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Detecting Subjectivity through Lexicon-Grammar Strategies

Databases, Rules and Apps for the Italian Language

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To Maria,
she is in every
elementary sentence
of my mind.

Contents

Chapter 1

Introduction

Consumers, as Internet users, can freely share their thoughts with huge and geographically dispersed groups of people, competing, this way, with the traditional power of marketing and advertising channels. Differently from the traditional word-of-mouth, which is usually limited to private conversations, the Internet used generated contents can be directly observed and described by the researchers. (Pang and Lee, 2008a, p. 7) identified the 2001 as the “beginning of widespread awareness of the research problems and opportunities that Sentiment Analysis and Opinion Mining raise, and subsequently there have been literally hundreds of papers published on the subject”.
The context that facilitated the growth of interest around the automatic treatment of *opinion* and *emotions* can be summarized in the following points:

- the expansion of the e-commerce (Matthews et al., 2001);
- the growth of the user generated contents (forum, discussion group, blog, social media, review website, aggregation site), that can constitute large scale databases for the machine learning algorithms training (Chin, 2005; Pang and Lee, 2008a);

- the rise of machine learning methods (Pang and Lee, 2008a);
- the importance of the on-line Word of Mouth (eWOM) (Gruen et al., 2006; Lee and Youn, 2009; Park and Lee, 2009; Chu and Kim, 2011);
- the customer empowerment (Vollero, 2010);
- the large volume, the high velocity and the wide variety of unstructured data (Russom et al., 2011; Villars et al., 2011; McAfee et al., 2012).

The same preconditions caused a parallel raising of attention also in economics and marketing literature studies. Basically, through user generated contents, consumers share positive or negative information that can influence, in many different ways, the purchase decisions and can model the buyer expectations, above all with regard to *experience goods* (Nakayama et al., 2010); such as hotels (Ye et al., 2011; Nelson, 1970) restaurants (Zhang et al., 2010), movies (Duan et al., 2008; Reinstein and Snyder, 2005) books (Chevalier and Mayzlin, 2006) or videogames (Zhu and Zhang, 2006; Bounie et al., 2005).

1.1 Research Context

Experience goods are products or services whose qualities cannot be observed prior to purchase. They are distinguished from *search goods* (e.g. clothes, smartphones) on the base of the possibility to test them before the purchase and depending on the information costs (Nelson, 1970). (Akerlof, 1970, p. 488-490) clearly exemplified the problems caused by the interaction of quality differences and uncertainty:

> "There are many markets in which buyers use some market statistic to judge the quality of prospective purchases. [...] The automobile market is used as a finger exercise to illustrate and develop these thoughts. [...] The individuals in this

> market buy a new automobile without knowing whether the car they buy will be good or a lemon[1]. [...] After owning a specific car, however, for a length of time, the car owner can form a good idea of the quality of this machine. [...] An asymmetry in available information has developed: for the sellers now have more knowledge about the quality of a car than the buyers. [...] The bad cars sell at the same price as good cars since it is impossible for a buyer to tell the difference between a good and a bad car; only the seller knows".

Asymmetric information could damage both the customers, when they are not able to recognize good quality products and services, and the market itself, when it is negatively affected by the presence of a smaller quantity of quality products, with respect to a quantity of quality products that would have been offered under the condition of symmetrical information (Lavanda and Rampa, 2001; von Ungern-Sternberg and von Weizsäcker, 1985).
However, it has been deemed possible for experience goods, to base an evaluation of their quality on the past experiences of customers that in previous "periods" had already experienced the same goods:

> "In most real world situations suppliers stay on the market for considerably longer than one 'period'. They then have the possibility to build up reputations or goodwill with the consumers. This is due to the following mechanism. While the consumers cannot directly observe a product's quality at the time of purchase, they may try to draw inferences about this quality from the past experience they (or others) have had with this supplier's products" (von Ungern-Sternberg and von Weizsäcker, 1985, p. 531).

Possible sources of information for buyers of experience goods are word of mouth and the good reputation of the sellers (von Ungern-Sternberg and von Weizsäcker, 1985; Diamond, 1989; Klein and Lef-

[1] A defective car discovered to be bad only after it has been bought.

fler, 1981; Shapiro, 1982, 1983; Dewally and Ederington, 2006).
The possibility to survey other customers' experiences increases the chance of selecting a good quality service and the customer expected utility. It is affordable to continue with this search, until the cost of such is equated to its expected marginal return. This is the "optimum amount of search" defined by Stigler (1961).
The rapid growth of the Internet drew the managers and business academics attention to the possible influences that this medium can exert on customers information search behaviors and acquisition processes. The hypothesis that the Web 2.0, as interactive medium, could make transparent the experience goods market by transforming it into a search goods market has been explored by Klein (1998), who has based his idea on three factors:

- lower search costs;
- different evaluation of some product (attributes);
- possibility to experience products (attributes) virtually, without physically inspecting them.

Actually, this idea seems too groundbreaking to be entirely true. Indeed, the real outcome of web searches depends on the quantity of available information, on its quality and on the possibility to make fruitful comparisons among alternatives (Alba et al., 1997; Nakayama et al., 2010).
Therefore, from this perspective, it is true that the growth of the user generated contents and the eWOM can truly reduce the information search costs. On the other hand, the distance increased by e-commerce, the content explosion and the information overload typical of the Big Data age, can seriously hinder the achievement of a symmetrical distribution of the information, affecting not only the market of experience goods, but also that of search goods.

1.2 Filtering Information Automatically

The last remarks on the influence of Internet on information searches inevitably reopen the long-standing problems connected to web information filtering (Hanani et al., 2001) and to the possibility of automatically "extracting value from chaos" (Gantz and Reinsel, 2011).
An appropriate management of online corporate reputation requires a careful monitoring of the new digital environments that strengthen the stakeholders' influence and independence and give support during the decision making process. As an example, to deeply analyze them can indicate to a company the areas that need improvements. Furthermore, they can be a valid support in the price determination or in the demand prediction (Bloom, 2011; Pang and Lee, 2008a).
It would be difficult, indeed, for humans to read and summarize such a huge volume of data about costumer opinions. However, in other respects, to introduce machines to the semantic dimension of human language remains an ongoing challenge.
In this context, business and intelligence applications, would play a crucial role in the ability to automatically analyze and summarize, not only databases, but also raw data in real time.
The largest amount of on-line data is semistructured or unstructured and, as a result, its monitoring requires sophisticated Natural Language Processing (NLP) tools, that must be able to pre-process them from their linguistic point of view and, then, automatically access their semantic content.
Traditional NLP tasks consist in Data Mining, Information Retrieval and Extraction of facts, objective information about entities, from semistructured and unstructured texts.
In any case, it is of crucial importance for both customers and companies to dispose of automatically extracted, analyzed and summarized data, which do not include only factual information, but also opinions regarding any kind of good they offer (Liu, 2010; Bloom, 2011).
Companies could take advantage of concise and comprehensive cus-

tomer opinion overviews that automatically summarize the strengths and the weaknesses of their products and services, with evident benefits in term of reputation management and customer relationship management.
Customer information search costs could be decreased trough the same overviews, which offer the opportunity to evaluate and compare the positive and negative experiences of other consumers who have already tested the same products and services.
Obviously, the advantages of sophisticated NLP methods and software, and their ability to distinguish factual from opinionated language, are not limited to the ones discussed so far; but they are dispersed and specialized among different tasks and domains, such as:

Ads placement: possibility to avoid websites that are irrelevant, but also unfavorable, when placing advertisements (Jin et al., 2007);

Question-answering: chance to distinguish between factual and speculative answers (Carbonell, 1979);

Text summarization: potential of summarizing different opinions and perspectives in addition to factual information (Seki et al., 2005);

Recommendation systems: opportunity to recommend only the items with positive feedback (Terveen et al., 1997);

Flame and cyberbullying detection: ability to find semantically and syntactically complex offensive contents on the web (Xiang et al., 2012; Chen et al., 2012; Reynolds et al., 2011);

Literary reputation tracking: possibility to distinguish disapproving from supporting citations (Piao et al., 2007; Taboada et al., 2006);

Political texts analysis: opportunity to better understand positive or negative orientations of both voters or politicians (Laver et al., 2003; Mullen and Malouf, 2006).

1.3 Subjectivity, Emotions and Opinions

Sentiment Analysis, *Opinion Mining*, *subjectivity analysis*, *review mining*, *appraisal extraction*, *affective computing* are all terms that refer to the computational treatment of *opinion*, *sentiment*, and *subjectivity* in raw text. Their ultimate shared goal is enabling computers to recognize and express emotions (Pang and Lee, 2008a; Picard and Picard, 1997).
The first two terms are definitely the most used ones in literature. Although they basically refer to the same subject, they have demonstrated varying degrees of success into different research communities. While *Opinion Mining* is more popular among web information retrieval researchers, *Sentiment Analysis* is more used into NLP environments (Pang and Lee, 2008a). Therefore, the coherence of our work's approach is the only reason that justifies the favor of the term *Sentiment Analysis*. All the terms mentioned above could be used and interpreted nearly interchangeably.
Subjectivity is directly connected to the expression of *private states*, personal feelings or beliefs toward entities, events and their properties (Liu, 2010). The expression *private state* has been defined by Quirk et al. (1985) and Wiebe et al. (2004) as a general covering term for opinions, evaluations, emotions, and speculations.
The main difference from objectivity regards the impossibility to directly observe or verify subjective language; but neither subjective nor objective implies *truth*: "whether or not the source truly believes the information, and whether or not the information is in fact true, are considerations outside the purview of a theory of linguistic subjectivity" (Wiebe et al., 2004, p. 281).
Opinions are defined as positive or negative views, attitudes, emotions or appraisals about a topic, expressed by an opinion holder in a given time. They are represented by Liu (2010) as the following quintuple:

$$o_j, f_{jk}, oo_{ijkl}, h_i, t_l$$

Where o_j represents the *object* of the opinion; f_{jk} its *features*; oo_{ijkl}, the positive or negative opinion *semantic orientation*; h_i the *opinion holder* and t_l the *time* in which the opinion is expressed.
Because the *time* can almost alway be deducted from structured data, we focused our work on the automatic detection and annotation of the other elements of the quintuple.
As regard the *opinion holder*, it must be underlined that "In the case of product reviews and blogs, opinion holders are usually the authors of the posts. Opinion holders are more important in news articles because they often explicitly state the person or organization that holds a particular opinion" (Liu, 2010, p. 2).
The *Semantic Orientation* (SO) gives a measure to opinions, by weighing their *polarity* (positive/negative/neutral) and *strength* (intense/weak) (Taboada et al., 2011; Liu, 2010). The polarity can be assigned to words and phrases inside or outside of a sentence or discourse context. In the first case it is called *prior polarity* (Osgood, 1952); in the second case *contextual* or *posterior polarity* (Gatti and Guerini, 2012).
We can refer to both opinion *objects* and *features* with the term *target* (Liu, 2010), represented by the following function:

$$T=O(f)$$

Where the *object* can take the shape of products, services, individuals, organizations, events, topics, etc., and the *features* are components or attributes of the object.
Each object *O*, represented as a "special feature", which is defined by a subset of features, is formalized in the following way:

$$F = \{f1, f2, \ldots, fn\}$$

Targets can be automatically discovered in texts through both synonym words and phrases W_i or indicators I_i (Liu, 2010):

$$W_i = \{w_i 1,\ w_i 2,\ \ldots,\ w_i m\}$$

$$I_i = \{i_i 1, i_i 2, \ldots, i_i q\}$$

Emotions constitute the research object of the *Emotion Detection* (Strapparava et al., 2004; Fragopanagos and Taylor, 2005; Alm et al., 2005; Strapparava et al., 2006; Neviarouskaya et al., 2007; Strapparava and Mihalcea, 2008; Whissell, 2009; Argamon et al., 2009; Neviarouskaya et al., 2009b, 2011; de Albornoz et al., 2012), a very active NLP subfield, that encroaches on *Speech Recognition* (Buchanan et al., 2000; Lee et al., 2002; Pierre-Yves, 2003; Schuller et al., 2003; Bhatti et al.; Schuller et al., 2004) and *Facial Expression Recognition* (Essa et al., 1997; Niedenthal et al., 2000; Pantic and Patras, 2006; Pal et al., 2006; De Silva et al., 1997). In this NLP based work, we focus on the Emotion Detection from written raw texts.
In order to provide a formal definition of sentiments, we refer to the function of Gross (1995):

$$P(sent,h)$$

$$Caus(s, sent, h)$$

In the first one, the *experiencer* of the emotion (*h*) is function of a *sentiment* (*Sent*), through a predicative relationship; the latter expresses a *sentiment* that is caused by a *stimulus* (*s*) on a person (*h*).

1.4 Structure of the Thesis

In this Chapter we introduced the research field of the Sentiment Analysis, placing it in the wider framework of Computational Linguistics and Natural Language Processing. We tried to clarify some terminological issues, raised by the proliferation and the overlap of terms in the literature studies on subjectivity. The choice of these topics has been justified through the brief presentation of the research context, which poses numerous challenges to all the Internet stakeholders.
The main aim of the thesis has been identified with the necessity to

treat both facts and opinion, expressed in the the Web in the form of raw data, with the same accuracy and velocity of the data stored in database tables.
Details about the contribution provided by this work to Sentiment Analysis studies are structured as follows.
Chapter 2 introduces the theoretical framework on which the whole work has been grounded: the Lexicon-Grammar (LG) approach, with an in-depth examination of the distributional and transformational analysis and the semantic predicates theory (Section 2.1).
The assumption that the elementary sentences are the basic discourse units endowed with meaning and the necessity to replace a unique grammar with plenty of lexicon-dependent local grammars are the founding ideas, from the LG approach, on which the research has been designed and realized.
The formalization of the sentiment lexical resources and tools as been performed through the tools described in Section 2.2.
Coherently with the LG method, our approach to Sentiment Analysis is lexicon-based. Chapter 3 provides a detailed description of the sentiment lexicon built *ad hoc* for the Italian language. It includes manually annotated resources for both simple (Section 3.3) and multiword (Section 3.4) units and automatically derived annotations (Section 3.5) for the adverbs in *-mente* and for the nouns of quality.
Because the word's meaning cannot be considered out of context, Chapter 3 explores the influences of some elementary sentence structures on the sentiment words occurring in them; while Chapter 4 investigates the effects on the sentence polarities of the so called Contextual Valence Shifters (CVS), namely intensification and downtoning (Section 4.2); Negation (Section 4.3); Modality (Section 4.4) and Comparison (Section 4.5).
Chapter 5 focuses on the three most challenging subtasks of the Sentiment Analysis: the sentiment polarity classification of sentences and documents (Section 5.1); the Sentiment Analysis based on features (Section 5.2) and the sentiment-based semantic role labeling (Sec-

tion 5.3). Experiments about these tasks are conduced through our resources and rules, respectively, on a multi-domain corpus of customer reviews, on a dataset of hotels comments and on a dataset that mixes tweets and news headlines.

Conclusive remarks and limitations of the present work are reported in Chapter 6.

Due to the large number of challenges faced in this work and in order to avoid penalizing the clarity and the readability of the thesis, we preferred to mention the state of the art works related to a given topic directly in the sections in which the topic is discussed. For easy reference, we anticipate that the literature survey on the already existent sentiment lexicons is reported in Section 3.2; the methods tested in literature for the lexicon propagation are presented in 3.5.1; works related to intensification and negation modeling, to modality detection and to comparative sentence mining are respectively mentioned in Sections 4.2.1, 4.3.1, 4.4.1 and 4.5.1; in the end, state of the art approaches to sentiment classification, the feature-based Sentiment Analysis and the Sentiment Role Labeling (SRL) tasks are cited in Sections 5.1.1, 5.2.1 and 5.3.1.

Some Sections of this thesis refer to works that, in part, have been already presented to the international computational linguistics community. These are the cases of Chapter 3 briefly introduced in Pelosi (2015a,b) and Pelosi et al. (2015) and Chapter 4 anticipated in Pelosi et al. (2015). Furthermore, the results presented in Section 5.1 have been discussed in Maisto and Pelosi (2014b), as well as the results of Section 5.2 in Maisto and Pelosi (2014a) and the ones of Section 5.3 in Elia et al. (2015).

Chapter 2

Theoretical Background

2.1 The Lexicon-Grammar Theoretical Framework

With *Lexicon-Grammar* we mean the method and the practice of formal description of the natural language, introduced by Maurice Gross in the second half of the 1960s, who, during the verification of some procedures from the transformational-generative grammar (TGG) (Chomsky, 1965) laid the foundations for a brand new theoretical framework.
More specifically, during the description of French complement clause verbs, through a transformational-generative approach, Gross (1975) realized that the English descriptive model of Rosenbaum (1967) was not enough to take into account the huge number of irregularities he found in the French language.
LG introduced important changes in the way in which the relationship between lexicon and syntax was conceived (Gross, 1971, 1975). It has been underlined, for the first time, the necessity to provide linguistic descriptions grounded on the systematic testing of syntactic and semantic rules along the whole lexicon, and not only on a limited set of

speculative examples.
Actually, in order to define what can be considered to be a *rule* and what must be considered an *exception*, a small sample of the lexicon of the analyzed language, collected in arbitrary ways, can be truly misleading. It is assumed to be impossible to make generalizations without verifying or falsifying the hypotheses. According with (Gross, 1997, p. 1),

> "Grammar, or, as it has now been called, linguistic theory, has always been driven by a quest for complete generalizations, resulting invariably in recent times in the production of abstract symbolism, often semantic, but also algorithmic. This development contrasts with that of the other Natural Sciences such as Biology or Geology, where the main stream of activity was and is still now the search and accumulation of exhaustive data. Why the study of language turned out to be so different is a moot question. One could argue that the study of sentences provides an endless variety of forms and that the observer himself can increase this variety at will within his own production of new forms; that would seem to confirm that an exhaustive approach makes no sense [...]
> But grammarians operating at the level of sentences seem to be interested only in elaborating general rules and do so without performing any sort of systematic observation and without a methodical accumulation of sentence forms to be used by further generations of scientists.".

In the LG methodology it is crucial the collection and the analysis of a large quantity of linguistic facts and their continuous comparison with the reality of the linguistic usages, by examples and counter-examples.
The collection of the linguistic information is constantly registered into LG tables that cross-check the lexicon and the syntax of any given

language. The ultimate purpose of this procedure is the definition of wide-ranging classes of lexical items associated to transformational, distributional and structural rules (D'Agostino, 1992).

What emerges from the LG studies is that, associating more than five or six properties to a lexical entries, each one of such entries shows an individual behavior that distinguishes it from any other lexical item. However, it is always possible to organize a classification around at list one *definitional property*, that is simultaneously accepted by all the item belonging to a same LG class and, for this reason, is promoted as distinctive feature of the class.

Having established this, it becomes easier to understand the necessity to replace "the" grammar with thousands of lexicon-dependent *local grammars*.

The choice of this paradigm is due to its compatibility with the purposes of the present work and with the computational linguistics in general that, in order to reach high performances in results, requires a large amount of linguistic data, which must be as exhaustive, reproducible and well organized as possible.

The huge linguistic datasets, produced over the years by the international LG community, provide fine-grained semantic and syntactic descriptions of thousands of lexical entries, also referred as "lexically exhaustive grammars" (D'Agostino, 2005; D'Agostino et al., 2007; Guglielmo, 2009), available for reutilization in any kind of NLP task[1].

The LG classification and description of the Italian verbs[2] (Elia et al., 1981; Elia, 1984; D'Agostino, 1992) is grounded on the differentiation of three different macro-classes: transitive verbs; intransitive verbs and complement clause verbs. Every LG class has its own definitional structure, that corresponds with the syntactic structure of the nuclear sentence selected by a given number of verbs (e.g. *V* for *piovere* "to rain" and all the verbs of the class 1; *N0 V* for *bruciare* "to burn" and

[1] LG descriptions are available for 4,000+ nouns that enter into verb support constructions; 7,000+ verbs; 3,000+ multiword adverbs and almost 1,000 phrasal verbs (Elia, 2014a).

[2] LG tables are freely available at the address `http://dsc.unisa.it/composti/tavole/combo/tavole.asp`.

the other verbs of the class 3; *N0 V da N1* for *provenire* "to come from" and the verbs belonging to the class 6; etc...). All the lexical entries are, then, differentiated one another in each class, by taking into account all the transformational, distributional and structural properties accepted or rejected by every item.

2.1.1 Distributional and Transformational Analysis

The Lexicon-Grammar theory lays its foundations on the Operator-argument grammar of Zellig S. Harris, the combinatorial system that supports the generation of utterances into the natural language.
Saying that the operators store inside information regarding the sentence structures means to assume the nuclear sentence to be the minimum discourse unit endowed with meaning (Gross, 1992b).
This premise is shared with the LG theory, together with the centrality of the *distributional analysis*, a method from the structural linguistics that has been formulated for the first time by Bloomfield (1933) and then has been perfected by Harris (1970). The insight that some categories of words can somehow control the functioning of a number of *actants* through a dependency relationship called *valency*, instead, comes from Tesnière (1959).
The *distribution* of an element A is defined by Harris (1970) as the sum of the contexts of A. Where the *context* of A is the actual disposition of its co-occurring elements. It consists in the systematic substitution of lexical items with the aim of verifying the semantic or the transformational reactions of the sentences. All of this is governed by verisimilitude rules that involve a graduation in the acceptability of the item combination.
Although the native speakers of a language generally think that the sentence elements can be combined arbitrarily, they actually choose a set of items along the classes that regularly appear together. The selection depends on the likelihood that an element co-occurs with

elements of one class rather than another[3].
When two sequences can appear in the same context they have an *equivalent distribution*. When they do not share any context they have a *complementary distribution*.
Obviously, the possibility to combine sentence elements is related to many different levels of acceptability. Basically, the utterances produced by the words co-occurrence can vary in terms of plausibility.
In the operator-argument grammar of Harris, the *verisimilitude of occurrence* of a word under an operator (or an argument) is an approximation of the likelihood or of the frequency of this word with respect to a fixed number of occurrence of the operator (or argument) (Harris, 1988).
Concerning *transformations* (Harris, 1964), we refer to the phenomenon in which the sentences A and B, despite a different combination of words, are equivalent to a semantic point of view. (e.g. *Floria ha letto quel romanzo = quel romanzo è stato letto da Floria* "Floria read that novel = that novel has been read by Floria" (D'Agostino, 1992)). Therefore, a *transformation* is defined as a function T that ties a set of variables representing the sentences that are in *paraphrastic equivalence* (A and B are partial or full synonym) and that follow the *morphemic invariance* (A and B possess the same lexical morphemes).
Transformational relations must not be mixed up with any derivation process of the sentence B from A and *vice versa*. A and B are just two correlated variants in which equivalent grammatical relations are realized (D'Agostino, 1992)[4]. That is why in this work we do not use directed arrows to indicate transformed sentences.
Among the transformational manipulations considered in this thesis while allying the Lexicon-Grammar theoretical framework to the Sen-

[3]Among the traits that mark the *co-occurrences classes*; we mention, by way of example, human and not human nouns, abstract nouns, verbs with concrete or abstract usages, etc. (Elia et al., 1981)

[4] Different is the concept of transformation in the generative grammar, that envisages an oriented passage from a deep structure to a superficial one: "The central idea of transformational grammar is that they are, in general, distinct and that the surface structure is determined by repeated application of certain formal operations called 'grammatical transformations' to objects of a more elementary sort" (Chomsky, 1965, p. 16).

timent Analysis field, we mention the following (Elia et al., 1981; Vietri, 2004).

Substitution. The substitution of polar elements in sentences is the starting point of this work, that explores the mutations in term of acceptability and semantic orientation in the transformed sentences. It can be found almost in every chapter of this thesis.

Paraphrases with support verbs[5] *, nominalizations and adjectivalizations.* This manipulation is essential, for example, in Section 3.3.4 and 3.3.5, where we discuss the *nominalization* (e.g. *amare = amore* "to love = love") and the *adjectivalization* (e.g. *amare = amoroso* "to love = loving") of the Italian psychological verbs; or in Section 3.5.2 when we account for the relation among a set of sentiment adjectives and adverbs (e.g. *appassionatamente = in modo appassionato* "passionately = in a passionate way").

Repositioning. Emphasis, permutation, dislocation, extraction are all transformation that, shifting the focus on a specific element of the sentence, influence its strength when the element is polarized.

Extension. We are above all interested in the expansion of nominal groups with opinionated modifiers (see Section 3.3.2).

Restructuring. The complement restructuring plays a crucial role in the Feature-based Sentiment Analysis for the correct annotation of the features and the objects of the opinions (see Sections 3.3.4 and 5.2).

Passivization. In our system of rules, passive sentences merely pos-

[5] The concept of operator does not depend on specific part of speech, so also nouns, adjectives and prepositions can possess the power to determine the nature and the number of the sentence arguments (D'Agostino, 1992). Because only the verbs carry out morpho-grammatical information regarding the mood, tense, person and aspect, they must give this kind of support to non-verbal operators. The so called *Support Verbs* (Vsup) are different from auxiliaries (Aux), that instead support other verbs. Support verbs (e.g. *essere* "to be", *avere* "to have", *fare* "to do") can be, case by case, substituted by stylistic, aspectual and causative equivalents.

sess the same semantic orientation of the corresponding active sentence.

Systematic correlation. Examples are the standard/crossed structures mentioned in Section 3.3.4.

2.1.2 Formal Representation of Elementary Sentences

While the generative grammar focused its studies on complex sentences, both the Operator grammar and the LG approach assumed the, respectively so called, nuclear or elementary sentences to be the minimum discourse units endowed with meaning. Above all because complex sentences are made from elementary ones, as stated by (Chomsky, 1957, p. 92) himself:

> "In particular, in order to understand a sentence it is necessary to know the kernel sentences from which it originates (more precisely, the terminal strings underlying these kernel sentences) and the phrase structure of each of these elementary components, as well as the transformational history of development of the given sentence from these kernel sentences. The general problem of analyzing the process of 'understanding' is thus reduced, in a sense, to the problem of explaining how kernel sentences are understood, these being considered the basic 'content elements' from which the usual, more complex sentences of real life are formed by transformational development".

This assumption shifts the definition of *creativity* from "recursivity" in complex sentences (Chomsky, 1957) to "combinatory possibility" at the level of elementary sentences (Vietri, 2004); but affects also the way in which the lexicon is conceived. (Gross, 1981, p. 48) made the following observation in this regard[6]:

[6] On this topic also Chomsky agrees that:

> “*Les entrées du lexique ne sont pas des mots, mais des phrases simples. Ce principe n'est en contradiction avec les notions traditionnelles de lexique que de façon apparente. En effet, dans un dictionnaire, il n'est pas possible de donner le sens d'un mot sans utiliser une phrase, ni de contraster des emplois différents d'un même mot sans le placer dans des phrases*”[7].

As it will be discovered in the following Sections, the idea that the entries of the lexicon can be sentences rather that isolated words is a principle that has been entirely shared among the sentiment lexical resources built for the present work.
With regard to formalisms, Gross (1992b) represented all the elementary sentences through the following generic shape:

$$N_0\ V\ W$$

Where N_0 stands for the sentence formal subject, V stands for the verbs and W can indicate all kinds of essential complements, including an empty one. While $N_0\ V$ represents a great generality, W raises more complex classification problems (Gross, 1992b). Complements indicated by W can be direct (N_i), prepositional ($Prep\ N_i$) or sentential ($Ch\ F$).

> “In describing the meaning of a word it is often expedient, or necessary, to refer to the syntactic framework in which this word is usually embedded; e.g., in describing the meaning of "hit" we would no doubt describe the agent and object of the action in terms of the notions "subject" and "object", which are apparently best analyzed as purely formal notions belonging to the theory of grammar” (Chomsky, 1957, p. 104).

But, without any exhaustive application of syntactic rules to lexical items, he feels compelled to point out that:

> “(...) to generalize from this fairly systematic use and to assign ‘structural meanings’ to grammatical categories or constructions just as ‘lexical meanings’ are assigned to words or morphemes, is a step of very questionable validity” (Chomsky, 1957, p. 104).

[7] “The entries of the lexicon are not words, but simple sentences. This principle contradicts the traditional notions of lexicon just into an apparent way. Indeed, into a dictionary, it is impossible to provide the meaning of a word without a sentence, nor to contrast different uses of the same word without placing it into sentences”. Author translation.

Information about the nature and the number of complement are contained in the verbs (or in other parts of speech that, case by case, play the a predicative function).
Gross (1992b) presented the following typology of complements, respectively approached for the Italian language by the LG researchers mentioned below:

frozen arguments (*C*): Vietri (1990, 2011, 2014d);

free arguments (*N*): D'Agostino (1992); Bocchino (2007);

sentential arguments (*Ch F*): Elia (1984).

2.1.2.1 The *Continuum* from Simple Sentences to Polyrematic Structures

Gross (1988, 1992b, 1993) recognized and formalized the concept of *phrase figée* "frozen sentence", which refers to groups of words that can be tied one another by different degrees of variability and cohesion (Elia and De Bueriis, 2008). They can take the shape of verbal, nominal, adjectival or adverbial structures.
The continuum, along which frozen expressions can be classified, varies according to higher or lower levels of *compositionality* and *idiomaticity* and goes from completely free structures to totally frozen expressions, as summarized below (D'Agostino and Elia, 1998; Elia and De Bueriis, 2008):

distributionally free structures: high levels of co-occurrence variability among words;

distributionally restricted structures: limited levels of co-occurrence variability;

frozen structures (almost) null levels of co-occurrence variability;

proverbs no variability of co-occurrence.

Idiomatic interpretations can be attributed to the last two elements of the *continuum*, due to their low levels of compositionality.
The fact that the meaning of these expressions cannot be computed by simply summing up the meanings of the words that compose them has a direct impact on every kind of Sentiment Analysis application that does not correctly approaches the linguistic phenomenon of idiomaticity.
We will show the role of multiword expressions in Section 3.4.

2.1.2.2 Against the Bipartition of the Sentence Structure

In the operator grammar, differently from the generative grammar, sentences are not supposed to have a bipartite structure,

$$\mathrm{S} \rightarrow NP + VP$$

$$VP \rightarrow V + NP$$[8]

but are represented as *predicative functions* in which a central element, the *operator*, influences the organization of its variables, the *arguments*. The role of operator must not be represented necessarily by verbs, but also by other lexical items that possess a predicative function, such as nous or adjectives.
This idea, shared also by the LG framework, is particularly important in the Sentiment Analysis field, especially if the task is the detection of the semantic roles involved into sentiment expressions (Section 5.3).
Sentences like (1) and (2) are examples in which the semantic roles of *experiencer of the sentiment* and *stimulus of the sentiment* are respectively played by “Maria” and *il fumo* “the smoke”. It is intuitive that, from a syntactic point of view, these semantic roles are differently distributed into the *direct* (the experiencer is the subject, such as in 1) and the *reverse* (the experiencer is the object, as in 2) sentence structures (see Section 3.3.3 for further explanations).

[8] Sentence = Noun Phrase + Verb Phrase; Verb Phrase = Verb + Noun Phrase.

(1) $[_{\text{Sentiment}}[_{\text{Experiencer}}\textit{Maria}]\ \textit{odia}\ [_{\text{Stimulus}}\textit{il fumo}]]$[9]
"Maria hates the smoke"

(2) $[_{\text{Sentiment}}[_{\text{Stimulus}}\textit{Il fumo}]\ \textit{tormenta}\ [_{\text{Experiencer}}\textit{Maria}]]$
"The smoke harasses Maria"

The indissoluble bond between the sentiment and the experiencer[10], that does not differ from (1) to (2), is perfectly expressed by the Operator-argument grammar function *Onn* for both the sentences; by the LG representation $N_0\ V\ N_1$; or by the function of Gross (1995) *Caus(s,sent,h)* (described in Section 1.3 and deepened in Section 3):

(1) *Caus(il fumo, odiare, Maria)*
(2) *Caus(il fumo, tormentare, Maria)*

The same can not be said of the sentence bipartite structure, that, representing the *experiencer* "Maria" inside (2) and outside (1) the verb phrase, unreasonably brings it closer or further from the sentiment, to which it should be attached just in the same way (Figure 2.1).

Moreover, it does not explain how the verbs of (1) and (2) can exercise distributional constraints on the noun phrase indicating the *experiecer* (that must be human, or at least animated) both in the case in which it is under the dependence of the same verb phrase (experiencer object, see 2b) and also when it is not (experiencer subject, see 2a):

(1a) $[_{\text{Sentiment}}\ [_{\text{Experiencer}} \begin{bmatrix} Maria \\ Il\ mio\ gatto \\ *Il\ televisore \end{bmatrix}]odia[_{\text{Stimulus}} il\ fumo]]$

"(Maria + My cat + *The television) hates the smoke"

[9] For the sentence annotation we used the notation of Jackendoff (1990): $[_{\text{Event}}\ ]$.
[10] *Un sentiment est toujours attaché à la personne qui l'éprouve* "A sentiment is always attached to the person that feels it" (Gross, 1995, p. 1)

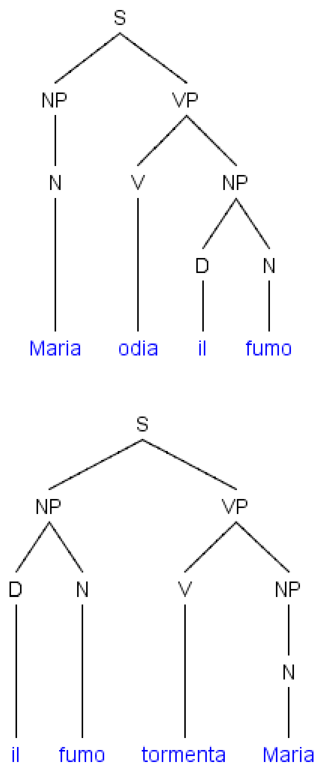

Figure 2.1: Syntactic Trees of the sentences (1) and (2)

(2a) $[_{\text{Sentiment}}[_{\text{Stimulus}} Il\ fumo] tormenta [_{\text{Experiencer}} \begin{bmatrix} Maria \\ Il\ mio\ gatto \\ *Il\ televisore \end{bmatrix}]]$

“The smoke harasses (Maria + My cat + *The television)”

According with (Gross, 1979, p. 872) the problem is that

> “rewriting rules (e.g. S $\rightarrow$ $NP\ VP$, $VP \rightarrow V\ NP$) describe only LOCAL dependencies. [...] But there are numerous syntactic situations that involve non-local constraints”.

While the Lexicon-Grammar and the operator grammar representations do not change, the representations of the paraphrases of (1,2) with support verbs (1b,2b) further complicate the generative grammar solution, that still does not correctly represent the relationships among the operators and the arguments (see Figure 2.2). It fails to determine the correct number of arguments (that are still two and not three) and does not recognize the predicative function, which is played by the nouns *odio* "hate" and *tormento* "harassment" and not by the verbs *provare* "to feel" and *dare* "to give".

(1b) $[_{\text{Sentiment}}[_{\text{Experiencer}}$ *Maria*$]$ *prova odio per* $[_{\text{Stimulus}}$ *il fumo*$]]$
"Maria feels hate for the smoke"

(2b) $[_{\text{Sentiment}}[_{\text{Stimulus}}$ *Il fumo*$]$ *dà il tormento a* $[_{\text{Experiencer}}$ *Maria*$]]$
"The smoke gives harassment to Maria"

For all these reasons, for the computational treatment of subjectivity, emotions and opinions in raw text, we preferred in this work the Lexicon-Grammar framework to other linguistic approaches, despite of their popularity in the NLP literature.

2.1.3 Lexicon-Grammar Binary Matrices

We said that the difference between the LG language description and any other linguistic approach regards the systematic formalization of a very broad quantity of data. This means that, given a set of properties P that define a class of lexical items L, the LG method collects and formalizes any single item that enters in such class (extensional classification), while other approaches limit their analyses only to reduced sets of examples (intensional classification) (Elia et al., 1981).
Because the presentation of the information must be as transparent, rigorous and formalized as possible, LG represents its classes through binary matrices like the one exemplified in Table 2.1.

They are called "binary" because of the mathematical symbols "+"

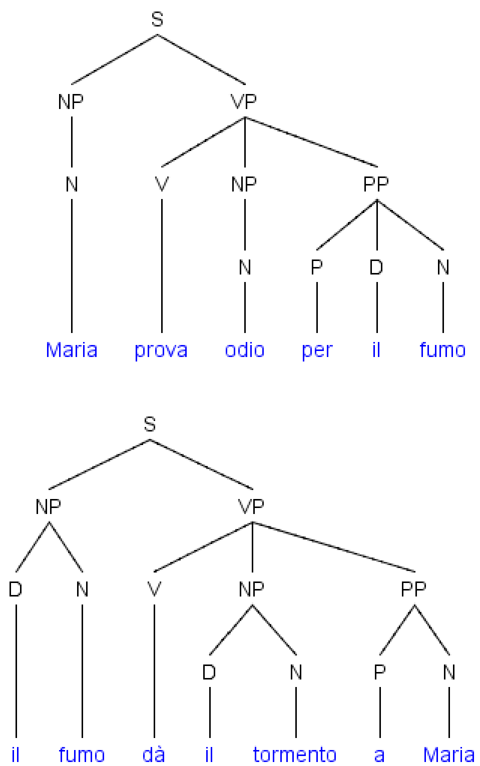

Figure 2.2: Syntactic Trees of the sentences (1b) and (2b)

and "–" respectively used to indicate the acceptance or the refuse of the properties *P* by each lexical entry *L*.
The symbol *X* unequivocally denotes an LG class and is always associated to a class definitional property, simultaneously accepted by all the items of the class (in the example of Table 2.1 P_1). Subclasses of *X* can be easily built by choosing another *P* as definitional property (e.g. L_2, L_3 and L_4 under the definitional substructure P_2).
The sequences of "+" and "–" attributed to each entry constitute the

X	P_1	P_2	P_3	P_4	P_n
L_1	+	−	−	−	+
L_2	+	+	−	−	−
L_3	+	+	+	+	+
L_4	+	+	+	+	+
L_n	+	−	−	−	+

Table 2.1: Example of a Lexicon-Grammar Binary Matrix

"lexico-syntactic profiles" of the lexical items (Elia, 2014a).
The properties, on which the classification is arranged, can regard the following aspects (Elia et al., 1981):

distributional properties, by which all the co-occurrences of the lexical items L with distributional classes and subclasses are tested, inside acceptable elementary sentence structures;

structural and transformational properties, through which all the combinatorial transformational possibilities, inside elementary sentence structures, are explored (see Section 2.1.1 for more in-depth explanations).

It is possible for a lexical entry to appear in more than one LG matrix. In this case we are not referring to a single verb that accepts divergent syntactic and semantic properties, but, instead, to two different *verb usages* attributable to the same morpho-phonological entry (Elia et al., 1981; Vietri, 2004; D'Agostino, 1992). Verb usages possess the same syntactic and semantic autonomy of two verbs that do not present any morpho-phonological relation.

2.1.4 Syntax-Semantics Interface

In the sixties, the hot debate about the syntax-semantics Interface opposed theories supporting the autonomy of the syntax from the semantics to approaches sustaining the close link between these two

linguistic dimensions.
Chomsky (1957), postulated the independence of the syntax from the semantics, due to the vagueness of the semantics and because of the correspondence mismatches among these two linguistic dimensions, but recognized the existence of a relation between the two, that deserves to be explored:

> "There is, however, little evidence that 'intuition about meaning' is at all useful in the actual investigation of linguistic form. [...]
> It seems clear, then, that undeniable, though only imperfect correspondences hold between formal and semantic features in language. The fact that the correspondences are so inexact suggests that meaning will be relatively useless as a basis for grammatical description. [...]
> The fact that correspondences between formal and semantic features exist, however, cannot be ignored. [...] Having determined the syntactic structure of the language, we can study the way in which this syntactic structure is put to use in the actual functioning of language. An investigation of the semantic function of level structure (...) might be a reasonable step towards a theory of the interconnections between syntax and semantics" (Chomsky, 1957, p. 94-102)

The contributions that come from the generative grammar, with particular reference to the theta-theory (Chomsky, 1993), assume the possibility of a mapping between syntax and semantics:

> "Every content bearing major phrasal constituent of a sentence (S, NP, AP, PP, ETC.) corresponds to a conceptual constituent of some major conceptual category[11]" (Jackendoff, 1990, p. 44)

[11] Object, Event, State, Action, Place, Path, Property, Amount

But their autonomy is not negated through this assumption: *thematic roles* are still considered to be part of the level of conceptual structure and not part of syntax (Jackendoff, 1990). This is confirmed, again, by (Chomsky, 1993, p. 17) when stating that "(...) the mapping of S-structures onto PF and LF are independent from one another". Here, the S-structure, generated by the rules of the syntax, is associated by means of different interpretative rules with representations in phonetic form (PF) and in logical form (LF).
Many contributions from the linguistic community define the concept of *thematic roles* through the linking problem between syntax (syntactic realization of predicate argument structures that determine the roles) and semantics (semantic representation of such structures) (Dowty, 1989; Grimshaw, 1990; Rappaport Hovav and Levin, 1998). Among the canonical thematic roles we mention the *agent* (Gruber, 1965), the *patient* Baker (1988), the *experiencer* (Grimshaw, 1990), the *theme* (Jackendoff, 1972), ect.

2.1.4.1 Frame Semantics

> "Some words exist in order to provide access to knowledge of such frames to the participants in the communication process, and simultaneously serve to perform a categorization which takes such framing for granted" (Fillmore, 2006, p. 381).

With these words, Fillmore (2006) depicted the Frame Semantics, which describes sentences on the base of *predicators* able to bring to mind the *semantic frames* (inference structures, linked through linguistic convention to the lexical items meaning) and the *frame elements* (participants and props in the frame) involved in these frames (Fillmore, 1976; Fillmore and Baker, 2001; Fillmore, 2006).
A frame semantic description starts from the identification of the lexical items that carry out a given meaning and, then, explores the ways in which the frame elements and their constellations are realized

around the structures that have such items as head (Fillmore et al., 2002).
This theoretical framework poses its bases on the Case grammar, a study on the combination of the *deep cases* chosen by verbs an on the definition of *case frames*, that have the function of providing "a bridge between descriptions of situations and underlying syntactic representations." by attributing "semantico-syntactic roles to particular participants in the (real or imagined) situation represented by the sentence (Fillmore, 1977, p. 61). A direct reference of Fillmore's work is the valency theory of Tesnière (1959).
Based on these principles, the FrameNet research project produced a lexicon of English for both human use and NLP applications (Baker et al., 1998; Fillmore et al., 2002; Ruppenhofer et al., 2006). Its purpose is to provide a large amount of semantically and syntactically annotated sentences endowed with information about the valences (combinatorial possibilities) of the items derived from annotated contemporary English corpus. Among the semantic domains covered, there are also *emotion* and *cognition* (Baker et al., 1998).
For the Italian language, Lenci et al. (2012) developed LexIt, a tool that, following the FrameNet approach, automatically explores syntactic and semantic properties of Italian predicates in terms of distributional profiles. It performs frame semantic analyses using both *La Repubblica* corpus and the *Wikipedia* taxonomy.

2.1.4.2 Semantic Predicates Theory

The Lexicon-Grammar framework offers the opportunity to create matches between sets or subsets of lexico-syntactic structures and their semantic interpretations. The base of such matches is the connection between the *arguments*, selected by a given predicative item listed in our tables, and the *actants* involved by the same semantic predicate. According with (Gross, 1981, p. 9),

> “*Soit* Sy *l’ensemble des formes syntaxiques d’une langue* [...]. *Soit* Se *un ensemble d’éléments de sens, les éléments de* Sy *seront associés à ceux de* Se *par des règles d’interprétation.* [...] *nous appellerons actants syntaxiques les sujet et complément(s) du verbe tels qu’ils sont décrits dans* Sy*; nous appelons arguments les variables des prédicats sémantiques. Dans certains exemples, il y a correspondance biunivoque entre actants et arguments, entre phrase simple et prédicat*”[12].

This is the basic assumption on which the Semantic Predicates theory has been built into the LG framework. It postulates a complex parallelism between the *Sy* and the *Se* that, differently from other approaches, can not ignore the idiosyncrasies of the lexicon, since “*il n’existe pas deux verbes ayant le même ensemble de propriétés syntaxiques*” (Gross, 1981, p. 10). Actually, the large number of structures in which the words can enter underlines the importance of a sentiment lexical database that includes both semantic and (lexicon dependent) syntactic classification parameters.

Therefore, the possibility to create intuitive semantic macro-classifications into the LG framework does not contrast with the autonomy of the semantics from the syntax (Elia, 2014b).
In this thesis we will refer to following three different predicates, all of them connected to the expression of subjectivity:

"Sentiment" (e.g. *odiare* "to hate"), that involves the actants *experiencer* and *stimulus*;

"Opinion" (e.g. *difendere* "to stand up for"), that implicates the actants *opinion holder* and *target* of the opinion;

[12] “Let *Sy* be the set of syntactic forms of a language [...]. Let it *Se* be the set of semantic elements, the elements from *Sy* will be associated to the ones of *Se* through interpretation rules. [...] We will call syntactic actants the subject and the complement(s) of the verb in the way in which they are described in *Sy*; we will call arguments the variables of semantic predicates. In some examples there is a one-to-one correspondence between actants and arguments, between simple sentence and predicate”. Author translation.

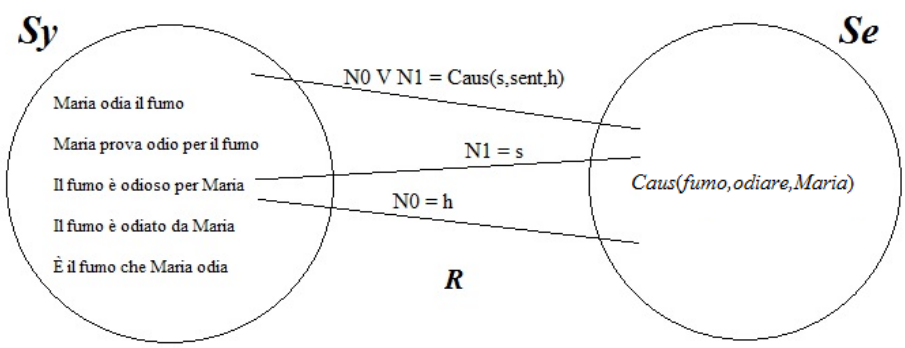

Figure 2.3: LG syntax-semantic interface

"Physical act" (e.g. *baciare* "to kiss"), that evokes the actants *patient* and *agent*.

As an example, the predicate in the sentence (1) from the LG class 43 will be associated to a Predicate with two variables, described by the mathematical function *Caus(s,sent,h)*.

(1) [$_{\text{Sentiment}}$[$_{\text{Experiencer}}$*Maria*] *odia* [$_{\text{Stimulus}}$*il fumo*]]]
"Maria hates the smoke"

The rules of interpretations which have been followed are:

1. the *experiencer* (*h* in the *Se*) corresponds to the formal subject (N_0 in *Sy*);

2. the sentiment *stimulus* (*t* in the *Se*) is the human complement (N_1 in *Sy*).

As shown in the few examples below, the syntactic transformations in which the same predicate is involved preserve the role played by its arguments.

Nominalization:

(1b) [$_{\text{Sentiment}}$ [$_{\text{Experiencer}}$*Maria*] *prova odio per* [$_{\text{Stimulus}}$*il fumo*]]
“Maria feels hate for the smoke”

Adjectivalization:

(1c) [$_{\text{Sentiment}}$ [$_{\text{Stimulus}}$*il fumo*] *è odioso per* [$_{\text{Experiencer}}$*Maria*]]
“The smoke is hateful for Maria”

Passivization:

(1d) [$_{\text{Sentiment}}$ [$_{\text{Stimulus}}$*il fumo*] *è odiato da* [$_{\text{Experiencer}}$*Maria*]]
“The smoke is hated by Maria”

Repositioning:

(1e) [$_{\text{Sentiment}}$ *è il* [$_{\text{Stimulus}}$*il fumo*] *che* [$_{\text{Experiencer}}$*Maria*] *odia*]
“It is the smoke that Maria hates”

As concerns the link among actants and arguments, the background of the research is the LEG-Semantic Role Labeling system of Elia (2014b), with particular reference to its psychological, evaluative and bodily predicates. The *granularity* of the verb properties, in this SRL system, are evidence of the strong dependence of the syntax from the lexicon and proof of its absolute independence from semantics. Special kinds of Semantic Predicates have been already used in NLP applications into a Lexicon-Grammar context; we mention Vietri (2014a); Elia et al. (2010); Elia and Vietri (2010) that formalized and tested the Transfer Predicates on the Italian Civil Code; Elia et al. (2013) that focused on the Spatial Predicates and Maisto and Pelosi (2014b); Pelosi (2015b); Elia et al. (2015) that exploited the Psychological Semantic Predicates for Sentiment Analysis purposes.

2.2 The Italian Module of Nooj

Nooj is the NLP tool used in this work for both the language formalization and the corpora pre-processing and processing, at the orthographical, lexical, morphological, syntactic and semantic levels (Silberztein, 2003).
Among the Nooj modules that have been developed, for more than twenty languages, by the international Nooj community, the Italian *Lingware* has been built by the Maurice Gross Laboratory from the University of Salerno.
The Italian module for NooJ can be any time integrated with other *ad hoc* resources, in form of electronic dictionaries and local grammars. The freely downloadable Italian resources[13] include:

- electronic dictionaries of simple and compound words;
- an electronic dictionary of proper names;
- an electronic dictionary of toponyms;
- a set of morphological grammars;
- samples of syntactic grammars.

This knowledge and linguistic based environment is not in contrast with hybrid and statistical approaches, that often require annotated corpora for their testing stages.
The Nooj annotations can go through the description of simple word forms, multiword units and even discontinuous expressions.
For a detailed description of the potential of the Italian module of Nooj, see Vietri (2014c).

[13] www.nooj-association.org

2.2.1 Electronic Dictionaries

If we tried to digit on a search engine the key-phrase "electronic dictionary", the first results that would appear in the SERP would concern CD-ROM dictionaries or machine translators.
Actually, electronic dictionaries (usable with all the computerized documents for the text recognition, for the information retrieval and for the machine translation) should be conceived as lexical databases intended to be used only by computer applications rather than by a wide audience, who probably wouldn't be able to interpret data codes formalized in a complex way.
In addition to the target, the differences between the two types of dictionary can be summarized in three points.

Completeness: human dictionaries may overlook information that the human users could extract from their encyclopedic knowledge. Electronic dictionaries, instead, must necessarily be exhaustive. They cannot leave anything to chance: the computer mustn't have possibility of error.

Explanation: human dictionaries can provide part of the information implicitly, because they can rely on human user's skills (intuition, adaptation and deduction). Electronic dictionaries, on the contrary, must respect this principle: the computer can only perform fully explained symbols and instructions.

Coding: unlike human dictionaries, all the information provided into the electronic dictionaries, related to the use of software for automatic processing of data and texts, must be accurate, consistent and codified.

Joining all these features enlarges the size and magnifies the complexity of monolingual and bilingual electronic dictionaries, which are, for this reason, always bigger than the human ones.
The Italian electronic dictionaries system, based on the Maurice

Gross's Lexicon-Grammar, has been developed at the University of Salerno by the Department of Communication Science; it is grounded on the European standard RELEX.

2.2.2 Local grammars and Finite-state Automata

Local grammars are algorithms that, through grammatical, morphological and lexical instructions, are used to formalize linguistic phenomena and to parse texts. They are defined "local" because, despite any generalization, they can be used only in the description and analysis of limited linguistic phenomena.
The reliability of "finite state Markov processes" (Markov, 1971) had already been excluded by (Chomsky, 1957, p. 23-24), who argued that

> "(..) there are processes of sentence-formation that finite state grammars are intrinsically not equipped to handle. If these processes have no finite limit, we can prove the literal inapplicability of this elementary theory. If the processes have a limit, then the construction of a finite state grammar will not be literally out of the question, since it will be possible to list the sentences, and a list is essentially a trivial finite state grammar. But this grammar will be so complex that it will be of little use or interest."

and remarked that

> "If a grammar does not have recursive devices (...) it will be prohibitively complex. If it does have recursive devices of some sort, it will produce infinitely many sentences."

Instead, Gross (1993) caught the potential of finite state machines, especially for those linguistic segments which are more limited from a combinatorial point of view.
The Nooj software, actually, is not limited to finite-state machines and regular grammars, but relies on the four types of grammars of the

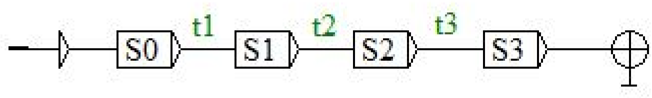

Figure 2.4: Deterministic Finite-State Automaton

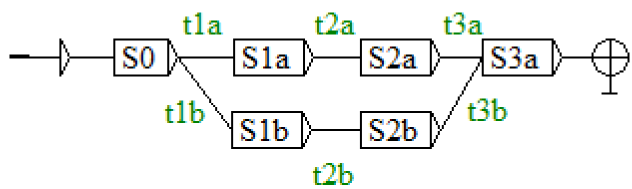

Figure 2.5: Non deterministic Finite-State Automaton

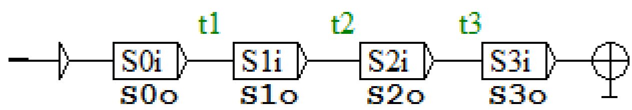

Figure 2.6: Finite-State Transducer

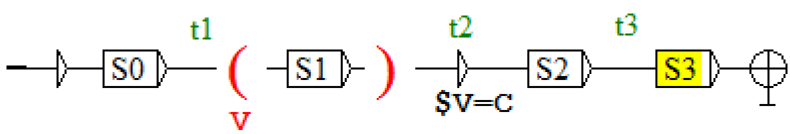

Figure 2.7: Enhanced Recursive Transition Network

Chomsky hierarchy. In fact, as we will show in this research, it is capable to process context free and sensitive grammars and to perform transformations in cascade.
Finite-State Automata (FSA) are abstract devices characterized by a finite set of nodes or "states" (S_i) connected one another by transitions (t_j) that allow us to determine sequences of symbols related to a particular path (see Figure 2.4).
These graphs are read from left to right, or rather, from the initial state (S_0) to the final state (S_3) (Gross, 1993). FSA can be *deterministic*, such as the one in Figure 2.4, or *non deterministic*, if they activate more then one path, as in Figure 2.5. A *Finite-State Transducer* (FST) tansduces the input symbols (S_ii) into the output ones (S_io), as in Figure 2.6. A *Recursive Transition Network* (RTN) is a grammar that contains embedded graphs (the S_3 node in Figure 2.7). An *Enhanced Recursive Transition Network* (ERTN) is a more complex grammar that includes variables (V) and constraints (C) (Silberztein, 2003, see Figure 2.7).
For simplicity, from now on we will just use the acronym FSA in order to indicate all the kinds of local grammars used to formalize different linguistic phenomena.
In general, the nodes of the graphs can anytime recall entries or semantic and syntactic information from the electronic dictionaries. FSA are inflectional or derivational if the symbols in the nodes are morphemes; syntactic if the symbols are words.

Chapter 3

SentIta: Lexicon-Grammar based Sentiment Resources

3.1 Lexicon-Grammar of Sentiment Expressions

The LG theoretical framework, with its huge collections and categorization of linguistic data, in the form of LG tables, built and refined over years by its researchers, offers the opportunity to systematically relate a large number of semantic and syntactic properties to the lexicon. The complex intersection between semantics and syntax, the greatest benefit of this approach, corrects the worse deficiency of other semantic strategies proposed in the Sentiment Analysis literature: the tendency to group together only on the base of their meaning words that have nothing in common from the syntactic point of view (Le Pesant and Mathieu-Colas, 1998)[1].

[1] On this purpose (Elia, 2013, p. 286) illustrates that

> "(...) the semantic intuition that drives us to put together certain predicates and their argument is not correlated to the set of syntactic properties of the verbs, nor is it «helped» by it, except in a very superficial way, indeed we might say that the granular nature of the syntax in the lexicon would be an obstacle for a mind that is organized in an efficient and

"*Classes d'objets*" is the expression introduced by Gross (1992a) to indicate the linguistic device that allow the language formalization from both a syntactic and semantic point of view. Arguments and Predicates are classified into subsets which are semantically consistent and that also share lexical and grammatical properties (De Bueriis and Elia, 2008).
According with (Gross, 2008, p. 1),

> "*Si un mot ne peut pas être défini en lui-même, c'est-à-dire hors contexte, mais seulement dans un environnement syntaxique donné, alors le lexique ne peut pas être séparé de la syntaxe, c'est-à-dire de la combinatoire des mots. La sémantique n'est pas autonome non plus: elle est le résultat des éléments lexicaux organisés d'une façon déterminée (distribution). Qu'il est soit ainsi est confirmé par les auteurs de dictionnaires eux-mêmes qui, timidement et sans aucune méthode, notent pour un prédicat donné, le ou les arguments qui permettent de séparer un emploi d'un autre. Pas de sémantique sans syntaxe donc, c'est-à-dire sans contexte.*"[2].

SentIta is a sentiment lexical database that directly aims to apply the Lexicon-Grammar theory, starting from its basic hypothesis: the minimum semantic units are the elementary sentences, not the words (Gross, 1975).
Therefore, in this work, the lemmas collected into the dictionaries and their Semantic Orientations are systematically recalled and computed into a specific context through the use of local grammars. On the base of their combinatorial features and co-occurrences contexts, the Sen-

rigorous logic way".

[2] "If a word can not be defined in itself, namely out of context, but only into a specific syntactic environment, then the lexicon can not be separated from the syntax, that is to say from the word combinatorics. Semantics is not autonomous anymore: it is the result of lexical elements organized into a determined way (distribution). This is confirmed by the dictionary authors themselves that, timidly and without any method, note for a specific predicate, the argument(s) that allow to separate one use from another. No semantics without syntax, that means without context". Author's translation.

tIta lexical items can take the following shapes (Buvet et al., 2005; Elia, 2014a):

operators, the predicates, that can be verbs, nouns, adjectives, adverbs, multiword expressions, prepositions and conjunctions,

arguments, the predicate complements, that can be nominal and prepositional groups or entire clauses.

As already specified in Section 2.2, the sentiment words and other oriented Atomic Linguistic Units (ALU) are listed into Nooj electronic dictionaries while the local grammars used to manipulate their polarities are formalized thanks to Finite State Automata.
Electronic dictionaries have then been exploited in order to list and to semantically and syntactically classify, into a machine readable format, the sentiment lexical resources. The computational power of Nooj graphs has, instead, been used to represent the acceptance/refuse of the semantic and syntactic properties through the use of constraint and restrictions.
Chapter 2 underlined the role played, in the elementary sentences, by the Predicates and the one assumed by its arguments. According to Le Pesant and Mathieu-Colas (1998),

> "*La structure prédicat/arguments semble plus opératoire que les découpages binaires classiques (sujet/prédicat).*
> [...] *C'est le prédicat qui détermine le nombre de positions constitutives de la phrase.*" [3]

Predicates must not be identified only with the category of verbs, but also with predicative nouns and adjectives that enter into support verb structures.
In the subgroup of sentiment expressions, starting from their syntactic structures, Gross identified two semantic types:

[3] The predicate/argument structure seems to be more operating than the classical binary subdivision (subject/predicate). [...] It is the predicate that determines the number of positions that constitute the sentence. Author's translation.

1. sentences with two arguments, where one is the *person* and the other is the *feeling* (e.g. *Maria è angosciata* "Maria is anguished");
2. sentences with three arguments, that differs from the first one for the presence of a *stimulus* that triggers the *feeling* into another *person* (e.g. *Gianni angoscia Maria* "Gianni anguishes Maria")

The notation for their representation is the same as the one used for the Semantic Predicates (Gross, 1981). The type 1 can be formalized by the following formula:

1. *P(sent,h)* e.g. *P(angoscia, Maria)*

in which the variable *h* is function of a sentiment *Sent*, through a predicative relationship.
The type 2, instead, can be expressed by the following formula:

2. *Caus(s, sent, h)* e.g. *Caus(Gianni, angoscia, Maria)*

in which a sentiment *Sent* is caused by a stimulus *s* on a person *h*. Both of them are outcomes of the following assumption: "*un sentiment est toujours attaché à la personne qui l'éprouve*"[4] (Gross, 1995, p. 1). At first glance, the problem connected to sentiment expressions seems to be easy to define and solve. Actually, upon a deeper analysis, it presents its challenging aspects, the quantity and the variability of sentiment expressions, which can vary both from a transformational and from a morpho-syntactic point of view. As displayed below, a sentiment expressed by a word can take the shape of verbs, nouns, adjectives or adverbs (Gross, 1995; D'Agostino, 2005; D'Agostino et al., 2007).

V: *angosciare* "to anguish", *angosciarsi* "to become anguished";

N: *angoscia* "anguish";

A: *angosciante* "anguishing", *angosciato, angoscioso* "anguished";

ADV: *angosciatamente, angosciosamente* "with anguish".

[4] "A sentiment is always attached to the person that feels it". Author's translation.

Such groups of words, related one another by the derivational morphology under a common root (e.g. *angosc-*), represent from the LG point of view *classes of paraphrastic equivalence* or, also, *paraphrastic constellations* (D'Agostino, 1992). These concepts are crucial when applied to the Sentiment Analysis field, because the connection of the words displayed above is related to a formal principle, that regards the sentence structure, and also a semantic principle, that concerns the distributional properties and the semantic roles of the arguments selected by the predicates (D'Agostino, 1992).
Nevertheless, from a syntactic point of view, Gross (1995) noticed that the terms of sentiment can occupy all the different nominal, adjectival, verbal or adverbial positions within the same sentence structure.

3.2 Literature Survey on Subjectivity Lexicons

The most used approaches in the Sentiment Analysis field can be divided and summarized in three main lines of research: lexicon-based methods, learning and statistical methods and hybrid methods.
The first ones coincide with the strategy that has been chosen to carry out the present work.
Lexicon-based approaches always start from the following assumption: the text sentiment orientation comes from the semantic orientations of words and phrases contained in it.
The most commonly used SO indicators are adjectives or adjective phrases (Hatzivassiloglou and McKeown, 1997; Hu and Liu, 2004; Taboada et al., 2006), but recently it became really common the use of adverbs (Benamara et al., 2007), nouns (Vermeij, 2005; Riloff et al., 2003) and verbs as well (Neviarouskaya et al., 2009a).
Hand-built lexicons are definitely more accurate than the automatically-built ones, especially in cross-domain Sentiment Analysis tasks. Nevertheless, to manually draw up a dictionary is

considered a painstakingly time-consuming activity (Taboada et al., 2011; Bloom, 2011). This is why the presence of a large number of studies on automatic polarity lexicons creation and propagation can be observed in literature. On this topic, it must be said that automatic dictionaries seem to be more unstable, but usually larger than the manually built ones (see Tables 3.1 and 3.2). Size, anyway, does not mean always quality: it is common for these large dictionaries to have scarcely detailed information, a large amount of entries could denote fewer details in description, e.g. the Maryland dictionary (Mohammad et al., 2009) does not specify the entries' part of speech, or, instead, could mean more noise.
Among the state of the art methods used to build and test those dictionaries we mention the Latent Semantic Analysis (LSA) (Landauer and Dumais, 1997); bootstrapping algorithms (Riloff et al., 2003); graph propagation algorithms (Velikovich et al., 2010; Kaji and Kitsuregawa, 2007); conjunctions (and or but) and morphological relations between adjectives (Hatzivassiloglou and McKeown, 1997); Context Coherency (Kanayama and Nasukawa, 2006a); distributional similarity (Wiebe, 2000); etc[5].
Word Similarity is a very frequently used method in the dictionary propagation over the thesaurus-based approaches. Examples are the Maryland dictionary, created thanks to a Roget-like thesaurus and a handful of affixe (Mohammad et al., 2009), and other lexicons based on WordNet, like SentiWordNet, built on the base of quantitative analysis of glosses associated to synsets (Esuli and Sebastiani, 2005, 2006a) or other lexicons based on the computing of the distance measure on WordNet (Kamps et al., 2004; Esuli and Sebastiani, 2005).
Pointwise Mutual Information (PMI) using *Seed Words* has been applied to sentiment lexicon propagation by Turney (2002); Turney and Littman (2003); Rao and Ravichandran (2009); Velikovich et al. (2010); Gamon and Aue (2005). *Seed words* are words which are strongly associated with a positive/negative meaning, such as *eccel-*

[5]More details about the lexicon propagation will be given in Section 3.5.1.

lente (“excellent”) or *orrendo* (“horrible”), by which it is possible to build a bigger lexicon, detecting other words that frequently occur alongside them. It has been observed, indeed, that positive words occur often close to positive seed words, whereas negative words are likely to appear around negative seed words (Turney, 2002; Turney and Littman, 2003).

PMI could be easily calculated in the past, using the Web as a corpus, thanks to the AltaVista’s NEAR operator. Today one must be content with the Google AND operator.

Learning and statistical methods for Sentiment Analysis intent usually make use of Support Vector Machine (Pang et al., 2002; Mullen and Collier, 2004; Ye et al., 2009) or Naïve Bayes classifiers (Tan et al., 2009; Kang et al., 2012).

In the end, as regards the hybrid methods it has to be cite the work of Read and Carroll (2009); Li et al. (2010); Andreevskaia and Bergler (2008); Dang et al. (2010); Dasgupta and Ng (2009); Goldberg and Zhu (2006); Prabowo and Thelwall (2009) and Wan (2009)[6].

A brief summary about the nature and the size of the most popular lexicons for the Sentiment Analysis is given in Tables 3.1 and 3.2.

A clarification needs to be done about the distinction between Polarity lexicons and Affect lexicon. The first ones are used in subjectivity detection, or in polarity and intensity classification systems; while the latter, going beyond the dichotomy positive/negative, refer to a more fine-grained emotion classification.

In the following paragraphs we will firstly describe some of the most famous Polarity lexicon and then we will briefly cite some databases for affect classification.

Another distinction will be made among the resources conceived for the English language and the ones created for other languages. The Italian language will especially be considered.

[6]These contributions will be deepened in Section 5.1.1.

Dictionary	**Author**	**Year**	**Entries**	**Language**
SO-CAL lexicon	Taboada	2011	5,000+	Eng
AFINN-111	Hansen	2011	2,400+	Eng
Sentilex	Silva	2010	7,000+	Port
Q-WordNet 3.0	Agerri et al.	2010	15,500+	Eng
DAL-2009	Whissell	2009	8,700+	Eng
MPQA lexicon	Wilson et al.	2005	8,000+	Eng
Hu-Liu lexicon	Hu et al.	2004	6,800+	Eng
Hatzivassiloglou lexicon	Hatzivassiloglou	1997	15,400+ pairs	Eng
General Inquirer	Stone	1961	9,800+	Eng

Table 3.1: Manually built Polarity Lexicons

Dictionary	**Author**	**Year**	**Entries**	**Language**
Sentix	Basile, Nissim	2013	59,700+	Ita
SentiWordNet	Baccianella et al.	2010	38,000+	Eng
Web-generated lexicon	Velikovich et al.	2010	178,000+	Eng
Maryland dictionary	Mohammad et al. e	2009	76,000+	Eng

Table 3.2: (Semi-)Automatically built Polarity Lexicons

3.2.1 Polarity Lexicons

SO-CAL dictionary. Taboada et al. (2011), due to the low stability of the automatically generated lexical databases, manually developed the SO-CAL dictionary. They hand tagged, with an evaluation scale that ranged from +5 to -5, the semantically oriented words they found into a variety of sources:

- the multi-domain collection of 400 reviews belonging to different categories, described in Taboada and Grieve (2004); Taboada et al. (2006);

- 100 movie reviews from the Polarity Dataset of Pang et al. (2002); Pang and Lee (2004),
- the whole General Inquirer dictionary (Stone et al., 1966)

The result was a dictionary of 2,252 adjectives, 1,142 nouns, 903 verbs, and 745 adverbs. The adverb list has been automatically generated by matching adverbs ending in "-*ly*" to their potentially corresponding adjective. Moreover, also a set of multiword expressions (152 phrasal verbs, e.g. "to fall apart" and 35 intensifier expressions, e.g. "a little bit") have been taken into account. In case of overlapping between a simple word (e.g. "fun", +2) and a multiword expression (e.g. "to make fun of", -1) with different polarity, the latter possess the higher priority in the annotation process.

AFINN. It is a list of English words that associates 1,446 words with a valence between +5 (positive) and -5 (negative) (Hansen et al., 2011). AFINN-111, that is its newest version, includes 2,477 words and phrases in its list. The drawing of the list started from a a set of obscene words and then gradually extended by examining Twitter posts. This has lead to a bias of 65% towards negative words compared to positive words (Nielsen, 2011).

Q-WordNet. It is a lexical resource consisting of WordNet senses automatically annotated by positive and negative polarity (Agerri and García-Serrano, 2010). It is grounded on the hypothesis that if a positive synset is matched in a gloss, then its synset can be also annotated as positive. Exceptions are the cases under the scope of a negation, that are classified as the opposite of the matched lemma.
What differentiates Q-WordNet from SentiWordNet is the fact that positive/negative labels are attributed to word senses at a certain level by means of a graded classification.

Multi-Perspective Question Answering Lexicon. The MPQA subjectivity lexicon (Wiebe et al., 2004; Wilson et al., 2005) is comprised by 8000+ subjectivity clues (words and phrases that may be used to express private states) annotated by type (*strongsubj* or *weakly-subj*) and prior polarity. Subjectivity clues and contextual features have been learned from two different kinds of corpora: a small amount of data manually annotated, at the expression-level, from the Wall Street Journal and newsgroup data and a large amount of data with existing document-level annotations from the Wall Street Journal. The focus is on three types of subjectivity clues:

- *hapax legomena*, words that appeared just once in the corpus;
- *collocations*, identified through fixed n-grams;
- *adjective and verb features*, identified using the results of a method for clustering words according to distributional similarity.

Hu-Liu lexicon. The Hu and Liu (2004) wordlist comprises around 6,800 English items (2,006 positive and 4,783 negative), including slang, misspellings, morphological variants and social media mark up.

Hatzivassiloglou Lexicon. Hatzivassiloglou and McKeown (1997), starting from a list of 1,336 manually labeled adjectives (657 positive and 679 negative terms), demonstrated that conjunctions between adjectives can provide indirect information about their orientation. In detail, the authors extracted the conjunctions through a two-level finite-state grammar, able to cover modification patterns and noun-adjective apposition, and tested their method on 21 million word from the Wall Street Journal corpus. This way they collected 13,426 conjunctions of adjectives, further expanded to a total of 15,431 conjoined adjective pairs.

Dictionary of Affect in Language. The Whissel (1989); Whissell (2009)

Dictionary of Affect (DAL) lists about 4,500 English words. Its more recent version (Whissell, 2009) is provided with 8,742 words manually annotated fro their *Activation*, *Evaluation*, *Imagery* Whissell (2009).

General Inquirer. It is an IBM 7090 program system developed at Harvard in the spring of 1961 for content analysis research problems in behavioral sciences (Stone et al., 1966; Stone and Hunt, 1963). It is based on the idea that, through the analysis of many variables at once, it is often possible to discover trends that can appear “latent" to casual observation.
The description of the “systematic” content analysis processes must be as “objective” as possible; the features of texts must be “manifest” and the results “quantitative”.
The lexicon attaches syntactic, semantic, and pragmatic information to part-of-speech tagged words. Among others, the categories related to polarity measures are the ones pertaining to the three semantic dimensions of Osgood (1952):

Positive: 1,915 words of positive outlook;

Negative: 2,291 words of negative outlook;

Strong: 1,902 words implying strength;

Weak: 755 words implying weakness;

Active: 2,045 words implying an active orientation;

Passive: 911 words indicating a passive orientation[7].

SentiWordNet. Esuli and Sebastiani (2006a) developed the SentiWordNet 1.0 lexicon based on WordNet 2.0 (Miller, 1995) by automatically associating each WordNet synset to three scores: *Obj(s)* for objective terms and *Pos(s)* and *Neg(s)* for positive and negative terms.

[7] Table 3.1 refers to the General Inquirer size only in terms of sentiment words.

Every score ranges from 0.0 to 1.0, and their sum is 1.0 for each synset. The values are determined on the base of the proportion of eight ternary classifiers (with similar accuracy levels but different classification behavior), that quantitatively analyze the glosses associated with every synset and assign them the proper label.

What differentiates SentiWordNet from other sentiment lexicons is the fact that the weighting process focuses on synonym sets, rather than on simple terms. The researchers intuitively observe that different senses of the same term could have different opinion-related properties.

SentiWordNet 3.0 (Baccianella et al., 2010) improves SentiWordNet 1.0. The main differences between them are the version of WordNet they annotate (3.0 for SentiWordNet 3.0), and the algorithm used to annotate WordNet, that in the 3.0. version, along with the semi-supervised learning step, also includes a random-walk step that perfects the scores.

Velikovich Web-generated lexicon. This dictionary of sentiment, that has been built through graph propagation algorithms and lexical graphs, counts 178,104 entries, which include not only simple words but also spelling variations, slang, vulgarity, and multiword expressions (Velikovich et al., 2010).

Maryland dictionary. The procedure on which Mohammad et al. (2009) built the Maryland lexicon can be split into two steps: the identification of a seed set of positive and negative words and the positive and negative annotation of the words synonymous in a Roget-like thesaurus.

Eleven antonym-generating affix patterns have been used to generate overtly marked words and their unmarked counterparts. This way, such patterns generated 2,692 pairs of valid English words listed in the Macquarie Thesaurus.

The main innovation introduced by Mohammad et al. (2009) is the autonomy from the manual annotation of any term in the dictionary, even if it could be used, when available, to improve both the correctness and the coverage of its entries.

3.2.2 Affective Lexicons

SentiSense. SentiSense (de Albornoz et al., 2012) is a semi-automatically developed affective lexicon, which consists of 5,496 words and 2,190 synsets.
Similarly to SentiWordNet or WordNet-Affect, it associates emotional meanings or categories to concepts (instead of terms) from the WordNet lexical database and can be used for both polarity and intensity classification and emotion identification.
Synsets are labeled with a set of 14 emotional categories, which are also related by an antonym relationships. Examples are *disgust/like*; *love/hate*; *sadness/joy*): *ambiguous, anger, anticipation, calmness, despair, disgust, fear, hate, hope, joy, like, love, sadness, surprise.*

SentiFul and the Affect Database. Neviarouskaya et al. (2009b, 2011) developed the SentiFul lexicon, by automatically expanding the core of sentiment lexicon through many different strategies:

- synonymy relation;
- direct antonymy relation;
- hyponymy relations;
- derivation and scoring of morphologically modified words;
- compounding of sentiment-carrying base components.

In summary, 4,190 new words, connected to the known ones through semantic relations, have been automatically extracted from WordNet and 4,029 lemmas have been automatically de-

rived with the morphological method. The starting point of the work has been the Affect Database of Neviarouskaya et al. (2007), that contained 364 emoticons; 337 popular acronyms and abbreviations (e.g. *bl*, "belly laughing"); words standing for communicative functions (e.g. "wow", "ouch", etc.); 112 modifiers (e.g. "very", "slightly", etc.); and 2,438 direct and indirect emotion-related entries (1,627 of which taken from WordNet-Affect).
In the Affect Database, emotion categories (*anger*, *disgust*, *fear*, *guilt*, *interest*, *joy*, *sadness*, *shame* an *surprise*) and intensity (from 0.0 to 1.0) was manually assigned to each entry by three independent annotators.

Appraisal Lexicon. The appraisal lexicon (Argamon et al., 2009) has been built through semi-supervised learning on a set of WordNet glosses containing adjectives and adverbs, among which only a small subset of the training data was manually labelled.
The construction of the lexicon is grounded on the Appraisal Theory, that is a linguistic approach for the analysis of subjective language. In this framework several sentiment-related features are assigned to relevant lexical items. The feature set, that allows more subtle distinctions than the most used binary classification Positive/Negative, includes the labels *orientation* (*Positive* or *Negative*), *attitude type* (*Affect*, *Appreciation*, *Judgment*), and *force* (*Low*, *Median*, *High*, or *Max*).

WordNet-Affect. WordNet-Affect is another extension of WordNet for the lexical representation of affective knowledge (Strapparava et al., 2004). Thanks to the synset model, it puts in relation a set of affective concepts with a number of affective words. In a first step in the WordNet-Affect creation, the "affective core" has been created starting from almost 2,000 terms directly or indirectly referring to mental states. Lexical and affective information have, then, been added to each item by creating for them specific frames. In the end, the senses of terms have been

mapped to their respective synsets in WordNet. The synsets have been specialized with a hierarchically organized set of emotional categories (namely *emotion*, *mood*, *trait*, *cognitive state*, *physical state*, *edonic signal*, *emotion-eliciting situation*, *emotional response*, *behaviour*, *attitude*, *sensation*). Furthermore, the emotional valences have been distinguished by four additional a-labels: *positive*, *negative*, *ambiguous*, and *neutral* (Strapparava et al., 2006).
WordNet-Affect contains 2,874 synsets and 4,787 words (Strapparava et al., 2004).

3.2.3 Subjectivity Lexicons for Other Languages

3.2.3.1 Italian Resources

The largest part of the state of the art works on polarity lexicons for Sentiment Analysis purposes focuses on the English language. Thus, Italian lexical databases are mostly created by translating and adapting the English ones, SentiWordNet and WordNet-Affect, among others. Basile and Nissim (2013) merged the semantic information belonging to existing lexical resources in order to obtain an annotated lexicon of senses for Italian, Sentix (Sentiment Italian Lexicon). Basically, MultiWordNet (Pianta et al., 2002), the Italian counterpart of WordNet (Miller, 1995; Fellbaum, 1998), has been used to transfer polarity information associated to English synsets in SentiWordNet to Italian synsets, thanks to the multilingual ontology BabelNet (Navigli and Ponzetto, 2012).
Every Sentix's entry is described by information concerning its part of speech, its WordNet synset ID, a positive and a negative score from SentiWordNet, a polarity score (from -1 to 1) and an intensity score (from 0 to 1).
The dictionary contains 59,742 entries for 16,043 synsets. Details

about its composition are reported in Table 3.3.

PoS	**Lemmas**	**Synsets**
noun	52,257	12,228
adjective	3,359	1,805
verb	2,775	1,260
adverb	1,351	750
all	59,742	16,043

Table 3.3: Sentix Basile and Nissim (2013)

Moreover, Steinberger et al. (2012) verified a triangulation hypothesis for the creation of sentiment dictionaries in many languages, namely English, Spanish, Arabic, Czech, French, German, Russian and also Italian.
The starting point is the semi-automatic generation of two pilot sentiment dictionaries for English and Spanish, that have been automatically transposed into the other languages, by using the overlap of the translations (triangulation), and then manually filtered and expanded. As regards the Italian lexicon, the authors collected 918 correctly triangulated terms and 1500 correctly translated terms from the starting dictionaries.
Hernandez-Farias et al. (2014) achieved good results in the SentiPolC 2014 task by semi-automatically translating in Italian different lexicons; namely, SentiWordNet, Hu-Liu Lexicon, AFINN Lexicon, Whissel Dictionary, etc...
Baldoni et al. (2012) proposed an ontology-driven approach to Sentiment Analysis, where tags and tagged resources are related to emotions. They selected representative Italian emotional words and used them to query MultiWordNet. The synsets connected to these lemmas were then processed with WordNet-Affect, in order to populate the emotion ontology only with the words belonging to synsets that represented affective information. The resulting ontology contains about 450 Italian words referring to the 87 emotional categories of On-

toEmotion, an ontology conceived for the categorization of emotion-denoting words. Furthermore, thanks to the SentiWordNet database every synset has been associated to the neutral, positive or negative scores.

3.2.3.2 Sentiment Lexical Resources for Different Languages

SentiLex-PT (Silva et al., 2010, 2012) is a sentiment lexicon for Portuguese made up of 7,014 lemmas, distributed in this way:

- 4,779 adjectives
  - e.g. castigado;PoS=Adj;TG=HUM:N0;POL:N0=-1;ANOT=JALC
- 1,081 nouns;
  - e.g. aberração.PoS=N;TG=HUM:N0;POL:N0=-1;ANOT=MAN
- 489 verbs
  - e.g. enganar.PoS=V;TG=HUM:N0:N1;POL:N0=-1;POL:N1=0;ANOT=MAN
- 666 verb-based idiomatic expressions
  - e.g. engolir em seco.PoS=IDIOM;TG=HUM:N0;POL:N0=-1;ANOT=MAN

The sentiment entries are all human nouns modifiers, compiled from different publicly available corpora and dictionaries.
The tagset used to describe the attributes of the lemmas is explained below.

- *part-of-speech* (ADJ, N, V and IDIOM);
- *polarity* (POL), that ranges between 1 (positive) and -1 (negative);
- *target of polarity* (TG), which corresponds to a human subject (HUM);
- *polarity assignment* (ANOT), that specifies if the annotation has been performed manually (MAN) or automatically, by the Judgment Analysis Lexicon Classifier (JALC).

Differently from Silva et al. (2010, 2012), that focused on the domain-specific features of the opinion lexicon of social judgment, Souza et al. (2011) proposed for the Portuguese language a domain-independent lexicon composed by 7,077 polar words (adjectives, verbs and nouns) and expressions.
As regards the dictionary population, the authors applied three different methods:

- corpus based approach, applied on 1,317 documents annotated using the Pointwise Mutual Information;
- thesaurus based approach on 44,077 words and their semantic relations from the TEP thesaurus (Maziero et al., 2008);
- translation based, from the Liu's English Opinion Lexicon (Hu and Liu, 2004).

Other contribution that deserve to be cited are Perez-Rosas et al. (2012) for Spanish; Mathieu (2006, 1999a, 1995) for French; Clematide and Klenner (2010), Waltinger (2010) and Remus et al. (2010) for German; Abdul-Mageed et al. (2011); Abdul-Mageed and Diab (2012) for Arabic and Chetviorkin and Loukachevitch (2012) for Russian.
As regards Multilingual Sentiment Analysis we can mention Balahur and Turchi (2012); Steinberger et al. (2012), Pak and Paroubek (2011), and Denecke (2008), among others.

3.3 SentIta and its Manually-built Resources

In this Section we will go in depth in the description of SentIta, the LG based Sentiment lexicon for the Italian language, that has been semi-automatically built on the base of the richness of both the Italian module of Nooj and the Italian Lexicon-Grammar resources.
The tagset used for the Prior Polarity annotation Osgood (1952) annotation of the resources is composed of four tags:

Lexical Item	Translation	Tag	Description	Score
meraviglioso	wonderful	+POS+FORTE	Intensely Positive	+3
colto	cultured	+POS	Positive	+2
rasserenante	calming	+POS+DEB	Weakly Positive	+1
nuovo	new	-	Neutral	0
insapore	flavourless	+NEG+DEB	Weakly Negative	-1
cafone	boorish	+NEG	Negative	-2
disastroso	disastrous	+NEG+FORTE	Intensely Negative	-3

Table 3.4: SentIta Evaluation tagset

Lexical Item	Translation	Tag	Description	Score
grande	big	+FORTE	Intense	+
velato	veiled	+DEB	Weak	-

Table 3.5: SentIta Strength tagset

POS *positive*

NEG *negative*

FORTE *intense*

DEB *weak*

Such labels, if combined together, can generate an evaluation scale that goes from -3 to +3 (see Table 3.4) and a strength scale that ranges from -1 to +1 (see Table 3.5).
Neutral words (e.g. *nuovo* “new”, with score 0 in the evaluation scale) have been excluded from the lexicon.
The main difference between the words listed in the two scales is the possibility to use them as indicators for the subjectivity detection task. Basically, the words belonging to the evaluation scale are “anchors” that begin the identification of polarized phrases or sentences, while the ones belonging to the strength scale are just used as intensity modifiers (see Section 4.2).

Details about the lexical asset available for the Italian language is summarized in Table 3.6. Here we report all the items contained in

Category	**Entries**	**Example**	**Translation**
Adjectives	5,381	*allegro*	cheerful
Adverbs	3,693	*tristemente*	sadly
Compound Adv	774	*a gonfie vele*	full steam ahead
Idioms	577	*essere in difetto*	to be in fault
Nouns	3,215	*eccellenza*	excellence
Psych Verbs	604	*amare*	to love
LG Verbs	651	*prendersela*	to feel offended
Bad words	182	*leccaculo*	arse licker
Tot	15,077	-	-

Table 3.6: Composition of SentIta

SentIta, including the ones automatically derived (namely, adverbs and nouns), that will be described in detail in Section 3.5.
Because hand-built lexicons are more accurate than the automatically built ones (Taboada et al., 2011; Bloom, 2011), we started the creation of the SentIta database with the manual tagging of part of the lemmas contained in the Nooj Italian dictionaries. In detail, adjectives and bad words have been manually extracted and evaluated starting from the Nooj Italian electronic dictionary of simple words, preserving their inflectional (FLX) and derivational (DRV) properties. Moreover, compound adverbs (Elia, 1990), idioms (Vietri, 1990, 2011), psych verbs and other LG verbs (Elia et al., 1981; Elia, 1984) have been weighted starting from the Italian LG tables, in order to maintain the syntactic, semantic and transformational properties connected to each one of them.

3.3.1 Semantic Orientations and Prior Polarities

In the Sentiment Analysis field, the *Semantic Orientation* is a subjectivity and an opinion measure that weights the polarity (positive/negative) and the strength (intense/weak) of an opinion. Other

concepts used to refer to SO are *sentiment orientation*, *polarity of opinion*, or *opinion orientation* (Taboada et al., 2011; Liu, 2010).
The *Prior Polarity*, instead, refers to the individual words' Semantic Orientation and differs from the SO because it is always independent from the context (Osgood, 1952). The second concept, generally used in sentiment dictionary population, has been exploited also to manually evaluate the words contained in the simple word dictionary of the Italian module of Nooj (Sdic_it.dic).
Before the description of the annotation process begins, it must be clarified that, at this stage of the work, the multiple meanings that a single word can possess have not been taken into account. In this sense, SentIta is different from the resources in which Prior Polarities are assigned to "concepts", rather than to mere words (e.g. SentiWordNet). Such procedure gives rise to the need to reconstruct the Prior Polarities starting from the various word meanings, transforming them actually in *Posterior Polarities* (Gatti and Guerini, 2012). An example is the word "cold" that possesses different meanings, and consequently different polarities, if associated to the words "beer" (with a low temperature, neutral) or "person" (emotionless, weakly negative) (Gatti and Guerini, 2012).
From our point of view, this distinction is redundant in a work that includes a syntactic module. We strongly support the idea that only the Prior Polarities must be contained in the lexicon and that the context should be used to compute them in a parallel module that is the syntactic one.
Indeed, our purpose is to reduce at the same time the presence of ambiguity, the computational time and the size of the electronic dictionaries. Therefore, the annotators of SentIta simply labeled the words of Sdic_it according to the meaning they thought dominant for each word. If, out of any context, the word "cold" can not be unequivocally associated to a positive or negative orientation, we preferred to attribute it a neutral polarity.

3.3.2 Adjectives of Sentiment

The annotation of the Sdic_it started with 34,000+ adjectives, by considering each word apart from any context. The first decision is binary and regards the choice between the positive or negative polarity; so the fist tags +POS or +NEG (that respectively correspond to the score +2, -2) are attached to the adjective under exam, as shown in the following examples.

```
colto,A+FLX=N88+DRV=ISSIMO:N88+POS
cafone,A+FLX=N88+DRV=ISSIMO:N88+NEG
```

A fine grained classification approach must include, during the Prior Polarity attribution, also the determination of the intensity of the oriented words. The strength of the SO is, therefore, defined with the combined use of the POS/NEG tags and the FORTE/DEB labels. The last two respectively increase or decrease of one point the intensity of the sentiment items. This way, as shown in Table 3.4, we could take into account three different degrees of positivity and as much levels of negativity scores.
As we will explain better in Section 4.2, we selected among the adjectives of Sdic_it a list of about 650 words that did not receive any polarity tag, but that have just been labeled with information about their intensity. This is the case of the items reported below, which are just examples from the SentIta Strenght list.

```
grande,A+FLX=N79+DRV=GRANDE:N88+DRV=GRANDE-C:N79+FORTE
velato,A+FLX=N88+DRV=ISSIMO:N88+DEB
```

Such words are not used to locate subjectivity in texts, but they can become really advantageous when the task is to compute the actual orientation of a phrase. The words endowed with the tag +FORTE are called *intensifiers* and the ones marked with +DEB *downtoners* (Taboada et al., 2011). Their function is, respectively, to increase or

decrease the score of the polarized words.
Details about the distribution of sentiment tag in the adjective dictionary are reported in Table 3.7.
Table 3.8 presents a summary, in term of percentage values, of the composition of the adjective dictionary in SentIta. In the upper part of the Table, percentages are evaluated on the base of SentIta, that accounts 5,381 adjectives, which in the Table are indicated by *tot oriented adj*. The differences between the positive and negative adjectives and the intensity modifiers are shown here.
The coverage of the SentIta adjectives, with respect to the whole number of adjectives contained in Sdic_it, at a first glance seems to be very low, but, if compared with the other part of speech, it becomes more significant.
For a LG treatment of adjectives see Section 3.3.5.

Score	**Adjectives**	**Entries**
+3	+POS+FORTE	111
+2	+POS	1,137
+1	+POS+DEB	110
-1	+NEG+DEB	770
-2	+NEG	2,375
-3	+NEG+FORTE	240
+	+FORTE	512
-	+DEB	126

Table 3.7: SentIta tag distribution in the adjective list

Adjectives	**Entries**	**Percentage (%)**
tot pos	1,358	25 (SentIta)
tot neg	3,385	63 (SentIta)
tot int	638	12 (SentIta)
tot oriented adj	5,381	16 (Sdic_it)
tot neutral adj	28,664	84 (Sdic_it)
tot adj Sdic_it	34,045	100

Table 3.8: Adjectives percentage values in SentIta

3.3.2.1 A Special Remark on Negative Words in Dictionaries and Positive Biases in Corpora

The most important aspect to notice in Table 3.8 is the fact that the positive items cover just the 25% of the total amount of oriented adjectives; while, with a percentage of 63%, negative adjectives predominate the dictionary.

Just as in SentIta, also other sentiment lexicons present an excess of negative items, such as the SO-CAL lexicon (Taboada et al., 2011), AFINN-111 (Nielsen, 2011) and the Maryland dictionary (Mohammad et al., 2009).

In texts, instead, exactly the opposite trend can be observed. The *Pollyanna hypothesis* asserts the universal human tendency to use positive words more frequently than negative ones, through the popular claim “people tend to look on (and talk about) the bright side of life” (Boucher and Osgood, 1969, p. 1).

The experimental results of Montefinese et al. (2014) and Warriner et al. (2013) confirmed the so-called *linguistic positivity bias*, the prevalence of positive words in different languages.

Garcia et al. (2012) also measured this bias by quantifying, in the context of online written communication, both the emotional content of words in terms of valence and the frequency of word usage in the whole indexable web. They provided strong evidence that words with a positive emotional connotation are used more often.

As regards the experiment in the Sentiment Analysis field that tried to solve the positive bias, we mention Taboada et al. (2011), that, upon noticing the presence of almost twice as many positive as negative words in their corpus, addressed the problem by increasing the SO of any negative expression by a fixed amount (of 50%). Voll and Taboada (2007) overcame the same problem by shifting the numerical cut-off point between positive and negative reviews.

In this research we chose to avoid the introduction of unpredictable errors, due to the difficulty to accurately evaluate to what extent positive and negative items are differently distributed in written texts.

3.3.3 Psychological and other Opinion Bearing Verbs

In the present Section we will go through the more complex annotation of verbs of sentiment from available Lexicon-Grammar matrices. We will return to the adjectives of sentiment in Section 3.3.5, where it will be addressed the issue of the adjectivalization of the psychological predicates.

3.3.3.1 A Brief Literature Survey on the Classification of Psych Verbs

The difference among the *direct* (Experiencer subject) and *reverse* (Experiencer subject) representations of thematic roles is underlined in the extensive body of scientific literature on psych verbs, e.g. Chomsky (1965); Belletti and Rizzi (1988); Kim and Larson (1989); Jackendoff (1990); Whitley (1995); Pesetsky (1996); Filip (1996); Baker (1997); Martín (1998); Arad (1998); Klein and Kutscher (2002); Bennis (2004); Landau (2010).
The thematic roles involved are the following:

Experiencer: the entity or the person that experiences the reaction;

Cause: "the thing, person, state of affairs that causes the reaction" (Whitley, 1995), "or cognitive judgment in the experiencer" (Klein and Kutscher, 2002).

These two main classes[8] correspond to three classes proposed by Belletti and Rizzi (1988), in which the reverse representation is split according to the presence of a direct or indirect object mapped with the role of *experiecer*.

[8] These classes of psych verbs are also known as the *Fear* class (direct) and the *Frighten* class (reverse) (Jackendoff, 1990; Pesetsky, 1996; Baker, 1997), on the base of the syntactic positions occupied by the thematic roles of the *experiencer* and the *cause* (*theme*).

Class I: verbs which have the *experiencer* as subject and the *cause* as direct object (e.g. *temere* “to be afraid of”);

Class II: verbs which have the *cause* as subject and the *experiencer* as direct object (e.g. *preoccupare* “to worry”);

Class III: verbs which have the *cause* as subject and the *experiencer* as indirect object in dative case (e.g. *piacere* “to like”[9]).

Transitivity is taken into account also by Whitley (1995) who, instead, identified four classes of psych verbs for the Spanish:

Class I: transitive-direct (e.g. *amar*, “to love”);

Class II: intransitive-direct (e.g. *gozar de*, “to enjoy”);

Class III: intransitive-reverse (e.g. *gustar*, “to like”);

Class IIII: transitive-reverse (e.g. *tranquilizar*, “to appease”).

3.3.3.2 Semantic Predicates from the LG Framework

Shifting the focus on the works realized into the Lexicon-Grammar framework, we find again the distinction among two types of possible constructions on the base of the syntactic position (subject or complement) of the person who feels the sentiment (Mathieu, 1999a; Ruwet, 1994) and, of course, the distinction between the transitive and intransitive verbs.
The (reverse) French verbs of sentiment that enter into the transitive structure $N_0\ V\ N_1$ have been examined by Mathieu (1995)[10]. In this structure N_0, the stimulus of the sentiment, can be a human, concrete or abstract noun, or a completive or infinitive clause and N_1, the experiencer of the sentiment is a human noun, or also other animated

[9] Note that if the Italian verb *piacere* is classified in this class of Belletti and Rizzi (1988), its English translation “to like” belongs to the first one.
[10] The analysis of Mathieu (1995) is based on the syntactic model of the LG French Table 4.

nouns, such as animals or gods (Ruwet, 1994, see example 3).

(3) $\begin{bmatrix} Luc \\ Ce\ tableau \\ Le\ mensonge \\ Que\ Luc\ soit\ venu \\ Trembler \end{bmatrix}$ $irrite\ Marie$ (Mathieu, 1995)

"(Luc + This table + The lie + That Luc has come + To tremble) irritates Marie"

Nevertheless, Ruwet (1994) argued that a number of predicates from this class[11] select an *Num* in position N_1 that do not play the role of Experiencer as happens in the example (5), differently from what happens in (4). According with Ruwet (1994), *le ministre* of (4) does not feel any sentiment, he is instead the object of a negative (public) judgment caused by the stimulus expressed by N_0.

(4) *La lecture d'Homère passionne Maxime* (Ruwet, 1994)
"Reading Homer moves Maxime"

(5) *Ses déclarations intempestives discréditent le ministre* (Ruwet, 1994)
"His untimely declarations discredit the Minister"

One of the main purposes of this thesis is to provide a Lexicon-Grammar based database for Sentiment Analysis tools. We decided to start from the LG works on psychological predicates because of their richness, but we do not look at the Ruwet (1994) objection as a limit for our data collection. It offers only a wider range of information which we associate to our data. Sentiment Analysis does not focus only on mental states, but searches for every kind of positive or negative statement expressed in raw texts; therefore also a positive or negative (public) judgment represents a valuable resource in this field.
The hypothesis is that the the Predicates under examination could be distinguished into three subsets: the ones indicating a mental state,

[11] Among the verbs pointed out by Ruwet (1994) there are *abuser, aigrir, anoblir, aplatir, avilir, berner, civiliser, compromettre, consacrer, corrompre, couler, dédouaner, démasquer, dénaturer,* etc.

that select the roles *experiencer* and *causer* (*amare* "to love", *odiare* "to hate"); the ones connected to the manifestation of judgments, that (following the Sentiment Analysis trend in terminology) involve the roles of *opinion holder* and *target* (e.g. *difendere* "to defend", *condannare* "to condemn") and the ones related to physical acts that select the roles *patient* and *agent* (e.g. *baciare* "to kiss", *schiaffeggiare* "to slap")[12]. The mapping between the syntactic representations of actants and the semantic representations of arguments is feasible and valuable, but, from a LG point of view, becomes a little bit more complex if compared with the generalizations described in the previous Paragraph. The big problem aroused by the LG method is that the Syntax-Semantics mapping can not ignore the idiosyncrasies of the lexicon.
In the following paragraphs we will show the distribution of Psychological Predicates among the classes 41, 42, 43 and 43B (3.3.3.3) and we will demonstrate that a large number of predicates, evoking judgment, physical positive/negative acts, but also psychological states, are distributed among other 28 LG classes, every one of which possesses its own definitional syntactic structure. The large number of structures in which these verbs can enter underlines the importance of a sentiment database that includes both lexiocn-based semantic and syntactic classification parameters.

3.3.3.3 Psychological Predicates

Among the verbs chosen for our sentiment lexicon a prominent position is occupied by the Predicates belonging to the Italian LG classes 41, 42, 43 and 43B, that constitute 47% of the total amount of verbs in SentIta (Table 3.11). From the lexical items contained in such LG classes, a list of 602 entries has been evaluated and hand-tagged with the same labels used to evaluate the adjectives.

[12] An experiment realized on these *frames* is reported in Section 5.3

In the following Paragraphs we will describe some of the peculiarities of the psych verbs from the classes 41, 42, 43 and 43B, questioning in many cases, their psychological nature. We will, then, briefly examine the presence of subjective verbs in other 28 LG classes.

Psych Verb	Translation	LG Class	Score
angosciare	"to anguish"	41	-3
piacere	"to like"	42	+2
amare	"to love"	43	+3
biasimare	"to blame"	43B	-2

Table 3.9: Examples from the Psych Predicates dictionary

LG Class	Tot Class	Psych Verbs	Positive items	Negative items	Intensifiers	Downtoners	Percentage (%)
41	599	525	136	325	45	19	**88**
42	114	8	4	4	0	0	**7**
43	298	39	19	20	0	0	**13**
43B	142	32	11	21	0	0	**23**
Tot	1,153	604	170	368	45	19	**52**

Table 3.10: Psych Predicates chosen for SentIta

LG Class 41: *Ch F V N₁*

The verbs from this LG class have as definitional structure $N_0\ V\ N_1$, in which

- N_0 is generally an infinitive or completive clause (direct or introducet by the phrase *il fatto (Ch F + di)* "the fact (that S + of)"; but, with few exceptions, it can be also a human, a concrete or an abstract noun;

SentIta Verbs	Tot Items	Positive items	Negative items	Intensifiers	Downtoners
Psych Verbs	604	170	368	45	19
Other Verbs	651	189	350	79	33
Tot	1,255	359	718	124	52

Table 3.11: All the Semantic Predicates from SentIta

- N_1 is a human noun (*Num*).

A great part of these verbs (436 entries), with homogeneous syntactic behavior, can be grouped together also because of a semantic homogeneity connected to their psychological nature (Elia, 1984), examples of this subset are reported below in their dictionary form.

```
addolorare,V+NEG+Sent+FLX=V3+DRV=RI+41
ingelosire,V+NEG+DEB+Sent+FLX=V201+41
perturbare,V+NEG+Sent+FLX=V3+41
rallegrare,V+POS+Sent+FLX=V3+DRV=RI+41
rincuorare,V+POS+DEB+Sent+FLX=V3+41
tormentare,V+NEG+FORTE+Sent+FLX=V3+DRV=RI+41
```
[13]

This Psychological subgroup, identified in the electronic dictionary through the tag *+Sent*, exactly like the French verbs from the LG class 4, enters into a reverse transitive psych-verb structure by selecting an *Experiencer* as object N_1 and a *Stimulus* as N_0, as exemplified in (6).

[13] "To grieve, to make jealous, to upset, to cheer up, to reassure, to torment".

$$(6)\ [_{\text{Sentiment}}[_{\text{Stimulus}}\textit{Le sue parole}] \begin{bmatrix} \textit{addolorano}^{[-2]} \\ \textit{ingelosiscono}^{[-1]} \\ \textit{perturbano}^{[-2]} \\ \textit{rallegrano}^{[+2]} \\ \textit{rincuorano}^{[+1]} \\ \textit{tormentano}^{[-3]} \end{bmatrix} [_{\text{Experiencer}}\textit{Maria}]]$$

“His words (grieve + make jealous + upset + cheer up + reassure + torment) Maria”

The objection of Ruwet (1994) on the psychological semantic homogeneity on this class can be applied also to the Italian LG class 41. The extract of the dictionary reported below explains it better than words.

```
danneggiare,V+NEG+Op+FLX=V4+41
esautorare,V+NEG+Op+FLX=V3+41
glorificare,V+POS+Op+FORTE+FLX=V8+41
ledere,V+NEG+Op+FLX=V34+41
miticizzare,V+POS+Op+FLX=V3+41
smascherare,V+NEG+Op+DEB+FLX=V3+41
```
[14]

122 items from the class 41 have been selected and marked with the tag *+Op* to indicate, according with Ruwet (1994), that they select an N_1 that does not plays the role of the *Experiencer*, but that represents just the *Target* of a positive or negative judgment. Differently from other verbs also tagged with the *+Op* label (e.g. *condannare* “to condemn”), here N_0 is not the *Opinion Holder*, but just the *Cause* that justifies the opinion conveyed by the verb (see example 7). The *Opinion Holder* is never expressed by the arguments of the predicates from the class 41, because it can be played in turn, by the public opinion or the people (Ruwet, 1994).

[14] “To damage, to reduce or deprive of the authority, to glorify, to wrong, to make into heroes, to unmask”.

(7) $[_{\text{Opinion}}[_{\text{Cause}}\textit{Le sue parole}] \begin{bmatrix} \textit{danneggiano}^{[-2]} \\ \textit{esautorano}^{[-2]} \\ \textit{glorificano}^{[+3]} \\ \textit{ledono}^{[-2]} \\ \textit{miticizzano}^{[+2]} \\ \textit{smascherarno}^{[-2]} \end{bmatrix} [_{\text{Target}}\textit{Maria}]]$

“His words (damage + reduce or deprive of the authority + glorify + wrong + make into heroes + unmask) Maria”

Another subgroup of the verbs from this class, marked in the LG table as accepting the property *V:= uso concreto* (“V:= concrete use”), possesses also a "concrete" meaning. This is the case of *abbattere* “to demolish” (fig: “to discourage”), *accendere* “to light” (fig: “to fire up”), *colpire* “to hit” (fig: “to move”), etc.
Of course, the semantic properties of the figurative verbs are not shared with their concrete homographs.
The automatic disambiguation of these metaphors is sometimes very simple, because it can be based on the divergent properties of the different LG classes to which the concrete and figurative words belong (8, 9).

Concrete usage (Class 20NR):

(8) *Carla accende il fiammifero* (Elia, 1984)
“Carla lights the match”

Figurative usage (Class 41):

(9) *Parlare di rivoluzione accende Arturo* (Elia, 1984)
“Talking about revolution fires up Arturo”

As exemplified, the verb *accendere* belongs also to the class 20NR, in which it does not accept a completive as N_0 (**Parlare di rivoluzione accende il fiammifero* “Talking about revolution lights the match”); neither a human noun as N_1 (**Carla accende il fratello* “Carla lights her brother”); or a body part noun. (**Carla accende la gamba del fratello* “Carla lights her brother’s leg”).

In other cases it proves more difficult, but it can be solved as well with the help of semantically annotated dictionaries. This happens in the examples below, in which the fact that this verb is marked in the class 20NR as accepting the property *Prep N_2strum*, makes it possible to automatically distinguish its concrete use (10) from the figurative one (11).

Concrete usage:

(10) $Carla\ accende\ il\ fuoco\ della \begin{bmatrix} stufa \\ griglia \\ cucina \end{bmatrix}$

"Carla lights the fire of the (stove + grill + cooker)

Figurative usage:

(11) $Carla\ accende\ il\ fuoco\ del(la) \begin{bmatrix} rivoluzione \\ cambiamento \\ passione \end{bmatrix}$

"Carla ignites the fire of (revolution + change + passion)"

LG Class 42: *Ch F V Prep N_1*

The verbs from the class 42 enter into an intransitive reverse psych-verb structure and are defined by the LG formula *N_0 V Prep N_1*, where

- N_0 is generally an infinitive or completive clause (direct or introducet by the phrase *il fatto (Ch F + di)* "the fact (that S + of)") but in few cases can be also a human (*Num*) or a non restricted noun (*Nnr*);
- N_1 is a human noun (*Num*), but can be also a body part or an abstract noun of the kind *discorso* " discourse", *mente* "mind", *memoria* "memory" (Elia, 1984).

Here we find a selection of Psychological Predicates so poor that can be entirely reported.

`aggradare,V+POS+Sent+42+FLX=V403+Prep=a`
`arridere,V+POS+Sent+42+FLX=V34+Prep=a`
`dispiacere,V+NEG+Sent+42+FLX=V37+Prep=a`
`spiacere,V+NEG+Sent+42+FLX=V37+Prep=a`
`piacere,V+POS+Sent+42+FLX=V37+DRV=RI+Prep=a`[15]

The importance of this LG class into SentIta is not given by the (very small) amount of entries it accounts, but depend on the extremely high frequency of the verb *piacere*, "to like".
Here the prepositions (*Prep*) have been associated directly in the dictionary, in order to avoid ambiguity with other verb usages.
The semantic annotation does not raise any problem, as can be deduced from the example (12).

(12) $[_{\text{Sentiment}}[_{\text{Stimulus}} \begin{bmatrix} Il\ fatto\ che\ si\ fumi \\ Che\ si\ fumi \\ Fumare \\ Il\ fumare \\ Il\ fumo \end{bmatrix}] \begin{bmatrix} aggrada^{[+2]} \\ dispiace^{[-2]} \\ piace^{[+2]} \end{bmatrix} a[_{\text{Experiencer}} \textit{Maria}]]$

"(The fact that people smokes + That people smokes + Smoking + The smoke) (pleases + regrets + is appreciated by) Maria"

The main difference with the class 41, added to its intransitivity, is the fact that in Italian a more easily accepted form is the permuted one (Elia et al., 1981, see example 13).

(13) $[_{\text{Sentiment}} A\ [_{\text{Experiencer}} \textit{Maria}]\ \textit{piace}^{[+2]}\ [_{\text{Stimulus}} \textit{fumare}]]$
"Maria likes smoking"

Again, a subset of verbs from this class can be marked as opinion indicator.

[15] "to please, to favor, to regret, to like"

Both N_0 and N_1 can be human nouns:

`incombere,V+NEG+Op+42+FLX=V21+Prep=loc+N0um+N1um`

`primeggiare,V+POS+Op+FLX=V4+Prep=su+N0um+N1um`

`contrastare,V+NEG+Op+FLX=V3+Prep=con+N0um+N1um`

`contare,V+POS+Op+FLX=V3+Prep=per+N0um+N1um`

Just N_1 can be a human noun:

`addirsi,V+42+POS+Op+FLX=V263+PRX+Prep=a+N1um`

`sconvenire,V+NEG+Op+FLX=V236+Prep=a+N1um`

`convenire,V+POS+Op+FLX=V236+Prep=a+N1um`

`costare,V+NEG+Op+FLX=V3+Prep=a+N1um`

Neither N_0, nor N_1 can be human nouns:

`degenerare,V+NEG+FORTE+Op+42+FLX=V3+DRV=BILE:N79+Prep=in`

`stridere,V+NEG+Op+FLX=V2+Prep=con`[16]

Not every verb of this subset accepts a human noun as N_1 (see examples 14 and 15)

(14) $[_{\text{Opinion}}[_{\text{Target}}\textit{Queste idee}]\textit{stridono}^{[-2]}\ \textit{con} \begin{bmatrix} \textit{i miei obiettivi} \\ \textit{la tua immagine} \\ *\textit{Maria} \end{bmatrix}]$

"These ideas are at odd with (my purposes + your image + *Maria)"

(15) $[_{\text{Opinion}}[_{\text{Target}}\textit{La situazione}]\textit{degenera}^{[-3]}\ \textit{in un} \begin{bmatrix} \textit{dramma} \\ \textit{conflitto} \\ *\textit{Maria} \end{bmatrix}]$

"The situation degenerates into a (drama + conflict + *Maria)"

In such cases the *Opinion Holder* remains implicit, but the judgment negatively affects the subject of the sentence instead of the N_1. Sentences like (16) and (17) raise to doubt whether N_1 can be the *Holder* of the opinion expressed by the sentence or not.

[16] "to loom over, to excel, to hinder, to worth, to suit, to be inconvenient, to be convenient, to cost, to degenerate, to clash"

(16) $[_{\text{Opinion}}[_{\text{Target}} \begin{bmatrix} Maria \\ Il\ fidanzamento \\ Che\ si\ sposti\ la\ riunione \end{bmatrix} \textit{conta}^{[+2]}\ \textit{per}\ [_{\text{Opinion Holder}} \textit{Arturo}]]$

"(Maria + The engagement + That the meeting is moved) matters to Arturo"

(17) $[_{\text{Opinion}}[_{\text{Target}} \begin{bmatrix} *Maria \\ Il\ fidanzamento \\ Che\ si\ sposti\ la\ riunione \end{bmatrix} \begin{bmatrix} conviene^{[+2]} \\ costa^{[-2]} \end{bmatrix} [_{\text{Opinion Holder}} \textit{ad}\ \ \textit{Arturo}]]$

"(*Maria + The engagement + That the meeting is moved) (is convenient + costs) for Arturo"

Actually, the verb does not provide any information regarding the active or passive role of N_1 in the expression of the opinion. The writer can be convinced about what "matters, is convenient or costs" for Arturo, but it remains a belief that is not confirmed in the text (16, 17). Therefore we chose to assign the *Opinion Holder* role to the N_1 of the class 42 only in the case in which the object corresponds to the personal pronouns "me" or "us" (18, 19).

(18) $[_{\text{Opinion}}[_{\text{Target}} \begin{bmatrix} Maria \\ Il\ fidanzamento \\ Che\ si\ sposti\ la\ riunione \end{bmatrix} \textit{conta}^{[+2]}\ \textit{per}\ [_{\text{Opinion Holder}} \textit{me}]]$

"(Maria + The engagement + That the meeting is moved) matters to me"

(19) $[_{\text{Opinion}}[_{\text{Target}} \begin{bmatrix} *Maria \\ Il\ fidanzamento \\ Che\ si\ sposti\ la\ riunione \end{bmatrix} [_{\text{Opinion Holder}} \textit{ci}] \begin{bmatrix} conviene^{[+2]} \\ costa^{[-2]} \end{bmatrix}]$

"(*Maria + The engagement + That the meeting is moved) (is convenient + costs) for us"

LG Classes 43 and 43B: *N_0 V Ch F* and *N_0 V il fatto Ch F*

The sentence structure that defines this class is *N_0 V N_1*

- N_0, in both the classes 43 and 43B, is generally a human noun (*Num*)
- N_1 is an infinitive clause or a completive one, which is direct for the 43 and introduced by *il fatto (Ch F + di)* "the fact (that S + of)") for the 43B.

The psychological (*Sent*), but also the opinion (*Op*) verbs from the class 43 share in many cases the acceptance or the refusal of a set of LG properties.

```
deprecare,V+Op+NEG+Class=43+FLX=V8
bestemmiare,V+Op+NEG+FORTE+Class=43+FLX=V11
criticare,V+Op+NEG+Class=43+FLX=V8
maledire,V+Op+NEG+FORTE+Class=43+FLX=V216
tollerare,V+Op+NEG+DEB+Class=43+FLX=V3

adorare,V+Sent+POS+FORTE+Class=43+FLX=V3
amare,V+Sent+POS+FORTE+Class=43+FLX=V3
ammirare,V+Sent+POS+Class=43+FLX=V3
odiare,V+Sent+NEG+FORTE+Class=43+FLX=V12
rimpiangere,V+Sent+NEG+DEB+Class=43+FLX=V31
```
[17]

As regards the distribution of N_0, it must be noticed that all these verbs accept a human noun, but only two of them (*condannare* "to comndemn" and *meritare* "to deserve") accept also a not restricted noun (*Nnr* not active), or a subjective clause introduced by *il fatto (Ch F + di)*. This fact is perfectly consistent with the animated nature of the *Experiencer* with respect to the Psychological verbs (20). However, it underlines that this class of verbs selects also an *Opinion Holder* as N_0 (except for the verb *meritare*).

[17] "to deprecate, to blaspheme, to criticize, to curse, to tolerate, to adore, to love, to admire, to hate"

(20) $[_{\text{Sentiment}}[_{\text{Experiencer}} Maria] \begin{bmatrix} adora^{[+3]} \\ odia^{[-3]} \end{bmatrix} [_{\text{Stimulus}} \begin{bmatrix} Arturo \\ che\ Arturo\ fumi \\ il\ fatto\ che\ Arturo\ fumi \\ il\ fumo \end{bmatrix}]]$

"Maria (adores + hates) (Arturo + that Arturo smokes + the fact that Arturo smokes + the smoke)"

(21) $[_{\text{Opinion}}[_{\text{Opinion Holder}} Maria] \begin{bmatrix} critica^{[-2]} \\ tollera^{[-1]} \end{bmatrix} [_{\text{Target}} \begin{bmatrix} Arturo \\ che\ Arturo\ fumi \\ il\ fatto\ che\ Arturo\ fumi \\ il\ fumo \end{bmatrix}]]$

"Maria (criticizes + tolerates) (Arturo + that Arturo smokes + the fact that Arturo smokes + the smoke)"

As far as the distribution of N_1 is concerned, all the psych and opinion items accept the pronoun *ciò*"this" and the Ppv *lo* "it/him/her" (apart from *inveire* "to inveigh"). The only verbs that refuse *Num* as complement are *auspicare* "to hope for", *inveire* "to inveigh", *lamentare* "to lament", *malignare* "to speak/think ill of", *meritare* "to deserve", *agognare* "to yearn for", *anelare* "to long for", *deilrare* "to talk nonsense" and *gustare* "to taste". The verbs that, instead, do not accept a *N-um* are fewer: *inveire* and *delirare*.
The property *N_1 dal fatto Ch F* is refused by every verb except for *apprezzare* "to admire", that, together with *sopportare* "to suffer", *desiderare* "to desire" and *bramare* "to crave", accept also the property *N_1 da N_2*. Other properties refused in bulk are *Ch N_0 V essere Comp* (save *malignare, sospettare* "to suspect", *temere* "to be afraid of"); *N_1 Agg* (save *sospettare, temere*) *N_1 = Agg Ch F* (save *sospettare*) *N_0 V essere Cong* (save *sospettare* and *malignare*) *N_1 = se F o se F* (save *benedire* "to bless ", *apprezzare* and *gustare*). *Ch F a N_2um* (save *approvare* "to approve").
Similar observations, but with an even higher homogeneity, can be

made on the class 43B that, differently from the 43, has the N_1 always introduced by *il fatto (Ch F + di)*.
The Psychological (*Sent*) and the opinionated (*Op*) verbs from the class 43B share sometimes the acceptance or the refusal of a set of LG properties.

```
attaccare,V+Op+NEG+Class=43B+FLX=V8
biasimare,V+Op+NEG+Class=43B+FLX=V3
lodare,V+Op+POS+Class=43B+FLX=V3
osannare,V+Op+POS+FORTE+Class=43B+FLX=V3
snobbare,V+Op+NEG+Class=43B+FLX=V3

assaporare,V+Sent+POS+Class=43B+FLX=V3
pregustare,V+Sent+POS+Class=43B+FLX=V3
schifare,V+Sent+NEG+FORTE+Class=43B+FLX=V3
sdegnare,V+Sent+NEG+FORTE+Class=43B+FLX=V16
spregiare,V+Sent+NEG+FORTE+Class=43B+FLX=V4[18]
```

Here, again, an N_0 different from a human noun can be accepted just by three verbs (*banalizzare* "to trivialize", *demitizzare* "to unidealize" and *pregiudicare* "to compromise").
The pronoun *ciò*"this", the Ppv *lo* "it/him/her" and a not human noun are accepted by all the *Sent* and *Op* verbs in complement position; while the *N_1 um* is refused by 2 psychological and 5 opinionated verbs. As regards the properties refused by almost all the verbs we account *N_1 dal fatto Ch F*; *N_1 da N_2* (save *difendere* "to defend") and *Ch F a N_2um* (save *apologizzare* "to make an apology for" and *vantare* "to praise").
Differently from the class 43, in which the passive transformation is not accepted in 3 cases, in the class 43B it is accepted by all the items.

[18]" to attack, to blame, to praise, to snub, to taste, to foretaste, to be disgusted by, to be indignant, to despise"

3.3.3.4 Other Verbs of Sentiment

We stated in Paragraph 3.3.3.2 that almost half of the SentIta verbs do not coincide with what is defined in literature as "psych verb". Moreover, a lot of psych verbs and other opinion-bearing items can be found in LG classes different from the ones classically identified as containing psychological predicates, namely 41, 42, 43, 43B (Elia, 2014a, 2013). In detail, a large number of verbs that can be used as sentiment and opinion indicators is classified over 28 other LG classes, described by as many definitional structures. This fact could be interpreted as the failure of the syntactic-semantic mapping hypothesis; but actually, into the LG framework, the semantic entropy of the lexicon can be decreased through the identification of classes of words that share sets of lexical-syntactic behaviors.
The main Lexicon-Grammar verbal subclasses are the mentioned below.

Intransitive verbs: LG classes from 1 to 15, on which LG researchers tested the acceptance or the refusal of 545 combinatorial and distributional properties, through 23,827 elementary sentences;

Transitive verbs: LG classes from 16 to 40, tested on 361 properties among 19,453 sentences;

Complement clause verbs: (transitive and intransitive) LG classes from 41 to 60, tested on 443 properties and 57,242 sentences (Elia, 2014a).

Table 3.12 shows the percentage values of opinionated verbs in each one of the Lexicon-Grammar verbal subclasses mentioned above. As we can see, the complement clause group contains the larger number of oriented items. When inserted in our electronic dictionaries, the lemmas from these LG classes are enriched with semantic information concerning the Types (*Sent*, sentiments, emo-

LG Class	**Verb usages**	**Oriented verbs**	**Percentages (%)**
Intransitive verbs	401	138	21
Transitive verbs	605	205	31
Complement clause verbs	760	308	47
Tot	1,766	651	100

Table 3.12: Polar verbs in the main Lexicon-Grammar verbal subclasses

tions, psychological states; *Op*, opinions, judgments, cognitive states; *Phy* physical acts), the Orientations (*POS*; *NEG*) and the Intensities (*STRONG*; *WEAK*) of the described lemmas.
Similarly to SentiLex (Silva et al., 2010, 2012), SentIta is provided with the specification of the argument(s) N_i semantically affected by the orientation of the verbs.
The presence of oriented verbs and the distribution of semantic tags are respectively described in Tables 3.13 and 3.14. For a complete presentation of LG verbal classes, their composition and their granularity, see Elia (2014a).

3.3.4 Psychological Predicates' Nominalizations

The nominal entities of SentIta that will described in this Section are all predicative forms, due to their correlation with the verbal predicates described above, e.g. *angosciare* "to anguish", *angoscia* "anguish" (D'Agostino, 2005).
The complex phenomenon related to the combinatorial constraints between sentiment V-n and specific verbs in simple sentences has been already explored by Balibar-Mrabti (1995) and Gross (1995) for the French language. In this regard, Gross (1995) specified that "*les*

Main LG Class	**LG Class**	**Verb usage**	**Oriented verbs**	**Percentages (%)**
Intransitive Verbs	2	122	34	28
	2A	40	9	23
	4	31	12	39
	9	72	35	49
	10	56	19	34
	11	80	29	36
Transitive Verbs	18	40	8	20
	20I	25	1	4
	20NR	83	15	18
	20UM	145	65	45
	21	29	2	7
	21A	65	44	68
	22	63	28	44
	23R	34	13	38
	24	72	18	25
	27	37	10	27
	28ST	12	1	8
Complement Clause Verbs	44	33	18	55
	44B	44	20	45
	45	31	23	74
	45B	21	16	76
	47	313	120	38
	47B	34	12	35
	49	96	12	13
	50	51	41	80
	51	36	19	53
	53	28	9	32
	56	73	18	25
Tot	-	1,766	651	37

Table 3.13: Polar verbs in other LG verb classes which contain at least one oriented item

Main LG Class	LG Class	Oriented Verbs	Sent	Op	POS	NEG	FORTE	DEB
Intransitive Verbs	2	34	7	24	8	26	0	0
	2A	9	4	2	1	8	0	0
	4	12	0	11	5	7	0	0
	9	35	10	25	11	24	0	0
	10	19	4	15	9	10	0	0
	11	29	25	4	0	29	0	0
Transitive Verbs	18	8	0	0	4	4	0	0
	20I	1	0	0	1	0	0	0
	20NR	15	5	8	4	11	0	0
	20UM	65	16	25	11	54	0	0
	21	2	0	2	0	2	0	0
	21A	44	9	14	17	6	11	10
	22	28	0	28	21	7	0	0
	23R	13	0	0	4	9	0	0
	24	18	0	0	0	1	15	2
	27	10	0	10	10	0	0	0
	28ST	1	0	0	0	1	0	0
Complement Clause Verbs	44	18	0	18	16	2	0	0
	44B	20	2	18	14	6	0	0
	45	23	6	16	7	15	1	0
	45B	16	5	10	7	9	0	0
	47	120	0	120	5	54	43	18
	47B	12	0	34	4	8	0	0
	49	12	0	12	4	8	0	0
	50	41	4	33	15	22	4	0
	51	19	1	14	10	9	0	0
	53	9	0	9	0	9	0	0
	56	18	1	9	1	9	5	3
tot	-	651	99	461	189	350	79	33

Table 3.14: Distribution of semantic labels into the LG verb classes that contain at least one oriented item

restrictions de noms de sentiment à certains verbes sont nombreuses et tellement inattendues que dans un premier temps, nous les avions traitées comme des expressions figées, c'est-à-dire comme de simples listes[19]*"*.
As regards Italian works in the LG framework we mention the works of D'Agostino (2005); D'Agostino et al. (2007) and Guglielmo (2009) that respectively explored the lexical micro-classes of the sentiments *ira* "anger", *angoscia* "anguish" and *vanità* "vanity", studying their nominal manifestation in support verb constructions.
Differently from ordinary verbs (discussed here in Sections 3.3.3), support verbs do not carry any semantic information; this role is just played here by the sentiment nouns; but they can modulate it, to a certain extent.
In the present research, the Nominalizations of Psychological verbs have been used to manually start the formalization of the SentIta dictionary dedicated to nouns. It comprehends 1000+ entries and includes list of 80+ human nouns, evaluated and added to this dictionary in order to use them in sentences like *N_0um essere un N_1sent* (e.g. *Max è un attaccabrighe*, "Max is a cantankerous").
Table 3.15 shows one example of Psych V-n for each LG class took into account during the annotation of Psychological Predicates.
A sample of the entries from this dictionary is given below. The LG

Psych verb	**V-n**	**V-n Translation**	**LG Class**	**Score**
angosciare	*angoscia*	"anguish"	41	-3
piacere	*piacere*	"pleasure"	42	+2
amare	*amore*	"love"	43	+3
biasimare	*biasimo*	"blame"	43B	-2

Table 3.15: Description of the Nominalizations of the Psychological Semantic Predicates

class is associated to a given item by the property "Class"; that let

[19] "The restrictions of nouns of sentiment to certain verbs are numerous and so unexpected that at first we treated them as frozen expressions, that is to say, as mere lists". Author's translation.

the grammar recognize the proper syntactic structures in which the nominalizations occur in real texts.

LG Class 41

```
bellezza,N+POS+Class=41+DASOLO+FLX=N41
calore,N+POS+Class=41+FLX=N5
contentezza,N+POS+Class=41+DASOLO+FLX=N41
dolcezza,N+POS+Class=41+DASOLO+FLX=N41
fascino,N+POS+Class=41+DASOLO+FLX=N5
```
[20]

LG Class 42

```
dispiacere,N+FLX=N5+42+NEG+DASOLO
dispiacevolezza,N+FLX=N41+42+NEG+DASOLO
dispiacimento,N+FLX=N5+42+NEG+DEB+DASOLO
piacere,N+FLX=N5+42+POS+DASOLO
piacevolezza,N+FLX=N41+42+POS+DASOLO
```
[21]

LG Class 43

```
approvazione,N+FLX=N46+43+POS+DASOLO
benedizione,N+FLX=N46+43+POS+DASOLO
bestemmia,N+FLX=N41+43+NEG+DASOLO
bramosia,N+FLX=N41+43+NEG+DEB+DASOLO
condanna,N+FLX=N41+43+NEG+DASOLO
```
[22]

LG Class 43B

```
denigrazione,N+FLX=N46+43B+NEG+FORTE+DASOLO
derisione,N+FLX=N46+43B+NEG+DASOLO
dileggio,N+FLX=N12+43B+NEG+DASOLO
disdegno,N+FLX=N5+43B+NEG+FORTE+DASOLO
disprezzo,N+FLX=N5+43B+NEG+FORTE+DASOLO
```
[23]

Table 3.16 presents the details about the distribution of sentiment tags into the Psych V-n dictionary. The size of the nouns dictionary is

[20] “Beauty, warmth, happiness, kindness, charm”.
[21] “Sorrow, displeasure, regret, pleasure, pleasantness”.
[22] “Approval, blessing, curse, yearning, condemnation”.
[23] “Detraction, derision, mockery, disdain, despise”.

LG Class	Nouns	Positive Items	Negative Items	Intensifiers	Downtoners	Percentages %
41	856	245	542	41	28	77
42	11	5	6	0	0	1
43	170	57	113	0	0	15
43B	74	21	53	0	0	7
Tot	1,111	328	714	41	28	100
%	100	30	64	4	3	-

Table 3.16: Nominalizations of the Psych Predicates chosen from SentIta

larger than the the verbs' one. This happens because the same predicate can possess more than one nominalization (e.g. the verb *amare* from the LG class 43 is related with the V-n *amabilità, amore, amorevolezza*).

3.3.4.1 The Presence of Support Verbs

To include V-n in a sentiment lexicon is particularly risky. In many cases it is misleading to use them out of any context because they often have a specific SO only if used with particular support verbs. Among the *Vsup* considered, we mention the following, with their equivalents (D'Agostino, 2005; D'Agostino et al., 2007).

- *essere in* "to be in": *patire di, soffrire di* "to suffer of", *stare in* "to be in", *andare in* "to go in" ;
- *avere* "to have": *avvertire* "to perceive", *patire, soffrire* "to suffer", *tenere* "to have", *sentire, provare* "to feel", *subire* "to undergo", *nutrire, covare* "to harbor", *provare un (senso + sentimento) di* "to ", "to feel a (sense + sentiment) of";
- *causare* "to cause": *dare* "to give", *suscitare* "to raise", *provocare*

"to provoke", *creare* "to create", *alimetare* "to instigate", *stimolare* "to inspire", *sviluppare* "to develop", *incutere* "to instill", *sollecitare* "to urge to", *donare, regalare, offrire* "to offer";

Sometimes it is even possible to have a SO switch by changing the word context. For example, the noun *pietà* "pity" and "compassion" is strongly negative into a fixed expression with the support verb *fare* (22), but it becomes positive when it co-occurs with the sentiment expression of (23).

(22) È proprio la sceneggiatura che fa *pietà* [-3]
"That's the script that is pitiful"

(23) Mary prova un sentimento di *pietà* [+2]
"Mary feels a sentiment of compassion"

Systematically evaluating the relationships that exist between each one of the psych nouns and each one of the support verbs that can be combined with them, through LG tables, can bring to an important conclusion: the fact that the support verb variants can influence the polarity of the V-n with which they occur is not an exception. For example, extensions of *Vsup* like *subire* "to undergo", *covare* "to harbor", *incutere* "to instill" bring a negative orientation with them; *donare, regalare, offrire* "to offer" are positively connoted; *perdere* "to lose", *abbandonare* "to abandon", *lasciare* "to leave" cause a polarity switch for whatever psych noun orientation.
Support verbs like the ones cited above can not be simply included into a Vsup list, but must be inserted in specific paths of a nouns grammars able to correctly manage their influence on V-n.

3.3.4.2 The Absence of Support Verbs

Another problem arises when a psych predicative noun from our collection presents different semantic behaviors when occurring without support verbs in real texts. This is the case of *calore* "warmth", from the verb *riscaldare* “to warm up” of the LG class 41, that possesses its psychological figurative meaning only together with specific structures (24), but assumes a physical interpretation when it occurs alone (26). Different is the case of *contentezza* “happiness” that preserves its psychological meaning in both the cases (25, 27).

(24) Le tue parole *invadono*$^{[+]}$ Maria di *calore*$^{[+2]}$ [+3]
“your words warm up Mary”

(25) Le tue parole *invadono*$^{[+]}$ Maria di *contentezza*$^{[+2]}$ [+3]
“your words overwhelm Mary with happiness”

(26) Che *calore*$^{[+2]}$! [0]
“what a heat!”

(27) Che *contentezza*$^{[+2]}$! [2]
“what a joy!”

In a banal way, we solved the problem by distinguishing in the dictionaries and recalling in the grammars the cases in which the nouns can occur alone from the cases in which a specific *Vsup* context is required to have a particular SO, by means of the special tag *+DASOLO* “alone”.

3.3.4.3 Ordinary Verbs Structures

In order to deeper examine how the presence of different verbs can affect the polarity of the Psychological V-n, we translated the list of 61 verbs of Balibar-Mrabti (1995) from the French and annotated them with semantic information. The sentence structure which they have been conceived for is N_0*sent V* N_1*um* (e.g. *una gioia intensa riempie Max* “an intense joy fills Max”) in which the subject N_0 plays the role of *Nsent*. Then, they have been tested into the structure N_0 *V* N_1*um di* N_2*sent* (e.g. *le tue parole riempiono Max di una gioia intensa* “your words fill Max with an intense joy”), that, in turn, is related with the

passive *Max è pieno di una gioia intensa* “Max is full of an intense joy”. This list of corresponding Italian verbs contains 47 entries, because of the exclusion of the duplicates from the LG class 41[24]. Among them, 11 give to the *Nsent* a negative connotation (e.g. *abbattere* “to lose heart”, *offuscare* “to confuse”, *corrodere* “to corrode”); 6 confer it a positive orientation (e.g. *rispeldere* “to shine”, *cullare* “to cling”, *illuminare*“to light up”); 18 intensify their polarity (e.g. *travolgere* ““to overwhelm””, *attraversare* “to undergo”, *riempire* “to fill”) and 12 simply possess a neutral orientation.
Their role can become crucial into two differently oriented sentences that make use of the same Nsent like (28a, b, c).

(28a) L'*amore*[+2] *tormenta*[-3] Maria [-3]
(28b) L'*amore*[+2] *illumina*[+2] Maria [+2]
(28c) L'*amore*[+2] *travolge*[+] Maria [+3]
“The love (torments + lights up + overwhelms) Maria”

Therefore, for sake of simplicity, we decided to put them into a FSA that assigns as sentence polarity the score of the verbs with tags NEG/POS (28a, b) and that uses the verbs with the tag FORTE as intensifiers (28c). A simplified version of this grammar is displayed in Figure 3.1. Here the paths marked with the number (1) represents the negative rule (28a); the paths (2) represent the positive rule (28b) and the paths marked with (3) exemplify the intensification rule (28c).
In this dictionary/grammar pair we did not mark the verbs with special tags; consequently other Psychological Predicated endowed with polarity and intensity tags can be matched in the corresponding paths.

[24]The verbs from this class are all compatible with this structure because they accept in the subject position an abstract noun and in position N_1 require always a human noun.

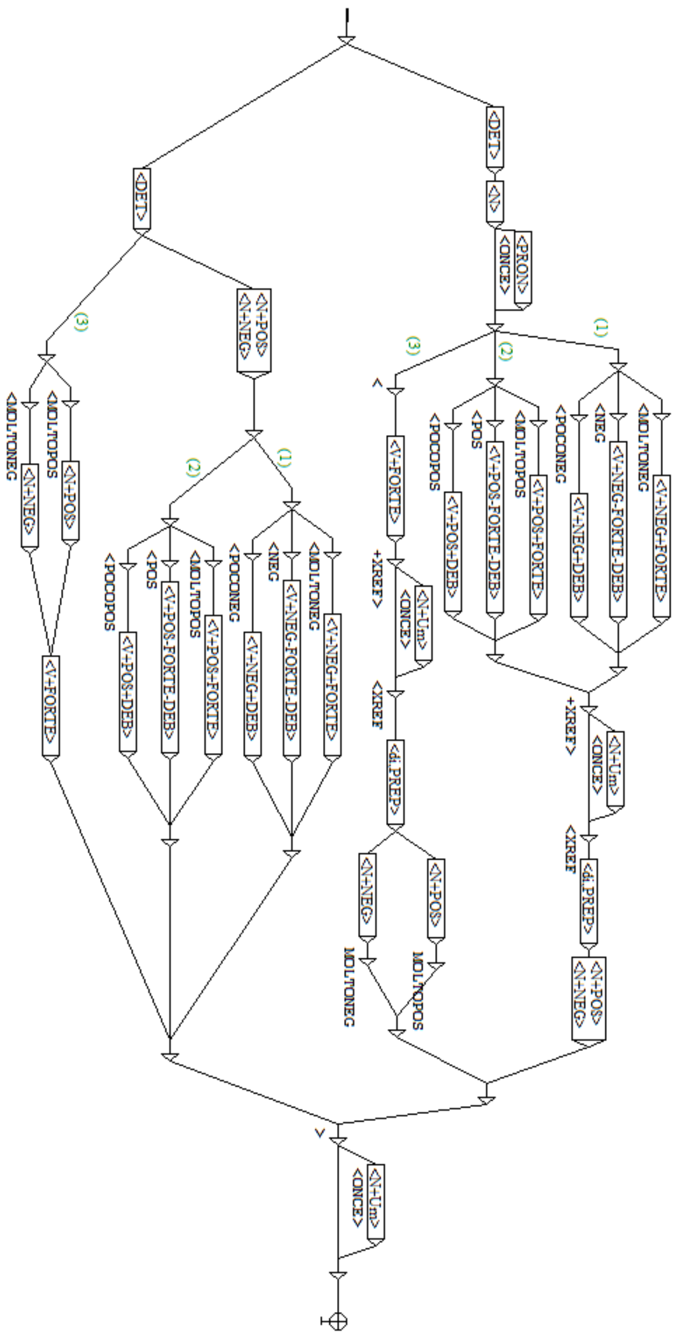

Figure 3.1: FSA for the interaction between Nsent and semantically annotated verbs

3.3.4.4 Standard-Crossed Structures

To conclude the work on sentiment V-n, we mention the case of the structures of the type "standard" ($N_0 sent\ V\ Loc\ N_1 um$) / "crossed" ($N_0 um\ V\ di\ N_1 sent$), exemplified below (D'Agostino, 2005; Elia et al., 1981).

(29) l'*amore*[+2] *brilla*[+] negli occhi di Maria [+3]
"love shines in Maria's eyes"

(30) gli occhi di Maria *brillano*[+] d'*amore*[+2] [+3]
"Maria's eyes shine with love"

To formalize this group of sentiment expressions we made use of 12 verbs from the LG class 12, interpreted into a figurative way, in which the $N_1 um$ "standard" position and the $N_0 um$ "crossed" position are designed by their body parts *Npc* through a metonymic process (Elia et al., 1981).
As happens in (29) and (30) such verbs can work as intensifiers (e.g *bruciare* "to burn") or can also have a negative polarity influence (only in the case of *dolere* "to hurt").

3.3.5 Psychological Predicates' Adjectivalizations

Paragraph 3.3.2 described the manually-built collection of opinion bearing adjectives that counts more than 5,000 items.
In this list, a subset of items in morpho-phonological relation with our predicates from the classes 41, 42, 43 and 43B has been automatically associated to the verbs of origin and to their respective LG classes. The result of this work is an electronic dictionary of 757 entries realized with a morphological grammar of Nooj (see Figure 3.2). It is displayed in the sample below.

```
angosciante,A+FLX=N79+DRV=ISSIMO:N88+NEG+Va+V=angosciare+Class=41
angosciato,A+FLX=N88+DRV=ISSIMO:N88+NEG+Va+V=angosciare+Class=41
angoscioso,A+FLX=N88+DRV=ISSIMO:N88+NEG+Va+V=angosciare+Class=41
piacente,A+FLX=N79+DRV=ISSIMO:N88+POS+Va+V=piacere+Class=42
piacevole,A+FLX=N79+DRV=ISSIMO:N88+POS+Va+V=piacere+Class=42
amato,A+FLX=N88+DRV=ISSIMO:N88+POS+Va+V=amare+Class=43
amorevole,A+FLX=N79+DRV=ISSIMO:N88+POS+Va+V=amare+Class=43
amoroso,A+FLX=N88+DRV=ISSIMO:N88+POS+Va+V=amare+Class=43
biasimevole,A+FLX=N79+DRV=ISSIMO:N88+NEG+Va+V=biasimare+Class=43B
```
[25]

Table 3.17 gives information about the distribution of its semantic tags; while Table 3.18 compares the sentiment selection of V-a with the whole dictionary of sentiment adjectives of SentIta in which it is contained.

Tag	**41**	**42**	**43**	**43B**	**Tot**
POS+FORTE	8	0	0	9	17
POS	133	3	35	11	182
POS+DEB	14	0	0	0	14
NEG+DEB	66	0	5	1	72
NEG	307	2	24	25	358
NEG+FORTE	49	0	6	2	57
FORTE	46	1	0	0	47
DEB	9	0	0	1	10
Tot	632	6	70	49	757

Table 3.17: Distribution of semantic tags in the dictionary of Adjectival Psych Predicates

The grammar resembles the ones used to derive the orientation of adverbs in *-mente* and quality nouns from the semantic information listed in the sentiment adjectives, that will be respectively treated in Sections 3.5.2 and 3.5.3. The process is similar: we copy and paste the dictionary that has to be semantically enriched into a Nooj text and we annotate it through the instructions of the grammar. We, then, export

[25] "Anguishing, anguished, anguishous, attractive, pleasing, beloved, loving, amorous, blameworthy".

Adjectives	**Entries**	**Percentages (%) on Adj Psych**	**Percentages (%) on SentIta**
Tot pos	213	28	4
Tot neg	487	64	9
Tot int	57	8	1
Tot Psych	757	100	14
Tot SentIta	5,381	-	100

Table 3.18: Percentage values of Psych Adjectivalizations in SentIta

the annotations and compile a brand new dictionary on their base.

Because the operations involve just the two dictionaries, we exclude any other lexical (.nod) and morphological (.nom) resource from the Nooj Preferences before applying the grammar to the dictionary-text. The grammar recognizes each verbal stem, checks if it belongs to the LG class of interest and then adds the adjectival suffixes listed into a .dic file (see Table 3.19). The difference from the grammars for the quick population of the adverbs in -m*ente* and the quality nouns is that here the morphological strategy is not exploited to discover the prior polarity of the words, since the adjective dictionary was already tagged with sentiment information. In fact, in the final annotation, the adjectives preserve all their semantic (`$2S`), inflectional and derivational (`$2F`) properties. The new information they acquire regard their nature of V-a (`+Va`), the connection with the psychological verb (`+V=$1L`) and the relative LG class of the predicate (`+Class=41`). Regarding the adjectival suffixes for the deverbal derivation we examined the ones that follow (Ricca, 2004a).

- morphemes for the adjectives formation (*-bile, -(t)orio, -evole, -(t)ivo, -(t)ore)-bondo, -ereccio, -iccio -ido, -ile, -ndo, -tario, -ulo*);
- morphemes for the formation of adjectives that coincide with the verb's past or present participle (*-to, -nte*);
- not typically deverbal morphemes (*-oso, -istico,-(t)ico, -aneo, -ardo, -ale, -ario*);

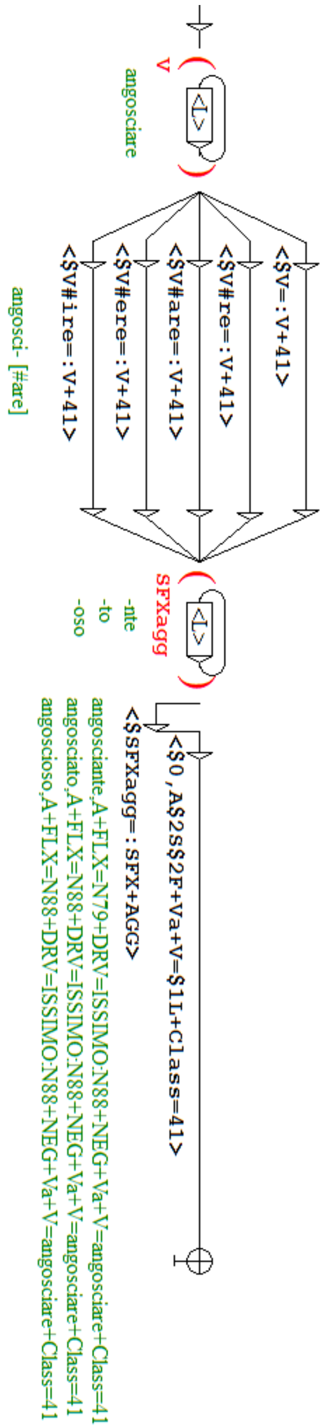

Figure 3.2: Extract of the morphological FSA that associates psych verbs to their adjectivalizations

- not typically adjectival morphemes (*-(t)ore, -trice, -ista, -one)*.

SFX	Adjectives
-t-o	309
-nt-e	159
-(t)or-e	100
-(t)iv-o	38
-os-o	38
-(t)ori-o	35
-evol-e	26
-o (conversion)	20
-(t)ic-o	8
-on-e	6
-ist-a	4
-istic-o	3
-al-e	3
-il-e	2
-bil-e	1
-bond-o	1
-nd-o	1
-tric-e	1
-icci-o	1
-ari-o	1
-erecci-o	0
-id-o	0
-tari-o	0
-ul-o	0
-ane-o	0
-ard-o	0

Table 3.19: Suffixes from the dictionary of Psych Adjectivalizations

As it can be seen in Table 3.19, some suffixes produced a large number of connections, some of them were less productive. Six morphemes did not produce any connection.
Furthermore, also a set of adjectives derived by conversion has been automatically connected to the respective verbs.

Psych verb	**Psych V-n**	**Psych V-a**	**V-a Translation**	**LG Class**	**Score**
angosciare	*angoscia*	angosciante angosciato angoscioso	“anguishing" “anguished" “anguishous"	41	-3
piacere	*piacere*	piacente piacevole	“attractive" “pleasing"	42	+2
amare	*amore*	amato amorevole amoroso	“beloved" “loving" “amorous"	43	+3
biasimare	*biasimo*	biasimevole	“blameworthy"	43B	-2

Table 3.20: Adjectivalizations of the Psych Predicates

LG class 43: *maligno* = *malignare* “mean = to speak ill of”
LG class 41: *schifo* = *schifare*“disgusting = to loathe”.

The average precision reached in the automatic association process is 97%. The list produced by Nooj has then been manually corrected in order to add it to the SentIta resources without any possible source of errors.
Table 3.20 shows examples of the connection between the verbs from the tables 41, 42, 43 and 43B and their respective nominalizations and adjectivalizations.
Actually, nouns can be associated to adjectives also independently from verbs (Gross, 1996), as happens in (31). Section 3.5.3 will deal with such cases.

(31) $Luc \begin{bmatrix} est\ généreux \\ a\ de\ la\ générosité \end{bmatrix} envers\ ses\ ennemis$ (Gross, 1996)

“Luc (is generous + has generosity) for his enemies”

Basically, we chose to associate the psych adjectives to the respective verbs in order to preserve their argument/actant selection, for Semantic Role Labeling purposes. This does not exclude that also other adjectives that do not belong to this subset can have the function of predicates in the sentences in which they occur, as happens in (31).

3.3.5.1 Support Verbs

As exemplified above, the sentiment expressions in which we inserted the adjectives from SentIta are of the kind *N_0 essere Agg val*. Where *Agg val* represents an adjective that expresses an evaluation (Elia et al., 1981) and the support verb for these predicates is *essere* "to be".
This verb gives its support also to the expression *N_0 essere un N_1-class* (e.g. *Questo film è una porcheria* "This movie is a mess"), that without it, together with the adjectives, would not posses any mark of tense (Elia et al., 1981).
A great part of the compound adverbs possess also an adjectival function (e.g. *a fin di bene* "for good", *tutto rose e fiori* "all peace and light", see Section 3.4.1); so, with good reason, they have been included in this support verb construction as well.
The support verbs' equivalents included in this case are the following (Gross, 1996).

- aspectual equivalents: *stare* "to stay", *diventare* "to become", *rimanere, restare* "to remain";
- causative equivalents: *rendere* "to make";
- stylistic equivalents: *sembrare* "to seem", *apparire* "to appear", *risultare* "to result", *rivelarsi* "to reveal to be", dimostrarsi, mostrarsi "to show oneself to be".

Among the Italian LG structures that include adjectives[26] we selected the following, in which polar and intensive adjectives can occur

[26] For the LG study of adjectives in French see Picabia (1978); Meunier (1999, 1984).

with the support verb *essere* (Vietri, 2004; Meunier, 1984):

- Sentences with polar adjectives:
  - *N_0 Vsup Agg Val*[27]

    L'idea iniziale era accettabile$^{[+1]}$

    "The initial idea was acceptable"
  - *V-inf Vsup Agg Val*

    Vedere questo film è demoralizzante$^{[-2]}$

    "Watching this movie is demoralizing"
  - *N_0 Vsup Agg Val di V-Inf*

    La polizia sembra incapace$^{[-2]}$ *di fare indagini*

    "The police seems unable to do investigate"
  - *N_0 Vsup Agg Val a N_1*

    La giocabilità è inferiore$^{[-2]}$ *alla serie precedente*

    "The playability is worse than the preceding series"
  - *N_0 Vsup Agg Val Per N_1*

    Per me questo film è stato noioso$^{[-2]}$

    "In my opinion this movie was boring"
- Sentences with adjectives as nouns intensifiers and downtoners:
  - *N_0 Vsup Agg Int di N_1*

    Una trama piena$^{[+]}$ *di falsità*$^{[-2]}$

    "A plot filled with mendacity"

---

[27] We preferred to use in these examples the notation *Agg Val* rather than *Psych V-a* because they can refer to both adjectivalizations of psych verbs and to other SentIta evaluative adjectives.

3.3.5.2 Nominal groups with appropriate nouns *Napp*

The support verb *avere* “to have” (and its equivalent *tenere*) has been observed into a transformation (*Nb Vsup Na V-a*), in which is involved a special kind of GN subject that contains *noms appropriés* “appropriate nouns” *Napp* (Harris, 1970; Guillet and Leclère, 1981; Laporte, 1997, 2012; Meydan, 1996, 1999).
Citing (Laporte, 2012, p. 1),

> “A sequence is said to be appropriate to a given context if it has the highest plausibility of occurrence in that context, and can therefore be reduced to zero. In French, the notion of appropriateness is often connected with a metonymical restructuration of the subject.”

and (Mathieu, 1999b, p. 122),

> “*On considère comme substantif approprié tout substantif Na pour lequel, dans une position syntaxique donnée, Na de Nb = Nb.*[28]”

we can clarify that “the notion of highest plausibility of occurrence of a term in a given context” (Laporte, 2012) should not be interpreted in statistic terms or proved by searches in corpora, but just intuitively defined through the paraphrastic relation *Na di Nb = Nb*.
According to (Meydan, 1996, p. 198), “the adjectival transformations with *Napp* (n.b. *(Na di Nb)Q essere V-a* =: *Il fisico di Lea è attraente* “The body of Maria is attractive”) can be put in relation through four types of transformations”, which correspond also to the structures included into our network of sentiment FSA. The obligatoriness of the modifiers and the appropriateness of the nouns are reflected in these transformations (Laporte, 1997).

[28] “It is considered to be appropriate substantive each substantive fro which, into a given syntactic position, Na of Nb = Nb”. Author’s translation.

- a nominal construction *Vsup Napp*:

  Nb Vsup Na V-a

  Lea ha un fisico attraente "Lea has an attractive body"

- a restructured sentence in which the GN subject is exploded into two independent constituents:

  Nb essere V-a Prep Na

  Lea è attraente (per il suo + di) fisico "Lea is attractive for her body"

- a metonymic sentence in which the *Napp* is erased:

  Nb essere V-a

  Lea is attractive "Lea is attractive"

- a construction in which the *Napp* is adverbalized:

  Nb essere Na-mente V-a

  Lea è fisicamente attraente "Lea is physically attractive"

The concept of appropriate noun has a crucial importance, not only in these adjectival expressions, but also when it appears as object of psychological predicates (see Section 3.3.4), as exemplified by (Mathieu, 1999b, p. 122):

N_0 *V (Dét N de Nhum)*$_1$ = N_0 *V (Nhum)*$_1$
Les soucis rongent l'esprit de Marie = Les soucis rongent Marie
"Worries torment the spirit of Mary = Worries torment Mary"

Moreover, into the Sentiment Analysis field, where the identification and the classification of the features of the opinion object even consist in a whole subfield of research (see Section 5.2), the *Napp* becomes a very advantageous linguistic device for the automatic feature analysis. See, for example, (32), in which *Na (Napp)* is the feature and the *Nb (N-um)* is the the object of the opinion.

(32) $[_{\text{Opinion}}[_{\text{Feature}} \begin{bmatrix} La\ risoluzione \\ L'obiettivo \end{bmatrix}]\ della\ [_{\text{Object}} fotocamera]$ è $eccellente^{[+3]}]$

(32a) $[_{\text{Opinion}}[_{\text{Object}} La\ fotocamera]\ ha\ una\ [_{\text{Feature}} \begin{bmatrix} risoluzione \\ obiettivo \end{bmatrix}]\ eccellente^{[+3]}]$

(32b) $[_{\text{Opinion}}[_{\text{Object}} La\ fotocamera]$ è $eccellente^{[+3]}]$

(32c) $[_{\text{Opinion}}[_{\text{Object}} La\ fotocamera]$ è $eccellente^{[+3]}\ per\ [_{\text{Feature}} \begin{bmatrix} la\ sua\ risoluzione \\ il\ suo\ obiettivo \end{bmatrix}]]$

"(The image resolution + The lens) of the camera is excellent"
"The camera has an excellent (image resolution + lens)"
"The camera is excellent"
"The camera is excellent for its (image resolution + lens)"

A useful classification of the nouns that can play the role of *Napp* for both human and not human nouns, and that can be exploited for the opinion feature classification, is the following (Meydan, 1996).

Napp of *Num*:

Npc = body parts;

Npabs = personality trait;

Ncomport = attitudes;

Nprédr = intentions.

Napp of *N-um*:

Npo = shape;

Nprop = ability;

Dnom = model.

3.3.5.3 Verbless Structures

Predicativity is not a property necessarily possessed by a particular class of morpho-syntagmatic structures (e.g. verbs, that carry information concerning person, tense, mood, aspect); instead, it is determined by the connection between elements (Giordano and Voghera, 2008; De Mauro and Thornton, 1985).
Also on the base of their frequency in written and spoken corpora and in informal and formal speech, together with Giordano and Voghera (2008), we consider verbless expressions syntactically and semantically autonomous sentences, which can be coordinated, juxtaposed and that can introduce subordinate clauses, just like verbal sentences. Among the verbless sentences available in the Italian language, we are interested here on those involving adjectives indicating appreciation (*Agg val*), e.g. *Bella questa!* "Good one!" (Meillet, 1906; De Mauro and Thornton, 1985).
Below we report a selection of customer reviews, from the dataset described in Section 5.1.3, that can give an idea of the diffusion of the verbless constructions in user generated contents.

- Movie Reviews: [*Molto bravi gli interpreti*], [*la mia preferita la sorella combina guai*]. [*Bella la fotografia*], [*i colori*].[29]
- Car Reviews: [*Ottimo l'impianto radio cd*], [*comodissimi i comandi al volante*].[30]
- Hotel Reviews: [*Posizione fantastica*] si raggiungono a piedi molti luoghi strategici di Londra, [*molto curato nel servizio e nel soddisfare le nostre richieste*].....[*ottimo servizio in camera*].[31]
- Videogame Reviews: [*Provato una volta*] e [*subito scartato*],

[29] http://www.mymovies.it/film/2013/abouttime/pubblico/?id=680439
[30] http://auto.ciao.it/Nuova_Fiat_500__Opinione_1336287/SortOrder/1
[31] http://www.tripadvisor.it/ShowUserReviews-g186338-d651511-r120264867-Haymarket_Hotel-London_England.html

[*odioso il modo in cui viene recensito*].[32]

- Smartphone Reviews: [*Utilissimo il sistema di spegnimento e riaccensione ad orari programmati*]. [*Telefonia e sensibilità OK*].[33]
- Book Reviews: [*Azzeccatissima la descrizione, anche psicologica e introspettiva, dei personaggi*].[34]

3.3.5.4 Evaluation Verbs

In this Paragraph we mention the use of the verbs of evaluation *Vval* (Elia et al., 1981), which represent a subclass of the LG class 43, grouped together through the acceptance of at least one of the properties $N_1 =: N_1\ Agg_1$ and $N_1 =: Agg_1\ Ch\ F$. Examples are *giudicare* "to judge", *trovare* "to consider", *avvertire* "to notice", *valutare* "to evaluate", etc.
Of course the $N_1\ Agg$ here can include an *Napp*, that takes the shape of $(Na\ di\ Nb)_1\ Agg$, just as happens with the psychological predicates of Mathieu (1999b).
They present a different role attribution with respect to support verbs constructions, since the N_0 of the evaluative verbs is always an *Opinion Holder* (33).

(33) $[_{\text{Opinion}}[_{\text{Opinion Holder}} Maria\,] considera \begin{bmatrix} [_{\text{Target}} Arturo]\ affascinante^{[+2]} \\ affascinante^{[+2]}\ [_{\text{Target}} che\ Arturo\ venga] \end{bmatrix}$

"Maria considers (Arturo fascinating + enchanting that Arturo comes)"

[32]http://www.amazon.it/review/RK6CGST4C9LXI
[33]http://www.amazon.it/Alcatel-Touch-Smartphone-Dual-Italia/product-reviews/B00F621PPG?pageNumber=3
[34]http://www.amazon.it/product-reviews/B007IZ1Q5S?pageNumber=3

The N_0 of support verb construction, instead, is always the target of the opinion (34). The Opinion Holder remains here unexpressed.

(34) $[_{\text{Opinion}}[_{\text{Target}} Arturo] \begin{bmatrix} \text{è} \\ rimane \\ sembra \end{bmatrix} davvero^{[+]}\ affascinante^{[+2]}]$

"Arturo (is + remain + seems) truly fascinating"

Into causative constructions the roles are again different (35).

(35) $[_{\text{Opinion}}[_{\text{Cause}} \begin{bmatrix} Maria \\ L'acconciatura \end{bmatrix}]\ rende\ [_{\text{Target}} Arturo] davvero^{[+]}\ affascinante^{[+2]}]$

"(Maria + The hairstyle) makes Arturo truly fascinating"

3.3.6 Vulgar Lexicon

The fact that "taboo language is emotionally powerful" (Zhou, 2010, p. 8) can not be ignored during the collection of lexical and grammatical resources for Sentiment Analysis purposes.
SentIta is provided with a collection of 182 bad words that include the following grammatical and semantic subcategories:

- Nouns, 115 entries, among which
  - 30 are human nouns (e.g *rompiballe* "pain in the ass");
  - 9 are nouns of body parts (e.g *cazzo* "dick");
- Verbs, 45 entries, among which
  - 17 are pro-complementary and pronominal verbs (e.g. 4 +PRXCOMP: *fottersene*, "to give not a fuck" and 13 +PRX *incazzarsi* "to get mad");

  – 17 allow the derivation of nouns in *-bile* “ble” (e.g. *trombabile* “bangable” from *trombare* “to screw”);
  – 4 are already included in the LG class 41 (e.g. *fregare* “to matter”);

- Adjectives, 16 entries , among which 10 are from SentIta (e.g. 5 +POS *cazzuto* “die-hard” and 5 +NEG *scoglionato* “annoyed”)
- Adverbs, 4 entries (e.g. *incazzosamente* “grumpily”);
- Exclamation, 8 entries (e.g. *vaffanculo* “fuck off”).

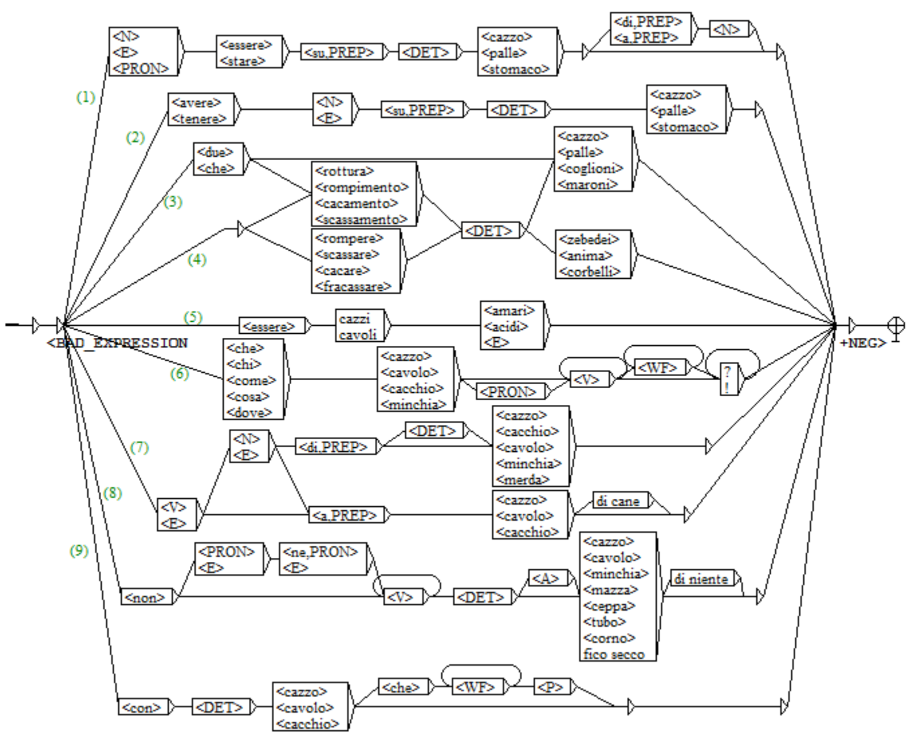

Figure 3.3: Frozen and semi-frozen expressions that involve the vulgar word *cazzo* and its euphemisms

Although some vulgar terms and expressions, e.g. with the functions of interjections or discourse markers, can be semantically empty, the great part of them have metaphorical functions that are relevant for the correct analysis of the sentiment in real texts. Examples are offense, imprecation, intensification of negation, etc...
The scatological and sexual semantic fields are among the most frequent in our lexicon. The male and female nouns derived from human body parts can have different kinds of orientations and functions, that go through the insult (*coglione* "asshole") and the praise (*figata* "cool thing").
In accord with the observations made up by Velikovich et al. (2010) in web corpora, our lexicon involves a set of racial or homophobic derogatory terms (e.g. *terrone*[35] "southern Italian", *culattone* "faggot").
The vulgar words in the SentIta database, especially the ones with an uncertain polarity, can be part of frozen or semi-frozen expressions that can make clear, for each occurrence, the actual semantic orientation of the words in context. A very typical Ialian example is *cazzo* "dick", with its more or less vulgar regional variants (e.g. *minchia*, *pirla*) and euphemisms (e.g. *cavolo* "cabbage", *cacchio* "dang", *mazza* "stick" , *tubo* "pipe", *corno* "horn", etc...). Figure 3.3 exemplifies the cases in which the context gives to the word(s) under examination a negative connotation. In detail, the FSA includes negative adverbial and adjectival functions (paths 1,2, 5, 7); exclamations (paths 3, 6, 9); interrogative forms (6) and intensification of negations (paths 8, 9). In path (4), it is also exemplified the frozen sentence from the LG class CAN ($N_0\ V\ (C_1\ di\ N)$= $\mathrm{N_0\ V\ C_1\ a\ N_2}$) that presents *cazzo* (Vietri, 2011) as C1 frozen complement. This frozen sentence, in particular, is also related to some monorematic compound nouns and adjectives included in the bad word list of Sentita.
However, a Sentiment Analysis tool, that works on user generated contents, must be aware of the fact that, in colloquial and informal situations, a word like *cazzo* can work simply as a regular intensifier, also

[35] term used with insulting purposes only by Northern Italians

for positive sentences (e.g. è così *bello*[+2] *cazzo*[+]! [+3] “it’s fucking nice!”). This is why it received in the dictionary just the tag attributed to intensifiers (+FORTE). In order to be annotated in texts with other orientations, it must occur as component of specific expressions.
As we can see in Table 3.21, although the majority of the entries in the bad words dictionary possess a negative connotation, 10% of them are positive (e.g. *strafigo* “supercool”). Moreover, the manual annotation of the whole list of bad words with sentiment tags confirmed the budding concept of the emotional power of taboo language: 84% of the vulgar lexicon is endowed with a defined semantic orientation (see Table 3.22).

Score	**Bad Words**	**Entries**
+3	+POS+FORTE	6
+2	+POS	12
+1	+POS+DEB	0
-1	+NEG+DEB	8
-2	+NEG	125
-3	+NEG+FORTE	6
+	+FORTE	3
-	+DEB	0

Table 3.21: SentIta tag distribution in the list of bad words

Bad Words	**Entries**	**Percentage (%)**
tot pos	18	10
tot neg	132	73
tot int	3	2
tot oriented	153	84
tot neutral	29	16
tot BW	182	100

Table 3.22: Bad Words percentage values in SentIta

Collateral Benefits of Exhaustive Vulgar Lexical and Grammatical Resources

The Web 2.0 offers the opportunity to Internet users to freely share almost everything in online communities, hiding their own identity behind the shelter of anonymity.
Flaming, trolling, harassment, cyberbullying, cyberstalking, cyberthreats are all terms used to refer to offensive contents on the web. The shapes can be different and the focus can be on various topics, e.g. physical appearance, ethnicity, sexuality, social acceptance, etc. (Singhal and Bansal, 2013); but they are all annoying (when not even dangerous, when the victims are children or teenagers) for the same reason: they make the online experience always unpleasant.
The detection and filtering of offensive language on the web is strongly connected to the Sentiment Analysis field, when one decide to handle it automatically. The occurrence of derogatory terms and phrases or the unjustified repetition of words with a strongly negative connotation can effectively help with this task.
Although taboo language is generally considered to be the strongest clue of harassment in the web (Xiang et al., 2012; Chen et al., 2012; Reynolds et al., 2011; Xu and Zhu, 2010; Yin et al., 2009; Mahmud et al., 2008), it must be clarified that the presence of bad words in posts does not necessarily indicate the presence of offensive behaviors.
We already explained that the words in our collection of vulgar terms, in some cases, are neutral or even positive. Profanity can be used with comical or satirical purposes, and bad words are often just the expression of strong emotions (Yin et al., 2009).
Thus, the well-known censoring approaches based only on keywords, that simply match words appearing in text messages with offensive words stored in blacklists, are clearly not meant to reach high levels of accuracy.
Consistent with this idea, in recent years many studies on offensive cyberbullying and flame detection integrated the bad words' context in their methods and tools.

Chen et al. (2012) exploited a Lexical Syntactic Feature (LSF) architecture to detect offensive content and identify potential offensive users in social media, introducing the concept of *syntactic intensifier* to adjust words' offensiveness levels based on their context.
Xiang et al. (2012) learned topic models from a dataset of tweet through Latent Dirichlet Allocation (LDA) algorithm. They combined topical and lexical features into a single compact feature space.
Xu and Zhu (2010) proposed a sentence-level semantic filtering approach that combined grammatical relations with offensive words in order to semantically remove all the offensive content from sentences.
Insulting phrases (e.g. get-a-life, get-lost, etc...) and derogatory comparisons of human beings with insulting items or animals (e.g. donkey, dog) were clues used by Mahmud et al. (2008) to locate flames and insults in text.

3.4 Towards a Lexicon of Opinionated Compounds

3.4.1 Compound Adverbs and their Polarities

Elia (1990) adapted to the Italian language the formal definition of "adverb" of1 2q Jespersen (1965), who, for the first time, included also special kinds of phrases and sentences in the category of the adverbs. In detail the structures included in this category are the following:

- traditional adverbs with a monolithic shape (e.g. *volentieri*, "gladly");
- traditional adverbs in *-mente* (e.g. *impetuosamente*, "impetuously");
- prepositional phrases (e.g. *a vanvera*, "randomly");

- phases derived from sentences with finite or non-finite verbs (e.g. *da levare il fiato*, “to take the breath away").

The first two types of adverbs will be treated separately in Section 3.5.2, due to the fact that they have been automatically derived from the SentIta adjective dictionary.
Compound adverbs, or *frozen* or *idiomatic adverbs* (the last two points of Jespersen’s list) can be defined as

> “(...) adverbs that can be separated into several words, with some or all of their words frozen, that is, semantically and/or syntactically noncompositional” (Gross, 1986, p. 2).

Therefore, just as happens in polyrematic expressions, the syntactic elements that compose such adverbs can not be freely shifted, substituted or deleted. This despite the fact that, from a syntactic point of view, they work just as simple adverbs.
Following the LG paradigm and according to their internal morphosyntactic structure, the compound adverbs have been classified in many languages; namely, English(Gross, 1986), French (Gross, 1990; Laporte and Voyatzi, 2008; Tolone and Stavroula, 2011), Italian (Elia, 1990; Elia; De Gioia, 1994a,b, 2001), Modern Greek (Voyatzi, 2006), Portuguese (Baptista, 2003), etc.
The LG description and classification of compound adverbs represents the intersection of two criteria corresponding to the phenomenon of the *multiword expressions* and to the *adverbial functions* (Tolone and Stavroula, 2011; Laporte and Voyatzi, 2008).
According to (Laporte and Voyatzi, 2008, p. 32)

> “(...) a phrase composed of several words is considered to be a multiword expression if some or all of its elements are frozen together, that is, if their combination does not obey productive rules of syntactic and semantic compositionality”.

The adverbial functions, instead, pertain to the adverbial roles, which can take the shape of circumstantial complements, or of complements which are not objects of the predicate of the clause in which they appear.
In LG descriptions compound adverbs are formalized as a sequence of parts of speech and syntactic categories. Their morpho-syntactic structures are described on the base of the number, the category and the position of the frozen and free components of the adverbials.
The Italian classification system for compound adverbs follows the same logic as the French one, with which it shares a strong similarity in terms of syntactic structures.
In this research, among the 16 classes of idiomatic adverbs selected by De Gioia (1994a,b), we worked on the ones reported in Table 3.23.
The comparative structures with *come* "like", treated by Vietri (1990, 2011), as idiomatic sentences, will be described in Section 3.4.2.
The adverbs belonging to the classes described in the first 9 rows of Table 3.23 have been manually selected and evaluated starting from the electronic dictionaries and the LG tables of Elia (1990); while the classes PF, PV and PCPN come from the LG tables of De Gioia (2001).
In the first classes, Elia (1990) recognized the following three abstract structures:

1. *Prep (E+Det) (E+Agg) C1 (E+Agg)*
   (a) PC
   (b) PDETC
   (c) PAC
   (d) PCA
2. *Prep (E+Det+Agg) C1 (E+Agg) Prep (E+Det+Agg) C2 (E+Agg)*
   (a) PCDC
   (b) PCPC

Class	**Structure**	**Example**	**Tranlation**
PC	Prep C	*contro voglia*	unwillingly
PDETC	Prep Det C	*con le cattive*	by any means necessary
PAC	Prep Agg C	*a pieni voti*	with flying colors
PCA	Prep C Agg	*a testa alta*	with your head held high
PCDC	Prep C di C	*con cognizione di causa*	with full knowledge
PCPC	Prep C Prep C	*di bene in meglio*	from good to better
PCONG	(Prep) C Cong C	*d'amore e d'accordo*	in armony
CC	C C	*niente male*	nothing bad
CPC	C Prep C	*l'ira di Dio*	a king's ransom
PF	Compound Sentence	*si salvi chi può*	every man for himself
PV	Prep V W	*seduta stante*	on the spot
PCPN	Prep C Prep N	*in onta a*	in spite of

Table 3.23: Classes of Compound Adverbs in SentIta

3. *(E+Prep) (E+Det) C1 (E+Cong+Prep) (E+Det+Agg) C2*
   (a) PCONG
   (b) CC
   (c) CPC

Table 3.24 shows the distribution of each one of the evaluation (POS/NEG), intensity (FORTE/DEB) and discourse tags[36] (SINTESI, NEGAZIONE, etc...) in every class of compound adverb.
As we can see in the two lower section of the Table 3.24, the percentage of compound adverbs that posses an orientation or that are significant for Sentiment Analysis purposes is the 51% of the total amount of compound adverbs under exam. Moreover, it must be observed that the 60% of the labels are connected to the intensity, while we have only the 30% of evaluation tags.
The presence of discourse tags seems to be marginal, but, if compared with other part of speech (or even with the *-mente* and monolithic adverbs, see Section 3.5.2), it reveals its significance.

3.4.1.1 Compound Adjectives of Sentiment

A great part of the polyrematic units with an adverbial function can also play the role of adjectives.

Adverbial function: *agire a fin di bene* “to act for good”

Adjectival function: *una bugia a fin di bene* “a white lie”

For simplicity, we did not distinguish the cases in which they posses just one function from the cases in which they can have both the roles. However, separating these two groups is often impossible,

[36]These tags annotate 70 discourse operators, able to summarize (e.g. *in parole povere* “in simple terms”), invert (e.g. *nonostante ció* “nevertheless”), confirm (e.g. *in altri termini* “in other terms”), compare (e.g. *allo stesso modo* “in the same way”) and negate (e.g. *neanche per sogno* “in your dreams”) the opinion expressed in the previous sentences of the text.

if one considers also their invariability and the fact that their function depends on semantic features rather then on morphological ones (Voghera, 2004):

AVV+AVVC+PC+PN without adjectival function:
in conclusione "in conclusion"

AVV+AVVC+PC+PN with adjectival function:
a vanvera (e.g. *parlare a vanvera* "to prattle", *un discorso a vanvera* "a prattle")

Therefore, we just did not make any distinction into the dictionaries, in order to avoid the duplication of the entries, but we recalled them also in the grammars dedicated to adjectives, as nouns modifiers and into constructions of the kind N_0 *(essere + E) Agg Val* (see Section 3.3.5).

3.4.2 Frozen Expressions of Sentiment

In this thesis oriented words are always considered in context. In this paragraph we will focus on the importance that the frozen sentences can have in a LG based module for Sentiment Analysis.
Traditional and generative grammar generally treat idioms as aberrations and many taggers and corpus linguistic tools just ignore multiword units and frozen expressions (Vietri, 2004; Silberztein, 2008).
The LG paradigm started with Gross (1982) the systematic and formal studies on frozen sentences, underling their non-exceptional nature from both the lexical and syntactic point of views. Indeed, idioms occupy in the lexicon a volume that is comparable with the one of the free forms (Gross, 1982).
This kind of approach opens plenty of possibilities in the field of Sentiment Analysis, in which the collection of lexical resources endowed with a defined polarity can not just run aground on simple words, but needs to be opened also to different kinds of oriented multiword ex-

Tag	**PC**	**CC**	**CPC**	**PAC**	**PCA**	**PCDC**	**PCONG**	**PCPC**	**PDETC**	**PF**	**PV**	**PCPN**	**Tot**
POS+FORTE	0	6	0	4	2	0	2	1	5	1	0	0	21
POS	1	5	2	9	15	10	1	0	14	0	0	0	57
POS+DEB	0	0	0	3	2	2	2	0	5	1	0	0	15
NEG+DEB	0	0	1	0	4	0	1	3	7	3	1	0	20
NEG	36	15	6	15	5	6	2	5	19	7	0	5	121
NEG+FORTE	0	0	0	1	1	1	2	2	3	1	1	0	12
FORTE	102	40	5	49	26	13	35	18	76	8	5	0	377
DEB	23	13	1	14	4	4	5	2	6	1	0	0	73
SINTESI	13	2	0	6	1	2	0	0	1	0	5	0	30
CONFERMA	5	2	0	0	0	0	0	0	5	0	0	1	13
INVERTE	4	2	0	8	0	0	0	0	7	0	1	0	22
COMP	3	0	0	1	0	0	0	0	1	0	0	0	5
NEGAZIONE	3	0	0	0	0	0	0	2	1	0	1	1	8
Tot	190	85	15	110	60	38	50	33	150	22	14	7	774
Tot Class	872	346	104	316	320	248	132	127	621	202	124	53	3,321
Percentage (%)	22	25	14	35	19	15	38	26	23	11	11	13	51
Evaluation tags (%)	19	31	60	29	48	50	20	33	35	59	14	71	32
Intensity tags (%)	66	62	40	57	50	45	80	61	55	41	36	0	58
Discourse tags (%)	15	7	0	14	2	5	0	6	10	0	50	29	10

Table 3.24: Composition of the compound adverb dictionary

pressions and frozen sentences.
According to (Vietri, 2014b, p. 32)

> (...) a verb, when co-occurring with a certain noun (or a set of nouns), produces a "special meaning" that it would not have been assigned if the noun was substituted. This type of meaning is conventionally defined "non-compositional", but this does not automatically imply, from a syntactic point of view, that idioms are "units".

On the base of this statement, strictly connected to the distributional properties of the idiomatic sentences, we included in our sentiment database more than 500 Italian frozen sentences that have been manually evaluated and then formalized with pairs of dictionary-grammar. This choice is connected to the purpose of lemmatizing them in lexical databases taking into account, through FSA, also their syntactic flexibility and lexical variation. Treating into a computational way idioms means to deal with the problems they pose in terms of relationship between "interpretation" and "syntactic constructions" (Vietri, 2014b).
The source of the work are the Lexicon-Grammar descriptions of idioms that take the shape of binary tables in which lexical entries are described on the base of syntactic and semantic properties.
The formal notation is the traditional one used in the LG framework. The symbol *C* is used in frozen sentences to indicate a fixed nominal position that can not be substituted by different items belonging to the same class or semantic field and that can not be morphogrammatically modified (Vietri, 2004).
The Lexicon-Grammar classification of Italian idioms includes more than 30 Lexicon-Grammar classes of idioms with ordinary verbs and support verbs. The most common support verbs are *avere* to "have", *essere* "to be", *fare* "to make". They differ from their ordinary counterparts because of their semantic emptiness. When they are implied in the formation of idiomatic constructions they present a very high lexical and syntactic flexibility that can take the shape of the following

phenomena (Vietri, 2014d):

- the alternation of support verbs with aspectual variants (e.g. *rimanere* “to remain”, *diventare* “to become”);
- the production of causative constructions (e.g. with verbs like *rendere* “to make”);
- the deletion of the support verb (e.g. *N0 Agg come C1*, *una donna astuta come una volpe* “a woman as sharp as a tack”).

Because of the complexity of their lexical and syntactic variability, that often affects the intensity of the idiom itself, we chose to reduce the sample of the idioms under examination for Sentiment Analysis purposes just to the frozen sentences with the support verb *essere* that include adjectives in their structure, namely PECO, CEAC, EAA, ECA and EAPC. Due to the fact that a large part of the idioms belonging to this subgroup contains adjectives evaluated in SentIta, we found interesting a comparison between the prior polarity of such adjectives involved in idioms and the polarity assigned to the idiom itself. The results of this evaluation of differences is reported in Table 3.25.

	PECO	**CEAC**	**EAA**	**ECA**	**EAPC**	**Tot**
Idioms in the LG Class	274	36	40	153	162	665
Idioms in SentIta	245	27	32	134	139	577
Adj of SentIta in Idioms	133	12	15	37	56	253

Table 3.25: Polar adjectives in frozen sentences

3.4.2.1 The Lexicon-Grammar Classes Under Examination: PECO, CEAC, EAA, ECA and EAPC

Vietri (1990) showed that the comparative frozen sentences of the type *N0 Agg come C1* (PECO) usually intensify the polarity of the adjective of sentiment they contain, as happens in (36), in which the SentIta adjective *bello*, endowed with a polarity score of +2, occurring into the idiom *Essere bello come il sole* changes its polarity in +3.

(36) Maria è *bella*$^{[+2]}$ come il sole [+3]
"Maria is as beautiful as the sun"

Actually, it is also possible for an idiom of this sort to be polarized when the adjective (e.g. *bianco*, "white") contained in it is neutral (37), or even to reverse its polarity as happens in (38) (e.g. *agile*, "agile", is positive).

(37) Maria è *bianca*$^{[0]}$ come un cadavere [-2]
"Maria is as white as a dead body" (Maria is pale)

(38) Maria è *agile*$^{[+2]}$ come una gatta di piombo [-2]
"Maria is as agile as a lead cat" (Maria is not agile)

In this regard, it is interesting to notice that the 84% of the idioms has a clear SO, while just the 36% of the adjectives they contain is polarized, see the examples in Table 3.26. This confirms the significance of a sentiment lexicon that includes also frozen expressions in its list. Indeed, a resource of this sort is able to disambiguate the cases in which the polarity of sentiment (or neutral) words is changed by the ironic nature of the idioms in which they occur (38), (39), (40).
The disambiguation rule is only one and consist in annotating always the longest match in the text analysis.

(39) Maria è *alta*$^{[0]}$ come un soldo di cacio [-2]
"Maria is knee-high to a grasshopper" (Maria is short)

(40) Maria è *asciutta*$^{[0]}$ come l'esca [-2]
"Maria is on the bones of its arse" (Maria is penniless)

Other idioms included in our resources are the ones belonging to the classes EAPC, that involve the presence of an adjective or a verb in its past participle form, a prepositional complement. These frozen expressions usually intensify the polarity of the adjective/past participle

Frozen Sentence	**Translation**	**Adj Polarity**	**Adj Score**	**Idiom Polarity**	**Idiom Score**
essere agile come una gatta di piombo	"to be as agile as a lead cat"	POS	+2	NEG	-2
essere agile come una gazzella	"to be as agile as a lead gazelle"	POS	+2	POS	+2
essere agile come uno scoiattolo	"to be as agile as a squirrel"	POS	+2	POS	+2
essere astuto come il demonio	"to be as clever as the devil"	-	0	POS	+2
essere astuto come una volpe	"to be as sharp as a tack"	-	0	POS	+2
essere astuto come uno zingaro	"to be as cunning as a gypsy"	-	0	NEG	-2

Table 3.26: Examples of idioms that maintain, switch or shift the prior polarity of the adjectives they contain

(see example below), but, just as the PECO ones, they can also switch it or shift it.

(41) Maria è *matta*[-2] da legare [-3]
"Maria is so crazy she should be locked up"

The LG class EAA, with definitional structure *N0 essere Agg e Agg* includes two adjectives that can be polarized or not. Example (42) shows that, in this case as well, the sentence polarity can be also opposite with respect to the adjectives ones.

(42) Maria è *bella*[+2] e *fritta*[0] [-2]
"Maria is cooked"

An example from the class CEACis reported in (43).

(43) L'anima è *nera*[0] come il carbone [-3]
"The soul is black like the coal"

Among the transformation that these idioms can have, we included *N0 avere C Agg* (44), that corresponds also to the most frequent one.

(44) Maria ha l'anima *nera*[0] come il carbone [-3]
"Maria has a black soul like the coal"

In the end we formalized the LG class ECA that accounts in its frozen elements the nominal element C1 and the Adjective.

(45) Maria è una gatta *morta*[0] [-2]
"Maria is a cock tease"

3.4.2.2 The Formalization of Sentiment Frozen Expressions

Due to their syntactic and lexical variation and to discontinuity, frozen expressions need to be formalized in an electronic context able to systematically list them in electronic databases and to take into account their syntactic variability. Basically, the final purpose is to take advantage of the large number of information listed into the LG matrices

while recognizing and annotating idioms in real texts.
One of the best solution is to link dictionaries, which contain the lists of Atomic Linguist Units and their syntactic and semantic properties, with syntactic grammars, which can make such words and properties interact into a FSA context (Silberztein, 2008). ALU are "the smallest elements that make up the sentence, i.e. the non-analyzable units of the language" (Silberztein, 2003). They can take the shape of simple words, affixes, multiword expressions and frozen expressions.
What makes different frozen expressions and the other ALU is discontinuity; as displayed in Figure 3.4, in fact, it is possible for adverbs to occur between the verb and the direct object (Vietri, 2004). That is why frozen sentences need both dictionaries and FSA to be recognized and annotated in a correct way: the dictionaries allow the recognition of idioms thanks to the *characteristic components* (word forms or sequences that occur every time the expressions occur and originate the recognition of the frozen expressions in texts (Silberztein, 2008)) and FSA let the machine compute them, despite of the many different forms that in real texts they can assume.
Figure 3.4 represents a simplified version the main graph of the FSA for the recognition and the sentiment annotation of idioms of the LG class PECO. It includes a metanode that allows the recognition of a nominal group in subject position (N0), an embedded graph for the verb and six nodes related to different Semantic Orientations.
The instruction XREF is used to exclude the linguistic material that can occur between the support verb and the idiom object when the annotation is performed. Figure 3.5 shows, as an example, the content of the metanode that annotates frozen expressions with +3 as Semantic Orientation (*MOLTOPOS*). Here we observe the interactions between the idiom dictionary and the restrictions reported in the syntactic grammar. In its structure, the grammar under examination looks exactly the same as the grammar for the identification of free sentences with the same syntactic shape. The difference are the syntactic and distributional constraints that, in the grammar, recall only the

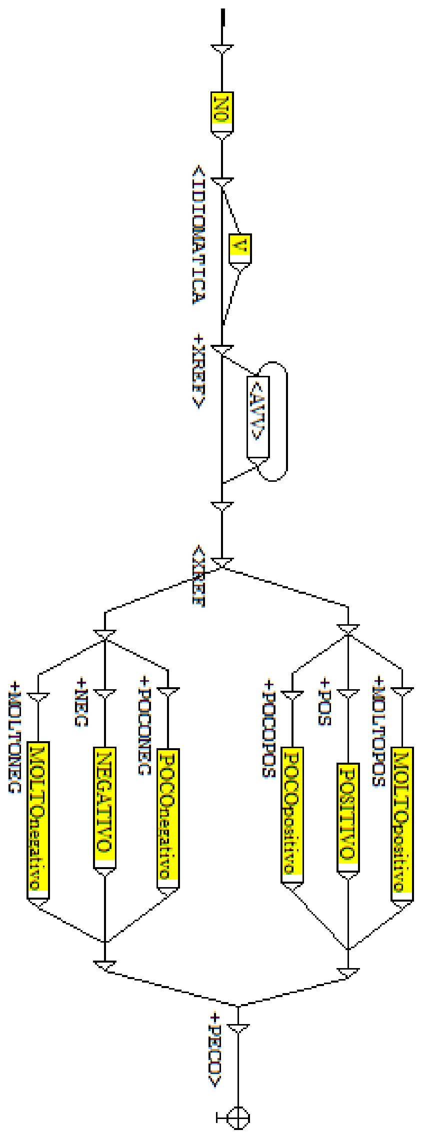

Figure 3.4: Extract of the FSA for the SO identification of idioms

properties and the lexical items associated, in the dictionary, with a specific characteristic component. To be more precise, the PECO dictionary, among others, lists the three entries shown below, which have been labeled with the semantic tags POS and FORTE (+3), as happens in the other subsets of SentIta.

Essere (forte+coraggioso) come un leone, "To be (strong+brave) like a lion"

```
leone,N+Class=PECO
+A=coraggioso+A=forte+AVV=come+AVV=quanto+DET=un
+Sent=POS+Int=FORTE
+N0um
+Vsup=essere+Vsup=diventare+Vsup=restare+Vsup=rimanere
+Vcaus=rendere
+N0essereunC1+N0esserecomeC1+N0esserepiu
```

Essere buono come il pane, "To be as good as bread"

```
pane,N+Class=PECO
+A=buono+AVV=come+AVV=quanto+DET=il+PREP=di
+Sent=POS+Int=FORTE
+N0um
+Vsup=essere+Vsup=diventare+Vsup=restare+Vsup=rimanere
+Vcaus=rendere
+N0esserediC1+N0esserecomeC1+N0esserepiu
```

Essere (astuto+furbo) come il demonio, "To be as clever as the devil"

```
demonio,N+Class=PECO
+A=astuto+A=furbo+AVV=come+AVV=quanto+DET=il
+Sent=POS+Int=FORTE
+N0um
+Vsup=essere+Vsup=diventare+Vsup=restare+Vsup=rimanere
+Vcaus=rendere
+N0esserepiu
```

As shown below, the characteristic components C (e.g. *leone* "lion", *pane* "bread", *demonio* "devil") have been used as Nooj entry in the electronic dictionary and have been associated to the other components of the frozen expressions (e.g. +A, +AVV, +DET). Moreover they have been described also with other information referring to the following properties, borrowed from the already cited LG tables:

distributional
 e.g. `+N0um; +Vsup; +Vcaus;`

transformational
 e.g. `+N0essereunC1, +N0esserecomeC1, +N0esserediC1, +N0esserepiu.`

All these properties are recalled in the idiom syntactic grammar in form of lexical and grammatical constraint.
The restrictions *+N0um* and *+Vsup; +Vcaus* are respectively meant for the distributional properties of sentence subject, that can or can not be a human, and of the support verb *essere* with its aspectual (*Vsup*) or causative (*Vcaus*) variants. While the support verbs *restare* and *rimanere* are always acceptable, *diventare* and *rendere* are not acceptable only in few cases (Vietri, 1990).
We chose to formalize the distributional restrictions in the syntactic grammars with the following instruction written under each involved node and into a related variable (*var*):

```
<$var=:$C$var>
```

It represents a constraint for the words that are allowed to appear into the nodes it restricts, which can be only the ones indicated in the dictionary by the same variable *var* for the entry *C*. As an example, the idiom *Essere (forte+coraggioso) come un leone*, that in the dictionary has as values for the variable *+A* only the adjectives *forte* "strong" and *coraggioso* "brave", can not accept in the grammar into the variable *A* other adjectives than the ones written above, if the variable goes with the restriction shown below.

```
<$A=:$C$A>
```

The same happens with the verb aspectual and causative variants (Vietri, 1990) with similar restrictions.

```
<$Vvar=:$C$Vvar>
<$Vcaus=:$C$Vcaus>
```

The symbols “=:” is used in Figure 3.5 when the inflection of the word in the variable is permitted (e.g. for the adjective, *essere furbi come il demonio*). Otherwise it is used the symbol “=”.
We preferred to treat transformational properties, instead, differently from Vietri (1990). In order to reduce the dimension of the grammar, that contains here also the polarity and intensity information, we wrote transformational constraints before the path starts in the following form:

```
<$C$var>
```

This instructs the FSA that the specific path is allowed just for the idioms that present in the dictionary the variable *var* for the entry *C*.
In the FSA in Figure 3.5 the PECO standard structure *Essere Agg come C1* is recognized by the path (2). The path (1) deletes the adjective if the idiom recognized by C possesses the specific transformational rule *+N0esserecomeC1*. Below are reported examples of idioms that satisfy this constraint. The ones preceded by the asterisk do not satisfy the restrictions.

essere come un leone “to be like a lion”
essere come il pane “to be like the bread”
**essere come il demonio* “to be like the devil”

In the path (3), the grammar performs the deletion of both the adjective and the adverb *come* for the idioms endowed with the property *+N0essereunC1* in the electronic dictionary.

essere un leone (di uomo) “to be a lion (man)”
**essere un pane* “to be a bread’
**essere un demonio (di uomo)* “to be a devil (man)”

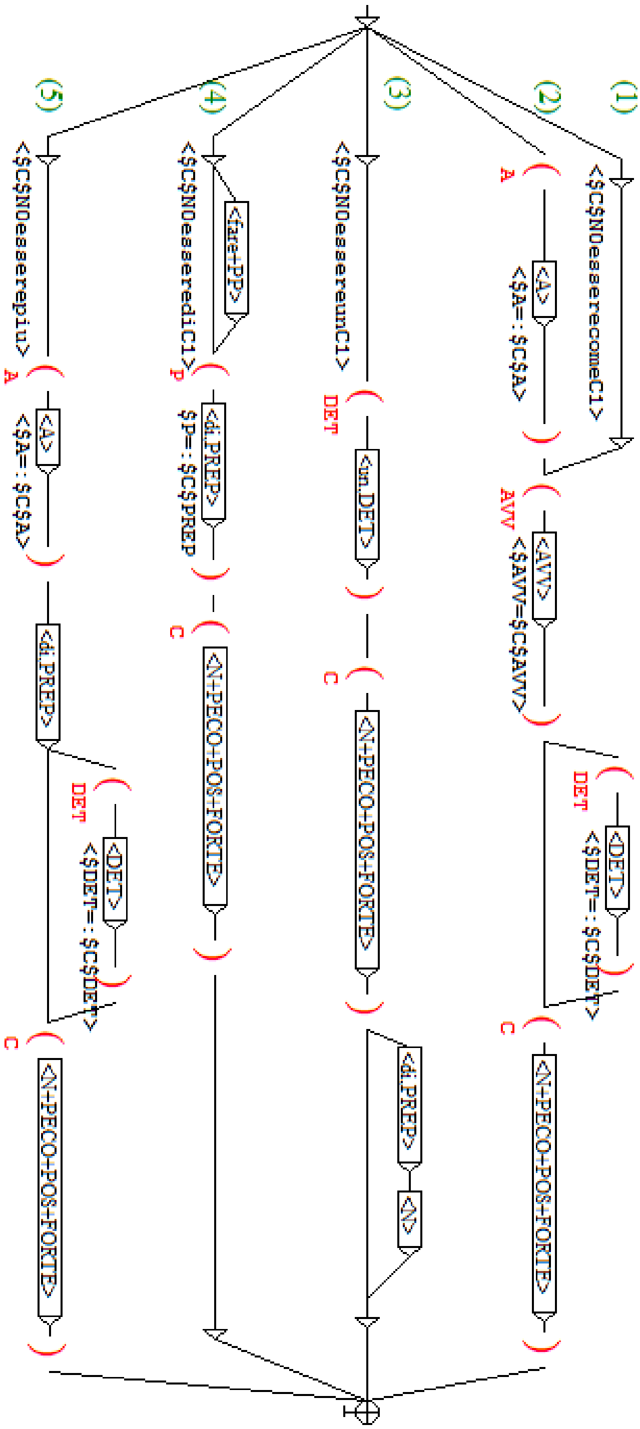

Figure 3.5: Extract of the FSA for the extraction of PECO idioms

Differently from **essere un pane*, that is not acceptable at all, **essere come il demonio* and **essere un demonio (di uomo)* are acceptable sentences that change the polarity of the basic idiom, probably because they are related with another comparative sentence with opposite meaning and orientation, e.g. *essere (brutto + cattivo) come il demonio* "to be (ugly + evil) like the devil" (Vietri, 1990).
The last two paths respectively refer to the correlation of PECO with other sentence structures such as *N0 essere di C1* (4), indicated by the property *+N0esserediC1*, and *N0 essere più Agg di C*, summarized in *+N0esserepiu* in the dictionary and in the path (5).

essere (fatto + E) di pane "to be made of bread"
**essere (fatto + E) di leone* "*to be made of lion"
**essere (fatto + E) di demonio* "*to be made of devil"

essere più (forte + coraggioso) di un leone "to be (stronger + braver) than a lion"
essere più buono del pane "to be better that the bread"
essere più (astuto + furbo) del demonio "to be cleverer that the devil"

While just the first idiom is allowed to walk through the path (4), the path (5) implies a property accepted by all the exemplified idioms.

3.5 The Automatic Expansion of SentIta

The present Section discusses the automatic enlargement of the manually built electronic dictionaries of SentIta.
Our work took advantage of derivation linguistic clues that put in relation semantically oriented adjectives with quality nouns and with adverbs in *-mente*. The purpose is making new words automatically derive the semantic information associated to the adjectives with which they are morpho-phonologically related.
Furthermore, we used as morphological Contextual Valence Shifters (mCVS) a list of prefixes able to negate or to intensify/downtone the

orientation of the words with which they occur.
We clarify in advance that the morphological method could have been applied also to Italian verbs, but we chose to avoid this solution because of the complexity of their argument structures. We decided, instead, to manually evaluate all the verbs described in the Italian Lexicon-Grammar binary tables, so we could preserve the different lexical, syntactic and transformational rules connected to each one of them.

3.5.1 Literature Survey on Sentiment Lexicon Propagation

The works on sentiment lexicon propagation follow three main research lines. The first one is grounded on the richness of the already existent thesauri, WordNet (Miller, 1995), among others. Although WordNet does not include semantic orientation information for its lemmas; semantic relations, such as synonymy or antonymy, are commonly used in order to automatically propagate the polarity, starting from a manually annotated set of seed words. Anyway, this approach presents some drawbacks, such as the lack of scalability, the unavailability of enough resources for many languages, including Italian, and the difficulty to handle newly coined words, which are not already contained in the thesauri. Furthermore, homographs which belong to different synsets, could present a diversity of meanings and polarities (Silva et al., 2010).
The second line of research is based on the hypothesis that the words that convey the same polarity appear close in the same corpus, so the propagation can be performed on the base of co-occurrence algorithms.
In the end, the morphological approach is the one that employs morphological structures and relations for the the assignment of the prior sentiment polarities to unknown words, on the base of the manipulation of the morphological structures of known lemmas.

In the following Paragraphs we will briefly describe the most interesting contributions pertaining to the just described research areas.

3.5.1.1 Thesaurus Based Approaches

Kamps et al. (2004) investigated the graph-theoretic model of WordNet's synonymy relation and, using elementary notions from graph theory, proposed a measure for the automatic attribution of the semantic orientation to adjectives. All the words listed in WordNet have been collected and related on the base of their occurrence in the same synset.
Although current WordNet-based measures of distance or similarity usually focus on taxonomic relations, and, in general, include in their algorithms the antonymy relation; the authors preferred to use only the synonymy relation.
Hu and Liu (2004) chose to limit the lexicon construction to the adjectives occurring in sentences that contained one or more product features, due to their defined interest on product features.
In their research, in order to predict the semantic orientations of such adjectives, the authors proposed a simple and effective method, grounded on the adjective synonym and antonym sets, discovered surfing the WordNet graphs.
Kim and Hovy (2004) proposed a system, for the automatic detection of opinion holders, topics and features for each opinion, that contains two modules: one for the determination of the word sentiment and another for the sentiment sentences.
In their System Architecture, it is interesting for the task in exam the stage in which the word sentiment classifier individually calculated the polarity of all the sentiment-bearing words. Their basic approach started from a small amount of seed words, sorted by polarity into a positive and a negative list. WordNet has been used to lengthen the initial list on the base of two very intuitive insights: synonyms of polar words, which usually preserve the orientation of the original lemma,

and antonyms of polar words that reverse the orientation of the original lemmas.
Esuli and Sebastiani (2005) presented a semi-supervised learning method for the orientation identification of subjective terms, based on the classification of their glosses.
The authors started from a representative seed set, built for both the positive and negative categories and from some lexical relations defined in WordNet (e.g. synonymy, hypernymy and hyponymy for the annotation of terms with the same orientation and direct antonymy and indirect antonymy for the terms with opposite orientation). Every time in which a new term is added to the original ones, it becomes part of the training set for the learning phase, performed with a binary text classifier. All the glosses of a given term, found in a machine-readable dictionary, are collocated into a vectorial form, thanks to standard text indexing techniques.
Esuli and Sebastiani (2006b) tested the following approaches:

- a two-stage method in which a first classifier groups the terms into the Subjective or Objective categories and another classifier tags the Subjective terms as Positive or Negative;
- other two binary classifiers based on learning algorithms categorise terms belonging to the Positive/not-Positive categories and the ones fitting the Negative/not-Negative categories;
- a method that simply considers Positive, Negative, and Objective as three categories with equal status.

Argamon et al. (2009) grounded on the Appraisal Theory a method for the automatic determination of complex sentiment-related attributes (e.g. type and force). The authors applied supervised learning to Word-Net glosses. The method started from small training sets of (positive or negative) seed words and then added them new sets of terms collected in the WordNet graph, along the synonymy and antonymy relations. This way, based on the WordNet glosses, each

term can received a vectorial representations thanks to standard text indexing techniques.
Dragut et al. (2010) based their research on few basic assumptions:

- the semantic relations between words with known polarities can be used to enlarge sentimental word dictionaries;
- two words are related if they share at least a synset;
- each synset has a unique polarity;
- the deduction can be performed just on few WordNet semantic relations, e.g. hyponymy, antonymy and similarity.

Thanks to these intuitions, given a sentimental seed dictionary, they deduced approximately an additional 50% of words endowed with a specific polarity, on top of the electronic dictionary WordNet.
Hassan and Radev (2010) applied a Markov random walk model to a large word relatedness graph with the purpose of producing a polarity estimate of the subjective words.
In detail, in their network, two nodes are linked if they are semantically related. Among the sources of information used as indicators of the relatedness of words we mention WordNet.
The hypothesis of the work is the following: a random walk that starts with a given word is more likely to firstly hit a word with the same semantic orientation than words with a different orientation.
Paulo-Santos et al. (2011), with a semi-supervised approach, created a small polarity lexicon (3000+ entries, 84.86% accuracy) for the Portuguese language, having as input only a limited collection of resources: a set of ten seed words, labelled as positive or negative; a common online dictionary; a set of extraction rules and an intuitive polarity propagation algorithm.
The authors implemented their task by converting the online dictionary into a directed graph, in which nodes correspond to words and edges correspond to synonyms, antonyms or other semantic relations between words. Thus, they propagated the polarities of the known

seed set to unlabelled words, applying a graph breadth-first traversal.
In their research, Maks and Vossen (2011) explored two approaches for the annotation of polarity (positive, negative and neutral) of adjective synsets in Dutch, using WordNet as lexical resource. The first approach is based on the translation of the English SentiWordNet 1.0 (Esuli and Sebastiani, 2006b) into Dutch and the respective transfer of the lemmas' polarity values. In the second approach WordNet is used in combination with a propagation algorithm, that starts with a seed list of synsets of known sentiment and extend the polarity values through WordNet making use of its lexical relations.

3.5.1.2 Corpus Based Approaches

Baroni and Vegnaduzzo (2004) observed the co-occurrences of polar adjectives into subjective texts. The ranking of a large list of adjectives, according to a subjectivity score, has been implemented without any knowledge-intensive external resource (e.g. lexical databases, human annotation, ect...). The authors made use just of an unannotated list of adjectives and a small seeds set of manually selected subjective adjectives.
The main idea of this work is taken from the Turney (2001) work on co-occurrence statistics applied on the web as a corpus, through the Web-based Mutual Information (WMI) method. Baroni and Vegnaduzzo (2004) obtained their subjectivity scores by computing the Mutual Information of pairs of adjectives taken from each set, using frequency and co-occurrence frequency counts on the World Wide Web, collected through queries to the AltaVista search engine.
Kanayama and Nasukawa (2006b) proposed an unsupervised method of lexicon construction for the annotation of polar clauses for domain-oriented Sentiment Analysis.
They grounded their work on unannotated corpora and anchored their research on the context coherency (the tendency for equal polarities to appear successively in contexts) achieving very satisfying re-

sults in terms of Precision.
Qiu et al. (2009) proposed a double propagation method which involved different kinds of relations between both sentiment words and features (words modified by the sentiment words).
With this method it has been possible to locate specific sentiment words from relevant reviews starting from a small set of seed sentiment words. Their research emphasized the fact that in reviews sentiment words always occur in association with features.
Double propagation basically means that both sentiment words and features can be reutilized to extract new sentiment words and new features, until no more sentiment words or features can be identified to continue the process. The relations are described, above all, by Dependency Grammars and trees Tesnière (1959), which represented the base for the design of the extraction rules.
In detail, the polarity of the new words is inferred using the following rules:

- Heterogeneous rule: the same polarity of known words is assigned to the novel words.
- Homogeneous rule: the same polarity of known words is assigned to the novel words, unless contrary words occur between them.
- Intra-review rule: in the cases in which the polarity cannot be inferred by dependency cues, it is assumed that the sentiment word takes the polarity of the whole review.

Maks et al. (2012) proposed a method, for the Dutch language, that is based on the idea that the words that express different types of subjectivity are distributed differently depending on the text types; therefore, they grounded their work on the comparison between three corpora: Wikipedia, News and News comments.
In order to perform their task, they used and test two different calculations, generally employed in Keyword Extraction tasks to identify the

words significantly frequent in a corpus with respect to other corpora: the Log-likelihood Technique and the Percentage Difference Calculations (DIFF). Their research revealed the better performances of the DIFF calculation.

Wawer (2012) introduced, for the Polish language, a novel iterative technique of sentiment lexicon expansion, which involved rule mining and contrast sets discovery. The research took advantages from two different textual resources: in a first stage, a small corpus endowed with morpho-syntactic annotations (The National Corpus of Polish), to acquire candidates for emotive patterns and evaluate the vocabulary, and, then, the whole web as corpus, to perform the lexical expansion.

The key idea of this work implies the fact that, if a word appears in the same extraction patterns as the seeds, so they belong to the same semantic class.

3.5.1.3 The Morphological Approach

Hatzivassiloglou and McKeown (1997) proposed a method for the sentiment lexicon expansion based on morphological relations between adjectives. They demonstrated that adjectives related in form almost always have different semantic orientations, e.g. "adequate-inadequate", "thoughtful-thoughtless", achieving 97% accuracy.

Moilanen and Pulman (2008) proposed five methods for the assignment of the prior sentiment polarities to unknown words based on known sentiment carriers. They started from a core sentiment lexicon which contained 41,109 entries, tagged with positive (+), neutral (N), or negative (-) prior polarities and, then, they employed a classifier society of five rule-driven classifiers, every one of which adopted a specific analytical strategy:

Conversion, that estimated zero-derived paronyms by retagging the unknown words with different POS tags.

Morphological derivation, that relied on derivational and inflectional morphology and is based on the words progressive transformation into shorter paronymic aliases, by using affixes and neoclassical combining forms. Also some polarity reversal affixes (e.g. *-less* and *not-so-*) were supported.

Affix-like Polarity Markers, that computed affix-like sentiment markers (e.g. *well-built, badly-behaving*), which usually propagates its sentiment orientation across the whole word.

Syllables, that split unknown words into individual syllables with a rule-based syllable chunker and, then, computed them, in order to connect them with the words contained in the original lexicon.

Shallow Parsing, that split and POS-tagged unknown word into virtual sentences.

Ku et al. (2009) employed morphological structures and relations for the opinion analysis on Chinese words and sentences. They classified the words into eight morphological types through Support Vector Machines (SVM) and Conditional Random Fields (CRF) classifiers.
Chinese morphological formative structures consist in three major processes: compounding, affixation, and conversion. Every word is composed of one or more Chinese characters, on the base of which the word's meaning can be interpreted.
The authors demonstrated that the injection of morphological information can truly improve the performances of the word polarity detection task.
Neviarouskaya (2010) proposed the expansion of the Sentiful lexicon grounding its task on the manipulation of the morphological structure, base and affixes, of known lemmas (Plag, 2003).
The derivation process, a linguistic device for the creation of new lemmas from known ones by adding prefixes or suffixes.
The results of the application of this method are 4,000+ new derived and scored sentiment words (1,400+ adjectives, almost 500 adverbs,

1,800 nouns and almost 350 verbs).
The author distinguished four types of affixes on the base of their roles in the sentiment feature attribution.

Propagating. The sentiment features are preserved and are inherited by new derived lexical units, often belonging to different grammatical categories (e.g. *en*-, -*ous*, -*fy*). The scoring function transfers the original polarity score to the new word without any variation.

Reversing. The affixes have the effect of changing the semantic orientation of the original lexeme. (e.g. *dis*-, -*less*). The scoring function simply switches the original score of the starting lemma.

Intensifying. The sentiment features are strengthened (e.g. *over*-, *super*-). The scoring function increases the score of the new word with respect to the score of the original lemma.

Weakening. The sentiment features are decreased (e.g. *semi*-), so the score of the derive word is proportionally reduced by the scoring function.

In the the approach of Neviarouskaya (2010), if a word is not already contained in the Sentiful lexicon, the algorithm checks the presence of the missing lemma into the Wordnet database, if the word actually exists there, it is taken into account for a future inclusion into the Sentiful lexicon. Its sentiment orientation is always deduced from the features of the starting word and the affixes used to derivate it.
Neviarouskaya et al. (2011) described methods to automatically generate and score a new sentiment lexicon, SentiFul, and expand it through direct synonymy and antonymy relations, hyponymy relations, derivation, and compounding with known lexical units.
The authors distinguished four types of affixes used to derive new words depending on the role they play with regard to sentiment features: propagating, reversing, intensifying, and weakening. They elaborated the algorithm for automatic extraction of new sentiment-

related compounds from WordNet by using words from SentiFul as seeds for sentiment-carrying base components and applying the patterns of compound formations.

Wang et al. (2011) proposed a morpheme-based fine-to-coarse strategy for Chinese sentence-level sentiment classification which used pre-existing sentiment dictionaries in order to extract sentiment morphemes and calculate their polarity intensity. Such morphemes are then reused to evaluate the sentence-level semantic orientation on the base of the sentiment phrases and their relevant polarity scores. The authors preferred morphemes to words as the basic tokens for sentiment classification because they are much less numerous than words.

Wang et al. (2011) derived the semantic orientation of unknown sentiment words on the base of their component morphemes (Yuen et al., 2004; Ku et al., 2009) thanks to a specific morpheme segmentation module, which applied the Forward Maximum Matching (FMM) word segmentation technique for the decomposition of words into strings of morphemes. Their approach can manage both unknown lexical sentiments and contextual sentiments for sentence-level sentiment classification, by taking into consideration multiple granularity-level sentiments (e.g. sentiment morphemes, sentiment words and sentiment phrases) in a morpheme-based framework.

3.5.2 Deadjectival Adverbs in *-mente*

As anticipated, this Section aims to enlarge the size of SentIta on the base of the morphological relations that connect the words and their meanings. In a first stage of the work, more than 5,000 labeled adjectives have been used to predict the orientation of the adverbs with which they were morphologically related. This Section explores the rules formalized to perform the task.

Adverbs are morphologically invariable and, consequently, they do not present any inflection. Anyway, the majority of them is characterized by a complex structure that includes an adjective base and the derivational morpheme *-mente* "-ly".

[[*veloce*]^{A} *-mente*]^{AVV} "fast-ly"

[[*fragile*]^{A} *-mente*]^{AVV} "delicate-ly"

[[*rapido*]^{A} *-mente*]^{AVV} "rapid-ly"

Therefore, thanks to a morphological FSA, in SentIta, the dictionary of sentiment adverbs has been derived from the adjectives one (see Figure 3.6). All the adverbs contained in the Italian dictionary of simple words have been put in a Nooj text and the above-mentioned grammar has been used to quickly populate the new dictionary by extracting the words ending with the suffix *-mente*, "-ly" (Ricca, 2004b) and by making such words inherit the adjectives' polarity.
The Nooj annotations consisted in a list of 3,200+ adverbs that, at a later stage, has been manually checked, in order to adjust the grammar's mistakes (e.g. *vigorosamente*, "vigorously", and *pazzamente*, "madly", that respectively come from the positive adjective "vigorous" and the negative adjective "mad", as adverbs, become intensifiers) and to add the Prior Polarity to the adverbs that did not end with the suffixes used in the grammar (e.g. *volentieri*, "gladly"; *controvoglia*, "unwillingly").
The manual check produced a set of 3,600+ adverbs of sentiment, that has been completed with 126 adverbs that did not end in *-mente*.
In detail, the Precision achieved in this task is 99% and the Recall is 88%. The distribution of semantic tags in this dictionary is reported in Table 3.27. Figure 3.6 shows the local grammar in which we formalized the rules for the adverbs formation. We started the word recognition anchoring it on the localization of an adjective stem (see the first node on the left, in the variable `Agg`).
Than, the automaton continues the word analysis by checking

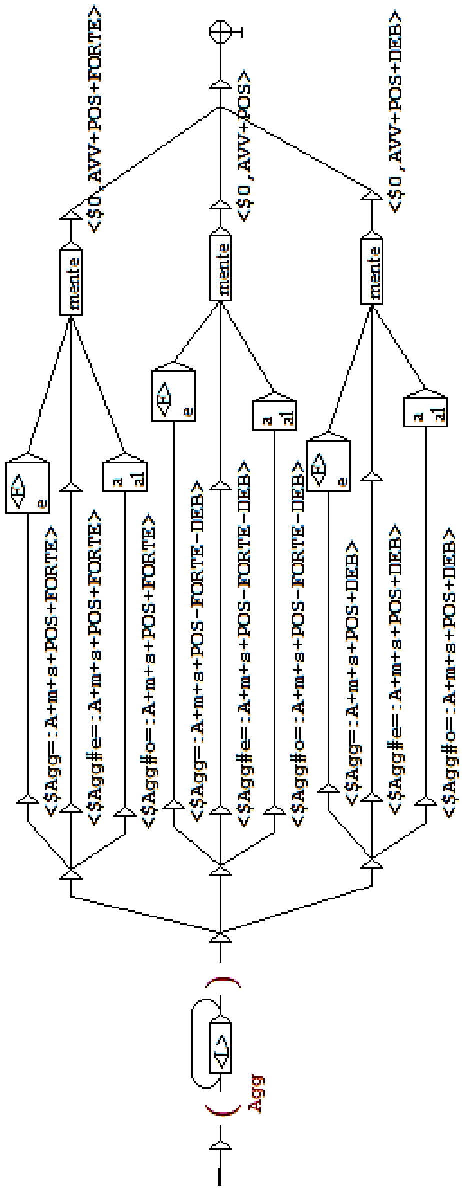

Figure 3.6: Extract of the FSA for the automatic annotation of sentiment adverbs

Tag	Automatically generated	Manually adjusted
POS+FORTE	82	89
POS	743	779
POS+DEB	61	55
NEG+DEB	436	456
NEG	1,273	1,466
NEG+FORTE	160	158
FORTE	366	482
DEB	84	163
SINTESI	0	9
CONFERMA	0	17
INVERTE	0	19
Tot	3,205	3,693
Tot Int	450	645
Tot Sent	2,755	3,003
Tot Discorso	0	42

Table 3.27: Composition of the adverb dictionary

that the adjective stem belongs to the sentiment dictionary (e.g. `$Agg=:A+POS+DEB`). Figure 3.6 represents just an extract of the bigger grammar that includes not only the positive (POS) adverbs, but also the negative ones.
Notice in the center of the FSA a multiplication of paths. This depends on the different inflectional classes of adjectives to which the suffix -*mente* is attached (Figure 3.28).
The rules used in the grammar to derive the adverbs are given in the following (see Table 3.29 and Figure 3.28):

- class 2, first path: nothing in the adjective changes (e.g. veloc-e, veloce-mente);
- class 2, second path: in the adjectives ending in *-re*, *-le* the *-e* is deleted [#e] (e.g. fragil-e, fragil-mente);
- class 1, third path: the *-o* is deleted [#o] and substituted by the

Adj Class	Number=s		Number=p	
	Gender=m	Gender=f	Gender=m	Gender=f
1	*-o*	*-a*	*-i*	*-e*
2	*-e*		*-i*	

Table 3.28: Adjective's inflectional classes Salvi and Vanelli (2004)

Adj Class	Adjective	Adverb			
		Deletion	Stem	Thematic Vowel	Suffix
1	*rapid-o*	#o	*rapid-*	*-a-*	*-mente*
2	*veloc-e*	-	*veloce-*	-	
	fragil-e	#e	*fragil-*	-	

Table 3.29: Rules for the adverb derivation

thematic vowel *-a* (e.g. rapid-o, rapid-a-mente).

Actually, in the FSA almost nothing about the inflection of the base adjectives has been specified. Because the adverbs of sentiment must be identified among the whole list of nooj adverbs and semantically annotated (and not generated from scratch), we did not find necessary to recall all the inflectional classes of the derived adjectives: just the deletion or the conservation of the final vowels was used to select the correct derivational rule.
Mistakes concerning the annotation of the adjectives regard those exceptions that were not enough productive to deserve a specific path in the local grammar. Examples are the adjectives in *-lento*: although they have the *-o* as last vowel, they do not require the thematic vowel *-a-*, but the *-e-* (e.g. *violento* becomes *violent-e-mente* rather than **violent-a-mente*).

3.5.2.1 Semantics of the *-mente* formations

The meaning of the deadjectival adverbs in *-mente* is not always predictable starting from the base adjectives from which they are derived.

Also the syntactic structures in which they occur influences their interpretation. Depending on their position in sentences, the deadjectival adverbs can be described as follows.

Adjective modifiers, they modify adjectives or other adverbs, even though two adverbs in *-mente* can appear close almost never.

- degree modifiers
  - intensifiers
    e.g. *altamente* “highly”, *enormemente* “enormously”
  - downtoners
    e.g. *moderatamente* “moderately”, *parzialmente* “partially”

Predicate modifiers, they are translatable with the paraphrase "in a A way", in which A is the adjective base.

- verb arguments
  e.g. Maria si comporta *perfettamente*
  “Maria acts perfectly”
- extranuclear elements
  e.g. Maria si reca *settimanalmente* a Milano
  “Maria goes weekly to Milan”

Sentence modifiers, they usually do not modify the sentence content, but they often give it coherence or work as discourse signals.

- evaluative adverbs, e.g. *stupidamente* “foolishly”
- modal adverbs, e.g. *necessariamente* “necessarily”
- circumstantial adverbs of time, e.g. *ultimamente* “lately”
- quantifiers over time, e.g. *frequentemente* “often”
- domain adverbs, e.g. *politicamente* “politically”

The French LG description of adverbs in *-mente* includes 3,200+ items represented in LG tables which classify the adverbs in a similar way. They refer to *sentential adverbs*, e.g. conjuncts, style disjuncts and attitude disjuncts that includes evaluative adverbs, adverbs of habit, modal adverbs, and subject oriented attitude adverbs, and *adverbs integrated into the sentence*, e.g. adverbs of subject oriented manner, adverbs of verbal manner, adverbs of quantity, adverbs of time, viewpoint adverbs, focus adverbs (Molinier and Levrier, 2000; Sagot and Fort, 2007).

3.5.2.2 The Superlative of the *-mente* Adverbs

As concern the superlative form of the adverbs in -mente, it must be underlined that they have been treated as adverbs derived from the superlative form of the adjectives. In fact, the rule for the adverb formation is selected by the inflectional paradigm of the superlative form and not by the adjective inflection. Moreover, the semantic orientation inherited by the superlative adverb is, again, the one belonging to the superlative adjective and not the one of the adjective itself. Therefore, the superlative adverbs FSA is almost the same of the one shown in Figure 1; the only difference is in the recognition of the base adjective, that is `A+SUP` rather than only `A`.

3.5.3 Deadjectival Nouns of Quality

The derivation of quality nouns (QN) from qualifier adjectives is another derivation phenomenon of which we took advantage for the automatic enlargement of SentIta. These kind of nouns allow to treat as entities the qualities expressed by the base adjectives.
A morphological FSA (Figure 3.7), following the same idea of the adverbs grammar, matches in a list of abstract nouns the stems that are

in morpho-phonological relation with our list of hand-tagged adjectives. Because the nouns, differently from the adverbs, need to have specified the inflection information, we associated to each suffix entry, in the QN suffixes electronic dictionary, the inflectional paradigm that they give to the words with which they occur (see Table 3.30).

As regards the suffixes used to form the quality nouns (Rainer, 2004), it must be said that they generally make the new words simply inherit the orientation of the derived adjectives. Exceptions are *-edine* and *-eria* that almost always shift the polarity of the quality nouns into the weakly negative one (-1), e.g. *faciloneria* “slapdash attitude". Also the suffix *-mento* differs from the others, in so far it belongs to the derivational phenomenon of the deverbal nouns of action (Gaeta, 2004). It has been possible to use it into our grammar for the deadjectival noun derivation by using the past participles of the verbs listed in the adjective dictionary of sentiment (e.g. V:*sfinire* “to wear out", A:*sfinito* “worn out", N:*sfinimento*; “weariness"). Basically, we chose to include it in our list of suffixes because of its productivity. This caused an overlap of 475 nouns derived by both the psychological predicates and the qualifier adjectives of sentiment. Just 185 psych nominalizations exceeded the coverage of our mophological FSA, proving the power of our methodology also in terms of Recall.

In about half the cases the annotations differed just in terms of intensity, the other mistakes affected the orientation also (see Table 3.33).
In general, the Precision achieved in this task is 93%, while the Precision performances of the automatic tagging of the QN compared with the manual tagging made on the corresponding nominalizations of the psych verbs is summarized in Table 3.34.

Tables 3.31 and 3.32 show the differences in productivity of all the suffixes (SFX) among the electronic dictionary of abstract nouns (*Abstr*); the sublists of QN that have their counterparts in the Psy V-n list (*Psy V-n=QN*) and the whole collection of QN (*QN tot*).
As regards the suffixes productivity *Abstr*, the suffixes that achieved the higher percentage values are *-ità*, *-ia* and *-(zione)*. The most pro-

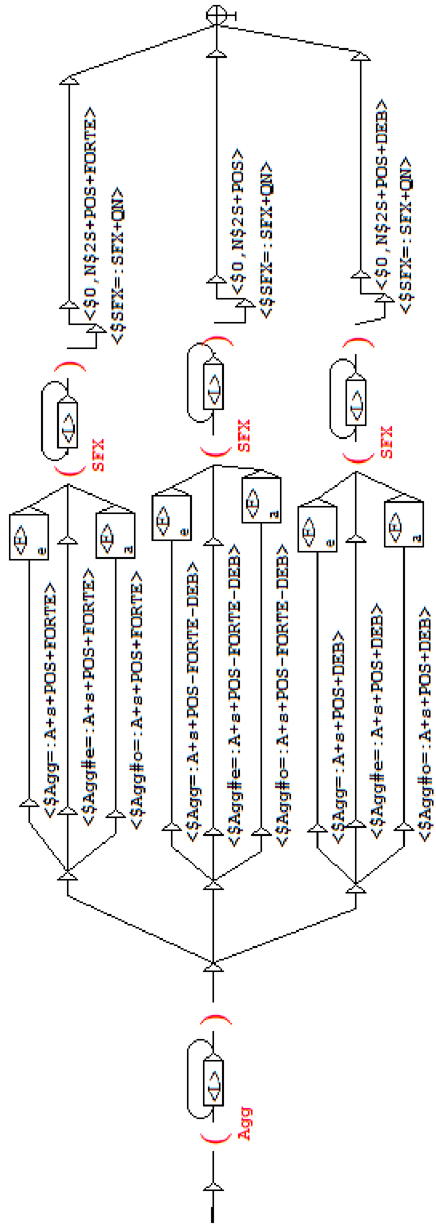

Figure 3.7: Extract of the FSA for the automatic annotation of quality nouns

Suffix (SFX)	**Inflectional paradigm (FLX)**	**Correct matches**	**Errors**	**Precision (%)**
-edin-e	N46	0	0	-
-età	N602	0	0	-
-izie	N602	0	0	-
-el-a	N41	0	1	0
-udine	N46	5	2	71.43
-or-e	N5	36	9	80
-zion-e	N46	359	59	85.89
-anz-a	N41	57	9	86.36
-itudin-e	N46	13	2	86.67
-ur-a	N41	142	20	87.65
-ment-o	N5	514	58	89.86
-izi-a	N41	14	1	93.33
-enz-a	N41	148	10	93.67
-eri-a	N41	71	4	94.67
-ietà	N602	27	1	96.43
-aggin-e	N46	72	2	97.3
-i-a	N41	145	3	97.97
-ità	N602	666	13	98.09
-ezz-a	N41	305	2	99.35
-igi-a	N41	3	0	100
-z-a	N41	2	0	100
tot	-	2,579	196	92.94

Table 3.30: Error analysis of the automatic QN annotation

Suffix (SFX)	**Suffix in Abstr**	**Suffix in Psy V-n=QN**	**Suffix in QN**
-ezz-a	498	73	305
-aggin-e	149	13	72
-itudin-e	31	1	13
-ietà	65	2	27
-igi-a	9	0	3
-izi-a	40	2	14
-enz-a	461	11	148
-anz-a	189	7	57
-eri-a	267	13	71
-ità	3,263	53	666
-or-e	297	6	36
-zion-e	2,866	87	359
-ur-a	1,700	11	142
-udin-e	39	3	5
-i-a	3,545	13	145
-el-a	15	0	0
-edin-e	4	0	0
-età	66	0	0
-izie	3	0	0
-z-a	30	2	2
-ment-o	2,520	150	514

Table 3.31: Presence of the QN suffixes in different dictionaries

Suffix (SFX)	**Suffix in Abstr**	**Suffix in Psy V-n=QN**	**Suffix in QN**
-ezz-a	3.1	16.33	6.28
-aggin-e	0.93	2.91	1.48
-itudin-e	0.19	0.22	0.27
-ietà	0.4	0.45	0.56
-igi-a	0.06	0	0.06
-izi-a	0.25	0.45	0.29
-enz-a	2.87	2.46	3.05
-anz-a	1.18	1.57	1.17
-eri-a	1.66	2.91	1.46
-ità	20.32	11.86	13.72
-or-e	1.85	1.34	0.74
-zion-e	17.85	19.46	7.4
-ur-a	10.59	2.46	2.93
-udin-e	0.24	0.67	0.1
-i-a	22.08	2.91	2.99
-el-a	0.09	0	0
-edin-e	0.02	0	0
-età	0.41	0	0
-izie	0.02	0	0
-z-a	0.19	0.45	0.04
-ment-o	15.69	33.56	10.59

Table 3.32: Productivity of the QN suffixes in different dictionaries

Correspondences	Differences	Different Orientation	Only Different Intensity
475	185	93	92

Table 3.33: About the overlap among Psych V-n dictionary and QN dictionary

	Precision	**Precision Orientation only**
QN<>Psy V-n	0.92	-
QN= Psy V-n	0.61	0.80

Table 3.34: Precision measure about the overlap of QN and Psy V-n

ductive suffixes for the *Psy V-n=QN* formation are *-(z)ione, -mento* and *-ezza,* while the ones most productive for the *QN tot* are *-ità, -(z)ione, -mento.*

3.5.4 Morphological Semantics

Our morphological FSA can, moreover, interact with a list of prefixes able to negate (e.g. *anti-*, *contra-*, *non-*, ect...) or to intensify/downtone (e.g. *arci-*, *semi-*, ect...) the orientation of the words in which they appear (Iacobini, 2004).
If the suffixes for the creation of quality nouns can interact with the preexisting dictionaries of the Italian module of Nooj, in order to automatically tag them with new semantic descriptions; the prefixes treated in this Section directly work on opinionated documents, so the machine can understand the actual orientation of the words occurring in real texts, also when their morphological context shifts

the polarity of the words listed in the dictionaries.
The collection of the suffixes that, from now on, we will call *Morphological Contextual Valence Shifters* (mCVS), is reported in Tables 3.35 and 3.36.

Prefixes	**Negation types**
non-	CDD
mis-	CR
a-	CR+PRV
dis-	CR+PRV
in-	CR+PRV
s-	CR+PRV
anti-	OPP
contra-	OPP
contro-	OPP
de-	PRV
di-	PRV
es-	PRV

Table 3.35: Negation suffixes.

They are endowed with special tags that specify the way in which they alter the meaning of the sentiment words with which they occur:

- FORTE: "strong", intensifies the Semantic Orientation of the words, making their polarity increase of one position in the evaluation scale (first path in Figure 3.8).
- DEB: "weak", downtones the Semantic Orientation of the words, making their polarity decrease of one position in the evaluation scale (second path in Figure 3.8).
- NEGAZIONE: "negation", works following the same rules of the negation formalised in the syntactic grammars (third path in Figure 3.8);
  - CR: "contrary"

Intensifiers	**Downtoners**
iper-	*bis-*
macro-	*fra-*
maxi-	*infra-*
mega-	*intra-*
multi-	*ipo-*
oltre-	*micro-*
pluri-	*mini-*
poli-	*para-*
sopra-	*semi-*
sovra-	*sotto-*
stra-	*sub-*
super-	-
sur-	-
ultra-	-

Table 3.36: Intensifier/downtoner suffixes

- OPP: “opposition”
- PRV: “deprivation”
- CDD: “contradiction”

Figure 3.8 shows the morphological FSA that combines the polarity and intensity of the adjectives of sentiment with the meaning carried on by the mCVS.
The shifting rules, in terms of polarity score, which are the same exploited in the syntactic grammar net (see Section 4), are summarized in this grammar, through the green comments on the right side of the automaton.
As regards the manipulation of the annotations of the resulting words we followed three parallel solutions:

- when the score doesn't change (e.g. the case of the intensification of words with starting polarity +3, or the case in which words with polarity -1 are decreased): the resulting word simply inherits the inflectional (*$2F*) and syntactic and semantic (*$2S*) information

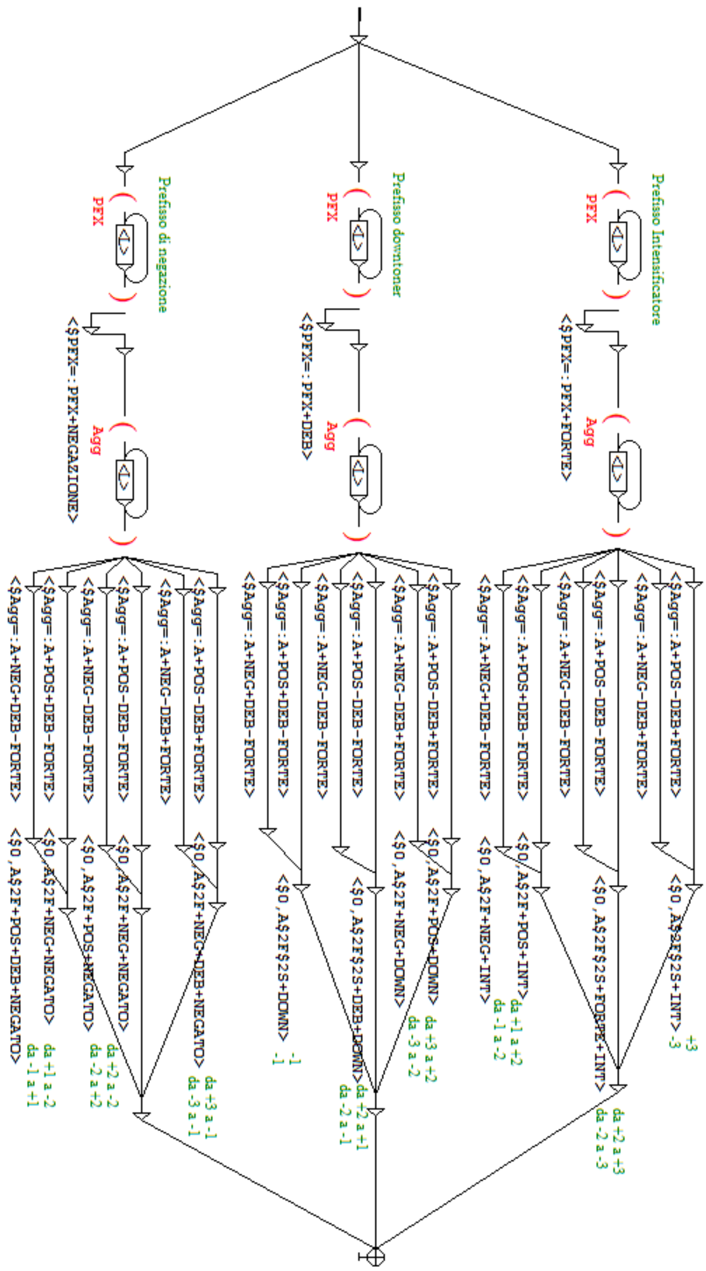

Figure 3.8: Morphological Contextual Valence Shifting of Adjectives

of the original word;

- when the intensity changes and the polarity remains steady (e.g. when the words with polarity +-2 are intensified or downtoned): the resulting word inherits the inflectional and syntactic and semantic information of the original word, but also obtain the tags FORTE/DEB;
- when both the intensity and the polarity change (in almost every case in which the words are negated): the resulting word just inherits the inflectional information, while the semantic tags are added from scratch.

We used the list of the sentiment adjectives as Nooj text in order to check the performances of our grammar. The discovery that the words containing the mCVS lemmatised in the dictionary are very few (just 29 adjectives, e.g. *straricco*, "very rich", *ultraresistente*, "heavy duty", *stramaledetto*, "damned", and 9 adverbs,e.g. *strabene*, "very well", *ultrapiattamente*, "very dully"), increases the importance of a FTA like the one described in this Paragraph.
It is also important to underline that all the synonyms of *poco* "few", also the ones that take the shape of morphemes, e.g. *ipo-*, *sotto-*, *sub-* do not seem be proper downtoners, but resemble the behaviour of the negation words that transform the sentiment words with which they occur into weakly negative ones, see Section 4.2 (e.g., *ipodotato*, "subnormal" *ipofunzionante*, "hypofunctioning"). Therefore, we excluded them from the dictionary of mCVS and we included it into a dedicated metanode of the morphological FSA, able to correctly compute its meaning.

Chapter 4

Shifting Lexical Valences through FSA

4.1 Contextual Valence Shifters

In Section 3.3.1 we provided the definitions of *Semantic Orientation*, the measure of the polarity and intensity of an opinion (Taboada et al., 2011; Liu, 2010), and of *Prior Polarity*, the individual words contex-independent orientation (Osgood, 1952). While the second concept is relevant during the population of sentiment dictionaries, the first one refers to the final semantic annotation that can be automatically or manually attributed to whole sentences and documents.
The need to make a distinction between these two measures is due to the semantic modifications that can come from the words surrounding contexts (Pang and Lee, 2008a). *Contextual Valence Shifters* are linguistic devices able to change the prior polarity of words when co-occurring in the same context (Kennedy and Inkpen, 2006; Polanyi and Zaenen, 2006).
From a computational point of view, Contextual Valence Shifting

is nothing more than an enhanced version of the term-counting method, firstly proposed by Turney (2002); but, from the distributional analysis perspective, it issues a number of challenges that deserve to be examined (Neviarouskaya et al., 2009a).
In this work we handle the contextual shifting by generalizing all the polar words that posses the same prior polarity. A network of local grammars as been designed on a set of rules that compute the words individual polarity scores, according to the contexts in which they occur.
In general, the sentence annotation is performed using six different metanodes, that, working as containers for the sentiment expressions, assign equal labels to the patterns embedded in the same graphs.
We used the FSA editor of Nooj to formalize our CVS rules, for their ease of use and their computational power; but nothing prevents the use of other strategies and tools for their application to texts. Consequently, in this chapter we will limit the discussion to the shifting rules, without any further mentions of their actual formalization, which, in a banal way, can be summarized into the treatment of embedded graphs as score boxes.

4.2 Polarity Intensification and Downtoning

4.2.1 Related Works

Amplifiers and *downtoners* (Quirk et al., 1985), *intensifiers* and *diminishers* (Polanyi and Zaenen, 2006), *overstatements* and *understatements* (Kennedy and Inkpen, 2006), *intensifiers* and *downtoners* (Taboada et al., 2011), are all couples of concepts that refer to the increasing or decreasing effects of special kinds of words on oriented lexical items.
Although the changes of the polarity scores are very intuitive, the simple addition and subtraction of a score to/from the base valence of a

term (Polanyi and Zaenen, 2006; Kennedy and Inkpen, 2006) has been criticized by Taboada et al. (2011), which instead associated different percentage values (positive for intensifiers and negative for downtoners) to each strength word.
Differently from both of these works, we decided to restrain the complexity of the rules by avoiding the distinction of degrees. In compensation, we did not limit the intensive function only to degree adverbs and adjectives, but we took under consideration also verbs and nouns.

4.2.2 Intensification and Downtoning in SentIta

The lexical items for the computational treatment of intensification in SentIta are the ones denoted by the tags FORTE and DEB.
As stated in the previous Chapter, Section 3.3, the lexical items endowed with these labels do not possess any orientation, but can modify the intensity of semantically oriented words.
The strength indicators included in the intensification FSA, that account for (but are not limited to) such modifiers, are the following:

- Morphological Rules:
  - the use of the absolute superlative suffixes *-issim-o* and *-errim-o*, that always increase the words' semantic orientations;
  - the use of intensifying or downtoning prefixes (e.g. *super-*, *stra-*, *semi-*, *micro-*), shown in Section 3.5.4.
- Syntactic Rules:
  - the repetition of more than one negative or positive words (that always increases the words' semantic orientations), e.g. *bello*[+2] *bello*[+2] *bello*[+2]*!* [+3] "nice nice nice");
  - the co-occurrence of words belonging to the strength scale (tags FORTE/DEB) with the sentiment words listed in the

evaluation scale (tags POS/NEG).

As generally assumed in literature, the adverbs intensify or attenuate adjectives (46), verbs (48) and other adverbs (49), while the adjectives modify the intensity of nouns (47). We adopted the simplest strategy for the polarity modification, the addition/subtraction of one point into the evaluation scale (Polanyi and Zaenen, 2006; Kennedy and Inkpen, 2006). Because this scale does not exceed the +/–3, words that starts from this polarity can not be increased beyond (e.g. *davvero*[+] *eccezionale*[+3] [+3] “truly exceptional”).

(46) *Parzialmente*[-] *deludente*[-2] anche il reparto degli attori [-1]
“Partially unsatisfying also the actor staff"

(47) Ciò che ne deriva (...) è una *terribile*[-2] *confusione*[-2] narrativa. [-3]
“What comes from it is a terrible narrative chaos"

(48) Alla guida *ci si diverte*[+2] *molto*[+] [+3]
“In the driver’s seat you have a lot of fun"

(49) Ne sono rimasta *molto*[+] *favorevolmente*[+2] colpita [+3]
“I have been very favourably affected of it"

Anyway, as already discussed in Section 3.3.4, also special subsets of verbs possess the power of intensifying or downtoning the polarity of the nominal groups or complement clauses they, case by case, affect in subject (50) or object (51) position (see Figure 3.1, Section 3.3.4).

(50) L’*amore*[+2] *travolge*[+] Maria [+3]
“The love overwhelms Maria”

(51) Le tue parole *invadono*[+] Maria di *contentezza*[+2] [+3]
“Your words overwhelm Mary with happiness”

Examples of intensifying/downtoning verbs, with the LG classes they belong, are reported below:

- the list of entries translated from the French work of Balibar-Mrabti (1995), e.g. *travolgere*[+] “to overwhelm”, *risplendere*[+] “to shine”;
- verbs from LG class 24 (15 intense, 2 weak), e.g. *aumentare*[+] “to increase”, *gonfiare*[+] “to amplify”, *calare*[–] “to go down”, *diminuire*[–] “to decrease”;
- verbs from LG class 41 (45 intense, 19 weak), e.g. *rivoluzionare*[+] “to revolutionize”, *sconquassare*[+] “to smash”, *moderare*[–] “to moderate”, *placare*[–] “to appease”;
- verbs from LG class 47 (43 intense, 18 weak), e.g. *strillare*[+] “to shout”, *sventolare*[+] “to show off”, *mormorare*[–] “to murmur”, *sussurrare*[–] “to whisper”;
- verbs from LG class 50 (4 intense, 0 weak), e.g. *assicurare*[+] “to assure”, *garantire*[–] “to guarantee”;
- verbs from LG class 56 (5 intense, 3 weak), e.g. *abbandonarsi*[+] “to abandon yourself”, *affrettarsi*[+] “to rush”, *accennare*[–] “to touch upon”, *esitare*[–] “to hesitate”.

As regards intensifying or downtoning nouns, we refer to the ones automatically derived from degree adjectives (220 intense, 95 weak), e.g. *sfrenatezza*[+] “wildness”, *abbondanza*[+] “abundance”, *labilità*[–] “evanescence”, *fugacità*[–] “fugacity”, and to the nominalizations of intensifying or downtoning verbs (41 intense, 95 weak), e.g. *rafforzamento*[+] “strengthening”, *fervore*[+] “fervor”, *affievolimento*[–] “weakening ”, *diminuzione*[–] “decrease”.
They can modify both other nouns (52) and verbs (53).

(52) La *sfrenatezza*[+] dell’*odio*[-3] di Maria [-3]
“The wildness of the Mary’s hate”

(53) Luca *difendeva*[+2] Maria con *fervore*[+] [+3]
“Luca was defending Maria with fervour”

Intensification, negation, modality and comparison can appear together in the same sentence. We will describe these eventuality in the further paragraphs.

4.2.3 Excess Quantifiers

Words that, at first glance, seem to be intensifiers but at a deeper analysis reveal a more complex behavior are *abbastanza* “enough” *troppo* “too much" and *poco* “not much". Because of their particular influence on polar words, their meaning, especially when associated to polar adjectives, have been associated in literature to other contextual valence shifters.[1] Examples are (Meier, 2003, p. 69) that proposed an interpretation that includes a *comparison* between extents,

> “*Enough*, *too*, and *so* are quantifiers that relate an extent predicate and the incomplete conditional (expressed by the sentential complement) and are interpreted as comparisons between two extents.
> The first extent is the maximal extent that satisfies the extent predicate. The second extent is the minimal or maximal extent of a set of extents that satisfy the (hidden) conditional, where the sentential complement supplies the consequent and the main clause the antecedent. [...] Intuitively, the value an object has on a scale associated with the meaning of the adjective or adverb I related to some standard of comparison that is determined by the sentential complement”. (Meier, 2003, p. 69)

(Schwarzschild, 2008, p. 316) that noticed the possibility of an *implicit negation*,

[1] When quantifiers like the ones under examination modify polar words, they compare such words with a threshold value that is defined by an infinitive clause in position N_1 (e.g. *The food is too good to throw (it) away*) (Meier, 2003; Schwarzschild, 2008).

> "In excessives, the infinitival complement, while it does not form a threshold description, it does contain an implicit negation. So, like other negative statements, excessives support *let alone* rejoinders[2]"

And, again, (Meier, 2003, p. 71) that transformed the infinitive clause into a *modal expression*:

> "In this paper, I will propose that the sentential complements of constructions with *too* and *enough* implicitly or explicitly contain a modal expression. [...] Evidence for this move is the fact that a modal expression (with existential force) can be added or omitted without changing the intuitive meaning of the sentences. [...] An explicit modal expression like *be able* or *be allowed* in the sentential complement makes them more precise, but it does not make them unacceptable".

In this research we noticed as well that the co-occurrence of *troppo*, *poco* and *abbastanza* with polar lexical items can provoke, in their semantic orientation, effects that can be associated to other contextual valence shifters. The *ad hoc* rules dedicated to these words (see Table 4.1) are not actually new, but refer to other contextual valence shifting rules that have been discussed in this Paragraph and/or will be explored in this Chapter.
Troppo and *poco* can also co-occur or can be negated, the rules to be applied in each case are reported in Table 4.2.
Troppo, *poco* and *abbastanza* are also able to give a polarity to words that in SentIta possess a neutral Prior Polarity. An exception is the case of *non troppo* + neutral words (Table 4.2), that does not produce generalizable effects (e.g. *non troppo decorato* "not so decorated" could have a weakly positive orientation, while same can not be said of *non*

[2] *This fuel is too volatile to use in a car engine* = *This fuel is too volatile to use in a car engine, let alone a lawn mower engine* = *This fuel should not be used in a car engine, let alone a lawn mower engine.* Example from Schwarzschild (2008).

	Positive Word	Neutral Word	Nagative Word
Examples	*bello*	*decorato*	*brutto*
troppo	Intensification	Negative Switch	Intensification
poco	Weakly Negative Switch	Weakly Negative Switch	Weak Negation
abbastanza	Downtoning	Weakly Positive Switch	Intensification

Table 4.1: The effects of *troppo, poco* and *abbastanza* on polar lexical items.

	Positive Word	Neutral Word	Nagative Word
Examples	*bello*	*decorato*	*brutto*
troppo poco	Strong Negation	Negative Switch	Downtoning
un poco troppo	Intensification	Negative Switch	Intensification
non troppo	Negative Switch	—	Weak Negation
non poco	Intensification	Weakly Positive Switch	Intensification

Table 4.2: The effects of the co-occurrence and the negation of *troppo, poco* with reference to polar lexical items.

troppo nuovo "not so new"). Therefore it has been excluded from the rules, in order to avoid additional errors.

4.3 Negation Modeling

4.3.1 Related Works

Negation modeling is an NLP research area that includes the automatic detection of negation expressions in raw texts and the determination of the *negation scopes*, that are the parts of the meaning modified by negation) (Jia et al., 2009).
Negation meets the Sentiment Analysis need of determining the correct polarity of opinionated words when shifted by the context. That is why we included it into our set of Contextual Valence Shifters (Polanyi and Zaenen, 2006; Kennedy and Inkpen, 2006).
In this paragraph we will survey the literature on negation modeling, going in depth through the state-of-the-art methods for the automatic

negation detection, from the pioneer work of Pang and Lee (2004) to more sophisticated techniques, such as some Semantic Composition methods, which even define the syntactic contexts of the polar expressions (Choi and Cardie, 2008).
Despite the large interest on negation in the biomedical domain (Harkema et al., 2009; Desclés et al., 2010; Dalianis and Skeppstedt, 2010; Vincze, 2010), maybe due to the availability of free annotated corpora (Vincze et al., 2008), this paragraph focuses on the more significant works on sentiment analysis.

Bag of Words: (Pang and Lee, 2004) demonstrated that using contextual information can improve the polarity-classification accuracy. By means of a standard bag-of-words representation, they handled negation modeling by adding artificial words to texts and without any explicit knowledge of polar expressions (e.g. *I do not NOT_like NOT_this NOT_new NOT_Nokia NOT_model*). The problem with this method is the duplication of the features, which are always represented in both their plain and negated occurrences (Wiegand et al., 2010).

Contextual Valence Shifters: Polanyi and Zaenen (2006) and Kennedy and Inkpen (2006) proposed a more sophisticated method that both switches (e.g. *clever*$^{[+2]}$:= *not clever*$^{[-2]}$) or shifts (*efficient*$^{[+2]}$:= *rather efficient*$^{[+1]}$) the initial scores of words, when negated or downtoned in context. As a general rule, polarized expressions are considered to be negated if the negation words immediately precede them.
Wilson et al. (2005, 2009) distinguished the following three types of binary relationship polarity features for negation modeling:

- *negation features*: negation expressions that negate polar expressions;
- *shifter features*: expressions that can be approximately equated with downtoners;

- *positive and negative polarity modification features*: special kind of polar expressions that modify other polar expressions turning their polarity into the positive or negative one.

Semantic Composition: Moilanen and Pulman (2007) exploited the syntactic representations of sentences, into a compositional semantics framework, with the purpose of computing the polarity of headlines and complex noun phrases. In this work, composition rules are incrementally applied to constituents, depending on the negation scope by means of negation words, shifters and negative polar expressions.
A similar approach is the one of Shaikh et al. (2007) that used verb frames, as a more abstract level of representation.
Choi and Cardie (2008) computed the phrases polarity in two steps: the assessment of polarity of the constituent and the subsequent application of a set of previously defined inference rules. For example, the rule [*Polarity([NP1]$^-$ [IN] [NP2]$^-$)* = +] can be applied to phrases like [[*lack*]$^-_{\mathrm{NP1}}$ [*of*]$_{\mathrm{IN}}$ [*crime*]$^-_{\mathrm{NP2}}$ *in rural areas*]).
Liu and Seneff (2009); Taboada et al. (2011) proposed compositional models able to mix together intensifiers, downtoners, polarity shifters and negation words, always starting from the words prior polarities and intensities.
The work of Benamara et al. (2012) goes beyond the studies mentioned above, since they specifically account for negative polarity items and for multiple negatives.
Socher et al. (2013) exploited Recursive Neural Tensor Network (RNTN) to compute two types of negation:

- negation of positive sentences, where the negation is supposed to changes the overall sentiment of a sentence from positive to negative;
- negation of negative sentences and their negation,where the overall sentiment is considered to become less negative (but not necessarily positive).

Negation Scope Detection: Jia et al. (2009) introduced the concept of scope of the negation term *t*. The scope identification[3] goes through the computing of a candidate scope (a subset of the words appearing after *t* in the sentence that represent the minimal logical units of the sentence containing the scope) and, then, a pruning of those words. The computational procedure that approximates the candidate scope considers the following elements: *static delimiters*, e.g. *because* or *unless* that signal the beginning of another clause; *dynamic delimiters*, e.g. *like* and *for*; and *heuristic rules focused on polar expressions*, that involve sentimental verbs, adjectives and nouns.

Morphological Negation modeling: In order to complete the literature survey on negation modeling, we can not fail to mention also morphological negation modeling. However, due to the fact that the scope of any morphological negation remains included into simple words (Councill et al., 2010), we deepened this aspect of the negation in Sections 3.5.1 and 3.5.4 of Chapter 3. We mention again, here, only the most significant contribution on this topic, Hatzivassiloglou and McKeown (1997); Plag (2003); Yuen et al. (2004); Moilanen and Pulman (2008); Ku et al. (2009); Neviarouskaya (2010); Neviarouskaya et al. (2011) and Wang et al. (2011).

4.3.2 Negation in SentIta

As exemplified in the following sentences, negation indicators do not always change a sentence polarity in its positive or negative counterparts (54); they often have the effect of increasing or decreasing the sentence score (55). That is why we prefer to talk about valence "shifting" rather than "switching".

[3] Scope Identification concerns the determination, at a sentence level, of the tokens that are affected by negation cues (Jia et al., 2009)

(54) Citroen *non*$^{[neg]}$ produce auto *valide*$^{[+2]}$ [-2]
"Citroen does not produce efficient cars"

(55) Grafica *non proprio*$^{[neg]}$ *spettacolare*$^{[+3]}$ [-1]
"The graphic not quite spectacular"

(Taboada et al., 2011, p. 277) made comparable considerations

> "Consider *excellent*, a +5 adjective: If we negate it, we get *not excellent*, which intuitively is a far cry from *atrocious*, a -5 adjective. In fact, *not excellent* seems more positive than *not good*, which would negate to a -3. In order to capture these pragmatic intuitions, we implemented another method of negation, a polarity shift (shift negation). Instead of changing the sign, the SO value is shifted toward the opposite polarity by a fixed amount (in our current implementation, 4). Thus a +2 adjective is negated to a -2, but the negation of a -3 adjective (for instance, *sleazy*) is only slightly positive, an effect we could call 'damning with faint praise.' [...] it is very difficult to negate a strongly positive word without implying that a less positive one is to some extent true, and thus our negator becomes a downtoner".

Just as (Benamara et al., 2012, p. 11):

> "(...) negation cannot be reduced to reversing polarity. For example, if we assume that the score of the adjective "excellent" is +3, then the opinion score in "this student is not excellent" cannot be -3. It rather means that the student is not good enough. Hence, dealing with negation requires to go beyond polarity reversal".

Even though the subtraction of a fixed amount of polarity points[4] seems to us a risky generalization, the authors confirmed the Horn's

[4] Other strategies for the automatic negation modeling have been proposed by Yessenalina and Cardie (2011), who combined words using iterated matrix multiplication, and Benamara et al. (2012), who, more in line with our research, computed negation on the base of its own types

ideas on the asymmetry between affirmative and negative sentences in natural language, differently from standard logic (Horn, 1989).
Such assumption complicates any attempt to automatically extract the meaning of negated phrases and sentences simply switching their affirmative scores.
Our hypothesis, that can be easily collocated into the compositional semantics approaches, is that the final polarity of a negated expression can be easily modulated, but only taking into account, at the same time, both the prior polarity of the opinionated expressions and the strength of the negation indicators (see Tables 4.3, 4.5 and 4.6).
Despite of any complexity, the finite-state technology offered us the opportunity to easily compute the negation influence on polarized expressions and to formalize the rules to automatically annotate real texts.
As regards the full list of negation indicators, we included in our grammar three types of negation (Benamara et al., 2012; Godard, 2013) that respectively include the following items. As we will show, each type has a different impact on the opinion expressions in terms of polarity and intensity.

Negation operators:

- *simple adverbs of negation:*
  `no,AVV+NEGAZIONE`
  `non,AVV+NEGAZIONE`
  `mica,AVV+NEGAZIONE`
  `affatto,AVV+NEGAZIONE+FORTE`
  `neanche,AVV+NEGAZIONE`
  `neppure,AVV+NEGAZIONE`
  `manco,AVV+NEGAZIONE`
  `senza,PREP+NEGAZIONE` [5]
- *compound adverbs of negation:*
  `neanche per sogno,AVV+AVVC+PC+PN+NEGAZIONE+FORTE`

[5] "not", "at all", "by no means", "neither"

```
per niente al mondo,AVV+AVVC+PCPC+PNPN+NEGAZIONE+FORTE
per nulla al mondo,AVV+AVVC+PCPC+PNPN+NEGAZIONE+FORTE
in nessun modo,AVV+AVVC+PDETC+PDETN+NEGAZIONE+FORTE
per niente,AVV+AVVC+PC+PAVV+NEGAZIONE+FORTE
per nulla,AVV+AVVC+PC+PAVV+NEGAZIONE+FORTE
niente affatto,AVV+AVVC+CC+AVVAVV+NEGAZIONE+FORTE
```
[6]

Negation operator Rules: Negative operators can appear alone (56) or, with a strengthening function, with another negation adverb (57).

(56) $\begin{bmatrix} Mica \\ Affatto \\ Per\ niente \end{bmatrix} bello\ l'hotel$

"Totally not cool the hotel"

(57) $L'hotel\ non\ è \begin{bmatrix} mica \\ affatto \\ per\ niente \end{bmatrix} bello$

"The hotel is not cool at all"

The general rules, concerning negation operators, formalized in the grammars in the form of FSA, are summarized in the Tables 4.3, 4.4, 4.5 and 4.6. The local grammar principle is to put in the same embedded graph all the structures that are supposed to receive the same score. Such score is indicated in the column Shifted Polarity.

Negative Quantifiers:

- *Adjectives*:

```
nessuno,A+FLX=A114+NEGAZIONE
niente,A+FLX=A605+NEGAZIONE
```
[7]

[6] "no way", "for anything in the world", "there's no way", "for nothing", "not at all"
[7] "nobody", "nothing"

Negation Operator	**Sentiment Word**	**Word Polarity**	**Shifted Polarity**
non	*fantastico*	+3	-1
	bello	+2	-2
	carino	+1	-2
	scialbo	-1	+1
	brutto	-2	+1
	orribile	-3	-1

Table 4.3: Negation rules.

Negation Operator	**Negation Operator**	**Sentiment Word**	**Word Polarity**	**Shifted Polarity**
non	*mica*	*fantastico*	+3	-2
		bello	+2	-3
		carino	+1	-3
		scialbo	-1	+2
		brutto	-2	+2
		orribile	-3	+1

Table 4.4: Negation rules with the repetition of negative operators.

Strong Negation Operator	**Sentiment Word**	**Word Polarity**	**Shifted Polarity**
per niente	*fantastico*	+3	-2
	bello	+2	-3
	carino	+1	-3
	scialbo	-1	+2
	brutto	-2	+2
	orribile	-3	+1

Table 4.5: Negation rules with strong operators.

Weak Negation Operator	Sentiment Word	Word Polarity	Shifted Polarity
poco	*fantastico*	+3	-1
	bello	+2	-1
	carino	+1	-1
	nuovo	0	-1
	scialbo	-1	+1
	brutto	-2	+1
	?*orribile*	-3	-1

Table 4.6: Negation rules with weak operators.

- *Adverbs*:

  `niente,AVV+NEGAZIONE`

  `nulla,AVV+NEGAZIONE`

  `poco,AVV+NEGAZIONE+DEB`

  `poco o niente,AVV+PCONG+NKN+NEGAZIONE+DEB`

  `poco o nulla,AVV+PCONG+NKN+NEGAZIONE+DEB mai,AVV+NEGAZIONE`[8]

- *Pronouns*:

  `nessuno,PRON+FLX=PRO717+NEGAZIONE`

  `niente,PRON+FLX=PRO719+NEGAZIONE`

  `poco,PRON+FLX=PRO721+NEGAZIONE+DEB`[9]

Negative Quantifiers Rules: As indicated in the dictionary extract above and as exemplified in the sentences below, negative quantifiers, which express both a negation and a quantification, can take the shape of different part of speech and, consequently, they can assume in sentences different syntactic positions.
We can directly observe that they change their function on the base of the different roles they assume.

Negative quantifiers as Adjectives: they tend to be pragmatically

[8] "nothing", "little", "little or nothing", "never"
[9] "not one", "few"

negative when occurring as adjectival modifiers (58, 59); just in the same way of lexical negation indicators (Potts, 2011).

(58) *Cortesia nessuna* [-2]
"No kindness"
(59) *Nessun servizio nelle stanze* [-2]
"No room service"

Negative quantifiers as Adverbs: they work exactly as *poco* when they occupy the adverbial position (60, 61), following the rules formalized in the next paragraph (see Table 4.6). As adverbs they can occur together with negation operators (61) or not (60).

(60) *Costa quasi niente* [+1]
" It costs almost nothing"
(61) *Non costa nulla* [+2]
" It doesn't cost anything"

Negative quantifiers as Pronouns: they seem to possess the same strengthening function of negative operators when occurring as pronouns (62, 63), the rules of reference are in Table 4.5.

(62) *Non lo consiglio a nessuno* [-3]
"I don't recommend it to anyone"
(64) *Non gliene frega niente a nessuno* [-3]
"Nobody cares"

Negative quantifiers in verbless sentences: into elliptical sentences (64, 65), they resemble the negation function of negative operators, following the rules of Table 4.3.

(65) *Niente di veramente innovativo* [-1]
"Nothing truly innovative"
(66) *Nulla da eccepire* [+1]
"No objections"

Lexical Negation:

$$\begin{bmatrix} \\ Nouns: \\ \\ \\ \\ Verbs: \\ \\ \\ \\ Adjectives: \\ \\ \end{bmatrix} \begin{bmatrix} mancanza \\ assenza \\ carenza \\ \\ mancare \\ difettare \\ scarseggiare \\ \\ mancante \\ carente \\ privo \end{bmatrix} di$$

[10]

Lexical negation Rules: lexical negation regards content word negators that always possess an implicit negative influence. Therefore, when they occur in texts their polarity is assumed to be negative.
Because they can co-occur with both the negative operators and quantifiers, their polarity can also be shifted to the positive one, by simply applying the negation rules conceived for the first two negation indicators.

4.4 Modality Detection

4.4.1 Related Works

Speculative Language Detection (Dalianis and Skeppstedt, 2010; Desclés et al., 2010; Vincze et al., 2008), *Hedge Detection* (Lakoff, 1973; Ganter and Strube, 2009; Zhao et al., 2010), *Irrealis Bloking* (Taboada et al., 2011), and *Uncertainty Detection* (Rubin, 2010) are all tasks that, completely or partially, overlap modal constructions.

[10] "lack, to lack in, to be laking of"

In order to account for the most popular annotate corpora in this NLP fields, we mention the BioScope corpus Vincze et al. (2008), which has been annotated with negation and speculation cues and their scopes; the FactBank, that has been annotated with event factuality (Saurí and Pustejovsky, 2009) and the CoNLL Shared Task 2010 (Farkas et al., 2010), which focused on hedges detection in natural language texts.
Modality has been defined by Kobayakawa et al. (2009) into a taxonomy that includes request, recommendation, desire, will, judgment, etc.
Taboada et al. (2011) did not consider *irrealis markers* to be reliable for the purposes of sentiment analysis. Therefore, they simply ignored the semantic orientation of any word in their scope. Their list of irrealis markers includes modals; conditional markers (e.g. "if"); negative polarity items (e.g. "any" and "anything"); some verbs ("to expect", "to doubt"); questions; words enclosed in quotes, which could not necessarily reflect the author's opinion).
According to Benamara et al. (2012) modality can be used to express possibility, necessity, permission, obligation or desire, through grammatical cues, such as adverbial phrases (e.g. "maybe", "certainly"); conditional verbal moods; some verbs (e.g. "must", "can", "may"); some adjectives and nouns (e.g. "a probable cause").
Relying on the categories of Larreya (2004); Portner (2009), they distinguished the following three types of modality, each one of which has been indicated to possess a specific effect on the opinion expression in its scope, in term of strength or degree of certainty.

Buletic Modality: it indicates the speaker's desires/wishes.

Cues: verbs denoting hope (e.g. "to wish").

Epistemic modality: it refers to the speaker's personal beliefs and affects the strength and the certainty degree of opinion expressions.

Cues: doubt, possibility or necessity adverbs (e.g. "perhaps", "definitely") and modal verbs (e.g. "have to", "may/can").

Deontic Modality: it indicates possibility/impossibility or obligation/permission.

Cues: same modal verbs of the epistemic modality, but with a deontic reading (e.g., "You must go see the movie").

4.4.2 Modality in SentIta

When computing the Prior Polarities of the SentIta items into the textual context, we considered that modality can also have a significant impact on the SO of sentiment expressions.
According to the literature trends, but without specifically focusing on the Benamara et al. (2012) modality categories, we recalled in the FSA dedicated to modality the following linguistic cues and we made them interact with the SentIta expressions:

Sharpening and Softening Adverbs:

- *simple adverbs* (32 sharp and 12 soft)

```
inequivocabilmente,AVV+FORTE+Focus=SHARP
necessariamente,AVV+FORTE+Focus=SHARP
relativamente,AVV+DEB+Focus=SOFT
suppergiù,AVV+DEB+Focus=SOFT
```

- *compound adverbs* (38 sharp and 26 soft)

```
con ogni probabilità,AVV+AVVC+PDETC+PDETN+Focus=SHARP
senza alcun dubbio,AVV+AVVC+PDETC+PDETN+Focus=SHARP
fino a un certo punto,AVV+AVVC+PAC+PDETAGGN+Focus=SOFT
in qualche modo,AVV+AVVC+PDETC+PDETN+Focus=SOFT
```

Modal Verbs: from the LG class 56 (dovere "have to", potere "may/can", volere "want"), that have as definitional structure *N_0 V (E + Prep) Vinf W*, and accept in position N_1 a direct or prepositional infinitive clause (all) and, only in the cases of *potere* and *volere*, a *N_1-um*.

Conditional and Imperfect Tenses: tenses are located after the texts preprocessing through the annotations *Tempo=IM* and *Tempo=C*.

Dealing with modality is very challenging in the Sentiment analysis field, because in this research area it is not enough to simply detect its indicators, but it is also necessary to manage its effects in term of polarity. We did not find appropriate to simplify the problem by ignoring all the semantic orientation of phrases and sentences in which modality can be detected (Taboada et al., 2011). In fact, as exemplified below, there are cases in which modality sensibly affects its intensity, and other cases in which it regularly shifts the sentence polarity into specific directions.

Uncertainty Degrees: the words annotated with the labels +SHARP and +SOFT, described above, just as intensifiers and downtoners, have the power of modifying the intensity of the words endowed with positive or negative prior polarities, with the same effects described in Section 4.2. We respectively selected them among the words tagged with the labels FORTE and DEB, with the only aim of providing an exhaustive module that can work well with both Modality Detection and Sentiment Analysis purposes.

"Potere" + Indicative Imperfect + Oriented Item: modal verbs occurring with an imperfect tense can turn a sentence into a weakly negative one (66) when combined with positive words, or into a weakly positive one when occurring with negative items (67). The effect is really close to the weak negation (see Table 4.6 in Section 4.3). This can be explained by the fact that the meaning

of the sentences of this kind always concerns subverted expectations.

(66) *Poteva*[Modal+IM] essere una trama *interessante*[+2] [-1]
"It could be an interesting plot"

(67) *Poteva*[Modal+IM] essere una trama *noiosa*[-2] [+1]
"It could be a boring plot"

"Potere" + Indicative Imperfect + Comparative + Oriented Items: also in this case, we use the explanation of subverted expectations. The terms of comparison are, obviously, the expected opinion object and the real one. If the expected object is better than the real one the sentence score is negative (68), if it is worse the sentence score is positive (69). The rules for the polarity score attribution are the ones displayed in Section 4.5.

(68) *Poteva*[Modal+IM] essere *più*[I-CW] *dettagliata*[+2] [-1]
"It might have been more detailed"

(69) *Poteva*[Modal+IM] andare *peggio*[I-OpW +2] [-1]
"It might have gone worse"

"Dovere" + Indicative Imperfect: Here, again, we face disappointment of expectations, but with a stronger effect: the negation does not regard the *possibility* of the opinion object to be good, but a *necessity*. Therefore we assumed the final score in these cases to follow the negation rules shown in Table 4.3 in Section 4.3 (70).

(70) Questo *doveva*[Modal+IM] essere un film *di sfumature*[+1] [-2]
"This one was supposed to be a nuanced movie"

"Dovere" + "Potere" + Past Conditional: Past conditional sentences (Narayanan et al., 2009) also have a particular impact on the opinion polarity, especially with the modal verb *dovere*, ("have to"). In such cases, as exemplified in (71), the sentence polarity is always negative in our corpus.

(71) Non$^{[\text{Negation}]}$ *avrei*$^{[\text{Aux+C}]}$ *dovuto*$^{[\text{Modal+PP}]}$ buttare via i miei soldi [-2]
“I should not have burnt my money"

The verb *potere*, instead, follows the same rules described above for the imperfect tense.

4.5 Comparative Sentences Mining

4.5.1 Related Works

Comparative Sentence Mining and *Comparison Mining Systems* are NLP techniques and tool that only in part coincide with the Sentiment Analysis field.
Sentences that express a comparison generally carry along with them opinions about two or more entities, with regard to their shared features or attributes (Ganapathibhotla and Liu, 2008). While the Sentiment Analysis main purpose is to identify details about such opinions; the Information Extraction main goals regard comparative sentence detection and classification. Therefore, if the object of the analysis and the basic information units are shared among the two approaches, their purposes can sometimes coincide but in other cases be different.
Among the few studies on the computational treatment of comparison (Jindal and Liu, 2006a,b; Ganapathibhotla and Liu, 2008; Fiszman et al., 2007; Yang and Ko, 2011), only Ganapathibhotla and Liu (2008) tried to extract the authors’ preferred entities and to identify the Semantic Orientation of comparative sentences, after their identification and classification.
With the following two examples, Ganapathibhotla and Liu (2008) showed the difficulty in the polarity determination of context-dependent opinion comparatives that, for a correct interpretation, al-

ways require domain knowledge, e.g. the word “longer” can assume positive (72) or negative (73) orientation depending on the product feature on which it is associated.

(72) “The *battery life* of Camera X is *longer* than Camera Y”
(73) “Program X’s *execution time* is *longer* than Program Y”

Since this work aims to provide a general purpose lexical and grammatical database for Sentiment Analysis and Opinion Mining, we did not face here the treatment of this special kind of opinionated sentences, just as we did not include in the lexicon items with domain-dependent meaning.
Concerning the comparative classification, the main types that have been identified in literature are the following:

- Gradable (direct comparison)
  - Non-equal
    - Increasing
    - Decreasing
  - Equative
  - Superlative
- Non-gradable (implicit comparisons)

According to Ganapathibhotla and Liu (2008); Jindal and Liu (2006a,b), a comparative relation can be represented in the following way:

ComparativeWord, Features, EntityS1, EntityS2, Type

Where *ComparativeWord* is the keyword used to express a comparative relation in a sentence; *Features* is a set of features being compared; *EntityS1* is the first term of comparison and *EntityS2* is the secon one.
This way, examples (72) and (73) are represented as follows:

(72) *longer, battery life, Camera X, Camera Y, Non-equal Gradable*

(73) *longer, execution time, Program X, Program Y, Non-equal Gradable*

Our work shares with Ganapathibhotla and Liu (2008) the following basic rules:

Increasing comparative + Negative item ⟶ Negative opinion ⟶ EntityS2 is preferred
Increasing comparative + Positive item ⟶ Positive opinion ⟶ EntityS1 is preferred
Decreasing comparative + Negative item ⟶ Positive opinion ⟶ EntityS1 is preferred
Decreasing comparative + Positive item ⟶ Negative opinion ⟶ EntityS2 is preferred

However, differently from our work, the authors simply switched the polarity of the opinions (and, consequently, the preferred entity) in the cases in which comparative sentences contained negation words or phrases. They underlined that, sometimes, this operation could appear problematic, e.g. "not longer" does not mean "shorter". Actually, the problem is that the authors did not take into account different degrees of positivity and negativity. As we will show in the next paragraphs of this Section, the co-occurrences of weakly positive/negative and intensely positive/negative Prior Polarities with comparison indicators can generate different final sentence scores.

As regards the automatic analysis of superlatives, we mention the work of Bos and Nissim (2006), that grounded the semantic interpretation of superlatives on the characterization of a *comparison set* (the set of entities that are compared to each other with respect to a certain dimension). The authors took into consideration the superlative modification performed by ordinals, cardinals or adverbs (e.g. intensifiers or modals), and also the fact that superlative can manifest itself both in predicative or attributive form.

Their superlative parser, able to recognise a superlative expression and its comparison set with high accuracy, provides a Combinatory Categorial Grammar (CCG) (Clark and Curran, 2004) derivation of the input sentence, that is, then, used to construct a Discourse Representation Structure (DRS) (Kamp and Reyle, 1993).

In this thesis we did not go through a semantic and logical analysis of comparative and superlative sentences, as well explained in the next paragraph, we just used them as CVS in order to accurately modify the polarity of the entities they involve.

4.5.2 Comparison in SentIta

In general, this work, which focuses on Gradable comparison, includes the analysis of the following comparative structures:

- equative comparative frozen sentences of the type *N0 Agg come C1* from the LG class PECO (see Section 3.4.2);
- opinionated comparative sentences that involve the expressions *meglio di*, *migliore di*, “better than", *peggio di*, *peggiore di*, “worse than", *superiore a*, “superior to" *inferiore a*, “less than" (74);
- adjectival, adverbial and nominal comparative structures that respectively involve oriented adjectives, adverbs and nouns from SentIta (75);
- absolute superlative (75)
- comparative superlative (76).

The comparison with other products (74) has been evaluated with the same measures of the other sentiment expressions; so the polarity can range from -3 to +3.
The superlative, that can imply (76) or not (75) a comparison with a whole class of items (Farkas and Kiss, 2000), confers to the first term of the comparison the higher polarity score, so it always increases the strength of the opinion. Its polarity can be -3 or +3.

(74) L'S3 è complessivamente *superiore all'*Iphone5 [+2]
“The S3 is on the whole superior to the iPhone5"

(75) Il suo motore era anche *il più brioso*[+2] [+3]
“Its engine was also the most lively"

(76) Un film *peggiore di* qualsiasi telefilm [-3]
"A film worse than whatever tv series"

We did not include the equative comparative in the Contextual Valence Shifters Section because it does not change the polarity expressed by the opinion words (77).

(77) [*Non*$^{\text{[Negation]}}$ *entusiasmante*$^{[+3]}$]$^{[-1]}$ *come* i PES degli anni precedenti
"Not exciting as the the past years PES".

In the next paragraphs we will go through the rules used in this FSA network to compute the Semantic Orientations of minority and majority comparative structures. As will be observed the variety and the complexity of co-occurrence rules can be easily managed using the finite-state technology.

4.5.3 Interaction with the Intensification Rules

Rule II: increasing comparative sentences, with increasing opinionated comparative items listed in SentIta with positive Prior Polarities, generate a positive opinion.
Comparative indicators are the following:

- increasing opinionated comparative words (I-Op-CW)
  e.g. *meglio* better = +2
- Intensifiers + increasing opinionated comparative words (Int + I-Op-CW)
  e.g. *molto meglio* a lot better = +3

Rule I: increasing comparative sentences which occur with positive items from SentIta generate a positive Opinion.
Comparative indicators are the following:

- Increasing Comparative Words (I-CW)
  e.g. *più* more”
- Intensifiers + Increasing comparative words (Int + I-CW)
  e.g. *molto più* a lot more”

The sentence score depends on the interaction of I-CWs, intensifiers and the prior polarity scores attributed to the SentIta words in the electronic dictionaries (see Table 4.7).

The sentence score just depends on the Prior polarity of the I-Op-CW.

Increasing comparative	**Examples**	**Positive Prior Polarities**		
		carino +1	*buono* +2	*prodigioso* +3
		Entity 1 Polarities		
I-CW + OpW[POS]	*più*	+1	+2	+3
Int + I-CW + OpW[POS]	*molto più*	+2	+3	+3

Table 4.7: Rule I: increasing comparative sentences with positive orientation

Decreasing comparative	**Examples**	**Positive Prior Polarities**		
		carino +1	*buono* +2	*prodigioso* +3
		Entity 1 Polarities		
D-CW + OpW[POS]	*meno*	-1	-2	-1
Int + D-CW + OpW[POS]	*molto meno*	-2	-3	-1

Table 4.8: Rule III: decreasing comparative sentences with negative orientation

Rule III: decreasing comparative sentences which occur with positive items from SentIta generate a negative opinion (see Table 4.8). Comparative indicators are the following:

- Decreasing Comparative Words (D-CW)
  e.g. *meno* less”

Increasing comparative	**Examples**	**Negative Prior Polarities**		
		distratto -1	*cafone* -2	*osceno* -3
		Entity 1 Polarities		
I-CW + $OpW^{[NEG]}$	*più*	-1	-2	-3
Int + I-CW + $OpW^{[NEG]}$	*molto più*	-2	-3	-3

Table 4.9: Rule IV: increasing comparative sentences with Negative Orientation

Decreasing comparative	**Examples**	**Negative Prior Polarities**		
		distratto -1	*cafone* -2	*osceno* -3
		Entity 1 Polarities		
D-CW + $OpW^{[NEG]}$	*meno*	+1	+1	+1
Int + D-CW + $OpW^{[NEG]}$	*molto meno*	+2	+2	+1

Table 4.10: Rule VI: decreasing comparative sentences with positive orientation

- Intensifier + Decreasing comparative word (Int + D-CW)
  e.g. *molto meno* much less”

Rule IV: this rule is perfectly specular to Rule I. Increasing comparative sentences which occur with Negative items from SentIta generate a negative opinion.
The sentence score depends again on the interaction of I-CW, Intensifiers and the prior polarity scores attributed to the SentIta words that appear in the same sentence (see Table 4.9).

Rule V: decreasing comparative sentences, with decreasing opinionated comparative items listed in SentIta with negative Prior Polarities, generate a negative opinion.
Comparative indicators are the following:

- decreasing opinionated comparative words (I-Op-CW)
  e.g. *peggio* worse = -2
- Intensifier + decreasing opinionated comparative word (Int + I-Op-CW)

Increasing comparative	**Examples**	**Positive Prior Polarities**		
		carino +1	*buono* +2	*prodigioso* +3
		Entity 1 Polarities		
N + I-CW + OpW$^{[POS]}$	*non più*	-1	-1	-1
N + Int + I-CW + OpW$^{[POS]}$	*non molto più*	-1	-1	-1

Table 4.11: Nagation of Rule I: Negated increasing comparative sentences with negative orientation

Decreasing comparative	**Examples**	**Positive Prior Polarities**		
		carino +1	*buono* +2	*prodigioso* +3
		Entity 1 Polarities		
N + D-CW + OpW$^{[POS]}$	*non meno*	+1	+2	+3
N+ Int + D-CW + OpW$^{[POS]}$	*non molto meno*	+1	+1	+2

Table 4.12: Negation of Rule III: Negated decreasing comparative sentences with positive orientation

e.g. *molto peggio* much worse = -3

Just as in Rule II, the sentence score just depends on the Prior Polarity of the I-Op-CWs.

Rule VI: decreasing comparative sentences which occur with negative items from SentIta generate a positive opinion (see Table 4.10).
Rule VI shares the comparative indicators with Rule III.

4.5.4 Interaction with the Negation Rules

Negation of the Rule I: increasing comparative sentences which occur with positive items from SentIta, when negated, generate a negative opinion.
Comparative indicators are, of course, the same of Rule I, with

Increasing comparative	**Examples**	**Negative Prior Polarities**		
		distratto -1	*cafone* -2	*osceno* -3
		Entity 1 Polarities		
N + I-CW + OpW$^{[NEG]}$	*non più*	+1	+1	-1
N+ Int + I-CW + OpW$^{[NEG]}$	*non molto più*	+1	+1	-2

Table 4.13: Negation of Rule IV: Negated increasing comparative sentences with negative orientation

Decreasing comparative	**Examples**	**Negative Prior Polarities**		
		distratto -1	*cafone* -2	*osceno* -3
		Entity 1 Polarities		
N + D-CW + OpW$^{[NEG]}$	*non meno*	-1	-2	-3
N+ Int + D-CW + OpW$^{[NEG]}$	*non molto meno*	-1	-2	-3

Table 4.14: Negation of RuleVI: Negated decreasing comparative sentences with positive orientation

the addition of negation indicators (N), e.g. *non* "not". The sentence score is always turned into the weakly negative one (see Table 4.11).

Negation of the Rule II: increasing comparative sentences in which occur increasing opinionated comparative items listed in SentIta with positive Prior Polarities, when negated, generate always a negative opinion.
Comparative indicators are the same of Rule II:

- Negation markers + Increasing Opinionated Comparative Words (N + I-Op-CW)
  e.g. *non meglio* "not better" = -2

- Negation markers + Intensifiers + Increasing Opinionated Comparative Words (N + Int + I-Op-CW)
  e.g. *non molto meglio* "not much better" = -1

Negation of Rule III: the negation of Rule III, that involves decreasing comparative sentences with positive items from SentIta, always generates positive opinions.
The different sentence scores, computed on the base of the interaction of comparative words and SentIta's Prior Polarities are reported in Table 4.12.

Negation of Rule IV: increasing comparative sentences which occur with negative items from SentIta generate in the great part of the cases positive opinions (see Table 4.13). The sentence score is influenced by the interaction of Negation markers, I-CW, Intensifiers and negative prior polarity scores.

Negation of Rule V: decreasing comparative sentences in which occur increasing opinionated comparative items listed in SentIta with negative Prior Polarities, when negated, generate a weakly negative opinion (*non (molto + E) peggio* "not (much + E) worse").

Negation of Rule VI: decreasing comparative sentences which occur with negative items from SentIta generate negative opinions if negated, see Table 4.14.

Chapter 5

Specific Tasks of the Sentiment Analysis

5.1 Sentiment Polarity Classification

Differently from the traditional topic-based text classification, sentiment classification aims to categorize documents through the classes *positive* and *negative*. The objective can be a simple binary classification or it can come after a more complex classification with a larger number of classes in the continuum between positive and negative (Pang and Lee, 2008a). The *rating-inference problem* (Pang and Lee, 2005; Leung et al., 2006, 2008; Shimada and Endo, 2008) regards the mapping of automatically detected document polarity scores on the fine-grained rating scales (e.g. 5/10) of existing *Collaborative Filtering* algorithms (Breese et al., 1998; Herlocker et al., 1999; Sarwar et al., 2001; Linden et al., 2003). The challenging problem of the sentiment classification is the fact that the sentiment classes, far from being unrelated to one another, represent opposing (binary classification) or ordinal categories (multi-class a and rating-inference).

5.1.1 Related Works

Many techniques have been discussed in literature to perform the Sentiment Polarity Classification. We divided them, in Section 3.2, in lexicon-based methods, learning methods and hybrid methods[1].
The first, which calculate the sentiment orientation of sentences and documents starting from the polarity of words and phrases they contain, are the methods that have been chosen for the present work. This is why they received an in-depth analysis in Chapter 3, where we discussed also the pros and cons of both the manual and automatic draft of sentiment lexical resources. In this respect, we mention again the major contribution related to knowledge-based solutions: Landauer and Dumais (1997); Hatzivassiloglou and McKeown (1997); Wiebe (2000); Turney (2002); Turney and Littman (2003); Riloff et al. (2003); Hu and Liu (2004); Kamps et al. (2004); Vermeij (2005); Gamon and Aue (2005); Esuli and Sebastiani (2005, 2006a); Kanayama and Nasukawa (2006a); Benamara et al. (2007); Kaji and Kitsuregawa (2007); Rao and Ravichandran (2009); Mohammad et al. (2009); Neviarouskaya et al. (2009a); Velikovich et al. (2010); Taboada et al. (2006, 2011).
Rule-based approaches, that take into account the syntactic dimension of the Sentiment Analysis, are the ones used by Mulder et al. (2004); Moilanen and Pulman (2007) and Nasukawa and Yi (2003).
The most used classification algorithms in learning and statistical methods are Support Vector Machines, which, trained on specific data-sets, map a space of unstructured data points onto a new structured space through a kernel function; and Naïve Bayes, which are probabilistic classifiers that connect the presence/absence of a class feature to the absence/presence of other features, given the class variable. Effective sentiment features exploited in supervised machine learning applications are terms, their frequencies and TF-IDF; parts

[1] In general, while hybrid methods are characterized by the application of classifiers in sequence approaches based on rules consists of an if-then relation among an antecedent and its associated consequent (Prabowo and Thelwall, 2009).

of speech; sentiment words and phrases; sentiment shifters ; syntactic dependency; etc.
Tan et al. (2009) and Kang et al. (2012) adapted Naïve Bayes algorithms for sentiment analysis.
Pang et al. (2002), with the purpose to test the hypothesis that sentiment classification can be treated just as a special case of topic-based categorization, with the positive and negative sentiment considered as topics, used SVM, Naïve Bayes and Maximum Entropy classifiers, with diverse sets of features.
Mullen and Collier (2004) employed the values *potency*, *activity* and *evaluative* from a variety of sources and created a feature space, classified by means of SVM.
Ye et al. (2009) compared SVM with other statistical approaches proving that SVM and n-gram outperform the Naïve Bayes approach.
The minimum-cut framework working on graphs has been used by Pang and Lee (2004).
Bespalov et al. (2011) performed sentiment classification via latent n-gram analysis.
Nakagawa et al. (2010) presented a dependency tree-based classification method grounded on conditional random fields.
Compositionality algorithms have been tested by Yessenalina and Cardie (2011) and Socher et al. (2013). Socher et al. (2013) proposed Recursive Neural Tensor Network, able to compute compositional vector representations for phrases of variable length or of syntactic kind, obtaining better performances of standard recursive neural networks, matrix-vector recursive neural networks, Naïve, bi-gram Naïve and SVM. Their output is the annotated corpus Stanford Sentiment Treebank, which represents a precious resource for the analysis of the compositional effects of sentiment in language.
Sentiment indicators can be used for sentiment classification in an unsupervised manner, this is the case of Turney (2002) and the other lexicon-based methods (Liu, 2012).
In the end, as regards the hybrid methods we mention the works of An-

dreevskaia and Bergler (2008) that integrated the accuracy of a corpus-based system with the portability of a lexicon-based system in a single ensemble of classifiers; Aue and Gamon that combined nine SVM-based classifiers; Dasgupta and Ng (2009) that firstly mined the unambiguous reviews through spectral techniques and afterwards exploited them to classify the ambiguous reviews by combining active learning, transductive learning, and ensemble learning; Goldberg and Zhu (2006) that presented an adaptation of graph-based learning algorithms for rating-inference problems and Prabowo and Thelwall (2009) that combined rule-based and machine learning classification algorithms.

5.1.2 DOXA: a Sentiment Classifier based on FSA

Using the command-line program noojapply.exe, we built Doxa, a prototype written in Java, by which users can automatically apply the Nooj lexicon-grammatical resources from Section 3 and rules from Section 4 to every kind of text, getting back a feedback of statistics that contain the opinions expressed in each case.
Doxa sums up the values corresponding to every sentiment expression and, then, standardizes the result for the total number of sentiment expressions contained in each review. Neutral sentences are simply ignored by both the FSA and Doxa.
The automatically attributed polarity score are compared with the stars that the opinion holder gave to his review. Then, through the statistics about the opinions expressed in every domain, Doxa tests the consistency of the sentiment lexical databases and tools, with respect to the rating-inference problem, in each document and in the whole corpus.
Figure 5.1 reports an example of the analysis on the domain of hotels reviews.

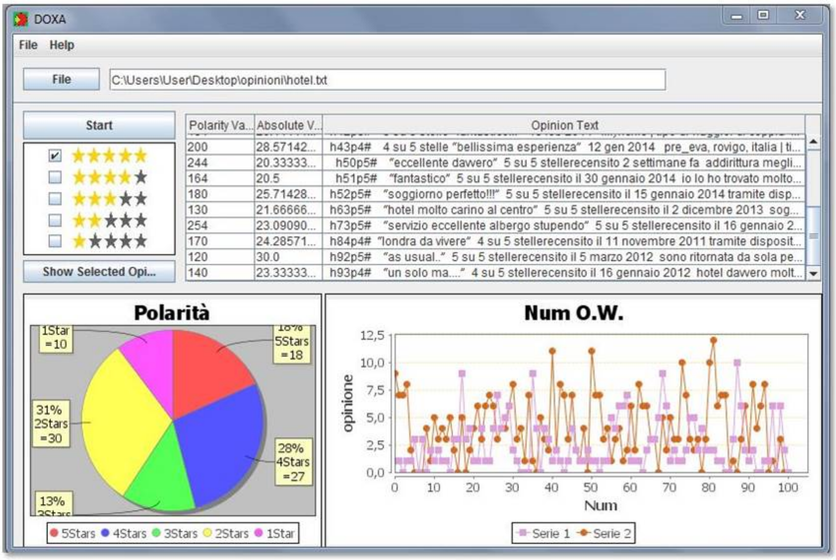

Figure 5.1: Doxa: the LG sentiment classifier based on the finite-state technology

5.1.3 A Dataset of Opinionated Reviews

Despite the fact that for the English language there is a large availability of corpora for sentiment analysis (Hu and Liu, 2004; Pang and Lee, 2004, 2005; Wiebe et al., 2005; Wilson et al., 2005; Thomas et al., 2006; Jindal and Liu, 2007; Snyder and Barzilay, 2007; Blitzer et al., 2007; Seki et al., 2007; Macdonald et al., 2007; Pang and Lee, 2008b, among others); the Italian language presents fewer contributions in this sense (Basile and Nissim, 2013; Bosco et al., 2013, 2014).

The dataset, used to evaluate the lexical and grammatical resources of the present work, has been built from scratch using Italian opinionated texts in the form of users' reviews and comments of e-commerce and opinion websites. It contains 600 texts units and refers to six different domains, for all of which different websites have been exploited:

Cars: `www.ciao.it`

Smartphones: `www.tecnozoom.it`, `www.ciao.it`, `www.amazon.it`, `www.alatest.it`,

Books: `www.amazon.it`, `www.qlibri.it`,

Movies: `www.mymovies.it`, `www.cinemalia.it`, `www.filmtv.it`, `www.filmscoop.it`,

Hotels: `www.tripadvisor.it`, `www.expedia.it`, `www.venere.com`, `it.hotels.com`, `www.booking.com`,

Videogames: `www.amazon.it`

Details about the corpus are shown in Table 1.

Text Features	**Cars**	**Smartphones**	**Books**	**Movies**	**Hotels**	**Games**	**Tot**
Neg Docs	50	50	50	50	50	50	300
Pos Docs	50	50	50	50	50	50	300
Text Files	20	20	20	20	20	20	120
Word Forms	17,163	19,226	8,903	37,213	12,553	5,597	101,655
Tokens	21,663	24,979	10,845	45,397	16,230	7,070	126,184

Table 5.1: Dataset of opinionated online customer reviews

Adjectives, as it is commonly recognized in literature (Hatzivassiloglou and McKeown, 1997; Hu and Liu, 2004; Taboada et al., 2006), seem to be the most reliable SO indicators, considering that the 17% of the adjectives occurring in the corpus are polarized, compared to the 3% of the adverbs, the 2% of nouns and the 7% of verbs.
Moreover, considering all the opinion bearing words in the corpus, the adjectives' patterns cover 81% of the total number of occurrences (almost 5000 matches), while the adverbs, the nouns and the verbs reach,

respectively, a percentage of 4%, 6%, and 2%. The remaining 7% is covered by the other sentiment expressions, that, in any case, contribute to the achievement of satisfactory levels of Recall.
As regards the Semantic Orientation, while in the dictionaries almost 70% of the words are connoted by a negative Prior Polarity, the number of positive and negative expressions in our perfectly balanced corpus lead to almost antipodal results: 64% of the sentiment expressions possess a positive polarity. In particular, it is positive 61% of the adjective expressions, 77% of the adverb expressions, 65% of the nouns expressions, and 51 % of the verb expressions.
The domain independent expressions have diametrically opposite percentages, only 34% of the occurrences is positive. This result is due to the presence of the really productive negative metanodes *troppo*, "too much" and *poco*, "not much". Inactivating them, in fact, the positive percentage reaches 58% of occurrences. Thus, it could be stated that, although the lexicon makes available a greater number of negative items, the real occurrences of the opinion words throw off balance in the direction of the positive items (see Section 3.3.2.1 to deepen the phenomenon of *positive biases*).

5.1.4 Experiment and Evaluation

In the sentiment classification task the information unit is represented by an opinionated document as a whole. The purpose of our sentiment tool is to classify such documents on the base of their overall Semantic Orientation.
To ground this task on a lexicon means to hypothesize that the polarities of opinion words can be considered indicators of the polarity of the document in which the words and the expressions are contained.
Our Lexicon-Grammar based sentiment lexical database confers to elementary sentences the status of minimum semantic units of the language. Therefore the indicators on which we grounded our classifi-

cation go beyond the limit of mere words to match entire elementary sentences or polar phrases from complex sentences.
Because the inference of the whole document SO depends on the correct annotation of its sentences and phrases, the evaluation phase involves both the sentence-level and the document-level performances of the tool.

5.1.4.1 Sentence-level Sentiment Analysis

This Paragraph presents the results pertaining to the Nooj output, which has been produced applying the SentIta LG sentiment resources to our corpus of costumer reviews.
For sake of clarity and for the reproducibility of the results, it must be pointed out that some of the lexical resources have been applied with higher priority attributions. Details about the preferences are given below:

- H1 to the sentiment *adverb* and *nouns dictionaries*;
- H2 to the sentiment *adjective dictionary*;
- H3 to the freely available dictionary *Contrazioni*, that belongs to the official Italian module of Nooj;
- H4 to an *high-level priority dictionary*, that contains what is commonly called a “stop word list”;
- H5 to a dictionary of *compound adverbs*.

In order to avoid ambiguity, as much as possible, the dictionary of the verbs of sentiment must have the same priority of the Italian standard dictionary (sdic), lower than any other mentioned resource.
Because our lexical and grammatical resources are not domain-specific, we observed their interaction with every single part of the corpus, which is composed of many different domains, each one of them characterized by its own peculiarities.

Moreover, in order to verify the performances of every part of speech (and of the expressions connected to them) we checked, as shown in Table 5.2, the Precision and the Recall applying separately every single metanode (A, ADV, N, V, D-ind[2]) of the main graph of the sentiment grammar.

Nodes	Cars	Smartphones	Movies	Books	Hotels	Videogames	Average
A	88	90	79	87.5	91.5	83.5	86.6
ADV	80.4	75.8	87.9	92.3	92	50*	79.7
N	81.8	85.7	82.8	77.8	85.3	85.7*	83.2
V	88.2*	57.1*	84.8	89.5	57.1*	100*	79.5
D-ind	87.9	83.5	78.1	76.7	90	94.7	87.9
Average	85.3	78.4	82.5	84.8	83.2	82.8	82.8

Table 5.2: Precision measure in sentence-level classification

The sentence-level Precision has been manually calculated, determining whereas the polarity and the intensity score of the expressions was correctly assigned, on all the concordances produced by Nooj. We made an exception for the expressions of the adjectives, which, due to the extremely large number of concordances, have been evaluated by extracting a sample of 1,200 matches (200 for each domain).
The values marked by the asterisks have been reported to be thorough, but they are not really relevant because of the small number of concordances on which they have been calculated.
The best performance has been reached in average by the cars dataset, while the lower values have been assigned to the movies dataset. The performances of the adjectives grammar are really satisfying, espe-

[2]Domain independent sentiment expressions (D-ind) refer to all the frozen and semi-frozen expressions that have been directly formalized in the FSA and include also the vulgar expressions.

cially if compared with the high number of matches they produced.
Even though the domain-independent node covers a small part of the matches (7%) it reached the best Precision results, if compared with the other metanodes.
Anyway, in many cases, just evaluating the polarity and the intensity of the expressions contained into a document is not enough to determine whereas such expression truly contributes to the identification of the polarity and the intensity of the document itself. Sometimes polarized sentences and phrases are not opinion indicators; especially in the reviews of movies and books, in which polarized sentences can just refer to the plot (78).

(78) *Le belle case sono dimora della degenerazione più bieca* [-3]
"pretty houses hosts the grimmest degeneracy").

An opinionated sentence can be considered not pertinent also is the case in which it does not directly refer to the object of the opinion, but mentions aspects that are just indirectly connected with the product. Examples of this are (79), that does not refer to the product, but to the delivery service; that in a book review does not refers to the object, but to another media product related to the book.

(79) *Apprezzo*[+2] *molto*[+] *Amazon per questo* [+3]
"I really appreciate Amazon for this"

(80) Il film non[Negation] mi era piaciuto[+2] [-2]
"I didn't like the movie"

In this work we chose to exclude the second sentence from the correct matches, but we considered worthwhile to include the first one, because of the high influence that this feature has on the numerical value that the opinion holder confers to his own opinion.
Table 5.3 corrects the results reported in Table 5.2 by excluding from the correct matches the ones that do not give their contribution to the individuation of the correct document SO. This makes the average sentence-level Precision drop of 8.7 points, reaching the percentage of

Nodes	Cars	Smartphones	Movies	Books	Hotels	Videogames	Average
A	-5	-5.5	-28	-10.5	-1	-1.5	-8.6
ADV	-2.2	0	-29.7	-7.7	0	0	-6.6
N	-11.4	-14.3	-39.5	-14.8	-5.9	-14.3	-16.7
V	0	0	-17.6	-15.8	0	0	-5.6
D-ind	-8.6	0	-13.3	-6.7	-2.5	-5.3	-6.1
Average	-5.4	-4	-25.6	-11.1	-1.9	-4.2	-8.7

Table 5.3: Irrelevant matches in sentence-level classification

74.1%, which we considered adequate.
We chose to present these two results separately because this way it is possible to distinguish the domains that are more influenced by this problem (e.g. movies and books) from the ones that are less affected by the pertinence problem (e.g. hotels and smartphones).

5.1.4.2 Document-level Sentiment Analysis

As far as the document-level performance is concerned (Table 5.4), we calculated the precision twice by considering in a first case as true positive the reviews correctly classified by Doxa on the base of their polarity and in a second case by considering as true positive the documents that received by our tool exactly the same stars specified by the Opinion Holder.
In detail, in the *Polarity only* row the True Positives are the documents that have been correctly classified by Doxa, with a polarity attribution that corresponds to the one specified by the Opinion Holder.
In the *Intensity also* row the True Positives are the document that received by Doxa exactly the same stars specified by the Opinion Holder.

Precision	**Cars**	**Smartphones**	**Movies**	**Books**	**Hotels**	**Videogames**	**Average**
Polarity only	71.0	72.0	63.0	74.0	91.0	72.0	74.0
Intensity also	32.0	45.0	25.0	33.0	49.0	34.0	36.3

Table 5.4: Precision measure in document-level classification

As we can see, the latter seem to have a very low precision, but upon a deeper analysis we discovered that is really common for the Opinion Holders to write in their reviews texts that do not perfectly correspond to the stars they specified. That increases the importance of a software like Doxa, that does not stop the analysis on the structured data, but enters the semantic dimension of texts written in natural language.

Recall	**Cars**	**Smartphones**	**Movies**	**Books**	**Hotels**	**Videogames**	**Average**
Sentence-level	72.7	79.6	64.8	65.7	72.1	58.8	69.0
Document-level	100	98.6	100	96.1	98.9	91.2	97.5

Table 5.5: Recall in both the sentence-level and the document level classifications

The Recall pertaining to the sentence-level performance of our tool has been manually calculated on a sample of 150 opinionated documents (25 from each domain), by considering as false negatives the sentiment indicators which have not been annotated by our grammar. The document-level Recall, instead, has been automatically checked with Doxa, by considering as true positive all the opinionated documents which contained at least one appropriate sentiment indicator.

So, the documents in which the Nooj grammar did not annotate any pattern were considered false negatives. Because we assumed that all the texts of our corpus were opinionated, we considered as false negatives also the cases in which the value of the document was 0.
Taking the F-measure into account, the best results were achieved with the smartphone's domain (77.0%) in the sentence-level task and with the hotel's dataset (94.8%) into the document-level performance.

5.2 Feature-based Sentiment Analysis

The purpose of the sentiment analysis based on features is to provide companies with customer opinions overviews, which automatically summarize the strengths and the weaknesses of the products and services they offer. In Section 1 we connected the definition of the opinion features to the following function (Liu, 2010):

$$T=O(f)$$

Where the *features* (f) of an *object* (O) (e.g. hotels) can be brand names (e.g. Artemide, Milestone), properties (e.g. cleanness, location), parts (e.g. rooms, apartments), related concepts (e.g. city, toponyms), or parts of the related concepts (e.g. city centre, tube, museum, etc...) (Popescu and Etzioni, 2007). Liu (2010) represented every object as a "special feature" (F) defined by a subset of features (f_i):

$$F = \{f_1, f_2, \ldots, f_n\}$$

Both F and f_i, grouped together under the noun *target* can be automatically discovered in texts through both synonym words and phrases W_i or other, direct or indirect, indicators I_i:

$$W_i = \{w_i 1, w_i 2, \ldots, w_i m\}$$

$$I_i = \{i_i 1, i_i 2, \ldots, i_i q\}$$

It is essential to discover not only the overall polarity of an opinionated document, but also its topic and features in order to discern the aspect of a product that must be improved, or whether the opinions extracted by the Sentiment Analysis applications are relevant to the product or not. For example, (81), an extract from a hotel review, expresses two opinions on two different kinds of features: the behavior of the staff (81a), and the beauty of the city in which the hotel is located (81b).

(81a) [$_{\text{Opinion}}$[$_{\text{Feature}}$Personale] *meravigliosamente accogliente*].
"Staff wonderfully welcoming".

(81b) [$_{\text{Opinion}}$[$_{\text{Feature}}$*Roma*] *è bellissima*].
"Rome is beautiful".

It is crucial to distinguish between the two topics, because just one of them, (81a), refers to an aspect that can be influenced or improved by the company.

5.2.1 Related Works

Pioneer works on feature-based opinion summarization are Hu and Liu (2004, 2006); Carenini et al. (2005); Riloff et al. (2006) and Popescu and Etzioni (2007). Both Popescu and Etzioni (2007) and Hu and Liu (2004) firstly identified the product features on the base of their frequency and, then, calculated the Semantic Orientation of the opinions expressed on these features. In order to find the most important features commented in reviews Hu and Liu (2004) used the association rule mining, thanks to which frequent itemsets can be extracted in free texts. Redundant and meaningless items are removed during a *Feature Pruning* phase. Experiments have been carried out on the first 100 reviews belonging to five classes of electronic products (`www.amazon.com` and `www.C|net.com`). Hu and Liu (2006) presented the algorithm ClassPrefix-Span that aimed to find special kinds of pat-

tern, the Class Sequential Rules (CSR), using fixed target and classes. Their method was based on the sequential pattern mining.
Carenini et al. (2005) struck a balance between supervised and unsupervised approaches. They mapped crude (learned) features into a User-Defined taxonomy of the entity's Features (UDF), that provided a conceptual organization for the information extracted. This method took advantages from a similarity matching, in which the UDF reduced the redundancies by grouping together identical features and then organized and presented information by using hierarchical relations). Experiments have been conducted on a testing set containing Pros, Cons and detailed free reviews of five products.
Riloff et al. (2006) used the subsumption hierarchy in order to identify complex features and, then, to reduce a feature set by removing useless features, which have, for example, a more general counterpart in the subsumption hierarchy. The feature representations used for opinion analysis are n-grams (unigrams, bigrams) and lexico-syntactic extraction patterns. Popescu and Etzioni (2007) presented OPINE, an unsupervised feature and opinion extraction system, that used the Web as a corpus to identify explicit and implicit features and relaxation-labelling methods to infer the Semantic Orientation of words. The system draws on WordNet's semantic relations and hierarchies for the individuation of the features (parts, properties and related concepts) and the creation of clusters of words.
Ferreira et al. (2008) made a comparison between the likelihood ratio test approach (Yi et al., 2003) and the Association mining approach (Hu and Liu, 2004). The e-product dataset (topical documents) and the annotation scheme (improved with some revisions) are the ones used by Hu and Liu (2004). In particular, the revised annotation scheme comprehended:

- part-of relationship with the product (e.g battery is a part of a digital camera);

- attribute-of relationship with the product (weight and design are attributes of a camera);

- attribute-of relationship with the product's feature (battery life is an attribute of the battery that is, in turn, a camera's feature).

Double Propagation (Qiu et al., 2009) focuses on the natural relation between opinion words and features. Because opinion words are often used to modify features, such relations can be identified thanks to the dependency grammar.
Because these methods have good results only for medium-size corpora, they must be supported by other feature mining methods. The strategy proposed by Zhang et al. (2010) is based on "no patterns" and part-whole patterns (meronymy):

- NP + Prep + CP: "battery of the camera";
- CP + with + NP: "mattress with a cover";
- NP CP or CP NP: "mattress pad";
- CP Verb NP: "the phone has a big screen".

Where NP is a noun phrase and CP a class concept phrase. The verbs used are "has", "have", "include", "contain", "consist", etc. "No" patterns are feature indicators as well. Examples of such patterns are "no noise" or "no indentation". Clearly, a manually built list of fixed "no" expression like "no problem" is filtered out from the feature candidates. Every sentence is POS-tagged using the Brill's tagger (Brill, 1995) and used as system input.
In order to find important features and rank them high Zhang et al. (2010) used a web page ranking algorithm named HITS (Kleinberg, 1999).
Somprasertsri and Lalitrojwong (2010) used a dependency based approach for the opinion summarization task. A central stage in their work is the extraction of relations between product features ("the topic of the sentiment") and opinions ("the subjective expression of the product feature") from online customer reviews. Adjectives and verbs

have been used in this study as opinion words. The maximum entropy model has been used in order to predict the opinion-relevant product feature relation. In general, in a dependency tree a feature can be of differing kinds:

- *Child*: the product feature is the subject or object of the verbs and the opinion word is a verb or a complement of a copular verb (opinions depend on the product features);

  e.g. I *like*$^{\text{(opinion)}}$ this *camera*$^{\text{(feature)}}$

- *Parent*: the opinion words are in the modifiers of product features, which include adjectival modifier, relative clause modifier, etc... (product features depend on the opinions),

  e.g. I have found that this camera takes *incredible*$^{\text{(opinion)}}$ *pictures*$^{\text{(feature)}}$

- *Sibling*: the opinion word may also be in an adverbial modifier, a complement of the verb, or a predicative (both opinions and product features depend on the same words);

  e.g. The *pictures*$^{\text{(feature)}}$ some time turn out *blurry*$^{\text{(opinion)}}$

- *Grand Parent*: the opinion words are adjectival complement of modifiers of product features (in the following example the word "good" is the adverbial complement of relative clause modifier of noun phrase "movie mode") (opinions depend on the words which depend on the product features);

  e.g. It has *movie mode*$^{\text{(feature)}}$ that works *good*$^{\text{(opinion)}}$ for a digital camera

- *Grand Child*: the product feature is the subject or object of the complements and the opinion word is a verb or a complement of a copular verb, for example (product features depend on the words which depend on the opinions);

  e.g. It's *great*$^{\text{(opinion)}}$ having the *LCD display*$^{\text{(feature)}}$

- *Indirect*: none of the above relations.

The Stanford Parser has been used by Somprasertsri and Lalitrojwong (2010) to parse documents in the pre-processing phase, before the dependency analysis stage. Definite linguistic filtering (POS based) pattern and the General Inquirer dictionary (Stone et al., 1966) has been used to locate noun phrases and to extract product feature candidate. The generalized iterative scaling algorithm (Darroch and Ratcliff, 1972) has been used to estimate parameters or weights of the selected features. Because it is possible to refer to a particular feature using several synonyms, Somprasertsri and Lalitrojwong (2010) used semantic information encoded into a product ontology, manually built by integrating manufacturer product descriptions and terminologies in customer reviews.
Wei et al. (2010) proposed a semantic-based method that made uses of a list of positive and negative adjectives defined in the General Inquirer to recognize opinion words and, then, extracted the related product features in consumer reviews.
Xia and Zong (2010) performed the feature extraction and selection tasks using word relation features, which seems to be effective features for sentiment classification because they encode relation information between words. They can be of different kinds: Uni (unigrams); WR-Bi (traditional bigrams); WR-Dp (word pairs of dependency relation); GWR-Bi (generalized bigrams) and GWR-Dp (dependency relations).
Gutiérrez et al. (2011) exploited Relevant Semantic Trees (RST) for the word-sense disambiguation and measured the association between concepts, at the sentence-level, using the association ratio measure.
Mejova and Srinivasan (2011) explored different feature definition and selection techniques (stemming, negation enriched features, term frequency versus binary weighting, n-grams and phrases) and approaches (frequency based vocabulary trimming, part-of-speech and lexicon selection and expected Mutual Information. Mejova's experimental results confirmed the fact that adjectives are important for polarity classification. Furthermore, they revealed that stemming

and using binary instead of term frequency feature vectors do not have any impact on performances and that the helpfulness of certain techniques depends on the nature of the dataset (e.g. size and class balance).

Concordance based Feature Extraction (CFE) is the technique used by Khan et al. (2012). After a traditional pre-processing step, regular expressions are used to extract candidate features. Evaluative adjectives, collected on the base of a seed list from Hu and Liu (2004), are helpful in the feature extraction task. In the end, a grouping phase found the appropriate features for the opinion's topic, grouping together all the related features and removing the useless ones. The algorithm used in this phase is based on the co-occurrence of features and uses the left and right feature's context.

Khan et al. selected candidate product features by employing noun phrases that appear in texts close to subjective adjectives. This intuition is shared with Wei et al. (2010) and Zhang and Liu (2011). The centrepiece of the Khan's method is represented by hybrid patterns, Combined Pattern Based Noun Phrases (cBNP) that are grounded on the dependency relation between subjective adjectives (opinionated terms) and nouns (product features). Nouns and adjectives can be sometimes connected by linking verbs (e.g. "camera produces fantastically good pictures"). Preposition based noun phrases (e.g. "quality of photo", "range of lenses") often represents entity-to-entity or entity-to-feature relations. The last stage is the proper feature extraction phase, in which, using an *ad hoc* module, the noun phrases of the cBNP patterns have been designated as product features.

5.2.2 Experiment and Evaluation

In order to give our contribution to the resolution of the opinion feature extraction and selection tasks, we both exploited the SentIta

database and other preexisting Italian lexical resources of Nooj, that consist of an objective dictionary that describes its lemmas with appropriate semantic properties; it has been used to define and summarize the features on which the opinion holder expressed his opinions.
In order to identify the relations between opinions and features, the lexical items contained in the just mentioned dictionaries have been systematically recalled into a Nooj local grammar, that provides, as feedback, annotations about the (positive or negative) nature of the opinion and about the semantic category of the features.
The objective lexicon consists in a Nooj dictionary of concrete nouns (Table 5.6), that has been manually built and checked by seven linguists. It counts almost 22,000 nouns described from a semantic point of view by the property *Hyper* that specify every lemma's hyperonym. The tags it includes are shown in Table 5.6. Through the software Nooj, it has been possible to create a connection between these dictionaries and an *ad hoc* FSA for the feature analysis.
As we will demonstrate below, the feature classification is strongly dependent on the review domains and topics, on the base of which specific local grammars need to be adapted (Engström, 2004; Andreevskaia and Bergler, 2008).
As shown in Figure 5.2, in the Feature Extraction phase the sentences or the noun phrases expressing the opinions on specific features are found in free texts. Annotations regarding their polarity (`BENEFIT/DRAWBACK`) and their intensity (`SCORE=[-3;+3]`) are attributed to each sentence on the base of the opinion words on which they are anchored. Obviously the graph reported in Figure 5.2 represents just an extract of the more complex FSA built to perform the task, which includes more than 100 embedded graphs and thousands of different paths, able to describe not only the sentences and the phrases anchored on sentiment adjectives, but also the ones that contain sentiment adverbs, nouns, verbs, idioms and other lexicon-independent opinion bearing expressions (e.g. *essere (dotato + fornito + provvisto) di* "to be

Label	Tag	Entries	Example	Traslation
body part,	Npc	598	*labbro*	lip
organism part,	Npcorg	627	*colon*	colon
text,	Ntesti	1,168	*rubrica*	address book
(part of) article of clothing,	Nindu	1,009	*vestaglia*	nightgown
cosmetic product,	Ncos	66	*rossetto*	lipstick
food,	Ncibo	1,170	*agnello*	lamb
liquid substance,	Nliq	341	*urina*	urine
potable liquid substance,	Nliqbev	29	*sidro*	cider
money,	Nmon	216	*rublo*	ruble
(part of) building,	Nedi	1,580	*torre*	tower
place,	Nloc	1,018	*valle*	valley
physical substance,	Nmat	1,727	*agata*	agate
(part of) plant,	Nbot	2,187	*zucca*	pumpkin
medicine,	Nfarm	415	*sedativo*	sedative
drug,	Ndrug	69	*mescalina*	mescaline
chemical element,	Nchim	1,212	*cloruro*	chloride
(part of) electronic device,	Ndisp	1,191	*motosega*	chainsaw
(part of) vehicle,	Nvei	1,082	*gondola*	gondola
(part of) furniture ,	Narr	450	*tavolo*	table
instrument,	Nstrum	3,666	*ventaglio*	fan
Tot	-	19,946	-	-

Table 5.6: Semantically Labeled Dictionary of Concrete Nouns

equipped with"; *essere un (aspetto + nota + cosa + lato) negativo* "to be a negative side").

The Contextual Valence Shifters that have been considered are the ones described in Chapter 4.

Differently from the other approaches proposed in Literature, the Feature Pruning task (Figure 5.3), in which the features extracted are grouped together on the base of their semantic nature, is performed in the same moment of the Extraction phase, just applying once the dictionaries-grammar pair to free texts. This happens because the grammar shown in Figure 5.3 is contained into the metanode NG (Nominal Group) of the feature extraction grammar.

Thanks to the instructions contained in this subgraph, the words described in our dictionary of concrete nouns as belonging to the same

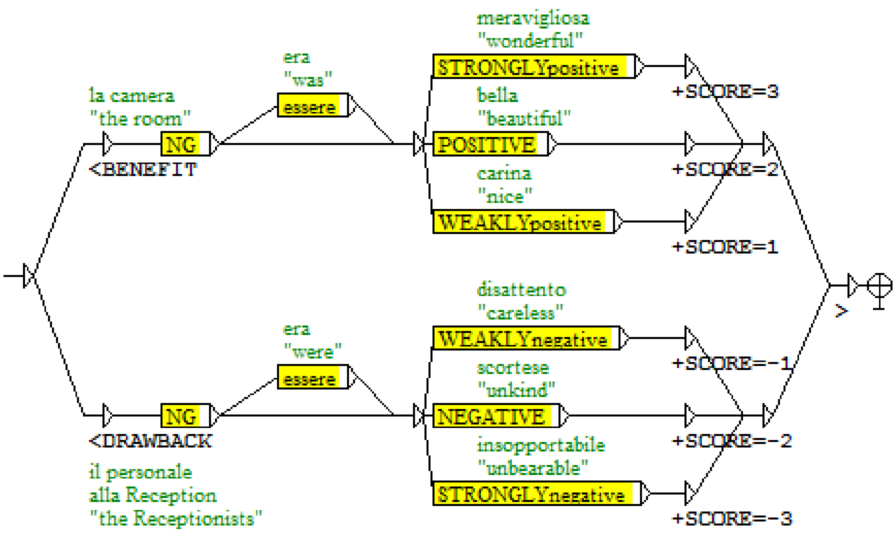

Figure 5.2: Extract of the Feature Extraction grammar

hyperonym receive the same annotation . The words labeled with the tags *Narr* (furniture, e.g. "bed") and *Nindu* (article of clothing, e.g. "bath towel") are annotated as "furnishings" (first path); the words labeled with the tags *Ncibo* (food e.g. "cake") and *NliqBev* (potable liquid substance, e.g. "coffee") receive the annotation "foodservice" (second path), and so on.

In order to perfect the results we also directly included in the nodes of the grammar the words that were important for the feature selection, but that were not contained in the dictionary of concrete nouns (abstract nouns e.g. *pranzo* "lunch", *vista* "view"); and the hyperonyms themselves that, in general, correspond with each feature class name (e.g. *arredamento* "furnishings", *luogo* "location").

Finally, we disambiguated terms that in the objective dictionary were associated to more than one tag by excluding the wrong interpretations from the corresponding node. For example, in the domain of

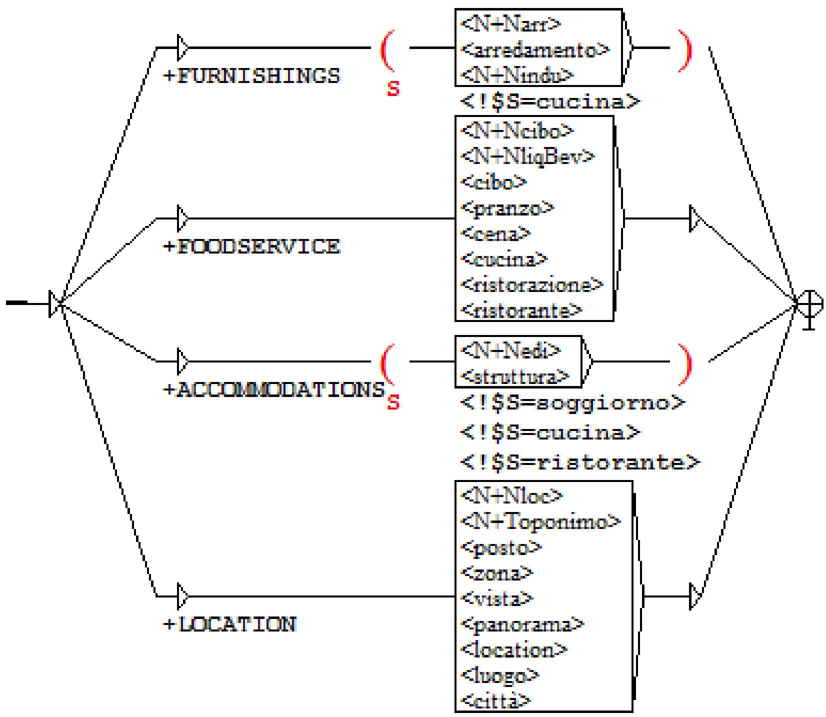

Figure 5.3: Extract of the Feature Pruning metanode

hotel reviews, if one comments the *cucina* “cooking” (first path) or the *soggiorno* “sojourn” (third path), he is clearly not talking about rooms (in Italian *cucina* means also “kitchen” and *soggiorno* “living room”), but, respectively, about the food service and the whole holiday experience.
The annotations provided by Nooj, once the lexical and grammatical resources are applied to texts written in natural language, can be on the form of XML (eXtensible Markup Language) tags. For this reason, they can be effortlessly recalled into an application that automatically applies the Nooj ad hoc resources and makes statistical

analyses on them. Therefore, we dedicated a specific module of Doxa to the feature-based sentiment analysis, that has been tested on a corpus composed of 1,000 hotel reviews, collected from websites like `www.tripadvisor.it`, `www.expedia.it` and `www.booking.com`. An extract of the automatically annotated corpus is reported below.

Review:

Sono stato in questo albergo quasi per caso, dopo aver subito un incidente e devo ammettere che se non fosse stato per la disponibilità, la cortesia e la professionalità di Mario, Pino e Rosa non avrei potuto risolvere una serie di cose. L'hotel è fantastico, silenzioso e decisamente pulito. La colazione ottima ed il responsabile della sala colazione gentilissimo.

"I happened to be in this hotel by accident and I must admit that if it hadn't been for the willingness, the kindness and the competence of Mario, Pino and Rosa I couldn't have solved a number of things. The hotel is fantastic, silent and definitely clean. Great the breakfast and very kind the responsible of the breakfast room".

Annotation:

Sono stato in questo albergo quasi per caso, dopo aver subito un incidente e devo ammettere che se non fosse stato per <BENEFIT TYPE="ATTITUDES" SCORE="2"> *la disponibilità* </BENEFIT>, <BENEFIT TYPE="ATTITUDES" SCORE="2"> *la cortesia* </BENEFIT> e <BENEFIT TYPE="ATTITUDES" SCORE="2"> *la professionalità* </BENEFIT> di Mario, Pino e Rosa non avrei potuto risolvere una serie di cose.
<BENEFIT TYPE="ACCOMMODATIONS" SCORE="3"> *L'hotel è fantastico* </BENEFIT>,
<BENEFIT TYPE="LOCATION" SCORE="2"> *silenzioso* </BENEFIT> e
<BENEFIT SCORE="3" TYPE="CLEANLINESS"> *decisamente pulito* </BENEFIT>.
<BENEFIT TYPE="FOODSERVICE" SCORE="3"> *La colazione ottima* </BENEFIT> ed

`<BENEFIT TYPE="ATTITUDES" SCORE="3">` *il responsabile della sala colazione gentilissimo* `</BENEFIT>`.

The evaluation presented in Table 5.7 shows that the method proposed in the present work performs very well with the hotel domain. We manually calculated, on a sample of 100 documents from the original corpus, the Precision on the Semantic Orientation Identification task (that regards the annotation of the sentences' polarity and intensity) and on the Feature Classification task (that regards the annotation of the types of the feature). Because the classes used to

Method	**Precision**		**Recall**	**F-score**
	SO Identification	**Classification**		
No residual category	93.3	92.4	72.3	81.1
Residual category	92.9	82.6	78.3	80.4

Table 5.7: F-score of Feature Extraction and Pruning

group the features have been identified *a priori* in our grammar, we also checked the results of our tool with the introduction of a residual category to annotate the features that do not belong to these classes. Even though this causes an increase on the Recall, a commensurate decrease of the Precision in the Classification task makes the value of the F-score similar to the one reached when the residual category is not taken into account. Significant examples of the sentences that have been automatically annotated in our corpus are given below:

(82) *Il responsabile della sala colazione gentilissimo*
"Very kind the responsible of the breakfast room"
`BENEFIT TYPE= "ATTITUDES" SCORE= "3"`

(83) *Le camere erano sporche*
"The rooms were dirty"
`DRAWBACK TYPE= "CLEANLINESS" SCORE= "-2"`

(84) *L'hotel è vicinissimo alla metro*
"The hotel is really close to the tube"
`BENEFIT TYPE= "LOCATION" SCORE= "3"`

In (82) the subjective adjective *gentilissimo* "very kind", recognised by the grammar as the superlative form (SCORE=+3) of the positive adjective *gentile* "kind" (SCORE=+2), makes the grammar recognize the whole sentiment expression and provides the information regarding its polarity and intensity. This is why the FSA associates the tag BENEFIT and the higher score to the feature that, in this case, is represented by a noun.
In (83) is shown that the "type" of the features can be indicated not only by nouns, but also by specific adjectives, as happens with *sporche* "dirty", that is both an opinion word that specifies that the whole expression is negative, and a feature class indicator that let the grammar classify it in the group of "cleanliness" rather than in the group of "accommodations" (that, instead, would be selected by the noun *camera* "room", described in our objective dictionary with the tags *Conc* "concrete" and *Nedi* "building").
In the end, sentence (84) attests the strength of the influence of the review domains: sometimes the lexicon is not enough to correctly extract and classify the product features. Domain-specific lexicon independent patterns are often required in order to make the analyses adequate (Engström, 2004; Andreevskaia and Bergler, 2008).

5.2.3 Opinion Visual Summarization

We said in Section 5.1 that Doxa is a prototype able to analyze opinionated documents from their semantic point of view. It automatically applies the Nooj resources to free texts, sums up the values corresponding to every sentiment expression, standardizes the results for the total number of sentiment expressions contained in the reviews and, then, provides statistics about the opinions expressed.

In this Section we show the Doxa improved functionalities dedicated to the sentiment analysis based on the opinion features. In the Hotel domain, this deeper analysis considerably increases the Precision on the sentences-level SO identification task, that goes from 81.3% to 93.3%, without any loss in the Recall, that holds steady, just rising of 0.2 percentage points, from 72.1% to 72.3% (see Table 5.7).
The feature-based module of Doxa, completely grounded on the automatic analysis of free texts, allows the comparison between more than one object on the base of different kinds of aspects that characterize them.
The regular decagon in the center of the spider graphs of Figure 5.4 represents the threshold value (zero) with which every group of opinion on the same object is compared: when a figure is larger than it, the opinion is positive; when it is smaller, the opinion is negative; when a feature's value is zero it means that the consumers did not express any judgment on that topic.
The automatic transformation of non-structured reviews in structured visual summaries has a strong impact on the work of company managers that must ground their marketing strategies on the analysis of a large amount of information, and on the individual consumers that need to quickly compare the Pros and Cons of the products or services they want to buy.

5.3 Sentiment Role Labeling

Semantic Roles, also called *theta* or *thematic roles* (Chomsky, 1993; Jackendoff, 1990, see Section 2.1.4), are linguistic devices able to identify in texts: "Who did What to Whom and How, When and Where" (Palmer et al., 2010, p. 1).
The main task of an SRL system is to map the syntactic elements of free text sentences to their semantic representation, through the identification of all the syntactic functions of clause-complements and their

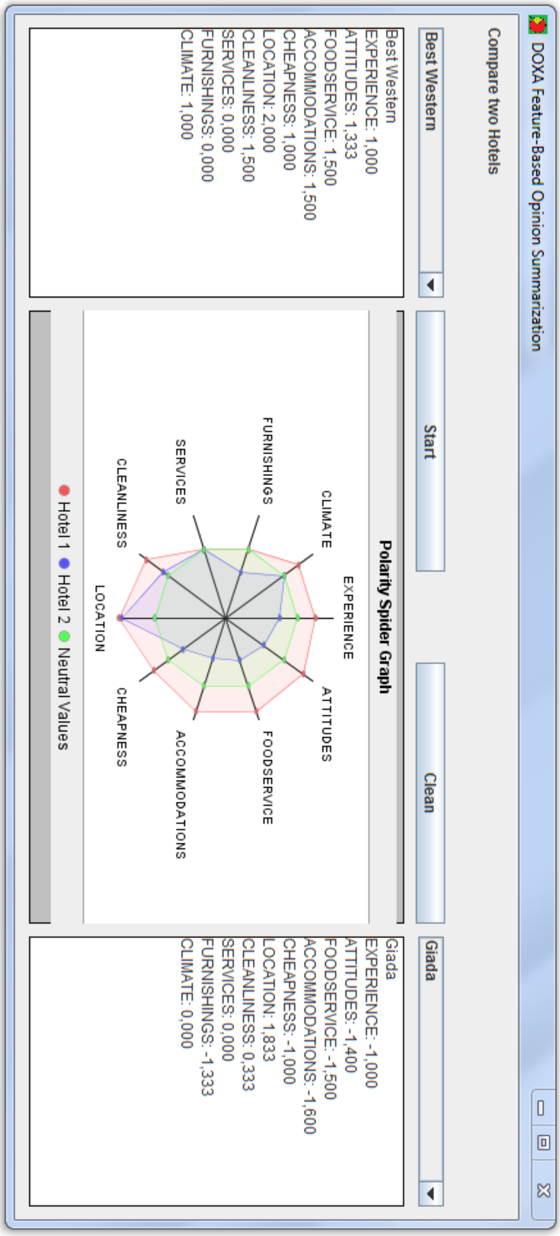

Figure 5.4: Doxa module for Feature-based Sentiment Analysis

labeling with appropriate semantic roles (Rahimi Rastgar and Razavi, 2013; Monachesi, 2009).
To work, an SRL system needs machine readable lexical resources, in which all the predicates and their relative arguments are specified. FrameNet (Baker et al., 1998; Fillmore et al., 2002; Ruppenhofer et al., 2006), VerbNet Schuler (2005) and the PropBank Frame Files (Kingsbury and Palmer, 2002) provide the basis for large scale semantic annotation of corpora (Giuglea and Moschitti, 2006; Palmer et al., 2010).
In this Section, according with the Semantic Predicates theory (Gross, 1981), we performed a matching between the definitional syntactic structures, attributed to each class of verbs, and the semantic information we attached in the database to every lexical entry.
This way we could create a strict connection between the *arguments*, selected by a given Predicate listed in our tables, and the *actants* involved into the same verb's Semantic Frame (Fillmore, 1976; Fillmore and Baker, 2001; Fillmore, 2006). In the experiment that we are going to describe, we focused on the following frames:

- "Sentiment" (e.g. *odiare* "to hate"), that involves the roles *experiencer* and *stimulus* ;
- "Opinion" (e.g. *difendere* "to stand up for"), that implicates the roles *opinion holder, target* of the opinion and *cause* of the opinion;
- "Physical act" (e.g. *baciare* "to kiss"), that evokes the roles *patient* and *agent.*

5.3.1 Related Works

A group of researches in the field of Semantic Role Labeling focused on the automatic annotation of the roles which are relevant to Sentiment Analysis and opinion mining, such as *source/ opinion holder, target/ theme/ topic.*

Bethard et al. (2004), with question answering purposes, proposed an extension of semantic parsing techniques, coupled with additional lexical and syntactic features, for the automatic extraction of propositional opinions. The algorithm used to identify and label semantic constituents, is the one developed by Gildea and Jurafsky (2002); Pradhan et al. (2003).
Kim and Hovy (2006) presented a Semantic Role Labeling system based on the Frame Semantics of Fillmore (1976), that aimed to tag the frame elements semantically related to an opinion bearing word expressed in a sentence, which is considered as the key indicator of an opinion. The learning algorithm used for the classification model is Maximum Entropy (Berger et al., 1996; Kim and Hovy, 2005). FrameNet II Ruppenhofer et al. (2006) has been used to collect frames related to opinion words.
Other works based on FrameNet are Houen (2011), that used Frame-Frame relations in order to expand the subset of polarity scored Frames found in the FrameNet database; Ruppenhofer et al. (2008); Ruppenhofer and Rehbein (2012) and Ruppenhofer (2013), which added opinion frames with slots for *source*, *target*, *polarity* and *intensity* to the FrameNet database to build SentiFrameNet, a lexical database enriched with inherently evaluative items associated to opinion frames.
Lexicon-based approaches are the one of Kim et al. (2008), that made use of a collection of communication and appraisal verbs, the SentiWordNet lexicon, a syntactic parser and a named entity recognizer for the extraction of opinion holders from texts; and the one of Bloom et al. (2007), that extracted domain-dependent opinion holders through a combination of heuristic shallow parsing and dependency parsing.
Conditional Random Fields (Lafferty et al., 2001) is the method used by Choi et al. (2005), that, interpreting the semantic role labeling task as an information extraction problem, exploited a hybrid approach that combines two very different learning-based methods: CRF for the

named entity recognition and a variation of AutoSlog (Riloff, 1996) for the information extraction. CRF have been also used by by Choi et al. (2006), who presented a global inference approach to jointly extract entities and relations in the context of opinion oriented information extraction, through two separate token-level sequence-tagging classifiers for opinion expression extraction and source extraction, via linear chain CRF (Lafferty et al., 2001).

5.3.2 Experiment and Evaluation

The starting point of our experiment on SRL are the LG tables of the Italian verbs, developed at the Department of Communication Science of the University of Salerno. Among the lexical entries listed in such matrices, we manually extracted all the verbs endowed with a positive or negative defined semantic orientation. Such verbs could be expression of *emotions*, *opinions* or *physical acts*. Details of this classification can be found in Section 3.3.3.
As an example, in Tables 5.8 and 5.9 we show a small group of verbs belonging to the Lexicon-Grammar class 45. This class includes all the verbs that can entry into a syntactic structure such as N_0 *V di* N_1, in which the “subject" (N_0) selected by the verb (*V*) is generally a human noun (*Num*) and the complement (N_1) is a completive (*Ch F*) or infinitive (*V-inf comp*) clause, usually introduced by the preposition “di" (see Table5.8). As shown in Table 5.9, our databases contain also semantic information concerning the nature, the semantic orientation and the strength of the Predicates in exam.
In detail, the tagset used in this experiment is the following:

1. Type
   (a) SENT, sentiment
   (b) OP, opinion
   (c) PHY, physical act

N0=Num	N0= il fatto Ch F	**Verb**	N1= che F	N1= che Fcong	di N1um	diN1-um	di N1 contro N2	prep V-inf comp
+	-	profittare	+	+	+	+	+	-
+	-	ridersene	+	+	+	+	-	-
+	-	risentirsi	+	+	+	+	-	+
+	-	strafottersene	+	+	+	+	-	-
+	-	vergognarsi	+	+	+	+	-	+

Table 5.8: Extract of the LG table of the verb Class 45

2. Orientation
   (a) POS, positive
   (b) NEG, negative
3. Intensity
   (a) FORTE, intense
   (b) DEB, feeble

Speaking in terms of Frame Semantics, we identified in the Opinion Mining and in the Sentiment Analysis field three Frames of interest, recalled by specific Predicates: *Sentiment*, *Opinion* and *Physical act*. The frame elements evoked by such frames are described below.

Sentiment

It refers to the expression of any given frame of mind or affective state.
The “sentiment" words can be put in connection with some WordNet Affect categories (Strapparava et al., 2004), such as *emotion, mood, hedonic signal*.
Examples are *sdegnarsi* “to be indignant" (class 10); *odiare* “to hate" (class 20); *affezionarsi* “to grow fond" (class 44B); *flirtare* “to flirt"

(class 9); *disprezzare* “to despise" (class 20); *gioire* “to rejoice" (class 45).
Predicates of that kind evoke as frame elements an *experiencer*, that feels the emotion or other internal states, and a *stimulus*, and event or a person that instigates such states (Gross, 1995; Gildea and Jurafsky, 2002; Swier and Stevenson, 2004; Palmer et al., 2005; Elia, 2013). This semantic frame summarizes the FrameNet ones connected to emotions, such as *Sensation*, *Emotions_of_mental_activity*, *Cause_to_experience*, *Emotion_active*, *Emotions*, *Cause_emotion*, ect...

Opinion. The type “Opinion", instead, is the expression of positive or negative viewpoints, beliefs or judgments, that can be personal or shared by most people. It comprehends, among the the WN-affect categories, *trait*, *cognitive state*, *behavior*, *attitude*. Examples are *ignorare* “to neglect" (class 20); *premiare* “to reward" (class 20); *difendere* “to defend" (class 27); *esaltare* “to exalt" (class 22); *dubitare* “to doubt" (class 45); *condannare* “to condemn" (class 49); *deridere* “to make fun of" (class 50).
The frame elements they evoke are an *opinion holder*, that states an opinion about an object or an event, and an *opinion target*, that represents the event or the object on which the opinion is expressed about (Kim and Hovy, 2006; Liu, 2012). Some predicates imply also the presence of a *cause* that motivates the opinion (see Section 3.3.3).
Into the FrameNet frame *Opinion* and *Judgment*, the *opinion holder* is called *Cognizer*, bu we preferred to use a word which is more common in the Sentiment Analysis and in the Opinion Mining literature.

Physical act

The type “Physical act" comprises verbs like *baciare* “to kiss" (class 18); *suicidarsi* “to commit suicide" (class 2); *vomitare* “to vomit" (class 2A); *schiaffeggiare* “to slap" (class 20); *sparare* “to shoot" (class 4);

palpeggiare “to grope" (class 18).
For this group of predicates the selected frame elements ara a *patient* that is the victim (for the negative actions) or the beneficiary (for the positive ones) of the physical act carried out by an *agent* (Carreras and Màrquez, 2005; Màrquez et al., 2008). It includes a large number of FrameNet frames, such as *Cause_bodily_experience*, *Shoot_projectiles*, *Killing*, *Cause_harm*, *Rape*, *Sex*, *Violence*, ect.

In order to perform the orientation and the intensity attribution, we manually explored the Italian LG tables of verbs and the SentIta semantic labels.
Thanks to lexical resources of this kind, it is possible to automatically extract and semantically describe real occurrences of sentences, like (85)

(85) $[_{\text{Sentiment}}[_{\text{Experiencer}}$ *Renzi*$^{(\text{N}_0)}]$ *si vergogna*$^{(\text{V})}$ $[_{\text{Stimulus}}$ *di parlare di energia in Europa*$^{(\text{N}_1)}]]$

“Renzi feels ashamed of talking about energy in Europe"

in which the syntactic structure of the verb, *vergognarsi* “to feel ashamed", N_0 *V (*di) Ch F*, is matched, by means of interpretation rules (e.g. V = N_0 *V (*di) Ch F* = *Caus(s, sent, h)*; $N_0 = h$; $N_1 = s$) to the semantic function *Caus(s, sent, h)*, that puts in relation an *experiencer h* and a *stimulus s* thanks to a Sentiment Semantic Predicate *sent* (Gross, 1995, Section 2.1.4).
Moreover, we provided our LG databases with the specification of the arguments (N_0, N_1, N_2, ect...) that are semantically influenced by the semantic orientation of the verbs. The purpose is to correctly identify them as *features* of the opinionated sentences and to work on their base also into feature-based sentiment analysis tasks.

The reliability of the LG method on the Semantic Role Labeling in the Sentiment Analysis task has been tested on three different

Verb	LG Class	Type	Orientation	Intensity	Influence
profittare	45	opinion	negative	-	N0
ridersene	45	opinion	negative	weak	N1
risentirsi	45	sentiment	negative	-	N0
strafottersene	45	opinion	negative	strong	N1
vergognarsi	45	sentiment	negative	strong	N0

Table 5.9: Examples of semantic descriptions of the opinionated verbs from the LG class 45

datasets, two of which have been extracted from social networks or web resources.
In detail, the first two datasets come from Twitter and the third is a free web news headings dataset provided by DataMediaHub (`www.datamediahub.it`, `www.humanhighway.it`).
The tweets have been downloaded using the hashtag that groups together the user comments on the election of the Italian President Mattarella (1) and the one that collects the comments on the Masterchef Italian TV show (2).

- Tweets: 46,393 tweets
  1. `#Mattarellapresidente`: 10,000 tweets
  2. `#Masterchefit`: 36,393 tweets
- News Headings : 80,651 titles

The LG based approach on which this experiment has been built includes the following basic steps:

- pre-processing pipeline, that includes two phases:
  - a cleaning up phase, carried out with Python routines, that

aims to distinguish in the datasets linguistic elements from structural elements (e.g. markup informations, web specific elements);

– an automatic linguistic analysis phase, with the goal to linguistically standardize relevant elements obtained from the cleaned datasets; in this phase texts are tokenized, lemmatized and POS tagged using TreeTagger (Schmid, 1994; Schmid et al., 2007) and, then, parsed using DeSR, a dependency parser (Attardi et al., 2009);

- LG based automatic analysis, in which the raw data are semantically labeled according with the syntactic/semantic rules of interpretation connected with each LG verb class.

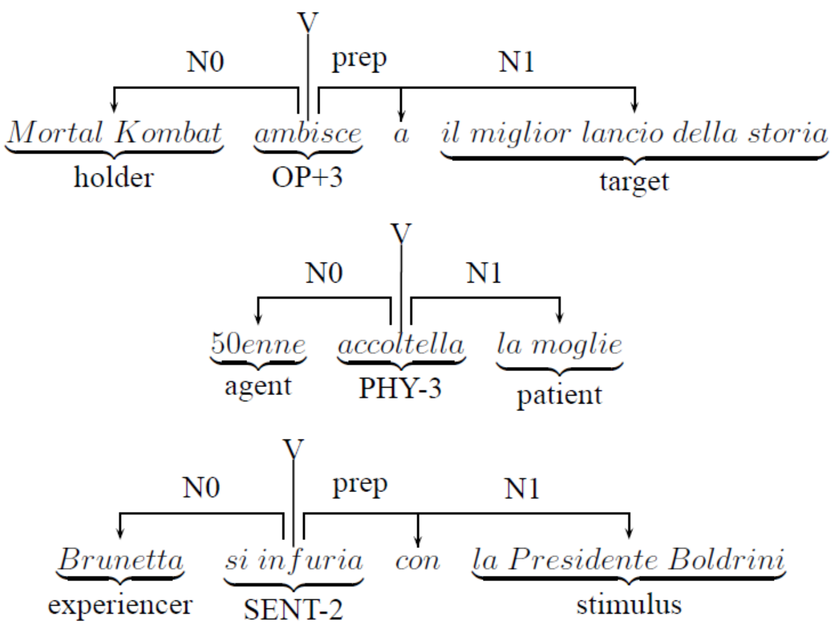

Figure 5.5: Examples of syntactically and semantically annotated sentences

Figure 5.5 presents three headlines examples processed both with the dependency syntactic parser and the semantic LG-based semantic analyzer.
Notice that the elements of the traditional grammar automatically identified by DeSR, such as subjects and complements, have been renamed according with the Lexicon-Grammar tradition.
The corpus, that counts 127,044 short texts, has been analyzed and semantically and syntactically annotated.
The representative sample on which the human evaluation has been performed, instead, has 42,348 texts.
The evaluation of the performances of our tool proved the effectiveness of the Lexicon-Grammar approach. The average F-scores achieved in the different datasets are 0.71 in the Twitter and 0.76 in the Heading corpus.

Chapter 6

Conclusion

The present research handled the detection of linguistic phenomena connected to subjectivity, emotions and opinions from a computational point of view.
The necessity to quickly monitor huge quantity of semistructured and unstructured data from the web, poses several challenges to Natural Language Processing, that must provide strategies and tools to analyze their structures from a lexical, syntactical and semantic point of views.
The general aim of the Sentiment Analysis, shared with the broader fields of NLP, Data Mining, Information Extraction, etc., is the automatic extraction of value from chaos (Gantz and Reinsel, 2011); its specific focus instead is on opinions rather than on factual information. This is the aspect that differentiates it from other computational linguistics subfields.
The majority of the sentiment lexicons has been manually or automatically created for the English language; therefore, existent Italian lexicons are mostly built through the translation and adaptation of the English lexical databases, e.g. SentiWordNet and WordNet-Affect.
Unlike many other Italian and English sentiment lexicons, SentIta,

made up on the interaction of electronic dictionaries and lexicon dependent local grammars, is able to manage simple and multiword structures, that can take the shape of distributionally free structures, distributionally restricted structures and frozen structures.
Moreover, differently from other lexicon-based Sentiment Analysis methods, our approach has been grounded on the solidity of the Lexicon-Grammar resources and classifications, that provide fine-grained semantic but also syntactic descriptions of the lexical entries. Such lexically exhaustive grammars distance themselves from the tendency of other sentiment resources to classify together words that have nothing in common from the syntactic point of view.
Furthermore, through the Semantic Predicate theory, it has been possible to postulate a complex parallelism among syntax and semantics that does not ignore the numerous idiosyncrasies of the lexicon.
According with the major contribution in the Sentiment Analysis literature, we did not consider polar words in isolation. We computed they elementary sentence contexts, with the allowed transformations and, then, their interaction with contextual valence shifters, the linguistic devices that are able to modify the prior polarity of the words from SentIta, when occurring with them in the same sentences.
In order to do so, we took advantage of the computational power of the finite-state technology. We formalized a set of rules that work for the intensification, downtoning and negation modeling, the modality detection and the analysis of comparative forms.
Here, the difference with other state-of-the-art strategies consists in the elimination of complex mathematical calculation in favor of the easier use of embedded graphs as containers for the expressions designed to receive the same annotations into a compositional framework.
With regard to the applicative part of the research, we conducted, with satisfactory results, three experiments on the same number of Sentiment Analysis subtasks: the sentiment classification of documents and sentences, the feature-based Sentiment Analysis and the seman-

tic role labeling based on sentiments.
This work exploited a method based on knowledge, but this does not run counter statistical strategies. All the semantically annotated datasets produced by our fine-grained analysis that can, indeed, be reused as testing sets for learning machines.
As concerns the limitations of this research, we mention, among others, the cases of irony, sarcasm and cultural stereotypes, which still remain open problems for the NLP in general and for the Sentiment Analysis in particular, since they can completely overturn the polarity of the sentences.
Sarcasm, hyperbole, jocularity, etc., are all rhetorical devices used to express *verbal irony*, a figurative linguistic process used to intentionally deny what it is literally expressed (Gibbs, 2000; Curcó, 2000). Therefore, irony could been interpreted as a sort of indirect negation (Giora, 1995; Giora et al., 1998), in which some expectations are violated (Clark and Gerrig, 1984; Wilson and Sperber, 1992). On this purpose, (Reyes et al., 2013, p. 243) affirms that irony is perceived "at the boundaries of conflicting frames of reference, in which an expectation of one frame has been inappropriately violated in a way that is appropriate in the other".
This linguistic device has been explored in both computational linguistics studies and in Opinion Mining works. Sets of potential indicators have been tested on large corpora through different approaches, obtaining encouraging results, over the state-of-the-art in some respects.
In detail, Tepperman et al. (2006) used prosodic, spectral, and contextual cues. Carvalho et al. (2009) selected as irony cues emoticons, onomatopoeic expressions for laughter, heavy punctuation marks, quotation marks and positive interjections. Davidov et al. (2010) exploited the meta-data provided by Amazon to locate gaps between the star ratings and the sentiments expressed in the raw reviews. Reyes and Rosso (2011) chose n-grams, part of speech n-grams, funny profiling, positive/negative profiling, affective profiling, and pleasantness pro-

filing. González-Ibánez et al. (2011) identified sarcasm through punctuation marks, emoticons, quotes, capitalized words, discursive terms that hint at opposition or contradiction in a text, temporal and contextual imbalance, character-grams, skip-grams and emotional scenarios concerning activation, imagery, and pleasantness. Maynard and Greenwood (2014) exploited the hashtag tokenization.

Among others, Veale and Hao (2009) carried out a very interesting study on creative irony focusing on ironic comparisons of the kind *A Topic is as Ground as a Vehicle* (Fishelov, 1993; Moon, 2008), which can consist on pre-fabricated similes, e.g. "as strong as an ox" (Taylor, 1954; Norrick, 1986; Moon, 2008), or on new and more emphatic and creative variations along the frozen similes, e.g. "as dangerous as a *toothless* wolf". The authors found out that the 2% of these elaborations subvert the original simile to achieve an ironic effect. The problem is that sarcasm, in general, is a phenomenon inherently difficult to analyze for machines and often for humans as well (Justo et al., 2014; Maynard and Greenwood, 2014). In addition, the barriers to the creation of brand new comparisons are very low (Veale and Hao, 2009).

In any case, the solutions to verbal irony proposed in literature seem far from being accurate and generalizable. They frequently lead to contradictory results, such as with the use of punctuation marks, which made Carvalho et al. (2009) and Tepperman et al. (2006) reach relatively high precision, but served as very weak predictors for Justo et al. (2014) and Tsur et al. (2010).

In this works, speaking in cost-benefit terms, we realized that the quantity of errors introduced by the use of irony cues would have gone over the errors caused by their absence. Therefore we limited the irony analysis to the cases of frozen comparative sentences described in Section 3.4.2, that can attribute a semantic orientation to neutral words (86) or reverse the orientation of polar words (87).

(86) Arturo è *bianco*$^{[0]}$ come un *cadavere* [-2]
"Arturo is as white as a dead body" (Arturo is pale)

(87) Maria è *agile*[+2] come una *gatta di piombo* [-2]
"Maria is as agile as a lead cat" (Maria is not agile).

Anyway, as can be noticed in (88) and (89), ironic comparisons can vary considerably from one case to another (Veale and Hao, 2009), and cannot be distinguished automatically from non-ironic comparisons (90), as long as we don not include (domain-dependent) encyclopedic knowledge into the analysis tools.

(88) La ripresa è *degna*[+2] di un *trattore con aratro inserito*
"The pickup is worthy of a tractor with an inserted plough"

(89) E quel tocco di piccante (...) è *gradevole*[+2] quanto lo sarebbe *una spruzzata di pepe su un gelato alla panna*
"And that touch of piquancy (...) is as pleasant as a spattering of pepper on a cream flavoured ice-cream"

(90) Gli spazi interni sono *comodi*[+2] come una *berlina* [+2]
"Inside spaces are as comfortable as a sedan".

Similar comments on the required encyclopedic knowledge can be made about cultural stereotypes as well (91, 92).

(91) La nuova fiat 500 è *consigliabile*[+2] molto di più ad una ragazza [-2]
"The new Fiat 500 is recommended a lot more to a girl"

(92) Un gioco per bambini di 12 anni [-2]
"A game for 12 years old child".

Appendix A

Italian Lexicon-Grammar Symbols

Agg Val Evaluative adjective

Agg Adjective

Avv Adverbe

C_i Constrained nominal group

Ch F Completive complement without specification of mood

Det Determiner

N_0 Sentence formal subject

$N_{1,2,3}$ Sentence complements

N_i Nominal group

N Noun

Napp Appropriate noun

Nconc Concrete noun

Npc Noun of body part

Nsent Noun of Sentiment

Num Human noun

N-um Not human noun

Ppv Pronoun in preverbal position

Prep Preposition

V Verb

V-a Adjectivalization

Vcaus Causative verb

V-n Nominalization

Vsup Support verb

Vval Evaluative verb

Vvar Support verb variant

Appendix B

Acronyms

ALU Atomic Linguistic Units

cBNP Combined Pattern Based Noun Phrases

CCG Combinatory Categorial Grammar

CFE Concordance-based Feature Extraction

CRF Conditional Random Field

CSR Class Sequential Rule

CVS Contextual Valence Shifters

DRS Discourse Representation Structure

ERTN Enhanced Recursive Transition Network

eWOM electronic Word of Mouth

FMM Forward Maximum Matching

FSA Finite State Automata

FST Finite State Transducers

LDA Latent Dirichlet Allocation

LG Lexicon-Grammar

LSA Latent Semantic Analysis

LSF Lexical Syntactic Feature

mCVS Morphological Contextual Valence Shifters

MPQA Multi Perspective Question Answering

NLP Natural Language Processing

PMI Pointwise Mutual Information

POS Part of Speech

PP Prior Polarity

QN Quality Noun

RNTN Recursive Neural Tensor Network

RST Relevant Semantic Tree

RTN Recursive Transition Network

SO Semantic Orientation

SVM Support Vector Machine

TGG Transformational-Generative Grammar

UDF User Defined taxonomy of entity Feature

WMI Web-based Mutual Information

XML eXtensible Markup Language

List of Figures

List of Tables

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