Text Mining Techniques for Knowledge Extraction from Technical Documents

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Preface

Chapter 1

Introduction

1.1 Goal

Il problema non è sostituire domain knowledge. Idea vecchia ha fallito. E' insostibuibile perchè:

- Technology, interessa gli ingegneri
- Social Science, decision making

PErchè fallita: da una parte è andata avanti la knowledge rappresentation. E' impossibile rappresentare la conoscenza con regole, ma con altri strumenti si può rappresentare (bottom-up).

Inoltre ho text mining, capaità di processare testi. Parte di intelligenza artificiale. Questi fenomeni non sostituioscono l'esperto ma ne cambiano il modo di operare.

Oggi si integra. Vogliamo un esperto di dominio che faccia meglio il suo mestiere.

Abbiamo oggi più potenza e correzione errori.

Oltre ad efficienza e potenza nel correggere gli errori. Ora c'è anche la possibilità dio maggiore specificità. L'obiettivo è qiuindi poratre domain knowledge sia su technology sia ai decisori sociali.

1.2 Problem

Foresight

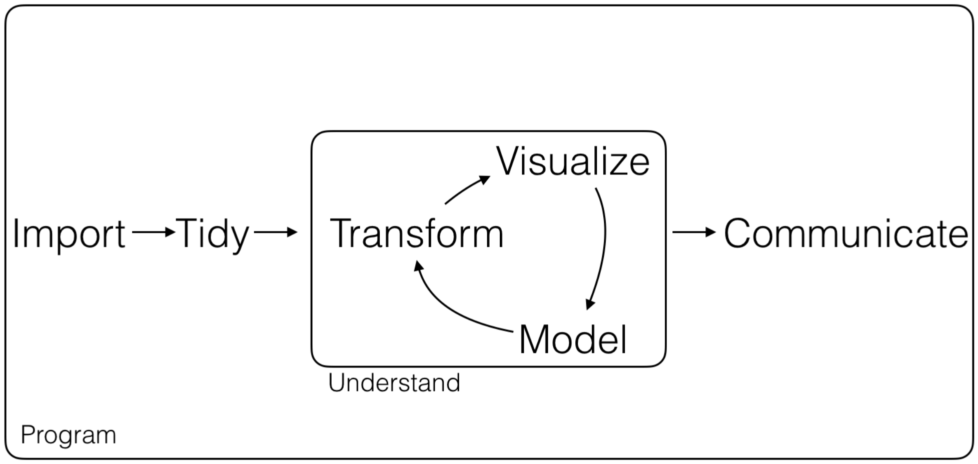

Figure 1.1: A general workflow for the process of data analysis. Readapted from Wickham (2016)

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Tipicamente occupaimo di attività ad altà ripetitività. Ti porti dietro metodologie ingegneristiche applicate a sistemi inernti, andnano a operare in sistemi socio-tecnici. Hai fatto il tuo mestieri (ricerca operativa ecc..). Negli ultimi anni però le aziende le attività a maggior valore aggiunto sono non ripetitive. R&S, Design, marketing, HR ecc.. e quindi gestione della conoscena. Su situazione che sembrano uniche il gestionale rischia di perdere rispetto al creativo. Come disciplina voglio presidiare queste aree: non ci occupaimo di casi unici, ma costruire modelli in grado di incorporare conoscenza per essere usati in questi. La tesi ha l'obbiettivo di esploration and exploitation queste direzioni. Hon trovato nella data science è più nello specifico nel text mining gli strumenti adatti.

Chapter 2

State of the Art

The analysis of technical documents require the design of processes that rely both on programming and Natural Language Processing techniques and on the understanding and knowledge of field experts. While the first techniques are codified and explicit, the second are sometimes implicit and always harder to systematize. In this section i treat these two groups of techniques in the same way to give to the reader a systematic literature review on these topics. For this reason the sections of this chapter has the subsequent structure:

- At a first level there are two sections 2.1 and 2.2, reviewing respectively the processes of *programming and Natural Language Processing* and of *undestanding and knowldege of field experts application*;
- Section 2.1 has a subsection for each of the *phases* showed in figure 1.1. These subsections goes from 2.1.1 to 2.1.7;
- Each subsection from 2.1.1 to 2.1.7 contains the relative Natural Language Processing *task* that are relevant for the analysis of technical documents, for example Document Retrieval 2.1.2.1, Part-Of-Speech-Tagging; 2.1.4.6 or Named Entity Recognition 2.1.5.5.
- Each task subsection describes the relevant *techniques* to perform that task. I use the word techniques to include mainly algorithms and procedures but also more generic methods or frameworks;
- Since the second section 2.2 describes less systematic phases, task and techniques this section opens with a first subsection 2.2.1 that focuses on the studies of the problems of using expert knowledge in an analytic process and which are the techniques to convert this knowledge in a format that is usable in a Natural Language Processing workflow.
- Finally, always section 2.2 has a subsection for each of the anlyzed technical *documents*. These subsections goes from 2.2.2 to 2.2.7.

2.1 Phases, Tasks, and Techniques

In this section I make a review of the most important techniques for Natural Language Processing in the context of technical documents analysis. The techniques (mainly algorithms) are grouped in phases (Import, Tidy, Transform, Model, Visualize, Communicate) showed in figure 1.1 and each phases is dived in the NLP tasks that are the most important for the analysis of technical documents. This standard process has been disclosed in the framework of the tidyverse (Wickham and Grolemund, 2016). The algorithms i reviewed in this section are summmarised in table tot, where the reader can see the relationship between tasks and techniques.

2.1.1 Program

Programming is a key activity to perform in order to effectively and efficiently perform text mining. It is not a phases per se because each phase is implemented trough programming. It is critical that an analysts has in mind the need of maximizing the probability that their analysis is reproducible, accurate, and collaborative. This goals can be reached only trough programming. The most used programming languages for text mining and natural language processing are R (R Development Core Team, 2008) and Python (Rossum, 1995). R and Python are both open-source programming languages with a large community of developers, and new libraries or tools are added continuously to their respective catalog. R is mainly used for statistical analysis and data science while Python is a more general purpose programming language. R has been developed by Academics and statisticians over two decades. R has now one of the richest ecosystems to perform data analysis and there are around 12000 packages available in CRAN (open-source repository of R). The rich variety of libraries makes R the first choice for statistical analysis. Another cutting-edge difference between R and the other statistical products is R-studio. RStudio is a free and open-source integrated development environment (IDE) for R. It includes a console, syntax-highlighting editor that supports direct code execution, as well as tools for plotting, history, debugging and workspace management. Finally, it is widely recognized the great performances that R has for data visualisation and communication. Python can pretty much do the same tasks as R: data wrangling, engineering, feature selection web scrapping, app and so on. Anyway, Python has great performances in the deployment and implementation of machine learning at a large-scale. Furthermore, Python codes are easier to maintain and more robust than R.

2.1.2 Import

The first activities to perform in a text mining pipeline is to find all the documents that contains useful information for the analysis and then import the corpus (the set of documents) in to the computer program. The present section is thus focused on techniques for document retrieval 2.1.2.1 and on the most popular documents digital formats 2.1.2.2.

2.1.2.1 Document Retrieval

Document retrieval is the process of matching a user query against a set of documents. A document retrieval system has two main tasks:

1- Find the documents that are relevant with respect to the user queries 2- Measure the relevance of the matching results

Building a query means to use field specific knowledge and logical rules to write a text string that is the composition of keywords and Boolean operators. The set of keywords (single words or phrases) is chosen in such a way that these are likely to be contained in the searched documents. Boolean operators can also be used to increment the performance of the query. The AND operator, for example is used to retrieve all the document that contains both of the terms at the left and the right of it, OR for document that contains at least one of the two words. Another important tool for making a good query are regular expressions. Regular expression (regexp) is a language for specifying text search strings, an algebraic notation for characterizing a set of strings. This language widely used in modern word processor and text processing tools. A regular expression search function will search through the corpus, returning all texts that match the pattern. For example, the Unix command-line tool grep takes a regular expression and returns every line of the input document that matches the expression. To evaluate the performance of a query is useful to understand the concepts of precision and recall.

Recall is the ratio of relevant results returned to all relevant results. Precision is the number of relevant results returned to the total number of results returned. Due to the ambiguities of natural language, full-text-search systems typically includes options like stop words to increase precision. Stop-words are words that filter all the document which contains them. On the other side, stemming to increase recall 2.1.4.3. The trade-off between precision and recall is simple: an increase in precision can lower overall recall, while an increase in recall lowers precision (Yuwono and Lee, 1996). Usually when a user performs a query, the main problem are false positives (the results that are returned by the systems but are not relevant to the user). False positives has a negative impact on the precision of the query. The retrieval of irrelevant documents is particularly strong for technical documents due to the inherent ambiguity of technical language. For this reason to understand and to use the rules of query building are fundamental to the technical document analysis, since without a good query is rare to have a good set of documents to analyze.

2.1.2.2 Documents Format

For the purpose of the present thesis documents are considered in a digital format, and there is no need to read it from a analogical source. From the computer science point of view, text is a human-readable sequence of characters and the words they form that can be encoded into computer-readable formats. There is no standard definition of a text file, though there are several common formats. The most common types of encoding are:

- ASCII, UTF-8 — plain text formats
- .doc for Microsoft Word — Structural binary format developed by Microsoft (specifications available since 2008 under the Open Specification Promise)
- HTML (.html, .htm), (open standard, ISO from 2000)
- Office Open XML — .docx (XML-based standard for office documents)
- OpenDocument — .odt (XML-based standard for office documents)
- PDF — Open standard for document exchange. ISO standards include PDF/X (eXchange), PDF/A (Archive), PDF/E (Engineering), ISO 32000 (PDF), PDF/UA (Accessibility) and PDF/VT (Variable data and transactional printing). PDF is readable on almost every platform with free or open source readers. Open source PDF creators are also available.
- Scalable Vector Graphics (SVG) - Graphics format primarily for vector-based images.
- TeX — Popular open-source typesetting program and format. First successful mathematical notation language.

For the R software there exist many packages that helps to import documents in several formats (Wickham et al., 2017).

2.1.3 Tidy

After that data are imported they have to be processed in such a way that it would be possible to perform the main task of data analysis (transformation, modelling and visualisation). This task of tidying data (usually referred to as data pre-processing) can be very time expensive, so it is important to have clear methods and techniques to perform this task.

Tidy data sets have structure and working with them is easy; they're easy to manipulate, model and visualize (Wickham et al., 2014). Tidy data sets main concept is to arrange data in a way that each variable is a column and each observation (or case) is a row. The characteristics of tidy data can be thus summarised as the points (Leek, 2015):

- Each variable you measure should be in one column
- Each different observation of that variable should be in a different row
- If you have multiple tables, they should include a column in the table that allows them to be linked

There main advantages of structuring the data in this way is that a consistent data structure make it easier to use the tools (programs) that work with it because they have an underlying uniformity. This lead to an advantage in reproducibility of code.

As stated before tidying data is not a trivial task, and applying this process to text is even harder for documents with respect to structured data (Silge and Robinson, 2016). On the other side, is clear that using tidy data principles can make many text mining tasks easier, more effective, and consistent with tools already in wide use . Treating text as data frames of individual words allows us to manipulate, summarize, and visualize the characteristics of text easily and integrate natural language processing into effective workflows already used.

Tidy text format is designed as being a table with one-token-per-row. A token unit of text that is meaningful for the analysis to be performed (for example letters, words, n-gram, sentences, or paragraphs). Tokenization is the process of splitting text into tokens. This one-token-per-row structure is in different from the ways documents are often stored in current analyses, mainly strings or document-term matrix. The term document matrix has each corpus word represented as a row with documents as columns. The document term matrix is the transposition of the TDM so each document is a row and each word is a column. The term document matrix or document term matrix is the foundation of bag of words text mining. The bag-of-words model is a simplifying representation of documents: a text is represented as the bag (multiset) of its words, disregarding grammar and even word order but keeping multiplicity (McTear et al., 2016).

2.1.4 Transform

Transforming in the context of Natural Language Processing is what in computational linguistic is called text normalization. Normalizing text means converting it to a more convenient, standard form. Most of the task of technical document analysis in fact relies on first separating out or tokenizing sentences and words, strip suffixes from the end of the word, determining the root of a word or transform the text using regular expressions.

2.1.4.1 Sentence Splitting

The analysis of technical documents require as first process, that the input text is segmented in sentences. Since documents do not encode this information in a non ambiguous manner (using dots) due to common abbreviations (e.g.: “Mr., Dr.”), a sentence splitting process that does not rely only on a trivial *dot based* rule is required. This issue in the technical documents domain is even more problematic due to the presence of formulas, numbers, chemical entity names and bibliographic references. Furthermore, since sentence splitting is one of the first processes of an NLP pipeline, errors in this early stage are propagated in the following steps causing a strong decrease for what concerns their accuracy. One of the most advanced techniques are machine learning techniques: given a training corpus of properly segmented sentences and a learning algorithm, a statistical model is built. By reusing the statistical model, the sentence splitter is able to split sentences on texts not used in the training phase. ItalianNLP lab systems uses this approach (Dell’Orletta, 2009, Attardi and Dell’Orletta (2009), Attardi et al. (2009)). For this reason this algorithm is used for the most of the application presented in this Thesis.

2.1.4.2 Tokenization

Since documents are unstructured information, these has to be divided into linguistic units. The definition of linguistic units is non-trivial, and more advanced techniques can be used (such as n-gram extraction) but most of the times these are words, punctuation and numbers. English words are often separated from each other by white space, but white space is not always sufficient. Solving this problems and splitting words in well-defined tokens defined as tokenization. In most of the application described in the present Thesis, the tokenizer developed by the ItalianNLP lab was integrated (Dell’Orletta, 2009; Attardi and Dell’Orletta, 2009; Attardi et al., 2009). This tokenizer is regular expression based: each token must match one of the regular expression defined in a configuration file. Among the others, rules are defined to tokenize words, acronyms, numbers, dates and equations.

2.1.4.3 Stemming

Stemming is a simpler but cruder methodology for chopping off of affixes. The goal of stemming is reducing inflected (or sometimes derived) words to their word stem, base or root form. The stem of a word and its morphological root do not need to be identical; it is sufficient that related words map to the same stem, even if this stem is not a valid root. One of the most widely used stemming is the simple and efficient Porter algorithm (Porter, 1980).

2.1.4.4 Lemmatisation

Lemmatization is the task of determining the root of a words. The output allow to find that two words have the same root, despite their surface differences. For example, the verbs *am*, *are*, and *is* have the shared lemma *be*; the nouns *cat* and *cats* both have the lemma *cat*. Representing a word by its lemma is important for many natural language processing tasks. Lemmatisation in fact diminish the problem of sparsity of document-word matrix. Furthermore lemmatisaion is important for document retrieval 2.1.2.1 web search, since the goal is to find documents mentioning motors if the search is for motor. The most recent methods for lemmatization involve complete morphological parsing of the word (Hankamer, 1989).

2.1.4.5 Words importance metrics

Once that a document has been tokenized and the tokens has been transformed, an analyst usually wants to measure how important a word is to a document in a collection or corpus. Some of the metrics adopted are:

- *Term Frequency*: the number of times that a term occurs in document.
- *Boolean frequency*: 1 if the term occurs in the document and 0 otherwise;
- *Term frequency adjusted for document length*: is raw count normalized for the number of words contained in the document
- *Logarithmically scaled frequency*: is raw count normalized for the natural logarithm of one plus the number of words contained in the document
- *Inverse document frequency*: is the logarithmically scaled inverse fraction of the documents that contain the word, obtained by dividing the total number of documents by the number of documents containing the term, and then taking the logarithm of that quotient. It is a measure of how much information the word provides, that is, whether the term is common or rare across all documents.
- *Term frequency–Inverse document frequency*: the product between *term frequency and inverse document frequency*. A high weight in tf–idf is reached by a high term frequency (in the given document) and a low document frequency of the term in the whole collection of documents; the weights hence tend to filter out common terms.

2.1.4.6 Part-of-Speech Tagging

The part of speech plays an central role in technical document analysis since it provides very useful information concerning the morphological role of a word and its morphosyntactic context: for example, if a token is a determiner, the next token is a noun or an adjective with very high confidence. Part of speech tags are used for many information extraction tools such as named entity taggers (see section 2.1.5.5) in order to identify named entities. In typical named entity task these are people and locations since tokens representing named entities follow common morphological patterns (e.g. they start with a capital letter). For the application to technical documents, technical entities (like the possible failures of a manufact) becomes more relevant. In this context a correct part-of-speech tagger becomes even more important since morphosyntactical rules can not be used. In addition part of speech tags can be used to mitigate problems related to polysemy since words often have different meaning with respect to their part of speech (e.g. “track”, “guide”). This information is extremely valuable in patent analysis, and some patent tailored part-of-speech tagger has been designed (see section 2.2.2). The literature on pos-tagger is huge, and goes behind the scope of the present thesis to make a complete review. In most of the application presented in this work, was employed the ILC postagger (Attardi, 2006). This postagger uses a supervised training algorithm: given a set of features and a training corpus, the classifier creates a statistical model using the feature statistics extracted from the training corpus.

2.1.5 Model

The goal of a model is to provide a simple low-dimensional summary of a dataset (Wickham and Grolemund, 2016). Ideally, the model will capture patterns generated by the phenomenon of interest (true signals), and ignore random variations (noise). A good model at the same time is able to capture the weak signals that cab be easily confounded with noise. These information is particularly valuable in the context of technical document analysis, where great technical insight could come weak quasi-invisible signals. (James et al., 2013)

Probabilistic models are widely used in text mining nowadays, and applications range from topic modeling, language modeling, document classification and clustering to information extraction. The present section contains a review of the most used methods used to model textual information.

2.1.5.1 N-Grams

An n-gram is a sequence of N n-gram words: a 2-gram (or bigram) is a two-word sequence of words like “credit card”, “3d printing”, or ”printing machine”, and a 3-gram (or trigram) is a three-word sequence of words like “3d printing machine”. Statistical model can be used to extract the n-grams contained in a document. A first approach has the of predicting the next item in a sequence in the form of a (n − 1)–order Markov model(Lafferty and Zhai, 2001). The algorithm begin with the task of computing P(w|h), the probability of a word w given a word h.The way to estimate this probability is using relative frequency counts. To do that the algorithms count the number of times h is followed by the w. With a large enough corpus it is possible to build valuable models, able to extract n-grams (Bellegarda, 2004). While this method of estimating probabilities directly from counts works for many natural language applications, in many cases a huge dimension of the corpus does make the model useful, and this is particularly true for technical documents (Brants et al., 2012). This is because technical language has a strong ratio of evolution; as new artifact are invented, new chunks are created all the time, and has no sense to continuously count every word co-occurrence to update our model(Gibson et al., 1994). A more useful method for chunk extraction fro technical document uses part-of-speech-tagging and regular expression. Once a document is pos-taggerd each word is associated whit a particular part of speech: each sentence is represented as a sequence of part-of-spech. Once this representation is ready, it is possible to extract only certain sequences of part-of-speeches, the ones that whit an high level of confidence are n-grams.

2.1.5.2 Document Classification

Classification is a general process that has the goal of taking an object, extract features, and assign to the observation one of a set of discrete classes. This process is largely used for documents (Borko and Bernick, 1963) and there exist many methods for document classification (Aggarwal and Zhai, 2012).

Regardless of technological sector, most organizations today are facing the problem of overload of information. When it comes to classify huge amount of documents or to separate the useful documents from the irrelevant, document classification techniques can reduce the process cost and time.

The simplest method for classifying text is to use expert defined rules. These systems are called expert systems or knowledge engineering approach. Expert rule-based systems are programs that consist of rules in the IF form condition THEN action (if condition, then action). Given a series of facts, expert systems, thanks to the rules they are made of, manage to deduce new facts. The expert systems therefore differ from other similar programs, since, by referring to technologies developed according to artificial intelligence, they are always able to exhibit the logical steps that underlie their decisions: a purpose that, for example, is not feasible from the human mind or black box-systems. There are many type of documents for which expert based classifiers constitute a state-of-the-art system, or at least part of it. Anyway, rules can be useless in situations such as: - data change over time - the rules are too many and interrelated

Most systems of documents classification are instead done via supervised learning: a data set of input observations is available and each observation is associated with some correct output (training set). The goal of the algorithm is to build a static model able to learn how to map from a new observation (test set) to a correct output. The advantages of this approach over the knowledge engineering approach are a very good effectiveness, considerable savings in terms of expert labor power, and straightforward portability to different domains.

In the supervised document classification process, is used a training set of N documents that have each been typically hand-labeled with a class: (d1, c1),....,(dN, cN). I say typically, because other less expensive methods could be designed, as it will be shown for the task of Named Entity Recognition (another supervised learning task, that classifies words instead of documents 2.1.5.5). The goal of the supervised document classification task is to learn a statistical model capable of assign a new document d to its correct class c C. There exist a class of these classifier, probabilistic classifiers, that additionally will tell us the probability of the observation being in the class.

Many kinds of machine learning algorithms are used to build classifiers (Aggarwal and Zhai, 2012), such as:

- *Decision Tree Classifiers*: Decision tree documents classifier are systems that has as output a classification tree (Sebastiani, 2002). In this tree internal nodes are terms contained in the corpus under analysis, branches departing are labeled by the weight (see section 2.1.3) that the term has in the test document, and leafs are labeled by categories. There exists many methods to automatically learn trees from data. A tree can be build by splitting the data source into subsets based on an test feature. This process is repeated on each derived subset in a recursive manner called recursive partitioning. The recursion is completed when the subset at a node has all the same value of the target variable, or when splitting no longer adds value to the predictions.

- *Rule Based Classifiers*: Rule-based classifiers are systems in which the patterns which are most likely to be related to the different classes are extracted from a set of test documents. The set of rules corresponds to the left hand side to a word pattern, and the right-hand side to a class label. These rules are used for the purposes of classification. In its most general form, the left hand side of the rule is a Boolean condition, which is expressed in Disjunctive Normal Form (DNF). However, in most cases, the condition on the left hand side is much simpler and represents a set of terms, all of which must be present in the document for the condition to be satisfied (Yang et al., 2004).

- *Support Vector Machines (SVM) Classifiers*: SVM Classifiers attempt to partition the data space with the use of linear or non-linear delineations between the different classes. The main principle of SVM algorithm is to determine separators in the feature space which can best separate the different classes (Joachims, 1998, Manevitz and Yousef (2001)).

- *Baeysian Classifiers*: Bayesian classifiers build a probabilistic classifier based on modeling the underlying word features in different classes. The idea is then to classify documents using the posterior probability of the documents belonging to the different classes on the basis of the word presence in the documents (Pop, 2006).

- *Neural Netword Classifiers*: The basic unit in a neural network is a neuron. Each neuron receives a set of inputs, which are denoted by the vector *Xi*, which are the values of the feature vector for a certain instance. Each neuron is also associated with a set of weights, which are used in order to compute a function of its inputs. Neural Networks Classifier are able, thank to a process called learning phase, to adjust their weights in such a way that the function is able to effectively classify new instances. Neural networks are nowadays one of the best method for documents classification, and are used in a wide variety of applications (Manevitz and Yousef, 2007). Great performances has also been reached by deep neural networks, which are neural networks whit a large number o neurons arranged in multiple layers (Lai et al., 2015, Kim (2014)).

2.1.5.3 Sentiment Analsysis

Sentiment analysis techniques are algorithms able to measure from text, people's opinions and emotions toward events, topics, products and their attributes (Pang et al., 2008). For example, businesses (particularly marketeers) are interested in finding costumers opinions about their products and services.

Thanks to the growth of social media (forums, blogs and social networks), individuals and organizations are producing a huge quantity of their written opinion. This has make it possible to scholars to study this phenomena and to develop many different and effective sentiment analysis techniques (Liu and Zhang, 2012). In the past decade, a considerable amount of research has been done by scholars and there are also numerous commercial companies that provide opinion mining services. However, measuring sentiment in documents and distilling the information contained in them remains a challenging task because of the diversity of documents from which is possible to extract sentiment.

The approaches to perform sentiment analysis are many. Among all, the most interesting for technical documents analysis are:

- *Dictionary Base Approaches* : This approach has the aim of collecting words that are clues for positive or negative sentiment. In literature these words are called opinion words, opinion-bearing words or sentiment words. Examples of positive opinion words are: good, nice and amazing. Examples of negative opinion words are bad, poor, and terrible. Collectively, they are called the opinion lexicon. The most simple and widely used techniques to produce a dictionary of opinion words is based on bootstrapping using a small set of seed opinion words and an online dictionary such as WordNet (Miller, 1995). The works that used this approach (Hu and Liu, 2004, Kim and Hovy (2004)), adopts a process that consist in two phases: first collect set of opinion words manually, then grow this set by searching in the WordNet for their synonyms and antonyms. The process stops when no more new words are found. After that a manual inspection can be carried out to remove and/or correct errors. Scholars has developed several opinion lexicons (Ding et al., 2008, Baccianella et al. (2010), Hu and Liu (2004), Philip et al. (1966), Wiebe et al. (1999)) The lexicon based approach has the characteristic of being strongly context specific. This is an advantage when the goal is to design a method able to extract sentiment in a specific context (Chiarello et al., 2017), but is a major shortcoming if the goal is to design a general purpose method.
- *Supervised Learning Approaches*: Sentiment analysis can be formulated as a document classification problem with three classes: positive, negative and neutral(Mullen and Collier, 2004). Training and test sets of documents are typically collected from product reviews, movies reviews or are created by scratch using manual annotation. Any learning algorithm can be applied to sentiment classification (naive Bayesian classification, and support vector machines (Prabowo and Thelwall, 2009)). The crucial phase for Supervised Learning sentiment analysis is the features presentation of the data. It was shown (Pang et al., 2002) that using uni-grams (a bag of individual words) as features in classification performed well with either naive Bayesian or SVM. Subsequent research used many more features and techniques in learning (Pang et al., 2008).

2.1.5.4 Text Clustering

The goal of clustering methods is to find groups of similar objects in the data thanks to the measure of a similarity function (Jain and Dubes, 1988, Kaufman and Rousseeuw (2009)). Clustering techniques has been widely applied in the text domain, where the objects of the clustering can be documents (at different level of granularity) or terms. In the context of technical documents analysis Clustering is especially useful documents retrieval (Anick and Vaithyanathan, 1997, Cutting et al. (1993)). Clustering problems has been and are studied widely outside the text domain. Methods for clustering have been developed focusing on quantitative/non-textual data (Guha et al., 1998, Han et al. (2001), Zhang et al. (1996)).

In the context of text analysis, the problem of clustering finds applicability for a number of tasks, such as Document Organization and Browsing (Cutting et al., 2017), Corpus Stigmatization using documents maps (Schütze and Silverstein, 1997) or word clusters (Baker and McCallum, 1998, Bekkerman et al. (2001)). It is useful also to use a Soft clustering approach, that associates each document with multiple clusters with a given probability.

However, standard techniques for cluster analysis (k-means or hierarchical clustering) do not typically work well for clustering textual data in general or more specific technical documents. This is because of the unique characteristics of textual data which implies the design of specialized algorithms for the task.

The distinguishing characteristics of the text representation are the following (Aggarwal and Zhai, 2012):

- There is a problem of course of dimensionality. The dimensionality of the bug-of-words representation is very large and the underlying data is sparse. In other words, the lexicon from which the documents are drawn may be of the order of millions, but a given document may contain only a few hundred words.This problem is even more serious for technical documents in which the lexicon is even more large.

- The words are correlated with one another and thus the number of concepts (or principal components) in the data is much smaller than the feature space. This necessitates the careful design of algorithms which can account for word correlations in the clustering process.
- The number of words (or non-zero entries) in the different documents may vary widely. Therefore, it is important to normalize the document representations appropriately during the clustering task.

The problems of sparsity and high dimensionality necessitate the design of specific algorithms text processing. The topic has been heavily studied in the information retrieval literature where many techniques have been proposed (Ricardo and Berthier, 2011).

2.1.5.5 Named Entity Recognition

Named Entity Recognition is the task of identifying entity names like people, organizations, places, temporal expressions or numerical expressions. An example of an annotated sentence for a NER extraction system tailored for user entity extraction from patents, is the following:

Traditionally, $< user >$ *guitar players* $< user/ >$ *or* $< user >$ *players* $< user/ >$ *of other stringed instruments may perform in any of a number of various positions, from seated, with the stringed instru- ment supported on the leg of theperformer, to standing or walking, with the stringed instrument suspended from a strap.*

Methods and algorithms to deal with the entity extraction task are different, but the most effective are the ones based on supervised methods. Supervised methods tackle this task by extracting relevant statistics from an annotated corpus. These statistics are collected from the computation of features values, which are strong indicators for the identification of entities in the analyzed text. Features used in NLP for NER purposes are divided in two main categories: - Linguistically motivated features, such as n-gram of words (sequences of n words), lemma and part of speech - External resources features as, for example, external lists of entities that are candidates to be classified in the extraction process.

The annotation methods of a training corpus can be of two different kinds: human based, which is time expensive, but usually effective in the classification phase; automatically based, which can lead to annotation errors due to language ambiguity. For instance driver can be classified both as a user (the operator of a motor vehicle), or not a user (a program that determines how a computer will communicate with a peripheral device). Different training algorithms, such as Hidden Markov Models (Eddy, 1996a), Conditional Random Fields (CRF) (Lafferty et al., 2001a) Support Vector Machines (SVM) (Hearst et al., 1998b), or Bidirectional Long Short Term Mermory-CRF Neural Networks (Lample et al., 2016, Misawa et al. (2017)) are used to build a statistical model based on features that are extracted from the analyzed documents in the training phase.

2.1.5.6 Topic Modelling

Topic modeling is a form of dimension reduction that uses probabilistic models to find the co-occurrence patterns of terms that correspond to semantic topics in a collection of documents (Crain et al., 2012). To understand topic modelling it is useful to understand its differences with clustering 2.1.5.4 and the problem they both solves: the course of dimensionality. Both these techniques has in fact the goal of representing documents in such a way that they reveals their internal structure and interrelations. Clustering measures the similarity (or dissimilarity) between documents to place documents into groups. Representing each document by considering the belonging to a group, clustering induces a low-dimensional representation for documents. However, it is often difficult to characterize a cluster in terms of meaningful features because the clustering is independent of the document representation, given the computed similarity. Topic modeling integrates soft clustering (assigning each element to a cluster with a given probability and not with a Boolean variable) with dimension reduction. Each document is associated with a number of latent topics: a topic can be seed as both document clusters and compact group of words identified from a corpus. Each document is assigned to the topics with different weights: this feature can be seen both as the degree of membership in the clusters, as well as the coordinates of the document in the reduced dimension space. The result is an understandable representation of documents that is useful for analyzing the themes in documents. Latent Dirichlet allocation (LDA) is a particularly popular method for fitting a topic model (Blei et al., 2003). It treats each document as a mixture of topics, and each topic as a mixture of words. This allows documents to “overlap” each other in terms of content, rather than being separated into discrete groups, in a way that mirrors typical use of natural language.

2.1.6 Visualize

Traditionally, statistical training has focused primarily on mathematical derivations and proofs of statistical tests: the process of developing the outputs (the paper, the report, the dashboard, or other deliverable) is less frequently analyzed. This problem influences also text mining (Parker, 2017). One of the most studied problems of output production is data visualisation. Data visualisation involves the creation and study of the visual representation of data (Friendly and Denis, 2001). Data visualization uses statistical graphics, plots, information graphics and other tools to communicate information in a clearl and efficient way. The main process of data visualisation is the visual encoding of numbers. Numerical data may be encoded in many ways, using a wide range of shapes: the main used are dots, lines, and bars (Wickham, 2016). The main goal of visualizations is to help users (students, researchers, companies and many others) analyze and reason about evidences hidden in data. It is possible thanks to the ability of visualisation to make complex data more accessible, understandable and usable. Tables are generally used where users will look up a specific measurement, while charts of various types are used to show patterns or relationships in the data for one or more variables.

Da visualisation has become in the last year a well enstablished discipline thanks to the increased amounts of data created by Internet activity and an expanding number of sensors in the environment are referred to as “big data” or Internet of things. It is important to undeline how the way this data is comunicated present ethical and analytical challenges for data visualization practitioner (Bikakis, 2018). The field of data science and practitioners called data scientists help address this challenge (Loukides, 2011).

Users of information displays are executing (consciously or not) particular analytical tasks such as making comparisons or determining causality (Tufte et al., 1990). The design principle of the information graphic should thus support the analytical task, showing the comparison or causality (Tufte, 2006).

Graphical displays and principles for effective graphical display is defined as the ability to communicate complex statistical and quantitative ideas with clarity, precision and efficiency (Mulrow, 2002). For this reason graphical displays should:

- show the data
- induce the viewer to think about the substance rather than about methodology, graphic design, the technology of graphic production or something else
- avoid distorting what the data has to say
- present many numbers in a small space
- make large data sets coherent
- encourage the eye to compare different pieces of data
- reveal the data at several levels of detail, from a broad overview to the fine structure
- serve a reasonably clear purpose: description, exploration, tabulation or decoration
- be closely integrated with the statistical and verbal descriptions of a data set

In litterature are identified eight types of quantitative messages that users may attempt to understand or communicate from a set of data and the associated graphs used to help communicate the message (Few, 2012):

- Time-series: A single variable is captured over a period of time, such as the unemployment rate over a 10-year period. A line chart may be used to demonstrate the trend.

- Ranking: Categorical subdivisions are ranked in ascending or descending order, such as a ranking of sales performance (the measure) by sales persons (the category, with each sales person a categorical subdivision) during a single period. A bar chart may be used to show the comparison across the sales persons.
- Part-to-whole: Categorical subdivisions are measured as a ratio to the whole (i.e., a percentage out of 100%). A pie chart or bar chart can show the comparison of ratios, such as the market share represented by competitors in a market.
- Deviation: Categorical subdivisions are compared against a reference, such as a comparison of actual vs. budget expenses for several departments of a business for a given time period. A bar chart can show comparison of the actual versus the reference amount.
- Frequency distribution: Shows the number of observations of a particular variable for given interval, such as the number of years in which the stock market return is between intervals such as 0-10%, 11-20%, etc. A histogram, a type of bar chart, may be used for this analysis. A boxplot helps visualize key statistics about the distribution, such as median, quartiles, outliers, etc.
- Correlation: Comparison between observations represented by two variables (X,Y) to determine if they tend to move in the same or opposite directions. For example, plotting unemployment (X) and inflation (Y) for a sample of months. A scatter plot is typically used for this message.
- Nominal comparison: Comparing categorical subdivisions in no particular order, such as the sales volume by product code. A bar chart may be used for this comparison.
- Geographic or geospatial: Comparison of a variable across a map or layout, such as the unemployment rate by state or the number of persons on the various floors of a building. A cartogram is a typical graphic used.

Data visualisation practionires has to consider whether some or all of the messages and graphic types above are applicable to their task and audience. The process of trial and error to identify meaningful relationships and messages in the data is part of exploratory data analysis.

2.1.6.1 The Grammar of Graphics

Even if trial and error is and will remain an important part of data visualisation, some works as tried to give to data visualisation practitioners a well structured framework able to guide the process of data visualisation. Among the many frameworks, the most used is the *Grammar of Graphics* (Wilkinson, 2006) and its implementation (Wickham et al., 2008). The grammar of graphics is a coherent system for describing and building graphs. Like other kind of grammars, it describes to basic rules to use the element of data visualization with the goal of comunicating some content. The main concept in the grammar of graphics is that graphs are made by multiple layers. Layers are responsible for creating the objects that we perceive on the plot. A layer is composed of four parts:

- *Data and aesthetic mapping*: Data are independent from the other components: we can construct a graphic that can be applied to multiple datasets. Along with the data, we need a specification of which variables are mapped to which aesthetics.
- *Statistical transformation*: A statistical transformation transforms the data, typically by summarizing them in some manner.
- *Geometric object*: Geometric objects control the type of plot that is created. For example, using a point geom will create a scatterplot, whereas using a line geom will create a line plot. Geometric objects can be classified by their dimensionality.
- *Position adjustment*: Sometimes there exist th need to tweak the position of the geometric elements on the plot, when otherwise they would obscure each other. This is most common in bar plots, where we stack or dodge (place side-by-side) the bars to avoid overlaps.

Multyple layers togheter are used to create complex plots.

Togheter with the layer the designer can control the *scale.* A scale controls the mapping from data to aesthetic attributes, and one scale for each aesthetic property used in a layer is needed. Scales are common across layers to ensure a consistent mapping from data to aesthetics.

After the decision of the scale, the designer has ti decid the *coordinate system* for the layer. A coordinate system maps the position of objects onto the plane of the plot. Position is often specified by two coordinates (x, y), but could be any number of coordinates. The Cartesian coordinate system is the most common coordinate system for two dimensions, whereas polar coordinates and various map projections are used less frequently. For higher dimensions, we have parallel coordinates (a projective geometry), mosaic plots (a hierarchical coordinate system), and linear projections onto the plane. Coordinate systems affect all position variables simultaneously and differ from scales in that they also change the appearance of the geometric objects.

Finally, the last element of the grammar are *facets*. Faceting makes it easy to create small multiples of different subsets of an entire dataset. This is a powerful tool when investigating whether patterns are the same or different across conditions. The faceting specification describes which variables should be used to split up the data, and how they should be arranged.

2.1.7 Comunicate

The last task to perform in the process of knowledge extraction from technical documents is communications. If it means to comunicate the results of an anlysis inside a team or to the world, it doesn not matter how great an analysis is unless it is impossibile to explain it to others (Wickham and Grolemund, 2016). For the purposes of the present thesis, the focus is on the review of technical mechanics of communication especialli in the R (R Core Team, 2018) enviroment, which is used to perform most of the analysis showed in the next chapters (3, **??**. One of the most important innovation for the task of communication in data science is R Markdown (Allaire et al., 2018). R Markdown provides an unified authoring framework for data science, combining code, results, and comments. R Markdown documents are fully reproducible and support dozens of output formats, like PDFs, Word files, slideshows, and more.

R Markdown files are designed to be used in three ways:

- For communicating to decision makers, who want to focus on the conclusions, not the code behind the analysis.
- For collaborating with other data scientists (including future you!), who are interested in both your conclusions, and how you reached them (i.e. the code).
- As an environment in which to do data science, as a modern day lab notebook where you can capture not only what you did, but also what you were thinking.

Togheter with reports (and usually contained in them) there are visualisation. Making graphics for communication follow all the rules and framework previously revised in section 2.1.6, but when a graph has to be used to comunicate to a wide audience there are some more rules to follow. The reason why this happen is that the audience likely do not share the background knowledge of the anlysit and do not be deeply invested in the data. To help others quickly build up a good mental model of the data, the analyst need to invest considerable effort in making plots as self-explanatory as possible. For this reason has been developed many tools to help data scientist to make effective comunication graphs(Wickham, 2016, Chang et al. (2017), Sievert et al. (2017), Pedersen (2018), Bastian et al. (2009)) .

2.2 Documents

In this section contains a review of the main classes of technical documents analyzed in the present work. The documents are patents, papers, Wikipedia, Social Media, Publicly Funded Projects and Human Resources Documentation. Before starting to analyze the state of the art techniques to perform knowledge extraction for these documents, the focus is on a task that has intentionally not been analyzed in section 2.1: understanding.

2.2.1 Understand

The most difficult challenge in technology intelligence is not how to detect the large trends- they are visible anyway. It is, rather, how to detect weak signals, or information that initially appears with low frequency, in unrelated or unexpected regions of the technology landscape, and associated with large noise (Apreda et al. 2016). These signals escape from traditional statistical detection techniques, exactly because it is difficult to distinguish them from pure statistical noise. Metadata are not the appropriate source of data for detecting weak signals. As a matter of fact, they can be detected only by using a fine-grained domain knowledge structure, or using the full text of documents. As an example, classification-based clustering has been shown to be flawed because the patent class used is usually only the first one listed in patents, generating loss of granularity (Benner and Waldfogel, 2008; Aharonson and Schilling, 2016).

Hypothesis

postulation

2.2.1.1 Domain Expertise

(collins)

Sheela Jasanow

Taleb?

2.2.1.2 The problem of byases

Each site typically contains a huge volume of opinionated text that is not always easily deciphered in long forum postings and blogs. The average human reader will have difficulty identifying relevant sites and accurately summarizing the information and opinions contained in them. Moreover, it is also known that human analysis of text information is subject to considerable biases, e.g., people often pay greater attention to opinions that are consistent with their own preferences. People also have difficulty, owing to their mental and physical limitations, producing consistent results when the amount of information to be processed is large. Automated opinion mining and summarization systems are thus needed, as subjective biases and mental limitations can be overcome with an objective sentiment analysis system.

2.2.1.3 The Importance of Lexicons for Technical Documents Analysis

2.2.2 Patents

Nowadays patent data can be used for planning technological strategy (Ernst, 2003). The focus on the technological usefulness of patent data is certainly a great advantage, but this huge research area could hide other useful application for patents. For example, in (Jin et al., 2015) the authors consider on one side patents as a source to collect information about technologies and products, and on the other side manuals, handbooks and market reports to collect market information. Since patents are only technological documents many potential patent reader (e.g. designers, marketers) could be taken aside. Despite this problem, some researchers (Bonino et al., 2010) affirm that there is an increasing variety of readers: not only technician and researchers but also marketers and designers who have grown an interest in patent analysis. Nevertheless, to our knowledge there are no researches that aim at facilitating information extraction for non-technological focused patent readers.

The bias that patent are only tech-oriented documents is due to two main reasons:

- Patents are produced to disclose and protect an invention, their content is mainly technical and legal.
- 80% of technical information is not available elsewhere (Terragno, 1979), so patents are one of the most comprehensive resources for technical analysis.

Focusing on the second point, our hypothesis is that also a fraction of all the other kinds of information (e.g. marketing and sociological information) is not contained elsewhere and it will appear in public documents (e.g. manual handbooks and market reports) in 6-18 months (Golzio, 2012).

Unfortunately there are four aspects reducing the non-tech readers' ability to analyze patents efficiently. First of all, an increasingly high number of patent filings generates a massive information overflow [Bergmann et al. (2008); secondly, analyzing patents takes a long time and requires skilled personnel (Liang and Tan, 2007); the quality of patent assessment process is decreasing (Burke and Reitzig, 2007, Philipp (2006)) because of the reduced assessment time available for patent examiners; finally, activities like patent hiding, proliferation and bombing, contribute to the generation of confusion and to the loss of time in research and analysis phases (Fantoni et al., 2013). These problems affect non-tech oriented patent readers as well as typical readers, even though the impact may be stronger on the firsts.

The main difference between typical and non-tech patent readers is the information they focus on. *Patent attorneys* and *Intellectual Property (IP) managers* are interested in reading patents for legal reasons to orient the IP direction. Analyzing patents is the core of their work, so they are experts in finding the information they need. Furthermore, they can spend most of their work-time on the activity. On the other hand, usually *marketers and designers* (taken as example of non-tech oriented readers) search users' behavioral changes and needs, market trends, designers' vision, R&D trends and competitors' strategies. In addition, they rarely work with patents, so they do not know what and how to search. Lastly, they have short time to spend on the activity, and they waste most of this time understanding the legal and technical jargon used in patents.

Due to the large amount of information contained in patents and the growing interest to exploit this information, huge efforts have been devoted to the development of systems source to automatically extract different kind of information from such an enormous and valuable data.

Many techniques introduced in order to extract textual information from patents come from extensive research advances in the Natural Language Processing field (NLP). NLP is an area of research and artificial intelligence which aims at teaching computers to understand and manipulate natural language text in order to performs different tasks such as information extraction, machine translation and sentiment analysis.

The field of technology intelligence has become so large in recent years that several efforts to review and summarize the various approaches have been undertaken (Abbas et al., 2014). There are several possible ways to classify the approaches. For example a used classification distinguish between Visualization techniques (Patent networks, Clustering) and Text mining (NLP-based, Property-function, Rule-based, Semantic analysis, Neural networks). Another possible classification is:

- *Metadata approaches*: methods that uses sources of information embedded in patents, such as claims structure or bibliographic information
- *Keyword approaches*: methods able to produce vector representations of the analyzed documents. Computed vectors can be used for many applications such as patent retrieval by keyword, or patent similarity matching. Even though this approach can be used for several tasks, it is not suitable to catch semantic relationships between entities in sentences. Furthermore, these methods use a blacklist to remove noisy words (Blanchard, 2007) or use predefined lexicons (Chiarello et al., 2017). The right design of such list dramatically impacts the final output of the analysis (Lee et al., 2009a, Lee et al. (2015a), Montecchi et al. (2013))
- *Natural Language Processing approaches*: methods based on grammatical and syntactical structures extracted by natural language processing tools, such as Part-of-Speech taggers and syntactical parsers. Unlike the keyword based approach, these methods are able to capture the relationships between the entities mentioned in sentences (Yoon et al., 2013a, Park et al. (2011a), Park et al. (2013)).

Each approach allows to capture different types of information from patents and build a knowledge base which can be exploited by patent analysis tools. For this reason the right approach to be chosen to develop a patent analysis system depends on the task to be solved, on the information to be analyzed and on the computational resources involved to solve the task. Choosing a good trade-off between these factors is a strict requirement in particular when analyzing big patent sets.

2.2.2.1 Metadata Approaches

Patent documents has the following metadata:

- Patent office
- Inventors
- Affiliation of the inventors
- Filling date
- Publication date
- Address of the affiliation of the inventor
- Patent classifications
- References
- Assignee
- Affiliation of the assignee
- Address of the affiliation of the assignee

Furthermore they contain text content:

- Title
- Abstract
- Keyword
- Summary page
- Drawing set
- Background of the invention
- Brief summary of the invention
- Brief description of the drawings
- Detailed description of the invention
- Claim set

This does not mean that metadata allow a unique identification. Disambiguation of metadata remains a challenge in most cases. Only recently documents have started to include a unique identifier, following the cooperation among the main producers and users. The unique identifiers refer to the publication (DOI, Digital Object Identifier) or the author (author ID). However, metadata are written and stored in a standardized way, so that it is possible to categorize them. Issues of disambiguation refer mainly to the identity of individual entities (e.g. distinguish between two authors with exactly the same name and surname) but not of categories (e.g. distinguish between the name of an author and the name of a university).

Metadata approaches for patent analysis exploit three types of information:

- bibliometric information
- patent structure information
- patent review process information.

In this approach are usually considered both patent and non-patent literature: for example patents with a high number of citations in papers usually indicate a strong correlation with the foundation of a technology.

On of the main problems addressed using metadata approaches is measure of the technology life cycle stage. The information about at which stage of maturity a technology is, is an important aspect taken into account by who decides to invest. Since the life cycle of a product is clearly related by patent grants evolution (Andersen, 1999), this lead research to investigate on patent indices that can be considered as appropriate life cycle stage indicators. The main effort has been directed in the identification of the three different technology life cycle stages: introduction, growth and maturity (Haupt et al., 2007). In this work, the author took into account that several studies have shown that a S-shape evolution of the number of patent applications or even a double-S-shape is typical. Consequently, the author defined the concept of patent activity index as an appropriate life cycle indicator only if its mean value differs significantly between the life cycle stages. The results of the work can be summarised as follow:

1. Backward literature citations increase significantly only at the transition from introduction to growth;
2. Backward patent citations increase significantly at both stage transitions;

3. The number of forward citations decreases significantly at the transition from introduction to growth;
4. The number of dependent claims is significantly higher at later technology life cycle stages than in earlier ones;
5. The number of priorities referred to in a patent application is significantly higher at later technology life cycle stages than in earlier ones;
6. Examination processes take longer in the phases of introduction and maturity than at the growth stage.

The main limit of these methods is the need of assumptions for what concerns the shapes of the stages curves.

For this reason furthuter works introduced an unsupervised method able to automatically detect the number of life cycle stages and the transition times of the technology of interest (Lee et al., 2016). Here, seven time series patent indicator were taken into account:

- patent activity which allows to model the evolution of a pattern. In particular increasing and decreasing patterns are considered a change for what concerns the research and development activity;
- the number of technology developers in the analyzed temporal series. It has been shown that a great number of competitor enters in the initial stages of a technology's life cycle, but this number lowers in the matu- rity stage
- the number of different patent application areas in the considered temporal series. This is an important indicator since it has been shown that the number of technology application areas are small in the first stages of their life cycles and in- creases in the later life cycle stages
- the number of backward citations. It has been shown that patents with an high number of backward citations have less relevance with respect to the patents with a lower number of citations
- the number of forward citations which expresses the technological value of a patent in the analyzed temporal period
- the duration of examination processes as the average time between the filing and granting dates.
- the number of claims belonging to the patent. The more the number of claims reported by the patents, the higher the correlation with novelty and the financial value is.

Another widely adressed problem using metadata is citation analysis. Publications, patents, technical standards or clinical guidelines include a section in which other documents are cited. Citation analysis argues that including the reference to another document is the result of an intentional act, whose meaning may differ according to the type of document, but is nevertheless always worth of consideration (Moed, 2006). The analysis of citations, initially developed in scientometrics and bibliometrics, has migrated to technology intelligence, following the initial concept of patent bibliometrics (Narin, 1994). Patent (or firms, or inventors) that cite the same prior art are clustered together. Patent citation networks are then generated (Karki, 1997, Érdi et al. (2013)). In fact, citations form a network structure, whose graph-theoretic properties can be interpreted in technology intelligence exercises (Lee and Kim, 2017). Patent citation networks have properties of small world (Cowan and Jonard, 2004) and their degree follows a power law distribution (Chen and Hicks, 2004). Patent citation analysis can be used to identify trajectory patterns and technology structure and paths, that is, knowledge flows among firms and among subsectors of an industry. In standard citation analysis all citations are considered equal. This counting approach can be criticized because "it relies on the assumption that patents are equally significant" (Gerken and Moehrle, 2012), which is in contrast with the empirical evidence on the large differences in patent value. This assumption is therefore removed in more advanced techniques in which the structure of citations from patents gets a qualification. It may be possible, however, that citations to other patents are strategically made by applicants, for example by citing their own patents or hiding other relevant citations). Backward citations may not be associated to technological novelty if they deliberately point only to the state of the art (Rost, 2011). Citations introduced by examiners are also another potential source of bias (Alcacer and Gittelman, 2006). Finally, it has been reported that the total number of citations increased over time, leading to "citation inflation" and the loss of value (Hall et al., 2001).

Derived from citation analysis, co-citation analysis argues that documents that are cited by the same documents should be considered part of the same cluster (Small, 2006, Small and Sweeney (1985)). A variant of this technique, called author co-citation analysis (White and Griffith, 1981), cluster documents that are cited by the same authors. Co-citation analysis can also be used to create classification systems of patents (Lai and Wu, 2005).

2.2.2.2 Keywords Approaches

In the keyword based approach each patent is represented as a vector where each component measure the importance of a specific keyword, like explained in section 2.1.4.5. The keywords to be taken into account depend on the patent set under analysis and on the goal of the task. Keywords can be extracted automatically using a text mining module, manually by experts or with hybrid methods where domain experts judge the relevance and the quality of the extracted keywords in order to limit the results to the most important keywords. Once keyword vectors are obtained, tasks such as patent similarity can be easily computed by using standard distance measures like cosine similarity. In addition, the keyword extraction allows to define more complex patent similarities measures (Moehrle, 2010) that can be exploited for the development of patent analysis tools (Lee et al., 2009b, Lee et al. (2015b)) such as mappers or patent search engines. The main goal of these works is to developed systems for building keyword-based patent maps to be used for technology innovation activities. The system is composed of a text mining module, a patent mapping module and a patent vacancies identification module. Once a specific technology field is taken into account for analysis and a related patent set is extracted, the modules of the system are sequentially executed. The text mining module automatically identifies relevant keywords in each patent of the considered patent set. Once all the keywords are extracted, only the ones with the highest relevance are selected for a further screening by domain experts. The final set of keywords resulting from the screening process is then considered for building the patent keyword vectors on the considered patent set. Specifically each component of the patent vector holds the frequency the corresponding keyword in the considered patent. Once all the keyword vectors are computed, the patent mapping module is executed to generate the patent map. The mapping is calculated by executing the Principal Component Analysis (PCA) algorithm on all the vectors. The PCA method allows to map n-dimensional vectors on a rectangular planar surface in order to generate the patent map. Intuitively this method allows to find the most meaningful 2 dimensional projection that filters out the correlated components of a n-dimensional vectors. The result of applying this method over the patent keyword vectors is a meaningful patent mapping, in which each patent is mapped over a 2-dimensional surface. Once the patent map is computed, a vacancy detection module is executed on the patent map. The vacancy detection module identifies sparse areas which can be considered good candidates for a research investigation. For each interesting vacancy, a list of related patents is obtained by selecting the ones which are located on the region boundaries. On the calculated list, a set of information for each patent is computed. This information is used to capture the importance of a patent in this patent list. Features considered strong indicators of the relevance of each patent are the number of citations [38] and the number of average citations by patents in the patent list. Finally, emerging and declining keywords are computed by taking into account the time series analysis of the considered keywords in the patent list. This allows to identify promising technology trends that can considered for further investigation.

The metadata and keyword approaches has a long tradition but suffers from several limitations. First, the initial query based on keywords is usually produced by human experts, either on an individual basis or organized as a panel. In practice, one of the best skills of research centers or consultancies specialised in technology intelligence has been, in the past, the ability to mobilize high level experts on an international basis in order to produce well crafted query lists. Unfortunately these lists, even if they are produced following elicitation procedures that respect state of the art recommendations in social sciences, are inevitably biased. Experts are extremely good in their field, but are not better that others if they have to evaluate matters that are outside their domain (Burgman, 2015). To the extent that emerging technologies are complex and fast evolving technologies, it is likely that experts have a narrow, or biased, perception of the dynamics. Experts tend to keep their existing R&D areas in mind, have personal and organizational inclinations, are subject to halo effects in favor of well known institutions or solutions, and may follow different criteria for selecting promising technologies (Kim and Bae, 2017). It has been shown that little differences in the wording of queries, or on the time window, may end up in completely different sets of documents, leading the analysis in different directions (Bassecoulard et al., 2007). In addition to these authors, several studies in recent years have called the attention to the risk that initial differences in the delineation process generate non-comparable descriptions of technologies (Mogoutov and Kahane, 2007, Youtie et al. (2008), Ghazinoory et al. (2013)). Following this line of concern,methodologies to update the keyword structure in an iterative, or evolutionary way has been proposed (Mogoutov and Kahane, 2007). Second, it has been shown that when experts are asked to decide on relatedness measures (e.g. synonyms, hypernims or hyponims), they do not apply systematic rules (Tseng et al., 2007, Noh et al. (2015)). Third, the query list is static. Once defined, it is used to extract documents from large corpora, which are then processed. In dynamic technologies, it is likely that the pace of technological changes exceeds the speed of updating of the query lists. It is difficult to convene panels of experts repeatedly, also because of the large costs incurred in expert selection and management (Tseng et al., 2007). As an example, with the advent of nanotechnology it was felt the need to introduce a new patent sub-class. The sub-class B82B was introduced in year 2000, but it did not incorporate the previous patents, so that a comparison across time is not feasible. A new sub-class, B82Y, was introduced in 2011 (Kreuchauff and Korzinov, 2017).

2.2.2.3 Natural Language Processing approaches

The impressive advancements of computational linguistics in the last two decades have made it possible to carry out analysis on the full content, not only the metadata, of large collections of texts. In text mining patterns are extracted from unstructured collection of documents, while in the metadata approach the patterns are extracted from structured documents or databases. This has opened the way to the "full text based scientometrics" (Boyack et al., 2013) and has created the conditions for the convergence between the citationist approach illustrated above, and the lexical approach. Text mining techniques have then been applied to the corpus of patent texts, with a number of extremely powerful results (Tseng et al., 2007, Joung and Kim (2017), Kreuchauff and Korzinov (2017), Ozcan and Islam (2017); Yoon and Kim, 2012). In turn, text mining can be applied for the search of specific words (or combination thereof) or in the search for patterns that are not defined ex ante. In the former case the most used techniques are combination of keywords, correspondence analysis or category specific terms. These approaches expand the search over the full text of patents but preserve the limitations of keyword-based search. On the contrary, the search for patterns is the object of the most largely used technique, namely topic modelling. Pattern recognition in patent texts is "still in its infancy" (Madani and Weber, 2016) but its applications are growing rapidly. A useful review of NLP techniques in patent analysis (Madani and Weber, 2016) identifies:

- the statistical approach that uses the Term Frequency-Inverted Document Frequency (TF-IDF) method to detect regularities
- the semantic approach uses SAO (Subject-Action-Object) and property-function structures in order to attribute meaning to the texts
- the corpus approach adopts ontology-based techniques.

In turn, all these three information retrieval approaches can be extended by using pattern recognition techniques, that are keyword-, patent- or concept-based.

Text mining has several limitations : it cannot consider synonyms and the co-occurrence of keywords, while the inclusion of compound words and n-gram expressions requires large computational power. In addition, in the case of patents, claims are written in "arcane legalese" in order to hide critical elements and confound potential competitors. The challenge here is how to maximize the substantive knowledge that can be generated by automatic processing of the full text. It has been remarked since long time that a promising direction for research into technology intelligence and foresight lies in the combination of methods. This recommendation requires the combination between domain-knowledge and powerful computational approaches. It is this combination that holds the best promise to generate methods for the identification of emerging technologies, and more generally, for technology intelligence, that are able to identify high-granularity information producing weak signals, that is, to distinguish accurately the signal from the noise in turbulent and dynamic technological landscapes.

By exploiting the information obtained by these steps, several information extraction tasks can be solved by other NLP tools such as: - Term extraction: the task of automatically extract relevant terms from a given corpus. Part of Speech tags are typically used by term extractors to narrow the terms search to a predefined term structure; - Named entity recognition: the task of automatically identify and classify named entities in text such as persons, organizations and locations. Named entity recognizers usually use Part of Speech tags in order to disambiguate the morphosyntactic role of tokens in a phrase, improving the performance of the extraction; - Relation extraction: the task of automatically build relations among entities in the analyzed text. In this context entities can be named entities or extracted terms. In addition, the syntactic role of the entities can be exploited to better categorize the relation type (e.g.: subject, object).

Technical domain language, as other linguistic domains, suffers from linguistic ambiguities. For instance the word “support” can have two totally different meanings when used as a noun or as a verb. By using part of speech taggers which are able to disambiguate the morphological role of each word in a sentence, more precise information extractions are possible and can be used in several applications (e.g. patent search engines). In addition part of speech taggers allow to perform textual lemmatization, which can further improve the performances of automatic patent analysis tools. Another key NLP tool used by several automatic patent analysis systems are syntactic parsers: by identifying the syntactic role of each word in document sentences, several patent analysis applications are possible.

The most well established system for patent analysis using NLP techniques is the extraction of the Subject-Action-Object (SAO) structures, which is also a common use of syntactic parsers in automatic patent analysis tools. Each SAO structure represents the subject (S), the action (A) and the object (O) in a patent sentence (Yoon and Kim, 2011). By automatically extracting SAO structures from patents, relationships between key technological components can be easily represented (Yoon et al., 2013b, Choi et al. (2011), Park et al. (2011b)).

Another techniques that is growing in patent literature analysis is Named Entity Recognition (for further details see section 2.1.5.5). The Named Entity Recognition (NER) is the task of identifying entity names like people, organizations, places, temporal expressions or numerical expressions.

Entity extraction tools used in patent analysis are largely based on NLP tools which can be applied to the analyzed text to extract entities that are important for the extraction purpose. For example, in the chemical field relevant entities are chemical components, proteins or product names. For the latter cases, adaptations of Named Entity Recognizers (NER) are commonly used for this task.

Methods and algorithms to deal with the entity extraction task are different, but the most effective are based on supervised methods. Supervised methods tackle this task by extracting relevant statistics from an annotated corpus. These statistics are collected from the computation of features values, which are strong indicators of the identification of entities in the analyzed text. Features used in NLP based entity recognition systems, are divided in two main categories:

- linguistically motivated features, such as n-grams of words, lemma and part of speech;
- external resources features as, for example, external lists of entities that are candidates to be classified in the extraction process.

The annotation methods of a training corpus can be of two different kinds: (a) human based, which is time expensive, but usually effective in the classification phase; (b) automatically based, which can lead to annotation errors due to language ambiguity. As an example *crack* can be classified both as a drawback (a fracture), or not drawback (short for crack cocaine). Different training algorithms, such as Hidden Markov Models (Eddy, 1996b), Neural Networks (Haykin and Network, 2004), Conditional Random Fields (Lafferty et al., 2001b) or Support Vector Machines (Hearst et al., 1998a), are used to build a statistical model based on the features that are extracted from the analyzed documents in the training phase. The same statistical model is later used in classification of unseen documents.

For what concerns the extraction of specific entities in patents, a major interest both in academia and commercial organizations has raised in the latest years, with the main aim of improving the accuracy of domain specific patent retrieval systems (Krallinger et al., 2015). In (Lee and Kang, 2014) the authors proposed a machine learning based patent NER system that identifies key terms in patent documents and recognizes products, services and technology names in patent summaries and claims. In this work a study was conducted to identify the most relevant features for this classification task and by using lexical features like word uni-grams, word bi-grams and word trig-rams, their NER system reached an F1 score (the harmonic mean of precision and recall) of 65.4%. The authors compared their NER tagging system resulting from the optimal feature selection method, with the human tagged corpus, showing that the kappa coefficient was 0.67. This result was better than the kappa coefficient between two human taggers (0.60).

Other entity extraction systems for the patent domain were proposed for the CHEMDNER (chemical compounds and drug names recognition) community challenge (Krallinger et al., 2015). The main aim of the organizers was to promote the development of novel, competitive and accessible chemical text mining systems. The best results were obtained by the *tmChem* system (Leaman et al., 2015), achieving a 0.8739 f-measure score. The authors proposed an ensemble system composed of two Conditional Random Fields based classifiers, each one using hard feature engineering such as lemmatization, stemming, lexical and morphological features. In addition, external lists of entities were exploited to recognize whether a token matched the name of a chemical symbol or element, each one used to compute features to be added in the final statistical model.

The described entity tagging systems have very good performances mainly for two reasons: firstly, chemical entity names (such as molecular formulas) have very common orthographic patterns; secondly, these entities surrounding contexts are very similar. In more generic cases, these two features can not be exploited for entity extraction from patents, since different words have totally different surrounding contexts. Another important key factor concerning the high performances of the described systems is that many external resources, such as lists of chemicals or product names, are available: this external knowledge can not be fully exploited in generic system.

2.2.3 Papers

2.2.4 Wikipedia

The use of Wikipedia as source of knowledge started more than a decade ago and has been validated repeatedly in a variety of text mining applications (text annotation, categorization, indexing, clustering, searching (Milne and Witten, 2008)). In addition to the large and growing size in terms of number of articles, the structure of Wikipedia has a number of useful features that make it a good candidate for text mining applications. First, Wikipedia pages are considered reliable in many knowledge fields, including the ones more interesting for technical analysis, i.e. engineering and computer science (Xu et al., 2015). The pages are regularly and systematically updated by a large global community of contributors, which includes many scientific and industrial authorities in the field. The use of Wikipedia as knowledge source for computerized text mining tools is established in the literature (Ferragina and Scaiella, 2012). In addition, it is powerful in disambiguation of terms, particularly through the use of redirect pages and disambiguation pages. This means that it can be used for detection and disambiguation of named entities (Bunescu and Paşca, 2006). Second, the pages include links to other pages motivated by clear reasons on content. There are many links between Wikipedia pages, which are clues for semantic relations. This makes Wikipedia a densely connected structure, creating a classical small world effect: according to an often cited estimate, it takes on average 4.5 clicks to reach an article from any other article (Dolan, 2008). Unfortunately it is not possible to disentangle the kind of semantic relation, introducing a distinction between equivalent relations (synonymy), hierarchical relations (hyponymy/ hyperonimy) and associative relations, but this limitation is not relevant for our applications. Third, it makes use of categories which do not have a hierarchical structure, but a tree-like structure. Fourth, it has the ability to evolve quickly (Lih, 2004), particularly after the development of systems such as Wikify (Mihalcea and Csomai, 2007, Cheng and Roth (2013)). Wikipedia has by design a dynamic structure, since it is constantly growing in the number of entries and changing in their content, when this is needed due to the advancements of knowledge (Ponzetto and Strube, 2007). Furthermore the new terms that appear on Wikipedia thanks to comprehensive contributions by volunteers around the world, cannot be found in other linguistic corpora, such as WordNet Miller, 1995. Indeed, Wikipedia is the expression of a large international community, that is, of a “real community agreement” (Bizer et al., 2009) or “community consensus” (Hepp et al., 2007), guaranteed by permanent collective monitoring of the quality and rigor of the entries (Bryant et al., 2005). Finally, Wikipedia is free-content and multilingual. This make it possible to freely collect the information contained in the web pages and allows the possibility for future developments of the dictionary in other languages. In our opinion multilanguage is an interesting feature for the dictionary, due to the fact that Industry 4.0 is a worldwide phenomena.

These properties make Wikipedia the ideal candidate for the goal of extracting technical knowledge from texts. Technical fields are in fact comprehensive, dynamically updated, and, as far as possible, expert-independent. In particular, Wikipedia entries allow an endogenous measurement of semantic relatedness.

This is an exceedingly important property for technical analysis: technologies can be mapped and can be defined as included in the perimeter of a knowledge field if and only it exhibits relatedness with other technologies already included in the perimeter. The inclusion of new technologies is therefore not dependent on experts' subjective views, but is endogenously generated by the technological community that writes the articles for the encyclopedia and includes hyperlinks in the text of newly added pages.

2.2.5 Social Media

Nowadays, more than ever before, companies, governments, and researchers can gather and access data about people on a massive scale. Monitoring public opinion is increasingly made possible thanks to the rise of Social Media. These ones are computer-mediated technologies that facilitate the creation and sharing of information, ideas, career interests and other forms of expression with friends, families, co-workers, and other users, via virtual communities and networks. There are many different Social Media platforms, each of which targets a different aspect of what users want or need: e.g., LinkedIn targets professional networking activities, Facebook provides a mean of connecting friends and family, and Twitter provides a platform from which to quickly broadcast thoughts and ideas. These platforms are incredibly popular: as of February 2017, Facebook sees an average of 1,871 billion active users, with 76% of them that logging in every day (Tuten and Solomon, 2017).

Being so widely used, Social Media platforms generate huge amount of data. In 2013 users were posting an average of over 500 million tweets every day (Krikorian, 2013). Social Media are not constrained by national, cultural, and linguistic boundaries differently from traditional data sources and records of human activities, such as newspapers and broadcast media. Moreover, traditional media requires time to compile relevant information for publication, while Social Media data is generated in real-time as events take place.

Virtually anyone who wishes to use all this information could collect and mine it. In 2009, the United States Geological Survey (USGS) began investigating the possibility of using SM data to detect earthquakes in real time (Ellis, 2015). Information about an earthquake spreads faster on Social Media than the earthquake itself can spread through the crust of the Earth (Konkel, 2013). Similarly, interesting work in Social Media forecasting also exists: EMBERS is a currently deployed system for monitoring civil unrests and forecasting events such as riots and protests (Ramakrishnan et al., 2014). Using a combination of Social Media and publicly-available, non-SM, researchers are able to predict not just when and where a protest will take place, but also why a protest may occur. These encouraging results have stocked the interest of researchers toward the possibilities opened by Social Media data, although some unanswered questions remain. If Social Media is useful for detecting real-time events, can it be used to make predictions about the future? What limitations does forecasting with Social Media data face? What methods lead researchers to positive results with Social Media data? However, some researchers are pessimist about Social Media analysis. According to (Ruths and Pfeffer, 2014, Weller (2015)), Social Media is noisy, and the data derived from it are of mixed quality: for every relevant post there may be millions that should be ignored. Learning with Social Media data sometimes requires robust statistical models. Nevertheless, researchers continue to investigate how best to make use of Social Media data. First studies show positive findings.

Social Media users not only react to and talk about events in real time, but also talk about and react to events that will happen in the future. This fact fuels the interesting possibility that Social Media data might be useful for forecasting events: making predictions about future events. Not only have researchers begun to investigate this line of questioning, earlier review articles on Social Media forecasting showcase early positive examples of predictive success (Kalampokis et al., 2013, O'Leary (2015), Schoen et al. (2013)). A lot of studies show that Social Media could be used to predict the future. At the same time, some works have been controversial (Schoen et al., 2013). It's clear that this domain of research is in its infancy, methodologies are different, common best practices are difficult to determine, and true replication of studies is near-impossible due to data sharing concerns (@ Weller, 2015). The use of data from Social Media for modelling real-world events and behavior has seen a growing interest since his first appearance in academic world around 2008. This increasing popularity is proportional to the leaps ahead made in computational social science. In the past, many sociological theories were hard to prove for the difficulties encountered in gathering indispensable data. Today, Social Media can record so many sides of human relationships on the web from millions of people all around the world. On the other hand, Social Media data cannot always provide a complete picture of what researchers might hope to see. The use of Social Media varies depending on age, culture, social background, gender and ethnicity. However, positive findings and the interest in fundamental dynamics of Social Media platforms explain the exponential growth in popularity of this field of research.

Social Media data has a huge potential but understanding if its application can be useful is not a trivial task. Forecasting models (data- or theory-driven) are important in many fields but Social Media data challenges researchers to find new ways to apply them. In natural sciences, aggregating techniques of data coming from network of sensors are important, but Social Media data challenges researchers to find new ways to increase their forecasting power. Researchers should first identify the methods through which Social Media challenges may be addressed to be able to make valid and reliable predictions. Among these difficulties, there are: noisy data, possible biases, a rapidly shifting Social Media landscape that prevents generalization and a need for domain-specific theory that brings all together.

Furthermore it is important to chose the best text source for Social Media analysis, among the many available. Previous studies found that researchers focused mainly on Twitter data (Giacomo, 2017). While Facebook is trying to compete, and Snapchat offers a unique perspective on the theme, Twitter remains the best indicator of the wider pulse of the world and what is happening in it. According to Hamad (Ahmed, 2017), there are at least six reasons that explain the importance of Twitter for Social Media analysis: 1. Twitter is a popular platform in terms of the media attention it receives, and it therefore attracts more research due to its cultural status; 2. Twitter makes it easier to find and follow conversations (i.e., by both its search feature and by tweets appearing in Google search results); 3. Twitter has hashtag norms which make it easier gathering, sorting, and expanding searches when collecting data; 4. Twitter data is easy to retrieve as major incidents, news stories and events on Twitter are tending to be centered around a hashtag; 5. The Twitter API is more open and accessible compared to other Social Media platforms, which makes it more favorable to developers creating tools to access data. This consequently increases the availability of tools to researchers; 6. Many researchers themselves are using Twitter and because of their favorable personal experiences, they feel more comfortable with researching a familiar platform. It is probable that a combination of the response from 1 to 6 led to more research on Twitter. However, this raises another distinct but closely related question: when research is focused so heavily on Twitter, what (if any) are the implications of this on methods? As for the methods that are currently used in analysing Twitter data i.e., sentiment analysis, time series analysis (examining peaks in tweets), network analysis etc., can these be applied to other platforms or are different tools, methods and techniques required?

Below has to be considered whether these methods would work for other Social Media platforms (Ahmed, 2017):

1. Sentiment analysis works well with Twitter data, as tweets are consistent in length (i.e.,) would sentiment analysis work well with, for example Facebook data where posts may be longer?
2. Time series analysis is normally used when examining tweets overtime to see when a peak of tweets may occur, would examining time stamps in Facebook posts, or Instagram posts, for example, produce the same results? Or is this only a viable method because of the real-time nature of Twitter data?
3. Network analysis is used to visualize the connections between people and to better understand the structure of the conversation. Would this work as well on other platforms whereby users may not be connected to each other i.e., public Facebook pages?
4. Machine learning methods may work well with Twitter data due to the length of tweets (i.e.,) but would these work for longer posts and for platforms that are not text based, i.e., Instagram?

Maybe at least some of these methods can be applied to other platforms, however they may not be the best methods, and may require the formulation of new methods and tools. In conclusion, Twitter is the best for Social Media analysis for now. Despite its smaller user base compared with Facebook, its responsiveness and openness to researchers' tool make possible gathering useful data.

Since the usage of social media has a wide impact on a great number of disciplines, here is exposed the main literature in the most technical related fields that are strongly related to social media analysis: economics and marketing.

2.2.5.1 Economics

This domain has raised the great interest of researchers. The first studies focused especially on market fluctuation and on aggregated measure, such as Dow Jones Industrial Average (DJIA). Most recent researches have gone further predicting single stock price and yield.

Great interest in Social Media analysis for economics has been on Stock market analysis. Stock price forecasting is an important and thriving topic in financial engineering and is considered a very difficult task, even outside Social Media. Many articles in this context present models based on sentiment analysis to make forecasts (Xu and Keelj, 2014, Kordonis et al. (2016), Cakra and Trisedya (2015), Cakra and Trisedya (2015), Wang and Wang (2016), Shen et al. (2016), Brown (2012), Rao and Srivastava (2012)), although some researchers realised more detailed models: Crone et al. (Crone and Koeppel, 2014) implemented neural networks and incorporated non-SM sources, and Shen et al. (Shen et al., 2016) developed a model that studies the connection between consumers' emotion and commodity prices.

The simplest task for stock market forecasting is predicting whether the following day will see rise or fall in stock prices. Comparison between researches is complicated by the fact that stock market volatility, and so the difficulty of prediction, may vary over time periods. High accuracy on this task was reported by Bollen et al. (Bollen et al., 2011), using sentiment analysis to achieve an accuracy of 87,6%. They investigated whether measurements of collective mood states derived from large-scale Twitter feeds are correlated to the value of the Dow Jones Industrial Average (DJIA) over time. They analysed the text content of daily Twitter feeds by two mood tracking tools, namely OpinionFinder, that measures positive vs negative mood, and Google-Profile of Mood States (GPOMS) that measures mood in terms of 6 dimensions (Calm, Alert, Sure, Vital, Kind, and Happy). They find that measures of "calm" on Twitter along with DJIA numbers from the previous three days provide the best up/down predictions. Further adding the emotion "happy" reduces rise/fall accuracy to 80% but does reduce error in terms of forecasting absolute DJIA values. Importantly, they find that positive/negative sentiment analysis through the popular OpinionFinder's tool leads to no improvement over just using previous DJIA values. In conclusion, researchers obtained good results forecasting up/down movements in the stock market.

Furthermore the topic of Sales and revenues is of great interest for people working on economics. For example, boosting movie ticket sales is an important task for producers and publishers, and this has been studied specifically on Social Media platforms like Twitter. Asur et al. (Asur and Huberman, 2010) showed how social media content can be used to predict movie success. In particular, they used the chatter from Twitter.com to forecast box-office revenues for movies. Specifically, using the rate of chatter from almost 3 million tweets, they constructed a linear regression model for predicting box-office revenues of movies in advance of their release. Then, they showed that the results outperformed in accuracy those of the Hollywood Stock Exchange and that there is a strong correlation between the amount of attention a given topic has (in this case a forthcoming movie) and its ranking in the future. They also analysed the sentiments present in tweets and demonstrated their efficacy at improving predictions after a movie has released. Cheng et al. (Cheng et al., 2013) obtained mixed results developing a model for predicting TV audience rating. They accumulated the broadcasted TV programs' word-of-mouse on Facebook and apply the Back-propagation Network to predict the latest program audience rating. They also presented the audience rating trend analysis on demo system which is used to describe the relation between predictive audience rating and Nielsen TV rating. Kim et al. (Kim et al., 2014) investigated the relationship between music listening behavior in Twitter and the Billboard rankings. They found that the play-counts extracted from tweets have strong relationships with the Billboard rank, whereas, interestingly, the artist popularity extracted from tweets has a weak correlation with future chart rankings. In addition, the number of weeks on chart information alone was insufficient to predict rank alone. With the features extracted from tweets, They built three regression models to predict the ranking. Among the proposed models, SVR (Support Vector Machine) showed the highest squared correlation coefficient (0.75). Although the combined model with the number of weeks on chart performed the best in rank prediction, the music listening behavior available in Twitter can generate an outstanding predictive model. They also built a hit prediction classifier with the features acquired in tweets and the number of weeks on chart. They classified the hit and non-hit songs in the Billboard Hot 100 and obtained a value of 83.9% accuracy, 83% precision, and 85.3% recall for classifying a hit song over the whole data set. The proposed feature showed a high performance both for rank prediction and hit classification. The previous week's twitter features and the number of weeks on chart are effective for predicting the Billboard rank of a song. Ahn et al. (Ahn and Spangler, 2014) focused on periodic forecasting problems of product sales based on social media analysis and time-series analysis. In particular, they presented a predictive model of monthly automobile sales using sentiment and topical keyword frequencies related to the target brand over time on social media. Their predictive model illustrates how different time scale-based predictors derived from sentiment and topical keyword frequencies can improve the prediction of the future sales. Tuarob et al. (Tuarob and Tucker, 2013) proposed a Knowledge Discovery in Databases (KDD) model for predicting product market adoption and longevity using large scale, social media data. In particular, the authors analysed the sentiment in tweets and use the results to predict product sales. The authors presented a mathematical model that can quantify the correlations between social media sentiment and product market adoption in an effort to compute the ability to stay in the market of individual products. The proposed technique involves computing the Subjectivity, Polarity, and Favorability of the product. Finally, the authors utilised Information Retrieval techniques to mine users' opinions about strong, weak, and controversial features of a given product model. The authors evaluated their approaches using the real-world smartphone data, which are obtained from www.statista.com and www.gsmarena.com. The findings show that tweets can be used to predict product sales for up to at least 3 months in advance for well-known products such as Apple iPhone 4, Samsung Galaxy S 4G, and Samsung Galaxy S II, thus the predictive ability varies across products.

2.2.5.2 Marketing

Scholars had a great focus in the last years on using Social Media Information for marketing. Chen et al. (Chen et al., 2015) conducted a survey study and a field study to explore the feasibility of using predicted personality traits derived from social media text for the purpose of ad targeting. In the survey study, they measured people's personalities and their responses to an advertisement tweet. They found that people with high openness and low neuroticism responded more favorably to a targeted advertisement, thus demonstrating the effects of the personality traits themselves. In the field study, they sent the advertisement tweets to real-world Twitter users, and found the same effects on users' responses using personality traits derived from users' tweet text. They demonstrate that aiming advertisements at users with particular personality traits improves click and follow rates by 66% and 87% respectively, representing a large increase in value for companies. These results suggest that the derived personality traits had the same effects as the personality traits measured by traditional personality questionnaires and can indeed improve ad targeting in real-world settings. Li et al. (Li et al., 2016) present a solution to the problem of predicting project success in a crowd-funding environment combined with innovative introduction of survival analysis based approaches. They used comprehensive data of 18 thousand Kick-starter (a popular crowd-funding platform) projects and 116 thousand corresponding tweets collected from Twitter. While the day of success is considered to be the time to reach an event, the failed projects are considered to be censored since the day of success is not known. They performed rigorous analysis of the Kick-starter crowd-funding domain to reveal unique insights about factors that impact the success of projects. Their experimental results show that incorporation of failed projects (censored information) can significantly help in building a robust prediction model. Additionally, they also created several Twitter-based features to study the impact of social network on the crowd-funding domain. Their study shows that these social network-based features can help in improving the prediction performance. They found that the temporal features obtained at the beginning stage (first 3 days) of each project will significantly improve the prediction performance. Even when just using Social Media information from the first three days of the project, they achieve an AUC of 0.90, reflecting very high classification performance.

2.2.6 Publicly Funded Projects

2.2.7 Human Resources Documentation

Text Mining has been used in the last years to manage human resources (HR) strategically, mainly with applications aiming at analyzing staff's opinions, monitoring the level of employee satisfaction, as well as reading and storing CVs for the selection of new personnel. In the context of human resources management, the text mining techniques are often utilized to monitor the state of health of a company by means of the systematic analysis of informal documents. These documents are both internal (e.g. curricula, job description) and external (e.g. Linkedin, social networks).

Nowadays in fact HR experts started to use text mining technique also with intelligence purposes. For this reason companies has to collect information about their employees, the HR market and their competitors, and to analyze enormous amount of documents. The aim of Competitive Intelligence in HR (Bolasco et al., 2005) is to select relevant information by automatic reading of this documents Once the material has been collected, it is classified into categories to develop a database, and analyzing the database to get answers to specific and crucial information for HR company strategies.

The typical queries to collect the documents, concern the skills or the technological sectors of the competitors or the names of the employees of a company with a certain profile of competences. This is not a trivial task, and before the introduction of Text Minig, there was a division that was entirely dedicated to the continuous monitoring of information and answering the queries coming from other sectors of the company. In these cases the return on investment by the use of automatic document analysis technologies was self evident when compared to results previously achieved by manual operators. In some cases, if a scheme of categories is not defined a priori, clusterization algotyrhm (2.1.5.4) are used to classify the set of documents (considered) relevant with regard to a certain topic, in clusters of documents with similar contents. The analysis of the key concepts present in the single clusters gives an overall vision of the subjects dealt with in the single texts (Gupta et al., 2009).

Futhermore it has to be considered that as intellectual capital has become one of the most strategic assets of successful organizations, the ability to manage the expertise, skills, and experience of employees has become a key factor in overcoming the increasing competitiveness of the global market (Colucci et al., 2003). In today's competitive business environment, companies need to accurately grasp the competency of their HR in order to be successful (Fazel-Zarandi and Fox, 2009).

As evidence of the increasing interest of TM techniques fot HR, an increasing number of publications are providing new research paths (Strohmeier and Piazza, 2013, Al-Zegaier et al. (2011), Zhao (2008), Çelik and Elçi (2012), Veit et al. (2001), Han and Lee (2016)). One study introduced an approach to improve the matching of profiles by searching job descriptions and applicant profiles using filters that represent the relevant skills and competencies (Paoletti et al., 2015). Nevertheless, several studies have found that résumés and work experience lists, which are composed of brief words or short sentences, are limited and have tried to improve HR solutions by adopting a semantic system approach, such as ontologies and text-mining methods. An example is the On-To-Knowledge project. The OnTo-Knowledge project focuses on the application-driven development of ontologies during the introduction of ontology-based knowledge management systems (Lau and Sure, 2002). One research study has suggested that a possible approach could be addressing an intelligent decision support system composed of case-based reasoning and ontology (Zhukova et al., 2014). Another research stressed the importance of HR recruiting, selecting individuals for teams based on different skills and qualifications, determining who to train and what training programs to offer, and recommending the right expert to individuals for acquiring information or learning from within the organization (Fazel-Zarandi and Fox, 2009). Another example of TM techniques often utilized to monitor the state of health of a company by means of the systematic analysis of informal documents is the case of ConocoPhilips, a fast-moving American company, which developed an internal system - the VSM (Virtual Signs Monitor) - able to find the intangible but crucial aspects of company life, the degree of experience and knowledge and the "productive" abilities. The approach chosen by Conoco was that of measuring the company mood by means of state of the art indicators (Ghoshal et al., 1997), which contrasts a new model based on completely different pillars, like stretch, discipline, trust and reciprocal support with the traditional managerial model founded on concepts of constraint, contract, control and compliance. This managerial model, according to Ghoshal's formulation encourages the cooperation and collaboration between the elements of an organisation, improving its results. Its collaboration with Temis enabled Conoco to refine its system for the monitoring of textual sources like e-mails, internal surveys of employees' opinions, declarations of the management, internal and external chat lines, all representing important means for sounding the evolution of company culture.

Furthrmore, Web-Based Human Resources Systems had a strong impact on the HR processes. The most widely well-known web-based HR systems are Linkedin and OilandGas (Walker, 2001). Their search systems are designed so that a user can input a query and look at the search results of résumés through keyword matching. With the special services of Linked-In (accessible to premium users only), users can also search for specialists and candidates from various industries. The OilandGas service is specialized for searching for experts in the oil and gas industry, using basically the same concept of discrete keywords matching. However, once this search process is completed, the recruiter has to download all the search results and résumés and then read through all the documents to pick the most suitable candidates.

2.2.7.1 The Key Role of Skills Assessment

The term "assessment" indicates the action of assessing the potential, the skills, the attitudes and the adequacy of a professional profile.

With the advent of the Fourth industrial revolution, it is increasingly important to carry out a continuous and precise assessment of skills. At the same time, it is essential to verify that the resources within the company are enough prepared to manage the phenomenon, or it is necessary to recruit new staff to face the challenge 4.0. Undoubtedly, the future demand for professional profiles will be conditioned by digital innovation and the ever more radical integration of new technologies. For these reasons, it is particularly sensitive to change.

The literature is very focused on identifying the professional profiles that will survive during the epochal change and which instead will be eliminated. Osborne and Frey's research is emblematic: they tried to define which would be the jobs that will resist and which not, according to the substitutability of individual skills (Frey and Osborne, 2017). The results are quite pessimist: they distinguished between High, Medium and Low risk of computerisation, and, according to their estimates, around the 47% of jobs is in the high risk category.

Moreover, there are opposing views on the social effects that the revolution will cause. Caruso outlines that the technological innovation could not improve worker' conditions, performances and relationships because they cannot be determined by any technical innovation in itself, being it always socially shaped (Caruso, 2017). On the other hand, the new technologies could represent an opportunity for the labour market and they could have positive impact on employment. The reason why it would probably happens is that 3d printing, Internet of Things, Augmented reality and Big data analytics demand a large quantity of new skills to be properly managed (Freddi, 2017). Furthermore, MacCrory et al., performed a data analysis on occupational skill requirements of 674 occupations to study the effects of recent changes in automation. They identified the three main consequences of technological innovation, which could be summarized in: a significant reduction in skills that compete with automation; a significant increase in skills which complement machines; : "a significant reduction in skills that compete with machines, an increase in skills that complement machines; finally, an increase in skills where machines are not enough advanced (MacCrory et al., 2014).

Chapter 3

Case Studies: Methods and Results

L'aprrocio metodologico generico...

This chapter describes the methods applied for the analysis of technical documents. The methods are ensamble of Natural Language Processing (NLP) and Text Mining *techniques* described in 2.1, re-designed depending on the analyzed document and the analysis goal. Not all the *techniques* have been applied to all the documents: table tot summarise the relations between the documents under analysis (introduced in section 2.2) and the NLP techniques.

Table documents vs tools

3.1 Patents

Patents contain a large quantity of information which is usually neglected. This information is hidden beneath technical and juridical jargon and therefore so many potential readers cannot take advantage of it. State of the art natural language processing tools and in particular named entity recognition tools, could be used to detect valuable concepts in patent documents. In this section we present three methodologies capable of automatically detecting and extracting threee of the multiple entities hidden in patents: the users of the invention, advantages and drawbacks of the invention and trademarks contained in patents. The results of the methodologies are described, togheter with example of applications of the extracted entities for intelligence tasks.

3.1.1 Users

In this section we show the approach used to extract the users of the invention described in a patent. The proposed process is shown in figure 3.1 and its phases are:

1. *Generation of an input list of users*: search all possible sources with the aim of creating an input list of users with the largest possible coverage (section 3.1.1.2);
2. *Patent set selection*: select the set of documents from which extract the users (section 3.1.1.3);
3. *Patent text pre-processing*: application of natural language processing tools on the documents with the aim of preparing them for the automatic user extraction;
4. *Automatic patent set annotation 1*: projection of the input list of users on the text to generate the Automatically Annotated Patent Set 1;
5. *Relevant sentences extraction*: selection of sentences containing at least one user to generate an informative training set;

6. *Automatic patent set annotation 2*: generation of a statistical model by a machine learning algorithm based on the training set sentences and automatically tagging the patent set to generate the Automatically Annotated Patent Set 2;
7. *Difference computation*: generation of the new list of users by computing the difference between the lists of users found in the automatically annotated patent set 1 and 2;
8. *Manual review*: manual selection of the entities that, in the new list of users, are effectively users. This new list will enrich the original list of users. This phase is described in section 3.1.1.6.

Before the description of each phases, in section 3.1.1.1 the concept of *user of the invetion* is explained by giving a definition of users and presenting the way that this concept is exploited in different knowledge fields.

3.1.1.1 Users: A key information hidden in patents

Patents are documents that must provide a detailed public disclosure of an invention (Idris, 2008). An *invention* is a new and useful process, machine, manufacture, or composition of matter, or any new and useful improvement thereof [1].

The notion of usefulness implies that the invention must have some value and not necessarily for a human entity. In fact, patents usually describe processes, machines or composition of matter which are useful for another process, machine or composition of matter.

Therefore, we distinguish between stakeholders and users, considering the definitions given by the authors in (Bonaccorsi and D'amico, 2017).

Definition 1: **Stakeholder** : *Stakeholders are entities on which the invention has or will have a positive or negative effect in order to show usefulness.*

This definition covers all possible entities that engage an active or passive relation with the invention.Given the logical condition of usefulness of patents, all patents must have stakeholder information. If a patent has not got any stakeholder information in it the patent application should be rejected.

Definition 2: **User**: *Users are animated or previously animated entities (human or animal, alive or dead), on which the invention has a positive or negative effect at an unspecified moment.*

Given definition 2, it is clear that every user is a stakeholder while non-users stakeholders include artifacts, machines, manufacturing or operational processes.

Corollary 1: **Multiple roles**: *Identities may have multiple roles as users.*

Our idea of users describes roles, not identities. Animated entities have an identity, as it happens for a specific person. A person has many roles as a user. For example, a *working mother* starts her day taking on the role of a *mom*, in which she is expected to feed her children and get them ready for school. At the office she shifts to the role of *project manager*, so she oversees projects in a timely and professional manner. *Working mother*, *mom* or *project manager* can be considered user roles attributed to the same person, or identity. From this definition it is clear that users are close to what social sciences define as "social roles".

Afterward, we can outline knowledge fields using the concept of user, with a twofold aim: help the reader to understand how the concept of users is interpreted in different knowledge fields; explain the background of the methodology we adopted.

3.1.1.1.1 Social sciences: social roles as users

In social sciences *social roles* are comparable with our definition of user. As defined in the psychological field (Dog, 2015), *"social roles refer to the expectations, responsibilities and behaviors we adopt in certain situations."*. The example of the working mother shown before, is the case of social roles.

The field of social sciences is the only one in which an attempt of automatic extraction of users has been done. In (Beller et al., 2014b) the authors extracted social roles from Twitter using heuristic methods. The

[1] http://www.uspto.gov

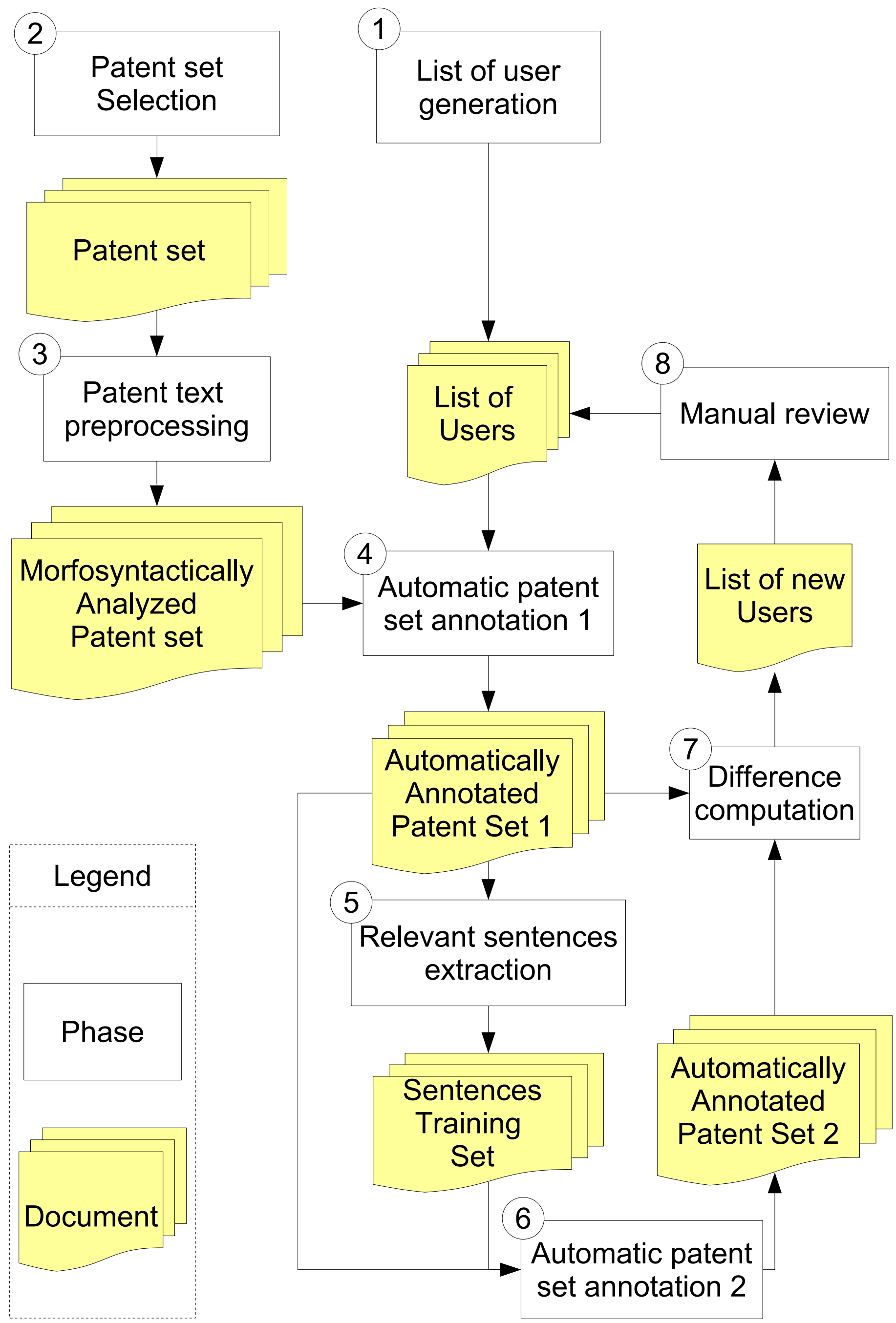

Figure 3.1: Process flow diagram of the proposed automatic user extraction system from patents. The diagram contains the representation of the documents and the operations performed on them. The process takes in input a patent set and a list of users and produces a list of new users as output.

authors looked for all the words preceded by constructions like "I'm a" and similar variations. This search resulted in 63.858 unique roles identified, 44.260 of which appeared only once. The result of the extraction process is noisy and only a low percentage of the extracted words are social roles. Despite of this noisy extraction, some entities are consistent with our definition of user, e.g. *doctor, teacher*, *mother* or *christian*.

Another work (Beller et al., 2014a) tries to identify social roles on Twitter exploiting a set of assumptions. The authors take into account roles, each one with a set of related verbs: if someone uses verbs from a set, that person may cover that particular social role. To sanitize the collection of positively identified users, the authors crowd-sourced a manual verification procedure, using the Mechanical Turk platform (Kittur et al., 2008). Also here some interesting extractions are performed, obtaining users like *artist, athlete, blogger, cheerleader, christian, DJ*, or *filmmaker*. These two works differ from the present study for what concerns the analyzed texts and the methods to extract the entities. Nevertheless, the extracted set of entities is consistent with our definition of user.

3.1.1.1.2 Human Resources Management: workers as users

In organizations, Human Resources Management is the function designed to maximize employees performance (Johnson, 2009). Employees are key actors and they can be considered users according to our definition.

Human Resources Management has tried to classify employees, especially in sub-fields like insurance, social security or work psychology. Usually, we refer to those as lists of jobs. Classifications were made with the goal of grouping similar jobs for educational requirements, job outlooks, salary ranges or work environments to facilitate social analysis and the placement of new workers. Such lists are relevant because, even if they represent just one subset of all the possible users, they contain valid information. Many institutions developed lists of jobs (lis, 1967).

3.1.1.1.3 Medicine: patients as users

Another field of interest is medicine, since patients can be considered users. Also in this case there are many lists of patients, illnesses and diseases (of Health and Services, 2018), which are valuable in terms of information contained.

3.1.1.1.4 Design and Marketing: between users and customers

In the field of *Design* the concept of user plays a central role and it overlaps with our definition of user. Many tools and theories like "User Centered Design" are based on the concept of user (ISO, 1999). As stated by the authors in (K., 2008), the quality of the design process is proportional to the user needs' satisfaction. It implies that a designer has to understand the user needs; as a consequence he has to discover whom are potential users.

3.1.1.2 List of users generation

To generate the input list of users, we used two different approaches: a bottom-up approach and a top-down approach. The bottom-up approach is based on the merge of lists from heterogeneous sources. In the present work we used the following lists of entities:

- *Lists of jobs* :(lis, 1967), 11.142 entities
- *Lists of sports and hobbies*[2]: 9.660 entities;

List of animals [3]: 600 entities;

- *Lists of patients* [4]: 14.609 users;

[2]http://www.notsoboringlife.com/list-of-hobbies/,http://www.notsoboringlife.com/list-of-hobbies/

[3]http://a-z-animals.com/animals/

[4]http://www.medicinenet.com/diseases/_and/_conditions/alpha/_a.htm, http://www.cdc.gov/DiseasesConditions/az/a.html

- *List of generic words*: manually generated. It contains users with a higher level of abstraction (such as *person* or *human being*), 56 items.

Bottom-up approach produced a list of 35.767 entries.

Afterwards, a top-down approach was applied. Starting from the list generated with the bottom-up approach, we looked for alternative methods to indicate a user, finding defined word patterns. The most relevant are:

- Patterns like “hobby_term + practitioner” for the hobbies;
- Patterns like “person who has + disease_term” or “suffering from + disease_term” for the diseases;
- Patterns like “practitioner of + sport_term” for sports.

Top-down approach generated a total of 41.090 entries.

The whole process generated a total of 76.857 users and gave us a reasonable number of terms to be used in the next step of the process.

Obviously our lists have a limited coverage and, therefore, they do not contain all variations of a certain user. For instance, the lists miss some users belonging to the classes mentioned above (e.g. new jobs emerged in the last years) and all the alternative ways for referring to a user we do not spotted in the top-down approach. For example our lists miss jobs like *data analyst*, *lap dancer*, *undertaker*, *mortician* and *thief* or patients with emerging diseases like *work-alcoholic* and *web-addicted*. In addition, our lists miss a class of users related to religious groups, containing users like *christians* or *jewish*. Such terms have intentionally **not** been introduced in the input list because we considered these terms as candidates to be extracted by the process in our case study .

3.1.1.3 Patent set selection

Our choice of patent sets aimed at challenging our system to find new users missing in the input list. To reproduce a patent set selection, we took into consideration the International Patent Classification (IPC) (Organization, 1971). IPC is a hierarchical system of patent classes representing different areas of technology. Then, we wondered which classes could contain new users according to our seed list. Furthermore, IPC class A, which is the first level in IPC differentiation, is based on human necessities. For this reason, we assumed that in this class we would have found likely users from patents texts.

3.1.1.4 Patent text analysis

Our Entity Extraction system is composed by a set of sequential phases. The first three phases are related to the linguistic annotation: sentence splitting and tokenization, part of speech tagging and lemmatization. Then, the patent set is analyzed by the entity extractor, specialized for users extraction. A more detailed description of each phase is:

- Sentence splitting and Tokenization: These processes split the text into sentences and then segment each sentence in orthographic units called tokens. In our system, sentence splitting plays a key role since thanks to a given word, it is possible to find sentences where the word is used. Finding correct boundaries for a specific word allows to dramatically reduce the space to retrieve its surrounding contexts.
- POS tagging and Lemmatization: The Part-Of-Speech tagging (or POS tagging) is the process of assigning unambiguous grammatical categories to words in context. It plays a key role in NLP and in many language technology systems. For the present application we used the most recent version of the Felice-POS-tagger described in (Dell’Orletta, 2009). Once the computation of the POS-tagged text is completed, the text is lemmatized according to the result of this analysis.
- Semi-automatic Users Annotation: The Users Extraction tool is based on supervised methods. Such methods require an entity annotated corpus in order to extract new entities from unseen documents. A semi-automatic method has been used to generate an annotated corpus of users to avoid manual annotation of a patent set. The method is a projection of the list of users on the patent set defined in

section @ref{patsel}. The list of users described in section @ref{sourc} is cleaned to avoid linguistic ambiguities when projecting these entities on the corpus. For example, the term *"guide"* has two different meanings when used as a verb or as a noun. Furthermore, as a noun it could indicate a component of a system (guide for mechanical parts) or a person (someone employed to conduct others) and therefore a user. Avoiding ambiguities is a crucial aspect to produce an informative training set, so ambiguous words were pruned.

The entity annotation schema for a single token is defined using a widely accepted BIO annotation scheme Ramshaw and Marcus (1999):

- **B-USE**: the token is the beginning of an entity representing an User;
- **I-USE**: the token is the continuation of a sequence of tokens representing an User;
- **O**: for all the other cases.

3.1.1.5 User Entity Extraction

The Users extraction problem is tackled by the implementation of a supervised classifier that is trained on an annotated patent set. Thus, the patent set is linguistically-annotated, using the steps described above and entity-annotated, exploiting the semiautomatic annotation process executed in the previous steps.

Given a set of features the classifier trains a statistical model using the feature statistics extracted from the corpus. For each new document the trained model assigns to each word the probability of belonging to one of the classes previously defined (B-USE, I-USE, O).

In our experiments the classifier has been trained using two different learning algorithms: Support Vector Machines (SVM) using the LIBSVM library (Hearst et al., 1998a) configured to use a linear kernel and Multi Layer Perceptron (MLP) implemented using the Keras library (Chollet, 2015). It has been proven that LSTM methods are well suited for similar NER task. Anyway, we chose SVM and MLP method to study how two wheel established state of the art classifiers perform on the specific task of user extraction from patents and to evaluate their performance in terms of precision and computational effort. We also think that the popularity of these methods increment the reproducibility of the work.

The classifier uses different kind of features extracted from the text:

- *linguistic features*, i.e. lemma, Part-Of-Speech, prefix and suffix of the analyzed token;
- *contextual features*, the linguistic characteristics of the context words of the analyzed token; in addition the entity category of the previous token is considered;
- *compositional features*, combinations of contextual features and linguistic features. i.e. Part-Of-Speech of the previous word and the lemma of the current word. These extra features allow to infer statistics on the interaction of the combined features that can not be captured by a linear SVM model.
- *word2vec features*: vector representations of words computed by the *word2vec* (Mikolov et al., 2013) tool.

Word2vec is a NLP tool able to produce word representations exploiting big corpora. The main property of the vectors produced by *word2vec* is that words sharing similar contexts have similar vector representations. By using word vectors instead of the corresponding words we were able overcome the problem of the limited lexical knowledge in the training phase. Using these features and excluding all the others (delexicalized model) we expected that the resulting user extraction system had a lower precision and an higher recall in the classification phase. We presumed to find new users not contained in the input seed list.

3.1.1.6 Manual Review of the new list of users

It is still possible that the classification process creates false positive results (words labeled as users that do not match the definition in section @ref{theuse}). Thus, it is necessary to make a manual review of the extracted entities with the aim of evaluating the output.

3.1.1.7 Results

The following section describes the performances of the automatic users extraction process on two different patent sets. To test the system four experiments were conducted}. Finally the performances and the outcomes of the system are shown and discussed.

Following the guidelines for the patent set selection described in section 3.1.1.3, we examined two patent sets belonging to the IPC class A:

- **A47G33**. The IPC definition of the subclass is *"religious or ritual equipment in dwelling or for general"*.
- **A61G1-A61G13**. The IPC definition of the subclass A61G1 is *"Stretchers"* while the definition of the subclass A61G13 is *"Operating tables; Auxiliary appliances therefor"*.

We extracted from the private Errequadro s.r.l. [5] database a random sample of 2.000 patents from each IPC class. For each patent set we applied the semiautomatic set annotation process by projecting the input list of users on the morphosyntactically analyzed patent set. After this process, each semi-automatically annotated patent set was split in two parts: the first was used as training set for the user extractor, and the second one was used as test set.

To build an informative training set, from the semi-automatically patent set we selected a subset of sentences containing at least one user. The size of the training set in both cases is approximately composed by 600.000 tokens. For each patent set table 3.1 shows the number of sentences of the training set, the number of sentences of the test set, and the number of distinct users in the training set (re-projected by the semi-automatic annotation process).

ref —> patent set-details

Table 3.1: Statistics related to the patent set groups analyzed in the case study

patent set group	*#Sentences - training*	*#Sentences - test*	*#Distinct users projected on training*
A47G33	13.364	214.029	126
A61G1-A61G13	15.108	2.520.350	121

We chose two orders of magnitude for the sentences test-set to test the efficiency of multiple configurations of the system.

To test the performances of the implemented user extractor, we devised four different configurations. Each configuration uses a specific learning algorithm and a set of features to build the statistical model. The main purpose of this procedure is to find the configurations that better perform in the user extraction task. In addition, the different behaviour of the system in the classification phase is studied. In table 3.2 are reported the detailed configurations used in our experiments.

Table 3.2: Context windows of the extracted features considering 0 as the current analyzed token.

Feature group	*Context Window*
Lemma unigrams	\([-2, -1, 0, 1]\)
Lemma bigrams	\([(-1 ,0), (0, 1)]\)
Word bigrams	\([(-1 ,0), (-2, -1), (0, 1), (1, 2)]\)
Word trigrams	\([(1, 0, 1) (-2, 1, 0)]\)
Pos unigrams	\([-2, -1, 0, 1]\)

[5] http://www.errequadrosrl.com/

Feature group	*Context Window*
Pos bigrams	\(([(-2, -1) (-1, 0), (0,1)])\)
Compositional feature #1	\((POS_{-1}, Lemma_{0})\)
Compositional feature #2	\((Lemma_{-1}, Lemma_{0})\)
Compositional feature #3	\((Lemma_{0}, Lemma_{1})\)
Compositional feature #4	\((POS_{0}, Lemma_{1})\)
Compositional feature #5	\((NER_{-1}, Lemma_{0})\)
Word2vec	$-2, -1, 0, 1, 2$

By using the first and the second configuration we expected to have a higher precision in the classification phase, since explicit lexical information is used in the training phase. For the same reason we expected to have low recall in classification phase. On the other hand, the third and fourth configurations are delexicalized: lexical information is provided by word vectors computed by word2vec_. In these two configurations we expected to have an higher recall and a lower precision, due to the characteristics of the computed vectors explained before. To limit errors when using the *word2vec* features, some linguistically motivated filtering rules were introduced. Specifically, sequences of tokens classified as users were constrained from the following categories: verbs, adjectives not preceded by articles, articles and adverbs.

To evaluate the whole user extraction process in each experiment, we defined some evaluation measures. Each measure was introduced to evaluate the characteristics of the extraction system concerning the configuration applied.

These measures are:

- Training time: time needed to create the statistical model using the training set;
- Test time: time needed to re-annotate the semi-automatically annotated patent set;
- Number of extracted users: number of unique entities classified as user in the automatically annotated patent set;
- Number of known users: number of distinct extracted users in the automatically annotated patent set and belonging to the list of user in input;
- Number of new users: number of distinct entities classified as user in the automatically annotated patent set and not belonging to the input list of users;
- Number of new correct users: number of distinct entities considered as user and as correct after a manual review;
- Precision: ratio between the number of new distinct correct users and the total number of new distinct users;
- Gain: ratio between the number of new distinct correct users and the number of re-projected distinct users on the training set.

Table 3.3 reports the values of the defined metrics across all the experiments run on the two patent sets.

Table 3.3: Comparison of the values of the defined metrics across all the experiments. The patent set annotation in the experiment (6) was not performed due to the computational costs. All the experiments were run on a machine provided with 10 AMD Opteron(tm) 6376 processors.

Experiment	Training time	Test Time	Extracted	Known	New	New correct	New wrong	Prec. (%)	Gain (%)
1 (SVM)	83m	321m	161	93	68	47	21	69.11	37.30
2 (MLP)	1911m	9091m	196	55	141	27	114	19.15	21.42
3 (MLP-W2V)	165m	246m	162	35	127	45	82	35.43	35.71

Experiment	Training time	Test Time	Extracted	Known	New	New correct	New wrong	Prec. (%)	Gain (%)
4 (SVM-W2V)	1265m	4310m	121	29	92	45	47	48.91	35.71
5 (SVM)	148m	3443m	302	120	182	88	108	48.35	72.72
6 (MLP)	1818m	—	—	—	—	—	—	—	—
7 (MLP-W2V)	333m	3530m	305	38	267	44	230	16.48	36.36
8 (SVM-W2V)	1268m	47020m	313	49	264	74	197	28.03	61.15

For what concerns training and test time of the automatic patent set annotation, it's clear that the configuration based on the SVM learning algorithm without the *word2vec* features performs better in both the experiments (1, 5). When the features based on *word2vec* are introduced, the configuration based on the MLP learning algorithm is the fastest both in training and test time (3, 6): it is due to the fact that keras implementation of this algorithm exploits all the available CPU cores of the system. On the other side, the MLP algorithm does not scale properly with a higher number of features, as seen in training and annotation time in the experiment (2). In addition, we could not perform the patent set annotation in the experiment (6), since it would have required more than 60 machine days to complete the process. When *word2vec* features are introduced, the patent set annotation based on the SVM algorithm is 10 times slower than the MLP algorithm.

For what concerns the precision in the automatic patent set annotation, the SVM configuration without *word2vec* features is clearly the more reliable: the precision values are from 1.5 to 2 times higher in the experiments (1, 5) in contrast to the other experiments. The higher precision is justified by the fact that the configurations based on *word2vec* features lack explicit lexical information: words with very similar contexts are represented by similar *word2vec* vectors, probably leading to errors in the classification phase. On the other hand, the use of *word2vec* vectors aims at extracting entities that would not be extracted by considering explicit lexical information only.

Finally, for what concerns information gain, the same amount of new information (21-37%) is extracted in the experiments on the A47G33 patent set. The gain values drastically change in the experiments on the A61G1-A61G13 patent set: in the experiments (5, 8) a gain between 61% and 72% is obtained: it is due to the size of this patent set in comparison to the A47G33 one. In the experiment (7), despite the introduction of *word2vec* features, a gain of 36% is obtained. This fact, in conjunction with the non-feasibility of the experimental configuration 6, shows how MLP systems lack in efficacy and efficiency (in entity extraction in patent domain) when the test-set has an order of magnitude of millions of sentences. We think that this result is relevant, based on our experience with practical applications.

Furthremore, a way to maximize the overall informative gain is to merge the results of all manually reviewed user extractions obtained by executing the patent set annotation process with all possible configurations.

The overall informative gain of the merging process is related to intersections that occur among the results obtained by the patent set annotation process in each configuration: the less the intersections, the more the overall informative gain obtained. In table 3.4 is shown the overall gain obtained by merging results of the manually reviewed extractions in each patent set.

Table 3.4: Gain obtained by merging correct entities extracted from each patent set annotation.

Configuration	A47G33 - Gain (%)	A61G1+A61G11 - Gain (%)
SVM	37.30	72.72
MLP	21.42	—
MLP-W2V	35.71	36.36

Configuration	A47G33 - Gain (%)	A61G1+A61G11 - Gain (%)
SVM-W2V	35.71	61.15
SVM - MLP	52.38	—
SVM - MLP-W2V	69.84	126.44
SVM - SVM-W2V	73.01	103.30
MLP - MLP-W2V	55.55	—
MLP - SVM-W2V	57.14	—
MLP-W2V - SVM-W2V	59.52	76.30
SVM - SVM-W2V - MLP-W2V	90.47	140.49
SVM - MLP - MLP-W2V	82.53	—
SVM - MLP - SVM-W2V	85.71	—
MLP - SVM-W2V - MLP-W2V	77.77	—
SVM - MLP - SVM-W2V - MLP-W2V	103.17	—

The table shows that the merging process of manually reviewed entities extracted from each patent set annotation run effectively contributes to increase the overall informative gain. For instance in the A47G33 patent set an overall gain of 103.17% is obtained, tripling the best result achieved by the extraction performed using the best single configuration. Good results are also achieved in the A47G33 patent set user extraction. In this case an overall gain of 140.49% is obtained, doubling the best result achieved by the extraction performed using the best single configuration.

The results shown in section 5 prove that if the goal of the extraction is to reach the maximal recall, an ensemble method (combining the output of multiple classifier) over-performs every single classifier method. Anyway, the ensemble approach has clear efficiency issues, because the time of analysis will be the sum of every single approach time (in hypotheses of non-parallelization). This leads to a trade off between the speed of the system and the quality of the results, and whoever would use the presented system can decide to gain benefit in one or in another direction.

Finally, tables 3.5 and 3.6 show an overview of extracted users randomly chosen from the A47G33 patent set (the only one in which were able to perform all experiments). Each table is divided in two blocks, representing the results of the extraction performed using a specific configuration. For each extracted user is shown the corresponding lemma (the root form), the frequency (how many times that user appears in the whole corpus) and the total number of patents containing the user. Users not contained in the starting user list, are highlighted in bold.

The table shows that the system was able to extract characteristic users of the patent set. The results are in fact not unexpected for the IPC class under analysis: this is an evidence of the correct performances of the proposed system. In other words, the results presented in the table show that it is possible to train a NER systems able to extract sparse and valuable information. Such users are the ones that an expert would manually extract but the NER system does it with an enormous saving in terms of time and efforts.

Other remarkable results are:

- many newly extracted entities have very low frequency in the patent set: it shows that the developed system is able to extract rare entities.
- table 3.6 shows that configurations using *word2vec* features are able to find new users with a higher frequency in the patent set: it was an expected result, since the *word2vec* configurations are not explicitly lexicalized and more able to generalize during extraction phase.
- The system is able to extract single words and multi-words.
- Taking into consideration the definition of user of an invention, the system extracts unusual and sometimes borderline users. Examples like *saint*, *angel*, *god* and *ghost* need discussion that is far beyond the purposes of the present paper. These results are a remarkable evidence of the human-like generalization ability of the described method.

Table 3.5: Extracted users from the A47G33 patent set using the SVM and DL configurations. New users extracted by the system are reported in bold.

Lemma	Frequency	# Patents	Lemma	Frequency	# Patents
female	801	109	child	402	102
child	426	108	cleregy member	128	5
guy	156	17	patient	113	11
patient	115	11	man	50	26
parent	70	31	young	48	32
man	51	26	**angel**	29	23
merchant	50	6	dog	20	7
soon	46	29	artisan	12	12
engineer	45	45	**male/female**	12	4
adult	39	23	hockey player	7	1
young	35	24	**professional**	7	7
society	32	21	tennis player	7	4
angel	29	23	football player	6	3
fund raiser	27	4	**ghost**	5	3
priest	22	4	children	5	5
cheerleader	15	4	manager	5	5
fund-raiser	11	4	**spider**	5	5
athlete	10	9	**vandal**	5	1
ghost	5	5	**athlete**	4	3
adulterant	3	3	mother	4	2
jew	3	3	soccer player	4	3
maid	3	1	squirrel	3	2
tourist	3	3	**maid**	3	1
indian	2	2	**god**	3	2
beginner	1	1	**mariner**	3	3
christians	1	1	**male-female**	2	2
datum entry operator	1	1	**manufacturer**	2	2
expert	1	1	**jew**	1	1
jewish	1	1	**merchandizers**	1	1
marinaro	1	1	**parishioner**	1	1

Table 3.6: Extracted users from the A47G33 patent set using the SVM-W2V and MLP-W2V configurations. New users extracted by the system are reported in bold.

Lemma	Frequency	# Patents	Lemma	Frequency	# Patents
child	152	68	clergy member	124	5
clergy member	124	5	**crowd**	36	3
man	50	26	basketball player	20	5
engineer	45	45	**him**	17	8
young	29	24	woman	16	8
choir	17	1	**saint**	14	2
infirm	13	8	**youth**	14	2
bride	9	4	**angel**	8	4
volunteer	8	6	**choir**	8	1
musician	6	6	musician	6	6
boy	3	1	**god**	5	1
children	3	3	children	3	3

girl	3	2	guy	3	3
creature	2	1	infant	3	3
deceased	2	1	priest	3	3
jewish	2	2	**bride**	2	2
person	2	2	**consumer**	2	2
mother	2	2	**everyone**	2	2
audience	1	1	**him/her**	2	2
boyfriend	1	1	**spectator**	2	2
derby member	1	1	farmer	2	1
gift giver	1	1	youngster	2	2
handicapped	1	1	**boyfriend**	1	1
jesus	1	1	**grandparent**	1	1
saint	1	1	**subject**	1	1
husband	1	1	clown	1	1
lady	1	1	husband	1	1
runner	1	1	runner	1	1
society	1	1	society	1	1
teenager	1	1	tennis player	1	1

The total number of users is 109. 28,2% (564 on 2.000) of patents in analysis contains at least one user. This result is an evidence of the fact that patents actually contain users information, and, considering the approach we followed, this percentage is an accurate lower approximation of the actual percentage of patents containing at least one user.

In figure 3.2 for each user on the x axes is shown the number of patents in which the user is contained. The distribution is skewed, with some occurrences showing large numbers and many others with just one or few occurrences. It is clear that there is a Pareto like distribution, with the first 20% of users covering 70% of total users in terms of occurrence. It means that some users are more likely to be cited in patents and many more users that rarely appear. Following this observations, we can divide users in three groups:

- *Group A*: users that appear in more than 100 patents (5% of the patent set). In our case these are *male*, *child* and *female*.
- *Group B*: users that appear in more than 20 patents (1% of the patent set). This group is composed by 13 different users. Some of these are *engineer*, *person*, *player*, *adult*, *angel* and _guy.
- *Group C*: users that appear in less then 20 patents. This group is composed by 93 different users. Some of these are *mother*, *athlete*, *priest*, *adulterant*, *golfer* and *hockey player*.

Further research means to study how these users differ from patent set to patent set. We expect to see similar distribution but with different content of users. Frequent and non-specific users comprise Group A: in other patent set we could see differences in terms of entities contained in this class but its content will stay non-specific. These results seem to be generic social roles indicating the gender or the age of a person. Group B is composed of mainly non-specific users and some specific users that change from patent set to patent set. This class helps to identify the core users of the patent set. Lastly, Group C contains non-frequent users that are both specific and non-specific, making it the most interesting of the three for the purposes of our work. In this group we find users that are market niches, so the patent that contains these users is of great interest for marketers and designers. These are both samples of the more generic users (for example a *mother* is a *female* and a *hockey player* is a *player*) or specific users of the patent-set (like *priest*, *fund-raiser*, *doll*, *spouse* and *clergy member*.

3.1.2 Advantages and Drawbacks

In this section we show the approach used to extract the advantages and the drawbacks of the invention described in a patent. More precisely, the system identifies textual elements which represent the advantages

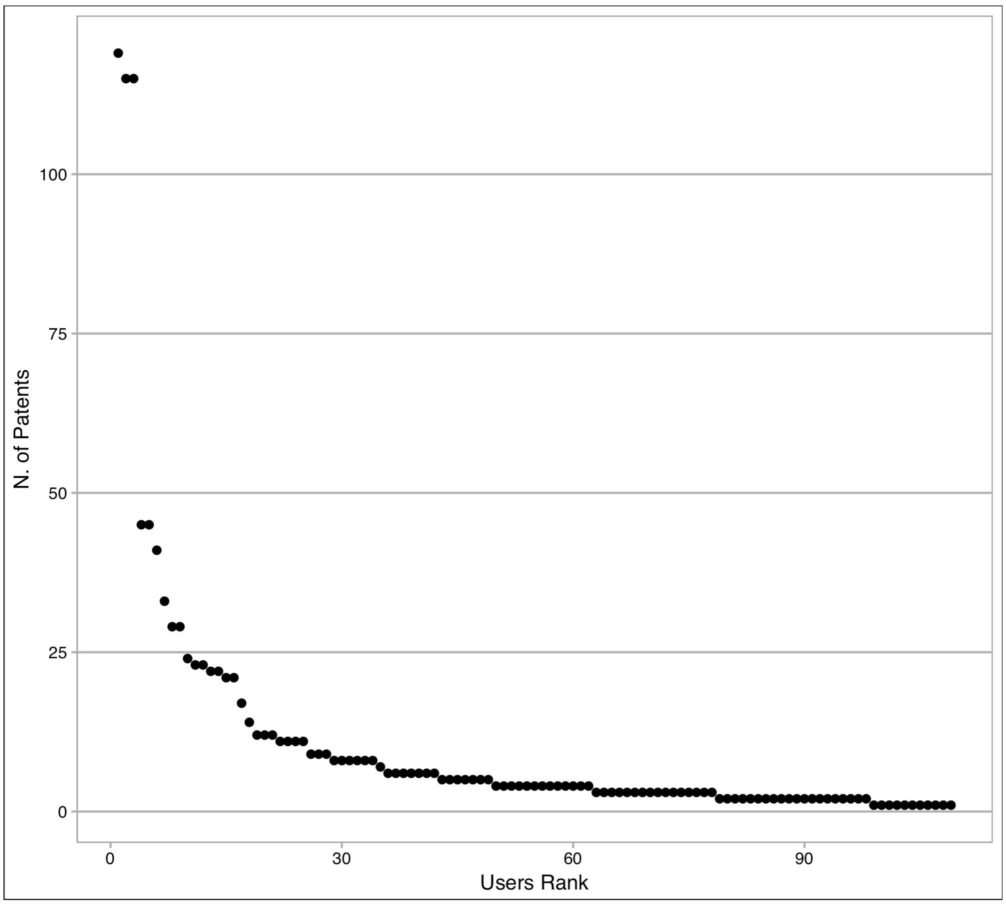

Figure 3.2: Process flow diagram of the proposed automatic user extraction system from patents. The diagram contains the representation of the documents and the operations performed on them. The process takes in input a patent set and a list of users and produces a list of new users as output.

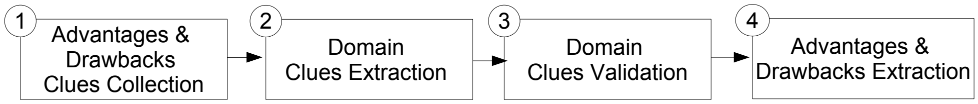

Figure 3.3: Main overview of the advantages and drawbacks extraction process from patents.

or the drawbacks described in a patent. Advantages and drawbacks information can strongly advantage designers in the phase of new product development or in the process of product improvement and marketers in the phase of customer understanding and product placing. Furthermore a patent based method has a strong advantage with respected to methods that extracts information using other type of documents (e.g. online reviews of products (Mirtalaie et al., 2018)): patents anticipate availability of products on the market by a factor varying from 6 to 18 months (Golzio, 2012).

The proposed extraction process is shown in figure 3.3 and its macro-phases are:

1. *Advantage and Drawback Clues Collection*: in this section we described the method to collect a reasonable number of generic advantage and drawback clues;
2. *Domain Clues Extraction*: in this section is shown how the generic clues are used in exploiting machine learning algorithm to extract new domain specific advantages and drawback clues;
3. *Domain Clues Validation* : since the new clues are automatically extracted, the output of the extraction phase surely contains a certain degree of noise. To clean this output a validation tool based on tweeter sentiment analysis is developed;
4. *Advantages and Drawbacks Extraction*: here the extracted clues (generic and domain specific) are expanded according to specific regular expression pattern in order to obtain the advantages and the drawbacks of the analyzed patent set.

Before the description of each phases, in section 3.1.2.1 the concepts of *advantages and disadvantages of an invention* are explained.

3.1.2.1 Advantages and drawbacks: an engineering point of view

An effective development of new products or the redesign of an existing one require the analysis of its positive and negative properties. Due to that, advantages and drawbacks of products are extremely valuable information for companies. Unfortunately, this information is not easy to obtain and manage: a strong evidence of that is the effort in the development of tools able to manage this information (Pahl and Beitz, 2013, Ulrich (2003)). Companies frequently make use of Quality Functional Deployment (QFD) and requisites lists, users' needs, users' requirements with the purpose of tracking advantages (Carnevalli and Miguel, 2008). On the other hand, companies use Failure mode and effects analysis (FMEA) to gather and study drawbacks, failure modes and their effects and causes (Liu et al., 2013) However, product developers can acquire QFD and FMEA data only from the users of the invention: this leads to the need of expensive processes of customer's voice listening whose results are often unclear. Moreover, this information is not disclosed to researchers since this is part of the company know-how.

The description of the brought advantages and solved drawbacks are critical requirements for the patentability of a product, as stated by the politics and the guidelines given by World Intellectual Property Organization (WIPO) on writing patents (Organization, 2004). As stated by WIPO, an invention is a *solution* to a specific *problem* . The problem that an invention solves is a negative effect that state-of-the-art technologies can not fully overcome; on the other side, a solution is a way to solve this problem. A solution can lead to some advantages with respect to the known art. Thus, starting from the definition of invention, it is clear how it can be characterized by the advantages that it brings and by the problems that it solves. Also, it is reasonable to assume that having a clear picture of both advantages and drawbacks of a technology is important for an effective design process [6]

[6] The most precise couple of words is **advantage** and **disadvantage**, but the reading is facilitated by using two very different

3.1.2.2 Clues of Advantages and drawbacks in patents

First of all we have to define the concept of clue to an advantage or a drawback. To describe with a certain degree of precision an advantage or a drawback, patent writers need to use sequences of words of a certain length. Since NER systems do not perform well on long sequence of tokens, we split the problem of extracting advantages and drawbacks in two parts: first we extract entities that are clues in the sequence of words that describes the advantage or the drawback; then we extract the surrounding words to collect the whole sequence that describes the advantage or the drawback.

To better understand these concepts some examples are:

- ease of access
- cook food quickly and economically
- benefits of keeping an outdoor cooker lid fixed

For the present work, we refer to advantages and drawbacks as a sequence of words of minimal length that express the advantage or the drawback. The three phrases of the example are three advantages. On the other hand clues are words that are likely to be contained in advantages or drawbacks phrases.

3.1.2.3 Advantages and Drawbacks Clue Collection

The approaches to generate a knowledge base of clues were two. The first approach was based on a manual collection of clues of advantages and drawbacks directly from patent texts. This process was performed on 2,000 patents, randomly chosen from the freepatent database [7]. With this approach we were able to collect 3,254 advantages and 5,142 drawback clues. Some examples of the extracted clues are shown in table 3.7.

Table 3.7: Examples of the clues collected with the first approach.

Advantages Clues	*Drawbacks Clues*
ability	aggravated
efficacy	breakage
ensure	damage
healthy	defect
innovative	error
optimum	improper
protect	leak
quick-release	problem
reinforce	unavailable
securely	wrong

The second approach consisted in looking for alternative methods to indicate advantages or drawbacks clues, looking defined word patterns. The most relevant are the negations of advantages to obtain drawbacks, and the negation of drawbacks to obtain advantages. Some examples of such constructions are shown in table 3.8.

Table 3.8: Examples of the clues collected with the second approach.

Advantages Clues	*Drawbacks Clues*
non damaged	out of
anti-corrosion	in need of comfort

words, therefore we decided to adopt the couple **advantage** and **drawback**.

[7] http://www.freepatentsonline.com/

Advantages Clues	*Drawbacks Clues*
loss reduction	non user-friendly
prevent	diminish comfort
defect free	issue with
reduce waste	problem with
reduction of	lacks of
cost less	lacks with
less severe	loss of
avoid disease	unfacilitate

At the end of this process, a total of 6.568 advantages and the 14.809 drawbacks formed the knowledge base for the system, and gave us a reasonable number of clues to be used in the next step of the process.

The first approach was restricted by the lists being extracted from a random and limited sample of patents. On the other side, the rules used in the second approach are non exhaustive, and this can create non-sense clues, due to all of the possible combinations of words. Anyway, it is reasonable to assume that a large set of non-domain dependent clues are collected and will be used in the next steps of the process.

It is important to underline that the list of advantages and drawbacks clues is designed to avoid linguistic ambiguities when projecting these entities on the corpus. For example *guide* has two different meanings[8] when used as a verb or as a noun: as a verb it means *"to assist something or someone to travel through, or reach a destination in, an unfamiliar area, as by accompanying or giving directions"*, so it could be the clue to an advantage; at the same time as a noun it assumes the mean of *"a book, pamphlet, etc., giving information, instructions, or advice; handbook"* thus indicating a product and not an advantage. Avoiding such ambiguities is a crucial aspect to produce an informative training set, so ambiguous words were avoided to be projected on patents.

3.1.2.4 Domain Clues Extraction

The domain-specific clues collection process takes in input the automatically annotated patent set 1. The analyzed patent set is automatically annotated using the domain-independent clues, and is used to extract new domain-specific clues. We decided for the present methods to analyze the whole text of the patents and not to focus only on a specific section.

Our system resorts to state-of-the-art NLP tools which are part of the linguistic analysis pipeline shown in figure 3.5. In addition we developed a specific advantages and drawbacks clues extraction tool, still based on Natural Language Processing techniques.

The automatic patent set annotation 2 process, as shown in figure 3.5, is composed by a set of sequential steps. The first three steps are related to the linguistic annotation: sentence splitting and tokenization, part of speech tagging and lemmatization. Once these three steps are completed the entity extractor collects the advantages and drawbacks clues from the analyzed patents.

Sentence splitting and Tokenization steps split the text into sentences and then segment each sentence in orthographic units called tokens.

The *Part-Of-Speech tagging* (or POS tagging) step assigns unambiguous grammatical categories to the tokens. For the present application we use the most recent version of the Felice-POS-tagger described in (Dell'Orletta, 2009). Once the computation of the POS-tagged text is completed, the text is automatically *lemmatized* in order to group inflected forms of a word in a single item. Some of the following steps of the entire extraction process exploit the lemmatized texts in order to achieve better extraction results.

Successively the *semi-automatic annotation of advantages and drawbacks clues* is performed. The advantages and drawbacks clues extraction tool is the key ingredient of the present paper, and it is based on supervised methods. Such methods require an entity annotated corpus in order to extract new entities from unseen

[8] www.dictionary.com

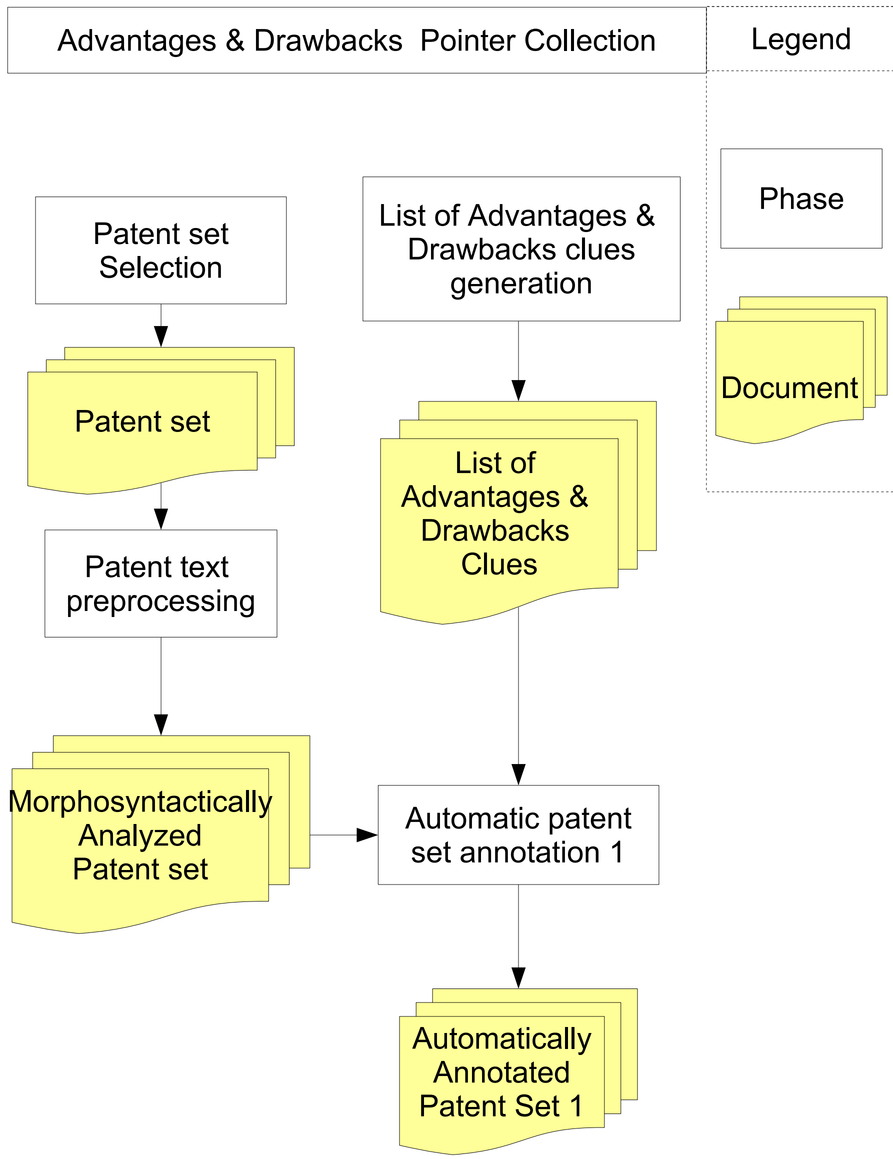

Figure 3.4: Main overview of the patent set annotation process.

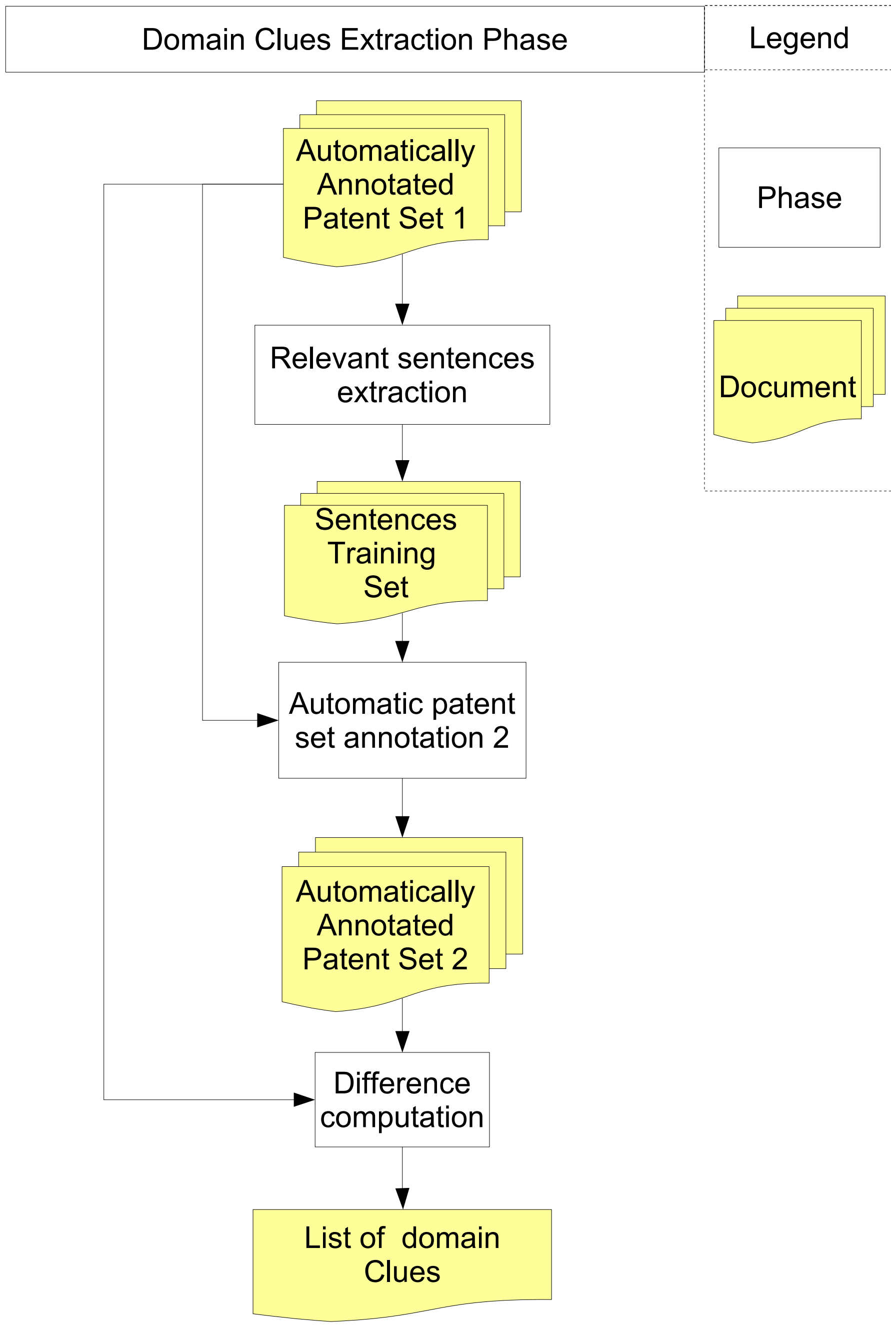

Figure 3.5: Overview of the domain specific advantages and failures clues extraction process.

documents. Since the manual annotation of a patent set is too expensive both in terms of time and manual effort, we apply a semi-automatic method to generate an advantage and drawback annotated corpus.

The entity annotation schema for a single token is defined using a widely accepted BIO annotation scheme (Ramshaw and Marcus, 1999):

- **B-ADV**: the token is the start of an entity representing an advantage clue;
- **I-ADV**: the token is the continuation of a sequence of tokens representing an advantage clue;
- **B-DRW**: the token is the start of an entity representing a drawback clue;
- **I-DRW**: the token is the continuation of a sequence of tokens representing a drawback clue;
- **O**: for the remaining case.

The *Advantages and Drawbacks Clues Extractor* is a supervised classifier that, given an annotated patent set, is trained on these examples. The patent set is: (a) linguistically-annotated, using the steps described above; (b) entity-annotated, exploiting the semiautomatic annotation process executed in the previous steps. Given a set of features the classifier trains a statistical model using the feature statistics extracted from the corpus. This trained model is then employed in the classification of unseen patents: it extracts new domain specific clues from patents and assigns them a probability score whether they are an advantage or a drawback. In our experiments the classifier has been trained using the Support Vector Machines (SVM) learning algorithm using the LIBSVM (**?**) library configured to use a linear kernel. The classifier uses two different kinds of features that are extracted from the text:

- **raw features**: prefix and suffix of the analyzed token; it works particularly well with advantages ending with -full -ious and with drawbacks starting with un- dis- etc..
- **word2vec features**: vector representations of words computed by the *word2vec* (Mikolov et al., 2013) tool.

Table 3.9 reports the detailed features chosen for the proposed advantage and drawbacks clues extractor.

Table 3.9: Context windows of the extracted features considering 0 as the current analyzed token.

Feature group	*Context Window*
Prefixes up to 4	0
Suffixes up to 4	0
Word2vec	$-2, -1, 0, 1, 2$
TAG	-1

By introducing prefixes and suffixes of the analyzed token, the classifier is able to identify frequent orthographic patterns which allow to maximize the precision in classification phase. On the other hand, the *word2vec* features are introduced in order to maximize the recall, since semantically similar clues should have similar *word2vec* vectors. Finally, the tag of the previous token is added to the final feature vector in order to improve the accuracy classification of multi-word clues.

3.1.2.4.1 Word2vec feature computation

While contextual, linguistic and compositional features are commonly used for entity extraction task in patents, from a computational linguistic point of view the presented system introduces the novelty of using *word2vec* features for entity extraction in patents.

Word2vec is a NLP tool able to produce word representations exploiting big corpora. The main property of the vectors produced by *word2vec* is that words that share similar contexts have similar vector representations. By using word vectors instead of the corresponding words we were able to overcome the problem of the limited lexical knowledge in the training phase.

To build our *word2vec* vectors we used the Skipgram model with a context window of 5 tokens. As reported in table 3.10, we used a corpus consisting of 48,194 different patents, containing more than 400,000,000 tokens.

The corpus was designed to contain patents belonging to different classes (12 in total) in order to acquire an extended knowledge of the contexts in which the words in general are surrounded. In addition, patents belonging to two of these classes are analyzed and, in the same section, detailed configurations of the entity extractor has been provided.

Table 3.10: Statistics of the documents on which the word2vec vectors have been learned. The patent sets of the analyzed case study are reported in bold.

Patent class	# Patents	# Tokens
A47G33	**2423**	**5.225.000**
A61G13	**2991**	**15.937.000**
A61G1	**5040**	**36.348.000**
A61H	**5199**	**41.831.000**
A61P25/24	5297	103.098.000
A63F1	5461	75.900.000
A63F3	4923	40.909.000
A63F7	4747	13.807.000
E02B3	3796	14.434.000
E04H9	2221	12.500.000
G01V11	1345	11.166.000
G08B13	4831	40.904.000
Total	48194	412.065.000

3.1.2.5 Clue validation using tweets sentiment analysis}

Figure 3.6 gives an overview of the activities performed to validate the collected clues using twtitter. Since the manual review of the new domain specific clues can be very time consuming, an innovative approach to automatic validation of these entities is proposed. The approach is based on the assumption that advantages of technological innovations can be considered positive factors by the users. Conversely, the drawbacks of the artifacts are considered negative factors impacting on the satisfaction of the users. Both advantages and drawbacks are common terms or chunks of terms commonly used in other contexts, too. Therefore, if we can identify a wide source of sentences tagged with a polarity score and containing advantages or drawbacks, the probability of assigning the proper polarity to advantages and drawbacks increases.

Social media platforms provide powerful venues for consumers to interact not only with brands but also with other consumers as they engage in the processes of curation, creation, and collaboration (Evans et al., 2010). Such virtual platforms are places where users discuss about products, about their features but also about problems and failures they experienced during the daily use. The way they discuss or describe products or services is often unambiguous and highly polarized.

Our approach to the automatic validation of advantages and drawbacks exploits the information contained in the Twitter platform [9]. More precisely, for each extracted advantage or drawback clue we collect a set of tweets in which the clue is mentioned. Once a significant number of tweets is collected (in our case 3,073,959 - around 2,738 per entity in average), they are analyzed by a sentiment classifier. The main idea behind this process is to assign to each clue a sentiment polarity score which should express the feeling of the user with respect to the considered clue on the social media.

The tweet collection can be easily performed by using the Twitter streaming API [10], which is freely available. By assigning a polarity score to each clue, we expect to detect tagging anomalies: entities tagged as advan-

[9]https://twitter.com
[10]https://dev.twitter.com/streaming/public

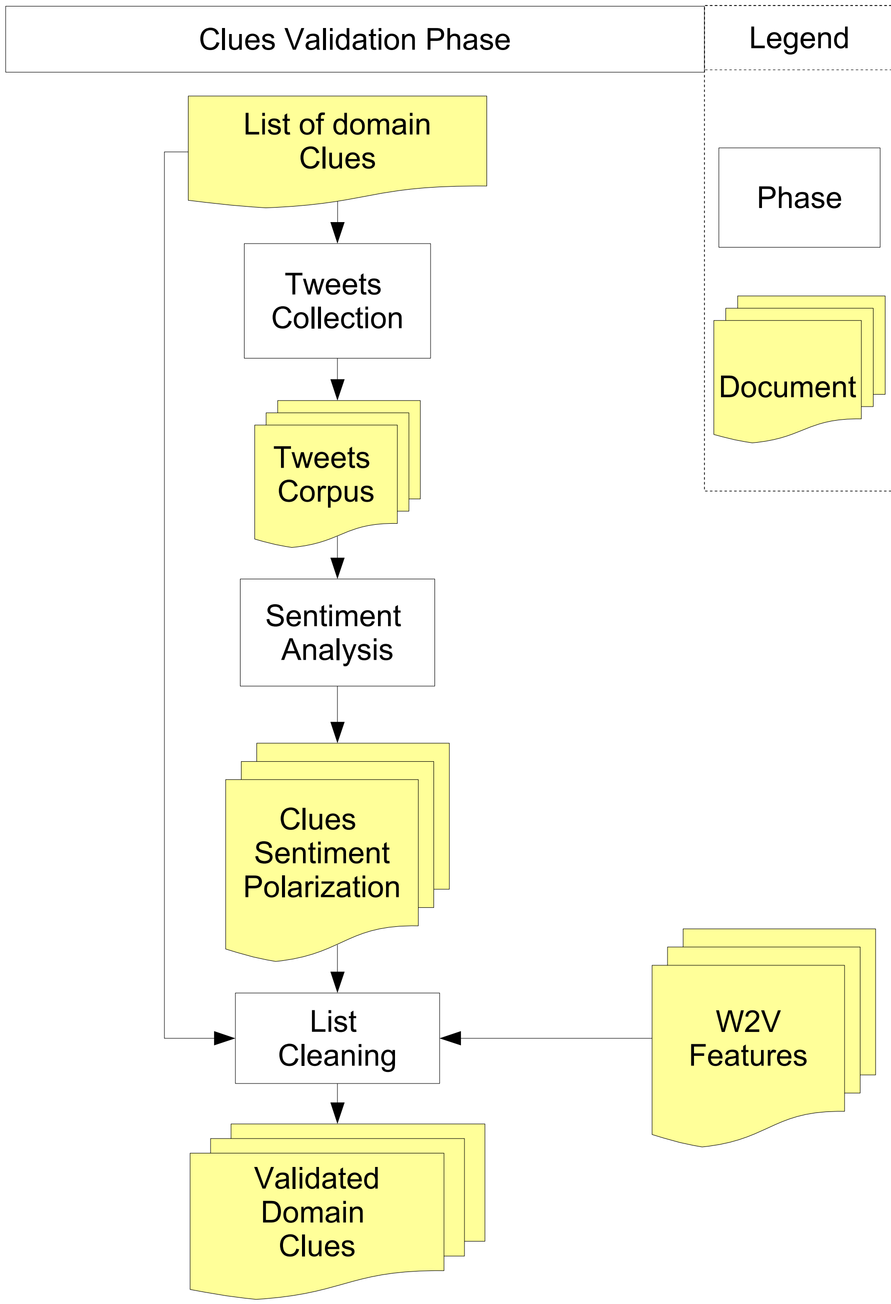

Figure 3.6: Overview of the domain specific advantages and failures clue validation process.

tages by the classifier are expected to have a positive polarity in the extracted tweets. Vice versa, entities tagged as drawbacks by the classifier are expected to have a negative polarity in the extracted tweets.

3.1.2.5.1 Sentiment Classifier: features, classification model and performance evaluation

In our sentiment classifier we focused on a wide set of features ranging across different levels of linguistic description. The whole set of features we started with is described below, organized into four main categories:

- raw and lexical text features
- morpho-syntactic features
- syntactic features
- lexicon features.

This proposed four-fold partition closely follows the different levels of linguistic analysis which is automatically carried out on the text being evaluated, (i.e. tokenization, lemmatization, morpho-syntactic tagging and dependency parsing) and the use of external lexical resources.

Raw and lexical text features are extracted considering the text available in the tweet. For this work we considered a number of tokens, character n-grams, word n-grams, lemma n-grams, char repetition sequences, mentions number, hashtags number and punctuation.

Morpho-syntactic and Syntactic Features consider the part of speech tags and the syntactic analysis of the text. Our sentiment analyzer extracts Part-Of-Speech n-grams (coarse and fine), coarse grained Part-Of-Speech distribution and syntactic dependency types n-grams.

To extract features based on lexicons we exploited three freely available resources. The Bing Liu Lexicon (Hu and Liu, 2004), which includes approximately 6,000 English words, the Multi–Perspective Question Answering Subjectivity Lexicon (Wilson et al., 2005), which consists of approximately 8,200 English words and the SentiWordNet 3.0 Lexicon (Baccianella et al., 2010) which consists of more than 117,000 words. For each word in these lexicons the associated polarity is provided. In addition, we manually developed a lexicon of positive and negative emoticons, which usually is a strong indicator of tweets polarity. By exploiting the described resources, the following features were extracted: positive/negative emoticon distribution, sentiment polarity n-grams, sentiment polarity modifiers, the distribution of sentiment polarity, the most frequent sentiment polarity and changes of polarity in tweet sections. A more detailed description of these features is provided in [Cimino et al. (2014).

In order to assign a sentiment polarity score to each tweet, we employed an adapted version of the ItaliaNLP Sentiment Polarity Classifier for the English language (Cimino et al., 2014). This classifier operates on morpho-syntactically tagged and dependency parsed texts and assigns to each document a score expressing its probability of belonging to a given polarity class. The highest score represents the most probable class. Given a set of features and a training corpus, the classifier creates a statistical model using the feature statistics extracted from the training corpus. This model is used in the classification of unseen documents. The set of features and the machine learning algorithm can be parametrized through a configuration file. For this work, we used a tandem Long Short Term Memory Recurrent Neural Network (LSTM) - Support Vector Machines (SVM) architecture.

3.1.2.5.2 Validation of the extracted clues

The sentiment classifier is employed to validate the advantage and drawback clues which were previously extracted from patents by the clue extractor. In order to do so, we exploited the output of the tweet classifier on the tweets we previously downloaded. Each tweet, as said before, contains one or more clues to be validated. The sentiment classifier assigns the likeliness to each tweet to positive, neutral or negative. Consequently by analyzing all the tweets we previously downloaded, we obtained for each clue the distribution of positive, neutral and negative tweets.

Then to make a decision regarding each clue we used another SVM based classifier. This classifier is trained on a gold set of advantages and drawbacks clues: we manually labeled 344 words as advantages and 193 words as drawbacks, obtaining the gold set. The features used by this classifier are a number of positive, neutral and negative tweets extracted in which the entities are mentioned and the *word2vec* vector representing the considered entity. In table 3.11 the classification results of the proposed approach over a 5-fold cross validation are reported. The obtained results show that the proposed entity validation method is suitable for the automatic advantages/drawbacks clues validation process.

Table 3.11: Classification results of the proposed validation method over a 5-fold validation.

Method	Global accuracy	*ADV Prec.*	*ADV Rec.*	*ADV F1*	*DRW Prec.*	*DRW Rec.*	*DRW F1*
SVM-W2V	87.71	89.89	91.29	90.57	83.35	80.66	81.92

3.1.2.6 Advantages and Drawbacks sentences extraction

The advantages and drawbacks extraction process is shown in figure 3.7. Once all the domain specific advantages and drawbacks clues are extracted, these are merged with the ones belonging to the original knowledge base, obtaining a final list which will be processed by the advantages and drawbacks sentences extractor. The advantages and drawbacks sentences extractor exploits predefined linguistic and clues filters which operate on the automatic pos–tagged patents. Specifically, for each advantage and drawback term identified in patents, we used a pos–clue-pattern constraining the start-token and the rest of the token pos. Since we were interested in phrases containing words belonging to specific morphological categories, we identified sequences of allowed pos–clue-pattern in order to cover most of the English morphosyntactic multi–words structures, using the following pattern:

(ADVClue|textbar DISClue)+Noun.*Noun.*Noun.

The pattern is applied to the previously lemmatized text in order to have less sparse and more informative extractions.

This choice was made because the pattern:

1. expresses an advantage or a drawback exhaustively;
2. increases the precision and the recall of the final output list of advantages and drawbacks;
3. allows to build a three-level named based tree over the final output list.

In particular, the tree is built by grouping terms which share at the first level the same clue, at the second level the same noun and at the third level the same noun. This grouping procedure allows to easily represent the final output list in a tree structure which can be easily navigated by the end user of the system.

3.1.2.7 Results: case study

In this section we describe the experimental use of the proposed process by applying it on four different patent sets.

To test the proposed methodology, we chose 4 patent sets composed of a sample of 3,000 patents each. The patent sets belong to 4 different IPC patent classes. The chosen classes and the definitions given by WIPO are reported in table 3.12.

Table 3.12: The patent IPC classes from which samples of 3,000 patents were chosen for the experimental analysis.

IPC name	*Definition*
A61G13	Operating tables and auxiliary appliances therefor
A61H	Physical therapy apparatus
A61C15	Devices for cleaning between the teeth
A47J37	Baking; Roasting; Grilling; Frying

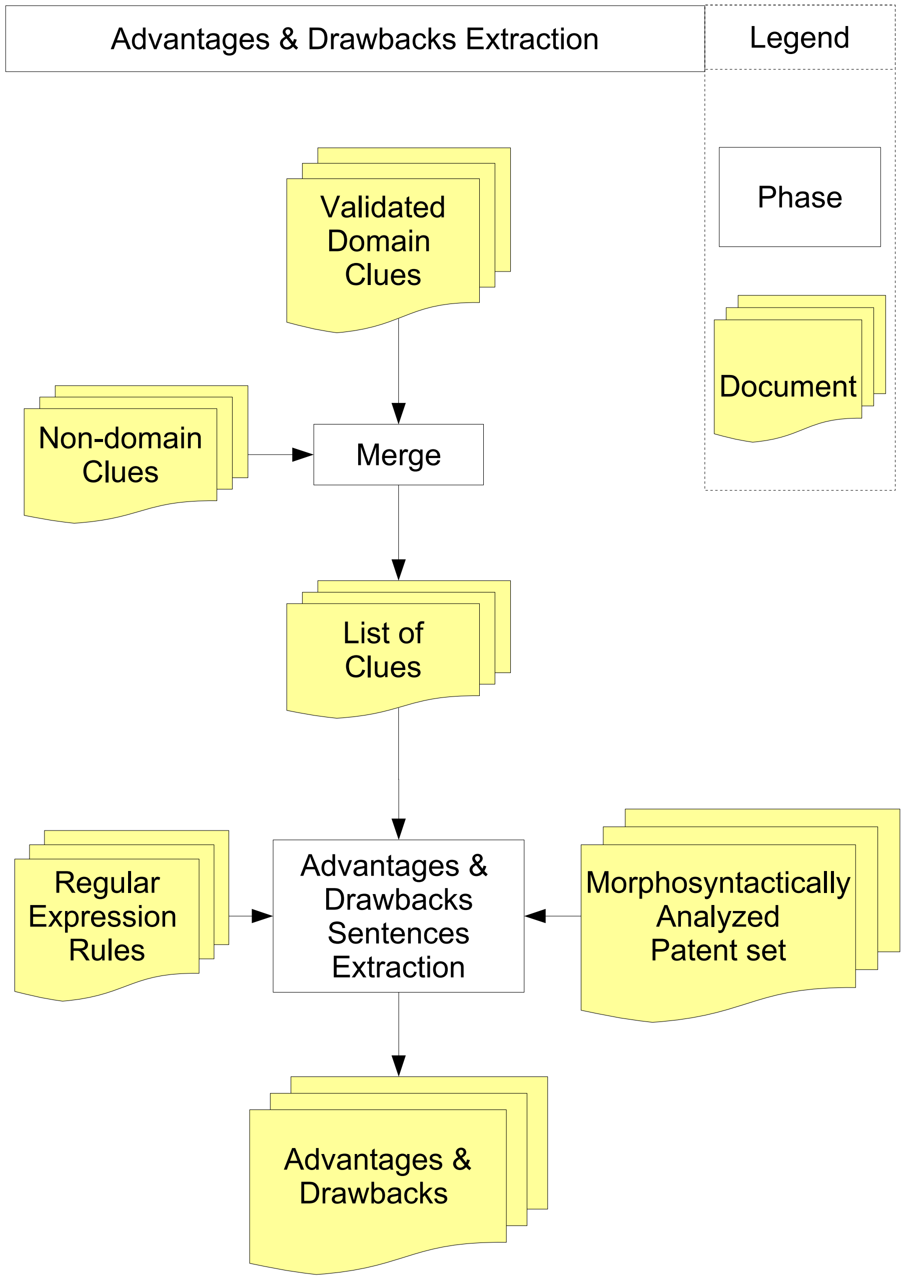

Figure 3.7: Overview of the advantages and failures extraction process.

Our choice of patent sets aimed at challenging our system to find new domain specific advantages and drawback clues in different domains. Furthermore, we only selected patent sets from the IPC class A, which is based on human necessities, to maximize the probability of finding advantages and drawbacks that impacts on the users and not only on other products/components.

Once the advantages and drawbacks are extracted, a manual review process was performed on the output of the system to compute the number of true positive clues. In this way we were able to compute the precision of the process for both the advantages and the drawbacks. The output of the clue extraction validated by the clue validator is analyzed in table 3.13.

The table shows that the number of the extracted true positive advantage clues is higher than the number of the extracted true positive drawback clues. On the other side, the automatic evaluation process has a lower performance on advantage clues in terms of precision.

A first hypotheses to explain these results is that our knowledge base contained more drawback clues than advantage clues. Another possible reason could be that the applicant is minded to describe the invention highlighting the positive effects of the invention.

Table 3.13: Number of clues filtered with the clue validator and number of true positive clues.

	# Advantage clues	*# Drawbacks clues*
Tot extracted clues	3607	1244
Automatically Validated clues	1976	576
True Positive	984	448
Precision	49.8%	77.8%

In order to assess the performance of the overall process, another important measure is the amount of new information that is obtained, which we call *information gain*. As shown in table 3.14, the percentage of new discovered clues decreases with the number of starting clues. Obviously, the more patent sets are analyzed, the less new generic and domain specific clues are extracted. The percentage of information gain (represented as delta in the table), stabilizes at a 5% value in the advantage clues case, and 1% in the drawback clues case. This trend could be an evidence that the clue extraction process has a natural saturation level.

Table 3.14: Information gained by applying the extraction process on different patent sets. Each row reports the percentage of information gained by incrementally adding the extracted entities to the knowledge base and the overall number of entities belonging to the extended knowledge base.

Patent set	Adv.	# Adv.	Draw.	# Draw.
Knowledge Base	N/A	6,568	N/A	14,809
A47J33	+23%	8,133	+3%	15,332
A61C15	+12%	9,178	+2%	15,644
A61G13	+5%	9,653	+1%	15,849
A61H	+5%	10,175	+1%	16,053

Tables 3.15 and 3.16 show the frequencies of a randomly chosen set of the new extracted advantages and drawbacks domain specific clues for each of the four analyzed patent sets. The results show that the domain specific clues clearly characterize the different technical areas of the patent sets. It is thus interesting to notice how valuable information is contained in the context specific clues them self. Further research can decide to stop here the process, without extracting the whole sentence.

Table 3.15: Extracted domain specific advantages clues with the measures of occurrences for each patent set.

A47J37 (Baking)	A61H (Therapy apparatus)	A61C15 (Teeth cleaning)	A61G13 (Operating tables)
transport 295	regenerative 144	elasticity 495	rigidity 784
integrity 246	waterproof 101	rigidity 461	ventilation 177
rigidity 233	hygienic 85	disinfection 247	hygiene 135
insure 180	ergonomically 77	precision 199	versatility 121
adjusting 164	disinfection 48	ergonomically 108	reliably 113
unobstructed 73	prevent excessive 39	economically 105	disinfection 56
uniformity 64	hemodynamics 25	waterproof 81	humidification 48
sensitivity 44	prophylaxis 22	hygienically 33	ergonomically 39
hygienic 30	prevent slippage 21	quick-connect 26	sanitation 20
selectively 34	smoothly 15	sanitation 24	non-invasive 12

Table 3.16: Extracted domain specific drawbacks clues with the measures of occurrences for each patent set.

A47J37 (Baking)	A61H (Therapy apparatus)	A61C15 (Teeth cleaning)	A61G13 (Operating tables)
accidental 61	infection 595	infection 446	syndrome 134
burnt 59	trauma 378	inconvenience 126	costly 72
malfunctioning 12	abrasion 106	irregularity 40	claustrophobia 38
time-consuming 8	fragmentation 37	pathogen 14	malfunctioning 36
non-compliant 6	paralysis 17	infected 8	unnecessarily 27
dirty 6	hematoma 15	unintentionally 6	discoloration 19
ignites 4	uncomfortably 8	abnormal 6	hyperglycemia 11
turbulence 4	undetectable 8	burn 4	unavoidable 10
cross-contamination 3	embarrassment 8	toxic 3	not linearly 8
violently 3	discoloration 8	erosive 3	catastrophic 6

Then, after the re-projection of the extracted clues on the text, the regular expression described in section is used to extract the sentences highlighted by the clues.

The number of advantages and drawbacks sentences extracted from each patent are shown in table 3.17. The table shows that the occurrence of sentences describing an advantage is higher than the ones containing a drawback 3.14. This result may be due to the fact that the applicant is minded to describe the invention by highlighting the positive effects of the invention.

Table 3.17: Number of sentences containing advantages and drawbacks for each analyzed patent set.

Patent class	*# Advantage sentences*	*# Drawbacks sentences*
A61G13	7,836	1,048
A61H	10,879	1,463
A61C15	9,551	1,572
A47J37	9,973	1,662
Total	38,239	5,745

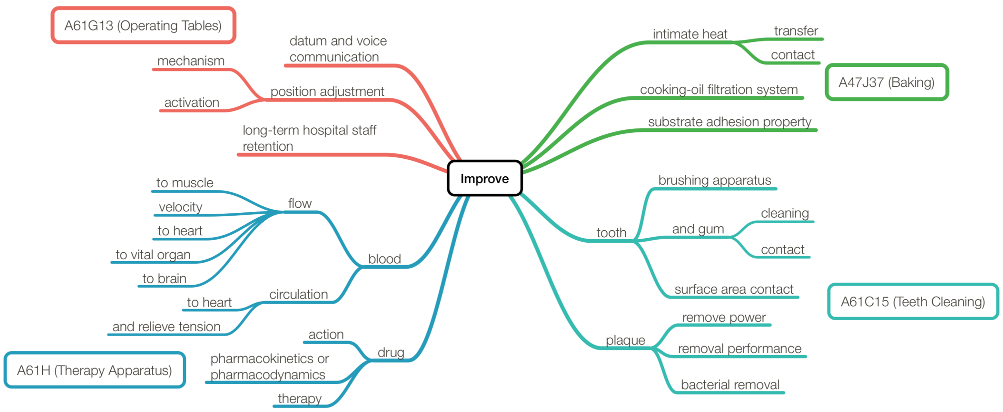

Figure 3.8: Sample of the tree based taxonomy extracted from the analyzed patent sets. The sample contains some of the leaves linked to the advantage clue Improve

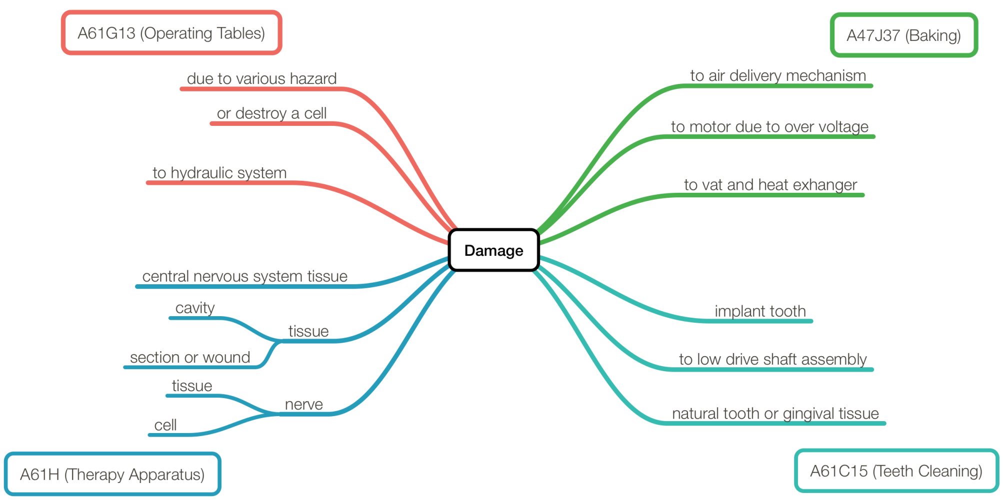

Figure 3.9: Sample of the tree based taxonomy extracted from the analyzed patent sets. The sample contains some of the leaves linked to the drawback clue Damage.

Figure 3.8 and 3.9 show two subsets of the taxonomies obtained by the extraction of the advantages and drawbacks for each of the four analyzed patent sets. The two figures respectively refers to a subset of the leaves linked to the advantage clue *Improve* and a subset of the leaves linked to the drawback clue _Damage. In both cases an additional trimming action is performed by removing those branches or leaves containing terms belonging to the stop-word list typical of patent lexicon (e.g. claim, embodiment, invention, comprise, figure, etc..). The figure shows that our process can extract highly informative sentences also starting from generic and non-contextual clues like *improve* or *damage*. Moreover the words that follow the generic clues are specific of the technical field of the analyzed products. Both the results are promising for future applications, especially for the design fields. In particular figure 3.8 allows designers to focus on the positive side of the effects provided by the product and to better meet the explicit and implicit user needs. Similarly, figure 3.9 helps designers to redesign of the product in a proactive way, to keep attention to the critical issues identified by the drawbacks and to conceive possible corrective actions to solve such drawbacks.

3.1.3 Trademakrs

3.2 Papers

3.3 Projects

3.4 Wikipedia

3.5 Twitter

3.6 Job Profiles

Chapter 4

Future Developments

4.1 Marketing

4.2 Research and Development

4.3 Design

4.4 Human Resources

Chapter 5

Conclusions

We have finished a nice thesis

Chapter 6

Glossary

Morphology= the study of the way words are built up from smaller meaning-bearing units called morphemes.

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