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Part I

Introduction

The information field human beings are living in has changed dramatically over the last years, effecting economy, technology, culture and society. And yet, its stronger mark has been over business systems (Rai et al., 2006; Jin et al., 2015b; Degryse, 2016; John Walker, 2014; O’Neil, 2016): companies have to master methods and tools to solve the information overload issue in order to strive and stay competitive (Levitin, 2014; Feng et al., 2015).

To understand what companies go through in terms of challenges, we have to wear their shoes. Let’s say that the amount of information (such as tactile, visual and sounds, rumors and conversations, the content of business papers) gathered in the location we live in starts to rise quickly. To survive such an environment, we would need new and more powerful senses; we would probably need outside systems to help us processing information. Considering the mole of digital information produced in the past 10 years, companies have found themselves in our hypothetical scenario: their digital universe is chaotic and constantly expanding. In fact, this very universe will grow from 2005 to 2020, from 130 exabytes to 40,000 exabytes (40 zettabytes) (Gantz and Reinsel, 2012), as shown in figure 1.

Moreover, new digital technologies have had an impact outside but most importantly inside companies (Lasi et al., 2014; Brettel et al., 2014; Rüßmann et al., 2015). Thanks to Industry 4.0, it is possible to create a low-budget digital copy of the company; in other terms, it is economically sustainable to extract information from any business process (Davies, 2015). Even though it seems a great advantage for companies, it leads to an information overload as an internal issue which should be handled as an external one.

Inside this rising pressure, the general goal of the present thesis is to understand how this information can be turned in to technical knowledge by technical experts (e.g. engineers, researchers, managers, marketeers). In order to do that, this work investigates:

- where valuable business information is hidden in certain documents
- which technical knowledge can be extracted from different sources of information
- what methods and software are available in order to reach this goal
- how these tools can be redesigned (if necessary) for being effective in non-standard contexts

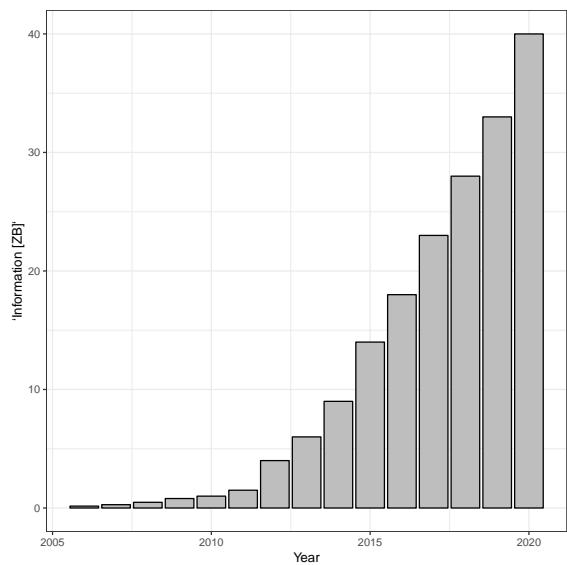


Figure 1: Hisogram of the eximated Zettabytes of information produced from 2005 to 2020.

Chapter 1

Scope of the Thesis

1.1 Sources of Information

Documents written in natural language contains knowledge by design. Their goal in fact is the explication of implicit knowledge (Masters, 1992; Graesser and Clark (1985)). With the growth of information of the last years also this kind of documents has grown in number and there exist a huge opportunity for business to manage this knowledge. The problem to address in order to take advantage of this opportunity, is understanding which sources of information are relevant to a certain company (Larose and Larose, 2014; Chemchem and Drias, 2015; Kasemsap, 2015). It is considered relevant all the information that helps the company building knowledge as a tool to achieve their goals (both vision and mission). Finding these sources requires a deep understanding of digital technologies and of business acumen , skills that not every company can have (Hecklau et al., 2016; Davenport and Patil, 2012; Provost and Fawcett, 2013; Van der Aalst, 2014). To understand the practical implications of this issue, it has been estimated that just a small portion of the digital universe has been explored with the purpose of extracting competitive gain (iView: IDC Analyze the future, 2012). The estimated percentage of untapped data is 25% and it is going to rise to 33% within 2020: it is likely that many of the potential sources of valuable knowledge are not taken in to consideration by companies and that a huge value is still hidden. This untapped value can be potentially found everywhere in the info-verse: users behaviors in social media, correlations among scientific studies, overlaps between medical and sociological studies, beneath complex analysis in legal documents and so on.

For these reasons an analytically process gains great value thanks to a correct decision of which documents mine to extract knowledge. To maximize this value the problem space has to be searched in term of business relevant knowledge content of documents. Since this problem space is huge (all the documents of which a company is stakeholder) in the present thesis this decision has been taken a-priori ensuring a wide set of document types in terms of their characteristics. These documents are:

1. *Patents*
2. *Scientific Papers*
3. *Wikipedia*
4. *Social Media*

Patents has their core in technical information. Despite this, some researchers (Bonino et al., 2010) affirm that there is an increasing variety of readers of patents: not only technician and researchers but also marketers and designers who have grown an interest in patent analysis. To our knowledge this thesis represent a first step the direction of these potential readers. Papers are similar to patents in terms of technical content but are not affected by the bias of being legal documents. If this makes technical information easier to find, it also brings a problem when there is the need of synthesizing the huge information coming from a corpus of papers. Wikipedia is distant from patents and papers. It (by design) contains encyclopedic and less objective information, which comes in a semi-structured form. Due to the bottom-up approach in which Wikipedia is developed, it has some reliability shortages to take in to account. Finally social media documents are far from the previous ones since they make use of a short, subjective and colloquial lexicon. It is another of the challenges addressed by this thesis to demonstrate that this sources contains exploitable technical information too.

1.2 Methods and Focus of the Analysis

Thanks to the improvement in the Artificial Intelligence (AI) field, *Natural Language Processing* (NLP) has dramatically increased its effectiveness in the last years (Russell and Norvig, 2016). Now powerful tools for the analysis of documents are available to every one that has a little understating of programming (Arnold, 2017, Benoit and Matsuo (2018), Wijffels (2018)). For this reason, the processes carried out in this thesis uses state of the art NLP techniques that only in few cases has been deeply modified in the design process. In other words the value of the output is not in the modified NLP algorithm but on the whole process of knowledge extraction that goes from the decision of which documents to analyze to the communication of the results.

Furthermore, despite the golden ages of AI and NLP we are living in, some problems this research area is trying to address are still having a huge impact on companies (Hand, 2007; Mining, 2006).

The first one is that the information overload is not manageable by machines alone and thus there is the need of understating which are the best practices in experts-machine interaction. In this context, it is interesting to notice that the way companies incorporate knowledge in their own artificial systems is drastically changed in the last 30 years. In fact, in the 1990s the main approach was knowledge engineering: machine learned how to perform analysis tasks thanks to the rules experts gave them. This idea has failed. In some contexts, it is impossible representing knowledge with explicit expert-driven rules. For this reason on

the 2010s inductive revolution developed; machines are used to extract knowledge from huge amounts of data in an inductive way.

This has led to a second major problem observed by literature: black boxes or systems whose working mechanism are unknown, except input and output. A recent paper (Pedreschi et al., 2018) tries to clarify the issue with black boxes and offers a few solutions. The authors point at a way similar to reversing, in which a program is stimulated with various inputs to study the outputs and understand its logic. In the same way, to study the mechanisms of a machine-learning model, it is possible to modify slightly the input only, and observe the result; or, foresee the right input for the needed output. It is still cutting edge, but it is already discussed and it is opening up to specific research, such as explainable AI.

Considering these problems and considering the general goal of the present thesis (i.e. to extract and synthesize technical knowledge from unstructured documents) we can state that we can not take aside the design of processes, which can provide correct knowledge exchange between human and machine, leading to:

- incorporate knowledge of the experts inside AI systems
- experts' ability to use in their process of decision making, inductively generated knowledge of machines

Chapter 2

Approach

2.1 Design Science Paradigm

Knowledge extraction systems are implemented within an organization for the purpose of improving the probability for that organisation to reach its goals. A wide literature exists on the design of these kind of systems and the main focus comes from Information Systems (IS) discipline. It is incumbent upon researchers in the IS to further knowledge that aids in the productive application of information technology to human organizations and their management (Editors, 2012) and to develop and communicate knowledge concerning both the management of information technology and the use of information technology for managerial and organizational purposes (Zmud, 1997). Hevner et al. (Bichler, 2006) argues that acquiring such knowledge involves two complementary but distinct paradigms: *behavioral science* and *design science* (March and Smith, 1995).

The *behavioral-science paradigm* has its roots in the research method of natural science (Makadok et al., 2018; Colquitt and Zapata-Phelan, 2007). Its goal is to develop and justify theories that explain (or predict) organizational phenomena (Zahra and Newey, 2009) about the analysis, design, implementation, management, and use of information systems. Such theories inform researchers and companies of the interactions among humans, machines, and organizations that must be managed if an information system has to be effective. These theories interact with design decisions made with respect to the system development methodology used (Fini et al., 2018).

The *design-science paradigm* is a problem solving paradigm and has its roots in engineering and the sciences of the artificial (Simon, 1996). Its goal is to create innovations: define the ideas, practices, technical capabilities, and products through which the analysis, design, implementation, management, and use of information systems can be effectively and efficiently accomplished (Denning, 1997; Tsichritzis, 1997). In this context the researchers switches his goal: the artifacts that are created in the research process are not exempt from natural laws or be-

havioral theories but relies on existing kernel theories that are applied, tested, modified, and extended through the experience, creativity, intuition, and problem solving capabilities of the researcher (George et al., 2016; Madhavji et al., 2015; Markus et al., 2002; Walls et al., 1992).

Since Design science creates and evaluates IT artifacts intended to solve identified organizational problems, the present thesis has as main approach this second paradigm. In Design Science, artifacts are represented in a structured form that may vary from software, formal logic, and rigorous mathematics to informal natural language descriptions. We will use all these representations at different level, for the different applications described.

Furthermore the thesis has been developed following the guidelines of design-science research. Hevner et al. (Bichler, 2006) provide a set of seven guidelines which help information systems researchers conduct, evaluate and present design-science research. The guidelines are summarised in table 2.1.

As previously discussed, design science is a problem solving paradigm. The fundamental principle of design-science research is that is the building and application of an artifact that permits to the researcher to gain new knowledge and understanding of a design problem and its solution. From this fundamental principle the seven guidelines are derived. That is, design-science research must end and must have as goal the *creation of an innovative, purposeful artifact (Guideline 1)* for a specified *problem domain (Guideline 2)*. Because the artifact has to be purposeful, researcher has to measure its utility for the specified problem: this imply that *evaluation of the artifact is crucial (Guideline 3)*. Novelty is similarly crucial since the artifact must *solve an unsolved problem or solving a known problem in a more effective or efficient manner (Guideline 4)*. In this way, design-science research is differentiated from the practice of design since artifact itself must be *rigorously defined, formally represented, coherent, and internally consistent (Guideline 5)*. The process of design of the artificial and also artifact itself, incorporates a search process whereby *a problem space is constructed and a mechanism posed or enacted to find an effective (not necessarily optimal) solution (Guideline 6)*. Finally, the results of the *design-science research must be communicated effectively (Guideline 7)*.

The communication phase is crucial, and the results of a design science based research has to be comprehensible and usable to:

- a technical audience (researchers who will extend them and practitioners who will implement them)
- a managerial audience (researchers who will study them in context and practitioners who will decide if they should be implemented within their organizations).

Table 2.1: Design-Science Research Guidelines

Guideline	Description
Design as an Artifact	<i>Design-science research must produce a viable artifact in the form of a construct, a model, a method, or an instantiation.</i>
Problem Relevance	<i>The objective of design-science research is to develop technology-based solutions to important and relevant business problems.</i>
Design Evaluation	<i>The utility, quality, and efficacy of a design artifact must be rigorously demonstrated via well-executed evaluation methods.</i>
Research Contributions	<i>Effective design-science research must provide clear and verifiable contributions in the areas of the design artifact, design foundations, and/or design methodologies.</i>
Research Rigor	<i>Design-science research relies upon the application of rigorous methods in both the construction and evaluation of the design artifact.</i>
Design as a Search Process	<i>The search for an effective artifact requires utilizing available means to reach desired ends while satisfying laws in the problem environment.</i>
Communication of Research	<i>Design-science research must be presented effectively both to technology-oriented as well as management-oriented audiences.</i>

2.2 Data Science Workflow

Many frameworks and models exists that describes the process of knowledge extraction from data (Kanehisa et al., 2013, Bellinger et al. (2004), Ackoff (1989), Liew (2007)). All this models brings contribution to the literature but with a focus on the *behavioral-science paradigm*, thus with the goal to develop theories about the analysis, design, implementation, management, and use of data analysis systems.

For the present thesis we adopted a more actionable framework popular in the field of data science: the Data Science Workflow (Wickham and Grolemund, 2016). We adopted this model because is a generic workflow that can be used as guideline to design any knowledge extraction system. The workflow is represented in figure 2.1.

The workflow is a model of the tools needed in a typical data science project. Since data science is a huge field, and there's no way that a model can master it, the goal of the model is to give a solid foundation in the most important tools. These tools are used in every data science project, but for most projects they are not enough. The tools represented in the model has been chosen following a rough Pareto 80-20 rule (Pareto et al., 1971).

The workflow is divided in the subsequent tasks:

- *Import*: take data stored in a file, database, or web API, and load it into a computer.
- *Tidy*: Tidying data means storing it in a consistent form that matches the semantics of the data-set with the way it is stored. In brief, when the data is tidy, each column is a variable, and each row is an observation. Tidy data is important because the consistent structure lets focus on questions about the data and not in its shape.
- *Transform*: Transformation includes narrowing in on observations of interest, creating new variables that are functions of existing variables, and calculating a set of summary statistics.
- *Visualize*: Visualisation is a fundamentally human activity. A good visualisation will show unexpected information, or raise new questions about the data. A good visualisation might also hint that the hypothesis is wrong, or there is the need to collect different data. Visualisations can surprise, but do not scale particularly well because they require a human to interpret them.
- *Model*: Model is complementary to visualize. Once the hypothesis are sufficiently precise, a model can answer them. Models are a fundamentally mathematical or computational tool, so they generally scale well. Even when they don't, it's usually cheaper to buy more computers than it is to buy more brains. But every model makes assumptions, and by its very nature a model cannot question its own assumptions. That means a model cannot fundamentally surprise.

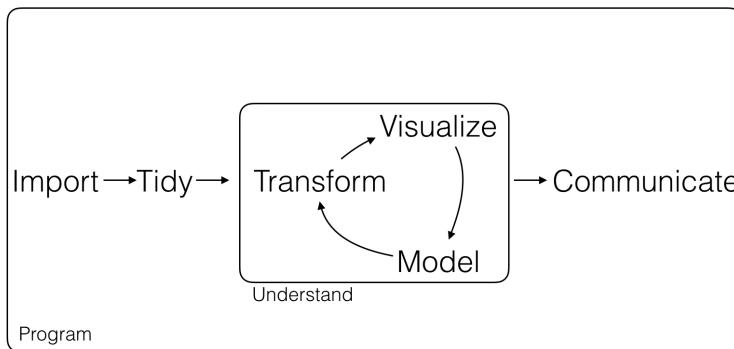


Figure 2.1: A general workflow for the process of data analysis. Readapted from Wickham (2016)

- *Communicate*: The last step is communication, an absolutely critical part of any project. As stated before communication phase is crucial, and the results of a design science based research has to be comprehensible and usable to a technical audience a managerial audience.
- *Program*: To design knowledge extraction tool programming is nowadays essential. There is no need to be an expert programmer to design effective knowledge extraction tool, but learning more about programming allows to automate common tasks, and solve new problems with greater ease.
- *Understand*: The greatest feature of a knowledge extraction system is not to detect the large trends- they are visible anyway; it is, rather, to detect weak signals, or information that initially appears with low frequency (Apreda et al., 2016). These signals escape from traditional statistical detection techniques, exactly because it is difficult to distinguish them from pure statistical noise. It is hard to distinguish weak-signals from noise only using algorithms: understanding the problem to be solved and having domain expertise is essential. For this reason *understand* is not only part of the process of analysis, but is maybe the most important task with respect to the present thesis.

A full state of the art on all of these tasks as been conducted in section 3.

Structure and Rationale

The selected documents to analyze, the exploitation of Natural Language Processing Techniques , the Design Science Approach and the Data Science Workflow helps to explain the structure of this thesis, since the decision of using these paradigm and tools had a direct impact on its form and content. The thesis is in fact structured as follow:

- *Part Number 2 “State of the Art”* makes a review of tools and techniques for Natural Language Processing and shows the documents used for knowledge extraction. In particular, the analysis of technical documents require the design of processes that rely both on Natural Language Processing techniques and on technical field experts. While the first techniques are codified and explicit, the second are sometimes implicit and always hard to systematize. In the State of the Art these two groups of techniques are treated in the same way to give to the reader a systematic literature review on these topics. Furthermore it is important to define the value in terms of new knowledge that documents can bring to companies. The goal of this state of the art is to demonstrate that a large literature on Techniques able to solve the problems described in section ?? exists, but weak or no effort exist in the literature in the systemic integration of these tools and in the design of holistic methods to solve these problems.
- *Part Number 3 “Methods and Results”* is the core Part of the thesis. This part describes the methods and processes designed for the analysis of technical documents following the guidelines of design research described in section 2.1. Since design research is a problem solving paradigm, each chapter (focalised on a different kind of document) starts with a brief description of the field of application of the method and with the framing of the problem to be solved. Then the methodology to solve the problem is described with the goal of being clear to a technical audience and a managerial audience. Each chapter closes with the results description that proves the utility, quality, and efficacy of the design artifact.
- *Part Number 4 “Applications of the Results”* is a collection of projects that describes the applications and results of the methods designed in *Part 3 “Methods and Results”*. The goal, again following the the guidelines of design

research (Bichler, 2006), is to provide clear and verifiable contributions in the areas of the design artifact, design foundations, and/or design methodologies.

- *Part Number 5 “Conclusions”* summarises the thesis, and its possible future developments. The thesis ends giving a more descriptive-science view of the results. In this last part we focus on a general method that has proven to be effective in the major part of the designs of the present thesis: **lexicons design**.

Part II

State of the Art

The analysis of technical documents require the design of processes that rely both on Natural Language Processing techniques and on technical field expertise. While the first techniques are codified and explicit, the second are sometimes implicit and always hard 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. This chapter can be seen as a background chapter as it illustrates the information that the reader should know to understand the rest of the dissertation. Furthermore it is important to define the value in terms of new knowledge that documents can bring to companies. For this reason the chapter of this part has the subsequent structure:

- At a first level there are two sections 3 and 4, reviewing respectively the processes of *programming and Natural Language Processing* and the *documents*;
- Section 3 has a subsection for each of the *phases* showed in figure 2.1. These subsections goes from 3.1 to 3.7;
- Each subsection from 3.1 to 3.7 contains the relative Natural Language Processing *task* that are relevant for the analysis of technical documents, for example Document Retrieval 3.2.1, Part-Of-Speech-Tagging; 3.4.6 or Named Entity Recognition 3.5.5.
- 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;
- Finally, section 4 has a subsection for each of the analyzed technical *documents*. These subsections goes from 4.1 to 4.4.

The goal of this state of the art is to demonstrate that a large literature on Techniques able to solve the problems described in section ?? exists, but weak or no effort exist in the literature in the systemic integration of these tools.

Chapter 3

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 2.1 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).

3.1 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.

3.2 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 3.2.1 and on the most popular documents digital formats 3.2.2.

3.2.1 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 3.4.3. 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.

3.2.2 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).

3.3 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

The 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.

In the context of the present Thesys, the Tidy task mean applying this process to text. It is clear that to tidy unstructured information is harder then to tidy structured data (Silge and Robinson, 2016). On the other side, 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).

3.4 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.

3.4.1 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.

3.4.2 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.

3.4.3 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).

3.4.4 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 3.2.1 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).

3.4.5 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.

3.4.6 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 3.5.5) 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 4.1). 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.

3.5 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.

3.5.1 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.

3.5.2 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: $(d_1, c_1), \dots, (d_N, c_N)$. 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 3.5.5). 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 $c \in C$. 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 3.3) 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).
- *Bayesian 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 Network Classifiers*: The basic unit in a neural network is a neuron. Each neuron receives a set of inputs, which are denoted by the vector X_i , 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).

3.5.3 Sentiment Analysis

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).

3.5.4 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 are 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 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 bag-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).

3.5.5 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, guitar players or players of other stringed instruments may perform in any of a number of various positions, from seated, with the stringed instrument supported on the leg of the performer, 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.

3.5.6 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 3.5.4 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.

3.6 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 clear 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.

Data visualisation has become in the last year a well established 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 (Ertug et al., 2018). It is important to underline how the way this data is communicated 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 literature 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 practitioners 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.

3.6.1 The Grammar of Graphics

Even if trial and error is and will remain an important part of data visualisation, some works has 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 communicating 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 the 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.

Multiple layers together are used to create complex plots.

Together 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 to decide 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.

3.7 Comunicate

The last task to perform in the process of knowledge extraction from technical documents is communications. If it means to communicate the results of an analysis inside a team or to the world, it does not matter how great an analysis is unless it is impossible 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 especially in the R (R Core Team, 2018) environment. 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.

Together with reports (and usually contained in them) there are visualisation. Making graphics for communication follow all the rules and framework previously revised in section 3.6, but when a graph has to be used to communicate 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 analysis 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 communication graphs(Wickham, 2016; Chang et al., 2017; Sievert et al., 2017; Pedersen, 2018; Bastian et al., 2009) .

3.8 Understand

The harder 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. It is hard to distinguish weak-signals from noise only using algorithms: understanding the problem to be solved and having domain expertise is essential. For this reason *understand* is not only part of the process of analysis, but is maybe the most important task with respect to the present thesis.

Unfortunately is difficult to design a process of analysis in such a way that the source of domain knowledge and they way they impact the analysis is clear. According to the survey carried out by Popper (Popper, 2008), expert panels are the second most used methodology, after the survey of the literature (see section 4.2

for automatic approach to this task). It is non-sense to gain technical knowledge that is valuable to carry on a text mining analysis by relying exclusively on algorithms, without the support of human experts that are acknowledgeable about the knowledge field, technologies, their inner functioning, and the range of practical problems they are intended to solve. Due to the ill-structured nature of knowledge field expertise systematisation in data science, it requires an extensive problem-formulation phase, which cannot be done by others than human experts (Bracken and Oughton, 2013).

It is usually necessary to involve experts into panels or focus groups, in which they have face-to-face interaction (FTF). It is well known that experts have a preference for methods involving personal communication, such as FTF, but this method delivers the least reliable results, as compared to other methods such as prediction markets, nominal groups and, above all, the Delphi technique (Woudenberg, 1991; Graefe and Armstrong, 2011).

Yet the use of experts creates a large number of problems. Even when experts are trained in data science, professionally engaged and personally committed to high standards of ethical integrity, they may introduce cognitive and motivational biases in the process (Kahneman and Egan, 2011). A crucial point in the literature is that not only lay people but also experts are subject to *cognitive biases*, and that cognitive abilities may moderate but not eliminate these effects (Stanovich and West, 2008). Therefore the issue cannot be solved by selecting better experts (Taleb, 2007).

In addition, experts often work in groups or panels, rather than in isolation or following the Delphi procedure, in which the revision of estimates is done separately and under the protection of anonymity (Meijering and Tobi, 2016; Makkonen et al., 2016). The group decision making process may add other peculiar distortions to the knowledge extraction exercise, as shown by the large literature on groupthink (Janis, 1972; Esser, 1998). These biases are difficult to overcome and require a dedicated attention. As the Expert Group of the European Commission has recommended: “in order to minimize cognitive bias in analysis, selection and interpretation of information, explicit tools and methodologies should be used” (Tuomi, 2013).

The issue of biases in data science technological analysis has been raised only recently in a few seminal papers, but it has not yet created a consistent literature, comparable to the large and robust literature in the field of forecasting and in many other areas of social sciences.

3.8.1 The problem of biases

The literature in the heuristic and biases tradition is now in the order of several thousand articles. A deliberately crude search for “heuristic and biases” delivers more than 208,000 items in Google Scholar, a more sober 5,298 items in JSTOR, and 2,463 items in Scopus (accessed January 19, 2018). Even looking at specialized branches of the field we find references in the hundreds: in the EBSCO Business

Source database the items are 453, in Pub Med they are 281. There is not a unique agreement on the terminology and the number. To make an example, Arnott (Arnott, 1998) mentions 37 heuristics and biases; a quite different list of 13 heuristics is discussed by Mousavi and Gigerenzer (Mousavi and Gigerenzer, 2014). There is a minority opinion that has contested the overall Kahneman-Tversky (Kahneman and Egan, 2011) paradigm, apparently without substituting it (Gigerenzer, 1991). There are several meta-analyses and systematic reviews that examine specific biases, which will be included in the reference list and in the discussion below.

What follows is a selection of topics that might be important in data science, and in particular for knowledge extraction from technical documents. In the following we start from the biases suggested by Goodwin (Goodwin, 2015) and we add a few ones, which we believe are relevant for the field. The list is not necessarily exhaustive but is focused on those biases that are more important for anticipating technological trends. We first describe the biases in general terms.

Framing effect

According to a famous experiment by Tversky and Kahneman (Tversky and Kahneman, 1981) people react differently to a decision problem according to the way it is “framed” in the task description, ignoring the content. In particular, framing a problem in terms of losses induces more risk-taking than framing in terms of gains. Risk or loss aversion occurs when people prefer a small reward with greater certainty than a large reward with less certainty. Framing a problem in terms of gains, or improvement, activates a different response (Tversky and Kahneman, 1981). This effect has been confirmed in a large number of studies. The literature review by Levin, Schneider and Gaeth (Levin et al., 1998) suggests to distinguish the effects of framing on risky choices, on the evaluation of attributes of alternatives, and of goal-related attributes. Experts are subject to framing effects not differently than novices (Loke and Tan, 1992) while in high level cognitive tasks the differences are remarkable (Larkin et al., 1980).

Several studies suggest that the framing can be mitigated or reduced to zero by warning on the effect (Cheng and Wu, 2010), using Decision Support Systems (Bhandari et al., 2008), creating heterogeneous groups (Yaniv, 2011), exposing people to dissenting minority views (Nemeth and Chiles, 1988), or using deliberately devil’s advocate or dialectical inquiry methods (Lord et al., 1984). However, other studies underline the importance of real conflict, or minority views, as opposed to artificially created situations (such as the devil’s advocate method, based on role playing) (Goodwin and Wright, 2010). Exposure to dissent and disagreement reduces the confidence in one’s own views, but also reduces the level of conformity and improves the accuracy (Nemeth et al., 2001). At the same time, it is critical that the dissent is centered around factual data, so that the discussion does not degenerate into issues of personalities (Keay, 2012). It is also critical that the judgment is repeated, so that people come to weight information according to its accuracy, considering discordant opinions and not discounting them (Harries et al., 2004).

According to Burgman (Burgman, 2015), “experts groups should be as diverse as possible, and systems for engagement should encourage people to listen and integrate information and reasoning from as many sources as possible, and to explore competing explanations”.

Different expert orientation than a framing in which gains and losses are compared and weighted. A related problem is that the framing of the problem may hinder the ability to identify rare events, or low predictability phenomena. A combination between quantitative modelling and scenario analysis is suggested to avoid blindness (Makridakis et al., 2009).

Anchoring

In producing numeric estimates of unknown quantities, people are heavily influenced by the information provided in the task description, even when it is not consistent or realistic (Gigerenzer, 2015). In other words, according to Kahneman and Tversky (Tversky and Kahneman, 1974), people “anchor” their estimate to the number provided in the description and incorporate new information by “adjusting” the estimate above and below the anchor. In this way people do not make efficient use of information available and may be distorted in their judgment (Thorsteinson et al., 2008). Furnham and Boo (Furnham and Boo, 2011) offers a literature review. The effect seems to be originated from the confirmatory testing of hypothesis that selectively activates anchor-consistent information in memory (Block and Harper, 1991; Chapman and Johnson, 1999).

In a classical experiment (Slovic et al., 2000) the authors asked thousands of forensic experts, trained formally in psychology and psychiatry, to estimate the probability that a given person with mental disorder would reiterate an offense after release from hospital. Two random assignments were used, one in which there was a suggestion to use a 1-40 scale to estimate probability, the other to use a 1-100 scale. Those using the 1-100 scale estimated that the probability to re-offend was approximately double than the one estimated by the other group. Another striking example was found by Ariely et al. (Ariely et al., 2003): the willingness to pay for consumption goods is influenced by an arbitrary anchor created by asking the subjects to remember the last two digits of their Social Security Number.

The magnitude of the bias is a function of personality and motivational orientation (Eroglu and Croxton, 2010) and of the social origin of the anchor value (Meub and Proeger, 2015), but not of cognitive abilities, so that experts are also subject to its effect (Mussweiler and Strack, 2000; Oechssler et al., 2009; Bergman et al., 2010). However, the level of knowledge of experts moderates the intensity of the anchoring effect (Wilson et al., 1996; Smith et al., 2013).

The extent to which the anchoring bias can be mitigated is the object of large research. George, Duffy and Auja (George et al., 2000) and Legerstee and Franses (Legerstee and Franses, 2014) report that after a training on the feedback from automated statistical program the accuracy of experts improves substantially, while Mussweiler et al. (Mussweiler, 2002) and Furnham and Boo (Furnham and Boo,

2011) suggest that using compensating strategies, such as consider-the-opposite strategy, may reduce the anchoring bias (see also Mussweiler and Strack (Mussweiler and Strack, 2001)). Providing experts with a feedback that uses metric knowledge (but not mapping knowledge) reduces the anchoring bias (Smith and Windschitl, 2015). Experts may receive incentives for the accuracy of their predictions, so that a loss function is defined and implemented (Lawrence and O'Connor, 2005). This does not eliminate biases in the adjustment: Franses, Legerstee and Paap (Franses et al., 2011) show that the loss functions of experts is typically asymmetric, so that underprediction is penalized more.

Overconfidence

A pervasive effect observed in many settings is the inability of individuals to evaluate correctly the degree of knowledge they have about issues or facts on which their judgment is requested (Shanteau et al., 1992). Moore and Healey (Moore and Healy, 2008) review a large literature, starting from a pioneering observation by Oskamp (Oskamp, 1965). The dominant effect is that people overestimate their own ability to perform accurate judgments (precision or accuracy), that is, they exhibit overconfidence in the form of overprecision, or unwarranted certainty (Koriat et al., 1980). They also overestimate their absolute ability or performance (overestimation) and their relative comparison within a group (overplacement) (Kruger and Dunning, 1999).

According to Plous “no problem in judgment and decision making is more prevalent and more potentially catastrophic than overconfidence” (Plous, 1993). In technical terms, people are not good in defining appropriately the confidence interval they assign to their own estimates (Lichtenstein et al., 1977). If confidence is defined at 90%, it means that about 90% of the probability intervals provided by experts will include the observed (true) values. In a classical experiment, on the contrary, Russo and Schoemaker (Russo and Schoemaker, 1992) found that only between 40% and 60% of the intervals suggested by managers included the true value of several economic variables, while respondents claimed they were 90% confident about the estimate. The overconfidence leads to illusion of competence (Castel et al., 2007).

Very importantly for our discussion, experts produce on average better estimates than non experts, but they are subject to overconfidence in the same way: “Experts are good at reporting relatively narrow intervals centered on true values, but they are no better than novices at reporting well calibrated, high-confidence interval” (McKenzie et al., 2008).

It has also been suggested that the willingness of people to revise their judgment in the light of feedback depends on their power and egocentrism. People who self-perceive themselves as powerful tend to be more self-confident and do not adjust their own judgments following external feedback (Bonaccio and Dalal, 2006).

Hindsight bias

Another distortion that makes it difficult to learn from past events and external knowledge is the hindsight bias. The hindsight bias, initially discussed by Fischhoff (Fischhoff, 2003), is the unjustified increase in the perceived probability of an event due to the knowledge of how the event actually took place, or outcome knowledge (Hawkins and Hastie, 1990). People who know the outcome of an event find it difficult to report objectively the predictions they made before the knowledge of the outcome.

For example, after the outcome of a disease, physicians may become unable to retrieve the reasons for their diagnosis, which at the time of execution was based on a prediction judgment (Arkes and Harkness, 1980; Arkes et al., 1981; Arkes and Freedman, 1984). As another example, Herrmann and Choi (Herrmann and Choi, 2007) examined the judgments of senior experts in foreign policy in Korea after the international political events were manifest and asked them to reconstruct their predictions, finding that “experts tend to forget what they used to believe and conclude in hindsight that they understand the causal forces driving developments” (Herrmann and Choi, 2007). Christensen-Szahansky and Willham (Christensen-Szalanski and Willham, 1991) offers a meta-analysis of 128 studies on the effect and Guilbault et al (Guilbault et al., 2004) update it.

This effect is also labeled “curse of knowledge”, or “curse of expertise”, that is, the tendency to be biased by one’s current knowledge in the evaluation of the knowledge of others (that is, the same person in an earlier perspective, or someone’s else) or the difficulty in discounting one’s privileged knowledge in judging what other people know or should know (Koriat and Bjork, 2006).

In other words, outcome knowledge compromises the ability of respondents to appreciate one’s own prior knowledge and another person’s naïve knowledge (Bernstein et al., 2012) and therefore produces an exaggerated perception of the a priori predictability, or obviousness, of outcomes after they become known (Fessel et al., 2009; Lassiter, 2010), leading to the inability to learn from the past and the underestimation of the informativeness of facts (Mazursky and Ofir, 1996).

Interestingly, expertise exacerbates the hindsight bias (Knoll and Arkes, 2017). Experts incorporate more easily new knowledge but tend to “go beyond the information given”. This means that they erroneously infer information that was not actually presented or consider old the newly presented information (Arkes and Freedman, 1984). They tend to take for granted elements that are in their knowledge, failing to examine whether the same level of knowledge is available to others. As shown by Tetlock and Lebow (Tetlock and Lebow, 2001), experts that have a preference for explanatory closure and are theory-driven, tend to exaggerate the degree to which “they knew it all along”.

Desirability bias

One of the fundamental assumptions of rational decision theory is that people are able to separate the judgment from the motivation, that is, the estimation of the

frequency or probability of an event, from the desirability of the event. Beliefs and desires should be *a priori* independent. A large and consistent literature shows that this is not the case: people systematically inflate the judged probability of desirable events, and diminish that of undesirable events. This is an example of motivational bias, or the influence of motivational factors, such as preferences or desires, on cognitive activities. This distortion is, in principle, of great importance if experts are asked to judge the future developments of technologies which they consider, for any possible reason, desirable. This seems to be plausible in data science, in which experts come from industry, academia, or consulting.

Initially discovered in the ‘50s, the desirability bias has been the object of an extensive empirical research. It is considered a case of motivated reasoning (Kunda, 1990), or interdependence between cognitive and motivational factors, and is also labelled wishful thinking. People distort their evaluation of probability in the direction of their preferred decision alternative (DeKay et al., 2009). It has been found not only in lay people (Lench and Bench, 2012), but in experts in a variety of fields, from professional investors to price forecasters , from political election voters , to sport fans . Interestingly, people exhibit the desirability bias not only when they have preferences before the choice (disposition), but also when the preferences are acquired during the decision process (Russo et al., 1996).

The explanations for this effect are multiple: people distort their judgment because the future prospects have an impact on their personal and affective future (Ayton et al., 1989; Wright et al., 1996; Lench and Ditto, 2008), or because there is high uncertainty and large amount of guessing on future prospects (Windschitl et al., 2010), or because the prospect horizon is very far (Vosgerau, 2010). A related distortion, called advocacy bias, refers to the conscious over-estimation of the prospects for technologies of products, when there is competition for resources. Here experts may inflate the probability of success in order to actively champion some technologies.

Of particular interest is the situation in which overoptimism, induced by the desirability bias, is associated to overconfidence, or the misplaced belief in the accuracy of one’s own judgments. Several studies show that overconfidence is frequently found in people with top managerial responsibilities in companies (Hribar and Yang, 2016). It is not known to what extent people involved in data science are also subject to this effect, but this is clearly an area for further research.

Chapter 4

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 and Social Media.

4.1 Patents

Nowadays patent data can be used for planning technological strategy (Azoulay et al., 2009; 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., 2015a) 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).

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, 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, 2013a).

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.

4.1.1 Metadata Approaches

Patent documents has the following metadata:

- Patent office
- Inventors
- Affiliation of the inventors
- Filing 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 further 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 maturity 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 increases in the later life cycle stages
- the number of backward citations. It has been shown that patents with a 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 addressed 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).

4.1.2 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 3.4.5. 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, 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 be 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 than 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).

4.1.3 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 data science 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, 2011b). 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 3.5.5). 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 tri-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.

4.2 Papers

Researchers are starting to increasingly design and rely on automated literature analysis using text mining techniques (Nuzzo et al., 2010; Azoulay et al., 2006). This task is particularly valuable in the starting stage of any study, when gathering knowledge about a scientific question or a problem is crucial in formulation of hypotheses and research planning. Furthermore, even if research communities and publishing houses are putting increasing efforts in delivering scientific articles as structured texts (Poelmans et al., 2012), nowadays a considerable part of digital scientific literature is available in layout-oriented data formats, like PDF, lacking any explicit structural or semantic information. As a consequence the bootstrap of textual analysis of scientific papers is often a time-consuming activity.

To understand how text mining techniques can help to extract knowledge from scientific papers, we can analyze the phases in which the literature review process (the process through which researchers extract knowledge from a corpus of documents) consists of. The tasks are:

- *locate* the best-available empirical evidence to answer specific research questions

- *appraise* which documents are valuable for the research
- *synthesize* the information in such a way that the results of the analysis are clear and can be communicated to the scientific community.

An ideal literature search would retrieve all relevant papers for inclusion (precision) and exclude all irrelevant papers (recall). However, researchers have proved that a lot of studies are not fully indexed, as well as a number of scientific papers are indexed incorrectly (Cooper, 1988; Okoli and Schabram, 2010; Edinger and Cohen, 2013).

In general an automatic systems able to extract knowledge from scientific papers and a process of literature review are structured in a similar way. The steps for the first type of process (with a particular focus on paper classification, see section 3.5.2) can be divided in paper collection, text processing, data division, feature extraction, feature selection, data representation, classifier training, applying a classification model, and performance evaluation (Khorsheed and Al-Thubaity, 2013; Weiss et al., 2010; Carlos and Thiago, 2015) (which are a subset of the generical tasks of natural language processing described in chapter 3).

Papers Collection has the aim of selecting all the papers that belong to a limited scientific domain, e.g., “industry 4.0” (Weiss et al., 2015; Chiarello et al., 2018). This task is not trivial, and domain experts has to work with computer scientists with the goal of building a query able to filter for all the relevant documents. Each sample text must then be labeled with one or more tags indicating a label to a certain class.

Text preprocessing has been discussed in section 3.4. Actually preprocessing is in this context a way to improve text classification by removing useless information (Weiss et al., 2010, Meyer et al. (2008)).

In *data division* papers are divided into two parts, training data and testing data. Based on training data, the classification statistical model will be trained. The testing data will be used to asses the performance of the resulting classification model. There is no ideal ratio of training data to testing data, but usually a split of 25% for training and 75% for testing is used.

Then the process of *feature extraction* is performed. Considering single words, the simplest of lexical features, as a representation feature in text classification has proven effective for a number of applications. The result of this step is a list of features and their corresponding frequency in the training data set (Weiss et al., 2010).

The result of the previous step is a collection of features. Clearly not all of these features are good for classification. The main reasons are:

- some classification algorithms are negatively affected when using many features due to what is called “curse of dimensionality”
- the over-fitting problem may occur when the classification algorithm is trained in all features

- some other features are common in most of the classes and thus do not add information to the classifier .

To solve these problems, there is the need of a *feature selection*. Many methods were proposed to select the most representative features for each class in the training data set (Zhao, 2012; Weiss et al., 2010, 2015).

The features obtained from the previous step gives the possibility to *represent the data* in matrix format, so that these can be used by the classification algorithm. Usually, the data are in the document-term matrix format with n rows and m columns wherein the columns correspond to the selected feature, and the rows correspond to the texts in the training data. Weighting methods, such as term frequency inverse document frequency (TFIDF) and term frequency (TF) are used to compute the value of each cell in this matrix, which represents the weight of the feature in the text (Meyer et al., 2008).

At this point of the process the *classifier can be trained*. The classification algorithm is trained using the document-term matrix. Many classical machine learning algorithms have been used in paper classification (Hotho et al., 2005; Aphinyanaphongs and Aliferis, 2003; Zhao, 2012). The result is a classification model to be tested by means of the testing data.

Finally, *Classification model evaluation* techniques are assessed to estimate future performance by measures such as accuracy, recall, precision, and f-measure, and to maximize empirical results (Weiss et al., 2015).

Researchers has also used unsupervised techniques to extract knowledge from papers corpora. In particular the interest have been increased about the manner in which important research topics evolve over time within the corpus of scientific literature (Zhou et al., 2017). One of the main method used in this context is topic modelling (see section 3.5.6). Topic models identify and measure latent topics within a corpus of papers documents (Séaghda and Teufel, 2014) in such a way that classes of topics has not to be decided apriori by researchers (Gargiulo et al., 2017; Yang et al., 2016; Paraschiv et al., 2015).

4.3 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, e.g. 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 Pașca, 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/hyperonymy) and associative relations, but this limitation is not relevant for our applications.

Third, 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 multi-language 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 if 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.

4.4 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 (Kriegerian, 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 unrest 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 in-

teresting 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 (e.g., 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 cre-

ating 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 e.g., 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 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 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.

4.4.1 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,?; 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 Koeppl, 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-mouth 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.

4.4.2 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.

Also the software engineering field, has helped marketing specialists using social media and other data sources, as, e.g., reviews, to improve products design specifically in the requirements design phase (Groen et al., 2017).

Part III

Methods and Results

This part describes the methods and processes designed for the analysis of technical documents following the guidelines of design research described in Part 1 of the present Thesis. The methods are ensamble of Natural Language Processing (NLP) and Text Mining *techniques* described in 3, re-designed depending on the analyzed document and the analysis goal.

Since design research is a problem solving paradigm, each chapter starts with a brief description of the field of application of the method and with the framing of the problem to be solved. Then the methodology to solve the problem is described with the goal of being clear to a technical audience and a managerial audience. Each chapter closes with the results description that proves the utility, quality, and efficacy of the design artifact.

Chapter 5

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. A deeper description of what patents are and how these documents are used to mine technical knowledge can be found in section 4.1

In this section we present three methodologies capable of automatically detecting and extracting three technical entities hidden in patents:

1- the users of the invention 2- advantages and drawbacks of the invention 3-trademarks.

The results of the methodologies are described, together with example of applications of the extracted entities for intelligence tasks.

5.1 Users

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 thereof¹.

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).

¹<http://www.uspto.gov>

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 Stakeholder (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 (individual entities or specific persons). 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.

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 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*, *logger*, *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.

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 (U.S.E.S., 1967).

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.

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 (Ulrich, 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.

Artificial Intelligence: utility-based agents

In artificial intelligence the concept of utility-based agent is to be taken into consideration to complete our list of concepts near to user. An utility-based agent or intelligent agent is an autonomous entity which observes through sensors and acts upon an environment using actuators (i.e. it is an agent) and directs its activity towards achieving goals (Russell and Norvig, 2016). Intelligent agents may also learn or use knowledge to achieve their goals. In our context Users are a subset of intelligent agents (only human and Animals). It is to be noticed that also some

products or components are intelligent agents. For example a reflex machine, such as a thermostat, is considered an example of an intelligent agent.

5.1.1 Method

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 5.1 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;
2. *Patent set selection*: select the set of documents from which extract the users;
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.

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* :(U.S.E.S., 1967), 11.142 entities

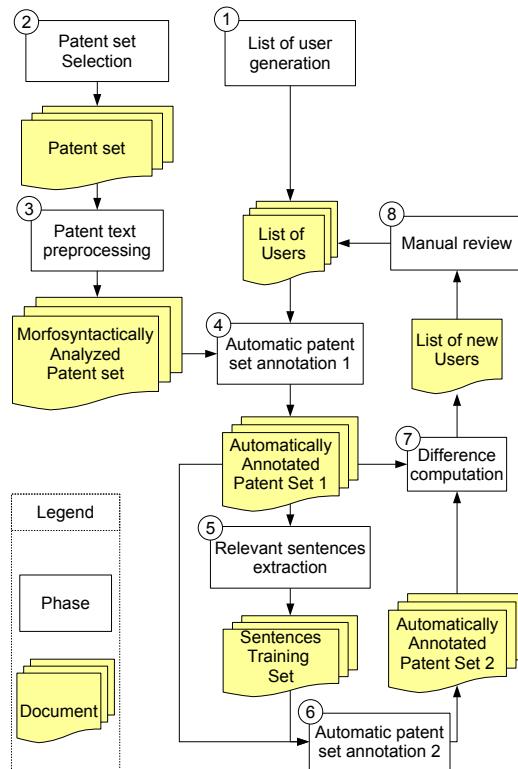


Figure 5.1: Process flow diagram of the proposed automatic user extraction system from patents. The diagram contains the representation of the documents and the operations performed on them. The process takes in input a patent set and a list of users and produces a list of new users as output.

- *Lists of sports and hobbies*²: 9.660 entities;

*List of animals*³: 600 entities;

- *Lists of patients*⁴: 14.609 users;
- *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 .

5.1.1.1 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,

²<http://www.notso boringlife.com/list-of-hobbies/>

³<http://a-z-animals.com/animals/>

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

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.

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. The list of users 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.

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 Long Short Term Memory Recurrent Neural Network (LSTM) (Chiu and Nichols, 2016) methods are well suited for similar NER task. Anyway, we chose SVM and MLP method to study how two well 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 a higher recall in the classification phase. We presumed to find new users not contained in the input seed list.

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{usersresults}). Thus, it is necessary to make a manual review of the extracted entities with the aim of evaluating the output.

5.1.2 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 @ref{patsetsel}, 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. We have chosen this database because of the reliability of the data given by this company with respect to the public available databases. Furthermore it is not always possible to have access to the full text of a patent for free. 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 5.1 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).

⁵<http://www.errequadrosrl.com/>

Table 5.1: Statistics related to the patent set groups analyzed in the case study

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

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 5.2 are reported the detailed configurations used in our experiments.

Table 5.2: Context windows of the extracted features considering 0 as the current analyzed token.

<i>Feature group</i>	<i>Context Window</i>
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	\([-2, -1, 0, 1]\)
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 5.3 reports the values of the defined metrics across all the experiments run on the two patent sets.

Table 5.3: 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.

	Training Experiment 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

	Training Experiment 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 5.4 is shown the overall gain obtained by merging results of the manually reviewed extractions in each patent set.

Table 5.4: 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
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 5.5 and 5.6 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 5.6 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 thesis. These results are a remarkable evidence of the human-like generalization ability of the described method.

Table 5.5: 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 5.6: 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 5.2 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 than 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

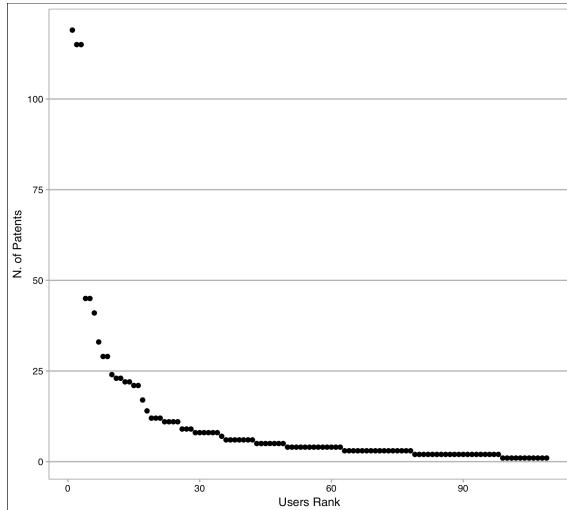


Figure 5.2: Distribution of the number of patents per user.

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*).

5.2 Advantages and Drawbacks

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 (Carnevali 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 re-

quirements 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 process⁶

5.2.1 Methodology

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 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 respect to methods that extracts information using other type of documents (e.g. online reviews of products (Mirtalaie et al., 2018a)): 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 5.3 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.

⁶The most precise couple of words is **advantage** and **disadvantage**, but the reading is facilitated by using two very different words, therefore we decided to adopt the couple **advantage** and **drawback**.

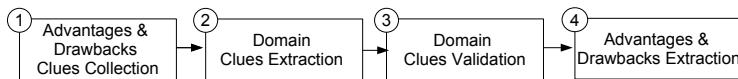


Figure 5.3: Main overview of the advantages and drawbacks extraction process from patents.

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.

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 database⁷. 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 5.7.

Table 5.7: Examples of the clues collected with the first approach.

<i>Advantages Clues</i>	<i>Drawbacks Clues</i>
ability	aggravated

⁷<http://www.freepatentsonline.com/>

<i>Advantages Clues</i>	<i>Drawbacks Clues</i>
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 5.8.

Table 5.8: Examples of the clues collected with the second approach.

<i>Advantages Clues</i>	<i>Drawbacks Clues</i>
non damaged	out of
anti-corrosion	in need of comfort
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.

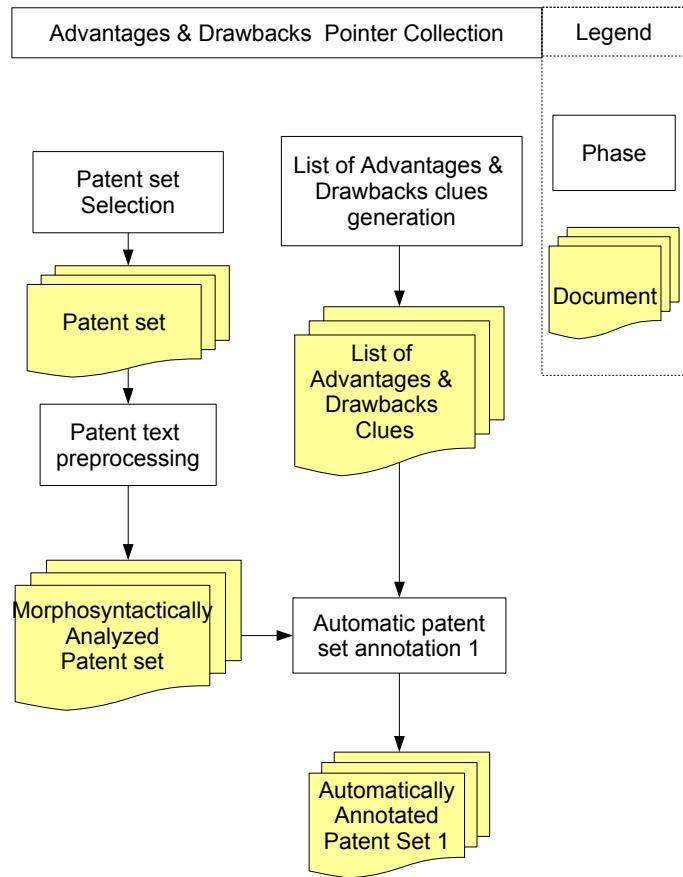


Figure 5.4: Main overview of the patent set annotation process.

For example *guide* has two different meanings⁸ 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.

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 5.5. 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 5.5, 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 thesis, and it is based on supervised methods. Such methods require an entity annotated corpus in order to extract new entities from unseen 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):

⁸www.dictionary.com

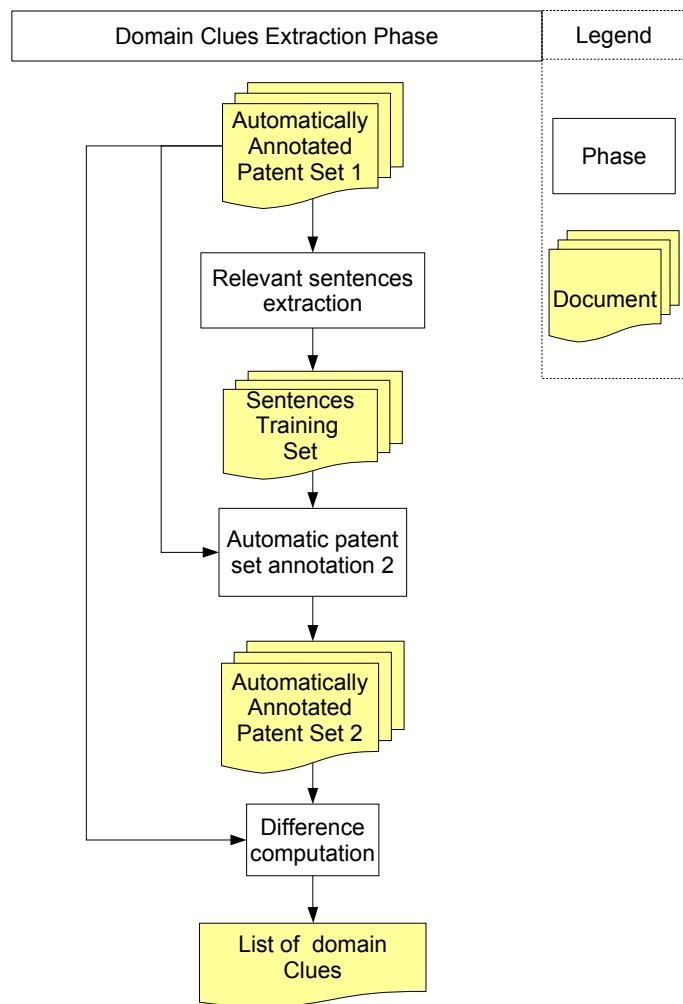


Figure 5.5: Overview of the domain specific advantages and failures clues extraction process.

- **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 (Hearst et al., 1998a) 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 5.9 reports the detailed features chosen for the proposed advantage and drawbacks clues extractor.

Table 5.9: Context windows of the extracted features considering 0 as the current analyzed token.

<i>Feature group</i>	<i>Context Window</i>
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.

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 5.10, 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 5.10: 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
<i>Total</i>	48194	412.065.000

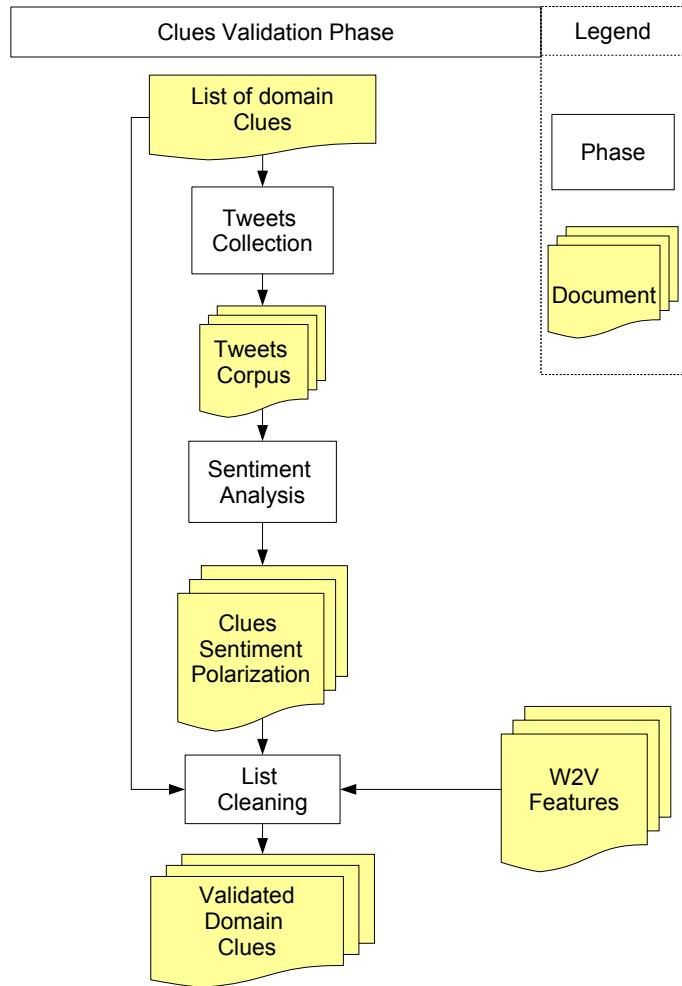


Figure 5.6: Overview of the domain specific advantages and failures clue validation process.

Clue validation using tweets sentiment analysis

Figure 5.6 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. Of course this method has a treat: some technical words can be used rarely in a non-technical context. For this reason we will rely on a big number of tweets in order to augment the probability of finding all the clues we want to measure.

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 advantages 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.

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:

⁹<https://twitter.com>

¹⁰<https://dev.twitter.com/streaming/public>

- 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.

Filtering and 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.

The classification results of the proposed approach over a 5-fold cross validation using the SVM-W2V are:

- Global accuracy: 87.71
- ADV Precision: 89.89
- ADV Recall: 91.29
- DRW Precision: 83.35
- DRW Recall: 80.66

The obtained results show that the proposed entity validation method is suitable for the automatic advantages/drawbacks clues validation process.

Advantages and Drawbacks sentences extraction

The advantages and drawbacks extraction process is shown in figure 5.7. 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| 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:

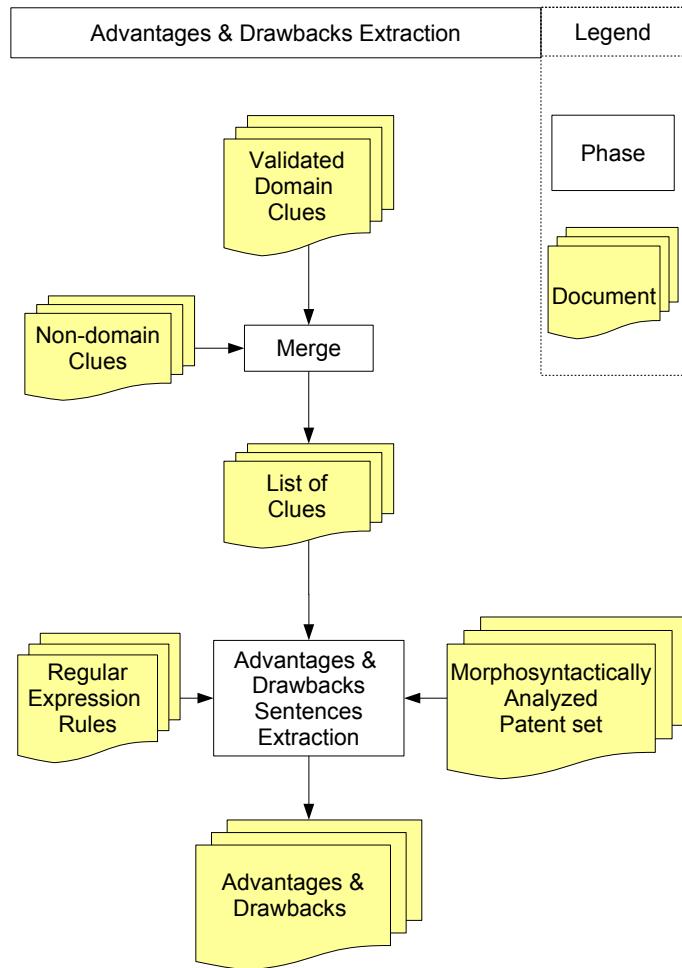


Figure 5.7: Overview of the advantages and failures extraction process.

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.

5.2.2 Results

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 5.11.

Table 5.11: The patent IPC classes from which samples of 3,000 patents were chosen for the experimental analysis.

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

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 5.12.

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

	# Advantage clues	# Drawbacks clues
<i>Tot extracted clues</i>	3607	1244
<i>Automatically Validated clues</i>	1976	576
<i>True Positive</i>	984	448
<i>Precision</i>	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 5.13, 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 5.13: 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 5.14 and 5.15 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 5.14: Extracted domain specific advantages clues with the measures of occurrences for each patent set.

A47J37 (Baking) transport 295	A61H (Therapy apparatus) regenerative 144	A61C15 (Teeth cleaning) elasticity 495	A61G13 (Operating tables) 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 5.15: Extracted domain specific drawbacks clues with the measures of occurrences for each patent set.

A47J37 (Baking) accidental 61	A61H (Therapy apparatus) infection 595	A61C15 (Teeth cleaning) infection 446	A61G13 (Operating tables) 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.

Table 5.16: Number of sentences containing advantages and drawbacks for each analyzed patent set.

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

The number of advantages and drawbacks sentences extracted from each patent are shown in table 5.16. The table shows that the occurrence of sentences describing an advantage is higher than the ones containing a drawback 5.13. 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.

Figure 5.8 and 5.9 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 5.8 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 5.9 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.

5.3 Trademakrs

The market interest for both patents and trademarks has increased during the last decades, with a significant increase in filing for both types of Intellectual Property. The academia also took attention to patent data and trademark data, but with different and (almost) disconnected research approaches. Furthermore, the analysis of patents to study R&D is predominant while less attention has been paid to trademarks (Griliches, 1981). Indeed, very few are the works where patents and trademarks are investigated together and not generically cited together as parts of the intellectual property right framework. Moreover cultural differences exist between United States and Europe (at least) and practical consequences can be observed in daily life: for example, even if Europe had an earlier and more

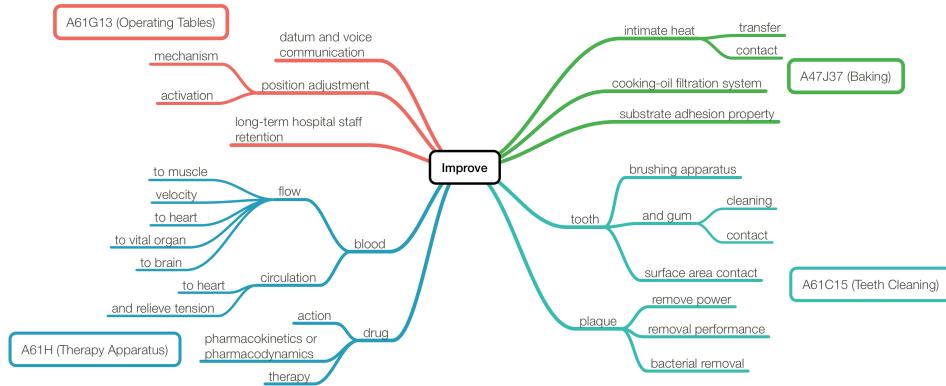


Figure 5.8: Sample of the tree based taxonomy extracted from the analyzed patent sets. The sample contains some of the leaves linked to the advantage clue Improve

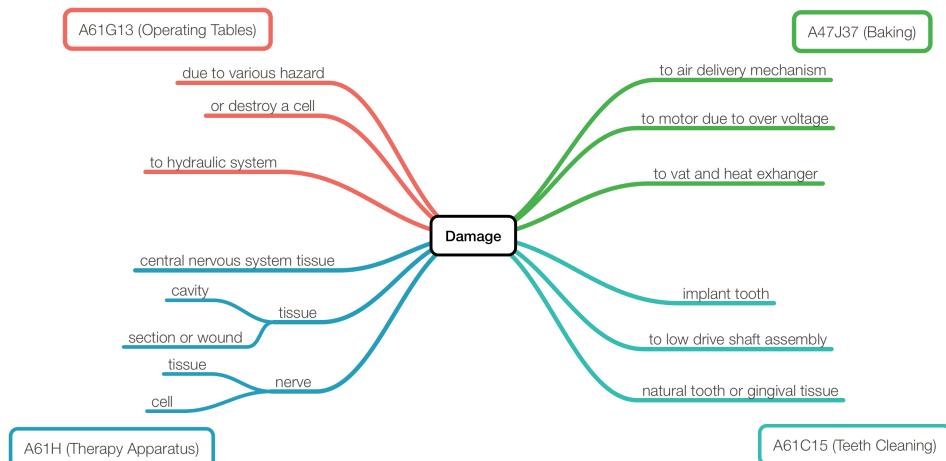


Figure 5.9: Sample of the tree based taxonomy extracted from the analyzed patent sets. The sample contains some of the leaves linked to the drawback clue Damage.

enduring interest in trademarking than the US the presence of the symbols ® and ™ in the product labels are more common in US than in Europe (MERCER et al., 2010). The difference exists also from an industrial perspective, across different sectors (Baroncelli et al., 2004). Indeed, trademarks have their larger use worldwide in the R&D intensive scientific equipment, pharmaceuticals sector and advertising intensive manufacturing industries (clothing, footwear, detergents and food products).

The present chapter studies the usage (if any) of *trademarks* and *trade symbols* within patent texts. The aim is to investigate possible indicators about IP strategies and innovation output utilizing information about the interlink between patents and trademarks. An additional goal is to understand if patent applicants make a right use of trademarks and trade symbols when writing a patent document. The analysis clearly stands at the boundary between patent and trademark research areas, and since such intermediate territory has not been investigated in depth, there are several research questions we would like to answer. The starting point is a sheer numerical evidence: we have found out that, at the date of 01/09/2017, a total of 2.162.962 patents worldwide (for details about the database and its coverage see section 3) contain a trademark symbol. It is therefore a not negligible phenomenon, worth of investigation and that should provide interesting insights about the mechanisms and strategies that companies adopt at the frontier between technical innovation and marketing.

The use of trademark symbols ™ and ® in patents from a legal perspective

It is evident from our preliminary analysis that there exist an high number of patent documents containing a trademark indication. In the present section we investigate what is the legal perspective of this usage.

In (Butler, 1969) the authors published a series of rules to standardize the use of trade terms in patents. They also specifies different rules in the case of use of trade terms in specifications and the use of trade terms in patent claims. The rules are:

1- A trade term is properly used in a specification if those skilled in the art can make the product designated by the trade term at the time the application is filed, using the specification and/or published literature that is implicated by the specification. 2- A trade term is also properly used in a specification if the product is generally known to persons skilled in the art and is readily obtainable at the time the application is filed, provided the composition of the product is a trade secret and there is reason to believe that whenever the composition of the product is modified the trade term will also be changed. 3- A trade term is also properly used in a specification if it designates a component of the embodiment which is not essential to the invention. 4- A trade term can be used in a claim only if its meaning has been adequately defined in the specifications, whereby it imparts specific limitations to the claim.”

The second rule is particularly interesting because it seems preventing early patenting or patenting before having produced and used a trade name. Rule number two

is even more interesting since it contains a case of a product that is a trade secret used to build another product subject to patent application.

Similar guidelines are contained in the European patent convention (Hall and Helmers, 2018). Here is state that is not desirable to use trademarks or trade names if such words merely denote origin or where they may relate to a range of different products. Anyway trademarks could be used in patent application to satisfy art.83, that states that the application shall disclose the invention in a manner sufficiently clear and complete for it to be carried out by a person skilled in the art. In this case the product must be sufficiently identified, without reliance upon the word. A special case are such words that have become internationally accepted as standard descriptive terms and have acquired a precise meaning (e.g. “Bowden” cable, “Belleville” washer, “Panhard” rod, “caterpillar” belt). In this case they may be allowed without further identification of the product to which they relate. It is clear specifications afflicts the analysis that we want to carry out. Always in the same document are given also guidelines for the usage of trademarks in claims. These are, as expected, different from the specifications. For claims we have the problem that it may not be guaranteed that the product or feature referred to is not modified while maintaining its name during the term of the patent. They may be allowed exceptionally if their use is unavoidable and they are generally recognised as having a precise meaning. It is the applicant’s responsibility then to ensure that registered trademarks are acknowledged as such in the description. From that we can deduce that the presence of a trademark in patents and more specifically in claims decreases the reproducibility of the invention and thus the quality of the patent. Also the US patent legislation (Jaffe, 2000) focuses on the use of trademarks in patents claims. Here the presence of a trademark or trade name in a claim is not considered improper but the examiner should analyze the claim to determine how the mark or name is used. In fact, the trademark or trade name should identify a source of goods, and not the goods themselves. In this case the claim scope is uncertain since the trademark or trade name cannot be used properly to identify any particular material or product. In fact, the value of a trademark would be lost to the extent that it became descriptive of a product, rather than used as an identification of a source or origin of a product. Thus, the use of a trademark or trade name in a claim to identify or describe a material or product would not only render a claim indefinite, but would also constitute an improper use of the trademark or trade name.

Finally, in (Pressman and Stim, 2018) the authors gives some guidelines on how to introduce trademarks when it is unavoidable. First, the trademark should be capitalized and used as an adjective (not a noun), followed by the generic name of the product or service. Furthermore when referring to the trademark there should also be a reference to the trademark owner.

5.3.1 Methodology

With respect to Users 5.1 and to Advantages and Distadvantages 5.2 the process to extract tradenames from patents is trivial. The main activity performed are

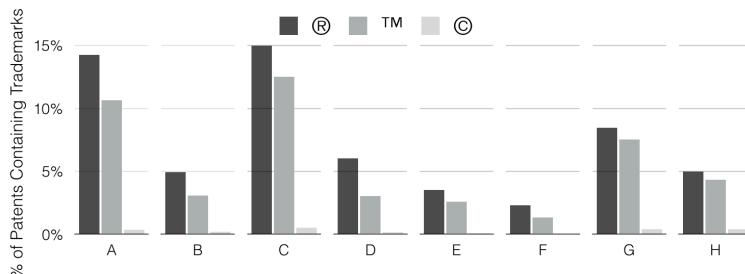


Figure 5.10: Histogram of the percentage of ® and ™ in patentes for each IPC class (limited to US patents). A (Human Necessities); B (Performing Operations; Transporting); C (Chemistry; Metallurgy); D (Textiles; Paper); E (Fixed Constructions); F (Mechanical Engineering; Lighting; Heating; Weapons; Blasting); G (Physics); H (Electricity).

(for details about the activities see section 3:

- Sentence splitting
- Tokenization
- Part-of-speech tagging
- Lemmatization

After that it is possible to identify tradenames searching for the symbols ™ and ®.

5.3.2 Results

The first investigation has the aim of understanding if the ™ and ® symbols has different content depending on different IPC (Organization, 1971) classes. The IPC classes are: The main evidence in figure 5.10 is that ® is used more than ™ in patent, with an average percent of presence of 7.4% and 5.6% respectively. The reason of this evidence could be that patents contains unregistered trademarks that are never converted to registered trademarks; another reason is the confusion between the ® and ™ symbol, usually considered as synonymous. Furthermore the writer will use the symbol only if he/she knows that the mark is protected, otherwise he/she will not indicate any symbols or will use ™ or ® without checking the right use. Another possible problem is that the word has become of common use and thus usually used without symbols. Furthermore, classes A (Human Necessities) and C (Chemistry; Metallurgy) clearly has more trade symbols than the other classes.

Secondly, from table 5.17 it is evident that the average ratio is 6.4 for ® (the usage is 6.4 times higher in the year span 2007-2014 than the span 1995-2002) and 5.4 for

TM (the usage is 5.4 times higher in the year span 2007-2014 than the span 1995-2002) thus the usage of trade-symbols in patent is growing and the presence of ® is increasing faster than the presence of TM. From the present results is not possible to say if this effect is due to an higher quality of the process of patent application (and thus an higher awareness of applicant and examiner) or of a positive trend in trademark registration. In particular for the IPC class E (fields constructions) the number of ® and TM has increased 10.5 and 9.0 times respectively. This could be an evidence of the fact that the number of trademark in the field of fixed constructions is increasing.

Table 5.17: For each IPC class the ratio of the percentage of patents containing at least one ® or TM character is computed for two patents sets 1995 to 2002 and from 2007 to 2014.

IPC Classes	Ratio ® 2007-2014 over ® 1995-2002	Ratio TM 2007-2014 over TM 1995-2002
A	5.9	5.0
B	6.2	5.4
C	5.9	5.2
D	5.6	5.7
E	10.5	9.0
F	7.5	6.2
G	4.6	3.2
H	5.1	3.2
Average	6.4	5.4

The Selected Tradenames

We a set of popular tradenames referring to (Morris, 2016). Then we filtered the ambiguous ones (the one that can refer to surnames), because this can create an overestimation of the number of patent citing it without the tradenames. The total number of tradenames is 38 and these are: amazon®, blackberry®, bose®, budweiser®, chiquita®, chrome®, cocacola®, ebay®, facebook®, fender®, firefox®, gibson®, gillette®, heineken®, ibanez®, intel®, iphone®, kellog®, kodak®, lego®, marlboro®, matlab®, mcdonald's®, nitinol®, nutella®, nylon®, photoshop®, polaroid®, postit®, powerpoint®, prozac®, sennheiser®, spotify®, teflon®, velcro®, whatsapp® and xanax®.

In figure 5.11 are shown the number of patent containing the tradenames with and without TM and ®; furthermore the information is divided for all the years, from 1995 to 2002 and from 2007 to 2014. In the previous analysis we noticed that ® is generally more used than TM. Now the goal is to understand if patent writers uses tradesymbols or not when citing tradenames, if there are any differences between different tradenames and if we can notice different behaviors in recent years. From figure 5.11 is evident that despite the fact that it is mandatory to use TM o ®, these symbols are not always used.

Trademark	All			1995-2002			2007-2014		
	TradeName Total	TradeName with ™ OR ®	TradeName without ™ OR ®	TradeName Total	TradeName with ™ OR ®	TradeName without ™ OR ®	TradeName Total	TradeName with ™ OR ®	TradeName without ™ OR ®
nylon®	431859	3838	428021	70340	174	70166	147870	1915	145955
teflon®	199084	47875	151209	29083	2237	26846	69305	23873	45432
intel®	131103	25148	105955	21741	857	20884	51497	13748	37749
chrome®	97493	2523	94970	11918	0	11918	39172	1545	37627
velcro®	75657	24860	50797	9459	925	8534	27864	12643	15221
nitinol®	54813	3031	51782	5186	136	5050	27298	1646	25652
kodak®	54619	772	53847	13219	64	13155	15013	416	14597
iphone®	40009	17523	22486	26	2	24	28718	12480	16238
blackberry®	37904	13967	23937	587	56	531	25709	9883	15826
facebook®	32903	10959	21944	0	0	0	22671	7551	15120
matlab®	26771	6086	20685	1526	149	1377	15270	3580	11590
firefox®	19280	5051	14229	7	0	7	13655	3687	9968
fender®	19127	53	19074	2367	2	2365	6083	37	6046
gibson®	18717	46	18671	2601	1	2600	7668	28	7640
amazon®	15840	2284	13556	309	21	288	9624	1431	8193
photoshop®	14595	3436	11159	1695	237	1458	7182	1824	5358
mcdonald's®	12405	346	12059	1891	19	1872	4684	221	4463
powerpoint®	11065	2958	8107	866	149	717	5715	1561	4154
ebay®	8304	1758	6546	284	49	235	5087	1040	4047
post-it®	6689	1069	5620	896	70	826	2651	452	2199
polaroid®	6293	195	6098	1375	24	1351	1308	81	1227
bose®	5922	121	5801	462	0	462	3126	72	3054
prozac®	3788	1899	1889	320	66	254	1919	1010	909
coca-cola®	3178	878	2300	283	41	242	1679	510	1169
kellogg®	2732	44	2688	0	0	0	801	27	774
gillette®	1799	77	1722	397	3	394	576	47	529
lego®	1597	700	897	168	16	152	755	360	395
marlboro®	1263	47	1216	335	0	335	384	23	361
xanax®	1202	680	522	92	3	89	638	433	205
spotify®	1142	258	884	0	0	0	622	115	507
ibanez®	694	11	683	113	0	113	295	8	287
whatsapp®	470	98	372	0	0	0	93	21	72
budweiser®	350	71	279	47	5	42	187	42	145
sennheiser®	211	6	205	47	0	47	76	3	73
heineken®	145	31	114	15	1	14	77	11	66
chiquita®	45	7	38	9	0	9	23	3	20
nutella®	41	23	18	1	0	1	26	16	10

Figure 5.11: Number of patents citing one of the 38 selected tradenames. The data are divided for any years, from 1995 to 2002 and from 2007 to 2014.

Tradenames Usage in Patents

It is relevant to understand if there exists any difference between different tradenames in the correct usage of trade symbols (a trade name has been cited in the patent texts with the trade symbol). Figure 5.12 illustrates in a bi-logarithmic plot the distribution of trade names correctly cited in patents with ® and ™ (Y-axis) versus the same trade names cited without using the proper symbol. Most of trade names are located under the diagonal. Those around the diagonal are those we can consider as well known trademarks and not so subject to genericization phenomena (green area). Conversely on the right we can find a red area where the ratio is even more shifted toward the absence of any indication of protected trademark. In the middle the orange area where many of the most famous trademarks fall down and that could be in phase of generalisation or conversely, since the trademark of a product is totally entangled with the owner (Iphone-Apple; Intel), inventors do not feel the reason to cite them as a trademark. A remark on Figure 5.12 is necessary: the plot presents a correct measurement of trademarks with ® and ™ plotted in the y axis, while the search for trademark with missing trademark symbols in some case can introduce undesired errors and include other meaning of the word. Take for example the case of Blackberry®: the datum is referring to mobile phones and accessories or software applications. In all the cases where ® or ™ are correctly written, it is probably true that the inventor is referring to the Blackberry® mobile phones, but machines for jam or juice production extracted out of the blackberry introduce false positive examples. Similarly Fender is probably located too far on the right because it is also a part of a car, bike, motorbike, boat, etc.. and Gibson could introduce citations of works performed by someone called Gibson, therefore if cleaned results are necessary the searching strategies for the trademarks without symbols have to be refined.

The Popularity of Tradenames in Patents

In figure 5.13 are plotted the trends of the numbers of patents that correctly cite a tradenames. We analyzed 12 different tradenames, divided in couples: each couple belong to a similar sector. We make use of a generalized additive model fitting function to better analyze the results and to make more easily to understand and compare the two element of each pair.

Each pair has been chosen to compare trademarks in homogeneous markets. Some of them shows:

- (d, e) similar trends but different incidence;
- (a, c) dissimilar behaviors (Amazon vs Ebay, Blackberry vs. Iphone: linear vs. exponential);
- (f) similar results (e.g. Gibson vs Fender in the music market have almost the same behavior and a reduced presence in patents)
- similar behavior but shifted in time (e.g. Firefox vs Chrome).

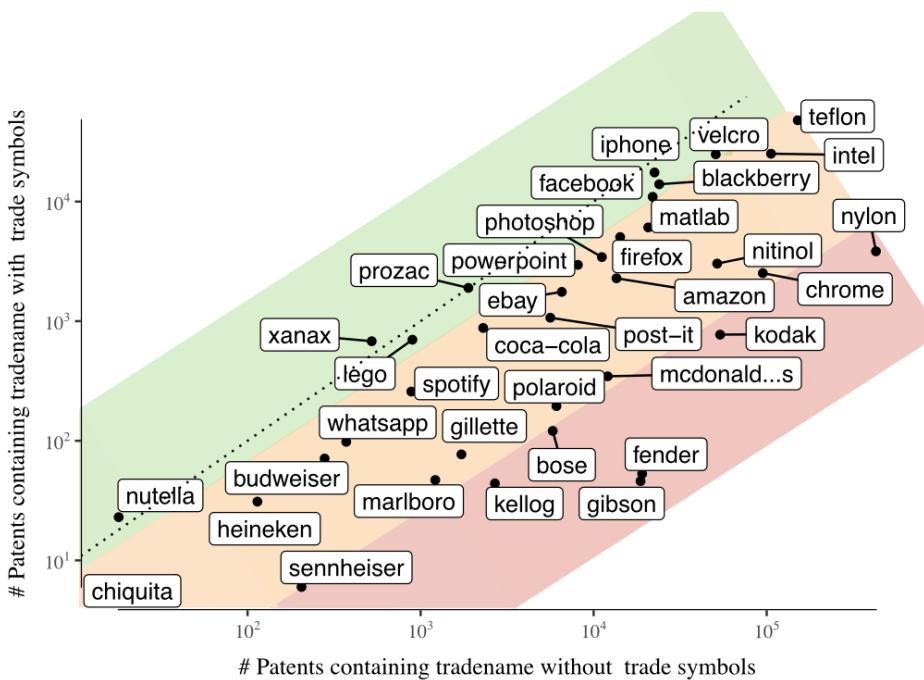


Figure 5.12: Plot of the trade names correctly cited in patents with ® and ™ on the y-axis and the same trade names cited without using the proper symbol on the x-axes. Both axes are on a logarithmic scale.

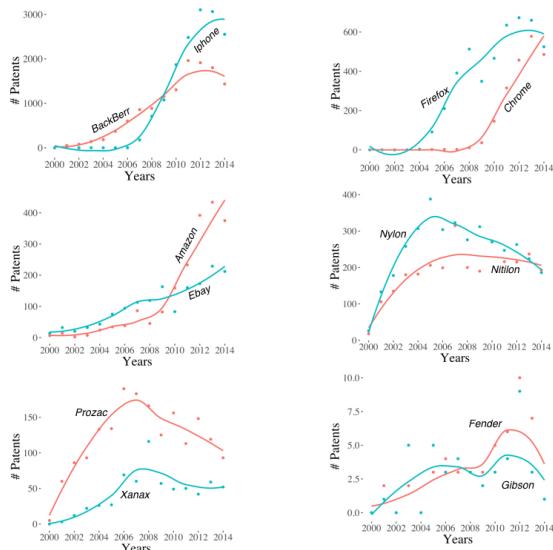


Figure 5.13: Plot of the trade names correctly cited in patents from 2000 to 2014.



Figure 5.14: Heat-map of the IPC-based similarities between trademarks.

The Similarity of Tradenames in Patents

Further information can be derived by analysing the IPC classes where the patent have been chosen by the assignees-attorneys-examiners. The choice of a class is not only matter of market segment but rather of market use. Moreover it is necessary to remark that from a formal point of view the IPC classes form a feature vector, denoted $y \in N639$. IPC classes form a complete dataset of 639 elements of such feature vector. Each tradename is represented in such a feature vector where the number of patents in each class constitutes the length of the vector along that direction (feature). Our training data is therefore $D = (x,y,z)$, where $x \in [1, \dots, 12]$, $y \in [1, \dots, 639]$, and z represents the patent numerosity $z \in [0..15*10^6]$. This dataset contains information about how z varies as a function of x and y . The matrix is quite empty since each product/brand addresses needs of specific market/s, after cleaning of the totally empty columns the matrix reduces to the dimensions of 12×479 and demonstrates a correct choice of the trademarks since they covered almost 75% of the IPC space.

With such a dataset a series of computations can be performed: here we show the results of the correlation analysis among the chosen trademarks to analyse their relative positioning on the invention landscape (not only the market); Correlation analysis is shown in Figure 5.14. The matrix is triangular owing to the symmetry of the relationship.

Chapter 6

Papers

There are fields (mature technologies) where patents anticipate papers, while in others (basic research) the opposite happens. For this reason, scientific literature is the place where companies and scholars gather information about the problems that researchers are facing in the development of new technologies. Anyway, standard approaches of knowledge extraction from papers requires skilled personnel, they are time consuming and lacks in reproducibility. Furthermore, the volume of scientific literature has grown rapidly raising an imminent question about how to extract knowledge from this source. On the other hand, this technical knowledge if managed, can be used to answer questions that 10 years ago would need the help of domain experts to be answered. In the present section is shown how text mining techniques can help to answer some of this questions. In particular, it is an essential problem when different classification codes are used in order to organize scientific knowledge on a specific domain, because a specific categorization in a certain scientific field is missing. This leads to unnecessary complications in the researchers' aims who want to quickly and easily find literature on a specific topic among the large amount of scientific publications, or want to effectively position a new research. Text mining techniques, and in particular topic modelling, can help scholars in solving this problems, if properly used together with domain expertise. A deeper description of what patents are and how these documents are used to mine technical knowledge can be found in section 4.2

In this section we present two methodologies capable of automatically segmenting a knowledge field. These selected knowledge field are: sustainable manufacturing and block-chain. The results of the methodologies are described, together with example of applications.

6.1 Sustainable Manufacturing: the 6R Framework

One of the most important objectives of Sustainable Manufacturing (SM) is developing innovative and viable engineered materials, manufacturing processes and systems to provide multiple life-cycle of products. In SM the old concept “from cradle to grave” is now transforming into “from cradle to cradle” (Jawahir and Bradley, 2016), tending toward multiple product life-cycles or even a “near-perpetual” product/material life. Scientific contributions in the sustainable manufacturing field mostly deals with energy and resource consumption. In this respect, two different main fields of causes can be identified: the process level and the material efficiency one. As a matter of facts, manufacturing processes have a significant role also in putting in place material efficiency strategies (Ingaraao, 2017). As far as the processes are concerned, a first classification of research contributions was discussed in the CIRP General Assembly (Duflou et al., 2012). There the authors state that research in manufacturing field, oriented to environmental impact reduction, can be clustered in 5 main sub-classes:

1. unit process level (Individual device or machine tool in the manufacturing system)
2. manufacturing system level,
3. facility,
4. multi-factory system up to considering the whole
5. supply chain level.

Another review paper was presented at the ASME international manufacturing science and engineering conference (Haapala et al., 2013). In that paper the authors scrutinize the research papers focusing more on the differentiation between manufacturing processes and manufacturing system. Considering the process level, Ingaraao (Ingaraao, 2017) clustered the scientific papers in 4 subsections: 1. effect of process parameters 2. role of machine tool architecture and related technology 3. applied process 4. manufacturing approach selection.

As concerns material efficiency options, a framework is presented by (Allwood, 2014). The authors there provide strategies within three main classes corresponding to principles: reduce, reuse and recycling. Within each class guidelines for material efficiency practices are detailed. As concerns material efficiency options, a framework is presented by Allwood (Allwood, 2014). There the authors provide strategies within three main classes (i.e. principle): reduce, reuse and recycling. Within each classes guideline for material efficiency practices are detailed. A good framework of all the possible reuses of materials is provided by Cooper (Cooper and Allwood, 2012). In this research the authors identify four main reuse strategies for metals: Remanufacture, Reshape (applying metal shaping processes, additive, subtractive, mass conserving) to obtain a new geometry, Relocate: (recovering component and applying little refurbishment, components reused in the same type of products), Cascade: recovering component and use it in another less demanding

use (downgrading). The role of manufacturing processes in putting in place material efficiency/reuse strategy was also outlined by Ingmarao (Ingmarao, 2017). In fact, manufacturing processes deserve to be considered as means for enabling material efficiency strategies. SM may be pursued by several strategies, such as re-designing and/or even changing manufacturing practices to conceive new-generation products, as well as by creating a closed-loop of environmentally-friendly material flow.

The 6R Framework

All the life-cycle stages of the product development (namely, design, production, use and post-use) should be considered carefully, with a particular attention to the design phase. This represents the real difference introduced by sustainable manufacturing concept with respect to traditional manufacturing, to lean manufacturing or even to green manufacturing, precursors of the SM. In a word, SM paradigm embraces those principles belonging to the 6R framework, namely: Reduce, Reuse, Recycle, Recover, Redesign and Remanufacture. The latter three principles were not included into the previous 3R framework. To a certain extent, it appears that the better definition of sustainability for any manufacturing operation provided so far is the extent to which these principles are applied. This statement justifies because in the search to find a common rationale behind the mess of SM applications, one possible way is to find common roots in the principles that inspired the same applications: namely principles, which allows to the decision maker either an effective way to search for new sustainable solutions or to a certain extent measure the “degree of sustainability”. The higher the number of principles that are satisfied, the higher the potential positive impact on sustainability can be for a given adopted solution. In this sense, far from stating that the 6R framework is a widespread and commonly adopted metric of SM, the starting assumption in this section is that 6R is the only approach, to the author’s knowledge, that provides a criteria of classification and selection of solution, and thus indirectly to provide a clear definition of what a SM application may look like. The true question nowadays is *if the 6R framework may capture the essence of SM*, provided that it is really critical to clearly define the SM paradigm rationale to the scientific community. This section aims to stimulate the reflection from the Italian perspective to this point, with a particular concern to the production technology side, by using an automatic classification of papers within the 6R framework and then by benchmarking approaches followed by the Italian Technologist research-network SOSTNERE on SM issues.

Sustainability (from sustain plus ability) refers to the set of properties of a given system (either natural or artificial), which allows the same system to maintain itself for an almost indefinite period of time. This concept was officially introduced in a document of the World Commission on Environment and Development (WCED) entitled “Our Common Future”, where the Sustainable Development was defined as follows: *“Sustainable development is development that meets the needs of the present without compromising the ability of future generations to meet their own needs”*(WCED, 1987). Starting from this general definition, further conceptualizations have been produced for manufacturing activities and/or processes, as

here briefly recalled. According to the Organization for Economic Co-operation and Development, Sustainable manufacturing is a formal name for an exciting new way of doing business and creating value. Different statements of sustainability in literature¹ share the same focus on the following three aspects: economy, environment and society. It is thus possible to summarize from the literature analyzed a possible definition for sustainable manufactured processes/products, according to the following set of prescriptions:

- (-) minimize business risk;
- (-) minimize negative environmental impacts;
- (-) conserve energy and natural resources;
- (-) are safe for employees, communities and consumers;

- (-) are economically sound;
- (+) a new way of creating value;
- (+) are socially and creatively rewarding for all working people;
- (+) providing access to basic services, green and decent jobs and a better quality of life for all ;
- (+) adopt sustainable infrastructures.

where the (-) sign stands for those prescriptions oriented to preservation of resources without any significant change of the present condition, while the (+) sign indicates those prescriptions aiming at ameliorating/modification of the trends with respect to traditionally manufactured processes/products. To summarize simplifying, sustainable manufacturing is all about minimizing business risks of any manufacturing operation while maximizing the new opportunities that arise from improving processes and products.

Fascinating in principle, these general statements are really difficult to deploy into real operations and production settings. The focus of the present analysis is to derive a clear definition of the concept of manufacturing sustainability based on clear and paper based evidences, rather than referring to general ethical or social principles, which appear to be a **top down** definition. Conversely, information extracted from all the scientific papers available on SM can provide a sort of **bottom up** statement. Evidences are relevant words and short concepts that can be related to sustainability, as it will be explained in the following paragraphs by also providing some sound examples from the Italian point of view.

6.1.1 Methodology

In this section, we describe the process involved to analyse the papers in the sustainable manufacturing field. To give a more detailed vision of the topic, we consider this field divided in 6 sub-classes (one for each principle), adopting the well known 6R framework. The goal of the process is both to identify which the topics in each of the 6R are, then to accurately measure the way this framework

¹<http://www.trade.gov/green/sm-101-module.asp>

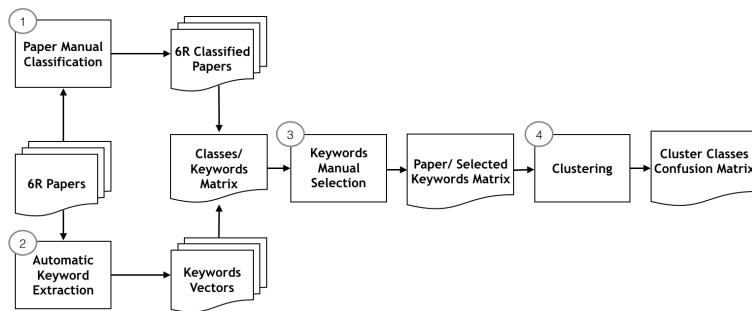


Figure 6.1: Flowchart of the 6R papers analysis process. The white boxes represent the activities and the yellow boxes the predicted documents. In the figure are also highlighted the input and the main outputs of the process.

corresponds to the topics of sustainable manufacturing. As seen in the flowchart of figure 1 the main activities of the process are four: Paper manual classification, Automatic Keywords Extraction, Keywords manual selection and Clustering. Each activity will be described in the next subsection.

Assignment of 6R principle meanings

The first critical issue is the selection criteria of 6R principles for the assignment. This was done by trying to assign a semantic specification of each R principle, as below explicated, built by summarizing all the possible definitions and concepts extracted by the selected bibliography (partially cited in the present section). The semantic specification provided below refers to the functional scope of each class, intended as an activity to be performed.

Reuse

Reuse is the action or practice of using something again, whether for its original purpose (conventional reuse) or to fulfill a different function (creative reuse or repurposing). Reuse involves taking, but not reprocessing, previously used items in order to save time, money, energy, and resources. In particular reuse is useful for machineries, especially when they are expensive, and for their components. Besides, technologies can be also reused and re-adapted to different situations. In addition, reuse is important because it minimizes disposal needs and costs.

Reduce

In pre-manufacturing it is possible to implement the reduction minimizing the use of resources. During the production phase, it refers to the use of energy and material, for example, it may involve the use of lower cost materials, the elimination of unnecessary product characteristics, the reduction of overhead costs or the readjustment of product processes. It implies a decrease of costs. As

a consequence, the derived effect of this principle is to minimize and optimize performance in terms of cost, time and waste and it focuses primarily on the first three stages of the four life cycle of the product before recalled.

Recycle

Recycle involves the process of converting material that would otherwise be considered waste, into new products and it corresponds to the breaking down of used items to make raw materials for the manufacture of new goods. Recycling can prevent the waste of potentially useful materials and reduce the consumption of fresh raw materials, thereby decreasing: energy usage, air pollution (from incineration) and water pollution (from landfilling). Recyclable materials include many kinds of glass, paper and cardboard, metal, plastic, tires, textiles and electronics.

Recover

Product recovery operations refer to operational processes (e.g. disassembling, sorting and cleaning) on products at the end of their use, in order to make them usable in n subsequent life-cycles. Differently from recycling, the product life-cycle is shortened, skipping all that phases of retreatment of wastes up to their second use. The risks of implementing product recovery operations is the uncertainty of returned product quality and quantity and for this reason recovering activities have only recently been considered in manufacture.

Redesign

The redesign activity involves the act of redesigning the next generation of products, which would use components, materials and resources recovered from the previous life-cycle or previous generation of products. It refers to the evaluation of ideas turning them into concrete innovative products obtained from products in their post-use phase.

Remanufacture

Remanufacture involves the re-processing of used products, to restore them to their original like-new state through the reuse of as many parts as possible without loss of functionality. It includes and exceeds the activity of recovering, because a remanufactured product should match the same customer expectation as a new one.

Despite this initial classification, some problem occurred for experts in assigning the papers to the different classes, due to the absence of the formalization that is needed to define unique criteria of belonging. This fact brought to the unbalance of the number of words within each class (corresponding to each principle), that drove to the fuzziness of the training set and, as a consequence, the difficulty in performing a real classification of scientific papers. This is the first critical issue of the followed approach so far, that may be overcome by alignment sessions of the decision makers.

Automatic Text analysis and Keywords extraction

In order to analyze the information coming from scientific papers belonging to topics encompassed within the 6R framework, we exploit text mining techniques, which employ methods from different fields of data mining to extract meaningful information 8. The second activity in our analysis process is thus devoted to transforming the set of papers in a set of numeric vectors to be elaborated by the clustering algorithm. To this aim, some text mining techniques are applied in sequence 12 to automatically extract meaningful information and knowledge from unstructured texts. The text mining process performed is summarized in the following. First, the information content of the document is converted into a structured form (vector space representation). In fact, most of text mining techniques are based on the idea that a document can be faithfully represented by the set of words contained in it (bag-of-words representation 9). According to this representation, each document j of a collection of documents is represented as an M -dimensional vector, where M is the number of words defined in the document collection, and $w(t_{ji})$ specifies the weight of the word t_i in document j . The simplest weighting method assigns a binary value to $w(t_{ji})$, thus indicating the absence or the presence of the word t_i , while other methods assign a real value to $w(t_{ji})$.

In the following, the text mining steps performed are described (for details about the activities see section 3:

- *Tokenization* is the first step of our text mining process, and consists in transforming a string of characters into a string of processing units called tokens that could be syllables, words, or phrases. Typically, with tokenization other operations are performed with the aim of making the text cleaner. Such operations are the removal of punctuation and other non-text characters, and the normalization of symbols (e.g., accents, apostrophes, hyphens, tabs and spaces). In the proposed system, the tokenizer removes all punctuation marks and splits each text into tokens corresponding to words, bigrams and trigrams.
- *Stop-word filtering* consists in eliminating the words which provide little or no information to the text analysis, or that, in our case, could make the clustering process fuzzier. Common stop-words belong to certain part of speech classes, such as articles, conjunctions, prepositions, pronouns, etc. Other stop-words are those that typically appear very often in sentences of the considered language (language-specific stop-words), or in the set of texts being analysed (domain-specific stop-words). In our case, this second group consists of typical words of the scientific articles such as “paper”, “state-of-the-art”, “present work”.
- *Stemming* is the process of reducing each word (i.e., token) to its root form. The purpose of this step is to group words with the same theme having closely related semantics. In the proposed system, the stemmer exploits the Snowball Stemmer for the English language, based on the Porter’s algorithm.
- *Feature representation* consists in building, for each text, the corresponding vector of numeric features. Indeed, in order to cluster the texts, we have to

represent them in the same feature space. In particular, we consider the F-dimensional set of features corresponding to the set of relevant stems.

Manual keywords selection

Keyword selection procedure was performed by hand from a team of 4 experts in the scientific field of sustainable manufacturing and with consolidated expertise on research and innovation. In order to prevent misunderstandings and difference in the judgement, a preliminary analysis of the single attitudes to classification was statistically performed and misalignment were eliminated by a guided training, based on the contemporary evaluation of a same sample from different experts so as to align the judgement. This process was done, as above mentioned, based on the 6R explicit framework and sharing the meaning of each principle.

It is clear that assignment of keywords to classes is not a trivial task and susceptible of interpretation. Disambiguation process would be required to explain the criteria of affinity to a given class, hopefully by referring to the functional scope of each class. Still an ambiguity may result, which can hardly be removed without a more profound specification with appropriate examples, which is out of the scope of the present paper.

According to this procedure the 6R refer to the following keywords:

- *Recover*: recovery, planning processes, renewable resources, new approach, waste recovery; process scrap recovery; energy recovery; heat recovery; collection; separation; design for environment; material recover optimization; recovery logistics;
- *Recycle*: recycle, adhesive technologies, materials conversions, government regulation; (Advanced) recycling technologies; Recyclability; End of first life; Down cycle; New/Old process scraps; Material scraps; Landfill taxes; Recycling benefit awarding; Secondary material production; Embodied energy saving; Environmental legislation
- *Redesign*: machining, cutting, lubrication, environment technologies, cryogenic; Material-efficient design; Design for Environment; New Materials; Eco-friendly design; Eco-friendly materials; Material reduction; Light-weighting; Design for Disassembly
- *Reduce*: reduce, optimize, waste minimization, consumption, energy pay-back, pollution, reduction, emission, saving; Energy reduction; Waste reduction; Resource reduction; Material usage reduction; Process sustainability optimization; Energy efficiency; Heat efficiency; Manufacturing efficiency; Doing with less;
- *Remanufacturing*: remanufacturing, material processing, eco-efficiency, renewable, innovations, nanocomposites; Product renewal; Product upgrade; Reconditioning; Part replacement; Modularity; Disassembly; Inspection; Separation; Re-Assembly; Design for Remanufacturing
- *Reuse*: reuse, replacing, material flow analysis, eco-efficiency; Component reuse; product re-conditioning; product upgrade; non-destructive recycling;

reuse supply chain; product maintenance; product repair; product monitoring;

It is clear that the keyword extraction is not a trivial task, since the outcome of the process may range from a useless single word to a meaningful group of combined words that, on the other hand, could become too specific to be significant for the training set of the search engines.

Paper Clustering

Document clustering is the application of the general process of cluster analysis to texts. The practical applications of document clustering systems are several and vary from automatic document organization to automatic topic extraction. For further details see section 3.5.4. Independently from the kind of algorithm, before the clustering phase, each document has to be represented as a set of features. These features are typically the n-grams contained in documents, so a critical activity for clustering effectiveness is the n-grams extraction (or feature selection). This goal is achieved with a series of sub-activity. These are typically tokenization (the process of parsing text data into smaller units), stemming and lemmatization (reducing all tokens to its semantic base), removing stop-words (less important words), and finally computing term frequencies (or other measures of the relationship between documents and words).

To get an exploratory view of the degree of precision with which the 6R framework represents the papers in analysis, the manually classified documents were clustered using a clustering Spherical K-Means Clustering algorithm (Buchta et al., 2012). We will then compare the output of the algorithm with the manual classification in the following paragraph.

Spherical k-means exploit cosine dissimilarities to perform prototype-based partitioning of term weight representations of the documents. Prototypes are centroids defined in the same feature space of the documents. The aim of the algorithm is to minimize, given a set of objects (documents in our case) and prototypes described in the same features space (the selected keywords) the cosine distance between each element and the closest prototype. This implies that the output of the algorithm is a membership matrix, in which each document is assigned to a certain prototype.

6.1.2 Results

In the present section, we describe the output of the application of the methodology on the 339 selected scientific papers on sustainable manufacturing extracted by the query “sustainable manufacturing” in the paper search field of the SCOPUS® database. Accordingly, apart the deliberate selection of the source database, no other filter was applied in the journal selection and this guarantees the significance of the journal sample selected. The main output, as highlighted in Figure 1, is

the distribution of documents among the 6R principles (i.e. classes) as manually classified, the automatic keywords representations of the classes and the outputs of the clustering algorithm (which is an unsupervised assignment of the documents) compared to the manual classification.

The assignment of a paper to a class was made by recognizing the application, or tools or scope of the paper to one 6R's principles. In this sense, for instance, a paper belonging to a recover might have as scope, or keywords or approach or an activity performed with the principal task to assure the recovery of a give good. It is thus clear, from the beginning, how complex may be to recognize just one principle more than a multiple possibility to satisfy more principles. This fact will be discussed in the followings.

Distributions of documents among the 6R

The main point coming out from the histogram in Figure 6.2 is that the distribution of scientific papers assigned to the 6R principles (classes) is not homogeneous. If the four classes Reduce, Recycle, Redesign and Remanufacture collect a comparable number of papers, the other two (Reuse, Recover) are poorly represented. One possible explanation of this is that cases of reuses or recoveries are less generalizable compared to other "R", and thus potentially less interesting for conferences and journals. Recovery and reuse, in fact, often refers to specific functions embedded into the product, and finding a general rule for assessing or designing such processes might be more difficult. They rather might find room in technical magazines, not included in the present analysis as concern processes. It worth noting that reuse and recover here refers to product and not explicitly to materials. Different approach concerns the design for reuse, which to a certain extent would belong to remanufacturing, as in the most of papers discussed, to mention a few, in the Annals of CIRP 18,19,20. It is difficult to think that the classification criteria, which plays a critical role into the assignment to classes, contributed to this situation, depending on the meaning assigned to each principle. Whether a different combination of classed have been provided, a different histogram would be expected to appear.

Keyword vector representation of 6R

After the phases of automatic keyword extraction and manual keyword selection, we derived the paper/selected keywords matrix. A sample of the elements of this matrix (keyword and their occurrence) is:

- *Recover*: Life cycle 5, environmental impact 4, raw material 3, cycle assessment 3, tossii fuel 3, energy payback 2, cleaner products 2, energy cost 2, energy usage 2, pv System 2, product process 2, managements System 2, new technologies 2, energy save 2, climate change 2, risk assessments 2
- *Recycle*: lite cycle 40, environmental impact 31, waste management 30, resource conservation recycle 25, solid waste 21, lite cycle assessment 18, recycle material 14, recycle process 12, reuse recycle 11, electronic equipment

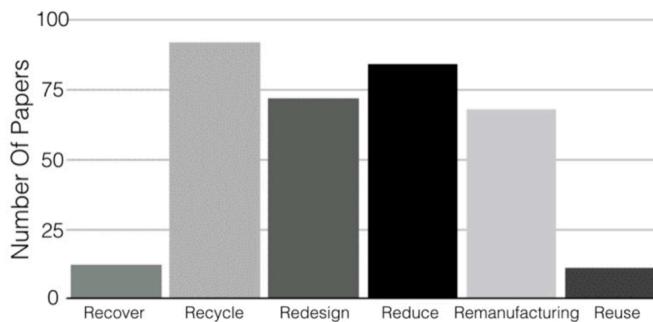


Figure 6.2: Histogram of the number of papers manually assigned to each of the 6R principles.

11, global warm 9, waste disposai 9, heavy metal 8, environment friendly 8, waste treatment 8, waste stream 8

- *Redesign*: manufacturing process 20, lite cycle assess 19, sustainable manufacturing 17, machine tool 14, naturai gas 14, cutting tool 13, raw material 13, tool life 13, cutting fluid 13, tool wear 13, mechanical engineering 12, System boundaries 11, machining process 11, manufacturing System 11, cutting speed 11, cutting zone 10
- *Reduce*: life cycle 40, environment impact 38, energy consumption 31, life cycle assessment 28, energy usage 22, energy requirements 18, solar energy 15, cleaner product 13, global warm 13, climate changes 12, solid waste 12, gas emission 11, solar celi 11, cutting conditions 11, co2 emissions 10, environmental management 10
- *Remanufacturing*: sustainable manufacturing 28, manufacturing process 22, remanufature product 18, supply chain 16, new product development 16, climate change 12, business model 12, product remanufacturing 12, manufacturing System 11, environmental performances 10, remanufacturing industry 10, management System 9, waste generation 9, design for environment 9, re-manufacture and recycle 8, automotive industry 7
- *Reuse*: life cycle 7, environment impact 7, energy usage 4, mechanical engineering 4, industriai ecology 4, cleaner product 3, life cycle assessement 3, environment management 3, design for manufacturing 3, environment protection agency 3, waste management 3, united nation 3, environment management System 2, process design 2, sustainable manufacturing 2, green chemistry 2

The keywords were divided according to the 6R principles (i.e. class), listing the number of the paper belonging to each class. The sample list of keywords and their occurrence, reflects the distribution of figure 6.2 and cannot thus be significant for classification but only for clustering purposes at the present.

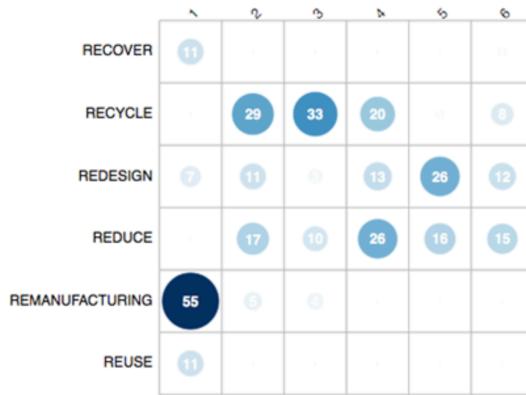


Figure 6.3: Matrix: comparing the manual classification and the clustering output.

Clusters/classes confusion matrix

To analyze from a semantic dimension how well 6R framework represent sustainable manufacturing definition through the scientific papers considered, the manually classified documents were clustered using a clustering Spherical K-Means Clustering algorithm. The results (the assignments of each paper to a cluster) was then compared with the manual classification. The number of resulted clusters was 6, having this number of clusters no specific relation with the number of 6R classes. The output of the clustering process is thus a 6x6 Matrix (Class(row)/Cluster (column)) shown in Figure 6.3. Numbers in the cells of the matrix represents centroids that can be characterized by the related keywords.

6.2 Sustainable Manufacturing: An Extended Mapping

The methodology described in section 6.1 has been then re-adapted to give an extended analysis of the 6R framework from a bottom-up perspective. In the present section, we map the state of the art of Sustainable Manufacturing using topic modelling, a widely used text mining techniques. The aim is to give a broad overview of how this knowledge field is approached world-wide and then, in section 3, to have a deeper look at the Italian way to sustainable manufacturing.

6.2.1 Methodology

The process of topic extraction is composed by the subsequent activities:

1. *Papers Collection*

2. *Keyword Extraction*
3. *Topic Modelling:* Number of topic selection
4. *Topic Modelling:* LDA Model fitting
5. *Manual topic labelling*

Each activity is described in the subsequent sections.

Papers collection

The analysis starts from a corpus of papers on sustainable manufacturing. The papers were downloaded from the Scopus database searching for the query:

*TITLE – ABS – KEY(sustainable.*manufacturing)*

At the date of 29/05/2018 the query results in 1,628 documents.

Keyword extraction

We represent each article as a set of keywords, merging Author Keywords and Index Keywords. The keywords are then “sanitized” following the subsequent rules:

- Eliminate duplicated keywords
- Eliminate brackets and its content
- Substitute non-alphanumeric character with a blank space
- Merge synonyms, alternative spelling and keywords pointing to similar concepts
- Eliminate scientific literature specific keywords like “article” and “review”
- Filter the generic keywords. The metrics for the threshold is the percentage of papers that contains the keywords. The value has been set to 7.5%.

Finally, we compute the Keywords Term Matrix. The matrix is composed of 1,628 documents and 26,272 keywords. Having a mathematical representation of the documents allows us to apply standard mathematical techniques to them.

Number of Topic Selection

The goal of the present section is to compute a topic model based on the keyword representation of the papers. A topic model allows examining a set of documents and discovering, based on the statistics of the words in each, what the topics might be and what each document’s balance of topics is. To deploy it for the purposes of the present paper, keywords will cluster to form a topic: each topic will represent a different view (say, principle) of sustainable manufacturing. This approach brings

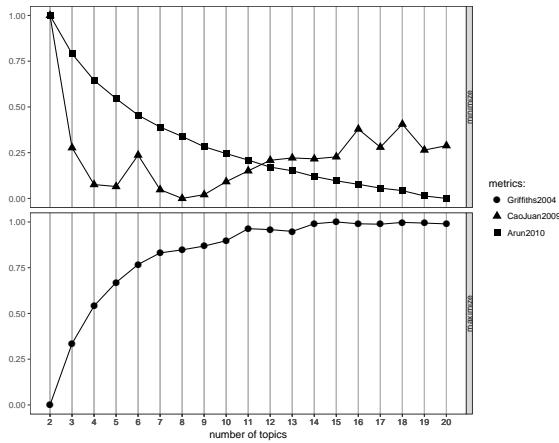


Figure 6.4: Relationship between the measures of the quality of the topic modelling output and the number of topics.

a new perspective to the definition of sustainable manufacturing with respect to the 6R's framework.

To compute the topic model, we use the Latent Dirichlet Allocation (LDA) algorithm. To select the number of topics for LDA, the most efficient and effective way is to calculate multiple metrics of the quality of the results in function of the number of topics. All existing methods require to train multiple LDA models to select one with the best performance. Several approaches tried to take the problem of automatically finding the right number of topics contained in a set of documents. Every approach follows the idea of computing distances (or similarities) between pair of topics varying the number of topics. We used four different methods to evaluate the output of a topic model for different value of k. These methods are:

- Caojuan2009 (Cao et al., 2009): Minimize the average cosine distance between every pair of topics. The best topic number K has a minimal final distance between topics in Latent Dirichlet Allocation
- Arun2010 (Arun et al., 2010): Minimize the symmetric KL-Divergence of the salient distribution that are derived from the matrices of factors. These matrices are the re-projections of the documents on the topics and of the topics on the vocabulary (the selected tokens). The divergence values are higher for non-optimal K values.
- Griffiths2004 (Griffiths and Steyvers, 2004): Maximize the likely of the data given the model built considering K topics. This is a problem of model selection using Bayesian statistics.

We computed these for measures fitting a LDA model for every K between 2 and 20. We choose the higher value because we wanted to obtain a reasonable number of topics representing the concepts (or we may say, principles) behind sustainable manufacturing. The results of the analysis are shown in figure 6.4. From this figure

is evident how the measure we want to minimize intersect each other at a value between 11 and 12 topics. We thus decided to visualize the results of the LDA models for a number of topics k between 7 and 15: the expert panel interviewed then allowed to decide that the best results was at 12 topics.

6.2.2 Results

We then extract the one-topic-per-term-per-row probabilities, beta. Beta measures what is the probability for each topic to produce a term. Figure 6.5 shows the top 5 terms for each topic. Here each topic has a different vertical position and a different color. Each topic is represented by a set of keywords and each keyword has a different position on the y axes. For each intersection topic/keyword, the dimension of a circle represent beta (what is the probability that topic to produce that term). It is possible for some keywords to belong to multiple topics: for example, optimization belongs to topic 1 and 9. It is easy to spot these keywords because typically (belonging to two different topics) are far from the group of keywords of the topics they belong.

Manual Labelling of the topics

To have a clearer representation of the topics, these were manually labelled by 6 independent experts in the field of manufacturing and sustainability. Then a seventh experts took in input the results of the manual naming and synthesized the label. The final results are the names of the 12 topics. These names are:

1. Smartness for Sustainability
2. Sustainable Machining
3. Manufacturing Environmental Efficiency
4. Modelling Manufacturing Sustainability
5. Welding Sustainability
6. AM Sustainability
7. Life-cycle Product Management
8. Advanced Material Sustainability
9. Production Management for Sustainability
10. Sustainable Energies
11. Innovation for Sustainability
12. Sustainable Logistic

This final picture provides a clear representation of how topics recognized are mostly homogeneous, provided there are few outlier keywords per each topic, as in figure 6.5. This “new perspective” of sustainable manufacturing represents a way of defining its contents by the grace of the tools or domain of interest involved. For instance, topic n.1 (smart sustainability) refers to the use of the new group of tools and approaches belonging to the Industry 4.0 stream, thus defining specific contents and criteria useful to pursue the sustainability in manufacturing.

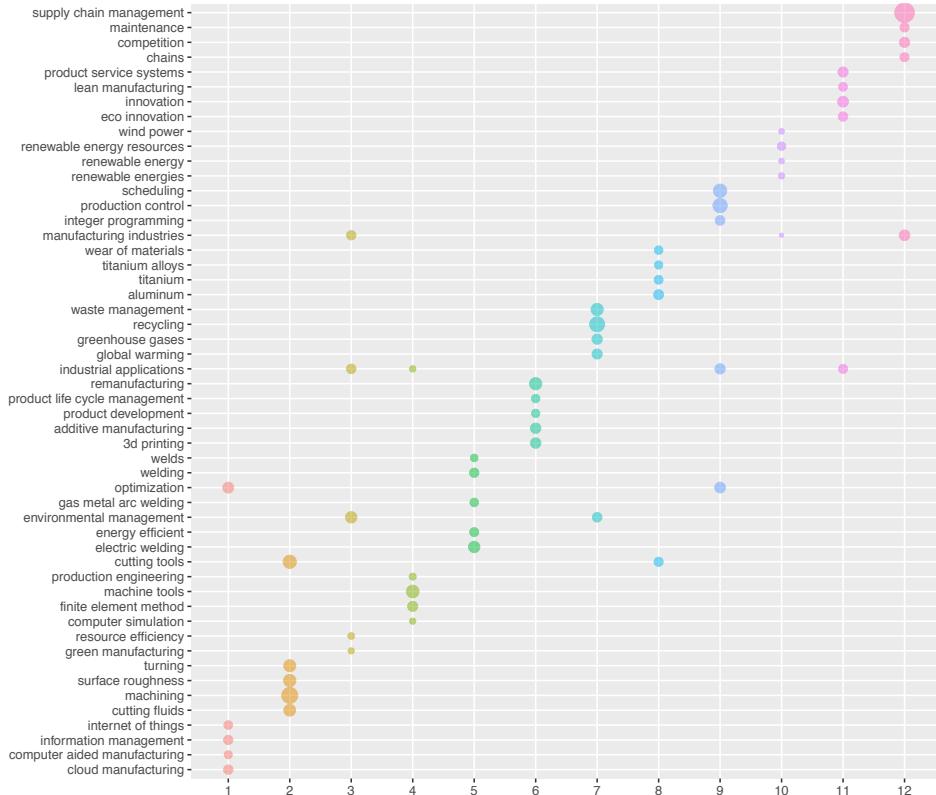


Figure 6.5: Content of the 12 topics. Each topic has a different vertical position and a different color. Each topic is represented by a set of keywords and each keyword has a different position on the y axes. For each intersection topic/keyword, the dimension of a circle represent beta (what is the probability that topic to produce that term).

6.3 Blockchain

In section 5.2 has been proposed a new usage of sentiment analysis to extract advantages (considered synonym of the words benefit, gain or profit) and disadvantages (drawback, failure) of technologies from patents with the aim of helping researchers and designers to effectively develop new products, analyzing positive and negative properties of an innovation. The main contributions of the present analysis is to list the problems of a technological field using this sentiment tool. We want to understand which are the problems that research is trying to solve for a technology and if there is any focus from researchers on the solution of certain technical problem. Furthermore using text mining techniques it is possible to correlate these problems between them and understand if there is any correlation between problems of technologies and if this map help researchers and companies to understand the research agenda.

This section thus proposes an innovative methodology for the (semi-automatic) extraction of technical knowledge from academic articles, using text mining techniques. Among many information related to technical knowledge, the methodology focus on the collection and the analysis of the problems of a technology. The meaning of problems of a technology is related to the concept of disadvantages of a technology but with a broader sense. In fact, using papers as a source makes it possible to collect not only technical disadvantages (typically described in patents) but also, organizational, business or even social problems, since these are faced by different intellectual fields in the scientific literature. We also propose a case study on the application of the method to the field of *block-chain*. We chose this technology because:

- It is highly innovative
- It is having an impact in many different field
- The problems of this technology are both technical and managerial

How Blockchain Technology Works

The blockchain can be exemplified as a process in which a set of subjects shares computer resources (memory, CPU, band) to make available all private users in which each participant has a copy of the data.

The use of cryptographic validation techniques generates the mutual trust of the participants in the data stored by the blockchain, which makes it comparable to the registries managed in a centralized manner by recognized and regulated authorities (banks, insurance companies, etc.) (Pilkington, 2016).

A blockchain is an open and distributed register that can store transactions between parties in a safe, verifiable and permanent way. Once written, the data in a block can not be retroactively altered without the modification of all the subsequent blocks, and this, due to the nature of the protocol and the validation scheme, would require the consensus of the majority of the network. (Iansiti and Lakhani, 2017)

The blockchain is a continuously growing list of records, called blocks, which are linked to each other and made safe by the use of cryptography. Each block in the chain contains a hash pointer (that is a link to the previous block), a timestamp and the transaction data.

The distributed nature and the cooperative model makes the validation process robust and secure, but it has considerable time and costs, due in large part to the *price of the electricity* needed to validate the blocks (Underwood, 2016). Authentication takes place through mass collaboration and is fueled by collective interests. The result of all this is a robust workflow where participants' data security expertise is not required. The use of this technology also makes it possible to overcome the problem of the infinite reproducibility of a digital asset and of the double expense without using a central server or an authority. (Karame et al., 2012)

There exist an overtrust about blockchain technology for businesses, and there exist a growing interest about the drawbacks of this technology (Eyal and Sirer, 2018; Lin and Liao, 2017; Yli-Huumo et al., 2016). Has been pointed out that a 51 percent attack would be enough to access or control a private blockchain because, in most cases, the organization that controls it already controls one hundred percent of the block creation. In fact, if someone could attack or damage the blocking tool on a private company server, would be possible to get complete management of the network and the ability to access and modify the data (Hampton, 2016). This is because the centralization due to the privatization of the blockchain leads to a single point of failure, or a central break point, which in a public blockchain could not happen as distributed, so there would be no central point to attack. This could have profound implications in financial crises or debt crises like the 2007-08 financial crisis.

6.3.1 Methodology

Considering our objectives, the approach we adopted for paper analysis is radically new with respect to the one traditionally established in the literature (bibliometric analysis and keyword approaches). These approaches do not allow a deeper understanding of the technical content described in the text. For this reason, we relied on text mining techniques supported by our technical knowledge base. For the sentiment computation in fact, we used a technical sentiment lexicon developed by the authors that extracts advantages and disadvantages of inventions from patents (5.2) and a novel dictionary lockup approach that incorporates weighting for valence shifters. Following a bottom up-approach, we redesigned and updated these lexicons for an optimal application to paper documents.

The workflow of the proposed methodology is shown in figure 6.6. The process starts with the collection of abstracts belonging to the same technological field. The abstracts are downloaded using the Scopus API, extracting all the documents that contain keywords of the selected technology in the title, abstract or keywords fields. The texts are then pre-processed using state of the art natural language processing tools (sentence splitter, tokenizer, lemmatization). Then, for each sentence we computed a negative sentiment polarity and took into consideration only

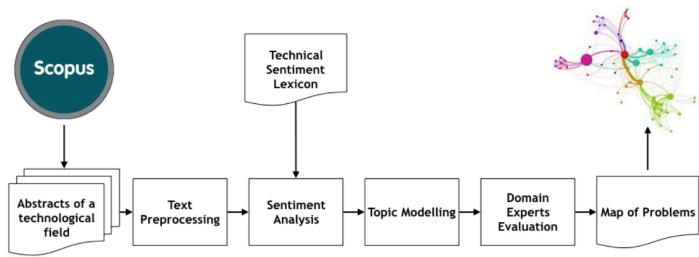


Figure 6.6: Proposed workflow for the problem extraction from papers.

the sentences having a negative polarity score below a threshold level. We applied topic modelling algorithm on the negative sentences with the aim of clustering. The output of topic modelling is evaluated by technology domain experts with the aim of labeling the identified clusters.

The application scenarios of our methodology have a wide range of users:

1. Companies that want to rapidly map a certain technological field
2. Policy maker that want to invest to solve problems of a technology to boost its innovation
3. Journals, to understand the hot-topic of a specific field
4. Research networks, to exploit possible collaborations and synergies between scholars.

Document collection and selection

The documents were extracted from Scopus searching for the query:

TITLE – ABS – KEY(blockchain OR blockchain OR block – chain)

At the date of 29/05/2018 the query results in 1,628 documents.

The term blockchain and its morphological variations is used in other fields different from computer science and economics, in particular in chemistry. For this reason we filtered from the data set all the papers belonging to one of the sequent All Science Journal Classification (ASJC) classes: chemistry, physics and astronomy, chemical engineering, biochemistry, genetics and molecular biology, pharmacology, toxicology and pharmaceutics, immunology and microbiology. The result of this lead us to a set of 1,364 papers.

To have a dataset with an higher precision, we also filtered using rules based on the content of the abstracts, since many conferences do not have an ASJC class in Scopus. This characteristic of the Scopus database could lead to bias in the results, especially for innovative technologies like block-chain for which the scientific discussion is stronger in conferences then in more structured journals.

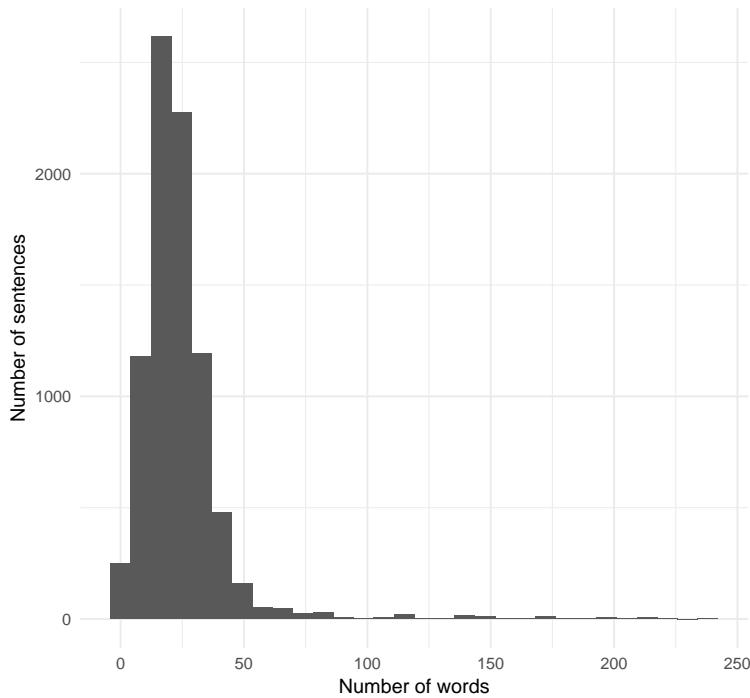


Figure 6.7: Histogram of the lengths of the sentences.

For this reason we analyzed the abstracts of the 264 articles belonging to one of the ASJC classes listed above (chemistry related) extracting the most frequent words and filtering for a blacklist of generic words contained in scientific articles. This results in a dictionary of words that has been used to search and filter all the papers containing in the abstract one or more of the words in the dictionary. The final number of selected papers is 1,276.

Sentence Splitting

A sentence splitter (for further details see section 3.4.1) is then applied to the abstract to divide the texts in sentences. From this step we had an output of 8,406 sentences.

The next step involved the measure of the sentences length. Some of the sentences in fact could be too long due to several factors for example the style of the author or an error in the sentences splitting phase). Since it is not a goal of the present work to analyze the style of the authors or to design a better sentence splitter, we decided to filter the sentences that are too long. The decision on the threshold level of number of words has been taken analyzing the distribution shown in figure 6.7. The 97% of the population of sentences contain a number of words that is lower than 53. Thus all the sentences contain more than 53 words has been filtered.

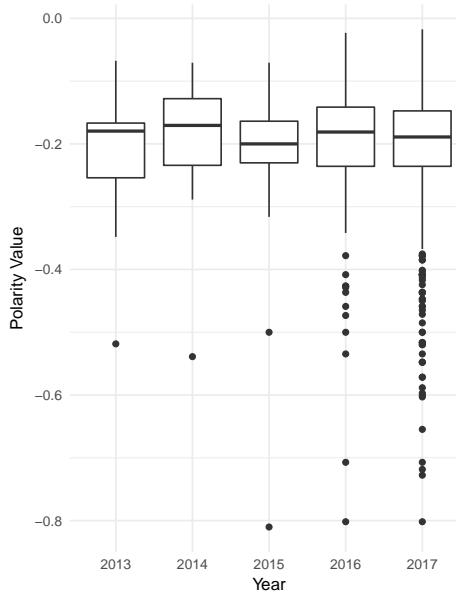


Figure 6.8: Box plots of the distributions by years of the polarities of the sentences having a negative polarity score.

From this step we had an output of 8143 sentences.

Polarity Computation

At this point has been possible to apply a sentiment polarity measurement on the sentences (Rinker, 2018). As output we had a polarity score between -1 (strongly negative) and 1 (strongly positive) for each sentence. Since we are interested in extracting the problems of the state-of-the-art blockchain systems, we visualize the distribution of the polarity scores of the sentences labeled as negative (having a polarity score lower than 0). The histogram of this distribution is shown in figure TOT. In this histogram are represented 1,108 different sentences. As we can see we have a distribution center in -0.2, with a tail that goes down to -0.8. This is an evidence that the system give a reasonable measures since it would be unreasonable to have more probable extreme values. Furthermore, the number of sentences having a polarity equal to 0 is 4,435 that is about the 50% of the sentences and the number of sentences having a positive polarity is 2,700 : it is reasonable that the higher number of sentences falls in these classes since the scientific jargon has to be neutral. The positive bias has been seen also for patent documents (see section 5.2)).

One interesting evidence we found is that the number of outliers (having a polarity values lower than the 95% of the population) is growing over the year as shown in figure 6.8. Even if the mean remains near to -0.2, int he last five years the number

of strongly negative sentences has increased. This shows how there has been a trend in the focus on the problems of blockchain.

Tokenization and Token Filtering

In the next phase we apply a state of the art natural language processing pipeline (see section 3 for more details) to the 1,108 negative sentences.

The tokenization process results in 220,094 tokens. To extract the meaningful words (words that adds information about the problem that the sentence is describing) we applied a series of filtering steps. As meaningful unit to analyze (token) we decided to use the lemma of the word. The 9,451 final token is a reasonable number considering the 1,108 sentences in input: we have a mean of 9 words per sentence. Considering the mean of 25 words per sentence shown in figure 6.7, we now have a summary of the sentences contains only the meaningful words. This output is a clean input for the topic modelling phase.

Topic modelling

Topic modeling is a method for unsupervised classification of documents which finds groups of documents fitting a statistical model to the data. In other words, these models captures word correlations in a collection of documents with a set of topics. Latent Dirichlet allocation (LDA) is a particularly popular method for fitting a topic model. 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 (for further details see section 3.5.6). If the topic modelling process is good, we have as output a structure where every topic is an understandable, meaningful and compact semantic cluster that in our case clearly represent a state-of-the-art problem of block chain technology.

Document Term Matrix

The first step is to take in input the 9,451 tokens and count how many times each one occurs in the 1,108 sentences. In this way we obtain a document-term matrix (DTM) where the documents are the sentences and the terms are our tokens (the lemmas). In our case the DTM has 1077 rows representing the sentences (31 sentences did not contain any relevant tokens) and 1147 tokens.

Definition of the Optimal Number of Topics: a Human-Machine Hybrid Approach

To fit a LDA model we have to give as a parameter the number of topic k that we think that best represent the corpus in analysis. In literature there exists many measurement to compute an optimal value of k . However it is worth to keep in

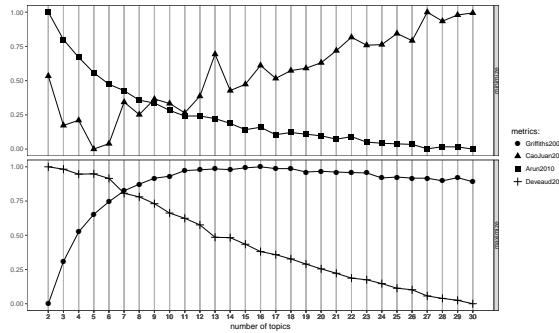


Figure 6.9: Measures of quality of the topic modelling results for growing number of topics. The figure is divided in metrics to minimize (top figure) and to maximized (bottom figure).

mind that these measures are not always correlated with expert judgement about topics interpretability and coherence. For this reason in the present section we use an hybrid approach in which we find an optimal neighborhood of value using state of the art k tuning methods and then we compute a graphical output for the 5 best k values to be evaluated by 4 different experts.

Several approaches tried to take the problem of automatically finding the right number of topics contained in a set of documents. Every approach follow the idea of computing distances (or similarities) between pair of topics varying the number of topics. We used four different methods to evaluate the output of a topic model for different value of k. These methods are:

- *Caojuan2009* (Cao et al., 2009): Minimize the average cosine distance between every pair of topics. The best topic number K has a minimal final distance between topics in Latent Dirichlet Allocation
- *Arun2010* (Arun et al., 2010): Minimize the symmetric KL-Divergence of the salient distribution that are derived from the matrices of factors. These matrices are the re-projections of the documents on the topics and of the topics on the vocabulary (the selected tokens). The divergence values are higher for non-optimal K values.
- *Griffiths2004* (Griffiths and Steyvers, 2004): Maximize the likely of the data given the model built considering K topics. This is a problem of model selection using Bayesian statistics.
- *Deveaud2014* (Deveaud et al., 2014): Maximize the information divergence between all pairs of topics. The optimal value k is the value for which LDA modeled the most scattered topics.

We computed these for measures fitting a LDA model for every K between 2 and 30. We choose the higher value because we wanted to obtain a reasonable number of topics representing the problems of blockchain. After a brain storming with experts it emerges that there can not exists more than 15 classes of problems. We

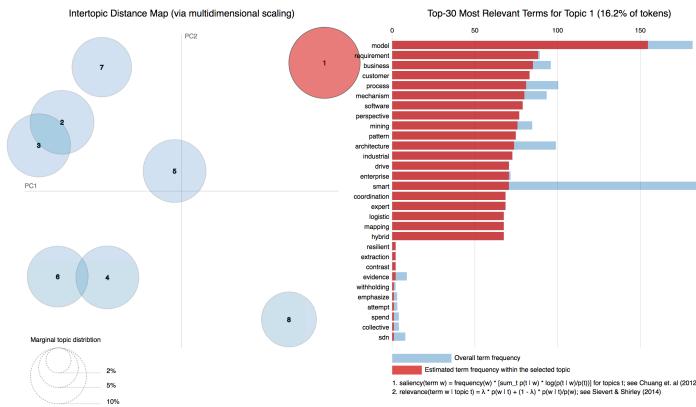


Figure 6.10: Screenshot of the shiny app used by experts to choose the optimal number of topics.

decide to take the double of this number to take in to consideration the biases of human experts. The results of the analysis are shown in figure 6.9. From this figure is evident how the measure we want to minimize interest each other at a value of 7 topics; the values we want to minimize are a little more unstable (especially (Arun et al., 2010)) and intersect both at level of 9 and 11. We thus decided to visualize and make choose the results of the LDA models for a number of topics k between 7 an 10.

To help experts in their decision process, an interactive map of the problem has been generated for 7, 8, 9, 10 and 11 topics. The map was created using Shiny (Chang et al., 2017). The interactive map of problems (a screen shot of the app is shown in figure 6.10) helped experts to understand the relationships between the problems. Here a multidimensional scaling algorithm compute the inter-topic distance that permits to visualize the distribution of topics in two dimensions. Clicking on a topic the experts can see its content, and for each word can see both at the estimated term frequency within the selected topic and at the overall term frequency.

The experts agreed for a total number of 8 topics as optimal.

6.3.2 Results

The output topic modelling phase is show in figure 6.11. The results of the topic modelling are visualized to make it possible for the expert to explore and label the topic representing the problems of block chain technology. Each point is a word, and word belonging to the same topic are grouped. The size of the label is proportional to the probability β that the word belong to that topic.

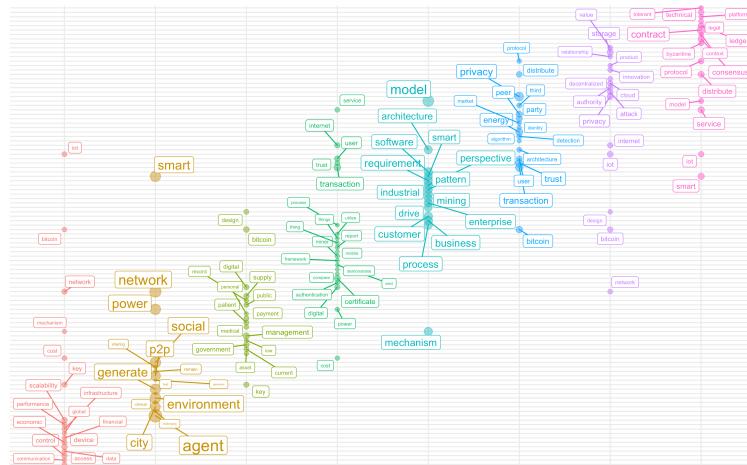


Figure 6.11: Content of the 8 topics of problems of blockchain. Each topic has a different vertical position and a different color. Each topic is represented by a set of keywords and each keyword has a different position on the y axes. For each intersection topic/keyword, the dimension of a circle represent beta (what is the probability that topic to produce that term)

6.4 Precision Agriculture

The agriculture is facing rapidly changing economic, social and environmental scenarios in 21st Century. Forecasts on worldwide population estimate that it might increase at about 9 billion by 2050 and led the Food and Agriculture Organization of the United Nations (FAO) to underline the growth of food needs of about 60% if compared to the annual average calculated between 2005 and 2007. The Committee on Agriculture and Rural Development of the European Parliament confirms these figures. In this regard, FAO focuses on how global agricultural and food systems can support the subsistence needs of the worldwide population according to different cultures and dietary habits of both developed and emerging countries.

Compared to past agricultural policies, nowadays trends related to technological evolution, socio-political changes, water shortages, as well as the increase in energy needs and the emergence of new pests and diseases that affect agricultural production acquire greater importance in the discussion between policy makers and companies concerning the future of agricultural activities.

In particular, technological innovation is necessary for the development of companies which aim to strengthen their production processes and organizational structures by exploiting automation and ICT within the cultivation and commercialization processes. Thus, digital technologies at the base of Precision Agriculture are the assets to leverage to deal with two major challenges for modern agriculture. On one hand, the need for an increase in production quantity by optimizing production factors. On the other hand, complying with production standards by combining

appropriate quality levels and limited environmental impact. Precision Agriculture is a modern approach for agricultural management that exploits cutting-edge technologies to monitor and optimize agricultural production processes.

The concept of Precision Agriculture was born in the United States in the early nineties, where the House of Representatives (Liaghat et al., 2010) defines it as “an integrated information- and production-based farming system that is designed to increase long term, site-specific and whole farm production efficiency, productivity and profitability while minimizing unintended impacts on wildlife and the environment”. Although it is a relatively well-known concept, Precision Agriculture still presents a low rate of adoption as reported by both academic surveys and professional reports (Pierpaoli et al., 2013).

Different definitions given by researchers, practitioners and policy makers have gradually allowed to deepen the understanding of the constituent elements of the concept as shown in the following table. Table 1 presents a literature review carried out on the Scopus database focusing on the analysis of the definitions of the concept of Precision Agriculture, and shows how technology emerges as the enabling aspect of Precision Agriculture. Anyway, authors focused also on other elements that refers to Precision Agriculture.

Pierce and Nowak (Pierce and Nowak, 1999) highlight the centrality of Technology and Benefits as the two key elements of Precision Agriculture. Zhang et al. (Zhang et al., 2002) strengthen these two distinctive elements, which compare in all subsequent analyses (Stafford, 2000; Kirchmann and Thorvaldsson, 2000), until the introduction of the concept of Sustainability (Bongiovanni and Lowenberg-DeBoer, 2004). Indeed, Bongiovanni emphasizes the environmental topic by underlining the role of Precision Agriculture to manage harvest production inputs in an environmentally friendly manner. Finally, Gertsis et al. (Gertsis and Vasilikiotis, 2018), define Precision Agriculture as “A modern farming management concept using digital techniques to monitor and optimize agricultural production processes”. They introduce the concepts of digital techniques and optimization of production processes by highlighting some possible concrete applications of Precision Agriculture. As emerged from the previous analysis, a fundamental role for the implementation of Precision Agriculture is played by digital technologies. In particular, object identification, georeferencing, measurement of physical and chemical parameters, satellite navigation, connectivity, data storage and analysis, process automation and vehicle driving are the most adopted (Schrijver et al., 2016). Precision agriculture is then based on a cyclical process of observation and acquisition of data, followed by an interpretation and evaluation of the information acquired, and by the implementation of a series of decisions that respond to them. Thanks to these technologies, farmers can increase production, optimize resources consumption (workforce included), costs and quantitative and qualitative production possibilities, according to the specific characteristics of the soil and cultivation. (Sawanta et al., 2016) shows that the implementation of digital technology in agriculture can increase total profitability from \$ 55 to \$ 110 per acre (1 acre = 4046.87 m²).

However, whether the Precision Agriculture is still far from being widely adopted

(Pierpaoli et al., 2013; Tey and Brindal, 2012). Indeed, the implementation difficulties related to the high initial investments and the lack of suitable skills among the farmers identified still represent significant obstacles. In fact, a study conducted by Pierpaoli et al. (Pierpaoli et al., 2013) identifies the so-called “non-adopters” farmers, (e.g. those who do not have sufficient skills or financial resources to manage the PA’s instruments). For these reasons measuring the concrete benefits of Precision Agriculture is not an easy task. However, Precision Agriculture is an increasingly pervasive concept within the agricultural sector and the constant evolution of technologies linked to it generates many opportunities which have not been fully explored yet.

Technologies advancements are directly linked also to another pervasive innovative concept in worldwide economy: Industry 4.0. This new paradigm grounds on the exploitation of digital technologies in the development of business processes and its enabling technologies are also used in Precision Agriculture . For example, Cyber-Physical Systems can be seen as one of the cornerstones for the development of innovative solutions to monitor and manage processes in agricultural businesses.

Starting from this relationship, the present chapter aims at analysing the technologies at the bases of the two domains to identify possible overlaps between Precision Agriculture and Industry 4.0.

6.4.1 Methodology

The work focuses on the creation of a dictionary which identifies the most innovative technologies that are applied in Precision Agriculture by investigating the overlaps with Industry 4.0 technologies to create clusters and to analyze the connections between them.

The dictionary aims to analyze the technologies related to the Precision Agriculture domain and to identify those belonging also to the Industry 4.0 paradigm. Concretely, the dictionary is a list of Precision Agriculture technologies that were identified by analysing papers retrieved from the international database. First of all, the twenty-five most cited scientific papers were identified by using the query “precision agriculture”, among those published between 2002 and 2017. Secondly, a text mining analysis on the 25 papers was conducted to identify the technologies mentioned and belonging to the Precision Agriculture domain. However, this list of technologies was not to be considered exhaustive because of the reduced number of analyzed sources, which however provided the basic information to build the analysis context. To face this limitation, and given the proximity of the founding concepts of Industry 4.0 and Precision Agriculture, the Technimetro® was used to expand the list of technologies at the base of the dictionary. Technimetro® (Chiarello et al., 2018) is a dictionary that contains over 1500 technologies belonging to the Industry 4.0 paradigm and was created by selecting the Industry 4.0 technologies found in manuals, technical documents and scientific publications on Scopus. The relationships between these technologies were studied through a text mining activity to describe possible clusters and to understand how technologies are linked one-another. Therefore, the present work attempted to understand if

the Technimetro® contains other Precision Agriculture technologies that were not identified with the analysis of the papers.

To answer this question, all abstracts of the publications on Precision Agriculture (published on SCOPUS from 2002 to 2017 for a total number of 4320 papers) were analyzed using the software “R”. In this way, technologies belonging to the Technimetro® that were mentioned in the Precision Agriculture publications were identified. Therefore, technologies extracted through the Technimetro® have been checked to manually eliminate not applicable terms. Technologies were removed with the help of control groups.

Finally, the new list of technologies obtained, was compared to the list of technologies identified at the beginning with the analysis of twenty-five papers for removing duplicates, so the dictionary was ready to use.

On one hand, this analysis confirmed the relationship between Industry 4.0 and Precision Agriculture domains, on the other hand, it allowed to create a list of over 1000 technologies referring to the Precision Agriculture domain, by expanding the list generated thanks to the analysis of the 25 most cited papers on Precision Agriculture. This analysis shows how the intersection between the technologies belonging to Industry 4.0 and Precision Agriculture is very broad and makes the two concepts very close from a technological point of view. To investigate the presence of possible technological clusters, a text mining on abstracts of papers belonging to the “Precision Agriculture” domain was performed.

The block diagram in Figure 6.12 describes the process to create the dictionary.

6.4.2 Results

The dictionary of Precision Agricultural Technologies includes 324 terms. Thanks to a graph, the most cited technologies and the connections between them allowed to identify at least 6 technology clusters. The graph in Figure 6.13 shows the structure of the dictionary containing the technologies related to Precision Agriculture and the relationships between the technologies that compose it. This representation allows to deepen the connections between the different clusters and technologies. The connections are represented by the lines that join the different nodes (which represent Precision Agriculture technologies) of the graph.

The size of the nodes varies proportionally to the number of papers they are cited in, instead their position depends on the number of connections between the different technologies: the most connected ones acquire a more central position into the graph and vice versa. A sample of the content of each cluster is:

- Monitoring: GPS, GIS, Data processing, GSM, Satellite, Ultrasound, Lidar, Broadband, Cellular, ...
- IoT: Wireless sensor network, Internet of things, RFID, Bluetooth, Zigbee, Wi-fi, Microcontroller, Arduino, ...

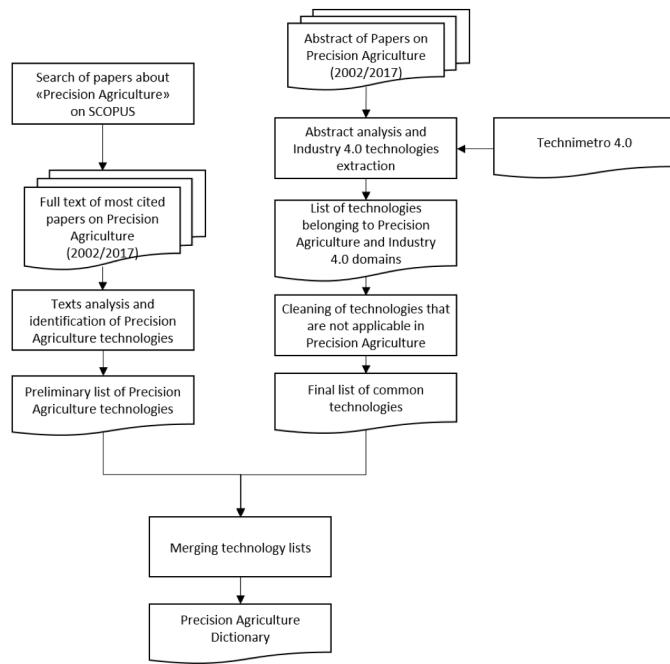


Figure 6.12: Process to create Precision Agriculture dictionary.

- Automation: Autonomous vehicle, Mobile Robot, Unmanned aerial vehicle, Agricultural robot, Computer vision, Data management, ...
- Decision: Artificial intelligence, Data mining, Expert systems, Forecasting, Machine learning, Semantic web, Smart grid, ...
- Hardware: Embedded system, Cyber-physical system, Manure spreader, Raspberry pi, CMOS, FPGA, ...
- Laser: Laser, Laser transmitter, Laser receiver, Laser surveying, Optical fiber, Photonic sensor, ...

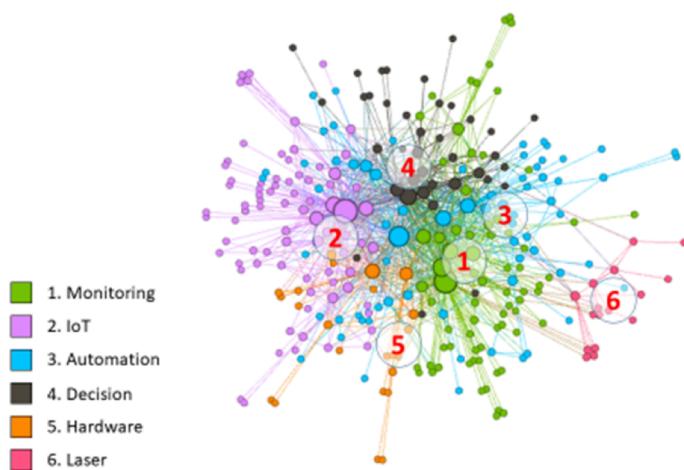


Figure 6.13: Graph of the Precion Agriculture technologies.

Chapter 7

Wikipedia

Wikipedia is a non-conventional source of technical knowledge, with respect to patent and papers. With respect to the literature on field delineation and clustering applied to science and technology we innovate by introducing this new source. In particular in the present chapter, Wikipedia is proposed as tool to map a technological field. The process start with a small number of documents following a procedure which is *expert-independent*, in order to minimize the distortions from subjective judgment. We then exploit the properties of Wikipedia in order to delineate the field and identifying the linkages between technologies. Further description of the structure of Wikipedia can be found in section 4.3

In this section we present two methodologies capable of automatically use Wikipedia information and its structure with the aim of mapping and analysing this content. The results of the methodologies are described, together with example of applications of the extracted entities for intelligence tasks.

7.1 Industry 4.0: Extracting and Mapping Technologies

Industry 4.0 is getting the center of the scene with respect to the future of production systems in advanced countries and to its economic and social implications. It is considered as the new fundamental paradigm shift in industrial production. The new paradigm is based on the advanced digitalization of factories, the Internet, and future-oriented technologies bringing intelligence in devices, machines, and systems (Lasi et al., 2014). Despite its growing popularity and the great expectations in terms of innovation impact, the concept of Industry 4.0 remains strongly linked to technologies and frameworks that have been heavily researched and analyzed in the last decades. In particular, Industry 4.0 can be seen as a smart recombination of existing technologies and some new technologies and their application to the manufacturing environment (Trappey et al., 2016). This recombinant nature

has led some authors to claim that it is nothing more than a re-labeling of old technologies, such as Computer Integrated Manufacturing (Apreda et al., 2016).

Yet other authors claim that this new wave of technology is fundamentally different from previous technologies and not just an amalgamation. In order to address the question whether Industry 4.0 is a new paradigm, or rather a re-labeling of existing technologies, a preliminary activity is needed, namely the delineation of the field and the clustering of technologies covered in the perimeter. It turns out that this activity is extremely challenging in the case of Industry 4.0, for a number of reasons we discuss in great detail. Faced with the complexity of Industry 4.0 existing delineation and clustering methodologies can be considered inadequate.

In this section we develop a novel approach, test it, and show its superior performance with respect to other approaches. The key features of the approach are as follows:

- i) the description of Industry 4.0 is offered in the form of an “enriched dictionary”, or an ordered and comprehensive collection of lemmas, each of which are associated to full scale definitions and descriptions and to explicit linkages to other lemmas;
- ii) the description of constituent technologies offered in the enriched dictionary is not obtained from individual experts, but is generated by accessing appropriate pages of the online encyclopedia Wikipedia;
- iii) the total number of technologies covered is more than 1200, linked with more than 39,000 semantic relations;
- iv) the perimeter of Industry 4.0 is not defined externally to the technology (by experts, government policies or other external sources) but is generated endogenously by examining the linkages between technologies described in the Wikipedia pages;
- v) the update of the descriptions of technologies in the dictionary takes place in real time due to the distributed, parallel and selfcontrolled activities of authors in the worldwide community of contributors to Wikipedia;
- vi) new technologies are automatically included in the dictionary if they exhibit a given threshold of connectivity with those already included in the perimeter.

Industry 4.0 as a multi-technology multi-stakeholder field

Industry 4.0 is the main keyword used by researchers, policy makers and entrepreneurs when describing how worldwide industrial systems will evolve in the near future by leveraging Internet connected technologies to generate new added value for organizations and society (Roblek et al., 2016). The growing interest is confirmed by the increasing number of academic papers focusing on topics that are related to the so-called “Fourth Industrial Revolution”. As shown in Figure 7.1 the query “Industry 4.0” generates 967 papers. Even if the query is very sharp

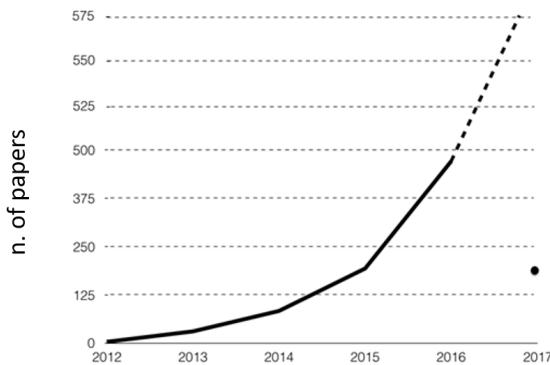


Figure 7.1: Trend of publications on Industry 4.0 (Title, Abstract, Keywords).
Source: Scopus. Date: 06/06/2017

and does not include all the research efforts on the single “enabling technology” it demonstrates an exponential growth of the topic. In Figure 7.1 a projection represented by the dotted line is included. The projection has been drawn by considering a constant increase of the derivative calculated as the average of the last 4 years. Our forecast is that in 2017 there will be 575 new papers in Scopus; this estimate is supported by the fact that about 200 papers have been already published before June 2017 (represented by the point). Since previous analyses in Scopus demonstrate a delay between publication and loading of 5–6 months our forecast seems to confirm a growing interest on the topic.

Table 7.1 shows how the scientific production on Industry 4.0 is divided among the main research fields (multiple attributions are possible in Scopus). In particular, it is possible to identify field specific-technologies that refers just to one or few sectors/business areas, and general purpose technologies that can be exploited in several sectors/business areas.

Formulated initially in Germany in 2011, the Industry 4.0 paradigm has been quickly translated, adapted and reinterpreted in developed and developing countries.

Despite this rapid and impressive convergence of interest (in itself a clear demonstration of the interdependence of policies across the world), there is no common ground in the definition and delineation of the field even if a first definition of the goal of industry 4.0 have been presented since 1998 (Council et al., 1998).

More precisely, while there is a reasonable convergence on the architectural definition of Industry 4.0, as defined in a relatively loose way, there is still considerable disagreement and misalignment with respect to constituent technologies (Riel et al., 2017; Smit et al., 2016; O’Halloran and Kvachko, 2015).

Furthermore, many constituent technologies are included in the definition of Industry 4.0, and hence described in these documents, from a variety of perspective that reflect mainly the huge variety of application domains. In other words, tech-

Table 7.1: Breakdown of industry 4.0 papers per research field. Source: SCOPUS date: 06/06/2017

Subject Area	Number of Publications
Engineering	645
Computer Science	410
Business, Management and Accounting	185
Decision Science	134
Material Science	90
Mathematics	87
Chemistry	52
Physics And Astronomy	45
Social Sciences	34
Energy	30

nologies are often described not only with respect to their fundamental engineering principles and related dimensions of performance, but with respect to specific applications to various manufacturing or service operations. In these applications the specific working of technologies and the associated dimensions of performance are indeed quite diverse.

Grangel and González (Grangel-González et al., 2016) develop a deductive rule-based system able to identify conflicts among AutomationML documents, named ALLIGATOR. It is interesting for the present work to notice how ALLIGATOR has the function to interoperate and align information models between a vast variety of areas (manufacturing, security, logistics) at a micro/plant level. In other words, this paper highlights the fact that one of the main problems of Industry 4.0 is the integration of models and concepts typically developed in their respective domains.

To offer an example of this state of affairs, let us consider the case of RFID (Radio Frequency Identification and Detection) technology. One of the main uses of RFID technology, that is, the detection of the location of a tag moving along a known path with known speed can indeed be applied for largely different purposes (safety, tracking, localisation) and in various company areas (production, logistics, maintenance). In practice, each of these applications will develop the basic technology in different directions. Depending on the applications we will find largely different descriptions of the technology involved. Figure 7.2 offers a Value Chain-like representation of Industry 4.0, showing the wide range of applications of constituent technologies.

An interesting consequence of this state of affairs is that there is disagreement also at the higher level of government documents describing Industry 4.0 as the main object for innovation and industrial policies: when describing the main components of Industry 4.0 the French government uses 47 technologies, against 39 technologies for the Italian government.

Summing up, the recombinant nature of Industry 4.0 creates several interrelated

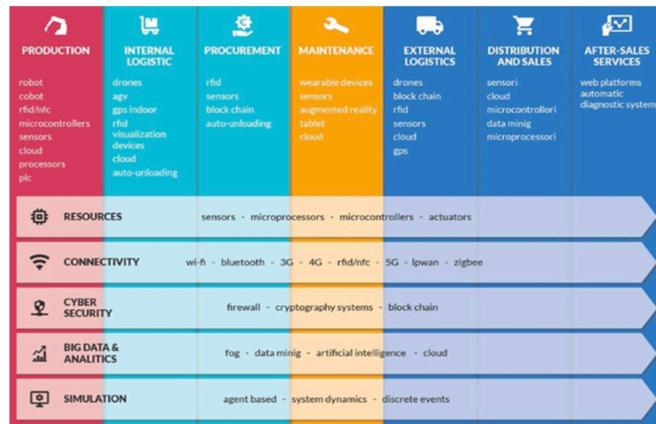


Figure 7.2: A Porter-like Value chain framework for Industry 4.0 (courtesy of Towel Publishing).

problems for profiling and mapping: - the number of constituent technologies is very large - the description and performance of constituent technologies depend critically on the specific application, hence on the business function/company area affected - the stakeholders are located in several organizational positions - the technical progress is very fast, with many (even if not all) constituent technologies facing rapid changes in their nature and performance.

Faced with this situation, a traditional approach to profiling and mapping would require a massive effort of keyword definition. A number of experts would be recruited in order to offer a representation of the field from their disciplinary or industry perspective. Extensive domain knowledge would be mobilized in such a way to build up detailed yet comprehensive maps of technologies. Based on these maps, governments, statistical offices and international organizations would work for a few years in line in the effort to identify the trends of technologies, the most important actors, the shares of individual countries or regions in the global landscape.

We strongly suggest this approach does not deliver the expected result. Keyword-based approaches to emerging technologies are too dependent on subjective judgments of experts. Even when the experts involved are top class and disinterested (often the best researchers or industrialists), their vision is inevitably partial. Even more importantly, keyword-based representations cannot be updated with the same speed of technology. The set of keywords identified by experts becomes inevitably obsolete in a few months. This section leverages on publications and open source repositories to design, develop and test a methodology that provides delineation and clustering of technologies of the Industry 4.0 paradigm. The methodology is based on a dictionary concerning the enabling technologies for industry 4.0 with full definitions and connections between them. Given the fast growth and the uncertainty that characterizes industry 4.0 technologies, the present methodology is designed to be a bottom-up and continuous evolving tool.

The structure and measurements made on the tool refer to July 2017.

Mapping and Clustering a complex emerging technology

The first task for mapping a new technology is field delineation, or the definition of the perimeter of the field. Industry 4.0 is not a new technology, but a novel combination of partly existing, partly new technologies driven by the convergence of their trajectories. As a matter of fact, it is clearly an example of emerging technology (Rotolo et al., 2015), as it shares the features of rapid growth, technological uncertainty, and market uncertainty.

The delineation of new fields of science and technology is an issue addressed since the late '70s, after the pioneering period of bibliometrics. Field delineation is a necessary step when existing classifications do not offer timely, reliable or comprehensive coverage of a topics, for example of a new technology or a new technological field. Moving beyond existing classifications require undertaking a search which, in general, may follow a lexical approach, a citationist approach, or a mix between the two (Small, 2006; Kreuchauff and Korzinov, 2017). In all cases there is a need to initialize the process, i.e. to identify a set of elements that constitute the starting point for searching.

The main approach has been based on keywords, to be identified in various regions of documents (title, abstract, keywords, full text of an article; title, abstract, claims, full text of a patent) and to be used as queries. A query is a structured sequence of words, connected by logical elements, such as "or", "and" and the like, to be launched on a database in order to build up profiling, indexing, or clustering a given field. In general the initial set of keywords are provided by experts in the field, usually organized in an expert panel.

There are several limitations of the keyword/expert approach. First, expert based keyword definition, or patent classification is a very expensive activity (Tseng et al., 2007). Second, the keyword selection is based on subjective judgment, and when experts are asked to decide on relatedness measures (e.g. synonyms, hypernyms or hyponyms), they do not apply systematic rules (Tseng et al., 2007, Noh et al. (2015)). Experts may be subject to a number of biases, such as for example the desirability bias (attributing higher probability of occurrence to preferred events) and many others (see section 3.8.1). Panels of experts are not immune by biases, such as group thinking. There is little research on the impact of expert subjective judgments on the delineation of emerging fields, but there is reason to believe it may be significant.

Third, the delineation of perimeter of emerging technologies is not robust to slight differences in the queries. As it has been shown by Zitt and Bassecoulard, little differences in the wording of queries, or on the time window, may end up in completely different sets of documents (Zitt and Bassecoulard, 2006). Therefore there is no proof that the method is reliable.

Finally, and more problematic for the case of Industry 4.0, the methodology is static, as it is based on a fixed sets of words. This set can (and in practice often is)

updated, but this introduces a delay in the process and does not deliver reliable results. Keeping updated a collection of keywords in a dynamic technological landscape is extremely difficult.

These limitations have become evident in the last two decades, after the efforts of many authors to produce reliable perimeters of the emerging field of Nanotechnology. The initial efforts have been based on a classical expert-based approach. Panel of experts provided lists of keywords that were transformed into database queries. Among them, a consulting company called Lux, the Fraunhofer ISI in Germany, and CWTS in the Netherlands were the most active. Most studies delivered largely different delineations (Youtie et al., 2008; Ghazinoory et al., 2013; Ozcan and Islam, 2017).

In turn, these limitations opened the way to massive efforts to reduce the dependence on experts and exploit systematically the new opportunities opened by text mining, following what has been called “full text based scientometrics” (Boyack et al., 2013). Starting from the late ‘90 s several attempts have been made to apply text mining techniques to the patent corpus and the field is currently burgeoning (Joung and Kim, 2017; Ozcan and Islam, 2017).

Summing up, the existing approaches to the delineation of emerging technologies, taken together, suffer from the following limitations: 1. dependence on expert judgment 2. lack of robustness to alternative definitions of the perimeter 3. delay in update of technologies (static approach) iv) lack of transparency in the modeling of technology.

We now turn to the second main task in text mining of technology documents, that is, *clustering*. Once the perimeter of the field is delineated, a task usually included in the mapping is clustering, or the creation of groups of entities in such a way to reduce the complexity of the representation. Within text mining the clustering of documents is based on various kinds of linkages that are considered a signal of similarity in topics (see section 3.5.4). In general, linkages among documents can be generated by citations (citationbased clustering) or by the extraction of features in texts (text-based clustering) (Leydesdorff and Hellsten, 2006; Wang and Koopman, 2017; Jaffe et al., 1993).

The most used approaches to clustering assume that members of a cluster:

- cite each other (citation analysis: (Jaffe et al., 1993; Moed, 2006; Verspagen, 2007; Lee and Kim, 2017));
- share certain words (co-word analysis: (Callon et al., 1983; Rip and Courtial, 1984; Leydesdroff, 1989; Engelsman and van Raan, 1994; Van Raan and Tijssen, 1993; Yoon and Park, 2004));
- share a reference in their bibliography (bibliographic coupling: (Glänzel and Czerwon, 1996; Kuusi and Meyer, 2007));
- share the same sub-fields in a classification (co-subfield analysis:(Chang et al., 2009));
- are cited by the same documents (co-citation analysis: (Small, 1973; Small and Sweeney, 1985));

– are cited by the same authors (author co-citation analysis: (White and Griffith, 1981)).

In the proposed methodology we exploit the hyperlink feature of Wikipedia in order to introduce a new approach to clustering. Hyperlinks are introduced by authors in order to establish a semantic linkage between the page and other pages. We exploit this feature as follows: members of the same cluster are those pages that share the hyperlinks to other pages, according to thresholds defined by an appropriate algorithm. Note that hyperlinks are only superficially similar to citations. The origin page cite another page by hyperlinking it, but in effect this linkage is not a citation (that is, a reference to a previous work) but a signal of semantic similarity, intended to guide the reader in the network of meanings. We suggest that the hyperlinks are similar to citations under some respect, but very different under some other respects. Like citations, hyperlinks are introduced in the text by authors and reflect intentionality. Unlike citations, they reflect semantic relations, not relations of credit assignment or tribute to scientific authority. Perhaps more importantly, citations are introduced only by the author(s) of a paper and remain unchanged after publication. Hyperlinks, on the contrary, are introduced also by subsequent readers of the Wikipedia page. If the introduction of hyperlinks is not considered appropriate by the community of contributors, as it may happen due to vandalism, they are immediately removed (see the discussion below). This means that they reflect all possible semantic connections among the pages, as collectively stated by a large community of authors, in a reliable and robust way. We believe this methodology offers a remarkable improvement with respect to existing approaches.

How is similarity measured by using Wikipedia

In general, semantic relatedness is a measure of the similarity between two terms. It can be computed by statistical methods without requiring a manually encoded taxonomy, for example by analyzing term co-occurrence in a large corpus (Resnik, 1999; Jiang and Conrath, 1997). Wikipedia has been largely exploited in the literature in order to compute semantic relatedness. Gabrilovich and Markovitch (Gabrilovich and Markovitch, 2007) developed an alternative to Latent Semantic Analysis and called this new technique Explicit Semantic Analysis (ESA). This methodology first uses a classifier that is centroid-based to map input text to a vector of weighted Wikipedia articles. Then the vectors are exploited to obtain the semantic relatedness between two terms by computing the cosine similarity. This technique could be applicable to individual words, phrases or even entire documents. Furthermore, the mapping developed in this work has been successfully utilized for documents categorization. A new version of this kind of systems was presented by Milne (Milne, 2007). While in Gabrilovich and Markovitch (Gabrilovich and Markovitch, 2007) the authors use the full text of Wikipedia articles to establish relatedness between terms, in this work only the internal hyperlinks are exploited. To compute the relatedness between two terms, they are first mapped to corresponding Wikipedia articles and then vectors are created containing the links to other Wikipedia articles that occur in these articles. The

main problem facing semantic relatedness using Wikipedia is the disambiguation of terms. Several strategies have been developed to solve this problem. A first approach, described in Strube and Ponzetto (Strube and Ponzetto, 2006), exploits the order in which entries occur in the disambiguation pages of Wikipedia to find the most likely correct meaning. On the other hand, Gabrilovich and Markovitch (Gabrilovich and Markovitch, 2007) avoids disambiguation entirely by simultaneously associating a term with several Wikipedia articles. Milne (Milne, 2007) approach hinges upon correct mapping of terms to Wikipedia articles. However, when terms are manually disambiguated, it has been shown that the systems of semantic relatedness computation are more accurate than the systems of automatic disambiguation (Medelyan et al., 2009).

Summing up, a consistent literature in the field of computational linguistics and text mining supports the notion that the use of Wikipedia articles as a knowledge base is justified and promising.

7.1.1 Methodology

In this section we give evidence of the methodological steps undertaken to build up the enriched dictionary referred to Industry 4.0. The dictionary contains technologies related to the Industry 4.0 paradigm, each of which is associated to the full set of relations with other technologies. The dictionary is semi-automatically generated using technical documents and the Wikipedia free online encyclopedia. The linkages between technologies have all a semantic content, since they are generated within the text of the articles of Wikipedia when a related topic or entry is considered necessary for the logical flow of the definition or description.

Figure 7.3 shows the methodological steps needed to generate the enriched dictionary. In the flow diagram three elements are graphically displayed: activities (rectangular shape), check points (diamond shape) and documents created from the procedure (sheet of paper shape).

Generation of the seed list

As input for our methodology we used technical documents, official government documents and the most cited academic papers in the field of industry 4.0. The selection of seed documents has been made by:

- taking the official government documents of the US government and of three large European countries (France, Germany, UK), all of which are strongly committed to the support of Industry 4.0 and are widely considered a benchmark in international documents (for example, OECD and European Union), plus a selection of technical documents cited in government papers, for a total of 10 documents;
- taking the 10 most cited papers on Industry 4.0 according to Scopus. The reference to Industry 4.0 was explicit in the title, abstract and keywords of the papers. The extraction was made on Scopus Database in June 2017.

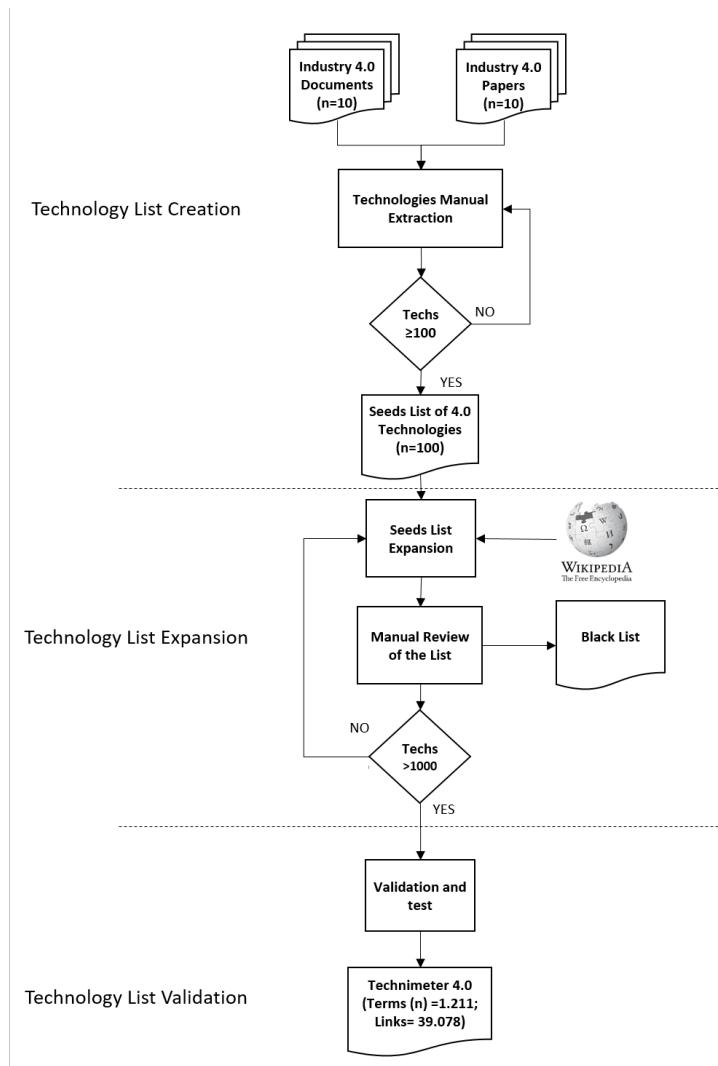


Figure 7.3: Flow diagram of the adopted methodology.

We deliberately limit ourselves to a small number of documents. The reason is explained in conjunction with the chosen stopping rules. The documents have been manually parsed by a team of Master students in Engineering Management at the University of Pisa. The assignment was “Understand each document and extract the enabling technologies for industry 4.0”. The manual search in the documents continued until the team reached the goal of 100 different technologies extracted. For our purposes 100 different technologies represents a reasonable seed list of technologies, which will be used as input for the automatic expansion phase.

Seed list expansion

For each term in the seed list the corresponding page in Wikipedia was found. All technologies identified in the seed were covered by Wikipedia. This is a preliminary confirmation of its relevance as a source of knowledge. These pages formed the initial glossary. The expansion procedure automatically retrieved the pages and identified all hyperlinks included in the description of the technology. The pages that are the target of hyperlinks are classified manually according to the following categorization:

- a. links to pages already in the seed: these pages are labeled “anchors”, since they provide robust indicators of technologies that are, at the same time, mentioned explicitly in the seed documents and referred to in Wikipedia pages that deal with other technologies;
- b. links to pages not in the seed: these are labeled “missing technologies” and are stored in memory for later treatment as potential candidates to inclusion in the dictionary;
- c. links to pages with non-technological content: they are labeled “stopwords” and are eliminated from the procedure. The overall procedure is iterated up to the point in which a number of at least 1000 different technologies is reached. At this point the procedure will stop. Updates and changes of the dictionary can originate from new entries (new technologies) or from updates to existing pages.

Given that the automatic extraction of Wikipedia pages can be run on a permanent basis, each version of the dictionary has a date. The current version, illustrated in the rest of the paper, is at the time point of July 15, 2017.

The stopping rule for the manual and the automatic expansion

The three stopping rules follow a sequential logic of order of magnitude: we start with approximately 101 documents, from which we extract 102 names of technologies, that, used as inputs to Wikipedia, deliver approximately 103 final technologies. More in detail we make use of:

1. 20 input documents: all technical documents taken as reference for Industry 4.0 share the same framework (i.e. DIN:SPEC 91345:2106). Many of the

documents contains the same information/terms/ technologies. Furthermore these documents are technology focused and therefore from a low number of documents we obtain a large number of technologies.

2. seed list of 100 technologies: as demonstrated in the past Wikipedia is a good source also for technical terms, therefore we assumed it was able to quickly expand the technologies related to Industry 4.0. For this reason the seed list is composed of no more than 102 entries.
3. output list of at least 1000 technologies: of the automatic expansion works correctly the technologies should increase by an order of magnitude in few iterations. Since the list has to be revised manually we decided for 103 entries as a target thus reducing the impact of manual review. As a matter of fact, the Wikipedia network of semantic linkages delivers a total number of technologies related to Industry 4.0 which exceeds this target, again confirming the validity of Wikipedia as a source of knowledge.

Structure of the enriched dictionary

The enriched dictionary can be defined as a set of enabling technologies for industry 4.0, associated to their definitions and to the linkages between them. The digital version of the tool is a hyperlinked text ¹.

For the purpose of publication in an academic paper the tool can be represented as a table in which we have:

- Column 1- Technologies: Enabling technologies for industry 4.0, or a broad categorisation of technologies following a clustering procedure (see below)
- Column 2- Url: Links of the Wikipedia pages of the enabling technologies for industry 4.0
- Column 3- Definitions: Glossary, snippets from wikipedia page of the definition of the enabling technologies for industry 4.0
- Column 4 Links: hyperlinks to other wikipedia pages from the wikipedia pages of enabling technologies for industry 4.0
- Column 5- Anchors: hyperlinks to other wikipedia pages that are enabling technologies for industry 4.0 from the wikipedia pages of enabling technologies for industry 4.

In the table shown in figure 7.4 shows a sample of the dictionary for four enabling technologies. An evidence is that there are conflicting definitions of “Augmented reality” (AR) and “Virtual reality” (VR); the first says that AR contrasts VR, while the second states that “AR systems may also be considered a form of VR”. This is an evidence of the ambiguity that exists in the definition of 4.0 technologies. Moreover, the table underlines how words such as “3D printing” and “Additive manufacturing” that are used in different ways within papers and technical documents (see Table 3), basically refer to the same concept. Table 7.4 also shows

¹ www.industria40senzaslogan.it

Enabling technology (A)	Wikipedia Page (B)	Definition (sample) (C)	Links (sample) (D)	Anchors (sample) (E)
3D printing	en.wikipedia.org/wiki/3D_printing	3D printing, also known as additive manufacturing (AM), refers to processes used to create a three-dimensional object in which layers of material are formed under computer control to create an object. [...] (same as 3D printing)	3D bioprinting; Actuator; Artificial brain; Artificial muscle; Biomaterials; Biotechnology; BioSprint Project; CAD; Delivery drone; Forber; Gene therapy; Injection molding; Inkjet; Laser-powered; Phosphor display; Magnetic refrigeration; (same as 3D printing)	Actuator; Artificial intelligence; Artificial photosynthesis; Biomaterials; Biotechnology; CNC; Computer-aided design; DMOZ; Electron beam melting; Home automation; Number; Internet of Things (same as 3D printing)
Additive Manufac- turing	en.wikipedia.org/wiki/3D_printing			
Augmented Reality	en.wikipedia.org/wiki/Augmented_reality	Augmented reality (AR) is a live direct or indirect view of a physical, real-world environment whose elements are augmented (or supplemented) by computer-generated sensory input such as sound, video, graphics or GPS data. It is related to a more general concept called computer-mediated reality, in which a view of reality is modified (possibly even diminished rather than augmented) by a computer. [...]	360° video; ARQuake; ARTag; ARToolKit; Abetton Live; Android; Augmented; Augobotics; Adobe Flash; Alexis Ohanian; Allosphere; Alternate reality game; American football; Android (operating system); Artificial reality; Audient; Augment (app); Augmented Reality Markup Language; Augmented reality browser; Augmented reality computing; Augmented reality; Augmented web; Australia Council for the Arts; Automotive head-up display; Automotive navigation system; BBC; Bionic contact lens; Blair MacIntyre; Blippar; Blob detection; Brain in a vat; Bruce H. Thomas; [...] 360° video; 3D audio effect; 3D computer graphics; A-ha; Augmented reality; Augmented reality browser; Augmented reality; Algorithm; Algorithm design; Allosphere; Alphenoxate; Alan Tower; Amnesty International; Amusement arcade; Analysis of algorithms; Andre Chung; Antonin Artaud; Anxiety disorder; Apple Inc.; Application security; Arcade game; [...]	Android (operating system); Bionic contact lens; Computer vision; Cyborg; DMOZ; EyeTap; GPS; Gesture recognition; Global Positioning System; Google Glass; Graphical user interface; Holography; iOS; MEMS; Mobile computing; QR code; RFID; Real-time computing; Smartphone; Speech recognition; Tablet computer; Ubiquitous computing; Ultrasound; Virtual Reality; Virtual retinal display XML
Virtual Reality	en.wikipedia.org/wiki/Virtual_reality	Virtual reality (VR) typically refers to computer technologies that create simulated environments, sometimes in combination with physical spaces or multi-sensory environments, to generate realistic images, sounds and other sensations that simulates a user's physical presence in a virtual or imaginary environment. [...]	3D computer graphics; ACM Computing Classification System; Algorithm; Artificial reality; Computer; Computer-aided design; Computer network; Computer security; Computer virus; Computing platform; Cryptography; Cyberspace; Data mining; [...]	

Figure 7.4: Sample of enabling technologies showing the table structure of dictionary.

the difference between links and anchors. Links include all hyperlinks found in Wikipedia pages. By nature, a certain fraction of these links contain information that is not relevant to our task. It is likely that, in the course of discussion of a given topics, authors quote an author (e.g. Bob Sproull in Virtual Reality), an institution (e.g. British Museum or California Institute of Technology) or an event or application (e.g. Coachella Valley Music and Arts Festival). These links do not add to our knowledge of the Industry 4.0 field. It can be seen that, following the definition of anchor given above, these terms are eliminated in column (E), which includes only the anchors, or those entries that are added to the body of knowledge.

7.1.2 Results

The dictionary is composed of 1.211 terms and 39.078 relationships between them. This generates a graph in which the node represents a technology and the edge represents a link in the Wikipedia page. The network structure naturally gives origin to graph-theoretic metrics. We exploit this property in order to generate a number of indicators that the readers may find it useful to examine.

Graph analysis and Sub-graph selection

Figure 7.5 gives an overview of the obtained. We compute for each node the indegree (horizontal axis), the out-degree (vertical axis) and the number of links to other Wikipedia pages that each node has (color of the node). Our results show that in terms of the analyzed variables we can identify 4 different clusters of nodes (or technologies) each one having a different behavior. The first group we take in consideration are the point having an indegree greater than 70 and an out-degree greater than 70. In this group on the top right of the page we have some outliers. These are terms like Microprocessor and Microcontroller, X86, 8-bit, 16-bit and 32-bit. Then we observe a sub-group centered on the coordinates (150, 100). Here

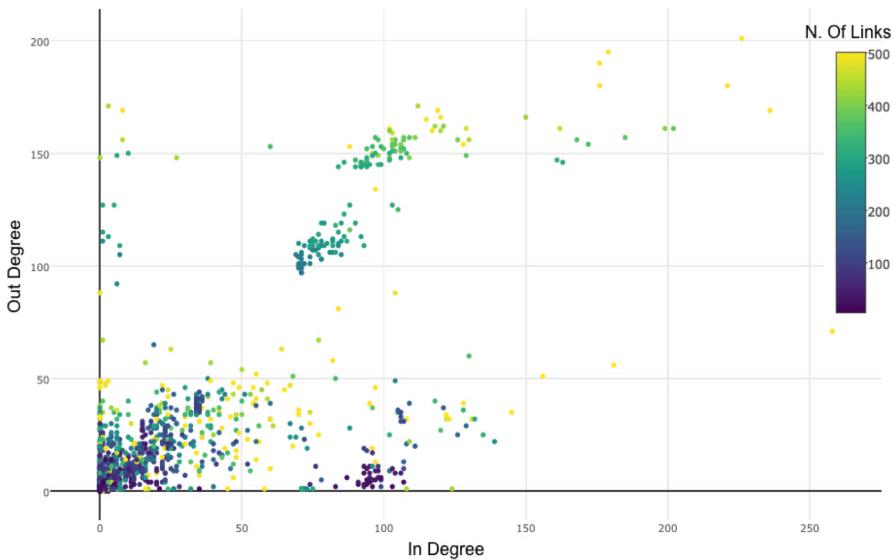


Figure 7.5: Plot of the in-degree and the out-degree of the nodes of the graph. The colour of the node represents the number of Wikipedia internal links.

we have terms like Program counter, Addressing mode, Instruction Cycle, Coprocessor, Symultaneus multitrading, SISD and MISD. Still within the first cluster we have another sub-group of terms centered in (80,110) with terms like Intel i860, Intel Atom, Intel 80286, Intel 80188 but also Bloomfield and Wolfdale. The second cluster is one in which the points have an in-degree greater than 70 and an out-degree smaller than 70. Here we have terms like Machine learning, Artificial Neural Network, Cognitive Computing, Software, Random Access Memory, Internet, Firmware and C++. The third group collects points having an in-degree lower than 70 and an out-degree greater than 70. Here we have terms like Processors, Micro-Operation, Micro-Assembler, Application specific integrated circuit. The last and most populated cluster has an in-degree smaller than 70 and an out degree smaller than 70.

This cluster is more precisely visualized in Figure 7.6, for which we have as before the in-degree (horizontal axis), the out-degree (vertical axis) and the number of links to other Wikipedia pages that each node has (color of the node). A jitter process has been implemented to the points on the graph in order to better visualize the overlapped points. In this plot only the technologies having both an in-degree and an outdegree lower than 70 are shown. This generates a subgraph composed by 931 nodes and 10673 edges.

Graph representation and cluster analysis

The structure of the graph offers it self naturally to clustering of technologies in order to obtain a readable mapping. The clustering algorithm receives as input

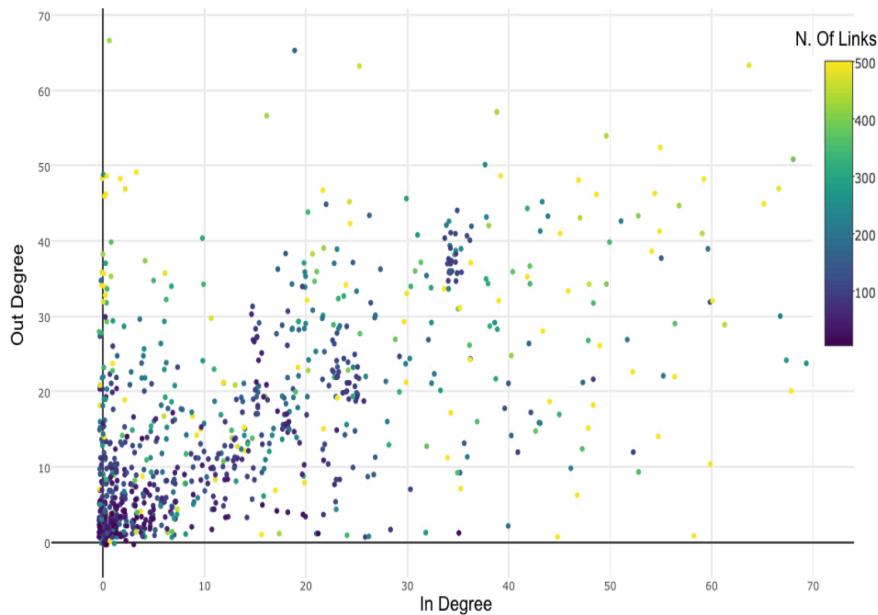


Figure 7.6: Plot of the in-degree and the out-degree of the nodes of the sub-graph. Selection of the nodes having an in-degree and an out-degree lower than 70. The colour of the node represent the number of Wikipedia internal links.

the collection of technology terms T of the analyzed subgraph and returns a set of terms clusters $C = \{C_1, C_2, \dots, C_n\}$ that cover the whole subgraph in analysis. Each cluster C_i is a subset of terms of T , and a term may belong to only one cluster. In Figure 7.7 we show a representation of the sub-graph made using Gephi software with its implementation of the Force Atlas algorithm (Bastian et al., 2009). In this representation, two nodes in the graph are represented closely if they share an edge. In this way also nodes that belongs to the same communities of nodes (nodes that can be grouped into sets such that each set is densely connected internally) but do not share any edge are represented closely. In other words, the visualization tends to be coherent with the clustering algorithm. The size of the node is proportional to its in-degree while the color express the cluster to which each node belong. Finally some of the labels of nodes and clusters are shown.

Each node is a technology and each edge represent a Wikipedia link between the pages. The size of the nodes is proportional to the in-degree, and the colors represent the clusters.

The algorithm we used to compute the modularity of each node and thus to assign a group to each of them is described in Blondel et al. (Blondel et al., 2008). The process resulted in 11 clusters. The content of each cluster is (for each cluster we can see the first 15 nodes in terms of in-degree):

1. *Big Data*: Virtual machine, Data mining, User interface, Algorithm, Com-

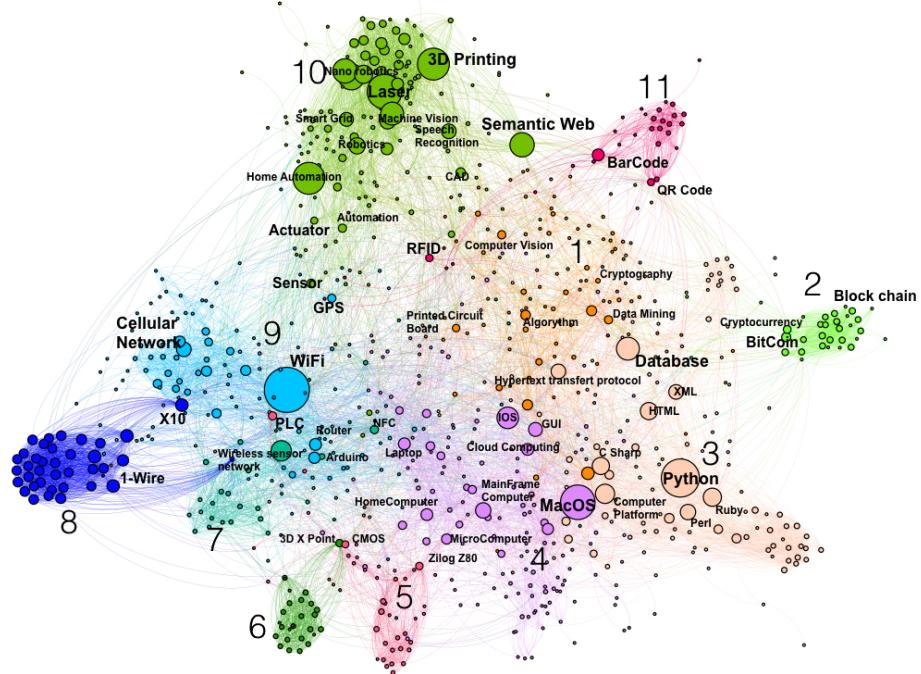


Figure 7.7: Representation of the graph of 4.0 technologies and of the clusters in which them are arranged.

- puter vision, Cryptography, Printed circuit board, Middleware, Real-time computing, Virtual reality, Augmented reality, Human-computer interaction, Multiprocessing, Decision support system, Supervised learning
2. *Transactions, digital certification, digital currency:* Bitcoin, Cryptocurrency, Bitcoin network, Cryptocurrency tumbler, Digital currency exchanger, Alternative currency, Dogecoin, Ethereum, Litecoin, Monero (cryptocurrency), Namecoin, Peercoin, Virtual currency, Auroracoin, Blockchain, Lisk, Primecoin, Ripple (payment protocol), Titcoin, Zerocoin
 3. *Programming languages:* Python (programming language), Database, Computing platform, Ruby (programming language), C Sharp (programming language), HTML, Perl, Hypertext Transfer Protocol, XML, Java (software platform), Haskell (programming language), .NET Framework, Lua (programming language), Sun Microsystems, BASIC
 4. *Computing:* MacOS, IOS, Mainframe computer, Graphical user interface, Cloud computing, Home computer, Laptop, Solaris (operating system), Microcomputer, Personal digital assistant, QNX, Read-only memory, Tablet computer, ASCII, DOS
 5. *Embedded Systems:* Programmable logic controller, Zilog Z80, CMOS, Zilog Z8, Toshiba TLCS, Zilog eZ80, NEC µPD780C, MOS Technology 6502, R800 (CPU), U880, Zilog Z180, Zilog Z800, Zilog Z8000, 1858 1, Hitachi HD64180
 6. *Intel:* 3D XPoint, Intel ADX, Intel Clear Video, Intel SHA extensions, Intel System Development Kit, Intel 1103, Intel AZ210, Intel Cluster Ready, Intel Compute Stick, Intel Display Power Saving Technology, Intel Mobile Communications, Intel Modular Server System, Intel PRO/Wireless, Intel Quick Sync Video
 7. *Internet of Things:* Wireless sensor network, Near field communication, Arduino, NetSim, Z-Wave, OPNET, Telemetry, RIOT (operating system), Routing protocol, TinyOS, Internet of things, NesC, MiWi, Nano-RK, LinuxMCE
 8. *Protocols & Architectures:* 1-Wire, Profibus, Smart meter, X10 (industry standard), Modbus, Local Interconnect Network, TTEthernet, Fleet Management System, Keyword Protocol 2000, Meter-Bus, MTConnect, OPC Unified Architecture, PROFINET, RAPIEnet, SAE J1587
 9. *Communication Network and Infrastructures:* Wi-Fi, Cellular network, Router (computing), Internet Protocol, Radiotelephone, ARPANET, Radio frequency, Digital subscriber line, General Packet Radio Service, Global Positioning System, CYCLADES, Beacon, Wireless, High Speed Packet Access, Evolution-Data Optimized
 10. *Production:* Laser, 3D printing, Home automation, Agricultural robot, Nanorobotics, Semantic Web, Machine vision, Nanotechnology, Robotics,



Figure 7.8: Wordcloud of the words belonging to the class 11 labelled as Identification. In this figure the size is proportional to the logarithm of the in- degree of each node that represents a word.

Information and communications technology, Speech recognition, Smart grid, Memristor, OLED, Computer-generated holography

11. *Identification:* Barcode, RFID, QR code, MaxiCode, Mobile tagging, Code 128, GS1 DataBar, High Capacity Color Barcode, Aztec Code, Barcode printer, Bicode, Codabar, CPC Binary Barcode, Interleaved 2 of 5, ITF-14

Let us examine more in depth a cluster, such as Identification (cluster 11). The size and colour of the words are proportional to the in-degree of the nodes as shown in Figure 7.8.

7.2 Industry 4.0: a Comparison with Industrie 4.0

The Industry 4.0 paradigm can be understood and implemented differently in different industrial eco-systems, depending on the country in which it is adopted. In the present section we make use of Wikipedia to build a network of pages regarding industry 4.0 in such a way that it is possible to map how a country is actually implementing the industry 4.0 paradigm. To analyze the differences between the industry 4.0 concept in the country of origin (Germany) and the rest of the world, our approach is thus to investigate the Wikipedia pages of Industrie 4.0 and Industry 4.0 and the pages they are connected to. Using clustering algorithm it is then possible to explore the different focus that countries have on different technological sub-field of Industry 4.0.

All aspects during our analyses and the description of the project, e.g. page names, consist of two parts: one in English and one in German. For simplicity and better

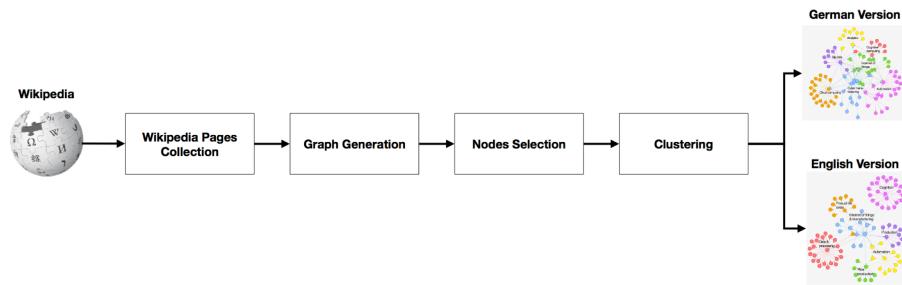


Figure 7.9: The workflow shows the steps we followed to generate the two graphs of industry 4.0 related concepts.

understandability, we will mostly refer to everything only by the English name.

7.2.1 Methodology

In the present section we explain the methodology we adopted to build and analyze the two graphs of Wikipedia pages representing the concepts linked to industry 4.0 in Germany and in the rest of the world. As a proxy of the world-wide vision of industry 4.0 we analyzed the English version of Wikipedia. The main steps of our methods are represented in the workflow of figure 7.9. The first step consisted of extracting all pages of interest from Wikipedia. Then the pages and their connections were used to build two graphs (the German and English version). The nodes of the graphs were then cleaned using a novel approach based on the categories of the Wikipedia pages. Finally a clustering algorithm was used to illustrate communities within the graph. These steps are described in the following sections.

Wikipedia Pages Collection

To list the pages connected to the concept of Industry 4.0, all Wikipedia pages that are linked to the page of Industry 4.0 (and Industrie 4.0) were downloaded. We will refer to these pages as level 1 connection. Then all the pages linked to the level 1 pages are collected and marked as level 2 pages. This process can be continued until a wanted level is reached: for the purposes of the present work we decided to show the effectiveness of the process stopping at level two. For each page, we collected the links to other pages and the categories of the page.

Graph Generation

Two pages that are linked by a link within Wikipedia share a certain relations of which we ignore the meaning. Thus, it is possible that the approach we described until now, also collects pages that are not relevant for the analysis. In our

case, this means that some of the extracted pages are not technologically related to the subject of Industry 4.0. Thus, the list of entries had to be cleaned from these non-relevant ones. To make the filtering process more efficient, we filtered considering the categories that had been extracted together with the pages. We considered as relevant all the categories of the pages of level 1. Then the level 2 pages were automatically considered to be relevant if they were in one of the formerly marked categories. For the nodes selection we also used a black-list of non-relevant Wikipedia pages (e.g. International Standard Name Identifier, International Standard Book Number, Digital object identifier, ISBN), previously developed by the authors in (see chapter 7.1). This list has been traduced in German for the purposes of the present work.

Clustering

In order to identify macro topics in the formerly created graphs, we applied clustering methods. The most beneficial results were found to be generated by applying a spin glass algorithm, which employs the spin glass model and uses simulated annealing to find communities in networks (Reichardt and Bornholdt, 2016). In this approach the community structure of the network is interpreted as the spin configuration that minimizes the energy of the spin glass with the spin states being the community indices.

7.2.2 Results

In this section we will focus on describing the differences that emerges between the two national technological approaches of industry 4.0 in Germany and in the rest of the world.

The collected pages

We collect 97 pages for the German graph and 95 pages for the English graph. A list of a sample of forty pages per language, alphabetically ordered is:

- **German Version:** Absatzwirtschaft, Automatisierung, Automatisierungsgrad, Automatisierungstechnik, Autonomic Computing, Autopoiesis, Betriebswirtschaftslehre, Corporate Evolution, Cyber-physisches System, Dataset, Daten, Datenabgleich, Datenarchitektur, Datenaustausch, Datenbasis, Datenelement, Datenfeld, Datenmanagement, Datenmodell, Datenmodellierung, Datensicherung, Datenstruktur, Datentyp, Denken, Dienst (Informatik), Dienstleistung, Digitales Objektgedächtnis, Elektronische Datenverarbeitung, Erfahrungskurve, Erinnerungsvermögen, Feld (Datentyp), Feldgerät, Fertigungsline, Fließbandabstimmung, Fließbandfertigung, Gegenwart, Geschichte der Produktionstechnik, Glauben, Gruppenfertigung, Halbzeug.

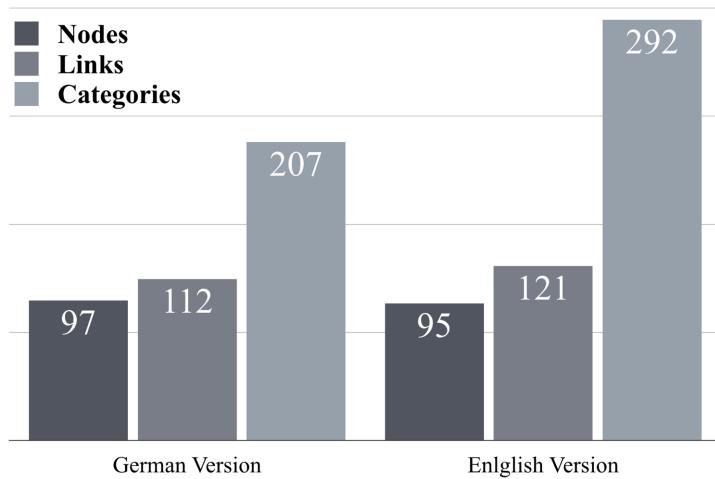


Figure 7.10: Number of nodes, links and categories for the German version of the graph (left) and the English version (right)

- **English Version:** Adaptive system, Agent-assisted automation, Ambient intelligence, AmbieSense, Analytics, Artificial intelligence, Automated reasoning, Automation, Autonomic computing, Autonomous car, Big data, Big Data Maturity Model, Big memory, Carrier cloud, Cloud-based design and manufacturing, Cloud analytics, Cloud collaboration, Cloud computing, Cloud computing comparison, Cloud computing security, Cloud database, Cloud engineering, Cloud Foundry, Cloud management, Cloud manufacturing, Cloud research, Cognitive computer, Cognitive computing, Community cloud, Competitions and prizes in artificial intelligence, Computer-aided engineering, Computer-aided technologies, Computer-integrated manufacturing, Computer vision, Continuous analytics, Control loop, Control system, Cyber-physical system, Cyber manufacturing, Datafication.

The Graphs

The dimension of the graphs in terms of nodes, links and categories are shown in Figure 7.10. From this figure is evident how the two graphs has almost the same number of nodes; by the way, the mean number of categories for the German version is close to 0.5 while its 0.3 for the English version. Beside these measure, as it would be even more evident from further analysis, there is the broader approach to industry 4.0 in the rest world with respect to the more focused vision that Germany has.

The resulting graphs are shown in figure 7.11 (respectively the German version on the left and the English version on the right). Here the vertices of the graphs represent the Wikipedia entries, while the links are depicted by arcs that are

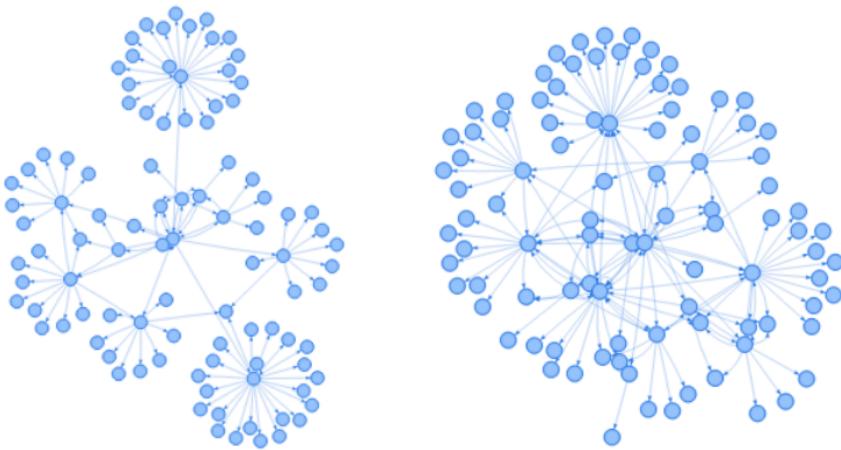


Figure 7.11: The German version (left) and the English version (right) of the Industry 4.0 related graphs.

directed from the originating page to the linked page. The structures of the two graphs and the difference in the number of links gives an evidence of the more focused network of concepts in Germany: the number of links is in fact lower for Germany, creating a more clustered graph.

Graph metrics

In this section we analyze the graphs using standard metrics. These measures allow investigations about relevant topology and specific features of a given graph. More precisely, we looked at the following measures:

- Graph diameter: calculates the longest shortest path in a graph, thus, the minimal distance between two nodes that are the furthest away from each other.
- Nodes Degree: Shows the number of nodes that every node is connected to. The mean value of the degree for the whole graph shows how interconnected the graph is: the higher the value, the more connections the nodes have with each other.
- Nodes Distance: Gives back the minimum number of edges that connect one node with each other. Here again, the mean value shows the interconnectivity of the graph: A lower value means that the way from one node to another is shorter, thus that the graph is more highly connected.

The results of these metrics for the two graphs are:

- German Version: Diameter= 4, Mean Degree= 2.38, Mean Distance= 3.25
- English Version: Diameter= 4, Mean Degree= 3.29, Mean Distance= 3

From the diameter measure we can see that all of the pages are connected through a maximum of 4 edges. This is not surprising, since it was a premise of the method when setting the level to 2. Considering the mean degree, a level of 2.38

for the German version and 3.29 for the English version shows how the nodes of the English graph are more interconnected. This can also be qualitatively observed when looking at the figures 3. Finally, the average distance from one node to another is higher in the German graph, supporting the finding of the measures discussed above.

These findings goes in line with what is said by a study of Acatech (Kagermann, 2006): in the USA, for example, the term Industry 4.0 is understood in a much wider meaning. Furthermore, Acatech study say that in Germany, the focus is mostly on technological dimensions, while in the USA, the development of the new business models in the area of big data analytics play a greater role, among others.

Clustering

Figure 7.12 shows the outcomes of the clustering process: the vertices of the graphs represent the Wikipedia pages, the links are depicted by arcs that are directed from the originating page to the linked page and the clusters are represented by the different colors of the nodes. In order to make these clusters comparable, the label of the German version are translated in English. The resulting, corresponding groups as well as the number of nodes they contain can be found in table 7.2.

Considering together figure 7.12 and table 7.2, it is evident how the central node of the graph (Industry 4.0) is contained in the first cluster Internet of things & manufacturing for both the graphs. It is also by design connected to all other clusters, so that no cluster is isolated from Industry 4.0 node.

As evident from table 7.2, the clusters in the two graphs are similar. We have the same five clusters in both graphs and a different one for each language. This shows that Industry 4.0 framework if considered at a more abstract level, is similar in different countries. This is not surprising, since there must be something that made policy and industry call it the same name, but it is a strong result for our methods, able to map bottom-up this phenomenon.

However, when looking at the clusters more closely, some interesting differences get clear. The cluster production, product life circle & flow production, which is completely missing in the English graph, is the one with the higher number of nodes in the German one. This shows how the topic of Industry 4.0 in Germany is much more concentrated on production than elsewhere. In the study of acatech (Kagermann, 2006), it is also explicitly stated that in Germany “ [...] the focus is on optimizing production processes in terms of quality, price and flexibility and delivering better financial returns overall”. The focus on production for Germany is also confirmed by a monitor paper written by the European Commission (Commission, 2016). To give a clearer view of this phenomena, we have to consider that the word production is very similar in meaning to manufacturing. The cluster including the latter (internet of things & manufacturing) has more than the double number of nodes in the English graph with respect to the German one, so it might be that it is rather the wording that makes the difference. Anyway, by

looking at the disposition of the cluster (see figure 7.12) internet of things & manufacturing in the two graphs, it can be observed that in the English version the cluster is strongly integrated with ITC-related topics (Data processing & Analytics, Cognition and Cloud Computing), adding the adjective cyber to the topic of manufacturing.

Additionally, also automation has more entries in the English version and is highly connected not only to internet of things & manufacturing, but also to could computing, which does not even exist in the German version of the graph: it is well known that Germany is not at the front when it comes to the integration of ICT in Industry 4.0. This found is again confirmed by the study of Acatech (Kagermann, 2006), where it is said that “Germany is currently lagging behind with regard to data-driven business models and the development of large platform ecosystems”.

The fact that cloud computing does not show up in the German graph is examined more closely. In fact, a Wikipedia page about this topic does exist in the German version of Wikipedia, but is not linked to the Industrie 4.0 page. As stated in section 4.3, contributors of the German version of Wikipedia tend to add only the most important connections between pages. This again shows that integrated ICT is not the most important topic in Germany now.

Another great difference in the number of nodes is in the cluster cognition, which seems to be more important in the German version of the graph. The German Wikipedia page describes this as a processing and rearrangement of information between a human and a system. Acatech study (Kagermann, 2006) does the same observation: “In Germany in particular, the focus is on integrating information, communication and manufacturing technologies”. This could explain even better the finding that the German graph lacks on the ICT side, giving a new interpretation: in Germany there is a different interpretation of the meaning of cognitive computing with respect to the rest of the world.

Finally, while the group of data, processing and analytics nearly has the same amount of nodes, the links of this cluster with the other clusters is quite different in the two graphs and also its content changes from one nation to the other. Words like big data does not even exist in the list of German pages related to industry 4.0 where it is limited to just data. This emphasizes the careful approach of Germany with this topic, which was also observed in (Wee et al., 2015). Germany seems to be rather conservative when it comes to new emerging technological trends or even buzz-worlds like Big Data.

Table 7.2: Clusters names and number of nodes per cluster for each version of the Industry Graph 4.0.

Cluster	# Nodes German	# Nodes English
1- Internet of things & manufacturing	12	28
2- Cognition	23	7
3- Data, processing & analytics	23	19
4- Automation	12	20
5- Cloud computing	-	21

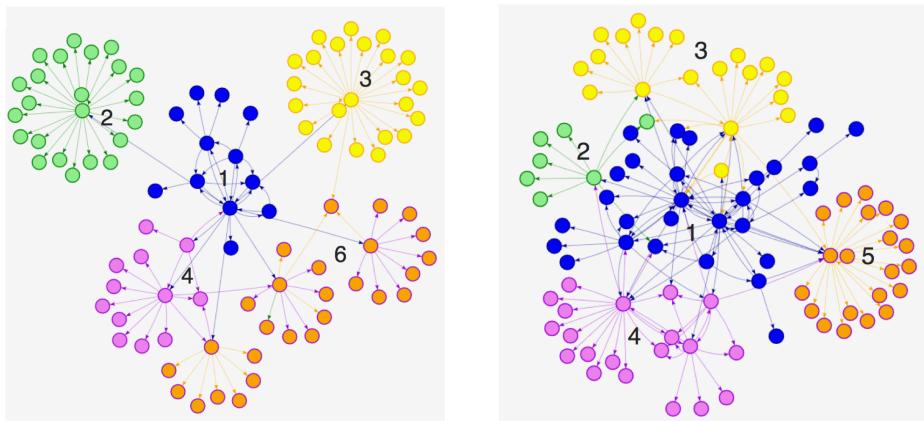


Figure 7.12: The German version (left) and the English version (right) of the Industry 4.0 clustered graphs.

Cluster	# Nodes German	# Nodes English
6- Production, product life circle and flow production	27	-

Chapter 8

Social Media

The technical knowledge generated by Social Media remains largely untapped. Some researchers proved that social media have been a valuable source to predict the future outcomes of some events such as box-office movie revenues or political elections. Social media are nowadays also used by companies to measure the sentiment of customers about their brand and products.

This chapter proposes a new social media based model to measure how users perceive new products from a technical point of view. This model relies on the analysis of advantages and drawbacks of products, which are both important aspects evaluated by consumers during the buying decision process. This model is based on a lexicon developed in a related work (see chapter 5.2) to analyse patents and detect advantages and drawbacks connected to a certain technology.

The results show that when a product has a certain technological complexity and fuels a more technical debate, advantages and drawbacks analysis is more efficient than sentiment analysis in producing technical-functional judgments.

8.1 Technical Sentiment Analysis

Nowadays, social media have become an inseparable part of modern life, providing a vast record of mankind's everyday thoughts, feelings and actions. For this reason, there has been an increasing interest in research of exploiting social media as information source of knowledge although extracting a valuable signal is not a trivial task since social media data is noisy and must be filtered before proceeding with the analysis. In this domain, sentiment analysis, which aims to determine the sentiment content of a text unit, is considered one of the best data mining method. It relies on different approaches (Collomb et al., 2014) and it has been used to answer research questions in a variety of fields comprised the measure of customers perception of new products (Mirtalaie et al., 2018b). In this section, we try to understand if sentiment analysis is really the best available method to

analyse consumer's perception of products, especially when we want to measure the perception of the technical content of the product. Thus we compare State of the art sentiment analysis techniques with a lexicon of advantages and drawbacks related to products.

8.1.1 Methodology

Our work started with the selection of an event able to polarise Twitter users' attention and products to analyse. In particular, we chose a premiere tradeshow for the video game industry, and two video game consoles disclosed during the event. We collected about 7 millions tweets about products published before, during and after the tradeshow. Since social media data is noisy (for example it may contains spam and advertising), before proceeding with the analyses, we filtered our dataset. In particular, after removing too short and non-English tweets, we manually classified a randomly extracted subset of posts to train a classifier which provide us the cleansed dataset. Then we conducted a sentiment analysis of the tweets using state of the art machine learning techniques. We classified each tweet as positive, negative or neutral. At this point we applied our lexicon identifying advantages tweets and drawbacks tweets. Finally we compared the outputs of the two analyses for the two product-related clusters of tweets. We found consistent differences between the extractions. The results shows that when a product has a certain technological complexity and fuels a more technical debate, advantages and drawbacks analysis is more able than sentiment in producing technical-functional judgements. For this reason we think that the proposed methodology performs better then standard sentiment analysis techniques when a product has a certain technological complexity and fuels a more technical social media discourse.

Selection of a triggering event and products

We chose the Electronic Entertainment Expo as event able to polarise users' attention. Commonly referred to as E3, it is a premier trade event for the video game industry, presented by the Entertainment Software Association (ESA). We chose two new video game consoles, disclosed at E3 2017, as products of which predicting the success or failure. The first is Xbox One X, a new high-end version of Xbox One with upgraded hardware and the other product is New Nintendo 2DS XL, a streamlined version of the handheld console New Nintendo 3DS XL.

Data collection

Twitter provides two possible ways to gather tweets: the Streaming Application Programming Interface (API) and the Search API. The first one allows user to obtain real-time access to tweets from an input query. The user first requests a connection to a stream of tweets from the server. Then, the server opens a streaming connections and tweets are streamed in as they occur, to the user. However, there are a few limitations of the Streaming API. First, language is not

specifiable, resulting in a stream that contains tweets of all languages, including a few non-Latin-based alphabets, that complicates further analysis. Instead, Twitter Search API is a Representational State Transfer API which allows users to request specific queries of recent tweets. It allows filtering based on language, region, geolocation, and time. Unfortunately, using the Search API is expensive and there is a rate limit associated with the query. Because of these issues, we decided to go with the Twitter Streaming API instead. For each product, we detected related hashtags and keywords and constructed a query to download relevant tweets. We chose to collect tweets not only after the tradeshow, but also before. For these reason, we initially identified some products keywords with their provisional names and we updated them at a later stage. Tweets have been downloaded from CNR (Consiglio Nazionale delle Ricerche, Istituto di Informatica e Telematica, Area di Pisa) since 11th June 2017 h. 10:00 to 31th July 2017 h. 15:00.

Data filtering

The initial dataset resulted to be very noisy, containing tweets written in different languages, advertising and posts related to different products or subjects. We chose to keep into account only English tweets because sentiment and advantages/drawbacks lexicon is in this language. The data set is filtered removing tweets with less than five words and non-English posts with a language classifier. We obtained 7.165.216 of filtered tweets.

At this point we created a golden set of relevant tweet to train a Supported Vector Machine classifier able to recognize relevant and unrelevant tweets. We defined characteristics that make a tweet: (i) relevant (posted by users or containing words or opinions related to our products of interests and their functionalities), (ii) irrelevant (tweets containing advertisings, links to e-commerce websites or messages related to other products or subjects). A researcher manually classified a subset made up of randomly extracted tweets. In particular, we extract a subset composed of 6.500 finding 105 positive results and 6.395 negative. SVM model was then trained using this dataset, and computed a probability for each tweet to be relevant or irrelevant. A threshold of 0.7 has been chosen to label a tweet as relevant. The final dataset of filtered tweets, made up of 66.796 posts. We clustered tweets using product-related keywords. Clustering posts allowed us to further filter the final dataset which contained a small number of irrelevant tweets (Table 8.1).

Table 8.1: Clusters of tweets.

	N° of tweets	% of tweets
Xbox One X	64885	0.9714
New N2DS	1706	0.0255
Irrelevant tweets	198	0.0030

Sentiment analysis

Table 8.2 presents the results of the sentiment analysis. We classified each tweet according to its sentiment into positive, negative, or neutral. We used an established methodology developed by (Cimino et al., 2014). We pre-processed the tweets by removing mentions (@ character), URLs, product hashtags, emoticons and single characters. As a result, for each tweet we obtained a probability of belonging to a mood class. After a manual analysis, we used a class prediction probability threshold of 0.6 to filter out low confidence prediction, i.e. tweets that cannot be classified as positive or negative with a high confidence are classified as neutral instead.

Table 8.2: Clusters of tweets.

	Positive	Negative	Neutral
Xbox One X	0.3599	0.0465	0.5937
New N2DS	0.5299	0.0158	0.4543
Overall	0.3642	0.0457	0.5901

Advantages and drawbacks analysis

To extract technical advantages and drawbacks from tweets we used the lexicon developed in chapter 5.2 that contains 657 Advantages words and 297 Drawbacks clues. These words are searched on our dataset finding different percentages of tweets with words from the lexicon in the two product-related clusters of tweets. Table 8.3 reports the results.

Table 8.3: Percentages of tweets containing or not words from our lexicon.

	Adv	Drw	Adv & Drw	No Adv or Drw	Adv or Drw
Xbox One X	0.0884	0.0374	0.0037	0.8705	0.1295
New N2DS XL	0.0662	0.0094	0.0000	0.9244	0.0756

8.1.2 Results

We adapted the advantages & drawbacks analysis to give as output a classification of each tweet. We classified data coming from the latter analysis in this way:

1. positive (tweets containing only advantages words)
2. negative (tweets containing only drawbacks)
3. neutral (tweets with no words of our lexicon or controversial tweets)

As we can see in figure 8.1, sentiment analysis is more able to polarise tweets. In

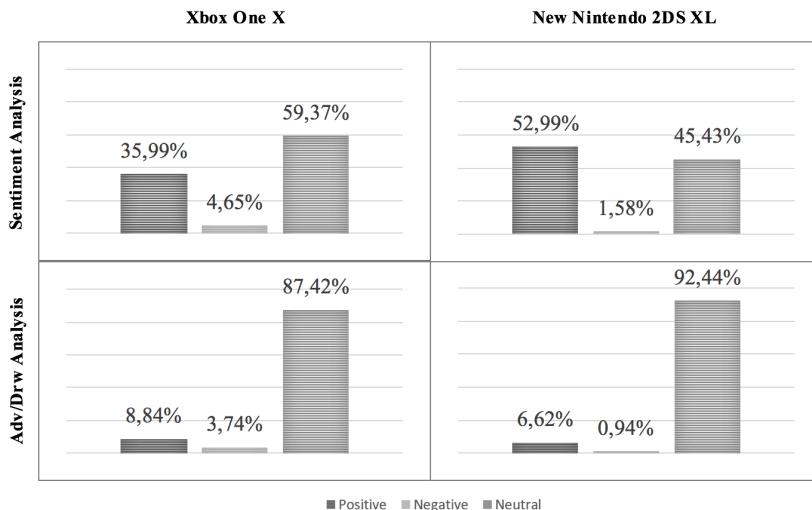


Figure 8.1: Comparison between Sentiment analysis and Advantages/Drawbacks analysis.

fact, with this analysis we found lower levels of neutral tweets, respectively 59.37 % for Xbox One X and 45.43% for the New Nintendo 2DS XL.

This was an expected result since this kind of analysis is designed to deal with colloquial language while our lexicon is technical, being derived from patents analysis. What surprised us is the different polarisation of the products that we see comparing the two analyses. In fact, while with sentiment analysis Nintendo achieves lower percentages of neutral tweets, with advantages and drawbacks analysis is the opposite, since Xbox tweets are more polarised. We also noted that we found more tweets with words of our lexicon in the Xbox subset than in the Nintendo one (8.3). We did the hypothesis that the differences between the percentages of tweets with words found for each product, and the differences of polarisation between the two analyses depend on the different marketing focus, target customer, and technological complexity of the two new video game consoles. Xbox One X targets hard-core gamers who really wants a premium experience ¹. With its marketing campaign, Microsoft pushed the technical supremacy of its new machine over the competitors' products, fuelling a debate about its technical features amongst the potential users.

As a result, the campaign produced a more technical social discourse that allowed us achieving better results. Instead, the new Nintendo handheld console has been developed targeting children and families providing a model that falls somewhere in the middle of the line of 3DS consoles ². We initially checked our hypothesis

¹<http://www.businessinsider.com/why-xbox-one-x-costs-500-2017-6?IR=T> (last access: 17/11/2017)

²http://www.nintendolife.com/news/2017/05/reggie_explains_the_reasoning_behind_the_new_2ds_xl (last access: 17/11/2017)

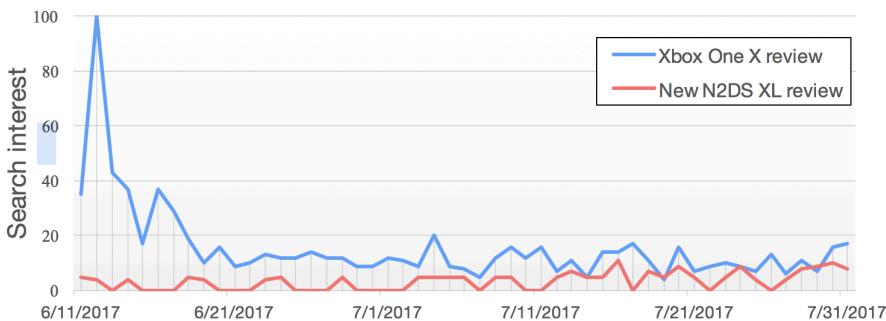


Figure 8.2: Google Trends comparison of search-terms “Xbox One X review” and “New Nintendo 2DS XL review” during the data collection period, since 11th June 2017 to 31st July 2017. Values on the vertical axis depict search interest compared to the highest point in the graph during the observation time. A value of 100 is the peak popularity for the term. On average, users searched for Xbox reviews with an approximately five times higher frequency.

using Google Trend to compare users’ search interest about technical review of the two products during the data collection period (Figure 8.2). Then, we analysed the number of technical articles related to the new products published by the 25 most popular video games and technology websites in the U.S, according to the ranking of SimilarWeb, a digital marketing intelligence company which publishes insights about websites. We used Google search engine to retrieve technical article within the web domains previously identified: we obtained 1.117 articles about Xbox and only 52 about Nintendo, proving that technical debate concerning Xbox is greater. This is and evidence of the fact that when a product has a certain technological complexity and fuels a more technical debate, advantages and drawbacks analysis is more able than sentiment in producing technical-functional judgements. The greater number of neutral tweets found with advantages and drawbacks analysis can also be explained with the Means-end chain model (Reynolds et al., 1995). Consumers express themselves basing on personal consequences linked with product use or basing on personal values satisfied by the product itself. For these reasons, tweets contain a more colloquial language which sentiment analysis is more able to interpret than the latter tool.

Part IV

Applications of the Results

It has been highlighted by the guidelines of design research (Bichler, 2006) that effective design-science research must provide clear and verifiable contributions in the areas of the design artifact, design foundations, and/or design methodologies. For this reason the present section is a collection of projects that describes the applications and results of the methods designed in *Part 3 “Methods and Results”*.

All the specific technologies from the previous chapters are exploited, and each chapter of the present part will show a specific application based on the technologies. The sequenct chapters provide an in depth view of the possible applications of the tools with respect to the previous ones that are more focused on how the tools where developed.

Chapter 9

A Novel Representation of Patents

Due to the complexity and volatility of user needs, companies increasingly ask product designers and engineers to create ideas that meet needs in novel and better ways, rather than just making existing technologies more attractive (Brown and Wyatt, 2010). As a matter of fact, these professionals are nowadays involved in the process of understanding in depth what users want and desire (Haley, 1968; Day et al., 1979). Unfortunately, it is well known that user needs are usually examined in separate business departments, such as marketing or business development, and are described in a language that is remote from the professional practice of product designers and engineers. The relation between the understanding of user needs by marketing departments and the development of new products by technical departments is a deeply troubled one. There is a large agreement within the design community that this state of affairs is not optimal and that dedicated efforts should be made to reconcile the engineering approach with a more articulated understanding of user needs, particularly of consumer needs (Pahl and Beitz, 2013; Eppinger and Ulrich, 1995).

A promising approach is based on the description of products in terms of advantages and disadvantages, or drawbacks. Users typically choose an artifact considering the advantages that it brings and the disadvantages that it solves. Advantages and drawbacks exist if they have an impact on the user and if they affect the product in terms of effectiveness (the level at which the product reaches its goals) and efficiency (how many resources does the product have to consume to reach its goals).

At the state of the art, the two main tools to manage advantages and drawbacks developed by the design community are QFD and FMEA/FMECA. Companies frequently make use of Quality Function Deployment (QFD) in order to generate lists of requisites, users' needs, users' requirements and to guide the design process (Carnevalli and Miguel, 2008). They use FMEA/FMECA to gather and

study drawbacks, failure modes and their effects and causes (Liu et al., 2013). On the other hand, the notion of advantages is also at the core of marketing techniques used in the segmentation of markets (benefit segmentation) and in the identification of alternative design solutions to achieve desired benefits (means-and-ends-chain analysis).

The interest in the description in terms of advantages and drawbacks is that it can be interpreted smoothly from the two sides of this troubled relationship: engineers can easily link them to performance specifications (usually described with a functional language) and hence technical specifications, while marketing experts can read them with the language of social sciences (for example, psychology, semiotics, sociology or anthropology). Given the promise of this description, why is it used so rarely?

There are several reasons. First, information on user needs is typically owned by users, and is stored in implicit and non codified formats. Second, and consequently, in order to access this information product developers must enter into direct and personal contact with users, listening and understanding the voice of the customer. Not only this is very expensive, but the experience shows that the earlier the stage of development of needs, the more ambiguous, fuzzy and uncertain the information obtained by users. Third, most of this information is not publicly disclosed but is kept confidential as company know-how. Researchers have hard time to access structured analyses of products based on advantages, even more so for descriptions based on drawbacks. Thus the goal of building up full scale descriptions based on advantages and drawbacks is still elusive.

In the present work we consider patents as a possible alternative information source for advantages and drawbacks. As stated by the World Intellectual Property Organization (WIPO), an invention is a solution to a specific technological problem (Organization, 2004). The problem that an invention solves in a technological field is a certain negative effect that the state-of-the-art technologies cannot overcome; on the other side, a solution is the way to solve this problem. A solution can lead to some advantages with respect to the known state of the art. Thus, starting from the definition of invention, it is clear how it can be characterized by its advantages and the problems it solves. Based on these definitions, the WIPO explicitly suggests as a guideline for applicants to write patents in this language. The applicant (the person or company that applies for the patent) is led to include this information in patent documents in order to have more chances of success in the patenting phase.

An important feature that makes patent information valuable is that the information that is contained in these documents today will be contained in other documents, like manuals, handbooks and market reports, to which designers are more accustomed, in the future: information anticipates availability of products on the market by a factor varying from 6 to 18 months (Golzio, 2012). In addition, these documents are freely accessible by many different databases nowadays (Kim and Lee, 2015).

To claim that patents include descriptions in terms of advantages and drawbacks is one thing, to show how this information can be used effectively, however, is a

completely different business. To test the hypothesis of the presence of advantages and drawbacks information in patents and to exploit this information for design purposes, there is a need to overcome two main problems:

- analyzing patents requires skilled personnel and long time (León-Rovira and Cho, 2007)
- due to the increase in the number of patent publications, there is a massive information overflow (Bergmann et al., 2008).

In this chapter we present a methodology for the extraction of information on advantages and drawbacks of technologies from patents, that is able to fully overcome these problems (as demonstrated in section 5.2) and with the final goal to make available patent-based structured information to the design community.

9.1 Towards Formal Definitions of Advantages and Drawbacks

Referring to section 5.2, we propose that all useful definitions of advantages and drawbacks can be collapsed into three categories, each with a positive or negative sign, as follows:

1. more/less wanted output obtained . A wanted output is a desired effect of the system.
2. more/less unwanted output obtained. An unwanted output is undesired effect of the system.
3. more/less resources needed. More resources needed to achieve a desired effect imply less efficiency.

This classification can be labelled ADIO classification (Advantages-Disadvantages-Input.Output). The operationalization of this classification for purposes of automatic information extraction and processing is the object of the rest of the paper.

9.2 Methodology

The goal of our system is to automatically extract short sentences that contain information about the advantages and the drawbacks of the technology from patent texts. Furthermore we propose a taxonomy that organizes the output of the system focusing on advantages and drawbacks that have impacts on the systems thus influencing its input or output. A flow diagram representing the adopted method for the automatic ADIO extraction and classification of a technology is shown in Figure 9.1. The method takes as entry a patent set representing the technology to analyze. The patent set and the list of advantages and drawbacks clues are entries

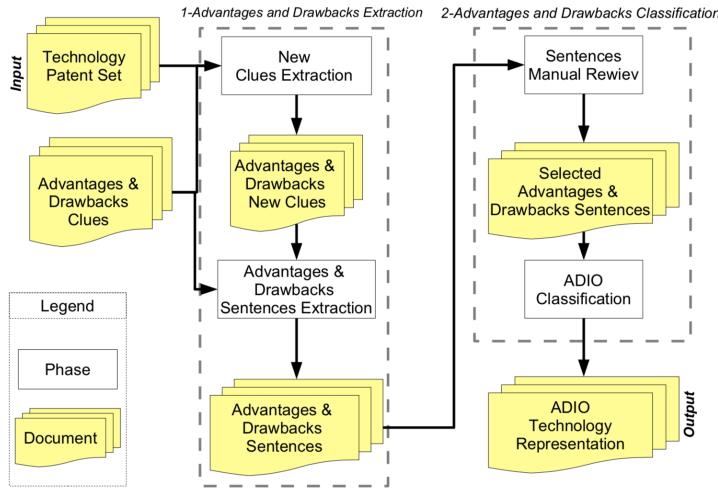


Figure 9.1: Work flow diagram followed to extract the ADIO technology representation from a patent set.

of the process of advantages and drawbacks extraction and generate the phrases containing the advantages and the drawbacks. Than they become the entry of the process of Advantages and Drawbacks classification that exploits human knowledge to classify the technology according to the ADIO representation.

9.2.1 Advantages and drawbacks extraction

The process of advantages and drawbacks extraction is the first of the two-macro processes used in our system. The first process starts from a patent set containing patents inherent to a technology and extract relevant sentences in output. Each sentence describes an advantage or a drawback of the specific technology. All steps of this process are fully automatic. The patent set should be very large, in the order of several hundred (in our case study $n > 1000$ items). To describe with a certain degree of precision an advantage or a drawback, patent applicants have to use sentences of a certain length. Since NER systems are designed to extract single words or short n- grams, we need to extract entities that are clues of the whole sentence that describes the advantage or the drawback. However our interest is not on the clue but rather on the words that follows the clue: the real advantage or the real drawback. We refer to these words as target. Considering the ADIO classification, proposed in the present work, these are words that help to classify whether the advantage or the drawback have an impact on the input (influencing efficiency) or the output (influencing effectiveness) of the system. The few examples above shows how clues are words that indicates a characteristic of a flow or its modification (positive or negative); the clue and target together specify the entity and direction of the modification of the flows that evolve within the system. A summary of these linguistic concepts and some examples are shown in

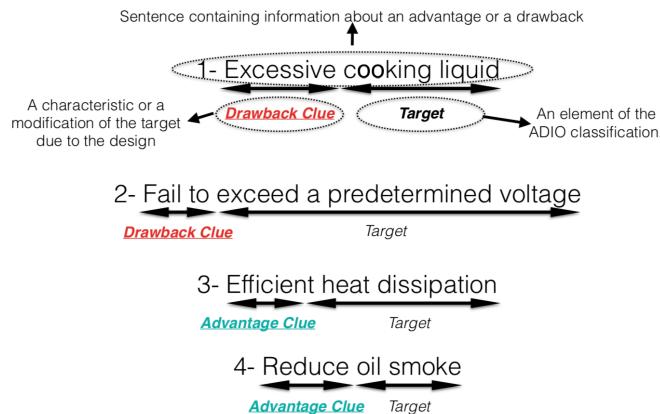


Figure 9.2: Examples of advantage or drawback sentences divided in its clue and target.

figure 9.2.

As stated above, we introduce a crucial concept, that of a “clue” for the identification of a complex text structure describing advantages or drawbacks. We describe here the process for collecting clues. The process is not trivial because the sources are heterogeneous, fragmented and sparse. For example, we can find lists of failures in repositories published in the car industry, lists of diseases or infections in medical treatises, lists of positive and negative words in sentiment analysis tool-chains. Some of them are very accurate but extremely short, domain specific and rarely occurring in patents (e.g. new diseases), while others are broad but ambiguous thus introducing noise in the analysis (e.g. sentiment annotated words). We followed a twofold approach. The first approach consisted in the manual collection of clues of advantages and drawbacks directly from patent texts. This process was performed on 2000 patents in several patent classes. This has led to collect 3.254 advantage-clues and 5.142 drawback-clues. The second approach consisted in looking for alternative methods to indicate advantages or drawbacks clues, finding defined word patterns. The most relevant are the negations of advantages to obtain drawbacks, and the negation of drawbacks to obtain advantages. It is worth noting the cases of suffixes like as -less or -friendly, - free and the like, and prefixes like as anti-, dis- , de-, un- and the like, that allow a rapid and systematic expansion of the database. At the end of the process, advantages numbered 6.568 and the drawbacks numbered 14.809. This is a fairly large knowledge base for the system, and gave us a reasonable number of clues to be used in the next step of the process. Example of clues are shown in section 5.2. The first approach has the limitation that lists were extracted from a random but relatively small sample of patents ($n= 2000$). Another limitation is that the rules used in the second approach are not exhaustive, and they can create non-sense clues, due to the possible combinations of words (e.g. “anti- ability” or “un-problem”). On the positive side, it is reasonable to assume that using these approaches it is possible to collect a

large set of clues that are relatively independent from the patent set. In addition, it is now clear how new clues could be easily extracted when changing patent sets. In order to obtain a larger and complete collection of clues it is unsuitable to use the manual extraction on each domain patent set. For this reason, new clues were iteratively used to train machine learning algorithms.

New Clues Extraction

In this section we briefly describe the system used to automatically extract new word clues from patent texts. The system is based on the work discussed in section 5.2. This process takes in input a corpus of patent documents regarding a certain technology. After the tokenization of the corpus, each token (word or n-gram) is represented by series of features. Then the advantage and drawback clues are re-projected on the text, generating a training set of words to be given as an input to a classifier system. The classifier builds a model able to detect words that have similar behavior (in terms of the selected features) with respect to the behavior described in the training set. The model is used to classify the words contained in patents as potential new advantages or drawbacks word clues. These new words clues are technology specific clues or generic clues that did not belong to the starting list of advantages and drawbacks generic word clues.

Advantages and Drawbacks Phrases extraction

Once all the new 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 extraction is the activity through which the system catches the shortest informative sentence containing each word clues. To do that the patents are processed through a phase of part-of-speech tagging (POS tagging). Starting from the clues, only the POS sequences that match a certain pattern were extracted. The pattern, expressed using a regex regular expression is:

$$(Clue) + Noun.\ast Noun.\ast Noun.\ast$$

This structure has proven to be able to catch a reasonable number of words of the target, exhaustively expressing an advantage or a drawback without catching very long phrases.

9.2.2 Advantages and Drawbacks ADIO classification

The process of advantages and drawbacks classification is the second of the two macro processes involved in our system. This process takes in input the advantages and drawback sentences extracted in the advantages and drawback extraction process and gives in output the ADIO representation of the technology.

Sentences Selection

As stated above, we suggest a clear classification of advantages and drawbacks in a 3*2 structure. After the extraction each sentence is assigned to one of the following classes:

1. more/less wanted output obtained. A wanted output is a desired effect of the system.
2. more/less unwanted output obtained. An unwanted output is undesired effect of the system.
3. more/less resources needed.

If a sentence does not belong to one of these classes it is not taken in to consideration for the next analysis, even if expresses advantages or the drawbacks of the invention. This classification makes it possible to represent the technology using the ADIO representation.

ADIO Technology Representation

Given the classification described above, we obtain three possible kind of advantages and three possible kinds of drawbacks. Considering a wanted or desired output, the achievement or the increase is an advantage, while the negation or the reduction is a drawback. On the other side, considering an input to the system or an unwanted output, negation and reduction constitute an advantage, while achievement and increase are clearly a drawback. It is important to specify that the both the input or the output (wanted or unwanted) could involve flows of matter, energy, or signal.

9.3 Results

9.3.1 Patent set

To test the proposed process, we selected a patent set composed of a sample of 3,000 patents. The patent sets belongs to the A47J37 IPC patent class defined as "*Baking; Roasting; Grilling; Frying*". We will refer to this patent set as cookers set.

9.3.2 Extraction of Advantages and Drawbacks

Total extracted advantages numbered 4129, drawbacks numbered 1835. After manual review of sentences the total number went to 2509 and 1532, respectively. During the manual review phase each sentence was assigned to one of the three classes of the taxonomy, considering the target of the sentence. The system itself

decides if a sentence indicates an advantage or a drawback, considering the clue. The results in terms of cardinality of the classes of the taxonomy are shown in Table 9.1. As we can see from this table, the sentences review process has led to a balance between the extracted advantages and drawbacks. It is interesting to see how the wanted outputs are more likely expressed as advantages (1786 sentences are advantageous wanted output while 660 are drawbacks); the situation is reversed for the unwanted output (431 sentences or that advantages and 682 for the drawbacks).

Table 9.1: Examples of clues of advantages and drawbacks extracted manually from patents.

Class	Number of Advantages Sentences	Number of Drawback Sentences
Input	292	190
Wanted Output	1786	660
Unwanted Output	431	682
TOT	2509	1532

9.3.3 A-D-I-O Representation

The two ADIO schemes for the advantages and drawbacks of cookers are shown respectively in Figure 9.3. The sentences shown in this figure are a sample of all of the 2662 extracted sentences. Furthermore these sentences are taken as-is from patents, misprints and errors included.

Both the results are promising for future applications in the design fields. In particular Figure 9.3 (a) 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 9.3 (b) 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.

9.4 Discussion

This chapter has proposed a method to extract and summarize sentences that describe advantages and drawbacks of technologies from patents. Advantages and drawbacks are considered as phenomena that influence the efficiency or the effectiveness of products by modifying their inputs or their outputs. Advantages and drawbacks information are useful for designers who want to design new products or to redesign old ones so to meet user needs in novel and better ways. The proposed approach allows patent readers to analyze a massive quantity of patents and to reduce the time needed for research and analysis.

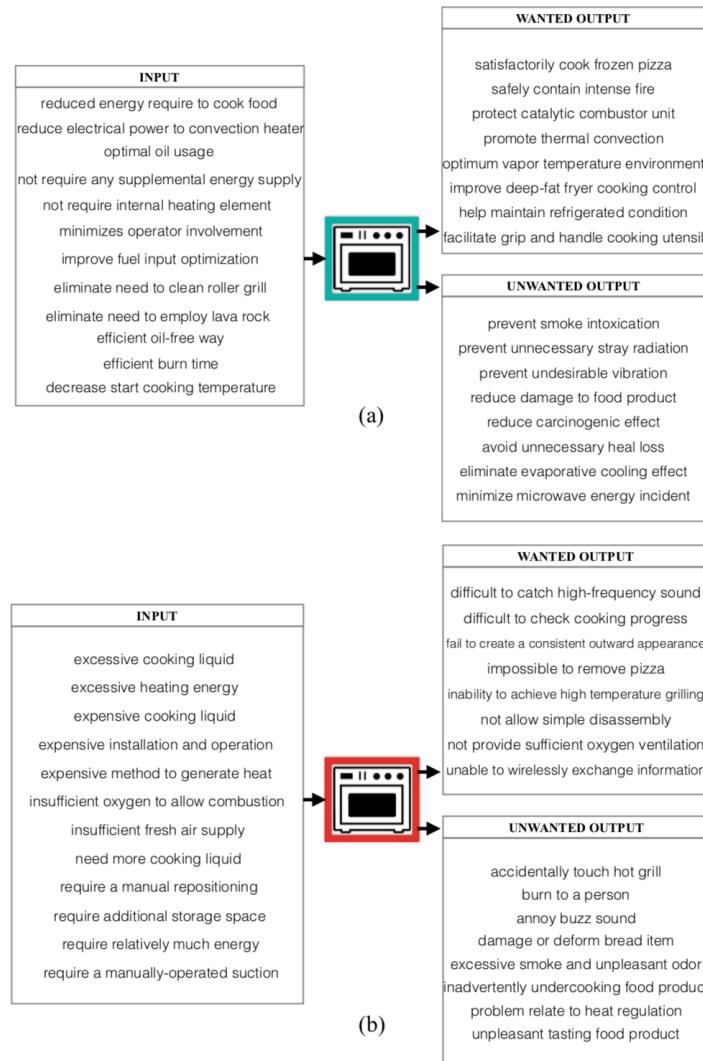


Figure 9.3: Examples of advantage or drawback sentences divided in its clue and target.

Chapter 10

Enriched dictionaries for Innovation

The demand for intelligence and foresight of technologies is increasing due to the need of companies and governments to make sense of the rapidly changing technology landscape and to make better decisions. In particular, emerging technologies exhibit not only rapid growth, but also strong conditions of technology and market uncertainty, so that traditional techniques of technology intelligence are challenged (Rotolo et al., 2015).

Technology intelligence makes large use of a statistical procedure called clustering. This multivariate technique is commonly used to place entities into relatively homogeneous groups, maximizing the difference with other groups, when entities are not subject to an existing classification. In technology intelligence this is the most interesting situation: if technologies were already fully classified, then they would already be established or mature.

It is important to remark that clustering, in one way or another, is almost a necessity in technology intelligence. The amount of data available on technologies, even on the last generation of technologies, is so large that a preliminary effort of clustering and profiling is generally considered a preliminary step for the analysis.

In technology intelligence the formation of clusters is generally based on words extracted from relevant documents (scientific publications, patents, technical standards). There are two main approaches to the extraction of words from documents: extracting from the metadata associated to the document, or extracting from the full text of the document. Examples of metadata are authors, affiliations, inventors, assignees, keywords, titles. This approach has generated a large literature that uses metadata in order to extract usable knowledge. Within this literature, a notable stream of studies has extracted usable knowledge from documents by clustering the metadata in order to obtain meaningful structures. This method is associated to the use of keywords, as we will see below.

More recently, a different approach has been introduced, based on the processing of the full text of documents. Following the remarkable advancements in computational linguistics, it has become possible to process the entire text of publications, patents, or technical standards to a large scale. Here the clustering exercise does not take place on metadata, but on words, or their combinations, included in the text of documents. The topic modeling is the most used approach. Topic modeling is a tool to extract structures of text from corpora without the help of external sources of knowledge (Blei et al., 2003). Once the words have been extracted from metadata or the full text, a clustering strategy must be designed based on an appropriate definition of similarity.

We then suggest the exploration of a novel approach, one that combines domain knowledge with powerful data science techniques, called *enriched dictionaries*. These are large and highly structured collections of words, associated to formal definitions and internal linkages, that are produced on the basis of domain knowledge of various kinds. In some cases they are publicly available, in other cases they are the result of dedicated and idiosyncratic research efforts. These dictionaries can be used in order to “filter” the semantic content of the full text of documents according to pre-defined structures, generated within the domain knowledge and validated at the state of the art. They can be used, therefore, within the so called supervised text mining approach. This section has two objectives: introducing the methodology of enriched dictionaries, and showing that it allows the joint use of several, and complementary, perspectives: one based on the abstract engineering principles of technologies (functional view), another on the advantages delivered by the technology (advantage view). These dimensions are kept separate in the literature and clustering exercises do not combine them. We show the power of clustering technologies using these views in a combined way.

10.1 An overview of dictionaries for technology intelligence

10.1.1 Publicly available dictionaries

One of the advantages of the dictionary approach is the possibility to utilize publicly available dictionaries, that is, available online with unrestricted, free access. We made systematic use of Wordnet, a large dictionary in English language made available and curated by Princeton University. Wordnet is a standard reference in computational linguistics.

Upon the basic Wordnet dictionary, several specialized or dedicated dictionaries have then been developed, which are also available with unrestricted, free access. We made use of the following dictionaries.

- Artifacts: a collection of terms referring to objects, inventions and tools. The dictionary is one of the Name categories available in the Wordnet-based

categorization dictionary from Provalis, free to download¹. Artifacts were chosen to explore texts in order to find structural indications for the components of an invention.

- Acts: a collection of terms referring to generic actions. This is another Name category from the Wordnet dictionary. Acts were selected in order to find verbal expressions referable to functions carried out by the objects described therein.

10.1.2 Research-based dictionaries

The dictionary methodology offers the flexibility to build up dedicated or specialized dictionaries, that represent the state of the art of a given knowledge domain. We make use of two dedicated dictionaries recently developed by the authors in an academic research context. Needless to say, in these cases the authors must give the readers or users of the dictionary full proof of the completeness of the dictionary, or the compliance with formal criteria for the definition of a dictionary. These proofs have been offered in a number of papers cited below.

Table 10.1: Sources and main characteristics of dictionaries.

Dictionary	Number of entries	Examples of chunks
Artifacts	12374	Acetanilid, Actuator, Aerogenerator, Agglomerator
Acts	5527	Abduction, Abidance, Accenting, Acquiring
Functional Verbs	11256	Abrade, Absorb, Abut, Accelerate
ADV/DIS	29902	Ability, Accelerate, Acceptance, Accessibility, Accident, Accidents, Aggravated, Aggravation

- Functional verbs: list of verbal expressions describing functions, or actions performed by artifacts on given objects (Fantoni et al., 2013; Apreda et al., 2016).
- Advantages and Disadvantages: list of terms referring to measurable benefits or drawbacks related to an object, chosen for their capacity to represent applications of an invention (see section 5.2).

Table 10.1 offers an overview of the dictionaries used for this analysis, with a few examples of terms.

¹<https://provalisresearch.com/products/content-analysis-software/wordstat-dictionary/>
wordnet-based-categorization-dictionary

10.2 The value added of enriched dictionaries

In order to illustrate the original contribution of the enriched dictionary approach, it is useful to refer to similar approaches, recently introduced in the literature. The starting point of this literature is similar to the one advocated in this paper, i.e. the need to supervise the full text mining with the help of list of words that reflect domain knowledge.

A natural candidate here is the list of words that describe technical functions, or the abstract characterization of the working principles of technologies (Cascini et al., 2004; Dewulf, 2006; Cascini et al., 2007; Cascini and Zini, 2008). The pioneering approach in this field is TRIZ, the patent-based methodology that has identified a number of abstract inventive principles (Petrov, 2002), whose application to patent texts has permitted the detection of evolutionary trends in specific technologies (Verhaegen et al., 2009; Wang et al., 2010; Yoon and Kim, 2011a; Park et al., 2013b). A variant of this approach combines the functional approach with lists of product attributes or properties (Yoon and Kim, 2012; Yoon et al., 2011; Kim et al., 2010). More recently, a similar approach has been introduced, suggesting that subject-action-object (SAO) linguistic patterns can be derived automatically from the full text of patents (Yoon and Kim, 2011b; Choi et al., 2012; Park et al., 2011b). A SAO textual sequence is considered an indication of the engineering principle that describes an action that is changing an object. Choi et al (Choi et al., 2012) reviews the state of the art of function-based technology databases (in particular, TRIZ and Creax) but suggest that SAO structures are more versatile and flexible in order to apply Natural Language Processing techniques.

Within this line of investigation the notion of technology tree (Tech Tree) has been introduced (Choi et al., 2012). It combines within a single representation taxonomies of products, technologies, and abstract functions. Similarity matrices are built along these dimensions and aggregated.

While these two approaches have generated a large and interesting literature, their main limitation is the lack of transparency. The queries obtained from the TRIZ inventive principles have not been published and there is no demonstration of their reliability (i.e. replicability under controlled conditions) with respect to all semantic variations of words. Similarly, the SAO queries, although intuitively clear, leave the readers and users with the problem of establishing the semantic content in the engineering sense, given that the notion of “action” may cover, in fact, many different meanings.

10.3 Methodology

The cited studies have suggested that a mixed approach to the clustering problem could be the best solution to achieve good results. In particular there is a need for placing more domain knowledge into the analysis, while keeping the enormous advantages of text mining and automatic knowledge representation techniques.

This is the starting point of the dictionary approach we propose. It suggests that the full text of technical documents is searched by using a structured list of words, generated from a substantive body of domain knowledge, formally defined, and organized in a hierarchical way.

A dictionary, in substance, is a collection of terms pertaining to a precise context and then selected following a logical pattern. The content of a dictionary may sensibly vary from case to case, comprising terms related to a precise technology, a technical field, a social group, or more generic parts-of-speech such as particular kinds of actions or nouns, and so on.

The main difference between a dictionary and a mere collection of keywords is in their respective scope, which is, for a dictionary, wider and far more complete, including all the synonyms, hypernyms and hyponyms of a term. By definition, a dictionary must include all the definitions and terms referring to the chosen context. The completeness has an important consequence for text mining applications. When a dictionary is used as a tool to filter the content in a collection of texts, the query is formed not only by principal words, but also by secondary words, such as synonyms. These secondary words would be lost if the analysis were based on words and keywords. Therefore dictionaries contribute to overcoming the biases introduced in the analysis by the subjective choice of keywords by experts.

To start with, the dictionary method was combined with topic modelling techniques in order to overcome one of the main limitations of topic modeling, that is, the extraction of irrelevant topics.

The starting assumption is the possibility of representing a document using the main topics cited in it. A topic is, basically, a collection of terms that delineate and describe an argument. Topics may be identified by using unsupervised or supervised methods. The unsupervised application of the method will have the result of giving generic topics, often irrelevant in specialized analysis. This outcome can be mitigated, but not eliminated, by the application of ranking techniques, such as Term Frequency-Inverse Document Frequency (TF-IDF), that allow the identification of coherent topics. Alternatively, analysts may refer to supervised methods, which are however resource-consuming in their design and implementation. The dictionary approach offers an excellent solution to the trade-off between relevance and precision of the search, which plays in favor of supervised methods, and the parsimony of the analysis, which on the contrary militates for the adoption of unsupervised methods.

In addition, if topics are clearly delineated, it becomes possible to identify similarities between documents that refer to technologies with a transversal, or cross-domain, potential for application. Dictionaries can be used for different purposes and help to identify latent structures from a variety of perspectives. We advocate the use of several dictionaries in parallel, on the same collection of texts, as a way to examine technologies with a variety of perspectives. Figure 10.1 illustrates the main steps of the methodology.

The basic idea of the process is that a document can be represented by the set of terms, numbers, graphic symbols and punctuation that compose meaningful sen-

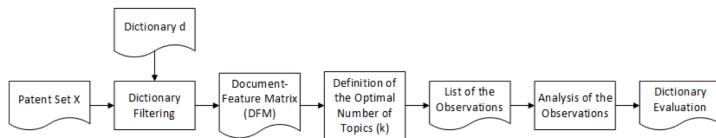


Figure 10.1: Steps of the dictionary approach to the text mining of patents.

tences. The “technical” objects belonging to this set are named Features. Starting from selected patent sets, a Document-Feature Matrix is created using different dictionaries as filters to select only the desired features; the obtained matrices are then used as the starting point to perform a topics number evaluation algorithm, based on the connections between documents with same or similar features. Topics are formally clusters of features, coupled because of their pertinence to the same concept; measuring the percentage of cohesion of a document to each topic recognized is, then, a method to collect information about the contents of the document itself.

Creation of the Document-Feature Matrix

A patent can be represented by a vector exhibiting the number of occurrences, if a given feature is included, and 0 otherwise. Since these features are ordered within dictionaries, all patents in a patent set can be represented with similar vectors. A collection of texts can be therefore represented as a matrix called Document-Feature. A Document Feature Matrix (DFM) is a algebraic matrix with N rows, corresponding to individual documents in the corpus, and M columns representing the features. With this formalization it is possible to measure the occurrences of features in every document contained in the corpus. It is a powerful tool to get a fast quantitative information about a document set, counting the features originated in the dictionaries, with the opportunity of selecting (or removing) some of them.

Each patent in the patent set is filtered using one of the four dictionaries at a time. The resulting list of words was processed in order to eliminate the generic words, or those words that, being diffused across most documents, do not have specific semantic content. This is done by using the stopwords labelled SMART in the text mining literature, in combination with a list of stopwords extracted from the text of patents and including some generic words in the legal language of patents (or “Patentes”), such as claim, invention, right, tool etc.

Due to the large number of entries in dictionaries and the exploratory nature of this work, we restricted the number of features considered for each of the DFM to 500. The selection was made automatically, by selecting the top 500 terms in terms of share of documents in which they appear. In some cases the selected patent text delivered no matching with the selected features. In this case the patents were eliminated. Thus the final DFM only includes documents with positive entries from the lists of features extracted from the analysis. It must be noted that DFM

are sparse matrices: sparsity is a mathematical parameter, varying from 0 to 1, that indicates how much systems are loosely coupled. In particular, it is a measure of the Z zero-valued elements in a matrix divided by the N x M total number of elements. Thus, a sparse matrix is a matrix in which large part of elements in cells are zeroes. Sparsity it is a good measure of how documents in a corpus differ from each other with respect to their Features.

Documents are iteratively examined in pairs: if two documents share a feature they are considered similar. Various metrics of similarity can be defined and computed. After a measure of similarity is defined, various clustering techniques can be applied as well. In this application we use the cosine similarity, which is largely adopted in the field. Cosine similarity is a measure of similarity between two non-zero vectors, that computes the cosine of the angle between them in an inner product space. Each document in the Document-feature Matrix is characterized by a vector where the value of each dimension corresponds to the number of times the feature appears in the document. Two documents, then, are similar if their cosine similarity is near to 1.

Given two n-dimensional vectors of attributes, x and y , their cosine similarity is calculated by the dot product of them, normalized by the product of the vector lengths. Results of the similarity measures are stored in a $N \times N$ matrix, in which documents are both upon rows and columns. It is a squared matrix with ones on its diagonal, indicating identities between patents and themselves, and the upper (or lower, for it is the same) half filled with similarity values for all the document couples. The most intuitive method to analyze which patents are more similar is to visualize them in a graph. To do so, it was used the igraph package , which contains a list of commands for creating and analyzing graphs. We can use our similarity matrices as a base to build the corresponding graphs, using them as they were adjacency matrices.

Adjacency Matrix

An Adjacency Matrix is a square matrix that represents a finite graph. In this case, the similarity matrix has in position (i,j) the inverse of the distance between vertices v_i and v_j . This gives to the graph not only information about whether two vertices are connected, but also a measure of their connection. It was chosen to set a threshold $t = 0.8$ for similarities in order to avoid representation of loose relations between vertices. To better visualize results, graphs were migrated from R to Gephi, a visualization software that simplifies this kind of operations. Gephi makes possible to assign colors to nodes as an intuitive way to label them; in our graphs four different colors were used to partition patents in their class, then Force Atlas layout algorithm was performed to see how well the graphs were clustered.

Optimal Number of Topics

Once created, a DFM can be interpreted as a graph showing similarity links between documents. In this context, in fact, similarity can be defined in terms of

the percentage of total features that are shared between documents. Features can also be grouped in topics. In turn, similarity between documents can be defined in terms of the percentage of topics shared between documents. Finally, documents that refer to the same topic, hence are similar among them, can be grouped in cluster. Within a cluster it is possible to define a metrics of cohesiveness: the larger the number of topics shared by documents, the larger the cohesiveness of the cluster they belong to.

The optimal number of topics is not defined once and for all, but it depends in subtle ways from the characteristics of the documents in the set and the list of features. Thus the optimal number is the result of an experimental approach. The R package `ldatuning` calculates several metrics and then delivers an estimate on the optimal number of topics for Latent Dirichlet Allocation (LDA) models. In our application, we chose the CAOJUAN metric to evaluate the number of topics. The decision to use just one metric was made due to computational reasons; we selected the model proposed by Cao Juan, since he demonstrated that LDA models perform in an optimal way when the average cosine distance of topics reaches the minimum. Starting from the assumption that less correlated topics are more independent, the author defined average dispersion as a metric to measure the topic structure, using cosine distance. A smaller average dispersion denotes a more stable topic structure, that is, a topic model which is defined in a better way.

10.4 Results

We now turn to the analysis of the topics resulting from the filtering procedure based on dictionaries, the construction of the DFM, the measurement of cosine similarity. We will use four measures to highlight the content of the patent sets:

- Average cosine distance of topics
- Average number of topics
- Average sparsity of DFM

The dictionaries were divided in two macro-classes, due to their nature: Non-Technical Dictionaries (Acts and Artifacts) versus Technical Dictionaries (Functional Verbs and Advantages & Disadvantages). The Blacklist set, filtered with canonical and “Patentese” stopwords, will be useful for a more complete understanding of the findings.

In order to test the dictionary approach to clustering, we trained the algorithm on a standard patent set, formed by patents belonging to four IPC classes whose technologies are largely known. Table 10.2 illustrates the International Patent Classification (IPC) classes included in the analysis (a random sample of 2.000 patents each).

The technologies examined are largely mature. As it is shown in Figure 10.2, in some of them the patenting activity started as early as XIX century. The maturity

Table 10.2: Patent sets under examination.

IPC Class	IPC Definition
A47J37	<i>KITCHEN EQUIPMENT; BAKING DEVICES; ROASTING DEVICES; GRILLING DEVICES; FRYING DEVICES</i>
A61C15	<i>DENTISTRY; APPARATUS OR METHODS FOR ORAL OR DENTAL HYGIENE</i>
A61G13	<i>TRANSPORT, PERSONAL CONVEYANCES, OR ACCOMMODATION SPECIALLY ADAPTED FOR PATIENTS OR DISABLED PERSONS; OPERATING TABLES OR CHAIRS; CHAIRS FOR DENTISTRY; FUNERAL DEVICES</i>
A61H	<i>PHYSICAL THERAPY APPARATUS, e.g. DEVICES FOR LOCATING OR STIMULATING REFLEX POINTS IN THE BODY; ARTIFICIAL RESPIRATION; MASSAGE; BATHING DEVICES FOR SPECIAL THERAPEUTIC OR HYGIENIC PURPOSES OR SPECIFIC PARTS OF THE BODY</i>

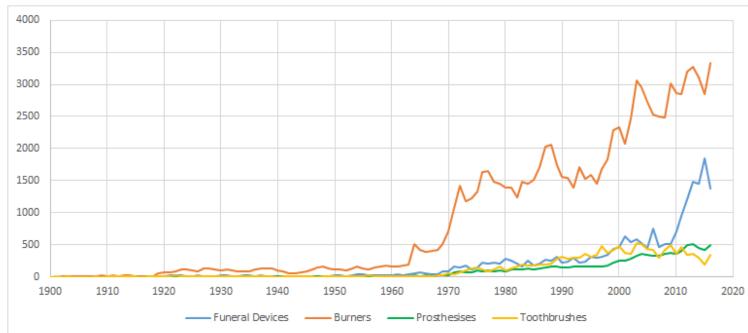


Figure 10.2: Technological history of the technologies in the selected patent sets.

of these technologies is a good starting condition for the training set: similarities and dissimilarities of the patents should be clearly visible.

By placing them together in the same patent set we deliberately include very different technologies. We ask the algorithm based on dictionaries to be able to discriminate technologies in a patent set which is, by construction, highly heterogeneous.

Table 10.3 offers a summary of measures derived from the application of dictionaries to the four patent sets combined together.

Two findings are visible in Table 10.3. First, there is large difference in the cohesiveness of the clustering based on Technical and Non-technical dictionaries. The average cosine distance calculated with the Artifacts and Acts dictionaries is ten times smaller than the average cosine distance for Advantages & disadvantages and the Functional dictionary. Second, Non-technical dictionaries give origin to a

Table 10.3: Summary of findings from the application of dictionaries to the combined patent sets.

Dictionary	Average cosine distance of topics	Average number of topics	Average sparsity of the DFM
Artifacts	0.002	16	98.3
Acts	0.004	11	97.9
Advantages and Disadvantages	0.016	32	94.3
Functional Verbs	0.029	37	73.8
Blacklist	0.031	40	63.3

Table 10.4: Findings from the application of the Acts dictionary to selected patent sets.

Dataset	Number of topics	Cosine distance of topics	Number of documents	Number of features	Average sparsity of the DFM (%)
Burners	2	0.001	496	306	97.8
Toothbrushes	6	0.002	494	311	97.8
Prosthesis	18	0.005	491	493	97.9
Funeral Dev.	16	0.007	491	470	98.2
Mean	11	0.004	493	395	97.9

much smaller number of topics.

Let us examine the differences between dictionaries more in detail. We start by examining the performance of each dictionary in extracting and clustering topics.

Non-technical Dictionaries

Table 10.4 shows the results of the application of the Acts dictionary to the four separate patent sets, while Table 10.5 shows the same for the Artifacts dictionary.

These two dictionaries were retrieved from the Wordnet categorization dictionary, which is a tool for linguistic analysis; thus, the terms comprised in them are of common use, and their suitability for the description of patents is not guaranteed. Taken together the Non-technical dictionaries deliver two main results. First, there

Table 10.5: Findings from the application of the Artifacts dictionary to selected patent sets.

Dataset	Number of topics	Cosine distance of topics	Number of documents	Number of features	Average sparsity of the DFM (%)
Burners	6	0.001	495	397	98.4
Toothbrushes	16	0.001	469	500	98.8
Prosthesis	18	0.003	487	500	98.0
Funeral Dev.	22	0.002	485	500	98.1
Mean	16	0.002	484	474	98.3

Table 10.6: Top ten words in selected topics extracted in the patent set Prosthesis with the aid of the Acts dictionary.

<i>Topic 3: Term</i>	Topic 3: Beta	<i>Topic 7: Term</i>	Topic 7: Beta
<i>Measuring</i>	0.322	<i>Manipulation</i>	0.160
<i>Measurement</i>	0.217	<i>Steering</i>	0.152
<i>Detecting</i>	0.210	<i>Dialysis</i>	0.145
<i>Performing</i>	0.033	<i>Cycling</i>	0.063
<i>Sending</i>	0.031	<i>Deactivation</i>	0.060
<i>Calibration</i>	0.030	<i>Dampening</i>	0.049
<i>Supplying</i>	0.024	<i>Shearing</i>	0.047
<i>Repositioning</i>	0.024	<i>Logging</i>	0.032
<i>Causing</i>	0.009	<i>Exercising</i>	0.029
<i>Comparing</i>	0.009	<i>Reaching</i>	0.023

is a difference in the optimal number of topics between simple technologies (Burners and Toothbrushes) and more complex and articulated technologies (Prosthesis and Funeral devices). In the case of the Acts dictionary, the optimal number of topics is 2-6 for the former technologies and 18-16 for the latter. Second, Non-technical dictionaries deliver clusters with an extremely low cosine distance, that is, with strong internal cohesiveness. In other words, Non-technical dictionaries produce an excellent clustering of documents. This suggests that they can be used to obtain a small number of non-technical topics, that allow a general identification of the content of documents, but not the identification of technical similarities and differences.

To provide an example of the potential of the dictionary methodology we show in Tables 10.6 and 10.7 the top ten words found in a selection of the topics extracted with the Non-technical dictionaries in the patent set Prosthesis. We need to test whether Non-technical dictionaries deliver topics that are satisfactory with respect to their potential to describe technologies.

In the case of the Artifacts dictionary, Topic 5 gives us information on components related to the body part interested by the prosthesis, while Topic 14 tells us about electrical tools and sensors that are involved in the invention. Also in this case, the two groups are useful to gather information about the basic composition of the set, but not enough on focus to have a satisfactory definition of the technologies.

Technical Dictionaries

Table 10.8 shows the results of the application of the Advantages & Disadvantages dictionary to the four separate patent sets, while Table 10.9 shows the same for the Functional dictionary. The technical dictionaries applied contain a large number of features, generating a large DFM. An overall look at Tables 10.8 and 10.9 shows several interesting findings. First of all, the technical dictionaries allow

Table 10.7: Top ten words in selected topics extracted in the patent set Prostheses with the aid of the Artifacts dictionary.

<i>Topic 5: Term</i>	Topic 5: Beta	<i>Topic 14: Term</i>	Topic 14: Beta
<i>Backrest</i>	0.498	<i>Electrode</i>	0.405
<i>Eyewash</i>	0.092	<i>Catheter</i>	0.233
<i>Armrest</i>	0.085	<i>Circuitry</i>	0.106
<i>Gasket</i>	0.060	<i>Sensor</i>	0.026
<i>Capacitor</i>	0.052	<i>Housing</i>	0.025
<i>Arms</i>	0.048	<i>Converter</i>	0.025
<i>Gurney</i>	0.045	<i>Emitter</i>	0.021
<i>Footplate</i>	0.025	<i>Cathode</i>	0.018
<i>Eyepiece</i>	0.019	<i>Anode</i>	0.018
<i>Headrest</i>	0.011	<i>Reflector</i>	0.011

Table 10.8: Findings from the application of the Advantages and Disadvantages dictionary to selected patent sets.

Dataset	Number of topics	Cosine distance of topics	Number of documents	Number of features	Average sparsity of the DFM (%)
Burners	32	0.015	500	500	95.9
Toothbrushes	30	0.014	500	500	95.0
Prostheses	32	0.021	497	500	92.3
Funeral Dev.	34	0.014	495	500	94.0
Mean	32	0.016	498	500	94.3

the identification of a much larger number of topics with respect to non-technical dictionaries: the average number is 32 for the Advantages & Disadvantages, and 37 for the Functional dictionary. This means that technical dictionaries show a higher power of discrimination of semantic content. This is an important finding for Technology intelligence, since a larger number of internally coherent topics is an extremely useful starting point for the interpretation of their content.

Second, in the case of the Functional dictionary the Document-Feature Matrix (DFMs) is less sparse: the average sparsity index is 73,8%, as opposed to around 98% for the non-technical dictionaries and 94,3% for the Advantages & Disadvantages dictionary. Third, the total number of documents used, i.e. the documents in which there is at least one matching between the words and the features of the dictionary, is larger in the case of technical dictionaries (in particular, it is 498 out

Table 10.9: Findings from the application of the Functional dictionary to selected patent sets.

Dataset	Number of topics	Cosine distance of topics	Number of documents	Number of features	Average sparsity of the DFM (%)
Burners	38	0.021	500	500	76.6
Toothbrushes	36	0.022	500	500	75.5
Prostheses	34	0.032	497	500	70.6
Funeral Dev.	38	0.041	495	500	72.4
Mean	37	0.029	498	500	73.8

Table 10.10: Top ten words in selected topics extracted in the patent set Prosthesis with the aid of the Advantages and Disadvantages dictionary.

<i>Topic 6: Term</i>	Topic 6: Beta	<i>Topic 28: Term</i>	Topic 28: Beta
<i>Adjustable</i>	0.564	<i>Worn</i>	0.155
<i>Accommodate</i>	0.046	<i>Comfort</i>	0.086
<i>Ergonomic</i>	0.032	<i>Wearing</i>	0.077
<i>Securely</i>	0.022	<i>Comfortable</i>	0.058
<i>Adjustability</i>	0.020	<i>Injury</i>	0.043
<i>Ability</i>	0.017	<i>Discomfort</i>	0.031
<i>Facilitate</i>	0.016	<i>Increase</i>	0.029
<i>Stabilizing</i>	0.011	<i>Reduce</i>	0.026
<i>Comfort</i>	0.010	<i>Uncomfortable</i>	0.025
<i>Stability</i>	0.010	<i>Tear</i>	0.024

of 500 for the Functional dictionary).

Fourth, the cosine distance of topics is approximately ten times larger in the case of technical dictionaries, meaning that clusters enjoy a over cohesiveness. These findings point to an important contribution of technical dictionaries, and in particular of the Functional dictionary, to Technology intelligence, that is, technology mapping, clustering, interpretation, and foresight.

The Functional dictionary offers a large number of features that find a matching with the text of the patents, so that the resulting DFM is less sparse. The fact that the total number of topics is larger also means that each of the topics is populated by a smaller number of features. Each topic, therefore, lends itself to a clear understanding of the technical content. The differences between topics have also a clear technical interpretation.

It can be said that technical dictionaries, as opposed to non-technical dictionaries, allow a fine-grained intelligence of the technical content of patent sets. This is in itself an important achievement, given that the topic modelling algorithm has not been previously trained, but is only filtered by the dictionary. In practice we achieve the precise results of supervised topic modeling with an effort which is more similar to that of the unsupervised approach.

In order to give a better understanding of the potential of the technical dictionary approach, let us examine more in detail in table 10.10 and 10.11 the top 10 words in some of the topics identified in one of the four patent sets examined, namely Prosthesis.

In Table 10.10 Topic 6 calls the attention to features of the prosthesis such as adjustability, facilitation and stability, that is, on ergonomic features. Topic 28 emphasizes comfort (as an advantage made possible by the invention) or discomfort (as a disadvantage addressed by the invention). The content of these topics, thanks to the power of the technical dictionary, is crystal clear.

Table 10.11: Top ten words in selected topics extracted in the patent set Prostheses with the aid of the Functional dictionary.

<i>Topic 15: Term</i>	Topic 15: Beta	<i>Topic 20: Term</i>	Topic 20 :Beta
<i>Distance</i>	0.054	<i>Arm</i>	0.238
<i>Coupling</i>	0.053	<i>Exercise</i>	0.082
<i>Position</i>	0.052	<i>Arms</i>	0.060
<i>Neck</i>	0.043	<i>Stretching</i>	0.042
<i>Line</i>	0.041	<i>Left</i>	0.025
<i>Parallel</i>	0.030	<i>View</i>	0.024
<i>View</i>	0.021	<i>Orientation</i>	0.023
<i>Form</i>	0.019	<i>Stretch</i>	0.021
<i>Orientation</i>	0.016	<i>Angle</i>	0.019
<i>Contact</i>	0.013	<i>Tension</i>	0.017

Table 10.12: Top ten words in selected topics extracted in the four patent sets with the aid of the Blacklist.

Dataset	Number of topics	Cosine Distance of Topics	Number of documents	Number of features	Average sparsity of the DFM (%)
Burners	40	0.016	500	500	66.5
Toothbrushes	40	0.025	500	500	65.7
Prostheses	40	0.040	500	500	59.2
Funeral Dev.	40	0.042	500	500	61.6
Mean	40	0.031	500	500	63.3

In Table 10.11 we see, in topic 15, the positioning of prosthesis on the neck of patients, and in topic 20, the orientation of arms with the support of prosthesis. Both these topics deal with the issue of placing the prosthesis around or over various parts of the human body. It is important to underline that, once generated, topics can also be combined together in further steps of the analysis.

Blacklist

Finally, the information power of technical dictionaries can be appreciated by comparing the results with those that would be obtained by filtering the texts with semantically poor words, such as generic words (stopwords) and “patentese” generic words. As stated above, the combination between generic and patentese stopwords is labelled Blacklist.

The Table 10.12 shows the clustering results using as filter a blacklist, composed by traditional and patentese stopwords. The following observations are in order. First, we observe a remarkable flatness in the number of topics: it equals 40, which is the maximum value that can be achieved by the algorithm. Second, Burners and Toothbrushes have a smaller distance value, confirming that these two patent sets are composed by more homogeneous types of features.

Summing up, it seems that the dictionaries deliver different results. On the one

hand, Non-technical dictionaries include more generic word expressions. Non-technical dictionaries deliver better performance if the goal is to provide a global representation of the technological field, since they generate a smaller number of topics and better indicators of effectiveness of clustering.

On the other hand, if the goal is to detect novelty and technological trends, or to identify the areas of exploration of emerging technologies, then Technical dictionaries perform better, as they generate a larger number of topics. Analysing these topics it is possible to get insights on technological differences among patents in the same patent set and to produce detailed technology maps. This is particularly important for innovations in the pre-paradigmatic stage.

10.5 Discussions

Patent clustering is a standard application in technology intelligence and has been common practice in the professional IP industry. In recent years, patent clustering based on text mining has gained large acceptance. In this section we have introduced a novel methodology to cluster patents. With respect to the existing literature we give a contribution by testing the use of dictionaries as a structured list of words to filter patent data and build up clusters. The clustering based on dictionaries is significantly different from the one provided by IPC classification. We have tested the use of multiple dictionaries on the same patent set. The resulting clusters allow a fine-grained interpretation, which is illuminating for purposes of technology intelligence. Kreuchauff and Korzinov (Kreuchauff and Korzinov, 2017) have developed a set of performance criteria to compare and evaluate the identification approaches proposed in the literature. These criteria include: degree of intervention of experts, portability, transparency, replicability, adaptability, updating capacity, and finally extent and relevance of data obtained. We suggest that the enriched dictionary approach satisfies all these criteria: it does not involve the role of experts, is portable and transparent (after publication of the dictionary in the open literature), it is therefore replicable to any technology, is adaptable and has capacity to update (particularly if based on Wikipedia), and offers broad and relevant data.

Chapter 11

Impact of Research from the Perspective of Users

A substantive interest has been developed in the last 15 years on the so-called “impact revolution”, namely the increasing demand for showcasing the results of publicly funded research in order to justify public expenditure. Public funders are increasingly required to demonstrate the relevance of funded research not only for scientific communities but also for the economy and society at large. In other words, there is an increasing demand to prove that the users and beneficiaries of research results are not only the traditional academic audience - researchers and university students - but include a large number of social actors. Let us use here the concept of “societal impact”, as opposed to academic impact, to include all dimensions of impact on the society and economy that are realized through impact pathways that go beyond the institutional research and teaching activities.

The issue of societal impact of public research has gained prominence in the specialized literature since the start of the century and has accelerated in recent years (Van der Meulen and Rip, 2000; Ernø-Kjølhede and Hansson, 2011; Bornmann, 2013; Bornmann and Marx, 2014; Bornmann and Haunschild, 2017). Indeed, a quick look at the most important journals in the field of innovation, research policy and research evaluation shows that the most largely cited, downloaded or read articles in the last five years are almost invariably dedicated to the issue of societal impact.

This follows from the adoption of societal impact of research as one dimension of evaluation of research, both ex ante and ex post, in many advanced countries.

As discussed by several authors, societal impact has become one of the criteria of ex ante project selection in several institutions and countries (Kanninen and Lemola, 2006; Dance, 2013). It is also a crucial chapter in the ex post research assessment in some countries, such as United Kingdom. Within the UK Research Excellence Framework (REF) the assessment of societal impact has been responsible for 20% of the total score, while an increase to 25% has been announced in September 2017

for the future exercise. The publication of REF case studies of societal impact has fueled a field of analysis (Derrick et al., 2014; Samuel and Derrick, 2015; Khazragui and Hudson, 2014). Some authors advocate impact analysis as a way to examine the effects of research agenda on the societal priorities (Cozzens et al., 2002).

This surge of policy interest, however, comes in a period in which the scientific analysis of the concept of societal impact and of the potential and limits of existing methodologies has not yet come to a general agreement. As succinctly stated by Lutz Bornmann, impact evaluation is “still in the infant stage” (Bornmann, 2013). And Bozeman and Sarewitz (Bozeman and Sarewitz, 2011) explained that “there has been remarkably little progress in the ability to measure directly, systematically, and validly the impacts of research on social change”, so that “we have no satisfactory analytical tools for characterizing the social impact (of research)” (Bozeman and Sarewitz, 2011).

This chapter is a contribution to the substantive and methodological work on the assessment of societal impact of research. From the substantive point of view, it introduces the notion of target group, or group of potential users of research, as a necessary component of the design and implementation of research projects. From the methodological point of view, the method strongly supports the idea, already advanced in the literature, that Text mining techniques are promising in this field, but suggests a major modification by introducing the Enriched dictionary methodology.

To be more precise we argue that a necessary component for impact assessment is the definition of users of research at a granular level. In addition, we suggest that the more researchers are able to define precisely their target groups the more they are likely to reach them effectively and to increase the impact. We develop a full scale, replicable and scalable methodology to identify the user groups mentioned in research-based texts, such as research proposals (*ex ante*), impact case studies (*ex post*), or publications. We test the methodology on the collection of case studies developed under the Research Excellence Framework (REF) in the United Kingdom. We examine three main dimensions of user target groups (frequency, intensity and specificity) and disaggregate the data by broad discipline.

11.1 Methodological challenges

11.1.1 Variability in the identification of outcomes and users

A first methodological issue is that in order to assess the societal impact of research, there is a need not only to identify observable elements that can be considered as an outcome of the research process, but also to define the actors that are affected, or benefit, from those outcomes. It turns that these elements are subject to huge variability across disciplines. Consequently, there are areas in which methodologies are more sophisticated and largely tested, and others in which there is remarkable lack of experience and methodological work (Stern et al., 2013; Mitton et al., 2007, Turcan (2015))

Among the former the health care sector is probably the one in which the impact assessment of research has made the largest progresses: a number of well structured research impact assessment methodologies have been developed and implemented. There in fact are as many as 16 different impact assessment models, according to Milat, Bauman and Redman (Milat et al., 2015). An important reason for this accumulation of experience and knowledge is that the outcomes that demonstrate the expected impact are clearly identified and standardized, and the categories of users are clearly observed, given a high degree of professionalism.

At the opposite side of the spectrum, there is still much uncertainty about the way in which the societal impact of research in social sciences and humanities (SSH) could be defined and observed, even less quantified and measured. The challenges associated with identifying the impact of outputs from these fields stem from a number of issues, most of which have been noted in earlier evaluation-based literature. According to certain theoretical perspectives the very notion of impact is problematic for SSH (Blasi et al., 2018). From a historical perspective, it has become increasingly clear that research across SSH has had a large influence on modern societies on a long time scale (Bod, 2013). It should be recognised therefore that a certain share of research need not be asked to demonstrate any impact, but be valued for its own sake (Small, 2013). It is part of the millennial history of humankind that some people, some ages of life, some resources are dedicated to the search for intangible and priceless goals such as beauty or truth. Research from the arts and humanities is needed in order to preserve in society the ability to interpret, appreciate, enjoy and valorize symbolic values inherited from the past. Should the many scholars from this field be interrupted or deprived, modern societies would rapidly become unable to coordinate, administer and govern themselves.

Consider the problem from the perspective of potential users of SSH research: the results or products are not necessarily used on the basis of direct access to scientific sources (as it happens more frequently with technological and biomedical research), but after some transformation and intermediation by specialised actors (e.g. journalists of popular magazines; social media). Furthermore they do not necessarily take the form of compelling evidence, or ultimate scientific authority, but enter into a social arena for public and political conversations and debate, where arguments may be advanced and refuted. In addition, audiences may be dispersed, non-institutionalized, or even transient (e.g. issue-based) and not professional. Finally, social behaviors are by definition slow to change, thus the impact of research is likely to be seen only after a long delay. This means that both outcomes and categories of users are much more difficult to identify and define.

11.1.2 Sources of information

Current approaches can be classified, according to Morton (Morton, 2015), as forward tracking, backward tracking, and evaluation of mechanisms. In forward tracking, researchers are asked to reconstruct the ways in which their research might be useful for given categories of users. Alternatively, users are asked to declare which kind of research results they are likely to utilize (Tang et al., 2000).

The strong limitation of this approach is that it relies heavily on the researcher's and research user's own recollections of research use (Nutley et al., 2007; Donovan, 2011). In some sense, this is also the limitation of the use of case studies of research impact: it is difficult to verify whether they are a random collection or they are biased in one way or another. Backward tracking suffers less from these subjective biases. If the sample of final outcomes is well designed, it can offer important lessons for researchers and policy makers. However, it comes with long delays with respect to actual research results.

It should be noted that this methodology is the one largely adopted in impact assessment of health-related research: once it is agreed that clinical guidelines are a suitable candidate for assessment, it is possible to trace back the impact using the citations to the medical literature. Evaluation of mechanisms is a partial methodology, which describes in great detail the pathways in which research results are channeled from their origin to the endpoint.

11.1.3 Text-based impact assessment

More recently, an interesting alternative approach has been suggested. Based on the availability of Machine learning and Text mining techniques, it has been argued that the evidence for the impact of research might be traced by extracting selected expressions from certain kinds of documents. We may distinguish between two kinds of documents: (a) produced by users of research; (b) produced by researchers themselves.

There are several suggestions to use documents produced by users of research. In one of the most developed efforts to conceptualize the social impact of research, called Public Value Mapping (PVM) Bozeman and Sarewitz (Bozeman and Sarewitz, 2011) suggested the use of three main sources of statements, from which it could be possible to trace the impact of research: government statements, academic literature, and public opinion polls containing public statements. More recently, Bornmann, Haunschild and Marx (Bornmann et al., 2016) have suggested to use the frequency of occurrence of policy-related words in policy documents as evidence of impact of research. In this section we will make these suggestions operational.

Yet another approach in the same line is to examine the documents produced within social media. A prominent approach is based on Altmetrics measures. The main tenet of Altmetrics is that citations, the basic unit of analysis of bibliometrics, capture only part of the impact of published research, so that "citation tracking has never been able to follow the less visible- but often more important- threads of invisible colleges, woven through personal connections and informal communications" (Priem et al., 2012). By accessing data on the personal use of published materials "Altmetrics could deliver information about impacts on diverse audiences, like clinicians, practitioners, and the general public, as well as help to track the use of diverse research products like datasets, software, and blog posts" (ib.). Sibebe et al. (Fausto et al., 2012) examine in this light the phenomenon of research blogging. There are however severe limitations that might make Altmetrics

problematic. The extent to which Altmetrics can capture traces of societal impact has recently been seriously contested (Bornmann and Marx, 2014). Social media are used more for internal discussions within scientific communities, rather than a bridge between the research community and society at large. According to Haustein there is lack of evidence that social media events can serve as appropriate indicators of societal impact (Haustein et al., 2016).

Among the documents produced by researchers, we might further distinguish between: (a) research proposals (*ex ante* documents) and (b) case studies produced after the realization of research projects (*ex post*, or documents produced within the research assessment process).

It is this type of documents we suggest to examine as a novel methodology to assess the potential societal impact of research. In the proposed method we follow type (b) documents and use the collection of case studies produced by UK researchers under the REF exercise. In future studies we plan to use archives of proposals made available in public sources in order to examine the *ex ante* representation of researchers.

The REF impact case studies, as already noted, have been the object of a large literature in recent years. Among these studies, King's College and Digital Science (London and Science, 2015) have indeed produced, using Text mining techniques, an interesting analysis of beneficiaries of UK research, publishing a fascinating infographics. This analysis, however, lists only a fairly small set of research users, most of which are defined with generic terms. It is our contention that much further work should be done in this direction. We propose a new lexicon-based methodology, called Enriched dictionary (see below), which allows a much more fine-grained analysis.

11.2 Methodology

Basically we suggest to examine carefully the full text of documents produced by researchers and extract, in a highly structured and theory-dependent way, information on potential users of research. Users are defined as categories of human agents that share some characteristics that are relevant with respect to the object of interest. In the present context users are social groups, or target groups, that are potentially affected by research results and that use these results for their own purposes. Before entering into a technical description of the methodology let us address the rationale of assuming users as an important dimension of research impact.

There are several compelling theoretical reasons for this choice. First, the literature has strongly underlined the interactive nature of societal research impact. As discussed above, the most recent literature and practice strongly suggest to abandon a unilinear model of impact, in which it is expected that researchers produce results, diffuse them in various channels, and see the results taken up by interested users. Let us call this approach a “percolation model”: researchers produce results that eventually percolate down into society, but without knowing

the ways in which they flow, the obstacles they meet, the timing of the process, or the final destination of the flows. On the contrary, it is strongly suggested to adopt an interactive model of interaction, in which researchers actively engage into systematic relation with potential users. In an interactive model there must be a reflexive activity on one side about the nature (characteristics, interests, behavior, style) of the other side. Researchers must build up a representation of their potential users, and vice versa. How could researchers engage with users if they do not know them? And how they could know potential users if they do not engage into some sort of analysis, even as simple as description and characterization? For interaction to take place, there must be some preliminary recognition of the existence, nature, attitudes of those that may utilize the research results. According to our methodological suggestion, it is this representation that is the preliminary object of interest for impact assessment. If researchers have a representation of their potential users, they will leave traces of this representation in their written texts. When they write research proposals they will promise to address the issues of these users, and when they write case studies of research impact they will report on the takeup or use of their research activities by these users.

Second, it has been shown that research activities have a huge variety of impact pathways, largely dependent on the scientific discipline. In turn, this implies that disciplines have at least partially different target groups. Research in political science is different from research in oncology not only because their scientific foundations, methods, objects and cognitive styles are different, but also because they talk to different user groups. The texts produced by researchers themselves are a necessary starting point to reconstruct the various impact pathways. Third, focusing on user groups has the advantage of shifting away the attention from discrete events or products to long term processes of interaction between research and society. The focus on discrete events or products is a typical feature of the narrow definition of research impact cultivated since long time in the so called “valorization of research”. This impact is defined and measured with reference to highly stylized entities, such as patents, licensing contracts, research contracts, and spinoff companies. These are clearly defined, legally enforced, highly visible and measurable entities. Defining and measuring impact is easier by focusing on these entities because they convey the meaning of knowledge transfer from research to the market, and because the final outcome can be defined in monetary terms. We suggest to focus on user groups as a relatively permanent social entity, which is defined by a specific combination of social status, needs, culture, practices and routines. User groups survive the individual personality of people. They are a permanent, although often entirely informal, characterization of society.

Finally, our methodology allows the large scale automatic analysis of large corpora. This means that the inevitable subjectivity in the reconstruction of impact by researchers in writing their proposals and/or impact case studies can be mitigated by examining large scale patterns. It is important to remark that the notion of users is consistent with other suggestions in the literature that adopt different definitions, such as stakeholders, constituencies, interest groups. Our definition is broader and admits more internal variability, as discussed below.

11.2.1 Operationalizing user groups using Natural Language Processing techniques

A simple implication of our methodology is that researchers “leave a trace” of their representation of users, or the groups of social agents that are most likely to use or uptake the results of their research activity. By using state-of-the-art Text mining technologies we are able to identify these traces in written texts and to give them unambiguous meaning. By assuming target groups as units of analysis we suggest to introduce a number of concepts, from which suitable indicators can be derived.

Definition 1 Stakeholders are entities influenced by the research activity. This definition covers all possible entities that engage an active or passive relation with the research activity.

Definition 2 Target groups are entities or groups of entities on which researchers claim to have an effect.

Given definition 2, it is clear that every target group is also a stakeholder, while the reverse does not hold true. Non-target stakeholders include the proponents themselves, managing authorities, funding agencies and so on. We need a formal technique for identifying target groups in the text of research documents. This technique has been developed as described in section 5.1.

Dictionaries are a peculiar type of written text, characterized by authoritativeness, saturation and update. In other words, a dictionary must be composed of entries established by some authority, most often an academic one and/or an authority established since long time by reputation (e.g. editorial initiatives of prestigious publishers). Saturation means that all words that are related to the domain of the dictionary must be included. It is a major flaw of a dictionary the lack of important entries. A dictionary is characterized by a property of semantic saturation: all words that have a meaning associated to a given field are included in the dictionary. Using this tool it will be possible to count the occurrences of target groups, and develop indicators of frequency and intensity. Finally, update means that dictionaries have an internal organization (for example, an editorial board) that examines all new expressions, discusses their acceptability in the dictionary, and make official and authoritative decisions about inclusion or exclusions.

These formal requisites, that used to be appropriate only for established dictionaries, are currently satisfied by a larger variety of sources. In particular, the huge power of Text mining techniques has made it possible to automatize at least some of the steps needed to create a formal dictionary. Section 5.1 illustrates the steps undertaken in order to build up an Enriched dictionary of users. It currently includes 76.857 entries, that have been shown to saturate the semantic field of users. It includes, among others, all jobs, work positions, professions, hobby, patient roles, sports, creative and entertainment roles, political, institutional and organizational roles, social roles, that have been classified in hundreds of official sources. In particular, this includes all stakeholders and target groups, as defined above.

Our Natural Language Processing (NLP) system follows the following steps. -

Table 11.1: Tokenization, lemmatization and annotation of a sentence in the corpus.

Doc_id	Token_id	Token	Lemma	Xpos	Target_group
1855	1	Each	Each	DT	NA
1855	2	year	Year	NN	NA
1855	3	,	,	,	NA
1855	4	in	in	IN	NA
1855	5	England	england	NN	NA
1855	6	alone	alone	RB	NA
1855	7	,	,	,	NA
1855	8	approximately	approximately	RB	NA
1855	9	152	152	CD	NA
1855	10	people	people	NN	People
1855	11	suffer	suffer	VBP	NA
1855	12	a	A	DT	NA
1855	13	stroke	stroke	NN	NA
1855	14	.	.	.	NA

Sentence splitting and Tokenization: this process splits the text into sentences and then segments each sentence in orthographic units called tokens. Sentence splitting plays a key role since thanks to a given word, it is possible to find all sentences in which the word is used. - POS tagging and Lemmatization: The Part-Of-Speech tagging (or POS tagging) is the process of assigning unambiguous grammatical categories to words in a specific context. It plays a key role in NLP and in many language technology systems. Once the computation of the POS-tagged text is completed, the text is lemmatized according to the result of this analysis. - Target groups Annotation: The Target groups Extraction tool is based on lexicon methods. Among the various lexicon methods we adopt, as stated above, the Enriched dictionary approach. With respect to users, we use a lexicon composed of 76.857 entries. By launching this Extraction tool we are able to capture all the different ways in which each target group can be expressed in a research document.

Table 11.1 shows the output of the NLP procedure for a sentence contained in the corpus (“Each year, in England alone, approximately 152,000 people suffer a stroke.”). As it can be seen, the automatic annotation system isolates the only word (“people”) that may be part of a target group.

11.3 From text extraction to indicators

After having extracted all possible expression of target groups in research documents, we are in a position to develop indicators with suitable statistical properties.

They are defined as follows.

Frequency

For a given document J, let us define T_j (number of target groups contained in J) and W_j (number of words contained in J). We then define:

$$F_j = \frac{T_j}{W_j} * 100$$

The frequency F of a document measures the percentage of words that are target groups. If a document shows high frequency it means that it cites many times target groups, even if it/they are always the same and they are generic. For example, an impact description that repeats many times the target group people will show high frequency.

Diversity

For a given document J, let us define Tu_j (number of different target groups contained in J) and Wu_j (number of different words contained in J). We then define:

$$D_j = \frac{Tu_j}{Wu_j} * 100$$

The diversity D of a document measures the percentage ratio of different words that are target groups. If a document has a high diversity it means that it cites many different target groups, even if they are generic.

Specificity

For a given target group i, let us define N (number of documents in the corpus) and n_i (number of documents that contains the target group i). We then define Si, the specificity of the target group i as:

$$S_i = \frac{\log(N/n_i)}{\log(N)}$$

The Specificity of a target group Si measures how rare, and thus specific, is a target group in the overall corpus. The specificity diminishes for target groups that occur very frequently in the corpus and increases for target groups that occur rarely (more specific target group). Let us take the example before, in which the annotation system identifies people as a target group. There will be a large amount of documents in which the word people will occur, so that the ratio between the

total number of documents in the corpus and the number of those that include the word people will be close to one. On the contrary, highly specific words (say, free climbers) will occur less frequently, so that the above ratio will increase. Since we are interested in giving a measure for each document, having defined S_i for each target group, if the document j contains k different target groups, we have that the specificity of the document j is:

$$S_j = \sum_{i=1}^k S_{i,j}/k$$

The specificity of a document S_j measures how rare, and thus specific, are the target groups contained in that document and it is the mean of the specificity of all the target groups that it contains. If a document contains only rare target group (not cited by other impact descriptions) that document exhibits high specificity. For the previous example, suppose we have a document repeating many times that the research has an impact on people. Since the target group people is a common one (thus having a low specificity S_i itself) the measure of the specificity of the document, resulting from the sum of low specificity values, will be low.

An interesting example of application of these principles comes from the scientific study of popular science, or divulgation. In these fields authors use a language which must be understood by lay people, not by professional scientists. For this reason they tend to use generic words, rather than highly specific and professional words. This is, incidentally, one of the reasons why professional scientists often disregard popular science as a literary genre: they perceive the generic nature of language used as too coarse. Scholars of popular science have used quantitative linguistic techniques to distinguish between generic and specific terms in the same semantic field (Jacobi, 1999)

11.3.1 The meaning of Frequency, Diversity and Specificity indicators for the analysis of research impact

The above definitions are building blocks of a model of engagement of researchers with their potential users. At the outset, it is important to examine whether researchers include users in their representation of research activity at all. Thanks to the use of an Enriched dictionary, which by definition saturates the semantic field, we are in a position to establish whether user-related expressions are found in researchers' texts or not. Since in the proposed method we use the impact case studies produced under the REF, the minimum level is by definition satisfied, as it was the condition for submitting the case study. At the same time, this indicator will be extremely useful for the ex ante evaluation of research proposals. The appropriateness of this indicator and its policy implications will be the object of future research. Authors of the REF documents are by definition aware of the existence of target groups of users.

Once the awareness level is satisfied, frequency comes into play. Frequency is a standard measure in computational linguistics and Text mining techniques, since it

gives evidence of the relative importance of words or expressions. The frequency by which target groups are mentioned in a document is a measure of their perceived importance. We are keen to examine the frequency by which users, or target groups, are mentioned in documents produced by researchers. Yet researchers may cite repeatedly a target group, but consider them as a unique entity. This approach is reasonable when the target group does not have internal differentiation (i.e. it is not segmented) and when the results of the research are equally useful for all its members.

But in many relevant cases this undifferentiated approach does not work. Representing and addressing users as a single target group may weaken the potential for impact.

There are two directions in which researchers can deepen their representation of target groups, and hence their impact. One is to address different target groups. This is similar to the notion of segmentation in consumer psychology: if target groups have sufficiently dissimilar characteristics with respect to the activity (in this case, the use of research results), then it is better to treat them differently. The other is to go in depth in addressing each of the target group, by refining their approach, using fine grained representations of the needs of the users. We capture these two directions by measuring diversity and specificity. It is our contention that the language used by researchers is a clear signal of their approach to research impact. A high level of diversity implies that researchers understand the need to mention, identify, enumerate target groups that have different names. They stop using generic words (say, people) and start to introduce some of the many criteria for segmentation. In addition, or in alternative, they discover that within their target groups it is possible to go deep in the fine grained representation, by adding specificity.

A spatial metaphor may help to capture the point: by increasing diversity of target groups researchers move horizontally, defining new regions of the space, while by increasing specificity they move vertically, drilling the ground in each of the regions. Frequency, diversity and specificity are not necessarily correlated. An interesting empirical issue is the relation between these two dimensions.

Let us articulate an example. Suppose an expected impact of a given research is on policy making. A low specificity situation arises when researchers speak about “policy makers”, or “government”. A more mature and engaged approach should articulate the policy making process by identifying several specific user groups in addition to the various layers of political and legislative decision making. For example, interest groups. These social actors are extremely important in shaping the policy agenda. A well developed body of research in political theory has examined the way in which new policy issues are generated, framed in the public conversation, and pushed forward in the policy arena until they become established in the policy agenda (Sabatier, 1987). Pittman (Pittman, 2006) argues that the most important factors leading to government interest there is the role of domestic advocacy, as well as the interest in their international standing. Second, intermediary organizations or boundary organizations, such as technical agencies and regulatory bodies (Agrawala et al., 2001). Third, opinion-makers such as

think tanks should be included. Many other examples could be added. These actors would be mentioned with more specific expressions.

Finally, researchers may engage into identifying user groups “by name and surname”, that is, as concrete and localized actors with whom they plan to enter into interaction. Counting or measuring them would be the final stage of maturity of research engagement with users.

11.4 Data

11.4.1 Description of the corpus

The corpus is composed of 6637 REF impact case studies. They generally follow a template illustrated in the REF criteria. The template has a Title and five main text sections, plus the name of the Submitting Institution and the Unit of Assessment. In addition to the Title of the case study, the text sections of the template and the indicative lengths, as recommended in the REF criteria are:

1. Summary of the impact, 100 words
2. Underpinning research, 500 words
3. References to the research, 6 references
4. Details of the impact, 750 words
5. Sources to corroborate the impact, 10 references

We take into consideration the sections Summary of the impact and Details of the impact. It is common practice in computational linguistics to examine the length of documents to be included in a corpus in order to ensure comparability. Figure 11.1 shows that the limits established by the REF criteria are not always respected. Nevertheless, since the distribution of the length is almost normal and there are not outliers it is appropriate to include all documents in the corpus.

Within the REF repository projects are classified using three criteria:

- Impact type: There are eight Summary Impact Types. These follow the PESTLE convention (Political, Economic, Societal, Technological, Legal, and Environmental) widely used in government policy development, with the addition of Health and Cultural impact types.
- Units of assessment (UOA): Institutions were invited to make REF submissions in 36 subject areas, called units of assessment (UOAs), each of which had a separate expert panel.
- Research subject areas: The REF Impact case studies are assigned to one or more Research Subject Areas (to a maximum of three) by text analysis of the ‘Underpinning research’ (Section 2 of the Impact case study template). This is a guide to text search that uses a disciplinary structure that is more fine-grained than the one in the 36 Units of assessment.

Figure 11.2 shows the number of documents per Unit of assessment.

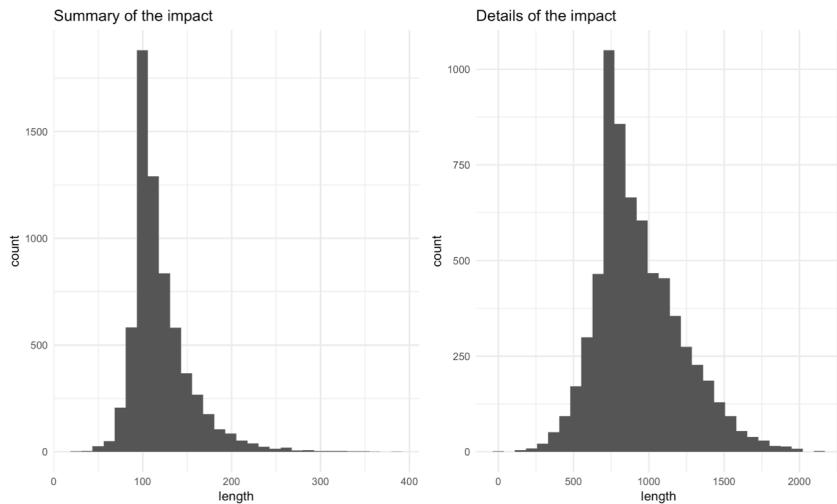


Figure 11.1: Distribution of number of words in relevant sections of the REF impact case studies.

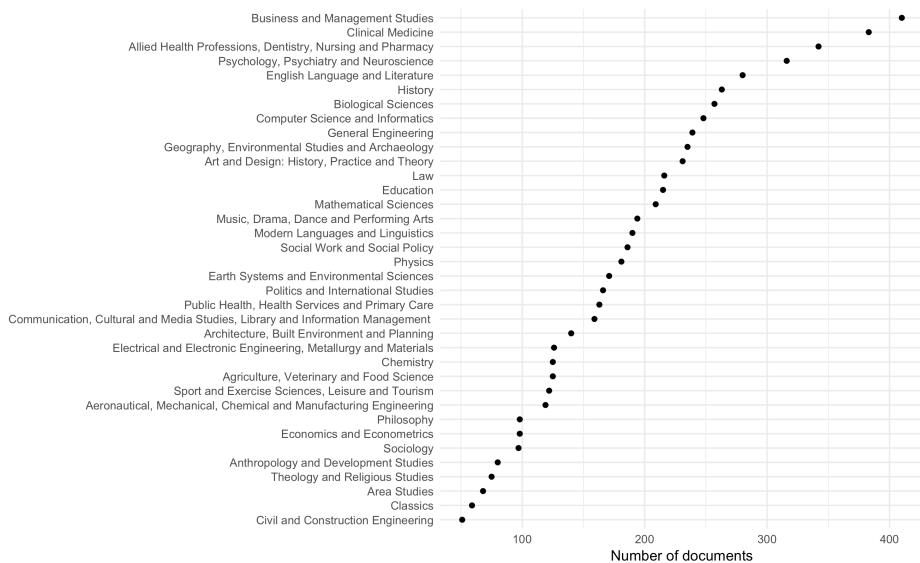


Figure 11.2: Number of documents per Unit of assessment (UoA) in REF impact case studies.

11.4.2 Preliminary analysis of the corpus

In this section we present a descriptive analysis of the content of the documents to give an evidence of two important facts: 1. The description of the impact contains target groups; 2. This information is enough to make a significant statistical analysis.

The corpus contains 8.230.598 words in total and 141.705 different words. By annotating the entire corpus with the entries of the Enriched dictionary we find that the total number of words referring to target groups is 169.037, while the number of different target groups is 1830, or 1.3% of different words. The number of documents that contain at least one target group is 6628, or 99,9% of the total. Only for nine documents we were unable to locate any word referring to a target group.

Figure 11.3 offers a vivid demonstration of the issue of specificity of words referring to target groups. As many as 37% of all projects include people, and as many as 25% mention company as isolated words. Among the top 20 occurrences we find extremely generic words such as public, community, individual, organization, user, or society. Slightly more specific are the words referring to the school or youth context (child, school, student, teacher) or the health context (patient, patients). In order to find more specific words we have to go further down the ranking. Please note that in all these cases these words do not appear in combination with other that might increase the specificity, but in isolation. Should the same word appear in combination with other more semantically connotated words, they would form a separate target group. As an example, the word people is considered part of a separate expression in the following examples: people with cystic fibrosis, people with primordial dwarfism, people with rheumatoid arthritis, ordinary people in extraordinary situation, people in senior management, people from different background, key policy people in UK government, specific community of people, young people in deprived community in Glasgow. Each of these expressions is considered as a separate target group and their Specificity is computed according to the formula above.

To see the difference in the use of words in sentences consider the following examples from REF case studies: “The validation of the exit poll forecast allowed people to see the power of social scientific methods, and may have helped them to establish a level of trust in evidence-based information” (generic use of the word people) and “Key components of this are nurturing people with cross-cultural understanding, diversity in thinking and global leadership skills” (more specific use). The NLP procedure developed for this analysis is able to accurately distinguish these situations.

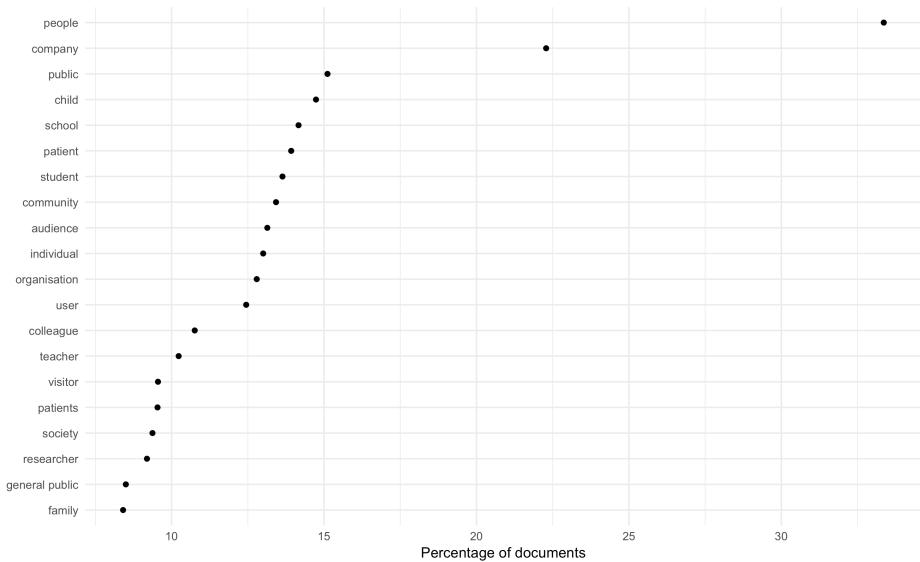


Figure 11.3: Top 20 occurrences of words referring to target groups in the corpus of REF impact case studies.

Table 11.2: Descriptive statistics of indicators of target groups in the corpus of REF impact case studies.

Indicator	Min	Max	1st quartile	3rd quartile	Mean	Median
Frequency:indicator	0	9.2	1.2	2.7	2	1.9
Frequency: absolute value	0	115	14	34	25469	22
Diversity: indicator	0	7.6	1.8	3.2	2.5	2.4
Diversity: absolute value	0	34	7	14	10518	10
Specificity	0	1	0.59	0.731	0.659	0.656

11.5 Results

11.5.1 Descriptive analysis

Table 11.2 offers a snapshot of the value of indicators calculated across the entire corpus. The minimum value of indicators (zero) is represented by the 9 documents without target groups. On average the REF impact case studies contain words that represent target groups as 2% of total words, and words that represent distinct target groups as 2.5% of different words. In absolute terms, the median REF impact case study contains 10 different words that refers to target groups, repeated 22 times in total.

There is not large variability in the number of different target groups, as the first

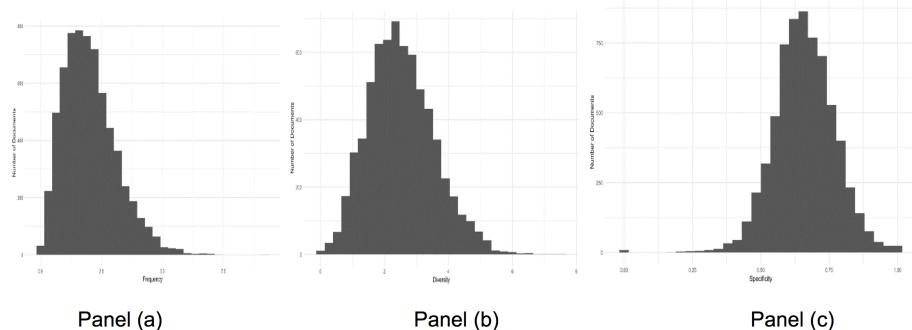


Figure 11.4: Top 20 occurrences of words referring to target groups in the corpus of REF impact case studies.

and third quartile at 7 and 14 are close to the median value. Interestingly, all distributions are close to the normal. A small number of documents use words that refer to target groups with much larger frequency and diversity. The document with maximum use of target groups identifies as many as 34 different words or combination of words. In terms of repetition, the document with the largest number of words uses 115 times a word representing target groups. When coming to specificity, the mean value of 0.659 implies a good level of specificity, given the range of the indicator. Figure 11.4 shows the distribution of documents by indicators.

11.5.2 Findings by subject area

We disaggregate the indicators with respect to the subject areas, or the Units of assessment (UoA), according to the REF nomenclature. This analysis offers a new perspective on the way in which the various disciplines describe their impact pathways. We use the conventional boxplot representation.

Figure 11.5 shows a surprising finding. On top of the ranking by frequency of occurrence of words that refer to target groups of users we find Humanities: not only Education (which by nature refers to children, students and teachers as user groups), but also Music and drama, Classics, Language and literature, and History. Or, in other words, disciplines that are not oriented towards users, but rather cultivate the goal of knowledge per se. At the bottom of the ranking we find, again surprisingly, Engineering disciplines, with a number of specializations, and Economics, that is, disciplines that, on the contrary, have a pragmatic orientation towards various target groups of users.

Figure 11.6 confirms a similar ranking by subject area when we use the Diversity indicator, with slight variations. In the case of diversity we find also Theology and religious studies, as well as Art and design. Almost all subject areas in Humanities consistently show up at the top when we investigate the frequency by which they mention users of research and the number of different target groups they are able

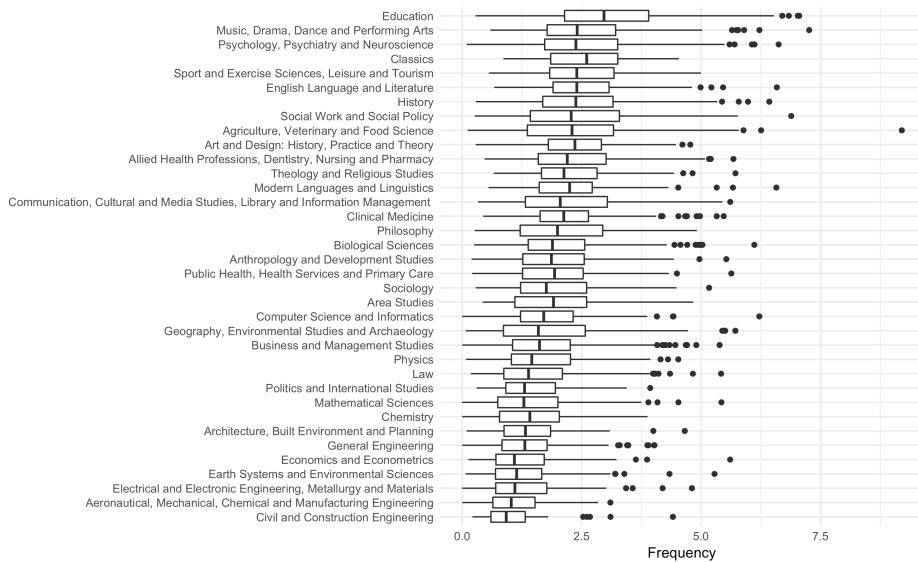


Figure 11.5: Boxplot of the Frequency indicator in the corpus of REF impact case studies by subject area (Unit of assessment)

to identify. This is a remarkable finding. It is true that this comes from documents that are themselves retrospective reconstruction of impact, but this feature applies to all subject areas in the same way.

This finding sheds light on one of the controversial issues in the literature on impact evaluation, that is, the role of Humanities and Arts. It seems that one of the tenets of the argument that Humanities and Arts are not sensitive to the audiences, or users, of their research results, is simply false. When asked to reflexively reconstruct their impact, they are systematically able to mention their target groups.

This comes at a cost, however. Humanities rank top in the Frequency and Diversity of target groups, but rank at the bottom when coming to their Specificity. Figure 11.7 shows an almost reverse ranking of subject areas when the indicator chosen is Specificity. At the top of the Specificity ranking we find Social Sciences, such as Economics, Politics, Anthropology and Law. This is another interesting finding. These disciplines have been able to target highly specific groups of users, following a process of academic specialization. They have low Frequency and low Diversity—that is, do not spend much emphasis on their target users, but have high Specificity—that is, they know whom to target.

Large part of Humanities are found at the bottom: Psychology, Education, Philosophy, Language and literature, Art and design. Engineering disciplines are more scattered.

Finally, by combining the three indicators it is possible to examine more closely the pattern of impact of subject areas.

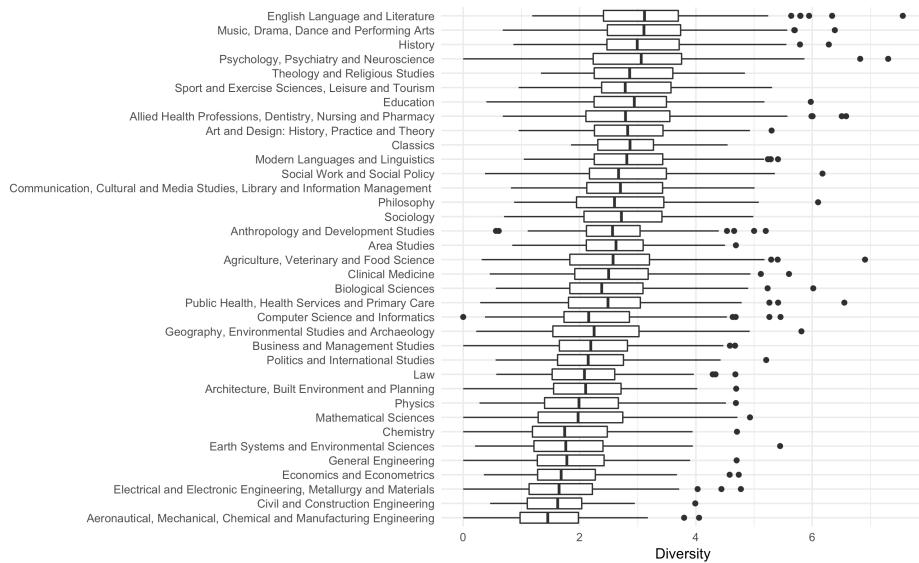


Figure 11.6: Boxplot of the Diversity indicator in the corpus of REF impact case studies by subject area (Unit of assessment)

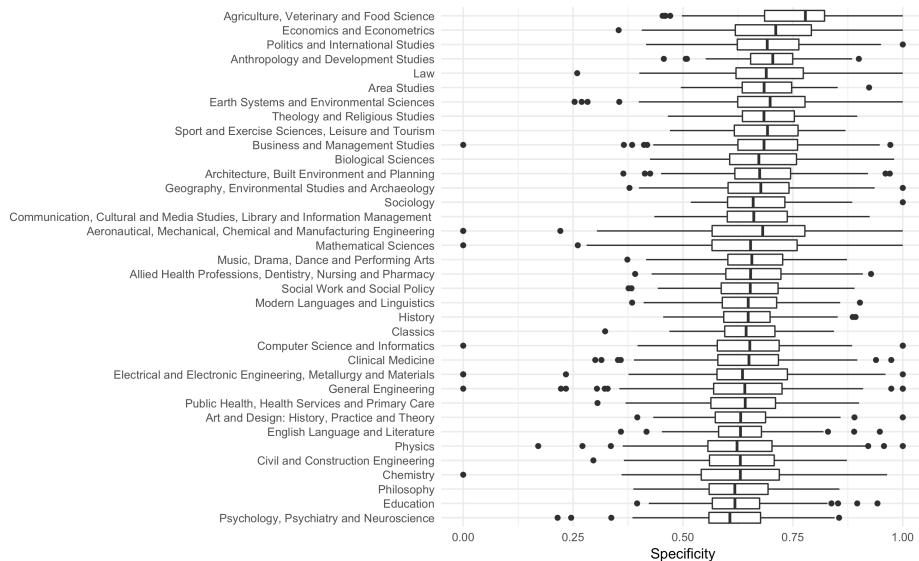


Figure 11.7: Boxplot of the Specificity indicator in the corpus of REF impact case studies by subject area (Unit of assessment)

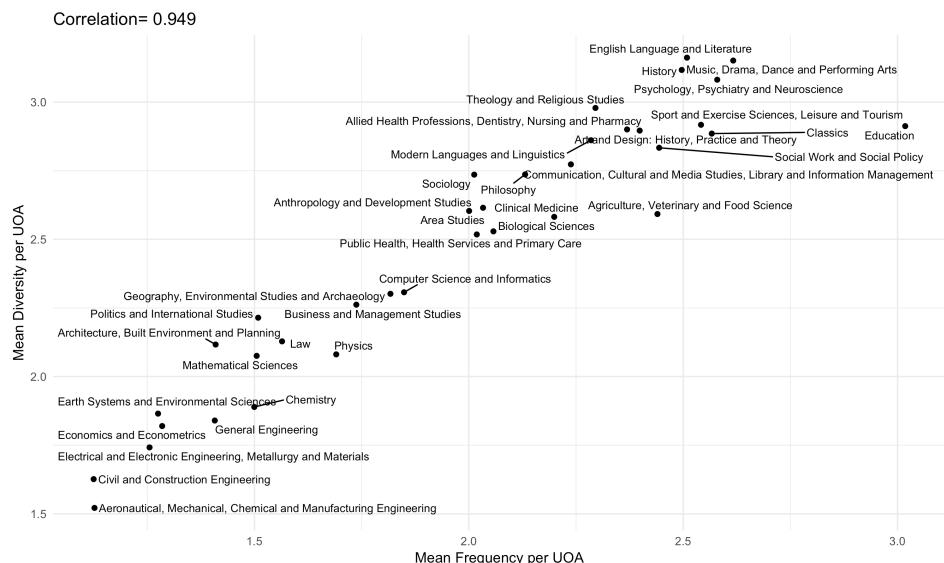


Figure 11.8: Scatterplot of the relation between Frequency and Diversity indicators in the corpus of REF impact case studies by subject area (Unit of assessment)

Frequency and Diversity are highly correlated (11.8). Humanities rank top in both indicators and are located in the top right region of the graph. Almost all disciplines in Engineering and Economics and Econometrics lie at the opposite corner. When coming to Specificity, correlation with the other indicators is on the contrary extremely low and is negative (- 0.016 with Intensity, - 0.146 with Diversity).

11.6 Discussion

The data show an intriguing disciplinary pattern: Humanities and Arts show remarkably higher frequency of terms related to users, but a significantly lower specificity. The opposite is found for many areas of STEM, namely Engineering and several Natural science disciplines.

The results for Humanities are very intriguing. Research in Humanities is often considered as pure, abstract, not engaged with society. This representation is used by those governments that argue that research funding in these areas should be cut because their impact on society cannot be demonstrated. For Social Sciences the situation is slightly different, but there is a presumption that only a few social sciences have an impact, in particular those with instrumental value, such as Economics. Our data tell a different story. When asked to demonstrate the impact of their research, scholars in Humanities and Arts use a very rich vocabulary of users and mention users very frequently, twice as much as scholars in STEM.

At the same time, they are less capable to transform their orientation in operational terms, by defining, identifying, targeting specific groups or audiences. At the opposite extreme, it seems that scholars in STEM mention very precise and well defined groups of users. This might be a result of the nature of their studies: researchers in Medicine follow specific targets in terms of disease and patients, or technologists have narrow industrial applications. This remarkable difference may create an imbalance in the assessment of research impact.

Research in STEM finds more easily and unambiguously the groups of potential users, so that its impact is easier to observe and operationalize. As it has been noted by the studies on REF, evaluators may find it easier to use concepts drawn from STEM to evaluate all types of research, simply because they point to more observable and discrete products of research. From the field of social studies of evaluation it is well known that measurements lead to a feedback loop so that the immediate availability of indicators may lead to believe that important things are only those that can be measured.

The notion of impact of research deserves further and intense research effort in the near future. We see several directions of research. First, apply the methodology to ex ante research documents, such as research proposals: do they include users? do they identify target groups with adequate Diversity and/or Specificity? Second, test whether there is a relation between the Specificity of identification of target groups and the assessment of the research, either ex ante (approval of a proposal) and ex post (score obtained in research assessment exercises). Third, extend the methodology to other kinds of documents.

Chapter 12

Defining Industry 4.0 Professional Archetypes

Worldwide industrial systems are evolving by leveraging Internet connected technologies to generate new added values for organizations and society. Researchers, policy makers and entrepreneurs refer to such phenomenon with the name of Industry 4.0.

An increasing number experts from different fields are focusing on this topic, bringing their contribution in terms of new technologies and methods. As a consequence of this process, the companies that are embracing the new paradigm need to manage new technologies and the new relations among them with a multidisciplinary approach. The result is an emerging need of new professional figures able to bridge the different fields.

Moreover, while the scientific interest in technological aspects of Industry 4.0 is constantly growing, the understanding of the future works and professional roles is slowed down by the heterogeneity, complexity and static nature of job description systems. These issues are usually addressed by qualitative methods thus making the results uncertain and partial.

The first step of the present chapter is to develop a data driven mapping of 4.0 competencies which benefit (rather than being disadvantaged) by the heterogeneity of the entities to map. Then we propose a classification of the groups of competencies with the aim of identifying and defining the archetypes of Industry 4.0 workers. Given the bottom-up process we adopted to reach our goal, also the relationships between them can be described.

12.1 Digital Competences Development

The radical technological change is going to affect the whole industrial environment and will radically transform, in several different ways, the world we live in (see

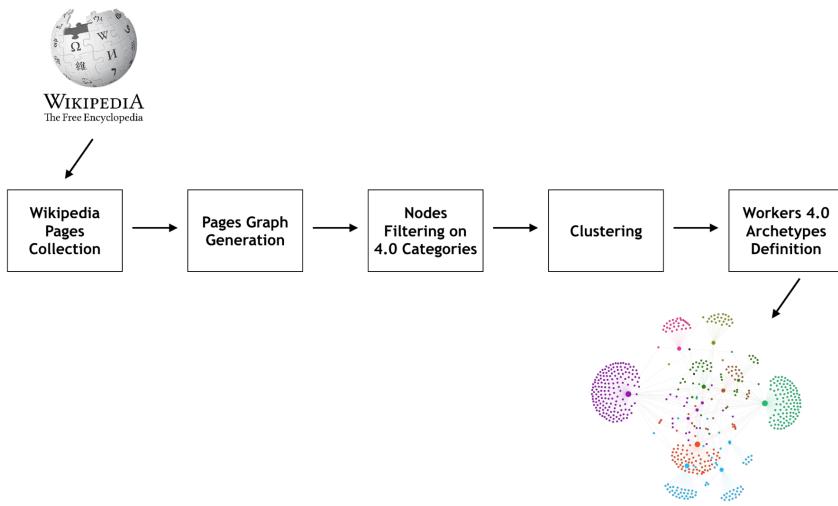


Figure 12.1: Flow diagram of the process of 4.0 Archetypes definition.

section 7.1). Consequently, the revolution is not just referred to the availability of new sophisticated machines, but also to the deep reconsideration of worker roles it brings with. On the one hand Industry 4.0 implementation may have negative impact on specific professional figures, which could be substituted by robots. In support of this theory, Osborne & Frey implemented a methodology to estimate the probability of job computerization using a Gaussian classifier (Frey and Osborne, 2017). The results are quite pessimist: they distinguished between High, Medium and Low risk of computerization: according to their estimates around the 47% of jobs is in the high risk category. On the other hand, another possible impact is represented by a significant increase of worker competences and the emersion of new professional profiles: our research mostly focused on the second prospect.

12.2 Methodology

In this chapter we show the process to built the graph of Wikipedia pages related to Industry 4.0. This graph will be then used by expert to define 4.0 workers archetypes. Figure 1 shows the process we adopted. The whole process takes in input a set of linked entities (e.g. Wikipedia pages) and gives as output a clustered graph.

Wikipedia Pages Collection

The process takes as input a set of entities linked between them. A link between two entities represent the existence of a relation between them. Here the concept of relation is intended as the sharing of a topic. In other words, two entities has to be

connected if they belong to the same topic. Any entities-links structure that meets this requirements can be used as input for the proposed process. For the purpose of the present work, we decided to use the free encyclopedia Wikipedia . Wikipedia is structured in such a way that each page contains links to other Wikipedia pages. The links from page to page are manually assigned by the contributors, so the structure of the links evolves dynamically. Furthermore each page is labeled by the contributors through categories with the intent of grouping together pages on similar subjects. To collect industry 4.0 related wikipedia pages we exploit this information and structure. In the date of 23/11/17 we collected three levels of pages typologies for a total of 4739 pages:

- L1, The Wikipedia page of industry 4.0 ¹ (*1 page*)
- L2, All the pages linked to L1 (*39 pages*)
- L3, All the pages linked to L2 (*4699 pages*)

For each page we collected the page name, the links and the categories.

Pages Graph Generation

Once we collected all the pages and the links between them, we represent this structure as a directed graph (S). It is composed of:

- A set of nodes (N): the Wikipedia pages.
- A set of edges (E): the links between the pages (considering also the direction of the edge)

S has 4739 nodes and 194.299 edges.

Nodes filtering on 4.0 Categories

Considering the content of Wikipedia, it is reasonable to assume that not all of the 4.739 pages are related to Industry 4.0.

To sanitize the set of nodes N we adopted a series of filtering rules based on the categories of the pages. The steps we followed were:

- Count the occurrence of each category we extracted. At this step we had 14.711 categories.
- Filter the categories having an occurrence minor or equal to 3. This threshold level has been chosen looking at the distribution of the occurrences (the number of pages per category). A change in the central node could make changes on the selection of this threshold level. At this step we had 1.605 categories.

¹https://en.wikipedia.org/wiki/Industry_4.0

- Manually screen the categories and select those related to industry 4.0, taken in to consideration the definition of Industry 4.0. At this step we had 337 categories.
- Selecting the nodes that contains at least one of the 337 categories.

As an example, the top 10 categories in terms of occurrence and the relative occurrences are: production and manufacturing (51), parallel computing (42), manufacturing (37), business terms (33), management (31), process management (29), engineering disciplines (28), internet of things(28), technology in society (26) and cloud computing (25). This list shows how the process is able to make categories correlated to Industry 4.0 emerge. We thus obtain a new graph S' that is a subgraph of S (all the nodes N' and the edges E' are a subset of N and E respectively). S' has 645 nodes and 703 edges. Of these nodes 75 are disconnected from the graph (both in-degree and out-degree equals to zero) and are thus not useful for the analysis we will conduct in section 3.4 . These nodes are filtered, obtaining a definitive S' having 570 nodes.

Clustering

We can assume that S' gives us a reasonable representation of Industry 4.0 related Wikipedia pages in terms of precision and recall.

It is thus possible now to analyze if the pages are arranged in clusters, or in other words, if there exists groups of similar pages.

To understand the concept of similarity we need to consider the nodes N_1 and N_2 , and the sets of all nodes connected to N_1 and N_2 , respectively L_1 and L_2 . The similarity of N_1 and N_2 is proportional to the module of the intersection between L_1 and L_2 . To investigate this similarity and to find clusters of similar pages, we grouped similar nodes via short random walks (Durrett, 2007). The approach finds ways to compute an intimacy relation between the nodes incident to each of the graph's edges. The process is non-supervised so it makes an optimal decision on the number of clusters. The output was 9 different communities.

The obtained graph is shown in Figure 12.2. The figure shows the nodes, the edges and the label of the nodes. The dimension of the nodes is proportional to the out-degree of each one (the number of tail edges adjacent to the vertex) and the color represent the community to which it belongs to. The label of the nodes (as center of the clusters) are shown for those having an out degree greater than 4. The table shows the correspondence between the community, the colors and the percentage of nodes per community.

Workers 4.0 Archetypes Definition

The authors generated a list representing the “Industry 4.0 workers archetypes” based on Wikipedia. The bias due to the profile of people writing this kind of

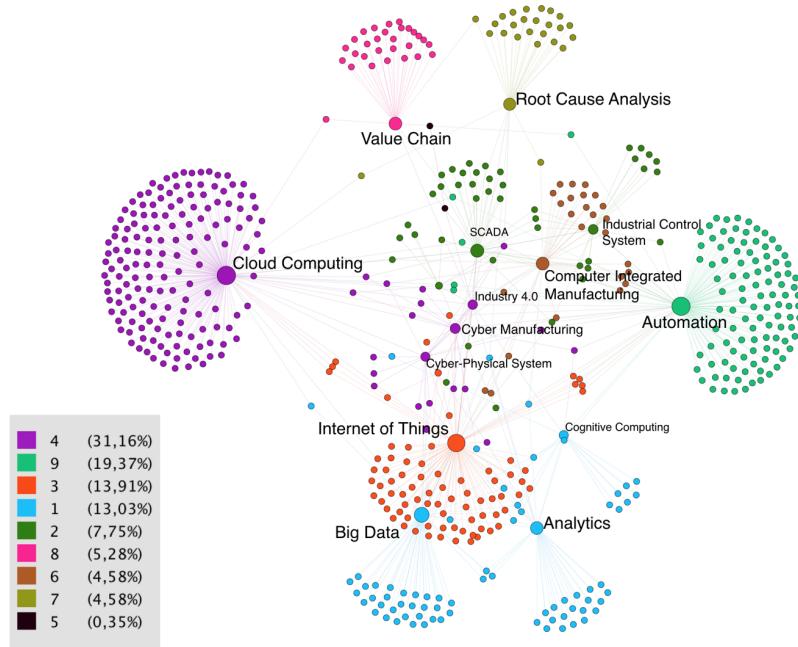


Figure 12.2: Representation of the graph S' . The nodes are the Wikipedia pages related to Industry 4.0. The arch between two nodes exists if there is a link between the pages. The labels of the nodes are shown only for nodes having an out-degree (number of tail edges adjacent to the vertex) greater than 4. The color of each node represent the community to which the node belongs. The table in the low-left shows the percentages of nodes for each community.

		Community Number									
		1	2	3	4	5	6	7	8	9	Total
Archetypes Names	the Architect	44	1	3	6	0	4	0	0	5	63
	the Prophet	21	0	4	0	0	0	0	0	7	32
	the Perfectionist	0	36	1	2	0	0	0	0	3	42
	the Geek	5	1	65	152	0	10	0	0	43	276
	the Investigator	0	0	0	0	0	2	26	0	2	30
	the Strategist	0	0	2	4	0	6	0	30	9	51
	Null	5	6	4	14	2	4	0	0	41	76
Total		75	44	79	178	2	26	26	30	110	570

Figure 12.3: Table of the accordance between the archetypes and communities. The total of pages for each archetypes is shown in the last column, the total of pages for each community is shown in the last row.

Wikipedia pages does not reduce the importance of this exercise, but it is fundamental to understand why the reader will find such a great emphasis on technologies, methodologies and tools as pages describing the archetypes in section 4. Skills, competences and professional figures (in the strict sense) are then behind and beyond the archetypes, which represent just the attitudinal profile of the workers that will be soon seek by companies adopting Industry 4.0 paradigm.

Table of Figure 12.3 shows the relation between the Archetypes and the communities (created by the text-mining procedure presented above). It also shows the total number of nodes per archetypes and per community.

From this table it emerges that:

- Group 1 (75 pages) has two nodes/centers: the page “Big Data” and the page “Analytics”. This is why from Group 1 derives two different Archetypes: “the Architect” (44 pages, centered in Big Data) and “the Prophet” (21, centered in Analytics). This is an evidence of the fact that these two archetypes are strongly related between them, since they belong differently from all the other groups.
- More than 80% of the pages referred to Group 2 (centered in the page “SCADA” and “Industrial Control system) were used for creating the

Archetype of “the Perfectionist”. It is important to underline that the page SCADA - acronym of Supervisory control and data acquisition- being a specific control system architecture, was discarded from the assignation to a specific archetypes. Our focus for designing “the Perfectionist” was the generic page “Industrial Control System”.

- Group 3, Group 4 and Group 9 are composed of pages we linked to the same Archetype: “The Geek”. In respect of Group 1, we made a different choice: we referred the most part of these three groups’ pages to just one Archetype, “nuanced” on the basis of the nearest technologies in the graph: “Cloud Computing”, “Automation” and “Internet of Things”. As the Geek was created starting from three different groups, it has three different declinations as shown in Figure 12.4. The geek, as will be explained in section 4, has to be seen as the expert of a specific family of similar technologies strongly related to industry 4.0.
- Group 6 is composed of 26 pages, that were referred to almost all the Archetypes. These pages are general purpose, and referring to Figure 12.2, this is also evident from their central position in the graph (there are related to every community). The predominance of pages referred to one Archetype (the Geek) did not allow us to consider this Group, centered in the page “Computer Integrated Manufacturing”, as another nuance of “the Geek”. Moreover, Group 6 is strictly related to Group 9, as the proximity of the clusters in the graph can easily show.
- In group 7, centered in “Root Cause Analysis” page, we found 100% of pages referable to the Archetype we called “The Investigator”.
- As in the previous group, also in Group 8 (centered in “Value Chain” page) the 100% of pages were referable to one Archetype: “the Strategist”

Figure 12.4 shows the same graph of Figure 12.2, associating to each group an Archetype. In this new version of the graph it is possible to identify the centers of each cluster, the position of the clusters (and the related archetype) in respect of the others, the interrelation among the clusters/archetypes.

12.3 The Archetypes

The term “archetype” has its origins in the Greek word “archein”, which means “original or old” and “typos” “pattern, model or type”. It is thus etymologically referred to the “original pattern” from which all other similar persons are derived, modeled or emulated. In this work we consider this etymological meaning, discarding any philosophical or psychoanalytic references which would mislead our research. As regards the personality many theories have been proposed over the years [11,12], but a common vision at the academic level has not been reached yet. Both Jung’s theory of personality types [13] and the Myers-Briggs indicator (MBTI) in the field of work psychology [14] come to several psychological types

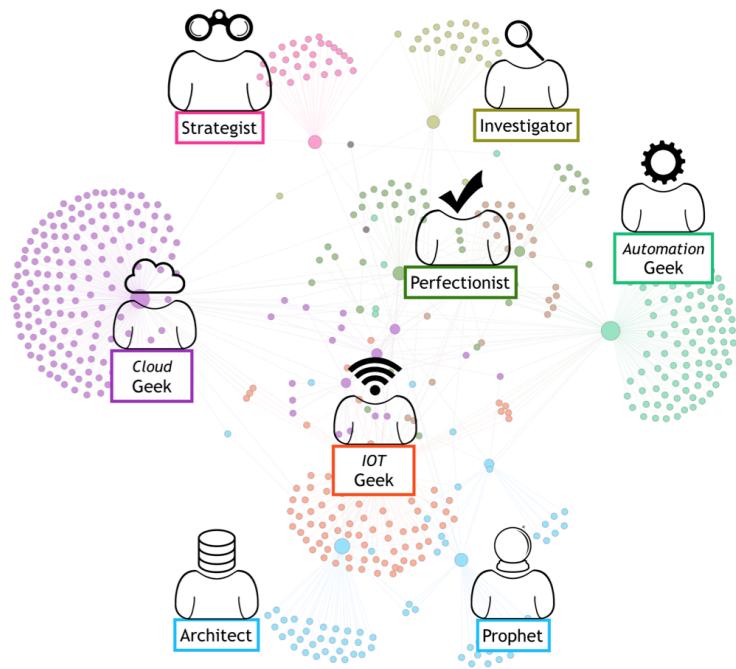


Figure 12.4: The different professional archetypes associated with each technological cluster.

defined through descriptions and traits. Some of them (e.g. the 16 psychological types of MBTI) are a standard for Human Resource managers and are largely used for resource classification and selection. It is important to underline that in the present work i) technologies and skills have been extracted in a scientific and repeatable manner, ii) they have been clustered following a well-known and accepted algorithm. Conversely, archetypes' names have been chosen with the intent to better communicate the research outcomes.

The archetype description sections are built following a common structure:

1. *The name of the archetype.* The choice of the name was made by the authors in order to have an evocative impact on the reader and reaching a communication goal. In some cases, the names are deliberatively imaginative, renouncing to respect a rigid scientific approach with the aim of charming and interesting the reader
2. *The list of the Wikipedia pages selected.* The pages represent the elements considered by the authors for defining the archetypes. The selection of the pages was done referring to the clusters identified with the data-mining as shown in section 3. All the Archetypes are referred at least to one group, with the exception of group 1, from which two different Archetypes were created, and groups 3,4 and 9, which all together participated in the creation of another Archetype (even if with three different declinations). In many cases the pages reported in the box are related to technologies, methodologies, tools: evidently the authors of Wikipedia pages related to Industry 4.0 are more interested in “hard” rather than “soft” topics, such as competencies or cultural aspects of the new paradigm.
3. *Industry 4.0 Emerging needs.* The authors presented shortly the needs that the companies face when introducing Industry 4.0 applications. The needs are mainly based upon the interpretation given by the acatech study [15], which represent one of the most effective key for understanding the new paradigm [16].
4. *The archetype.* We have already explained what we meant with the word “archetype” and the rationale behind the choice of the specific names. The explanation of the archetype given in this section is based on the interpretation of the Wikipedia pages selected and on the semantic fields they refer to. We tried to describe the inner nature of the individuals referable to each specific archetype, defining the peculiar traits of their mindset and their most marked features. The aim was also to describe them so to make them recognizable in our daily experience.
5. *Keywords.* The keywords are taken from the column “categories” of the clustered list of selected Wikipedia pages. Strikethrough in the body of the text indicates where the authors decided of deleting misleading words: we kept them for making clear and transparent the procedure behind this cleaning activity. The reasons for deleting some words were: a) they were too generic and did not characterize the archetype, b) they were too specific and

they made the archetype losing its capacity of encompassing more aspects, c) even if they survived to the “cleaning” after the data-mining, they were referred to another semantic field (disambiguation).

The Architect

The Wikipedia pages selected: Big data; Data blending; Data quality; Cognitive computing; Data fusion; Data science; Unstructured data; Data lake; Data set; Data; Data lineage; Data transmission; Radio-frequency identification; Data philanthropy; Datafication

Industry 4.0 Emerging needs

When taking a decision in Industry 4.0 paradigm it is more important than ever that the individuals can access, collect and process data and information. Data can be gathered from machinery, equipment and tools thanks to sensors, actuators and information processing systems, linked to a communication layer. Big data is a buzzword usually linked to Industry 4.0 and used to describe mass data that cannot be analyzed adopting common procedures, but requires advanced applications and technologies. Thus, in the new paradigm, it is important not just collecting the data, but also collecting and processing them in an innovative way and shaping them in a form that make them usable for the company decision-makers and other employees.

The archetype: The Architect

The Architect is the individual that is at ease in managing, transforming and processing data. He/she has a clear idea of the importance of data and understand which data are useful, in which context and for who. The Architect likes formalized information and the possibility of shaping them, has an innate capacity of breaking the problems and find the best solutions: this capacity is fundamental when having to deal with different sources of information and numerous data and inputs. He/she is precise and reliable, has a great aptitude for visualization and for problem solving.

Key words: big data; data management; distributed computing problems; technology forecasting; transaction processing, artificial intelligence; cognitive science business intelligence; data; information technology management, computer data, automatic identification and data capture; privacy; radio-frequency identification; ubiquitous computing; wireless, big data, types of analytics, online analytical processing

The Prophet

The Wikipedia pages selected: Analytics; User behavior analytics; Business analytics; Data mining; Data analysis; Continuous analytics; Machine learning; Data visualization; Cultural analytics; Predictive analytics; Natural language processing; Customer analytics; Business intelligence; Analytic applications; News analytics; Statistics; Behavioral analytics; Predictive engineering analytics

Industry 4.0 Emerging needs

The implementation process of the Industry 4.0 paradigm involves different stages. At one advanced stage of this process the company should be able, starting from the data collected, to simulate future scenarios and select the most likely one [15]. To do so the company needs to have analyzed and assessed a number of data and projected the “digital shadow” of its assets in the future. Forecasting and the recommendations based on it became the key elements on which building the development of the company. The analysis of the different scenarios is the basis for building the business success. For reaching these targets it is fundamental to have constructed proper “digital shadows” of the assets and have understood the interactions among them.

The archetype: The Prophet

The Prophet is an individual with strong analytical thinking skills, able to examine in details specific situations in a critical way. He/she has a future-oriented mindset: is at ease in thinking about next steps, possible scenarios and with a medium-to-long-term vision. Starting from the analysis of data and adopting also statistical methods, the Prophet investigate the problems (creative thinking) and identify possible solutions (complex problem solving) in order to reach the best case scenario he designed.

Key words: analytics; business intelligence; business terms; financial data analysis; formal sciences; data mining; formal sciences; cybernetics; learning; machine learning; actuarial science; big data; business intelligence; financial crime prevention; prediction; statistical analysis; types of analytics; financial technology; information management; data; formal sciences; information; mathematical and quantitative methods (economics); research methods; statistics; artificial intelligence; computer security; human behavior; machine learning; computational fields of study; data analysis; particle physics; scientific method; data; information technology governance; statistical charts and diagrams; visualization (graphic); artificial intelligence; computational fields of study; computational linguistics; natural language processing; speech recognition; business intelligence; business software stubs; applied data mining; business analytics; market research; marketing performance measurement

The Perfectionist

The Wikipedia pages selected: Industrial control system; Instrumentation; Control valve; Overall equipment effectiveness; Enterprise resource planning; Distributed control system; Control system; Lean manufacturing; Total productive maintenance; Programmable logic controller; Risk; Control System Security; Control loop

Industry 4.0 Emerging needs

Since the First Industrial Revolution, quality improvement has been one of the critical aspects for developing any business. In the current age of high competition and

mass production, this has become, along with price strategies, the main element for expanding the market. Thus, quality control has become a central issue to consider before establishing any industrial undertaking and the best way for ensuring the best allocation of resources and highest level of production. In Industry 4.0 paradigm quality has become even more important, mainly because the increased flexibility of machinery, processes and procedures allow to intervene continuously for analyzing the parameters, identify machine faults or quality issues with a high degree of confidence and in advance. Flexibility and agility (which denotes the ability to implement changes in real-time, including changes to the company's business model) are two key factors that allow a constant improvement.

The archetype: the Perfectionist

The Perfectionist is the individual who is never satisfied of the actual conditions: it could be his/her current personal situation, the preparation for an exam, the functioning of a process or a machinery. He/she always thinks that things can be done better, in a shorter time, with less resources, involving different teams, collaborating more (or less). The Perfectionist likes tests: he/she tries, monitors, checks the results, thinks about it (possibly analyzing data and empirical results) and then suggests - or decides - how to make things work right.

Key words: control engineering; industrial automation; industry; manufacturing; telemetry; lean manufacturing; automation; control theory; systems engineering; systems theory; industrial computing; programmable logic controllers; measuring instruments; sensors; business terms; computer-aided engineering; erp software; enterprise resource planning terminology; information technology management; management; production and manufacturing; supply chain management terms; commercial item transport and distribution; inventory; management; process management; production and manufacturing; actuarial science; environmental social science concepts; financial risk; risk; applications of distributed computing; control engineering; industrial automation; control devices; valves; applications of distributed computing; control engineering; industrial automation; business terms; commercial item transport and distribution; computer security; computer security procedures

The Geek

The Wikipedia pages selected: Cloud computing; Smart grid; Productivity; Cyber manufacturing; Artificial intelligence; Embedded system; Cyber-physical system; Cybernetics; system; Manufacturing; Computer network; Cloud manufacturing; Computer security; Internet of things; Information technology; Distributed computing; Service-oriented architecture; Automation; Adaptable robotics; Automation Technician; Developmental robotics; Industrial Engineering

Industry 4.0 Emerging needs

Beside the aspects related to a new organizational structure and a different work culture, Industry 4.0 is strongly determined by the new technologies, both hardware and software. It is impossible to implement Industry 4.0 applications without

considering technical aspects. The enabling technologies (Clouds, Augmented reality, Simulation, IoT, etc.) must be known in the company in order to make the new paradigm real. Technologies are so specific and so many, that it is important to have an extensive knowledge of them (even if not deep) and be able to integrate them for finding the most effective custom-made solution to solve specific problems.

The archetype: the Geek

The Geek is the archetype of an individual extremely passionate in new technologies and its applications. He/she is interested in everything is new and innovative, in seeing beyond and within things: how technological applications work, why and at what extend their capacities can be brought. Integration is always an important aspect: the Geek appreciate the ideas of combining, breaking and keeping just some aspects for recombining and then creating something new. He/she has a kinesthetic learning (or tactile learning) and has a kinesthetic approach to the work: he/she needs make tests (rather than thinking or planning), piloting solutions (rather than have someone else doing the job) and working on the field. The geek is always up-to-date on the newest technology and is always willing to be the first in creating something new. As the number of pages referable to the Geek were numerous, the authors decided to create three different nuances represented by three different logos, one for each field of expertise of the Geeks.

Key words: ambient intelligence; emerging technologies; internet of things; computers; information-theoretically secure algorithms; information technology; media technology decentralization; distributed computing; architectural pattern (computer science); enterprise application integration; service-oriented (business computing); software design patterns; web services; cloud computing; cloud infrastructure; big data; industrial revolution; industrial automation; industrial computing; technology forecasting; computer systems; industrial computing; industry; internet companies; manufacturing; computer systems; physical systems industry; manufacturing ambient intelligence; emerging technologies; smart grid; artificial intelligence; computational fields of study; computational neuroscience; cybernetics; formal sciences; technology in society; unsolved problems in computer science; cybernetics computer networking; computer networks; telecommunications engineering; computer network security; crime prevention; cryptography; cybercrime; cyberwarfare; e-commerce; information governance; national security; secure communication; security technology; weapons countermeasures; economic growth; industry; production and manufacturing; production economics; electrical engineering; embedded systems; cloud computing; automation; engineering disciplines; adaptable robotics; robot kits; robotics stubs; industrial automation; technicians; machine learning; robot control; engineering disciplines; industrial engineering; operations research; production and manufacturing

The Investigator

The Wikipedia pages selected: Root cause analysis; A3 problem solving; Failure mode and effects analysis; Quality control; Business process mapping; Forensic

engineering; Business process; DMAIC; Incident management; Value stream mapping; Design of experiments; Pareto chart; 5S (methodology)

Industry 4.0 Emerging needs

Industry 4.0 paradigm enables to a constant check on procedures, processes and systems, as they are all integrated and all the information are conveyed to a same “repository” (the communication layer). All these aspects can be then monitored in a totally new way: it is possible, for example, to have data in real time and the decisions can be taken according to information which can be transferred almost at the same time they are created by one or more devices or tools. Thanks to the high amount of information than can be analyzed, also mistakes can be treated in a different way: in Industry 4.0 it becomes easier to focus and investigate on the causes of a failure – and solve it -, rather than on finding out who is to blame.

The archetype: the Investigator

The Investigator is the individual who is naturally curious: as a proper scout he/she wants to understand what is working and what is not. He/she is never satisfied with the explanation he/she receives and is always searching for a mistake, a bug or just another way for reaching at the same conclusion. The Investigator is eager for analyzing what is already known and what is new, he/she likes going into details and understanding how things works and how they could work in a different way. When identified the problem the Investigator is not necessarily interested in finding the fix, he/she rather prefer to have some other problems to break and leaving someone else the possibility of coming up with a solution (that he/she would love to analyze again).

Key word: business terms; problem solving; process management; production and manufacturing; quality; quality management; six sigma; design for x; management; quality control; statistical process control; business process; enterprise modelling; process management; lean manufacturing; commercial item transport and distribution; inventory; japanese business terms; lean manufacturing; manufacturing; methodology; process management; quality control tools; business process; data management; design of experiments; experiments; industrial engineering; quantitative research; statistical theory; systems engineering; reliability analysis; reliability engineering; systems analysis; engineering disciplines; engineering failures; forensic disciplines; materials science; business software; disaster preparedness; enterprise modelling; firefighting in the united states; itil; incident management; categorical data; statistical charts and diagrams

The Strategist

The Wikipedia pages selected: Value chain; Core competency; SWOT analysis; Business model; Delta Model; Strategic management; Balanced scorecard; Game theory; Strategic planning; Control (management); Porter's five forces analysis; Strategic thinking

Industry 4.0 Emerging needs

If Industry 4.0 allows the companies to foresee different scenario based on data and information, it doesn't guarantee to the entrepreneurs to select the right one or take the correct decision. Data should be read correctly, but also the strategy for reaching the preferred scenario should be decided in the proper way. In particular, one of the most dangerous risk is not being able to redefine properly the company business model, which should be constantly monitored, assessed and, according to the most updated information, modified.

The archetype: the Strategist

The Strategist is the individual who has a mind wide open: he/she thinks to the outcomes of each activity and reflect on the different ways for reaching the target. Strategic thinking, strategic management and planning are its most marked qualities: he likes thinking to all the possible outputs in a comparative way. He/she is also a pragmatist, as starting from the analysis of the current situation he/she doesn't like to create different scenarios (as the Prophet does) but rather reaching the result established in the more effective way. Even if the Strategist is not an entrepreneur, he has some of its qualities and this is why this archetype can be referred to the "entrepreneurial mindset". The Strategist is visionary, risk-taker, creative, with a strong willingness to challenge the status quo and he has diplomatic and leadership skills.

Key words: distribution (business); michael porter; process management; supply chain management; value proposition; business models; management; strategic management; types of marketing; business planning; business software; business terms; management; control (social and political); control theory; artificial intelligence; formal sciences; game theory; john von neumann; mathematical economics; business terms; strategic management; business intelligence; strategy; systems thinking

12.4 Discussions

The present section can be seen as a first step of a long journey. As stated in introduction our Archetypes are intended in the etymological sense, as original models, and we assume that they are emerging in the digital economy. Thanks to the data-mining exercise we were able to place the clusters of Wikipedia pages in a graph, analyzing them according to the contents, the position in the graph and the relation among them. This recurrence of same pages in almost all the clusters let us concluding that some topics are common to all the Archetypes, independently to the cluster they were originated. For example, being able to read and exploit data is a transversal issue and all the Archetypes (and all the workers referable to them) should be used to work with them. Another constant in all the cluster is the reference to technologies: they are central in the new paradigm, it is unavoidable for a digital worker knowing them. Even if the "Fourth Industrial Revolution" doesn't end with a bunch of IT tools, they are at the center of the new paradigm and workers must be used to play with them [17].

To conclude and anticipate the further developments, in figure 12.5 we give an interpretation of the position of the archetypes in the graph. We can cluster the Archetypes according to the general company area they could be referred. The areas are:

1. Business. The Strategist and the Investigator are the main actors. In this area the decision regarding the future and the strategy of the company are taken: it is important to have people who have always the big picture clear in their mind (the Strategists) and are good in analyzing the situation for what it is (the Investigator).
2. Data. The Architect and the Prophet suits well here. This area is referred to the acquisition, collection and management of data. This area is perfectly suitable for someone who is comfortable in analyzing and structuring data (the Architect) and for who has a future-oriented mindset, always based on the actual inputs coming from the company functions (the Prophet).
3. Process. The Geek (automation) is the only major player in this area. The process area is where the core activities of a company are performed.

The connection between the three areas are ensured by three Archetypes:

- The Perfectionist, is the bridge between the process area and the business area: in both of them is useful to have someone who is comfortable in solving problems and making things work always better.
- The Geek (cloud) is the bridge among the Data area, where he/she contribute with the knowledge of technologies, and the Business area, where Archetypes will benefit from these technologies for new business development.
- Finally, the Geek (IoT) is the connection among the Process area and the Data area, representing the bridge between the core activities and the usage of information coming from them.

A possible next step of our study will be identifying at which function of the Porter value chain model each Archetype suits better. Then, having placed the Archetypes in their most suitable function, it will be then possible to allocate for each Archetype the most appropriate 4.0 professional profiles, so to follow their attitudes and exploit better their skills. At this stage, as the new paradigm is still emerging, we cannot go further in our research, but the road-map is now clear and the first step is taken.

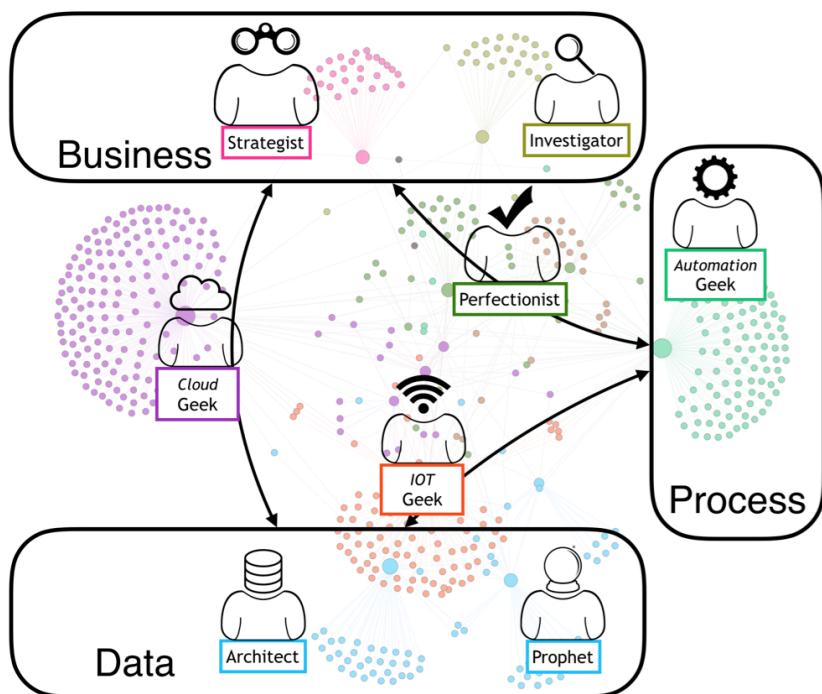


Figure 12.5: The Archetypes grouped by business areas. The image also shows the strategic roles of Perfectionist, Cloud Geek and IOT Geek, who represent the bridges between different functions.

Part V

Conclusions

The thesis has faced the problem of Mining Technical Knowledge from documents with a particular focus on Engineering Management Methods and Natural Language Processing Techniques. Its main goals are three:

- understand which information sources contain the most untapped value and which methods and tools can be used to uncover that.
- understand how management engineering can cover those areas.
- designing analysis algorithms, which can provide correct knowledge exchange between human and machine, leading to incorporate knowledge of the experts inside machine-learning systems and improve the usage that experts' makes of machine outputs in their process of decision making.

The designed solutions make large use of the Design Science Approach, the Data Science Workflow and Natural Language Processing Techniques.

In *Part Number 2 “State of the Art”* has made a review of tools and techniques for Natural Language Processing and shows the documents used for knowledge extraction. In particular, the analysis of technical documents require the design of processes that rely both on Natural Language Processing techniques and on technical field expertise. While the first techniques are codified and explicit, the second are sometimes implicit and always hard to systematize. In the State of the Art these two groups of techniques are treated in the same way to give to the reader a systematic literature review on these topics. Furthermore it is important to define the value in terms of new knowledge that documents can bring to companies. The goal of this state of the art is to demonstrate that a large literature on Techniques able to solve the problems discussed in section ?? exists, but week or no effort exist in the literature in the systemic integration of these tools and in the design of holistic methods to solve these problems.

Part Number 3 “Methods and Results” has been the core Part of the thesis. This part describes the methods and processes designed for the analysis of technical documents following the guidelines of design research described in section 2.1. Since design research is a problem solving paradigm, each chapter (focalised on a different kind of document) starts with a brief description of the field of application of the method and with the framing of the problem to be solved. Then the methodology to solve the problem is described with the goal of being clear to a technical audience and a managerial audience. Each chapter closes with the results description that proves the utility, quality, and efficacy of the design artifact.

Part Number 4 “Applications of the Results” is a collection of projects that describes the applications and results of the methods designed in *Part 3 “Methods and Results”*. The goal, again following the the guidelines of design research (Bichler, 2006), is to provide clear and verifiable contributions in the areas of the design artifact, design foundations, and/or design methodologies.

In this Part a brief summary of the thesis is made, and its future developments are described. Before that, a more descriptive-science view of the results is given. In the next chapter we give a general method that has proven to be effective in the major part of the designs of the present thesis: **lexicons design**.

Chapter 13

Lexicons Design for Mining Technical Knowledge

In this work as been shown that text mining techniques are being adopted in many different fields to face the problem of extracting meaningful information hidden in unstructured data. Hybrid processes (human-machine) of knowledge extraction are usually the best solution for companies to achieve great results and to ensure the conformity of the output of the knowledge extraction process. Anyway, state-of-art literature on Natural Language Processing (NLP) lacks in process management studies. In particular, researchers have not yet studied the best way to integrate NLP outputs with human activities. To our best knowledge, the present thesis is a first step in the desired direction. Such a process and the design of new methods for human-machine (or better engineers machine) interaction , started with the present thesis, bring some valuable contribution to the literature:

- Minimize the introduction of errors and biases made by human intervention;
- Maximize the human effort only on value added tasks such as knowledge validation and consolidation;
- Decrease the overall time of the process.

From this thesis emerges the fact that *Information Extraction from texts for developing technical dictionaries (a Knowledge Base), is a effective approach to follow in order to increase the knowledge base of a specific field.* Many of the designs presented in this thesis uses this approach.

In section 5.1 a dictionary of *users of inventions* has been developed, containing more than 76.000 entries, and this dictionary has been used to analyze projects texts 11. In section 5.2 a dictionary of *advantages and drawbacks* has been extracted from patents using twitter to validate its content. The dictionary contains a total of 6.568 advantages and the 14.809 drawbacks and has been used to classify

problems of different technologies in patents 9 and papers 6.3. This dictionary has also been used to design a novel technical sentiment analysis, which has been used to analyze the sentiment about two innovative products in section 8.1.

Sections 6.1, 6.4 and 7.1 developed dictionaries for respectively sustainable manufacturing, precision agriculture and industry 4.0 with the aim of giving a clear picture to both academics and practitioners about the state of the art of technologies in these fields. In particular in section 7.1 the dictionary is an enriched dictionary: the enriched dictionary can be defined as a set of enabling technologies for industry 4.0, associated to their definitions and to the linkages between them.

In this final chapter of the thesis we give a descriptive-science view of the results. We thus present a general method that has proven to be effective in the major part of the designs of the present thesis: **lexicons design**.

13.1 The Knowledge Bases and Technical Lexicons

A Knowledge Base is an organized repository of knowledge - in a computer system or an organization - consisting of concepts, data, objectives, requirements, rules, or specifications. Technical Lexicons (or Dictionaries) are lists of keywords and expressions linked to a specific topic and they are used to extract information through the research of these keywords in raw texts. All the methods that use these lists of keywords are named Dictionary-based Approaches.

For using these approaches, the first thing to do is the construction of these dictionaries. For some applications - i.e. biomedical fields - there are already existing dictionaries that can be used for text mining; in other applications, these dictionaries need to be constructed. The development of dictionary is a task still too human-dependent: in fact, for building these lists, domain experts must select keywords from texts and clear them from words that are too general for that domain; this process must be repeated iteratively until a satisfactory result is achieved, in relation with the purpose. These tasks rely too much on the intervention of experts and the subsequent analysis are greatly influenced from their choices and opinions. Experts intervention is also too time consuming and expensive.

Another way to increase the Knowledge Base is through the Named-Entity Recognition Techniques. Named-entity recognition (NER) - also known as entity identification, entity chunking and entity extraction- is a subtask of Information Extraction that seeks to locate and classify named entities in text into pre-defined categories as names, locations, quantity, and others. These techniques usually take an unlabeled text and produce an annotation on it, extracting the entities of some predefined categories.

13.2 The history of Lexicons Design

In order to map the main techniques used for Lexicons Design, 23 papers have been analysed and mapped.

In 2014, Song et al (Song et al., 2015b) developed a hybrid dictionary-based bio-entity recognition technique based on the expansion of the bio-entity dictionary by combining different data sources and using the approximate string matching technique and the shortest path edit distance algorithm. The technique also adopts text mining techniques in the merging stage of similar entities such as Part of Speech (POS) expansion, stemming, and the exploitation of the contextual cues to further improve the performance.

In 2015, Yang and Garibaldi (Yang and Garibaldi, 2015) described a hybrid information extraction system to automatically identify risk factors for heart disease in medical records. Their approaches rely on several natural language processing (NLP) techniques such as machine learning, rule-based methods, and dictionary-based keyword spotting to cope with complicated clinical contexts inherent in a wide variety of risk factors.

In 2016, Arif-Uz-Zaman et al (Arif-Uz-Zaman et al., 2017) used text mining for industrial application, proposing a text mining approach to extract accurate failure time data from WOs (work orders which detail maintenance activities on the asset) and DD (downtime data which details when the asset was taken offline). Texts are pre-processed and the WOs are manually labeled as potential failure or non-failure. Then a keyword dictionary is developed from the WOs. Labels and the keyword dictionary are used to classify each DDs downtime event as a failure or non-failure.

Kim and Joung (Joung and Kim, 2017) proposed a technical keyword-based analysis of patents to monitor emerging technologies, and used a keyword-based model in contents-based patent analysis. Technical keywords are extracted using a commercial NLP software package, then selected using a TF-IDF function. After that, a technical keyword-context matrix is constructed. The relatedness between pairs of keywords is then identified , and patent documents are clustered by using a hierarchical clustering algorithm based on patent document vectors. As a result, emerging technologies can be monitored by identifying clusters composed of technical keywords.

In 2017, Rezaeian et al (Rezaeian et al., 2017) described a three-step methodological framework for science foresight on the basis of published research papers, consisting of life-cycle analysis, text mining and knowledge gap identification by means of automated clustering. Moro et al Amado et al. (2018)] presented a research literature analysis based on a text mining semi-automated approach with the goal of identifying the main trends in Big Data in Marketing. The study includes dictionaries built by keywords extraction, experts' judgment and usage of sources as Bloomberg and Google Finance. Text mining results in a matrix structure used as input to the LDA algorithm of Topic Modeling, that groups articles in logical topics characterized by key relevant terms.

Baechle et al (Baechle et al., 2017) presented a method to examine several de-identified clinical notes and discover associations between Chronic Obstructive Pulmonary Disease and medical terms. A natural language processing system is leveraged to annotate and structure clinical notes. In order to analyse the performance of retrieved results, dictionaries of terms for diseases, medications, and symptoms have been created using clinical domain knowledge.

Fan et al (Chen et al., 2017) used a Bio-Dynamic Topic Modeling (DTM) for revealing topics and their evolution in biomedical literature. The system of Bio-DTM mainly includes four components, documents pre-processing, bio-dictionary construction with the use of medical sources, dynamic topic models, topics analysis and visualization.

Finally, Karystianis et al (Karystianis et al., 2017) proposed a knowledge-driven, rule-based approach to identify targeted information from abstracts of epidemiological studies. Their methodology involved the design and implementation of generic rules that enable the recognition of mentions of elements in the right context in epidemiological study abstracts, using dictionaries of targeted elements. Since the dictionaries are concept specific for the outcomes and exposures, they are manually crafted because of their quickly development.

Regarding the NER techniques, in 2008 Sasaki et al (Sasaki et al., 2008) suggested a novel way to improve the NER performance by adding Named Entities (NEs) to an NE dictionary without retraining. In their approach, known NEs are identified in parallel with Part-of-Speech (POS) tagging based on a general word dictionary and an NE dictionary. Then, statistical NER is trained on the POS/PROTEIN tagger outputs with correct NE labels attached. In particular, they use CRF models to predict the label of entities.

In 2009, Yang et al (Xu et al., 2009) conducted a Named Entity Mining (NEM) by using click-through data collected at a web search engine, employing the Weak Supervised Latent Dirichlet Allocation (WS-LDA) topic model technique that generates the click-through data, and learning the topic model by weak supervision from humans. The method then applies the acquired patterns into the click-through data to mine new named entities. It outputs the top ranked named entities for each class, as well as patterns of each class.

In 2014, Mahalakshmi et al (Mahalakshmi et al., 2018) described a way for automating the test process from the early stages of requirement elicitation in the development of software. They proposed a semi-supervised technique to generate test cases by identifying named entities in the given set of use cases. The Named Entity Recognizer model used is Maximum Entropy Model (MEM), that is trained by a set of features extracted from the use cases. The Named Entities found are saved in the NE dictionary in their domain which can be referred in future for other set of use cases.

Also in 2014, Konkol et al (Konkol et al., 2015) proposed a new feature for NER based on latent semantic and explored the effect of unsupervised morphological information on these methods and on the NER system in general. Rather than using gazetteers -lists of named entities of the same type- made by human experts

as semantic features, they use words and phrases clusters and use word similarity based on semantic spaces to create these clusters. These clusters are then used to represent the local semantic information. They also used topic models - LDA in particular- and enrich features by a language-independent unsupervised stemming. In 2015, Chen et al (Liu et al., 2015) investigated the effect of semantic features based on word embeddings on DNR and compare them with semantic features based on three drug dictionaries. They propose a Conditional Random Fields-based system for Drug Name Recognition. Rather than using classical semantic features based on drug dictionaries manually constructed by experts, they use word embeddings. The skip-gram model, an unsupervised algorithm, is used to induce word embeddings on unlabelled biomedical texts.

Song et al (Song et al., 2015a) presented a comprehensive text-mining system that integrates dictionary-based entity extraction and rule-based relation extraction in a highly flexible and extensible framework. They developed an extensible rule engine based on dependency parsing for relation extraction in order to develop a predictive model that was effective in general. A set of rules is applied to identify whether a relation exists in a sentence and to determine its relation type.

In 2017, Natarajan et al (Murugesan et al., 2017) described an hybrid named entity tagging composed of three modules: the first is for text processing, which includes basic NLP pre-processing, feature extraction, and feature selection; the second is for training and model building with bidirectional Conditional Random Fields to parse the text in both directions (forward and backward); the final module is for post-processing, which includes surrounding text features, parenthesis mismatching, and two-tier abbreviation algorithm.

Rinaldi et al (Basaldella et al., 2017) showed an approach that uses a two-stage pipeline, combining a dictionary- based entity recognizer with a machine-learning classifier. First, the dictionary stage annotates the terms that appear in selected domain ontologies. Subsequently, the machine learning stage uses this information as a feature for two machine learning algorithms, Conditional Random Fields and Neural Networks, to select the relevant entities only.

Unanue et al (Unanue et al., 2017) proposed two deep learning methods to create a highly accurate Drug Name Recognition and Clinical Concept Extraction system that avoids conventional, time-consuming feature engineering and to develop more specialized word embeddings by using health domain datasets. Two deep learning methods are the Bidirectional LSTM and the Bidirectional LSTM-CRF. A CRF model is set as the baseline to compare the deep learning systems to a traditional machine learning approach and the same features are used for all the models.

To solve the issue of biomedical names ambiguity in knowledge extraction, Huang et al (Huang et al., 2018) presented a novel approach to disambiguating gene/protein names by using context graphs. In order to obtain the domain knowledge, a context graphs is built by examining the co- occurrence word relationship in a set of abstract of document, rather than by relying on expensive experts' judgements. They propose a method that integrates the word frequency, dispersion degree and concentration degree. Finally, entity resolution is performed by applying a Support Vector Machine.

Venkatasubramanian et al (Remolona et al., 2017) developed an approach that integrates a variety of machine learning and natural language processing methods to extract information from journal articles and store them semantically in an ontology. In this work, identification of key terms - such as chemicals, drugs, processes, anatomical entities, etc. - from abstracts, and the classification of these terms into 25 classes are presented. They tested two methods - a multi-class classifier (SVM) and a multi-label classifier (HOMER)- on an annotated data set for the pharmaceutical industry.

In 2018, Gupta et al (Gupta et al., 2018) propose a hybrid approach that combines dependency-based parse tree with distributed semantics for generating structured information frames about particular findings from the free-text mammography reports. To do this, they follow three steps: Extraction of relation through tokenization, sentence splitting, POS tagging, Dependency Parsing and Relation extraction; Clustering of relations through Word2Vec and k-means method; Association of relations with their arguments and construction of information frames. Chen et al (Wang et al., 2018) present a workflow for information extraction and knowledge discovery from textual geoscience data. They set up a hybrid corpus combining the generic and geology terms from geology dictionaries to train word segmentation rules of the Conditional Random Fields model. Then, they parsed documents and get a corpus constituted of content-words. Finally, they use a statistical method to analyze the semantic links between content words, and they use a knowledge graph to visualize these links and to map a clear overview of key information in an unstructured document. Also in 2018, An et al (An et al., 2018) propose a novel approach based on preposition semantic analysis network, where a preposition is the word that defines the relationship between two neighbouring words. In the case of patents, prepositions aid in revealing the relationships between keywords related to technologies. Patent documents largely consist of technical terms and, if the relationships between the keywords are well identified, the keyword analysis can be a useful tool for revealing the overall technological structure of the invention and the technological landscape.

13.3 A Map for Lexicons Design

After the identification of the main techniques for dictionaries construction and for NER techniques used in the 23 papers, techniques were grouped into three classes: pre-processing tools, NER supervised tools and NER unsupervised tools. Table presented in figure 13.1 shows what of these techniques were used in the analysed papers. In the table, there is also a column that indicates the presence of expert intervention, a column that indicates the year of publication of papers and a column that gives an indication about the number of documents used as datasets for the analysis described in papers.

The use of experts for crafting of Knowledge Base and Technical lexicons has evolved in time: at first, knowledge extraction was a completely human task in which domain experts selected manually keywords from raw texts. To date, with the development of text mining techniques just described, experts' intervention

Paper	Year of publication	Dimension of Data Set (N of documents)	Pre-Processing				NER Supervised Tools			NER unsupervised tools			
			Sentence splitting	Token	Lemma	Stemming	POS Tagging	Chunk	Word frequency	Dependency parsing tree	SVM	NB	MEM
1) Extracting failure time data from industrial maintenance records using text mining	2016	11786	X	X				X	X	X			
2) Developing a hybrid dictionary-based bio-entity recognition technique	2014	340		X	X	X							
3) Science foresight using life-cycle analysis, text mining and clustering A case study on natural ventilation	2017	92	X	X		X			X				X
4) Research trends on Big Data in Marketing: A text mining and topic modeling based literature analysis	2017	1560	X	X				X				X	X
5) A hybrid model for automatic identification of risk factors for heart disease	2015	1304	X	X		X	X	X		X	X		X
6) Big data driven co-occurring evidence discovery in chronic obstructive pulmonary disease patients	2017	64371 (summaries)	X	X			X	X					X
7) Revealing topics and their evolution in biomedical literature using Bio-DTM: a case study of eprints	2017	5394	X	X		X		X		X			X
8) Monitoring emerging technologies for technology planning using technical keyword based analysis from patent data	2016	151	X	X	X			X					
9) Evaluation of a rule-based method for epidemiological document classification towards the automation of systematic reviews	2017	51											X
10) How to make the most of NE dictionaries in statistical NER	2008	2404 abstracts	X	X			X			X			
11) Effects of Semantic Features on Machine Learning-Based Drug Name Recognition Systems: Word Embeddings vs. Manually Constructed Dictionaries	2015	17,3 GB of texts	X	X			X	X		X			X
12) Automatic information extraction from unstructured mammography reports using distributed learning	2018	300300	X	X			X		X			X	X
13) Information extraction and knowledge graph construction from geoscience literature	2018	NA		X		X		X		X			
14) BCC-NER: bidirectional, contextual clues named entity tagger for gene/protein mention recognition	2017	20000 sentences	X	X	X		X	X	X				X
15) Named Entity Mining from Click-Through Data Using Weakly Supervised Latent Dirichlet Allocation	2009	1000 queries	X									X	X
16) Named Entity Recognition for Automated Test Case Generation	2014	139	X					X			X		
17) Entity recognition in the biomedical domain using a hybrid approach	2017	97	X	X	X	X			X		X		
18) Recurrent neural networks with specialized word embeddings for health domain named-entity recognition	2017	426				X			X		X		
19) Latent semantics in Named Entity Recognition	2014	NA			X							X	
20) A novel approach for entity resolution in scientific documents using context graphs	2017	2000 abstracts	X	X				X	X				
21) Hybrid ontology-learning materials engineering system for pharmaceutical products: Multi-label entity recognition and concept detection	2017	1730 abstracts	X	X			X		X				X
22) PKDE4: Entity and relation extraction for public knowledge discovery	2015	2384	X	X	X		X	X	X	X			X
23) Deriving technology intelligence from patents: Preposition-based semantic analysis	2018	2838	X				X	X	X			X	X

Figure 13.1: Summary of state-of-art techniques for lexicons design.

has been reduced but not eliminated: although their intervention is considered too subjective, expensive and time-consuming, their contribution is still fundamental in the process of keywords selection and filtering, and in phase of dictionaries check and analysis check.

Chapter 14

Future Developments

One of the main evidence looking at the state-of-art literature on the topic of knowledge extraction from documents is the lacks in management studies. In particular, researchers did not study the best way to integrate NLP outputs with human activities yet. This work is a first step in the desired direction, but the research agenda is still long.

Among the many possible future works the most important at this time is the development of measurements of efficiency and effectiveness of human-machine processes for the knowledge extraction from texts. To do so we will focus on specific areas of applications and understand how to measure the impact of our designs on the day-to-day work of our stakeholders.

For this reason, in further research we will investigate the impact of the methods on the design and marketing processes. A first type of impact involves more effectiveness of the process. Our tools can be used in the design or the redesign of existing products; the users or the advantages of the inventions for example, can help marketer in communicate the positive effects of a product/system, helping them in the product positioning. A second type of impact can bring efficiency. The use of the proposed methods are clearly less time and money expensive with respect to the manual analysis of documents made by experts.

Another interesting area of research is the extraction of new lexicons that could be connected with the ones described in this thesis. A taxonomy instead of a dictionary could dramatically improve the quality of the output of our systems.

Finally, it is important to underline that further areas of research can focus on using our methodologies for the extraction of new types of entities, even far from the explored field. The challenge is to understand which other group of words contained in documents can add value to different stakeholders, and how to use design science, data science and natural language processing to solve their problems.

Glossary

Algorithm: In mathematics and computer science, an algorithm is an unambiguous specification of how to solve a class of problems. Algorithms can perform calculation, data processing and automated reasoning tasks.

Artificial Intelligence: Artificial intelligence (AI), sometimes called machine intelligence, is intelligence demonstrated by machines, in contrast to the natural intelligence displayed by humans and other animals. In computer science AI research is defined as the study of “intelligent agents”: any device that perceives its environment and takes actions that maximize its chance of successfully achieving its goals. Colloquially, the term “artificial intelligence” is applied when a machine mimics “cognitive” functions that humans associate with other human minds, such as “learning” and “problem solving”.

Bias: Bias is disproportionate weight in favor of or against one thing, person, or group compared with another, usually in a way considered to be unfair.

Bibliometrics: Bibliometrics is statistical analysis of written publications, such as books or articles. Bibliometric methods are frequently used in the field of library and information science, including scientometrics. For instance, bibliometrics are used to provide quantitative analysis of academic literature or for evaluating budgetary spending. Citation analysis is a commonly used bibliometric method which is based on constructing the citation graph, a network or graph representation of the citations between documents. Many research fields use bibliometric methods to explore the impact of their field, the impact of a set of researchers, the impact of a particular paper, or to identify particularly impactful papers within a specific field of research. Bibliometrics also has a wide range of other applications, such as in descriptive linguistics, the development of thesauri, and evaluation of reader usage.

Blockchain: A blockchain, originally block chain is a growing list of records, called blocks, which are linked using cryptography. Each block contains a cryptographic hash of the previous block, a timestamp, and transaction data (generally represented as a merkle tree root hash).

Business Intelligence: Business intelligence (BI) comprises the strategies and technologies used by enterprises for the data analysis of business information. BI technologies provide historical, current and predictive views of business operations. Common functions of business intelligence technologies include reporting, online

analytical processing, analytics, data mining, process mining, complex event processing, business performance management, benchmarking, text mining, predictive analytics and prescriptive analytics. BI technologies can handle large amounts of structured and sometimes unstructured data to help identify, develop and otherwise create new strategic business opportunities. They aim to allow for the easy interpretation of these big data. Identifying new opportunities and implementing an effective strategy based on insights can provide businesses with a competitive market advantage and long-term stability.

Business Process Management: Business process management (BPM) is a discipline in operations management in which people use various methods to discover, model, analyze, measure, improve, optimize, and automate business processes. BPM focuses on improving corporate performance by managing business processes. Any combination of methods used to manage a company's business processes is BPM. Processes can be structured and repeatable or unstructured and variable. Though not required, enabling technologies are often used with BPM.

Citation Analysis: Citation analysis is the examination of the frequency, patterns, and graphs of citations in documents. It uses the pattern of citations, links from one document to another document, to reveal properties of the documents. A typical aim would be to identify the most important documents in a collection. A classic example is that of the citations between academic articles and books. The judgements produced by judges of law to support their decisions refer back to judgements made in earlier cases so citation analysis in a legal context is important. Another example is provided by patents which contain prior art, citation of earlier patents relevant to the current claim.

Cloud Computing: Cloud computing is shared pools of configurable computer system resources and higher-level services that can be rapidly provisioned with minimal management effort, often over the Internet. Cloud computing relies on sharing of resources to achieve coherence and economies of scale, similar to a public utility.

Cognitive Computing: Cognitive computing (CC) describes technology platforms that, broadly speaking, are based on the scientific disciplines of artificial intelligence and signal processing. These platforms encompass machine learning, reasoning, natural language processing, speech recognition and vision (object recognition), human "computer interaction, dialog and narrative generation, among other technologies. Contents Definition Use cases Cognitive analytics⁴ See also⁵ References⁶ Further readingDefinition

Communication: Communication (meaning "to share") is the act of conveying meanings from one entity or group to another through the use of mutually understood signs and semiotic rules.

Computer Science: Computer science is the study of the theory, experimentation, and engineering that form the basis for the design and use of computers. It is the scientific and practical approach to computation and its applications and the systematic study of the feasibility, structure, expression, and mechanization of the methodical procedures (or algorithms) that underlie the acquisition, repre-

sentation, processing, storage, communication of, and access to, information. An alternative, more succinct definition of computer science is the study of automating algorithmic processes that scale. A computer scientist specializes in the theory of computation and the design of computational systems. See glossary of computer science.

Confidence: Confidence has a common meaning of a certainty about handling something, such as work, family, social events, or relationships. Some have ascribed confidence as a state of being certain either that a hypothesis or prediction is correct or that a chosen course of action is the best or most effective. Self-confidence is having confidence in one's self. Arrogance or hubris in this comparison is having unmerited confidence—believing something or someone is capable or correct when they are not. Overconfidence or presumptuousness is excessive belief in someone (or something) succeeding, without any regard for failure. Confidence can be a self-fulfilling prophecy as those without it may fail or not try because they lack it and those with it may succeed because they have it rather than because of an innate ability.

Cosine Similarity: Cosine similarity is a measure of similarity between two non-zero vectors of an inner product space that measures the cosine of the angle between them. The cosine of 0 is 1, and it is less than 1 for any angle in the interval radians. It is thus a judgment of orientation and not magnitude: two vectors with the same orientation have a cosine similarity of 1, two vectors oriented at relative to each other have a similarity of 0, and two vectors diametrically opposed have a similarity of -1, independent of their magnitude. The cosine similarity is particularly used in positive space, where the outcome is neatly bounded in. The name derives from the term “direction cosine”: in this case, unit vectors are maximally “similar” if they’re parallel and maximally “dissimilar” if they’re orthogonal (perpendicular). This is analogous to the cosine, which is unity (maximum value) when the segments subtend a zero angle and zero (uncorrelated) when the segments are perpendicular.

Data: Data is a set of values of qualitative or quantitative variables.

Data Science: Data science is an interdisciplinary field that uses scientific methods, processes, algorithms and systems to extract knowledge and insights from data in various forms, both structured and unstructured, similar to data mining.

Design: Design is the creation of a plan or convention for the construction of an object, system or measurable human interaction. Design has different connotations in different fields (see design disciplines below). In some cases, the direct construction of an object (as in pottery, engineering, management, coding, and graphic design) is also considered to use design thinking.

Design Methods: Design methods is a broad area that focuses on:
 Divergence
 — Exploring possibilities and constraints of inherited situations by applying critical thinking through qualitative and quantitative research methods to create new understanding (problem space)
 Transformation
 — Redefining specifications of design solutions which can lead to better guidelines for traditional and contemporary design activities (architecture, graphic, industrial, information, interaction, et al.)
 Convergence
 — and/or multidisciplinary response

Prototyping possible scenarios for better design solutions that incrementally or significantly improve the originally inherited situationSustainability “ Managing the process of exploring, redefining and prototyping of design solutions continually over timeArticulation - the visual relationship between the parts and the whole.

Design Science: Design Science was introduced in 1957 by R. Buckminster Fuller who defined it as a systematic form of designing. He expanded on this concept in his World Design Science Decade proposal to the International Union of Architects in 1961. The term was later used in S. A. Gregory's 1966 book of the 1965 Design Methods Conference 4 where he drew the distinction between scientific method and design method. Gregory was clear in his view that design was not a science and that design science referred to the scientific study of design. Herbert Simon in his 1968 Karl Taylor Compton lectures 5 used and popularized these terms in his argument for the scientific study of the artificial (as opposed to the natural). Over the intervening period the two uses of the term (systematic designing and study of designing) have co-mingled to the point where design science has come to have both meanings.

Document: A document is a written, drawn, presented, or memorialized representation of thought. The word originates from the Latin *documentum*, which denotes a “teaching” or “lesson”. In the past, the word was usually used to denote a written proof useful as evidence of a truth or fact. In the computer age, “document” usually denotes a primarily textual computer file, including its structure and format, e.g. fonts, colors, and images. Contemporarily, “document” is not defined by its transmission medium, e.g., paper, given the existence of electronic documents. “Documentation” is distinct because it has more denotations than “document”. Documents are also distinguished from “realia”, which are three-dimensional objects that would otherwise satisfy the definition of “document” because they memorialize or represent thought documents are considered more as dimensional representations. While documents are able to have large varieties of customization, all documents are able to be shared freely, and have the right to do so, creativity can be represented by documents, also. History, events, examples, opinion, etc. all can be expressed in documents.

Efficacy: Efficacy is the ability to get a job done satisfactorily. The word comes from the same roots as effectiveness, and it has often been used synonymously, although in pharmacology a distinction is now often made between efficacy and effectiveness. The word efficacy is used in pharmacology and medicine to refer both to the maximum response achievable from a pharmaceutical drug in research settings, and to the capacity for sufficient therapeutic effect or beneficial change in clinical settings.

Efficiency: Efficiency is the (often measurable) ability to avoid wasting materials, energy, efforts, money, and time in doing something or in producing a desired result. In a more general sense, it is the ability to do things well, successfully, and without waste. In more mathematical or scientific terms, it is a measure of the extent to which input is well used for an intended task or function (output). It often specifically comprises the capability of a specific application of effort to produce a specific outcome with a minimum amount or quantity of waste, expense,

or unnecessary effort. Efficiency refers to very different inputs and outputs in different fields and industries.

Entrepreneurship: Entrepreneurship is the process of designing, launching and running a new business, which is often initially a small business. The people who create these businesses are called entrepreneurs.need quotation to verify.

Expert System: In artificial intelligence, an expert system is a computer system that emulates the decision-making ability of a human expert. Expert systems are designed to solve complex problems by reasoning through bodies of knowledge, represented mainly as “then rules rather than through conventional procedural code. The first expert systems were created in the 1970s and then proliferated in the 1980s. Expert systems were among the first truly successful forms of artificial intelligence (AI) software.

Feature Selection: In machine learning and statistics, feature selection, also known as variable selection, attribute selection or variable subset selection, is the process of selecting a subset of relevant features (variables, predictors) for use in model construction. Feature selection techniques are used for four reasons:simplification of models to make them easier to interpret by researchers/users,shorter training times,to avoid the curse of dimensionality,enhanced generalization by reducing overfitting (formally, reduction of variance).

Forecasting: Forecasting is the process of making predictions of the future based on past and present data and most commonly by analysis of trends. A commonplace example might be estimation of some variable of interest at some specified future date. Prediction is a similar, but more general term. Both might refer to formal statistical methods employing time series, cross-sectional or longitudinal data, or alternatively to less formal judgmental methods. Usage can differ between areas of application: for example, in hydrology the terms “forecast” and “forecasting” are sometimes reserved for estimates of values at certain specific future times, while the term “prediction” is used for more general estimates, such as the number of times floods will occur over a long period.

Grammar: In linguistics, grammar is the set of structural rules governing the composition of clauses, phrases, and words in any given natural language. The term refers also to the study of such rules, and this field includes phonology, morphology, and syntax, often complemented by phonetics, semantics, and pragmatics.

Heuristic: A heuristic technique often called simply a heuristic, is any approach to problem solving, learning, or discovery that employs a practical method, not guaranteed to be optimal, perfect, logical, or rational, but instead sufficient for reaching an immediate goal. Where finding an optimal solution is impossible or impractical, heuristic methods can be used to speed up the process of finding a satisfactory solution. Heuristics can be mental shortcuts that ease the cognitive load of making a decision. Examples that employ heuristics include using a rule of thumb, an educated guess, an intuitive judgment, a guesstimate, stereotyping, profiling, or common sense.

Industrial Engineering: Industrial engineering is a branch of engineering which deals with the optimization of complex processes, systems, or organizations. Industrial engineers work to eliminate waste of time, money, materials, person-hours, machine time, energy and other resources that do not generate value. According to the Institute of Industrial and Systems Engineers, they create engineering processes and systems that improve quality and productivity.

Information: Information is any entity or form that provides the answer to a question of some kind or resolves uncertainty. It is thus related to data and knowledge, as data represents values attributed to parameters, and knowledge signifies understanding of real things or abstract concepts. As it regards data, the information's existence is not necessarily coupled to an observer (it exists beyond an event horizon, for example), while in the case of knowledge, the information requires a cognitive observer.

Information Technology: Information technology (IT) is the use of computers to store, retrieve, transmit, and manipulate data, or information, often in the context of a business or other enterprise. IT is considered to be a subset of information and communications technology (ICT).

Knowledge: Knowledge is a familiarity, awareness, or understanding of someone or something, such as facts, information, descriptions, or skills, which is acquired through experience or education by perceiving, discovering, or learning.

Knowledge Base: A knowledge base (KB) is a technology used to store complex structured and unstructured information used by a computer system. The initial use of the term was in connection with expert systems which were the first knowledge-based systems. Contents1 Original usage of the term Knowledge base properties Internet as a knowledge base See also5 NotesOriginal usage of the term

Latent Dirichlet Allocation: In natural language processing, latent Dirichlet allocation (LDA) is a generative statistical model that allows sets of observations to be explained by unobserved groups that explain why some parts of the data are similar. For example, if observations are words collected into documents, it posits that each document is a mixture of a small number of topics and that each word's presence is attributable to one of the document's topics. LDA is an example of a topic model.

Lexicon: A lexicon, word-hoard, wordbook, or word-stock is the vocabulary of a person, language, or branch of knowledge (such as nautical or medical). In linguistics, a lexicon is a language's inventory of lexemes.

Literature Review: A literature review or narrative review is a type of review article. A literature review is a scholarly paper, which includes the current knowledge including substantive findings, as well as theoretical and methodological contributions to a particular topic. Literature reviews are secondary sources, and do not report new or original experimental work. Most often associated with academic-oriented literature, such reviews are found in academic journals, and are not to be confused with book reviews that may also appear in the same publication. Literature reviews are a basis for research in nearly every academic field. A narrow-scope literature review may be included as part of a peer-reviewed journal

article presenting new research, serving to situate the current study within the body of the relevant literature and to provide context for the reader. In such a case, the review usually precedes the methodology and results sections of the work.

Machine Learning: Machine learning is a field of artificial intelligence that uses statistical techniques to give computer systems the ability to “learn” (e.g., progressively improve performance on a specific task) from data, without being explicitly programmed.

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

Named-Entity Recognition: Named-entity recognition (NER) (also known as entity identification, entity chunking and entity extraction) is a subtask of information extraction that seeks to locate and classify named entity mentions in unstructured text into pre-defined categories such as the person names, organizations, locations, medical codes, time expressions, quantities, monetary values, percentages, etc.

Natural Language Processing: Natural language processing (NLP) is a subfield of computer science, information engineering, and artificial intelligence concerned with the interactions between computers and human (natural) languages, in particular how to program computers to process and analyze large amounts of natural language data.

Neural Network: The term neural network was traditionally used to refer to a network or circuit of neurons. The modern usage of the term often refers to artificial neural networks, which are composed of artificial neurons or nodes. Thus the term may refer to either biological neural networks, made up of real biological neurons, or artificial neural networks, for solving artificial intelligence (AI) problems. The connections of the biological neuron are modeled as weights. A positive weight reflects an excitatory connection, while negative values mean inhibitory connections. All inputs are modified by a weight and summed. This activity is referred as a linear combination. Finally, an activation function controls the amplitude of the output.

Patent: A patent is a form of intellectual property. A patent gives its owner the right to exclude others from making, using, selling, and importing an invention for a limited period of time, usually twenty years. The patent rights are granted in exchange for an enabling public disclosure of the invention. People who are employed to do research are often obligated by their employment contracts to assign inventions to their employer. In most countries patent rights fall under civil law and the patent holder needs to sue someone infringing the patent in order to enforce their rights. In some industries patents are an essential form of competitive advantage in others they are irrelevant.

Policy: A policy is a deliberate system of principles to guide decisions and achieve rational outcomes. A policy is a statement of intent, and is implemented as a procedure or protocol. Policies are generally adopted by a governance body within an organization. Policies can assist in both subjective and objective decision making. Policies to assist in subjective decision making usually assist senior management

with decisions that must be based on the relative merits of a number of factors, and as a result are often hard to test objectively, e.g. work-life balance policy. In contrast policies to assist in objective decision making are usually operational in nature and can be objectively tested, e.g. password policy.

Precision Agriculture: Precision agriculture (PA), satellite farming or site specific crop management (SSCM) is a farming management concept based on observing, measuring and responding to inter and intra-field variability in crops. The goal of precision agriculture research is to define a decision support system (DSS) for whole farm management with the goal of optimizing returns on inputs while preserving resources.

Programming Language: A programming language is a formal language, which comprises a set of instructions used to produce various kinds of output. Programming languages are used to create programs that implement specific algorithms.

Radio-Frequency Identification: Radio-frequency identification (RFID) uses electromagnetic fields to automatically identify and track tags attached to objects. The tags contain electronically-stored information. Passive tags collect energy from a nearby RFID reader's interrogating radio waves. Active tags have a local power source (such as a battery) and may operate hundreds of meters from the RFID reader. Unlike a barcode, the tag need not be within the line of sight of the reader, so it may be embedded in the tracked object. RFID is one method for Automatic Identification and Data Capture (AIDC).

Regular Expression: A regular expression, regex or regexp (sometimes called a rational expression) is, in theoretical computer science and formal language theory, a sequence of characters that define a search pattern. Usually this pattern is then used by string searching algorithms for “find” or “find and replace” operations on strings, or for input validation.

Research Excellence Framework: The Research Excellence Framework is the successor to the Research Assessment Exercise. It is an impact evaluation which assesses the research of British higher education institutions. It was first used in to assess the period. REF is undertaken by the four UK higher education funding bodies: Research England, the Scottish Funding Council (SFC), the Higher Education Funding Council for Wales (HEFCW), and the Department for the Economy, Northern Ireland (DfE).

Scientific Literature: Scientific literature comprises scholarly publications that report original empirical and theoretical work in the natural and social sciences, and within an academic field, often abbreviated as the literature. Academic publishing is the process of contributing the results of one’s research into the literature, which often requires a peer-review process. Original scientific research published for the first time in scientific journals is called the primary literature. Patents and technical reports, for minor research results and engineering and design work (including computer software), can also be considered primary literature. Secondary sources include review articles (which summarize the findings of published studies to highlight advances and new lines of research) and books (for large projects or broad arguments, including compilations of articles). Tertiary sources might

include encyclopedias and similar works intended for broad public consumption.

Semantic Field: In linguistics, a semantic field is a set of words grouped semantically (by meaning) that refers to a specific subject. The term is also used in anthropology, computational semiotics, and technical exegesis.

Social Media: Social media are interactive computer-mediated technologies that facilitate the creation and sharing of information, ideas, career interests and other forms of expression via virtual communities and networks. The variety of stand-alone and built-in social media services currently available introduces challenges of definition however, there are some common features: Social media are interactive Web .0 Internet-based applications. User-generated content, such as text posts or comments, digital photos or videos, and data generated through all online interactions, is the lifeblood of social media. Users create service-specific profiles for the website or app that are designed and maintained by the social media organization. 4 Social media facilitate the development of online social networks by connecting a user's profile with those of other individuals or groups.

Social Science: Social science is a category of academic disciplines, concerned with society and the relationships among individuals within a society. Social science as a whole has many branches, each of which is considered a social science. The social sciences include, but are not limited to: anthropology, archaeology, communication studies, economics, history, human geography, jurisprudence, linguistics, political science, psychology, public health, and sociology. The term is also sometimes used to refer specifically to the field of sociology, the original "science of society", established in the 19th century. For a more detailed list of sub-disciplines within the social sciences see: Outline of social science.

Statistical Model: A statistical model is a mathematical model that embodies a set of statistical assumptions concerning the generation of some sample data and similar data from a larger population. A statistical model represents, often in considerably idealized form, the data-generating process.

Strategic Management: In the field of management, strategic management involves the formulation and implementation of the major goals and initiatives taken by an organization's top management on behalf of owners, based on consideration of resources and an assessment of the internal and external environments in which the organization operates. need quotation to verify.

Taxonomy: Taxonomy (general) is the practice and science of classification of things or concepts, including the principles that underlie such classification.

Technology Intelligence: Technology Intelligence (TI) is an activity that enables companies to identify the technological opportunities and threats that could affect the future growth and survival of their business. It aims to capture and disseminate the technological information needed for strategic planning and decision making. As technology life cycles shorten and business become more globalized having effective TI capabilities is becoming increasingly important.

Topic Model: In machine learning and natural language processing, a topic model is a type of statistical model for discovering the abstract "topics" that occur in a

collection of documents. Topic modeling is a frequently used text-mining tool for discovery of hidden semantic structures in a text body. Intuitively, given that a document is about a particular topic, one would expect particular words to appear in the document more or less frequently: “dog” and “bone” will appear more often in documents about dogs, “cat” and “meow” will appear in documents about cats, and “the” and “is” will appear equally in both. A document typically concerns multiple topics in different proportions thus, in a document that is 10% about cats and 90% about dogs, there would probably be about 9 times more dog words than cat words. The “topics” produced by topic modeling techniques are clusters of similar words.

Trademark: A trademark, trade mark, or trade-mark is a recognizable sign, design, or expression which identifies products or services of a particular source from those of others, although trademarks used to identify services are usually called service marks.⁴⁵ The trademark owner can be an individual, business organization, or any legal entity. A trademark may be located on a package, a label, a voucher, or on the product itself. For the sake of corporate identity, trademarks are often displayed on company buildings.

Trait Theory: In psychology, trait theory (also called dispositional theory) is an approach to the study of human personality. Trait theorists are primarily interested in the measurement of traits, which can be defined as habitual patterns of behavior, thought, and emotion. According to this perspective, traits are aspects of personality that are relatively stable over time, differ across individuals (e.g. some people are outgoing whereas others are not), are relatively consistent over situations, and influence behavior. Traits are in contrast to states, which are more transitory dispositions.

Word-Sense Disambiguation: In computational linguistics, word-sense disambiguation (WSD) is an open problem of natural language processing and ontology. WSD is identifying which sense of a word (i.e. meaning) is used in a sentence, when the word has multiple meanings. The solution to this problem impacts other computer-related writing, such as discourse, improving relevance of search engines, anaphora resolution, coherence, inference, et cetera.

Wordvec: Wordvec is a group of related models that are used to produce word embeddings. These models are shallow, two-layer neural networks that are trained to reconstruct linguistic contexts of words. Wordvec takes as its input a large corpus of text and produces a vector space, typically of several hundred dimensions, with each unique word in the corpus being assigned a corresponding vector in the space. Word vectors are positioned in the vector space such that words that share common contexts in the corpus are located in close proximity to one another in the space.

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