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PhD Thesis

Semantically-enabled Browsing of Large Multilingual Document Collections

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A mis padres.

A Beatriz.

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Acronyms

API: Application Programming Interface

CQ: Competency Question

GUI: Graphical User Interface

IDE: Integrated Development Environment

LD: Linked Data

LOD: Linked Open Data

UML: Unified Modeling Language

URI: Uniform Resource Identifier

URL: Uniform Resource Locator

WUI: Web User Interface

Chapter 1

Introduction

Huge amounts of textual documents are produced daily in digital format. Every second, more than two thousand blog entries are published, nine thousand tweets are written, and more than two million emails are sent on the internet¹. The number of scientific publications per year has increased by 8-9% in the last decade (Rob Johnson and Mabe, 2018). More than one million papers, about two per minute, were submitted to the PubMed database, the leading database of references and abstracts on life sciences and biomedical research, during last year. Statistics on judicial activity are similar. More than 168,000 procedural documents and 3,000 judicial notices were published in the Official Journal of the European Union in 2019 ². Unlike the academic domain where articles are mostly published in English, legal documents are usually available in multiple languages. The Court of Justice of the European Union had to translate over 1 million texts into its 24 official languages, with 552 possible language combinations, in just one year. These numbers make it virtually impossible for an expert in an academic or legal domain to stay abreast by only reading a few articles nowadays. Navigating the growing torrent of textual data and exploring their content is not only necessary, but has become a crucial job that experts must add to their daily tasks.

Document retrieval techniques are being used nowadays to facilitate text review in such big collections. Major digital publishers specialized in scientific³, technical⁴, and

¹<https://www.internetlivestats.com/one-second>

²<https://curia.europa.eu>

³<https://www.nature.com>

⁴<https://www.elsevier.com>

medical⁵ content provide search engines to make it easier to browse their collections of scientific articles. Given a few keywords, a list of relevant papers is retrieved and offered for reading. Legal documents are also exploited through similar solutions. The Spanish⁶, American⁷ and European⁸ intellectual property registration offices, for example, allow exploring their patent collections by search engines guided by keywords and/or categories. These categories are available because documents are manually categorized by their authors according to the International Patent Classification (IPC) system. It contains approximately 70,000 different codes for different technical areas. This label-based browsing⁹ has been also adopted by several academic search engines¹⁰ to organize papers by research areas, or even by evaluation tasks to browse state-of-the-art methods¹¹. In the natural language processing domain, research papers are organized into 256 tasks such as 'knowledge representation', 'question-answering', 'machine translation' and so on. However, while there are initiatives to normalize research areas, the use of keywords by authors in the form of tags to categorize their scientific papers is still insufficient and some text processing tasks are required to set labels to articles following a uniform criteria. One of the main reasons that limits its widespread use is the difficulty that authors have in picking labels that describe their research work in sufficient detail.

But what happens when a new research field or a new category emerges?. Searches guided by keywords or tags are useful when the domain is known, but when new categories appear these mechanisms may be insufficient. Researchers use reviewing to keep abreast of new discoveries. It helps to spark new ideas and approaches for their projects. But the problem is not all researchers are asked to peer review and those who are might struggle to fit it into their busy schedules, especially when the article is outside their area of expertise. Exist academic reports that identify the hottest and emerging specialty areas in scientific research from the last years¹². The methodology used in these reports assumes that cumulatively, and over time, citations in research

⁵<https://pubmed.ncbi.nlm.nih.gov>

⁶<https://www.oepm.es>

⁷<https://www.uspto.gov/>

⁸<https://www.epo.org>

⁹<https://patents.google.com>

¹⁰<https://academic.microsoft.com>

¹¹<https://paperswithcode.com>

¹²https://discover.clarivate.com/ResearchFronts2019_EN

leave a trail that highlights progress and advancements across a range of fields. By regularly tracking these citations and unpacking the patterns and groupings of how papers are cited, in particular clusters of papers that are frequently cited together, new research areas take shape. After an in-depth analysis, reports describe the research lines covered by these groups of research articles. Such reports also exist on patent collections to discover technology trends¹³.

Therefore, identifying relationships between documents is key to facilitating their exploration. A documentary exploration does not stop when a relevant article is found, but starts from its content shaping the area of interest through its relations. Most academic¹⁴ and legal¹⁵ search engines provide a list of related documents for each text and offer navigating through them. The relationship between two documents can be based on references, when documents are cited by others¹⁶, or content, when documents share a thematic area, etc. The chains of articles derived from that related content can lead to more complex structures when cross-relations are considered. A document can be related to another that, in turn, is related to a third one that can be also related to the first article. This content-guided exploration helps to browse document collections by areas of interest not necessarily aligned with a list of predefined categories. A visual overview of an academic field, for example, can be provided by showing graphs of articles with similar content¹⁷.

While these initiatives are valuable efforts to address access to huge amounts of documents, they are still insufficient to make the most out of the knowledge available within the textual collection. On an individual level, the knowledge derived from a text comes from the concepts evoked by its words (Griffiths et al., 2007). On a collective level, the knowledge derived from a document collection emerges from the relationships among its texts (Kenter and de Rijke, 2015). Two modes of knowledge inferences are needed, a *bottom-up* from documents to collection-aware units, and a *top-bottom* from document relationships to specific info in texts. A semantic awareness is desirable to interpret the relationships and guide the exploration. The focus is on why some texts are related and what concepts are key to those relationships. But analyzing

¹³https://www.wipo.int/tech_trends

¹⁴<https://www.semanticscholar.org>

¹⁵<https://patents.google.com>

¹⁶<http://citationgecko.com>

¹⁷<https://www.connectedpapers.com>

and comparing texts on a large scale requires addressing some challenges imposed by external conditions that have appeared in recent years:

- **Complexity:** The increasing variety of topics, subjects, in those ever growing collections, has forced a reconsideration of the way to compare them. The operations required to compute each comparison should be simplified as much as possible.
- **Efficiency:** The algorithms, besides being accurate enough, must be also efficient in order to be applied on a large scale. Brute-force techniques cannot be applied to compare all items in a huge corpus.
- **Explainability:** The associations between documents must be explained in such a way that the relationship itself provides knowledge about the content of the texts. It is not enough that one text is related to another, it is necessary to explain why it is so.
- **Multilinguality:** In addition, the increasing availability of texts written in different natural languages also makes it necessary to address comparison in multilingual collections. In these collections, external translation systems cannot be considered as the only applicable solution, since they increase processing costs and potentially introduce a bias in the relationships that are obtained.

In our work we aim at facilitating the exploration of huge collections of documents written in multiple languages. We address the problem of comparing them on a large scale while enabling a semantic-aware exploration through their content. Our proposal automatically discovers thematic associations between texts using probabilistic topic models and organizes document collections so that they can be efficiently and transparently browsed through the related content regardless of their language.

1.1 Contributions

The following contributions are presented in this thesis:

- **Scalable Framework for Topic Modeling:** We introduce a text processing model that supports the creation of probabilistic topic models. Based on this

abstraction, we implement a framework that becomes the foundation of this thesis research, which is used as a tool for supporting performance analysis and algorithm design.

- **Lifecycle Management of Topic Models:** To facilitate the exploitation of trained topic models, we propose a unified form to publish and (re)use models based on Web services available from online repositories.
- **Hierarchical Thematic Annotations:** To study the problem of representativeness in high dimensional topic models, we exploit the relationships between texts derived from their topic distributions. We show how the distances vary between the same texts when the dimensions of the model change, and how less representative topics can influence their calculation. Our analytical and experimental results show that as more topics are available in the model, less representative are the distance measurements based on densities. During the study, we identified hierarchies in the topic distributions that maintain their representativeness regardless of the dimensions of the model, and without losing the ability to measure distances. We propose a method to annotate texts using topic hierarchies, and a distance metric based on this hierarchical representations.
- **Support for Large-scale Document Similarity Comparisons:** We present an efficient mechanism to index and retrieve related documents, described by hierarchical annotations, while allowing the exploration of the collection by the themes inferred from its texts.
- **Discovery of Cross-lingual Document Relations:** We introduce a technique to transform probabilistic topics from different languages into a single representation space based on shared concepts where texts can be thematically related regardless of the language used.

1.2 Thesis Structure

The thesis is structured as follows:

Chapter 2 describes the main concepts handled throughout the thesis, analyses the state of the art and identifies the main limitations. *Chapter 3* presents the research

problems and hypotheses that guide our work, as well as assumptions and restrictions and details the methodology that has been followed. *Chapter 4* describes the software architecture proposed to analyze huge document collections and the format suggested to distribute and reuse the topic models built in this thesis. *Chapter 5* details the text annotation algorithm based on probabilistic topics. *Chapter 6* shows how to store and search documents efficiently from large collections when they are annotated with topic hierarchies. *Chapter 7* explains the method to relate texts written in different languages from their main topics without the need of supervision. The approach to relate multi-lingual texts from their representations based on topic hierarchies is evaluated in *Chapter 8*, where the results are explained in detail. *Chapter 9* describes real-world projects where contributions from this thesis have been used. Finally, *Chapter 10* introduces conclusions and future lines of work.

1.3 Publications

The following publications support the research work presented in this thesis:

- *Chapter 4:*
 - **Carlos Badenes-Olmedo**, José Luis Redondo-Garcia, and Oscar Corcho. Distributing Text Mining tasks with librAIry. Proceedings of the 17th ACM Symposium on Document Engineering (DocEng). Association for Computing Machinery, Valletta, Malta. 2017.
 - Victoria Kosa, Alyona Chugunenko, Eugene Yuschenko, **Carlos Badenes-Olmedo**, Vadim Ermolayev, and Aliaksandr Birukou. Semantic saturation in retrospective text document collections. Information and Communication Technologies in Education, Research, and Industrial Applications (ICTERI) PhD Symposium, vol. 1851, pages 1-8. CEUR-WS. 2017
 - Victoria Kosa, David Chaves-Fraga, Dmitriy Naumenko, Eugene Yuschenko, **Carlos Badenes-Olmedo**, Vadim Ermolayev, Aliaksandr Birukou, Nick Bassiliades, Hans-Georg Fill, Vitaliy Yakovyna, Heinrich C. Mayr, Mykola Nikitchenko, Grygoriy Zholtkevych, and Aleksander Spivakovsky. Cross-Evaluation of Automated Term Extraction Tools by Measuring Terminological Saturation. Information and Communication Technologies in Education,

Research, and Industrial Applications, pages 135-163. Springer International Publishing. 2018

- *Chapter 5:*

- **Carlos Badenes-Olmedo**, José Luis Redondo-García, and Oscar Corcho. Efficient Clustering from Distributions over Topics. Proceedings of the 9th International Conference on Knowledge Capture (K-CAP), Article 17, 1–8. Association for Computing Machinery, Austin, TX, USA. 2017.
- **Carlos Badenes-Olmedo**, Jose Luis Redondo-Garcia, and Oscar Corcho. An initial Analysis of Topic-based Similarity among Scientific Documents based on their Rhetorical Discourse Parts. Proceedings of the 1st Workshop on Enabling Open Semantic Science (SemSci) co-located with 16th International Semantic Web Conference (ISWC 2017), 15-22. Vienna, Austria. 2017.

- *Chapter 6:*

- **Carlos Badenes-Olmedo**, José Luis Redondo-García, and Oscar Corcho. Large-scale Semantic Exploration of Scientific Literature Using Topic-based Hashing Algorithms. Semantic Web, vol. 11, no. 5, pp. 735-750. 2020

- *Chapter 7:*

- **Carlos Badenes-Olmedo**, José Luis Redondo-García, and Oscar Corcho. Scalable Cross-lingual Document Similarity through Language-specific Concept Hierarchies. Proceedings of the 10th International Conference on Knowledge Capture (K-CAP). Association for Computing Machinery, 147–153. Marina Del Rey, CA, USA. 2019
- **Carlos Badenes-Olmedo**, José Luis Redondo-García, and Oscar Corcho. Legal document retrieval across languages: topic hierarchies based on synsets. arXiv e-prints, arXiv:1911.12637. 2019
- Ahmet Soylu, Oscar Corcho, Brian Elvesaeter, **Carlos Badenes-Olmedo**, Francisco Yedro, Matej Kovacic, Matej Posinkovic, Ian Makgill, Chris Taggart, Elena Simperl, Till C. Lech, and Dumitru Roman. Enhancing Public

Procurement in the European Union through Constructing and Exploiting an Integrated Knowledge Graph. Proceedings of the 19th International Semantic Web Conference (ISWC). 2020

Chapter 2

State of the Art

2.1 Related Work

In this chapter we analyze the current state of the art and limitations to facilitate the exploration of large and multilingual document collections. First, the tasks derived from processing the texts and enabling a semantic-aware exploration of the corpus are described. Then, an overview of the existing methods that perform these tasks is introduced. And finally, for each research area involved, the limitations that must be addressed to achieve the ultimate goal of facilitating documentary exploration are presented. The concepts that will be used throughout the rest of the thesis are here introduced.

In order to browse large and multilingual document collections we need to process them in a way that is computationally affordable and provides enough knowledge to understand the relationships that arise. The annotation of human-readable documents is a well-known problem in the Artificial Intelligence (AI) domain in general and Information Retrieval (IR) and Natural Language Processing (NLP) fields in particular. Vector space models (VSM) (Salton, 1983) were proposed to represent texts as vectors where each entry corresponds to a different term and the number at that entry corresponds to how many times that term is present in the text. The objective was twofold, on the one hand to make document collections manageable since we move from having lots of terms for each text to only one vector per document with defined dimension, and on the other hand to have representations based on metric spaces where calculations can be made, for example comparisons by measuring vector distances. The definition and

number of dimensions for each vector are key aspects in a VSM. Traditional retrieval tasks over large collections of textual documents highly rely on individual features like term frequencies (TF) (Hearst and Hall, 1999). A representational space is created where each term in the vocabulary is projected by a separate and orthogonal dimension. All terms in a document are treated as equally descriptive. To overcome this problem, Term-Frequency Inverse-Document Frequency (TF-IDF) (Christopher D. Manning and Schütze, 2008) relativizes the relevance of each term with respect to the entire corpus. TF-IDF calculates the importance of a term for a document, based on the number of times the term appears in the document itself (term frequency - TF) and the number of documents in the corpus, which contain the term (document frequency - DF). The absence of semantic information and the notion of word sequences, and the high-number of dimensions are the main drawbacks of these approaches that lead to the emergence of other techniques.

New ways of characterizing documents based on the automatic generation of models surfacing the main themes covered in the corpus are developed during recent years. Among them, text embedding proposes transforming texts into low-dimensional vectors by prediction methods based on (i) word sequences or (ii) bag-of-words. The first approach assumes words with similar meanings tend to occur in similar contexts. It considers word order relevant and is based on Neural Models (NM) that learn word vectors from pairs of target and context words, where context words are taken as words observed to surround a target word. Document vectors are usually created by taking the word vectors they contain or by considering them as target and context items. Skip-gram with negative sampling (Word2Vec) (Mikolov et al., 2013) and Global Vectors (GloVe) (Pennington et al., 2014) are indeed the most popular methods to learn word embeddings due to its training efficiency and robustness (Levy et al., 2015). The second approach does not consider the order of the words to be relevant, but their frequency is. It assumes words with similar meanings will occur in similar documents. Topic models (Blei et al., 2003; Deerwester et al., 1990; Hofmann, 2001) are the main methods based on this approach. This second approach is used in our work since *we are not only interested in representing words and documents, but we also seek internal structures that can provide knowledge about the collection as a whole.*

Probabilistic Topic Models (PTM) (Blei et al., 2003; Hofmann, 2001) are statistical methods based on bag-of-words that analyze the words of the original texts to discover

the themes that run through them, how those themes are connected to each other, or how they change over time. PTM do not require any prior annotations or labeling of the documents. The topics emerge, as hidden structures, from the analysis of the original texts. These structures are topics distributions, per-resource topic distributions or per-resource per-word topic assignments. In turn, a topic is a distribution over terms that is biased around those words associated to a single theme. This interpretable hidden structure annotates each resource in the collection and these annotations can be used to perform deeper analysis about relationships between resources. Topic-based representations bring a lot of potential when applied over different IR tasks, as evidenced by recent works in different domains such as scholarly (Gatti et al., 2015), health (Lu et al., 2016; Tapi Nzali et al., 2017), legal (Greene and Cross, 2016; O'Neill et al., 2017), news (He et al., 2017) and social networks (Cheng et al., 2014). Topic modeling provides us an algorithmic solution to organize and annotate large collections of textual documents according to their topics.

The simplest generative topic model is *Latent Dirichlet Allocation* (LDA) (Blei et al., 2003). Along with *Latent Semantic Analysis* (LSA) (Deerwester et al., 1990) and *Probabilistic Latent Semantic Analysis* (pLSA) (Hofmann, 2001) are part of the field known as topic modeling. They are well-known latent variable models for high dimensional data, such as the bag-of-words representation for textual data or any other count-based data representation. They try to capture the intuition that documents can exhibit multiple themes. Each document exhibits each topic in different proportion, and each word in each document is drawn from one of the topics, where the selected topic is chosen from the per-document distribution over topics. All the documents in a collection share the same set of topics, but each document exhibits these topics in a different proportion. Texts are described as a vector of counts with W components, where W is the number of words in the vocabulary. Each document in the corpus is modeled as a mixture over K topics, and each topic k is a distribution over the vocabulary of W words. Formally, a topic is a multinomial distribution over words of a fixed vocabulary representing some concept. Depending on the function used to describe that distribution there are different algorithms to create topic models. While LSA and pLSA propose a singular value decomposition, LDA, influenced by the generative Bayesian framework to avoid some of the over-fitting issues that were observed with

pLSA, suggests the use of a Dirichlet function. It is a continuous multivariate probability distribution parameterized by a vector of positive reals whose elements sum to 1. It is continuous because the relative likelihood for a random variable to take on a given value is described by a probability density function, and is multivariate because it has a list of variables with unknown values. In fact, the Dirichlet distribution is the conjugate prior of the categorical distribution and multinomial distribution and is responsible for, unlike LSA and pLSA, LDA can infer topic distributions in texts that have not been used during training.

Topic models are not restrictive clustering models where each document is assigned to one cluster, but allows documents to exhibit multiple topics. The topics covered in a set of documents are discovered from the own corpus and feature vectors are topic distributions expressed as vector of probabilities. Taking into account this premise, the similarity between two topic-based resources is based on the distance between their topic distributions, which can be also seen as two probability mass functions. A commonly used metric is the *Kullback-Liebler* (KL) divergence:

$$KL(P, Q) = \sum_{i=1}^K p(x_i) \log \frac{p(x_i)}{q(x_i)} \quad (2.1)$$

However, it presents two major problems: (1) when a topic distribution is zero, KL divergence is not defined and (2) it is not symmetric, which does not fit well with semantic similarity measures that are usually symmetric (Rus et al., 2013).

Jensen-Shannon (JS) divergence (Lin, 1991; Rao, 1982) solves these problems considering the average of the distributions as below (Celikyilmaz et al., 2010):

$$JS(P, Q) = \sum_{i=1}^K p_i * \log \frac{2 * p_i}{p_i + q_i} + \sum_{i=1}^K q_i * \log \frac{2 * q_i}{q_i + p_i} \quad (2.2)$$

where K is the number of topics and p, q are the topics distributions

It can be transformed into a similarity measure as follows (Dagan et al., 1999) :

$$sim_{JS}(D_i, D_j) = 10^{-JS(p,q)} \quad (2.3)$$

where D_i, D_j are the documents and p, q the topic distributions of each of them.

Hellinger (He) distance is also symmetric and is used along with JS divergence in various fields where a comparison between two probability distributions is required (Blei and Lafferty, 2007; Boyd-Graber and Resnik, 2010; Hall et al., 2008):

$$He(P, Q) = \frac{1}{\sqrt{2}} \cdot \sqrt{\sum_{i=1}^K (\sqrt{p_i} - \sqrt{q_i})^2} \quad (2.4)$$

It can be transformed into a similarity measure by subtracting it from 1 (Rus et al., 2013) such that a zero distance means max. similarity score and vice versa:

$$sim_{He}(D_i, D_j) = 1 - He(p, q) \quad (2.5)$$

However, all these metrics are not well-defined distance metrics, that is, they do not satisfy triangle inequality (Charikar, 2002). This inequality considers $d(x, z) \leq d(x, y) + d(y, z)$ for a metric d (Griffiths et al., 2007) and places strong constraints on distance measures and on the locations of points in a space given a set of distances. As a metric axiom, the triangle inequality must be satisfied in order to take advantage of the inferences that can be deduced from it. Thus, if similarity is assumed to be a monotonically decreasing function of distance, this inequality avoids the calculation of all pairs of similarities by considering that if x is similar to y and y is similar to z , then x must be similar to z .

S2JSD was introduced by (Endres and Schindelin, 2003) to satisfy the triangle inequality. It is the square root of two times the *JS* divergence:

$$S2JSD(P, Q) = \sqrt{2 * JS(P, Q)} \quad (2.6)$$

2.2 Research Areas

This thesis aims to enable a semantic-aware exploration of the knowledge arising from large and multilingual document collections by exploiting the capabilities of topic models and their metric spaces. There are several research areas of ongoing related work.

The first one is **topic creation and reuse**, key for understanding the steps needed to transform the unstructured data from a text into numerical values based on probabilistic topics. *The way in which topic models are created and reused is crucial to addressing large-scale analysis.*

The second area is **topic explainability**, which refers to the capacity of topics to capture and describe the content of a text. Topic explainability is important for *making understandable the relationships that are derived from topic distributions*.

The third area is **document similarity**, where the ability to measure the *semantic difference between texts from the distance between their topic distributions is addressed*.

Finally, the fourth area is **multilingual topics**, as we aim to explore collections of texts written in different languages through their topic-based relationships. A *strategy to relate the topics of each language is needed*.

These four areas are closely related to each other. Having efficient thematic representations of texts, distance metrics based on shared themes, and mechanisms to abstract the particularities of a language to represent the themes, may help to organize large multilingual document collections.

Each area and its limitations are described below. A summary can be found in Table 2.1.

| Area | Scope | Limitation |
|----------------------------|--|---|
| large-scale topic creation | process texts and train topic models from large corpora | no scalable frameworks that integrates both tasks |
| topic reuse | calculate distributions from existing topic models | no unified models for changing topic models |
| topic explainability | describe and relate documents by topics | high dimensional models makes them difficult to interpret |
| document similarity | compare topic distributions by measuring their distances | unaffordable complexity in large collections |
| multilingual topics | topic distributions across languages | parallel or comparable training data required |

Table 2.1: Research areas and limitations.

2.2.1 Topic Creation and Reuse

Textual content usually includes non-relevant information and keeping only what can bring value for the involved agents (general consumers, experts, companies, investors...) becomes a challenge. A necessary first step before leveraging documents for knowledge-intensive tasks is to preprocess them following different techniques. Recent studies (Westergaard et al., 2017) have shown that mining full-text articles gives consistently better results than only using sections or summaries. Given the size limitations and concise nature of summaries, they often omit descriptions or results that are considered to be less relevant but still are important for some IR tasks (Divoli et al., 2012). Since this behavior is present in many other domains, our interest is focused on processing full texts, not only summaries or parts of texts, as we will show in the remainder of this thesis.

Exists a broad set of algorithms able to analyze text for producing annotations at very different levels of granularity: from minimal units such as terms and entities, to descriptors at the level of the entire collection such as summaries or topics. Methods to perform Part-of-Speech (PoS) tagging, Named Entity Recognition (NER) tasks, or topic modeling following the LDA or any other approach. But their implementations have been designed to work in an isolated, non-collaborative way (Agerri et al., 2014; Manning et al., 2014). They have not paid special attention to facilitating their interoperability and use closed formats to manage their data which increase the technological dependence and limits their reuse and their expansion possibilities. For example, a topic model trained in Mallet¹⁸ can only make inferences if it is used from Mallet itself or using its libraries, since ***there is no unified format for distributing topic models*** and each resource defines its own. In that example, the fact that Mallet is implemented in Java prevents reusing their models from Python or any other programming language. However, there are NLP tools (e.g. spaCy¹⁹) that have been provided through open services decoupled from their technical development (e.g Explosion²⁰).

Some approaches have advanced in this direction and offer the creation and exploitation of topic models through an API based on libraries²¹ or web services²²(Lisena

¹⁸<http://mallet.cs.umass.edu>

¹⁹<https://spacy.io>

²⁰<https://github.com/explosion/spacy-services>

²¹<https://bab2min.github.io/tomotopy>

²²<https://github.com/D2KLab/ToModAPI>

et al., 2020), but they are focused on the operations that can be performed on the model rather than abstracting the topic model as a resource. Others provide local²³ or remote²⁴ ecosystems where create and reuse learning models, but their format is not open and cannot be used out of the environment. To the best of our knowledge, the efforts made do not propose a unified model to exchange topic models, understood as an already accepted standards-based format. In this thesis we propose *reusable topic models and a scalable framework to create and use them*.

2.2.2 Topic Explainability

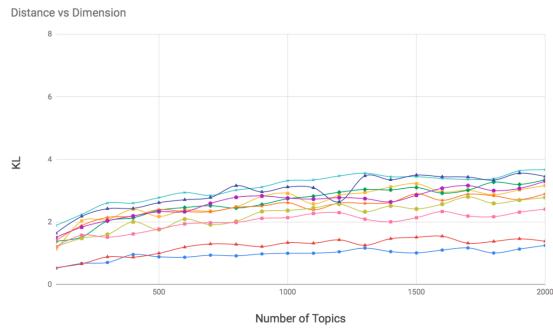
Even though distance metrics mentioned in Section 2.1 have been proposed and used in the SoA, making sense out of the similarity score based on compare topic distributions is not easy. As shown in figure 2.1, given a set of pairs of documents, their similarity scores vary according to the number of topics. So the distances between the same pairs fluctuate from being more to less distant when changing the number of topics, and are hence difficult to use for relate semantically documents. In this conditions, which of those distances is better representing the underlying collection?

Distances between documents based on topic distributions, because it is a vector space, generally increase as the number of dimensions of the space increases. This is due to the fact that as the number of topics describing the model increases, the more specific the topics will be. Topics shared by a pair of documents can be broken down into more specific topics that are not shared by those documents. *Document similarity is then dependent on the model used to represent documents when considering this type of metrics.*

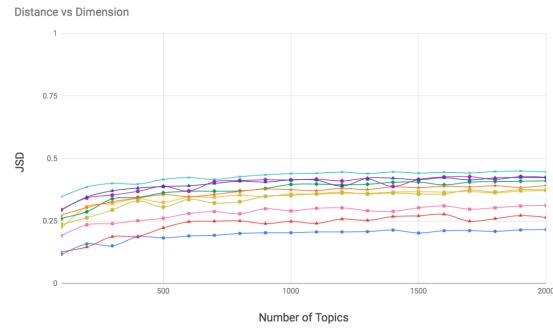
Each topic is drawn from a Dirichlet distribution with parameter β , while each document's mixture is sampled from a Dirichlet distribution with parameter α . These two priors, α and β , are also known as hyper-parameters of a topic model and they set the probability that a document or a word, respectively, contains more than one topic. We know that absolute distances between documents vary when we tune those hyper-parameters differently, but we also see that “relative distances” also change. Imagine that we have two documents, A and B, and one topic model, M1. The distance from the topic distribution of A to B is less than from A to C. However, in a

²³<https://onnx.ai/>

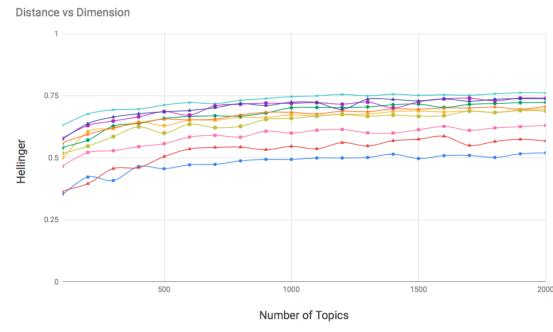
²⁴<https://vespa.ai>



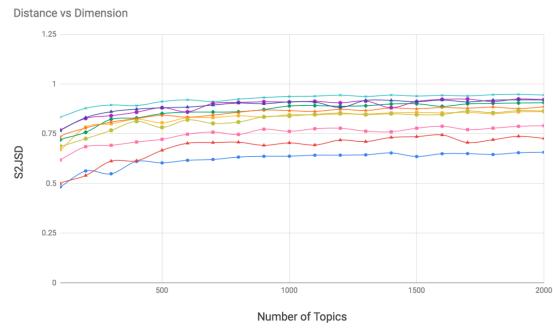
(a)



(b)



(c)



(d)

Figure 2.1: Distance values of 10 pairs of documents calculated in topic models with 100-to-2000 dimensions. The Kullback-Liebler(a), Jensen-Shannon Divergence(b), Hellinger(c) and S2JSD(c) metrics are considered.

second topic model, M2, trained with the same documents as M1 but with different hyper-parameters, the distance from the topic distribution of A to C is less than to B (cross-lines in fig 2.1). This behaviour highlights the *difficulty of establishing absolute similarity thresholds and the complexity to measure distances taking into account all dimensions*. If we consider that documents are similar when their distance is lower than 0.2, a pair of documents may be similar when they are represented in low-dimensional topic models, and not similar when high-dimensional models are used to represent them. Distance thresholds should be model-dependent rather than general and metrics flexible enough to handle dimensional changes. In this thesis we have gone beyond the thematic and low-dimensional feature space created by topic models and propose a *hierarchical feature space suitable for big real-world data sets, where documents are only described by their most relevant topics*.

2.2.3 Document Similarity

In addition, document similarity comparisons are too costly to be performed in huge collections of data and require more efficient approaches than having to calculate all pairwise similarities. Using a naive approach creating a similarity matrix with all document comparisons takes $O(n^2)$ time (where n is the number of documents), so obtaining all possible pairs of similarities in a large collection of documents (e.g. a corpus of 32 million patents) can be unfeasible because of the exponential cost of comparing every pair of elements. Many different approaches have been proposed to reduce this complexity. For instance, computation can be approximated by a nearest neighbors (ANN) search problem (Indyk and Motwani, 1998). ANN search is an optimization problem that finds nearest neighbors of a given query in a metric space of n points.

Due to the low storage cost and fast retrieval speed, hashing is one of the most popular solutions for ANN search (Zhen et al., 2016). This technique transforms data points from the original feature space into a binary-code space, so that similar data points have larger probability of collision (i.e. having the same hash code). This type of formulation for the document similarity comparison problem has proven to yield good results in the metric space (Krstovski and Smith, 2011) due to the fact that ANN search has been designed to handle distance metrics (e.g. cosine, Euclidean, Manhattan). But distance metrics between topic distributions should be information-

theoretically motivated metrics (e.g. Hellinger, Kullback-Leibler divergence, Jensen-Shannon divergence) since they compare density functions.

These challenges can be tackled by hashing methods based on clusters of topics to measure similarity, instead of directly using their weights. Hashing methods transform the data points from the original feature space into a binary-code Hamming space, where the similarities in the original space are preserved. They can learn hash functions (data-dependent) or use projections (data-independent) from the training data (Wang et al., 2016). Data-independent methods, unlike data-dependent ones do not need to be re-calculated when data changes, i.e. adding or removing documents to the collection. Taking large-scale scenarios into account (e.g. Document clustering, Content-based Recommendation, Duplicate Detection), data independency is a key feature along with the ability to infer hash codes individually (for each document) rather than on a set of documents. Data-independent hashing methods depend on two key elements: (1) data type and (2) distance metric. For vector-type data, as introduced in section 2.1, based on l_p distance with $p \in [0, 2]$ lots of hashing methods have been proposed, such as p-stable Locality-Sensitive Hashing (LSH) (Datar et al., 2004), Leech lattice LSH (Andoni and Indyk, 2006), Spherical LSH (Terasawa and Tanaka, 2007), and Beyond LSH (Andoni et al., 2014). Based on the θ distance many methods have been developed such as Kernel LSH (Kulis and Grauman, 2012) and Hyperplane hashing Vijayanarasimhan et al. (2014). But only few methods handle density metrics in a simplex space, where topic distributions are projected. A first approach transformed the H_e divergence into an Euclidean distance so that existing ANN techniques, such as LSH and k-d tree, could be applied Krstovski et al. (2013). But this solution does not consider the special attributions of probability distributions, such as Non-negative and Sum-equal-one. Recently, a hashing schema (Mao et al., 2017) has been proposed taking into account the symmetry, non-negativity and triangle inequality features of the S2JSD metric for probability distributions. For set-type data, Jaccard Coefficient is the main metric used. Some examples are K-min Sketch (Li et al., 2012), Min-max hash (Ji et al., 2013), B-bit minwise hashing (Li and König, 2010) and Sim-min-hash (Zhao et al., 2013).

All of them have demonstrated efficiency in the search for similar documents, but none of them considers the search for documents (1) by thematic areas or (2) by similarity levels, nor they offer (3) an *explanation about the similarity obtained beyond*

the vectors used to calculate it. In addition, binary-hash codes drop a very precious information: the topic relevance. This thesis proposes a *hash function-based approach that allows efficiently searching for related documents while maintaining topic-based annotation, preserving notion why two documents are related.*

2.2.4 Multilingual Topic Alignment

When the IR task is also cross-language, document retrieval must be independent of the language of the user’s query. At execution time, the query in the source language is typically translated into a target language with the help of a dictionary or a machine-translation system. But for many languages we may not have access to translation dictionaries or a full translation system, or they can be expensive to execute, or expensive to train (lot of data required) in an online search system. In such situations it is useful to rely on smaller annotation units derived from the text so the full content does not need to be translated, for instance by finding correspondences with regard to the topics discussed in both the query and the documents being searched.

Some methods uses document-aligned corpora, where documents are grouped and constrained to the same topic distribution during training to align the different languages (De Smet and Moens, 2009a; Fukumasu et al., 2012; Mimno et al., 2009a; Ni et al., 2009; Zhang et al., 2013), or theme-aligned corpora, where similar themes and ideas appear in all languages(Boyd-Graber and Blei, 2009). Multilingual Probabilistic Topic Models (MuPTM) (Vulić et al., 2015) have emerged in this area as a group of language-independent generative machine learning models that can be used on theme-aligned multilingual texts. They are based on LDA, adding supervised associations between languages by using *parallel* corpora, with sentence-aligned documents (e.g. Europarl²⁵ corpus), or *comparable* comparable, with theme-aligned documents (e.g. Wikipedia²⁶ articles), in multiple languages. Once a MuPTM has been generated, documents can be represented by data points in a single feature space based on topics to detect similarities among them exploiting inference results and using distance metrics. Due to its generic language-independent nature and the power of inference on unseen documents, MuPTM’s have found many interesting applications in many different cross-lingual tasks. They have been used on cross-lingual event clustering

²⁵<https://ec.europa.eu/jrc/en/language-technologies/dcep>

²⁶<https://www.wikipedia.org/>

(De Smet and Moens, 2009b), document classification (De Smet et al., 2011; Ni et al., 2011), semantic similarity of words (Mimno et al., 2009b; Vulić and Moens, 2012), information retrieval (Ganguly et al., 2012; Vulić and Moens, 2013), document matching (Platt et al., 2010; Zhu et al., 2013), and others.

Other methods are based on word alignments from bilingual dictionaries instead of aligned corpora. Topic models emerge as distributions over crosslingual equivalence classes of words (Hao and Paul, 2018; Jagarlamudi and Daumé, 2010; Zhang et al., 2010). A recent approach is placed between word and document alignments. It proposes crosslingual topic models using the language-independent categories assigned to each wikipedia article(Piccardi and West, 2020). Instead of using bags-of-words to represent texts, which would be language dependent, it explores the references of each article and represents them through bags-of-links, using the categories of each reference to represent the texts.

In short, *the requirement of parallel/comparable corpora or dictionaries limits the usage of these models in many situations*. There are not many document collections that can be used for training since large parallel corpora are rare in most of the use cases, especially for languages with fewer resources. Moreover, in order to incorporate new languages or update the existing associations, these models must be re-trained with documents from all languages at the same time, making it difficult to scale to large corpora (Hao et al., 2018; Moritz and Ičhler, 2017). We take MuPTM a step further by making it cross-lingual through representations based on topic hierarchies. Documents from multi-language corpora are described by expressions of language independent concepts and can then be efficiently browsed and related with other languages without the need for translation or parallel or comparable corpora. In this thesis we propose to *automatically infer cross-lingual topics to browse multi-lingual document collections without the need for parallel or comparable corpus*.

Chapter 3

Methodology

The work presented in this thesis aims to facilitate the exploration of huge collections of multilingual documents through thematic associations inferred from their content. It assumes that, given a multilingual corpus, similar documents will contain the same topics. Each of the challenges arising from this objective defines a working dimension and guides the research carried out in this thesis.

The first dimension focuses on **scalability**, in order to create the text processing flows that are required to create or apply learning models. The workload required to process a corpus varies according to the number of documents, the length of texts and the kind of knowledge (annotations) that need to be inferred from the text. If the design of the workflow is scalable, there is no need to modify the processing logic when working with larger collections of documents, since adding a reasonable amount of computational resources is enough to perform it. These resources can be machines (i.e horizontal scaling) or processing units (e.g CPU, RAM) in an existing machine (i.e vertical scaling).

The second dimension covers the **representativeness** of the text annotations when projected into spaces where they are manipulated. The idea behind these spaces is to represent documents as points (or vectors in a vector space) that are close together when the texts are semantically similar, and far apart when they are semantically distant. The ability of these spaces to create meaningful representations is also studied in this work.

In the third dimension, we explore the usage of data structures that efficiently **cluster** texts from their representations based on probabilistic topics. Divisions of

space into semantically-related regions are convenient to allow browsing large document collections. The *representativeness* covered in the previous dimension enables the interpretation of the relations and regions obtained.

And finally, the fourth dimension handles the **multilingualism** of collections that contain documents in several languages. On a multilingual space, documents are described and related across languages.

This chapter introduces our main hypothesis (section 3.1), and the associated research challenges (section 3.2), and presents the research methodology (section 3.3).

3.1 Research Hypotheses

We define our main hypothesis as follows:

Hypothesis 1 *Large multilingual document collections can be automatically analyzed to discover appropriate thematic relations that facilitate a semantically-enabled text browsing.*

Our hypothesis can be divided into four different sub-parts, which are related to the aforementioned scalability, representativeness, clustering, and multilinguality dimensions. First, by *distributing across different computation nodes both natural language processing tasks and representational models we can efficiently process huge collections of documents (**H1.1**)*.

Second, it is possible to *semantically relate documents by comparing their most relevant topics (**H1.2**)*. Furthermore, for this purpose we hypothesize that the use of *topic hierarchies (**H1.2.1**) and similarity metrics based on relevance levels (**H1.2.2**) help quantifying the semantic distance between texts*. Third, by *dividing the representational space into regions based on topics and relevance levels we can search for related documents without having to calculate all pairwise comparisons and without discarding the notion of topics for further processing (**H1.3**)*.

And finally, by *abstracting the topic representations into concept-based descriptions across languages we can relate documents in various languages without having to translate them (**H1.5**)*.

A summary of the hypotheses and how they tackle our research dimensions can be found in Table 3.1.

| Hypothesis | Research Dimension |
|---|--|
| H1: Large multilingual document collections can be automatically analyzed to be semantically-browsed through thematic relations | D1: Scalability, D2: Representativeness, D3: Clustering, D4: Multilingualism |
| H1.1: it is possible to efficiently annotate documents on a large scale by distributing across different computation nodes natural language processing tasks and representation models | D1: Scalability |
| H1.2: it is possible to semantically relate texts from their most relevant topics | D2: Representativeness |
| H1.3: it is possible to find relevant documents with similar topic distributions without calculating all pairwise comparisons and without discarding the notion of topics from their representation | D3: Clustering |
| H1.4: it is possible to relate documents in different languages without having to translate them, by using language agnostic concepts from their main topics | D4: Multilingualism |

Table 3.1: Hypotheses and research dimensions.

3.2 Research Challenges

Several research challenges emerge from these hypotheses. First, in order to facilitate reusing existing topic models by processing systems with different architectures and technological stacks, we need to define *topic-model programming interfaces*. Second, in order to describe and thematically relate documents, we must address how to produce *explainable topic-based associations*. Third, by working with huge collections of documents described by topics, we need to handle *large-scale comparisons of topic distributions*. Finally, in order to explore multilingual document collections from shared topic-based representational spaces, we have to provide *automatic cross-lingual topic alignment*. Each of these research challenges are described below and covered throughout this thesis.

3.2.1 Scalable Creation and Inference of Topics

Although some initiatives to facilitate the reuse of machine-learning models exist in the literature as discussed in section 2.2.1, there are still some restrictions that limit the use of topic models. Technical dependencies or closed data formats are the main reasons that prevent or make reproducibility of these models difficult by imposing conditions to work with them. It is common to provide the model only through its functionality, rather than its properties, which prevents it from being used for a different purpose than when it was created. *Reuse of topic models is limited by incompatibility problems (RCInterface1)*.

The properties and functions offered by a topic model, instead of being uniform, vary according to the method used to build it. This limits the ability to reproduce the work done in this area and reuse topic models without losing information or knowledge. *There is no standard to specify the attributes and operations that a topic model can provide (RCInterface2)*. Sometimes topics are described by the top ten or five most relevant words, and occasionally these word lists are not accompanied by weights, making a density-based analysis impossible. These differences in presenting the models can sometimes limit their reusability if they cannot infer new topic distributions even when the learning algorithm allows for it.

3.2.2 Explainable Topic-based Relations

In order to facilitate the exploration of document collections, vector space models are often used to semantically relate texts based on their word distributions. As described in Section 2.1, these models first create a dictionary with the words used in the collection, and then represent documents by vectors whose dimensions correspond to each word in the dictionary. In large collections, these models need to be adapted to make operations on vectors more manageable. As a result, a new abstraction method based on emerged topics that reduces the dimensions of vectors. Topics are described by word distributions over the entire vocabulary and documents by vectors containing topic distributions. Despite the extensive use of these representation models, *there is no common criteria for identifying the most representative topics in a document (RCExplainable1)*.

In addition, since similarity metrics over this representation space are based on accumulating the difference in topic densities, *it is difficult to explain the distance between topic distributions (RCExplainable2)*. And, unless a minimum distance threshold can be defined or a set of n-top topics agreed, *there is no common criterion for determining whether two documents are related (RCExplainable3)*.

3.2.3 Large-scale Comparisons of Topic Distributions

There are many scenarios where we need to find related documents (e.g. a researcher doing literature review, or an R&D manager analyzing project proposals). Experts can benefit from discovering those connections to achieve these goals, but brute-force pairwise comparisons are not computationally adequate when the size of the corpus is too large. Some algorithms in the literature divide the search space into regions containing potentially similar documents, which are later processed separately from the rest in order to reduce the number of pairs compared. However, *there are no mechanisms that efficiently partition the topic-based search space without compromising the ability for thematic exploration (RCComparison1)*.

In addition, documents from the same region should be compared and *there are no similarity metrics that compare partial distributions of topics (RCComparison2)*.

3.2.4 Unsupervised Cross-lingual Topic Alignment

With the ongoing growth in the number of texts in different languages, we need annotation methods that enable browsing multilingual corpora. As discussed in section 2, multilingual probabilistic topic models have recently emerged as a group of semi-supervised machine learning models that can be used to perform thematic explorations on collections of texts in multiple languages. However, *there are no approaches that abstract the representation of probabilistic topics in language-independent spaces without translating texts or aligning documents (**RCCrossLingual1**)*. Existing approaches require parallel or comparable training data to create a language-independent space.

A summary of the challenges covered in this work and how they map to the hypotheses is presented in table 3.2.

3.3 Research Methodology

The research presented in this thesis is based on four dimensions or research areas as discussed in section 3.2. Each one is motivated by different research problems that we need to solve in order to achieve our ultimate goal of making it easier to explore large multilingual document collections through their topics. Once a dimension is tackled, the next one is considered, and so on. This iterative and incremental methodology allows refining the research results by evaluating them with more experiments and addressing increasingly complex research problems.

Figure 3.1 shows the dimensions on which the research of this thesis has been built. The top of the pyramid is only reached once the lower dimensions are dealt with successfully. They are presented as a chain of four steps. The first step describes the motivation to perform a given task coming from real-world problems that we had to deal with, and is represented by a brown arrow. In the context of this task, the research problem arises and is framed by a pink arrow. For each of them a solution is proposed and evaluated according to a specific criterion. The proposed solution is represented by a green arrow and the evaluation with a blue arrow. Once a proposal has been validated, the next dimension of the pyramid is achievable and all the previous research problems are added to the new research problem as conditions to be taken into account.

| Research Challenge | Hypotheses |
|--|---|
| RCInterface1: reuse of topic models is limited by incompatibility problems | H1.1: documents can be efficiently annotated on a large scale by distributing across different computation nodes both natural language processing tasks and representation models |
| RCInterface2: there is no standard that unifies the representation of topic models | H1.1: documents can be efficiently annotated on a large scale by distributing across different computation nodes both natural language processing tasks and representation models |
| RCExplainable1: there is no common criteria for identifying the most representative topics in a document | H1.2: texts can be semantically related from their most relevant topics, H1.3: documents with similar topic distributions can be found without calculate all pairwise comparisons and without losing the ability to explore them through their topics |
| RCExplainable2: it is difficult to understand the distance between topic distributions | H1.2: texts can be semantically related from their most relevant topics |
| RCExplainable3: there is no common criterion for determining whether documents are related | H1.2: texts can be semantically related from their most relevant topics |
| RCComparison1: there are no mechanisms that efficiently partition the topic-based search space without compromising the ability for thematic exploration | H1.3: documents with similar topic distributions can be found without calculate all pairwise comparisons |
| RCComparison2: there are no similarity metrics that compare partial distributions of topics | H1.3: documents with similar topic distributions can be found without calculate all pairwise comparisons |
| RCCrossLingual1: there are no approaches to abstract probabilistic topics in language-independent spaces without translating texts or aligning documents | H1.4: documents in different languages can be related without having to translate them using language agnostic concepts from their main topics |

Table 3.2: Open Research Challenges and Hypotheses.

Technical objectives (i.e., develop a new resource) or research objectives (i.e., discover the solution to a problem) guide the solution proposal before moving on to the next dimension. They are presented below, organized by the research problem associated with each dimension.

3.3.1 Scalable Creation and Inference of Topics

This first dimension arose when we had to analyze a huge collection of documents describing research and innovation projects to discover which research areas are being addressed, measure their presence in the collection, and characterize them so their presence can be inferred in unseen documents. Such a high volume of data made difficult to process it manually, so we needed to automate the required processing to draw insights from it. Probabilistic topics allow describing research areas, so we defined a *distributed text-processing model for creating large probabilistic topic models (RO1)* and a *Web service template to distribute them (RO2)*. In this way, the models themselves could be easily integrated into scalable text processing pipelines. As a result, we created a *scalable platform for topic modeling (TO1)*, and produced a *model-as-a-service repository with pre-trained topic models (TO2)*. The efficiency of this solution was validated by processing a corpus of 100,000 documents collected from the CORDIS dataset²⁷, which contains descriptions of projects funded by the European Union under a framework programme since 1990 (Badenes-Olmedo et al., 2017b).

The main contributions under this dimension are described in Chapter 4 as follows:

- a software architecture to process big volumes of textual documents in a distributed and decoupled manner;
- the definition of a model-as-a-service template for probabilistic topic models;
- an implementation of the architecture, librAIry, following those design principles.

3.3.2 Explainable Topic-based Relations

In the second dimension we needed to browse scientific papers through their content-based relations. The problem of massively annotating documents with topic distributions came up. We had to *create annotations based on topic models in a way that*

²⁷<https://data.europa.eu/euodp/es/data/dataset/cordisH2020projects>

*was computationally affordable and enabled a semantic-aware exploration of the knowledge inside them (**RO3**). Once documents were annotated, a metric that compares documents and facilitates their interpretation from topic annotations (**RO4**) was required. As a result, we integrated the annotation method into the topic model service (**TO3**) and implemented a text comparison metric based on partial representations of topics. These proposals were validated by classifying 500,000 scientific articles from the Open Research Corpus²⁸ in domains such as Computer Science, Neuroscience and Biomedicine (Badenes-Olmedo et al., 2017a, 2019a, 2017c).*

The main contributions under this dimension are described in Chapter 5 as follows:

- a clustering algorithm based on probabilistic topic distributions;
- a hash function to transform topic distributions into topic hierarchies;
- a similarity metric based on topic sets.

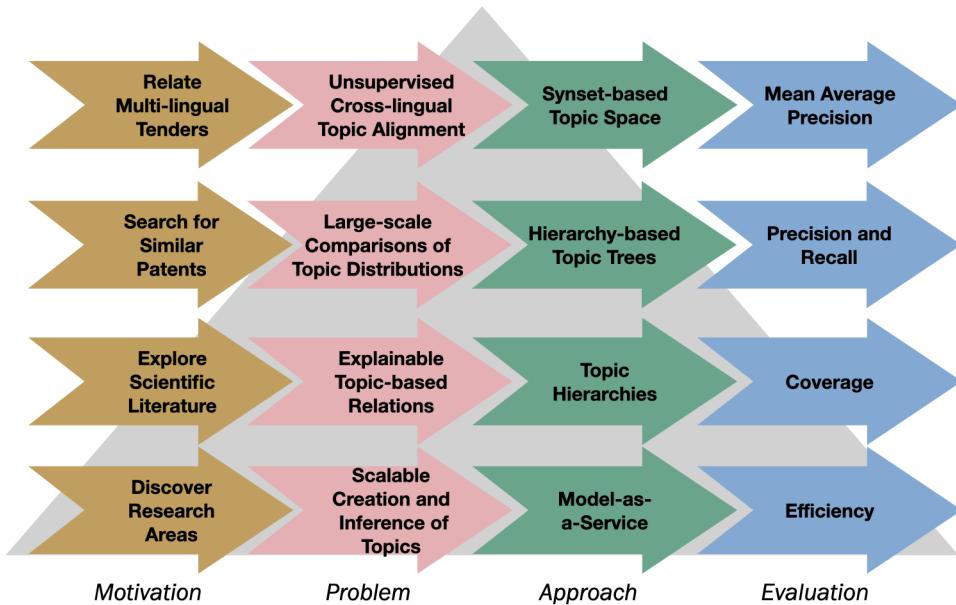


Figure 3.1: Research dimensions of the thesis. The first ones must be overcome before reaching higher dimensions.

²⁸<https://allenai.org/data/open-research-corpus>

3.3.3 Large-scale Comparisons of Topic Distributions

This dimension covered the search for similar documents based on their most relevant topics. Thanks to having dealt with the above two dimensions, large collections of documents could be annotated with topic hierarchies and text distances could be measured from their annotations. Now, the aim was to find similar documents without losing the exploratory capacity offered by topics. Similarity comparisons were too costly to be performed in such huge collections of data and required more efficient approaches than having to calculate all pairwise similarities. We applied *techniques based on approximate nearest-neighbors to organize documents in regions with similar topic hierarchies (RO5)*. As a result, we developed *a system to automatically find similar documents (TO4)*. It was validated on a collection of one million texts retrieved from the United States patents corpus²⁹. The relations between patents derived from their manual categorization were compared with those automatically obtained from their topic distributions (Badenes-Olmedo et al., 2019a, 2020).

The main contributions under this dimension are described in Chapter 6 as follows:

- a data structure to partition the search space and organize documents described by topic hierarchies;
- a corpus browser that leverages these representations to automatically relate documents.

3.3.4 Unsupervised Cross-lingual Topic Alignment

Finally, a new dimension on top of the previous ones emerged to relate texts coming from different languages. In particular, since document relations were based on their topics, this dimension was focused on aligning topics without supervision from models trained with texts in different languages. Since each language defined its own vocabulary, the topics were model-specific and could not be directly compared. We abstracted the *topic representations to create a single space out of the particularities of the language (RO6)*. This approach was validated on the English, Spanish, French, Italian and Portuguese editions of the JCR-Acquis³⁰ corpora and revealed promising results on

²⁹<https://www.uspto.gov/ip-policy/economic-research/research-datasets>

³⁰<https://ec.europa.eu/jrc/en/language-technologies/jrc-acquis>

classifying and sorting documents by similar content across languages (Badenes-Olmedo et al., 2019a,b).

The main contributions under this dimension are described in Chapter 7, as follows:

- an algorithm to represent probabilistic topics using concept sets;
- a repository of aligned topic models from the English, Spanish, French, Italian and Portuguese editions of the JRC-Acquis corpus.

Table 3.3 summarizes the research objectives (ROs), technical objectives (TOs) and connects them with the research challenges (RCs) from Table 3.2.

| Research Objective | Research Challenge |
|---|--|
| RO1: Define a distributed text-processing model for creating large probabilistic topic models | RCInterface1 |
| RO2: Define a template to package probabilistic topic models as web services | RCInterface2 |
| RO3: Define annotations based on topics that enable a semantic-aware exploration of the knowledge inside a corpus | RCExplainable1 |
| RO4: Define a metric based on topic annotations that compares documents and facilitates their interpretation | RCExplainable2, RCExplainable3 |
| RO5: Define nearest-neighbor techniques to organize documents in regions with similar topic hierarchies | RCComparison1, RCComparison2 |
| RO6: Define a transformation of the topic-based annotations to create a unique representational space out of the particularities from each language | RCCrossLingual1 |
| T01: Create a scalable platform for topic modeling | RCInterface1, RCInterface2 |
| T02: Create a repository of Topic-based web services | RCInterface2 |
| T03: Integrate the annotation method based on topic hierarchies into the topic model service | RCExplainable2, RCComparison2 |
| T04: Create a system capable of finding similar documents automatically | RCExplainable2, RCExplainable3, RCComparison1, RCCrossLingual1 |

Table 3.3: Research and technical objectives and their related challenges.

Chapter 4

Creation and Publication of Probabilistic Topic Models

This chapter present *librAIry* (Badenes-Olmedo et al., 2017b), our framework to exploit probabilistic topic models through a service-oriented approach. In doing so, we reuse existing techniques and standards, which aim to make our results reusable and interoperable with other alternative approaches.

4.1 Topic Modeling Framework

Topic models have been successfully used in multiple domains in the last years (Greene and Cross, 2016; He et al., 2017; O’Neill et al., 2017; Tapi Nzali et al., 2017). Each of them has different characteristics. Some with longer texts, others with shorter texts, some with millions of documents, others with only a few hundred or thousands, some have only one computing unit to process them, others have multiple nodes distributed among several distributed machines. Adapting to such diversity, topic modeling algorithms have evolved to be more efficient in challenging situations (Liu et al., 2015). However, the methods are only focused on the learning process and a topic model life-cycle is broader than just the creation of the model (Fig. 4.1.) It covers a first stage of *document preparation*, where texts are divided first into phrases and then into words that are normalized before being counted to create bags-of-words (BoW). The next stage seeks patterns among word distributions, is the *training* stage, and as a result a topic model is created. The model is then packaged for distribution, this is the *publi-*

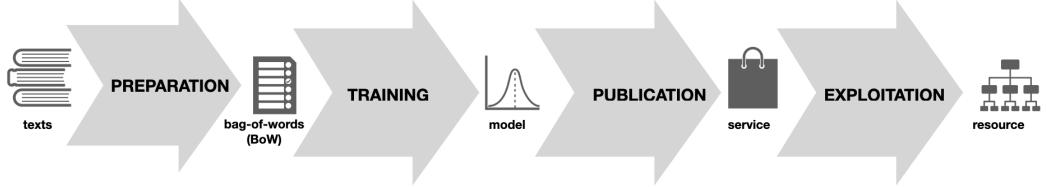


Figure 4.1: Topic model life-cycle. First texts are processed to retrieve tokens and build bags-of-words (BoW). They are then used to train a model that identifies patterns among words and builds topics. The model, which is also enabled to make inferences in unseen texts, is published as a service in an online repository. Finally, the service is used as resource in a particular solution, for example to categorize documents.

cation stage. And finally the model can be reused, it is the *exploitation* stage. In order to have a framework that covers the entire process of creating, publishing and reusing probabilistic topic models in both large- and small-scale, we have focused on adapting techniques and standards widely used in software engineering domain. In this section we cover the first two stages of the life-cycle: text preparation and model training. In Section 4.2.1 we describe how the models are published, and in section 4.2.2 how they can be exploited.

libraIry is a framework that covers the entire topic model life-cycle by combining learning algorithms with natural language processing methods and software distribution techniques. The main objective is to ***facilitate the creation of reusable probabilistic topic models by minimizing their technical dependencies***. Methods and algorithms proposed in this thesis have been implemented and evaluated in this framework, which therefore serves as the technological basis for our research.

Our design requirements, which have guided our development process, can be organized into three categories:

- **Corpora representation requirements**, which tackle the modeling of document collections and its metadata. This includes texts and their related annotations.
- **Task distribution requirements**, which refer to event management to notify changes in document collections. Coordination of this information is crucial for robust and reproducible results.

- **Process execution requirements**, which capture the operations involved in creating a topic model. The parallel task execution leads to the creation of models.

The rest of the section describes how we have adapted existing techniques and standards in *libraIry* to address each of the requirements categories described above. An open, distributed and scalable framework has been developed whose source code is publicly available for reuse³¹.

4.1.1 Corpora Representation for Topic Modeling

Inspired by a Staged Event-Driven Architecture (SEDA) that exchanges messages and handle status changes, our framework is based on *resources* and *actions*. A *resource* can be a *document* that represents raw texts (e.g. a full-text research paper), or a *snippet* of text with a logical part (e.g. sections, summaries or even phrases grouped by their rhetoric), or a *domain* that contains a dataset of texts (e.g. a conference proceedings) or even an *annotation* made on them (e.g. review comments, named-entities, topics). *Actions* can be executed on resources to change their status (e.g. *create*, *update* or *delete*).

To better illustrate this model, take a sample of the research articles published at the latest K-CAP conference³² (see Fig. 4.2). A *document* resource is created for each publication and contains the full text of the article. Each *document* is then associated with several *snippets*, one for each section of the article (e.g. abstract, introduction, conclusions, etc). Finally, a *domain* is created that groups all these *documents* under the same conference. This initial representation can be extended with *annotations*, that can provide more detailed information at different levels (e.g. named-entities, keywords or topics).

Resources, and *actions* are individually addressable and linkable (Turchi et al., 2012) following the Linked Data principles(Bizer et al., 2009). Each of them has: (1) a name, (2) a retrievable (or dereferenceable) HTTP URI so that it can be looked up, (3) a descriptive information provided by using standard notation (e.g. JavaScript Object Notation (JSON)) when it is looked up by URI, and (4) links to other URIs so that other resources can be discovered from it.

³¹<https://github.com/librairy>

³²<http://www.k-cap.org/2019>

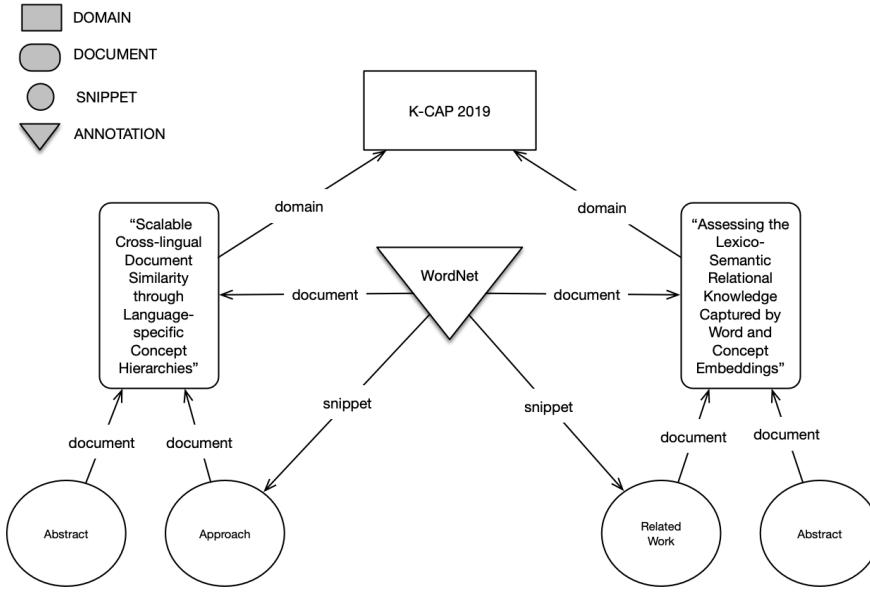


Figure 4.2: Representation of two scientific papers published at the International Conference on Knowledge Capture (K-CAP, 2019) that mention the same entity, *Wordnet*, in different sections.

More details about each of them is shown below.

4.1.1.1 Domain

A *domain* is an aggregation of *documents*. It is described as a group with parts separately described. A default *domain* is created and every *document* belongs, at least, to one *domain* (Fig 4.3).

A *domain* contains the following information:

- **uri:** identifier created from the resource type (i.e *domains*) and a Universally Unique Identifier (UUID) (e.g *domains/88b86fa6-11c8-11eb-adc1-0242ac120002*)
- **creation-time:** date when resource was created. It follows the ISO-8601³³.
- **name:** label associated to the resource.
- **description:** additional information about it.

³³<https://www.iso.org/standard/40874.html>



Figure 4.3: Relation between *domain* and *document*.

4.1.1.2 Document

A *document* is a resource consisting primarily of text. Examples include research papers, articles, books or patents. It follows the Open Archives Initiative for Object Reuse and Exchange³⁴ (OAI-ORE) and the Dublin Core Metadata Initiative³⁵ (DCMI).

A *document* contains the following information:

- **uri:** identifier created from the resource type (i.e *documents*) and a UUID (e.g *documents/809af686-11c8-11eb-adc1-0242ac120002*)
- **creation-time:** date when resource was created. It follows the ISO-8601.
- **publishedOn:** date when resource was published. It follows the ISO-8601.
- **publishedBy:** an entity responsible for making the document available. It can be a person, an organization or a service. It may be different from the entity that conceptually formed the resource (e.g. wrote the document), which is recorded as *authoredBy*. This entity should be identified by a valid Uniform Resource Identifier (URI) such as WebId³⁶, orcid³⁷ or internal URI.
- **authoredOn:** the time the *document* was conceptually formed. The author time should be present if different from *publishedOn*. It must be a formatted timestamp following ISO-8601.
- **authoredBy:** an entity primarily responsible for making the content of the *document*. It may be a list to indicate multiple authors. Each of them identified by a valid URI such as WebId, orcid or internal URI.

³⁴<http://www.openarchives.org>

³⁵<http://dublincore.org>

³⁶<http://www.w3.org/wiki/WebID>

³⁷<http://orcid.org>



Figure 4.4: Relation between *document* and *snippet*.

- **retrievedFrom:** a URI identifying the repository or source from which the document was derived. This property should be accompanied with *retrievedOn*.
- **retrievedOn:** the time the *document* was retrieved on. If this property is present, the *retrievedFrom* must also be present. It must be a formatted timestamp following ISO-8601.
- **format:** the physical or digital manifestation of the resource. Typically, it includes the media-type (i.e the IANA code³⁸) of the *document*.
- **language:** the language(s) in which the document was written. It is defined by RFC-1766³⁹ with a two-letter language code followed, optionally, by a two-letter country code.
- **title:** a name given to the *document*. It is a name by which the *document* is formally known.
- **description:** it may include but is not limited to an abstract, or a free-text account of the content.
- **rights:** information about rights held in and over the *document*.
- **content:** raw text from the *document*.

Furthermore, a *document* can contain zero or more *snippets* and a *snippet* can belong to one or more *documents*. Since *librAIry* can also discover relations among *documents*, a *document* may contain zero or more references to other *documents* (Fig. 4.4).

³⁸<http://www.iana.org>

³⁹<http://www.ietf.org/rfc/rfc1766.txt>

4.1.1.3 Snippet

A *snippet* is a resource that is included either physically or logically in a *document*. In a scientific *document*, for example, it may be the *abstract* section or a logical set of sentences sharing the same rhetorical class (e.g. approach, background, related-work, etc). As seen above (Fig. 4.4), a *snippet* can belong to one or more *documents*.

It contains the following information:

- **uri**: identifier created from the resource type (i.e *snippets*) and a UUID (e.g *snippets/7a5a46c8-11c8-11eb-adc1-0242ac120002*)
- **creation-time**: date when resource was created. It follows the ISO-8601.
- **sense**: content-type. It refers to a section or any other criteria under which the following text makes sense.
- **content**: partial text retrieved from the full-text of a *document*.

4.1.1.4 Annotation

Annotations are data retrieved from resources that can be used to relate them. They are basically key-value data structures associated to *domains*, *documents* or *snippets*. Examples are entities mentioned in a text, or topics covered in a collection. Any resource can have zero or multiple annotations, which can be shared among several resources (Fig. 4.5)

It contains the following information:

- **uri**: identifier created from the resource type (i.e *annotations*) and a UUID (e.g *annotations/73671e68-11c8-11eb-adc1-0242ac120002*)
- **creation-time**: date when resource was created. It follows the ISO-8601.
- **key**: a category or type associated with the information it contains (e.g. entity, comment, topic, keywords, etc). Recommended best practice is to use a controlled vocabulary.
- **value**: a note about the resource in the form of free text.

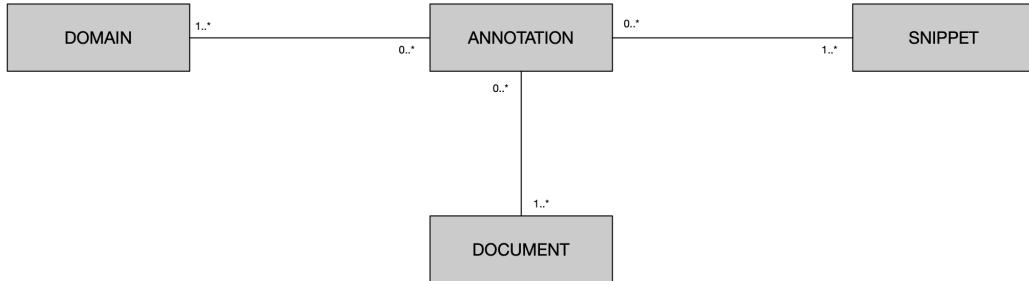


Figure 4.5: Relation between *annotations* and other resources.

4.1.2 Event-oriented Processing Workflow

Along with the resources mentioned above, there are two additional elements that provide a crucial behavior to the framework: *modules* and *events*. An *event* is a non-persistent time-based occurrence that describes a new action performed on a resource. *Modules* are responsible for carrying out operations on the resources (e.g. tokenize a *document* or create a topic model from a *domain*). *Events* are broadcasted so that any *module* is aware of the changes made to the resources and can perform actions on one or more resources in response to a new state reached by a given resource. These actions are paralleled since modules are replicated through distributed environments.

The framework follows a publisher/subscriber approach where *modules* can publish and read *events* to notify and to be notified about the state of a *resource* (Fig. 4.6). An *event* notifies a performed *action* (i.e. a resource and its new state), and follows the Representational State Transfer (REST) paradigm (Fielding and Taylor, 2002). It contains the resource type and the new state reached by a specific resource (i.e *created*, *deleted* or *updated*). For example, when a new *domain* is created, an *event* message is published to the channel: *domain.created*. A channel is a space where *events* are published and *modules* can be subscribed to read only some *events*. The actions performed by a module depend on the events to which it is subscribed. Therefore, the workflow of the framework is neither static nor explicitly defined. A distributed dynamic workflow emerges according to the *modules* subscribed to the *event* channels.

We used the Advanced Message Queuing Protocol (AMQP) as the messaging standard to avoid any technical dependency to the message broker (i.e the server that



Figure 4.6: Resource states.

sends and receives messages). This protocol defines: *exchanges*, *queues*, *routing-keys* and *binding-keys* to communicate publishers (i.e message senders) and consumers (i.e message readers). *Exchanges* are like message inboxes, and *queues* are subscribed to them by specifying the message types they are interested in with a *binding-key*. A message sent by a publisher to an exchange is routed with a *routing-key* and consumers matching that *routing-key* with their *binding-key* (used to connect the *queue* to that *exchange*), will receive the message. This mechanism allows sending and receiving messages between consumers and producers by means of shared keys (i.e. *routing-keys* and *binding-keys*). A key follows the structure: *resource.status*. Since a wildcard-based definition can be used to set the key, this paradigm allow modules both listening to individual type events (e.g. *domains.created* for new *domains*), or multiple type events (e.g. *#.created* for all new resources).

4.1.3 Module-based Model Training

A microservice-oriented style has been used to define the framework architecture. Through multiple services the system analyzes texts, creates probabilistic topic models, publishes them as new services and uses them to annotate texts. A service is equivalent to a functionality, and each functionality is materialized by a *module* in the system. A *module* is then a cohesive and independent process (Dragoni et al., 2016) with a specific purpose (i.e functionality) based on the *events* to which it responds. These *events* correspond to the routing- and binding- keys attached to the module.

There are four types of *modules* (Fig. 4.7):

- **Harvester:** creates resources such as *documents*, *snippets* and *domains*, from local or remote repositories with textual files. We have developed harvesters to create scientific resources from Elsevier⁴⁰ or any other digital repository⁴¹ that

⁴⁰<https://github.com/librairy/harvester-elsevier>

⁴¹<https://github.com/librairy/harvester-research>

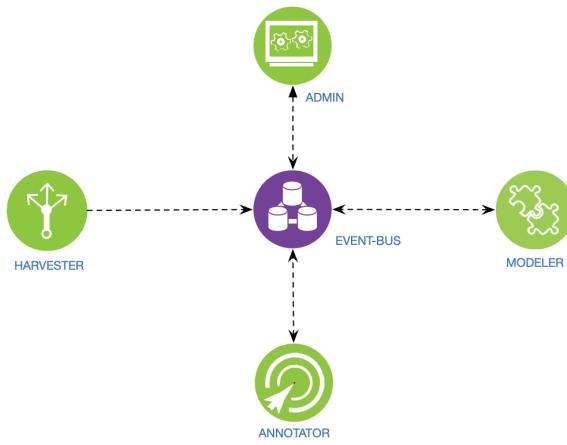


Figure 4.7: Modules (in green) publishing or receiving events from the messenger service (in purple).

follows the Open Archives Initiative Protocol for Metadata Harvesting (OAI-PMH)⁴²; as well as more general ones to retrieve public datasets from datos.gob.es⁴³ or resources located on local folders⁴⁴.

- ***binding-queue*** (i.e listening for): nothing
- ***routing-key*** (i.e publishing to): *document.created*, *snippet.created*, *domain.(created;updated)*
- **Annotator:** creates *annotations* (e.g named-entities, bag-of-words, topic distributions, etc) in *documents*, *snippets* or *domains*. We have developed an NLP Annotator⁴⁵ that creates bag-of-words from a given text by normalizing its content through natural language processing tasks such as named entity recognition, lemmatization or part-of-speech (PoS) tagging. The source code⁴⁶ is publicly available for reuse. Topic models are also annotators in this framework, as will be seen in section 4.2.1.

- ***binding-key***: *document.(created;updated)*, *snippet.(created;updated)*
- ***routing-key***: *annotation.(created;deleted)*

⁴²<https://github.com/cbadenes/camel-oaipmh>

⁴³<https://github.com/librairy/harvester-datosGobEs>

⁴⁴<https://github.com/librairy/harvester>

⁴⁵<http://librairy.linkeddata.es/nlp>

⁴⁶<https://github.com/librairy/nlp>

- **Modeler:** creates probabilistic topic models for *domains* from the bag-of-word *annotations* of each *document*. We have developed a LDA Modeler⁴⁷ as well as a W2V Modeler⁴⁸ (the latter for testing purposes).
 - **binding-key:** *domain.(created;updated)*, *annotation.created*
 - **routing-key:** *annotation.(created;deleted)*
- **Administrator:** performs user-driven tasks such as reading/writing/updating resources or database queries. As with the other modules, the source code⁴⁹ is publicly available for reuse. Together with the API, we have also developed a web interface⁵⁰ to visualize documents, their relationships and the topics associated with each *domain*.
 - **binding-key:** *#.#*
 - **routing-key:** *domain.(created;updated;deleted)*,
document.(created;updated;deleted), *snippet.(created;updated;deleted)*,
annotation.(created;updated;deleted)

Figure 4.8 shows a sequence diagram that illustrates how modules work collaboratively to create a topic model from documents added to the framework. Each module provides an Application Program Interface (API) over HTTP, that follows the web standards for the RESTful API development, and a Avro⁵¹-based interface over TCP for efficiency reasons. Among them the communication is done over TCP.

4.2 Reusable Topic Modeling

In order to use an existing topic model in our framework, which is micro-services-oriented, the model itself needs to be a service. This approach decouples the resources used to train a probabilistic topic model (e.g. data format or algorithm implementation), from the resources required to make inferences and thus avoids unexpected incompatibilities. In this way, we simultaneously facilitate the reuse of topic models and also their scalable execution.

⁴⁷<https://github.com/librairy/modelerTopics-service>

⁴⁸<https://github.com/librairy/modeler-w2v>

⁴⁹<https://github.com/librairy/api>

⁵⁰<https://github.com/librairy/explorer>

⁵¹<https://avro.apache.org>

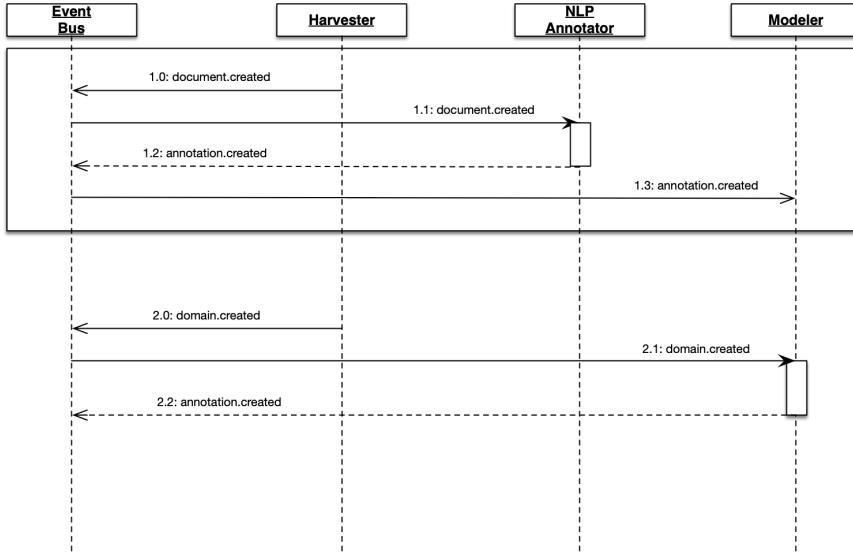


Figure 4.8: Sequence of *events* exchanged between modules to create a topic model from the *documents* added to a *domain*.

4.2.1 Topic Model Publication

We propose distribute topic models as services hosted in online repositories. Models are packaged as OS-level virtualization software that can run reliably applications from one computing environment to another. A model becomes a standalone and executable software package that includes everything needed to use it: code, data, runtime libraries, system tools and settings.

There are several technologies that can virtualize services. Among them, Docker⁵² stands out as a de facto standard due to its wide adoption. It is a platform as a service (PaaS) environment that use operating service-level virtualization to deliver software in packages called *containers*. Containers are isolated from one another and bundle their own software, libraries and configuration files. All containers are run by a single operating system kernel and therefore use fewer resources than virtual machines.

Topic Models in *librAIry* are packaged as Docker *containers* and published in online repositories⁵³ so they can be easily downloaded and run on any machine or software

⁵²<https://www.docker.com/>

⁵³<https://hub.docker.com/repositories>

solution. Containers not only offers virtualization advantages, but also version and license control, since they handle some information that we use to characterize our models:

- **repository**: model name (e.g. dbpedia-model).
- **author**: model creator (e.g. librAIry)
- **version**: model version (e.g. 3.0)
- **license**: model license (e.g. Apache 2.0)

4.2.2 Topic Model Exploitation

Once a topic model has been packaged as a virtual service (i.e. Docker containers), either assembled as a *annotator* in librAIry or as an online service accessible via its HTTP (based on a Swagger interface, Fig. 4.9) or TCP (based on an Avro⁵⁴ interface) API, it should support all tasks that can be performed on a topic model. Taking into account the **reproducibility** of a model, the *conditions under which the model has been created*, in relation to the corpus (i.e. number of documents, vocabulary size, language,...), about NLP tasks (i.e stopwords, PoS filtering) and about the model itself (i.e. hyperparameters) should be collected and provided by the service. Taking into account the **exploration** of a model, the *topics and their word distributions* must also be available. The word distribution is usually omitted when publishing topic models providing only the top10 or top5 words per topic. This limits the capacity of the model to be exploited in tasks where that information is required, for example this thesis (as will be seen in chapter 4). And finally, taking into account the topic **inference** in new texts, which is the most extended ability of these models, the service must be able to calculate topic distributions from texts.

A summary of the tasks, and their purposes, provided by a topic model can be found in Table 4.1.

In order to cover these tasks by topic services, the API must offer operations that, individually or partially, allow them to be achieved. A topic model is: *reproducible* (T1) when its hyperparameters and the configuration of the training set are known,

⁵⁴<https://github.com/librairy/modeler-service-facade/blob/master/src/main/avro/model.avpr>

jrc-en-model^{1.0}

[Base URL: librairy.linkeddata.es/jrc-en-model]
<http://librairy.linkeddata.es/jrc-en-model/v2/api-docs>

Collection of legislative texts (EN) from the European Union generated between years 1958 and 2006

[librAry - Website](#)

[Send email to librAry](#)

[Apache License Version 2.0](#)

/classes topic classification

POST /classes topics details in a text

/inferences topic distributions

POST /inferences topics details in a text

/settings model details

GET /settings params and stats about the model

/topics topic details

GET /topics list of topics

GET /topics/{id} topic info

GET /topics/{id}/neighbours topic neighbours

GET /topics/{id}/words topic words

Figure 4.9: Swagger-based web interface of a probabilistic topic model service created with *librAIry*.

| Task | Purpose |
|---------------------|-------------------------------|
| T1: Reproducibility | create a similar model |
| T2: Exploration | browse topics and words |
| T3: Inference | calculate topic distributions |

Table 4.1: Tasks and scopes provided by a topic model.

explorable (T2) when the word distributions of each topic are known, and is *interpretable* (T3) when the presence of each topic can be measured in a text. Table 4.2 summarizes the operations offered by a topic model-as-a-service to support the tasks provided by a topic model.

| Operations | Tasks |
|---|---------------------|
| O1: reading of model hyperparameters (i.e alpha, beta, and number of topics) | T1: Reproducibility |
| O2: reading of pre-processing tasks (i.e stop-words, normalization, PoS filtering) | T1: Reproducibility |
| O3: reading of learning parameters (i.e number of iterations, seed, likelihood) | T1: Reproducibility |
| O4: reading of topics described by word distributions (i.e topic relevance) | T2: Exploration |
| O5: reading of words described by topic distributions (i.e word relevance) | T2: Exploration |
| O6: calculation of topic distributions in texts (i.e vector of topic distributions) | T3: Inference |

Table 4.2: Operations offered by a Probabilistic Topic Model.

The rest of the section describes how the model implements these operations through service methods. A topic model-as-a-service is online available for review⁵⁵.

⁵⁵<http://librairy.linkeddata.es/jrc-en-model>

4.2.2.1 Reproducibility Tasks

Through a single request to the model API, a list of parameters is provided to support the O1, O2, and O3 operations. The method is available by both a HTTP-GET request on */settings* resource and by a TCP request on *getSettings* method. An online example is available here⁵⁶.

A detailed list of the parameters provided by the topic model is shown below:

- **algorithm**: method used to train the model (e.g. LDA, LLDA).
- **date**: when the model was created. It follows the ISO-8601.
- **params**: configuration of the learning process.
 - **seed**: numerical value to ensure consistent results (e.g. 1066).
 - **lowercase**: if true, text is converted to lowercase.
 - **topics**: number of topics.
 - **language**: language of texts.
 - **iterations**: number of sampling iterations.
 - **entities**: if true, NER tasks are performed.
 - **max-doc-ratio**: maximum word presence per document ratio (e.g. 0.9).
 - **min-freq**: minimum word presence per number of document (e.g. 5).
 - **alpha**: prior distribution over topic weights in each document (e.g. 0.1)
 - **beta**: prior distribution over word weights in each topic (e.g. 0.01)
 - **part-of-speech**: word classes used in the model (e.g. NOUN, VERB, ADJECTIVE)
 - **top-words**: number of words used to describe a topic (e.g. 10)
 - **stop-words**: list of words removed from the corpus (e.g. quantity, datum)
- **stats**: statistics after the learning process.
 - **loglikelihood**: how much the model fits with the training set.
 - **vocabulary**: number of unique words.

⁵⁶<http://librairy.linkeddata.es/jrc-en-model/settings>

- **topic-coherence**: distance between topics from their top words (e.g min, max, mean, mode).
- **topic-distance**: distance between topics from their word distributions (e.g min, max, mean, mode).
- **corpus**: number of documents in the training set.

4.2.2.2 Exploration Tasks

The exploration task, with its respective operations of reading topics (O4) and words (O5), is broken down into four services:

- **Topic List(O4)**. By means of the HTTP-GET `/topics`⁵⁷ resource and the TCP `getTopics` method, all the topics of the model are listed. Each topic is described with an increasing unique *identifier* (from 0 to the maximum number of topics), a label or *name* in case it has been established, and a *description* with the most relevant words (based on their density distributions).
- **Topic Detail(O4)**. By means of the HTTP-GET `/topics/_id_`⁵⁸ resource and the TCP `getTopic` method, a topic identified by *id* is described by providing its *identifier*, *name*, *description* and *entropy* (i.e how different is with respect the other topics).
- **Topic Words(O5)**. By means of the HTTP-GET `/topics/_id_/words`⁵⁹ resource and the TCP `getTopicWords` method, a list of word distributions for the topic identified by *id* is provided. Every word has its weight (i.e relevance score) with respect to the topic.
- **Topic Neighbours(O4)**. By means of the HTTP-GET `/topics/_id_/neighbours`⁶⁰ resource and the TCP `getTopicNeighbours` method, a list of topics related to the topic identified by *id* is provided. The distance between topics is measured from their word distributions.

⁵⁷<http://librairy.linkeddata.es/jrc-en-model/topics>

⁵⁸<http://librairy.linkeddata.es/jrc-en-model/topics/0>

⁵⁹<http://librairy.linkeddata.es/jrc-en-model/topics/0/words>

⁶⁰<http://librairy.linkeddata.es/jrc-en-model/topics/0/neighbours>

4.2.2.3 Inference Tasks

A single request with the text to be analyzed returns a list with the presence of each topic (O5) in that text. The method is available by both a HTTP-POST request to */inferences* or a TCP request to the *createInference* method, with a JSON message containing the text to be analyzed.

4.3 Summary

In Section 4.1 we have described *librAIry*, the framework to cover the entire topic model life-cycle in a scalable way. Algorithms and tools coming from different technologies work collaboratively to process and analyze huge collections of textual resources creating and using probabilistic topic models.

We tested and validated *librAIry* by using the framework in some real world scenarios such as DrInventor⁶¹, where thousands of scientific publications were processed, TheyBuyForYou⁶², where hundreds of thousands of public procurement texts were analyzed, or CorpusViewer⁶³, where millions of patents were automatically organized. Thus, *librAIry* has proven to be a text processing framework and addresses the first technical objective of this thesis (T01, *create a scalable platform for topic modeling*).

librAIry has been designed to represent corpora by organizing the data in three levels of detail: *snippets* to reflect parts or pieces of texts, *documents* to represent full texts, and *domains* to group documents. Transversally there are *annotations*, which allow providing more details to any of them. Figure 4.2 shows how two scientific articles published in the same conference and that mention a same resource in their papers can be represented. On this representation model based on SEDA architectures, actions over resources and status change notification events are introduced, which enable to distribute the processing of resources. Figure 4.7 shows the four modules involved in processing the resources. *Harvester* modules create new *documents*, *snippets* and *domains*. *Annotator* modules react to each new resource and introduce *annotations*. *Modeler* modules create new topic models for each new *domain*. And *Admin* modules perform administrative tasks and allow users to read the data. As shown in figure 4.8,

⁶¹<http://drinventor.eu>

⁶²<https://theybuyforyou.eu>

⁶³<https://www.plantl.gob.es/tecnologias-lenguaje/actividades/plataformas/Paginas/corpus-viewer.aspx>

modules coordinate their actions by reacting to the notifications. The actions are then executed in parallel through a distributed workflow and the first research objective of this thesis is addressed (R01, *define a distributed text-processing model for creating large probabilistic topic models*).

In Section 4.2 we propose the publication of topic models as web services that can be used in a scalable way from external solutions or integrated into the *libraIry* framework. Regardless of their API, since they works both over HTTP and over TCP, there are three types of tasks that guide the definition of the service: *reproducibility*, *exploration*, and *inference*. Tables 4.1 and 4.2 detail the operations supported by the service to cover these tasks. The definition of a topic model-as-a-service covers the second research objective of this thesis (R02, *define a template to package probabilistic topic models as web services*).

And finally, in order to facilitate the reuse of the topic models published as web services, section 4.2.1 presents an online repository based on virtual services. This covers the second technical objective of the thesis (T02, *create a repository of topic-based web services*).

Chapter 5

Explainable Topic-based Associations

As stated in Chapter 3, one of our hypotheses aims to determine whether it is possible to semantically relate texts from their most relevant topics (H1.2). In particular, our goal is to determine whether two documents can be related by identifying their most representative topics.

However, as seen in Section 2.2.2, interpreting how documents are related from their topic distributions is hard when using density-based measures. The same pair of documents may vary their distance from each other when using topic models with different dimensions to represent them, as shown in figure 2.1. High dimensional models create more specific topics than models with fewer dimensions, and this topic specificity influences the way in which topic distributions are related.

In order to better understand the relations derived from topic distributions, Section 5.1 compares scientific articles from their representations based on full-content, abstracts (i.e manual summaries), or summaries created automatically. Two types of metrics are considered: (i) *internal-representativeness*, focused on describing the content, and *external-representativeness*, focused on discovering relations (Badenes-Olmedo et al., 2017a).

In Section 5.2, once we know how the topics are used to represent and relate texts, we propose a new topic-based annotation based only on the most representative topics and a new distance measure that takes advantage of these representations (Badenes-Olmedo et al., 2017c). The main goal is not only to cluster texts through their most

relevant topics, but also to facilitate the interpretation of their relations.

5.1 Topic-based Relations

This section studies the ability of topic distributions to capture the representativeness of a text through the relations that can be derived from it. In particular, it examines the performance offered by topic-based representations to describe scientific articles from their full-texts compared to representations based on summaries (e.g. *abstract*). The objective is twofold, to analyze comparisons based on topic distributions on the one hand, and to identify strengths and weaknesses when using *abstracts* to compare scientific articles on the other hand. Two novel measures are proposed based on the capability of the summary to substitute the original paper (Figure 5.1): (1) *internal-representativeness*, which evaluates how well the summary represents the original full-text and (2) *external-representativeness*, which evaluates the summary according to how the summary is able to produce a set of related texts that are similar to what the original full-text has triggered.

Recent studies (Sciences and life, 2016; Westergaard et al., 2017) have shown that text mining of full research articles give consistently better results than using only their corresponding abstracts. Given the size limitations and concise nature of abstracts, they often omit descriptions or results that are considered to be less relevant but still are important in certain Information Retrieval tasks. Thus, when other researchers cite a particular paper, 20% of the keywords that they mention are not present in the abstract (Divoli et al., 2012).

An analysis about the *representativeness* of research article summaries based on topic distributions is presented, considering those based exclusively on abstracts and those based on their discursive structure (*approach*, *challenge*, *background*, *outcomes* and *future work*) (Simone Teufel, 2010). The *representativeness* of a summary with respect to the original full-text is assumed as the degree of relation with the original one (*internal-representativeness*), along with the capacity of mimicking the full text when finding related items (*external-representativeness*). In order to quantify this notions of internal-external representativeness, a probabilistic topic model is trained to have a vectorial representation of each text retrieved from a paper: full content-based and summary-based (Figure 5.1). The vectorial representations of full-papers

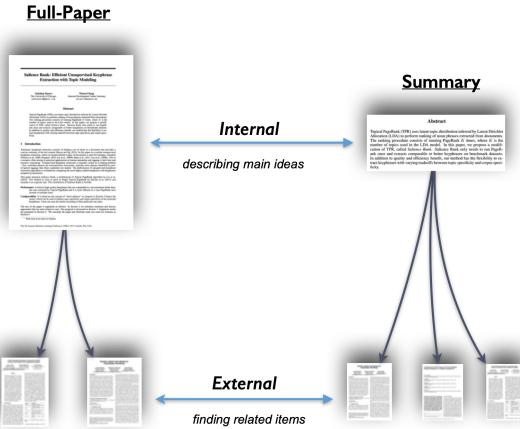


Figure 5.1: Internal and External Representativeness.

is used to measure the distance between them and those derived from abstract or summaries (*internal-representativeness*), and also to find similar documents (*external-representativeness*) based on the distance between their vectorial representations. An upper distance threshold is specified to filter less similar pairs and compose a set of related papers for each paper. Then, a comparison in terms of *precision* and *recall* is performed between sets obtained by only using the vectorial representation of full-papers, against sets produced by using other kind of summaries.

5.1.1 Research Articles Summaries

Some approaches have been proposed to summarize scientific articles (Cohan and Goharian, 2015) taking advantage of the citation context and the document discourse model. We have used the scientific discourse annotator proposed by (Ronzano and Saggion, 2015) to automatically create summaries from research papers by classifying each sentence as belonging to one of the following scientific discourse categories: *approach*, *challenge*, *background*, *outcomes* and *future work*. These categories were identified from the schemata proposed by (Teufel et al., 2009) with an original purpose of characterizing the content of Computer Graphics papers.

The annotator is based on a Support Vector Machine classifier that combines both lexical and syntactic features to model each sentence in a paper. The tool⁶⁴ was in-

⁶⁴<http://backingdata.org/dri/library/>

tegrated in our *libraIry* framework through the *Rhetoric Module*⁶⁵ to automatically annotate research papers with their rhetorical content.

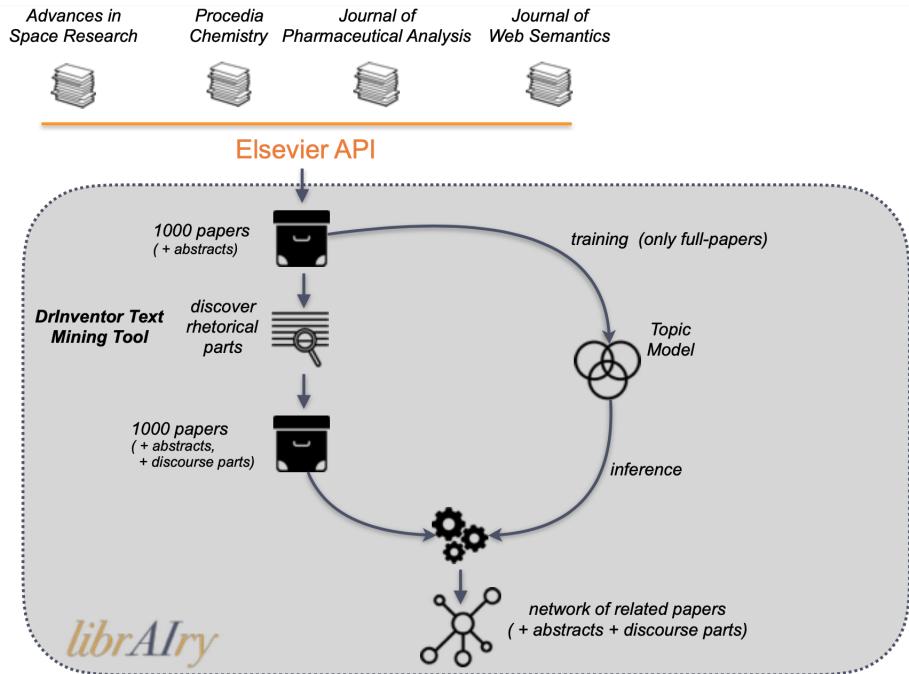


Figure 5.2: Experiment to analyze the ability of topic-based representations to create relations from summaries *vs* full-texts.

5.1.2 Feature Vectors

A representational model is required not only to measure distances between text fragments but, more importantly, to help to understand the differences in their content. As seen in Section 2.2.2, topic models are widely used to uncover the latent semantic structure from text corpora. In particular, Probabilistic Topic Models represent documents as a mixture of topics, where topics are probability distributions over words. Latent Dirichlet Allocation (LDA)(Blei et al., 2003) is the simplest *generative* topic model that makes it possible to characterize documents not previously used during the training task. This is a key feature for our evaluations because, although the model used for the experiments will be trained from the full-content of papers, it will be also used to describe the texts summaries.

⁶⁵<https://github.com/librairy/annotator-rhetoric>

Thus, we have used a LDA model to describe the inherent topic distribution of papers in the corpus. Some hyper-parameters need to be estimated: the *number of topics* (k), the concentration parameter (α) for the prior placed on documents' distributions over topics and the concentration parameter (β) for the prior placed on topics' distributions over terms. Since the target of this experiment is not to evaluate the quality of the representational model, but to compare their topic distributions, we accepted as valid values those widely used in the literature: $\alpha = 0.1$, $\beta = 0.1$, and $k = 2 * \sqrt{n/2} = 44$ where n is the size of the corpus.

5.1.3 Similarity Measure

Feature vectors in Topic Models are topic distributions expressed as vectors of probabilities. Hence we opt for *Jensen-Shannon divergence* (JSD) (See Section 2.1) instead of the commonly used *Kullback-Liebler divergence* (KLD). The reason for this is that KLD is not defined when a topic distribution is zero and is not symmetric, what does not fit well with semantic similarity measures which in general are symmetric (Rus et al., 2013). JSD considers the average of the distributions as follows :

$$JSD(p, q) = \sum_{i=1}^T p_i * \log \frac{2 * p_i}{p_i + q_i} + \sum_{i=1}^T q_i * \log \frac{2 * q_i}{q_i + p_i} \quad (5.1)$$

where T is the number of topics and p, q are the topics distributions.

And the *similarity measure* used in our analysis is based on the JSD transformed into a similarity measure as follows (Dagan et al., 1999) :

$$\text{similarity}(D_i, D_j) = 10^{-JSD(p,q)} \quad (5.2)$$

where D_i, D_j are the documents and p, q the topics distributions of each of them.

5.1.4 Experiments

The corpus used in the experiments was created by combining journals in different scientific domains such as *Advances in Space Research*, *Procedia Chemistry*, *Journal of Pharmaceutical Analysis* and *Journal of Web Semantics* (Figure 5.2). In total 1,000 papers were added, 250 from each journal. Both the abstract and the *full-content* of

these documents were directly retrieved from the Elsevier API⁶⁶ by using our *Harvester module*⁶⁷. The code used to perform the analysis along with the results obtained are publicly available⁶⁸.

Since the annotation process to automatically discovers the rhetorical parts of a research paper (Section 5.1.1) is sensitive to the structure of the phrases that are used when writing the text, only 20% of papers in the corpus could be fully annotated with all the fragments considered. In fact, these categories are not present in the same proportion in the corpus: *approach* (90%), *background* (78%), *outcome* (73%), *challenge* (57%) and *future work* (21%)

5.1.4.1 Internal Representativeness

The *internal-representativeness* of a text measures the similarity of a summary against the original full-text. This measure is based on the JSD between the topic distribution of each of them.

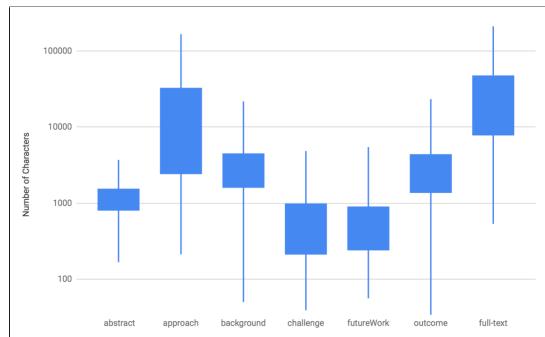


Figure 5.3: length of summaries

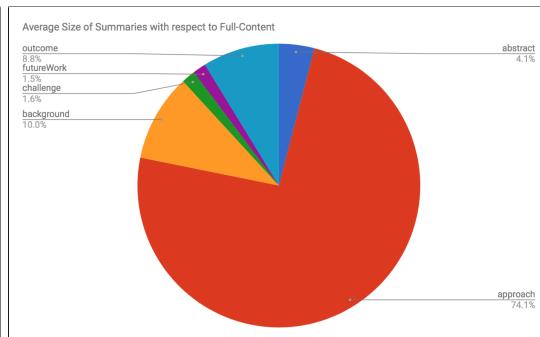


Figure 5.4: length of text parts

Since LDA considers documents as *bag-of-words*, the text length (e.g. full-content or summaries) affects the accuracy of the topic distributions inferred by the topic model described in Section 5.1.2. The occurrences of words in short texts are less discriminative than in long texts where the model has more word counts to know how words are related (Hong and Davison, 2010). In view of the above, the *approach*, the *background* and the *outcome* content of a paper generate more accurate topic distributions than those created from other approaches such as the abstract (Figure 5.3). Also, the relative

⁶⁶<https://dev.elsevier.com>

⁶⁷<https://github.com/librairy/harvester-elsevier>

⁶⁸<https://github.com/librairy/study-semantic-similarity>

presence of each of them in a paper (figure 5.4) shows an unexpected result when compared to the IMRaD format (Nair and Nair, 2014). This style proposes to distribute the content of an abstract, and by extension the full-paper, as follows: *Introduction*(25%), *Methods*(25%), *Results*(35%) and *Discussion*(15%). However, the results (figure 5.4) show that *Method* section (*approach* content) is more extensive than *Results* section (*outcome* content) in our corpus.

All pairwise similarities between full-papers, abstracts and rhetorical-based summaries are calculated to measure the *internal-representativeness* of a summary with respect to the original text, i.e. the topic-based similarity value (equation 5.2) between the probability distributions of the full-text and each of the summaries. Results (table 5.1) suggest than summaries created from the *approach* content are more representative than others, i.e. the distribution of topics describing the text created from the *approach* content is the most similar to the one corresponding to the full-content of the paper.

| | Min | Lower Quartile | Upper Quartile | Max | Dev | Median |
|-----------------|---------------|----------------|----------------|---------------|---------------|---------------|
| abstract | 0.0489 | 0.9109 | 0.9840 | 1.0000 | 0.1443 | 0.9741 |
| approach | 0.0499 | 0.9969 | 1.0000 | 1.0000 | 0.0872 | 0.9998 |
| background | 0.0463 | 0.8967 | 0.9937 | 0.9988 | 0.2037 | 0.9822 |
| challenge | 0.0426 | 0.7503 | 0.9517 | 0.9940 | 0.2224 | 0.8829 |
| futureWork | 0.0000 | 0.6003 | 0.9435 | 0.9948 | 0.2842 | 0.8814 |
| outcome | 0.0485 | 0.9267 | 0.9925 | 0.9990 | 0.1721 | 0.9835 |

Table 5.1: Internal-Representativeness

5.1.4.2 External-Representativeness

The *external-representativeness* metric tries to measure how different is the set of related documents obtained from summaries with respect to those derived from the original full-text. In terms of *precision*, *recall* and *f-measure*, a comparison has been performed to analyze the behavior of the summaries when trying to discover related content compared to use the full-text of the article.

By using the same topic model previously created, similarities among all pairs of documents were also calculated according to equation 5.2. Then, a minimum score or similarity threshold is required to define when a pair of papers are related. Each

threshold is used to create a gold-standard which relates articles to others based on their similarity values. In order to discover that lower bound of similarity, a study about trends in the similarity scores (fig 5.5) as well as distributions of topics in the corpus (fig 5.6) was performed. We can see that topics are not equally balanced across papers. This fact generates separated groups of strongly related papers. We think this phenomena is due to our usage of a corpus created from journals where different domains are equally balanced. Then, we considered a similarity score equals to 0.99 (fig 5.5) as the threshold from which strong relations appear. However, to cover different interpretations of similarity, from those based on sharing general ideas or themes to those that imply to share a more specific content, the following list of thresholds was considered in the experiments: 0.5, 0.6, 0.7, 0.8, 0.9, 0.95 and 0.99.

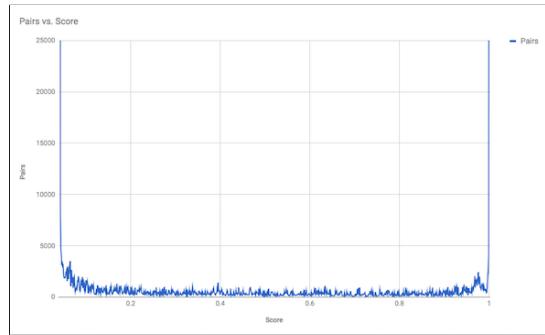


Figure 5.5: number of pairwises by similarity score (rounded up to two decimals)

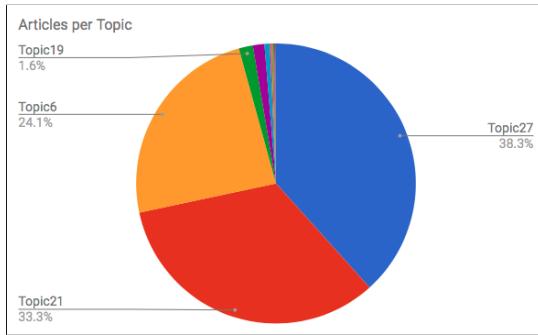


Figure 5.6: topics per article with value above 0.5

For each similarity threshold, a gold-standard was created based on considering as related those papers with a similarity value upper than the selected threshold. Results (figure 5.7) comparing the related papers inferred from the full-content with those inferred from the partial-content representation (i.e. abstract or rhetorical parts) suggest that strongly related papers are mainly discovered by using the summary created from the *approach* section. The reason for this may be based on the average size of this type of summaries or the particular content included in this part of a paper. While other summaries include more general-domain words, the *approach* content includes more specific words that describe the method or the final objective of the paper. So, for higher similarity thresholds, i.e. for strongly related papers, the recommendations discovered by using the *approach* are more precise than those discovered by using the abstract.

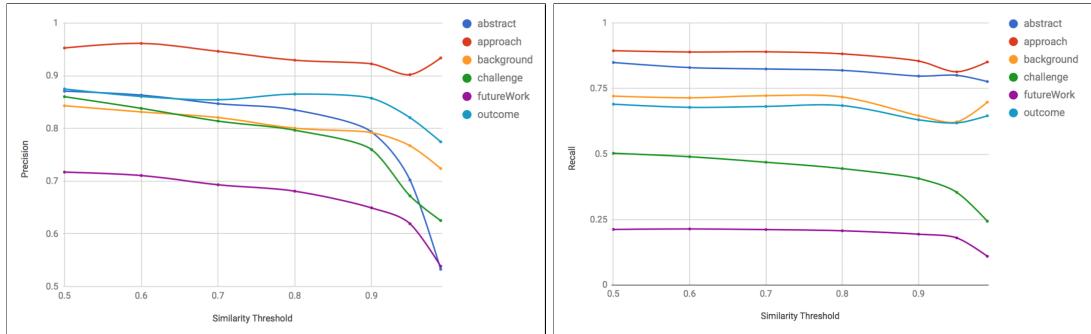


Figure 5.7: Precision at different similarity thresholds

Figure 5.8: Recall at different similarity thresholds

In terms of *recall* (figure 5.8), the upward trend followed by the *approach*, the *outcome* and the *background* content remarks the assumption of summaries containing key words allow to discover more similar papers than others. Moreover, since *recall* overlooks false-negatives classifications, it suggests that these parts of a research paper share more words than others with strongly related papers but they may also present commonalities with highly related papers, except in case of *approach* which still exhibits higher *precision*.

As expected, only summaries created from the *approach*, the *outcome* and the *background* content maintain high accuracy values (fig 5.9) even for high similarity thresholds. Along with the results showed in figure 5.10, where the same three rhetorical classes present the lowest standard deviation over the *f-measure*, they can be considered as the most robust summaries containing the ideas that better characterize the paper compared to others.

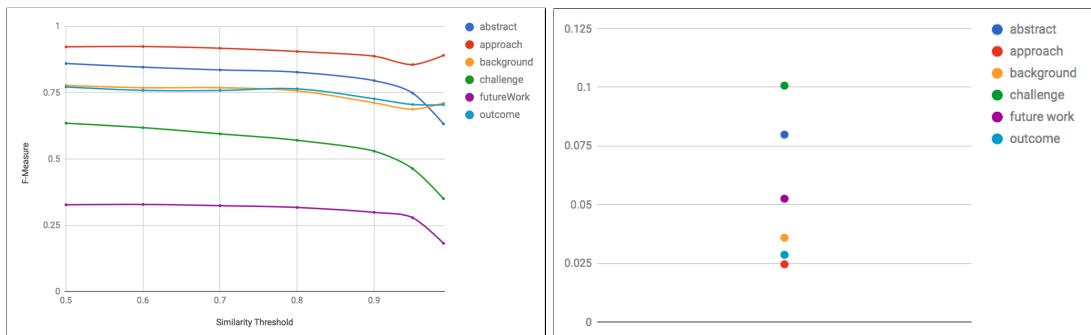


Figure 5.9: f-measure performance

Figure 5.10: f-measure deviation

5.1.5 Conclusion

Topic-based relations have been studied among scientific documents based on their abstract sections with respect to summaries corresponding to their scientific discourse categories. For this purpose, two novel measures have been proposed: (1) *internal-representativeness* and (2) *external-representativeness*.

Results show that summaries created from the *approach*, *outcome* or *background* content of a paper describe more accurately its full-content in terms of overall ideas and related documents than abstracts. Although those summaries are more extensive in number of characters than other with similar *precision* such as the abstract content, they have proven to be particularly helpful discovering strongly related papers, i.e. papers with a similarity value close to 1.0.

5.2 Topic-based Clustering

Once we have a better understanding of the behavior of topic models to represent texts, and the relationships that can be derived, we examine their usefulness in browsing document collections. A way to explore the knowledge inside document collections is by moving from one information element to another based on certain criteria that relates them. This approach requires to calculate a similarity matrix with all possible comparisons between elements, so we can later select the most pertinent ones. Since computing a $n \times n$ matrix takes $O(n^2)$ time, obtaining all possible pairs of similarities in a large collection of documents can be unfeasible because of the exponential cost of comparing every pair of elements.

In order to reduce the complexity, some approaches have introduced mechanisms (mainly pre-election methods) to alleviate the problem of making this calculation over the whole set of pairs in the collection. However those methods are still quite costly.

In this section we propose a novel clustering technique based on topic model distributions that reduces the complexity to find relations between documents in a large corpus of textual documents, without compromising efficiency and providing additional information about relations. A detailed description of our algorithm is given in Section 5.2.1. The experiments to verify the efficiency and effectiveness of our clustering algorithms using real data, and demonstrate that our approach is competitive enough against both a centroid-based and a density-based clustering baselines are described

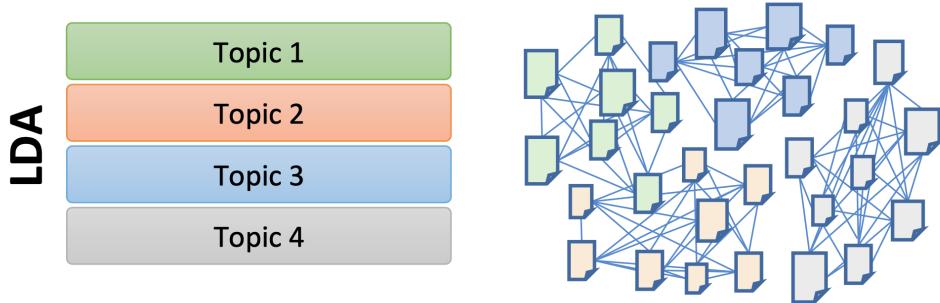


Figure 5.11: Probabilistic Topic Models, and in particular Latent Dirichlet Allocation (LDA), can efficiently divide the search space and speed up the process of finding relations among documents inside big collections.

in Section 5.2.2. The most relevant results and conclusions are finally presented in Section 5.2.3.

5.2.1 Most Relevant Topics

Our algorithm to identify the most relevant topics draw inspiration from other clustering techniques to divide the initial space of elements into smaller sub-groups where the complexity of calculating all possible distances is significantly reduced. Existing unsupervised approaches based on centroids or density measures require to make comparisons between elements to find groups of similar elements in the collection. They usually follow an iterative methodology to produce the final solution, based on calculating distances between the elements inside each intermediate state. A naïve approach would need to calculate all possible distances between elements, which takes $O(n^2)$ time for a $n \times n$ matrix. That makes it impossible to apply such techniques on large collections of documents, since the cost of comparing each element with the others escalates quickly. For those big volumes of data, a clustering task that only takes linear time to discover the clusters can significantly alleviate this problem. For example, a classification method that does not require any other data except the element information to assign the item to the corresponding cluster will take $O(n)$ time to compose those groups.

The classification method needs to take advantage of both the vectorial representations of the documents and the similarity measure used to relate them in a corpus.

Since the representational model considered is based on Probabilistic Topic Models (and more specifically on LDA), the classification method leverages on the particular behavior of Dirichlet distributions, which describes each document by a density vector where the sum of all the probability values must be equal to 1.0. Thus, analyzing the relations between the topics that compose a topic distribution becomes more important than comparing their probability values with another topic distribution.

Our hypothesis is that, *given a collection of topic distributions, an unsupervised classification with high precision and linear computing time can be performed by considering only the topic distribution of each document and without needing to further compare it with other document's distributions.*

All algorithms have been compared in terms of *cost*, *effectiveness* and *efficiency* (Halkidi et al., 2001). *Cost* is based on the number of pairwise similarity values. *Effectiveness* handles relevance measures such as *precision* and *recall*. And *efficiency* tries to measure the overall balance between *cost* and *effectiveness*. More details about those measures will be included in Section 5.2.2.

5.2.1.1 Trends-based Clustering Method

Topic distributions are formalized as probability distributions following a Dirichlet distribution, so their probability values sum to 1. In this way, the relevance of a topic is influenced and at the same time influences the relevance of the others items in the distribution. Our first approach named *Trends on Dirichlet distribution-based Clustering* (TDC) considers changes in the relevance, i.e. probability values of the topics instead of directly relying on the scores associated to a given topic distribution (Figure 5.12). It expresses the oscillations between topic weights considering a fixed order between them. The order can be any, as long as it remains constant in all distributions. Thus, a *probability-vector* composed by n density values is translated to a *trend-expression* made out of $n - 1$ trend-values such as (1) upward, (2) downward and (0) sustained. This *trend-expression* will identify the cluster the distribution falls into, and therefore the corresponding item belongs to. TDC is defined as:

$$TDC(P) = T \quad (5.3)$$

where: $T_i = 1$, when $P_i < P_{i+1}$
 $T_i = 2$, when $P_i > P_{i+1}$
 $T_i = 0$, when $P_i = P_{i+1}$

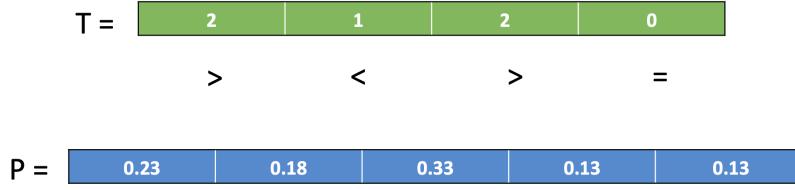


Figure 5.12: TDC considers variations across consecutive topics inside a document's topic distribution.

For example, given the distribution $P_1 = [0.23, 0.18, 0.33, 0.13, 0.13]$, the assigned cluster will be $T = 2120$. The first value is 2 because 0.23 is greater than 0.18 (same for other values).

5.2.1.2 Ranking-based Clustering Method

We propose a clustering technique named *Ranking on Dirichlet distribution-based Clustering* (RDC) that only considers the top n topics from the ranked list of probability distributions to classify similar topic distributions (Figure 5.13). It is based on the focal document selection proposed by (Towne et al., 2016) to validate LDA-based similarity algorithms against human perception of similarity. RDC is defined as:

$$RDC(P) = R \quad (5.4)$$

where $\forall i \in R, R_i \geq R_{i+1}$ and $\forall j \in P, R_1 \geq P_j$

This is based on the assumption that the highest weighted topics have a high influence in the rest of topics in terms of calculating distances, when comparing continuous multivariate probability distributions. Since similarity measures (Section 2.1) based on probability distributions are oriented to determine the uncertainty of the distribution, when a mixture of probability distributions is considered, as in the case of Topic Models, the top n distributions (i.e. the most relevant topics) should be sufficient to allow us grouping similar distributions. Taking into account the above considerations, the RDC algorithm classifies a topic distribution according to only n highest probability values. For instance, given the following topic distribution: $P_2 = [0.23, 0.18, 0.33, 0.13, 0.13]$, the assigned cluster is 3 from RDC-1 because that is the topic with the highest weight.

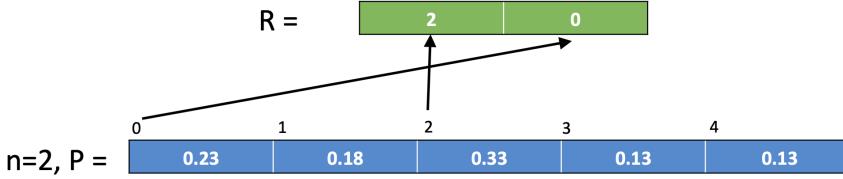


Figure 5.13: RDC only considers the top n topics from the ranked list of probability distributions.

5.2.1.3 Cumulative Ranking-based Clustering Method

A variant of the previous algorithm, named *Cumulative Ranking on Dirichlet distribution-based Clustering* (CRDC), also aims to discover the most representative topics that can help to group similar topic distributions. While RDC is based on a fixed number of topics, CRDC is based on the cumulative sum of the weights of the highest topics (Figure 5.14). The number of topics is now dynamically determined by a threshold, and once this threshold is reached no more topics are considered. CRDC is defined as:

$$CRDC(P) = C \quad (5.5)$$

where $\forall i \in C, C_i \geq C_{i+1}$ and $\sum_{i=1}^T C_i \geq w$ with T size of C , and w a cumulative weight threshold.

For instance, considering a CRDC algorithm with a cumulative weight threshold of 0.9, and the following topic distribution: $P_3 = [0.36, 0.58, 0.05, 0.01]$. The assigned cluster will be 21 . To come up with this cluster, a ranked list of topics based on their weights is first calculated, $R_p = 2|1|3|4$. Then, a sum of weights according to the order described by R_p is performed. When the accumulated sum is greater than the threshold, the topics taking part of the sum will be selected to “label” the cluster. In this case, the cumulative weight threshold is 0.9 therefore using only the first two topics we exceed the threshold: $w = 0.58 + 0.36 = 0.94$

5.2.2 Experiments

In this section we present the experimental setup for evaluating our trends-based (TDC), ranking-based (RDC) and cumulative ranking-based (CRDC) clustering approaches, considering both JS divergence and He distance as similarity measures. We describe the datasets and baseline algorithms that will be used for comparison.

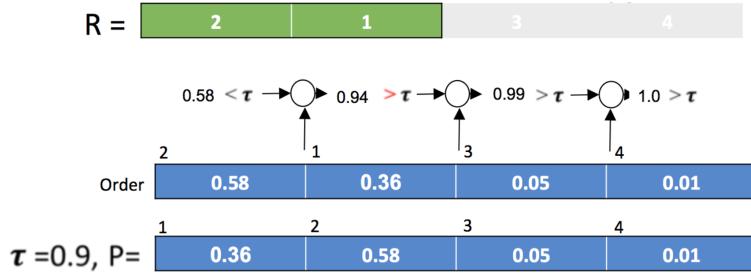


Figure 5.14: CRDC only considers the top n topics until the sum of the weights of the highest topics exceeded a given threshold.

5.2.2.1 Datasets

We used two datasets to evaluate the performance of the algorithms. The first dataset, DIRICHLET-RANDOM-MIXTURE (DRM), is synthetic (Badenes-Olmedo et al., 2017d). To generate the dataset, we sampled k probabilistic distributions from a *randomly k -dimensional selector* based on Dirichlet distributions. This implies that all probabilities must sum to 1 for each sampled point. The number of sampled points from this mixture of Dirichlet distributions is $n = 1000$.

The second dataset has been created from a collection of research papers published in the *Advances in Engineering Software* (AIES) journal. They were retrieved from the Springer API by using the librAIry (Badenes-Olmedo et al., 2017b) framework and a Topic Model based on LDA was created from them. The sample is also composed by $n = 1000$ documents.

Topic models were trained from these datasets by using the criteria described by (Steyvers et al., 2006): $\alpha = 50/k$, $\beta = 0.01$ and $k = 2 * (\sqrt{(n/2)})$, where k is the number of topics and n is the number of documents. Since both datasets contain 1000 documents (n), the hyper-parameters α and β are assigned as follow: $\alpha = 1.136$, and $\beta = 0.01$, and the number of topics is fixed to $k = 44$. Further tuning of the settings is not crucial in this evaluation process, because we are not focusing on the quality of the model but on the efficiency when calculating similarities from their representational distributions.

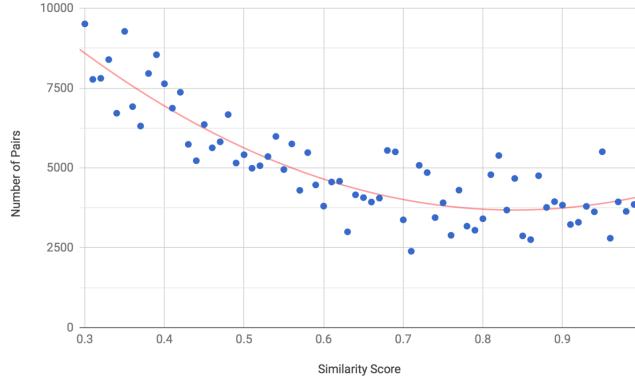


Figure 5.15: Similarity values grouped by frequency in AIES

5.2.2.2 Settings

Since there is no unified criteria to select a threshold inside the distance scores spectrum that allows us to determine when two documents are similar, we decided to study the distribution of similarity values calculated from all pairwise comparisons. In Figure 5.15, the result of grouping all similarities by the two most representative decimals, i.e. the first two decimals of the similarity value, is shown. Then, a polynomial function (red line) is approximated to describe the trend of these values. In this function, the similarity score 0.83 emerges as a global minimum and has been used for filtering out the non-similar document pairs.

5.2.2.3 Baselines

We compare the performance of TDC, RDC and CRDC algorithms against the following baselines:

- *K-Means* as a centroid-based clustering approach.
- *DBSCAN* as a density-based clustering approach.
- *Random*, which randomly selects R from the dataset

Initially, *K-Means* (Bahmani et al., 2012) randomly composes a set of centroids and assigns each point of the sample to its nearest cluster based on a distance measure. Then, a new set of centroids is calculated from the previous ones according to the assigned points. This process is repeated until the set of centroids does not

change significantly between consecutive iterations or a maximum number of iterations is reached. The *scalable K-Means* approach used in our experiments is an improved version of *k-means* which obtains an initial set of centers ideally close to the optimum solution. The algorithm implemented at the Apache Commons Math library⁶⁹ was used in the experiments. Based on empirical results, the best configuration is: $k = \text{number - of - topics} = 44$ and $\text{maxIterations} = 50$

A widely known density-based algorithm is *DBSCAN* (Ester et al., 1996), which compose clusters from the neighborhood of each point considering at least a minimum number of points and a given radius. Thus, it requires to specify the radius of the point's neighborhood, *Eps*, and the minimum number of points in the neighborhood *MinPts*. Based on empirical results, the best results were obtained with the following configuration: $\text{eps} = 0.1$ and $\text{minPts} = 50$

The *Random* algorithm takes as input a parameter m and randomly divides the dataset into m equal-sized groups of similar documents. For the evaluation, m was set to the number of topics, the dimension of the dataset.

With respect to the proposed algorithms and taking into account empirical results, the RDC algorithm is set to use the *top1* highest topics, and the cumulative weight threshold for the CRDC algorithm is set to 0.9.

5.2.2.4 Evaluation

A gold-standard is created for each dataset and distance metric considered. They are created by calculating all pairwise similarities from their documents. Since the $n \times n$ similarity matrix requires $O(n^2)$ time to be calculated, the selected size of datasets has not been too large $n = 1000$.

We considered three measures to evaluate our algorithms with respect to the baseline:

- ***cost***: based on the number of similarity score calculations required by the algorithm:

$$\text{cost} = (\text{reqSim} - \text{minSim}) / (\text{totalSim} - \text{minSim}) \quad (5.6)$$

The *minSim* corresponds to the number of similar documents obtained from using the *threshold* score previously mentioned in section 5.2.2.2. The *totalSim*

⁶⁹<http://commons.apache.org/proper/commons-math/>

corresponds to the Cartesian product of existing documents: $totalSim = n * n = 1,000,000$. And the $reqSim$ corresponds to the number of similarities calculated by the algorithm.

- ***effectiveness***: based on *precision* and *recall*. It expresses the quality of the algorithm:

$$effectiveness = \frac{precision^2 + recall^2}{2} \quad (5.7)$$

- ***efficiency***: based on the previous ones, it express a compromise between quality and performance:

$$efficiency = effectiveness - cost \quad (5.8)$$

5.2.2.5 Results

The code used to evaluate the algorithms along with the results obtained are publicly available(Badenes-Olmedo et al., 2017d).

In terms of ***effectiveness*** (Figures 5.16 and 5.17), the results highlight that *K-Means* and *CRDC* outperform the other algorithms. *K-Means* was expected to be a top performer because the algorithm itself performs comparisons to map clusters. The fact that *CRDC* has such good performance encourages us to think that, in fact, the most relevant topics when they altogether exceed a certain high weight threshold, are those that best represent the document and allow to group together similar documents. However, as shown in tables 5.2, 5.3, 5.5 and 5.4, considering a fixed number of more relevant topics (*RDC*) or considering the trend of their weights (*TDC*) does not seem to perform so well on aggregating similar documents, since their *precision* and *recall* values are very low in both cases. It is surprising that the *DBSCAN* has such low value. Taking a look at its *precision* and *recall* values, and also seeing the number of groups that each algorithm has created (Figure 5.18), we believe that having a corpus containing a very cohesive set of documents (all papers in corpus belong to the same journal) affects the performance of this algorithm since it divides the corpus into a lower number of groups. This way, it obtains high values of *recall* because most of the pair-wise distances are computed, but very low *precision*.

The results also show that the behavior of the algorithms does not differ significantly when using different similarity measures, for example JS divergence (Figure 5.16) and

He distance (Figure 5.17). This highlights the importance of the documents' topic distributions to successfully classify them into smaller groups of similar items, while other particular aspects such as the distance or similarity metric used to compare them are less influential.

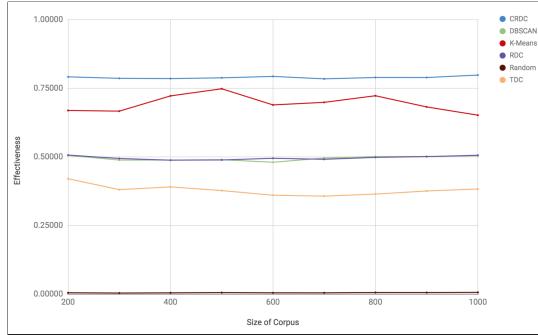


Figure 5.16: Effectiveness (JS-based) in AIES

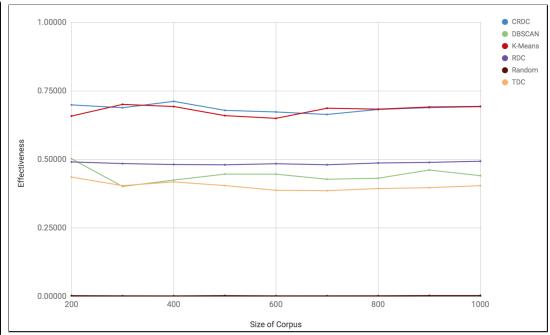


Figure 5.17: Effectiveness (He-based) in AIES

| Size | CRDC | DBSCAN | K-Means | RDC | TDC | Random |
|------|-------------|--------|-------------|------|------|--------|
| 200 | 0.94 | 0.10 | 0.96 | 0.31 | 0.42 | 0.12 |
| 300 | 0.93 | 0.15 | 0.94 | 0.30 | 0.39 | 0.08 |
| 400 | 0.93 | 0.15 | 0.89 | 0.29 | 0.39 | 0.09 |
| 500 | 0.92 | 0.30 | 0.90 | 0.28 | 0.38 | 0.09 |
| 600 | 0.92 | 0.19 | 0.88 | 0.28 | 0.38 | 0.08 |
| 700 | 0.92 | 0.20 | 0.91 | 0.28 | 0.38 | 0.09 |
| 800 | 0.92 | 0.12 | 0.89 | 0.30 | 0.39 | 0.10 |
| 900 | 0.92 | 0.13 | 0.87 | 0.30 | 0.40 | 0.10 |
| 1000 | 0.93 | 0.13 | 0.90 | 0.30 | 0.40 | 0.10 |

Table 5.2: Precision (JS-based) in AIES

In terms of *cost* (Figures 5.19 and 5.20), the best clustering algorithm, as expected, is based on *random* selection. This is due to the fact that the number of pairs compared by this algorithm is always the minimum, given the dataset is simply randomly divided into m equal-sized groups, where m is equals to the number of topics, i.e. dimension of the dataset. Since *K-Means* and *DBSCAN* make comparisons between documents until their internal condition is satisfied, they are the most inefficient approaches. *K-Means* involves the highest cost because it compares all the documents with the 44 centroids

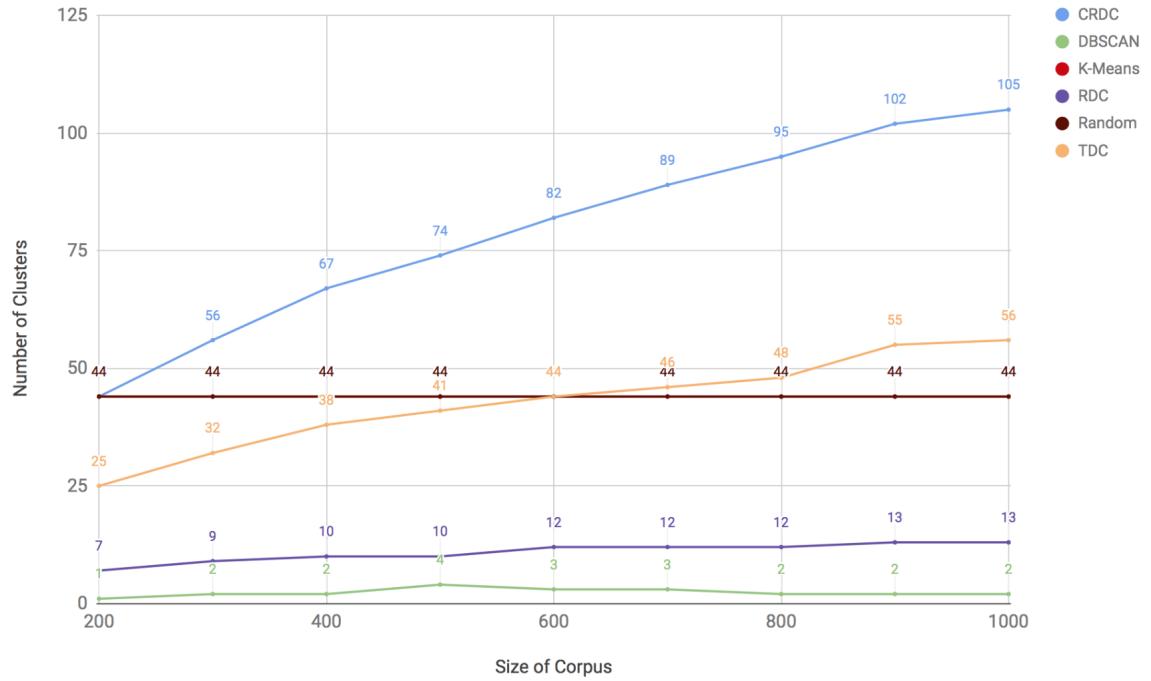


Figure 5.18: Clusters in AIES

| Size | CRDC | DBSCAN | K-Means | RDC | TDC | Random |
|------|-------------|-------------|-------------|------|------|--------|
| 200 | 0.75 | 0.07 | 0.84 | 0.23 | 0.08 | 0.33 |
| 300 | 0.74 | 0.08 | 0.83 | 0.23 | 0.06 | 0.32 |
| 400 | 0.76 | 0.09 | 0.76 | 0.22 | 0.06 | 0.32 |
| 500 | 0.73 | 0.08 | 0.74 | 0.21 | 0.08 | 0.31 |
| 600 | 0.72 | 0.08 | 0.73 | 0.21 | 0.06 | 0.30 |
| 700 | 0.71 | 0.10 | 0.76 | 0.21 | 0.06 | 0.30 |
| 800 | 0.73 | 0.11 | 0.78 | 0.22 | 0.07 | 0.31 |
| 900 | 0.73 | 0.12 | 0.80 | 0.22 | 0.08 | 0.32 |
| 1000 | 0.74 | 0.15 | 0.77 | 0.23 | 0.08 | 0.32 |

Table 5.3: Precision (He-based) in AIES

in each iteration.

Among our proposals, the main reason for an algorithm to present a higher cost is due to the number of groups the corpus is divided into (see Figure 5.18). The greater the number of groups, the fewer the number of later comparisons that have to be made

| Size | CRDC | DBSCAN | K-Means | RDC | TDC | Random |
|------|------|-------------|---------|-------------|------|--------|
| 200 | 0.92 | 1.00 | 0.79 | 0.96 | 0.02 | 0.87 |
| 300 | 0.91 | 0.89 | 0.84 | 0.96 | 0.02 | 0.84 |
| 400 | 0.92 | 0.92 | 0.90 | 0.96 | 0.02 | 0.86 |
| 500 | 0.91 | 0.94 | 0.88 | 0.96 | 0.03 | 0.85 |
| 600 | 0.91 | 0.94 | 0.87 | 0.96 | 0.02 | 0.83 |
| 700 | 0.91 | 0.92 | 0.90 | 0.96 | 0.02 | 0.83 |
| 800 | 0.92 | 0.92 | 0.88 | 0.96 | 0.02 | 0.83 |
| 900 | 0.92 | 0.95 | 0.86 | 0.96 | 0.02 | 0.83 |
| 1000 | 0.92 | 0.93 | 0.89 | 0.97 | 0.02 | 0.84 |

Table 5.4: Recall (JS-based) in AIES

| Size' | CRDC | DBSCAN | K-Means | RDC | TDC | Random |
|-------|------|-------------|---------|-------------|------|--------|
| 200 | 0.84 | 1.00 | 0.65 | 0.96 | 0.02 | 0.82 |
| 300 | 0.84 | 0.98 | 0.76 | 0.95 | 0.02 | 0.78 |
| 400 | 0.84 | 0.98 | 0.79 | 0.94 | 0.02 | 0.79 |
| 500 | 0.85 | 0.94 | 0.87 | 0.95 | 0.02 | 0.78 |
| 600 | 0.86 | 0.96 | 0.80 | 0.95 | 0.02 | 0.76 |
| 700 | 0.85 | 0.98 | 0.80 | 0.95 | 0.02 | 0.76 |
| 800 | 0.85 | 0.99 | 0.81 | 0.95 | 0.02 | 0.76 |
| 900 | 0.85 | 0.99 | 0.75 | 0.95 | 0.02 | 0.77 |
| 1000 | 0.86 | 1.00 | 0.74 | 0.96 | 0.02 | 0.78 |

Table 5.5: Recall (He-based) in AIES

and, therefore, the lower the cost of the algorithm.

The behavior of the *DBSCAN* algorithm depends remarkably on the similarity metric used. We think that this may be due to the way in which both measures satisfy the triangle inequality condition, since one is based on divergence (JS) and the other on distance (He). This property, which defines $distance(a, b) \leq distance(a, c) + distance(c, b)$, is very important in the calculations that *DBSCAN* makes to discover the groups, since it only calculates the distances between near points.

Finally, in terms of *efficiency* (Figures 5.21, 5.22), regardless of the similarity measure used, the algorithm that yields the best performance according to the results obtained is *CRDC*. Overall, *CRDC* demonstrates a high accuracy classification and a

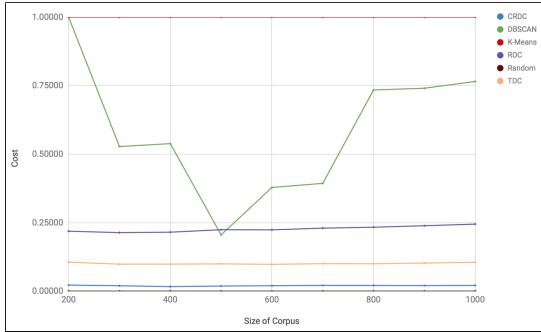


Figure 5.19: Cost (JS-based) in AIES

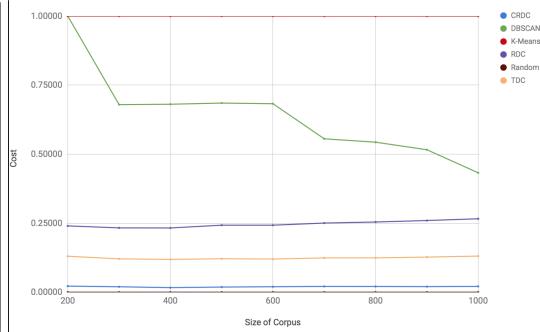


Figure 5.20: Cost (He-based) in AIES

lower cost by improving the performance offered by centroid-based or density-based approaches.

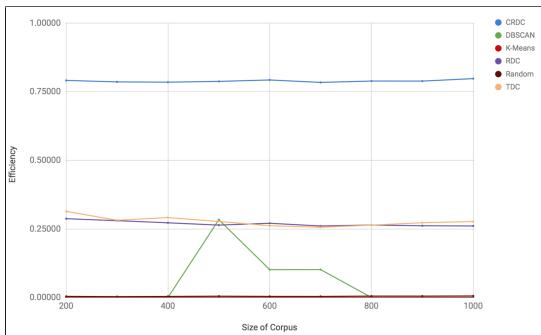


Figure 5.21: Efficiency (JS-based) in AIES

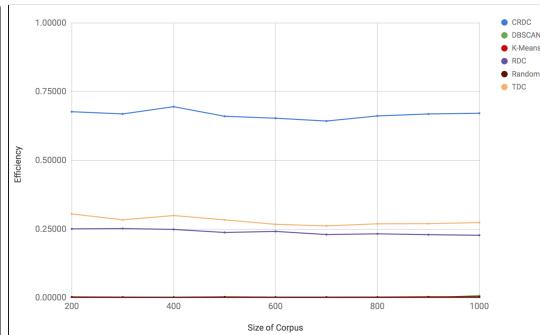


Figure 5.22: Efficiency (He-based) in AIES

We have also created a synthetic dataset, DRM (Section 5.2.2.1), composed of 1000 Dirichlet distributions with the same dimensions than topics in AIES: $k = 44$. Unlike AIES, topic distributions have been randomly generated which imply that the similarity values are not so high: $\min = 0.06$, $\text{mean} = 0.18$ and $\max = 0.61$. Following the same criteria than before (Section 5.2.2.2), the similarity threshold is now fixed to 0.34 (Figure 5.23). Results in terms of *effectiveness* (Figure 5.24) show a poor performance of the RDC and CRDC algorithms. The reason is that both are based on the fact that the highest weighted topics are shared between similar distributions. However, this condition is not satisfied when the similarity value between them is low.

To confirm this behavior, we created a third dataset (DRM2) with the same size but with only 4 dimensions (4 topics). The goal is to achieve more similar distributions

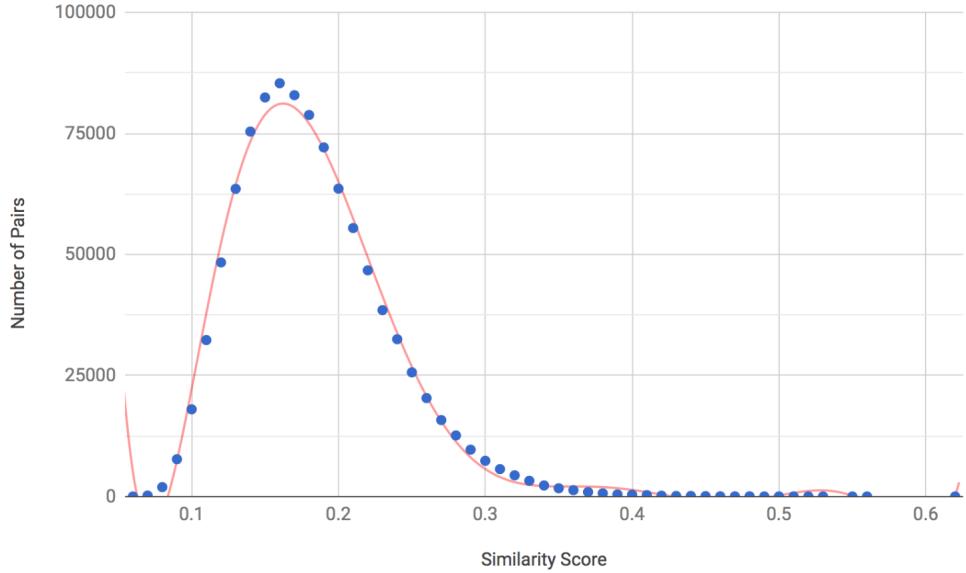


Figure 5.23: Similarity values grouped by frequency in DRM

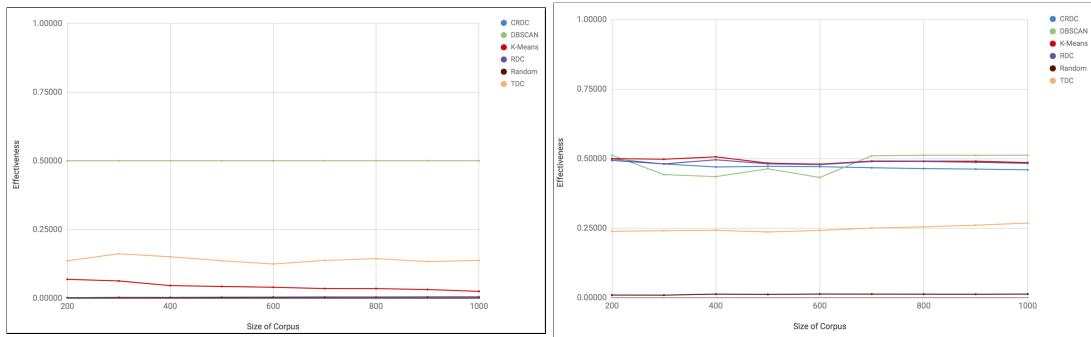


Figure 5.24: Effectiveness (JS based) in DRM

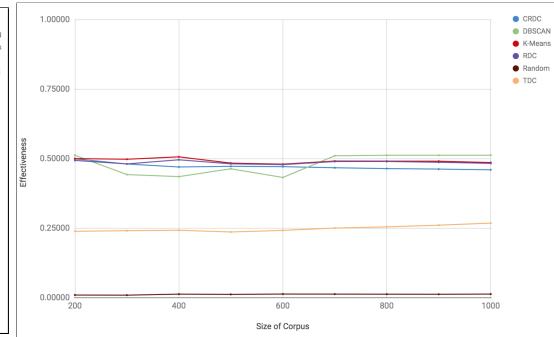


Figure 5.25: Effectiveness (JS based) in DRM2

than in DRM even though they are also randomly generated. Since the similarity values range from $\min = 0.04$, $\text{mean} = 0.34$ to $\max = 0.99$, the similarity threshold is now fixed to 0.66 (more details in section 5.2.2.2). The results (Figure 5.25) show an improvement in the accuracy of both the RDC and CRDC algorithms. Although scores are still not as high as for the AIES dataset, the increase compared to the DRM dataset shows that their *precision* and *recall* improve when the similarity threshold is higher. On the other hand, both the DBSCAN and TDC algorithms show similar behavior in both datasets, which means that their performance is not affected by the

similarity threshold.

5.2.3 Conclusion

Processing a continuously growing collection of human generated documents requires techniques that divide the space into smaller regions containing potentially similar documents. Some algorithms in the literature tackle this problem from an unsupervised point of view, but they incur in high temporal costs and may not be suited for the domain being studied.

Three novel unsupervised clustering algorithms, *TDC*, *RDC* and *CRDC*, are described in this paper relying on the distributions inferred from a topic modeling algorithm (LDA). They are presented as a means to identify a smaller set of documents where only the similarity function has to be computed. They leverage on the particular behavior of Dirichlet distributions describing topic distributions, where the highest weighted topics have a high influence on the rest of topics. This also means that given a topic distribution, the relations between their topic weights such as order or trends between them, are more important than the density values.

Although we initially thought that using only a fixed number of topics with higher weights of a topic distribution (*RDC*), or taking into account only the trend changes between the weights of consecutive topics (*TDC*), could be enough to classify similar topic distributions, the results obtained have shown that these properties are not sufficient. Results in terms of *efficiency*, *effectiveness* and *cost* have been shown comparing the proposed algorithms with existing centroid-based and density-based clustering techniques. They reveal that obtaining the most representative topics of a topic distribution by comparing the sum of their weights with respect to the rest (*CRDC*) is a promising approach, which improves the *efficiency* obtained by other centroid-based and density-based approaches. While *K-Means* takes $O(n^k * \log n)$ and *DBSCAN* takes $O(n * \log n)$ time to classify n documents in a collection, the proposed algorithms only take linear time ($O(n)$) because they do not require any other data except their own topic distribution to assign it to a cluster.

5.3 Summary

In Section 5.1, we have analyzed the representativeness of topics to describe texts. In the particular case of scientific articles, it is concluded that the abstracts are not sufficiently representative to describe, by means of topics, the content of a paper. This behavior suggests that texts with greater vocabulary that emphasize key terms through repetition, favor topic-based representation.

Taking into account the relevance of topics to describe texts, we analyze in Section 5.2 the behavior of topic distributions to calculate distances between documents using topic models with different dimensions. By using clustering techniques at the topic level, the most representative topics of a topic distribution are identified regardless of the number of dimensions that the model has. A topic-based representation is then proposed that covers the third research objective of this thesis (*R03, define annotations based on topics that enable a semantic-aware exploration of the knowledge inside a corpus*).

A new distance metric is also proposed that takes advantage of such representation to compare documents. Its performance is analyzed by automatically clustering the JRC-Acquis corpus according to EUROVOC categories. Tables XX and XY show results with high precision and recall in unsupervised classification tasks. This new way of relating documents from their most representative topics covers the fourth research objective of this thesis (*R04, define a metric based on topic annotations that compares documents and facilitates their interpretation*).

In order to perform the experiments, both the representation based on the most relevant topics and the distance metric based on these representations have been implemented in *libraIry*. This partially covers the third and fourth technical objectives (*T03, integrate the annotation method base on topic hierarchies into the topic model service*) (*T04, create a system capable of finding similar document automatically*).

Chapter 6

Large-scale Comparisons of Topic Distributions

As we showed in Section 5.2, topic groupings based on cumulative ranking are useful mechanisms for simplifying representations based on topic distributions. Relevant topics are those whose accumulated weight exceeds a threshold, after ordering them and starting from the top, and have shown a promising performance to cluster documents (Section 5.2.2.5). This suggests that *similar documents share the most relevant topics*. However, this definition has two main limitations: it depends on the manual tuning of a parameter, the threshold; and it does not measure degrees of similarity since it only establishes whether or not two documents are similar. As shown in Chapter ch:hypothesis, we hypothesize that is possible to find relevant documents with similar topic distributions without calculating all pairwise comparisons and without discarding the notion of topics from their representation. In this chapter we introduce levels of relevance between topics and present our approach to compare documents through hierarchical representations of their topic distributions in large-scale (Badenes-Olmedo et al., 2019b).

6.1 Hashing Topic Distributions

One of the greatest advantages of using Probabilistic Topic Models (PTM) in large document collections is the ability to represent documents as probability distributions over a small number of topics, thereby mapping documents into a low-dimensional

latent space (the K-dimensional probability simplex, where K is the number of topics). A document, represented as a point in this simplex, is said to have a particular topic distribution. As seen in Section 5.2, the low-dimensional feature space created by topic models could also be suitable for document similarity tasks, especially on big real-world data sets, since topic distributions are continuous and not as sparse as discrete-term feature vectors and can be explained in terms of relevance.

Hashing methods transform the data points from the original feature space into a binary-code Hamming space, where the similarities in the original space are preserved. They can learn hash functions (data-dependent) or use projections (data-independent) from the training data Wang et al. (2016). Data-independent methods unlike data-dependent ones do not need to be re-calculated when data changes, i.e. adding or removing documents to the collection. Taking large-scale scenarios into account (e.g. Document clustering, Content-based Recommendation, Duplicate Detection), this is a key feature along with the ability to infer hash codes individually (for each document) rather than on a set of documents.

Data-independent hashing methods depend on two key elements: (1) data type and (2) distance metric. For vector-type data, as introduced in Section 2.1, based on l_p distance with $p \in [0, 2]$ lots of hashing methods have been proposed, such as p-stable Locality-Sensitive Hashing (LSH) Datar et al. (2004), Leech lattice LSH Andoni and Indyk (2006), Spherical LSH Terasawa and Tanaka (2007), and Beyond LSH Andoni et al. (2014). Based on the θ distance many methods have been developed such as Kernel LSH Kulis and Grauman (2012) and Hyperplane hashing Vijayanarasimhan et al. (2014). But only few methods handle density metrics in a simplex space. A first approach transformed the $H\epsilon$ divergence into an Euclidean distance so that existing ANN techniques, such as LSH and k-d tree, could be applied Krstovski et al. (2013). But this solution does not consider the special attributions of probability distributions, such as Non-negative and Sum-equal-one. Recently, a hashing schema Mao et al. (2017) taking into account the symmetry has been proposed, non-negativity and triangle inequality features of the S2JSD metric for probability distributions. For set-type data, Jaccard Coefficient is the main metric used. Some examples are K-min Sketch Li et al. (2012), Min-max hash Ji et al. (2013), B-bit minwise hashing Li and König (2010) and Sim-min-hash Zhao et al. (2013).

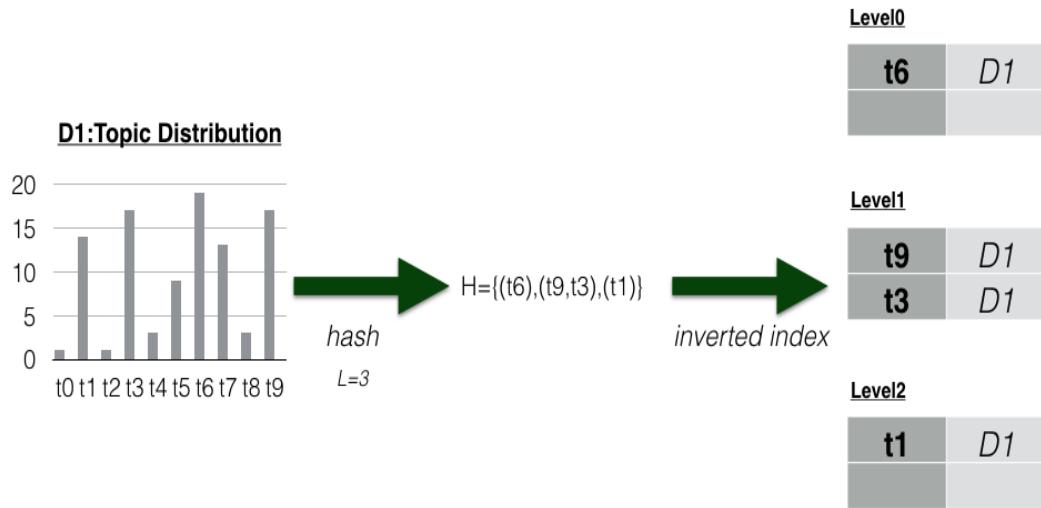


Figure 6.1: Hash method based on hierarchical set of topics from a given topic distribution

All of them have demonstrated efficiency in the search for similar documents, but none of them allows the search for documents (1) by thematic areas or (2) by similarity levels, nor they offer (3) an explanation about the similarity obtained beyond the vectors used to calculate it. Binary-hash codes drop a very precious information: the topic relevance.

A new hierarchical set-type data is proposed. Each level of the hierarchy indicates the importance of the topic according to its distribution. Level 0 contains the topics with the highest score. Level 1 contains the topics with highest score once the first ones have been eliminated, and so on. From a vector of components, where each of the components is the score of topic t , a vector containing set of topics is proposed, where each of the dimensions means a topic relevance. Thus, for the topic distribution $q = [0.3, 0.15, 0.4, 0.15]$, a hierarchical set of topics may be $h = \{(t2), (t0), (t1, t3)\}$. It means that topic $t2$ (0.4) is the most relevant, then topic $t0$ (0.3) and, finally, topics $t1$ (0.15) and $t3$ (0.15). This is just an example about the data structure that will support the different hashing strategies. In Section 6.1.3 some approaches to create hash codes based on this data structure are described.

6.1.1 Data Type

A traditional approach to text representation usually requires encoding of documents into numerical vectors. Words are extracted from a corpus as feature candidates and based on a certain criterion they are assigned values to describe the documents: term-frequency, TF-IDF, information gain, and chi-square are typical measures. But this causes two main problems: huge number of dimensions and sparse distribution. The use of topics as feature space has been extended to mapping documents into low-dimensional vectors. However, as shown in Figures ?? to ??, the distance metrics based on probability densities vary according to the dimensions of the model and reveal the difficulty of calculating the similarity values using the vectors with the topic distributions.

Since hashing techniques can transform both vector and set-based data Mao et al. (2017) Ji et al. (2013) into a new space where the similarity (i.e. closeness of points) in the original feature space is preserved, a new set-based data structure is proposed in this paper. It is created from clusters of topics organized by relevance levels and it aims to extend the ability of building queries with topic-based restrictions over the searching space while maintaining high level of accuracy.

The new hierarchical set-type data describes each document as a sequence of sets of topics sorted by relevance. Each level of the hierarchy expresses how important those topics are in that document. In the first level (i.e level 0) are the topics with the highest score. In the second level (i.e level 1) are the topics with the highest score once the first ones have been removed, and so on. In this work, several clustering approaches have been considered to assign topics to each level.

In a feature space created from a PTM with eight topics, for example, each data point p is described by a eight-dimensional vector with the topic distributions: $vp = [t_0, t_1, t_2, t_3, t_4, t_5, t_6, t_7]$. Then, given a point $q_1 = [0.18, 0.15, 0.2, 0.05, 0.14, 0.11, 0.09, 0.08]$, the three-level hierarchical set of topics may be $h = [\{t_2\}, \{t_0\}, \{t_1, t_4\}]$. It means that t_2 is the most relevant topic, then topic t_0 and finally topics t_1 and t_4 . This is just an example about the data structure that will support the hashing strategies. In section 6.1.3 some approaches to create hash codes based on this data structure are described.

Domain-specific features such as vocabulary, writing style, or speech type, have a major influence on the topic models, but not in the hashing algorithms described in

this article. The methods for creating hash codes are agnostic of these particularities since they are only based on the topic distributions generated by the models.

6.1.2 Distance Metric

Since documents are described by set-type data, the proposed distance metric is based on the Jaccard coefficient. This metric computes the similarity of sets by looking at the relative size of their intersection as follows:

$$J(A, B) = \frac{|A \cap B|}{|A \cup B|} \quad (6.1)$$

where A and B are set of topics.

More specifically, d_J is based on the Jaccard distance, which is obtained by subtracting the Jaccard coefficient J from 1:

$$d_J(A, B) = 1 - J(A, B) \quad (6.2)$$

The proposed distance measure d_H used to compare hash codes created from set of topics is the sum of the Jaccard distances d_j for each hierarchy level, i.e. for each set of topics:

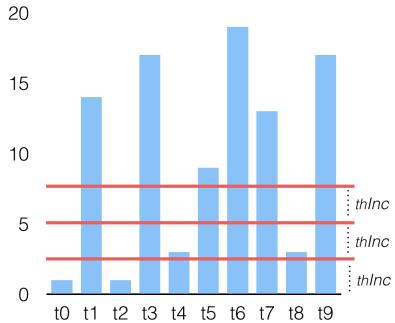
$$d_H(H_1, H_2) = \sum_{l=1}^L \left(d_J(H_1(x_l), H_2(x_l)) \right) \quad (6.3)$$

where H_1 and H_2 are hash codes, $H_1(x_l)$ and $H_2(x_l)$ are the set of topics up to level l for each hash code H and L is the maximum hierarchy level. A corner case is $L = T$, where T is the number of topics in the model.

6.1.3 Hash Function

The hash function clusters topics based on relevance levels. Three approaches are proposed depending on the criteria used to group topics: threshold-based, centroid-based and density-based.

Threshold-based Hashing



$$H = \{(t1, t3, t5, t6, t7, t9), (), (t4, t8)\}$$

Figure 6.2: Threshold-based Hierarchical Hash (L=3)

6.1.3.1 Threshold-based Hierarchical Hashing Method

This approach is just an initial and naive way of grouping topics by threshold values into each relevance level. They can be manually defined or automatically generated by thresholds dividing the topic distributions as follows:

$$th_{inc} = \frac{1}{(L + 1) \cdot T} \quad (6.4)$$

where L is the number of hierarchy levels, and T the number of topics.

If $L = 3$ and $T = 10$ for a topic distribution td defined as follows:

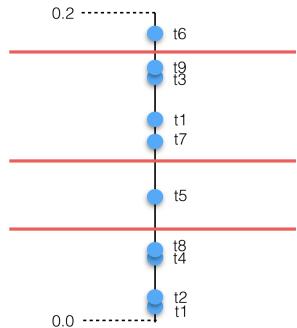
$$td = [0.017, 0.141, 0.010, 0.172, 0.030, \\ 0.090, 0.199, 0.133, 0.031, 0.171] \quad (6.5)$$

Then, a threshold-based hierarchical hash H_T , with an automatically created threshold defined by equation 6.4, is equals to $H_T = \{(t1, t3, t5, t6, t7, t9), (), (t4, t8)\}$ with $th_{inc} = 0.025$ (Fig 6.2).

6.1.3.2 Centroid-based Hierarchical Hashing Method

This approach assumes topic distributions can be partitioned into k clusters where each topic belongs to the cluster with the nearest mean score. It is based on the k-Means clustering algorithm, where k is obtained by adding 1 to the number of hierarchy levels. Unlike the previous method, threshold values used to define the hierarchy levels may

Centroid-based Hashing



$$H = \{(t6), (t9, t3, t1, t7), (t5)\}$$

Figure 6.3: Centroid-based Hierarchical Hash ($L=3$)

vary between documents, i.e. for each topic distribution, since they are calculated for each distribution separately.

Following the previous example, if $L = 3$ and $T = 10$ for a topic distribution td defined in equation 6.5, then a centroid-based hierarchical hash H_C equals to $H_C = \{(t6), (t9, t7, t3, t1), (t5)\}$ (Fig 6.3).

6.1.3.3 Density-based Hierarchical Hashing Method

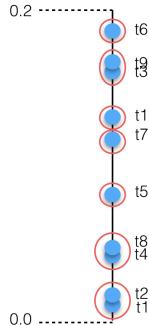
This approach also considers relative hierarchical thresholds for each relevance level. Now, a topic distribution is described by points in a single dimension. In this space, topics closely packed together are grouped together. This approach does not require a fixed number of groups. It only requires a maximum distance (eps) to consider two points close and grouped together. This value can be estimated from the own distribution of topics (e.g. variance).

Following the above example, if $L = 3$ and td is the topic distribution defined in equation 6.5, then a density-based hierarchical hash H_D is equals to $H_D = \{(t6), (t9, t3), (t1)\}$ when eps equals to the variance of the topic distribution (Fig 6.4).

6.1.4 Online-mode Hashing

Hashing methods are batch-mode learning models that require huge data for learning an optimal model and cannot handle unseen data. Recent work address online mode

Density-based Hashing



$$H = \{(t6), (t9, t3), (t1)\}$$

Figure 6.4: Density-based Hierarchical Hash ($L=3$)

by learning algorithms Huang et al. (2018) that get hashing model accommodate to each new pair of data. But these approaches require the hashing model to be updated during each round based on the new pairs of data.

Our methods rely on topic models to build hash codes. These models do not require to be updated to make inferences about data not seen during training. In this way, the proposed hashing algorithms can work on large-scale and real-time data, as the size and the novelty of the collection does not influence the annotation process.

6.2 Experiments

As mentioned in Section 2.2.2, it is difficult to interpret the similarity score calculated by metrics in a probability space. Since all of them are based on adding the distance between each dimension of the model (eq. 2.1, 2.2 and 2.4), distributions that share a fair amount of the less representative topics may still get higher similarity values than those that share the most representative ones specially if the model has a high number of dimensions.

Figures 6.5 and 6.6 show overlapped topic distributions of two pairs of documents. In the first case (fig 6.5), none of the most representative topics of each document is shared between them. However, the similarity score calculated from divergence-based metrics (eq 2.2) is higher than in the second case (fig 6.6), where the most representative topic is shared (topic 26). This behavior is due to the sum of the distances between the less representative topics (i.e. topics with a low weight value) being greater than

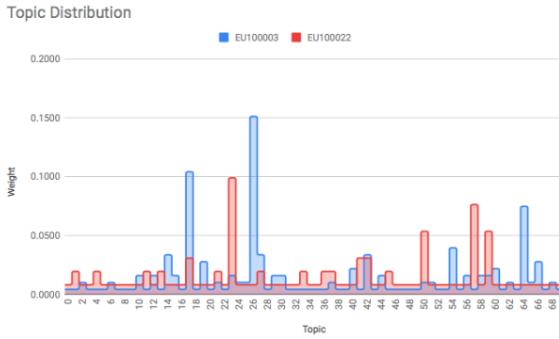


Figure 6.5: Topic Distribution of two documents. Similarity score, based on JSD, is equals to 0.74

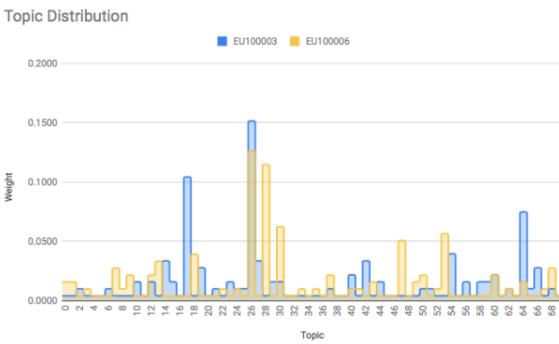


Figure 6.6: Topic Distribution of two documents. Similarity score, based on JSD, is equals to 0.71

the sum of the distances between the most representative ones (i.e. topic with a high weight value). In high-dimensional models, that sum may be more representative than the one obtained with the most relevant topics, which are fewer in number than the less relevant ones.

The following experiments aim to validate that **hash codes based on hierarchical set of topics not only make it possible to search for similar documents with high accuracy, but also to extend queries with new restrictions and to offer information that helps explaining why two documents are similar.**

6.2.1 Datasets and Evaluation Metrics

Three datasets Badenes-Olmedo et al. (2019c) are used to validate the proposed approach. The OPEN-RESEARCH⁷⁰ dataset consist of 500k research papers in Computer Science, Neuroscience, and Biomedical randomly selected from the Open Research Corpus Waleed et al. (2018). The CORDIS⁷¹ dataset contains 100k documents describing research and innovation projects funded by the European Union under a framework programme since 1990. The PATENTS dataset consists of 1M patents randomly selected from the USPTO⁷² collection. For each dataset, documents are mapped to two latent topic spaces with different dimensions using LDA. We perform parameter estimation using collapsed Gibbs sampling for LDA Griffiths and Steyvers (2004) from the open-source librAIry Badenes-Olmedo et al. (2017b) software. It is a framework that combines natural language processing (NLP) techniques with machine learning algorithms on top of the Mallet toolkit McCallum (2002), an open-source machine learning package. The number of topics varies to study their influence on the performance of the algorithm (i.e. CORDIS-70 indicates a latent space created with 70 topics).

Experiments use JS divergence as an information-theoretically motivated metric in the probabilistic space created by topic models. Since it is a smoothed and symmetric alternative to the KL divergence, which is a standard measure for comparing distributions Cha (2007), it has been extensively used as state-of-the-art metric over topic distributions in literature Towne et al. (2016)Aletras et al. (2017)Mao et al. (2017). Our upper bound is created from the brute-force comparison of the reference documents with all documents in the collection to obtain the list of similar documents.

In this scenario the goal is to minimize the accuracy loss introduced by hashing algorithms. Since this is a large-scale problem and an accuracy-oriented task, recall is not a good measure to be considered and precision is only relevant for sets much smaller than the total size of data (between 3-5 candidates).

All the experimental results are averaged over random training/set partitions. For each topic space, 100 documents are selected as references, and the remaining documents as search space. As noted above, only p@5 will be used to report the results of the experiments.

⁷⁰<https://labs.semanticscholar.org/corpus/>

⁷¹<https://data.europa.eu/euodp/data/dataset/cordisref-data>

⁷²<https://www.uspto.gov/learning-and-resources/ip-policy/economic-research/research-datasets>

6.2.2 Retrieving Similar Documents

It is challenging to create an exhaustive gold standard, given the significant amount of human labour that is required to get a comprehensive view of the subjects being covered in it. In order to overcome this problem, the list of similar documents to a given one is obtained after comparing the document with all the documents of the repository and sorting the result. We have observed that different distance functions perform similarly in this scenario (figs ?? to ??), so we have decided to use only the JS divergence (eq. 2.2) in our experiments.

Only the top N documents obtained from this method are used as reference set to measure the performance of the algorithms proposed in this paper. The value of N is equals to 0.5% of the corpus size (i.e. if the corpus size is equal to 1000 elements, only the top 5 most similar documents are considered relevant for a given document). This value has been considered after reviewing datasets used in similar experiments Krstovski et al. (2013)Mao et al. (2017). In those experiments, the reference data is obtained from existing categories, and the minimum average between corpus size and categorized documents is around 0.5%.

Once the reference list of documents similar to a given one is defined, the most similar documents through the proposed methods (i.e. threshold-based hierarchical hashing method (thhm), centroid-based hierarchical hashing method (chhm) and density-based hierarchical hashing method (dhhm)) are also obtained. An inverted index has been implemented by using Apache Lucene⁷³ as document repository. The source code of both the algorithms and tests is publicly available Badenes-Olmedo et al. (2019c).

Let's look at an example to better understand the procedure. We want to measure the accuracy and data size ratio used to identify the top5 similar documents to a new document d_1 from a corpus of 1000 documents . The similarity between d_1 and all the documents in the corpus is calculated based on JS divergence. The top50 (0.5%) documents with the highest values will be the set of documents considered as similar to d_1 . As we are going to use an ANN-based approach, we need the hash expressions of all documents to measure similarity. The data structure proposed in this work is a hierarchy of sets of topics, so that the most similar documents are those that share most of the topics at the highest levels of the hierarchy.

⁷³<http://lucene.apache.org>

OPEN-RES-100 (p@5)

| LEVEL | THHM | | CHHM | | DHHM | |
|-------|------|--------|-------------|--------|------|--------|
| | mean | median | mean | median | mean | median |
| 2 | 0.22 | 0.20 | 0.86 | 1.00 | 0.66 | 0.80 |
| 3 | 0.23 | 0.20 | 0.87 | 1.00 | 0.81 | 1.00 |
| 4 | 0.27 | 0.20 | 0.89 | 1.00 | 0.86 | 1.00 |
| 5 | 0.27 | 0.20 | 0.92 | 1.00 | 0.89 | 1.00 |
| 6 | 0.27 | 0.20 | 0.94 | 1.00 | 0.92 | 1.00 |

Table 6.1: Precision at 5 (*mean* and *median*) of threshold-based (THHM), centroid-based (CHHM) and density-based (DHHM) hierarchical hashing methods on Open Research dataset using a model with 100 topics. LEVEL column indicates the number of hierarchies used.

OPEN-RES-500 (p@5)

| LEVEL | THHM | | CHHM | | DHHM | |
|-------|------|--------|-------------|--------|------|--------|
| | mean | median | mean | median | mean | median |
| 2 | 0.23 | 0.20 | 0.76 | 0.80 | 0.67 | 0.80 |
| 3 | 0.24 | 0.20 | 0.80 | 1.00 | 0.71 | 0.80 |
| 4 | 0.25 | 0.20 | 0.83 | 1.00 | 0.74 | 0.80 |
| 5 | 0.25 | 0.20 | 0.86 | 1.00 | 0.81 | 1.00 |
| 6 | 0.24 | 0.20 | 0.89 | 1.00 | 0.86 | 1.00 |

Table 6.2: Precision at 5 (*mean* and *median*) of threshold-based (THHM), centroid-based (CHHM) and density-based (DHHM) hierarchical hashing methods on Open Research dataset using a model with 500 topics. LEVEL column indicates the number of hierarchies used.

CORDIS-70 (p@5)

| LEVEL | THHM | | CHHM | | DHHM | |
|-------|------|--------|-------------|--------|------|--------|
| | mean | median | mean | median | mean | median |
| 2 | 0.18 | 0.20 | 0.92 | 1.00 | 0.66 | 0.70 |
| 3 | 0.20 | 0.20 | 0.92 | 1.00 | 0.80 | 0.80 |
| 4 | 0.22 | 0.20 | 0.94 | 1.00 | 0.86 | 1.00 |
| 5 | 0.23 | 0.20 | 0.91 | 1.00 | 0.89 | 1.00 |
| 6 | 0.19 | 0.20 | 0.92 | 1.00 | 0.91 | 1.00 |

Table 6.3: Precision at 5 (*mean* and *median*) of threshold-based (THHM), centroid-based (CHHM) and density-based (DHHM) hierarchical hashing methods on CORDIS dataset using a model with 70 topics. LEVEL column indicates the number of hierarchies used.

| CORDIS-150 (p@5) | | | | | | | |
|------------------|------|--------|-------------|--------|------|--------|--|
| LEVEL | THHM | | CHHM | | DHHM | | |
| | mean | median | mean | median | mean | median | |
| 2 | 0.19 | 0.20 | 0.88 | 1.00 | 0.78 | 0.80 | |
| 3 | 0.19 | 0.20 | 0.92 | 1.00 | 0.80 | 1.00 | |
| 4 | 0.25 | 0.20 | 0.91 | 1.00 | 0.82 | 1.00 | |
| 5 | 0.25 | 0.20 | 0.91 | 1.00 | 0.83 | 1.00 | |
| 6 | 0.27 | 0.20 | 0.91 | 1.00 | 0.86 | 1.00 | |

Table 6.4: Precision at 5 (*mean* and *median*) of threshold-based (THHM), centroid-based (CHHM) and density-based (DHHM) hierarchical hashing methods on CORDIS dataset using a model with 150 topics. LEVEL column indicates the number of hierarchies used.

The representational model for this example only considers 8 topics, that is, a document is described by a vector with 8 dimensions where each dimension corresponds to a topic (i.e $[t_0, t_1, t_2, t_3, t_4, t_5, t_6, t_7]$) and its value will be the weight of that topic in the document, for example $d_1 = [0.18, 0.15, 0.2, 0.05, 0.14, 0.11, 0.09, 0.08]$. The hierarchy level (L) will be equal to 2, i.e. the hash expression has two hierarchical sets of topics: $h = \{h_0, h_1\}$.

According to methods described at Section 6.1.3, there are 3 ways to create the hierarchical hash codes for documents:

1. threshold-based (thhm): 2 thresholds are defined as described in section 6.1.3.1, for example 0.15 and 0.1 . h_0 includes the topics with a weight greater than 0.15, and h_1 the remaining topics with a weight greater than 0.1. Then $h_0 = \{t_0, t_1, t_2\}$ and $h_1 = \{t_4, t_5\}$. Based on the hash expression $h = \{(t_0, t_1, t_2), (t_4, t_5)\}$, the documents that share more topics in those levels (i.e $h_0 = (t_0 \text{ OR } t_1 \text{ OR } t_2)$, $h_1 = (t_4 \text{ OR } t_5)$) or in other levels but with less relevance are ordered. Since there are many topics in the expression, potentially many documents are similar when sharing at least one of them. This increases the data ratio. Accuracy is also affected, as the algorithm is not able to bring under the same bucket similar documents. In short, the hash expression is not representative of the document, for the given exploratory task.
2. centroid-based (chhm): sets of topics are created using a clustering algorithm based on centroids as described in section 6.1.3.2. The cardinalities of the hierarchical groups are generally more uniform with this method. Since $k = L + 1 = 3$

PATENTS-250 (p@5)

| LEVEL | THHM | | CHHM | | DHHM | |
|-------|------|--------|-------------|--------|-------------|--------|
| | mean | median | mean | median | mean | median |
| 2 | 0.03 | 0.00 | 0.71 | 0.80 | 0.67 | 0.80 |
| 3 | 0.08 | 0.00 | 0.91 | 1.00 | 0.90 | 1.00 |
| 4 | 0.11 | 0.00 | 0.95 | 1.00 | 0.95 | 1.00 |
| 5 | 0.12 | 0.00 | 0.95 | 1.00 | 0.96 | 1.00 |
| 6 | 0.11 | 0.00 | 0.97 | 1.00 | 0.97 | 1.00 |

Table 6.5: Precision at 5 (*mean* and *median*) of threshold-based (THHM), centroid-based (CHHM) and density-based (DHHM) hierarchical hashing methods on Patents dataset using a model with 250 topics. LEVEL column indicates the number of hierarchies used.

PATENTS-750 (p@5)

| LEVEL | THHM | | CHHM | | DHHM | |
|-------|------|--------|-------------|--------|-------------|--------|
| | mean | median | mean | median | mean | median |
| 2 | 0.02 | 0.00 | 0.77 | 0.80 | 0.76 | 0.80 |
| 3 | 0.04 | 0.00 | 0.94 | 1.00 | 0.95 | 1.00 |
| 4 | 0.06 | 0.00 | 0.97 | 1.00 | 0.97 | 1.00 |
| 5 | 0.08 | 0.00 | 0.97 | 1.00 | 0.97 | 1.00 |
| 6 | 0.06 | 0.00 | 0.97 | 1.00 | 0.97 | 1.00 |

Table 6.6: Precision at 5 (*mean* and *median*) of threshold-based (THHM), centroid-based (CHHM) and density-based (DHHM) hierarchical hashing methods on Patents dataset using a model with 750 topics. LEVEL column indicates the number of hierarchies used.

in this example, $h_0 = \{t0, t2\}$ and $h_1 = \{t1, t4\}$. The number of representative topics at each level of the hierarchy is usually lower, and this causes the data ratio used to discover similar documents to decrease as well. This approach increases the precision because now the hierarchy is more selective to distinguish similar documents. However, the size of region of similar candidates is still high.

3. density-based (dhhm): now the clustering algorithm is based on how dense certain regions in the topic relevance dimensions are as described in section 6.1.3.3. It can group topics that have unbalanced distributions and, therefore, generates more discriminating hash expressions than with the previous algorithm. In the example, we would have a hash expression like this: $h_0 = \{t2\}$ and $h_1 = \{t0\}$. This significantly reduces the data ratio used to discover similar documents and does not excessively penalize accuracy. Obviously, increasing L (i.e. number of hierarchies) increases precision, but with $L > 3$ that gain is not so significant.

OPEN-RES-100 (data-ratio)

| LEVEL | THHM | | CHHM | | DHHM | |
|-------|------|--------|------|--------|-------------|--------|
| | mean | median | mean | median | mean | median |
| 2 | 99.8 | 99.9 | 45.2 | 45.9 | 4.9 | 2.5 |
| 3 | 99.9 | 99.9 | 74.4 | 77.6 | 13.4 | 10.7 |
| 4 | 99.9 | 99.9 | 87.4 | 90.2 | 27.2 | 22.8 |
| 5 | 99.9 | 99.9 | 95.4 | 96.3 | 49.9 | 42.6 |
| 6 | 99.9 | 99.9 | 97.9 | 98.7 | 72.2 | 65.8 |

Table 6.7: Data size ratio used (*mean* and *median*) of threshold-based (THHM), centroid-based (CHHM) and density-based (DHHM) hierarchical hashing methods on Open Research dataset and 100 topics.

OPEN-RES-500 (data-ratio)

| LEVEL | THHM | | CHHM | | DHHM | |
|-------|------|--------|------|--------|-------------|--------|
| | mean | median | mean | median | mean | median |
| 2 | 95.9 | 96.3 | 22.2 | 22.1 | 1.4 | 0.3 |
| 3 | 99.1 | 99.2 | 43.9 | 43.7 | 5.1 | 4.1 |
| 4 | 99.6 | 99.6 | 57.1 | 57.3 | 11.7 | 10.3 |
| 5 | 99.6 | 99.6 | 70.7 | 70.7 | 28.8 | 22.0 |
| 6 | 99.9 | 99.9 | 81.5 | 80.6 | 50.3 | 40.1 |

Table 6.8: Data size ratio used (*mean* and *median*) of threshold-based (THHM), centroid-based (CHHM) and density-based (DHHM) hierarchical hashing methods on Open Research dataset and 500 topics.

| CORDIS-70 (data-ratio) | | | | | | | |
|------------------------|------|--------|------|--------|-------------|--------|--|
| LEVEL | THHM | | CHHM | | DHHM | | |
| | mean | median | mean | median | mean | median | |
| 2 | 99.9 | 99.9 | 51.3 | 56.3 | 5.1 | 5.0 | |
| 3 | 99.9 | 99.9 | 84.8 | 89.5 | 10.5 | 10.6 | |
| 4 | 99.9 | 99.9 | 96.1 | 97.6 | 20.8 | 19.5 | |
| 5 | 99.9 | 99.9 | 98.9 | 99.4 | 35.0 | 32.7 | |
| 6 | 99.9 | 99.9 | 99.7 | 99.8 | 53.1 | 51.2 | |

Table 6.9: Data size ratio used (*mean* and *median*) of threshold-based (THHM), centroid-based (CHHM) and density-based (DHHM) hierarchical hashing methods on CORDIS dataset and 70 topics.

As it can be seen in tables 6.1 to 6.6, the mean and median of precision are calculated to compare the performance of the methods. In this assessment environment, the variance is not robust-enough because score values don't follow a normal distribution. We consider the result obtained as significant, based on the fact that mean and median values are fairly close. The centroid-based method (chhm) and the density-based method (dhhm) show a similar behaviour to the one offered by the use of brute force by means of JS divergence.

In terms of efficiency, we consider the times to compare pairs of topic distributions constant, and we focus on the number of comparisons needed. Thus, algorithms with larger candidate spaces will be less efficient than others when the accuracy in both is the same. Tables 6.7-6.12 show the percentage of the corpus used by each of the algorithms to discover similar documents. Tables 6.1-6.6 show the accuracy of each algorithm for each of these scenarios. Density-based algorithm (dhhm) shows better balance between accuracy and volume of information (efficiency). It uses smaller samples (i.e lower ratio size) than others in all tests and even when it only uses a subset that is a 6.2% (Table 6.10) of the entire corpus, it obtains an accuracy of 0.808 (Table 6.4).

The precision achieved by the algorithm based on density (dhhm), which is much more restrictive than the others, suggests that few topics are required to represent a document in order to obtain similar ones. In addition, the number of topics does not seem to influence the performance of the algorithms, since their precision values are similar among the datasets of the same corpus. This shows that hashing methods based on hierarchical set of topics are robust to models with different dimensions.

The behavior of the algorithms have also been analyzed when the number of topics

CORDIS-150 (data-ratio)

| LEVEL | THHM | | CHHM | | DHHM | |
|-------|------|--------|------|--------|-------------|--------|
| | mean | median | mean | median | mean | median |
| 2 | 99.9 | 99.9 | 40.9 | 41.2 | 3.1 | 2.9 |
| 3 | 99.9 | 99.9 | 75.3 | 76.7 | 6.2 | 6.1 |
| 4 | 99.9 | 99.9 | 90.0 | 92.1 | 12.1 | 11.8 |
| 5 | 99.9 | 99.9 | 96.4 | 96.9 | 21.6 | 20.6 |
| 6 | 99.9 | 99.9 | 98.1 | 98.9 | 36.5 | 33.9 |

Table 6.10: Data size ratio used (*mean* and *median*) of threshold-based (THHM), centroid-based (CHHM) and density-based (DHHM) hierarchical hashing methods on CORDIS dataset and 150 topics.

PATENTS-250 (data-ratio)

| LEVEL | THHM | | CHHM | | DHHM | |
|-------|-------|--------|------|--------|-------------|--------|
| | mean | median | mean | median | mean | median |
| 2 | 99.9 | 99.9 | 43.2 | 32.7 | 35.1 | 23.0 |
| 3 | 99.9 | 100.0 | 82.4 | 100.0 | 78.2 | 100.0 |
| 4 | 99.9 | 100.0 | 96.5 | 100.0 | 95.1 | 100.0 |
| 5 | 99.9 | 99.9 | 99.2 | 100.0 | 98.9 | 100.0 |
| 6 | 100.0 | 100.0 | 99.8 | 100.0 | 99.7 | 100.0 |

Table 6.11: Data size ratio used (*mean* and *median*) of threshold-based (THHM), centroid-based (CHHM) and density-based (DHHM) hierarchical hashing methods on Patents dataset and 250 topics.

PATENTS-750 (data-ratio)

| LEVEL | THHM | | CHHM | | DHHM | |
|-------|------|--------|------|--------|-------------|--------|
| | mean | median | mean | median | mean | median |
| 2 | 99.9 | 100.0 | 35.2 | 23.6 | 31.8 | 19.9 |
| 3 | 99.9 | 99.9 | 81.4 | 99.8 | 79.6 | 98.8 |
| 4 | 99.9 | 99.9 | 96.5 | 99.9 | 95.5 | 99.5 |
| 5 | 97.7 | 96.6 | 99.0 | 99.9 | 98.6 | 99.7 |
| 6 | 99.1 | 98.6 | 99.7 | 99.9 | 99.5 | 99.8 |

Table 6.12: Data size ratio used (*mean* and *median*) of threshold-based (THHM), centroid-based (CHHM) and density-based (DHHM) hierarchical hashing methods on Patents dataset and 750 topics.

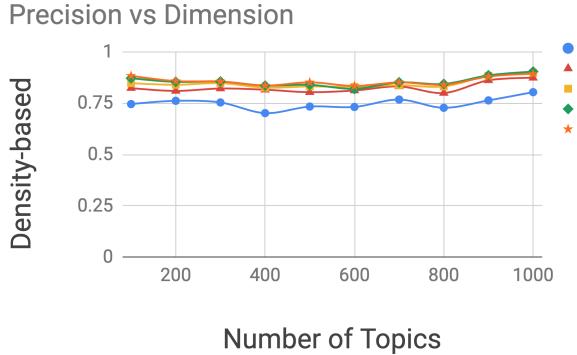


Figure 6.7: Precision at 5 (*mean*) of threshold-based hashing method when number of topics varies in CORDIS dataset.

in the model varies. Models with 100, 200, 300, 400, 500, 600, 700, 800, 900 and 1000 topics were created from the CORDIS corpus. For each model, the p@5 of the hashing methods is calculated taking into account the hierarchy levels: 2, 3, 4, 5 and 6. Figures 6.7 to 6.9 show the results obtained for each algorithm. It can be seen how the performance, i.e precision, of each of the algorithms is not influenced by the dimensions of the model.

6.2.3 Exploration

In a certain domain, we may want to retrieve similar documents to one given. For example, searching for articles in the Biomedical domain that are similar to an article about Semantic Web. In terms of topics this kind of search requires to narrow down the initial search space to a subset with only documents that contain the topics that better describe the queried domain.

Existing hashing techniques based on a binary-code Hamming space do not allow to customize the search query beyond the reference document itself. However, the algorithms proposed in this work allow adding new restrictions to the initial query based on the reference document, since they use a hierarchy of set of topics as hash codes.

Through the following example we describe the workflow to enable such retrieval operations. For simplicity we consider hash expressions with only two hierarchy levels. The reference document d_1 has the following hash expression: $h = \{h_0, h_1\} = \{(t10), (t18)\}$.

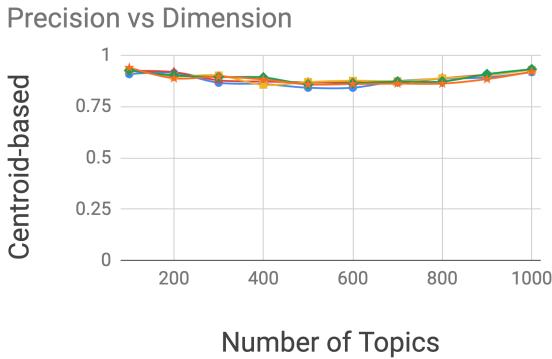


Figure 6.8: Precision at 5 (*mean*) of centroid-based hashing method when number of topics varies in CORDIS dataset.

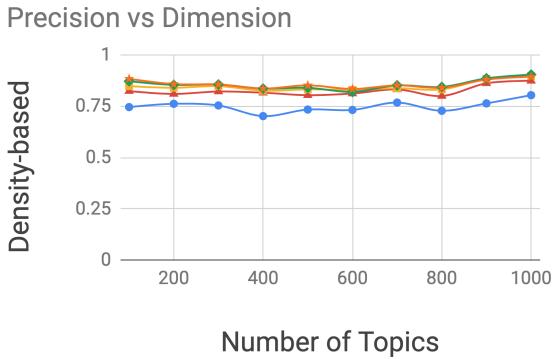


Figure 6.9: Precision at 5 (*mean*) of density-based hashing method when number of topics varies in CORDIS dataset.

The first query, $Q1$, searches for documents similar to the reference document d_1 among all documents in the corpus. One of the ways to formalise this query looks like this: $Q1 = h_0 : t10^100 \text{ or } h_0 : t18^50 \text{ or } h_1 : t10^50 \text{ or } h_1 : t18^100$. It sets a maximum boost (100) when the same restrictions as the reference document ($t10$ in h_0 and $t18$ in h_1) are fulfilled, and a lower boost (50) for the others ($t18$ in h_0 and $t10$ in h_1). In the specific case of applying this query to the CORDIS dataset, we observed that most of the retrieved documents included topic $t18$ (fig 6.10).

But if we were only interested in similar documents to d_1 that have topic $t10$, we could restrict the previous query $Q1$ to express this condition in the following way: $Q2 = (h_0 : t10^100 \text{ or } h_1 : t10^50) \text{ and } (h_1 : t10^50 \text{ or } h_1 : t18^100)$. The result obtained by $Q2$ (fig 6.10) shows that the condition has been considered since there is a balance between topics $t10$ and $t18$ among the documents similar to d_1 .

| OPEN-RESEARCH-100 | | | |
|-------------------|---------|---------|-------|
| hash | q1 | q2 | ratio |
| thhm | 499,755 | 160,660 | 67.8 |
| chhm | 356,111 | 1,976 | 99.44 |
| dhhm | 49,068 | 766 | 98.43 |

Table 6.13: Number of documents similar to a given one (q1) and also in a specific domain (q2) for threshold-based (thhm), centroid-based (chhm) and density-based (dhhm) hierarchical hashing methods.

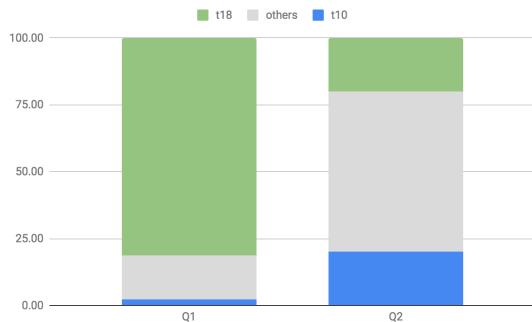


Figure 6.10: Most relevant topics in similar documents from using a document as query (Q1) and setting topic t10 as mandatory (Q2).

This type of restrictions based on the semantics offered by topics in the hash expression get enabled thanks to the methods proposed in this work.

6.3 Summary

The usefulness of topics created by probabilistic models when exploring document collections on large-scale has been widely studied in the literature. Each document in the corpus is described by probability distributions that measure the presence of those topics in their content. These vectors can also be used to measure the similarity between documents by using metrics such as Jensen-Shannon divergence (see Section 2.1). But with large amounts of items in the collection, discovering the entire set of nearest neighbors to a given document would be infeasible. Due to the low storage cost and fast retrieval speed, hashing is one of the popular solutions for approximate nearest neighbors. However, existing hashing methods for probability distributions only focus on the efficiency of searches from a given document, without handling complex queries

or offering hints about why one document is considered more similar than another.

In this chapter we have introduced a new data structure to represent hash codes, based on topic hierarchies created from the topic distributions. This approach has proven to obtain high-precision results and can accommodate additional query restriction. In doing so, we have showed a new way to annotate documents by topic inferences made from topic models. This addresses the technical objective of this thesis T03 (*integrate the annotation method based on topic hierarchies into the topic model service*).

This way of encoding documents can also help to understand why two documents are similar, based on the intersection of topics at hierarchies of relevance. We have proposed a method to compare and organize huge document collections based on similar topic-based annotations, thus addressing the research objective R05 (*define nearest-neighbor techniques to organize documents in regions with similar topic hierarchies*).

In addition, we have implemented the technique to compare documents in our librAIry framework, encouraging the achievement of the T04 technical objective (create a system capable of finding similar documents automatically).

Chapter 7

Cross-lingual Document Similarity

7.1 Synset-based Representational Space

7.2 Cross-lingual Models

7.3 Summary

Chapter 8

Evaluation

8.1 Evaluation Metrics

8.2 Text Representativeness

8.3 Large-scale Text Processing

libraIry has been used in some real scenarios such as a research-paper repository for the European project DrInventor⁷⁴, a support to decision makers for analyzing patents and public aids for the ICT sector, and also as a book recommender for an online content platform. This has allowed us to identify some weak and strong points of the framework and iterate over the architecture to come with the described solution.

The following modules have been developed⁷⁵: (1) a ***general-purpose harvester*** which retrieves text and meta-information from PDF files in local or remote file-system; (2) a ***research paper-oriented harvester*** focused on collecting and processing more specific textual files (e.g. scientific papers) creating both *documents* and *parts* inferred from the rhetorical classes of the paper; (3) a ***Stanford CoreNLP-based Annotator*** which discovers named-entities, compounds and lemmas from *documents* and *parts*; (4) a ***Topic Modeler*** based on Latent Dirichlet Allocation (LDA) which creates probabilistic topic models for each *domain* in the framework. They are annotated with the set of topics (i.e. ranked list of words) discovered from the corpus, and both *documents* and *parts* of that domain are also annotated by the vector of probabilities to belong

⁷⁴<http://drinventor.eu>

⁷⁵<https://github.com/librairy>

to these topics. It uses the Spark implementation of the algorithm; and (5) a ***Word Embedding Modeler*** which creates a *word2vec* model from the *documents* contained in a *domain*.

Due to linear scalability and high performance features, Cassandra has been used to support the column-oriented storage functionality, Elasticsearch as document-oriented storage and Neo4j as graph-oriented storage.

All modules in *libraIry* have been packaged as Docker⁷⁶ containers and uploaded to Docker-Hub⁷⁷ to facilitate the installation of the system.

Maximizing information re-usability and minimize irrelevant data, becomes specially important when the system handles large collections of data (around million of documents). Fine-grained resource definitions have been key to achieve this, so modules execute actions only when really necessary. When a new *domain* is created, for instance, a new Topic Model is trained for that *domain* and is used to calculate the semantic similarity between the *documents* (and the *parts*) in that domain. If a new *document* (or *part*) is added to that *domain*, the model is trained again and the semantic similarities are re-calculated. However, this becomes unfeasible when the domain is frequently updated and it is composed by a large number of documents. One solution has been to define a new type of resource between domains and documents, models, that describes the representational state (e.g. topic model) of a collection of documents. Thus the model is only re-trained when a significant amount of *documents* are added to the sampling data set and not to the entire *domain*. This less transient model is used to calculate semantic similarities between the *document* collection (and *parts*) inside a *domain* in a more efficient way. Following this more precise execution of tasks, the routing-keys should include the URI of the implied resource into the definition, not only in the content of the message. It would allow modules listening to both the type of a resource or to a specific resource (or subsets, via regular expressions).

While the storage modules are always used to save/update/delete a resource, they are not always required from the end-user. The graph storage, for instance, makes sense when a path between two *documents* or *parts* is requested for a given *domain*. However, some *domains* are not intended to be explored by their linked resources. A

⁷⁶<https://www.docker.com>

⁷⁷<https://hub.docker.com/u/librairy/>

more fine/grained definition of resources will allow graph-storage being only used when necessary.

On the other hand, distributed execution of NLP tasks (not only in threads, but also in machines) has proved to be especially useful to handle large collection of *documents*. It requires less processing time than a monolithic solution (e.g. CoreNLP application) and it also provides a dynamic load balancing between modules.

8.4 Topic-based Clustering

8.5 Cross-lingual Similarity

8.6 Conclusions

Chapter 9

Experiments

9.1 Polypharmacy and Drug-drug Interactions

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9.2 Corpus Viewer

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9.3 ODS Classifier

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9.4 Drugs4Covid

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Chapter 10

Conclusions

10.1 Assumptions and Restrictions

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10.2 Contributions

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10.3 Impact

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10.4 Limitations

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10.5 Future Work

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