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PhD Thesis

Semantically-enabled browsing of large multilingual document collections

Author: Carlos Badenes-Olmedo

Supervisors: Prof. Dr. Oscar Corcho

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Presidente: Dr. Xxx Xxx

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Suplente: Dr. Xxx Xxx

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A mis padres.

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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 data is daily produced or captured in any imaginable domain offering the possibility of extracting knowledge from them. Much of them are presented in the form of textual documents (e.g. scientific papers in digital journals, news in online channels, books in documentary repositories), making necessary for experts to browse through many of these texts to find relevant data. In the context of research publications, for example, personalized recommendations based on papers content is a key feature for performing a smart selection of relevant resources over big collections of scientific content.

Griffiths et al. (2007) argued the knowledge in a text arose from the relations established between their words through the concepts they evoked. Similarly, **?** highlighted the knowledge derived from relations between documents in a collection and summarized the process in three stages. First, by processing the items following different annotation techniques (entities, keywords, etc) that allow machines to programmatically leverage on their content. Then, creating a vectorial representation based on those features for each document. And finally, comparing them following some distance/divergence functions .

It becomes crucial to provide mechanisms for programmatically processing this raw data discarding all the noisy, non-relevant information and keeping only the data that can bring value for the involved agents (general consumers, experts, companies, investors...). While some specific tools already allow for advanced sense-making operations, others opt for composing a solution where different analysis techniques are integrated under a uniform data schema. However, this integration involves significant

efforts on reconciling data sources, coordinating processing operations, and efficiently exploiting results from the execution of those techniques. There is the need for a more flexible paradigm where tools and algorithms for textual document analysis, from different programming languages and technologies, can operate independently and in a collaborative manner creating a common document oriented work-flow through their actions.

Once data has been processed, texts are usually converted into numeric vectors to operate with them. The definition and number of dimensions for each vector are key aspects when vector space models (VSM) create these representations. In a common and simple approach, term frequencies guide the creation of a space where each word in the vocabulary is represented by a separate and orthogonal dimension. Term Frequency-Inversed Document Frequency (TFIDF) measures the term frequency of each term in a text and multiplies it by the logged inverse document frequency of that term across the entire corpus. Despite its simplicity, TFIDF may suffer from an ignorance of n-gram phrases, complications with incremental updates upon addition of new documents, and a large number of dimensions. To deal with such issues, variants of TFIDF have been proposed to incorporate n-grams as new terms, and/or to adjust for the timing of the use of vocabulary across the time line of the corpus.

Other techniques, known as text embedding, attempt to address the high-number of dimensions and the loss of semantic information in TFIDF models, by transforming each text into a low-dimensional vector. Text embedding methods can be grouped into two categories: (i) count based methods based on bag of words (where the order of words are ignored), and (ii) prediction based methods based on sequence of words (where the order of words is taken into account). Neural models are an example of the second approach where word vectors are learned using a shallow neural network trained from pairs of (target word, context word), where context words are taken as words observed to surround a target word. The assumption behind neural models is that words with similar meanings tend to occur in similar contexts. Document vectors can then be created out of word vectors through an averaging strategy or by considering each document as a special context token, hence obtaining document vectors directly. Topic models are an example of the first approach where each document is represented as a probability distribution of how relevant that document is to a given number of topics (and thus a lower-dimensional space). Each topic is selected as a weighted

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average of a subset of terms and document vectors are learned from the corpus on the assumption that words with similar meanings will occur in similar documents. This brings a lot of potential when applied over different Information Retrieval (IR) tasks, as evidenced by recent works in different domains such as scholarly Hall et al. (2008)Gatti et al. (2015), health Paul and Dredze (2014) Lu et al. (2016) Tapi Nzali et al. (2017), legal O'Neill et al. (2017)Greene and Cross (2016), news He et al. (2017) and social networks Ramage et al. (2010)Cheng et al. (2014).

This thematic and low-dimensional feature space 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.

However, document similarity comparisons are too costly to be performed in such huge collections of data and require more efficient approaches than having to calculate all pairwise similarities. Create 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 can be unfeasible because of the exponential cost of comparing every pair of elements. Computation can be approximated by nearest neighbors (ANN) search problem. 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 Liu et al. (2014) Andoni et al. (2013) 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 due to the fact that ANN search has been designed to handle distance metrics (e.g. cosine, Euclidean, Manhattan) Ravichandran et al. (2005)Petrovic et al. (2010)Krstovski and Smith (2011), even in high-dimensional simplex spaces handling information-theoretically motivated metrics (e.g. Hellinger, Kullback-Leibler divergence, Jensen-Shannon divergence) as demonstrated by Mao et al. (2017).

However, the smaller space created by existing hashing methods loses the exploratory capabilities of topics to support document similarity. The notion of topics is lost and therefore the ability to make thematic explorations of documents. Moreover, metrics in simplex space are difficult to interpret and the ability to explain the

similarity score on the basis of the topics involved in the exploration can be helpful. While other models based on vector representations of documents are simply agnostic to the human concept of themes, topic models can help finding the reasons why two documents are similar.

When the information extraction 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 apply 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 this case, it may be advisable to automatically learn cross-lingual topics to browse multi-lingual document collections.

In this work we facilitate the exploration of large document collections with texts written in different languages. We address the problem of programmatically generating annotations for each of the items inside big collections of textual documents, in a way that is computationally affordable and enables a semantic-aware exploration of the knowledge inside it. Our proposal automatically discovers thematic associations between texts and organizes the collection so that it can be browsed through related content.

1.1   Contributions

The work presented in this thesis makes the following contributions:

- **Topic Creation and Inference**: We define a large-scale text processing architecture following web standards and software architecture best practices for the creation and using of probabilistic topic models.

- **Topic Model Repository**: We propose a format to publish topic models that facilitates their reuse.

- **Relevance-oriented Thematic Annotations**: We present a method to annotate texts by topic hierarchies inferred from their content.

- **Massive Document Comparisons**: We leverage multi-level topic annotations to efficiently index and retrieve related documents while allow exploring the collection by themes.

- **Cross-lingual Document Relations**: We introduce a technique to transform probabilistic topics from different languages into a single representation space where texts can be thematically related regardless of the language used.

1.2   Thesis Structure

The thesis is structured as follows:

Chapter 2 introduces the state of the art, along with the main concepts that we will be handling throughout the thesis.

Chapter 3 identifies the research problems and presents the hypotheses that guide this work.

Chapter 4 describes the processing architecture and the distribution format of the topic models on which the work presented in this thesis is built.

Chapter 5 details the text annotation algorithm from probabilistic topics.

Chapter 6 shows how to efficiently store and search documents 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 for translation. This approach is evaluated in 8, where the results are explained in detail.

Chapter 9 provides information on real-world projects where contributions from this thesis have been used.

Finally, *Chapter 10* describes conclusions and future lines of work.

1.3   Publications

The following publications have been accepted (in chronological order) during the research work presented in this thesis:

1. **Carlos Badenes-Olmedo**, José Luis Redondo-Garcia, and Oscar Corcho. Distributing Text Mining tasks with librAIry. Proceedings of the 17th ACM Sympo-

sium on Document Engineering (DocEng). Association for Computing Machinery, Valletta, Malta. 2017.

2. **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.

3. **Carlos Badenes-Olmedo**, Ronald Denaux, Martine De Vos, Daniel Garijo, Jose Manuel Gomez-Perez, Agnieszka Lawrynowicz, Pasquale Lisena, Raul Palma, Raphaël Troncy, and Daniel Vila. K-CAP2017 Satellites: Workshops and Tutorials. Proceedings of the 9th International Conference on Knowledge Capture (K-CAP), Article 1e, 1–6. Association for Computing Machinery, Austin, TX, USA. 2017

4. Jose Manuel Gomez-Perez, Ronald Denaux, Daniel Vila and **Carlos Badenes-Olmedo**. Hybrid Techniques for Knowledge-based NLP - Knowledge Graphs meet Machine Learning and all their Friends. Proceedings of Workshops and Tutorials of the 9th International Conference on Knowledge Capture (K-CAP), 69–70. CEUR-WS, Austin, TX, USA. 2017

5. **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.

6. 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

7. Beatriz López-Centeno, **Carlos Badenes-Olmedo**, Ángel Mataix-Sanjuan, Katie McAllister, José M Bellón, Pascual Balsalobre, Juana Benedí, Saye Khoo, María J

Calvo-Alcántara, and Juan Berenguer. Polypharmacy in HIV-infected and non-HIV-infected individuals in the region of Madrid (Spain): A population-based study. Proceedings of the 10th GeSIDA Conference, Spain. 2018.

8. Victoria Kosa, David Chaves-Fraga, Dmitriy Naumenko, Eugene Yuschenko, **Carlos Badenes-Olmedo**, Vadim Ermolayev, Aliaksandr Birukou. The influence of the order of adding documents to datasets on terminological saturation. Technical Report TS-RTDC-TR-2018-1, Dept of Computer Science, Zaporizhzhia National University, Ukraine. 2018.

9. 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

10. **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

11. **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

12. Beatriz López-Centeno, **Carlos Badenes-Olmedo**, Ángel Mataix-Sanjuan, Katie McAllister, José M Bellón, Sara Gibbons, Pascual Balsalobre, Leire Pérez-Latorre, Juana Benedí, Catia Marzolini, Ainhoa Aranguren-Oyarzábal, Saye Khoo, María J Calvo-Alcántara, Juan Berenguer. Polypharmacy and drug-drug interactions in HIV-infected subjects in the region of Madrid, Spain: a population-based study. Clinical infectious diseases : an official publication of the Infectious Diseases Society of America, ciz811. 2019

13. **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. Pre-press, no. Pre-press, pp. 1-16. 2020

Chapter 2

Related Work

2.1   Text Processing

2.2   Document Embeddings

2.3   Document Similarity

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2.4   Summary

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Chapter 3

Research Objectives

The work presented in this thesis aims to facilitate the exploration of large collections of multilingual documents through thematic associations inferred from their content. 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 infer 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 studied in this work.

In the third dimension, data structures that efficiently **sorting** texts from their representations based on probabilistic topics were studied. Divisions of space into semantically-related regions are necessary 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 (3.1), its associated research challenges (3.2) and presents the research methodology (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, sorting, and multilinguality dimensions respectively. First, by *distributing both natural language processing tasks and representational models we can efficiently process big collections of documents(**H1.1**).*

Second, we can *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**) can 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 losing the ability to rely on topics for further processing down the line (**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 objectives 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: Sorting, D4: Multilingualism
H1.1: it is possible to efficiently annotate documents on a large scale by distributing 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 documents with similar topic distributions without calculate all pairwise comparisons and without losing the ability to explore them through their topics	D3: Sorting
H1.4: it is possible to relate documents in different languages without having to translate them 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 Topic-model Programming Interface

Although some initiatives to standardize the format of machine-learning models and to provide tools that facilitate their transformation among the most widespread proprietary formats already exist in the literature, there are still some software restrictions that can limit their reuse. These models may hold certain software dependencies that e.g. force using a specific version of a programming language (python2 vs python3[1]) or an operating system (e.g., linux kernel vs on-cloud environments[2]) to load them or to launch the service that deploys them (e.g., ONNX[3]). This limits their ability to be reused in domains that are not familiar with these technological stacks. *Integrating pre-trained topic models into general-purpose systems is not easy **(RCInterface1)**.*

Topic models, as many other machine learning models, may be distributed in a proprietary or standard format with software dependencies or by directly providing the data. However, *there is no standard way to specify the topics and the operations that can be performed on them **(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 it.

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[1] https://www.python.org
[2] https://vespa.ai
[3] https://onnx.ai

3.2.2 Explainable Topic-based Associations

In order to facilitate the exploration of document collections, vector space models are often used to semantically relate texts based on their word distributions. 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 topics emerged 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 is defined or a 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 finding related documents in a large corpus is desirable (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 Automatic Cross-lingual Topic Alignment

With the ongoing growth in the number of digital articles in different languages, we need annotation methods that enable browsing multi-lingual corpora. 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 table3.2

3.3 Research Methodology

The research presented in this thesis is based on four dimensions or research areas. 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 us 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. 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

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

Research Challenge	Hypotheses
RCInterface1: integrating pre-trained topic models into general-purpose systems is not easy	H1.1: documents can be efficiently annotated on a large scale by distributing natural language processing tasks and representation models
RCInterface2: there is no standard presentation of topics that facilitates their reuse	H1.1: documents can be efficiently annotated on a large scale by distributing 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.

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 that they can be assigned to new documents. Such a high volume of data made difficult to process it manually, so we needed to automatize 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 processing pipelines. As a result, we created a *platform for large-scale text analysis (**TO1**)*, and produced a *model-as-a-service repository with pre-trained topic models(**T02**)*. The efficiency of this solution was validated by processing a corpus of 100,000 documents collected from the CORDIS dataset[4], 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 Section 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 Associations

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*

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[4]https://data.europa.eu/euodp/es/data/dataset/cordisH2020projects

*was computationally affordable and enabled a semantic-aware exploration of the knowledge inside it (**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 Open Research Corpus[5] in domains such as Computer Science, Neuroscience and Biomedicine (Badenes-Olmedo et al., 2017c) (Badenes-Olmedo et al., 2017a) (Badenes-Olmedo et al., 2019a).

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

- a clustering algorithm based on probabilistic topic distributions;

- a hash function to transform topic distributions into topic hierarchies;

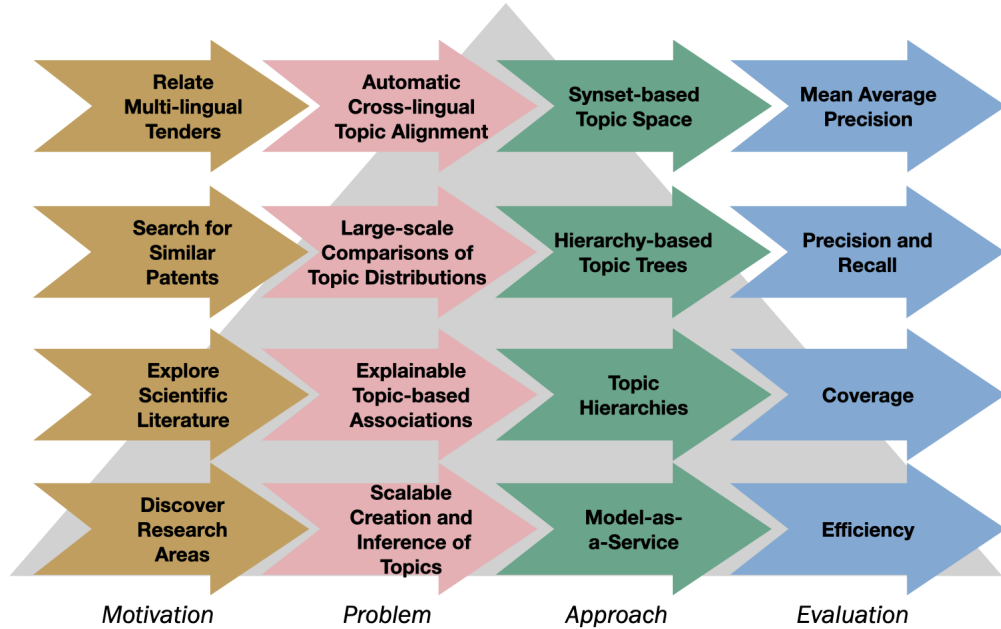- a similarity metric based on topic sets;

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

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[5] 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 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 corpus[6]. The relations between patents derived from their manual categorization were compared with those automatically obtained from their topic distributions (Badenes-Olmedo et al., 2020)(Badenes-Olmedo et al., 2019a).

The main contributions under this dimension are described in Section 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 Automatic 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

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[6]https://www.uspto.gov/ip-policy/economic-research/research-datasets

Portuguese editions of JCR-Acquis[7] corpora and revealed promising results on classifying and sorting documents by similar content across languages (Badenes-Olmedo et al., 2019b)(Badenes-Olmedo et al., 2019a).

The main contributions under this dimension are described in Section 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.

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[7]`https://ec.europa.eu/jrc/en/language-technologies/jrc-acquis`

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 enables a semantic-aware exploration of the knowledge inside a corpus	RCExplainable1
R04: Define a metric based on topic annotations that compares documents and facilitates their interpretation	RCExplainable2, RCExplainable3
RO5: Define nearest-neighbors techniques to organize documents in regions with similar topic hierarchies	RCComparison1, RCComparison2
R06: Define a transformation of the topic-based annotations to create a unique representational space out of the particularities from each language	RCCrossLingual1
TO1: Create a platform for large scale text processing	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 document automatically	RCExplainable2, RCExplainable3, RCComparison1, RCCrossLingual1

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

Chapter 4

Scalable Creation and Inference of Topics

This chapter presents *librAIry*[8], our text management platform that combines natural language processing techniques with automatic learning algorithms to analyze large collections of documents. It serves as a technological framework where we can implement the advances of our research and measure its performance.

4.1 Document Workflow

Given the huge amount of textual data about any domain that is daily being produced or captured in any imaginable domain, it becomes crucial to provide mechanisms for programmatically processing this raw data so we can make sense out of it: discarding all the noisy, non-relevant information and keeping only the data that can bring value for the involved agents (general consumers, experts, companies, investors...).

While some specific tools already allow for advanced sense-making operations, others opt for composing a solution where different analysis techniques are integrated under a uniform data schema. However, this integration involves significant efforts on reconciling data sources, coordinating processing operations, and efficiently exploiting results from the execution of those techniques. There is the need for a more flexible paradigm where tools and algorithms for textual document analysis, from different programming languages and technologies, can operate independently and in a collaborative manner

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[8]http://librairy.linkeddata.es

creating a common document oriented workflow through their actions. In the context of the scientific publications, the personalized recommendation of research papers based on their content is a key novel feature for performing a smart selection of relevant resources over very big collections of scientific content. From the set of values and different attributes extracted from the papers and by generating advanced knowledge models about the information they contain we can bridge across the different relevant pieces of information and allow users to navigate them in a more efficient and powerful way. This knowledge about a specific document is frequently acquired by different techniques focused on revealing certain aspects of it, that are later combined to achieve one particular task.

The architecture presented in this thesis aims to ease the way different software modules work together and lays the foundation for efficiently process big volumes of textual documents in a distributed, decoupled manner.

4.2 librAIry

librAIry is a framework where different text mining tools, available in various languages and technologies, can operate in a distributed, high-performance and isolated manner creating a common workflow through their actions. Instead to work towards a pre-defined sequence of actions, synchronization across modules is achieved through the aggregation of the operations executed by them in response to an emergent chain of events. This raises both technical and functional challenges to coordinate multiple executions. From the technical point of view, isolated environments and communication mechanisms are provided so initially dissimilar tools can be executed with maximum guarantees. From the functional point of view, all executions are coordinated to reach a final result as aggregation of partial results derived from each execution.

4.2.1 Functional Features

The architecture is articulated around three main concepts: (1) the **resource** such as *document*, a *part-of-a-document*, or a *domain*. (2) the **actions** performed over them: *create*, *update* or *delete* a resource. And (3) the new **state** that is reached by the resource after an action is performed, such as *created*, *updated* or *deleted*. An **event** is a message containing details about those three aspects, published on a shared
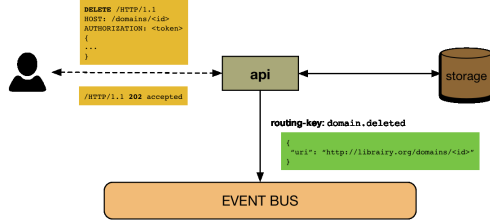
Figure 4.1: Domain deleted flow.

event-bus available for all the modules deployed in the framework. This will, in turn, allow that any module can perform actions on one or more resources in response to a new state reached by a given resource. Actions executed in parallel from distributed environments.

4.2.1.1 Resources

Two main kinds of resources are considered: those derived from external sources such as (1) *documents* from textual files (e.g. a research paper), (2) *parts* from logical divisions of a *document* (e.g. rhetorical classes or sections), and (3) *domains* from sets of *documents* (e.g. a conference or journal), and those derived from processing the previous ones such as *annotations*.

To better illustrate this model, consider to explore the research papers published at the SIGGRAPH conference in 2016[9]. First, every paper will be materialized as a new *document* containing the full-text. Immediately after, the *document* will be automatically associated to several *parts*, each of them grouping sentences by rhetorical class (e.g. approach, background, challenge, future work and outcome) and by section (e.g abstract, introduction). Finally, a new *domain* will be created grouping all these *documents*. Different analysis will be performed extending the initial set of resources with more annotations at several representational levels: at *document level*, full-text based annotations are provided such as named-entities, compounds and descriptive tags. At *relational level*, connection between resources are found (e.g. semantic similarity-based relationships). And finally, at *domain level* annotations such as tags and summaries are composed describing the corpus of *documents*.

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[9]http://s2016.siggraph.org

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4.2.1.2   Event-based Paradigm

An event illustrates a performed action, i.e. a resource and its new state. It follows the Representational State Transfer (REST)Fielding and Taylor (2002) paradigm, but taking into account the state reached after an action, i.e *created*, *deleted* or *updated*. Thus, an event contains the resource type and the new state reached by a specific resource.

4.2.1.3   Linked Data Principles

Data in *librAIry* is individually addressable and linkable Turchi et al. (2012) following the Linked Data principles defined by T. Berners-Lee Bizer et al. (2009). Thus, resources (i.e. a *domain*, a *document*, a *part* or an *annotations*) have: (1) a URI as name, (2) a retrievable (or dereferenceable) HTTP URI so that it can be looked up, (3) a useful 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.

4.2.2   Framework Architecture

Following a publisher/subscriber approach, all the modules in the framework can publish and read events to notify and to be notified about the state of a resource. Therefore, the system flow is not unique and is not explicitly implemented, instead distributed and emergent flows can appear according to particular actions on resources.

4.2.2.1   Event-Bus

We use the Advanced Message Queuing Protocol (AMQP) as the messaging standard in *librAIry* to avoid any cross-platform problem and any dependency to the selected message broker. This protocol defines: *exchanges*, *queues*, *routing-keys* and *binding-keys* to communicate publishers and consumers.A message sent by a publisher to an exchange is tagged with a routing-key. Consumers matching that routing-key with the binding-key used to link the queue to that exchange will receive the message. In *librAIry* this 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
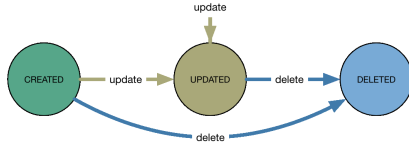
Figure 4.2: Resource states.

(e.g. ́domains.created ́for new domains), or multiple type events (e.g. #.created for all new resources).

4.2.2.2 API

A HTTP-Rest Application Program Interface (API) was designed for interaction with end-users. Any external operation motivated by a user will be handled here. Some of them, usually those related to reading operations, will be completely managed by this module getting all the data from the internal storage. However, those operations implying a modification of the status of some resource (e.g. creation of a *document*), may be also performed by other modules listening for that type of event asynchronously. This module publishes to the following routing-keys: *domain.(created;updated;deleted)*, *document.(created;updated;deleted)*, *part.(created;updated;deleted)*, and *annotation.(created;updated;deleted)*.

4.2.2.3 Storage

Multiple types of data can be handled in this ecosystem. Inspired in the Data Access Object (DAO) pattern, we have created a Unified Data Manager (UDM) providing access to any type of data used in the system. Three types of databases have been considered:

- **column-oriented database**: Focused on unique identified and/or *structured data*. This storage allow us searching key elements across resources.

- **document-oriented database**: Focused on indexing raw text. This storage allow us to execute advanced search operations over all the information gathered about a textual resource.

- **graph database**: Focused on relations. This storage allow us exploring resources through the relationships between them.
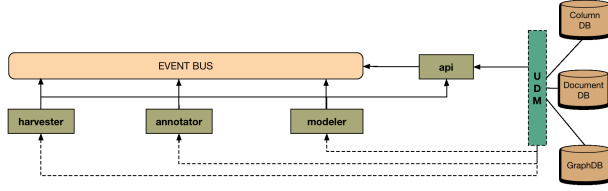
Figure 4.3: Modules.

4.2.2.4 Modules

The modules composing *librAIry* have been designed following the microservices architectural style. A module is a cohesive (i.e. it implements only functionalities strongly related to the concern that it is meant to model Dragoni et al. (2016)) and independent process working on the framework with a specific purpose. This purpose is defined by both the routing-key and the binding-key associated to the events handled by the module.

These are the main types of modules identified in *librAIry*:

- **Harvester**: creates system resources such as *documents*, *parts* and *domains*, from local or remote located textual files.

  – Listening for: nothing

  – Publishing to: *document.(created)*, *part.(created)*, *domain.(created;updated)*

- **Annotator**: retrieves named-entities, compounds, lemmas and other annotations resulting of Natural Language Processing (NLP) task execution from *documents* and *parts*.

  – Listening for: *document.(created;updated)*, *part.(created;updated)*

  – Publishing to: *annotation.(created;deleted)*

- **Modeler**: builds representational models from a given *domain*.

  – Listening for: *domain.(created;updated)*

  – Publishing to: *annotation.(created;deleted)*

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4.3 Model-as-a-Service

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4.4 Summary

In *librAIry*, existing algorithms and tools coming from different technologies can work collaboratively to process and analyze large collections of textual resources which has been successful applied to some real scenarios [10].

A new model definition based on the previously mentioned principle of maximizing information re-usability and minimize irrelevant data is being studied to create a more fine-grained resource design. New domains, in the sense of particular vocabularies or specific textual formats, are also being analyzed to be included into the system via specific harvesters or more precise annotators. Moreover, a template-based mechanism oriented to facilitate the integration of new tools and techniques into the system is being built to make easier to develop new modules as well as increasing the available modules at Docker-Hub.

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[10]`http://drinventor.dia.fi.upm.es`

Chapter 5

Explainable Topic-based Associations

5.1   Topic Relevance

5.2   Topic-based Clustering

5.3   Summary

Chapter 6

Large-scale Comparisons of Topic Distributions

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 DrInventor [11], 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 developed[12]: (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

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[11]http://drinventor.eu
[12]https://github.com/librairy

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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 Docker [13] containers and uploaded to Docker-Hub [14] 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

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[13]https://www.docker.com
[14]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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