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LOV-ES: Guiding the Ontology Selection to Structure Textual Data using Topic Modeling

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Abstract

On-line availability of text corpora nowadays allow data practitioners to build complex knowledge combining various sources. One common shared challenge lays in the modelisation of intermediate knowledge structures able to gather at once the various topics present in the texts. Practically, practitioners often go through the creation of vocabularies. In order to help these domain experts, we design LOV-ES: a solution able to help them in this creative process, guiding them in the selection and the combination of already existing vocabularies available online. Technically, our solution relies on LDA to detect topics and on the LOV to then propose candidate vocabularies.

Keywords

Topic Modeling, Textual source, LDA, LOV, Vocabulary Recommender

1. Introduction

Since its early days, natural language processing has *knowledge acquisition* as a prominent goal. Formally, we would like to have machines able to read text and express its embedded knowledge in a formal representation so to rely on it to later solve various problems. One of the first tasks to tackle in this context is therefore to have an ontology able to capture the knowledge structure of the considered texts: the *ontology induction*.

Ontology induction (constructing an ontology) and ontology population (mapping textual expressions to concepts and relations in the ontology) have been explored by the community [1]. In particular, early efforts have been made to bridge Semantic Web and ontology learning [2, 3]; and machine learning approaches were developed [4, 5], some being unsupervised [6]. Nevertheless, as highlighted by Tsujii [7], most approaches induce and populate a deterministic ontology, which does not capture the uncertainty among entities and relations. Moreover, they focus on inducing ontology over individual words rather than arbitrarily large meaning units.

In parallel, the Semantic Web community has been structuring many knowledge domains in an open manner, *i.e.* sharing their datasets and their ontologies, see *e.g.* the LOD-cloud¹ and the LOV-dataset² providing data on respectively open linked datasets and vocabularies. As a consequence, in this article, we propose to rely on these available resources to design

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¹LOD: more than 1 255 datasets. <https://lod-cloud.net/>

²LOV: more than 800 vocabularies. <https://lov.linkeddata.es/dataset/lov>

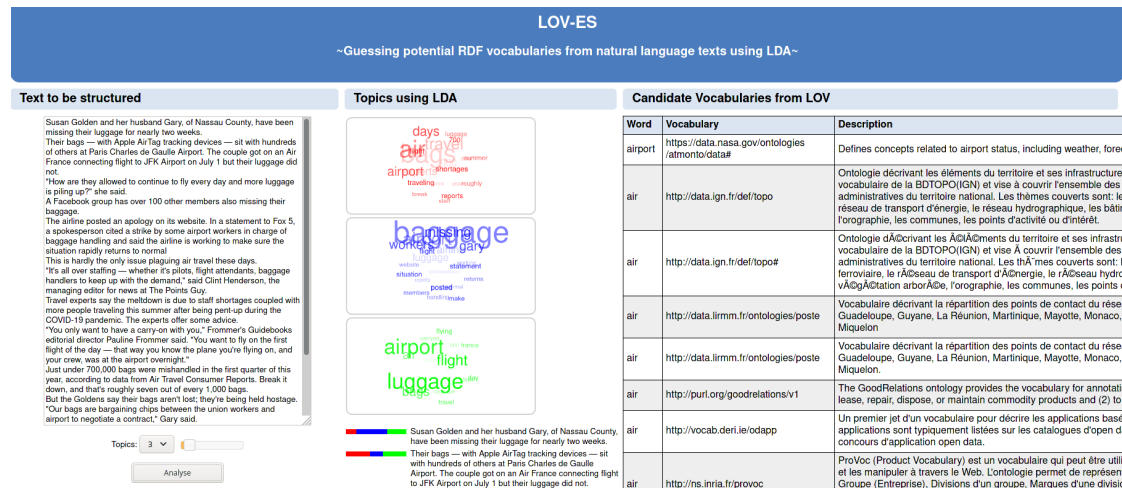


Figure 1: Screenshot of the LOV-ES interface.

a vocabulary recommender from text, aiming to guide and help data practitioners in their ontology selection and design process. Following a similar goal, domain-specific solutions have been designed *e.g.* for medical data [8].

In this article, we propose an end-to-end solution named LOV-ES for Linked Open Vocabulary Enhanced Selection. We show how LDA and SPARQL [9] can be associated to obtain a list of candidate vocabularies. Moreover, we propose a metric to rank the vocabularies against each other (combining words' weights and vocabulary frequencies in the list) in order to suggest the most relevant results.

2. Vocabulary Suggestion using LDA

The LOV initiative created in 2014 [10] has contributed to the deployment of Linked Data providing a high-quality catalogue of reusable vocabularies for the description of data on the Web. Currently, the LOV gathers around 800 vocabularies in more than 50 languages ranging from English to French. The task of Topic Modeling consists of discovering abstract semantic themes, or *topics*, hidden within data. Among existing topic model techniques, Latent Dirichlet Allocation (LDA) [11] and its extensions have been successfully applied to many data types and application domains, including bioinformatics, computer vision, and social network analysis, in addition to text mining and analytics [12].

The proposed architecture performs two main tasks: (1) applying LDA to identify underlying topics of a given text block, and (2) ranking candidate vocabularies considering their relevance to the topics. In detail, we rely on the original version of LDA [11] based on two hyperparameters α (controlling the prior distribution over topic weights in each document) and β (setting the prior distribution over word weights in each topic), respectively set to 0.1 and 0.01. Each topic word bag resulting from applying LDA is then used to build a SPARQL query aiming at extracting candidate vocabularies. Typically, the words are given to the SPARQL endpoint

taking advantage of the VALUES variable passing method as presented schematically below:

```

SELECT ?word ?voc WHERE {
  VALUES ?word { "word1" "word2" "word3" } # Word list from an LDA bag.
  ?voc a lod:Vocabulary . ?voc dterms:description ?description . [...]
  FILTER ( CONTAINS ( STR(?description),?word ) ) }

```

The rest of the query then returns candidate vocabularies ?voc if occurrences of ?word are present within the vocabulary description, making the assumption that specific words would be present to describe more generic vocabularies.

Once candidate vocabularies are obtained. We apply the following metric to give each vocabulary a score of relevancy. Formally, considering k topics, we have for each topic t a bag containing n_t words and their associated weights *i.e.* $\{(w_{i,t}, p_{i,t})\}_t$, with $i \in [1, n_t]$ and $t \in [1, k]$. As there might be multiple possible candidate vocabularies for a single word, we obtained (after running the k SPARQL queries) k lists containing c_t 3-tuples of the form $(voc_j, w_{i,t}, p_{i,t})$, with $j \in [1, c_t]$, $i \in [1, n_t]$ and $t \in [1, k]$. Moreover, a specific vocabulary can be suggested multiple times for a single topic *e.g.* a vocabulary about travel may be returned two times considering the bag {"plane", "trip"}. To rank the list, we propose to first attribute an aggregated weight for each vocabulary per topic, summing the weights of the words it matches while normalising by the sum of the weights in the 3-tuple list for the considered topic; and then to combine the topics summing the aggregated weights of same vocabularies together:

$$\forall V \in vocList, \text{score}(V) = \sum_{t=1}^k \frac{\sum_{voc_i=V} p_{i,t}}{c_t \sum_{i=1}^{c_t} p_{i,t}}, \text{ considering } k \text{ lists of } c_t \text{ 3-tuples}$$

We then just have to decreasingly sort the *score* of each vocabulary of *vocList* to provide an ordered list of suggestions.

The graphical user interface takes as input a text block split by line and allows to select the number of topics to be identified, ranging from 2 to 10. By clicking on the *Analyse* button, word clouds are generated corresponding to detected topics, graphically the larger a word, the more weight it has in the topic. In parallel, a ranking list of candidate vocabularies is displayed by descending order of relevancy (using the scoring function aforementioned) including among other information: the link to the vocabulary, its description and various explanations to describe the internal step of the process. In particular, it provides information referring to the distribution of words over topics after applying the scoring metric. Figure 1 presents our pure JavaScript Web-App: LOV-ES.

3. Related Work

Most of existing works focusing on the task of ontology research relies on the content of ontology and user query to perform vocabulary recommendation [13]. In these works, the core idea consists of using a set of keywords or ontology metadata to describe the domain to suggest

appropriate ontology according to the user query. Swoogle³, Sindice.com⁴ or Watson⁵ are semantic search engines performing a search of ontology resources using the aforementioned methodology. Among proposed works, some of them have especially focused on the LOV ecosystem. Initially consisting of a full-text inverted index and a ranking algorithm based on the term popularity [10], related works have extended the recommendation capabilities of the LOV search engine proposing ranking metrics [14, 15, 16] and evaluation parameters [17]. Recently, Sarwar et al. [18] have addressed the task as an information retrieval problem, introducing a framework-based on text categorisation and unsupervised learning techniques. To overcome the well-known limitations related to domain coverage and keyword-based searching/matching, LOV-ES benefits from NLP-powered techniques allowing it to consider full text data to performing ontology resource recommendation.

4. Conclusion

This article presents LOV-ES: a solution combining an LDA-based model together with a novel scoring metric to extract relevant vocabularies from the LOV catalog in order to structure a text. A pure JavaScript Web-App is openly available from:

<https://dgraux.github.io/LOV-ES/> ↗

with the aim of guiding data practitioners selecting relevant vocabularies to structure textual knowledge. Currently working exclusively with resources released on LOV, it constitutes the main limitation of the proposed solution. In future work, we plan to extend the coverage of available vocabularies by aggregating resources from other catalogs. In addition, several approaches for estimating LDA parameters have been proposed in the literature and should be considered in an improved version of LOV-ES, together with an evaluation of the results.

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³<https://ebiquity.umbc.edu/project/html/id/53/Swoogle>

⁴<https://sindice.com/>

⁵<http://watson.kmi.open.ac.uk>

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