Detecting Knowledge Innovation through Automatic Topic Labeling on Scholar Data

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Abstract

Knowledge innovation can be detected by scientific and technology production. A challenge on knowledge innovation analysis is the identification of knowledge areas in text documents - called topic modeling - and presenting the related concepts in an understandable way. The most used and reliable approaches are based on manual labeling, which is impracticable when we analyze a huge period of time, a large number of documents or different domains. We propose a method of automatic labeling. Evaluation results pointed that the proposed method can effectively generate labels for topics with a similar efficiency of human generated labels.

1. Introduction

Knowledge Innovation is essential to generate value and competitive advantage to a company or a nation. However, strategic analyzes like assessing the growth of innovation areas, potential opportunities and identifying leading institutions, become difficult as the human effort and time spent in these tasks grow.

The main challenge is to extract – from textual datasets such as publications, patents and projects – knowledge areas and correlate them. In this scenario, we can use topic models, which are a suite of algorithms for discovering the main subjects from a large collection of unstructured documents [2].

In all algorithms used to extract topics from document collections, subjects are in majority represented by a unigram language model or multinominal word distribution, which is a set of words with associated probabilities of belonging to the collection. In Figure 1, we illustrate an example of topic model for a subject entitled “mining algorithms” with words ordered by their probabilities, and three possible kinds of labels: single terms, phrases formed from the model and labels created by humans. All of the labels try to explain the topic subject.

Frequently, few words can completely represent the contents of a collection, as for example, “bioinformatics” or “clustering” topics. Human indexers often use two-word phrases [4]. Sentences, unlike words, are very specific and good to describe concepts of a document, like titles of articles, but fail to represent the general concept of a corpus.

While the multinomial word distributions are quite intuitive, it demands some familiarity with the domain and the collection. Users without this background knowledge will not be able to recognize concepts from a set of words, to identify the main subject or to compare different themes. This is common in scientific and technological domains when usually a topic is not recognizable in some groups while it is extremely meaningful to others. For example, in Figure 1, “mining algorithms” is a common term for the computer science domain, but users from another knowledge area can have problems to understand the concept hidden in the words. “Mining” could be related to computer, geological or military domains. Other words as “model” and “work” do not provide much information when they are presented individually.

Figure 1. Possible labels for a topic model example.

These problems are also present in detecting knowledge innovation, because of the main scholar nature of the data. The detection of knowledge areas and subsequently innovation areas needs the collaboration of many experts and the study of terminologies, concepts and related areas. Many times this knowledge are not trivial to extract from a list of words, especially
when dealing with new, multidisciplinary or collaborative topics. When it comes to broader topics with massive data the problem is even bigger because the collaborative work between researchers to detect and represent the knowledge take even more time and costs more.

To improve the interpretation of topics, most of the works use as labels the top words in the distribution [2, 3, 9]. Another option is to create labels manually with the aid of someone who have expertise in that particular collection [4]. Usually, this is the most reliable option but requires a hard work from experts and it is difficult to apply when dealing with a huge amount of data. Semi-supervised approaches are another way to assign labels, as: i)classification [10, 15], where a user labels a training set, and ii)active learning [6], where the system receives feedback from experts about the created label, being also human-dependent. In this scenario, a big challenge is to automatically generate comprehensible labels, which could be applied on collections with different sizes with the same efficiency.

In this paper, we study this problem within topic models and knowledge detection and present a fast and scalable process for labeling. This process uses different methods to extract candidate labels, score and rank them, and finally select the best options.

To evaluate this proposal, we used a scholar dataset of abstracts and the results suggest that we can effectively represent a topic via the generated labels communicating the knowledge areas present in the corpus.

The rest of this paper is organized as follows. In Section 2, we present the definitions necessary to understand the steps involved in our proposal. In Section 3, we describe our process to generate automatically topic labels, followed by the evaluations described in Section 4. In Section 5, we compare and discuss related works and in Section 6, we conclude with some future works.

2. Definitions

Given a collection of documents \( \{d_1, d_2, ..., d_{|C|}\} \), where \( d_i \) is the document number \( i \), a vocabulary \( V = \{w_1, w_2, ..., w_{|V|}\} \) and a set of latent topics extracted from \( C \) (the knowledge areas), we have the problem of generating meaningful labels for each topic. To facilitate the understanding we use the following definitions:

**Definition 1.** A topic model \( \theta \) in \( C \) is a probability distribution of words such that \( \theta = \{ p(w_1|\theta), p(w_2|\theta), ..., p(w_{|V|}|\theta) \} \) and \( \sum_{w \in V} p(w|\theta) = 1 \). A “temporal text mining” topic, for example, would assign higher probabilities to the words “mining”, “text” and “temporal” and lower probabilities to uncorrelated words.

**Definition 2.** A label \( l \) for a topic model \( \theta \) is a word or sequence of words that expresses the thematic of \( \theta \). We will be using words and phrases as labels. By this definition, it comes out that there could be more than one label for a topic model since synonyms would be valid labels for a topic model \( \theta \).

Given a topic model \( \theta \) extracted from \( C \), the problem of assigning a label \( l \) for \( \theta \) can be broken into four major steps:

1. Identifying a set of candidate labels \( L = \{l_1, l_2, ..., l_n\} \).
2. Computing \( S(l_i, \theta) \), a score of the relevance of a label \( l_i \) to the topic \( \theta \).
3. Ranking \( L \) based on \( S \).
4. Selecting the top relevant label or labels for \( \theta \).

To identify label candidates, we can use candidates from a thesaurus, an ontology of the domain, a reference collection or the corpus itself. Most domains do not have a reliable thesaurus or ontology for extracting candidate labels, so we assume in this work that the candidate labels can be extracted from the collection being used.

For the other three tasks we can use probabilistic methods for topic models [14] that computes the probability of a label \( l \) relative to \( \theta \), but this tends to give high scores to uninformative labels because often we have meaningless topic words, which do not characterize the theme, mixed with the representative ones. For example, the topic from Figure 1 includes the words “results” and “show” with higher probability then informative words like “mining” and “system”.

Another way is to use traditional methods for cluster labeling and extend these to topic models. They can be differentiated into internal labeling and external or differential labeling methods [5].

Internal labeling select and score labels depending only on the contents of the cluster of interest, being more efficient and modular. External labeling select labels based on the difference between all clusters, this can be more costly but could discard common terms from the sets. We can extend these definitions for topics using topic models instead of clusters.

The main methods for internal labeling of clusters are [5]: (1) Frequency label, which is the most used and get the most frequent words from a cluster (words with highest probability, in our case); (2) Centroid labels, that give higher scores to words that appear in the centroid (the most relevant document of a topic, in our case) and; (3) Title labels, which gets the title of the centroid document as the label (in this case the label will often be a sentence, which is not desirable as we are using only words and phrases).
As for external or differential labeling we have [5]: (1) Pointwise mutual information, which in the field of information theory measures the degree of dependence of two random variables (in our case the term and topic) and; (2) Chi-square test that assess the significance of violating the hypothesis that “the presence of a word w and the membership of a cluster are independent events”.

These are some known methods to score and subsequently rank the labels. We will be adapting and extending these approaches, focusing on internal labeling because of its efficiency and because our process already filters uncommon and general terms from topics. The main challenge is to produce labels that are discriminative across topics, relevant for the understanding of the content and general enough to cover the main concepts of the topic.

In the next section, we will detail the methods proposed for each of the steps required to automatically generate the topic labels.

3. Proposal: Topic labeling process

The Figure 2 shows the process of generating labels for topics. The major subtasks are Candidate selection, Score and ranking and Label selection.

![Figure 2 – Topic Labeling Process](image)

In the next subsections, we describe all the methods used in each subtask.

3.1 Candidate Selection

To select a list of candidate labels L for a topic \( \theta \), we first need a way to extract primitive labels from documents. In our approach, we create a sample of the collection’s documents, extracting candidates only from the most relevant documents.

Each document in the collection has a probability associated for each topic, which is the proportion of words from the text that are associated to the topic. The most relevant documents for a topic \( \theta \) are those that have the highest associated probability within \( \theta \). To avoid noise in L and to maintain the scalability of the algorithm when using massive amounts of data, we take a sample of the documents in the collection based on this associated probability. Instead of using the entire collection, we use the top D documents of \( \theta \), where the number of documents D to be used in candidate selection is an input parameter received by the algorithm. With this parameter D, we do not have to apply the algorithm in the entire collection. Whenever necessary, we can increase the collection with more documents and the labels will only change if they belong to D. This characteristic makes this solution scalable to use with data intensive environments and with frequently changing sets.

After sampling the collection and retrieving D documents, we extract primitive labels from them. These primitive labels will be matched with the top W words of the multinomial distribution of \( \theta \) (the list of words sorted by probability) to generate the candidate labels. The number of words W will be an input for the algorithm alongside D. Figure 3 shows a formal description of the algorithm.

![Figure 3 – Candidate Selection Algorithm](image)

As a result, this step provides as candidate labels for \( \theta \), a list of words and phrases that match or contain some word from W.

If we use all terms from the source documents, most of them will be stopwords. Using primitive labels will also produce labels with uninformative terms that appear frequently in the documents, for example, “paper” or “results” for a scientific domain. Matching the primitive labels with the words from W could ensure that the candidates contains words related with the main concepts of the topic.

The parameter W selects only the most relevant words of a topic. This input is important because the number of words used will influence the number of candidate labels chosen.

The main part of the algorithm is the extraction of primitive labels. For this task, we use two approaches: one that generates labels only from text content (section 3.1.1) and one that uses keywords, subjects and classifications from the documents (section 3.1.2).

3.1.1 Text Methods are based on the fast keyword extraction algorithm [1], which in turn is based on the fact that labels frequently contain multiple words, but they rarely contain punctuation or stop words. The input
of the algorithm is a list of stop words, phrase (punctuation) and word delimiters (spaces). All word or sequence of words between phrase delimiters and stopwords are considered as a primitive label. The advantages of this algorithm are its simplicity, efficiency and independence from language, document type or domain. An example of the algorithm output is shown in Table 1.

<table>
<thead>
<tr>
<th>Original Text</th>
<th>Output</th>
</tr>
</thead>
<tbody>
<tr>
<td>Temporal Text Mining (TTM) is concerned with discovering temporal patterns in text information collected over time. Since most test information bears some time stamps, TTM has many applications in multiple domains, such as summarizing events in news articles and revealing research trends in scientific literature.</td>
<td>“time stamps”, “summarizing events”, “discovering temporal patterns”, “news articles”, “concerned”, “test information bears”, “applications”, “test information collected”, “temporal text mining”, “TTM”, “multiple domains”, “scientific literature”, “revealing research trends”, “time”</td>
</tr>
</tbody>
</table>

Table 1 – Output of extraction algorithm

In this article, we will name the combination between the algorithm of candidate selection and the primitive label extraction algorithm as Text Selection 1 or TS1. Some variations will be:

**TS2:** If the final candidate label has more than two words and this bigram contains a word included in the list of W top words, we will add these bigrams to the final set. This action is based on the preference of two-word phrases by human indexers [4].

**TS3:** Similar to TS2, we add bigrams if each final candidate label has more than two words and trigrams if it has more than three words. This is a form to favor short phrases in the set.

**3.1.2 Keyword Methods.** In this approach, we extract as primitive labels the keywords described by authors on each document and descriptors (i.e., classes) based on any classification schema (for example, taxonomies). The methods created are:

**KS1:** The documents keywords provided by authors are grouped as the final candidate set.

**KS2:** In addition to keywords, we use the descriptors as final candidates, too.

**KS3:** Similarly to TS3, we generate word, bigrams and trigrams for each of the final candidate labels in the set.

It is important to emphasize that not all collections have labels provided by humans in its documents. Initially, we may think that they are relevant descriptors and consequently the best candidates for a topic labeling. Unfortunately, they use to be common and general, reducing their ability to describe concepts for a topic.

The use of the descriptors of a classification reduces the generality, since these classes have restricted and specific meanings.

In our experiments, we will be comparing these methods and its variations to find differences and similarities among them and their respective performances.

### 3.2 Score and ranking

To score, we use three statistical methods: term frequencies (section 3.2.1), modified label degree (section 3.2.2) and degree/frequency ratio (section 3.2.3).

**3.2.1 Term Frequency (tf)** usually gives higher scores to stop words and non-descriptive terms when used in raw textual corpora. However, in the candidate selection of text methods, we remove stop words. In addition, by matching the list of top words W with the phrases and words, we remove a second list of irrelevant terms. Then, the tf can be used as a mechanism for removing longer sentences, which are infrequent and to highlight short labels that appear often. These frequent terms could be more general and less informative.

**3.2.2 Modified Label Degree.** The degree (deg) of a word in a collection C is defined as the sum of the frequency of the word in C and the number of times the word appears as a substring of another candidate label.

For a phrase, the degree is the sum of the degrees of its words. As this definition benefit only the longest keywords, we are defining the label degree (ldeg) as the sum of the frequency of the label and the number of times it appears as a substring of another candidate label.

This definition favors primarily unigrams because they appear more frequently, i.e., common terms such as “data” can appear in “data mining”, “data analysis”, “data warehouse”, even though those terms represent different concepts.

One solution is to balance the score, decreasing the weight of words and increasing the score of terms that make a perfect match.

Thus, we define a new function to balance words called **modified label degree** (mdeg), which gives one point for each label which appears as a substring of another candidate label and two points for every occurrence of the term, the formal notation would be: mdeg = ldeg + 2*tf. Then, comparing “data” and “data mining” with a “data mining” term would grant “data” a score of one and “data mining” a score of two. This can be especially useful when used together with candidate labels generated by TS2, TS3 and KS3, which creates bigrams and trigrams from longer terms. Then terms like “data mining models” and “data mining
algorithms” can be broken down in bigrams and favor “data mining” instead of the unigram “data”.

3.2.3 Degree/Frequency Ratio. The last approach is a ratio between the degree and the frequency of a term. Since deg favors words that occur in longer candidate keywords and tf terms with higher occurrence regardless of length, the deg(l)/tf(l) would favor terms that predominantly occur in longer candidate keywords.

An example of the scores produced by each method on a mini-set of label candidates can be seen in Table 2 for clarity.

<table>
<thead>
<tr>
<th>Label candidates</th>
<th>Candidate: “data mining”</th>
</tr>
</thead>
<tbody>
<tr>
<td>“data mining”, “data mining algorithms”, “data mining applications”, “learning algorithms”, “data”, “classifier”</td>
<td>tf</td>
</tr>
<tr>
<td></td>
<td>1</td>
</tr>
</tbody>
</table>

With the candidate labels ranked, the last task is to select from the ranking discriminative labels.

3.3 Label Selection

After we have a set of labels ordered by the score function S, the last step is to choose labels to identify each topic. A question that arises in this step is if one label is always sufficient to represent the topic or a set of labels will be necessary to clarify the thematic of the topic.

In the second case, when more than one label is required, the additional labels need to represent complementary concepts, instead of being a synonym of the first. We call this an intra-topic selection problem.

For example, in a topic about “data mining”, a second label “mining” is an irrelevant label since both represent similar concepts. Other labels such as “algorithms” and “learning” could provide a broader view and help the interpretation of the topic’s contents.

To solve this issue, we compare the selected labels to find if one of them is a substring of the other. If so, the label is discarded and the next one in the ranking replaces it.

In our experiment, we use both individual labels and a set of labels for comparison purpose. The intra-topic labeling approach will be used whenever there is a set of labels in the result.

4. Evaluation and results

In this section, we present the experiments to evaluate the effectiveness and relevance of each of the labeling methods introduced.

4.1 Evaluation Setup

4.1.1 Dataset. We use a dataset containing titles, abstracts, keywords and descriptors from KDD conference proceedings. Scholar collections often offer challenges for labeling, because they frequently have new terms on the collection and specific terms that are not of common knowledge.

To create the dataset, we downloaded articles from the conference proceedings, from 2004 to 2014, at the ACM digital library.

The collection has 1.483 documents with 10,506 unique terms. Title and abstract were extracted from each article and tokenized to be used in the topic model algorithm. The keywords and subject descriptors were extracted and stored to be used with the keywords methods.

4.1.2 Topic Extraction. We use the dataset as input for the statistical topic model algorithm LDA [3]. The LDA algorithm needs a parameter K, representing the number of topics to extract from the text. We are using a stability analysis approach for topic models described in [7] to infer automatically the best value for the collection. The method infers K based on the stability of the top M words in the multinomial distribution of each topic. Using M = 10, we find that the best for K is 37, then 37 topics were extracted from the collection.

Table 3 shows some of the topics extracted and the top 10 words with highest probabilities. Note that it is difficult, even for a human (especially with no background context), to interpret some topics only using the words. As an example, topic 2 is about optimization methods.

4.1.3 Method Application. With the topics extracted, the next step is to apply our methods for automatic label generation.

First, we have to set the two parameters required by the candidate selection algorithm: The number of documents to sample D and the number of top words from the multinomial word distribution W. As our methods will not be applied in the entire collection, these two parameters can have a heavy influence on the output. These parameters need to be estimated and in
our empirical tests, we found a value around ten as a good one. Decreasing W would reduce the number of candidates and this can increase noise terms in the final set. Increasing it would add words with fewer probabilities and consequently, less relevant for the topic. The same can be said for D. Decreasing it would favor specific candidates of few documents, while increasing it would include documents where the proportion of the topic is lower and then introducing more candidates unrelated to the topic. Therefore, we are using D = W = 10 as the input parameters when applying the candidate selection algorithm. Note that the time complexity of the methods depends on W and on the size of the primitive label set, which in turn depends on D. Because of the modularity of the method, it can be applied one topic at a time or even in parallel, but as we work with sampling, higher values for D and W would mean more processing. The additional steps of adding bigrams and trigrams adds one more matching with W to filter those new candidates.

As notation for the methods, we have for text-based methods: TS1 for the main candidate selection algorithm, TS2 and TS3 as its respective variations. For keyword methods, we similarly use KS1, KS2 and KS3. For the score functions, we are using: TF, MDeg, and Deg/TF.

Possible combinations between candidate selection methods and score functions are shown in Table 4. The combinations of candidate selection methods and score functions give us 15 methods to use in the experiments. Note that we only use MDeg in TS1, since the degree already counts terms that make partial matches. This is the same reason for not using MDeg with KS3.

Finally, the label selection is applied. For all combinations that use text methods, we will select the top label as the final label and a set of the three top-ranked labels as another option. In the keyword methods, we are choosing only the first ranked label since we have few keywords per document.

For notation purposes, we will be appending a “top-1” when we talk about the method with only one label and a “top-3” for the three labels set. For example, a TS1-TF with only one label selected will be called “TS1-TF (top-1)” and so on.

<table>
<thead>
<tr>
<th>Combination</th>
<th>Candidate Selection</th>
<th>Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>TS1-TF, TS2-TF, TS3-TF</td>
<td>TS1, TS2, TS3</td>
<td>TF</td>
</tr>
<tr>
<td>TS1-MDeg</td>
<td>TS1</td>
<td>MDeg</td>
</tr>
<tr>
<td>TS1-DTF, TS2-DTF, KS3-DTF</td>
<td>TS1, TS2, TS3</td>
<td>Deg/TF</td>
</tr>
</tbody>
</table>

### 4.2 Evaluation Execution

To evaluate the quality and coverage of the automatic labels, we compared the created labels with human generated labels.

The experiment was made with the help of a group of seven people (all of them specialists in Computer Science), who were introduced to the set of topics and their respective final labels generated automatically by our proposal. A baseline method consisting of the top five terms of the topics was included as a label for comparison purposes.

After this, the group was asked to:

1. Define a label to each extracted topic, according to their understanding of its contents. They had access and could read the documents of the sample, to help the interpretation of the knowledge area.
2. Score each label with a value from one to five, according to how well the label represents the topic.
3. Score each label from one to five according to how semantically similar an automatic label is to the manual label.

The values from three to five of the representation score were defined as good scores. Labels with these values for the score could be used to represent a topic satisfactorily. The higher value (five) means that the label represents completely and exactly a topic. The minimum value (one) means that the label is unrelated or inappropriate.

Likewise, the values from three to five of the similarity score mean that both the automatic and human labels could be used to represent the topic. A value of five means that the labels are almost or identical and a value of one means they are unrelated.

The similarity score helps us to address some limitations encountered in the quantitative evaluation of labels based on the equality comparison between human and automatic labels. If two labels are synonyms or can be used interchangeably, lexically comparing both will give lower scores even if they were a semantical match.

### 4.3 Results

Table 5 shows some topics where most of the participants agreed on a manual label and the results of the algorithms tested. We show the top-3 ranked label set to facilitate the comparison between the top-1 and top-3 options.
At first sight, we can see that the combination between keyword-based methods and the Deg/TF ratio results in the strangest methods. It happens because Deg/TF helps longer labels containing frequent words inside. Longer labels in a keyword set tend to be document specific keywords and so, the score is not considering more general terms. The combination with MDeg is not satisfactory as well. The keywords tend to have around two words and so the score given to substrings of this function do not provide better results.

For KS methods, the best approach seems to use the TF score function. Using only keywords seems to produce better labels for the topics. Adding descriptors and bigrams only made the labels too general.

For the TS methods, TF and MDeg had good results, with TS1-TF and TS1-MDeg matching the human labels in the top-1 more than any other does. The DTF functions select related labels, but not as accurate as the other two methods. It could be used to highlight other aspects of the topic.

To assess the quality of the labels, we can view the Table 6, which contains the average score given by the human annotators to the labels generated by each method for all topics. The results confirm our suspicions, giving a low score to KS methods combined with DTF score functions and higher scores with TF and MDeg functions for both methods.

**Basic Results:** In general, DTF had a worse performance compared to the other score functions. The best score functions overall were TF and MDeg, which had achieved better performances in the TS methods. The TF was the best function in both keyword and text-based methods. We can see that the variations that added bigrams and trigrams to the sets (TS2, TS3 and KS3) ended up not giving higher scores for these methods.

The MDeg did not do well with keyword-based approaches; this could be because of the size of the candidates. If the collection has mostly bigrams and trigrams, it becomes difficult to match substrings between terms.

The baseline method, which used the top-5 words from the distribution as a label set, did not go well too. The method scored worse than all other methods in both measures besides the DTF combined with KS.

Another observation is that the TF and MDeg methods for TS have an average score of three, thus we can conclude that, in average, the labels generated were good for representing the knowledge topic.

**Top-3 vs Top-1:** We had consistent increases in both representation and similarity measures when using a top-3 selection approach (a set of three top-ranked labels as the final label set) compared with a top-1 selection regardless of the method selected.

**Representation vs Similarity:** All methods had gotten fewer similarity scores than representation scores. For TS methods combined with TF and MDeg we still have an average score of three which is regarded as a good similarity between the human description and the automatic description.

These results suggest that the TS1-TF and TS1-MDeg are best methods when we are using text-based approaches, when we only have text as a source. The KS1-TF is the best choice if we have some type of labels associated with the text such as author keywords.

The other suggestion is that it is possible to generate good labels for topic models without processing the entire corpus. This can be promising for big data environments or when using dynamic collections, where processing the entire collection each time a new document appears is infeasible.

### 5. Related work

Most works in multinomial topic models have been using the distribution over words to represent the knowledge of a topic [2, 3, 9].

Some works have used external databases to generate labels for topic models, especially Wikipedia articles [10, 16]. While the articles of an online encyclopedia is a useful context database, we could argue that for frequently changing datasets with specific terms, such as scholar domains and innovative knowledge areas, the label results could be too general.

While not directly related with topic models, a few works have been using only phrase extraction methods to group documents [8, 17]. These approaches have an intensive processing since the methods use all terms of the entire collection to detect and represent areas.

[13] proposed a method for labeling topics induced by hierarchical topic modelling, based on ontological alignment, and optionally expanding topics based on a thesaurus or WordNet. The experiments give good results, but the method is limited because it relies on both a hierarchical topic model and a pre-existing ontology.

In [11], we are introduced to a method for selecting the best word from the distribution to represent a topic model. The drawback is that often a topic cannot be represented by a single word, or is not explicit in the distribution, for example, a “dog, cat, duck…” distribution would not be about dog or cat, but about animals, a concept latent in the distribution. As our work considers phrases from most relevant documents, we can represent topics with those and although the lack of explicitness of terms is a problem for our method too, we can access terms that could be in the context of one of the words and therefore select good representations as part of phrases(for example, “cat fish animals”).

The most related work is [14], which proposed some unsupervised approaches for automatically labeling
Table 5 – Automatic Labels x Human Labels

<table>
<thead>
<tr>
<th>Method</th>
<th>Human</th>
<th>Label</th>
<th>Representation (top-1)</th>
<th>Representation (top-3)</th>
<th>Similarity (top-1)</th>
<th>Similarity (top-3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>TS1-TF</td>
<td>social networks, nodes, connection subgraphs</td>
<td>clusters, clustering, algorithms</td>
<td>active learning, labeled data, labels</td>
<td>collaborative filtering, recommender systems, users</td>
<td></td>
<td></td>
</tr>
<tr>
<td>TS2-TF</td>
<td>social networks, large social network graphs, nodes</td>
<td>clusters, clustering, algorithms</td>
<td>labeled data, labels, unlabeled data</td>
<td>collaborative filtering, recommender systems, users</td>
<td></td>
<td></td>
</tr>
<tr>
<td>TS3-TF</td>
<td>social networks, large social network graphs, networks graphs</td>
<td>clusters, clustering, algorithms</td>
<td>labeled data, active learning, labels</td>
<td>collaborative filtering, recommender systems, users</td>
<td></td>
<td></td>
</tr>
<tr>
<td>TS1-MDeg</td>
<td>social networks, social network, graph</td>
<td>clustering, clusters, subspace cluster</td>
<td>active learning, label, labeled data</td>
<td>collaborative filtering, recommender systems, users</td>
<td></td>
<td></td>
</tr>
<tr>
<td>TS1-DTF</td>
<td>social network, large network, data structures</td>
<td>real data, categorical objects, subspace clustering</td>
<td>binary classification, active learning, active labeling</td>
<td>tag recommender, recommendation based, recommender systems</td>
<td></td>
<td></td>
</tr>
<tr>
<td>TS2-DTF</td>
<td>large network, social network, large networks</td>
<td>real data, categorical objects, real world</td>
<td>classification algorithm, binary classification, learning algorithm</td>
<td>tag recommender, recommendation based, filtering methods</td>
<td></td>
<td></td>
</tr>
<tr>
<td>TS3-DTF</td>
<td>social communication, communication network, compressing social</td>
<td>real data, quality hierarchical, approach seamlessly</td>
<td>fully supervised, classification algorithm, label efficient</td>
<td>user preferences, user posts, reputable user</td>
<td></td>
<td></td>
</tr>
<tr>
<td>KS1-TF</td>
<td>social networks</td>
<td>clustering</td>
<td>active learning</td>
<td>recommender systems</td>
<td></td>
<td></td>
</tr>
<tr>
<td>KS2-TF</td>
<td>social networks</td>
<td>clustering</td>
<td>learning</td>
<td>recommendation</td>
<td></td>
<td></td>
</tr>
<tr>
<td>KS3-TF</td>
<td>networks</td>
<td>data mining</td>
<td>active learning</td>
<td>data mining</td>
<td></td>
<td></td>
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<td>KS1-MDeg</td>
<td>quality</td>
<td>clustering</td>
<td>data mining</td>
<td>subspace clustering</td>
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<tr>
<td>KS2-MDeg</td>
<td>experimentation</td>
<td>episode mining</td>
<td>information search and retrieval</td>
<td>learning</td>
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<tr>
<td>KS1-DTF</td>
<td>user generated content</td>
<td>minimum description length principle</td>
<td>interactive and online data mining</td>
<td>hybrid content and collaborative filtering</td>
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<td></td>
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<tr>
<td>KS2-DTF</td>
<td>user generated content</td>
<td>minimum description length principle</td>
<td>interactive and online data mining</td>
<td>user profiles and alert services</td>
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<td></td>
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<tr>
<td>KS3-DTF</td>
<td>learning</td>
<td>kernel</td>
<td>Misclassification</td>
<td>filtering</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Top-5 words</td>
<td>graph, graphs, network, nodes, networks</td>
<td>clustering, cluster, clusters, objects, experiments</td>
<td>training, labeled, classification, classifier, supervised</td>
<td>users, recommendation, user, system, collaborative</td>
<td></td>
<td></td>
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Table 6 - Average scores for label generation methods

<table>
<thead>
<tr>
<th>Method/Measure</th>
<th>Representation (top-1)</th>
<th>Representation (top-3)</th>
<th>Similarity (top-1)</th>
<th>Similarity (top-3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>TS1-TF</td>
<td>3.69</td>
<td>3.83</td>
<td>3.15</td>
<td>3.53</td>
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<tr>
<td>TS2-TF</td>
<td>3.34</td>
<td>3.50</td>
<td>3.08</td>
<td>3.17</td>
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<td>TS3-TF</td>
<td>3.22</td>
<td>3.45</td>
<td>3.01</td>
<td>3.32</td>
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<tr>
<td>TS1-MDeg</td>
<td>3.75</td>
<td>3.85</td>
<td>3.13</td>
<td>3.55</td>
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<td>------</td>
<td>------</td>
<td>------</td>
<td>------</td>
</tr>
<tr>
<td>TS1-DTF</td>
<td>2.64</td>
<td>3.52</td>
<td>2.30</td>
<td>2.36</td>
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<tr>
<td>TS2-DTF</td>
<td>2.58</td>
<td>3.48</td>
<td>2.27</td>
<td>2.36</td>
</tr>
<tr>
<td>TS3-DTF</td>
<td>2.54</td>
<td>3.36</td>
<td>2.07</td>
<td>2.34</td>
</tr>
<tr>
<td>KS1-TF</td>
<td>3.45</td>
<td>-</td>
<td>2.87</td>
<td>-</td>
</tr>
<tr>
<td>KS2-TF</td>
<td>2.71</td>
<td>-</td>
<td>2.03</td>
<td>-</td>
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<tr>
<td>KS3-TF</td>
<td>2.60</td>
<td>-</td>
<td>1.89</td>
<td>-</td>
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<tr>
<td>KS1-MDeg</td>
<td>2.54</td>
<td>-</td>
<td>1.96</td>
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<tr>
<td>KS2-MDeg</td>
<td>2.12</td>
<td>-</td>
<td>1.25</td>
<td>-</td>
</tr>
<tr>
<td>KS1-DTF</td>
<td>1.72</td>
<td>-</td>
<td>1.37</td>
<td>-</td>
</tr>
<tr>
<td>KS2-DTF</td>
<td>1.35</td>
<td>-</td>
<td>1.30</td>
<td>-</td>
</tr>
<tr>
<td>KS3-DTF</td>
<td>1.22</td>
<td>-</td>
<td>1.19</td>
<td>-</td>
</tr>
<tr>
<td>Top-5 words</td>
<td>2.02</td>
<td>-</td>
<td>1.31</td>
<td>-</td>
</tr>
</tbody>
</table>

topics, generating label candidates by extracting either bigrams or noun chunks from the entire document collection; and ranking the label candidates based on KL-divergence with a given topic. The best method uses bigrams exclusively, in the form of the top-1000 bigrams based on the Student’s t-test. [10] argue that the best method performs worse than the baseline and that for large text collections the scoring method is intractable. Other drawback is that the labels must be bigrams. In our methods, some of these problems were addressed since we do not use the entire collection for labeling and included words and n-grams as candidates. Since their experiments do not inform the values of the parameters used for their methods, a comparison with our experiments was not possible.

At last, other works have extended topic models to work with n-grams [12, 18]. Those were limited by using only one type of topic model algorithm, and as with the word distributions, many grams are irrelevant because of the latent nature of the text.

6. Conclusion

The challenge of extracting and representing knowledge areas from text data are essential for knowledge innovation analysis. The areas can be used as a map of the contents of the source data. The representation is important to contextualize the researchers in the thematic of the areas detected, facilitating the communication and collaboration between researchers from different areas. For these tasks, we used a topic modeling approach.

Topic modeling over time turned out to be a very attractive area of study, with many applications in both machine learning and text mining domains. Despite the amount of works concerning the use of such models, no methods could provide a fast and robust automatic label generation process for extracting useful labels for the representation of the topic contents. The use of these models in real world applications is thus limited without understandable labels. With the recent and future predictions of data growth, fast and scalable approaches would be preferred over resource consuming ones.

In this work, we deal with the problem of generating automatic labels from a multinomial topic model to detect and represent knowledge. We introduce both text-based and keyword-based methods for candidate selection from a sample of a document collection. We use some statistical scores to rank these labels according to the characteristics of the sampling (such as being small). Finally, we select labels taking into consideration intra-topic issues and generate sets of one label and three labels.

Our results, evaluated qualitatively by human annotators on a conference proceedings data set, shows that term frequencies and our new score function, modified degree, give us the best ranking of label candidates for text-based label generation. For keyword-based generation, a simple term frequency approach was the preferred method.

The main contributions of this work are:

1. A new candidate selection algorithm for labeling topic models, which considers the association between the model and the labels via its words, dropping out stop-words and frequent topic-irrelevant labels, to increase the chance of getting relevant general terms.

2. A method that is:

(1) Fast and scalable, since we are generating labels based in a sampling of documents instead of the entire collection, which can be used as a post-processing step for labeling existing topics independent of the collection size;

(2) Incremental friendly, because adding documents to the topic only alter the labeling if they enter in the
document sample and if so, we only need to apply the labeling to the particular topic (thanks to the internal labeling approach);

3. A new score function, modified label degree, which balances n-gram phrases and words. Given the experiments, the function is suggested to be a good one for ranking labels.

Although we get good results for the labels generated, we have to bring the automatic labels closer to the human generated ones, since they are less similar to each other, even being representative of the topic.

Future work could make use of a label selector for automatic selection of the best number of labels to represent the topic instead of using top-1 or top-3 labels. Another direction could be to apply the methods in another context or using external bases for label generation to assess if the method can generate satisfactory results for contextual labeling as well. Application to cluster labeling is trivial too, given a term representation of clusters. Hierarchical topic models present a challenge for our method, because of our sampling of the collection. A solution could be to sample discriminative documents inside each topic instead of top documents. Finally, we could test the methods with different kinds of data sets, such as social network data or email messages, which do not have a formal language as scholar data and which are getting important for knowledge innovation as new sources of information.

7. Acknowledgments

We would like to thank CAPES, CNPq and FAPERJ, as also those who participated on the experiment.

8. References