Fast Top-\(k\) Area Topics Extraction with Knowledge Base

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Abstract

What are the most popular research topics in Artificial Intelligence (AI)? We formulate the problem as extracting top-\(k\) topics that can best represent a given area with the help of knowledge base. We theoretically prove that the problem is NP-hard and propose an optimization model, FastKATE, to address this problem by combining both explicit and latent representations for each topic. We leverage a large-scale knowledge base (Wikipedia) to generate topic embeddings using neural networks and use this kind of representations to help capture the representativeness of topics for given areas. We develop a fast heuristic algorithm to efficiently solve the problem with a provable error bound. We evaluate the proposed model on three real-world datasets. Experimental results demonstrate our model\’s effectiveness, robustness, real-time (return results in \(< 1s\)), and its superiority over several alternative methods.

1 Introduction

Automatically extracting top-\(k\) topics of a given area is fundamental in the historical analysis of the given area. With the ability of solving this problem, not only can we gain an accurate overview of the given area, but it can also help make our society more efficient, such as giving suggestions on how to optimize the allocation of resources (e.g., research fundings) to more representative and important topics. This can also provide guidances to newcomers of the area. However, there are too many topics in almost any areas, and for any researcher, it is non-trivial for him/her to extract the top-\(k\) topics of the given area in a short period of time, especially if the researcher is a newcomer to the area. Therefore it is important to find a way to automatically solve this problem.

Unlike much research has been conducted on the topic extraction problem, their main focus is basically on document topic extraction, but not on area topic extraction. For example, in (Blei, Ng, and Jordan 2003), latent dirichlet allocation (LDA) model is used to model topics in documents and abstracts, where topics are represented as multinomial distributions over words. Topics can also be represented as keyphrases (or topical phrases), and under this perspective, keyphrases extraction task can also be viewed as topic extraction task. Different models such as frequency-based (Salton and Buckley 1997), graph-based (Mihalcea and Tarau 2004), clustering-based (Grineva, Grinev, and Lizorkin 2009) and so on have been explored to address the keyphrase extraction problem, but still focus on a document instead of an area.

The problem of area topic extraction is novel, non-trivial and poses a set of unique challenges as follows: (1) How to formulate the problem and using what kind of datasets and how to use it is not clear. (2) How to capture the representativeness of topics for a given area is another challenging issue. (3) The number of candidate topics in a given area may be very large. There are 14,449,404 page titles (including categories) in Wikipedia and even after we do some preprocessing on it, we still get 9,355,550 topics. Thus how to develop an efficient algorithm to apply it in practice is important too. (4) Since there are no standard benchmarks that can perfectly match this problem, how to quantitatively evaluate the results is also a challenging issue.

To address these challenges, in this paper, we give a formal definition of the problem and develop an optimization model to efficiently solve it. Our contributions can be summarized as follows:

- To the best of our knowledge, this is the first attempt to formulate and address the area topic extraction problem. We formulate the problem as extracting top-\(k\) topics that can best represent a given area with the help of knowledge base. We theoretically prove that the problem is NP-hard.

- We propose an optimization model, FastKATE, to address this problem by combining both explicit and latent representations for each topic. We leverage a large-scale knowledge base (Wikipedia) to generate topic embeddings using neural networks and use this kind of representations to help capture the representativeness of topics for given areas. We develop a fast heuristic algorithm to efficiently solve the problem with a provable error bound.

- We evaluate the proposed model on three real-world datasets. Experimental results demonstrate our model\’s effectiveness, robustness, real-time (return results in \(< 1s\)), and its superiority over several alternative methods.
2 Problem Formulation

We first provide necessary definitions and then formally define the problem.

Definition 1. Knowledge Base and Topic. A knowledge base is represented as a triple $KB = (C, R, X)$, where $C$ represents a set of topics, $R$ represents a set of relations between topics, and $X$ represents a set of co-existences between topics, i.e., each $x_i \in X$ is a sequence of topics $\{t_{i1}, t_{i2}, t_{i3}, \ldots\}$, where $t_{ij} \in C$.

This definition is a variation of that in (McGuinness, Van Harmelen, and others 2004; Tang et al. 2015). In our work, $X$ represents a corpus consisting of massive documents, and each document is a sequence of topics. Relations $R$ may have various types; we focus on sub-topic and super-topic relations in our work.

Each topic $t \in C$ in a knowledge base $KB$ already has a corresponding topical phrase, such as “Artificial Intelligence”. To help grasp the relations/similarities between these topical phrases, we also represent each topic $t \in C$ as a vector $v_t \in \mathbb{R}^n$ in a latent feature space, where $n$ is the dimension of the feature space, which will be detailed in section 5.1. Thus each topic in our work has both explicit representation (i.e., topical phrase) and latent representation (i.e., vector).

Definition 2. Area. In this paper, an area $r$ is essentially also a topic in $C$. Thus it has the same form and attributes as other topics in $C$. An area may be also a topic of some other area. For example, Machine Learning is an area, and it can also be viewed as a topic of Artificial Intelligence area.

We leverage a knowledge base to help extract topics from a given area in our work. We formally define the problem as follows.

Problem 1. Extracting top-$k$ topics in a given area.

The input of this problem includes an external knowledge base $KB = (C, R, X)$, a given area $r \in C$ and the number $k \in \mathbb{Z}^+$ of topics needed to be extracted.

The output of this problem is a set of top-$k$ topics $T^k = \{t | t \in C\}$ which can represent the given area best.

Our goal is to learn a function $f$ from the given input so as to extract the top-$k$ topics which can represent the given area best. More specifically, $f$ is defined as:

$$f : \{r, k, KB = (C, R, X) | r \in C, k \in \mathbb{Z}^+\} \rightarrow \{T^k = \{t | t \in C\}\}.$$

This problem is equivalent to selecting $k$ topics from the topics set $C$ that can represent the given area $r$ best. We use $D(T^k, C, r)$ to denote the degree of how well a set of $k$ topics $T^k \subseteq C$ can represent all topics in $C$ on the given area $r$. Without loss of generality, we assume $D(T^k, C, r) \geq 0$. And since adding new topics to $T^k$ should not reduce the representativeness of previous extracted topics, $D(T^k, C, r)$ should be monotonically non-decreasing. We also assume reasonably that topics added in early steps should not help (actually it may damage) topics added in later steps increase the value of the goal function. This means that a topic added in later steps contribute equal or possibly less to the goal function compared with that when the same topic is added in early steps. This is intuitive and reasonable because if a topic is added in later steps, some previous added topics may already have a good representation of the area, and thus this topic’s contribution to the goal function may be decreased. We will show that this attribute implies the goal function’s submodularity (Svitkina and Fleischer 2011) in the following section. Then our problem can be reformulated as follows:

$$T^k = \arg\max_{T^k \in C, |T^k| = k} D(T^k, C, r),$$

where $D(T^k, C, r)$ is a non-negative and monotonically non-decreasing function.

3 The Proposed Model

We propose FastKATE (Fast top-$K$ Area Topics Extraction) to address the problem. In general, FastKATEnot only represents topics in explicit forms (phrases) as in knowledge bases, but also represents topics as vectors in a latent feature space, and uses a neural network-based method to learn topic embeddings from an external large-scale knowledge base. FastKATE further incorporates domain knowledge from the knowledge base to assign “general weights” to different topics to help solve the problem. We develop a heuristic algorithm to efficiently solve the defined problem and we prove our algorithm is at least $(1 - 1/e)$ of the optimal solution. We further develop a fast implementation of our algorithm which can return results in real-time.

3.1 Topics Representation

We first generate $C$ and use it as candidate topics and then train embeddings $v_t \in \mathbb{R}^n$ for each topic $t \in C$. We use Wikipedia as our knowledge base $KB$ to help generate candidate topics and train topics embeddings. We extract 14,449,404 titles of all articles and categories from Wikipedia, and convert them into lower forms and remove possible duplicates and those consisting of punctuations from these titles. Finally we get 9,355,550 titles as candidate topics. Then we use an unsupervised neural network-based method to learn the embeddings of these topics. We then preprocess the Wikipedia corpus to keep only candidate topics in the corpus, and use the preprocessed Wikipedia corpus as our training data. We adopt a similar method to that used in Word2Vec (Mikolov et al. 2013). We treat each topic as a single token, and use a Skip-Gram model to generate each topic’s embedding. In the Skip-Gram model, the training objective is to find topic embeddings that are useful for predicting surrounding topics. More formally, given a sequence of training topics, $t_1, t_2, t_3, \ldots, t_N$, the objective of the Skip-Gram model is to maximize the average log probability

$$\frac{1}{N} \sum_{i=1}^{N} \sum_{-c \leq j \leq c, j \neq 0} \log p(t_{i+j} | t_i).$$
where \( c \) is the size of the training context (also denoted as window size), and \( p(t_{i+j} | t_i) \) is defined using the softmax function:

\[
p(t_0 | t_I) = \frac{\exp(v_{t_0}^T \cdot v_{t_I})}{\sum_{i=1}^{T} \exp(v_{t_i}^T \cdot v_{t_I})}
\]

where \( v_{t_I} \) and \( v_{t_0} \) are the embeddings of “input topic” \( t_I \) and “output topic” \( t_0 \) respectively, and \( T \) is the number of total candidate topics. Because \( T \) is very large, this calculation is very computationally expensive. Thus we adopt a common approximation in our model: Negative Sampling (NEG) (Mikolov et al. 2013), which can speed up the training process greatly. Using NEG, \( \log p(t_0 | t_I) \) is replaced by:

\[
\log \sigma(v_{t_0}^T \cdot v_{t_I}) + \sum_{i=1}^{l} E_{t_i \sim \text{Noise}(t)}[\log \sigma(-v_{t_i}^T \cdot v_{t_I})],
\]

where \( \sigma(x) = 1/(1+\exp(-x)) \), \( \text{Noise}(t) \) is the noise distribution of topics, and \( l \) is the number of negative samples of each topic. Thus the task is to distinguish the target topic \( t_0 \) from draws from the noise distribution \( \text{Noise}(t) \). We also do subsampling (Mikolov et al. 2013) of frequent topics in our model to counter the imbalance between rare and frequent topics: each topic \( t_i \) in the training set is discarded with probability computed by the formula:

\[
P(t_i) = 1 - \frac{\delta}{F(t_i)},
\]

where \( F(t_i) \) is the frequency of topic \( t_i \) and \( \delta \) is a chosen threshold, typically around \( 10^{-5} \).

**Algorithm 1: Top-k Area Topics Extraction**

**Input:** Area \( r \), knowledge base \( KB = (C, R, X) \), the number \( k \) of topics to extract, general weights \( \{w_j^f\}_3 \) of topics in \( C \).

**Output:** The top-k topics set \( T^k \).

1. \( T = \emptyset; \)
2. while \( |T| < k \) do
   1. \( m = -1; \)
   2. foreach \( t_I \in C \setminus T \) do
      1. \( s = 0; \)
      2. foreach \( t_J \in C \) do
         1. \( s += w_j^f D(T \cup \{t_I\}, \{t_J\}, r); \)
      3. if \( s > m \) then
         1. \( t = t_I; \)
         2. \( m = s; \)
   3. \( T = T \cup \{t\}; \)
3. return \( T; \)

### 3.2 Top-k Area Topics Extraction

As stated in section\( \square \) our problem is formulated as an optimization problem:

\[
T^{k*} = \arg \max_{T^k \in C, |T^k| = k} D(T^k, C, r),
\]

where \( D(T^k, C, r) \) is a function that denotes the degree of how well a set of \( k \) topics \( T^k \subseteq C \) can represent all topics in \( C \) on the given area \( r \).

**NP-hardness.** We first prove the problem is NP-hard by reducing Dominating Set Problem (Karp 1972; Gary and Johnson 1979) to this problem as follows.

**Proof.** For \( t_i, t_j \in C \), we first define the relativeness between \( t_i, t_j \) as \( I(t_i, t_j) \in [-1, 1] \), and if \( I(t_i, t_j) \geq 0 \), we assign an undirected edge \( e_{ij} \) between \( t_i \) and \( t_j \); otherwise, there is no edge between \( t_i \) and \( t_j \). Thus we get an undirected graph \( G = (C, E) \) of all concepts in \( C \), where \( E \) is the set of all edges in \( G \).

Then we define \( D(T^k, \{t_i\}, r) = D(T^k, \{t_i\}, r) = 1 \) if \( \exists t_a \in T^k \) such that \( e_{ai} \in E; D(T^k, \{t_i\}, r) = 0 \) otherwise. And then we define \( D(T^k, C, r) \) as:

\[
D(T^k, C, r) = \sum_{t_i \in C} D(T^k, \{t_i\}, r).
\]

We then show that if we can find the maximum value \( M = \max D(T^k, C, r) \), we can also decide that for the given number \( k \in \mathbb{Z}^+ \), whether there exists a dominating set \( G^* = \{C^*, E^*\} \) where \( C^* \subseteq C \) and \( E^* \subseteq E \) such that \( |G^*| \leq k \). The reduction process is as follows: we compare \( M \) with \( |C| \) which is the number of concepts in \( C \), and according to our definition of \( D(T^k, C, r) \) and \( D(T^k, \{t_i\}, r) \), it must hold that \( M \leq |C| \). If \( M = |C| \), then \( \forall t_i \in C \) such that \( \exists t_a \in E \), which means there exists a dominating set \( G^* \) such that \( |G^*| \leq k \); if \( M < |C| \), then \( \forall t_i \in C \) such that \( \forall t_a \in T^k, e_{ai} \notin E \), which means there does not exist a dominating set \( G^* \) such that \( |G^*| \leq k \).

**Heuristic Algorithm.** Since the problem is NP-hard, we propose an approximate heuristic algorithm in our model to solve it, as outlined in Algorithm\( \square \) and detailed as follows. The main idea is that we select topics one by one, and in the \( i \)-th step, we select topic \( t_j^* \) such that

\[
t_j^* = \arg \max_{t_j \in C, t_j \notin T^i} D(T^i \cup \{t_j\}, C, r),
\]

where \( t_i^* \) is the selected topics set before the \( i \)-th step. To calculate \( D(T^i \cup \{t_j\}, C, r) \), we introduce the general weight \( w_j^f \) to measure the importance of topic \( t_i \) in the given area \( r \). We call \( w_j^f \) general weight because this value will be set by utilizing some domain knowledge and may probably be not very precise and can only measure the importance of \( c_i \) in area \( r \) to some general extent. We will demonstrate the calculation process of \( w_j^f \) in the following part. Then we define \( D(T^i \cup \{t_j\}, C, r) \) as:

\[
D(T^i \cup \{t_j\}, C, r) = \sum_{t_h \in T^i \cup \{t_j\}} \sum_{t_i \in C} w_j^f D(\{t_h\}, \{t_i\}, r),
\]

and define \( D(\{t_h\}, \{t_i\}, r) \) as:

\[
D(\{t_h\}, \{t_i\}, r) = S(t_h, t_i),
\]

where \( S(t_h, t_i) \) represents the relativeness between \( t_h \) and \( t_i \).
After we get the embeddings of topics in section 3.1, we can calculate $S(t_h, t_l)$ as follows:

$$S(t_h, t_l) = \frac{\mathbf{v}_{t_h} \cdot \mathbf{v}_{t_l}}{\|\mathbf{v}_{t_h}\| \cdot \|\mathbf{v}_{t_l}\|},$$

where $\mathbf{v}_{t_h}$ and $\mathbf{v}_{t_l}$ are the embeddings of $t_h$ and $t_l$ respectively.

**General Weight Calculation.** To calculate the general weight $w^r_i$ of topic $t_i \in C$ in the given area $r$, we incorporate the domain knowledge from an external large-scale knowledge base into our model. This shares a similar idea as Distant Supervision (Mintz et al. 2009). We still use Wikipedia as our knowledge base here, and use category information of the given area $r$ as the domain knowledge to help calculate $w^r_i$. The idea behind the calculation of general weight is that topics in shallower depth of subcategories of $r$ are probably more important in area $r$. More specifically, we calculate $w^r_i$ in the following steps:

- Find the category that $r$ represents in Wikipedia, which is also denoted as $r$.
- For the given area $r$, extract its all subcategories $SC = \{\{t_0\}, \{t_{11}, t_{12}, \ldots\}, \{t_{21}, t_{22}, \ldots\}, \ldots\}$ recursively from Wikipedia, where $t_0$ is the root category $r$ and $t_{mn}$ represents the $n$-th subcategory in depth $m$.
- Calculate the general weight $w^r_i$ of topic $t_i \in C$ as:

$$w^r_i = g(n),$$

where $n$ is the depth of topic $t_i$ in $r$’s subcategories if $t_i \in SC$; otherwise $w^r_i = 0$ (or equivalently set $n = \infty$ if we want to put all topics in $SC$). $g(n)$ is a monotonically decreasing function of $n$, and can be selected empirically.

**Algorithm 2:** Fast Top-$k$ Area Topics Extraction

**Input:** Area $r$, high-quality candidate topics set $C'^r_{d_1}$, contributive topics set $C'_{d_2}$, the number $k$ of topics to extract, general weights $\{w^r_i\}_i$ of topics in $C$.

**Output:** The top-$k$ topics set $T^k$.

$T = \emptyset$;

while $|T| < k$ do

$|T| = 1$;

foreach $t_i \in C'^r_{d_1} \setminus T$ do

$s = 0$;

foreach $t_j \in C'^r_{d_2}$ do

$s += w^r_{ij} D(T \cup \{t_i\}, \{t_j\}, r)$;

if $s > m$ then

$t = t_i$;

$m = s$;

$T = T \cup \{t\}$;

return $T$;

3.3 Algorithmic Analysis

We argue that Algorithm [1] has at least an $(1 - 1/e)$-approximate of the original NP-hard problem. We first prove that the goal function of the original optimization problem is non-negative, monotonically non-decreasing, and submodular, and then we use these properties to prove its error bound. By definition the goal function is non-negative and monotonically non-decreasing; thus we only show its submodularity as follows.

**Proof.** As stated before, the problem is formulated as follows:

$$T^{k*} = \arg \max_{T^k \in C, |T^k| = k} D(T^k, C, r),$$

where $D(T^k, C, r)$ is the goal function which represents the degree of how well topics set $T^k$ can represent $C$ in the given area $r$. For a given topic $t_j \notin T^k$, we first denote $a_1 = D(T^k \cup \{t_i\}, C, r) - D(T^k, C, r)$, which means the increment to the goal function by adding $t_i$ to $T^k$. Then we add a topic $t_j \neq t_i$ and $t_j \notin T^k$ to $T^k$, and denote $a_2 = D(T^k \cup \{t_j, t_i\}, C, r) - D(T^k \cup \{t_j\}, C, r)$. By the attribute of $D(T^k, C, r)$ we assume in section 3.1, we have $a_2 \leq a_1$, which means the goal function is submodular.

Since the goal function of our problem is monotonically increasing, nonnegative and submodular, the solution generated by Algorithm [1] is at least $(1 - 1/e)$ of the optimal solution (Nemhauser, Wolsey, and Fisher 1978; Kempe, Kleinberg, and Tardos 2003).

3.4 Fast Implementation

The time complexity of Algorithm [1] is $O(k|C|^2)$, where $k$ is the number of topics needed to be extracted and $|C|$ is the number of elements in $C$. In practical use, $k \leq 100$, but $|C|$ may be (tens of) millions of order of magnitude (i.e., we extract 9,355,550 candidate topics from Wikipedia as mentioned above). Thus Algorithm [1] still seems infeasible and may take unbearable time to return results (which is actually the case in our experiments). However, we observe the following two facts:

- Most of the candidate topics in the whole set are not relevant to a given area.
- When the general weight of a topic is little enough, this topic’s contribution to the whole sum ($s$ in Algorithm [1]) may be little enough too.

From the above two observations, we think of the following two strategies which can greatly speed up our algorithm:

- We only keep topics within a depth $d_1$ in the given area’s category as high-quality candidate topics from the original set.
- Since the general weight function $g(n)$ of a topic is monotonically decreasing with the topic’s depth $n$, thus we can choose a depth $d_2$ (with a well-defined $g(n)$) such that the contributions of all topics below this depth are small enough and can be discarded without calculation.

And this can lead to a much faster algorithm with time complexity $O(k|C'^r_{d_1}| |C'_{d_2}|)$, as summarized in Algorithm [2], where $C'^r_{d_1}$ and $C'_{d_2}$ represent high-quality candidate topics set and contributive topics set respectively, and in practical use we have $|C'^r_{d_1}| \ll |C|, |C'_{d_2}| \ll |C|$.
We train our model on one of the largest public knowledge base (Wikipedia). As there are no standard datasets with ground truth and also it is difficult to create such a data set of ground truth, for evaluation purpose, we collect three real-world datasets and choose five representative areas in computer science: Artificial Intelligence (AI), Computer Vision (CV), Machine Learning (ML), Natural Language Processing (NLP), and Software Engineering (SE) to compare the performance of our model with several alternative methods. But our model is not restricted to these areas and can be applied to any other areas theoretically. The datasets and codes are publicly available, and a demo is ready.—Inputs are: (1) area name in the form of a topical phrase (words are connected by a underline, such as “artificial intelligence”). (2) k: the number of topics needed to be extracted. Outputs are: (1) Extracted k topics ranked by and accompanied with their scores (\(S_{i, t}\) in Section 3.2). (2) Running time.

### 4 Experimental Results

We train our model on one of the largest public knowledge base (Wikipedia). As there are no standard datasets with ground truth and also it is difficult to create such a data set of ground truth, for evaluation purpose, we collect three real-world datasets and choose five representative areas in computer science: Artificial Intelligence (AI), Computer Vision (CV), Machine Learning (ML), Natural Language Processing (NLP), and Software Engineering (SE) to compare the performance of our model with several alternative methods. But our model is not restricted to these areas and can be applied to any other areas theoretically. The datasets and codes are publicly available, and a demo is ready.—Inputs are: (1) area name in the form of a topical phrase (words are connected by a underline, such as “artificial intelligence”). (2) k: the number of topics needed to be extracted. Outputs are: (1) Extracted k topics ranked by and accompanied with their scores (\(S_{i, t}\) in Section 3.2). (2) Running time.

### 4.1 Datasets

We download Wikipedia data from wikidump as our knowledge base \(KB\), use its (preprocessed) titles of all articles and categories as \(X\), use the text of all articles as \(X\) and use its category structures as \(R\). After we preprocess the titles as stated in section 3.1 we get 9,355,550 candidate topics in \(C\). As stated in section 3.1 we use full text of Wikipedia to train topics embeddings and view each topic as a whole in Word2Vec model, and we use Gensim to help implement our model. The parameter settings are as follows: vector size = 200, window size = 10, min count of each topic = 2, threshold (\(\delta\)) for downsampling = 0.0001, min sentence length = 2, num workers = 64; for other parameters, we use default settings in Gensim. The collected three real-world datasets for evaluation are detailed as follows.

1. Wikipedia dump
2. Microsoft Academic Graph (MAG)
3. Microsoft Fields of Study (FoS)
4. ACM CCS dataset

ACM CCS classification tree. ACM CCS classification tree is a poly-hierarchical ontology and contains 2,126 nodes in total. In this tree (actually a directed acyclic graph), each node can be viewed as a topic and each non-leaf node has several children nodes as its sub-topics. Although different nodes may have different number and different granularity of nodes in its sub-tree, it still provides us a guidance that what may be top topics in a given area.

Microsoft Fields of Study (FoS). Microsoft Fields of Study (FoS) from its Microsoft Academic Graph (MAG) is a directed acyclic graph where each node also represent a topic and it contains 49,038 nodes in total. Each node in the graph is accompanied with a “level” representing its depth/Granularity in the graph. The network has 4 different levels in total. Each node has super-nodes of different levels as its super-topics and each super-topic is accompanied with a confidence value. The confidences of all super-nodes of the same level of one topic sum to 1. This dataset can also provide us a guidance that what may be top topics in a given area.

Domain Experts Annotated Dataset. As there are actually no standard datasets/benchmarks which perfectly match our problem, we also let domain experts directly annotate top-k (= 15) topics in the five given areas without giving any single dataset for reference.

For the first two datasets, we let domain experts select top-k topics based on each given area’s sub-topics to match our problem better. Because there may be too much nodes in certain area’s sub-topics, we instruct domain experts to first select a larger set of topics than needed and then do secondary screening from them. Since we need to do annotations in all three datasets, we set up the following criterions to reduce subjectivity in the annotation process and help domain experts reach an agreement:

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1. https://github.com/thuzifast/KATE
2. https://dumps.wikimedia.org/enwiki/latest/
3. https://radimrehurek.com/gensim/models/word2vec.html
4. http://www.acm.org/about/class/class/2012
5. https://www.microsoft.com/en-us/research/project/microsoft-academic-graph/
• Selected topics should be more significant than other topics in the given area.
• Selected topics should cover the whole given area as far as possible. This implies that they should not be too similar with each other in the given area, such as Artificial Neural Networks and Neural Networks should be viewed as the same topic in AI area.

After we get the results of each domain expert, we count the number of each selected topic and rank them by their counts, and choose the top- \( k \) from them as the ground truth of the given area. We empirically set \( k = 15 \) in our experiment.

### 4.2 Evaluation Metrics

To quantitatively evaluate the proposed model, we consider the following two metrics.

**Presion@k.** Since the number of extracted results are set to the same \( k \) for domain experts and machines, we use Presion@\( k \) to measure the performance of different methods. Since the order is also important in the extracted results, we introduce another metric as follows.

**Mean Average Precision (MAP).** For a single result (such as a ranked list in our experiments), AP is defined as follows:

\[
AP = \frac{1}{n} \sum_{k=1}^{n} \frac{P(k)}{\min(m, n)}
\]

where \( m \) is the number of all correct items (i.e., the length of human-annotated ranked list); \( n \) is the length of the machine extracted ranked list (which is the same as \( m \) in our experiments); \( P(k) \) equals 0 when the \( k \)-th item is incorrect or equals the precision of the first \( k \) items in the ranked list. MAP is then calculated by averaging the APs over all results.

### 4.3 Comparison Methods

For each given area \( r \), we first extract all its subcategories within a depth of \( d_1 = 3 \), and use them as candidate topics \( C_{d_1}^r \). We then extract all articles \( X^r \subseteq X \) of these candidate topics from Wikipedia for LDA and TextRank methods here, where \( X \) represents the corpus in Wikipedia as introduced in section 2.

• **Topic TF-IDF (TFIDF):** We calculate each candidate topic’s tf-idf \(^{(Jones 1973)}\) value in the whole Wikipedia corpus (viewing each article as a document), and rank all candidate topics by these values.

• **LDA:** We train LDA \(^{(Blei, Ng, and Jordan 2003)}\) model on all documents in \( X^r \). For each candidate topic \( t_i \in C_{d_1}^r \) (note that this is in the form of a topical phrase, and it is not the extracted topics in LDA which is actually multinomial distributions over words), we calculate its weight \( w_i \) as follows:

\[
w_i = \sum_{j=l}^{\left|X^r\right|} \sum_{t_i \in \theta_j} \theta_{jt_i} \alpha_{t_i},
\]

where \( K_{\theta} \) is the number of topics extracted by the LDA model, \( \theta_{jt_i} \) is the probability of \( j \)-th topic of the LDA model in the \( i \)-th article, and \( \alpha_{t_i} \) is the probability of \( t_i \) in \( l \)-th topic of the LDA model. When training, we remove those documents with < 100 words. We utilize Gensim\(^{4}\) to help implement this model, and we use all default parameters of it except we set \( K_{\theta} = 500 \).

• **TextRank:** We run TextRank \(^{(Mihalcea and Tarau 2004)}\) algorithm on each article in \( X^r \), and for each candidate topic \( t_i \in C_{d_1}^r \) (in the form of a topical phrase), we calculate its weight \( w_i \) as follows:

\[
w_i = \sum_{j=1}^{\left|X^r\right|} \text{weight}_{ij},
\]

where \( \text{weight}_{ij} \) is the weight generated by TextRank of \( t_i \) in \( j \)-th article of \( X^r \).

• **FastKATE:** This is our model outlined in Algorithm\(^{[\star]}\) Due to the unbearable running time of Algorithm\(^{[\star]}\) we think it is impractical and thus do not compare its result with others. We empirically select \( g(n) = \exp(4 - n) \). We select two different settings of \( d_1, d_2 \) to compare their performances and time costs: (1) \( d_1 = d_2 = 3 \) (denoted as FastKATE-1), (2) \( d_1 = 3, d_2 = 1 \) (denoted as FastKATE-2).

### 4.4 Results and Analysis

**Accuracy Performance.** Table\(^{[\star]}\) lists the performances of different methods used in the problem of extracting top-\( k \) topics in a given area. In terms of Precision@\( k \), our model FastKATE-2 performs consistently the best on all three datasets and in all five areas. In terms of MAP, our model FastKATE-2 performs the best in 11/14 cases. This suggests our model can not only extract more correct top-\( k \) topics but also rank them in more accurate order. We can also see that FastKATE-1 (it is different from FastKATE-2 only in parameter settings) performs the second best in most cases, which suggests that even with different parameter settings, our model is still very effective comparing to other methods so that our model is also robust.

We note that average performances of all methods on the first two datasets (ACM CCS and Microsoft FoS) are worse than on the third dataset, which is annotated by domain experts directly, and we think the third dataset is more capable of reflecting the performances of different methods on this problem.

It is beyond our expectation that FastKATE-2 performs better than FastKATE-1 in most cases, because FastKATE-2 uses smaller contributive topics set than FastKATE-1.

\(^{4}\)https://radimrehurek.com/gensim/models/ldamodel.html
In this paper, we formally formulate the problem of top-k area topics extraction. We propose FastKATE in which topics have both explicit and latent representations. We leverage a large-scale knowledge base (Wikipedia) to learn topic embeddings and use this kind of representations to help capture the representativeness of topics for given areas. We propose a heuristic algorithm together with a fast implementation to efficiently solve the problem and prove it is at least \((1-1/e)\) of the optimal solution. Experiments on three real-world datasets and in five different areas validate our model’s effectiveness, robustness, real-timeness (return results in < 1s), and its superiority over other methods. In
future, we plan to integrate more knowledge bases and also try to apply our model to a broader range of problems.

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