Multi-label dataless text classification with topic modeling

Daochen Zha1 · Chenliang Li2

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Abstract
Manually labeling documents is tedious and expensive, but it is essential for training a traditional text classifier. In recent years, a few dataless text classification techniques have been proposed to address this problem. However, existing works mainly center on single-label classification problems, that is, each document is restricted to belonging to a single category. In this paper, we propose a novel Seed-guided Multi-label Topic Model, named SMTM. With a few seed words relevant to each category, SMTM conducts multi-label classification for a collection of documents without any labeled document. In SMTM, each category is associated with a single category-topic which covers the meaning of the category. To accommodate with multi-label documents, we explicitly model the category sparsity in SMTM by using spike and slab prior and weak smoothing prior. That is, without using any threshold tuning, SMTM automatically selects the relevant categories for each document. To incorporate the supervision of the seed words, we propose a seed-guided biased GPU (i.e., generalized Pólya urn) sampling procedure to guide the topic inference of SMTM. Experiments on two public datasets show that SMTM achieves better classification accuracy than state-of-the-art alternatives and even outperforms supervised solutions in some scenarios.

Keywords Dataless text classification · Topic model · Multi-label text classification · Spike and slab prior

1 Introduction
Multi-label text classification is a fundamental task for textual information organization and management. The task assumes that each document is associated with one or more categories. For example, the paper “statistical topic models for multi-label document classification” [41] can be assigned to multiple categories: topic model, document classification and machine learning simultaneously. In the past decade, many researchers have developed approaches dedicated to automatic multi-label text classification, typically in a supervised
manner: (1) manually labeling some sample documents, (2) training a model based on these labeled documents and (3) assigning category labels automatically on unlabeled documents with the trained model. These approaches often require a considerable number of labeled documents to train a high-quality classifier. However, manually building a multi-label training set is much more expensive than a single-label counterpart because an annotator needs to consider every possible category for each document. The quality of training set is also hard to control since a user may easily miss some categories when annotating a document.

Many research efforts have been made to reduce the labeling cost in multi-label text classification. Active learning, such as [27,52], iteratively selects the most informative documents from the unlabeled documents for human annotation. Semi-supervised learning, such as [42], trains a model with both labeled and unlabeled documents. These approaches still need a significant number of labeled documents and remain expensive.

Recently, a weakly supervised setting has emerged to be a promising solution, called dataless classification. Without any labeled document, dataless setting assumes that there is a small set of seed words relevant to each category. Seed words are much easier to obtain because categories are often meaningful. For example, for topic model we can easily select some seed words such as “topic,” “LDA,” “Dirichlet.” In dataless setting, users only need to focus on how to use some seed words to precisely describe each category rather than manually labeling a large number of documents. This makes it easier to train a high-quality classifier.

In this paper, we propose a Seed-guided Multi-label Topic Model to conduct multi-label dataless classification, named SMTM. In SMTM, each category is associated with a single category-topic which covers the meaning of the category. Typically, a document only uses a limited number of category-topics, which we call category sparsity. We model the category sparsity of the documents by using spike and slab prior and weak smoothing prior [16,30]. The spike and slab prior allows us to set up a binary variable between a document and a category. This binary variable works as an “on/off” switch to decide whether the category is “selected” by the document. The binary variables are naturally decided in a probabilistic manner and can successfully model the category sparsity of the documents in dataless setting. To effectively use the seed words, SMTM resorts to word co-occurrence information in the corpus. Specifically, we propose a seed-guided biased GPU sampling procedure for topic
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inference based on the generalized Poïya urn (GPU) model [33]. The proposed sampler promotes the relevant category-topics under a document and the relevant words under a category-topic in “the rich get richer” manner. In this sense, the semantics of the seed words are propagated during the topic inference procedure. The words that co-occur frequently with the seed words become more likely to be generated from the corresponding category-topic. With few seed words, SMTM is able to continually discover more relevant words which are further used to classify documents.

We evaluate our approach on two public datasets. Experimental results show that SMTM significantly outperforms the state-of-the-art dataless baselines and achieves competitive performance with supervised approaches. We also evaluate some variants of SMTM and discuss the results. Overall, the main contributions of this paper are summarized as follows

- We propose a novel Seed-guided Multi-label Topic Model for multi-label dataless text classification, named SMTM. SMTM is devised to explicitly model the category sparsity of multi-label documents by using spike and slab prior and weak smoothing prior. To the best of our knowledge, this is the first work to classify documents into relevant categories in a multi-label and dataless manner.
- We introduce a simple yet effective seed-guided biased GPU sampler to guide topic learning process of SMTM. With a few seed words provided for each category, the seed-guided biased GPU sampler can identify the relevant words for each category based on higher-order word co-occurrence patterns, leading to promising classification accuracy in multi-label setting.
- Our extensive experiments on two public datasets show that the proposed SMTM achieves significantly better classification accuracy than the existing dataless alternatives in terms of both Macro-$F_1$ and Macro-$AUC$ metrics. Also, SMTM even achieves better performance than some supervised solutions in some scenarios.

The rest of the paper is organized as follows. In Sect. 2, we summarize the related works of this paper. In Sect. 3, we formalize the problem of multi-label dataless text classification. We then present the proposed SMTM model in detail in Sect. 4. Section 5 shows the experimental settings, results and discussions. Finally, we conclude the paper in Sect. 6.

2 Related work

Since our work is related to multi-label text classification, dataless text classification and topic modeling, we review the relevant works from these areas in this section.

2.1 Dataless text classification

Supervised text classifiers are often hindered by the need for a large number of labeled documents. One thread of the solutions is dataless classification, a weakly supervised setting that only requires some seed words for each category. The earliest works focus on building a pseudo-training set based on the given seed words, which we call classification based. Liu et al. [31] proposed to use seed words to build an initial training set from the unlabeled documents. Then EM algorithm is applied to train a classifier. Ko and Seo [19] proposed to construct context clusters based on seed words. Then a Naïve Bayes classifier is learned accordingly by using bootstrapping algorithm. One problem of these approaches is the difficulty of controlling the quality of the pseudo-training set, which may lead to unpredictable noisy information into the training procedure.
With the development of semantic representations, some researchers proposed to embed categories, which are represented with seed words, and documents to a shared semantic space. Then the classification is conducted by searching the nearest category for each document, which we call *semantic based*. Chang et al. [3] built a dataless classifier by using Explicit Semantic Analysis (ESA) [12] based on Wikipedia, showing that dataless classifier is competitive with Naive Bayes in binary classification. Song and Roth [43] adapted the semantic method to hierarchical classification and evaluated the effectiveness of a few semantic representations in dataless setting. They found that ESA [12] performs the best in dataless classification. Song et al. [44] further adapted the ESA-based method to cross-lingual dataless classification. For multi-label datasets, they treated the multi-label classification as independent binary classification problems and labeled the top K relevant documents as positive for each category. However, the ESA-based method is not well suited for multi-label text classification. A drawback of this strategy is that it does not consider the imbalanced nature of multi-label datasets. This simple adaptation has been included in our experiments.

Another line of dataless classification research is built upon probabilistic models, which we call *probabilistic model based*. Druck et al. [10] constrained discriminative probabilistic models with seed words by using generalized expectation (GE) criteria. Chen et al. [6] proposed to use probabilistic topic models to conduct dataless classification. Li et al. [24] associated each document with a single category-topic as well as some general topics and then used explicit word co-occurrence to guide topic models to conduct single-label classification. Probabilistic models bring promising results in dataless classification. However, existing approaches all assume that each document is restricted to belonging to one category so that are not well suited for multi-label dataless classification.

Our work differs from these works in that we aim to conduct multi-label text classification in dataless setting. To the best of our knowledge, this is the first work to classify documents in a multi-label and dataless manner.

### 2.2 Multi-label text classification and topic models

Topic models have many applications in a broad range. Latent Dirichlet Allocation (LDA) [2] is a probabilistic topic model that extracts latent topics underlying a document collection in an unsupervised manner. In the past decade, researchers have adapted LDA to single-label supervised learning, such as Supervised Topic Model [34], DiscLDA [21] and MedLDA [53].

The first topic model designed for multi-label learning is Labeled-LDA (L-LDA) [38]. L-LDA makes a one-to-one correspondence for each category and each topic. In topic inference, L-LDA assumes that each document only uses topics that correspond to its associated categories. They further extended L-LDA to partially Labeled-LDA by allowing one or more topics for each category [39]. Rubin et al. [41] improved L-LDA by considering two conditions. They developed Prior-LDA by considering relative frequencies of categories and Dependency-LDA by considering dependencies between category labels. Soleimani and Miller [42] proposed a semi-supervised multi-label topic model (MLTM) to model documents in sentence level. MLTM assigns a category label to a document if and only if at least one sentence in the document is attributed to that category label. MLTM is reported to achieve the state-of-the-art classification results in terms of Macro-AUC [42] and thus is included in our experiments.

There is another line of research on discriminative approaches for multi-label text classification. There is a large body of research in this line. Since supervised solution is not the concern of this paper, we only include some representative works. The most simple and
frequently used strategy is to adapt single-label classification solutions to the multi-label setting, that is, multi-label classification problem is transformed into a few binary classification problems so that the problem can be solved using binary classifiers [47,48]. Besides these adaptation-based techniques, many researchers have proposed to model interdependencies between categories (i.e., category correlation) [13,22,40,49]. Recently, some researchers have also adopted neural network techniques for multi-label classification [1,5,9,32].

Most existing works of multi-label text classification assume that there is a set of training documents. Since training documents are often expensive, some strategies have been proposed to save human annotating efforts for multi-label classification. Active learning [27,52] and semi-supervised learning [42] are two popular strategies. However, they still require labeled documents and the performance of these approaches still degrades significantly when the size of the training set is not large enough. Tao et al. [46] designed an unsupervised framework for multi-label text classification based on the structure of Library of Congress Subject Headings (LCSH). The limitation of their approach is that the labels of LCSH are pre-defined so that their approach is not suited for general multi-label classification tasks.

Different from these works, we aim to conduct multi-label text classification by using some seed words instead of labeled documents. Our approach works in a weakly supervised manner such that a lot of human efforts can be saved.

3 Problem formalization

In this section, we formalize the problem of multi-label dataless text classification. Let \( D \) be a set of documents where \( D \) is the number of documents in the corpus. The vocabulary is denoted by \( \mathcal{W} = \{1, 2, \ldots, W\} \) where \( W \) is the vocabulary size. Each document \( d \in D \) is represented as \( \{w_1, w_2, \ldots, w_{N_d}\} \) where \( w_i \in \mathcal{W} (i \in \{1, 2, \ldots, N_d\}) \) and \( N_d \) is the number of tokens in document \( d \). Let \( \mathcal{C} = \{1, 2, \ldots, C\} \) be a set of labels within the corpus where \( C \) is the number of labels and each \( c \in \mathcal{C} \) is associated with a seed set \( S_c \). Note that \( S_c \) is often small in size since users can only provide a limited number of seed words. Given all such \( S_c \), the problem of multi-label dataless classification is to assign a label set \( \mathcal{L}_d \) to each document \( d \) where \( \mathcal{L}_d = \{c : c \in \mathcal{C}\} \).

4 Our approach

In this section, we present the proposed Seed-guided Multi-label Topic Model for multi-label dataless text classification, named SMTM. We first describe the generative process and inference of our model. Then we introduce the proposed seed-guided biased GPU sampler, which enables effective supervision of seed words for multi-label dataless text classification.

4.1 Generative process and inference

In the paradigm of topic modeling, a hidden topic \( t \) is represented as a distribution \( \phi_t \) over the vocabulary, i.e., \( \sum_{w \in \mathcal{W}} \phi_{t,w} = 1 \). The most probable words under a topic are expected to convey the corresponding semantic theme. A document \( d \) is characterized by a distribution over hidden topics \( \theta_d \). A specific word \( w \) in a document is generated by firstly sampling a topic \( t_w \): \( t_w \sim \theta_d \). Then word \( w \) is generated according to the word distribution \( \phi_{t_w} \): \( w \sim \phi_{t_w} \). Usually, a Dirichlet prior is introduced over the distributions \( \phi_t \) and \( \theta_d \), to alleviate the overfitting problem.
The purpose of SMTM is to identify the categories associated with each document by only using a few seed words for each category. It then becomes natural to represent each category as a hidden topic. The most probable words under a hidden topic present the semantic meaning of the corresponding category. Here, we make a one-to-one correspondence between a category and a topic.1 We call the topics as category-topics in SMTM. Besides the category-topics, a document collection would contain general semantic information that is useless to help the classification. The representative examples include the common function words, the semantic information covered by all the category-topics. For example, given a document collection covering three sports relevant categories: football, basketball and tennis, the information relevant to the season schedule, medical treatment and salary would appear widely in each category. Including these words would hurt the discriminative ability of each category-topic.

A background topic is often used to model the irrelevant information regarding the target task in the literature of topic modeling [4,24,35]. Following the previous works, we further introduce a background topic to model the general semantic information underlying the whole collection. That is, we have $C$ category-topics and a single background topic, where $C$ is the number of categories covered by the collection. Consider a sentence in a document that is assigned web and education in Delicious dataset: “I regularly update my blog, podcast, workshop curricula and social bookmarks.” This sentence is expected to use a mixture of three topics, i.e., web, education and the background topic, where the two category-topics are expected to cover the highly related words (e.g., “blog,” “podcast,” “curricula”) and the background topic is expected to include other background words (e.g., “regularly,” “update”).

In SMTM, we introduce a binary variable $x_{d,i}$ for word $w_{d,i}$ (i.e., the word at position $i$ in document $d$). This variable works as a switch to determine whether word $w_{d,i}$ is generated by the background topic. The setting $x_{d,i} = 0$ indicates that the associated word is generated by the background topic. Otherwise, word $w_{d,i}$ is generated from a category-topic associated with the document. The variable $x_{d,i}$ is sampled from a Bernoulli distribution with parameter $\lambda$. Here, we treat $\lambda$ as a global parameter for all the documents. A beta prior with a symmetric hyperparameter $\pi$ is added for parameter $\lambda$, which allows the value of $\lambda$ to be iteratively estimated in a data-driven manner.

The generative story of a document in SMTM is as follows. For a multi-label document, SMTM first selects some candidate-topics which include some category-topics and a background topic. For each position in the document, SMTM then uses one of the candidate-topics and generates a word accordingly. Intuitively, the selected category-topics should correspond to the categories that this document belongs to. Although a text collection could contain a lot of categories, we observe that each document is likely to belong to only a small number of categories (i.e., category sparsity). Table 2 illustrates the statistics of the two document collection used for evaluation. Given about 20 categories covered by the two collections, respectively, we observe that each document belongs to no more than two categories on average (last column in Table 2). This suggests that each document typically has very few dominating category-topics, i.e., the categories of the document. A key challenge for the efficacy of SMTM is an appropriate mechanism to model this category sparsity for each document. This sparsity modeling is similar to L-LDA [38], in which each document is restricted to using topics that correspond to its categories. However, assigned categories are not available in the dataless setting where no training document is used. Here, we propose to automatically select the categories for each document in a probabilistic manner (with the supervision of seed words). Specifically, we utilize spike and slab prior and weak smoothing

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1 Category and category-topic are considered equivalent and exchangeable in this work when the context has no ambiguity.
prior together to enable the sparsity and the smoothness of the category-topic distribution for a document in SMTM.

The spike and slab prior is a well-known method to realize “on” and “off” switch selector in probabilistic topic models [16, 50]. It has been used to learn focused terms or focused topics for better topic inference [30, 50, 51]. In SMTM, spike and slab prior allows us to associate each document with a set of auxiliary topic selectors which determine whether each corresponding category-topic appears or not. In other words, these topic selectors indicate whether each corresponding category is “selected” by a document. Specifically, we introduce an auxiliary Bernoulli variable $\alpha_{d,c}$ to control the presence of category-topic $c$ in document $d$. The category $c$ is assigned to document $d$ when $\alpha_{d,c} = 1$. On the other hand, document $d$ does not belong to category $c$ when $\alpha_{d,c} = 0$. Inspired by Lin et al. [30], we use a regular smoothing prior $\gamma_0$ and a weak smoothing prior $\gamma_1 (\gamma_0 \gg \gamma_1)$ to decouple the sparsity and smoothness, such that the prior of category-topic distribution for document $d$ is defined to be $\gamma_0 \alpha_d + \gamma_1 \mathbf{1}$, where $\alpha_d = \{\alpha_{d,c}\}_{c=1}^C$ and $\mathbf{1}$ is the vector with all elements being 1. Note that the number of categories associated with a document is document dependent. Hence, for each document, $\alpha_{d,c}$ is then sampled from a Bernoulli distribution with a document dependent parameter $\alpha_d$. A Beta prior with hyperparameters $p$ and $q$ is introduced over $\alpha_d$, such that the parameter $\alpha_d$ is estimated according to the content of document $d$.

Another strategy is to simply regard all the category-topics as candidate-topics. However, we find that the sparsity modeling strategy can improve the classification performance (see Table 3). For clarity, we summarize all the notations and counters used in Table 1. The graphical representation of SMTM is shown in Fig. 1, and the generative process is formally described as follows:

1. Sample a background word distribution $\phi_0 \sim \text{Dirichlet}(\beta_0)$
2. Sample $\lambda \sim \text{Beta}(\pi)$
3. For each category-topic $c \in \{1, \ldots, C\}$:
   (a) Sample a word distribution $\phi_c \sim \text{Dirichlet}(\beta_1)$
4. For each document $m_d \in \{m_1, \ldots, m_D\}$:
   (a) Sample $\alpha_d \sim \text{Beta}(p, q)$
   (b) For each category-topic $c \in \{1, \ldots, C\}$:
      (i) Sample selector $\alpha_{d,c} \sim \text{Bernoulli}(\alpha_d)$
   (c) Selected category-topic set $A_d = \{k : \alpha_{d,k} = 1\}$
   (d) Sample a category-topic distribution $\theta_d \sim \text{Dirichlet}(\gamma_0 \alpha_d + \gamma_1 \mathbf{1})$
   (e) For each position $i \in \{1, \ldots, N_d\}$:
      (i) Sample $x_{d,i} \sim \text{Bernoulli}(\lambda)$
      (ii) If $x_{d,i} = 0$, sample $w_{d,i} \sim \text{Multinomial}(\phi_0)$ If $x_{d,i} = 1$,
          (1) Sample $z_{d,i} \sim \text{Multinomial}(\{\theta_{d,k} : k \in A_d\})$
          (2) Sample $w_{d,i} \sim \text{Multinomial}(\phi_{z_{d,i}})$.

Here, $z_{d,i}$ is sampled from the selected category-topic set $A_d$. Since $\gamma_0 \gg \gamma_1 (\gamma_1 = 10^{-7})$, we can get $\sum_{k \in A_d} \theta_{d,k} = 1$ in the numerical sense [30], which results in a much simpler inference procedure. The variables $[\beta_0, \beta_1, p, q, \pi, \gamma_0, \gamma_1]$ are the hyperparameters for the corresponding prior distributions. More information regarding the prior distributions can be found in [15].

In SMTM, $\alpha_{d,k}$ is the key to enable multi-label dataless text classification. With the supervision of the seed words (detailed in Sect. 4.2), the value of $\alpha_{d,k}$ is determined in a probabilistic manner. The switch will be “on” (i.e., $\alpha_{d,k} = 1$) when a document is highly
Table 1 Notations used in the generative process (top); the counters used in the Gibbs sampling equations (bottom)

| Symbol | Description |
|--------|-------------|
| $D$    | The number of documents in the corpus |
| $C$    | The number of categories in the corpus |
| $W$    | The vocabulary size |
| $N_d$  | The number of word in document $d$ |
| $w_{d,i}$ | The word at position $i$ in document $d$ |
| $x_{d,i}$ | Category word indicator about whether $w_{d,i}$ is generated from a category-topic |
| $z_{d,i}$ | The category-topic assignment for $w_{d,i}$ |
| $\alpha_{d,c}$ | Category selector of category $c$ in document $d$ |
| $\alpha_d$ | All category selectors in document $d$ |
| $\phi_c$ | Word distribution of category-topic $c$ |
| $\phi_0$ | Word distribution of background topic |
| $\theta_d$ | Category-topic distribution for document $d$ |
| $\lambda$ | Bernoulli distribution over category word indicator |
| $\beta_0$, $\beta_1$ | Dirichlet priors |
| $\gamma_0$, $\gamma_1$ | Regular smoothing prior, weak smoothing prior |
| $\pi$, $p$, $q$ | Beta prior |
| $n_0$ | The number of words assigned to background topic |
| $n_1$ | The number of words assigned as one of the category-topics |
| $n_{0,w}$ | The number of times word $w$ is assigned to background topic |
| $n_{c,w}$ | The number of times word $w$ is assigned to category-topic $c$ |
| $n_{d,c}$ | The number of words assigned to category-topic $c$ in document $d$ |
| $n_{d,-}$ | The sum over $n_{d,c}$ of document $d$ |
| $|\alpha_d|$ | The sum of the values of category selectors in document $d$ |

Fig. 1 Graphical representation of SMTM

related to a category or “off” (i.e., $\alpha_{d,k} = 0$) when the document covers less semantic information of the category. That is, the model finds a category set for the document that best fits the document. The sparsity modeling for the document, in turn, enhances the quality of topi-
cal words, which further improves the quality of category assignments for other documents. This category selection process continues until a global convergence is reached.

Before introducing how we incorporate the supervision of seed words, we first introduce the inference algorithm for the above described model. We utilize Gibbs sampling for the approximate inference and parameter learning [14]. Since \( x_{d,i} \) and \( z_{d,i} \) are correlated in SMTM, we jointly sample \( x_{d,i} \) and \( z_{d,i} \) as follows:

\[
P(x_{d,i}, z_{d,i} | w, z_{\neg di}, n, \alpha, \beta_0, \beta_1, \gamma_0, \gamma_1, \pi) \propto \begin{cases} 
\frac{n_0^{\alpha_d+\beta_0}}{n_0^{\alpha_d+\beta_0}+n_1^{\alpha_d+\beta_0}+2\pi} \times \frac{n_0^{\gamma_0+\beta_1}}{n_0^{\gamma_0+\beta_1}+2\pi} 
& x_{d,i} = 0 \\
\frac{n_0^{\alpha_d+n_{c,d}^{\alpha_d+\beta_0}+\gamma_0+\gamma_1}}{n_0^{\alpha_d+n_{c,d}^{\alpha_d+\beta_0}+\gamma_0+\gamma_1}+\pi} \times \frac{n_0^{\gamma_0+\gamma_1}}{n_0^{\gamma_0+\gamma_1}+\pi} 
& z_{d,i} = c, x_{d,i} = 1
\end{cases}
\]  

(1)

where \( n_0 \) is the number of words assigned to the background topic, \( n_1 \) is the number of words assigned to the category-topics, \( n_{0,w} \) is the number of times word \( w \) is assigned to background topic, \( n_{c,w} \) is the number of times word \( w \) is assigned to category-topic \( c \), \( n_{d,c} \) is the number of words assigned to category-topic \( c \) in document \( d \), \( W \) is the vocabulary size, symbol \( \neg di \) means that the current assignment is excluded from the count. After sampling all \( x_{d,i} \) and \( z_{d,i} \), we then sample each category-topic selector \( \alpha_{d,c} \) as follows:

\[
P(\alpha_{d,c} | w, z, x, \alpha_{\neg d,c}, \beta_0, \beta_1, \gamma_0, \gamma_1, \pi) \propto \begin{cases} 
\Gamma(n_{d,c} + \gamma_0 + \gamma_1) \times \Gamma(|\alpha_d^{\neg c}| \gamma_0 + C \gamma_1 + n_{d,c}^{\neg c}) 
& \alpha_{d,c} = 1 \\
\Gamma(\gamma_0 + \gamma_1) \times \Gamma(|\alpha_d^{\neg c}| \gamma_0 + C \gamma_1 + n_{d,c}^{\neg c}) 
& \alpha_{d,c} = 0
\end{cases}
\]  

(2)

where \( \Gamma(\cdot) \) is the standard Gamma function, \( n_{d,c} \) is the sum of \( n_{d,c} \) over categories, \( |\alpha_d| \) is the number of category-topics selected by document \( d \), symbol \( \neg c \) means that category \( c \) is excluded from the count.

### 4.2 Seed-guided biased GPU sampler

Without any supervision, SMTM is just an unsupervised probabilistic topic model. It is difficult to learn the relevant categories for the documents in a purely unsupervised manner. Here, we propose a seed-guided Gibbs sampling procedure by incorporating the seed words through the generalized Polya urn (GPU) model [33] in topic inference.

**Biased GPU promotion** The generalized Pólya urn (GPU) model represents the discrete probability as colored balls in an urn. The probability of seeing a ball in a color is linearly proportional to the number of balls in that color in the urn. Traditional Gibbs samplers for conventional LDA models follow the simple Pólya urn (SPU) model. In SPU, when a ball in a particular color is drawn, that ball along with a new ball in the same color is put back, often expressed as “the rich get richer.” If we perform this repeatedly, the distribution of the colored balls in the urn follows a Dirichlet multinomial distribution. The GPU differs from SPU in that, when a ball in a particular color is drawn, a certain number of balls in each color are put back along with the drawn ball. This idea has been used in topic modeling for encoding word relatedness knowledge [7,8,23,25,37]. That is, a new ball in the same color and also a
certain number of balls in similar colors are put back along with the drawn ball. Different from these existing works, we propose a biased GPU sampler to guide the sparsity-oriented topic inference of SMTM under the supervision of seed words. By analogy with the GPU model, given a ball of category-topic $c$, we can put back more balls of category-topic $c$ into document $d$ if $d$ is expected to be more likely to belong to category $c$. On the contrary, if we find that document $d$ is less relevant to category $c$, a smaller number of balls of category-topic $c$ will be put back instead. In this sense, the categories that are more related to a particular document will “get more richer” under this sampling strategy. A similar procedure can also be applied to guide the word distribution learning for the category-topics in SMTM. Now we explain the strategies for promoting the category-topic distribution and the word distribution.

Promotion for the category-topic distribution We observe that a document is likely to belong to a particular category if the document contains the seed words of that category. Thus, we bias the category-topic distribution to prefer a particular category when this document has at least one seed word of that category. More formally, let $I(d, c)$ be an indicator such that $I(d, c) = 1$ when document $d$ contains at least one seed word of category $c$, and $I(d, c) = 0$ otherwise. The amount of promotion by the biased GPU sampler in SMTM is then calculated as follows:

$$u_{c,d} = \begin{cases} 1 & I(c, d) = 1 \\ \mu & I(c, d) = 0 \end{cases}$$

(3)

$$P_{c,d} = \frac{u_{c,d}}{\sum_{c'} u_{c',d} \times C}.$$  

(4)

In Eq. 3, $\mu$ is a tunable parameter in the range of $[0, 1]$ to control the importance of observing seed words in a document. Based on Eq. 4, when $\mu = 1$, no supervision from the seed words is utilized for the calculation of category-topic distributions. That is, the SPU model is recovered instead (i.e., $P_{c,d} = 1$). When $\mu = 0$, the categories covered by a document are restricted to the ones whose seed words appear in the document.

Promotion for the word distribution Similarly, we can promote the probabilities of the relevant words for each category-topic. Inspired by Li et al. [24], we use explicit word co-occurrences to estimate the word relevance:

$$p(w|s) = \frac{df(w,s)}{df(s)}$$  

(5)

$$v(w, c) = \frac{1}{|S_c|} \sum_{s \in S_c} p(w|s)$$  

(6)

$$v_n(w, c) = \max \left( \frac{v(w, c)}{\sum_{c'} v(w, c')}, \varepsilon \right)$$  

(7)

where $df(s)$ is the document frequency of a seed word $s$, $df(w, s)$ is the number of documents containing both word $w$ and seed word $s$, $S_c$ is the set of seed words for category $c$, $\varepsilon$ is a small value to avoid zero ($\varepsilon = 0.01$). Based on the above equations, if word $w$ co-occurs very frequently with seed words of category $c$, $v_n(w, c)$ will have a larger value. Similar to Eq. 4, the promotion for word $w$ under category-topic $c$ is calculated as follows:

$$\tilde{P}_{w,c} = \frac{v_n(w, c)}{\sum_{w'} v_n(w', c)} \times W.$$  

(8)

Model inference By using GPU model, the joint probability of the words in any topic is not invariant to the permutations of those words. The exact inference, therefore, becomes
Algorithm 1 One iteration of sampling for SMTM

1: /* update $x_{d,i}$ and $z_{d,i}$ */
2: for $d \in \{1, 2, \ldots, D\}$ do
3: for $i \in \{1, 2, \ldots, N_d\}$ do
4: if $x_{d,i} = 0$ then
5: $n_0 \leftarrow n_0 - 1$
6: $n_{0,w_{d,i}} \leftarrow n_{0,w_{d,i}} - 1$
7: else
8: $n_1 \leftarrow n_1 - 1$
9: $n_{d,z_{d,i}} \leftarrow n_{d,z_{d,i}} - P_{z_{d,i},d}$ /* See Eq. 4 */
10: $n_{z_{d,i},w_{d,i}} \leftarrow n_{z_{d,i},w_{d,i}} - \tilde{P}_{w_{d,i},z_{d,i}}$ /* See Eq. 8 */
11: end if
12: sample $x_{d,i}$ and $z_{d,i}$ /* See Eq. 1 */
13: if $x_{d,i} = 0$ then
14: $n_0 \leftarrow n_0 + 1$
15: $n_{0,w_{d,i}} \leftarrow n_{0,w_{d,i}} + 1$
16: else
17: $n_1 \leftarrow n_1 + 1$
18: $n_{d,z_{d,i}} \leftarrow n_{d,z_{d,i}} + P_{z_{d,i},d}$ /* See Eq. 4 */
19: $n_{z_{d,i},w_{d,i}} \leftarrow n_{z_{d,i},w_{d,i}} + \tilde{P}_{w_{d,i},z_{d,i}}$ /* See Eq. 8 */
20: end if
21: end for
22: end for
23: /* update $\alpha_{d,c}$ */
24: for $d \in \{1, 2, \ldots, D\}$ do
25: for $c \in \{1, 2, \ldots, C\}$ do
26: $|\alpha_{d,c}| \leftarrow |\alpha_{d,c}| - \alpha_{d,c}$
27: sample $\alpha_{d,c}$ /* See Eq. 2 */
28: $|\alpha_{d,c}| \leftarrow |\alpha_{d,c}| + \alpha_{d,c}$
29: end for
30: end for

intractable. Following the work in [37], we treat each word as if it were the last word, leading to a sampling procedure similar to standard Gibbs sampling based on Eqs. 1 and 2. The details of the biased GPU sampling process of SMTM are described in Algorithm 1. When updating $x_{d,i}$ and $z_{d,i}$, $n_{d,z_{d,i}}$ and $n_{z_{d,i},w_{d,i}}$ are sampled based on $P_{z_{d,i},d}$ and $\tilde{P}_{w_{d,i},z_{d,i}}$, respectively. A larger $P_{z_{d,i},d}$ or $\tilde{P}_{w_{d,i},z_{d,i}}$ will encourage $z_{d,i}$ to be sampled from the corresponding category-topic. With the two sampling strategies, the topic inference procedure is effectively supervised by the semantics of the seed words.

4.3 Multi-label classification

As mentioned above, SMTM automatically selects the relevant categories for each document in a probabilistic manner. For multi-label classification, we assign category label $c$ to document $d$ when the corresponding category-topic is “selected” by the document (i.e., $\alpha_{d,c} = 1$). For the purpose of performance evaluation, we can also derive a ranking of documents for each category in the descending order of $p(c|d)$. We follow the work in [23] to estimate $p(c|d)$ indirectly by using the summation over words (SW) strategy:

$$p(c|d) \propto \frac{1}{N_d} \sum_{i=1}^{N_d} p(c|w_{d,i})$$

(9)

where $p(c|w_{d,i})$ can be obtained by using Bayes’ theorem.
Table 2  Statistics of the two datasets

| Dataset | #categories | #documents | #vocabulary | #avgLen | #cardinality |
|---------|-------------|------------|-------------|---------|-------------|
| Ohsumed | 23          | 12,929     | 12,711      | 96.67   | 1.66        |
| Delicious| 20          | 21,670     | 33,769      | 140.97  | 1.96        |

#categories: the total number of categories in the dataset; #documents: the total number of documents in the dataset; #vocabulary: the size of the vocabulary; #avgLen: the average number of tokens for each document; #cardinality: the average number of categories of a document

5 Experiment

In this section, we conduct extensive experiments to evaluate the performance of SMTM on two real-world multi-label datasets. We show that SMTM outperforms existing dataless alternatives. We further examine the scenarios in which SMTM achieves comparable or even better classification performance than the supervised learning solutions. At last, we investigate the impact of different parameter settings and convergence rate, as well as qualitative case study.

5.1 Datasets

Two public multi-label datasets are used for performance comparison. The first dataset (called Ohsumed) contains medical abstracts from MEDLINE database. Following Joachims [18], we consider the 13,929 unique abstracts in the first 20,000 abstracts. The task is to classify the documents into 23 cardiovascular diseases categories. There are 6286 training documents and 7643 documents for testing. Each document is associated with 1.7 categories on average. In our experiments, we use the standard training/test split. The second dataset (called Delicious) consists of tagged Web pages retrieved from social bookmarking service delicious [54]. Following the work in [39], we use the 20 most common tags for evaluation. For each document, we consider the tags annotated by at least 5 users. There are 21,670 documents, and each document is associated with 2 categories on average. We conduct fourfold cross-validation for this dataset. Both datasets were used previously in evaluating MLTM [42]. The datasets are tokenized with NLTK. The stop words, the words shorter than 3 characters and the words appearing in fewer than 5 documents are removed from both datasets. Table 2 summarizes the statistics of the two datasets after preprocessing.

Following the seed word selection process used in [6], we manually select the seed words for each category based on the topical words derived by standard LDA model:

1. Run standard LDA on the collection to infer latent topics.
2. Manually assign category labels to each topic. If a topic appears not related to any category, we do not assign a category label on that topic.
3. Manually choose at most 10 seed words based on the most probable 50 words for each labeled topic.

Note that standard LDA is an unsupervised model that effectively clusters semantically related words, which helps us conduct human selection. There are other approaches that could be

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2 https://github.com/WHUIR/SMTM.
3 http://disi.unitn.it/moschitti/corpora.htm.
4 http://nlp.uned.es/social-tagging/delicioust140/.
used for seed words extraction. (e.g., synonymous words or external dictionary). However, the procedure applied here uses no external resource, but merely needs a minimal amount of manual filtering [6]. After the seed words selection, on average, each category contains 4.3 and 4.1 seed words for Ohsumed and Delicious, respectively. And a category has a maximum of 7 seed words for both datasets. These seed words are included in Appendix A.

5.2 Metrics

For performance evaluation, we utilize macro-averaged $F_1$ (Macro-$F_1$) and Macro-AUC [17,41,42]. Macro-$F_1$ and Macro-AUC are the averaged $F_1$ and AUC (i.e., area under ROC curve) scores of all categories, respectively. Let $TP_c$, $FP_c$ and $FN_c$ be the number of true positive, false positive and false negative, respectively, for category $c$. Then we can obtain Macro-$F_1$ metric as follows:

$$\text{Macro-}F_1 = \frac{1}{C} \sum_{c=1}^{C} \frac{2 \times TP_c}{2 \times TP_c + FP_c + FN_c}$$

Macro-AUC is a ranking-based metric, i.e., it tests the ranking prediction of the most relevant documents for each category. For each category $c$, we first derive a correlation score $S(c, d)$ for each document $d$ based on the classifier. Then we obtain a receiver operating characteristic (ROC) curve by plotting the true positive rate against false positive rate with various threshold settings. The area under the ROC curve is computed for each category, and Macro-AUC is the average area across categories. A random decision rule gives Macro-AUC = 0.5; a perfect prediction achieves Macro-AUC = 1.

5.3 Baselines

For thorough comparison, we evaluate SMTM against state-of-the-art supervised and dataless classifiers, as well as some variants of SMTM. We first consider three supervised baselines:

- SVM A widely used supervised text classifier. We use a linear kernel and one-vs-rest scheme with TF-IDF weighting. The SVM implementation in sklearn toolkit is used. We tune the penalty parameter $C$ on the set $\{10^i | i = -5, -4, \ldots, 4, 5\}$.

- L-LDA The labeled LDA [38] is a topic modeling-based supervised approach for multi-label classification. The parameters are tuned, and the best result is reported.

- MLTM The recently proposed semi-supervised multi-label topic model with sentence-level modeling [42]. We use the implementation provided by the authors and use their recommended settings. In our experiments, we report the results with full training set, which yields the best results for this model.

Tuning decision threshold based on the training set is an important step for supervised multi-label text classification [11,41]. For the supervised classifiers (i.e., SVM, L-LDA and MLTM), the threshold is selected using a fourfold cross-validation. As mentioned in the related work, there are three types of dataless classification techniques, i.e., classification based, semantic based and probabilistic model based. For thorough comparison, we consider the state-of-the-art solutions from each type:

5 https://nlp.stanford.edu/software/tmt/tmt-0.4/.

6 NLTK is used to split the documents into sentences.

7 https://github.com/hsoleimani/MLTM.
– SVM\textsuperscript{s}, L-LDA\textsuperscript{s} and MLTM\textsuperscript{s} The straightforward classification-based approaches. We build a pseudo-training set by associating a training document with a category if the document contains at least one seed word of that category. Then we train a supervised classifier accordingly. We build three dataless classifiers in this setting by using SVM, L-LDA and MLTM, respectively. The threshold selection process is the same to supervised selection strategy but conducted over the pseudo-training set.

– ESA The Explicit Semantic Analysis-based dataless classification using Wikipedia [3], which is the state-of-the-art semantic-based solution. The recommended setting is used in our evaluation. We use bootstrapping described in [44] since bootstrapping is reported to improve the results of ESA-based methods. We treat the problem as independent binary classification problems and follow [44] by labeling the top $K$ relevant documents as positive for each category, where $K$ is tuned and the best result is reported.

– WMD Word mover’s distance is a state-of-the-art word embedding-based metric for measuring document distances [20], which is also a semantic-based solution. Similar to ESA, we conduct classification based on semantic distances between documents and categories which are represented with seed words. We implement WMD with the pre-trained 300-dimensional word embeddings\textsuperscript{8} from Google News based on Word2Vec [36].

– DescLDA Descriptive LDA [6] is a state-of-the-art probabilistic model-based dataless classifier. Similar to semantic-based solutions, we label the top $K$ relevant documents as positive for each category.

Note that STM [24] explicitly models only one category for each document so that it is not directly applicable to multi-label classification. We further consider some variants of the proposed model by removing or replacing some components in SMTM:

– SMTM – sparsity Recall that we explicitly model the category sparsity in SMTM. Here, we remove the sparsity part in our model. That is, we do not use binary selectors $\alpha$. Then we adopt the same top $K$ strategy used in the baselines to conduct multi-label classification.

– SMTM – category promotion A variant without the promotion for category-topic distribution. We simply set $\mu = 1$ (see Eq. 3), so that no supervision from the seed words is utilized for the calculation of category-topic distribution for a document.

– SMTM – word promotion A variant without the promotion for word distribution. We fix $\tilde{P}_{w,c} = 1$ (see Eq. 8) so that no bias is incorporated in the sampling process of the words under each category-topic.

– SMTM + word embedding Recall that SMTM uses explicit word co-occurrences in the target corpus to estimate $P(w|s)$ (see Eq. 5). We further consider a variant of SMTM that estimates $P(w|s)$ from word embeddings learned from a large external corpus, i.e., the pre-trained 300-dimensional word embeddings from Google News based on Word2Vec. Formally, let $\cos(s, w)$ denote the cosine similarity between the vector representations of seed word $s$ and word $w$, where $\cos(s, w) \in [-1, 1]$. Equation 5 is rewritten as

$$P(w|s) = \frac{\cos(s, w) + 1}{2}$$

such that $P(w|s) \in [0, 1]$. For SMTM, we set $\mu = 0.3$, $\pi = 1$, $p = q = 1$, $\beta_0 = \beta_1 = 0.01$, $\gamma_0 = 50/C$ and $\gamma_1 = 10^{-7}$. Fast convergence of SMTM is observed in our experiments. We conduct the classification after running SMTM for 100 iterations. The averaged result over 10 runs is reported. For fair comparison, the same seed words are used for all dataless methods.

\textsuperscript{8} https://code.google.com/archive/p/word2vec/.
Table 3 Performance comparison on the two datasets

| Method          | Ohsumed | Delicious |
|-----------------|---------|-----------|
|                 | #F1    | #AUC     | #F1    | #AUC     |
| SVM             | 0.629  | 0.921    | 0.461  | 0.846    |
| L-LDA           | 0.520  | 0.861    | 0.401  | 0.763    |
| MLTM            | 0.463  | 0.874    | 0.286  | 0.780    |
| SVM^s           | 0.418  | 0.789    | 0.340  | 0.754    |
| L-LDA^s         | 0.411  | 0.818    | 0.321  | 0.745    |
| MLTM^s          | 0.278  | 0.805    | 0.296  | 0.781    |
| ESA             | 0.424  | 0.851    | 0.343  | 0.775    |
| WMD             | 0.264  | 0.753    | 0.268  | 0.783    |
| DescLDA         | 0.358  | 0.781    | 0.297  | 0.743    |
| SMTM            | 0.480  | 0.872    | 0.370  | 0.793    |
| SMTM – sparsity | 0.437  | 0.864    | 0.346  | 0.788    |
| SMTM – category promotion | 0.448 | 0.866 | 0.334 | 0.786 |
| SMTM – word promotion | 0.450 | 0.861 | 0.362 | 0.789 |
| SMTM + word embedding | 0.451 | 0.845 | 0.364 | 0.783 |

The best and the second best results by dataless classifiers are highlighted in boldface and underlined, respectively. #F1: Macro-F1 score; #AUC: Macro-AUC score

5.4 Results and discussion

The classification performance over the two datasets is reported in Table 3. We observe that SMTM significantly outperforms all other dataless methods in terms of both Macro-F1 and Macro-AUC on both datasets. Among all dataless baselines in comparison, ESA delivers the best Macro-F1 scores on the two datasets, however, with an expensive external knowledge base. We can also find that our approach is much better than DescLDA. Note that DescLDA is also built upon probabilistic topic models but designed for single-label classification. This suggests that our approach successfully discovers the underlying topical structure of multi-label documents, leading to better classification results.

As expected, the supervised classifiers like SVM and L-LDA obtain better classification performance than all the dataless classifiers. However, we observe that our approach does the best to close the gap. In fact, the gap between SMTM and L-LDA is small in terms of Macro-F1, and SMTM even achieves better Macro-AUC scores than L-LDA. The results of MLTM on both datasets are comparable with the ones reported in [42]. An interesting finding is that SMTM outperforms MLTM on both datasets in terms of Macro-F1. Note that SMTM and MLTM are both probabilistic topic model-based techniques. The superiority of SMTM over MLTM confirms again that explicitly modeling category sparsity of the documents is an effective mechanism for multi-label dataless classification.

SMTM is superior to all its variants. This suggests that the proposed sparsity modeling and promotion strategies are effective. The performance loss when removing either promotion strategy (i.e., promotion for the category-topic distribution or the word distribution) validates that the two promotion strategies are complementary so that their combination leads to better classification accuracy. Interestingly, SMTM + word embedding, though with an external resource, underperforms SMTM in all settings. This suggests that using the semantic knowledge in target collection could be more effective than resorting to an external resource, possibly due to the discrepancy in domains.
5.5 Comparison of SMTM and supervised classifiers

Though SMTM is significantly superior to dataless baselines, from Table 3, we observe that SVM is significantly better than our model. Thus, supervised classifiers should be preferred when training data are large in volume and of high quality. Here, we are interested in conducting a deeper comparison of SMTM and supervised classifiers. Specifically, we will discuss a few scenarios in which our dataless classifier will be a more desired choice than supervised classifiers.

First, to better understand the performance of our model, we visualize the $F_1$ per category in Fig. 2. We observe that, surprisingly, SMTM outperforms L-LDA in terms of $F_1$ for about one third of the categories on both datasets. For some categories, SMTM also surpasses SVM. The categories for which SMTM outperforms SVM by more than 3% are Neoplasms in the Ohsumed dataset, and java, education in the Delicious dataset. One possible reason is that these categories are better described by the seed words than the labeled documents. This suggests that seed words could be very strong indicators for some categories, which are even better than labeled documents. That is, seed words could possibly substitute the labeled documents for some categories and result in an even better text classifier. Thus, our approach could possibly be used only to a part of the categories that are precisely described by seed words so that labeled documents are not required for those categories. In this sense, human efforts can be saved with only slight or even no performance loss.

Second, the volume of training data is critical to the effectiveness of supervised classifiers. Here, we would like to find the number of training instances at which SVM starts to outperform SMTM. Following the work in [6], we randomly create the subsets from training documents such that the proportion of documents under each category is identical to that of the whole training set. The performance pattern of SVM in terms of Macro-$F_1$ is shown in Fig. 3a. It takes about 1000 training documents for SVM to obtain comparable performance with SMTM on both datasets. Note that SMTM only uses about 4 seed words for each category on average. SMTM would be a desired choice when a large number of labeled documents are not available.

Third, in many applications, there is only a “partial” set of category labels for a document in the training set [45]. To prepare a multi-label dataset, a user has to consider every possible category for each document. It is likely that the user will miss some proper categories. When a user provides a particular category label for a document, we know that the category is proper.

![Fig. 2 Visualizing per category performance in terms of $F_1$. The categories are numbered in increasing order of $F_1$ scores obtained by SVM. The dataless classifier SMTM outperforms L-LDA for 7/23 categories on the Ohsumed dataset and 7/20 categories on the Delicious dataset. SMTM also occasionally outperforms SVM](image-url)
Multi-label dataless text classification with topic modeling

The number of training documents

Macro-$F_1$

SVM (Ohsumed)  
SVM (Delicious)  
SMTM (Ohsumed)  
SMTM (Delicious)

Fig. 3  Performance comparison of SMTM and SVM. a plots the performance of SVM with different number of training documents; b plots the performance of SVM with different weak label ratios, that is, only that ratio of category labels is kept for each document.

However, for the categories not provided, we cannot conclude that they are not proper. Regularly, “partial” category labels will degrade the performance of supervised classifiers. To simulate this scenario, here, we construct the document datasets with partial category labels. Specifically, we set a specific ratio of the category labels for each document and train an SVM classifier accordingly. For example, given a document with 10 distinct labels, we randomly pick 8 labels from the document for model training, when the ratio is set to be 80%. The result is reported in Fig. 3b. We observe that the performance of SMTM is close to SVM using about 50% to 70% of the category labels for each document. For supervised classifiers, it is expensive to ask human annotators to carefully consider all the categories and assign a perfect category label set for each document. Our dataless classifier will be preferable when the quality of labeled documents cannot be guaranteed.

5.6 Impact of parameters and the number of iterations

Our model has a few parameters. We study the impact of those parameters by varying each parameter, respectively, with other parameters fixed. Note that we do not consider $\gamma_1$ and fix it to $10^{-7}$ since the Gibbs sampling algorithm holds only when $\gamma_1$ is very small. In our experiments, we find that our model is not sensitive to most parameters, except $\mu$ and $\gamma_0$. The performance patterns of SMTM with different $\mu$ and $\gamma_0$ values are plotted in Fig. 4. The two parameters can be well interpreted. $\mu$ controls the importance of observing seed words. Small $\mu$ value indicates that the appearance of a seed word is a very strong indicator...
of the corresponding category. $\gamma_0$ controls the category sparsity of each document and can be understood as a “threshold” of assigning a category label. A small $\gamma_0$ value means a document will be assigned more category labels, that is, a category will be included even when this category is only weakly related to a document. A large $\gamma_0$ results in a small number of category labels for each document, which means a category will be included only when this category is highly related to a document. We can observe that a larger $\gamma_0$ (i.e., about 1 to 5) leads to better performance, consistent with the assumption that the category-topic distribution for a document is sparse. In our evaluation, we set $\gamma_0 = 50/C$ on both datasets, which is a typical value for topic models. For other insensitive parameters, we also set them to typical values.

Fast convergence of SMTM is observed. The performance with respect to the number of iterations is plotted in Fig. 5. We observe stable performance after about 10 iterations.

5.7 Topic visualization and case study

Table 4 shows the most probable words under some sample category-topics learned from the Delicious dataset by using SMTM and L-LDA. Observe that, in addition to the seed words, SMTM discovers other relevant words for each category. For example, SMTM finds “obama” in category politics and “desktop” in category computer, although both are not seed words. We also observe that some irrelevant words are discovered by L-LDA, e.g., “new,” “one,” “use” and “would.” Note that L-LDA uses a large number of labeled documents in learning. The above observations show that SMTM can discover meaningful category-topics that are comparable with supervised topic models.

Table 5 shows three documents in the Delicious dataset. We make the following observations. First, most of the words are generated from the background topic in SMTM. It is reasonable because regularly only those words highly relevant to a category are expected to be generated from the corresponding category-topic. Second, each document only uses category-topics that correspond to its prediction, which provides evidence of the effect of sparsity modeling of SMTM. Third, SMTM can correctly classify a document even if the document contains no seed word. For example, in the second document, there is no seed word of politics. Nevertheless, SMTM successfully associates the document with politics. An explanation is that some words in the document (e.g., “democratic,” “obama”) frequently co-occur with the seed words of politics and are identified as relevant words by our model.
Table 4  Top 10 words learned from the Delicious dataset by SMTM (left) and L-LDA (right) for sample categories

| Category  | SMTM top 10 words                        | L-LDA top 10 words                        |
|-----------|------------------------------------------|------------------------------------------|
| Style     | *style*, color, styles, fonts, div, cascading colors width, font, sheets | *style*, css, color, use, page, font, name, display, styles, fonts |
| Politics  | government, obama, political, mccain, politics, presidential campaign, senate, democracy, federal | government, political, new, people, world, obama, public, campaign, mccain, would |
| Computer  | mac, computer, desktop, hardware, screen, windows, drive, apple, linux, usb | mac, computer, use, windows, software, free, download, file, new, apple |
| Culture   | music, art, culture, artists, artist, film festival, stock, songs, arts | art, music, new, one, culture, artists, time, work, world, video |

The seed words of SMTM are highlighted in boldface, and irrelevant words are underlined.

Table 5  Topic assignments of some documents in the Delicious dataset. The words and punctuations that are removed in the preprocessing step are shaded with gray. Black words are generated from background topic; red from *education*; blue from *web*; purple from *politics*. The seed words are underlined. Note that there is no seed word in the second document.

| Ground Truth: web, education | Prediction: web, education |
|-------------------------------|-----------------------------|
| Hi! My *name* is Wesley Fryer. I am thrilled to be a 21st century digital learner. We live in the most exciting *age* of earth history for anyone with ideas they want to share with a global audience! As I process the world and the *web* I regularly update my *blog*, *podcast*, workshop curricula and social bookmarks. (You can add me to your own *del.icio.us network*! I frequently contribute to *Technology and Learning’s Blog* and Google’s *Education blog*. The Infinite Thinking Machine – A fairly complete list of the websites I maintain, social networks to which I regularly contribute, and other *web* 2.0 sites I utilize is available on claimid.com/wfryer. |

| Ground Truth: politics | Prediction: politics |
|-----------------------|---------------------|
| It’s time for presumed Democratic nominee Barack Obama to turn his attention to a running mate. To help, we bring you the second installment of VP Madness, where users decide who Obama should choose as his #2. Vote in the head-to-head match ups below to determine which *candidates* advance to face each other in the next round. You can view the latest results by clicking the button at the bottom of the page. The winner will be revealed on July 15. Plenty of time for Obama to consider your choice. In the GOP Edition, former Arkansas Governor (and former presidential candidate) Mike Huckabee was chosen as John McCain’s best bet. |

| Ground Truth: education | Prediction: web, education |
|-------------------------|-----------------------------|
| A note about the resources presented. The following is a collection of audio video and multimedia *learning tools for use by faculty and students*. To use any of the tools below you can link to this page as needed or simply right-click your mouse on the title, then copy the *web address* (shortcut, URL, link location) to your system’s clipboard and paste the direct URL into your *code*. The use of these objects is free for nonprofit *educational use* with proper attribution to the CIP as author. |

This also explains why SMTM can discover relevant words in addition to seed words, as illustrated in Table 4. Fourth, some documents may be irrelevant to a particular category even though it contains relevant words of that category. For example, the third document mentions “web” only to tell the readers how to use the tools, but not to talk about the *web*. Unfortunately, “web” is the seed word of *web* in our experiments. It is not a surprise that SMTM mistakenly associates the document with *web* since seed words are assumed to be strong indicators of corresponding categories. Our model could be further improved by considering these conditions.
6 Conclusion and future works

In this paper, we proposed a novel Seed-guided Multi-label Topic Model for multi-label dataless text classification, named SMTM. Without any labeled data or external resource, SMTM only needs few seed words relevant to each category to conduct multi-label classification. The experimental results on two public datasets show that SMTM outperforms existing state-of-the-art dataless baselines and some supervised techniques. We further discussed some scenarios in which SMTM is a more desired choice than supervised solutions. Our approach is preferable when training data are not large or the quality of the data cannot be guaranteed. It is also desirable to use our approach only on the precisely described categories so that labeled documents are not required for those labels.

For future works, we plan to test whether dataless setting is applicable to extreme multi-label classification. Our experiments are conducted on two normal-sized multi-label datasets. In real applications, the number of categories could reach hundreds of thousands or millions. It is interesting to check whether SMTM can work in this situation. In our evaluation, we used LDA-based strategy to select seed words for each category. However, this strategy may not work well when the dimension of the category space is extremely high. It is also necessary to develop more advanced strategies to select seed words.

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Appendix

A. Seed words for evaluation

We manually label some seed words for Delicious and Ohsumed based on standard LDA model. The seed words for Delicious are listed as follows:

| Category   | Seed words                                                      |
|------------|----------------------------------------------------------------|
| Politics   | Politics, government, political, democracy, senate              |
| Design     | Design, css, gallery, designers, designer, graphic              |
| Programming| Programming, php, javascript, python, ruby                     |
| java       | java, eclipse, tomcat, applet                                  |
| Reference  | Reference                                                       |
| internet   | internet, traffic                                              |
| Computer   | Computer, mac, drive, desktop, screen, hardware                 |
| Education  | Education, students, learning, school, teachers                |
| web        | web, html, ajax                                                |
| Language   | Language, languages, French                                    |
| Science    | Science, scientific, brain, scientists, researchers             |
| Writing    | Writing, fiction, tales                                        |
| Culture    | Culture, art, music                                            |
| History    | History, collections, historical, ancient                      |
| Philosophy | Philosophy, ethics                                             |
| Books      | Books, book, chapter, reading, authors, readers                |
| English    | English                                                         |
| Religion   | Religion, Christian, church, religious, fathers, testament, Jesus|
| Grammar    | Grammar, idioms, verbs, verb, sentence, clause, punctuation     |
| Style      | Style                                                           |

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And the seed words for Ohsumed are listed as follows:

| Category                          | Seed words                                                 |
|-----------------------------------|------------------------------------------------------------|
| Bacterial Infections and Mycoses  | Bacterial, infections, mycoses, sepsis                     |
| Virus Diseases                    | Virus, viral, measles, herpes, influenza                   |
| Parasitic Diseases                | Parasite, parasites, malaria, falciparum, leishmaniasis    |
| Neoplasms                         | Neoplasms, neoplasm, cancer, carcinoma, tumor              |
| Musculoskeletal Diseases          | Musculoskeletal, spine, osteomyelitis                      |
| Digestive System Diseases         | Digestive, gastric, hepatitis, bowel, biliary              |
| Stomatognathic Diseases           | Stomatitis, teeth, parotid, periodontal                    |
| Respiratory Tract Diseases        | Respiratory, lung, pneumonia, bronchial                    |
| Otorhinolaryngologic Diseases     | Otolaryngologist, ear, hearing, otitis                     |
| Nervous System Diseases           | Nervous, nerve, neurologic, dementia, neurological         |
| Eye Diseases                      | Eye, eyes, cataract                                        |
| Urologic and Male Genital diseases| Urologic, urological, genital, bladder, prostate, prostatic|
| Female Genital Diseases and       | Genetic, pregnancy, endometrial, endometriosis            |
| pregnancy Complications           |                                                            |
| Cardiovascular Diseases           | Cardiovascular, ventricular, heart, cardiac, hypertension  |
| Hemic and Lymphatic Diseases      | Lymphadenopathy, anemia, sickle, thrombocytopenia          |
| Neonatal Diseases and Abnormalities| Neonatal, neonates, abnormalities, congenital, anomalies   |
| Skin and Connective Tissue Diseases| Skin, connective, tissue, rheumatoid, psoriasis, dermal    |
| Nutritional and Metabolic Diseases| Nutritional, nutrition, metabolic, glucose, insulin, diabetes, diabetic |
| Endocrine Diseases                | Endocrine, thyroid, parathyroid                            |
| Immunologic Diseases              | Immunologic, immunodeficiency, leukemia                    |
| Disorders of Environmental Origin | Disorders, injuries, trauma, fracture                      |
| Animal Diseases                   | Animal animals                                             |
| pathological Conditions, Signs and Symptoms | Pathological postoperative                                 |

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Daochen Zha received his Bachelor degree in school of computer science from Wuhan University in 2018. He is currently a Ph.D candidate at the department of computer science and engineering, Texas A&M University. His research interests focus on data mining, machine learning and its applications.

Chenliang Li received PhD from Nanyang Technological University, Singapore, in 2013. Currently, he is an Associate Professor at School of Cyber Science and Engineering, Wuhan University, China. His research interests include information retrieval, text/web mining, data mining and natural language processing. He is a co-recipient of Best Student Paper Award Honorable Mention in ACM SIGIR 2016, and serves as an editorial board member of JASIST.