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Leveraging Label Information in Representation Learning for Multi-label Text Classification

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ABSTRACT OF THE THESIS

Leveraging Label Information in Representation Learning
for Multi-label Text Classification

by

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The thesis studies the problem of multi-label text classification, and argues that it could benefit from bringing the question into the stage of language understanding. In specific, rather than limit the use of annotated labels to providing supervision in classification only, we also rely on them as auxiliary information to guide the learning of an effective representation that is tangent to the down-stream task. Two approaches are discussed: a) learn a label-word attention layer for composition of word embedding into document vectors; b) learn a high-level latent abstraction via an auto-encoder generative model with structured priors conditional on labels. We introduce two designs of label-enhanced representation learning: Label-embedding Attention Model (LEAM) and Conditional Variational Document model (CVDM) with application on real-world datasets, in order to demonstrate their ability in promoting the classification performances with improved interpretability.

The thesis of Jiayu Wu is approved.

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CHAPTER 1

Introduction

1.1 Motivation and Challenges

Multi-label classification is a common task in natural language processing (NLP). It assigns the most relevant label(s) to a given text document, and is widely applied for review categorization, tag recommendation, information retrieval, etc. The rapid growth in modern data scale is making it increasingly important as well as challenging.

Conventionally, text data can be processed with manually designed label taxonomy and naive labeling methods like regular expression matching. It is obviously not accurate nor efficient enough, and fails to achieve a generalizable understanding of the language.

Going beyond keyword matching, most statistical models and machine learning techniques favor well-defined, fix-length inputs, while the representation of textual data is non-trivial in NLP. Word entities are discrete in form while rich in connotation, and the serial correlation in natural utterances also makes feature extraction more difficult.

In addition, multi-label classification can be harder than the single-label multi-class problem, due to the huge solution space and the potential label structure. Traditional machine learning techniques like binary relavence and label powerset suffers from a high computational cost and unbalanced label distributions. Meanwhile, deep learning methods usually require considerable annotated training samples as well as high computational power, and the model tend to be domain-specific and hard to interpret.

This thesis attempts to look into these challenges, and argues that using label information as auxiliary knowledge in the learning of text representation can facilitate the down-stream classification task and increase model interpretability. Intuitively, instead of assigning labels after finishing the reading, we make the algorithm 'aware of' the task and the possible labels to choose from even before it looks at the text. In this way, the representation of the messy textual data is not only aided by contextual information, but also more tangent to the classification task.

We introduce two approaches to this end: a) learn a label-attention layer after the word embedding layer, and b) learn a latent semantic vector for each document via generative model.

1.2 Outline and Contributions

This thesis is organized in five parts. In the first chapter, we introduce the multi-label text classification task with its main challenges, and state the purpose of this thesis. In Chapter 2, we formally define the task, and review previous literature on the learning of text representation and the training of multi-label classification models respectively, with specific interests in recent advances by using auxiliary knowledge in representation learning. The methodology will then be detailed in the next chapter. We discuss two models: Lable-Embedding Attention Model (LEAM) and Conditional Variational Document Model (CVDM). In Chapter 4, we assess both models on real-world datasets to demonstrate how the classification is boosted and made more interpretable with the use of label-enhanced representation, and some abalative analysis is also presented. Finally, conclusion and discussions will be presented.

The contributions of our work are as follows:

1. argue that using labels information in the stage of text representation learning can facilitate the multi-label classification tasks with improved model interpretability;

2. introduce two sorts of label-enhanced representation learning methods and construct the models for multi-label classification:

    - LEAM: multi-label extension of the multi-class LEAM [42] that introduces attention mechanism between word and label embedded in the same space

- CVDM: latent variable model under the neural variational inference framework with latent prior conditioned on labels.

3. demonstrate that LEAM significantly improves multi-label classification performances, and the decision is made more interpretable due to the learnt attention weights, and scales well to a large number of labels and unbalanced samples.

4. show that CVDM achieves classification performance comparable to benchmark generative methods as well as discriminative classification methods, with a more flexible and generalizable neural network structure.

CHAPTER 2

Preliminaries

2.1 Task Statement

Consider a corpus with N documents. Each document $\mathbf{d}$ is a sequence $\{\mathbf{w}_1, \mathbf{w}_2, ..., \mathbf{w}_i, ..., \mathbf{w}_m\}$ where $\mathbf{w}$'s are word tokens, and m is the length of the document. In order to extract numerical features from it, we denote the p-dimensional vector representing a word token $\mathbf{w}$ as $\mathbf{x}$, and the vector representation of a document $\mathbf{X_d}$.

Since each document $\mathbf{d}$ is associated with an indefinite number of labels, we represent the label with a binary vector $\mathbf{Y_d} = \left[\mathbf{y}^1, \mathbf{y}^2, ..., \mathbf{y}^l, ..., \mathbf{y}^L\right]^\intercal, \mathbf{y}^l \in \{0, 1\}$ where L is the number of potential labels in total. We drop the subscript $\mathbf{d}$ for simplicity, thus the objective is to predict a set of most relevant labels $\mathbf{Y}$ for a document $\mathbf{d}$ represented by $\mathbf{X}$.

The task could be decomposed into two phases in modeling: design or learn a quantitative representation of the text documents, and perform multi-label classification on that representation. We are especially interested in the mapping of a sequence of word entities to a fixed length document vector or a latent variable $\mathbf{Z}$ with the help of the annotated labels:

$$\mathbf{X} = f\left(\mathbf{x}_1, \mathbf{x}_2, ..., \mathbf{x}_i, ..., \mathbf{x}_m; \mathbf{Y}\right) \quad \text{and/or} \quad \mathbf{Z} = f\left(\mathbf{X}; \mathbf{Y}\right).$$

2.2 Representation Learning

The representation of textual data is a prevalent challenge in modeling language. Natural utterances are sequences of discrete entities of indefinite lengths, while the semantic nuances as well as the syntactic rules entailed are hard for even human learners to command. In contrast, most modeling and learning algorithms prefer well-defined, fixed-length numerical data and tend to be limited to differentiable functions. Therefore, an important problem in language processing is to extract from the textual data numerical features capable of representing various linguistic properties of the text [11].

2.2.1 Word representation

"Without grammar, very little can be conveyed; without vocabulary, nothing can be conveyed" [46] . Word tokens are commonly used as the lowest level modeling components in NLP as the basic abstract units of meaning. Representing a word is the design or learning of a mathematical object associated with each word, often a vector [40].

Discrete symbols

Regarding word tokens as discrete symbols, a generic way is to represent each word by a one-hot vector, the vector dimension is then the size of the vocabulary denoted as $|V|$. With a high volume of vocabulary, such representation is extremely sparse as well as high-dimensional, and lacks a similarity measure between words.

To capture the relationship between words, graphically structured dictionary (taxonomy) that links synonym and hypernym together are designed, an example is the word-net [23]. However, it requires massive human expertise and labor, as the constant development of language is making an accurate and up-to-date dictionary hard to maintain. Nevertheless, the similarity is still hard to quantify objectively.

Word embedding

In recent years, the pursuit of word embedding has become popular, especially deep neural network models motivated by the development in computation power and the success of pre-trained feature extractors in the field of computer vision. Empirical evidences have shown that the effectiveness of word embedding can be the key to improvement on various NLP task, including and not limited to text classification [3][26].

Word embedding is real-valued, fixed-length dense feature vector of the word, of which the dimension is usually far more compact than the vocabulary size. It is also called distributed representation [3][40], because it is usually learned unsupervised with the assumption known as distributional hypothesis [1][12], that is, similar words should have similar contexts. The learnt representation not only is reduced in dimension, but also provides a simple word similarity measure by distance or angle (ex. cosine similarity) between vectors. Hopefully, each embedding dimension represents a meaningful latent syntactic or semantic feature of the word [40], which even makes word analogy possible, such as *man:woman* $\sim$ *king:queen*.

In general, word embedding can be learnt from global or local co-occurence information. The former is by factorization or low-rank approximation on a global relational matrix from a general corpus. An example is Latent Semantic Analysis (LSA) [8] that applies SVD to a term-document matrix. The later is to build a predictive model for the local context of each word, where neural language models (NNLM) are prevalent. NNLM solve for a language model that is capable of predicting the most probable word given its context, and the vector representation (usually the first hidden layer) corresponding to each word can be output as word embedding $\mathbf{x}$.

Many efforts have been made towards higher efficiency and performance since the first large NNLM proposed by Bengio in 2003 [3]. Word2Vector introduces two popular frameworks, Skip-Gram and Continuous Bag-of-Words, which can be seen as a two-layer network with an efficient architecture providing nice semantic properties [22]. Interestingly, there is also a proven connection to the global embedding methods, as it implicitly factorizes globally shifted word-context matrices with pair-wise information measures [18]. Another prominent word embedding architecture, GloVe [26], leverages both the local context window and the global co-occurrence matrix via a bilinear regression model. ELMO further model the different usage of the same word by learning multiple levels of syntactic and semantic information about words in-context [27]. A most recent advance in 2018, BERT, achieves state-of-the-art performances on a vast of tasks via a transformer neural architecture and two novel objectives: predict masked words and next sentences [9].

Word embedding is significant as a pre-train method widely used in NLP, which makes learning transferable between various text domains and tasks. The embedded features can be used directly for down-stream task, or fine-tuned over specific tasks [9][29]. It is notable that, both the application of word embedding and the training of language models require the composition of the representations of single words into that of the training units - sentences or documents.

2.2.2 Document representation

Bag-of-words

A simple way to represent document is to add up all one-hot word vectors, resulting in a document vector that is an occurrence count of the vocabulary. It is called bag-of-words (BoW), because only content is preserved and the order information discarded. It can be generalized to n-gram model which counts all unique contiguous sequences of n tokens instead of single words, such that some multi-word expressions can be identified.

Although BoW does not tap into the word-level nuances, it is still a simple and useful feature extractor for documents. Intuitively, similar documents tend to have similar distributions over the tokens, and occurrence of certain words can be indicative of the document semantic. Representing the word distribution by count, however, can be biased by the varying lengths of documents and certain words frequent in the whole corpus (ex. 'the', 'is'). Therefore, Term Frequency Inverse Document Frequency (TFIDF) is motivated, which uses the frequency normalized by length and rescaled by how often they appear in the whole corpus to penalize words that dominate. The resulting value corresponding to each word indicates how informative the word is in distinguishing this document from the others.

Neural networks and attention

As for the composition of word embedding, there are studies showing that simply averaging [45] or max-pooling [31] achieves excellent performance given a good enough embedding. Nonetheless, there are also more sophisticated methods attempting to incorporate structural or temporal correlation. Neural networks, as powerful approximator for complex nonlinear functions, are popular choices for not only learning of language models but also down-stream NLP tasks.

The local context and serial correlation between words motivates the prevalent use of convolutional networks (CNN) and recurrent networks (RNN) [27][53]. Long-short Term

Memory (LSTM), a variant of RNN, stands out due to its ability to reduce the gradient vanishing of signal faraway, which improves the performances over longer sentences. Bi-direction LSTM benefits from the context after the word as well as that comes before it, by concatenating two feature vectors learnt on both direction. It achieves excellent performances in language model architectures like ELMO as well as in various NLP tasks [48][50]. However, RNN has the drawback that the sequential computation cannot be parallelized, hence takes longer time to train.

Attention mechanism is an important technique to promote the efficiency in modeling distant dependency, while maintaining a simple, interpretable and parallelizable structure. Attention models dynamically 'pay attention to' (put more weight on) certain parts of the input that is more relevant to the task at hand than others, and can be flexibly incorporated to different levels of representation or threads of inputs [6]. Not only can it incorporates other structures like RNNs [2], Transformer architecture bypasses the inefficient RNNs by modeling sequences purely based on a stack of multi-head self-attention over position embedding and content embedding [41].

In text classification tasks, attention models are mainly used for better document representation. An example is HAN proposed by Yang et al. that achieves a SOTA performance with both word-level and sentence-level attention [49].

2.2.3 Latent Variable Inference

Another way to extract a compact representation of messy raw data is via latent variable inference or generative statistical models [25], which is useful not only for signal generation like in machine translation or question answering, but also for obtaining efficient and hopefully interpretable latent representations.

Latent variable models assumes that there exists a hidden variable underlying the observed data $\mathbf{X}$, denoted as $\mathbf{Z}$. It can be considered as the hidden structure from which the observed data are generated, or as a high-level abstraction of the data. Thus the marginal data probability can be defined via Bayes rule: $p(\mathbf{X}) = \int p(\mathbf{Z}, \mathbf{X}) d\,\mathbf{Z}$. By introducing an approximator $q(\mathbf{Z})$, the evidence lower bound (ELBO) can be derived by Jensen's Inequality (see appendix):

$$\log p(\mathbf{X}) \geq ELBO = \mathbb{E}_q[\log p(\mathbf{X}, \mathbf{Z})] - \mathbb{E}_q[\log q(\mathbf{Z})] = E_q[\log p(\mathbf{X})] - D_{KL}(q(\mathbf{Z}) \parallel p(\mathbf{Z} \mid \mathbf{X}))$$

EM algorithm can be used to iteratively update $q(\mathbf{Z})$ when the posterior distribution is in a known form. However, the posterior is intractable in most cases, then Monte Carlo sampling or Variational Bayes may be sought for approximation.

In language processing, topic models are widely explored, which explains text by a specified number of unobserved classes [5][13]. It considers document with BoW encoding, and assumes a probabilistic generative process that each document corresponds to a topic sampled from a corpus-specific multinomial distribution over all potential topics, then each word in that document is sampled from a topic-specific multinomial distribution over the whole vocabulary:

$$\begin{aligned} \mathbf{y}_l &\sim \text{Multinomial}(\boldsymbol{\theta}), \qquad \boldsymbol{\theta} \sim p(\alpha_0) \\ \mathbf{w}_i &\sim \text{Multinomial}(\beta_l) \end{aligned}$$

Here $\mathbf{y}_l$ is the discrete latent variable indicating the l-th topic, $\boldsymbol{\theta}$ is a corpus-level parameter sampled from the a prior distribution with hyperparameter α_0, and β_l parameterizes the word distribution corresponding to the topic $\mathbf{y}_l$. It can also be generalized to document models, where latent semantics are assumed represented by a continuous vectors instead of discrete topic.

A successful model, Latent Dirichlet allocation (LDA) relies on the conjugate prior, Dirichlet distribution $\boldsymbol{\theta} \sim \text{Dirichlet}(\alpha_0), \alpha_0 \geq 0$, for analytical computation to the posterior over the discrete latent topics [5]. There are also extensions to incorporate annotated labels and even multi-label information, like in semi-supervised LDA or Multi-label Topic Model [33]. All these methods require certain assumption for approximation and meticulous derivation for tractable computation.

Whereas, more expressive models are in increasing demand to accommodate more complex and diverse problem with different sources of information, where closed-form derivation are often non-trivial and hard to generalize. Variational auto-encoder (VAE) introduced the idea to learn a approximate posterior probability $q(\mathbf{Z} \mid \mathbf{X})$ parameterized by an neural inference network, rather than rely on analytic approximation as in traditional variational Bayes [16]. They propose a different variational lower bound that matches the approximate posterior to a prior (see Appendix):

$$\log p(\mathbf{X}) \geq \mathcal{L}_{VAE} = \mathbb{E}_{q(\mathbf{Z} \mid \mathbf{X})}[\log p(\mathbf{X} \mid \mathbf{Z})]] - D_{KL}(q(\mathbf{Z} \mid \mathbf{X}) \parallel p(\mathbf{Z}))$$

$q(\mathbf{Z} \mid \mathbf{X})$ and $p(\mathbf{Z})$ are usually assumed to follow distributions easy to sample from, such as gaussian or uniform distribution, thus it is capable of learning complicated non-linear distributions with strong generalisation ability as well as simple computation.

The success of VAE motivates a vast of extensions under the Neural Variational Inference framework, for signal generation as well as latent variable inference [37]. Miao et al. proposed several neural topic and document models (NVDM, NVTM), where the inference is conditioned on easy samples from multivariate gaussian, and the model architectures are designed to discretize the variable while preserving some conjugacy property [20][21]. However, a drawback to these models is that they are fully unsupervised, so the learning can not make full use of the known context, and the learnt latent topics are not always coherent.

2.3 Multi-label Classification

Assigning multiple labels is natural for many real scenarios including text processing, as each document usually belongs to more than one semantic categories. It is a more challenging than single-label problem, as the solution space grows exponentially with the the size of the labels L and the distribution of available samples over the labels can be very unbalanced. For example, among the 90 labels in the benchmark dataset Reuters, some labels have thousands of training sample, whereas the least populated label is seen only once in the training.

The related models can be categorized into two types: problem transformation methods, and algorithm adaptation methods [38].

The former transform the multi-label task into single-label classification or regression problems, and choose corresponding algorithm to solve it. A common example is the Binary

Relevance (BR), also referred to as one-vs-all, which independently train one binary classifier per label to tell apart it against all the others. To further consider the label correlations, there are label powerset (LP) that train a multi-class classifier on all unique label combinations [39], and classifier chains (CC) that train a chain of binary classifiers [30]. They are mostly strong baselines with simple intuition and implementation, however, the computational cost usually scales with the label size.

Algorithm adaptation methods extend specific learning algorithms to handle multi-label data directly. Ensemble tree methods are widely explored, Clare and King extend entropy to multi-label scenario [7], and FastXML improves the accuracy by learning a hyperplane to split instances rather than selecting a feature subset at each node [28]. Ranking-based methods are also popular choices, such as Rank-SVM [10], ML-KNN [52]. They are more computationally efficient than most problem transformation methods, yet the selection of a decision threshold is usually required.

BP-MLL was one of the first to use neural network for multi-label tasks by a pairwise ranking loss [51]. More recent research, however, reported that binary cross entropy loss with rectified linear units (ReLU) outperforms the pairwise ranking loss with higher efficiency [24]. Such feed-forward architectures are easy to execute, yet they relied on the parameter itself to exploit the dependency across labels.

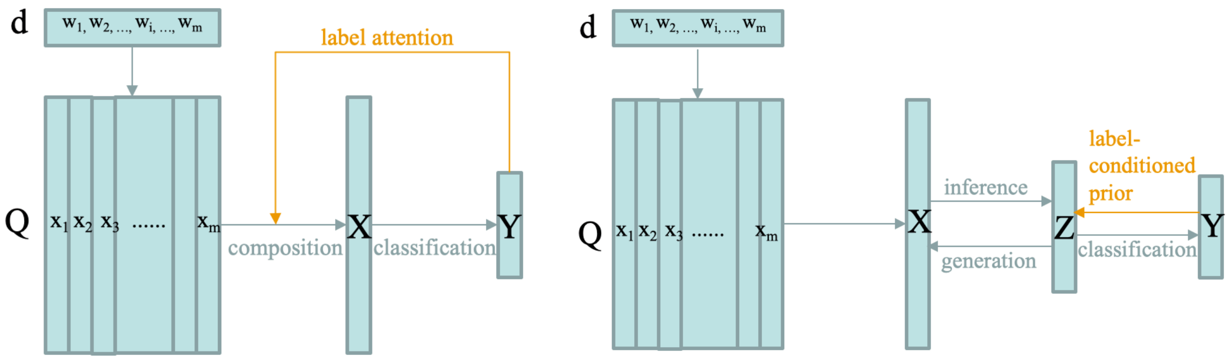
More sophisticated architectures are proposed in many recent works. Wei et al. proposed a modified architecture for multi-label image classification [44]. SGM use RNN to sequentially generate label predictions in order to learn label correlation, and using label co-occurrence statistic in network initialization is also proven to better capture label dependencies [17]. Label embedding methods are greatly improves the efficient when the label space is huge and sparse, which compress the label Y to a low dimensional latent space, and decompress the predicted embedding to the original label space [4].

CHAPTER 3

Methodology

3.1 Leveraging Label Information

We introduce two approaches to leverage the annotated labels $\mathbf{Y}$ in the representation of textual data, in the scenarios of discriminative learning and generative learning respectively. As illustrated in Figure 3.1, the former enhance the document representation by introducing attention between label-word pairs, and the later imposes structure in latent representation by matching the posterior to label-conditioned priors. Both are capable of producing representation of the original document that are more tangent to the down-stream classification task.



(a) Discriminative

(b) Generative

Figure 3.1: Illustration of the use of label information

Label attention

As mentioned before, several text classification models use the attention mechanism for a good representation of the text sequence [19][49]. Nevertheless, these model mainly focus on self-attention that applies attention to each word-word pair from the text itself, while auxiliary information are less explored even though the attention between words and labels is directly related to the target task.

Label-Embedding Attentive Model (LEAM) is a recent state-of-the-art text classification model proposed by Wang et al.[42]. It embeds words and labels to the same latent space, and aggregates the word embedding into the document representation attended by the label embedding. Moreover, the prediction is made more interpretable by outputting the attention weights for each word as a by-product, which may also provide informational anchors for human speed reading and assessment.

Despite the novel idea and excellent results, the original work did not analyze the effect of the pre-trained embedding and attention structures in the architecture. We will detail the model in Section 3.2, and implement it for experiments on real-world multi-label tasks and further compare some ablative methods.

Conditional VAE

The vanilla VAE framework has the drawback that its inference process is fully unsupervised without leveraging auxiliary knowledge. It not only limits its interpretability, but also reduces the inference ability. Namely, the inference network either matches all the latent representations closely together to the one prior $p(\mathbf{Z})$, though they can be multi-modal in nature (ex. from different classes), or fail to learn an effective inference because the generative objective dominates the objective function [54]. Many research have contributed to improving the quality of autoencoder-based representation learning [36][37], either by modifying objective function [54] or imposing structured prior [14].

Conditional VAE (CVAE), is motivated by the need to generate more diverse signals (images or answers) conditioned on certain context attributes [32][47][55]. It defines a prior network to learn the prior distribution conditional on known attributes (ex. classes), and the variational lower bound conditional on the attributes can be rewritten in accordance (see Appendix) [34]. CVAE is also applied on the task of zero-shot image classification, to aid the prediction of unseen classes by sharing prior network between the seen classes with the unseen ones [43].

We intend to incorporate the idea into NVDM to build a supervised generative model for text categorization. The proposed model will be described in Section 3.3 and compare with traditional supervised LDA in the experiments.

3.2 Multi-label LEAM Model

We denote the embedding of a word $\mathbf{w}$ as e-dimensional vector $\mathbf{x}$, and construct a embedding matrix concatenating all the words in the whole document as: $\mathbf{Q} = \{\mathbf{x}_1, ..., \mathbf{x}_i, ..., \mathbf{x}_m\} \in \mathbb{R}^{(e \times m)}$. We also embed the labels $\mathbf{Y}$ into the same embedding space, denoted as $\mathbf{C} = \{\mathbf{c}_1, ..., \mathbf{c}_l, ..., \mathbf{c}_L\} \in \mathbb{R}^{(e \times L)}$. Then we align all the label-word pairs via the cosine similarity:

$$\mathbf{G} = \frac{\mathbf{C}^{\intercal}\mathbf{Q}}{|\mathbf{C}| \cdot |\mathbf{Q}|} \tag{3.1}$$

$\mathbf{G} \in \mathbb{R}^{(L \times m)}$ measures the similarity between each label and word token with respect to the document, in order to determine how relevant a word is to each label. Nonetheless, the local context can impact the word meaning, so an $1 - d$ convolution with ReLU activation is added on to obtain an alignment between the label and each $2r + 1$ gram window center at word $\mathbf{w}_i$:

$$a = \{a_1, ..., a_i, ..., a_m\} \qquad a_i = ReLU\left(\mathbf{G}_{i-r:i+r} W + b\right) \tag{3.2}$$

Then the attention $\boldsymbol{\alpha}$ is obtained by max-pooling and softmax, resulting in the weights for each word in the document, and finally the composition of the document vector is computed as the weighted average:

$$\boldsymbol{\alpha} = \{\alpha_1, ..., \alpha_i, ..., \alpha_m\} \qquad \alpha_i = \text{softmax}\left(\text{max-pooling}\left(a_i\right)\right) \tag{3.3}$$

$$\mathbf{X} = \sum_i^m \alpha_i \, \mathbf{x}_i \tag{3.4}$$

The label-attended document representation $\mathbf{X}$ can be used as the input to a multi-label classification algorithm, the embedding weights and attention parameters can be learnt or fine-tuned simultaneously with the classifier. In our experiments, we compare on different datasets the effect of using a pre-trained word embedding and learn the embedding from random initialization in the target corpus.

An interesting byproduct of LEAM, is the attention weights on each word $\boldsymbol{\alpha}$, such that we may highlight the most 'important' (more weights in the representation composition) words in the document. It will also be exemplified in the experiments. In addition, there are several potential variants of LEAM architecture. The word-label alignment can be computed in alternative ways. Some of them will be compared in the experiments.

3.3 Conditional Variational Document Model

We propose Conditional Variational Document Model (CVDM) by introducing class-conditioned priors into NVDM by Mian et al. [20], and use a KL-divergence based ranking score for classification prediction similar to VZSL by Wang et al.[43].

We denote the BoW encoded document as $\mathbf{X}$, and assume there exists a high-level semantic abstraction notated by a p-dimensional latent variable $\mathbf{Z}$. The posterior distribution $p(\mathbf{Z} \mid \mathbf{X})$ is approximated by a isotropic Gaussian distribution parameterized by an inference network $f(\cdot; \phi)$:

$$q_\phi(\mathbf{Z} \mid \mathbf{X}) \sim N(f_\mu(\mathbf{X}; \phi), f_\sigma^2(\mathbf{X}; \phi) I_p) \tag{3.5}$$

In order to leverage the label information, we assume the prior distribution of latent variable $\mathbf{Z}$ is conditional on the label set $\mathbf{Y}$, and the distribution parameters are learnt by a prior network $g_\mu(\cdot; \psi)$, which can be a multi-layer perceptron or a simple linear transformation:

$$p(\mathbf{Z} \mid \mathbf{Y}, \mathbf{A}) = \prod_l^L \left[p(\mathbf{Z} \mid \mathbf{y}^l)\right]^{\mathbf{y}^l} = \prod_l^L \left[N(g_\mu(\mathbf{a}^l; \psi), g_\sigma^2(\mathbf{a}^l; \psi) I_p)\right]^{\mathbf{y}^l} \tag{3.6}$$

Here $\mathbf{A} = \left[\mathbf{a}^1, ..., \mathbf{a}^l, ..., \mathbf{a}^L\right]$ are the attributes associated with each label, they can be learnt from random initialization or use additional features, for example, features extracted by TF-IDF over all the documents associated with each label.

For better interpretability, we assume each document is generated over a mixture of labels following a similar intuition to topic models. In specific, each label defines a multinomial distribution over the vocabulary parameterized by β_l, and the occurrence of each label follows a Bernoulli distribution parameterized by $\boldsymbol{\theta}$ that is conditioned on samples from the latent variable $\hat{\mathbf{Z}}$:

$$\begin{cases} \mathbf{y}^l \sim \text{Bernoulli}\left(\theta_l\right), & \boldsymbol{\theta} = \text{sigmoid}(\hat{\mathbf{Z}}U) = [\theta_1, ..., \theta_l, ..., \theta_L] \\ \mathbf{w} \sim \text{Multinomial}(\beta_l), & \beta = \text{softmax}(V) = [\beta_1, ..., \beta_l, ..., \beta_L] \end{cases} \tag{3.7}$$

where $U \in \mathbb{R}^{(p \times L)}, V \in \mathbb{R}^{(L \times |V|)}$ are learnable weight parameters. Therefore, by sampling $\tilde{\mathbf{Z}}$ from the posterior and compute topic distribution parameter $\tilde{\boldsymbol{\theta}}$, the label indicator $\mathbf{y}^l$ can be integrated out as:

$$\log p(\mathbf{X}; \tilde{\boldsymbol{\theta}}, \beta) = \sum_i^m \left[\log p(\mathbf{w}_i; \tilde{\boldsymbol{\theta}}, \beta)\right] = \sum_i^m \left[\log \sum_l^L \left[p(\mathbf{w}_i; \beta_l) p(\mathbf{y}^l; \tilde{\theta}_l)\right]\right] = \log(\tilde{\boldsymbol{\theta}} \cdot \beta) \tag{3.8}$$

We may derive the variational lower bound as follows:

$$\begin{aligned} \log p(\mathbf{X} \,|\, \mathbf{Y}, \mathbf{A}) &\geq \mathbb{E}_{q(\mathbf{Z} \,|\, \mathbf{X}; \phi)} \left[\log p(\mathbf{X}; \boldsymbol{\theta}, \beta)\right] - D_{KL}(q(\mathbf{Z} \,|\, \mathbf{X}; \phi) \parallel p(\mathbf{Z} \,|\, \mathbf{Y}, \mathbf{A}; \psi)) \\ &= \mathbb{E}_{q(\mathbf{Z} \,|\, \mathbf{X}; \phi)} \left[\log p(\mathbf{X}; \boldsymbol{\theta}, \beta)\right] - \mathbb{E}_{q(\mathbf{Z} \,|\, \mathbf{X}; \phi)} \left[\log q(\mathbf{Z} \,|\, \mathbf{X}; \phi)\right] \\ &\qquad + \sum_l^L \mathbf{y}^l \cdot \mathbb{E}_{q(\mathbf{Z} \,|\, \mathbf{X}; \phi)} \left[\log p(\mathbf{Z} \,|\, \mathbf{a}^l; \psi)\right] \\ &= \mathbb{E}_{q(\mathbf{Z} \,|\, \mathbf{X}; \phi)} \left[\log p(\mathbf{X}; \boldsymbol{\theta}, \beta)\right] - \sum_l^L \mathbf{y}^l \cdot D_{KL}(q(\mathbf{Z} \,|\, \mathbf{X}; \phi) \parallel p(\mathbf{Z} \,|\, \mathbf{a}_l; \psi)) + const. \end{aligned}$$

Since the last term is an additive constant, we may formulate the CVAE Likelihood as:

$$\mathcal{L}_{CVAE} = \frac{1}{N} \sum_d^N \left[\log(\mathbf{X}; \boldsymbol{\theta}; \theta, \beta) - \sum_l^L \mathbf{y}_d^l \cdot D_{KL}(q(\mathbf{Z}_d \,|\, \mathbf{X}_d; \phi) \parallel p(\mathbf{Z}_d \,|\, \mathbf{a}_d^l; \psi))\right] \tag{3.9}$$

A trivial solution to maximize L_{CVAE}, however, is to learn the same prior distribution $p(\mathbf{Z} \,|\, \mathbf{y}_l; \psi)$ for each label, which reduces the model to the original VAE with a standard gaussian prior. Therefore, we augment the objective with a margin regularizer. We encourage $q(\mathbf{Z} \,|\, \mathbf{X}; \phi)$ to be far away from irrelevant labels by penalizing the maximum-margin between the next best label. Since the hard maximum is non-differentiable, we use the smooth surrogate log-sum-exponential trick:

$$\mathcal{L}_{REG} = \log \sum_l^L (1 - \mathbf{y}^l) \cdot \exp\left[-D_{KL}(q(\mathbf{z} | \, \mathbf{X}; \phi) \parallel p(\mathbf{z}_d | \, \mathbf{a}_d^l; \psi))\right] \tag{3.10}$$

The final objective function to be optimized is:

$$\begin{aligned}\mathcal{L} \;&= \tfrac{1}{N}\textstyle\sum_d^N \{\log p(\mathbf{X}_d;\theta,\beta) - \sum_l^L \mathbf{y}_d^l \cdot D_{KL}(q(\mathbf{Z}_d\,|\,\mathbf{X}_d;\phi) \parallel p(\mathbf{Z}_d\,|\,\mathbf{a}_d^l;\psi)) \\ &\qquad -\lambda \cdot log \textstyle\sum_l^L (1-\mathbf{y}^l)\cdot \exp\left[-D_{KL}(q(\mathbf{z}|\,\mathbf{X};\phi) \parallel p(\mathbf{z}_d|\,\mathbf{a}_d^l;\psi))\right]\}\end{aligned} \tag{3.11}$$

Given the trained model parameters, the prediction on a testing document $\mathbf{X}$ from that corpus can be obtained by first encoding the feature $\mathbf{X}$ into variable $\mathbf{Z}$, and sample a latent variable or use the mean as $\hat{\mathbf{Z}}$, then selecting the most probable labels. The generative learning process has provided a natural choice of scoring: KL-divergence measuring the distance between the latent variable to the label-conditioned priors:

$$\hat{\mathbf{y}}_l = \mathbb{1}\left[\text{sigmoid}(-D_{KL}(q(\mathbf{Z}\,|\,\mathbf{X};\phi) \parallel p(\mathbf{Z}\,|\,\mathbf{a}_l;\psi))) > T\right] \tag{3.12}$$

Here T is a decision threshold. Since the KL-divergence term is greater than 0, the resulting score is always less than .5, so we select T empirically by grid-search on the interval $(0, 0.5]$ to find a T with minimum macro-F1 score.

CHAPTER 4

Experiments

4.1 Experiment setting

We evaluate LEAM and CVDM empirically on three English text datasets: Reuters, Delicious and anon-Rev. The first two are public annotated datasets, and the last one is an anonymous business review datasets provided by Stratifyd Inc. The data attributes are listed in Table 4.1. Here we define Label Density (LD) as the average number of labels per sample divided by the size of labels, in order to quantify to which a dataset is multi-label: $LD = \frac{1}{N}\sum_{d=1}^{N} \frac{|\mathbf{Y}_d|}{|L|}$.

Dataset	#labels	LD	#train set	%multi-label	#test set	#Vocab
Reuters	90	0.0137	7769	15.09	3019	11411
Delicious	20	0.1539	7764	87.77	3757	8520
anon-Rev	54	0.0390	14765	52.49	3692	9828

Table 4.1: Data Description

The Reuters is a benchmark financial newswire dataset for document classification, and we use its "ApteMod" subeset[1], and keep only the alphabetic vocabulary appear at least three times. The Delicious dataset[2] [56] contains tagged web pages retrieved from the social bookmarking site delicious.com with 20 common tags, we adopted the preprocessed and partitioned version by Soleimani and Miller[3] [33]. The anon-Rev dataset contains online

[1]http://kdd.ics.uci.edu/databases/reuters21578/reuters21578.html

[2]http://nlp.uned.es/social-tagging/delicioust140/

[3]https://github.com/hsoleimani/MLTM/tree/master/Data

reviews on banking services, labeled by the keyword matching method. In all experiments, we split the training data into train and validation by a ratio of 4:1 for threshold selection and tuning purpose.

For the Delicious dataset, we use the same preprocessing procedure by Soleimani and Miller [33] for a fair comparison with their experiment results in section 4.4. This version uses a larger stopword set, and performs word stemming in order to obtain a more compact BoW representation. As a result, GloVe embedding is of little use and some sequential info can be lost, so we will focus on CVDM for this dataset.

In LEAM implementation, we employ 300 dimensional word embedding and set the convolution window size as 8, a maximum length of $m = 100$ is fixed for each document. We train a two-layer MLP with 256 hidden units and binary cross entropy loss as the multi-label classifier. In *LEAM, we learn the embedding weights from random initialization. In the pre-trained version (GloVe-LEAM), we use $300 - d$ GloVe embedding pre-trained on Wikipedia 2014 + Gigaword 5 as embeddings weights initialization, and the Out-Of-Vocabulary (OOV) words are initialized from a mean embedding over the whole vocabulary.

As for CVDM, we set the inference network to be a two-layer MLP with 256 hidden units each, and the latent variable dimension is set to $p = 60$. The prior net uses a simple linear transformation, and in *CVDM, we learn a 128-dimension label attributes $\mathbf{A}$ from random initialization while the TFIDF-CVDM uses 128-dimension TF-IDF features. The regularization parameter λ is set to 1, and in each epoch we alternatively update the encoder and the decoder.

We compare our models with two strong baselines based on neural network methods, BoW-MLP and GloVe-MLP. The former takes BoW encoded documents as input, while the later learns embedding weights from GloVe initialization and the document vector is built by mean-pooling over word vectors. Both train two-layer MLP as classifiers.

We use Adam Optimizer [15] with an initial learning rate of 0.001 and a minibatch size of 128, dropout regularization is employed on each hidden layer with a 0.5 rate. The performances are evaluated on the testing set unseen in training if not specified otherwise.

4.2 Evaluation metric

The evaluation for multi-label classification should be different than those for single-label targets, since the prediction for each example can be partially right as well as being completely right or miss. We introduce several metrics to assess and compare the performance in our experiments. The true label set is notated as binary vector $\mathbf{Y}$, and similarily the predicted as $\hat{\mathbf{Y}}$.

If we consider only the complete right cases as accurate prediction, we have a simple and strict measure **Exact Match Ratio** [35] :$EMR = \frac{1}{N}\sum_{d=1}^{N} \mathbb{1}(\mathbf{Y}_d = \hat{\mathbf{Y}}_d)$.

In order to account for partial correctness, Godbole et al. adopted **Hamming Score** to measure **Multilable Accuracy** as a symmetric measure of the distance between two binary vectors:

$$Accuracy = \frac{1}{N}\sum_{d=1}^{N} \frac{|\,\mathbf{Y}_d \cap \hat{\mathbf{Y}}_d|}{|\,\mathbf{Y}_d \cup \hat{\mathbf{Y}}_d|}$$

and corresponding **Precision**, **Recall** and **F1** measures:

$$Precision = \frac{1}{N}\sum_{d=1}^{N} \frac{|Y_d \cap \hat{\mathbf{Y}}_d|}{|\hat{\mathbf{Y}}_d|} \qquad Recall = \frac{1}{N}\sum_{d=1}^{N} \frac{|\,\mathbf{Y}_d \cap \hat{\mathbf{Y}}_d|}{|\,\mathbf{Y}_d\,|} \qquad F1 = \frac{1}{N}\sum_{d=1}^{N} \frac{2|\,\mathbf{Y}_d \cap \hat{\mathbf{Y}}_d|}{|\,\mathbf{Y}_d\,| + |\hat{\mathbf{Y}}_d|}$$

These are also called **Micro** measures, where True Positive (TP) and False Positive (FP) are counted globally and averaged per sample. Because they care more about positives then negatives, more frequent labels may dominate the measure. To alleviate that, we also have **Macro** measures, where statistics are computed for and averaged over each classes such that they are given the same weight:

$$macro - F1 = \frac{1}{L}\sum_{l=1}^{L} \frac{2|\,\mathbf{Y}^l \cap \hat{\mathbf{Y}}^l|}{|\,\mathbf{Y}^l\,| + |\hat{\mathbf{Y}}^l|}$$

As mentioned before, thresholding can affect the classification accuracy, especially for ranking-based algorithms. Therefore, to assess and compare the ranking performance, **ROC-AUC** can be used, which is the area under the receiver operating characteristic. Similarly, it also has Micro and Macro measures [33].

4.3 LEAM Results and Analysis

Table 4.2 compares the LEAM results on Reuters and anon-Rev. The performances over training processes are plotted in Figure 4.1 and Figure 4.2 respectively, in which the middle one display the testing macro-F1, the left one shows the micro-F1 and the right one training macro-F1. It can be observed that micro-F1 hardly tells apart different models, while macro measure is less biased by high-frequency labels.

	Reuters				anon-Rev			
Model	Macro-F1	Micro-F1	Accuracy	macro-AUC	Macro-F1	Micro-F1	Accuracy	One-Error
BoW-MLP	0.4378	0.8396	0.8470	0.0891	0.4947	0.7118	0.6770	0.1153
GloVe-MLP	0.3593	0.8188	0.8191	0.1165	0.3987	0.6846	0.6517	0.1454
*LEAM	0.3860	0.8349	0.8351	0.1050	**0.5358**	**0.7406**	**0.7106**	**0.0921**
GloVe-LEAM	**0.4798**	**0.8464**	**0.8580**	**0.0847**	0.5129	0.7004	0.6696	0.1278

Table 4.2: LEAM Results Comparison

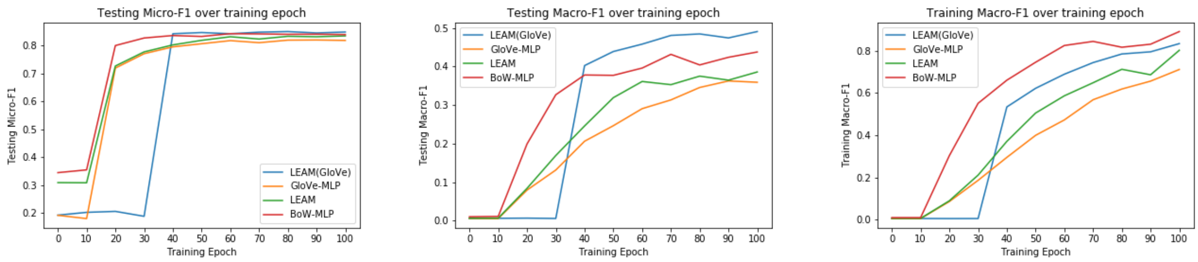


Figure 4.1: Reuters Performance over Training Epoches

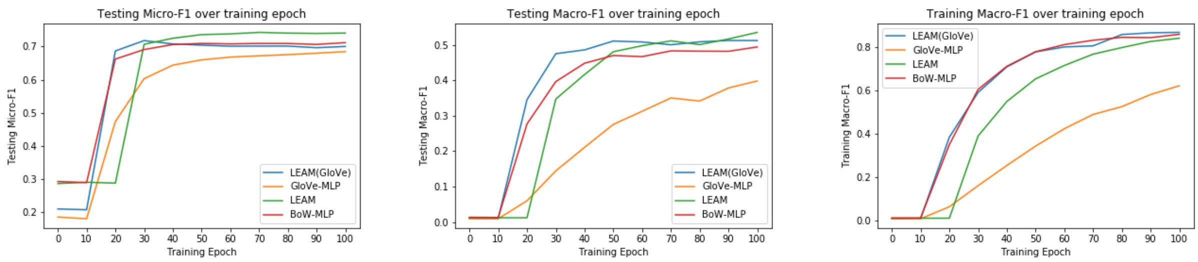


Figure 4.2: anon-Rev Performance over Training Epoches

We can observe that LEAM achieves the best performances on both datasets.

On Reuters, the pre-trained GloVe initialization greatly improves Macro-F1 that indicates better predictions on rare classes, and is less prone to overfit. As for anon-Rev, *LEAM is slightly better. We hypothesize that it is related to the difference in vocabulary domain. GloVe is trained on newswire stories and encyclopedia, and is closer to the domain of Reuters collection. Whereas, non-Rev tend to use informal language with a relative smaller vocabulary, and the label distribution is more balanced, hence the word embedding can be learnt more effectively within the corpus.

In Figure 4.1 it can be observed that GloVe-LEAM achieves the best testing macro-F1 by a large margin, while the training performance and the micro measure of the strong baseline BoW-MLP is almost as good if not better, which demonstrates that LEAM is less prone to overfit or influenced by the unbalanced label distribution, even when the data sparsely populates on a large number of labels in Reuters.

Compared to GloVe-MLP, GloVe-LEAM is only different in the one-layer label embedding and the one-layer attention, however the improvement in performance is substantial. A good word embedding itself does not suffice and the convergence can be very slow even though our network is shallow, which further illustrates that the label attention mechanism effectively promotes the representation of sequence with a simple and interpretable structure.

Table 4.3 shows some samples where the word is in a bold font if the learnt attention weights is greater than 0.015 (among 100 in length). Keywords indicative of the label is marked, even if they do not share the same etymology with label words. For example, 'crop' is identified for label 'grain', 'merge' and 'profitable' for label 'acq', while some phrases are less stressed such as time, places and prevalent transitions of 'someone said'. Comparison between GloVe-LEAM and *LEAM on the same text (Line 1 and 2) indicates that the pre-trained embedding facilitates the learning of more spiky attention weights, while *LEAM is slightly inferior in distinguishing irrelevant words like 'osaka' or 'japan', probably because the learnt embedding is not sufficient in capturing the distance between entities such that the label-word alignments are harder to learn.

LEAM is also able to identify phrases even though we use single word embedding, for example, 'net loss' is frequently recognized for the label 'earn', likely due to the use of convolution over label-word alignment. Interestingly, the prediction also seems to capture some correlation between labels, for example, 'crude' and 'oil-gas' are predicted together when the text is lack of evidence for 'crude'.

Ture Label	**Predicted Label**	**Model**	**Highlighted Content**
'acq'	'acq'	GloVe-MLLEAM	**sumitomo** bank aims quick recovery **merger sumitomo** bank ltd lt **sumi** certain lose status japan **profitable** bank result **merger heiwa** sogo bank financial analysts said osaka based **sumitomo** around trillion yen ... interview said **merger** initially **reduce sumitomo profitability** ...
'acq'	'acq'	ML-LEAM	sumitomo bank **aims** quick **recovery** merger sumitomo bank **ltd lt certain lose** status **japan profitable bank result merger heiwa** sogo bank financial analysts said **osaka** based **sumitomo** around trillion yen ... interview said **merger** initially **reduce** sumitomo **profitability** ...
'earn'	'earn'	GloVe-MLLEAM	tribune swab fox cos inc lt th **qtr loss shr loss cts** vs nil **net loss** vs **profit** year **shr loss cts vs profit** five cts **net loss vs profit** note earnings restated ... dividends company release revenues
'earn' 'crude' 'nat-gas'	'earn'	GloVe-MLLEAM	energy ... **loss energy** development partners ltd said operating loss ... non cash **writeoff oil gas** properties taken first quarter resulted **net loss** mln dlrs dlrs per share ... **reserves** december totaled mln **barrels oil** mln **cubic** feet **natural** gas
'grain' 'sugar'	'sugar'	GloVe-MLLEAM	rain boosts central queensland **sugar cane crop** good rains ... **sugar cane** crops ... **sugarproducers** asociation spokesman said ... **crops** beginning look healthy **greener putting** growth since rains ...

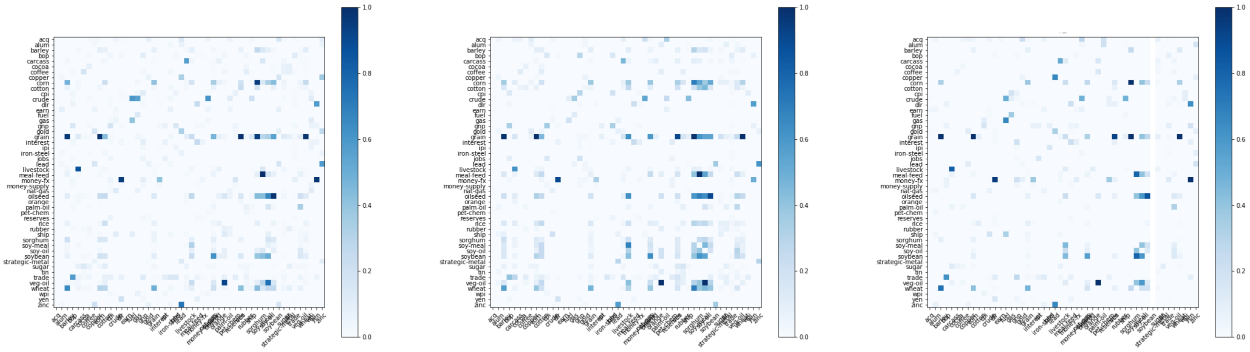
Table 4.3: Reuters Highlight Samples

To further illustrate the inferred label correlation, in Figure 4.4 we compare the true label correlation with the learnt. The correlation is computed as the co-occurrence matrix divided by label counts by row, a subset of the most frequent 50 labels are selected and the diagonal ones are set to zero for the sake of visualization. It is clear in the heatmap that the learnt label correlation on the right reflects a similar pattern to the ground truth on testing set and the training samples it learns from.

Ablative analysis

We also explore some ablative methods with the GloVe-LEAM structures, the results with the same experiment setting is compared in Table 4.4.

Firstly we consider to modify the convolution layer, and it turns out to be important to take into account the local context, as sparing it greatly affects the result. We also try to change the convolution position from the attention layer to after word embedding for a direct computation of label-phrase similarity, or use it to composite the attended single-word



(a) Training labels (b) Testing labels (c) Predicted testing labels

Figure 4.3: Reuters label correlation heatmap (subset of 50)

	GloVe-	Convolutional Layer					Attention	
Reuters	LEAM	W/O Conv	Emb Conv	Comp Conv	Emb + Att	Emb + Comp	mean-pooling	multi-head
macro-F1	**0.4798**	0.3947	0.3718	0.4189	0.3907	0.4584	0.4696	0.3363
micro-F1	0.8464	0.8375	0.8313	0.8455	0.8333	0.8492	**0.8503**	0.7773

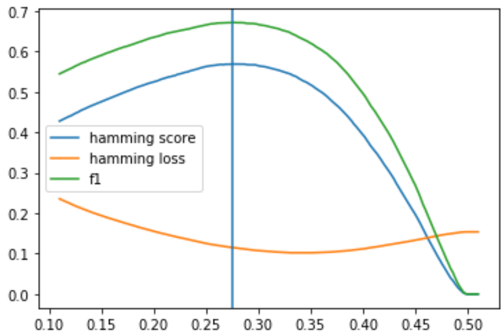
Table 4.4: Ablative Analysis on Reuters

embeddings into the document representation, neither achieves a result as good. Moreover, adding extra convolution layer also does not boost the performance.

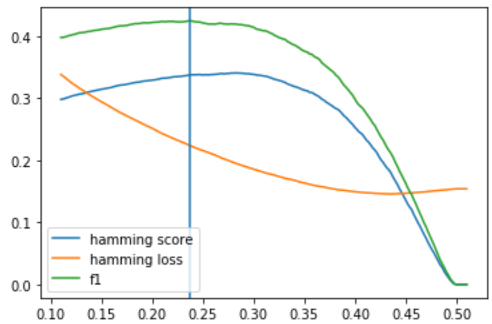
In LEAM we take the maximum over all label attentions assuming that each word is associated with only one label. Since it is plausible to consider each word as realted to more than one labels, we also experiment with alternative ways to compute attention. We try mean-pooling over all label attentions, and for the Reuters dataset the result makes little difference. Another possible architecture is to reserve the multiple label attention layers, and use a Binary Relavance based MLP classffier. However, the results is not as good, the reason might be that the optimization becomes harder with a larger number of parameters. It is notable that You et al. achieved an excellent performance with such multi-representation attention structure paired with bi-LSTM on datasets with more extreme label sizes [50], and it is worthwhile to explore the interaction between network structure and data characteristics in the future work.

4.4 CVDM Results and Analysis

Since CVDM prediction is based on ranking loss, we compare the performances over the ROC-AUC score in sync with realted works. In order to make the final label prediction, we adopt the empirical method, that is, to find the optimal threshold on a validation set or via cross-validation if the computational power is sufficient. Figure displays a sample of threshold selection curve with maximum macro-F1 criterion, where a clear peak can be observed.



(a) Training threshold



(b) Validation threshold

Figure 4.4: Empirical threshold selection on Delicious

We compare CVDM on all three datasets in Table 4.5. CVDM achieves a comparable performance to the discriminative baselines on the Delicious dataset, where the vocabulary is cleaned and stemmed for better BoW representation. Meanwhile, the model performs worse on Reuters and anon-Rev. The potential reasons can be that the their data processing is more coarse with more words reserved for more local contextual information. Moreover, CVDM may be harder to scale to a large number of labels, since a separate prior distribution is required for each label.

*CVDM and TFIDF-CVDM makes only small differences, which indicates that the prior distributions does not necessarily require concrete semantic information, but serves as anchors that separate examples with different labels. Nevertheless, more content-relevant features can be useful when some labels are not seen during training in the situation of zero-shot or few-shot learning, where the prior network helps transfer knowledge between classes.

	Reuters		anon-Rev		Delicious	
Model	Macro-AUC	Micro-AUC	Macro-AUC	Micro-AUC	Macro-AUC	Micro-AUC
BoW-MLP	0.9515	0.9839	**0.9138**	**0.9553**	**0.7762**	0.8015
*LEAM	**0.9641**	**0.9879**	0.8917	0.9465	0.7422	0.7713
*CVDM	0.9560	0.9834	0.8416	0.9268	0.7598	0.8016
TFIDF-CVDM	0.9478	0.9820	0.8479	0.9294	0.7724	**0.8107**

Table 4.5: General Comparison of Results

Our model is also comparable to other STOA generative models on the Delicious dataset as illustrated in Table 4.6. The models other than ours are implemented by Soleimani and Miller [33], and the code and results can be rechieved online[4]. They developed Multi-label Topic Model (MLTM) where each label is associated with indefinite number of latent topics, and compair it with Binary Relevance and also other supervised topic models (Partially labeled LDA, semi-supervised LDA) with different model assumptions. It is notable that these models approximate the analytical posterior estimates by Monte Carlo sampling, rather than using neural network methods. We adopt the same data preprocessing procedure and dimension of latent variable for a fair comparison.

Delicious	BR	PLLDA	ssLDA	MLTM	*CVDM	CVDM (TFIDF)
macro-AUC	0.6193	0.7009	0.7696	0.7756	0.7598	0.7724
micro-AUC	0.6551	0.7007	0.8104	0.8147	0.8016	0.8107

Table 4.6: Comparison between generative models

We display in Table 4.7 the label semantic inferred by TFIDF-CVDM, where the words with the highest probability for each label-specific distribution (β^l) are listed. Although the top-words are mostly relevant to the label, they are also heavily influenced by high-frequency words, for example, 'use' is ranked high for most labels. It suggests that the reconstruction

[4]https://github.com/hsoleimani/MLTM

model $p(\mathbf{X} \,|\, \mathbf{Z})$ is likely not good enough. Therefore, we also try optimizing only the KL-divergence term with the margin regularizer, and the resulted macro-AUC is only about 0.1 lower than the original model. It could possibly be fixed by adjusting the weights of each term in the objective function for better optimization, and another possible improvement is to penalize the similarity between label distribution for more interpretable results.

Topic	Top-words
internet	use, see, page, web, document, name, type, system, click, applic
writing	use, make, first, write, great, comment, year, mean, thing, post
reference	work, free, list, take, realli, use, common, page, right, featur
education	one, know, read, way, design, call, good, number, com, mean

Table 4.7: Top-words for some topics

CHAPTER 5

Conclusion and Future Work

In conclusion, we study the problem of multi-label text classification, and argues that the use of annotated labels should not limit to providing supervision for the classification task, but also guiding the learning of natural language representation. We discuss two approaches specifically, and empirically show that they promote the classification performances with improved interpretability.

Label-embedding Attention Model (LEAM) learns a label-word attention layer for the composition of word embedding into document vectors. It uses a simple and efficient architecture to achieve excellent performances especially for unbalanced data, and the simple structure also provides better interpretability with the attention weights on each word. In our experiments, we analyze the architecture to explore the effect of the attention layer and the convolution layer, and demonstrate its merits in identifying multi-word expressions and capturing word-label and label-label correlations.

Conditional Variationl Document Model (CVDM) learns explicitly a probabilistic latent variable, and encourages it to contain label information by minimizing its distance to a prior distribution conditional on the label attributes, meanwhile the measure of distance - KL-divergence also serves as ranking score for prediction. The variational scheme and sampling procedure makes it more tolerant to noise, and the explicit high-level latent abstraction also provide more interpretability. Our model achieves comparable ranking performance to benchmark generative topic models, while being more flexible and generalizable with neural variational inference rather than traditional variational bayes that relies on analytic approximation.

We also identify the limitations of our methods:

The training of LEAM is not stable enough as certain random seed gives poor results, so cross-validation is needed in pratical use. Moreover, the effect of pre-trained word embedding could be affect by the domain of the corpus, and we have not experiment on data with more extreme number of labels (ex. over 100).

CVDM breaks down when the label amount grows, and it is possible that similar labels or hierarchical label relationship is hard to be distinguish by the separately learned latent priors and the coarse-grained BoW distribution. Another problem is that the current decision rule is not disciplined since the classification score derived from a divergence measure is not well-distributed. In addition, the topic generative model does not fit very well as we show in the experiments.

Therefore, future works may consider the following aspects:

1. Use LEAM representation with more advanced classification algorithms, and extend the experiments to extreme multi-label problems;

2. Explore variational attention mechanism on LEAM;

3. Re-construct CVAE with more realistic latent structures, such as hierarchical VAE or semi-supervised VAE;

4. Modify CVAE objective function with different topic diversity regularization or divergence measures such as wasserstein distance.

CHAPTER 6

Appendix

Evidence Lower Bound (ELBO)

$$
\begin{aligned}
\log p(\mathbf{X}) &= \log \int_{\mathbf{Z}} p(\mathbf{X}, \mathbf{Z}) \\
&= \log \int_{\mathbf{Z}} p(\mathbf{X}, \mathbf{Z}) \frac{q(\mathbf{Z})}{q(\mathbf{Z})} \\
&= \log \left(\mathbb{E}_q \left[\frac{p(\mathbf{X}, \mathbf{Z})}{q(\mathbf{Z})} \right] \right) \\
&\geq \mathbb{E}_q[\log p(\mathbf{X}, \mathbf{Z})] - \mathbb{E}_q[\log q(\mathbf{Z})] = ELBO \text{ by Jensen Inequality} \\
&= E_q[\log p(\mathbf{X})] - D_{KL}(q(\mathbf{Z}) \parallel p(\mathbf{Z} \mid \mathbf{X}))
\end{aligned}
$$

VAE Objective

$$
\begin{aligned}
\log p(\mathbf{X}) &= \log \int_{\mathbf{Z}} p(\mathbf{X}, \mathbf{Z}) \frac{q(\mathbf{Z} \mid \mathbf{X})}{q(\mathbf{Z} \mid \mathbf{X})} \\
&= \log \left(\mathbb{E}_{q(\mathbf{Z} \mid \mathbf{X})} \left[\frac{p(\mathbf{X}, \mathbf{Z})}{q(\mathbf{Z} \mid \mathbf{X})} \right] \right) \\
&\geq \mathbb{E}_{q(\mathbf{Z} \mid \mathbf{X})}[\log p(\mathbf{X} \mid \mathbf{Z})]] - D_{KL}(q(\mathbf{Z} \mid \mathbf{X}) \parallel p(\mathbf{Z})) = \mathcal{L}_{VAE}
\end{aligned}
$$

CVAE Objective

$$
\mathcal{L}_{CVAE} = \log p(\mathbf{X} \mid \mathbf{A}) \geq \mathbb{E}_{q(\mathbf{Z} \mid \mathbf{X}, \mathbf{A})}[\log p(\mathbf{X} \mid \mathbf{Z}, \mathbf{A})]] - D_{KL}(q(\mathbf{Z} \mid \mathbf{X}, \mathbf{A}) \parallel p(\mathbf{Z} \mid \mathbf{A}))
$$

Complete experiment results

Model	Macro-F1	Micro-F1	Hamming Score	Hamming Loss	EMR	Precision	Recall	One-Error	Macro-AUC	Micro-AUC
BoW-MLP	0.4378	0.8396	0.8470	0.0043	0.7906	0.8769	0.8765	0.0891	0.9515	0.9839
GloVe-MLP	0.3593	0.8188	0.8191	0.0048	0.7595	0.8498	0.8516	0.1165	0.9629	0.9883
*LEAM	0.3860	0.8349	0.8351	0.0043	0.7787	0.8614	0.8668	0.1050	0.9641	0.9897
GLoVe-LEAM	0.4798	0.8464	0.8580	0.0041	0.7940	0.8927	0.8894	0.0847	0.9752	0.9918
CVDM	0.2650	0.6811	0.7433	0.0102	0.6446	0.8519	0.7594	0.1785	0.9560	0.9833
CVDM (TFIDF)	0.2938	0.7285	0.7691	0.0079	0.6810	0.8390	0.7926	0.1765	0.9478	0.9820

Table 6.1: Reuters Results

Model	Macro-F1	Micro-F1	Hamming Score	Hamming Loss	EMR	Precision	Recall	One-Error	Macro-AUC	Micro-AUC
BoW-MLP	0.4947	0.7118	0.6770	0.0206	0.4672	0.7433	0.8059	0.1153	0.9138	0.9553
GloVe-MLP	0.3987	0.6846	0.6517	0.0232	0.4347	0.7370	0.7685	0.1454	0.8917	0.9465
*LEAM	0.5358	0.7406	0.7106	0.0192	0.4848	0.7920	0.8249	0.0921	0.9284	0.960
GLoVe-LEAM	0.5129	0.7004	0.6696	0.0226	0.4450	0.7662	0.7815	0.1278	0.9227	0.9567
CVDM	0.2955	0.5024	0.5166	0.0494	0.2985	0.7363	0.590	0.2725	0.8371	0.9261
CVDM (TFIDF)	0.2564	0.4937	0.4981	0.0485	0.2814	0.7123	0.5737	0.2963	0.9223	0.9224

Table 6.2: anon-Rev Results

Model	Macro-F1	Micro-F1	Hamming Score	Hamming Loss	EMR	Precision	Recall	One-Error	Micro-AUC	Macro-AUC
BoW-MLP	0.4361	0.4762	0.3347	0.1486	0.0511	0.4554	0.5072	0.3899	0.7762	0.8015
*LEAM	0.3958	0.4348	0.2987	0.1639	0.0391	0.4192	0.4523	0.4621	0.7422	0.7713
CVDM	0.4182	0.4590	0.3270	0.2490	0.0138	0.6958	0.3750	0.4679	0.7598	0.8016
CVDM (TFIDF)	0.4338	0.4704	0.3354	0.2432	0.0144	0.7089	0.3810	0.4493	0.7724	0.8107

Table 6.3: Delicious Results

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