Hierarchical Metadata-Aware Document Categorization under Weak Supervision

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ABSTRACT

Categorizing documents into a given label hierarchy is intuitively appealing due to the ubiquity of hierarchical topic structures in massive text corpora. Although related studies have achieved satisfying performance in fully supervised hierarchical document classification, they usually require massive human-annotated training data and only utilize text information. However, in many domains, (1) annotations are quite expensive where very few training samples can be acquired; (2) documents are accompanied by metadata information. Hence, this paper studies how to integrate the label hierarchy, metadata, and text signals for document categorization under weak supervision. We develop HiMeCat, an embedding-based generative framework for our task. Specifically, we propose a novel joint representation learning module that allows simultaneous modeling of category dependencies, metadata information and textual semantics, and we introduce a data augmentation module that hierarchically synthesizes training documents to complement the original, small-scale training set. Our experiments demonstrate a consistent improvement of HiMeCat over competitive baselines and validate the contribution of our representation learning and data augmentation modules.

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1 INTRODUCTION

Document categorization is an important task in text mining, with many real applications such as sentiment analysis [39], location prediction [4] and scientific paper tagging [21]. Given a large text corpus, automatically inferring the category of each document not only enables effective organization of the data, but also benefits downstream tasks like document retrieval [47]. Hierarchical document categorization [7, 12] further considers relationships among categories and classifies documents into a given label hierarchy. Leveraging such hierarchical structures is shown to be effective and necessary due to their pervasiveness in web directories\(^1\), business category lists\(^2\) and many other domains (Figure 1).

Although recent studies on hierarchy-aware neural models [24, 44, 55] and pre-trained language models [5, 38] greatly improve the performance of (hierarchical) text categorization, they are less concerned with two challenges in real applications:

**Limited Training Data.** Neural classifiers are data hungry and require a significant amount of manually labeled training documents

\(^1\)https://en.wikipedia.org/wiki/Yahoo!_Directory
\(^2\)https://www.yelp.com/developers/documentation/v3/all_category_list
to achieve good performance. In some scientific domains (e.g., arXiv papers and GitHub repositories), to obtain a large training set is expensive because annotations have to be acquired from domain experts. In these scenarios, it would be favorable to perform classification without much annotation effort. To be specific, one may only expect very few (e.g., 5) training examples for each category.

Heterogeneous Signals. Documents on the Web are often accompanied by metadata information. We raise three examples in Figure 1: each GitHub repository has its creator and several topic tags; each arXiv paper has its author(s); each Amazon review is associated with a user and a product. These signals, as potential category indicators, should be considered together with the plain text sequence. Moreover, the label hierarchy, which reflects category dependencies and correlation, should also be viewed as one type of signal. In recognition of these heterogeneous signals, how can we jointly leverage them during category inference?

In this paper, to tackle the two challenges, we develop HiMeCat, an embedding-based generative framework for Hierarchical Metadata-aware document Categorization under weak supervision. HiMeCat features a hierarchical generative process in the embedding space to simultaneously model (1) category dependencies via a top-down generative assumption along the label hierarchy, (2) metadata information via a joint generative assumption that documents are dependent on both their categories and metadata, and (3) textual semantics via a document-word generative assumption. This hierarchical generative process guides the two important steps of our method: (1) representation learning: Maximizing the likelihood of the hierarchical generative process yields an embedding learning objective which jointly optimizes the representations of the label hierarchy, metadata and texts to effectively exploit the heterogeneous signals; (2) data augmentation: Following the hierarchical generative process allows us to synthesize training documents that augment the original, small-scale training set, which overcomes the limited training data challenge. Combining real and synthesized training data, we train a neural classifier for hierarchical text categorization under weak supervision and a data augmentation module guided by a novel hierarchical generative process allows us to synthesize training documents that augment the original, small-scale training set, which overcomes the limited training data challenge.

2 PRELIMINARIES

2.1 Problem Definition

The inputs of our hierarchical metadata-aware text categorization task are a collection of documents \( D = \{d_1, ..., d_n\} \) and a label hierarchy \( T \). Each document \( d_i \in D \) has both text and metadata information. We explain these concepts one by one.

Text. In this paper, text refers to all free-text fields of a document. For example, in Figure 1, a GitHub repository has its description and README file as text information; an arXiv paper has its title and abstract. To simplify our discussion, we concatenate all these fields into one word sequence, denoted as \( w_1w_2...w_n \).

Metadata. Each document can have multiple types of metadata (e.g., an Amazon review has both user and product information). Given a specific metadata type, there may be an arbitrary number (could be zero) of metadata instances associated with a document (e.g., a repository may have no tags, and a paper can have more than one author). For a document \( d \), we represent its metadata as a set of metadata instances \( M_d = \{m_{1}...m_{|M_d|}\} \).

Label Hierarchy. We assume the label hierarchy \( T \) has a tree structure. Each node \( l \in T \) represents a category. If, in some cases, \( T \) is a directed acyclic graph (DAG), we follow [55] and convert \( T \) to a tree by distinguishing each label node as a single-path node.

Formally, we define our task as follows:

Problem Definition. Given a collection of documents \( D \) and a label hierarchy \( T \), where each leaf category \( l \in T \) is characterized by a small set of training documents \( D_l \subset D \), the task is to assign appropriate category labels to the remaining documents \( D \setminus (\cup_l D_l) \). The labels of each document should form a path in \( T \).

2.2 The Von Mises-Fisher Distribution

The von Mises-Fisher (vMF) distribution [8, 26] will be extensively used in our proposed framework. It defines a probability density over a unit sphere and is parameterized by a mean direction vector \( \mu \) and a concentration parameter \( \kappa \). Formally, let \( S^{p-1} = \{x \in \mathbb{R}^p : ||x||_2 = 1\} \) denote the \( p \)-dimensional unit sphere. The probability density function for \( x \in S^{p-1} \), \( ||\mu||_2 = 1, \kappa > 0 \) is given by

\[
f_{\text{vMF}}(x|\mu, \kappa) = c_p(\kappa) \exp(\kappa \cdot \cos(x, \mu)).
\]

Here, the normalization constant \( c_p(\kappa) \) is

\[
c_p(\kappa) = \frac{\kappa^{p/2-1}}{2\pi^{p/2}I_{p/2-1}(\kappa)}.
\]

where \( I_r(\cdot) \) represents the modified Bessel function of the first kind at order \( r \) [8, 26]. Intuitively, the vMF distribution is an analogue of the Gaussian distribution on a sphere. The distribution concentrates around the mean direction \( \mu \), and is more concentrated if \( \kappa \) is large.

3 MODEL

3.1 A Hierarchical Generative Process

Motivation. In recognition of various types of information (i.e., the label hierarchy, weak supervision, metadata, and text), we propose a probabilistic generative process to characterize these heterogeneous signals. By adopting the vMF distribution, our generative process is defined in a spherical space (i.e., \( S^{p-1} \)) instead of a Euclidean one (i.e., \( \mathbb{R}^p \)). The motivation of doing so is inspired by two lines of related studies. First, the vMF distribution has demonstrated its
Label & Metadata → Document. Our second step generates document embeddings according to their metadata and label information (if applicable). Consider how we humans write a document given a topic category (or a tag/product). We need to first have a general idea of the article, which can be represented as the document embedding \( d \). To impose the coherence between \( d \) and its category/meta-data information, we assume

\[
p(d|l_d, M_d) \propto \exp(d^T l_d) \cdot \prod_{m_d \in M_d} \exp(d^T m_d),
\]

where \( l_d \) is the category label of \( d \) (here, we are referring to the leaf label of \( d \)); \( m_d \) is a metadata instance of \( d \); the corresponding embedding variables are in bold. Following the derivation above, by assuming all embedding vectors reside on a sphere, we can rewrite Eq. (6) as

\[
p(d|l_d, M_d) \propto \prod_{z \in \{l_d\} \cup M_d} c_p(1) \exp(d^T z) = \prod_{z \in \{l_d\} \cup M_d} f_{\text{vMF}}(d|z, 1), \quad \forall d \in \mathbb{S}^{p-1}.
\]

One unique problem we need to address here is that label and metadata information can be missing. For example, due to supervision scarcity, only a small proportion of documents in \( \mathcal{D} \) have label information. Besides, a GitHub repository may have many tags. In general, suppose \( V \) instances \( z_1, ..., z_V \) are missing in \( \{l_d\} \cup M_d \). In this case, we assume their embeddings \( z_1, ..., z_V \) can be any vector on the sphere with equal probability (i.e., \( z_1, ..., z_V \sim U(\mathbb{S}^{p-1}) \)) i.i.d.). Let \( \mathcal{O}_d = \{l_d\} \cup M_d \backslash \{z_1, ..., z_V\} \) be the remaining observable instances. Therefore, Eq. (7) becomes

\[
p(d|l_d, M_d) \propto \prod_{z \in \mathcal{O}_d} c_p(1) \exp(d^T z) = \prod_{z \in \mathcal{O}_d} f_{\text{vMF}}(d|z, 1).
\]

The second-to-last step holds because \( \int_{\mathbb{S}^{p-1}} c_p(1) \exp(d^T z_i) \, dz_i = 1 \) (i.e., the probability density function of a vMF distribution integrates to 1 over the whole sphere). Eq. (8) tells us that, when some label/metadata information is missing, we only need to consider the remaining observable part (i.e., \( \mathcal{O}_d \)) in the conditional probability.

Document → Word. Based on the document embedding \( d \), a sequence of words \( w_1, ..., w_n \) is then generated to describe the overall semantics of \( d \). Similar to Eqs. (3) and (6), we assume the probability of word \( w_t \) appearing in document \( d \) to be

\[
p(w_t|d) \propto \exp(w_t^T d).
\]

Again, we rewrite the probability using a vMF distribution:

\[
p(w_t|d) = f_{\text{vMF}}(w_t|d, 1) = c_p(1) \exp(w_t^T d), \quad \forall w_t \in \mathbb{S}^{p-1}.
\]

Eqs. (5), (8) and (10) together fully specify our proposed hierarchical generative process.
3.2 Joint Representation Learning

Guided by the hierarchical generative process, we aim to jointly learn the embeddings of all labels, metadata instances, documents and words. Our learning objective can be divided into two parts: one for modeling the label hierarchy information (corresponding to the first step in our generative process), and the other for modeling corpus statistics and metadata information (corresponding to the second and third steps).

**Objective for Label Hierarchy.** Given a parent–child label pair \((l_p, l_c)\), our goal is to maximize the log-likelihood \(\log p(l_c | l_p)\) during embedding learning. Inspired by studies on knowledge graph embedding [3, 42], we adopt the following margin-based ranking objective:

\[
\min \left( 0, \log p(l_c | l_p) - \log p(l_c' | l_p') - \gamma \right),
\]

where \(\gamma > 0\) is a margin hyperparameter and \((l_p', l_c')\) is a negative training sample. Given the positive pair \((l_p, l_c)\), we generate the negative pair by replacing the parent label with any other label in \(T\) while keeping the child label. According to this corruption strategy, our objective can be defined as

\[
\mathcal{J}_L = \sum_{l_c \in T \setminus \{ \text{ROOT} \}} \sum_{l_p' \in T \setminus \{ l_p, l_c \}} \min \left( 0, \log p(l_c | l_p) - \log p(l_c' | l_p') - \gamma \right).
\]

Based on the definition of \(p(l_c | l_p)\) in Eq. (5), we have

\[
\log p( l_c | l_p ) - \log p( l_c' | l_p' ) = \log \left( \frac{c_p(1) \exp(t_p^T l_p)}{c_p(1) \exp(t_{p'}^T l_p')} \right) - \log \left( \frac{c_p(1) \exp(t_p^T l_{p'})}{c_p(1) \exp(t_{p'}^T l_p)} \right) = t_p^T l_p - t_{p'}^T l_{p'}.
\]

Therefore,

\[
\mathcal{J}_L = \sum_{l_c \in T \setminus \{ \text{ROOT} \}} \sum_{l_p' \in T \setminus \{ l_p, l_c \}} \min \left( 0, t_p^T l_p - t_{p'}^T l_{p'} - \gamma \right).
\]

**Objective for Metadata and Corpus.** Given the label and metadata information of a document \(d\), the log-likelihood of observing the document and its word sequence is

\[
\log p(d, w_{1:n} | d, M_d) = \log \left( p(d | d, M_d) \prod_{i=1}^{n} p(w_i | d) \right).
\]

According to Eqs. (8) and (10), it can be written as

\[
\sum_{z \in O_d} \log f_{\text{MB}}(d | z, 1) + \sum_{i=1}^{n} \log f_{\text{MB}}(w_i | d, 1) + \text{const}.
\]

Again, we adopt the margin-based ranking objective to push the negative pairs distant enough from the positive pairs \((z, d)\) and \((d, w_i)\). Formally,

\[
\mathcal{J}_{\text{MC}} = \sum_{d \in D} \sum_{d' \in D \setminus \{d\}} \left( \sum_{z \in O_d} \min \left( 0, \log f_{\text{MB}}(d | z, 1) - \log f_{\text{MB}}(d' | z, 1) - \gamma_M \right) \right) + \sum_{i=1}^{n} \min \left( 0, \log f_{\text{MB}}(w_i | d, 1) - \log f_{\text{MB}}(w_i | d', 1) - \gamma_C \right).
\]

Following the derivation in Eq. (13), we have

\[
\mathcal{J}_{\text{MC}} = \sum_{d \in D} \sum_{d' \in D \setminus \{d\}} \left( \sum_{z \in O_d} \min \left( 0, d^T z - d'^T z - \gamma_M \right) + \sum_{i=1}^{n} \min \left( 0, w_i^T d - w_i^T d' - \gamma_C \right) \right).
\]

To summarize, our joint representation learning step can be formulated as the following optimization problem:

\[
\max \mathcal{J} = \mathcal{J}_L + \mathcal{J}_{\text{MC}},
\]

s.t. \(\|\theta\|_2 = 1, \forall \theta \in T \setminus M \cup D \cup V\).

Here, \(M\) is the set of metadata instances appearing in the dataset, and \(V\) is the vocabulary (i.e., the set of words).

**Optimization.** Given the constraint that all embedding vectors live on a sphere, directly performing stochastic gradient descent in the Euclidean space is not an effective way to optimize the objective. Instead, following recent studies on hyperbolic embedding [33, 34] and spherical embedding [29, 45], we apply the Riemannian gradient method [2] to learn the embeddings.

According to [29], on a unit sphere, the relationship between the Riemannian gradient \(\nabla^R\) and the Euclidean gradient \(\nabla^E\) is

\[
\nabla^R \mathcal{J}(\theta) = (I - \theta \theta^T) \nabla^E \mathcal{J}(\theta).
\]

Based on Eqs. (14) and (18), the Euclidean gradient of each embedding vector is easy to compute. For example, given a parent-child label pair \((l_p, l_c)\), we have

\[
\nabla^E \mathcal{J}_L(l_c) = \sum_{l_p' \in T \setminus \{ l_p, l_c \}} 1(l_p^T l_p - l_{p'}^T l_{p'} < \gamma) \cdot (l_p - l_{p'}),
\]

\[
\nabla^E \mathcal{J}_L(l_p) = \sum_{l_p' \in T \setminus \{ l_p, l_c \}} 1(l_p^T l_p - l_{p'}^T l_{p'} < \gamma) \cdot l_{p'},
\]

\[
\nabla^E \mathcal{J}_{\text{MC}}(l_p') = 1(l_p^T l_p - l_{p'}^T l_{p'} < \gamma) \cdot (-l_p), \quad \forall l_p' \in T \setminus \{ l_p, l_c \}.
\]

where \(1(\cdot)\) is the indicator function. Then, following Eq. (20), we can obtain the Riemannian gradient \(\nabla^R \mathcal{J}(l_c)\), \(\nabla^R \mathcal{J}(l_p)\), and \(\nabla^R \mathcal{J}(l_p')\).

The gradient of other embedding vectors can be calculated in a similar way. After knowing the Riemannian gradient, we update the parameters in the following form [2, 29]:

\[
\theta_{t+1} = \theta_t - \alpha_t \nabla^R \mathcal{J}(\theta_t) / \|\nabla^R \mathcal{J}(\theta_t)\|_2,
\]

where \(\alpha_t\) is the learning rate at step \(t\). Intuitively, this update can be viewed as an addition along the Riemannian gradient direction followed by a projection onto the unit sphere.

Since computing the gradient requires enumerating all labels or documents, in our actual computation, we adopt the negative sampling strategy [3, 32] to accelerate this process. To be specific, for each positive pair \((l_p, l_c), (z, d)\) or \((d, w_i)\), we sample 5 negative pairs to estimate the gradient.

3.3 Hierarchical Data Augmentation

Now we proceed to tackle the limited training data challenge. After representation learning, we have obtained the embedding vectors of all observed labels, metadata instances, documents and words. Using these embeddings, we can generate synthesized training documents for each category. Formally, given a category \(l\), we aim to create a document set \(D_l^*\) to augment its original training set
Algorithm 1 Hierarchical Data Augmentation

1: Input: embedding vectors \((l, d, w_i)\), \(\#\) synthesized docs per category (\(\beta\))
2: Generate a bottom-up traverse order of \(T\)
3: for \(l\) in the traverse order do
4: if \(l\) is a leaf category then
5: \(D^*_l = \emptyset\)
6: for \(i = 1\) to \(\beta\) do
7: Generate \(d^*\) according to Eq. (24)
8: \(w^*_l, w^*_2, \ldots, w^*_n\) according to Eq. (25)
9: \(D^*_l = D^*_l \cup \{d^*\}
10: end for
11: else
12: for \(x \in \text{Child}(l)\) do
13: \(D^*_{x, \text{sample}} \leftarrow \text{sample}_{|\text{Child}(l)|} \) docs from \(D^*_x\)
14: end for
15: \(D^*_l = \bigcup_{x \in \text{Child}(l)} D^*_{x, \text{sample}}\)
16: end if
17: end for
18: Output: \(\{D^*_l : l \in T\}\)

\(D_l\). To implement this idea, we seek guidance from our proposed generative process once again.

Data Augmentation for a Leaf Category. Recall Figure 2(a). If \(l\) is a leaf category, it will directly participate in the generation of document embeddings according to Eq. (8). If we denote a synthesized document as \(d^*\) (to distinguish it from a “real” document \(d\)), the generation probability will become

\[
p(d^*|l, M_{d^*}) \propto \prod_{z \in O_{d^*}} f_{\text{MF}}(d^*|z, \kappa).
\]

Note that we do not have any metadata information of the synthesized document. Therefore, the only observable variable here in \(\{l\} \cup M_{d^*}\) is the label \(l\). Also, it is not necessary to generate documents associated with a certain metadata instance because our goal is to predict the label, instead of the metadata information, of a document. Substituting \(O_{d^*} = \{l\}\) into Eq. (23), we have

\[
p(d^*|l, M_{d^*}) = f_{\text{MF}}(d^*|l, \kappa).
\]

After getting the document embedding \(d^*\), we continue our generative process to create a sequence of words describing \(d^*\). In principle, we should follow Eq. (10) and sample words from \(f_{\text{MF}}(\cdot|d^*, 1)\). However, in practice, we expect that the generated word embedding \(w^*\) can be mapped back to a concrete word that has occurred in our vocabulary \(V\). In [19], Kumar and Tsvetkov propose a way that first samples an vector \(e\) from a continuous distribution, and then find the nearest neighbor of \(e\) in the embedding space among all \(w \in V\). In contrast, we directly require the generated word to reside in the neighborhood of \(d^*\) in our joint embedding space. In this way, Eq. (10) degenerates to a discrete softmax function:

\[
p(w^*|d^*) = \frac{f_{\text{MF}}(w^*|d^*, 1)}{\sum_{w \in V_N(d^*)} f_{\text{MF}}(w|d^*, 1)} = \frac{\exp(w^T d^*)}{\sum_{w \in V_N(d^*)} \exp(w^T d^*)},
\]

where \(V_N(d)\) is the set of top-\(N\) nearest neighbors of \(d^*\) in the embedding space among all \(w \in V\). Using Eq. (25) repeatedly, we can obtain a sequence of words \(w^*_1, w^*_2, \ldots, w^*_n\) as the content of \(d^*\).

Data Augmentation for a Non-Leaf Category. In our hierarchical generative process, a non-leaf label does not directly generate documents. Instead, it determines the embeddings of its children, and the child categories further determine its lower-level descendants. Formally, given a non-leaf label \(l\), let \(T_l \subseteq T\) be the subtree with root \(l\) and \(\text{Leaf}(T_l)\) be the leaf descendants of \(l\). Then,

\[
p(D^*_l, T_l | l) = p(T_l | l) \cdot \prod_{x \in \text{Leaf}(T_l)} p(D^*_x | x). \tag{26}
\]

After the joint representation learning step, all label embeddings have been fixed. Therefore, for any parent-child pair \((l_p, l_c)\), the probability \(p(l_c | l_p) = c_p(1) \exp(l_c^T l_p)\) is fixed. Thus,

\[
p(T_l | l) = p(\text{Child}(l) | l) \cdot \prod_{x \in \text{Child}(l)} p(\text{Child}(x) | x) \cdot \ldots = \text{const.}
\]

Here, \(\text{Child}(l)\) is the set of \(l\)’s children. Putting Eqs. (26) and (27) together, we know that the generation of \(D^*_l\) solely depends on \(\text{Leaf}(T_l)\) in the current data augmentation step. That being said, for a leaf category \(x \in \text{Leaf}(T_l)\), the documents \(D^*_x\) sampled from \(p(D^*_x | x)\) can also be viewed as the documents \(D^*_l\) sampled from \(p(D^*_l | T_l | l)\). This is intuitive because training samples of a leaf category are naturally training samples of its ancestor categories. We have discussed how to generate synthesized documents for a leaf category. Therefore, we can directly have

\[
D^*_l = \bigcup_{x \in \text{Child}(l)} D^*_x. \tag{28}
\]

If we adopt a bottom-up order to generate \(D^*_l\), this can also be written in a recursive way:

\[
D^*_l = \bigcup_{x \in \text{Child}(l)} D^*_x. \tag{29}
\]

In practice, some non-leaf categories have more children than their siblings have. Thus, if we directly apply Eq. (29), they will have more synthesized training data. To avoid class imbalance, we fix \(|D^*_l| = \beta = \text{const.}\) for any \(l \in T\). When applying Eq. (29), we sample \(\beta\) documents from \(D_l\) and put them into \(D^*_l\). Algorithm 1 completely summarizes our data augmentation process.

3.4 Hierarchical Classifier Training

After hierarchical data augmentation, every (leaf or non-leaf) category \(l\) has a set of synthesized training documents \(D^*_l\) and a set of real training data \(D_l\). (If \(l\) is a non-leaf category, we follow the idea of creating \(D^*_l\) and let \(D_l = \bigcup_{x \in \text{Child}(l)} D_x\).) Each training document \(d \in D_l \cup D^*_l\) has a sequence of words, whose embedding vectors are already learned in joint representation learning.

Now, based on the augmented training data, we need to train a hierarchical text classifier. Hierarchical text classification has been extensively studied for decades with many effective models proposed (see Section 5 for a detailed discussion). The main goal of this paper is to tackle signal heterogeneity and supervision scarcity instead of proposing a novel neural architecture for hierarchical classification. Therefore, we simply adopt the top-down training strategy [7, 18, 22] that classifies documents at the top layer and then propagates the results to the next layer until the leaves. For each non-leaf category \(l \in T\), we need to train a flat classifier that assigns documents to its child classes \(\text{Child}(l)\) for more fine-grained predictions. We adopt Kim-CNN [17], a popular convolutional architecture, as our flat text classifier. The embeddings \(\{w : w \in V\}\) trained in the joint representation learning step are used as initialization embeddings of the input layer.
The model adopted here can be easily improved by replacing Kim-CNN with a more advanced flat classifier (e.g., [41, 51]) or by adding a hierarchical regularization (e.g., [12, 14, 35]). However, since we would like to demonstrate the contribution of our embedding and augmentation modules when comparing with baselines, we keep the classifier as simple as possible.

4 EXPERIMENTS

4.1 Experimental Setup

Datasets. We use three datasets from different domains.3 The statistics of the datasets can be found in Table 1.

| Dataset | #Docs | #Classes | #Leaves | #Training | #Testing |
|---------|-------|----------|---------|-----------|----------|
| GitHub  | 1,596 | 18       | 14      | 70        | 1,526    |
| ArXiv   | 26,400| 94       | 88      | 440       | 25,960   |
| Amazon  | 147,000| 166      | 147     | 735       | 146,265  |

We use three datasets from different domains.

• GitHub [54]. This dataset is collected by paperswithcode.com. It contains 1,596 GitHub repositories implementing state-of-the-art machine learning algorithms for different tasks (e.g., object detection, question answering, speech synthesis, etc.). The tasks form a taxonomy which is viewed as the label hierarchy.

• ArXiv. This dataset is crawled from arXiv.org. There are 5 level-1 categories (i.e., cs, math, physics, q-bio, and q-fin) and 88 level-2 categories. For each category, we randomly sample 300 papers to constitute the dataset.

• Amazon [27]. This dataset is a large collection of Amazon product reviews. The label of each review is its product category (e.g., automotive, car care, beauty, skin care, etc.). These categories are organized into a catalog taxonomy [25]. We select 147 large leaf categories and sample 1,000 reviews for each of them.

According to our weakly supervised setting, we use 5 documents per leaf category for training and all the other documents for testing.

Baseline Methods. We evaluate the performance of HiMeCat against the following classification/embedding algorithms:

• HierSVM [7] is a supervised hierarchical classification method. It adopts a top-down classification strategy and trains an SVM for each non-leaf node to distinguish its child categories.

• WeSHClass [30] is a weakly supervised hierarchical classification method. It adopts LSTM to generate data for pre-training and iteratively refines results based on the hierarchy.

• PCEM [48] is a weakly supervised hierarchical classification method. It proposes a path-cost sensitive hierarchical classifier and applies an EM technique to utilize the unlabeled data.

• HiGitClass [54] is a weakly supervised hierarchical classification method. It uses heterogeneous network embedding to encode relationships between categories, text and metadata and then leverages WeSHClass to train a hierarchical classifier.

Evaluation Metrics. We use Micro and Macro F1 scores as evaluation metrics. Denote $TP_l$, $FP_l$ and, $FN_l$ as the instance numbers of true positive, false positive and false negative for a category $l \in T$. The Leaf Micro F1 is defined as $\frac{TP_l}{TP_l + FP_l + FN_l}$ and $R_l = \frac{\sum_{l \in \text{Leaf}(T)} TP_l}{\sum_{l \in \text{Leaf}(T)} (TP_l + FN_l)}$. The Leaf Macro F1 is defined as $\frac{1}{|T|} \sum_{l \in \text{Leaf}(T)} \frac{TP_l}{TP_l + FP_l + FN_l}$, where $P_l = \frac{TP_l}{TP_l + FN_l}$ and $R_l = \frac{TP_l}{TP_l + FP_l}$. Following previous works [30, 48], we also calculate the Overall Micro/Macro F1, which is defined accordingly on $T \setminus \{(\text{ROOT})\}$ instead of Leaf(T).

4.2 Performance Comparison

Table 2 shows the categorization performance of compared algorithms on the three datasets. We repeat each experiment five times and report the average F1 scores. To measure statistical significance, we conduct a two-tailed paired t-test to compare HiMeCat and each baseline approach. The significance level (“p-value < 0.05”) of each result is also marked in Table 2.

We observe that: (1) HiMeCat consistently outperforms the compared baseline methods on all three datasets. In most cases, the performance gap is statistically significant. The improvement of HiMeCat over the best baseline is 8.3%, 13.0% and 47.5% on GitHub, ArXiv and Amazon, respectively. (2) For the three metadata-aware text categorization methods, HiMeCat performs better than HiGitClass and MetaCat, indicating the importance of considering label hierarchy and incorporating it into representation learning. (3) Although Metapath2vec and Poincaré are assumed to be strong tools for metadata and hierarchy embedding respectively, they do not achieve competitive performance when we need to jointly embed these signals. This observation also emphasizes the contribution of our joint representation learning module. (4) Despite the great success of BERT in many supervised NLP tasks, it does not perform
Table 2: {Leaf, Overall}×{Micro, Macro} F1 scores of compared algorithms on the three datasets. *: significantly worse than HiMeCat (p-value < 0.05). **: significantly worse than HiMeCat (p-value < 0.01).

|                | Leaf | GitHub | Overall | ArXiv | Amazon |
|----------------|------|--------|---------|-------|--------|
|                | Micro | Macro  | Micro   | Macro | Micro  | Macro |
| HiSVM [7]      | 0.1861** | 0.1388** | 0.4862** | 0.2457** | 0.0538** | 0.0460** | 0.4066** | 0.0750** | 0.0248** | 0.0217** | 0.2218** | 0.0494** |
| WeSChClass [30] | 0.1727** | 0.1559** | 0.3332** | 0.1924** | 0.0604** | 0.0602** | 0.3077** | 0.0797** | 0.0483** | 0.0500** | 0.1234** | 0.0640** |
| PCEM [48]      | 0.2519** | 0.1234** | 0.5299** | 0.1766** | 0.1090** | 0.0717** | 0.4440 | 0.0963** | 0.0675** | 0.0439** | 0.2189** | 0.0659** |
| HiGitClass [54] | 0.3984 | 0.3902* | 0.5073** | 0.4084** | 0.1738** | 0.1656** | 0.3928** | 0.1880** | 0.0903** | 0.0876** | 0.1677** | 0.1040** |
| MetaCat [52]   | 0.3762** | 0.3403** | 0.5411** | 0.3865** | 0.0790** | 0.0768** | 0.3071** | 0.0935** | 0.1008** | 0.0994** | 0.1703** | 0.1083** |
| Metapath2vec [6] | 0.2814** | 0.2805** | 0.4592** | 0.3212** | 0.1360** | 0.1344** | 0.3419** | 0.1534** | 0.0666** | 0.0666** | 0.1334** | 0.0806** |
| Poincaré [33]  | 0.2730** | 0.1980** | 0.4302** | 0.2218** | 0.1336** | 0.1296** | 0.2995** | 0.1454** | 0.0645** | 0.0607** | 0.1202** | 0.0739** |
| BERT [5]       | 0.2889** | 0.2561** | 0.4675** | 0.3097** | 0.1316** | 0.0812** | 0.4203** | 0.1100** | 0.0891** | 0.0520** | 0.2361** | 0.0771** |
| HiMeCat        | 0.4254 | 0.4209 | 0.5820 | 0.4535 | 0.2038 | 0.1938 | 0.4509 | 0.2191 | 0.1552 | 0.1553 | 0.2748 | 0.1770 |

Table 3: Ablation analysis of the joint embedding module. -: the dataset does not have such metadata. * and **: the same as Table 2.

|                | GitHub | Overall | ArXiv | Overall | Amazon | Overall |
|----------------|--------|---------|-------|---------|--------|---------|
|                | Leaf   | Micro   | Micro | Macro   | Micro  | Macro   |
| HiMeCat        | 0.5820 | 0.4535  | 0.4509 | 0.2191  | 0.2748 | 0.1770  |
| No-Hierarchy   | 0.5649* | 0.4385  | 0.4353 | 0.2007* | 0.2640* | 0.1658* |
| No-Metadata    | 0.5282* | 0.3949** | 0.4208* | 0.1951** | 0.2196** | 0.1117** |
| No-User/Author | 0.5626** | 0.4238** | 0.4208* | 0.1951** | 0.2578** | 0.1520** |
| No-Tag         | 0.5649* | 0.4263** | -      | -       | 0.2304** | 0.1134** |
| No-Product     | -      | -       | -      | -       | -      | -       |

Figure 3: Performance of HiMeCat with different embedding dimensions ($p$).

Figure 4: Performance of HiMeCat with different numbers of synthesized training samples per class ($\beta$).
Many efforts have been put on how to utilize the label hierarchy to improve text classification. For example, Dumais and Chen [7] and Liu et al. [22] adopt a top-down training strategy and use SVMs to distinguish child categories of the same parent. In contrast, bottom-up classification [1] backpropagates the labels from the leaves to the top layer. Gopal and Yang [12, 14] propose a recursive regularization framework encouraging the similarity between the child classifiers and the parent classifier. Peng et al. [35] extend this regularization to deep graph-CNN models. Wehrmann et al. [44] and Huang et al. [15] combine the ideas of training a local classifier per level and optimizing the global classification results to mitigate exposure bias. The global structure of hierarchies is also used in many other models, such as meta-learning [46], reinforcement learning [24] and tree/graph based neural networks [55]. However, these fully supervised methods rely heavily on the amount of human-labeled training data. Under weakly supervised settings, hierarchical dataless classification [36] jointly embeds class labels and documents using Explicit Semantic Analysis; WeSHClass [30] models topic semantics in the word2vec embedding space and applies a self-training scheme; PCEM [48] introduces a path-cost sensitive classifier for semi-supervised hierarchical classification; HierCon [21] projects documents and taxonomy categories into a common concept space and calculates their fine-grained similarity. However, these studies are not concerned with metadata information.

### Metadata-Aware Text Classification

Several previous studies try to incorporate metadata information into a text classifier. For example, Ghani et al. [11] use HTML meta tags to help hypertext classification; Steyvers et al. [37] leverage author information in topic classification; Tang et al. [39] learn user and product representations for sentiment analysis; Zhang et al. [53] employ user biography data for tweet localization. Chen et al. [4] encode user mobility data and social network information for joint time and location prediction; Kim et al. [16] propose a general framework to inject categorical metadata signal into a deep text classifier. However, these models assume a fully supervised setting. Zhang et al. [54] present a weakly supervised hierarchical classification approach to classify GitHub repositories. Later, they also propose a flat metadata-aware text categorization framework [52]. Mekala et al. [28] explore to incorporate metadata as additional supervision for text classification with seed words only. However, in these studies, the label hierarchy is not leveraged in the embedding space.

#### Tree and Metadata Embedding

Recent studies on non-Euclidean embedding models, such as Poincare [33], Lorentz [34], hyperbolic cones [10] and spherical tree embedding [31], consider to preserve a tree structure in the embedding space. Along another line of work, heterogeneous network embedding algorithms [6, 9, 50] are widely used to learn representations of metadata. HHNE [43] further considers to perform heterogeneous network embedding in a hyperbolic space. Despite their respective success in capturing hierarchy and metadata information, to the best of our knowledge, there lacks a framework which allows simultaneous modeling of tree-structure dependencies, text semantics and metadata signals.

### 6 CONCLUSIONS

We present HiMeCat, an embedding-based generative framework for hierarchical metadata-aware document categorization under weak supervision. The framework is featured by a joint hierarchy-metadata-text representation learning module and a hierarchical data augmentation module. We propose a generative process in the spherical space to guide the design of both modules. Through experiments on three datasets from different domains, we show the superiority of HiMeCat towards competitive baselines in our task. We also conduct ablation studies to validate the contribution of our proposed embedding and augmentation modules. Interesting future work include: (1) discovering new categories from the unlabeled dataset and put them into the existing hierarchy and (2) integrating
different forms of weak supervision (e.g., annotated documents and class-related keywords) in hierarchical text classification.

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