Pairwise Instance Relation Augmentation for Long-tailed Multi-label Text Classification

Lin Xiao, Pengyu Xu, Liping Jing and Xiangliang Zhang

Abstract—Multi-label text classification (MLTC) is one of the key tasks in natural language processing. It aims to assign multiple target labels to one document. Due to the uneven popularity of labels, the number of documents per label follows a long-tailed distribution in most cases. It is much more challenging to learn classifiers for data-scarce tail labels than for data-rich head labels. The main reason is that head labels usually have sufficient information, e.g., a large intra-class diversity, while tail labels do not. In response, we propose a Pairwise Instance Relation Augmentation Network (PIRAN) to augment tailed-label documents for balancing tail labels and head labels. PIRAN consists of a relation collector and an instance generator. The former aims to extract the document pairwise relations from head labels. Taking these relations as perturbations, the latter tries to generate new document instances in high-level feature space around the limited given tailed-label instances. Meanwhile, two regularizers (diversity and consistency) are designed to constrain the generation process. The consistency-regularizer encourages the variance of tail labels to be close to head labels and further balances the whole datasets. And diversity-regularizer makes sure the generated instances have diversity and avoids generating redundant instances. Extensive experimental results on three benchmark datasets demonstrate that PIRAN consistently outperforms the SOTA methods, and dramatically improves the performance of tail labels.

Index Terms—Multi-label Learning, Text Classification, Long-tailed Classification, Transfer Learning, Data Augmentation.

1 INTRODUCTION

Compared with single label text classification, multi-label text classification (MLTC) is more complicated as it assigns multiple labels to one document. Strong co-occurrences and interdependencies exist among multiple labels. For example, an article on the topic of religion is likely to talk about ethic as well, but unlikely to talk about weather. MLTC has been widely applied to diverse tasks from automatic annotation for topic recognition [1], [2], [3] to bioinformatics [4], [5], web mining [6], question answering [7], tag recommendation [8] and etc.

Long-tailed distribution of the number of documents per label is a general issue in MLTC. Figure 1 shows the number of papers in the different fields of computer science on AAPD dataset collected from arXiv website. As shown in figure 1 the long tail categories with very few training instances, e.g., the label named “Quantitative Biology Quantitative Methods”. It results the MLTC model performing exceptionally well on head labels (categories with a large number of training instances, e.g., the label named “Computer Sciences Information Theory”), and the high-risk of over-fitting and inferior performance on tail labels separates hyperplane heavily skewed to the tail labels.

Label correlations may provide helpful extra information, such information can help the classification of tail labels. Thus, the exploitation of label correlations has been widely accepted as a key solution of current multi-label learning approaches. To exploit label correlations, some approaches explore external knowledge such as existing label hierarchies [9], [10], [11] or label semantic information [12], [13], [14]. The co-occurrence of labels in training data is utilized in [15], [16]. Although these approaches exploit label correlations in different ways to help alleviate long-tailed problem. However, they all train head labels and tailed labels together, as we know, it will make the head labels dominate the learning procedure, which will sacrifice the prediction precision of head labels and recall of tail labels.

Many studies solve such long-tailed problem by artificially balancing strategies, such as data re-sampling strategies [17], [18], [19], [20] and class-sensitive loss function [21], [22], [23], [24], [25], [26], which are designed to assign equal learning opportunities for each label. Although such balancing strategies can alleviate the long-tailed problem to some extent, it may bring the following problems: (1) instance re-sampling tends to over-fit by duplicating tail data and damage feature representation when abandoning head
data; (2) loss re-weighting may cause unstable training especially when the label distribution is extremely imbalanced. In other words, both strategies over-fitting on tail labels is still a big issue because of the limited intra-class diversity.

Transfer learning, as an alternative strategy, can promote the classification performance of the tail labels by transferring knowledge from head labels. Recently, several approaches based on transfer learning were proposed for long-tailed MLTC. LEAP [27] transfers the intra-class variance, OLTR [28] transfers semantic deep features and HTTN [29] transfers the meta-knowledge between classifier parameters and label prototype. What they have in common is they learn rules or distributions of parameters from head labels, then transfer such meta-knowledge to tail labels. However, they cannot deliver adaptive adjustment to tail labels, i.e., transferring adapted meta-knowledge suitable for tail labels with few-shot instances. To address this limitation, in this paper, we generate new instances for tail labels based on “localization” to alleviate the few-shot challenge. “Localization” means that we generate the new instances for tail labels by adding the pairwise instance relations on their prototypes, pairwise instance relations preserve instances neighbor structure of head labels which are expected to enlarge the intra-class diversity of tail labels. The classifiers of tail labels are then built in a many-shot situation. Compared to the previous transfer-based methods, the proposed relation transfer explicitly complements what the tail labels need.

The model is named Pairwise Instance Relation Augmentation Network (PIRAN), which has two main modules. The first module is a Relation Collector, which is implemented with the aid of head labels to get adequate instance relationships. The second module is called Tail Instance Generator, which transfers the relations to tail labels and generates new instances for tail labels in the feature space. As demonstrated in Figure 2 we transfer the instance relations from head label to tail label, and then aggregate them with the prototype of tail label (with the green circle) to generate new instances for tail labels. The generated instances enrich the tail label distribution.

To ensure the quality of the generated instances, we have to be aware of several issues. On the one hand, the variance of the new generated data may be too different from the variance of head labels. The transferred relations may drag the tail distribution with a wide spread. On the other hand, the generated data may be too similar when the transferred relations cause little perturbation to the feature space governed by a tail label. We thus constrain the new generations from two regularizers, consistency and diversity. For consistency, it contains two aspects, one is generation consistency, which ensures the new generations similar to the original tail prototype. Another is called variance consistency, which helps the variance of head and tail labels keep close. For the regularizer of diversity, it makes the generated representations be different, and effectively enlarges the intra-class diversity for tail labels.

To make a summary, our main contributions are:

- A Pairwise Instance Relation Augmentation Network (PIRAN) is proposed to tackle the long-tailed problem in multi-label text classification. PIRAN takes advantage of the pairwise relations from the data-rich head labels to generate new instances for data-poor tail labels with the aid of Relation Collector and Instance Generator.
- To make the validity of new generations for tail labels, PIRAN designs two regularizers, consistency and diversity, which not only ensures the effectiveness of generation but also enlarges the intra-class diversity of tail labels.
- The evaluation results on three widely-used benchmark datasets show that PIRAN outperforms the SOTA baselines, especially on the prediction of tail labels.

The rest of the paper is organized via four Sections. Section 2 discusses the related work. Section 3 describes the proposed PIRAN model for multi-label text classification. The experimental setting and results are discussed in Section 4. A brief conclusion and future work are given in Section 5.

2 RELATED WORK

In this section, we review previous literature from three aspects, multi-label text classification, long tail classification and long-tailed multi-label text classification.

2.1 Multi-label Text Classification

Multi-label classification is with wide applications in many areas, especially for text classification. Traditional methods can be grouped into two major categories: namely, problem transformation and algorithm adaptation. Problem transformation maps the MLTC task into multiple single-label learning tasks, such as BR [30], LP [31], CC [32]. Algorithm adaptation extends specific multi-class algorithms to deal with multi-label classification problems such as Rank-SVM [8], ML-DT [33], ML-KNN [34]. Briefly, the key idea of transformation methods is to fit data to algorithm, while the key idea of algorithm adaptation methods is to fit algorithm to data.

Recent years, with the development of neural network, it have become the promising solution for the multi-label classification. Among them, recurrent convolutional neural network (RCNN) [35] captures contextual information with the recurrent structure and constructs the representation of text using a convolutional neural network. XML-CNN [36] captures the local correlations from the consecutive context windows. Although obtains promising results, but it suffer from the limitation of window size so it cannot determine the long-distance dependency of text. Besides them, attention mechanism is introduced to yield unusually brilliant results on MLTC. SGM [37] uses sequence generation model with attention structure to solve the MLTC task. AttentionXML [38] proposes a multi-label attention to capture the most relevant parts of texts to each label and uses the label probabilistic label tree to tackle MLTC. However, most of them ignore the correlation among labels. An initialization method [15] is proposed to treat some neurons in the final hidden layer as dedicated...
neurons for each pattern of label co-occurrence. Some methods are proposed to capture label correlations by exploiting label structure or label content. DXML \cite{39} constructs the label graph from the label co-occurrence to supervise the MLTC. EXAM \cite{13} leverages the interaction mechanism to explicitly compute the word-level interaction signals for the text classification. Although multi-label learning benefits from the exploration of label correlation, these methods can not well handle long tail problem because most of them treat the labels equally. In this case, infrequently occurring tail labels are harder to predict than head labels since they have little training documents which make the whole learning model dominates by the head labels \cite{40}.

2.2 Long Tail Classification

Data re-sampling \cite{18}, \cite{20}, \cite{41}, \cite{42}, \cite{43} is one traditional solution for long-tail learning. It typically over-samples the training data from tail labels, or equivalently to under-sample head labels. Another traditional solution is re-weighting, it modifies the loss function that is used to train the model \cite{24}, \cite{26}, \cite{44}, \cite{45}. Their common idea is to assign a higher loss to samples from tail labels, thereby providing a stronger supervisory signal for the model to learn these labels. Recent studies show a trend of decoupling long-tailed classification into two separate stages: representation learning and classifier learning \cite{46}, \cite{47}. BBN \cite{47} proposes a unified Bilateral-Branch Network (BBN) integrating “conventional learning branch” and “re-balancing branch”. The former branch is equipped with the typical uniform sampler to learn the universal patterns for recognition, the later branch is coupled with a reversed sampler to model the tail data. Similar idea is used in \cite{46}. Both of them empirically prove that re-balancing methods may hurt feature learning to some extent. Transfer learning as an effective strategy, it transfer the knowledge learned from data-rich head classes with abundant training instances to help data-poor tail classes. \cite{48} gradually transfer meta-knowledge learned from the head to the tail through a recursive approach. In \cite{28}, an integrated algorithm is developed with dynamic meta-embedding. It handles tail recognition robustness by relating visual concepts among head and tail label embedding. LEAP \cite{27} expands the distribution of tail labels during training by transferring the intra-class angular distribution learned from head labels to tail labels. All the methods mentioned above are proposed to deal with long-tailed multi-class problems, the characteristic of multi-label is not fully considered.

2.3 Long-tailed Multi-label Text Classification

For MLTC task, the re-sampling strategy may not necessarily result in a more balanced distribution of classes due to the label correlations. For example, a document that contains tail labels, e.g. “Condensed Matter Statistical Mechanics” and “Symbolic Computation”, is likely to be also associated with head labels, e.g. “Computer Science”. To solve the multi-label long-tailed problem, some methods take advantage of label correlations and extra label information to alleviate the imbalance between head labels and tail labels in some extent, they still can not well handle long tail problem. To tackle the long-tailed multi-label problem, \cite{49} proposes a linear ensemble by using DNN and linear classifier for head and tail labels respectively. \cite{50} introduces the label semantics and then employ soft n-gram interaction matching to tackle tail labels. ZACNN \cite{14} introduces a neural architecture that incorporates label descriptors and the hierarchical structure of the label spaces for few and zero-shot multi-label text prediction. HTTN \cite{29} learns meta-knowledge for mapping prototypes learned by few-shot to those by many-shot.

It is worth mentioning that above-discussed related work gain the knowledge mainly from the head labels but they don’t consider whether the transferred knowledge is suitable for tail labels. Different from them, we transfer the pairwise correlations to generate the new instances for tail labels. And the generated instances adapt the correlation of each pair instances in head labels to tail labels. The classifiers of tail labels are then built in a many-shot situation. Comparing to the parameter-level knowledge transfer, the proposed data augmentation with correlation transfer explicitly complements what the tail labels need.

3 Proposed Method

Let $D = \{(x_i, y_i)\}_{i=1}^{N}$ be a set of $N$ documents with corresponding labels $Y = \{y_{i} \in \{0, 1\}^l\}$, here $l$ is the total number of labels. Each document contains a sequence of words, $x_i = \{w_{i1}, \cdots, w_{ij}, \cdots, w_{in}\}$, where $w_j \in \mathbb{R}^k$ is the $j$-th word vector (e.g., encoded by word2vec \cite{51}), and $n$ is the number of words in the document. Multi-label text classification (MLTC) aims to learn a classifier from $D$, which can assign the most relevant labels to the new given documents. In this study, we divide the label set into two parts: head labels that are associated with many documents (higher than a given threshold), and tail labels that are associated with few documents (lower than a given threshold). The number of head labels and tail labels are $l_{head}$ and $l_{tail}$, respectively.

In long-tailed multi-label text classification task, head labels have sufficient documents that can be used to train high-performance classifiers. On the contrary, there are only few-shot documents for tail labels to build their classifiers. The imbalanced distribution over labels often causes poor performance on tail labels when head and tail labels are treated with no difference. Here, we consider to design a data augmentation strategy to calibrate this biased distribution and alleviate the difficulties for few-shot tail label learning. A Pairwise Instance Relation Augmentation Network (PIRAN) is proposed to transfer the instance relations from head labels to tail labels for generating new instances to enlarge the intra-class diversity of tail labels. The overall architecture of PIRAN is shown in Figure 2. Besides the Semantic Extractor for learning comprehensive document representation, PIRAN has two other main modules, Relation Collector and Tail Instance Generator. Relation Collector captures the instance correlation from head labels, and Tail Instance Generator applies these correlation pairs to tail labels to generate new instances.

3.1 Document Representation by Semantic Extractor

To capture the forward and backward sides contextual information of each word, we adopt the bidirectional long short-term memory (Bi-LSTM) \cite{52} language model to learn the word embedding for each input document. At time-step $p$, the hidden state can be updated with the aid of input and $(p-1)$-th step output.

$$
\overrightarrow{h_p} = LSTM(\overrightarrow{h_{p-1}}, w_p)
$$

$$
\overleftarrow{h_p} = LSTM(\overleftarrow{h_{p-1}}, w_p)
$$

where $w_p$ is the embedding vector of the $p$-th word in the corresponding document, and $\overrightarrow{h_p}, \overleftarrow{h_p} \in \mathbb{R}^k$ indicate the forward and backward word context representations respectively.
Then, the whole document can be represented by Bi-LSTM as follows.

\[
H = (\overrightarrow{h}, \overrightarrow{H}), \quad \overrightarrow{H} = (\overrightarrow{h_1}, \overrightarrow{h_2}, \ldots, \overrightarrow{h_n})
\]

In this case, the whole document set can be taken as a matrix \( H \in \mathbb{R}^{2k \times n} \). As mentioned above, a multi-label document may be tagged by more than one label. To capture the components relevant to different labels in each document, we adopt the multi-head attention mechanism as the Semantic Extractor. The multi-head document representation can be obtained by

\[
A = \text{softmax}(W_2 \tanh(W_1 H)) \quad M_s = A_s H^T \quad r = f_a(M)
\]

where \( W_1 \in \mathbb{R}^{d_a \times 2k} \) and \( W_2 \in \mathbb{R}^{d \times d_a} \) are so-called attention parameters to be trained. The dimension parameter \( d_a \) can be set arbitrarily. The matrix \( A \in \mathbb{R}^{s \times n} \) is the multi-head attention score for \( n \) words in the document. Here, \( s \) is the number of heads in the multi-head attention mechanism, and \( r \) means the \( \tau \)-th head of attention. The multi-head document representation \( M \in \mathbb{R}^{s \times 2k} \) is obtained by using linear combination of the context words with the aid of attention score \( A \). The comprehensive document representation \( r \in \mathbb{R}^{d} \) is produced by aggregating the multi-head representation \( M \) with an aggregation function \( f_a \). The Semantic Extractor is shared between head and tail labels, and it can be replaced with any modern language model such as BERT [53], GPT-3 [54] and etc.

Once having the comprehensive document representation, we can build the multi-label text classifier. Mathematically, the predicted probability of each label for a document can be estimated via

\[
\hat{y} = \text{sigmoid}(W_a r)
\]

where \( W_a \in \mathbb{R}^{1 \times d} \) is the classifier parameter for all labels, including both the classifier parameter of head labels \( W_{head} \) and tail labels \( W_{tail} \). The sigmoid function is used to transfer the output value into a probability. The cross-entropy is often used for constructing the loss function for multi-label text classification task [55].

\[
\mathcal{L} = -\frac{1}{N} \sum_{i=1}^{N} \sum_{j=1}^{l} y_{ij} \log(\hat{y}_{ij}) + (1 - y_{ij}) \log(1 - \hat{y}_{ij})
\]

where \( N \) is the number of training documents, \( l \) is the number of labels, \( \hat{y}_{ij} \in [0, 1] \) is the predicted probability, and \( y_{ij} \in \{0, 1\} \) indicates the ground truth of the \( i \)-th document along the \( j \)-th label. To prevent the predicted scores from being biased toward frequent head labels, we re-train the classifier of tail labels according to data augmentation strategy with the aid of Relation Collector and Tail Instance Generator.

### 3.2 Relation Collector

Instances belonging to head labels demonstrate abundant pairwise relations that are missing in tail labels. The pairwise relations preserve instances neighbor structure information. To generate instances for tail labels, we can copy these pairwise relations and adjust them in the tail cases. For example, the most intuitive operation is to transfer the pairwise relations to tail labels by scaling operations. To get the transferable pairwise relations, Relation Collector is designed to make an efficient collection. Specifically, for each head label, we sample \( p \) pairs of instances and measure the difference between each pair of them. The collected relations for a head label is \( \{c_1, \cdots, c_p\} \), where one relation \( c \) is calculated as follows

\[
c = r_1 - r_2
\]

\( c \) is the difference between the two sampled instances \( r_1 \) and \( r_2 \) in one pair. From all head labels, we extract in total \( l_h \times p \) relations to transfer for tail instance generation. It is analogous to allow some teachers (head labels) to impart knowledge (instance relations) to their students (tail labels) from what they have.

### 3.3 Instance Generator

For a tail label \( j \), we sample \( q \) documents and get their representation \( \{r_{j1}, \cdots, r_{jq}\} \) by the trained multi-head Semantic Extractor.
Note that \( q \) can be a small value, e.g., 1 to 5. Then, we use the average function to get the prototype of the tail label,

\[
o^j = \text{avg}\{r_1^j, \cdots, r_q^j\}
\]

Although the multi-head semantic extractor can map the documents of tail labels to comprehensive representations, the obtained prototype \( o^j \) is not capable to govern the same region that could be reached at the condition that tail label \( j \) has a sufficient number of instances. To make an instance-rich environment for label \( j \), we can generate new instances centering at prototype \( o^j \) by transferring the collected relations from head labels.

By using the \( p \) relations from one head label \( b \), we can generate \( p \) instances for a label \( j \).

\[
g_z^{jb} = W(o^j + c_z^b), \quad z = \{1, \cdots, p\}
\]

where \( c_z^b \) is one of the \( p \) relations from head label \( b \), and \( g_z^{jb} \) is one new generated instance. Trainable parameter \( W \) works as scaling operation to make the perturbation \( c_z^b \) on prototype \( o^j \) be adapted to the tail label setting.

The parameter \( W \) is trained by constraining the new generations on two regularizers, consistency and diversity. They are reflected in three loss functions defined below, generation and variance consistency, generation diversity.

\[
\mathcal{L}_{\text{gen}} = \sum_{j=1}^{l_t} \sum_{k=1}^{l_h} \sum_{z=1}^{p} \|o^j - g_z^{jb}\|^2
\]

\[
\mathcal{L}_{\text{div}} = -\sum_{j=1}^{l_t} \sum_{k=1}^{l_h} \sum_{z=1}^{p} (|Q_h^T g_z^{jb} - \frac{1}{p} \sum_{z=1}^{p} Q_h^T g_z^{jb}|)^2 \quad (10)
\]

\[
\mathcal{L}_{\text{var}} = \sum_{j=1}^{l_t} \sum_{k=1}^{l_h} \sum_{z=1}^{p} (|Q_h Q_h^T g_z^{jb} - g_z^{jb}|)^2 \quad (11)
\]

The loss \( \mathcal{L}_{\text{gen}} \) is called generation consistency. It is designed to make the new generations for one tail label be close to its label prototype, so that the overall distribution of the generated instances is roughly located close to the few-shot distribution. However, if the new generations are too close, the generated instances will be redundancy and invalid due to the low intra-class diversity. Therefore, generation diversity \( \mathcal{L}_{\text{div}} \) is designed to combat this problem by measuring the projected variance of generated instances. The projected space is spanned by \( Q \), which are the eigenvectors calculated from the head labels’ covariance matrix:

\[
\sum_{k=1}^{l_h} \sum_{z=1}^{n_z} (r_{bz} - o_b)^T (r_{bz} - o_b)
\]

where \( o_b \) is the prototype of head label. The intra-class variance are evaluated from individual documents of head labels to tail labels. We take the top 100 eigenvectors as preserving 95% information. The variance consistency is introduced by \( \mathcal{L}_{\text{var}} \) that measures the reconstruction loss of generated instances in the space of \( Q \). This further ensures the generated instances for tail labels have a consistent variance w.r.t. the head labels. These three loss functions are combined with coefficients \( \alpha = 1, \beta = 1, \gamma = 0.1 \) to be the instance correlation transfer loss. These coefficients were set by grid search to reach the best performance on training \( W \).

\[
\mathcal{L}_{\text{transfer}} = \alpha \mathcal{L}_{\text{gen}} + \beta \mathcal{L}_{\text{var}} + \gamma \mathcal{L}_{\text{div}} \quad (13)
\]

### 3.4 Classifier Adjustment

Once we have the new instances and their representations for tail labels, we use these representations to adjust the tail classifier parameter \( W_{\text{tail}} \). such that the tail class prediction

\[
\hat{y} = \text{sigmoid}(W_{\text{tail}} g_z^{jb})
\]

can minimize the loss function defined in Eq. (5). The adjusted
Datasets.

4.1 Experimental Setting

In this section, we evaluate the proposed model PIRAN on three datasets by comparing with seven state-of-the-art methods in terms of widely used metrics, P@k, nDCG@k (k = 1, 3, 5) and F1-score.

4.1 Experimental Setting

Datasets. Three multi-label text datasets are employed for evaluation: AAPD, RCV1 and EUR-Lex. Their label distributions all show the long-tailed distribution.

- **AAPD** [37] collects the abstract and the corresponding subjects of 55840 papers from arXiv in the field of computer science.
- **Reuters Corpus Volume I (RCV1)** [56] contains more than 80K manually categorized news belonging to 103 classes.
- **EUR-Lex** [57] is a collection of documents about European Union law belonging to 3714 subjects (labels).

For these three data sets, only last 500 words were kept for each document. Once the document has less than the predefined number of words, we extend it by padding zeros. These widely used benchmark datasets have defined the training and testing split. We follow the same data usage for all evaluated models. The datasets have been adjusted by many-shot instances.

Algorithm 1 illustrates the procedure of PIRAN in detail. The lines 1-5 present the learning process of Semantic extractor and classifier parameters. The lines 6-9 show the procedure of Relation Collector which obtains the instance relations from head labels. The lines 10-17 present the Instance Generator procedure of tail labels with the aid of instance relations, which obtains from head labels. The line 18 updates the parameter of tail labels by using the new generations.

Given a testing document, it will first go through the Semantic Extractor to have its representation vector \( r \), and then get the predicted label by \( \hat{y} = \text{sigmoid}(W_a r) \). \( W_a \) is composed of \( W_{head} \) and \( W_{tail} \). \( W_{tail} \) is the parameter of tail labels, which has been adjusted by many-shot instances.

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**Baseline Models.** To verify the effectiveness of PIRAN, we selected the seven most representative baseline models in three groups.

1) **Multi-Label Methods:**

- **DXML:** [39] tries to explore the label correlation by considering the label structure from the label co-occurrence graph.
- **XML-CNN:** [36] adopts Convolutional Neural Network (CNN) and a dynamic pooling technique to extract high-level feature for multi-label text classification.
- **AttentionXML:** [38] builds the label-aware document representation for multi-label text classification.

2) **Long-Tailed Multi-Class Methods:**

- **OLTR** [28] learns dynamic meta-embedding in order to share visual knowledge between head and tail classes.
- **LEAP** [27] transfers the intra-class diversity learned from head labels to tail labels.

3) **Long-Tailed Multi-Label Methods:**

- **LTMCN** [49] introduces an ensemble method to tackle long-tailed multi-label training. The DNN and linear classifier are combined to deal with the head label and tail label respectively.
- **HTTN** [29] captures meta-knowledge from head to tail for mapping few-shot network parameters to many-shot network parameter.

**Parameter Setting**

For all three datasets, we use Glove [51] to get the word embedding in 300-dim. LSTM hidden state dimension is set to \( k = 150 \). The parameter \( d_1 = 100 \) for \( W_1 \) and \( W_2, s = 4 \) for \( M \) and \( d = 100 \) for \( r \) and \( W_{tail} \). The whole model is trained via Adam [58] with the learning rate being 0.01. The baselines OLTR and LEAP deal with the long tail problem on the image recognition, the Semantic Extractor used was the ResNet-10, ResNet-32 and others. For a fair comparison, we replace the Semantic Extractor with Bi-LSTM with attention. All experiment results reported in this paper are averaged from five independent runs. The parameters of all baselines are either adopted from their original papers or determined by experiments. For AAPD, RCV1 datasets, we set the number of tail labels as 24 (44.4%) and 60 (60%), respectively. For Eurlex dataset, we set the number of tail label be 2476 (66.7%).

**Evaluation Metrics.** We use the metric, precision at top \( K (P@k) \) and the Normalized Discounted Cumulated Gains at top \( K \) (nDCG@k), F1-score to evaluate the prediction performance. \( P@k \) and \( nDCG@k \) are defined according to the predicted score vector \( \hat{y} \in \mathbb{R}^l \) and the ground truth label vector \( y \in \{0, 1\}^l \) as follows.

\[
P@k = \frac{1}{k} \sum_{l \in \text{rank}_k(\hat{y})} y_l
\]

\[
DCG@k = \sum_{l \in \text{rank}_k(\hat{y})} \frac{y_l}{\log(1 + l + 1)}
\]

\[
nDCG@k = \frac{\sum_{l=1}^{\min(k, ||y||_0)} \frac{1}{\log(1+l)}}{\sum_{l=1}^{\min(k, ||y||_0)} 1}
\]

where \( \text{rank}_k(y) \) is the label indexes of the top \( k \) highest scores of the current prediction result. \( ||y||_0 \) counts the number of relevant labels in the ground truth label vector \( y \). F1-score is the harmonic mean of Precision and Recall, Precision(\( P_i \)), Recall(\( R_i \)), and F1-score can be computed as below:

\[
F1 = 1 + \frac{1}{||l||} \sum_{i \in l} \frac{2P_i R_i}{P_i + R_i}
\]

\[
P_i = \frac{TP_i}{TP_i + FN_i}
\]

\[
R_i = \frac{TP_i}{TP_i + FN_i}
\]

where \( TP_i, TN_i, FP_i, FN_i \) denote the true positives, true negatives, false positives and false negatives for the category \( i \) in label set \( l \), respectively.

**4.2 Comparison Results and Discussion**

Table 2, Table 3 and Table 4 show the averaged performance of all test documents. According to the formula of P@K and
TABLE 2
Comparing PIRAN with baselines on AAPD dataset.

|      | P@1 | P@3 | P@5 | nDCG@3 | nDCG@5 | F1-score |
|------|-----|-----|-----|--------|--------|----------|
| DXML | 80.54 | 56.30 | 39.16 | 77.23 | 80.99 | 65.13 |
| XML-CNN | 76.25 | 54.34 | 37.84 | 72.01 | 76.40 | 65.52 |
| AttentionXML | 83.02 | 58.72 | 40.56 | 78.01 | 82.32 | 68.79 |
| OLTR | 78.96 | 56.28 | 38.00 | 74.66 | 78.58 | 62.48 |
| LEAP | 82.23 | 60.00 | 40.95 | 79.36 | 83.21 | 68.09 |
| LTMCP | 78.51 | 56.02 | 38.46 | 75.19 | 76.05 | 63.59 |
| HTTN | 82.79 | 58.69 | 40.18 | 77.15 | 81.32 | 68.47 |
| PIRAN | 83.94 | 60.61 | 41.65 | 79.57 | 83.74 | 69.81 |

TABLE 3
Comparing PIRAN with baselines on RCV1 dataset.

|      | P@1 | P@3 | P@5 | nDCG@3 | nDCG@5 | F1-score |
|------|-----|-----|-----|--------|--------|----------|
| DXML | 94.04 | 78.65 | 54.38 | 89.83 | 90.21 | 75.76 |
| XML-CNN | 95.75 | 78.63 | 54.94 | 89.89 | 90.77 | 75.92 |
| AttentionXML | 95.62 | 78.72 | 54.22 | 90.21 | 90.59 | 77.95 |
| OLTR | 93.79 | 61.36 | 44.78 | 74.37 | 77.05 | 56.44 |
| LEAP | 95.64 | 78.84 | 54.90 | 89.97 | 90.74 | 79.52 |
| LTMCP | 90.76 | 73.26 | 51.62 | 84.31 | 85.12 | 74.28 |
| HTTN | 94.00 | 75.79 | 53.87 | 86.90 | 87.65 | 76.27 |
| PIRAN | 95.87 | 79.21 | 54.76 | 90.40 | 91.09 | 79.84 |

TABLE 4
Comparing PIRAN with baselines on EUR-Lex dataset.

|      | P@1 | P@3 | P@5 | nDCG@3 | nDCG@5 | F1-score |
|------|-----|-----|-----|--------|--------|----------|
| DXML | 80.41 | 66.74 | 56.33 | 70.03 | 63.18 | 53.28 |
| XML-CNN | 78.20 | 65.93 | 53.81 | 68.41 | 60.54 | 51.98 |
| AttentionXML | 78.36 | 66.01 | 53.97 | 68.74 | 63.29 | 52.75 |
| OLTR | 65.62 | 52.34 | 42.69 | 55.73 | 50.57 | 22.64 |
| LEAP | 80.02 | 64.09 | 51.73 | 68.16 | 61.57 | 47.64 |
| LTMCP | 75.23 | 60.12 | 49.36 | 64.89 | 58.23 | 48.10 |
| HTTN | 79.58 | 65.28 | 54.92 | 68.46 | 63.71 | 53.34 |
| PIRAN | 80.56 | 67.37 | 56.47 | 70.39 | 65.21 | 54.68 |

nDCG@K, we know P@1 = nDCG@1, thus only nDCG@3 and nDCG@5 are listed. The best result is marked in bold. From Table 2, Table 3 and Table 4, we can make several observations about these results. Firstly, XML-CNN is worse than DXML and AttentionXML, it proposes a dynamic max pooling scheme that captures richer information from different regions of the document and a hidden bottleneck layer for better representations of documents as well as for reducing model size, but it ignores the label correlation, which is in fact the key focus for multi-label learning. DXML explores the label correlation by the label graph to alleviate the long tail problem in MLTC. AttentionXML tries to capture the important parts of texts most relevant to each label, and establishes the relationship between labels and documents, so as to help tail labels capture sufficient semantic information. DXML and AttentionXML can get the satisfying results. Secondly, for LEAP and OLTR, they all use the transfer strategy to transfer information from the head labels to help the tail labels. Since they are specially designed for long-tailed multi-class classification and don’t consider the characteristics of MLTC, thus they are not good at MLTC task. Thirdly, HTTN and LTMCP are both specially designed for long-tailed MLTC task. Both of them train the documents belonging to the head label and the tail label respectively. LTMCP combines linear model and DNN to train the documents belonging to tail label and head label respectively, which ignores the label correlations between the head label and tail labels. HTTN transfers the meta-knowledge from the data-rich head labels to data-poor tail labels. But it doesn’t consider whether the transferred information suits for tail labels. As expected, PIRAN consistently outperforms all baselines on all experimental datasets. It further confirms that the proposed Pairwise Instance Relation Augmentation Network is effective for long-tailed multi-label text classification by doing the data augmentation for tail labels.

4.3 Significance Analysis
To prove that PIRAN can significantly improves the multi-label text classification performance on whole labels. The P-value is known as the probability value. It is defined as the probability of getting a result that is either the same or more extreme than the actual observations. The P-value is known as the level of marginal significance within the hypothesis testing that represents the probability of occurrence of the given event. If the P-value is small, then there is stronger evidence in favour of the alternative hypothesis. We give the statistics comparison (P-Value) on the superior baselines on three datasets in terms on F1-score. All experiment results reported in our paper are averaged from five independent runs, thus we list the five results of the superior baseline and PIRAN on Table 5. AttentionXML, LEAP and HTTN are the strongest baselines on AAPD, RCV1 and EUR-Lex respectively, which are selected as the comparison algorithms for significance calculation. As we all know, P-value < 0.05, the result is statistically significant. As shown in Table 5, the P-Value are 0.00019, 0.00037, 0.00013 on three datasets respectively, thus
we can make the conclusion that the improvement of PIRAN is statistically significant.

4.4 Tail labels Performance Verification

In order to further verify the performance of these methods on tail labels, we compare the tail label results of PIRAN with that of the strong competitors in multi-label methods (AttentionXML), long-tailed multi-label methods (LEAP) and multi-label methods (HTTN). Table 6 reports the average of the F1-scores for all tail labels in three datasets. AttentionXML only alleviates the long-tailed problem by constructing the relation between labels and documents, therefore, the performance on the tail labels is poor. LEAP and HTTN are specially designed for long-tailed task. In order to improve the classification performance of tail labels, they try different explorations. LEAP seeks to expand the distribution of the tail classes during training, so as to alleviate the distortion of the feature space and propose to augment each instance of the tail classes with certain disturbances in the deep feature space. HTTN transfers the meta-knowledge from the data-rich head labels to data-poor tail labels. The meta-knowledge is the mapping from few-shot network parameters to many-shot network parameters, which aims to promote the generalizability of tail classifiers. HTTN is designed for multi-label learning, the design of HTTN comprehensively considers the characteristics of multi label data. And LEAP is designed for multi-class task, therefore, the performance on the tail labels is worse than HTTN. PIRAN transfers the instance correlations from head labels to tail labels for generating new instances to enlarge the intra-class diversity of tail labels, PIRAN truly solves the problem of the imbalance between head labels and tail labels in MLTC task. The results show that PIRAN performs better than the other three strong baselines, verifying again the effectiveness of PIRAN on addressing the tail classification problem.

\[
L_{\text{div}} = \text{div} \quad \text{and} \quad L_{\text{var}} = \text{var}
\]

\[
W \quad \text{and} \quad W_{\text{gen}}
\]

\[
L_{\text{dis}} = \text{dis} \quad \text{and} \quad L_{\text{gen}} = \text{gen}
\]

4.5 Ablation Test

To evaluate the design of different components in PIRAN, we report the ablation test results in the following setting. The first one is PIRAN without data augmentation (denoted as No-Aug). The second one is PIRAN with data augmentation that however simply generates instances without the constrain of transfer parameter $W$ (denoted as Aug-w/o-C). The third one is PIRAN with data augmentation that generates instances with $W$ but without diversity and variance constraint (i.e., just using loss $L_{\text{gen}}$ to train $W$, no $L_{\text{div}}$ and $L_{\text{var}}$, denoted as Aug-w-gen). The fourth one is PIRAN with data augmentation that generates instances with $L_{\text{gen}}$ and $L_{\text{div}}$ to ensure the validity of generation instances, denoted as Aug-w-gen-div). The last one is the complete PIRAN (denoted as Complete). Figure 4 shows the prediction results on three datasets in terms of F1-score. There are four interesting observations:

- It is always preferable to consider the three constraints added in the relation transfer, generation consistency, generation diversity and distribution consistency, as shown by the superior performance of Complete. It proves that PIRAN can generate high-quality instances for tail labels and use the new instances to improve the performance of tail labels.
- The result of Aug-w/o-C is the worst, because simple transfer of the correlations without $W$ cannot ensure the effectiveness of the generated instances. It even generates noisy instances to harm the classifier. In other words, learning transfer parameter $W$ is the key to generate high-quality instance.
- The result of No-Aug is better than Aug-w/o-C, it shows that generating inaccurate instances will greatly affect the performance. For Aug-w/o-C, it generates a lot of noise data, which really disturbs the learning of tail labels.
- Compared with Aug-w-gen, the model of Aug-w-gen-div can obtain the better result, because the constraint of $L_{\text{div}}$ avoids redundancy in generating instances. Aug-w-gen-div can effectively enlarge the diversity of tail labels, thus it obtains better result than Aug-w-gen model.
- The result of Complete is always better than Aug-w-gen, showing the usefulness of $L_{\text{div}}$ and $L_{\text{dis}}$ on improving the classification performance.

Therefore, we can confirm the effectiveness of the three regularizers we designed in PIRAN. The regularizer of $L_{\text{gen}}$ makes the generations are similiar with tail label’s prototype. Coupling with the regularizer of $L_{\text{div}}$ can effectively enlarge the intra-class diversity of tail labels. Furthermore, $L_{\text{var}}$ further keeps the generated instances for tail labels have a consistent variance with head labels.

4.6 Sensitivity of the Number of New Generations for Tail Labels

We investigate the performance of PIRAN with different number of new generations for tail labels in AAPD, RCV1 and EUR-Lex dataset. Figure 5 shows the performance of PIRAN when the number of generated instances $p$ varies from 300 to 1800 for AAPD, from 120 to 720 for RCV1, from 10 to 250 for EUR-Lex, and show their influence on F1-score. For AAPD dataset, when the number of new generations $p$ is changed from 300 to 1200, the classification performance becomes better. However, the performance improvement reaches a limit when $p$ is as large as 1200. When the number of generated instances $p$ is changed from 1200 to 1800, the classification performance is slowly decreased. There is the same trend on the RCV1 dataset, when $p$ is increased from 120 to 480, F1-score is steadily improved. With the number of $p$ become larger, the performance of PIRAN is degraded. For EUR-Lex, as the number of new generations $p$ grows from 10 to 50, the performance dramatically improve, because the number of instance in tail labels mostly only contain 1-3 documents. Therefore, the new generations can effectively improve the classification performance of EUR-Lex at the case of extreme data scarcity.
TABLE 5

| Dataset  | Methods          | 1   | 2   | 3   | 4   | 5   | avg | P-value |
|----------|------------------|-----|-----|-----|-----|-----|-----|---------|
| AAPD     | AttentionXML     | 68.77 | 68.85 | 68.91 | 68.56 | 68.86 | 68.79 | 0.00019 |
|          | PIRAN            | 69.32 | 69.89 | 70.17 | 69.69 | 69.98 | 69.81 |         |
| RCV1     | LEAP             | 79.48 | 79.64 | 79.35 | 79.44 | 79.49 | 79.52 | 0.00037 |
|          | PIRAN            | 79.75 | 79.93 | 79.88 | 79.73 | 79.91 | 79.84 |         |
| EUR-Lex  | HTTN             | 53.56 | 53.78 | 53.21 | 53.29 | 52.86 | 53.34 | 0.00013 |
|          | PIRAN            | 54.79 | 54.87 | 54.36 | 54.45 | 54.93 | 54.08 |         |

Fig. 5. Sensitivity of PIRAN to the number of new generations for tail labels ($p$).

Fig. 6. Sensitivity of PIRAN to the number of head labels ($l_{head}$).

TABLE 6

|         | AAPD | RCV1 | EUR-Lex |
|---------|------|------|---------|
| AttentionXML | 17.22 | 12.30 | 1.09 |
| LEAP     | 16.19 | 10.17 | 0.06 |
| HTTN     | 23.26 | 16.23 | 1.30 |
| PIRAN    | 25.90 | 18.78 | 1.96 |

4.7 Sensitivity of the Number of Head labels

We vary the number of head labels $l_{head}$ to see how the proposed model is affected by different number of head labels. Figure 6 shows the result of different numbers of head labels on AAPD, RCV1 and EUR-Lex evaluation. From the result we can see, for AAPD, from 42 to 30, the classification performance is greatly improved, because when the number of head label is set to 42, some of them are actually tail labels. However, when it is decreased from 30 to 12, the classification performance is going down due to the few diversity can be transferred. The same trend is shown in RCV1 dataset. when the number of head labels is changed from 20 to 60, the classification performance is greatly improved. However, when the number of head labels increased from 60 to 80, the result is degraded. For EUR-Lex, for the different number of tail labels, the results don’t change dramatically. From 619 to 1238, the classification performance is improved, because the richer instance relationships are brought. However, when the number of head labels increases from 1238 to 2476, the performance of PIRAN decreases. The reason is that many labels are really only few-shot, When they are used to learn
Q, Q may introduce noise.

In summary, extensive experiment results demonstrate that the proposed PIRAN can achieve competitive performance compared with baselines. In particular, PIRAN has excellent performance on tail label prediction.

5 CONCLUSIONS AND FUTURE WORK
A Pairwise Instance Relation Augmentation Network (PIRAN), in this paper, is proposed for long-tailed multi-label text classification. It makes use of the instance relations in head labels, and then transfers these relations to tail labels which help tail labels generate new instances in feature space. Two regularizers (diversity and consistency) are imposed to ensure the generation of high-quality instances in feature space by considering generation consistency, variance consistency and generation diversity. Experiments show that PIRAN consistently outperforms the state-of-the-art baselines and furthermore reveals the performance advantage in predicting long-tailed labels.

In real applications, more precious information can be collected, such as label description, label topology (e.g., hierarchical structure) and etc. Therefore, it is interesting to extend the current model with such extra information. In the future work, we will transfer the instance correlation from head labels to tail labels by considering the label semantic or label co-occurrence between head and tail labels.

REFERENCES
[1] Z. Yang, D. Yang, C. Dyer, X. He, A. Smola, and E. Hovy, “Hierarchical attention networks for document classification,” in Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, 2016, pp. 1480–1489.
[2] H. Kazawa, T. Izumitani, H. Taira, and E. Maeda, “Maximal margin labeling for multi-topic text categorization,” Advances in neural information processing systems, vol. 17, 2004.
[3] N. Ueda and K. Saito, “Parametric mixture models for multi-labeled text,” Advances in neural information processing systems, vol. 15, 2002.
[4] M.-L. Zhang and Z.-H. Zhou, “Multilabel neural networks with applications to functional genomics and text categorization,” IEEE transactions on Knowledge and Data Engineering, vol. 18, no. 10, pp. 1338–1351, 2006.
[5] A. Elisseeff and J. Weston, “A kernel method for multi-labelled classification,” in Advances in neural information processing systems, 2002, pp. 681–687.
[6] L. Tang, S. Rajan, and V. K. Narayanan, “Large scale multi-label classification via metalabeler,” in Proceedings of the 18th international conference on World wide web, 2009, pp. 211–220.
[7] A. Kumar, O. Irosy, P. Ondruska, M. Iyyer, J. Bradbury, I. Gulrajani, V. Zhong, R. Paulus, and R. Socher, “Ask me anything: Dynamic memory networks for natural language processing,” in International Conference on Machine Learning, 2016, pp. 1378–1387.
[8] I. Katakas, G. Tsoumakas, and I. Vlahavas, “Multilabel text classification for automated tag suggestion,” in Proceedings of the ECML/PKDD, vol. 18. Citeseer, 2008, p. 5.
[9] L. Cai and T. Hofmann, “Hierarchical document categorization with support vector machines,” in Proceedings of the thirteenth ACM international conference on Information and knowledge management, 2004, pp. 78–87.
[10] N. Cesa-Bianchi, C. Gentile, and L. Zaniboni, “Hierarchical classification: combining bayes with svm,” in Proceedings of the 23rd international conference on Machine learning, 2006, pp. 177–184.
[11] B. Chen, X. Huang, L. Xiao, Z. Cai, and L. Jing, “Hyperbolic instance model for hierarchical multi-label classification,” in Proceedings of the AAAI Conference on Artificial Intelligence, vol. 34, no. 05, 2020, pp. 7496–7503.
[12] L. Xiao, X. Huang, B. Chen, and L. Jing, “Label-specific document representation for multi-label text classification,” in Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), 2019, pp. 466–475.
[36] J. Liu, W.-C. Chang, Y. Wu, and Y. Yang, “Deep learning for extreme multi-label text classification,” in Proceedings of the 40th International ACM SIGIR Conference on Research and Development in Information Retrieval, 2017, pp. 115–124.

[37] P. Yang, X. Sun, W. Li, S. Ma, W. Wu, and H. Wang, “Sgm: sequence generation model for multi-label classification,” in Proceedings of the 27th International Conference on Computational Linguistics, 2018, pp. 3915–3926.

[38] R. You, Z. Zhang, Z. Wang, S. Dai, H. Mamitsuka, and S. Zhu, “Attentionxml: Label tree-based attention-aware deep model for high-performance extreme multi-label text classification,” Advances in Neural Information Processing Systems, vol. 32, pp. 5820–5830, 2019.

[39] W. Zhang, J. Yan, X. Wang, and H. Zha, “Deep extreme multi-label learning,” in Proceedings of the 2018 ACM on International Conference on Multimedia Retrieval, 2018, pp. 100–107.

[40] H. Jain, Y. Prabhu, and M. Varma, “Extreme multi-label loss functions for recommendation, tagging, ranking & other missing label applications,” in Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, 2016, pp. 935–944.

[41] C. Drummond, “Class imbalance and cost sensitivity: Why undersampling beats oversampling,” in ICML-KDD 2003 Workshop: Learning from Imbalanced Datasets, vol. 3, 2003.

[42] H. Han, W.-Y. Wang, and B.-H. Mao, “Borderline-smote: a new oversampling method in imbalanced data sets learning,” in International conference on intelligent computing. Springer, 2005, pp. 878–887.

[43] B. Mateusz, M. Atsuto, and M. A. Mazurowski, “A systematic study of the class imbalance problem in convolutional neural networks,” Neural Networks, pp. S0893 608 018 302 107–, 2017.

[44] K. Cao, C. Wei, A. Gaidon, N. Arechiga, and T. Ma, “Learning imbalanced datasets with label-distribution-aware margin loss,” in Proceedings of the 33rd International Conference on Neural Information Processing Systems, 2019, pp. 1567–1578.

[45] C. Huang, Y. Li, C. C. Loy, and X. Tang, “Learning deep representation for imbalanced classification,” in Proceedings of the IEEE conference on computer vision and pattern recognition, 2016, pp. 5375–5384.

[46] B. Kang, S. Xie, M. Rohrbach, Z. Yan, A. Gordo, J. Feng, and Y. Kalantidis, “Decoupling representation and classifier for long-tailed recognition,” in International Conference on Learning Representations, 2019.

[47] B. Zhou, Q. Cui, X.-S. Wei, and Z.-M. Chen, “Bnn: Bilateral-branch network with cumulative learning for long-tailed visual recognition,” in Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2020, pp. 9719–9728.

[48] Y.-X. Wang, D. Ramanan, and M. Hebert, “Learning to model the tail,” in Advances in Neural Information Processing Systems, 2017, pp. 7029–7039.

[49] M. Yuan, J. Xu, and Z. Li, “Long tail multi-label learning,” in 2019 IEEE Second International Conference on Artificial Intelligence and Knowledge Engineering (AIKE). IEEE, 2019, pp. 28–31.

[50] S. Macavaney, F. Dernoncourt, W. Chang, N. Goharian, and O. Frieder, “Interaction matching for long-tail multi-label classification,” arXiv preprint arXiv:2005.08805, 2020.

[51] J. Pennington, R. Socher, and C. Manning, “Glove: Global vectors for word representation,” in Proceedings of the 2014 conference on empirical methods in natural language processing (EMNLP), 2014, pp. 1532–1543.

[52] S. Hochreiter and J. Schmidhuber, “Long short-term memory,” Neural computation, vol. 9, no. 8, pp. 1735–1780, 1997.

[53] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, “Bert: Pre-training of deep bidirectional transformers for language understanding,” arXiv preprint arXiv:1810.04805, 2018.

[54] T. B. Brown, B. Mann, N. Ryder, M. Subbiah, J. Kaplan, P. Dhariwal, A. Neelakantan, P. Shyam, G. Sastry, A. Askell et al., “Language models are few-shot learners,” arXiv preprint arXiv:2005.14165, 2020.

[55] J. Nam, J. Kim, E. L. Mencia, I. Gurevych, and J. Fünnkranz, “Large-scale multi-label text classification-revisiting neural networks,” in Joint european conference on machine learning and knowledge discovery in databases. Springer, 2014, pp. 437–452.

[56] D. D. Lewis, Y. Yang, T. G. Rose, and F. Li, “Rcv1: A new benchmark collection for text categorization research,” Journal of machine learning research, vol. 5, no. Apr, pp. 361–397, 2004.

[57] E. L. Mencia and J. Fünnkranz, “Efficient pairwise multilabel classification for large-scale problems in the legal domain,” in Joint European Conference on Machine Learning and Knowledge Discovery in Databases. Springer, 2008, pp. 50–65.

[58] D. P. Kingma and J. Ba, “Adam: A method for stochastic optimization,” arXiv preprint arXiv:1412.6980, 2014.