GUDN: A novel guide network for extreme multi-label text classification

Abstract
The problem of extreme multi-label text classification (XMTC) is to recall some most relevant labels for a text from an extremely large label set. Though the methods based on deep pre-trained models have reached significant achievement, the pre-trained models are still not fully utilized. Label semantics has not attracted much attention so far, and the latent space between texts and labels has not been effectively explored. This paper constructs a novel guide network (GUDN) to help fine-tune the pre-trained model to instruct classification later. Also, we use the raw label semantics to effectively explore the latent space between texts and labels, which can further improve predicted accuracy. Experimental results demonstrate that GUDN outperforms state-of-the-art methods on several popular datasets. Our source code is released at https://github.com/wq2581/GUDN.

1 Introduction
Extreme multi-label text classification (XMTC) aims to match the most relevant labels for a text from an extremely large number of labels. For example, see Figure 1, when you read about the text of the NBA on Wikipedia, you will find many related labels such as player names, team names, team city, and even other related sports. It is emphasized that extreme multi-label text classification is a challenging task that differs from multi-class or usual multi-label text classification because the labels in XMTC tasks may reach hundreds of thousands or even more. This task has attracted many research interests due to the wide downstream applications, such as advertisement recommendation, user profiling, or web search.

Many works have been proposed to solve the XMTC problem, including [Prabhu and Varma, 2014; Bhatia et al., 2015; Babbar and Shoelkopf, 2016], in some ways, they achieved relatively impressive results. However, they cannot break through the limitations of traditional methods to achieve high prediction accuracy. Deep learning methods have started to shine in XMTC tasks in recent years. X-Transformer [Chang et al., 2019] used the pre-trained model, e.g., BERT [Devlin et al., 2018] effectively extracted features from raw texts so that accuracy can be improved significantly. Nevertheless, X-Transformer is not satisfied when it comes to calculating costs. LightXML [Jiang et al., 2021] later improved the X-Transformer to make it lighter, faster, and LightXML also reached state-of-the-art. However, the easily accessible but critical label semantics are not taken into account by LightXML.

C2AE [Yeh et al., 2017] explored the latent space between texts and labels by using a sparse linear network making new development for the multi-label classification tasks. RankAE [Wang et al., 2019] further improved C2AE and spread it to extreme multi-label text classification. DXML [Zhang et al., 2018] used the label structure to build a graph then revealed the potential relationship between texts and labels. Some recent works, such as [Mittal et al., 2021a] indicated that label metadata such as label structure or label description is helpful for XMTC. However, the above methods do not use label metadata effectively. Additionally, using sparse linear layers to find latent space is insufficient. [Mittal et al., 2021a] have shown that the effective extraction of descriptive label semantic features can provide an immediate performance boost. Because from the perspective of natural language, there must be some connection between text semantics and label semantics. However, these connections have not been exploited effectively.

Considering that descriptive label semantics are underutilized to find the latent space and the sparse linear network is not robust for feature extraction. We use BERT to extract...
specific label semantic features from raw labels. The ability to extract features of BERT has been widely recognized, and raw labels are more semantical than label one-hot vectors or Bag-Of-Words (BOW). Furthermore, we propose a guide network (GUDN) to combine BERT to improve the performance of XMTC tasks. The contributions of our work are summarized as follows:

- A novel guide network (GUDN) that includes two modules of guide and two loss functions is proposed to instruct the BERT on extracting features to relieve the classification pressure.
- GUDN considers raw label semantics and combines a deep pre-trained model to extract features, which is more effective than previous work for finding the latent space between texts and labels.
- We perform experiments on four benchmark datasets, and the results show that GUDN helps XMTC tasks. GUDN reaches new state-of-the-art results on several datasets.

The rest of this paper will give a specific description of the XMTC problem. In Section 2, we introduce some remarkable work. In Section 3, the proposed methods are described in detail. Moreover, the experimental results are discussed in Section 4. In Section 5, we summarize this paper and indicate future work.

2 Related Work

Since the XMTC problem was presented, many approaches have been exquisitely constructed and successful. Embedding-based methods reduce label redundancy under the low-rank assumption to alleviate the storage and computing overhead. SLEEC [Bhatia et al., 2015] capture label correlations non-linearly to reduce the adequate number of labels and cluster the data to speed up the training stage. [Tagami, 2017] advanced SLEEC, which fixed the problem including data partition unreasonable, objective function indirect, and the prediction speed slow. However, the long-tail distribution caused by the extremely extensive labels tends to undermine this assumption. For tree-based methods, label sets are hierarchically divided to generate a label tree. FastXML [Prabhu and Varma, 2014] is a typical tree-based instance which optimizes the ranking loss function. [Wydmuch et al., 2018; Prabhu et al., 2018] developed the probabilistic label trees (PLT) [Jasińska et al., 2016].

Though the tree structure reduces the prediction time, accuracy is affected as the tree grows deep. OVA methods such as Dismec [Babbar and Shoelkopf, 2016], Slice [Jain et al., 2019], Bonsai [Khandagale et al., 2020] intended to create a binary classifier for each label so that the prediction accuracy undoubtedly improve significantly. However, OVA approaches need too many calculated resources, making them unacceptable in real-world applications.

Deep learning (DL) methods have flourished for XMTC tasks in recent years. XML-CNN [Liu et al., 2017] is the first successful DL method using CNN networks to get text representation. C2AE first proposed the hypothesis of a latent space between labels and texts and conducted a preliminary exploration. RankAE also deemed that every text can be represented from text features and labels, so a common latent space must exist between text features and labels. RankAE proposed a margin-based ranking loss and dual-attention mechanism to find the latent space to improve C2AE.

DXML also hopes to find the latent space to help establish the connection between texts and labels. Hence, DXML creatively considers the label structure information, label metadata. In fact, they use the raw label semantics when constructing the label graph. However, the feature extractor has dramatically reduced the label semantics due to the label graph hiding the semantics. Also, the label feature extractor of RankAE and DXML is not strong enough. LAHA [Huang et al., 2019] used the attention mechanism to integrate labels and text semantics but did not try to find the latent space. In view of the [Mittal et al., 2021a; Mittal et al., 2021b] emphasized the importance of label metadata. We fully consider the label semantics and use the deep pre-trained network to extract features from the raw labels directly.

Inspired by the success of deep pre-training models in natural language processing, X-Transformer [Chang et al., 2019] tamed the pre-trained Transformer to handle XMTC tasks. Considering the X-Transformer’s computational complexity and the model’s size, LightXML [Jiang et al., 2021] intends to improve it to obtain a light and fast model. LightXML has reached the most advanced level. However, X-Transformer and LightXML fine-tuned BERT [Devlin et al., 2018] to extract text features but did not fully use BERT because only fine-tuned to obtain features without guidance, which is still tricky for improving the prediction accuracy of extreme classification. We use the guide network to guide BERT further and use BERT to extract label semantics.

3 Proposed Method

This section will give a detailed description of the proposed method. GUDN is end-to-end and easily extensible. On the whole, the three parts of the proposed model are feature extractor, guide network, ranking classifier. Firstly, the feature extractor extracts the features of texts and labels, and then the features of texts and labels are input into the guide network. A close relationship is established through the guide network for texts and labels, and the relationship is fed back to the feature extractor for continuous optimization. Finally, the ranking classifier obtains accurate semantic information to classify. The proposed framework is shown in Figure 2.

3.1 Preliminaries

Let $D = \{(x_1, y_1), (x_2, y_2), ..., (x_n, y_n)\}$ represent the training dataset with $n$ samples where $x_i \in \mathbb{R}^d$ is the input of raw text and $y_i \in \{0, 1\}^L$ denotes one-hot vector of true label. The real semantic labels which belong to a sample text also as a part of input during the training stage, note that each raw text length is equal to the $d$ and the sum of the number of labels is $L$. We want to find a function $f$ to map $x_i$ and $y_i$. If the $y_{ij} = 1$ then the function $f$ will output a high score, wherein $j \in [1, L]$. The mapping function $f$ can be expressed
as follows:

\[ f(x_i, k) = W_k B(x_i), \quad (1) \]

where \( B(x_i) \) represents the \( i \)-th text features generated from an encoder \( B \) and \( W \) is the classifier, usually a full connected layer. \( f \) output the score of \( k \)-th label. If the score is high, the label has a high possibility belongs to the text.

### 3.2 Feature Extractor

We follow X-Transformer and LightXML [Chang et al., 2019; Jiang et al., 2021] using the BERT [Devlin et al., 2018] to get features for the BERT has proven powerful in natural language processing tasks. Thinking of previous methods only takes the label one-hot vector lacking semantic information as the input of the sparse linear network, which is not sufficient for finding the latent space between labels and texts. We use the feature extractor with raw label semantic information to help find the latent space.

A single BERT (12 layers and 768 hidden dimensions) is used to extract the text features. At the same time, the labels share the same BERT with texts to get the label features. Sharing one BERT can significantly reduce the model size and complexity to accelerate convergence. Text features and label features are extracted asynchronously in the training phase.

Label description is usually shorter and has less semantic information than text, so we concatenate the output of the last ten layers “[CLS]” token as the extracted features of labels to enrich semantic information. The output of the feature extractor are text features \( E_t \), and the label features \( E_l \). Like the LightXML, high dropout rates are used to avoid overfitting.

### 3.3 Guide Network

Relying directly on the simple classified network to link texts to labels is like being lost in the sea without a guide which is unstable and uncertain. A simple and effective way to solve this problem is to create a guide mechanism for labels and texts. In the previous work, [Yeh et al., 2017; Zhang et al., 2018; Wang et al., 2019] both provide a bridge between texts and labels, that is to say, try to find a latent space between texts and labels, and the sparse linear network is trained to guide the classification. However, the bridge is not strong enough. The guide is not skilled sufficient because the raw label semantics have not been used, and only the simple linear network is not enough to get good label representations. So we proposed the guide network to solve the above problems.

The success of the guide network resides in two guides. The first guide instructs BERT to learn the most representative label features from text features. Thus, the latent space between text and label semantics is effectively found. The other one can directly establish a mapping relationship between label features and labels to reduce the pressure on the ranking classifier. Finally, the guide network helps us find a certain way from the texts to the true labels. The loss functions \( L_{feature} \) and \( L_{link} \) will be the solid bridges in the guide network. Through bridge \( L_{feature} \), text space and label space can blend, while labels and label features can be connected through bridge \( L_{link} \). Their expressions are as follows:

\[
L_{feature}(E_t, E_l) = \frac{1}{2n} \sum_{i=1}^{n} \| E_{ti} - E_{li} \|^2, \quad (2)
\]
$L_{\text{link}}(y, \hat{y}) = \sum_{i=1}^{n} \sum_{j=1}^{L} -y_{ij} \log(\hat{y}_{ij}) - (1 - y_{ij}) \log(1 - \hat{y}_{ij}).$

(3)

Equation 2 is mean square error loss (MSE) which is calculated from label features $E_i$ and text features $E_t$, while Equation 3 is the binary cross-entropy loss (BCE) calculated from true label $y$ and predicted label $\hat{y}$. $\hat{y}$ is not produced from text features but label features. The sum loss of the guide network $L_{\text{guide}}$ be the sum of $L_{\text{feature}}$ and $L_{\text{link}}$, which is described as follows:

$$L_{\text{guide}} = L_{\text{feature}} + L_{\text{link}}.$$  

(4)

Theoretically, minimizing $L_{\text{guide}}$ can make the feature extractor and ranking classifier not dependent on the guide network anymore. We do not use label information during the test stage because the feature extractor and ranking classifier have become possible to find a way from text to the correct labels alone after being guided by the guide network.

In effect, the guide network is not limited to the classification problems in extreme cases described in this paper. It is also suitable for multi-label and multi-category classification, and the network structure is simple and can be easily extended.

### 3.4 Ranking Classifier

We set up a fully connected layer to rank and get the final result in classified networks. For medium-size datasets Eurlex-4K, AmazonCat-13K, Wiki10-31K, Wiki-500K, we do not change the original output space of the ranking classifier. However, for the large-scale dataset Wiki-500K, we go after LightXML to adopt a dynamic negative sampling strategy. The $b$ label clusters with the highest recall probability are selected from the output space, and then the candidate labels are selected from clusters.

The final candidate set contains all positive samples and many “hard negative” samples. This strategy not only compresses the output space but also enhances accuracy effectively. In general, label clustering is required before dynamic negative sampling, generally according to BOW, but [Chang et al., 2019] also gives new insights like positive instance feature aggregation. In this work, we still use BOW for simplicity. The final classification loss is also BCE loss which can be expressed as follows:

$$L_{\text{class}}(y, \hat{y}') = \sum_{i=1}^{n} \sum_{j=1}^{L} -y_{ij} \log(\hat{y}_{ij}') - (1 - y_{ij}) \log(1 - \hat{y}_{ij}'),$$

(5)

where $y_{ij}$ is the ground truth, and $\hat{y}_{ij}'$ is the labels predicted by text information, they are both $L$-dimensional one-hot vectors.

### 3.5 Training and Prediction

GUDN is finally implemented since we have constructed the feature extractor, guide network, and ranking classifier. The goal of GUDN is to minimize the objective function $L_{\text{overall}}$, which contains two losses $L_{\text{guide}}$ and $L_{\text{class}}$, where $L_{\text{guide}}$ is the loss caused by the guide network, $L_{\text{class}}$ is the classification loss. The overall loss function is:

$$L_{\text{overall}} = L_{\text{guide}} + L_{\text{class}}.$$  

(6)

We sum the two losses in the guide network and the classification loss because GUDN would be incomplete without any of them. We want the three losses to interact to help GUDN prediction accuracy achieve the best results. It is challenging to optimize with all three losses, but GUDN is not very complex, making convergence possible.

We take full advantage of all available information during the training stage, especially label semantics. We first get text features and label features through the feature extractor. They contain the most primitive and crucial semantic information. Then text features and label features be entered into the guide network. Regarding the feature loss as a guideline, the guide network help train the feature extractor and the ranking classifier. Only the feature extractor and the ranking classifier remain after guidance, making the model lighter and suitable for time-sensitive and widespread user applications. Finally, GUDN gives the predicted results fast and accurately.

### 4 Experiment

We perform experiments on Linux (Ubuntu 20.04.1). The experiments use four Nvidia GeForce RTX 3090 GPUs to do calculations in parallel, every GPU memory is 24GB, but the training phase occupies less than 20GB. Also, we have Intel(R) Xeon(R) Gold 6254 CPU @ 3.10GHz.

| Datasets     | TRN  | TST  | LBL  | SPL  | LPS  |
|--------------|------|------|------|------|------|
| Eurlex-4K    | 15339| 3809 | 3903 | 25.73| 3.31 |
| AmazonCat-13K| 1186239| 306782| 13330| 448.57| 5.04 |
| Wiki10-31K  | 14146 | 6616 | 30938| 8.52 | 18.64|
| Wiki-500K   | 1813391| 783743| 501070| 23.62| 4.89 |

Table 1: A specific description of datasets. $TRN$ and $TST$ are the numbers of the training set and the number of testing sets, respectively. $LBL$ refers to the number of labels. $SPL$ represents the average sample per label, and $LPS$ is the average label per sample.

### 4.1 Datasets and Evaluation Metrics

The datasets for the experiments are collected from [Bhatia et al., 2016]. Eurlex-4K, AmazonCat-13K, Wiki10-31K, and Wiki-500K are four very representative datasets we used. Eurlex-4K is text data about European Union law, containing nearly four thousand labels formed according to EU-ROVOC descriptors. Amazon-13K is a product-to-product recommendation dataset, and in this dataset, labels are product categories. Wiki10-31K and Wiki-500K are excerpts from Wikipedia articles with labels of thirty-one thousand and five hundred thousand, respectively. Details about the four datasets can be queried in Table 1.

We use a simple but intuitive evaluation metric used extensively in XMTC tasks called P@k. The calculation formula
DXML and RankAE, GUDN uses a deep pre-trained BERT to encode the text, and they are all based on a pre-trained model BERT to encode the text, and they used to be state-of-the-art. Comparing X-Transformer and LightXML, we also use BERT as the backbone network. With feature loss as the guideline, under the guidance of the guide network, GUDN also achieves significant results.

From Table 2 we can see that the GUDN reaches state-of-the-art on Eurlex-4K, especially for P@5. We also gain some advantages on AmazonCat-13K, Wiki-500K, and Wiki10-31K. It is not hard to see that GUDN does not perform as well on AmazonCat-13K, Wiki10-31K, and Wiki-500K as it does on Eurlex-4K.

| Datasets       | P@1  | XML-CNN | DXML | AttentionXML | RankAE | X-Transformer | LightXML | GUDN | Difference |
|----------------|------|---------|------|--------------|--------|---------------|----------|------|------------|
| Eurlex-4K      | P@03 | 75.32   | -    | 87.12        | 79.52  | 87.22         | 87.03    | 88.13 | +0.50      |
| AmazonCat-13K  | P@03 | 60.14   | -    | 73.99        | 65.14  | 75.12         | 75.89    | 77.06 | +1.17      |
| Wiki10-31K     | P@05 | 49.21   | -    | 61.69        | 53.18  | 62.90         | 63.36    | 65.49 | +2.13      |
| Wiki-500K      | P@01 | 93.26   | -    | 95.92        | -      | 96.70         | 96.77    | 97.06 | +0.06      |
| Wiki50K        | P@03 | 77.06   | -    | 82.41        | -      | 83.85         | 84.02    | 84.19 | +0.17      |
| Wiki50K        | P@05 | 61.40   | -    | 67.31        | 68.58  | 68.76         | 69.76    | 70.74 | -0.47      |
| Wiki10-31K     | P@03 | 66.23   | 70.88 | 78.48        | 72.07  | 78.71         | 78.96    | 78.58 | -0.38      |
| Wiki-500K      | P@05 | 56.11   | 61.31 | 69.37        | 62.07  | 69.62         | 69.85    | 69.86 | +0.01      |

Table 2: Comparison of experimental results with several representative DL methods on Eurlex-4K, AmazonCat-13K, Wiki10-31K, Wiki-500K. The font in bold indicates the best score, and the underlined font indicates the sub-best score. The ‘Difference’ represents the difference between the experimental results of GUDN and the results of using state-of-the-art methods.

of P@k is as follows:

\[ P(\hat{y}|k) = \frac{1}{k} \sum_{i \in \text{rank}_k(\hat{y})} y_i, \]

where \( k \) is a given constant is usually 1, 3, 5. For the predicted results \( \hat{y} \), we rank them by probability, then the top \( k \) with the highest probability be selected and record their index number. If the \( k \) indexes have more values of 1 corresponding to the label vector position, the score of P@k is higher.

4.2 Experiments Setting

We set the length of the input texts to 512. As for the labels that are impossible to reach 512 lengths, we regard all the labels corresponding to a text as a whole which can also be thought to a text, then input the whole of labels to the feature extractor. Note that when the text length is more than 512, we have to decide which part of the text to keep. The reserved part of the text could be the head, the tail, or even the middle. Some information is lost after dividing, but the head contains the most vital information, so we only take the first 512 words.

In terms of training epochs, we set 40 epochs for datasets Eurlex-4K and Wiki10-31K, 20 epochs for datasets Wiki-500K and AmazonCat-13K due to their large sample number. For all the datasets, the training batch size is 8, and the testing batch size is 16.

4.3 Experimental Results and Discussion

The experimental results are shown in Table 2. We experiment with four datasets and compare the results of GUDN with six representative deep learning approaches. The data of the six deep models are obtained from their original papers. Among these six most representative models, DXML [Zhang et al., 2018], and RankAE [Wang et al., 2019] were similar to the CAE [Yeh et al., 2017] trying to find a latent space between texts and labels. Although their achievements have been surpassed, their ideas are still inspiring. Compared with DXML and RankAE, GUDN uses a deep pre-trained BERT [Devlin et al., 2018] to directly extract the raw label semantics, which is more conducive to finding the latent space.

As far as we know, XML-CNN was the first to use the deep network for the XMTC task. The results of AttentionXML [You et al., 2018] showed that the accuracy was significantly improved compared to XML-CNN, and AttentionXML still retained one best performance. The primary opponents of GUDN are X-Transformer [Chang et al., 2019], and LightXML [Jiang et al., 2021], and they are all based on a pre-trained model BERT to encode the text, and they used to be state-of-the-art. Comparing X-Transformer and LightXML, we also use BERT as the backbone network. With feature loss as the guideline, under the guidance of the guide network, GUDN also achieves significant results.

From Table 2 we can see that the GUDN reaches state-of-the-art on Eurlex-4K, especially for P@5. We also gain some advantages on AmazonCat-13K, Wiki-500K, and Wiki10-31K. It is not hard to see that GUDN does not perform as well as AmazonCat-13K, Wiki10-31K, and Wiki-500K as it does on Eurlex-4K.

4.4 Detail Analysis

In this section, an in-depth analysis of the experimental data is displayed. We explored why GUDN does not perform as well as Eurlex-4K on other datasets. According to our analysis, the label settings in dataset Eurlex-4K are more consistent with the semantics in natural language, which has solid semantic features and represents its corresponding text. At the same time, there are many symbolic labels in AmazonCat-13K, Wiki10-31K, and Wiki-500K, which are just representative symbols without semantic information, such as ‘++++’ and ‘08P01B’ (extracted from Wiki10-31K). Therefore, we conclude that GUDN is sensitive to semantic information, which impairs the performance of GUDN on datasets with weak label semantics, but is favorable for GUDN on datasets with strong label semantics. We further clarify this conclusion in ablation experiments.

4.5 Ablation Study

A single BERT model, BERT with feature guide (help find the latent space) and BERT with link guide (reduce the pressure of ranking classifier), are tested to prove that the guide network helps BERT effectively extract features to solve the XMTC problem. It should be mentioned that when we only use a single BERT model, GUDN is equivalent to LightXML [Jiang et al., 2021], but we cannot reproduce it to the same accuracy, and that is regrettable. The impact of different modules on accuracy is shown in Table 3.
Table 3: Comparison of ablation results on four datasets of each network module. GUD-F and GUD-L represent feature guide and link guide, respectively.

| Modules     | Eurlex-4K | AmazonCat-13K | Wiki10-31K | Wiki-500K |
|-------------|-----------|---------------|------------|-----------|
|             | P@1      | P@3          | P@5        | P@1      | P@3          | P@5        | P@1      | P@3          | P@5        |
| BERT        | 86.68    | 75.04        | 63.03      | 96.10    | 82.89        | 67.01      | 88.76    | 77.65        | 68.51      |
| BERT+GUD-F  | 87.93    | 76.64        | 65.02      | 96.56    | 83.98        | 67.66      | 89.62    | 77.98        | 69.67      |
| BERT+GUD-L  | 87.21    | 75.09        | 63.93      | 96.12    | 83.10        | 67.28      | 89.21    | 77.63        | 68.94      |

It can be seen clearly from Table 3 that the model using the guide network has better prediction accuracy compared to only using a single BERT. It also proves that the guide network helps fine-tunes BERT to catch the label-aware features, guiding texts and labels to set a close connection, then find the latent space. According to Table 3, we find that the accuracy of dataset Eurlex-4K increases most obviously, which also indicates that the guide network is sensitive to label semantics. We also find that both the feature guide and the linked guide contribute to the accuracy, and both are indispensable. Feature guide contributes more to accuracy improvement, and the model works best when the two guides work together.

Table 4: Experimental results on the Eurlex-4K and Wiki10-31K datasets, comparing the improvement of P@k over basic BERT using one-hot vectors and using raw labels as input.

|         | P@k | Raw labels | One-hot vectors |
|---------|-----|------------|-----------------|
| Eurlex-4K |    |            |                 |
| P@1     | +1.25 | +0.03 |
| P@3     | +1.60 | +0.32 |
| P@5     | +1.99 | +0.13 |
| Wiki10-31K |       |            |                 |
| P@1     | +0.86 | +0.15 |
| P@3     | +0.33 | +0.18 |
| P@5     | +1.16 | +0.10 |

We conducted experiments on datasets Eurlex-4K and Wiki10-31K to examine whether using raw label semantics to find the latent space is better than using one-hot vectors and helps improve prediction accuracy. Experimental results of prediction accuracy improvement of P@k over basic BERT are shown in Table 4 and the results of the decay of feature losses with epochs are shown in Figure 3. We can discover that using label semantics improves the prediction accuracy more than using one-hot vectors while significantly reducing feature losses. This result indicates that using raw label semantics is better than using one-hot vectors to find the latent space.

Besides, it can be found that using raw label semantics on dataset Eurlex-4K has a more remarkable improvement in accuracy than on dataset Wiki10-31K. Because the labels in dataset Eurlex-4K are more in line with natural language norms than those in dataset Wiki10-31K, thus provides richer semantic information to facilitate the exploration for the latent space between texts and labels.

Figure 3: On Eurlex-4K and Wiki10-31K, the experimental results of the decay of feature losses with epochs when using raw labels and using one-hot vectors are compared.

SimaesXML [Dahiya et al., 2021] did an exciting piece of work. They focus on dealing with the few-shot or zero-shot problems caused by the long-tail of labels. Furthermore, SimaesXML is also considered for short texts with insufficient semantics using only one title as a text. Effectively solving the XMTC problem under such a tricky situation caught our attention.

5 Conclusion and Future work

This paper constructs a novel guide network for XMTC tasks. The experimental results show that we achieve competitive performance in multiple datasets, especially Eurlex-4K. The ablation experiments prove that the guide network does help fine-tune BERT, and the feature guide and the link guide play their respective roles. However, GUDN is sensitive to the semantics of labels, which means that GUDN does not apply to datasets where labels lack semantics but impressive power for semantically rich labels.
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