Joint Embedding of Words and Category Labels for Hierarchical Multi-label Text Classification

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Abstract

Text classification has become increasingly challenging due to the continuous refinement of classification label granularity and the expansion of classification label scale. To address that, some research has been applied onto strategies that exploit the hierarchical structure in problems with a large number of categories. At present, hierarchical text classification (HTC) has received extensive attention and has broad application prospects. Making full use of the relationship between parent category and child category in text classification task can greatly improve the performance of classification. In this paper, We propose a joint embedding of text and parent category based on hierarchical fine-tuning ordered neurons LSTM (HFT-ONLSTM) for HTC. Our method makes full use of the connection between the upper-level and lower-level labels. Experiments show that our model outperforms the state-of-the-art hierarchical model at a lower computation cost.

Keywords: Joint embedding; Hierarchical Fine-Tuning; Ordered neurons LSTM.

1. Introduction

Many important real-world classification problems consist of a large number of usually very similar categories, which are organized into a class hierarchy or taxonomy[1][40]. Taking a news article as an example, it may be related to three categories of "Sports", "Basketball" and "NBA". It can be found that there is an inclusion relationship between the three categories from left to right, that is to say, the categories have a hierarchical structure. The hierarchy between these categories is important information, while the flat classifiers ignores the hierarchy by “flattening”it to the leaf nodes level. So the flat classification method can only perform well on two or a few categories, but it is difficult to classify accurately on a large number of closely related categories[1][2]. To address that, the method of HTC is proposed and widely concerned.

HTC methods are traditionally divided into two categories, namely local, and global approaches[1][8][9]. The local approaches create a unique classifier for each node/each parent node/each level in the taxonomy, while global approaches create a single classifier for the entire taxonomy[1][8]. At present, the state-of-the-art local hierarchical classifier is HDLTex[26], which displayed superior performance over traditional non-neural-based models with a top-down structure. However, it has a disadvantage of parameter explosion, which leads to high computation cost. In the work of [28] the authors propose a unified global deep neural-based classifier HATC that overcomes the problem of exploding models. However, HATC suffers the inherited disadvantage of the global approach: The classifier constructed is not flexible enough to cater for
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changes to the category structure[2]. In addition, the accuracy of HATC and HDLTex are equal to or slightly worse than that of the state-of-the-art flat classifiers[28].

In this paper, we propose a local hierarchical text classification method can achieve better performance than the first two methods at a lower computation cost. Neural networks such as CNN and LSTM can only learn the semantic features of the language, and can't deal with the hierarchical structure of the language. Instead of using these neural networks, we applied a neural network ONLSTM [35] that can model the hierarchical structure of the language. In addition, we use the method of text and parent category joint embedding and hierarchical fine-tuning technology, which can effectively utilize the data in the upper levels to contribute categorization in the lower levels. The contribution of our paper is as follows:

1). We propose a local hierarchical text classification method based on the joint embedding of text and parent category.

2). We propose a hierarchical fine-tuning ONLSTM model, which applies the hierarchical fine-tuning technology to a long-term and short-term memory model variant (ONLSTM) [35] for HTC.

3). The performance of our method is better than the existing state-of-the-art hierarchical classifiers and the state-of-the-art flat classifiers. The deeper the category label level, the more obvious the advantages of our method are compared with other methods.

2. Related Work

In contrast to traditional flat classification, the key challenge of HTC is how to make better use of the hierarchical relationship of category labels to improve performance [1]. Generally speaking, hierarchical classifiers can be divided into two broad approaches [1,8,9], namely global and local.

The traditional global approaches [10-13] are mostly based on the specific flat model, and rely on the static, human curated features as input. In the global method, a single classification model is built on the training set, which is usually relatively complex [1][2]. The hierarchical structure of the whole class is considered in one run of the classification algorithm. The advantage of learning a single global model for all classes is that the total size of the global classification model is usually much smaller than the total size of all local models learned by any one local classifier method. However, because the discriminant features in the parent category may not be discriminant in the subcategory, it is usually difficult to use different feature sets in different category levels by using the global method. Besides, the global classifier constructed may not be flexible enough to cater for changes to the category structure[1][2].
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The local approaches[14][15][16][17][18] use the hierarchy structure to build classifiers using local information, which includes top-down and bottom-up types. In the top-down approach, [1] further subdivide the local classification method into three subgroups according to the way of using local information in the training phase: local classifier per node (LCN), local classifier per parent node (LCPN) and local classifier per level (LCL), where LCN trains a binary classifier for each child node, LCPN trains a multi-class classifier for each parent node, LCL trains a multi-class classifier for the entire hierarchy level. The top-down approach is essentially a strategy for avoiding class-prediction inconsistencies across class levels during the testing phase, when using a local hierarchical classification method[41]. The disadvantage of this approach is that the error propagates from high level to low level, and when the classifier goes deep into the hierarchy, error propagation will cause more and more significant performance degradation [36].

In recent years, deep learning approaches[29][30][31][32][33][34] have achieved surpassing achievements in comparison to previous machine learning algorithms[3][4][5][6][7] in text classification. Hierarchical classification based on deep learning has become the mainstream. Kowsari et al. proposed a local hierarchical classification method called HDLTex[26], HDLTex combines deep neural networks in the top-down fashion where a separate neural network (either CNN or RNN) is built at each parent node to classify its children. This method achieves the best performance in the local hierarchical classification method, but there is a disadvantage of parameter explosion. Koustuv et al. proposed an end-to-end global natural attention based model call HATC [28], which sequentially predicted the category label of the next level, conditioned on a dynamic document representation obtained based on a variant of an attention mechanism[27], which solved the problem of parameter explosion. However, both HATC and HDLTex perform comparably with or slightly worse than the state-of-the-art flat classifiers in terms of accuracy [28].

3. The Proposed Method

3.1. Overview of Proposed Method

This paper studies the text classification problem with tree structure in the category hierarchy, that is, there is a parent-child relationship between the upper and lower levels, a parent category contains many subcategories, while a subcategory has only one parent category [2]. The classification process is shown in Figure 1, where W means to transfer the parameters of the upper level ONLSTM training to the lower level ONLSTM. \( c_i \) refers to the category label of level i, which is obtained by mapping the probability
distribution of the output of softmax layer to its corresponding semantic words. ⊕ indicates that the parent category label of the upper prediction is spliced with its corresponding text.

Fig. 1. Joint Embedding of Text and Parent Category Based on HFT-ONLSTM Model.

First, we concatenate the predicted parent category label with its corresponding text, and then embed it in the same vector space through the word embedding matrix[19][20][21] (since the first level of category label does not have a parent category label, there is no need to embed the parent label). Then, the vector representation of the joint embedded parent category label and text is put into the deep learning model for training. The deep learning model we used in this paper consists of two parts. The first part is ONLSTM, a variant of long-term and short-term memory model [35], and the second part is a two-layer multi-layer perceptron (MLP). During the training, we transferred the parameters of ONLSTM trained in the upper levels to the lower levels, and then finely tuned parameters of ONLSTM for lower levels.

In general, our proposed hierarchical text classification method can be summarized into four parts: Joint embedding of text and parent category, Hierarchical Fine-Tuning, Ordered Neurons LSTM(ONLSTM) and MLP. We will introduce these four parts in detail below.

1) Joint embedding of words and labels

In this paper, we will only focus on hierarchical classification that involves tree structured class taxonomies. In a tree structure category, a parent category contains one or more subcategories, while a subcategory belongs to only one parent category. This relationship can be understood as that a parent category restricts all its child categories.
It can also be said that the text belonging to the subcategory must also belong to the parent category. We use the method of joint embedding of parent category and text to put this restriction relationship into the classification process. This method adds the information of parent category in the text, which can play a constraint role in the process of subcategory classification and greatly improve the effect of subcategory classification. Specifically, we first extract the corresponding parent category of each text in the text preprocessing stage and then stitch it together with the corresponding text. Finally, the parent category and text are embedded in the same space.

2) Hierarchical Fine-Tuning

Hierarchical fine tuning[24][25] refers to transferring the training parameters of some layers in the classification model of the upper level category to the corresponding layer in the classification model of the lower level category for training according to the hierarchy of the category. Because of the high correlation between the target task and the pre-training task in the hierarchical text classification task, the hierarchical fine tuning can be used to make full use of the information of the parent training in the subcategory training process to improve the classification performance. The parameters of parent category training model can be used as initialization parameters of child category training model, which can not only acquire prior knowledge, but also accelerate convergence [42]. We transfer the ONLSTM parameters from the upper level to the lower level for training, and then fine-tune the parameters of ONLSTM. We only fine tune between adjacent layers. We repeat this process from the top level to the bottom of the hierarchy. When the dataset is large enough, it can accelerate the convergence, and when the dataset is small, it can improve the classification accuracy more effectively.

3) Ordered Neurons LSTM (ONLSTM)

A natural sentence can usually be expressed as a hierarchical structure. If these structures are extracted, they are what we call grammatical information. The ONLSTM model can learn this hierarchical structure naturally in the process of training. In the LSTM, updates between neurons are independent of each other and unrelated. To this end, Yikang Shen et al. has made changes to the LSTM unit by adding two gates[35]: master forget gate and master input gate, which use the new activation function \( cumax(x) \) to control the information to be stored and forgotten based on the state of the neurons in front of it. Here \( cumax(x) \) is the abbreviation of \( cumsum(softmax(x)) \). By introducing such a gate mechanism, the renewal rules of interdependence among neurons are established, and the order and hierarchical differences among neurons are made. A step by step explanation of a ONLSTM cell is as following:

\[
\begin{align*}
    f_t &= \sigma(W_fx_t + U_fh_{t-1} + b_f) \\
    i_t &= \sigma(W_ix_t + U_hi_x_t + b_i) \\
    o_t &= \sigma(W_ox_t + U_ho_x_t + b_o) \\
    c_t &= \tanh(W_cx_t + U_hc_x_t + b_c) \\
    h_t &= \sigma(W_hf_c + Uohon_c + b_h) \\
\end{align*}
\]
\[ i_t = \sigma(W_i x_t + U_i h_{t-1} + b_i) \]  
\[ o_t = \sigma(W_o x_t + U_o h_{t-1} + b_o) \]  
\[ c_t = \tanh(W_c x_t + U_c h_{t-1} + b_c) \]  
\[ f_t = \text{cumax}(W_f x_t + U_f h_{t-1} + b_f) \]  
\[ \tilde{i}_t = 1 - \text{cumax}(W_i x_t + U_i h_{t-1} + b_i) \]  
\[ \omega_t = f_t \odot \tilde{i}_t \]  
\[ \tilde{f}_t = \tilde{f}_t \odot (f_t \odot \tilde{i}_t + 1 - \tilde{i}_t) \]  
\[ \tilde{c}_t = \tilde{c}_t \odot \tilde{i}_t + \tilde{i}_t \odot c_t \]  
\[ h_t = o_t \odot \tanh(c_t) \]  

In the above description, \( b \) is a bias vector, \( W \) is a weight matrix, and \( x_t \) is the input to the memory cell at time \( t \). The indices refer to input, cell memory, forget, output gates, master forget gate and master input gate respectively. Where \( \sigma \) denotes the logistic sigmoid function and \( \odot \) denotes elementwise multiplication.

4) MLP

This part is a two-layer multi-layer perceptron (MLP). The first layer is tanh nonlinear transformation layer, and the second layer is softmax nonlinear transformation layer. In this part, the features extracted from the previous part are extracted by tanh and softmax non-linear changes in turn, and the correlation between these features is extracted. The first function of the two-layer multilayer perceptron is to enhance the expression ability of neural network, and the second is to map the features to the output space.

3.2. Classification process

Formally, suppose we are given a collection \( T \) of \( n \) texts and a collection \( C \) of categories corresponding to the \( n \) texts, where \( T = (x_1, x_2, ..., x_n) \), \( C = (c_{11}, c_{12}, ..., c_{1k}), (c_{21}, c_{22}, ..., c_{2k}), ..., (c_{n1}, c_{n2}, ..., c_{nk}) \), where \( x_n \) represents the \( n \)-th text and \( c_{nk} \) represents the \( k \)-th level label of \( n \)-th text. The text representation \( z \) is obtained by connecting the text with its corresponding parent category label. For example, in Equation 12, we get the text representation \( z_{i,j} \) by connecting the \( i \)-th text \( x_i \) in the text set and its corresponding \((j-1)\)-level label \( c_{i,j-1} \), where the \((j-1)\)-level label represents the parent category label of the \( j \)-level label.

\[ z_{i,j} = \begin{cases} x_i, & j = 1 \\ c_{i,j-1} \oplus x_i, & 1 < j \leq k \end{cases} \]
After obtaining the text representation $z_{i,j}$ through the above steps, we will convert it into semantic vector $w$ through word embedding. In addition, in the following, we will use $w^j_t$ to represent all text representations of the $j$-th level label at time $t$. Finally, we will extract the syntactic structure information in the word vector representation $w^j_t$ through ONLSTM to obtain the text representation.

$$h^j_t = \text{ONLSTM}^j(w^j_t, h^j_{t-1}, W^j_{on-lstm})$$ (13)

Equation 13 shows the training process of the ONLSTM layer in the classification model of the $j$-th level label, $h^j_t$ denotes the hidden state vector of input sequence at $t$ time. $W_{on-lstm}^{j-1}$ denotes the weight parameters of ONLSTM network when classifying $j$-1 level categories. The equation here is to transfer the weight parameters of the ONLSTM layer trained by the upper level of category label classification model to the ONLSTM layer of the lower level of category label classification model as initialization parameters. Final output text feature representation.

Finally, a two-layer multi-layer perceptron is employed to enhance the expressive power of neural networks and predicts the probability distribution over classes at level $j$:

$$d_j = \tanh(W_1 h^j_T + b_1)$$ (14)

$$y_j = \text{softmax}(W_2 d_j + b_2)$$ (15)

The parameters of the network are trained to minimise the cross-entropy of the predicted distributions $\hat{y}$ and true distributions $y$.

$$L(\hat{y}, y) = -\sum_{n=1}^{N} \sum_{c=1}^{C^j} y_n^c \log \hat{y}_n^c$$ (16)

Where $y_n^c$ is the ground-truth label; $\hat{y}_n^c$ is prediction probabilities; $N$ denotes the number of training samples and $C^j$ is the number of categories at level $j$.

4. Experiment

4.1. Dataset

We evaluate our method on two widely-studied datasets: Web of Science (WOS) and DBpedia. Web of Science (WOS) dataset is created by [26] through collecting data and meta-data on 46985 published papers available from the Web Of Science. The WOS dataset contains 46985 documents, 7 parent categories and 134 subcategories. Compared to WOS, The DBpedia dataset is larger in two aspects: the number of data instances and the number of hierarchical levels. The DBpedia ontology was first used in [29] for flat text classification. [28] instead use the DBpedia ontology to construct a dataset which contains 381,025 documents with a three-level taxonomy of classes. Details of these two datasets are shown in Table 1.

Table 1. Dataset description.
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| Level 1 Categories | WOS | DBpedia |
|-------------------|-----|---------|
|                   | 7   | 9       |
| Level 2 Categories | 134 | 70      |
| Level 3 Categories | NA  | 219     |
| Number of documents | 46985 | 381025 |

4.2. Hyperparameters

For WOS, We use a 300 dimensional pre-training word vector trained by glove as our pre-trained word embeddings which does not participate in model training, and then add a 0.25 dropout after it, and then add an ONLSTM with 500 hidden units and 0.25 dropout, then add a full connection layer with 500 units, a 0.5 dropout layer, and a batch normalization layer in turn. The last layer is a fully connected layer whose numbers of units is category number. We use the standard Adam optimizer[23] with the learning rate of 0.001 to optimize all the trainable parameters. If the validation accuracy is no longer improved after 3 epoch, we reduce the learning rate to 0.1 times. The batch size is set to 64. In addition, We employ early stopping to select the best model.

For DBpedia, other hyperparameters are exactly the same as WOS, except that the hidden layer size of ONLSTM is 300.

4.3. Empirical Results

Table 2 shows the results from our experiments. we compare against the current state-of-the-art flat classifiers such as FastText[37], Bi-directional LSTM with max/mean pooling[36][23] and the Structured Self-attentive classifier[24].we also compare against the current state-of-the-art hierarchical classifier HDLTex[26] and HATC[28].

| Flat Classifiers | WOS | DBpedia |
|------------------|-----|---------|
|                  |     |         |
|                  |     |         |
|                  |     |         |
|                  |     |         |

| Hierarchical Classifiers | WOS | DBpedia |
|--------------------------|-----|---------|
| HDLTex                   | 99.16 | 90.45 |
| HATC                     | 99.42 | 89.24 |
| Our method               | 99.43 | 90.92 |

Table 2. Comparison of experimental results.
Table 2 shows the accuracy of the state-of-the-art classifiers and our classifier on two data sets of DBpedia and WOS. $l_1$, $l_2$, $l_3$ refer to the classification accuracy of this level when providing the real category of text in the upper level. Overall [28] refers to the classification accuracy of the last level labels of text without providing real parent categories, that is, the parent categories used in the classification process is the parent categories predicted by the classifier itself. Because the flat classifier does not deal with the middle levels of the category hierarchy, but only considers the classification of the last level, so the flat classifier has only overall accuracy. From table 2, we can see that our classification model is not only superior to the state-of-the-art flat classification models, but also superior to the state-of-the-art hierarchical classification models. Through a more detailed analysis of the data in Table 2, we can see that in the hierarchical classification model, the difference between the classification accuracy of our model and that of the other two models increases level by level, indicating that the deeper the level of our model in the HTC, the more obvious the advantages of our model compared with other hierarchical models.

Table 3. Number of parameters.

| Model      | Number of parameters/million | DBpedia | WOS |
|------------|------------------------------|---------|-----|
| HDLTex     | 5000                         |         |     |
| HATC       | 34                           |         |     |
| Our Method | 83                           | 57      |     |

Table 3 shows the comparison between the state-of-the-art hierarchical classification models and our classification model in terms of model parameters. Our model is a level by level classification model. The number of parameters is obtained by adding all the parameters of each level classification model. The parameters of each level include the parameters participating in training and the parameters not participating in training. From table 3, we can see that the total parameters of HDLTex are much larger than those of HATC and our model, while the total parameters of HATC are the smallest. However, Our method is local, and the number of parameters is close to the number of HATC parameters. It is the least number of parameters in the current local hierarchical text classification method, so our method has the highest cost performance. we can see from table 2 and table 3 that our classification model achieves the optimal performance with lower computation cost.

5. Conclusion

In this paper, we propose a local hierarchical text classifier with less parameters and better performance. The model performance is not only better than the state-of-the-art
hierarchical classifiers, but also better than the state-of-the-art flat classifiers. Our experiments show that the deeper the label level, the larger the label scale, and the better the performance of our model compared with other hierarchical classification models. Because in our model, we use the joint embedding of text and parent category method and hierarchical fine-tuning technology to make full use of the hierarchical relationship between categories, which directly proves that the use of the relationship between labels can greatly improve the performance of text classification. In this paper, we mainly study the text classification method that the category structure is a tree structure, and we do not test it in the text that the category structure is a directed acyclic graph structure. In the future work, we will analyze and study the hierarchical classification that involves directed acyclic graph structured class taxonomies.

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