Abstract

Text classification is a primary task in natural language processing (NLP). Recently, graph neural networks (GNNs) have developed rapidly and been applied to text classification tasks. Although more complex models tend to achieve better performance, research highly depends on the computing power of the device used. In this article, we propose TENT to obtain better text classification performance and reduce the reliance on computing power. Specifically, we first establish a dependency analysis graph for each text and then convert each graph into its corresponding encoding tree. The representation of the entire graph is obtained by updating the representation of the non-leaf nodes in the encoding tree. Experimental results show that our method outperforms other baselines on several datasets while having a simple structure and few parameters.

1 Introduction

Text classification is an essential problem in NLP. There are numerous applications of text classification, such as news filtering, opinion analysis, spam detection, and document organization (Aggarwal and Zhai, 2012). Recently, GNNs have developed rapidly. GNNs learn the representation of each node by aggregating the information of neighboring nodes and can retain structural information in the graph embedding. Therefore, many graph-based methods are applied to text classification and achieve good performance. Yao et al. (2019) proposed TextGCN, which is the first method to employ a Graph Convolutional Network (GCN) in the text classification task. They built a heterogeneous graph containing word nodes and document nodes for the corpus and transformed the text classification task into a node classification task.

TextGCN outperformed other traditional methods and attracted much attention, which has led to increasingly more applications of graph-based methods in text classification. In Huang et al. (2019); Zhang et al. (2020), the text classification task was converted into the graph classification task. They built text-level co-occurrence graphs for each data. Huang et al. (2019) employed a Message Passing Mechanism (MPM) and outperformed TextGCN. A Gated Graph Neural Network (GGNN) was employed in Zhang et al. (2020) and achieved state-of-the-art performance.

However, the performance improvement comes with more complex structures and more parameters. This makes text classification research increasingly dependent on computing power.

Recently, a model called Encoding Tree Learning (ETL) (Wu et al., 2021) was proposed to boost graph classification performance while focusing on reducing model complexity. In particular, based on structural optimization, ETL simplifies the input data from graphs into encoding trees, which not only retains the crucial features of datasets but also excludes many other features that worsen the model in a given task. Consequently, significant promotions are achieved with only 22% volumes of computation of another popular baseline method (i.e., Graph Isomorphism Network (GIN-0) (Xu et al., 2019)). In view of the universal adoption of GNNs in text classification, we believe ETL provides a promising method for achieving better results in an environmentally friendly manner (i.e., less computational consumption).

In this work, we propose a novel model for text classification named TENT. We build individual graphs for each document through dependency parsing and then transform the graph into its corresponding encoding tree. The ETL model classifies the entire document by learning the representation of the encoding tree. We conduct several experiments to verify the advantages of our method over...
the baselines. To sum up, our contributions are as follows:

- We propose a novel graph neural network method that obtains encoding trees from dependency parsing graphs of documents for text classification.

- The results demonstrate that our method not only outperforms several text classification baselines but is also much simpler in structure than other graph-based models.

2 Method

In this section, we will introduce TENT in detail. First, we will explain how to construct a graph for each text. Then, we introduce ETL, a simple and effective graph classification model. Finally, we will show how to predict the label for a given text based on the learned representations. The architecture of our model is illustrated in Figure 1.

2.1 Graph Construction

In previous graph-based text classification models, there are two ways to construct a graph for text. In Yao et al. (2019), the corpus is constructed into a heterogeneous graph containing word nodes and document nodes. The weight of the edge connecting the word nodes is the point-wise mutual information (PMI) of the two words. The weight of the edge connecting the word node and the document node is the TFIDF value of the word in this document. The advantage of using this method to construct a graph is that it can explicitly model the global word co-occurrence and can easily adapt to graph convolution. However, building a large graph of the entire corpus consumes a considerable amount of memory, and the new incoming text is difficult to classify. The other method is to construct a graph for each text. Huang et al. (2019); Zhang et al. (2020) construct a graph for a textual document by representing unique words as vertices and co-occurrences between words as edges. The relationship between words appearing in a fixed-size sliding window can be described in the co-occurrence graph. This method reduces the memory consumption and is friendly to new text.

However, the graphs constructed by the above methods do not contain rich semantic information. In addition, the method based on co-occurrence treats the words at different positions equally, which causes a lack of position information in the representations of graph nodes. The transformed encoding tree will retain more features if the original graph contains rich semantic information. Therefore, we use the dependency parsing information of the text to construct a graph in TENT. Take a document with $l$ words $D = \{w_1, \ldots, w_i, \ldots, w_l\}$, where $w_i$ is the $i$th word of document. The dependency parsing result of the document is $DP = \{r_{ij}|i \neq j; i, j < l\}$, where $r_{ij}$ denotes the dependency relation of words $i$ and $j$. The graph $G = (V, E)$ for a text is defined as:

$$V = \{w_i|i \in [0, l]\},$$

$$E = \{e_{ij}|r_{ij} \in DP\},$$

Figure 1: The architecture of TENT.
2.2 Encoding Tree Learning

ETL (Wu et al., 2021) is a novel deep learning architecture based on structural optimization (Wu et al., 2021; Pan et al., 2021). Structural optimization is designed to transform the original structure of data into a simplified form while retaining key features. Given a graph $G = (V, E)$, the encoding tree after structural optimization with given height $h$ is computed by $ET = SO(G)$, where $ET = (V_T, E_T)$, $V_T = (V^0_T, \ldots, V^h_T)$ and $V^0_T = V$. SO refers to the structural optimization algorithm that transforms the graphs into encoding trees. After the text is transformed into an encoding tree, all words are the leaf nodes, and the structural information and crucial features of the graph can be retained. Figure 2 shows an example of a text and its corresponding encoding tree. We can see that the encoding tree divides the words of the text. The information contained in each non-leaf node can be interpreted as the semantic information of all its child nodes, so non-leaf nodes at different levels contain semantic information with different granularities. In addition, the two words "Tom" and "Jerry" that are farther apart in the original text are closer in the encoding tree while retaining the correct semantic information.

ETL develops a hierarchical reporting scheme to update the hidden features of the non-leaf nodes in the encoding tree. The information of non-leaf nodes is updated by aggregating the information from their child nodes. Finally, ETL can obtain a representation of the entire graph by using the structure of the encoding tree and the features of the leaf nodes. The number of layers of the ETL is the same as the height of the encoding tree. The $i_{th}$ layer of ETL on encoding tree $T = (V_T, E_T)$ can be expressed as:

$$x^i_v = MLP^1(\sum_{n \in C(v)} x^{i-1}_n),$$

where $v \in V_T$, $x^i_v$ is the feature vector of node $v$ with height $i$, and $C(v)$ is the child nodes of $v$. ETL starts from the leaf node layer and learns the representation of each node layer by layer until reaching the root node. Finally, all feature vectors of the nodes are used to compute a representation of the entire encoding tree $x_T$:

$$x_T = Concat(Pool(\{x^i_v|v \in V^i_T\})_{|i = 0, 1, 2, \ldots, h}),$$

where $x^i_v$ is the feature vector of node $v$ with height $i$ in $T$, and $h$ is the height of $T$. $Pool$ in Equation 4 can be replaced with a summation or averaging function.

2.3 TENT

By converting the graph into an encoding tree, the data structure becomes simpler, and the hierarchical information and main features of the graph are retained in the encoding tree. In ETL, the node feature vector is aggregated in one direction owing to the hierarchical structure of the encoding tree. We can conclude that the structure of ETL is simple and the convergence is strong. We feed the encoding trees $T = (T_1, T_2, \ldots, T_n)$ and feature matrix to TENT. Each word is represented by the Glove (Pennington et al., 2014) vector and one-hot position encoding vector, and we concatenate these two vectors as feature matrix $F$. The representation of the entire graph can be obtained from Equation 4, and then the predicted label of the original text is computed as:

$$y_i = softmax(Wx_{T_i} + b),$$

where $T_i \in T$, $x_{T_i}$ is the representation of encoding tree $T_i$; and $W$ and $b$ are the weight and bias, respectively. The goal of training is to minimize the cross-entropy between the ground truth label and predicted label:

$$loss = -\sum_i g_i \log(y_i),$$

where $g_i$ is the one-hot vector of the ground truth label.
3 Experiments

In this section, we evaluate the TENT model and report the experimental results.

3.1 Experimental Setup and Baselines

Datasets. We utilize datasets including R8, R52, MR, and Ohsumed. R8 and R52 are subsets of the Reuters 21578 dataset. MR is a movie review dataset used for sentiment classification in which each review is a single sentence. The Ohsumed corpus, which is designed for multilabel classification, is from the MEDLINE database. In this paper, we only use single-label data like other GNN-based text classification models (Yao et al., 2019; Huang et al., 2019). We employ StanfordNLP (Qi et al., 2018) to build the dependency graphs for all datasets. The statistics of our datasets are summarized in Table 1.

| Datasets | # Training | # Test | Categories | Avg. Length |
|----------|------------|--------|------------|-------------|
| MR       | 7108       | 3554   | 2          | 20.39       |
| Ohsumed  | 3357       | 4043   | 23         | 193.79      |
| R52      | 6532       | 2568   | 52         | 106.29      |
| R8       | 5485       | 2189   | 8          | 98.87       |

Table 1: Summary statistics of datasets.

Baselines. In this paper, we aim to boost model performance while reducing model complexity; thus, we select the popular baselines of various methods. We divide the baseline models into three categories: (i) traditional deep learning methods, including the CNN (Kim, 2014) and LSTM (Liu et al., 2016); (ii) word embedding methods, including fastText (Joulin et al., 2017) and SWEM (Shen et al., 2018); and (iii) graph-based methods for text classification, including the spectral approach-based TextGCN (Yao et al., 2019), S²GC (Zhu and Koniusz, 2021), and nonspectral method-based Huang et al. (2019). S²GC was recently proposed as a simpler and more effective network than the GCN.

Settings. We randomly divide the training set into the training set and the validation set at a ratio of 9:1. We use the Adam optimizer with an initial learning rate of $10^{-3}$ and set the dropout rate to 0.5. The height of the encoding tree is between 2 and 12. We set the sum or average function as the initial function of $\text{Pool}$ in Equation 4. For word embedding, we use pretrained GloVe with the dimension of 300, and the out-of-vocabulary (OOV) words are randomly initialized from the uniform distribution $[-0.01, 0.01]$. We concatenate the GloVe vector and one-hot position encoding as a representation of graph nodes.

3.2 Experimental Results

Table 2 presents the performance of our model and baselines. Graph network-based methods generally outperform other types of methods because of the inclusion of graph information. We can observe that the performance of our model is generally better than those of other graph network-based methods. Traditional deep learning methods (CNN and RNN) perform well on MR dataset with relatively short text lengths but are not as good at processing long text. The word embedding-based methods (fastText and SWEM) use word embedding with contextual information and perform better on the R52 and Ohsumed datasets than traditional deep learning methods.

TextGCN is the first method to apply a graph neural network method in text classification. TextGCN learns the representation of nodes through corpus-level co-occurrence graphs. Huang et al. (2019) uses the co-occurrence window and message passing mechanism to learn the representation of nodes.

| Model                  | MR       | R8       | R52      | Ohsumed   |
|------------------------|----------|----------|----------|-----------|
| CNN(Non-static)        | 77.75± 0.72 | 95.71± 0.52 | 87.59± 0.48 | 58.44± 1.06 |
| RNN(Bi-LSTM)           | 77.68± 0.86 | 96.31± 0.33 | 90.54± 0.91 | 49.27± 1.07 |
| fastText               | 75.14± 0.20 | 96.13± 0.21 | 92.81± 0.09 | 57.70± 0.49 |
| SWEM                   | 76.65± 0.63 | 95.32± 0.26 | 92.94± 0.24 | 63.12± 0.55 |
| TextGCN                | 76.74± 0.20 | 97.07± 0.10 | 93.56± 0.18 | 68.36± 0.56 |
| Huang et al. (2019)    | -        | 97.80± 0.20 | 94.60± 0.30 | 69.40± 0.60 |
| S²GC                   | 76.70± 0.00 | 97.40± 0.10 | 94.50± 0.20 | 68.50± 0.10 |
| TENT                   | 77.03± 0.12 | 98.12± 0.09 | 95.02± 0.18 | 68.79± 0.12 |

Table 2: Test accuracy(%) of models on text classification datasets. Some results of baselines are from (Huang et al., 2019). The average standard deviation of our model is reported based on ten runs.
S$^2$GC is an extension of the Markov Diffusion Kernel used to make the information aggregation in graphs more efficient. The graph learning method enables each node to learn a better node representation by using the information of its farther neighbors and accordingly performs well on all datasets. The TENT model encodes a graph and extracts features through structural optimization algorithms and employs the ETL model to combine features. The representations of non-leaf nodes in the encoding tree are obtained by a facile method. The results show that TENT performs better on the MR, R8, and R52 datasets than other graph-based methods and achieves competitive performance on the Ohsumed dataset. Notably, TENT does not have a complicated structure and numerous parameters, but it still generally outperforms other baselines. Next, we will conduct further analysis of the height of the encoding tree, the position encoding, and the number of parameters.

### 3.3 Height of the Encoding Tree

The height of the encoding tree plays an important role in TENT. Different height encoding trees reflect divergent hierarchical information, and the utilization of leaf node information is also disparate. Figure 3 shows the test performance of different height encoding trees on the 4 datasets. The increase in the height of the encoding tree will increase the number of nodes in the encoding tree and the number of learning iterations of ETL. For datasets with different average lengths, the optimal height of the encoding tree is different. For the MR dataset, a height of 2 is the best. For the Ohsumed dataset with an average length of nearly 200, the best performance occurs when the height is 11. Therefore, a suitable height will improve the quality of the extracted features of the encoding tree and make better use of the information of original texts.

### 3.4 Position Encoding

Position encoding (PE) distinguishes the same words in different positions. By adding position encoding to the representations of words, the information of the leaf nodes of the encoding tree will be more abundant. There are various position encoding methods. For example, in the Transformer (Vaswani et al., 2017) model, the position encoding is determined based on trigonometric functions. The $d$-dimensional position embedding of a word in position $t$ is determined by:

$$PE_{t,2i} = \sin(t/10000^{2i/d}),$$

$$PE_{t,2i+1} = \cos(t/10000^{2i/d}).$$  \hspace{1cm} (7)

We concatenate or add the Transformer PE and word vector as the representation of leaf nodes. Here, 512-dimensional PE is used for concatenation, and 300-dimensional PE is utilized for addition. Table 3 shows the effect of different position encodings on the performance of the model. The model performs best with one-hot position encoding. Transformer PE pays attention to the relative positions of words, and the dimension $d$ of the vector can be customized. The dimension of one-hot PE is the same as the length of the longest text in the data. Each position in the text is regarded as a feature. Although the dimension of the vector increases, it makes the representation contain more information. Because the representation of

| Model           | MR     | R8     | R52    | Ohsumed |
|-----------------|--------|--------|--------|---------|
| TENT(Add PE)    | 75.72±0.13 | 97.72±0.04 | 93.73±0.18 | 62.25±0.22 |
| TENT(Concat PE) | 75.83±0.30 | 97.58±0.08 | 93.81±0.16 | 64.74±0.25 |
| TENT            | 77.03±0.12 | 98.12±0.09 | 95.02±0.18 | 68.79±0.12 |

Table 3: Test accuracy(%) of models on text classification datasets with different position encodings.
leaf nodes does not change with training, the model needs more information initially, so one-hot PE is more suitable for our model.

3.5 The Efficiency of TENT

As we mentioned in the first part, for text classification or other NLP tasks, increasing the complexity of the neural network model and the number of network parameters can often achieve better performance. Therefore, the problem is that the development of NLP tasks highly depends on computing power. With the development of deep learning, increasingly more people are paying attention to this problem. The proposal of ETL, in which model promotion is achieved by decreasing model complexity, provides a solution for this type of problem.

In the graph-based baseline models, the computational complexity of TextGCN, S₂GC and Huang et al. (2019) is $O(hm)$, where $h$ is the number of diffusion steps and $m$ is the number of edges. The computational complexity of ETL is $O(n)$, where $n$ is the number of nodes, which is much smaller than that of graph-based baseline models. In addition, we also compare the parameters and floating-point operations per second (FLOPs) of the models. Since S₂GC and Huang et al. (2019) do not have a complete model code implementation, we only compare the proposed model with TextGCN. Table 4 shows the comparison of the parameters of TENT and TextGCN. We set the height of the encoding tree $h \in [2, 12]$ and use 2 as the step size and then run TENT and TextGCN on the same dataset. We can observe that the parameters of TENT gradually increase as the height increases, but the model with the most parameters is still dozens of times smaller than TextGCN.

Moreover, we further compare the number of FLOPs of TENT and TextGCN on the same parameter settings. We set the hidden size of TENT to 96 and the batch size to 4. We calculate the FLOPs of the TENT and TextGCN models on four datasets. The results are shown in Figure 5. We can see that the calculation amount of TENT is also less than that of TextGCN. The performance of our model is not only better than those of other models, but the numbers of parameters and calculations are also very small, which further proves that our model is simple and effective. Our model makes the extraction of features not completely dependent on the deep learning network and greatly reduces the requirements for the computing power of the neural network.
4 Conclusion

In this paper, we propose a novel and simple graph-based method for text classification. We build a dependency parsing tree for each text and construct a structural information encoding tree for each graph. Our model uses the structure of the encoding tree to learn the representation of each text. The experimental results prove the effectiveness of the model and show that this model achieves better performance than the classic model with a simple structure and very few parameters.

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