TextRGNN: Residual Graph Neural Networks for Text Classification

Jiayuan Chen, Boyu Zhang, Yinfei Xu, Meng Wang

Abstract

Recently, text classification model based on graph neural network (GNN) has attracted more and more attention. Most of these models adopt a similar network paradigm, that is, using pre-training node embedding initialization and two-layer graph convolution. In this work, we propose TextRGNN, an improved GNN structure that introduces residual connection to deepen the convolution network depth. Our structure can obtain a wider node receptive field and effectively suppress the over-smoothing of node features. In addition, we integrate the probabilistic language model into the initialization of graph node embedding, so that the non-graph semantic information of can be better extracted. The experimental results show that our model is general and efficient. It can significantly improve the classification accuracy whether in corpus level or text level, and achieve SOTA performance on a wide range of text classification datasets.

Introduction

Text classification is one of the basic problem in natural language processing. It has a broad applications in many aspects such as News Categorization, Topic Analysis, Sentiment Analysis and so on. Text representation learning is the basic problem in text classification. Traditionally, handmade features such as sparse lexical features (e.g., word bag and n-gram) are used to represent text (Aggarwal and Zhai 2012; Forman 2008). With the development of deep learning, deep models have achieved good performance in the field of text classification, including convolutional neural network (CNN) (Kim 2014), recursive neural network (RNN) (Liu, Qiu, and Huang 2016) and Transformer (Devlin et al. 2018).

With the development of graph neural network, its application in text classification has attracted more and more attentions. In (Kipf and Welling 2016), graph convolution neural network (GCN) is applied in text classification task for the first time, and it shows better performance than traditional CNN models. Later, TextGCN (Yao, Mao, and Luo 2018) is proposed in, which builds a single large graph from a complete corpus, including both words and documents as nodes. In (Zhang et al. 2020), TextGCN is improved by TextING, and their inductive model outperformed the state-of-the-art text classification methods. (Lin et al. 2021) proposed BertGCN and achieved excellent results by combining large-scale pretrained BERT with TextGCN. In these works, the graph convolution used in the model has spectral convolution and non spectral convolution, but their network structure is basically similar, which is essentially a two-layer graph convolution structure. In addition, their models are single graph processing methods, without considering the combination of non graph semantic extraction model.

In this work, we make two improvements on the original graph processing framework and propose a general and effective network framework.

Firstly, we fuse the traditional feed-forward neural networks with graph convolution neural networks. In previous models such as TextGCN and TextING, graph nodes were initialized using one-hot vectors (shallow embedding) or pre-trained GloVe embedding. Although GCNs are capable of capturing the graphic structure information inside the text, such as syntactic and semantic parse trees, they do not pay enough attention to the sequential order of text. Therefore, during node embedding initialization, we weighted average the node features obtained by word2vec with the one-hot vector of the node, which not only increases utilization of word order and contextual information, but also ensures integrity of information before graph convolution. In addition, the introduction of word2vec with corpus training can also accelerate the model training.

Secondly, although deepening the network will obtain more information about neighbor nodes, it will also make the node features over-smoothing, resulting in the decline of classification accuracy. Therefore, the structure of two-layer graph convolution is considered to be a suitable structure and has been widely used in the previous model (Yao, Mao, and Luo 2018; Lin et al. 2021). However, our model changes the original two-layer network to a three-layer residual structure with shortcut connection. By deepening the depth, a wider receptive field of each node can be obtained, and the residual connection can effectively adjust smoothness of node features. Applying this residual convolution structure to the existing models can effectively improve the performance of the original model. To sum up, our contributions include:

- We propose a novel graph convolution network framework, in which word2vec is added for node initialization, and residual connection is introduced to expand the network depth.
- Our model is a general structural paradigm that performs well on both the text level and corpus level graphs.
• Results on several datasets demonstrate that our method outperforms state-of-the-art methods in both using pre-trained embedding and non-pretrained models.

Related Work

Text Classification

Text classification is a classical problem in natural language processing (NLP), which is widely used in real life. Traditional text classification research mainly focuses on Feature Engineering and classification algorithms. Then, text classification models based on deep learning are becoming more and more popular, including word embedding models (Deerwester et al. 2010; Bengio et al. 2001) and deep neural networks such as CNN (Kim 2014) and RNN (Liu, Qiu, and Huang 2016). These methods have achieved better classification results. With the development of graph neural network, some graph-based classification models appear gradually. However, these models focus on how to build a better graph model and ignore how to better extract the information from the graph. The model proposed in this paper presents a better graph neural network structure and skills of node representation initialization.

Graph Neural Networks

The in-depth study of graph neural networks has attracted more and more attention. In the early work, recurrent neural networks were used to process the data represented as directed acyclic graphs in the graph domain (Frasconi and Gori 1998). (Gori, Monfardini, and Scarselli 2005) introduced graph neural network (GNN) as a generalization of the recurrent neural network, which can directly deal with more general graph classes. After summarizing the previous work including spectral representation of the graphs, Chebyshev expansion of the graph Laplacian (Defferrard, Bresson, and Vandergheynst 2016) and so on, kipf and welling proposed a simplified graph neural network model, called graph convolution neural network (GCN) (Kipf and Welling 2016), which has achieved the most advanced classification results on many benchmark graphic datasets. Then (Velickovi et al. 2017) Introduced the attention mechanism into the graph neural network and proposed Graph Attention Networks (GAT). (Yao, Mao, and Luo 2018; Huang et al. 2019; Zhang et al. 2020) have deeply studied the application of graph neural network in text classification. Their respective models build different graphs, hoping to capture more text information. Our model proposes a general graph processing structure based on text classification, improves the graph embedding processing framework in the original method, and can be extended to graphs with different characteristics. It also makes a preliminary attempt for the application of some deep learning models in GNN.

Proposed Framework

Since our model is a general method and effective on both corpus level (Yao, Mao, and Luo 2018) and text level (Huang et al. 2019) graphs, we skip how to construct graphs in this section.

Node Embedding Initialization

Using graph neural network can achieve good performance for text classification. However, further improvement of classification accuracy is rather limited, since graph structure can not capture all the semantic features in the text. In this work, a lightweight feed-forward neural network word2vec (CBOW) is added to extract implicit contextual information, and the preliminary features are fed into GNN during node initialization. Compared with original node initialization such as pre-train GloVe embedding, the trained word2vec carries more accurate semantic information and can dramatically improve the text classification accuracy.

As shown in Figure 1, we modify the traditional initialization of graph node embedding. The original one-hot vector and the feature vector extracted by word2vec (Mikolov et al. 2013a) is weighted averaged as input of the graph neural network.

The node vector obtained by word2vec is a distributed representation of words. We use $C(v)$ to denote the context of word $v$. Taking the CBOW (Mikolov et al. 2013b) model of the word2vec as an example, node embedding $H_v$ is obtained by optimizing $p(v|C(v))$. Therefore, word2vec obtains word embedding $H_v$ by optimizing the words and their context in the article by random gradient ascending.

$$H_v = g_\theta(C(v), v), \quad \forall v \in V \quad (1)$$

where $\theta$ represents the parameters of the model and $g$ represents the obtained word2vec model after the training of experimental corpus.

Node vector initialization through word2vec will preserve the correlation between word nodes and obtain the semantic information existing in the word context. One-hot and word2vec are used for node embedding, respectively. The final vector is then obtained by averaging the two results,

$$H_v^0 = \alpha H_v + (1 - \alpha) H_v, \quad \forall v \in V \quad (2)$$

where $H_v^0$ represents the representation of node $v$, $\alpha$ is a hyper-parameter, $H_v$ and $H_v$ represent the results of one-hot vector and word2vec, respectively. Our initialization method includes the results of word2vec and one-hot, with assigned different weights to them.

Using one-hot initialization alone such as TextGCN (Yao, Mao, and Luo 2018), it will ignore relations between words. Our model combines the one-hot vector and the embedding of probabilistic language model. It not only carries out a latent semantic extraction through word2vec but also integrates one-hot to prevent information loss during word2vec processing. Compared with the pre-trained GloVe (Huang et al. 2019; Zhang et al. 2020), the word2vec we use is trained with the tested corpus, and the semantic information implied in word embedding is more accurate. Numerous Experiments are product to verify fast convergence and high classification accuracy of our initialization methods.

Residual Graph Convolutional Networks

The structure of the convolution neural network part of the model is shown in Figure 1. By passing the input node features through a three-layer graph convolution network with
residual connections, a softmax classifier is delivered to obtain the final result.

**Graph Convolutional Network** Graph convolutional neural network is a stack of graph convolutional layers. For graph $G = (V, E)$, where $V$, $(|V| = n)$ and $E$ are the sets of nodes and edges, respectively. We denote the adjacency matrix as $A$ and use $D$ to represent the degree matrix. A basic $k^{th}$ GCN layer is defined in (Kip.F. and Welling 2016) as

$$H^{(k)} = \sigma(\tilde{A}H^{(k-1)}W^{(k)})$$  

$$\tilde{A} = (D + I)^{-\frac{1}{2}}(I + A)(D + I)^{-\frac{1}{2}}$$

where $\tilde{A}$ is a normalized variant of the adjacency matrix (with self-loops). $\sigma(\cdot)$ is activation function (ReLU). $W^{(k)}$ is the learnable parameter matrix and $H^{(k)}$ represents node features.

This architecture of convolution layer can aggregate information from neighbors and combines that with information from the node itself. The output node embeddings of the last layer are fed into the softmax classifier for classification,

$$Z = softmax(H^{(3)})$$  

**Residual Connection** In (Wu et al. 2019), it is proved that stacking multiple rounds of message passing in graph convolutional network is equivalent to applying a low-pass graph filter. It will produce a smoothed version of the input feature on the graph. It is the reason that three-layer graph convolution network will lead to over-smoothing of node in the application of text classification.

In other words, over-smoothing makes the node features between adjacent nodes become more and more similar, which limits the classification accuracy. While our model introduces residual connection, as shown in the bottom part (our method) of Figure[1] a shortcut connection is added between the first convolution layer output and the second convolution layer output. The input nodes features of the next layer can be expressed as

$$H^{(k)} = \lambda_1\sigma(\tilde{A}H^{(k-1)}W^{(k)}) + \lambda_2W^*H^{(k-1)}$$

where $W^*$ is a learnable parameter to match the dimension (since the two embedding dimensions may be different), $W^{(k)}$ are parameters in graph convolution, $\lambda_1$ and $\lambda_2$ are hyper-parameters.

One point should be mentioned is that the effect of our residual connection is different from that in (He et al. 2016). Our structure here is not only to suppress over-smoothing but also to aggregate and update node information more finely. As shown in Equation [7] graph spectral convolution can be represented by polynomials of graph Laplacian (Hamilton 2020),

$$f *_{G} h = p_{N}(L)f,$$

where $f$ is the Fourier transform of input features, $h$ is a filter and $L = D - A$ ($D$ is the degree matrix) represents graph Laplacian. From this point of view, it can be found that the network structure of our model is similar to the higher-order expansion of Taylor formula compared with the original two-layer network. This results in a more precise mapping of node features to text categories.

**Experiments**

In this section, we evaluate our model on two experimental tasks. Specifically, we want to determine

- Can our model achieve better results and faster convergence in text classification.
- Whether our improved network structure and node representation initialization is a general approach.
Table 1: The statistics of the datasets. Note that the datasets statistics are from (Yao, Mao, and Luo 2018)

| Dataset   | # Docs | # Training | # Test | # Words | # Nodes | # Classes | Average Length |
|-----------|--------|------------|--------|---------|---------|-----------|----------------|
| 20 NG     | 18,846 | 11,314     | 7,532  | 42,757  | 61,603  | 20        | 221.26         |
| R8        | 7,674  | 5,485      | 2,189  | 7,688   | 15,362  | 8         | 65.72          |
| R52       | 9,100  | 6,532      | 2,568  | 8,892   | 17,992  | 52        | 69.82          |
| Ohsumed   | 7,400  | 3,357      | 4,043  | 14,157  | 21,557  | 23        | 135.82         |
| MR        | 10,662 | 7,108      | 3,554  | 18,764  | 29,426  | 2         | 20.39          |

Experimental setup

Baseline. We compare our method with the following baseline models. These baseline models can be roughly divided into two categories, including models based on deep learning and models based on graph neural network. We show the results separately from other models with pre-trained BERT models.

- CNN: proposed by (Kim 2014), perform convolution neural network on word embeddings to get representation of text.
- LSTM: defined in (Liu, Qiu, and Huang 2016), view text as a sequence of words and use the last hidden state as the representation of the text.
- Graph-CNN: a graph CNN model that operates convolutions which Cheby-shav filter is used over word embedding similarity graphs (Defferrard, Bresson, and Vandergheynst 2016).
- LEAM: label-embedding attentive models (Wang et al. 2018), which embeds the words and labels in the same joint space for text classification. It utilizes label descriptions.
- TextGCN: proposed by (Yao, Mao, and Luo 2018), a graph model was constructed based on corpus and the graph convolutional neural network was used for classification.
- Huang et al. (2019): GNN based method for text classification which produce a text level graph for each input text.
- TextING: a graph-based text classification method for inductive word representations via graph neural networks, proposed by (Zhang et al. 2020).
- BertGCN: a model proposed by (Devlin et al. 2018) that combines large scale pretraining and graph neural networks.

Datasets. In order to fully compare our model with the conventional network model, we tested it on five widely used datasets. The statistics of the preprocessed datasets are summarized in Table 1

- MR is a movie review dataset for binary emotion classification. Each review contains only one sentence. There are 5331 positive comments and 5331 negative comments in the corpus (Pang and Lee 2005).
- R8 and R52 (all term versions) are two subsets of the Reuters 21578 dataset. R8 has 8 categories, including 5485 training documents and 2189 test documents. R52 has 52 categories, including 6532 training documents and 2568 test documents.
- Ohsumed corpus was established by William Hersh and his colleagues. Its document comes from the medical information database medline10. It contains the titles and/or abstracts of 270 medical journals from 1987 to 1991, including 348566 documents.
- 20NG collects about 20000 newsgroup documents and is evenly divided into 20 newsgroup sets with different topics. It is one of the international standard newsgroup sets for text classification, text mining and information retrieval.

Implementation Details. Our model is implemented based on TextGCN (Yao, Mao, and Luo 2018) and (Huang et al. 2019) model, and improved on their open-source code. For the former, we migrated it from Tensorflow to Pytorch. In order to fair comparison, in addition to the structure of initialization vector and convolution neural network, the parameters in the experiment are in accordance with TextGCN and (Huang et al. 2019) model used in the paper. These parameters include the dimension of word embedding, learning rate, the sliding window size, dropout rate, dataset division, and so on. For the specific model in word2vec, we use Continuous Bag-of-Word Model (Mikolov et al. 2013b) and the window size is 5. For the two weights $\alpha$ and $\lambda$ in the model related to the dataset, we will analyze them in the parameter sensitivity section. For baseline models using pre-trained word embeddings, we used 300-dimensional GloVe (Pennington, Socher, and Manning 2014) word embeddings (TextGCN maintains the original one-hot embedding).

Experimental Results

Table 2 presents the test performance of our model as well as the baselines. We can see that our model has achieved the state-of-the-art result on the four datasets of 20NG, R8, R52 and Ohsumed. -C and -T in the table 2 represent corpus level graph and text level graph respectively, which are proposed by (Yao, Mao, and Luo 2018) and (Huang et al. 2019). Since the original Text level GCN was not tested on MR and 20NG datasets, our experiment did not expand our text level model on these two datasets.

From experimental results presented in Table 2 we can see that our node feature extraction framework performs well for both text level graphs and Corpus level graphs, and has greatly improved the classification accuracy based on the original model. This also shows that our framework is a general graph neural network structure, which can be applied to other graph models. The performance of the Text level model is obviously better than that of Corpus level model.
because the baseline model has great advantages. The test accuracy of the model has been greatly improved on 20NG and Ohsumed. This is because the average text length of the two data sets is long, which leads to the low accuracy of text classification. Our model deepens the network depth, carries out finer node information dissemination, and extracts more semantic information in combination with word2vec. Compared with traditional deep learning models such as LSTM (Liu, Qiu, and Huang 2016) and graph structure based models (Zhang et al. 2020), our model combines the two methods and achieves better classification accuracy than them.

The reasons for the performance improvement of our model after deepening one layer of network are different for different levels of graphs. For the text level graph, the deeper network means that each word obtains a deeper feeling field. The corpus level graph is a heterogeneous graph, including document nodes and word nodes. Therefore, comparing 2-hop convolution to 3-hop convolution for document nodes, the additional information includes the word features connected by document nodes containing the same word.

Since whether there is large scale pre-trained word embedding will have a great impact on the results, we present the results on these models separately in Table 3. The * in the table represents our model. Because the pre-trained word embedding is used, we do not add a word2vec module, but only change the structure of the original convolution network to the residual convolution structure we proposed. However, due to the limitation of computing resources (CUDA memory), we only tested on the two smallest datasets R8 and R52. The experimental results show the generality of our method. In the model with pre-trained word embedding, our convolution network can also significantly improve the classification accuracy.

| Model          | 20NG       | R8         | R52         | Ohsumed     | MR          |
|----------------|------------|------------|-------------|-------------|-------------|
| CNN-non-static | 82.15 ± 0.52 | 95.71 ± 0.52 | 87.59 ± 0.48 | 58.44 ± 1.06 | 77.75 ± 0.72 |
| LSTM           | 65.71 ± 1.52 | 93.68 ± 0.82 | 85.54 ± 1.13 | 41.13 ± 1.17 | 75.06 ± 0.44 |
| LEAM           | 81.91 ± 0.24 | 93.31 ± 0.24 | 91.84 ± 0.23 | 58.58 ± 0.79 | 76.95 ± 0.45 |
| Graph-CNN      | 81.42 ± 0.32 | 96.99 ± 0.12 | 92.75 ± 0.22 | 63.86 ± 0.53 | 77.22 ± 0.27 |
| TextGCN        | 86.34 ± 0.09 | 97.07 ± 0.10 | 93.56 ± 0.18 | 68.36 ± 0.56 | 76.74 ± 0.20 |
| (Huang et al. 2019) | −         | 97.80 ± 0.20 | 94.60 ± 0.30 | 69.40 ± 0.60 | −           |
| TextING        | −          | 98.04 ± 0.25 | 95.48 ± 0.19 | 70.42 ± 0.39 | −           |
| our method-C   | **88.72 ± 0.10** | **97.52 ± 0.33** | **94.54 ± 0.11** | **69.05 ± 0.28** | **78.15 ± 0.16** |
| our method-T   | −          | **98.21 ± 0.13** | **95.62 ± 0.21** | **70.86 ± 0.35** | −           |

Analysis of Training Efficiency

Although adding word2vec will bring additional training overhead, it can make the model converge faster and balance the additional consumption. Figure 2 shows the training process of the text level model on R8 dataset with or without word2vec, where * is the added model. It can be seen from the figure that the introduction of the traditional language model makes the training more efficient. This is because of the shortcomings of shallow embedding, that is, the one-hot vector do not leverage node feature information, which increases the consumption of feature extraction process. In terms of memory consumption, compared with the memory occupied by various graphs constructed based on corpus, the memory occupied by word2vec model is almost negligible.

Compared with BERT, it seems meaningless to use word2vec for pre-train. But in fact, GCN and BERT need to be trained together when BertGCN is fine tuned. Therefore, we can use word2vec to pre train GCN. In this sense, word2vec is equivalent to a pre module of GCN pre-training model.

Table 4: Results of ablation studies on R8(We run all models for 10 times and use mean results.)

| Setting                              | Acc.     |
|--------------------------------------|----------|
| **Original (corpus level)**          | **97.52**|
| (1)one-hot                           | 97.31    |
| (2)word2vec+Doc2vec (Le and Mikolov 2014) | 97.37    |
| (3)word2vec+2-layers                 | 97.20    |
| (4)baseline (TextGCN)                | 97.07    |

Ablation Study

Ablation experiments were carried out for the two modules in our model for further analysis. Since the test on the R8 dataset is the most efficient, we carried out experiments on it, and the results are shown in Table 4.

In (1), we retain the residual graph convolution neural network structure and initialize the nodes with one-hot vectors. Compared with the results of the baseline model, it can be seen that the three-layer network structure with residual con-
connection has significantly improved the classification accuracy.

In (2), since there are document nodes in the corpus level graph, we use doc2vec proposed by Le and Mikolov (2014). In the original model, we refer to the method of fastText (Joulin et al. 2017) and initialize the document-node features by taking the mean of the feature vectors of the document containing word nodes. But the result is not as good as the original model, which shows that the document feature vector trained by doc2vec is not as accurate as the result of word-node vectors accumulation. Further, although the traditional neural network model CBOW does not have the excellent performance as Bi-LSTM and BERT (Devlin et al. 2018), it is very suitable in improving the defects of graph neural network information extraction. Similarly, a more complex deep learning model for parallel feature embedding may not improve the accuracy.

In (3), we use the basic two-layer graph convolution neural network used by predecessors. From Table 4 we can see that using word2vec can improve the classification accuracy, but the improvement effect is not as high as the three-layer residual network structure.

Parameter Sensitivity

Figure 3 shows test accuracies with different weights on R8 datasets. $\alpha$ is the weights used for the weighted average of network input. $\lambda$ is the weights used for the weighted average of the second layer and the third layer output. It can be seen from the Figure that the weight has a great impact on the efficiency of the model. For $\alpha$, the accuracy of the model is the highest when one-hot embedding accounts for about 0.4, and the model performs best when $\lambda_1$ is equal to 0.3. However, through the comparison between (a)/(b) and (c)/(d), it can be found that different models have different optimal parameters. When experimenting with each dataset, we find the best $\alpha$ and $\lambda$ for each dataset through the search algorithm. It is worth mentioning that for the weight $\alpha$ during node embedding initialization, most datasets achieve the best effect when weighted average the weight around the golden section ratio.

**Analysis of Structure**

As shown in Figure 4, we made some changes to the devised structure and carried out a variety of experiments. For full verification, we tested on different levels of graph models, and used R8 and Ohsumed datasets. The experimental results are shown in Table 4. On the corpus level model, we expand the network to four layers (Fig. 4c). The experimental results on two datasets show that this can not further improve the classification accuracy, but lead to a decline in performance. This is consistent with our analysis in the experimental results section. On the text level model, we add an additional short cut connection (Fig. 4b). The experimental results are very close to the original model, and even have a slight improvement on the Ohsumed dataset, which means that we may find a more effective structure in the subsequent experiments. In addition, as shown in Figure 4(d), we also introduced the global graph attention mechanism (Velickovi et al. 2017; Thekumparampil et al. 2018) for experiments. However, the experimental results show that this structure can not improve the accuracy of classification, and will greatly increase the computational consumption.

Table 5: Test results after structural fine tuning. We used the average of five experiments. (a) (b) (c) corresponds to the structure in Fig. 4

| Model                  | Ohsumed | R8   |
|------------------------|---------|------|
| Text level(a)          | 70.86   | 98.21|
| Text level(b)          | 70.90   | 97.83|
| Corpus level(a)        | 69.05   | 97.52|
| Corpus level(c)        | 68.42   | 94.59|
| Corpus level(d)        | 68.20   | 96.34|
Discussion

Other graph neural networks such as GraphSAGE (Hamilton, Ying, and Leskovec 2017) have paid attention to the over-smoothing problem, but they have adopted other methods. In the future, we will try to migrate this structure to other graph neural networks and other downstream tasks of natural language processing, such as reasoning (Wang et al. 2019) and question answering (Han, Cheng, and Wang 2020). For the residual connection method, (Pham et al. 2016) mentioned a similar propagation mechanism called skip connection. In addition, although residual connection is added, the number of network layers cannot be extended to a very large number. To solve this problem, we will try other structures in the future, such as the bottleneck structure in ResNet, and try to migrate some classical structures of computer vision to graph neural network.

References

Aggarwal, C. C.; and Zhai, C. X. 2012. A survey of text classification algorithms. In Mining text data, 163–222. Springer.

Bengio, Y.; Ducharme, R.; Vincent, P.; and Jauvin, C. 2001. A Neural Probabilistic Language Model. In NIPS, 932–938.

Deerwester, S.; Dumais, S. T.; Furnas, G. W.; Landauer, T. K.; and Harshman, R. 2010. Indexing by latent semantic analysis. Journal of the Association for Information Science and Technology, 391–407.

Defferrard, M.; Bresson, X.; and Vandergheynst, P. 2016. Convolutional Neural Networks on Graphs with Fast Localized Spectral Filtering. In NIPS, 3844–3852.

Devlin, J.; Chang, M. W.; Lee, K.; and Toutanova, K. 2018. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. arXiv preprint arXiv:1810.04805.

Forman, G. 2008. BNS feature scaling: an improved representation over tf-idf for svm text classification. In CIKM, 263–270.

Frasconi, P.; and Gori, M. 1998. A general framework for adaptive processing of data structures. IEEE Transactions on Neural Networks, 768–786.

Gori, M.; Monfardini, G.; and Scarselli, F. 2005. A new model for learning in graph domains. 729–734.

Hamilton, W.; Ying, R.; and Leskovec, J. 2017. Inductive Representation Learning on Large Graphs. In NIPS, 1024–1034.

Hamilton, W. L. 2020. Graph Representation Learning. Synthesis Lectures on Artificial Intelligence and Machine Learning, 81–82.

Han, J.; Cheng, B.; and Wang, X. 2020. Open Domain Question Answering based on Text Enhanced Knowledge Graph with Hyperedge Infusion. In EMNLP, 1475–1481.

He, K.; Zhang, X.; Ren, S.; and Sun, J. 2016. Deep Residual Learning for Image Recognition. 770–778.

Huang, L.; Ma, D.; Li, S.; Zhang, X.; and Wang, H. 2019. Text Level Graph Neural Network for Text Classification. In EMNLP, 3444–3450.

Joulin, A.; Grave, E.; Bojanowski, P.; and Mikolov, T. 2017. Bag of Tricks for Efficient Text Classification. In ACL, 427–431.

Kim, Y. 2014. Convolutional Neural Networks for Sentence Classification. arXiv preprint arXiv:1408.5882.

Kipf, T. N.; and Welling, M. 2016. Semi-Supervised Classification with Graph Convolutional Networks. arXiv preprint arXiv:1609.02907.

Le, Q. V.; and Mikolov, T. 2014. Distributed Representations of Sentences and Documents. In ICML, 1188–1196.

Lin, Y.; Meng, Y.; Sun, X.; Han, Q.; and Wu, F. 2021. BertGCN: Transductive Text Classification by Combining GCN and BERT. In ACL.

Liu, P.; Qiu, X.; and Huang, X. 2016. Recurrent Neural Network for Text Classification with Multi-Task Learning. In IJCAI, 2873–2879.

Mikolov, T.; Chen, K.; Corrado, G.; and Dean, J. 2013a. Efficient Estimation of Word Representations in Vector Space. In ICLR.

Mikolov, T.; Sutskever, I.; Kai, C.; Corrado, G.; and Dean, J. 2013b. Distributed Representations of Words and Phrases and their Compositionality. In NIPS, 3111–3119.

Pang, B.; and Lee, L. 2005. Seeing stars: Exploiting class relationships for sentiment categorization with respect to rating scales. In ACL, 115–124.

Pennington, J.; Socher, R.; and Manning, C. 2014. Glove: Global Vectors for Word Representation. In EMNLP, 1532–1543.

Pham, T.; Tran, T.; Phung, D.; and Venkatesh, S. 2016. Column Networks for Collective Classification. In AAAI.

Thekumparampil, K. K.; Wang, C.; Oh, S.; and Li, L. J. 2018. Attention-based Graph Neural Network for Semi-supervised Learning. arXiv preprint arXiv:1803.03735.
Velikovi, P.; Cucurull, G.; Casanova, A.; Romero, A.; Liò, P.; and Bengio, Y. 2017. Graph Attention Networks. arXiv preprint arXiv:1710.10903.

Wang, X.; Kapanipathi, P.; Musa, R.; Yu, M.; Talamadupula, K.; Abdelaziz, I.; Chang, M.; Fokoue, A.; Makni, B.; and Mattei, N. 2019. Improving Natural Language Inference Using External Knowledge in the Science Questions Domain. In AAAI, 7208–7215.

Wu, F.; Zhang, T.; Souza, A.; Fifty, C.; Yu, T.; and Weinberger, K. Q. 2019. Simplifying graph convolutional networks. In ICML, 6861–6871.

Yao, L.; Mao, C.; and Luo, Y. 2018. Graph Convolutional Networks for Text Classification. In AAAI, 7370–7377.

Zhang, Y.; Yu, X.; Cui, Z.; Wu, S.; Wen, Z.; and Wang, L. 2020. Every Document Owns Its Structure: Inductive Text Classification via Graph Neural Networks. In ACL, 334–339.