Heterogeneous Graph Neural Networks for Multi-label Text Classification

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Abstract

Multi-label text classification (MLTC) is an attractive and challenging task in natural language processing (NLP). Compared with single-label text classification, MLTC has a wider range of application in practice. In this paper, we propose a heterogeneous graph convolutional network model to solve the MLTC problem by modeling tokens and labels as nodes in a heterogeneous graph. In this way, we are able to take into account multiple relationships including token-level relationships. Besides, the model allows a good explainability as the token-label edges are exposed. We evaluate our method on three real-world datasets and the experimental results show that it achieves significant improvements and outperforms state-of-the-art comparison methods.

1 Introduction

In the real world, we have seen an explosion of information on the internet, such as tweets, microblogs, news articles, blog posts, etc. A practical issue is to assign classification labels to those instances. Such labels may be emotion tags for tweets and micro-blogs (Wang et al., 2016; Li et al., 2020b), or topic category tags for news articles and blog posts (Yao et al., 2019). Multi-label text classification (MLTC) is the problem of assigning one or more labels to each instance.

A major challenge for MLTC is the class imbalance. In practice, the number of labels may vary across the training data, and the frequency of each label may differ as well, thus bringing difficulties to model training and evaluation (Quan and Ren, 2010). In Table 1, we show some examples of tweets, micro-blogs and news articles, labeled with emotion tags or news topics. As can be seen from those examples, there is a various number of coexisting labels. Another challenge is the explainability for such a model trained on MLTC by figuring out the trigger words and phrases to class labels. In the table, it is easy to tell that in S1, the emotion Anxiety is very likely to be triggered by the word confusion. However, S2 might be more complicated, there are two possible triggering phrases makes me sad and burst into tears and two emotion labels. There might be different opinions on which phrase triggers which emotion.

Deep learning has been applied for MLTC due to their strong ability in learning semantic representations. Convolutional Neural Networks (CNNs) (Kim, 2014) have been proved to achieve satisfying results for multi-label emotion classification (Wang et al., 2016; Feng et al., 2018). Many Recurrent Neural Networks (RNNs)-based models (Tang et al., 2015) are also playing an important role in MLTC (Huang et al., 2019; Yang et al., 2018; Nam et al., 2017). Recently, with the breakthrough in pre-trained models, BERT (Devlin et al., 2019) achieves state-of-the-art performance in up to 11 NLP tasks. Existing work has applied BERT to solve MLTC problem successfully with very com-

| Text | Labels |
|------|--------|
| S1 我不知道类似这样的困惑到底还要持续多久，(I don't know how long the confusion like this will last.) | Anxiety |
| S2 nothing happened to make me sad but i almost burst into tears like 3 times today | Pessimism, Sadness |
| S3 i would start my process now but i’m too busy enjoying this self hatred wave I’m on | Anger, Fear, Disgust, Pessimism, Sadness |
| S4 ...The price of BASF AG shares improved on Thursday due to its better than expected half year results. At 0900 GMT BASF was up 51 pfennigs at 42.75 marks... | C15, C151, C152, CCAT |

Table 1: Examples of multi-label emotion classification. Data source explained in Sec. 4.1. Note that in S4, the labels are: C15 (Performance), C151 (Accounts/Earnings), C152 (Comment/Forecasts), CCAT (Corporate/Industrial).
petitive performance (Li et al., 2019b). Besides, as a new type of neural network architecture with growing research interest, Graph Convolutional Networks (GCNs) have been applied to solving multiple NLP tasks (Yao et al., 2019). Different from CNN and RNN-based models, GCNs could capture the relations between words and texts if we model the texts as graphs. (Yao et al., 2019).

To tackle the mentioned challenges and investigate different perspectives, we propose a heterogeneous graph convolutional network for multi-label text classification. It models each token and class label as nodes in a heterogeneous graph, allowing various types of edges to be considered: token-token, token-label, and label-label. Then we apply graph convolution to graph-level classification. As GCN shows competitive performance for semi-supervised learning (Ghorbani et al., 2019), we can then ease the impact of data imbalance. Finally, since the token-label relationships are exposed in the heterogeneous graph, one can easily identify the triggering tokens to a specific class, providing a good explainability for multi-label classification.

The contributions of our work are as follows: (1) We transfer the MLTC task to a link prediction task within a heterogeneous graph, and propose two approaches for predicting output labels. In this way, our model is able to provide token-level explanation for the classification. (2) To the best of our knowledge, this is the first work that considers token-label relationships within a manner of a graph neural network for MLTC. (3) We conduct extensive experiments on three representative datasets and achieve competitive results, we also demonstrate comprehensive analysis and ablation studies to show the effectiveness of our proposed model for label nodes and token-label edges. ¹

2 Related Work

Multi-label Text Classification Many existing works focus on single-label text classification, while limited literature is available for multi-label text classification. In general, these methods fall into three categories: problem transformation, label adaptation and transfer learning. Problem transformation is to transform the multi-label classification task into a set of single-label tasks (Jabreel and Moreno, 2019; Fei et al., 2020). Some models also take label correlations into consideration, such as Seq2Emo (Huang et al., 2019) and CNN-CLR (Wang et al., 2016). However, this method is not always applicable and computationally expensive, as there may be hundreds of classes. Label adaptation is to rank the predicted classes or set a threshold to filter the candidate classes. (Chen et al., 2017) proposed a novel method to apply an RNN for multi-label generation with the help of text features learned using CNNs. RM-CNN (Feng et al., 2018) applied a ranking-based multi-label convolutional neural network model for MLTC. Please note that there is a research topic named extreme multi-label text classification (Liu et al., 2017), where the pool of candidate labels is extremely large. In this work, however, we do not target on the extreme case.

Graph Neural Networks in NLP Previous research has introduced GCN-based methods for NLP tasks by formulating the problems as graph-structural tasks. A fundamental task in NLP is text classification. Many works have shown that it is possible to utilize inter-relations of documents or tokens to infer the labels (Yao et al., 2019; Zhang et al., 2019a). Besides, some NLP tasks focus on learning relationships between nodes in a graph, such as learning prerequisites between concepts (Li et al., 2019a) and leveraging dependency trees predicted by GCNs for machine translation (Bastings et al., 2017). Though GCNs have been applied to multi-label classification for images (Chen et al., 2019), application on texts is still very limited. Heterogeneous Graph Neural Network (HGNN), as a variation of GCN, has been applied to many real-world networks, such as academic graphs and review graphs (Yang et al., 2020; Zhang et al., 2019b), where multiple types of nodes and relations are considered, hence the name heterogeneous. In the work of (Zhang et al., 2019b), they model authors and papers as two types of nodes in a heterogeneous graph to predict the paper venues, and apply different propagation rules for different neighboring groups (types). Another work by (Li et al., 2020a) models document texts and concept texts as different types of nodes in a heterogeneous graph to inference concept node relations.

3 Method

In this section, we first provide task definition and preliminaries, then we introduce our proposed heterogeneous graph convolution network for multi-label text classification.

¹We release our code in placeholder.link.
3.1 Task Definition

In multi-label text classification task, we are given the training data \( \{D, Y\} \). For the \( i \)-th sample, \( D^i \) contains a list of tokens \( D^i = \{w_1, w_2, ..., w_m\} \) and \( Y^i \) is a list of binary labels \( Y^i = \{y_1, y_2, ..., y_n\} \), \( y \) is 1 if the class label is positive. The task for MLTC is to predict \( Y^i \) given \( D^i \) in testing.

3.2 Preliminary

Graph convolutional neural networks (GCN) (Kipf and Welling, 2017) is a type of deep architecture for graph-structural data. In a typical GCN model, we define a graph as \( G = (V, E) \), where \( V \) is a set of nodes and \( E \) is a set of edges. Normally, the edges are represented as an adjacency matrix \( A \), and the node representation is defined as \( X \). In a multi-layer GCN, the propagation rule for layer \( l \) is defined as:

\[
H^{(l)} = \sigma \left( \text{norm}(A^{(l-1)})H^{(l-1)}W^{(l-1)} \right)
\]

where \( \text{norm}(A) = \tilde{D}^{-\frac{1}{2}} \tilde{A} \tilde{D}^{-\frac{1}{2}} \) is a normalization function, \( H \) denotes the node representation, and \( W \) is the parameter matrix to be learned. \( \tilde{A} = A + I_{|V|} \), \( \tilde{D} \) denotes the degree matrix of \( \tilde{A} \). In general, in the very first layer, we have \( H^0 = X^0 \).

3.3 Heterogeneous Graph Convolutional Networks for MLTC

In this paper, we expand the node types and edge types from the GCN model by introducing heterogeneous graph convolution networks (HGCNs). For each training sample, we construct an undirected heterogeneous graph. We define two types of nodes: token node and label node, and the node representations are \( X_{\text{token}} \) and \( X_{\text{label}} \). Thus, there are three types of relations between the nodes, defined by the adjacency matrices: \( A_{\text{token}} \) (between token nodes), \( A_{\text{label}} \) (between label nodes), and \( A_{\text{token,label}} \) (between token nodes and label nodes).

We show the model overview in Figure 1. It consists of two main components: a pre-trained BERT encoder\(^2\) and heterogeneous graph convolutional layers. In the HGCN model, we have a list of token nodes \( X_{\text{token}} \) in orange ellipses, and a list of label nodes \( X_{\text{label}} \) in blue ellipses. Besides, there are edges between token nodes \( A_{\text{token}} \), edges between label nodes \( A_{\text{label}} \), and edges between token and label nodes \( A_{\text{token,label}} \). We explain them in greater detail below.

\(^2\)https://huggingface.co/bert-base-multilingual-cased

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{model_overview.png}
\caption{HGCN model overview.}
\end{figure}

Node representations \( X \): In the very first layer, to initialize token nodes, we encode the input data \( D^i = \{w_1, w_2, ..., w_m\} \) using a pre-trained BERT model, where we take the representation of each token including [CLS] token as \( X_{\text{token}} \). For the label nodes, we initialize them using one-hot vectors.

Adjacency matrix \( A \): In our experiments, to initialize token node adjacency matrix \( A_{\text{token}} \), we use the token nodes to construct an undirected chain graph, where we consider an input sequence as its natural order, i.e. in \( A_{\text{token}} \): \( A_{i,i+1} = 1 \). Since it is an undirected graph, the adjacency matrix is symmetric, i.e. \( A_{i+1,i} = 1 \). We also add self-loop to each token: \( A_{i,i} = 1 \). In other words, \( A_{\text{token}} \) is a symmetric \( m \)-by-\( m \) matrix with an upper bandwidth of 1, where \( m \) is the number of token nodes.

We initialize \( A_{\text{label}} \) with an Identity matrix, and \( A_{\text{token,label}} \) with a zero value matrix. In the later layers, we re-construct \( A_{\text{token,label}} \) for layer \( l \) by applying Cosine-similarity between \( X_{\text{token}} \) and \( X_{\text{label}} \) of the current layer:

\[
A_{\text{token,label}}^l = \text{cosine}(X_{\text{token}}^l, X_{\text{label}}^l)
\]

The value is normalized into the range of [0,1]. After this update, the model conducts graph convolution operation as in Eq. 1.

In Figure 1, we are not showing self-loops, so \( A_{\text{label}} \) is not visible. We show only a subset of edges from \( A_{\text{token}} \) and \( A_{\text{token,label}} \). Note that we use dashed lines at the first HGCN layer because \( A_{\text{token,label}} \) is a zero value matrix.

We also investigate other possible ways to build \( A_{\text{token}} \) including dependency parsing trees (Huang et al., 2020) and random initialization, but our method gives the best result. Such ways may not bring useful information to the graph: the help from dependency relations maybe limited in the case of classification, and random initialization brings noises. As we focus more on the network convolution, we leave investigating more methods for initialization as future work.
Predictions At the last HGCN layer, we are able to reconstruct $A_{\text{last,token,label}}$ using Eq. 2. For each label node $j$, we sum up the edge weights from $A_{\text{last,token,label}}$ to get a score,

$$score(j) = \sum_{v_i \in V_{\text{token}}} A_{i,j}$$ (3)

where $V_{\text{token}}$ is the set of all token nodes in the last HGCN layer. Then we apply a Softmax function over all the labels, so that the scores are transformed to probabilities of labels. Finally, to make the prediction, we rank the probabilities in a descending order, and experiment with two methods: top-k and threshold. Top-k method: we choose the top-k labels from the ranking as predicted labels; Threshold method, we select an empirical threshold, and keep the labels whose weights are greater or equal to the threshold. As the predictions are in forms of probabilities, we also convert the ground truths into probability distribution. We use the Mean-Square-Error as the loss function. Another way is to apply the normal cross-entropy for classification, however, it achieves slightly worse results, so it is not included in the evaluation.

4 Experiments

4.1 Datasets

We applied three public datasets for our experiments: SemEval, Ren_CECps and RCV1-V2.

**SemEval** (Mohammad et al., 2018) contains a list of subtasks on labeled tweets data. In our experiments, we focus on the Task1 (E-c) challenge: multi-label classification tweets on 11 emotions. 3

**Ren_CECps** (Quan and Ren, 2010) is a Chinese blog emotion corpus which contains manual annotation of eight emotional categories. Different from SemEval-2018, it not only provides sentence-level emotion annotations, but also contains word-level annotations, where in each sentence, emotional words are highlighted.

**RCV1-V2** (Lewis et al., 2004) consists of manually-labeled news articles from Reuters Ltd. Each news article has a list of topic class labels, i.e., CCAT for Corporate/industrial, G12 for Internal politics. We followed the same setting of Yang et al. (2018) and Nam et al. (2017), and do MLTC on the top 103 classes.

4.2 Metrics

We follow other works and report the following three evaluation metrics.

**Micro/Macro F1** We report micro-average and macro-average F1 scores as did by (Baziotis et al., 2018; Huang et al., 2019), and both metrics consider true positives, false negatives and false positives. We report both because in the datasets, the training samples are not evenly distributed.

**Jaccard Index** We follow the Jaccard index used by (Mohammad et al., 2018; Baziotis et al., 2018; Huang et al., 2019), as always referred as multi-label accuracy. The definition is given below:

$$J = \frac{1}{N} \sum_{i=1}^{N} \frac{|Y^i \cap \hat{Y}^i|}{|Y^i \cup \hat{Y}^i|}$$ (4)

where $N$ is the number of samples, $Y^i$ denotes the ground truth labels and $\hat{Y}^i$ denotes system predicted labels.

4.3 Experimental Results

We apply two graph convolutional layers for all datasets by default for our HGCN model. The hyper-parameters can be found in Table 4. We apply 5 different random seeds and report the average.

We compare with BERT-based baselines. We first take the representation of [CLS] token from pre-trained BERT model, on top of that, two baseline methods are conducted: BERT+single, where we train a separate BERT-based binary classification model for each of the $N$ classes; and BERT+multi, where we jointly train a multi-label classification model and the final output layer is an $N$-dimensional vector indicating the existence of each class.

**SemEval** Illustrated in Table 5, we compare with the following baseline models: NTUA-SLP (Baziotis et al., 2018) is the winner team of the SemEval-2018 Task1 challenge, the model applies attention mechanism and transfer learning with the help of labeled data from other datasets; DATN-2 (Yu et al., 2018) is a transfer learning method which is trained with external labeled data; BNet (Jabreel and Moreno, 2019) is a RNN-based method that transforms the task into a binary classification problem; TECap(Fei et al., 2020) is a topic-enhanced
| Dataset | #train | #dev | #test | #class | #avg label | #token max | #token median | #token mean |
|---------|--------|------|-------|--------|-----------|------------|--------------|-------------|
| SemEval | 6,839  | 887  | 3,260 | 8      | 2.37      | 499        | 26           | 32.08       |
| Ren_CECPs | 27,299 | -    | 7,739 | 11     | 1.37      | 36         | 17           | 16.42       |
| RCV1-V2 | 20,647 | 3,000 | 783,144 | 103 | 3.20 | 9,380 | 198 | 259.06 |

Table 2: Dataset statistics

| Method | Macro F1 | Micro F1 | Jaccard |
|--------|----------|----------|---------|
| NTUA-SLP | 0.5280 | 0.7010 | 0.5880 |
| Transfer | 0.5510 | - | - |
| BNet | 0.5640 | 0.6920 | 0.5900 |
| TECap | 0.5760 | - | - |
| Seq2Emo | - | 0.7089 | 0.5919 |

Table 3: Label number distributions.

| Method | Macro F1 | Micro F1 | Jaccard |
|--------|----------|----------|---------|
| LCo-BERT | 0.5672 | 0.8137 | 0.7696 |
| CNN-CLR | 0.3868 | 0.2889 | - |
| RM-CNN | 0.4219 | - | - |
| TECap | 0.4550 | 0.5310 | - |
| MN-NICER | 0.5520 | - | - |
| BERT+single | 0.6268 | 0.8508 | 0.7665 |
| BERT+multiple | 0.5344 | 0.6365 | 0.4669 |
| BERT+HGCN (topk) | 0.7136 | 0.8614 | 0.7565 |
| BERT+HGCN (thd) | 0.7159 | 0.8732 | 0.7749 |

Table 4: Hyper-parameters chosen in our experiments.

| Method | Macro F1 | Micro F1 | Jaccard |
|--------|----------|----------|---------|
| LCo-BERT | 0.5672 | 0.8137 | 0.7696 |
| CNN-CLR | 0.3868 | 0.2889 | - |
| RM-CNN | 0.4219 | - | - |
| TECap | 0.4550 | 0.5310 | - |
| MN-NICER | 0.5520 | - | - |
| BERT+single | 0.6268 | 0.8508 | 0.7665 |
| BERT+multiple | 0.5344 | 0.6365 | 0.4669 |
| BERT+HGCN (topk) | 0.7136 | 0.8614 | 0.7565 |
| BERT+HGCN (thd) | 0.7159 | 0.8732 | 0.7749 |

Table 5: Results on SemEval 2018 E-c task.

| Method | Macro F1 | Micro F1 | Jaccard |
|--------|----------|----------|---------|
| LCo-BERT | 0.5672 | 0.8137 | 0.7696 |
| CNN-CLR | 0.3868 | 0.2889 | - |
| RM-CNN | 0.4219 | - | - |
| TECap | 0.4550 | 0.5310 | - |
| MN-NICER | 0.5520 | - | - |
| BERT+single | 0.6268 | 0.8508 | 0.7665 |
| BERT+multiple | 0.5344 | 0.6365 | 0.4669 |
| BERT+HGCN (topk) | 0.7136 | 0.8614 | 0.7565 |
| BERT+HGCN (thd) | 0.7159 | 0.8732 | 0.7749 |

Table 6: Results on Ren_CECPs dataset.

| Method | Macro F1 | Micro F1 | Jaccard |
|--------|----------|----------|---------|
| LCo-BERT | 0.5672 | 0.8137 | 0.7696 |
| CNN-CLR | 0.3868 | 0.2889 | - |
| RM-CNN | 0.4219 | - | - |
| TECap | 0.4550 | 0.5310 | - |
| MN-NICER | 0.5520 | - | - |
| BERT+single | 0.6268 | 0.8508 | 0.7665 |
| BERT+multiple | 0.5344 | 0.6365 | 0.4669 |
| BERT+HGCN (topk) | 0.7136 | 0.8614 | 0.7565 |
| BERT+HGCN (thd) | 0.7159 | 0.8732 | 0.7749 |

Table 7: Results on RCV1-V2 dataset.
5 Analysis

In this section, we first focus on ablation study of the proposed model. We then demonstrate the explainability of the model with several case studies where we identify keywords that trigger certain labels. Moreover, we study and examine the meaning of label representations learned by the model.

5.1 Ablation Study

We study the impact of BERT embeddings, the number of heterogeneous graph convolutional layers and the two prediction methods. We conduct experiments on the SemEval dataset, and show the study results in Table 8.

In the first group, we choose top-k as the prediction method, and test with 1 and 2 HGCN layers; at the same time, we compare freezing (freeze) with not freezing the BERT model. One can notice that during training, when BERT is freezed, and applying 1 layer and 2 layers of HGCN, the performance drops by around 0.11 on Micro F1, 0.08 on Macro F1 and 0.08 on Jaccard. If BERT is not freezed, it helps a lot in improving the performance. The HGCN layers rely on token embeddings directly from BERT, so the model benefits from the fine-tuned BERT model.

In the second group, We fine-tune BERT parameters and choose threshold method as the prediction method, and compare the impact of the number of HGCN layers. Comparing with the same number of HGCN layer setting with the first group, we could notice that threshold is outperforming top-k method. The former is more adjustable since it enables variable number of positive labels for each testing sample, which fits better to the nature of the data; while the later method shares a global k for the number of positively predicted labels of each testing sample. Moreover, HGCN has the best performance when the number of layer is 2. More layers may lower the performance, as other works(Li et al., 2018) have shown that increasing the layer number results in greater difficulty in training.

5.2 Token-label Relations

As our proposed model provides token-label relations, we further study token-level explanations via a case study and a quantitative analysis.

Case Study We show a few examples by visualizing the token-label weights in Figure 2. Specifically, we take the reconstructed $A_{token, label}$ and normalize the matrix so that all values sum up to 1. We select a sample from SemEval test set (S2 in Table 1), as shown in Figure 2a: nothing happened to make me sad but i almost burst into tears like 3 times today (labels: pessimism and sadness). In such a heatmap, columns are tokens while rows are the class labels. It is very obvious that the two rows of pessimism and sadness are highlighted, indicating a higher score in the model prediction. We can notice that there is a strong negative emotional word sad from nothing happened to make me sad, and the following piece almost burst into tears like 3 times today may also expressing a negative emotion. Here, our model computes a higher score to the text chunk almost burst into tears and a relatively lower score to make me sad, by looking at the corresponding columns, which means our model could discover implicit emotion semantics though no strong emotion word exists. 4

When doing classification, both special tokens of BERT [CLS] and [SEP] contain useful semantic information of the whole sequence, so the color tends to be brighter.
We show another example from Ren_CECps test set in Figure 2b: 阴沉的天，加上暗红色的地板，让房间显得压抑异常。 (The gloomy sky, together with the dark red floor, made the room look very depressing.) The ground truth labels are Sorrow and Anxiety. Our model successfully predicts these two class labels; moreover, the model also suggests that Hate as a possible label, which is reasonable in this particular example. Besides, in the annotation of the original dataset by (Quan and Ren, 2010), we found that two keywords are highlighted for this example: 阴沉 (gloomy): Surprise=0, Sorrow=0, Love=0, Joy=0, Hate=0, Expect=0, Anxiety=0.6, Anger=0; and 压抑 (depressing): Surprise=0, Sorrow=0.5, Love=0, Joy=0, Hate=0, Expect=0, Anxiety=0.7, Anger=0. Our model also captures such a trend successfully by showing a higher score near or on these token columns.

Quantitative Analysis So far, we have demonstrated that our model is able to identify the triggering words for each individual class from the confidence score of the token-label edges. To further show the quality of the identified triggering words, we compute the mean square error (MSE) between our best performed model and the ground-truth annotations for the test set of Ren_CECps. Similar to previous analysis, we first normalize the constructed token-label adjacency matrix $A_{token\_label}$, then construct a token-label matrix $A_{golden}$ from ground-truth annotations (for each sentence, there is only a few keywords, we assign zero to other non-keyword tokens). Then we are able to compute MSE score between the two aforementioned matrices: $MSE(A_{token\_label}, A_{golden})$. We also reconstruct the token-label matrix from the BERT+single model as a comparison. BERT+single has an MSE score of 0.0909 and BERT+HGCN has 0.0021. BERT+HGCN has a significant lower MSE score compared with BERT+single. The T-test between the two models based on the predictions is 0.0165, showing a significant difference. Please note that the other baseline model, BERT+multi fails to provide any token-label information, as there is no token-level connections to the final classification prediction layer (on sentence-level [CLS] is connected) and thus cannot be compared.

5.3 Label Correlations
As we model class labels as nodes in the heterogeneous graph, we can then investigate if and how the learned label node representations are meaningful. After training HGCN, we take the label node representations of the last HGCN layer and
calculate cosine similarity between each label pair. We assume that the meaningful representations of a label pair should have a small angle in the latent space (i.e., their cosine similarity tends to the value of 1) if they have a positive correlation, and a large angle if they have a negative correlation. We also compare with label correlations by looking at the model predictions. We collect model predictions in the test set and each label is represented as a binary vector with the dimension to be the size of test set, and then calculate Pearson correlation between each label pair. Similarly, if Pearson correlation tends to the value of 1 then it means a positive relationship; if the value tends to -1 then it means a negative relationship.

**Emotions in Semeval** We evaluate on SemEval and visualize the results in Figure 3. Pearson correlations in the testing data is shown in Figure 3a, which we consider as the ground truth. We can see that there are highly-correlated emotions: anger and disgust, pessimism and sadness, optimism and joy. Besides, the emotion sadness always appears with anger, disgust and fear. Such observations are compatible with our intuition.

We also show Pearson correlations for BERT-multi and HGCN. In Figure 3b, BERT-multi model missed some strong negative relationships, i.e., anger and joy, disgust and joy; and some positive relationships, i.e., pessimism and sadness. In Figure 3c, HGCN captures most of the label correlations in the ground truth, i.e., disgust has a strong positive correlation with anger, joy and optimism, joy and disgust. While it also captures the correlation between love and surprise, though not presented in the ground truth, this label correlation does not contradict our intuition because both two emotions are positive. Besides, we also calculate cosine similarities of the representations of label nodes from HGCN in Figure 3d. As we expected, the label node representations learned by HGCN properly reflect most of the positive correlations, such as anger with disgust, fear with pessimism etc., and negative correlations, such as anger with joy, love, optimism, and joy with sadness etc. By comparing cosine similarities of node representations and Pearson correlations of model predictions, we show that label node representations learned by HGCN are meaningful.

**Selected News Topics from RCV1-V2** In RCV1-V2 we select 9 topics randomly: government, (financial) performance, commodity market, consumer prices, domestic markets, acquisitions, funding and domestic politics. Due to the limited space, we only show Pearson correlations and cosine similarities between each pair of our HGCN model with the best performance in Figure 4. For the Pearson correlation, we could notice that the model captures strong positive relationships between the following pairs: commodity market and market, government and domestic politics, (financial) performance and domestic markets. These relationships are consistent with our real life, i.e., government news and domestic politics news are semantically very similar. We see a similar trend in the heatmap of cosine similarity for the mentioned label pairs. And in this way, more positive relations are found than negative ones, for example, domestic markets and funding, market and consumer prices.

### 6 Conclusion

In this work, we propose a heterogeneous graph model to solve the MLTC problem. We solve MLTC as link prediction, and propose two approaches for predicting output labels. Our model is able to provide token-level explanation for the classification. Experiments on three public datasets show that our model achieved promising scores.
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