Enhancing Mixup-Based Graph Learning for Language Processing via Hybrid Pooling

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Abstract

Graph neural networks (GNNs) have recently been popular in natural language and programming language processing, particularly in text and source code classification. Graph pooling which processes node representation into the entire graph representation, which can be used for multiple downstream tasks, e.g., graph classification, is a crucial component of GNNs. Recently, to enhance graph learning, Manifold Mixup, a data augmentation strategy that mixes the graph data vector after the pooling layer, has been introduced. However, since there are a series of graph pooling methods, how they affect the effectiveness of such a Mixup approach is unclear. In this paper, we take the first step to explore the influence of graph pooling methods on the effectiveness of the Mixup-based data augmentation approach. Specifically, 9 types of hybrid pooling methods are considered in the study, e.g., $M_{\text{sum}}(P_{\text{att}}, P_{\text{max}})$. The experimental results on both natural language datasets (Gossipcop, Politifact) and programming language datasets (Java250, Python800) demonstrate that hybrid pooling methods are more suitable for Mixup than the standard max pooling and the state-of-the-art graph multiset transformer (GMT) pooling, in terms of metric accuracy and robustness.

1 Introduction

Since the text, as well as the source code, can be represented as graph-structured data, graph neural networks (GNNs) have been recently applied for both natural language processing (NLP) [1], and programming language (PL) understanding [2, 3], and achieved remarkable results, e.g., work [4] processes source code as syntax tree and data flow and then utilizes GNNs to learn such representations for downstream tasks. This hot trend makes GNN more and more important in the NLP field.

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1 - Introduction

Typically, to train a GNN model with competitive performance, high-quality training data is necessary. However, preparing the labeled training data is not always easy due to the need for huge human effort with domain knowledge. Especially for the PL datasets, understanding code is the premise of labeling code. To alleviate the data labeling issue, data augmentation is one of the techniques that enhances the training data by adding diverse new data automatically generated from the original data during training. In which, Mixup [5] is one simple yet efficient data augmentation method that linearly mixes two data and their labels to create new cases. Although Mixup is initially proposed for image classification tasks, recent research demonstrates that it is also a good way to augment graph-structured data [6].

However, different from other data types (e.g., image) where the influence factors of Mixup that could affect the performance of the trained model are widely studied [7][8], and multiple variants of Mixup are proposed [9][10][11][12][13][14][15][16]. The analysis of Mixup for graph-structured data is still in an early stage. There might be various potential factors that could affect the training of GNNs when using Mixup. For instance, as an important component in GNNs, graph pooling transforms node representation into a graph representation used for downstream tasks. Moreover, generally, Mixup is applied to the transformed graph representation. This raises the question: how different graph pooling methods affect the effectiveness of Mixup?

In this paper, we tackle this problem by empirically analyzing the difference when Mixup is applied in different graph representations generated by different pooling methods. Specifically, we focus on two types of graph pooling methods, standard pooling methods, and hybrid (mixture) pooling methods. For the standard pooling, the Max pooling, which is the most widely used one, and the state-of-the-art graph multiset transformer pooling (GMT) are considered. For the hybrid pooling, we extend the prior work [17] and design 9 types of hybrid pooling strategies, e.g., $M_{\text{concat}}(P_{\text{att}}, P_{\text{max}})$. From another perspective, GMT and hybrid pooling methods are considered advanced.

In the experiments, we evaluate the clean accuracy and the robustness of the trained GNN models by using Mixup with different pooling methods. The results on NLP datasets (Gossipcop and Politifact used for fake news detection) and PL datasets (Java250 and Python800 used for problem classification) demonstrate that advanced pooling methods are more suitable for Mixup than max pooling methods. Specifically, in fake news detection, hybrid pooling outperforms max pooling by up to 3.16% accuracy and 31.91% robustness. In program classification, hybrid pooling surpasses max pooling by up to 1.46% accuracy and 10.21% robustness.

In summary, the contributions of this paper are as follows:

- This is the first work that explores the potential influence of graph pooling methods on Mixup-based graph-structured data augmentation.
- We discuss and further extend the hybrid pooling methods from existing works.
- The comprehensive empirical analysis demonstrates that hybrid pooling is a better way for Mixup-based graph-structured data augmentation.


2 Background and Related Work

2.1 Graph Data Classification

Researchers have proposed multiple approaches for the text classification task that analyze the data based on its graph structure. In which, [18] constructs text graph data by using the words and documents as nodes. To further enhance text classification performance, [19] proposes the graph-based word interaction to capture the contextual word relationships.

Similar to the text data, source code data can also be represented in graph structures. [20] mainly integrates four separate subgraph representations of source code into one joint graph data. Furthermore, to advance the generalization, [21] offers four code rewrite rules, such as variable renaming, comment deletion, etc., as a data augmentation for graph-level program classification. Different from the above works, our study focuses on Mixup-based graph classification.

2.2 Mixup

Due to its effectiveness in graph-structured data processing and the promising performance on graph-specific downstream tasks, e.g., graph classification, GNN has recently received considerable attention. Meanwhile, as a sophisticated data augmentation method, Mixup [5] is widely used in computer vision, and natural language processing and has recently been applied in the training process of GNNs.

[22] proposes two basic strategies of Mixup for augmenting data. One is wording embedding-based, and another is sentence embedding-based. After these two different kinds of embedding, the feature of input data can be mixed to synthesize the new data in vector space. To solve the difficulty in mixing text data in the raw format, [23] mixes text data from transformer-based pre-trained architecture. [24] increases the size of augmented samples by interpolating text data in hidden space. [25] generates extra labeled sequences in each iteration to augment the scale of training data. Unlike previous work, some researchers consider the raw text itself to augment the input data. [26] synthesizes the new text data from two raw input data by span-based mixing to replace the hidden vectors.

In our work, we do not simply employ Mixup for graph-structured data classification. Instead, we explore how different pooling strategies affect the effectiveness of Mixup.

2.3 Graph Pooling Methods

Graph pooling [27] plays a crucial role in capturing relevant structure information of the entire graph. [28] [29] [30] propose the basic graph pooling methods, such as summing or averaging all of the node features. However, such pooling methods treat every node information identically, which could lose the structural information. To solve this problem, [31] [32] [33] [34] drop nodes with lower scores using a learnable scoring function, which can compress the graph and alleviate the impact of irrelevant nodes to save the important structural information. Additionally, to locate the tightly related communities on a graph, [35] [36] [37] [38] consider the graph pooling as the
node clustering problem, where nodes are specifically aggregated to the same cluster. To combine these advantages, [39] first cluster nearby nodes locally and drop clusters with lower scores. In addition, there exists a kind of attention-based pooling methods [40, 41, 42, 43] that scores nodes with an attention mechanism to weight the relevance of nodes to the current graph-level task. Besides, different from the above standard pooling methods, [17] leverages a mixture of sum pooling and max pooling methods for graph classification.

Our study considers Mixup with both hybrid pooling and standard pooling on graph-level classification.

3 Mixup-Based Graph Learning via Hybrid Pooling

3.1 Overview

Figure 1 shows the overview of graph classification where the Manifold-Mixup technique is applied after the hybrid pooling layer. Concretely, first, GNNs process the graph-structured data and transform them to the node attributes \( \{x^i_V\}_{i=1}^n \). Then, after pooling all node embedding with the 3 types of readout functions-SUMPOOL, MAXPOOL, and AttentionPOOL, the hybrid pooling function produces the entire graph embedding. Finally, after the hybrid pooling layer, Manifold-mixup is applied to randomly mix selected two graph embedding \( \tilde{x}^G_i, \tilde{x}^G_j \) and their ground truth labels \( y^G_i, y^G_j \) with one-hot values as new training set for the classifier.

3.2 Graph-level hybrid pooling

Recent research has shown several methods with different levels of granularity for representing graphs, each with a different level of granularity, e.g., node-level representation and graph-level representation. Our work focuses on graph-level representation and its related downstream tasks.

Generally, GNNs learn the graph representation by exploiting the graph structure as an inductive bias. The GNN architecture proposed by [44] is the most popular and
3.2 Graph-level hybrid pooling

widely used in the applications. Briefly speaking, first, given a node with its initialized information, GNN computes the representation by iteratively aggregating its adjacent nodes (Aggregate). Then, it combines this aggregated representation with the existing node representation (Update). After that, a final representation of the complete graph is created by pooling this node representation. The primary areas where the various models differ are how they handle the aggregation, update, and pooling.

Mathematically, given a graph-structured data $G(V, \varepsilon)$, where $V$ is the vertex set and $\varepsilon$ represents the edge set, we simply formulate the entire graph $x_G$ representation as follows:

$$H^k_u = \text{GNN} \left( H^{k-1}_u, W, \sum_{v \in N(u)} H^{k-1}_v \right)$$

$$H^G = P \left( H^k_{u,u \in V}, V \right)$$

where $H^{k-1}_u$ and $H^{k-1}_v$ denote the matrix representation of node $u$ and $v$ ($u, v \in V, uv \in \varepsilon$) at the $(k-1)$-th iteration. Meanwhile, $H^G$ also refers the latent vector of the entire graph $x_G$. Let $N(u)$ be the set of neighbor nodes of $u$. Firstly, neural network GNN($\cdot$) is used to iteratively update the latent vector of each node via the message aggregated from the neighborhood $\sum_{v \in V(u)} H^{k-1}_v$, wherein $W$ represents the trainable parameter matrix. After that, the pooling method $P(\cdot)$ is used to construct the vector representation of the entire graph, which captures the global information, after the $k$ steps of iteration.

We consider three standard pooling methods in our study, which are as follows:

$$P_{\text{att}}(H, V) = \sum_{i=1}^{\text{Num}(V)} \sigma \left( W H^i_k + b \right) \odot \phi \left( W H^i_k + b \right)$$

$$P_{\text{sum}}(H, V) = \sum_{i=1}^{\text{Num}(V)} H^i_k$$

$$P_{\text{max}}(H, V) = \max_{i=1}^{\text{Num}(V)} H^i_k$$

where $\phi$ represents the nonlinear activation function and $H^i_k$ refers to the final vector representation of the $i$-th node, wherein $\sigma \left( W H^i_k + b \right)$ acts as a soft attention mechanism. We leverage the global attention pooling $P_{\text{att}}$ as it better captures relevant global features for graph-level tasks. Finally, we examine three hybrid pooling functions as:

$$M_{\text{sum}}(P, H) = H^G_{P_1} + H^G_{P_2}$$

$$M_{\text{mul}}(P, H) = H^G_{P_1} \odot H^G_{P_2}$$

$$M_{\text{concat}}(P, H) = W \left( [H^G_{P_1} \parallel H^G_{P_2}] \right) + b$$

where $H^G_{P_1}, H^G_{P_2}$ means the embedding vector of the entire graph produced by pooling methods $P_1, P_2 (P_1 \neq P_2)$, wherein, $W$ is a linear transformation matrix to reduce the dimension ($\mathbb{R}^{2d} \to \mathbb{R}^d$).

To conclude, the hybrid pooling layer, which consists of the pooling function and
### 3.3 Mixup via hybrid pooling

Mixup employing the hybrid pooling layer is shown as:

\[
\tilde{x}_{G}^{\text{mix}} = \lambda \tilde{x}_{i}^{G} + (1 - \lambda) \tilde{x}_{j}^{G}
\]

\[
y_{G}^{\text{mix}} = \lambda y_{i}^{G} + (1 - \lambda) y_{j}^{G}
\]

where, \( \tilde{x}^{G} \) is the graph embedding and \( y^{G} \) refers to its label embedding with one-hot value, wherein \( \lambda \) means the Mixup ratio.

### 4 Experimental Setup

#### 4.1 Dataset and Model

**Dataset.** We conduct our study on both traditional NLP and PL tasks. For the NLP, we consider the famous task User Preference-aware Fake News Detection (UPFD) [45], which is a text-level text binary classification problem. For the PL, we consider function level problem multi-classification task provided by Project_CodeNet [46]. Two popular programming languages, Java and Python, are included in our study.
4.1 Dataset and Model

Table 2: Details of datasets and DNNs. #Training, #Ori Test, and #Robust Test represent the number of training data, original test data, and test data for generalization evaluation, respectively.

| Dataset     | Task              | #Training | #Clean Test | #Robust Test | Model               |
|-------------|-------------------|-----------|-------------|--------------|---------------------|
| Gossipcop   | Fake news detection | 62        | 221         | 314          | GCN                 |
|             |                   |           |             |              | GCN-Virtual         |
|             |                   |           |             |              | GIN                 |
|             |                   |           |             |              | GIN-Virtual         |
| Politifact  | Fake news detection | 1092      | 3826        | 5464         | GIN                 |
|             |                   |           |             |              | GIN-Virtual         |
| Java250     | Problem classification | 48000     | 15000       | 75000        | GCN                 |
|             |                   |           |             |              | GIN                 |
| Python800   | Problem classification | 153600    | 48000       | 240000       | GAT                 |
|             |                   |           |             |              | GraphSAGE           |

UPFD contains two sets of tree-structured fake and real news propagation graphs derived from Twitter. Given a single graph, the source news is represented by the root node, and leaf nodes represent Twitter users who retweeted the root news. Edges reflect the 1) connection between users and the 2) connection between the user and root news that have been retweeted. Moreover, UPFD also includes 4 different node feature types, which are 10-dimensional Profile feature that is derived from ten user profile attributes, 300-dimensional Spacy feature encoded using spacy Word2vec, 768-dimensional Bert feature encoded by BERT, and 310-dimensional Content feature composed of the sum of Spacy and Profile. In general, fake news detection can be considered a binary classification, since GNNs output a negative or positive prediction given a graph of user preference.

Project_CodeNet provides two datasets, Java250 and Python800. Java250 consists of 250 classification problems, where each problem has 300 Java programs. Python800 contains 800 classification problems, and each problem has 300 Python programs. The raw data of these two datasets are transformed into graph representation based on the simplified parse tree. We follow the same process as the original paper to divide the datasets into training, validation, and test sets in our experiment.

Model. We build 4 different GNN architectures for each dataset. In the text classification, we follow the recommendation of [45] and build Graph Convolution Network (GCN) [47], Graph Isomorphism Network (GIN) [30], Graph Attention Network (GAT) [48], and GraphSAGE [49] models. GCN, which is a variant of a convolution neural network, is dedicated to operating graph-structured data. GAT mainly uses the attention mechanism for graph message passing. GIN is designed to generalize the Weisfeiler-Lehman (WL) test. GraphSAGE effectively generates node embeddings for previously undiscovered data by utilizing node feature information. In program classification, we use GNN models (GCN, GCN-Virtual, GIN, and GIN-Virtual) provided by [46]. Especially to enhance the aggregation phase of GNNs, virtual nodes, which involve adding an artificial node to each network and connecting it in both directions to all other graph nodes, are offered. To sum up, Table 2 shows the details of used datasets and models in our experiment.
4.2 Experiment Settings

We implement the hybrid pooling layer based on the open-source library PyG (Pytorch Geometric) [50]. The training epochs we set for Project_CodeNet and UPFD are 100 and 200, respectively. The batch size is set to 80 for Project_CodeNet and 128 for UPFD. For the optimizer, we use Adam [51] with the learning rate $10^{-3}$ for all the models. For Mixup ratio, $\alpha = 0.1$ is our default setting. To alleviate overfitting, we adopt early stopping with patience 20. To reduce the impact of randomness, we train each GNN model five times by using different random seeds. We present the average experimental results with standard deviation in the later Section. All the experiments were conducted on a server with 2 GPUs of NVIDIA RTX A6000.

4.3 Evaluation Metrics

We evaluate the trained model from two perspectives, clean accuracy (Accuracy) and robustness accuracy (Robustness). The general accuracy means the percentage of correctly identified data among the given test data. The robustness reflects the generalization ability of the trained model [52]. For clean accuracy, we evaluate the models on the default test set provided by the original datasets. For the robustness accuracy, we create a new test set following previous works [53, 54, 55] which focus on evaluating the robustness of GNNs. In detail, given the structured data, we attack the local connectivity of a node to its neighbors and change the topological feature to generate new data.

5 Results Analysis

Table 3: Detailed accuracy and robustness results (%) of trained GCN models on NLP datasets. A gray background highlights results that are better than MAXPOOL. The best average results are marked by red color.

| Dataset | Accuracy | Robustness |
|---------|----------|------------|
| | Profile | Spacy | Bert | Content | Average | Profile | Spacy | Bert | Content | Average |
| Base | 96.84 ± 0.58 | 95.12 ± 0.54 | 95.51 ± 0.52 | 95.91 ± 0.54 | 96.01 ± 0.55 | 95.94 ± 0.54 | 95.91 ± 0.54 | 95.98 ± 0.54 | 96.02 ± 0.55 | 96.01 ± 0.55 |
| MAXPOOL | 78.28 ± 0.98 | 67.81 ± 1.23 | 66.64 ± 1.05 | 67.65 ± 1.22 | 67.63 ± 1.23 | 67.65 ± 1.22 | 67.65 ± 1.22 | 67.68 ± 1.22 | 67.70 ± 1.23 | 67.69 ± 1.23 |
| GMT | 93.17 ± 0.86 | 91.60 ± 0.85 | 91.61 ± 0.86 | 91.62 ± 0.87 | 91.63 ± 0.88 | 91.63 ± 0.88 | 91.63 ± 0.88 | 91.64 ± 0.88 | 91.65 ± 0.89 | 91.65 ± 0.89 |
| Mixup | 94.11 ± 0.79 | 94.11 ± 0.79 | 94.11 ± 0.79 | 94.11 ± 0.79 | 94.11 ± 0.79 | 94.11 ± 0.79 | 94.11 ± 0.79 | 94.11 ± 0.79 | 94.11 ± 0.79 | 94.11 ± 0.79 |

We study the influence of pooling methods on the Mixup training first, then go deeper into the hyperparameter settings of Mixup.
5.1 Pooling Methods Analysis

Table 4: Average results (%) of GAT, GraphSAGE, and GIN models on NLP datasets. Results that are better than MAXPOOL are highlighted by gray background. The best average results are marked by red color.

| Accuracy | Gossipcop | Politifact | Robustness | Gossipcop | Politifact |
|----------|-----------|------------|------------|-----------|------------|
| **GAT**  |           |            |            |           |            |
| Base     | 96.00     | 80.81      | 94.22      | 79.26     |            |
| MAXPOOL  | 95.43     | 80.38      | 94.46      | 76.19     |            |
| Type1    | 96.51     | 81.36      | 94.88      | 81.11     |            |
| Type2    | 96.33     | 80.98      | 94.30      | 77.54     |            |
| Type3    | 96.80     | 81.41      | 94.44      | 76.19     |            |
| Type4    | 93.32     | 79.69      | 91.64      | 76.35     |            |
| Type5    | 96.33     | 79.31      | 93.66      | 76.27     |            |
| Type6    | 94.68     | 81.36      | 93.28      | 75.56     |            |
| Type7    | 94.78     | 80.29      | 93.86      | 75.66     |            |
| Type8    | 95.35     | 80.58      | 94.09      | 77.89     |            |
| Type9    | 95.77     | 81.07      | 94.20      | 79.19     |            |
| **GraphSAGE** |           |            |            |           |            |
| Base     | 95.26     | 81.75      | 94.64      | 79.89     |            |
| MAXPOOL  | 94.82     | 81.12      | 86.35      | 74.26     |            |
| Type1    | 96.46     | 82.39      | 93.95      | 81.05     |            |
| Type2    | 96.22     | 81.27      | 92.87      | 79.24     |            |
| Type3    | 96.01     | 81.71      | 95.89      | 79.69     |            |
| Type4    | 95.10     | 81.42      | 92.70      | 77.77     |            |
| Type5    | 95.09     | 80.41      | 93.74      | 76.94     |            |
| Type6    | 93.84     | 80.80      | 94.56      | 77.03     |            |
| Type7    | 94.19     | 80.33      | 92.36      | 75.45     |            |
| Type8    | 94.70     | 80.89      | 93.58      | 77.00     |            |
| Type9    | 95.15     | 81.66      | 93.43      | 78.90     |            |
| **GIN**  |           |            |            |           |            |
| Base     | 95.21     | 82.06      | 80.80      | 69.80     |            |
| MAXPOOL  | 94.75     | 82.21      | 76.01      | 72.98     |            |
| Type1    | 95.91     | 82.98      | 90.25      | 71.05     |            |
| Type2    | 95.47     | 82.52      | 71.97      | 70.21     |            |
| Type3    | 95.38     | 82.53      | 78.46      | 70.83     |            |
| Type4    | 94.80     | 81.52      | 81.86      | 78.69     |            |
| Type5    | 94.30     | 81.42      | 84.73      | 79.11     |            |
| Type6    | 95.99     | 81.93      | 84.27      | 78.06     |            |
| Type7    | 95.00     | 81.67      | 82.64      | 77.68     |            |
| Type8    | 95.74     | 80.96      | 71.42      | 65.30     |            |
| Type9    | 94.96     | 82.17      | 81.45      | 79.62     |            |

Table 5 presents the detailed results of GCN models on NLP datasets. Table 6 shows the average results of the GAT, GraphSAGE, and GIN models. The detailed results of these three models can be found in Appendix A.1. From the results, first, we can see that Mixup is a powerful technique for augmenting graph-structured data. Compared to the model trained without Mixup (Base in the tables), the Mixup-trained models are more accurate and robust. Then, concerning different pooling methods, we can see that the basic and widely used max pooling method (MAXPOOL) and the state-of-the-art GMT pooling methods (GMT) are not the best choice for Mixup training. There are always some hybrid pooling methods that achieve better results than them. More specifically, on average, the type 1 hybrid pooling method can achieve better results than the max pooling method in most cases (9 out of 10 cases). Moreover, maybe surprisingly, the gap between using advanced pooling methods and max pooling methods can be up to 2.55% of clean accuracy (Gossipcop, Type1, Profile) and 23.27% of robustness (Gossipcop, Type4, Profile).

Table 6 presents the results of PL datasets. We can see that the advanced graph pooling methods are more helpful than the max pooling method for Mixup when dealing with PL data, where the best results are always from the hybrid pooling methods. Similar to the results of traditional NLP datasets, the type 1 pooling method outperforms the
5.1 Pooling Methods Analysis

Table 5: Accuracy and robustness (%) of trained models on PL datasets. Results that are better than MAXPOOL are highlighted by gray background. The best average results are marked by red color.

|       | Accuracy | Robustness |
|-------|----------|------------|
|       | Java250  | Python800  | Java250  | Python800  |
| Base  | 92.29 ± 0.17 | 93.73 ± 0.03 | 92.05 ± 2.10 | 93.37 ± 1.65 |
| MAXPOOL | 92.39 ± 0.08 | 93.94 ± 0.07 | 92.29 ± 2.14 | 93.63 ± 1.32 |
| GMT   | 92.50 ± 0.02 | 94.29 ± 0.06 | 93.65 ± 1.67 | 93.80 ± 1.02 |
| Type1 | 92.51 ± 0.25 | 93.66 ± 0.02 | 93.63 ± 2.07 | 93.16 ± 2.46 |
| Type2 | 92.71 ± 0.45 | 94.99 ± 0.12 | 94.27 ± 1.43 | 93.94 ± 1.89 |
| Type3 | 91.99 ± 0.11 | 93.90 ± 0.08 | 93.62 ± 2.02 | 93.15 ± 1.67 |
| Type4 | 91.86 ± 0.16 | 93.72 ± 0.04 | 93.18 ± 1.25 | 93.77 ± 2.01 |
| Type5 | 92.78 ± 0.09 | 93.09 ± 0.21 | 92.91 ± 1.87 | 93.17 ± 1.47 |
| Type6 | 91.96 ± 0.10 | 92.45 ± 0.19 | 91.98 ± 1.87 | 93.19 ± 1.68 |
| Type7 | 92.81 ± 0.09 | 93.66 ± 0.12 | 94.74 ± 2.56 | 94.97 ± 2.01 |
| Base  | 92.57 ± 0.04 | 93.54 ± 0.26 | 94.07 ± 1.41 | 93.12 ± 1.86 |
| MAXPOOL | 93.35 ± 0.05 | 94.15 ± 0.05 | 95.11 ± 2.02 | 92.28 ± 1.65 |
| GMT   | 93.13 ± 0.11 | 95.19 ± 0.11 | 95.69 ± 1.03 | 95.12 ± 1.83 |
| Type1 | 93.11 ± 0.17 | 94.31 ± 0.19 | 95.01 ± 1.63 | 94.38 ± 1.76 |
| Type2 | 93.95 ± 0.06 | 94.72 ± 0.01 | 94.22 ± 3.25 | 94.47 ± 1.38 |
| Type3 | 93.21 ± 0.10 | 93.97 ± 0.08 | 94.51 ± 2.32 | 94.71 ± 2.06 |
| Type4 | 93.42 ± 0.14 | 93.52 ± 0.15 | 94.96 ± 2.01 | 94.32 ± 2.11 |
| Type5 | 94.81 ± 0.12 | 94.22 ± 0.01 | 94.41 ± 1.09 | 94.49 ± 1.68 |
| Type6 | 93.14 ± 0.15 | 97.33 ± 0.05 | 92.89 ± 1.32 | 92.99 ± 1.68 |
| Type7 | 93.08 ± 0.22 | 94.42 ± 0.14 | 93.31 ± 1.40 | 93.53 ± 2.12 |
| Type8 | 95.63 ± 0.03 | 95.90 ± 0.06 | 94.37 ± 2.13 | 95.59 ± 1.22 |
| Base  | 94.66 ± 0.07 | 93.39 ± 0.18 | 95.91 ± 2.34 | 95.48 ± 1.28 |
| MAXPOOL | 93.84 ± 0.31 | 94.27 ± 0.21 | 95.66 ± 2.04 | 96.13 ± 1.34 |
| GMT   | 92.49 ± 0.26 | 93.88 ± 0.33 | 94.17 ± 1.87 | 92.77 ± 1.87 |
| Type1 | 94.68 ± 0.27 | 93.19 ± 1.03 | 94.22 ± 0.76 | 94.62 ± 0.75 |
| Type2 | 93.32 ± 0.34 | 94.18 ± 0.39 | 93.11 ± 2.01 | 94.14 ± 2.01 |
| Type3 | 90.00 ± 0.29 | 94.96 ± 0.09 | 96.54 ± 2.26 | 96.56 ± 1.09 |
| Type4 | 91.21 ± 0.23 | 94.39 ± 0.26 | 95.11 ± 1.34 | 95.15 ± 1.54 |
| Type5 | 91.04 ± 0.31 | 93.78 ± 0.11 | 94.38 ± 1.76 | 93.51 ± 1.76 |
| Type6 | 92.17 ± 0.31 | 93.54 ± 0.15 | 94.16 ± 2.11 | 93.59 ± 2.11 |
| Type7 | 92.35 ± 0.29 | 92.99 ± 0.25 | 93.04 ± 1.98 | 91.37 ± 1.55 |
| Type8 | 92.69 ± 0.45 | 92.43 ± 0.19 | 92.71 ± 2.31 | 91.64 ± 1.65 |
| Type9 | 93.31 ± 0.33 | 93.29 ± 0.21 | 94.35 ± 1.78 | 94.19 ± 1.34 |
| Base  | 94.60 ± 0.06 | 94.06 ± 0.08 | 93.12 ± 1.46 | 94.57 ± 1.28 |
| MAXPOOL | 92.57 ± 0.36 | 94.46 ± 0.16 | 94.17 ± 2.11 | 96.09 ± 2.13 |
| GMT   | 92.66 ± 0.49 | 93.01 ± 0.22 | 93.92 ± 1.86 | 93.57 ± 1.24 |
| Type1 | 93.01 ± 0.62 | 92.39 ± 0.32 | 93.70 ± 2.24 | 93.98 ± 1.76 |
| Type2 | 92.47 ± 0.23 | 93.49 ± 0.14 | 93.73 ± 2.01 | 93.87 ± 1.22 |
| Type3 | 92.89 ± 0.20 | 92.52 ± 0.19 | 92.59 ± 2.24 | 92.11 ± 1.77 | 93.34 ± 1.58 |
| Type4 | 92.39 ± 0.39 | 93.43 ± 0.23 | 93.47 ± 1.88 | 92.98 ± 1.68 |

max pooling method in most situations (11 out of 12 cases). Unlike the NLP datasets, the type 3 pooling method consistently achieves better results than max pooling. In PL datasets, the gap between using advanced and max pooling methods can be up to 1.46% of clean accuracy (GIN, Java250, Type6) and 10.21% of robustness (GIN, Python800, Type3).

From the results of both traditional NLP datasets and PL datasets, we can conclude that the graph pooling method has a significant impact on the effectiveness of the Mixup data augmentation technique when dealing with graph-structured datasets. The type 1 ($\mathcal{M}_{\text{sum}}(P_{\text{att}}, P_{\text{max}})$) advanced pooling method is the best choice among our considered candidates and is recommended to be used in the graph representation.
Although the type 1 hybrid pooling method is the best for producing high-performance when dealing with graph-structured data. However, the potential influence of $\alpha$, which is the key hyperparameter in the Mixup technique, on the effectiveness of the Mixup training is still unclear. In this part, we tend to explore such influence using the dataset Politifact with Profile node embedding. We set the $\alpha$ from 0.05 to 0.5 in 0.05 intervals.

Table 6: Results (%) of Mixup-trained GCN models (dataset: Politifact) using the hybrid pooling layer with different $\alpha$ settings. The best results are marked by red color.

| Alpha | Accuracy | Robustness |
|-------|----------|------------|
| 0.05  | 76.38 ± 0.38 | 76.02 ± 1.28 |
| 0.10  | 76.12 ± 0.48 | 75.99 ± 1.38 |
| 0.15  | 76.02 ± 0.58 | 75.94 ± 1.38 |
| 0.20  | 75.98 ± 0.68 | 75.90 ± 1.38 |
| 0.25  | 75.94 ± 0.78 | 75.86 ± 1.38 |
| 0.30  | 75.90 ± 0.88 | 75.82 ± 1.38 |
| 0.35  | 75.86 ± 0.98 | 75.78 ± 1.38 |
| 0.40  | 75.82 ± 1.08 | 75.74 ± 1.38 |
| 0.45  | 75.78 ± 1.18 | 75.70 ± 1.38 |
| 0.50  | 75.74 ± 1.28 | 75.66 ± 1.38 |

Table 6 presents the detailed results of GCN models on the Politifact dataset when using the Mixup training strategy with different $\alpha$ settings. And Figure 2 depicts the trend of average (row Average) in Table 6 results of all the models. The detailed results of other models can be found in Appendix A.2. First, we can see that although both the accuracy and robustness difference between using different $\alpha$ is not that big, i.e., the gap between accuracy (robustness) is 1.3% (1.23%). The smaller $\alpha$ can produce models with better performance, which is consistent with the conclusion of the original Mixup work [5]. Especially for the robustness, there is a clear decreasing trend when $\alpha$ becomes bigger.

Then, we analyze how $\alpha$ affects each type of graph pooling methods. Column Std shows the standard deviation of the results of each pooling method. We can see that, in the type level, $\alpha$ also does not greatly impact the Mixup training. The maximum standard deviation is only 1.84% (accuracy of type 3). Maybe interestingly, we can find the two most stable and least stable types, i.e., type 4 ($M_{\text{sum}}(P_{\text{att}}, P_{\text{max}})$) pooling method always has the smallest standard deviation values while Type 3 ($M_{\text{concat}}(P_{\text{att}}, P_{\text{max}})$) always has the biggest ones.

In conclusion, Mixup for graph-structured data with hybrid graph pooling is resilient to the $\alpha$ setting. Moreover, small $\alpha$ is recommended in the practical usage of Mixup. Although the type 1 hybrid pooling method is the best for producing high-performance models, type 4 is the most stable method that is least affected by $\alpha$.

6 Threats to Validity

The internal threat to validity comes from implementing the GNNS, each pooling method, and the Mixup for graph-structured data. The implementation of GNNS is based on [50].
7 Conclusions

In this paper, we comprehensively investigated how the graph pooling methods impact the effectiveness of Mixup when dealing with graph-structured data. We considered the basic max pooling method, the state-of-the-art GMT pooling method, and nine different hybrid pooling methods defined by ourselves. In the empirical analysis part,

and the implementation of Mixup for graph data is based on the official released project of Mixup [5].

External validity threats lie in the selected NLP and PL tasks, datasets, and GNNs. We consider both the traditional NLP tasks (text level) and PL tasks (source code level) in the study and include two datasets for each task. Particularly, for the NLP task, we consider two well-studied datasets and four types of node embedding. For the PL task, we include two popular programming languages (Java and Python). For the GNN models, we consider six famous graph neural networks: GCN, GCN-Virtual, GIN, GIN-Virtual, GAT, and GraphSAGE.

The construct threats to validity mainly come from the parameters of Mixup, randomness, and evaluation measures. Mixup only contains the parameter $\alpha$ that controls the weight of mixing two input instances. We follow the recommendation of the original Mixup algorithm and investigate the impact of this parameter. Moreover, further, we explore the impact of $\alpha$ in our study. To reduce the impact of randomness, we repeat each experiment five times with different random seeds and report the average and standard deviation results. Finally, concerning the evaluation measures, we consider both the test accuracy on original test data and the robustness of corrupted test data. The latter one is specific for evaluating the generalization ability of GNNs.

7 Conclusions

The accuracy and robustness trendings with different $\alpha$ are depicted in Figure 2.

Figure 2: Accuracy and robustness trendings with different $\alpha$. 
we conducted experiments on both traditional NLP tasks (fake news detection) and PL tasks (problem classification) using six types of GNN architecture. The experimental results demonstrated that the pooling method significantly impacts the effectiveness of Mixup, where hybrid pooling methods outperform the max pooling and GMT pooling methods in terms of producing accurate and robust models. The hyperparameter $\alpha$ has a limited impact on Mixup for augmenting graph-structured data. This study gave the lesson that, when using Mixup in GNNs, carefully choosing the pooling methods could help produce better models.

Limitations
The main limitation of this work is the selection of standard pooling methods. Besides the max pooling method and GMT pooling method, there are multiple other methods proposed in the literature, e.g., MincutPool [37], and TopKPool [32]. We only considered the basic one and the SOTA one. In future work, we plan to study more pooling methods and give more comprehensive conclusions.

References

[1] Zonghan Wu, Shirui Pan, Fengwen Chen, Guodong Long, Chengqi Zhang, and S Yu Philip. A comprehensive survey on graph neural networks. IEEE transactions on neural networks and learning systems, 32(1):4–24, 2020.

[2] Elizabeth Dinella, Hanjun Dai, Ziyang Li, Mayur Naik, Le Song, and Ke Wang. Hoppity: Learning graph transformations to detect and fix bugs in programs. In International Conference on Learning Representations (ICLR), 2020.

[3] Wenhan Wang, Ge Li, Bo Ma, Xin Xia, and Zhi Jin. Detecting code clones with graph neural network and flow-augmented abstract syntax tree. In 2020 IEEE 27th International Conference on Software Analysis, Evolution and Reengineering (SANER), pages 261–271. IEEE, 2020.

[4] Miltiadis Allamanis, Marc Brockschmidt, and Mahmoud Khademi. Learning to represent programs with graphs. In International Conference on Learning Representations, 2018.

[5] Hongyi Zhang, Moustapha Cisse, Yann N. Dauphin, and David Lopez-Paz. mixup: Beyond empirical risk minimization. In International Conference on Learning Representations, 2018.

[6] Yiwei Wang, Wei Wang, Yuxuan Liang, Yujun Cai, and Bryan Hooi. Mixup for node and graph classification. In Proceedings of the Web Conference 2021, pages 3663–3674, 2021.

[7] Linjun Zhang, Zhun Deng, Kenji Kawaguchi, and James Zou. When and how mixup improves calibration. arXiv preprint arXiv:2102.06289, 2021.
[8] Linjun Zhang, Zhun Deng, Kenji Kawaguchi, Amirata Ghorbani, and James Zou. How does mixup help with robustness and generalization? *arXiv preprint arXiv:2010.04819*, 2020.

[9] Vikas Verma, Alex Lamb, Christopher Beckham, Amir Najafi, Ioannis Mitliagkas, David Lopez-Paz, and Yoshua Bengio. Manifold mixup: Better representations by interpolating hidden states. In *International Conference on Machine Learning*, pages 6438–6447. PMLR, 2019.

[10] Cecilia Summers and Michael J Dinneen. Improved mixed-example data augmentation. In *2019 IEEE Winter Conference on Applications of Computer Vision (WACV)*, pages 1262–1270. IEEE, 2019.

[11] Hongyu Guo, Yongyi Mao, and Richong Zhang. Mixup as locally linear out-of-manifold regularization. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 33, pages 3714–3722, 2019.

[12] Ryo Takahashi, Takashi Matsubara, and Kuniaki Uehara. Ricap: Random image cropping and patching data augmentation for deep cnns. In *Asian conference on machine learning*, pages 786–798. PMLR, 2018.

[13] Sangdoo Yun, Dongyoon Han, Seong Joon Oh, Sanghyuk Chun, Junsuk Choe, and Youngjoon Yoo. Cutmix: Regularization strategy to train strong classifiers with localizable features. In *Proceedings of the IEEE/CVF international conference on computer vision*, pages 6023–6032, 2019.

[14] Jang-Hyun Kim, Wonho Choo, and Hyun Oh Song. Puzzle mix: Exploiting saliency and local statistics for optimal mixup. In *International Conference on Machine Learning*, pages 5275–5285. PMLR, 2020.

[15] Yuan Wu, Diana Inkpen, and Ahmed El-Roby. Dual mixup regularized learning for adversarial domain adaptation. In *European Conference on Computer Vision*, pages 540–555. Springer, 2020.

[16] Xudong Mao, Yun Ma, Zhenguo Yang, Yangbin Chen, and Qing Li. Virtual mixup training for unsupervised domain adaptation. *arXiv preprint arXiv:1905.04215*, 2019.

[17] Van-Anh Nguyen, Van Nguyen, Trung Le, Quan Hung Tran, Dinh Phung, et al. Regvd: Revisiting graph neural networks for vulnerability detection. In *2022 IEEE/ACM 44th International Conference on Software Engineering: Companion Proceedings (ICSE-Companion)*, pages 178–182. IEEE, 2022.

[18] Liang Yao, Chengsheng Mao, and Yuan Luo. Graph convolutional networks for text classification. In *Proceedings of the AAAI conference on artificial intelligence*, volume 33, pages 7370–7377, 2019.

[19] Yufeng Zhang, Xueli Yu, Zeyu Cui, Shu Wu, Zhongzhen Wen, and Liang Wang. Every document owns its structure: Inductive text classification via graph neural networks. *arXiv preprint arXiv:2004.13826*, 2020.
[20] Yaqin Zhou, Shangqing Liu, Jingkai Siow, Xiaoning Du, and Yang Liu. Devign: Effective vulnerability identification by learning comprehensive program semantics via graph neural networks. Advances in neural information processing systems, 32, 2019.

[21] Miltiadis Allamanis, Henry Jackson-Flux, and Marc Brockschmidt. Self-supervised bug detection and repair. Advances in Neural Information Processing Systems, 34:27865–27876, 2021.

[22] Hongyu Guo, Yongyi Mao, and Richong Zhang. Augmenting data with mixup for sentence classification: An empirical study. arXiv preprint arXiv:1905.08941, 2019.

[23] Lichao Sun, Congying Xia, Wenpeng Yin, Tingting Liang, Philip S Yu, and Lifang He. Mixup-transformer: dynamic data augmentation for nlp tasks. arXiv preprint arXiv:2010.02394, 2020.

[24] Jiaao Chen, Zichao Yang, and Diyi Yang. Mixtext: Linguistically-informed interpolation of hidden space for semi-supervised text classification. arXiv preprint arXiv:2004.12239, 2020.

[25] Rongzhi Zhang, Yue Yu, and Chao Zhang. Seqmix: Augmenting active sequence labeling via sequence mixup. arXiv preprint arXiv:2010.02322, 2020.

[26] Soyoung Yoon, Gyuwan Kim, and Kyumin Park. Ssmix: Saliency-based span mixup for text classification. arXiv preprint arXiv:2106.08062, 2021.

[27] Zhitao Ying, Jiaxuan You, Christopher Morris, Xiang Ren, Will Hamilton, and Jure Leskovec. Hierarchical graph representation learning with differentiable pooling. Advances in neural information processing systems, 31, 2018.

[28] James Atwood and Don Towsley. Diffusion-convolutional neural networks. Advances in neural information processing systems, 29, 2016.

[29] Martin Simonovsky and Nikos Komodakis. Dynamic edge-conditioned filters in convolutional neural networks on graphs. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 3693–3702, 2017.

[30] Keyulu Xu, Weihua Hu, Jure Leskovec, and Stefanie Jegelka. How powerful are graph neural networks? arXiv preprint arXiv:1810.00826, 2018.

[31] Muhan Zhang, Zhicheng Cui, Marion Neumann, and Yixin Chen. An end-to-end deep learning architecture for graph classification. In Proceedings of the AAAI conference on artificial intelligence, volume 32, 2018.

[32] Hongyang Gao and Shuiwang Ji. Graph u-nets. In International conference on machine learning, pages 2083–2092. PMLR, 2019.

[33] Junhyun Lee, Inyeop Lee, and Jaewoo Kang. Self-attention graph pooling. In International conference on machine learning, pages 3734–3743. PMLR, 2019.
REFERENCES

[34] Cătălina Cangea, Petar Veličković, Nikola Jovanović, Thomas Kipf, and Pietro Liò. Towards sparse hierarchical graph classifiers. *arXiv preprint arXiv:1811.01287*, 2018.

[35] Yao Ma, Suhang Wang, Charu C Aggarwal, and Jiliang Tang. Graph convolutional networks with eigenpooling. In *Proceedings of the 25th ACM SIGKDD international conference on knowledge discovery & data mining*, pages 723–731, 2019.

[36] Yu Guang Wang, Ming Li, Zheng Ma, Guido Montúfar, Xiaosheng Zhuang, and Yanan Fan. Haarpooling: Graph pooling with compressive haar basis. 2019.

[37] Filippo Maria Bianchi, Daniele Grattarola, and Cesare Alippi. Spectral clustering with graph neural networks for graph pooling. In *International Conference on Machine Learning*, pages 874–883. PMLR, 2020.

[38] Hao Yuan and Shuiwang Ji. Structpool: Structured graph pooling via conditional random fields. In *Proceedings of the 8th International Conference on Learning Representations*, 2020.

[39] Ekagra Ranjan, Soumya Sanyal, and Partha Talukdar. Asap: Adaptive structure aware pooling for learning hierarchical graph representations. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 34, pages 5470–5477, 2020.

[40] Yujia Li, Daniel Tarlow, Marc Brockschmidt, and Richard Zemel. Gated graph sequence neural networks. *arXiv preprint arXiv:1511.05493*, 2015.

[41] Jia Li, Yu Rong, Hong Cheng, Helen Meng, Wenbing Huang, and Junzhou Huang. Semi-supervised graph classification: A hierarchical graph perspective. In *The World Wide Web Conference*, pages 972–982, 2019.

[42] Dzmitry Bahdanau, Kyunghyun Cho, and Yoshua Bengio. Neural machine translation by jointly learning to align and translate. *arXiv preprint arXiv:1409.0473*, 2014.

[43] Jinheon Baek, Minki Kang, and Sung Ju Hwang. Accurate learning of graph representations with graph multiset pooling. *arXiv preprint arXiv:2102.11533*, 2021.

[44] Justin Gilmer, Samuel S Schoenholz, Patrick F Riley, Oriol Vinyals, and George E Dahl. Neural message passing for quantum chemistry. In *International conference on machine learning*, pages 1263–1272. PMLR, 2017.

[45] Yingtong Dou, Kai Shu, Congying Xia, Philip S Yu, and Lichao Sun. User preference-aware fake news detection. In *Proceedings of the 44th International ACM SIGIR Conference on Research and Development in Information Retrieval*, pages 2051–2055, 2021.
A. Additional Results

A.1 Pooling Methods Analysis

Table 7, 8, and 9 present the detailed results of GAT, GraphSAGE, and GIN models on NLP datasets with 4 different types of node embedding. Similar to the results of the GCN model (Table 3), type 1 \(M_{sum}(P_{att}, P_{max})\) is still the recommended pooling method which achieves better results than max pooling method in most cases (10 out of 12 cases).
Table 7: Detailed accuracy and robustness results (%) of trained GAT models on NLP datasets. Results that are better than MAXPOOL are highlighted by gray background. The best average results are marked by red color.

| Method | Politifact | Type2 | GMT | Type9 | Average | Politifact | Type2 | GMT | Type9 | Average |
|--------|------------|-------|-----|-------|---------|------------|-------|-----|-------|---------|
| Robustness | 77.23 ± 0.55 | 94.81 ± 0.24 | 78.73 ± 0.67 | 76.89 ± 0.99 | 76.93 ± 1.28 | 76.71 ± 0.97 | 93.12 ± 0.16 | 92.38 ± 0.42 | 77.65 ± 1.52 | 78.89 ± 1.88 | 94.41 ± 0.11 | 94.38 ± 0.23 | 77.61 ± 0.32 | 79.45 ± 1.00 | 90.38 ± 1.50 |

Table 8: Detailed accuracy and robustness results (%) of trained GraphSAGE models on NLP datasets. Results that are better than MAXPOOL are highlighted by gray background. The best average results are marked by red color.

| Method | Politifact | Type2 | GMT | Type9 | Average | Politifact | Type2 | GMT | Type9 | Average |
|--------|------------|-------|-----|-------|---------|------------|-------|-----|-------|---------|
| Robustness | 75.37 ± 1.11 | 79.41 ± 0.66 | 82.78 ± 0.33 | 86.07 ± 2.14 | 80.81 ± 0.85 | 75.26 ± 0.69 | 77.61 ± 0.47 | 79.54 ± 0.19 | 84.52 ± 0.62 | 79.28 |
## A.1 Pooling Methods Analysis

Table 9: Detailed accuracy and robustness results (%) of trained GIN models on NLP datasets. Results that are better than MAXPOOL are highlighted by gray background. The best average results are marked by red color.
### Table 10: Results (%) of Mixup-trained GAT models (dataset: Politifact) using the hybrid pooling layer with different $\alpha$ settings. The best results are marked by red color.

| Model | $\alpha$ | Accuracy | Std | Hy | Accuracy | Std |
|-------|--------|----------|-----|-----|----------|-----|
| Type2 | 0.05   | 76.36    | 0.19 | 76.91 | 76.14    | 0.19 |
| Type3 | 0.10   | 76.91    | 0.19 | 76.91 | 76.14    | 0.19 |
| Type4 | 0.15   | 76.91    | 0.19 | 76.91 | 76.14    | 0.19 |
| Type5 | 0.20   | 76.91    | 0.19 | 76.91 | 76.14    | 0.19 |
| Type6 | 0.25   | 76.91    | 0.19 | 76.91 | 76.14    | 0.19 |
| Type7 | 0.30   | 76.91    | 0.19 | 76.91 | 76.14    | 0.19 |
| Type8 | 0.35   | 76.91    | 0.19 | 76.91 | 76.14    | 0.19 |
| Type9 | 0.40   | 76.91    | 0.19 | 76.91 | 76.14    | 0.19 |
| Type10| 0.45   | 76.91    | 0.19 | 76.91 | 76.14    | 0.19 |
| Type11| 0.50   | 76.91    | 0.19 | 76.91 | 76.14    | 0.19 |

### A.2 Alpha Analysis

### Table 11: Results (%) of Mixup-trained GraphSAGE models (dataset: Politifact) using the hybrid pooling layer with different $\alpha$ settings. The best results are marked by red color.

| Model | $\alpha$ | Accuracy | Std | Hy | Accuracy | Std |
|-------|--------|----------|-----|-----|----------|-----|
| Type2 | 0.05   | 76.36    | 0.19 | 76.91 | 76.14    | 0.19 |
| Type3 | 0.10   | 76.91    | 0.19 | 76.91 | 76.14    | 0.19 |
| Type4 | 0.15   | 76.91    | 0.19 | 76.91 | 76.14    | 0.19 |
| Type5 | 0.20   | 76.91    | 0.19 | 76.91 | 76.14    | 0.19 |
| Type6 | 0.25   | 76.91    | 0.19 | 76.91 | 76.14    | 0.19 |
| Type7 | 0.30   | 76.91    | 0.19 | 76.91 | 76.14    | 0.19 |
| Type8 | 0.35   | 76.91    | 0.19 | 76.91 | 76.14    | 0.19 |
| Type9 | 0.40   | 76.91    | 0.19 | 76.91 | 76.14    | 0.19 |
| Type10| 0.45   | 76.91    | 0.19 | 76.91 | 76.14    | 0.19 |
| Type11| 0.50   | 76.91    | 0.19 | 76.91 | 76.14    | 0.19 |

### A.2 Alpha Analysis

Table 10 [11] and [12] present the results of GAT, GraphSAGE, and GIN models on Politifact dataset when using Mixup training strategy with different $\alpha$ settings [0.05 - 0.5]. We can see the conclusion in Section 5.2 Mixup for graph-structured data with hybrid graph pooling is resilient to the $\alpha$ setting can still stand.
Table 12: Results (%) of Mixup-trained GIN models (dataset: Politifact) using the hybrid pooling layer with different $\alpha$ settings. The best results are marked by red color.

| Model | $\alpha$ | Accuracy | Robustness |
|-------|---------|-----------|------------|
| Type1 | 0.05    | 75.87 ± 2.14 | 73.22 ± 1.34 |
|       | 0.10    | 78.28 ± 0.93 | 74.42 ± 2.45 |
|       | 0.15    | 75.72 ± 1.83 | 75.06 ± 3.78 |
|       | 0.20    | 74.96 ± 1.14 | 75.06 ± 1.45 |
|       | 0.25    | 78.43 ± 1.45 | 76.76 ± 0.34 |
|       | 0.30    | 77.98 ± 0.26 | 75.21 ± 1.95 |
|       | 0.35    | 77.52 ± 0.46 | 74.87 ± 0.87 |
|       | 0.40    | 76.77 ± 0.69 | 74.87 ± 1.34 |
|       | 0.45    | 78.13 ± 1.59 | 74.87 ± 1.34 |
|       | 0.50    | 77.38 ± 0.38 | 73.59 ± 1.23 |
| Average |         | 78.03 ± 2.34 | 73.34 ± 0.65 |

| Model | $\alpha$ | Accuracy | Robustness |
|-------|---------|-----------|------------|
| Type2 | 0.05    | 76.47 ± 0.45 | 75.98 ± 2.85 |
|       | 0.10    | 77.92 ± 2.85 | 76.37 ± 2.85 |
|       | 0.15    | 76.37 ± 2.85 | 76.37 ± 2.85 |
|       | 0.20    | 75.57 ± 2.75 | 76.37 ± 2.85 |
|       | 0.25    | 76.37 ± 2.85 | 76.37 ± 2.85 |
|       | 0.30    | 75.72 ± 1.45 | 76.37 ± 2.85 |
|       | 0.35    | 76.62 ± 1.14 | 76.37 ± 2.85 |
|       | 0.40    | 76.62 ± 1.14 | 76.37 ± 2.85 |
|       | 0.45    | 76.69 ± 0.56 | 76.37 ± 2.85 |
|       | 0.50    | 77.58 ± 0.66 | 76.37 ± 2.85 |
| Average |         | 77.59 ± 0.66 | 76.65 ± 0.56 |

| Model | $\alpha$ | Accuracy | Robustness |
|-------|---------|-----------|------------|
| Type3 | 0.05    | 79.34 ± 0.26 | 79.34 ± 0.69 |
|       | 0.10    | 77.74 ± 0.74 | 77.74 ± 0.74 |
|       | 0.15    | 78.58 ± 2.23 | 78.58 ± 2.23 |
|       | 0.20    | 77.83 ± 1.45 | 77.83 ± 1.45 |
|       | 0.25    | 78.88 ± 1.05 | 78.88 ± 1.05 |
|       | 0.30    | 77.23 ± 1.05 | 77.23 ± 1.05 |
|       | 0.35    | 79.04 ± 0.69 | 79.04 ± 0.69 |
|       | 0.40    | 77.83 ± 2.39 | 77.83 ± 2.39 |
|       | 0.45    | 79.34 ± 0.26 | 79.34 ± 0.26 |
|       | 0.50    | 77.98 ± 1.71 | 77.98 ± 1.71 |
| Average |         | 77.75 ± 0.66 | 77.75 ± 0.66 |

| Model | $\alpha$ | Accuracy | Robustness |
|-------|---------|-----------|------------|
| Type4 | 0.05    | 79.19 ± 0.91 | 79.19 ± 0.91 |
|       | 0.10    | 77.74 ± 1.71 | 77.74 ± 1.71 |
|       | 0.15    | 79.49 ± 1.14 | 79.49 ± 1.14 |
|       | 0.20    | 78.24 ± 1.14 | 78.24 ± 1.14 |
|       | 0.25    | 79.33 ± 1.75 | 79.33 ± 1.75 |
|       | 0.30    | 78.58 ± 1.59 | 78.58 ± 1.59 |
|       | 0.35    | 77.92 ± 1.71 | 77.92 ± 1.71 |
|       | 0.40    | 76.98 ± 1.26 | 76.98 ± 1.26 |
|       | 0.45    | 77.38 ± 1.71 | 77.38 ± 1.71 |
|       | 0.50    | 77.75 ± 1.71 | 77.75 ± 1.71 |
| Average |         | 77.51 ± 1.71 | 77.51 ± 1.71 |