Online cross-layer knowledge distillation on graph neural networks with deep supervision

Jiongyu Guo¹ · Defang Chen² · Can Wang²

Received: 8 November 2022 / Accepted: 14 July 2023 / Published online: 8 August 2023
© The Author(s), under exclusive licence to Springer-Verlag London Ltd., part of Springer Nature 2023

Abstract
Graph neural networks (GNNs) have become one of the most popular research topics in both academia and industry communities for their strong ability in handling irregular graph data. However, large-scale datasets are posing great challenges for deploying GNNs in edge devices with limited resources and model compression techniques have drawn considerable research attention. Existing model compression techniques such as knowledge distillation mainly focus on convolutional neural networks. Only limited attempts have been made recently for distilling knowledge from GNNs in an offline manner. As the performance of the teacher model does not necessarily improve as the number of layers increases in GNNs, selecting an appropriate teacher model will require substantial efforts. To address these challenges, we propose a novel online knowledge distillation framework called Alignahead++ in this paper. Alignahead++ transfers structure and feature information in a student layer to the previous layer of another simultaneously trained student model in an alternating training procedure. Meanwhile, to avoid over-smoothing problem in GNNs, deep supervision is employed in Alignahead++ by adding an auxiliary classifier in each intermediate layer to prevent the collapse of the node feature embeddings. Experimental results on four datasets including PPI, Cora, PubMed and CiteSeer demonstrate that the student performance is consistently boosted in our collaborative training framework without the supervision of a pre-trained teacher model and its effectiveness can generally be improved by increasing the number of students.

Keywords Online knowledge distillation · Graph neural networks · Cross-layer alignment · Deep supervision

1 Introduction
Recent years have witnessed the great success of graph neural networks (GNNs) in tackling irregular data and facilitating their downstream tasks such as node classification [1–3], link prediction [4, 5] and node clustering [6]. However, the large-scale datasets and high-capacity architectures increase the computing and memory costs, making the deployment of large models difficult in platforms with limited resources. To address the above issues, mainstream model compression techniques such as knowledge distillation are explored and have achieved great success in compressing convolutional neural networks (CNNs) [7–13]. The most common form of knowledge distillation is offline KD where the compressed student model mimics the soft targets or hidden feature maps extracted from a well-trained teacher model, thus boosting the performance of student model and even outperforming the teacher model [11]. Comparing with CNNs, GNNs will encounter additional complexity in that besides soft targets or feature maps, it shall take into consideration graph topological structure in knowledge distillation.

There exist only a few recent works in distilling knowledge from GNNs. Yang et al. [14] modeled the local structure preserving (LSP) as the pairwise similarity of connected node features transferred from a pre-trained teacher model to a student model, which was the first
attempt of knowledge distillation from GNNs. The subsequent researches mainly focus on adding auxiliary modules [15] to assist training or introducing more effective knowledge [16, 17] to capture comprehensive graph information or graph-free settings [18]. Existing KD methods for GNNs are mostly offline (see Fig. 1a), i.e., the common teacher-student manner. An important part in offline knowledge distillation is to select a qualified teacher model. In CNNs, the teacher models are large models with more learning capacity and parameters. However, this does not apply to GNNs due to the over-smoothing problem [19–21], i.e., the performance of GNNs does not necessarily improve as the number of layers increases. Selecting a qualified teacher model for student model is thus a time-consuming and laborious task as it requires substantial efforts and experiments. Furthermore, training costs, privacy and heterogeneous data sources between teacher and student are all issues that need to be addressed in distilling from GNNs.

Inspired by recent works that the student performance can be boosted by learning from other peers [22–24], as shown in Fig. 1b, we propose a strategy called Alignahead++, where each student model layer learns the structure information and feature information from the next layer of another student model in an alternating training procedure. Theoretical analysis proves that Alignahead++ strategy with alternate training can spread structure and feature information over all layers of the two student models after several epochs and each student layer can effectively capture the global structure information. Meanwhile, previous studies have shown that with the increasing number of layers in GNNs, the over-smoothing problem will deteriorate significantly, i.e., the connected node embeddings will converge to a fixed point and thus degrade the performance of the model on downstream tasks. A disastrous training error will be back-propagated from the last layer to earlier layers in deep GNNs if only the last layer is supervised, which will disrupt the shallow feature embeddings. Therefore, we borrow the idea from the deep-supervised learning [25, 26], adding an auxiliary classifier to each intermediate layer of GNNs, and then apply supervision to the predictions of each auxiliary classifier.

One important issue in Alignahead++ is selecting the auxiliary classifier. Different from conventional data such as image data, graph data need to consider structure information in its feature embeddings. As multilayer perceptron (MLP) (commonly used in CNNs) cannot express the structure of the underlying graph data, we introduce structure-aware projection heads in Alignahead++, which uses a single GNN layer of the corresponding student model to capture the graph structure. Experiments show that the effect of a single GNN layer is better than that of a single MLP layer, and only one layer is sufficient. Although our framework will increase a small number of parameters and time consumption, this is within an acceptable range. To verify the effectiveness of Alignahead++, we conduct experiments on different public datasets and different GNN architectures. The main contributions of this paper are highlighted as follows:

- We propose an online knowledge distillation framework called Alignahead++ for GNNs which is combined with the deep-supervised learning to supervise each intermediate layer.
- Each student layer is aligned ahead with the layer in different depth of another student model, which helps to
spread structure and feature information over all layers after a couple of training iterations.

- The introduced deep supervision module posing label supervision on intermediate layers alleviates the over-smoothing problem in deep GNNs.
- Experimental results on various datasets and model architectures demonstrate that Alignahead++ framework can effectively improve the performance of student models.

The earlier version of this paper [27] was accepted by 2022 International Joint Conference on Neural Network (IJCNN 2022). In this work, we combine the Alignahead strategy with deep-supervised learning, termed as Alignahead++, to further improve the performance of the previously proposed online knowledge distillation framework and alleviate the over-smoothing problem in deep GNNs. In addition, we conduct a series of more detailed experiments, such as (a) two student models with different structures; (b) different layer numbers and structures (GNNs or MLPs) of auxiliary classifier and (c) sensitivity analysis of new hyperparameters.

The rest of this paper is organized as follows. We introduce the related work of deep-supervised learning and knowledge distillation in GNNs in Sect. 2. In Sect. 3, we introduce our proposed Alignahead++ strategy. Section 4 shows the experimental results, such as the node classification results on four kinds of datasets, sensitivity analysis of hyperparameters and the exploration of auxiliary classifiers. Finally, we conclude this paper in Sect. 5.

2 Related work

2.1 Knowledge distillation

Knowledge distillation is one of the most popular techniques in model compression [7], which utilizes a powerful but cumbersome teacher model to boost a compressed student model. Hinton et al. [8] first proposed the concept of knowledge distillation, trying to transfer the soft targets, i.e., the teacher model predictions to the student models. It is believed that the soft targets can capture the relationship among classes and apply regularization during the training. In addition to soft targets, feature maps in the intermediate layers are another form of knowledge [9–12]. Romero et al. [9] first put forward FitNet to reduce the distance of feature embeddings between teacher models and student models. Agoruyko et al. [10] considered the attention mechanism and extracted attention maps instead of features. SemCKD [11] utilizes the attention mechanism to automatically assign adaptive intermediate features for student model. SimKD [13] achieves incredible effect just by reusing the teacher’s classifier. Lin et al. [28] proposed a novel one-to-all spatial matching knowledge distillation approach to solve the inconsistency of semantic information in the same location between teacher model and student model. Zhao et al. [29] divided the classic KD loss into two parts, i.e., target class knowledge distillation (TCKD) and non-target class knowledge distillation (NCKD), and further proved the influence of these two parts with experiments.

However, training a large teacher model in advance is time-consuming and requires high computing resources. In a worse case, we cannot even get a teacher model. The online knowledge distillation [22–24] is proposed to address these issues, where a group of student models are trained simultaneously by aggregating and aligning their outputs. Compared with the offline knowledge distillation mentioned above, online knowledge distillation can still boost the performance of the student model when reducing the training costs. Deep mutual learning [22] trained a group of student models collaboratively by learning the soft targets from each other. OKDDip [24] introduced multiple auxiliary peers and one team leader, proposing a novel two-level online knowledge distillation framework.

2.2 Graph neural networks

The recently proposed graph neural networks [1–3, 30–32] have achieved great success in processing irregular data, such as 3D point clouds [33] and protein property [34]. Kipf et al. [1] proposed the graph convolution network (GCN), which propagates node features by spectral graph convolutions. GraphSAGE [3] further improved the scalability by sampling neighbor nodes and aggregating their features. Graph attention network (GAT) [2] performs attention-based message passing to upgrade graph representations.

However, as the number of layers increases, GNNs face the challenge of over-smoothing, that is, deep node feature embeddings will converge to a stationary point and become indistinguishable, which will degrade the performance of the model on downstream tasks. Li et al. [19] showed GCN model is actually a special form of Laplacian smoothing and first found the potential concerns of over-smoothing. Rong et al. [35] retarded the convergence of over-smoothing by randomly removing a certain number of edges from the input graph at each epoch, thus alleviating the over-smoothing problem. Some researchers try to design GNNs that can memorize initial node features to alleviate this problem, such as DeeperGCN [36] and GCNII [32]. Our work is perpendicular to DeeperGCN and other work mentioned above, that is, Alignahead++ can be used in any form of GNN models.
2.3 Deeply supervised learning

Deeply supervised networks (DSNs) [26] which added extra supervision to the hidden layer of convolutional neural networks (CNNs) were proposed to speed up the convergence of CNNs and solve the vanishing gradient problem. This technique has shown good ability in various tasks, such as image classification [26], machine translation [37] and image retargeting [38].

Zhang et al. [39] proposed the self-distillation with the idea of deep supervision, where a single student model uses its deep predictions, feature maps and label to supervise its shallow layers. In GNNs, there is little research on deep supervision applications. Elinas et al. [40] made the first attempt to combine deep supervision with GNNs.

2.4 Knowledge distillation on graph neural networks

Knowledge distillation has achieved great success in computer vision and natural language processing tasks [13, 41]. However, due to the particularity of graph data, that is, both feature embeddings and topological structures need to be considered, existing knowledge distillation methods cannot be directly applied to GNNs.

LSP [14] was the first attempt of knowledge distillation on GNNs. It aligned the local structure of the student nodes with the corresponding teacher nodes based on the kernel function. Yang et al. [17] proposed a well-designed student model as a combination of label propagation and feature transformation. Joshi et al. [16] extended the LSP module to global structure preservation (GSP) module and combined it with contrastive learning. GraphAKD [15] adaptively reduces the discrepancy between student and teacher models by training an additional generator and discriminator. Yang et al. [42] proposed a general knowledge distillation framework for GNNs and introduced node-specific distillation temperatures rather a fixed temperature to get better performance.

The work in this paper, Alignahead++, combines deep supervision with Alignahead, which alleviates the over-smoothing problem of the deep GNNs and can further improve the performance of shallow GNNs.

3 Method

This section is organized into three subsections. Section 3.1 gives a brief introduction of local structure preserving. In Sect. 3.2, we will detail our proposed Alignahead++. In the last section, we will explain why the structure and feature information will flow from layer to layer.

3.1 Local structure preserving (LSP)

The core idea of LSP [14] is to force the nodes of the student model to imitate the local structure of the teacher nodes. The similarity $L_{ij}$ between node $i$ and its neighbor nodes $j(i, j) \in \varepsilon$ in the feature space is calculated with one of the following kernel functions and then normalized with a softmax function

$$D(z_i, z_j) = \begin{cases} \frac{\| z_i - z_j \|_2^2}{z_i \cdot z_j} & \text{Euclidean} \\ (z_i \cdot z_j + c)^d & \text{Poly} \\ e^{-\frac{1}{2}\| z_i - z_j \|_2^2} & \text{RBF} \end{cases}$$

(1)

$$L_{ij} = \frac{e^{D(z_i, z_j)}}{\sum_{(i,j) \in \varepsilon} (D(z_i, z_j))}$$

(2)

where $z_i$ and $z_j$ are the node features. The local structure $L_i$ of node $i$ is quantified as the probability distribution of similarity between node $i$ and its neighbor nodes.

The student model is trained with KL divergence to mimic the local structure of the certain teacher layer in the feature space:

$$L_{isp} = \frac{1}{N} \sum_{i=1}^{N} D_{KL}(L_i^s || L_i^t).$$

(3)

3.2 The proposed Alignahead++

This section introduces the proposed Alignahead++ detailedy. We will start by explaining the motivation behind the previous Alignahead strategy. Although the method based on offline knowledge distillation has achieved some success in GNNs, the pre-training process of the teacher model faces various challenges. Online knowledge distillation eliminates the tedious pre-training process of teacher model and improves performance by simultaneously training a group of student models. Besides, LSP aligns only one layer between the student model and the teacher model but wastes information on the other layers. Therefore, we take advantage of the alternating training of online knowledge distillation and propose Alignahead strategy, where one student layer is aligned ahead with the layer in different depth of the another student model. In each round of alternate training, the structure information of each student layer is transferred to the previous layer of another student model, and finally the structure information will spread over all layers.
However, Alignahead strategy only considers the structure information of graph data while ignoring the rich semantic information contained in node feature embeddings. The intermediate semantic information of teacher model is always transferred to student model as knowledge in CNNs and has achieved great success [9–11, 43, 44]. In Alignahead, the similarity between node feature embeddings calculated by kernel function only contains the relationship strength of two nodes, but the semantic information of each node itself is lost. Therefore, we add an additional auxiliary classifier in each intermediate layer to make full use of the semantic information containing in nodes by transferring classification results in different semantic spaces. For the auxiliary classifier, we use a single GNN layer just the same as the backbone network instead of MLP commonly used in CNNs, because GNN layer has structure-aware function compared with MLP. Besides, student models trained by Alignahead still suffers from over-smoothing problem, so we introduce deep supervision technique, where we add the supervision of label to the each intermediate layer predictions to prevent node feature embeddings in the deep layer from becoming indistinguishable. Our collaborative training framework with two student models is illustrated in Fig. 2 and contains three parts of loss: label loss, deeply supervised loss and Alignahead loss. Next, we will talk about these three types of losses.

### 3.2.1 Label loss

This part of loss is conventional, that is, label-based supervision is carried out on the backbone network predictions. Suppose we have two student models $S_1$ and $S_2$ with the same architecture, the intermediate layer number is $H$. Then the ground-truth loss of $S_1$ and $S_2$ is

$$
L_{ce}^{S_1} = \text{CrossEntropy}(p_1^{S_1}, y) \\
L_{ce}^{S_2} = \text{CrossEntropy}(p_1^{S_2}, y)
$$

(4)

where $L_{ce}^{S_1/S_2}$ is a cross-entropy loss function calculated with the student predictions $p_1^{S_1/S_2}$ and the label $y$.

### 3.2.2 Deeply supervised loss

Deep supervision introduces the label information from the dataset to each layer of the backbone network directly by adding an additional auxiliary classifier in all intermediate layers. The auxiliary classifier is chosen a single GNN layer with the same structure as the backbone network.

Let $f_i^{S_1}$ and $f_i^{S_2}$ represent the feature embeddings of node $j$ in the layer $i$. Since the last layer of the student model itself is a classifier, there is no need to add an auxiliary classifier. Thus, the feature embeddings of the last layer are the final predictions of the model, that is

$$f_H^{S_1/S_2} = p_H^{S_1/S_2}
$$

(5)

### Algorithm 1: Alignahead++ for collaborative distillation

**Input:** The parameters $\theta_1$ and $\theta_2$ of the student $S_1$ and $S_2$ with auxiliary classifiers; The calculated local structure and intermediate layer predictions; hyper-parameter $\alpha, \beta, \lambda$ and label $y$.

**Output:** $S_1$ and $S_2$ with excellent performance.

1. Initialization parameters $\theta_1$ and $\theta_2$.
2. while $epochs \leq \text{max\_epoch}$ do
   3. // Training loss of $S_1$
   4. Obtain the structure loss $L_{str}^{S_1}$ with Equ. (8) and Equ. (9).
   5. Obtain the feature loss $L_{fea}^{S_1}$ with Equ. (11) and Equ. (12).
   6. Obtain the deeply-supervised loss $L_{ds}^{S_1}$ with Equ. (7).
   7. Obtain the label loss $L_{ce}^{S_1}$ with Equ. (4).
   8. Construct the total loss for $S_1$ as Equ. (14) and Equ. (16).
   9. **Update** the parameter $\theta_1$ while keeping $\theta_2$ fixed.
10. // Training loss of $S_2$
11. Obtain the structure loss $L_{str}^{S_2}$ with Equ. (8) and Equ. (10).
12. Obtain the feature loss $L_{fea}^{S_2}$ with Equ. (11) and Equ. (13).
13. Obtain the deeply-supervised loss $L_{ds}^{S_2}$ with Equ. (7).
14. Obtain the label loss $L_{ce}^{S_2}$ with Equ. (4).
15. Construct the total loss for $S_1$ as Equ. (15) and Equ. (17).
16. **Update** the parameter $\theta_2$ while keeping $\theta_1$ fixed.

end
For the other layers, feature embeddings need to be mapped into the class semantic space through their respective auxiliary classifiers. We have tried two types of auxiliary classifier, i.e., MLP and one single GNN layer. During the training process, the auxiliary classifiers and the backbone network are updated simultaneously. Compared with MLP, GNN layer can capture the topology information (including the neighbor structure of the nodes), that is,

\[ p_{i,j}^{S_1/S_2} = \begin{cases} 
    \text{GNN}(f_{i,j}^{S_1/S_2}, j_{i,k}^{S_1/S_2}), & (j, k) \in e \\
    \text{MLP}(f_{i,j}^{S_1/S_2}) 
\end{cases} \]

(6)

where \( p_{i,j}^{S_1/S_2} \) are the predictions of node \( j \) in layer \( i \) of two student models. In addition, it is natural and reasonable to use classifiers consistent with the backbone network structure. For the above reasons, GNN layer is more suitable as the auxiliary classifier. But anyway, we explore the performance of these two classifiers and the effect of the layer numbers in the experiment section.

Similar with the label loss, the target of deeply supervised loss is the intermediate layer predictions. In order to simplify the form, the last-layer predictions are still added in the calculation of deeply supervised loss.

\[
L_{ds}^{S_1} = \sum_{i=1}^{H} \text{CrossEntropy}(p_i^{S_1}, y) \\
L_{ds}^{S_2} = \sum_{i=1}^{H} \text{CrossEntropy}(p_i^{S_2}, y)
\]

(7)
3.2.3 Alignedahead loss

Alignedahead loss is divided into two parts, namely, structure loss and feature loss. Structure loss is used to capture the relationship between nodes, while feature loss is used to supervise the semantic information of nodes themselves. We will start by introducing the structure loss.

For two student models $S_1$ and $S_2$ with $H$ layers, we use $l_{ij}^{S_1}$ and $l_{ij}^{S_2}$ to represent the local structure of node $j$ in the $i$-th layer. As mentioned above, the local structure $l_{ij}^{S_1/S_2}$ is quantified as the probability distribution of similarity between node $i$ and its neighbor nodes in layer $j$. For $S_1$, its local structure of $i$-th layer is required to match the $(i+1)$-th layer of $S_2$ and the final layer $H$ is required to match the first layer. The structure loss is calculated as the sum of KL divergence loss over all layers

$$L_{str}^{S_1} = \sum_{i=1}^{H} l_{ij}^{S_1}, \quad L_{str}^{S_2} = \sum_{i=1}^{H} l_{ij}^{S_2},$$

where

$$L_{str}^{S_1} = \frac{1}{N} \sum_{j=1}^{N} D_{KL}(p_{ij}^{S_1} \| p_{ij}^{S_1}),$$

$$L_{str}^{S_2} = \frac{1}{N} \sum_{j=1}^{N} D_{KL}(p_{ij}^{S_2} \| p_{ij}^{S_2}).$$

Next it comes to feature loss. Similar to the structure loss, feature loss also adopts Alignedahead strategy. We align the predictions $p_{ij}^{S_1}$ of $S_1$ in layer $i$ with $p_{ij+1}^{S_2}$ of $S_2$ in layer $i+1$ and take the sum of KL divergence of all layers as the feature loss

$$L_{fea}^{S_1} = \sum_{i=1}^{H} L_{fe}^{S_1}, \quad L_{fea}^{S_2} = \sum_{i=1}^{H} L_{fe}^{S_2},$$

where

$$L_{fe}^{S_1} = \frac{1}{N} \sum_{j=1}^{N} D_{KL}(p_{ij}^{S_1} \| p_{ij}^{S_1}),$$

$$L_{fe}^{S_2} = \frac{1}{N} \sum_{j=1}^{N} D_{KL}(p_{ij}^{S_2} \| p_{ij}^{S_2}).$$

3.2.4 The combination of loss

We will talk about how to get the final loss function in this section. For the intermediate layer predictions of the student model, they are constrained by both the labels and the previous layer of the peer model, which can correspond to labels and soft targets in the offline knowledge distillation.

**Table 1** The meanings of the first two loss terms when $\lambda$ and $\beta$ take extreme values

| $\beta$ | $\lambda$ | $\beta$ |
|--------|----------|--------|
| 1      | 0        | 1      |
| 0      | Label loss | Label loss |
| 1      | Deeply supervised loss | Feature loss |

Therefore, we use the hyperparameter $\lambda$ to balance the two parts of loss

$$L_{ds-fea}^{S_1} = \lambda L_{fe}^{S_1} + (1-\lambda)L_{str}^{S_1}$$

$$L_{ds-fea}^{S_2} = \lambda L_{fe}^{S_2} + (1-\lambda)L_{str}^{S_2}$$

Then combine it with label loss and structure loss

$$L_{S_1} = (1-\beta)L_{ce}^{S_1} + \beta L_{ds-fea}^{S_1} + \alpha L_{str}^{S_1}$$

$$L_{S_2} = (1-\beta)L_{ce}^{S_2} + \beta L_{ds-fea}^{S_2} + \alpha L_{str}^{S_2}$$

where $\lambda, \beta \in [0, 1]$. The second loss term is divided by the number of layers $H$ to match the magnitude of label loss. We fix $\alpha = 1$, since we have found in our previous work [27] that the experiment results are not sensitive to the value of this hyperparameter. In order to show the role of the other two hyperparameters more clearly, Table 1 shows the meanings of the first two loss terms when they take extreme values. In the experiment section, we will also conduct sensitivity studies on these two hyperparameters. Two student models $S_1$ and $S_2$ are trained alternately as shown in Algorithm 1. Then, we analyze the additional algorithmic complexity introduced by the Alignedahead++ framework. Set the kernel function as RBF, and get the complexity of LSP as $O(V^2 \cdot F \cdot L)$, where $V$ is the number of nodes, $F$ is the feature dimension, and $L$ is the number of layers. Set the auxiliary classifier as one layer MLP and we can get the complexity introduced by the it is $O(V \cdot L \cdot F \cdot F')$, where $F'$ is the number of classes. Therefore, with $N$ student models, the additional computational complexity introduced by Alignedahead++ framework is $O(V^2 \cdot F \cdot L \cdot N + V \cdot L \cdot F \cdot F' \cdot N)$

3.3 Why the structure and feature information spread over all layers?

This section will explain why the structure and feature information spreads over all layers. For convenience, we will only focus on structure information, and it is the same with feature information. Figure 3 reveals the flow of structure information during an alternating training
procedure. It can be seen that each student layer is aligned ahead with the next layer of another student model and the last layer is to match the first layer specially. In this way, the two student models exchange structure information with each other and propagate it in different layer depth.

Table 2 shows the distribution of structure information of two student models with three hidden layers in six iterations. Theoretically, the structure information of each layer is circulated once inside the two student models. Take the layer-1 of the Student-1 model as an example, it gathers the structure information in $l_1^2$, $l_2^1$, $l_3^2$, $l_2^2$, $l_1^3$, and $l_1^1$ one-by-one, and returns to the initial state in the sixth iteration. That is to say, the layer-1 of the Student-1 model indeed collects the structure information from all layers of two student models within the first six iterations. Similar phenomenon also happens in other layers, making the structure information spread over all layers.

### 4 Experiments

We first introduce four benchmark datasets, the experimental settings, three popular graph neural network architectures and compared methods adopted in our experiments in Sect. 4.1. Sections 4.2 and 4.3 detail the experimental results with different methods in four datasets and demonstrate that Alignahead++ can alleviate the oversmoothing problem in deep GNNs. Next, we explore the performance of the student models with different hyperparameters choice and two different architectures in Sects. 4.4 and 4.5, respectively. Finally, we explore the effect of auxiliary classifiers and student numbers.

### 4.1 Datasets, model architectures and compared methods

Four benchmark datasets are used in our experiments, and their summary is shown in Table 3 and listed as follows:

- PPI [45] consists of 24 graphs corresponding to different human tissues, where 20 graphs are used for training, two graphs are used for validation, and another 2 graphs are used for testing. The average node
numbers for each graph are 2372. Each node has 50 features, consisting of positional gene sets, motif gene sets and immunological signatures. The number of labels is 121 and a node can have multiple labels at the same time.

- Cora [46, 47] and CiteSeer [48] consist of citation networks on computer science, and both two are widely used in GNNs. Each node represents a paper, and the edge directly connected between nodes represents the citation relationship. The feature is a binary vector indicating the presence or absence of a word in the paper, and the label represents the topic.
- PubMed [49] is the citation network on diabetes in PubMed database. The meanings of nodes and edges are the same as Cora. Node features are TF/IDF-weighted word frequencies, and the label represents the type of diabetes.

The adopted models are briefly listed as follows:

- GCN [1] propagates node features by defining spectral graph convolutions on graph data. It is the most widely used baseline model in GNNs.
- SAGE [3] updates node features by sampling neighbor nodes and aggregating their information. SAGE-mean and SAGE-pool are used as student models.
- GAT [2] introduces the attention mechanism to automatically assign weights to nodes’ neighbors. In the PPI dataset, we adopt GAT with different layers and feature dimensions.

The results of three methods are presented in comparison:

- Baseline means the student model is trained with the labels alone.
- Alignahead is our previous work proposed specifically for GNNs [27]. Each student model layer learns the structure information from the next layer of another student model in an alternating training procedure.
- OC is the ablation model of Alignahead. It keeps the setting of online knowledge distillation but changes cross-layer matching to one-to-one correspondence, which means each layer of the student model is matched with the corresponding layer of the peer model.
- Alignahead++ means the student models are trained with our proposed online cross-layer distillation framework combined with deep supervision, as shown in Algorithm 1.

In the case of the PPI dataset, we train all the three student models on the visible graph to make predictions on completely invisible graphs. We refer to the experiment settings of [14], where the learning rate, weight decay, optimizer and epochs are 0.005, 0, Adam and 300, respectively. We adopt the RBF kernel function for distance calculation in LSP module, and σ is 100, while on other four datasets, we apply GCN [1] and two variants of SAGE [3] as student models to predict the unknown nodes on the visible graph. We adopt one set of experiment settings from [3], where the learning rate, weight decay, optimize are 0.001, 0.0001, Adam, respectively; we also set up 300 epochs and the RBF kernel function is adopted for all models. For the auxiliary classifiers, we use one GNN layer that is consistent with the trunk model, such as the GAT model using one GAT layer as the auxiliary classifier, mapping the intermediate feature domain to the classification domain. For the hyperparameters, we take α = 1, β = 0.4 and λ = 0.2. For the three methods of OC, Alignahead and Alignahead++, we only report the higher metric in the two student models. All our experiments are performed on an NVIDIA 2080Ti GPU.

4.2 Node classification on PPI

On the PPI dataset, we use three GNN architectures, namely GAT, GCN and SAGE-pool. For each GNN, we take different layers and feature dimensions for experiments. The experimental results are shown in Table 4.

It can be seen that student models trained with our new proposed Alignahead++ consistently achieve better performance compared to those trained with labels or Alignahead strategy. The comparison between the results of one-to-one correspondence (OC) and Alignahead demonstrates Alignahead can indeed help the student layer learn...
global semantics by flowing structure information. By introducing feature information and combining with deep supervision, Alignahead++ can deliver more comprehensive and accurate information, further improving the performance of student models. Due to the addition of auxiliary classifiers, the model capacity and training time are increased. Nevertheless, knowledge distillation is generally aimed at small capacity models, which makes the increased costs affordable.

In addition, we find that when the layer number of GCN reaches 10, Alignahead++ has the biggest improvement compared with Alignahead. It is probably due to the reason that GNNs suffer from over-smoothing problem, that is, the feature embeddings of nodes in deep layer become indistinguishable as the layer number increases. We believe that our Alignahead++ can alleviate the over-smoothing [19–21] problem to some extent and delve more deeply in the next section.

Then, we explore the F1-score in GAT models with different structures under different methods during training, and the results are shown in Fig. 4. We start drawing from the F1-score of Alignahead++ greater than 0.9 without OC method to prevent curves from tangling together. It can be seen that our Alignahead++ always outperforms Alignahead and Baseline, demonstrating the superiority of Alignahead++.

### 4.3 Node classification on citation datasets

We conduct experiments with GCN as well as two variants of SAGE (SAGE-mean and SAGE-pool) on the Cora, PubMed, and CiteSeer datasets. The goal is to train these student models to classify unknown nodes on the visible graph. For GCN and two variants of SAGE, we adopt two versions of framework, one with 3 layers and the other with 10 layers. Both of them have 128 feature dimensions in each layer. Two student models with the same architecture are used for training. The results are shown in Table 5.

The three GNN models with 10 layers perform worse than those with 3 layers due to the existence of over-smoothing problem. For the GNN models with three layers, we find that Alignahead++ has limited enhancement in small datasets. In particular, the Alignahead++ method has few advantages in PubMed datasets, which is a very simple classification task and only needs to be divided into 3 classes, resulting in insufficient differentiation between various methods. When the number of layers increases to 10, the superiority of our Alignahead++ method becomes

---

**Table 4** The results of GAT, GCN and SAGE-pool student models on PPI

| Model   | Layers | Feature dimensions | Baseline F1-score | Baseline OC F1-score | Alignahead F1-score | Alignahead OC F1-score | Alignahead++ F1-score | Alignahead++ OC F1-score |
|---------|--------|--------------------|-------------------|----------------------|---------------------|------------------------|------------------------|--------------------------|
| GCN     | 2      | 256                | 0.6153            | 0.6176               | 0.11                | 0.68                   | 0.6183                 | 0.17                     | 0.73                     | 0.6245                 |
| GCN     | 2      | 512                | 0.6397            | 0.6599               | 0.37                | 0.72                   | 0.6606                 | 0.79                     | 0.76                     | 0.6743                 |
| GCN     | 3      | 512                | 0.6163            | 0.6512               | 0.89                | 0.85                   | 0.6715                 | 1.45                     | 0.90                     | 0.7050                 |
| GCN     | 5      | 512                | 0.6130            | 0.6865               | 0.53                | 1.15                   | 0.7018                 | 0.91                     | 1.25                     | 0.7160                 |
| GCN     | 10     | 512                | 0.4085            | 0.5280               | 2.38                | 1.87                   | 0.5173                 | 3.37                     | 2.06                     | 0.6620                 |
| SAGE-pool | 3   | 128                | 0.9018            | 0.9292               | 0.16                | 0.67                   | 0.9316                 | 0.26                     | 0.75                     | 0.9393                 |
| SAGE-pool | 3   | 256                | 0.9582            | 0.9810               | 0.55                | 0.71                   | 0.9818                 | 0.81                     | 0.84                     | 0.9851                 |
| SAGE-pool | 4   | 64                 | 0.7798            | 0.8050               | 0.07                | 0.67                   | 0.8056                 | 0.13                     | 0.74                     | 0.8284                 |
| SAGE-pool | 4   | 128                | 0.8848            | 0.9300               | 0.21                | 0.69                   | 0.9338                 | 0.36                     | 0.78                     | 0.9495                 |
| SAGE-pool | 4   | 256                | 0.9540            | 0.9801               | 0.75                | 0.82                   | 0.9815                 | 1.13                     | 0.92                     | 0.9863                 |
| GAT [3,3,3,3] | 32 |                      | 0.9090            | 0.9085               | 0.13                | 0.83                   | 0.9105                 | 0.34                     | 1.03                     | 0.9140                 |
| GAT [3,3,3,3] | 64 |                      | 0.9736            | 0.9757               | 0.37                | 0.93                   | 0.9770                 | 0.79                     | 1.18                     | 0.9791                 |
| GAT [3,3,3,3] | 128 |                     | 0.9820            | 0.9832               | 0.89                | 1.02                   | 0.9836                 | 1.45                     | 1.22                     | 0.9873                 |
| GAT [2,2,2,2,2] | 128 |                 | 0.9780            | 0.9796               | 0.53                | 0.97                   | 0.9800                 | 0.91                     | 1.15                     | 0.9846                 |
| GAT [2,2,2,2,2] | 256 |                     | 0.9882            | 0.9891               | 2.38                | 1.62                   | 0.9897                 | 3.37                     | 1.93                     | 0.9908                 |

The layers of GAT represent the attention heads in each layer.

Bold values indicate the best performance.

---

© Springer
apparent. The Alignahead++ method significantly outperforms the other methods on all datasets and all three GNN models.

In addition, we plot the accuracy curves of GCN and SAGE-mean on Cora dataset when the number of layers increases gradually from 2 to 20, which is shown in Fig. 5. As the number of layers increases, the accuracy of all three methods decreases, but Alignahead++ decreases more slowly than other methods, which shows that Alignahead++ can effectively alleviate the over-smoothing problem in deep GNNs. Besides, Alignahead and Baseline become extremely unstable when deepening GNNs, that is, the accuracy curves fluctuate sharply, while the accuracy curve of Alignahead++ method is always flat.

4.4 Sensitivity analysis

In this section, we explore the impact of different values of $\beta$ and $\lambda$ on the results when fixing $\alpha = 1$. The same experiment settings as the Sect. 4.2 are used. The student model is a five-layer GAT, and the number of attention heads and feature dimensions of each layer is 2 and 128. We take 0, 0.2, 0.4, 0.6, 0.8 and 1 for $\beta$ and $\lambda$, respectively. The results are shown in Table 6.

When $\beta$ and $\lambda$ do not take extreme values (0 or 1), the performance of the model is relatively stable with around 0.9845 $F_1$-score, demonstrating the robustness of our method. Besides, when both $\beta$ and $\lambda$ take 1, we find that the performance of the model deteriorates rapidly. Under the current hyperparameter settings, the model cannot obtain any label information referring to Table 1, which naturally leads to this result. Furthermore, we find that the performance of the model does not seem to be affected when

---

**Fig. 4** $F_1$-score curves of different GAT models during training. The small images magnify the results of the first 50 epochs.
Table 5 The results of different GNNs on citation datasets

| Dataset | Model  | Layers | Feature dimensions | Baseline | OC | Alignahead | Alignahead++ |
|---------|--------|--------|--------------------|----------|----|------------|--------------|
|         |        |        |                    | Acc      | Acc| Capacity (M) | Time (s)     | Acc          | Capacity (M) | Time (s) | Acc      |
| Cora    | GCN    | 3      | 128                | 0.772    | 0.770 ± 0.002 | 0.22 | 0.023 | 0.776 ± 0.001 | 0.22 | 0.031   | 0.785 ± 0.004 |
| Cora    | GCN    | 10     | 128                | 0.616    | 0.614 ± 0.001 | 0.33 | 0.062 | 0.659 ± 0.005 | 0.34 | 0.075   | 0.705 ± 0.004 |
| Cora    | SAGE-mean | 3     | 128                | 0.818    | 0.818 ± 0.002 | 0.43 | 0.026 | 0.790 ± 0.004 | 0.44 | 0.028   | 0.802 ± 0.006 |
| Cora    | SAGE-mean | 10    | 128                | 0.592    | 0.593 ± 0.003 | 0.67 | 0.065 | 0.606 ± 0.008 | 0.68 | 0.088   | 0.727 ± 0.01   |
| Cora    | SAGE-pool | 3     | 128                | 0.706    | 0.712 ± 0.005 | 2.54 | 0.028 | 0.747 ± 0.012 | 2.58 | 0.036   | 0.762 ± 0.008 |
| Cora    | SAGE-pool | 10    | 128                | 0.516    | 0.500 ± 0.007 | 2.89 | 0.060 | 0.530 ± 0.01   | 3.05 | 0.081   | 0.572 ± 0.005 |
| PubMed  | GCN    | 3      | 128                | 0.771    | 0.766 ± 0.004 | 0.10 | 0.027 | 0.780 ± 0.003 | 0.10 | 0.035   | 0.771 ± 0.002 |
| PubMed  | GCN    | 10     | 128                | 0.730    | 0.675 ± 0.016 | 0.21 | 0.068 | 0.719 ± 0.012 | 0.22 | 0.090   | 0.740 ± 0.007 |
| PubMed  | SAGE-mean | 3     | 128                | 0.795    | 0.797 ± 0.002 | 0.20 | 0.028 | 0.791 ± 0.001 | 0.20 | 0.036   | 0.785 ± 0.003 |
| PubMed  | SAGE-mean | 10    | 128                | 0.750    | 0.754 ± 0.006 | 0.43 | 0.068 | 0.756 ± 0.005 | 0.43 | 0.083   | 0.765 ± 0.003 |
| PubMed  | SAGE-pool | 3     | 128                | 0.753    | 0.759 ± 0.004 | 0.50 | 0.033 | 0.769 ± 0.002 | 0.53 | 0.041   | 0.767 ± 0.003 |
| PubMed  | SAGE-pool | 10    | 128                | 0.650    | 0.642 ± 0.007 | 0.84 | 0.079 | 0.666 ± 0.014 | 1.00 | 0.108   | 0.704 ± 0.008 |
| CiteSeer| GCN    | 3      | 128                | 0.633    | 0.617 ± 0.007 | 0.51 | 0.024 | 0.607 ± 0.022 | 0.51 | 0.030   | 0.647 ± 0.014 |
| CiteSeer| GCN    | 10     | 128                | 0.249    | 0.253 ± 0.003 | 0.62 | 0.058 | 0.486 ± 0.015 | 0.63 | 0.080   | 0.553 ± 0.009 |
| CiteSeer| SAGE-mean | 3     | 128                | 0.686    | 0.651 ± 0.017 | 1.02 | 0.028 | 0.665 ± 0.021 | 1.02 | 0.037   | 0.709 ± 0.008 |
| CiteSeer| SAGE-mean | 10    | 128                | 0.429    | 0.454 ± 0.013 | 1.25 | 0.055 | 0.418 ± 0.024 | 1.26 | 0.078   | 0.579 ± 0.012 |
| CiteSeer| SAGE-pool | 3     | 128                | 0.632    | 0.609 ± 0.009 | 1478 | 0.044 | 0.642 ± 0.008 | 14.82| 0.048   | 0.663 ± 0.004 |
| CiteSeer| SAGE-pool | 10    | 128                | 0.436    | 0.397 ± 0.009 | 15.13| 0.075 | 0.491 ± 0.004 | 15.29| 0.080   | 0.512 ± 0.006 |

Bold values indicate the best performance

![Graph](image1.png) ![Graph](image2.png)

Fig. 5 The accuracy of GCN and SAGE-mean with different layers on Cora. The feature dimensions are 128

$\lambda = 1$ and $\beta$ does not take the extreme values, that is, deep-supervised loss does not play a role here referring to Table 1. Next is our explanations. For shallow GNNs, each layer can capture the label information from the last layer by using Alignahead strategy when the over-smoothing problem is relatively light, making deep-supervised loss
redundant. As the number of layers deepens, the over-smoothing problem becomes more serious, and the node features of the last layer become indistinguishable, making the intermediate layer cannot obtain the accurate label information. The huge error accumulated by back propagation degrades the model performance. At this time, adding the supervision of label in the intermediate layer can restrain the accumulation of error in the back propagation and guide the evolution of the intermediate layer to the right direction.

Therefore, we perform sensitivity analysis on CiteSeer dataset and the student model is a 10-layer GCN with 128 feature dimensions. We fix $\beta = 0.4$ and $\lambda$ was taken from 0 to 1 with an interval of 0.1. The result is shown in Fig. 6. It is not difficult to find that with the increase of $\lambda$, the classification accuracy generally decreases, indicating that deep-supervised loss plays an important role in deep GNNs.

4.5 Two different student models

In addition to two identical student models, in this section we try to explore the performance of two different student models with the Alignahead++ method. Due to the limitations of Alignahead method, the two student models need to have the same number of layers. For the case of student model $S_1$ has $l_1$ layers and student model $S_2$ has $l_2$ layers, in which $l_1 > l_2$, one feasible method is to arbitrarily choose $l_2$ layers from student model $S_1$ to align with student model $S_2$. We select four groups of student models to conduct experiments on PPI dataset, in which all GAT models have 2 attention heads. Table 7 records the experimental results. We find that Alignahead++ method is superior to the competitors and the relatively poor student model tends to improve more in training.

4.6 The effect of auxiliary classifiers

The auxiliary classifiers, which are the key modules in Alignahead++, translate the unknown semantic space of the intermediate layers into the label semantic space. In CNNs, auxiliary classifiers are usually stacked by several convolutional layers, followed by one or two MLPs.
However, unlike images, graph data are irregular and carry structure information. Using MLPs directly as the auxiliary classifier is likely to lose structure information and affect model performance. We explore the differences between MLP and GNN as the auxiliary classifier and the effect of layer number on PPI dataset, which are shown in Table 8. We use two GNN models, that is, four-layer SAGE-mean with 128 feature dimensions and six-layer GAT with 2 attention heads and 64 feature dimensions.

We find that GNN is indeed superior to MLP as an auxiliary classifier and increasing the number of auxiliary classifier layers does not always improve the student model performance. One possible reason is that more layer may cause the over-smoothing problem. Considering the training costs and model capacity, one layer of GNN auxiliary classifier is sufficient.

### 4.7 The number of student models

In this section, we explore the effect of the number of student models on the experimental results. If the student number is greater than 2, each model will capture information from all remaining models. The $i$-th layer’s structure and feature loss of the $k$-th model become

\[
L_{S_i}^k = \frac{1}{M-1} \sum_{h=1/h\neq k}^M \sum_{j=1}^N D_{KL}(S_{i+1,j}||S_{i,j})
\]

\[
L_{p_{S_i}}^k = \frac{1}{M-1} \sum_{h=1/h\neq k}^M \sum_{j=1}^N D_{KL}(p_{S_i,j}||p_{S_{i+1,j}})
\]

where $M$ is the number of student models. To make the student models have more room for improvement, we use the GAT with a smaller architecture on PPI dataset. The student model is a four-layer GAT, and the number of attention heads and feature dimensions of each layer is 2 and 42. We use the same parameter settings as in Sect. 4.2.

As shown in Table 9, increasing the student numbers does improve the model performance, especially when it is less than 4 in Alignahead. For Alignahead++, however, two student models are sufficient. When the number increases further, the Max F1 score hardly changes, which indicates that the model performance has reached its limit. Since the model training time linearly increases as the student numbers increase, two or three student models are generally appropriate.

### 5 Conclusion

In this paper, we propose an online knowledge distillation framework specifically for graph neural networks, where two student models extract information from each other in an alternating training procedure. Specifically, we design a strategy called Alignahead to align one student layer with the next layer of another student model, resulting in the information spreading over all layers after several iterations. We further develop a new framework with our existing approach, namely Alignahead++, which introduces feature information except structure information by adding auxiliary classifier in each intermediate layer, to alleviate the over-smoothing problem in deep GNNs with deep supervision. We conduct experiments with GAT, GCN and two variants of SAGE on four datasets: PPI, Cora, PubMed and CiteSeer. The results show that the new proposed Alignahead++ is superior to Alignahead and other compared methods. We summarize the following advantages of Alignahead++. First, Alignahead++ can further improve the performance of shallow GNNs. Second, Alignahead++ can alleviate the over-smoothing problem in deep GNNs. Third, Alignahead++ can accelerate the convergence speed of GNNs. Beyond that, we
find that increasing the student numbers generally improves the performance further and our framework exhibits high robustness with different hyperparameter settings.

In the future, we will consider student models with different layer numbers, other GNN models and datasets with different properties to demonstrate the applicability and effectiveness of our proposed framework. In addition, since not all information from different layers has the same effect on the final task, we are interested to explore appropriate information weighting method for better training. More importantly, we will continue to explore the application of Alignahead++ framework in unsupervised learning and its practice in other more complex graph learning tasks (e.g., community detection, link prediction).

Acknowledgements This work is supported by the Starry Night Science Fund of Zhejiang University Shanghai Institute for Advanced Study (Grant No: SN-ZJU-SIAS-001) and National Natural Science Foundation of China (Grant No: U1866602). The authors would like to thank anonymous reviewers for their helpful comments.

Data availability The datasets analyzed during the current study are available in the next four links. Cora: https://linqs-data.soe.ucsc.edu/public/lbc/cora.tgz. CiteSeer: http://www.cs.umd.edu/~sen/lbc-proj/data/citeeseer.tgz. PubMed: https://linqs-data.soe.ucsc.edu/public/Pubmed-Diabetes.tgz. PPI: https://data.dgl.ai/dataset/ppi.zip.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

References

1. Kipf TN, Welling M (2017) Semi-supervised classification with graph convolutional networks. In: International conference on learning representations
2. Velickovic P, Cucurull G, Casanova A, Romero A, Liò P, Bengio Y (2018) Graph attention networks. In: International conference on learning representations
3. Hamilton WL, Ying Z, Leskovec J (2017) Inductive representation learning on large graphs. In: Advances in neural information processing systems, pp 1024–1034
4. Kipf TN, Welling M (2016) Variational graph auto-encoders. In: NeurIPS workshop on Bayesian deep learning
5. Peng Z, Huang W, Luo M, Zheng Q, Rong Y, Xu T, Huang J (2020) Graph representation learning via graphical mutual information maximization. In: The web conference, pp 259–270
6. Wang C, Pan S, Hu R, Long G, Jiang J, Zhang C (2019) Attributed graph clustering: a deep attentional embedding approach. In: Proceedings of international joint conference on artificial intelligence, pp 3670–3676
7. Bucilua C, Caruana R, Niculescu-Mizil A (2006) Model compression. In: Proceedings of the 12th ACM SIGKDD international conference on knowledge discovery and data mining, pp 535–541
8. Hinton G, Vinyals O, Dean J (2015) Distilling the knowledge in a neural network
9. Romero A, Ballas N, Kahou SE, Challang A, Gatta C, Bengio Y (2015) Fitnets: hints for thin deep nets. In: International conference on learning representations
10. Zagoruyko S, Komodakis N (2017) Paying more attention to attention: improving the performance of convolutional neural networks via attention transfer. In: International conference on learning representations
11. Chen D, Mei J, Zhang Y, Wang C, Wang Z, Feng Y, Chen C (2021) Cross-layer distillation with semantic calibration. In: Proceedings of the AAAI conference on artificial intelligence, pp 7028–7036
12. Zhang H, Chen D, Wang C (2022) Confidence-aware multi-teacher knowledge distillation. In: International conference on acoustics, speech and signal processing
13. Chen D, Mei J-P, Zhang H, Wang C, Feng Y, Chen C (2022) Knowledge distillation with the reused teacher classifier. In: Proceedings of the IEEE conference on computer vision and pattern recognition, pp 11933–11942
14. Yang Y, Qiu J, Song M, Tao D, Wang X (2020) Distilling knowledge from graph convolutional networks. In: Proceedings of the IEEE conference on computer vision and pattern recognition, pp 7072–7081
15. He H, Wang J, Zhang Z, Wu F (2022) Compressing deep graph neural networks via adversarial knowledge distillation. In: Proceedings of the 28th ACM SIGKDD international conference on knowledge discovery and data mining
16. Joshi CK, Liu F, Xun X, Lin J, Foo C-S (2021) On representation knowledge distillation for graph neural networks. arXiv preprint arXiv:2111.04964
17. Yang C, Liu J, Shi C (2021) Extract the knowledge of graph neural networks and go beyond it: an effective knowledge distillation framework. In: The web conference, pp 1227–1237
18. Deng X, Zhang Z (2021) Graph-free knowledge distillation for graph neural networks. In: Proceedings of the international joint conference on artificial intelligence, pp 2321–2327
19. Li Q, Han Z, Wu X-M (2018) Deeper insights into graph convolutional networks for semi-supervised learning. In: Proceedings of the AAAI conference on artificial intelligence, pp 3538–3545
20. Liu M, Gao H, Ji S (2020) Towards deeper graph neural networks. In: Proceedings of the 26th ACM SIGKDD international conference on knowledge discovery and data mining, pp 338–348
21. Chen D, Lin Y, Li W, Li P, Zhou J, Sun X (2020) Measuring and relieving the over-smoothing problem for graph neural networks from the topological view. In: Proceedings of the AAAI conference on artificial intelligence, pp 3438–3445
22. Zhang Y, Xiang T, Hospedales TM, Lu H (2018) Deep mutual learning. In: Proceedings of the IEEE conference on computer vision and pattern recognition, pp 4320–4328
23. Arin R, Pereyra G, Passos A, Ormándi R, Dahl GE, Hinton GE (2018) Large scale distributed neural network training through online distillation. In: International conference on learning representations
24. Chen D, Mei JP, Wang C, Feng Y, Chen C (2020) Online knowledge distillation with diverse peers. In: Proceedings of the AAAI conference on artificial intelligence, pp 3430–3437
25. Szegedy C, Liu W, Jia Y, Sermanet P, Reed SE, Anguelov D, Erhan D, Vanhoucke V, Rabinovich A (2015) Going deeper with convolutions. In: Proceedings of the IEEE conference on computer vision and pattern recognition, pp 1–9
26. Lee CY, Xie S, Gallagher P, Zhang Z, Tu Z (2015) Deeply-supervised nets. In: Artificial intelligence and statistics, pp 562–570
27. Guo J, Chen D, Wang C (2022) Alignahead: online cross-layer knowledge extraction on graph neural networks. arXiv preprint arXiv:2205.02468
28. Lin S, Xie H, Wang B, Yu K, Chang X, Liang X, Wang G (2022) Knowledge distillation via the target-aware transformer. In: Proceedings of the IEEE conference on computer vision and pattern recognition, pp 10905–10914

29. Zhao B, Cui Q, Song R, Qiu Y, Liang J (2022) Decoupled knowledge distillation. In: Proceedings of the IEEE conference on computer vision and pattern recognition, pp 11943–11952

30. Klicpera J, Bojchevski A, Günnemann S (2019) Predict then propagate: graph neural networks meet personalized pagerank. In: International conference on learning representations

31. Wu F, Jr AHS, Zhang T, Fifty C, Yu T, Weinberger KQ (2019) Simplifying graph convolutional networks. In: International conference on machine learning, pp 6861–6871

32. Chen M, Wei Z, Huang Z, Ding B, Li Y (2020) Simple and deep graph convolutional networks. In: International conference on machine learning, pp 1725–1735

33. Shi W, Rajkumar RR (2020) Point-gnn: graph neural network for 3d object detection in a point cloud. In: Proceedings of the IEEE conference on computer vision and pattern recognition, pp 1708–1716

34. Shen ZA, Luo T, Zhou Y-K, Yu H, Du P-F (2021) NPI-GNN: predicting NCRNA–protein interactions with deep graph neural networks. Brief Bioinform 22(5):51

35. Rong Y, bing Huang W, Xu T, Huang J (2019) Dropedge: towards deep graph convolutional networks on node classification. In: International conference on learning representations

36. Li G, Xiong C, Thabet A, Ghanem B (2020) Deepergcn: all you need to train deeper gcns. arXiv preprint arXiv:2006.07739

37. Huang C, Zhou H, Zaiane OR, Mou L, Li L (2022) Non-autoregressive translation with layer-wise prediction and deep supervision. In: Proceedings of the AAAI conference on artificial intelligence, pp 10776–10784

38. Mei Y, Guo X, Sun D, Pan G, Zhang J (2021) Deep supervised image retargeting. In: Proceedings of the IEEE international conference on multimedia and expo, pp 1–6

39. Zhang L, Song J, Gao A, Chen J, Bao C, Ma K (2019) Be your own teacher: improve the performance of convolutional neural networks via self distillation. In: International conference on computer vision, pp 3712–3721

40. Elinas P, Bonilla EV (2022) Addressing over-smoothing in graph neural networks via deep supervision. arXiv preprint arXiv:2202.12508

41. Jiao X, Yin Y, Shang L, Jiang X, Chen X, Li L, Wang F, Liu Q (2019) Tinybert: distilling bert for natural language understanding. arXiv preprint arXiv:1909.10351

42. Yang C, Guo Y, Xu YL, Shi C, Liu J, Wang C, Li X, Guo N, Yin H (2023) Learning to distill graph neural networks. In: Proceedings of the sixteenth ACM international conference on web search and data mining

43. Ahn S, Hu SX, Damianou AC, Lawrence ND, Dai Z (2019) Variational information distillation for knowledge transfer. In: Proceedings of the IEEE conference on computer vision and pattern recognition, pp 9163–9171

44. Yue K, Deng J, Zhou F (2020) Matching guided distillation. In: European conference on computer vision, pp 312–328

45. Zitnik M, Leskovec J (2017) Predicting multicellular function through multi-layer tissue networks. Bioinformatics 33(14):i190–i198

46. Bojchevski A, Günnemann S (2018) Deep gaussian embedding of graphs: unsupervised inductive learning via ranking. In: International conference on learning representations

47. McCallum A, Nigam K, Rennie JDM, Seymore K (2004) Automating the construction of internet portals with machine learning. Inform Retr 3:127–163

48. Sen P, Namata G, Bilgic M, Getoor L, Gallagher B, Eliassi-Rad T (2008) Collective classification in network data. AI Mag 29:93–106

49. Namata G, London B, Getoor L, Huang B, Edu U (2012) Query-driven active surveying for collective classification. In: 10th International workshop on mining and learning with graphs, vol 8, p 1

50. Yang C, An Z, Cai L, Xu Y (2021) Hierarchical self-supervised augmented knowledge distillation. In: Proceedings of the international joint conference on artificial intelligence, pp 1217–1223

51. Xu G, Liu Z, Li X, Loy CC (2020) Knowledge distillation meets self-supervision. In: European conference on computer vision, pp 588–604

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.