Weakly-supervised Graph Meta-learning for Few-shot Node Classification

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ABSTRACT

Graphs are widely used to model the relational structure of data, and the model of graph machine learning (ML) has a wide spectrum of applications ranging from drug design in molecular graphs to friendship recommendation in social networks. Prevailing approaches for graph ML typically require abundant labeled instances in achieving satisfactory results, which is commonly infeasible in real-world scenarios since labeled data for newly emerged concepts (e.g., new categorizations of nodes) on graphs is limited. Though meta-learning has been applied to different few-shot graph learning problems, most existing efforts predominately assume that all the data from those seen classes is gold-labeled, while those methods may lose their efficacy when the seen data is weakly-labeled with severe label noise. As such, we aim to investigate a novel problem of weakly-supervised graph meta-learning for improving the model robustness in terms of knowledge transfer. To achieve this goal, we propose a new graph meta-learning framework – Graph Hallucination Networks (Meta-GHN) in this paper. Based on a new robustness-enhanced episodic training, Meta-GHN is meta-learned to hallucinate clean node representations from weakly-labeled data and extracts highly transferable meta-knowledge, which enables the model to quickly adapt to unseen tasks with few labeled instances. Extensive experiments demonstrate the superiority of Meta-GHN over existing graph meta-learning studies on the task of weakly-supervised few-shot node classification.

1 INTRODUCTION

Graphs serve as a common language for modeling a plethora of structured and relational systems, such as social networks [27], knowledge graphs [40], and academic graphs [16, 36]. Many central tasks in graph machine learning (ML), such as node classification [18], link prediction [11], and community detection [46], have received much research attention due to their significant impacts in addressing real-world problems. To harness the inherent structure among data, significant methodological advances have been made in graph ML, which have produced promising results in applications from diverse domains [12, 18, 38].

Many prevailing graph ML methods typically rely upon the availability of sufficient labeled data [8, 48]. In contrast, the long-tail property of real-world graphs makes those methods less effective for learning new concepts when only limited labeled data is available [1, 8, 16]. A powerful graph ML model should be able to quickly learn never-before-seen class labels using only a handful of labeled data. Dealing with such few-shot concepts1 is important and corresponds to many practical applications. For example, many social networking platforms such as Facebook and Twitter need to consistently promote new features or new social media groups to users. Based on the limited user interactions, the deployed model is required to provide high-quality recommendations for other users regarding these new concepts. Inspired by the recent success of meta-learning in image domain [34], increasing research efforts have been made in graph meta-learning [16, 19, 22, 48] for solving the problem of few-shot learning on graph-structured data.

In essence, a meta-learning model learns across diverse meta-training tasks sampled from those seen classes with a large quantity of labeled data, and can be naturally generalized to a new task (i.e., meta-test task) with unseen classes during training [34]. Such a learning-to-learn procedure enables the model to accumulate knowledge from previous experiences, and has led to significant progress in few-shot learning (FSL) problems. Following this learning paradigm, researchers have proposed to use graph neural networks (GNNs) as the backbone to extrapolate meta-knowledge on graphs, which demonstrates promising results [8, 16, 48].

Despite some exciting progress, the research of graph meta-learning overall remains in its infancy. In general, existing endeavors predominately focus on the supervised setting, where abundant gold-labeled nodes can be accessed from those seen classes during the meta-training process. This assumption is often infeasible since collecting such auxiliary knowledge is laborious and requires intensive domain-knowledge, especially when considering the heterogeneity of graph-structured data. An alternative solution is to adopt automatic labeling tools based on heuristics, crowd-sourcing, or weak-learners [47]. Though using such weakly-labeled data is more practical, one companion issue is that those labels usually contain a significant amount of noise. As shown in the previous research studies [30, 45], most of the existing FSL models are highly vulnerable to noise or outliers, thus the model performance on unseen tasks would be largely degraded if the model is meta-learned on those weakly-labeled data. Therefore, it is imperative to investigate the problem of weakly-supervised graph meta-learning, in order to push forward the frontiers of few-shot learning on graphs.

As a research problem has been little explored, weakly-supervised graph meta-learning is challenging to solve, mainly due to the difficulty of extracting highly transferable meta-knowledge from weakly-labeled node classes. To suppress the negative impacts of mislabeled nodes during the meta-training process, a principled noise-resistant approach...

1In this paper, we primarily focus on the task of few-shot node classification.
A graph meta-learning model is highly desired: (i) on the one hand, the existing literature of learning with noisy labels is tailored for independent and identically distributed (i.i.d.) data such as image and text. The inability of modeling relational data like graphs that lie in non-Euclidean space could largely jeopardize their effectiveness. Hence, it is necessary to develop new frameworks that can consider the dependencies among nodes and mitigate the inaccurate supervision signals; (ii) on the other hand, in order to extract meta-knowledge during the meta-training process, graph meta-learning models will be trained with diverse node classification tasks from disjoint label spaces. It requires the model to quickly adapt to never-before-seen labels, which poses great challenges to existing denoising algorithms since they are optimized in a static learning environment (i.e., a single task). Hence, how to bridge the gap between the two learning paradigms and design a graph meta-learning model that can effectively denoise and efficiently adapt to different tasks is vital to be explored.

To address the aforementioned challenges, we present a new graph meta-learning framework – Graph Hallucination Networks (Meta-GHN) which is learned with our robustness-enhanced episodic training paradigm, for solving the problem of weakly-supervised few-shot node classification on graphs. As shown in cognitive studies, humans mainly perceive and learn novel concepts from noisy inputs by comparing and summarizing [33]. Motivated by this, instead of directly using a few weakly-labeled nodes (i.e., K-shot) to extract meta-knowledge in each episode, Meta-GHN first hallucinates K noise-reduced node representations from K-set of weakly-labeled nodes and leverage such “clean” node representations to meta-learn the graph FSL model. To obtain each noise-reduced (clean) node representation in a meta-training task, Meta-GHN randomly samples a set of weakly-labeled nodes and learn expressive node representations that captures both node attributes and topological structure information. Afterwards, by aggregating and comparing the information among the sampled nodes within a set, Meta-GHN is able to provide a better estimation of confidence score for each node and further summarize a clean representation of the corresponding target class. By learning across a pool of weakly-supervised node classification tasks, the proposed Meta-GHN can be meta-learned not only to denoise from weakly-labeled data, but also to extrapolate the knowledge from seen to unseen node classes. Finally, with K-shot clean-labeled nodes from unseen classes, the learned Meta-GHN can quickly adapt to new tasks using few fine-tuning steps.

In summary, the main contributions of our work are:

- **Problem**: We investigate a new problem – weakly-supervised graph meta-learning, which can mitigate the limitation of existing graph meta-learning methods and push forward the frontiers of few-shot learning on graphs.

- **Algorithm**: We propose a principled framework Meta-GHN that is capable of extracting highly transferable meta-knowledge from weakly-labeled data, in order to solve unseen node classification tasks with few labeled nodes.

- **Evaluation**: We perform extensive experiments on various real-world datasets to corroborate the effectiveness of our approach. The experimental results demonstrate the superior performance of Meta-GHN over existing efforts.

## RELATED WORK

### Meta-Learning

Meta-learning, also known as learning-to-learn, has been widely used in various domains to address few-shot learning problems. Generally, existing meta-learning methods follow the episodic training paradigm, and fall into three broad categories: **metric-based** [21, 30, 34, 35, 39], **optimization-based** [10, 20, 26, 28], and **memory-based** [32, 50]. Metric-based approaches try to learn generalizable matching metrics between query and support set across different tasks. For example, Prototypical Networks [34] learn a matching metric by taking the mean of support sets as prototypes, and classify query instances by calculating their Euclidean distances to the computed prototypes. Relation Network [35] trains an auxiliary network to learn a non-linear metric between each query and the support set; Optimization-based approaches focus on learning an initialization of model parameters that can quickly adapt to new tasks by fine-tuning with few labeled examples. For example, in [29], Meta-Learner LSTM interprets stochastic gradient descent update rules as a gated recursive model with trainable parameters, in order to learn the update rules of model parameters. MAML [10] seeks a proper parameter initialization by second-order gradient descent method so that the model can achieve better generalization performance after a few steps of gradient descent. Meta-SGD [20] goes further in meta-learning by arguing to learn the weights initialization, gradient update direction and learning rate within a single step. Memory-based approaches use the memory mechanism to extract valuable knowledge acquired in the meta-training phase to assist meta-testing. For instance, MANN [52] learns new tasks by reminiscence mechanism in virtue of physical memory, CMN [50] uses the key-value memory network paradigm to obtain an optimal video representation in a larger space.

### Graph Neural Networks

Graph neural networks [2, 3, 12, 18, 38] have recently achieved momentous success in transforming the information of a graph into low-dimensional latent representations. Originally inspired by graph spectral theory, spectral-based graph convolutional networks (GCNs) [6, 13, 18, 41] extend convolution operation in the spectral domain to network representation learning. Among them, the model proposed by Kipf et al. [18] has become the most prevailing one by using a linear filter. SGC [41] reduces the extra complexity of GCN by eliminating the non-linearity between the GCN layers and folding the convolution functions into a linear transformation. In addition to spectral-based graph convolution models, spatial-based graph neural networks that follow message passing scheme also have been extensively investigated [12, 38, 42]. Instead of training individual embeddings for each node, those methods learn a set of aggregator functions to aggregate features from a node’s local neighborhood. For example, GAT [38] proposes to learn hidden representations by introducing a self-attention strategy when aggregating neighborhood information of a node. GIN [42] extends the idea of parameterizing universal multiset functions with neural networks to graph-structured data. Recently, different robust graph neural networks such as RGCN [49], PA-GNN [37] has been proposed in the community. However, those methods mostly focus on defending adversarial attacks and cannot be leveraged for mitigating the noise of weakly-labeled data. Another recent work PTA [9] is a decoupled GNN that can mitigate...
label noise using adaptive weighting, while it cannot transfer the knowledge to unseen classes.

**Graph Few-shot Learning.** The effectiveness of prevailing graph ML methods such as GNNs largely relies on sufficient labeled instances. However, those methods fail to address graph few-shot learning problems, where the unseen concepts during testing phase only have few labeled instances [48]. Among recent advances of few-shot learning on graphs, a major line of work aims to solve the task of node classification [8, 16, 19, 22, 23, 48]. Among them, Meta-GNN, GPN and G-Meta are three representative ones. Specifically, Meta-GNN [48] uses gradient-based meta-learning to optimize a GNN model for few-shot node classification. GPN [8] extends prototypical networks to graph-structured data by considering the importance of each node. G-META [16] uses local subgraphs to transfer subgraph-specific information. Note that other methods such as GFL [43] and MetaTNE [19] are different from our scenario since they are focusing on multiple networks and plain networks, respectively. In addition to few-shot node classification, other graph ML tasks including graph classification [4, 24] and link prediction [1, 44] has also been studied under the few-shot learning setting. Unlike previous works, we propose a weakly-supervised graph meta-learning framework, which eliminates the dependency of gold-labeled data during meta-training.

## 3 PROBLEM STATEMENT

Following the commonly used notations, in this paper, we use calligraphic fonts, bold lowercase letters, and bold uppercase letters to denote sets (e.g., \( V \)), vectors (e.g., \( x \)), and matrices (e.g., \( X \)), respectively. The \( i \)-th row of a matrix \( X \) is denoted by \( x_i \), and the transpose of a matrix \( X \) is represented as \( X^T \). For the other special notations, we will illustrate them in the corresponding sections.

Formally, consider an attributed graph \( G = (V, E, X) \), where \( V \) denotes the set of nodes \( \{v_1, v_2, \ldots, v_n\} \) and \( E \) denotes the set of edges \( \{e_1, e_2, \ldots, e_m\} \). Each node is associated with an attribute vector \( v_i \in \mathbb{R}^d \) and \( X = [x_1^T, x_2^T, \ldots, x_n^T] \in \mathbb{R}^{n \times d} \) denotes all the node features. More concretely, we represent the attributed graph as \( G = (A, X) \), where \( A = \{0, 1\}^{n \times n} \) is an adjacency matrix representing the network structure. Accordingly, we formulate the studied problem as follows:

**Problem Definition 1.** **Weakly-supervised Few-shot Node Classification:** Given an attributed graph \( G = (A, X) \), and the node label set \( Y = \{y_1, y_2, \ldots, y_c\} \) that can be divided two subsets: the seen labels \( Y_{\text{train}} \), and the unseen labels \( Y_{\text{test}} \). Specifically, we have substantial weakly-labeled nodes for \( Y_{\text{train}} \), and few-shot clean-labeled nodes (i.e., support set \( S \)) for each class in \( Y_{\text{test}} \). The problem aims to study how to predict labels for the unlabeled nodes (i.e., query set \( Q \)) from those few-shot node classes \( Y_{\text{test}} \), by leveraging the knowledge of weakly-labeled nodes from \( Y_{\text{train}} \).

Following previous research [48], if \( Y_{\text{test}} \) consists of \( N \) classes and the support set \( S \) includes \( K \) labeled nodes per class, this problem is named \( N \)-way \( K \)-shot node classification problem. In essence, the objective of this problem is to learn a meta-classifier that can be adapted to new classes with only a few labeled nodes. Therefore, how to extract highly transferable meta-knowledge from weakly-labeled data from \( Y_{\text{train}} \) is the key for solving the studied problem.

## 4 PROPOSED APPROACH

In this section, we introduce the details of the proposed Meta-GHN. To better explain how it works, we show its framework in Figure 1. Based on our robustness-enhanced episodic training, Meta-GHN facilitates graph meta-learning on weakly-labeled nodes by hallucinating noise-reduced node representations. With the noise-reduced node representations, Meta-GHN further extracts highly transferable meta-knowledge and perform few-shot node classification on novel classes using optimization-based meta-learning. In the following subsections, we elaborate three key parts: robustness-enhanced episodic training, graph hallucination networks, and meta-optimization, respectively.

### 4.1 Robustness-enhanced Episodic Training

The effectiveness of few-shot learning algorithms largely benefits from the episodic training paradigm [39]. Briefly, the key idea of episodic training is to mimic the real test environment by sampling data from \( Y_{\text{train}} \) and the model learns over such meta-training tasks in a large number of episodes. Following this idea, graph FSL methods construct a pool of few-shot node classification tasks according to the seen labels. For each meta-training task \( T_i = (S_i, Q_i) \), the model is trained to minimize the loss of its predictions for the query set \( Q_i \), and goes episode by episode until convergence. Thus, in this way, the model gradually collects meta-knowledge across those meta-training tasks and then can be naturally generalized to the meta-testing task \( T_{\text{test}} = (S, Q) \) with unseen classes \( Y_{\text{test}} \).

However, existing graph FSL methods commonly assume that the labels of nodes from \( Y_{\text{train}} \) are clean, which is invalid under the studied weakly-supervised setting. To suppress the label noise during the meta-training process, we propose a robustness-enhanced episodic training mechanism in this work. Instead of sampling \( N \)-way \( K \)-shot nodes from \( Y_{\text{train}} \) to construct the support set in each meta-training episode, we sample \( N \)-way \( K \)-set nodes, where each set contains \( M \) nodes from a class (and likewise the query set):

\[
T_i = (S_i, Q_i),
S_i = \{V_1^{(i)}, V_2^{(i)}, \ldots, V_K^{(i)}\},
Q_i = \{V_1^{(i)} q_1^{(i)}, V_2^{(i)} q_2^{(i)}, \ldots, V_K^{(i)} q_K^{(i)}\},
\]

(1)

where the nodes in \( V_k = \{v_1, v_2, \ldots, v_M\} \) are sampled from the same class. For each meta-training task \( T_i \), the support set contains \( N \) classes and \( K \times M \) weakly-labeled nodes per class.

Furthermore, for each set of \( M \) weakly-labeled nodes, the proposed framework Meta-GHN will try to generate a noise-reduced node representation to improve the effectiveness of episodic training under the weakly-supervised setting. Thus we can get the noise-reduced support and query sets:

\[
S'_i = \{(c_1^{(i)}, y_1^{(i)}), (c_2^{(i)}, y_2^{(i)}), \ldots, (c_K^{(i)}, y_K^{(i)})\},
Q'_i = \{(c_1^{(i)} q_1^{(i)}, c_2^{(i)} q_2^{(i)}, \ldots, c_K^{(i)} q_K^{(i)})\},
\]

(2)

where \( c_k \) denotes the noise-reduced node representation generated from \( V_k \) and \( y_k \) denotes its corresponding target class.

With the noise-reduced node representations, our model could further extract highly transferable meta-knowledge and solve the weakly-labeled graph meta-learning problems. It is worth mentioning that, during the meta-testing phase, our model only
uses $N$-way $K$-shot clean-labeled nodes and does not require extra knowledge from the unseen classes, which is fair when comparing to other methods.

### 4.2 Graph Hallucination Networks

Moreover, we propose a new family of graph neural networks, called Graph Hallucination Networks (GHN) to facilitate graph meta-learning on weakly-labeled nodes. In essence, GHN is composed of two key building blocks, including (1) a node representation learning module that embeds each node; and (2) a clean node hallucination module for deriving noise-reduced node representations from each sampled set. The details are as follows:

**Node Representation Learning.** The initial step of conducting graph meta-learning is to learn expressive node representations that capture both graph structure and node features. To achieve this, we first design a GNN-based encoding module in GHN. Specifically, it is built with multiple GNN layers that encode each node to a low-dimensional latent representation. The core operation in GNNs is the message passing scheme, in which information is propagated from each node to its neighborhoods with specific deterministic propagation rules. In general, a GNN layer can be defined as:

$$
\begin{align*}
    h^l_i &= \text{TRANSFORM}^l \left( h^{l-1}_i, h^{l-1}_{N_i} \right), \\
    h^{l-1}_{N_i} &= \text{AGGREGATE}^l \left( h^{l-1}_j \mid j \in N_i \cup \{i\} \right),
\end{align*}
$$

where $h^l_i$ is the node representation of node $i$ at layer $l$ and $N_i$ is the set of neighboring nodes of $v_i$. TRANSFORM and AGGREGATE are two key functions of GNNs. Furthermore, by stacking multiple GNN layers, the model is able to capture the long-range node dependencies in the graph.

It is worth noting that the encoding module is compatible with arbitrary GNN-based architecture [12, 18, 38]. To improve the model efficiency on large graphs, we employ Simple Graph Convolution (SGC) [41] in this work. Specifically, SGC utilizes a simplified graph convolution pre-processing followed by standard multi-class logistic regression. Let $\tilde{A} = A + I$ denotes the “normalized” adjacency matrix with added self-loops, $\tilde{D}$ is the corresponding degree matrix of $\tilde{A}$, the node representation with $L$ layers propagation can be computed by:

$$
Z = \tilde{A} \cdots \tilde{A} \tilde{X} \sum_{l=1}^{L} \tilde{X} \Theta,
$$

where $Z \in \mathbb{R}^{d' \times d'}$ denotes node representation matrix and the $\Theta \in \mathbb{R}^{d' \times d'}$ is a learnable parameter matrix. This way the encoding model is linear, but still has the same increased “receptive field” of a $L$-layer GCN [18].

**Clean Node Hallucination.** However, the previously learned node representations from seen classes $Y_{\text{train}}$ are unable to represent their corresponding classes since they are likely mislabeled in practice. Hence, our clean node hallucination module aims at generating a noise-reduced node representation for each set $V_k$ and leverage those hallucinated “clean” nodes to learn the concept of each class.

To compute a clean representation with the $M$ labeled nodes from a sampled set $V_k$, one straightforward solution is taking the average of all the embedded nodes belonging to that set:

$$
P_k = \frac{1}{|V_k|} \sum_{i \in V_k} z_i,
$$

where $z_i$ is the learned node representations from the graph representation learning module of node $v_i$. This process can be considered as computing the prototype of a set of weakly-labeled nodes, which is similar to the idea of prototypical networks [34]. But differently, we use the computed prototypes to further hallucinate clean node representations rather than directly training the meta-leaner. The reason is that directly taking the mean vectors of the embedded nodes as the clean node representation could be ineffective due to the existence of mislabeled nodes. Also for each target class, our model will generate $K$ prototypes from the sampled $K$ sets.

Specifically, our clean node hallucination module will try to estimate a confidence score $\alpha_i$ about whether the node $v_i$ is a correctly labeled sample. For example, a “machine learning” paper on the citation network is mistakenly collected into the “data mining” category. To effectively avoid confusion when learning the concept of...
“data mining”, our clean node hallucination module should assign a low confident score for the mislabeled node, while applying high scores for other nodes that represent “data mining” papers.

As suggested by cognitive science [33], humans mainly perceive and learn novel concepts from noisy inputs by comparing and summarizing. To identify the confidence score of each labeled node, GHN will compute the confidence score of each sample with message passing. As shown in Figure 1, we first build a full-connected perception graph using M sampled nodes from each set \( V_k \), then we develop a node re-weighting layer using graph attention mechanism to aggregate and compare the information among weakly-labeled nodes. The node re-weighting layer can be defined as follows:

\[
s_i = \sigma \left( \sum_{v_j \in V_k} a_{ij} w^T \begin{bmatrix} x_i \vert \vert \Delta_j \end{bmatrix} \right),
\]

(6)

where \( w \in \mathbb{R}^{2d'} \) is the learnable parameter vector, \( \sigma \) is a nonlinear activation function, i.e., sigmoid function. \( s_i \) denote the confidence score of node \( v_i \) and \( \Delta_j = z_i - p_k \) captures the difference between the embedding of node \( v_i \) and the prototype of \( V_k \). By incorporating the distance between each node and the prototype, GHN can better perceive the concept of the corresponding class and compute the final confidence score. Specifically, \( a_{ij} \) is the attention weight between nodes \( v_i \) and \( v_j \), we compute it via a shared attention mechanism:

\[
a_{ij} = \frac{\exp(\text{LeakyReLU}(a^T \begin{bmatrix} w^T z_i \vert \vert w^T z_j \end{bmatrix}))}{\sum_{m \in V_k} \exp(\text{LeakyReLU}(a^T \begin{bmatrix} w^T z_i \vert \vert w^T z_m \end{bmatrix}))},
\]

(7)

where \( z_i = [z_i \vert \vert \Delta_i] \) and the attention vector \( a \) is a trainable weight vector that assigns importance to different node during aggregation.

After obtaining the confidence scores of the weakly-labeled nodes in each set \( V_k \), GHN is able to hallucinate (generate) a clean node representation by summarizing these noisy labeled nodes with their weights. Based on the computed attentional weights from Eq. (6), we can obtain a clean representation \( c_k \):

\[
c_k = \frac{\sum_{i \in V_k} s_i z_i}{\sum_{i \in V_k} s_i}.
\]

(8)

**Node Classification.** With the noise-reduced support set \( S_k' \) that contains \( K \) hallucinated clean node representations for each of the \( N \) classes, GHN will try to classify each instance to its corresponding class label. This can be done with a feed-forward layer:

\[
y_k = \text{softmax}(W_c^T c_k + b_c),
\]

(9)

where \( W_c \in \mathbb{R}^{d' \times N} \) and \( b_c \in \mathbb{R}^N \) are learnable weight matrix and bias, respectively. Under the episodic training framework, the objective of each meta-training task is to minimize the cross-entropy loss function for performing node classification. Specifically, the training loss for each hallucinated instance \( c_k \) is computed by:

\[
\mathcal{L} = -\log p(y_k^* \vert c_k),
\]

(10)

where \( y_k^* \) is the corresponding label of set \( V_k \). As the training instances are computed by the clean node hallucination module, GHN is able to reduce the negative impacts of mislabeled nodes during the meta-learning process. By minimizing the above loss function, GHN is able to learn a generic classifier for a specific \( N \)-way \( K \)-set meta-training task and further extract highly transferrable meta-knowledge from weakly-labeled data.

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**Algorithm 1:** The learning algorithm of Meta-GHN.

**Input:** Task distribution \( p(T) \) over the input graph \( G = (A, X) \)

**Output:** The well-trained graph meta-learning model Meta-GHN

1. Randomly initialize the parameters \( \theta \) of GHN
2. while not converge do
   3. Randomly sample a batch of tasks from \( p(T) \) with weakly-supervised support set \( S_t \) and query set \( Q_t \) for each task \( T_t \)
4. for each task \( T_t \) do
5.   // Clean node Hallucination
6.   for each \( V_k \in \{S_t, Q_t\} \) do
7.     Compute the node representations for nodes in \( V_k \)
8.     Hallucinate a clean node representation \( \tilde{c}_k \)
9.   Obtain the noise-reduced support set \( S_k' \) and query set \( Q_k' \)
10. Evaluate \( \nabla_{\theta} \mathcal{L}_{T_t}(f_{Q_t}) \) using \( S_k' \) and \( \mathcal{L}_{Q_t} \) in Equation (10)
11. Compute adapted parameters \( \theta' \) according to Eq. (11)
12. Update \( \theta \leftarrow \theta - \beta \nabla_{\theta} \sum_{T \sim p(T)} \mathcal{L}_{Q_t}(f_{Q_t}) \) with \( Q_k' \) by Eq. (12)
13. return Meta-learned graph meta-learning model Meta-GHN

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4.3 Meta-optimization

Having the proposed Graph Hallucination Networks (GHN), we are able to hallucinate noise-reduced support set \( S_k' \) and query set \( Q_k' \) for each meta-training task. Upon that, we train the model via meta-learning, such that the meta-learned GHN model (Meta-GHN) is capable of effectively adapting to new tasks with few labeled instances. Specifically, we follow the idea of model-agnostic meta-learning [10] to learn Meta-GHN in an optimization-based fashion, in order to better exploit the clean-labeled support nodes during meta-testing and make fast and effective adaptation to a new task through a small number of gradient steps.

**Meta-training.** In the meta-training stage, we expect to obtain a good initialization of GHN, which is inherently generalizable to unseen tasks, and explicitly encourage the initialization parameters to perform well after a small number of gradient descent updates on a new learning task. When learning a specific task \( T_t \), we begin with feeding the nodes from the noise-reduced support set \( S_k' \) to GHN, and calculate the cross-entropy loss \( \mathcal{L}_{T_t} \) as formulated in Eq. (10). We consider a GHN model represented by a parameterized function \( f_\theta \) with parameters \( \theta \), the optimization algorithm first adapts the initial model parameters \( \theta \) to \( \theta' \) for each learning task \( T_t \) independently. Specifically, the updated parameter \( \theta' \) is computed using \( \mathcal{L}_{T_t} \) on the hallucinated node representation and the corresponding class label. Formally, the parameter update with one gradient step can be expressed as:

\[
\theta' = \theta - \alpha \nabla_{\theta} \mathcal{L}_{T_t}(f_\theta),
\]

(11)

where \( \alpha \) controls the meta-learning rate. Note that Eq. (11) only includes one-step gradient update, while it is straightforward to extend to multiple gradient updates [10].

Our model Meta-GHN is trained by optimizing for the best performance of \( f_\theta \) with respect to \( \theta \) across all meta-training tasks. More concretely, the meta-objective function is defined as follows:

\[
\min_{\theta} \sum_{T \sim p(T)} \mathcal{L}_{T_t}(f_\theta) = \min_{\theta} \sum_{T \sim p(T)} \mathcal{L}_{T_t}(f_\theta - \alpha \nabla_{\theta} \mathcal{L}_{T_t}(f_\theta)),
\]

(12)
where $p(T)$ is the distribution of meta-training tasks. Since the meta-optimization is performed over parameters $\theta$ with the objective computed using the updated parameters (i.e., $\theta'$) for all tasks, correspondingly, the model parameters are optimized such that one or a small number of gradient steps on the target task will produce maximal effectiveness.

Formally, we leverage stochastic gradient descent (SGD) to update the model parameters $\theta$ with the instances from $Q'_t$, such that the model parameters $\theta$ are updated as follows:

$$\theta \leftarrow \theta - \beta \nabla \theta \sum_{T_i \sim p(T)} L_{T_i}(f_{\theta'}),$$

where $\beta$ is the meta step size. The detailed learning process of Meta-GHN is presented in Algorithm 1.

**Meta-testing.** After training on a considerable number of meta-training tasks, we expect that the Meta-GHN model has been gradually meta-learned well for handling unseen one-shot node classification tasks. Its generalization performance will be measured on the test episodes, which contain clean-labeled nodes sampled from $Y_{test}$ instead of $Y_{train}$. For each meta-testing episode, we fine-tune the classifier meta-learned classifier Meta-GHN with the provided support set $S$ and classify each query node in $Q$ into the most likely class. Specifically, in the meta-testing phase, we will remove the Hallucination layer, and simply feed the $N$-way $K$-shot (not $N$-way $K$-set) clean-labeled support set from unseen classes to Meta-GHN to update the model parameters via one or a small number of gradient descent steps.

## 5 EXPERIMENTS

In this section, we will start with the experimental setup and then present our experiment results to answer the following research questions: **RQ1:** Is the proposed Meta-GHN effective in solving the weakly-supervised few-shot node classification? **RQ2:** Can Meta-GHN achieve satisfying performance on a variety of noise levels? **RQ3:** How does each module in Meta-GHN contribute to the final performance and what are the impacts of model parameters?

### 5.1 Experiment Settings

**Evaluation Datasets.** In our experiments, we adopt three datasets used in previous research [7, 16] for few-shot node classification. The summary of statistics is presented in Table 1.

- **Amazon** [25] is built with the products in “Electronics” on Amazon. In this network, products are considered as nodes and their attributes are constructed with the corresponding product description. We use low-level product categories to define the class label and the complementary relationship (“bought together”) between products to connect the nodes.
- **DBLP** [36] is a citation network constructed with data extracted from DBLP in which nodes denoting papers and node attributes are from paper abstracts. The citation relations among papers are used to create links between nodes and the paper venue is utilized to define the class label.
- **ogbn-arxiv** [15] is a benchmark dataset from the Open Graph Benchmark (OGB). This network includes all Computer Science (CS) ARXIV papers indexed by MAG, in which each node denotes a paper with its subject area as the class label. The links between nodes indicate the citation relation. The node attributes are obtained by averaging the Word2Vec embeddings of their title and abstract.

We follow the same train/validation/test splits and data preprocessing procedure as in [8] for Amazon and DBLP datasets. For ogbn-arxiv dataset, we retrieve the network with the public OGB package and split it for few-shot learning node classification scenario.

**Label Corruption.** To explore the performance of different methods for graph meta-learning on weakly-labeled data, we follow previous work [5, 14, 17, 31] and inject two representative types of label noise to the datasets. Specifically, for a dataset with $P$ classes, 
- **Symmetric Noise** (Sym) corrupts each label class uniformly to all the other classes with probability $\epsilon/(P - 1)$; and 
- **Asymmetric Noise** (Asym) flips a label to a different class with probability $\epsilon$.

To make the evaluation more realistic, both training and validation data will be perturbed. More details can be found in Section A.1.

**Compared Methods.** In the experiments, we compare the proposed model GPN with two different categories of methods: (1) **GNN-based methods** covering three representative semi-supervised node classification methods GCN, SGC, GraphSAGE and PTA which are adapted for few-shot learning scenarios as in [8, 48]. (2) **Graph meta-learning methods** Meta-GNN, GPN and G-Meta, which are the state-of-the-arts for graph few-shot node classification:

- **GCN** [18]: It learns node representations with stacked layers of first-order approximation of spectral graph convolutions.
- **SGC** [41]: This linear model reduces the unnecessary complexity of GCN by successively collapsing the convolution functions between consecutive layers into a linear transformation.
- **GraphSAGE** [12]: It can efficiently generate node embeddings by uniformly sampling a fixed size of neighbors and then aggregating the feature information from the neighbors.
- **PTA** [12]: It is a decoupled GNN which is robust to label noise using adaptive weighting strategy.
- **Meta-GNN** [48]: It applies MAML [10] to Simple Graph Convolution (SGC) for few-shot node classification in graphs.
- **GPN** [8]: This Graph Prototypical Network can learn highly representative class prototypes with a GNN-based network encoder and node valuator. It predicts node labels by measuring their similarity with prototypes.
- **G-Meta** [16]: It constructs a local subgraph for each node and regards the centroid embedding of subgraphs as the prototypes. It is optimized with both the prototypical loss and MAML.

It is worth noting that existing methods for learning with noisy labels cannot be applied to few-shot node classification without principled modifications and only achieve very poor performance.
We evaluate the proposed Meta-GHN and all the baseline models on different weakly-supervised node classification tasks including the content in Section A.2. The proposed model is implemented in PyTorch. Specifically, we employ a 2-layer propagation SGC for the node representation learning module. As for the clean node hallucination module, we use one aggregation layer and the negative slope for the LeakyReLU in it is set to be 0.2. The meta-learning rate $\alpha$ is set to be 0.1 and the meta step size $\beta$ is 0.001. For model training, the task number in each batch is 5 and the query size $K'$ is 5. For constructing the meta-training episodes, unless otherwise notice, we let the set size $M$ to be 5 for both the support and query set. We train the model with 20,000 episodes or stop earlier when the performance on validation set converges. For details about reproducibility of Meta-GHN and all the baselines, please refer to the content in Section A.2.

5.2 General Comparisons (RQ1)

We evaluate the proposed Meta-GHN and all the baseline models on different weakly-supervised node classification tasks including 5-way-1-shot, 5-way-3-shot, 10-way-1-shot, and 10-way-3-shot. For each of the datasets, we inject either the symmetric noise or the Asymmetric noise with noise ratio $\epsilon = 30\%$. Following previous work of few-shot node classification, we adopt Accuracy (ACC) as the evaluation metric for evaluating performance. We randomly sampled 100 meta-test tasks from the test node classes and evaluate each method on these tasks. The process is repeated for 10 times and the resulted mean ± standard deviation is reported in Table 2. In the following, we elaborate our in-depth observations and analysis based on the results:

- In general, the proposed Meta-GHN can significantly outperform all the baseline methods on weakly-supervised node classification tasks for different datasets corrupted by either symmetric or Asymmetric label noise. Take the benchmark ogbl-arxiv dataset as an example, we find that Meta-GHN can achieve 8.0% and 3.1% improvement for the 5-way-3-shot task with symmetric and Asymmetric noise if we compare it with the best performing baseline. On Amazon dataset, the improvements are more substantial.

### Table 2: Test accuracy for weakly-supervised few-shot node classification (30% label noise) on different datasets.

|       | Amazon |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |
|-------|--------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
|       | 5-way 1-shot | Symmetric | Asymmetric | Symmetric | Asymmetric | Symmetric | Asymmetric | Symmetric | Asymmetric | Symmetric | Asymmetric | Symmetric | Asymmetric | Symmetric | Asymmetric | Symmetric | Asymmetric | Symmetric | Asymmetric | Symmetric | Asymmetric | Symmetric | Asymmetric | Symmetric | Asymmetric | Symmetric | Asymmetric | Symmetric | Asymmetric |
|       | 5-way 3-shot |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |
|       | 10-way 1-shot |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |
|       | 10-way 3-shot |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |
|       | Meta-GNN | 0.403 ± 0.021 | 0.480 ± 0.018 | 0.601 ± 0.028 | 0.650 ± 0.024 | 0.279 ± 0.034 | 0.325 ± 0.031 | 0.555 ± 0.023 | 0.563 ± 0.029 |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |
|       | GNN | 0.408 ± 0.015 | 0.463 ± 0.023 | 0.629 ± 0.024 | 0.651 ± 0.027 | 0.263 ± 0.011 | 0.314 ± 0.026 | 0.535 ± 0.011 | 0.579 ± 0.016 |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |
|       | G-Meta | 0.488 ± 0.025 | 0.496 ± 0.024 | 0.614 ± 0.018 | 0.658 ± 0.022 | 0.336 ± 0.025 | 0.376 ± 0.021 | 0.463 ± 0.021 | 0.504 ± 0.019 |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |
|       | Meta-GHN | 0.694 ± 0.033 | 0.652 ± 0.010 | 0.750 ± 0.021 | 0.725 ± 0.021 | 0.567 ± 0.027 | 0.559 ± 0.025 | 0.627 ± 0.028 | 0.615 ± 0.022 |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |

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in our preliminary experiments, due to the space limit, we do not include those methods in this paper.

**Model Implementation.** The proposed model is implemented in PyTorch. Specifically, we employ a 2-layer propagation SGC for the node representation learning module. As for the clean node hallucination module, we use one aggregation layer and the negative slope for the LeakyReLU in it is set to be 0.2. The meta-learning rate $\alpha$ is set to be 0.1 and the meta step size $\beta$ is 0.001. For model training, the task number in each batch is 5 and the query size $K'$ is 5. For constructing the meta-training episodes, unless otherwise notice, we let the set size $M$ to be 5 for both the support and query set. We train the model with 20,000 episodes or stop earlier when the performance on validation set converges. For details about reproducibility of Meta-GHN and all the baselines, please refer to the content in Section A.2.
We can conclude that Meta-GHN is effective in solving the challenging problem of weakly-supervised graph meta-learning.

- GNN-based methods such as GCN, SGC are originally proposed for semi-supervised node classification and require abundant clean labeled data to achieve satisfying classification accuracy. Thus, they obtain poor performance while adapted for weekly-supervised few-shot learning scenarios. Though PTA can mitigate label noise to some extent, it is unable to transfer the knowledge from seen classes to unseen classes. For the graph FSL methods, they still fall behind the proposed Meta-GHN on the weakly-labeled data. This observation verifies the assumption that most of the existing FSL models is vulnerable to label noise.
- Powered by the well-designed Graph Hallucination Networks under the robustness-enhanced episodic training framework, Meta-GHN is able to generate the noise-reduced node representation and achieve the best few-shot node classification performance on the noisy label data. It is also worth noting that noise usually have larger impact on meta-learning relying on fewer shot. However, compared with the graph meta-learning methods, the improvement of Meta-GHN on N-way-1-shot tasks is larger than that on N-way-3-shot tasks. This illustrates Meta-GHN’s power on denoising for the practical few-shot learning scenarios.

5.3 Robustness Analysis (RQ2)
To examine the robustness of Meta-GHN on data with different noise levels, we show its performance in Figure 2 by varying the noise ratio. Firstly, on the data with no injected noise (i.e., \( \epsilon = 0 \)), Meta-GHN can still outperform the state-of-the-art for graph few-shot learning, which shows it is powerful in extrapolating the knowledge from seen to unseen node classes. Then if we inject the noise, the performance of all the baseline methods is degraded as the noise ratio increases, which is in accordance with our assumption. In addition, we also find that symmetric noise leads to larger decrease in the performance compared to Asymmetric in both 5-way 1-way and 10-way 1-way tasks. The main reason is that corrupting a label to a wider range of node classes may lead to a more challenging weakly-supervised meta-learning task. However, when we increase the noise ratio for either the symmetric or Asymmetric noise, the performance of Meta-GHN does not decrease very much. It can obtain larger improvement compared with the baselines in the data with higher noise level. This verifies the effectiveness of Meta-GHN in achieving robust performance on weakly-labeled data.

5.4 Ablation Study (RQ3)
To investigate the contribution of each component in Meta-GHN, we compare it with its variants in Figure 3 for an ablation study. Specifically, Meta-GHN-naive can be considered as a naive variant by excluding both robustness-enhanced episodic training and clean node hallucinate. Meta-GHN-MLP and Meta-GHN-mean denote the variants that calculate the confidence score for each node using a fully connecting layer and taking the average, respectively. As shown in the reported results, Meta-GHN-naive is highly vulnerable to label noise and unable to obtain competitive results with other variants on weakly-labeled few-shot node classification. Based on the proposed robustness-enhanced episodic training, Meta-GHN-mean uses the simplest way to compute the noise-reduced node representations, but can significantly outperforms Meta-GHN-naive, which verifies the importance of using the new episodic training paradigm. In the meantime, though Meta-GHN-MLP can improve Meta-GHN-mean by assigning weighted confidence score to each node, it still fall behind our approach, which shows the clean node hallucination module can better estimate the confidence score of each weakly-labeled node via message passing.

5.5 Parameter Analysis (RQ3)
In this subsection, to further understand the model design, we analyze the sensitivity of Meta-GHN to the support size \( K \) and the set size \( M \). Due to the space limit, here we show the results under the task of 5-way 1-shot with symmetric noise (\( \epsilon = 0.3 \)), similar patterns can be observed for other cases.

First, we summarize the performance of Meta-GHN with various support size \( K \) on ogbn-arxiv in Figure 4 (a). As we increase the
size of the support set, we can see that all the models obtain better performance, which is in accordance to our expectation. Since GPN relies on the support set to compute class prototypes, its performance is extremely sensitive to the number of set. The proposed Meta-GHN can achieve the best performance on different 5-way K-shot tasks. This demonstrates the superiority of Meta-GHN for solving weakly-supervised graph few-shot learning problems.

Next, we investigate the performance of Meta-GHN by varying the set size M and show the results of 5-way 1-shot (Sym) on the three datasets. From Figure 4 (b), we find that by increasing the set size M, the performance of Meta-GHN gradually improves, which indicates that larger set size is helpful to hallucinate noise-reduced node representations. Also, the model performance become stable when M ≥ 5, thus 5 is the appropriate value for M to obtain satisfying performance considering both efficiency and effectiveness.

6 CONCLUSION

In this paper, we introduce a novel graph meta-learning framework Graph Hallucination Networks (Meta-GHN) to solve few-shot learning problems under the weakly-supervised setting. Unlike existing methods, our approach does not require abundant golden labeled data from seen classes and can meta-learned to denoise for extracting highly transferable meta-knowledge from weakly-labeled data. Essentially, Meta-GHN leverages robustness-enhanced episodic training to hallucinate clean node representations by comparing and summarizing from weakly-labeled data in a meta-learning fashion. By training a pool of weakly-supervised few-shot learning tasks, Meta-GHN can be effectively generalized to the target unseen task. The empirical results over different datasets demonstrate the effectiveness of our proposed model versus the existing graph meta-learning state-of-the-arts.

A REPRODUCIBILITY SUPPLEMENTARY

A.1 Label Noise Injection

To enable our experiments on few-shot node classification with weakly-labeled data, we need to inject label noise to the training data. We focus on two representative types of label noise: symmetric and asymmetric noise [5]. In fact, the noise injection can be done by flipping the labels following the transition probabilities defined in a corruption matrix T, in which T_{ij} denotes the probability of flipping class c_{i} to class c_{j}. In Figure 5, we visualize the examples of corruption matrix for the dataset containing 5 label classes. For injecting noise of ratio ε to a dataset with P classes:

- **Symmetric noise** flips a label uniformly to all the other classes, s.t. T_{ii} = 1 − ε and T_{ij} = ε/(P − 1) if i ≠ j.
- **Asymmetric noise** flips a label to a different class with probability ε, s.t. T_{ii} = 1 − ε and ∃i ≠ j, T_{ij} = ε.

A.2 Implementation Details

**Implementation of Meta-GHN.** We implement the proposed Meta-GHN model in PyTorch. For the node representation learning module, we employ a SGC with 2-layer propagation. As for the clean node hallucination module, it uses one aggregation layer and we finetune the negative slope for the Leaky ReLU in the score calculation. We grid search for task numbers in {1, 5, 10, 15, 20, 25}, meta learning rate α in [1 × 10⁻⁴, 5 × 10⁻⁴], 1 × 10⁻³, 5 × 10⁻³, 1 × 10⁻², 5 × 10⁻², 5 × 10⁻¹, 1 × 10⁻¹] and meta step size β in [1 × 10⁻⁵, 5 × 10⁻⁵, 1 × 10⁻⁴, 5 × 10⁻⁴, 1 × 10⁻³, 5 × 10⁻³, 1 × 10⁻², 5 × 10⁻², 1 × 10⁻¹]. The optimal values are selected when the model achieve the best performance for validation set. We select the meta-learning rate α to be 0.1 and the meta step size β to be 0.001. For each task, we train the model for 20,000 episodes or early stop if the validation performance doesn’t increase for 10 consecutive episodes.

**Implementation of Baselines.** We test all the baseline methods with the publicly released implementations. In the experiments, we fine-tune the hyperparameters to report their best performance.

- **GCN.** It utilizes two graph convolutional layers (32, N dimensions) to learn the node representations for N-way-K-shot tasks.
- **SGC.** After the feature pre-processing step, it learns the node representations with 2-layer feature propagation.
- **GraphSAGE.** We set the search depth to 2 and the neighborhood sample size to 35 for both two layers (32, N dimensions). Relu function is used for non-linearity and the mean-pooling aggregator is selected for comparison.
- **PTA.** We set the propagation step to 10 and the parameter α is 0.1. We use two-layer neural network (32, N dimensions) with ReLu function for non-linearity.
- **Meta-GNN.** A 2-layer SGC is used for network embedding. Each batch contains 5 tasks. As suggested in the original paper, we set task-learning rate α₁ = 0.5 and meta-learning rate α₂ = 0.003.
• GPN. It employs a 2-layer (32, 16 dimensions) GCN as network encoder. The node valuator relies on two score aggregation layers. We use the optimal learning rate $\alpha = 0.005$.

• G-Meta. It takes the 2-hop neighbors into consideration and employs two graph convolutional aggregation layers (32, 32 dimensions) for representation learning. We select the optimal update learning rate $\alpha = 0.01$ meta learning rate $\beta = 0.001$.

REFERENCES

[1] Bai, J., Lee, D. B., and Hwang, S. J. Learning to extrapolate knowledge: Transductive few-shot out-of-graph link prediction. NeurIPS (2020).

[2] Cao, S., Li, W., and Xu, Q. Deep neural networks for learning graph representations. In AAAI (2016).

[3] Chang, S., Han, W., Tang, J., Qi, G.-J., Aggarwal, C. C., and Huang, T. S. Heterogeneous network embedding via deep architectures. In KDD (2015).

[4] Chauhan, J., Nathani, D., and Kaul, M. Few-shot learning on graphs via super-classes based on graph spectral measures. In ICLR (2019).

[5] Chen, P., Liao, B. B., Chen, G., and Zhang, S. Understanding and utilizing deep neural networks trained with noisy labels. In ICML (2019).

[6] Defferrard, M., Bresson, X., and Vandergheynst, P. Convolutional neural networks on graphs with fast localized spectral filtering. In NeurIPS (2016).

[7] Ding, K., Li, J., Bhansali, R., and Liu, H. Deep anomaly detection on attributed graphs. In SDM (2019).

[8] Ding, K., Wang, J., Li, J., Shu, K., Liu, C., and Liu, H. Graph prototypical networks for few-shot learning on attributed networks. In CIKM (2020).

[9] Dong, H., Chen, J., Feng, F., He, X., Bi, S., Ding, Z., and Cui, P. On the equivalence of decoupled graph convolution network and label propagation. In The Web Conference (2021).

[10] Finn, C., Abbeel, P., and Levine, S. Model-agnostic meta-learning for fast adaptation of deep networks. In ICML (2017).

[11] Grover, A., and Leskovec, J. node2vec: Scalable feature learning for networks. In KDD (2016).

[12] Hamilton, W., Ying, Z., and Leskovec, J. Inductive representation learning on large graphs. In NeurIPS (2017).

[13] Henaff, M., Bruna, J., and LeCun, Y. Deep convolutional networks on graph-structured data. arXiv preprint arXiv:1506.05163 (2015).

[14] Hendrycks, D., Mazeika, M., Wilson, D., and Gimpel, K. Using trusted data to train deep networks on labels corrupted by severe noise. In NeurIPS (2018).

[15] Hu, W., Fey, M., Zitnik, M., Dong, Y., Ren, H., Liu, B., Catasta, M., and Leskovec, J. Open graph benchmark. Datasets for machine learning on graphs. In NeurIPS (2020).

[16] Huang, K., and Zitnik, M. Graph meta learning via local subgraphs. In NeurIPS (2020).

[17] Jiang, L., Zhou, Z., Leung, T., Li, L.-J., and Fei-Fei, L. MentorNet: Learning data-driven curriculum for very deep neural networks on corrupted labels. In ICML (2018).

[18] Kipf, T. N., and Welling, M. Semi-supervised classification with graph convolutional networks. In NeurIPS (2017).

[19] Lan, L., Wang, P., Du, X., Song, K., Tao, J., and Guan, X. Node classification on graphs with few-shot novel labels via meta transformed network embedding. In NeurIPS (2020).

[20] Li, Z., Zhou, F., Chen, F., and Li, H. Meta-sgd: Learning to learn quickly for few-shot learning. arXiv preprint arXiv:1707.09835 (2017).

[21] Liu, L., Zhou, T., Long, G., Jiang, J., and Zhang, C. Learning to propagate for graph meta-learning. In NeurIPS (2019).

[22] Liu, Z., Fang, Y., Liu, C., and Hoi, S. C. Relative and absolute location embedding for few-shot node classification on graph. In AAAI (2021).

[23] Liu, Z., Zhang, W., Fang, Y., Zhang, X., and Hoi, S. C. Towards locality-aware meta-learning of tail node embeddings on networks. In CIKM (2020).

[24] Ma, N., Bo, J., Yao, J., Zhang, Z., Yao, C., Yu, Z., Zhou, S., and Yan, X. Adaptive-step graph meta-learner for few-shot graph classification. In CIKM (2020).

[25] McAuley, J., Pandey, R., and Leskovec, J. Inferring networks of substitutable and complementary products. In KDD (2015).

[26] Mishra, N., Rohanimanesh, M., Chen, X., and Abbeel, P. A simple neural attentive meta-learner. In ICLR (2018).

[27] Qi, G.-J., Aggarwal, C., Tian, Q., Ji, H., and Huang, T. Exploring context and content links in social media: A latent space method. TPAMI (2011).

[28] Ravi, S., and Larochelle, H. Optimization as a model for few-shot learning. In ICLR (2017).

[29] Ravi, S., and Larochelle, H. Optimization as a model for few-shot learning. In International Conference on Learning Representations (ICLR) (2017).

[30] Ren, M., Trakatilou, E., Ravi, S., Swersky, K., Tenenbaum, J. B., Larochelle, H., and Zemel, R. S. Meta-learning for semi-supervised few-shot classification. In ICLR (2018).

[31] Ren, M., Zeng, W., Yang, B., and Urtasun, R. Learning to reweight examples for robust deep learning. In ICMl (2018).

[32] Santoro, A., Bartunov, S., Botvinick, M., Wierstra, D., and Lillicrap, T. Meta-learning with memory-augmented neural networks. In ICLR (2016).

[33] Schmidt, R. A., and Bjork, R. A. New conceptualizations of practice: Common principles in three paradigms suggest new concepts for training. Psychological science (1992).

[34] Shu, J., Swersky, K., and Zemel, R. Prototypical networks for few-shot learning. In NeurIPS (2017).

[35] Sung, F., Yang, Y., Zhang, L., Xiang, T., Torr, P. H., and Hospedales, T. M. Learning to compare: Relation network for few-shot learning. In CVPR (2018).

[36] Tang, J., Zhang, J., Yao, A., Li, L., Zhang, L., and Su, Z. Arnettminer: extraction and mining of academic social networks. In KDD (2008).

[37] Tang, X., Li, Y., Sun, Y., Yao, H., Mitra, P., and Wang, S. Transferring robustness for graph neural network against poisoning attacks. In WSDM (2020).

[38] Velečková, P., Cucurull, G., Casanova, A., Romero, A., Liu, P., and Bengio, Y. Graph attention networks. In ICLR (2018).

[39] Vinyals, O., Blundell, C., Lillicrap, T., Wierstra, D., et al. Matching networks for one shot learning. In NeurIPS (2016).

[40] Wang, Q., Mao, Z., Wang, B., and Guo, L. Knowledge graph embedding: A survey of approaches and applications. In TKDE (2017).

[41] Wu, F., Zhang, T., Souza Jr, A. H. D., Fifty, C., Yu, T., and Weinberger, K. Q. Simplifying graph convolutional networks. In ICML (2019).

[42] Xu, K., Hu, W., Leskovec, J., and Jegelka, S. How powerful are graph neural networks? In ICLR (2019).

[43] Yao, H., Zhang, C., Wei, Y., Jiang, M., Wang, S., Huang, J., Chowla, N. V., and Li, Z. Graph few-shot learning via knowledge transfer. In AAAI (2020).

[44] Zhang, C., Yao, H., Huang, C., Jiang, M., Li, Z., and Chowla, N. V. Few-shot knowledge graph completion. In AAAI (2020).

[45] Zhang, J., Zhao, C., Ni, B., Xu, M., and Yang, X. Variational few-shot learning. In ICCV (2019).

[46] Zhang, T., and Wu, B. A method for local community detection by finding core nodes. In ASONAM (2012).

[47] Zhang, W., Wang, Y., and Qiao, Y. Metalearner: Learning to hallucinate clean representations for noisy-labeled visual recognition. In CVPR (2019).

[48] Zhou, F., Cao, C., Zhang, K., Trauebek, G., Zhong, T., and Geng, J. Meta-gnn: On few-shot node classification in graph meta-learning. In CIKM (2019).

[49] Zhu, D., Zhang, Z., Cui, P., and Zhu, W. Robust graph convolutional networks against adversarial attacks. In KDD (2019).

[50] Zhu, L., and Yang, Y. Compound memory networks for few-shot video classification. In ECCV (2018).