Self-supervised Auxiliary Learning for Graph Neural Networks via Meta-Learning

Dasol Hwang, Jinyoung Park, Sunyoung Kwon, Kyung-Min Kim, Jung-Woo Ha, and Hyunwoo j. Kim

Abstract—In recent years, graph neural networks (GNNs) have been widely adopted in representation learning of graph-structured data and provided state-of-the-art performance in various application such as link prediction and node classification. Simultaneously, self-supervised learning has been studied to some extent to leverage rich unlabeled data in representation learning on graphs. However, employing self-supervision tasks as auxiliary tasks to assist a primary task has been less explored in the literature on graphs. In this paper, we propose a novel self-supervised auxiliary learning framework to effectively learn graph neural networks. Moreover, we design first a meta-path prediction as a self-supervised auxiliary task for heterogeneous graphs. Our method is learning to learn a primary task with various auxiliary tasks to improve generalization performance. The proposed method identifies an effective combination of auxiliary tasks and automatically balances them to improve the primary task. Our methods can be applied to any graph neural networks in a plug-in manner without manual labeling or additional data. Also, it can be extended to any other auxiliary tasks. Our experiments demonstrate that the proposed method consistently improves the performance of link prediction and node classification on heterogeneous graphs.

Index Terms—Graph Neural Network, Self-supervised Learning, Auxiliary Learning, Meta Learning, Meta-Path

1 INTRODUCTION

Recently, it has been leading a surge of interest in learning Graph Neural Networks (GNNs) for effective representation learning on graph-structured data. GNNs [1] are powerful representation learning method for graph and have shown superior performance in a variety of tasks such as node classification [2], link prediction [3], and graph classification [4]. The representation learned by GNN yields state-of-the-art performance in a wide range of applications including social network analysis [5], citation network analysis [2], recommender systems [6], [7], [8], physics [9], and drug discovery [10], visual understanding [11], [12]. As the success of GNNs [13], [14], the need for better representation learning for graphs has emerged. Most state-of-the-art approaches for deep learning, such as pre-training and fine-tuning [15], transfer learning [16], multi-task learning [17], self-supervised learning [18], meta-learning [19], have been extended to graphs, taking into account the characteristics of the graphs. Despite the wide development range of learning strategies for graphs, learning with auxiliary (pre-text) tasks has been less explored for further improving generalization performance.

Learning with auxiliary tasks is to jointly learn representation for multiple tasks while sharing the representation of those. This method can generalize better by learning effective representations. However, few approaches have been generalized to graph-structured data due to their fundamental challenges. First, graph structure (e.g., the number of nodes/edges, and diameter) and its meaning can significantly differ between domains. So, these should assume that the auxiliary tasks are carefully selected with substantial domain knowledge and expertise in graph characteristics. Also, it causes that auxiliary tasks can dominate training and harm generalization on the primary task, i.e., negative transfer [16]. To solve these challenges, we propose an auxiliary learning method to learn with the auxiliary tasks by focusing on improving the primary task.

Recent works show that they can be further improved by self-supervised learning on graphs. Self-supervised tasks can be designed based on node attributes and graph structure information: node property (e.g., degree, centrality, clustering coefficient, PageRank score etc.) prediction [20], context prediction [21], graph partitioning [18], cluster detection [22], graph kernel [23], graph completion [18] and attribute masking [21]. These tasks can be utilized as the auxiliary task and assume that they are carefully selected with substantial domain knowledge and expertise in graph characteristics to assist the primary task. Furthermore, since most graph neural networks operate on homogeneous graphs, which have a single type of nodes and edges, these auxiliary tasks are not specifically designed for heterogeneous graphs, which have multiple types of nodes and edges. Heterogeneous graphs commonly occur in real-world applications, for instance, a music dataset has multiple types of nodes (e.g., user, song, artist) and multiple types of relations (e.g., user-artist, song-film, song-instrument). To leverage on the heterogeneous graph, we introduce meta-path prediction as a self-supervised auxiliary task to encourage rich information of heterogeneous graphs.

In this paper, we propose a framework to train a graph...
neural networks with automatically selected auxiliary self-supervised tasks which assist the primary task without manual labeling or additional data. This can be formulated as a meta-learning problem. Our approach first generates meta-paths from heterogeneous graphs without manual labeling and train a model with meta-path prediction (auxiliary task) to assist the primary task such as link prediction and node classification. Furthermore, it can be extended to any other auxiliary tasks such as supervised and self-supervised task. Our method can be adopted to existing GNNs in a plug-in manner, enhancing the model performance.

Our contributions are as follows: 1) We propose a self-supervised learning method on a heterogeneous graph via meta-path prediction without manual labeling or additional data. 2) Our framework automatically selects auxiliary tasks (meta-paths) to assist the primary task via meta-learning. 3) We develop Hint Network that helps the learner network to benefit from challenging auxiliary tasks. To the best of our knowledge, this is the first auxiliary task with meta-paths specifically designed for leveraging heterogeneous graph structure. Our experiments show that various auxiliary tasks improve the representational power and meta-path prediction provides a significant improvement as the auxiliary task. Moreover, we confirm that the gains can be further improved to explicitly optimize auxiliary tasks for the primary task via meta-learning and Hint network, built on various state-of-the-art GNNs for homogeneous graphs and heterogeneous graphs.

2 RELATED WORK

2.1 Graph Neural Networks

Graph neural networks (GNNs) have been proposed to learn the representations of graph-structured data. It was developed by extending the existing deep learning approaches to graph data. Motivated by the success of CNNs, Kipf & Welling [2] presented a popular graph neural network called GCN, which developed spectral approaches into spatial approaches by localizing first-order approximation of graph convolutions. Graph attention network (GAT) [24] which adopts the attention mechanism to learn the attention coefficient of connected node pair is proposed. [25] demonstrated that the existing message passing method can not distinguish structurally different graphs. Then it proposed a graph isomorphism network (GIN) that can complement it. SGC [26] is a simplified model by removing non-linearity between GCN layers. [27] proposed graph transformer network (GTN) which learns new graph structures by softly selecting edge types and composite relations for generating useful multi-hop connections. Based on the variants of GNNs, they have provided promising results in a wide range of applications on graphs.

2.2 Self-supervised Learning

Self-supervised learning methods are constantly being explored in order to effectively utilize rich unlabeled data. It is a novel learning framework to train deep learning models by assigning supervision to unlabeled data by itself. In the computer vision domain, various self-supervised learning methods have been developed for general semantic understanding of images. Relative positioning [28] aims to train networks to predict relative position of two regions in the region patches of an image. [29] was inspired by Jigsaw Puzzle and designed a pretext task to train a model to solve the puzzle. Following this, various self-supervised learning method proposed: rotation [30], colourization [31], exemplar [32], image inpainting [33] and image clustering [34].

Inspired by self-supervised learning in computer vision, recent works show promising results that self-supervised learning can be effective for GNNs. Hu et al. [21] has introduced several strategies for pre-training GNNs in the graph-level tasks, such as attribute masking, context prediction, and structural similarity prediction. [18] incorporates self-supervision into GCNs and introduced three novel self-supervised tasks (node clustering, graph partitioning, graph completion) for GCNs on multi-task learning. These self-supervised learning tasks can be utilized as auxiliary tasks. However, one problem of learning with auxiliary tasks is that all the auxiliary tasks may not be beneficial for the target applications. So, we studied auxiliary learning for GNNs that explicitly focuses on the primary task.

2.3 Learning with Auxiliary tasks

Multi-task learning (MTL) [35] is usually used to improve the performance of all tasks by utilizing useful information from multiple relevant tasks. MTL has difficulties which not exist in learning for a single task. There may be conflicts between how to learn each task. Therefore, learning with multiple auxiliary tasks can harm generalization on the primary task referred to as negative transfer. Auxiliary Learning is a learning strategy to employ auxiliary tasks to assist the primary task. It is similar to multi-task learning, but auxiliary learning cares only the performance of the primary task. A number of auxiliary learning methods are proposed in a wide range of tasks [17], [36], [37]. AC-GAN [38] proposed an auxiliary classifier for generative models. Our approach generates meta-paths on heterogeneous graphs to make new labels and trains models to predict meta-paths as auxiliary tasks.

2.4 Meta-learning

Meta-learning aims at learning to learn models efficiently and effectively, and generalizes the learning strategy to new tasks. It has been proved to be effective on few-shot learning. Meta-learning includes black-box methods to approximate gradients without any information about models [39], [40], optimization-based methods to learn an optimal initialization for adapting new tasks [19], [41], [42], learning loss functions [41], [43] and metric-learning or non-parametric methods for few-shot learning [44], [45], [46]. In contrast to classical learning algorithms that generalize across samples, meta-learning generalizes across tasks. In contrast to classical learning algorithms that generalize the concept across samples, meta-learning generalizes across tasks. In this paper, we use meta-learning to learn a concept across tasks and transfer the knowledge from auxiliary tasks to the primary task.

Recent works on meta-learning for graphs have emerged. [47] is one-shot relational learning framework to
learn a differentiable metric to match entity pairs. MetaGNN [48] and Meta-Graph [49] are gradient-base meta-learning approaches in few-shot setting for node classification and link prediction. MetaR [50] is a meta relational learning framework to focus on transferring relation-specific meta information in few-shot link prediction. Besides, G-META [51] can learn transferable knowledge faster via meta gradients by leveraging local subgraphs. [52] introduces a novel meta-learner that explicitly relevant tasks on a graph that explains the relations of predicted classes in few-shot learning. Meta-learning for graphs is specialized in learning a learner and the few-shot learning. Our proposed method can learn how to assist the primary task by optimizing a weighting function rather than a model via meta-learning and transfer knowledge across tasks.

3 Method

The goal of our framework is to learn with multiple auxiliary tasks to improve the performance of the primary task. In this work, we demonstrate the benefits of our framework with various auxiliary tasks. Especially, we evaluate meta-path prediction as auxiliary tasks. The meta-paths capture diverse and meaningful relations between nodes on heterogeneous graphs [53]. However, learning with auxiliary tasks for graphs has multiple challenges: identifying useful auxiliary tasks, balancing the auxiliary tasks with the primary task, and converting challenging auxiliary tasks into solvable (and relevant) tasks. To address the challenges, we propose SELF-supervised Auxiliary LeArNing (SELAR).

Our framework consists of two main components:

- We propose a novel framework that learns weight functions to softly select auxiliary tasks and balance them with the primary task via meta-learning.
- We introduce Hint Networks to convert challenging auxiliary tasks into more relevant and solvable tasks to the primary task learner.

3.1 Meta-path Prediction as a self-supervised task

Most existing graph neural networks have been studied focusing on homogeneous graphs that have a single type of nodes and edges. However, in real-world applications, heterogeneous graphs [54], which have multiple types of nodes and edges, commonly occur. Learning models on the heterogeneous graphs requires different considerations to effectively represent their node and edge heterogeneity.

**Heterogeneous graph.** Let $G = (V,E)$ be a graph with a set of nodes $V$ and edges $E$. A heterogeneous graph [55] is a graph equipped with a node type mapping function $f_v : V \rightarrow T^v$ and an edge type mapping function $f_e : E \rightarrow T^e$, where $T^v$ is a set of node types and $T^e$ is a set of edge types. Each node $v_i \in V$ (and edge $e_{ij} \in E$ resp.) has one node type, i.e., $f_v(v_i) \in T^v$, (and one edge type $f_e(e_{ij}) \in T^e$ resp.). In this paper, we consider the heterogeneous graphs with $|T^v| > 1$ or $|T^e| > 1$. When $|T^v| = 1$ and $|T^e| = 1$, it becomes a homogeneous graph.

**Meta-Path.** Meta-path [53], [56] is a path on a heterogeneous graph $G$ that a sequence of nodes connected with heterogeneous edges, i.e., $v_1 \xrightarrow{t_1} v_2 \xrightarrow{t_2} \ldots \xrightarrow{t_l} v_{l+1}$, where $t_i \in T^e$ denotes an $l$-th edge type of the meta-path. The meta-path can be viewed as a composite relation $R = t_1 \circ t_2 \ldots \circ t_l$ between node $v_1$ and $v_{l+1}$, where $R_1 \circ R_2$ denotes the composition of relation $R_1$ and $R_2$. The definition of meta-path generalizes multi-hop connections and is shown to be useful to analyze heterogeneous graphs. For instance, in Book-Crossing dataset, ‘user-item-written.series-item-user’ indicates that a meta-path that connects users who like the same book series.

We introduce meta-path prediction as a self-supervised auxiliary task to improve the representational power of graph neural networks. To our knowledge, the meta-path prediction has not been studied in the context of self-supervised learning for graph neural networks in the literature.

**Meta-path prediction.** Meta-path prediction is similar to link prediction but meta-paths allow heterogeneous composite relations. The meta-path prediction can be achieved in the same manner as link prediction. If two nodes $u$ and $v$ are connected by a meta-path $p$ with the heterogeneous edges $(t_1, t_2, \ldots, t_l)$, then $y^p_{u,v} = 1$, otherwise $y^p_{u,v} = 0$. The labels can be generated from a heterogeneous graph without any manual labeling. They can be obtained by $A_p = A_{u_1} \cdots A_{u_l} A_{v_l}$, where $A_t$ is the adjacency matrix of edge type $t$. The binarized value at $(u,v)$ in $A_p$ indicates whether $u$ and $v$ are connected with the meta-path $p$. In this paper, we use meta-path prediction as a self-supervised auxiliary task.

Let $X \in \mathbb{R}^{V \times d}$ and $Z \in \mathbb{R}^{V \times d'}$ be input features and their hidden representations learnt by GNN $f$, i.e., $Z = f(X; w, A)$, where $w$ is the parameter for $f$, and $A \in \mathbb{R}^{|V| \times |V|}$ is the adjacency matrix. Then link prediction and meta-path prediction are obtained by a simple operation as

$$\hat{y}_{u,v} = \sigma(\Phi_t(z_u)^T \Phi_t(z_v)), \quad (1)$$

where $\Phi_t$ is the task-specific network for task $t \in T$ and $z_u$ and $z_v$ are the node embeddings of node $u$ and $v$, e.g., $\Phi_0$ (and $\Phi_1$ resp.) for link prediction (and the first type of meta-path prediction resp.).

**The architecture** is shown in Fig. 1 for link prediction, especially meta-path prediction as auxiliary tasks. To optimize the model, as the link prediction and the meta-path prediction, cross entropy is used. The graph neural network $f$ is shared by the link prediction and meta-path prediction and there is a task-specific function $\Phi$ for each task. As any auxiliary learning methods, the auxiliary task samples (meta-paths) should be carefully chosen and properly weighted so that the auxiliary task (meta-path prediction) does not compete with link prediction (primary task) especially when the capacity of GNNs is limited. To address these issues, we propose our framework that automatically selects meta-paths and balances them with the primary task via meta-learning.

3.2 Self-Supervised Auxiliary Learning

Our framework SELAR is learning to learn a primary task with multiple auxiliary tasks to assist the primary task. This
can be formally written as

\[
\min_{\mathbf{w}, \Theta} \mathbb{E}_{(x,y) \sim D^{pr}} \left[ L^{pr}(\mathbf{w}^*(\Theta)) \right] \\
\text{s.t. } \mathbf{w}^*(\Theta) = \arg\min_{\mathbf{w}} \mathbb{E}_{(x,y) \sim D^{pr+au}} \left[ L^{pr+au}(\mathbf{w}; \Theta) \right],
\]

where \( L^{pr}(\cdot) \) is the primary task loss function to evaluate the trained model \( f(x; \mathbf{w}^*(\Theta)) \) on meta-data (a validation set), \( L^{pr+au}(\mathbf{w}; \Theta) \) is the loss function to train a model on training data \( D^{pr+au} \) with the primary and auxiliary tasks. To avoid cluttered notation, \( f, x, \) and \( y \) are omitted. Each task \( T_i \) has \( N_i \) samples, \( T_0 \) and \( \{T_i\}_{t=1}^{T} \) denote the primary and auxiliary tasks respectively. The proposed formulation in Eq. (2) learns how to assist the primary task by optimizing \( \Theta \) via meta-learning. The nested optimization problem given \( \Theta \) is a regular training with properly adjusted loss functions to balance the primary and auxiliary tasks. The formulation can be more specifically written as

\[
\min_{\mathbf{w}, \Theta} \frac{1}{M} \sum_{i=1}^{M} L^t(y_i^{(0,\text{meta})}, f_i^{(0,\text{meta})}; \mathbf{w}^*(\Theta)) \\
\text{s.t. } \mathbf{w}^*(\Theta) = \arg\min_{\mathbf{w}} \sum_{i=1}^{T} \sum_{t=1}^{N_i} \frac{1}{N_i} \mathbb{V}(\cdot; \Theta) \ell^t(y_i, \hat{y}_i),
\]

where \( \ell^t \) and \( f^t \) denote the loss function and the model for task \( t \). We overload \( \ell^t \) with its function value, i.e., \( \ell^t(y_i, \hat{y}_i) \) where \( \hat{y}_i = f^t(x_i^{(t,\text{train})}; \mathbf{w}) \). The embedding vector of \( i_{th} \) sample for task \( t \) denotes \( \xi^t_{(i_{th})} \). The input of the weighting function is \( \xi^t \), i.e., \( \mathbb{V}(\xi^t; \Theta) \). In our experiment, \( \xi^t \) is the concatenation of the loss value, one-hot representation of task types, and the label of the sample (positive/negative), i.e., \( \xi^t = [\ell^t; \ell^t; y_i^{(t,\text{train})}] \in \mathbb{R}^T+2 \).

To derive our learning algorithm, we first shorten the objective function in Eq. (3) and Eq. (4) as \( L^{pr}(\mathbf{w}^*(\Theta)) \) and \( L^{pr+au}(\mathbf{w}; \Theta) \). This is equivalent to Eq. (2) without expectation. Then, our formulation is given as

\[
\min_{\mathbf{w}, \Theta} L^{pr}(\mathbf{w}^*(\Theta)) \text{ s.t. } \mathbf{w}^*(\Theta) = \arg\min_{\mathbf{w}} L^{pr+au}(\mathbf{w}; \Theta),
\]

To circumvent the difficulty of the bi-level optimization, as previous works [19], [41] in meta-learning we approximate it with the updated parameters \( \hat{\mathbf{w}} \) using the gradient descent update

\[
\mathbf{w}^*(\Theta) \approx \hat{\mathbf{w}}^k(\Theta) = \mathbf{w}^k - \alpha \nabla_{\mathbf{w}} L^{pr+au}(\mathbf{w}^k; \Theta),
\]

where \( \alpha \) is the learning rate for \( \mathbf{w} \). We do not numerically evaluate \( \hat{\mathbf{w}}^k(\Theta) \) instead we plug the computational graph of \( \hat{\mathbf{w}}^k(\Theta) \) in \( L^{pr}(\mathbf{w}^*(\Theta)) \) to optimize \( \Theta \). Let \( \nabla_{\Theta} L^{pr}(\mathbf{w}^*(\Theta)) \) be the gradient evaluated at \( \Theta^k \). Then updating parameters \( \Theta \) is given as

\[
\Theta^{k+1} = \Theta^k - \beta \nabla_{\Theta} L^{pr}(\hat{\mathbf{w}}^k(\Theta)),
\]

where \( \beta \) is the learning rate for \( \Theta \). This update allows softly selecting useful auxiliary tasks (meta-paths) and balance them with the primary task to improve the performance of the primary task. Without balancing tasks with the weighting function \( \mathbb{V}(\cdot; \Theta) \), auxiliary tasks can dominate training.

**Algorithm 1** Self-supervised Auxiliary Learning

**Input:** training data for primary/auxiliary tasks \( D^{pr}/D^{au} \), mini-batch size \( N_{pr}, N_{au} \)

**Output:** network parameter \( \mathbf{w}^K \) for the primary task

1: for \( k = 1 \) to \( K \) do
2: \( D^{pr}_m \leftarrow \text{MiniBatchSampler}(D^{pr}, N_{pr}) \)
3: \( D^{au}_m \leftarrow \text{MiniBatchSampler}(D^{au}, N_{au}) \)
4: for \( c = 1 \) to \( C \) do \( \triangleright \) Cross Validation
5: \( D^{pr}_m(\text{train}), D^{pr}_m(\text{meta}) \leftarrow \text{CVSplit}(D^{pr}_m, c) \)
6: \( \hat{\mathbf{w}}^k(\Theta) \leftarrow \mathbf{w}^k - \alpha \nabla_{\mathbf{w}} L^{pr+au}(\mathbf{w}^k; \Theta) \)
7: with \( D^{pr}_m(\text{train}) \cup D^{au}_m \) \( \triangleright \) Eq. (6)
8: \( g_c \leftarrow \nabla_{\Theta} L^{pr}(\hat{\mathbf{w}}^k) \) with \( D^{pr}_m(\text{meta}) \) \( \triangleright \) Eq. (7)
9: end for
10: Update \( \Theta^{k+1} \leftarrow \Theta^k - \beta \sum_c g_c \) \( \triangleright \) Eq.(9)
11: \( \mathbf{w}^{k+1} = \mathbf{w}^k - \alpha \nabla_{\mathbf{w}} L^{pr+au}(\mathbf{w}^k; \Theta^{k+1}) \)
12: with \( D^{pr}_m \cup D^{au}_m \) \( \triangleright \) Eq. (8)
13: end for

![Fig. 1. The SELAR framework for self-supervised auxiliary learning. Our framework learns how to balance (or softly select) auxiliary tasks to improve the primary task via meta-learning. In this paper, the proposed formulation is link prediction (or node classification) and auxiliary tasks are meta-path predictions to capture rich information of a heterogeneous graph.](image-url)
and degrade the performance of the primary task.

The model parameters $w^k$ for tasks can be updated with optimized $\Theta^{k+1}$ in (7) as

$$w^{k+1} = w^k - \alpha \nabla_w L^{pr+au}(w^k; \Theta^{k+1}).$$

(8)

Remarks. The proposed formulation can suffer from the meta-overfitting [57], [58] meaning that the parameters $\Theta$ to learn weights for softly selecting meta-paths and balancing the tasks with the primary task can overfit to the small meta-dataset. In our experiment, we found that the overfitting can be alleviated by meta-validation sets [57]. To learn $\Theta$ that is generalizable across meta-training sets, we optimize $\Theta$ across $k$ different meta-datasets like $k$-fold cross validation using the following equation:

$$\Theta^{k+1} = \Theta^k - \beta E \left[ \nabla_{\Theta} L^{pr}(\hat{w}^k(\Theta^k)) \right],$$

(9)

where $D_{pr(meta)} \sim CV$ is a meta-dataset from cross validation. We used 3-fold cross validation and the gradients of $\Theta$ w.r.t different meta-datasets are averaged to update $\Theta^k,$ see Algorithm 1. The cross validation is crucial to alleviate meta-overfitting and more discussion is Section 5.2.

### 3.3 Hint Networks

Meta-path prediction is generally more challenging than link prediction and node classification since it requires the understanding of long-range relations across heterogeneous nodes. The meta-path prediction gets more difficult when mini-batch training is inevitable due to the size of datasets or models. Within a mini-batch, important nodes and edges for meta-paths are not available. Also, a small learner network, e.g., 2-layer GNNs, with a limited receptive field, inherently cannot capture long-range relations. The challenges can hinder representation learning and damage the generalization of the primary task. We proposed a Hint Network (HintNet) which makes the challenging tasks more solvable by correcting the answer with more information at the learner’s need. Specifically, the Hintnet corrects the answer of the learner with its own answer from the augmented graph with hub nodes, see Fig. 2.

The amount of help (correction) by HintNet is optimized maximizing the learner’s gain. Let $V_H(\cdot)$ and $\Theta_H$ be a weight function to determine the amount of hint and its parameters which are optimized by meta-learning. Then, our formulation with HintNet is given as

$$\min_{w,\Theta} \frac{1}{M_0} \sum_{i=1}^{M_0} \ell^0(y_{i,(0,\text{meta})}^{(0,\text{meta})}, f(x_{i,(0,\text{meta})}^{(0,\text{meta})}, w^*(\Theta, \Theta_H))),$$

(10)

$$\text{s.t. } w^*(\Theta) = \text{argmin}_w \sum_{t=0}^T \sum_{i=1}^{N_t} \frac{1}{N_t} V(\cdot, \ell^t; \Theta)\ell^t(y_i, \hat{y}_i(\Theta_H),$$

(11)

where $\hat{y}_i(\Theta_H)$ denotes the convex combination of the learner’s answer and HintNet’s answer, i.e., $\hat{y}_i(\Theta_H) = V_H f_t^H(x_{i,(\text{train})}^t; w) + (1 - \nu_H) f_t(x_{i,(\text{train})}^t; w) \text{ and } V_H = \nu_H \xi_i(\text{train}; \Theta_H).$ The input of the weighting function for HintNet is $\xi_i(\text{train}) = [\ell^t; \ell^t_H; \ell_i^t; \hat{y}_i(\text{train})] \in \mathbb{R}^{T+3}.$

Fig. 2. HintNet helps the learner network to learn even with challenging and remotely relevant auxiliary tasks. As our framework selects effective auxiliary tasks, our framework with HintNet learns $V_H$ to decide to use hint $\hat{y}_i$ in the orange line from HintNet or not via meta-learning. $\hat{y}$ in the blue line denotes the prediction from the learner network.

### 4 Experiments

We evaluate our proposed methods on four public benchmark datasets of heterogeneous graphs. Our experiments answer the following research questions: Q1. Is meta-path prediction effective for representation learning on heterogeneous graphs? Q2. Can the meta-path prediction be further improved by the proposed methods (e.g., SELAR, HintNet)? Q3. Can our proposed methods benefit from auxiliary tasks in the primary task performance? Q4. Why are the proposed methods effective, any relation with hard negative mining?

#### 4.1 Settings

**Datasets.** We use two public benchmark datasets from different domains for link prediction: Music dataset Last-FM and Book dataset Book-Crossing, released by KGNN-LS [8]. RippleNet [7]. The Last-FM dataset with a knowledge graph has 122 types of edges, e.g., “artist.origin”, “musician.instruments.played”, “person.or.entity.appearing.in.film”, and “film.actor.film”, etc. Book-Crossing with a knowledge graph has 52 types of edges, e.g., “book.genre”, “literary.series”, “date.of.first.publication”, and “written.work.translation”, etc.

**Table 1:**

| Datasets     | # Nodes | # Edges | # Edge type | # Features |
|--------------|---------|---------|-------------|------------|
| Last-FM      | 15,084  | 73,382  | 122         | N/A        |
| Book-Crossing| 110,739 | 442,746 | 52          | N/A        |
| ACM          | 8,994   | 25,922  | 4           | 1,902      |
| IMDB         | 12,772  | 37,288  | 4           | 1,256      |

We use two datasets for node classification: citation network datasets ACM and Movie dataset IMDB, used by HAN [53] for node classification tasks. ACM has three types nodes (Paper(P), Author(A), Subject(S)), four types of edges (PA, AP, PS, SP) and labels (categories of papers). IMDB contains three types of nodes (Movie (M), Actor (A),
TABLE 2
Link prediction performance (AUC) of GNNs trained by various learning strategies.

| Dataset        | Base GNNs | Vanilla w/o meta-path | w/ meta-path | Ours SELAR | SELAR+Hint |
|----------------|-----------|------------------------|-------------|-----------|-----------|
| Last-FM        | GCN       | 0.7963                 | 0.7889      | 0.8235    | 0.8296    | 0.8121    |
|                | GAT       | 0.8115                 | 0.8115      | 0.8263    | 0.8294    | 0.8302    |
|                | GIN       | 0.8199                 | 0.8217      | 0.8242    | 0.8361    | 0.8350    |
|                | SGC       | 0.7703                 | 0.7766      | 0.7718    | 0.7827    | 0.7975    |
|                | GTN       | 0.7836                 | 0.7744      | 0.7865    | 0.7988    | 0.8067    |
| Avg. Gain      |           |                        |             | +0.0106   | +0.0190   | +0.0200   |
| Book-Crossing  | GCN       | 0.7039                 | 0.7031      | 0.7110    | 0.7182    | 0.7208    |
|                | GAT       | 0.6891                 | 0.6968      | 0.7075    | 0.7345    | 0.7360    |
|                | GIN       | 0.6979                 | 0.7210      | 0.7338    | 0.7526    | 0.7513    |
|                | SGC       | 0.6860                 | 0.6808      | 0.6792    | 0.6902    | 0.6926    |
|                | GTN       | 0.6732                 | 0.6758      | 0.6724    | 0.6858    | 0.6850    |
| Avg. Gain      |           |                        |             | +0.0055   | +0.0108   | +0.0263   | +0.0267   |

TABLE 3
The average of the task-specific weighted loss.

| Meta-paths (Last-FM) | Avg. | Meta-paths (Book-Crossing) | Avg. |
|----------------------|------|-----------------------------|------|
| user-item-actor-item | 7.675| user-item-literary.series-item-user | 6.439|
| user-item*           | 7.608| item-genre-item              | 6.217|
| user-item-appearing.in.film-item | 7.372| user-item-user-item         | 6.163|
| user-item-instruments-item | 7.049| user-item-user            | 6.126|
| user-item-user-item  | 6.878| item-user-item              | 6.066|
| user-item-artist.origin-item | 6.727| item-user-item           | 6.025|

* primary task

Director (D)), four types (MA, AM, MD, DM) of edges and labels (genres of movies). Last-FM and Book-Crossing do not have node features, while ACM and IMDB have node features, which are bag-of-words of keywords and plots. Statistics of the datasets are in Table 1.

Baselines. We evaluate our methods with five graph neural networks: GCN [2], GAT [24], GIN [25], SGCConv [26] and GTN [27]. Our methods can be applied to both homogeneous graphs and heterogeneous graphs. We compare five learning strategies: Vanilla, standard training of base models only with the primary task samples; w/o meta-path, learning a primary task with sample weighting function \( V(\xi; \Theta) \); w/ meta-path, training with the primary task and auxiliary tasks (meta-path prediction) with a standard loss function; SELAR proposed in Section 3.2, learning the primary task with optimized auxiliary tasks by meta-learning; SELAR+Hint introduced in Section 3.3.

Implementation details. All the models are randomly initialized and optimized using Adam [59] optimizers. For a fair comparison, the number of layers is set to two and the dimensionality of output node embeddings is the same across models. The node embedding \( z \) for Last-FM has 16 dimensions and for the rest of the datasets 64 dimensions. Since datasets have a different number of samples, we train models for a different number of epochs; Last-FM (100), Book-Crossing (50), ACM (200), and IMDB (200). For link prediction, the neighborhood sampling algorithm [60] is used and the neighborhood size is 8 and 16 in Last-FM and Book-Crossing respectively. For node classification, the neighborhood size is 8 in all datasets. For the experiments on link prediction using SELAR+Hint, we train a learner network with attenuated weights as a regularization, i.e., \( V_H(\xi_i^{(t,\text{train})}; \Theta_H)^\gamma f_t(x_i^{(t,\text{train})}; w) + (1 - V_H(\xi_i^{(t,\text{train})}; \Theta_H)^\gamma) f_H(x_i^{(t,\text{train})}; w) \), where \( 0 < \gamma \leq 1 \). In all the experiments, hyperparameters such as learning rate and weight-decay rate are tuned using validation sets for all models. The test performance was reported with the best models on the validation sets. We report the mean performance of three independent runs. Our experiments were mainly performed based on NAVER Smart Machine Learning platform (NSML) [61], [62]. All the experiments use PyTorch [63] and the geometric deep learning extension library provided by Fey & Lenssen [64].

4.2 Link Prediction with meta-path prediction

Link prediction results. We used five types of meta-paths of length 2 to 4 for auxiliary tasks. Table 2 shows that our methods consistently improve link prediction performance for all the GNNs, compared to the Vanilla and the method using Meta-Weight-Net [41] only without meta-paths (denoted as w/o meta-path). Overall, a standard training with meta-paths shows 1.1% improvement on average on both Last-FM and Book-Crossing whereas meta-learning
that learns sample weights degrades on average on Last-FM and improves only 0.6% on average on Book-Crossing, e.g., GCN, SGC and GTN on Last-FM and GCN and SGC on Book-Crossing, show degradation 0.2% compared to the standard training (Vanilla). As we expected, SELAR and SELAR with HintNet provide more optimized auxiliary learning resulting in 1.9% and 2.0% absolute improvement on Last-FM and 2.6% and 2.7% on the Book-Crossing dataset. Further, in particular, GIN on Book-crossing, SELAR and SELAR+Hint provide ∼5.5% and ∼5.3% absolute improvement compared to the vanilla algorithm.

**Task selection results.** Our proposed methods can identify useful auxiliary tasks and balance them with the primary task. In other words, the loss functions for tasks are differentially adjusted by the weighting function learned via meta-learning. To analyze the weights of the tasks, we calculate the average of the task-specific weighted loss learned by SELAR+HintNet for GAT. Table 3 shows tasks in descending order of the task weights. ‘user-item-actor-item’ has the largest weight followed by ‘user-item’ (primary task), ‘user-item-appearing.in.film-item’, ‘user-item-instruments-item’, ‘user-item-user-item’ and ‘user-item-artist.origin-item’ on the Last-FM. It indicates that the preference of a given user is closely related to other items connected by an actor, e.g., specific edge type ‘film.actor.film’ in the knowledge graph. Moreover, our method focuses on ‘user-item’ interaction for the primary task. On the Book-Crossing dataset, our method has more attention to ‘user-item’ for the primary task and ‘user-item-literary.series-item-user’ which means that users who like a series book have similar preferences.
4.3 Recommender system with meta-path prediction

To evaluate our framework in the recommendation scenario on music dataset Last-FM, we use top-K recommendation Recall@K (R@K), which is the proportion of the relevant items among those selected as the K item with the highest predicted probability for each user. We compare our proposed method to the baseline methods to demonstrate its effectiveness on recommendation. We use SVD [65], LibFM [66], LibFM+TransE [66], [67], PER [68], CKE [69], RippleNet [7] and KGGN-LS [8] as recommendation baselines and GCN [2], GAT [24], GIN [25], SGC [26] and GTN [27] as GNN base models. The performance comparison results in top-K recommendation are presented in Table 4. SELAR consistently improve the performance on Last-FM, compared to the vanilla learning scheme. In particular, SELAR improved the Recall@2 of GAT by 1.9% absolute gains compared to the vanilla. SELAR on GTN and GCN shows 17% and 13% improvements from the vanilla in Recall@850 and Recall@100, respectively. Also, SELAR performed as much as KGGN-LS, a model designed for user-specific recommendations, and yielded high performance in the rest of evaluation metrics except Recall@10.

4.4 Node Classification with meta-path prediction

Similar to link prediction above, Table 5 shows that our SELAR consistently enhances node classification performance of all the GNN models and the improvements are more significant on IMDB which is larger than the ACM dataset. We believe that ACM dataset is already saturated and the room for improvement is limited. However, our methods still show small yet consistent improvement over all the architecture on ACM. We conjecture that the efficacy of our proposed methods differs depending on graph structures. However, it is worth noting that introducing meta-path prediction as auxiliary tasks remarkably improves the performance of primary tasks such as link and node prediction with consistency compared to the existing methods. “w/o meta-path”, the meta-learning to learn sample weight function on a primary task shows marginal degradation in five out of eight settings. Remarkably, SELAR improved the F1-score of GAT on the IMDB by (4.46%) compared to the vanilla learning scheme.

4.5 Extended to various auxiliary tasks

To demonstrate that our methods can be extended to include other auxiliary tasks, we experiment with multiple self-supervised tasks on a graph as auxiliary tasks. The details of auxiliary tasks we used are elaborated below.

Degree prediction is to predict the degree for each node in the graph. The goal of this auxiliary task is to learn local structure information by quantifying the node connectivity as a local measure. Specifically, we first calculate the degree \(d(i) = \sum_{j=1}^{N} A_{ij} \) for all node and group the degree into three categories \(c_i\): the top 20%, bottom 20% of the degree magnitude, and the rest. We use randomly selected \(|D|\) samples from nodes \(V\), i.e., \(D \subset V\). The loss of this auxiliary task can be formulated as the cross entropy loss as follows

\[
L_{\text{degree}} = \frac{1}{|D|} \sum_{i=1}^{|D|} \ell(f(x_i; w), c_i)
\]  

Pairwise Node Distance [20] is designed to predict the distance between different node pairs. It aims to encourage the GNNs to learn global topology information via a pairwise comparison. We use the shortest path length as a measure of the distance between nodes. We can calculate the shortest path length \(sp_{ij}\) for all node pairs \((u_i, u_j)\). We group the node pairs in a graph into four categories and use only randomly selected \(|E'|\) samples from all edges \(E\), i.e., \(E' \subset E\). We can denote the pairwise distance loss function as follows

\[
L_{\text{dist}} = \frac{1}{|E'|} \sum_{(u_i, u_j) \in E'} \ell((f(u_i; w) - f(u_j; w), c_{sp_{ij}})
\]  

PageRank prediction aims to predict the PageRank score, which indicates the importance of each node in the graph. The assumption of the PageRank [70] algorithm is that the more important nodes, the more nodes are connected, and the nodes with many important nodes are important. Predicting these PageRank scores can learn the importance of nodes based on their structural roles of each node in the whole graph. \(PR(i) = \sum_{j \in E} PR(j)\), denotes the PageRank score of \(i\)-th node. We can divide label categories similar to degree prediction and construct the cross entropy loss as Eq.(12).

Node clustering first generates a cluster set via the existing graph clustering algorithm (K-means). It is a self-supervised task that predicts which cluster target node belongs to. Given the node set \(V, A_k \subset V\) denote a subset of the nodes belong to \(k\) cluster in the graph. The Clustering algorithm will output \(K\) disjoint subsets \(A_1, \ldots, A_k\). Each node is assigned a label indicating which cluster it belongs to, i.e., \(y_u = k\) if \(u \in A_k \forall k = 1, \ldots, K\). This task allows models to infer latent cluster structure in the graph. It can learn that features are more similar between nodes of the same cluster, and that nodes belonging to different clusters are dissimilar. In the graph, you can learn information that features are more similar between nodes of the same cluster, and that nodes belonging to different clusters are dissimilar.

Graph partitioning is a self-supervised task that predicts which partition each node is assigned to. To this, we first separate nodes into \(K\) disjoint subsets \(P_1, \ldots, P_K \subset V\) through METIS [71] algorithm. This partition algorithm generates partitions to minimize the number of connected edges (edge-cut) between partitions. These partitions have the following conditions: \(\bigcup_{k=1}^{K} P_k = V\), \(\forall k = 1, \ldots, K\) and \(P_i \cap P_j = \emptyset\), \(\forall i, j = 1, \ldots, K\). These partition indices are assigned as self-supervised labels. It is similar to above the notion of node clustering, but graph partitioning relies on the edges and is based on topology, and node clustering assumes feature similarity based on nodes. This task can learn to distinguish node properties based on graph topology.

To evaluate the benefits from various combinations of the auxiliary tasks described above in node classification on IMDB, we compare our SELAR with standard multi-task learning (denote as MTL). We conducted experiments on all base models based on six auxiliary tasks: Degree, node degree prediction; Distance, pairwise node distance prediction; PageRank, PageRank score prediction; Clustering, node clustering label prediction; Partition, graph partition-
| Base GNNs | Combination of auxiliary tasks | MTL      | SELAR     |
|----------|--------------------------------|----------|-----------|
| GCN      | Degree                         | 0.5886   | 0.6074    |
|          | Distance                       | 0.5880   | 0.6080    |
|          | PageRank                       | 0.5906   | 0.5919    |
|          | Partition                      | 0.5835   | 0.6127    |
|          | Clustering                     | 0.5841   | 0.5878    |
|          | Degree+Distance                | 0.5975   | 0.5983    |
|          | Degree+Distance+PageRank       | 0.5908   | 0.5993    |
|          | Degree+Distance+PageRank+Partition | 0.5864  | 0.6255    |
|          | Degree+Distance+PageRank+Meta-path | 0.6162  | 0.6317    |
|          | Degree+Distance+PageRank+Partition+Clustering+Meta-path | **0.6096** | 0.6036 |
| GAT      | Degree                         | 0.5679   | 0.5689    |
|          | Distance                       | **0.5627** | 0.5598    |
|          | PageRank                       | 0.5371   | 0.5697    |
|          | Partition                      | 0.5507   | 0.5542    |
|          | Clustering                     | 0.5488   | 0.5533    |
|          | Degree+Distance                | 0.5586   | 0.5735    |
|          | Degree+Distance+PageRank       | 0.5741   | 0.6010    |
|          | Degree+Distance+PageRank+Partition | 0.5910  | 0.6115    |
|          | Degree+Distance+PageRank+Meta-path | 0.6029  | 0.6164    |
|          | Degree+Distance+PageRank+Partition+Clustering+Meta-path | **0.6132** | 0.6100    |
| GIN      | Degree                         | 0.5714   | 0.5863    |
|          | Distance                       | 0.5727   | 0.5746    |
|          | PageRank                       | 0.5782   | 0.5799    |
|          | Partition                      | 0.5708   | 0.5754    |
|          | Clustering                     | **0.5706** | 0.5705    |
|          | Degree+Distance                | 0.5700   | 0.5772    |
|          | Degree+Distance+PageRank       | 0.5713   | 0.5815    |
|          | Degree+Distance+PageRank+Partition | 0.5690  | 0.5741    |
|          | Degree+Distance+PageRank+Meta-path | 0.5863  | 0.5939    |
|          | Degree+Distance+PageRank+Partition+Clustering+Meta-path | 0.5654  | 0.5833    |
| SGC      | Degree                         | 0.5698   | 0.5802    |
|          | Distance                       | 0.5822   | 0.5898    |
|          | PageRank                       | 0.5826   | 0.5839    |
|          | Partitioning                   | 0.5885   | 0.5960    |
|          | Clustering                     | **0.5854** | 0.5805    |
|          | Degree+Distance                | 0.5770   | 0.5850    |
|          | Degree+Distance+PageRank       | 0.5713   | 0.5804    |
|          | Degree+Distance+PageRank+Partitioning | 0.5717  | 0.5859    |
|          | Degree+Distance+PageRank+Meta-path | 0.5786  | 0.5992    |
|          | Degree+Distance+PageRank+Partitioning+Clustering+Meta-path | 0.5797  | 0.5868    |
| GTN      | Degree                         | 0.6152   | 0.6161    |
|          | Distance                       | 0.6100   | 0.6387    |
|          | PageRank                       | 0.6029   | 0.6184    |
|          | Partition                      | **0.6288** | 0.6224    |
|          | Clustering                     | **0.6170** | 0.6170    |
|          | Degree+Distance                | **0.6270** | 0.6229    |
|          | Degree+Distance+PageRank       | 0.5966   | 0.6149    |
|          | Degree+Distance+PageRank+Partition | 0.6143  | 0.6199    |
|          | Degree+Distance+PageRank+Meta-path | 0.6135  | 0.6218    |
|          | Degree+Distance+PageRank+Partition+Clustering+Meta-path | 0.6152  | 0.6184    |

Table 6 shows that employing multiple auxiliary tasks could benefit to various extents. It seems to work...
well by employing auxiliary tasks that are known to learn transferable representations. As we expected, in combinations of multiple auxiliary tasks, SELAR consistently outperforms most base models trained by MTL. For instance, SELAR provides more optimized auxiliary learning resulting in 1.5%, 2.9%, 2.9% and 3.3% improvement on GIN, GTN, GCN and GAT trained by degree prediction, pairwise node distance, graph partitioning and PageRank prediction respectively. Particularly, SELAR provides 3.6% improvement compared to MTL in trained GCN with degree prediction, pairwise node distance, PageRank prediction and graph partitioning. Interestingly, learning with various auxiliary tasks combinations, especially SELAR, on GTN improves 4.1% on average across all auxiliary task combinations compared to the vanilla learning scheme (only primary task). We observe that a model with more capacity (e.g., GTN) on heterogeneous graph can be helpful for the primary task by learning to perform well in various auxiliary tasks.

4.6 Meta cross-validation

Meta cross-validation, i.e., cross-validation for meta-learning, helps to keep weighting function from over-fitting on meta data. Table 7 evidence that our algorithms as other meta-learning methods can overfit to meta-data. As in Algorithm 1, our proposed methods, both SELAR and SELAR with HintNet, with cross-validation denoted as ‘3-fold’ alleviates the meta-overflowing problem and provides a significant performance gain, whereas without meta cross-validation denoted as ‘1-fold’ the proposed method can underperform the vanilla training strategy.

5 ANALYSES

The effectiveness of meta-path prediction and the proposed learning strategies are answered above. To address the last research question Q4, why the proposed method is effective, we provide analysis on the weighting function $V(\xi; \Theta)$ learned by our framework. Also, we show the evidence that meta-overflowing occurs and can be addressed by cross-validation as in Algorithm 1.

Fig. 3. Weighting function $V(\cdot)$ learnt by SELAR+HintNet. $V(\cdot)$ gives overall high weights to the primary task positive samples (red) in (a). $V(\cdot)$ decreases the weights of easy samples with a loss ranged from 0 to 1. In (b), the adjusted cross entropy, i.e., $-V(\xi; \Theta) \log(\hat{y})$, by $V(\cdot)$ acts like the focal loss, which focuses on hard examples by $-(1 - p_t)^\gamma \log(\hat{y})$.

5.1 Weighting Function

Our proposed methods can automatically balance multiple auxiliary tasks to improve the primary task. To understand the ability of our method, we analyze the weighting function and the adjusted loss function by the weighting function, i.e., $V(\xi; \Theta), V(\xi; \Theta)\ell^t(\tilde{y}, \hat{y})$. The positive and negative samples are solid and dash lines respectively. We present the weighting function learnt by SELAR+HintNet for GAT which is the best-performing construction on Last-FM. The weighting function is from the epoch with the best validation performance. Fig. 3 shows that the learnt weighting function attends to hard examples more than easy ones with a small loss range from 0 to 1.

Also, the primary task-positive samples are relatively less down weighted than auxiliary tasks even when the samples are easy (i.e., the loss is ranged from 0 to 1). Our adjusted loss $-V(\xi; \Theta)\ell^t(\tilde{y}, \hat{y})$ is closely related to the focal loss, $-(1 - p_t)^\gamma \log(p_t)$. When $\ell^t$ is the cross-entropy, it becomes $V(\xi; \Theta) \log(p_t)$, where $p$ is the model’s prediction for the correct class and $\gamma$ is defined as $p$ if $y = 1$, otherwise $1 - p$ as [72]. The weighting function differentially evolves over iterations. At the early stage of training, it often focuses on easy examples first and then changes its focus over time. Also, the adjusted loss values by the weighting function learnt by our method differ across tasks. To analyze the contribution of each task, we calculate the average of the task-specific weighted loss on the Last-FM and Book-Crossing datasets. Especially, on the Book-Crossing, our method has more attention to ‘user-item’ (primary task) and ‘user-item-litterary.series.item-user’ (auxiliary task) which is a meta-path that connects users who like a book series.

| Model | Vanilla | SELAR 1-fold | SELAR 3-fold | SELAR+Hint 1-fold | SELAR+Hint 3-fold |
|-------|---------|--------------|--------------|------------------|------------------|
| GCN   | 0.7963  | 0.7885       | 0.8296       | 0.7834           | 0.8121           |
| GAT   | 0.8115  | 0.8287       | 0.8294       | 0.8290           | 0.8302           |
| GIN   | 0.8199  | 0.8234       | 0.8361       | 0.8244           | 0.8350           |
| SGC   | 0.7703  | 0.7691       | 0.7827       | 0.7702           | 0.7975           |
| GTN   | 0.7836  | 0.7897       | 0.7988       | 0.7915           | 0.8067           |
Fig. 4. Weighting function $V(\cdot)$ tendency curves learnt by SELAR+Hint on Last-FM for each base model (GCN, GAT, GIN, SGC and GTN). In each row, left is the first epoch, the epoch with the best validation performance, and the last epoch respectively. The positive sample of the primary task is a red solid line and negative sample is a dashed line.
implies that two users who like a book series likely have a similar preference.

5.2 Weighting function at different training stages

The weighting functions of our methods dynamically change over time. In Fig. 4, each row is the weighting function learned by SELAR+HintNet for GCN [2], GAT [24], GIN [25], and SCG [26] in order on Last-FM. From left, columns are from the first epoch, the epoch with the best validation performance, and the last epoch respectively. The positive and negative samples are illustrated in solid and dash lines respectively in Fig. 4. At the begging of training (the first epoch), one noticeable pattern is that the weighting function focuses more on ‘easy’ samples. At the epoch with the highest performance, easy samples are down-weighted and the weight is large when the loss is large. It implies that hard examples are more focused. At the last epoch, most weights converge to zero when the loss is extremely small or large in the last epoch. Since learning has almost completed, the weighting function becomes relatively smaller in most cases, e.g., GCN, GAT, and GIN. Especially, for GCN and GAT in the epoch with the highest performance, the weights are increasing and it means that our weighting function imposes that easy samples to smaller importance and more attention on hard samples. Among all tasks, the scale of weights in the primary task is relatively high compared to that of auxiliary tasks. This indicates that our method focuses more on the primary task.

6 CONCLUSION

We proposed a framework that learns to softly select auxiliary tasks to improve the primary task. The auxiliary tasks can be further improved by our proposed method SELAR, which automatically balances auxiliary tasks to assist the primary task via a form of meta-learning. Besides, we introduced meta-path prediction as self-supervised auxiliary tasks on heterogeneous graphs. Our experiments show that the representation learning on heterogeneous graphs can benefit from meta-path prediction which encourages to capture rich semantic information. The learnt weighting function identifies more beneficial auxiliary tasks (meta-paths) for the primary tasks. Within a task, the weighting function can adjust the cross entropy like the focal loss, which focuses on hard examples by decreasing weights for easy samples. Moreover, when it comes to challenging and remotely relevant auxiliary tasks, our HintNet helps the learner by correcting the learner’s answer dynamically and further improves the gain from auxiliary tasks. Our framework based on meta-learning provides learning strategies to balance primary task with different auxiliary tasks. Further, our method identifies easy/hard (and positive/negative) samples between tasks or within each task. We demonstrated the effectiveness of our proposed methods to improve the representational power of GNNs in node classification, link prediction and recommender system. Interesting future directions include applying our framework to other domains (e.g., computer vision, natural language processing).

REFERENCES

[1] William L. Hamilton, Rex Ying, and Jure Leskovec. Representation learning on graphs: Methods and applications. IEEE Data Eng. Bull., 40(3):52–74, 2017.
[2] Thomas N. Kipf and Max Welling. Semi-supervised classification with graph convolutional networks. In ICLR, 2017.
[3] David Liben-Nowell and Jon M. Kleinberg. The link prediction problem for social networks. In CIKM, pages 556–559, 2003.
[4] Zhantao Ying, Jiaxuan You, Christopher Morris, Xiang Ren, William L. Hamilton, and Jure Leskovec. Hierarchical graph representation learning with differentiable pooling. In NeurIPS, pages 4805–4815, 2018.
[5] Daixin Wang, Peng Cui, and Wenwu Zhu. Structural deep network embedding. In SIGKDD, pages 1225–1234, 2016.
[6] Rianne van den Berg, Thomas N Kipf, and Max Welling. Graph convolutional matrix completion. arXiv preprint arXiv:1706.02263, 2017.
[7] Hongwei Wang, Fuzheng Zhang, Jialin Wang, Miao Zhao, Wenjie Li, Xing Xie, and Minyi Guo. Ripplenet: Propagating user preferences on the knowledge graph for recommender systems. In ACM, pages 417–426, 2018.
[8] Jie Zhou, Gangu Cui, Zhengyang Zhang, Jure Leskovec, Miao Zhao, Wenjie Li, and Zhongyuang Wang. Knowledge-aware graph neural networks with label smoothness regularization for recommender systems. In SIGKDD, pages 968–977, 2019.
[9] Peter Battaglia, Razvan Pascanu, Matthew Lai, Danilo Jimenez Rezende, et al. Interaction networks for learning about objects, relations and physics. In NeurIPS, pages 4502–4510, 2016.
[10] Zhenqin Wu, Bharath Ramsundar, Evan N. Feinberg, Joseph Gomes, Caleb Geniesse, Aneesh S Pappu, Karl Leswing, and Vijay Pande. Moleculenet: a benchmark for molecular machine learning. Chemical science, 9(2):513–530, 2018.
[11] Jianwei Yang, Jiasen Lu, Stefan Lee, Dhruv Batra, and Devi Parikh. Graph r-cnn for scene graph generation. In ECCV, pages 670–685, 2018.
[12] Seong Jae Hwang, Sathya N. Ravi, Zirui Tao, Hyunwoo J. Kim, Maxwell D. Collins, and Vikas Singh. Tensorize, factorize and regularize: Robust visual relationship learning. In CVPR, pages 1014–1023, 2018.
[13] Zonghan Wu, Shirui Pan, Fengwen Chen, Guodong Long, Chengqi Zhang, and S Yu Philip. A comprehensive survey on graph neural networks. IEEE, 2020.
[14] Jie Zhou, Gangu Cui, Zhengyang Zhang, Cheng Yang, Zhiyuan Liu, Lifeng Wang, Changcheng Li, and Maosong Sun. Graph neural networks: A review of methods and applications. arXiv preprint arXiv:1812.08434, 2018.
[15] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. BERT: pre-training of deep bidirectional transformers for language understanding. In NAACL-HLT, pages 4171–4186, 2019.
[16] Sinno Jialin Pan and Qiang Yang. A survey on transfer learning. IEEE Transactions on knowledge and data engineering, 22(10):1345–1359, 2009.
[17] Shubham Toshniwal, Hao Tang, Liang Lu, and Karen Livescu. Multitask learning with low-level auxiliary tasks for encoder-decoder based speech recognition. In Interspeech, pages 3532–3536, 2017.
[18] Yunming You, Tianlong Chen, Zhangyang Wang, and Yang Shen. When does self-supervision help graph convolutional networks? In International Conference on Machine Learning, pages 10871–10880. PMLR, 2020.
[19] Chelsea Finn, Pieter Abbeel, and Sergey Levine. Model-agnostic meta-learning for fast adaptation of deep networks. In ICML, pages 1126–1135, 2017.
[20] Wei Jin, Tyler Derr, Haochen Liu, Yeqi Wang, Suhang Wang, Zitao Liu, and Jiliang Tang. Self-supervised learning on graphs: Deep insights and new direction. arXiv preprint arXiv:2006.10141, 2020.
[21] Weihua Hu, Bowen Liu, Joseph Gomes, Marinka Zitnik, Percy Liang, Vijay Pande, and Jure Leskovec. Strategies for pre-training graph neural networks. In ICLR, 2020.
[22] Ziniu Hu, Changjun Fan, Ting Chen, Kai-Wei Chang, and Yizhou Sun. Pre-training graph neural networks for generic structural feature extraction. In ICLR 2019 Workshop: Representation Learning on Graphs and Manifolds, 2019.
[23] Nicolo Navarin, Dinh V Tran, and Alessandro Sperduti. Pre-training graph neural networks with kernels. arXiv preprint arXiv:1811.06930, 2018.
[71] George Karypis and Vipin Kumar. A fast and high quality multilevel scheme for partitioning irregular graphs. *SIAM Journal on Scientific Computing*, 20(1):359–392, 1998.

[72] Tsung-Yi Lin, Priya Goyal, Ross Girshick, Kaiming He, and Piotr Dollár. Focal loss for dense object detection. In *ICCV*, pages 2980–2988, 2017.