ABSTRACT
With the tremendous expansion of graphs data, node classification shows its great importance in many real-world applications. Existing graph neural network based methods mainly focus on classifying unlabeled nodes within fixed classes with abundant labeling. However, in many practical scenarios, graph evolves with emergence of new nodes and edges. Novel classes appear incrementally along with few labeling due to its newly emergence or lack of exploration. In this paper, we focus on this challenging but practical graph few-shot class-incremental learning (GFSCIL) problem and propose a novel method called Geometer. Instead of replacing and retraining the fully connected neural network classifier, Geometer predicts the label of a node by finding the nearest class prototype. Prototype is a vector representing a class in the metric space. With the pop-up of novel classes, Geometer learns and adjusts the attention-based prototypes by observing the geometric proximity, uniformity and separability. Teacher-student knowledge distillation and biased sampling are further introduced to mitigate catastrophic forgetting and unbalanced labeling problem respectively. Experimental results on four public datasets demonstrate that Geometer achieves a substantial improvement of 9.46% to 27.60% over state-of-the-art methods.

CCS CONCEPTS
- Information systems → Data mining. - Theory of computation → Graph algorithms analysis.

KEYWORDS
Node Classification; Graph Neural Network; Few-Shot Learning; Class-Incremental Learning

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1 INTRODUCTION
Graphs data are ubiquitously used to reveal the interactions among various entities, such as academic graphs, social networks, recommendation systems, etc. During the past several years, node classification [1–5] has received considerable interests and achieved remarkable progress with the rise of graph neural networks (GNNs). In contrast, real-world networks evolve with the emergence of new nodes and edges, thereby generating novel classes. For example, in academic networks, the publication of new research papers produces new interdisciplines; Industrial development brings about new types of commodities in online e-commerce; The addition of new users leads to the emergence of new social groups. Classes of nodes are expanding incrementally and usually accompanied by few labeling due to its newly emergence or lack of exploration.

Take a toy academic graph in Figure 1 for further illustration. Originally, there are abundant labeled nodes for “Transfer Learning” and “Multi-task Learning” (i.e., base classes). With the knowledge evolution, new nodes appear and introduce additional citation relationships (edges). A new emerging research topic “Incremental Learning” (i.e., novel class) has also turned up with few labeled nodes. A critical problem to be solved is to classify the remaining unlabeled nodes into either a base class or a novel class, where novel class only have few labeled samples. We term this kind of node classification among all encountered classes (base classes and novel classes altogether) in dynamic graphs as graph few-shot class-incremental learning (GFSCIL).

Prior works. Classical GNN-based methods [6–8] mainly focus on classifying the nodes within a set of fixed classes with abundant labelling. However, due to the few-shot and class-incremental nature, these methods fail to solve GFSCIL problem. Some advanced methods aim at addressing part of the problem of GFSCIL. On one hand, to tackle the few-shot node classification problems in graphs, MAML-based studies transfer the knowledge from base classes to
never-before-seen classes with only a handful of labeled information. Whereas, these methods [9–11] all make a strong prior N-way K-shot assumption that the unlabeled nodes belong to a fixed set of N novel classes. Meanwhile, the classification of base classes and novel classes are separated into two models, which prevents from judging the results under a unified metric. On the other hand, although class-incremental learning has achieved significant progress in computer vision tasks [12–14], class-incremental node classification in graphs has not been fully explored. Existing methods are dedicated to independent and identically distributed data (e.g., images), which has no explicit interactions. Graph data lies in non-Euclidean space and the network structure evolves dynamically. The emergence of new edges changes and complicates the node correlations, thus bringing more challenges.

### Challenges

A naive approach for GFSCIL is to finetune the base model on both base classes and novel classes. However, there are three main challenges that need to be addressed: (1) How to find a way out of “forgetting old”? Catastrophic forgetting phenomenon [15–17] describes the performance degradation on old classes when incrementally learning novel classes. In GFSCIL, the growing number of novel classes makes the model suffer from forgetting base classes. (2) How to overcome the unbalanced labeling between base classes and novel classes? In GFSCIL, the labeling between large-scale base classes and few-shot novel classes is unbalanced. Directly training on few-shot samples may cause over-fitting problem. (3) How do we capture the dynamic structure as the network evolves? The structure of graphs are highly dynamic in GFSCIL. The arrival of new nodes and edges make more complex connections, which is a big challenge for expressive node representations.

### Our Work

To address the aforementioned problems, we leverage the concept of metric learning and propose a new method for **Graph Few-Shot Class-Incremental Learning via Prototypical Representation**, named **GEOMETER**. Instead of replacing and retraining the fully connected neural network classifier, **GEOMETER** predicts the ever-expanding class of a node by finding the nearest prototype representation. Prototype is a vector representing a class in the metric space. We propose class-level multi-head attention to learn the dynamic prototype representation of each class. When novel classes popping up, **GEOMETER** learns and adjusts the representation based on the geometric relationships of intra-class proximity, inter-class uniformity and inter-class separability in the metric space. In order to avoid forgetting old, **GEOMETER** iteratively takes the previous model as the teacher, and guides the student model’s representation of old classes with knowledge distillation. **GEOMETER** adopts pretrain-finetune paradigm with well-designed biased sampling strategy to further alleviate the impact of unbalanced labeling.

To summarize, the main contributions of our works are as follows:

- We investigate a novel problem for node classification: **graph few-shot class-incremental learning** (GFSCIL). To the best of our knowledge, this is the first work to study this challenging yet practical problem.
- We propose a novel model **GEOMETER** to solve GFSCIL problem. With the novel classes popping up, **GEOMETER** learns and adjusts the attention-based prototypes based on the geometric relationships of proximity, uniformity and separability of representations.
- **GEOMETER** proposes teacher-student knowledge distillation and biased sampling strategy to further mitigate the catastrophic forgetting and unbalanced labeling in GFSCIL.

We conduct extensive experiments on four real-world node classification datasets to corroborate the effectiveness of our approach. **GEOMETER** achieves a substantial improvement of nearly 9.46% to 27.60% in multiple sessions of GFSCIL over state-of-the-art baselines.

## 2 RELATED WORK

### 2.1 Few-Shot Node Classification

In recent years, few-shot node classification on graph has attracted increasing attention. These works can be categorized into two types: (1) optimization based approaches, and (2) metric based approaches. Optimization-based approaches leverage MAML [18] to learn a better GNN initialization on base classes, and quickly adapt to novel classes with few-shot samples. Meta-GNN [9] firstly incorporates the meta-learning paradigm into GNNs for few-shot node classification. G-Meta [10] proposes to use local subgraphs to learn the transferable knowledge across tasks. Liu et al. [11] further design the relative and absolute embedding of nodes and achieves promising performance. However, these methods divide the classification of novel classes and old classes into two separate models, which cannot carry out a unified classification of the unknown nodes in GFSCIL. Metric-based methods propose to learn a transferable metric space, which is closely related to our work. Ding et al. propose GPN [19] for few-shot learning on attributed graphs by combining prototype network with GNNs. Yao et al. [20] incorporate prior knowledge learned from auxiliary graphs to further transfer the knowledge to a new target graph. Whereas, the growing of new labels in GFSCIL will make the prototypes overlapping, and the accuracy of the classification will decline sharply.

### 2.2 Class-Incremental Learning

Class-incremental learning aims to learn a unified classifier to recognize the ever-expanding classes over time, which is extensively studied in the field of computer vision [12–14, 21]. iCaRL [13] adopts an "episodic memory" of class exemplars and incrementally learns the nearest-neighbor classifier for novel classes. Castro et al. [21] propose a distillation measure to retain the knowledge of old
classes, and combines it with the cross-entropy loss for end-to-end training. Hou et al. [14] propose the multi-class incremental setting and raises the imbalance challenge between old classes and novel classes. However, among these works, the training samples of novel classes are all large-scale. In many real-world scenarios, the novel classes often lack of labeling due to its newly emergence or lack of exploration. Recently, the FSCIL problem has just been put forward in image classification [22, 23]. Tao et al. [22] firstly propose this FSCIL problem and utilize a neural gas (NG) network to learn and maintain the topology of the feature manifold of various classes. Cheraghian et al. [23] further introduce a distillation algorithm with semantic information. Except in the field of computer vision, few-shot class-incremental learning also shows practical significance in graphs and remains an under-explored problem. To the best of our knowledge, this is the first study of FSCIL for node classification in graphs, which we denoted as GFSCIL.

3 PROBLEM STATEMENT

In this section, we provide problem statement and definitions. In the base stage, we have an initial graph \( G^{base} \). In streaming sessions, suppose we have \( T \) snapshots of evolving graph, denoting as \( G^{stream} = \{ G^1, \ldots, G^T \} \). Take the \( t \)-th session as an example, its corresponding graph represents as \( G^t = (V^t, E^t, X^t) \). Suppose we have \( N_t \) nodes and \( M_t \) edges. \( V^t \) is the node set \( \{ v_1, v_2, \ldots, v_{N_t} \} \), and \( E^t \) is the edge set \( \{ e_1, e_2, \ldots, e_{M_t} \} \). The feature vector of node \( v_i \) is represented as \( x_i \in \mathbb{R}^{d} \), and \( X^t = [x_1, \ldots, x_{N_t}] \in \mathbb{R}^{N_t \times d} \) denotes all the node features. We denote \( \{ C^{base}, C^1, \ldots, C^T \} \) as sets of classes from base stage to the \( T \)-th streaming session. \( C^{base} \) is the set of base classes with large training samples. In \( t \)-th streaming session, \( \Delta C^i \) novel classes are introduced with few-shot samples, where \( \forall i, j, \Delta C^i \cap \Delta C^j = \emptyset \) and \( C^i = C^{i-1} + \Delta C^i \). We denote the totally encountered class in \( t \)-th session as \( C^t = C^{base} + \sum_{i=1}^{T} \Delta C^i \).

**Definition 1. Prototype Representation** A prototype representation is a representative embedding of one class. The node embeddings of one class tend to cluster around its prototype representation in the same metric space. Prototype representation is first proposed in [24], which regards the mean of its support set as class’s prototypes.

4 METHODOLOGY

We first give an overview of the proposed Geometer, as illustrated in Figure 2. Geometer intends to predict the node class by finding the nearest attention-based prototype representation. When novel classes emerging, we learn and adjust prototypes based on geometric metric learning and teacher-student knowledge distillation. Our approach follows the episode meta learning process, and different biased sampling are designed to overcome the unbalanced labeling among base classes and novel classes.

4.1 Attention-based Prototype Representation

The evolution of the network makes the influence of nodes unequal and non-static. In addition, weakly-labeled few-shot data usually contains a significant amount of noise. Therefore, direct
average of support node features cannot be fully representative and is highly vulnerable to the noise or outliers. In order to learn the expressive prototype representation of each class, we propose a two-level attention-based prototype representation learning method as shown in Figure 3.

4.1.1 Node-level Graph Attention Network. Graph neural network is typically expressed as a message-passing process in which information can be passed from one node to another along edges directly. Node-level graph attention network $f_G(.)$ computes a learned edge weight by performing masked attention mechanism [25]. The attention score $a_{ij}$ between node $v_i$ and $v_j$ is normalized across all node $v_i$’s neighbors $N_i$ as

$$a_{ij} = \frac{\exp\left(\text{LeakyReLU}\left(\text{a}^T \left[\text{W}h_i^l \| \text{W}h_j^l\right]\right)\right)}{\sum_{k \in N_i} \exp\left(\text{LeakyReLU}\left(\text{a}^T \left[\text{W}h_i^l \| \text{W}h_k^l\right]\right)\right)},$$

(1)

where $h_i^l$ and $h_j^l$ represent the node features of $l$-th GNN layer, $\text{a} \in \mathbb{R}^{d^l}$ and $\text{W} \in \mathbb{R}^{d^l \times d^l}$ are weight matrices. $\|$ denotes vector concatenation. Then, graph attention network computes a weighted average of the transformed features of the neighbor nodes as the new representation, followed by a nonlinear function $\sigma$. The $(l+1)$-th layer hidden state of node $v_i$ is calculated via

$$h_{i}^{l+1} = \sigma\left(\sum_{j \in N_i} a_{ij} \cdot \text{W}h_j^l\right).$$

(2)

We denote the $L$-th layer hidden state output of node $v_i$ as $f_G(x_i) = h_i^L$. As usual, we build a 2-layer graph attention network for feature extraction.

4.1.2 Class-level Multi-head Attention. Due to the dynamic structure and stochastic label noise, GEOMETRER proposes class-level multi-head attention to learn the class prototype as follows. In streaming fashion of GFSCIL, the importance of nodes changes dynamically as the network evolves. The degree centrality is one of simplest way to measure the importance of nodes. The large-degree nodes are often referred to as hubs, which has a stronger influence in the networks. Therefore, an initial prototype $\hat{p}_i$ of class $i$ is calculated by degree-based weighted-sum of support node embeddings:

$$\hat{p}_i = \sum_{j \in S_i} \frac{\text{degree}(v_j)}{\sum_{j' \in S_i} \text{degree}(v_{j'})} \cdot f_G(x_j).$$

(3)

where $S_i$ is the support set of class $i$, $f_G(x_j)$ is the node representation of $v_j$ obtained by node-level graph attention network, degree($v_j$) is the degree centrality of node $v_j$. Apart from considering the structural information, i.e. degree centrality, different support node features plays an important role in learning a representative class prototype. In order to fully characterize the relationship between node features and prototypes, class-level multi-head attention calculates the attention score between the initial prototype and support node representations to obtain an expressive prototype representation. To be specific, we take the linear transformation of initial prototype $\hat{p}_i$ as the query $Q$ and then concatenate the initial prototype and support node representations as $h_i^{spt}$:

$$h_i^{spt} = \text{CONCATENATE}(\hat{p}_i, \|_{j \in N_i} f_G(x_j)).$$

(4)

We take the linear transformation of $h_i^{spt}$ as the key $K$ and value $V$. GEOMETRER adopts the scaled dot-product attention [26], which is calculated via

$$\text{ATTENTION}(Q, K, V) = \text{softmax}\left(\frac{QR^T}{\sqrt{d_k}}\right)V,$$

(5)

where $Q = W_Q \hat{p}_i$, $K = W_K h_i^{spt}$, $V = W_V h_i^{spt}$, $W_Q, W_K, W_V$ are three weight matrices, and $d_k$ is the dimension of $Q$ and $K$. Finally, the residual connection is adopted to obtain the final prototype representation $p_i$ of class $i$:

$$p_i = \hat{p}_i + \text{ATTENTION}(\hat{p}_i, h_i^{spt}, h_i^{spt}).$$

(6)

4.2 Geometric Metric Learning

In GFSCIL problem, as the graph evolves, novel node classes obtain new prototypes in the metric space. With the increase of growing classes, the performance of node classification is greatly reduced due to the overlapping of prototype representations. As a consequence of few-shot samples of novel classes, parameter update only based on node classification results is prone to overfitting novel classes, or is greatly affected by the support set sample distribution. Therefore, we propose to learn the prototype representation from geometric relationships. As shown in Figure 2(c), we propose geometric loss functions from three aspects: intra-class proximity, inter-class uniformity and inter-class separability.

4.2.1 Intra-Class Proximity. Intra-class proximity indicates that the nodes of same classes should be closely clustered. Therefore, in the metric space, the distance between the node embedding and its corresponding class prototype representation should be relatively close. We use squared Euclidean distance $d(\cdot)$ to measure the distance between node features and class prototype, and define the intra-class proximity loss $L_P$ as follows:

$$L_P = \sum_{k=1}^{C} \frac{1}{N_k} \sum_{i=1}^{N_k} -\log \frac{\exp\left(-d(f_G(x_i), p_k)\right)}{\sum_{k' \in C} \exp\left(-d(f_G(x_i), p_{k'})\right)},$$

(7)
where \( \|C^k\| \) is the total number of encountered classes up to \( k \)-th streaming session, \( n_k \) is the number of node samples of class \( k \), \( \alpha_k \in [0, 1] \) is a weighting factor, which is used to adjust the impact of unbalanced labeling of base classes and novel classes in total loss function.

### 4.2.2 Inter-Class Uniformity

Inter-class uniformity describes the positional uniformity of different prototypes in metric space. Specifically, a prototype center \( p_c \) is denoted by the mean of all prototypes:

\[
     p_c = \frac{1}{\|C^k\|} \sum_{i=1}^{\|C^k\|} p_i. \tag{8}
\]

Geometrically, taking the prototype center \( p_c \) as the coordinate origin, each normalized prototype relative to the center \( \frac{p_j - p_c}{\|p_j - p_c\|}, \forall j \) is distributed on a unit sphere. As the prototypes of the novel classes are increasingly projected onto the unit sphere, we propose that the distribution of prototypes should tend to be uniform. The distribution of class prototypes are adjusted based on the division of sphere angle. Therefore, we define the following inter-class uniformity loss function \( L_U \) based on cosine similarity distance as

\[
     L_U = \frac{1}{\|C^k\|} \sum_{i=1}^{\|C^k\|} \left\{ 1 + \max_{j \in\{C^k\}\setminus i} \left( \frac{(p_i - p_c)}{\|p_i - p_c\|} \cdot \frac{(p_j - p_c)}{\|p_j - p_c\|} \right) \right\}, \tag{9}
\]

where 1 is used as a bias to ensure that the value is always non-negative, and the purpose of taking the maximum value of cosine similarity here is to focus on the angular distribution of adjacent prototypes. By defining the inter-class uniformity, the unbalanced labeling class prototypes are inclined to be evenly distributed on the sphere. Especially for novel classes with few-shot labeled nodes, the inter-class geometric relations provide important guidance for the learning of prototype representations.

### 4.2.3 Inter-Class Separability

Before finetuning, the feature extractor is more suitable for old classes representation. The prototypes of novel classes are likely to overlap with the old class prototypes, which greatly affects the accuracy of node classification. Therefore, we propose inter-class separability in geometric metric learning, which describes that the prototypes of novel classes and old classes should keep a distance in the metric space. The inter-class separability loss \( L_S \) is denoted as

\[
     L_S = \frac{1}{\Delta C^k} \sum_{i \in \Delta C^k-1} \min_{j \in C^k-1} \exp \left( -d \left( p_i, p_j \right) \right), \tag{10}
\]

where \( d(\cdot) \) is the squared euclidean distance, \( \Delta C^{k-1} \) is the set of labels of \( (k - 1) \)-th session, \( \Delta C^k \) is the novel classes of \( k \)-th session. The definition of inter-class separability is a supplement to inter-class uniformity. With the addition of novel classes, in order to avoid the error diffusion caused by the inaccurate classification of old categories, expanding the distance between old and novel class prototypes in metric space helps to further enhance the classification accuracy in GFSCIL settings.

### 4.3 Teacher-Student Knowledge Distillation

Due to the class-incremental nature of GFSCIL problem, **GEOMETER** applies the idea of teacher-student knowledge distillation to further mitigate "forgetting old" during finetuning. In contrast to the classic teacher-student knowledge distillation techniques [27–29] used to compress large model into lightweight model with better inference efficiency, we regard the model before streaming as the teacher model and new model as the student model. Knowledge distillation technique is used to transfer the classification ability of previous model, while preserving the interrelationships of the old classes in the metric space. Temperature-scaled softmax [12] is utilized to soften the old classes logits of teacher model and student model. The modified logits \( y_s'(i) \) of class \( i \) by applying a temperature scaling function in the softmax are calculated as

\[
     y_s'(i) = \frac{\exp \left( \frac{d \left( f_T(x^{(i)}), p_i \right)}{\tau} \right)}{\sum_j \exp \left( \frac{d \left( f_T(x^{(j)}), p_j \right)}{\tau} \right)}, \tag{11}
\]

where \( \tau \) is the temperature factor. Generally, we set \( \tau > 1 \) to increase the weight of smaller logit values and encourages the network to better reveal inter-class relationships learned by the teacher model. **GEOMETER** proposes to calculate the KL-divergence of the softened logits to make the student model gain the experience of classifying old classes \( C^{k-1} \) from teacher model. The teacher-student knowledge distillation loss \( L_{KD} \) on \( k \)-th session is calculated as

\[
     L_{KD} = \frac{1}{\|C^{k-1}\|} \sum_{i=1}^{\|C^{k-1}\|} y_s'(i) \cdot \log \frac{y_s'(i)}{y_T'(i)}, \tag{12}
\]

where \( C^{k-1} \) is the set of old classes of \( (k - 1) \)-th streaming session and \( y_s'(i) \) and \( y_T'(i) \) are the modified logits. **GEOMETER** proposes the teacher-student knowledge distillation to avoid the catastrophic forgetting caused by the growing addition of novel classes. Meanwhile, it makes **GEOMETER** a system of checks and balances related to geometric losses.

### 4.4 Episode Meta Learning

In this section, we discuss the learning process of **GEOMETER**. We adopt the episode paradigm in learning process, which has shown great promise in few-shot learning. Instead of directly training or finetuning on batches of data, a set of tasks \( T \) are generated by imitating the \( N \)-way- \( K \)-shot few-shot scenario. Each task \( T \) includes support set \( S \) and query set \( Q \). In GFSCIL setting, two different bias sampling strategies are adopted in both pretraining and finetuning stages.

In the base stage, all base classes have a large number of training samples. However, in streaming sessions, the novel classes follows few-shot labeling. **GEOMETER** adopts biased sampling strategy in pretraining stage to generate class-imbalanced support sets by mimicking the circumstances encountered during finetuning. Specifically, the number of sampling number of each class in support set \( S \) follow a uniform distribution \( U[1, K_{max}] \). The size of query set still maintains a fixed number \( K_{query}y \). During meta training, intra-class proximity and inter-class uniformity loss are utilized. Therefore, the loss function \( L_{train} \) is as follows, with hyper-parameters \( \lambda_p \) and \( \lambda_U \):

\[
     L_{train} = \lambda_p L_p + \lambda_U L_U. \tag{13}
\]

In the streaming sessions, the biased sampling adopts different strategies to obtain the class-imbalanced query set \( Q \). In order to avoid "forgetting old" and "overfitting new" problem, a higher proportion of the old samples will be sampled when sampling the
query set. This helps to fully retain the classification accuracy on old classes during meta-fine-tuning. During meta-finetuning, three geometric losses and the knowledge distillation losses are taken into account, and the loss function $L_{\text{finetune}}$ is calculated as

$$L_{\text{finetune}} = \lambda_p L_p + \lambda_U L_U + \lambda_S L_S + \lambda_{KD} L_{KD},$$

where $\lambda_p$, $\lambda_U$, $\lambda_S$ and $\lambda_{KD}$ are hyper-parameters.

5 EXPERIMENT

5.1 Experimental Setup

5.1.1 Datasets. We evaluate the proposed Geometer on four real-world representative datasets: Cora-ML, Flickr, Amazon and Cora-Full. We summarize the statistics of these datasets in Table 1.

| Dataset     | Data Field | Nodes | Edges | Features | Class |
|-------------|------------|-------|-------|----------|-------|
| Cora-ML     | Academic   | 2,995 | 16,316| 2,879    | 7     |
| Flickr      | Social network | 7,575 | 479,476 | 12,047 | 9     |
| Amazon      | E-commerce | 13,752| 491,722| 767     | 10    |
| Cora-Full   | Academic   | 19,793| 126,842| 8,710   | 70    |

5.1.2 Experiment Settings. We divide the dataset into base stage and several streaming sessions respectively. For Cora-ML, Flickr and Amazon datasets, we select five classes as novel classes and the rest as base classes, and adopt the 1-way 5-shot GFSCL setting, which means we have 6 sessions (i.e., 1 base + 5 novel) in total. While for Cora-Full dataset, we adopt 5-way 5-shot GFSCL setting, by choosing 20 classes as base classes and splitting the remaining 50 classes into 10 streaming sessions. We set 2-layer GNNs with 512 neurons of hidden layer. The learning rate of base class is 1e-3, and the learning rate during fine-tuning is 1e-4. The temperature factor $\tau$ is 2.

5.1.3 Baseline Methods.

- **GAT (FT)**: Graph attention network (GAT) [25] is one of the state-of-the-art methods for node classification. We first pre-train a 2-layer GAT model with a fully connected neural network classifier on the base classes. During streaming sessions, we replace and retrain the parameters of the fully connected neural network classifier on the support set of both base classes and novel classes.
- **GAT+ (FT)**: It adopts the same architecture of GAT (FT). The difference is that we fine-tune all training parameters on support set on different streaming sessions.
- **GPN** [19]: GPN is a superior method for few-shot node classification. It exploits graph neural networks and meta-learning on attributed networks for metric-based few-shot learning.
- **GFL** [20]: It is the first work that resorts to knowledge transfer to improve semi-supervised node classification in graphs. It integrates local node-level and global graph-level knowledge to learn a transferable metric space, which is shared between auxiliary graphs and the target.
- **PN* [24]**: Prototype Network firstly proposed for few-shot image classification. We adopt the key idea and implement PN* for node classification.
- **PN* (FT)**: The training process is the same as PN*, but in the test process it fine-tunes all trained parameters before making prediction on the query set.
- **iCaRL* [13]**: iCaRL is a class-incremental methods for image classification. We replace the feature extractor as a two-layer GAT network.

We only modify the dataset partition to satisfy the graph few-shot class-incremental settings for GAT, GPN and GFL, while other settings are the same as its original implementation. PN and iCaRL are two methods proposed in image classification tasks. To explore its performance on node classification, we utilize GNN-based backbone for feature extraction, and we marker with asterisk (*) for clarification. The above baselines can be can be summarized into four categories: (1) GNN methods with fully connected neural network classifier, which is a widely used architecture for node classification. (2) Representative graph few-shot learning models includes GPN and GFL. (3) Prototype network methods. (4) Class-incremental learning baselines.

5.2 Performance Comparison

We run Geometer and other baselines 10 times with different random seeds and report the average test accuracy over all encountered classes in Table 2 and Figure 4. From the comprehensive views, we make the following observations:

(1) Firstly, our proposed model Geometer outperforms other baselines across Cora-ML, Amazon and Cora-Full datasets. For example, Geometer achieves 13.49% to 24.15% performance improvement over the best baseline model in 10 streaming sessions on Cora-Full dataset. Meanwhile, as shown in Figure 4, Geometer does not suffer dramatic performance degradation as other baselines, strongly demonstrating the superiority of our approach.

(2) Secondly, by integrating the idea of metric learning, GFL, as the state-of-the-art model of graph few-shot learning, shows competitive performance at the base stage and first session on Flickr dataset. However, it is worth noting that Geometer achieves supreme results as more streaming session arrives and achieves substantial improvements.

(3) GNN methods with fully connected neural network classifier largely fall behind other baselines. Those two methods need to replace and retrain the fully connected neural network classifier, which relies on sufficient training samples of each node classes. Therefore, with the increase of few-labeling novel classes, the performance of node classification deteriorates dramatically. PN* (FT) and iCaRL show better performance in several datasets, which shows metric-based methods with finetuning are more suitable for solving the GFSCL problems.

5.3 Ablation Study

In this section, we analyze our Geometer model with several degenerate models from four aspects. Due to space limitations, the ablation studies are conducted on two representative datasets: Cora-ML and Amazon.

(1) **GNN backbone**: Due to the dynamic evolution of graph, Geometer utilizes graph attention network to capture the node features. In the ablation study, we replace it with two well-known GNN backbone GCN and GraphSage for comparison. As shown in
Table 2: Comparison results of node classification accuracy in GFSCIL settings on Cora-Full and Flickr dataset. GEOMETER’s improvement is calculated relative to the best baseline.

| Session | Cora-Full (5-way 5-shot GFSCIL setting) | Flickr (1-way 5-shot GFSCIL setting) |
|---------|----------------------------------------|-------------------------------------|
|         | GAT (FT) | GAT+ (FT) | GPN | GFL | PN* | PN* (FT) | iCaRL* | GEOMETER (Ours) | impr. | GAT (FT) | GAT+ (FT) | GPN | GFL | PN* | PN* (FT) | iCaRL* | GEOMETER (Ours) | impr. |
| Base    | 80.53±1.32% | 81.11±0.79% | 73.82±1.94% | 76.02±0.94% | 74.88±0.89% | 74.18±0.72% | 73.92±1.06% | 79.88±0.96% | -1.52% |
| Session 1 | 33.13±2.51% | 37.10±1.51% | 55.95±1.52% | 60.50±0.74% | 56.60±1.11% | 58.07±0.92% | 59.33±1.79% | 69.48±1.66% | +14.84% |
| Session 2 | 25.39±1.59% | 26.34±0.98% | 49.49±1.57% | 52.85±1.88% | 48.59±0.66% | 53.97±0.97% | 54.05±0.70% | 61.34±0.92% | +13.49% |
| Session 3 | 17.48±1.59% | 17.41±1.43% | 43.41±1.66% | 43.88±2.84% | 39.70±1.25% | 43.76±0.92% | 44.65±0.55% | 53.61±0.81% | +20.07% |
| Session 4 | 12.09±1.35% | 12.12±0.78% | 39.03±1.29% | 38.22±1.81% | 37.33±2.07% | 41.83±0.91% | 40.52±1.56% | 48.24±1.46% | +15.30% |
| Session 5 | 10.04±1.56% | 8.54±0.39% | 35.12±1.98% | 38.69±2.50% | 32.66±0.21% | 37.35±0.73% | 36.25±1.06% | 44.97±1.03% | +16.23% |
| Session 6 | 8.63±0.88% | 7.01±0.80% | 33.34±1.35% | 33.94±3.53% | 30.83±2.09% | 36.56±0.84% | 33.46±1.16% | 42.93±0.88% | +17.42% |
| Session 7 | 7.76±0.62% | 5.79±0.42% | 31.98±1.03% | 32.60±1.65% | 29.52±1.92% | 34.70±0.20% | 32.68±1.44% | 42.82±1.14% | +23.40% |
| Session 8 | 6.99±0.72% | 5.38±0.49% | 30.63±1.64% | 28.32±1.78% | 28.39±1.97% | 33.97±1.24% | 31.02±1.48% | 41.01±0.96% | +20.72% |
| Session 9 | 5.95±0.75% | 4.49±0.40% | 30.53±1.80% | 21.95±1.71% | 27.65±2.19% | 33.71±0.75% | 30.73±1.76% | 40.49±0.97% | +20.11% |
| Session 10 | 5.51±0.95% | 3.92±0.61% | 28.33±1.48% | 21.77±1.50% | 26.07±1.89% | 31.67±0.55% | 29.21±1.71% | 39.32±0.78% | +24.15% |

Figure 4: Comparison results of node classification accuracy in GFSCIL settings on Cora-ML and Amazon datasets.

Figure 5: Ablation study of different GNN backbone on Cora-ML and Amazon dataset.

Figure 5, the performance of GCN and GraphSage falls behind graph attention network especially in Amazon dataset, since these two model fails to capture the complex correlations in message-passing.

(2) Prototype representation method: GEOMETER proposes class-level multi-head attention to learn the class prototype. Three degenerate prototype representation methods are considered in ablation study—i.e. means of support node embedding (Average), weighted-sum of node embedding by node degree (Weighted-sum), and average node embeddings as the initial prototype in multi-head attention mechanism (Attention (Average)). Results on two datasets are presented in Figure 6. Since the unequal and non-static node influence, attention-based methods helps to better characterize the relationship of nodes and classes. On Amazon dataset, GEOMETER and Attention (Average) show close performance, while the introduction of degree-based weighted-sum further improve accuracy of prototype representation on Cora-ML dataset.

(3) Loss functions: GEOMETER proposes four different loss functions to finetune the prototype representation, and the effects of inter-class uniformity, inter-class separability and knowledge distillation are compared in Table 3. In general, with the pop-up of novel classes, the best classification results are obtained when the four loss functions are combined together. Different loss functions optimize the classification effect from different aspects, and the deletion of any loss function will have a significant impact on performance.
Biased sampling strategy: In episode meta learning, due to the imbalanced labeling of base and novel classes, different biased sampling strategies are adopted in pretraining stage and finetuning stage. In ablation study, we compare the performance with only one strategy is adopted or without biased sampling strategy in Figure 7. When we discard any biased sampling strategy, the learning process degenerates into a MAML-based learning strategy, and our method always shows better performance. If only one biased sampling strategy is adopted, partial sessions on Amazon datasets will have better results, but overall requires a combination of two biased sampling strategies.

5.5 Case Study

In order to explore the effects of geometric losses and knowledge distillation technique, we use t-SNE method to project the node embeddings and prototype representations of base stage and 5 streaming sessions on Amazon dataset, as shown in Figure 9. The visualization shows that as the novel classes arrive, most nodes are well clustered, and the prototypes are uniformly distributed around the prototype center. It is worth noting that a hard novel class (colored in light purple) emerges in streaming session 2. Since Geometer takes into account the geometric relationships in the metric space and adapt knowledge distillation, the following novel classes in the subsequent streaming sessions actively distance with the light purple class, thereby avoiding the dramatic drop in performance caused by prototype representations overlapping.

6 CONCLUSION

In this paper, we propose Geometer for Graph Few-Shot Class-Incremental Learning (GFSCIL). As far as we known, this is the first work to deal with this challenging yet practical problem. The core idea of Geometer is to adjust the prototype representation in metric space from the aspects of geometric relationship and knowledge distillation, so as to realize the classification of ever-expanding classes with few-shot samples. Extensive experiments on
Figure 9: A t-SNE visualization of the query node embeddings and prototypes of GEOMET (ours) on Amazon dataset.

four public datasets show that GEOMET significantly outperforms the state-of-the-art baselines. In the future, we would like to extend our framework to address more challenging problem, like the open-set classification in graphs.

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A APPENDIX

To support the reproducibility of the results in this paper, we have released our code and data. We implement the Geometer model based on Pytorch framework. All the evaluated models are implemented on a server with two CPUs (Intel Xeon E5-2630 × 2) and four GPUs (NVIDIA GTX 2080 × 4).

A.1 Dataset

In this paper, we evaluate the proposed Geometer on four public datasets as follows:

- **Cora-ML** [30] is an academic network about machine learning papers. The dataset contains 7 different classes, in which each node represents a paper and each edge represents the citation relationship between two papers.

- **Flickr** [31] is a photo-sharing social network from Flickr. Each node represents one picture uploaded to the Flickr website and the node feature contains information of low-level feature from NUS-WIDE Dataset. Flickr forms the edges between images from the same location, submitted to the same gallery, sharing common tags, taken by friends, etc.

- **Amazon** [32] is the segments of Amazon co-purchase e-commerce network, in which each node is an item and each edge denotes the co-purchasing relationship by a common user. The node features are bag-of-words encoded product reviews, and class labels are given by the product category.

- **Cora-Full** [30] is a well-known citation network labeled based on the paper topic, which has 70 different classes of papers. Among the academic networks we know, it has the largest network size and the largest number of categories.

1 The implementation code and details of our model is available at https://github.com/RobinLu1209/Geometer.