Few-Shot Learning on Graphs: From Meta-Learning to LLM-empowered Pre-Training and Beyond

Yuan Fang
Singapore Management University
Singapore
yfang@smu.edu.sg

Yuxia Wu
Singapore Management University
Singapore
yieshah2017@gmail.com

Xingtong Yu
Singapore Management University
Singapore
xingtongyu@smu.edu.sg

Shirui Pan
Griffith University
Gold Coast, Australia
s.pan@griffith.edu.au

Abstract

Graph representation learning has become central to many graph-based tasks, driving advancements in various domains such as web search, recommendation systems, and social network analysis. Traditionally, these methods rely on end-to-end supervised learning paradigms that require abundant labeled data, which can be costly and difficult to obtain. To address this limitation, few-shot learning on graphs has emerged as a promising approach, allowing models to generalize with minimal supervision and overcome data scarcity in real-world applications. This tutorial offers an in-depth exploration of recent advancements in few-shot learning for graphs, providing a comparative analysis of state-of-the-art methods and identifying future research directions. We categorize these approaches into two main taxonomies: (1) a problem taxonomy that examines various types of data scarcity problems and their applications, and (2) a technique taxonomy that outlines key strategies for tackling these challenges, including meta-learning, pre-training methods from both the pre-LLM and LLM eras. The tutorial will conclude by summarizing key insights from the literature and discussing future avenues for research, aiming to equip participants with a deep understanding of few-shot learning on graphs and inspire innovation in this rapidly growing field.

CCS Concepts

• **Information systems → World Wide Web**; **Data mining**; • **Computing methodologies → Learning paradigms**; **Artificial intelligence**.

Keywords

Graph Neural Networks, Deep Learning, Large Language Models

ACM Reference Format:
Yuan Fang, Yuxia Wu, Xingtong Yu, and Shirui Pan. 2025. Few-Shot Learning on Graphs: From Meta-Learning to LLM-empowered Pre-Training and Beyond. In *Companion Proceedings of the ACM Web Conference 2025 (WWW Companion '25), April 28-May 2, 2025, Sydney, NSW, Australia.* ACM, New York, NY, USA, 4 pages. https://doi.org/10.1145/3701716.3715854

WWW Companion '25, Sydney, NSW, Australia

ACM ISBN 979-8-4007-1331-6/25/04
https://doi.org/10.1145/3701716.3715854

1 General Information

Title. Few-Shot Learning on Graphs: From Meta-Learning to LLM-empowered Pre-Training and Beyond.

Contributors. There are four contributors to this tutorial.

- **Yuan Fang** is an Assistant Professor at the School of Computing and Information Systems, Singapore Management University (SMU). Before joining SMU, he was a data scientist at DBS Bank and a research scientist at A*STAR. He obtained a PhD Degree in Computer Science from the University of Illinois at Urbana-Champaign in 2014, and a Bachelor of Computing with First Class Honors from the National University of Singapore in 2009 as the top student in Computer Science. His research focuses on graph-based learning and mining, as well as its applications in recommendation systems, social network analysis and bioinformatics. He is a senior member of IEEE, and has been recognized among the world's Top 2% Scientist (2024, Stanford). His research has been published in top conferences and journals such as NeurIPS, KDD, WWW, SIGIR, and TKDE. One of his works has been ranked as the Top 1 among the Most Influential Papers of WWW'23 (Sep 2024, Paper Digest), and another was featured in VLDB'13 Best Papers Collection (2015, VLDBJ).
- **Yuxia Wu** is a research scientist at the School of Computing and Information Systems, SMU. She received her Ph.D. degree from Xi'an Jiaotong University in 2023. Her research interests include graph data mining, recommender systems and natural language processing. She has published over 20 papers in top journals and conferences, such as IEEE TKDE, TMM, WWW, and EMNLP.
- **Xingtong Yu** is currently a research scientist with the School of Computing and Information Systems, Singapore Management University. He received his bachelor's degree from the School of the Gifted Young, University of Science and Technology of China in 2019, and the PhD degree from the University of Science and Technology of China in 2024. His current research focuses on graph-based machine learning, prompting on graphs, and graph foundation models. His research has been published in top conferences and journals such as WWW, AAAI, and TKDE. One of his works has been ranked as the Top 1 among the Most Influential Papers of WWW'23 (Sep 2024, Paper Digest).
- **Shirui Pan** is a Professor and an ARC Future Fellow with the School of Information and Communication Technology, Griffith University, Australia. Before joining Griffith in 2022, he was

Senior Lecturer (Associate Professor) with the Faculty of Information Technology, Monash University. He received his Ph.D degree in computer science from University of Technology Sydney (UTS), Australia. He is a Senior Member of IEEE and ACM, and a Fellow of Queensland Academy of Arts and Sciences (FQA). His research focuses on artificial intelligence and machine learning, with significant contributions to graph machine learning methods for solving hard AI problems for real-life applications, including graph classification, anomaly detection, recommender systems, and multivariate time series forecasting. His research has been published in top conferences and journals including NeurIPS, ICML, KDD, TPAMI, TNNLS, and TKDE. He is recognized as one of the AI 2000 AAAI/IJCAI Most Influential Scholars in Australia (2023, 2022), and one of the World's Top 2% Scientists (since 2021). His research received the 2020 IEEE ICDM Best Student Paper Award (2020), and the 2024 IEEE CIS TNNLS Outstanding Paper Award. He has eight papers recognized as the Most Influential Papers in KDD (x1), IJCAI (x5), AAAI (x1), and CIKM (x1) (Feb 2022). He received a prestigious Future Fellowship (2022-2025), one of the most competitive grants from the Australian Research Council (ARC).

2 Topic and Relevance

Scope. The tutorial topic covers the following aspects.

1. Introduction & Overview: Background and preliminaries of few-shot learning on graphs, including fundamental concepts and techniques related to graphs.

- Graph preliminaries: Graph data, graph representation learning approaches and graph-related tasks;
- Few-shot learning on graphs: few-shot learning settings and overview of techniques on graphs.

2. Problems & Applications: A discussion on different problem settings and applications of few-shot learning on graphs.

- Label scarcity problems, involving different types of class-based and instance-based label scarcity.
- Structure scarcity problems, involving long-tailed distribution and cold-start learning problems.
- Applications of various problem settings, such as cold-start recommendation on user-item graphs and user classification in social networks.

3. Technical Approaches: A review of existing few-shot learning techniques on graphs including meta-learning approaches, pre-training methods in the pre-LLM and LLM era, and hybrid methods.

- Meta-learning approaches tailored for graph data include (1) structure-based enhancement focusing on exploiting graph structures to enhance the learning of the prior; (2) adaptation-based enhancement methods enhancing the adaptation mechanism for few-shot learning on graphs.
- Pre-training methods in the pre-LLM era encompass (1) contrastive and generative pre-training strategies; (2) downstream adaptation techniques such as fine-tuning, prompt tuning, and parameter-efficient fine-tuning.
- Pre-training methods in the LLM era include (1) LLM-based models that describe graph data in natural language, allowing pre-training similar to language models; (2) GNN+LLM-based models integrating the advantages of GNNs and LLMs to better capture the semantic and structural information.

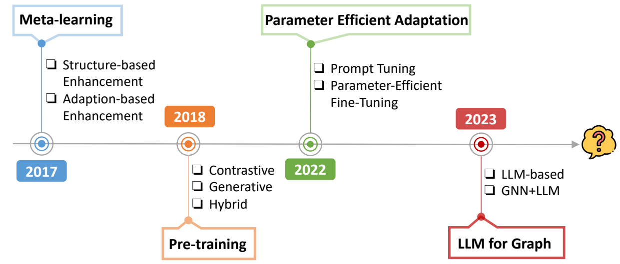

Figure 1: Timeline of few-shot learning research on graphs.

- Hybrid approaches combine meta-learning and pre-training strategies by leveraging pre-training to learn a general task-agnostic prior while drawing adaptation insights from similar meta-training tasks to enhance few-shot performance.

4. Future Directions: A discussion of open challenges and future directions for few-shot learning on graphs.

- Future avenues in problem settings such as the few-shot learning on large-scale, complex, or cross-domain graphs.
- Future avenues in techniques such as model interpretability and foundation models.

Importance and Timeliness. Few-shot learning on graphs rapidly gains attention as graph-structured data becomes increasingly prevalent across various domains, including social networks, recommender systems, Web search and retrieval, knowledge graphs, and molecular research. The challenge of learning from limited labeled data is critical in real-world applications, where labeled data are often scarce or costly to obtain. As the landscape of machine learning shifts towards more data-efficient methods, particularly with the rise of pre-training techniques and LLMs, understanding how these advancements apply to graph-based tasks is more important than ever. This tutorial addresses the urgent need for a comprehensive overview of few-shot learning on graphs, an emerging field poised to drive future innovations in AI, web technologies, and beyond. It is timely, given the rapid evolution of pre-training and LLM techniques (Figure 1), offering attendees a fresh perspective on cutting-edge approaches for learning from minimal data on graphs.

Relevance to the Web Conference. The Web Conference focuses on advances in Web technologies, which have become increasingly intertwined with graph-structured data. Few-shot learning on graphs is highly relevant to the core topics of the conference, including social network analysis, recommender systems, Web search and retrieval, and knowledge graphs. As Web applications continue to evolve, effectively leveraging limited labeled data emerges as a crucial challenge. This tutorial is aligned with the conference's relevance to AI and machine learning, providing attendees with valuable insights into data-efficient learning methods that can be applied to a wide range of Web applications. Moreover, the exploration of pre-LLM and LLM-era pre-training methods for graphs is especially timely, as it promotes the effective exploitation of LLMs and generative AI methods in Web technologies.

Qualification of Presenters. The presenters of this tutorial are recognized experts in graph representation learning, few-shot learning and language models. With a proven track record of research

Table 1: Summary of tutorial schedule.

	Part	Presenter(s)	Duration
1.	Introduction & Overview	Shirui Pan	30 mins
2.	Problems & Applications	Yuan Fang	30 mins
3.	Technical Approaches	Yuxia Wu Xingtong Yu	50 mins 50 mins
4.	Future Directions	Yuan Fang	20 mins

and contributions in these areas, they have published extensively in top-tier conferences in the topics covered by this tutorial.

3 Style

This will be a lecture-style tutorial aimed at providing a comprehensive overview and systematic analysis of this fast-growing direction.

4 Schedule

This tutorial will be conducted over a half-day (3 hours). An overview of the schedule is presented in Table 1, with detailed explanations of each section as follows.

4.1 Introduction and Overview (30 mins)

- Presenter: Shirui Pan
- Preliminary of graph representation learning;
- Overview of few-shot learning on graphs.

Graph-structured data, arising from interactions among data objects in many domains, has led to increased interest in tasks such as node classification, link prediction, and graph classification. Various graph representation learning techniques have been developed to address these tasks, including GNNs and graph transformers, which rely on rich graph structures and substantial amounts of labeled data. However, in real-world applications, labeled data is often scarce, which severely limits the performance of these methods. In light of this challenge, few-shot learning on graphs [12] has garnered significant attention across diverse fields including social network analysis, recommender systems, and molecular research. This session will begin with an introduction to classic graph representation methods, providing the necessary background to understand few-shot learning on graphs. We will then introduce two different problem settings of few-shot learning in graphs. Finally, we will provide an overview of the current progress and recent advancements in few-shot learning on graphs, highlighting key methodologies and their applications.

4.2 Problems & Applications (30 mins)

- Presenter: Yuan Fang
- Taxonomy of few-shot problems on graphs;
- Real-world applications of different problem settings.

Few-shot learning on graphs has gained significant research interest due to the frequent data scarcity issues in real-world graphs. This session provides an overview of key challenges in few-shot learning on graphs and their applications across various domains, including social networks, e-commerce, molecular analysis, *etc.* Based on the type of data scarcity, we categorize few-shot learning problems on graphs into two groups: *label scarcity* and *structure scarcity*. On one hand, similar to the challenges faced in NLP and CV, label scarcity, or the lack of labeled data, remains an important challenge in few-shot learning on graphs. In this session, we will introduce *class-based* label scarcity problems [3, 6] including label scarcity in new classes, base classes and both, and *instance-based* label scarcity problems [4] such as node-level, edge-level and graph-level. On the other hand, unlike text and image data, graphs possess a non-euclidean topological structure. As a result, structure scarcity in graphs emerges as a second challenge that could adversely impact the learning of effective representations. In this session, we will cover two subtypes of structure scarcity problems: long-tailed distribution and cold-start learning problems.

4.3 Technical Approaches (100 mins)

1) Overall Taxonomy & Meta-learning Approaches (25 mins).

- Presenter: Yuxia Wu
- Overall taxonomy of technical approaches;
- Review and comparison of meta-learning techniques for few-shot learning on graphs.

In this session, we will begin with an overall taxonomy of technical approaches, from meta-learning to pre-training methods across both the pre-LLM and LLM eras. Following this, we will delve into meta-learning approaches, a crucial paradigm in few-shot learning that enables models to generalize across tasks with minimal labeled data. We will provide a formal overview of standard meta-learning techniques, establishing a theoretical and practical understanding. This will be followed by a systematic review of recent advancements in meta-learning, focusing on extended methodologies that address the challenges of few-shot learning in graph data through structure-based and adaptation-based enhancements [9, 10].

2) Pre-training: Pre-LLM (25 mins).

- Presenter: Yuxia Wu
- Review and comparison of pre-training techniques for graphs;
- Review and comparison of few-shot adaptation strategies for pre-trained graph models.

Pre-training methods have gained significant attention due to their ability to leverage large amounts of unlabeled data and their flexibility in adapting to a wide range of downstream tasks. In the context of graph-based learning, pre-training typically involves the use of self-supervised techniques to learn a graph encoder that captures intrinsic, task-agnostic properties of graphs, such as node attributes and local or global structural features. This graph encoder, enriched with prior knowledge, can then be fine-tuned for specific downstream tasks in an adaptation stage. In this session, we will provide a comprehensive taxonomy of pre-training and adaptation strategies in the pre-LLM era [2, 3]. For pre-training methods, we will cover contrastive and generative models. In terms of adaptation techniques, we will provide discussions on fine-tuning, prompt tuning, and parameter-efficient fine-tuning strategies.

3) Pre-training: LLM Era (30 mins).

- Presenter: Xingtong Yu
- Review and comparison of LLM-based pre-training for graphs;
- Review and comparison of LLM+GNN-based pre-training;
- Review and comparison of their adaptation strategies for few-shot learning on graphs.

With the advent of LLMs, pre-training methodologies have gained a new dimension, especially in their ability to capture rich semantic relationships from large-scale textual data. Integrating LLM-powered pre-training into graph encoders enables these models to capture both structural and semantic properties of graphs, yielding more robust and versatile graph representations. In this session, we will explore state-of-art pre-training approaches including LLM-based and GNN+LLM-based methods [1, 5].

4) Hybrid Approaches & Overall Summary (20 mins).

- Presenter: Xingtong Yu
- Review and comparison of hybrid approaches integrating meta-learning and pre-training;
- Overall summary and discussion of the advantages and limitations of each line of techniques.

In real-world scenarios, we often have access to abundant unlabeled data suitable for pre-training, along with a well-annotated base set for meta-learning. This setup allows hybrid approaches to combine the advantages of each method effectively by employing the unlabeled data to establish a task-agnostic prior via pre-training while drawing on insights from similar tasks during meta-training to enable task-specific adaptation. We will introduce the related works using various pre-training and adaptation strategies [7, 8]. This session will conclude with an overall summary, highlighting the strengths and limitations of different methods.

4.4 Future Directions (20 mins)

- Presenter: Yuan Fang
- Future avenues in problem settings
- Future avenues in techniques

In this section, we will explore future opportunities arising from new problem settings and innovative technical approaches. For the problem settings, we will discuss structure scarcity learning problems and the few-shot learning on large-scale graphs, complex graphs (3D, dynamic, multi-modal) and cross-domain graphs. In terms of future techniques, we will cover advancements in interpretability and the development of foundation models tailored for graphs, which can be pre-trained on extensive graph data and adapted across diverse downstream tasks and domains.

5 Audience

Target Audience: This tutorial is designed for a broad audience from academia and industry, catering to both newcomers and experienced professionals in deep learning on graphs, large language models, and related fields. Attendees will gain a comprehensive understanding of these topics and their practical applications, making them valuable and accessible for all expertise levels.

Prerequisites: While there are no strict prerequisites, a basic understanding of graph learning and language models is preferred. The tutorial will also cover all necessary foundations, providing a clear and comprehensive introduction to these topics to ensure accessibility for all participants.

Potential Learning Outcomes: After this tutorial, the audience would benefit from the following potential outcomes.

- Comprehensive understanding: Attain a thorough understanding of few-shot learning problems and methodologies on graphs, as well as the impact of LLMs on advancing these techniques.
- Familiarity with advanced techniques: Gain insights into state-of-the-art meta-learning approaches and pre-training strategies, encompassing both pre-LLM and LLM-driven advancements.
- Awareness of emerging research directions: Cultivate awareness of key future directions in the field, including the enhancement of interpretability, tackling cross-domain learning challenges, and the development of foundational models.
- Broader application understanding: Understand the potential real-world applications of these techniques in both academic and industrial settings, enabling participants to apply these insights to their own research.

6 Previous Editions

As this tutorial covers a novel direction, it has not been presented before. It will be the first time we introduce this topic at a conference, and the Web Conference 2025 will be a timely venue.

7 Tutorial Materials

All the attendees of the tutorial will be provided with a comprehensive set of materials, including our preprint survey paper [11], a GitHub repository organizing key works with links to their code/data, available at https://github.com/smufang/fewshotgraph and presentation slides of the tutorial.

8 Video Teaser

A video teaser is available at https://youtu.be/3ACNzgqcDZQ.

Acknowledgments

This research / project is supported by the Ministry of Education, Singapore, under its Academic Research Fund (AcRF) Tier 1 grant (22-SIS-SMU-054). Any opinions, findings and conclusions or recommendations expressed in this material are those of the author(s) and do not reflect the views of the Ministry of Education, Singapore.

References

[1] Jiawei Liu, Cheng Yang, Zhiyuan Lu, Junze Chen, Yibo Li, Mengmei Zhang, Ting Bai, Yuan Fang, Lichao Sun, Philip S Yu, et al. 2023. Towards graph foundation models: A survey and beyond. *arXiv preprint arXiv:2310.11829* (2023).
[2] Yixin Liu, Ming Jin, Shirui Pan, Chuan Zhou, Yu Zheng, Feng Xia, and S Yu Philip. 2022. Graph self-supervised learning: A survey. *TKDE* 35, 6 (2022), 5879–5900.
[3] Zemin Liu, Xingtong Yu, Yuan Fang, and Xinming Zhang. 2023. Graphprompt: Unifying pre-training and downstream tasks for graph neural networks. In *WWW*. 417–428.
[4] Linhao Luo, Yuan-Fang Li, Gholamreza Haffari, and Shirui Pan. 2023. Normalizing flow-based neural process for few-shot knowledge graph completion. In *SIGIR*. 900–910.
[5] Xubin Ren, Jiabin Tang, Dawei Yin, Nitesh Chawla, and Chao Huang. 2024. A survey of large language models for graphs. In *KDD*. 6616–6626.
[6] Xiangguo Sun, Hong Cheng, Jia Li, Bo Liu, and Jihong Guan. 2023. All in One: Multi-Task Prompting for Graph Neural Networks. In *KDD*. 2120–2131.
[7] Zhen Tan, Ruocheng Guo, Kaize Ding, and Huan Liu. 2023. Virtual Node Tuning for Few-shot Node Classification. In *KDD*. 2177–2188.
[8] Zhihao Wen and Yuan Fang. 2024. Prompt tuning on graph-augmented low-resource text classification. *IEEE TKDE* (2024).
[9] Zhihao Wen, Yuan Fang, and Zemin Liu. 2021. Meta-Inductive Node Classification across Graphs. In *SIGIR*. 1219–1228.
[10] Cheng Yang, Chunchen Wang, Yuanfu Lu, Xumeng Gong, Chuan Shi, Wei Wang, and Xu Zhang. 2022. Few-shot link prediction in dynamic networks. In *WSDM*. 1245–1255.
[11] Xingtong Yu, Yuan Fang, Zemin Liu, Yuxia Wu, Zhihao Wen, Jianyuan Bo, Xinming Zhang, and Steven CH Hoi. 2024. Few-shot learning on graphs: from meta-learning to pre-training and prompting. *arXiv preprint arXiv:2402.01440* (2024).
[12] Chuxu Zhang, Kaize Ding, Jundong Li, Xiangliang Zhang, Yanfang Ye, Nitesh Chawla, and Huan Liu. 2022. Few-Shot Learning on Graphs: A Survey. In *IJCAI*.