Research Statement

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18 December 2025

I. Background and Overview

Graphs are prevalent in real-world applications, for they can model not only individual data entities, but also interactions between these entities. Example graphs include social networks, transportation and communication systems, financial networks, citation networks, and biochemical graphs [WPC20]. To gain insights into such data, my research (Figure 1) has undertaken *graph learning and mining*. I particularly focus on three topics: a) learning graph representations, B) multi-modal graph learning, and C) data efficiency for graph learning, as well as their various applications.

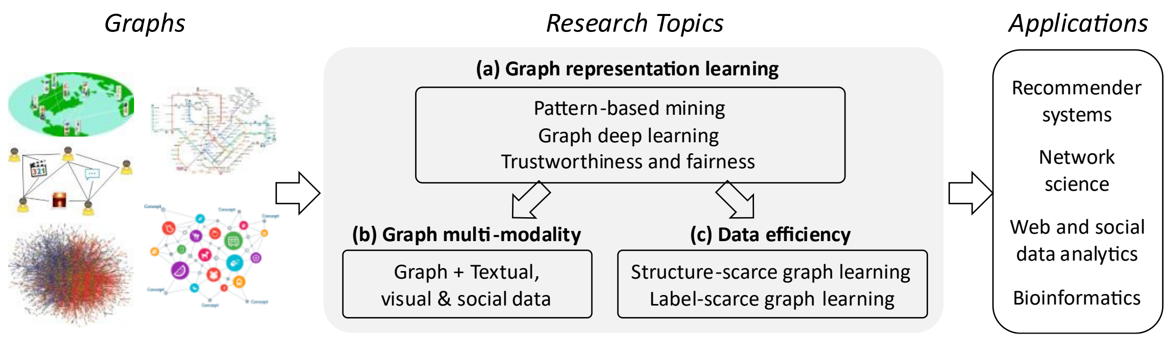

Figure 1: Overall research theme – Graph learning and mining.

Overall, my research is driven by the need to develop principled methodology for various fundamental problems on graphs. My work on graph representations investigates the underlying principles and mechanisms in graph-structured data, which builds a mathematical and algorithmic foundation for exploring different aspects and applications on graphs. On top of the fundamental graph representation learning, my choice of specific research problems has been motivated by opportunities and challenges in graph learning and mining. On one hand, given the variety and volume of multi-modal data associated with graph structures, there is an urgency to leverage graph multi-modality to augment traditional problems on graphs. Hence, I have explored the setting of graphs augmented by textual, visual and social data. These data often complement the graph structures to enable more effective and robust learning. On the other hand, one of the biggest hurdles faced by the deep learning community is data efficiency, particularly the lack of labelled data. The same problem persists in graph learning, where we need to address two aspects of data efficiency: when the structures are scarce, and when the labels are scarce. Addressing these research problems is crucial to not only the understanding of fundamental principles on graphs, but also the enabling of practical applications on graphs.

II. Summary and Evolution of My Research

As new opportunities and challenges arise, my research has evolved around several important topics in graph learning and mining (Table 1).

My early research has studied the fundamental principles of graph representations based on structural patterns, ranging from simple links [VLDB13] to more complex semantic structures, most notably the concept of *metagraph* [ICDE16, TKDE19]. Metagraph is a representative semantic structure, which have since been widely used in the community for various applications and problems on graphs [ZYL17, SZC19], including in some of my own research [MET17, TKDE20, CIKM21]. Since I started my career as an assistant professor, my research on graph representations has gradually taken on deep learning-based approaches, given the superior performance of neural networks. Nonetheless, such more recent work [KDD19, TKDE20, IJCAI21, AAAI23a] are built upon the insights of pattern-based representations. In addition to performance-oriented methods, in recent years I have also explored the trustworthiness and fairness in representation learning [TOIS23, AAAI23b, NeurIPS23a]. This line of work has become increasingly important, as it addresses critical concerns about the ethical and societal impacts of artificial intelligence [KUR22].

Building upon graph representation learning, my research has also explored graph multi-modality, given the opportunities presented in the big data era. Specifically, abundant multi-modal data, including textual, visual and social data, are often associated with graphs. These data encompass rich information to complement graph structures and can be immensely valuable to enhancing graph learning models for various graph-based applications. While my earlier works [TACL14, IJCAI17] leverage shallow structural patterns in addition to multi-modal data, more recent studies [SIGIR23, KDD25a, KDD25b] have leveraged graph neural networks, Transformers or large language models for deeper semantic-structural integration.

While deep learning has been widely adopted in different communities including graph learning, its success critically depends on the availability of large-scale labelled data. This limitation has motivated research on data-efficient learning, in which we aim to learn a strong model even without large-scale data. Hence, my more recent research has paid significant attention to the data efficiency problem on graphs, in which there is not only the label-scarcity issue [AAAI21b, SIGIR21], but also the structure-scarce issue [CIKM20, KDD20, KDD21]. Recently, graph pre-training on large-scale label-free graphs has emerged as a promising direction [AAA21a, CIKM21, NeurIPS23b]. Inspired by prompt-based learning in large language models, I have furthered our graph pre-training research into prompt learning on graphs [WWW23, CIKM23, AAAI24, KDD25c]. These studies have established a parameter-efficient adaptation for pre-trained graph models, showcasing great generalization ability across different downstream tasks with limited task-specific labels. Building on these insights, our work [WWW25] takes a further step towards generalization across graph datasets, advancing the development of graph foundation models [TPAMI25].

Topics	Subtopics	Period	Selected publications
(a) Graph representation learning	Pattern-based mining	2010–2019	VLDB13, ICDE16, MET17, TKDE19
	Deep graph learning	2018–present	KDD19, TKDE20, IJCAI21, WWW22, AAAI23a, WWW24
	Trustworthiness & fairness	2022–present	TOIS23, AAAI23b, NeurIPS23a
(b) Graph multi-modality learning		2013–present	TACL14, IJCAI17, SIGIR23, KDD25a, KDD25b
(c) Data-efficient graph learning	Structure-scarce graphs	2019–2023	KDD20, CIKM20, KDD21, TKDE23
	Label-scarce graphs	2020–present	AAAI21a, AAAI21b, SIGIR21, CIKM21, WWW23, CIKM23, NeurIPS23b, AAAI24, KDD25c, WWW25, TPAMI25

Table 1: Topical and chronological evolution of my research.

III. Notable Recognition of Research

Research output. I have published over 100 conference and journal papers in leading data mining, machine learning and the broader AI venues such as KDD, WWW, SIGIR, NeurIPS, ICLR, AAAI, TKDE, TPAMI, etc. My publications have garnered a total citation of 4911 and h-index of 39 on Google Scholar as of the time of writing. Most notably, our recent work on GraphPrompt [WWW23] has been recognized among the Most Influential WWW Papers (ranked #1 in WWW'23) by Paper Digest in Sep 2024, and our work on PageRank [VLDB13] has been featured in the special issue on Best Papers of VLDB'13 (only 4 selected out of 127). Our poster on graph foundation models have won the Outstanding Poster Award at the China Computer Federation (CCF)'s 1st Graph Machine Learning Conference in 2025.

Fundings and grants. My research activities were or are supported in part by Singapore's Ministry of Education (MOE Tier 2), A*STAR, AI Singapore, Alibaba Group and DBS Bank, as well as SMU internal funding. Including the period before joining SMU, I served or am serving as the PI, Co-PI or project-level PI across 8 projects. Since I joined SMU in July 2018, as the PI or project-level PI, I have secured a total external funding size of SGD 1.6 million (~USD 1.2 million), and managed and executed externally funded projects worth SGD 2.1 million in total.

Academic supervision. In conjunction with my research, I have supervised or co-supervised doctoral students and research staff who have become promising young researchers and practitioners. In total, four PhD students have graduated: Zhihao Wen (2023), Zhongzhou Liu (2024), Jianyuan Bo (2025), and Ran Liu (2025), and one Doctor of Engineering student have graduated: Brindha PRIYADARSHINI (2025). They are now with prestigious employers such as Ant Group, TikTok, Huawei, and UOB. Zhihao and Zhongzhou were awarded the prestigious SMU Presidential Doctoral Fellowship, Zhongzhou also received the NeurIPS Scholar Award (2023), while Brindha were named a Top 50 Asia Women Tech Leaders (2025). My former postdoctoral fellow, Zemin Liu, joined Zhejiang University as an Assistant Professor in May 2024. My former research assistant, Jiaqi Shi, joined the University at Buffalo as an Assistant Professor in Fall 2024.

Professional activities. I was a keynote/invited speaker or panelist at the Social Networks Analysis Forum, 8th China Conference on Data Mining (2020), 5th International Symposium on Cognitive and Semantic Computing in Taiyuan, China (2025), and various prestigious workshops collated at WSDM'23, RecSys'23, WWW'24 and WWW'25. I served as an Associate Chair, Area Chair, Senior PC or PC member and Session Chair on various top conferences, and reviewers for leading journals. I also served on the Organizing Committees of top conferences: KDD'21 Registration Co-Chair, WSDM'23 Workshop Co-Chair, and WWW'24 Volunteers Co-Chair. For professional societies, I have been the Secretary of Singapore ACM SIGKDD Chapter since 2022 and served as the PC Co-Chair for the local chapter's Symposium in 2023 and 2024. I have also been elevated to a Senior Member of IEEE in 2024.

IV. Key Research Findings by Area

(a) Graph representation learning

Learning effective graph representations has been and remains a core problem for graph-based tasks.

Pattern-based approaches. My earlier research revolved around directly utilizing structural patterns in graphs. In real-world applications, entities are often interlinked to form heterogeneous graphs, where different semantics exist between nodes. For instance, on a social network, various relationships between users exist: classmates, family, colleagues, etc. We proposed *metagraph representations* [ICDE16] as a novel concept to characterise these different semantic relationships, which have shown strong results in many graph-based applications such as social recommendation [ICDE16] and bioinformatics [MET17]. Taking a step further, we have also explored metagraphs as a universal form of node and edge representations [TKDE19], demonstrating its superior performance in more downstream tasks. Apart from using metagraphs as explicit representations, they can also serve as a tool for graph deep learning [TKDE20] and pre-training [CIKM21].

Graph deep learning. I have also investigated various techniques of graph embedding and neural networks for representation learning on different kinds of graphs. On general graphs, we have studied the node-wise adaptation [IJCAI21] and edge-centric message-passing [AAAI23a] for graph neural networks. On heterogenous graphs, our research has investigated adversarial learning [KDD19] and metagraph-guided embedding [TKDE20]. On dynamic graphs, I have studied the Hawkes process on graph neural networks [WWW22] and the Transformer-based approach [WWW24]. Due to the ability to fit complex, nonlinear functions, deep graph representation learning often achieves state-of-the-art performance in various domains such as bioinformatics and recommender systems.

Trustworthiness and fairness. Traditionally, graph representation learning focuses on improving performance in graph-based applications but pays little attention to the trustworthiness and fairness of the model predictions. My recent work on structural fairness in graph neural networks [AAAI23b] aims to develop methods for learning fair representations of nodes, particularly focusing on addressing the disparities in structural resources (e.g., social capital) among these nodes. The goal is to ensure that the algorithmic outcomes are equitable, regardless of the varied structural resources of the nodes. The fairness concept can also be extended to user-item bipartite graphs in recommender systems. On this bipartite graph, we investigated the issue of popularity bias [TOIS23], aiming to achieve fairness for both users and sellers, regardless of their existing popularity (Figure 2). On recommender systems, we also explored propensity estimation for causality-based recommender systems [NeurIPS23a]. This study enables a more practical setup for causality-based recommendations that are not only effective but also more trustworthy and explainable, by producing outcomes grounded in causal effect rather than mere correlations in historical data.

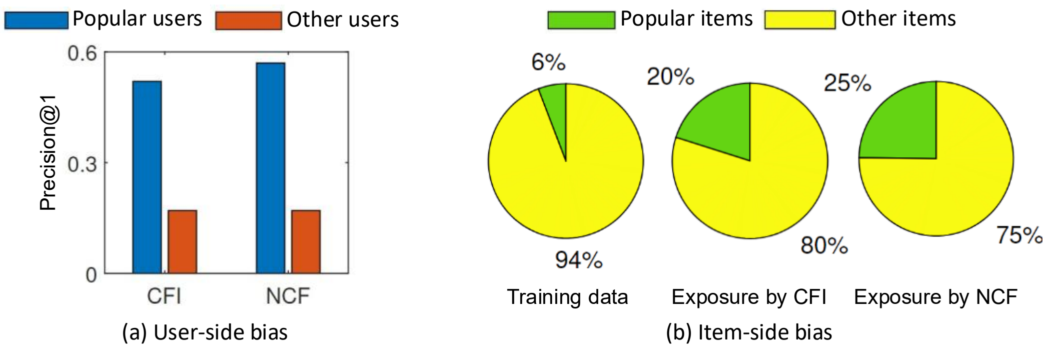

Figure 2: Popularity bias in conventional recommender models, e.g., CFI [LZL18] and NCF [HLZ17]. (a) User-side bias: popular users enjoy much higher recommendation accuracy than others; (b) Item-side bias: popular items receive much more exposure (20–25%) than their proportion in the training data (6%).

(b) <u>Graph multi-modality learning</u>

Many problem statements often involve other kinds of data in addition to explicit graph structures, including visual, textual, and social data. These data either enable us to construct new graphs, or to complement existing graphs to improve learning or to enable new tasks. We refer to such research as multi-modal graph learning, with the goal of exploiting additional knowledge from one or more complementary modalities beyond graph structures.

In an earlier work [IJCAI17], we exploited knowledge graphs to improve the object detection task in images. Specifically, knowledge graphs contain commonsense knowledge that can relate different objects in an image, e.g., pets like cats and furniture like dining table often appear together in households. Such knowledge would improve detection recalls in home scenes: the detections of pet and furniture mutually reinforce each other, should one of them has low initial confidence. Besides visual data, textual information on text-attributed graphs [SIGIR23], such as abstracts for papers on a citation graph (Figure 3), or item descriptions in a recommender system, can enrich the interactions between nodes. Moreover, social meta-data could also be used to construct auxiliary graphs. In our entity linking study [TACL14], we constructed spatial and temporal graphs for entities appearing on Twitter (known as X now), so that entities close to each other in either space or time can be connected based on the meta-data of the tweets (i.e., timestamps and geotags). The connections reveal the relatedness between entities, which proves beneficial to the entity linking task.

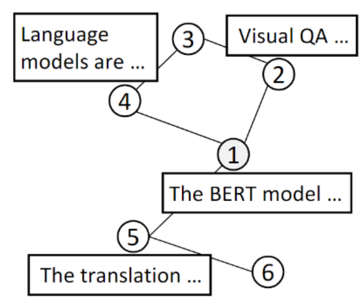

Figure 3: An example text-attributed citation graph, where each node represents a paper with a textual description (e.g. title or abstract).

While our earlier studies [TACL14, IJCAI17] only leveraged shallow structural patterns in addition to multi-modal data, more recent work focuses [SIGIR23, KDD25a, KDD25b] on deeper semantic-structural integration, building upon graph neural networks, Transformers or large language models (LLMs). Specifically, we pioneer joint training paradigms for graph and language models [SIGIR23, KDD25a], and further explore graph quantization paradigms that quantize graph nodes into textual tokens for direct consumption by LLMs, thereby leveraging their strong semantic understanding and reasoning capabilities [KDD25b].

(c) Data efficiency in graph learning

Learning with data efficiency has gained significant traction in recent years as a means to overcome the requirement of large-scale labelled data in conventional supervised deep learning. We have explored two major aspects of data efficiency in graph learning.

Structure-scarce graph learning. On many graphs, we observe that there is often a long tail of nodes with very few links. In general, the node degrees vary considerably across the network and are not uniformly distributed (Figure 4a). Learning representations for these structure-scarce "tail" nodes are more challenging than nodes with rich structures (Figure 4b), presenting a novel problem that is often neglected by conventional graph learning. Leveraging the power of meta-learning, we formulated the problem as a few-shot regression task and proposed meta-tail2vec [CIKM20], a first attempt on this problem. However, meta-tail2vec is a two-stage method that improves the tail node embedding through a post-processing step. Thus, we further proposed an end-to-end tail node representation learning framework for graph neural networks [KDD21]. Similarly, the cold-start recommendation problem also suffers from the scarcity of structures connecting new users and items. Thus, we formulated the cold-start problem as a few-shot link prediction task [KDD20] and addressed it from the model and data levels with a co-adaptation meta-learner.

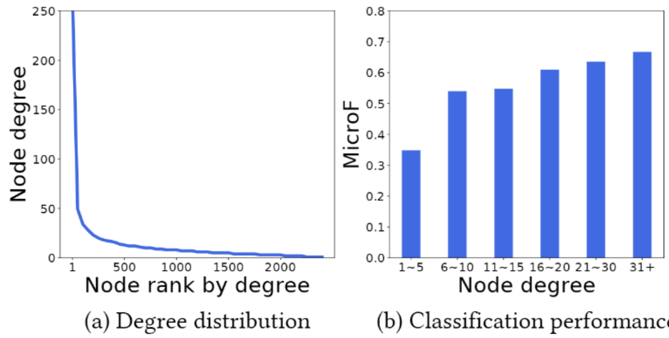

Figure 4: Relationship between node degrees and the quality of learned representations on a typical graph.

Label-scarce graph learning. Similar to other supervised models, state-of-the-art graph neural networks depend on abundant labelled data to achieve optimal performance. However, in real-world applications, many tasks often lack abundant labelled data. One common scenario is the few-shot node classification on graphs, in which some novel classes only have one or few examples. For instance, on a citation graph, while Markov chains is a mature topic with many labelled examples, algorithmic explainability and fairness is relatively new with few labelled examples. To address few-shot learning on graphs, we resort to the framework of meta-learning, while simultaneously exploiting graph-specific characteristics including the long-range dependencies between nodes, and the global graph contexts [AAAI21b]. We have also explored inductive graph learning across graphs, where the trained model on an existing set of graphs can be transferred to new graphs in the same feature space, reducing the need for labels on the new graphs [SIGIR21].

Meanwhile, to make use of the vast availability of "label-free" graphs (i.e., graphs without any label for downstream tasks), pre-training has emerged as a promising direction to capture inherent graph properties in a task-agnostic manner, which can be transferred to different downstream tasks. To capture such properties, we designed various pre-training objectives [AAAI21a, CIKM21, NeurIPS23b]. Conventionally, the pre-trained graph models can be adapted to diverse downstream tasks through fine-tuning using task-specific labels. However, full fine-tuning is not only inefficient, but also suboptimal especially when there are few task-specific labels due to the divergence between pre-training and downstream objectives. To address the objective differences, we draw inspiration from prompt-based learning in pre-trained language models, in which prompts are designed to generalize the pre-trained model to a wide range of downstream tasks using limited task-specific labels. Consequently, we designed GraphPrompt [WWW23], one of the pioneering studies that attempt to unify pre-training and downstream tasks in a prompt-tuning framework for graph learning, enabling the generalization to new downstream tasks. We further applied prompt-based learning to address anomaly detection in e-commerce [CIKM23] and handle heterogeneous graphs [AAAI24], and devised a Chain-of-Thought-style prompt learning strategy for graph models [KDD25c].

Finally, graph prompt learning establishes a natural pathway toward graph foundation models (GFMs) [TPAMI25], which seek a broader generalization across not only tasks but also graph datasets. Our most recent work, SAMGPT [WWW25], is one of the earlier attempts to enable multi-domain graph pre-training and downstream adaptation on graph structures, advancing the development of GFMs.

V. Future Research Agenda

My future work will still be anchored on graph learning and mining, as many research questions and opportunities remain open in the three major topics of my research (Figure 1).

Towards trustworthy and fair graph learning. While we have conducted some preliminary work in trustworthiness [NeurIPS23a] and fairness [TOIS23, AAAI23b], both our research and the broader literature in the community are still in their early stages, with many challenges remaining.

First, different perspectives of fairness and various forms of biases exist. For example, fairness can be defined based on statistical parity and equal opportunities, while various biases such as self-selection, conformity, exposure, and popularity are prevalent in recommender systems [CDW23]. These definitions may sometimes conflict with each other, driving the outcomes in opposing directions. Thus, it is crucial to design an adaptive framework that can accommodate different definitions of fairness and bias on graphs in a coherent manner.

Second, how do we study various related concepts in trustworthy graph learning systematically? For example, fairness and explainability are often not independent but have intricate relationships. A decision that can be explicitly explained often helps mitigate perceived unfairness. Thus, considering two or more aspects jointly could improve the trustworthiness of graph learning.

Towards multi-modal graph foundation models. Recently, large language models (LLMs) or foundation models [BHA21] have unified the pre-training of a broad range of language-based data across many domains, enabling an exciting array of downstream tasks. Given their successes, it is intriguing to ask: *Is it possible to develop a graph foundation model [LYL23] on broad graph data across diverse domains, which can be subsequently used to address a wide range of downstream tasks on graphs?*

The first major hurdle towards this goal lies in the challenge that graphs from different domains often exhibit divergent characteristics. In LLMs, textual contents from multiple domains are inherently connected through a common set of natural language tokens (i.e., words). In contrast, for multi-domain graphs, the tokens (i.e., nodes of the graphs) can have little overlap across graphs in different domains, ranging from users on a social network, to corporations in a financial network and atoms in a molecular graph. As a result, directly applying existing graph pre-training techniques to multi-domain graphs often leads to domain conflicts, as our preliminary study shows (Figure A5). Thus, it is imperative to study pre-training methodologies for multi-domain graphs. Meanwhile, the domains must be carefully scoped *within the same discipline* to ensure there are some common tokens across domains. For example, protein-protein interactions, gene regulatory networks, and metabolic pathways are multi-domain graphs within the biomedical discipline, while customer relationships and transaction networks are multi-domain graphs within the finance discipline. In each discipline, there could be a set of explicit or latent common tokens to bridge the multi-domain graphs for synergistic pre-training.

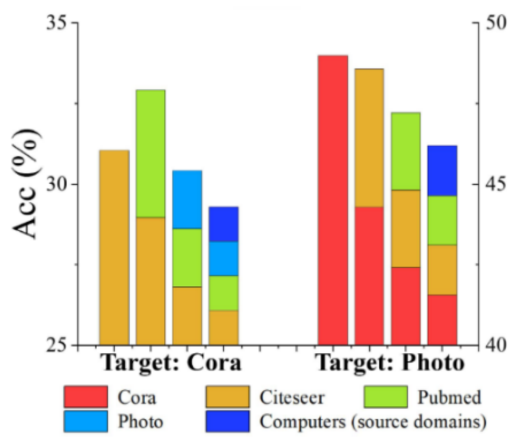

Figure A5: Accuracy of one-shot node classification tasks on two target domains, as more source domains are added to pre-training using a popular graph pre-training approach [VFH19]. Pre-training with more source domains often results in reduced accuracy, indicating domain conflicts.

Second, how can we integrate large-scale visual and textual data to complement graph learning? Our existing research on graph multi-modal learning [TACL14, IJCAI17, SIGIR23] has shed light on this possibility, albeit on a smaller scale. Towards multi-modal graph foundation models, it would be crucial to explore the integration of graph structures with existing large language and vision models. One plausible starting point is our research on text-attributed graphs [SIGIR23], where we align the graph and language models with each other. However, considering the scale of the LLMs, injecting the smaller graph models into existing LLMs presents a more feasible direction.

Third, I plan to investigate parameter-efficient fine-tuning techniques for pre-trained graph models beyond our prompt-based work [WWW23], such as adapter learning and low-rank adaptation [ACL24]. These techniques would further enhance the generalization ability across different downstream tasks in a parameter-efficient manner, potentially contributing to the development of graph foundation models, driving future research on offering universal transferability and adaptability to broad graph data and tasks.

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