THE HONG KONG POLYTECHNIC UNIVERSITY
香港理工大學

Department of Computing
電子計算學系

COMP RESEARCH STUDENT SEMINAR

Date : 5 February 2025 (Wed)
Time : 15:00 - 16:00
Venue : FJ303 (Face-to-face)

Causally Motivated Personalized Federated Invariant Learning with Shortcut-Averse Information-Theoretic Regularization

Abstract

Exploiting invariant relations and mitigating spurious correlation (a.k.a., shortcut) between representation and target across varied data distributions can tackle the challenging out-of-distribution (OOD) generalization problem. In personalized federated learning (PFL), heterogeneous data distribution across local clients offers the inherent prerequisites to extract the invariant features that maintain invariant relation with target. Nevertheless, personalized features are closely entangled with spurious features in PFL since they exhibit similar variability across different clients, which makes preserving personalization knowledge and eliminating shortcuts two conflicting objectives in PFL. To address the above challenge, we analyse the heterogeneous data generation on local clients through the lens of structured causal model and propose a crucial causal signature which can distinguish personalized features from spurious features with global invariant features as the anchor. Then the causal signature is quantified as an information-theoretic constraint that facilitates the shortcut-averse personalized invariant learning on each client. Theoretical analysis demonstrates our method, FedPIN, can yield a tighter bound on generalization error than the prevalent PFL approaches when train-test distribution shift exists on clients. Moreover, we provide a theoretical guarantee on the convergence rate of FedPIN in this paper. The results of extensive experiments show that our method can achieve superior OOD generalization performance compared with the state-of-the-art competitors.

Mr Xueyang TANG
PhD candidate
Department of Computing

About the Speaker

Mr Xueyang TANG received her bachelor's degree in excellent engineer program for electronics and information engineering from Huazhong University of Science and Technology in 2018. He is now a PhD. student at the Department of Computing at The Hong Kong Polytechnic University, under the supervision of Dr Jingcai GUO. His research interest focuses on personalized federated learning, causality and out-of-distribution generalization, vision-language models, hallucination in large language models.

Fast Graph Condensation with Structure-based Neural Tangent Kernel

Mr Lin WANG
PhD candidate
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About the Speaker

Mr Lin WANG graduated with a Bachelor's degree from the Northwestern Polytechnical University in 2019 and subsequently earned his Master's degree there in 2022. He is currently pursuing a PhD in the Department of Computing at The Hong Kong Polytechnic University under the supervision of Professor LI Qing. His research interests encompass graph neural networks, data mining, recommender systems, and machine learning.

Abstract

The rapid development of Internet technology has given rise to a vast amount of graph-structured data. Graph Neural Networks (GNNs), as an effective method for various graph mining tasks, incurs substantial computational resource costs when dealing with large-scale graph data. A data-centric manner solution is proposed to condense the large graph dataset into a smaller one without sacrificing the predictive performance of GNNs.

However, existing efforts condense graph-structured data through a computationally intensive bi-level optimization architecture also suffer from massive computation costs. In this paper, we propose reforming the graph condensation problem as a Kernel Ridge Regression (KRR) task instead of iteratively training GNNs in the inner loop of bi-level optimization. More specifically, We propose a novel dataset condensation framework (GC-SNTK) for graph-structured data, where a Structure-based Neural Tangent Kernel (SNTK) is developed to capture the topology of graph and serves as the kernel function in KRR paradigm. Comprehensive experiments demonstrate the effectiveness of our proposed model in accelerating graph condensation while maintaining high prediction performance. The source code is available on https://github.com/WANGLin0126/GCSNTK.