Murata laboratory, Dept. of Computer Science, Science Tokyo (artificial intelligence, network science, machine learning)

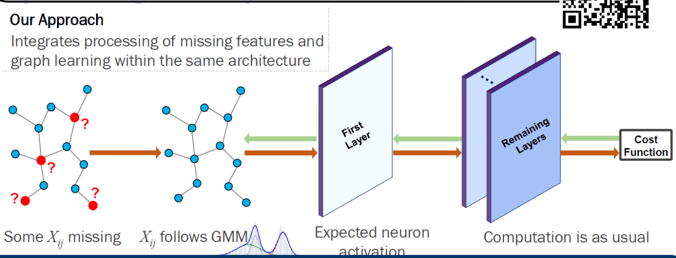
Finding Knowledge from Networks

Focusing on network (graph) structures such as friendships and traffic networks, we study the elucidation and control of information and disease propagation, prediction of future structures, and graph neural networks (GNNs).

GNN for Graphs with Missing Values

Missing feature imputation and graph learning are integrated within the same neural network architecture. The missing data is represented by a Gaussian mixture model (GMM), and the expected activation of neurons in the first hidden layer of the GCN is computed. It achieves higher performance and robustness than previous methods.

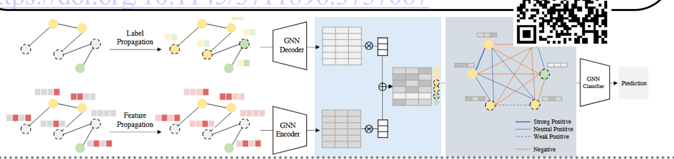
Hibiki Taguchi, Xin Liu, Tsuyoshi Murata, "Graph Convolutional Networks for Graphs Containing Missing Features", Future Generation Computer Systems, Vol.117, pp.155-168, Elsevier, 2021.
https://doi.org/10.1016/j.future.2020.11.016



Accurate GNN under Extreme Feature Missingness

In real-world graphs, a large portion of node features is often missing due to sensitive information and other constraints. In such scenarios, directly applying GNNs may fail to achieve optimal performance on tasks such as node classification. To address this issue, we propose a novel framework that revisits and further exploits the potential of classical Label Propagation (LP). In particular, we focus on leveraging Feature Propagation (FP) in situations where only partial features are available. Our method, named GOODIE, adopts a hybrid approach that obtains embeddings from both the Label Propagation branch and the Feature Propagation branch. GOODIE outperforms existing state-of-the-art methods not only when features are scarce but also when they are abundantly available.

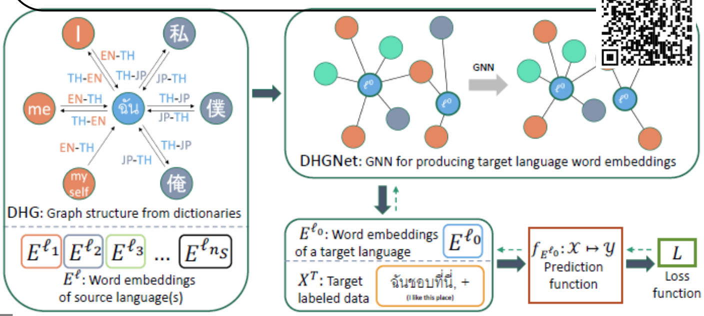
Sukwon Yun, Xin Liu, Yunhak Oh, Junseok Lee, Tianlong Chen, Tsuyoshi Murata, Chanyoung Park, "Oldie but Goodie: Re-illuminating Label Propagation on Graphs with Partially Observed Features", Proceedings of the 31st ACM SIGKDD Conference on Knowledge Discovery and Data Mining (KDD 2025), pp.3704-3715, 2025.
https://doi.org/10.1145/3711896.3737067



Cross-lingual transfer for Text Classification

In transfer learning, which uses training data from resource-rich languages to solve classification problems in resource-poor languages, task-specific training data for resource-rich languages is often difficult to obtain. As an alternative, we propose CLTC using task-independent word embeddings of resource-rich languages and dictionaries between the two languages. We construct a heterogeneous vertex graph from the dictionaries between the two languages and built a high-performance graph neural network with two-stage aggregation at the word and language levels, resulting in higher performances.

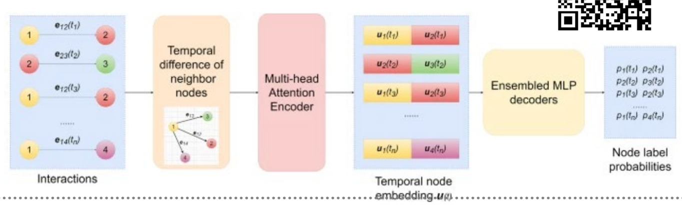
Nuttapong Chairatanakul, Noppayut Sriwatanasakdi, Nontawat Charoenphakdee, Xin Liu, Tsuyoshi Murata, "Cross-lingual Transfer for Text Classification with Dictionary-based Heterogeneous Graph", Findings of the Association for Computational Linguistics: EMNLP 2021, pp.1504–1517, 2021.
https://doi.org/10.18653/v1/2021.findings-emnlp.130



GNN for predicting donations on YouTube

In recent years, online live streaming platforms such as YouTube Live and Twitch have rapidly gained popularity. However, little research has been conducted on donation (tipping) systems in these live streaming platforms. In this study, we construct a continuous-time dynamic graph that models interactions among viewers based on real-time chat messages, and propose a method to predict real-time donations on live streaming platforms. We further propose a novel model, Temporal Difference Graph Neural Network (TDGNN), which identifies potential donors during live streaming. The proposed model is capable of predicting the exact time when donations will occur.

Jin Ruidong, Xin Liu, Tsuyoshi Murata, "Predicting Potential Real-time Donations in YouTube Live Streaming Services via Continuous-time Dynamic Graph", Machine Learning, Vol.113, pp.2093–2127, 2024.
https://doi.org/10.1007/s10994-023-06449-z



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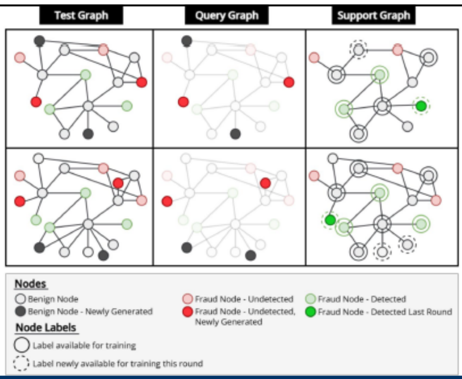
https://www.net.comp.isct.ac.jp/

Fraud Detection using GNN

With the increasing digitalization of financial institutions and activities, the development of reliable models for fraud detection has become increasingly important. In this study, we propose a new scenario for graph-based fraud detection, termed Multi-round Adversarial Fraud Detection. In this scenario, the fraud detection model is iteratively trained and evaluated on an adversarially evolving graph. To further improve performance, we introduce a module called Temporally Pre-trained Node Embedder (TPNE), which leverages self-supervised pre-training to explicitly disentangle and enhance temporal information across multiple rounds.

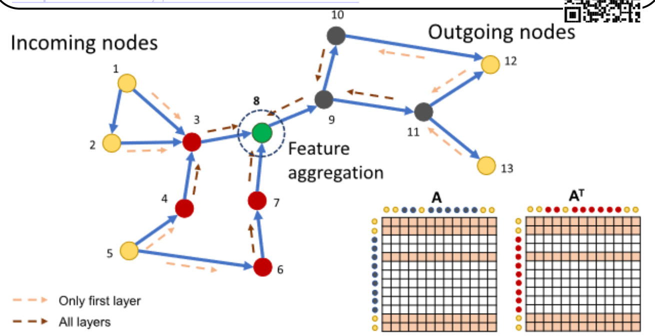
Hafizh Adi Prasetya, Xin Liu, Tsuyoshi Murata, Akiyoshi Matono, "A Multi-rounded Adversarial Scenario for Graph-based Promo Fraud Detection", Social Network Analysis and Mining, Vol.16, No.24, pp.1-30, 2026.
https://doi.org/10.1007/s13278-025-01566-0



Approximation of Centralities with GNN

Graphs arise naturally in numerous situations, including social graphs, transportation graphs, and web graphs. One of the important problems in these graphs is to identify the most important nodes. We propose the first graph neural network (GNN) based model to approximate betweenness and closeness centrality. In GNN, each node aggregates features of the nodes in multihop neighborhood. We use this feature aggregation scheme to model paths and learn how many nodes are reachable to a specific node. We demonstrate that our approach significantly outperforms current techniques while taking less amount of time through extensive experiments on a series of synthetic and real-world datasets.
https://github.com/sunilkmaurya/GNN_Ranking

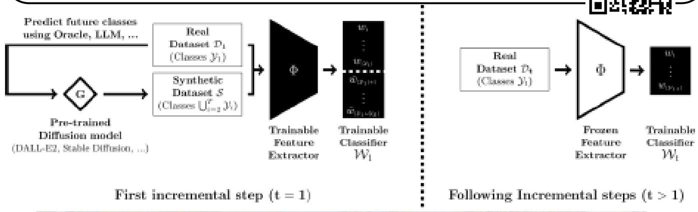
Sunil Kumar Maurya, Xin Liu, Tsuyoshi Murata, "Graph Neural Networks for Fast Node Ranking Approximation", ACM Transactions on Knowledge Discovery from Data, Vol.15, No.5, Article No.78, 32 pages, 2021.
https://doi.org/10.1145/3446217

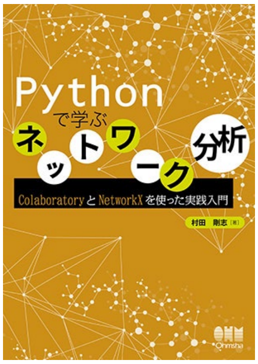


Continual Learning in Deep Learning

In class-incremental learning (CIL), where new classes are introduced after an initial training phase, deep learning models are known to suffer from catastrophic forgetting, leading to a significant degradation in performance on previously learned classes. Furthermore, exemplar-free CIL represents an especially challenging setting, as it sequentially learns new classes without storing any past data. In this study, we propose a method that leverages a pre-trained text-to-image diffusion model to generate synthetic images of future classes and uses them to train the feature extractor. Experimental results on standard benchmarks, CIFAR100 and ImageNet-Subset, demonstrate that the proposed method improves existing state-of-the-art approaches for exemplar-free CIL.

Quentin Jodelet, Xin Liu, Yin Jun Phua, Tsuyoshi Murata, "Future-proofing class-incremental learning", Machine Vision and Applications, Vol.36, No.16, pp.1-16, 2025.
https://doi.org/10.1007/s00138-024-01635-y





"Network Analysis in Python -- A Practical Introduction with Colaboratory and NetworkX", Tsuyoshi Murata, Ohmsha (2019)
https://www.ohmsha.co.jp/book/9784274224256/

"Graph Neural Networks – Implementation with PyTorch", Tsuyoshi Murata, Ohmsha (2022)
https://www.ohmsha.co.jp/book/9784274228872/

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