Murata laboratory, Dept. of Computer Science, Tokyo Tech (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(deep learning for graphs).

Prediction of Emergency Medical Service Demand

We propose a bipartite graph convolutional neural network for predicting ambulance demand (high/low) using a hospital-region bipartite graph of ambulance data in Tokyo. It outperforms traditional machine learning algorithms, statistical models, and state-of-the-art graph-based methods.

Ruidong Jin, Tianqi Xia, Xin Liu, Tsuyoshi Murata, Kyoung-Sook Kim, “Predicting Emergency Medical Service Demand With Bipartite Graph Convolutional Networks”, IEEE Access, Vol. 9, pp.9903-9915, 2021.
https://doi.org/10.1109/ACCESS.2021.3050607

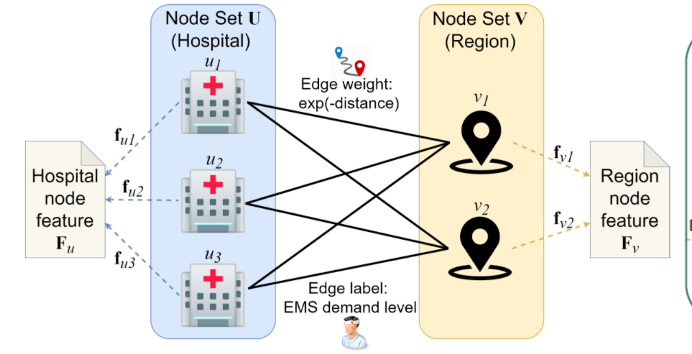
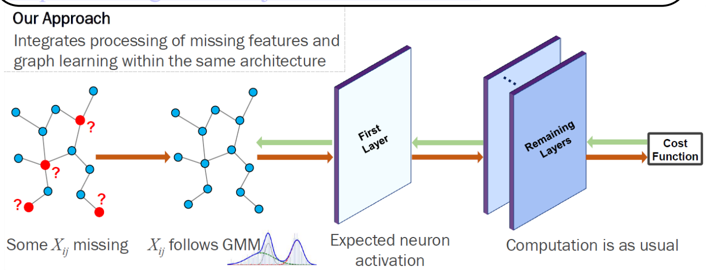


FIGURE 1. The hospital-region EMS bipartite graph.

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



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

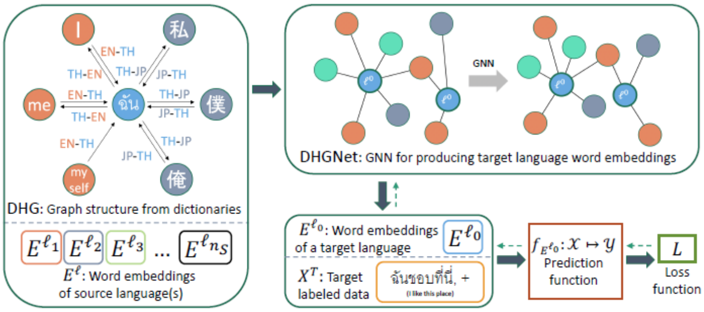
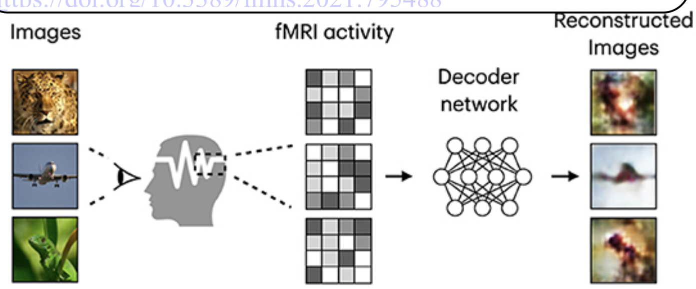


Image Reconstruction from fMRI

Brain imaging techniques and machine learning have been used to understand the processing of visual information in the human brain. Accurate reconstruction of perceived images from brain activity measured by fMRI is one of the most challenging tasks in brain imaging technology. This survey paper shows state-of-the-art deep learning methods for image reconstruction from fMRI and presents a fair performance evaluation across standardized metrics.

Zarina Rakhimberdina, Quentin Jodelet, Xin Liu, Tsuyoshi Murata, “Natural Image Reconstruction From fMRI Using Deep Learning: A Survey”, Frontiers in Neuroscience, Vol. 15, Article 795488, 19 pages, 2021.
https://doi.org/10.3389/fnins.2021.795488

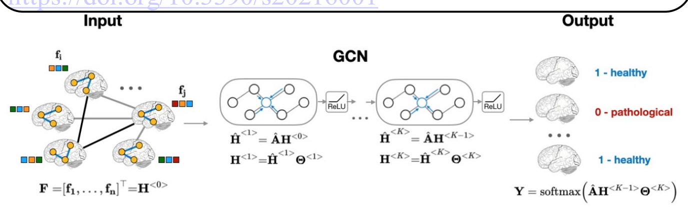


Murata Laboratory, Artificial Intelligence Course, Department of Computer Science, School of Computing, Tokyo Institute of Technology
http://www.net.c.titech.ac.jp/

Accurate Diagnosis of Cognitive Functions

Advances in brain imaging technology and machine learning have raised hopes for machine learning models to diagnose brain diseases. We propose a multi-model ensemble based on population graphs that incorporates not only representations of the patient's brain, but also representations of similar patients' brains. Our method achieves better performance than state-of-the-art methods in the experiments of ABIDE dataset.

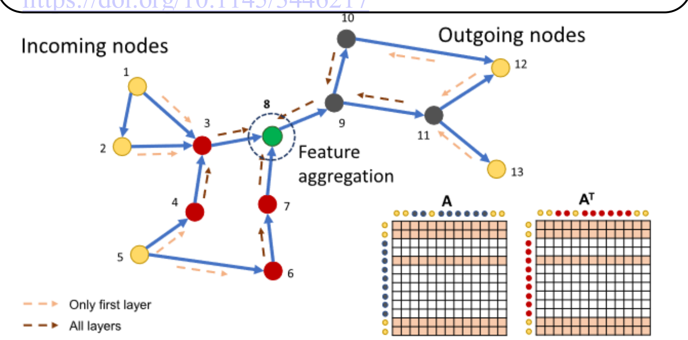
Zarina Rakhimberdina, Xin Liu, Tsuyoshi Murata, “Population Graph-Based Multi-Model Ensemble Method for Diagnosing Autism Spectrum Disorder”, Sensors, Vol.20, No.21, 18 pages, 2020.
https://doi.org/10.3390/s20216001



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. As the criteria for finding influential central nodes, betweenness centrality and closeness centrality are two commonly used node ranking measures. Both of these are based on an assumption that the information flows between the nodes via the shortest paths. However, exact calculations of these centrality measures are computationally expensive and prohibitive, especially for large graphs. Previous approximation methods are either less efficient or suboptimal or both. 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

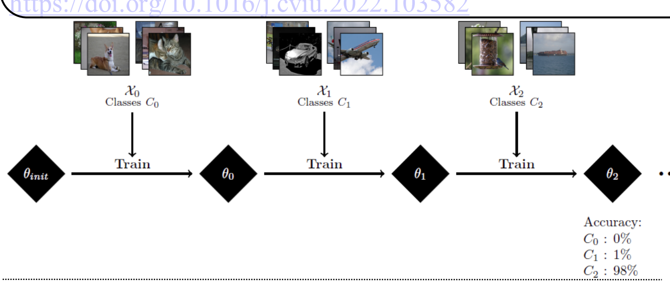
Sunil Kumar Maurya, Xin Liu, Tsuyoshi Murata, “Graph Neural Networks for Fast Node Ranking Approximation”, ACM Transactions on Knowledge Discovery from Data, Vol.15, No.5, Article No.78, 32 pages, 2021.
https://doi.org/10.1145/3446217

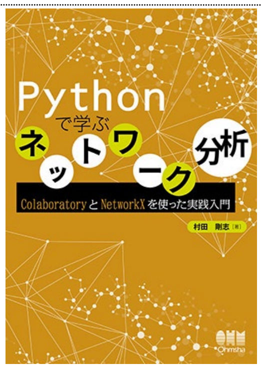


Continual Learning in Deep Learning

When incrementally trained on new classes, deep neural networks are subject to catastrophic forgetting which leads to an extreme deterioration of their performance on the old classes while learning the new ones. Using a small memory containing few samples from past classes has shown to be an effective method to mitigate catastrophic forgetting. However, due to the limited size of the replay memory, there is a large imbalance between the number of samples for the new and the old classes in the training dataset resulting in bias in the final model. To address this issue, we propose to use the Balanced Softmax Cross-Entropy and show that it can be seamlessly combined with state-of-the-art approaches for class-incremental learning in order to improve their accuracy while also potentially decreasing the computational cost of the training procedure. We further extend this approach to the more demanding class-incremental learning without memory setting and achieve competitive results with memory-based approaches.

Quentin Jodelet, Xin Liu, Tsuyoshi Murata, “Balanced Softmax Cross-Entropy for Incremental Learning with and without Memory”, Computer Vision and Image Understanding, Vol.225, Article 103582, 11 pages, 2022.
https://doi.org/10.1016/j.cviu.2022.103582





“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/

Murata Laboratory
5th floor, West 8 building, Ookayama
http://www.net.c.titech.ac.jp/