Machine Learning with Graphs:
Paper Presentations

Arlei Silva

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As part of this course, you are expected to present one research paper on machine learning with graphs. Presentations will take place at the end of the semester and can be done in groups of up to three students. The group is free to select a paper of their interest or one from the list provided below.

Paper Proposal (02/25)

This is the deadline for officially selecting a paper. In case two groups select the same paper, the earliest group wins.

Paper Presentations (04/12 and 04/14)

Presentations will be short (10-20 minutes). The exact duration will be provided once the number of students taking the class is known. At the end of the presentation, other students will have the chance to ask questions. You will be evaluated in terms of the clarity of the presentation, slides, answers, and questions.

Candidate List of Papers

This is a short list of recent papers related to the topics of the course:

- Network science: [8, 12, 15, 21]
- Problems/applications: [1, 3, 32, 9]
- Spectral graph theory: [22, 11, 24, 26]
- Graph kernels: [25, 6, 16, 7]
- Optimization on graphs: [10, 2, 30, 27]
- Graphical models: [28, 18, 4]

- Graph and non-linear embedding: [5, 19, 13, 23]
- Graph neural networks: [20, 14, 31, 17]

References

[1] Carlo Abrate and Francesco Bonchi. Counterfactual graphs for explainable classification of brain networks. *arXiv preprint arXiv:2106.08640*, 2021.

[2] Yoshua Bengio, Prateek Gupta, Tegan Maharaj, Nasim Rahaman, Martin Weiss, Tristan Deleu, Eilif Benjamin Muller, Meng Qu, Pierre-luc St-charles, Olexa Bilaniuk, et al. Predicting infectiousness for proactive contact tracing. In *International Conference on Learning Representations*, 2020.

[3] Austin R Benson, Rediet Abebe, Michael T Schaub, Ali Jadbabaie, and Jon Kleinberg. Simplicial closure and higher-order link prediction. *Proceedings of the National Academy of Sciences*, 115(48):E11221–E11230, 2018.

[4] George T Cantwell and Mark EJ Newman. Message passing on networks with loops. *Proceedings of the National Academy of Sciences*, 116(47):23398–23403, 2019.

[5] Sudhanshu Chanpuriya, Cameron Musco, Konstantinos Sotiropoulos, and Charalampos Tsourakakis. Node embeddings and exact low-rank representations of complex networks. *Advances in Neural Information Processing Systems*, 33, 2020.

[6] Corinna Coupette and Jilles Vreeken. Graph similarity description: How are these graphs similar? *arXiv preprint arXiv:2105.14364*, 2021.

[7] Simon S Du, Kangcheng Hou, Russ R Salakhutdinov, Barnabas Poczos, Ruosong Wang, and Keyulu Xu. Graph neural tangent kernel: Fusing graph neural networks with graph kernels. *Advances in Neural Information Processing Systems*, 32:5723–5733, 2019.

[8] Justin Eldridge, Mikhail Belkin, and Yusu Wang. Graphons, mergeons, and so on! In *Advances in Neural Information Processing Systems*, pages 2307–2315, 2016.

[9] Deisy Morselli Gysi, Ítalo Do Valle, Marinka Zitnik, Asher Ameli, Xiao Gan, Onur Varol, Susan Dina Ghiassian, JJ Patten, Robert A Davey, Joseph Loscalzo, et al. Network medicine framework for identifying drug-repurposing opportunities for covid-19. *Proceedings of the National Academy of Sciences*, 118(19), 2021.

[10] Qian Huang, Horace He, Abhay Singh, Ser-Nam Lim, and Austin Benson. Combining label propagation and simple models out-performs graph neural networks. In *International Conference on Learning Representations*, 2020.

[11] James R Lee, Shayan Oveis Gharan, and Luca Trevisan. Multiway spectral partitioning and higher-order cheeger inequalities. *Journal of the ACM (JACM)*, 61(6):1–30, 2014.

[12] Yanchen Liu, Nima Dehmamy, and Albert-László Barabási. Isotopy and energy of physical networks. *Nature Physics*, 17(2):216–222, 2021.

[13] Zhonghua Liu, Zhihui Lai, Weihua Ou, Kaibing Zhang, and Ruijuan Zheng. Structured optimal graph based sparse feature extraction for semi-supervised learning. *Signal Processing*, 170:107456, 2020.

[14] Eli Meirom, Haggai Maron, Shie Mannor, and Gal Chechik. Controlling graph dynamics with reinforcement learning and graph neural networks. In *International Conference on Machine Learning*, pages 7565–7577. PMLR, 2021.

[15] Lu Mi, Hang Zhao, Charlie Nash, Xiaohan Jin, Jiyang Gao, Chen Sun, Cordelia Schmid, Nir Shavit, Yuning Chai, and Dragomir Anguelov. Hdmapgen: A hierarchical graph generative model of high definition maps. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 4227–4236, 2021.

[16] Marion Neumann, Roman Garnett, Christian Bauckhage, and Kristian Kersting. Propagation kernels: efficient graph kernels from propagated information. *Machine Learning*, 102(2):209–245, 2016.

[17] Giannis Nikolentzos and Michalis Vazirgiannis. Random walk graph neural networks. *Advances in Neural Information Processing Systems*, 33:16211–16222, 2020.

[18] Victor Garcia Satorras and Max Welling. Neural enhanced belief propagation on factor graphs. In *International Conference on Artificial Intelligence and Statistics*, pages 685–693. PMLR, 2021.

[19] Michael T Schaub, Jean-Charles Delvenne, Renaud Lambiotte, and Mauricio Barahona. Multiscale dynamical embeddings of complex networks. *Physical Review E*, 99(6):062308, 2019.

[20] Michael Sejr Schlichtkrull, Nicola De Cao, and Ivan Titov. Interpreting graph neural networks for nlp with differentiable edge masking. In *International Conference on Learning Representations*, 2020.

[21] C Seshadhri, Aneesh Sharma, Andrew Stolman, and Ashish Goel. The impossibility of low-rank representations for triangle-rich complex networks. *Proceedings of the National Academy of Sciences*, 117(11):5631–5637, 2020.

[22] Daniel A Spielman and Nikhil Srivastava. Graph sparsification by effective resistances. *SIAM Journal on Computing*, 40(6):1913–1926, 2011.

[23] Zhiqing Sun, Zhi-Hong Deng, Jian-Yun Nie, and Jian Tang. Rotate: Knowledge graph embedding by relational rotation in complex space. In *International Conference on Learning Representations*, 2018.

[24] Yuichi Tanaka, Yonina C Eldar, Antonio Ortega, and Gene Cheung. Sampling signals on graphs: From theory to applications. *IEEE Signal Processing Magazine*, 37(6):14–30, 2020.

[25] Matteo Togninalli, Elisabetta Ghisu, Felipe Llinares-López, Bastian Rieck, and Karsten Borgwardt. Wasserstein weisfeiler-lehman graph kernels. *arXiv preprint arXiv:1906.01277*, 2019.

[26] Zekun Tong, Yuxuan Liang, Changsheng Sun, David S Rosenblum, and Andrew Lim. Directed graph convolutional network. *arXiv preprint arXiv:2004.13970*, 2020.

[27] Nguyen Tran, Henrik Ambos, and Alexander Jung. Classifying partially labeled networked data via logistic network lasso. In *ICASSP 2020-2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 3832–3836. IEEE, 2020.

[28] Binghui Wang, Jinyuan Jia, and Neil Zhenqiang Gong. Semi-supervised node classification on graphs: Markov random fields vs. graph neural networks. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 35, pages 10093–10101, 2021.

[29] Zheng Wang, Feiping Nie, Rong Wang, Hui Yang, and Xuelong Li. Local structured feature learning with dynamic maximum entropy graph. *Pattern Recognition*, 111:107673, 2021.

[30] Han Xie, Jing Ma, Li Xiong, and Carl Yang. Federated graph classification over non-iid graphs. *Advances in Neural Information Processing Systems*, 34, 2021.

[31] Yongyi Yang, Tang Liu, Yangkun Wang, Jinjing Zhou, Quan Gan, Zhewei Wei, Zheng Zhang, Zengfeng Huang, and David Wipf. Graph neural networks inspired by classical iterative algorithms. *arXiv preprint arXiv:2103.06064*, 2021.

[32] Marinka Zitnik, Marcus W Feldman, Jure Leskovec, et al. Evolution of resilience in protein interactomes across the tree of life. *Proceedings of the National Academy of Sciences*, 116(10):4426–4433, 2019.