Learning Embeddings of Events in Continuous-time Dynamic Graphs

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Abstract

Graphs are crucial structures for modeling relationships between objects and have a wide range of applications such as social networks, drug design, and recommender systems. Deep learning on the Euclidean domain (e.g. images, text, speech) has achieved remarkable success and many studies try to generalize the deep learning methods to graph data for performing downstream tasks like node classification and link prediction.

Graph neural networks use message passing to create node embeddings (vector representation of nodes) which can be used for many tasks including node/graph classification, clustering, community detection, and link prediction. Most graph neural networks focus on static graphs by assuming that the graph will not change so there will be no change in features and no addition or removal of nodes and edges. However, most real-life problems have dynamic underlying structures i.e. graphs that evolve over time. For instance, the changes can be new friendships in social networks or new interactions between a customer and the items in recommendation systems.

We focus on continuous-time dynamic graphs where the data is represented as a sequence of timestamped events. We propose interaction2vec, an event-centric perspective on continuous-time dynamic graphs by embedding the edges (interactions) to vectors. Our interaction2vec framework's effectiveness is investigated with the following experiments: finding significant events, link classification in a heterogeneous continuous-time dynamic graph, and future link prediction.

References

[1] A. Bordes, N. Usunier, A. Garcia-Duran, J. Weston, and O. Yakhnenko. Translating embeddings for modeling multi-relational data. In C. J. C. Burges, L. Bottou, M. Welling, Z. Ghahramani, and K. Q. Weinberger, editors, *Advances in Neural Information Processing Systems*, volume 26. Curran Associates, Inc., 2013.

[2] S. M. Kazemi, R. Goel, K. Jain, I. Kobyzev, A. Sethi, P. Forsyth, and P. Poupart. Representation learning for dynamic graphs: A survey, 2020.

[3] S. Kumar, X. Zhang, and J. Leskovec. Predicting dynamic embedding trajectory in temporal interaction networks. In *Proceedings of the 25th ACM SIGKDD international conference on Knowledge discovery and data mining*. ACM, 2019.

[4] E. Rossi, B. Chamberlain, F. Frasca, D. Eynard, F. Monti, and M. Bronstein. Temporal graph networks for deep learning on dynamic graphs, 2020.

[5] R. Trivedi, M. Farajtabar, P. Biswal, and H. Zha. Dyrep: Learning representations over dynamic graphs. In *International Conference on Learning Representations*, 2019.

[6] D. Xu, C. Ruan, E. Korpeoglu, S. Kumar, and K. Achan. Inductive representation learning on temporal graphs, 2020.