



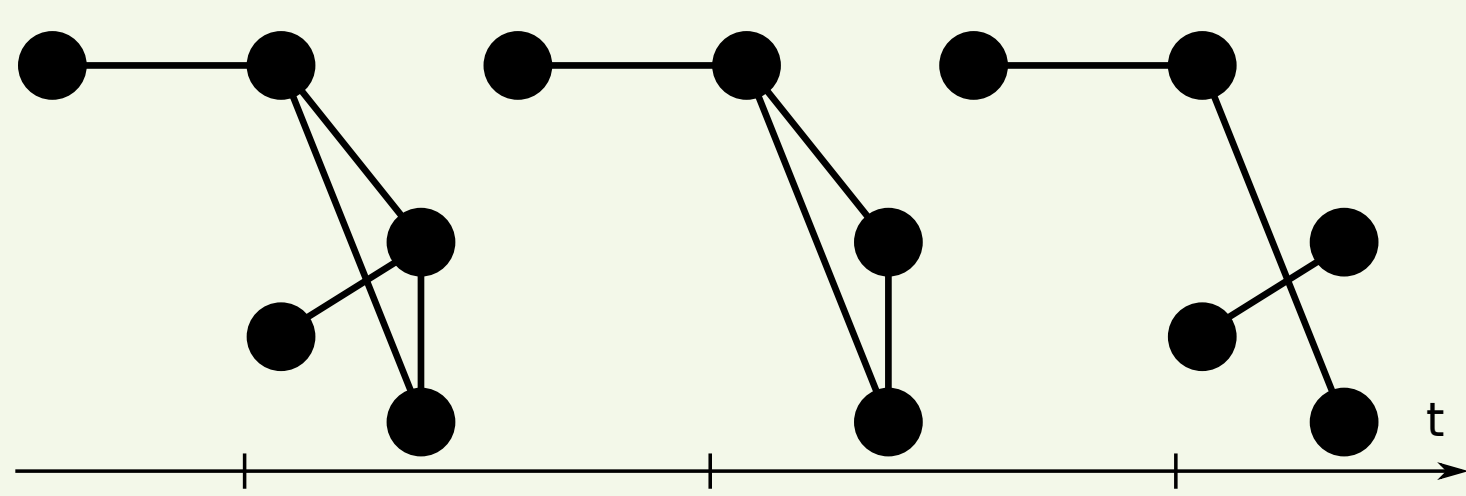
Motivation

- Dynamic graphs constitute useful data representations for problems of various natures, making them a recent focus of Machine Learning
- The handling of changing node and edge sets are challenging, especially the deletion of nodes

- In this dissertation, **two approaches** are developed to address the changing structure:
 - Graph preprocessing creating a substitute graph of equal size processed by a GNN for attribute-dynamic graphs afterward
 - Expressive GNN handling the structural dynamics directly

Structural-Dynamic Graph

A **Structural-Dynamic Graph (SDG)** consists of node and edge sets (with possible additional attributes) that change over time.



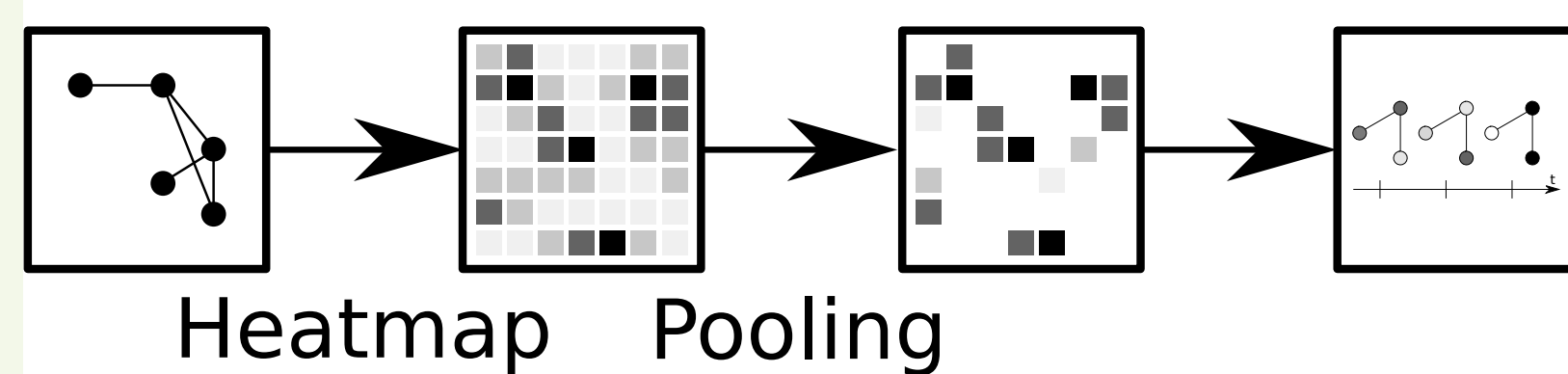
Preprocessing

Node/Edge Activity [1]

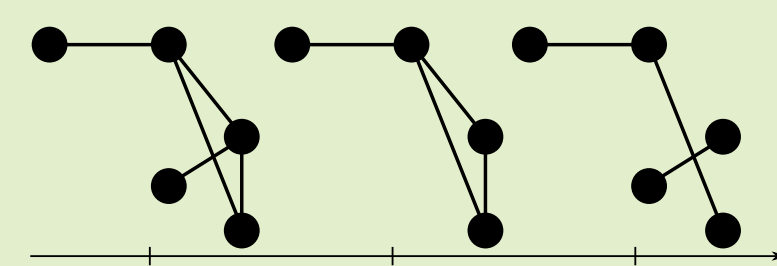
The **Activity** of a node or edge is a boolean and dependent on the existence of the node/edge. Active nodes/edges are considered in the calculations, while inactive nodes/edges enable the learning of the deletion history.

Local Activity Encoding [2]

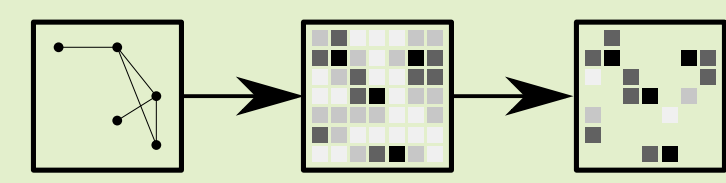
Based on the activity and **occurring incident events** of nodes (and edges), additional information are stored in a **heatmap**. Subsequent **pooling** creates graphs of equal sizes for each timestamp. Thus, a processable graph stream can be passed to an attribute-dynamic GNN.



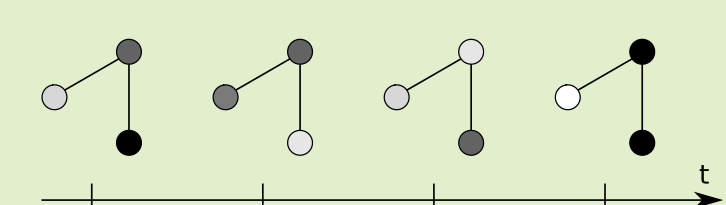
Dynamic Graph



Preprocessing

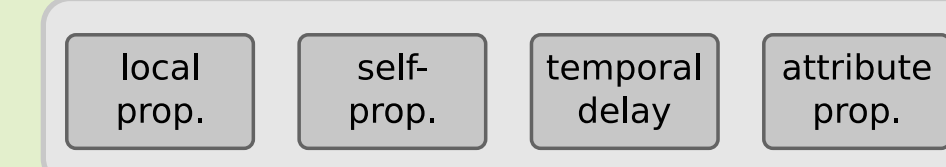


Attr.-Dyn. GNN

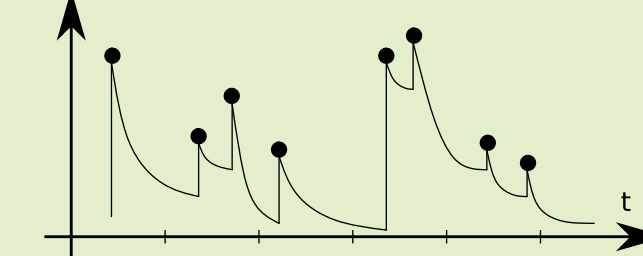


Fully Dynamic GNN

Embedding



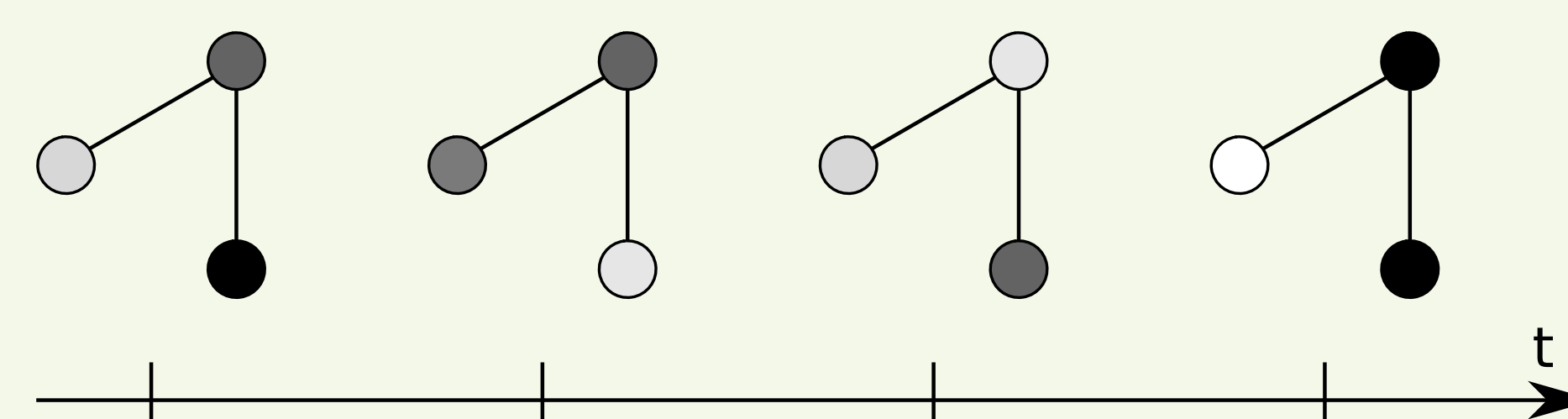
Decoder



Expressivity?

Attribute-Dynamic GNN [3]

An **attribute-dynamic graph** contains a fixed node and edge set whose attributes change over time.



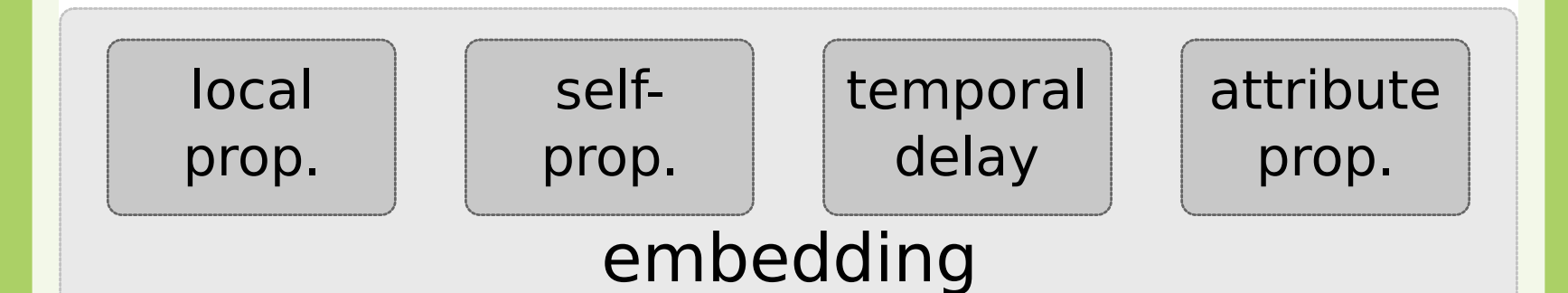
Learning on such a graph may use its structural and temporal information as well as the constitution of the attribute space.

Fully Dynamic GNN [1]

Embedding

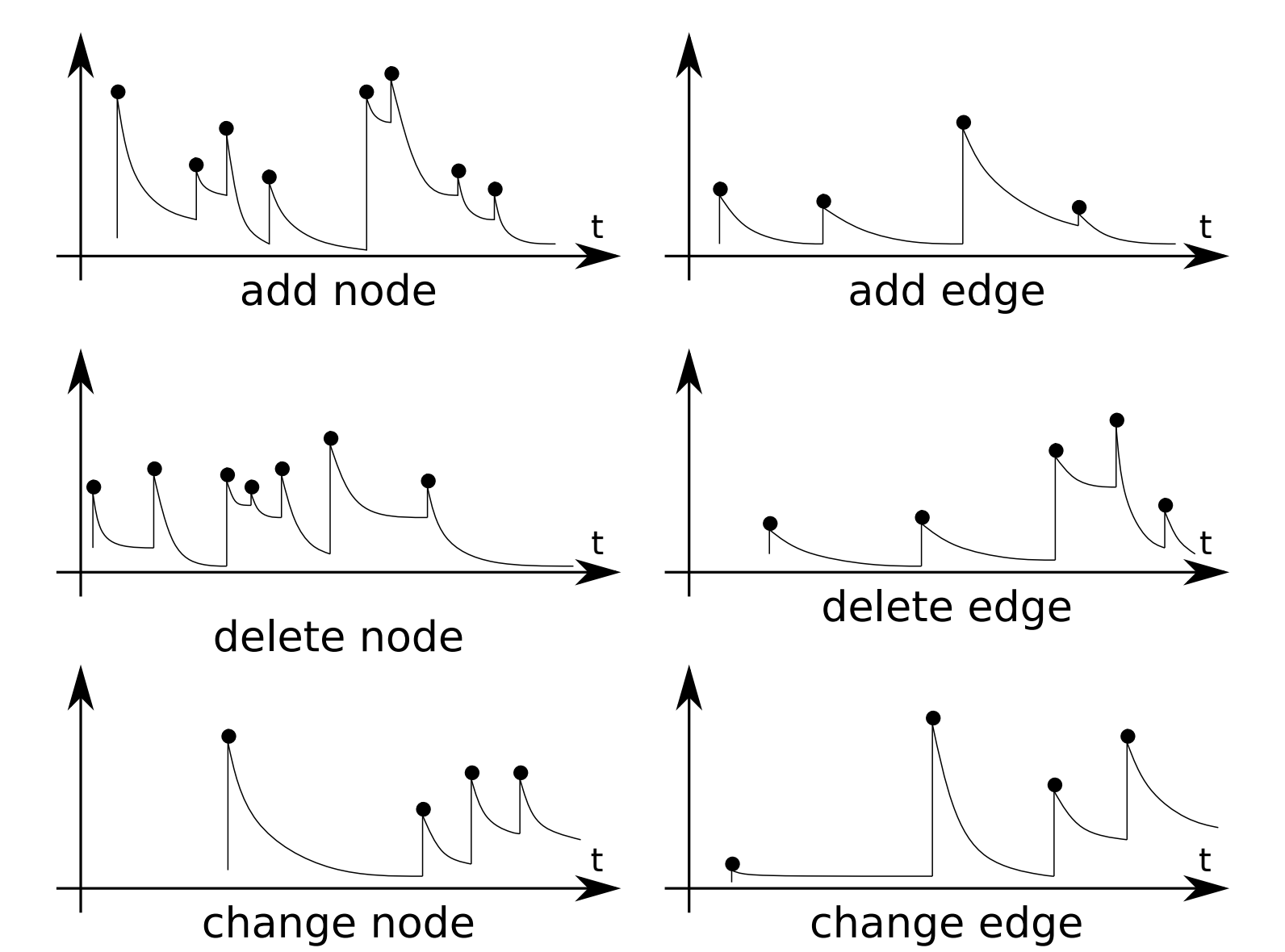
The node and edge embeddings utilize the node/edge activities and are composed of a combination of

- historical information realized with **self-attention**,
- local information given by a **neighborhood attention**,
- the **temporal delay** between recent events,
- and its **attribute embedding**.



Decoder

Given the node and edge embeddings, a **Temporal Point Process (TPP)** is used to decode the encoded information respecting a certain task. For an **Event Prediction**, one TPP is trained per event type of the SDG.



Future Work: Analysis of the Expressive Power

- Handling structural-dynamic graphs is an ongoing challenge for state-of-the-art GNNs
- There is first research on the **Expressivity** and **Explainability** of GNNs working for dynamic graphs

- To warrant the application of the provided approaches, it is essential to examine the expressivity of the models
- Currently, we set up a baseline practice in [4] for analyzing the expressivity of given GNNs

References

- [1] Moallem-Oureh, Alice and Beddar-Wiesing, Silvia and Nather, Rüdiger and Thomas, Josephine M. *FDGNN: Fully Dynamic Graph Neural Network*, 2022, arXiv preprint <https://arxiv.org/pdf/2206.03469.pdf>
- [2] Beddar-Wiesing, Silvia *Using local activity encoding for dynamic graph pooling in structural-dynamic graphs: student research abstract*, 2022, Proceedings of the 37th ACM/SIGAPP Symposium on Applied Computing, <https://dl.acm.org/doi/pdf/10.1145/3477314.3506969>
- [3] Moallem-Oureh, Alice *Continuous-time generative graph neural network for attributed dynamic graphs: student research abstract*, 2022, Proceedings of the 37th ACM/SIGAPP Symposium on Applied Computing, <https://dl.acm.org/doi/pdf/10.1145/3477314.3508018>
- [4] Beddar-Wiesing, Silvia and D'Inverno, Giuseppe Alessio and Graziani, Caterina and Lachi, Veronica and Moallem-Oureh, Alice and Scarselli, Franco and Thomas, Josephine Maria *Weisfeiler-Lehman goes Dynamic: An Analysis of the Expressive Power of Graph Neural Networks for Attributed and Dynamic Graphs*, 2022, arXiv preprint, <https://arxiv.org/pdf/2210.03990.pdf>