Project Kick-Off

Graphs in Artificial Intelligence and Neural Networks

Josephine Thomas, Silvia Beddar-Wiesing, Alice Moallemy

5th of May 2021

Thank you!

gain

UNI KASSEL
VERSITÄT

Intelligent
Embedded Systems

Fraunhofer
IEE

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1 Introduction of group members

2 What is the purpose of the kick-off?

3 What is GAIN all about?

4 Project Overview
- Graph Neuronal Networks and Graph Learning Problems
- Structure-Dynamic Graphs
- Attribute-Dynamic Graphs
- Explainability
- Generation of Graphs with GNNs

5 Strategy

Introduction: Josephine Thomas

- Diploma in physics (TU Berlin)
- Doctoral thesis on ’Using non-linear dimension reduction to embedd networks into hyperbolic space’ (TU Dresden)
- Data Scientist (Fraunhofer IEE)

Introduction: Silvia Beddar-Wiesing

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- B.Sc. in Mathematics
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- B.Sc. in Mathematics
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- M.Sc. in Computer Science
  Computational Intelligence and Data Analytics
- Research Assistant at
  - Fraunhofer IEE Kassel
  - Intelligent Embedded Systems, University of Kassel

Introduction: Silvia Beddar-Wiesing

- B.Sc. in Mathematics
  Combinatorial Optimization
- M.Sc. in Computer Science
  Computational Intelligence and Data Analytics
- Research Assistant at
  - Fraunhofer IEE Kassel
  - Intelligent Embedded Systems, University of Kassel
- Current Research Topic:
  Machine Learning for structure-dynamic Graphs

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- M.Sc. Mathematics (University of Kassel)
- Application focus in Computer Science

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$\rightarrow$ Next personal goal:
Causing a GNN revolution with GAIN.

Introduction: Prof. Dr. Bernhard Sick

- Director Department Intelligent Embedded Systems (IES)
- 24 researchers, 12 external doctoral candidates
- Focus on Machine Learning and Artificial Intelligence
  - Basic research: e.g. uncertainty modeling, active learning, collaborative learning
  - Applications: e.g. autonomous driving, future energy systems, physics and materials
- Mentor of GAIN and HyMeKI

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- ... you to give us feedback regarding our strategy.

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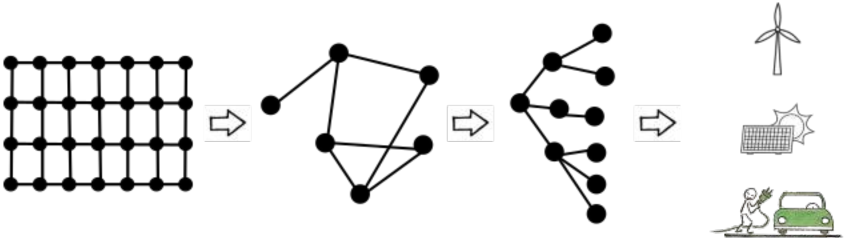

Research Topics

0. Survey on dynamic GNN's and analysis of graph types

1. Develop GNN's with different dynamics

   - changing node/link attributes
   - changing numbers of nodes and links
   - fully dynamic model

2. Explainable GNN's

3. Generation of graphs with GNN's

Graph Neural Network (GNN)

Message Passing for Structure Learning

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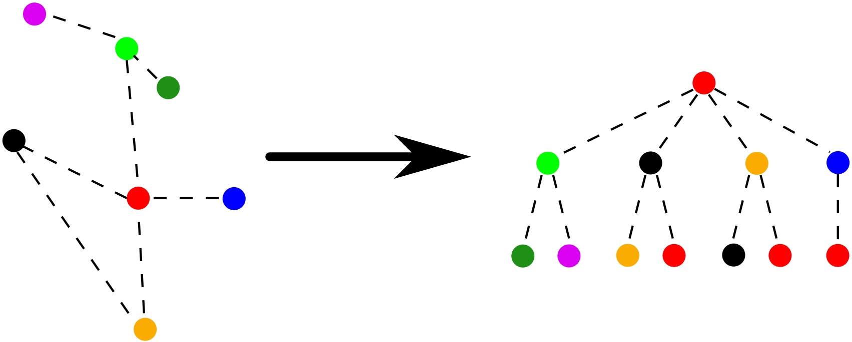

Graph Learning Problems

Graph Learning Problems

Node-/Edge-/(Sub-)Graph-Level		
Supervised	Unsupervised	Semi-Supervised
Classification	Clustering	Transductive Class./Regr.
Regression	Embedding	Inductive Class./Regr.
Temporal Predictions	Temporal Pattern Detection	Temporal Predictions
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- *Temporal and Structural Learning:* Spatio-Temporal GNN [Kapoor et al. 2020]

Structure-Dynamic Graphs

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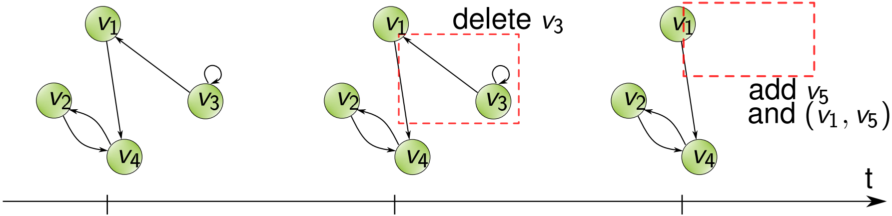

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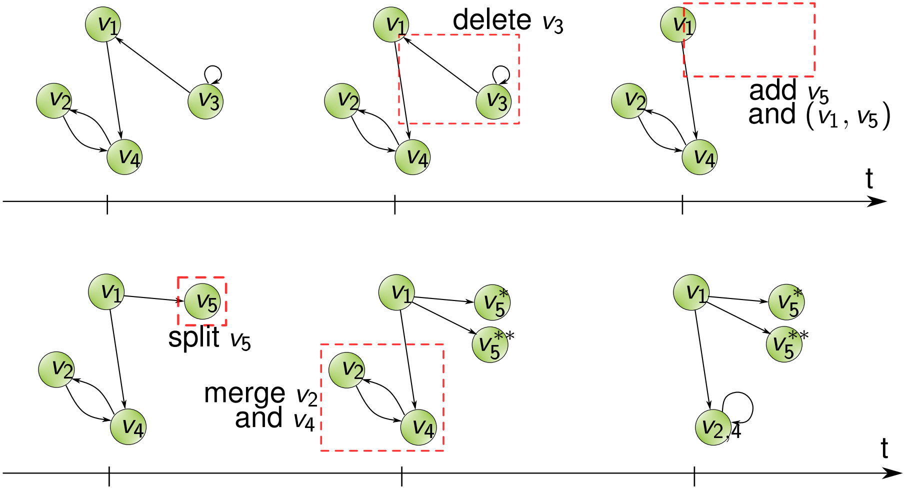

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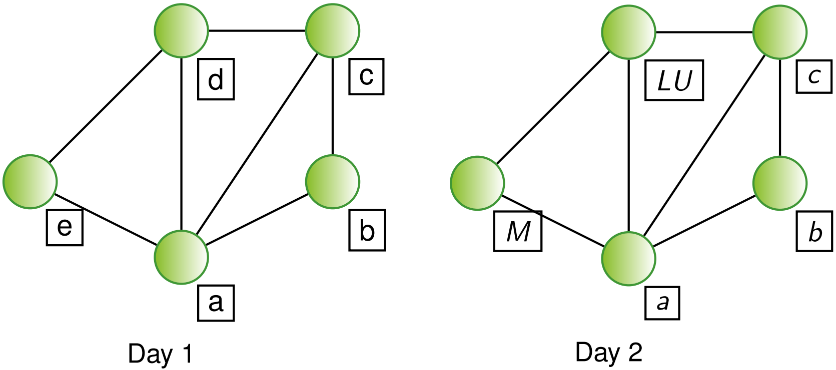
*How to consider additional **Properties** for the **Embedding**?*

- Graph Property Preservation
- Smoothness
- Efficiency

Attribute-Dynamic Graphs



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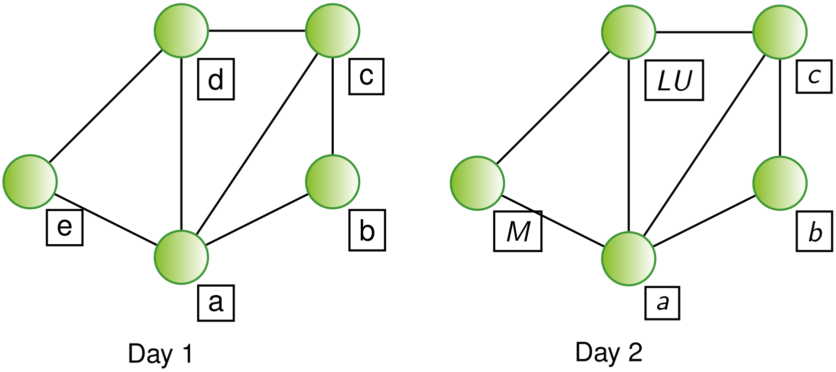

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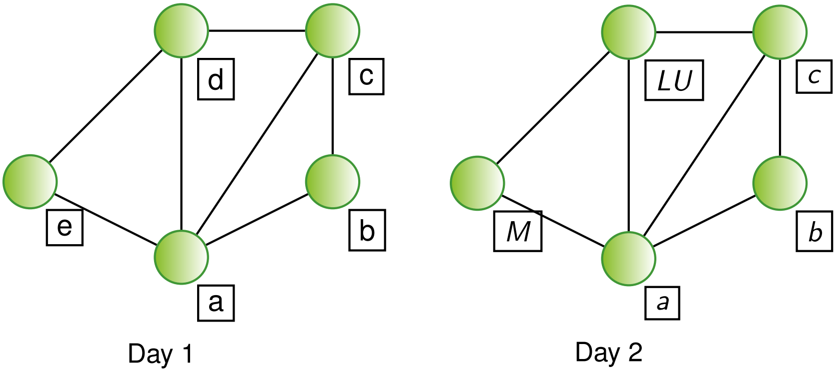

- **static** in the structure of their nodes and edges
- **dynamic** in the node and edge attributes.

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- **discrete-time dynamic (DTD)**

$$\mathcal{G}_d = (g_1, g_2, \ldots, g_T), \quad \text{where}$$

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Example for an event:

at time stamp t,

$\epsilon = (t,$ add $, v)$ that is,
add a node called v into
graph g.

$\epsilon = (t, v, a)$ that is,
the attribute of node v in
graph g equals a.

Example: COVID-19 Forecasting

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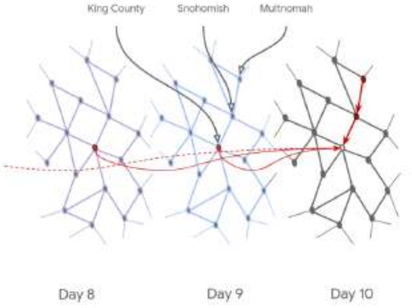

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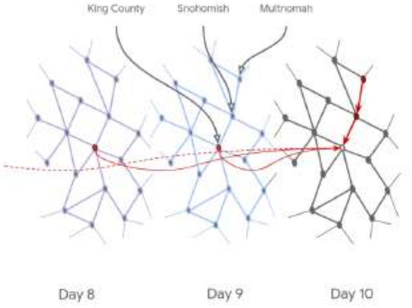

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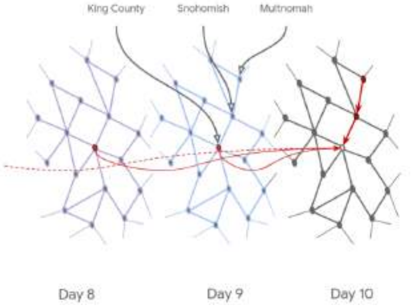

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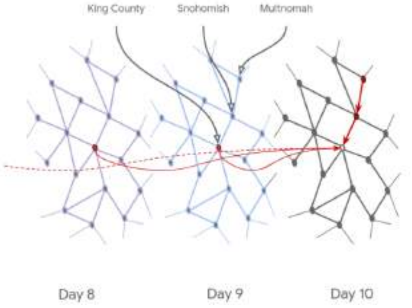

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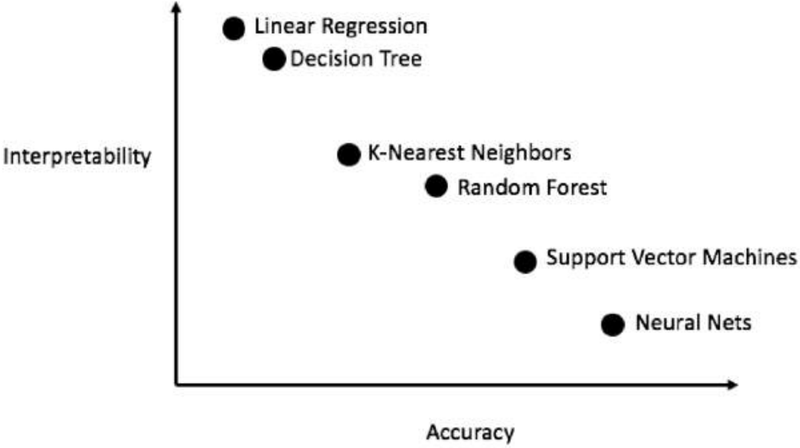

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Explainability: Techniques

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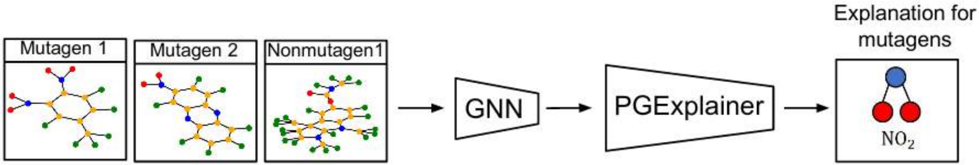

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Generation of Graphs with GNNs

Adding additional instances to an otherwise too small data set

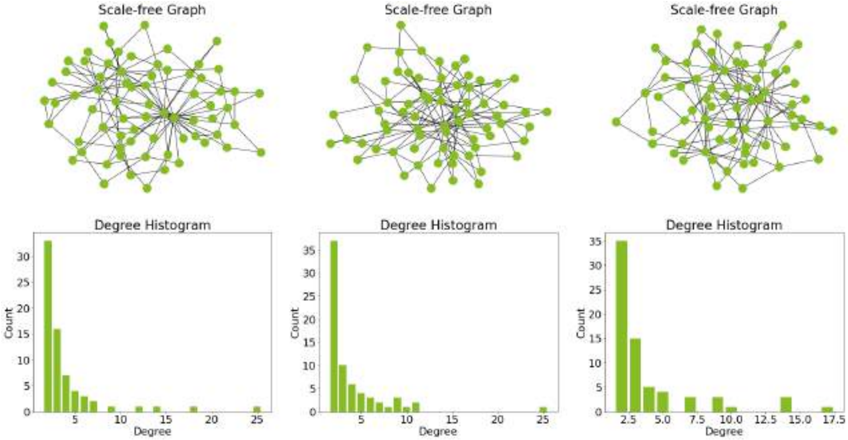
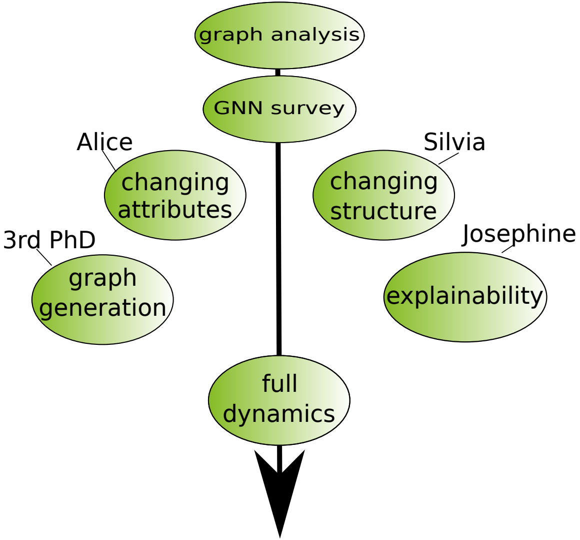


figure is self made

Strategy


graph analysis
GNN survey
Alice
changing attributes
Silvia
changing structure
3rd PhD
graph generation
Josephine
explainability
full dynamics

Contact

Thank you for your attention!
Questions?

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