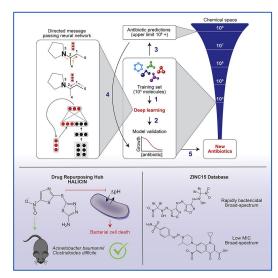


Paper presentations

- Starting next week
 - Presenters: share the slides on Monday
 - Listeners: skim the papers and attend
- Topic assignment
 - 40/50 selected a topic
 - All topics will be presented
 - Not all papers will be presented
- Paper assignment
 - In groups of 1 or 2 it's fine
 - 10/40 did not select a paper
 - No paper presentation no credits!
 - If you know your paper, but didn't register it on Moodle – do it now



Stokes et al., A Deep Learning Approach to Antibiotic Discovery, 2020



Figure 1: Google Maps estimated time-of-arrival (ETA) prediction improvements for several world regions, when using our deployed graph neural network-based estimator. Numbers represent relative reduction in negative ETA outcomes compared to the prior approach used in production. A negative ETA outcome occurs when the ETA error from the observed travel duration is over some threshold and acts as a measure of accuracy.

Derrow-Pinion et al., ETA Prediction with Graph Neural Networks in Google Maps



Projects

Format

- Team: 3 people
- Assignment: Implement and apply deep learning on graphs
- Coding: Python, PyTorch Geometric, Google Colab
- Handouts (pdf) with point assignments will be provided
- Deliverables
 - pdf report (background and results)
 - jupyter notebook (code and comments)
 - * presentation of notable projects

Project 1

- Duration: 3 weeks
- Dates: out Oct 11 due Nov 1
- Topic
 - o intro to GNNs and PyTorch geometric
 - node and graph level tasks
 - o graph visualization and statistics

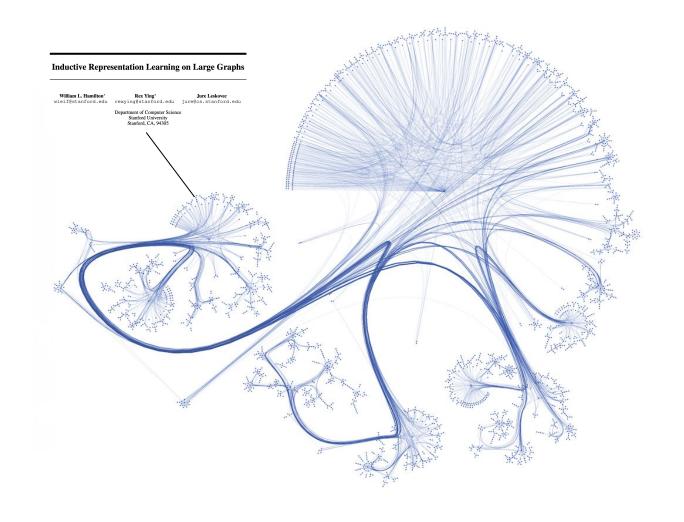


Fig.: Complete directed homogeneous graph with 3 vertices.



Part 2 - Cora Citation Dataset

- Transductive Setting
- 2708 Scientific publications
- 5429 Citation Links
- 7 categories for classification
- Bag-of-Word feature vector
- torch_geometric.datasets.Planetoid
 - Planetoid(name='Cora', split='public')
- Task 2.1: Data Exploration



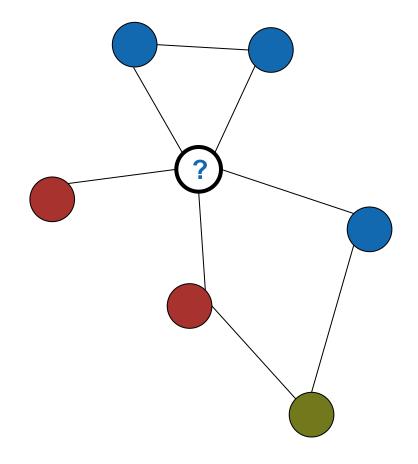




2.2 Label Propagation with full observations

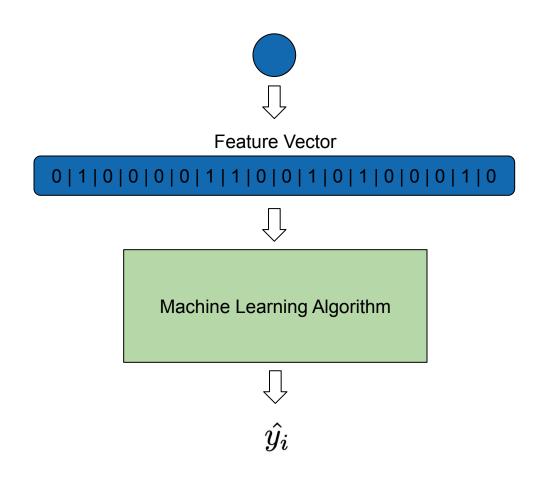
- What if we only learn from structure?
- For this task you are allowed to consider all the labels, except for the current node to be classified.
- We want to implement a nearest neighbour predictor solely based on the structure of the graph.

$$\hat{y}_i = Majority(\{y_j \mid j \in \mathcal{N}(i)\})$$



2.3 Baseline without Graph Structure

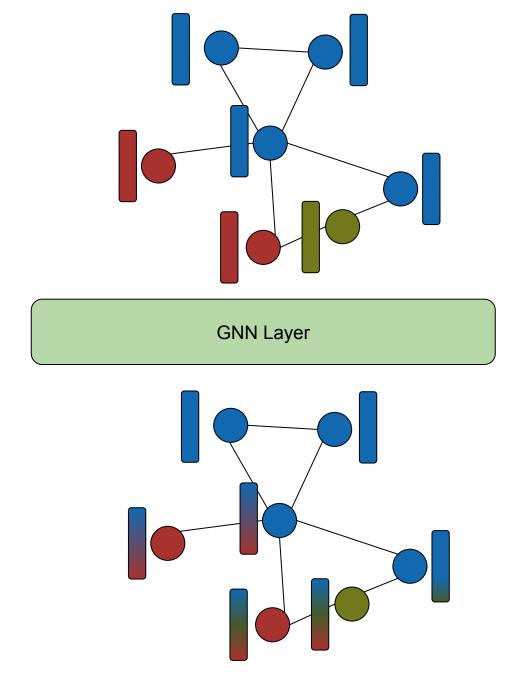
- What is the simplest model, which can solve our task? How much do we gain from sophisticated architectures?
- We establish a baseline by training a predictor on the node features





2.4 Untrained GNNs

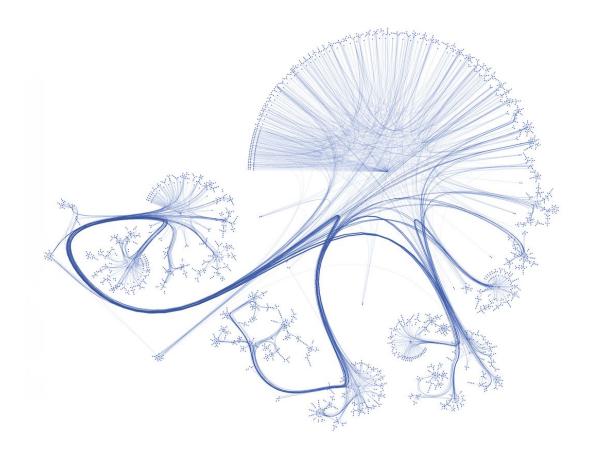
- GNNs have a very powerful prior!
- Random projections can be used for dimensionality reductions
- Due to the nature of message passing GNNs with random initialization already exhibit interesting properties
- The goal of this task is to understand these properties:
 - Compare their performances
 - Visualizing embedding spaces





2.5 Trained GNNs

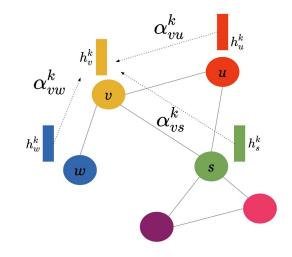
- Example Notebook for different architectures
- Train the GNN and put it into perspective to previously obtained numbers
- We encourage you to play around with different ideas you might have on how to combine available PyTorch / Pytorch Geometric Layers

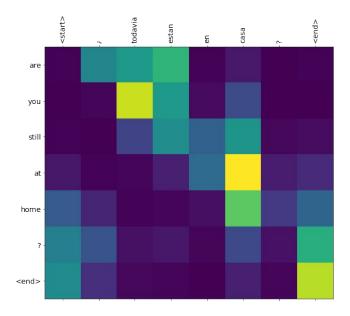




2.6 Visualizing Graph Attention Networks

- Attention has become a popular mechanism to investigate neural network computations.
 - Although a bit controversial recently
- Still, we can get an intuition and see if it aligns with our priors
- The goal, train and visualize a graph attention network:
 - Are the attention weights channeling information in a meaningful way?

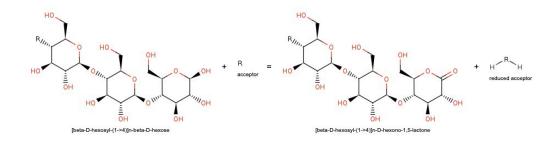






Part 3 - ENZYMES Dataset

- Inductive Setting: Many Graphs (600)
- Graph Classification
- 6 categories / classes (EC Number)
 - "The Enzyme Commission number (EC number)
 is a numerical classification scheme for enzymes,
 based on the chemical reactions they catalyze" Wikipedia
- Small Notebook to explain advanced mini-batching on graphs







Part 3 - ENZYMES Dataset

Implement a GNN with good classification accuracy:

- Baseline Performance: reach 40%
- Push Performance: reach 60% (get close)
- State of The Art: reach 70+% (Bonus)

Part 4 - Custom Message Passing

- Custom Implementation of <u>GraphSAGE</u>
- The notebook contains a skeleton to implement/subclass the MessagePassing class from Pytorch Geometric

$$h_v^{(l)} = W_l \cdot h_v^{(l-1)} + W_r \cdot AGG(\{h_u^{(l-1)}, \forall u \in N(v)\})$$

$$AGG(\{h_u^{(l-1)}, \forall u \in N(v)\}) = \frac{1}{|N(v)|} \sum_{u \in N(v)} h_u^{(l-1)}$$

Final thoughts

- Questions
 - Discuss within the group
 - Discuss between the groups
 - Ask on Moodle: in the Q&A forum or privately
- Please
 - Start early
 - Make the reports and notebooks easily readable
 - Check that the code runs
 - Don't plagiarise (see <u>Plagiarism Prevention</u>)
- This is the 1st edition of the course, so there will be hiccups. Thank you for your patience!



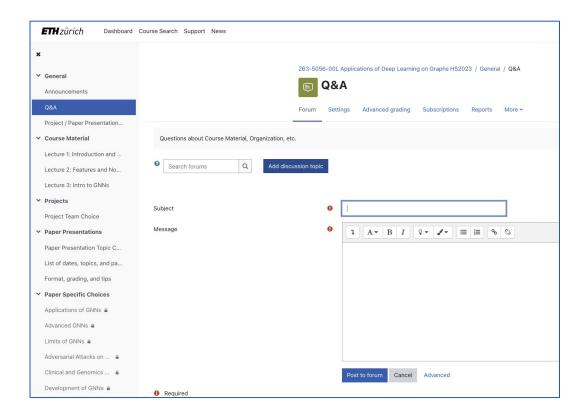


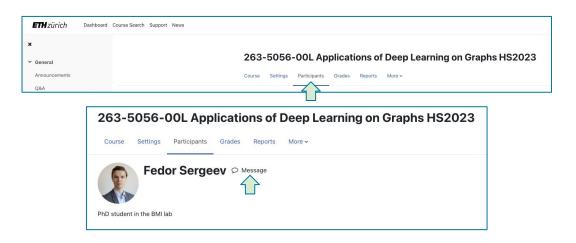


Contact

- Through the Q&A forum
 - a. Go to the ADL Moodle.
 - b. Open the Q&A forum in the General section
 - c. Click "Add discussion topic"
 - d. Type in your question and "Post to forum"

- Privately
 - a. Go to the ADL Moodle.
 - b. Open participants
 - c. Find a TA (Fedor Sergeev or Manuel Burger)
 - d. Click on the name
 - e. Click on "Message"







BIOMEDICAL INFORMATICS