

Graph Neural Networks
Introductory lecture
Advanced ML using NN
spring 2021

Introduction to Graph Neural Networks (GNN)

Mats Greneth
24/3 2021

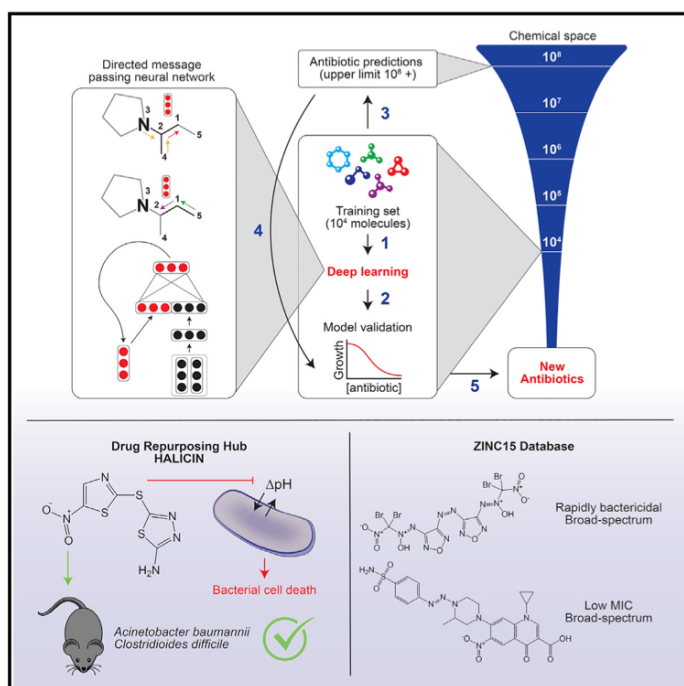
Recent GNN application

Article

Cell

A Deep Learning Approach to Antibiotic Discovery

Graphical Abstract



Authors

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In Brief

A trained deep neural network predicts antibiotic activity in molecules that are structurally different from known antibiotics, among which Halicin exhibits efficacy against broad-spectrum bacterial infections in mice.

Highlights

- A deep learning model is trained to predict antibiotics based on structure
- Halicin is predicted as an antibacterial molecule from the Drug Repurposing Hub
- Halicin shows broad-spectrum antibiotic activities in mice
- More antibiotics with distinct structures are predicted from the ZINC15 database

Stokes et al., 2020, Cell 180, 688–702
February 20, 2020 © 2020 Elsevier Inc.
<https://doi.org/10.1016/j.cell.2020.01.021>

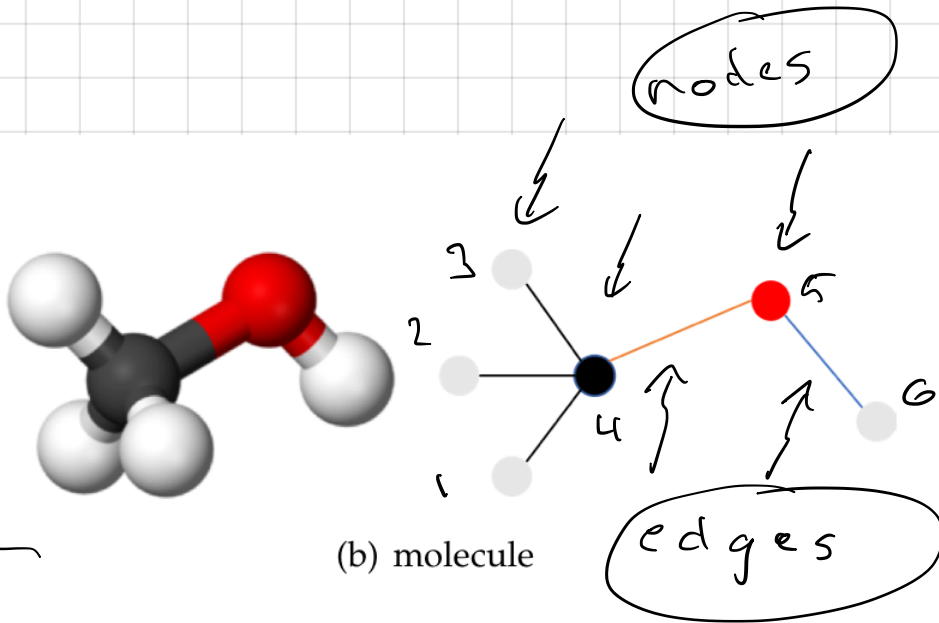
Outline

- ~ what is a graph, how describe
- ~ Graph learning tasks
- ~ GNN vs. CNN
- ~ GNN layers
- ~ Homework

• Watch the Youtube videos for more general discussion!

What is a graph?

It's a collection of nodes and edges
 $i \in \{1, \dots, n\}$ $\rightarrow$ $\{(i \rightarrow j)\}$



Structure given by Adjacency matrix

$$A_{ij} = 1 \text{ if edge } i \rightarrow j$$

$\uparrow$ $n \times n$ matrix

$$A_{ij} = 0 \text{ if no edge}$$

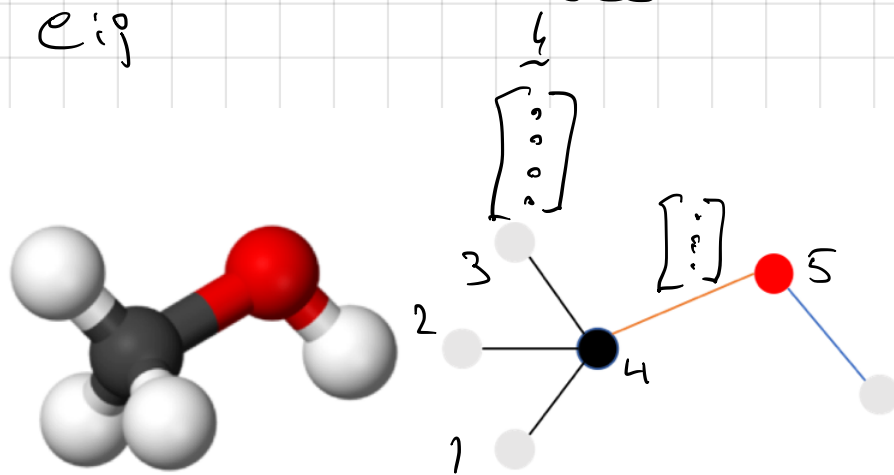
We will consider undirected graphs $A_{ji} = A_{ij}$

$$A = \begin{bmatrix} 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 1 & 1 & 1 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

$\leftarrow$ symmetric

But there will be more information than the structure

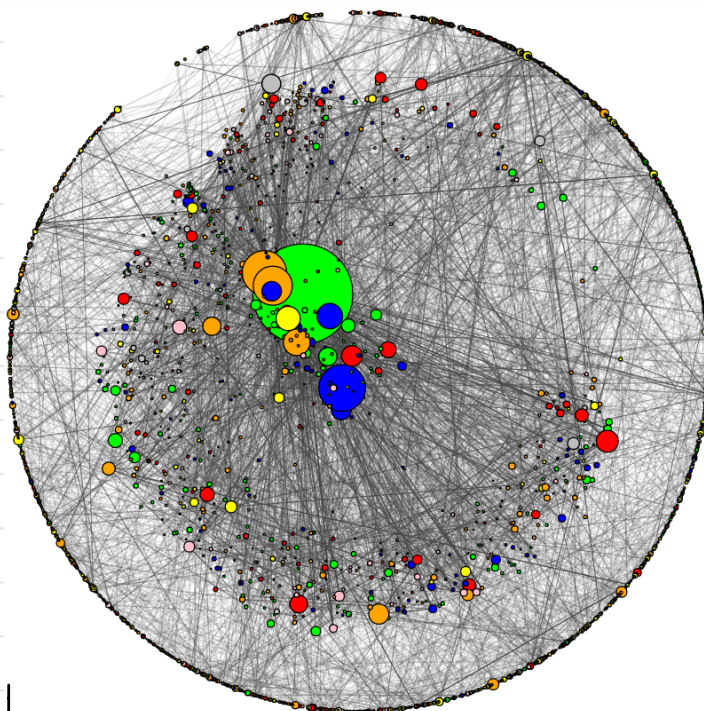
Feature vectors on nodes and edges



(b) molecule

Ex. c_{45} = distance 4 to 5 (scalar, not vector)
 x_3 = label of type of molecule

Example Cora dataset



Citation
network of
papers.
↑
nodes

2708 nodes

1433 dim.
feature
vector

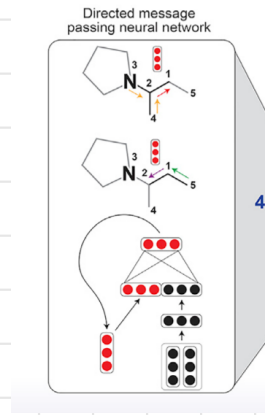
↑
based on
keywords

7 classes
of papers

Machine learning tasks on graphs

Graph classification

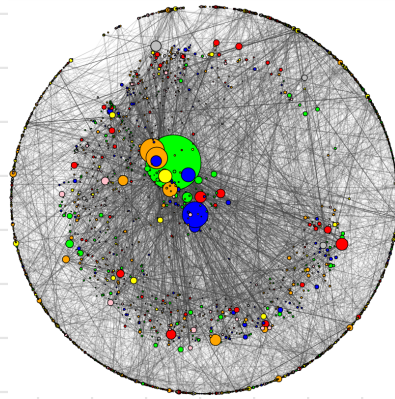
E.g. Does the molecule have antibiotic properties or not



many graphs

Node classification

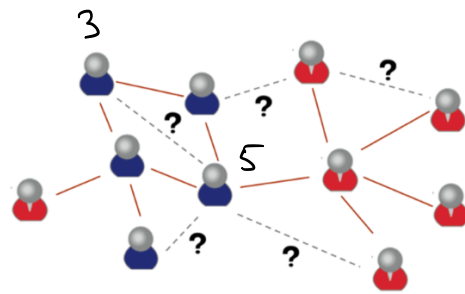
E.g. is the paper in class A, B, C, etc.?



single graph

Link prediction

E.g. Is there a link (edge) between node 3 and 5?



(e) social network

Supervised learning:

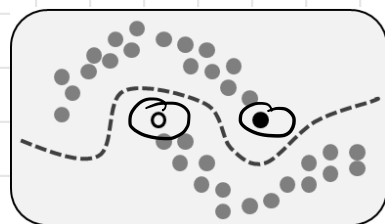
Graph classification is typically supervised:
set of labeled graphs, use for training.

⇒ Semi-supervised learning:

Ex two labeled data points,

many unlabeled

use clustering to extract info. from unlabeled data points.



Node prediction is typically of this type.

Ex. Cora 140 labeled nodes
out of 2708 nodes

Use info about how papers are related (citation graph)

E.g. homophilous graph: adjacent

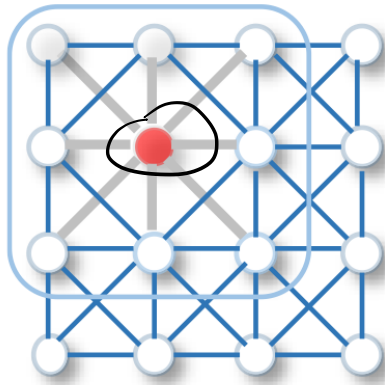
Unsupervised:

GNN do clustering even when not trained.

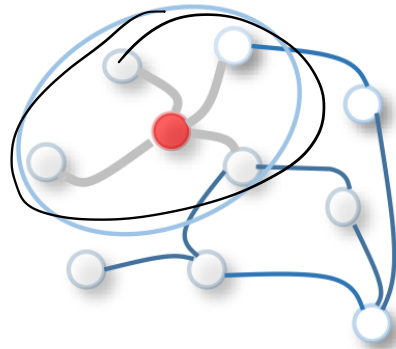
nodes more likely to share properties.

Convolutions on graphs

CNN filter



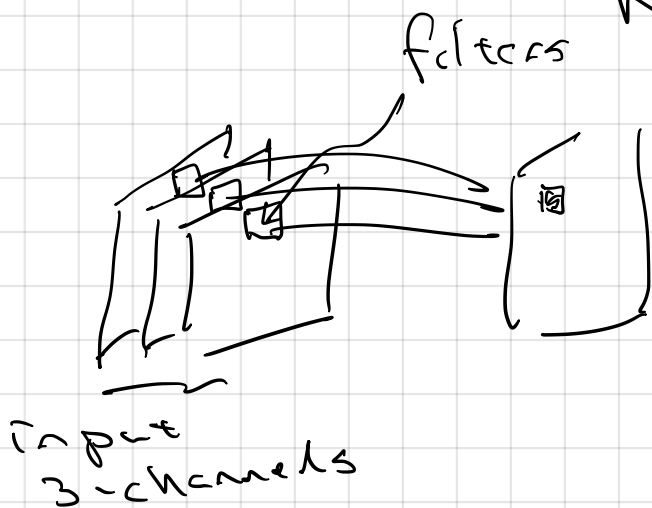
GNN filter



A Comprehensive Survey on Graph Neural Networks

Zonghan Wu, Shirui Pan, Member, IEEE, Fengwen Chen, Guodong Long, Chengqi Zhang, Senior Member, IEEE, Philip S. Yu, Fellow, IEEE

Standard CNN work on grids, regular structure: each "node" has fixed number of neighbors



different filter: weights to all pixels

3x3 filter has 9 trainable weights

How to set up similar object on graph?

Clearly: We want to use adjacency matrix A_{ij}

Problem: not fixed number of adjacent nodes, how many weights?

Graph convolutional layers, some examples

Basic graph convolution

add "self-loops" to A

$$\tilde{A} = A + I$$

$$\tilde{A} = \begin{pmatrix} 1 & 1 & 0 & 0 \\ 1 & 2 & 0 & 0 \\ 0 & 0 & 2 & 1 \\ 0 & 0 & 1 & 2 \end{pmatrix}$$

SEMI-SUPERVISED CLASSIFICATION WITH
GRAPH CONVOLUTIONAL NETWORKS

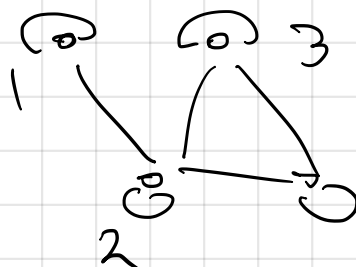
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its degree matrix

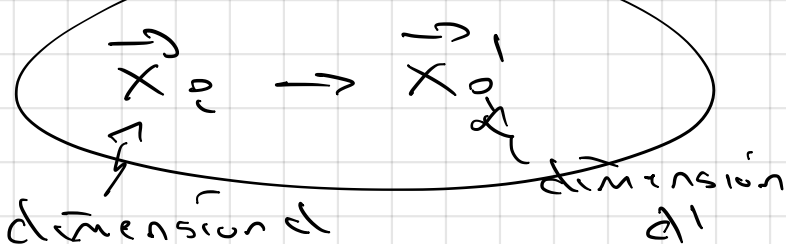
$$\tilde{D}: \text{diagonal } \tilde{D}_{ii} = \sum_j \tilde{A}_{ij} = \tilde{d}_i$$

$$D_{ij} = 0 \quad i \neq j$$



- Convolution takes a graph to an isomorphic graph, same structure, i.e. same A_{ij} .

Gives new node feature vectors



make feature matrix X
 $n \times d'$

$$X = \begin{pmatrix} - & x_1 & - \\ - & x_2 & - \\ - & x_3 & - \end{pmatrix}$$

$$X' = \sigma \left(\underbrace{\tilde{D}^{-1/2} \tilde{A} \tilde{D}^{-1/2}}_{n \times n} X W \right)$$

non-linearity $\rightarrow$
ReLU, tanh.

$n \times d$

weight matrix
 $d \times d'$

- Same weights on all nodes!

equivalently

$$\vec{x}_i' = \sigma \left(\underbrace{\sum_j \frac{\tilde{A}_{ij}}{\sqrt{\tilde{d}_i \tilde{d}_j}}}_{\text{collect from adjacent neighbors}} \underbrace{\omega^T \vec{x}_j}_{\text{linear transform to } d' \text{ dim vector}} \right)$$

just like a single dense NN layer

collects information
isotropically from neighbors.
"one-hop" per layer

Warning! Too many layers may smear out information over the graph.

No edge info used except for A

- Simple variation that uses an edge weight e_{ij} (scalar edge feature)

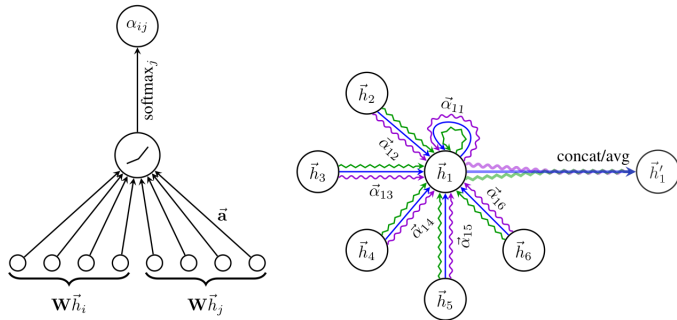
$$\vec{x}_i' = \sigma \left(\omega_1 \vec{x}_i + \omega_2 \sum_j e_{ij} \vec{x}_j \right)$$

"heavy" edges weighed more

Graph Attention layers

The basic layer is isotropic, all adjacent nodes are treated the same.

We may want to be more selective,



GRAPH ATTENTION NETWORKS

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Attention gives selective feedback from adjacent nodes.

$$\vec{x}'_i = \sigma \left(\sum_j \alpha_{ij} W \vec{x}_j \right)$$

d' d $d' \times d$ weight matrix

attention coefficients

$$\alpha_{ij} = \text{softmax}(\Sigma_{ij}) = \frac{e^{\Sigma_{ij}}}{\sum_k e^{\Sigma_{ik}}}$$

$$\Sigma_{ij} = \sigma' \left(\vec{a} \cdot \underbrace{[W \vec{x}_i || W \vec{x}_j]}_{\text{concatenation}} \right) A_{ij}$$

attention vector $d \sim 2d'$

trainable weights

$$d' \left\{ \begin{bmatrix} W \vec{x}_i \\ W \vec{x}_j \end{bmatrix} \right\} 2d'$$

One can also have multiple attention heads

$W^k, Q^k, k=1, \dots, K$

$$\vec{x}'_i = \frac{1}{K} \sum_k \vec{x}_i^k$$

concatenation over heads

Pooling layers

- Convolutional layers: graph $\rightarrow$ same graph (new features)
- How do we get output for graph classification? $\leftarrow$ single label
 - We may want to decrease or unify graph size.

Use pooling layers: Pool nodes together.

- Global pooling $\Leftrightarrow$ graph $\rightarrow$ 1 node

E.g. global mean pool

$$\vec{X}^1 = \frac{1}{n} \sum_i \vec{X}_i$$

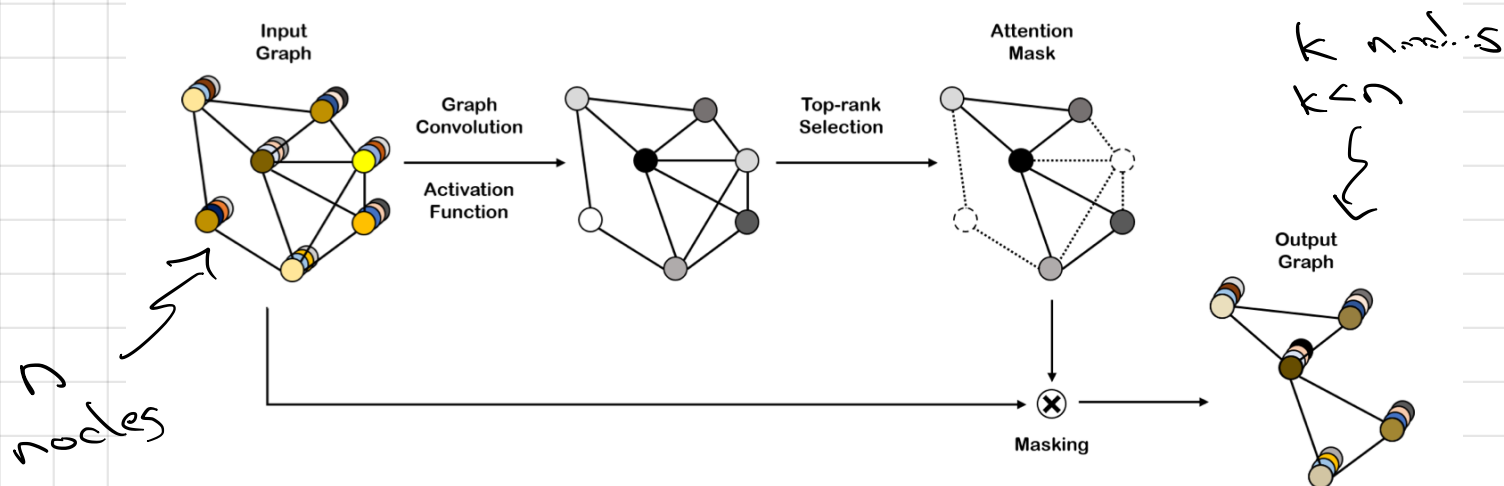
$\nearrow$
MLP $\rightarrow$ classifier

$\nwarrow$
single feature vector

Example -

Self-Attention Graph Pooling

Junhyun Lee^{*1} Inyeop Lee^{*1} Jaewoo Kang¹



Select the k most important nodes

Self-attention
$$Z_i = \sigma \left(\sum_j \tilde{A}_{ij} \frac{\vec{a}_i \cdot \vec{x}_j}{\sqrt{\tilde{d}_i \tilde{d}_j}} \right)$$

$\nearrow$ scalar value of each node

$\vec{a}$ attention vector

Keep k nodes with highest Z -value

$$\tilde{A}_{ij} \rightarrow A_{\text{mask}}(ij) \quad \vec{x}_i' = \vec{x}_i Z_i$$

$\nwarrow$ $n \times n$ $\nearrow$ $k \times k$

Bottom line: Put together conv. layers + pooling layers depending on the task

Beware of overdoing.

Homework A

- Walk through

Graph Neural Networks, Assignment A

Course: Advanced machine learning using neural networks, TIF360/FYM360

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David Fitzek, davidfi@chalmers.se

- Recommended GNN library for the h.w.

The screenshot shows a web browser displaying the PyTorch Geometric documentation. The browser's address bar shows the URL `pytorch-geometric.readthedocs.io`. The page has a dark sidebar on the left with a search bar and a list of navigation links under the heading "NOTES". The main content area has a white background and contains the following sections:

- PYTORCH GEOMETRIC DOCUMENTATION**: A heading followed by a paragraph stating that PyTorch Geometric is a geometric deep learning extension library for PyTorch.
- Notes**: A list of links including Installation, Introduction by Example, Creating Message Passing Networks, Creating Your Own Datasets, Advanced Mini-Batching, Memory-Efficient Aggregations, TorchScript Support, Colab Notebooks, and External Resources.
- Package Reference**: A list of links for `torch_geometric`, `torch_geometric.nn`, `torch_geometric.data`, `torch_geometric.datasets`, `torch_geometric.transforms`, `torch_geometric.utils`, and `torch_geometric.io`.
- INDICES AND TABLES**: A list of links for the Index and Module Index.

At the bottom of the page, there is a copyright notice: "© Copyright 2021, Matthias Fey Revision c711bb22." and a note: "Built with Sphinx using a theme provided by Read the Docs." A "Next" button is visible in the bottom right corner.

