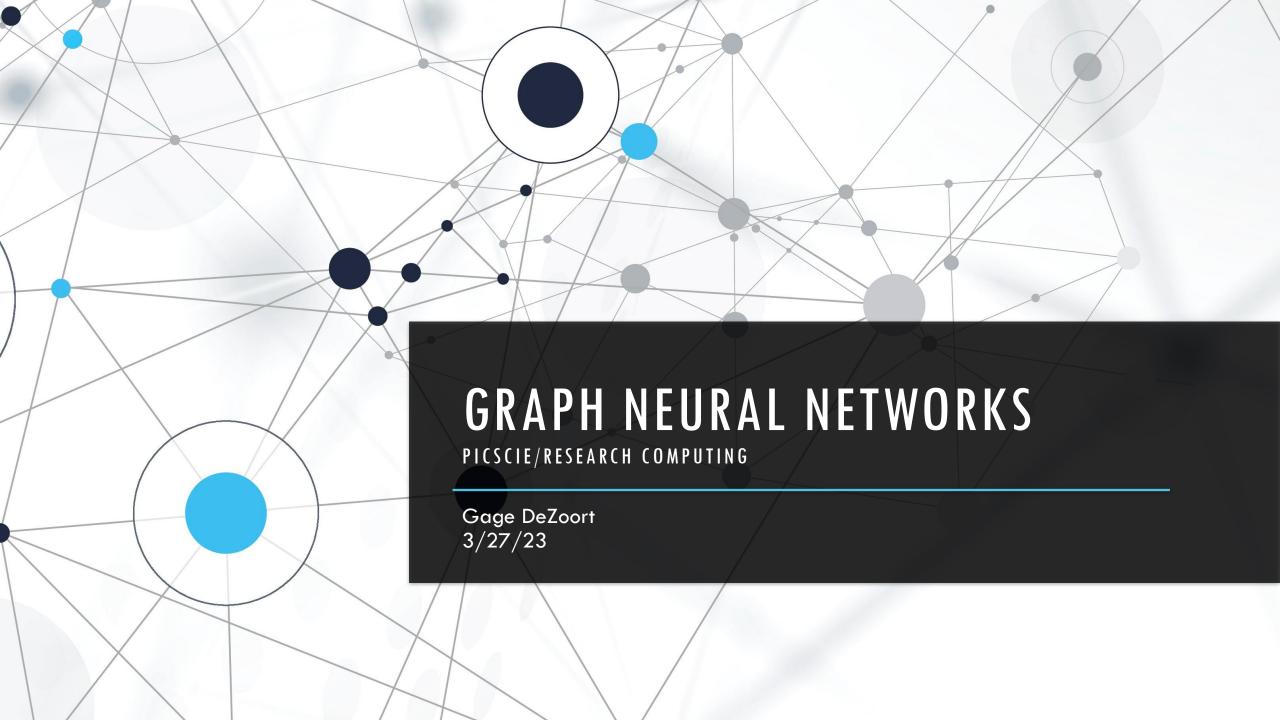
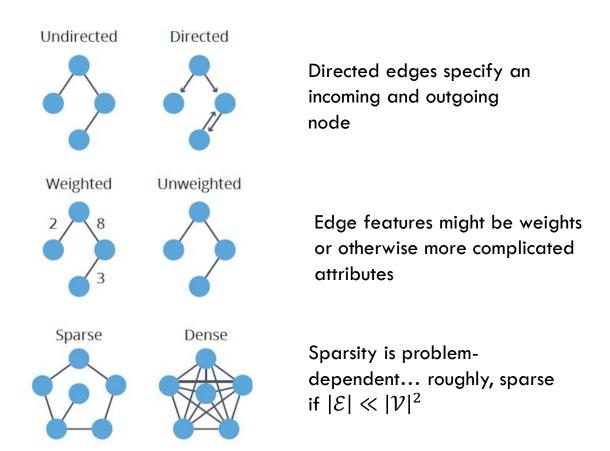
Setup Instructions: 1. Navigate to https://github.com/GageDeZoort/prc_gnn_tutorial 2. Click on gnn_tutorial_3_27_23.ipynb 3. Change "github" to "githubtocolab" in your searchbar, i.e.: https://colab.research.google.com/github/GageDeZoort/prc_gnn_tutorial 4. If you want to use a GPU (none of the cells require one), you can request one on Colab through Edit->Notebook Settings



GRAPHS

- Graphs represent relational data
 - Entities \rightarrow Nodes: $u \in \mathcal{V}$
 - Node features: $x_u \in \mathbb{R}^{d_{\mathcal{V}}}$
 - Relations \rightarrow Edges: $(u, v) \in \mathcal{E}$
 - Edge features: $e_{uv} \in \mathbb{R}^{d_{\mathcal{E}}}$

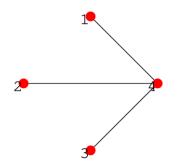


Graph Algorithms in Neo4j: Graph Algorithm Concepts

EDGE REPRESENTATIONS



- Entities \rightarrow Nodes: $u \in \mathcal{V}$
 - Node features: $x_u \in \mathbb{R}^{d_{\mathcal{V}}}$
- Relations \rightarrow Edges: $(u, v) \in \mathcal{E}$
 - Edge features: $e_{uv} \in \mathbb{R}^{d_{\mathcal{E}}}$



Edge Representations

Adjacency Matrices $A_{adjacency} \in \mathbb{R}^{d_{\mathcal{V}} \times d_{\mathcal{V}}}$

$$\begin{pmatrix}
0 & 0 & 0 & 1 \\
0 & 0 & 0 & 1 \\
0 & 0 & 0 & 1 \\
1 & 1 & 1 & 0
\end{pmatrix}$$

Incidence Matrices $A_{incidence} \in \mathbb{R}^{d_{\mathcal{V}} \times d_{\mathcal{E}}}$

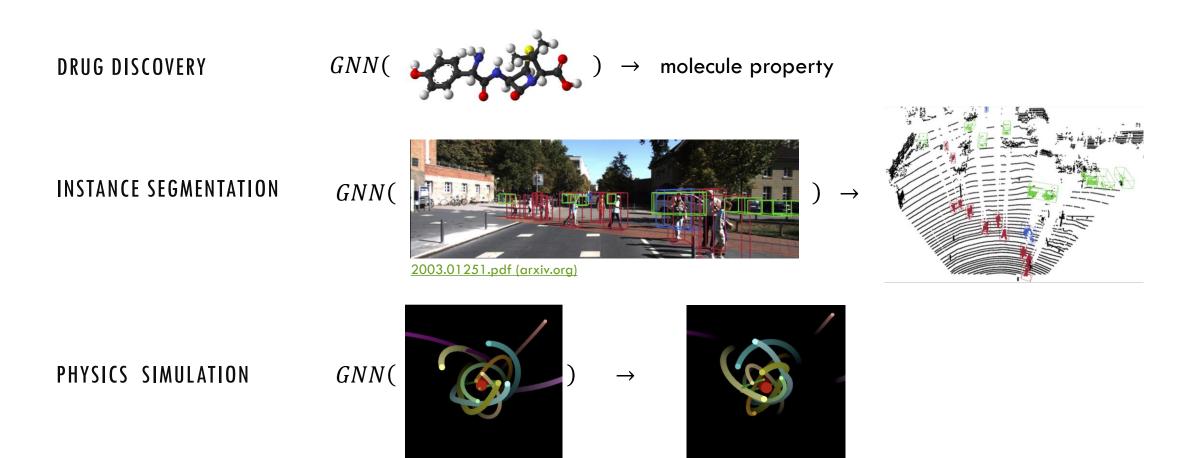
$$\begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ 1 & 1 & 1 \end{pmatrix}$$



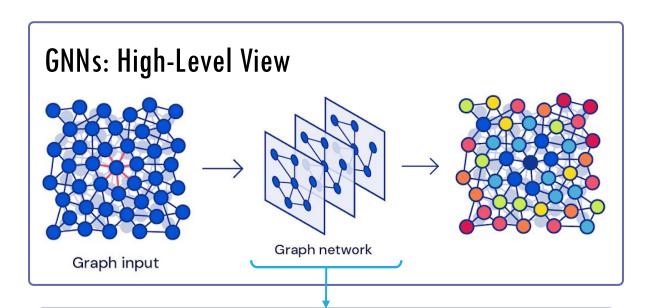
Sparse Index Lists (COO) $I_{COO} \in \mathbb{R}^{2 \times d_{\mathcal{E}}}$

$$\begin{bmatrix} 1 & 2 & 3 \\ 4 & 4 & 4 \end{bmatrix}$$

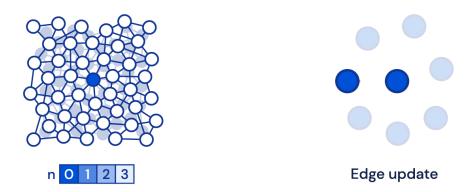
GRAPH LEARNING TASKS



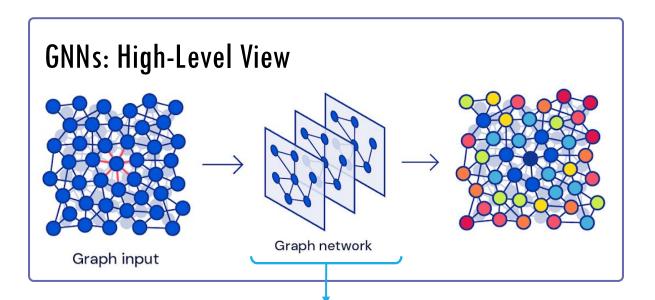
[1612.00222] Interaction Networks for Learning about Objects, Relations and Physics (arxiv.org)



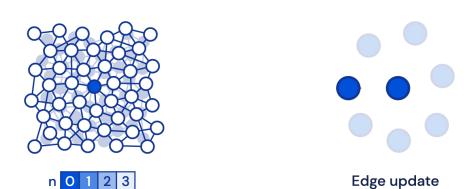
GNN Layers, Neural Message Passing



"Messages" computed from each node's neighborhood are used to update graph features... k iterations \rightarrow info from k-hop neighborhood



GNN Layers, Neural Message Passing



"Messages" computed from each node's neighborhood are used to update graph features... k iterations \rightarrow info from k-hop neighborhood

Message Passing (MPNN) Layers:

Framework for many equivariant graph updates

At each layer k, compute messages in each node's neighborhood:

$$oldsymbol{m}_{uv}^{(k)} = \psi^{(k)}\left(oldsymbol{h}_{u}^{(k-1)}, oldsymbol{h}_{v}^{(k-1)}, oldsymbol{e}_{uv}^{(k-1)}
ight)$$

Aggregate messages in a permutation-invariant way:

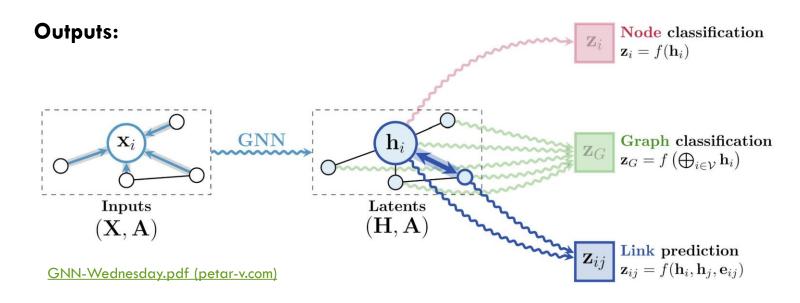
Messages passed only from u's direct neighbors $\boldsymbol{a}_{u}^{(k)} = \bigoplus_{v \in N(u)}^{\text{Messages passed only from u's direct neighbors}$ $\boldsymbol{a}_{u}^{(k)} = \bigoplus_{v \in N(u)}^{\text{Messages passed only from u's direct neighbors}$ $\boldsymbol{a}_{u}^{(k)} = \bigoplus_{v \in N(u)}^{\text{Messages passed only from u's direct neighbors}$ $\boldsymbol{a}_{u}^{(k)} = \bigoplus_{v \in N(u)}^{\text{Messages passed only from u's direct neighbors}$ Any permutation invariant operation (e.g. sum, mean, max)

Update the node's state based on the messages it received:

$$\mathbf{h}_{u}^{(k)} = \phi^{(k)}(\mathbf{h}_{u}^{(k-1)}, \mathbf{a}_{u}^{(k)})$$

Generic MPNN Layers:

$$\boldsymbol{h}_{u}^{(k)} = \phi^{(k)} \left[\boldsymbol{h}_{u}^{(k-1)}, \bigoplus_{v \in N(u)} \psi^{(k)} \left(\boldsymbol{h}_{u}^{(k-1)}, \boldsymbol{h}_{v}^{(k-1)}, \boldsymbol{e}_{uv}^{(k-1)} \right) \right]$$





Tutorial Agenda

- O. Software Setup
- 1. Graph-Structured Data
 - 1. Karate Club (node classification)
 - 2. ENZYMES (graph classification)
- 2. Graph Neural Networks
 - 1. GCN Math
 - 2. Training on Cora
- 3. Long Exercise: graph-level training with ENZYMES (Optional)
- Message Passing Under the Hood (Optional)