

Stanford CS224W: **Graph Neural Networks**

CS224W: Machine Learning with Graphs

Jure Leskovec, Stanford University

<http://cs224w.stanford.edu>



ANNOUNCEMENTS

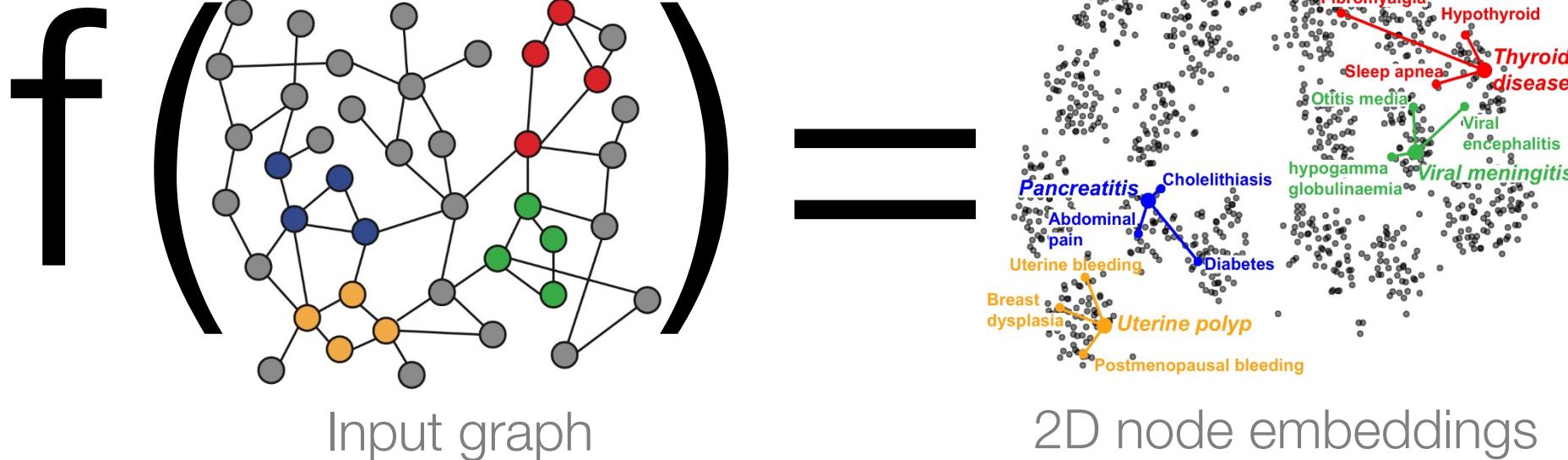
- **Today (10/07):** Colab 1 due, Colab 2 out
- **Next Thursday (10/14):** HW 1 due, HW 2 out
- **Project proposals due on Tuesday 10/19**
 - If you are looking for project partners, check out / add yourself to our pinned Ed post ("Project Partner Thread")
-- reach out to each other!
 - We strongly encourage groups of 3, but groups of 1 or 2 are allowed

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Recap: Node Embeddings

- **Intuition:** Map nodes to d -dimensional embeddings such that similar nodes in the graph are embedded close together

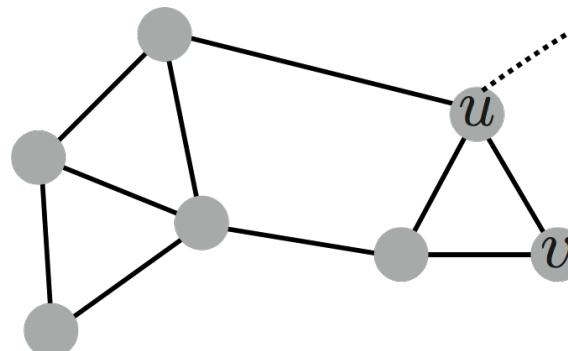


How to learn mapping function f ?

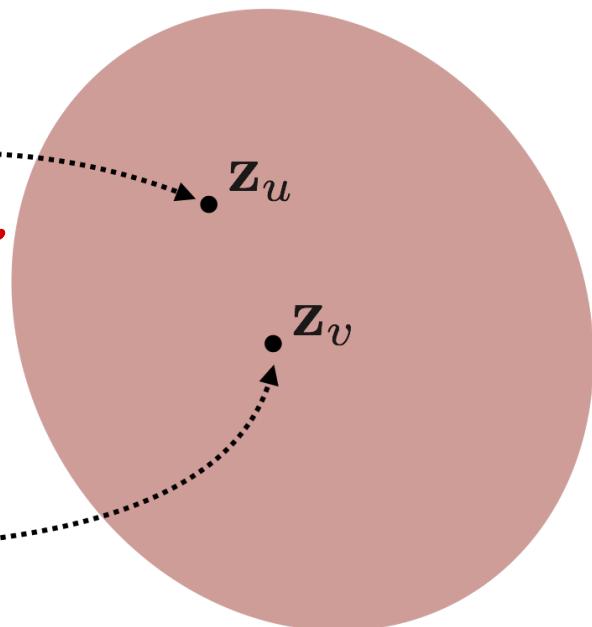
Recap: Node Embeddings

Goal: $\text{similarity}(u, v) \approx z_v^T z_u$

Need to define!



encode nodes

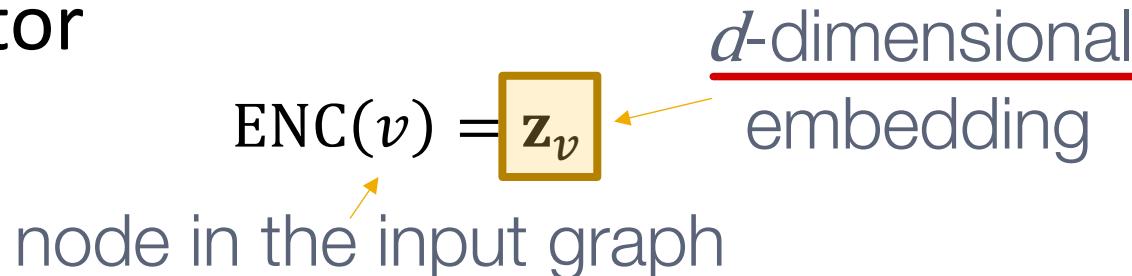


Input network

d -dimensional
embedding space

Recap: Two Key Components

- **Encoder:** Maps each node to a low-dimensional vector



- **Similarity function:** Specifies how the relationships in vector space map to the relationships in the original network

$$\text{similarity}(u, v) \approx \mathbf{z}_v^T \mathbf{z}_u$$

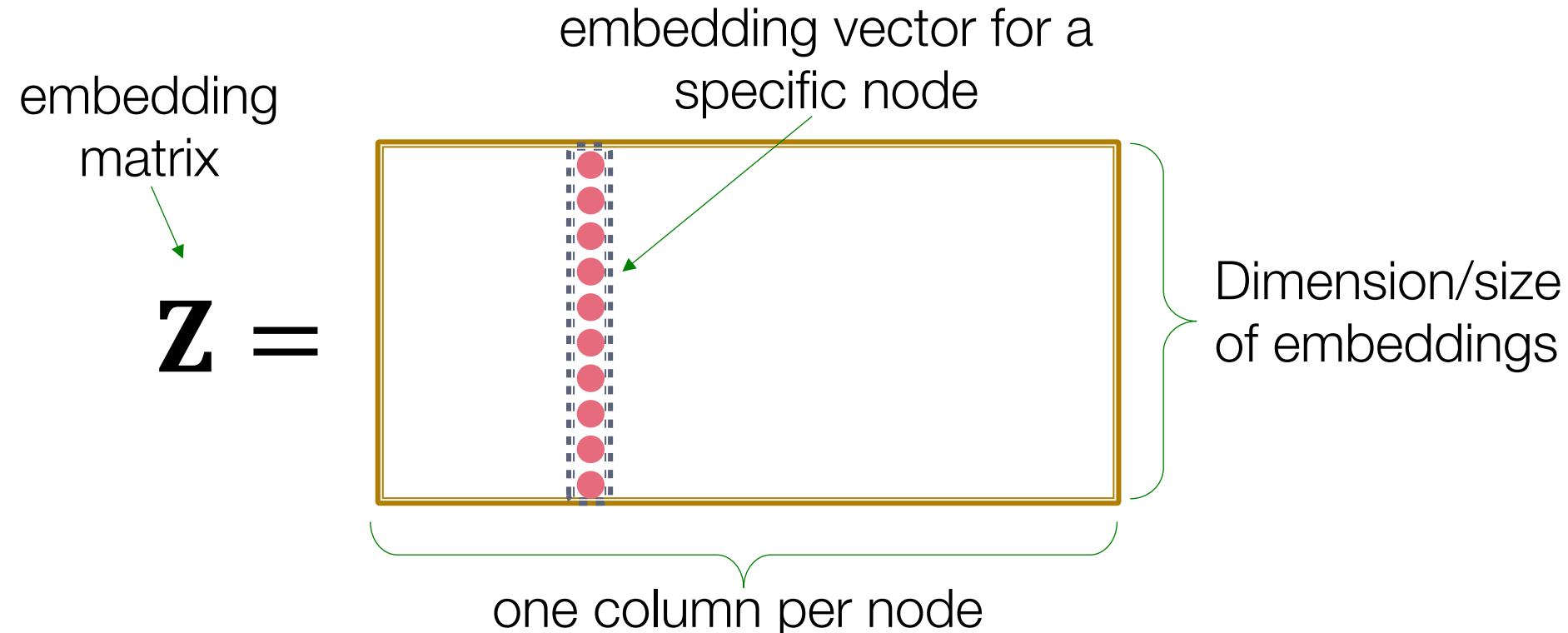
Similarity of u and v in the original network

Decoder

dot product between node embeddings

Recap: “Shallow” Encoding

Simplest encoding approach: **Encoder is just an embedding-lookup**



Recap: Shallow Encoders

- Limitations of shallow embedding methods:
 - **$O(|V|)$ parameters are needed:**
 - No sharing of parameters between nodes
 - Every node has its own unique embedding
 - **Inherently “transductive”:**
 - Cannot generate embeddings for nodes that are not seen
during training
 - **Do not incorporate node features:**
 - Nodes in many graphs have features that we can and should leverage

Today: Deep Graph Encoders

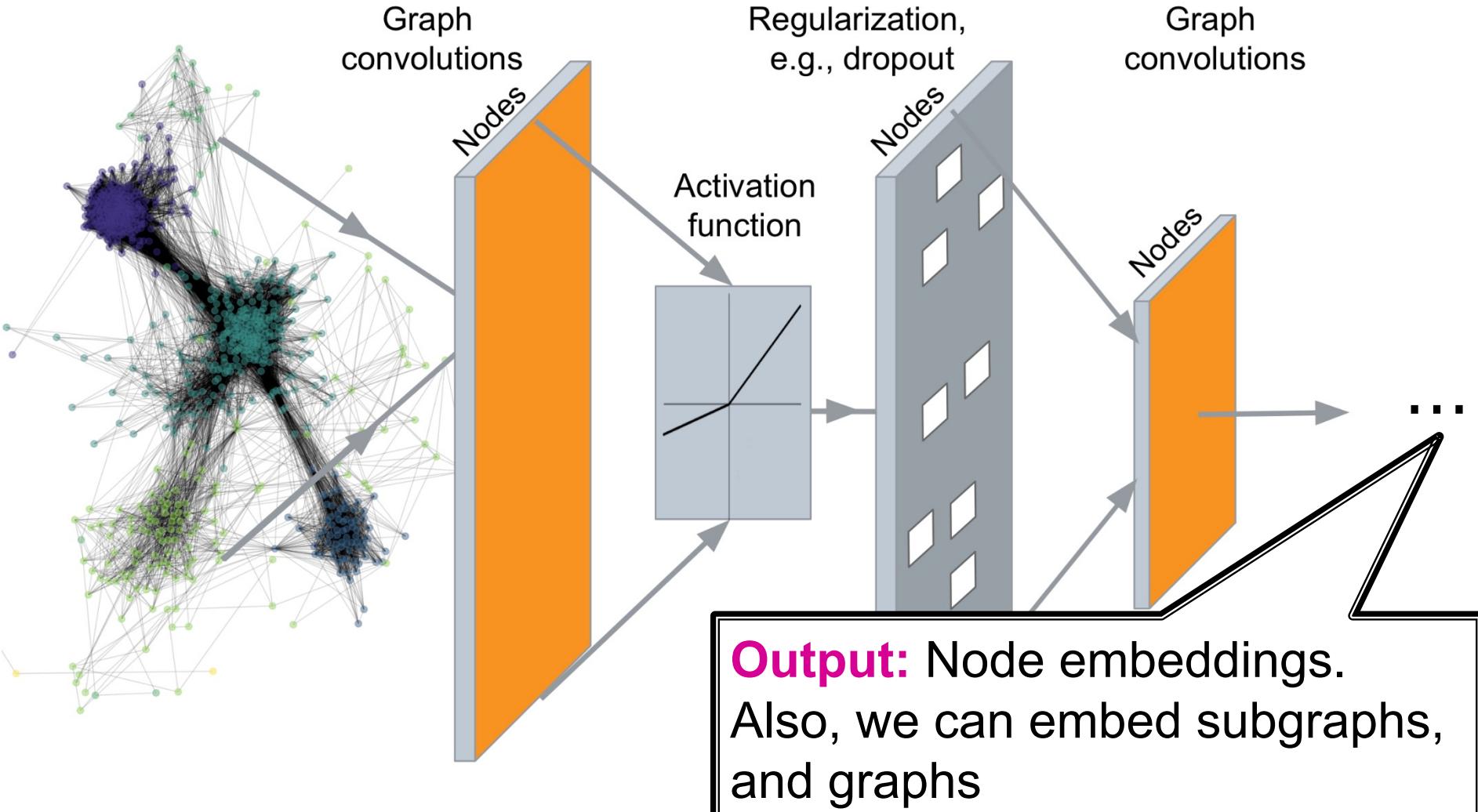
- **Today:** We will now discuss deep learning methods based on **graph neural networks (GNNs)**:

$$\text{ENC}(v) =$$

**multiple layers of
non-linear transformations
based on graph structure**

- **Note:** All these deep encoders can be **combined with node similarity functions** defined in the Lecture 3.

Deep Graph Encoders

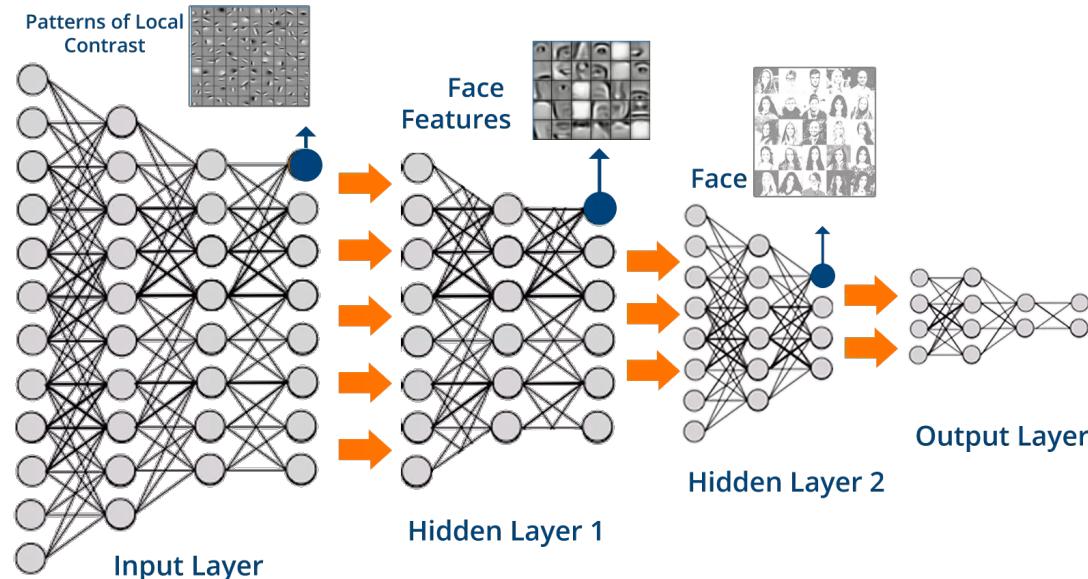
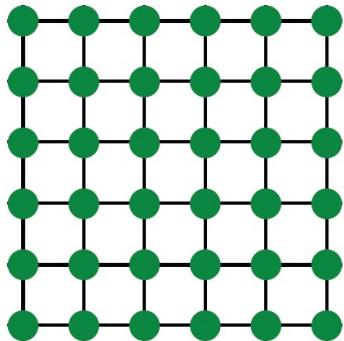


Tasks on Networks

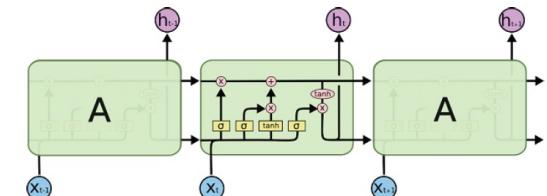
Tasks we will be able to solve:

- Node classification
 - Predict a type of a given node
- Link prediction
 - Predict whether two nodes are linked
- Community detection
 - Identify densely linked clusters of nodes
- Network similarity
 - How similar are two (sub)networks

Modern ML Toolbox



Text/Speech

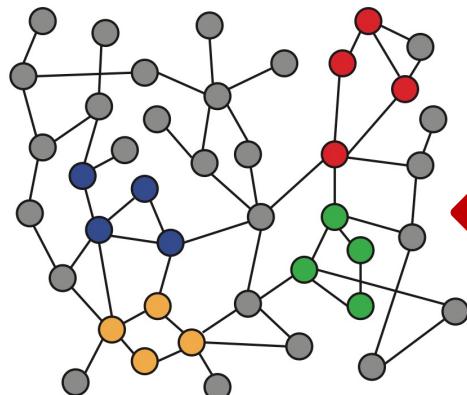


Modern deep learning toolbox is designed
for simple sequences & grids

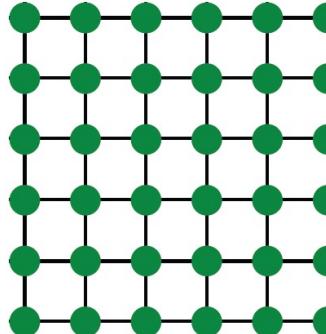
Why is it Hard?

But networks are far more complex!

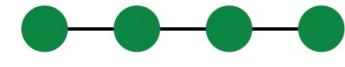
- Arbitrary size and complex topological structure (i.e., no spatial locality like grids)



Networks



Images



Text

- No fixed node ordering or reference point
- Often dynamic and have multimodal features

Outline of Today's Lecture

1. Basics of deep learning



2. Deep learning for graphs

3. Graph Convolutional Networks

**4. GNNs subsume CNNs and
Transformers**

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Machine Learning as Optimization

- **Supervised learning:** we are given input \mathbf{x} , and the goal is to predict label \mathbf{y} .
- **Input \mathbf{x} can be:**
 - Vectors of real numbers
 - Sequences (natural language)
 - Matrices (images)
 - Graphs (potentially with node and edge features)
- **We formulate the task as an optimization problem.**

Machine Learning as Optimization

- Formulate the task as an optimization problem:

$$\min_{\Theta} \mathcal{L}(y, f(x))$$

Objective function

- Θ : a set of **parameters** we optimize
 - Could contain one or more scalars, vectors, matrices ...
 - E.g. $\Theta = \{Z\}$ in the shallow encoder (the embedding lookup)

- \mathcal{L} : **loss function**. Example: L2 loss

$$\mathcal{L}(y, f(x)) = \|y - f(x)\|_2$$

- Other common loss functions:
 - L1 loss, huber loss, max margin (hinge loss), cross entropy ...
 - See <https://pytorch.org/docs/stable/nn.html#loss-functions>

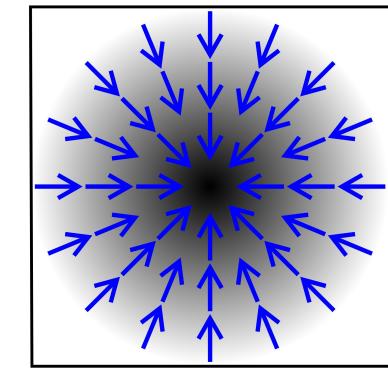
Loss Function Example

- One common loss for classification: **cross entropy (CE)**
- Label \mathbf{y} is a categorical vector (**one-hot encoding**)
 - e.g. $\mathbf{y} = \begin{array}{c|c|c|c|c} \text{o} & \text{o} & \text{1} & \text{o} & \text{o} \end{array}$ \mathbf{y} is of class "3"
- $f(\mathbf{x}) = \text{Softmax}(g(\mathbf{x}))$
 - Recall from lecture 3: $f(\mathbf{x})_i = \frac{e^{g(\mathbf{x})_i}}{\sum_{j=1}^C e^{g(\mathbf{x})_j}}$ $g(\mathbf{x})_i$ denotes i -th coordinate of the vector output of func. $g(\mathbf{x})$
 - where C is the number of classes.
 - e.g. $f(\mathbf{x}) = \begin{array}{c|c|c|c|c} \text{0.1} & \text{0.3} & \text{0.4} & \text{0.1} & \text{0.1} \end{array}$
- $\text{CE}(\mathbf{y}, f(\mathbf{x})) = -\sum_{i=1}^C (y_i \log f(\mathbf{x})_i)$
 - y_i and $f(\mathbf{x})_i$ are the **actual** and **predicted** values of the i -th class.
 - **Intuition:** the lower the loss, the closer the prediction is to one-hot
- **Total loss over all training examples:**
 - $\mathcal{L} = \sum_{(\mathbf{x}, \mathbf{y}) \in \mathcal{T}} \text{CE}(\mathbf{y}, f(\mathbf{x}))$
 - \mathcal{T} : training set containing all pairs of data and labels (\mathbf{x}, \mathbf{y})

Machine Learning as Optimization

- How to optimize the objective function?
- Gradient vector: Direction and rate of fastest increase
Partial derivative

$$\nabla_{\Theta} \mathcal{L} = \left(\frac{\partial \mathcal{L}}{\partial \Theta_1}, \frac{\partial \mathcal{L}}{\partial \Theta_2}, \dots \right)$$



<https://en.wikipedia.org/wiki/Gradient>

- $\Theta_1, \Theta_2 \dots$: components of Θ
- Recall **directional derivative** of a multi-variable function (e.g. \mathcal{L}) along a given vector represents the instantaneous rate of change of the function along the vector.
- Gradient is the directional derivative in the **direction of largest increase**.

Gradient Descent

- **Iterative algorithm:** repeatedly update weights in the (opposite) direction of gradients until convergence
$$\Theta \leftarrow \Theta - \eta \nabla_{\Theta} \mathcal{L}$$
- **Training:** Optimize Θ iteratively
 - **Iteration:** 1 step of gradient descent
- **Learning rate (LR) η :**
 - Hyperparameter that controls the size of gradient step
 - Can vary over the course of training (LR scheduling)
- **Ideal termination condition:** gradient = 0
 - In practice, we stop training if it no longer improves performance on **validation set** (part of dataset we hold out from training).

Stochastic Gradient Descent (SGD)

■ Problem with gradient descent:

- Exact gradient requires computing $\nabla_{\Theta} \mathcal{L}(y, f(\mathbf{x}))$, where \mathbf{x} is the **entire** dataset!
 - This means summing gradient contributions over all the points in the dataset
 - Modern datasets often contain billions of data points
 - Extremely expensive for every gradient descent step

■ Solution: Stochastic gradient descent (SGD)

- At every step, pick a different **minibatch** \mathcal{B} containing a subset of the dataset, use it as input \mathbf{x}

Minibatch SGD

- **Concepts:**
 - **Batch size:** the number of data points in a minibatch
 - E.g. number of nodes for node classification task
 - **Iteration:** 1 step of SGD on a minibatch
 - **Epoch:** one full pass over the dataset (# iterations is equal to ratio of dataset size and batch size)
- **SGD is unbiased estimator of full gradient:**
 - But there is no guarantee on the rate of convergence
 - In practice often requires tuning of learning rate
- Common optimizer that improves over SGD:
 - Adam, Adagrad, Adadelta, RMSprop ...

Neural Network Function

- **Objective:** $\min_{\Theta} \mathcal{L}(y, f(\mathbf{x}))$
- In deep learning, function f can be very complex
- **Example:**
 - To start simple, consider linear function
$$f(\mathbf{x}) = \mathbf{W} \cdot \mathbf{x}, \quad \Theta = \{\mathbf{W}\}$$
 - Then, if f returns a scalar, then \mathbf{W} is a learnable **vector**
$$\nabla_{\mathbf{W}} f = \left(\frac{\partial f}{\partial w_1}, \frac{\partial f}{\partial w_2}, \frac{\partial f}{\partial w_3}, \dots \right)$$
 - But, if f returns a vector, then \mathbf{W} is the **weight matrix**

$$\nabla_{\mathbf{W}} f = \begin{bmatrix} \frac{\partial f_1}{\partial w_{11}} & \frac{\partial f_2}{\partial w_{12}} \\ \frac{\partial f_1}{\partial w_{21}} & \frac{\partial f_2}{\partial w_{22}} \end{bmatrix}$$

Jacobian
matrix of f

Intuition: Back Propagation

- **Goal:** $\min_{\Theta} \mathcal{L}(y, f(\mathbf{x}))$
 - To minimize \mathcal{L} , we need to evaluate the gradient:
$$\nabla_{\mathbf{W}} \mathcal{L} = \left(\frac{\partial f}{\partial \mathbf{w}_1}, \frac{\partial f}{\partial \mathbf{w}_2}, \frac{\partial f}{\partial \mathbf{w}_3} \dots \right)$$
which means we need to derive derivative of \mathcal{L} .
- **Overview of Back-propagation:**
 - \mathcal{L} is composed from some set of predefined building block functions $g(\cdot)$
 - For each such g we also have its derivative g'
 - Then we can automatically compute $\nabla_{\Theta} \mathcal{L}$ by evaluating appropriate funcs. g' on the minibatch \mathcal{B} .

Back-propagation

- How about a more complex function:

$$f(\mathbf{x}) = W_2(W_1 \mathbf{x}), \Theta = \{W_1, W_2\}$$

- Recall chain rule:

$$\frac{df}{dx} = \frac{dg}{dh} \cdot \frac{dh}{dx} \text{ or } f'(x) = g'(h(x))h'(x)$$

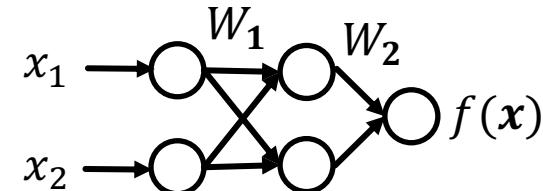
- Example: $\nabla_{\mathbf{x}} f = \frac{\partial f}{\partial (W_1 \mathbf{x})} \cdot \frac{\partial (W_1 \mathbf{x})}{\partial \mathbf{x}}$

- Back-propagation: Use of chain rule to propagate gradients of intermediate steps, and finally obtain gradient of \mathcal{L} w.r.t. Θ .

In other words:
 $f(\mathbf{x}) = W_2(W_1 \mathbf{x})$
 $h(x) = W_1 \mathbf{x}$
 $g(z) = W_2 z$

Back-propagation Example (1)

- **Example:** Simple 2-layer linear network
- $f(\mathbf{x}) = g(h(x)) = W_2(W_1 \mathbf{x})$
- $\mathcal{L} = \sum_{(x,y) \in \mathcal{B}} \left\| (y, -f(x)) \right\|_2$
 - The loss \mathcal{L} sums the L2 loss in a minibatch \mathcal{B} .
- **Hidden layer:**
 - Intermediate representation of input \mathbf{x}
 - Here we use $h(x) = W_1 \mathbf{x}$ to denote the hidden layer
 - $f(\mathbf{x}) = W_2 h(\mathbf{x})$



Back-propagation Example (2)

■ Forward propagation:

Compute loss starting from input

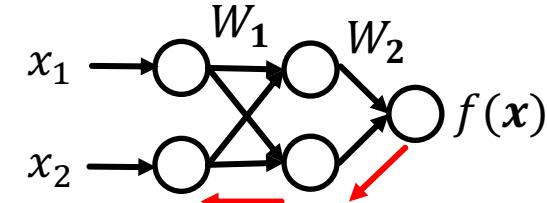
$$\begin{array}{ccccccc} \textcolor{blue}{x} & \xrightarrow{\text{Multiply } W_1} & h & \xrightarrow{\text{Multiply } W_2} & \textcolor{violet}{g} & \xrightarrow{\text{Loss}} & \mathcal{L} \\ & & & & & & \end{array}$$

Remember:

$$f(\mathbf{x}) = W_2(W_1 \mathbf{x})$$

$$h(x) = W_1 \mathbf{x}$$

$$g(z) = W_2 z$$



■ Back-propagation to compute gradient of

$$\Theta = \{W_1, W_2\}$$

Start from loss, compute the gradient

$$\frac{\partial \mathcal{L}}{\partial W_2} = \frac{\partial \mathcal{L}}{\partial f} \cdot \frac{\partial f}{\partial W_2},$$



Compute backwards

$$\frac{\partial \mathcal{L}}{\partial W_1} = \frac{\partial \mathcal{L}}{\partial f} \cdot \frac{\partial f}{\partial W_2} \cdot \frac{\partial W_2}{\partial W_1}$$



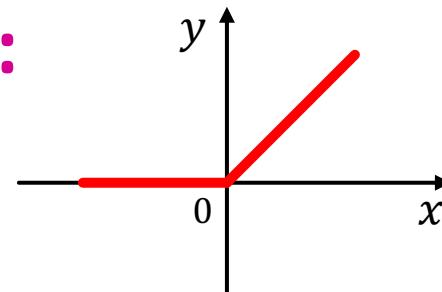
Compute backwards

Non-linearity

- Note that in $f(\mathbf{x}) = W_2(W_1 \mathbf{x})$, $W_2 W_1$ is another matrix (vector, if we do binary classification)
 - Hence $f(\mathbf{x})$ is still linear w.r.t. \mathbf{x} no matter how many weight matrices we compose
- We introduce non-linearity:

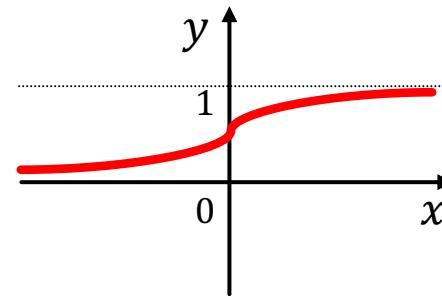
- Rectified linear unit (ReLU)

$$\text{ReLU}(x) = \max(x, 0)$$



- Sigmoid

$$\sigma(x) = \frac{1}{1 + e^{-x}}$$

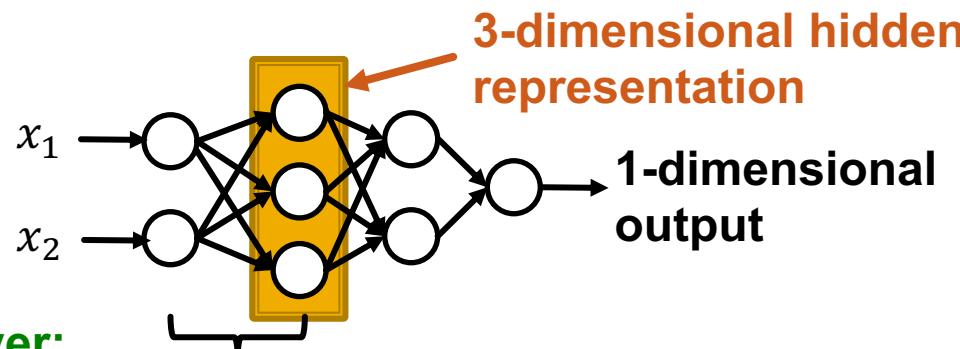


Multi-layer Perceptron (MLP)

- Each layer of MLP combines linear transformation and non-linearity:

$$\mathbf{x}^{(l+1)} = \sigma(W_l \mathbf{x}^{(l)} + b^l)$$

- where W_l is weight matrix that transforms hidden representation at layer l to layer $l + 1$
 - b^l is bias at layer l , and is added to the linear transformation of \mathbf{x}
 - σ is non-linearity function (e.g., sigmod)
- Suppose \mathbf{x} is 2-dimensional, with entries x_1 and x_2



Every layer:
Linear transformation +
non-linearity

Summary

- **Objective function:**

$$\min_{\Theta} \mathcal{L}(y, f(\mathbf{x}))$$

- f can be a simple linear layer, an MLP, or other neural networks (e.g., a GNN later)
- Sample a minibatch of input \mathbf{x}
- **Forward propagation:** Compute \mathcal{L} given \mathbf{x}
- **Back-propagation:** Obtain gradient $\nabla_{\mathbf{W}} \mathcal{L}$ using a chain rule.
- Use **stochastic gradient descent (SGD)** to optimize for Θ over many iterations.

Outline of Today's Lecture

1. Basics of deep learning



2. Deep learning for graphs



3. Graph Convolutional Networks

4. GNNs subsume CNNs and
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Content

- **Local network neighborhoods:**
 - Describe aggregation strategies
 - Define computation graphs
- **Stacking multiple layers:**
 - Describe the model, parameters, training
 - How to fit the model?
 - Simple example for unsupervised and supervised training

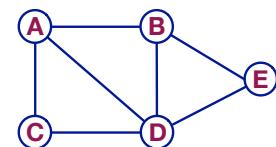
Setup

- Assume we have a graph G :
 - V is the **vertex set** — *nodes*
 - A is the **adjacency matrix** (assume binary) *→ 푸시 anweighted 가중*
 - $X \in \mathbb{R}^{m \times |V|}$ is a matrix of node features
 - v : a node in V ; $N(v)$: the set of neighbors of v .
- **Node features:**
 - Social networks: User profile, User image
 - Biological networks: Gene expression profiles, gene functional information
 - When there is no node feature in the graph dataset:
 - Indicator vectors (one-hot encoding of a node)
 - Vector of constant 1: [1, 1, ..., 1]

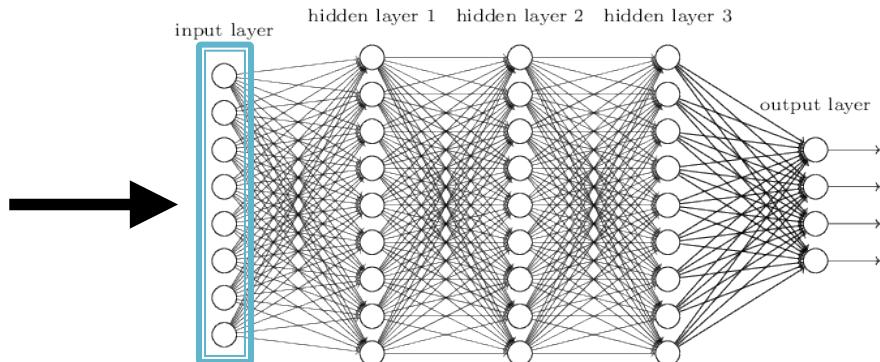
领悟
知识点

A Naïve Approach

- Join adjacency matrix and features
- Feed them into a deep neural net:



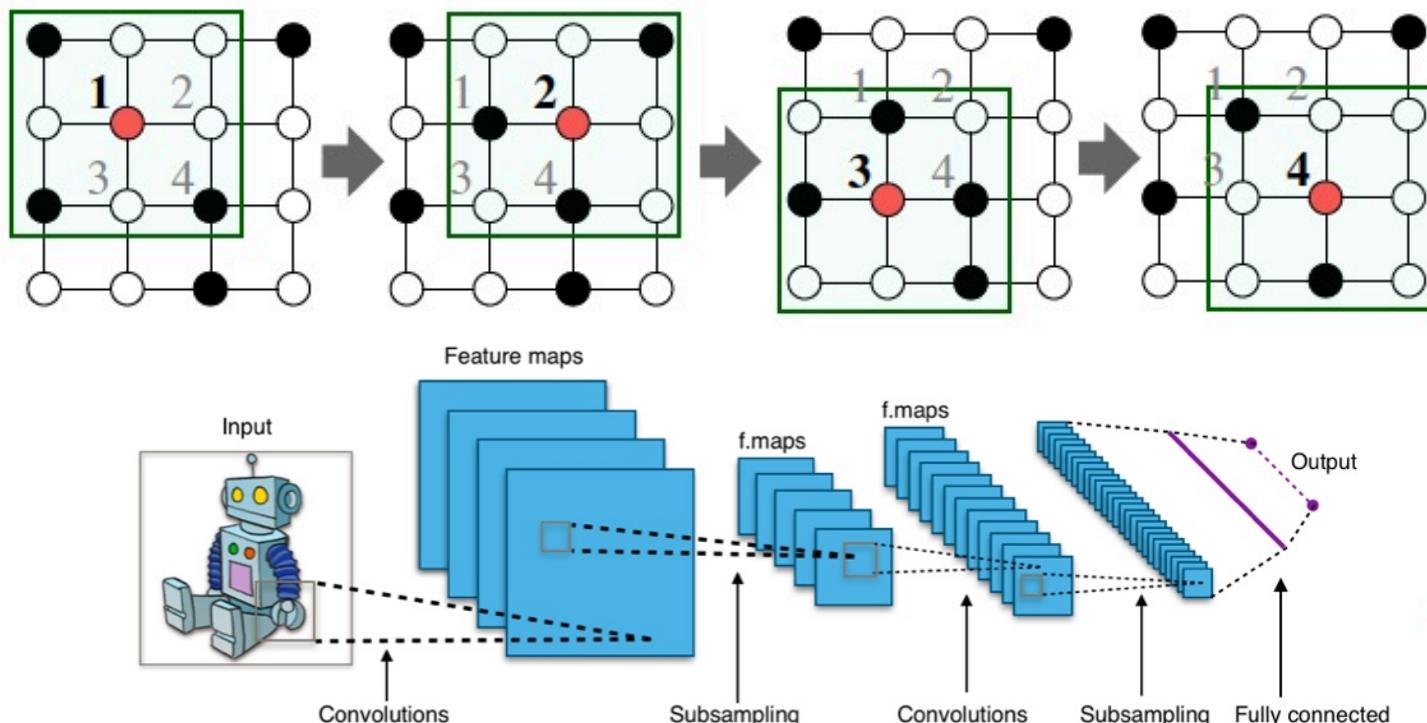
	A	B	C	D	E	Feat
A	0	1	1	1	0	1 0
B	1	0	0	1	1	0 0
C	1	0	0	1	0	0 1
D	1	1	1	0	1	1 1
E	0	1	0	1	0	1 0



- Issues with this idea:
 - $O(|V|)$ parameters \Rightarrow training unstable, easily overfit.
 - Not applicable to graphs of different sizes
 - Sensitive to node ordering 수행이 안감

Idea: Convolutional Networks

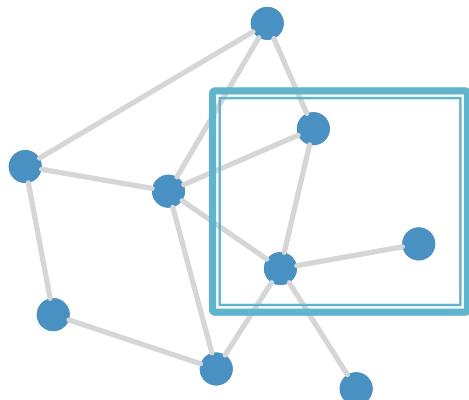
CNN on an image:



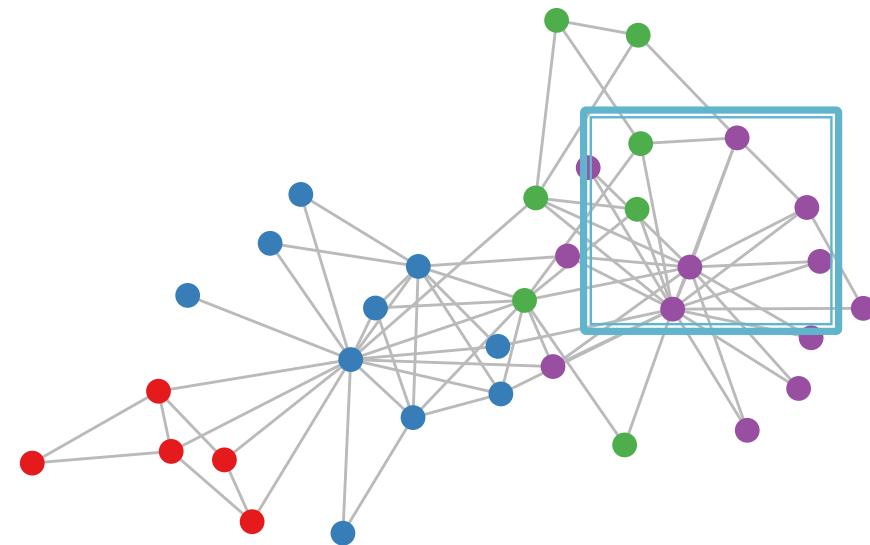
Goal is to generalize convolutions beyond simple lattices
Leverage node features/attributes (e.g., text, images)

Real-World Graphs

But our graphs look like this:



or this:



- There is no fixed notion of locality or sliding window on the graph
- Graph is permutation invariant

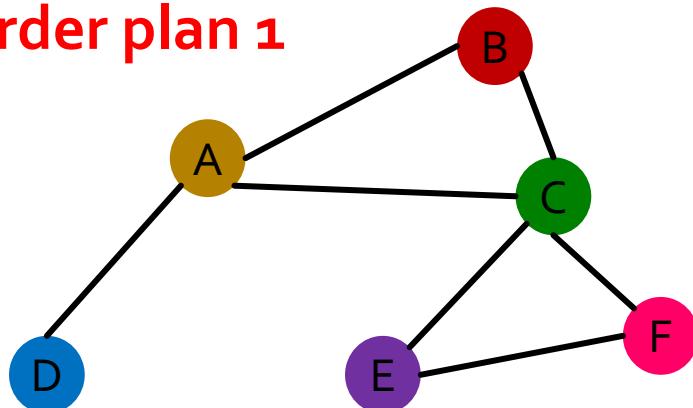
Permutation Invariance

- Graph does not have a canonical order of the nodes!
- We can have many different order plans.

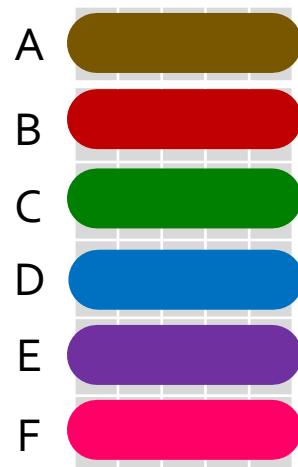
Permutation Invariance

- Graph does not have a canonical order of the nodes!

Order plan 1



Node features X_1



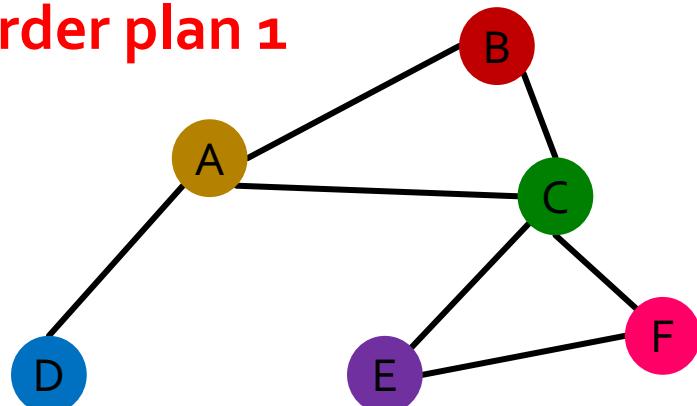
Adjacency matrix A_1

	A	B	C	D	E	F
A	Gray	Blue	Blue	Blue	Gray	Gray
B	Blue	Gray	Gray	Gray	Gray	Gray
C	Blue	Blue	Gray	Gray	Blue	Blue
D	Blue	Gray	Gray	Gray	Gray	Gray
E	Gray	Gray	Blue	Gray	Gray	Blue
F	Gray	Gray	Gray	Blue	Gray	Gray

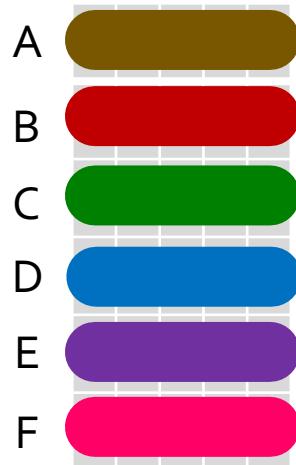
Permutation Invariance

- Graph does not have a canonical order of the nodes!

Order plan 1



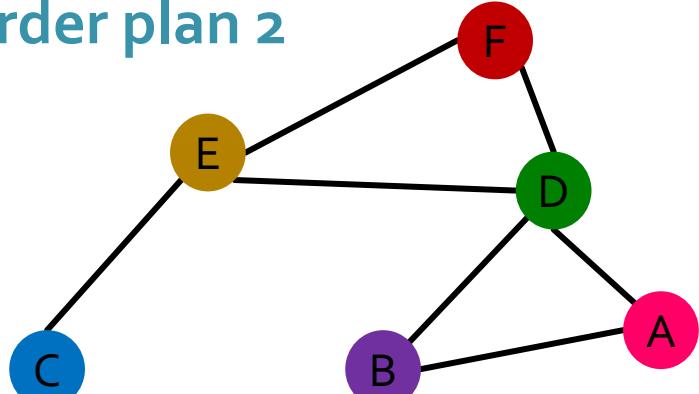
Node features X_1



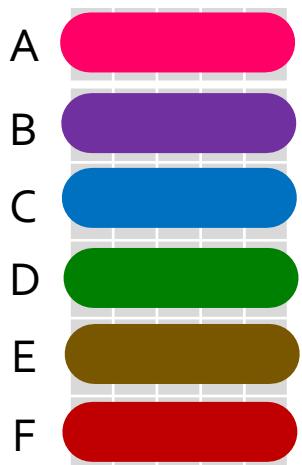
Adjacency matrix A_1

	A	B	C	D	E	F
A	grey	blue	blue	blue	blue	grey
B	blue	grey	blue	blue	blue	grey
C	blue	blue	grey	blue	blue	blue
D	blue	blue	blue	grey	blue	blue
E	grey	grey	blue	blue	grey	blue
F	grey	grey	blue	blue	blue	grey

Order plan 2



Node features X_2



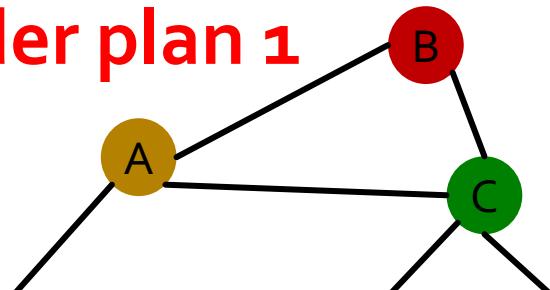
Adjacency matrix A_2

	A	B	C	D	E	F
A	grey	blue	blue	blue	blue	grey
B	blue	grey	grey	blue	blue	blue
C	grey	grey	grey	blue	blue	blue
D	blue	blue	blue	grey	blue	blue
E	grey	grey	blue	blue	grey	blue
F	grey	grey	blue	blue	blue	grey

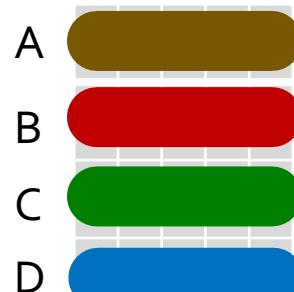
Permutation Invariance

- Graph does not have a canonical order of the nodes!

Order plan 1



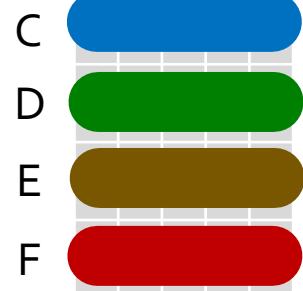
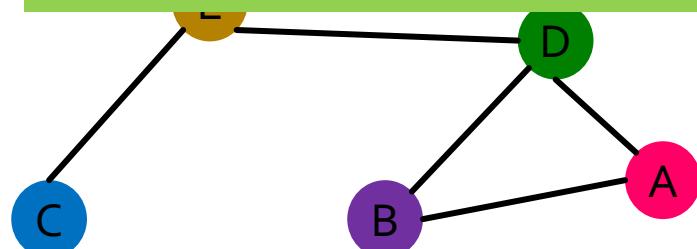
Node feature X_1



Adjacency matrix A_1

	A	B	C	D	E	F
A	Gray	Blue	Blue	Blue	Blue	Gray
B	Blue	Gray	Blue	Blue	Blue	Gray
C	Blue	Blue	Gray	Blue	Blue	Gray
D	Blue	Gray	Gray	Gray	Blue	Gray

Graph and node representations
should be the same for Order plan 1
and Order plan 2



	B	C	D	E	F
B	Blue	Gray	Gray	Blue	Gray
C	Gray	Gray	Gray	Blue	Gray
D	Blue	Blue	Gray	Gray	Blue
E	Gray	Gray	Blue	Gray	Blue
F	Gray	Gray	Gray	Blue	Gray

Permutation Invariance

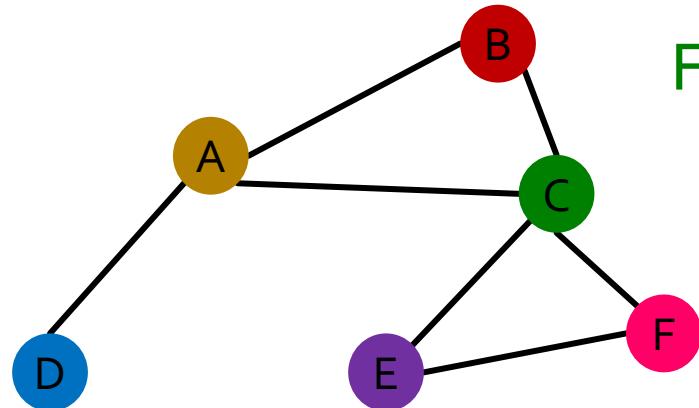
What does it mean by “graph representation is same for two order plans”?

- Consider we learn a function f that maps a graph $G = (A, X)$ to a vector \mathbb{R}^d then

$$f(A_1, X_1) = f(A_2, X_2)$$

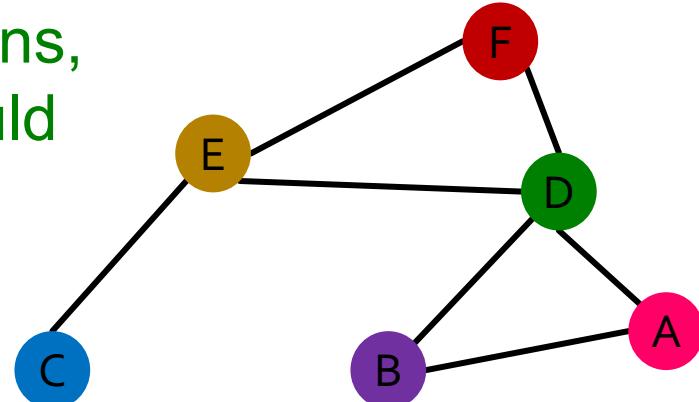
A is the adjacency matrix
 X is the node feature matrix

Order plan 1: A_1, X_1



For two order plans,
output of f should
be the same!

Order plan 2: A_2, X_2



Permutation Invariance

What does it mean by “graph representation is same for two order plans”?

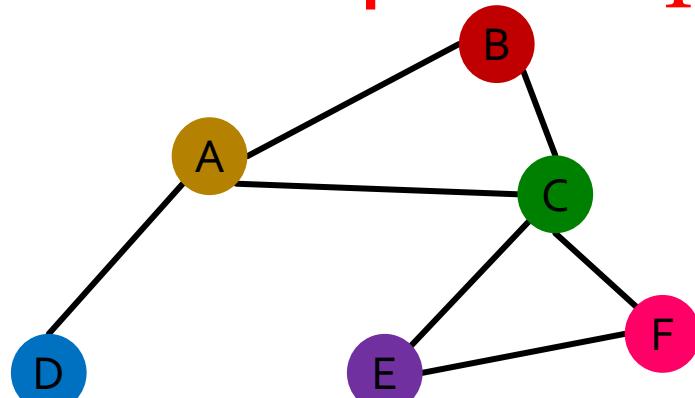
- Consider we learn a function f that maps a graph $G = (A, X)$ to a vector \mathbb{R}^d .
 A is the adjacency matrix
 X is the node feature matrix
- Then, if $f(A_i, X_i) = f(A_j, X_j)$ for any order plan i and j , we formally say f is a **permutation invariant function**.

For a graph with m nodes, there are $m!$ different order plans.

Permutation Equivariance

Similarly for node representation: We learn a function f that maps nodes of G to a matrix $\mathbb{R}^{m \times d}$.

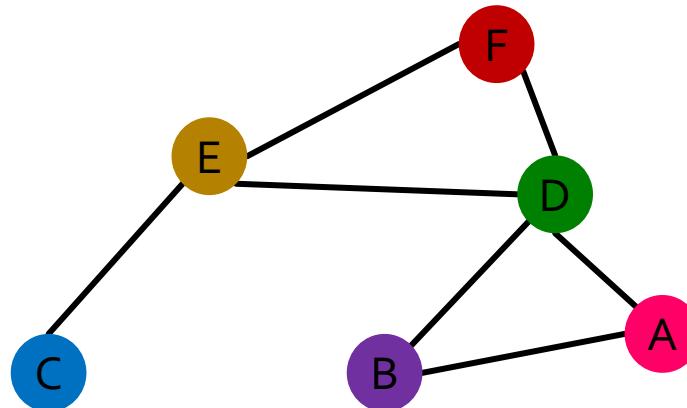
Order plan 1: A_1, X_1



$$f(A_1, X_1) =$$

A		
B		
C		
D		
E		
F		

Order plan 2: A_2, X_2



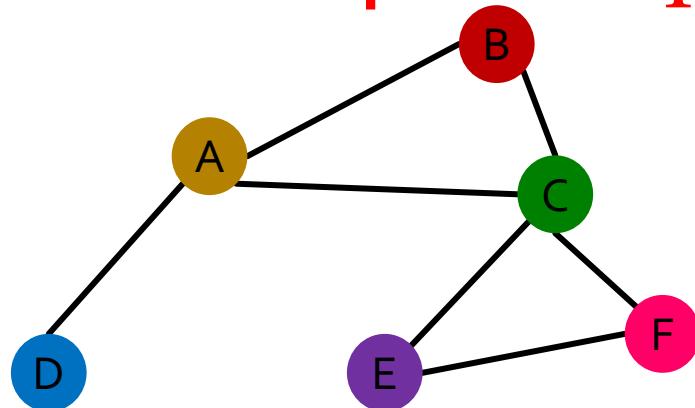
$$f(A_2, X_2) =$$

A		
B		
C		
D		
E		
F		

Permutation Equivariance

Similarly for node representation: We learn a function f that maps nodes of G to a matrix $\mathbb{R}^{m \times d}$.

Order plan 1: A_1, X_1

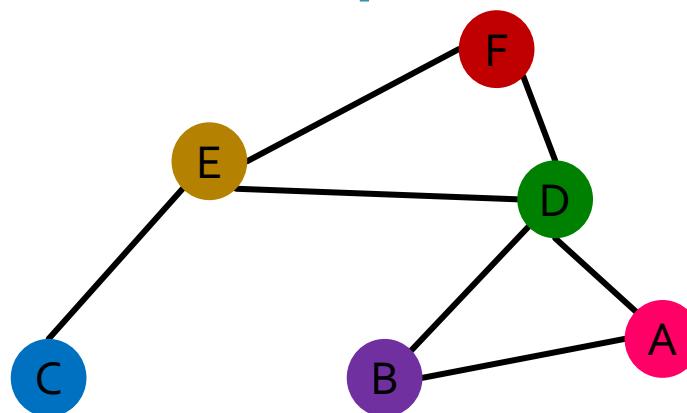


Representation vector
of the brown node A

A	[brown]	[brown]
B	[red]	[red]
C	[green]	[green]
D	[blue]	[blue]
E	[purple]	[purple]
F	[pink]	[pink]

$$f(A_1, X_1) =$$

Order plan 2: A_2, X_2



$$f(A_2, X_2) =$$

For two order plans, the vector of node
at the same position is the same!

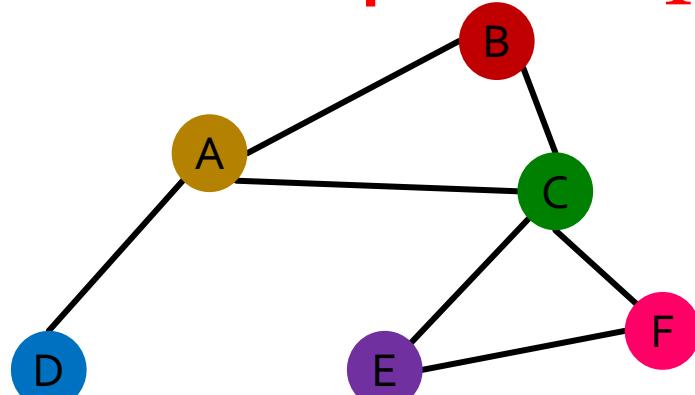
A	[red]	[red]
B	[purple]	[purple]
C	[blue]	[blue]
D	[green]	[green]
E	[brown]	[brown]
F	[pink]	[pink]

Representation vector
of the brown node E

Permutation Equivariance

Similarly for node representation: We learn a function f that maps nodes of G to a matrix $\mathbb{R}^{m \times d}$.

Order plan 1: A_1, X_1

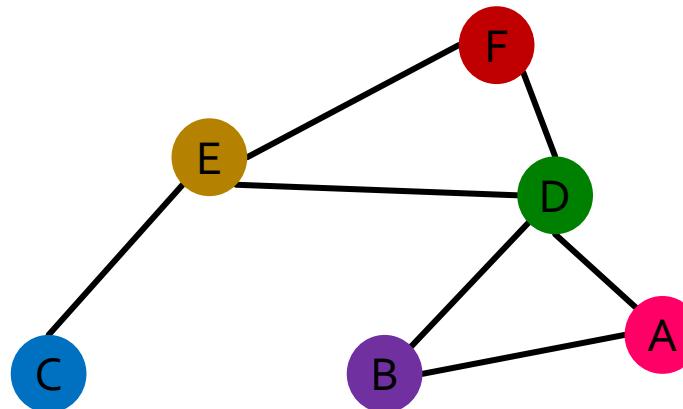


$$f(A_1, X_1) = \begin{matrix} & \text{A} & \text{B} & \text{C} & \text{D} & \text{E} & \text{F} \\ \text{A} & \text{B} & \text{C} & \text{D} & \text{E} & \text{F} & \\ \boxed{\text{B}} & \boxed{\text{C}} & \boxed{\text{C}} & \boxed{\text{D}} & \boxed{\text{E}} & \boxed{\text{F}} & \\ & \text{B} & \text{C} & \text{D} & \text{E} & \text{F} & \\ & \text{B} & \text{C} & \text{D} & \text{E} & \text{F} & \end{matrix}$$

Representation vector of the brown node C

For two order plans, the vector of node at the same position is the same!

Order plan 2: A_2, X_2



$$f(A_2, X_2) = \begin{matrix} & \text{A} & \text{B} & \text{C} & \text{D} & \text{E} & \text{F} \\ \text{A} & \text{B} & \text{C} & \text{D} & \text{E} & \text{F} & \\ \boxed{\text{B}} & \boxed{\text{C}} & \boxed{\text{D}} & \boxed{\text{E}} & \boxed{\text{F}} & \boxed{\text{A}} & \\ & \text{B} & \text{C} & \text{D} & \text{E} & \text{F} & \\ & \text{B} & \text{C} & \text{D} & \text{E} & \text{F} & \end{matrix}$$

Representation vector of the brown node D

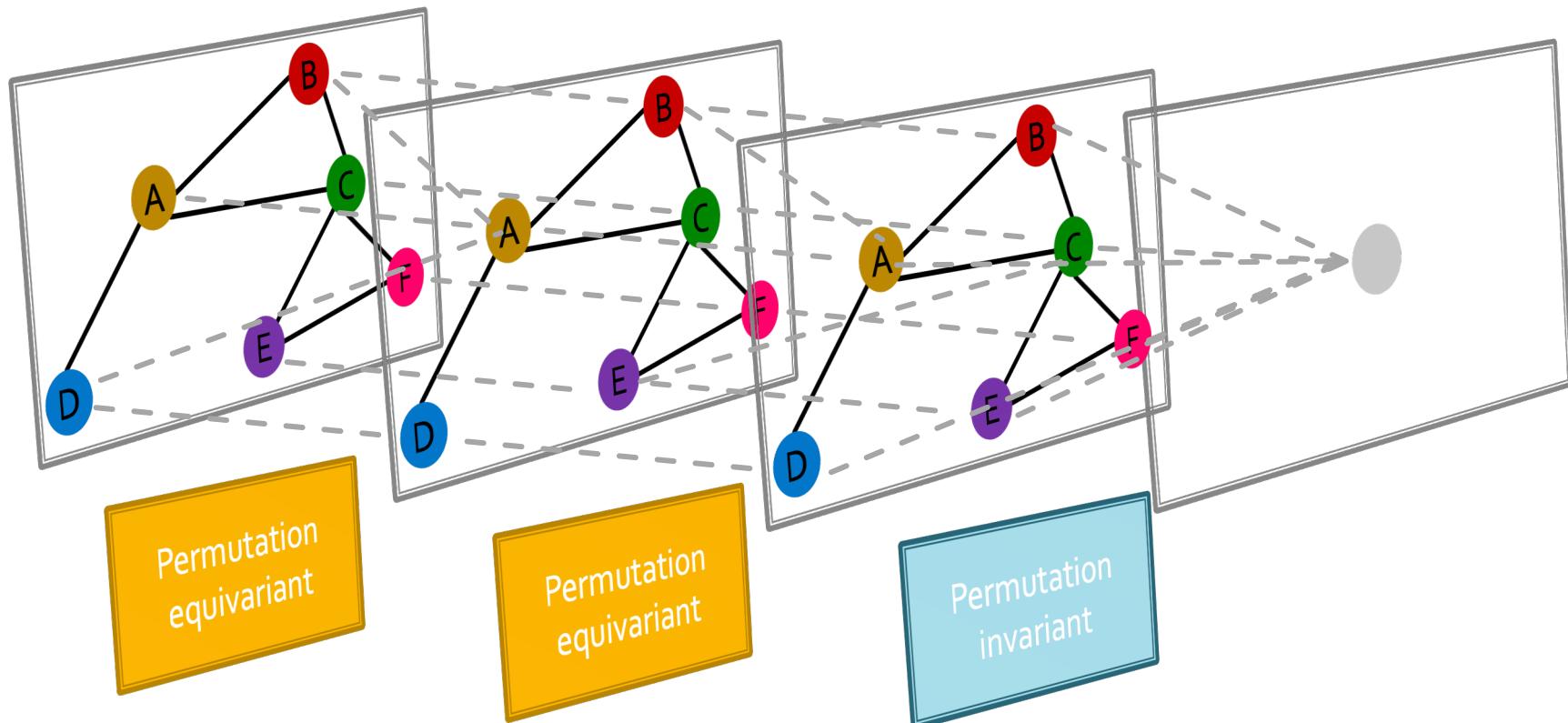
Permutation Equivariance

For node representation

- Consider we learn a function f that maps a graph $G = (A, X)$ to a matrix $\mathbb{R}^{m \times d}$
 - graph has m nodes, each row is the embedding of a node.
- Similarly, if this property holds for any pair of order plan i and j , we say f is a **permutation equivariant function**.

Graph Neural Network Overview

- Graph neural networks consist of multiple permutation equivariant / invariant functions.

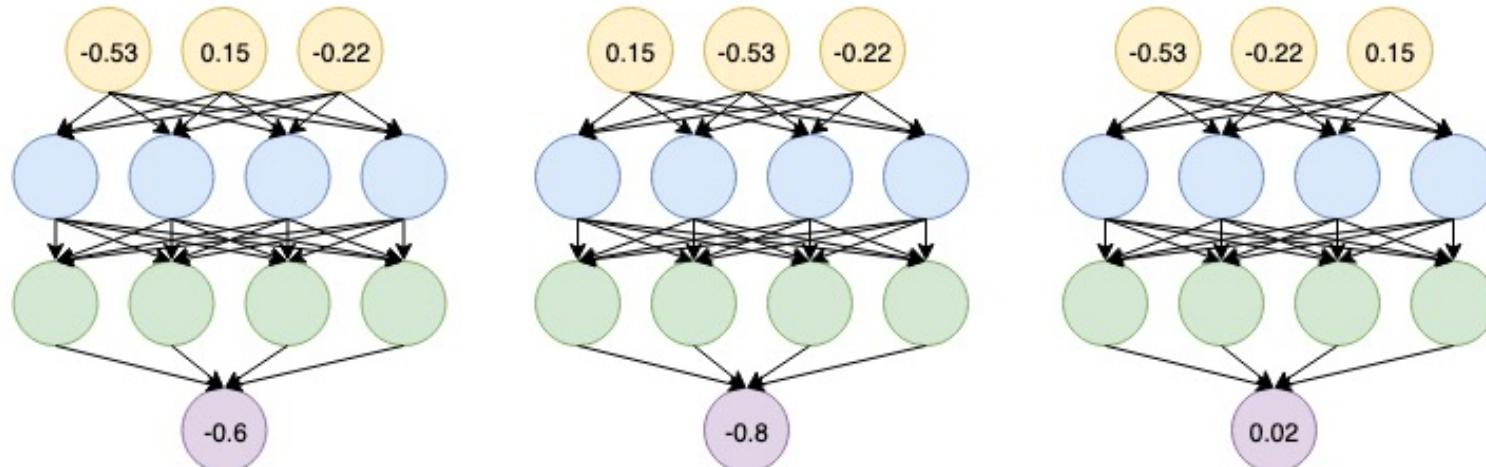


Graph Neural Network Overview

Are other neural network architectures, e.g.,
MLPs, permutation invariant / equivariant?

- No.

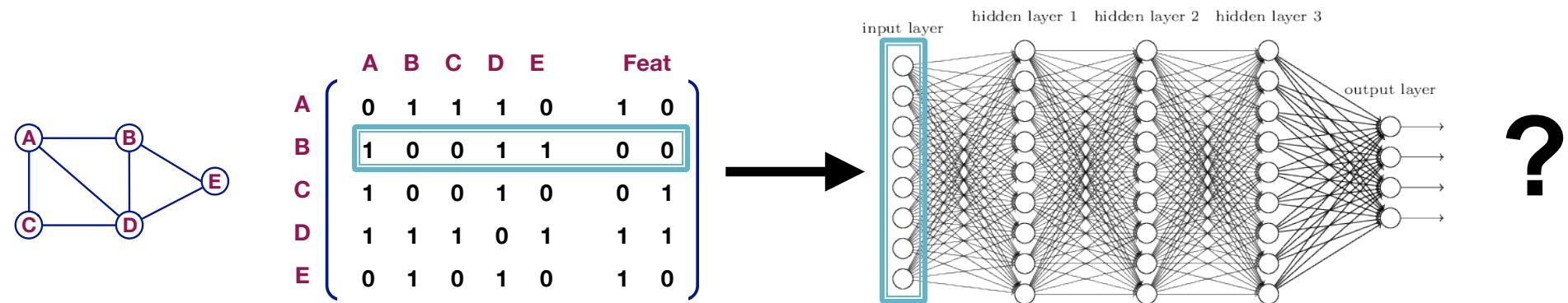
Switching the order of the
input leads to different
outputs!



Graph Neural Network Overview

Are other neural network architectures, e.g.,
MLPs, permutation invariant / equivariant?

- No.

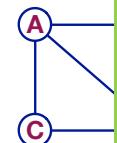


This explains why **the naïve MLP approach fails for graphs!**

Graph Neural Network Overview

- Are any neural network architecture, e.g.,

Next: Design graph neural networks that are permutation invariant / equivariant by **passing and aggregating information from neighbors!**



Outline of Today's Lecture

1. Basics of deep learning



2. Deep learning for graphs



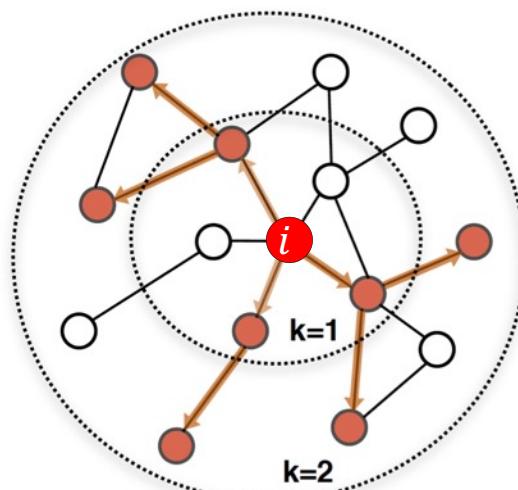
3. Graph Convolutional Networks



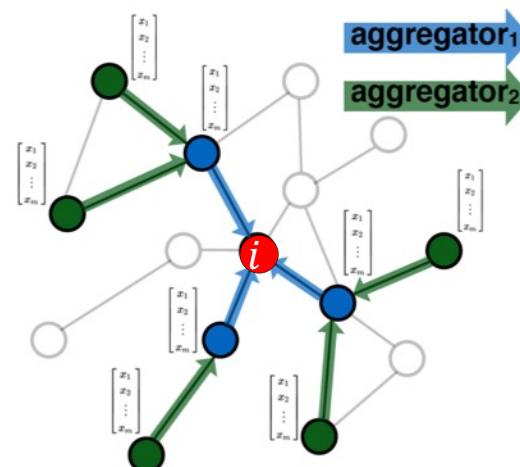
4. GNNs subsume CNNs and
Transformers

Graph Convolutional Networks

Idea: Node's neighborhood defines a computation graph



Determine node computation graph

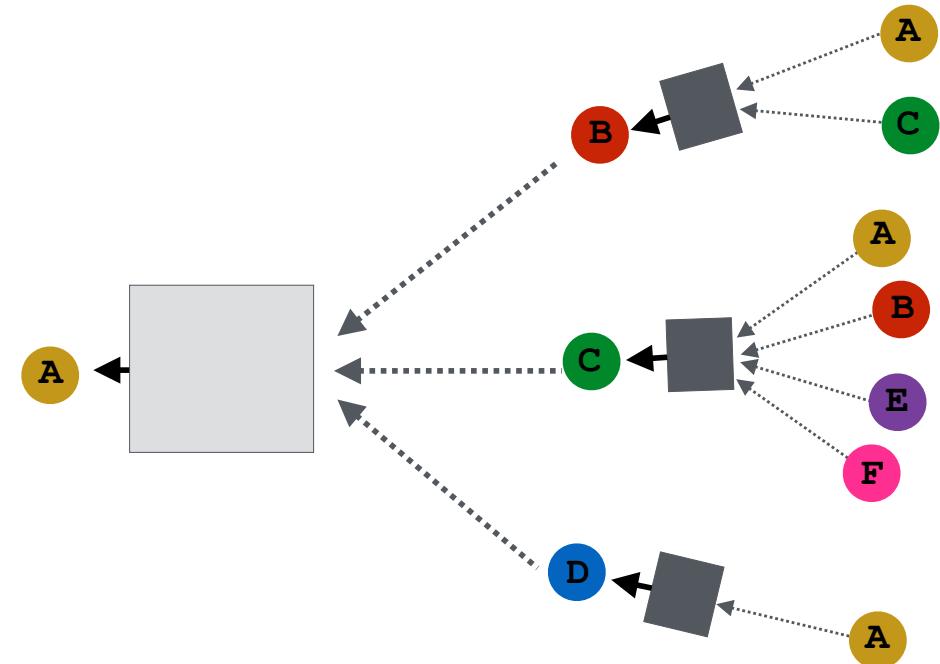
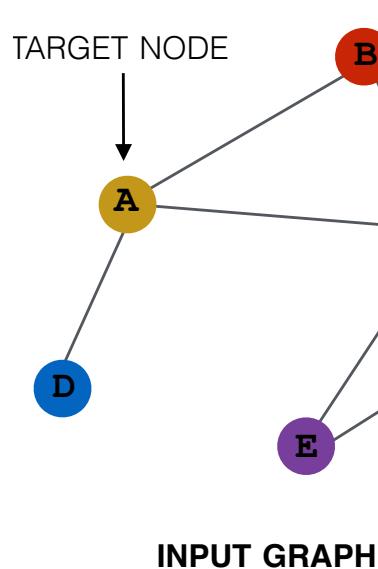


Propagate and transform information

Learn how to propagate information across the graph to compute node features

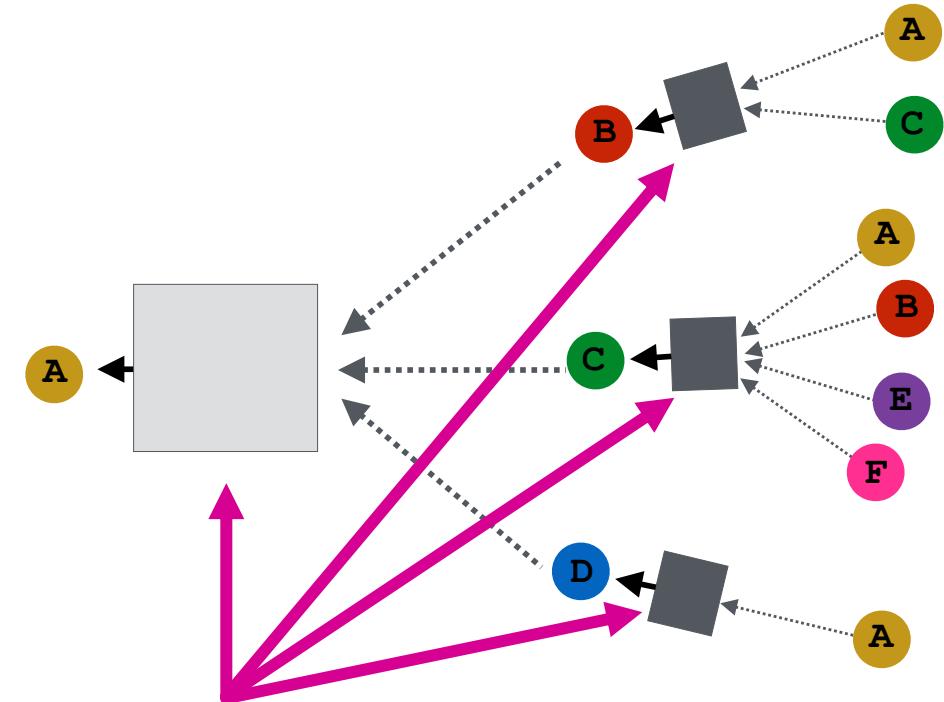
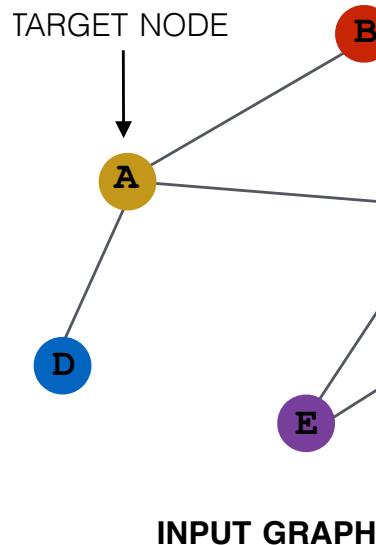
Idea: Aggregate Neighbors

- **Key idea:** Generate node embeddings based on **local network neighborhoods**



Idea: Aggregate Neighbors

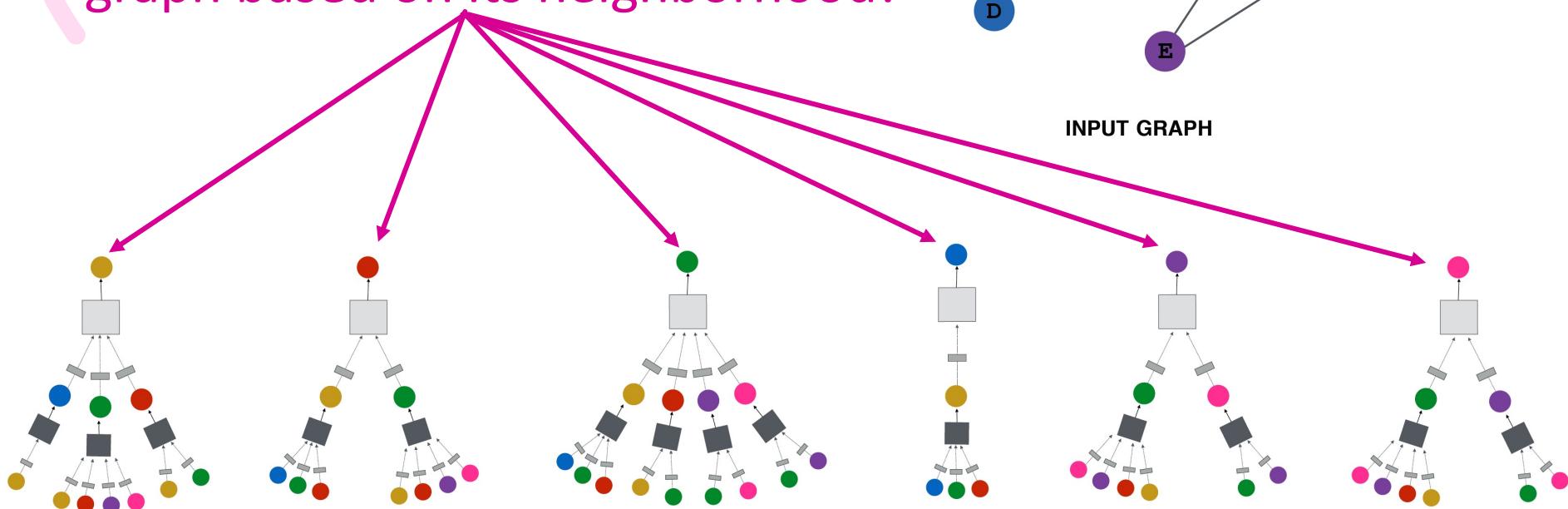
- **Intuition:** Nodes aggregate information from their neighbors using neural networks



Idea: Aggregate Neighbors

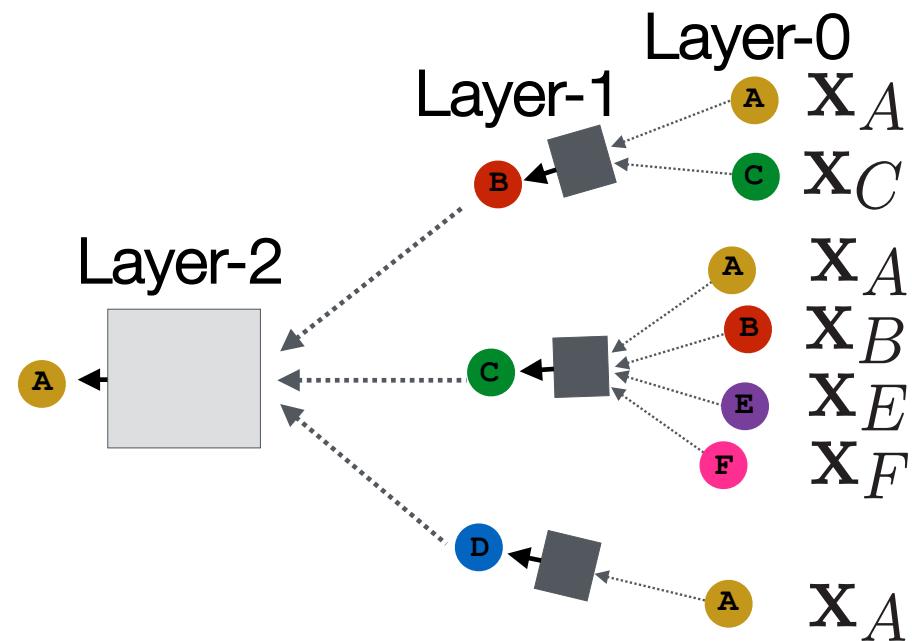
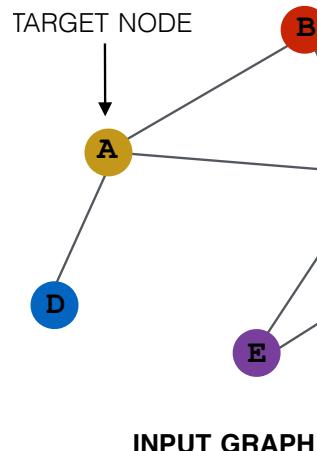
- **Intuition:** Network neighborhood defines a computation graph

Every node defines a computation graph based on its neighborhood!



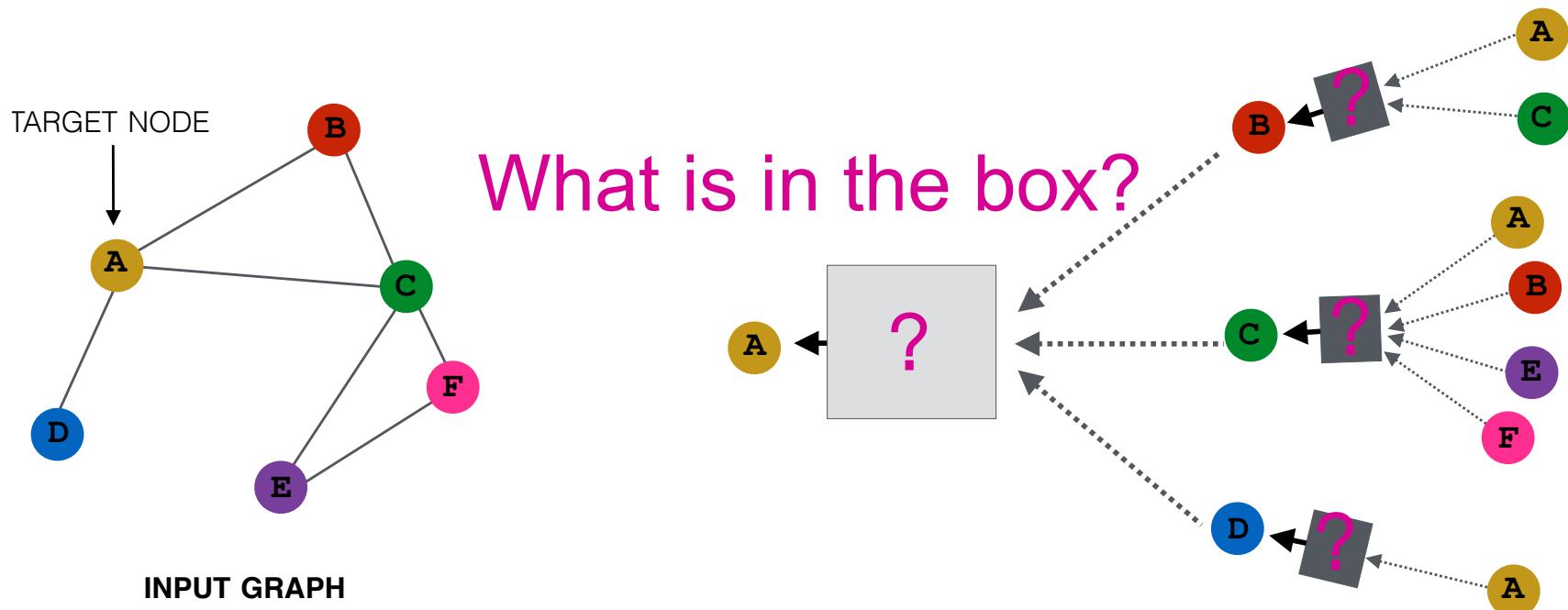
Deep Model: Many Layers

- Model can be **of arbitrary depth**:
 - Nodes have embeddings at each layer
 - Layer-0 embedding of node v is its input feature, x_v
 - Layer- k embedding gets information from nodes that are k hops away



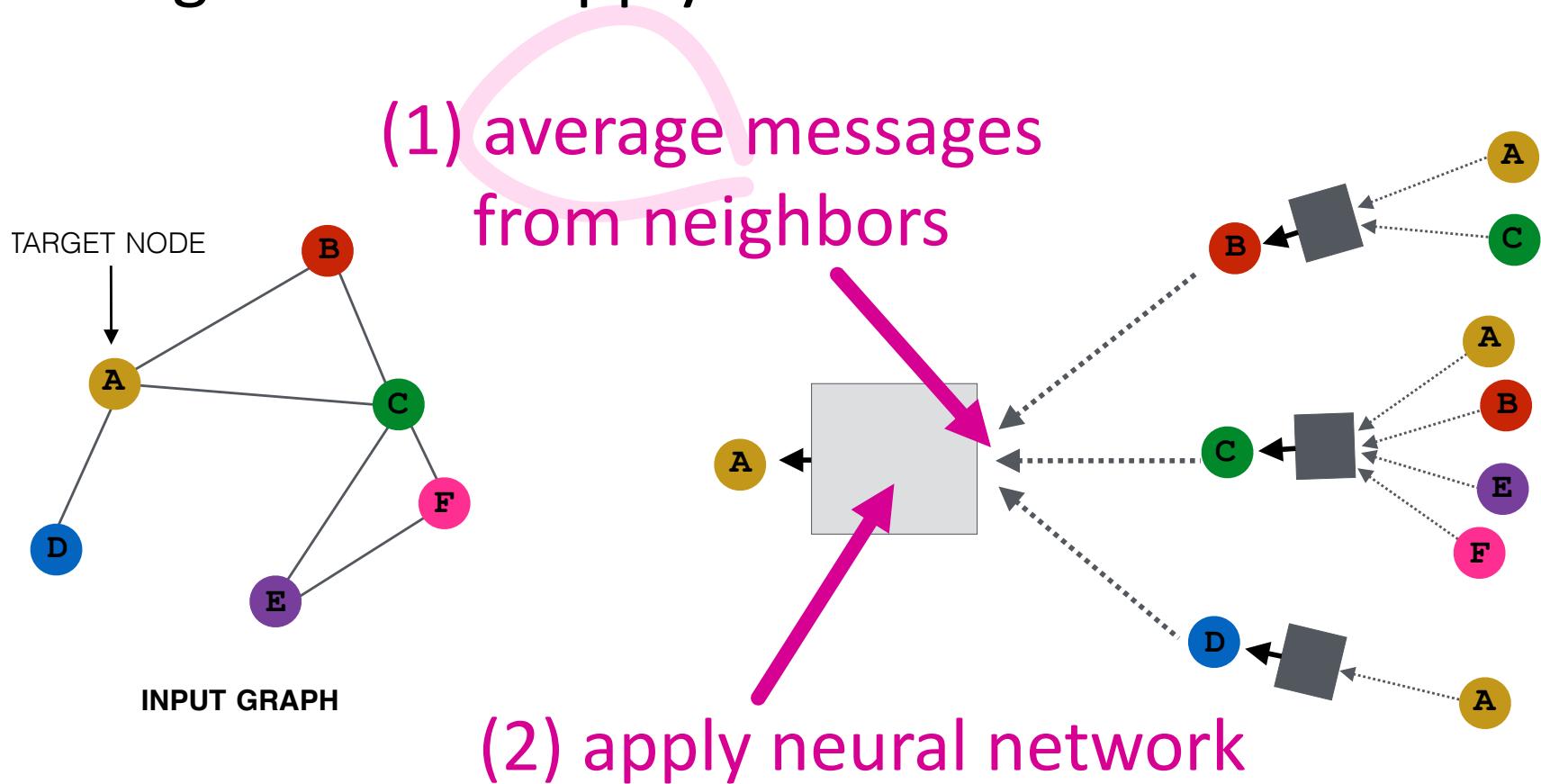
Neighborhood Aggregation

- **Neighborhood aggregation:** Key distinctions are in how different approaches aggregate information across the layers



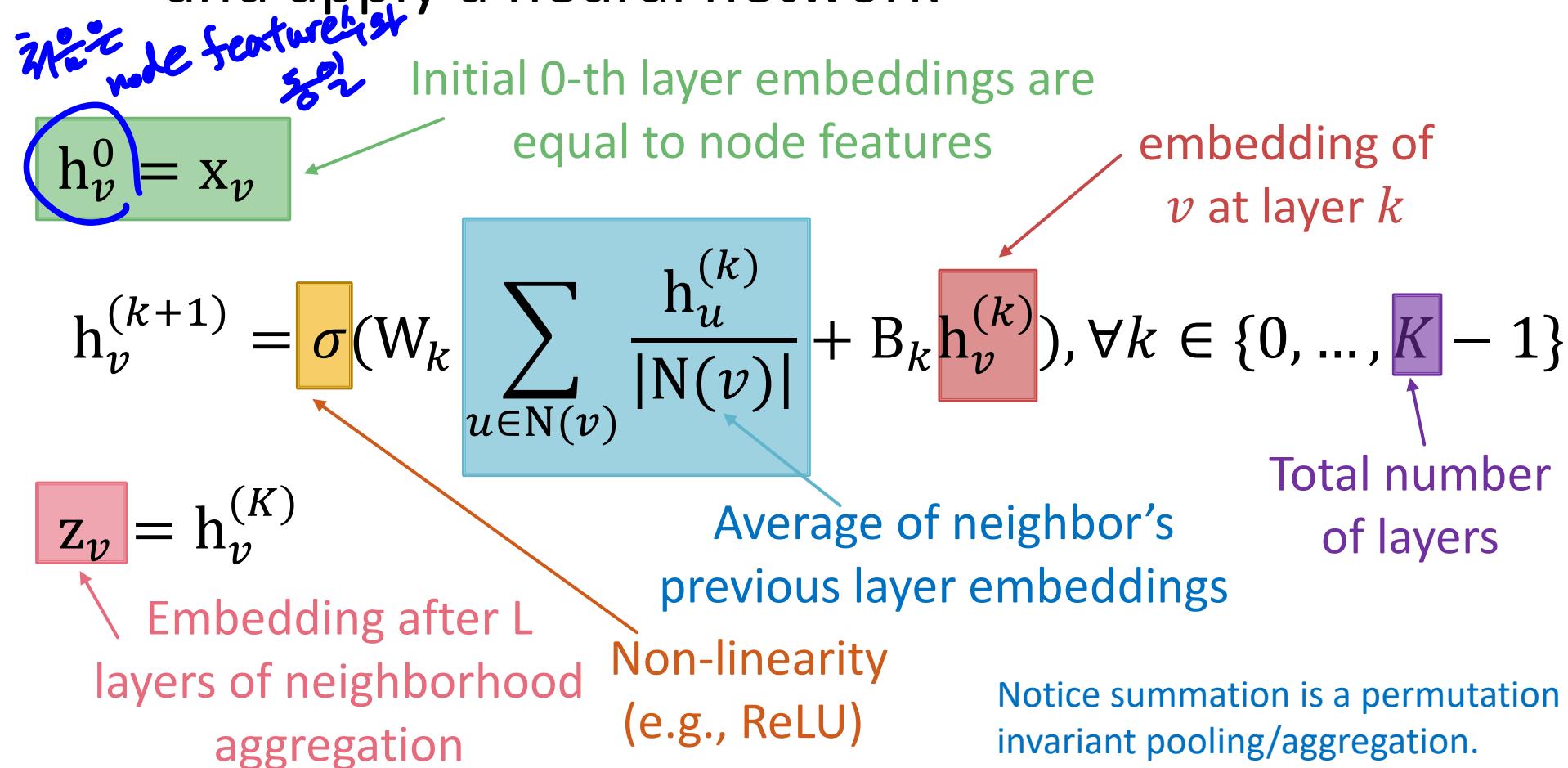
Neighborhood Aggregation

- **Basic approach:** Average information from neighbors and apply a neural network



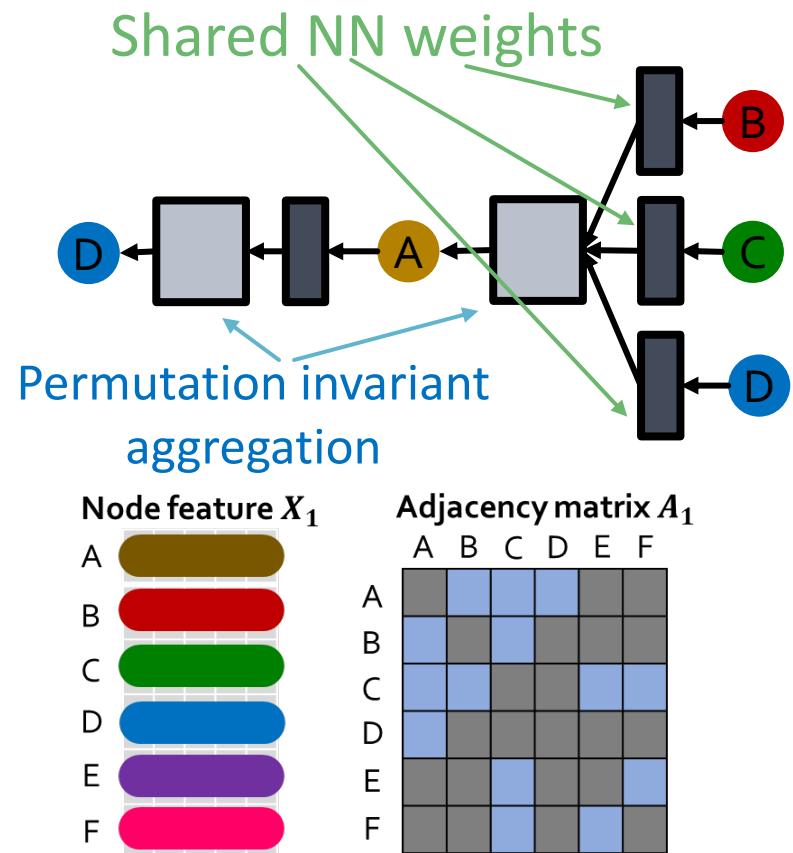
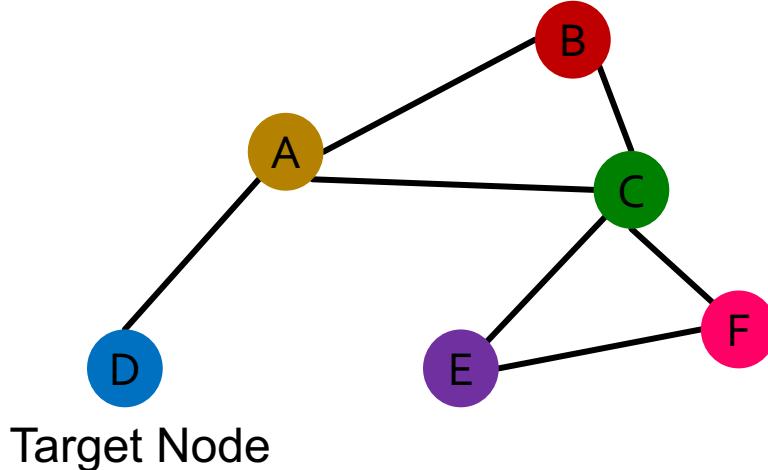
The Math: Deep Encoder

- **Basic approach:** Average neighbor messages and apply a neural network



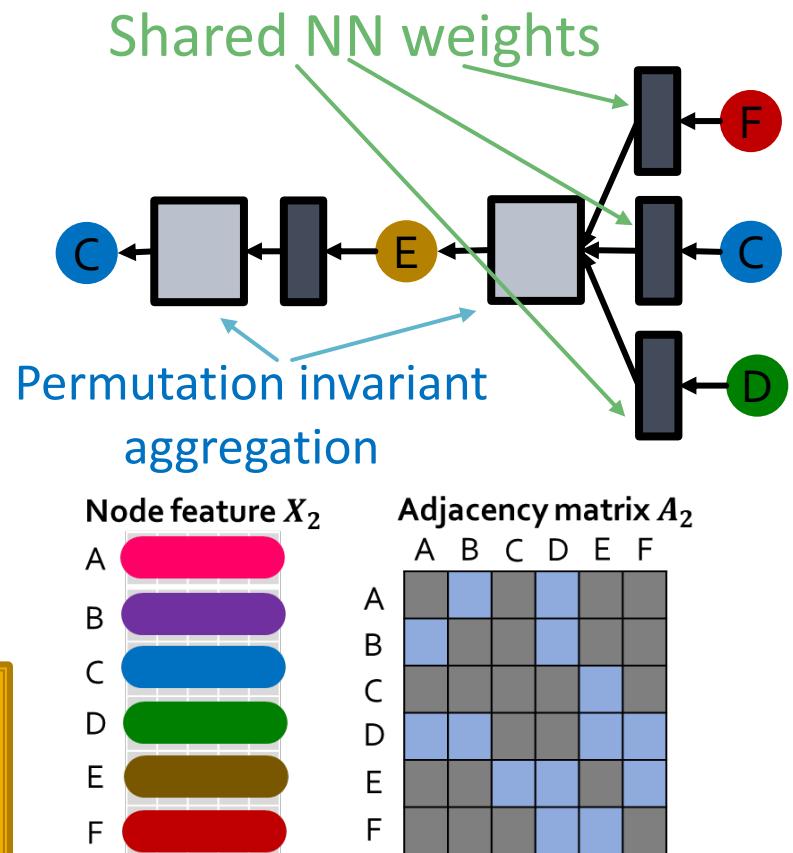
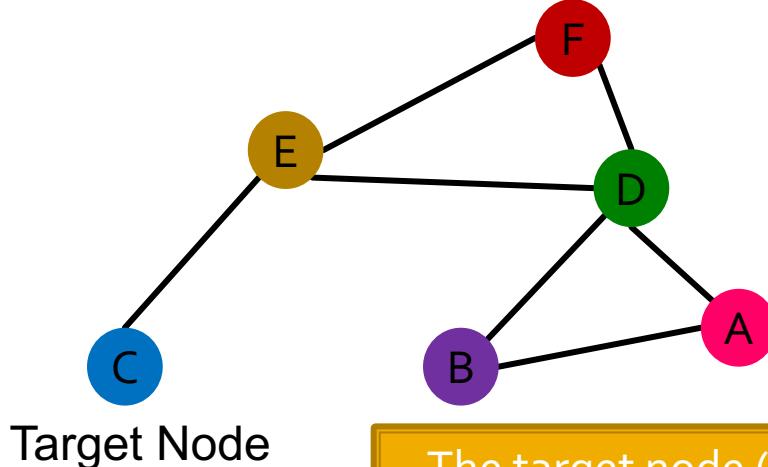
Equivariant Property

Message passing and neighbor aggregation in graph convolution networks is permutation equivariant.



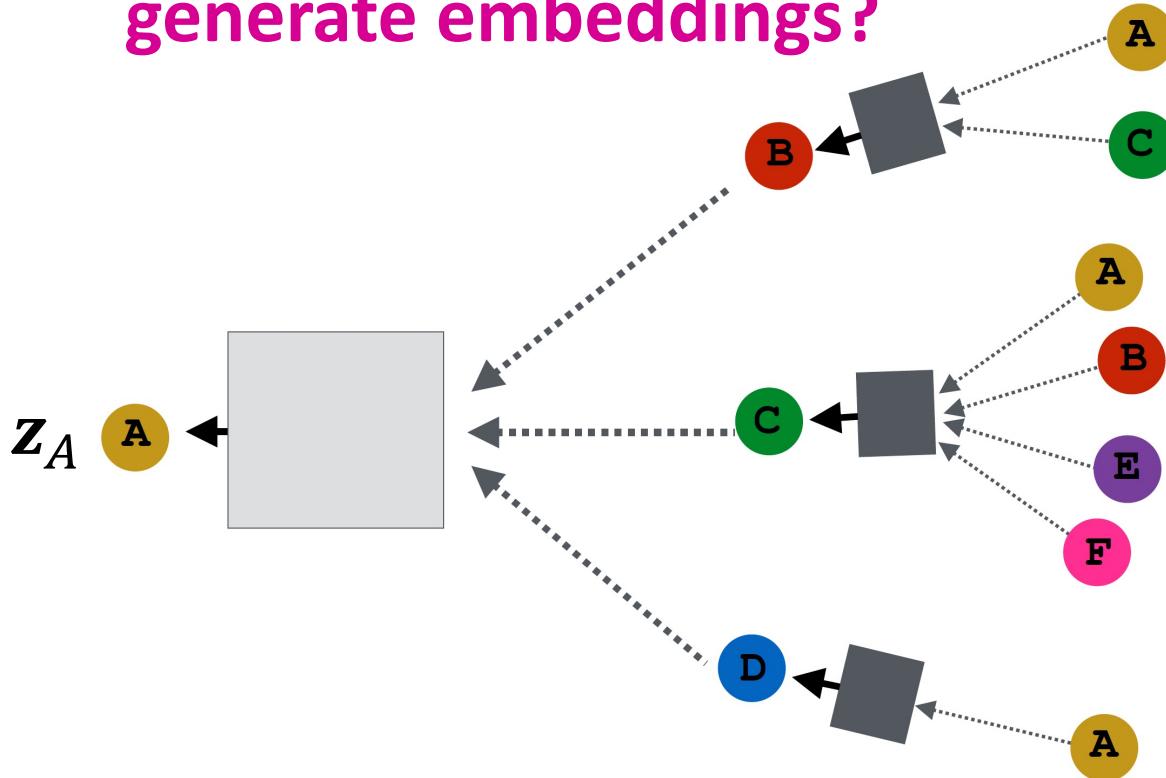
Equivariant Property

Message passing and neighbor aggregation in graph convolution networks is permutation equivariant.



Training the Model

How do we train the GCN to generate embeddings?



Need to define a loss function on the embeddings.

Model Parameters

Trainable weight matrices
(i.e., what we learn)

$$\begin{aligned} h_v^{(0)} &= x_v \\ h_v^{(k+1)} &= \sigma(W_k \sum_{u \in N(v)} \frac{h_u^{(k)}}{|N(v)|} + B_k h_v^{(k)}), \forall k \in \{0..K-1\} \\ z_v &= h_v^{(K)} \end{aligned}$$

Final node embedding

We can feed these **embeddings into any loss function** and run SGD to **train the weight parameters**

h_v^k : the hidden representation of node v at layer k

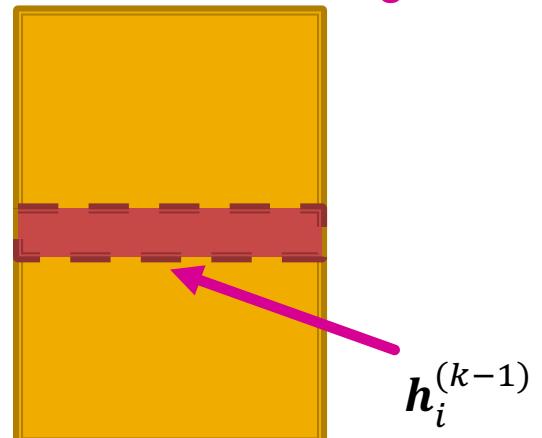
- W_k : weight matrix for neighborhood aggregation
- B_k : weight matrix for transforming hidden vector of self

Matrix Formulation (1)

- Many aggregations can be performed efficiently by (sparse) matrix operations
- Let $H^{(k)} = [h_1^{(k)} \dots h_{|V|}^{(k)}]^T$ Matrix of hidden embeddings $H^{(k-1)}$
- Then: $\sum_{u \in N_v} h_u^{(k)} = A_{v,:} H^{(k)}$
- Let D be diagonal matrix where $D_{v,v} = \text{Deg}(v) = |N(v)|$
 - The inverse of D : D^{-1} is also diagonal:
 $D_{v,v}^{-1} = 1/|N(v)|$
- Therefore,

$$\sum_{u \in N(v)} \frac{h_u^{(k-1)}}{|N(v)|}$$

$H^{(k+1)} = \underbrace{D^{-1}}_{\text{Adjacency.}} \underbrace{A}_{\text{averaging.}} H^{(k)}$

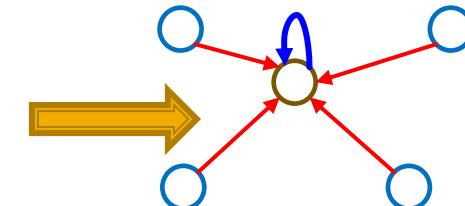


Matrix Formulation (2)

- Re-writing update function in matrix form:

$$H^{(k+1)} = \sigma(\tilde{A}H^{(k)}W_k^T + H^{(k)}B_k^T)$$

where $\tilde{A} = D^{-1}A$



$$H^{(k)} = [h_1^{(k)} \dots h_{|V|}^{(k)}]^T$$

- Red: neighborhood aggregation
- Blue: self transformation
- In practice, this implies that efficient sparse matrix multiplication can be used (\tilde{A} is sparse)
- **Note:** not all GNNs can be expressed in matrix form, when aggregation function is complex

How to Train A GNN

- Node embedding \mathbf{z}_v is a function of input graph
- **Supervised setting:** we want to minimize the loss \mathcal{L} (see also Slide 15):

$$\min_{\Theta} \mathcal{L}(\mathbf{y}, f(\mathbf{z}_v))$$

- \mathbf{y} : node label
- \mathcal{L} could be L2 if \mathbf{y} is real number, or cross entropy if \mathbf{y} is categorical
- **Unsupervised setting:**
 - No node label available
 - **Use the graph structure as the supervision!**

Unsupervised Training

- “Similar” nodes have similar embeddings

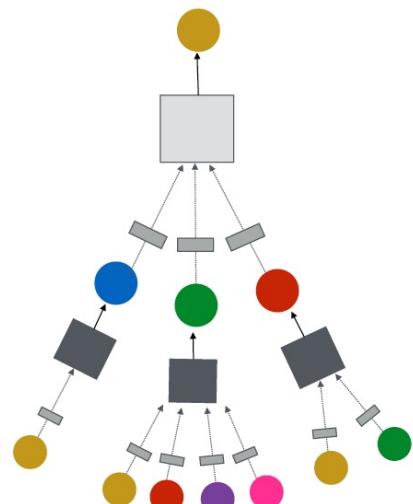
$$\mathcal{L} = \sum_{z_u, z_v} \text{CE}(y_{u,v}, \text{DEC}(z_u, z_v))$$

- Where $y_{u,v} = 1$ when node u and v are **similar**
- **CE** is the cross entropy (Slide 16)
- **DEC** is the decoder such as inner product (Lecture 4)
- **Node similarity** can be anything from Lecture 3, e.g., a loss based on:
 - **Random walks** (node2vec, DeepWalk, struc2vec)
 - **Matrix factorization**
 - **Node proximity in the graph**

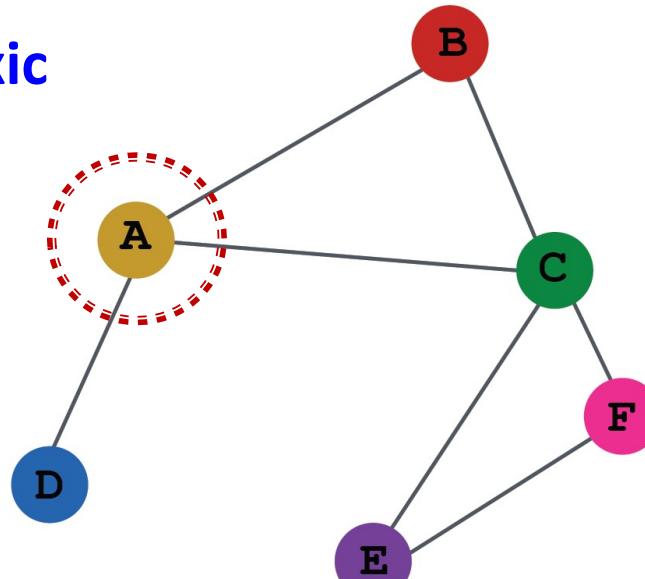
Supervised Training

Directly train the model for a supervised task
(e.g., node classification)

Safe or toxic
drug?



Safe or toxic
drug?

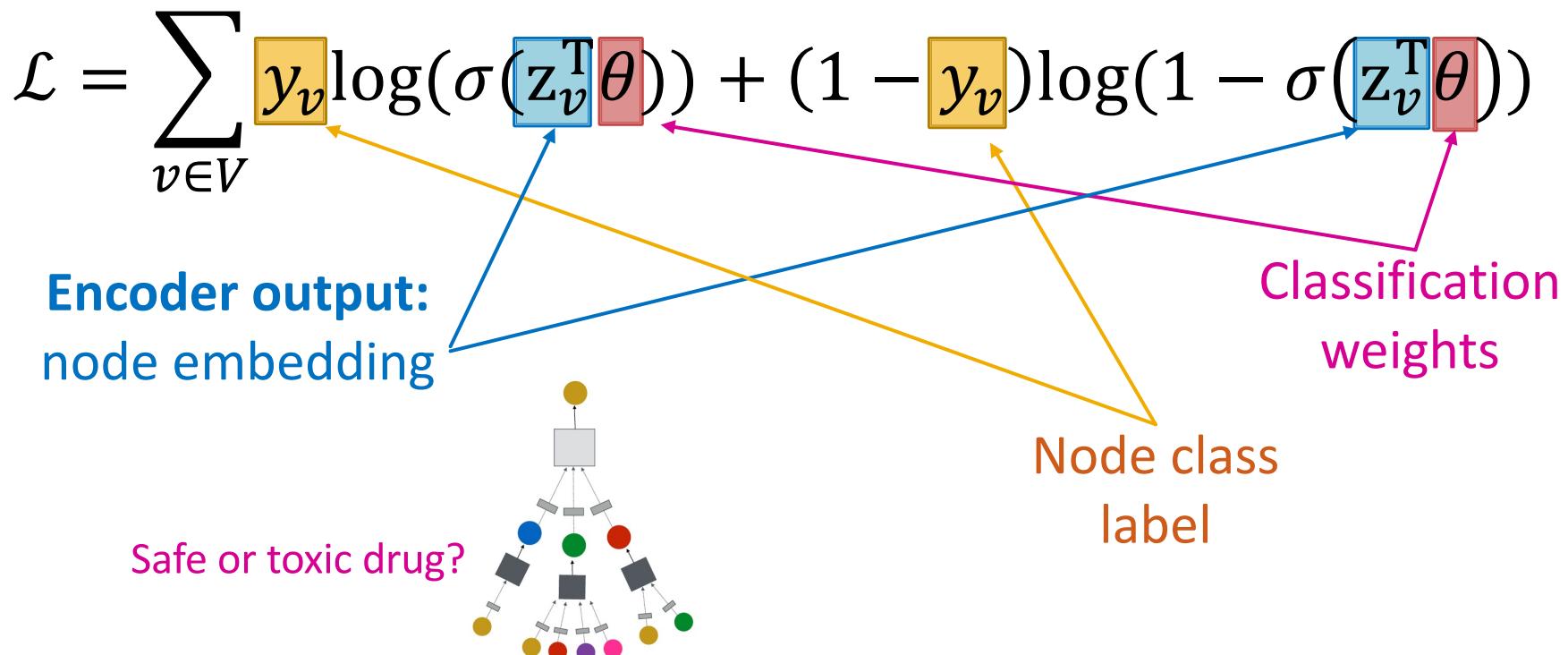


E.g., a drug-drug
interaction network

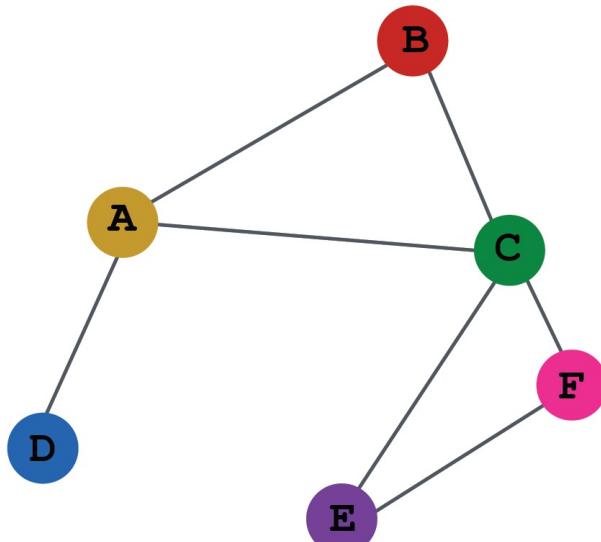
Supervised Training

Directly train the model for a supervised task
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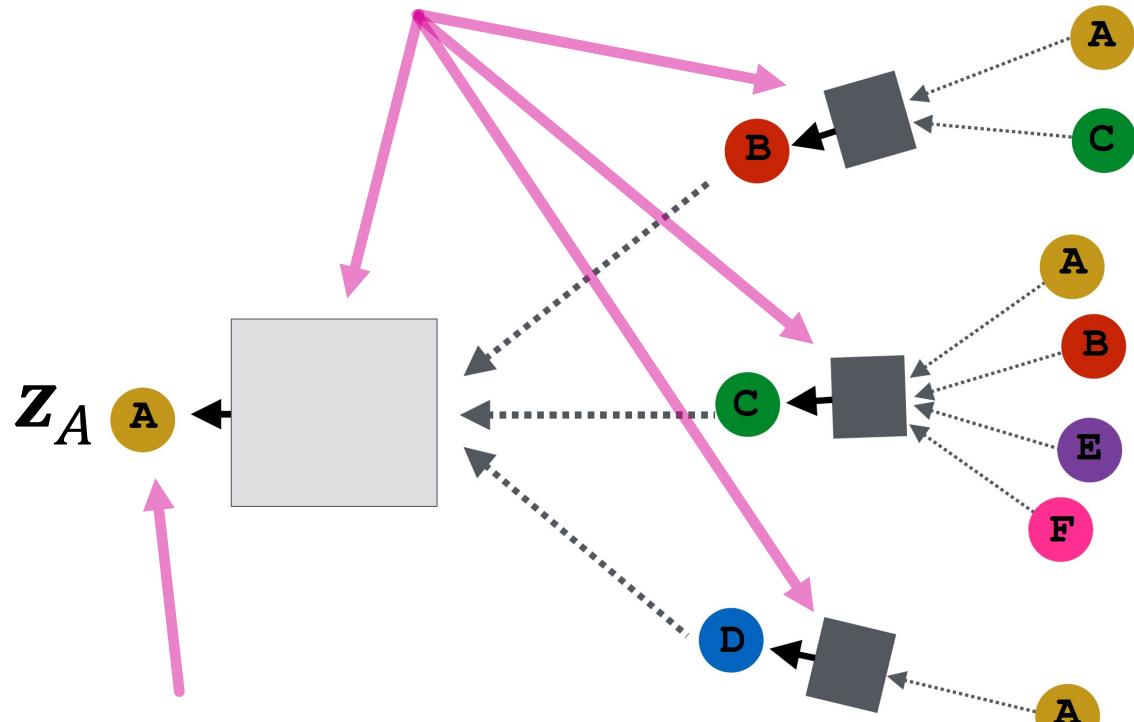
- Use cross entropy loss (Slide 16)



Model Design: Overview

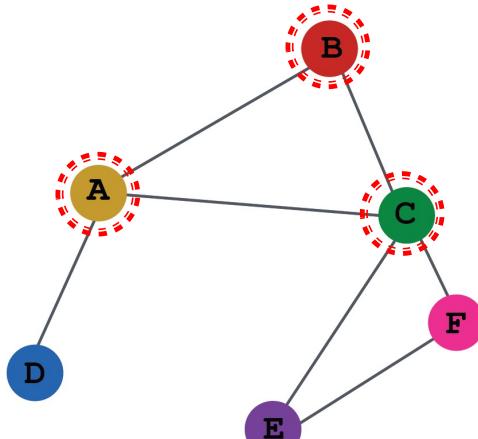


(1) Define a neighborhood aggregation function



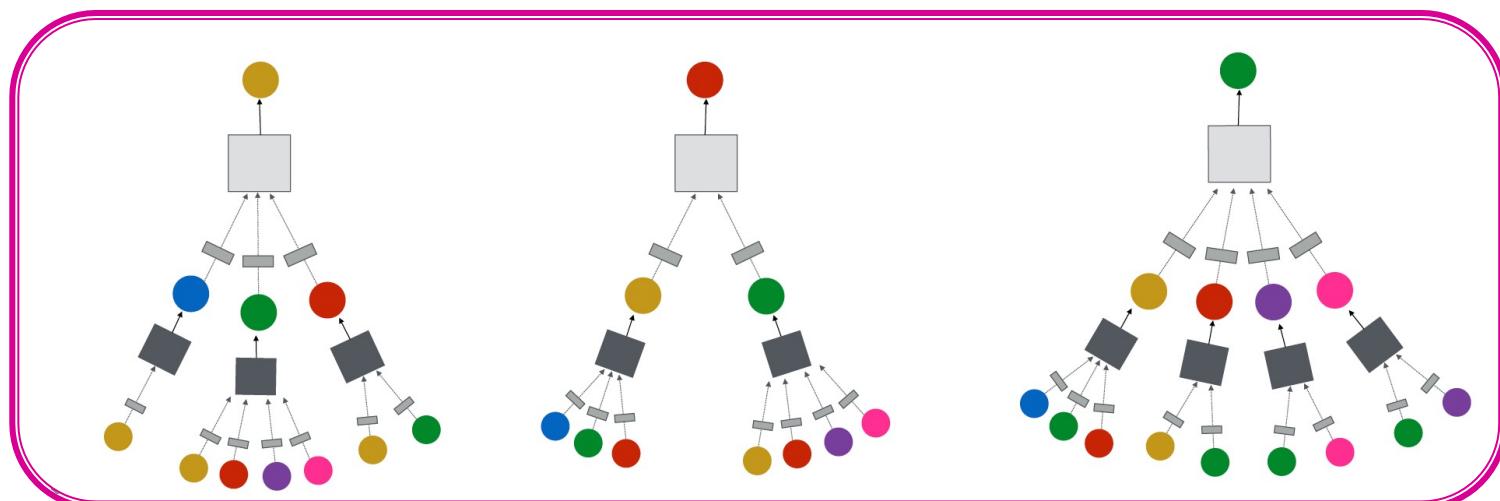
(2) Define a loss function on the embeddings

Model Design: Overview

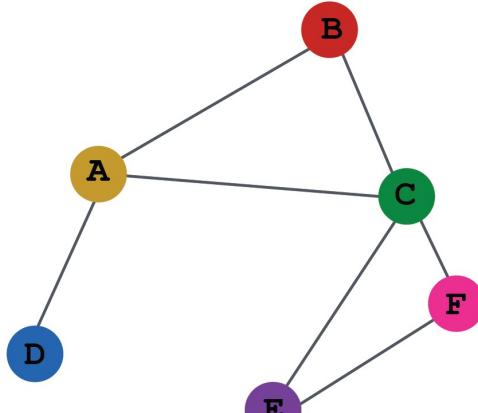


INPUT GRAPH

(3) Train on a set of nodes, i.e.,
a batch of compute graphs



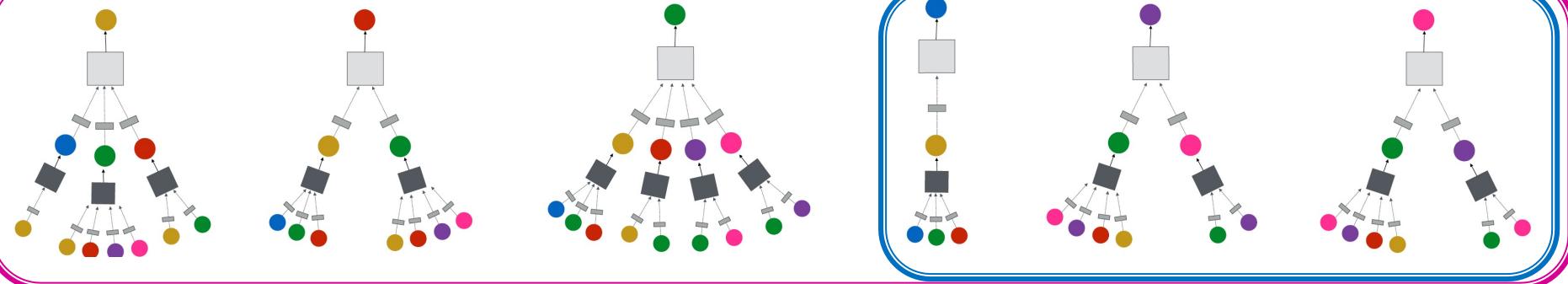
Model Design: Overview



INPUT GRAPH

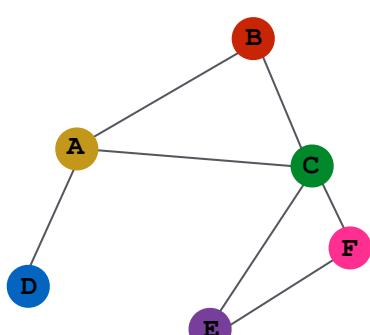
(4) Generate embeddings
for nodes as needed

Even for nodes we never
trained on!

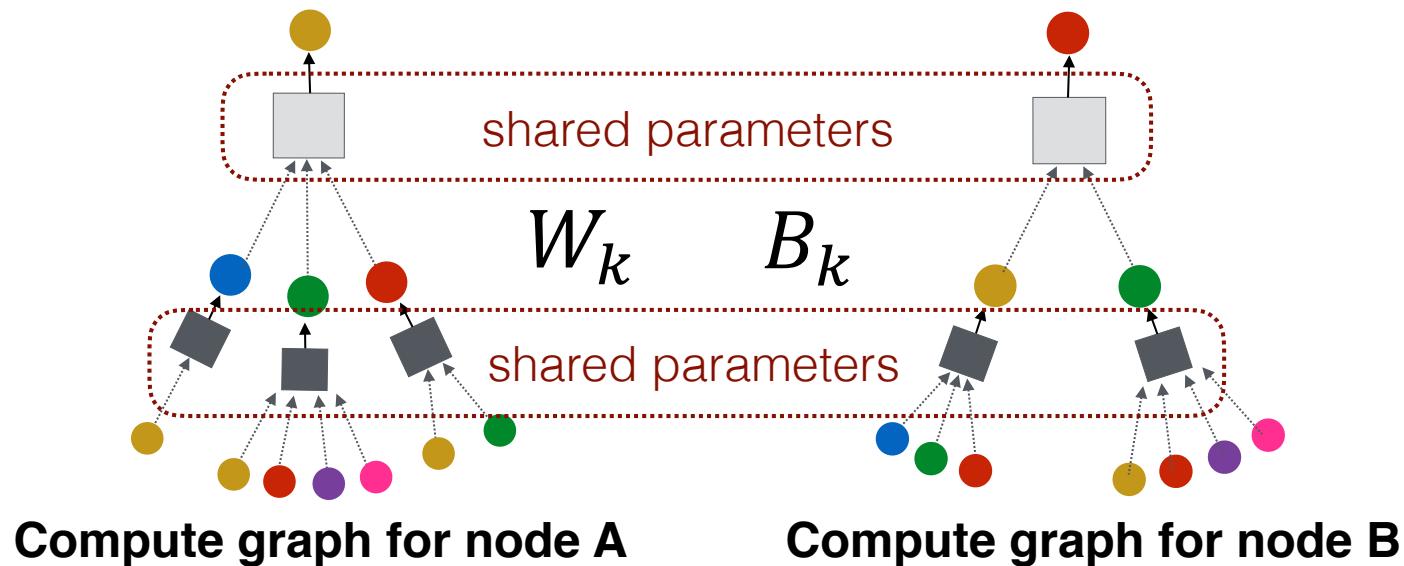


Inductive Capability

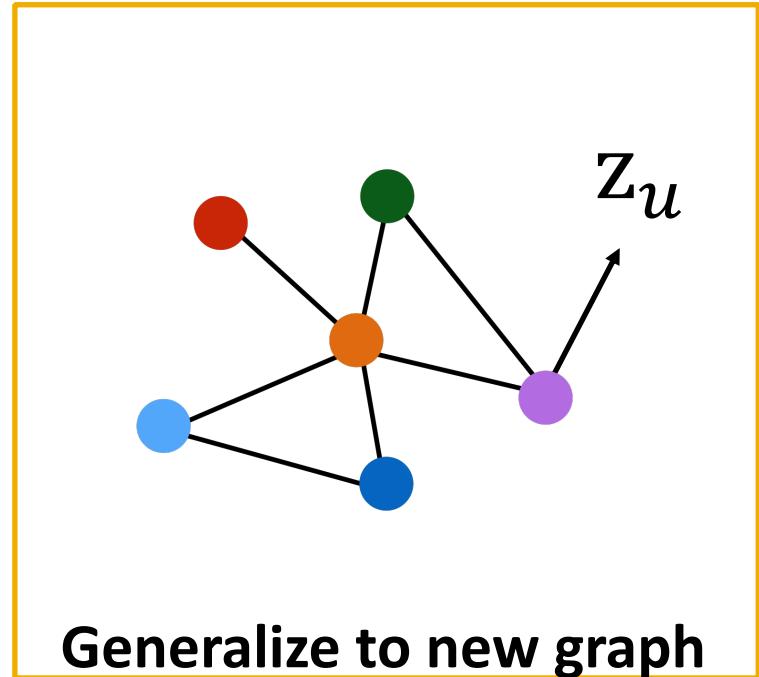
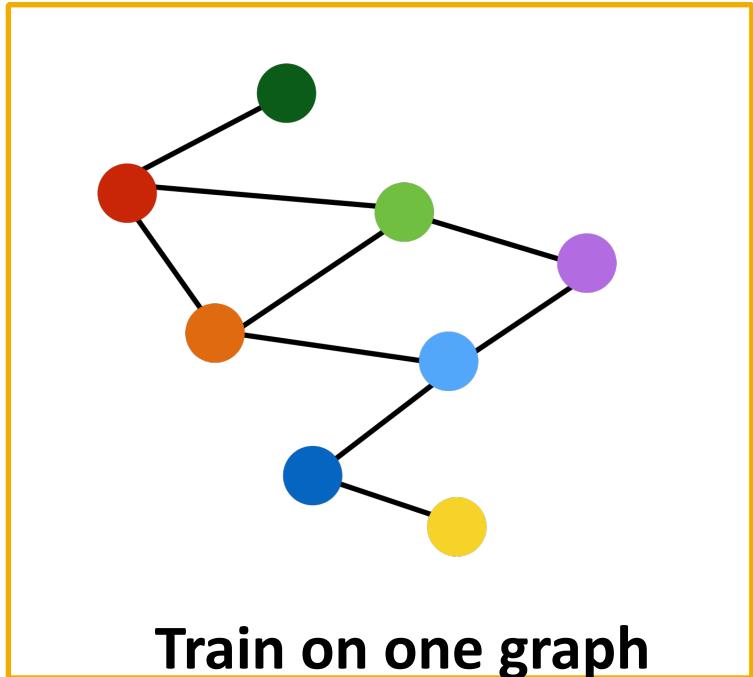
- The same aggregation parameters are shared for all nodes:
 - The number of model parameters is sublinear in $|V|$ and we can **generalize to unseen nodes!**



INPUT GRAPH



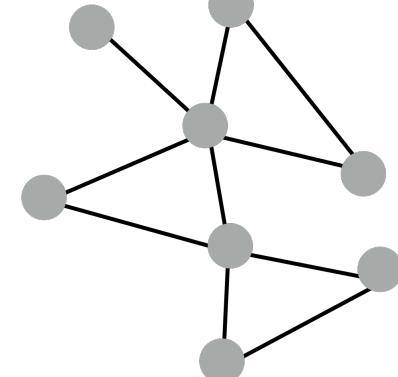
Inductive Capability: New Graphs



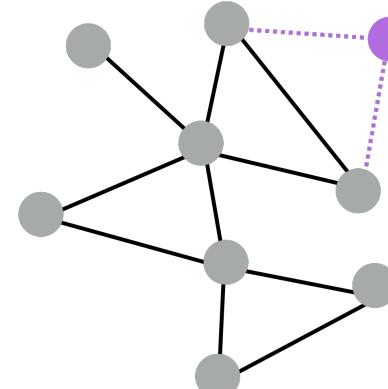
Inductive node embedding → Generalize to entirely unseen graphs

E.g., train on protein interaction graph from model organism A and generate embeddings on newly collected data about organism B

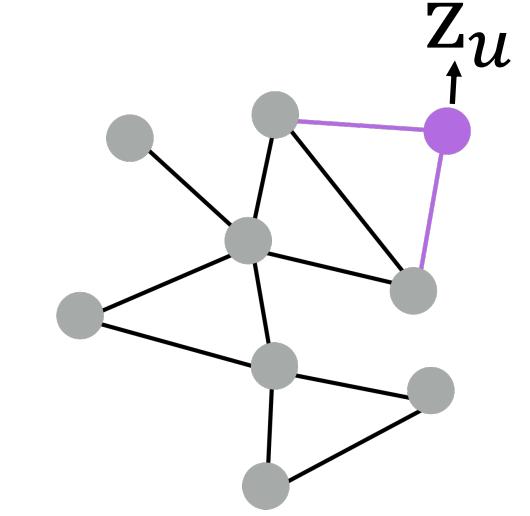
Inductive Capability: New Nodes



Train with snapshot



New node arrives



Generate embedding
for new node

- Many application settings constantly encounter previously unseen nodes:
 - E.g., Reddit, YouTube, Google Scholar
- Need to generate new embeddings “on the fly”

Outline of Today's Lecture

1. Basics of deep learning



2. Deep learning for graphs



3. Graph Convolutional Networks



4. GNNs subsume CNNs and
Transformers

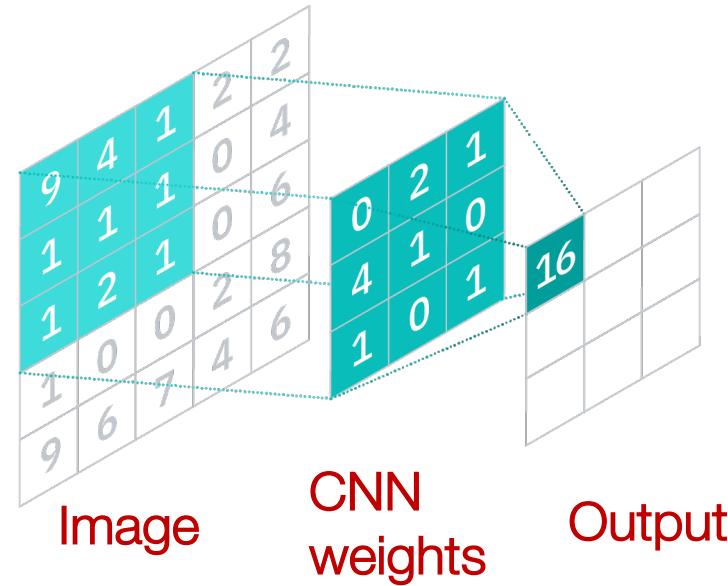
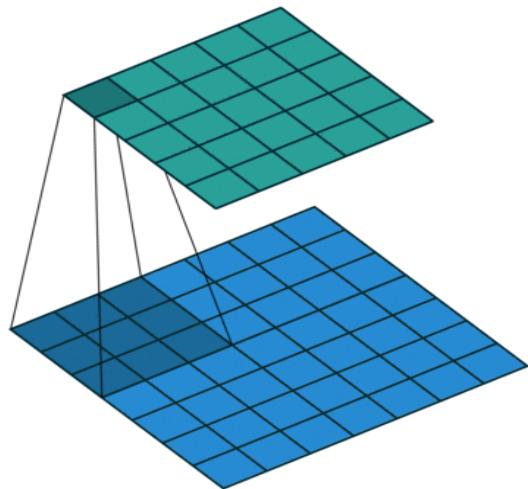


Architecture Comparison

- How does GNNs compare to prominent architectures such as Convolutional Neural Nets, and Transformers?

Convolutional Neural Network

Convolutional neural network (CNN) layer with 3x3 filter:

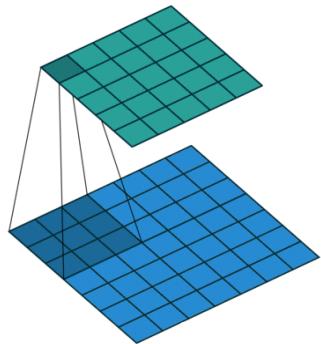


$$\text{CNN formulation: } h_v^{(l+1)} = \sigma(\sum_{u \in N(v) \cup \{v\}} W_l^u h_u^{(l)}), \quad \forall l \in \{0, \dots, L-1\}$$

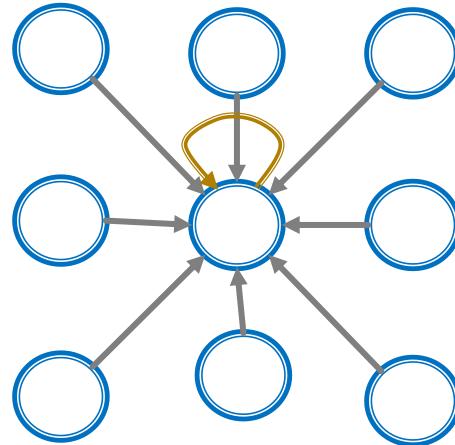
$N(v)$ represents the 8 neighbor pixels of v .

GNN vs. CNN

Convolutional neural network (CNN) layer with 3x3 filter:



Image

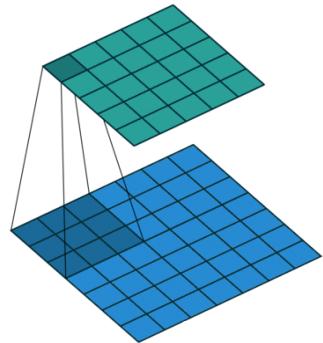


Graph

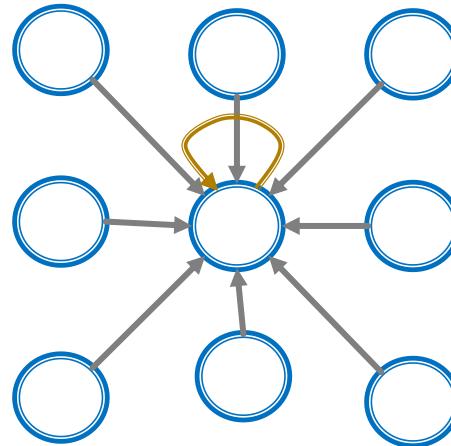
- GNN formulation (previous slide): $h_v^{(l+1)} = \sigma(\mathbf{W}_l \sum_{u \in N(v)} \frac{h_u^{(l)}}{|N(v)|} + B_l h_v^{(l)})$, $\forall l \in \{0, \dots, L-1\}$
- CNN formulation:
if we rewrite:
$$h_v^{(l+1)} = \sigma(\sum_{u \in N(v) \cup \{v\}} W_l^u h_u^{(l)})$$
$$h_v^{(l+1)} = \sigma(\sum_{u \in N(v)} \mathbf{W}_l^u h_u^{(l)} + B_l h_v^{(l)})$$
, $\forall l \in \{0, \dots, L-1\}$

GNN vs. CNN

Convolutional neural network (CNN) layer with 3x3 filter:



Image



Graph

$$\text{GNN formulation: } h_v^{(l+1)} = \sigma(\mathbf{W}_l \sum_{u \in N(v)} \frac{h_u^{(l)}}{|N(v)|} + B_l h_v^{(l)}), \forall l \in \{0, \dots, L-1\}$$

$$\text{CNN formulation: } h_v^{(l+1)} = \sigma(\sum_{u \in N(v)} \mathbf{W}_l^u h_u^{(l)} + B_l h_v^{(l)}), \forall l \in \{0, \dots, L-1\}$$

Key difference: We can learn different W_l^u for different “neighbor” u for pixel v on the image. The reason is we can pick an order for the 9 neighbors using **relative position** to the center pixel: $\{(-1, -1), (-1, 0), (-1, 1), \dots, (1, 1)\}$

GNN vs. CNN

Convolutional neural network (CNN) layer with 3x3 filter:



- CNN can be seen as a special GNN with fixed neighbor size and ordering:
 - The size of the filter is pre-defined for a CNN.
 - The advantage of GNN is it processes arbitrary graphs with different degrees for each node.

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GNN vs. CNN

Convolutional neural network (CNN) layer with 3x3 filter:

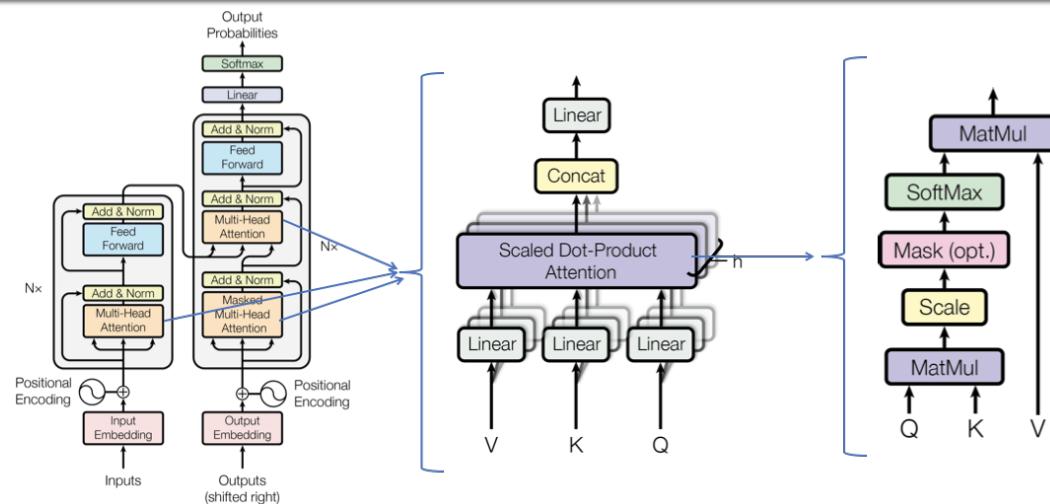


- CNN can be seen as a special GNN with fixed neighbor size and ordering.
- CNN is not permutation equivariant.
 - Switching the order of pixels will leads to different outputs.

Key difference: We can learn different W_l^u for different “neighbor” u for pixel v on the image. The reason is we can pick an order for the 9 neighbors using **relative position** to the center pixel: $\{(-1, -1), (-1, 0), (-1, 1), \dots, (1, 1)\}$

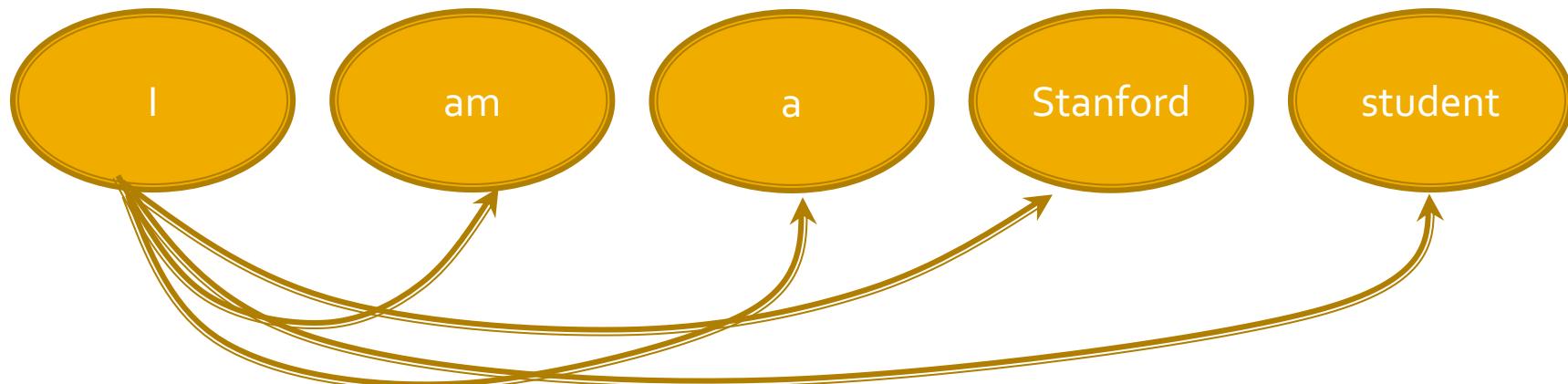
Transformer

Transformer is one of the most popular architectures that achieves great performance in many sequence modeling tasks.



Key component: self-attention

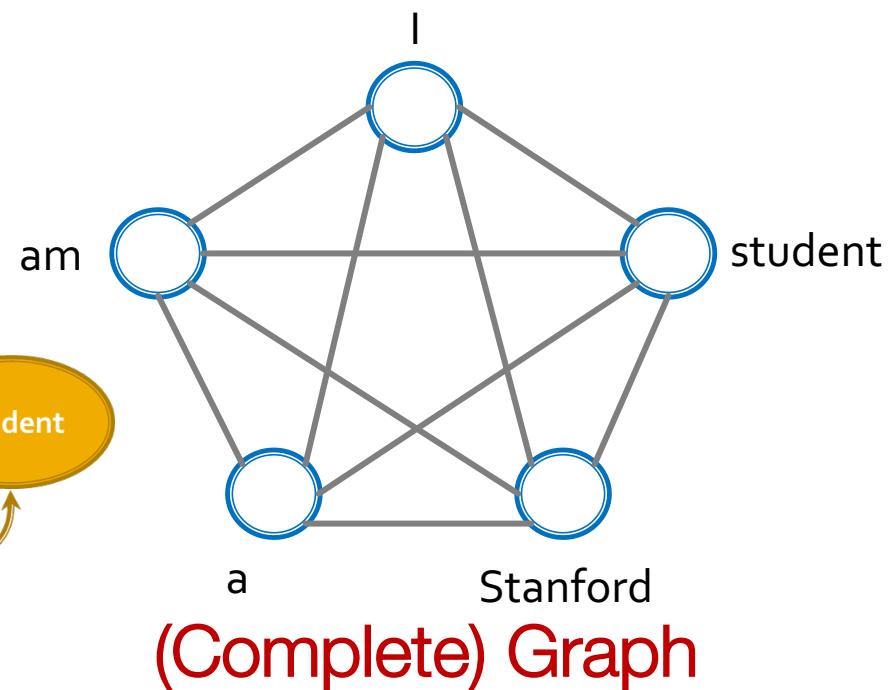
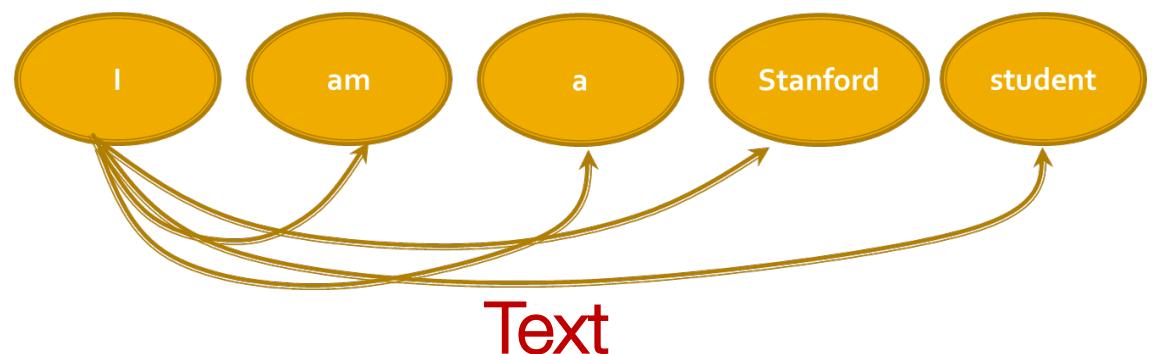
- Every token/word attends to all the other tokens/words via matrix calculation.



GNN vs. Transformer

Transformer layer can be seen as a special GNN that runs on a fully-connected “word” graph!

Since each word attends to **all the other words**, **the computation graph** of a transformer layer is identical to that of a GNN on the **fully-connected “word” graph**.



Summary

- In this lecture, we introduced
 - Basics of neural networks
 - Loss, Optimization, Gradient, SGD, non-linearity, MLP
 - Idea for Deep Learning for Graphs
 - Multiple layers of embedding transformation
 - At every layer, use the embedding at previous layer as the input
 - Aggregation of neighbors and self-embeddings
 - Graph Convolutional Network
 - Mean aggregation; can be expressed in matrix form
 - GNN is a general architecture
 - CNN and Transformer can be viewed as a special GNN