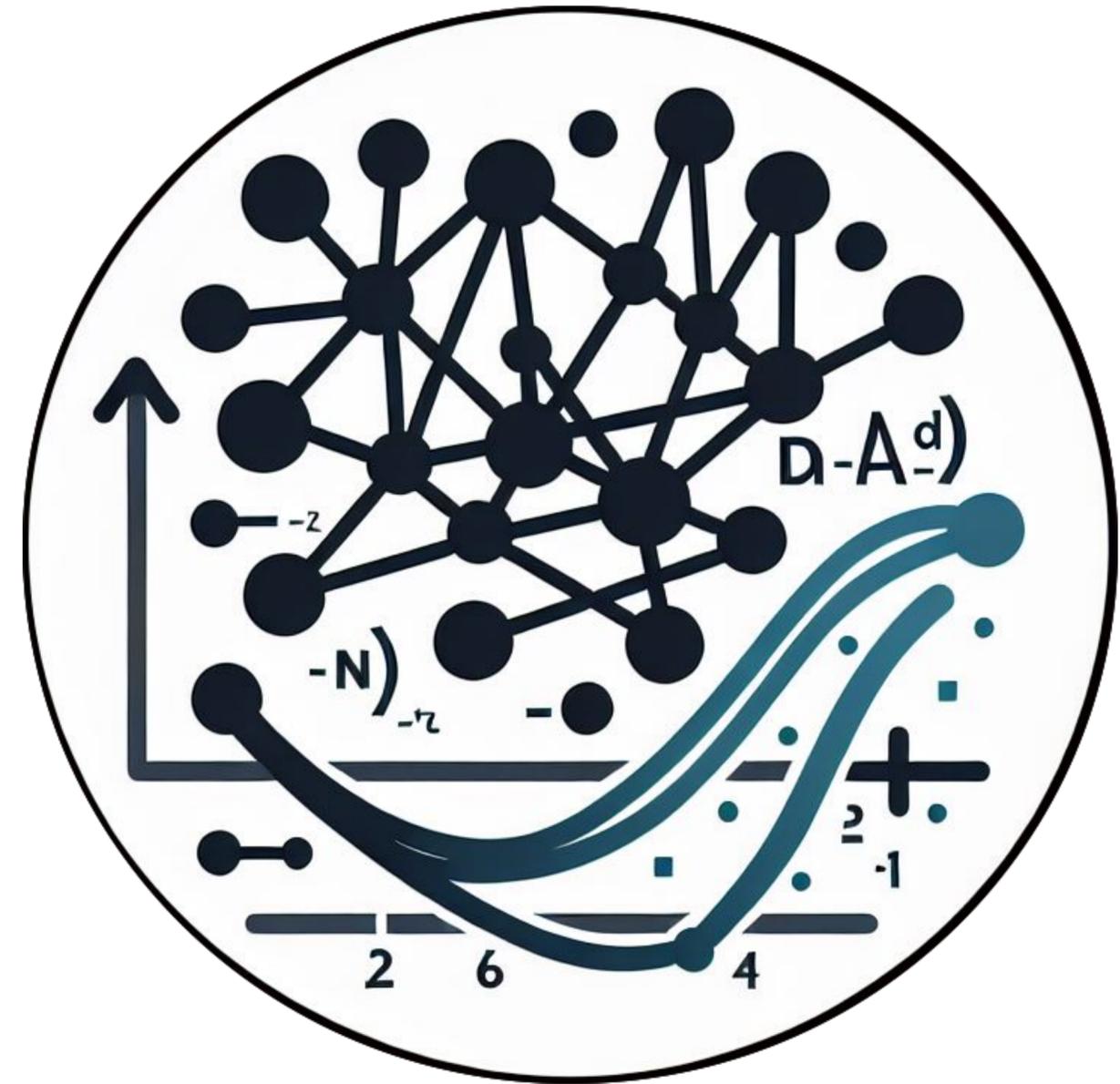


Graph Neural Nets

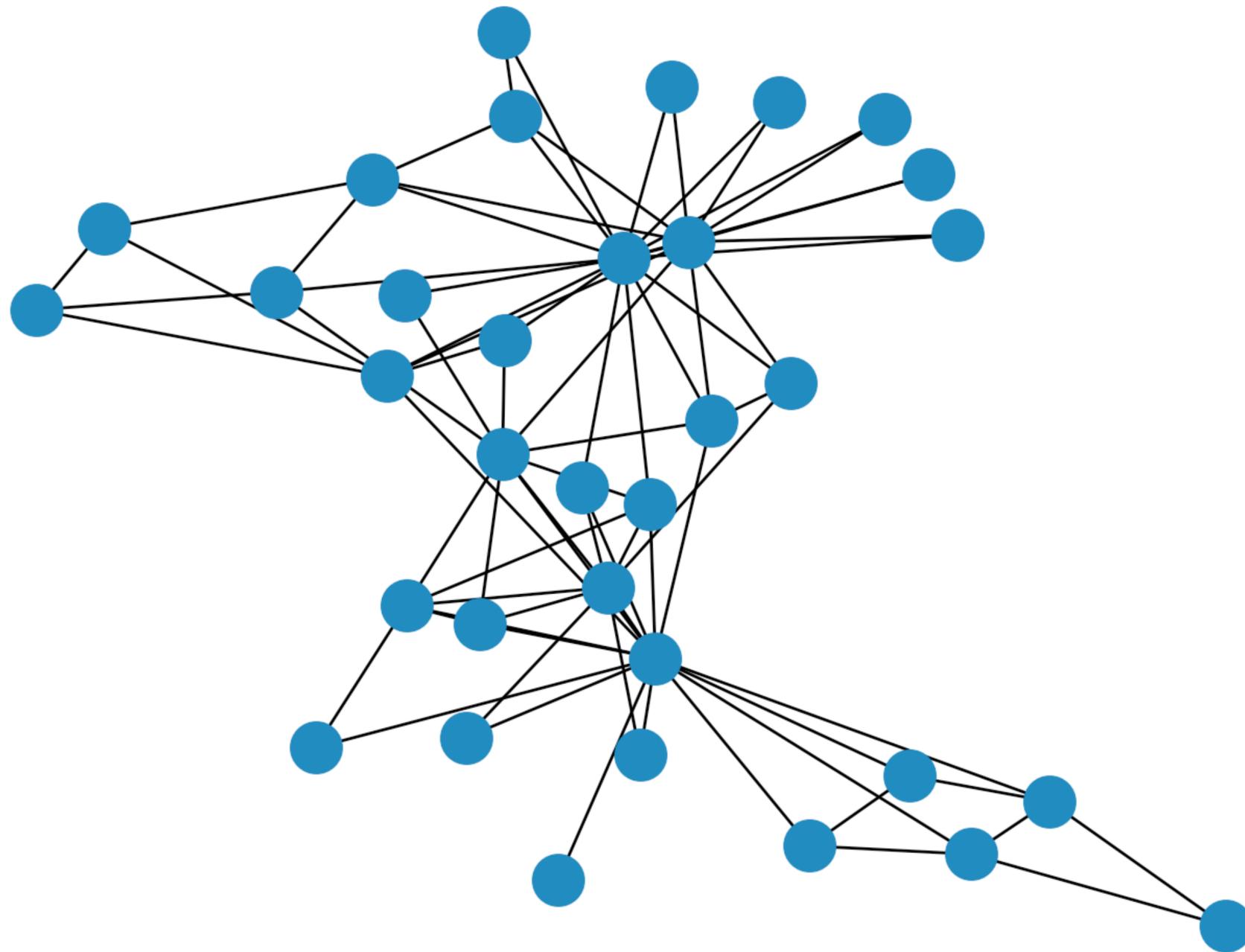


Deep Learning for Engineers

Andrew Ning

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Motivation

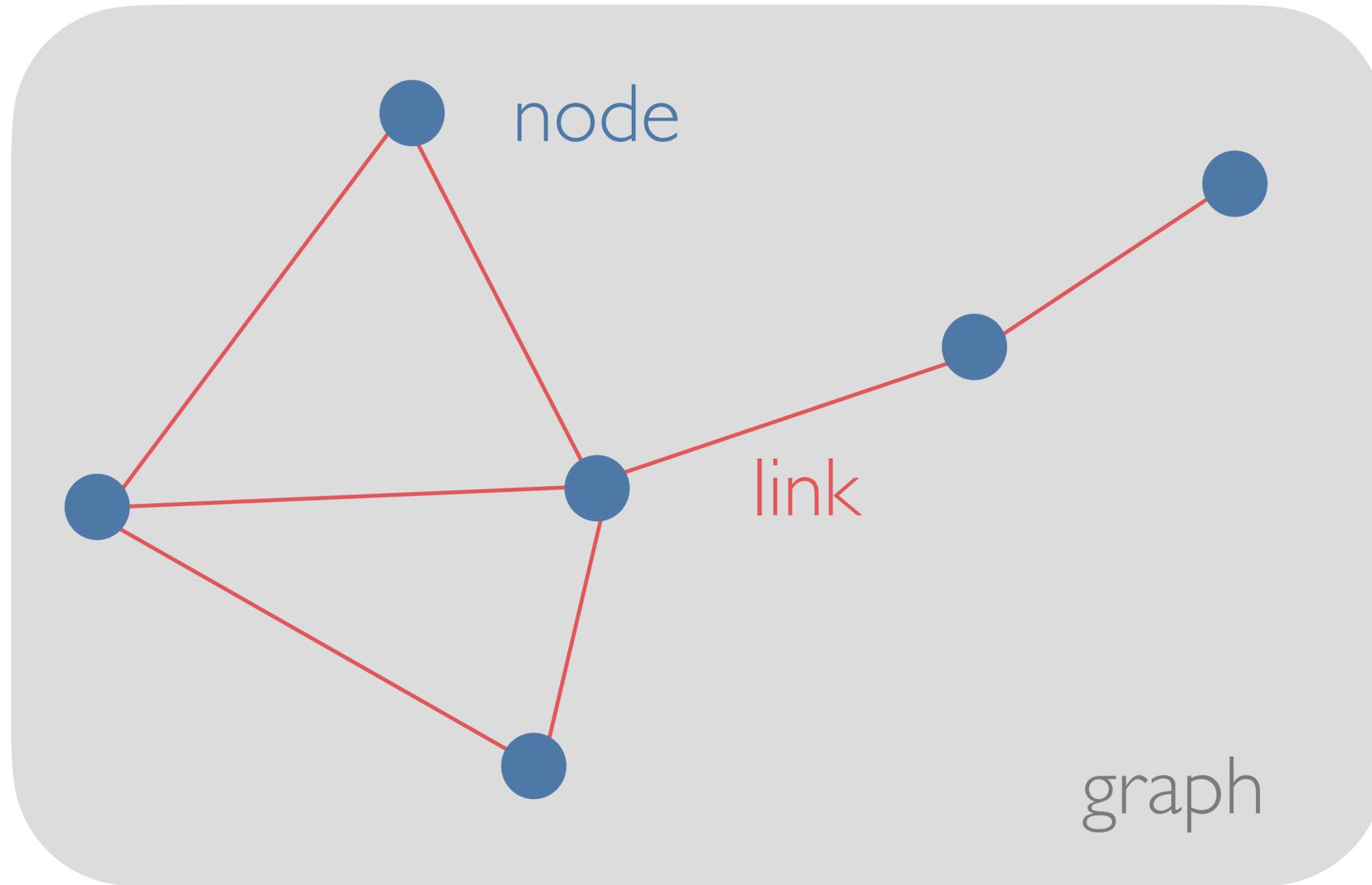


Challenges

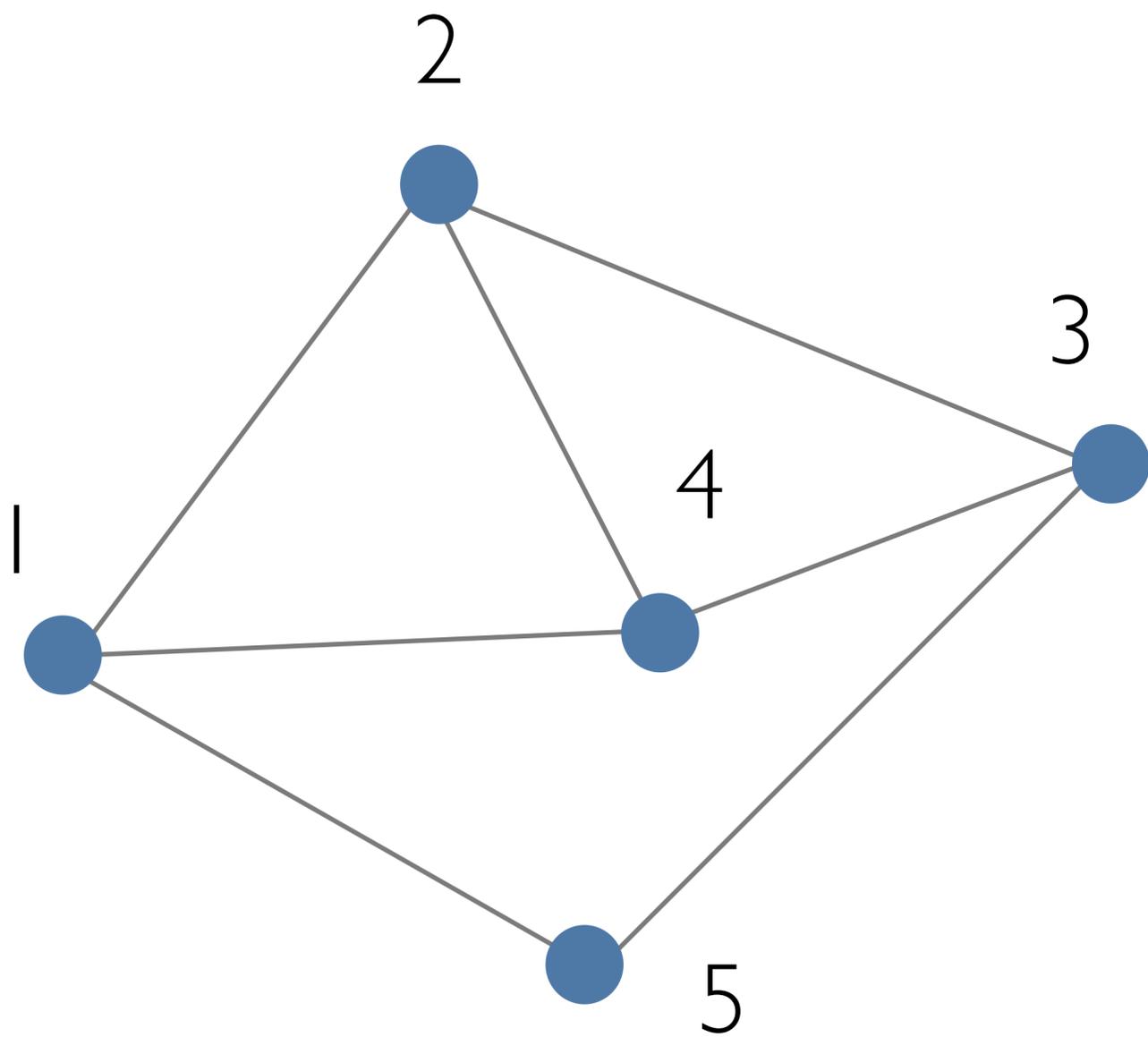
as compared to structured data

- structure is complex and requires more memory
- no natural ordering (would also like functionality to not be sensitive to this ordering)
- less obvious how to deal with different size inputs (graphs)

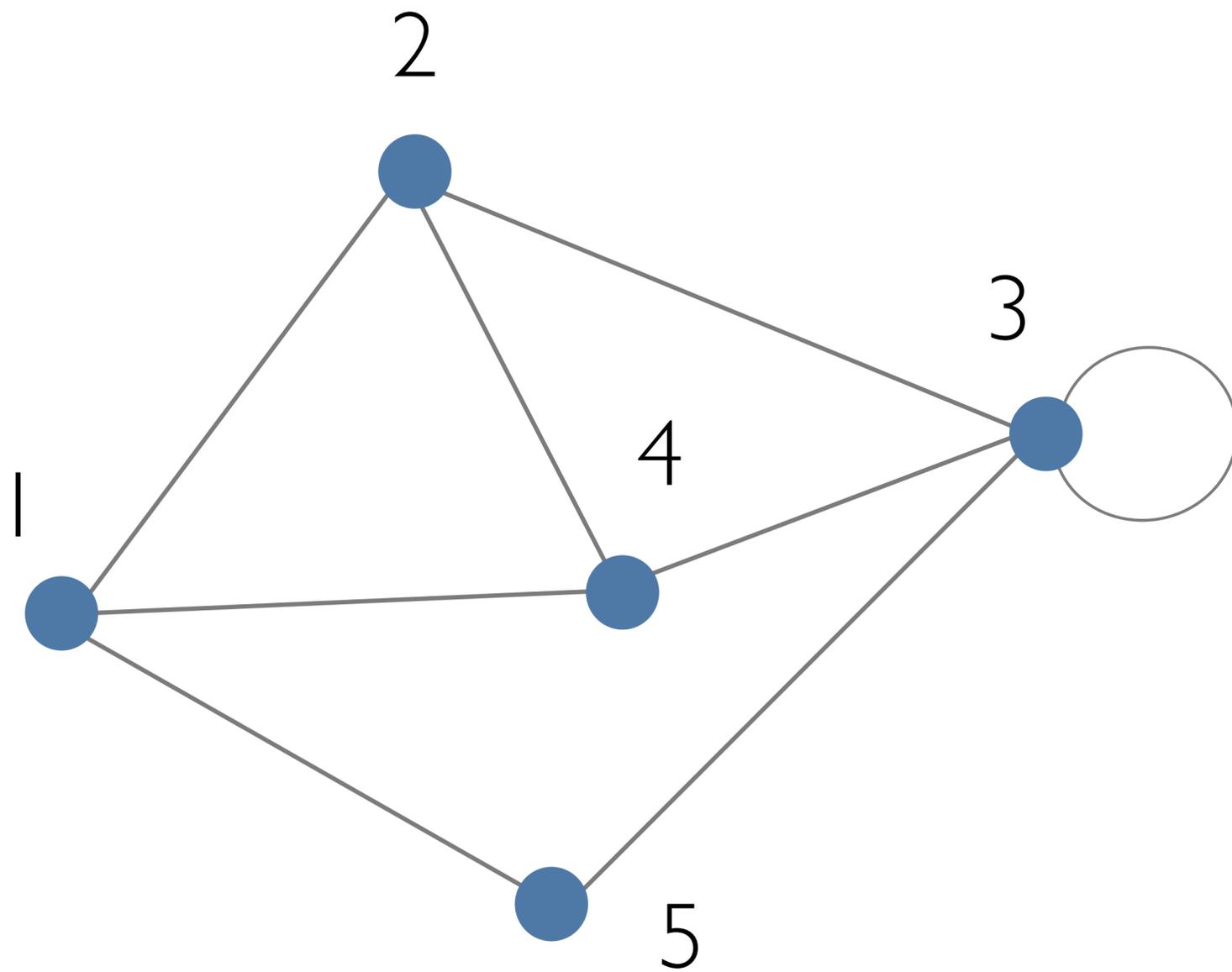
Node, link, and graph classification/regression



Adjacency matrix



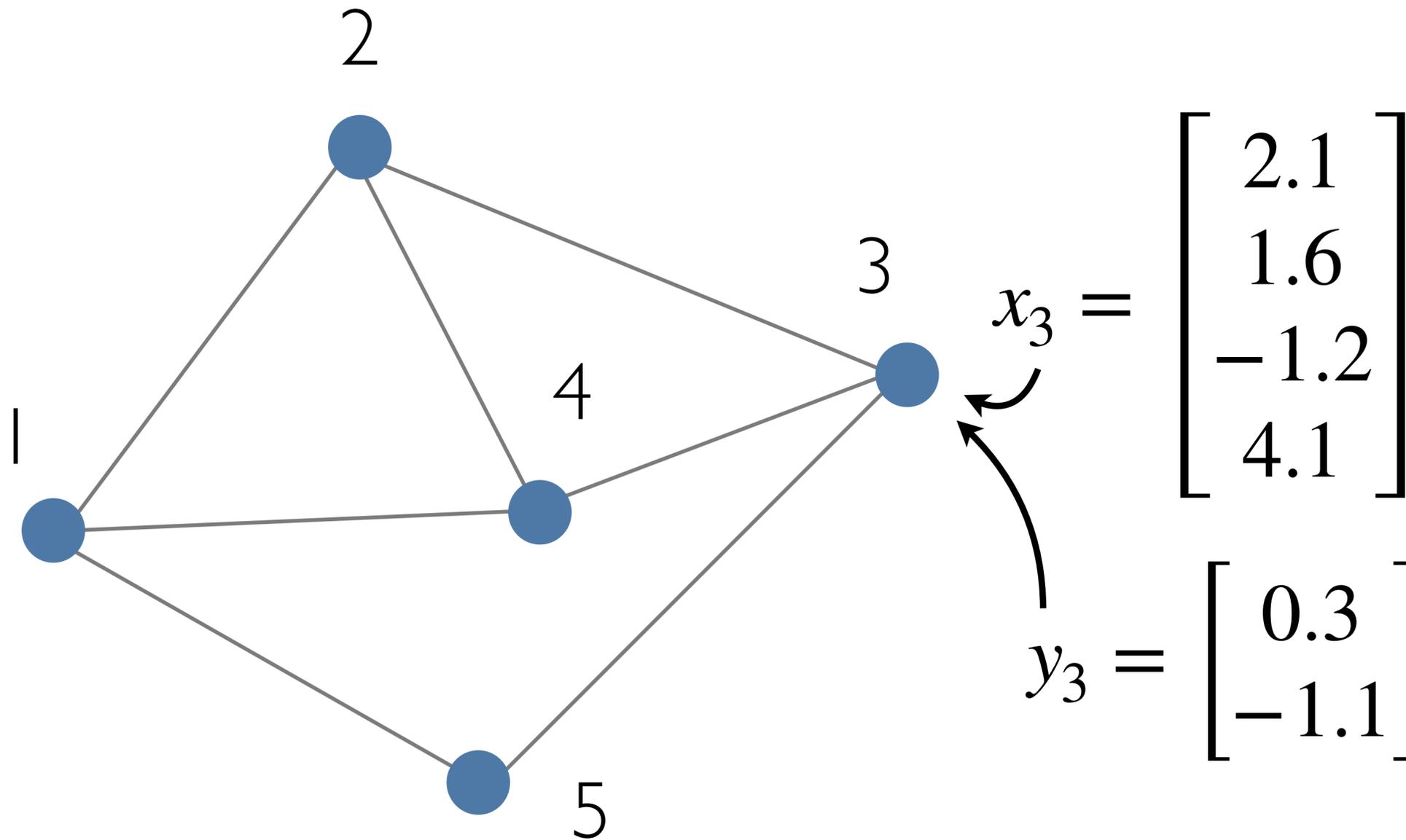
Adjacency matrix



$$A_{ij} = \begin{cases} 1 & \text{connected} \\ 0 & \text{otherwise} \end{cases}$$

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

Features and (Node) Targets/Labels

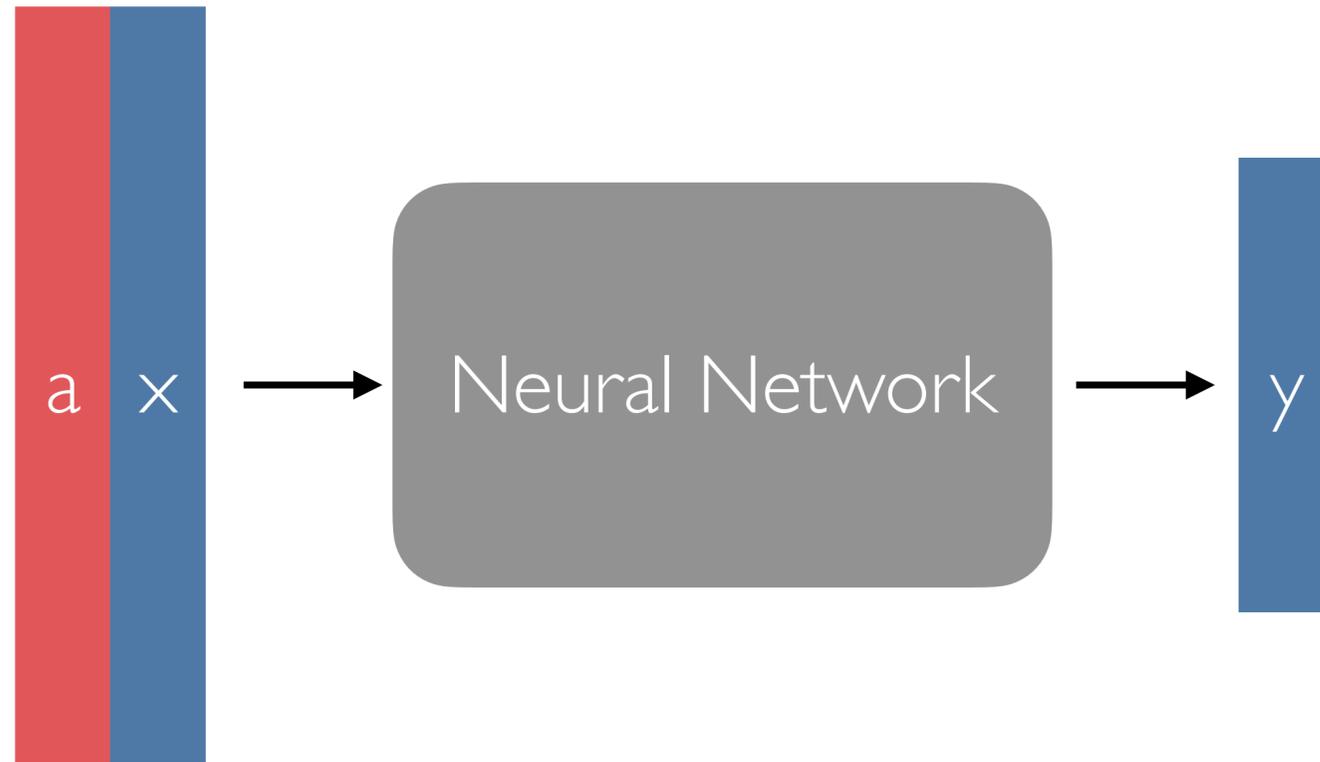


$$X \in \mathcal{R}^{n \times d}$$

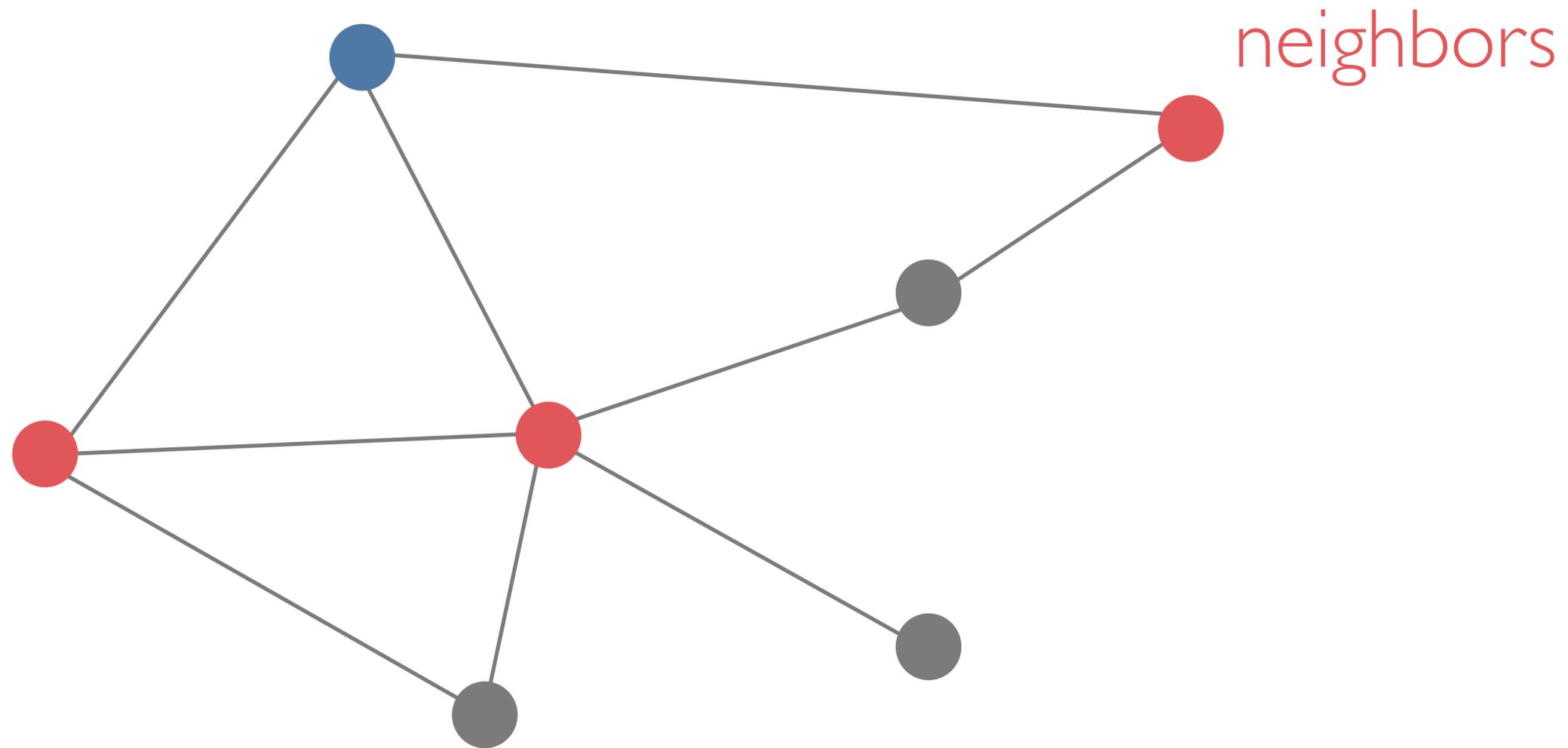
n: number of nodes

d: dimension of x

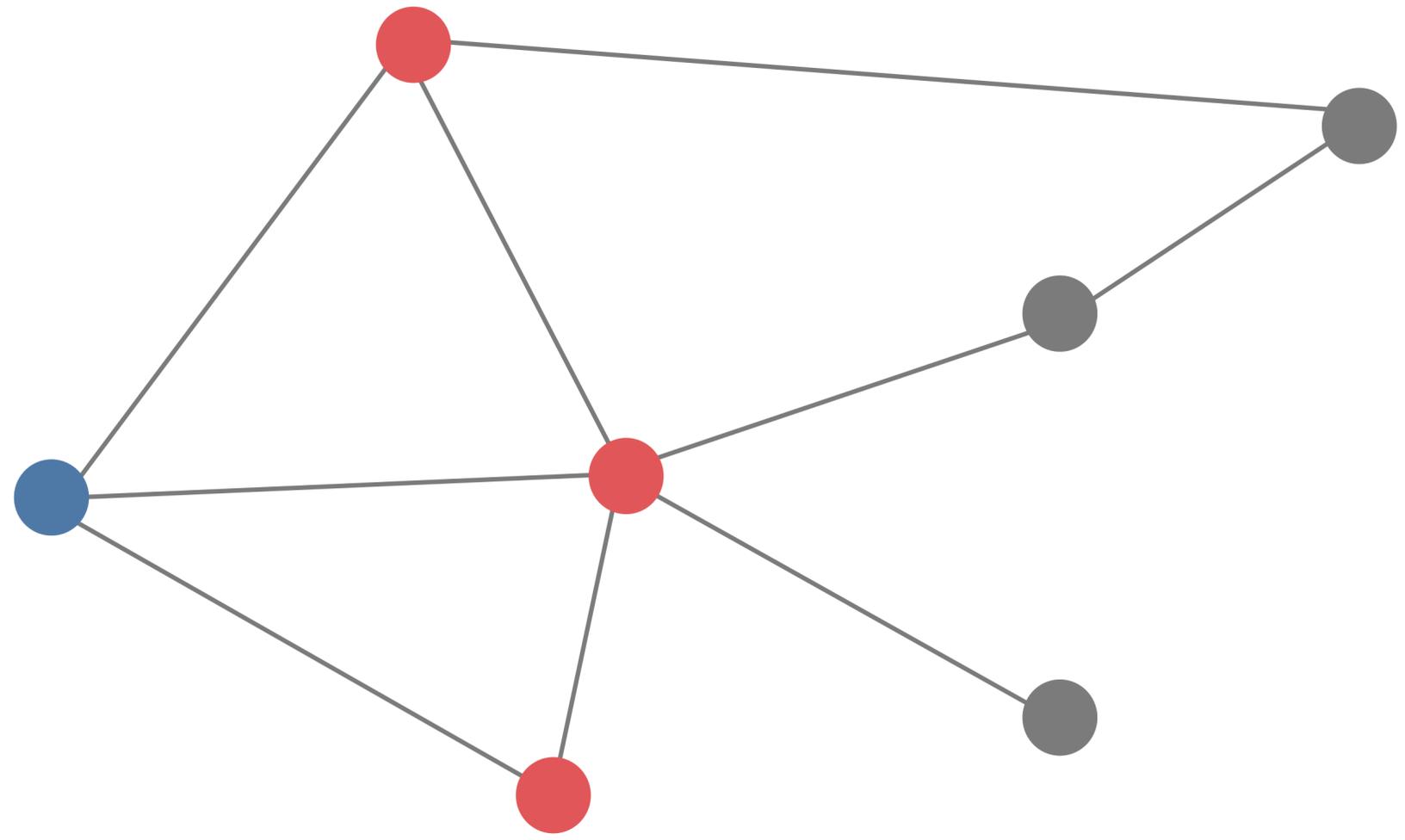
First Approach



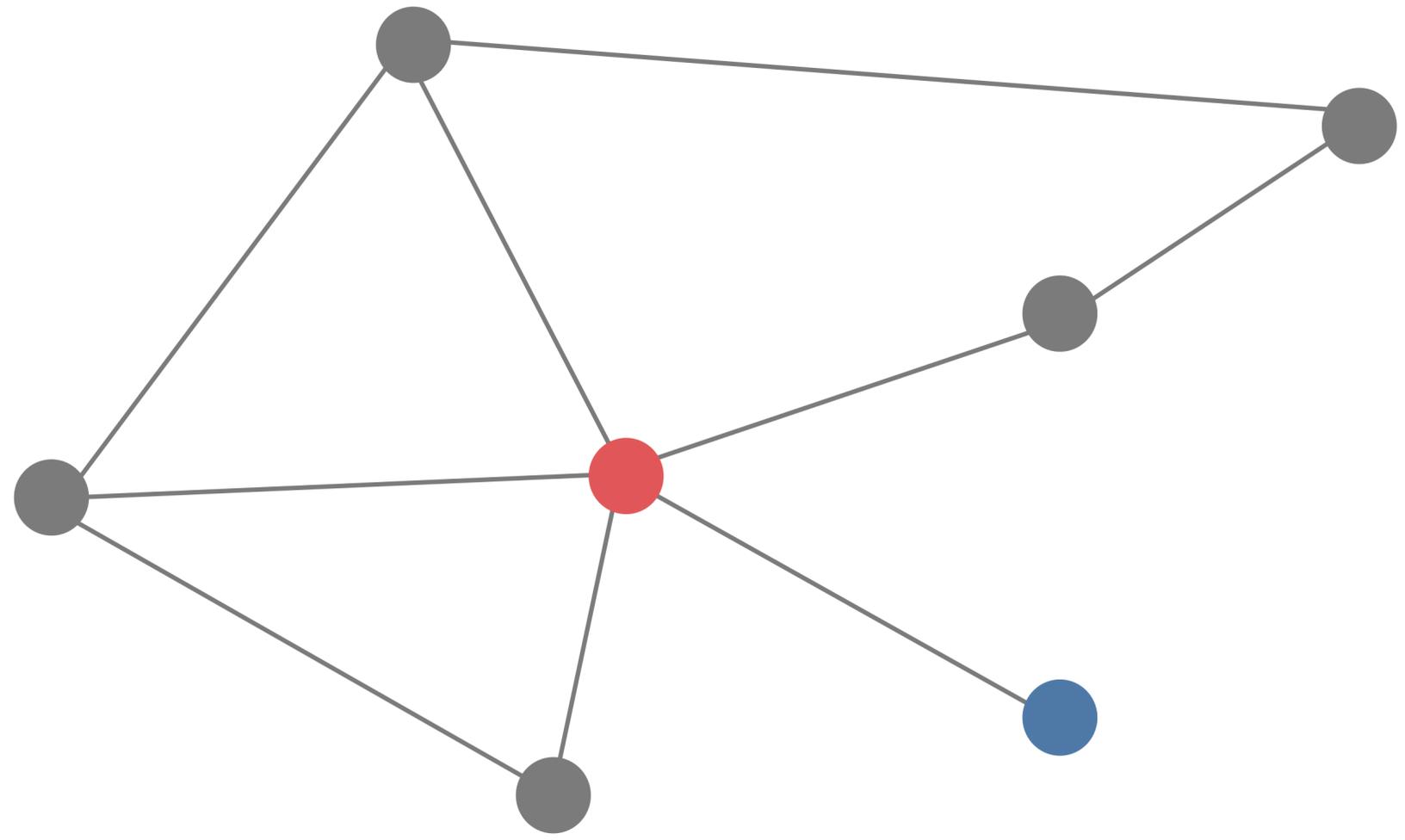
Neighbors



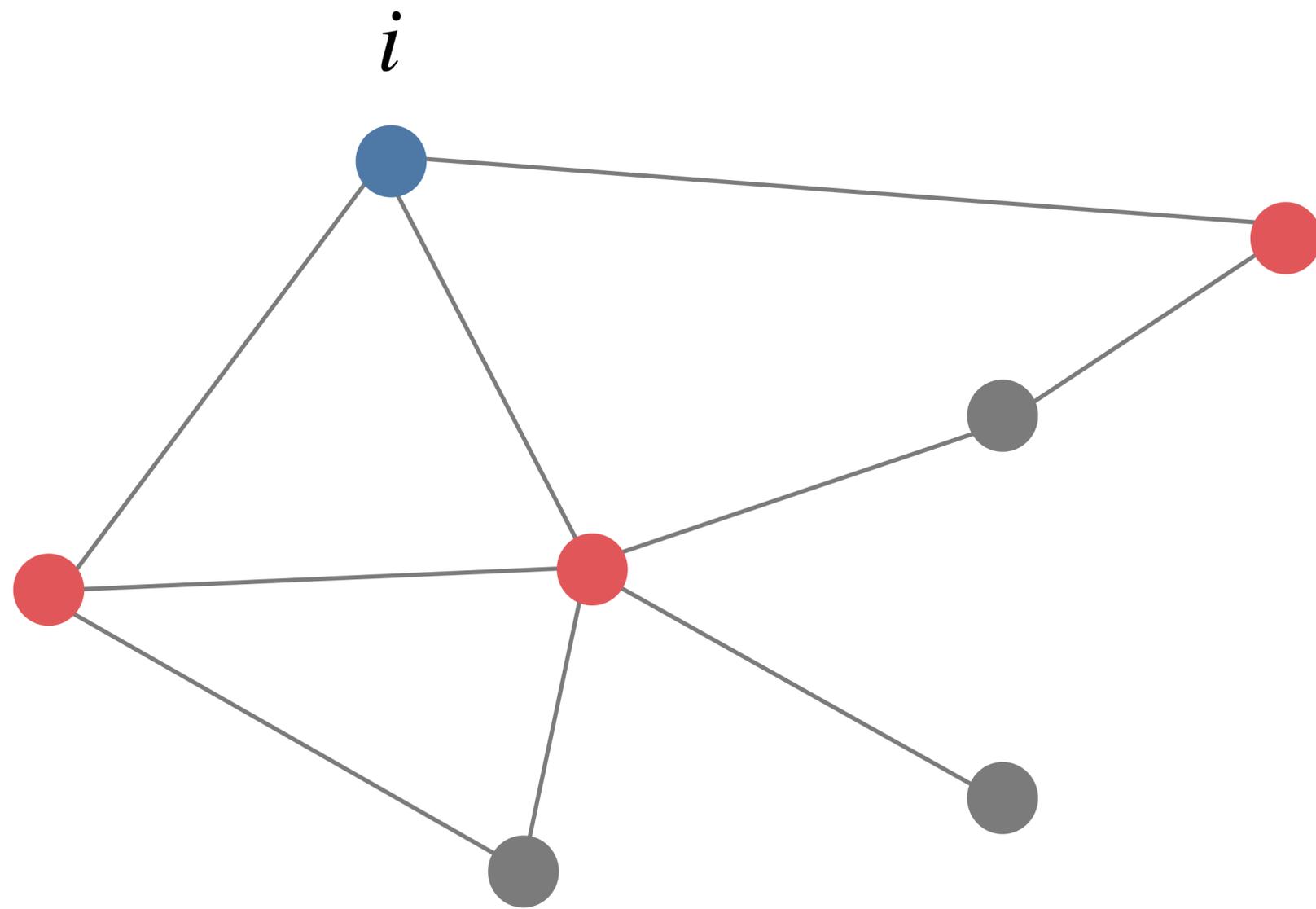
Neighbors



Neighbors



Neighbors

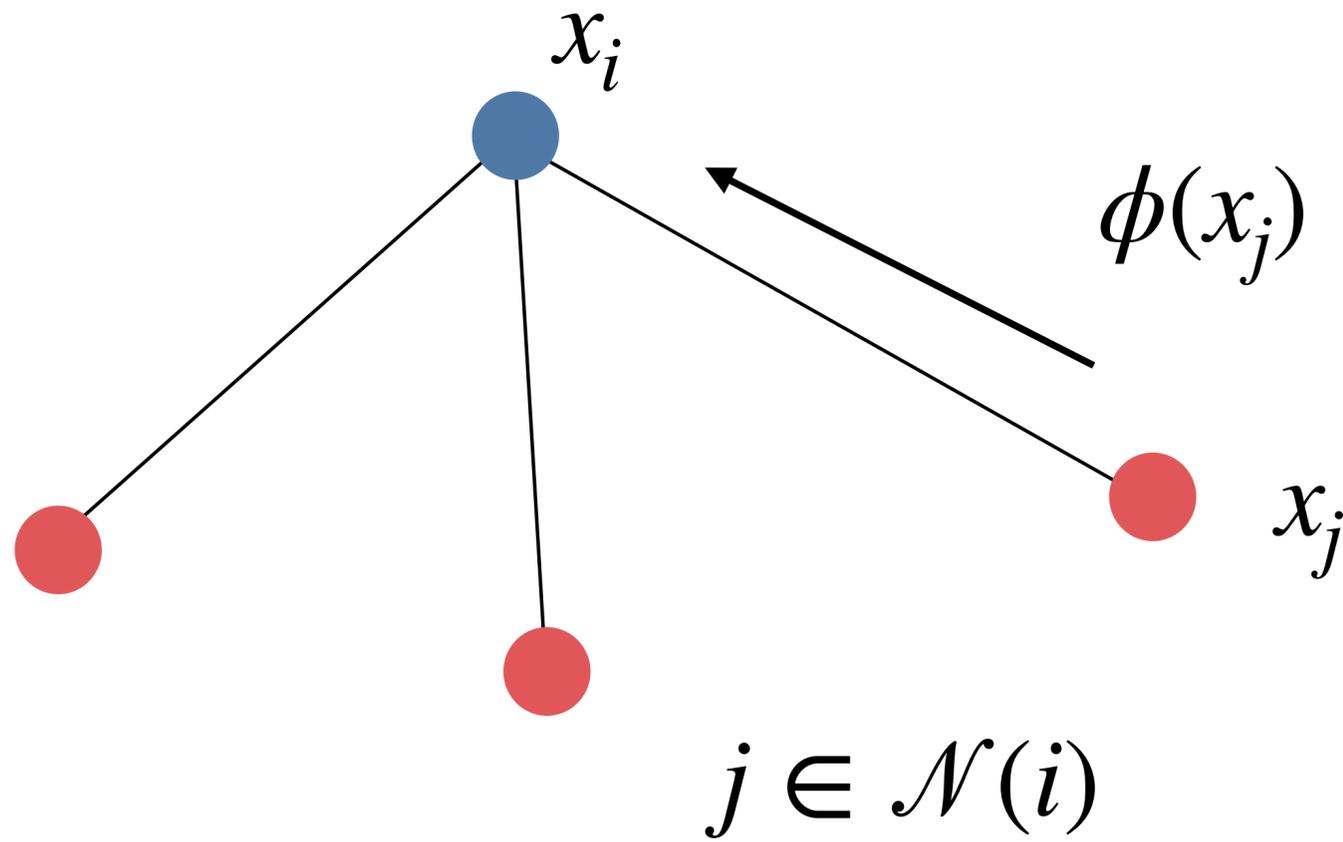


$$\mathcal{N}(i) = \{j : a_{ij} \in A\}$$

Message Passing GNN

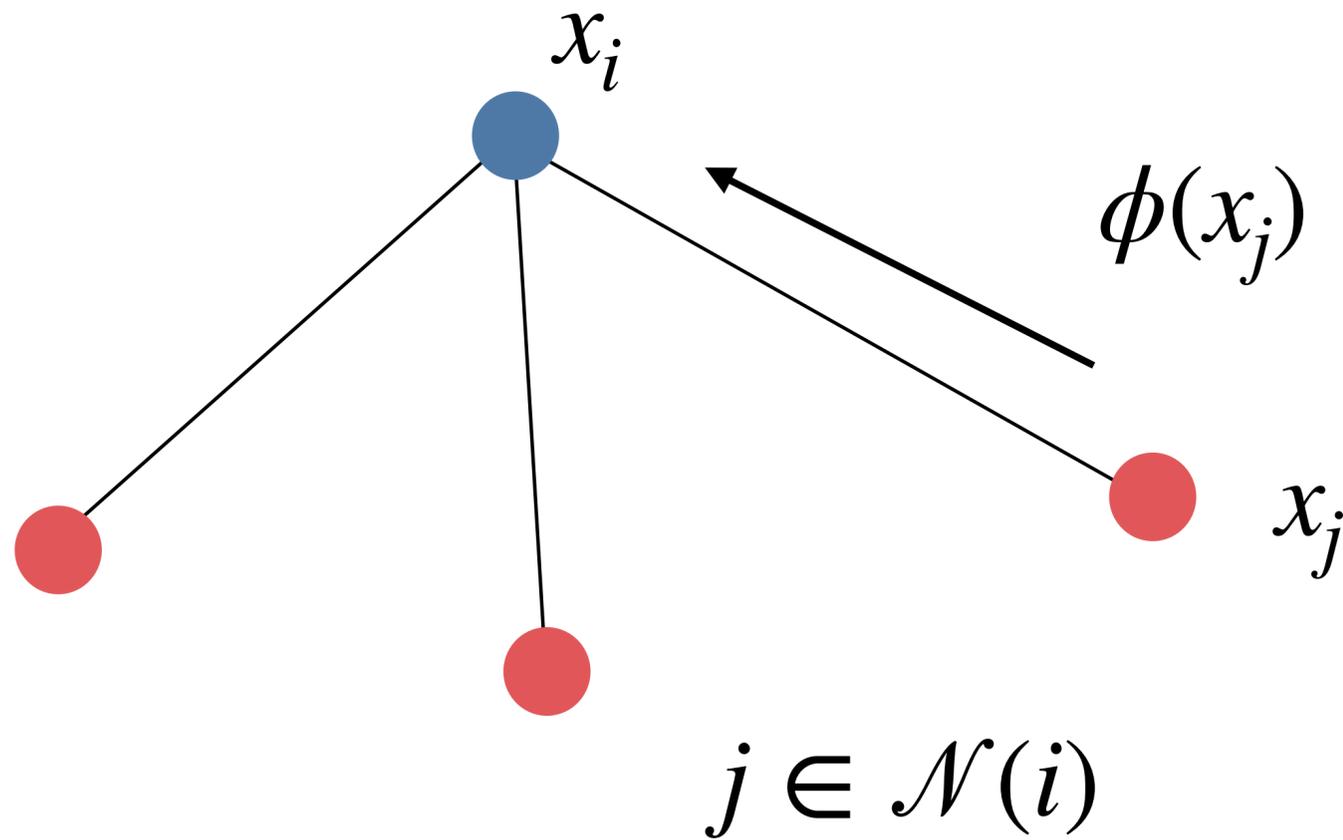
- 1) Each node constructs a **message** for its neighbors
- 2) Messages are sent and each node **aggregates** messages from all its neighbors
- 3) Each node **updates** its attributes

Create a message



message passing function

Create a message



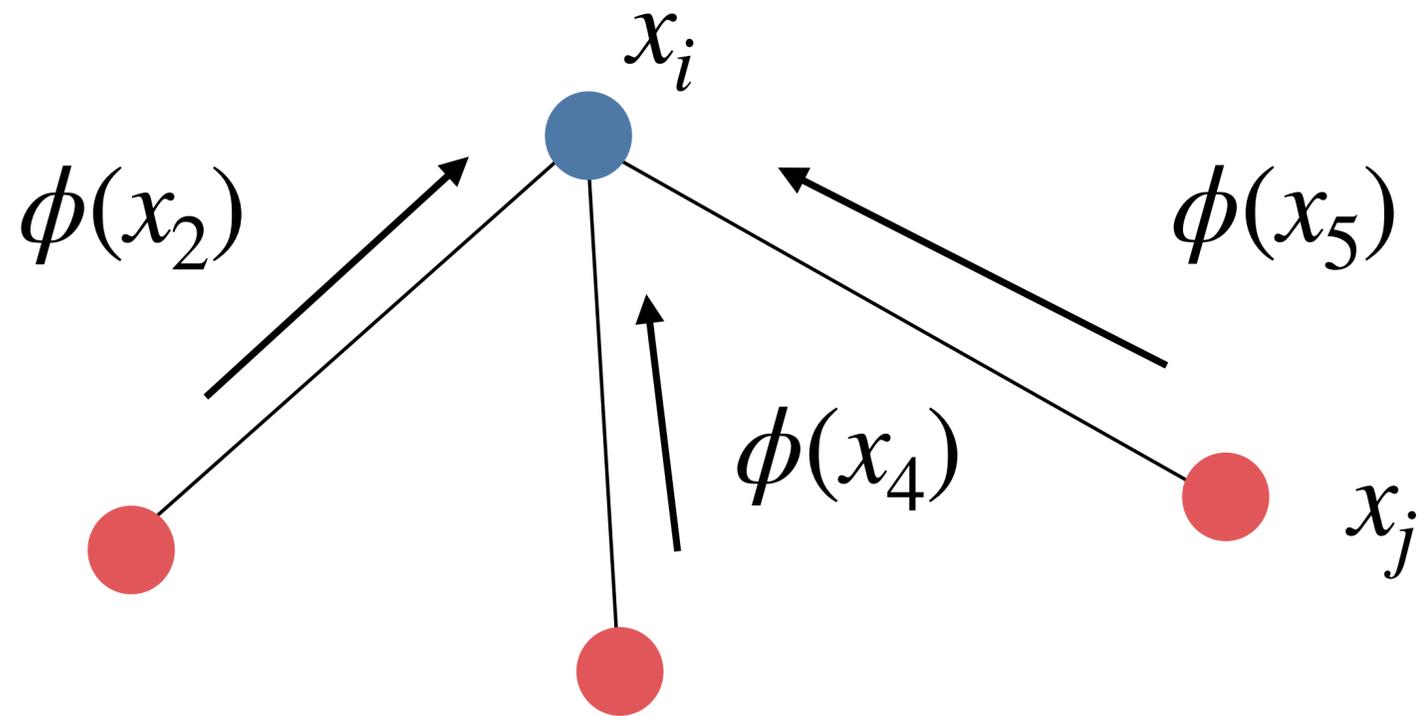
message passing function

simple: Wx_j

more general form:

$$\phi(x_j, x_i)$$

Aggregate



Aggregate

$$x_{agg} = \sum_{j \in \mathcal{N}(i)} \phi(x_j, x_i) \quad (\text{sum})$$

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Aggregate

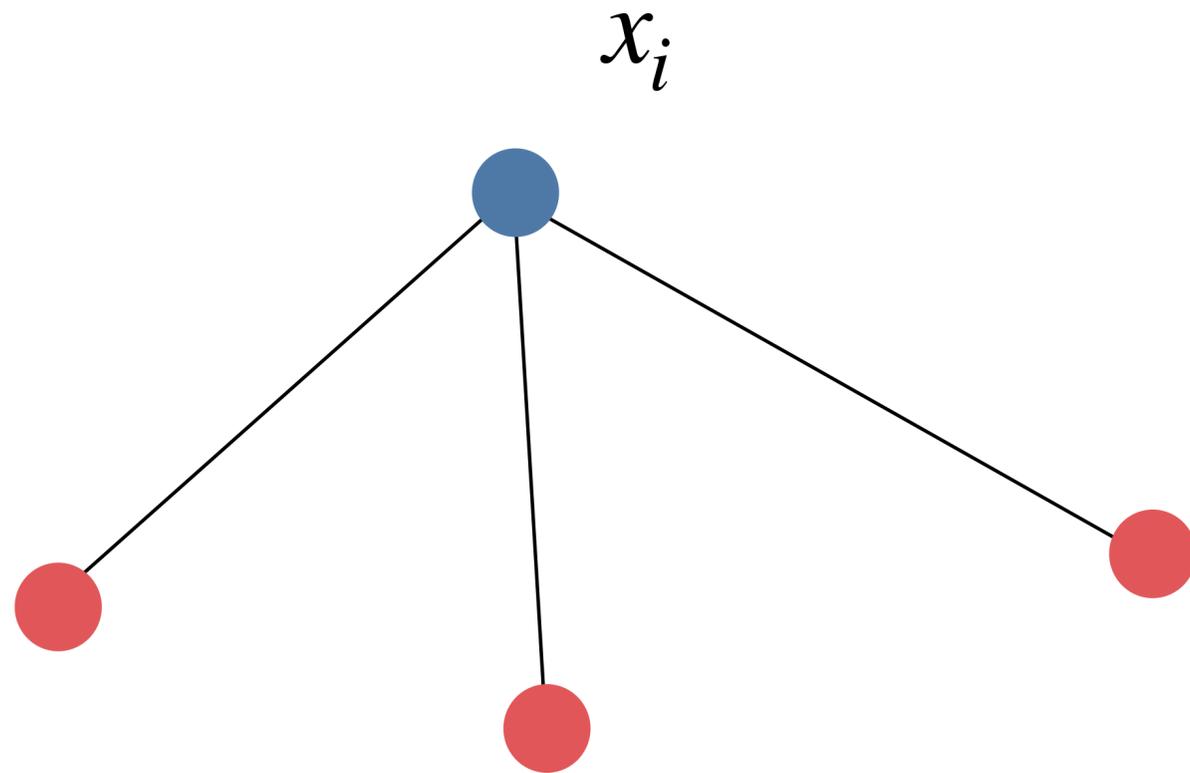
$$x_{agg} = \sum_{j \in \mathcal{N}(i)} \phi(x_j, x_i) \quad (\text{sum})$$

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$$x_{agg} = \max_{j \in \mathcal{N}(i)} \phi(x_j, x_i) \quad (\text{max or min})$$

$$x_{agg} = \bigoplus_{j \in \mathcal{N}(i)} \phi(x_j, x_i) \quad \text{some other function that is } \textit{order invariant}$$

Update



hidden state
(dimension size may change)

hidden state (dimension size may change) → $x_i^{(k+1)} = \gamma(x_{agg}, x_i^{(k)})$

some function →

All Together

$$x_i^{(k+1)} = \gamma(x_i^{(k)}, \bigoplus_{j \in \mathcal{N}(i)} \phi(x_j^{(k)}, x_i^{(k)}))$$

— update

— message passing

— aggregation

ϕ, γ are learned functions (e.g., Neural Networks)

Simple version

nonlinear activation function

$$x_i^{(k+1)} = \sigma \left(W_{self}^{(k)} x_i^{(k)} + W_{neighbor}^{(k)} \sum_{j \in \mathcal{N}(i)} x_j^{(k)} + b^{(k)} \right)$$

Like a CNN kernel, *for a given layer k*, W and b are same for every node across graph

Graph Convolutional Network (GCN)

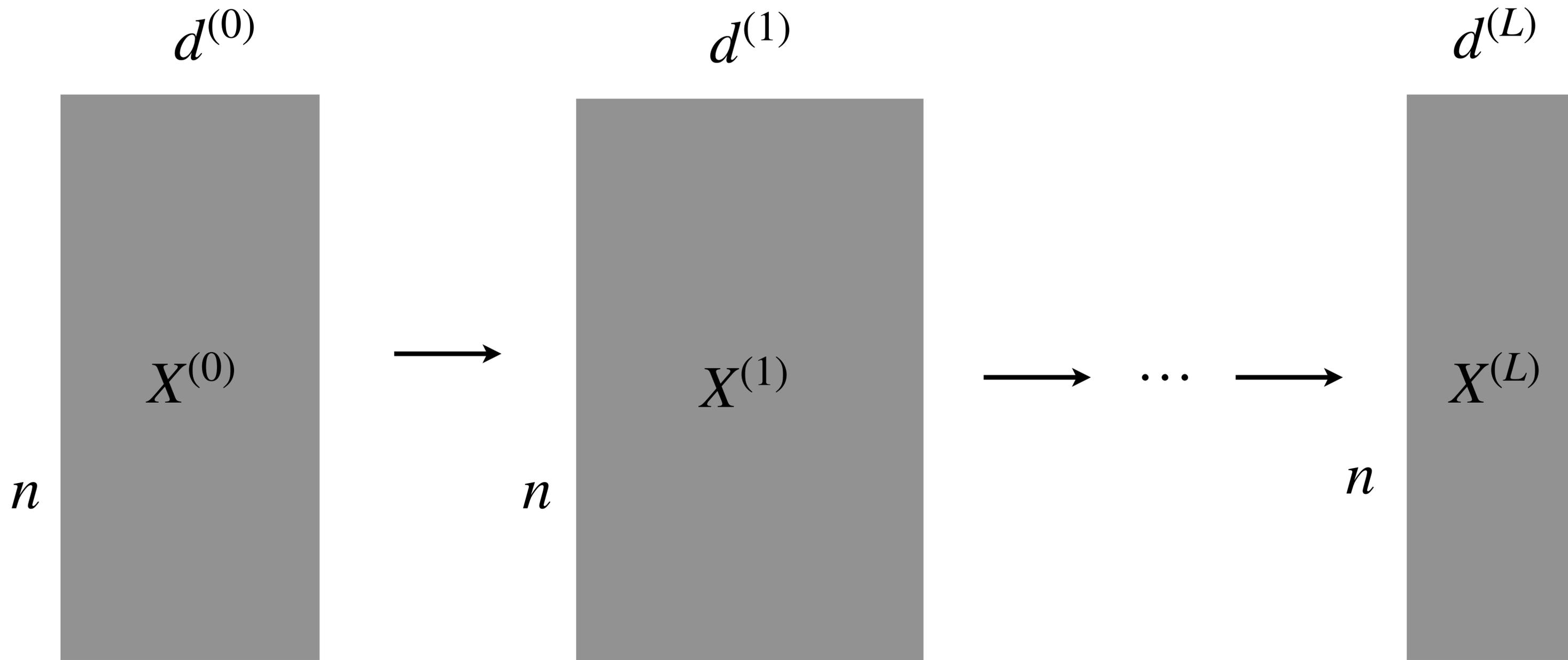
$$x_i^{(k+1)} = \sigma \left(W^{(k)} \sum_{j \in \mathcal{N}(i) \cup \{i\}} \frac{x_j^{(k)}}{\sqrt{|\mathcal{N}(i)| |\mathcal{N}(j)|}} + b^{(k)} \right)$$

sum over neighbors and self

Matrix form (for some GNNs)

$$Y = \tilde{A}XW$$

Network of Layers



Node, link, and graph classification/regression

$$X^{(L)} =$$



node

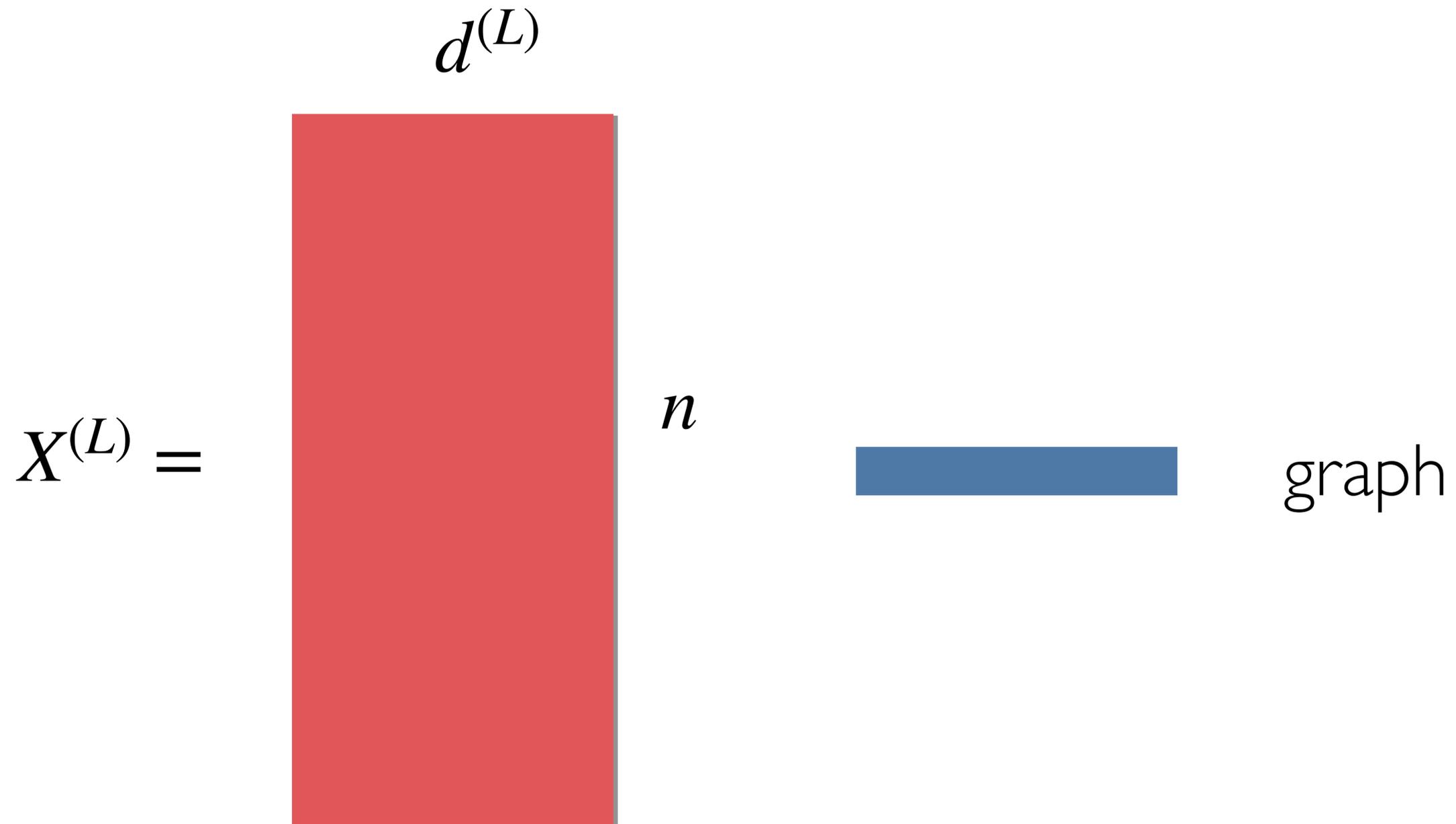
Node, link, and graph classification/regression

$$X^{(L)} =$$



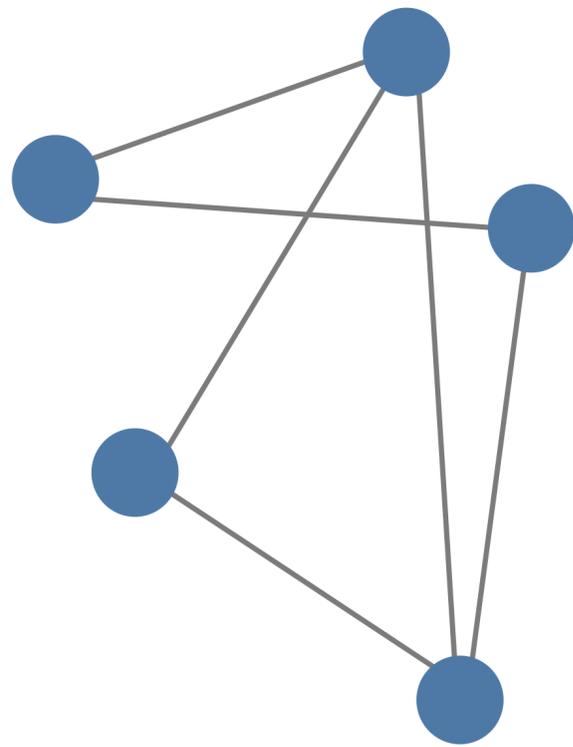
edge

Node, link, and graph classification/regression

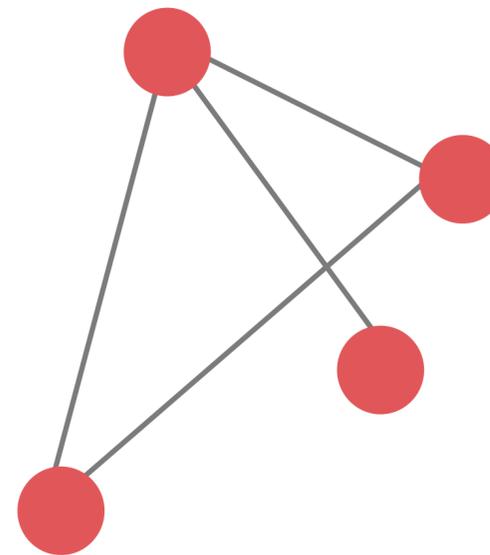


Testing

inductive: test on graphs not seen in training (basically like what we've done)



train

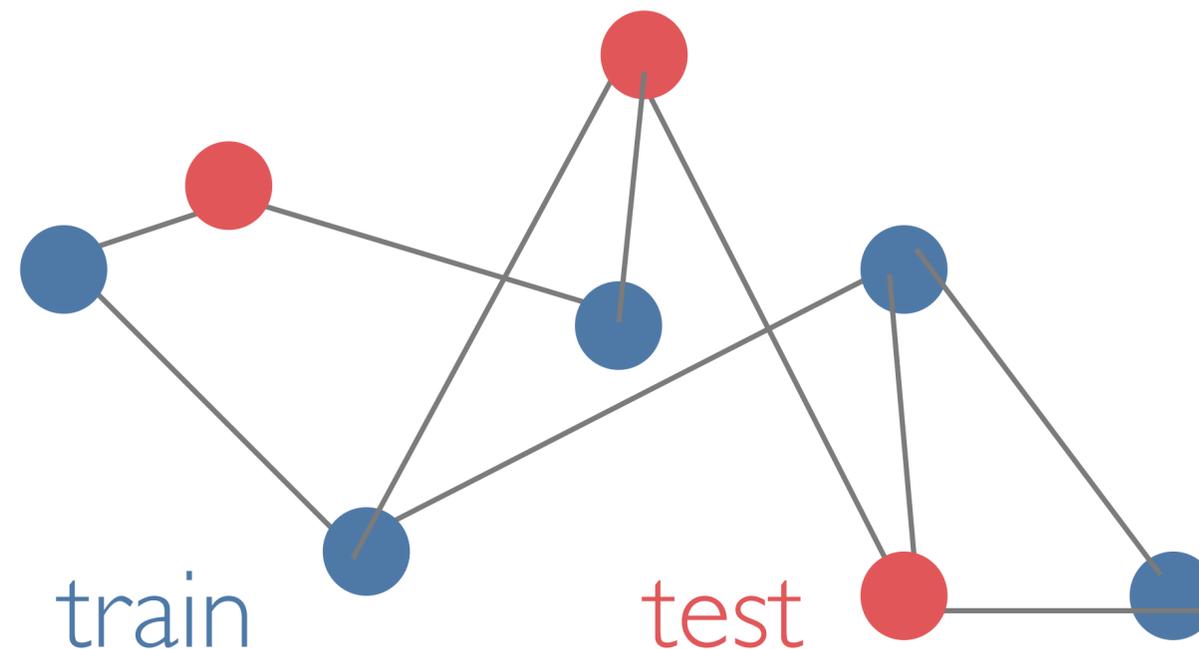


test

Testing

inductive: test on graphs not seen in training (basically like what we've done)

transductive: train and test on same graphs. features of all nodes are visible, but during training labels/targets for some testing nodes are hidden



Graph Attention Networks

$$x_{agg} = \sum_{j \in \mathcal{N}(i)} \alpha_{i,j} W x_j$$