

Graph Neural Networks

Graph Convolutional Networks

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Graph Convolutional Networks (GCNs)

- ❖ GCNs are convolutional in nature: they update each node's embedding by aggregating information from neighboring nodes.
- ❖ This structure introduces a *relational inductive bias*, encouraging the model to prioritize information from a node's local neighborhood.
- ❖ Each layer in the GCN is a function that, given node embeddings and the adjacency matrix, outputs new node embeddings:

$$H_1 = F(X, A, \phi_0)$$

$$H_2 = F(H_1, A, \phi_1)$$

$$H_3 = F(H_2, A, \phi_2)$$

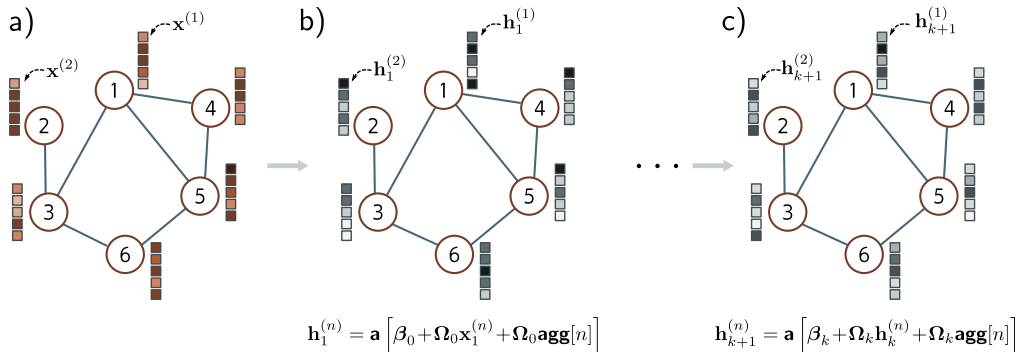
$$\vdots$$

$$H_K = F(H_{K-1}, A, \phi_{K-1})$$

where H_i represents the node embeddings at layer i , A is the adjacency matrix, and ϕ_i denotes parameters for mapping from layer i to $i + 1$.

Message Passing in GCNs

- ❖ A basic GCN layer takes an input graph with adjacency matrix A and node embeddings. The adjacency matrix is hidden in the function $\text{agg}[n]$.
- ❖ Intuitively, each node aggregates messages from its neighbors to update its embedding.



Aggregation and Update in GCNs

- ❖ There are various forms of the aggregation function, but it must be invariant to the ordering of inputs.
- ❖ For instance, at each node n in layer k , we can aggregate information by summing the embeddings of neighboring nodes:

$$\text{agg}[n, k] = \sum_{m \in \text{ne}[n]} h_k^{(m)}$$

where $\text{ne}[n]$ denotes the set of neighboring nodes of node n .

- ❖ Using the adjacency matrix A , we can represent this aggregation more concisely:

$$\begin{aligned} H_{k+1} &= a \left[\beta_k \mathbf{1}^T + \Omega_k H_k + \Omega_k H_k A \right] \\ &= a \left[\beta_k \mathbf{1}^T + \Omega_k H_k (A + I) \right] \end{aligned}$$