Graph Convolutional Networks

Exploiting domain sparsity

Self-attention (I)

$$\{oldsymbol{x}_i\}_{i=1}^t = \{oldsymbol{x}_1, oldsymbol{x}_2, \cdots oldsymbol{x}_t\} &\sim oldsymbol{X} \in \mathbb{R}^{n imes t}, \quad oldsymbol{x}_i \in \mathbb{R}^n$$
 $oldsymbol{h} = oldsymbol{lpha}_1 oldsymbol{x}_1 + oldsymbol{lpha}_2 oldsymbol{x}_2 + \cdots + oldsymbol{lpha}_t oldsymbol{x}_t = oldsymbol{X} oldsymbol{a} \in \mathbb{R}^n$
 $oldsymbol{lpha}_i > 0$
 $oldsymbol{X} \doteq egin{bmatrix} | oldsymbol{a} & | oldsymb$

Input layer / samples

$$\mathcal{X} = \{m{x}^{(i)} \in \mathbb{R}^n \mid m{x}^{(i)} ext{ is a data sample}\}_{i=1}^m$$
 input samples

$$\mathcal{X} = \{m{x}^{(i)}: \Omega o \mathbb{R}^c, m{\omega} \mapsto m{x}^{(i)}(m{\omega})\}_{i=1}^m$$

$$\Omega = \{1, 2, \cdots, T/\Delta t\} \subset \mathbb{N}, \quad c \in \{1, 2, 5+1, \cdots\}$$
 sampling interval

$$\Omega = \{1, \cdots, h\} \times \{1, \cdots, w\} \subset \mathbb{N}^2, \quad c \in \{1, 3, 20, \cdots\}$$

four-momentum

$$\Omega = \mathbb{R}^4 \times \mathbb{R}^4, \quad c = 1$$

$$m{x}(\omega_1,\omega_2) = egin{pmatrix} r(\omega_1,\omega_2) \ g(\omega_1,\omega_2) \ b(\omega_1,\omega_2) \end{pmatrix}$$

GCN

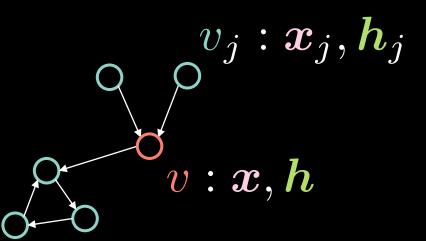
: adjacency vector

$$\alpha_j \stackrel{\downarrow}{=} 1 \Leftrightarrow v_j \to v$$

$$d = \| {oldsymbol a} \|_1$$
 : degree (# of incoming edges)

$$\mathbf{h} = f(\mathbf{U}\mathbf{x} + \mathbf{V}\mathbf{X}\mathbf{a}d^{-1})$$
 $f(\cdot): (\cdot)^+, \sigma(\cdot), \tanh(\cdot)$

$$\{\boldsymbol{x}_i\}_{i=1}^t \leadsto \boldsymbol{H} = f(\boldsymbol{U}\boldsymbol{X} + \boldsymbol{V}\boldsymbol{X}\boldsymbol{A}D^{-1}) \quad D = \operatorname{diag}(d_i)$$



Residual gated GCN

Residual gated GCN
$$h^{\ell} \qquad \qquad \begin{matrix} & & & & & & & & & \\ & & & & & & & \\ h^{\ell} & & & & & & \\ & & & & & & \\ h^{\ell+1} \rightarrow h = x + \left(Ax + \sum_{v_j \rightarrow v} \eta(e_j) \odot Bx_j\right)^+ \\ & & & & & \\ \eta(e_j) = \sigma(e_j) \Big(\sum_{v_k \rightarrow v} \sigma(e_k)\Big)^{-1} & h^{\ell}_j \\ & & & & \\ e_j = Ce^x_j + Dx_j + Ex, & e^h_j = e^x_j + (e_j)^+ \end{matrix}$$