ch1: Hypergraph

理解:

$\mathcal{G} = (\mathcal{V}, \mathcal{E}, W)$

$\mathcal{G}$: hypergraph

$\mathcal{V}$: vertices   U: Vertex Weight Matrix   order:V

X: Vertex Feature Matrix   Y: Vertex Label Matrix

$\mathcal{E}$: hyperedges   W: Hyperedge Weight Matrix   size:E

$$H \in |\mathcal{V}| * |\mathcal{E}| \qquad H(v,e) = \begin{cases} 1 & \text{if } v \in e \\ 0 & \text{if } v \notin e \end{cases}$$

$$d(v) = \sum_{e \in \mathcal{E}} H(v,e) * w(e) \qquad D_v$$

$$d(e) = \sum_{v \in \mathcal{V}} H(v,e) \qquad D_e$$

$$\Delta = D_v - HWD_e^{-1}H^T$$

$$\Delta = I - D_v^{-1/2}HWD_e^{-1}H^TD_v^{-1/2}$$

ch2: Spectral Hypergraph Theory

理解:

1: 推导超图的拉普拉斯矩阵

$$g \star x = \phi((\phi^T g) \odot (\phi^T x)) = \phi g(\wedge)(\phi^T x)$$
$$g(\wedge) = diag(g(\lambda_1), ..., g(\lambda_n))$$

$$g \star x \approx \sum_{k=0}^{K} \theta_k T_k(\tilde{\Delta}) x$$
$$\tilde{\Delta} = \frac{2}{\lambda_{max}} \Delta - I$$

$$K = 2 \qquad \lambda_{max} = 2$$
$$g \star x \approx \theta_0 x - \theta_1 D_v^{-1/2} H W D_e^{-1} H^T D_v^{-1/2} x$$

$$\theta_0 = (1/2)\theta D_v^{-1/2} H D_e^{-1} H^T D_v^{-1/2} \qquad \theta_1 = (-1/2)\theta$$
$$g \star x \approx (1/2)\theta D_v^{-1/2} H (I + W) D_e^{-1} H^T D_v^{-1/2} x$$
$$\approx \theta D_v^{-1/2} H W D_e^{-1} H^T D_v^{-1/2} x$$

$$X^{t+1} = \sigma(D_v^{-1/2} H W D_e^{-1} H^T D_v^{-1/2} X^t \Theta)$$

ch3: Hypergraph Generation and Transformation

理解：
隐式：距离、特征
显式：属性、网络

ch4: Hypergraph Learning Architecture

理解:
超图游走

(1) Features

$X \in R^{|V| \times d}$ $Y \in R^{|E| \times d'}$

Externel + Internal(local+global) + Identity

(2) Transformation

Reductive Transformation

$(E, X, Y) \Rightarrow A$ hyperedges to edges

clique expansion + adaptive expansion

Non-reductive Transformation

star/line/tensor expansion

(3) Message

whose: v-v v-e e-v

what : e-consistent + e-dependent

how : fixed-pooling + learnable-pooling

(4) Training