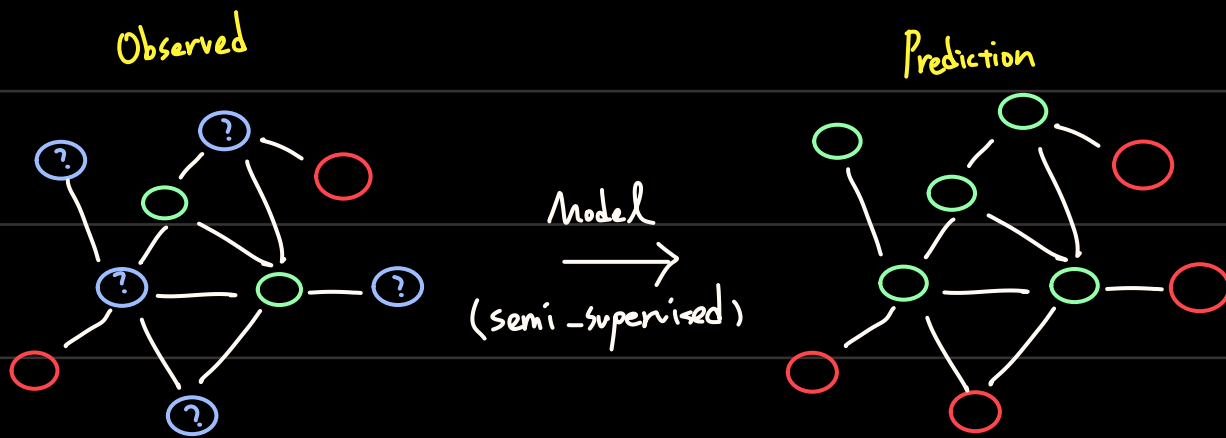


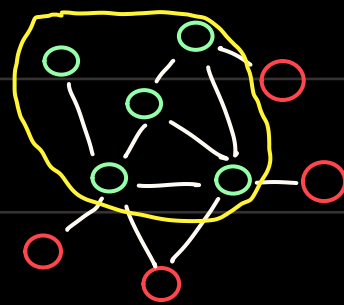
# Message Passing and Node Classification

Question: How do we know labels of all other nodes



We can use correlation exist in networks (collective classification)

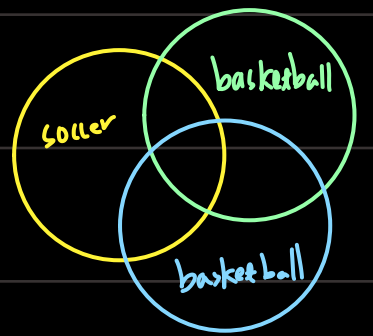
Correlation: nearby nodes have same class



Phenomenon:

Homophily: The tendency of individuals to associate and bond with similar others

Influence: Social connections can influence the individual characteristics of a person



Property

Classification label of a node  $v$  in network may depend on:

- ① Features of  $v$
  - ② Labels of the nodes in  $v$ 's neighborhood
  - ③ Features of the nodes in  $v$ 's neighborhood
- } KNN

Semi-Supervised Learning:

Given  $G=(V,E)$ , Few Node Labels  $\rightarrow$  Plz predict class for unlabeled nodes in  $G$

Assump  $G$  exist Homophily property (Markov property)

e.g. Binary Classification:

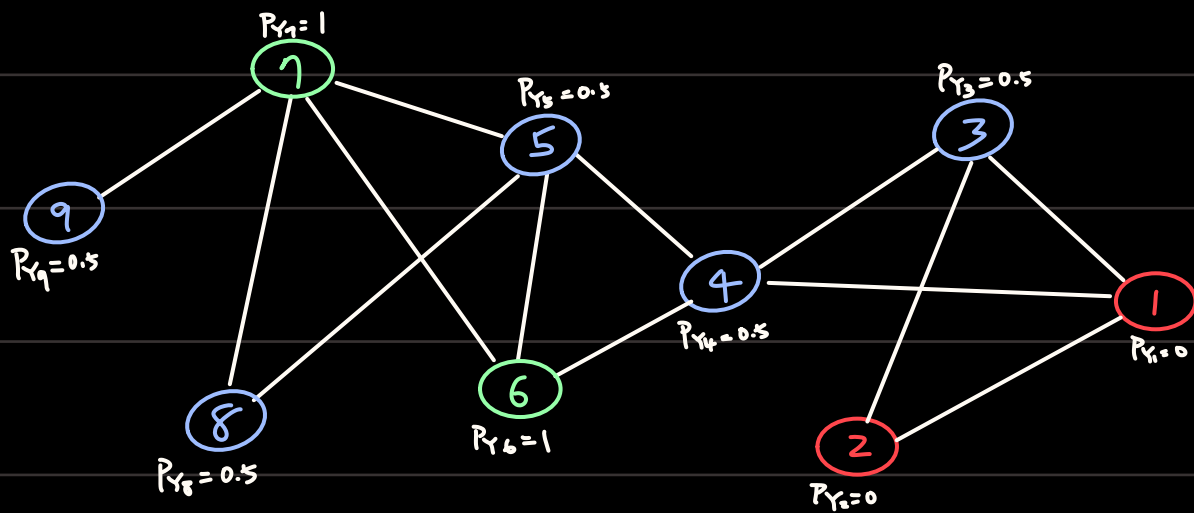
$G=(V,E)$ ,  $|V|=m$ , Adjacency matrix  $A \in \{0,1\}^{m \times m}$  with labels  $Y=\{0,1\}^m$ , where  $m \gg n$

(根本是 K-Nearest Neighbors)

Def Relational Classifiers  $v \rightarrow P(Y_v = ?)$

For some class  $c$ ,  $P(Y_v = c) = \text{weighted average of } P(Y_m = c), m \in N(v)$

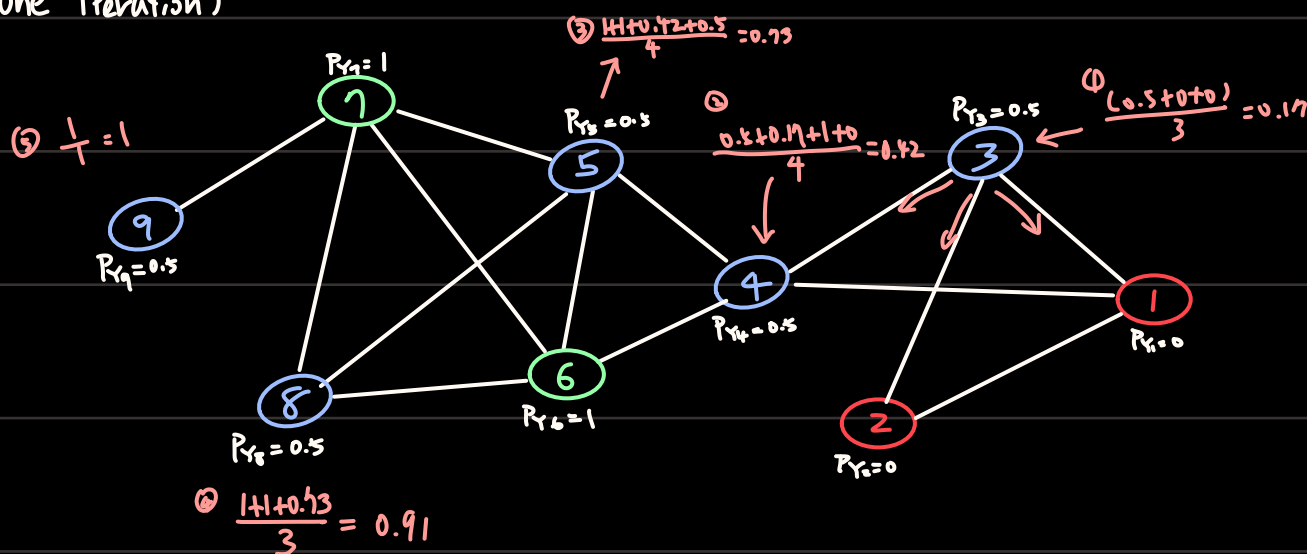
Init: labeled:  $Y_v = 1$  unlabeled:  $Y_v = 0.5$



Update:

$$P(Y_v = c) = \frac{1}{\sum_{(v,m) \in E} A_{v,m}} \sum_{(v,m) \in E} A_{v,m} P(Y_m = c), \text{ where } A_{v,m} \text{ is edge weight of } (v,m)$$

(one iteration)



→ After convergence:  $\begin{cases} 1 & \text{if } P(Y_v) > 0.5 \\ 0 & \text{o.w} \end{cases}$

Challenges: ① Convergence not guaranteed

② Model cannot use node feature information

## Def Iterative Classification

Given  $G = G(V, E)$ , some of nodes with labels, each  $v \in V$  have feature  $f_v$

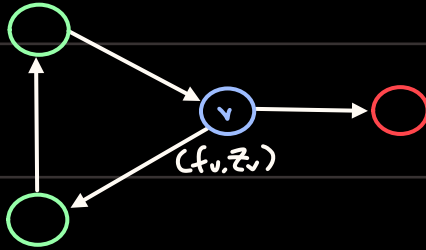
Train 2 Classifier:  $\hat{Q}_1(f_v)$ : predict node label based on node feature vector  $f_v$

the summary  $z_v$ :  $Q_2(f_v, z_v)$ : predict label based on feature vector  $f_v$  and summary  $z_v$  of labels of  $v$ 's neighbors

- ① Histogram of the number (or fraction) of each label in  $N_{\text{dev}}$

- ④ Most common label in  $N_{cr}$

- ③ Number of different labels in  $N_{uv}$



Algorithm:  $G = G(V, E)$ , some  $v \in V$  have labels

Step 1: classify based on node attributes alone

train 2 clf e.g. SVM - RFs

- ①  $\hat{y}_i(f_v)$  predict  $Y_v$  based on  $f_v$

- ②  $x_{21}(f_v, z_v)$  to predict  $Y_v$  based on  $f_v$  and  $z_v$

Step 2 Iterate till convergence

Test unknow:  $Q_1(f_v) = Y_v$ , compute  $Z_v \rightarrow Q_2 = Y_v$

Iterate  $v \in V$  {

Update  $z_v$  based on  $Y_u \forall u \in N(v)$

Update  $z_v$  based on  $Y_u \forall u \in N(v)$       ① class label not changed (Convergence not guaranteed)  
Update  $Y_v$  based on the new  $z_v(\Phi_2)$  } until ② reach max iteration

Update  $Y_v$  based on the new  $z_v(q_i)$  } until  $\phi$  reach max iteration

### Example: Web Page Classification

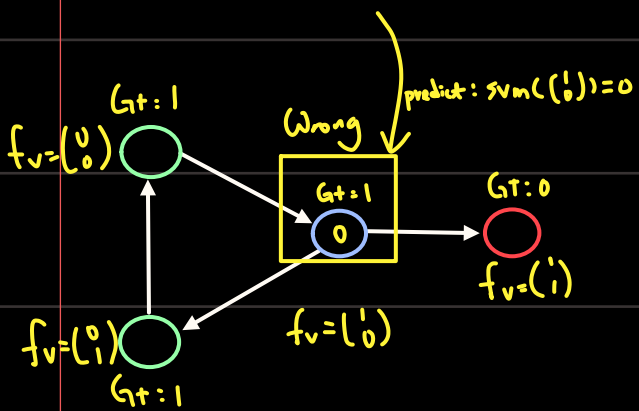
Input :  $G = G(V, E)$  ,  $V$ : Web Pages  $E$ : Hyper-link between Web pages (directed)

Given

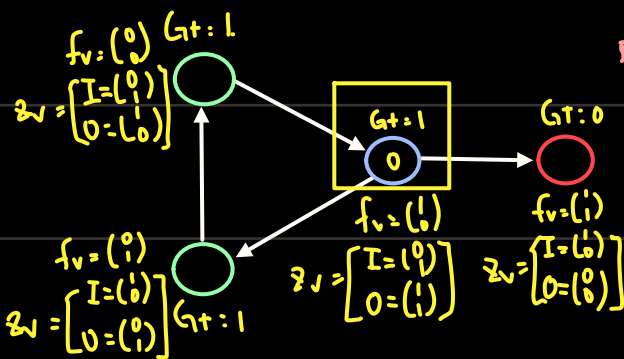
Node features: Webpage description (for simplicity, only consider 2 binary features)

→ Plz predict the topic of the webpage

- ①  $\hat{y}_v(f_v)$  predict  $Y_v$  based on  $f_v$   
 $\text{train: } \hat{y}_i = \text{sum}([(\%), (\%), (\%)]) \leftrightarrow [1, 1, 0]$

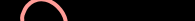


- ②  $\alpha_2(f_v, z_v)$  to predict  $Y_v$  based on  $f_v$  and  $z_v$   
 $z_v \rightarrow 1$ : incoming neighbor feature,  $0$ : outgoing neighbor feature



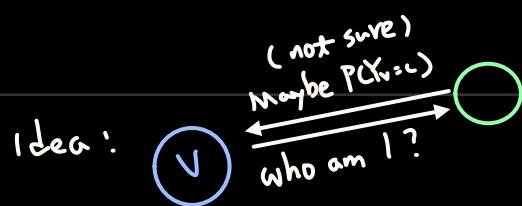
Rules:  $I_0 = 1$  if one of incoming labeled 0  
 $I_1 = 1$ , " " " " " "  
 $O_0 = 1$ , " outgoing  
 $O_1 = 1$ , " " "

$$\text{train: } \mathcal{Q}_2 = \text{smc}(\{f_u, I, 0\} \mid \forall m \in \text{Ncv}\}) \quad \forall v \in V$$

Test:  $z_v = [I, 0]$    $\mathcal{Q}_2(\{(f_v, I, 0) \mid \forall n \in \text{Ncr}(v)\})$   
 $\parallel$   
 $\forall_v$

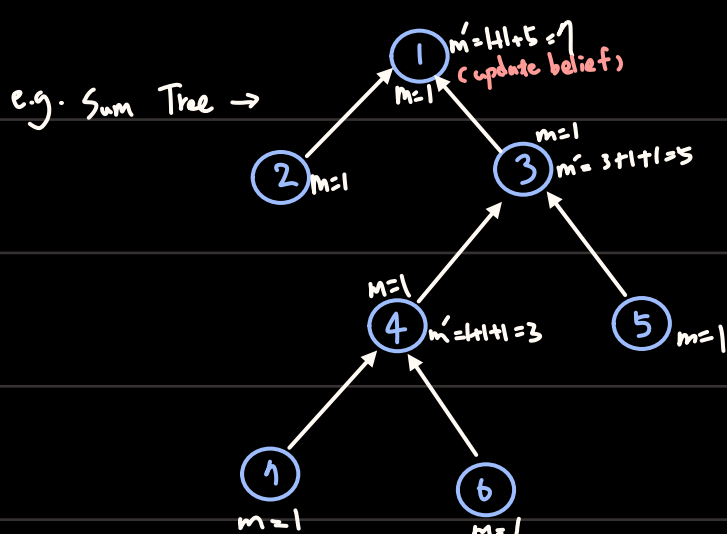
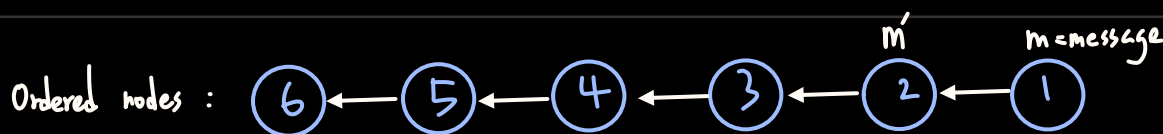
## (Dynamic Programming)

Def Collective Classification: Belief Propagation



Message Passing Concept:

Condition: Each node can only pass message to its neighbors (conclude received from in-link neighbors and pass to out-link)



Notation:

Label-label potential matrix  $\psi$ :  $\psi(Y_i, Y_j) = P(\text{node } j \text{ is being in class } Y_j | j's \text{ neighbor } i \text{ in class } Y_i)$

Prior belief  $\alpha$ :  $\alpha(Y_i) = P(\text{node } i \text{ being in class } Y_i)$

$m_{i \rightarrow j}(Y_j)$ : <sup>(estimation)</sup> i's message of j being in class  $Y_j$

$L$ : the set of all labels

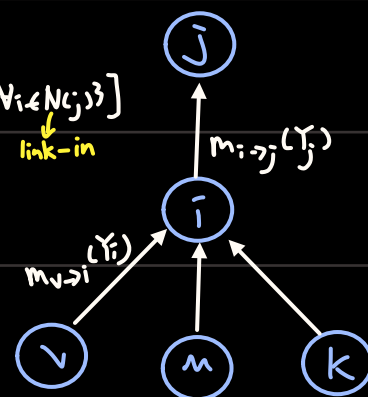
Algorithm:

Given  $G=(V, E)$  directed

Init: all message = 1 (Prior)

Iter each node  $i \in V$ :  $m_{i \rightarrow j}(Y_j) = \sum_{Y_i \in L} \underbrace{\psi(Y_i, Y_j) \cdot \alpha(Y_i)}_{P(Y_j|Y_i) \cdot P(Y_i) = P(Y_i, Y_j)} \prod_{k \in N_{in}(j)} m_{k \rightarrow i}(Y_i) \forall Y_j \in L \} = E[P(Y_j) | r_i | \{V_i \in N_{in}(j)\}]$   
 $\downarrow$  only link-in neighbors

Convergence  $\rightarrow$  belief of node i being in class  $Y_i$ :  $b_i(Y_i) = \alpha(Y_i) \prod_{j \in N_{out}(i)} m_{j \rightarrow i}(Y_j)$



Very Similar to Bellman Equation (But focus on j's link-out neighbors)

$\forall s_i \in N_{out}(s_j)$ , State  $s_j$  take an action to the state  $s_i$  with policy  $\pi$ , and define the value function  $V_\pi(s_j)$

$$V_\pi(s_j) = E_\pi \left[ \sum_{k=0}^{\infty} \gamma^k R_{t+k+1} | S_t = s_j \right] = \sum_a \pi(a|s_j) \sum_{s_i \in N_{out}(s_j)} \sum_{\substack{r \\ \text{link-out}}} P(s_i, r | s_j, a) [r + \gamma V_\pi(s_i)]$$

