

VE444: Networks

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Homophily

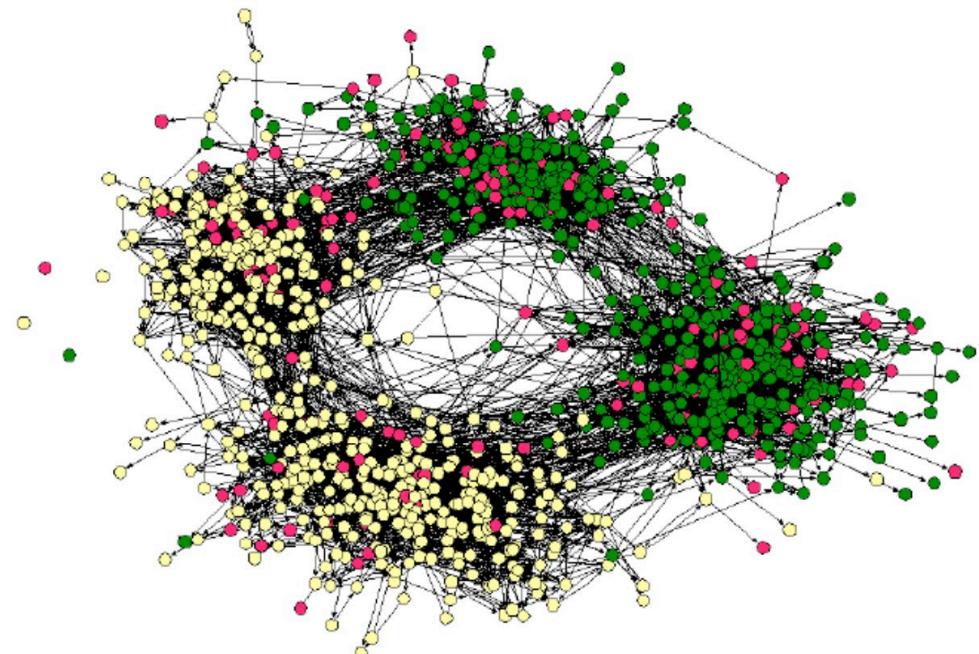
Networks in their surrounding contexts

- **Homophily**: the tendency of individuals to associate and bond **with similar others**
 - “*Birds of a feather flock together*”
 - “similarity begets friendship” – Plato
 - “love those who are like themselves” -- Aristotle
 - It has been observed in a vast array of network studies, based on a variety of attributes (e.g., age, gender, organizational role, etc.)
 - **Example**: people who like the same music genre are **more likely to establish a social connection** (meeting at concerts, interacting in music forums, etc.)

Correlations Exist in Networks

Example:

- Real social network
 - Nodes = people
 - Edges = friendship
 - Node color = race
- People are segregated by race due to homophily



(Easley and Kleinberg, 2010)

Homophily and Friendship

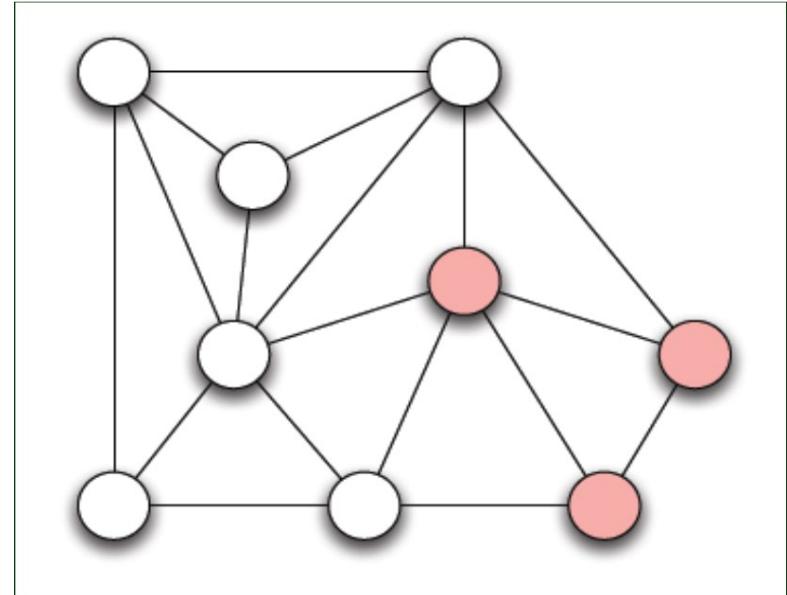
- For an individual, he has two types of characteristics
 - Intrinsic: gender, race, mother tongue, etc
 - Changeable: where he lives, expertise, what he likes, etc
- Homophily is the external reason for the creation of social networks
 - Common in race, locations, expertise, interests
- One key question in social sciences
 - Commonality → friendship ? (selection)
 - Friendship → commonality ? (social influence)
 - **Example:** I recommend my “peculiar” musical preferences to my friends, until one of them grows to like my same favorite genres ☺

Measuring homophily

- Given a social network where the nodes have only two properties: red and white
- The information we can have:
 - The number of nodes (n), the number of links (e)
 - The ratio of different colors: $p, q = 1 - p$
 - The number of links (s) where the two end nodes have the same color
- If not homophily?

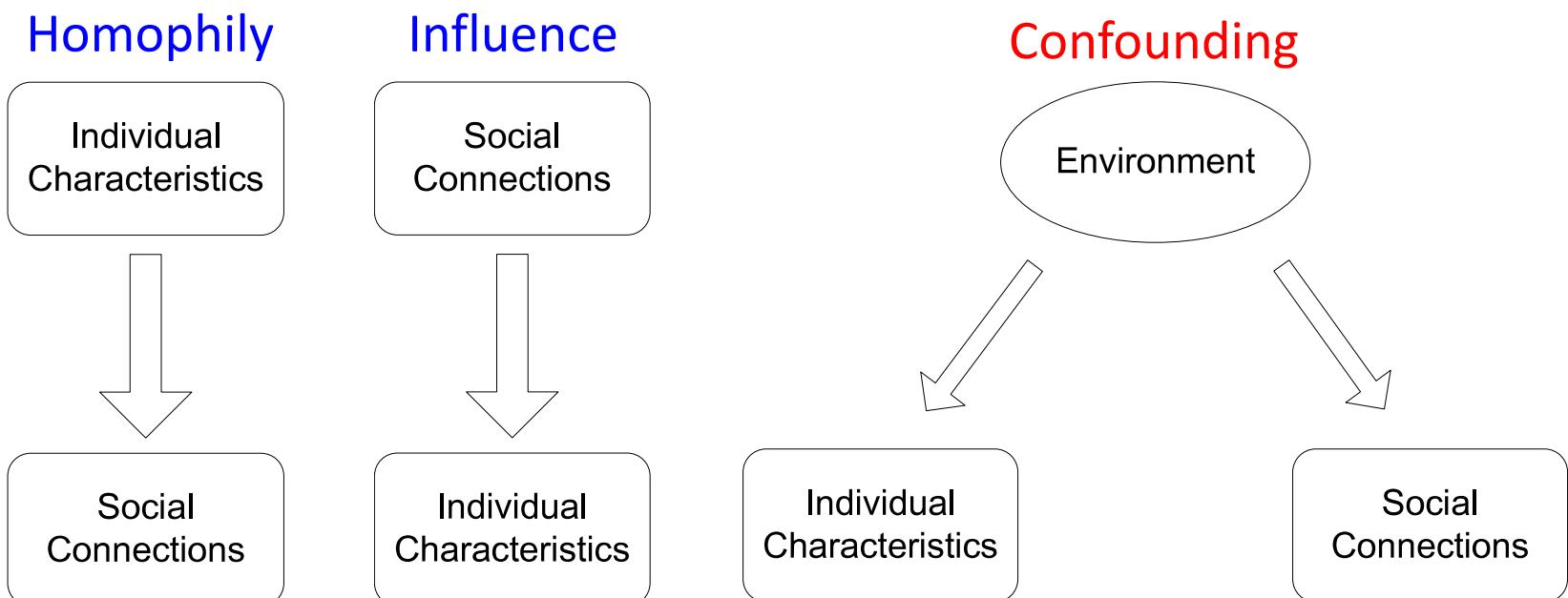
Measuring homophily

- Homophily test: If the fraction of cross-attributes edges is significantly less than $2pq$, then there is evidence for homophily.
- Example:
 - The number of nodes $n = 9$
 - The number of links $e = 18$
 - The ratio of red nodes $p = 1/3$
 - The ratio of white nodes $q = 2/3$
- Statistical significance test required
- Inverse homophily



Correlations Exist in Networks

- Individual behaviors are **correlated** in a network environment
- Three main types of dependencies that lead to correlation:



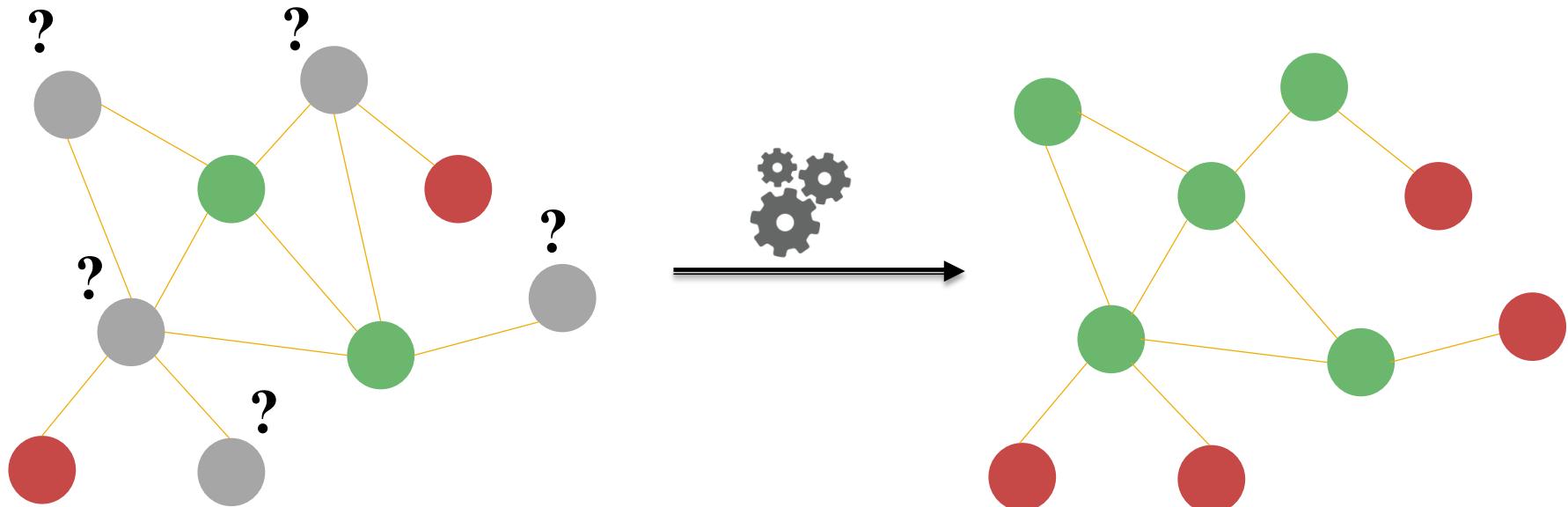
Application of homophily

- How do we **leverage this correlation** observed in networks to help predict node labels?
- Similar nodes are typically close together or directly connected:
 - “**Guilt-by-association**”: If I am connected to a node with label X , then I am likely to have label X as well.
 - Example: **Malicious/benign web page**: Malicious web pages link to one another to increase visibility, look credible, and rank higher in search engines

Fake Review Spam Detection

- Behavioral analysis
 - individual features, geographic locations, login times, session history, etc.
- Language analysis
 - use of superlatives, lots of self-referencing, rate of misspellings, many agreement words, ...
- Easy to fake: **individual behaviors, content of review**
- Hard to fake: **graph structure**
 - Graphs capture relationships between reviewers, reviews, stores

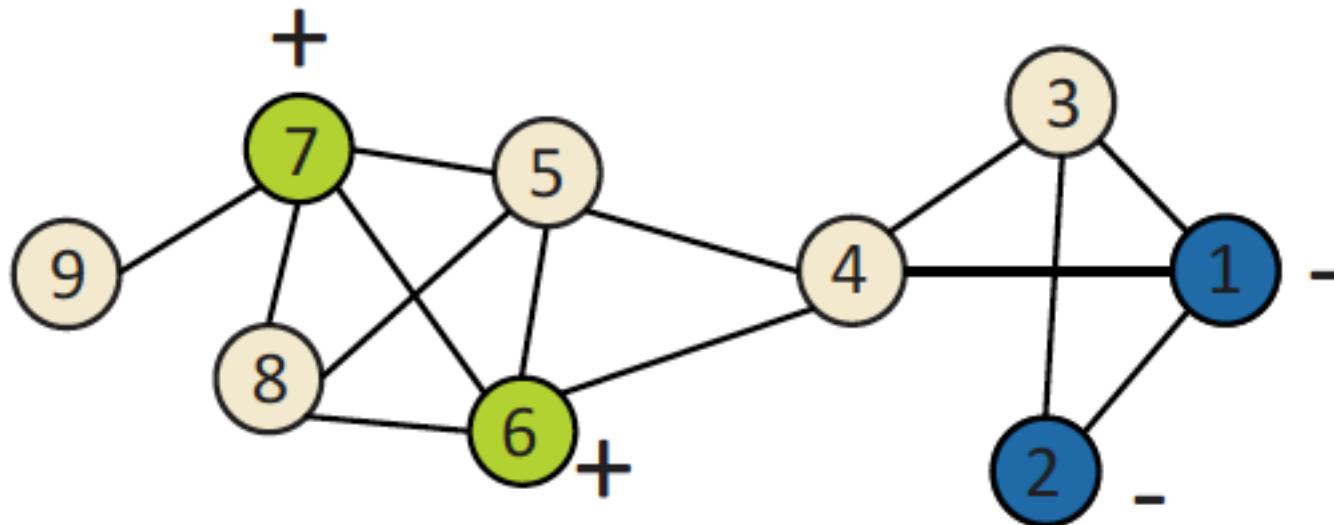
Node Classification



- Given labels of some nodes
- Let's predict labels of unlabeled nodes
- This is called semi-supervised node classification

Classification with Network Data

- How do we leverage this correlation observed in networks to help predict node labels?



How do we predict the labels for the nodes in beige?

Available information

- Classification label of an object O in network may depend on:
 - Features of O
 - Labels of the objects in O 's neighborhood
 - Features of objects in O 's neighborhood

Collective classification overview

- **Markov Assumption:** *the label Y_i of one node i depends on the labels of its neighbors N_i*

$$P(Y_i|i) = P(Y_i|N_i)$$

- Collective classification involves 3 steps:

Local Classifier

- Assign initial labels

Relational Classifier

- Capture correlations between nodes

Collective Inference

- Propagate correlations through network

Collective Classification: Overview

Local Classifier

- Assign initial labels

Local Classifier: Used for initial label assignment

- Predicts label based on node attributes/features
- Standard classification task
- Does not use network information

Relational Classifier

- Capture correlations between nodes

Relational Classifier: Capture correlations based on the network

- Learns a classifier to label one node based on the labels and/or attributes of its neighbors
- This is where network information is used

Collective Inference

- Propagate correlations through network

Collective Inference: Propagate the correlation

- Apply relational classifier to each node iteratively
- Iterate until the inconsistency between neighboring labels is minimized
- Network structure substantially affects the final prediction

Probabilistic Relational Classifier

- **Basic idea:** Class probability of Y_i is a weighted average of class probabilities of its neighbors
- For labeled nodes, initialize with ground-truth Y labels
- For unlabeled nodes, initialize Y uniformly
- **Update** all nodes in a random order until convergence or until maximum number of iterations is reached

Probabilistic relational classifier

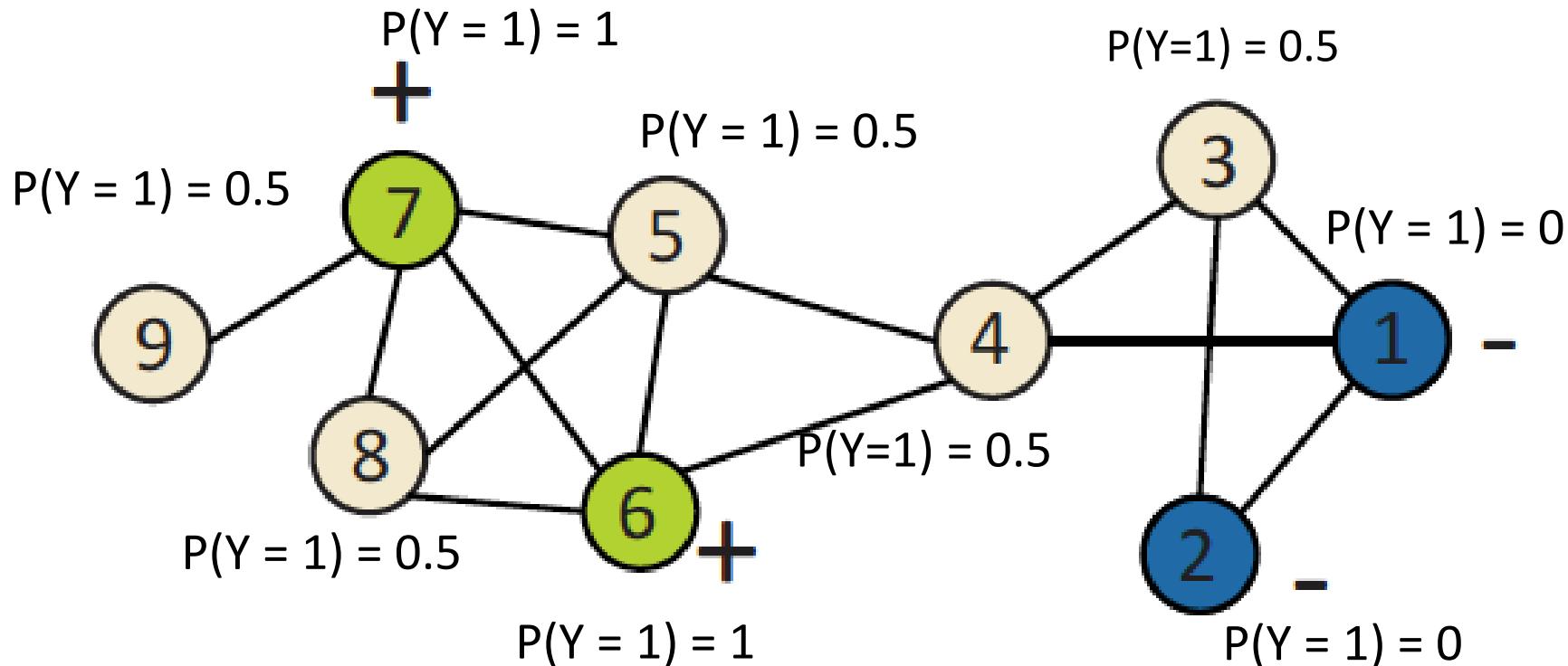
- **Repeat** for each node i and label c

$$P(Y_i = c) = \frac{1}{|N_i|} \sum_{(i,j) \in E} W(i,j) P(Y_j = c)$$

- $W(i,j)$ is the edge strength from i to j
- N_i is the number of neighbors of i
- **Challenges:**
 - Convergence is not guaranteed
 - Model cannot use node feature information

Probabilistic relational classifier example

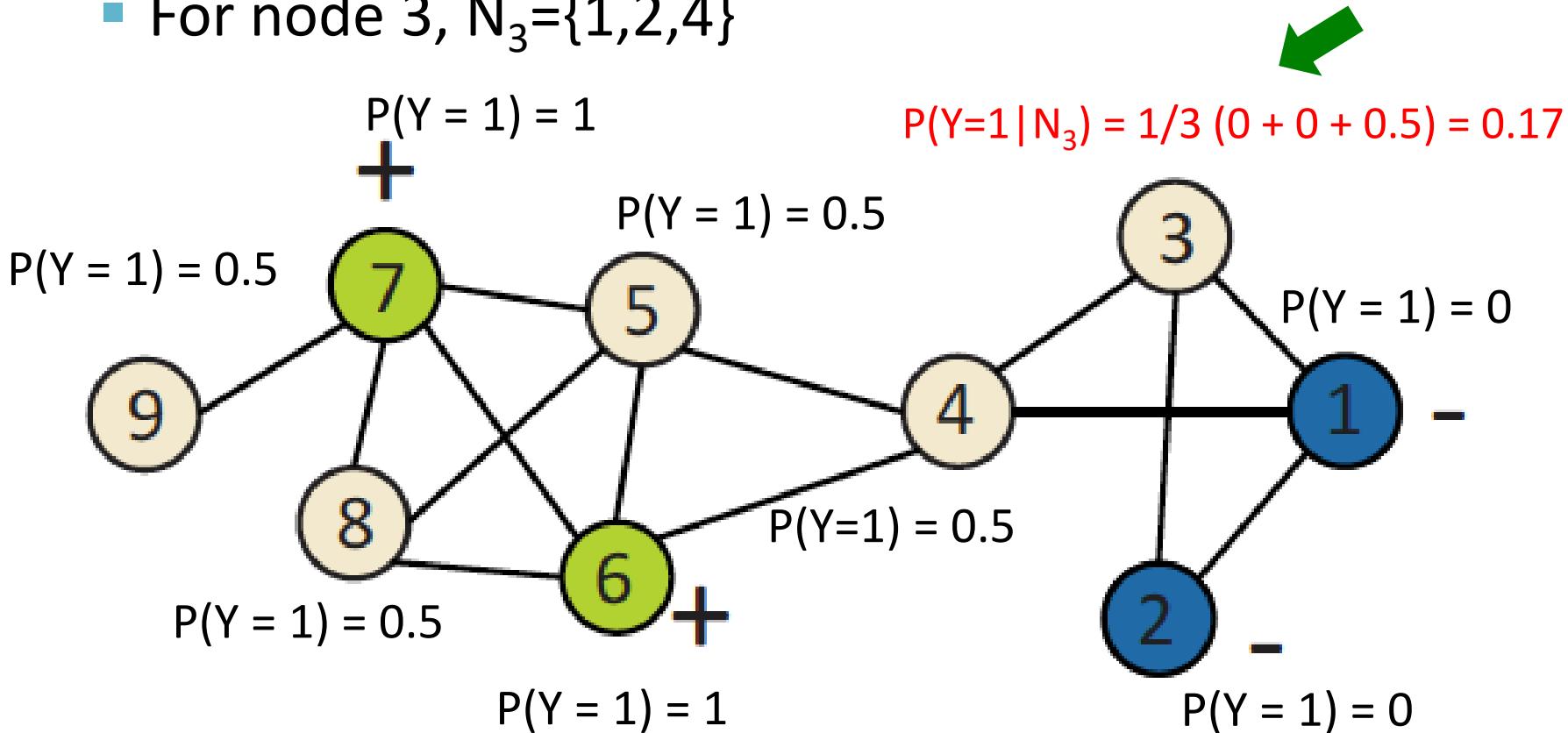
Initialization: All labeled nodes to their labels, and all unlabeled nodes uniformly



Probabilistic relational classifier example

- Update for the 1st Iteration:

- For node 3, $N_3 = \{1, 2, 4\}$



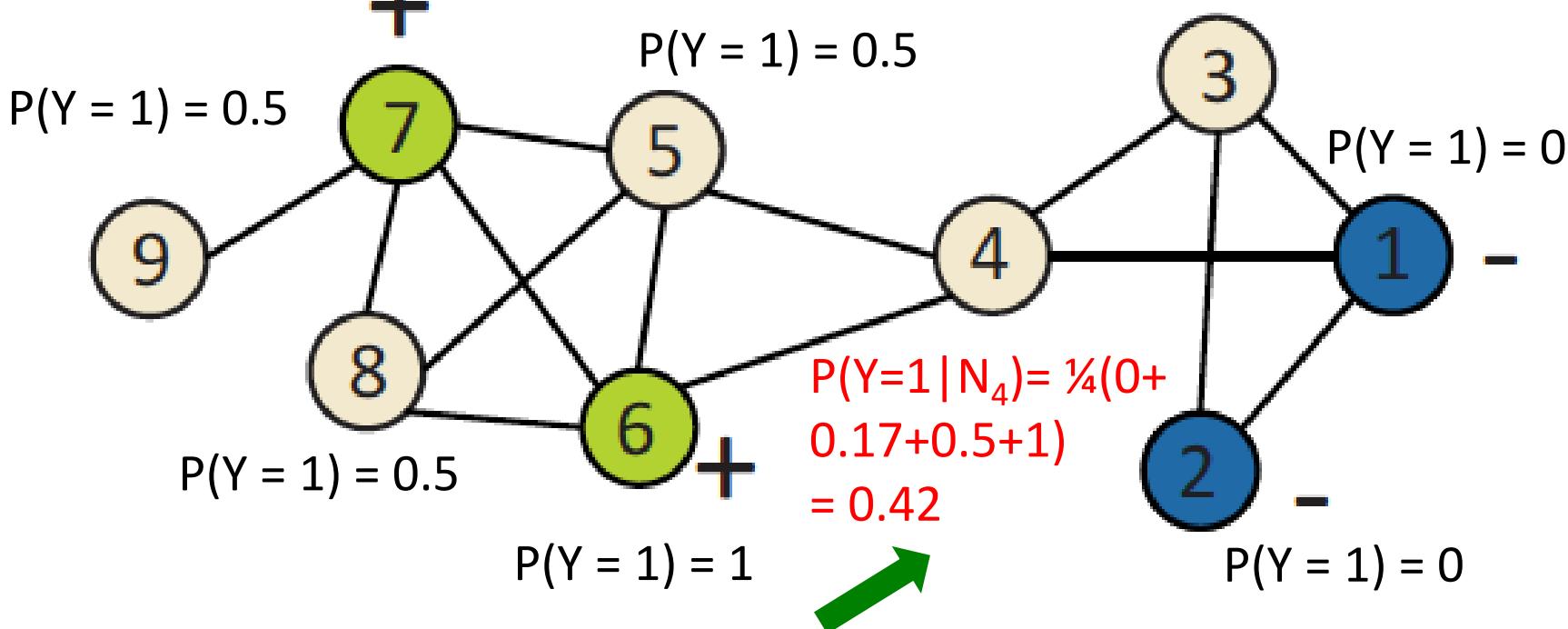
Probabilistic relational classifier example

- Update for the 1st Iteration:

- For node 4, $N_4 = \{1, 3, 5, 6\}$

$$P(Y = 1) = 1$$

+



Probabilistic relational classifier example

- Update for the 1st Iteration:

- For node 5, $N_5 = \{4, 6, 7, 8\}$

$$P(Y = 1) = 1$$

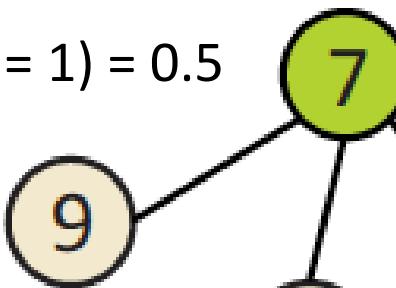
+

$$P(Y=1 | N_5) =$$

$$\frac{1}{4} (0.42 + 1 + 1 + 0.5) = 0.73$$

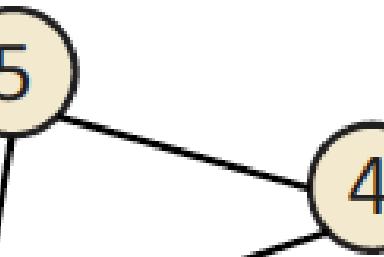


$$P(Y = 1) = 0.5$$



$$P(Y = 1) = 0.5$$

$$P(Y = 1) = 1$$



$$P(Y=1 | N_4) = 0.42$$

+

$$P(Y=1) = 0.17$$



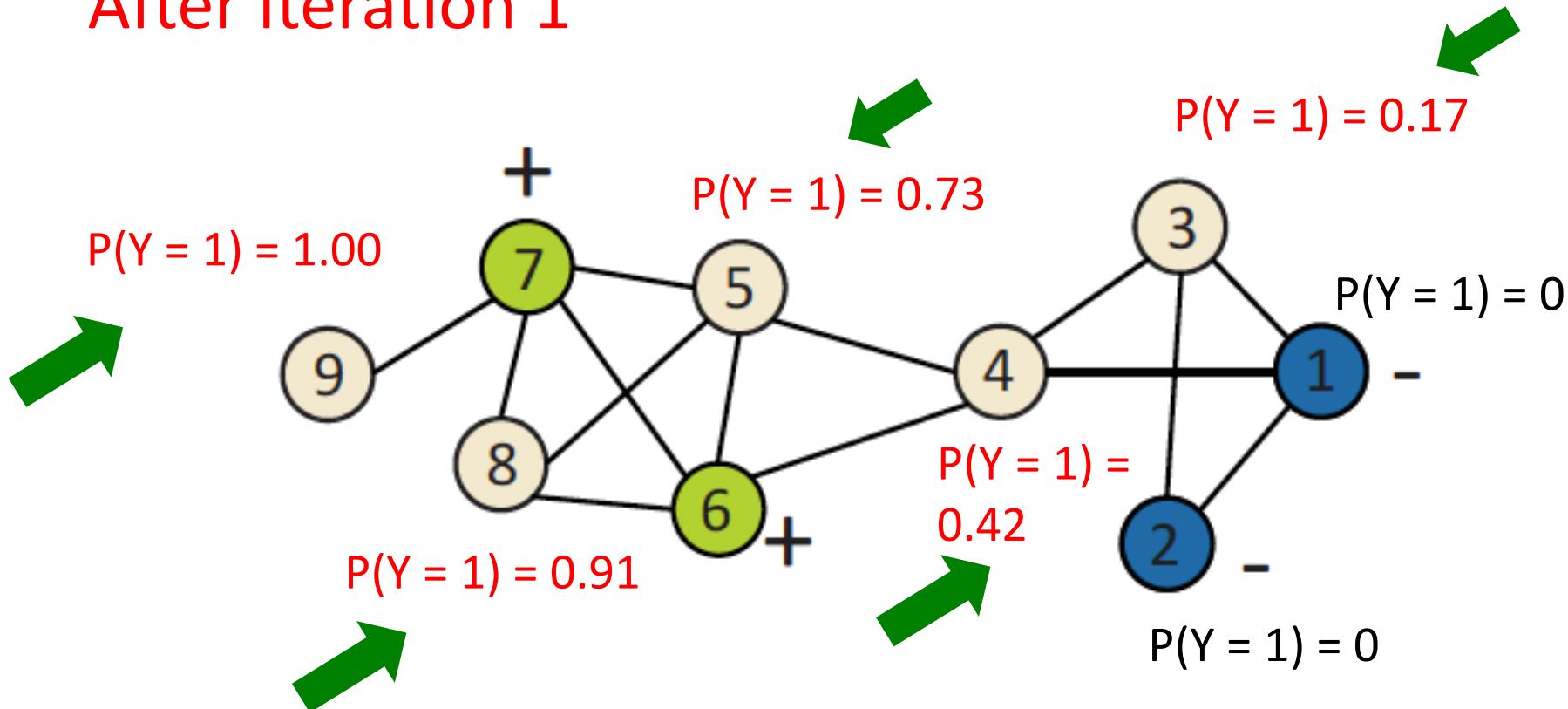
$$P(Y = 1) = 0$$



$$P(Y = 1) = 0$$

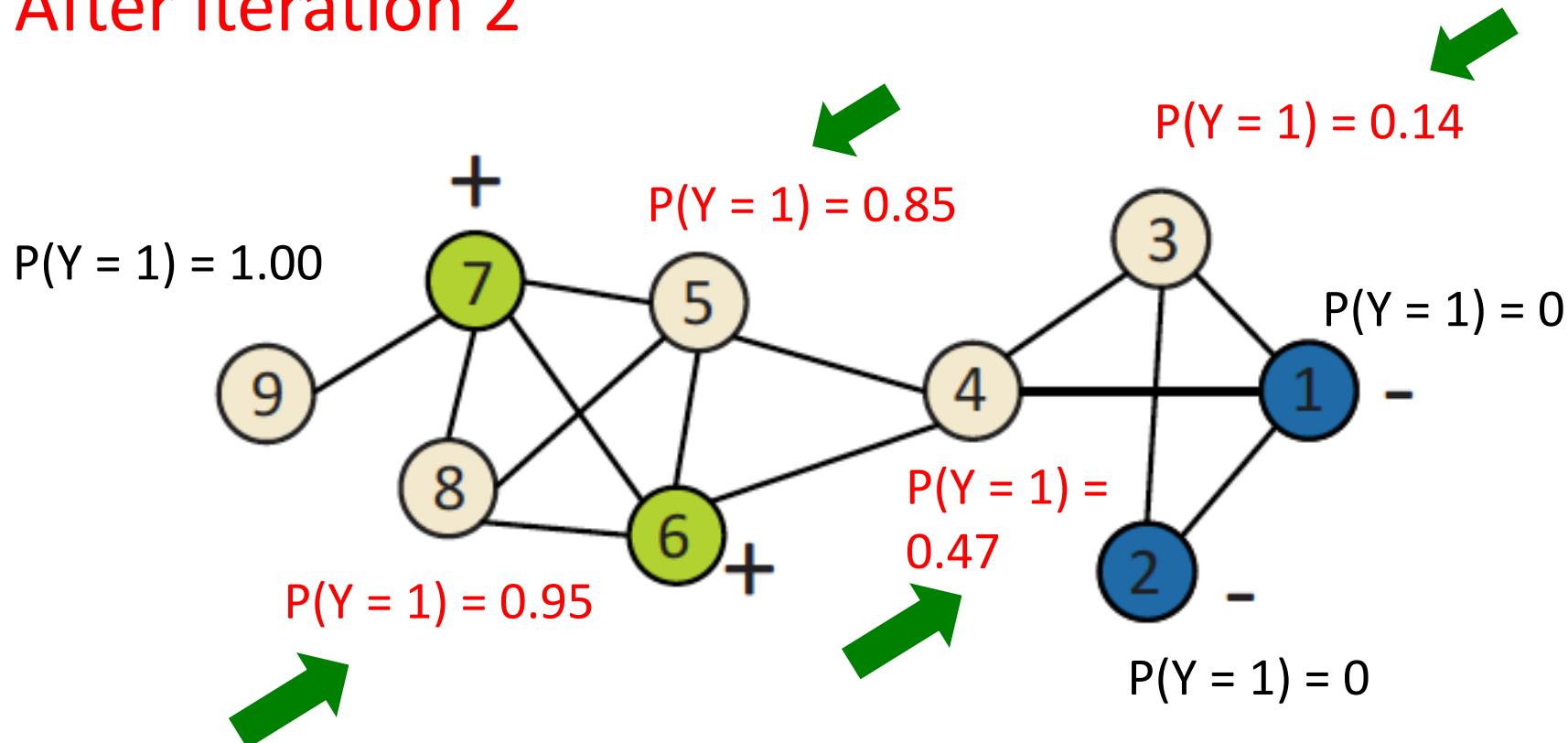
Probabilistic relational classifier example

After Iteration 1



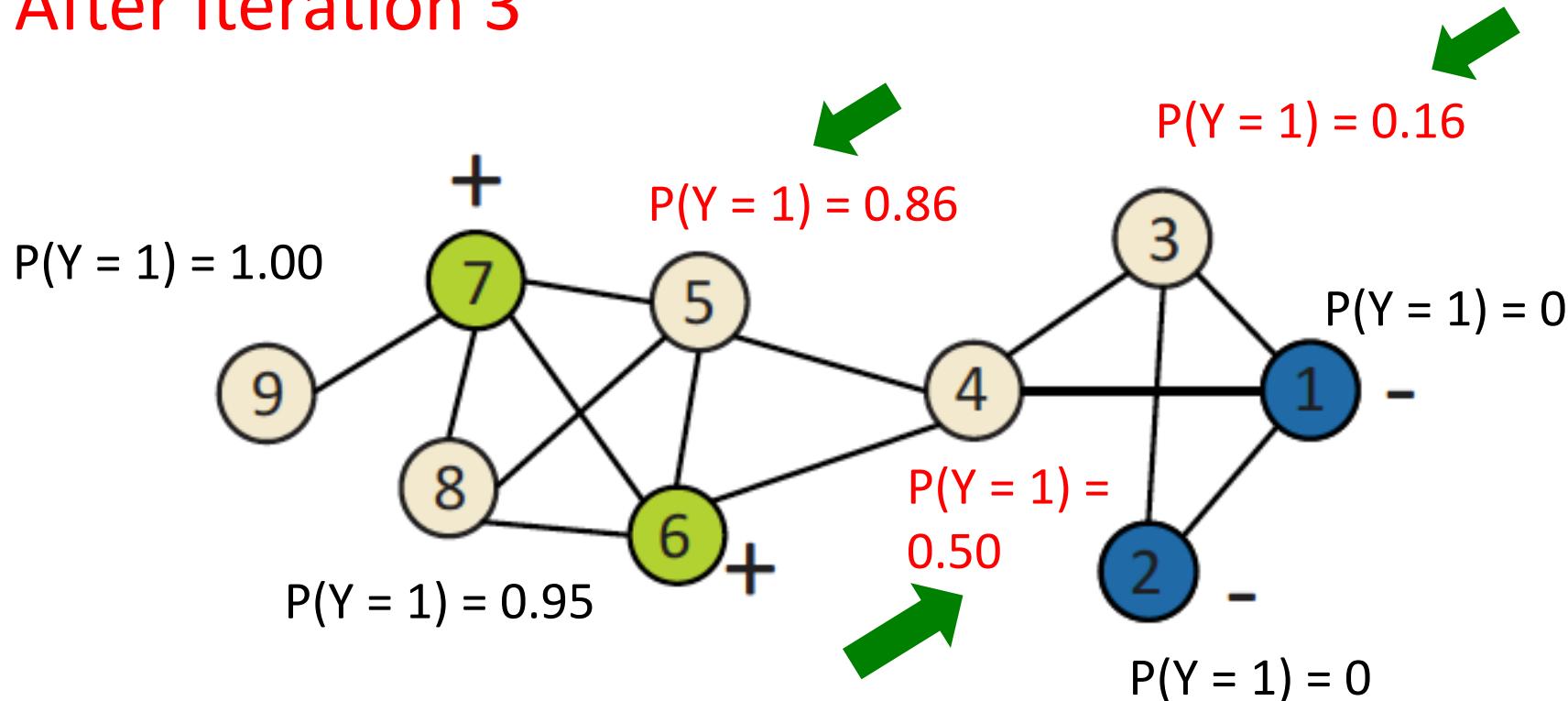
Probabilistic relational classifier example

After Iteration 2



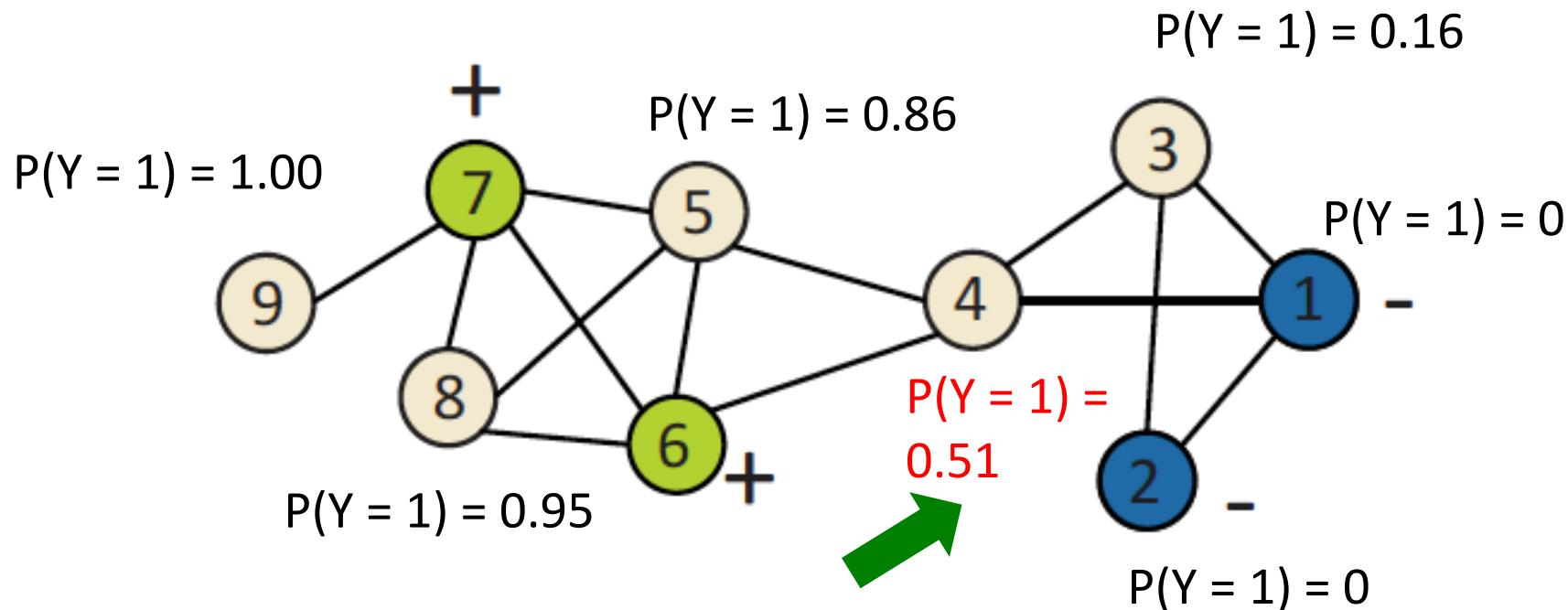
Probabilistic relational classifier example

After Iteration 3



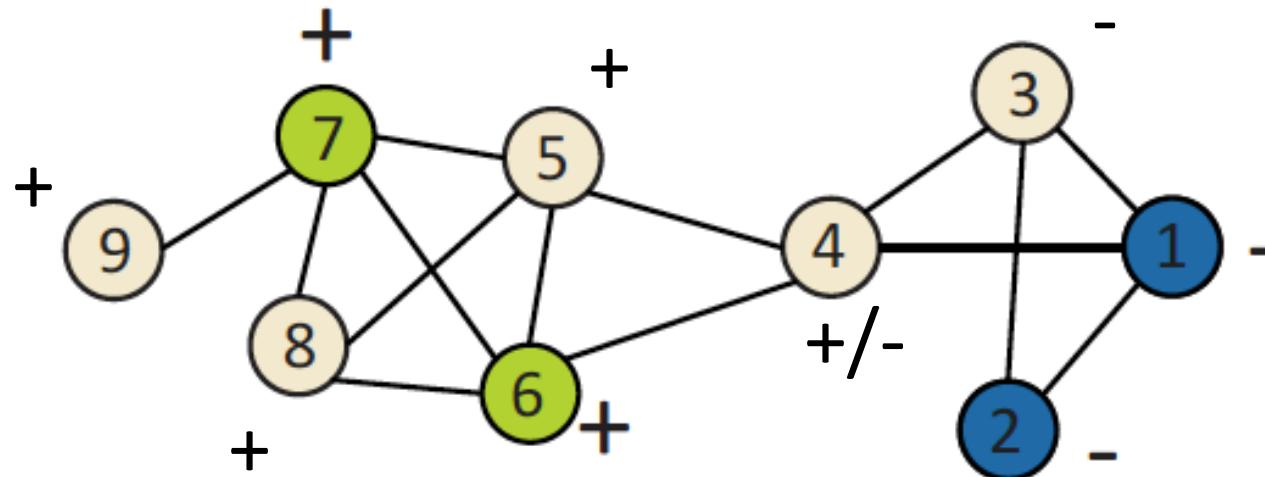
Probabilistic relational classifier example

After Iteration 4



Probabilistic relational classifier example

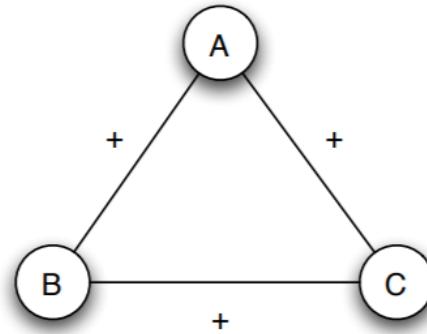
- All scores stabilize after 5 iterations:
 - Nodes 5, 8, 9 are + ($P(Y_i = 1) > 0.5$)
 - Node 3 is - ($P(Y_i = 1) < 0.5$)
 - Node 4 is in between ($P(Y_i = 1) = 0.5$)



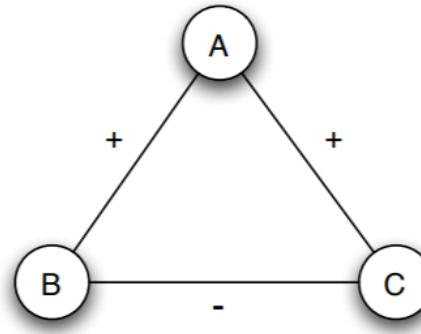
Structural Balance

**Local effects can have global
consequences that are observable
at the level of the network as a
whole**

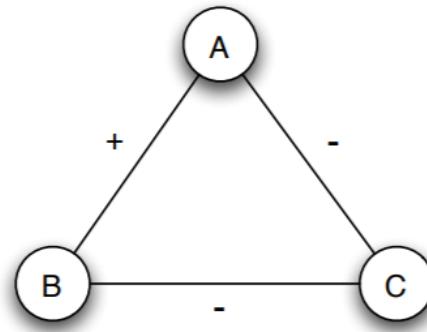
Starting from the local



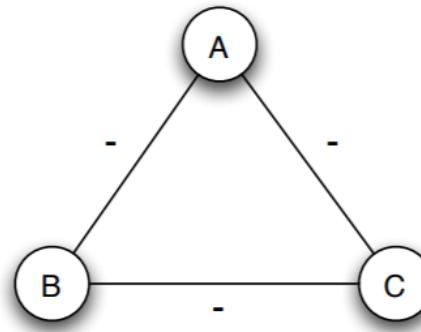
(a) *A, B, and C are mutual friends: balanced.*



(b) *A is friends with B and C, but they don't get along with each other: not balanced.*



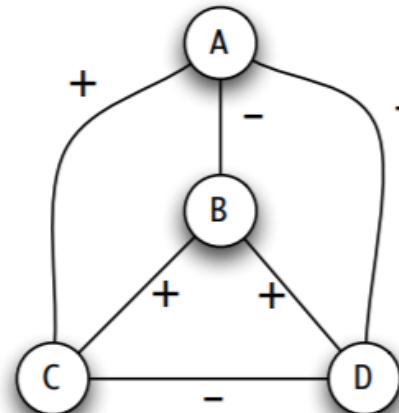
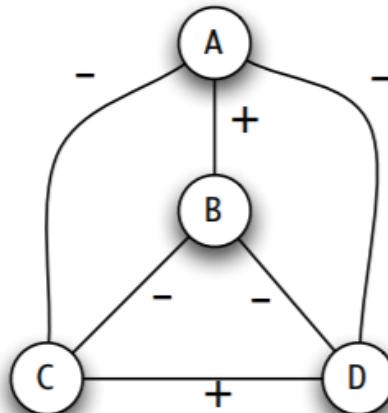
(c) *A and B are friends with C as a mutual enemy: balanced.*



(d) *A, B, and C are mutual enemies: not balanced.*

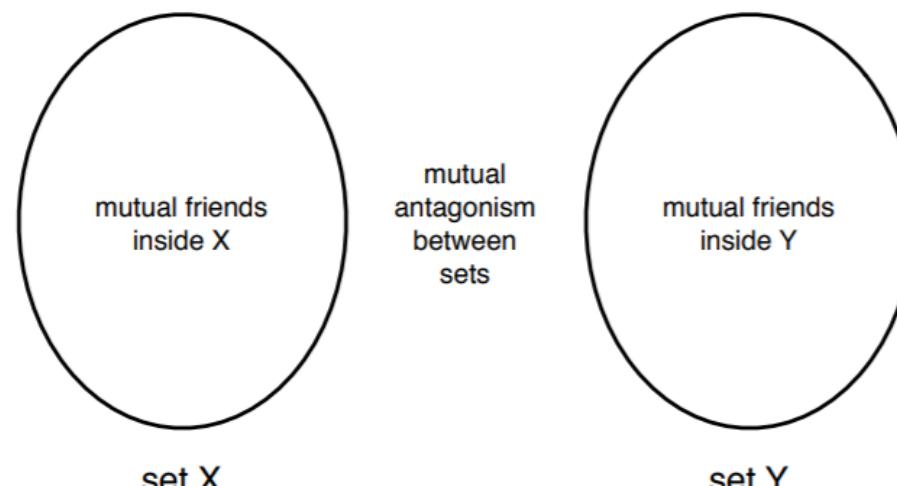
Structural balance

- **Structural balance property:** For every set of three nodes, if we consider the three edges connecting them, either all three of these edges are labeled +, or else exactly one of them is labeled +.



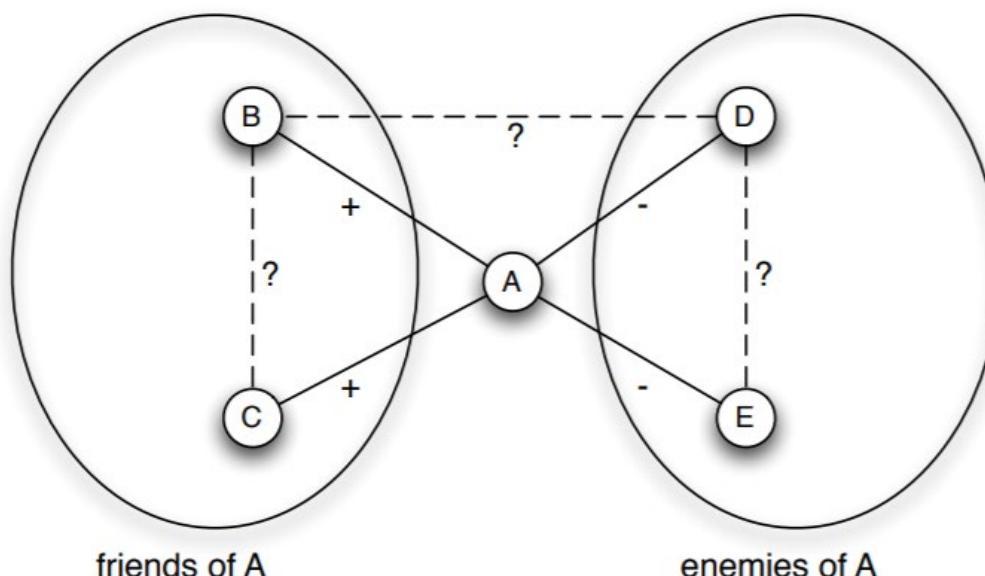
Structure of a balanced networks

- **Balance theorem:** If a labeled complete graph is balanced, then either all pairs of nodes are friends, or else the nodes can be divided into two groups, X and Y , such that every pair of nodes in X like each other, every pair of nodes in Y like each other, and everyone in X is the enemy of everyone in Y .



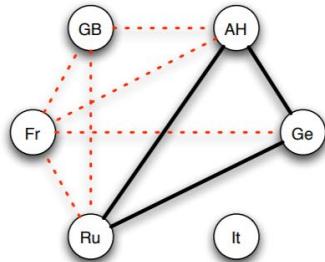
Proving the Balance Theorem

- To satisfy balance theorem, we have to
 - (1) every nodes in X are friends
 - (2) every nodes in Y are friends
 - (3) every node in X is an enemy of every node in Y

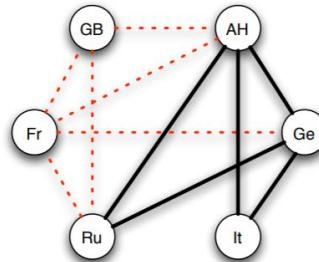


Balance: good or bad?

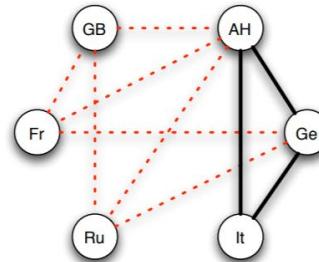
- Search for balance can lead to two implacably opposed alliances



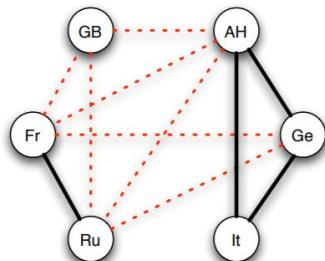
(a) *Three Emperors' League 1872–81*



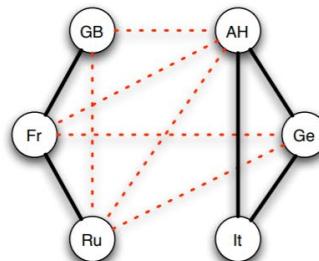
(b) *Triple Alliance 1882*



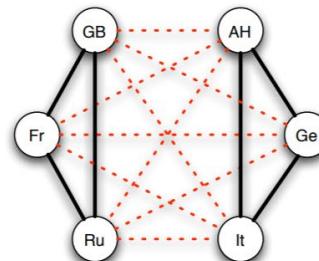
(c) *German-Russian Lapse 1890*



(d) *French-Russian Alliance 1891–94*



(e) *Entente Cordiale 1904*



(f) *British Russian Alliance 1907*