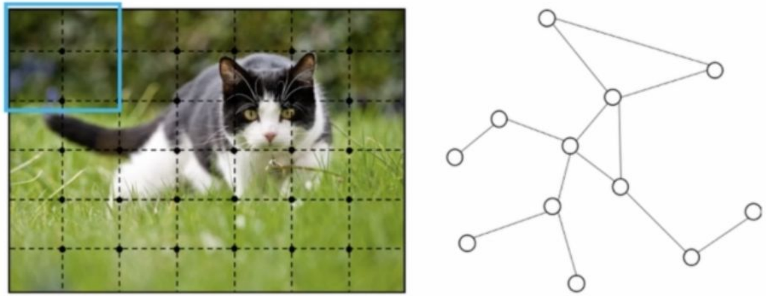


Message Passing and Representations

All knowledge is connected to all other knowledge. The fun is in making the connections.

- Arthur Aufderheide

Jay Urbain, Ph.D.

Electrical Engineering and Computer Science Department

Milwaukee School of Engineering

Credits:

Message Passing

Intuition:

- Correlations (dependencies) exist in networks.
- Similar nodes are connected.

Key concept is collective classification:

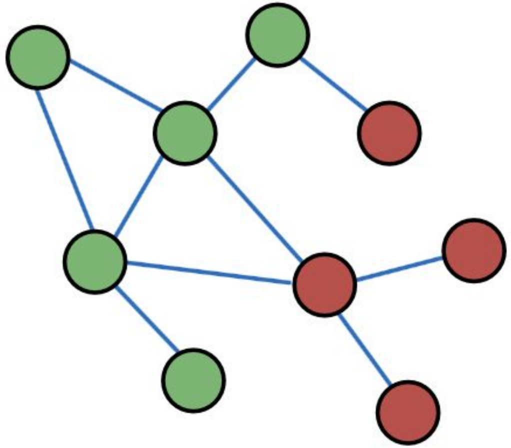
- Idea of assigning labels to all nodes in a network together.

Review a couple of techniques:

- Relational classification
- Iterative classification

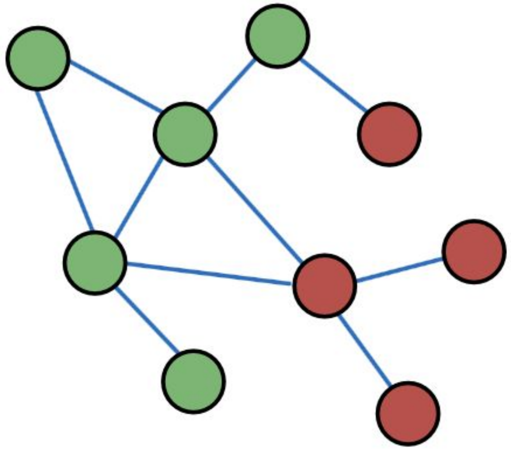
Correlations exist in networks

- Behaviors of nodes are correlated across the links of the network
- Correlation: Nearby nodes have the same class (color)



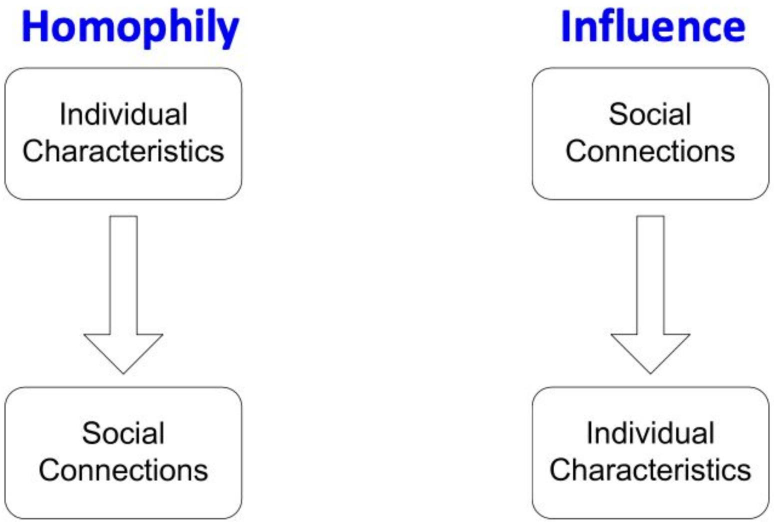
Correlations exist in networks

- Why are behaviors of nodes correlated?



Correlations exist in networks

- Why are behaviors of nodes correlated?

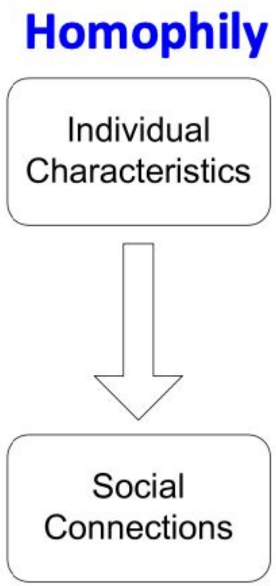


Social Homophily

Homophily

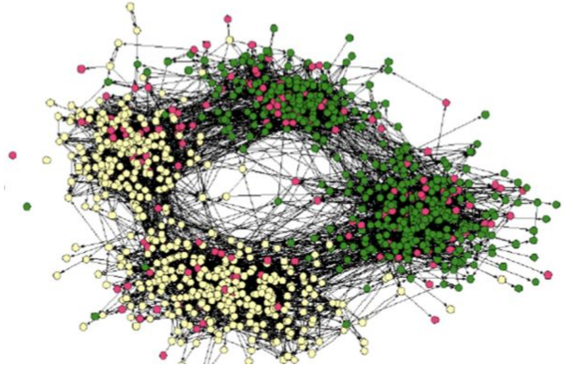
- Tendency for people to seek out or be attracted to those who are similar to themselves.
- "Birds of a feather flock together"
- Observed in a vast array of network studies, based on a variety of attributes (e.g., age, gender, organizational role, etc.)

Example: Researchers who focus on the same research area are more likely to establish a connection (meeting at conferences, interacting in academic talks, etc.)



Example: Homophily

(Easley and Kleinberg, 2010)



Online social network

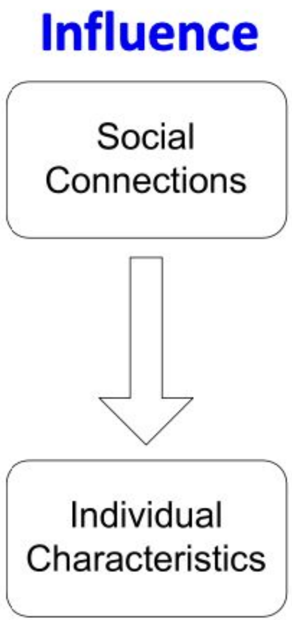
- Nodes = people
- Edges = friendship
- Node color = interests (sports, profession, arts, etc.)

People with the same interest are more closely connected due to homophily

Example: Social Influence

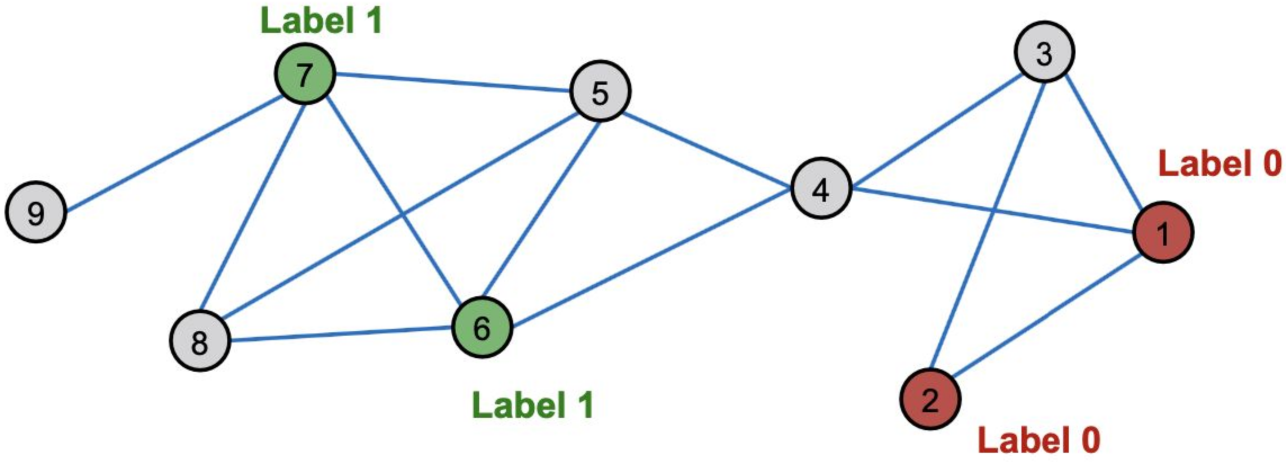
Influence: Social connections can influence the individual characteristics of a person.

Example: You’re influenced by the behavior of people with your group(s). Activities, interests, clothes, video games, etc.



Classification with network data

- How do we leverage this correlation observed in networks to help predict node labels?
- For example, predict the class (color) of the gray nodes?



Idea: Guilt by association

Similar nodes are typically close together or directly connected in the network:

- Guilt-by-association: If I'm connected to a node with label X, then I'm more likely to have label X as well.
- Example: Financial web pages link to one another to increase visibility, look credible, and rank higher in search engines.

Idea: Node Features

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

- Features of v
- Labels of the nodes in v's neighborhood
- Features of the nodes in v's neighborhood

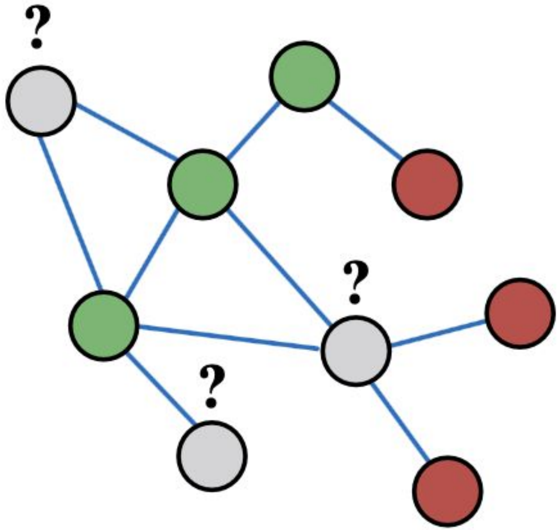
Semi-supervised learning

Given:

- Graph
- Some labeled nodes

Find: Class (red/green) of remaining nodes

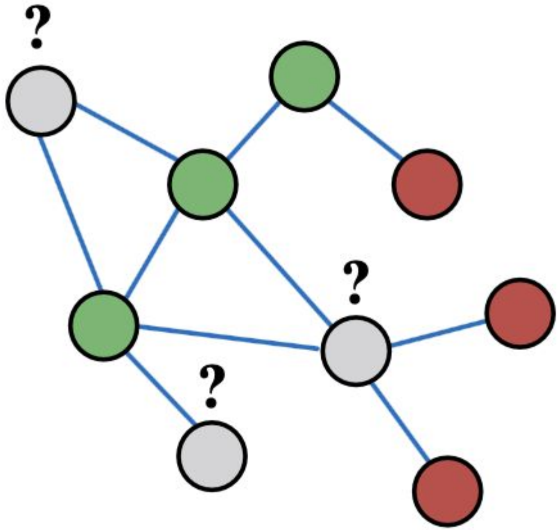
- Main assumption: There is *homophily* in the network



Semi-supervised learning

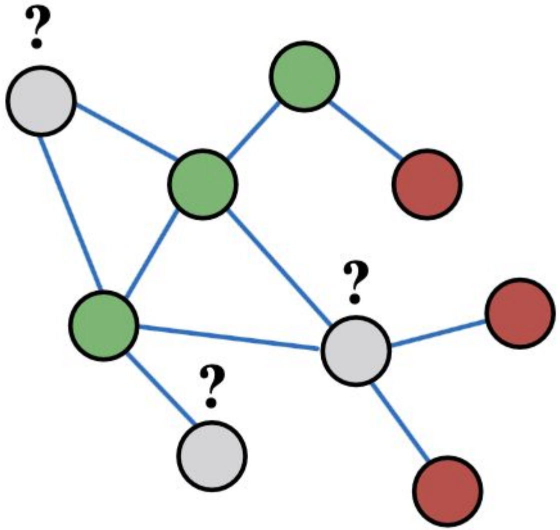
Example task:

- Let A be a $\boldsymbol{n \times n}$ adjacency matrix over n nodes
- Let $\mathbf{Y} = \{0,1\}^n$ be a vector of labels:
  - $Y_v = 1$ (Class 1, green)
  - $Y_v = 0$ (Class 0, red)
  - Unlabeled node needs to be classified (grey)
- Goal: Predict which unlabeled nodes are likely Class 1, and which are likely Class 0

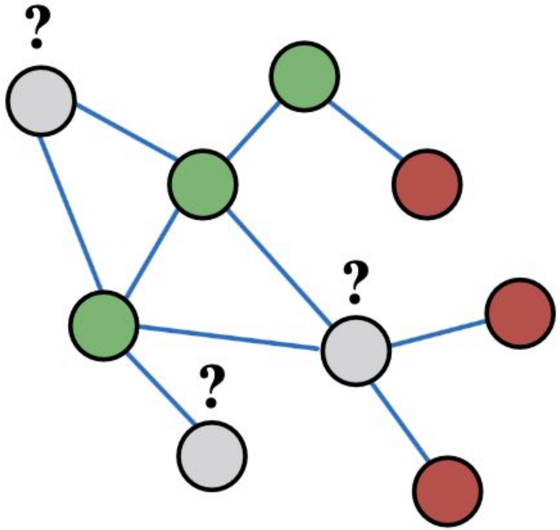


Problem setting

- How to predict the labels Y_v for the unlabeled nodes $\boldsymbol{v}$ (grey)?
- Each node v has a feature vector f_v
- Labels for some nodes are given (1 for green, 0 for red)
- Task: Find $P(Y)$ given all features and the network

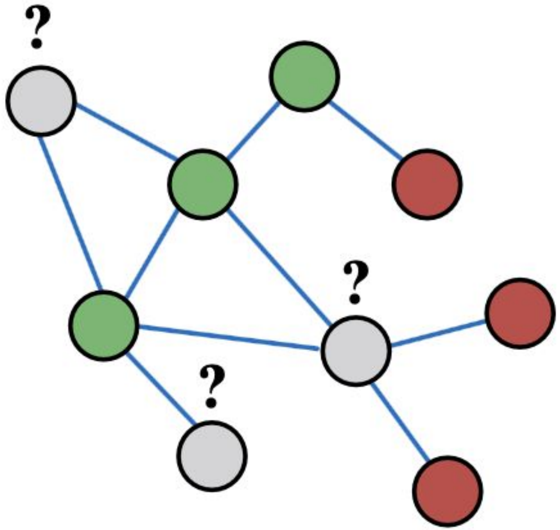


Applications?



Applications?

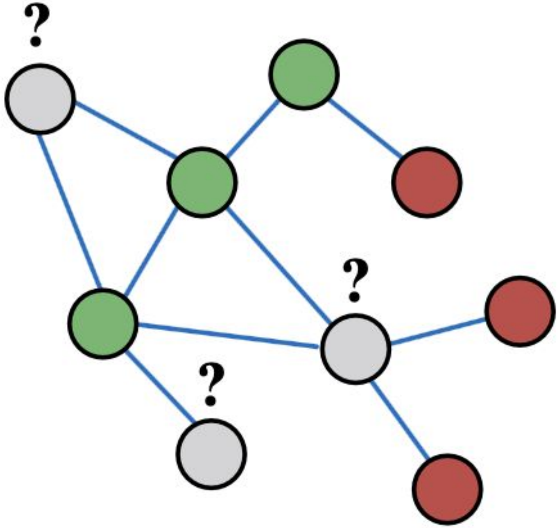
- Document classification
- Part of speech tagging
- Link prediction
- Optical character recognition
- Image/3D data segmentation
- Entity resolution in sensor networks
- Spam and fraud detection



Semi-supervised binary node classification

Focus on a couple of approaches:

- Relational classification
- Iterative classification



Probabilistic Relational Classifier

Idea: Propagate node labels across the network

- Class probability Y_v of node v is a weighted average of class probabilities of its neighbors.
- For labeled nodes v, initialize label Y_v with ground-truth label Y_v*.
- For unlabeled nodes, initialize Y_v = 0.5.
- Update all nodes in a random order until convergence or until maximum number of iterations is reached.

Probabilistic Relational Classifier

- Update for each node v and label c (e.g. 0 or 1)

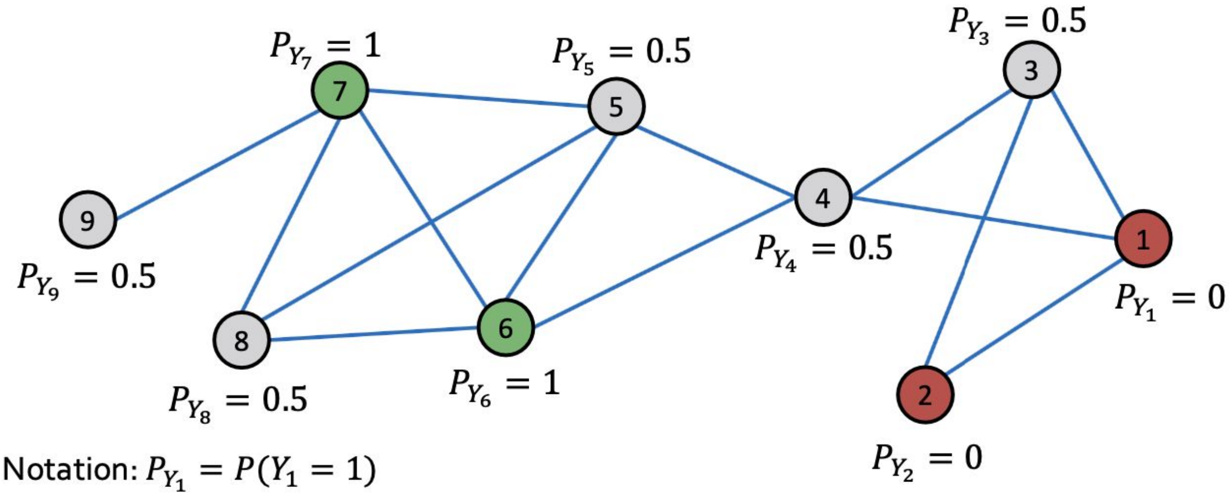
$$P(Y_v = c) = \frac{1}{\sum_{(v,u)\in E} A_{v,u}} \sum_{(v,u)\in E} A_{v,u} P(Y_u = c)$$

  - If edges have strength/weight information, $A_{v,u}$ can be the edge weight between v and u
  - $P(Y_v) = c$ is the probability of node v having label c
- Challenges:
  - Convergence is not guaranteed

Example Initialization

Initialization:

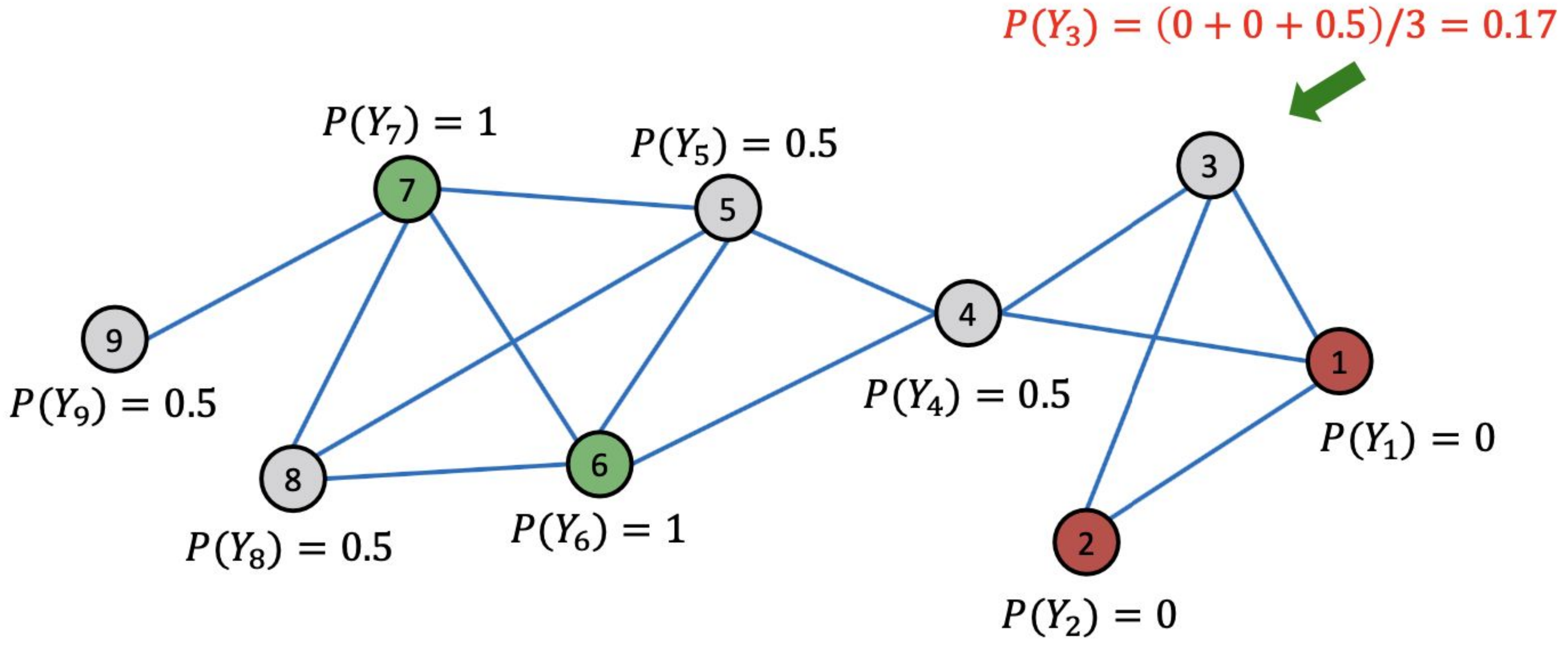
- All labeled nodes with their labels
- All unlabeled nodes 0.5 (belonging to class 1 with probability 0.5)



Notation: $P_{Y_1} = P(Y_1 = 1)$

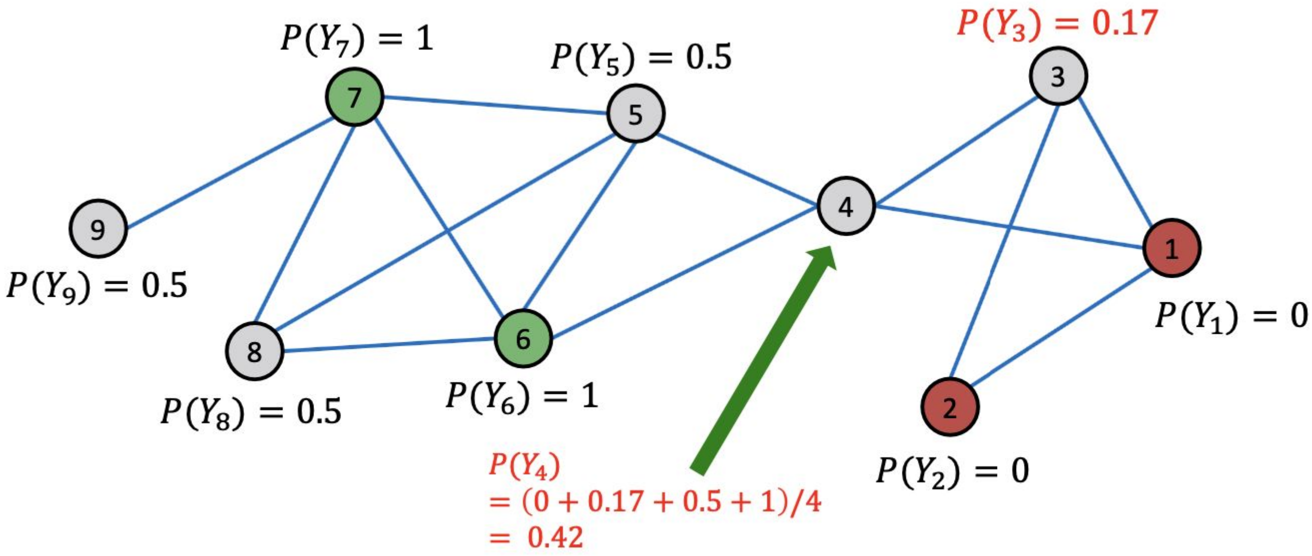
Example: first iteration node 3

- Update for the 1st Iteration: For node 3, $N($ =\{1,2,4\}



Example: first iteration node 4

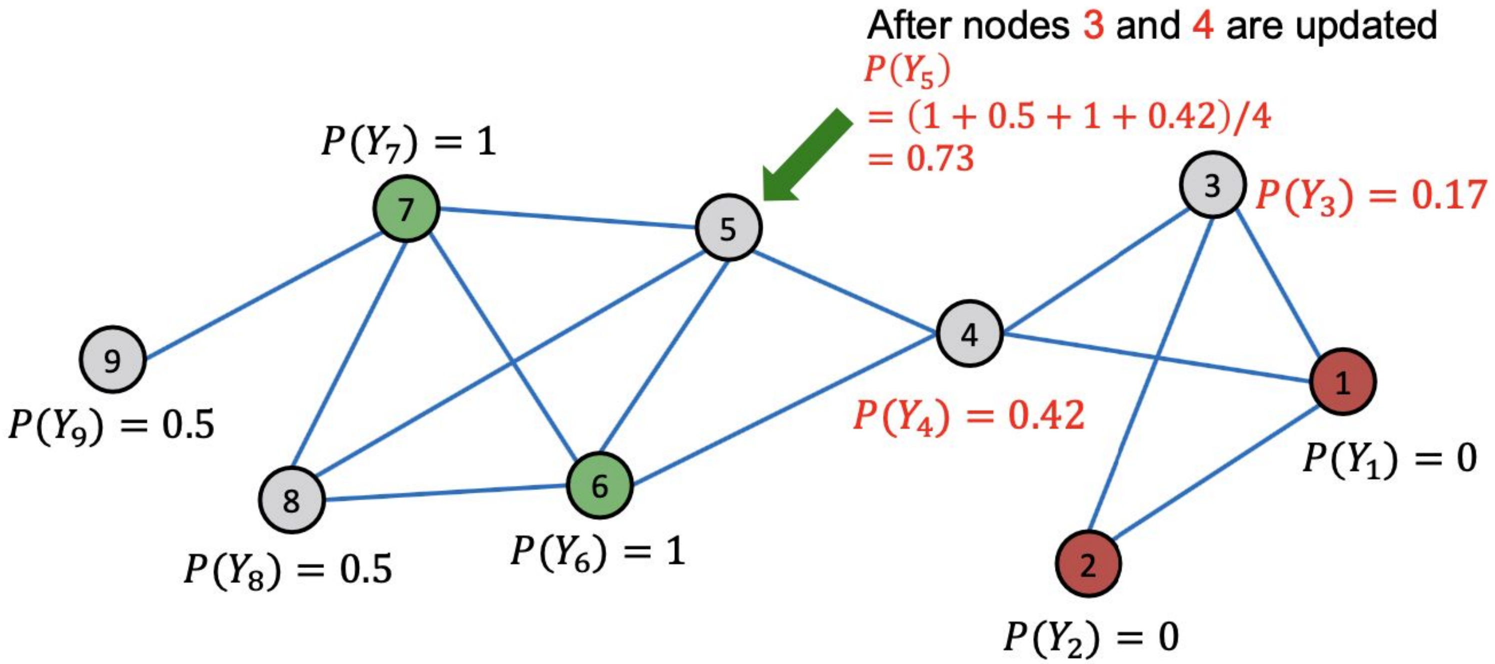
- Update for the 1st Iteration: For node 4, $N = \{1,3,5,6\}$



After Node 3 is updated

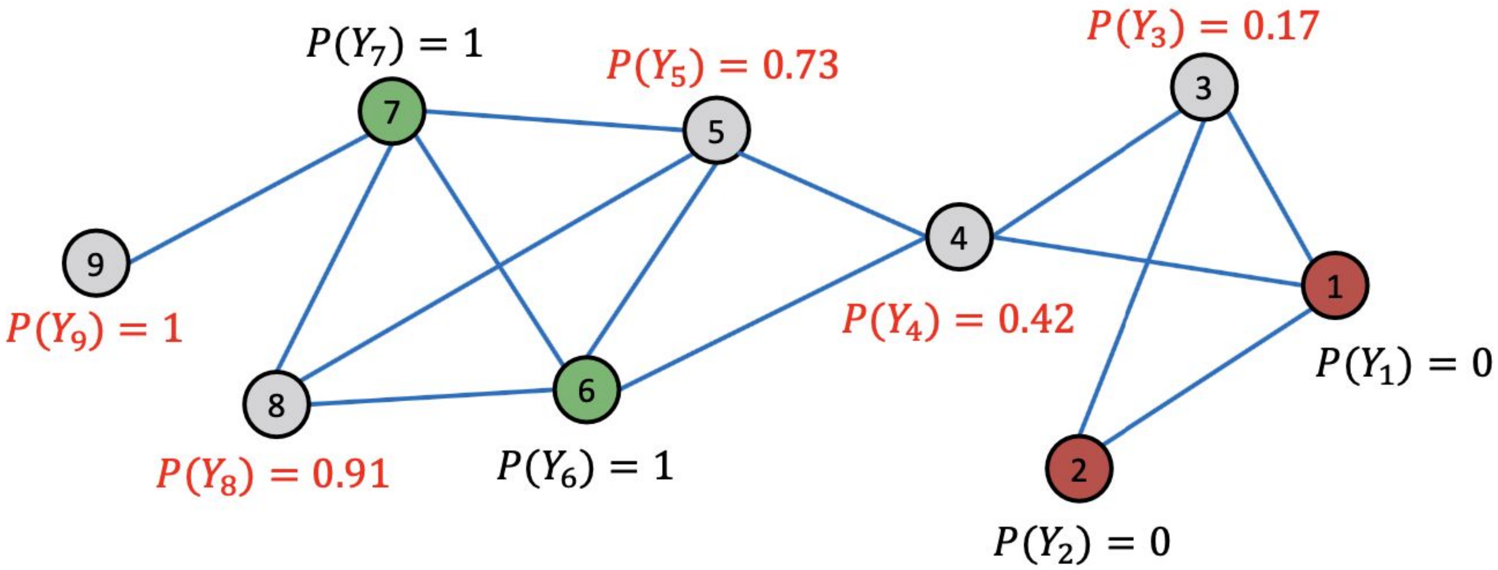
Example: first iteration node 5

- Update for the 1st Iteration: For node 5, N_5 = {4,6,7,8}

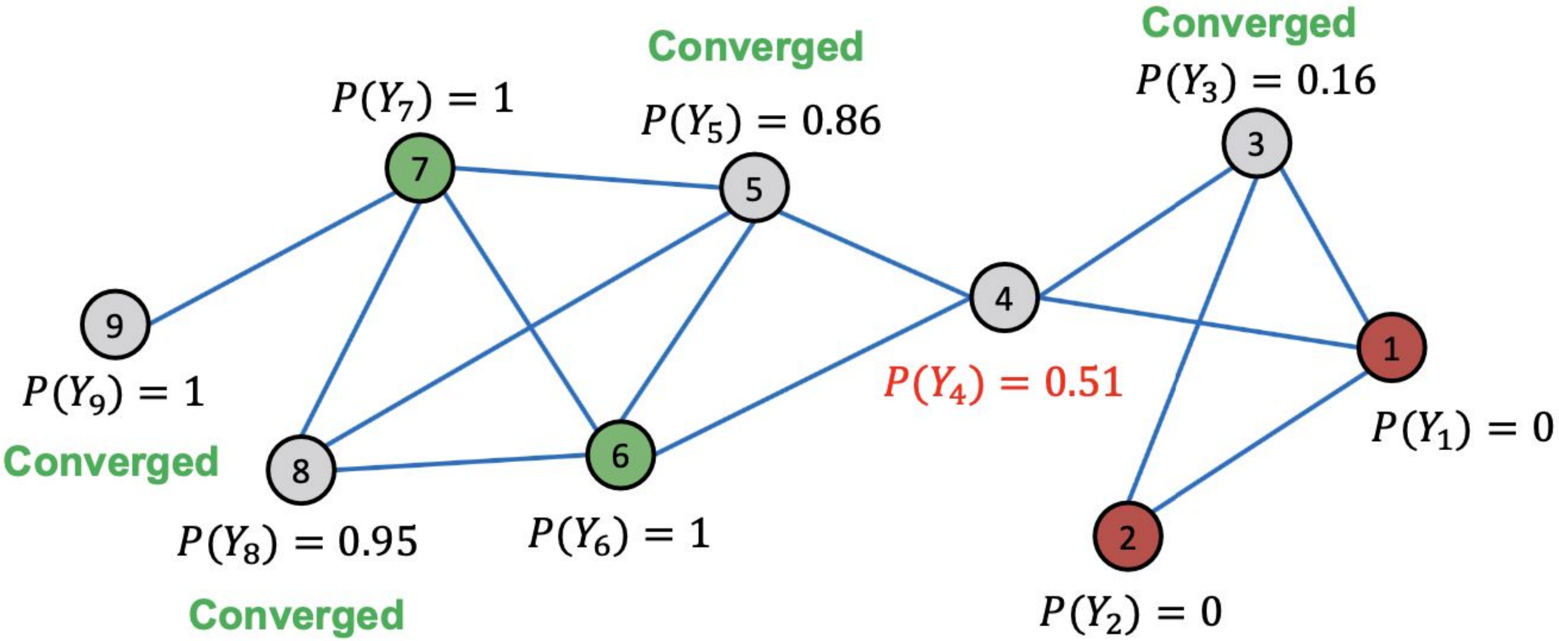


Example: After 1st iteration

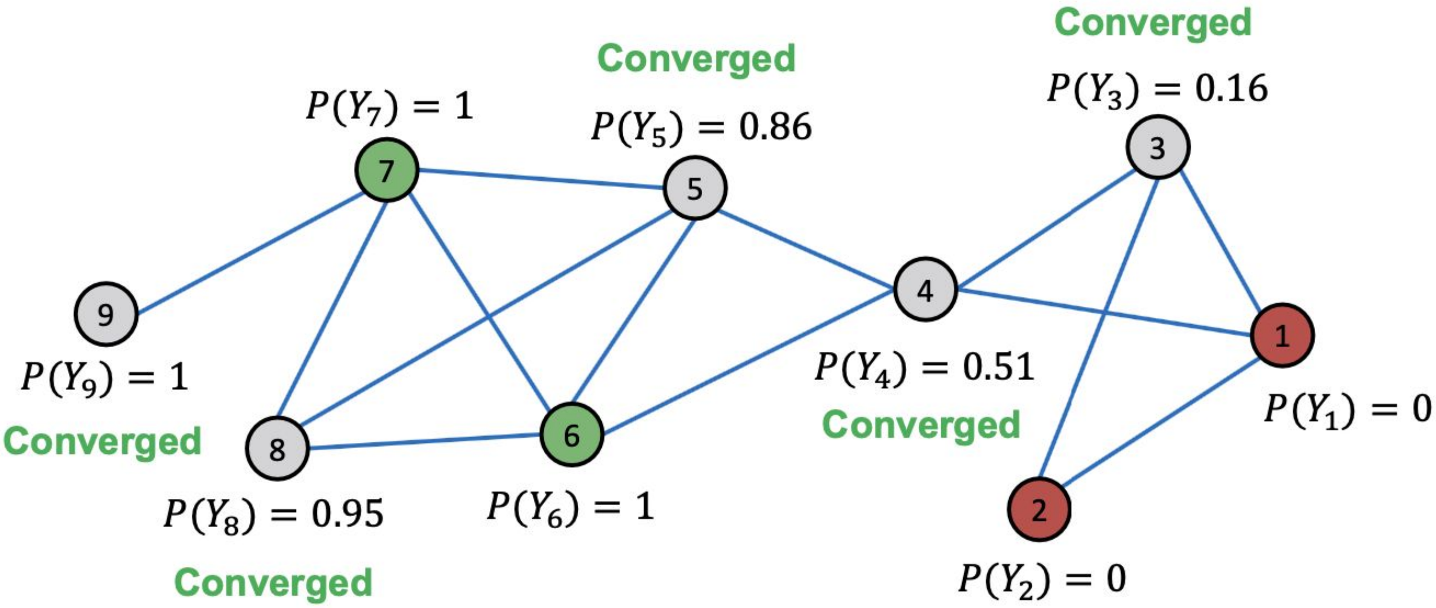
- Update for the 1st Iteration: For node 5, N_5 = {4,6,7,8}



Example: After 4th iteration



Example: Convergence

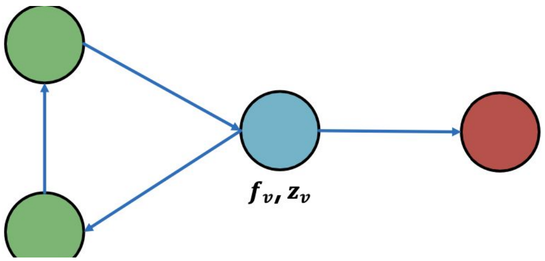


Iterative Classification

- Input: Graph
- f_v : feature vector for node v
- Some nodes v are labeled with Y_v
- Task: Predict label of unlabeled nodes *i*
- Approach: Train two classifiers:
  - $\phi_1(f_v)$ = Predict node label based on node feature vector f_v. This is called base classifier.
  - $\phi_2\,(f_v\,, z_v)$ = Predict label based on node feature vector f_v and summary z_v of labels of v's neighbors. This is called relational classifier.

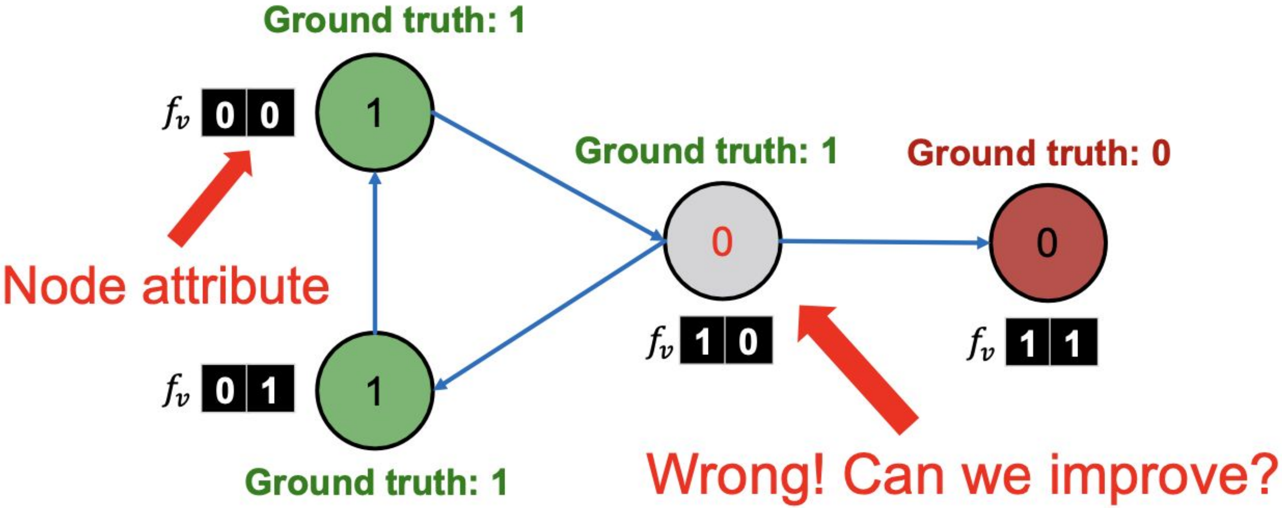
Computing summary z_v

- z_v **= vector that captures labels around node** v
  - Histogram of the number (or fraction) of each label in N_v



Example: Web page classification

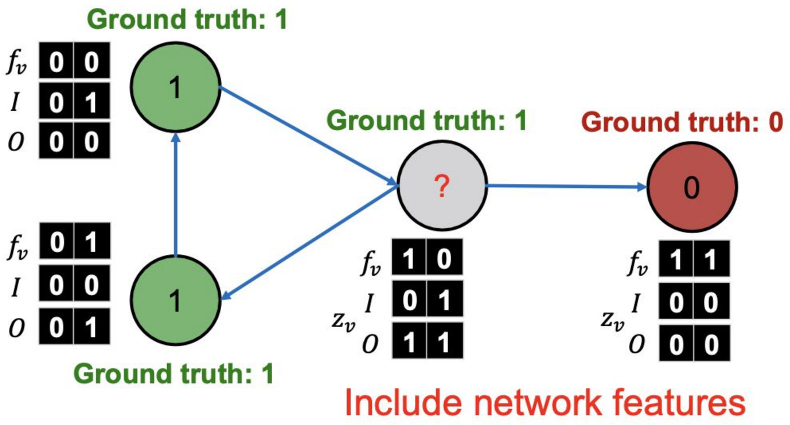
Baseline: Train a classifier (e.g., linear classifier) to classify pages based on node attributes.



Example: Web page classification

Each node maintains vectors z_v of neighborhood labels:

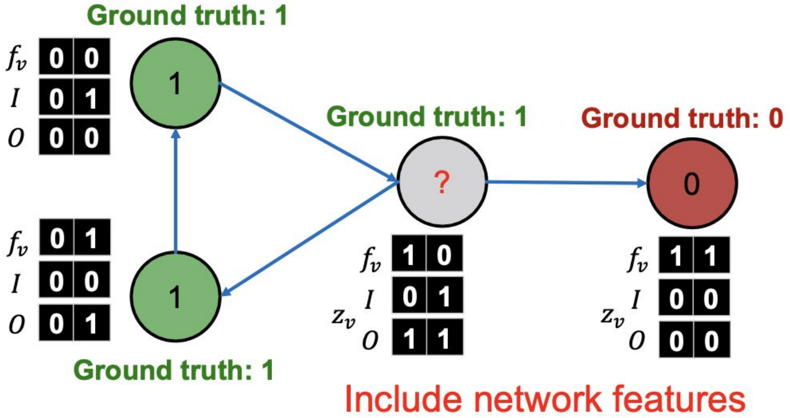
- I = Incoming neighbor label information vector.
- O = Outgoing neighbor label information vector.
- I_0 = 1 if at least one of the incoming pages is labelled 0.



Example: Web page classification.

On **training labels**, train two classifiers:

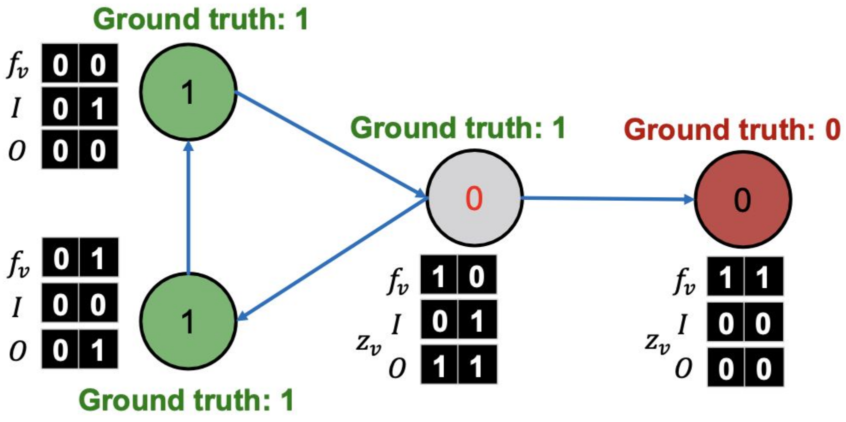
- Node attribute vector only: $\phi_1(f_v)$
- Node attribute and link vectors z_v: $\phi_2(f_v, z_v)$



Example: Web page classification.

On the **unlabeled set**:

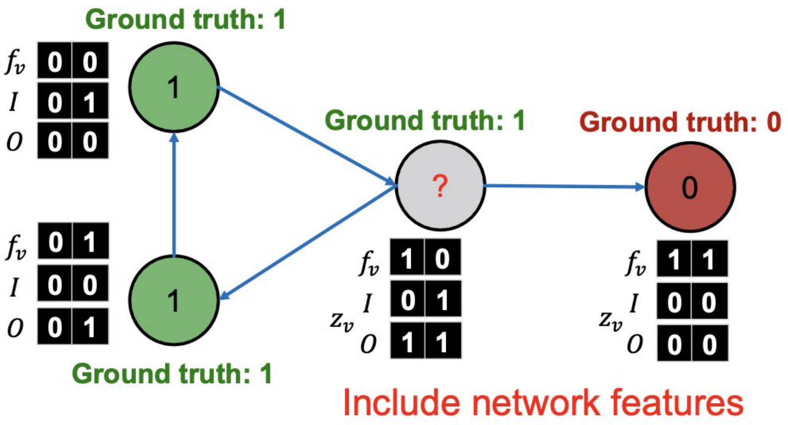
- Use trained node feature vector classifier ϕ_1 to set Y_v



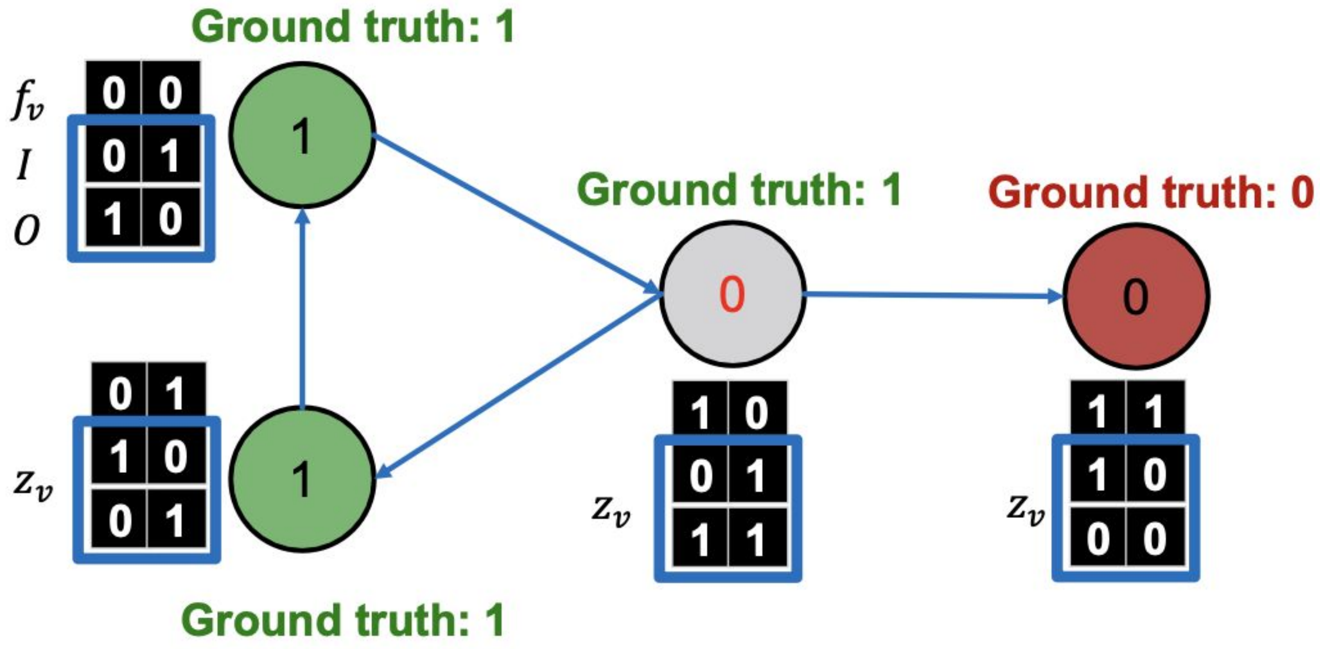
Example: Web page classification - 2. Apply classifier

On **training labels**, train two classifiers:

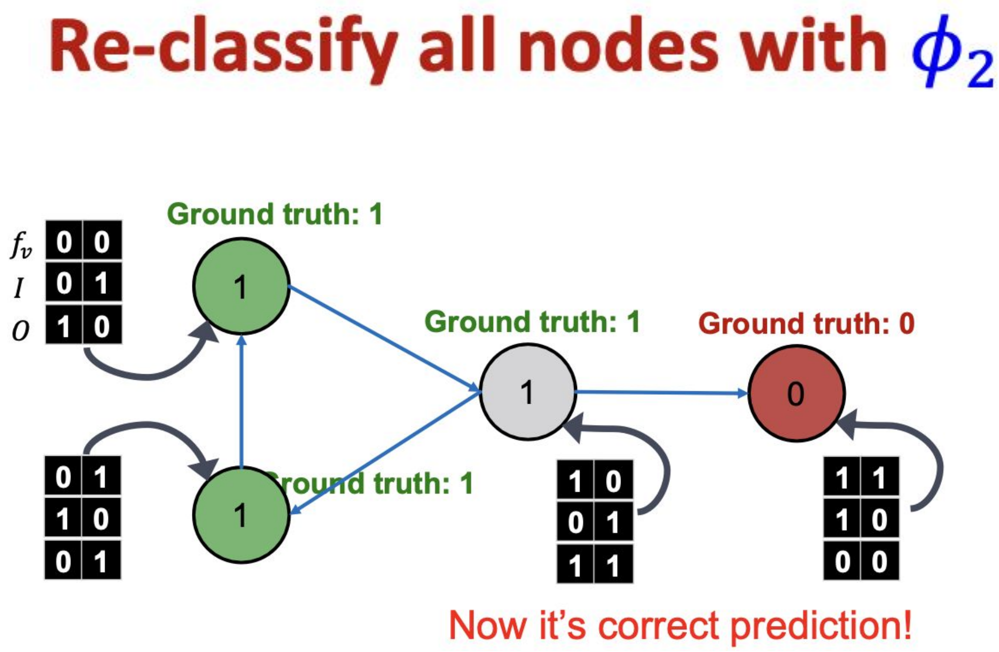
- Node attribute vector only: $\phi_1(f_v)$
- Node attribute and link vectors z_v: $\phi_2(f_v, z_v)$



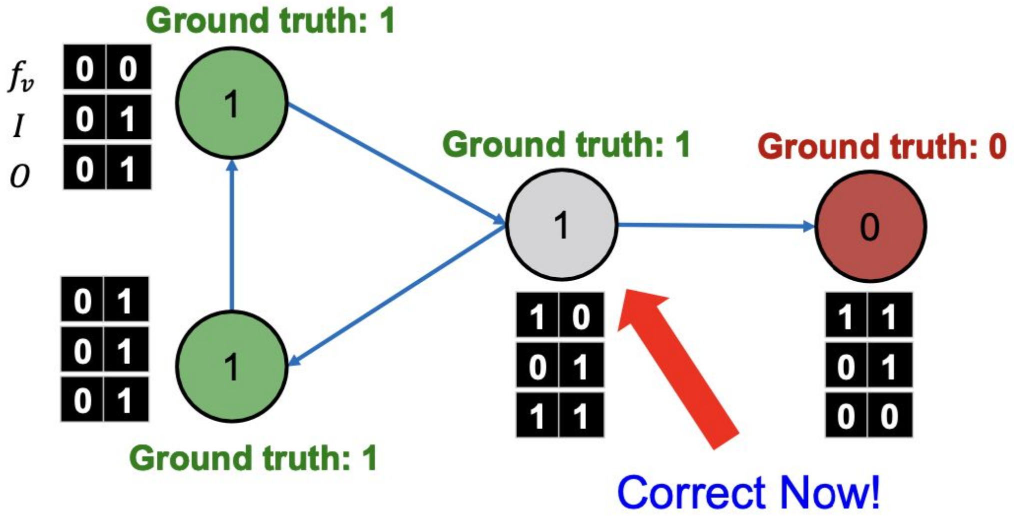
Example: Web page classification - Update relational features



Example: Web page classification - Reclassify all nodes with phi_2



Example: Web page classification - Continue to iterate



Summary

Two approaches to collective classification:

- Relational classification
  - Iteratively update probabilities of node belonging to a label class based on its neighbors
- Iterative classification
  - Improve over collective classification to handle attribute/feature information
  - Classify node v based on its features as well as labels of neighbors