Applications

Node Classification

Acknowledgement: Jure Leskovec, Stanford University

Overview

- Node Classification
- Relational Classifiers
- Iterative Classification
- Belief Propagation

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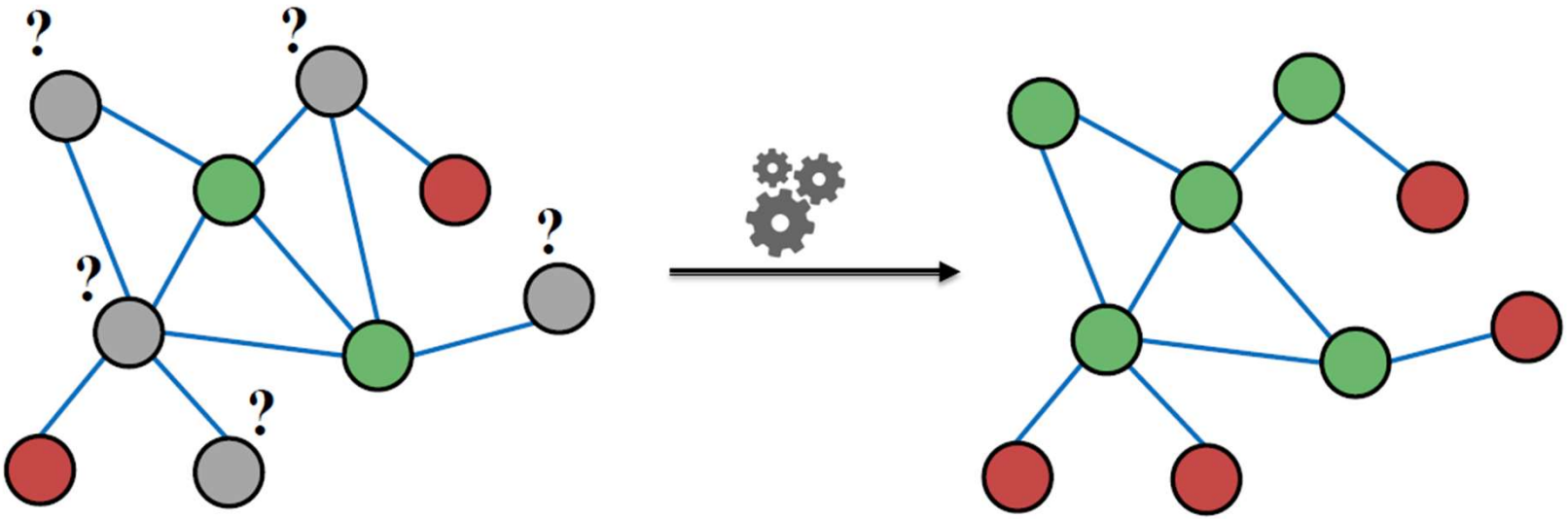
Node Classification

- Given a network with labels on some nodes, how do we assign labels to all other nodes in the network?
- Example:
  - In a network, some nodes are fraudsters and some other nodes are fully trusted.
  - How do you find the other fraudsters and trustworthy nodes?
- Can utilize a variety of techniques
  - Machine Learning
  - SNA

Node Classification



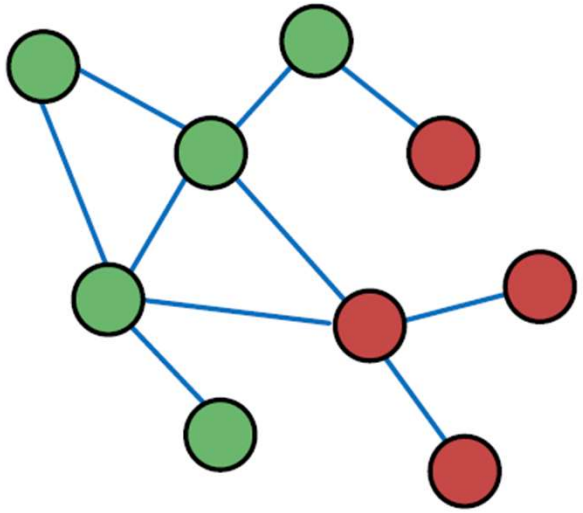
- Given labels of some nodes
- Let's predict labels of unlabeled nodes
- This is called semi-supervised node classification

Node Classification

- **A framework for Node Classification: Message Passing**
- **Intuition: Correlations** exist in networks.
  - In other words: Similar nodes are connected
- **Key concept** is **collective classification**: Idea of assigning labels to all nodes in a network together
- **We will look at three techniques:**
  1. **Relational classification**
  2. **Iterative classification**
  3. **Belief propagation**

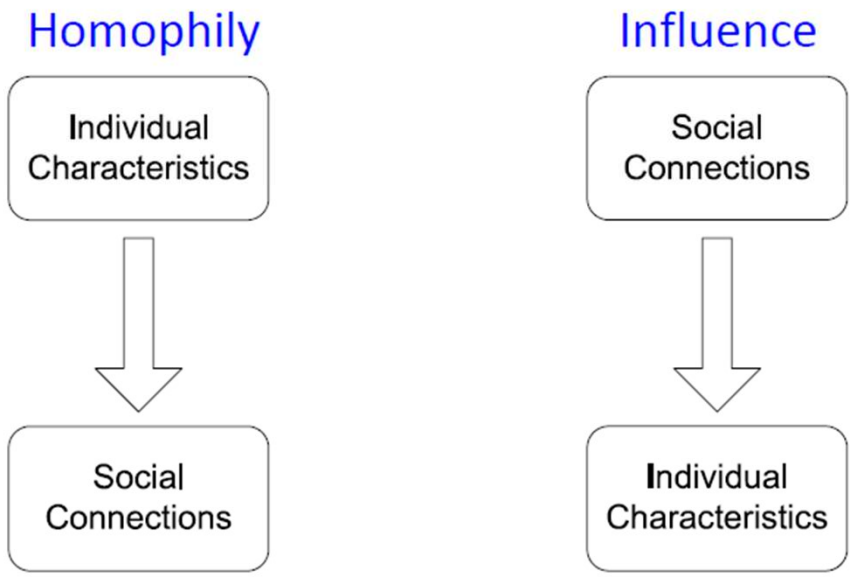
Correlations exist in the Network

- Individual behaviors are **correlated** in the network
- **Correlation**: nearby nodes have the same color (belonging to the same class)



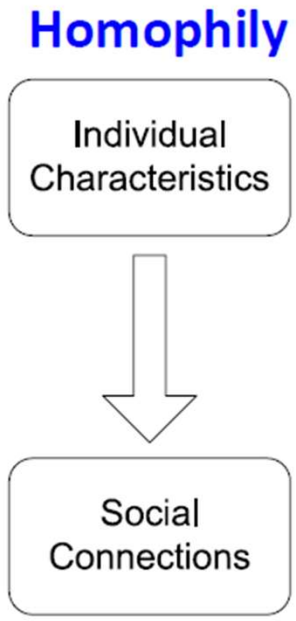
Correlations exist in the Network

- **Main types of dependencies that lead to correlation:**



Homophily

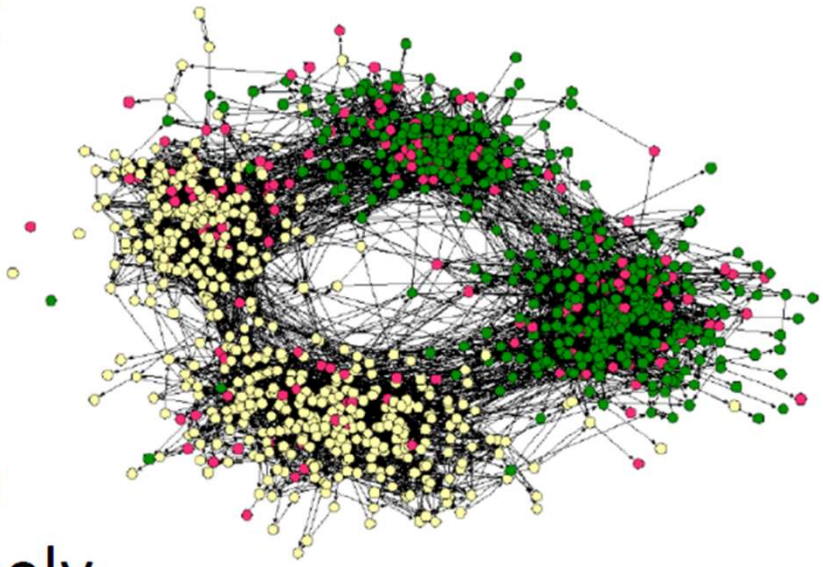
- **Homophily**: The tendency of individuals to associate and bond with similar others
  - *"Birds of a feather flock together"*
  - It has been observed in a vast array of network studies, based on a variety of attributes (e.g., age, gender, organizational role, etc.)
  - **Example**: Researchers who focus on the same research area are more likely to establish a connection (meeting at conferences, interacting in academic talks, etc.)



Homophily: Example

Example of homophily

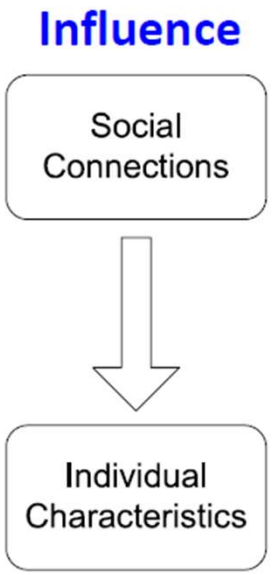
- Online social network
  - Nodes = people
  - Edges = friendship
  - Node color = interests (sports, arts, etc.)
- People with the same interest are more closely connected due to homophily



(Easley and Kleinberg, 2010)

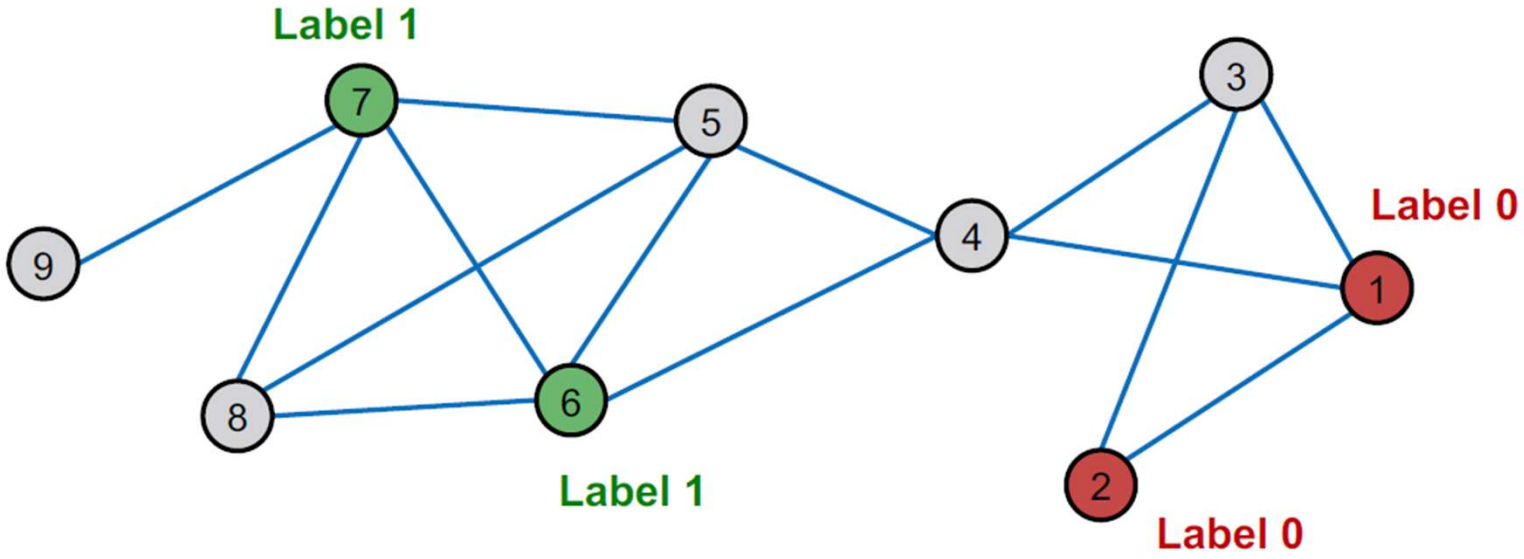
Influence

- **Influence**: Social connections can influence the individual characteristics of a person.
  - **Example**: I recommend my musical preferences to my friends, until one of them grows to like my same favorite genres!



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 grey?

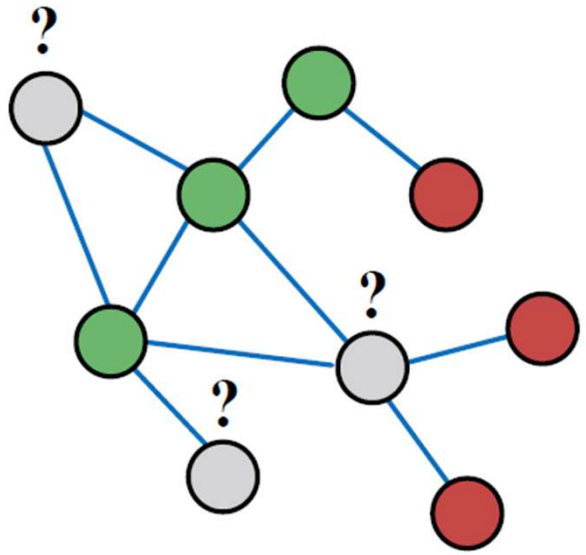
Motivation

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

Motivation

- **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
- Few 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 $n \times n$ adjacency matrix over n nodes
- Let $\mathrm{Y} = \{0, 1\}^n$ be a vector of **labels**:
  - $\mathrm{Y}_v = 1$ belongs to Class 1
  - $\mathrm{Y}_v = 0$ belongs to Class 0
  - There are unlabeled node needs to be classified
- **Goal:** Predict which **unlabeled** nodes are likely **Class 1**, and which are likely **Class 0**

Approach: Collective Classification

- **Many 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

Collective Classification Overview

- **Intuition**: Simultaneous classification of interlinked nodes using correlations
- Probabilistic framework
- Markov Assumption: *the label Y_v of one node v depends on the labels of its neighbors N_v*

$$P(Y_v) = P(Y_v|N_v)$$

- Collective classification involves 3 steps:

Local Classifier	Relational Classifier	Collective Inference
• Assign initial labels	• Capture correlations between nodes	• Propagate correlations through network

Collective Classification Overview

Local Classifier

- Assign initial labels

Relational Classifier

- Capture correlations between nodes

Collective Inference

- Propagate correlations through network

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

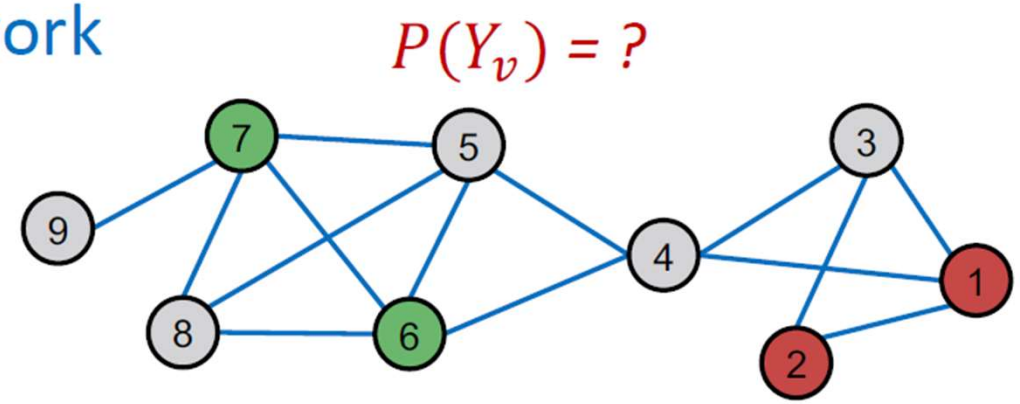
- Learns a classifier to label one node based on the labels and/or attributes of its neighbors
- This is where network information is used

Collective Inference: Propagate the correlation

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

Problem Setting

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



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Probabilistic Relational Classifier

- **Basic idea:** 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

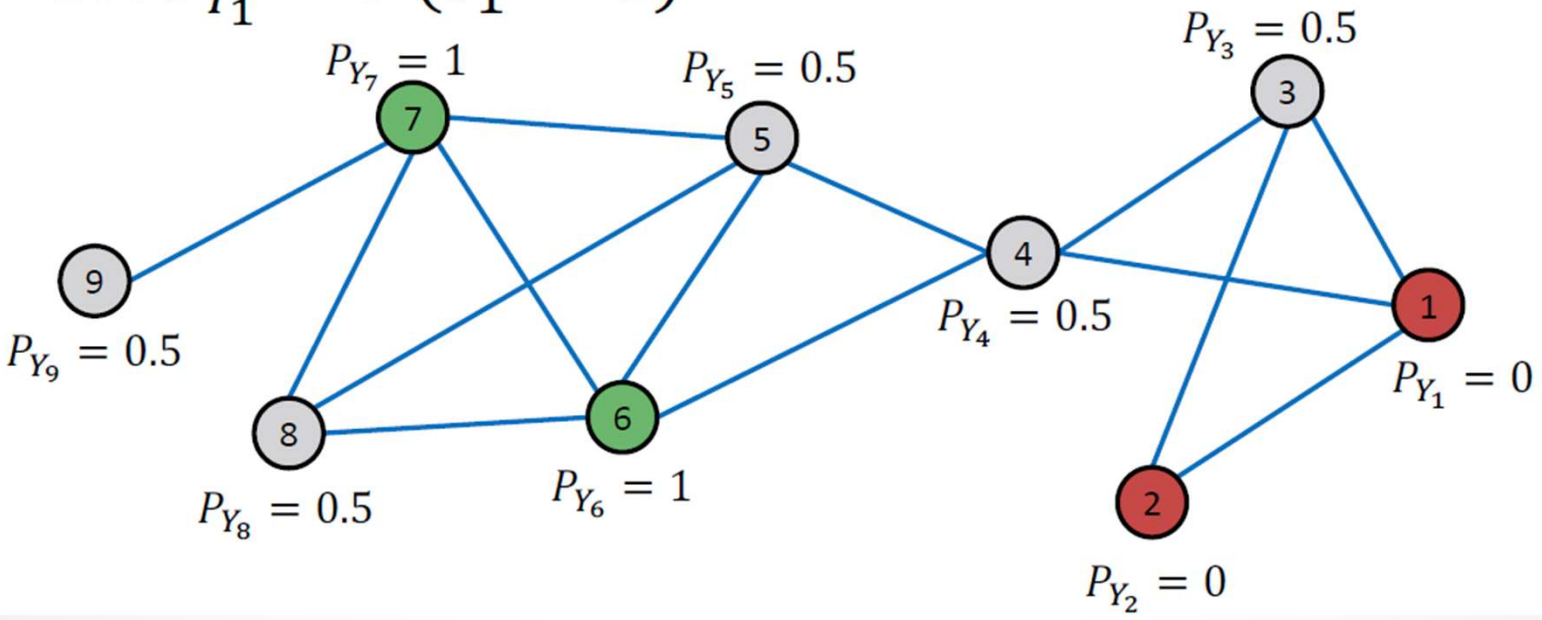
- Challenges:
  - Convergence is not guaranteed
  - Model cannot use node feature information

Example: Initiation

Initialization:

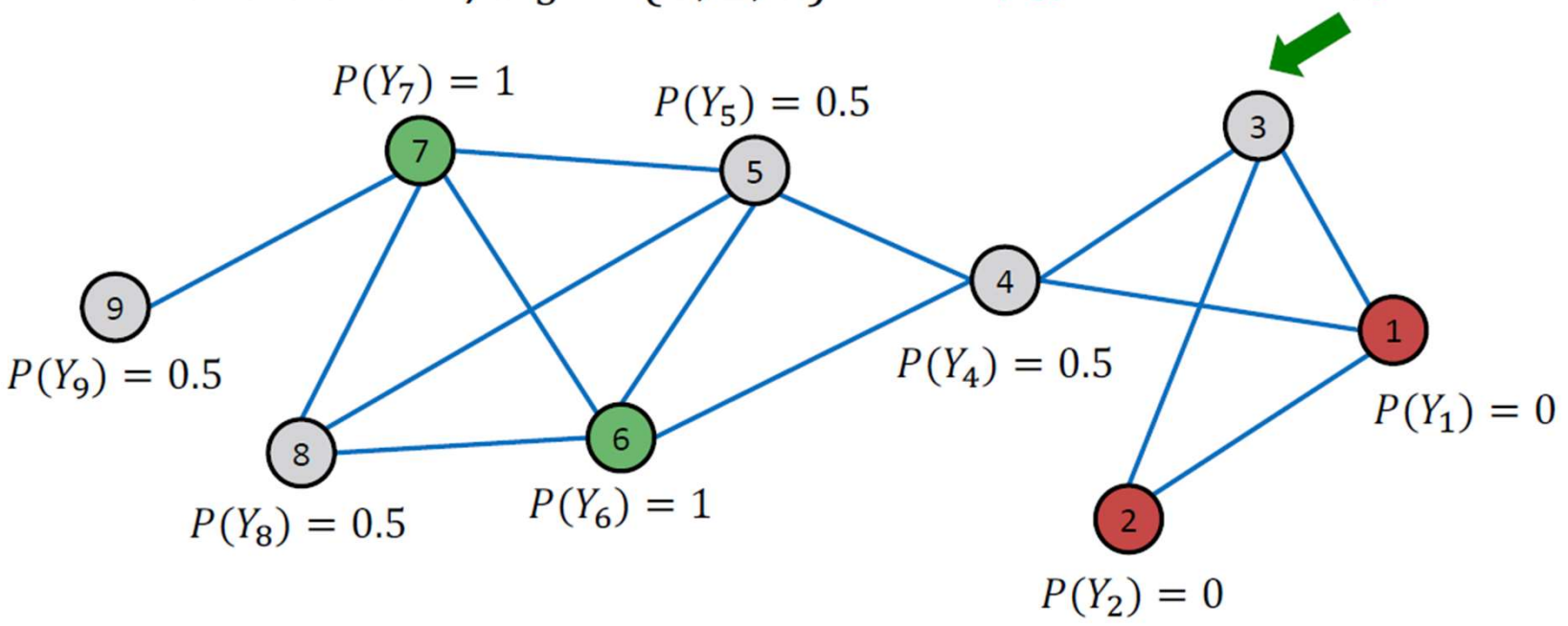
- All labeled nodes with their labels
- All unlabeled nodes 0.5 (belonging to class 1 with probability 0.5)

Let $P_{Y_1} = P(Y_1 = 1)$



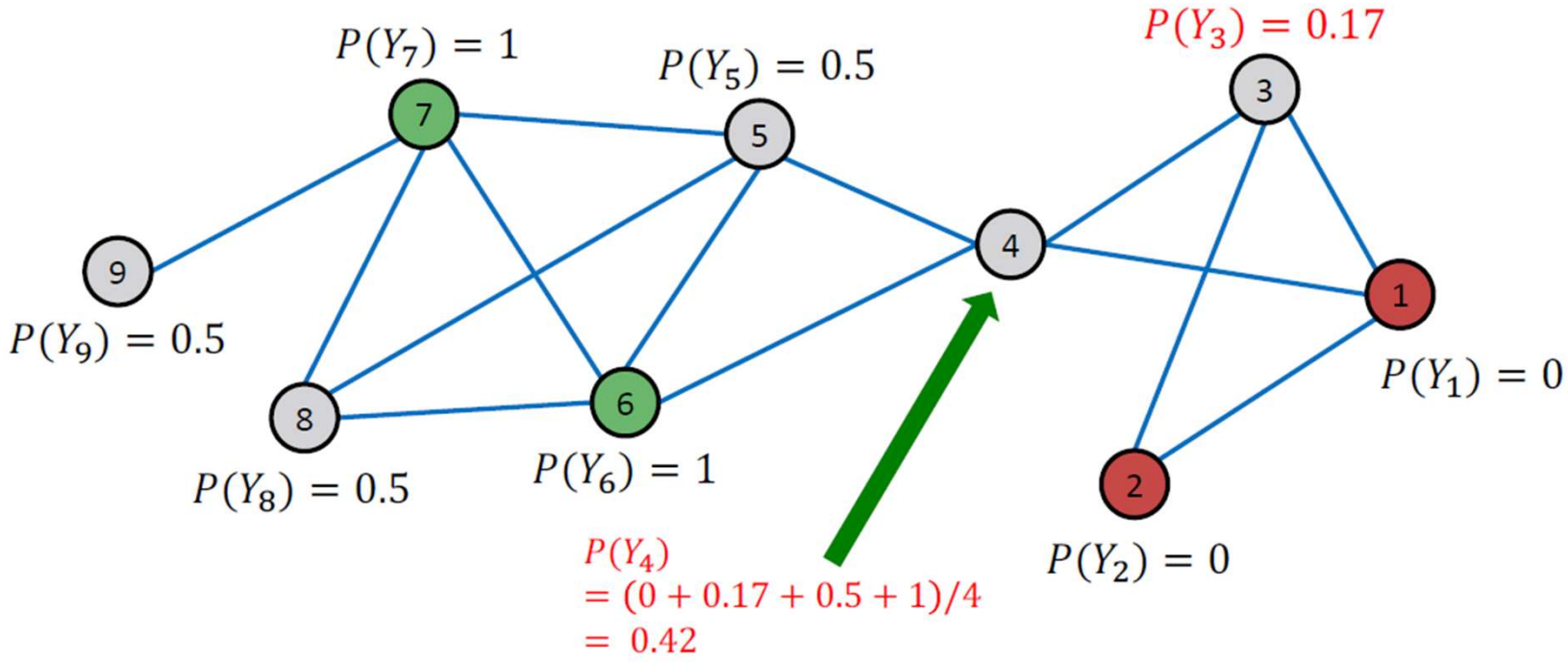
Example: 1st Iteration, Update Node 3

- Update for the 1st Iteration:
  - For node 3, $N_3 = \{1, 2, 4\}$



Example: 1st Iteration, Update Node 4

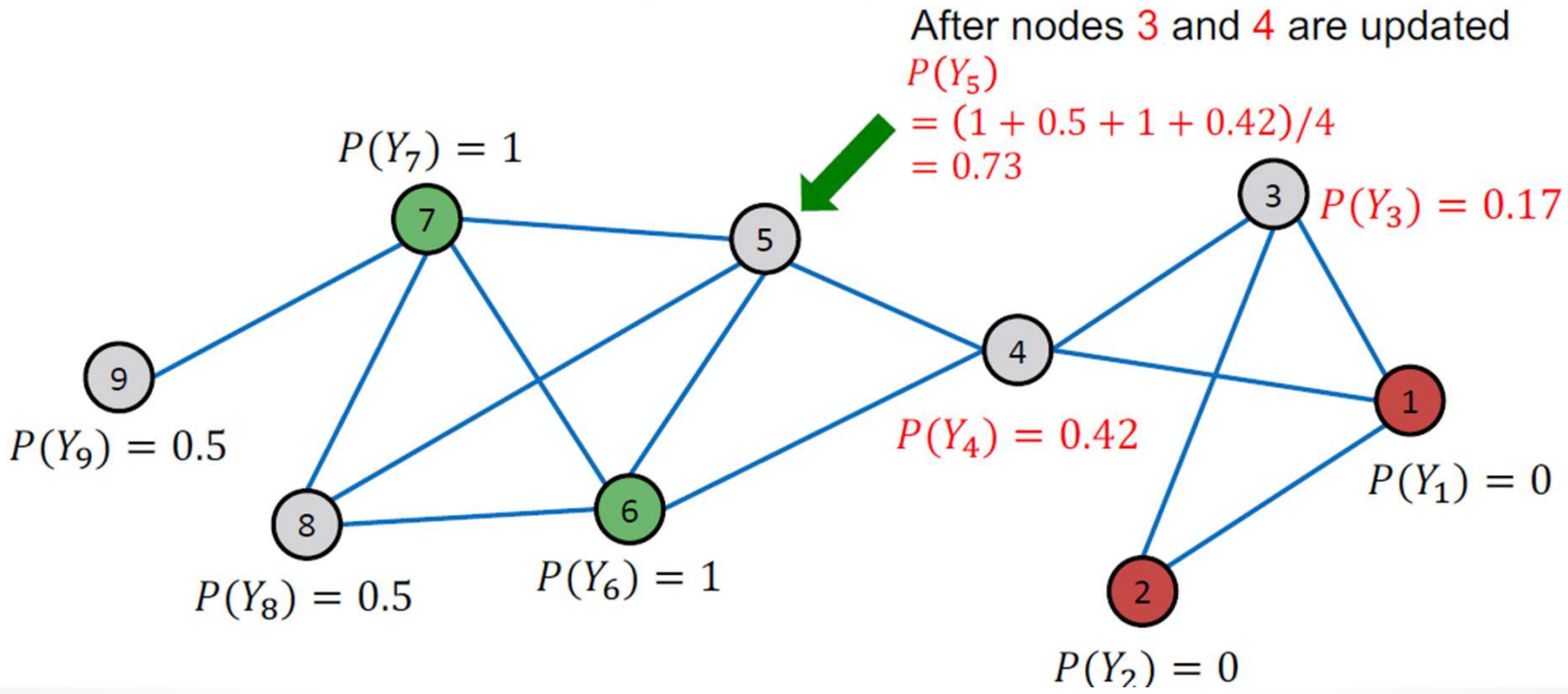
- Update for the 1st Iteration:
  - For node 4, $N_4 = \{1, 3, 5, 6\}$



After Node 3 is updated

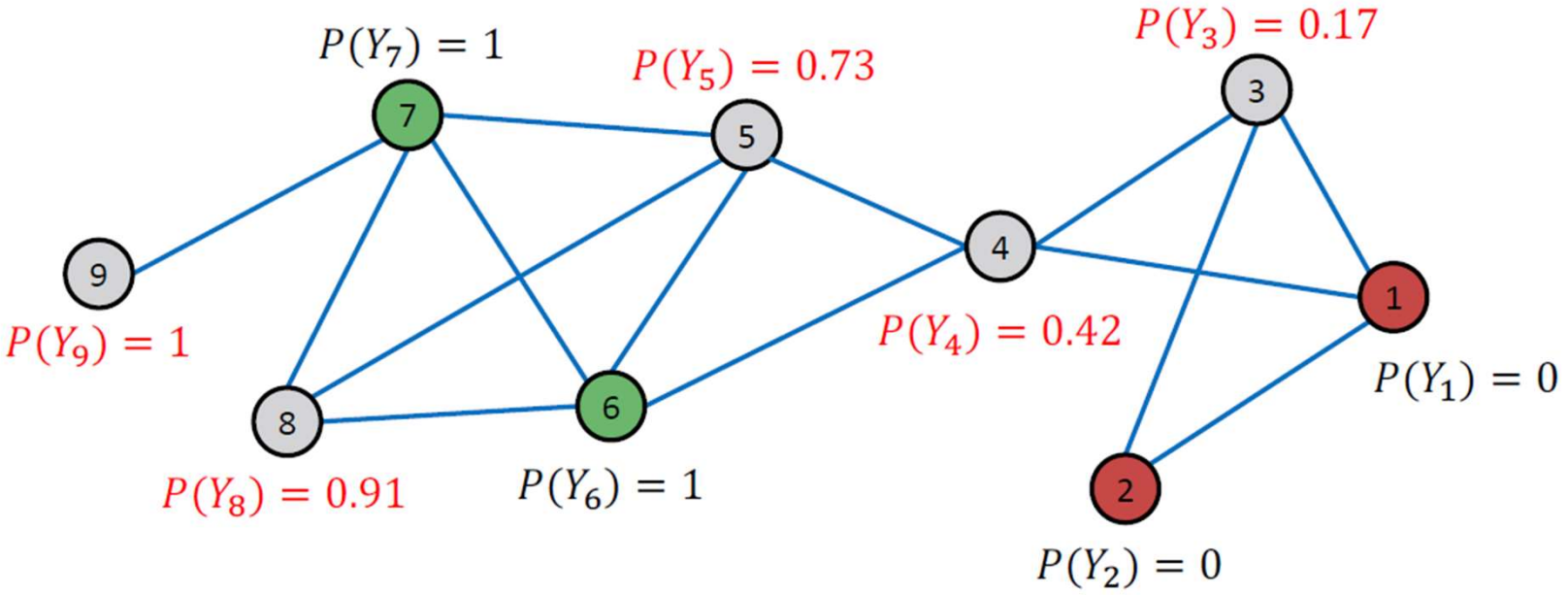
Example: 1st Iteration, Update Node 5

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

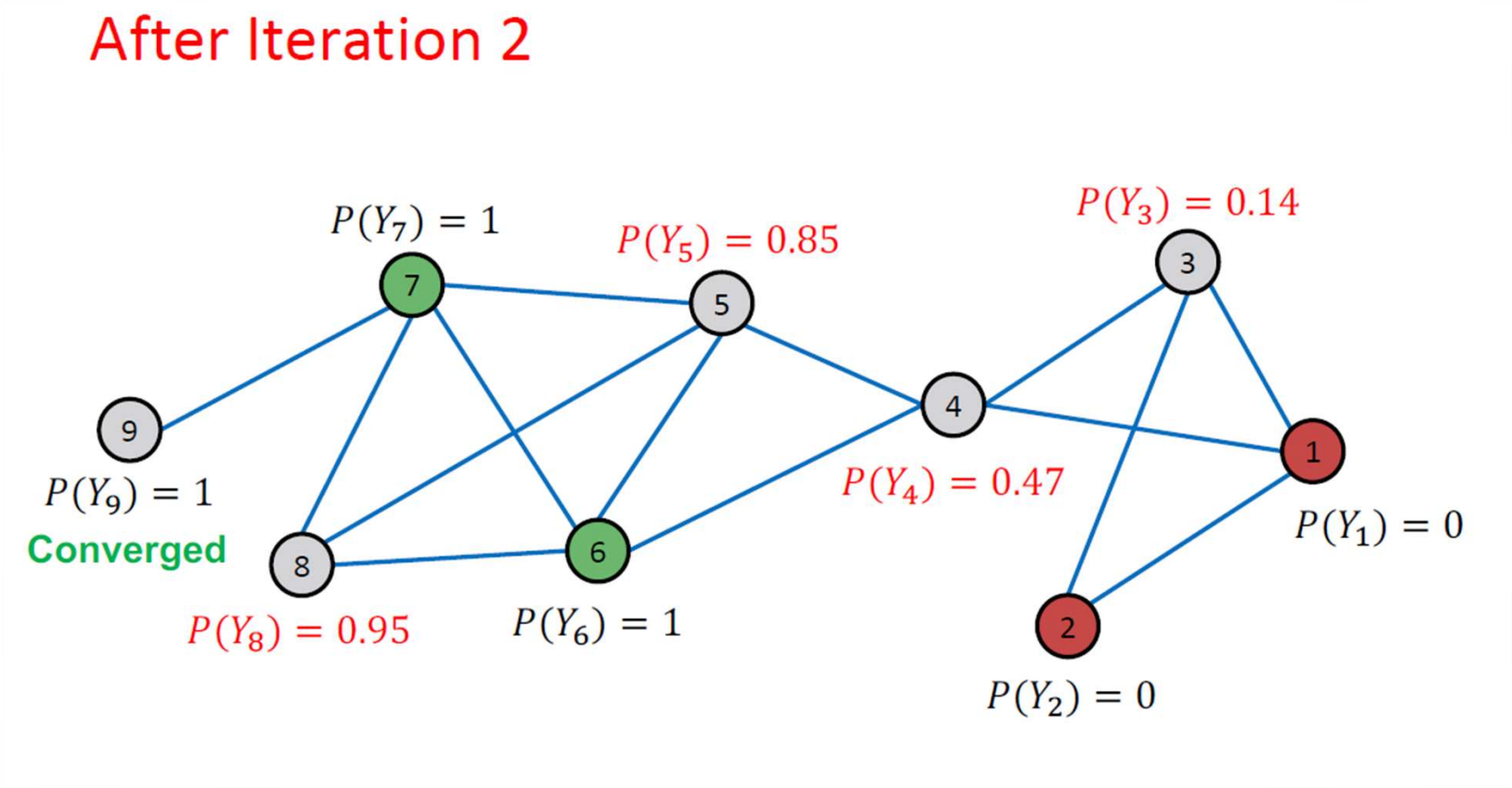


Example: After 1st Iteration

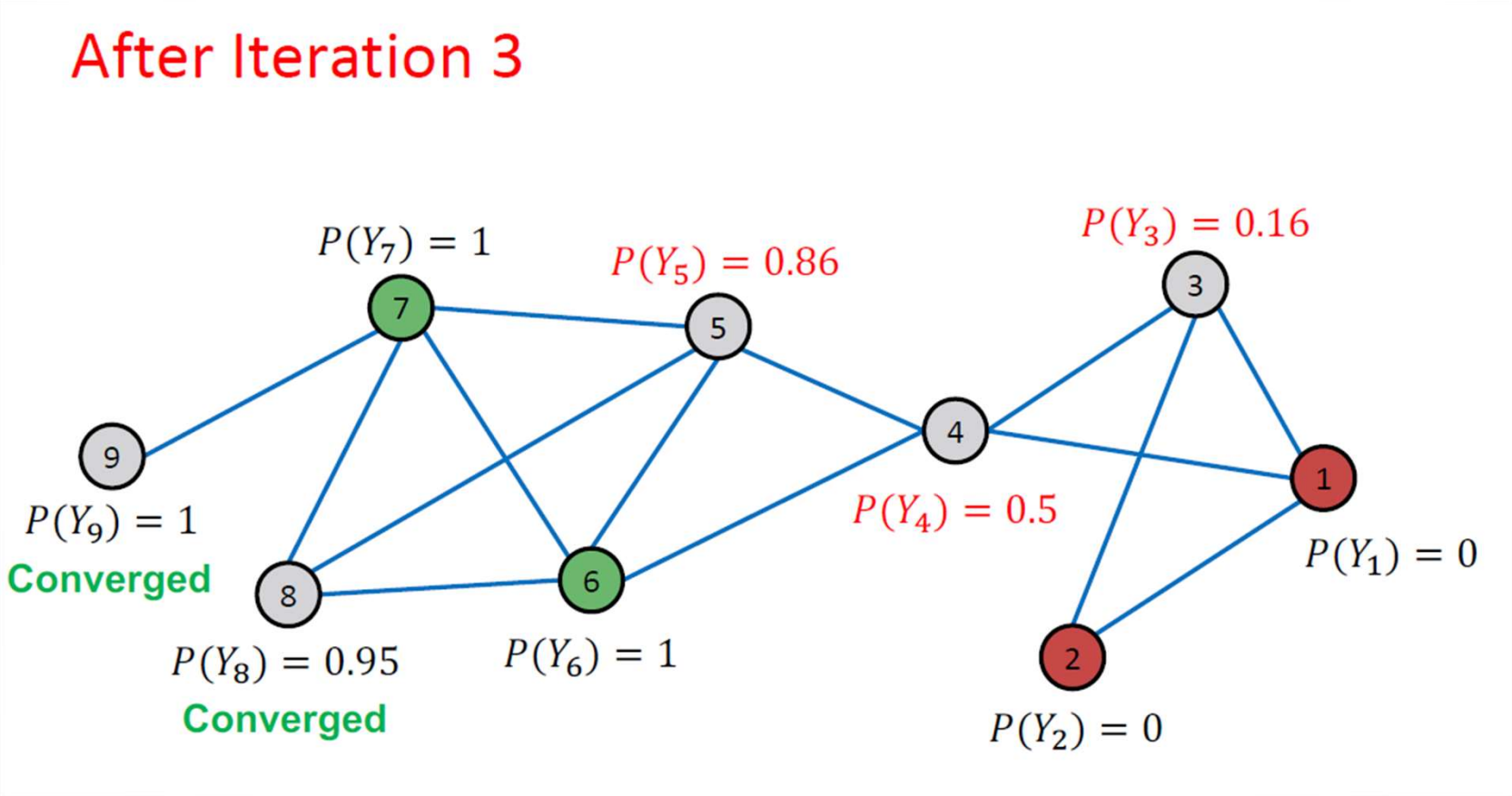
After Iteration 1 (a round of updates for all unlabeled nodes)



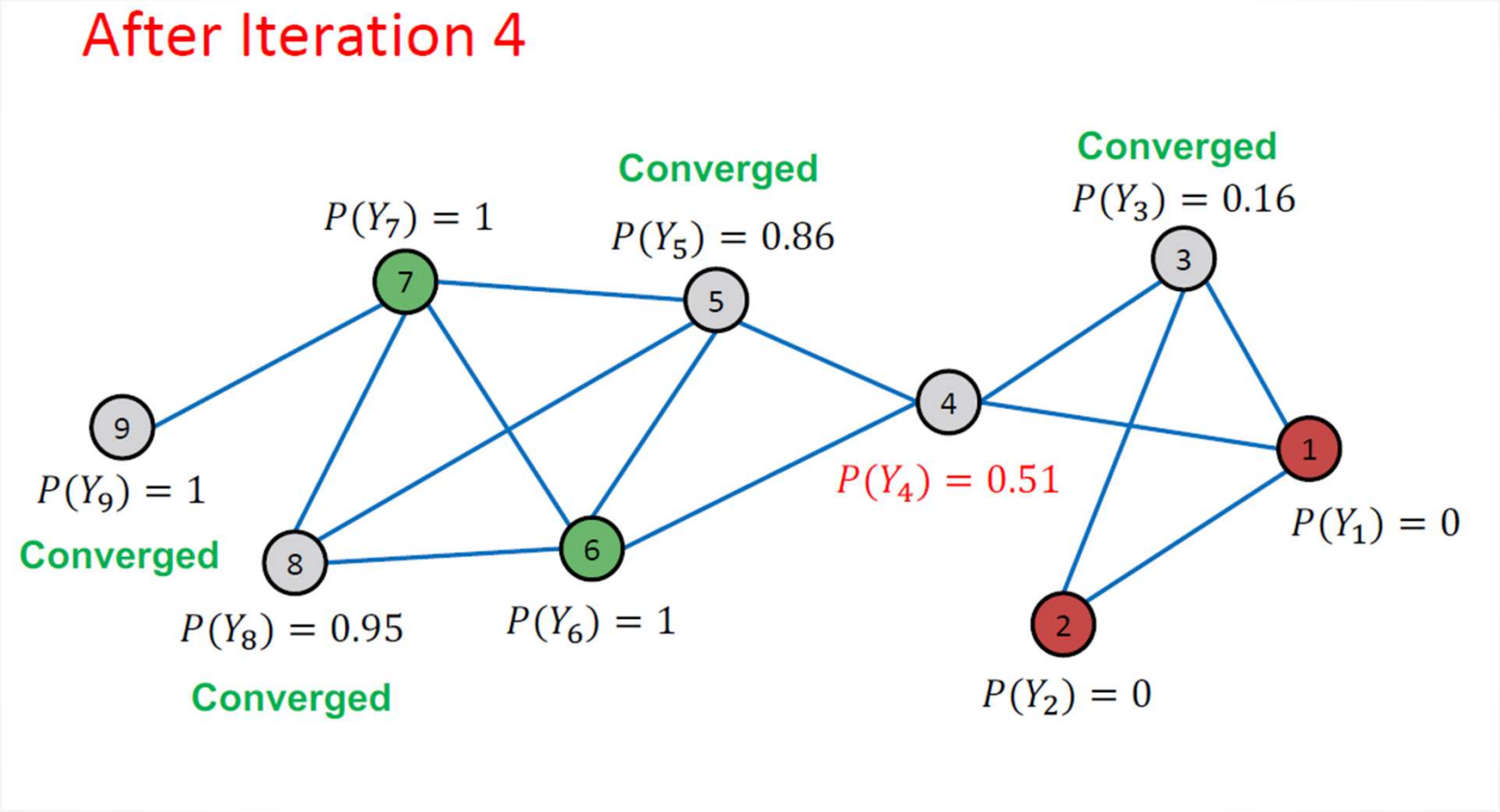
Example: After 2nd Iteration



Example: After 3rd Iteration

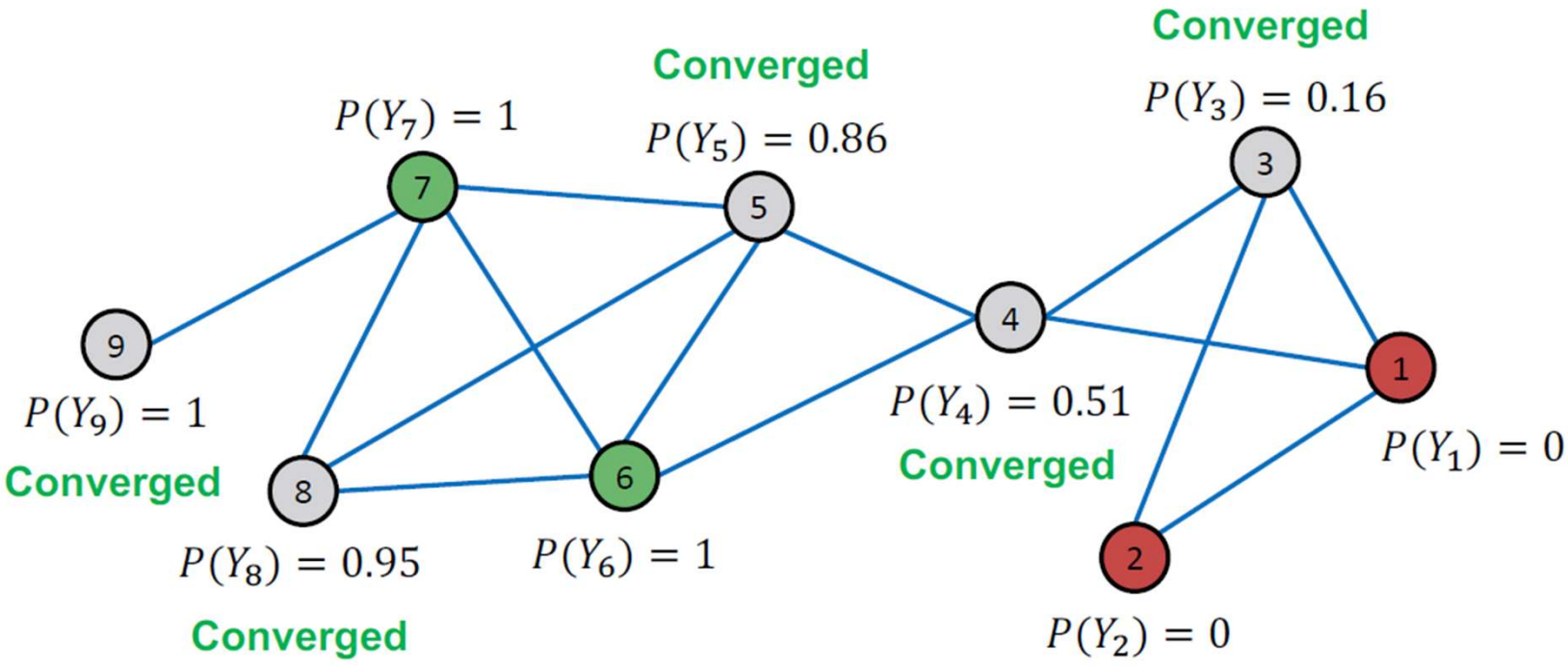


Example: After 4th Iteration



Example: After Convergence

- All scores stabilize after 4 iterations. We therefore predict:
  - **Nodes 4, 5, 8, 9 belong to class 1** ($P_{Y_v} > 0.5$)
  - **Nodes 3 belong to class 0** ($P_{Y_v} < 0.5$)



Overview

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Iterative Classification

- Relational classifiers do not use node attributes. How can one leverage them?

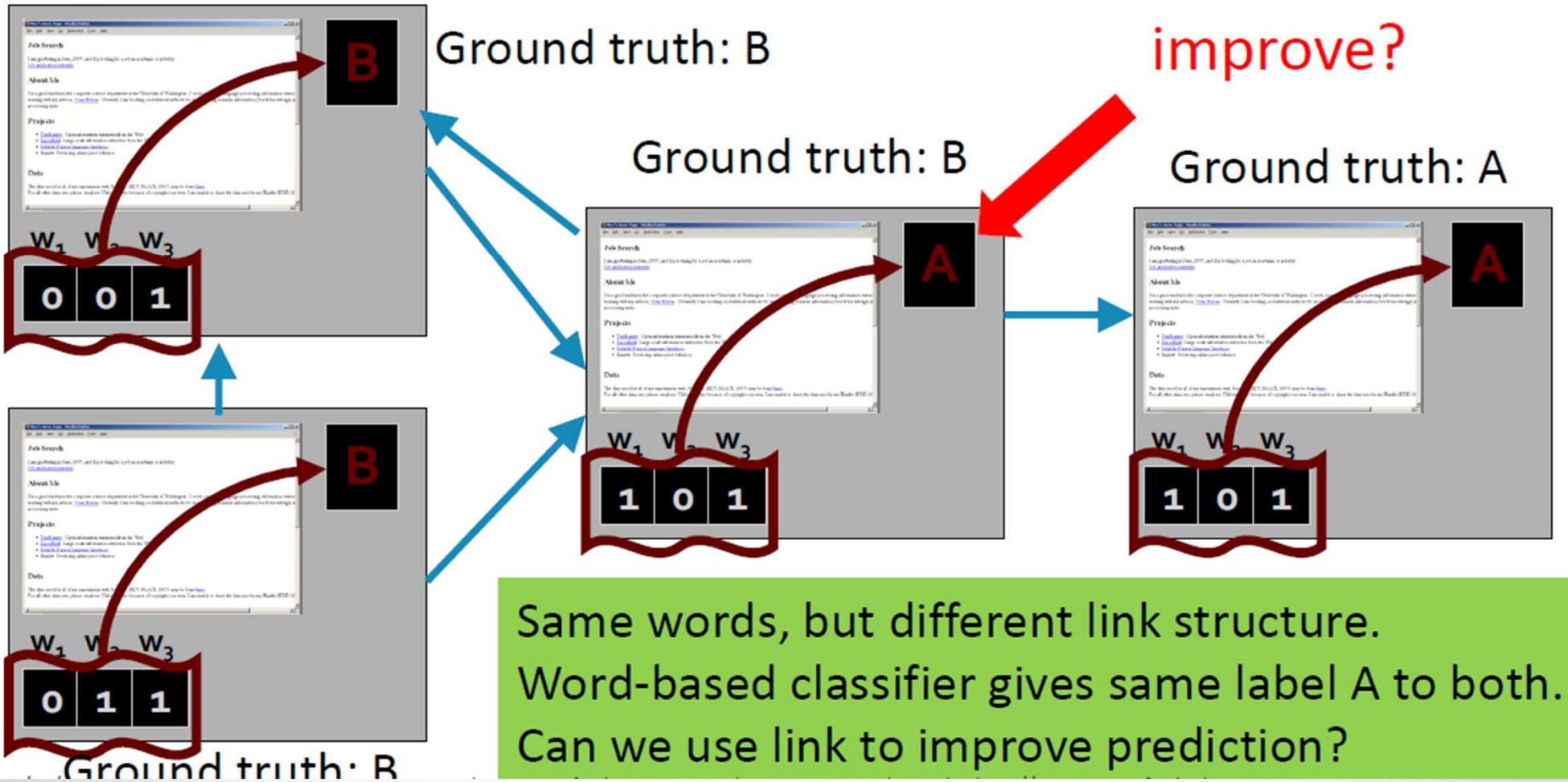
- Main idea of iterative classification: Classify node *i* based on its attributes as well as labels of neighbor set N_i
  - Create a flat vector a_i for each node *i*
  - Train a classifier to classify using a_i
  - Node may have various number of neighbors, so we can aggregate using: count , mode, proportion, mean, exists, etc.

Iterative Classifiers – Basic Architecture

- **Bootstrap phase**
  - Convert each node *i* to a flat vector a_i
  - Use local classifier $f(a_i)$ (e.g., SVM, kNN, …) to compute best value for Y_i
- **Iteration phase:** Iterate till convergence
  - Repeat for each node *i*
    - Update node vector a_i
    - Update label Y_i to $f(a_i)$. This is a hard assignment
  - Iterate until class labels stabilize or max number of iterations is reached
- Note: Convergence is not guaranteed
  - Run for *max* number of iterations

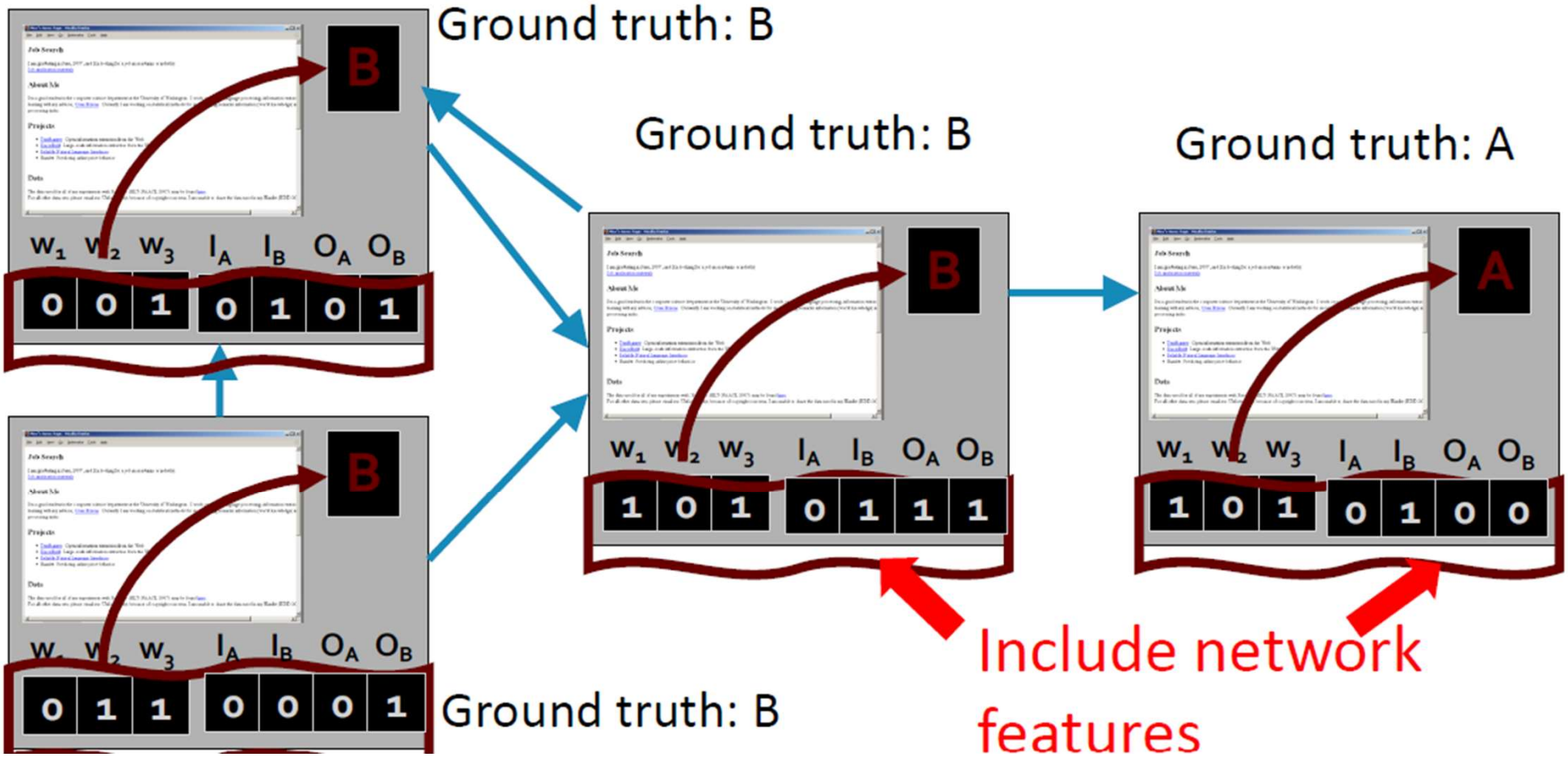
Example: Web Page Classification

- w_1, w_2, w_3, … represent presence of words
- Baseline: train a classifier (e.g., k-NN) to classify pages based on words



Example: Web Page Classification

- Each node maintains a vector of neighborhood labels: (I_A, I_B, O_A, O_B). I = In, O = Out
- I_A = 1 if at least one of the incoming pages is labelled A. Similar definitions for I_B, O_A, and O_B

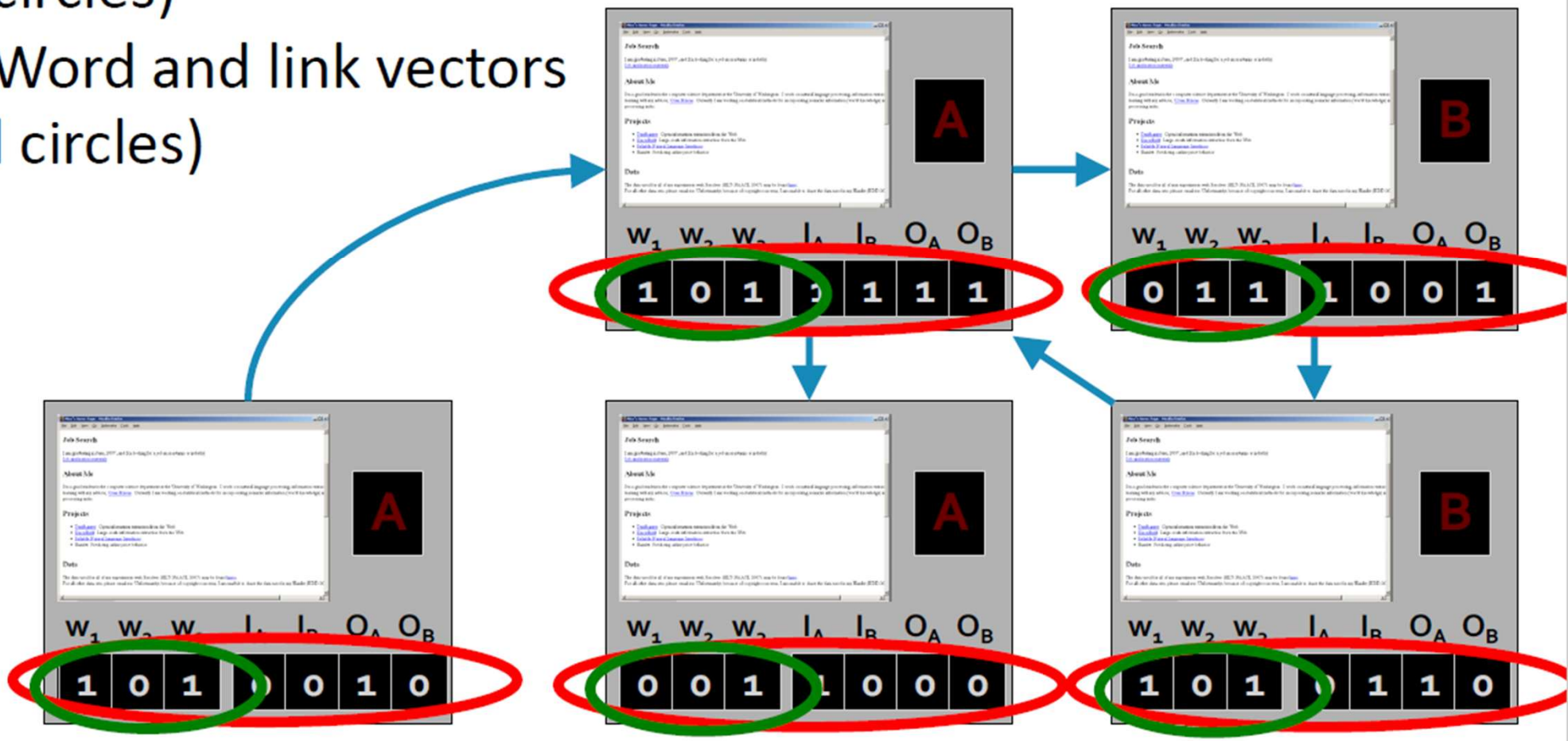


Training set

1. Train
2. Bootstrap
3. Iterate
   a. Update relational features
   b. Classify

On a different **training set**, train two classifiers:

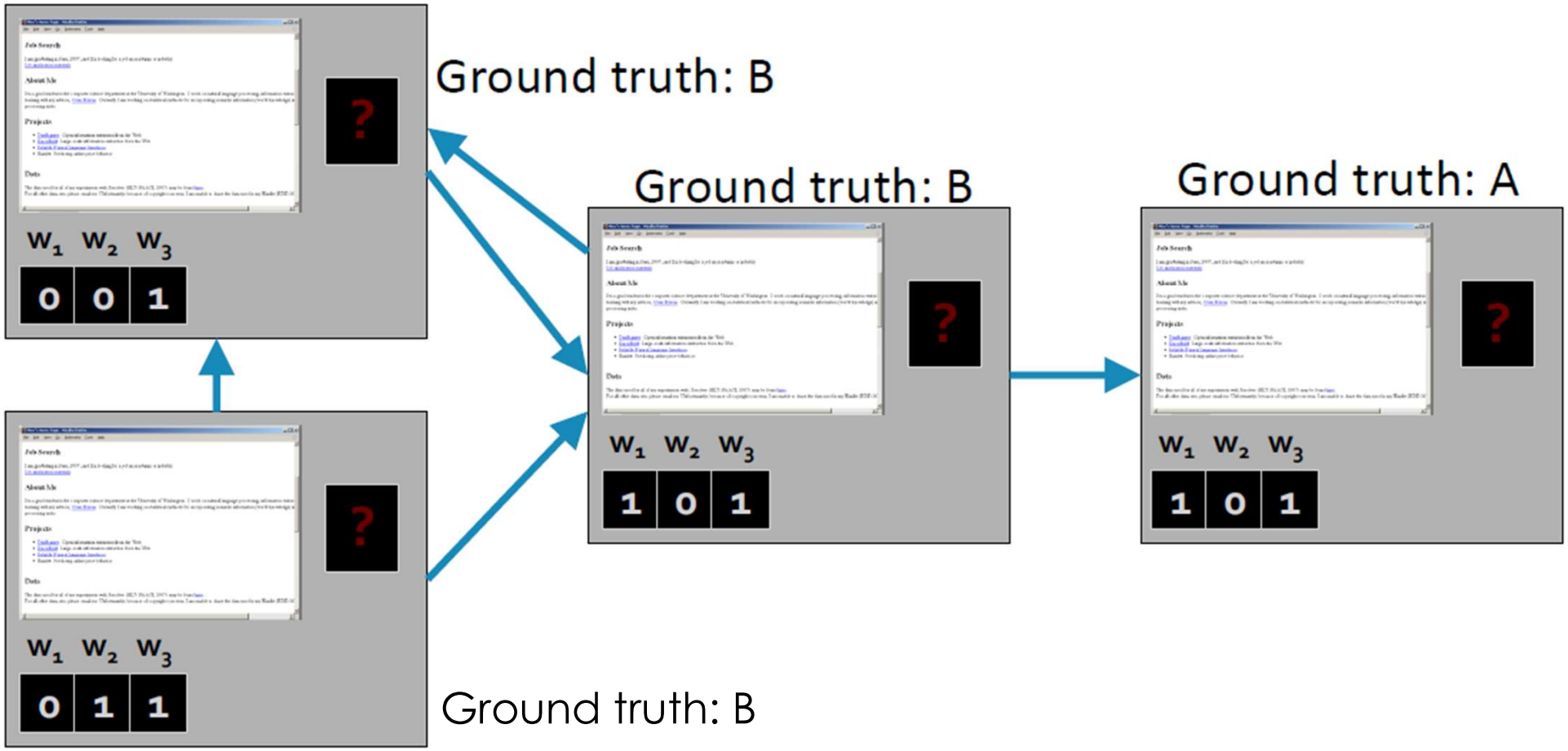
1. Word vector only (green circles)
2. Word and link vectors (red circles)



On test set

1. Train
2. Bootstrap
3. Iterate
   a. Update relational features
   b. Classify

Use trained word-vector classifier to bootstrap on test set



On test set

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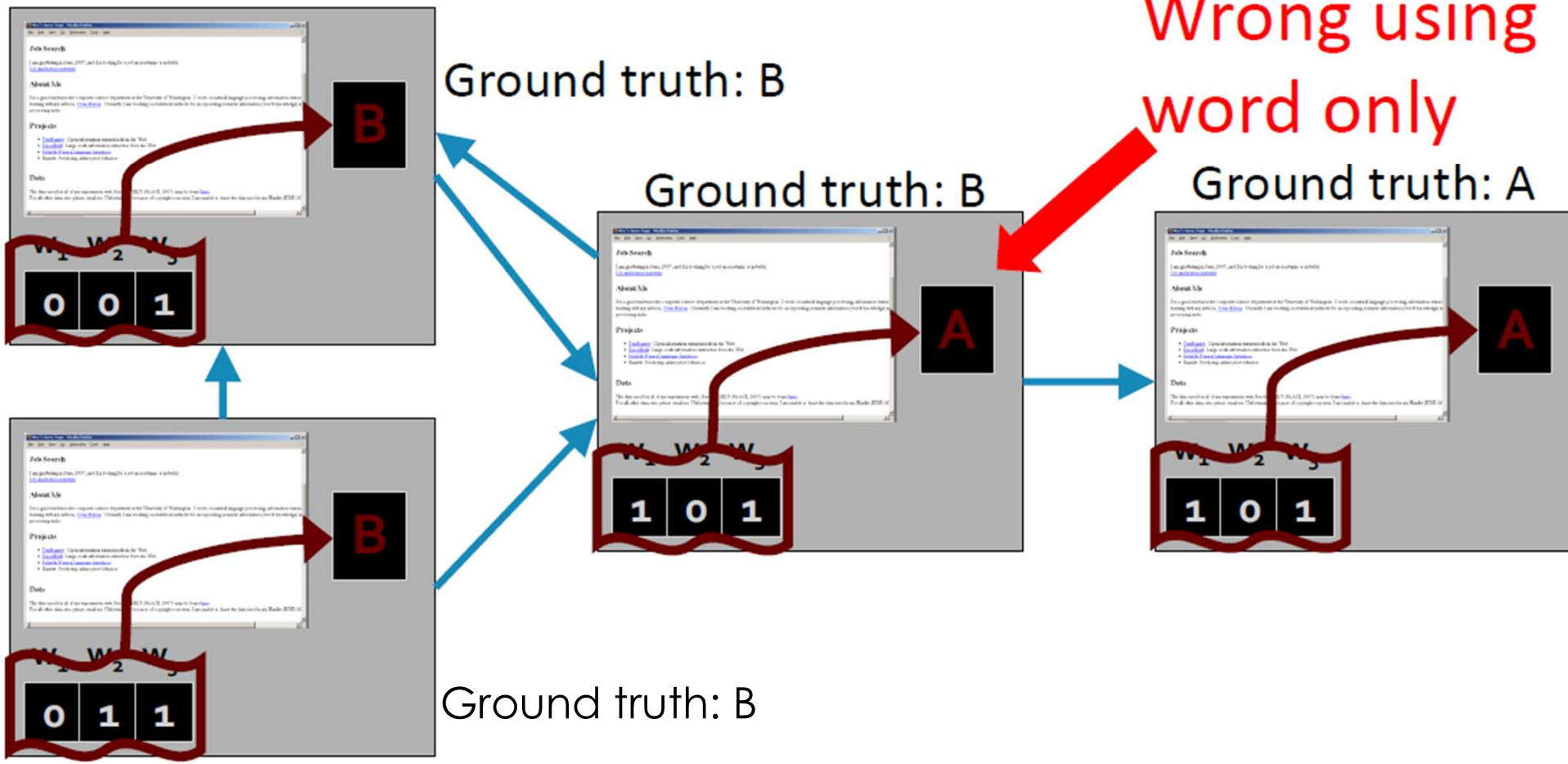
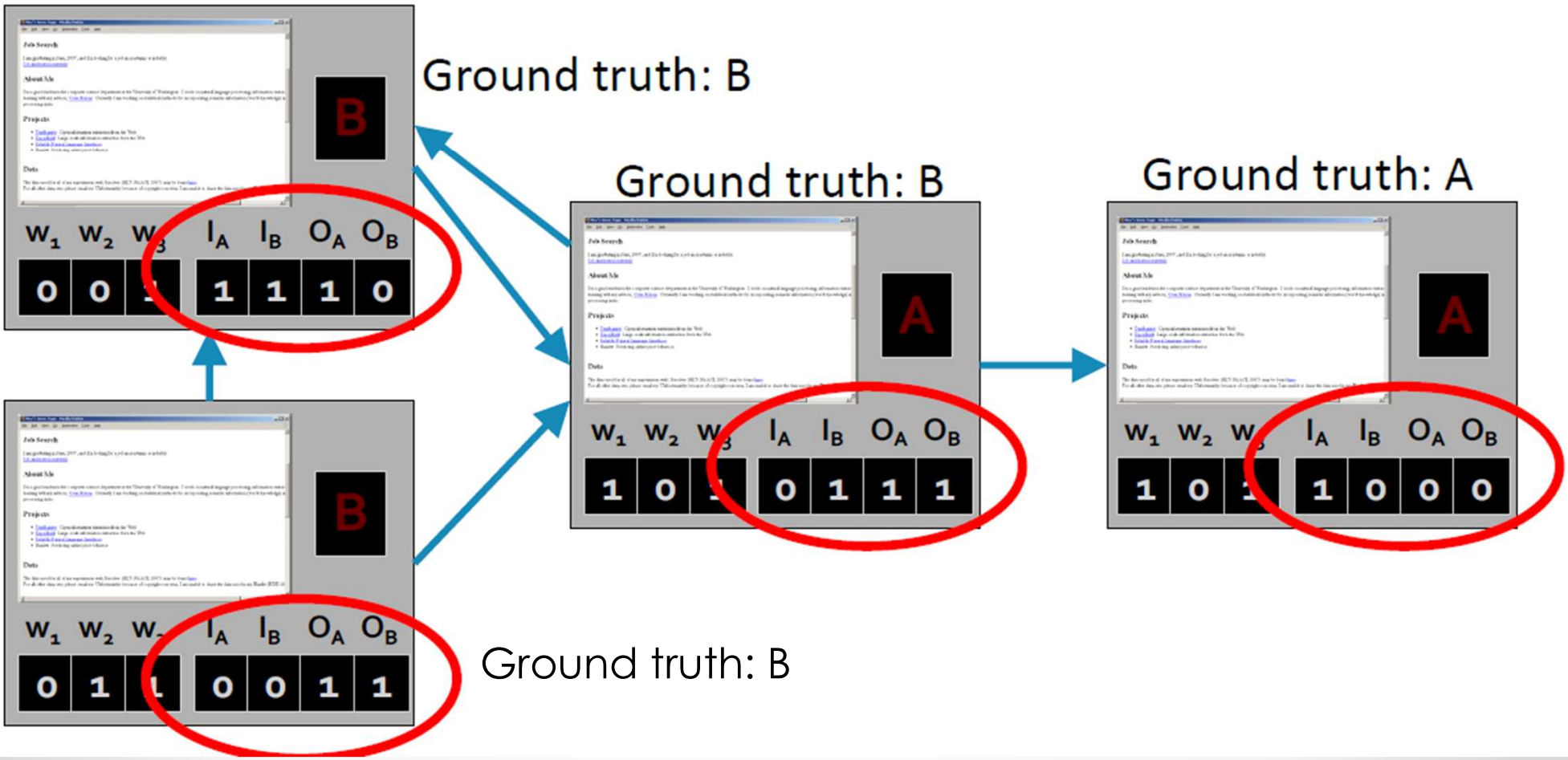


On test set

1. Train
2. Bootstrap
3. Iterate
   - a. Update relational features
   - b. Classify

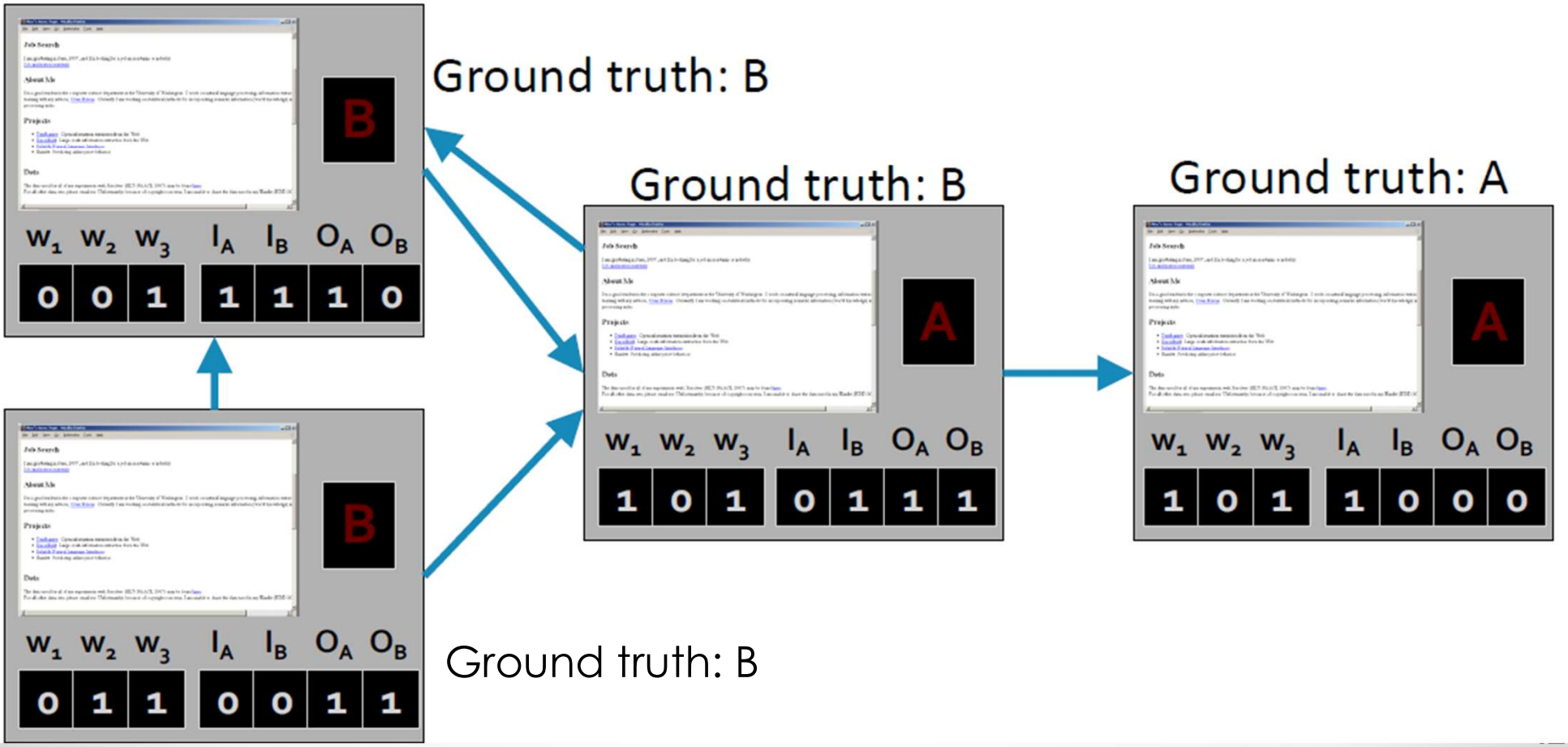
Update neighborhood vector for all nodes



On test set

1. Train
2. Bootstrap
3. Iterate
   a. Update relational features
   b. Classify

Reclassify all nodes



On test set

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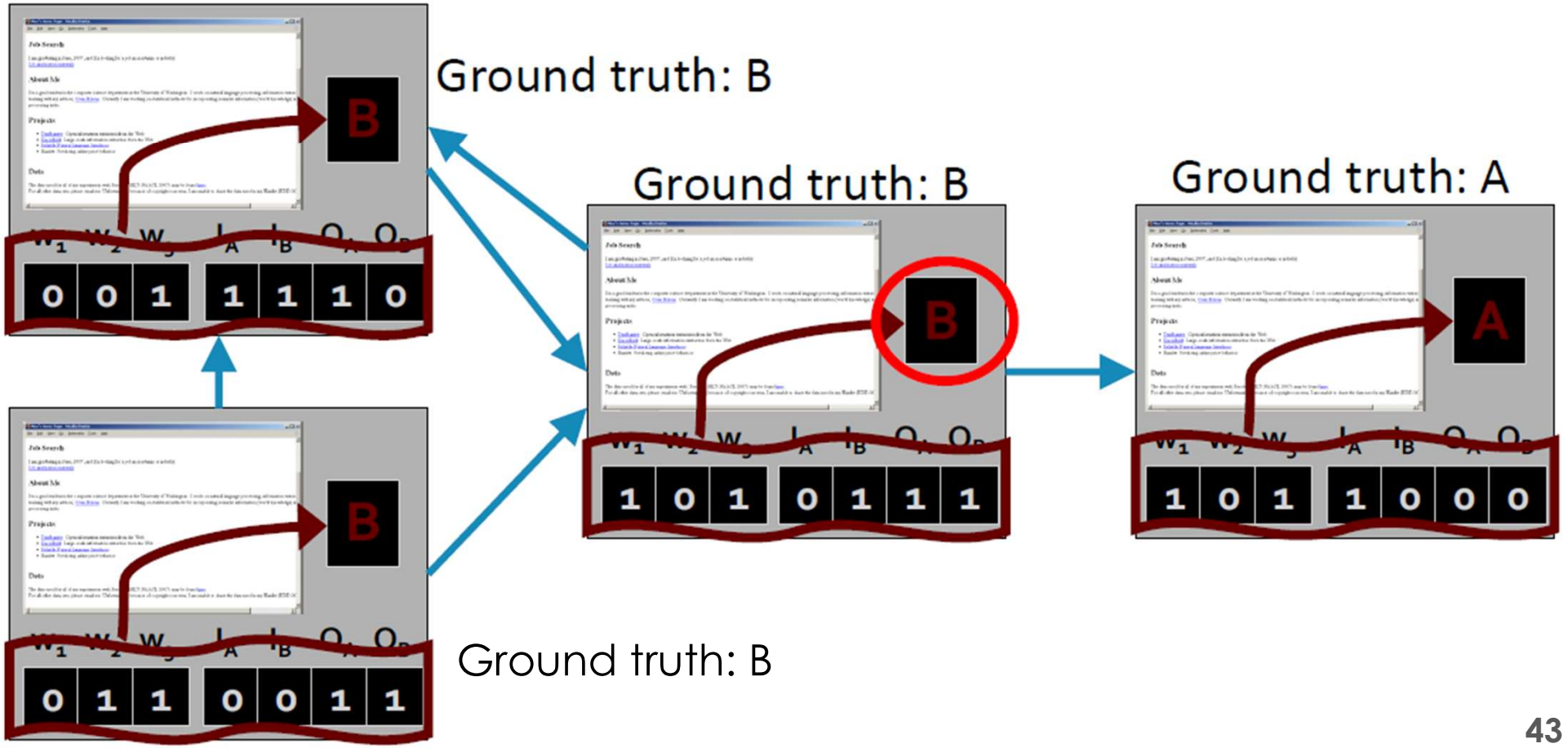
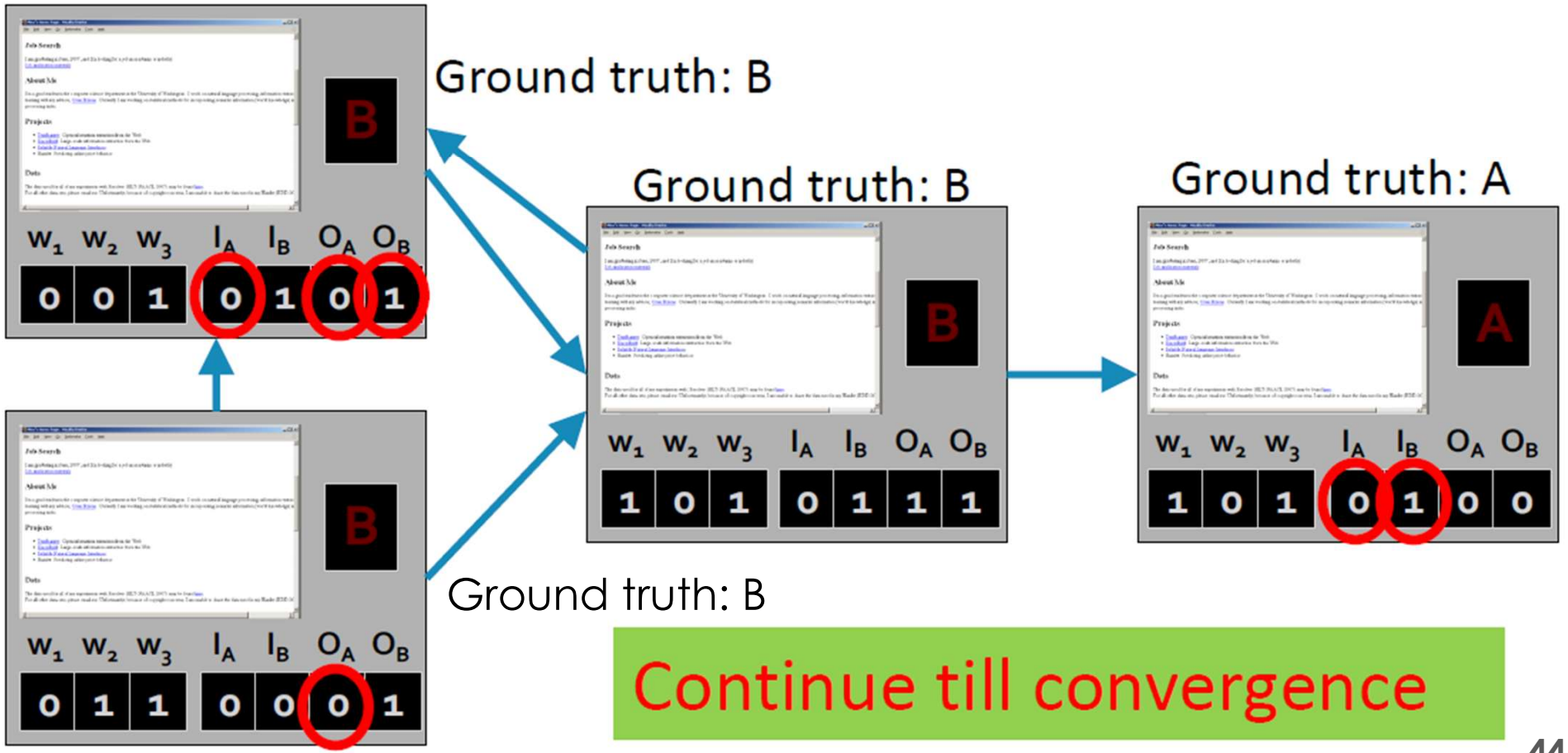
3. Iterate
   a. Update relational features
   b. Classify

Reclassify all nodes



On test set

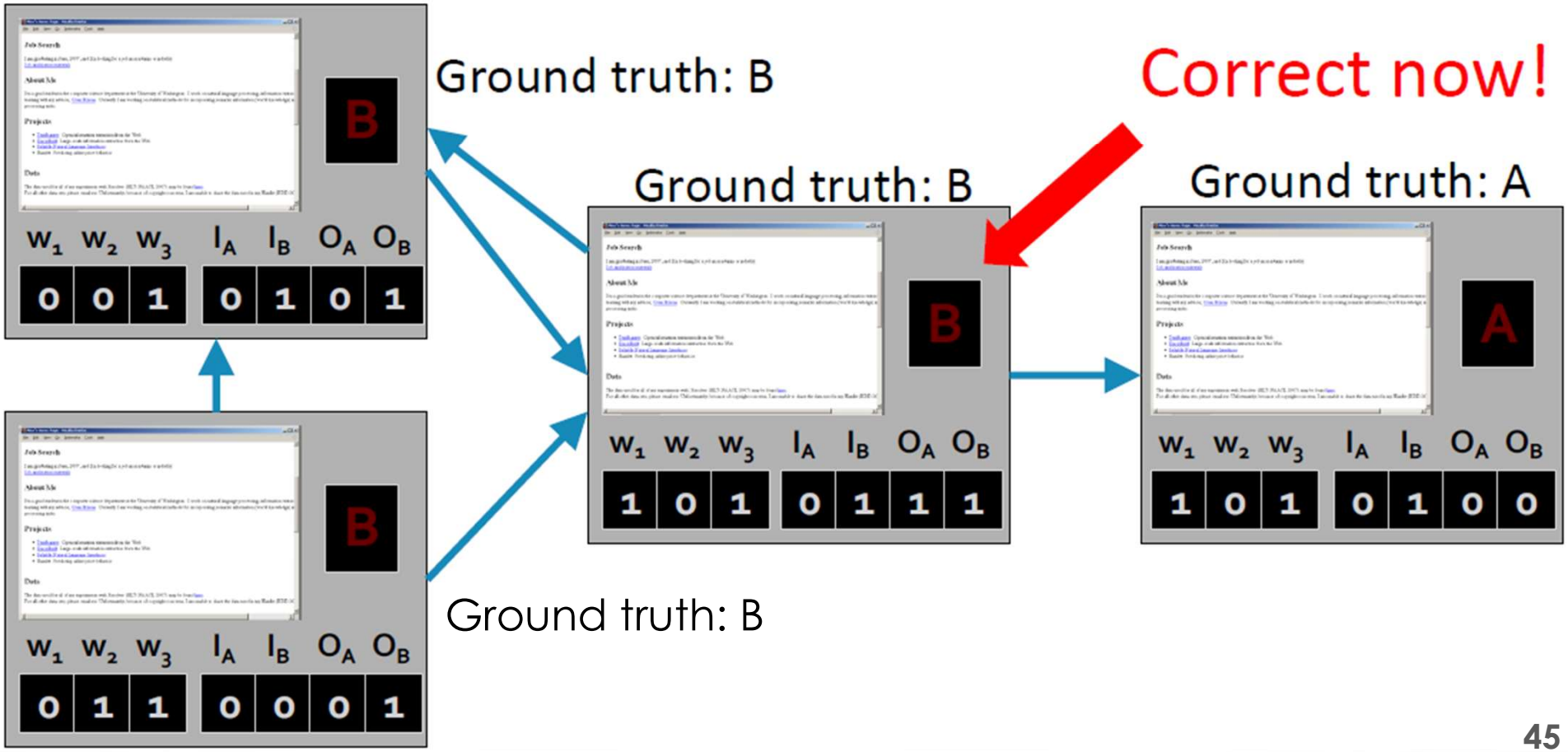
1. Train
2. Bootstrap
3. Iterate
   - a. Update relational features
   - b. Classify



Continue till convergence

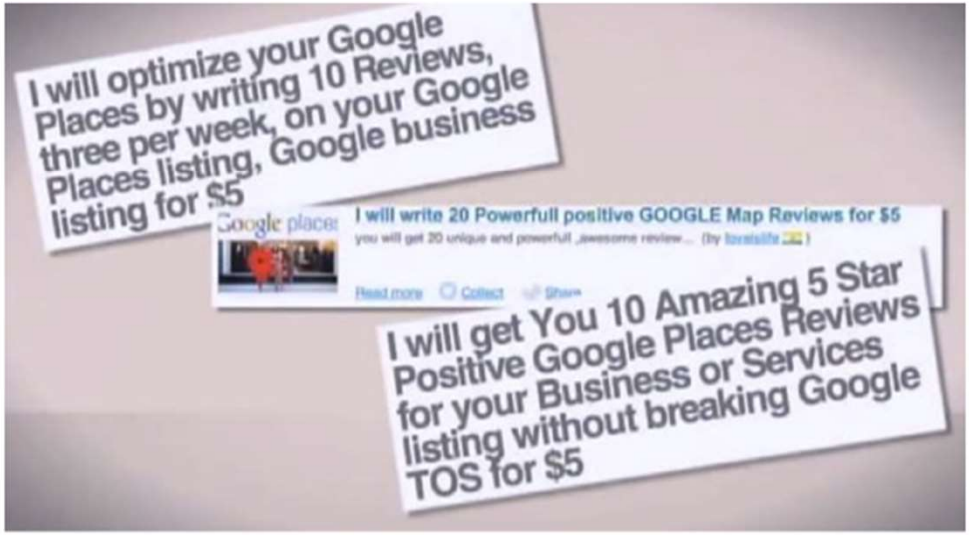
Final

1. Train
2. Bootstrap
3. Iterate
   a. Update relational features
   b. Classify



Example: Fake Reviewer/Review Detection

- Review sites are an attractive target for spam: a +1 star increase in rating increases revenue by 5-9%!
- Often hype/defame spam
- Paid spammers



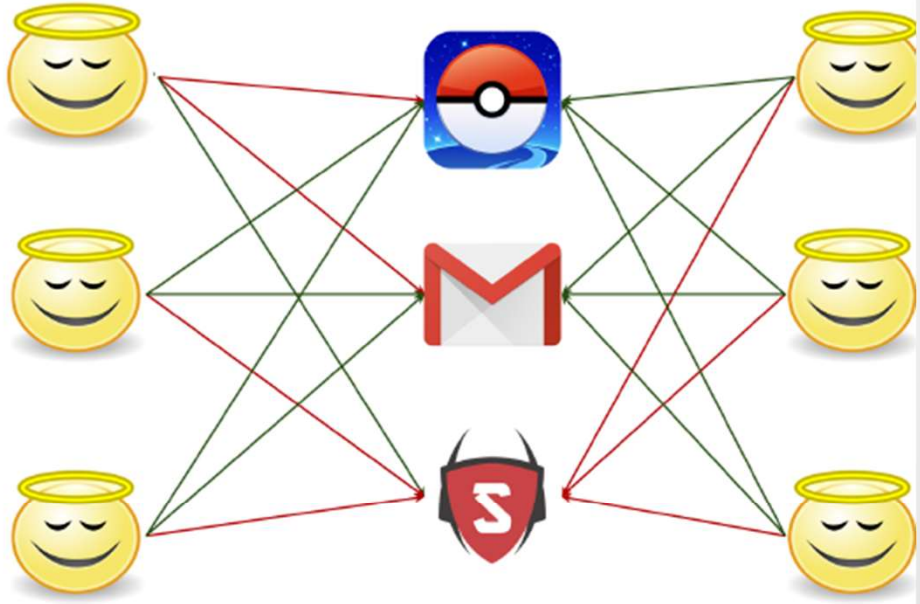
Reference: S. Kumar, et al. REV2: Fraudulent User Prediction in Rating Platforms, Proceedings of the Eleventh ACM International Conference on Web Search and Data Mining, 2018.

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

Problem Setup

- **Input**: bipartite rating graph as a weighted signed network:
  - Nodes: users, products
  - Edges: rating scores between -1 and +1

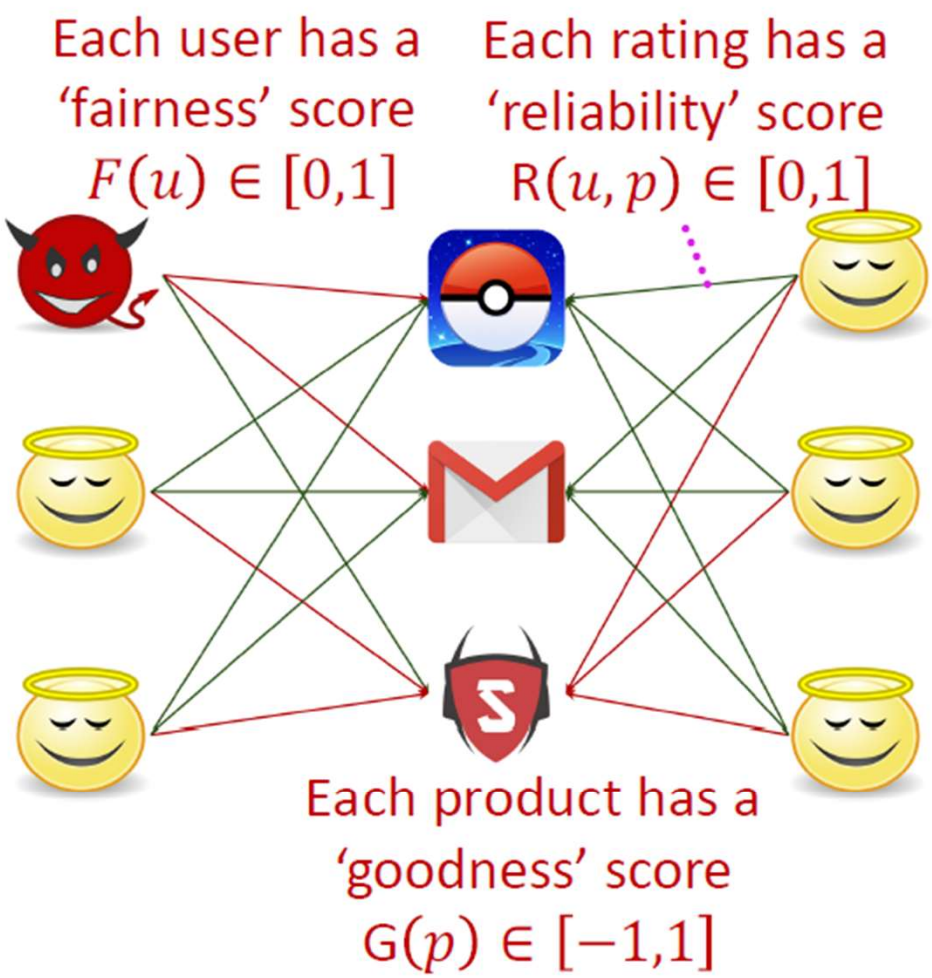


- **Output**: set of users that give fake ratings

Red edges = -1 rating
Green edges = +1 rating

Solution Formulation

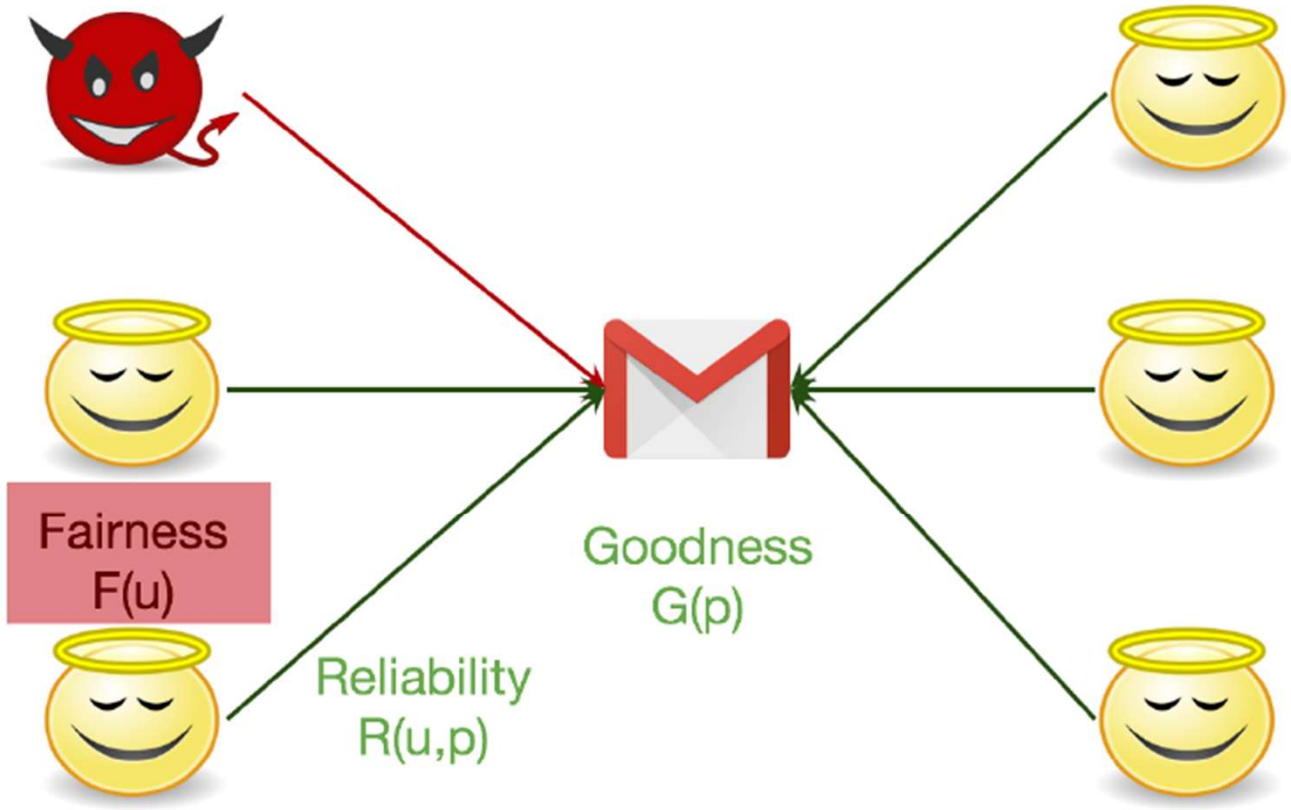
- **Basic idea**: Users, products, and ratings have intrinsic quality scores:
  - Users have fairness scores
  - Products have goodness scores
  - Ratings have reliability scores
- All values are unknown
- How can one calculate the values for all nodes and edges simultaneously?
- **Solution: Iterative classification**



Fairness of users

- Fixing goodness and reliability, fairness is updated as:

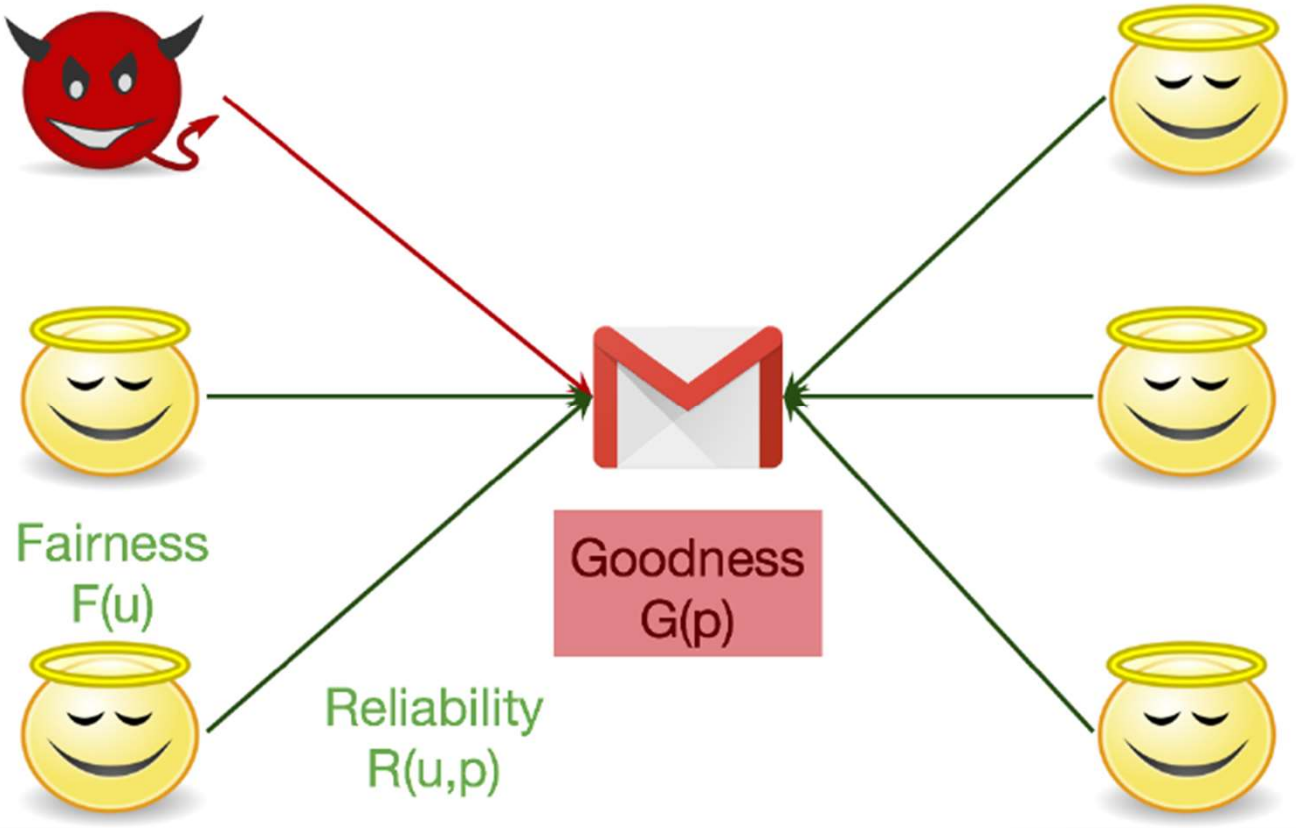
$$F(u) = \frac{\sum_{(u,p)\in \mathrm{Out}(u)} R(u,p)}{|\mathrm{Out}(u)|}$$



Goodness of products

- Fixing fairness and reliability, goodness is updated as:

$$G(p) = \frac{\sum_{(u,p)\in In(p)} R(u,p) \cdot score(u,p)}{|In(p)|}$$



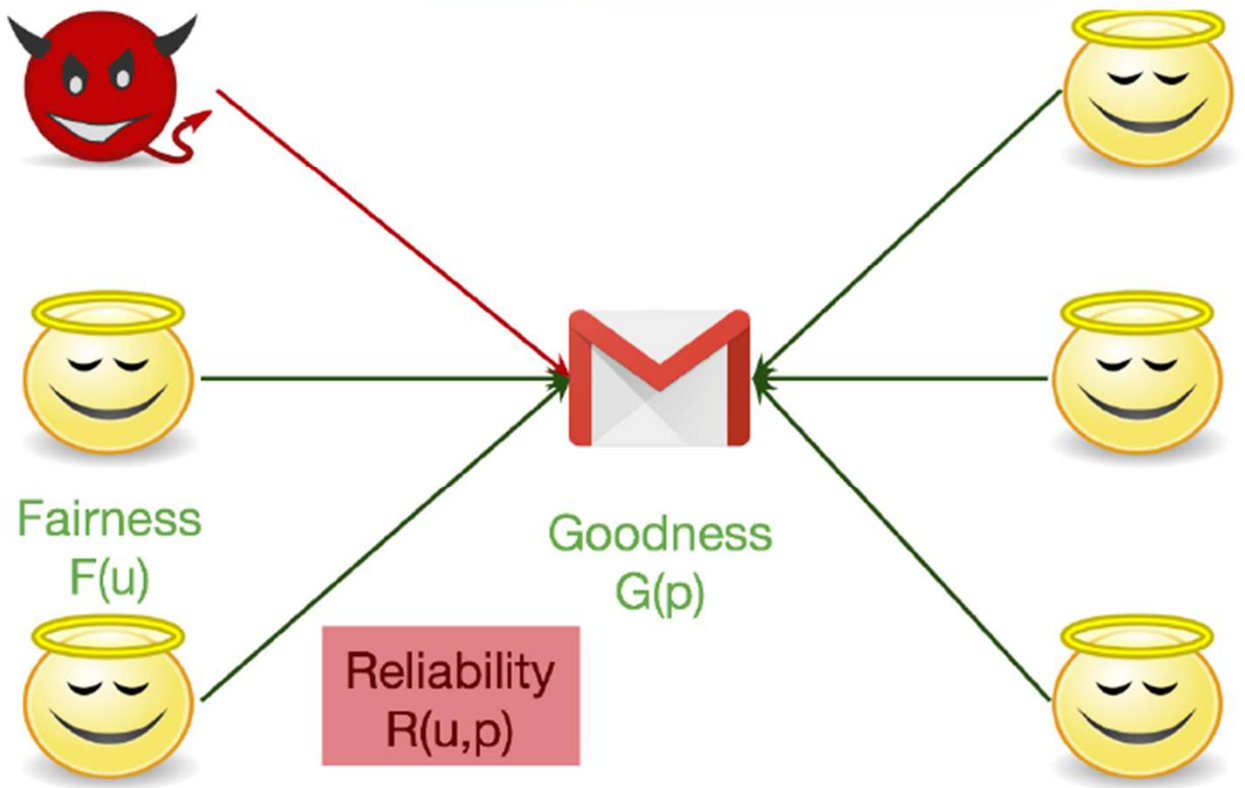
Reliability of ratings

- Fixing fairness and goodness, reliability is updated as:

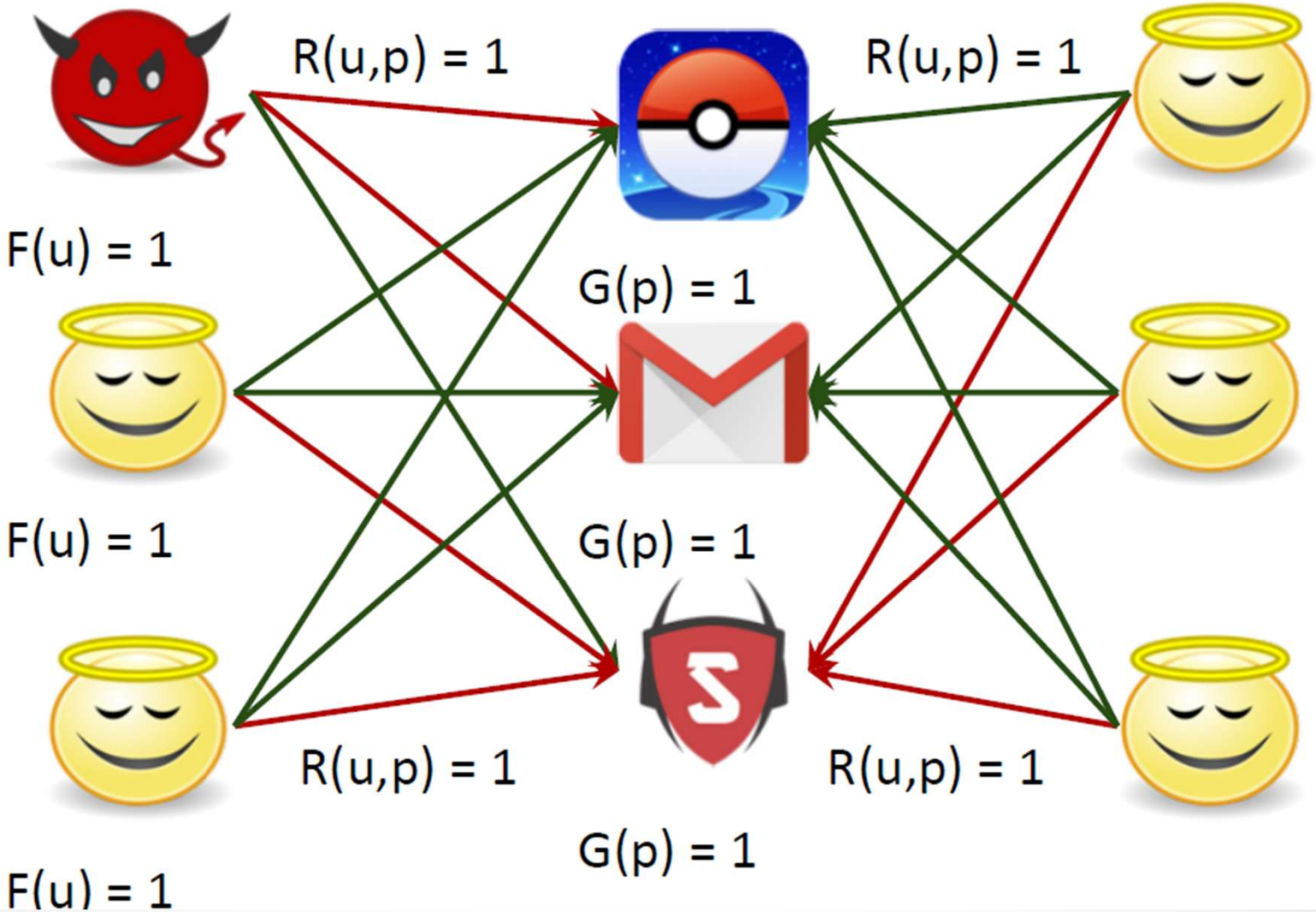
How fair is the user who gives the rating

How close is the rating from the goodness of product

$$R(u,p) = \frac{1}{\gamma_1 + \gamma_2}(\gamma_1 \cdot F(u) + \gamma_2 \cdot (1 - \frac{|\text{score}(u,p) - G(p)|}{2}))$$

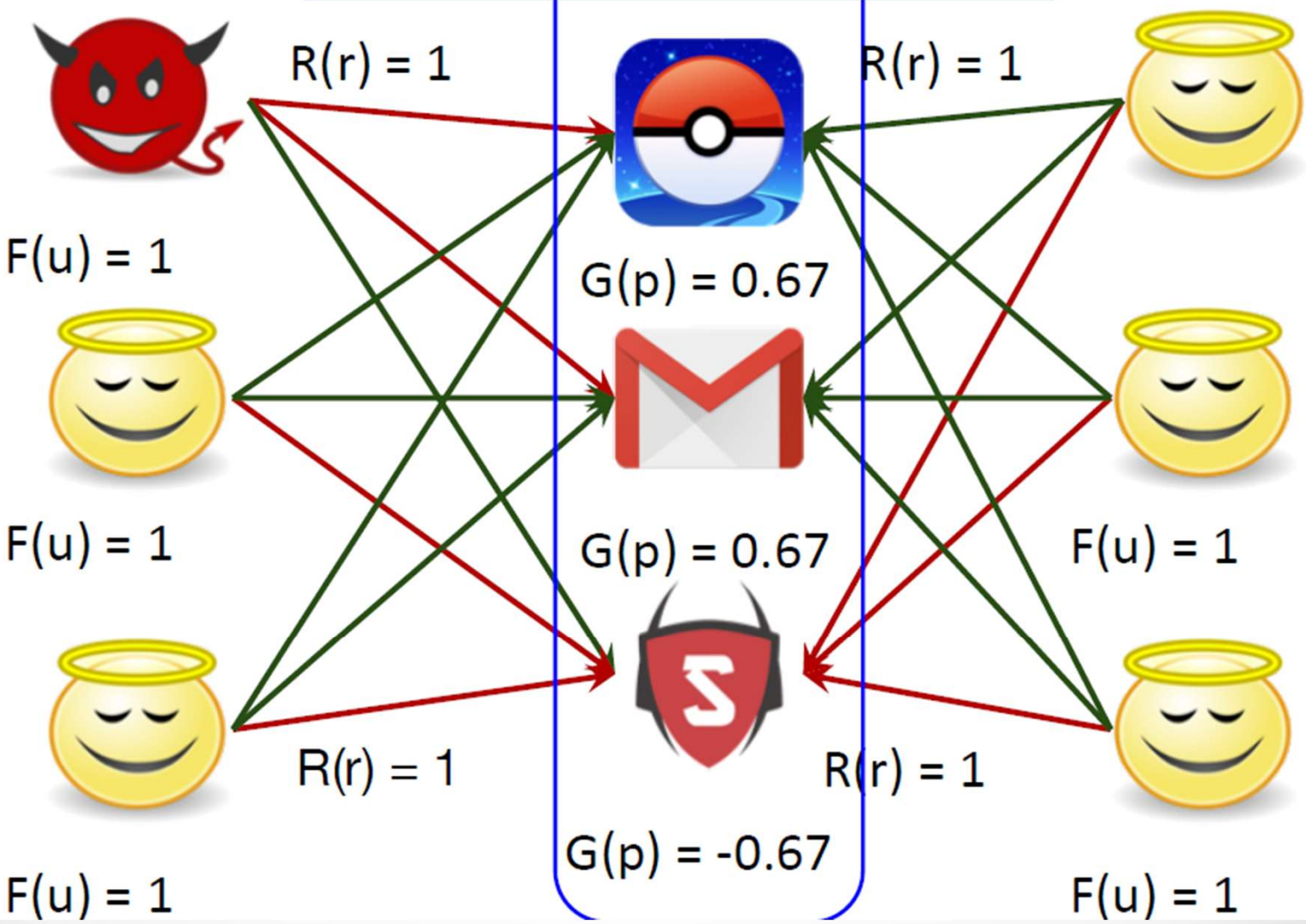


Initialization to best scores



Updating Goodness – Iteration 1

$$G(p) = \frac{\sum_{(u,p)\in In(p)} R(u,p) \cdot score(u,p)}{|In(p)|}$$



Updating Reliability – Iteration 1

$$R(u,p) = \frac{1}{\gamma_1 + \gamma_2}(\gamma_1 \cdot F(u) + \gamma_2 \cdot (1 - \frac{|\text{score}(u,p) - G(p)|}{2}))$$

Both gamma values are set to 1









R(r) = 0.58

R(r) = 0.58

F(u) = 1

G(p) = 0.67

R(r) = 0.92

F(u) = 1

F(u) = 1

G(p) = 0.67

F(u) = 1

R(r) = 0.92

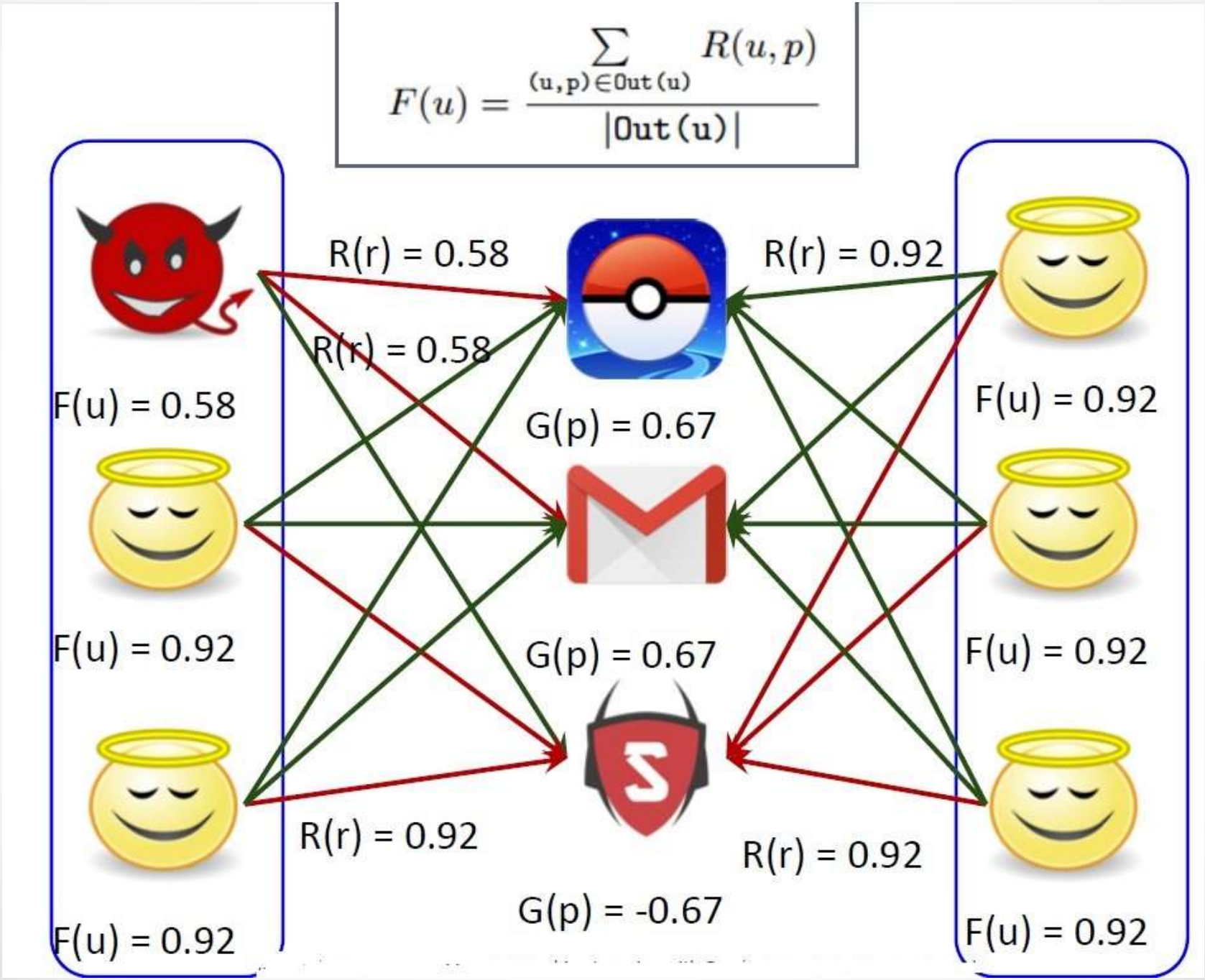
G(p) = -0.67

R(r) = 0.92

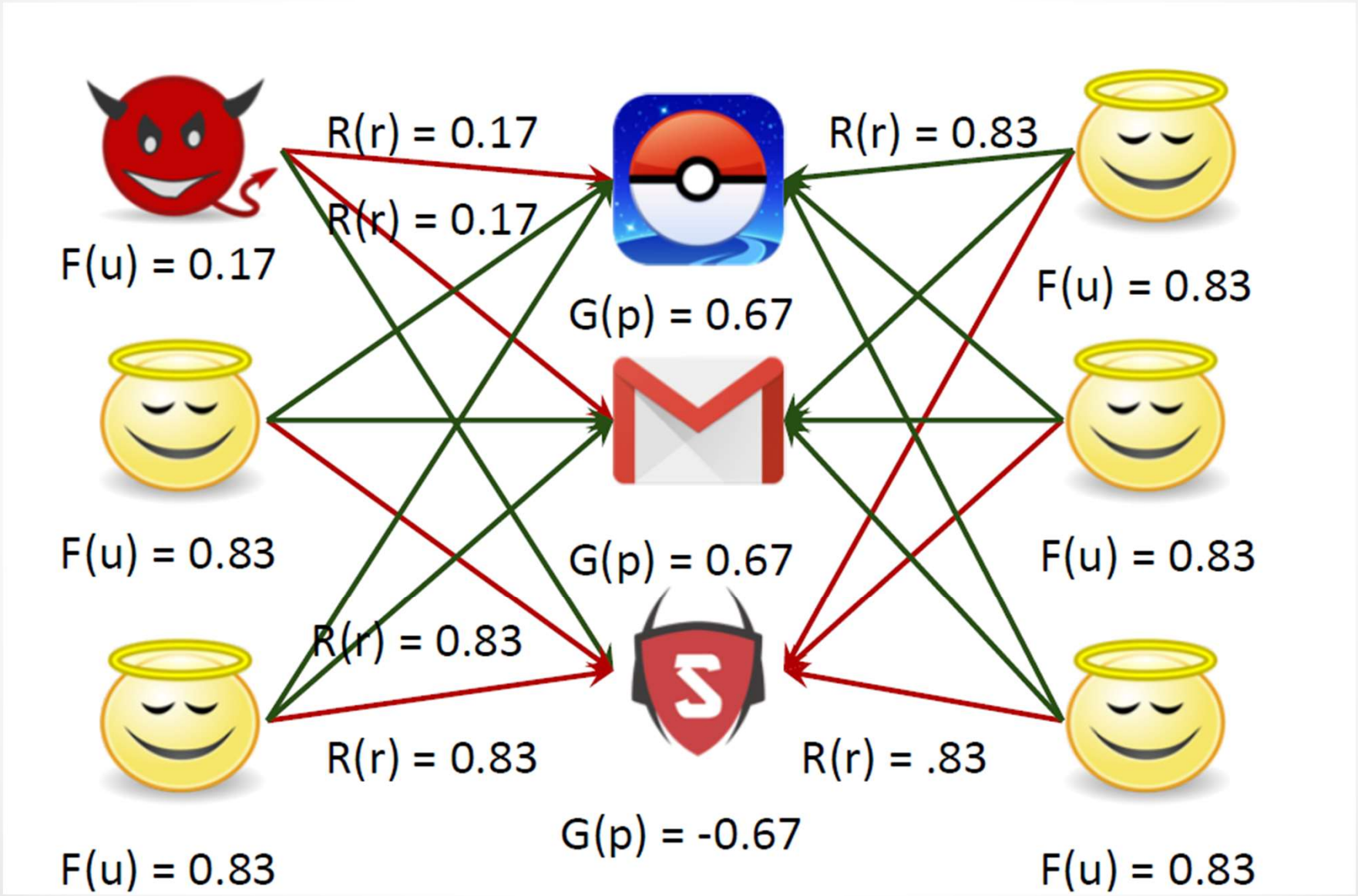
F(u) = 1

Updating Fairness – Iteration 1

$$F(u) = \frac{\sum_{(u,p) \in Out(u)} R(u,p)}{|Out(u)|}$$

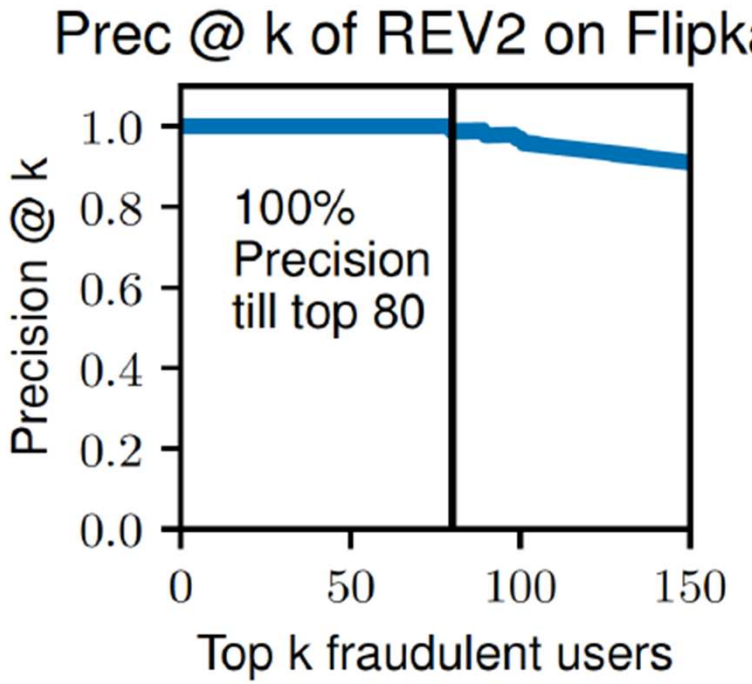


After Convergence



Performance

- Low fairness users = Fraudsters
- 127 of 150 lowest fairness users in Flipkart were real fraudsters



Properties of solution

- Guaranteed to converge
- Number of iterations till convergence is upper-bounded
- Time–complexity: linear in the number of edges in the graph

Overview

- Node Classification
- Relational Classifiers
- Iterative Classification
- Belief Propagation

Loopy Belief Propagation

- Belief Propagation is a dynamic programming approach to **answering probability queries in a graph** (e.g. probability of node v belonging to class 1)
- Iterative process in which neighbor nodes "talk" to each other, **passing messages**

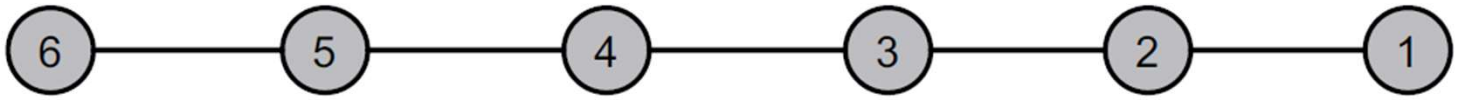
"I (node v) believe you (node u) belong to class 1 with likelihood …"

- **When consensus is reached, calculate final belief**

Message Passing: Basics

- **Task**: Count the number of nodes in a graph*
- **Condition:** Each node can only interact (pass message) with its neighbors

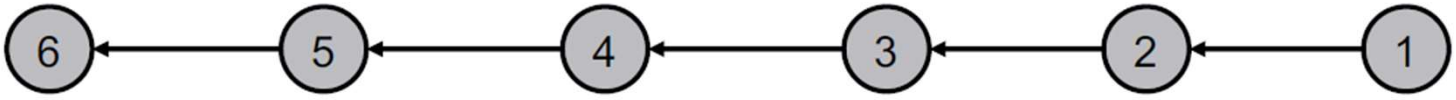
- **Example**: path graph



* Potential issues when the graph contains cycles.
We'll get back to it later!

Message Passing: Algorithm

- **Task**: Count the number of nodes in a graph
- **Algorithm**:
  - Define an ordering of nodes (that results in a path)
  - Edge directions are according to order of nodes
    - Edge direction defines the order of message passing
  - For node i from 1 to 6
    - Compute the message from node i to $i + 1$ (number of nodes counted so far)
    - Pass the message from node i to $i + 1$



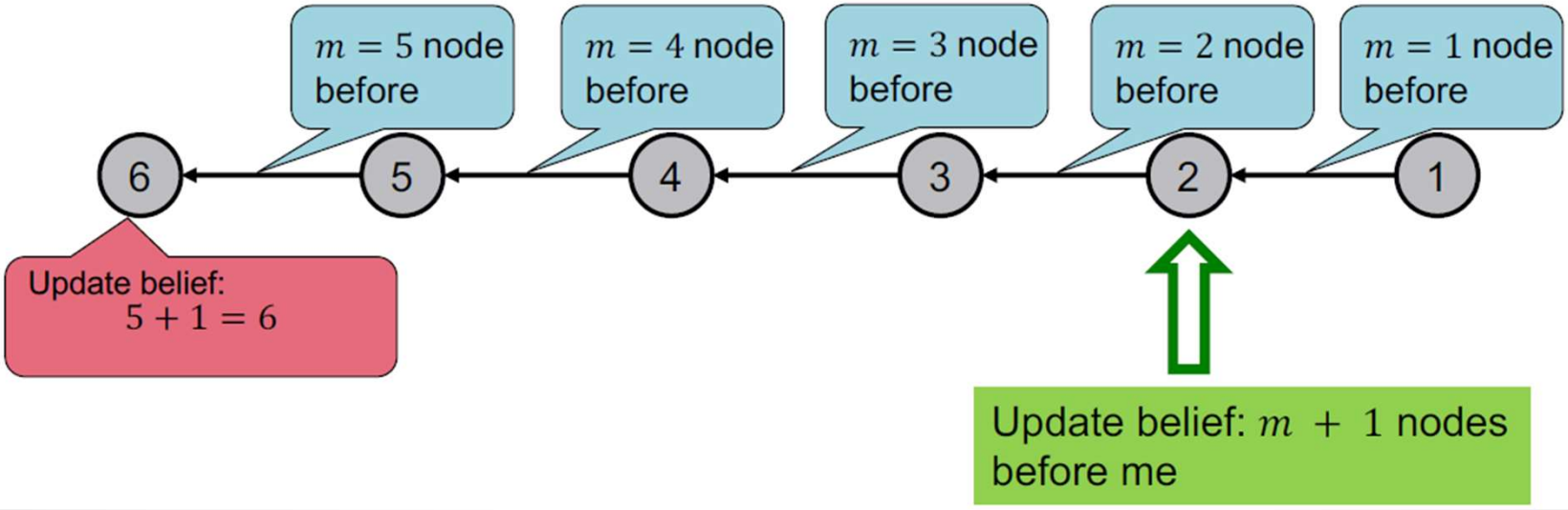
Message Passing: Basics

Task: Count the number of nodes in a graph

Condition: Each node can only interact (pass message) with its neighbors

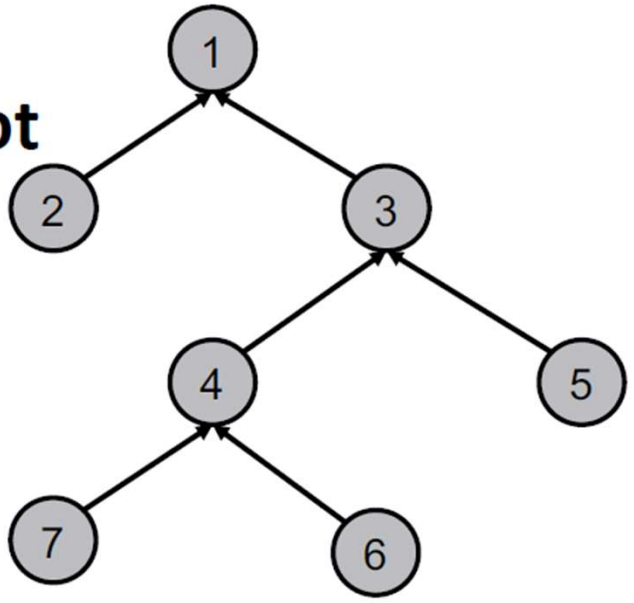
Solution: Each node listens to the message from its neighbor, updates it, and passes it forward

m: the message

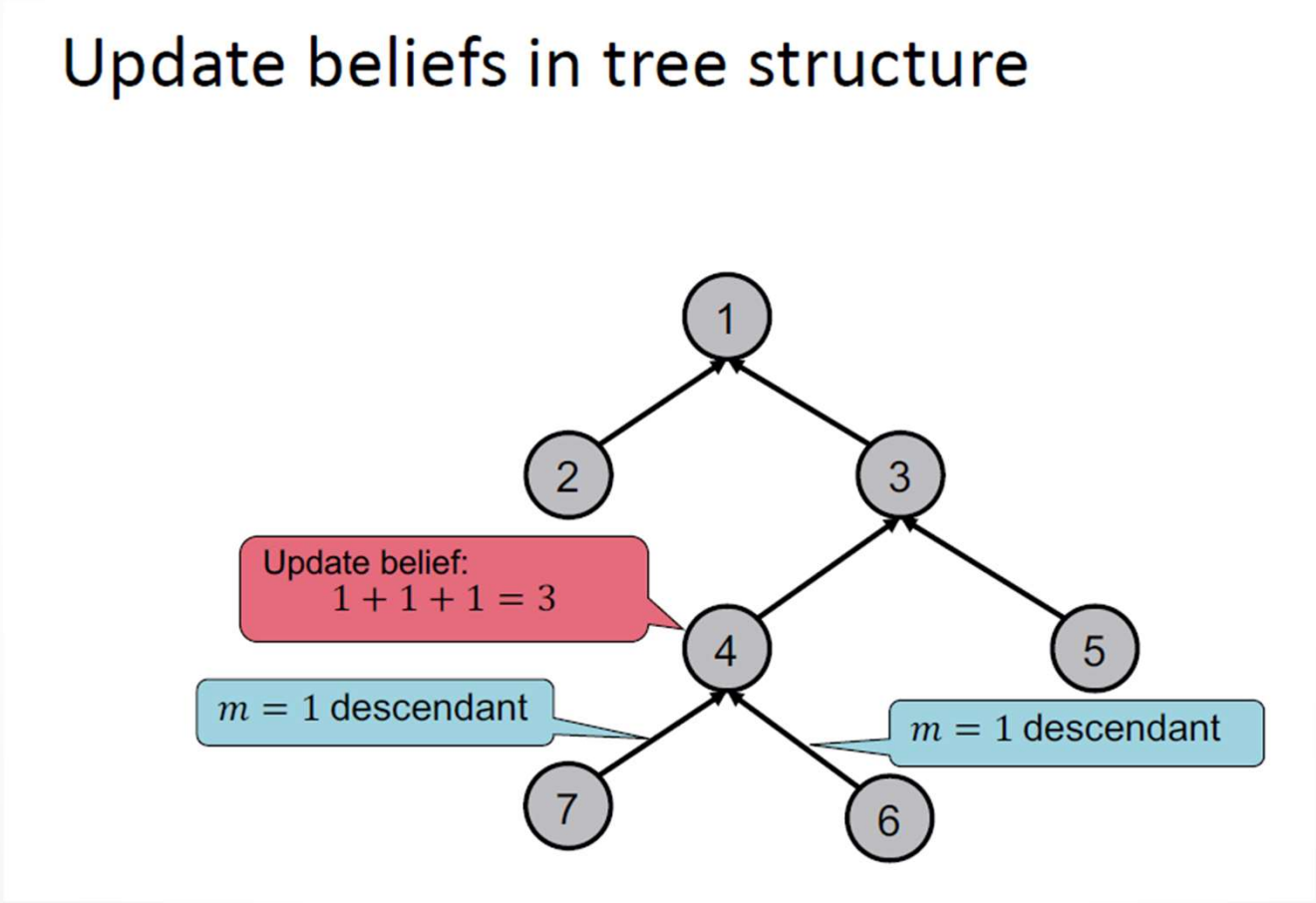


Generalizing to a Tree

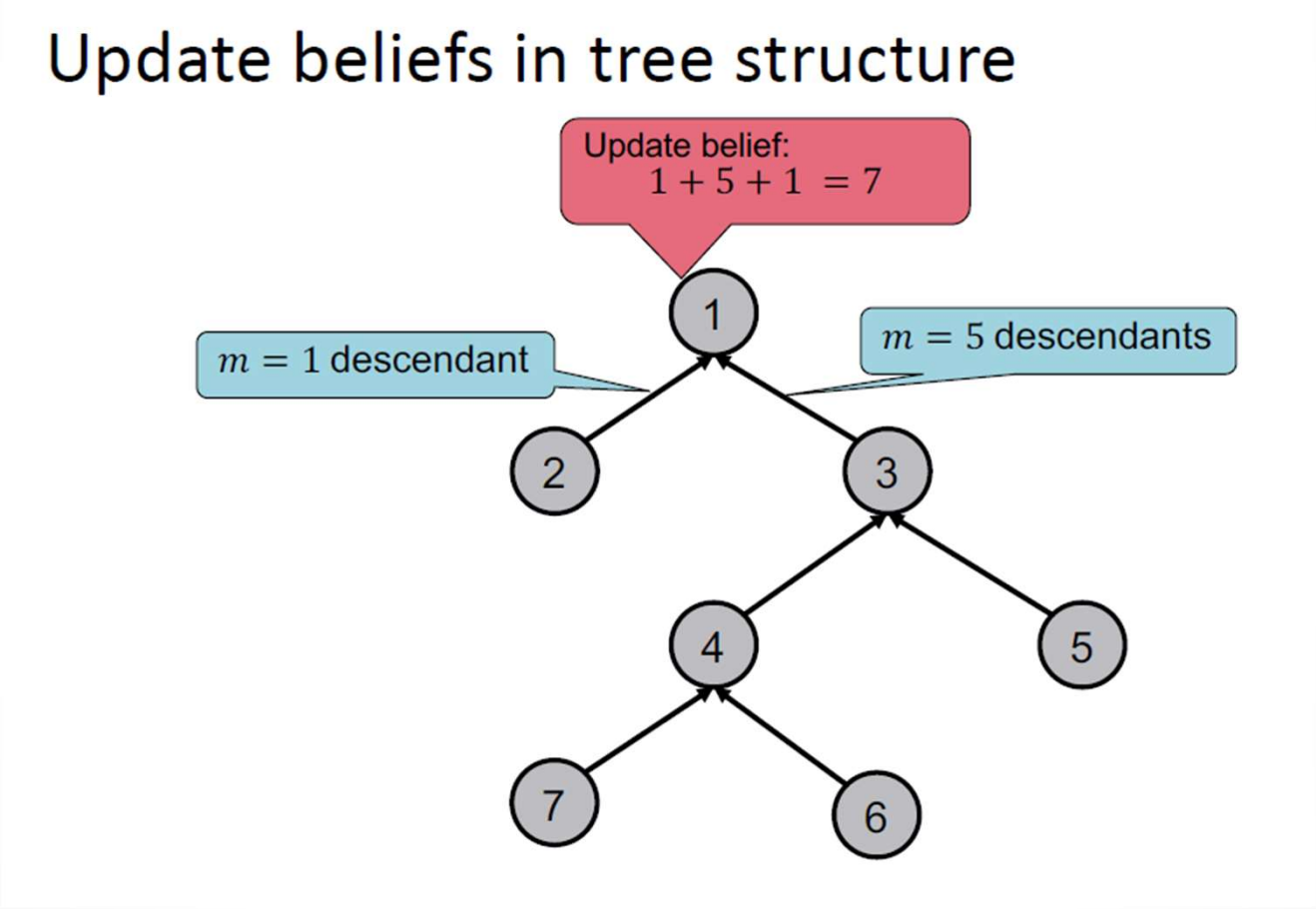
- We can perform message passing not only on a path graph, but also on a tree-structured graph
- Define order of message passing from **leaves** to **root**



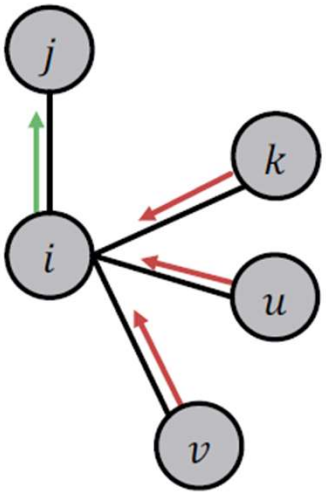
Message Passing in a Tree



Message Passing in a Tree



Loopy BP Algorithm



What message will i send to j?

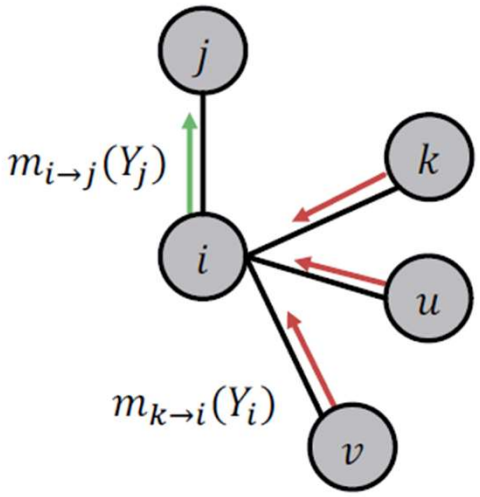
- It depends on what i hears from its neighbors
- Each neighbor passes a message to i its beliefs of the state of i

I (node i) believe that you (node j) belong to class Y_j with probability …

Notation

- ***Label-label potential matrix*** ψ : Dependency between a node and its neighbor. $\boldsymbol{\psi}(Y_i, Y_j)$ is proportional to the probability of a node j being in class Y_j given that it has neighbor i in class Y_i.
- ***Prior belief*** ϕ : $\phi(Y_i)$ is proportional to the probability of node i being in class Y_i.
- $m_{i \to j}(Y_j)$ is i's message / estimate of j being in class Y_j.
- $\mathcal{L}$ is the set of all classes/labels

Loopy BP Algorithm



1. Initialize all messages to 1
2. Repeat for each node:

All messages sent by neighbors from previous round

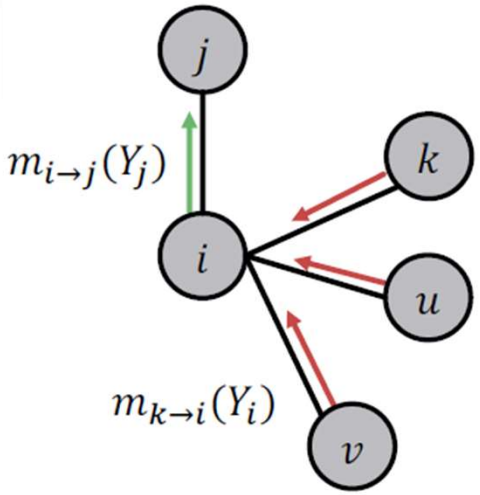
Label-label potential

$$m_{i\to j}(Y_j) = \sum_{Y_i\in\mathcal{L}} \psi(Y_i, Y_j)\,\phi_i(Y_i) \prod_{k\in N_i\setminus \mathrm{j}} m_{k\to i}(Y_i), \forall Y_j \in \mathcal{L}$$

Sum over all states

Prior

Loopy BP Algorithm



After convergence:

$b_i(Y_i)$ = node i's belief of being in class Y_i

All messages from neighbors

Prior

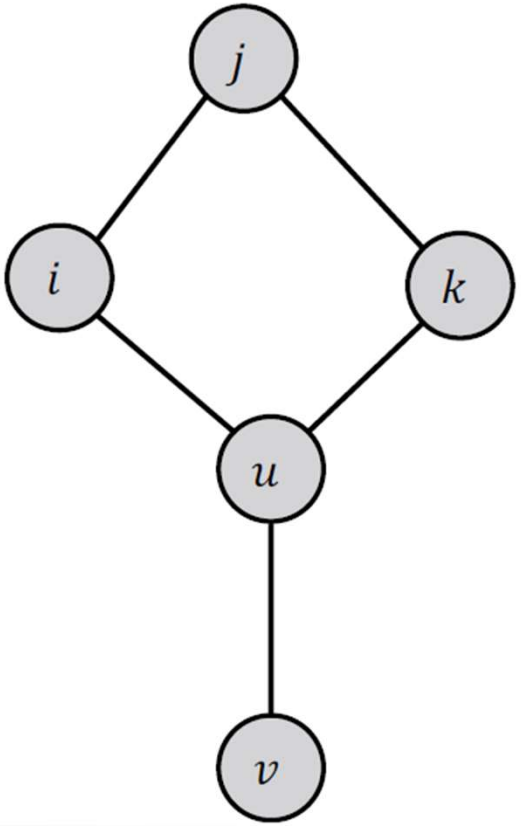
$$b_i(Y_i) = \phi_i(Y_i) \prod_{j \in N_i} m_{j \to i}(Y_i), \quad \forall Y_i \in \mathcal{L}$$

Example: Loopy Belief Propagation

- Now we consider a graph with cycles
- There is no longer an ordering of nodes
- We apply the same algorithm as in previous slides:
  - Start from arbitrary nodes
  - Follow the edges to update the neighboring nodes

Example: Loopy Belief Propagation

What if our graph has cycles?

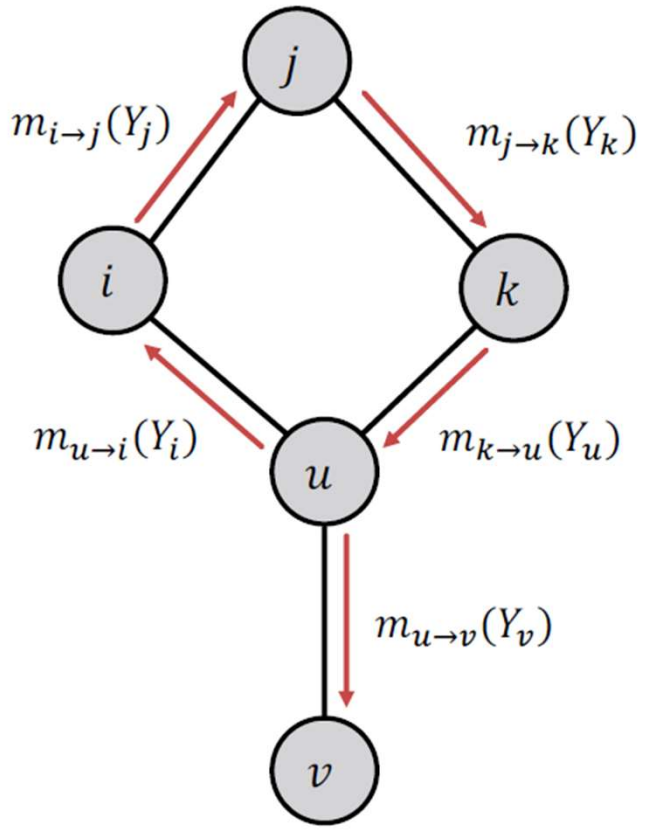


Messages from different subgraphs are **no longer independent**!

But we can still run BP, but it will pass messages in loops.

Example: Loopy Belief Propagation

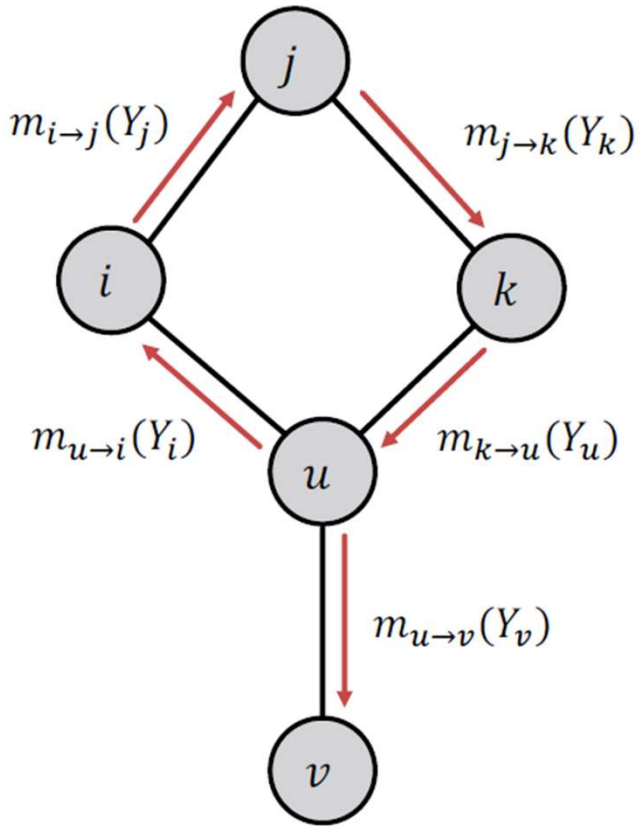
What if our graph has cycles?



Messages from different subgraphs are **no longer independent**!

But we can still run BP, but it will pass messages in loops.

What can go wrong?



- **Beliefs may not converge**
  - Message $m_{u\to i}(Y_i)$ is based on initial belief of i, not a **separate evidence** for i
  - The initial belief of i (which could be incorrect) is reinforced by the cycle $i \to j \to k \to u \to i$
- However, in practice, Loopy BP is still a good heuristic for complex graphs which contain many branches.

In most real-world graphs, cycles are few or have weak connections

Belief Propagation - Analysis

- **Advantages**:
  - Easy to program & parallelize
  - General: can apply to any graph model with any form of potentials
    - Potential can be higher order: e.g. $\boldsymbol{\psi}(Y_i, Y_j, Y_k, Y_v \ldots)$
- **Challenges**:
  - Convergence is not guaranteed (when to stop), especially if many closed loops
- **Potential functions** (parameters)
  - Require training to estimate

Summary

- Three collective classification algorithms:
  - **Relational models**
    - Weighted average of neighborhood properties
    - Cannot take node attributes while labeling
  - **Iterative classification**
    - Update each node's label using own and neighbor's labels
    - Can consider node attributes while labeling
  - **Belief propagation**
    - Message passing to update each node's belief of itself based on neighbors' beliefs