

# **Supervised Belief Propagation:** Scalable Supervised Inference on Attributed Networks

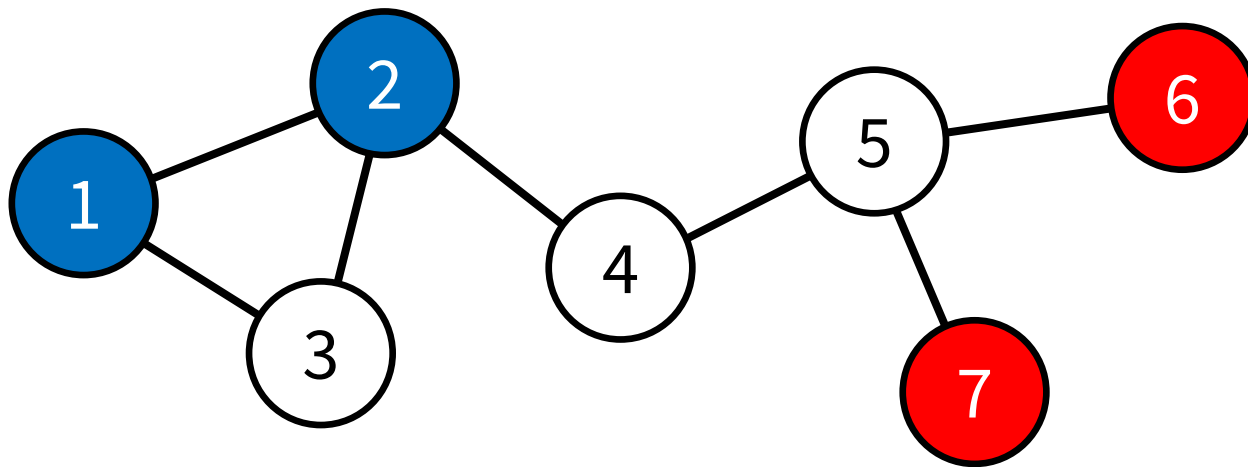
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# Outline

1. **Introduction**
2. Proposed Method
3. Experiments
4. Conclusion

# Network of Political Blogs

- We are given a network of political blogs
- Each blog is either **Liberal** or **Conservative**
- Only some blogs have been observed



# Node Classification

- How can we classify unobserved nodes?
- This problem is called **node classification**
- **Real-world applications:**
  - Fraud detection in auction networks
  - User labeling in social networks
  - Malware detection in file-machine networks

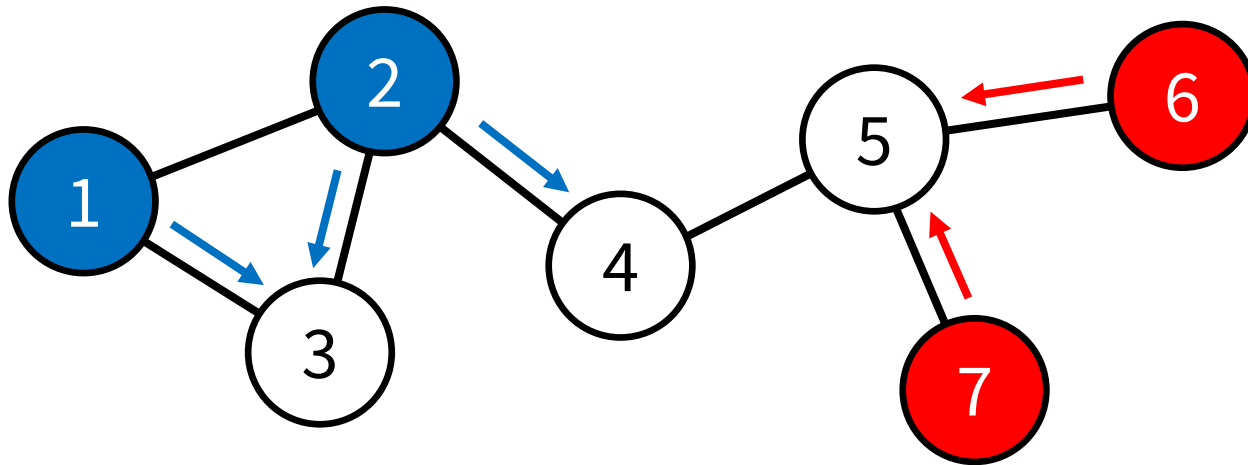
# Loopy Belief Propagation

- Widely used method for node classification
- Uses an **affinity table** to model the network
- For any pair of connected nodes
  - the probability of having a same label is  $\epsilon$
  - the probability of having different labels is  $1 - \epsilon$

	Label 1	Label 2
Label 1	$\epsilon$	$1 - \epsilon$
Label 2	$1 - \epsilon$	$\epsilon$

# LBP in the Network of Blogs

- LBP propagates information when  $\epsilon > 0.5$
- This is called the property of **homophily**
- Nodes 3 and 4 as liberal, 5 as conservative



# Two Assumptions of LBP

- LBP assumes **homophily** and **uniformity**
- Homophily ( $\epsilon > 0.5$ ):
  - Adjacent nodes are likely to have a same label
  - This is called *guilt-by-association* in literature
- Uniformity ( $\epsilon$  is globally applied):
  - All edges have a same **propagation strength**

# Attributed Network

- Let's say the network is **attributed**:
  - Each edge  $(i, j)$  is attached with a feature vector  $\theta_{ij}$
- Then, these assumptions may break

Node 1	Node 2	Features
1	3	(15,3,0)
1	3	(5, -1,0)
...		
5	7	(0,0,10)



# LBP in Attributed Networks

- Edges have distinct and different features
- Are the edges uniform?
  - **No.** Their strengths depend on their features
- Do the nodes represent homophily?
  - **Not sure.** Some can even represent heterophily
- Moreover, it is difficult to choose a proper  $\epsilon$
- **Not appropriate for attributed networks!**

# Research Question

- **Question.** How can we classify nodes in an attributed network with high accuracy?
- **Challenges:**
  - Domain knowledge is not given
  - Different values of  $\epsilon$  should be modeled
  - Edges may follow the heterophily
- We propose **Supervised belief propagation!**

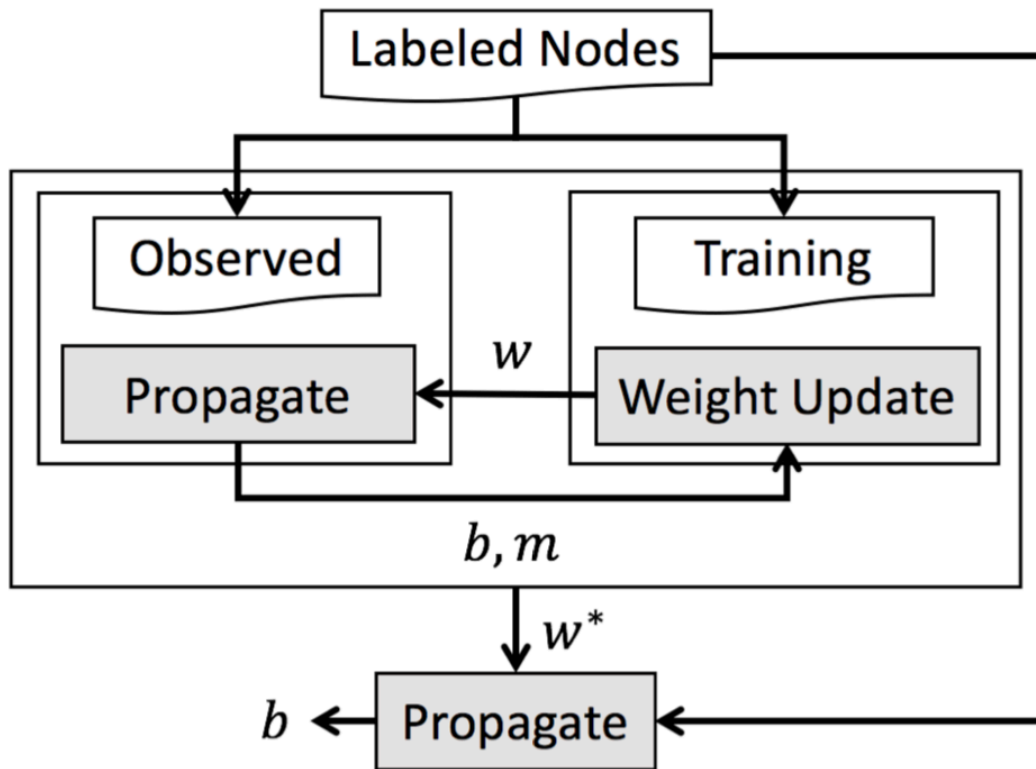
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# Supervised Belief Propagation

- Node classification method for attr. networks
- Learns the **weight vector**  $w$  as a parameter
- Alternates the following steps until  $w$  converges:
  - Propagation step
  - Weight update step
- Then, uses the optimal  $w$  in final classification

# Flowchart of SBP



# Alternating Updates

- The process is similar to an EM algorithm
- **In the propagation step:**
  - SBP uses the current  $w$  in classification
  - This is similar to the **expectation** in EM
- **In the weight update step:**
  - SBP updates  $w$  toward a local optimum
  - This is similar to the **maximization** in EM

# Return Values of SBP

- We assume a network of binary labels
  - Name one label as **pos.**, the other as **neg.**
- SBP returns the belief  $b_i$  of every node  $i$ :
  - The probability of node  $i$  for being positive
- Then we classify node  $i$  based on  $b_i$ :

$$\text{Label of node } i = \begin{cases} \text{pos.} & \text{if } b_i > 0.5 \\ \text{neg.} & \text{if } b_i < 0.5 \end{cases}$$

# Key Ideas of SBP

- **Idea 1.** Model learnable prop. strengths
- **Idea 2.** Introduce a differentiable loss
- **Idea 3.** Iteratively update the parameter



# Idea 1. Prop. Strength

- To model the strength  $\epsilon_{ij}$  as a function:

$$\epsilon_{ij} = \left(1 + \exp(-\theta_{ij}^T w)\right)^{-1}$$

where

- $\theta_{ij}$  is the feature vector of edge  $(i, j)$
- $w$  is the **weight vector** to be optimized

# Idea 2. Differentiable Loss

- To use a differentiable loss  $E(w)$ :

$$E(w) = \lambda \|w\|_2^2 + \sum_p \sum_n h(b_n - b_p)$$

where

- $h = (1 + \exp(-x/d))^{-1}$  is an increasing func.
- $p$  and  $n$  are positive and negative nodes, resp.
- $b_i$  is the belief of node  $i$  for being positive

# Idea 3. Gradient Update

- To update  $w$  with the gradient descent:

$$w \leftarrow w - \text{clip} \left( \alpha \frac{\partial E(w)}{\partial w}; \beta \right)$$

where

- $\alpha$  is a step size parameter
- $\text{clip}(\cdot; \beta)$  restricts the size of each update to  $\beta$

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# Experimental Settings

- MovieLens is a user-movie bipartite network
- Each edge has an integer rating of 1-5
- We classify the movies into “recomm.” and not

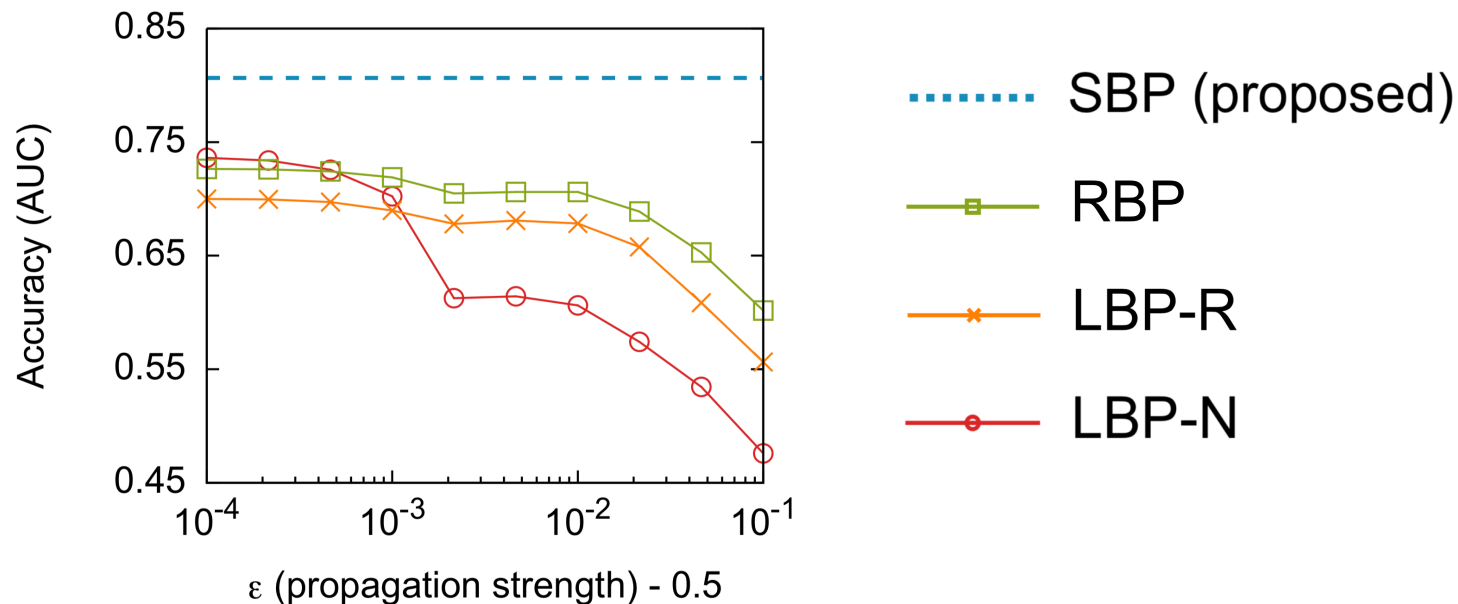
Dataset	Nodes	Edges	Attributes
Epinions-R <sup>2</sup>	189,028	1,152,005	ratings and trusts
Epinions-S <sup>3</sup>	131,828	841,372	signs (trusts or distrusts)
MovieLens <sup>4</sup>	9,940	1,000,209	ratings (1 to 5)

# Experimental Questions

- **Q1.** How sensitive are previous methods to  $\epsilon$ ?
- **Q2.** How accurately does SBP classify nodes?
- **Q3.** How does  $E(w)$  change during iterations?
- **Q4.** How does the running time scale?

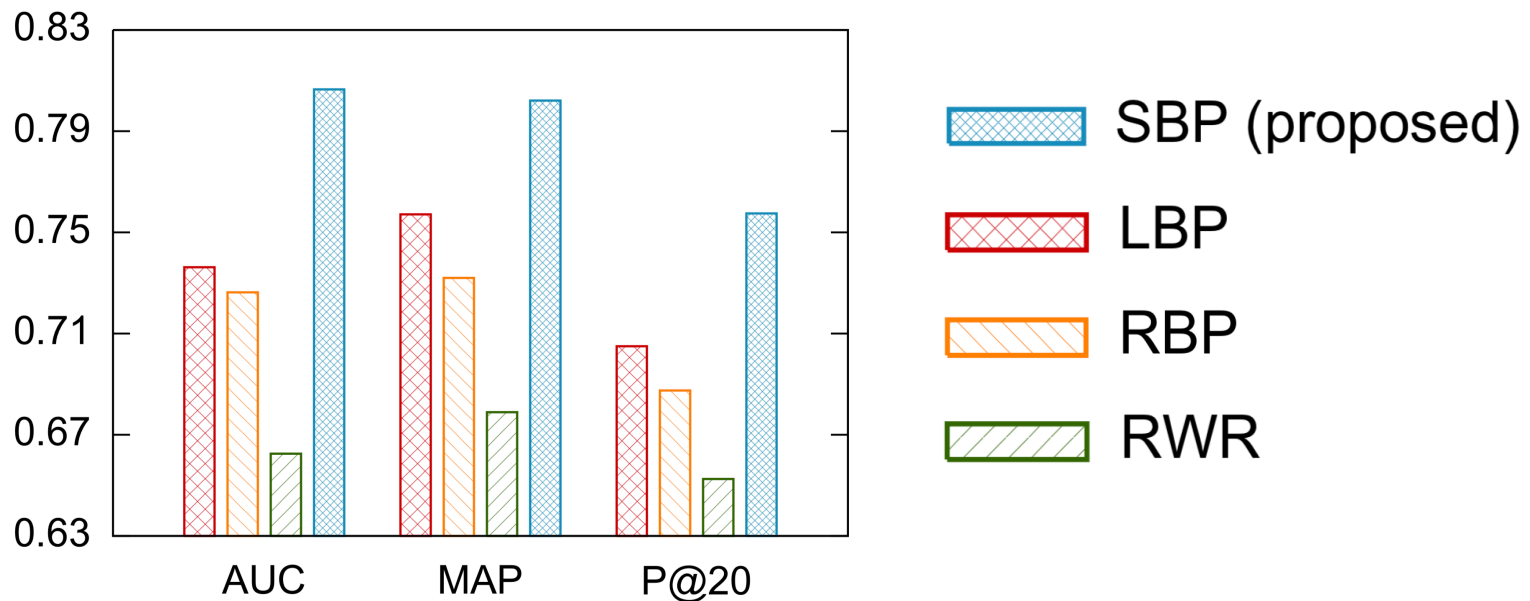
# Sensitivity to Prop. Strength

- **Q1.** How sensitive are previous methods to  $\epsilon$ ?
- **Ans.** Previous methods highly depend on its val.



# Classification Accuracy

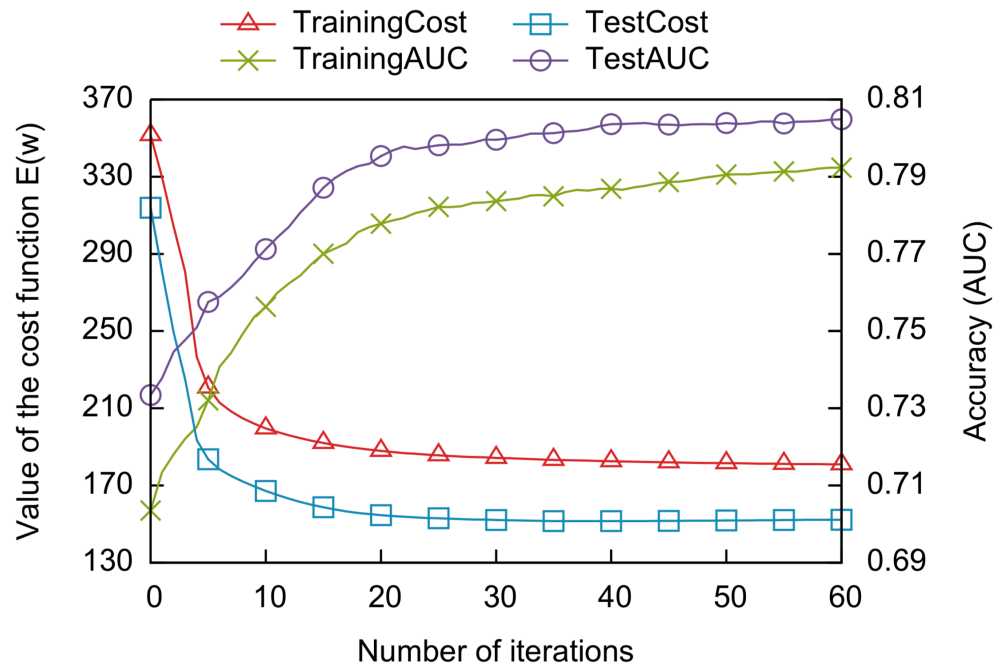
- **Q2.** How accurately does SBP classify nodes?
- **Ans.** SBP shows the best AUC, MAP, and P@20





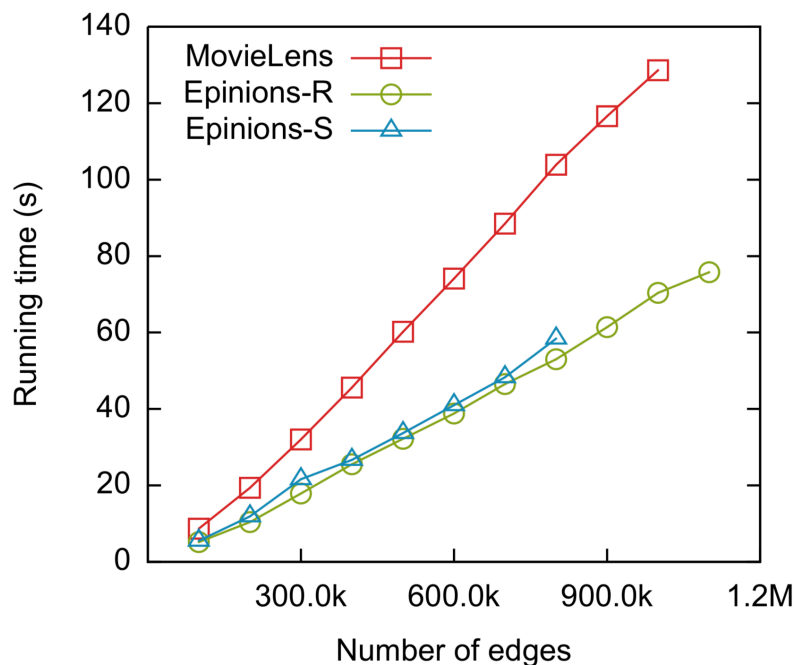
# Cost Minimization

- **Q3.** How does  $E(w)$  change during iterations?
- **Ans.** It is minimized for both train. and test sets



# Linear Scalability

- **Q4.** How does the running time scale?
- **Ans.** It scales linearly with the number of edges



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# Conclusion

- **Method:** **Supervised belief propagation**
- **Key ideas:**
  - Consider rich feature vectors in propagation
  - Learn the propagation strength of each edge
- **Contributions:**
  - Generalize previous LBP-based methods
  - Provide up to 15.6% higher AUC
  - Linearly scalable with the number of edges

# Thank you!

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<https://datalab.snu.ac.kr/sbp/>