Graph-based Security and Privacy Analytics via Collective Classification with Joint Weight Learning and Propagation

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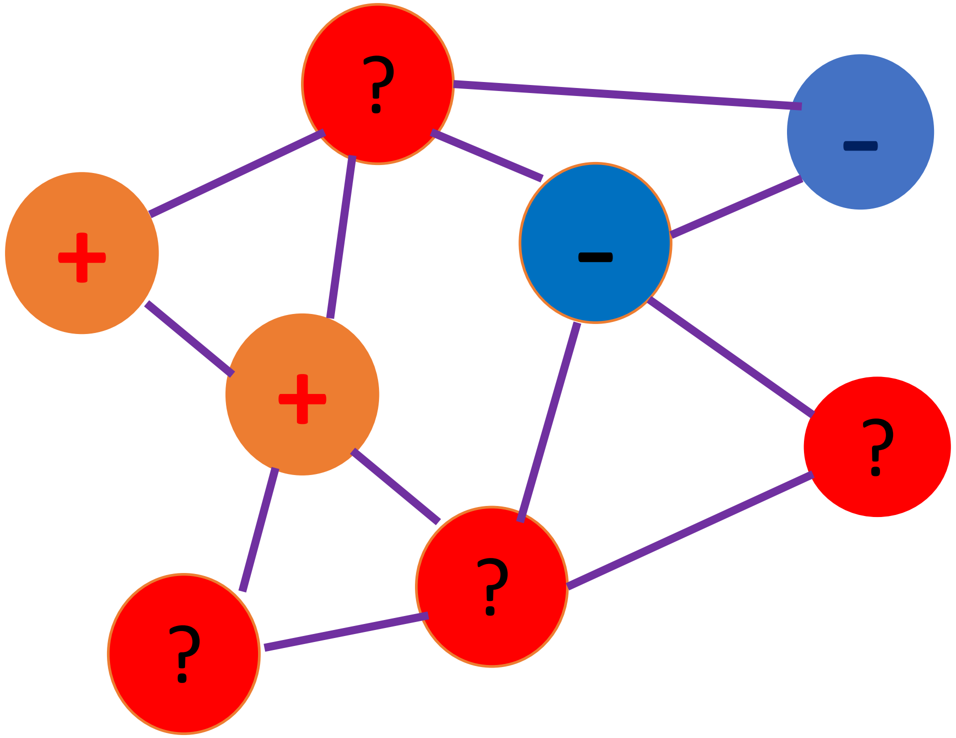
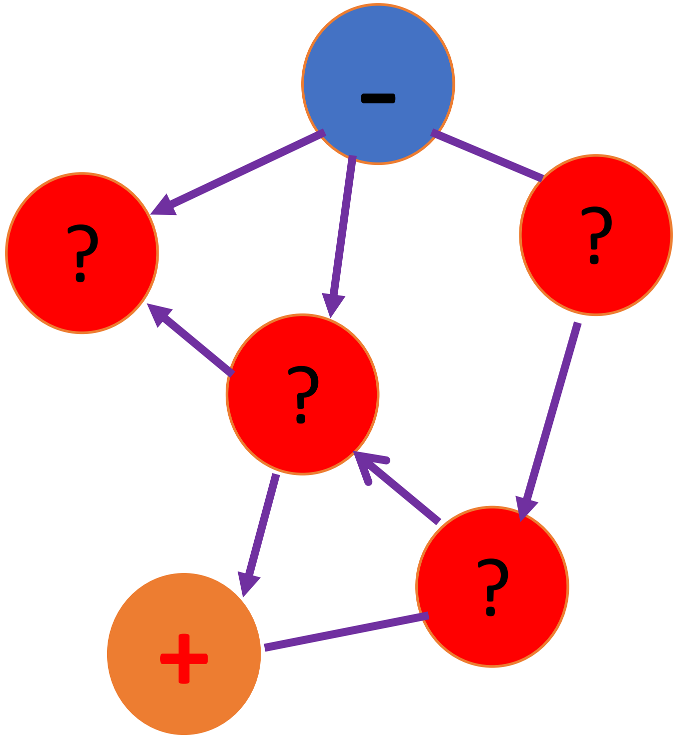
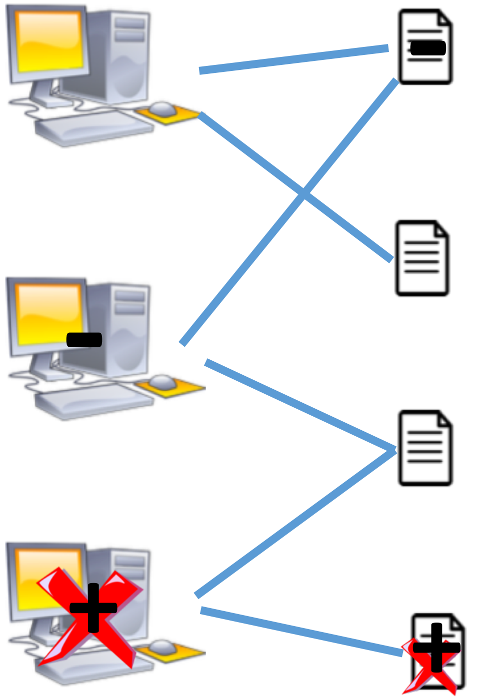
What is Collective Classification?





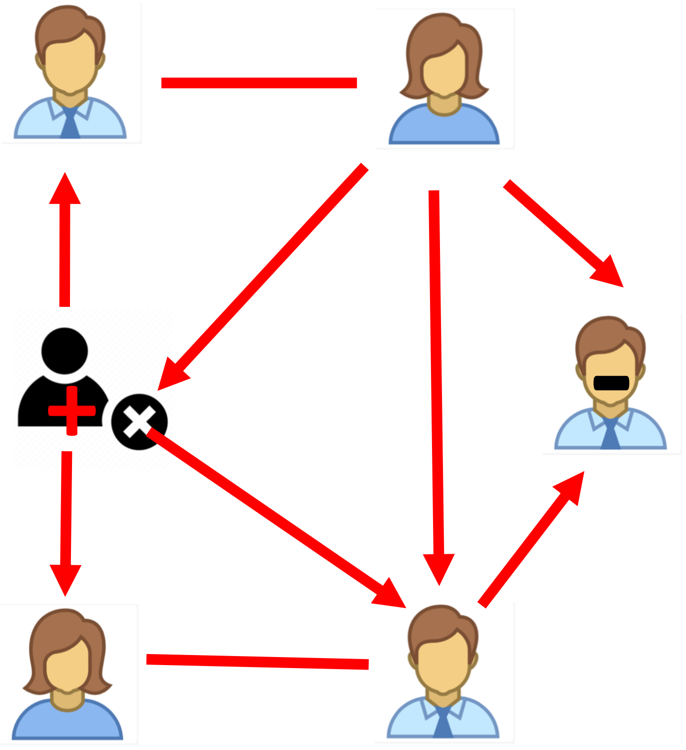
Modeling Security & Privacy Problems as Collective Classification

Malware detection



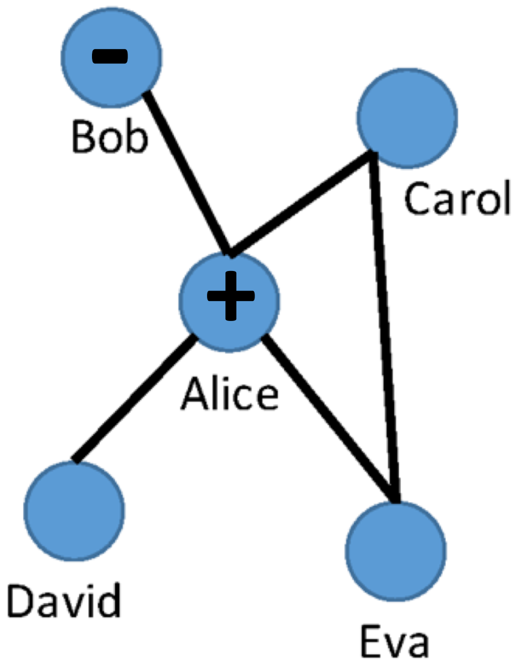
Host-file graph

Sybil detection



Social graph

Attribute inference



Social graph

Existing Collective Classification Methods

- Studied by multiple research communities
  - Networking, security, machine learning, data mining, etc.

- Classified as Random walk (RW) and Loopy belief propagation (LBP)

- Three key steps:
  - Step I: assign nodes' prior scores based on a training dataset
  - Step II: assign (fixed/equal) weight to every edge in the graph
  - Step III: obtain nodes' posterior scores by propagating nodes' prior scores among the weighted graph; larger posterior score indicates a higher likelihood to be positive

Fundamental Limitation of Existing Methods

- Assign small weights to a large number of homogeneous edges
  - *homogeneous* edge (u,v) => u and v *have the same label => large weight*
- Assign large weights to a large number of heterogeneous edges
  - *heterogeneous* edge (u,v) => u and v *have different labels => small weight*
- Limited success in security and privacy problems having a large amount of heterogeneous edges
  - e.g., Sybil detection in weak-trust social networks (like Twitter)

Our Work: Joint Weight Learning and Propagation

- Jointly learning edge weights and propagating posterior scores
- Applicable to both RW-based and LBP-based methods
- Applicable to both undirected and directed graphs
- Applicable to various graph-based security and privacy problems
    - Sybil detection in social networks
    - Fake review detection
    - Attribute inference in social networks
    - Malware detection
    - Malicious website detection
    - …

Outline

- Background
- Methodology
- Evaluation
- Conclusion

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Collective Classification

- Nodes' posterior scores are solutions to a system of equations:

$$\mathbf{p} = f(\mathbf{q}, \mathbf{W}, \mathbf{p})$$

  - **q, p**: nodes' prior and posterior scores
  - **W**: edge weight matrix
  - ***f***: different methods use different function *f*

- Iteratively updating the posterior scores:

$$\mathbf{p}^{(t+1)} = f(\mathbf{q}, \mathbf{W}, \mathbf{p}^{(t)}),\ \mathbf{p}^{(0)} = \mathbf{q}.$$

LBP on Undirected Graphs

- Function f

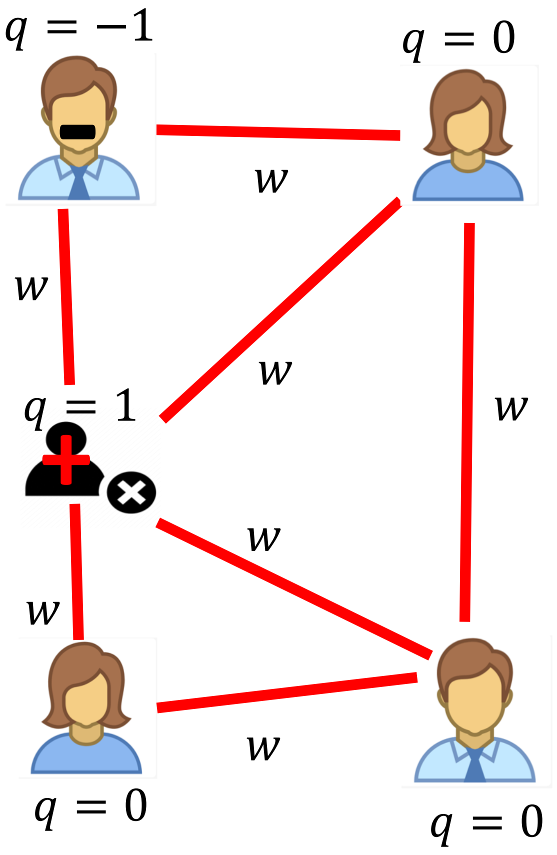
$$f(\mathbf{q}, \mathbf{W}, \mathbf{p}) = \mathbf{q} + \mathbf{W}\mathbf{p},$$

- Nodes' prior scores

$$q_u = \begin{cases} \theta & \text{if } u \in L_P \\ -\theta & \text{if } u \in L_N \\ 0 & \text{otherwise,} \end{cases}$$

  - L_p, L_N: labeled positive and labeled negative nodes
  - $\theta > 0$: strength of the prior

- Edge weight
  - $w_{uv}>0$: u, v likely to have the same label
  - $w_{uv}<0$: u, v likely to have different labels
  - $\mathrm{w}_{\mathrm{uv}}=\mathrm{w} > 0$, i.e., assume ***all edges*** homogeneous!



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Motivation

- Existing methods assign large weights to a large number of heterogeneous edges
- Existing methods assign small weights to a large number of homogeneous edges
- Can we adaptively learn edge weights such that heterogeneous (homogeneous) edges have small (large) weights?

Goals

- Goal 1: *final* posterior scores of labeled nodes should be close to nodes' labels

- Quantifying Goal 1:

$$L(\mathbf{W}) = \frac{1}{2} \sum_{l \in L} (p_l - y_l)^2,$$

  - $y_l = 1$, if l is labeled positive
  - $y_l = -1$, if l is labeled negative
  - L(W): loss function over the training dataset

Goals

- Goal 2: edge weights and *final* posterior scores be *consistent*
  - u and v predicted the *same label* => edge (u,v) *homogeneous*
  - u and v predicted *different labels* => edge (u,v) *heterogeneous*

- Quantifying Goal 2:
  - $p_u p_v > 0$ => $w_{uv} > 0$
  - $p_u p_v < 0$ => $w_{uv} < 0$
  - C(W): regularization term

$$\mathrm{C}(\mathbf{W}) = \sum_{(u,v)\in E} p_u p_v w_{uv},$$

Learning Edge Weights via Gradient Descent

- Optimization problem:

$$\min_{\mathbf{W}} \mathcal{L}(\mathbf{W}) = \mathrm{L}(\mathbf{W}) - \lambda \mathrm{C}(\mathbf{W}), \qquad f(\mathbf{q}, \mathbf{W}, \mathbf{p}) = \mathbf{q} + \mathbf{W}\mathbf{p},$$

- Gradient descent: $w_{uv} \leftarrow w_{uv} - \gamma \frac{\partial \mathcal{L}(\mathbf{W})}{\partial w_{uv}},$

- Solving a linear system for each edge:

$$\frac{\partial \mathbf{p}}{\partial w_{uv}} = \mathbf{1}_v + \mathbf{W} \frac{\partial \mathbf{p}}{\partial w_{uv}}.$$

Computationally infeasible for large graphs!

Alternative Goals

- Computational challenge due to two goals using final posterior scores
- Instead, quantify the two goals using the current posterior scores
- Given posterior scores $p^{(t)}$ and edge weights $W^{(t-1)}$, we learn $W^{(t)}$
  - Goal 1’: posterior scores $p^{(t+1)}$of labeled nodes should be close to their labels
  - Goal 2’: edge weights $W^{(t)}$ and posterior scores $p^{(t)}$ should be *consistent*

Joint Weight Learning and Propagation

- Propagating posterior reputation scores $p^{(t)}$:

$$\mathbf{p}^{(t+1)} = f(\mathbf{q}, \mathbf{W}^{(t)}, \mathbf{p}^{(t)}).$$

- Learning weight matrix $W^{(t)}$:

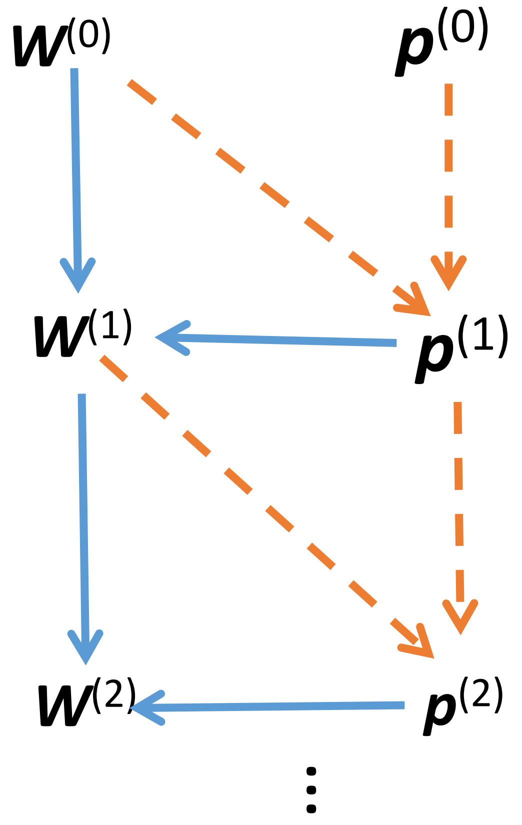
$$\min_{\mathbf{W}^{(t)}} \mathcal{L}(\mathbf{W}^{(t)}) = \frac{1}{2}\sum_{l \in L}(p_l^{(t+1)} - y_l)^2 - \lambda \sum_{(u,v)\in E} p_u^{(t)} p_v^{(t)} w_{uv}^{(t)},$$

- Gradient descent ($p^{(t)}$ is known):

$$\frac{\partial \mathcal{L}(\mathbf{W}^{(t)})}{\partial w_{uv}^{(t)}} = \sum_{l \in L}(p_l^{(t+1)} - y_l)\frac{\partial p_l^{(t+1)}}{\partial w_{uv}^{(t)}} - \lambda p_u^{(t)} p_v^{(t)}.$$

LBP for undirected graphs:

$$\frac{\partial p_l^{(t+1)}}{\partial w_{uv}^{(t)}} = \begin{cases} p_v^{(t)} & \text{if } u = l \\ p_u^{(t)} & \text{if } v = l \\ 0 & \text{otherwise} \end{cases}$$



Computationally efficient!

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Experimental Setup

- Application scenarios
  - Security problem: Sybil detection & fake review detection
  - Privacy problem: Attribute inference attack

- Datasets

Dataset	#Nodes	#Edges	Ave. degree
Twitter	41,652,230	1,468,364,884	71
Sina Weibo	3,538,487	652,889,971	369
Yelp	520,230	718,144	3
Google+	5,735,175	30,644,909	11

Experimental Setup

- Training datasets
  - Twitter: 3000 Sybils and 3000 benign users
  - Sina Weibo: 980 labeled users
  - Yelp: 1000 fake reviews and 1000 genuine reviews
  - Google+: 75% users who have at least one city

- Evaluation metrics
  - AUC
  - Learnt edge weights
  - Scalability

Compared Methods

- RW-based methods
  - For undirected graphs: RW-N, RW-P, RW-B, RW-FLW
  - For directed graphs: RW-N-D, RW-P-D
- LBP-based methods
  - For undirected graphs: LBP-U, LBP-FLW-U
  - For directed graphs: LBP-D
- Our proposed methods
  - LBP-JWP-w/o, LBP-JWP-L1, LBP-JWP-L2, LBP-JWP

AUC Performance

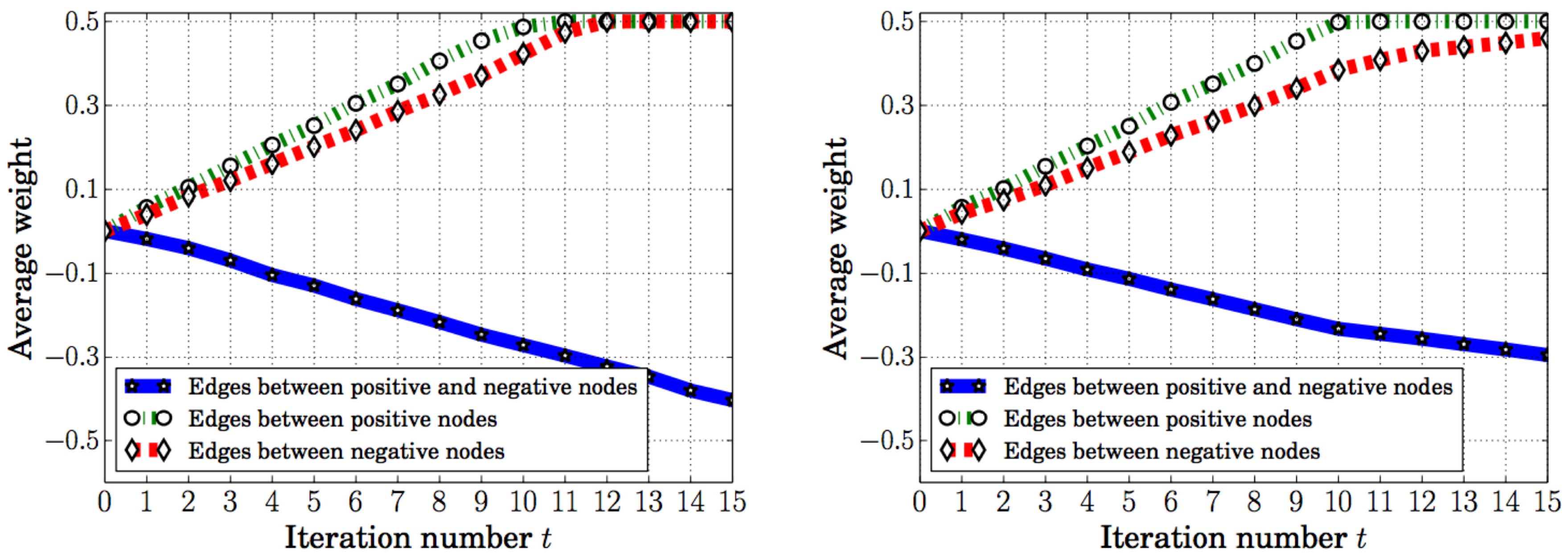
Methods		Twitter	Sina Weibo	Yelp	Google+
RW	RW-N-U	0.57	0.61	0.55	0.59
	RW-P-U	0.58	0.61	0.57	0.58
	RW-LFW-U	0.53	0.54	0.48	0.57
	RW-B-U	0.63	0.68	0.58	0.63
LBP	LBP-U	0.64	0.68	0.58	0.66
	LBP-FLW-U	0.62	0.66	0.58	0.66
Ours	LBP-JWP-w/o-U	0.69	0.74	0.60	0.69
	LBP-JWP-L1-U	0.65	0.70	0.59	0.66
	LBP-JWP-L2-U	0.68	0.72	0.60	0.68
	LBP-JWP-U	**0.73**	**0.77**	**0.62**	**0.72**

Methods		Twitter	Sina Weibo
RW	RW-N-D	0.60	0.66
	RW-P-D	0.63	0.64
LBP	LBP-D	0.72	0.80
Ours	LBP-JWP-w/o-D	0.75	0.82
	LBP-JWP-L1-D	0.72	0.79
	LBP-JWP-L2-D	0.73	0.80
	LBP-JWP-D	**0.78**	**0.85**

Our methods consistently outperform existing ones

Jointly edge weight learning and propagation indeed enhances performance

Learnt Edge Weights



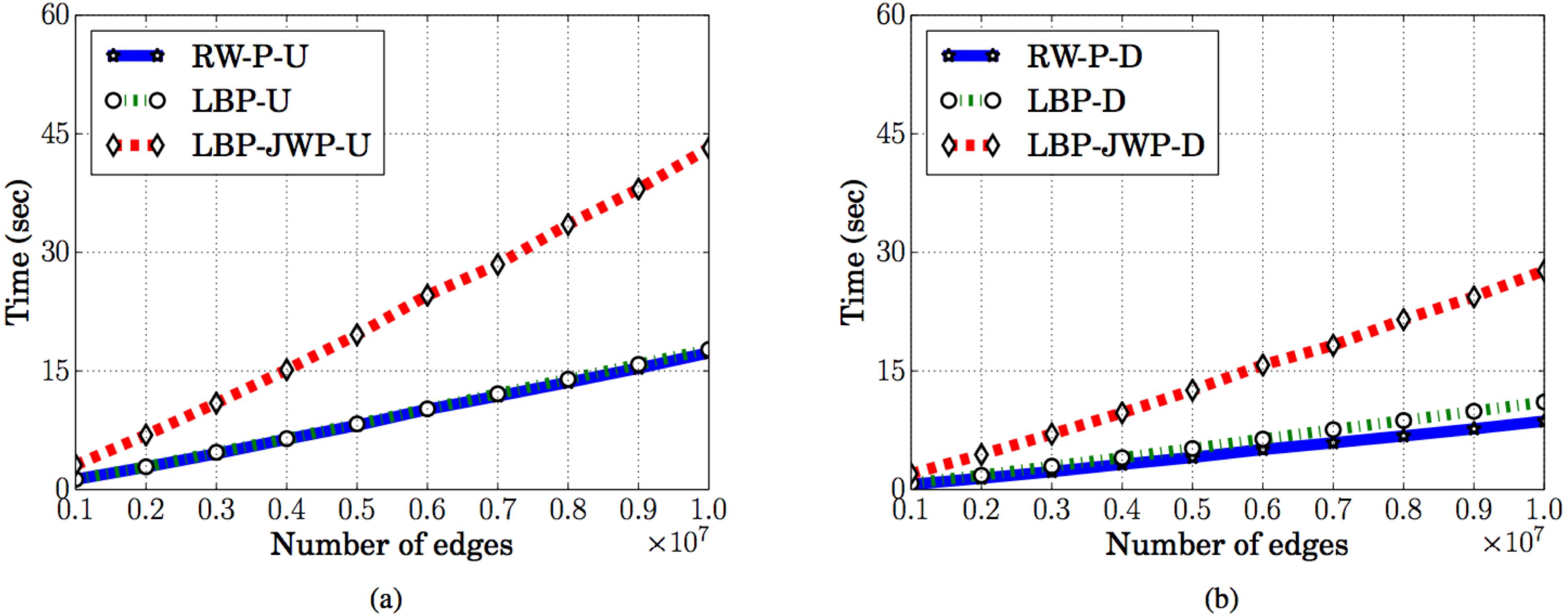
(a) LBP-JWP-U

(b) LBP-JWP-D

The average edge weights between positive nodes and negative nodes decrease

The average edge weights between negative (or positive) nodes increase

Scalability



Our methods are only 2-3 times slower than state-of-the-art methods

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Conclusion

- We propose a general framework to learn edge weights for graph-based security and privacy analytics
- Our framework is applicable to both RW-based and LBP-based methods, and both undirected and directed graphs
- Iteratively learning edge weights can enhance performance for various graph-based security and privacy applications, with an acceptable computational overhead