Personalized Ranking in Signed Networks using Signed Random Walk with Restart

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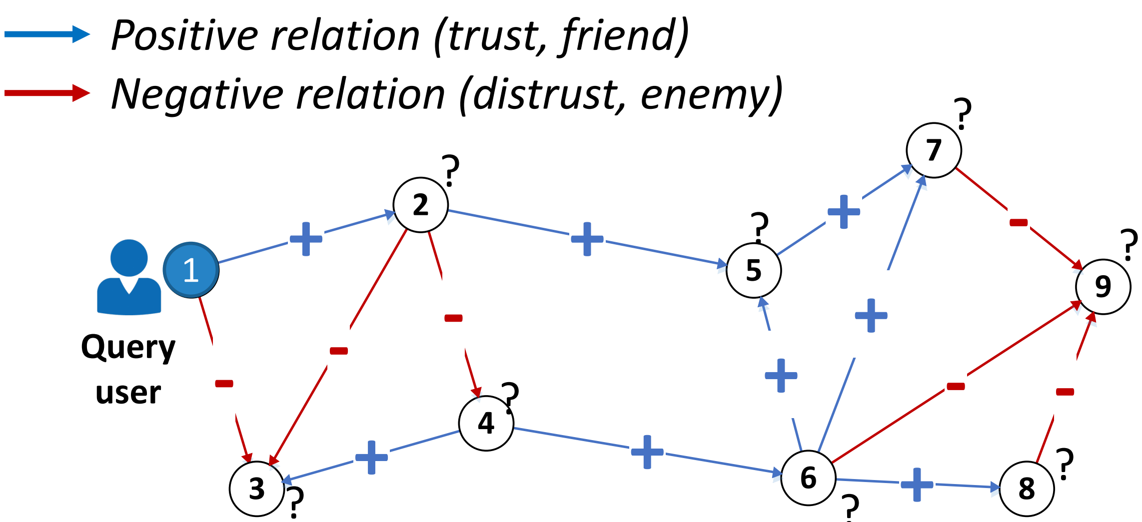
Outline

1. Introduction
2. Proposed Method
3. Experiment
4. Conclusion

Research Question

Q. How can we rank users in signed networks?

- How to find friends or enemies of a query user?



Signed social network

Node	Trust score	Distrust score
1	Query user	
2	0.3	0
3	0	0.3
4	…	…
5	…	…
6	…	…
7	…	…
8	..	…
9	…	…

Goal: to rank nodes w.r.t. the query user using the scores

Problem Definition

Personalized Ranking in Signed Networks

Given: a signed network and a query node s

- $\boldsymbol{A}$: signed adjacency matrix of the network

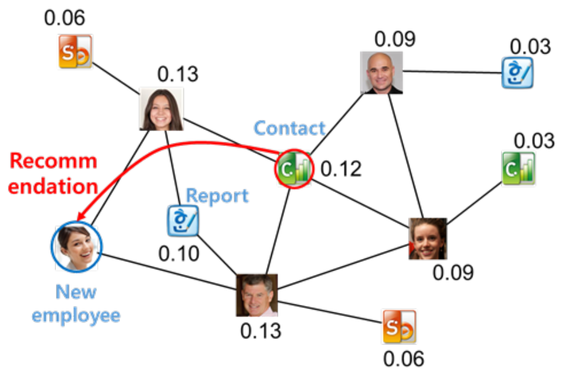
Find: relevance scores with respect to the query node s

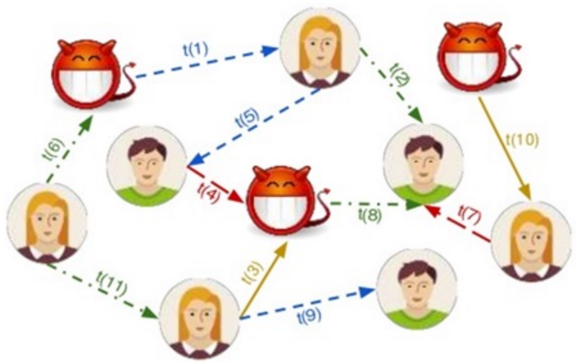
- $\boldsymbol{r}^{+}$: trust score vector
- $\boldsymbol{r}^{-}$: distrust score vector

Applications

Ranking is an important tool for graph analysis

- Recommendation
- Link prediction
- Anomaly detection



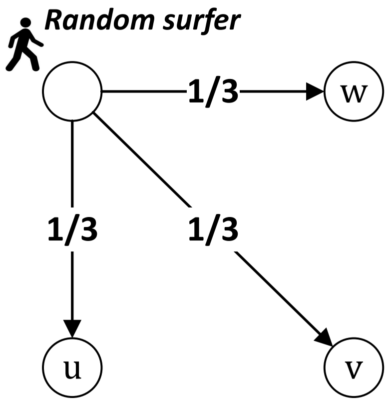


- **Recommendation**
  - Friends, movies, documents
- **Anomaly detection**
  - Spammer, trolls, frauds

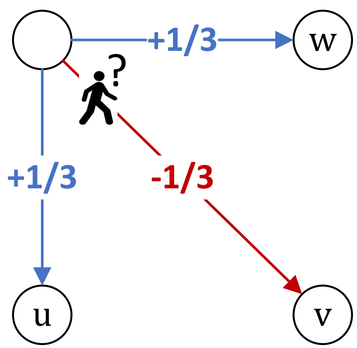
Challenges

Traditional ranking models cannot handle negative edges

- Random walk based models: *PageRank* or *Random Walk with Restart (RWR)*
- Traditional random surfer assumes only positive edges



Traditional random surfer only consider positive edges



No rules for handling negative edges

Challenge: How to deal with negative edges?

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Proposed Method – Overview

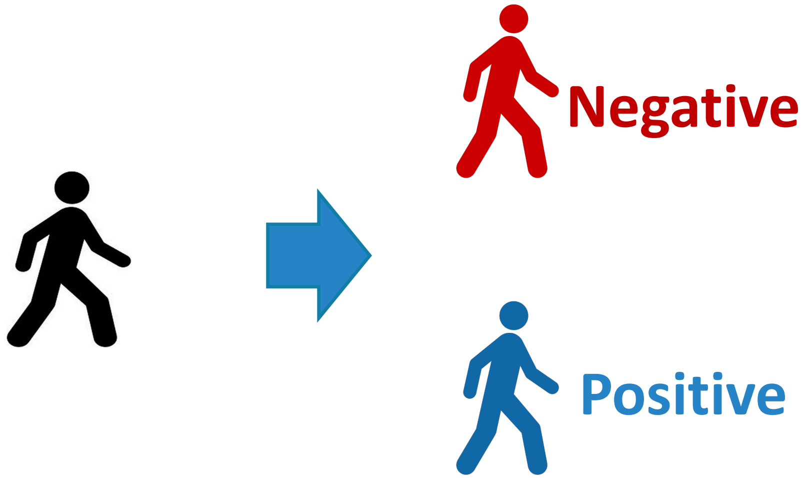
Idea 1) Introduce a sign into a random surfer

Idea 2) Adopt balance theory to the signed surfer

Idea 3) Introduce balance attenuation factors

Proposed Method – Idea 1

Idea 1) Introduce a sign into a random surfer



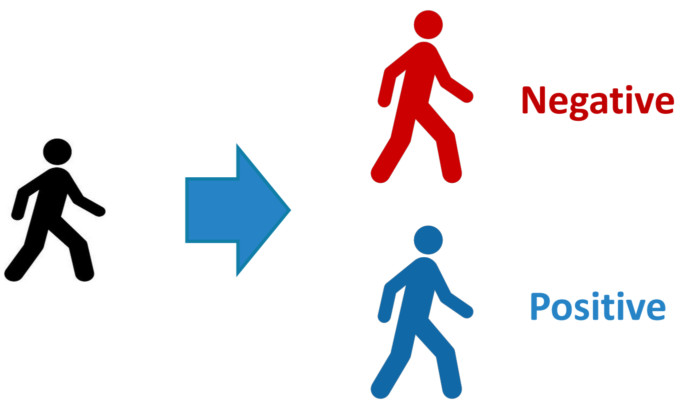
Traditional random surfer

Signed random surfer

Proposed Method – Idea 2

Idea 2) Adopt balance theory to the signed surfer

Signed Random Surfer



Traditional random surfer

Signed random surfer

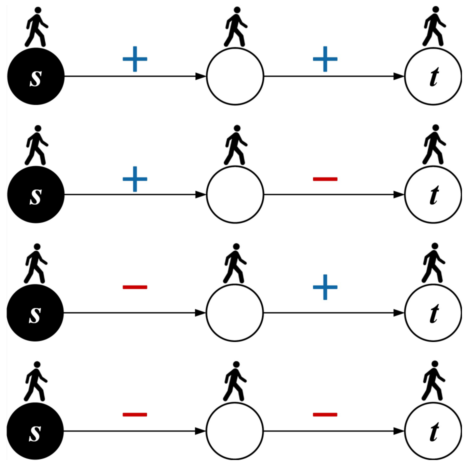
Balance Theory

1) Friend of my friend is my friend
2) Enemy of my friend is my enemy
3) Friend of my enemy is my enemy
4) Enemy of my enemy is my friend

Proposed Method – Idea 2

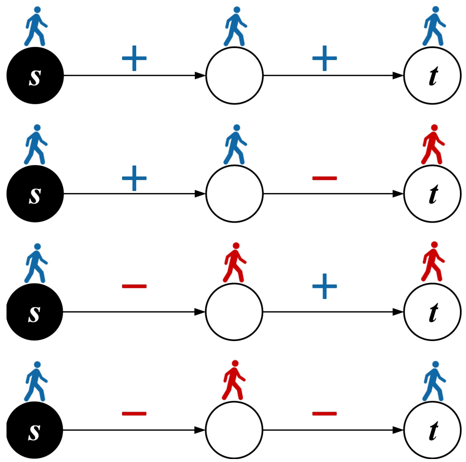
Idea 2) Adopt balance theory to the signed surfer

- Flip the sign of the surfer if she encounters a negative edge



Traditional random surfer

Cannot identify node t



Signed random surfer

Consistent with balance theory

Proposed Method – SRWR (1)

Signed Random Walk with Restart Model

- **Suppose the positive surfer starts from seed node s**
- **Action 1: Signed Random Walk**
  - The surfer randomly moves to one of neighbors from a node with prob. $1-c$
  - *She flips her sign if she encounters a **negative** edge*
- **Action 2: Restart**
  - The surfer goes back to the query node s with prob. c
  - *Her sign should become **positive** at the query node*

c is the restart probability

Proposed Method – SRWR (2)

Signed Random Walk with Restart

- Produces two probabilities on each node

- $\boldsymbol{r}_u^+$: the probability that the positive surfer is at node u after SRWR from the seed node s
  - interpreted as a trust score on node u w.r.t. node s

- $\boldsymbol{r}_u^-$: the probability that the negative surfer is at node u after SRWR from the seed node s
  - interpreted as a distrust score on node u w.r.t. node s

Details

Formulation of SRWR (1)

Signed Random Walk with Restart

$$\boldsymbol{r}^{+} = (1-c)\left(\widetilde{\boldsymbol{A}}_{+}^{T}\boldsymbol{r}^{+} + \widetilde{\boldsymbol{A}}_{-}^{T}\boldsymbol{r}^{-}\right) + c\boldsymbol{q}$$

$$\boldsymbol{r}^{-} = (1-c)\left(\widetilde{\boldsymbol{A}}_{-}^{T}\boldsymbol{r}^{+} + \widetilde{\boldsymbol{A}}_{+}^{T}\boldsymbol{r}^{-}\right)$$

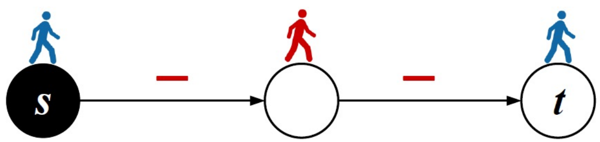
where

- $\widetilde{\boldsymbol{A}}$: semi-row normalization matrix
  - $\widetilde{\boldsymbol{A}} = \boldsymbol{D}^{-1}\boldsymbol{A}$ and $\boldsymbol{D} = \boldsymbol{diag}\left(\boldsymbol{sum}(|\boldsymbol{A}|, row)\right)$
- $\widetilde{\boldsymbol{A}}_{+}$: positive semi-row normalization matrix
- $\widetilde{\boldsymbol{A}}_{-}$: negative semi-row normalization matrix
  - $\widetilde{\boldsymbol{A}} = \widetilde{\boldsymbol{A}}_{+} - \widetilde{\boldsymbol{A}}_{-}$ and $\left|\widetilde{\boldsymbol{A}}\right| = \widetilde{\boldsymbol{A}}_{+} + \widetilde{\boldsymbol{A}}_{-}$

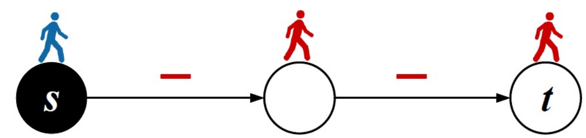
Proposed Method – Idea 3

Idea 3) Introduce balance attenuation factors

- To consider the uncertainty of enemy's friendship
- *CASE-4. Enemy of enemy is my friend?*

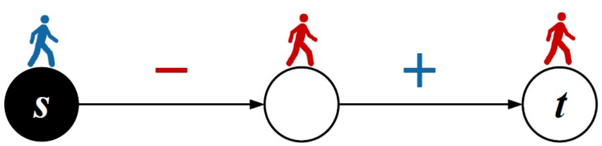


Positive with probability β

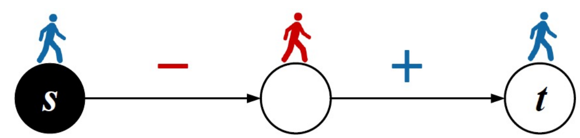


Negative with probability $1-\beta$

- *CASE-3. Friend of enemy is my enemy?*



Negative with probability γ



Positive with probability $1-\gamma$

Details

Formulation of SRWR (2)

SRWR with balance attenuation factors

$$\boldsymbol{r}^{+} = (1-c)\left(\widetilde{\boldsymbol{A}}_{+}^{T}\boldsymbol{r}^{+} + \beta\widetilde{\boldsymbol{A}}_{-}^{T}\boldsymbol{r}^{-} + (1-\gamma)\widetilde{\boldsymbol{A}}_{+}^{T}\boldsymbol{r}^{-}\right) + c\boldsymbol{q}$$

$$\boldsymbol{r}^{-} = (1-c)\left(\widetilde{\boldsymbol{A}}_{-}^{T}\boldsymbol{r}^{+} + \gamma\widetilde{\boldsymbol{A}}_{+}^{T}\boldsymbol{r}^{-} + (1-\beta)\widetilde{\boldsymbol{A}}_{-}^{T}\boldsymbol{r}^{-}\right)$$

where

- β: balance attenuation factor for enemy's enemy
- γ: balance attenuation factor for enemy's friend

- *The uncertainty of a friend's friendship* could be considered by adding other factors similarly to the proposed approach.

Outline

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

Experiment Setting

Goal: Effectiveness of ranking in signed networks

- Q1. How effective is our proposed method **SRWR** for predicting signs of edges?
- Q2. How helpful is **SRWR** for identifying trolls who are abnormal users compared to other ranking models?

Datasets

Name	# of nodes	# of edges	Description
Epinions	131,828	841,372	Online Social Network
Slashdot	79,120	515,397	Online Social Network
Wikipedia	7,118	103,675	Wikipedia Voting Network

Sign Prediction Task

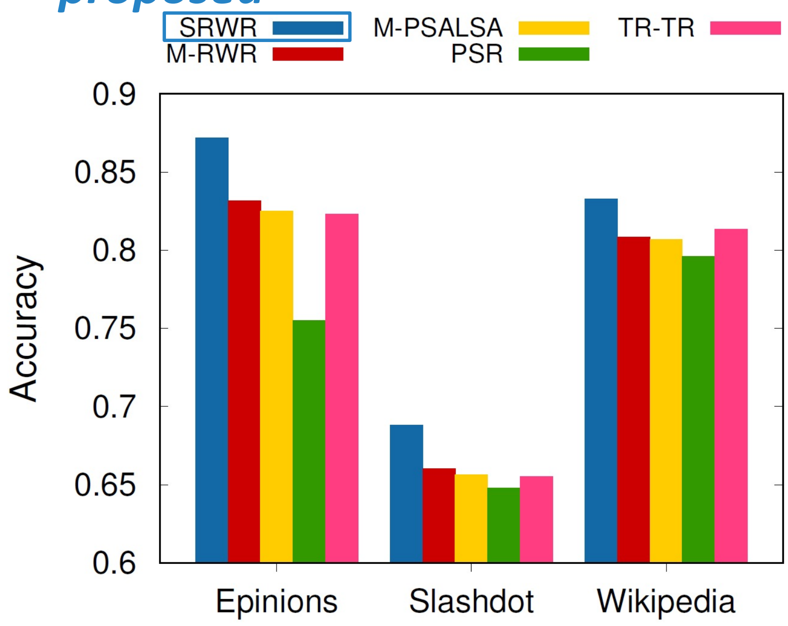
Given a signed network containing the missed signs of edges, predict those signs

- Randomly select 5,000 seed nodes
- For each seed node s,
  - extract 20% out-going edges from the seed node as a test set (20% positive and negative links, respectively)
  - compute $\boldsymbol{r}^{+}$ and $\boldsymbol{r}^{-}$ w.r.t. the seed node s
  - for each extracted edge $(s \rightarrow u)$,
    - If $\boldsymbol{r}_u^{+} > \boldsymbol{r}_u^{-}$, then predict the sign as positive; otherwise it is considered as negative.
- Measure the prediction accuracy : $\frac{\#\ correct\ predictions}{\#\ test\ edges}$

Result – Sign Prediction Task

Q1. How effective is our proposed method SRWR model for predicting signs of edges?

proposed



Our model outperforms other ranking models

- **Shows improvement in terms of accuracy**

Troll Prediction Task

Given a signed network, identify trolls using a personalized distrust ranking

- **Assumption.** Trolls are likely to be enemies of each normal user ⇒ trolls would be ranked high in a personalized distrust ranking w.r.t. the user

In the Slashdot dataset,

- It has a blacklist having 96 trolls
- We search trolls in the top-k distrust ranking $\boldsymbol{r}^{-}$

Result – Troll Prediction Task

Q2. How helpful is SRWR for identifying trolls who are abnormal users compared to other ranking models? *(Slashdot)*

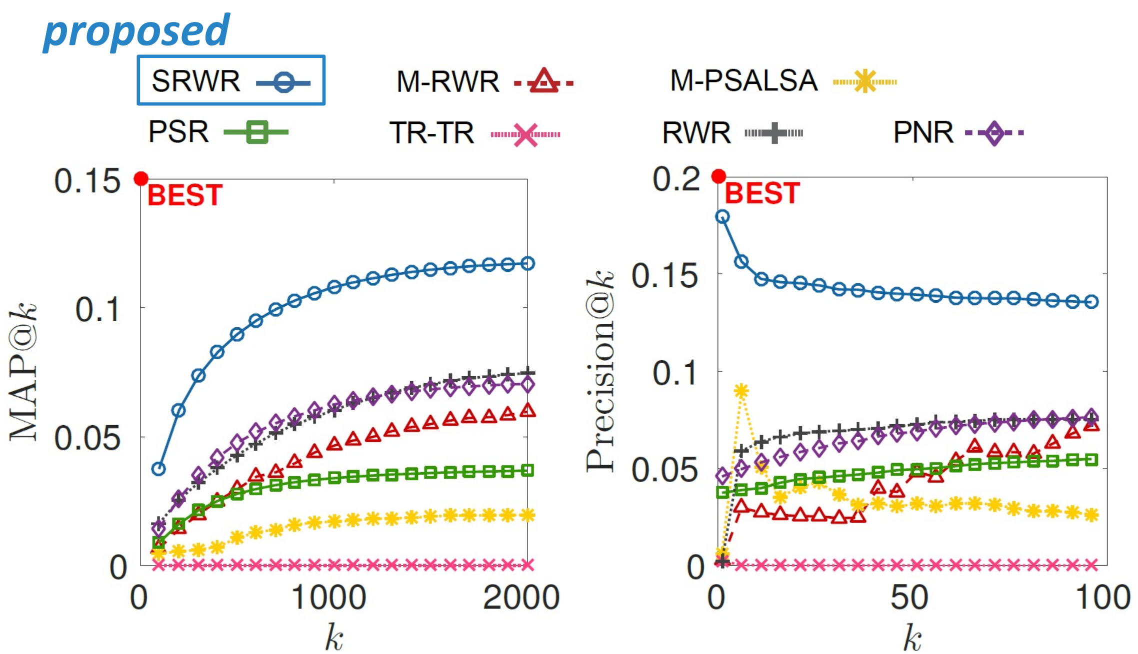
- ***Blue**: querying user (freejung)* & ***Red**: trolls*

	SRWR (proposed)		M-RWR		M-PSALSA		PSR		TR-TR	
Rank	**Trust Ranking**	**Distrust Ranking**	**Trust Ranking**	**Distrust Ranking**	**Trust Ranking**	**Distrust Ranking**	**Trust Ranking**	**Distrust Ranking**	**Trust Ranking**	**Distrust Ranking**
1	**freejung**	**Twirlip+o**	**freejung**	**freejung**	CleverNic	**freejung**	**freejung**	manifest3	**freejung**	inTheLoo
2	CmdrTaco	**Klerck**	CmdrTaco	TheJesusC	CmdrTaco	**Klerck**	CmdrTaco	rpiquepa	daoine	(TK14)Des
3	TomorrowP	CmdrTaco	CleverNic	Fnkmaster	Bruce+Per	**CmderTaco**	TomorrowP	JonKatz	Jamie+Zaw	westbake
4	Gryll	**%24%24%24**	FortKnox	Professor	John+Carm	spinlocke	Gryll	johnnyb	KshGoddes	2forshow
5	CleverNic	JonKatz	TomorrowP	rqqrtnb	**%24%24%24**	JonKatz	autosentr	**TrollBurg**	shadowspa	43Percent
6	FortKnox	CleverNic	gleam	dubba-dum	kfg	twitter	CleverNic	HanzoSan	turg	ABeowulfC
7	autosentr	HanzoSan	Gryll	drhairsto	NewYorkCo	StarManta	meowsquea	kalka	ryanr	abigsmurf
8	meowsquea	ekrout	autosentr	howcoome	**freejung**	tomstdeni	FortKnox	p00p	slothdog	AdiBean
9	Ethelred+	**CmderTaco**	quadong	khuber	AKAImBatm	Doc+Ruby	Ethelred+	fimbulvet	TheIndivi	airjrdn
10	SolemnDra	manifest3	meowsquea	Skapare	FortKnox	**stratjakt**	SolemnDra	HBergeron	avitzur	alewar

- The ***query user*** is ranked 1st in our trust ranking
- ***Many trolls*** are ranked high in our distrust ranking

Result – Troll Prediction Task

Q2. How helpful is SRWR for identifying trolls who are abnormal users compared to other ranking models?



Our model outperforms other ranking models

- **Achieve best accuracy**

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Conclusion

We propose ***Signed Random Walk with Restart*** for computing ranking scores in signed social networks

- *Idea 1)* Introduce a sign into a random surfer
- *Idea 2)* Adopt balance theory to the surfer
- *Idea 3)* Introduce balance attenuation factors

Main Results

- Make random walks interpretable in signed networks
- Achieve *best* performance in applications on signed networks
  - Sign prediction & troll identification tasks

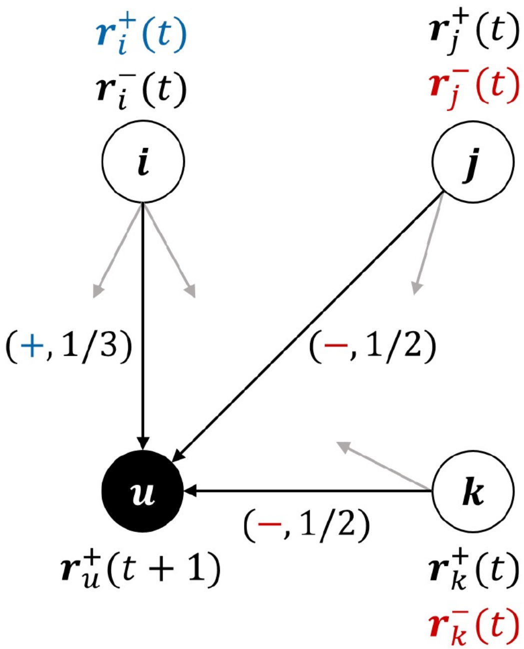
Formulation of SRWR (1)

Note that each node has two probabilities:

- $\boldsymbol{r}_u^+(t)$: the probability that the positive surfer visits node u at time t starting from the seed node s
  - interpreted as a trust score on node u w.r.t. node s
- $\boldsymbol{r}_u^-(t)$: the probability that the negative surfer visits node u at time t starting from the seed node s
  - interpreted as a distrust score on node u w.r.t. node s

Formulation of SRWR (2)

Formulation on trust score $r_u^+(t+1)$



(a) An example of a positive probability, $\mathbf{r}_u^+(t+1)$

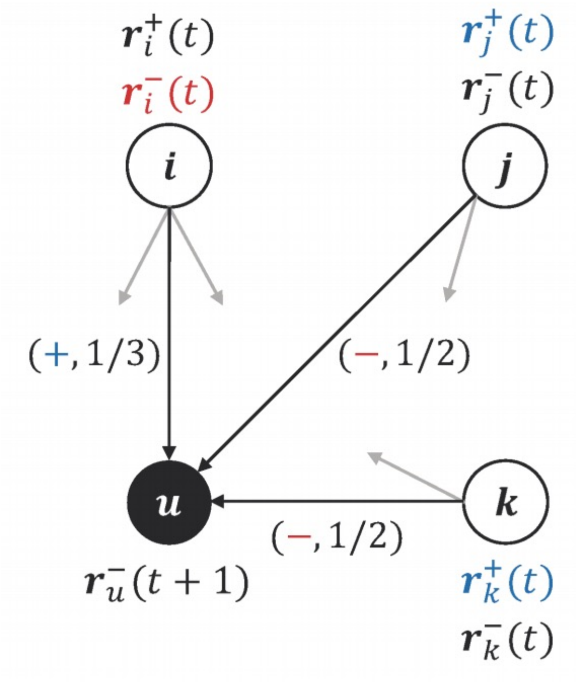
- Focus on how to make the surfer positive on node u at time $t+1$

$$\boldsymbol{r}_u^+(t+1) = \underbrace{(1-c)\left(\frac{\boldsymbol{r}_i^+(t)}{3} + \frac{\boldsymbol{r}_j^-(t)}{3} + \frac{\boldsymbol{r}_k^-(t)}{2}\right)}_{\text{Signed random walk}} + \underbrace{c\mathbf{1}(u=s)}_{\text{Restart}}$$

- $\mathbf{1}(u=s)$ is an indicator function returns 1 if $u=s$ and 0 otherwise.

Formulation of SRWR (3)

Formulation on distrust score $r_u^-(t+1)$



(b) An example of a negative probability, $\mathbf{r}_u^-(t+1)$

- Focus on how to make the surfer negative on node u at time $t+1$

$$\boldsymbol{r}_u^-(t+1) = (1-c)\underbrace{\left(\frac{\boldsymbol{r}_i^-(t)}{3} + \frac{\boldsymbol{r}_j^+(t)}{3} + \frac{\boldsymbol{r}_k^+(t)}{2}\right)}_{\text{Signed random walk}}$$

- Note that we do not consider “restart” since the surfer becomes positive when performing “restart”

Formulation of SRWR (4)

Formulation on SRWR scores

$$\mathbf{r}_u^+ = (1-c)\left(\sum_{v \in \overleftarrow{\mathbf{N}}_u^+} \frac{\mathbf{r}_v^+}{|\overrightarrow{\mathbf{N}}_v|} + \sum_{v \in \overleftarrow{\mathbf{N}}_u^-} \frac{\mathbf{r}_v^-}{|\overrightarrow{\mathbf{N}}_v|}\right) + c\mathbf{1}(u=s)$$

$$\mathbf{r}_u^- = (1-c)\left(\sum_{v \in \overleftarrow{\mathbf{N}}_u^-} \frac{\mathbf{r}_v^+}{|\overrightarrow{\mathbf{N}}_v|} + \sum_{v \in \overleftarrow{\mathbf{N}}_u^+} \frac{\mathbf{r}_v^-}{|\overrightarrow{\mathbf{N}}_v|}\right)$$

$\overleftarrow{\boldsymbol{N}}_u^+$: set of in-neighbors positively connected from node u

$\overleftarrow{\boldsymbol{N}}_u^-$: set of in-neighbors negatively connected from node u

$\overrightarrow{\boldsymbol{N}}_u$: set of out-neighbors from node u

Formulation of SRWR (5)

Vectorize the previous equations (matrix-vector form)

$$\boldsymbol{r}^{+} = (1-c)\left(\widetilde{\boldsymbol{A}}_{+}^{T}\boldsymbol{r}^{+} + \widetilde{\boldsymbol{A}}_{-}^{T}\boldsymbol{r}^{-}\right) + c\boldsymbol{q}$$

$$\boldsymbol{r}^{-} = (1-c)\left(\widetilde{\boldsymbol{A}}_{-}^{T}\boldsymbol{r}^{+} + \widetilde{\boldsymbol{A}}_{+}^{T}\boldsymbol{r}^{-}\right)$$

where

- $\widetilde{\boldsymbol{A}}$: semi-row normalization matrix
  - $\widetilde{\boldsymbol{A}} = \boldsymbol{D}^{-1}\boldsymbol{A}$ and $\boldsymbol{D} = \boldsymbol{diag}\left(\boldsymbol{sum}(|\boldsymbol{A}|, row)\right)$
- $\widetilde{\boldsymbol{A}}_{+}$: positive semi-row normalization matrix
- $\widetilde{\boldsymbol{A}}_{-}$: negative semi-row normalization matrix
  - $\widetilde{\boldsymbol{A}} = \widetilde{\boldsymbol{A}}_{+} - \widetilde{\boldsymbol{A}}_{-}$ and $\left|\widetilde{\boldsymbol{A}}\right| = \widetilde{\boldsymbol{A}}_{+} + \widetilde{\boldsymbol{A}}_{-}$

Formulation of SRWR (6)

SRWR with balance attenuation factors

$$\boldsymbol{r}^{+} = (1-c)\left(\tilde{\boldsymbol{A}}_{+}^{T}\boldsymbol{r}^{+} + \beta\tilde{\boldsymbol{A}}_{-}^{T}\boldsymbol{r}^{-} + (1-\gamma)\tilde{\boldsymbol{A}}_{+}^{T}\boldsymbol{r}^{-}\right) + c\boldsymbol{q}$$

$$\boldsymbol{r}^{-} = (1-c)\left(\tilde{\boldsymbol{A}}_{-}^{T}\boldsymbol{r}^{+} + \gamma\tilde{\boldsymbol{A}}_{+}^{T}\boldsymbol{r}^{-} + (1-\beta)\tilde{\boldsymbol{A}}_{-}^{T}\boldsymbol{r}^{-}\right)$$

where

- β**:** balance attenuation factor for enemy's enemy
- γ**:** balance attenuation factor for enemy's friend

- *The uncertainty of a friend's friendship* could be considered by adding other factors similarly to the proposed approach.

Competitors

RWR on an absolute adjacency matrix

M-RWR (Modified RWR)

- RWR on both a positive subgraph ($\boldsymbol{r}^{+}$) and a negative subgraph ($\boldsymbol{r}^{-}$)

M-PSALSA

- Personalized SALSA: RWR version of HITS

PSR (Personalized Signed Spectral Rank)

- $M_{PSR} = (1-c)\boldsymbol{D}^{-1}\boldsymbol{A}^{T} + c\boldsymbol{e}_{s}\boldsymbol{1}^{T}$: the left eigenvector ($\boldsymbol{r}^{d}$)

PNR (Personalized Negative Rank)

- **PNR($\boldsymbol{r}^{-}$) = RWR($\boldsymbol{r}^{+}$) – PSR($\boldsymbol{r}^{d}$)**

Metrics

Precision@k (l is the total number of interesting items)

- Precision at the cut-off k: $\frac{\#\, rel.\, items\ @\ top{-}k}{k}$

Recall@k

- Recall at the cut-off k: $\frac{\#\, rel.\, items\ @\ top{-}k}{l}$

AP@k

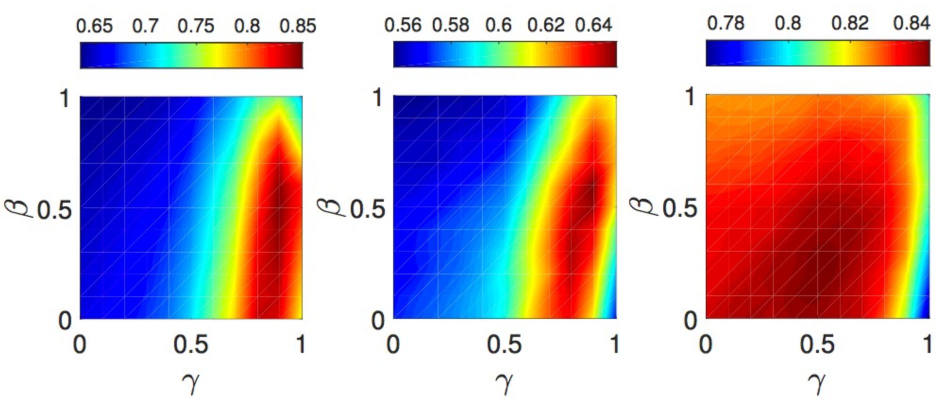
- For a query, $AP@k = \frac{1}{min(l,k)}\left(\sum_{t=1}^{k} Precision@t\right)$

MAP@k (Mean Average Precision @ k)

- For multiple queries, $\mathrm{M}AP@k = \frac{1}{N}\left(\sum_{i=1}^{N} AP@k\right)$

Result – Sign Prediction Task

Sign prediction accuracy according to balance attenuation factors (B.A.F.s)



(a) Epinions (b) Slashdot (c) Wikipedia

$$\boldsymbol{r}^{+} = (1-c)\left(\widetilde{\boldsymbol{A}}_{+}^{T}\boldsymbol{r}^{+} + \widetilde{\boldsymbol{A}}_{-}^{T}\boldsymbol{r}^{-}\right) + c\boldsymbol{q}$$

$$\boldsymbol{r}^{-} = (1-c)\left(\widetilde{\boldsymbol{A}}_{-}^{T}\boldsymbol{r}^{+} + \widetilde{\boldsymbol{A}}_{+}^{T}\boldsymbol{r}^{-}\right)$$

- Ideal balance theory does not apply well to real-world signed networks
  - ⇒ not best when $\gamma = \beta = 1$
- Epinions and Slashdot show the similar tendency
  - ⇒ Wikipedia is a voting network
- Our model is flexible by controlling B.A.F.s

Balance Attenuation Factors

β: balance attenuation factor for enemy's enemy

γ: balance attenuation factor for enemy's friend

Sign Prediction Task

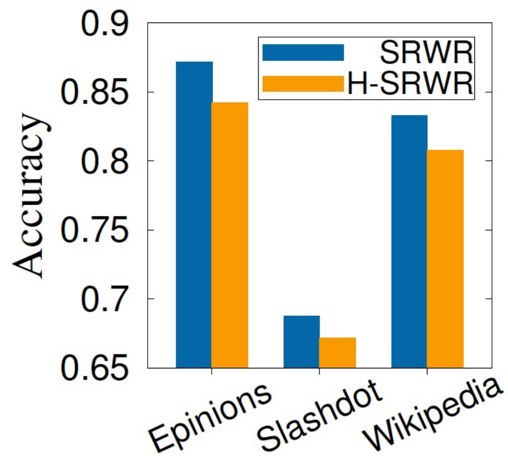
- Epinions: $\beta = 0.5, \gamma = 0.9$
- Slashdot: $\beta = 0.5, \gamma = 0.9$
- Wikipedia: $\beta = 0.5, \gamma = 0.5$

Troll Prediction Task

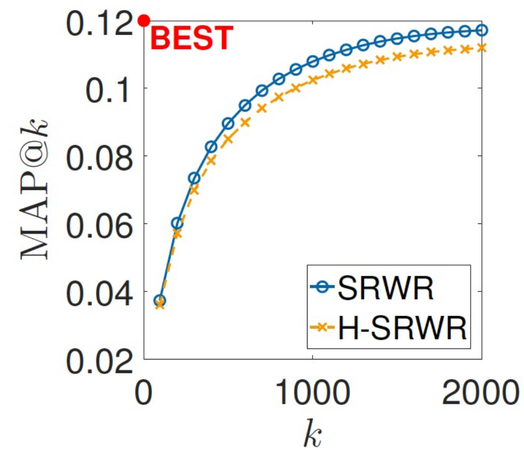
- Slashdot: $\beta = 0.1, \gamma = 1.0$

Balance Attenuation Factors

Q3. How effective are the balance attenuation factors of SRWR for the applications in signed networks?



(a) Accuracy of the sign prediction task



(b) MAP@k of the troll identification task

Result – Troll Prediction Task

Querying user: CmderTaco & Red: trolls

seed_user: CmderTaco [11745] [troll] [degree: 164]

-:	TOP-20 TRUST RANKING (+)			TOP-20 DISTRUST RANKING (-)		
-:	USER NAME	USER ID	ISTROLL	USER NAME	USER ID	ISTROLL
1:	CmderTaco	11745	TROLL	JonKatz	32742	NORMAL
2:	CLIT	11554	NORMAL	Klerck	35211	TROLL
3:	CmdrTaco	11768	NORMAL	Ralph+JewHater+Nader	51758	NORMAL
4:	xeno	69681	NORMAL	CmdrTaco	11768	NORMAL
5:	cyborg_monkey	13935	TROLL	Gendou	23950	TROLL
6:	sllort	58169	TROLL	Lockwood's+Guppy	37606	NORMAL
7:	TRoLLaXoR	65510	TROLL	prizog	50415	NORMAL
8:	Hello+Kitty	27229	NORMAL	Bible_Study_Guys	6368	NORMAL
9:	Big_Ass_Spork	6394	TROLL	Esther+Sassaman	20559	NORMAL
10:	%24%24%24%24%24exyGal	263	TROLL	bsd+is+dying+lololol	8682	NORMAL
11:	trollercoaster	65521	TROLL	undetrerbrucke	66503	NORMAL
12:	YourMissionForToday	70498	TROLL	Mr+Fred+M+Rogers	43103	NORMAL
13:	Pr0n+K1ng	50234	TROLL	Mendax+Veritas	40739	NORMAL
14:	Fucky+the+troll	23090	TROLL	Anti-Spork	3476	NORMAL
15:	TrollBridge	65515	TROLL	internet	29417	NORMAL
16:	negativekarmanow+tm	44633	TROLL	MsGeek	43477	NORMAL
17:	Sexual+Asspussy	56351	TROLL	btempleton	8733	NORMAL
18:	Carp+Flounderson	9795	TROLL	geekotourist	23872	NORMAL
19:	Subject+Line+Troll	60800	TROLL	Alan+Cox	1901	NORMAL
20:	Tasty+Beef+Jerky	61929	TROLL	The+WIPO+Troll	63887	TROLL

Result – Troll Prediction Task

Q2. How helpful is SRWR for identifying trolls who are abnormal users compared to other ranking models?

Best