Networks with Signed Edges

CS224W: Social and Information Network Analysis
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http://cs224w.stanford.edu

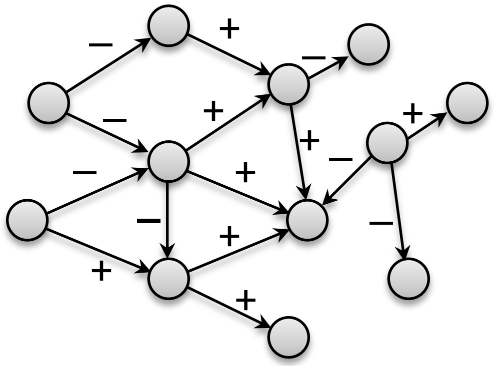
Interesting Datasets

- **Some example datasets:**
  - Author Citation/Collaboration Networks
    - ANetMiner and Microsoft Academic Graph
  - Pinterest (to be released):
    - Users: age, gender, boards they own
    - Boards: title, creation time, pins that belong to a board
    - Pins: title, description, link, image, creation time
  - Datasets on Reddit: https://www.reddit.com/r/datasets/
    - Presidential candidate endorsements by newspaper
    - 25M presidential debate tweets
    - Vehicle mobility data in Cologne, Germany

More at: http://cs224w.stanford.edu/resources.html

Real Large Signed Networks

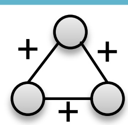
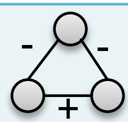
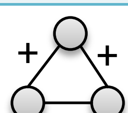
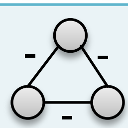
- Each link A→B is **explicitly** tagged with a sign:
  - Epinions: Trust/Distrust
    - Does A trust B's product reviews? (only positive links are visible to users)
  - Wikipedia: Support/Oppose
    - Does A support B to become Wikipedia administrator?
  - Slashdot: Friend/Foe
    - Does A like B's comments?
  - **Other examples:**
    - Online multiplayer games



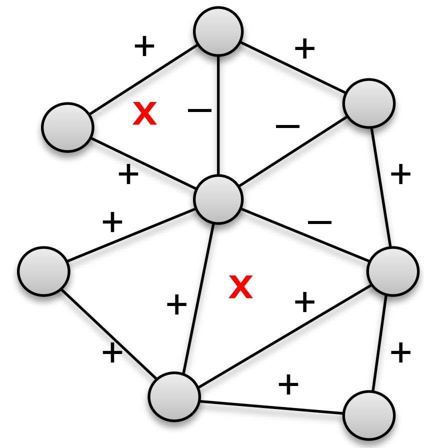
	Epinions	Slashdot	Wikipedia
Nodes	119,217	82,144	7,118
Edges	841,200	549,202	103,747
+ edges	85.0%	77.4%	78.7%
− edges	15.0%	22.6%	21.2%

Balance in Our Network Data

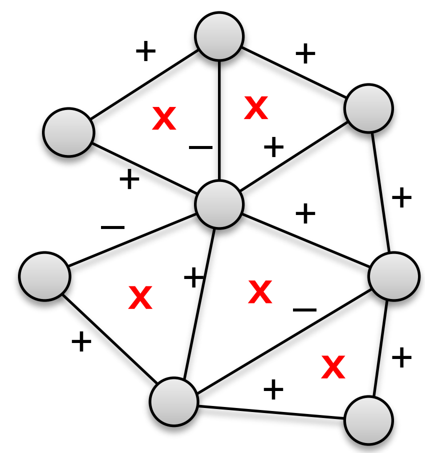
- **Does structural balance hold?**
  - Compare frequencies of signed triads in real and "shuffled" signs

	Triad	Epinions		Wikipedia		Consistent with Balance?
		P(T)	P_0(T)	P(T)	P_0(T)	
Balanced		0.87	0.62	0.70	0.49	✓
Balanced		0.07	0.05	0.21	0.10	✓
Unbalanced		0.05	0.32	0.08	0.49	✓
Unbalanced		0.007	0.003	0.011	0.010	✗

P(T) … fraction of a triads
P_0(T)… triad fraction if the signs would appear at random



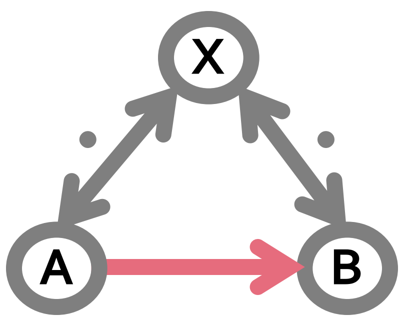
Real data



Shuffled data

Evolving Directed Networks

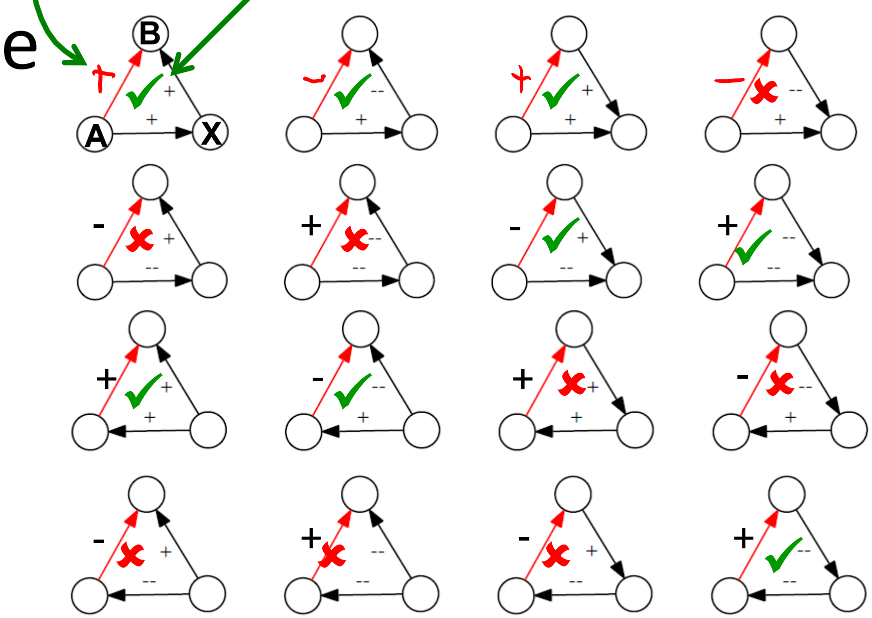
- **New setting:** Links are **directed**, created over time
  - Node **A** links to **B**
  - Directions and signs of links from/to X provide context



- How many △ are now explained by balance?
  - Only half (8 out of 16)

Edge sign according to the balance theory

Do people close such triads with the "balanced" edge?



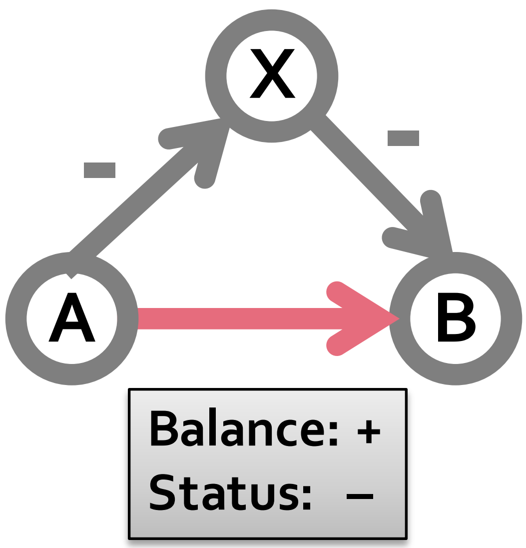
16 signed directed triads

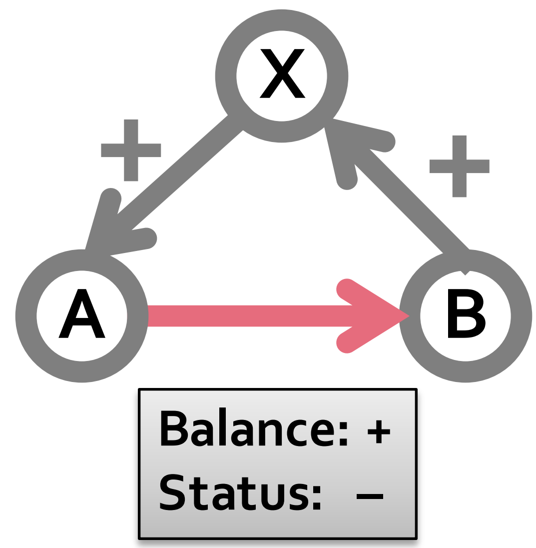
(in directed networks people traditionally applied balance by ignoring edge directions)

Alternate Theory: Status

- **Status** in a network [Davis-Leinhardt '68]
  - **A** $\xrightarrow{+}$ **B** :: **B** has higher status than **A**
  - **A** $\xrightarrow{-}$ **B** :: **B** has lower status than **A**
    - Note the notion of status is now implicit and governed by the network (rather than the number of edits)
  - **Apply this principle transitively over paths**
    - Can replace each **A** $\xrightarrow{-}$ **B** with **A** $\xleftarrow{+}$ **B**
    - Obtain an all-positive network with same status interpretation

Status vs. Balance



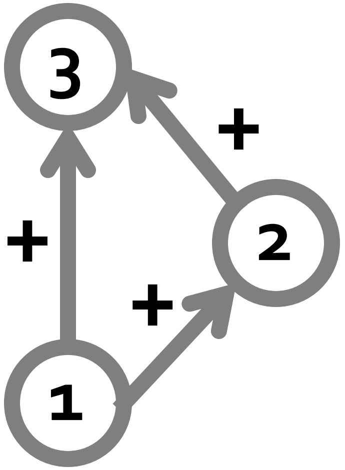


Status and balance give different predictions!

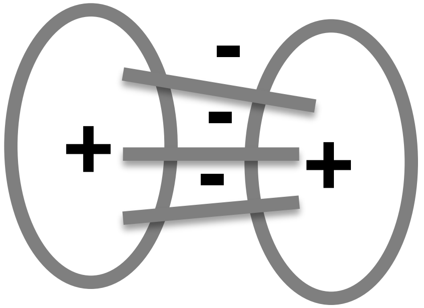
Status vs. Balance

At a global level (in the ideal case):

- **Status ⇒ Hierarchy**
  - All-positive directed network should be approximately **acyclic**

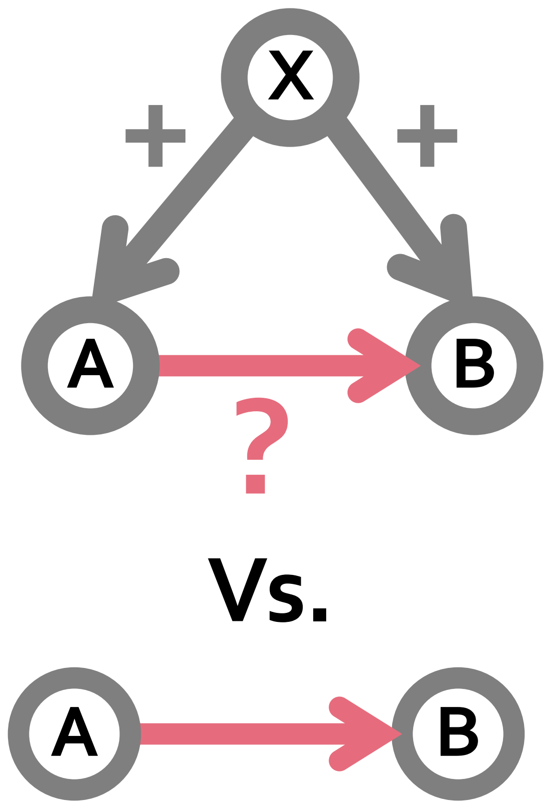


- **Balance ⇒ Coalitions**
  - Balance ignores directions and implies that subgraph of negative edges should be approximately **bipartite**



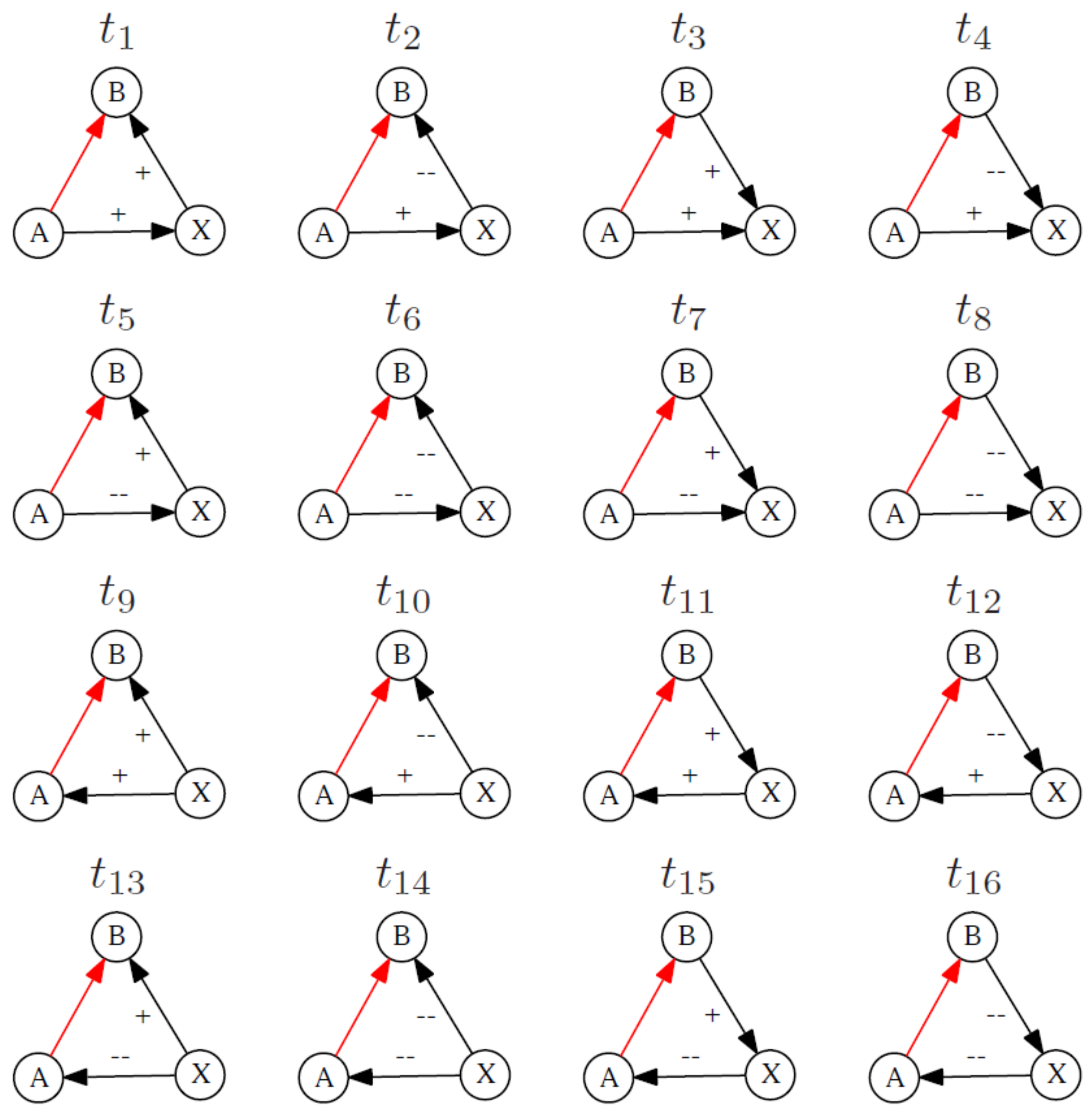
Theory of Status

- **Edges are directed:**
  - X has links to A and B
  - Now, A links to B (triad A-B-X)
  - **How does sign of A → B depend signs from/to X?**
    $P(A \xrightarrow{+} B \mid X)$ vs. $P(A \xrightarrow{+} B)$
- **We need to formalize:**
  - **1) Links are embedded in triads:** Triads provide context for signs
  - **2) Users are heterogeneous** in their linking behavior



1) Context: 16 Types

- Link A → B appears in **context X:** A → B | X
- **16 possible contexts:**



Note: Context of a link is uniquely determined by the directions and signs of links from/to **X**

2) Heterogeneity in linking behavior

- Users differ in frac. of + links they give/receive
- For a user U:
  - Generative **baseline:** Frac. of **+** given by **U**
  - Receptive **baseline:** Frac. of **+** received by **U**

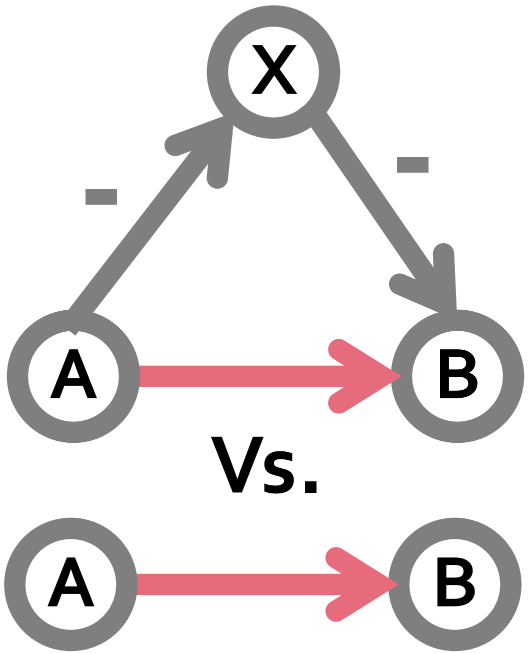
Basic question:

- How do **different link contexts** cause users to **deviate from their baselines**?
  - Link contexts as modifiers on a person's predicted behavior
  - **Def:** **Surprise**: How much behavior of A/B **deviates** from his/her **baseline** when A/B is in **context X**

Computing Surprise

- **Intuition:** How much behavior of user A in **context X deviates** from his/her **baseline** behavior
  - **Baseline:** For every user $\boldsymbol{A}$:
    $p_g(A_i)$… **generative baseline** of A_i
    - Fraction of times A_i gives a plus
  - **Context:** $(A_1, B_1 | X_1), \ldots, (A_n, B_n | X_n)$
    … all instances of triads in context $\boldsymbol{X}$
    - $(\mathbf{A_i}, \mathbf{B_i}, \mathbf{X_i})$ … an instance where when user $\mathbf{A_i}$ links to user $\mathbf{B_i}$ the triad of type **X** is created.
    - Say k of those triads closed with a plus
      - $\boldsymbol{k}$ out of $\boldsymbol{n}$ times: $\mathbf{A_i} \xrightarrow{+} \mathbf{B_i}$

Context X:

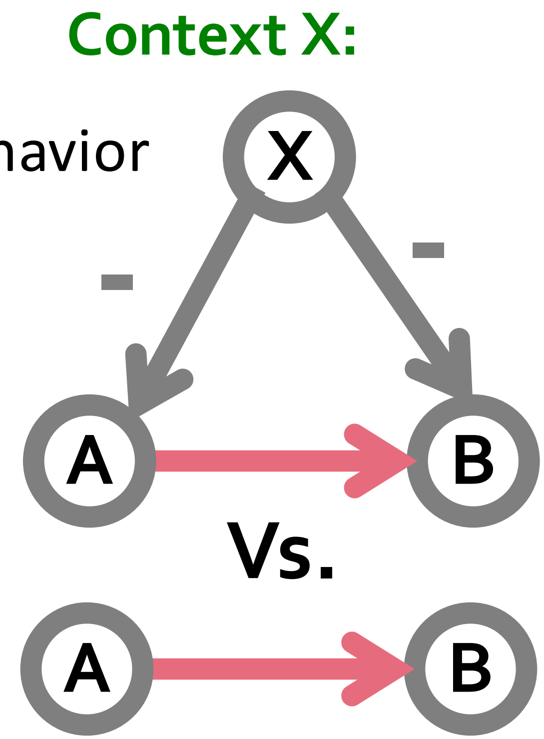


Computing Surprise

- **Surprise:** How much behavior of user A in **context X** **deviates** from his/her **baseline** behavior
  - **Generative surprise of context *X*:**

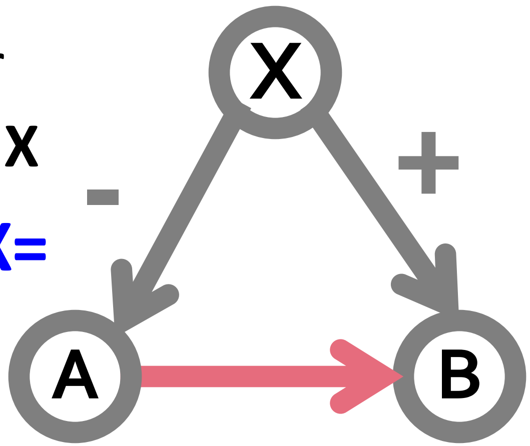
$$s_g(X) = \frac{k - \sum_{i=1}^{n} p_g(A_i)}{\sqrt{\sum_{i=1}^{n} p_g(A_i)(1 - p_g(A_i))}}$$

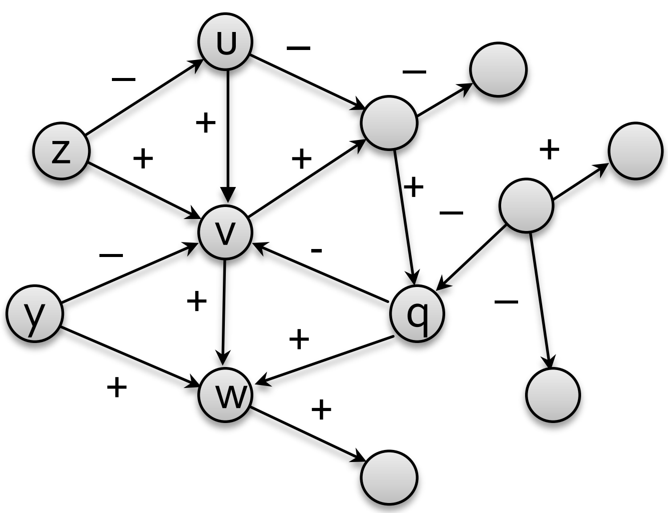
    - **$p_g(A_i)$** … **generative baseline** of **A_i**
    - **Context X:** $(A_1, B_1 | X_1), \ldots, (A_n, B_n | X_n)$
    - ***k*** of instances of triad ***X*** closed with a plus edges
  - Receptive surprise is similar, just use **$p_r(A_i)$**



Example: Computing Surprise

- **Surprise:** How much behavior of user **deviates** from **baseline** when in **context X**
  - **Generative surprise of context X=**



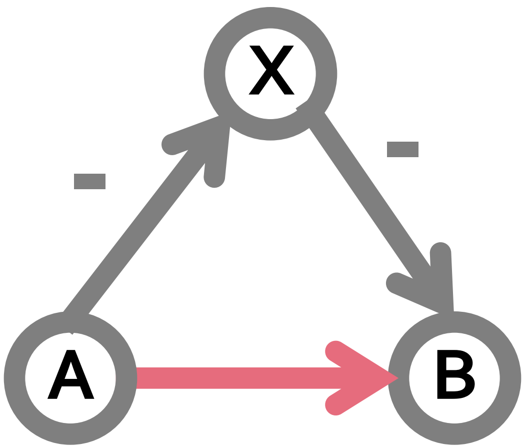


$$s_g(X) = \frac{k - \sum_{i=1}^{n} p_g(A_i)}{\sqrt{\sum_{i=1}^{n} p_g(A_i)(1 - p_g(A_i))}}$$

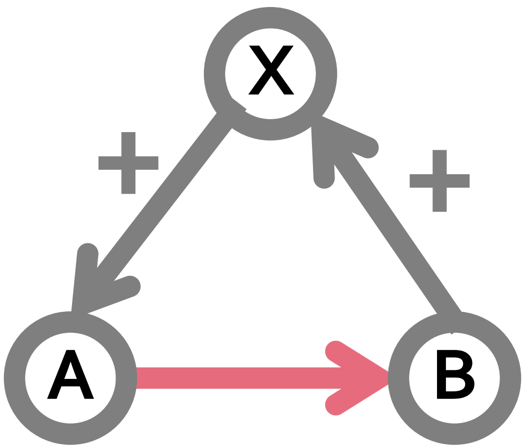
We have 3 triads of context X: (z,u,v), (y,v,w), (q,v,w)
They all close with a plus: So k=3
$P_g(u)=1/2=0.5 \quad P_g(v)=2/2=1$
$S_g(X)=(3-2.5)/\sqrt{(0.5*0.5+1*0+1*0)}$ **= 1**

Status: Two Examples

- **Assume status theory is at work**
- **What sign does status predict for edge A → B?**
  - We have to look at this separately from the viewpoint of A and from the viewpoint of B



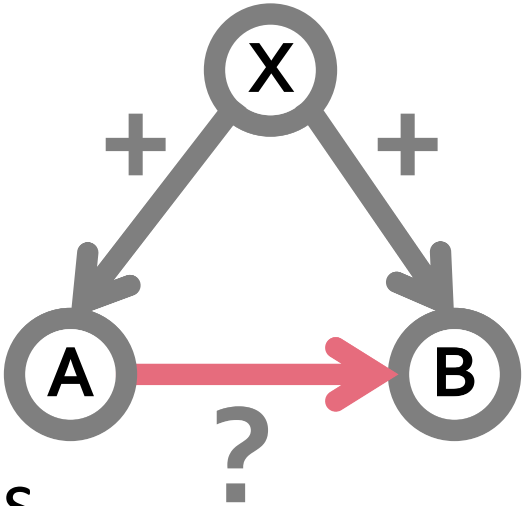
Gen. surprise of A: –
Rec. surprise of B: –



Gen. surprise of A: –
Rec. surprise of B: –

Joint Positive Endorsement

- **X** positively endorses **A** and **B**
- Now **A** links to **B**



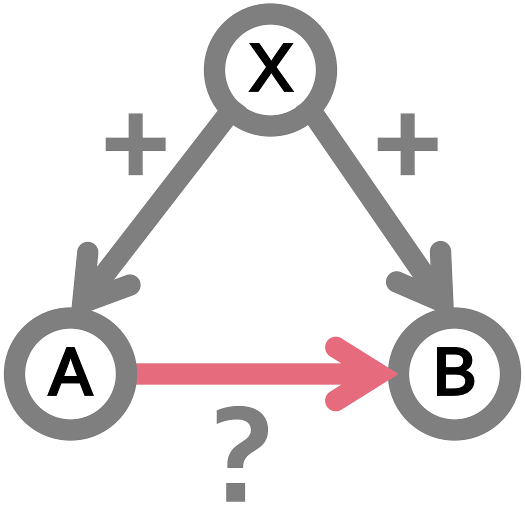
A puzzle:

- In our data we observe:
  Fraction of positive links deviates
  - **Above generative baseline of A: $S_g(X) > 0$**
  - **Below receptive baseline of B: $S_r(X) < 0$**

- **Why?**

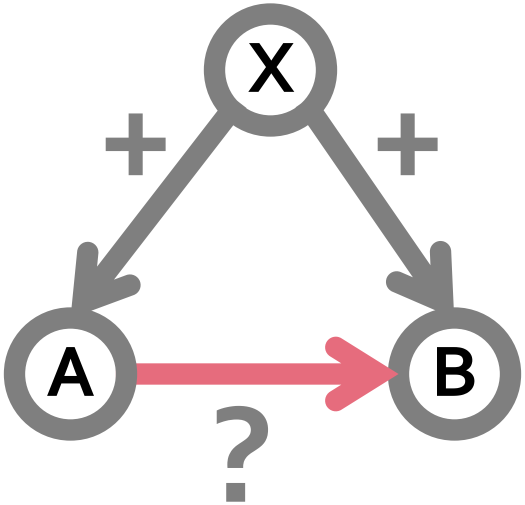
Joint Positive Endorsement

- **A's viewpoint:**
  - Since **B** has a positive evaluation, **B** is likely of high status
  - Thus, evaluation **A** gives is **more likely to be positive** than A's baseline behavior



Joint Positive Endorsement

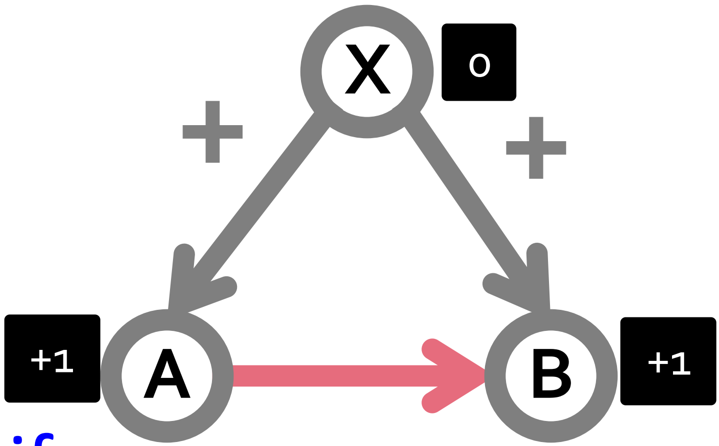
- **B's viewpoint:**
  - Since **A** has positive evaluation, **A** is likely to be high status
  - Thus, evaluation **B** receives is **less likely to be positive** than the baseline evaluation B usually receives



Surprise of A→B deviates in different directions depending on the viewpoint!

Consistency with Status

- **Determine node status:**
  - Assign ***X*** status 0
  - Based on signs and directions of edges set status of **A** and **B**
- Surprise is **status**-consistent, if:
  - Gen. surprise is status-consistent if it has **same** sign as status of **B**
  - Rec. surprise is status-consistent if it has the **opposite** sign from the status of **A**
- Surprise is **balance**-consistent, if:
  - If it completes a balanced triad



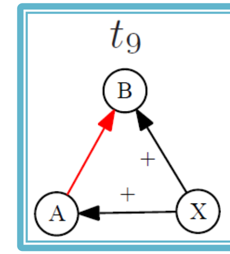
Status-consistent if:
Gen. surprise > 0
Rec. surprise < 0

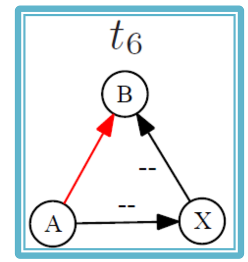
[CHI '10]

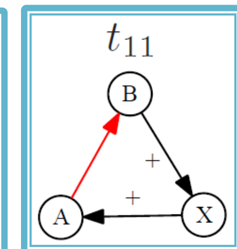
Status vs. Balance (Epinions)

- **Predictions by status and balance:**

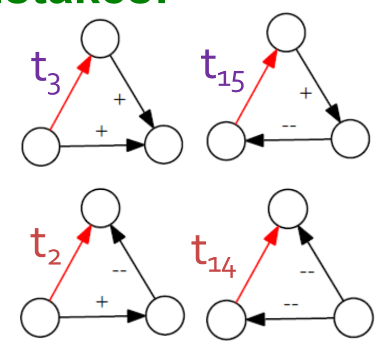
t_i	count	$P(+)$	$S_g(t_i)$	$S_r(t_i)$	B_g	B_r	S_g	S_r
t_1	178,051	0.97	95.9	197.8	✓	✓	✓	✓
t_2	45,797	0.54	-151.3	-229.9	✓	✓	✓	●
t_3	246,371	0.94	89.9	195.9	✓	✓	●	✓
t_4	25,384	0.89	1.8	44.9	○	○	✓	✓
t_5	45,925	0.30	18.1	-333.7	○	✓	✓	✓
t_6	11,215	0.23	-15.5	-193.6	○	○	✓	✓
t_7	36,184	0.14	-53.1	-357.3	✓	✓	✓	✓
t_8	61,519	0.63	124.1	-225.6	✓	○	✓	✓
t_9	338,238	0.82	207.0	-239.5	✓	○	✓	✓
t_{10}	27,089	0.20	-110.7	-449.6	✓	✓	✓	✓
t_{11}	35,093	0.53	-7.4	-260.1	○	○	✓	✓
t_{12}	20,933	0.71	17.2	-113.4	○	✓	✓	✓
t_{13}	14,305	0.79	23.5	24.0	○	○	✓	✓
t_{14}	30,235	0.69	-12.8	-53.6	○	○	✓	●
t_{15}	17,189	0.76	6.4	24.0	○	○	●	✓
t_{16}	4,133	0.77	11.9	-2.6	✓	○	✓	●
Number of correct predictions					8	7	14	13

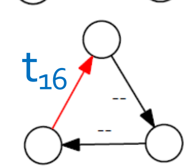






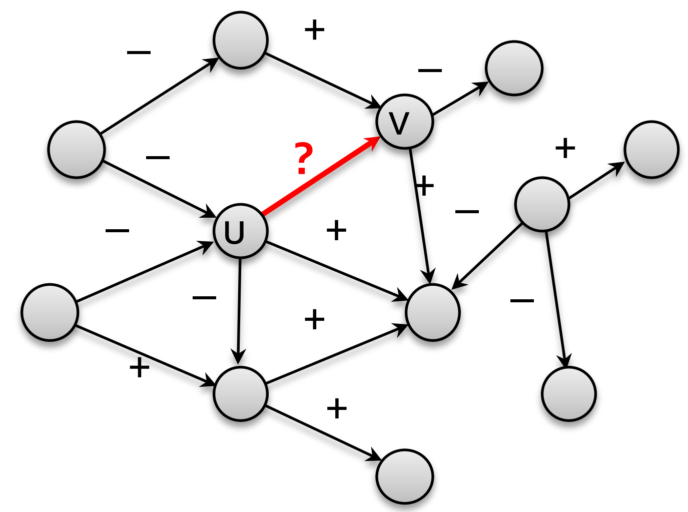
Mistakes:



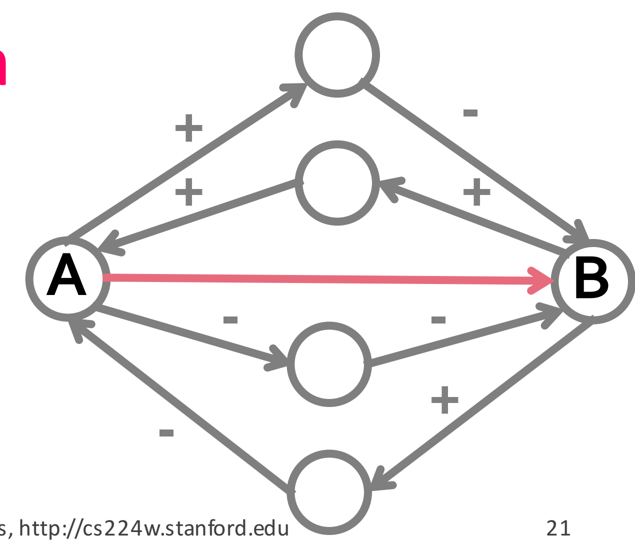


Predicting Edge Signs

Edge sign prediction problem

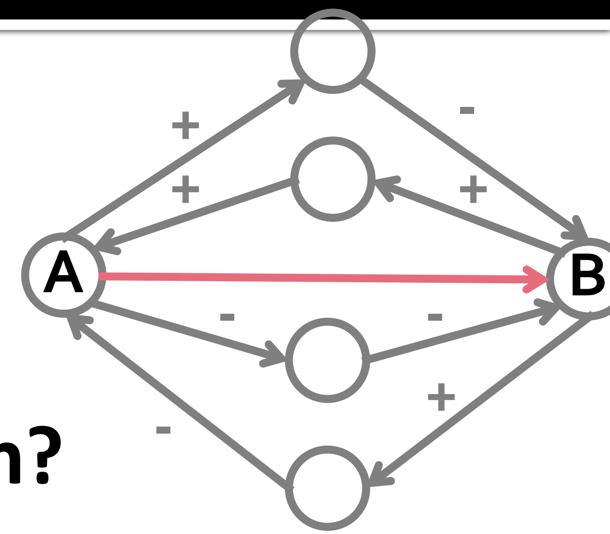


- Given a network and signs on all but one edge, predict the missing sign
- **Friend recommendation:**
  - Predicting whether you know someone vs. Predicting what you think of them



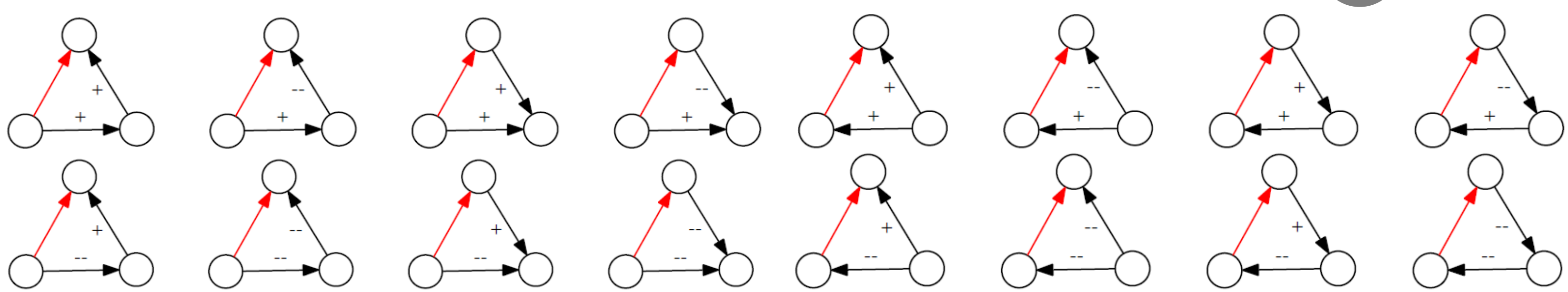
- **Setting:**
  - **Given edge *(A,B)*, predict its sign:**
  - **Let's look at signed triads *(A,B)* belongs to:**

Features for Learning



For the edge (A,B) we examine
Its network context:

- **In what types of triads does our red-edge participate in?**



- Each triad then "votes" and we determine the sign

Balance and Status: Complete Model

Triad	Bal
const	
$\bullet \xrightarrow{+} \bullet \xrightarrow{+} \bullet$	1
$\bullet \xrightarrow{+} \bullet \xrightarrow{-} \bullet$	-1
$\bullet \xrightarrow{-} \bullet \xrightarrow{+} \bullet$	-1
$\bullet \xrightarrow{-} \bullet \xrightarrow{-} \bullet$	1
$\circ \xrightarrow{+} \circ \xleftarrow{+} \circ$	1
$\circ \xrightarrow{+} \circ \xleftarrow{-} \circ$	-1
$\bullet \xrightarrow{-} \bullet \xleftarrow{+} \bullet$	-1
$\circ \xrightarrow{-} \circ \xleftarrow{-} \circ$	1
$\circ \xleftarrow{+} \circ \xrightarrow{+} \circ$	1
$\bullet \xleftarrow{+} \bullet \xrightarrow{-} \bullet$	-1
$\circ \xleftarrow{-} \circ \xrightarrow{+} \circ$	-1
$\circ \xleftarrow{-} \circ \xrightarrow{-} \circ$	1
$\circ \xleftarrow{+} \circ \xleftarrow{+} \circ$	1
$\circ \xleftarrow{+} \circ \xleftarrow{-} \circ$	-1
$\circ \xleftarrow{-} \circ \xleftarrow{+} \circ$	-1
$\circ \xleftarrow{-} \circ \xleftarrow{-} \circ$	1

Balance and Status: Complete Model

Triad	Bal	Stat
const $\bullet \xrightarrow{+} \bullet \xrightarrow{+} \bullet$	1	1
$\bullet \xrightarrow{+} \bullet \xrightarrow{-} \bullet$	-1	0
$\bullet \xrightarrow{-} \bullet \xrightarrow{+} \bullet$	-1	0
$\bullet \xrightarrow{-} \bullet \xrightarrow{-} \bullet$	1	-1
$\circ \xrightarrow{+} \circ \xleftarrow{+} \circ$	1	0
$\circ \xrightarrow{+} \circ \xleftarrow{-} \circ$	-1	1
$\bullet \xrightarrow{-} \bullet \xleftarrow{+} \bullet$	-1	-1
$\circ \xrightarrow{-} \circ \xleftarrow{-} \circ$	1	0
$\circ \xleftarrow{+} \circ \xrightarrow{+} \circ$	1	0
$\bullet \xleftarrow{+} \bullet \xrightarrow{-} \bullet$	-1	-1
$\circ \xleftarrow{-} \circ \xrightarrow{+} \circ$	-1	1
$\circ \xleftarrow{-} \circ \xrightarrow{-} \circ$	1	0
$\circ \xleftarrow{+} \circ \xleftarrow{+} \circ$	1	-1
$\circ \xleftarrow{+} \circ \xleftarrow{-} \circ$	-1	0
$\circ \xleftarrow{-} \circ \xleftarrow{+} \circ$	-1	0
$\circ \xleftarrow{-} \circ \xleftarrow{-} \circ$	1	1

Balance and Status: Complete Model

Triad	Bal	Stat	Epin	Slashd	Wikip
const			-0.2	0.02	-0.2
$\bullet \xrightarrow{+} \bullet \xrightarrow{+} \bullet$	1	1	**0.5**	**0.9**	**0.3**
$\bullet \xrightarrow{+} \bullet \xrightarrow{-} \bullet$	-1	0	**-0.5**	**-0.9**	**-0.4**
$\bullet \xrightarrow{-} \bullet \xrightarrow{+} \bullet$	-1	0	**-0.4**	**-1.1**	**-0.3**
$\bullet \xrightarrow{-} \bullet \xrightarrow{-} \bullet$	1	-1	**-0.7**	**-0.6**	**-0.8**
$\circ \xrightarrow{+} \circ \xleftarrow{+} \circ$	1	0	0.3	0.4	0.05
$\circ \xrightarrow{+} \circ \xleftarrow{-} \circ$	-1	1	-0.01	-0.1	-0.01
$\bullet \xrightarrow{-} \bullet \xleftarrow{+} \bullet$	-1	-1	**-0.9**	**-1.2**	**-0.2**
$\circ \xrightarrow{-} \circ \xleftarrow{-} \circ$	1	0	0.04	-0.07	-0.03
$\circ \xleftarrow{+} \circ \xrightarrow{+} \circ$	1	0	0.08	0.4	0.1
$\bullet \xleftarrow{+} \bullet \xrightarrow{-} \bullet$	-1	-1	**-1.3**	**-1.1**	**-0.4**
$\circ \xleftarrow{-} \circ \xrightarrow{+} \circ$	-1	1	-0.1	-0.2	0.05
$\circ \xleftarrow{-} \circ \xrightarrow{-} \circ$	1	0	0.08	-0.02	-0.1
$\circ \xleftarrow{+} \circ \xleftarrow{+} \circ$	1	-1	-0.09	-0.09	-0.01
$\circ \xleftarrow{+} \circ \xleftarrow{-} \circ$	-1	0	-0.05	-0.3	-0.02
$\circ \xleftarrow{-} \circ \xleftarrow{+} \circ$	-1	0	-0.04	-0.3	0.05
$\circ \xleftarrow{-} \circ \xleftarrow{-} \circ$	1	1	-0.02	0.2	-0.2

Edge Sign Prediction

- **Prediction accuracy:**

	Balance	Status	Triads
Epinions	80%	82%	93.5%
Slashdot	84%	72%	94.4%
Wikipedia	64%	70%	81%

- **Observations:**
  - **Signs can be modeled from local network structure alone!**
    - Status works better on Epinions and Wikipedia
    - Wikipedia is harder to model:
      - Votes are publicly visible

Generalization

- **Do people use these very different linking systems by obeying the same principles?**
  - How generalizable are the results across the datasets?

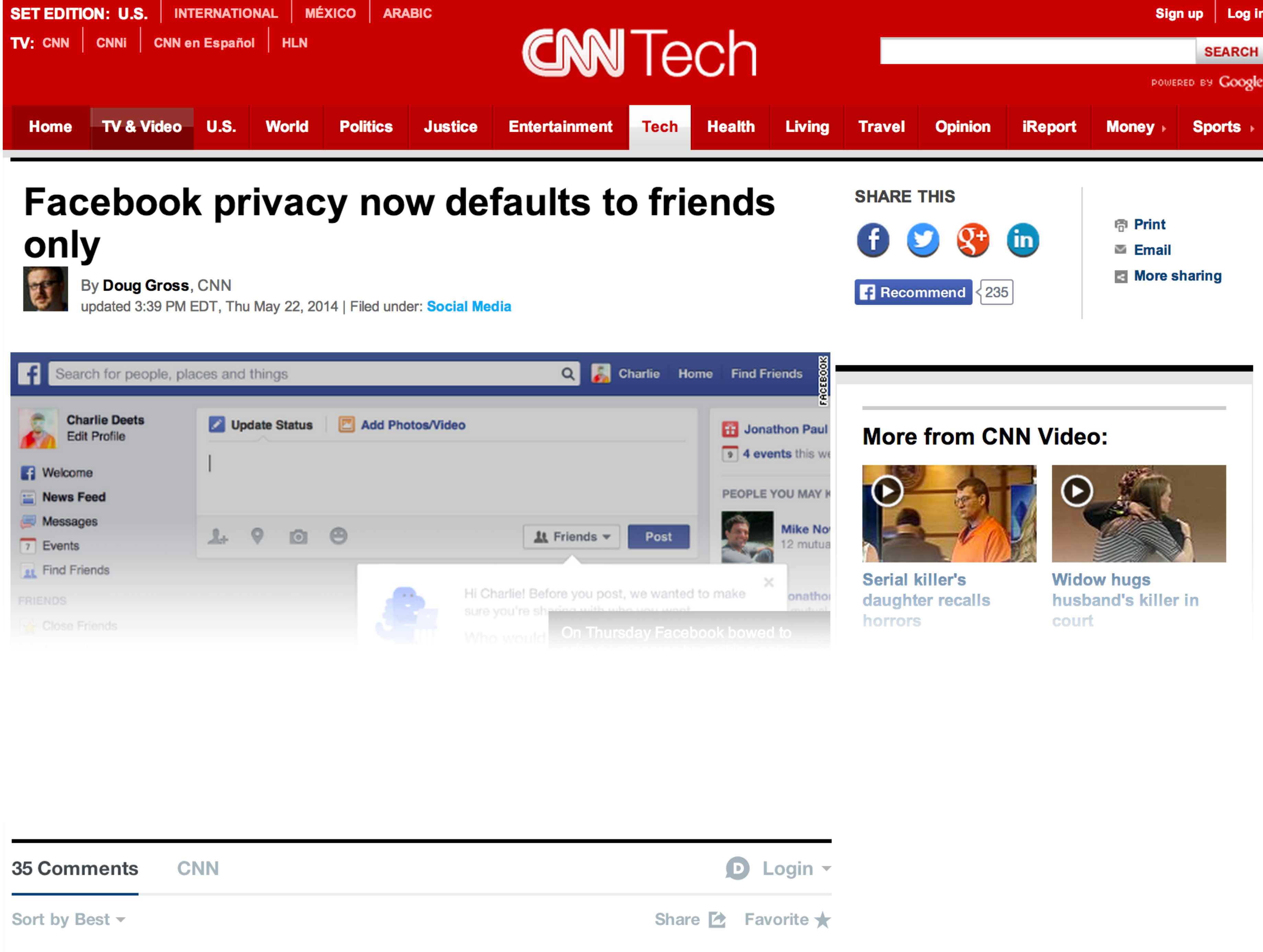
Train on row, test on column	Epinions	Slashdot	Wikipedia
Epinions	0.9342	0.9289	0.7722
Slashdot	0.9249	0.9351	0.7717
Wikipedia	0.9272	0.9260	0.8021

- Nearly **perfect generalization** of the models even though networks come from very different applications!

Summary: Signed Networks

- **Signed networks provide insight into how social computing systems are used:**
  - Status vs. Balance
  - Role of embeddedness and public display
  - More evidence that networks are globally organized based on status
- **Sign of relationship can be reliably predicted from the local network context**
  - ~90% accuracy sign of the edge
  - People use signed edges consistently regardless of particular application
    - Near perfect generalization of models across datasets

What about the effect of evaluations on the target T?



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Facebook privacy now defaults to friends only

By **Doug Gross**, CNN

updated 3:39 PM EDT, Thu May 22, 2014 | Filed under: Social Media

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On Thursday Facebook bowed to

More from CNN Video:

Serial killer's daughter recalls horrors

Widow hugs husband's killer in court

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35 Comments CNN Login

Sort by Best Share Favorite

Join the discussion…

Tom · 7 hours ago

If you're posting something to facebook, it shouldn't be anything you wouldn't print and tape to the front door of a local grocery store.

21 · Reply · Share ›

ccw101 → Tom · 7 hours ago

I hate Facebook for the fact the only person you have control over is yourself. I have seen full grown adults get angry at their own children and rip them a new one on their Facebook home page!

If adults can be so ST***id then what do kids do?

Facebook is scary. And has given people the opportunity to use it to cause home break in's, ruined reputations, fights , suicides etc.

8 · Reply · Share ›

IAmNotATroll → ccw101 · 7 hours ago

Come now, I thoroughly enjoy watching my in-laws publicly argue and shred each other to pieces over Facebook.

8 · Reply · Share ›

Furby → IAmNotATroll · 6 hours ago

I had a distant cousin try to blackmail my mom on FB publically. Me and her became real close after that - and not in the way you want to get close to someone. Some people are just plain dumb

How do people react to evaluations they receive?

How does positive/negative feedback influence subsequent user behavior?

Positively Evaluated → ?

Negatively Evaluated → ?

Evaluations can affect

Post quality (How well you write)

Community bias (How people perceive you)

Posting frequency (How regularly you post)

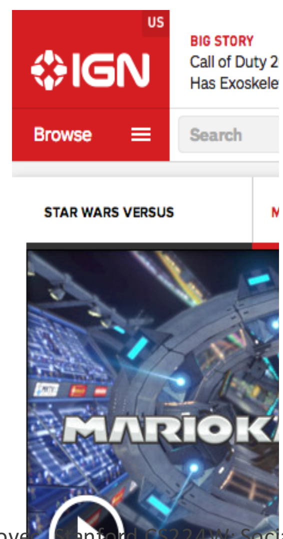
Voting behavior (How you vote on others)

Four large comment-based news communities with

1.2M articles, 1.8M registered users, 42M posts, 140M votes, 1 year

CNN

IGN



Breitbart

allkpop

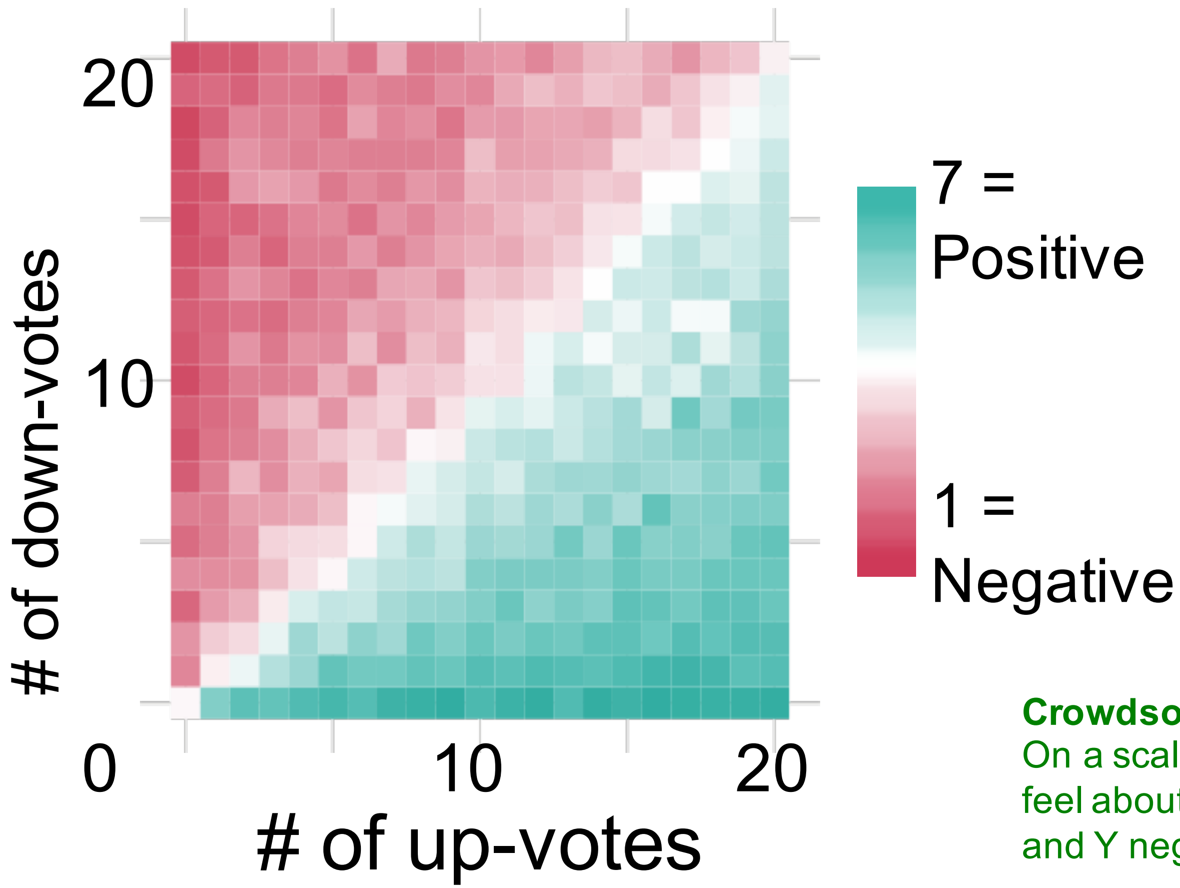
How do we measure community feedback?

Number of up-votes

Up-votes minus Down-votes

Fraction of up-votes

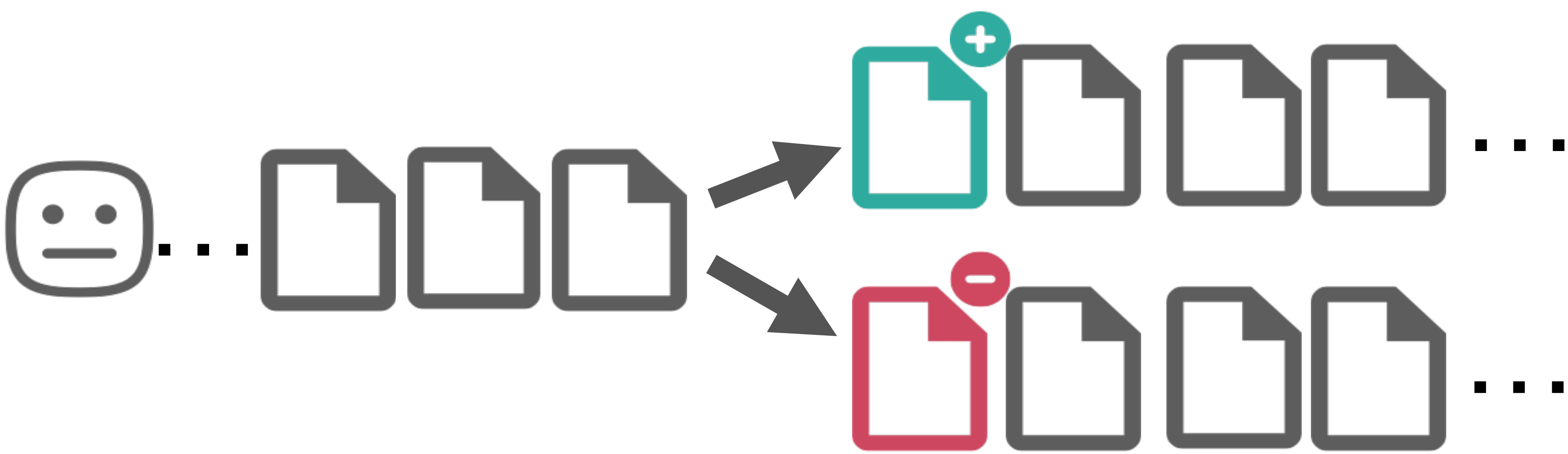
User ratings were independent of the total number of votes



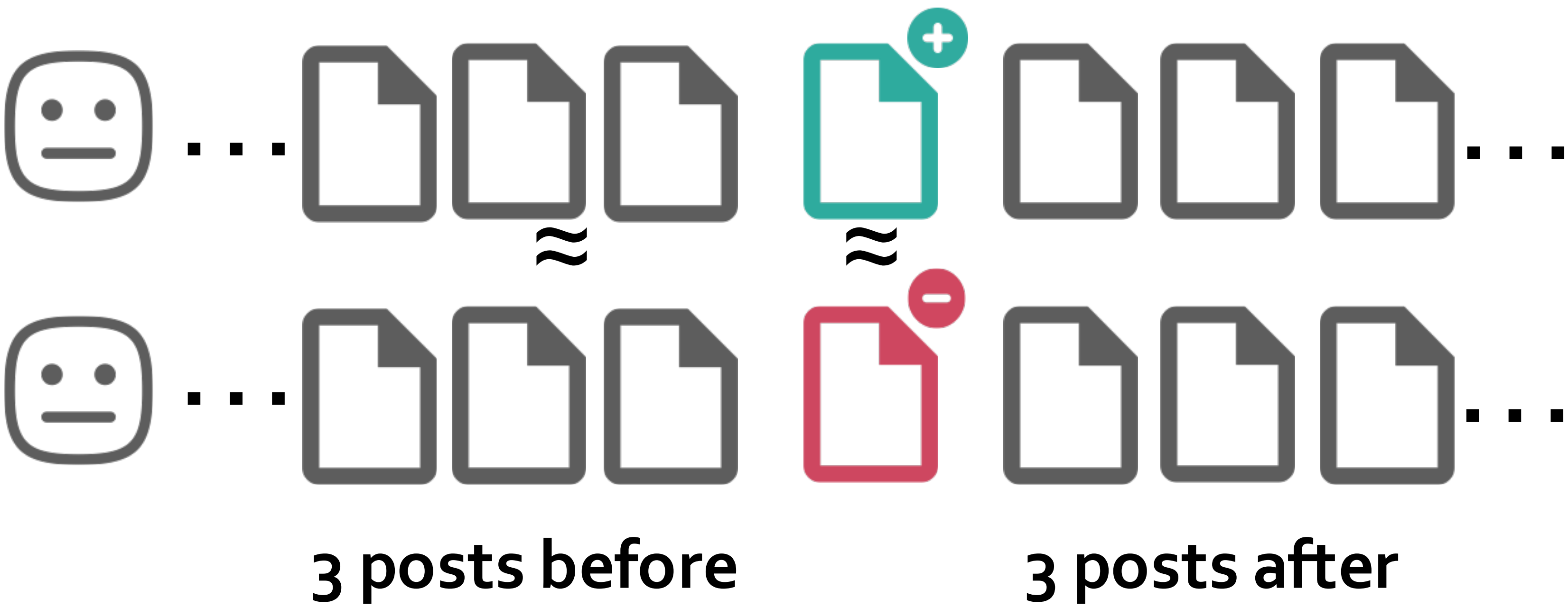
Crowdsourcing exercise:
On a scale 1-7 how would you feel about getting X positive and Y negative votes?

Fraction of up-votes: R^2=0.92

What happens after you give a user a positive, or a negative evaluation?



Compare similar pairs of users who were evaluated differently on similar content



Rosenbaum, P. R., & Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects.

Matching pairs of users

- **Match pairs of users where one got positive and one got negatively evaluated.**
- **Match based on similar history**
  - text quality, number of posts, overall proportion of up-votes, etc.

Text quality determined by training a machine learning model using text features, validated using crowd workers.

Evaluations can affect

Post quality (How well you write)

Community bias (How people perceive you)

Posting frequency (How regularly you post)

Voting behavior (How you vote on others)

How much of a future evaluation can be explained by textual effects?

Text quality drops significantly after a negative evaluation, but does not change after a positive evaluation

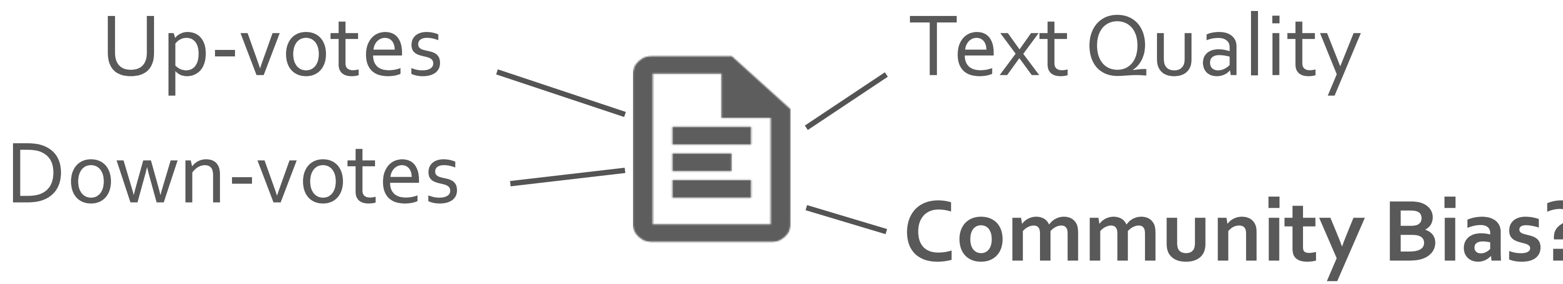
$p < 0.05$ in all communities

To learn more about these types of effects, see Kanouse, D. E., & Hanson Jr, L. R. (1987). Negativity in evaluations.

Evaluations can affect

Community bias (How people perceive you)

How does community perception of a user change after an evaluation?

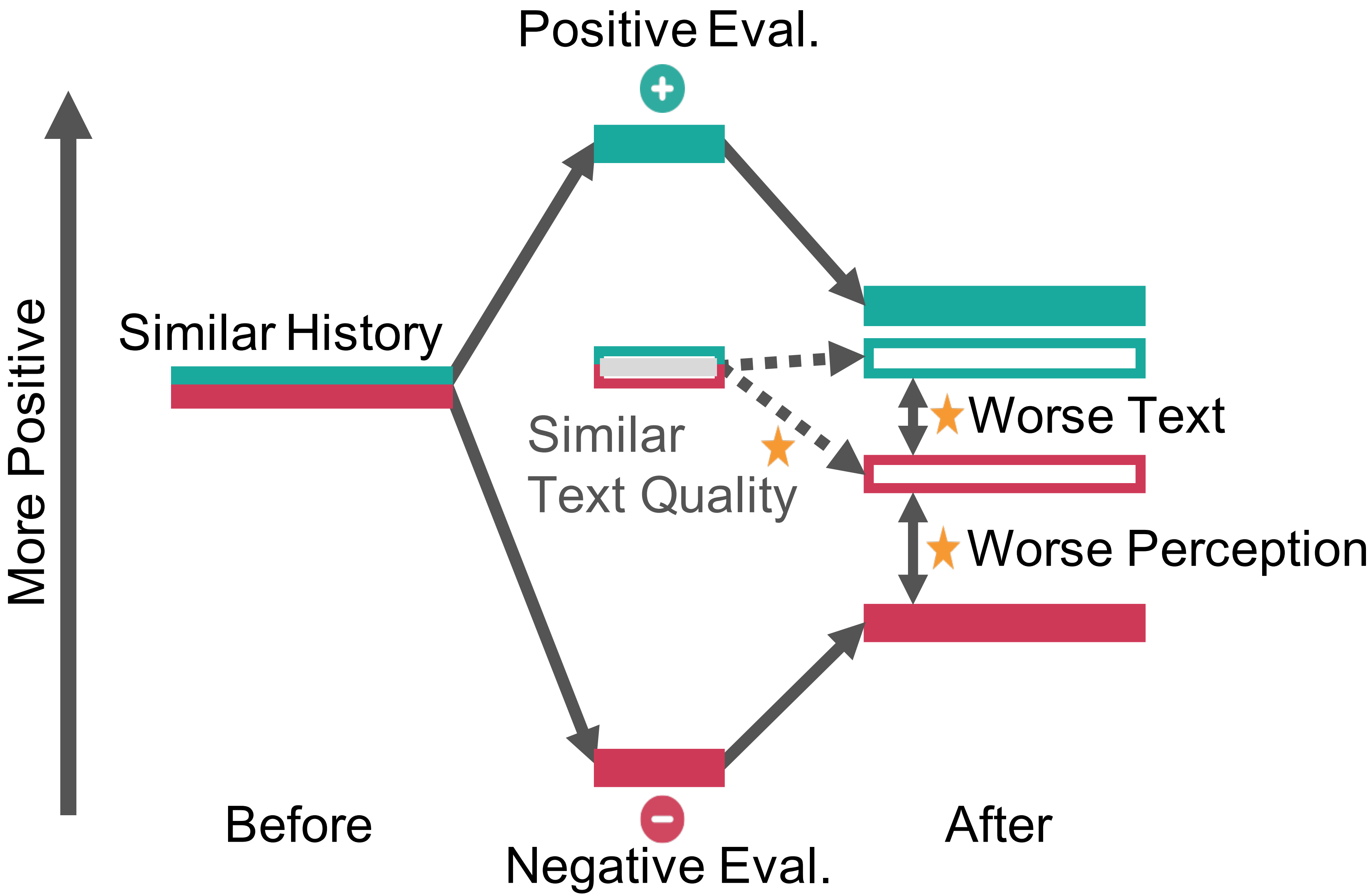


Actual Evaluation P/(P+N)	**0.9**
Judged Text Quality	**0.8**
Community Bias	**0.9-0.8 = +0.1**

Community Effects

Posts made after a negative evaluation were perceived worse than those made after a positive evaluation

$p < 0.05$ in all communities

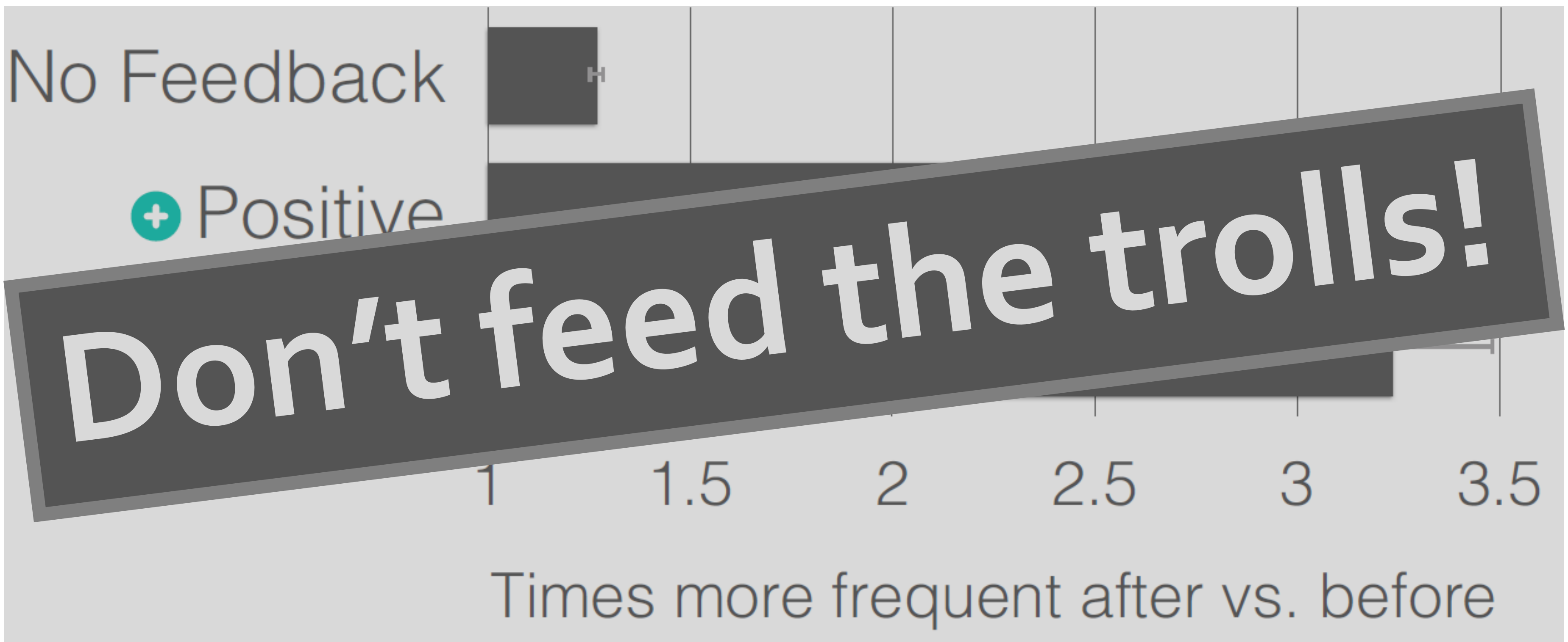

Positive Eval.
More Positive
Similar History
Similar
Text Quality
Worse Text
Worse Perception
Before
After
Negative Eval.

Evaluations can affect

Posting frequency (How regularly you post)

Does feedback regulate post *quantity*?

Users who receive negative feedback post more frequently

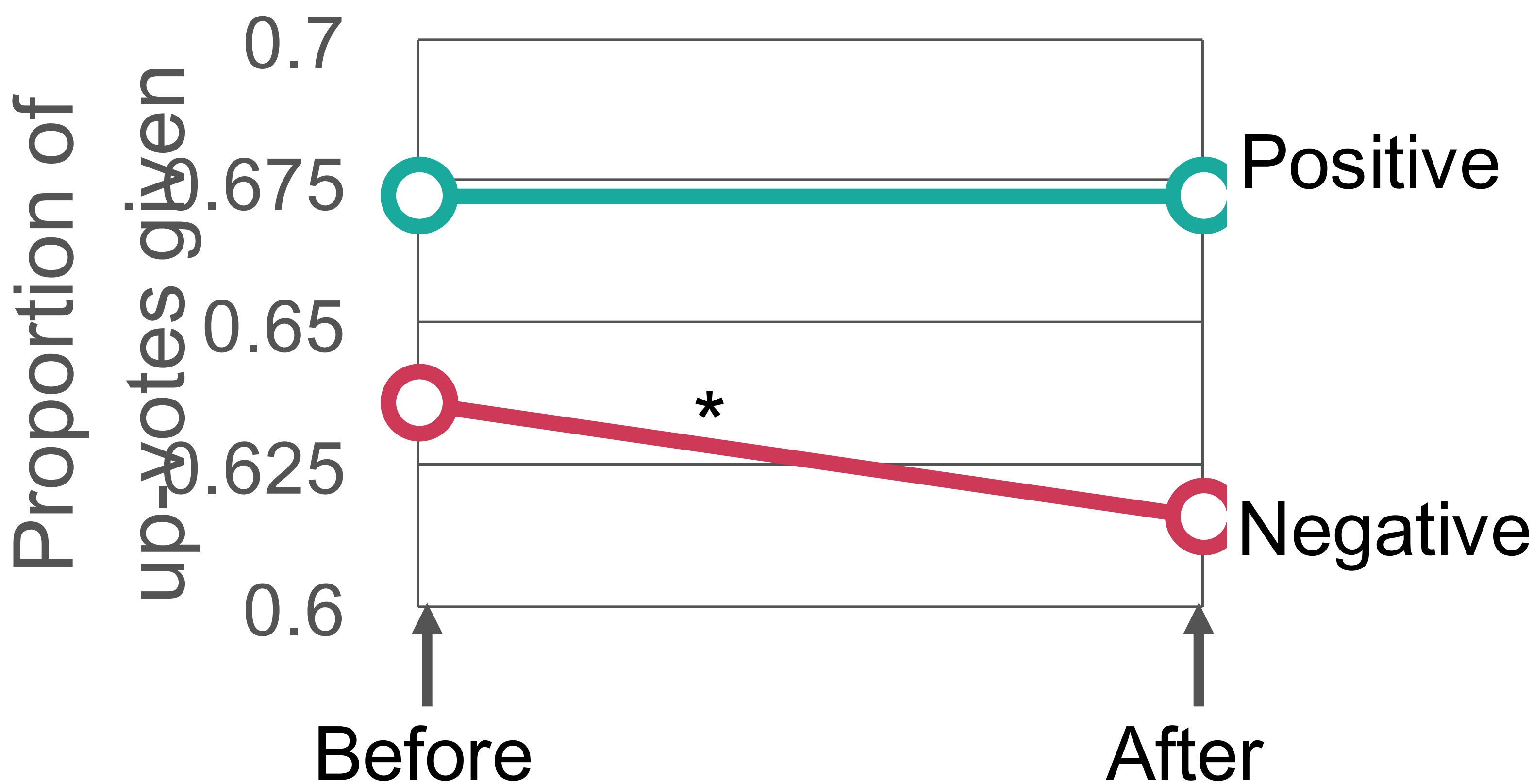


Evaluations can affect

Voting Behavior (How you vote on others)

Does feedback result in subsequent backlash?

Users who receive negative feedback are more likely to down-vote others



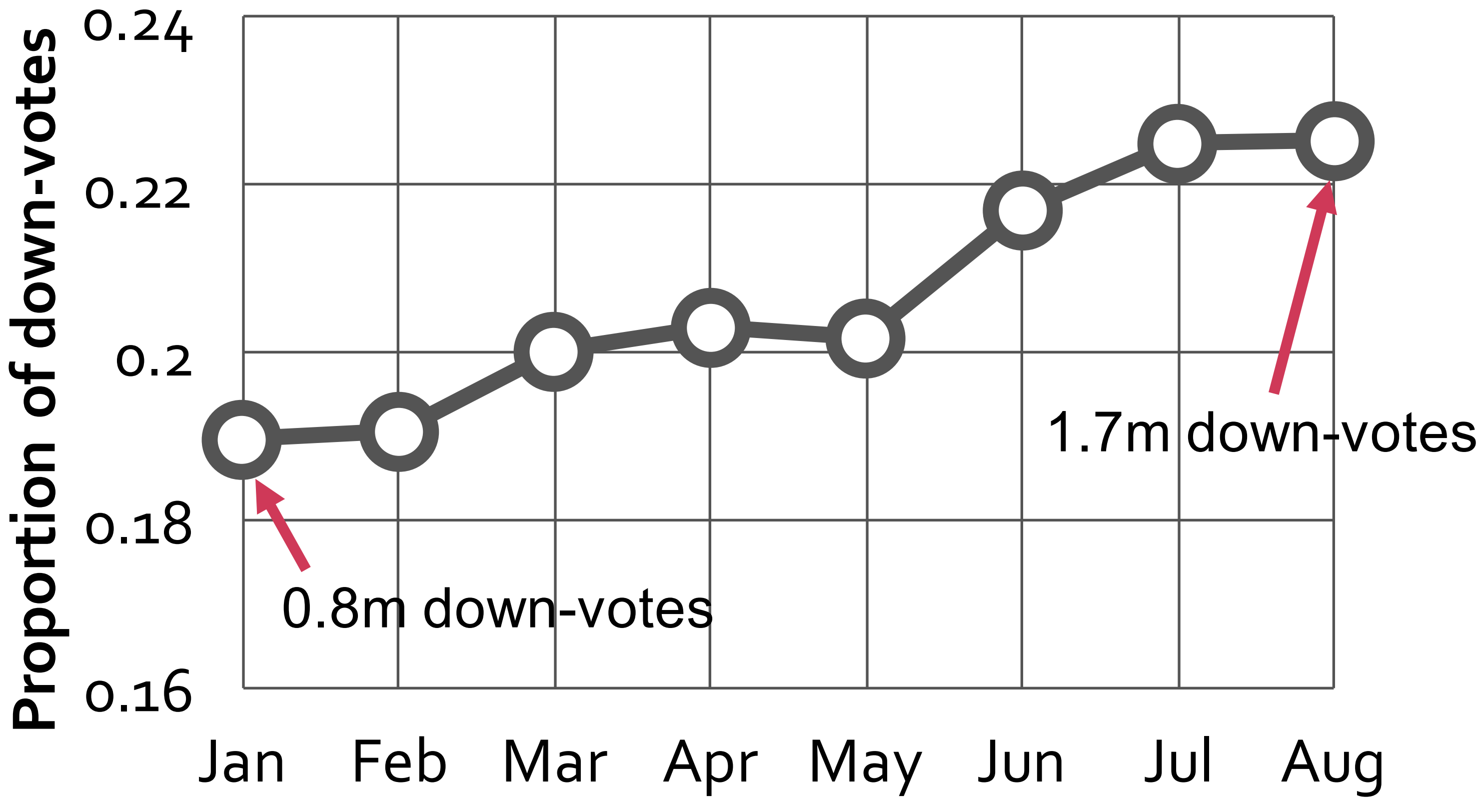
Conclusion

Negatively-evaluated users write worse (and more!), are themselves evaluated worse by the community, and evaluate other community members worse.

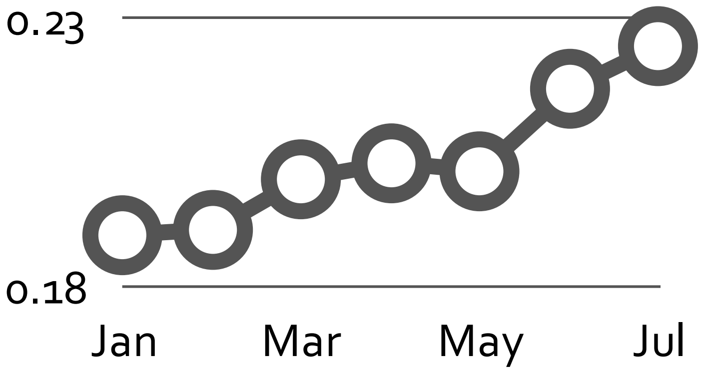
Positively-evaluated users, on the other hand, don't do any better.

Is there a downward spiral in online communities?

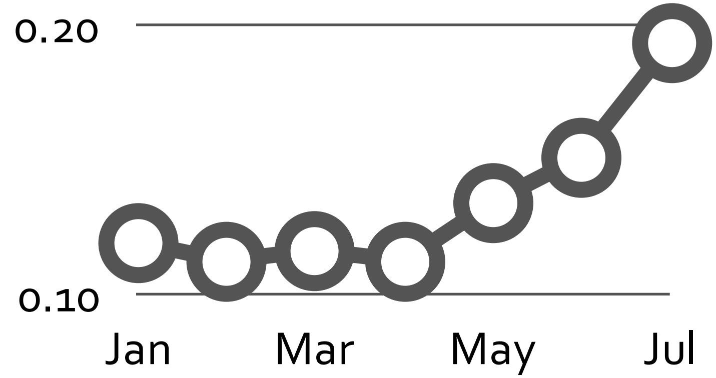
The proportion of down-votes is increasing over time



CNN



IGN



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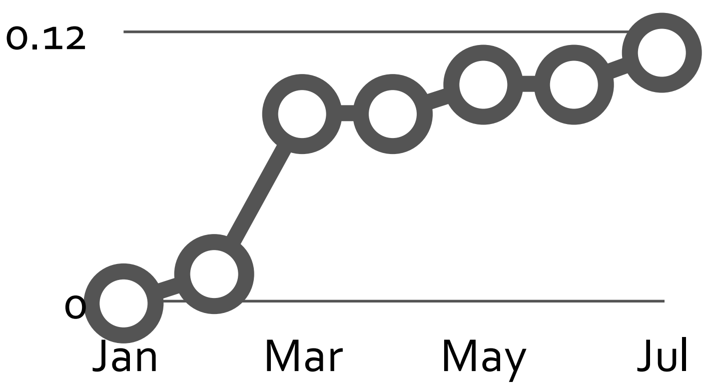

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