Signed networks: Theories of Structural Balance and Status

CS224W: Social and Information Network Analysis Jure Leskovec, Stanford University

http://cs224w.stanford.edu



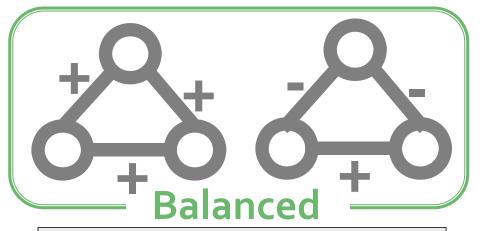
Signed networks

- Networks with positive and negative relationships
- Consider an undirected complete graph
- Label each edge as either:
 - Positive: friendship, trust, positive sentiment, ...
 - Negative: enemy, distrust, negative sentiment, ...
- Examine triples of connected nodes A,B, C

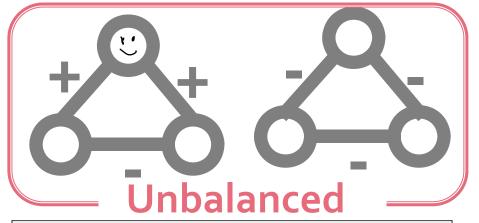
Theory of Structural Balance

Consider edges as undirected

- Start with intuition [Heider '46]:
 - Friend of my friend is my friend
 - Enemy of enemy is my friend
 - Enemy of friend is my enemy
- Look at connected triples of nodes:



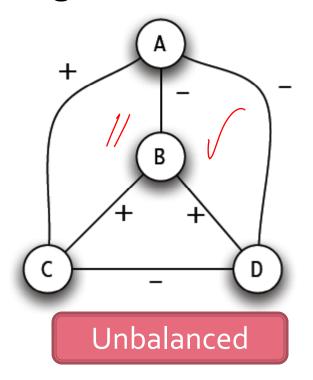
Consistent with "friend of a friend" or "enemy of the enemy" intuition

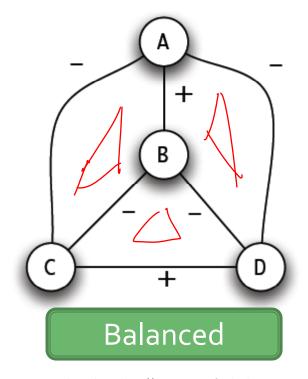


Inconsistent with the "friend of a friend" or "enemy of the enemy" intuition

Balanced/unbalanced networks

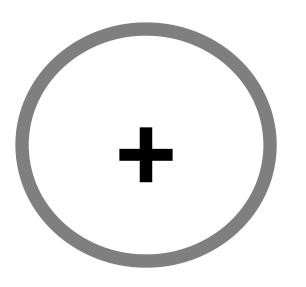
 Graph is balanced if every connected triple of nodes has all 3 edges labeled +, or else exactly 1 edge is labeled +.

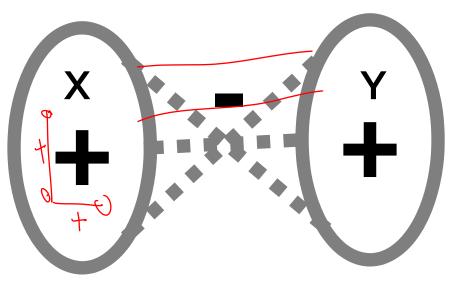




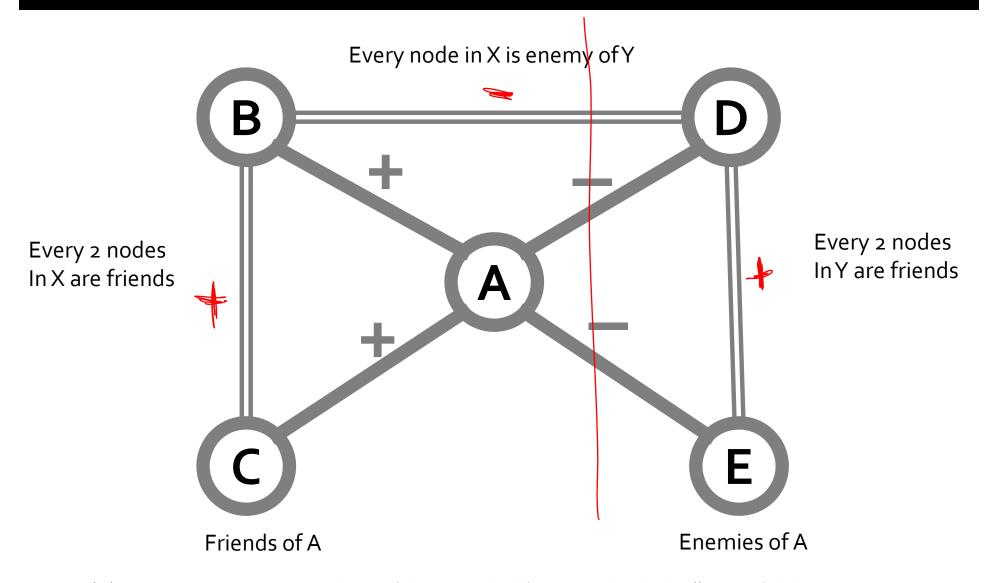
Local balance → **Global factions**

- Balance implies global coalitions [Cartwright-Hararx]
 - If all triangles are balanced, then either:
 - The network contains only positive edges, or
 - Nodes can be split into 2 factions linked by negative edges



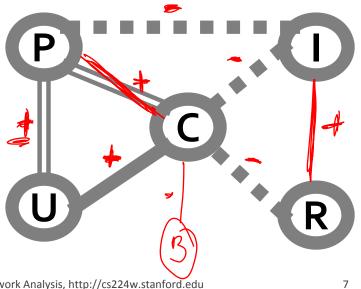


Analysis of balance

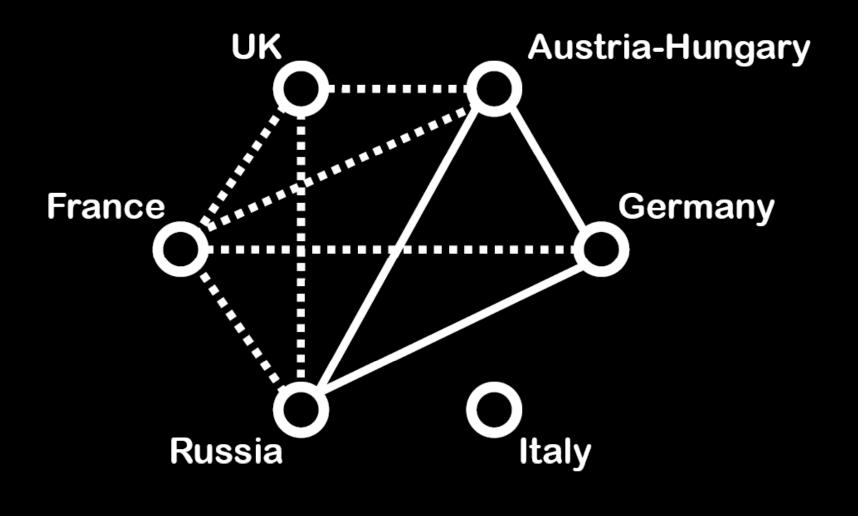


Example

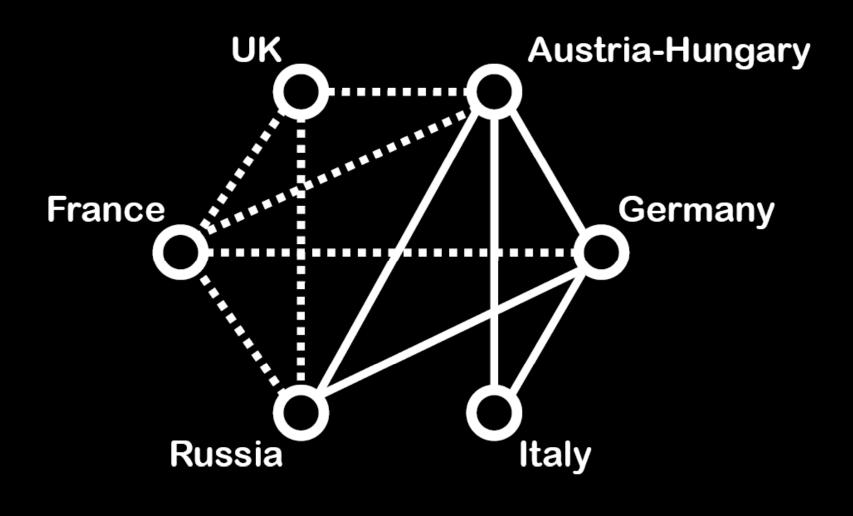
- International relations:
 - Positive edge: alliance
 - Negative edge: animosity
- Separation of Bangladesh from Pakistan in 1971: US supports Pakistan. Why?
 - USSR was enemy of China
 - China was enemy of India
 - India was enemy of Pakistan
 - US was friendly with China
 - China vetoed Bangladesh

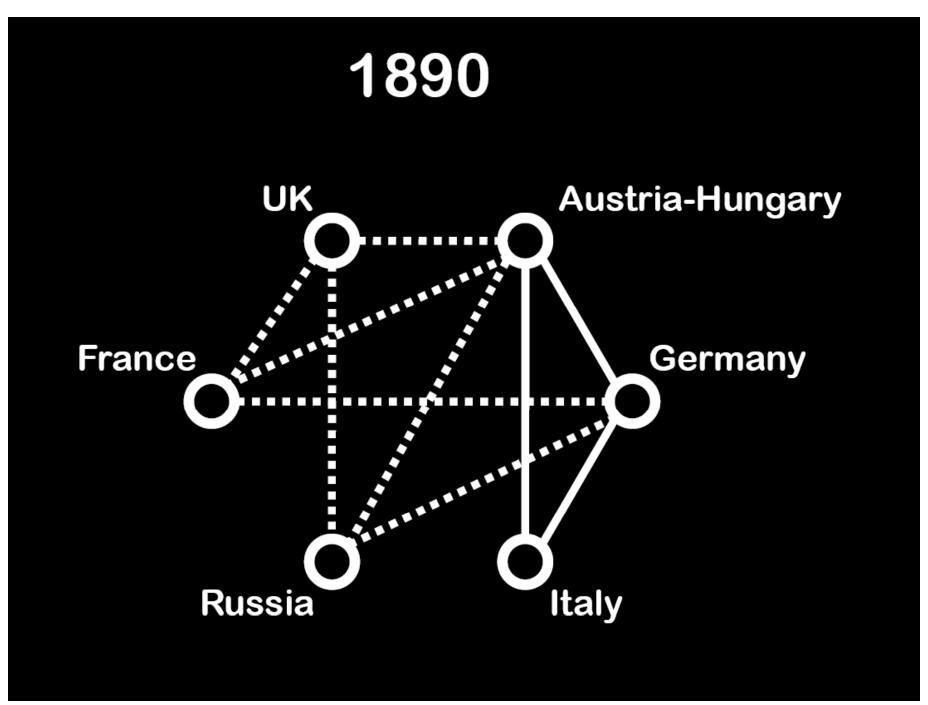


1872-1881

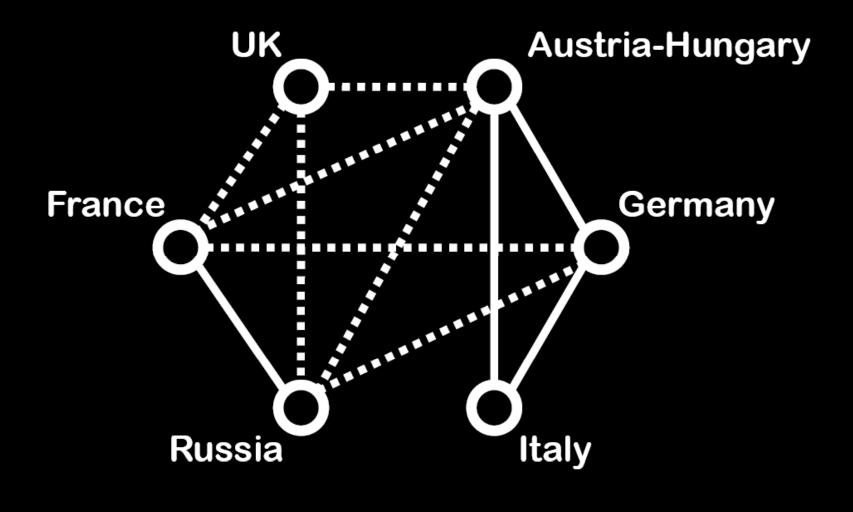


1882

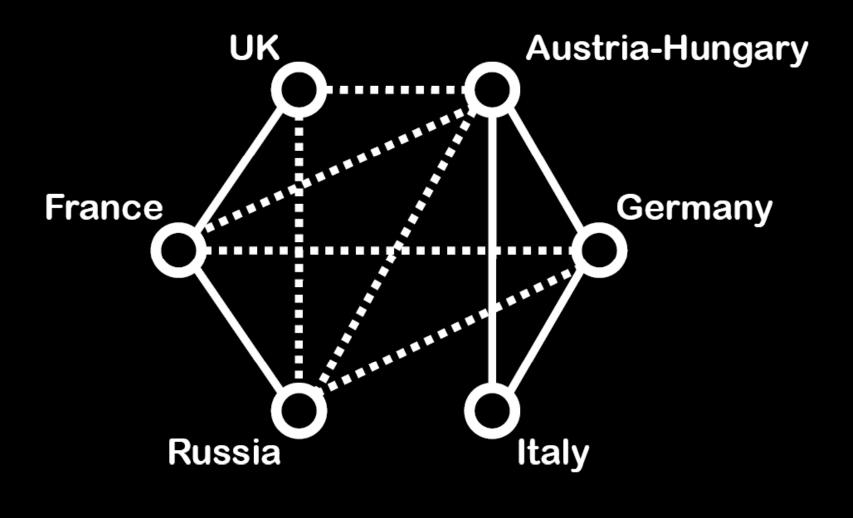




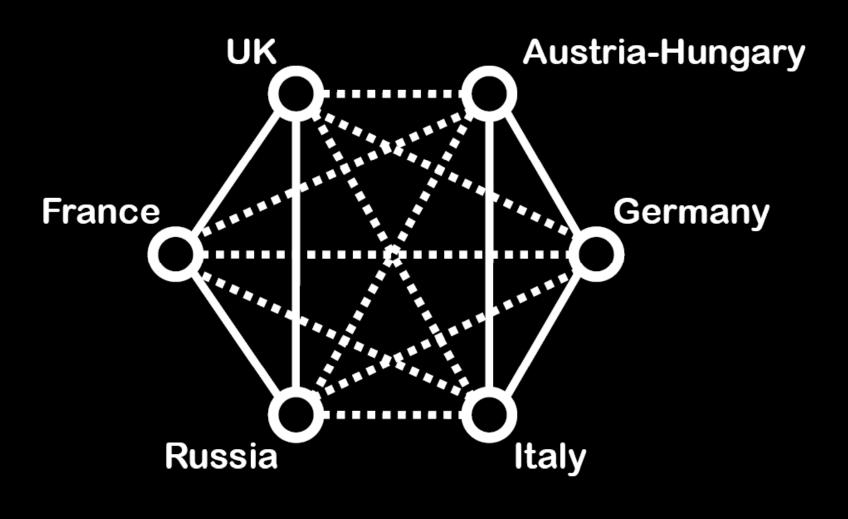
1891-1894



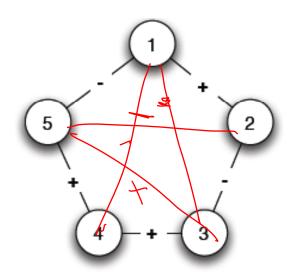
1904



1907

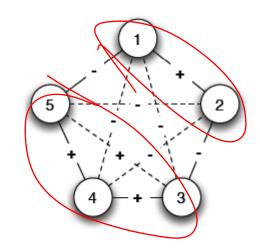


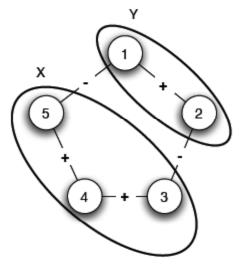
Balance in general networks



Balanced?

- Def 1: Local view
 - Fill in the missing edges to achieve balance
- Def 2: Global view
 - Divide the graph into two coalitions
- Defs are equivalent!

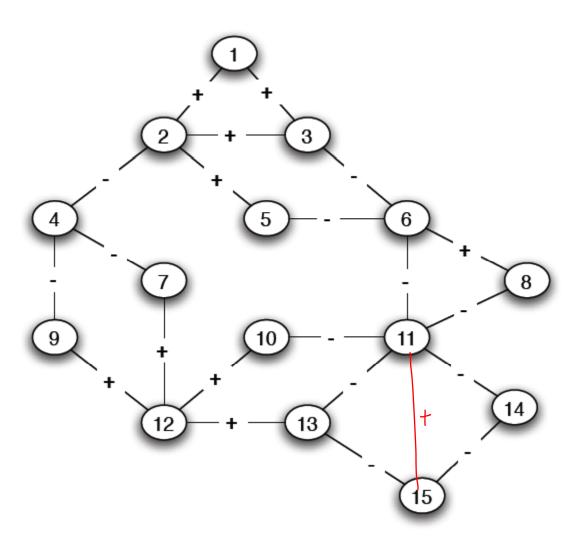




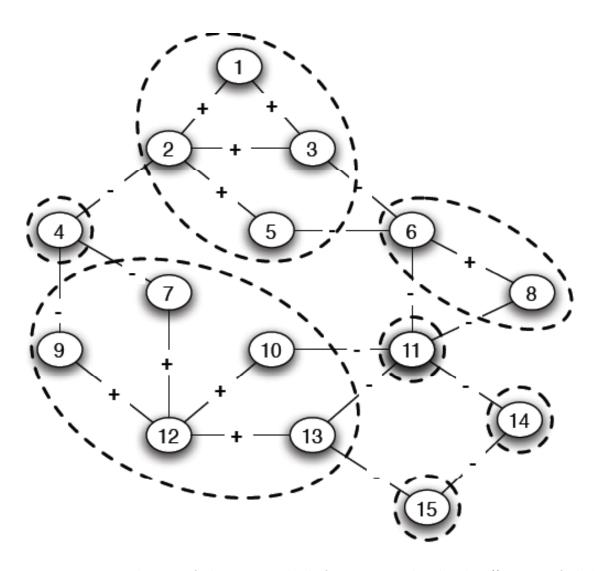
Is a signed network balanced?

- A graph is balanced if and only if it contains no cycle with an odd number of negative edges.
- How to compute this?
 - Find connected components on + edges
 - For each component create a super-node
 - Connect components A and B if there is a negative edge between the members
 - Assign super-nodes to sides using BFS

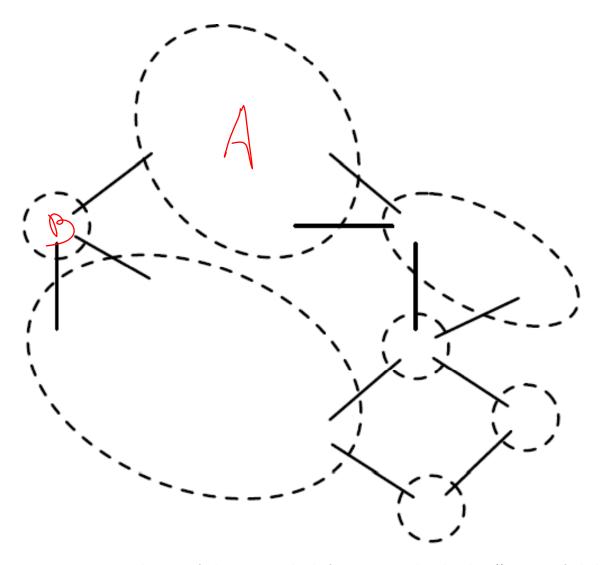
Signed Graph: Is it balanced?



Positive connected components

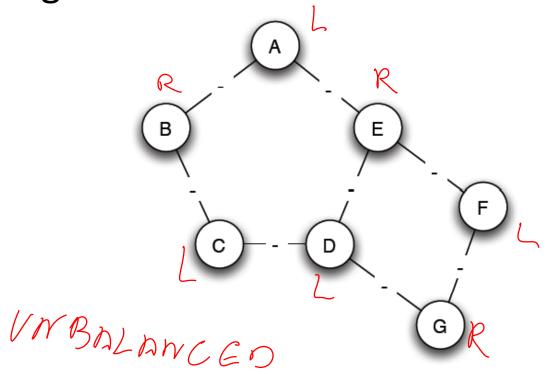


Reduced graph on super nodes



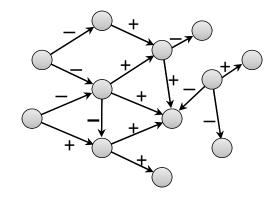
BFS on reduced graph

- Using BFS assign each node a side
- Graph is unbalanced if any two super-nodes are assigned the same side



Real Large Signed Networks

- Each link $A \rightarrow B$ is **explicitly** tagged with a sign:
 - Epinions: Trust/Distrust
 - Does A trust B's product reviews?(only positive links are visible)
 - 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 [Szell et al. 2010]



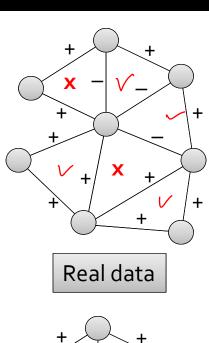
	Epinions	Slashdot	Wikipedia
Nodes	119,217	82,144	7,118
Edges	841,200	549,202	103,747
+ edges	85.0%	77.4%	78.7%
edges	15.0%	22.6%	21.2%

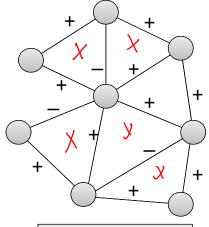
Balance in our network data

Does structural balance hold?

	Triad	Epin	ions	Wikipedia		Dalanca	
	IIIau	P(T)	P _o (T)	P(T)	P _o (T)	Balance	
→ >	+ +	o.87 —	0.62	0.70	0.49	✓	
	·	0.07	0.05	0.21	0.10	✓	
	+ +	0.05	0.32	0.08	0.49	✓	
		0.007	0.003	0.011	0.010	×	

P(T) ... probability of a triad $P_o(T)$... triad probability if the signs would be random





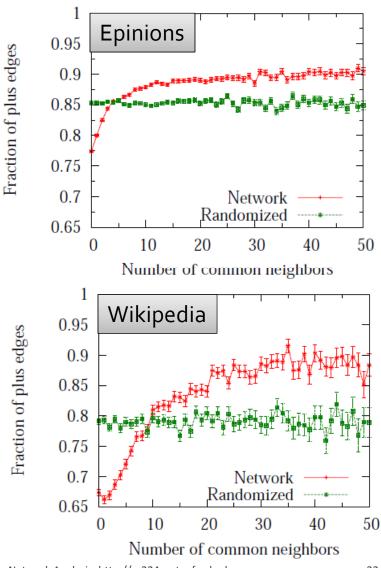
Shuffled data

Global factions: Embeddedness

- Embeddedness of ties:
 - Positive ties tend to be more embedded



- Positive ties tend to be more clumped together
- Public display of signs (votes) in Wikipedia further attenuates this



Global Structure of Signed Nets

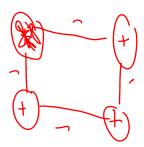
	Si	ze	Clust	ering	Component	
	Nodes Edges		Real	Rnd	Real	Rnd
Epinions: —	119,090	123,602	0.012	0.022	0.308	0.334
->Epinions: +	119,090	717,027	0.093	0.077	0.815	0.870
Slashdot: –	82,144	124,130	0.005	0.010	0.423	0.524
Slashdot: +	82,144	425,072	0.025	0.022	0. <u>90</u> 6	0.909
Wikipedia: –	7,115	21,984	0.028	0.031	0.583	0.612
→Wikipedia: +	7,115	81,705	0.130	0.103	0. <u>87</u> 0	0.918

Clustering:

- +net: more clustering than baseline
- -net: less clustering than expected

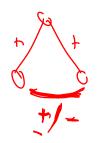


+/-net: smaller than expected



Evolving directed networks

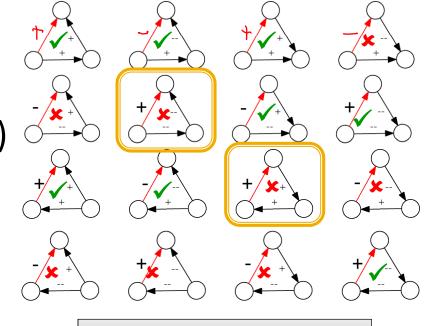
Our networks are really directed







Half (8 out of 16)

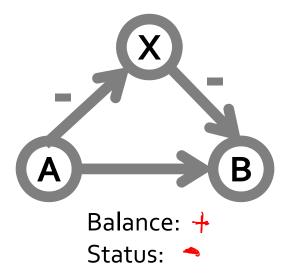


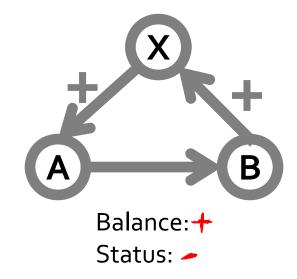
16 *2 signed directed triads

- Is there a better explanantion:
 - Yes. Theory of Status.

Alternate theory: Status

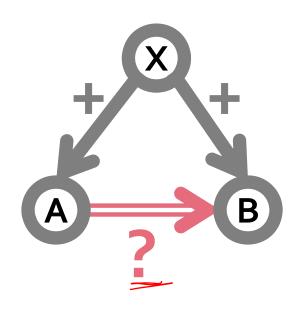
- Links are directed and created over time
- Status theory [Davis-Leinhardt '68, Guha et al. '04, Leskovec et al. '10]
 - Link A → B means: B has higher status than A
 - Link A → B means: B has lower status than A
- Status and balance can give different predictions:

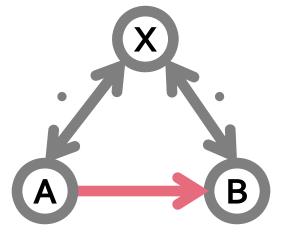




Theory of Status

- Edges are directed
- Edges are created over time
 - X has links to A and B
 - Now, A links to B (triad A-B-X)
 - How does sign of A-B depend signs of X?
- We need to formalize:
 - Links are embedded in triads provides context for signs
 - Users are heterogeneous in their linking behavior

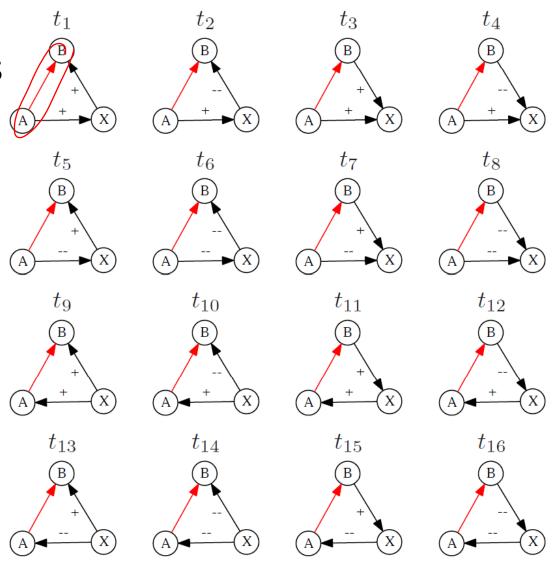




16 types of contexs

Link (A,B) appears in the context (A,B; X)

16 different contextualized links:

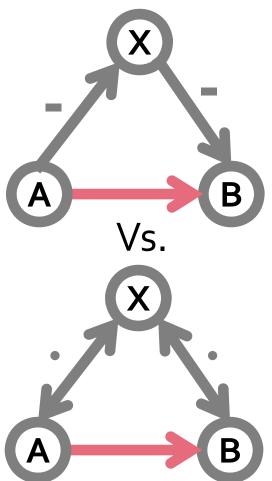


Generative (Receptive) Surprise

- Surprise: How much behavior of user deviates from baseline in context t:
 - (A₁, B₁; X₁),..., (A_n, B_n; X_n) ...
 instances of contextualized link t
 - k of them closed with a plus
 - $p_g(A_i)$... generative baseline of A_i
 - empirical prob. of A_i giving a plus
- Then: generative surprise of triad type t: $k \sum_{i=1}^{n} p_{\sigma}(A_{i})$

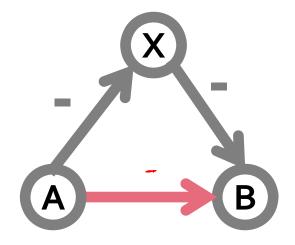
et:

$$s_{g}(t) = \frac{k - \sum_{i=1}^{n} p_{g}(A_{i})}{\sqrt{\sum_{i}^{n} p_{g}(A_{i})(1 - p_{g}(A_{i}))}}$$



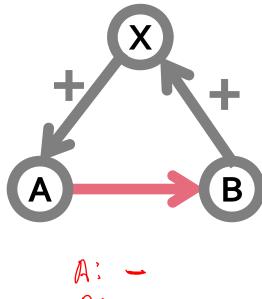
Status: Two Examples

Two basic examples:



Gen. surprise of A:

Rec. surprise of B:

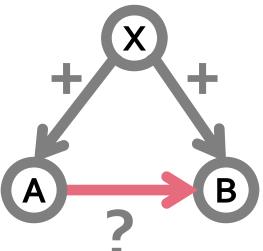


Joint positive endorsement

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

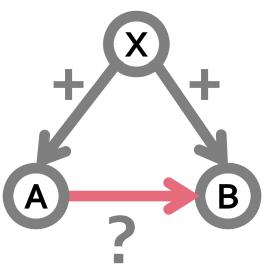
A puzzle:

- In our data we observe:
 Fraction of positive links deviates
 - Above generative baseline of A $\Lambda \gamma^{(h)}$
 - Below receptive baseline of B
- Why?



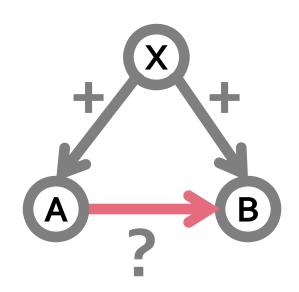
A story: Soccer team

- Ask every node: How does skill of B compare to yours?
 - Build a signed directed network
- We haven't asked A about B
- But we know that X thinksA and B are both better than him
- What can we infer about A's answer?



A story: Soccer team

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



How does A evaluate B?

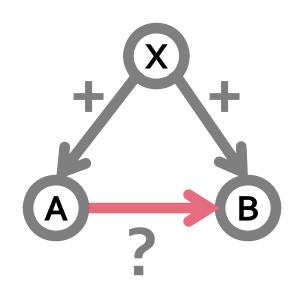
A is evaluating someone who is better than avg.

→ A is more positive than average



A story: Soccer team

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



How is B evaluated by A?

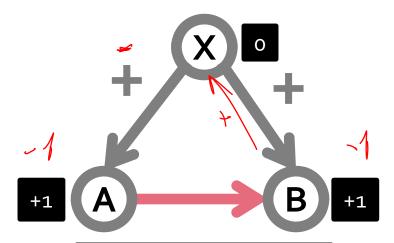
B is evaluated by someone better than average.

→ They will be more negative to B than average

Sign 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



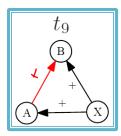
- Surprise is **status**-consistent, if:
 - Gen. surprise is status-consistent if it has same sign as status of B
 - Rec. surprise is status-consistent
 if it has the opposite sign from the status of A
- Surprise is balance-consistent, if:
 - If it completes a balanced triad

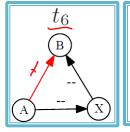
Gen. surprise > 0 Rec. surprise < 0

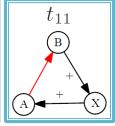
Status vs. Balance (Epinions)

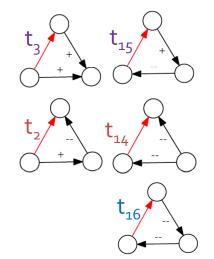
Predictions:

	- 1100							
t_i	count	P(+)	Bout	i) Ar Sin	B_{out}	B_{in}	S_{out}	S_{in}
t_1	178,051	0.97	95.9	197.8	√	✓	√	\checkmark
t_2	45,797	0.54	-151.3	-229.9	\checkmark	\checkmark	\checkmark	
t_3	246,371	0.94	89.9	195.9	\checkmark	\checkmark		\checkmark
t_4	25,384	0.89	1.8	44.9	0	0	\checkmark	\checkmark
t_5	45,925	0.30	18.1	-333.7	0	\checkmark	\checkmark	\checkmark
t_6	11,215	0.23	-15.5	-193.6	Q	0	\checkmark	V
$\frac{t_6}{t_7}$	36,184	0.14	-53.1	-357.3	\checkmark	\checkmark	V	\checkmark
t_8	61,519	0.63	124.1	-225.6	\checkmark	0	\checkmark	A .
t_9	338,238	0.82	207.0	-239.5	\checkmark	6	(🗸)	\checkmark
t_{10}	27,089	0.20	-110.7	-449.6	\checkmark	\checkmark	V	\checkmark
t_{11}	35,093	0.53	-7.4	-260.1	0	0	\checkmark	\checkmark
t_{12}	20,933	0.71	17.2	-113.4	0	\checkmark	\checkmark	√
t_{13}	14,305	0.79	23.5	24.0	0	0	\checkmark	\checkmark
t_{14}	30,235	0.69	-12.8	-53.6	0	0	\checkmark	
t_{15}	17,189	0.76	6.4	24.0	0	0		\checkmark
t_{16}	4,133	0.77	11.9	-2.6	\checkmark	0	✓	•
Number of correct predictions					8	7	14	13









From Local to Global Structure

- Fraction of edges of the network that satisfy Balance and Status?
- Observations:
 - No evidence for global balance beyond the random baselines
 - Real data is 80% consistent vs. 80% consistency under random baseline
 - Evidence for global status beyond the random baselines
 - Real data is 80% consistent, but 50% consistency under random baseline

From Local to Global Structure

- Both theories make predictions about the global structure of the network
- Structural balance Factions
 - Find coalitions
- Status theory Global Status
 - Flip direction and sign of minus edges
 - Assign each node a unique status so that edges point from low to high

From Local to Global Structure

- Fraction of edges of the network that satisfy Balance and Status?
- Observations:
 - No evidence for global balance beyond the random baselines
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 - Evidence for global status beyond the random baselines
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Predicting edge signs

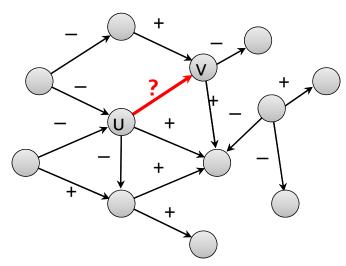
Edge sign prediction problem

 Given a network and signs on all but one edge, predict the missing sign

Machine Learning formulation:

- Predict sign of edge (u,v)
- Class label:
 - +1: positive edge
 - -1: negative edge
- Learning method:
 - Logistic regression

$$P(+|x) = \frac{1}{1 + e^{-(b_0 + \sum_{i=0}^{n} b_i x_i)}}$$



- Dataset:
 - Original: 80% +edges
 - Balanced: 50% +edges
- Evaluation:
 - Accuracy and ROC curves
- Features for learning:
 - Next slide

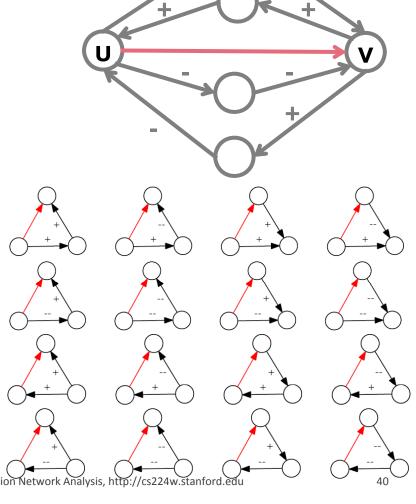
Features for learning

For each edge (u,v) create features:

Triad counts (16):

 Counts of signed triads edge u→v takes part in

- Node degree (7 features):
 - Signed degree:
 - d⁺_{out}(u), d⁻_{out}(u), d⁺_{in}(v), d⁻_{in}(v)
 - Total degree:
 - d_{out}(u), d_{in}(v)
 - Embeddedness of edge (u,v)



Edge sign prediction

Classification accuracy:

Epinions: 93.5%

Slashdot: 94.4%

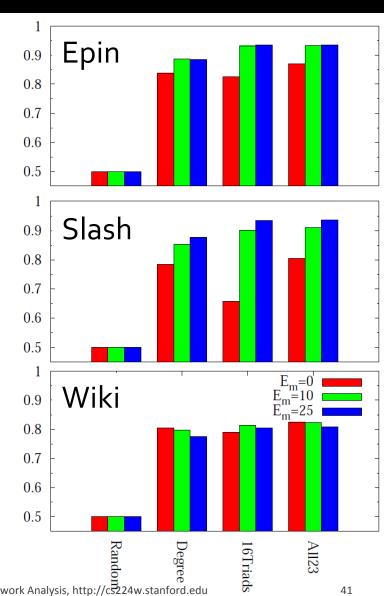
Wikipedia: 81%

 Signs can be modeled from local network structure alone

 Trust propagation model of [Guha et al. '04] has 14% error on Epinions

 Triad features perform less well for less embedded edges

- 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 "dataset", predict on "column"

All23	Epinions	Slashdot	Wikipedia
Epinions	0.9342	0.9289	0.7722
Slashdot	0.9249	0.9351	0.7717
Wikipedia	0.9272	0.9260	0.8021

 Almost perfect generalization of the models even though networks come from very different applications

Conclusions

Status vs. Balance, Consistent use of signs

