

Jure will **not** hold office hours tomorrow (Wed 10/8).
Alternative office hours will be held on Friday 10/10 5-6pm.

Human Evaluations and Signed Networks

CS224W: Social and Information Network Analysis
Jure Leskovec, Stanford University
<http://cs224w.stanford.edu>



How the Class Fits Together

Observations

Small diameter,
Edge clustering

Patterns of signed
edge creation

Viral Marketing, Blogosphere,
Memetracking

Scale-Free

Densification power law,
Shrinking diameters

Strength of weak ties,
Core-periphery

Models

Erdős-Renyi model,
Small-world model

Structural balance,
Theory of status

Independent cascade model,
Game theoretic model

Preferential attachment,
Copying model

Microscopic model of
evolving networks

Kronecker Graphs

Algorithms

Decentralized search

Models for predicting
edge signs

Influence maximization,
Outbreak detection, LIM

PageRank, Hubs and
authorities

Link prediction,
Supervised random walks

Community detection:
Girvan-Newman, Modularity

People Express Opinions

In many online applications users express positive and negative attitudes/opinions:

- Through actions:

- Rating a product/person
- Pressing a “like” button

- Through text:

- Writing a comment, a review

- **Success of these online applications is built on people expressing opinions**

- Recommender systems
- Wisdom of the Crowds
- Sharing economy

amazon.com.



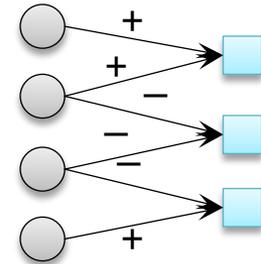
WIKIPEDIA
The Free Encyclopedia



People & Evaluations

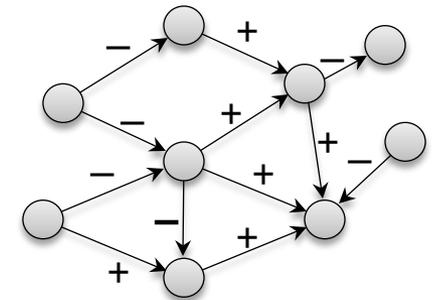
- **About items:**

- Movie and product reviews



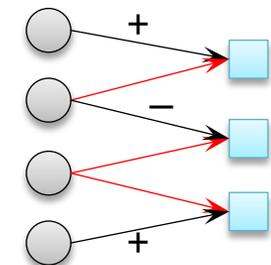
- **About other users:**

- Online communities



- **About items created by others:**

- Q&A websites



User-User Evaluations

- **Many on-line settings where one person expresses an opinion about another (or about another's content)**
 - **I trust you** [Kamvar-Schlosser-Garcia-Molina '03]
 - **I agree with you** [Adamic-Glance '04]
 - **I vote in favor of admitting you into the community** [Cosley et al. '05, Burke-Kraut '08]
 - **I find your answer/opinion helpful** [Danescu-Niculescu-Mizil et al. '09, Borgs-Chayes-Kalai-Malekian-Tennenholtz '10]

Evaluations: Some Issues

Some of the central issues:

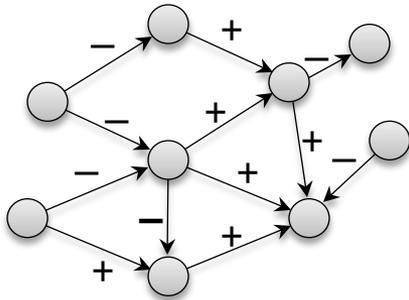
- **Factors:**

What factors drive one's evaluations?

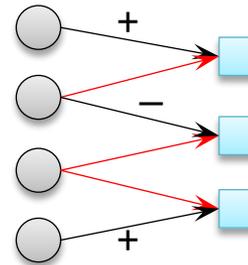
- **Synthesis:**

How do we create a composite description that accurately reflects cumulative opinion of the community?

Evaluations: the Setting



Direct

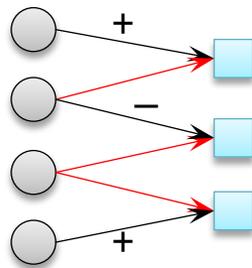
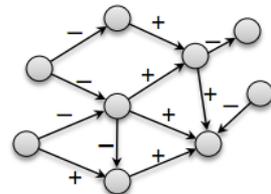


Indirect

- **Direct:** User to user
- **Indirect:** User to content (created by another member of a community)
- **Where online does this explicitly occur on a large scale?**

Evaluations: the Data

- **Wikipedia adminship elections**
 - Support/Oppose (120k votes in English)
 - 4 languages: EN, GER, FR, SP
- **Stack Overflow Q&A community**
 - Upvote/Downvote (7.5M votes)
- **Epinions product reviews**
 - Ratings of others' product reviews (13M)
 - 5 = positive, 1-4 = negative

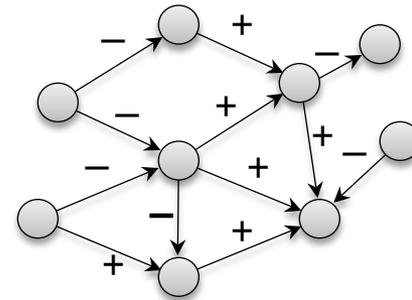


Two ways to look at this

- There are two ways to look at this:
One person evaluates the other via a positive/negative evaluation



First we focus on a
single evaluation
(without the context
of a network)



Then we will focus on
evaluations in the
context of a network

Human Evaluations

- What drives human evaluations?



- How do properties of **evaluator A** and **target B** affect A's vote?
 - **Status** and **Similarity** are two fundamental drivers behind human evaluations

Definitions

■ **Status:**

Level of recognition, merit, achievement, reputation in the community

- Wikipedia: # edits, # barnstars
- Stack Overflow: # answers

■ **User-user Similarity:**

- Overlapping topical interests of **A** and **B**
 - **Wikipedia:** Similarity of the articles edited
 - **Stack Overflow:** Similarity of users evaluated

Relative vs. Absolute Assessment

- How do properties of **evaluator A** and **target B** affect A's vote?



- **Two natural (but competing) hypotheses:**
 - **(1)** Prob. that B receives a positive evaluation depends primarily on the characteristics of B
 - There is some objective criteria for user B to receive a positive evaluation

Relative vs. Absolute Assessment

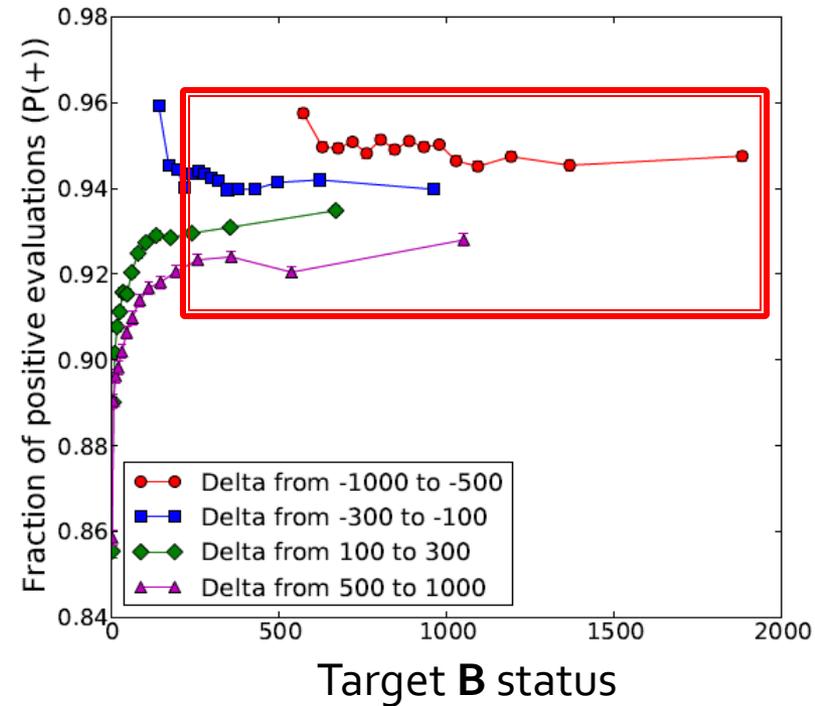
- How do properties of **evaluator A** and **target B** affect A's vote?



- **Two natural (but competing) hypotheses:**
 - (2) Prob. that B receives a positive evaluation depends on relationship between the characteristics of A and B
 - User A compares herself to user B and then makes the evaluation

Effects of Status

- **How does status of B affect A's evaluation?**
 - Each curve is fixed status difference: $\Delta = S_A - S_B$
- **Observations:**
 - **Flat curves:** Prob. of positive eval. $P(+)$ doesn't depend on B's status
 - **Different levels:** Different values of Δ result in different behavior

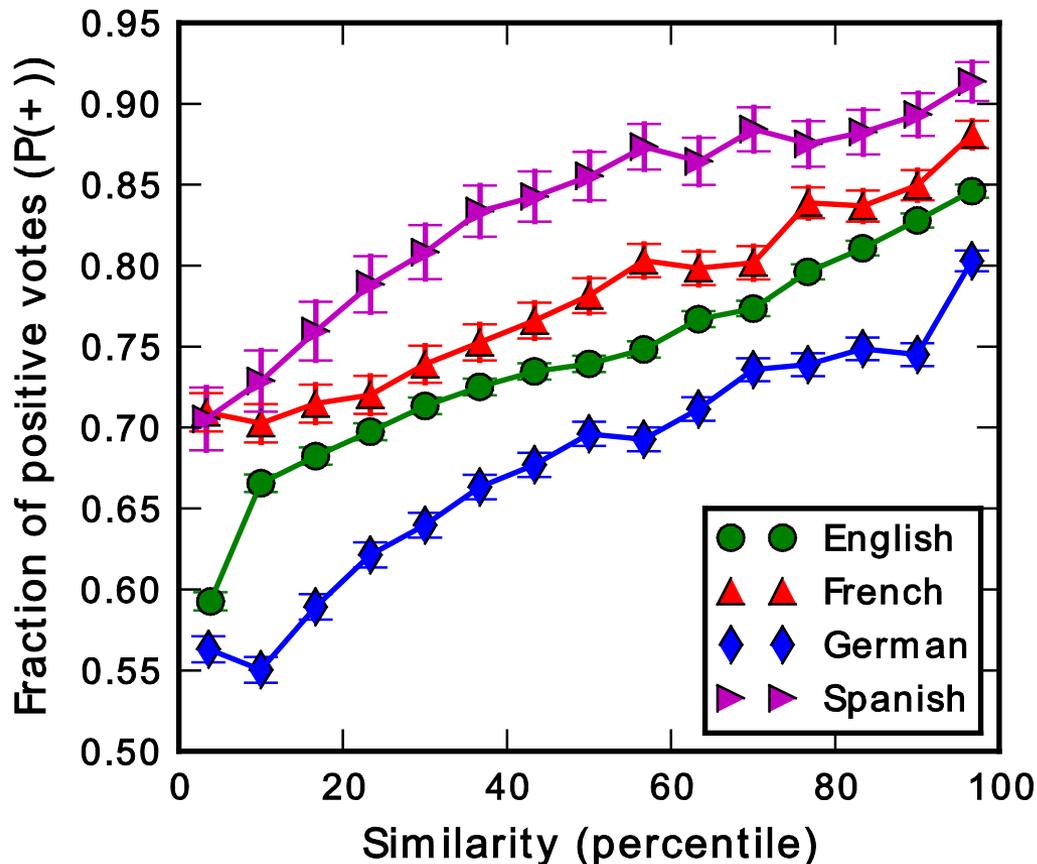


We keep increasing status of B, while keeping the status difference ($S_A - S_B$) fixed

Effects of Similarity

- **How does prior interaction shape evaluations? 2 hypotheses:**
 - **(1)** Evaluators are more supportive of targets in their area
 - “The more similar you are, the more I like you”
 - **(2)** More familiar evaluators know weaknesses and are more harsh
 - “The more similar you are, the better I can understand your weaknesses”

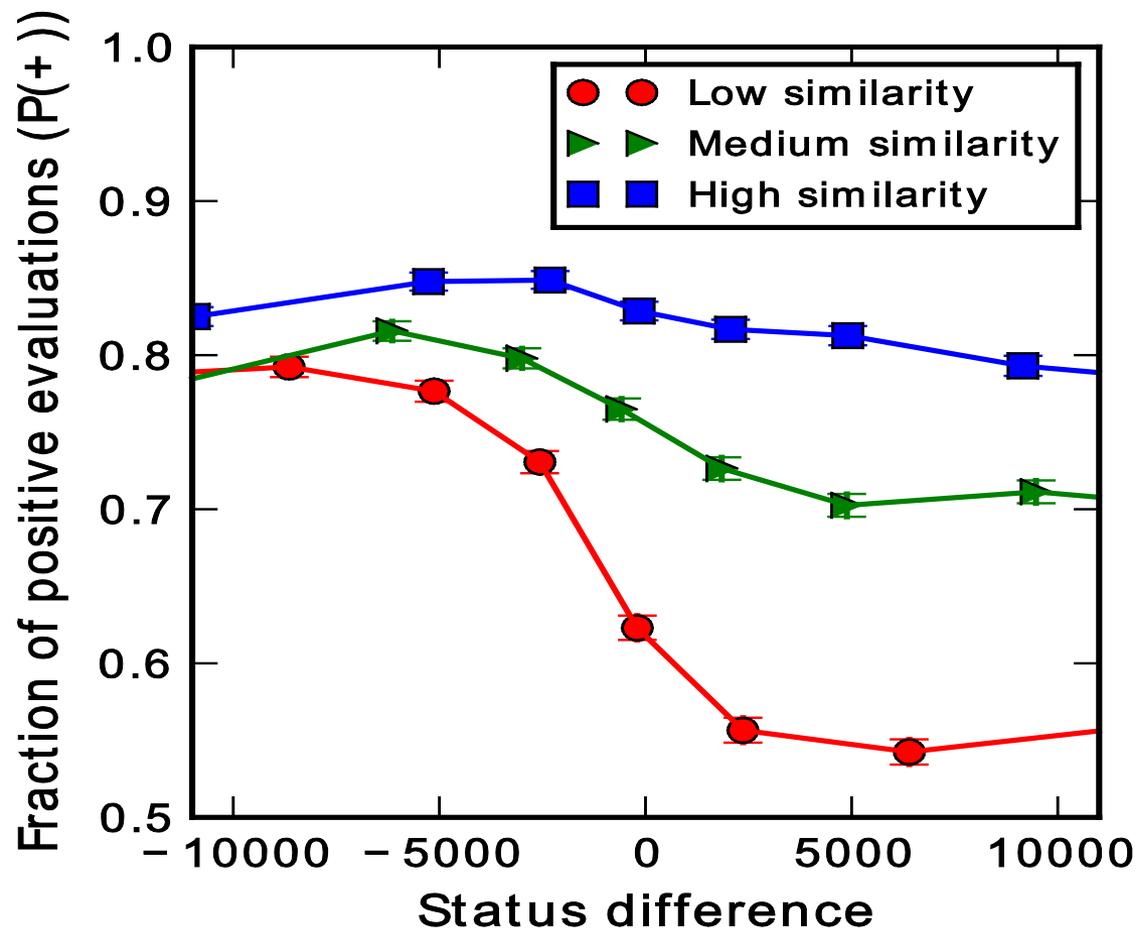
Effects of Similarity



Prior interaction/ similarity boosts positive evaluations

Similarity: For each user create a set of words of all articles she edited. The similarity is then the Jaccard similarity between the two sets of words. Then sort the user pairs by similarity and bucket them into percentile.

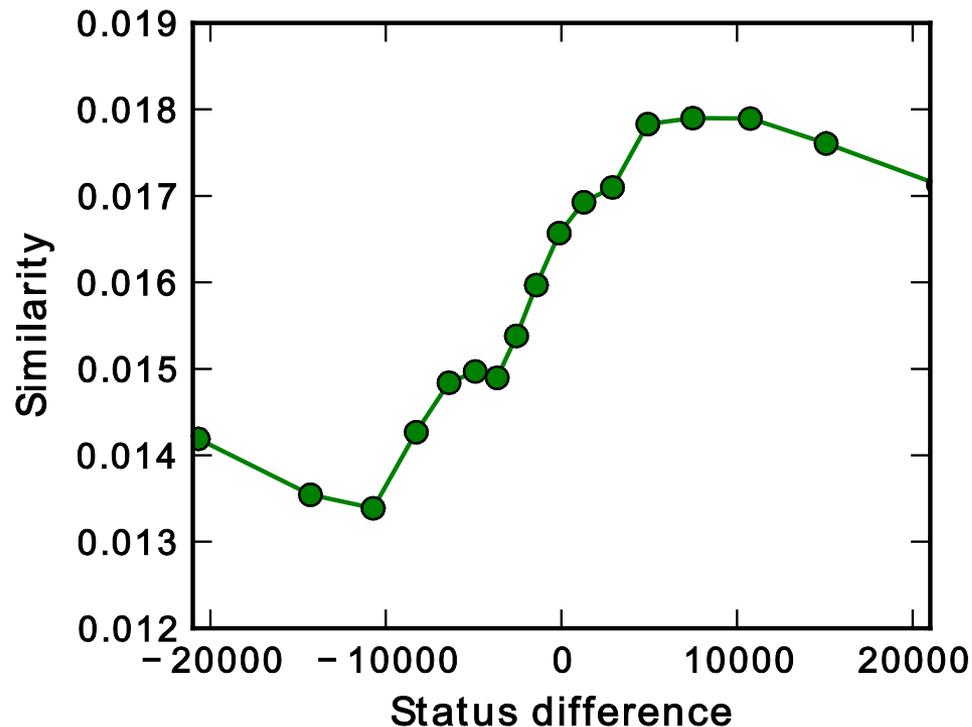
Status & Similarity



Status is a proxy for quality when evaluator does not know the target

Status & Similarity

■ Who shows up to evaluate?

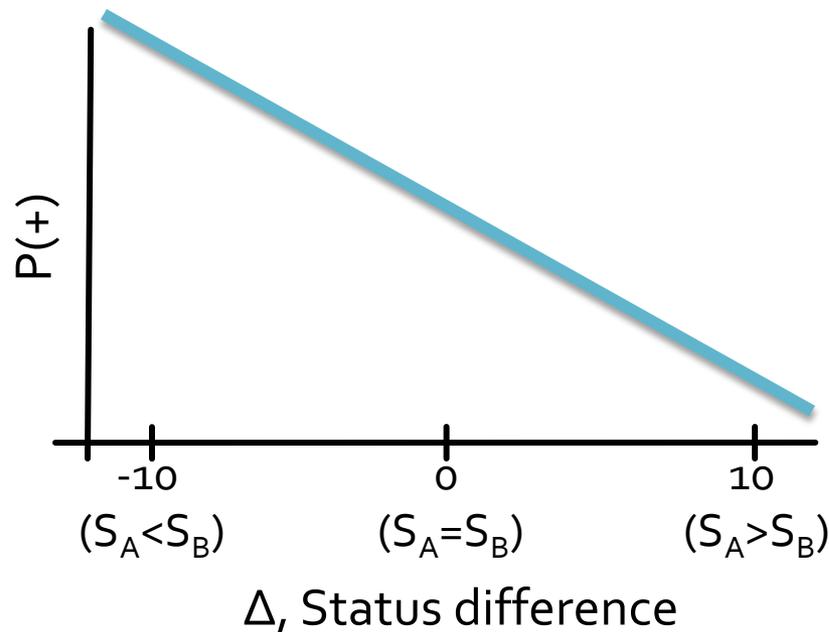


Elite evaluators
vote on targets in
their area of
expertise

- Selection effect in who gives the evaluation
 - If $S_A > S_B$ then A and B are more likely to be similar

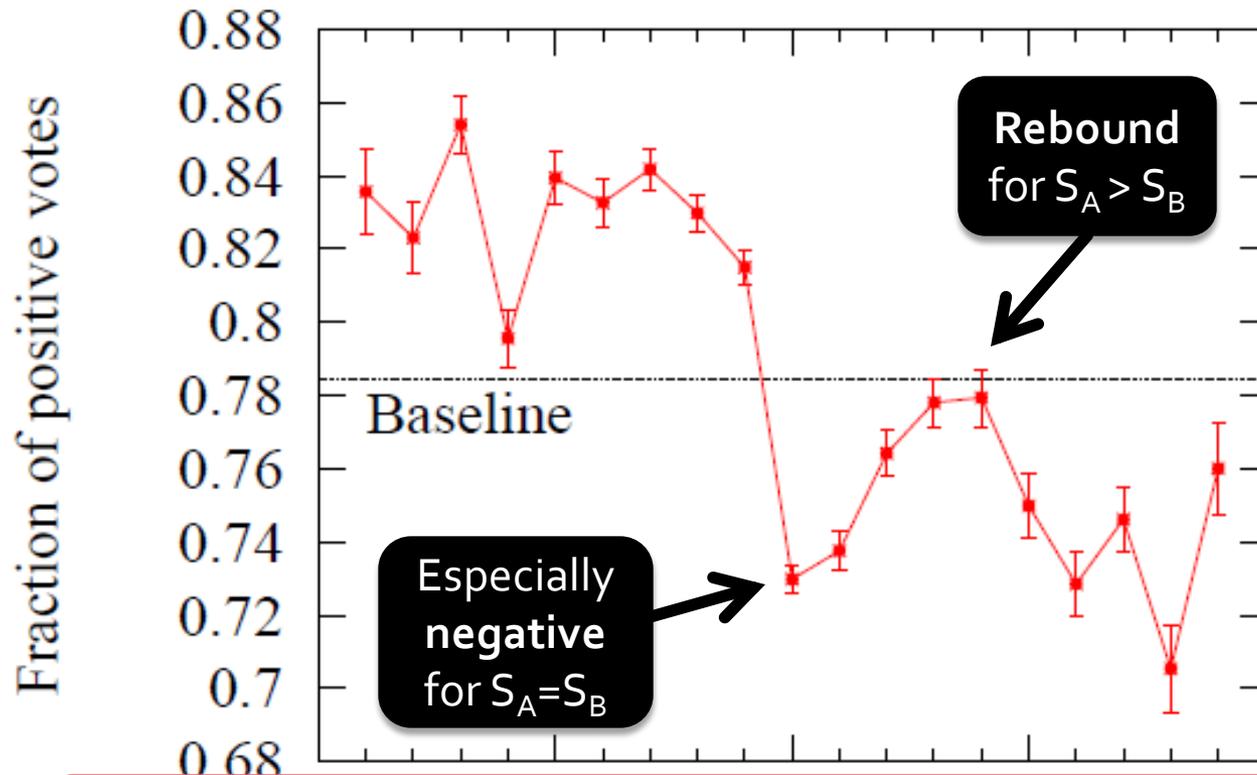
A Puzzle

- What is $P(+)$ as a function of $\Delta = S_A - S_B$?
 - Based on findings so far:
Monotonically decreasing



A Puzzle: The Mercy Bounce

- What is $P(+)$ as a function of $\Delta = S_A - S_B$?

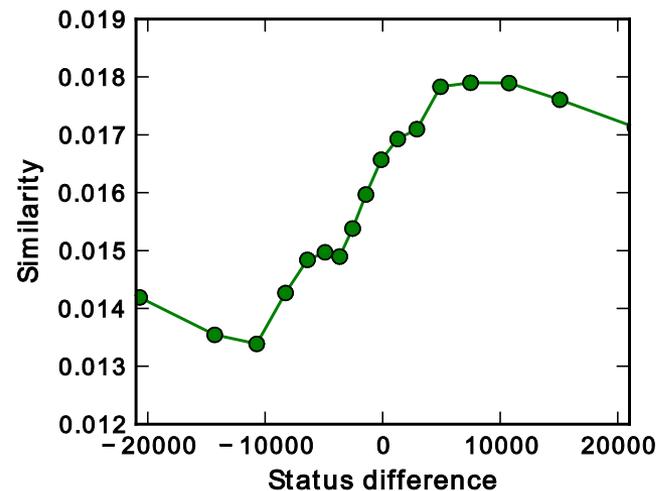
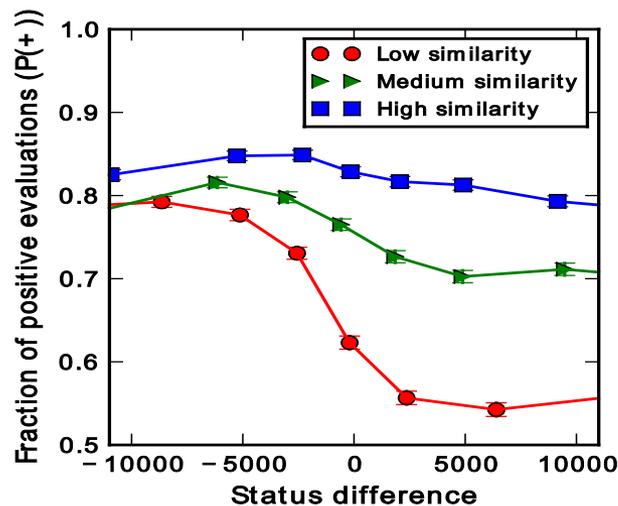


Computed over
120k votes

How can we explain this?

The Mercy Bounce

- **Why low evals. of users of same status?**
 - Not due to users being tough on each other
 - **But due to the effects of similarity**



- **So: High-status evaluators tend to be more favorably disposed**

Aggregating Evaluations

- **So far:** Properties of individual evaluations
- **But:** Evaluations need to be “summarized”
 - Determining rankings of users or items
 - Multiple evaluations lead to a group decision
- **How to aggregate user evaluations to obtain the opinion of the community?**
 - Can we guess community’s opinion from a small fraction of the makeup of the community?

Ballot-blind Prediction

- **Predict Wikipedia adminship election results without seeing the votes**
 - Observe identities of the first k ($=5$) people voting (but *not* how they voted)
 - Want to predict the election outcome
 - Promotion vs. no promotion
- **Why is it hard?**
 - Don't see the votes (just voters)
 - Only see first 5 voters (out of ~ 50)



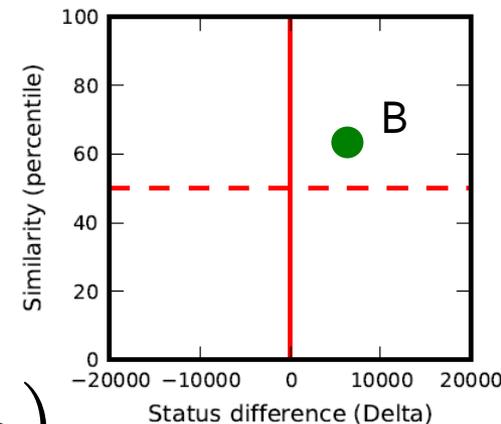
Ballot-blind: The Model

- Want to model prob. user A votes + in election of user B
- Our model:

$$P(A = + | B) = P_A + d(\Delta_B, S_B)$$

- P_A ... empirical fraction of +votes of A
- $d(S, \Delta)$... avg. deviation in fraction of +votes
 - When A s evaluate B from a particular (S, Δ) quadrant, how does this change their behavior?

- Predict 'elected' if: $\sum_{i=1}^k P(A_i = + | B) > w$



Ballot-blind Prediction

- **Based on only who showed to vote predict the outcome of the election**

Number of voters seen	Accuracy
5	71.4%
10	75.0%
all	75.6%

- **Other methods:**
 - Guessing gives 52% accuracy
 - Logistic Regression on status and similarity features: 67%
 - If we see the first $k=5$ votes 85% (gold standard)

Theme: Learning from implicit feedback

Audience composition tells us something about their reaction

Summary

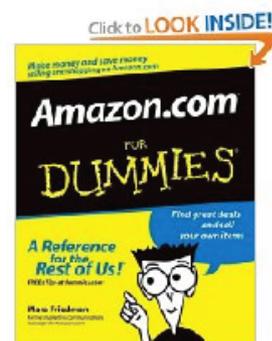
- **Social media sites are governed by** (often implicit) **user evaluations**
- Wikipedia voting process has an **explicit**, **public** and **recorded** process of **evaluation**
- **Main characteristics:**
 - Importance of relative assessment: **Status**
 - Importance of prior interaction: **Similarity**
 - Diversity of individuals' response functions
- **Application: Ballot-blind prediction**

Important Points

- **Status seems to be salient feature**
- **Similarity** also plays important role
- Audience composition helps predict audience's reaction
- **What kinds of opinions do people find helpful?**

What do People Find Helpful?

- What do people think about our recommendations and opinions?



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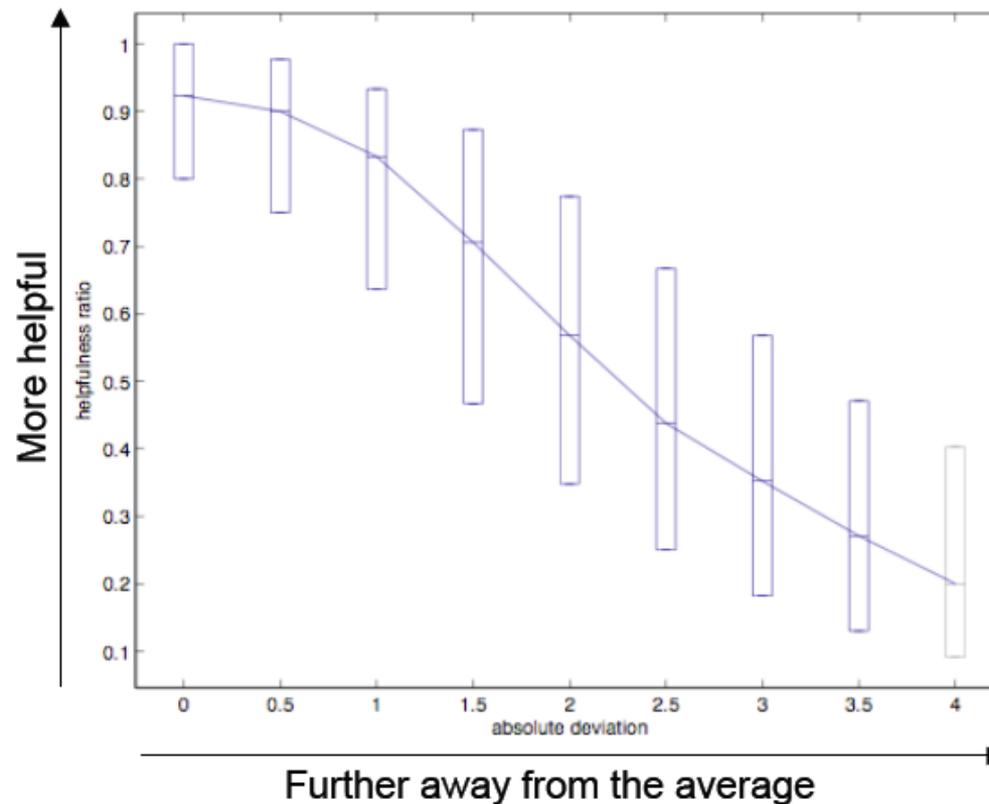
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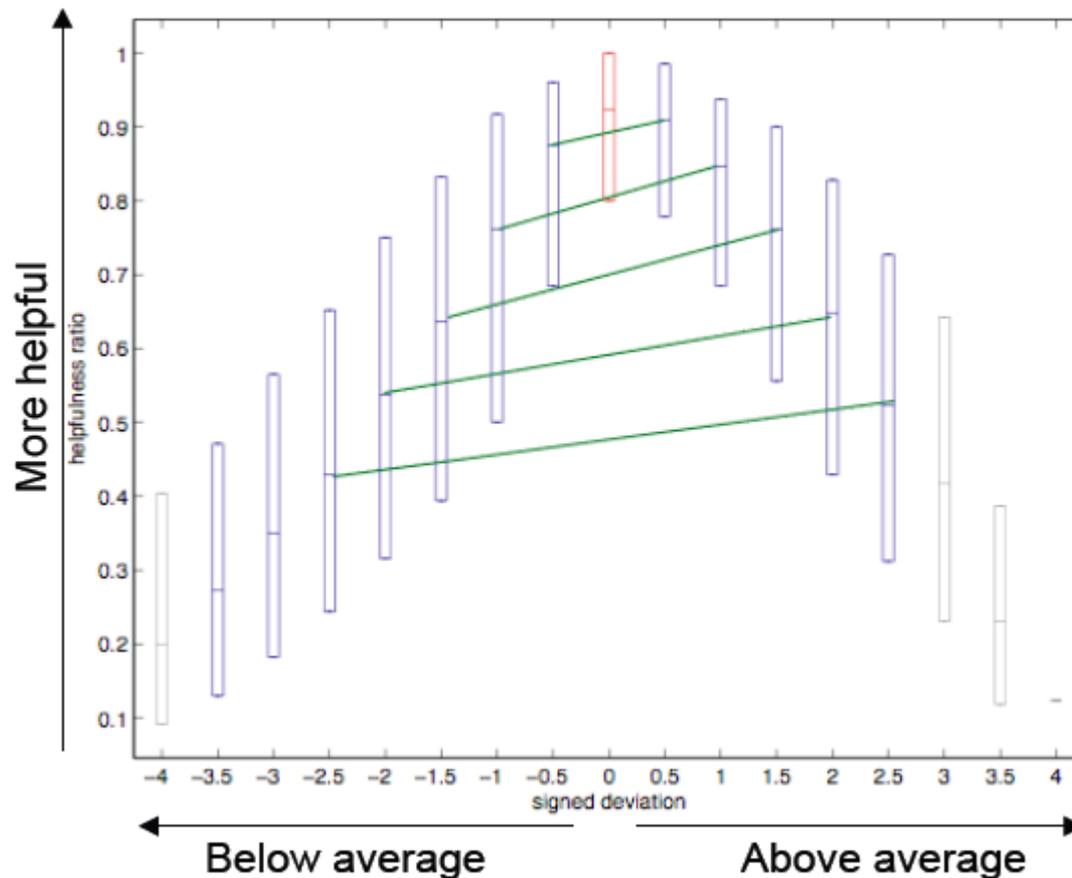
Review Helpfulness: Conformity

- Are **conforming** opinions more helpful?



Review Helpfulness: Deviation

- Are **Positive** reviews are more helpful?



Slight bias towards positive reviews

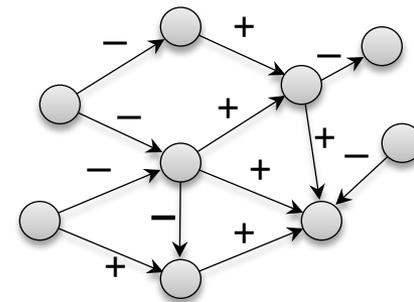
**Evaluations happen in a
context of a network!**

Two ways to look at this

- There are two ways to look at this:
One person evaluates the other via a positive/negative evaluation



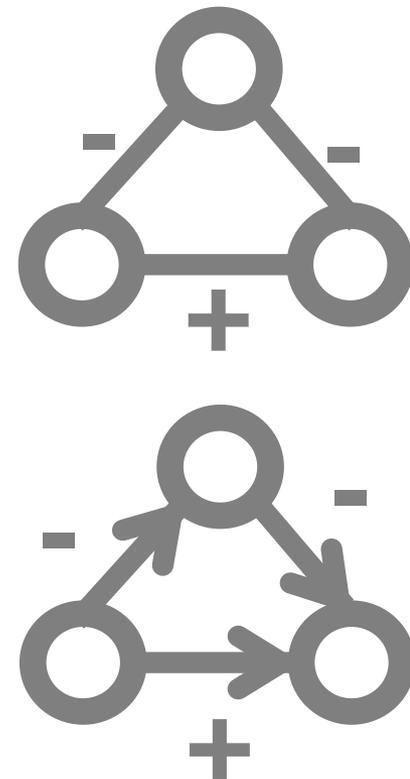
So far we focused on a
single evaluation
(without the context
of a network)



Now we will focus on
evaluations in the
context of a network

Signed Networks

- **Networks with positive and negative relationships**
- Our basic unit of investigation will be **signed triangles**
- First we talk about **undirected** networks then **directed**
- **Plan:**
 - **Model:** Consider two soc. theories of signed nets
 - **Data:** Reason about them in large online networks
 - **Application:** Predict if A and B are linked with + or -

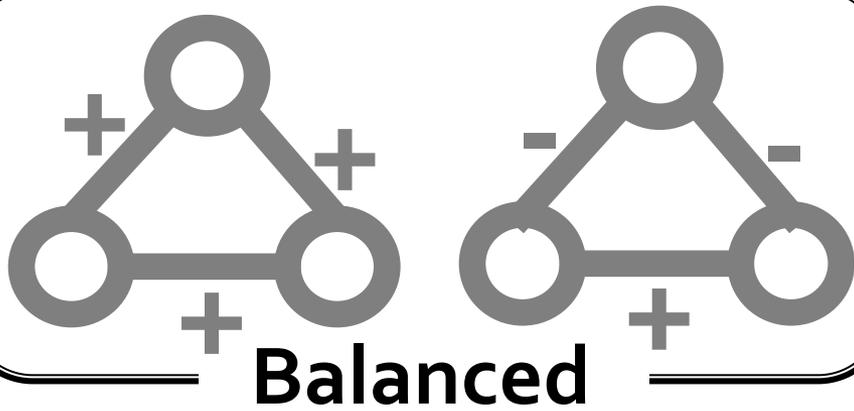


Signed Networks

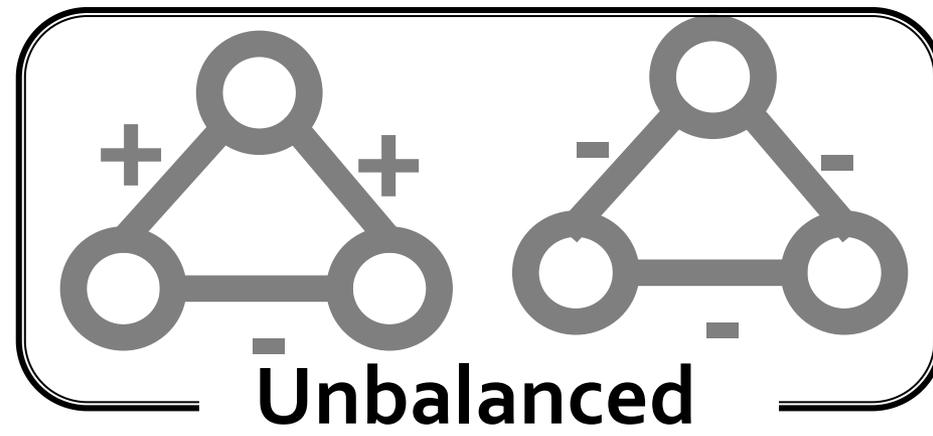
- Networks with **positive** and **negative** relationships
- Consider an undirected complete graph
- Label each edge as either:
 - **Positive**: friendship, trust, positive sentiment, ...
 - **Negative**: enemy, distrust, negative sentiment, ...
- Examine triples of connected nodes A, B, C

Theory of Structural Balance

- **Start with the 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:



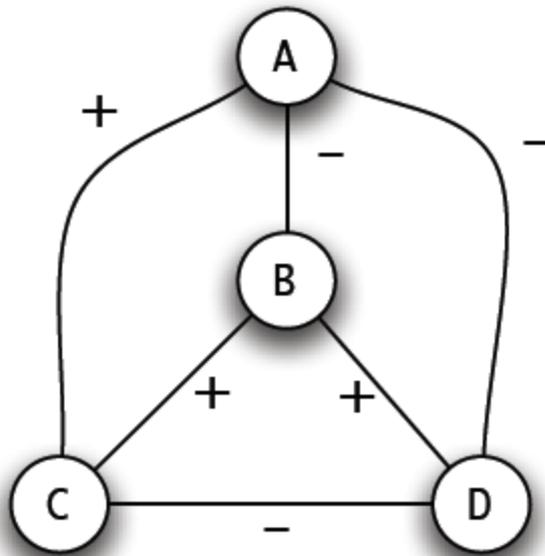
Consistent with "friend of a friend" or "enemy of the enemy" intuition



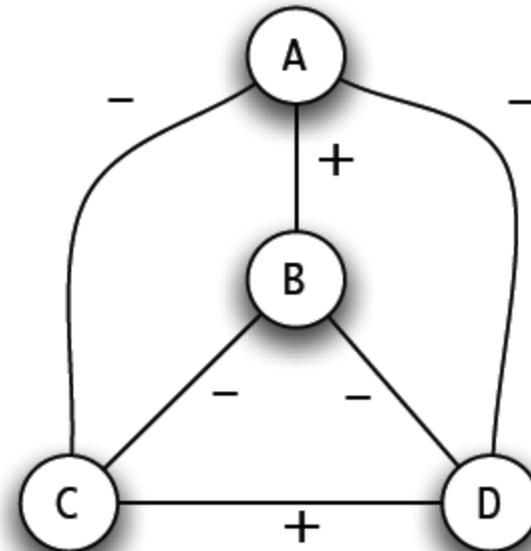
Inconsistent with the "friend of a friend" or "enemy of the enemy" intuition

Balanced/Unbalanced Networks

- Graph is **balanced** if every connected triple of nodes has:
 - All 3 edges labeled +, or
 - Exactly 1 edge labeled +



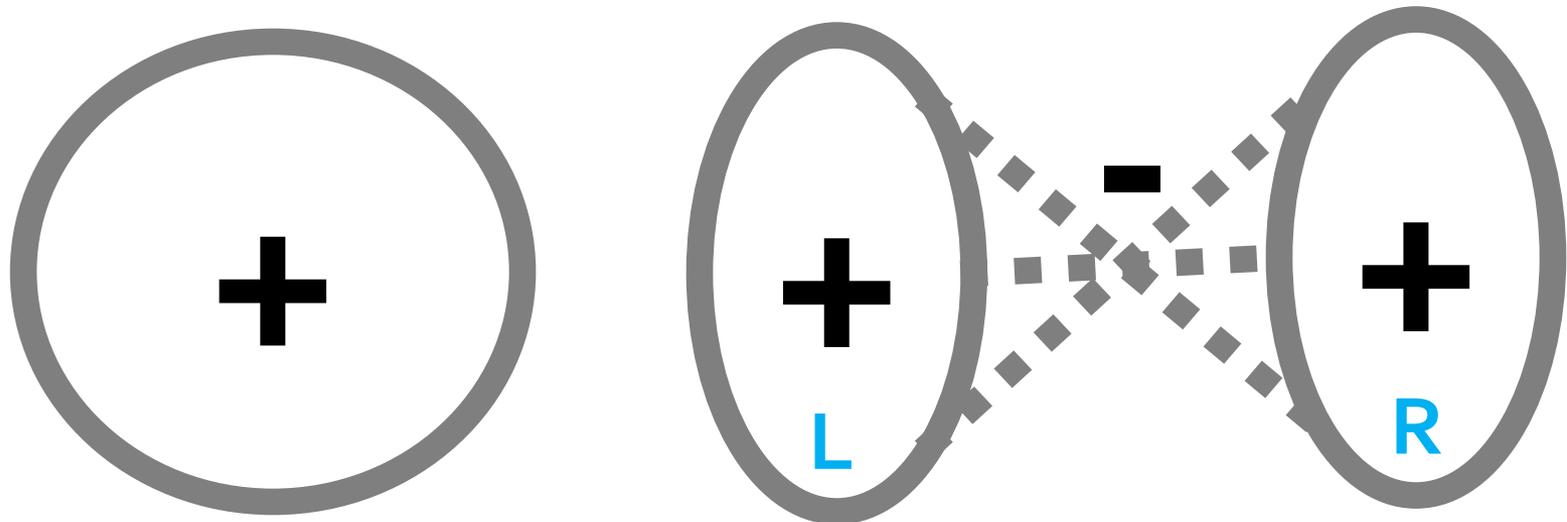
Unbalanced



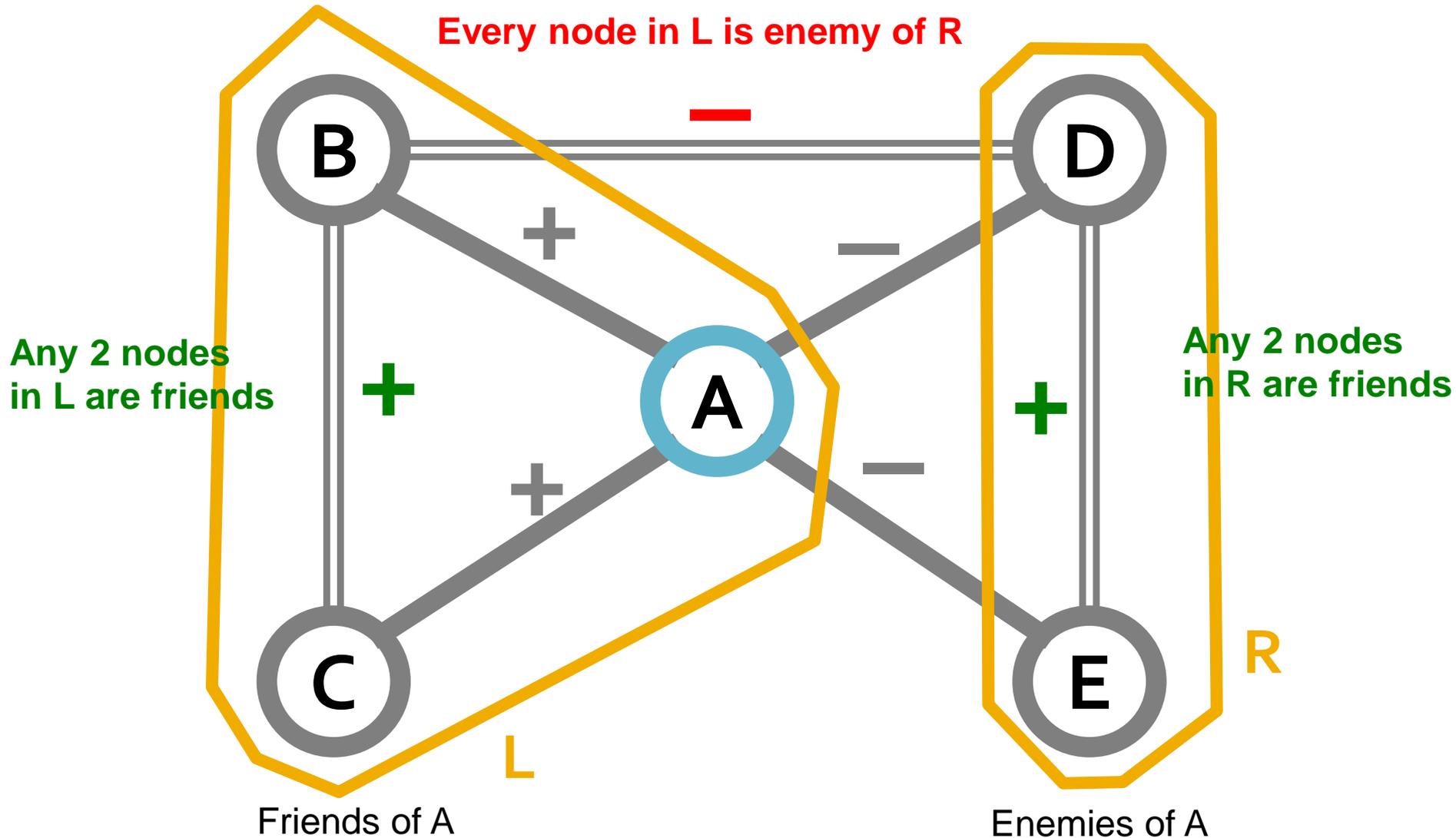
Balanced

Local Balance \rightarrow Global Factions

- **Balance implies global coalitions** [Cartwright-Harary]
- If all triangles are balanced, then either:
 - The network contains only positive edges, or
 - Nodes can be split into 2 sets where negative edges only point between the sets



Analysis of Balance



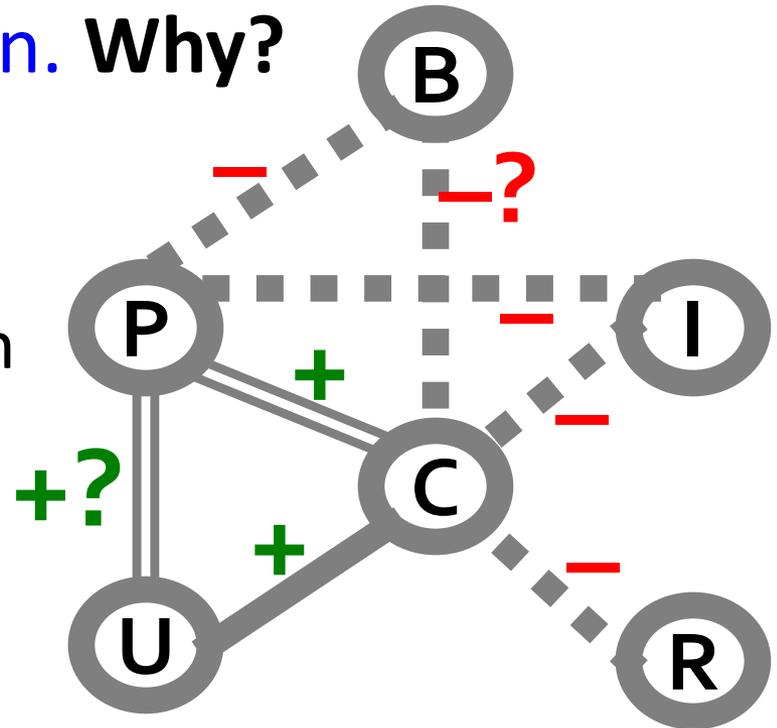
Example: International Relations

- **International relations:**

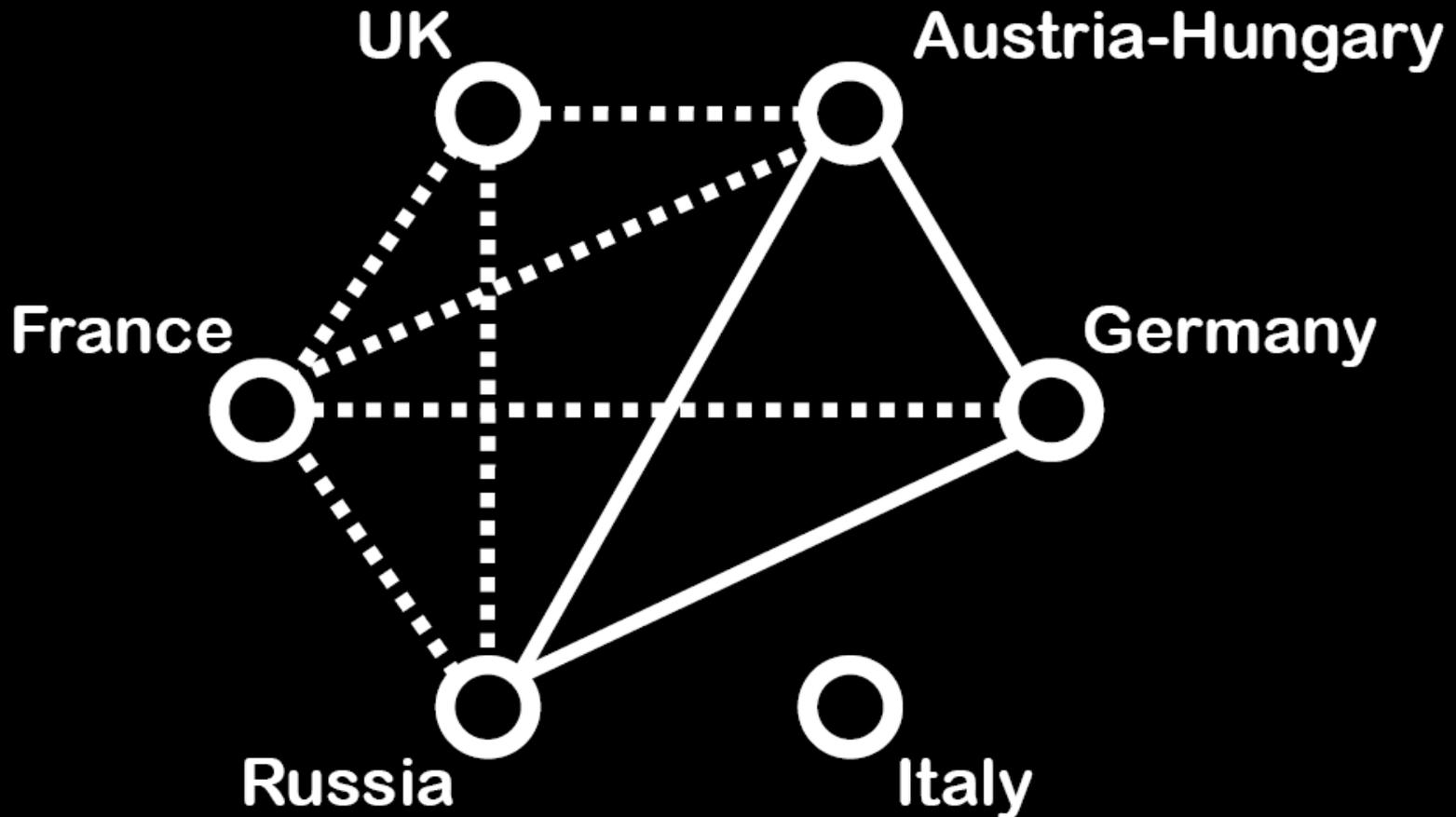
- **Positive** edge: alliance
- **Negative** edge: animosity

- Separation of Bangladesh from Pakistan in 1971: **US supports Pakistan. Why?**

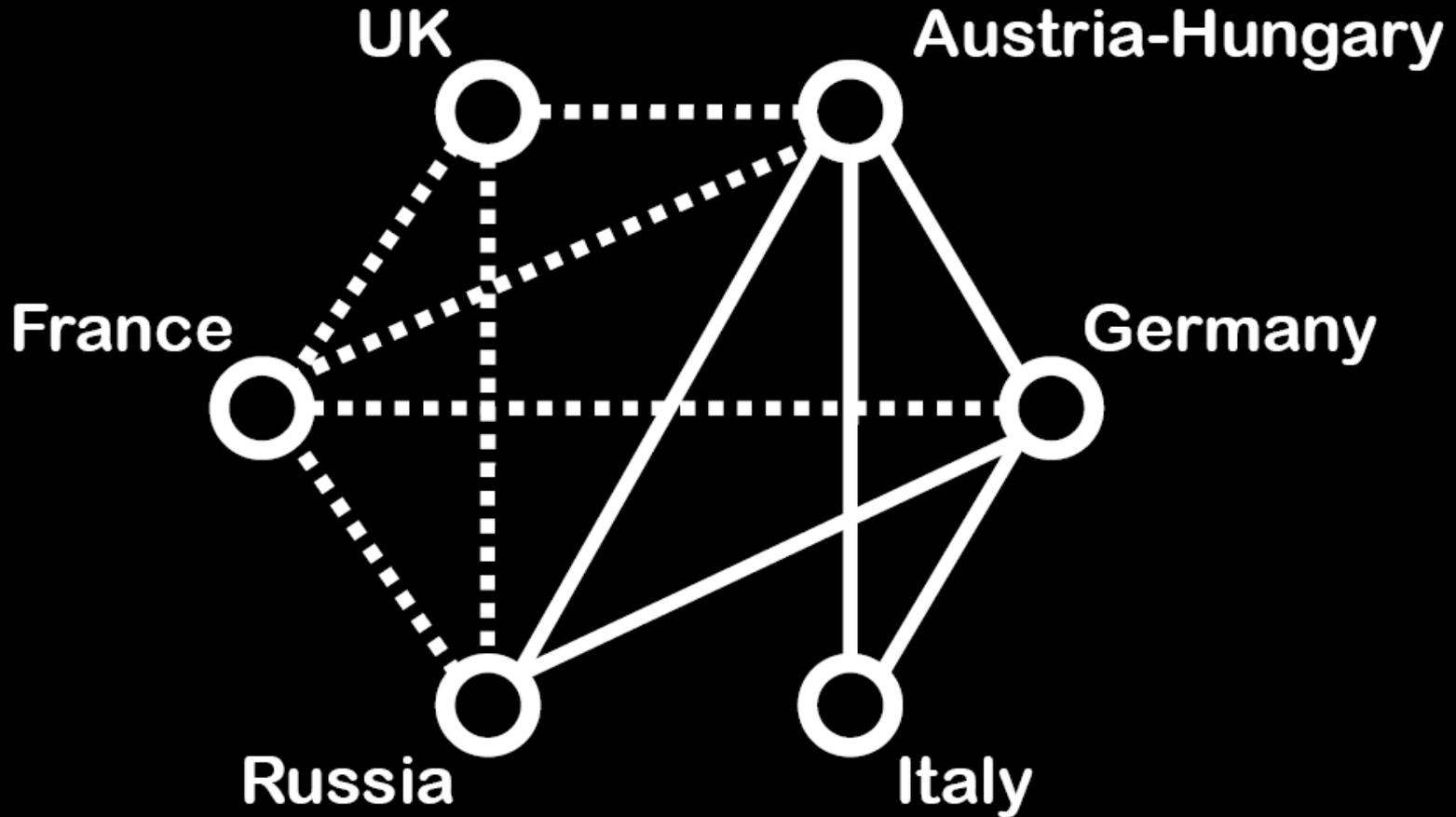
- USSR was enemy of China
- China was enemy of India
- India was enemy of Pakistan
- US was friendly with China
- China vetoed Bangladesh from U.N.



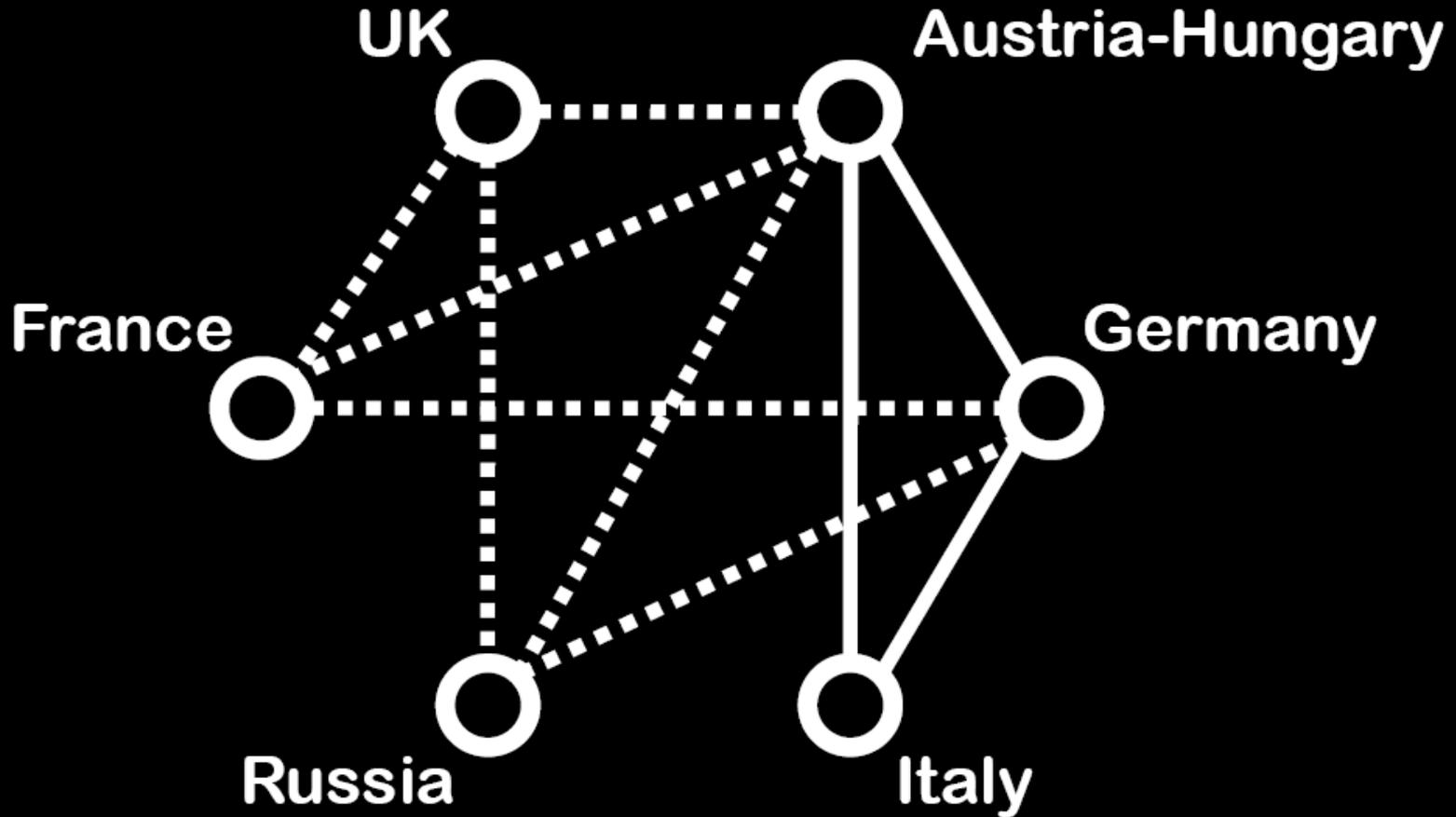
1872-1881



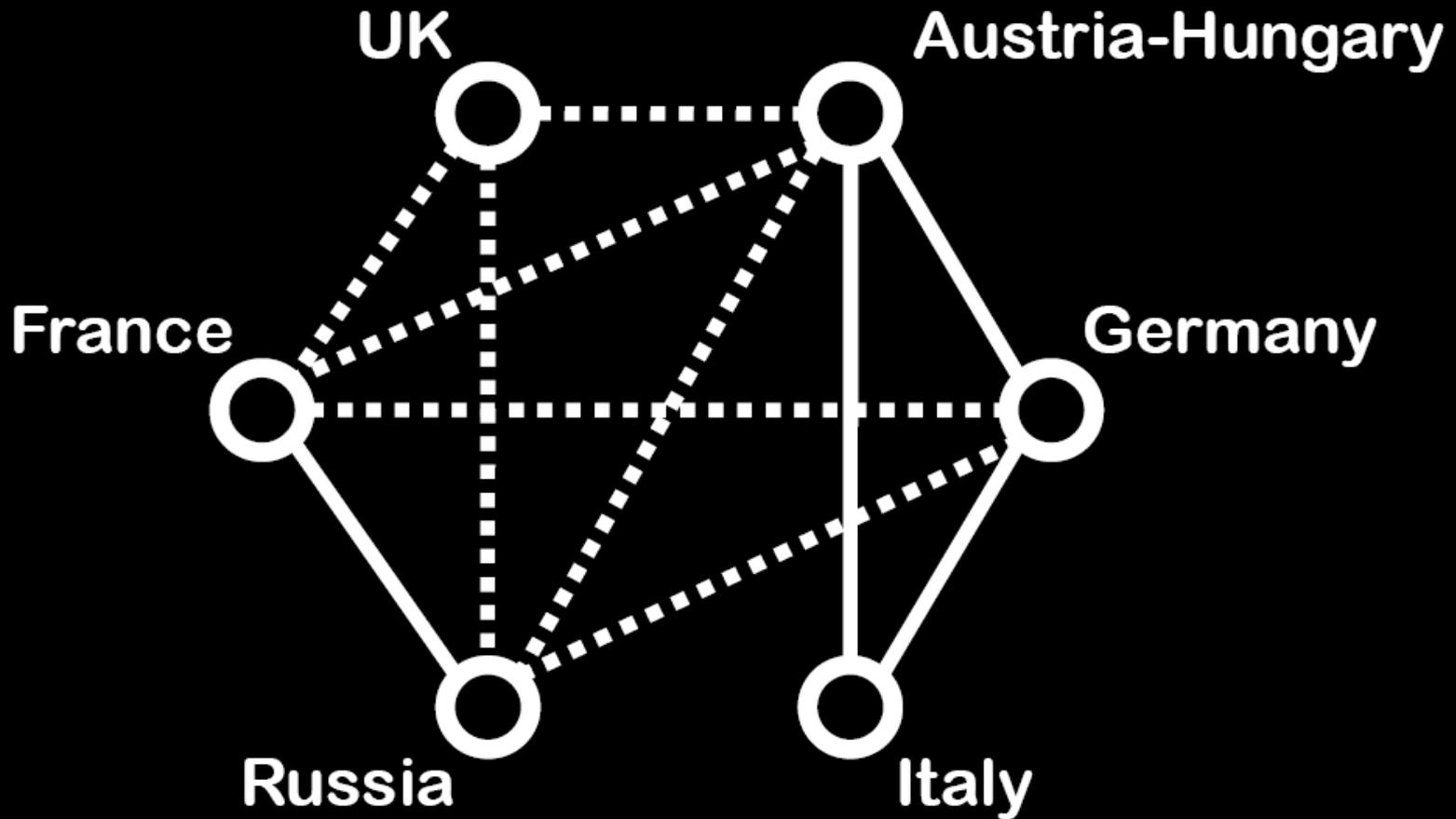
1882



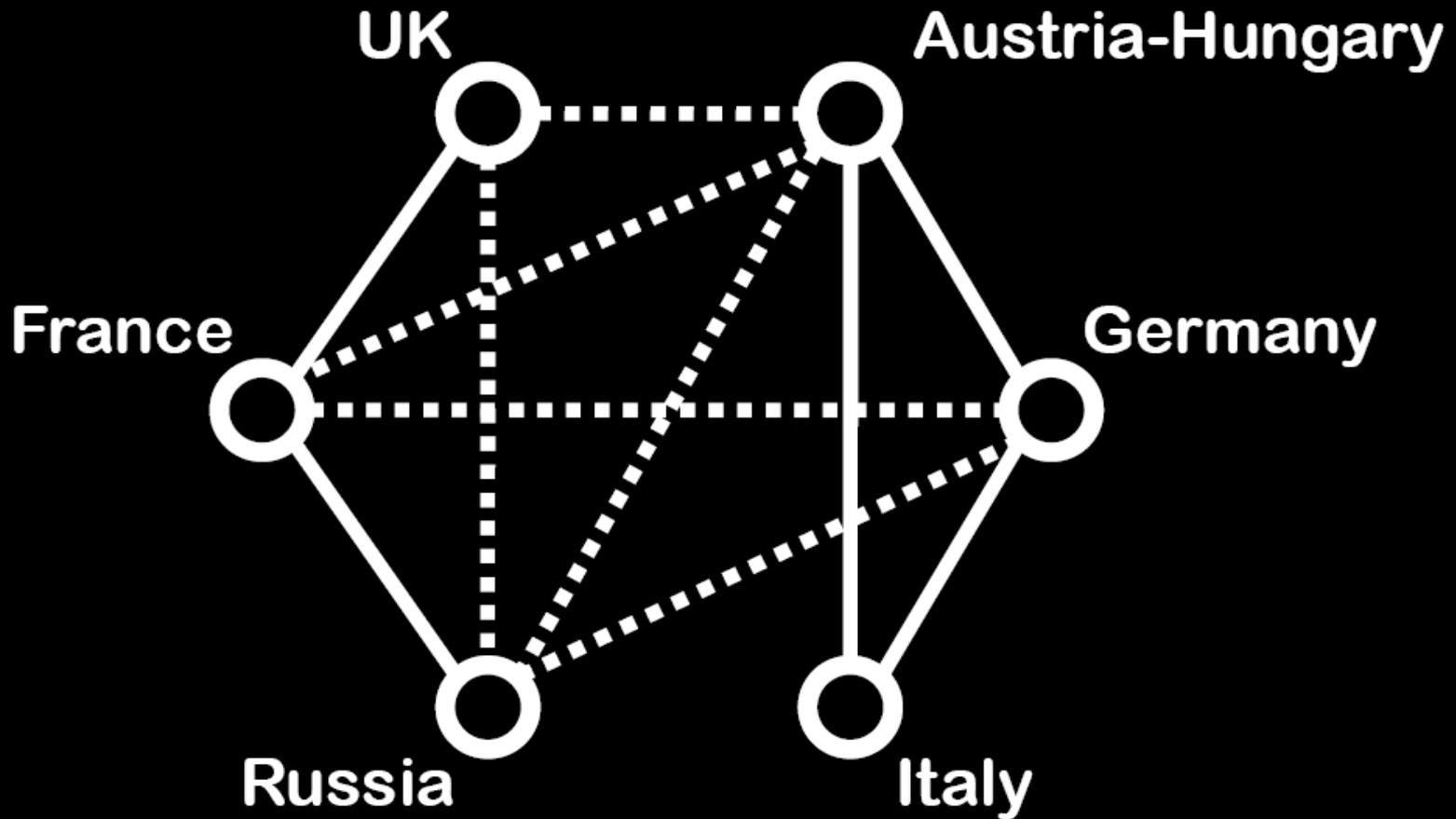
1890



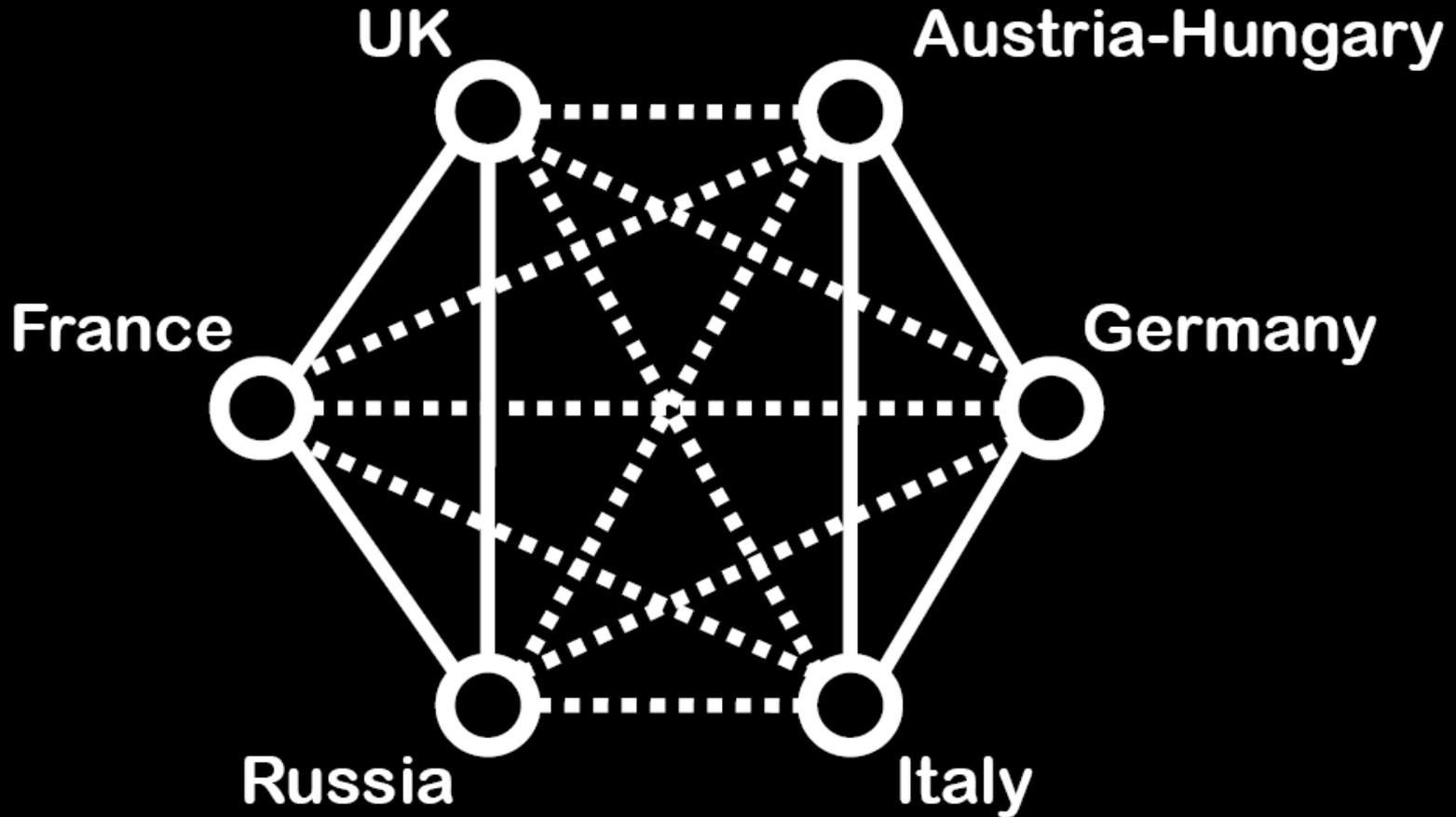
1891-1894



1904

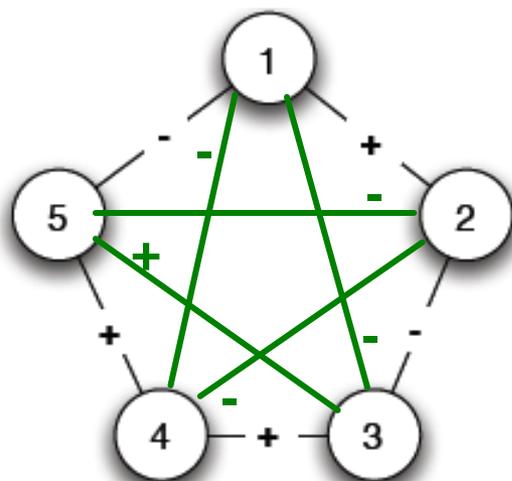


1907



Balance in General Networks

- So far we talked about complete graphs



Balanced?

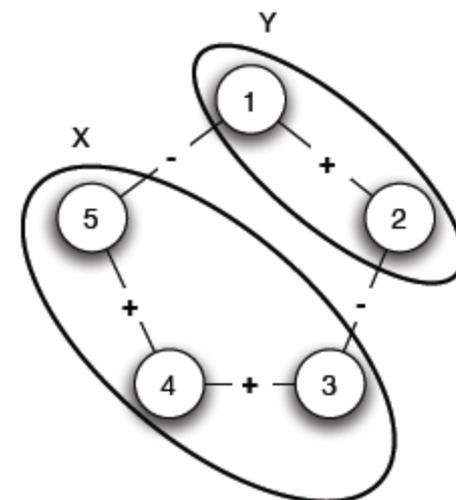
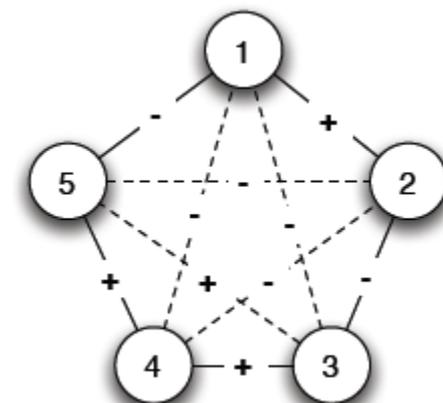
Def 1: Local view

Fill in the missing edges to achieve balance

Def 2: Global view

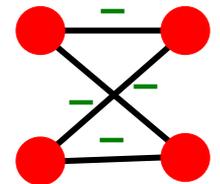
Divide the graph into two coalitions

The 2 definitions are **equivalent!**

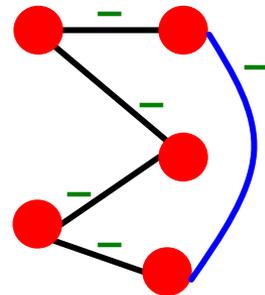


Is a Signed Network Balanced?

- 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
 - If we find a component of nodes on +edges that contains a – edge \Rightarrow **Unbalanced**
 - 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

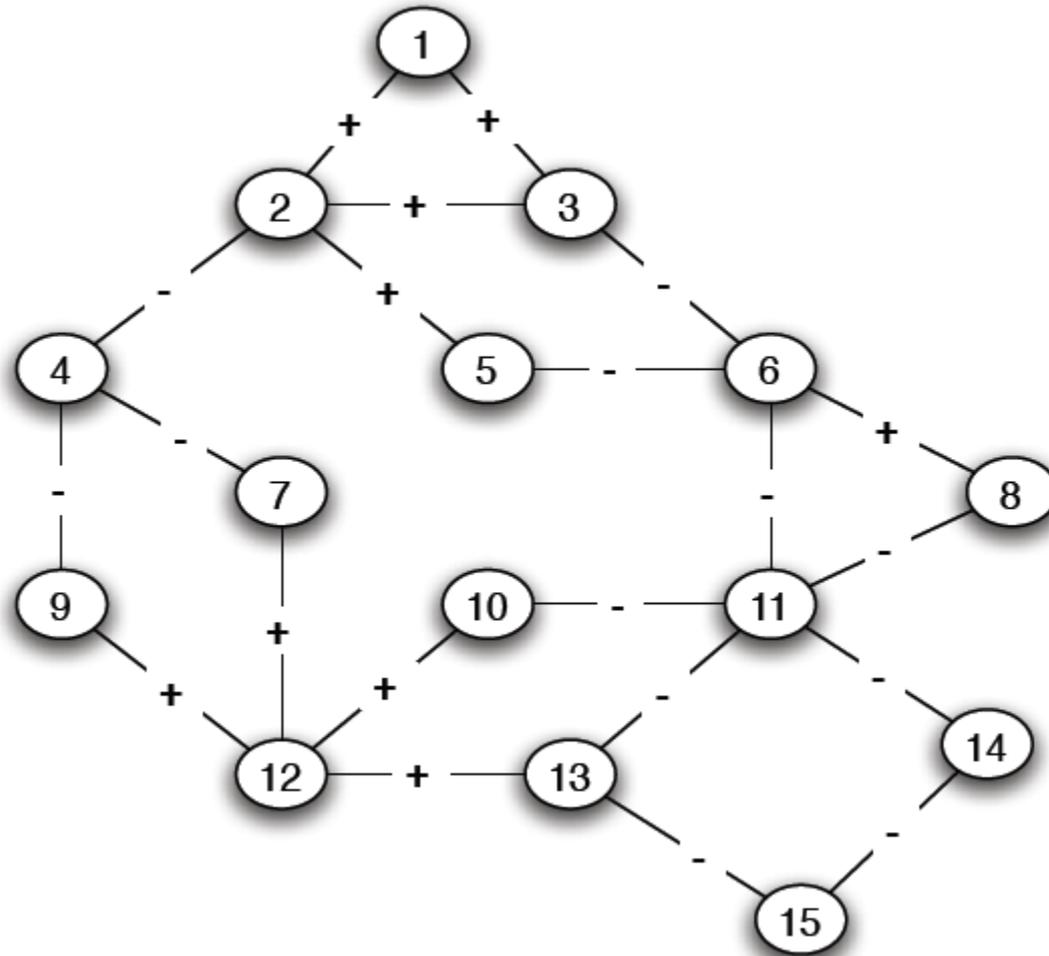


Even length cycle

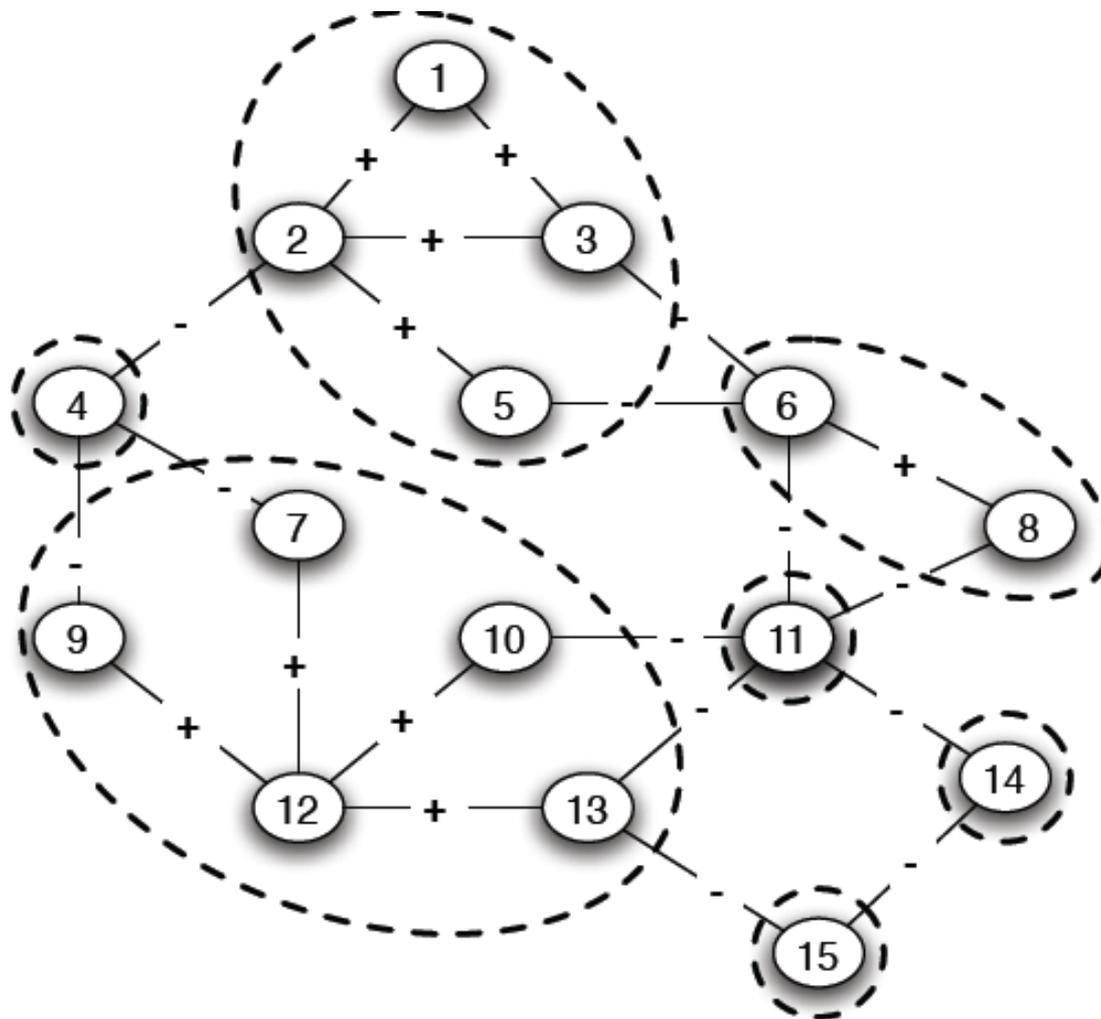


Odd length cycle

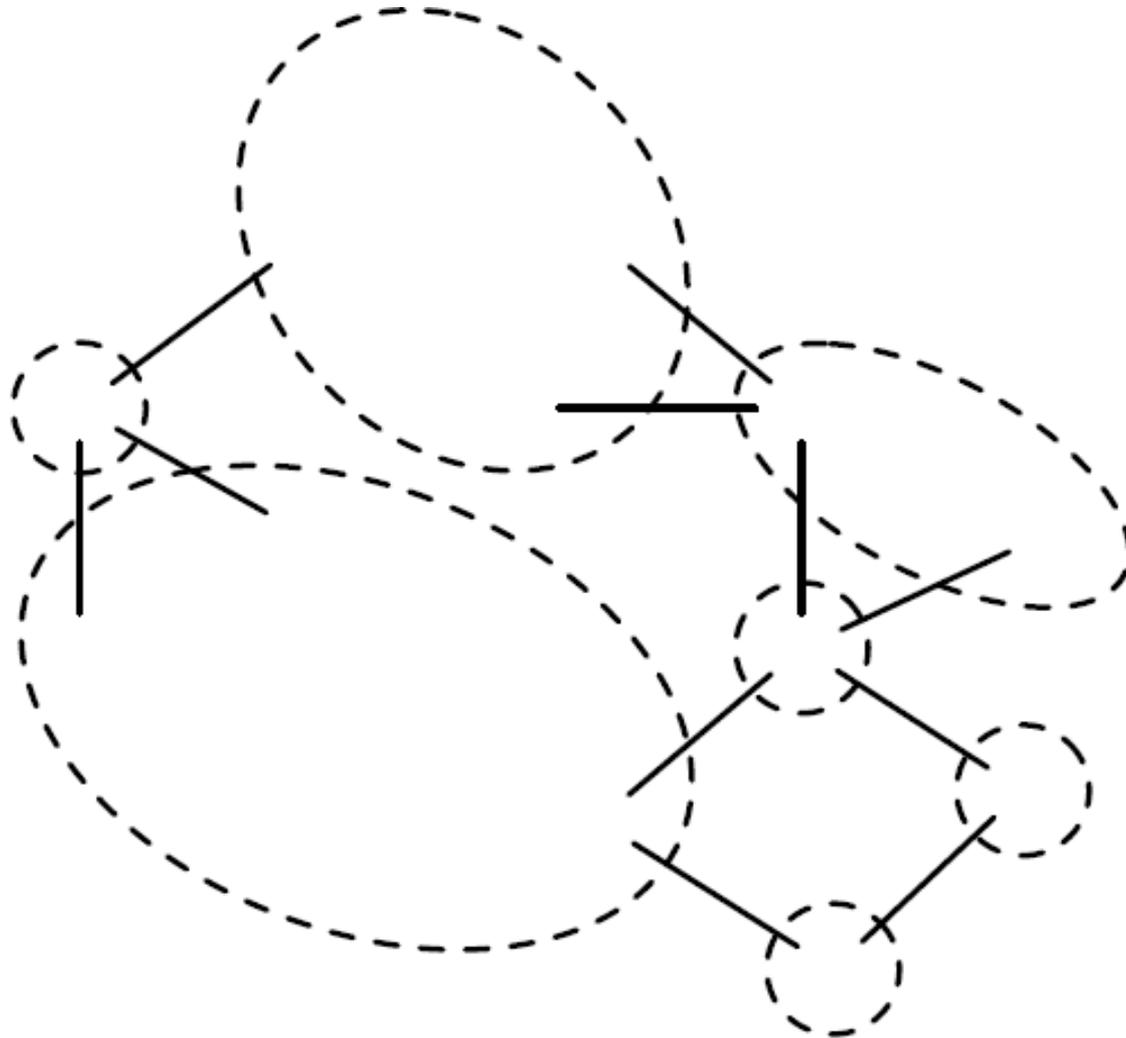
Signed Graph: Is it Balanced?



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 connected super-nodes are assigned the **same side**

