

How People Evaluate One Another in Social Media

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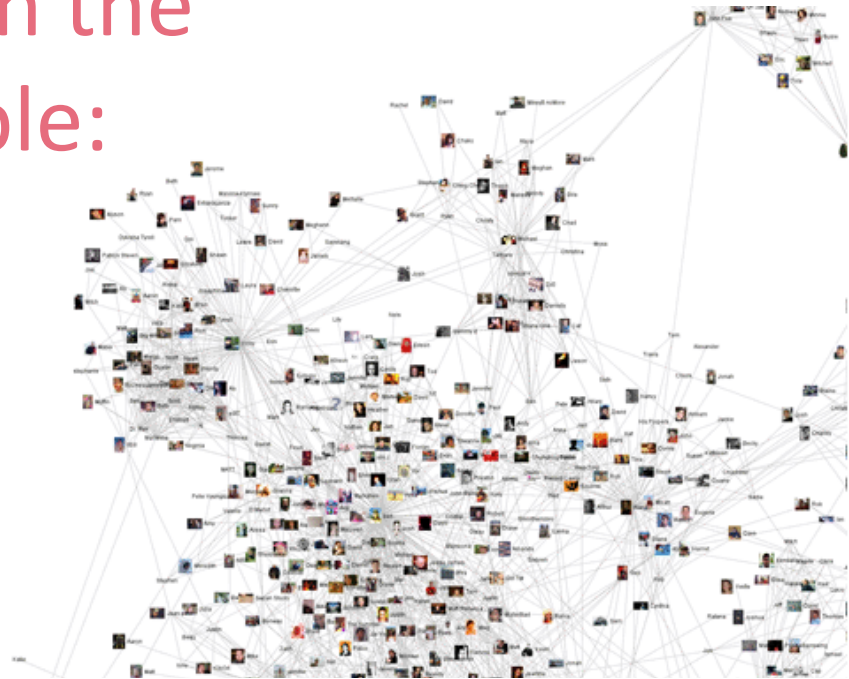


Social Networks and Social Media

Science advances when the invisible becomes visible:

- Social interaction is leaving digital traces on-line

- Can we recognize fundamental patterns of human behavior from raw digital traces?



People have Opinions

People express positive and negative attitudes/opinions:

- Through actions:

- Rating a product
- Pressing “like” button

- Through text:

Sentiment analysis

[Pang-Lee '08]

- Writing a comment, a review

amazon.com.



WIKIPEDIA
The Free Encyclopedia



last.fm
the social music revolution



Slashdot
News for Nerds. Stuff that matters.



Epinions.com



People Express Opinions

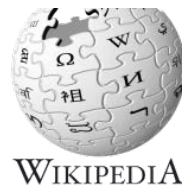
■ About items:

- Movie and product reviews



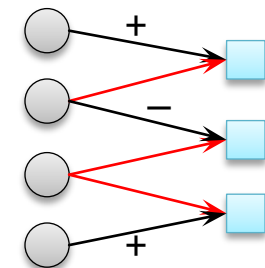
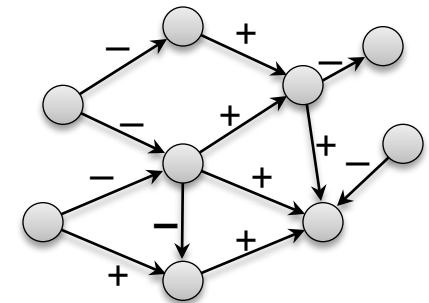
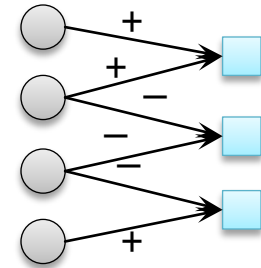
■ About other users:

- Online communities



■ About items created by others:

- Q&A websites

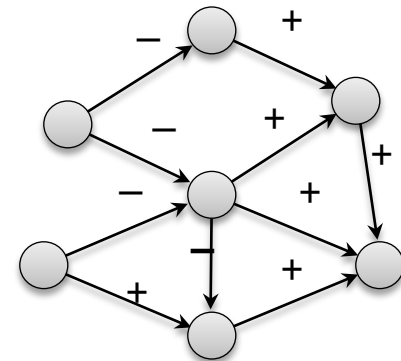


This talk: Users evaluating others

- Any user A can evaluate any user B:



- Positive (+) vs. negative (-) evaluation
- In what (online) settings does this process naturally occur at large scale?
 - Epinions:** Trust/Distrust (1M evals)
 - Does A trust B's product reviews?
 - Wikipedia:** Support/Oppose (150k votes)
 - Does A support B to become Wiki admin?
 - Stackoverflow:** Up/down vote (6M votes)
 - Does A think B contributed a good answer?



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 a user 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 characteristics of A and B
 - **Similarity**: Prior interaction between A and B
 - **Status**: A compares status of B to her own status

Status (level of contribution)

Three ways to quantify status S :

- Total number of **edits** of a user:
 - The more edits the user made the higher status she has
- Total number of **answers** of a user:
 - The more answers given by the user the higher status she has

Status: How to model?

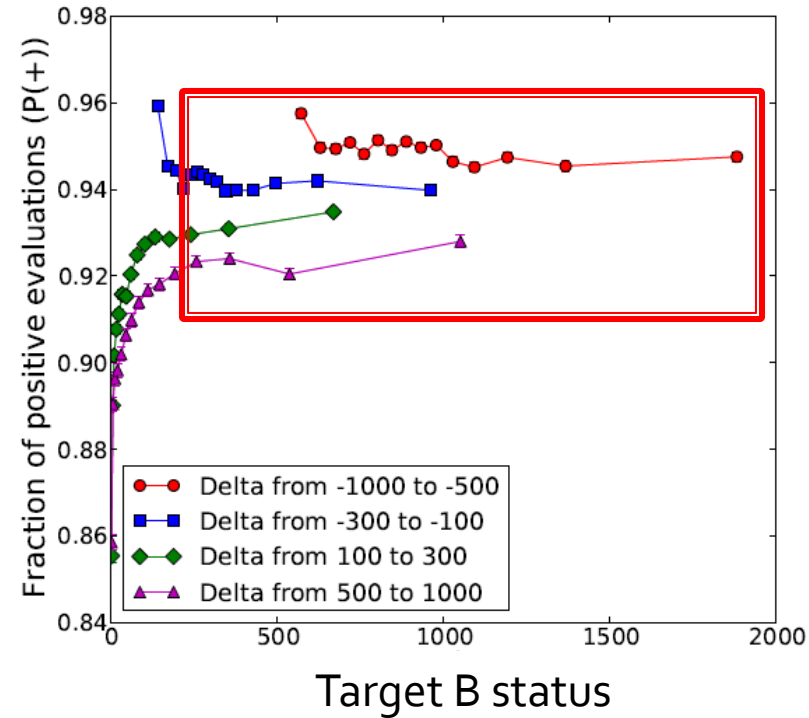
- How does the prob. of A evaluating positively depend on the status of A and status of B?



- Model it as a function of status S_A of A and S_B of B separately?
- Model as the status difference $S_A - S_B$?
- Model as the status ratio S_A / S_B ?

Status: Relative Assessment (1)

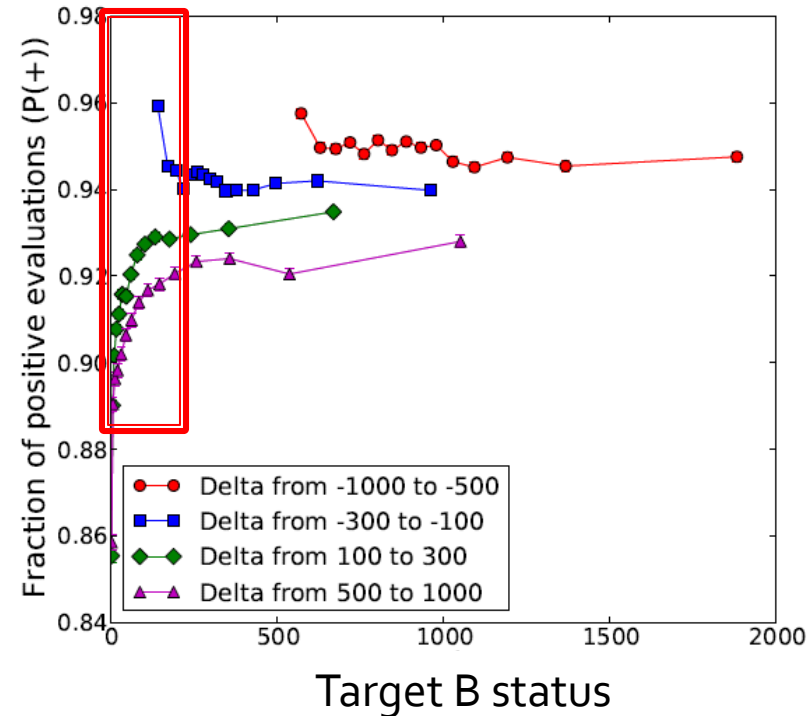
- How does status of B affect A's evaluation?
 - Each curve is fixed status difference: $\Delta = S_A - S_B$
- Observations:
 - Flat curves: Prob. of positive evaluation doesn't depend on B's status
 - Different levels: Different values of Δ result in different behavior



Status difference remains salient even as A and B acquire more status

Status: Relative Assessment (2)

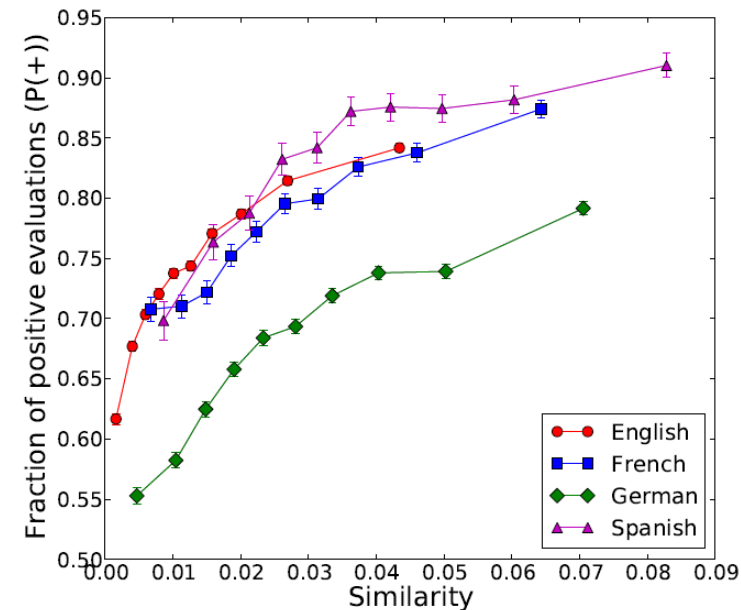
- How does status of B affect A's evaluation?
 - Each curve is fixed status difference: $\Delta = S_A - S_B$
- Observations:
 - Below some threshold targets are judged based on their absolute status
 - And independently of evaluator's status



Low-status targets are evaluated based on absolute status

Effects of Similarity

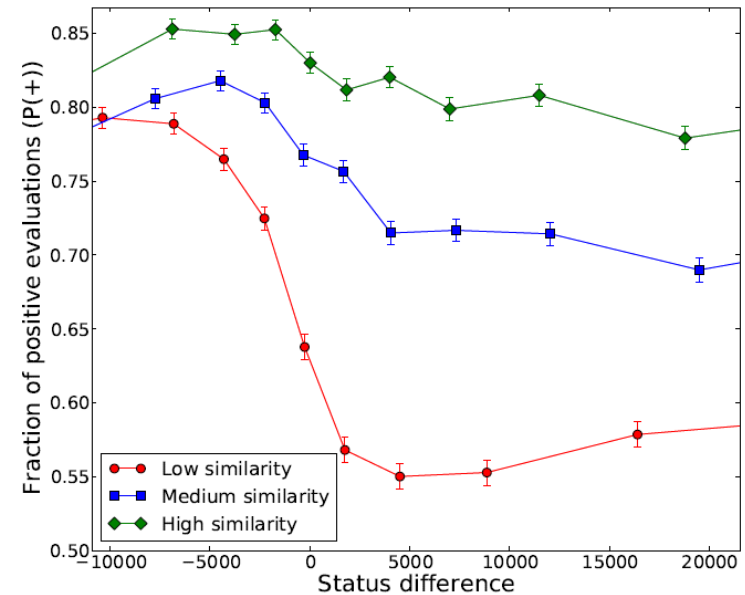
- How does prior interaction shape evaluations?
 - (1) Evaluators are more supportive of targets in their area
 - (2) More familiar evaluators know weaknesses and are more harsh
- Observation:
 - Prior interaction/similarity increases prob. of a positive evaluation



Prior interaction/
similarity boosts
positive evaluations

Relating Status and Similarity (1)

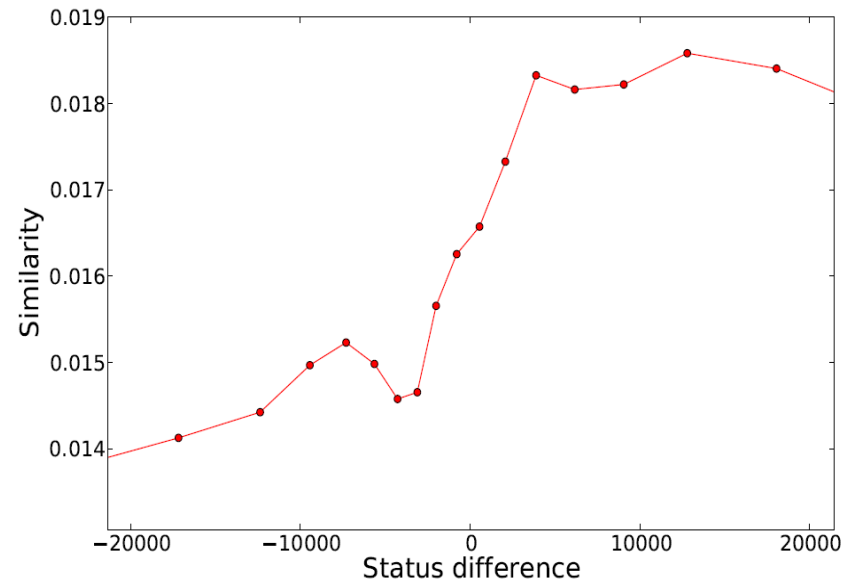
- Observation:
 - Evaluation depends less on status when evaluator A is more informed
- Consequence:
 - Evaluators use status as proxy for quality in the absence of direct knowledge of B



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

Relating Status and Similarity (2)

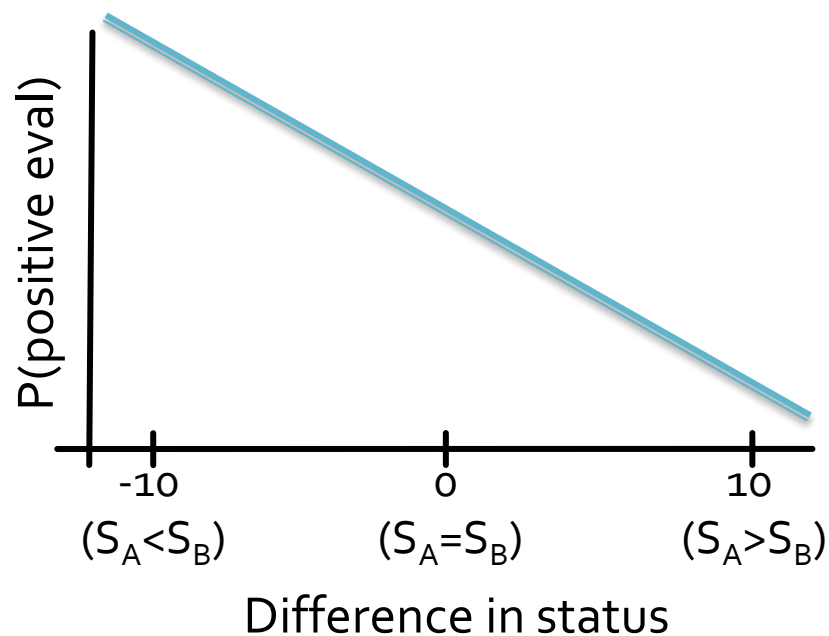
- Observation:
 - Evaluators with higher status than the target are more similar to the target
- Selection bias:
 - High-status evaluators are more similar to the target



Elite evaluators
vote on targets in
their area of
expertise

Puzzle: Status

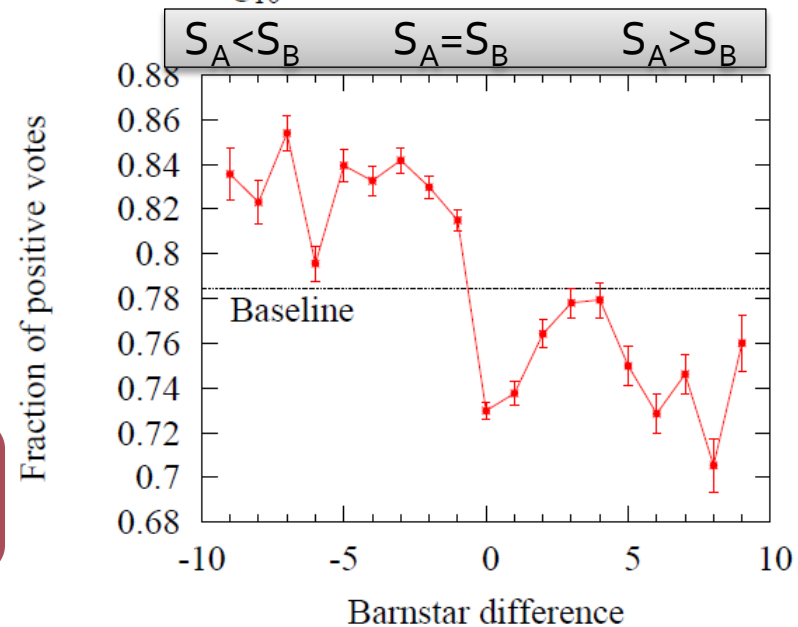
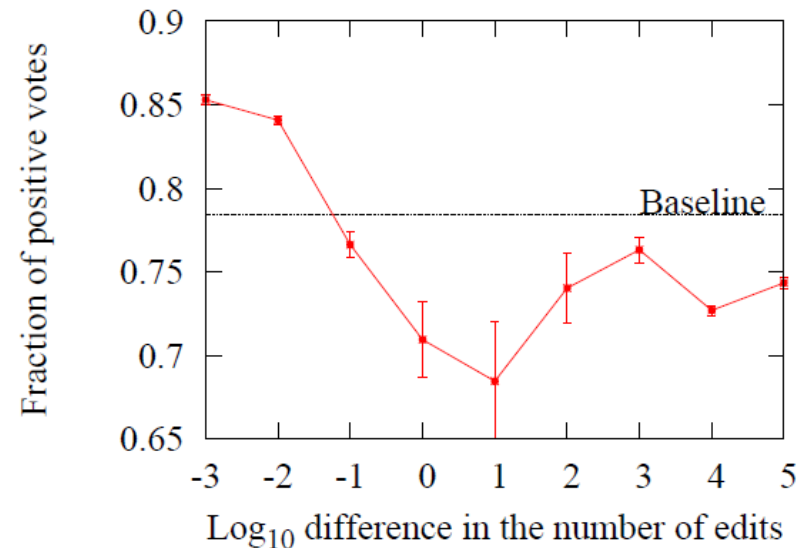
- Evaluator A evaluates target B
- Prob. of positive evaluation of A as a function of status difference: $\Delta = S_A - S_B$
 - Hypothesis: Monotonically decreases



Puzzle: Status

- Prob. of positive evaluation of B as a function of status difference: $\Delta = S_A - S_B$
- Observations:
 - A is especially negative when status equals: $S_A = S_B$
 - “Mercy bounce” for $S_A > S_B$

How to explain the bounce?



Why most harsh at zero difference?

How to explain low aggregate evaluations given by users to others of same status?

- Not due to users being tough on each other
 - Similarity increases the positivity of evaluations

Possible (but wrong) explanation:

- Most targets have low status (small $\Delta > 0$)
- Low-status targets are judged on abs. status
 - The rebound persists even for high-status targets

Explanation: Differential Status

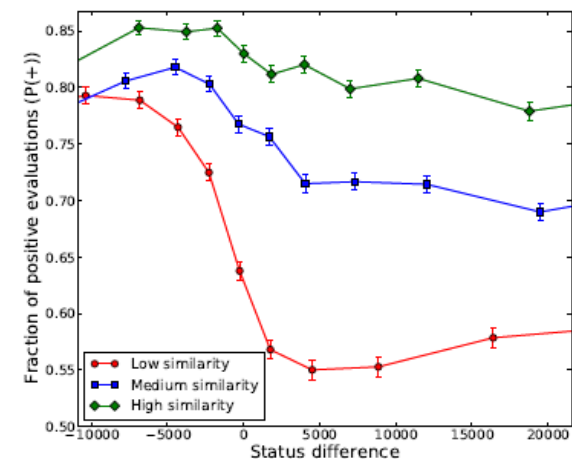
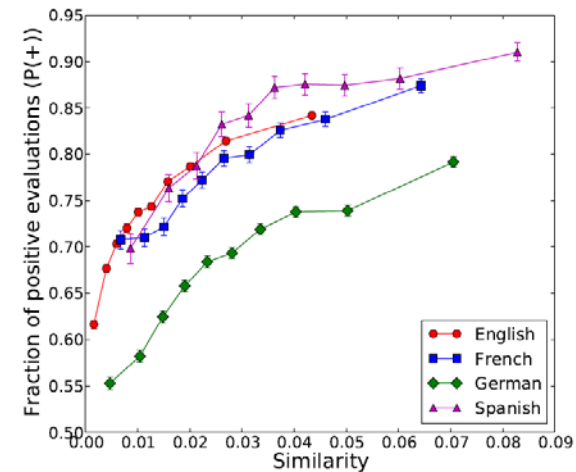
Model ingredients:

■ Similarity:

- Highly similar users are more positive

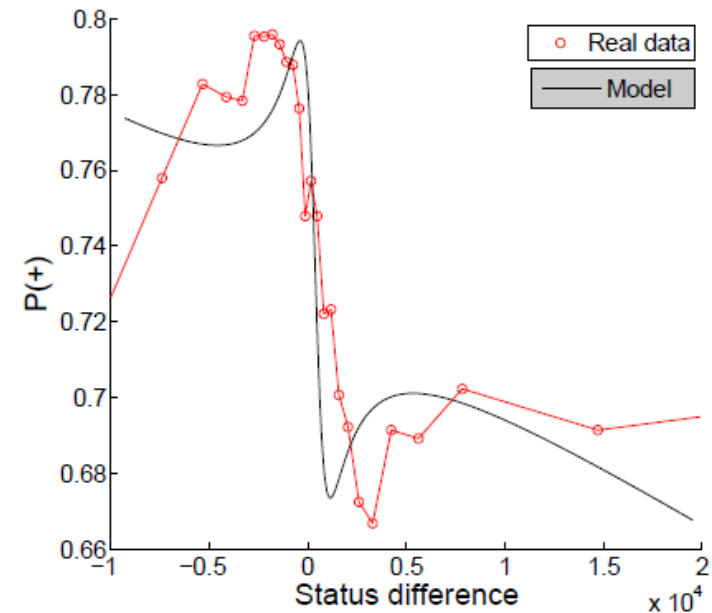
■ Selection bias:

- High-similarity users are overrepresented among high-status evaluators



Explanation: Differential Status

- The rebound not the effect of harshness of same status evaluators...
... but a combination of
- how low-status users are evaluated
- who shows up to evaluate users



Application: Predicting outcomes

- Predict the outcome using only properties of evaluators without looking at their votes
 - **Wikipedia:** Based on only who showed to up to vote predict the outcome of the election
- **Simple model:**
 - Target status
 - Evaluator status
 - Similarity

Application: Ballot-blind prediction

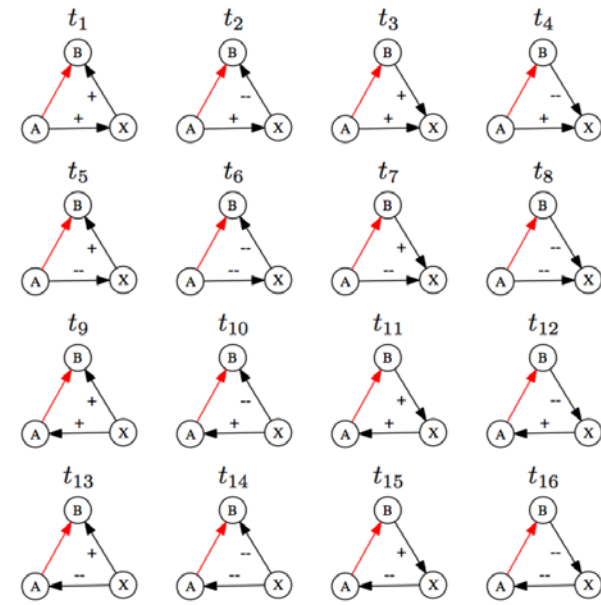
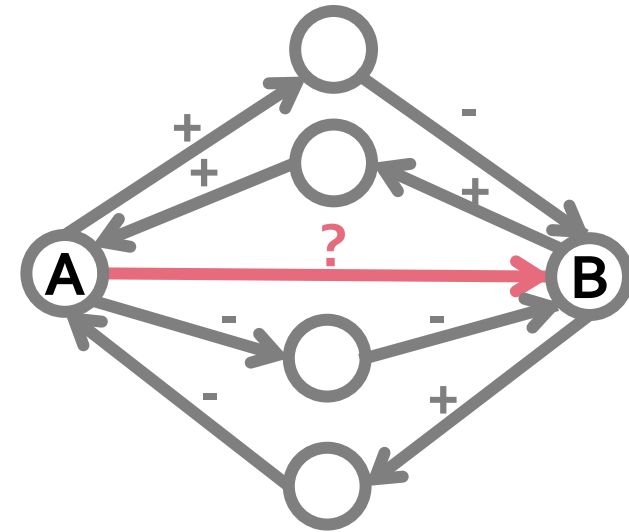
- Based on only who showed to up to evaluate predict the outcome of the Wiki election

| Number of votes | E | Relative gain over LogReg |
|-----------------|-------|---------------------------|
| 5 | 71.4% | 12.8% |
| 10 | 75.0% | 23.8% |
| all | 75.6% | 25.7% |

- **Method:**
 - Divide the Status-Similarity space, each cell prob. + vote
- **Baseline:**
 - Guessing gives 50% accuracy
 - Logistic Regression based on the target status (67% acc)

Application: Predicting evaluations

- How will A evaluate B?
- Model:
 - Count the triads in which edge $A \rightarrow B$ is embedded
 - Predictive accuracy: $\sim 95\%$
- Evaluations can be modeled from local network structure alone!

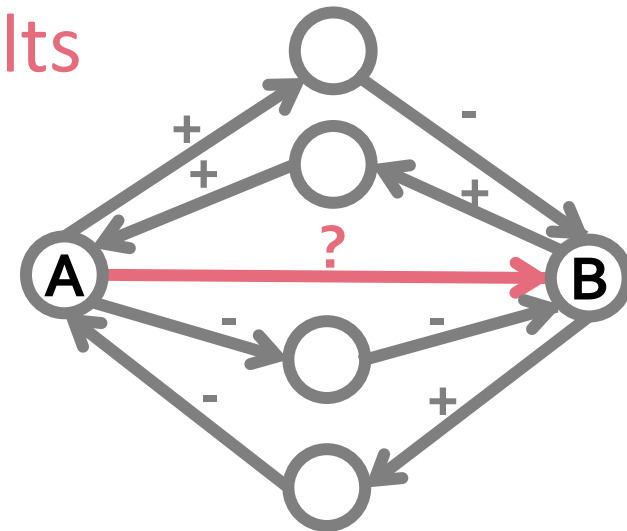


Application: Predicting evaluations

- How do people evaluate in different contexts?

How generalizable are the results across the datasets?

- Wikipedia: Support/Oppose
 - Epinions: Trust/Distrust
 - Stackoverflow: Up/Down vote
- Almost **perfect generalization** of the models even though evaluations have very different meaning



Conclusions

- Social media sites are governed by (often implicit) user evaluations
- Wikipedia voting process has an explicit, public and recorded process of evaluation
 - Similarly, Epinions and Stackoverflow
- Main characteristics:
 - Importance of relative assessment: Status
 - Importance of prior interaction: Similarity

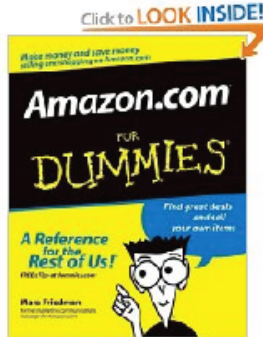
Conclusion and reflections

- Online social systems are globally organized based on status
- Users use evaluations consistently regardless of a particular application
 - Near perfect generalization across datasets
- 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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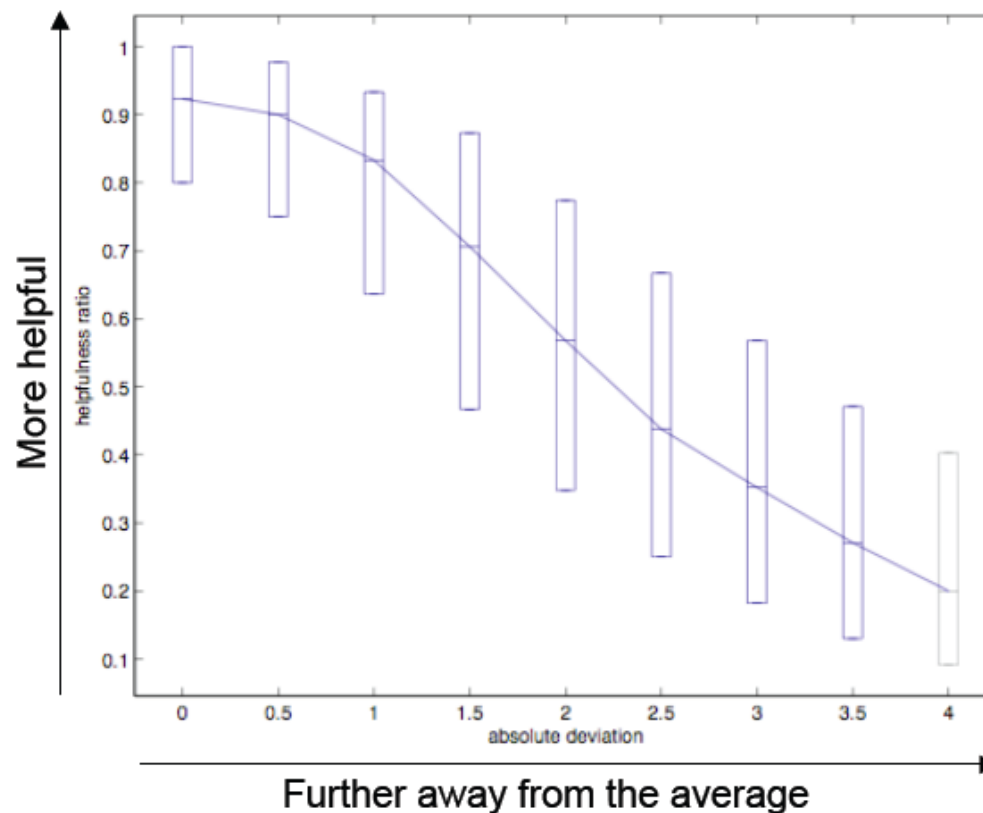
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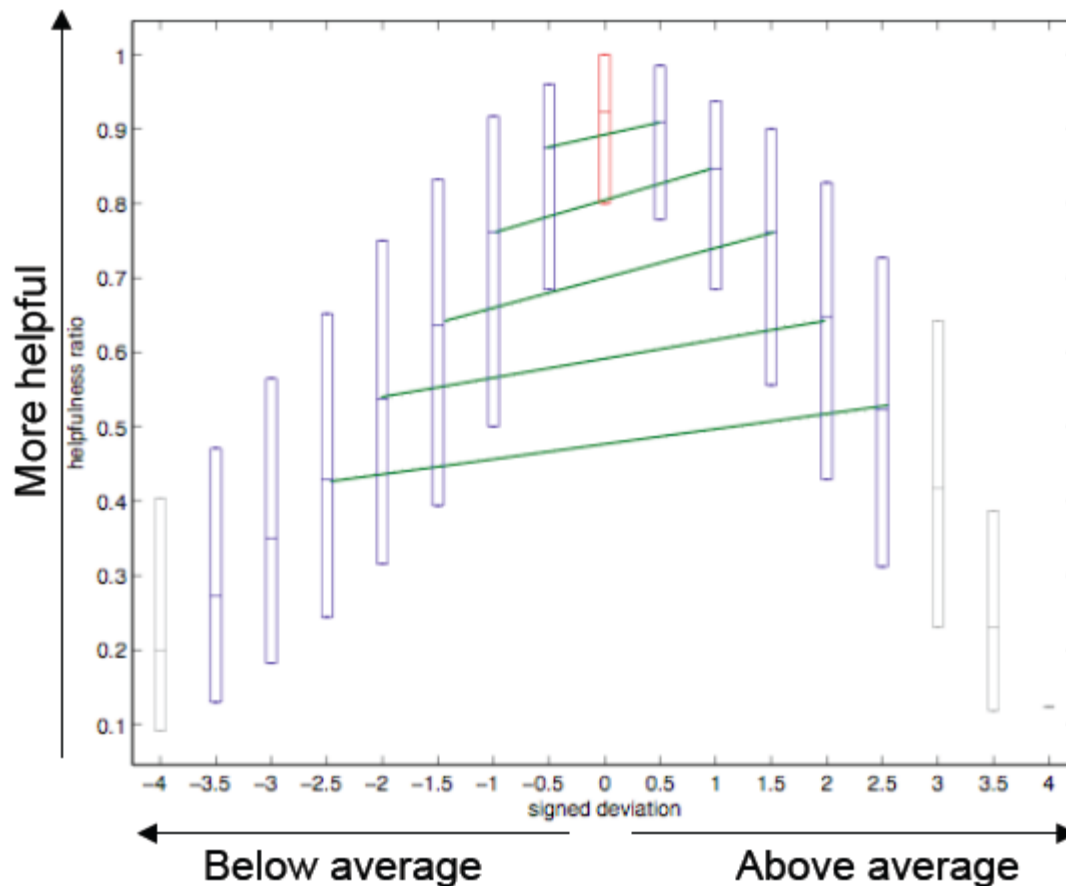
Review helpfulness: Conformity

- People find **conforming** opinions more helpful



Review helpfulness: Deviation

- **Positive** reviews are more helpful



Future Directions

- Predict the outcome of group evaluations from small set of evaluations
 - Seeing just a few votes, what's the final outcome
- Predicting outcomes without explicit user feedback
 - Based on who showed up, predict outcome

Future Directions

- Understanding the dimensions of the opinion:
 - Status vs. Similarity
 - Agreement with the statement vs. Statement is technically correct
- Status and reputation mechanisms
 - What reputation/merit mechanisms should we build into the social systems to achieve desirable behavior?

THANK YOU!

