Finding the Bias and Prestige of Nodes in Networks based on Trust Scores

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About

- Assistant Professor in Computer Science and Engineering department at IIT Kanpur
- Data Mining, Databases, Bioinformatics

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- Data Networks (please read as Social Networks)
- Trust and Bias in social platforms

Trust Networks

- A network where entities indicate trust of other entities by rating each other
- *Positive* ratings represent trust, friend, etc.
- *Negative* ratings represent mistrust, foe, etc.
- Example
  - P2P networks
  - Epinions rating reviews
  - Slashdot rating comments

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- Basic question: How to rank nodes?

Ranking

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- Ranking on a signed graph
    - Eigentrust, Pagetrust
- Solution does not guarantee convergence
- Removes negative weights

Neutral Ratings

- Neutral ratings are marked with edge weight 0
- Very different from a no-edge
- Consider node A with only 1 negative in-link
- Consider node B with 1 negative in-link and 100 neutral in-links
- Node B has more prestige than node A

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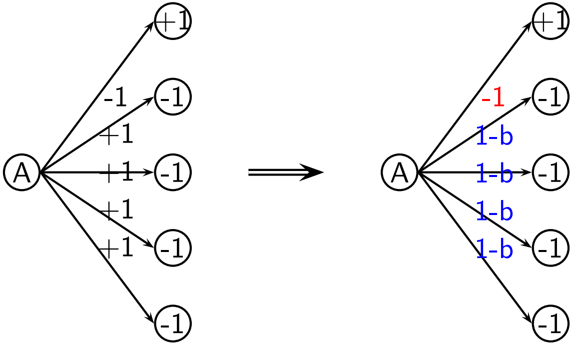
- Bias is the average difference of the weight that a node assigns to another to the actual rating of that other node
- Thus, deserve is the expected weight of an incoming edge comning from an unbiased node
- How to identify and remove bias from nodes?

Removing Bias

- If a node weights another node which has negative rating positively, then it is positively biased
- Thus, the amount of this positive bias should be removed from the positive edge weights
- However, if this node weights some other negatively, then nothing should be done to that edge weight



Effect of Bias

- An auxiliary variable to capture the effect of bias

$$X_{kj} = \begin{cases} 0 & \text{if } (bias(k) \times w_{kj}) \leq 0 \\ |bias(k)| & \text{otherwise} \end{cases}$$

- If edge weight and bias are oppositely signed, then no correction is needed
- Otherwise, the amount of bias needs to be corrected

$$w'_{kj} = w_{kj}(1 - X_{kj})$$

Formulae for Bias and Deserve

- Bias of a node i is defined in terms of deserve of all its neighbours j, i.e., where ij is an edge

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$$deserve(j) = \frac{1}{|d^i(j)|} \sum_{k \in d^i(j)} \left(w_{kj}(1 - X_{kj}) \right)$$

Computing Bias and Deserve

- Iterative algorithm
- Start with random values of deserve
- Compute bias using these
- In next iteration, update deserve
- Then update bias again
- So on

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- Running time needed per iteration is $O(m)$ for a graph with m edges

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THANK YOU!