# Edge prediction and Miscellaneous topics 

Social and Technological Networks

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## Link prediction

- Given a network
- Can you predict which links are likely to form in future in a reasonable time interval?
- May be because two people become friends
- Or they are already friends, but the link becomes visible


## Link prediction

- Basic idea:
- Similar people are likely to form links
- Homophily
- People with similar attributes/interests form links
- If we have external attributes (locations, interests) then we use them
- Also, friends of friends often become friends
- Predict links based on common friends and neighborhoods
- Note that this indirectly incorporates homophily effects


## Prediction methods

- Give a score to each pair of nodes based on how likely they are to form link
- Example scoring strategies:
- Graph distance (shortest path length)
- Number of common neighbors
- Jaccard similarity of neighborhoods
- Preferential attachment
- Random walk (hitting time based methods)
- How soon does a random walk from $x$ hit $y$ ?
- Others


## Results

- In reality, many unknown external factors affect links
- So raw accuracy itself is low
- However, we can compare them with baselines like random links
- Most methods perform much better than random links
- Nowell, Kleinberg. Link prediction problem. CIKM 03.


## Friendship paradox

- Your friends have more friends than you do!
- Are you less social than others?


## Friendship paradox

- The paradox:
- If you ask everyone to report their degrees and take average, you get the average degree
- If you ask everyone to report the average degrees of their friends and take the averages of all,
- you get more than the overall average degree!
- Most of us have some popular friends (hence they are popular)
- If you pick a random friend of a random person, (random edge)
- This friend is relatively likely to be popular, since popular nodes have more edges
- Average degree of nodes:
- A node with degree $\mathrm{d}(\mathrm{v})$ contributes $\mathrm{d}(\mathrm{v})$ once
- Average degree of a friend:
- Each person picks a friend and counts degree
- A node with degree $d(v)$ contributes $d(v)$ times, with total contribution $\mathrm{d}(\mathrm{v})^{2}$
- A few nodes with relatively high $\mathrm{d}(\mathrm{v})$ can skew the count
- https://en.wikipedia.org/wiki/Friendship_paradox
- S. L. Feld, Why your friends have more friends than you do, American journal of sociology, 1991


## Identify spouses or romantic partners

## Identify spouses or romantic partners

- Tie strengths are important
- Romantic ties tend to be of high strength, more likely to transmit information
- Do you expect romantic links to have high embeddedness (number/fraction of common friends)?
- People have clusters of friend circles
- Work, school, college, hobbies
- Edges in these have high embeddedness, even if they are not strong friends

- Spouses usually know some friends in eachothers different circles
- The edge does not have high embeddedness
- Compared to links in groups such as school/college


## Dispersion

- But, it has a dispersed structure:
- There are several mutual friends, but the mutual friends are not well connected among themselves


## Dispersion

- dispersion between $u, v$
- Notations:
$-C(u, v)$ : Common friends of $u, v$
- $G_{u}$ : Subgraph induced by $u$ and all neighbors of $u$
- duv : distance measured in $\mathrm{G}_{\mathrm{u}-\{\mathrm{u}, \mathrm{v}\} \text { : Without using } \mathrm{u}}$ or v

$$
\operatorname{disp}(u, v)=\sum_{s, t \in C(u, v)} d_{u v}(s, t)
$$

## Dispersion

$$
\operatorname{disp}(u, v)=\sum_{s, t \in C(u, v)} d_{u v}(s, t)
$$

- Increases with more mutual friends
- Increases when these friends are far in the graph
- It is possible to use other distance measures
- Good results with $d=1$ if no direct edge, 0 otherwise


## Normalized dispersion

- Use norm(u,v) $=\operatorname{disp}(u, v) / e m b e d(u, v)$
- 48\% accuracy
- Apply recursively, to weigh higher nodes with high dispersion
- Gives 50.5\% accuracy
- 60\% accuracy for married couples
- High accuracy considering hundreds of friends
- Works better than usual machine learning based on posts, visits, photos etc
- Best results with combination of features
- Backstrom and Kleinberg. Romantic partnerships and dispersion of social ties, ACM CSCW 2014

