## Social Networks Characteristics \& Link Prediction

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## The small world effect

- The average distance in the topology is very small compared to the size of the network.
- Facebook avg distance is $\sim 5$



## Power law degree distribution

- Only a few nodes have lots of links. Most nodes' links are very small in the network
- See: M. Faloutsos, P. Faloutsos, C. Faloutsos: On power-law relationships of the Internet topology

Degree distribution of facebook


## Clustering effect

- There are many small groups in a social network where each member of the group knows each other.
- Results in many fully connected subgraphs.



## Link prediction

- Predict the likelihood of a future association between two nodes
- This is typically achieved by utilizing some notion of similarity between the two nodes


## Preferential Attachment

- Intuition: users with many friends tend to create more connections in the future
- Lets $N(u)$ denote the set of friends of node $u$
- Then, use $|N(u)|^{*}|N(v)|$ as a measure for scoring the likelihood of a link between node $u$ and node $v$


Caveat?

## Graph Distance

- Define similarity as the negative length of the shortest path between nodes $A$ and $B$
- Recall that due to the small-world effect this distance is typically small
- Thus, it may be hard to differentiate pairs using shortest-paths



## Count Common Neighbours

- Intuition: two strangers who have a common acquaintance may be introduced by that friend.



## Friends-measure

- Count \#common-friends + \#connections_between_neighbors



## Jaccard Coefficient

- Use proportion of the common friends as a similarity metric
- $\operatorname{Jaccard}(N(A), N(B))=|N(A) \cap N(B)| /|N(A) \cup N(B)|$

Example


## Consider neighbors in-common



## Consider neighbors not in-common



## Jaccard Coefficient

- $\operatorname{Jaccard}(A, B)=2 /(2+8)=20 \%$



## Caveat - 1: Common friends beyond 1-hop


$\operatorname{sim}(A, B)=0$
Simpler case:
common friend-of-friend

Should we increase $\operatorname{sim}(A, B)$ because of this node?


## Caveat - 2: Popularity of common neighbor



## Adamic/Adar index

- The Adamic/Adar index computes the sum of the inverse logarithmic degree centrality of the neighbours shared by the two nodes

$$
A(x, y)=\sum_{u \in N(x) \cap N(y)} \frac{1}{\log |N(u)|}
$$

$N(x)$ : set of neighbours of node $x$
For $u \in N(x) \cap N(y):|N(u)| \geq 2$ (why?)


## Reduce weigh of common neighbor (u) with many connections (|N(u)|)



## Adamic/Adar Example

## $A(x, y)=$ $\sum_{u \in N(x) \cap N(y)} \frac{1}{\log |N(u)|}$

$A($ John, Helen $)=1 / \log (3)=0.63$



## Adamic/Adar Example

## $A(x, y)=$ $\sum_{u \in N(x) \cap N(u)} \frac{1}{\log |N(u)|}$

A $($ John, Maria $)=1 / \log (2)=1$


## Adamic/Adar Example

## $A(x, y)=$ $\sum_{u \in N(x) \cap N(u)} \frac{1}{\log |N(u)|}$

$A($ Helen, Maria $)=1 / \log (3)+1 / \log (2)=1.63$



## Caveat - 1: Need to look beyond 1-hop


$\operatorname{sim}(A, B)=0$
Simpler case:
common friend-of-friend


## SimRank: two nodes are similar if they are referenced by similar nodes

- Recursive calculation in the same spirit as pageRank
- In the example bellow u references both $\mathrm{a}, \mathrm{b}$ and this contributes to their similarity



## Motivation

- A similarity measure that exploits the object-to-object relationships found in many domains of interest
- Web page X "points to" Web page $Y$
- Customer "buys" product
- Customer X transfers money to Customer Y
- May be used to cluster objects, such as for collaborative filtering in a recommender system


## Intuition

- Concentrate on structural content
- Can be combined with other similarity metrics that consider content similarity
- Two nodes are similar if they are referenced by similar nodes
- Accounts $X, Y$ are similar if they both receive money from some account $Z$



## SimRank Recursive Computation

- Initialize:
- $s(a, b)=\left\{\begin{array}{l}1, \text { if } a=b \\ 0, \text { otherwise }\end{array}\right.$
- Iteratively compute ( $\mathrm{a} \neq \mathrm{b}$ ):

$$
s(a, b)=\frac{C}{|I(a)||I(b)|} \sum_{i=1}^{|I(a)|} \sum_{j=1}^{|I(b)|} s\left(I_{i}(a), I_{j}(b)\right)
$$

- Where
- $I(x)=$ in-neighbors of $x$
- $\mathrm{I}_{\mathrm{i}}(\mathrm{x})=\mathrm{i}^{\text {th }}$ in-neighbor of x and $\mathrm{C}<1$ (decay factor)


## Explanation

$$
s(a, b)=\frac{C}{|I(a)||I(b)|} \sum_{i=1}^{|I(a)| I(b) \mid} \sum_{j=1} s\left(I_{i}(a), I_{j}(b)\right)
$$

- Nodes receive the average similarity of their in-neighbors multiplied by the decay factor C
- Special case: $s(a, b)=0$ if $\|(a) \mid=0$ or $||(b)|=0$
- i.e. nodes have no in-neighbors


## Example



Assume $\mathrm{C}=0.8$

## Iterate



## Updated SimRank

$$
\begin{aligned}
& s(u, u)=1 \\
& s(a, b)=0.8^{*} s(u, u)=0.8 \\
& s(a, x)=0.8^{*} s(u, a)=0 \\
& s(x, y)=0,8^{*} s(a, b)=0,8^{*} 0,8=0,64
\end{aligned}
$$

## SimRank propagation



Assume $\mathrm{C}=0.8$

## SimRank in bipartite graphs

- Bipartie graph: two disjoint classes of nodes $\mathrm{V}_{1}, \mathrm{~V}_{2}$
- e.g. $\mathrm{V}_{1}=\{$ customers $\}, \mathrm{V}_{2}=\{$ items $\}$
- Edges only between nodes in $\mathrm{V}_{1}$ to nodes in $\mathrm{V}_{2}$



## Intuition-1

- People are similar if they purchase similar objects



## Intuition-2

- Items are similar if they are purchased by similar people



## Bipartite SimRank

- SimRank between persons $A$ and $B,(A \neq B)$

$$
s(A, B)=\frac{C_{1}}{|O(A)||O(B)|} \sum_{i=1}^{|O(A)|} \sum_{j=1}^{|O(B)|} s\left(O_{i}(A), O_{j}(B)\right)
$$

- SimRank between items $x$ and $y$, $(x \neq y)$

$$
s(x, y)=\frac{C_{2}}{|I(x)||I(y)|} \sum_{i=1}^{\mid I(x)} \sum_{j=1}^{|I(y)|} s\left(I_{i}(x), I_{j}(y)\right)
$$

- The similarity between persons $A$ and $B$ is the average similarity between the items they purchased
- O(A) are the out-neighbors (items) for person A
- The similarity between items $x$ and $y$ is the average similarity between the people who purchased them


## Modified SimRank in bipartite graphs



