

OSU CS419/519 Document Analysis



#### Social Network Analysis

# Link Prediction and Network Visualization

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Lecture slides credit: Lada Adamic, Univ. Michigan, Jure Leskovec, Stanford University

## Plan for today

 An introduction to link prediction in networks

David Liben-Nowell and Jon Kleinberg.
The Link-Prediction Problem for Social Networks.
In Journal of the American Society for Information Science and Technology, 58(7):1019–1031, May 2007

http://cs.carleton.edu/faculty/dlibenno/papers/link-prediction/link.pdf earlier version published in CIKM 2003

 Network Visualization with Gephi



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#### Link Prediction in Networks

- The link prediction task:
  - Given  $G[t_0, t_0]$  a graph on edges up to time  $t_0$  output a ranked list L of links (not in  $G[t_0, t_0]$ ) that are predicted to appear in  $G[t_1, t_1]$



G[t<sub>0</sub>, t'<sub>0</sub>]

- Evaluation:
  - $n = |E_{new}|$ : # new edges that appear during the test period  $[t_1, t_1]$
  - Take top n elements of L and count correct edges

# Link Prediction via Proximity

Predict links in a evolving collaboration network

|          | training period |        |                             | Core    |             |             |
|----------|-----------------|--------|-----------------------------|---------|-------------|-------------|
|          | authors         | papers | collaborations <sup>1</sup> | authors | $ E_{old} $ | $ E_{new} $ |
| astro-ph | 5343            | 5816   | 41852                       | 1561    | 6178        | 5751        |
| cond-mat | 5469            | 6700   | 19881                       | 1253    | 1899        | 1150        |
| gr-qc    | 2122            | 3287   | 5724                        | 486     | 519         | 400         |
| hep-ph   | 5414            | 10254  | 47806                       | 1790    | 6654        | 3294        |
| hep-th   | 5241            | 9498   | 15842                       | 1438    | 2311        | 1576        |

- Core: Since network data is very sparse
  - Consider only nodes with in-degree and out-degree of at least 3

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# Link Prediction via Proximity

- Methodology:
  - For each pair of nodes (x,y) compute score c(x,y)
    - For example: # of common neighbors c(x,y) of x and y
  - Sort pairs (x,y) by the decreasing score c(x,y)
    - Note: Only consider/predict edges where both endpoints are in the core (deg. > 3)
  - Predict top n pairs as new links
  - See which of these links actually appear in  $G[t_1, t'_1]$



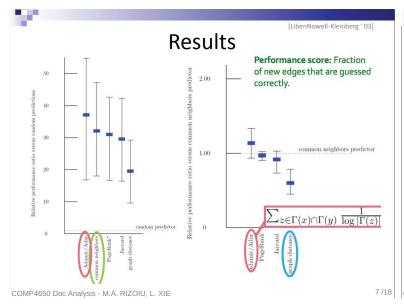
# Link Prediction via Proximity

- Different scoring functions c(x,y)
  - Graph distance: (negated) Shortest path length
  - Common neighbors:  $|\Gamma(x) \cap \Gamma(y)|$
  - Jaccard's coefficient:  $|\Gamma(x) \cap \Gamma(y)|/|\Gamma(x) \cup \Gamma(y)|$
  - Adamic/Adar:  $\sum_{z \in \Gamma(x) \cap \Gamma(y)} 1/\log |\Gamma(z)|$
  - Preferential attachment:  $|\Gamma(x)| \cdot |\Gamma(y)|$

 $\Gamma(x)$  ... neighbors of node x

• PageRank:  $r_x(y) + r_y(x)$ 

- =  $r_x(y)$  ... stationary distribution weight of y under the random walk: = with prob. 0.15, jump to x
  - with prob. 0.85, go to random neighbor of current node
- Then, for a particular choice of c(·)
  - For every pair of nodes (x,y) compute c(x,y)
  - Sort pairs (x,y) by the decreasing score c(x,y)
  - Predict top n pairs as new links



#### **Link Prediction**

- One useful task
  - -Can be tackled with 3 hrs of SNA primer
- -Simple scoring preforms reasonably well
- -Lots of possible scoring functions
- How can this be improved?

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# Network visualization

- How to make sense of a large network? 1000s of nodes 10,000s of nodes 1,000,000 of nodes?
- What are efficient methods for displaying information about a network, manipulating it, and zooming in to reveal insight?

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# Tools for analyzing social network (non-exhaustive)

Gephi (visualization and basic network metrics)

**NetworkX** – programming in Python

- extensive functionality
- scales to large networks by taking advantage of existing C, Fortran libraries for large matrix computations
- open source
- http://networkx.lanl.gov/

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# Elements of Graph Visualization with Gephi

- Data graph structure, node labels, edge properties ...
- Graph Layout
- Styling color/size/font for nodes and edges

#### Fruchterman-Reingold layout

It simulates the graph as a system of mass particles. The nodes are the mass particles and the edges are springs between the particles. The algorithms try to minimize the energy of this physical system. It has become a standard but remains very slow.

Thomas Fruchterman & Edward Reingold

Author: Date: Kind:

Force-directed Complexity:  $O(N^2)$ 1 to 1 000 nodes Graph size: No

1991

Use edge weight:

<sup>1</sup> Fruchterman, T. M. J., & Reingold, E. M. (1991). Graph Drawing by Force-Directed Placen

Software: Practice and Experience, 21(11). COMP4000 DUC AHAIYSIS - IVI.A. KIZUIU, L. AIE

#### ForceAtlas layout

Home-brew layout of Gephi, it is made to spatialize Small-World / Scale-free networks. It is focused on quality (meaning "being useful to explore real data") to allow a rigor ous interpretation of the graph (e.g. in SNA) with the fewest biases possible, and a good readability even if it is slow

Author: Mathieu Jacomy 2007 Date: Force-directed Complexity: O(N2) 1 to 10 000 nodes Graph size:

Use edge weight:



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#### Yifan Hu Multilevel layout

It is a very fast algorithm with a good quality on large graphs. It combines a force-directed model with a graph coarsening technique (multilevel algorithm) to reduce the complexity. The repulsive forces on one node from a cluster of distant nodes are approximated by a Barnes-Hut calculation, which treats them as one super-node. It stops automatically.

Author: Yifan Hu Date: 2005 Force-directed + multilevel Kind:

O(N\*log(N)) Complexity: Graph size: 100 to 100 000 nodes

Use edge weight:

1 Y. F. Hu, Efficient and high quality force-directed graph drawing. The Mathematica Journal, 10

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#### So how to choose a layout? In general, select one according to the feature of the topology you want to highlight: emphasis emphasis DIVISIONS COMPLEMENTARITIES ForceAtlas, Yifan Hu, OpenOrd Frushterman-Reingold

emphasis RANKING

Circular, Radial Axis

emphasis GEOGRAPHIC REPARTITION

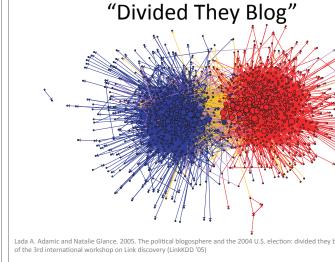
GeoLayout

**Graphic Adjustements** 

Label Adjust

Expansion - Contraction

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Lada A. Adamic and Natalie Glance. 2005. The political blogosphere and the 2004 U.S. election: divided they blog. In Proceedings

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### Gephi comes with great tutorials

- -http://gephi.org/users/
- -esp http://gephi.org/tutorials/gephi-tutorial-layouts.pdf
- Lots of good, online walk-throughs
  - -http://www.martingrandjean.ch/introduction-tonetwork-visualization-gephi/

# Other Options for Network Visualization

- GraphViz underlying engine for many
- Pajek
- NodeXL http://nodexl.codeplex.com/
- Network package + visualization
  - -NetworkX/Python (example in your tutorial)
  - -iGraph / R
- Web applications
- -D3.js
- -Sigma.js