Graphs / Networks

Centrality measures, algorithms, interactive applications

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Partly based on materials by Professors Guy Lebanon, Jeffrey Heer, John Stasko, Christos Faloutsos, Parishit Ram (GT PhD alum; SkyTree), Alex Gray
Centrality
= “Importance”
Why Node Centrality?

What can we do if we can rank all the nodes in a graph (e.g., Facebook, LinkedIn, Twitter)?

• Find **celebrities** or influential people in a social network (Twitter)

• Find “**gatekeepers**” who connect communities (headhunters love to find them on LinkedIn)

• What else?
More generally

Helps **graph analysis, visualization, understanding**, e.g.,

- Let us **rank** nodes, group or study them by centrality
- Only show subgraph formed by the **top 100 nodes**, out of the millions in the full graph
  - **Similar to google search results** (ranked, and they only show you 10 per page)
  - Most graph analysis packages already have centrality algorithms implemented. **Use them!**

Can also compute edge centrality.
Here we focus on node centrality.
Degree Centrality (easiest)

Degree = number of neighbors

- For directed graphs
  - **In degree** = No. of incoming edges
  - **Out degree** = No. of outgoing edges
- For undirected graphs, only **degree** is defined.

- Algorithms?
  - Sequential scan through edge list
  - What about for a **graph stored in SQLite**?
Computing Degrees using SQL

Recall simplest way to store a graph in SQLite:

\begin{verbatim}
edges(source_id, target_id)
\end{verbatim}

1. If slow, first create index for each column

2. Use \texttt{group by} statement to find \texttt{in degrees}

\begin{verbatim}
select count(*) from edges group by source_id;
\end{verbatim}
Betweenness Centrality

High betweenness = “gatekeeper”

Betweenness of a node $v$

$$= \sum_{s \neq v \neq t \in V} \frac{\sigma_{st}(v)}{\sigma_{st}}$$

- Number of shortest paths between $s$ and $t$ that goes through $v$
- Number of shortest paths between $s$ and $t$

= how often a node serves as the “bridge” that connects two other nodes.

Betweenness is very well studied. [http://en.wikipedia.org/wiki/Centrality#Betweenness_centrality](http://en.wikipedia.org/wiki/Centrality#Betweenness_centrality)
(Local) Clustering Coefficient

A node’s clustering coefficient is a measure of how close the node’s neighbors are from forming a clique.

- 1 = neighbors form a clique
- 0 = No edges among neighbors

(Assuming undirected graph)

“Local” means it’s for a node; can also compute a graph’s “global” coefficient.

Computing Clustering Coefficients...

Requires **triangle counting**

Real social networks have a lot of triangles

- Friends of friends are friends

Triangles are **expensive** to compute

(neighborhood intersections; several approx. algos)

Can we do that quickly?

Algorithm details:
Faster Clustering Coefficient Using Vertex Covers
http://www.cc.gatech.edu/~ogreen3/_docs/2013VertexCoverClusteringCoefficients.pdf
Super Fast Triangle Counting
[Tsourakakis ICDM 2008]

But: triangles are expensive to compute
(3-way join; several approx. algos)
Q: Can we do that quickly?
A: Yes!

#triangles = 1/6 \( \sum (\lambda_i^3) \)

(and, because of skewness,
we only need the top few eigenvalues!)
Power Law in Eigenvalues of Adjacency Matrix

Eigenvalue

Eigen exponent = slope = -0.48
Wikipedia graph 2006-Nov-04
≈ 3.1M nodes ≈ 37M edges

1000x+ speed-up, >90% accuracy
More Centrality Measures…

- Degree
- Betweenness
- Closeness, by computing
  - Shortest paths
  - “Proximity” (usually via random walks) — used successfully in a lot of applications
- Eigenvector
- …
PageRank (Google)

PageRank: Problem

Given a directed graph, find its most interesting/central node

A node is important, if it is connected with important nodes (recursive, but OK!)
Given a directed graph, find its most interesting/central node

Proposed solution:
use random walk; spot most “popular” node
(-> steady state probability (ssp))

PageRank: Solution

A node has high ssp, if it is connected with high ssp nodes
(recursive, but OK!)

“state” = webpage
Let $B$ be the transition matrix: transposed, column-normalized,

(Simplified) PageRank
(Simplified) PageRank

$$B \ p = \ p$$

How to compute SSP:
http://www.sosmath.com/matrix/markov/markov.html
(Simplified) PageRank

• $B \mathbf{p} = 1 \times \mathbf{p}$

• Thus, $\mathbf{p}$ is the eigenvector that corresponds to the highest eigenvalue ($=1$, since the matrix is column-normalized)

• Why does such a $\mathbf{p}$ exist?
  – $\mathbf{p}$ exists if $B$ is nxn, nonnegative, irreducible
    [Perron–Frobenius theorem]
(Simplified) PageRank

• In short: imagine a particle randomly moving along the edges
• Compute its steady-state probability (ssp)

Full version of algorithm:
  with occasional random jumps
Why? To make the matrix irreducible
Full Algorithm

- With probability \(1-c\), fly-out to a random node
- Then, we have

\[
p = c \mathbf{B} \mathbf{p} + \frac{(1-c)}{n} \mathbf{1} \Rightarrow \\
p = \frac{(1-c)}{n} [\mathbf{I} - c \mathbf{B}]^{-1} \mathbf{1}
\]
How to compute PageRank for huge matrix?

Use the power iteration method

http://en.wikipedia.org/wiki/Power_iteration

\[ p = c \ B \ p + \frac{(1-c)}{n} \ 1 \]

Can initialize this vector to any non-zero vector, e.g., all “1”s
PageRank Explained with Javascript

http://www.cs.duke.edu/csed/principles/pagerank/
PageRank for graphs (generally)

You can compute PageRank for any graphs

Should be in your algorithm “toolbox”

• Better than simple centrality measure (e.g., degree)

• Fast to compute for large graphs (O(E))

But can be “misled” (Google Bomb)

• How?
Personalized PageRank

Make one small variation of PageRank

• Intuition: not all pages are equal, some more relevant to a person’s specific needs
• How?
Personalized PageRank

With probability $1-c$, fly-out to a random node some preferred nodes.

Can initialize this vector to any non-zero vector, e.g., all “1”s.
Why learn Personalized PageRank?

For recommendation

- If I like webpage A, what else do I like?
- If I bought product A, what other products would I also buy?

Visualizing and interacting with large graphs

- Instead of visualizing every single nodes, visualize the most important ones

Very flexible — works on any graph
Related “guilt-by-association” / diffusion techniques

- **Personalized PageRank**
  (= Random Walk with Restart)

- “Spreading activation” or “degree of interest” in Human-Computer Interaction (HCI)

- Belief Propagation
  (powerful inference algorithm, for fraud detection, image segmentation, error-correcting codes, etc.)
Why are these algorithms popular?

• **Intuitive to interpret**
  uses “network effect”, homophily

• **Easy to implement**
  Math is relatively simple (mainly matrix-vector multiplication)

• **Fast**
  run time linear to \#edges, or better

• **Probabilistic** meaning
Human-In-The-Loop Graph Mining

Apolo: Machine Learning + Visualization

CHI 2011
Finding More Relevant Nodes

Citation network
Finding More Relevant Nodes

Citation network
Finding More Relevant Nodes

Apolo uses **guilt-by-association** (Belief Propagation, similar to personalized PageRank)
Demo: Mapping the Sensemaking Literature

Nodes: 80k papers from Google Scholar (node size: #citation)
Edges: 150k citations
The cost structure of sensemaking


245 citations 8 versions
The cost structure of sensemaking


245 citations 8 versions
Key Ideas (Recap)

Specify **exemplars**

Find **other** relevant nodes (BP)
Apolo’s Contributions

1. Human + Machine

   It was like having a partnership with the machine.

2. Personalized Landscape

Apolo User
Apolo 2009
Apolo 2010
Apolo 2011

22,000 lines of code. Java 1.6. Swing. Uses SQLite3 to store graph on disk.
User Study

Used citation network

Task: Find related papers for 2 sections in a survey paper on user interface

• Model-based generation of UI
• Rapid prototyping tools

Past, Present and Future of User Interface Software Tools

Brad Myers, Scott E. Hudson, and Randy Pausch

Human Computer Interaction Institute
School of Computer Science
Carnegie Mellon University
Pittsburgh, PA 15213-3891
Between subjects design
Participants: grad student or research staff
"Model-based"

"Prototyping"

Apolo

Google Scholar

10 papers for each section
Apolo

“Model-based”

“Prototyping”

Google Scholar

10 papers for each section

Expert judges rated papers

\[
\begin{align*}
1 + 0 &= 1 \\
1 + 1 &= 2 \\
0 + 0 &= 0 \\
\vdots
\end{align*}
\]
Higher is better.

Apolo wins.

Statistically significant, by two-tailed t test, $p < 0.05$
Apolo: Recap

A mixed-initiative approach for exploring and creating personalized landscape for large network data

Apolo = ML + Visualization + Interaction
Practitioners’ guide to building (interactive) applications

Think about scalability early

- Identify candidate scalable algorithms early on

Use iterative design approach, as in Apolo and industry

- Why? It’s hard to get it right the first time
- **Create prototype, evaluate, modify prototype, evaluate, ...**
- Quick evaluation helps you identify **important fixes early** — save you a lot of time overall
Practitioners’ guide to building (interactive) applications

What kinds of prototypes?

• Paper prototype, lo-fi prototype, high-fi prototype

Important to involve REAL users as early as possible

• Recruit your friends to try your tools
• Lab study (controlled, as in Apolo)
• Longitudinal study (usage over months)
• Deploy it and see the world’s reaction!

• To learn more:
  • CS 6750 Human-Computer Interaction
  • CS 6455 User Interface Design and Evaluation
If you want to know more about people…

http://amzn.com/0321767535