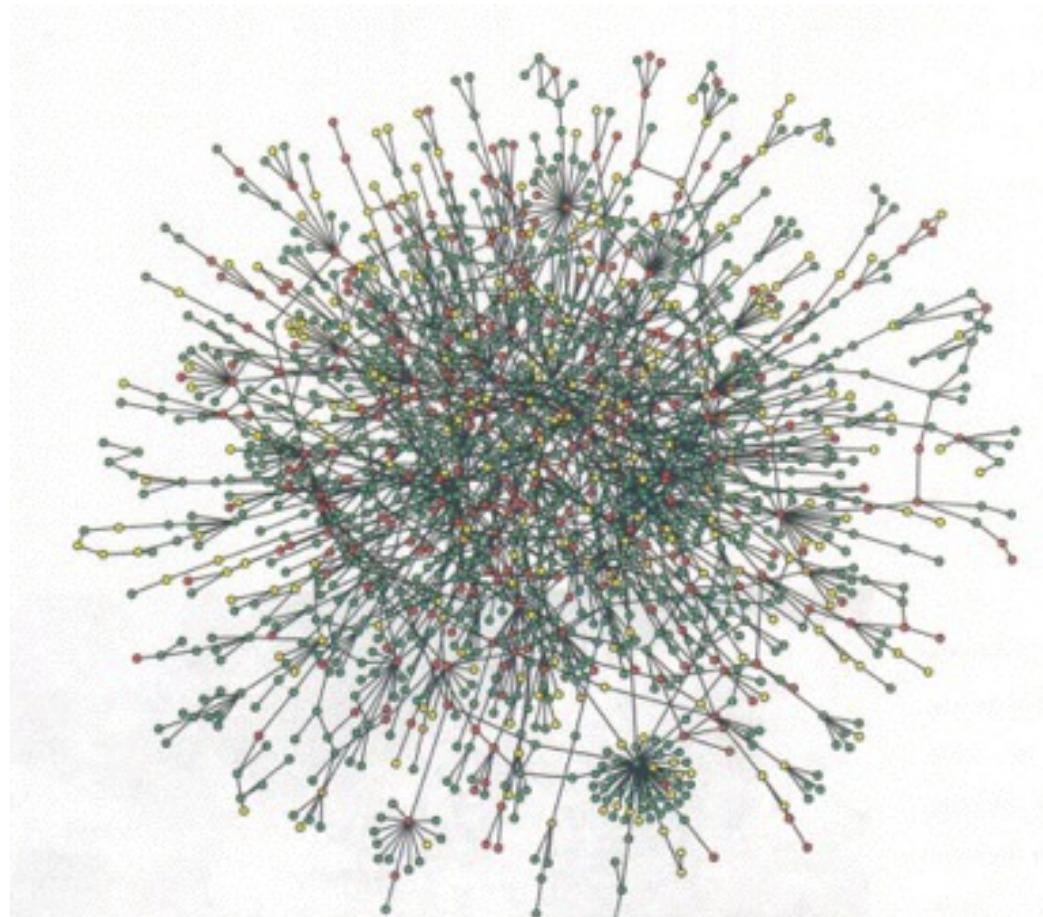


Visualizing Networks

Lynn Cherny
@arnicas

4 Nov 2014

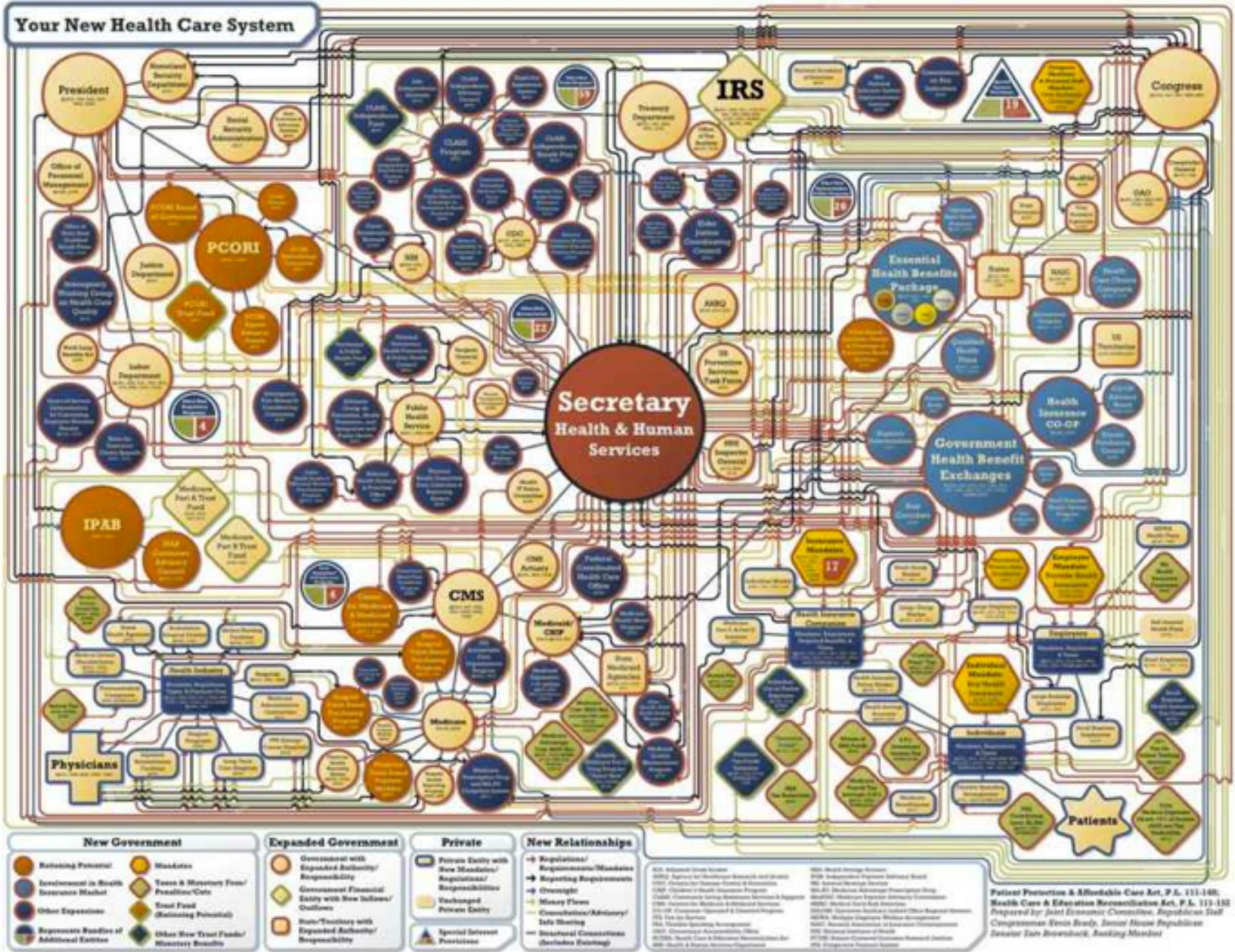
The Hairball: A Metaphor for Complexity



MAP OF INTERACTING PROTEINS in yeast highlights the discovery that highly linked, or hub, proteins tend to be crucial for a cell's survival. Red denotes essential proteins [their removal will cause the cell to die]. Orange represents proteins of some importance [their removal will slow cell growth]. Green and yellow represent proteins of lesser or unknown significance, respectively.

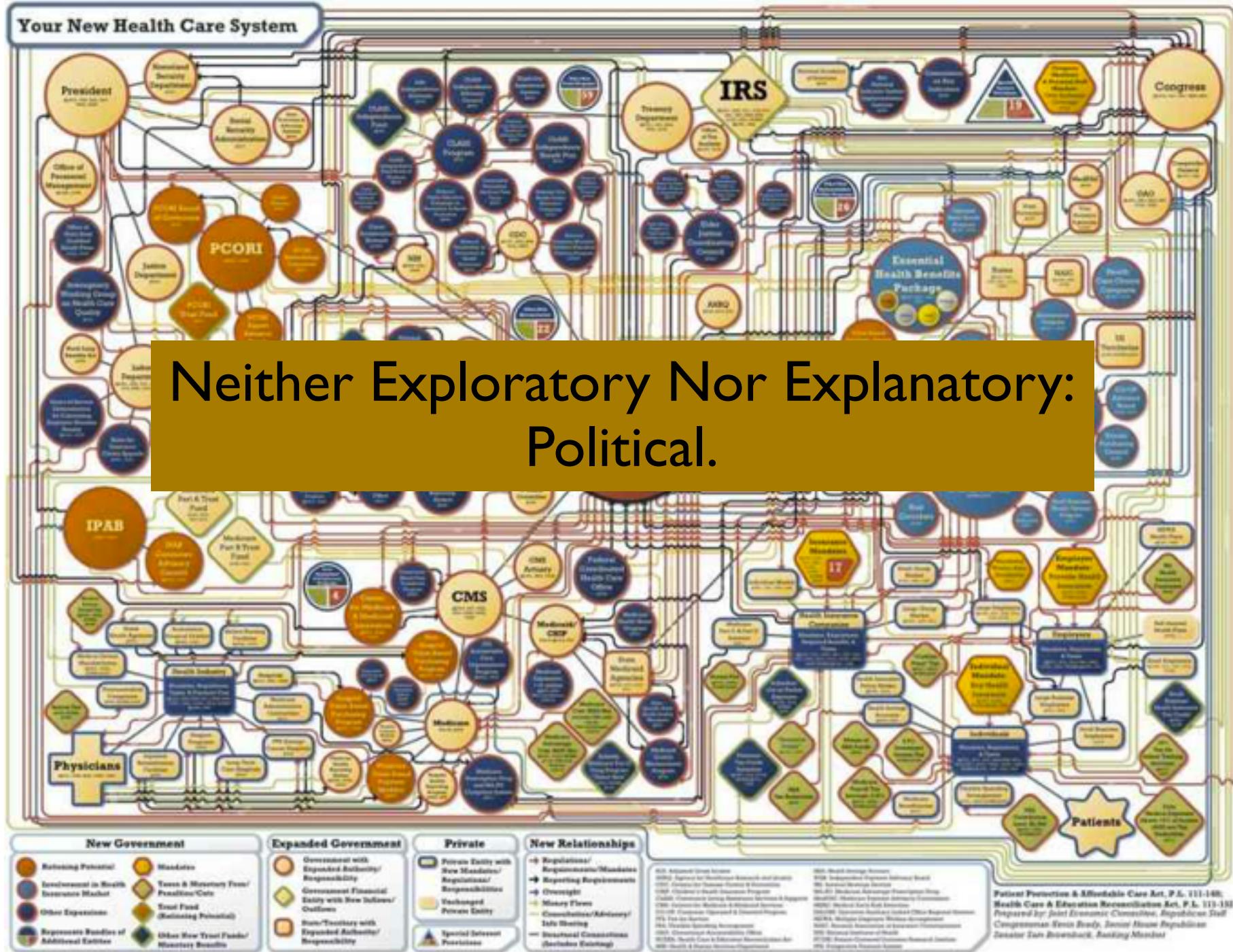


Your New Health Care System

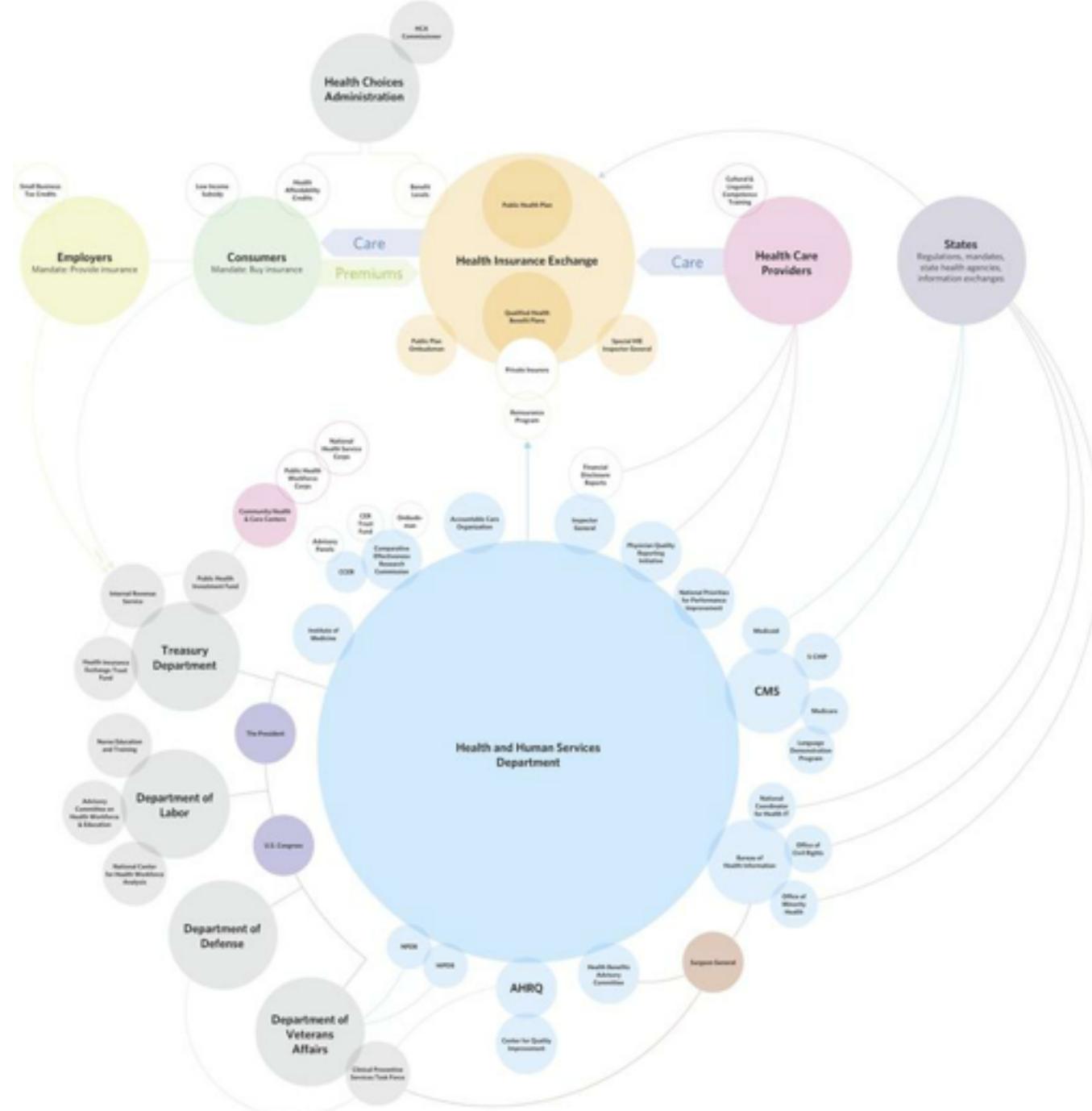


Patient Protection & Affordable Care Act, P.L. 111-148; Health Care & Education Reconciliation Act, P.L. 111-132
Prepared by Joint Economic Committee, Republican Staff
Congressman Kevin Brady, Senior House Republican
Senator Tom Coburn, Ranking Democrat

Your New Health Care System



Organizational Chart of the House Democrats' Health Plan



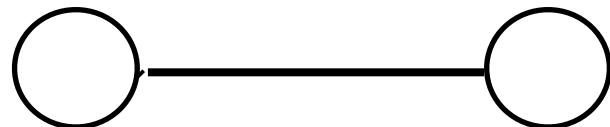


“By releasing your chart, instead of meaningfully educating the public, you willfully obfuscated an already complicated proposal. There is no simple proposal to solve this problem. You instead chose to shout ‘12! 16! 37! 9! 24!’ while we were trying to count something.”

WHAT IS A NETWORK?

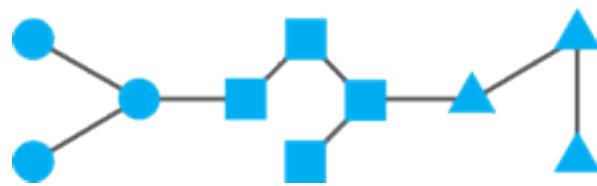
It's not a visualization. Think of it as a data structure.

- Data relationship: entities + relationships to other objects (node/edge, vertex/link)



- Nodes and Edges may have attributes, eg.
 - gender, age, weight, tv prefs
 - connection date, frequency of contact, type of exchange, directionality of relationship
 - attributes may be calculated from network relations too

Node Shape



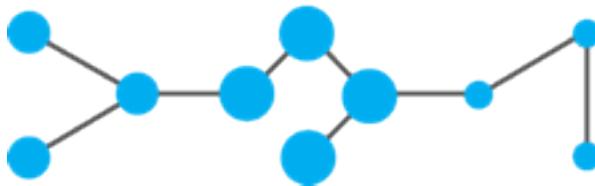
Node Shape



Node Color



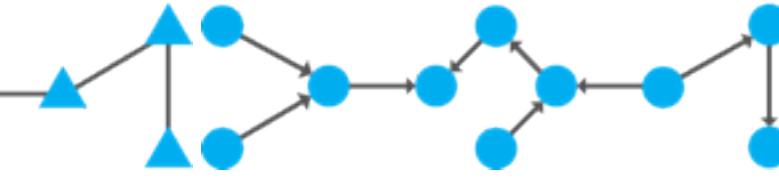
Node Size



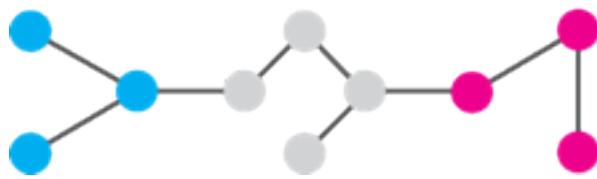
Node Shape



Edge Direction



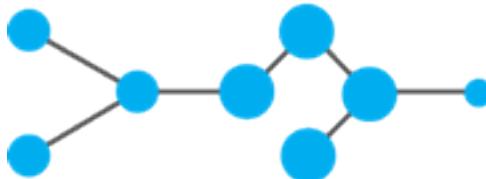
Node Color



Edge Color



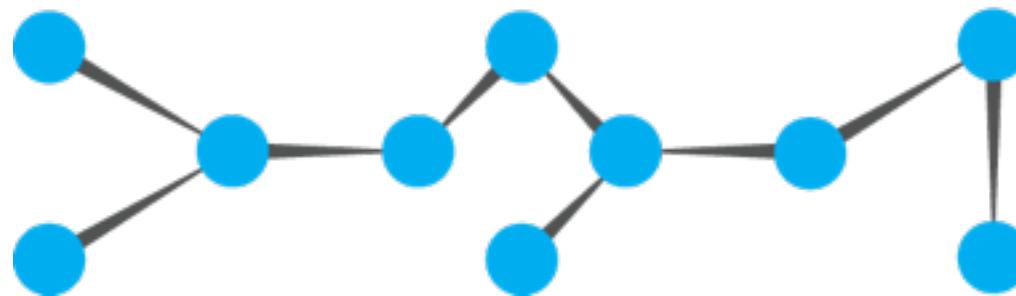
Node Size



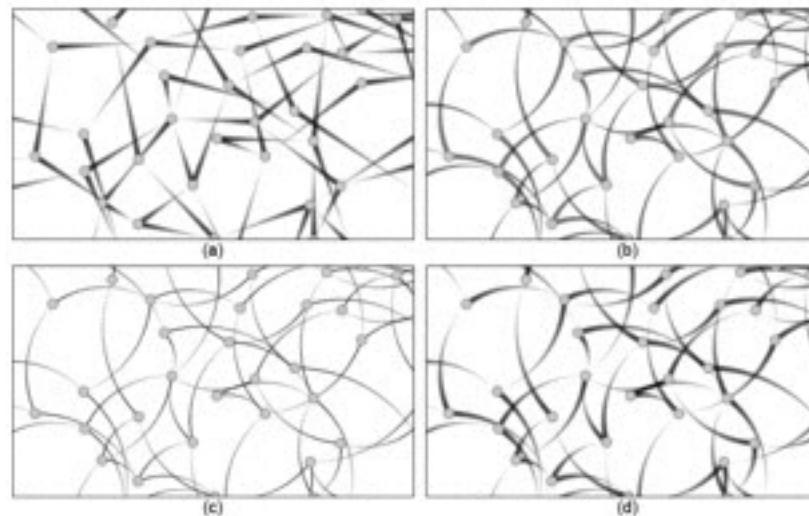
Edge Size



Edge Tapering

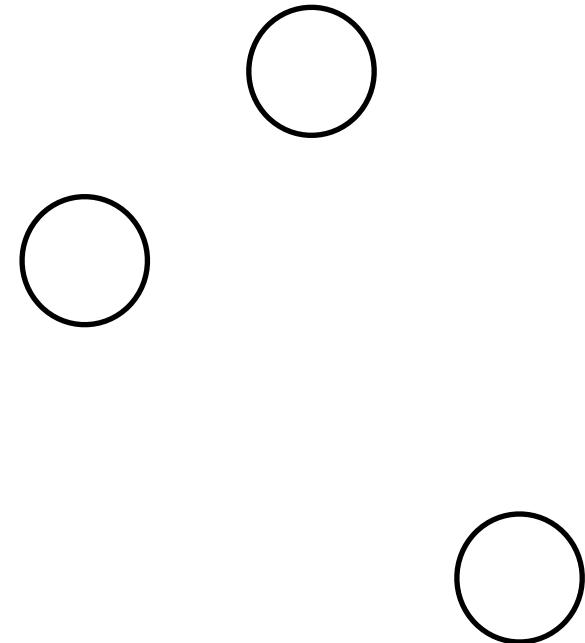
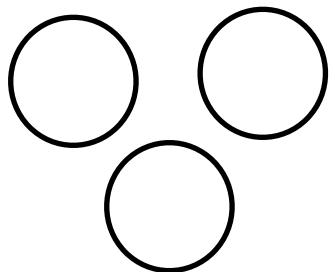


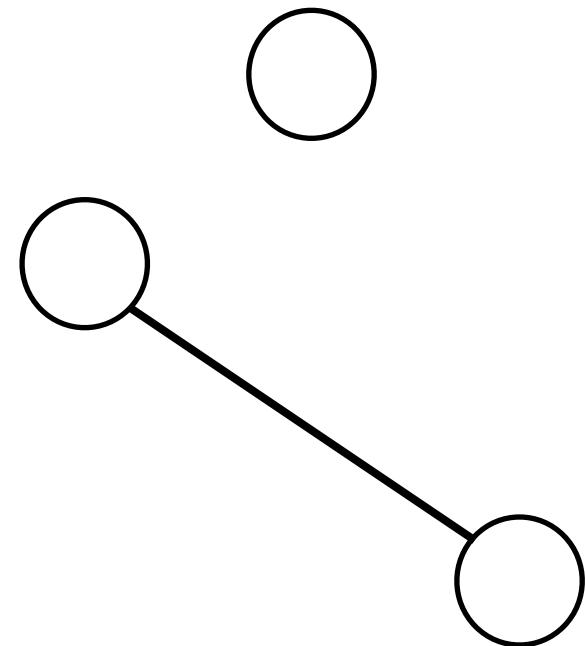
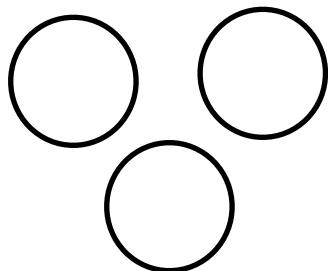
Best!

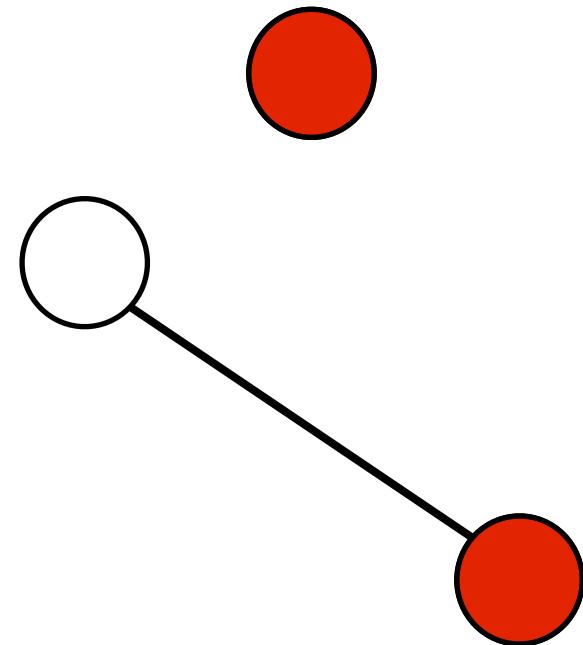
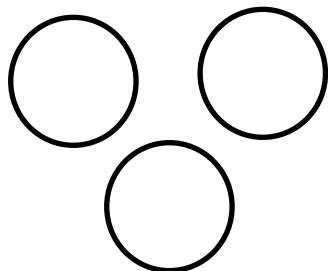


A User Study on Visualizing Directed Edges in Graphs"

Danny Holten and Jarke J. van Wijk, 27th SIGCHI Conference on Human Factors in Computing Systems (Proceedings of CHI 2009),





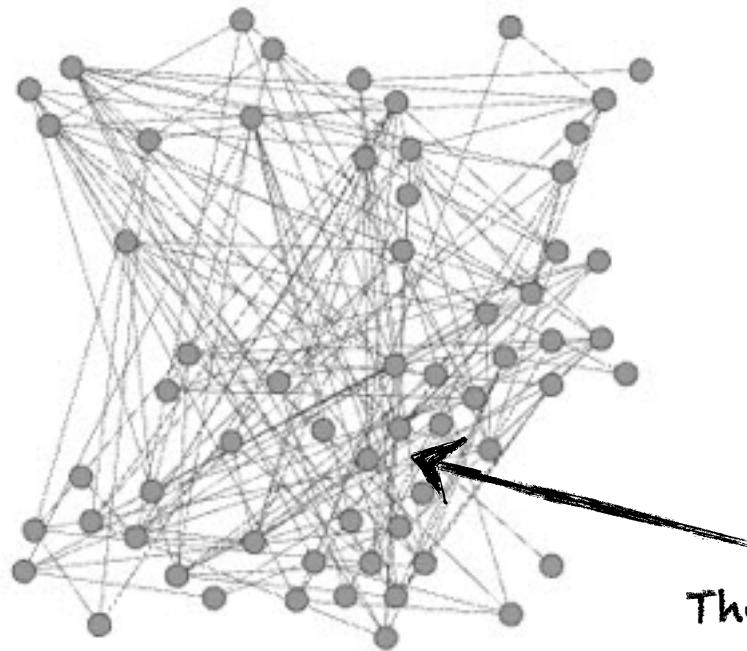




It's a natural human trait to see visual similarity and proximity as meaningful.

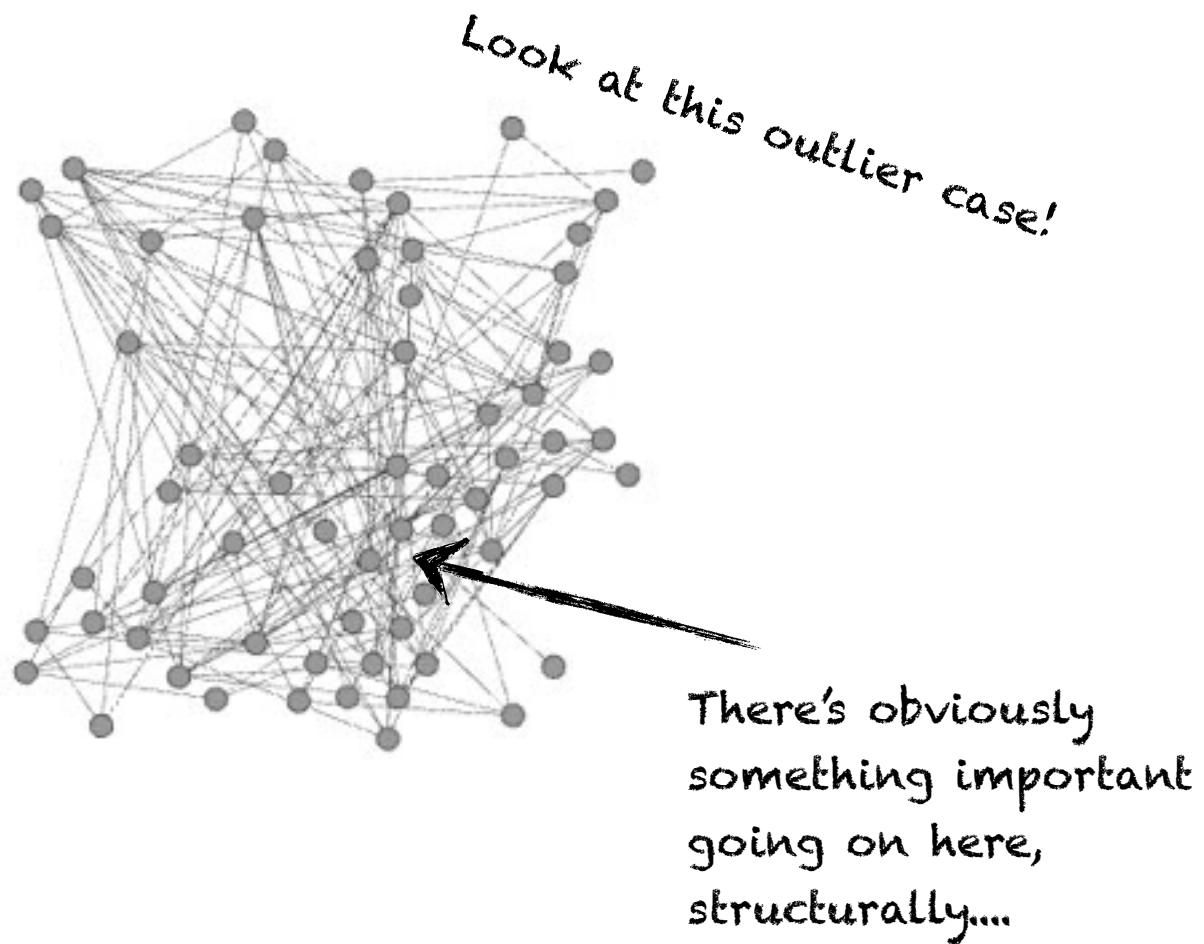
Be very careful about your display choices and layout methods!

Reading a network visualization

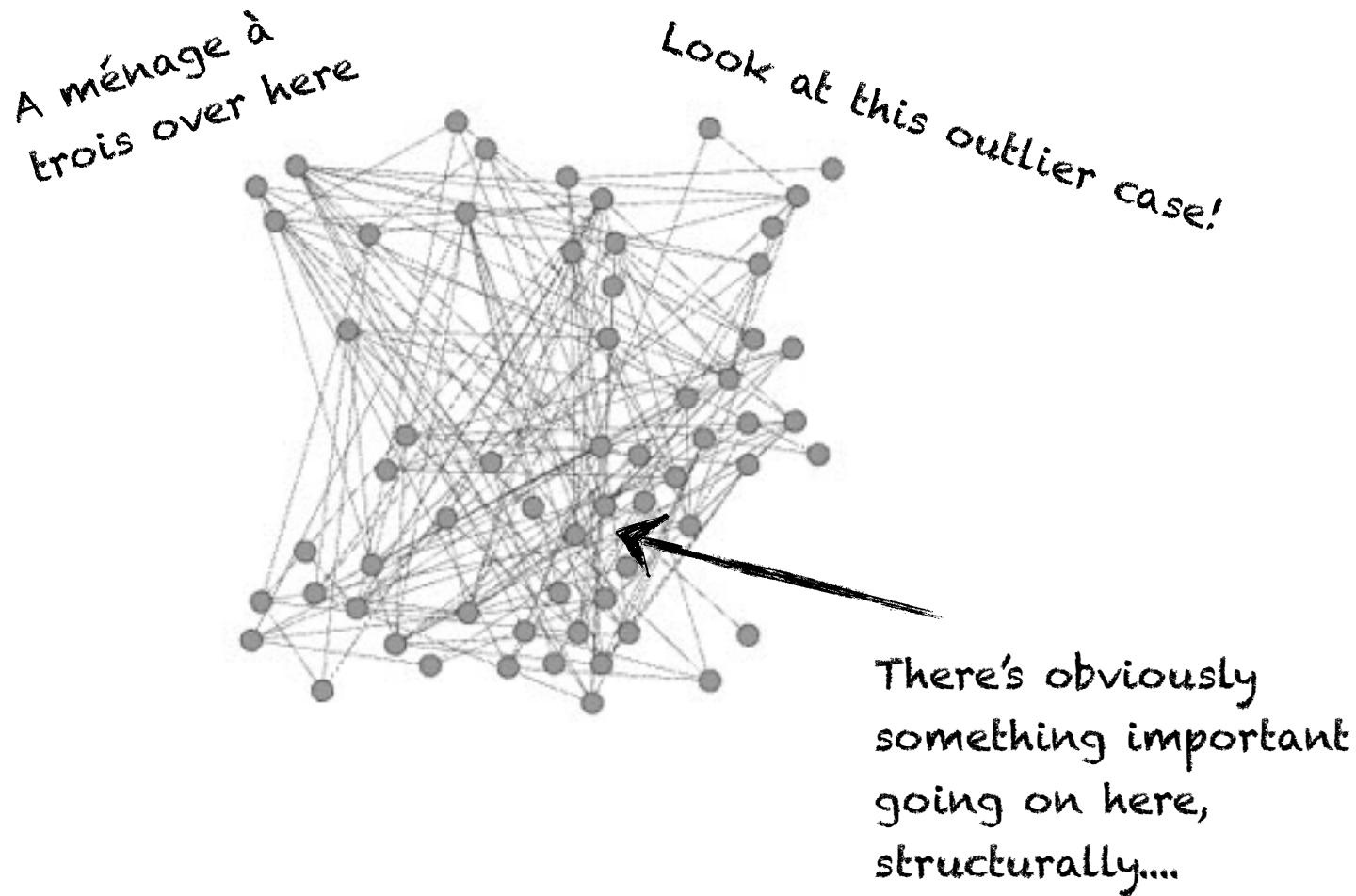


There's obviously
something important
going on here,
structurally....

Reading a network visualization

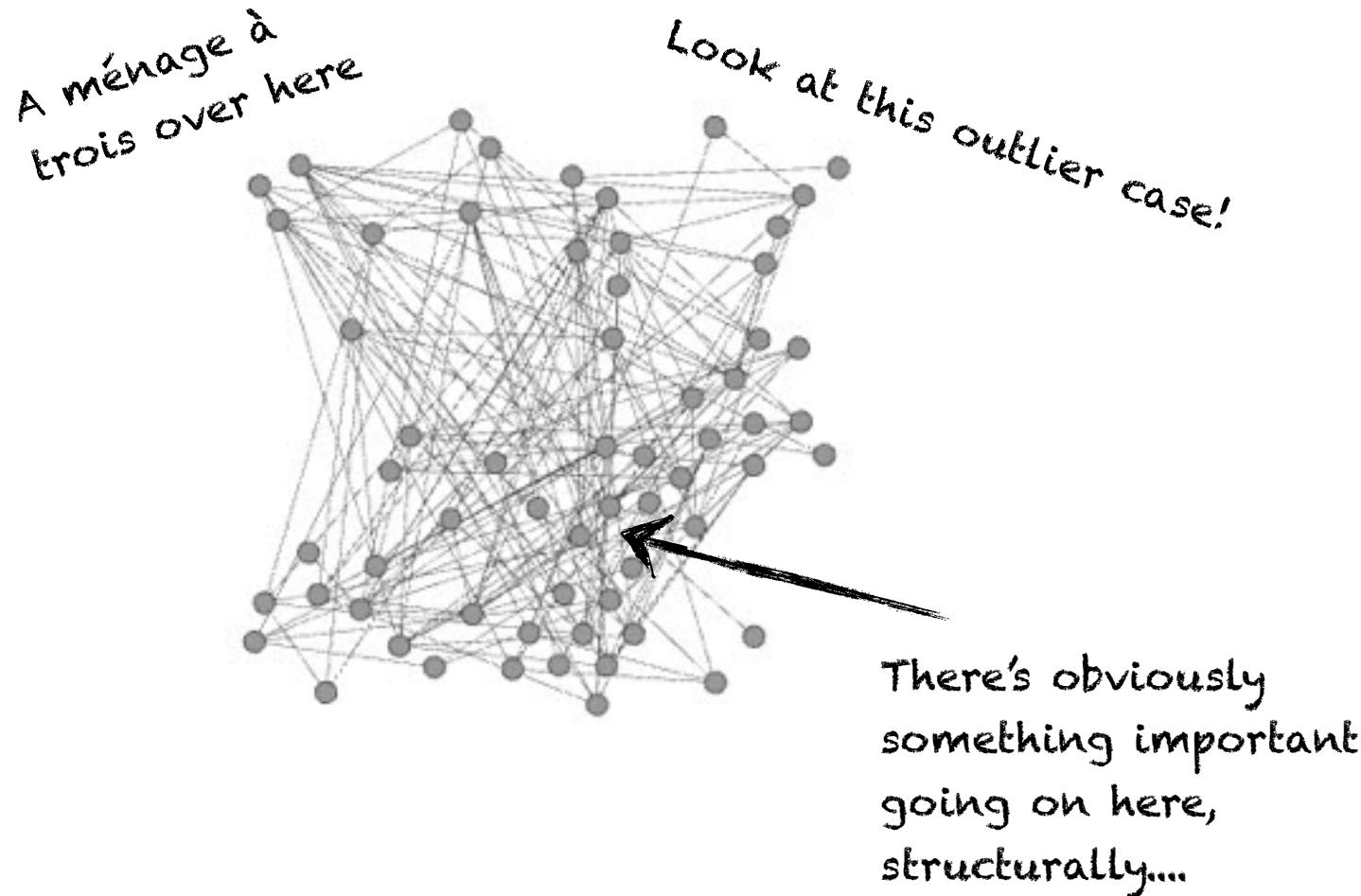


Reading a network visualization



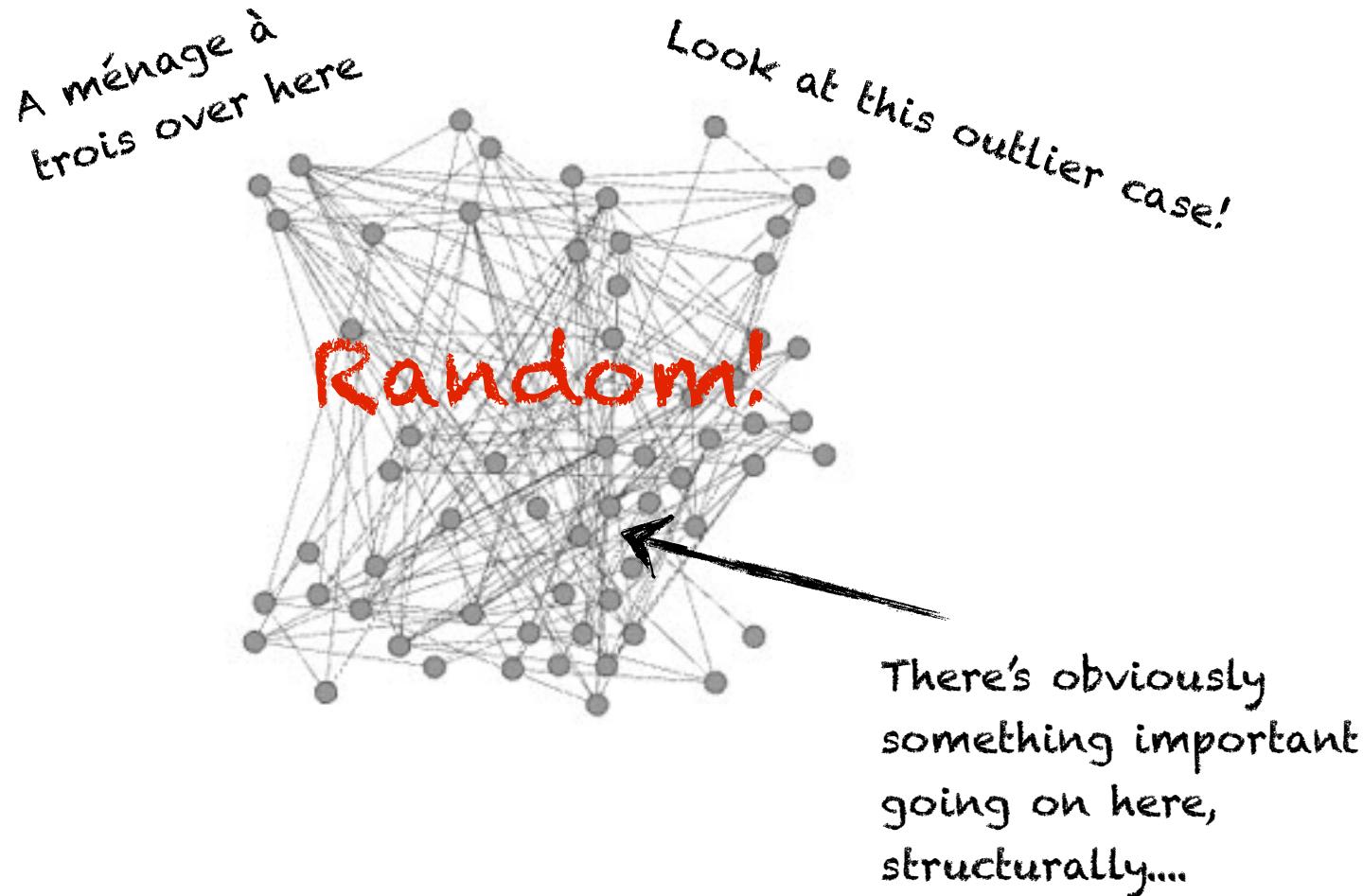
MIS?

Reading a network visualization



MIS?

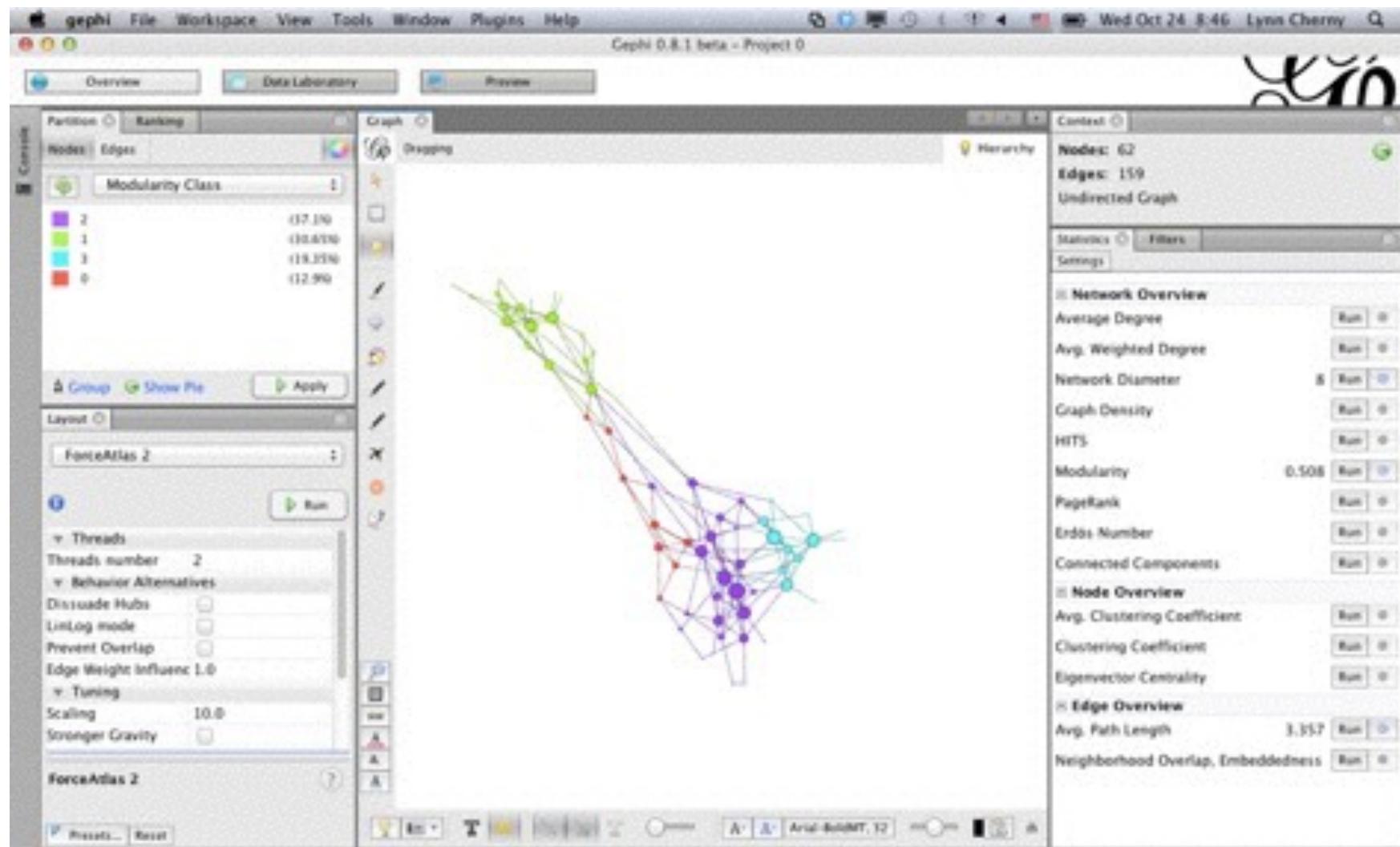
Reading a network visualization



TOOLS AND CONCEPTS FOR TODAY

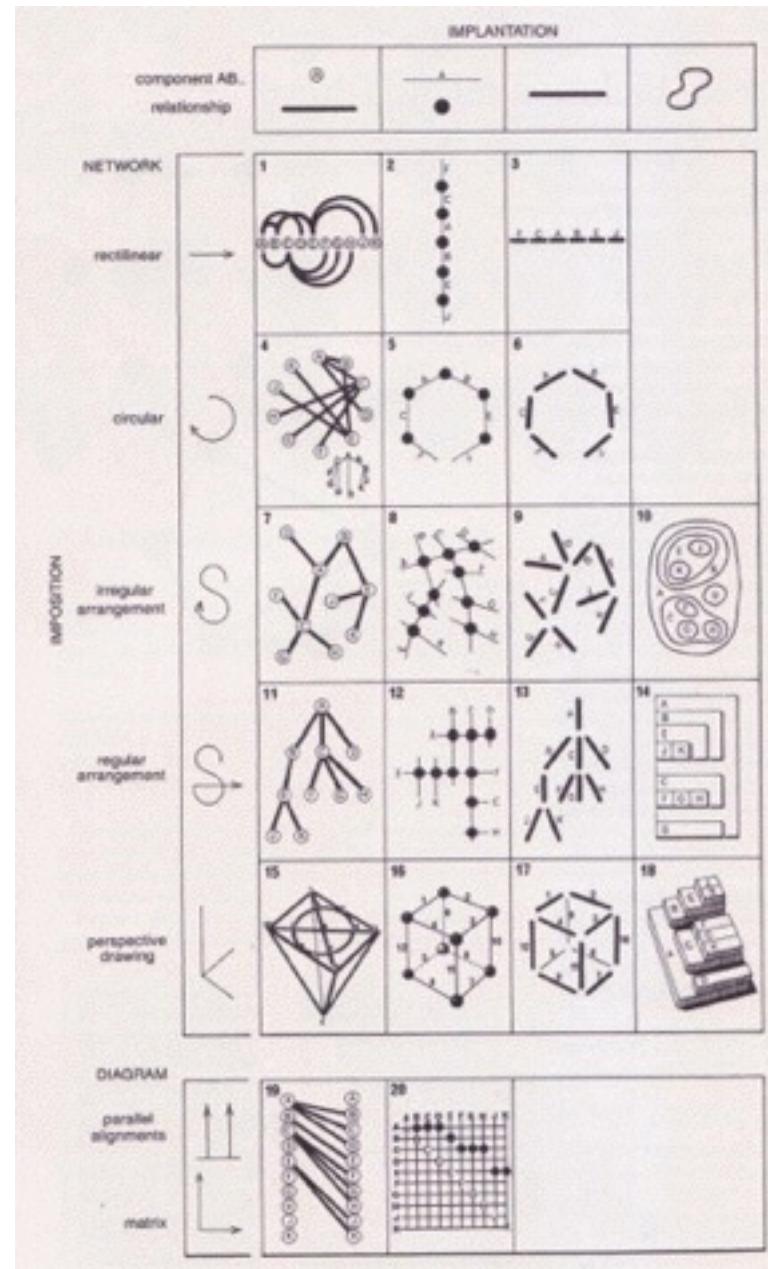
Creating network layouts...

Gephi (and a little D3)



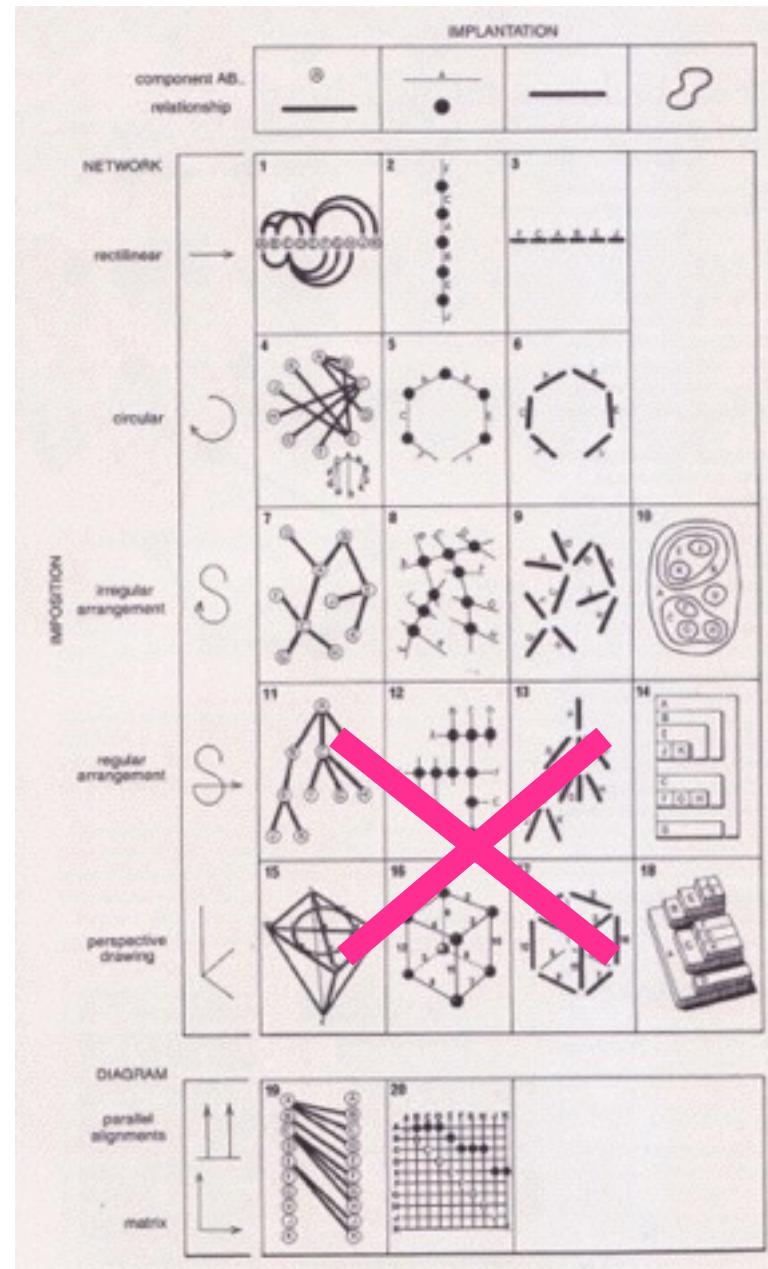
J Bertin: Semiology of Graphics

Linear
Circular
Irregular
Regular (Tree)
3D
Matrix /
Bipartite

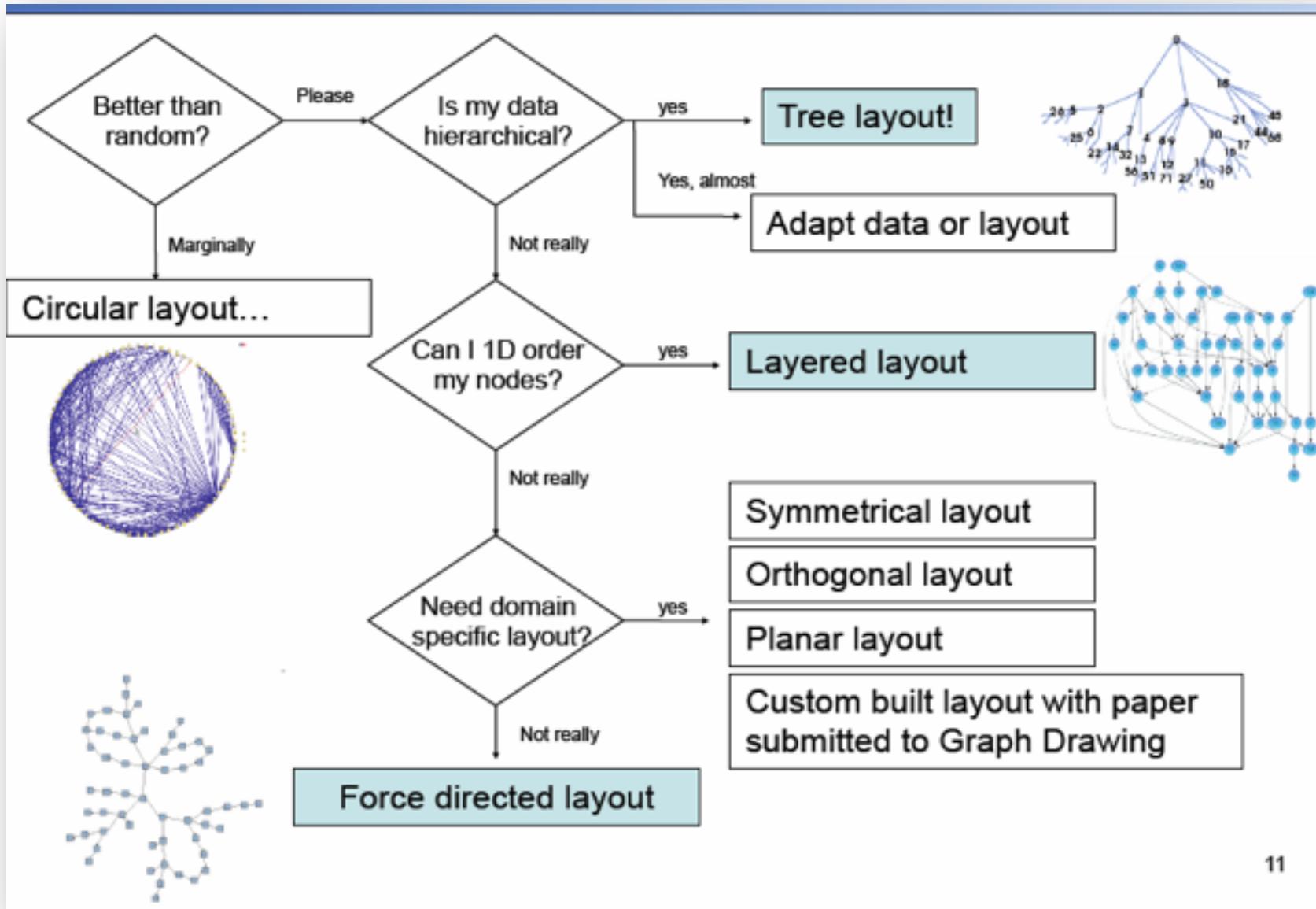


J Bertin: Semiology of Graphics

Linear
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Algorithmic Approaches

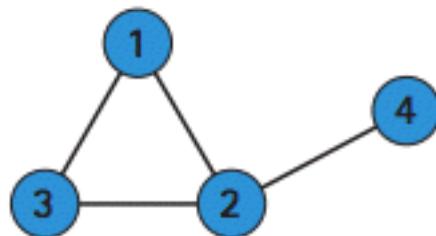


MATRIX LAYOUTS / REPRESENTATIONS

Adjacency matrix

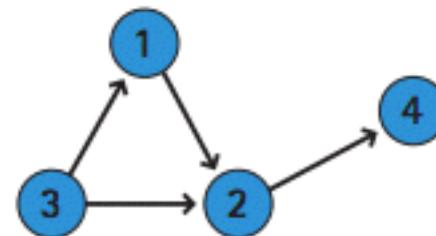
$$A_{ij} = \begin{pmatrix} A_{11} & A_{12} & A_{13} & A_{14} \\ A_{21} & A_{22} & A_{23} & A_{24} \\ A_{31} & A_{32} & A_{33} & A_{34} \\ A_{41} & A_{42} & A_{43} & A_{44} \end{pmatrix}$$

Undirected network

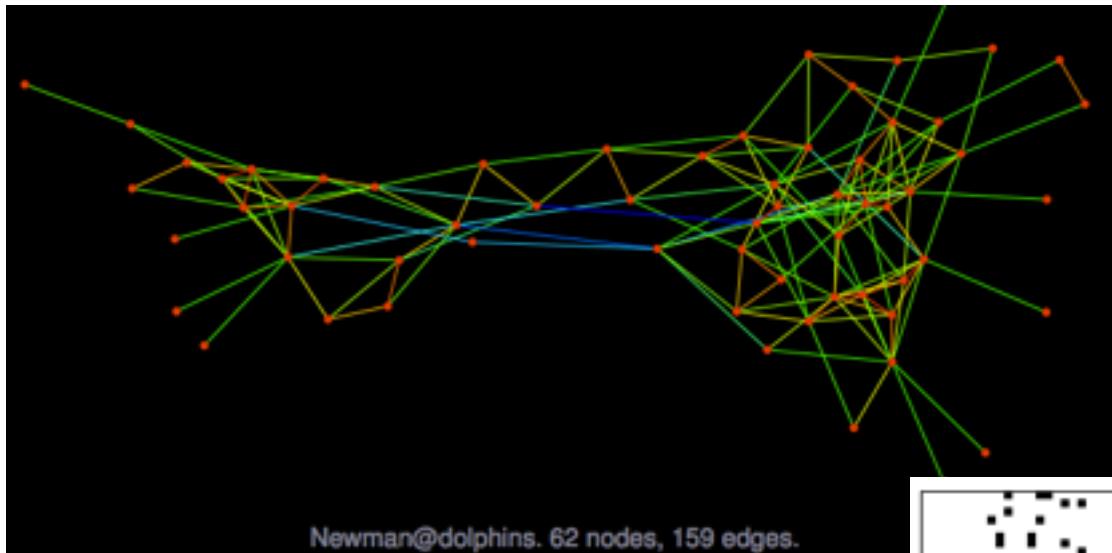


$$A_{ij} = \begin{pmatrix} 0 & 1 & 1 & 0 \\ 1 & 0 & 1 & 1 \\ 1 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{pmatrix}$$

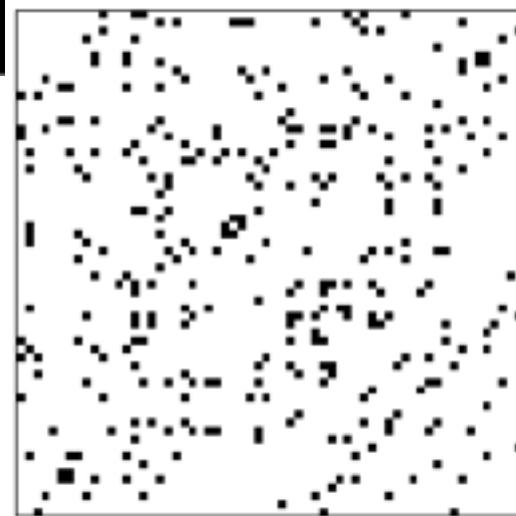
Directed network



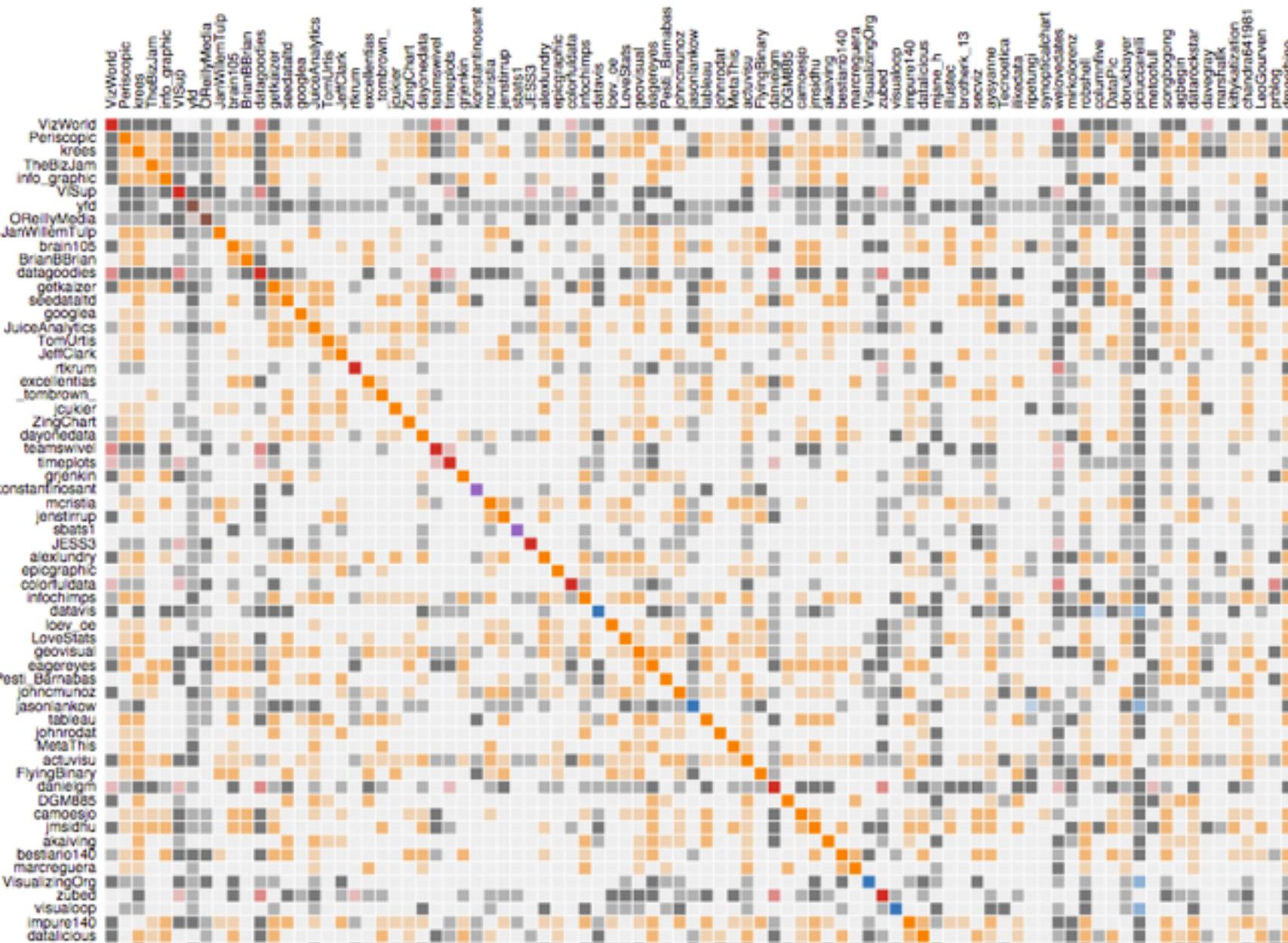
$$A_{ij} = \begin{pmatrix} 0 & 0 & 1 & 0 \\ 1 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{pmatrix}$$



Real social networks are generally quite sparse.



Sample with High Eigenvector Centrality



Data Set

Nodes: 88

Edges: 2591

Order (From Top Left) By:

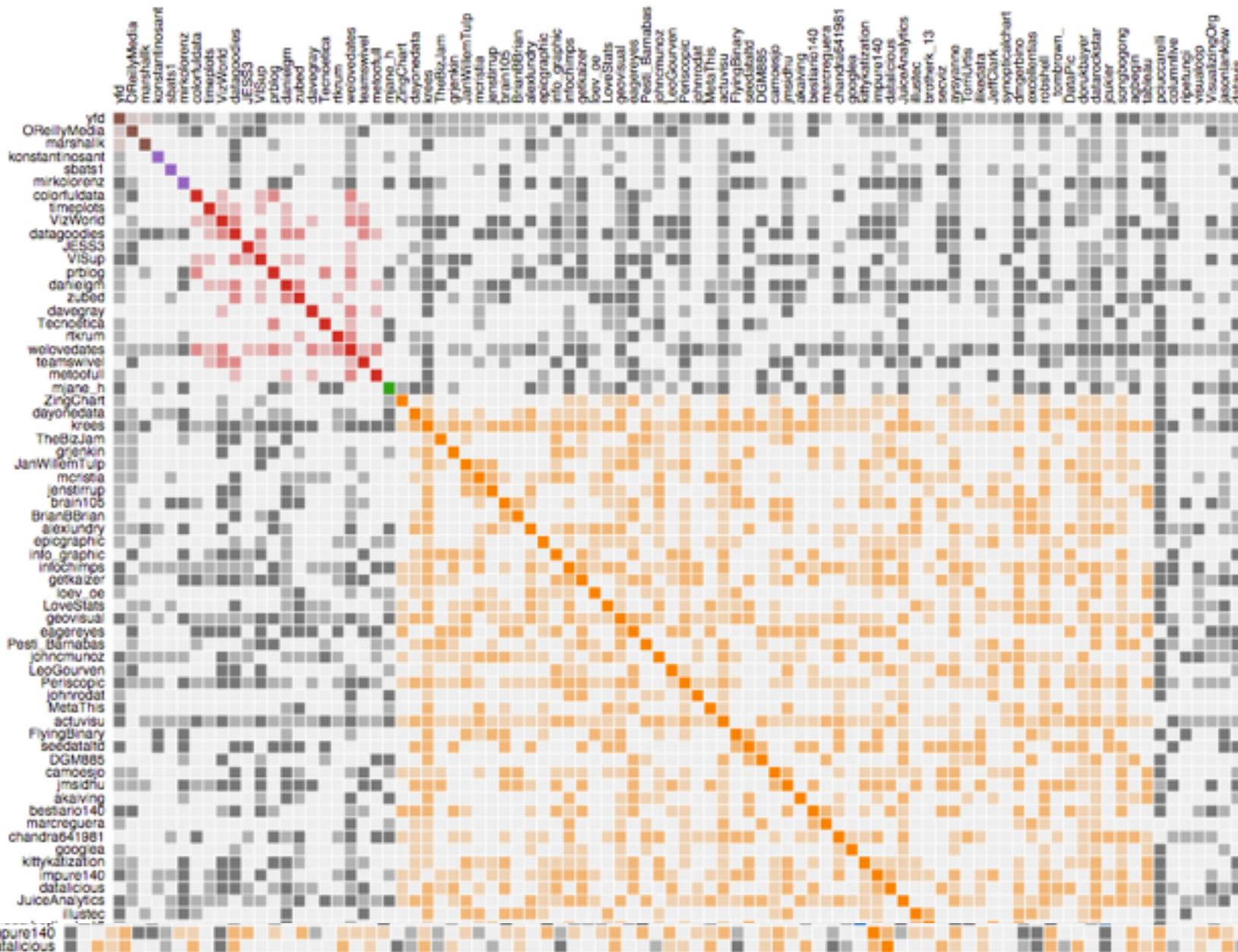
Eigenvector Centrality

Nodes shown represent a high eigenvector-scoring subset of the full 1644 node dataset from Moritz Stefaner's crawl of infovis tweeters in Summer 2011.

Cells are colored by partition joint membership. Grey cells indicate links between nodes that don't share a partition.

Based on Mike Bostock's [Les Mis Co-occurrence Matrix Example](#). Built with D3 by Lynn Chemey from NetworkX analysis with accompanying talk slides and blog post.

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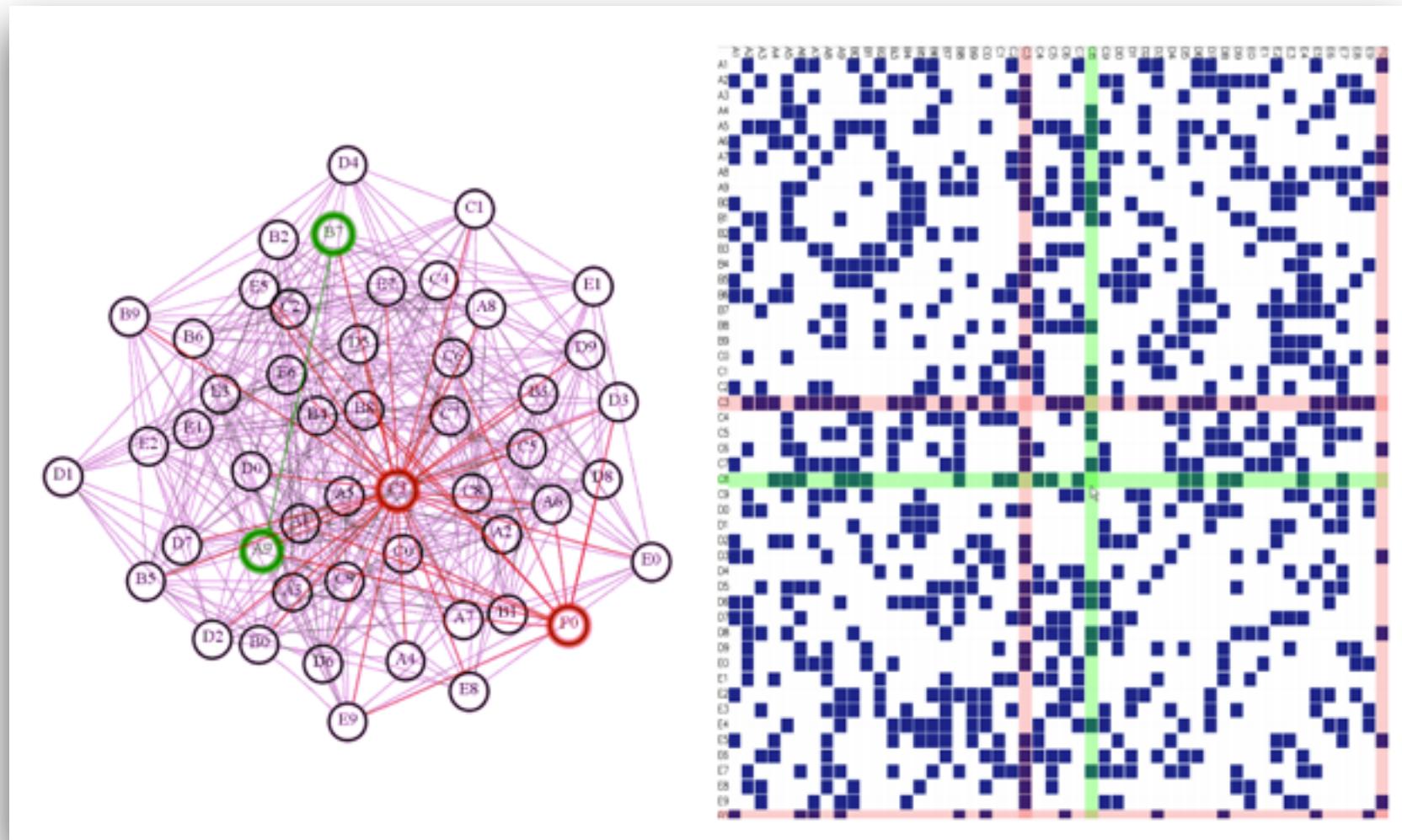
Partition(Color)

Nodes shown represent a high eigenvector-scoring subset of the full 1644 node dataset from Moritz Stefaner's crawl of infovis tweeters in Summer 2011.

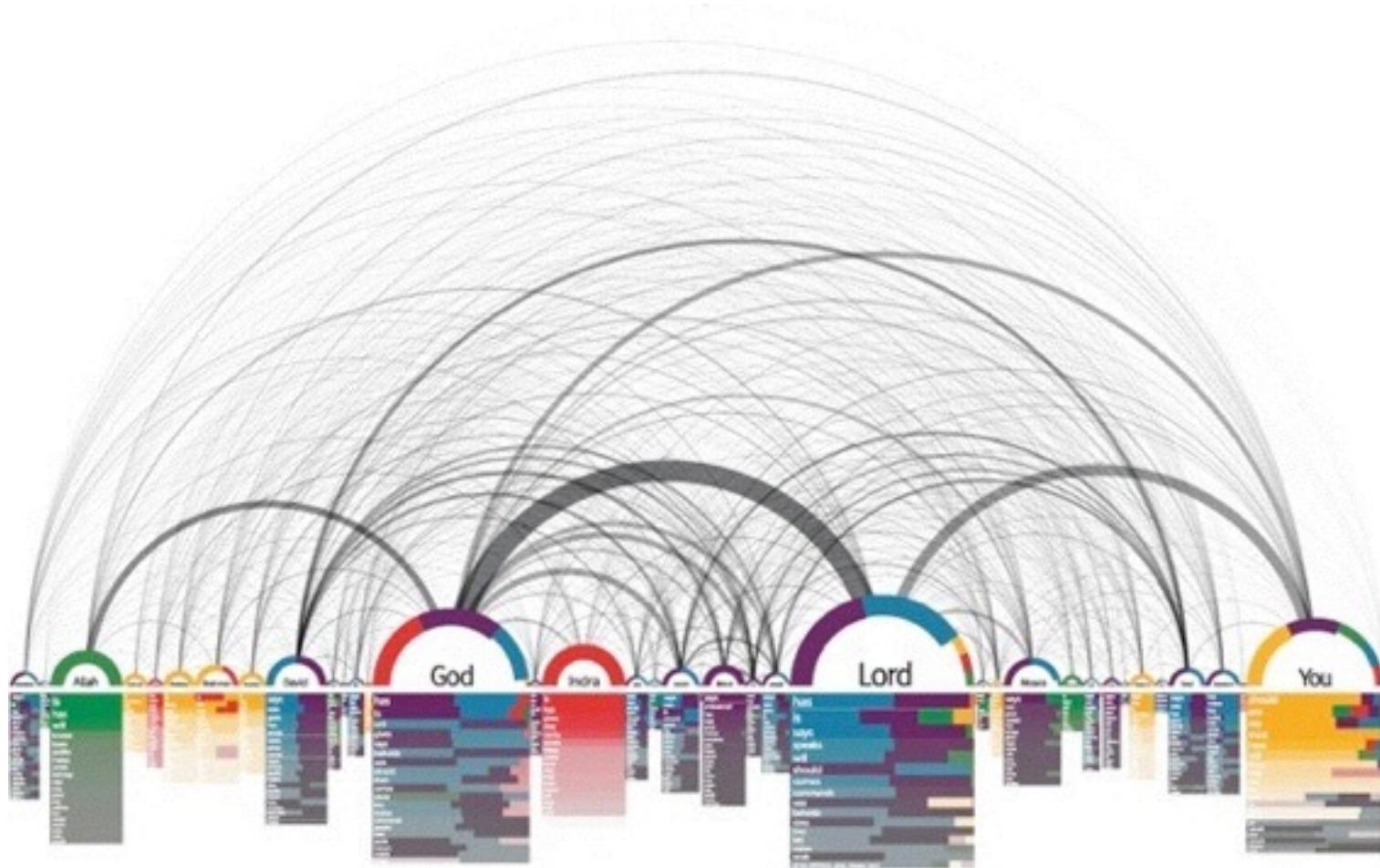
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Based on Mike Bostock's [Les Mis Co-occurrence Matrix Example](#). Built with [D3](#) by Lynn Cherny from NetworkX analysis with accompanying [talk slides](#) and [blog post](#).

Readability: Matrix Better (except for path finding)



ARC / LINEAR LAYOUTS



Philipp Steinweber and Andreas Koller
Similar Diversity, 2007

Topics in *Da Vinci Code* (by me)

Color text by:

Chapter Excitement Rating (like blocks)

Shared Topics (like arcs)



Topics in *Da Vinci Code* (by me)

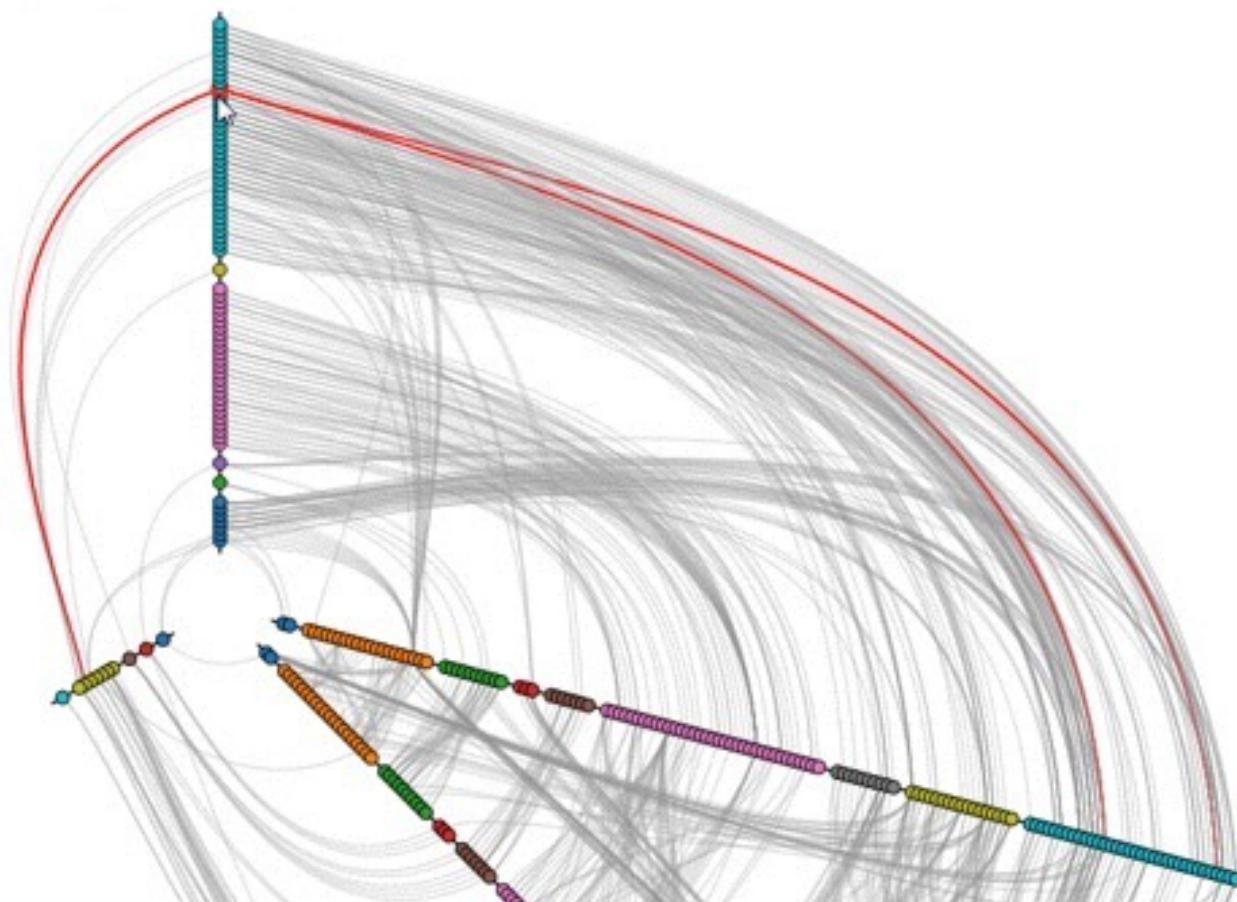
Color text by:

Chapter Excitement Rating (like blocks) Shared Topics (like arcs)



Hive Plots

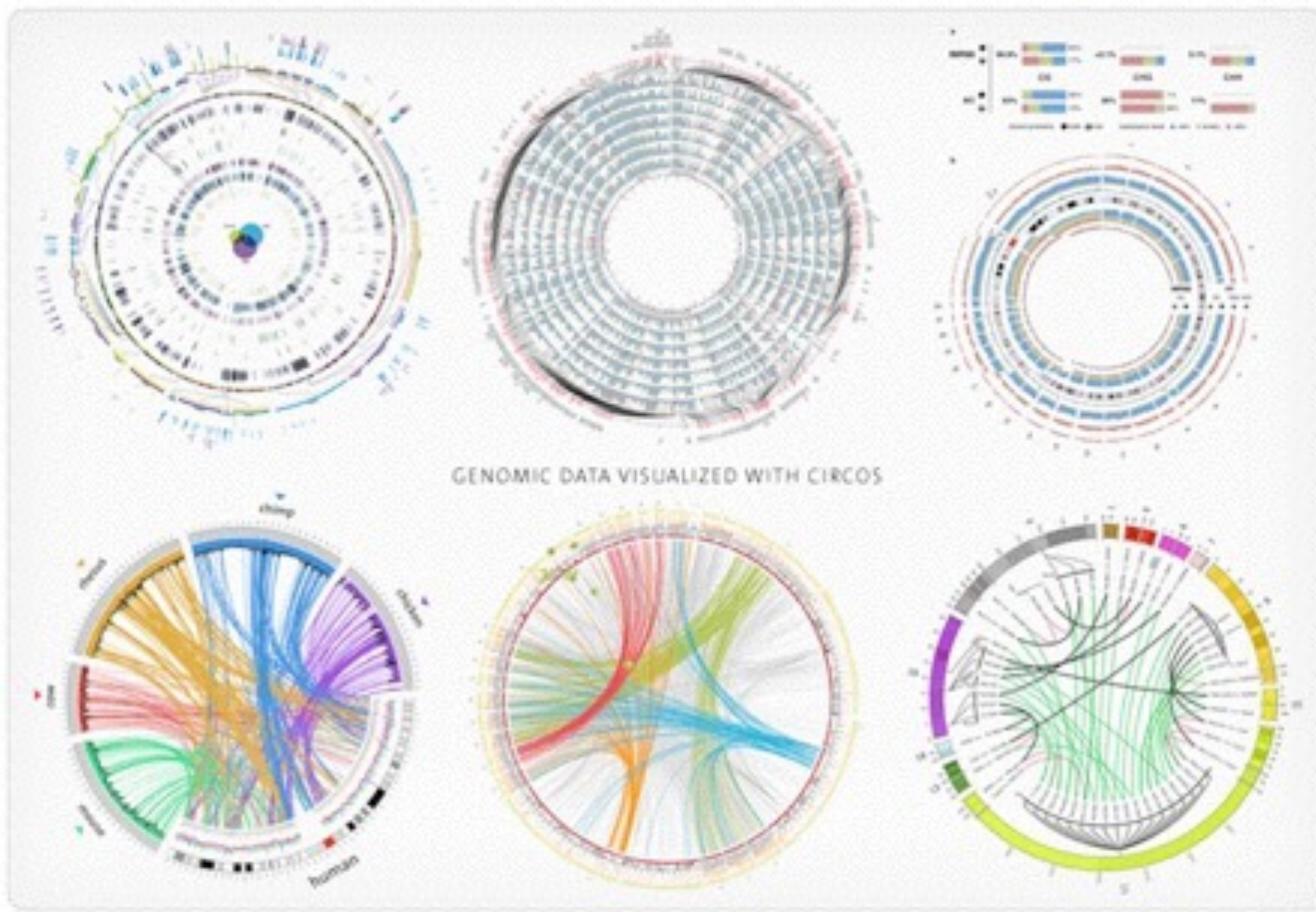
flare.vis.operator.layout.IcicleTreeLayout



CIRCULAR / CHORD LAYOUTS

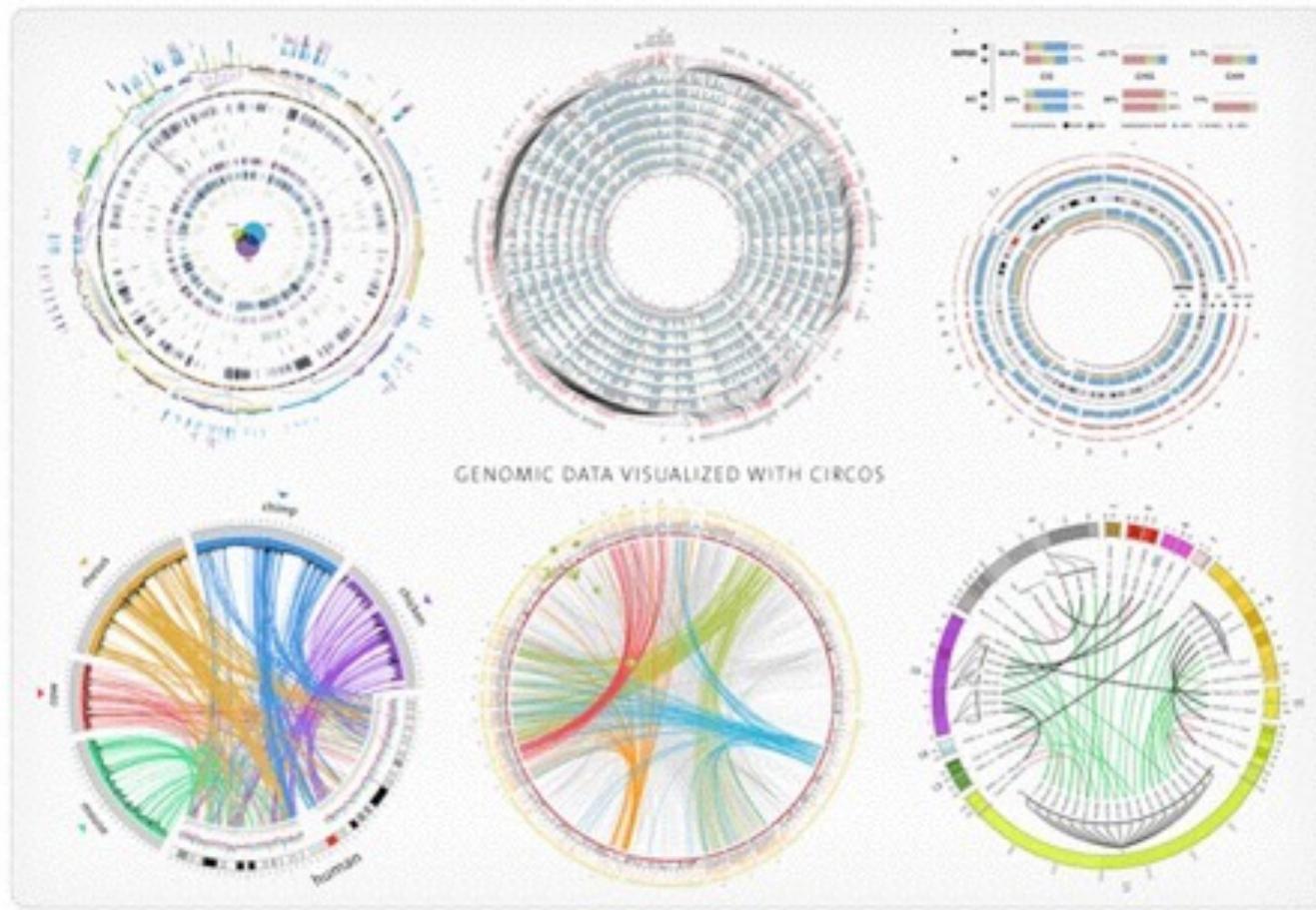
Circos

"If it's round, Circos can probably do it"



Circos

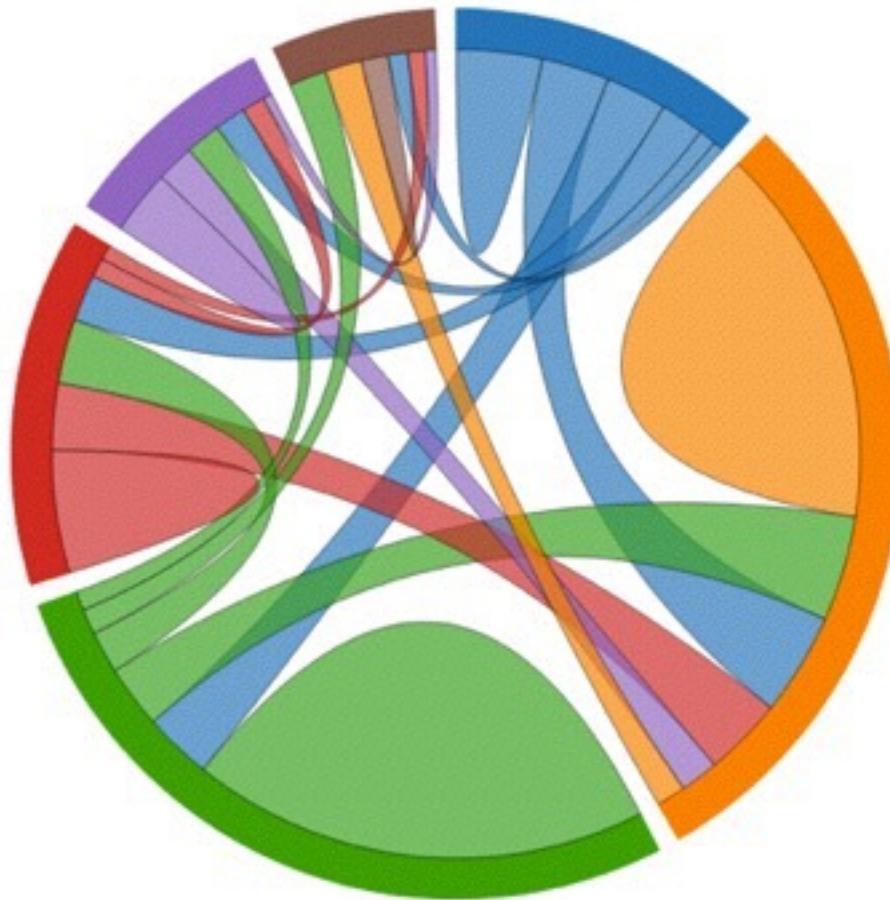
"If it's round, Circos can probably do it"



TIL (shocking): It's all perl code!?

Computed Relations Between Nodes as Chord Diagram

Nodes shown represent a high-scoring subset of the full 1644 node dataset from [Moritz Stefaner's crawl of infovis tweeters](#) in Summer 2011.



Select Data Set:

Full Data (1644)

Nodes: 1644

Edges: 73922

Computed Source/Target Matrix

	0	1	2	3	4	5
0	2663	2107	1896	1360	544	332
1	3182	11823	3263	2456	1192	911
2	2111	1958	14203	1302	597	784
3	1452	2071	1983	3803	598	461
4	964	1183	1096	712	2009	282
5	617	1151	1162	528	333	833

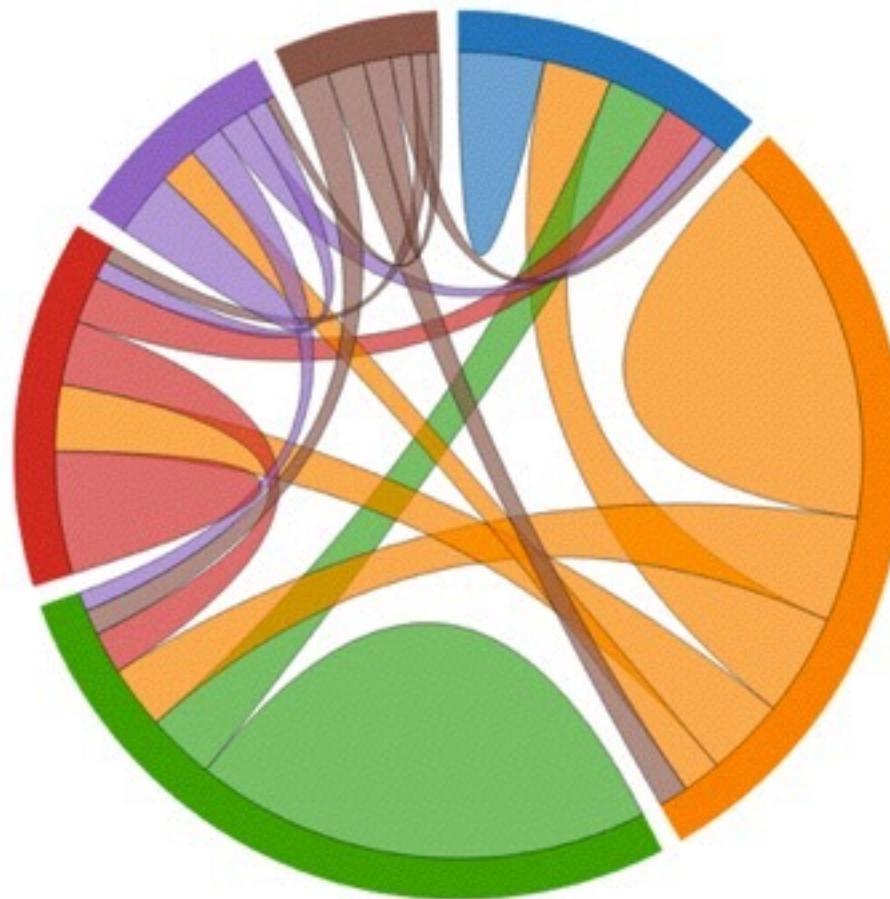
Color chords by larger:

Source Target

Built with [D3](#) by [Lyon Cherry](#) from
NetworkX analysis with accompanying [talk](#)
[slides](#) and [blog post](#).

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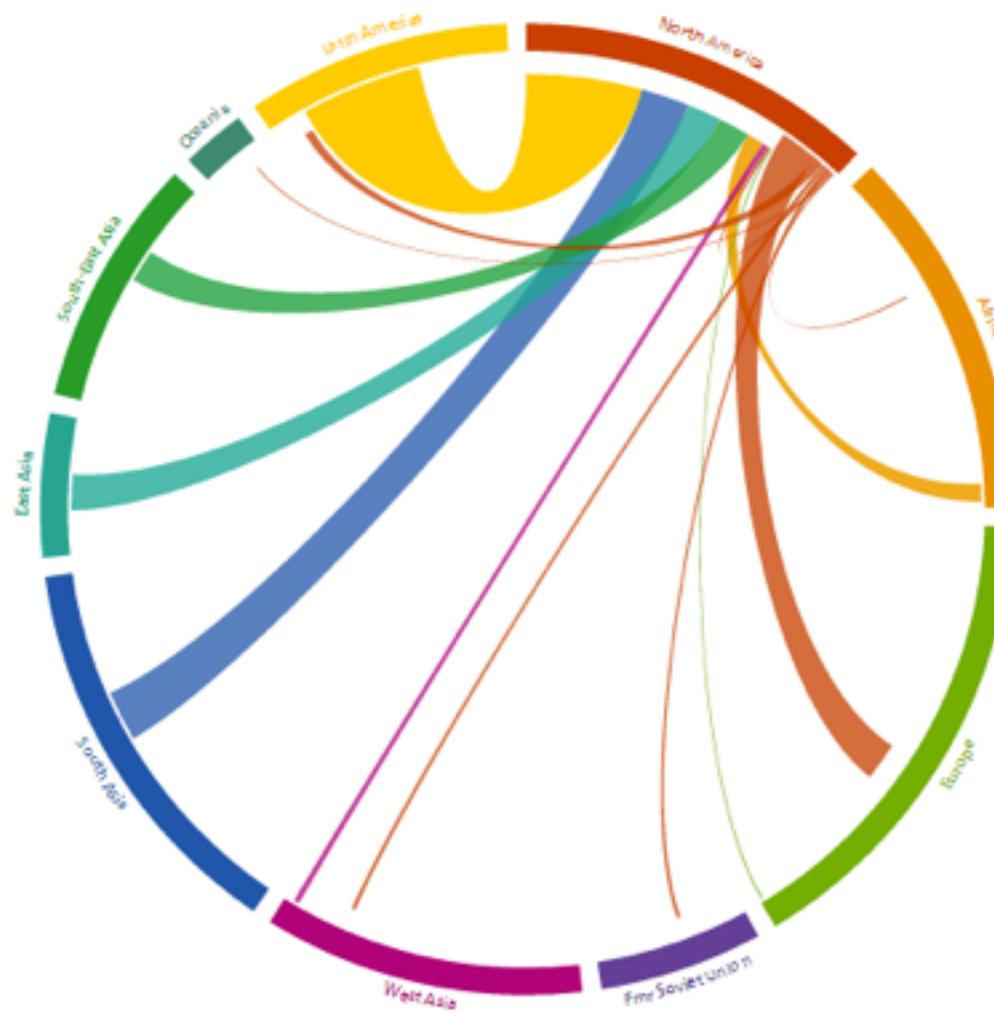
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Color chords by larger:

Source Target

Built with [D3](#) by [Lynn Cherny](#) from
NetworkX analysis with accompanying [talk](#)
[slides](#) and [blog post](#).

A Nice UI Improvement - Differentiate Source/ Destination



Hierarchical Edge Bundling demo by @mbostock



D3: <http://bl.ocks.org/1044242>

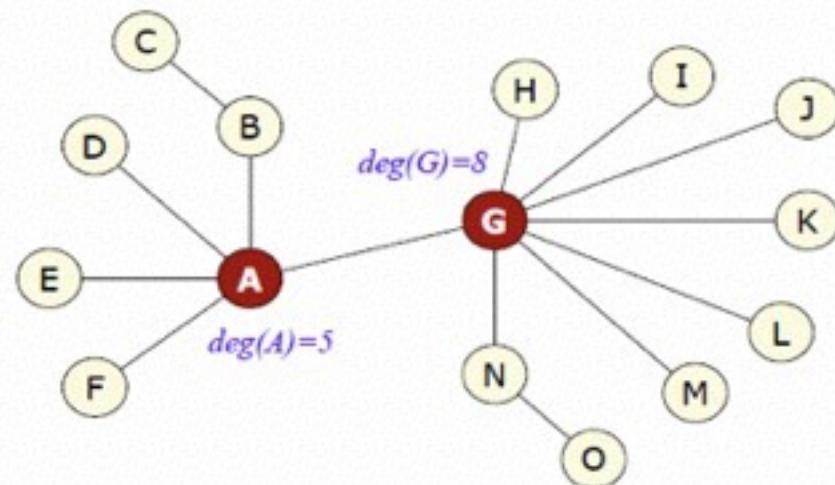
"Hierarchical Edge Bundles: Visualization of Adjacency Relations in Hierarchical Data", Danny Holten, IEEE Transactions on Visualization and Computer Graphics (TVCG; Proceedings of Vis/InfoVis 2006), Vol. 12, No. 5, Pages 741 - 748, 2006.

SIMPLE CALCULATIONS ON NETWORKS CAN TELL YOU LOADS

Often you need to visualize the structure/role of the graph elements as part of the visualization: So, do some simple math.

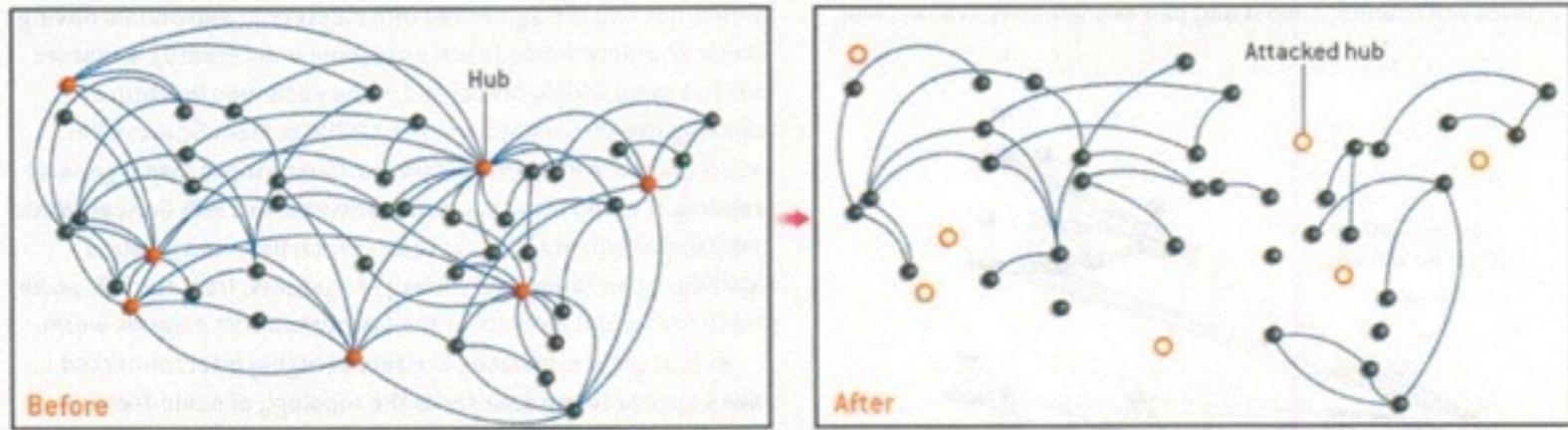
Degree (In, Out)

- “Degree” is a measure of the edges in (directed), out (directed), or total (in directed or undirected graphs) to a node
- “Hub” nodes have high in-degree. In scale-free networks, we see preferential attachment to the popular kids.



The Threat of Hub-Loss

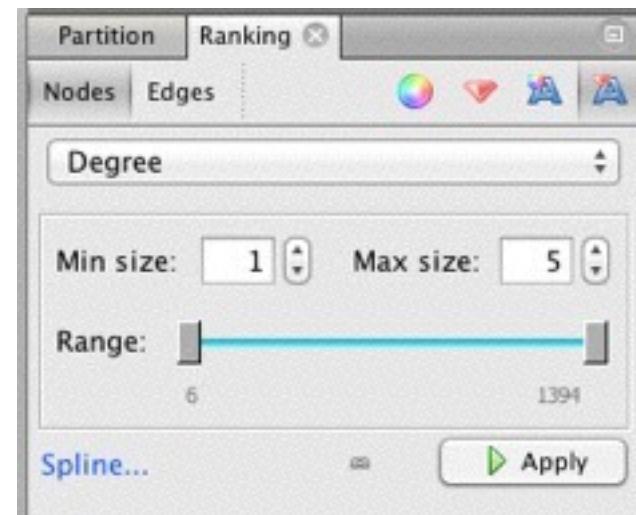
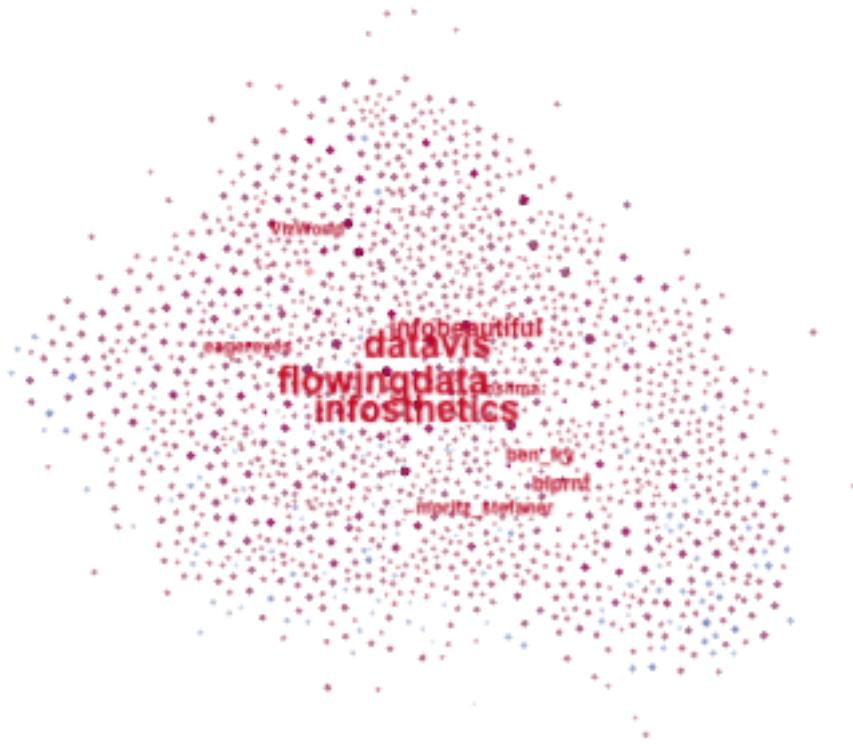
Scale-Free Network, Attack on Hubs



Visualization Aside: If Some Names are Huge, the Others are Invisible-?

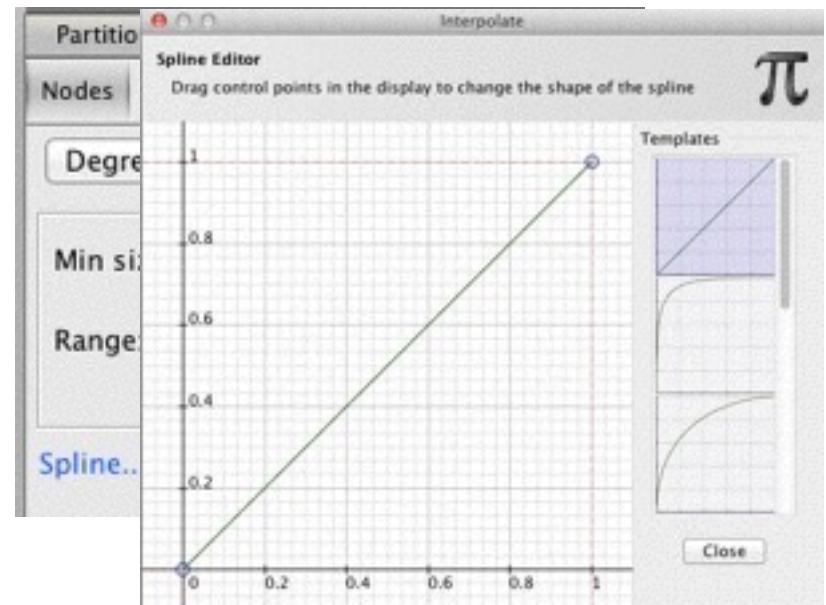
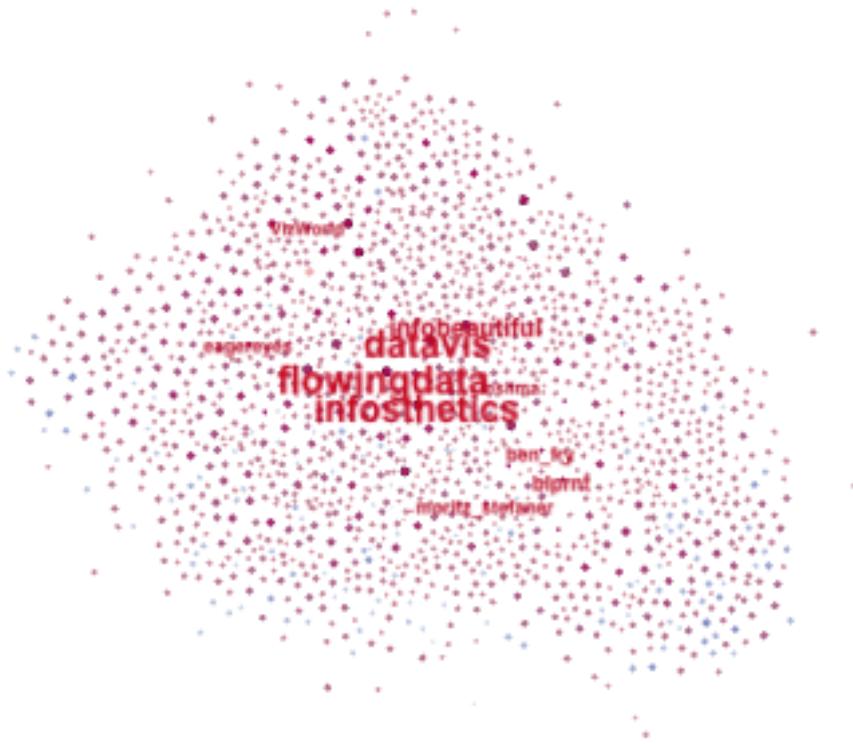


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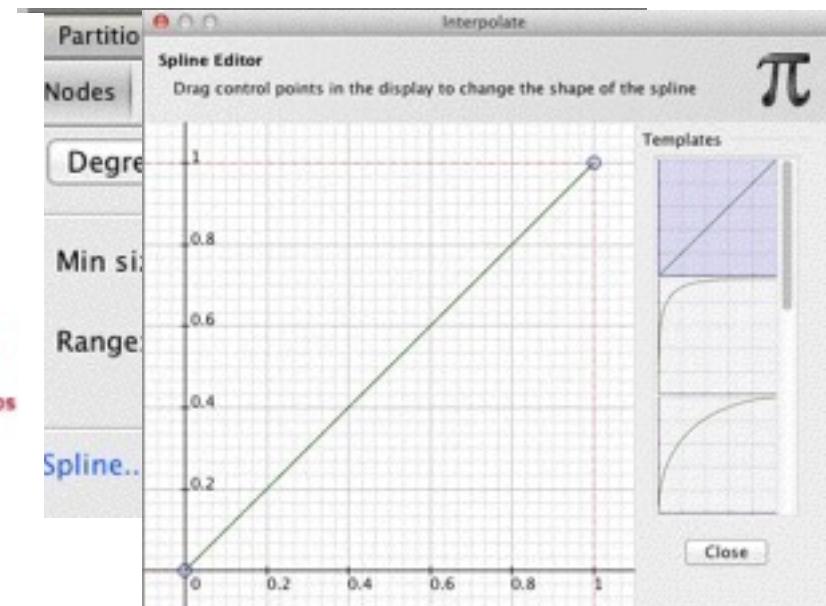
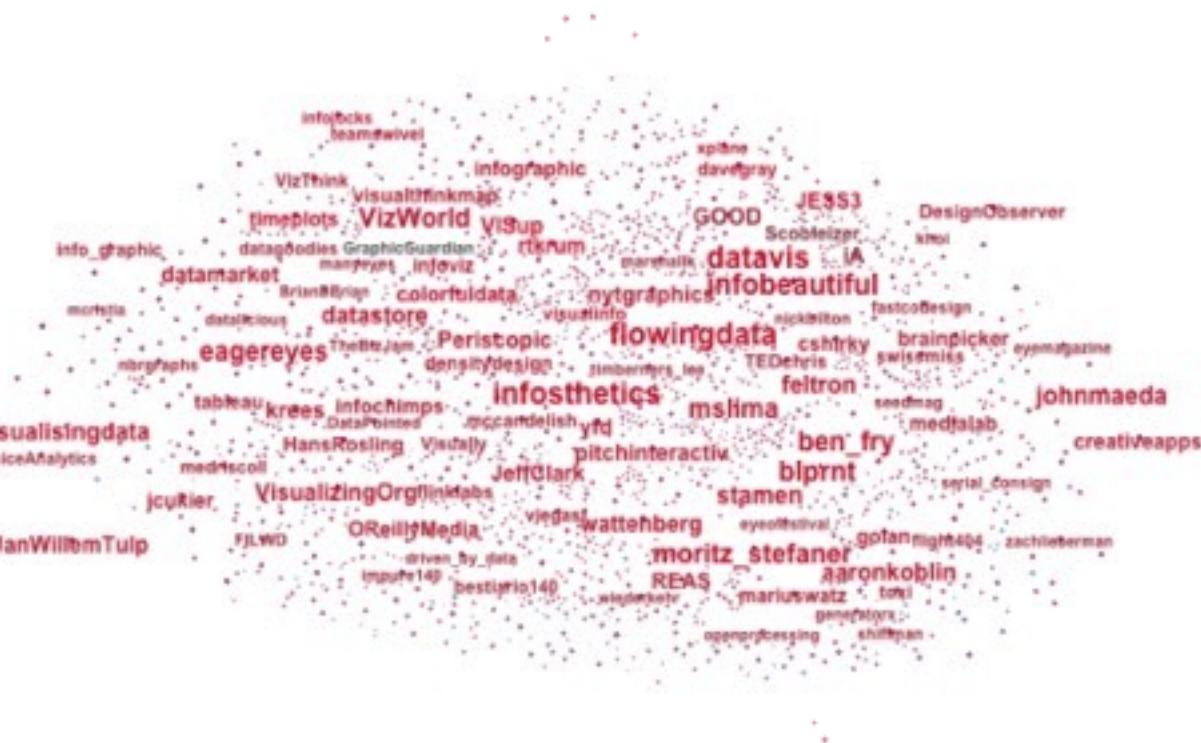


Gephi Panel

Visualization Aside: If Some Names are Huge, the Others are Invisible-?



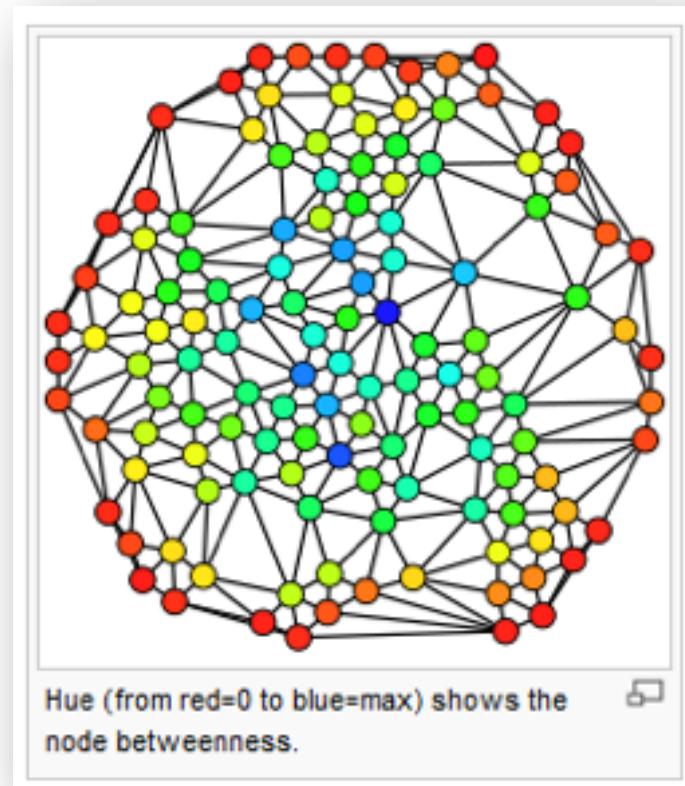
Visualization Aside: If Some Names are Huge, the Others are Invisible-?



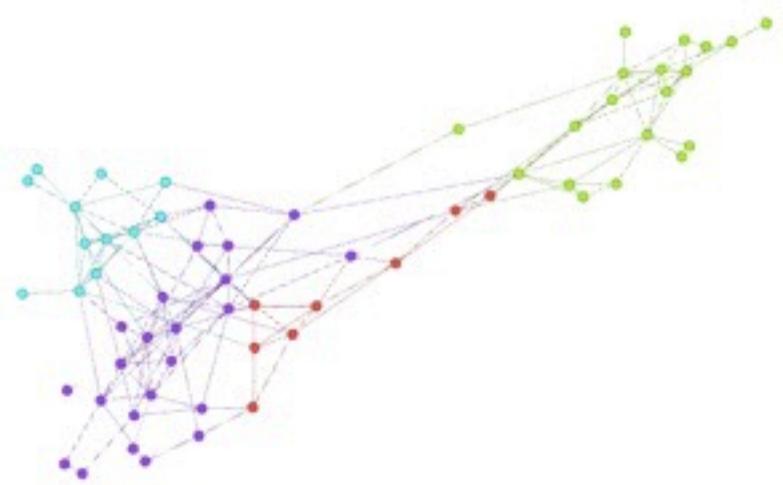
Betweenness

A measure of connectedness between
(sub)components of the graph

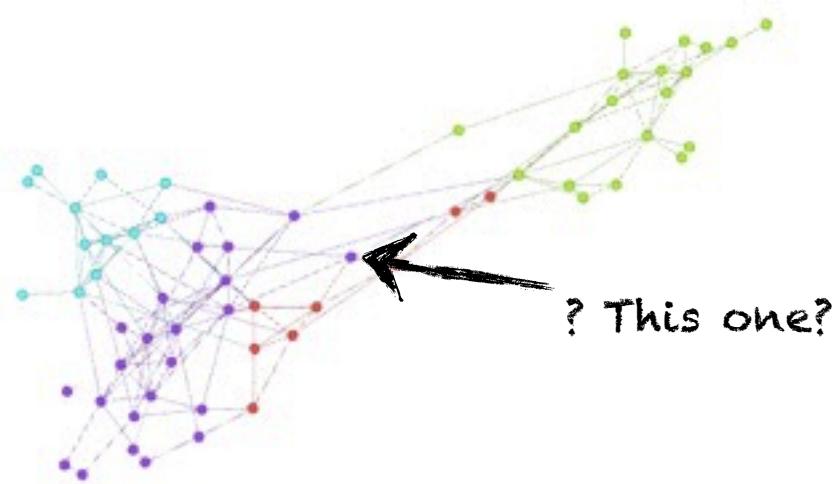
“Betweenness centrality thus tends to pick out boundary individuals who play the role of brokers between communities.”



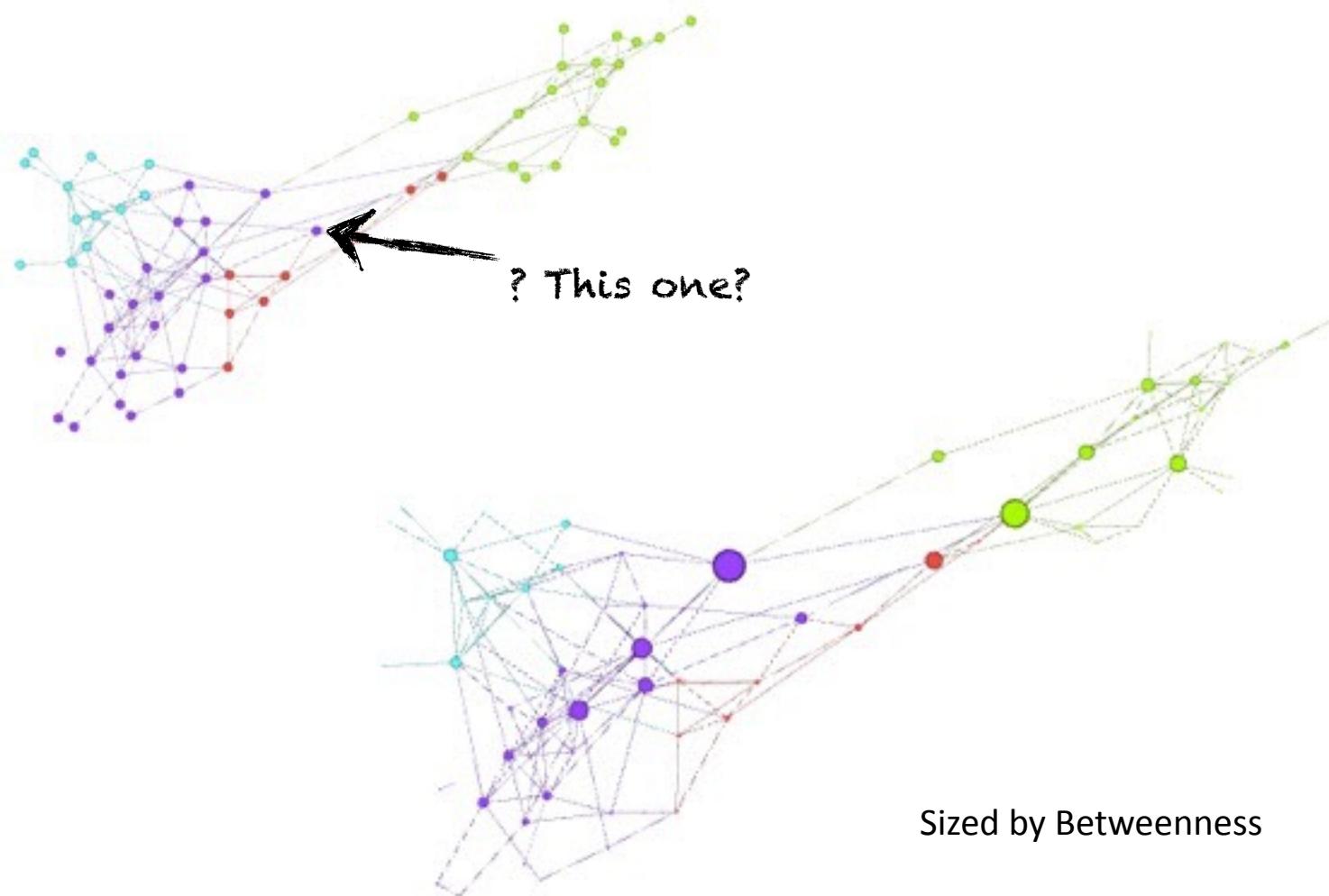
Judging By Eye Will Probably Be Wrong...



Judging By Eye Will Probably Be Wrong...



Judging By Eye Will Probably Be Wrong...



Eigenvector Centrality

- Intuition: A node is important if it is connected to other important nodes
- A node with a small number of influential contacts may outrank one with a larger number of mediocre contacts

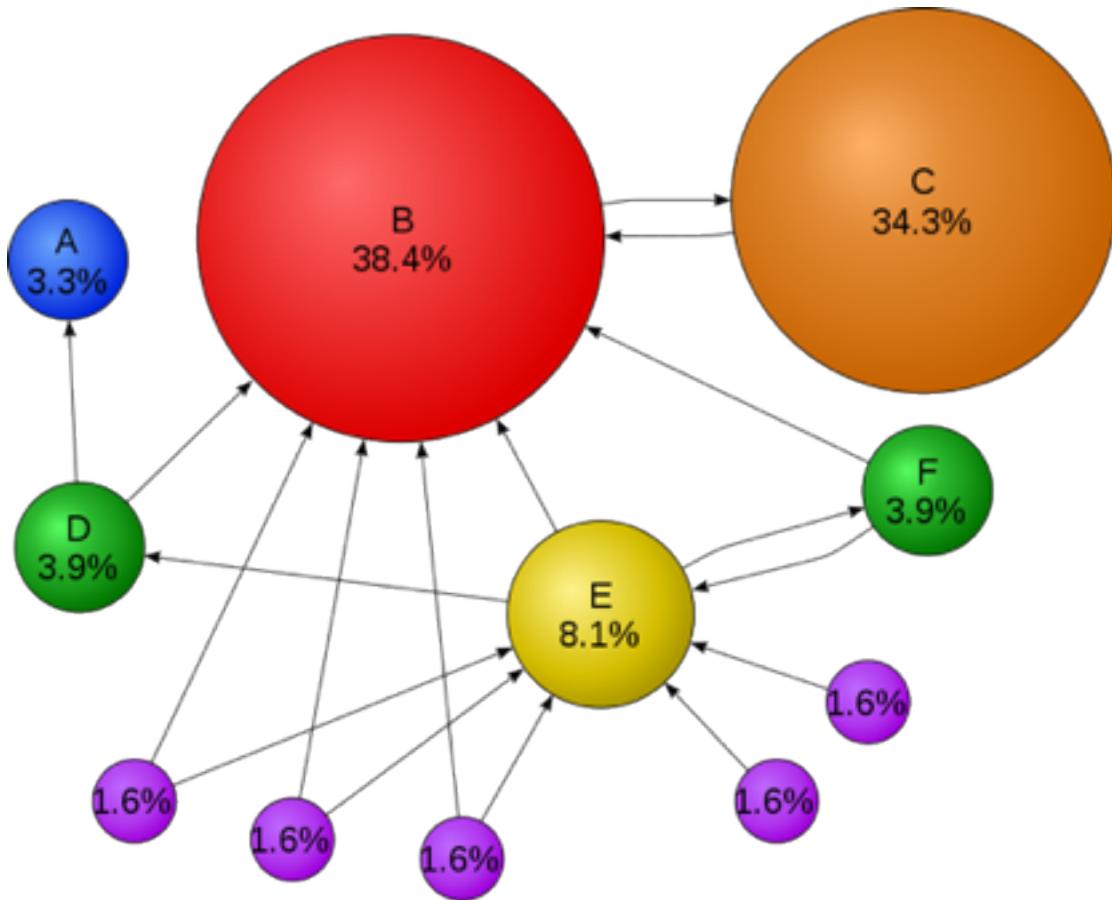
adjacency matrix A :

$$\begin{pmatrix} 0 & 0 & 1 & 0 & 1 & 0 \\ 1 & 0 & 1 & 1 & 1 & 0 \\ 0 & 1 & 0 & 1 & 1 & 0 \\ 1 & 1 & 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 1 & 1 & 1 & 0 \end{pmatrix}$$

centrality matrix x :

$$\begin{pmatrix} 0.38374 \\ 0.833698 \\ 0.730143 \\ 0.833698 \\ 0.30813 \\ 1. \end{pmatrix}$$

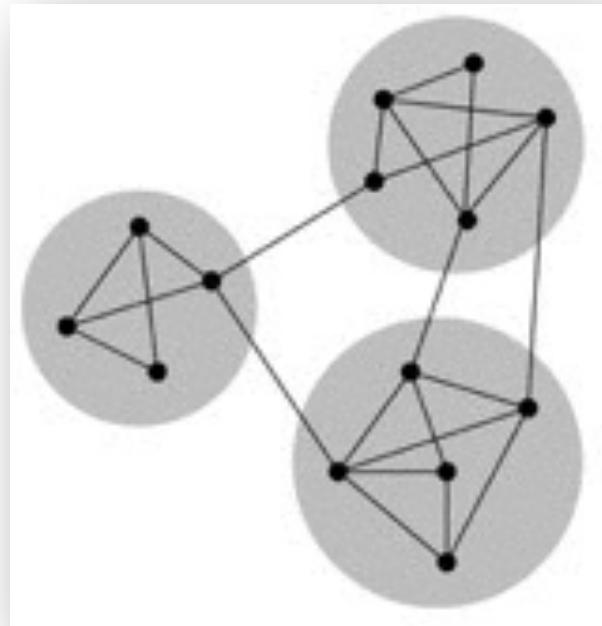
Pagerank



Community Detection Algorithms

E.g., the Louvain method, in Gephi as “Modularity.”

Many layout algorithms help you intuit these structures, but don't rely on perception of layout!



You can even do it in your browser now...

john-guerra's block #ecdde32ab4ad91a1a240 October 31, 2014

Javascript Network Clustering Library



netClustering allows you to detect clusters in networks using the Clauset, Newman and Moore community detection algorithm directly from the browser, as simple as:

```
netClustering.cluster(nodes, edges);
```

[Open in a new window.](#)

You can even do it in your browser now...

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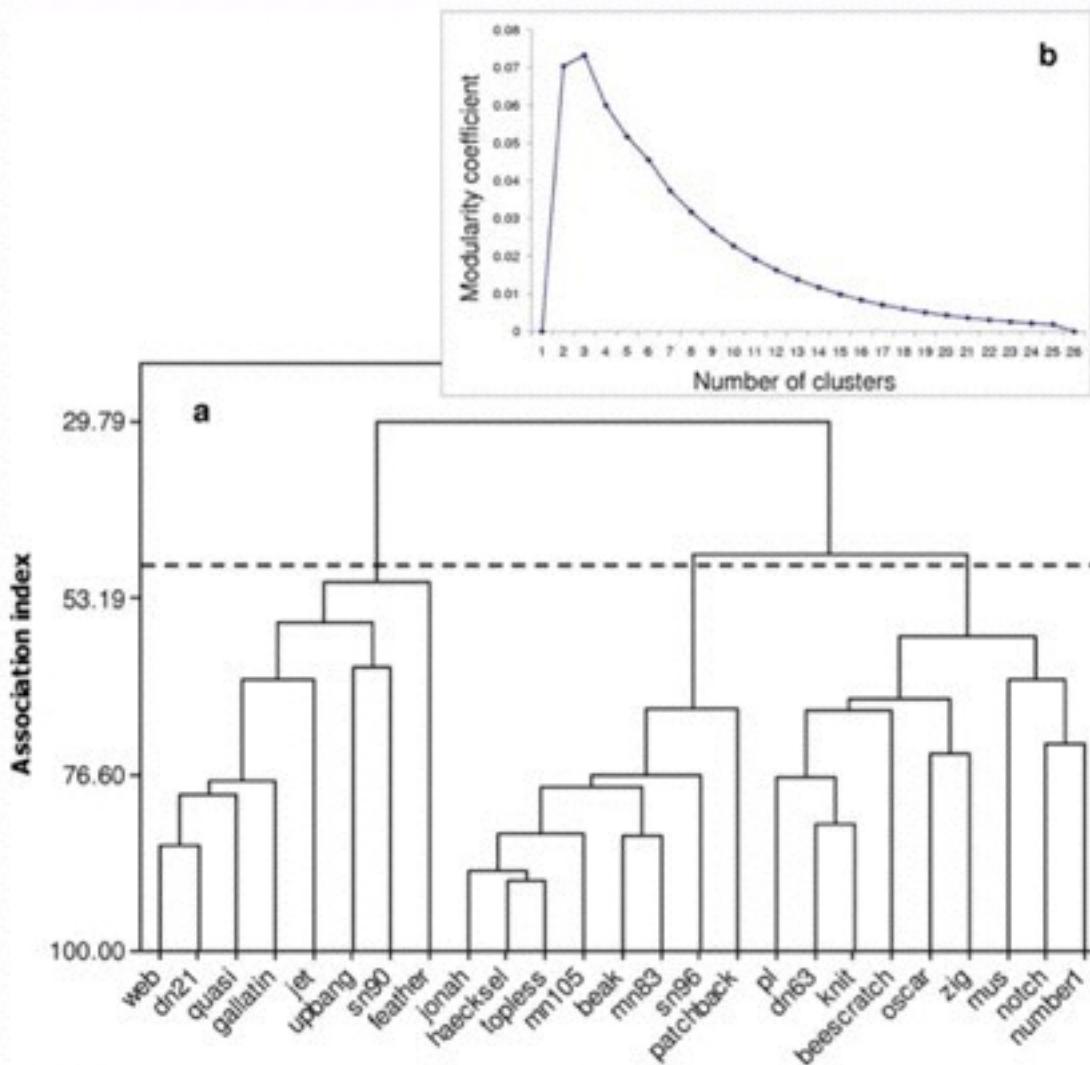
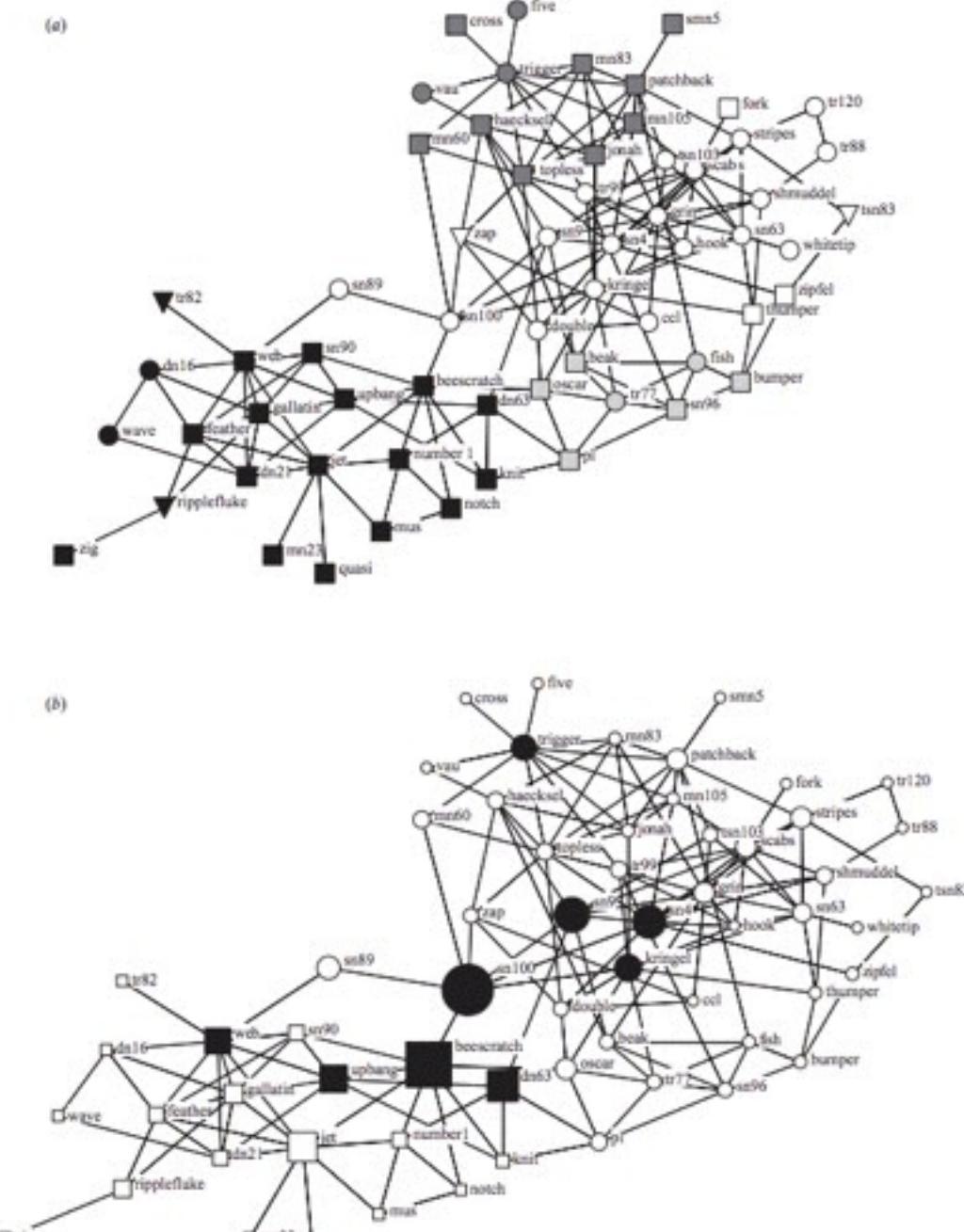
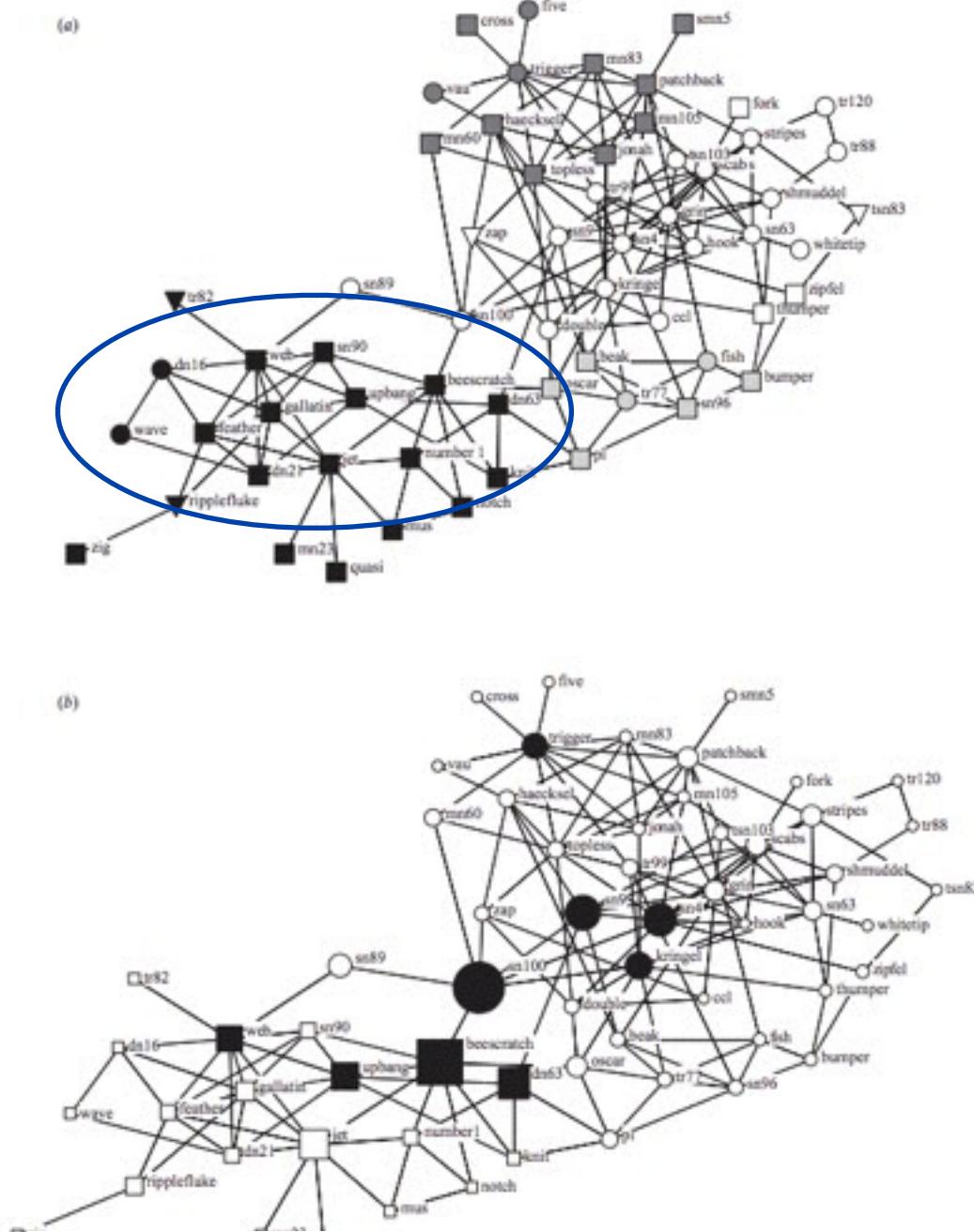


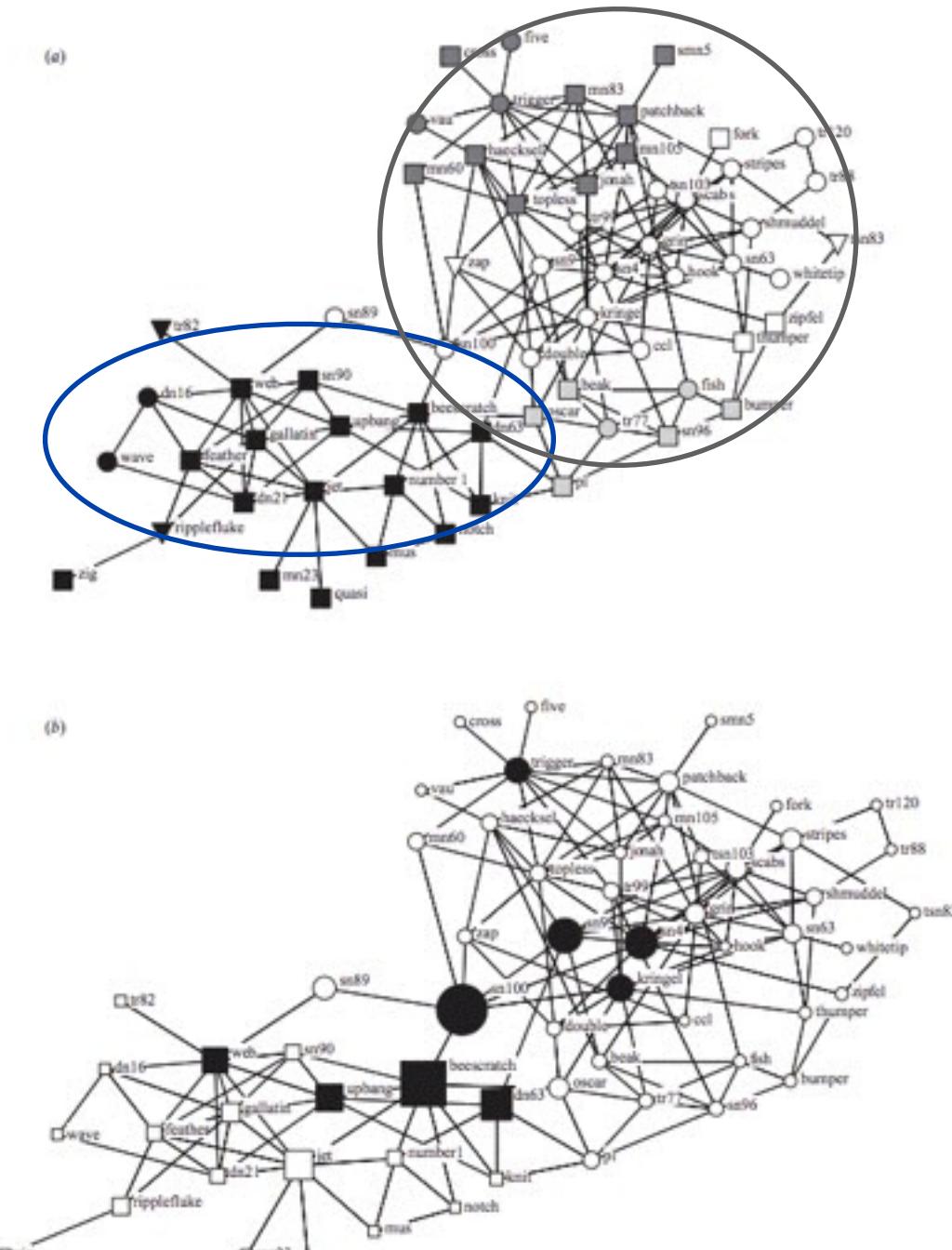
Figure 1. (a) Average linkage cluster analysis of the male association matrix, based on half-weight index (the association index). There appears to be three clusters of individuals spending more time together, the dashed line represents the more parsimonious split in the network which is given by the peak in the modularity coefficient (b).



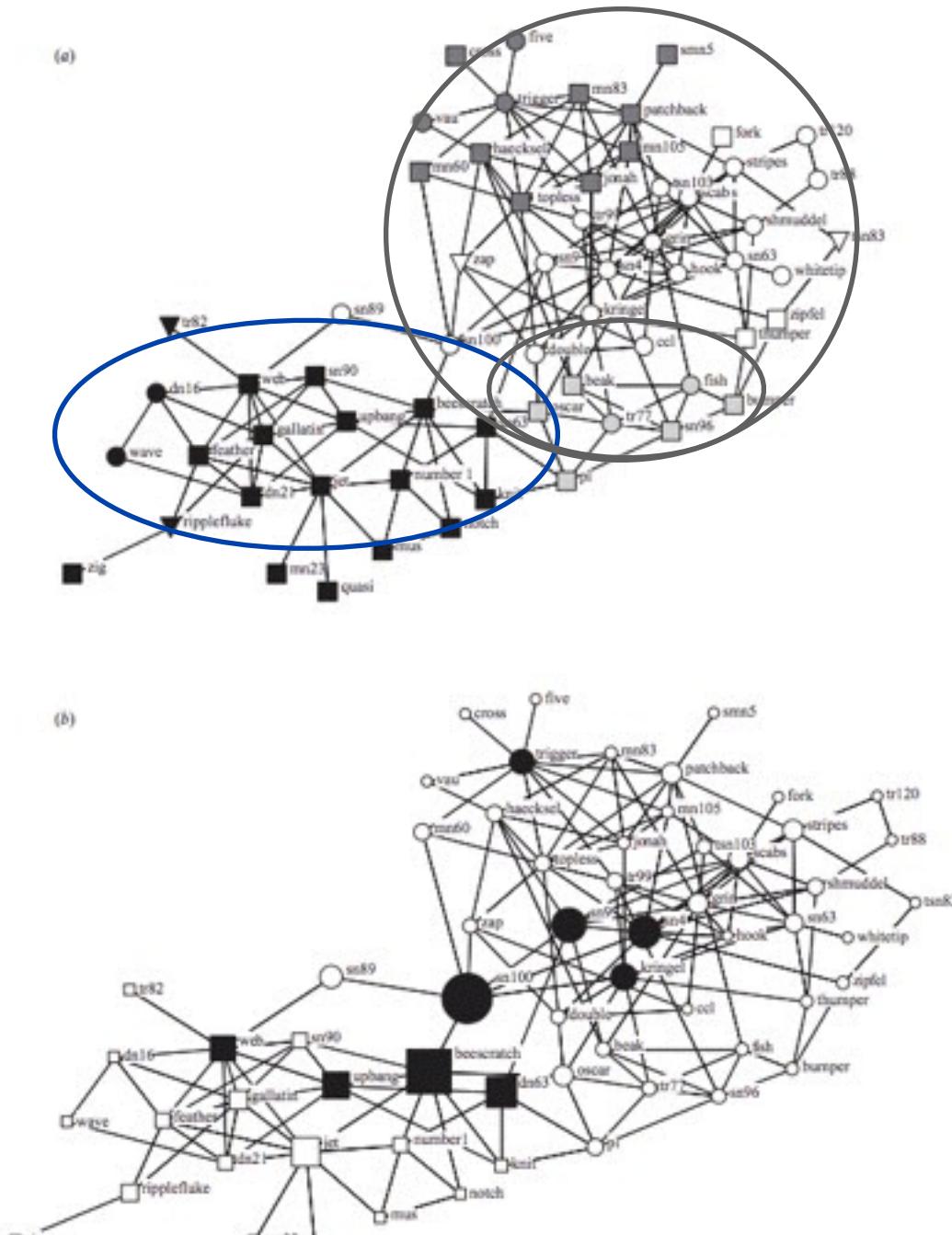
□ Figure 1. Communities and sub-communities identified in the dolphin social network using the betweenness-based algorithm of Girvan & Newman (2002). (a) Vertex shading indicates community membership: vertices in black are all part of one community, while all other vertices are part of the second community. This second community is further divided into three sub-communities by the algorithm; these are represented by the shading (white, light grey and dark grey). Females are represented as circles, males as squares and individuals with unknown gender as triangles. (b) Individuals with high betweenness values (greater than 7.32) are represented by black symbols. The size of the black symbol is directly related to the betweenness of the vertex.



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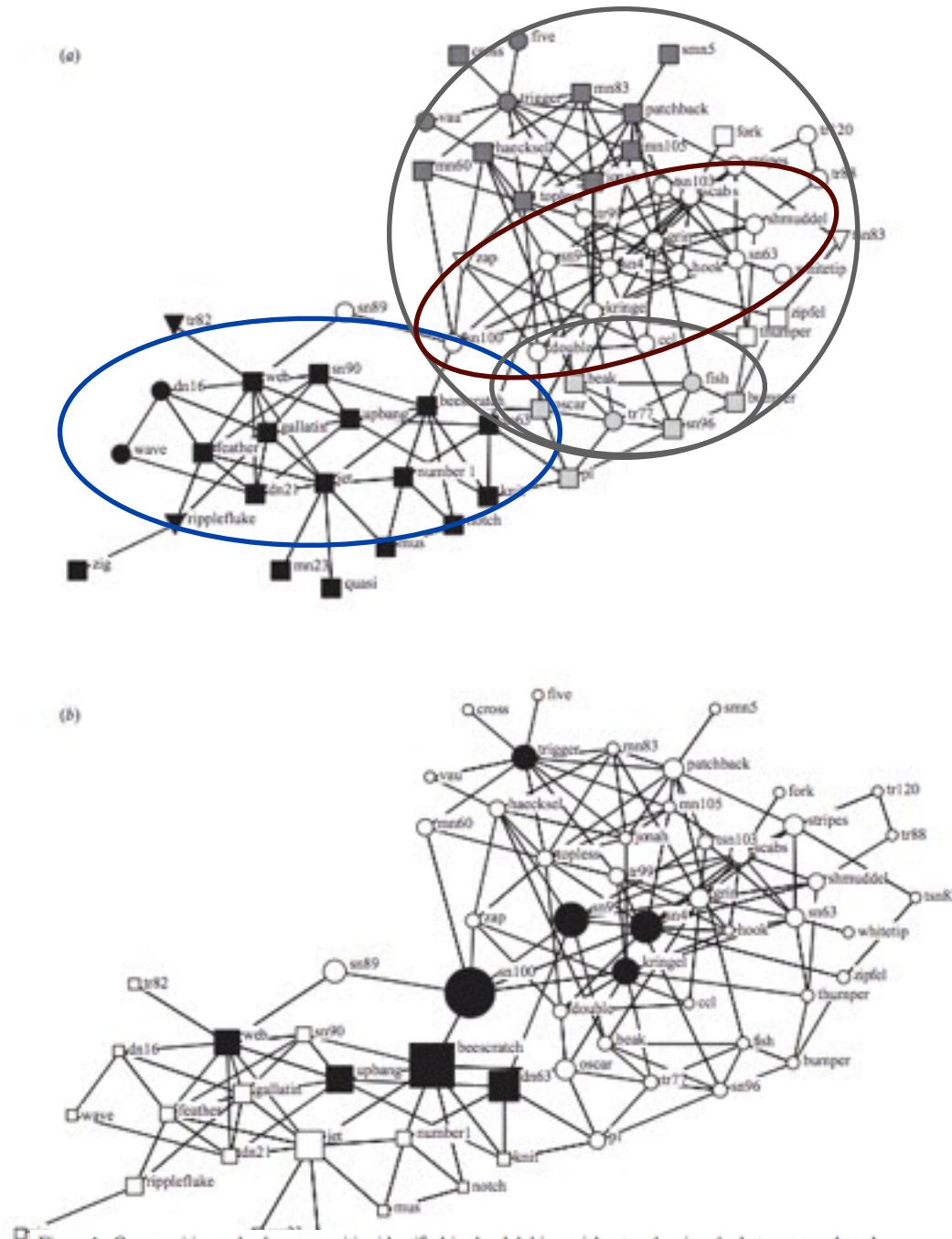


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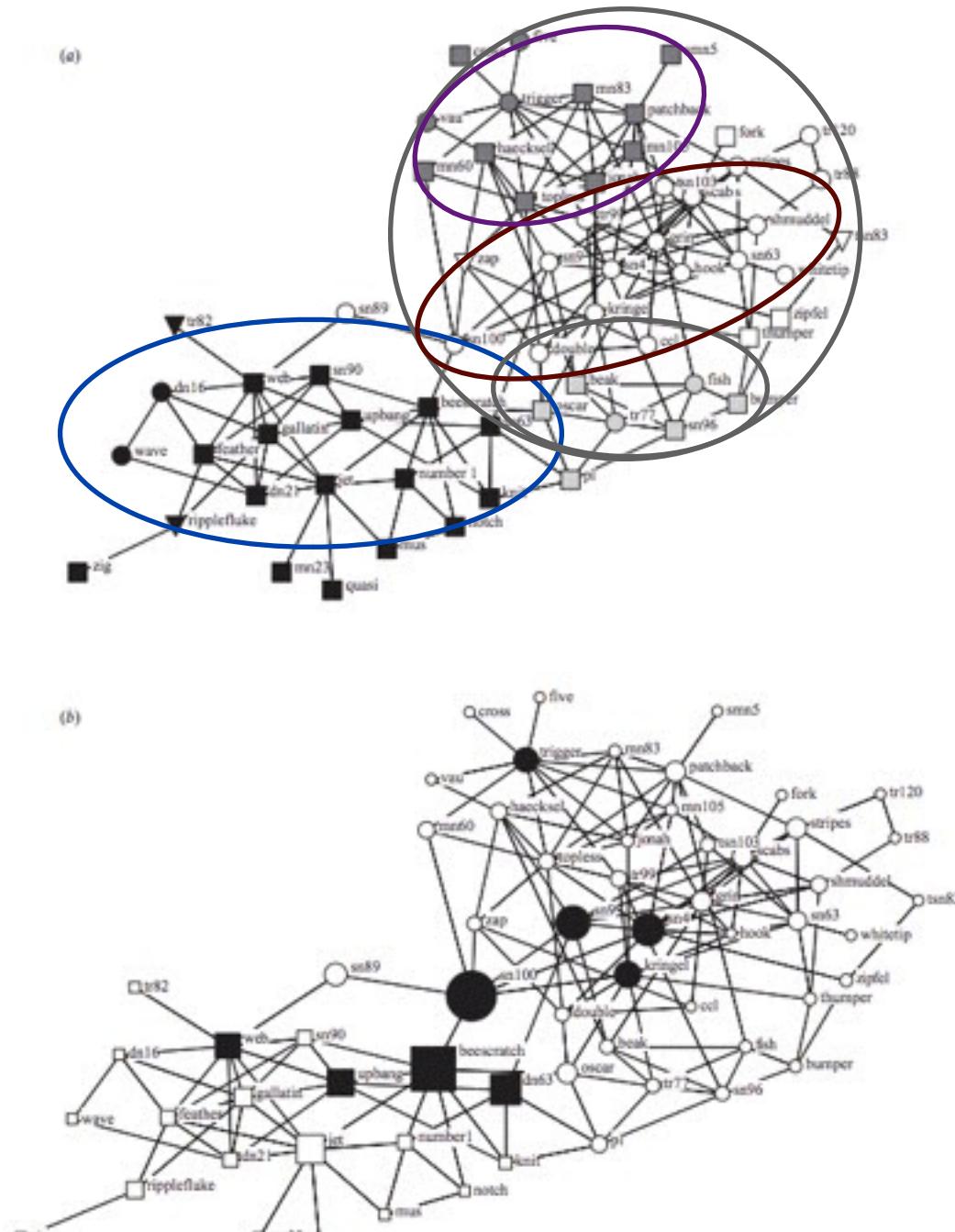
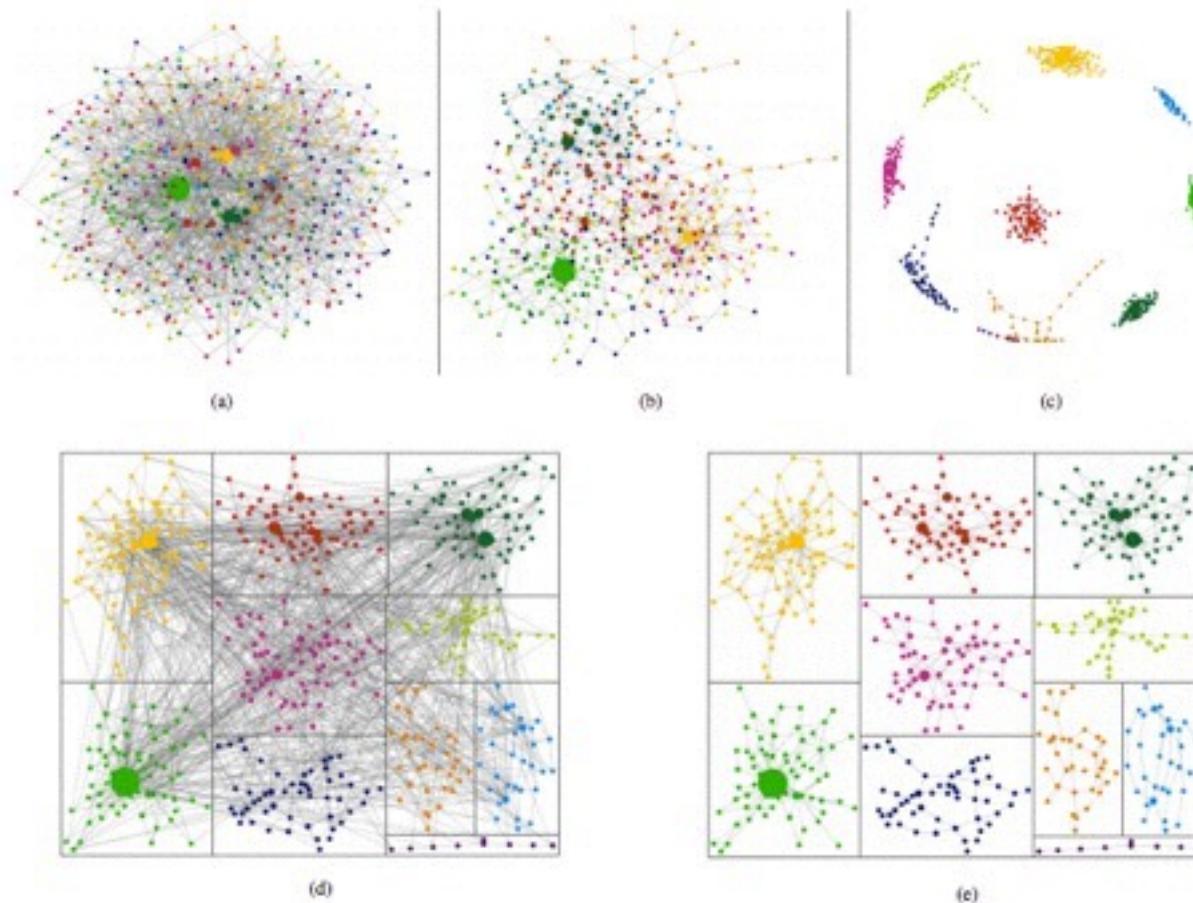
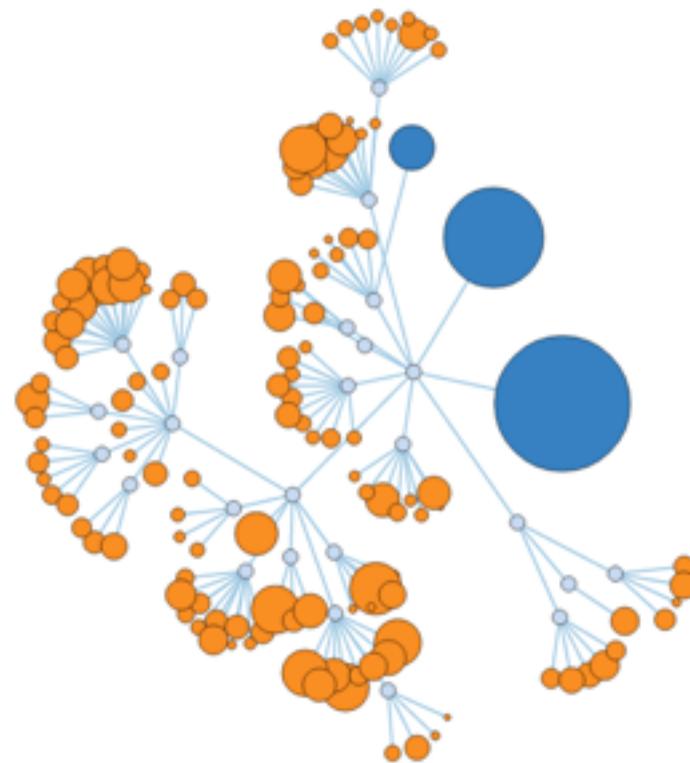


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Figure 6. Scale-free network with 10 clusters detected by the Clauset-Newman-Moore algorithm. Vertices are colored by cluster membership and sized by betweenness centrality. (a) Harel-Koren layout of the clustered graph. (b) Harel-Koren layout after removing inter-cluster edges. (c) Fruchterman-Reingold layout after removing inter-cluster edges. (d) GIB showing inter-cluster edges and (e) GIB showing intra-cluster edges.







ALGORITHMIC LAYOUTS

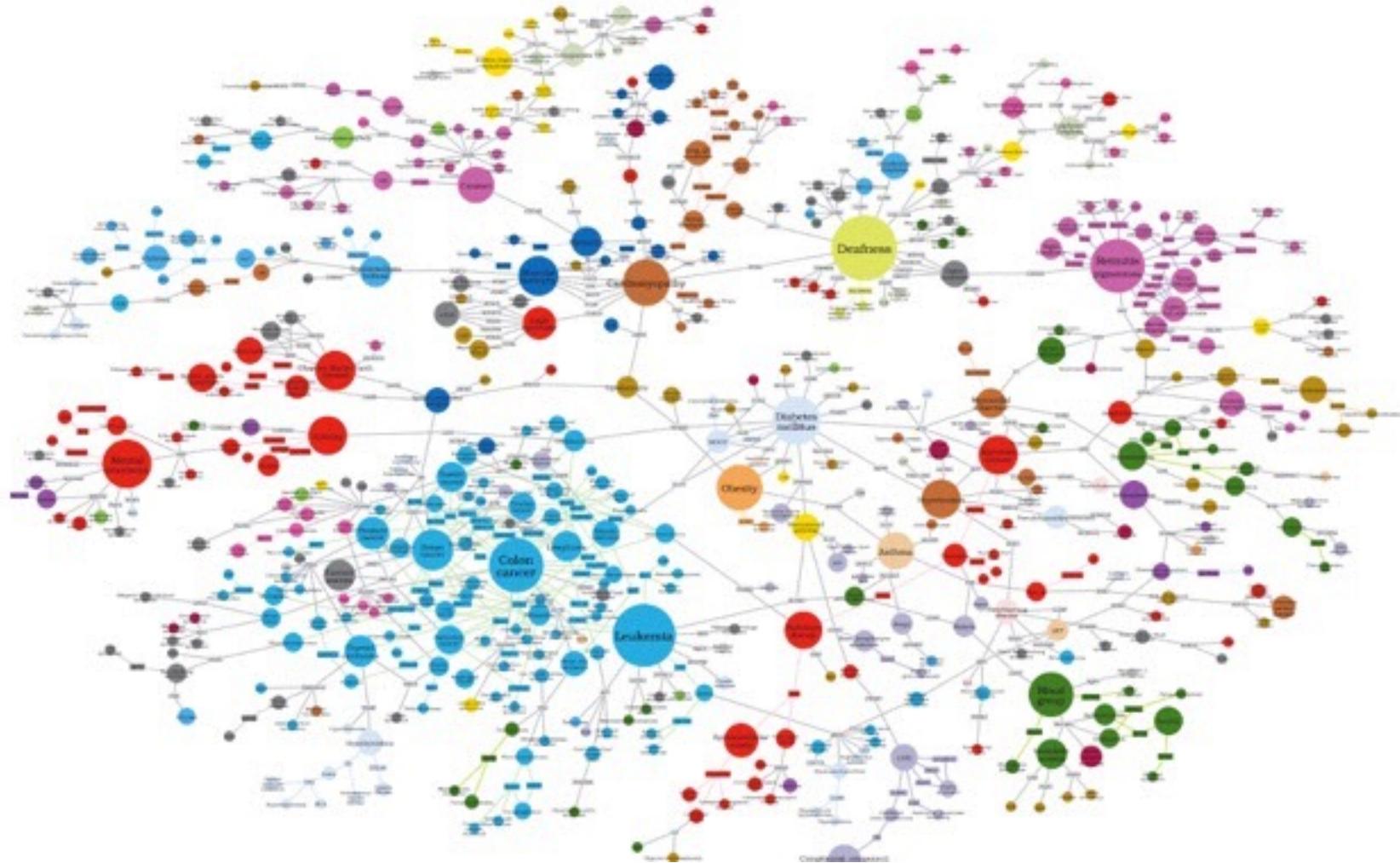
Gephi / D3.js / Other tools

Gephi → Sigma.js / D3

- Gephi.org: Open source, runs on Mac, Linux, PC
 - Can be run from a python-esque console plugin or UI
 - Can be run “headless” for layouts with Java or Python (I have code for this)
 - Plugins include a Neo4j graph db access, and streaming support
- Sigma.js :
 - Will display a gexf gephi layout file with minimal work, using a plugin interpreter for sigma site export
 - Also offers a force-directed layout plugin for graphs without x&y coords
 - Does CANVAS drawing, not SVG
- Export JSON from Gephi and load into D3 network layout

The human disease network

Goh K-I, Cusick ME, Valle D, Childs B, Vidal M, Barabasi A-L. [2007] Proc Natl Acad Sci USA 104:8685-8690



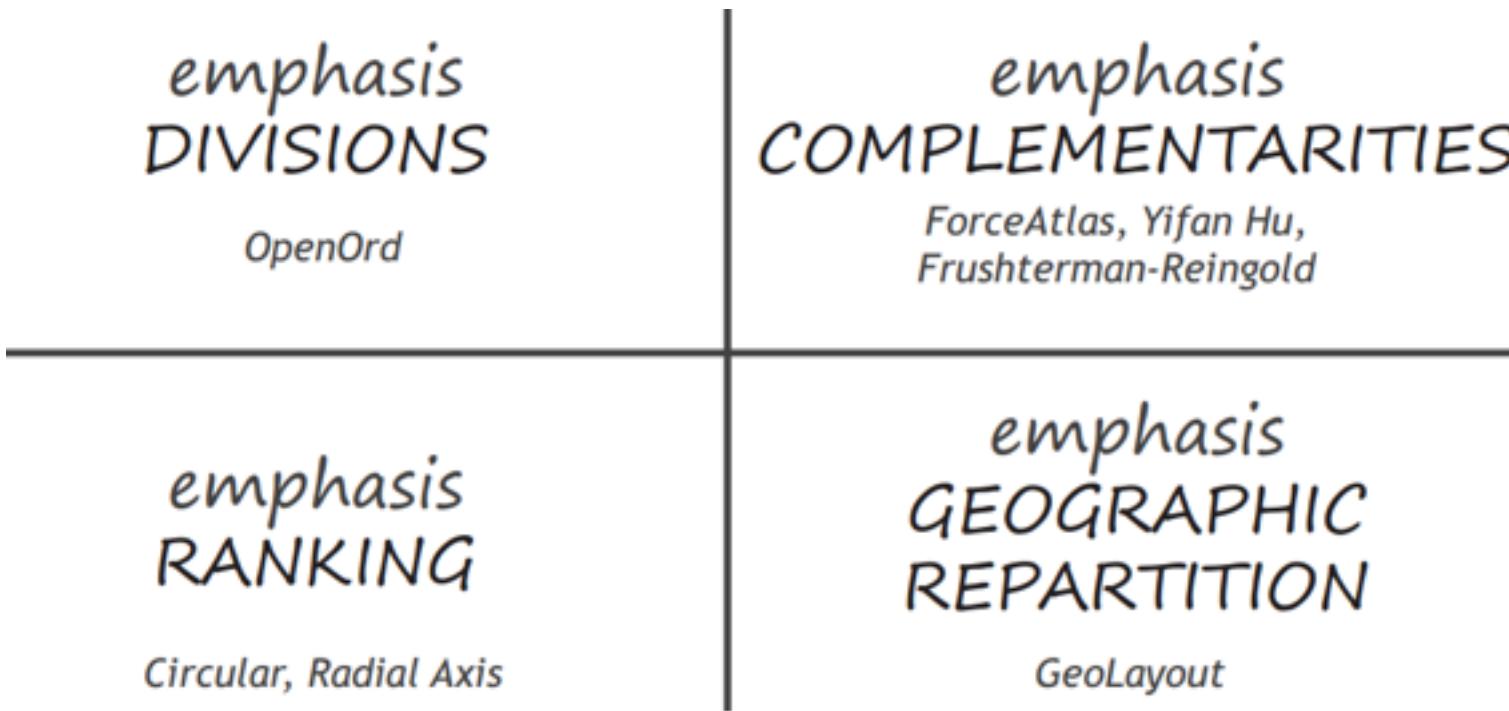
Movie:



Movie:



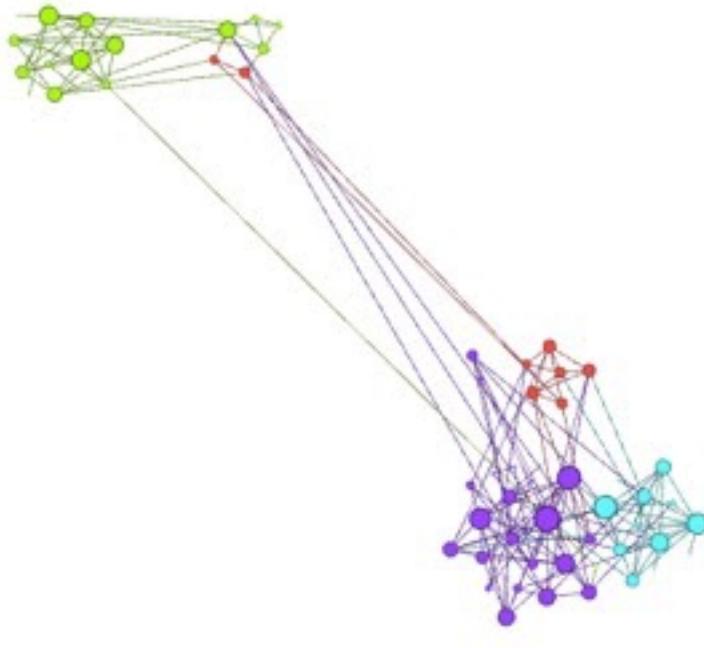
Sample Layout Plugins in Gephi



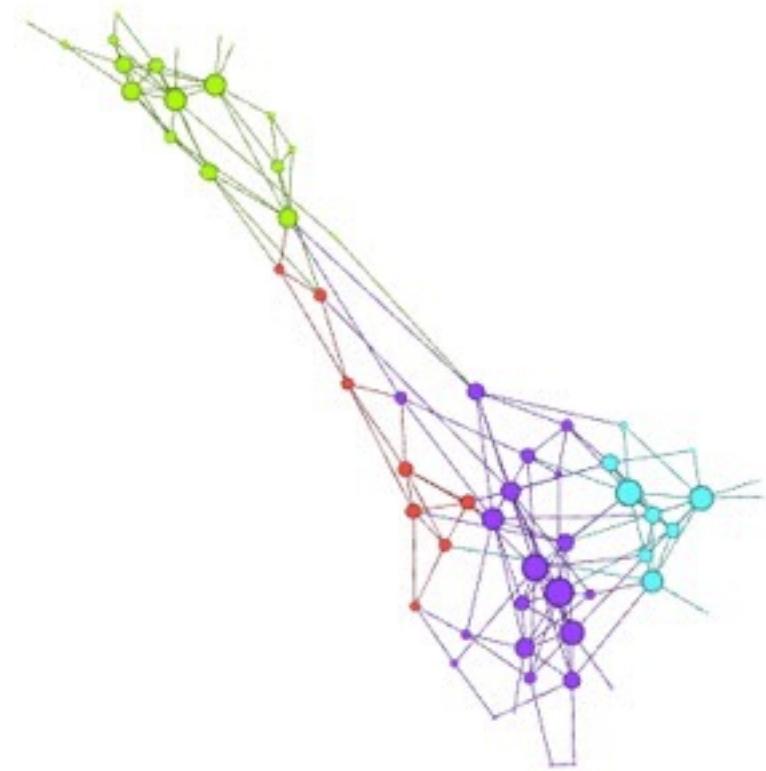
Gephi Plugin Layout Details

Layout	Complexity	Graph Size	Author	Comment
Circular	$O(N)$	1 to 1M nodes	Matt Groeninger	Used to show distribution, ordered layout
Radial Axis	$O(N)$	1 to 1M nodes	Matt Groeninger	Show ordered groups (homophily)
Force Atlas	$O(N^2)$	1 to 10K nodes	Mathieu Jacomy	Slow, but uses edge weight and few biases
Force Atlas 2	$O(N * \log(N))$	1 to 1M nodes	Mathieu Jacomy	(does use weight)
OpenOrd	$O(N * \log(N))$	100 to 1M nodes	S. Martin, W. M. Brown, R. Klavans, and K. Boyack	Focus on clustering (uses edge weight)
Yifan Hu	$O(N * \log(N))$	100 to 100K nodes	Yifan Hu	(no edge weight)
Fruchterman-Rheingold	$O(N^2)$	1 to 1K nodes	Fruchterman & Rheingold!	Particle system, slow (no edge weight)
GeoLayout	$O(N)$	1 to 1M nodes	Alexis Jacomy	Uses Lat/Long for layout

Dolphins Again

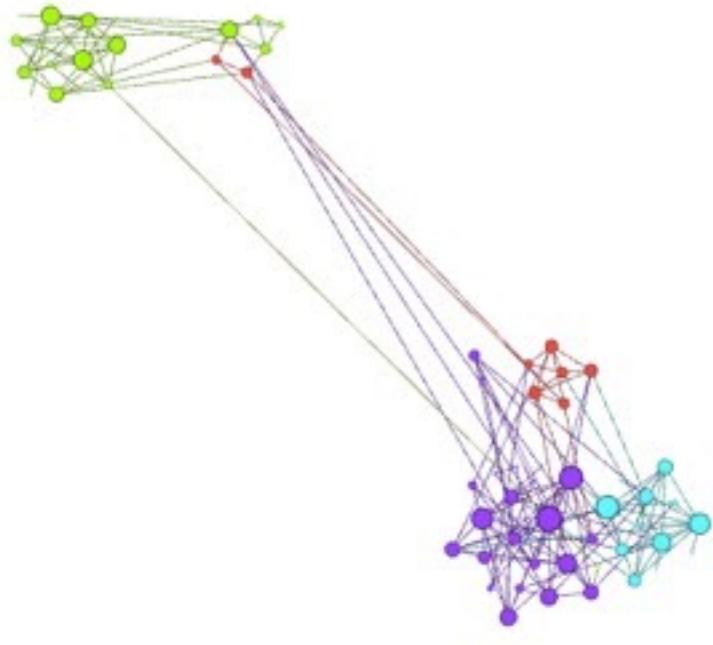


OpenOrd + “No Overlap”

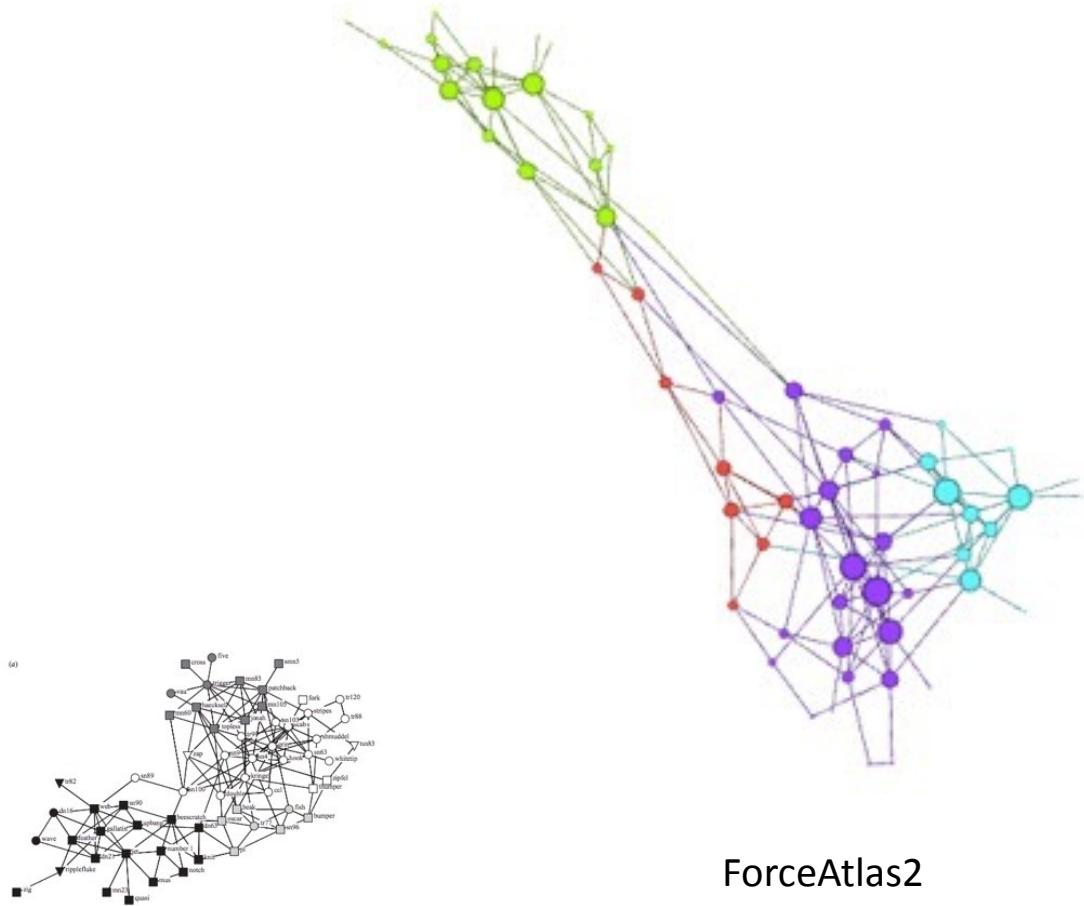


ForceAtlas2

Dolphins Again

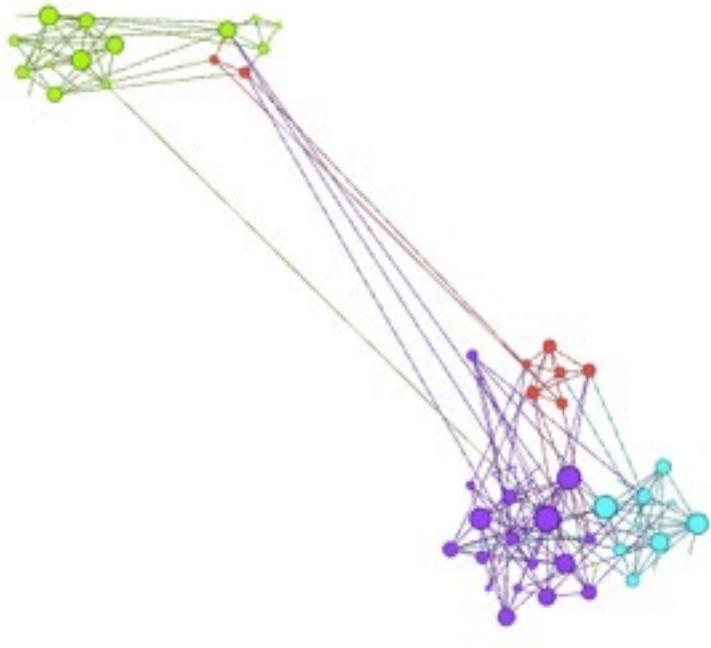


OpenOrd + “No Overlap”

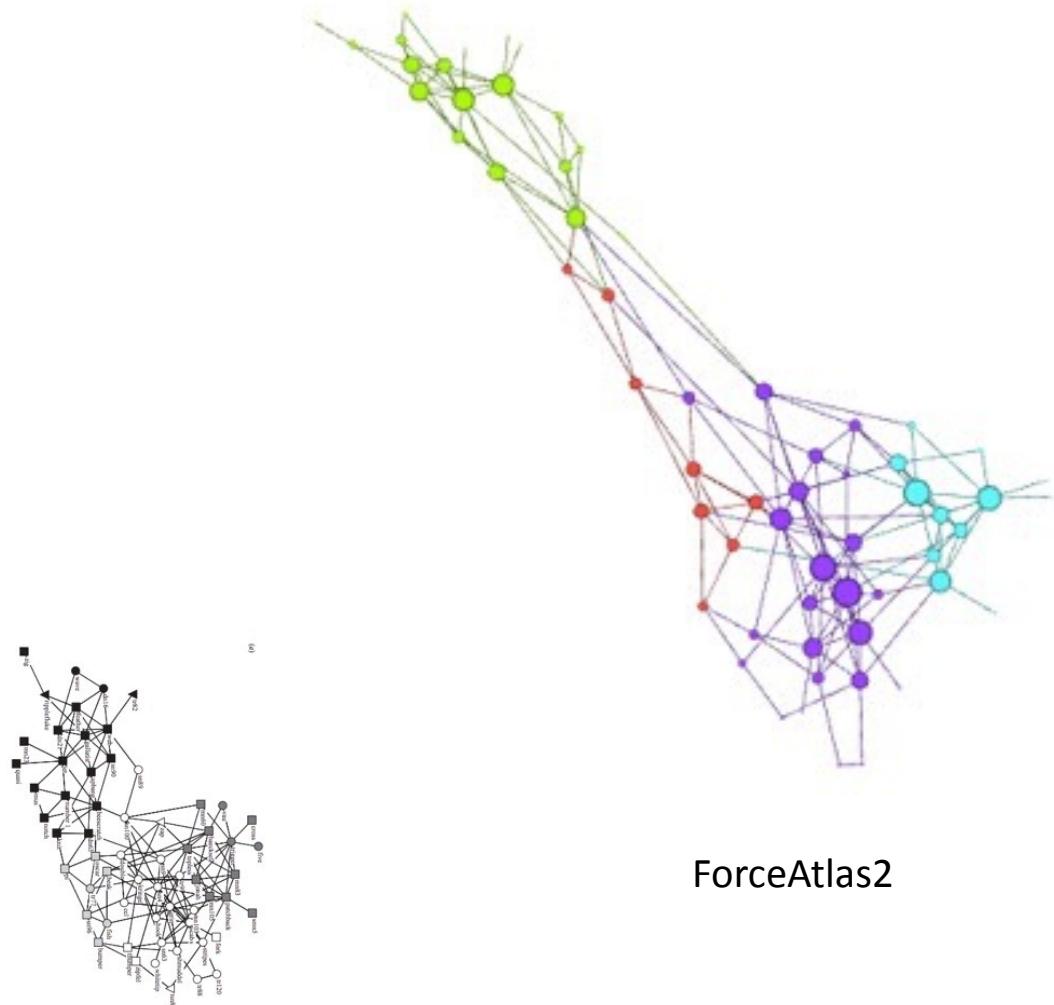


ForceAtlas2

Dolphins Again

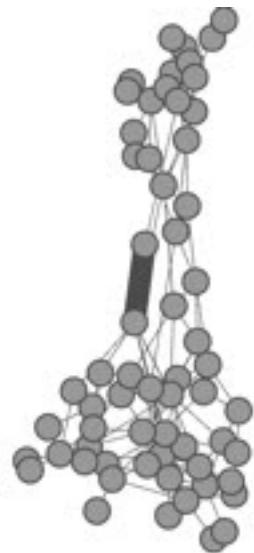
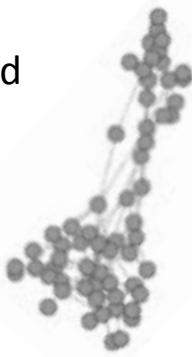


OpenOrd + "No Overlap"

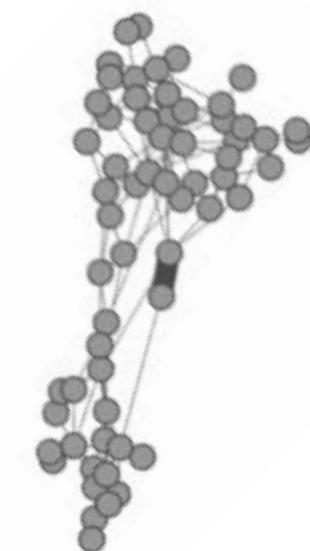


ForceAtlas2

Unweighted
dolphins,
Force Atlas

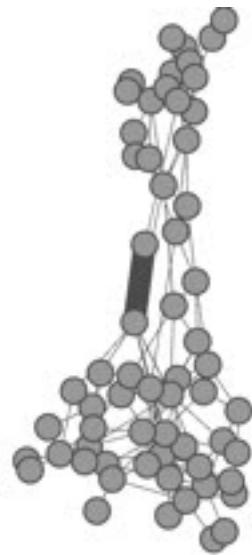


Weight 2: Force Atlas

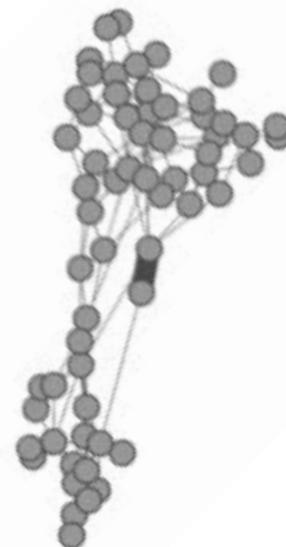


Weight 4: Force Atlas

Unweighted
dolphins,
Force Atlas



Weight 2: Force Atlas



Weight 4: Force Atlas



Weight 4: Yifan Hu

Graph Rendering Performance

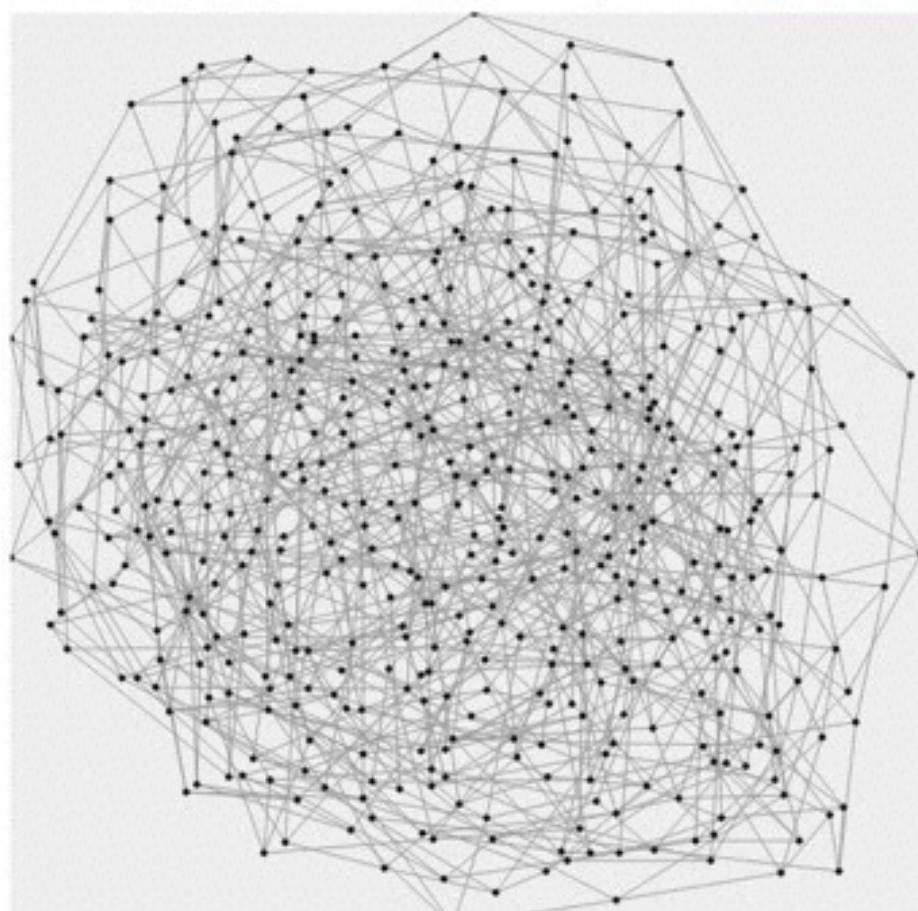
Test rendering performance for different size random graphs with X nodes and 2X edges

First Frame Took: 38 ms

Render Time per Frame: 16 ms (62 FPS)

Library: D3 Sigma.js Processing.js D3 Canvas

Graph size: 500 nodes 1.000 nodes 2.500 nodes 5.000 nodes Start Animation



Canvas/SVG benchmarks from the d3.js group:

[https://docs.google.com/spreadsheets/ccc?
key=0AtvIFoSBUC5kdEZJNVFySG9wSHZka0NsOT
ZDSkt3Nnc#gid=0](https://docs.google.com/spreadsheets/ccc?key=0AtvIFoSBUC5kdEZJNVFySG9wSHZka0NsOTZDSkt3Nnc#gid=0)

Graph Rendering Performance

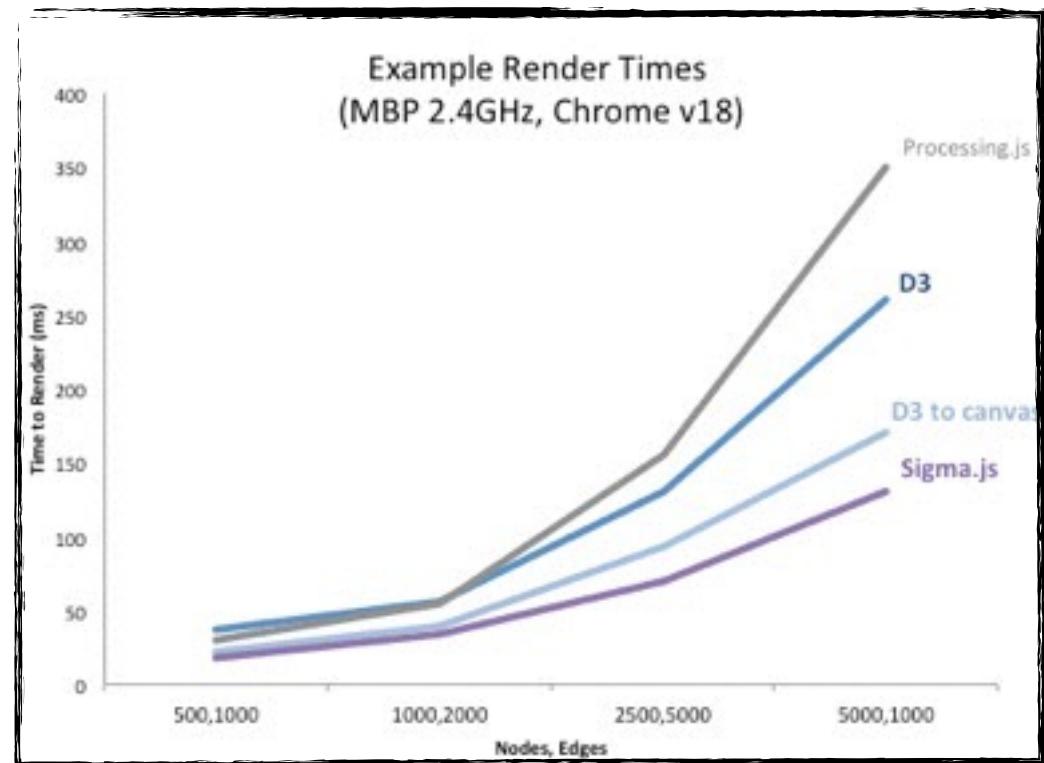
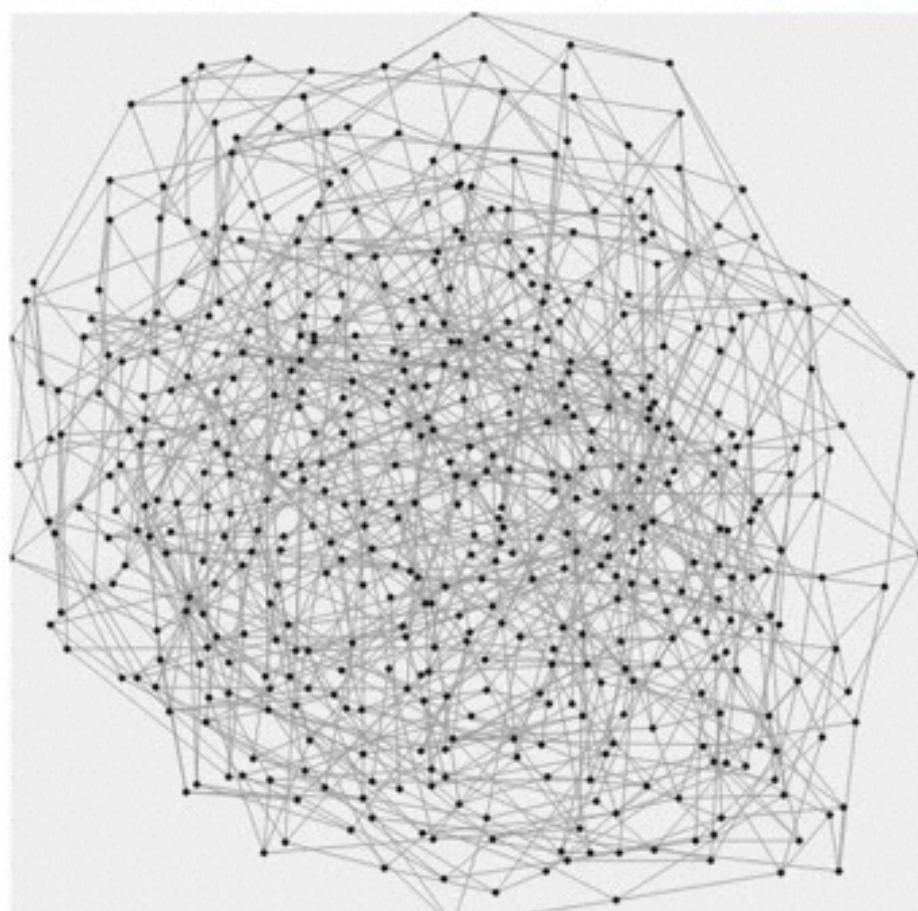
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**FINAL DESIGN THOUGHTS...
BY HAND? BY ALGORITHM-?**

Optimizing “Aesthetic” Constraints

Minimize edge crossings

Minimize area

Minimize line bends

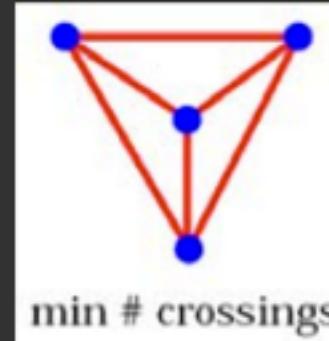
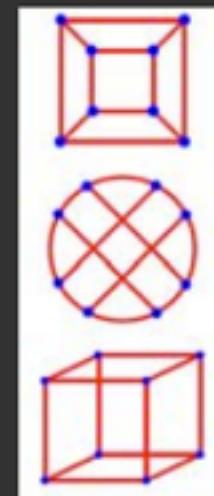
Minimize line slopes

Maximize smallest angle between edges

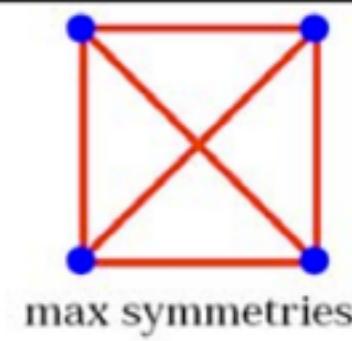
Maximize symmetry

but, can't do it all.

Optimizing these criteria is often NP-Hard, requiring approximations.

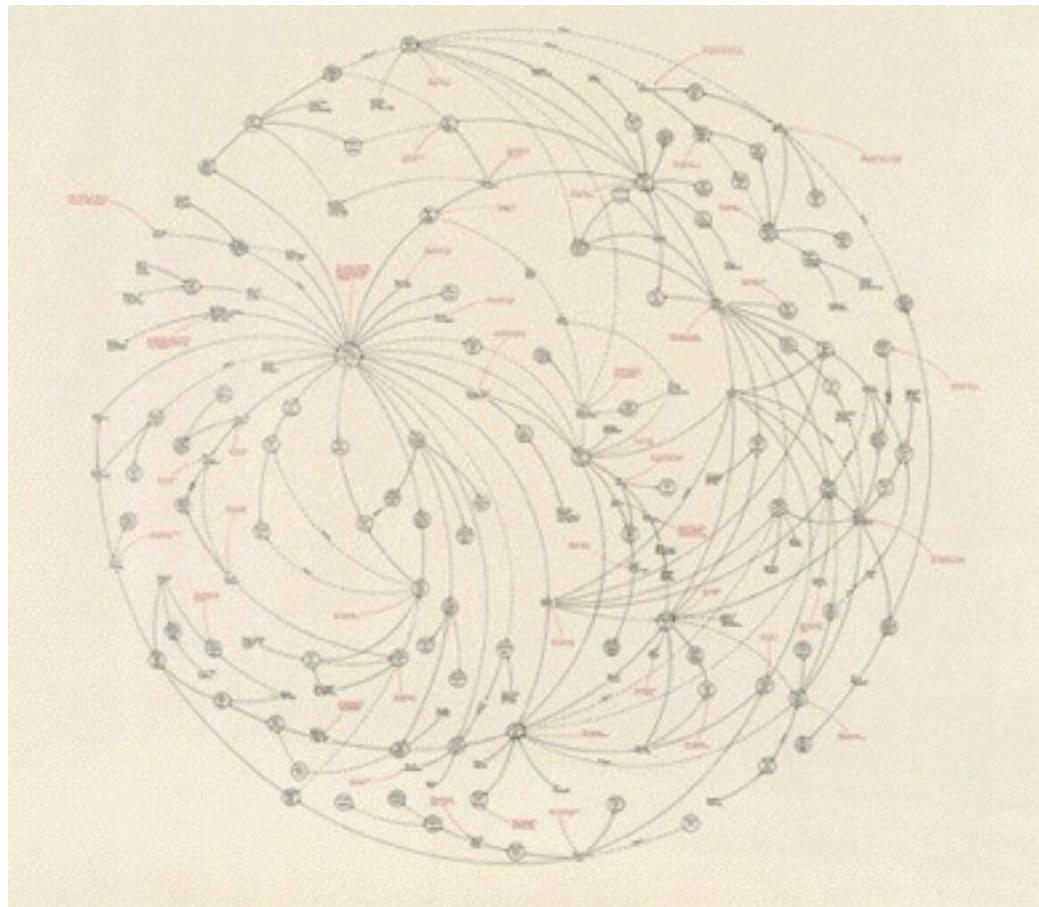


min # crossings



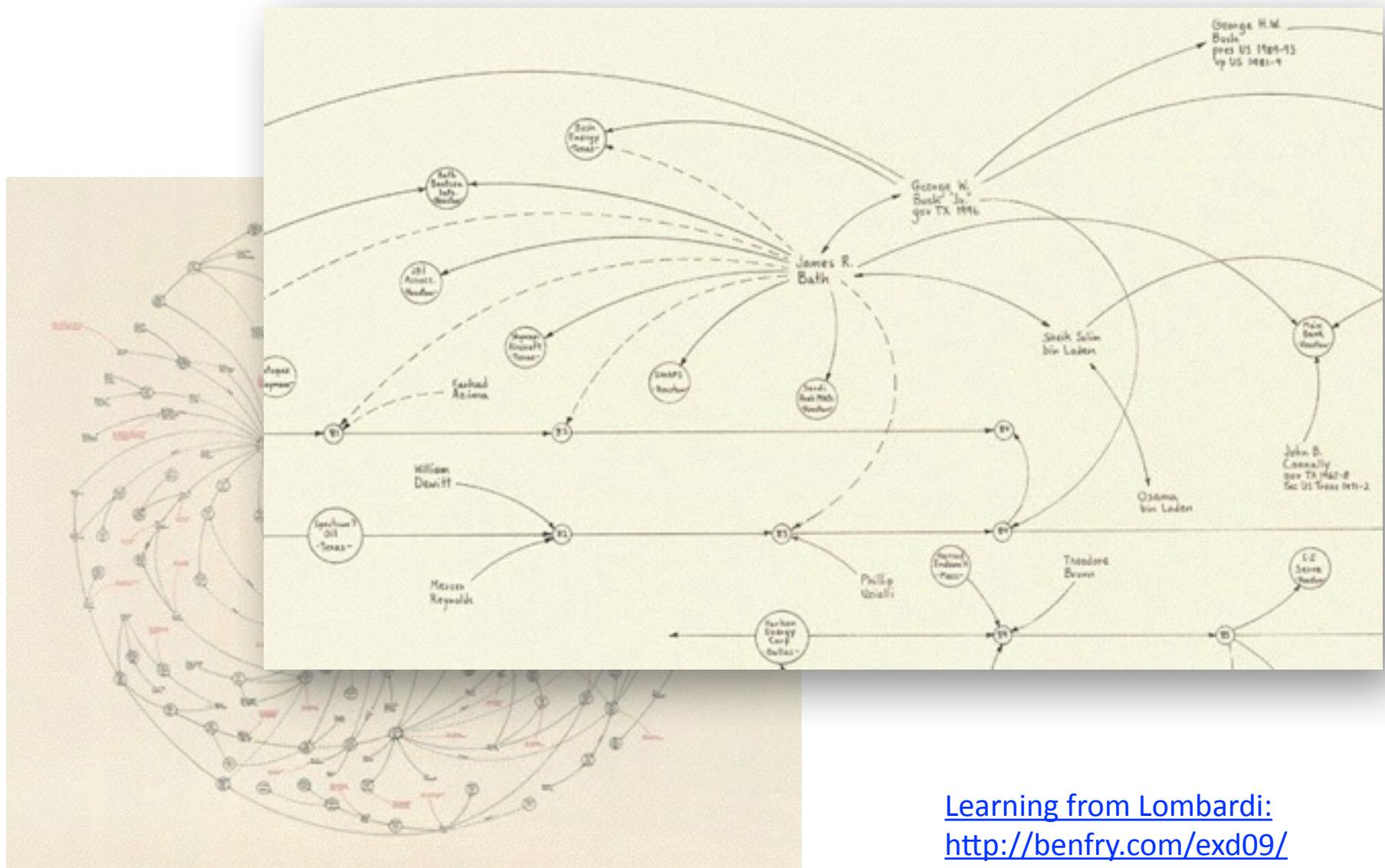
max symmetries

Conspiracy Theorist Mark Lombardi

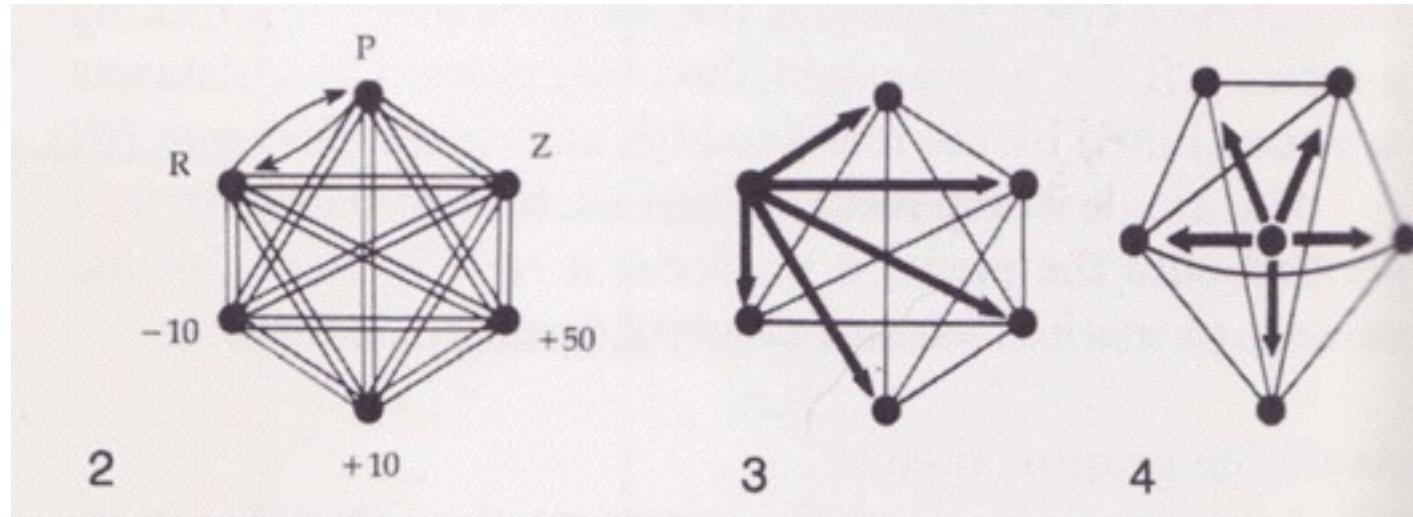


[Learning from Lombardi:](http://benfry.com/exd09/)
<http://benfry.com/exd09/>

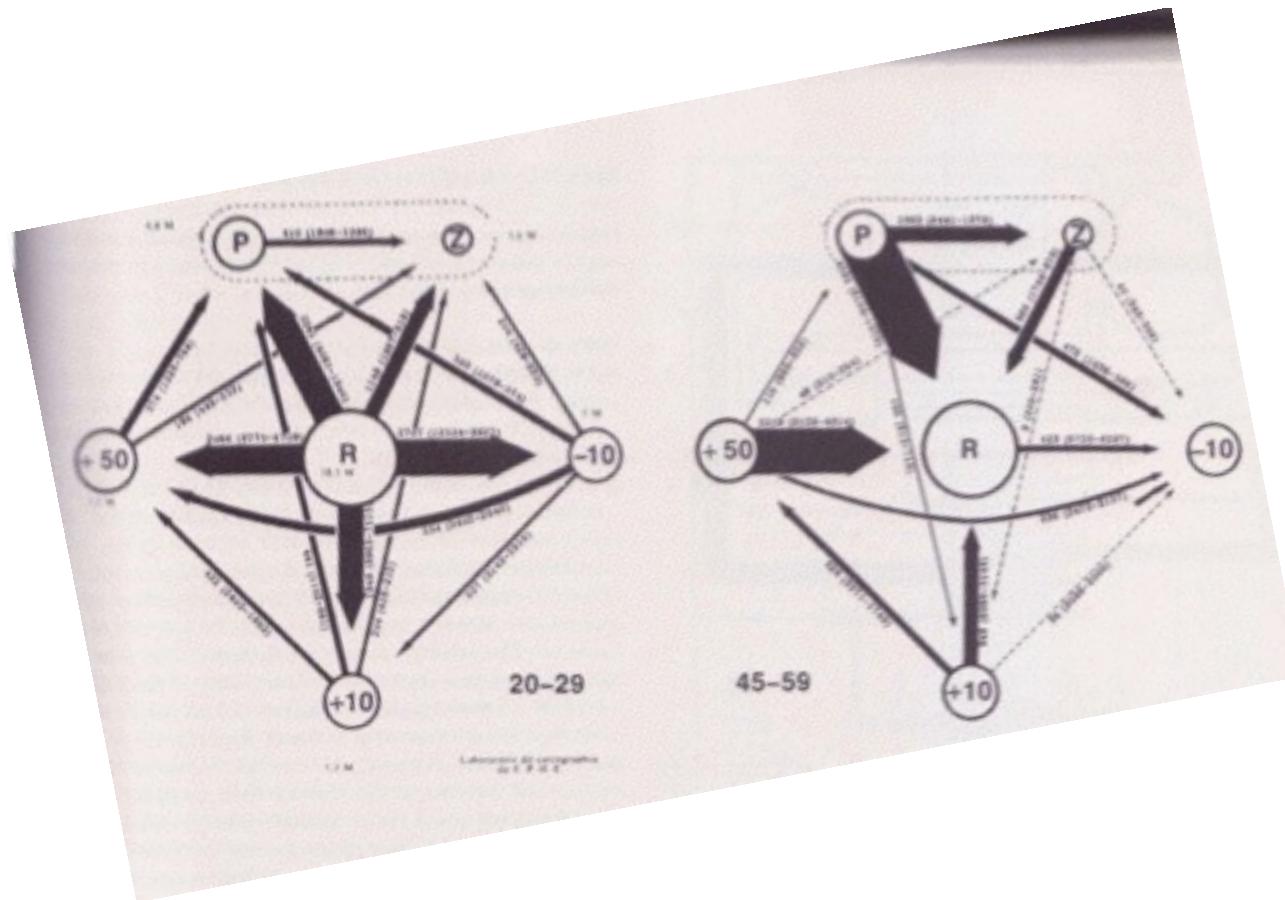
Conspiracy Theorist Mark Lombardi

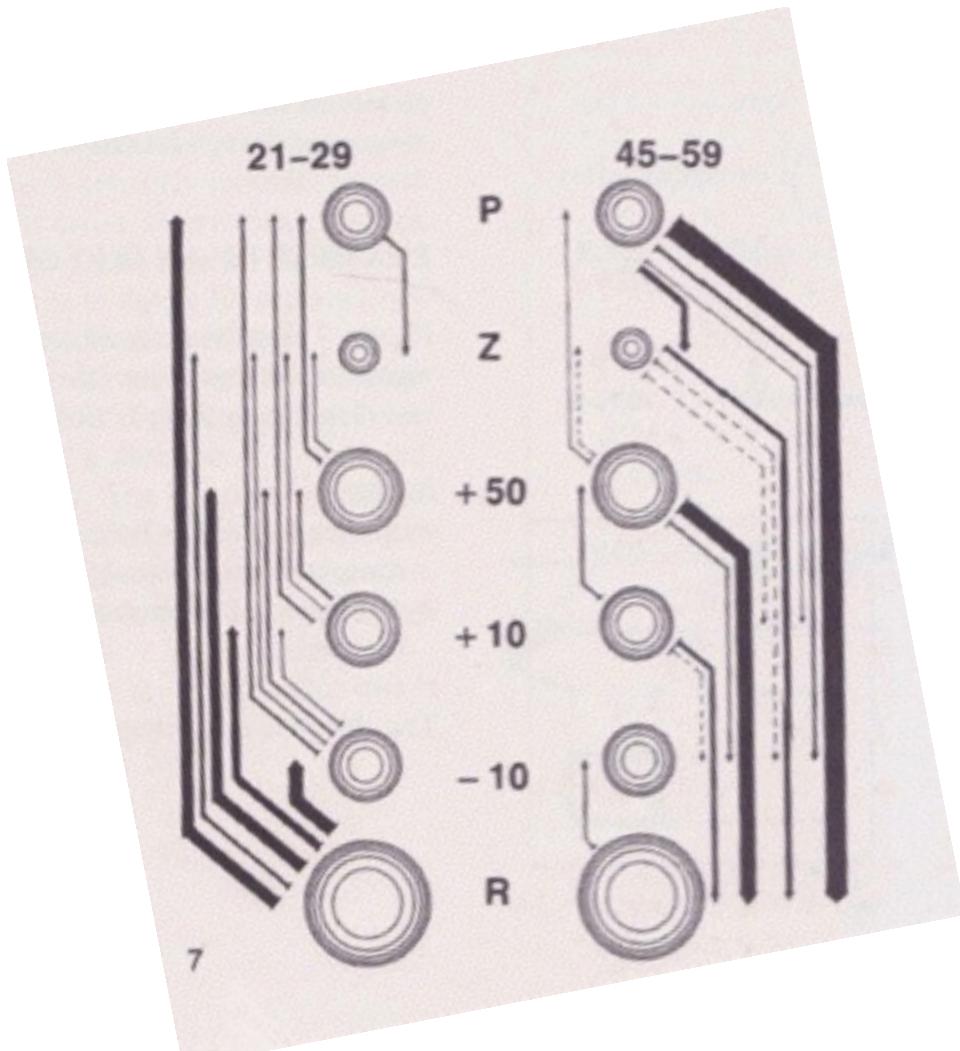


J. Bertin Again...



Age Groups and Movement to/from Paris to Rural Spots





(P) Paris

(Z) Paris Suburbs

(+50) Communes of >50K

(+10) Communes of >10K

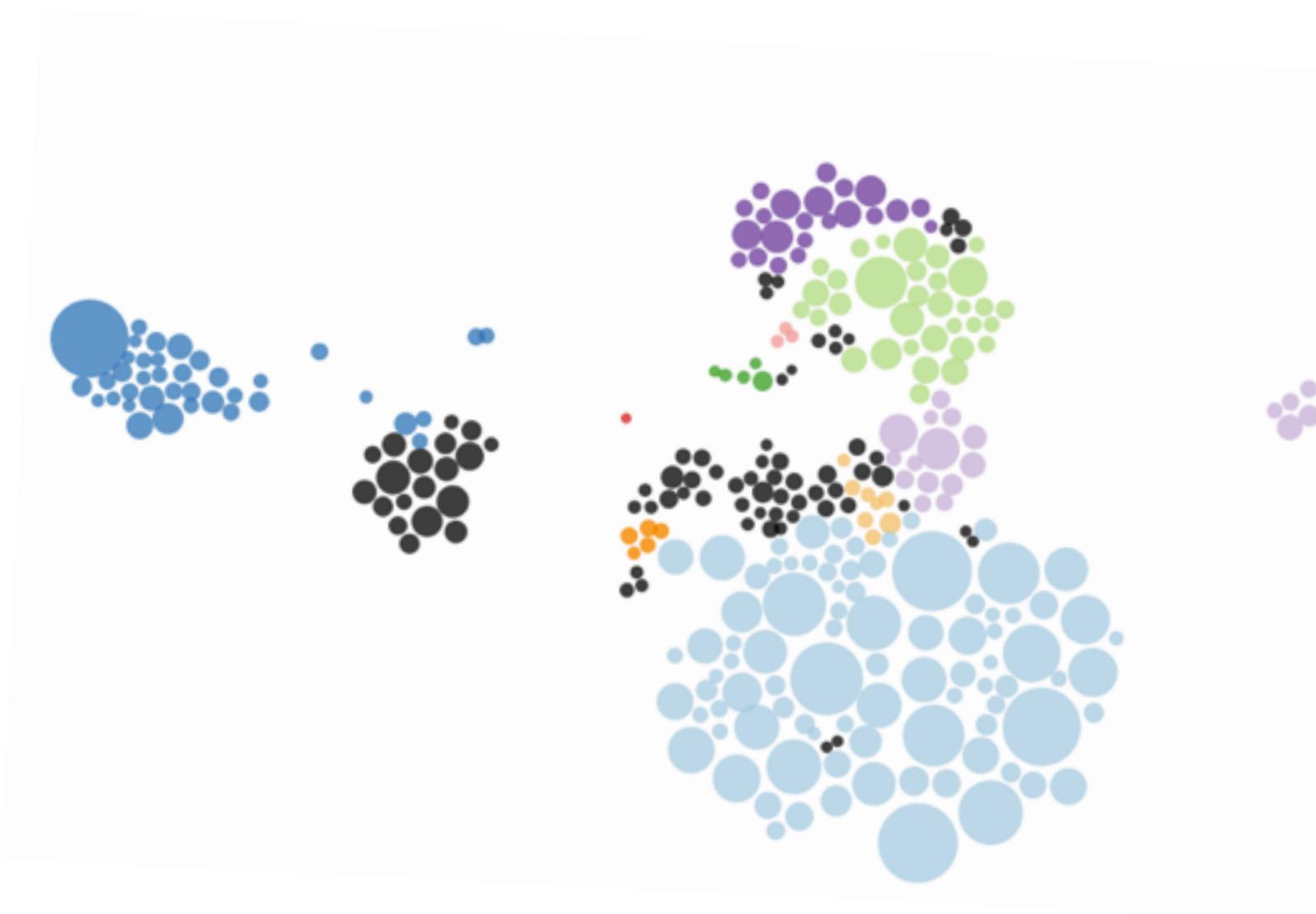
(-10) Communes of <10K

(R) Rural

Hybrid Method: Use algorithmic layout, and then adjust nodes by hand.



Minimize Info: Less is More



Color by important data value, sized by degree, no edges

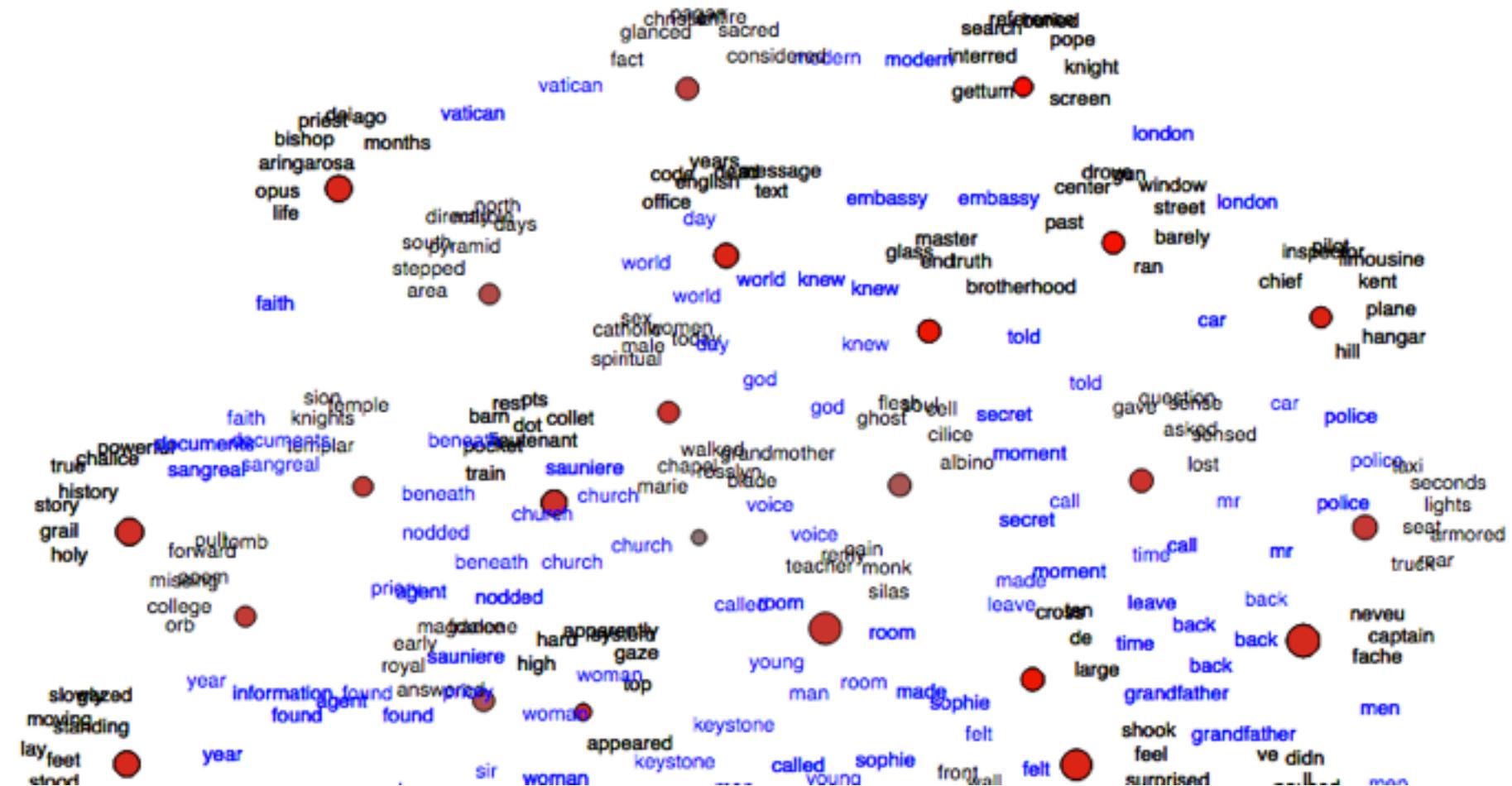
'DaVinci Code' LDA Topic Words

Topic node sized by number of topic assignments, colored by relative excitement score as tallied off Mechanical Turk ratings by chapter. Mouse over to see details and network relations.

Blue words are found in more than one topic. NB: This layout has a lot of overlaps because there is no collision detection for the labels, but I abandoned it when I realized it wasn't very illuminating anyway. [Blog post/slides](#) by Lynn Cherny.

Filter Topics By...

All Most Exciting Less Exciting



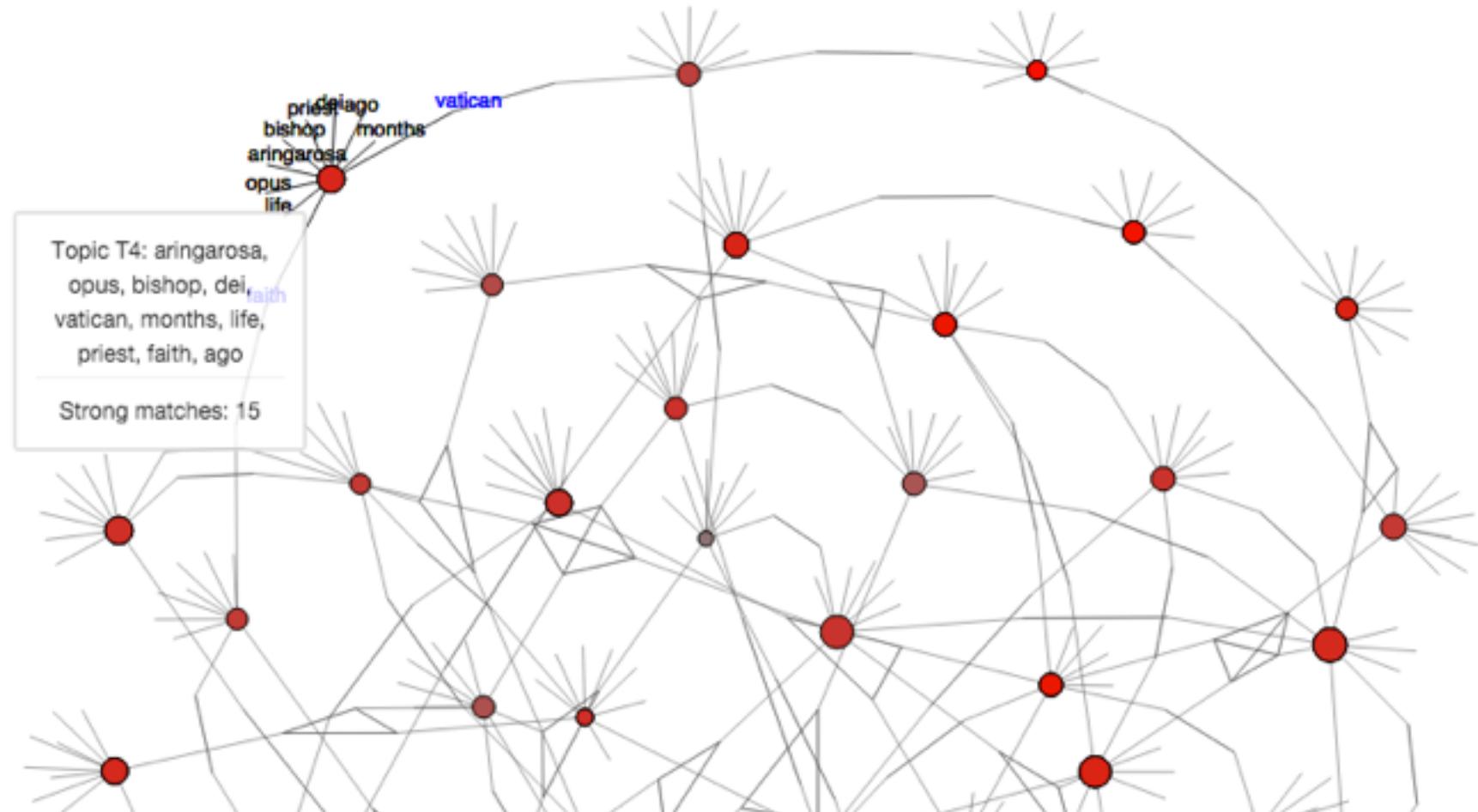
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Filter Topics By...

All Most Exciting Less Exciting



Brian Keegan's “15 Minutes of Fame as a B-List GamerGate Celebrity”



 **Brian Keegan** @bkeegan 29 Oct
I took @waxpancake's #gamergate data and made a RT network of accounts. Big cluster is core GG, lower left anti-GG.
pic.twitter.com/OE3ebhir5f

 **Alrenous** @Alrenous [Follow](#)
I would assume the lowerV left< black hole is Quinn, Gawker, or Sarkeesian, and is surrounded by a botnet. [@bkeegan](#) [@Outsideness](#)
2:36 AM - 30 Oct 2014
1 FAVORITE   

Brian Keegan's “15 Minutes of Fame as a B-List GamerGate Celebrity”



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2:36 AM - 30 Oct 2014
1 FAVORITE

 ROGUE☆ @RogueStarGamez Follow
How diverse is #GamerGate? Lower left is AntiGG forces. ProGG is the center.
AntiGG is INSULAR. Data does not lie.
2:40 PM - 29 Oct 2014
145 RETWEETS 133 FAVORITES

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2:40 PM - 29 Oct 2014

145 RETWEETS 133 FAVORITES

Wrap it up on design...

Reminders

- Do data analysis / **reduction** - why would you want to show 1T of network data?
- **Calculate** and reveal important facts about node relationships.
- Consider your **visual encodings**:
 - visualization, not data vomit.
- Make it **interactive** - details on demand.
 - Help people find things in your network! (Search?)
 - Show more on hover/click

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too much data
=Not always good
data science!

More Reminders!

- Different layouts communicate different things to your viewer - choose wisely.
 - Take care: people will infer things from proximity/similarity even if it was not intended!
- Consider if it has to be a “network” display at all: Is it the stats you care about? The important nodes who branch sub-communities? The ones with the most in/out links? Graph those instead.

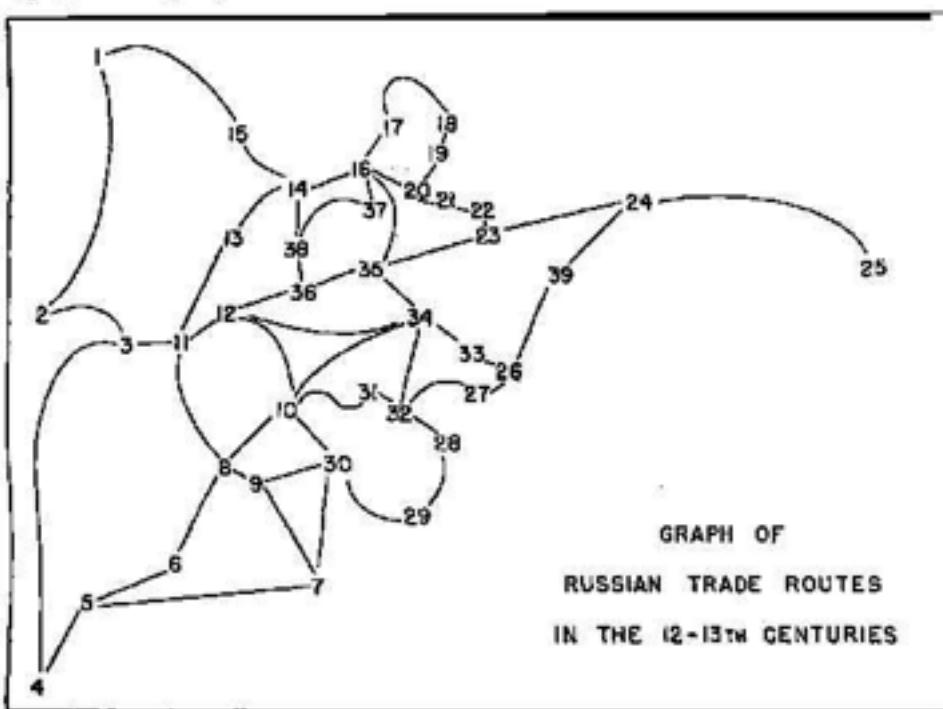
The Map is Not the Territory...

Figure 1. *Russian trade routes in the 12th - 13th centuries.*



The Map is Not the Territory...

Figure 2. *Graph of Russian trade routes in the 12th - 13th centuries.*



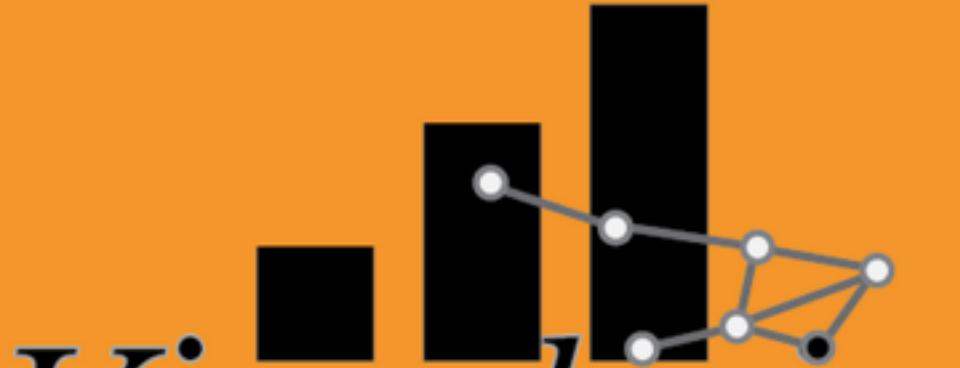
Thanks!
@arnicas
lynn@ghostweather.com

Dec 11-12, NYC

Two days of tutorials with
Naomi B. Robbins and Lynn
Cherny

December 11-12, 2014, NYC

Learn how to communicate data clearly in charts and
graphs, both static and interactive, followed by a deep-dive
into network visualization techniques.



Visualizing DATA

Design for Communication, Interactivity,
& Network Displays

http://www.ghostweather.com/workshops/nyc_visdata.html

lynn @ ghostweather.com

A Few More References

Jeff Heer class slides: <http://hci.stanford.edu/courses/cs448b/w09/lectures/20090204-GraphsAndTrees.pdf>

A great in-progress book on networks: <http://barabasilab.neu.edu/networksciencebook/>

Mark Newman's new book- [NetWorks: An Introduction](#)

Eyeo Festival videos from [Moritz Stefaner, Manuel Lima, Stefanie Posavec](#)

Journal of Graph Algorithms and Applications:
<http://jgaa.info/home.html>

Jim Vallandingham's D3 network tutorials:
<http://flowingdata.com/2012/08/02/how-to-make-an-interactive-network-visualization/>,
http://vallandingham.me/bubble_charts_in_d3.html

Brian Keegan's post about [GamerGate tweets and the dangers of network vis](#)

Robert Kosara's post: <http://eagereyes.org/techniques/graphs-hairball>

Lane Harrison's post: <http://blog.visual.ly/network-visualizations/>

MS Lima's book [Visual Complexity](#)

Jason Sundram's tool to drive Gephi layout from command line: <https://github.com/jsundram/pygephi>

A couple articles on community structure:

[Overlapping Community Detection in Networks: State of the Art and Comparative Study](#) by Jierui Xie, Stephen Kelley, Boleslaw K. Szymanski

[Empirical Comparison of Algorithms for Network Community Detection](#) by Leskovec, Lang, Mahoney

My posts on [NetworkX with D3](#) and [Twitter network vis with Gephi](#)