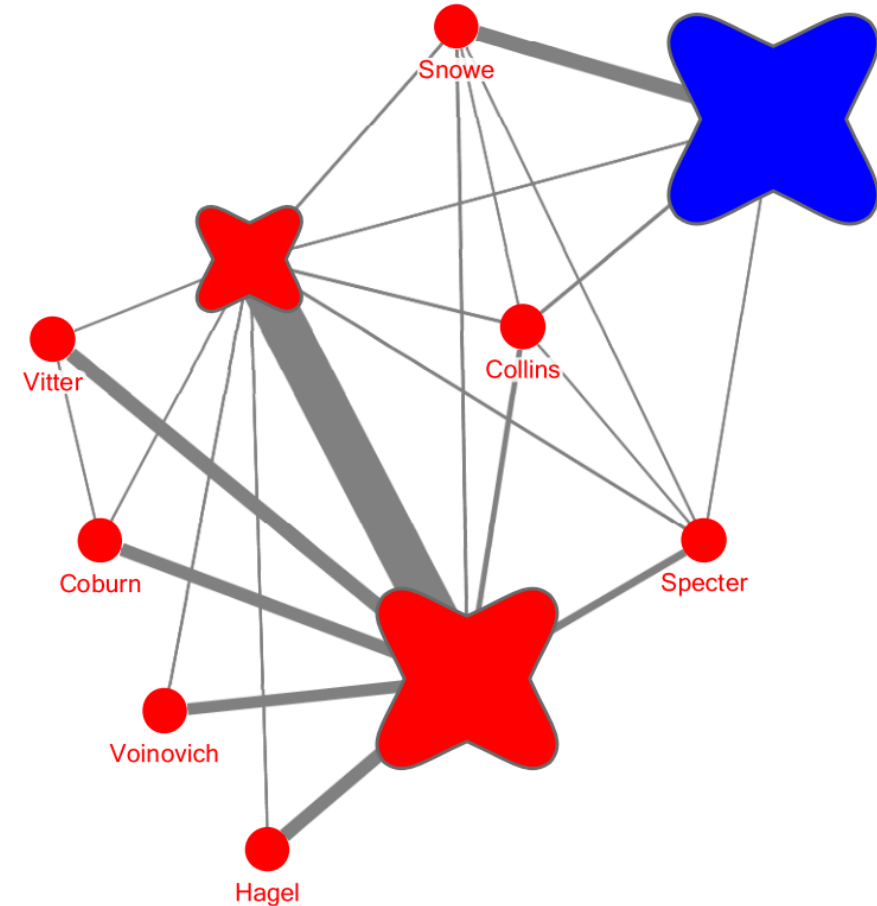
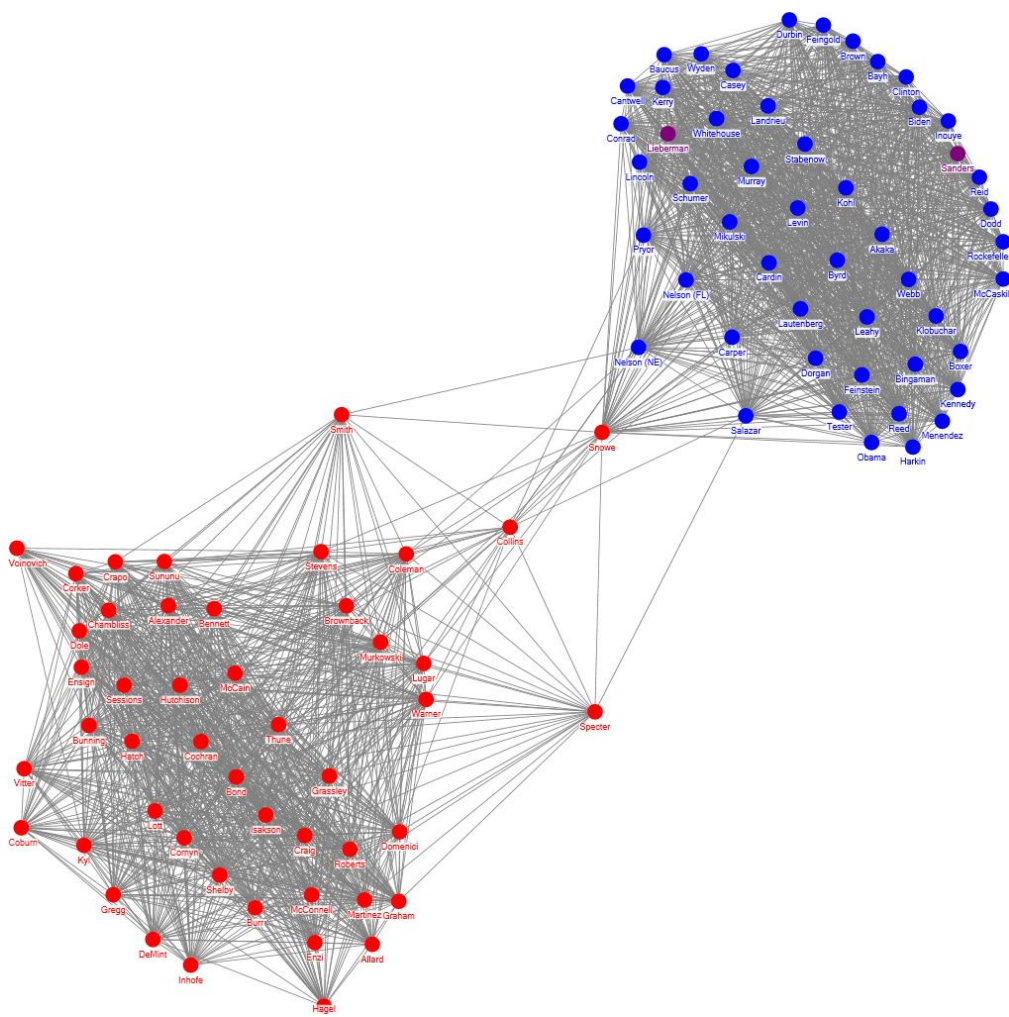


CS 7280-03 Special Topics on Visualization in Network Science

Lecture 2



Professor Cody Dunne

<https://codydunne.github.io/cs7280-f16/>
c.dunne@northeastern.edu

Email

Projects

<https://codydunne.github.io/cs7280-f16/#final-project>

Graph Drawing 2017

Hosted in September by IBM
Cambridge, MA, USA

Cody Dunne, Northeastern University

c.dunne@northeastern.edu

T. Alan Keahey, IBM Watson Health

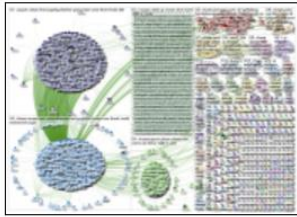
alan.keahey@us.ibm.com



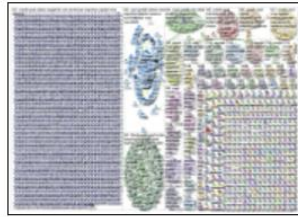
HW2 Tools and Teams

These are [network graphs](#) created with [NodeXL](#), a template for graphing network data in Excel® (2007, 2010, 2013 and 2016).

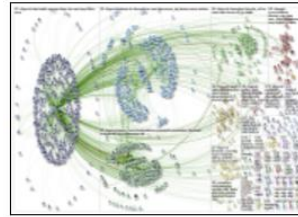
Recent graphs:



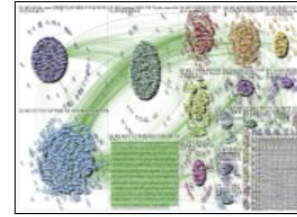
[\(Chase Bank\) OR \(JP Mor...](#)



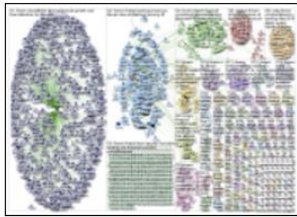
[%22Credit Card%22 \(PNC ...](#)



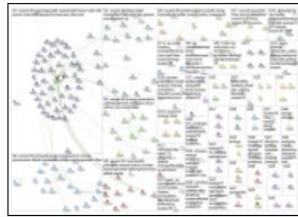
[DHgovuk Twitter NodeXL ...](#)



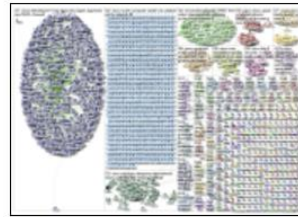
[북한 Twitter NodeXL SNA ...](#)



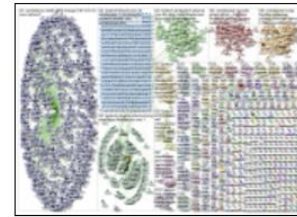
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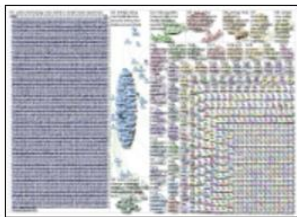
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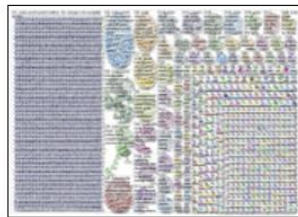
[#cisco 2016-09-12 23-19-...](#)



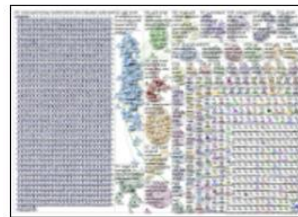
[#BIO2016 OR IAMBiotech ...](#)



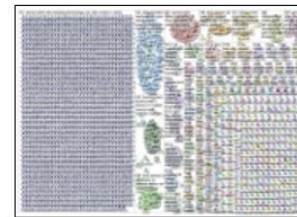
[Technology Policy 2016-...](#)



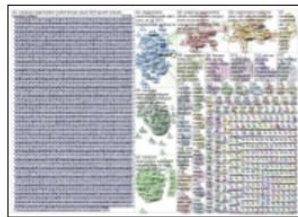
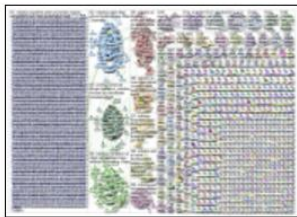
[Solar \(panel OR Photovo...](#)



[Smart Grid 2016-09-12 2-...](#)



[Sensor Tech 2016-09-12 ...](#)



Reading Discussions

<https://codydunne.github.io/cs7280-f16/schedule/>

<https://piazza.com/northeastern/fall2016/cs728003/>

Discussion:
Illuminating the Path

The Science of Analytical Reasoning

- **R1:** Build upon theoretical foundations of reasoning, sense-making, cognition, and perception to create visually enabled tools to support collaborative analytic reasoning about complex and dynamic problems.
- **R2:** Conduct research to address the challenges and seize the opportunities posed by the scale of the analytic problem. The issues of scale are manifested in many ways, including the complexity and urgency of the analytical task, the massive volume of diverse and dynamic data involved in the analysis, and challenges of collaborating among groups of people involved in analysis, prevention, and response efforts.

Table 2.2. How information visualization amplifies cognition.

1. Increased resources	
High-bandwidth hierarchical interaction	The human moving gaze system partitions limited channel capacity so that it combines high spatial resolution and wide aperture in sensing the visual environments [Resnikoff, 1989].
Parallel perceptual processing	Some attributes of visualizations can be processed in parallel compared to text, which is serial.
Offload work from cognitive to perceptual system	Some cognitive inferences done symbolically can be recoded into inferences done with simple perceptual operations [Larkin & Simon, 1987].
Expanded working memory	Visualizations can expand the working memory available for solving a problem [Norman, 1993].
Expanded storage of information	Visualizations can be used to store massive amounts of information in a quickly accessible form (e.g., maps).
2. Reduced search	
Locality of processing	Visualizations group information used together, reducing search [Larkin & Simon, 1987].
High data density	Visualizations can often represent a large amount of data in a small space [Tufte, 1983].
Spatially-indexed addressing	By grouping data about an object, visualizations can avoid symbolic labels [Larkin & Simon, 1987].

3. Enhanced recognition of patterns	
Recognition instead of recall	Recognizing information generated by a visualization is easier than recalling that information by the user.
Abstraction and aggregation	Visualizations simplify and organize information, supplying higher centers with aggregated forms of information through abstraction and selective omission [Card et al., 1991; Resnikoff, 1989].
Visual schemata for organization	Visually organizing data by structural relationships (e.g., by time) enhances patterns.
Value, relationship, trend	Visualizations can be constructed to enhance patterns at all three levels [Bauer et al., 1999].

4. Perceptual inference	
Visual representations make some problems obvious	Visualizations can support a large number of perceptual inferences that are extremely easy for humans [Larkin & Simon, 1987].
Graphical computations	Visualizations can enable complex, specialized graphical computations [Hutchins, 1996].

5. Perceptual monitoring	
	Visualizations can allow for the monitoring of a large number of potential events if the display is organized so that these stand out by appearance or motion.

6. Manipulable medium	
	Unlike static diagrams, visualizations can allow exploration of a space of parameter values and can amplify user operations.

Visual Representations and Interaction Technologies

- **R1:** Create a science of visual representations based on cognitive and perceptual principles that can be deployed through engineered, reusable components. Visual representation principles must address all types of data, address scale and information complexity, enable knowledge discovery through information synthesis, and facilitate analytical reasoning.
- **R2:** Develop a new suite of visual paradigms that support the analytical reasoning process. These visualizations must:
 - Facilitate understanding of massive and continually growing collections of data of multiple types
 - Provide frameworks for analysis of spatial and temporal data
 - Support understanding of uncertain, incomplete, and often misleading information
 - Provide user- and task-adaptable, guided representations that enable full situation awareness while supporting development of detailed actions
 - Support multiple levels of data and information abstraction
 - Facilitate knowledge discovery through information synthesis, which is the integration of data based on their meaning rather than the original data type.
- **R3:** Develop a new science of interactions that supports the analytical reasoning process. This interaction science must provide a taxonomy of interaction techniques ranging from the low-level interactions to more complex interaction techniques and must address the challenge to scale across different types of display environments and tasks.

Basic Principles for Effective Vis

- Norman, 1993; Illuminating the Path
 - **Appropriateness Principle** – The visual representation should provide neither more nor less information than that needed for the task at hand. Additional information may be distracting and makes the task more difficult.
 - **Naturalness Principle** – Experiential cognition is most effective when the properties of the visual representation most closely match the information being represented. This principle supports the idea that new visual metaphors are only useful for representing information when they match the user's cognitive model of the information. Purely artificial visual metaphors can actually hinder understanding.
 - **Matching Principle** – Representations of information are most effective when they match the task to be performed by the user. Effective visual representations should present affordances suggestive of the appropriate action.

Basic Principles for Effective Vis

- Tversky et al., 2002
 - **Principle of Congruence** – The structure and content of a visualization should correspond to the structure and content of the desired mental representation. In other words, the visual representation should represent the important concepts in the domain of interest.
 - **Principle of Apprehension** - The structure and content of a visualization should be readily and accurately perceived and comprehended.

Data Representations and Transformations

- **R1:** Develop both theory and practice for transforming data into new scalable representations that faithfully represent the content of the underlying data.
- **R2:** Create methods to synthesize information of different types and from different sources into a unified data representation so that analysts, first responders, and border personnel may focus on the meaning of the data.
- **R3:** Develop methods and principles for representing data quality, reliability, and certainty measures throughout the data transformation and analysis process.

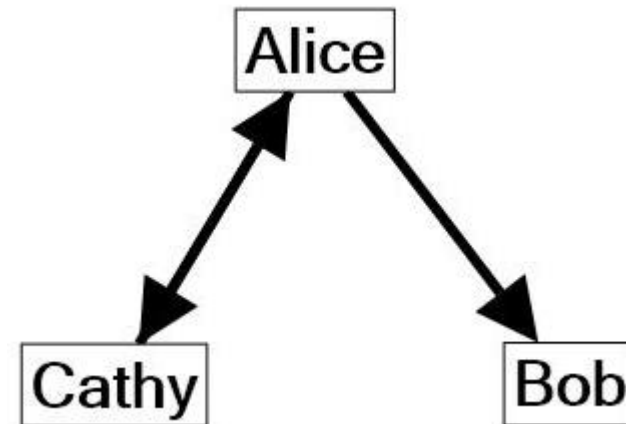
Node-Link Visualization

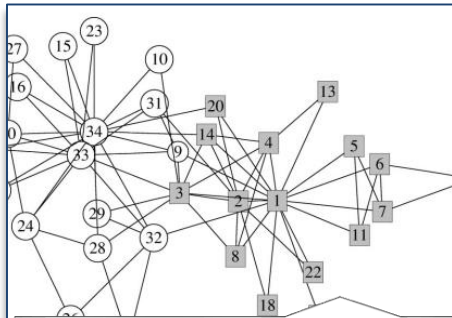
Graph \approx Network

Node \approx Vertex \approx Entity

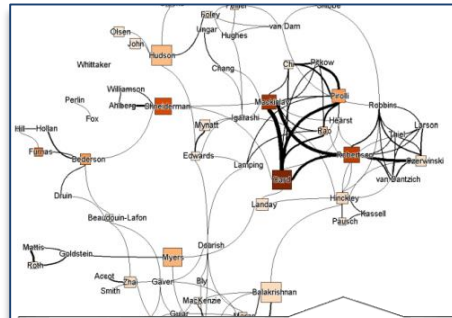
Edge \approx Link \approx Relationship

Node 1	Node 2
Alice	Bob
Alice	Cathy
Cathy	Alice

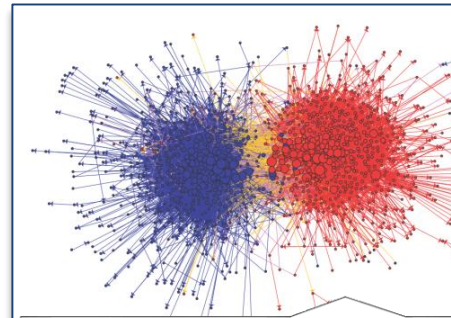




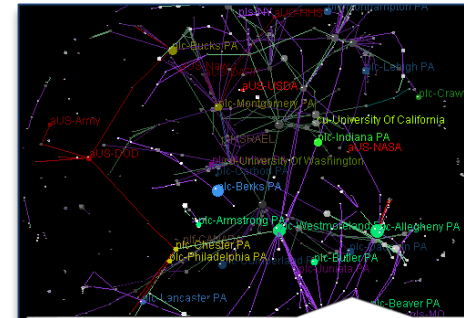
Sociology



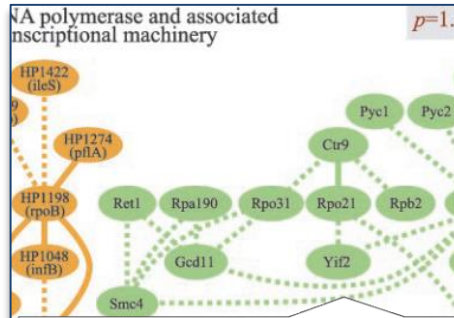
Scientometrics



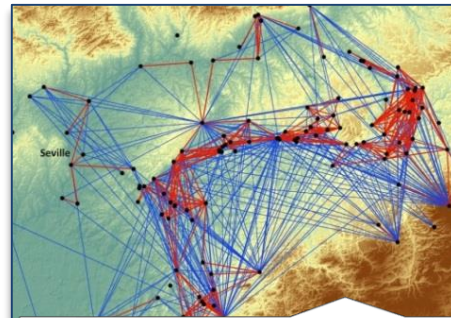
Politics



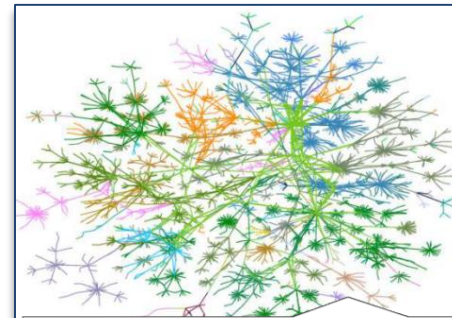
Urban Planning



Medicine

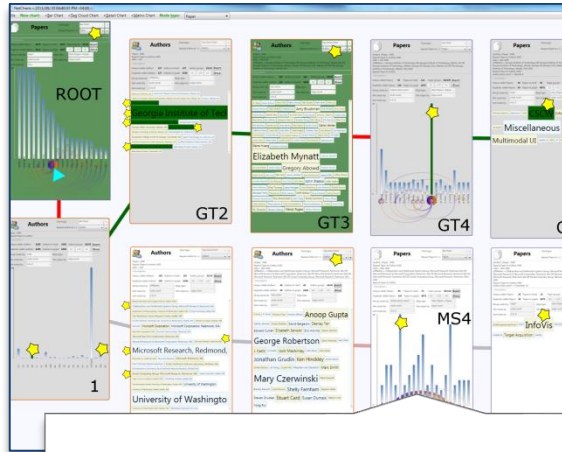


Archaeology

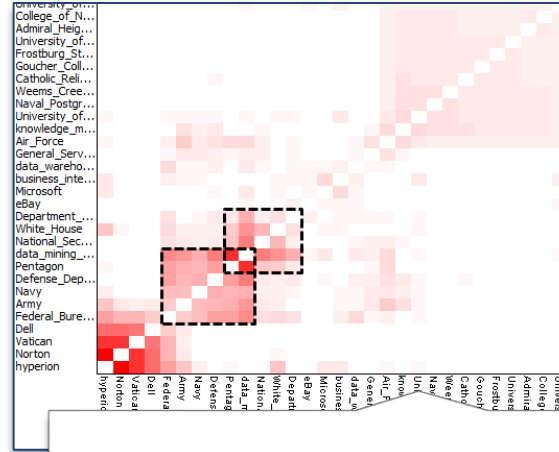


Computer Networks

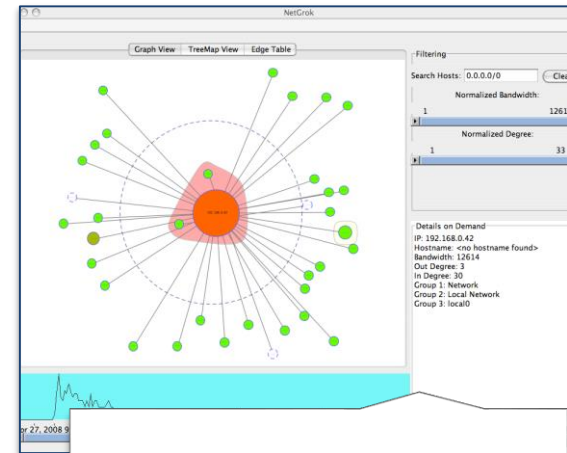
Alternate visualizations...



Dunne et al., 2012



Gove et al., 2011



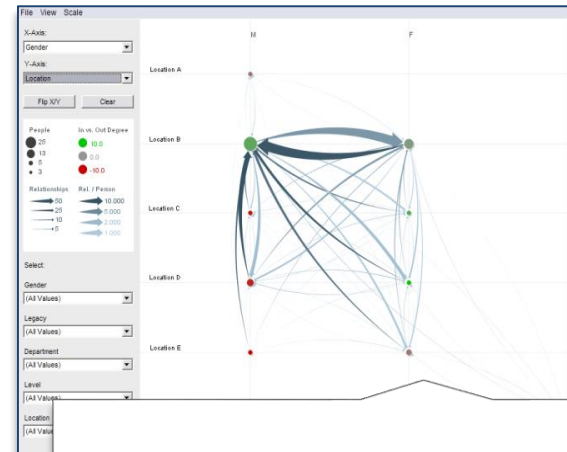
Blue et al., 2008



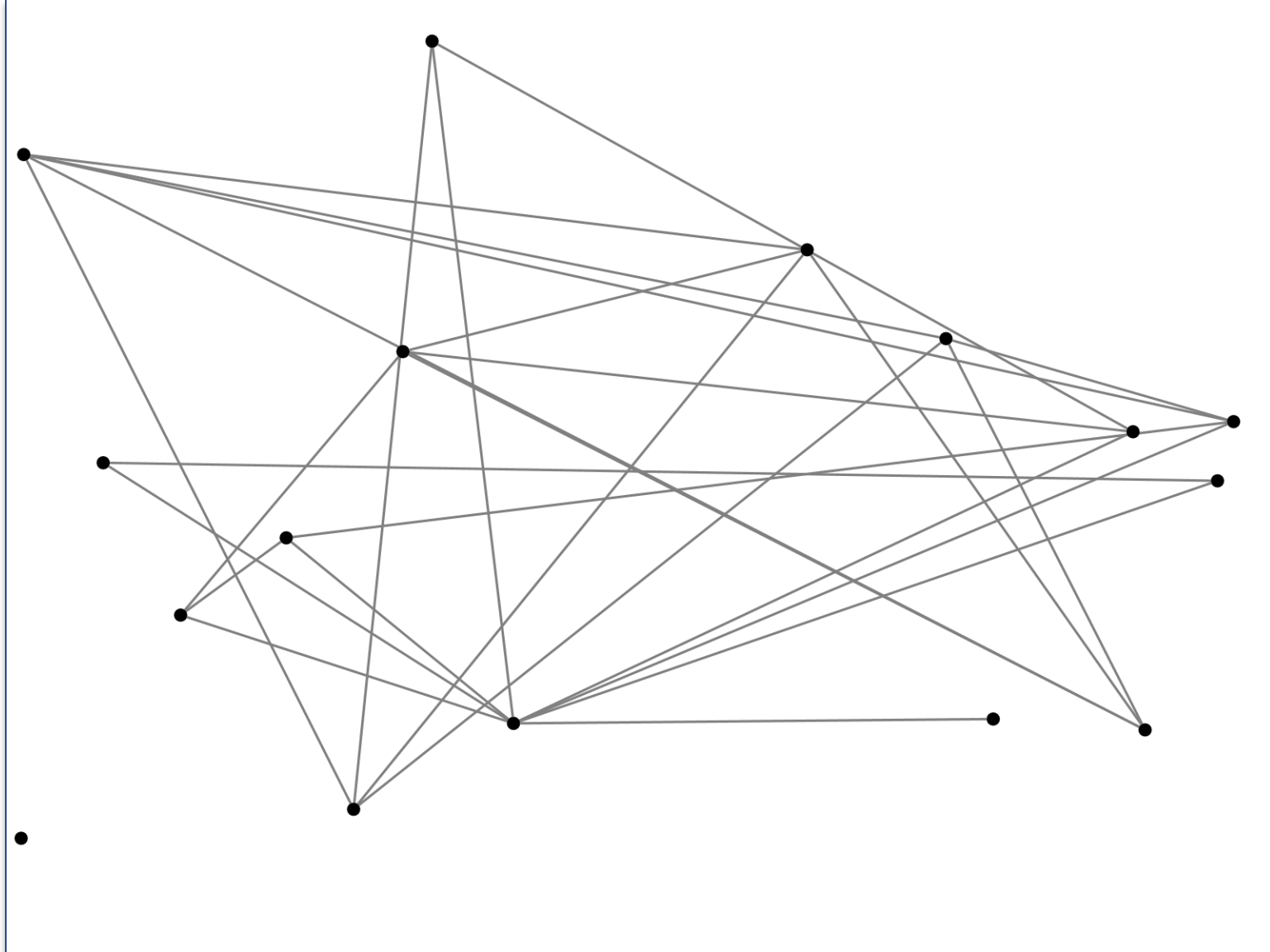
Henry & Fekete,
2006

	Vertex count	Component count	Component sizes	Duplicate edge count	Start
6E-3	213	45		18	
6E-3	270	33		45	
6E-3	303	19		90	
6E-3	337	11		132	
6E-3	346	9		148	
6E-3	334	6		142	
7E-3	333	12		121	
E-3	311	21		67	
8E-3	280	42		31	
7E-3	211	50			

Freire et al., 2010



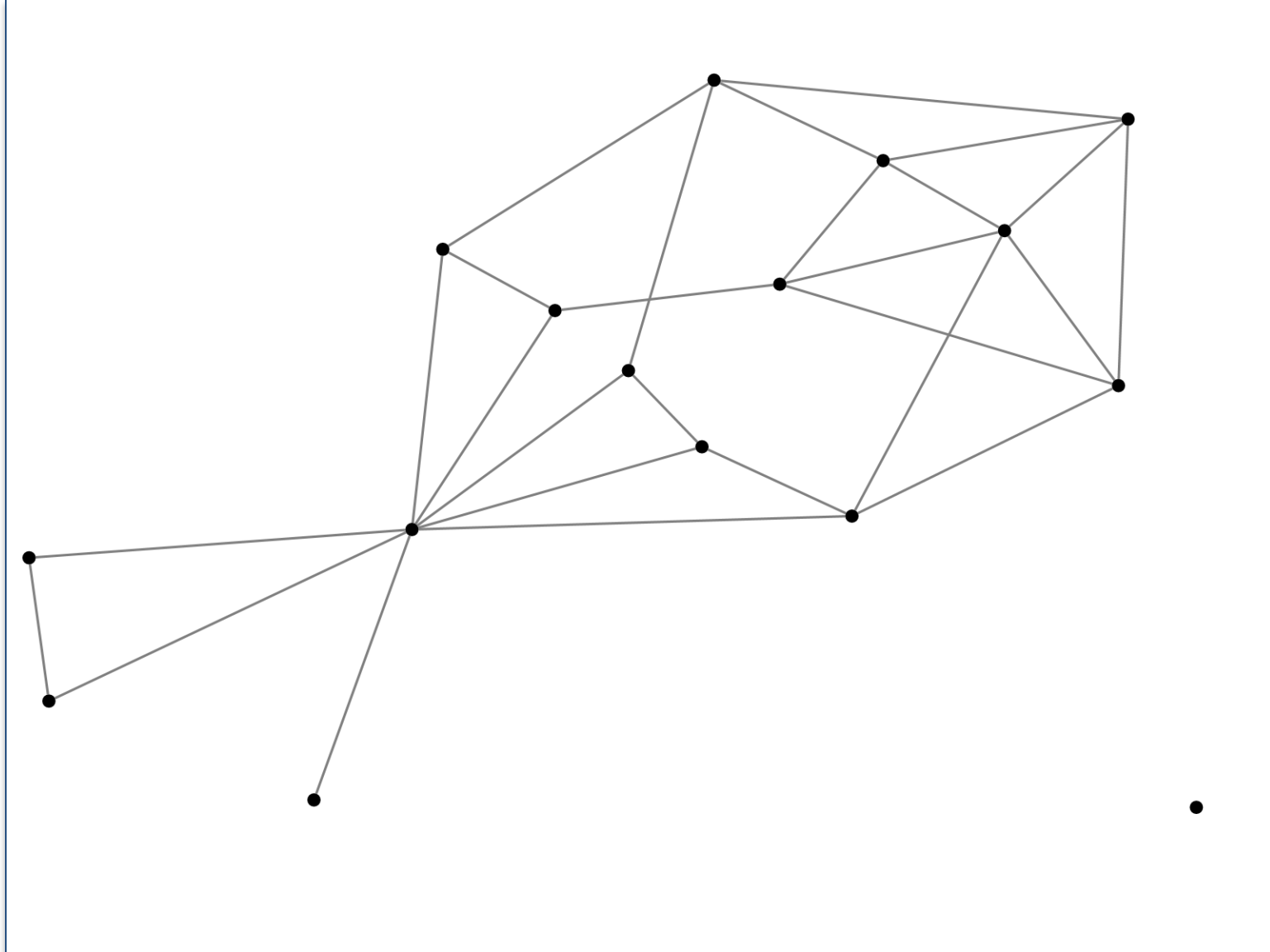
Wattenberg, 2006



Florentine Families

Random layout

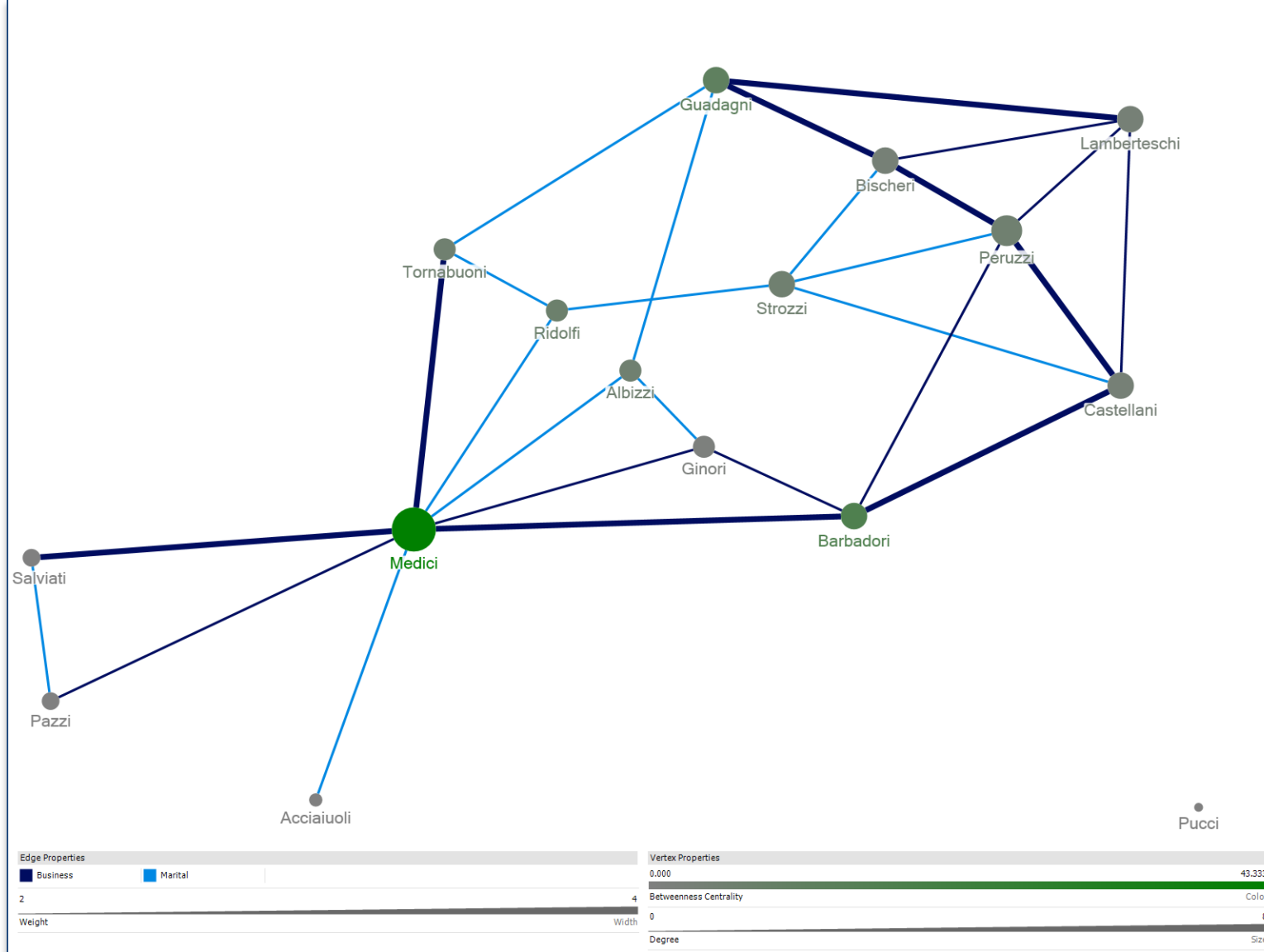
Data source: John Padgett, Breiger & Pattison (1986)



Florentine Families

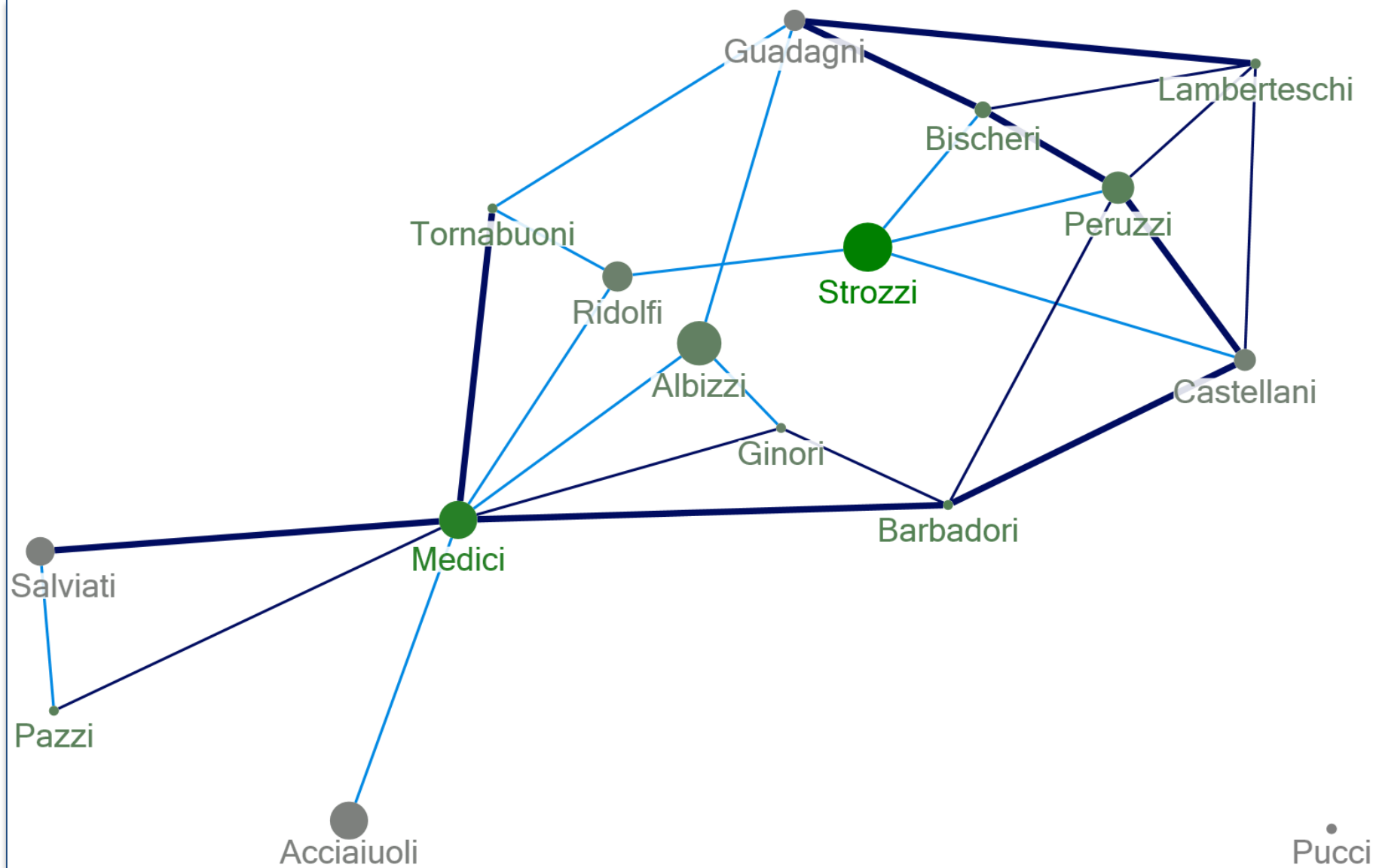
Fruchterman & Reingold (1991) layout

Data source: John Padgett, Breiger & Pattison (1986)



Florentine Families

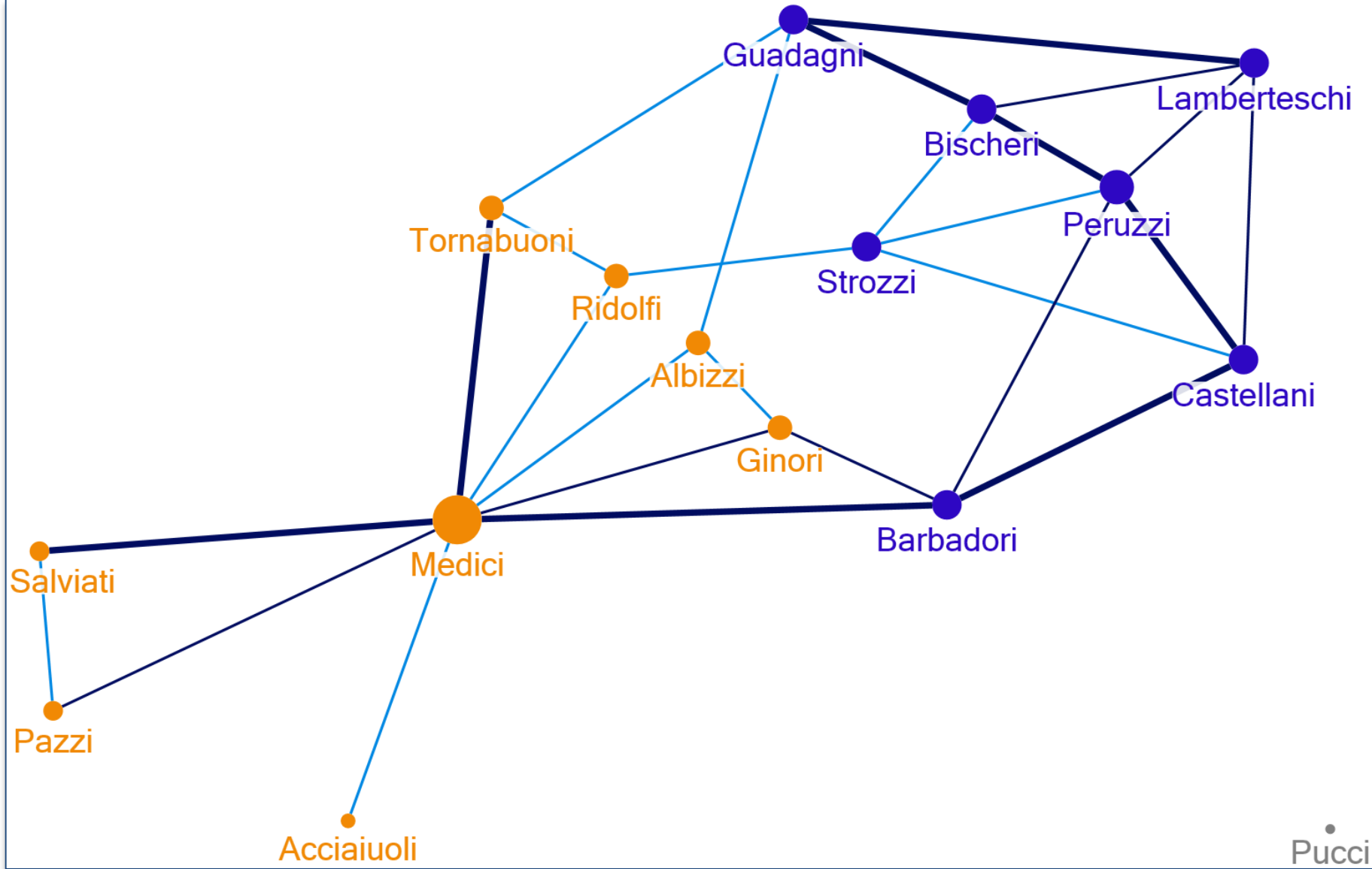
Metric coding: betweenness centrality and degree
 Data source: John Padgett, Breiger & Pattison (1986)



Florentine Families

Attributes: Council seats 1282-1344, net wealth in 1427, financial ties, marriage ties

Data: John Padgett, Breiger & Pattison (1986)

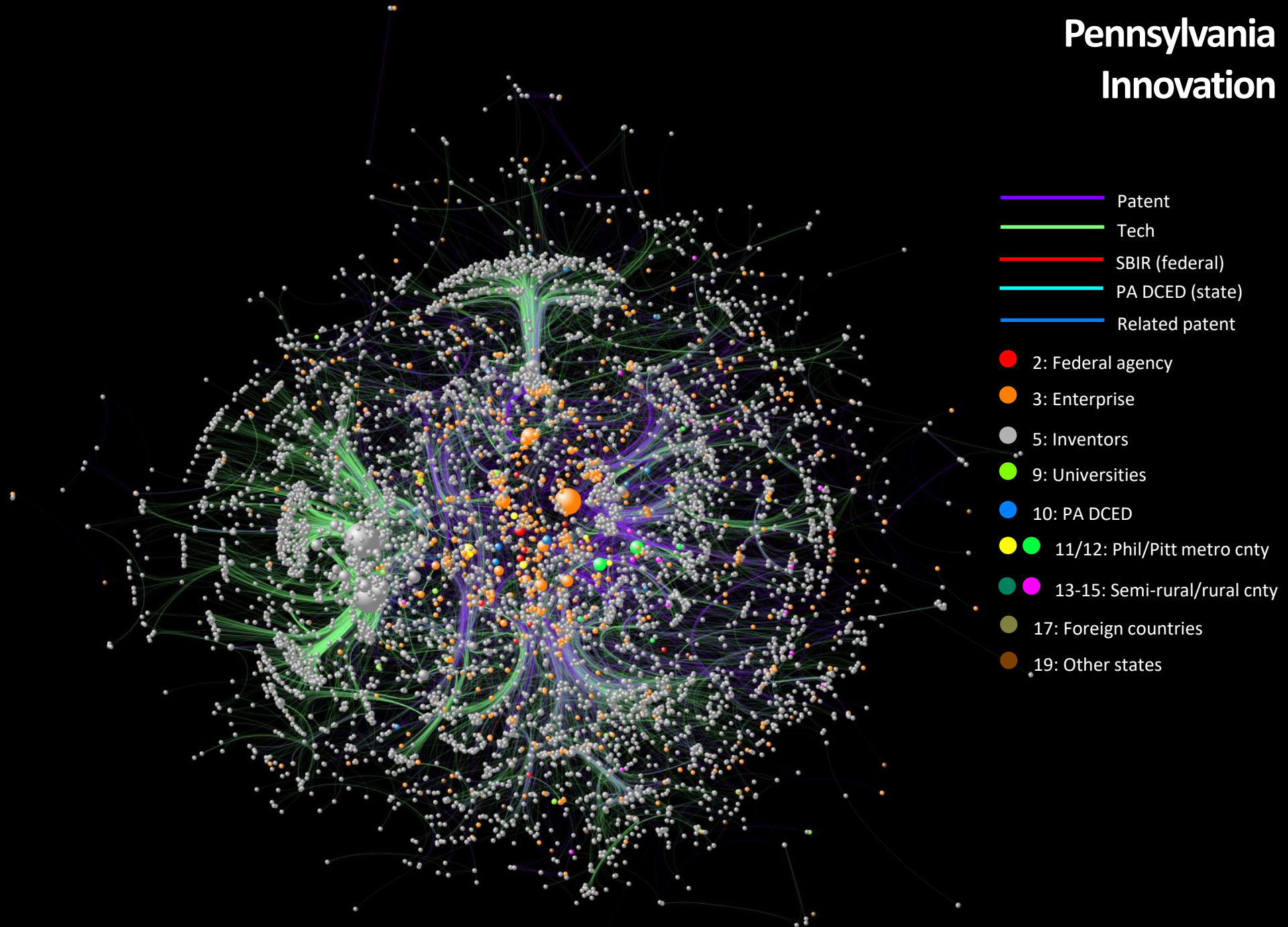


Florentine Families

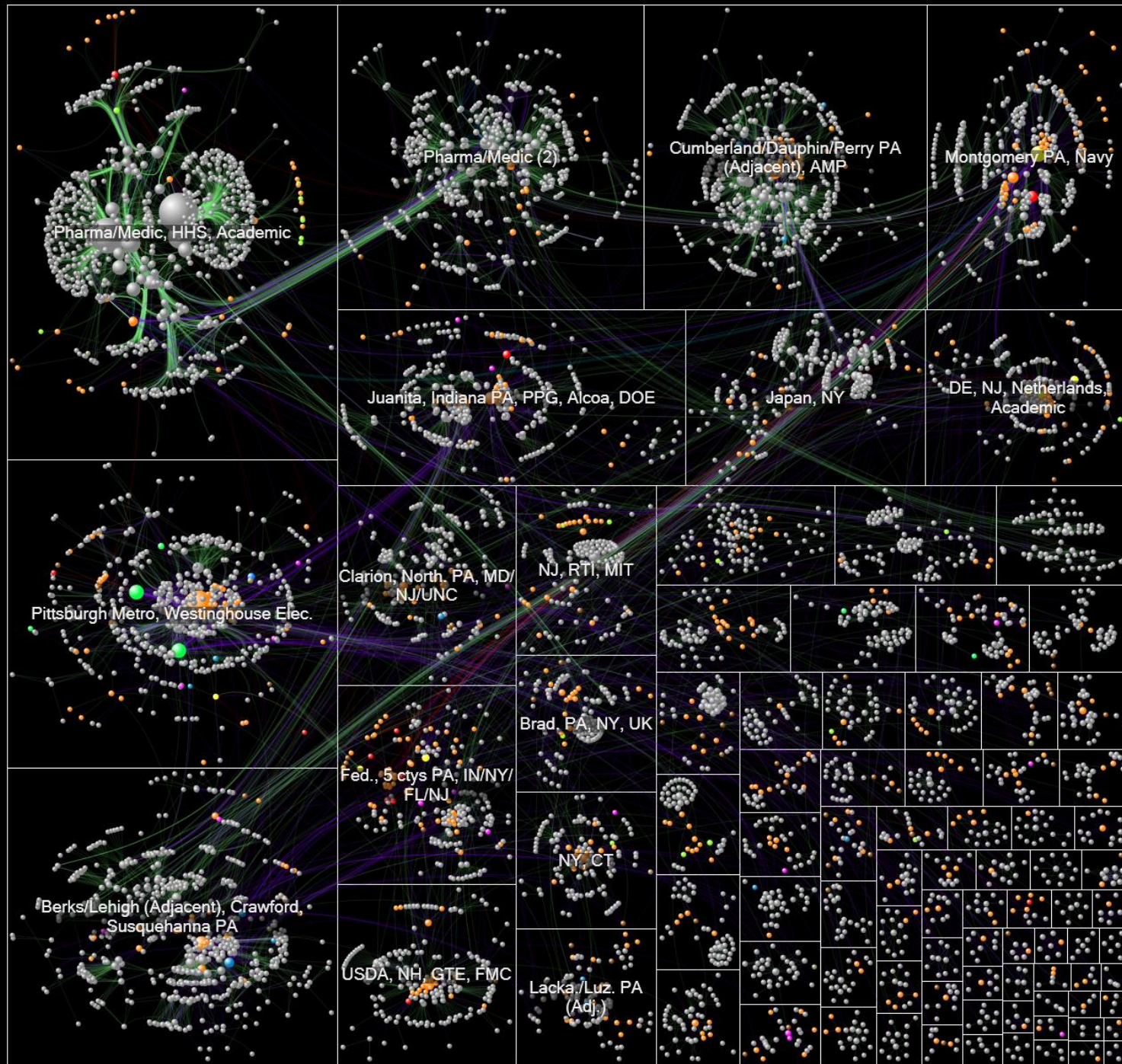
Cluster coding: Girvan & Newman (2002)

Data: John Padgett, Breiger & Pattison (1986)

Pennsylvania Innovation

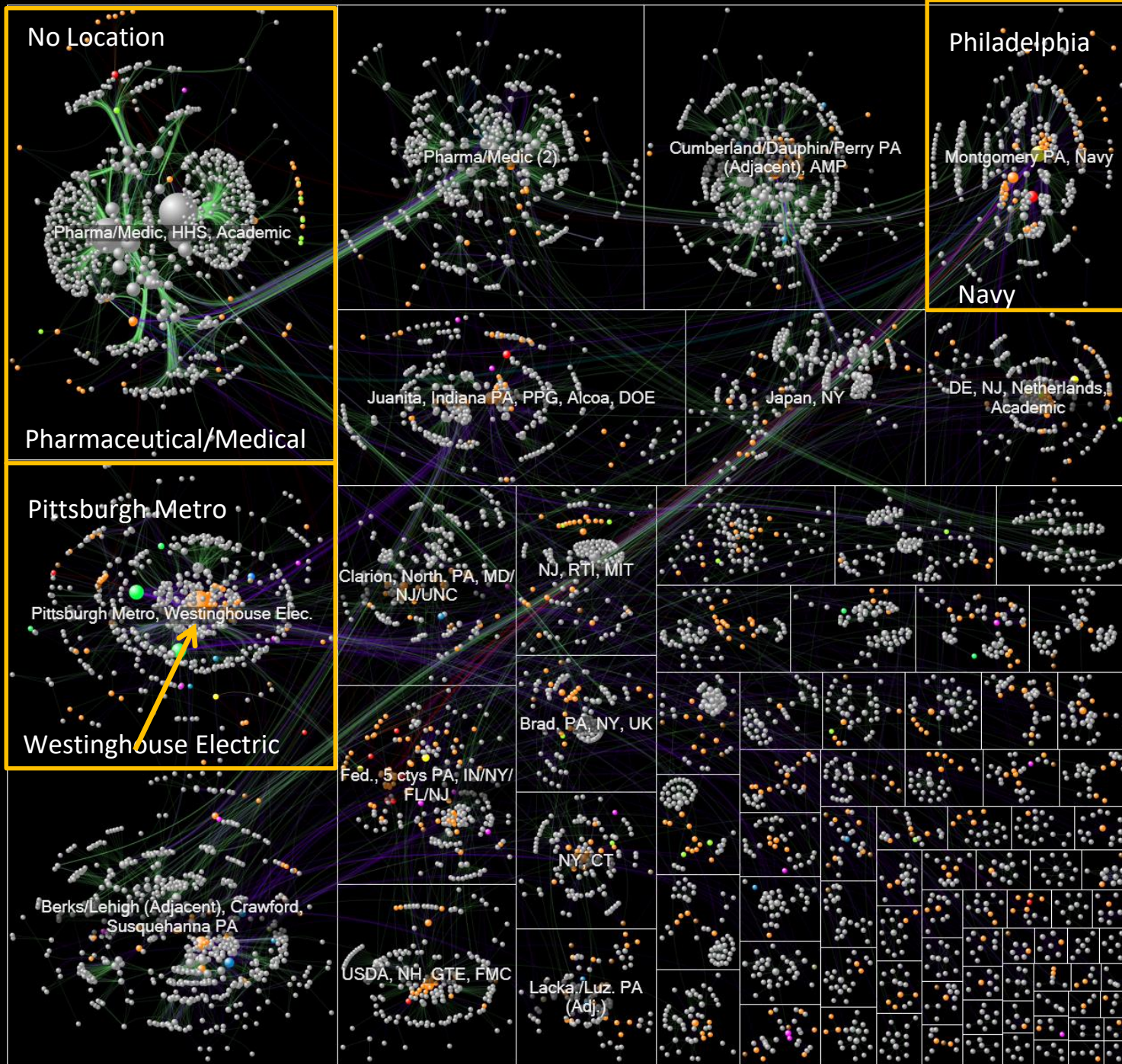


Pennsylvania Innovation



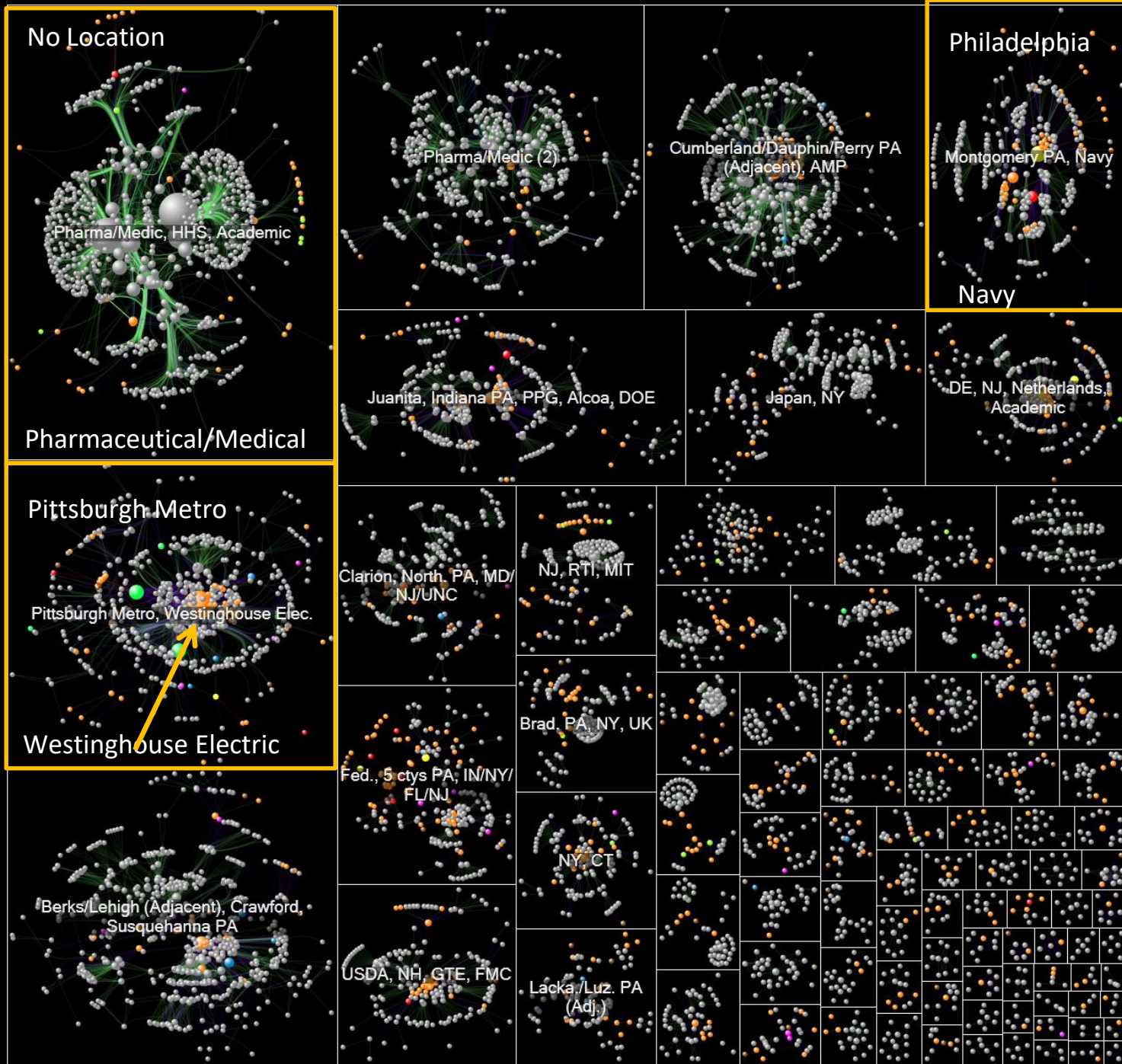
- Patent
- Tech
- SBIR (federal)
- PA DCED (state)
- Related patent
- 2: Federal agency
- 3: Enterprise
- 5: Inventors
- 9: Universities
- 10: PA DCED
- 11/12: Phil/Pitt metro cnty
- 13-15: Semi-rural/rural cnty
- 17: Foreign countries
- 19: Other states

Pennsylvania Innovation



- Patent
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Pennsylvania Innovation

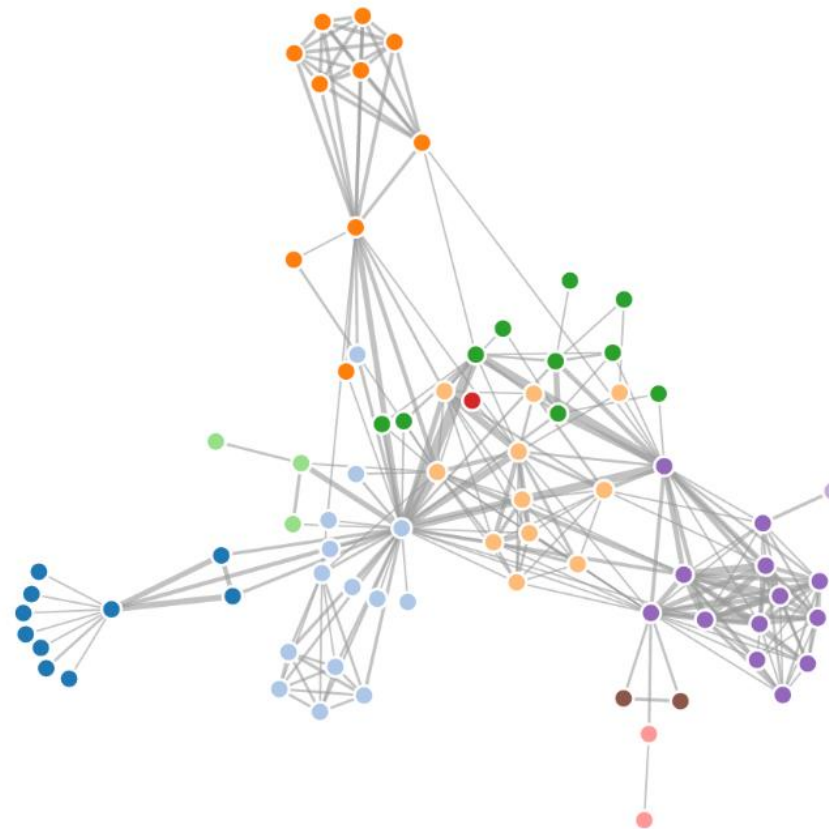


- Patent
- Tech
- SBIR (federal)
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- Related patent
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- 10: PA DCED
- 11/12: Phil/Pitt metro cnty
- 13-15: Semi-rural/rural cnty
- 17: Foreign countries
- 19: Other states

Technical Tips



Force-Directed Graph



Choose Graph:

FAVORITE GRAPHS

HB/blckhole

Bai/rw5151

HB/bcsstm13

HB/jagmesh6

HB/watt_1

HB/lshp1882

HB/plat1919

HB/bcsstk26

Bai/dw256A

Bai/tols2000

Bai/dw1024

Bai/rdb2048

Pajek/CSphd

GHS_indef/laser

BAI

bfwa398

bfwa62

bfwb398

bfwb62

bfwb782

bwm200

cdde1

cdde2

cdde3

cdde4

cdde5

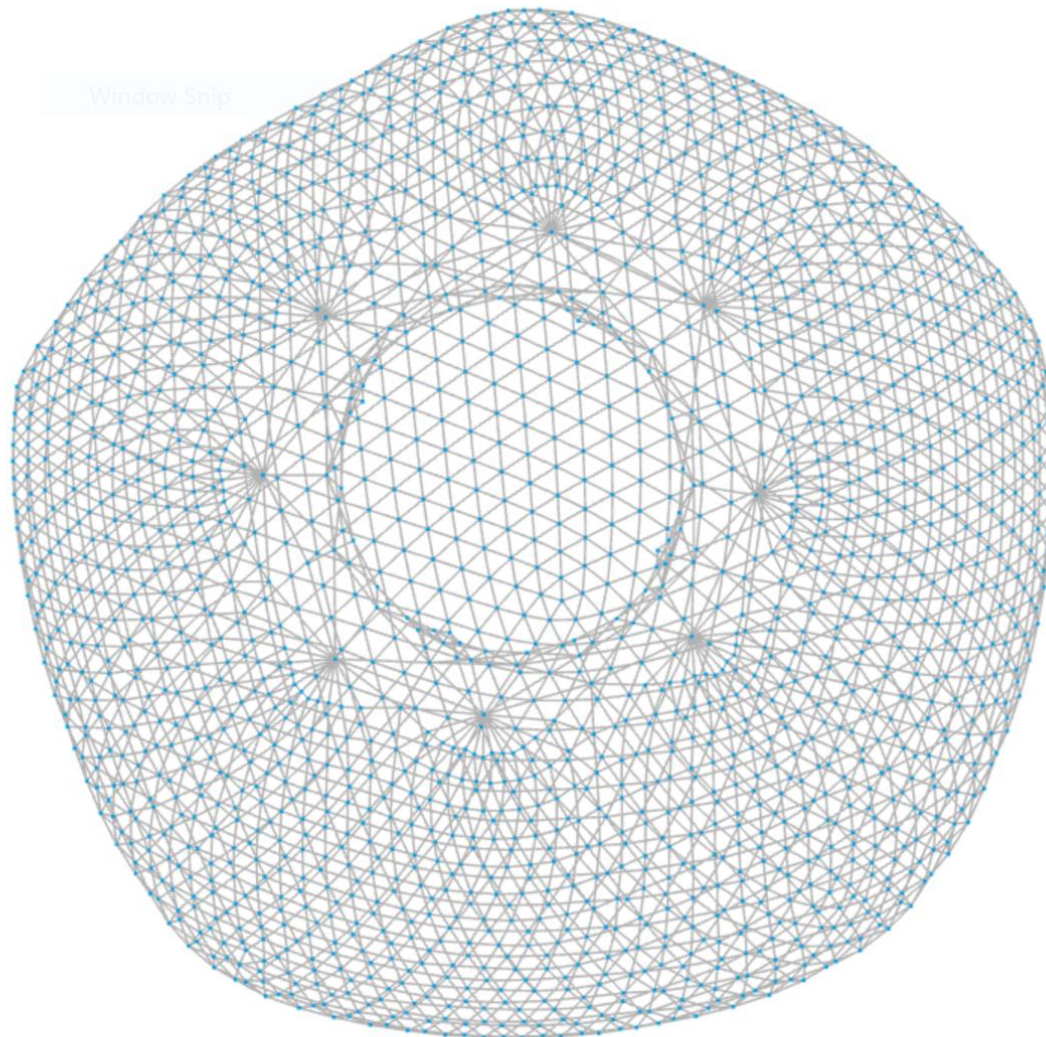
cdde6

ck104

ck400

ck656

dw256A



Window Snip

Layout Settings

- Spring Coeff:
- Spring Length:
- Gravity Coeff:
- Drag Coeff:
- Theta Coeff:

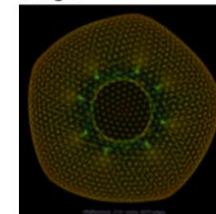
Reset to default

HB/blckhole

Nodes: 2121

Edges: 6370

Image:

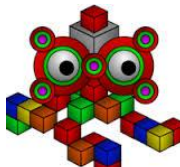

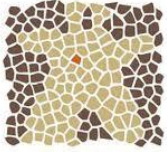
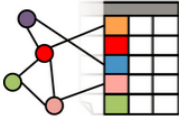


Graph Technology

- Visualisation
 - Rich client applications
 - Browser-based tools
- Analytics
 - Graph processing languages & engines
- Search
 - Indexes
- Storage
 - Graph Databases
 - Graphs in RDBMS. NoSQL DBs

“which should I use? does it scale? is it web-based?”
“how do I get data into it?”

Gephi 	vis.js 	D3.js 	WebGL 	VivaGraphJS 	IBM i2 
Alchemy.js 	sigma.js 	Linkurious.js 	three.js 	Watson Network Data API 	

Tinkerpop 	Gremlin 	Apache Giraph 	GraphX 	Pregel Cypher
--	--	--	---	------------------

neo4j 	titan 	cassandra 	Solr 
		APACHE HBASE HBase 	Lucene 
			elastic Elastic Search 

Recommendations for browser-based rendering

Sizes in UI terms; for graphs 10M elements="small"

Size of Graph			Preferred Technology	accessible flexible ← SVG	Preferred Libraries	→ Canvas	scalable → WebGL ⁶
S	Small	c 5K elements	SVG	✓ D3	✓ D3	✓ VivaGraph	
M	Medium	c 25K elements	Canvas	!! Custom ²	✓ D3 ¹	✓ VivaGraph	
L	Large	c 50K elements	WebGL	!! Custom ³	!! Custom ³	✓ VivaGraph	
XL	Extra Large	c 500K elements	Pre-Process!! WebGL++		!! Custom ³	!! Custom ³	
XXL	Huge	c 5M+ elements	Pre-Process!! WebGL++			!! Custom	

[1] D3 supports canvas with some difficulty

[2] Custom SVG renderers may do well up to 25K; use Canvas options instead

[3] With effort, you *could* write a custom SVG or Canvas renderer to reach 50K (SVG) or more (Canvas)

For XXL graphs think of the user - try to pre-process: e.g. filter, aggregate, cluster, etc

Recommendations for graph layout on the web

	Size of Graph		Preferred Technology	Preferred Libraries		
				Client CPU	Server CPU ⁴	Server GPU ⁴
S	Small	c 1K elements	Client	✓ D3 force ¹ ✓ WebCola ²	✓ WND ⁵	
M	Medium	c 25K elements	Server CPU/GPU	✓ VivaGraphJS ³ ✓ Custom	✓ WND ⁵	
L	Large	c 50K elements	Server CPU/GPU		✓ WND ⁵	
XL	Extra Large	c 500K elements	Pre-process!! Server GPU	See note 6		
XXL	Huge	c 5M+ elements	Pre-process!! Server GPU			

Investment needed!

[1] D3 standard layout only scales to 1K elements; you could push D3 using a custom layout but requires work

[2] WebCola produces more readable layouts at a performance cost

[3] VivaGraphJS scales better but is harder to integrate

[4] Server-side layout requires more implementation effort, but results in dramatically more readable layouts for the same delay

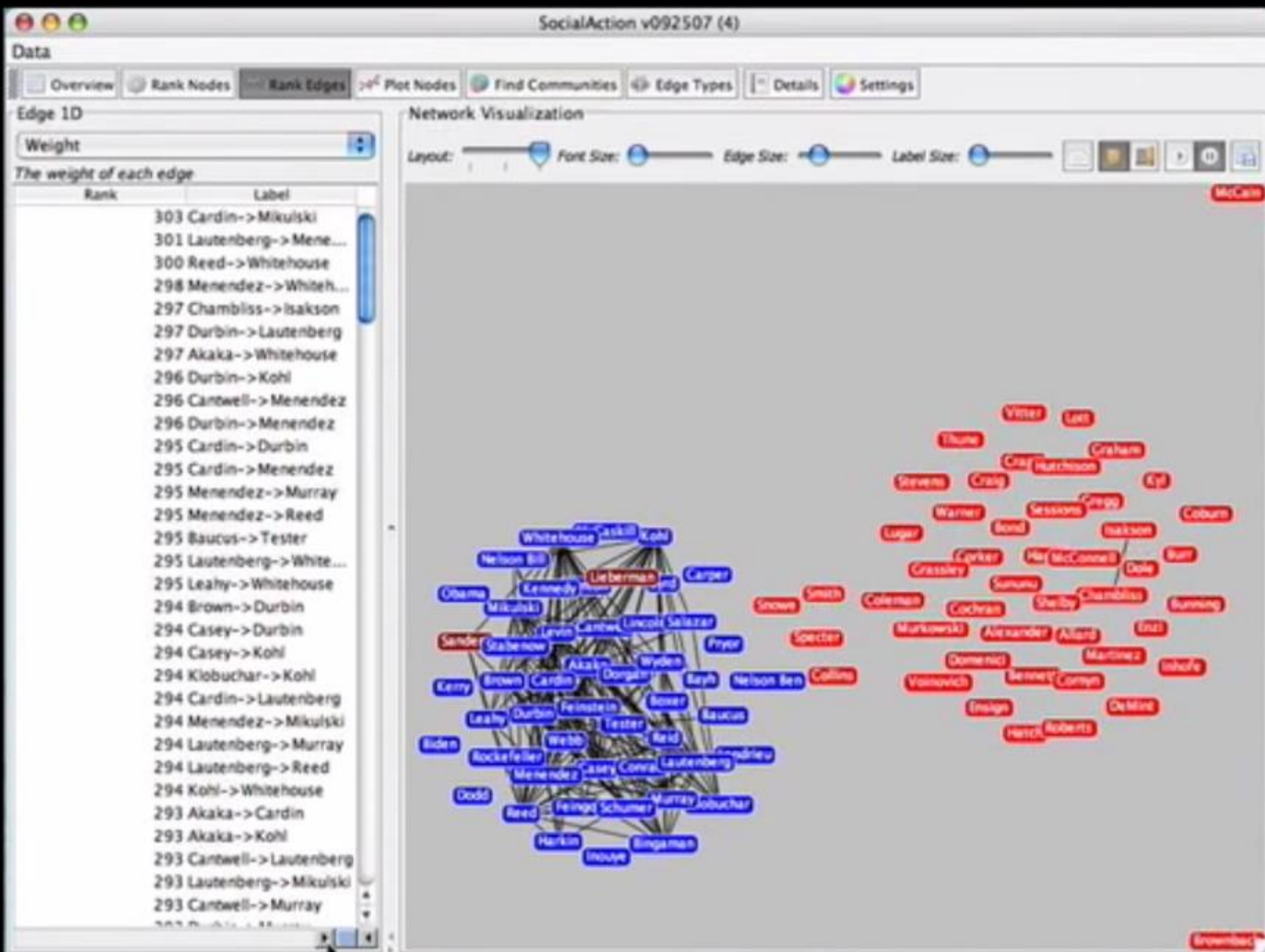
[5] Watson Network Data API (WND) provides many layout algorithms for varied use cases

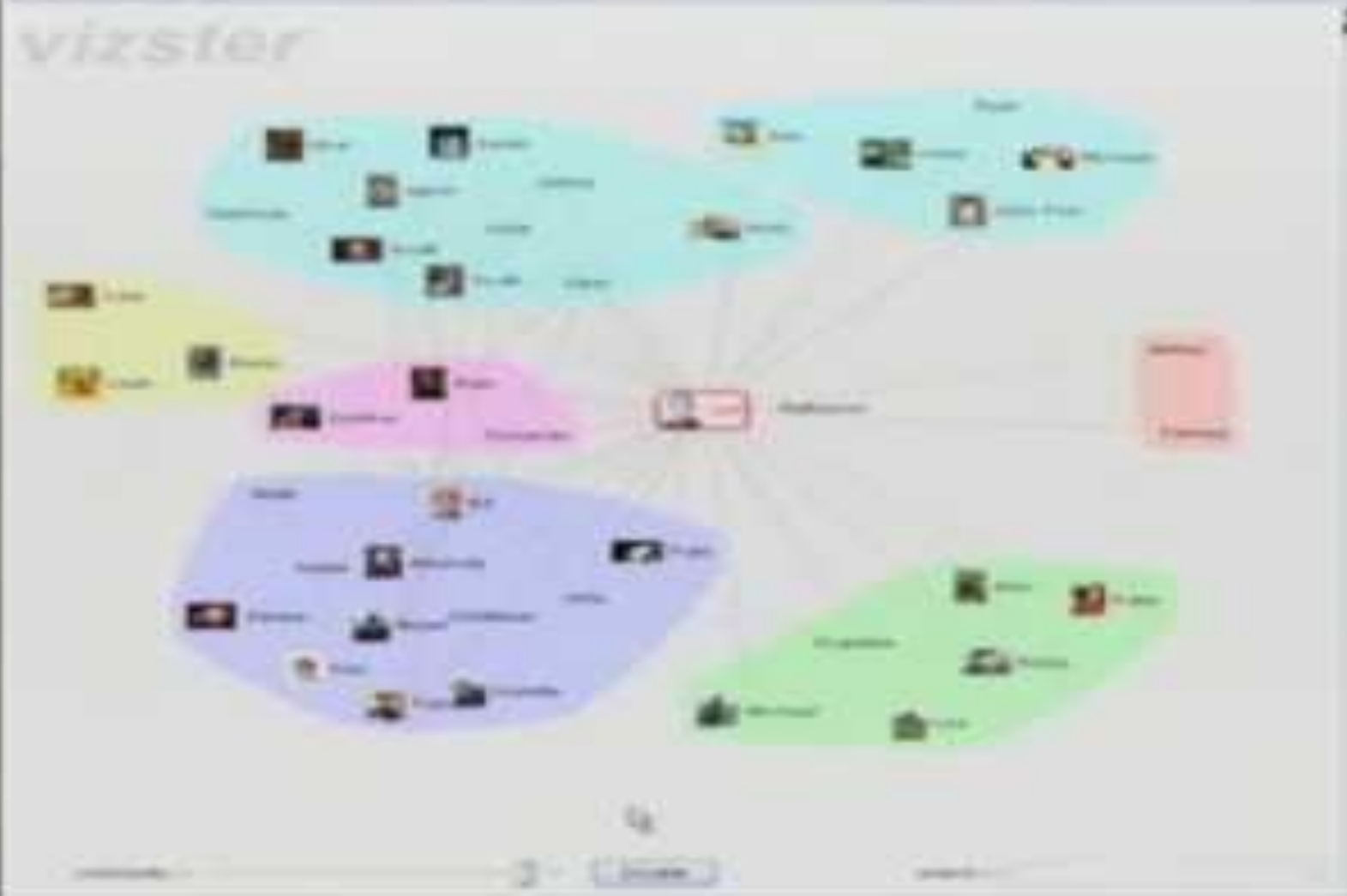
[6] Beyond 50K requires a combination of multi-scale algorithms, filtering, aggregation, GPU-acceleration to achieve fitness-for-purpose and speed

Recommendations for interactivity

Size of Graph			Interactivity		
			Pan/Zoom	Selection	Live Editing
S	Small	c 5K elements	✓ Adaptive Client Side Redraw	✓ Client CPU compute	✓ Client-side
M	Medium	c 25K elements			✓ Hybrid
L	Large	c 50K elements	✓ Scene Tree Transformations	✓ GPU rendering or server-side query	✓ Server-side
XL	Extra Large	c 500K elements			
XXL	Huge	c 5M+ elements	✓ Server-side		

Interaction & Coordinated Views





Jeff

- Full Name** Jeff
- First Name** J
- Last Name** J
- Age** 30
- Gender** Male
- Location** Berkeley, CA
- Education** Stanford, CA
- Occupation** Working student
- Interests**
 - Public music, reading, writing, editing, carpentry, painting, beer drinking, politics, computer education.
 - Computer education, education, computer science, education.
- Work**
 - Google, The Open Group, software TV presentation, software team projects, software for Open, software within team, the user interface in the morning.
- Skills**
 - The great things about of software, structured app, good-looking, fast, powerful, simple.
- CV Skills**
 - collaboration, communication, education, being curious, being inspired.
- Other**
 - is interested in computer, music, being user-friendly, professional, being, giving, and being an artist.
- Member Since** 2005-10-01
- Last Update** 2005-10-01
- Last Modified** 2005-10-01
- About**
 - Can't standing for too long, but not always.
- About My About**
 - people, computer, education, and software, and software, and software.



Visualizing a Large Packet Trace

Details on Demand, Searching and Filtering

Search

Search All Fields

135	CC9-2011	Taniguchi, Tomonari, Kawanishi &	Experiments in Basic-IRF Clustering and its Role in Deep	2008	COLING - Frontiers
136	CC9-1112	Ts. Kawahara and Kurohashi	Chinese Dependency Parsing with Large Scale Automata	2008	International Conference O
137	CC9-1088	Tajiri and Tsuji	Stat-Reduce Dependency DAG Parsing	2008	International Conference O
138	CC9-1048	Yoshida, Anzai and Matsumoto	Japanese Dependency Parsing Using a Truncated Mo	2008	International Conference O

Cluster Network

Main menu Overview Rank Nodes Attribute Nodes Rank Edges Plot Nodes Find Communities Edge Types Graph Readability Details Settings

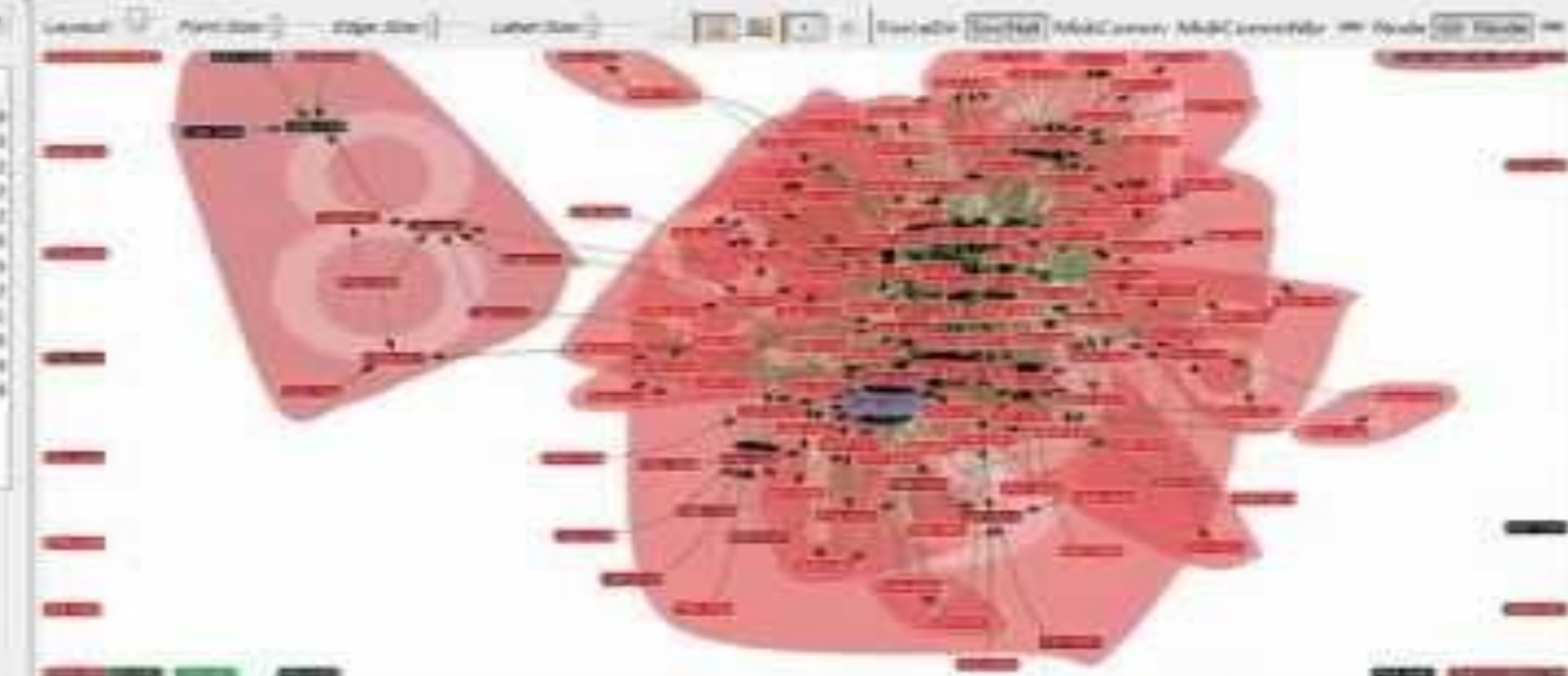
Community

Neumann's Community

ID	Number of Nodes
0	99
1	3
2	2
3	2
4	2
5	6
6	3
7	2
8	6
9	11
10	4
11	14

- Nodes & Edges
- Show Subgraph Only
- Compress Graph
- Output Communities
- Output Communities (GML)
- Layout Communities

Network Visualization



Details 100 articles loaded

- Ted Cruz Has a Chance to Win. Here's the Path.
- Graying Firms Wrestle With Making Room for Younger Lawyers
- UH professors read mean reviews from RateMyProfessors website
- 5 Are Stabbed at University of California in Merced
- One Downside of an Up Economy: Employee Turnover
- 2010 August - DealBook
- Risking Your Neck to Run With the Unicorns cap that
- Denying the Will of Okinawans
- Achenblog
- Readers React to Rising Death Rates of Middle-Aged White Americans
- Britain, Concerned About Russian Crash, Halts Flights From Egyptian Resort

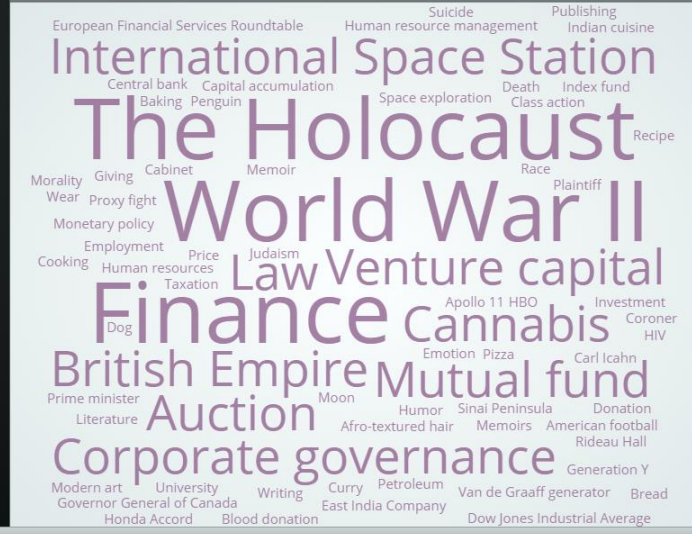
News Network show/hide: companies, organizations, people



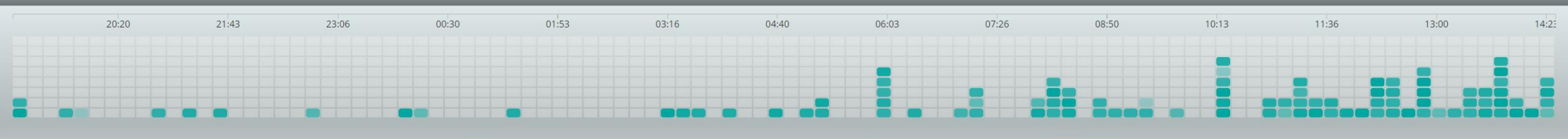
Locations 111 found, view in map list



Topics People Companies Organizations



Timeline news articles across 0 days, 19 hrs, 30 min, 24 sec up to the current date: 11/4/2015





START

RESUME

CHANGE SIZE
(CURRENT: 250,000)

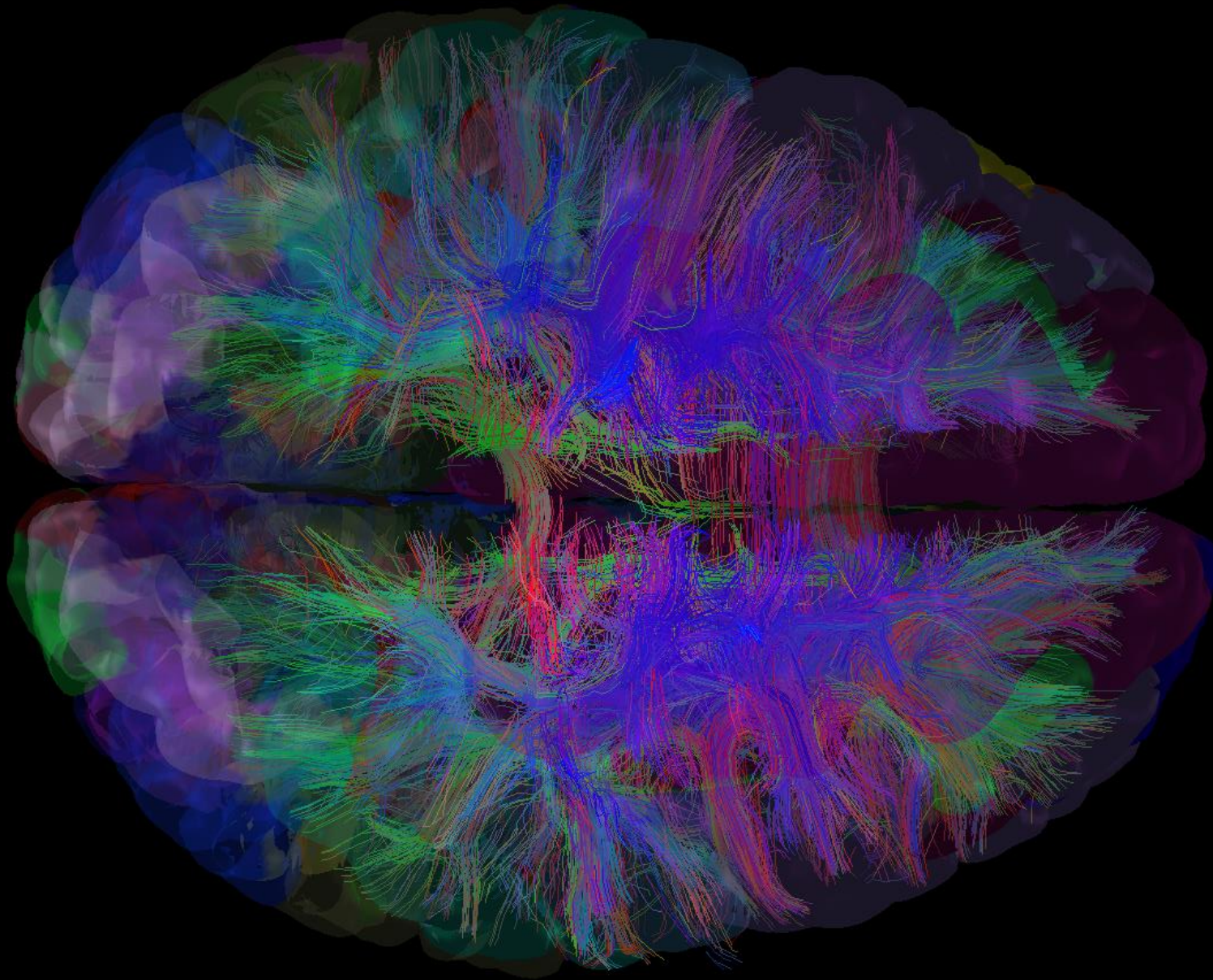
©2016 owen corneil



WIKIGALAXY

LAUNCH

100,000 wikipedia articles, 500 thematic nebulas, one galaxy.



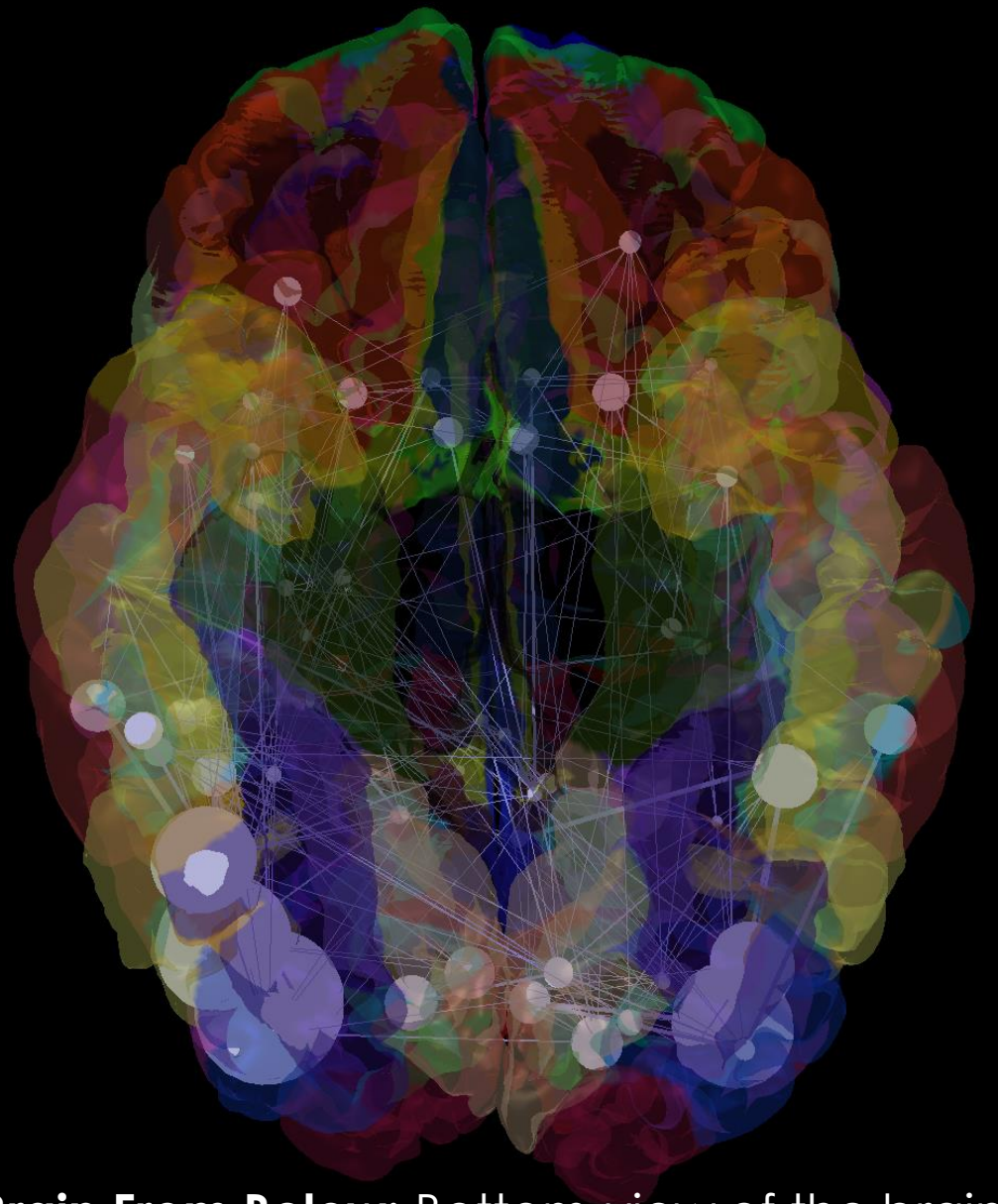
How does the complex pattern of activity in the 100 billion neurons of our brain underlie our understanding of the environment, our thoughts and behavior? We are in a new area of neuroscience that is making prodigious leaps towards understanding neural functions, and is informing related fields. Human vision research in particular has uncovered general principles such as multilayer processing, which inspires neural network models for machine learning. A crucial question in neuroscience of how the wiring of brain regions relates to their function. Cutting edge research generated a model showing that physical connections predict the activity of brain networks in response to visual stimuli.

Our 3D brain and neural network visualization renders structural connectivity, function, and predicted activity. The relationship between these features is compared across participants viewing different types of images. A novel way to depict uncertainty metrics enhances the interpretability of the data.

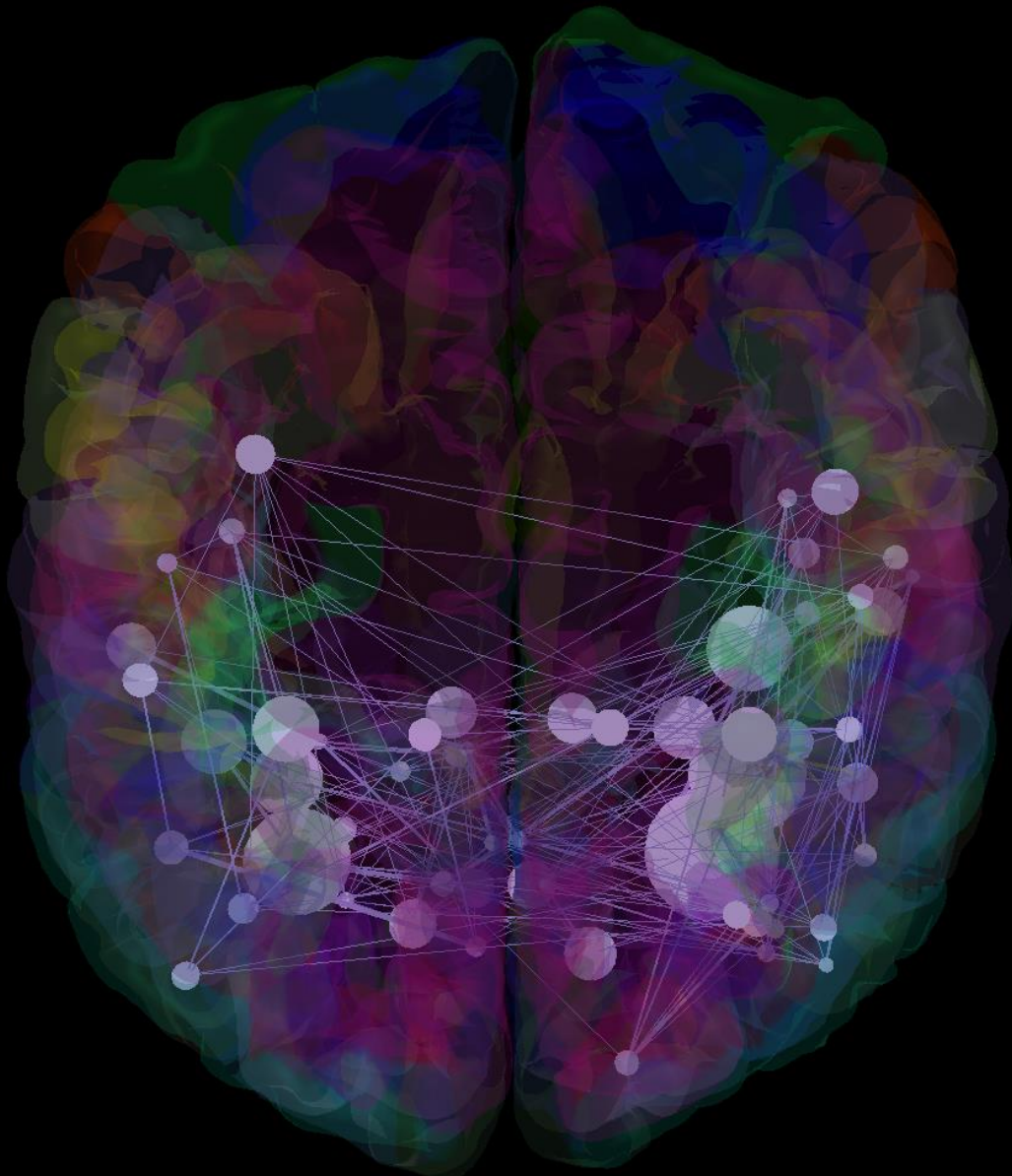
Brain From Above Tract And Regions: Top-view of the brain with color-coded brain regions and physical connections



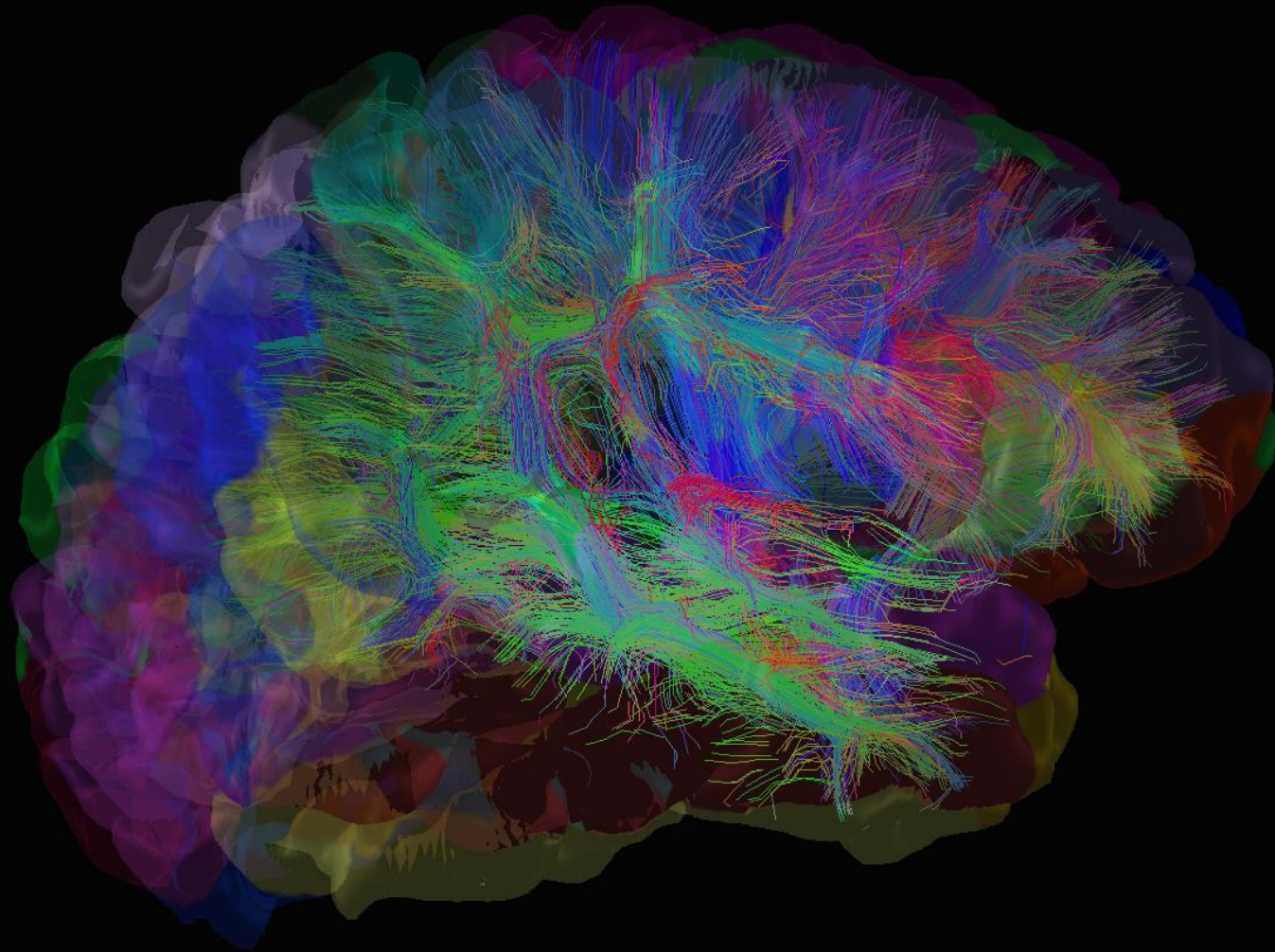
Brain From Back: Back-view of the brain with the network of activity and connections overlaid onto colored brain regions



Brain From Below: Bottom-view of the brain with the network of activity and connections overlaid onto colored brain regions



Brain From Above: Top-view of the brain with the network of activity and connections overlaid onto colored brain regions



Brain From Side: Side-view of the brain with color-coded brain regions and physical connections

HW2 Tools and Teams