http://poloclub.gatech.edu/cse6242

CSE6242 / CX4242: Data & Visual Analytics

Analytics Building Blocks

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Associate Director, MS Analytics

Machine Learning Area Leader, College of Computing

Georgia Tech

Partly based on materials by

Professors Guy Lebanon, Jeffrey Heer, John Stasko, Christos Faloutsos

Collection

Cleaning

Integration

Analysis

Visualization

Presentation

Dissemination

Building blocks. Not Rigid "Steps".

Collection

Cleaning

Integration

Analysis

Visualization

Presentation

Dissemination

Can skip some

Can go back (two-way street)

- **Data types** inform **visualization** design
- **Data size** informs choice of **algorithms**
- **Visualization** motivates more **data cleaning**
- **Visualization** challenges algorithm assumptions
  e.g., user finds that results don't make sense

How “**big data**” affects the process?

(Hint: almost **everything** is harder!)

- Collection
- Cleaning
- Integration
- Analysis
- Visualization
- Presentation
- Dissemination

The Vs of big data (3Vs originally, then 7, now 42)

Volume: “billions”, “petabytes” are common

Velocity: think Twitter, fraud detection, etc.

Variety: text (webpages), video (youtube)…

Veracity: uncertainty of data

Variability

Visualization

Value

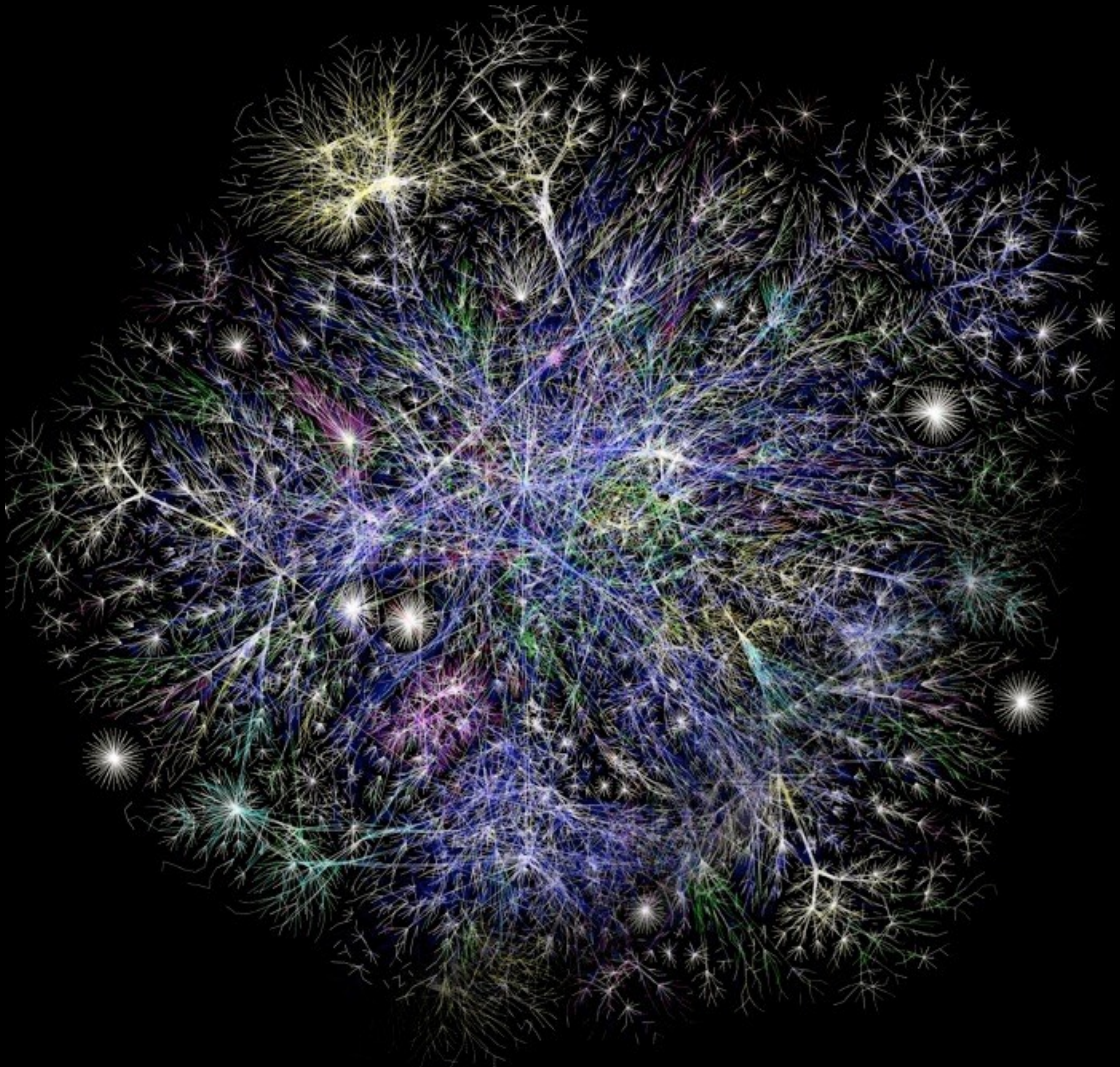
http://www.ibmbigdatahub.com/infographic/four-vs-big-data
http://dataconomy.com/seven-vs-big-data/
https://tdwi.org/articles/2017/02/08/10-vs-of-big-data.aspx

Two Example Projects

from Polo Club

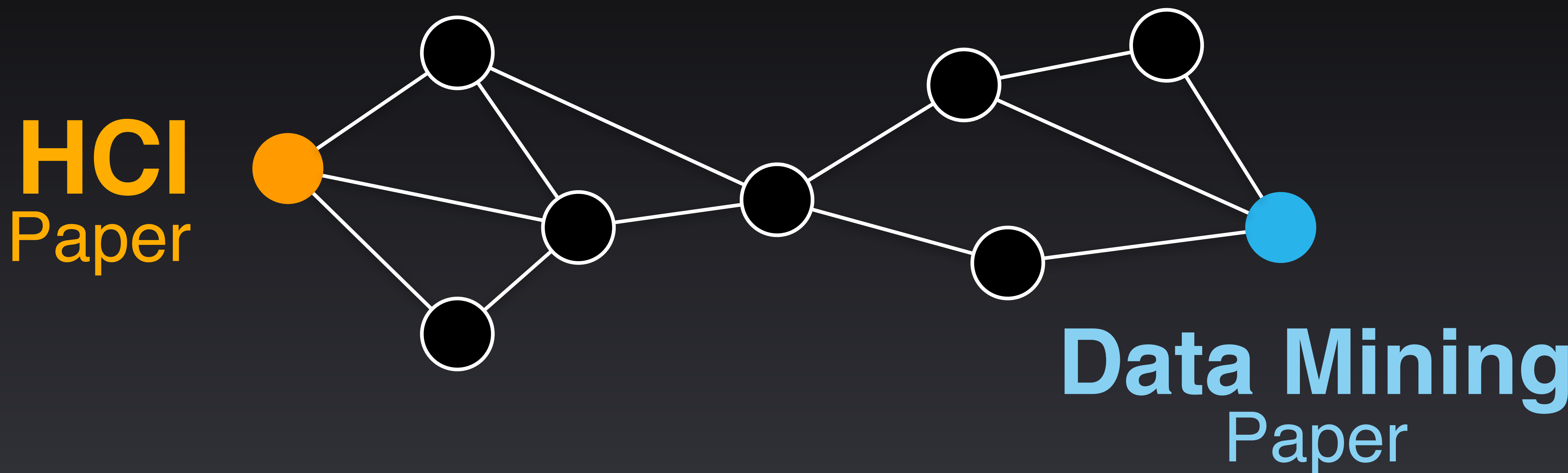
Apolo Graph Exploration:
Machine Learning + Visualization

Apolo: Making Sense of Large Network Data by Combining Rich User Interaction and Machine Learning.
Duen Horng (Polo) Chau, Aniket Kittur, Jason I. Hong, Christos Faloutsos. CHI 2011.



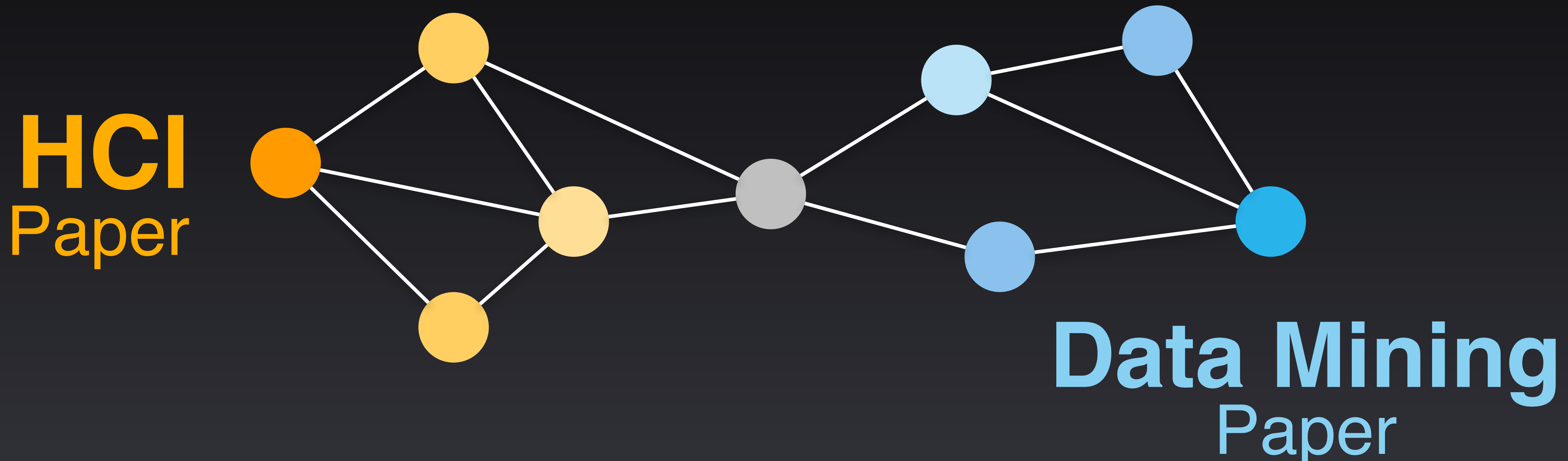

Beautiful Hairball
Death Star
Spaghetti

Finding More Relevant Nodes



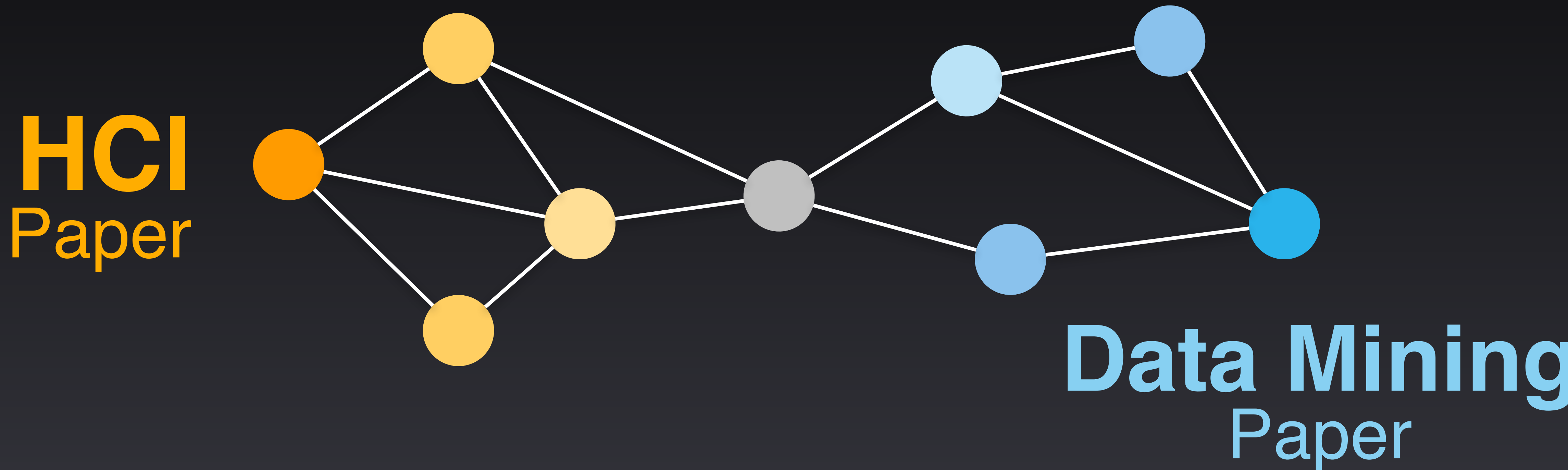
Citation network

Finding More Relevant Nodes



Citation network

Finding More Relevant Nodes

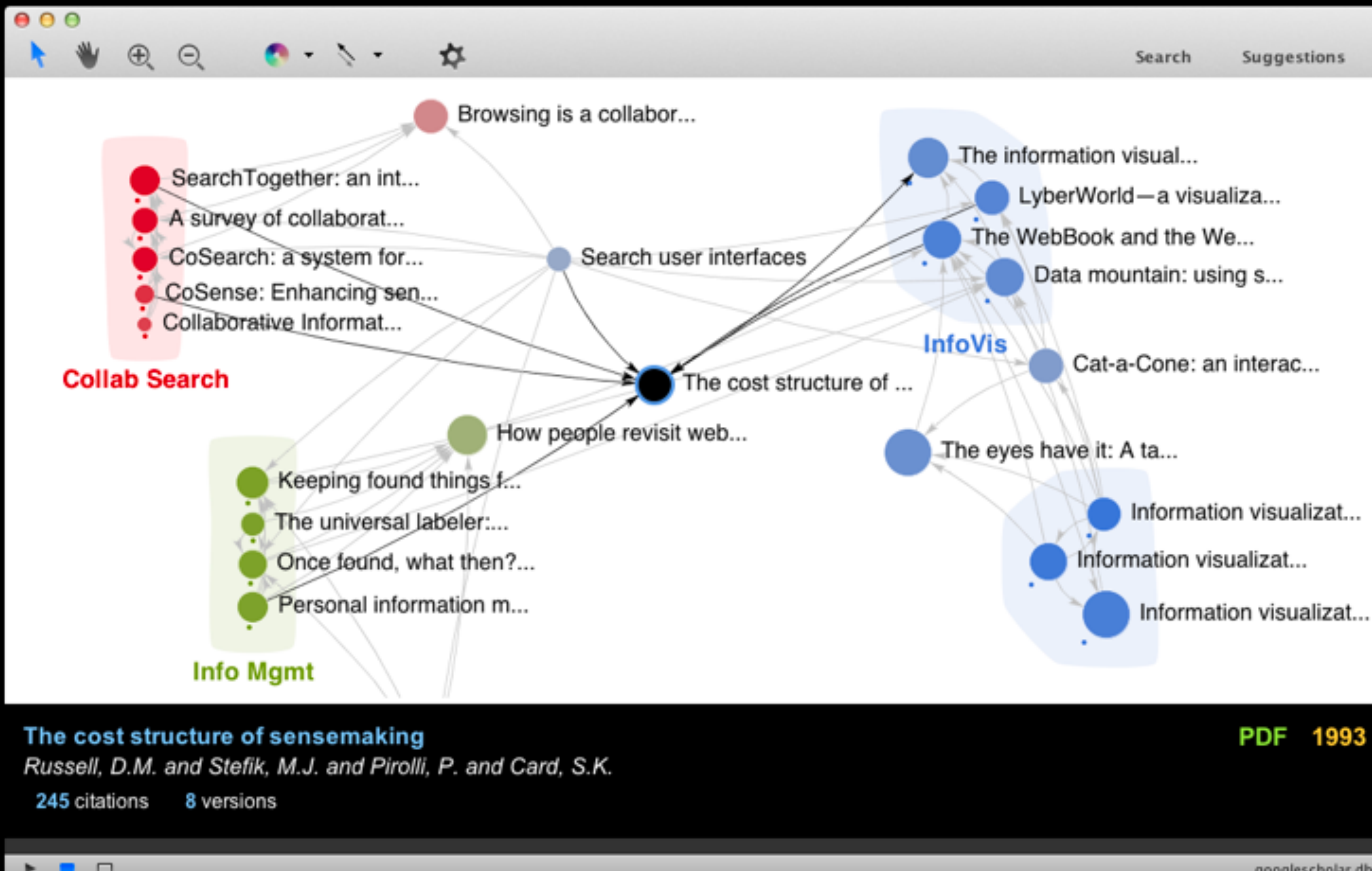


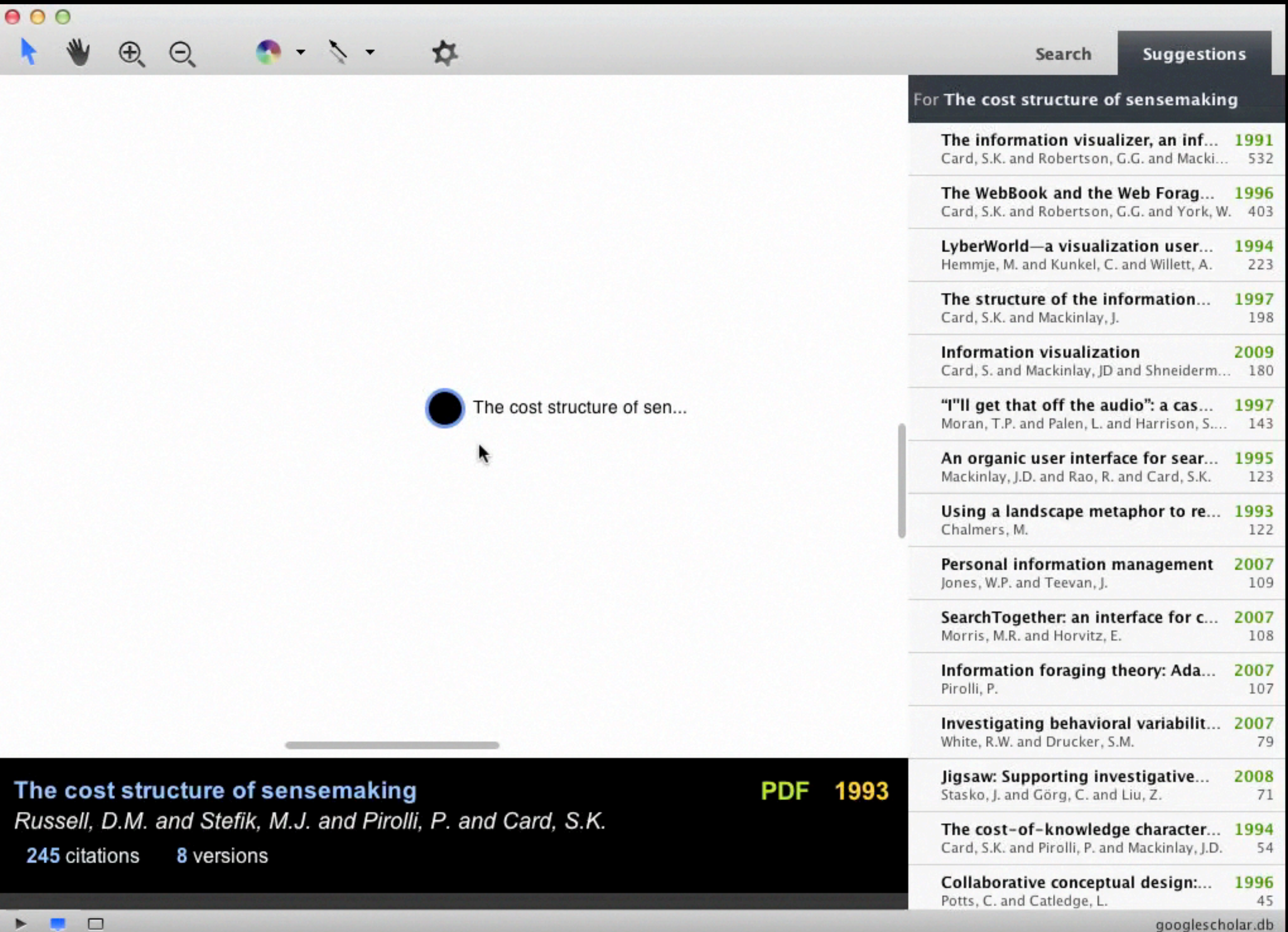
Citation network

Apolo uses **guilt-by-association**
(Belief Propagation)

Demo: Mapping the Sensemaking Literature

Nodes: 80k papers from Google Scholar (node size: #citation)
Edges: 150k citations




Search
Suggestions
For The cost structure of sensemaking
The information visualizer, an inf... 1991
Card, S.K. and Robertson, G.G. and Macki... 532
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Collaborative conceptual design:... 1996
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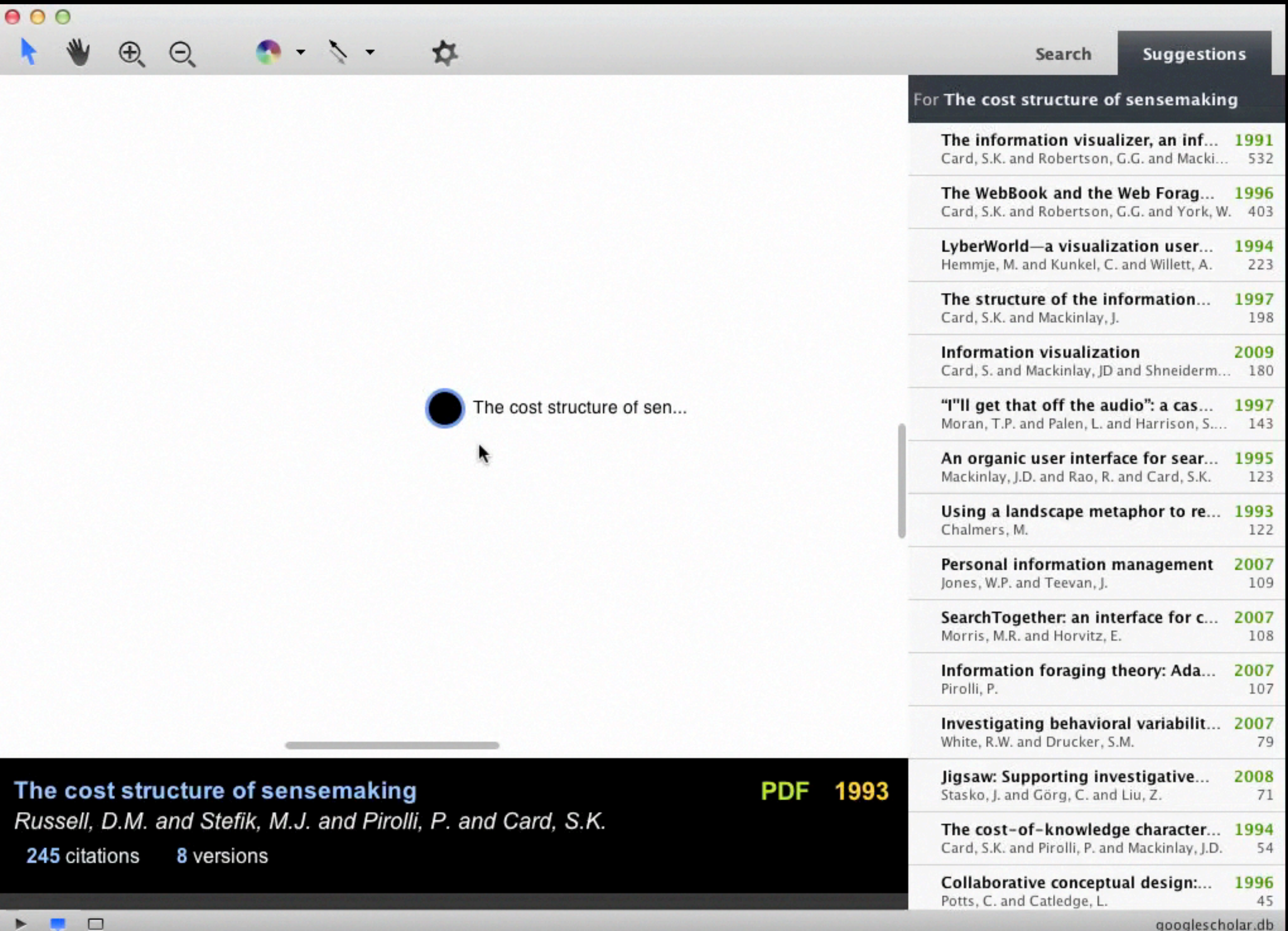
The cost structure of sen...
The cost structure of sensemaking
PDF 1993
Russell, D.M. and Stefik, M.J. and Pirolli, P. and Card, S.K.
245 citations 8 versions
googlescholar.db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Russell, D.M. and Stefik, M.J. and Pirolli, P. and Card, S.K.
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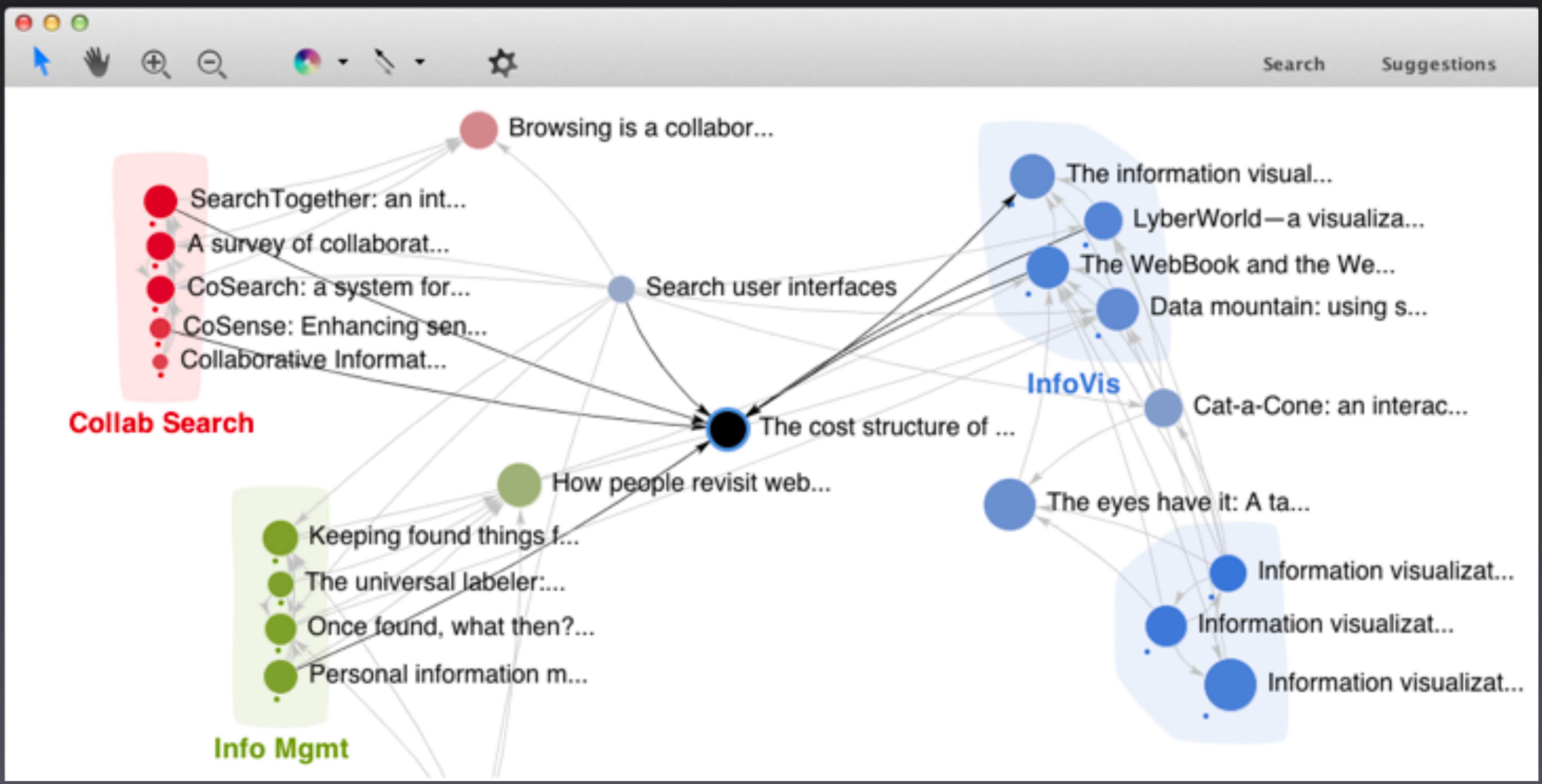
Key Ideas (Recap)

Specify exemplars

Find other relevant nodes (BP)



What did **Apolo** go through?

Collection	Scrape Google Scholar. No API. 😩
Cleaning	
Integration	
Analysis	Design inference algorithm (Which nodes to show next?)
Visualization	Interactive visualization you just saw
Presentation	Paper, talks, lectures
Dissemination	You will a new Apolo prototype (called Argo)

Apolo: Making Sense of Large Network Data by Combining Rich User Interaction and Machine Learning

Duen Horng (Polo) Chau, Aniket Kittur, Jason I. Hong, Christos Faloutsos
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ABSTRACT

Extracting useful knowledge from large network datasets has become a fundamental challenge in many domains, from scientific literature to social networks and the web. We introduce Apolo, a system that uses a mixed-initiative approach—combining visualization, rich user interaction and machine learning—to guide the user to incrementally and interactively explore large network data and make sense of it. Apolo engages the user in bottom-up sensemaking to gradually build up an understanding over time by starting small, rather than starting big and drilling down. Apolo also helps users find relevant information by specifying exemplars, and then using a machine learning method called Belief Propagation to infer which other nodes may be of interest. We evaluated Apolo with twelve participants in a between-subjects study, with the task being to find relevant new papers to update an existing survey paper. Using expert judges, participants using Apolo found significantly more relevant papers. Subjective feedback of Apolo was also very positive.

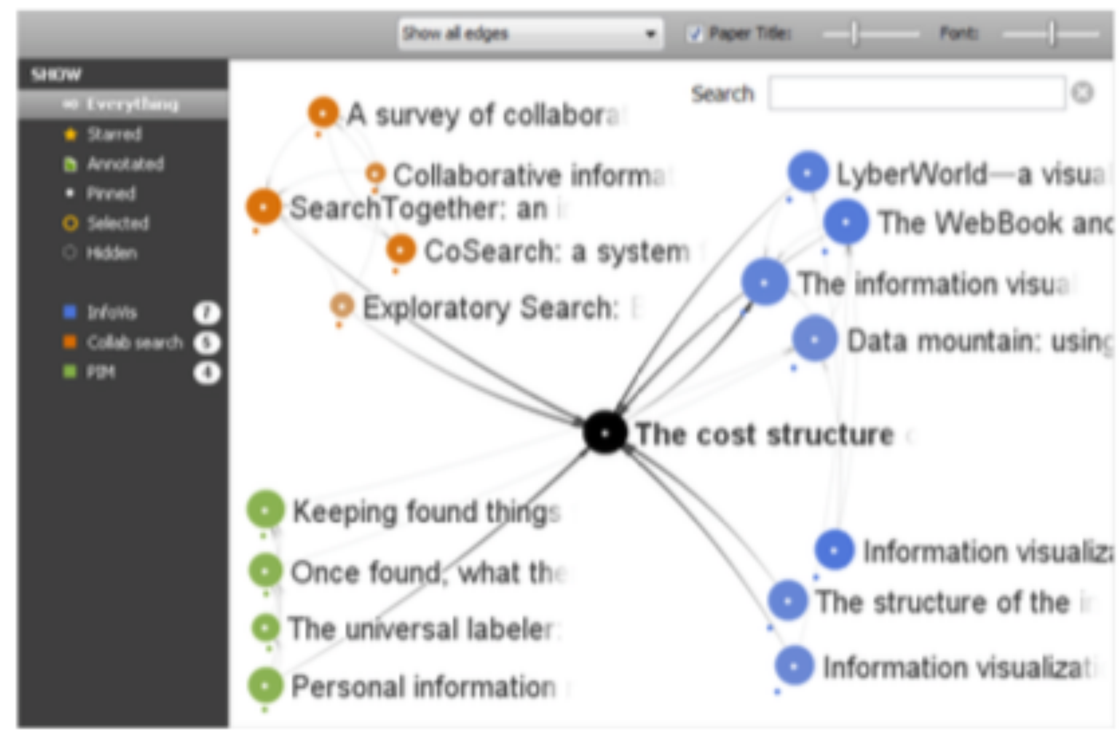


Figure 1. Apolo displaying citation network data around the article *The Cost Structure of Sensemaking*. The user gradually builds up a mental model of the research areas around the article by manually inspecting some neighboring articles in the visualization and specifying them as exemplar articles (with colored dots underneath) for some ad hoc groups, and instructs Apolo to find more articles relevant to them.

Apolo: Making Sense of Large Network Data by Combining Rich User Interaction and Machine Learning. Duen Horng (Polo) Chau, Aniket Kittur, Jason I. Hong, Christos Faloutsos. *ACM Conference on Human Factors in Computing Systems (CHI) 2011*. May 7-12, 2011.

back; H.5.2 Information Interfaces and Presentation: User

the new domain to understand and contribute to it

NetProbe:
Fraud Detection in Online Auction

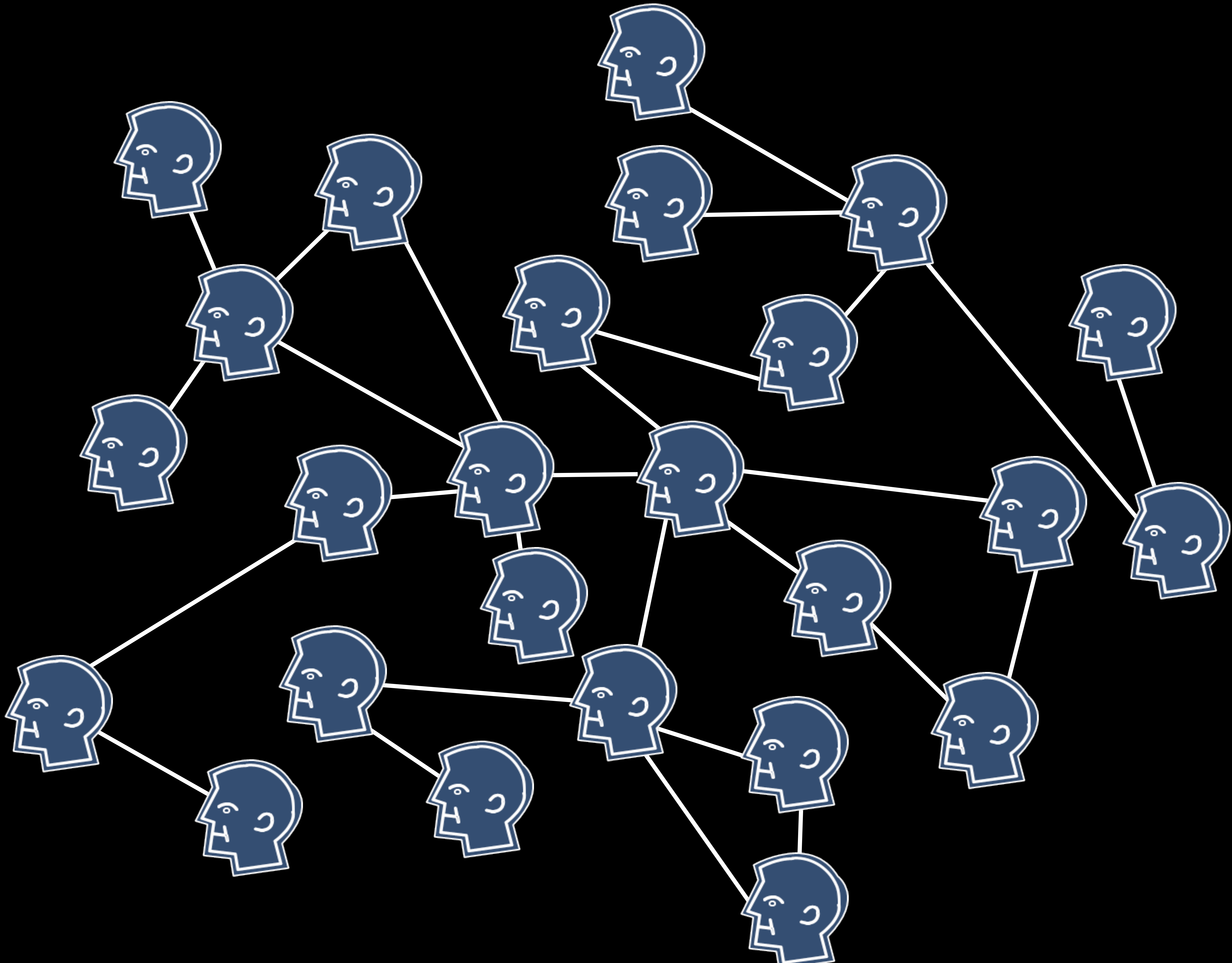
NetProbe: A Fast and Scalable System for Fraud Detection in Online Auction Networks. Shashank Pandit, Duen Horng (Polo) Chau, Samuel Wang, Christos Faloutsos. WWW 2007

NetProbe: The Problem

Find **bad sellers** (**fraudsters**) on eBay who don't deliver their items

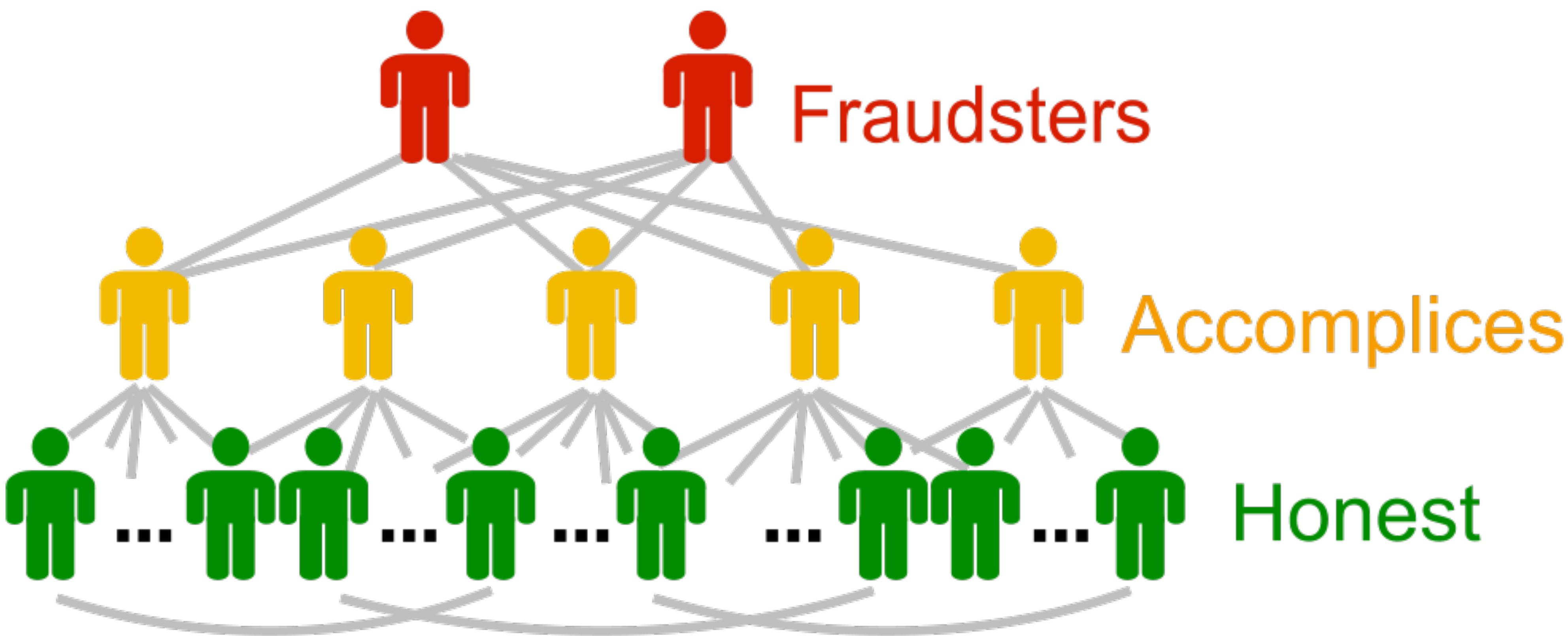
Non-delivery fraud is a common auction fraud

source: https://www.fbi.gov/contact-us/field-offices/portland/news/press-releases/fbi-tech-tuesday---building-a-digital-defense-against-auction-fraud



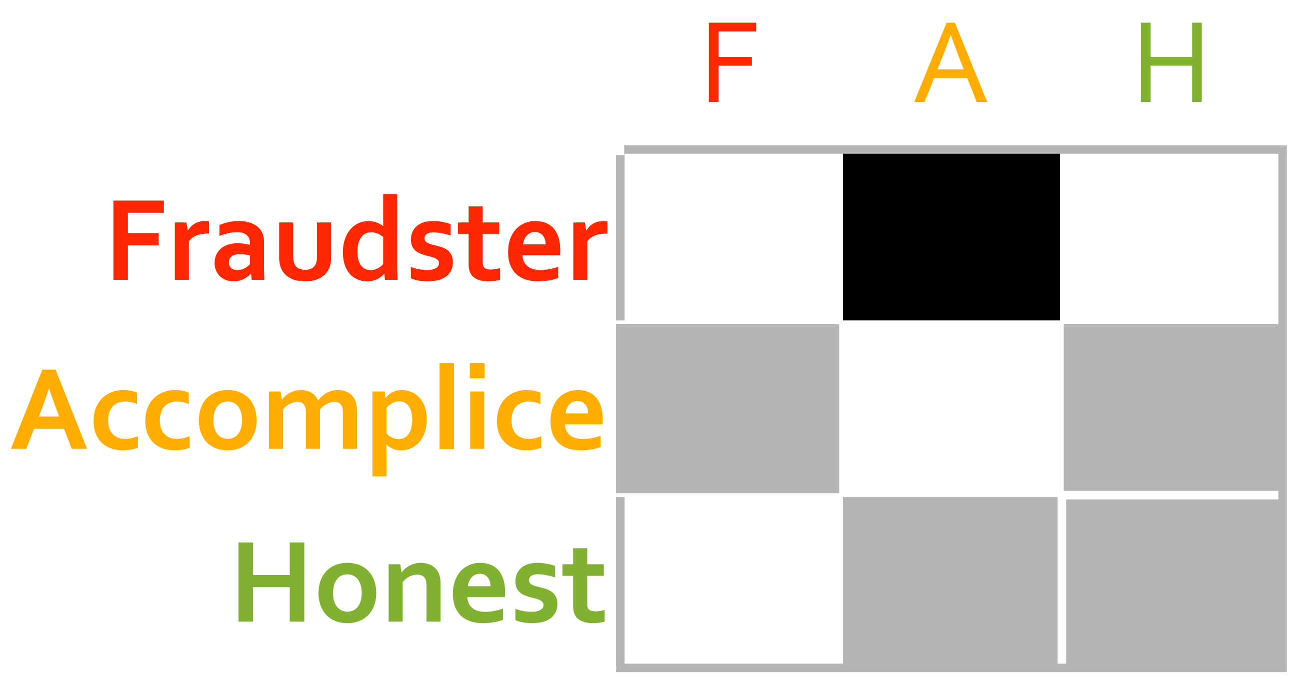
NetProbe: Key Ideas

- Fraudsters **fabricate their reputation** by "trading" with their accomplices
- Fake transactions form **near bipartite cores**
- How to detect them?

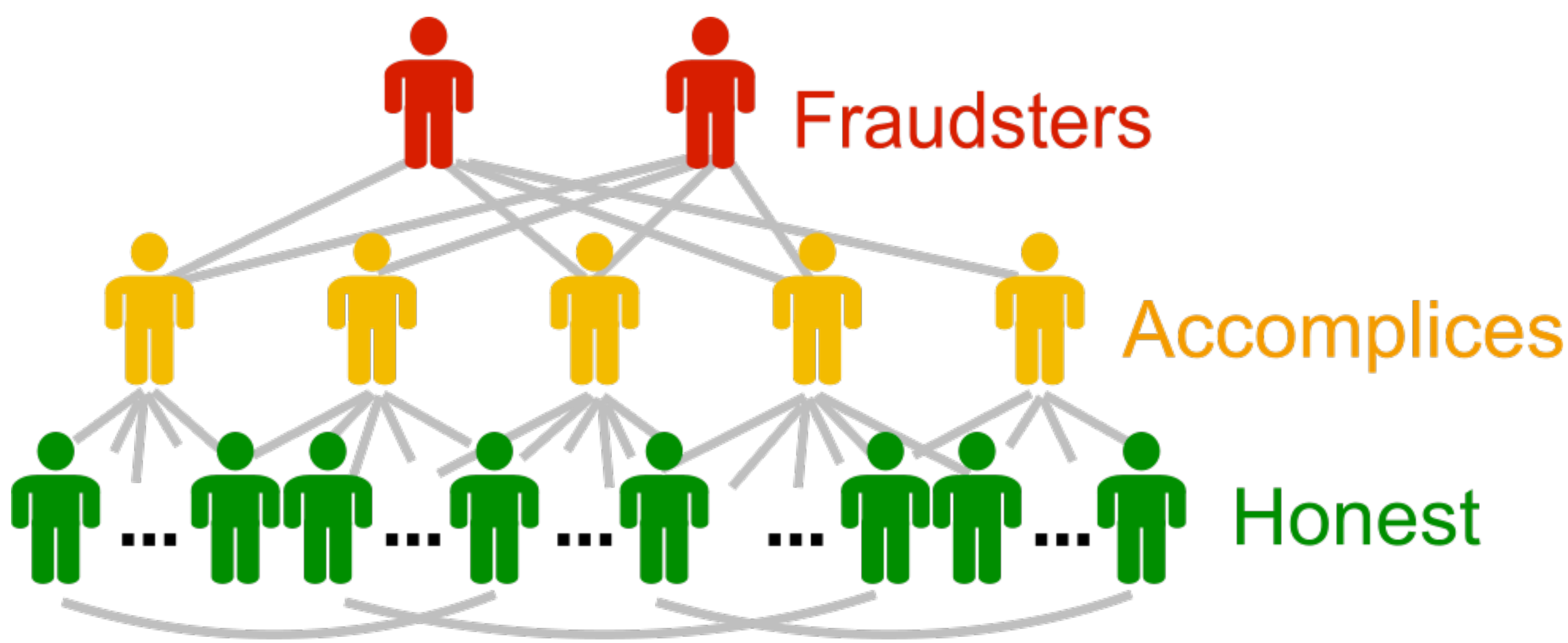


NetProbe: Key Ideas

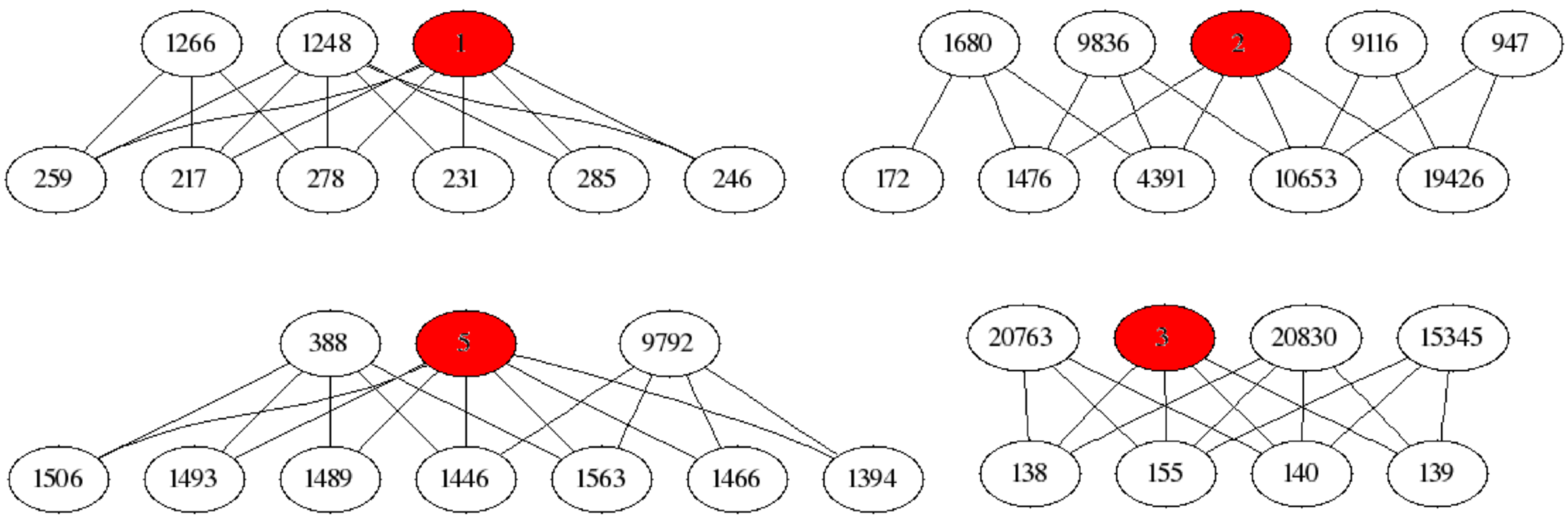
Use **Belief Propagation**



Darker means more likely



NetProbe: Main Results



ebay

USA TODAY

CNNMoney.com
A Service of CNN, Fortune & Money

THE WALL STREET JOURNAL.

MSNBC

KDKA 2

PITTSBURGH TRIBUNE-REVIEW

Symantec

ebay

USA TODAY

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THE WALL STREET JOURNAL.

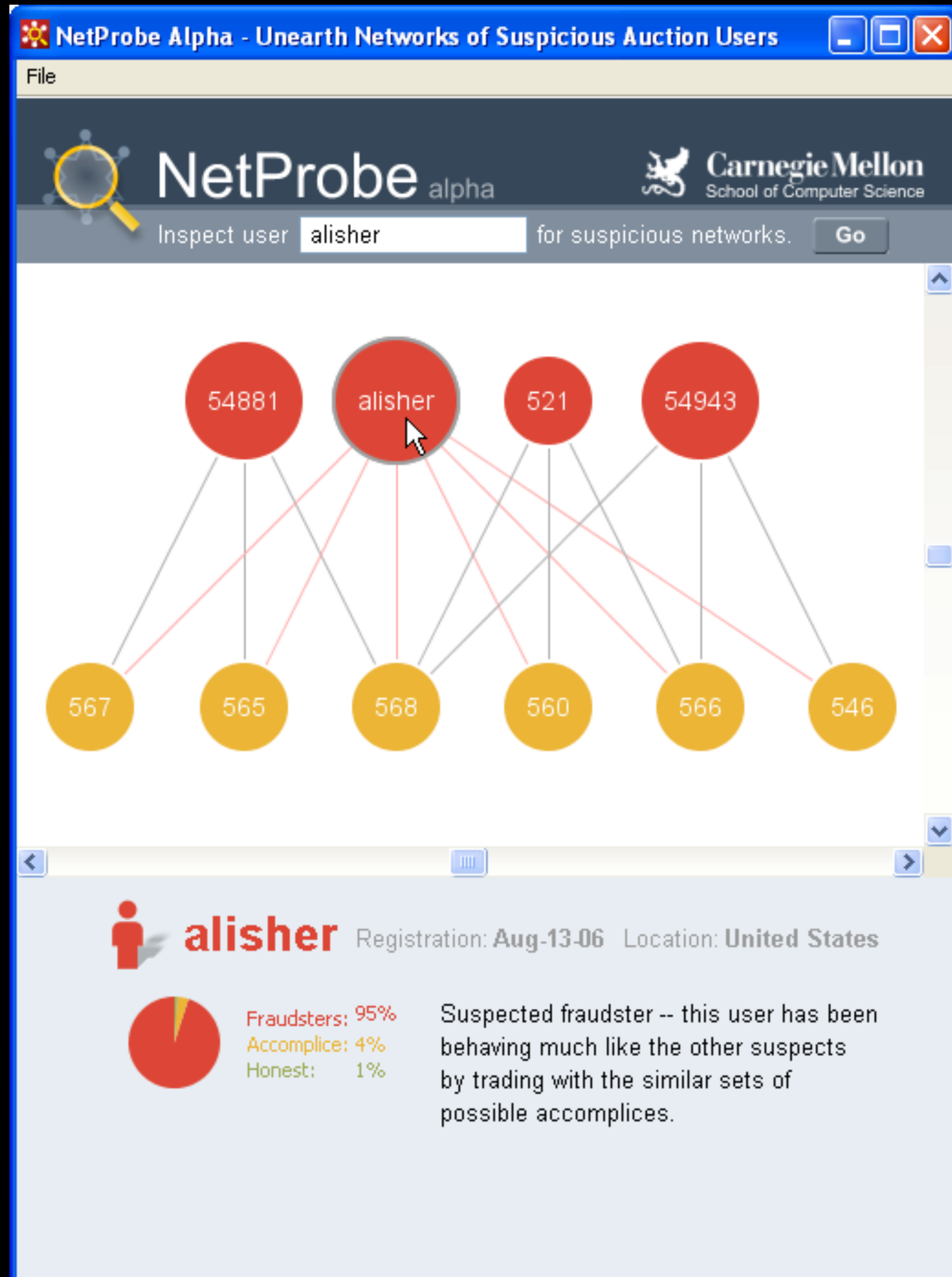
MSNBC

KDKA 2

PITTSBURGH TRIBUNE-REVIEW

Symantec.

“Belgian Police”


NetProbe Alpha - Unearth Networks of Suspicious Auction Users
File
NetProbe alpha
Carnegie Mellon
School of Computer Science
Inspect user
alisher
for suspicious networks.
Go
54881
alisher
521
54943
567
565
568
560
566
546
alisher
Registration: Aug-13-06
Location: United States
Fraudsters: 95%
Accomplice: 4%
Honest: 1%
Suspected fraudster -- this user has been behaving much like the other suspects by trading with the similar sets of possible accomplices.

What did **NetProbe** go through?

Collection	Scraping (built a “scraper”/“crawler”)
Cleaning	
Integration	
Analysis	Design detection algorithm
Visualization	
Presentation	Paper, talks, lectures
Dissemination	Not released

NetProbe: A Fast and Scalable System for Fraud Detection in Online Auction Networks

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Pittsburgh, PA 15213, USA
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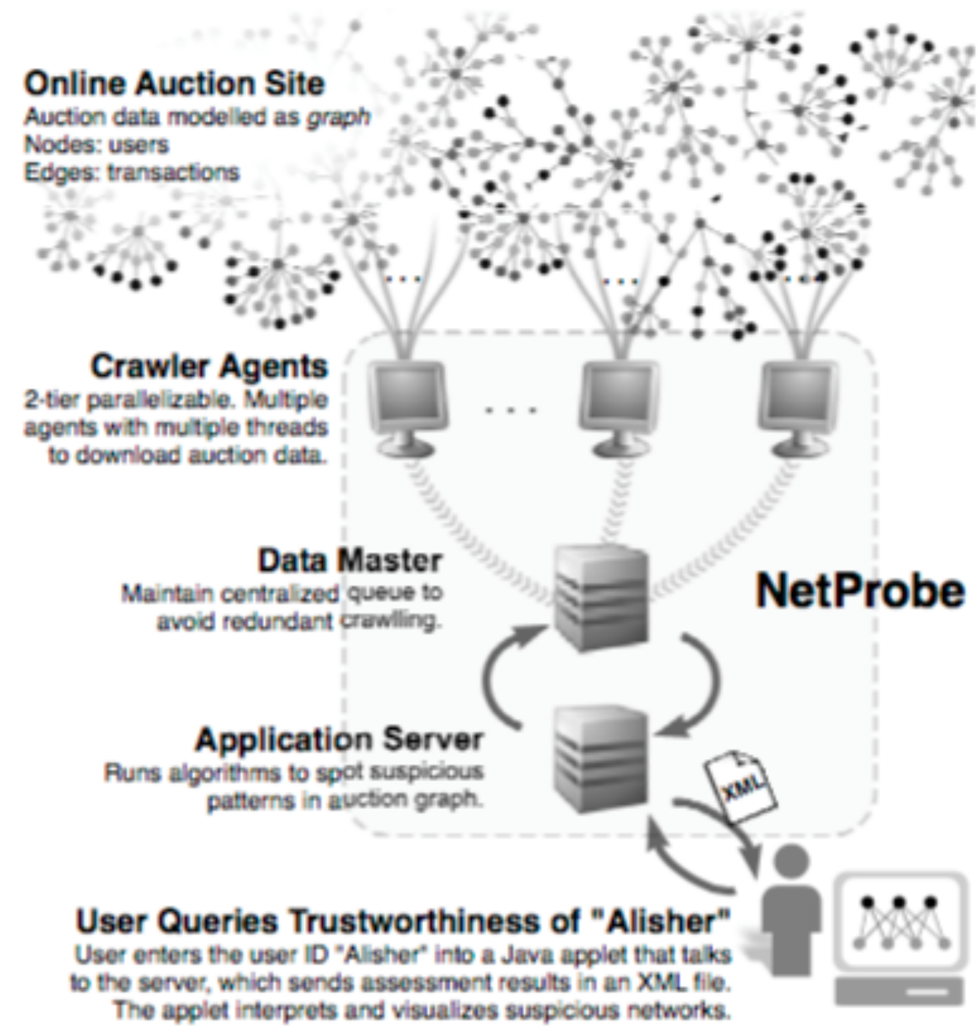
ABSTRACT

Given a large online network of online auction users and their histories of transactions, how can we spot anomalies and auction fraud? This paper describes the design and implementation of NetProbe, a system that we propose for solving this problem. NetProbe models auction users and transactions as a *Markov Random Field* tuned to detect the suspicious patterns that fraudsters create, and employs a *Belief Propagation* mechanism to detect likely fraudsters. Our experiments show that NetProbe is both efficient and effective for fraud detection. We report experiments on synthetic graphs with as many as 7,000 nodes and 30,000 edges, where NetProbe was able to spot fraudulent nodes with over 90% precision and recall, within a matter of seconds. We also report experiments on a real dataset crawled from eBay, with nearly 700,000 transactions between more than 66,000 users, where NetProbe was highly effective at unearthing hidden networks of fraudsters, within a realistic response time of about 6 minutes. For scenarios where the underlying data is dynamic in nature, we propose *Incremental NetProbe*, which is an approximate, but fast, variant of NetProbe. Our experiments prove that Incremental NetProbe



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Categories and Subject Descriptors

1. INTRODUCTION

Homework 1 (out next week; tasks subject to change)

Collection

Cleaning

Integration

Analysis

Visualization

Presentation

Dissemination

- Simple “End-to-end” analysis
- Collect data using API
  - Store in SQLite database
- Create graph from data
- Analyze, using SQL queries (e.g., create graph’s degree distribution)
- Visualize graph using **Gephi**
- Describe your discoveries