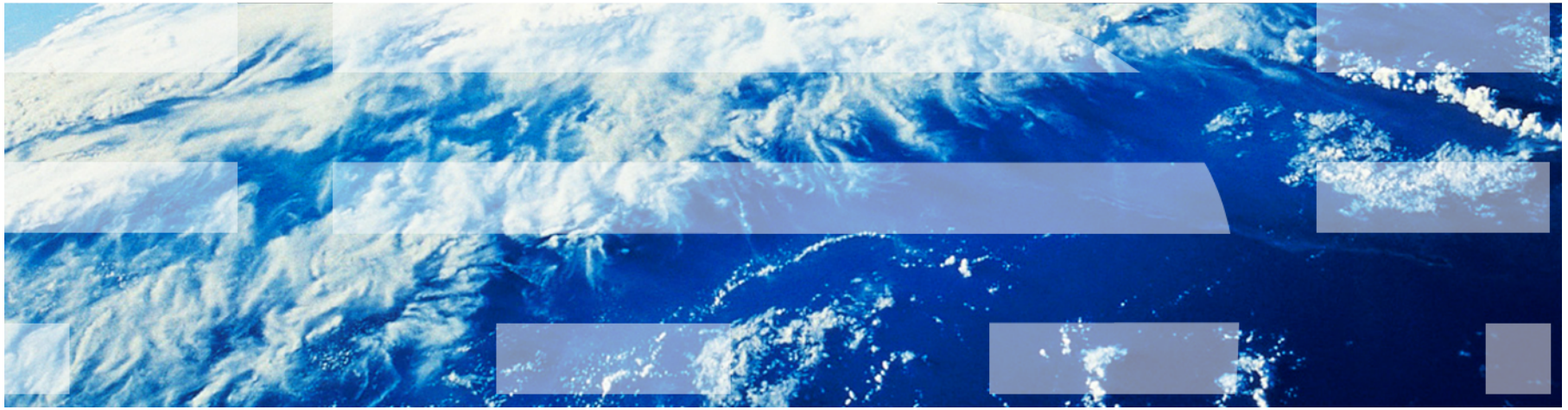
E6893 Big Data Analytics Lecture 1:

Overview of Big Data Analytics

Ching-Yung Lin, Ph.D.

Adjunct Professor, Dept. of Electrical Engineering and Computer Science

IBM Chief Scientist, Graph Computing and Distinguished Researcher



September 10th, 2015

Big Data

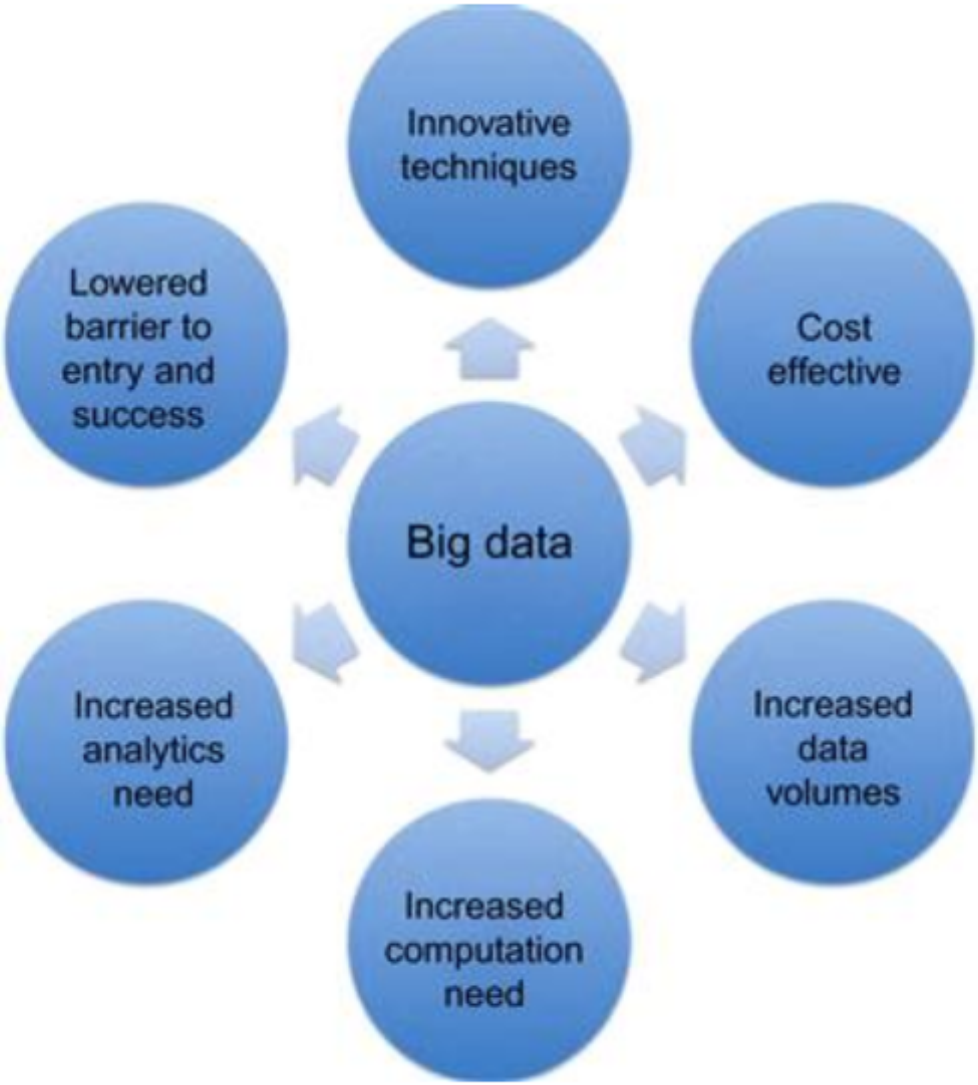
Definition and Characteristics of Big Data

"*Big data is high-**volume**, high-**velocity** and high-**variety** information assets that demand **cost-effective**, **innovative** forms of information processing for **enhanced insight and decision making***." -- Gartner

which was derived from:

"*While enterprises struggle to consolidate systems and collapse redundant databases to enable greater operational, analytical, and collaborative consistencies, changing economic conditions have made this job more difficult. E-commerce, in particular, has exploded data management challenges along three dimensions: **volumes, velocity and variety**. In 2001/02, IT organizations much compile a variety of approaches to have at their disposal for dealing each*." – Doug Laney

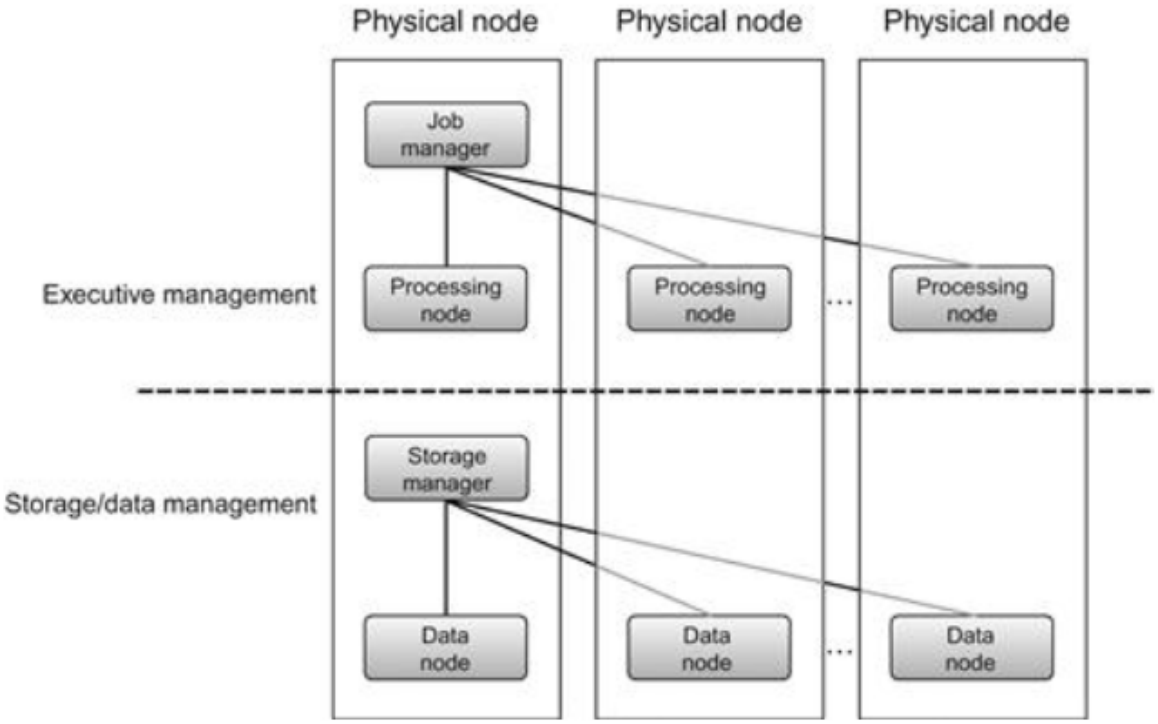
What made Big Data needed?



"Big Data Analytics", David Loshin, 2013

Key Computing Resources for Big Data

- Processing capability: CPU, processor, or node.
- Memory
- Storage
- Network



"Big Data Analytics", David Loshin, 2013

Techniques towards Big Data

- Massive Parallelism
- Huge Data Volumes Storage
- Data Distribution
- High-Speed Networks
- High-Performance Computing
- Task and Thread Management
- Data Mining and Analytics
- Data Retrieval
- Machine Learning
- Data Visualization

➔ Techniques exist for years to decades. Why did Big Data become hot now?

Why Big Data now?

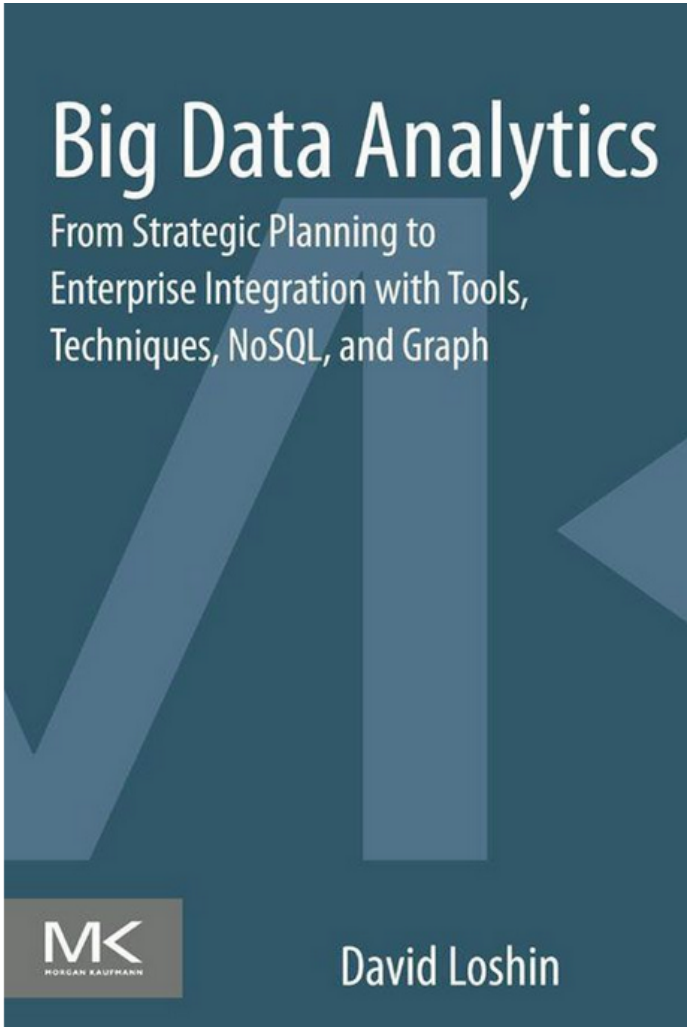
- More data are being collected and stored
- Open source code
- Commodity hardware

Contrasting Approaches in Adopting High-Performance Capabilities

Aspect	Typical Scenario	Big Data
Application development	Applications that take advantage of massive parallelism developed by specialized developers skilled in high-performance computing, performance optimization, and code tuning	A simplified application execution model encompassing a distributed file system, application programming model, distributed database, and program scheduling is packaged within Hadoop, an open source framework for reliable, scalable, distributed, and parallel computing
Platform	Uses high-cost massively parallel processing (MPP) computers, utilizing high-bandwidth networks, and massive I/O devices	Innovative methods of creating scalable and yet elastic virtualized platforms take advantage of clusters of commodity hardware components (either cycle harvesting from local resources or through cloud-based utility computing services) coupled with open source tools and technology
Data management	Limited to file-based or relational database management systems (RDBMS) using standard row-oriented data layouts	Alternate models for data management (often referred to as NoSQL or "Not Only SQL") provide a variety of methods for managing information to best suit specific business process needs, such as in-memory data management (for rapid access), columnar layouts to speed query response, and graph databases (for social network analytics)
Resources	Requires large capital investment in purchasing high-end hardware to be installed and managed in-house	The ability to deploy systems like Hadoop on virtualized platforms allows small and medium businesses to utilize cloud-based environments that, from both a cost accounting and a practical perspective, are much friendlier to the bottom line

"Big Data Analytics", David Loshin, 2013

Reading Reference for Lecture 1



Chapter 1: Market and Business Drivers for Big Data Analysis

Chapter 2: Business Problems Suited to Big Data Analytics

Chapter 3: Achieving Organizational Alignment for Big Data Analytics

Chapter 4: Developing a Strategy for Integrating Big Data Analytics into the Enterprise

Chapter 5: Data Governance for Big Data Analytics: Considerations for Data Policies and Processes

Chapter 6: Introduction to High-Performance Appliances for Big Data Management

Chapter 7: Big Data Tools and Techniques

Chapter 8: Developing Big Data Applications

Chapter 9: NoSQL Data Management for Big Data

Chapter 10: Using Graph Analytics for Big Data

Chapter 11: Developing the Big Data Roadmap

5 Key Big Data Use Case Categories

Big Data Exploration

Find, visualize, understand all big data to improve decision making

Enhanced 360º View of the Customer

Extend existing customer views (MDM, CRM, etc) by incorporating additional internal and external information sources

Security/Intelligence Extension

Lower risk, detect fraud and monitor cyber security in real-time

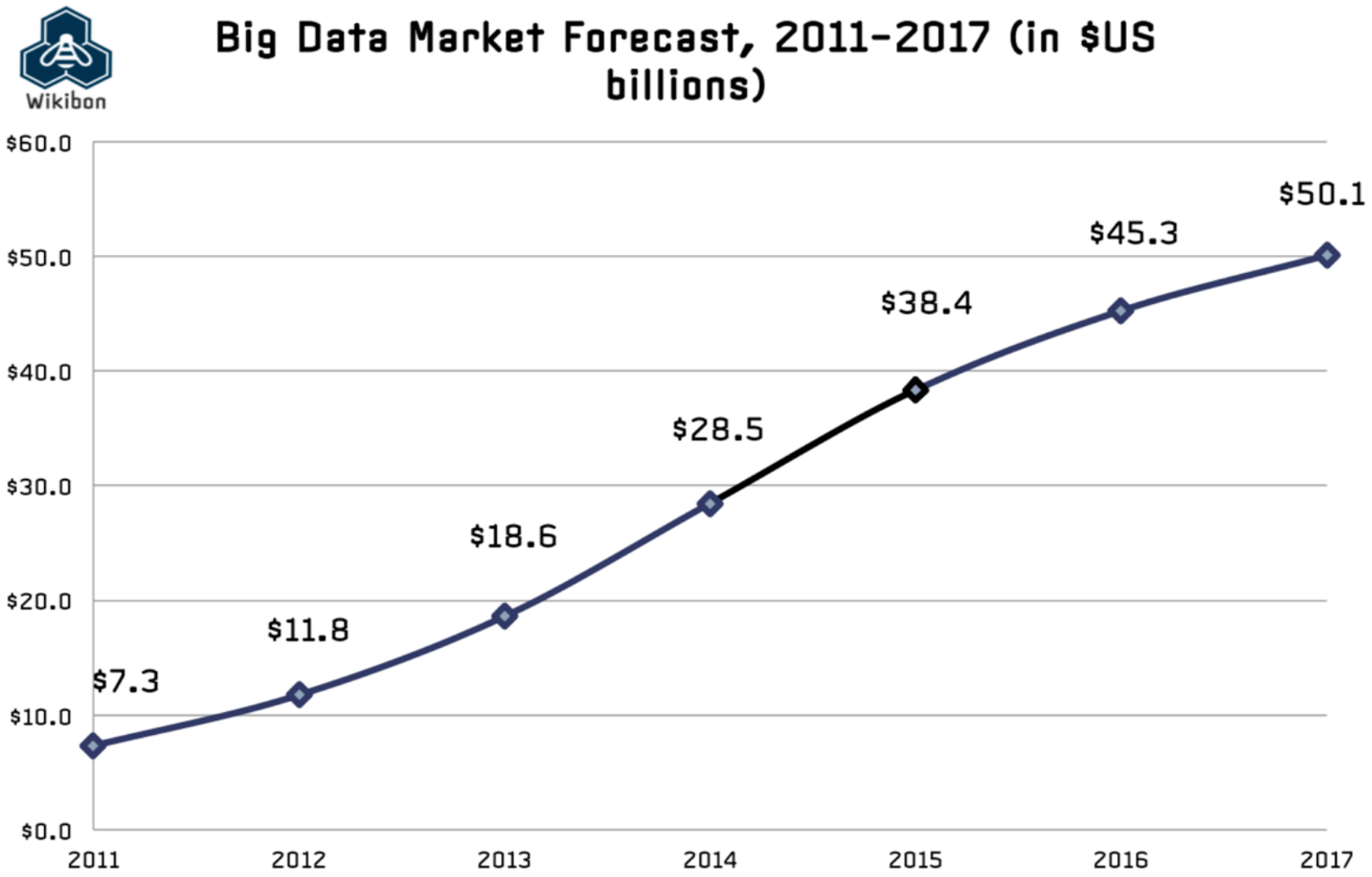
Operations Analysis

Analyze a variety of machine data for improved business results

Data Warehouse Augmentation

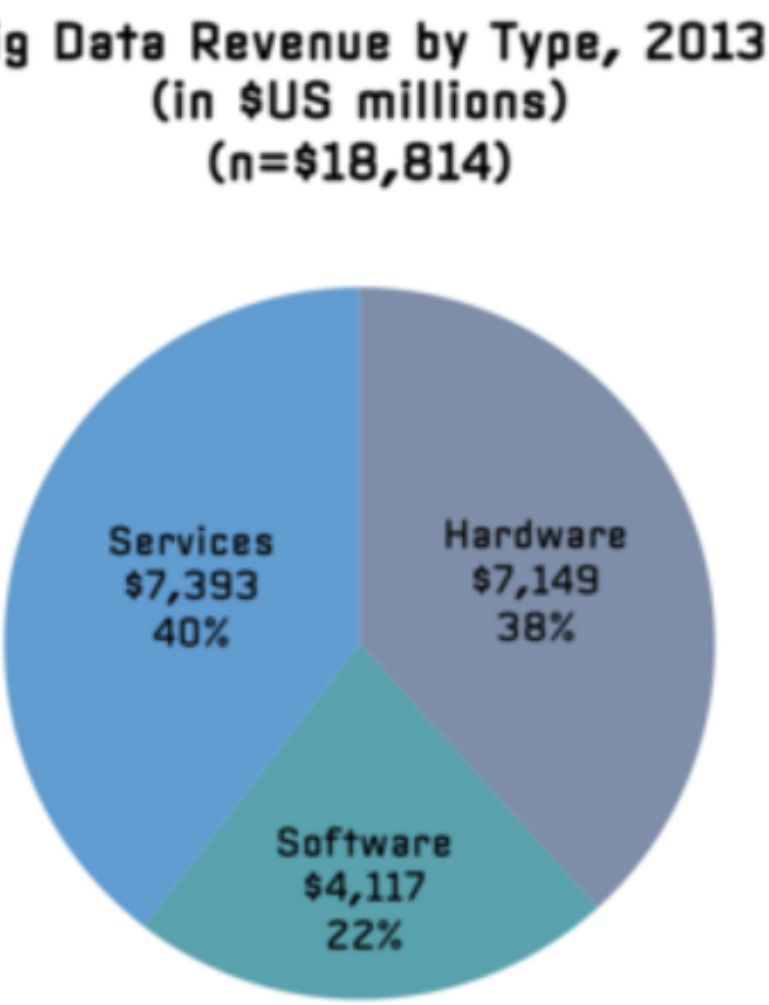
Integrate big data and data warehouse capabilities to increase operational efficiency

Big Data Market



http://wikibon.org/wiki/v/Big_Data_Vendor_Revenue_and_Market_Forecast_2013-2017

Big Data Market



http://wikibon.org/wiki/v/Big_Data_Vendor_Revenue_and_Market_Forecast_2013-2017

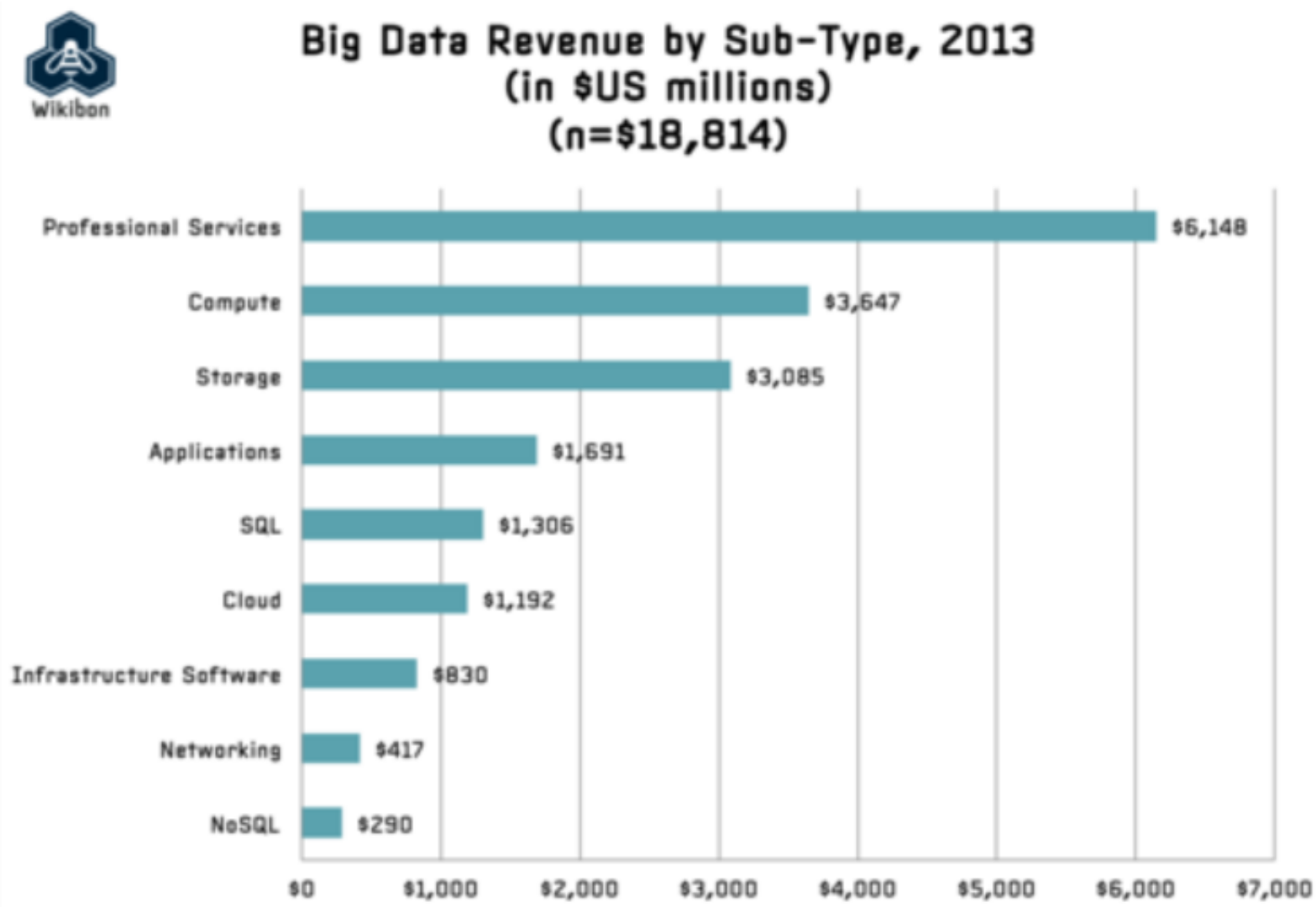
Big Data Market

2013 Worldwide Big Data Revenue by Vendor ($US millions)

Vendor	Big Data Revenue	Total Revenue	Big Data Revenue as % of Total Revenue	% Big Data Hardware Revenue	% Big Data Software Revenue	% Big Data Services Revenue
IBM	$1,368	$99,751	1%	31%	27%	42%
HP	$869	$114,100	1%	42%	14%	44%
Dell	$652	$54,550	1%	85%	0%	15%
SAP	$545	$22,900	2%	0%	76%	24%
Teradata	$518	$2,665	19%	36%	30%	34%
Oracle	$491	$37,552	1%	28%	37%	36%
SAS Institute	$480	$3,020	16%	0%	68%	32%
Palantir	$418	$418	100%	0%	50%	50%
Accenture	$415	$30,606	1%	0%	0%	100%
PWC	$312	$32,580	1%	0%	0%	100%
Deloitte	$305	$33,050	1%	0%	0%	100%
Pivotal	$300	$300	100%	15%	50%	35%
Cisco Systems	$295	$50,200	1%	72%	12%	16%

http://wikibon.org/wiki/v/Big_Data_Vendor_Revenue_and_Market_Forecast_2013-2017

Big Data Revenue by Sub-Type, 2013

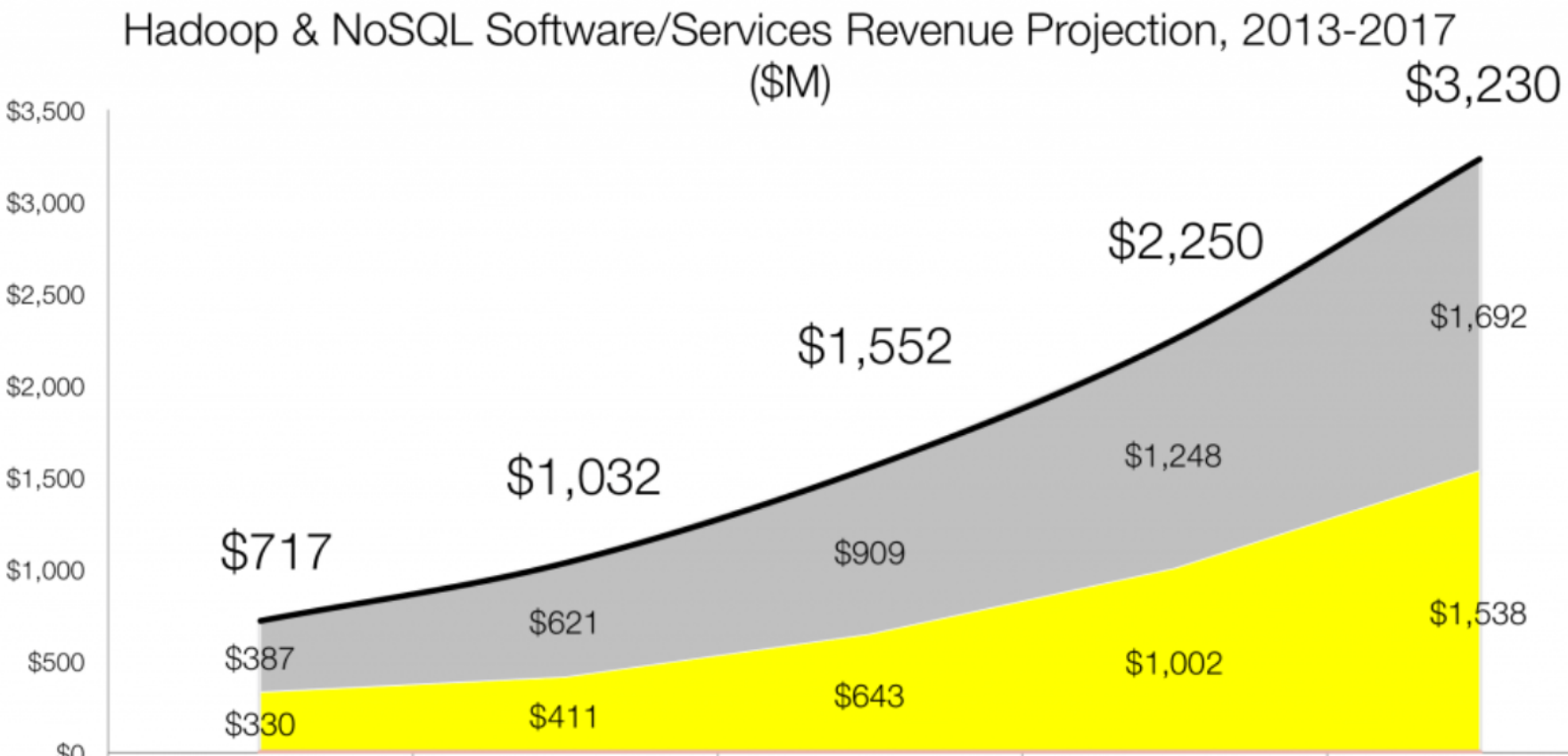


Big Data Market further breakdown

http://wikibon.org/wiki/v/Big_Data_Database_Revenue_and_Market_Forecast_2012-2017

USD: billions	2014	2015	2016	2017
Big Data XaaS Revenue	$1.71	$2.43	$2.87	$3.19
Big Data Professional Services Revenue	$9.24	$12.31	$14.06	$15.30
Big Data Application (Analytic and Transactional) Revenue	$3.24	$4.94	$6.05	$6.89
Big Data NoSQL Database Revenue	$0.73	$1.14	$1.41	$1.62
Big Data SQL Database Revenue	$2.00	$2.48	$2.74	$2.91
Big Data Infrastructure Revenue	$0.67	$0.93	$1.08	$1.19
Big Data Networking Revenue	$0.67	$0.89	$1.02	$1.11
Big Data Storage Revenue	$4.39	$5.85	$6.68	$7.27
Big Data Compute Revenue	$5.23	$6.70	$7.50	$8.06
Total Big Data Revenue	$27.9	$37.7	$43.4	$47.5

- NoSQL DB ==> Distributed DB, Document-Orinted DB, Graph NoSQL DB, and In-Memory NoSQL DB.
- "It is not uncommon for an enterprise IT organization to support multiple NoSQL DBs alongside legacy RDBMSs. Indeed, there are single applications that often deploy two or more NoSQL solutions, e.g., pairing a document-oriented DB with a graph DB for an analytics solution." [Dec 2013]



	2013	2014	2015	2016	2017
Hadoop	$387	$621	$909	$1,248	$1,692
NoSQL	$330	$411	$643	$1,002	$1,538
Total	$717	$1,032	$1,552	$2,250	$3,230
CAGR		44%	50%	57%	47%

http://wikibon.com/hadoop-nosql-software-and-services-market-forecast-2013-2017/

Course Structure

Class Data	Number	Topics Covered
09/10/15	1	Introduction to Big Data Analytics
09/17/15	2	Big Data Platforms
09/24/15	3	Big Data Storage and Processing
10/01/15	4	Big Data Analytics Algorithms — I (recommender)
10/08/15	5	Big Data Analytics Algorithms — II (clustering)
10/15/15	6	Big Data Analytics Algorithms — III (classification)
10/22/15	7	Spark and Data Analytics
10/29/15	8	Linked Big Data — I (graph DB)
11/05/15	9	Linked Big Data — II (graph analytics)
11/12/15	10	Big Data Application (Guest Speaker)
11/19/15	11	Final Project Proposal Presentation
11/26/15		*Thanksgiving Holiday*
12/03/15	12	Big Data Application (Guest Speaker)
12/10/15	13	Big Data Application (Guest Speaker)
12/17/15 & 12/18/15	14-15	**Two-Day Big Data Analytics Workshop – Final Project Presentations**

Course Grading

- 3 Homeworks: 50%
  - -- Individual work; Language Requirement: Java, JavaScript, Python, C/C++, Perl
  - -- Report and source code
  - Data Store & Processing
  - Analytics
  - In-Memory and Graph Computing

- Final Project: 50%
  - -- Teamwork: 2 - 3 students per team (on campus); 1+ per team for CVN
  - Proposal (slides)
  - Final Report (paper, up to 12 pages)
  - Workshop Presentation (Oral and Demo)
  - Open Source

Course Information

- Website:

  http://www.ee.columbia.edu/~cylin/course/bigdata/

- Textbook:

  -- None, but reference book(s) and/or articles/papers will be provided each lecture.

Sapphirine Big Data Analytics Open Source Applications

- **Goal:** Create a Big Data open source toolsets for various industries (and disciplines)

- **Dataset and Use Cases:** Welcome!!

Crowdsourcing of our collective effort!!

Other Issues

- Professor Lin:
  - Office Hours:
    Thursday 9:30pm – 10:00pm (SIPA 415, lecture room) (every week)
  - Contact: c {dot} lin {at} columbia {dot} edu (the same as <cl300>)
  - Telephone: 914-945-1897
- TAs:
  Ghazel Fazelnia <gf2293>, EE; Office Hours and Location: TBD
  We are recruiting more TAs..

Apache Hadoop

The Apache™ Hadoop® project develops open-source software for reliable, scalable, distributed computing.

The Apache Hadoop software library is a framework that allows for the distributed processing of large data sets across clusters of computers using simple programming models. It is designed to scale up from single servers to thousands of machines, each offering local computation and storage. Rather than rely on hardware to deliver high-availability, the library itself is designed to detect and handle failures at the application layer, so delivering a highly-available service on top of a cluster of computers, each of which may be prone to failures.

The project includes these modules:

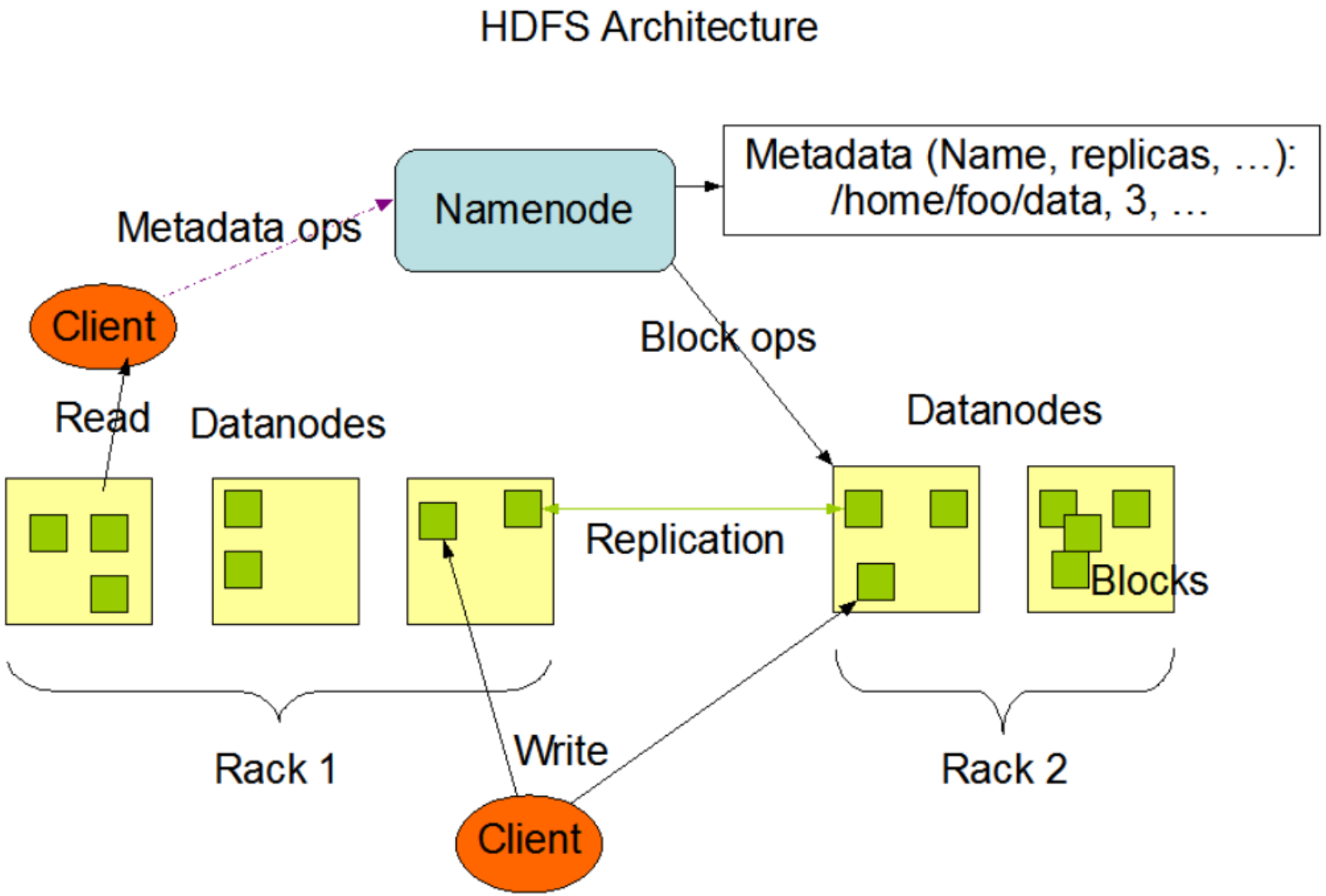
- **Hadoop Common**: The common utilities that support the other Hadoop modules.
- **Hadoop Distributed File System (HDFS™)**: A distributed file system that provides high-throughput access to application data.
- **Hadoop YARN**: A framework for job scheduling and cluster resource management.
- **Hadoop MapReduce**: A YARN-based system for parallel processing of large data sets.

http://hadoop.apache.org

Hadoop-related Apache Projects

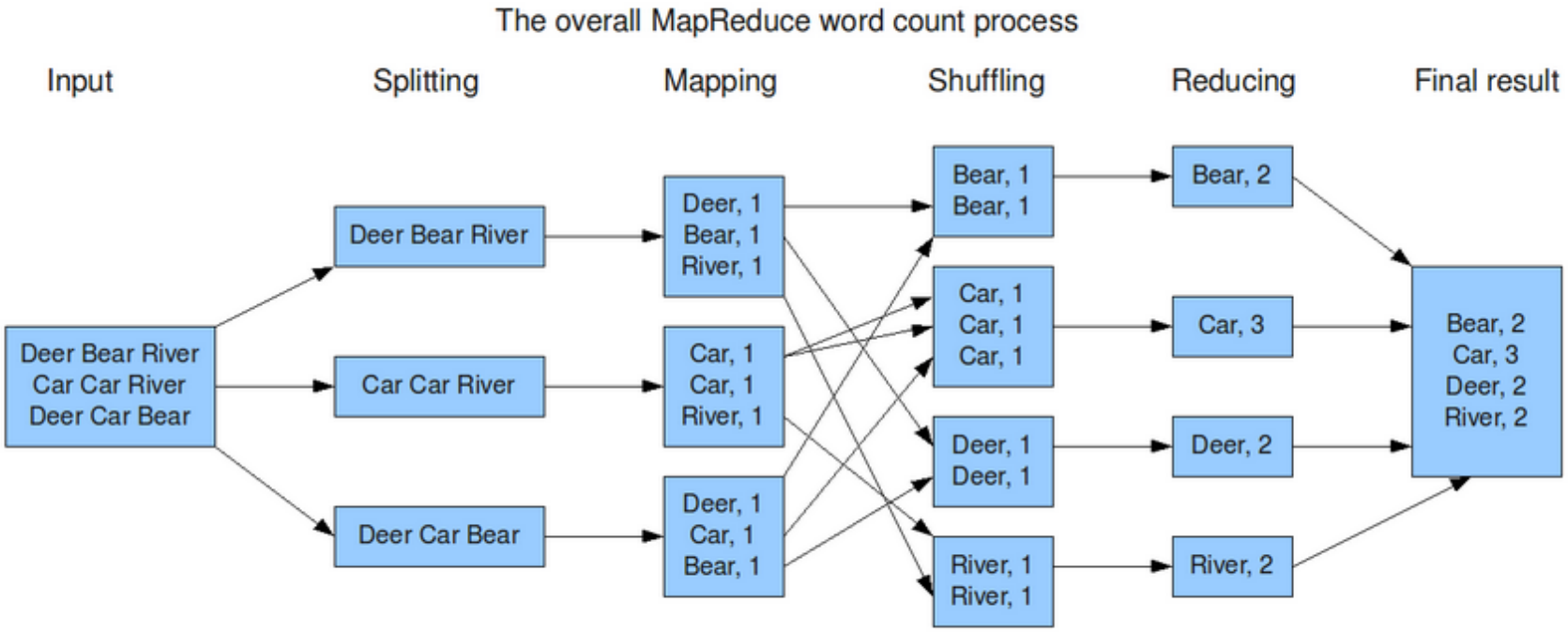
- Ambari™: A web-based tool for provisioning, managing, and monitoring Hadoop clusters.It also provides a dashboard for viewing cluster health and ability to view MapReduce, Pig and Hive applications visually.
- Avro™: A data serialization system.
- Cassandra™: A scalable multi-master database with no single points of failure.
- Chukwa™: A data collection system for managing large distributed systems.
- HBase™: A scalable, distributed database that supports structured data storage for large tables.
- Hive™: A data warehouse infrastructure that provides data summarization and ad hoc querying.
- Mahout™: A Scalable machine learning and data mining library.
- Pig™: A high-level data-flow language and execution framework for parallel computation.
- Spark™: A fast and general compute engine for Hadoop data. Spark provides a simple and expressive programming model that supports a wide range of applications, including ETL, machine learning, stream processing, and graph computation.
- Tez™: A generalized data-flow programming framework, built on Hadoop YARN, which provides a powerful and flexible engine to execute an arbitrary DAG of tasks to process data for both batch and interactive use-cases.
- ZooKeeper™: A high-performance coordination service for distributed applications.

Hadoop Distributed File System (HDFS)



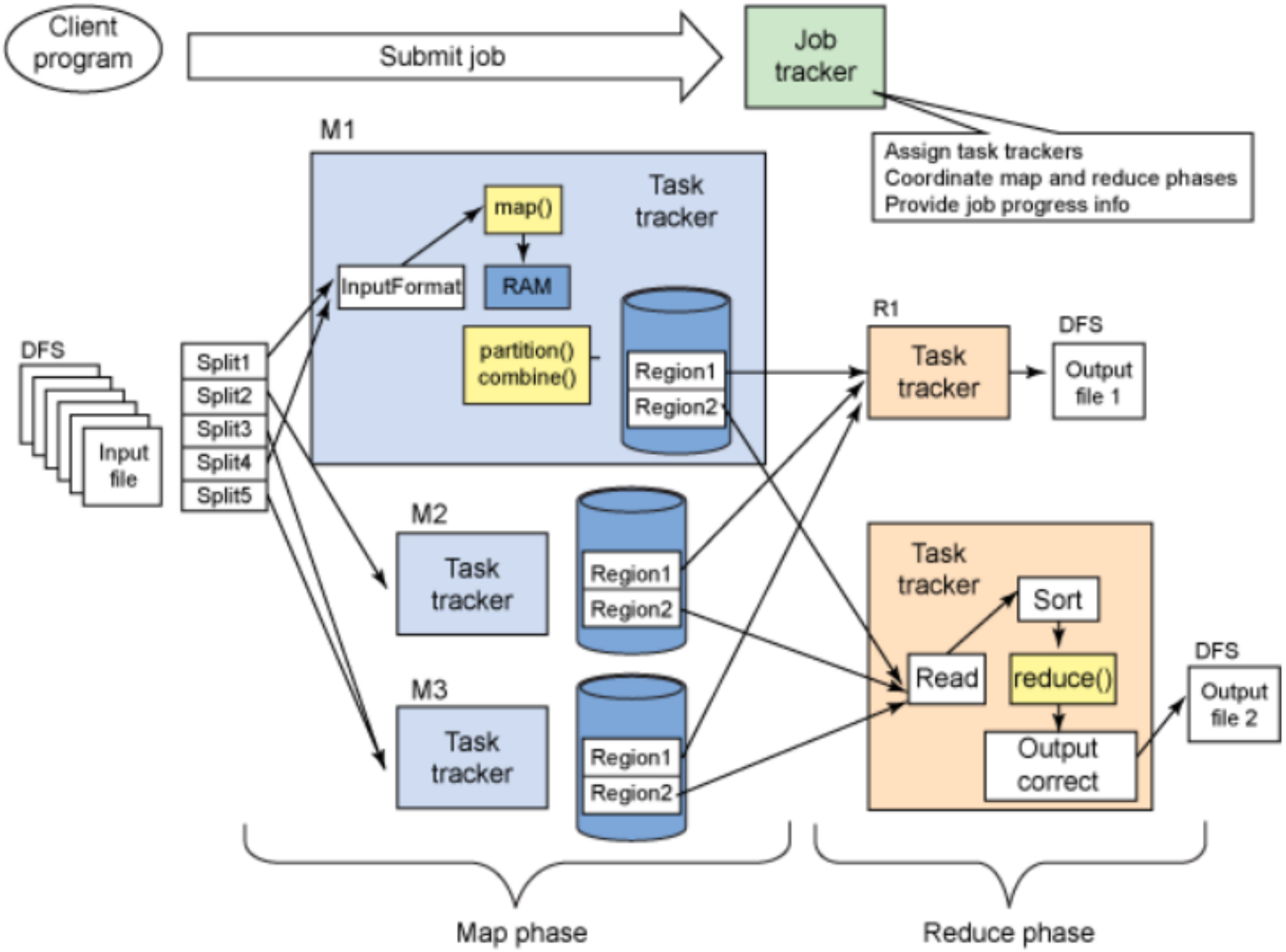
http://hortonworks.com/hadoop/hdfs/

MapReduce example



http://www.alex-hanna.com

MapReduce Data Flow



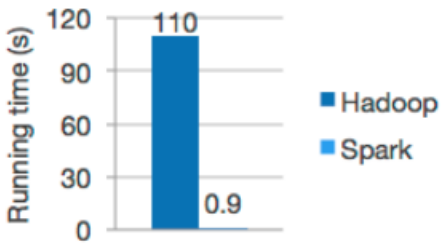
http://www.ibm.com/developerworks/cloud/library/cl-openstack-deployhadoop/

Building on top of HDFS

Speed

Run programs up to 100x faster than Hadoop MapReduce in memory, or 10x faster on disk.

Spark has an advanced DAG execution engine that supports cyclic data flow and in-memory computing.



Logistic regression in Hadoop and Spark

Ease of Use

Write applications quickly in Java, Scala or Python.

Spark offers over 80 high-level operators that make it easy to build parallel apps. And you can use it *interactively* from the Scala and Python shells.

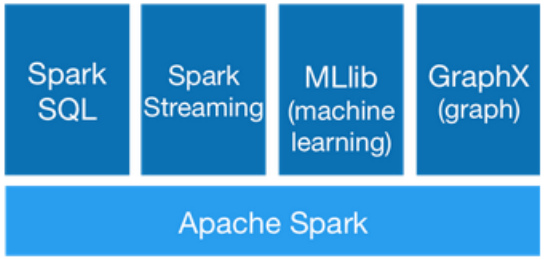
```
file = spark.textFile("hdfs://...")

file.flatMap(lambda line: line.split())
    .map(lambda word: (word, 1))
    .reduceByKey(lambda a, b: a+b)
```

Word count in Spark's Python API

Generality

Combine SQL, streaming, and complex analytics.

Spark powers a stack of high-level tools including Spark SQL, MLlib for machine learning, GraphX, and Spark Streaming. You can combine these frameworks seamlessly in the same application.



Linked Big Data — IBM System G

NoSQL Database

- Key-Value Store
- Document Store
- Tabular Store
- Object Database
- Graph Database (property graphs, RDF graphs)

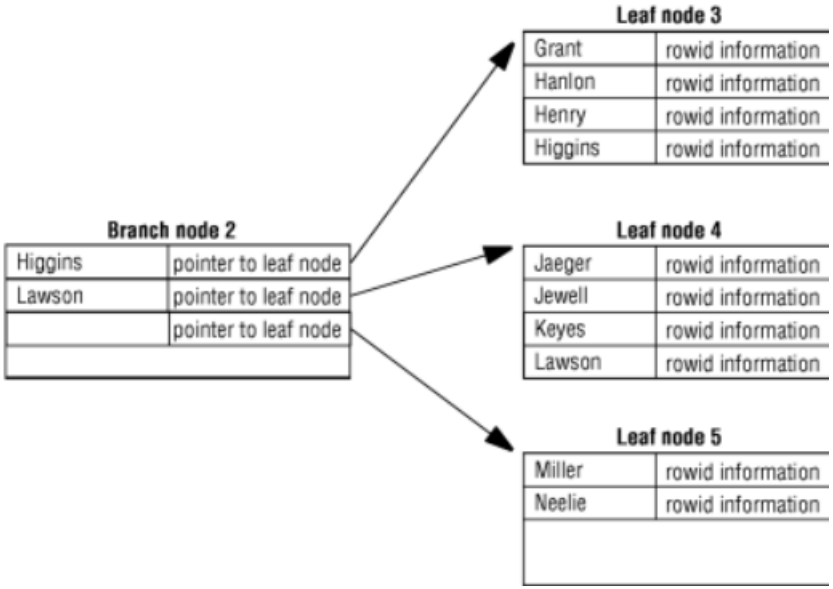
Key Value Store

Example Data Represented in a Key–Value Store

Key	Value
…	
"BMW"	{"1-Series", "3-Series", "5-Series", "5-Series GT", "7-Series", "X3", "X5", "X6", "Z4"}
"Buick"	{"Enclave", "LaCrosse", "Lucerne", "Regal"}
"Cadillac"	{"CTS", "DTS", "Escalade", "Escalade ESV", "Escalade EXT", "SRX", "STS"}
…	

- Get(*key*), which returns the value associated with the provided *key*.
- Put(*key*, *value*), which associates the *value* with the *key*.
- Multi-get(*key1*, *key2*,.., *keyN*), which returns the list of values associated with the list of *keys*.
- Delete(*key*), which removes the entry for the *key* from the data store.

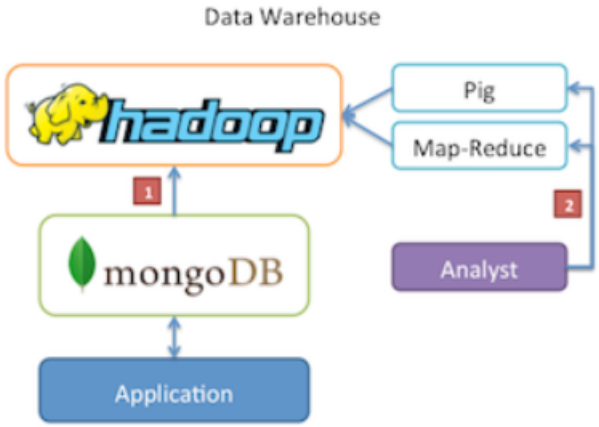
"Big Data Analytics", David Loshin, 2013



IBM Informix K-V store

Example Application: Spatio-Temporal Analysis

Document Store



The following diagram highlights the components of a MongoDB insert operation:

```
db.users.insert (          ← collection
   {
     name: "sue",          ← field: value
     age: 26,              ← field: value
     status: "A"           ← field: value
   }
)
```

document

The components of a MongoDB insert operations.

The following diagram shows the same query in SQL:

```
INSERT INTO users                          ← table
            ( name, age, status )          ← columns
VALUES      ( "sue", 26, "A" )             ← values/row
```

The components of a SQL INSERT statement.

Relational data model

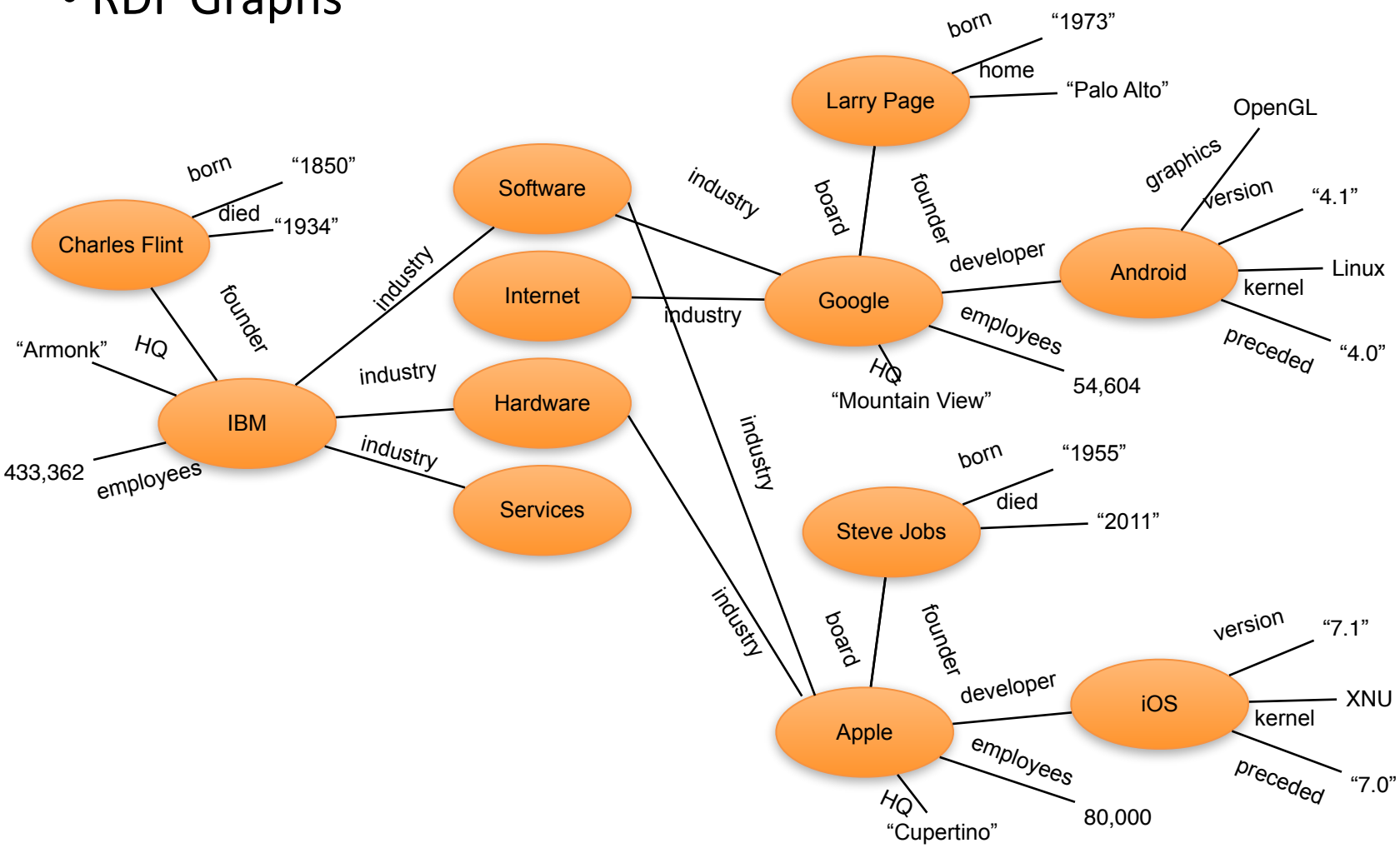
Highly-structured table organization with rigidly-defined data formats and record structure.

Document data model

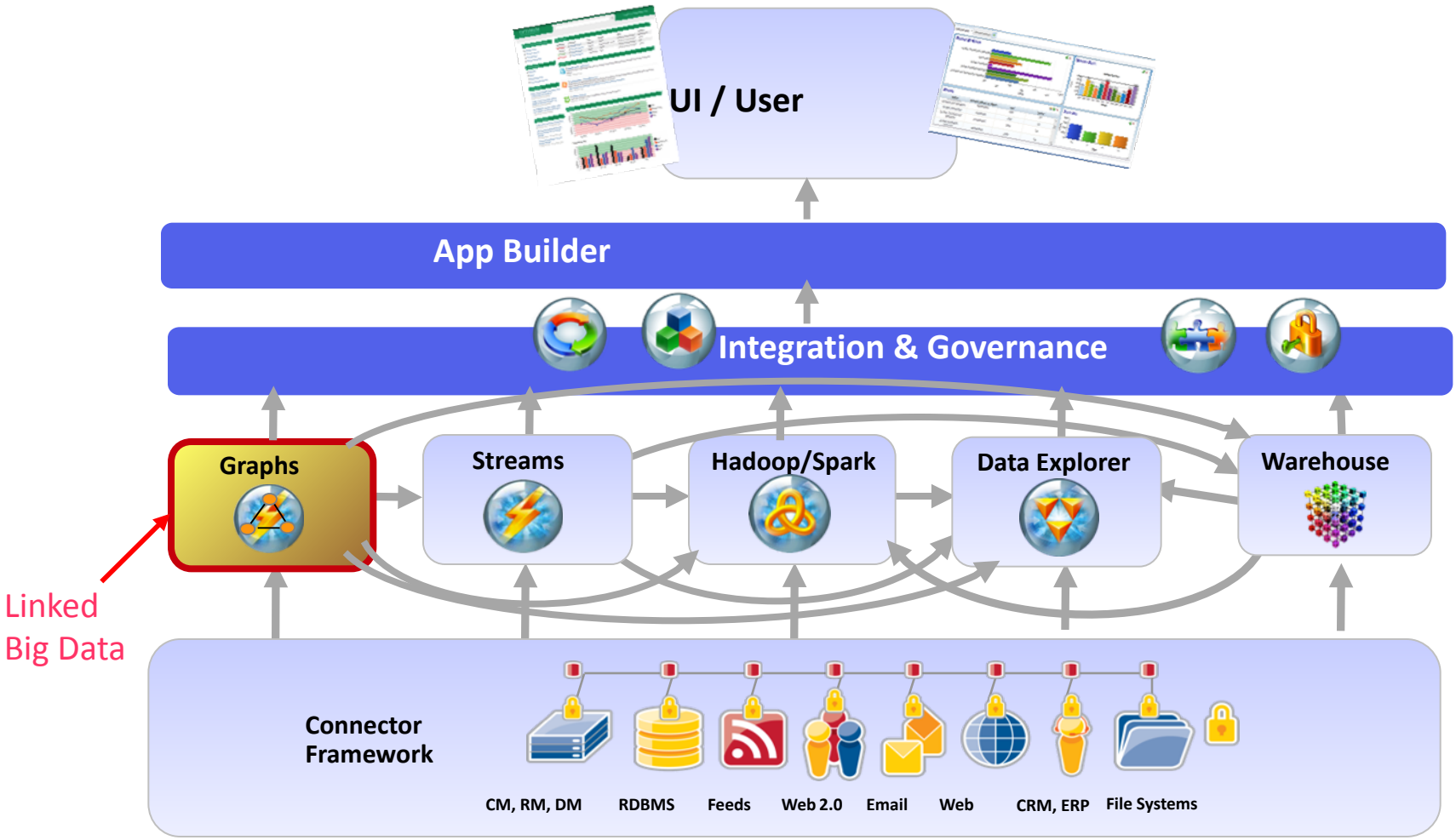
Collection of complex documents with arbitrary, nested data formats and varying "record" format.

Graph Data

- Property Graphs
- RDF Graphs

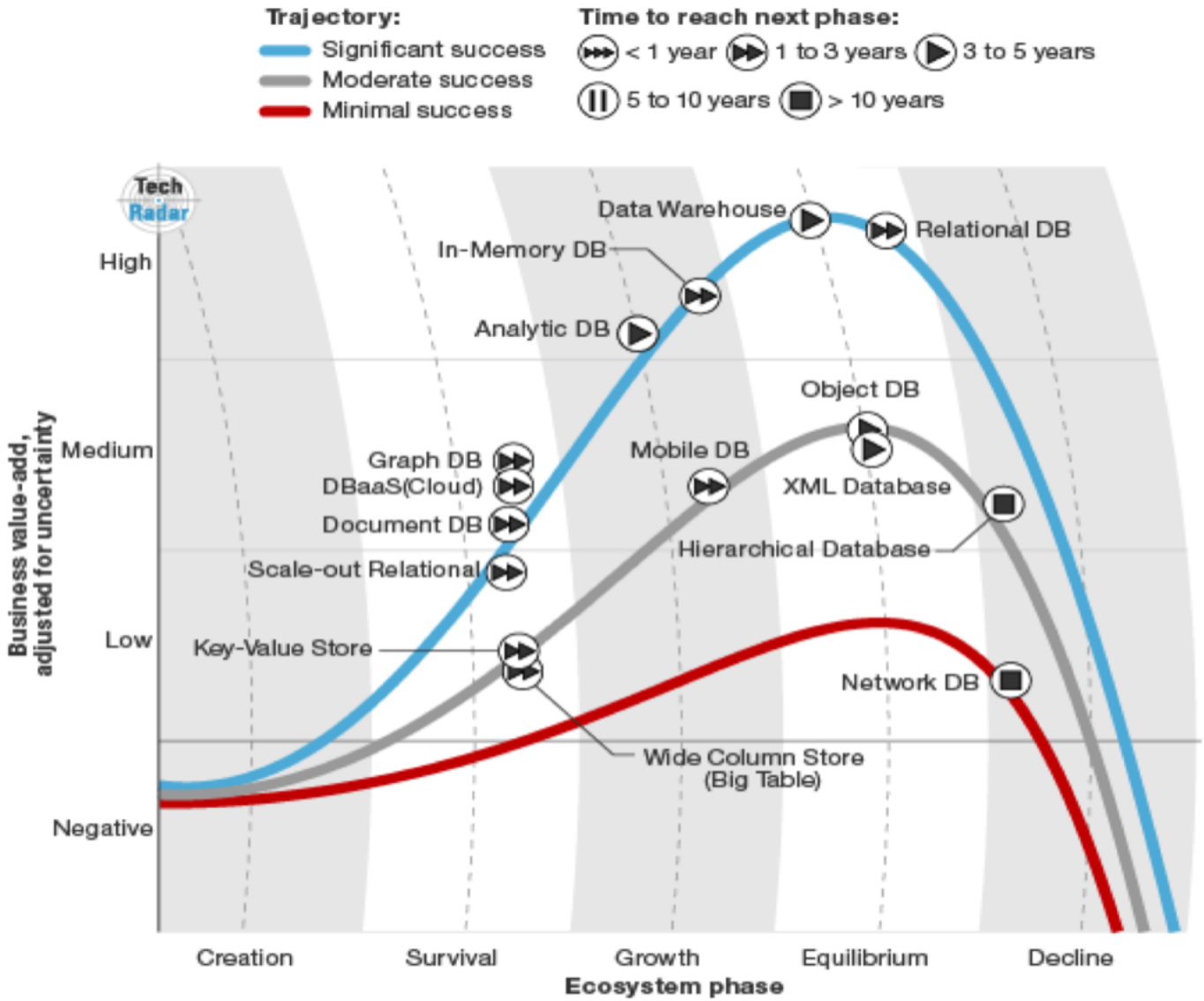


Graph is a missing pillar in the existing Big Data foundation



Volume ==> Hadoop / Spark; Velocity ==> Streams; Variety ==> Graphs

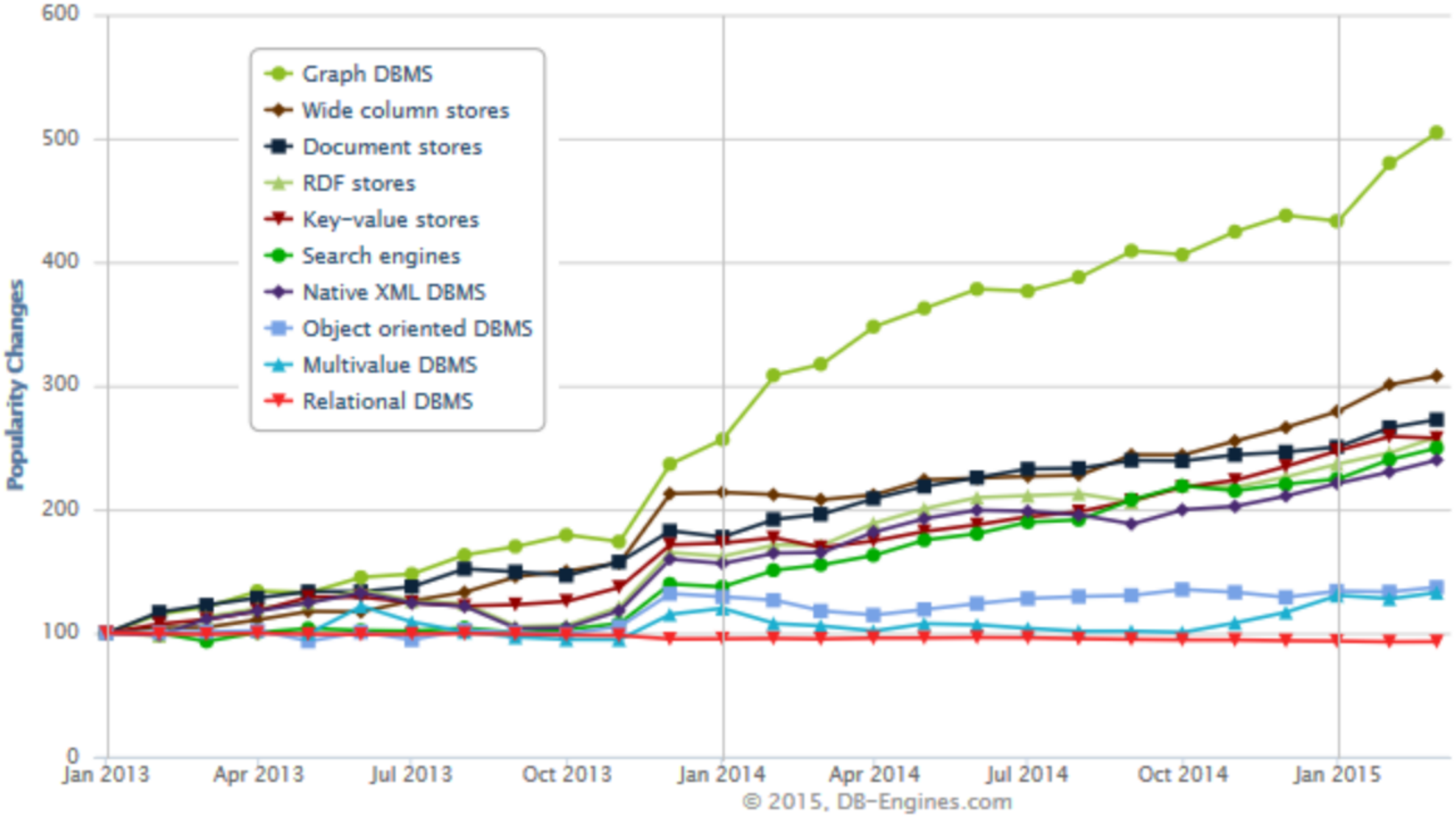
Forrester: Over 25% of enterprise will use Graph DB by 2017



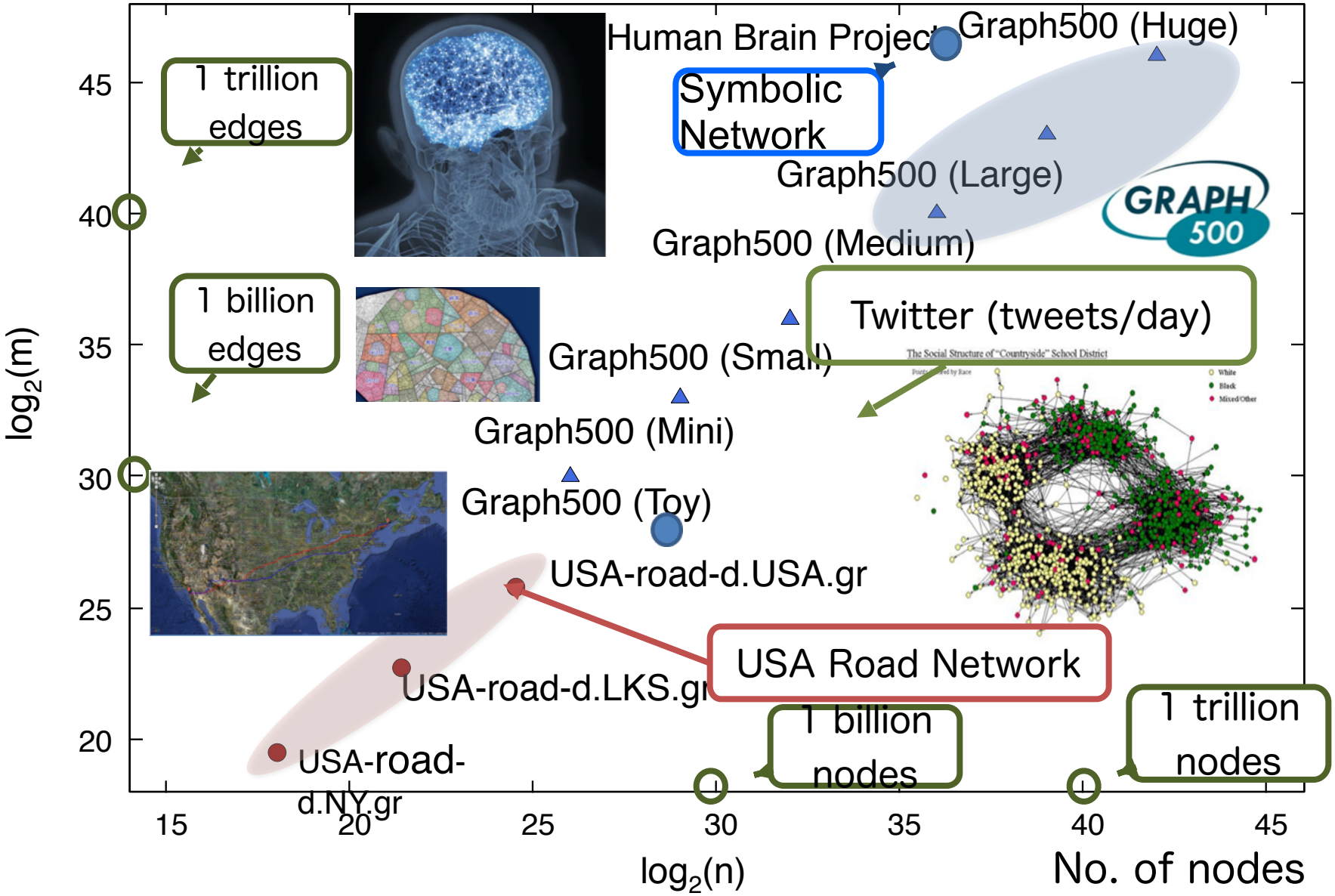
TechRadar: Enterprise DBMS, Q12014

Graph DB is in the significant success trajectory, and has the highest business value among the upcoming DBs.

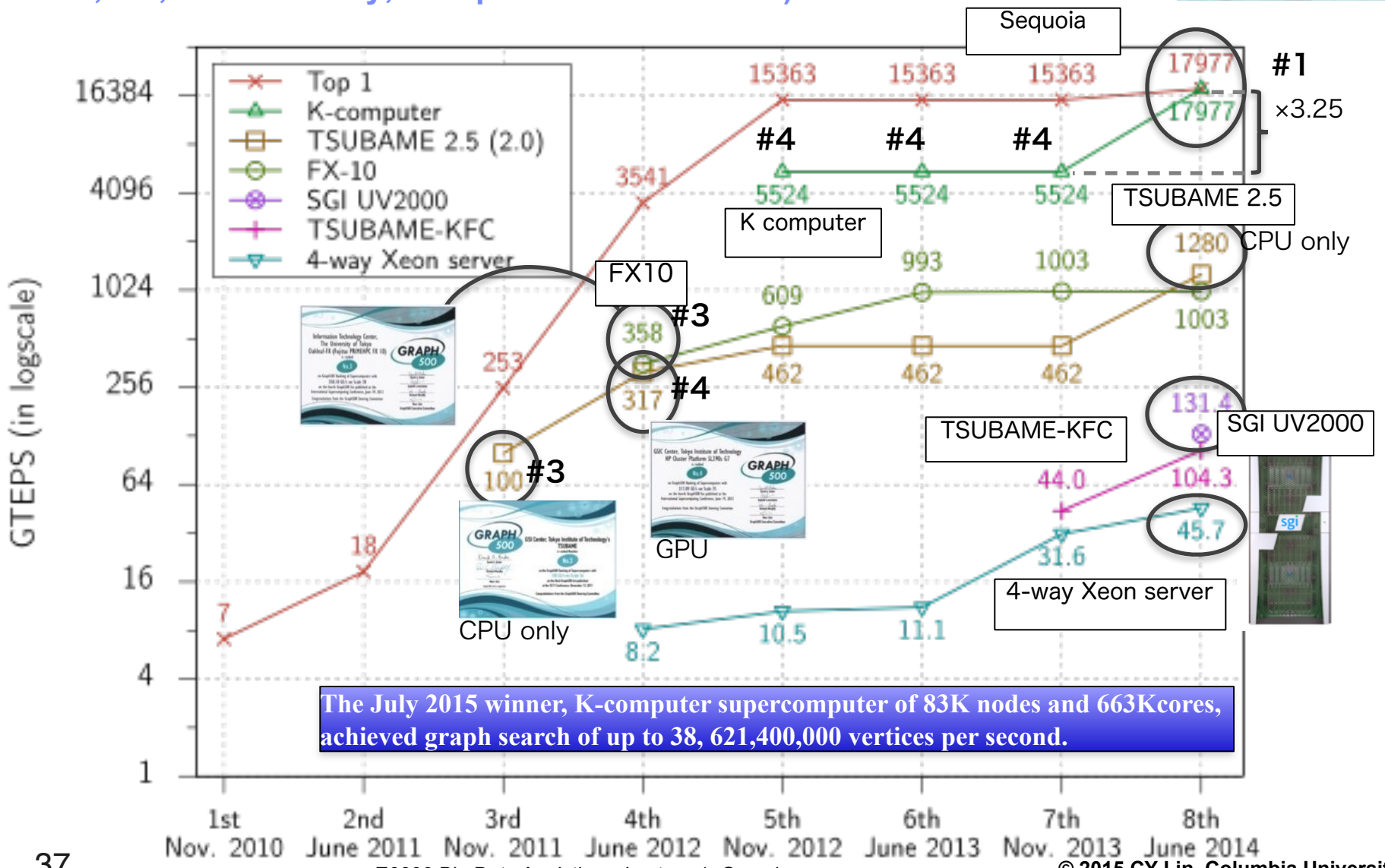
GraphDB has the largest Popularity Change among DBMS lately



Comparison of linked data size



July 2015: IBM Research's Software powered all Top 3 winners of Graph 500 benchmark and 9 out of the Top 10 winners (supercomputers in US, Japan, France, UK, and Germany; except Tianhe 2 in China).

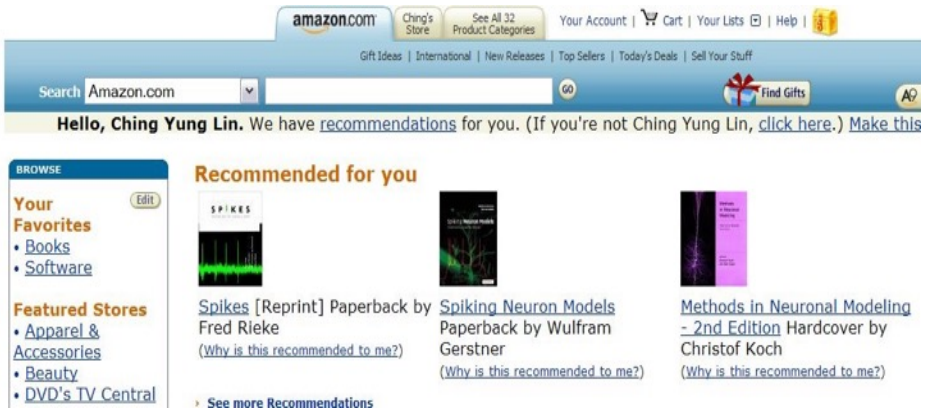


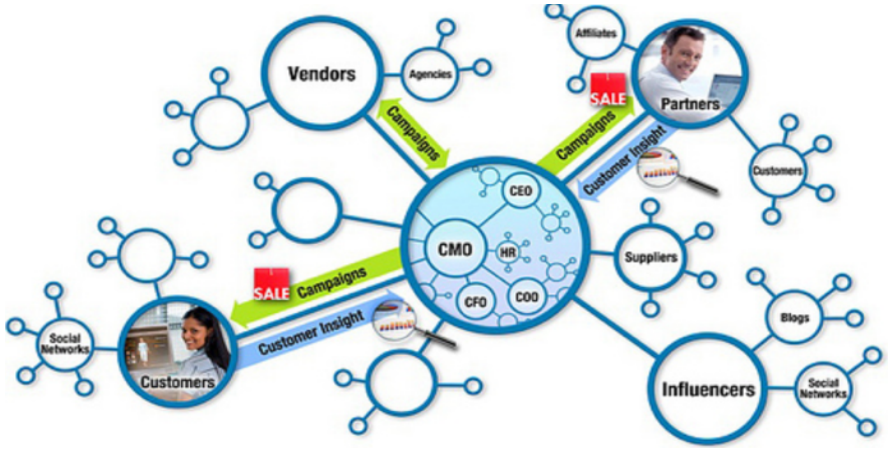
Big Data Analytics Example Use Cases

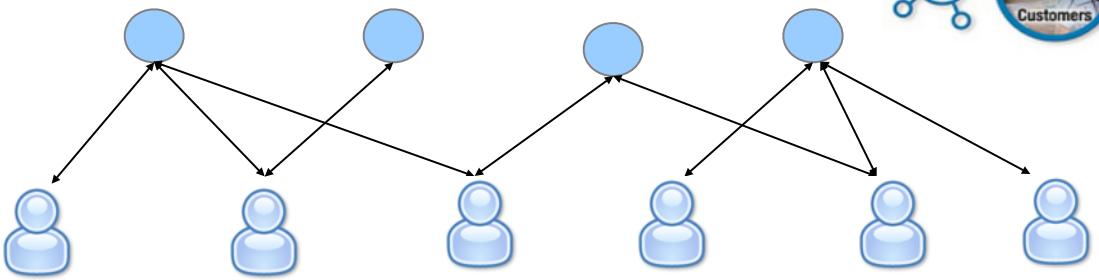
1. Expertise Location
2. Recommendation
3. Commerce
4. Financial Analysis
5. Social Media Monitoring
6. Telco Customer Analysis
7. Watson
8. Data Exploration and Visualization
9. Personalized Search
10. Anomaly Detection (Espionage, Sabotage, etc.)
11. Fraud Detection
12. Cybersecurity
13. Sensor Monitoring (Smarter another Planet)
14. Celluar Network Monitoring
15. Cloud Monitoring
16. Code Life Cycle Management
17. Traffic Navigation
18. Image and Video Semantic Understanding
19. Genomic Medicine
20. Brain Network Analysis
21. Data Curation
22. Near Earth Object Analysis

Category 1: 360º View

Recommendation



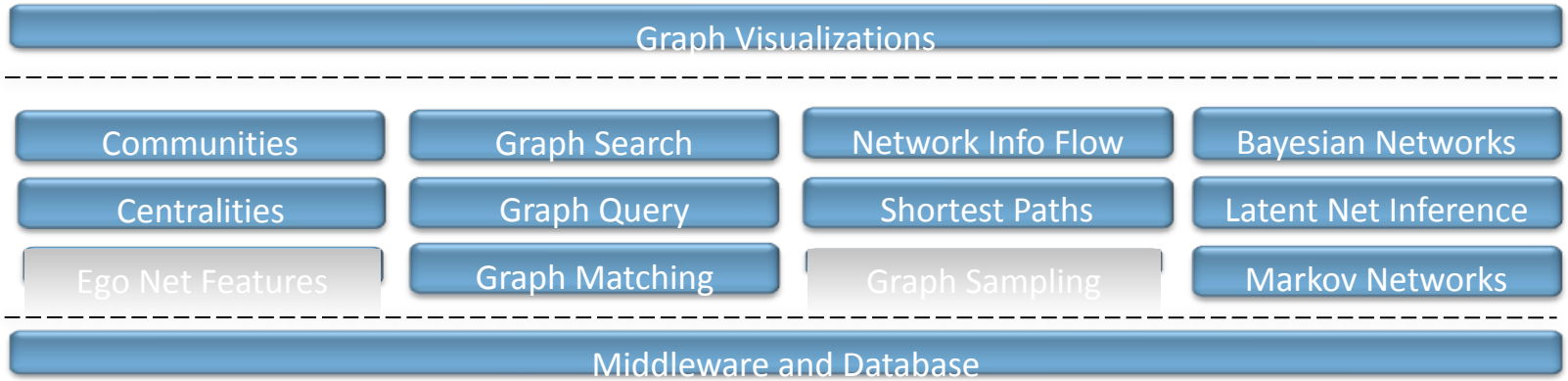




Enhancing:

Coremetrics An IBM Company

unica



Use Case 1: Social Network Analysis in Enterprise for Productivity

Production Live System used by IBM GBS since 2009 – verified ~$100M contribution

15,000 contributors in 76 countries; 92,000 annual unique IBM users

25,000,000+ emails & SameTime messages (incl. Content features)

1,000,000+ Learning clicks; 14M KnowledgeView, SalesOne, …, access data

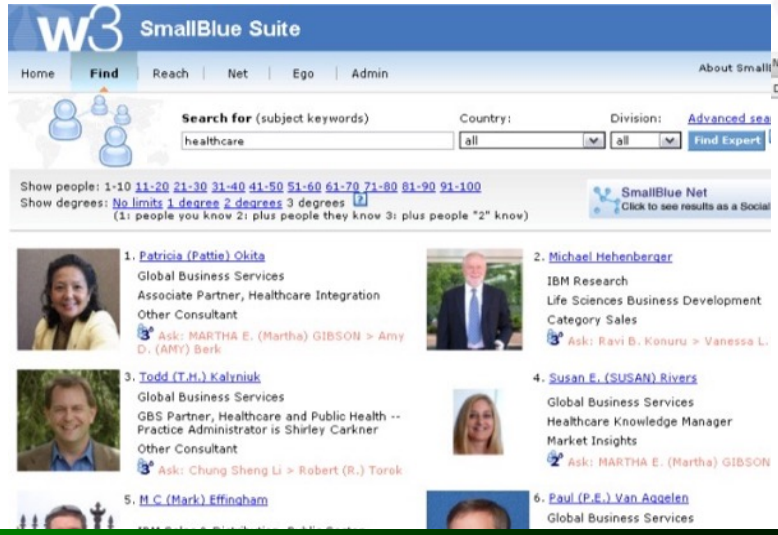
1,000,000+ Lotus Connections (blogs, file sharing, bookmark) data

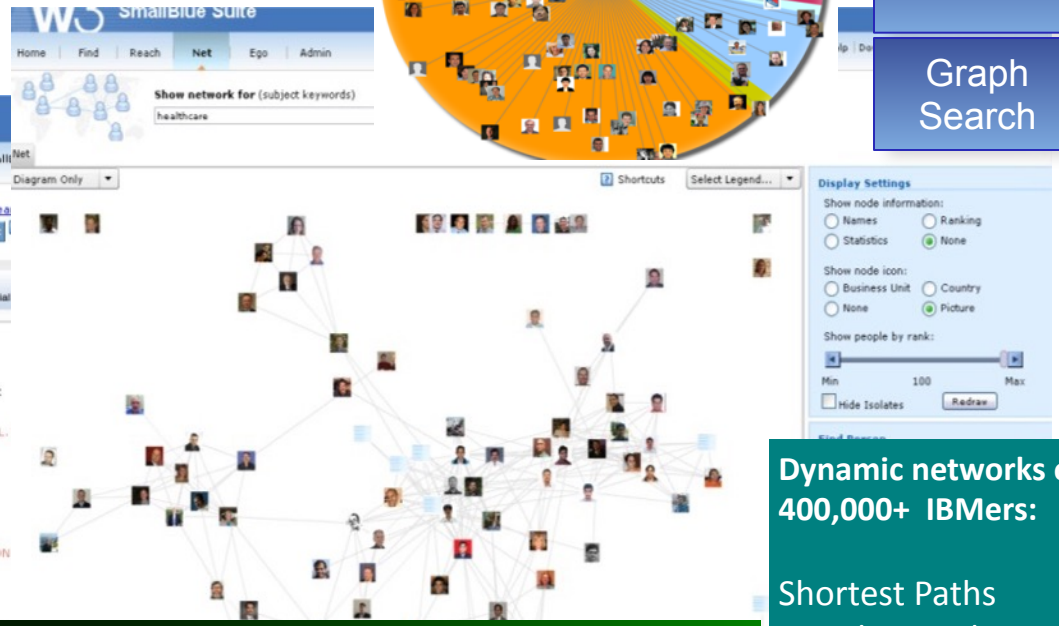
200,000 people's consulting project & earning data

Shortest Paths

Centralities

Graph Search





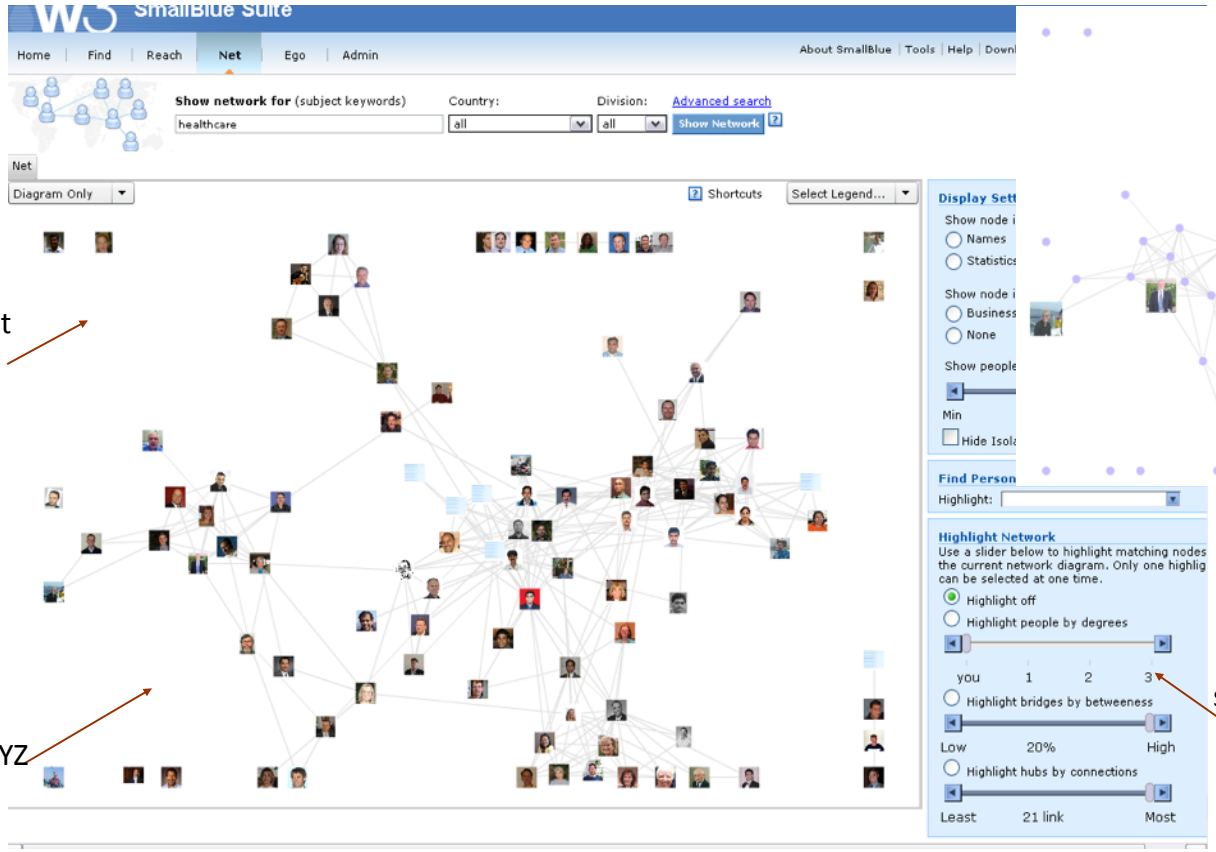
Dynamic networks of 400,000+ IBMers:

Shortest Paths
Social Capital
Bridges
Hubs
Expertise Search
Graph Search
Graph Recomm.

– On BusinessWeek four times, including being the Top Story of Week, April 2009
– Help IBM earned the 2012 Most Admired Knowledge Enterprise Award
– Wharton School study: $7,010 gain per user per year using the tool
– In 2012, contributing about 1/3 of GBS Practitioner Portal $228.5 million savings and benefits
– APQC (WW leader in Knowledge Practice) April 2013:
"The Industry Leader and Best Practice in Expertise Location"

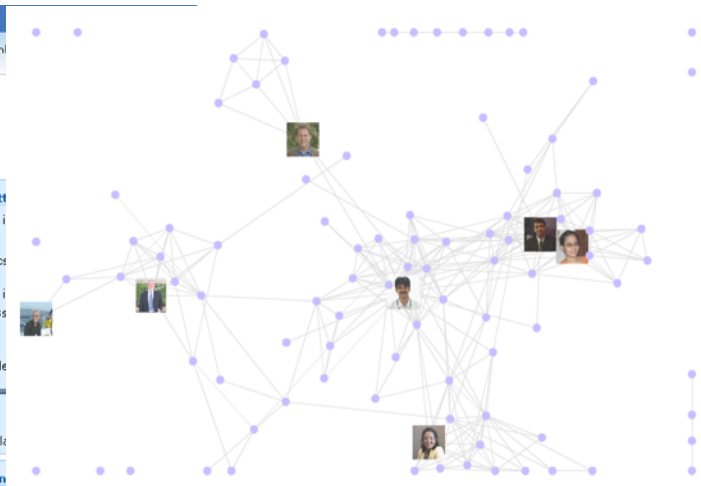
Finding and Ranking Expertise – Social Network Analysis

- Decades of Social Science studies demonstrates that (social) network structure is the key indicator determining a person's influence, organizational operation efficiency, social capital to get help, potential to be successful, etc.
- Who are the key bridges? Who have the most connections? How do these experts cluster?
- Analogy – Google founders utilized the concept of network analysis on webpages to create ranking.



Independent experts on healthcare

A cluster of XYZ experts



Influencers are the one with high 'Betweeness' and 'Degree' value

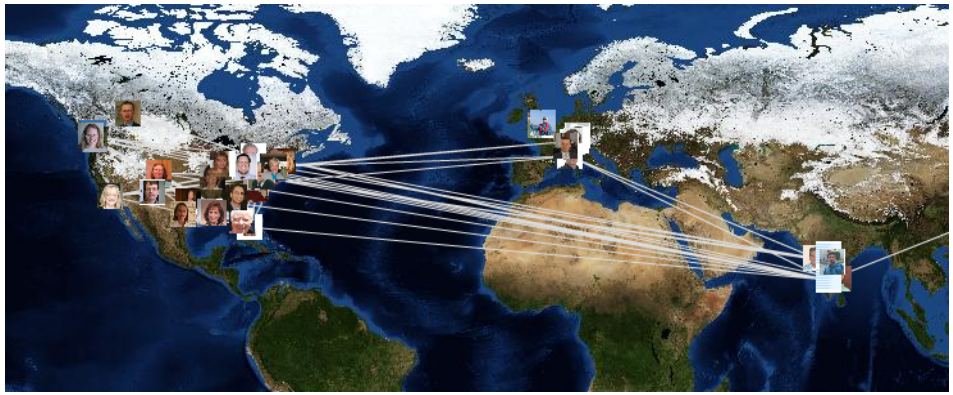
UI to highlight experts based on my social proximity, the number of experts she connects, or the 'social bridges' importance

SmallBlue analyzes underlining dynamic network structure in enterprise

User Interface of finding knowledgeable and influential colleagues

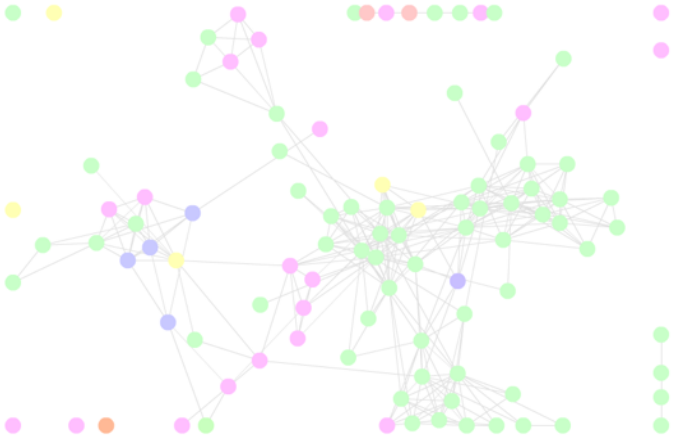
- Search for the most knowledgeable colleagues within organization or my 3-degree network for who knows topic XYZ (or within a country, a division, a job role, or any group/community)
- Based on IBM HR requirements, adding the 'sponsored search' for business department needs
- IBM HR gives a list of about 10,000 IBMers whose name should not be listed in the search result – mostly high level managers, lawyers, people involving acquisition, etc.
- A list of 2,000+ words that are inappropriate to search in enterprise.

Visualize social roles of individuals in company

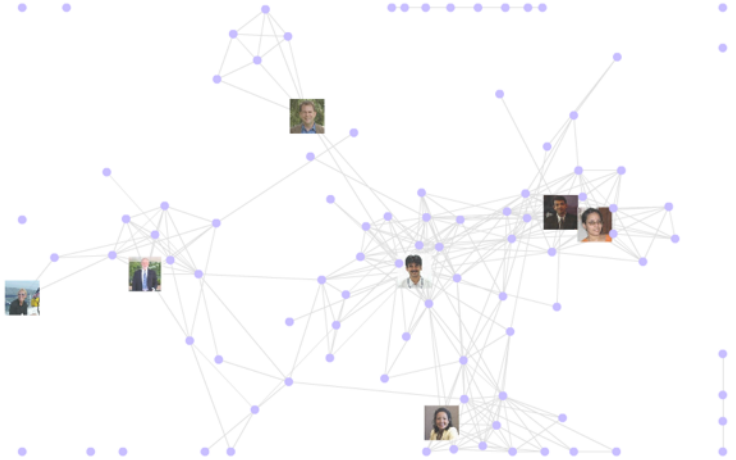


Example: Healthcare experts in the world

Example: Healthcare experts in the U.S.



Connections between different divisions



Key social bridges

Shortest Paths between two people in enterprise

- **Example: Is Tom a right person to me?**

His official job role, title, contact info

His self-described expertise

His public communities

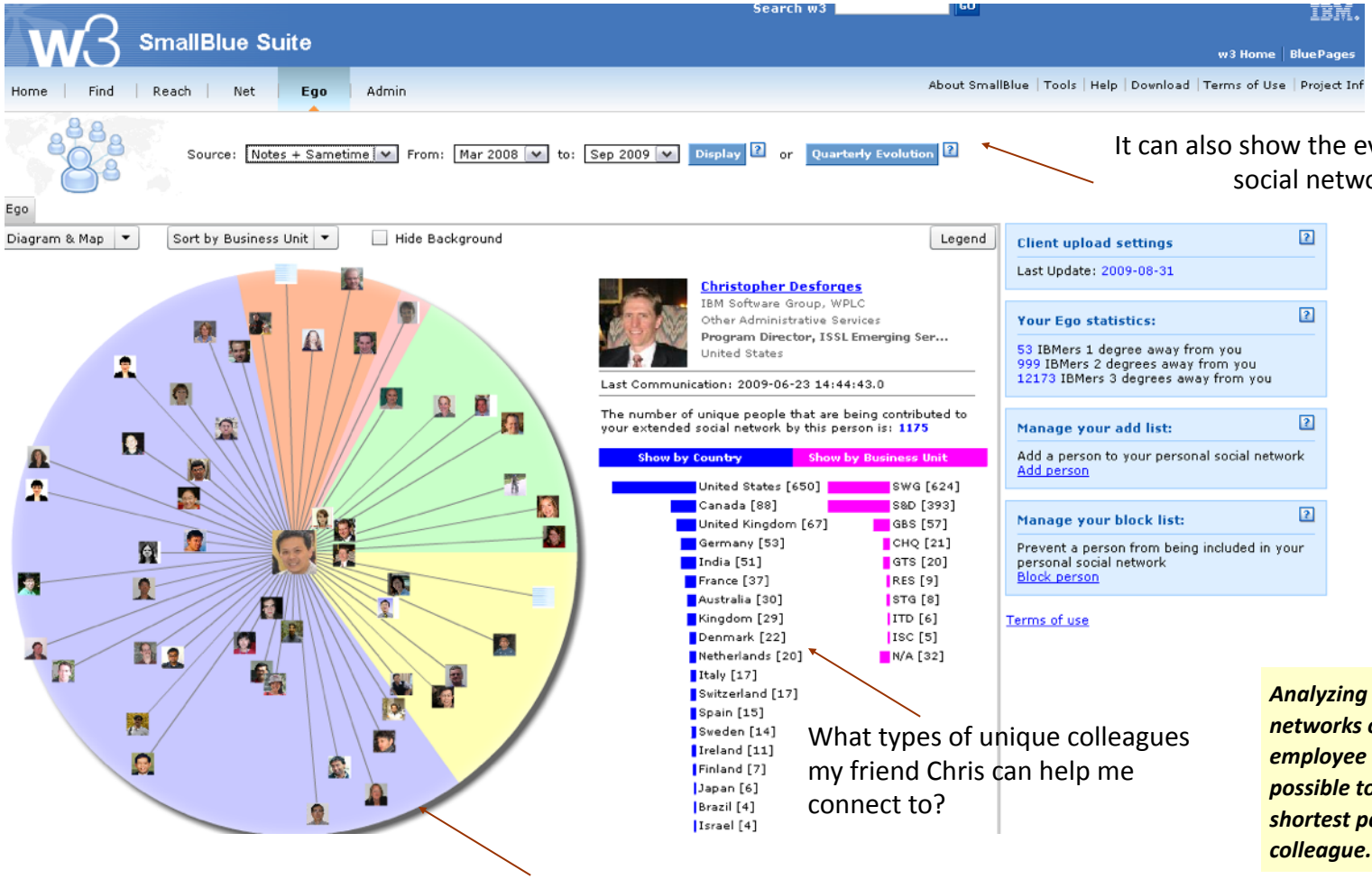
The public interest groups he is in

His blogs

My various paths to Tom. SmallBlue can show the paths to any colleagues up to 6-degree away

Personal social network capital management

- What is a friend's social capital to me? Am I losing an 'important' friend?

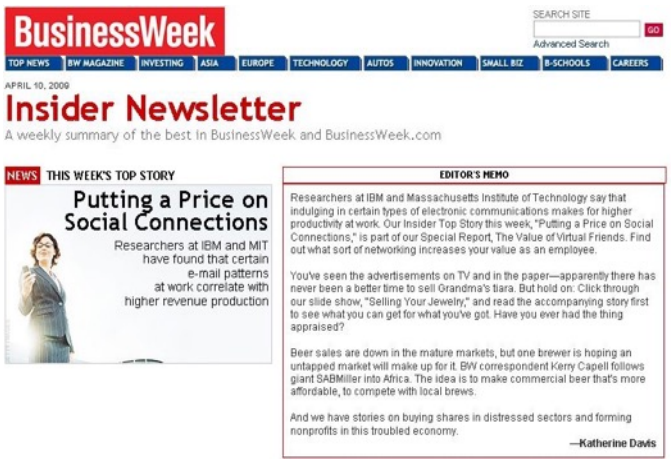


It can also show the evolution of my social network..

What types of unique colleagues my friend Chris can help me connect to?

Evolutionalry personal social network

Analyzing existing social networks of every employee That makes it possible to find the shortest path to any colleague..

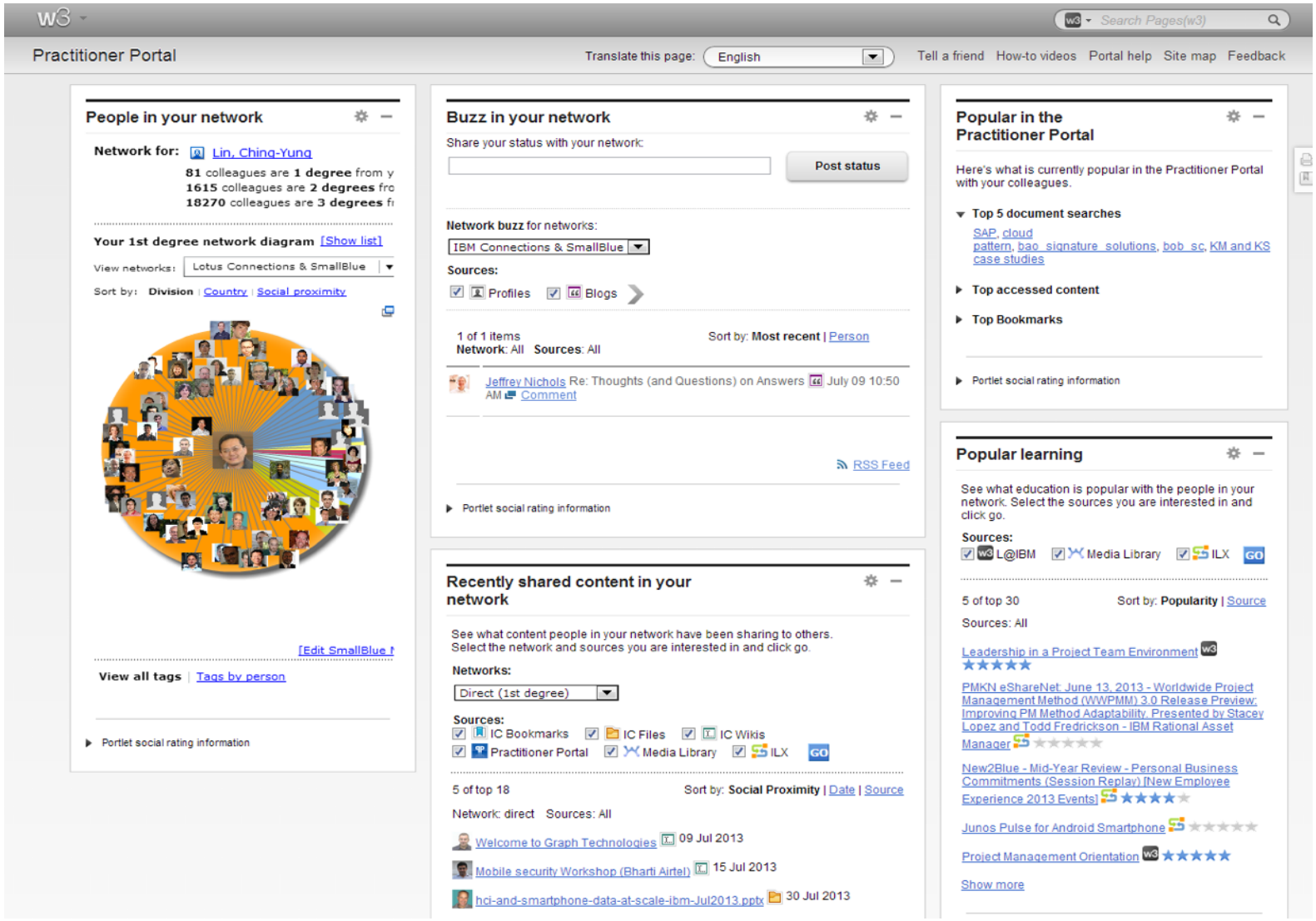


Productivity effect from network variables

- An additional person in network size ~ $986 revenue per year
- Each person that can be reached in 3 steps ~ $0.163 in revenue per month
- A link to manager ~ $1074 in revenue per month
- 1 standard deviation of network diversity (1 - constraint) ~ $758
- 1 standard deviation of btw ~ -$300K
- 1 strong link ~ $-7.9 per month

- Structural Diverse networks with abundance of structural holes are associated with higher performance.
  - *Having diverse friends helps.*
- Betweenness is negatively correlated to people but highly positive correlated to projects.
  - *Being a bridge between a lot of people is bottleneck.*
  - *Being a bridge of a lot of projects is good.*
- Network reach are highly corrected.
  - *The number of people reachable in 3 steps is positively correlated with higher performance.*
- Having too many strong links — the same set of people one communicates frequently is negatively correlated with performance.
  - *Perhaps frequent communication to the same person may imply redundant information exchange.*

Use Case 2: Recommendation



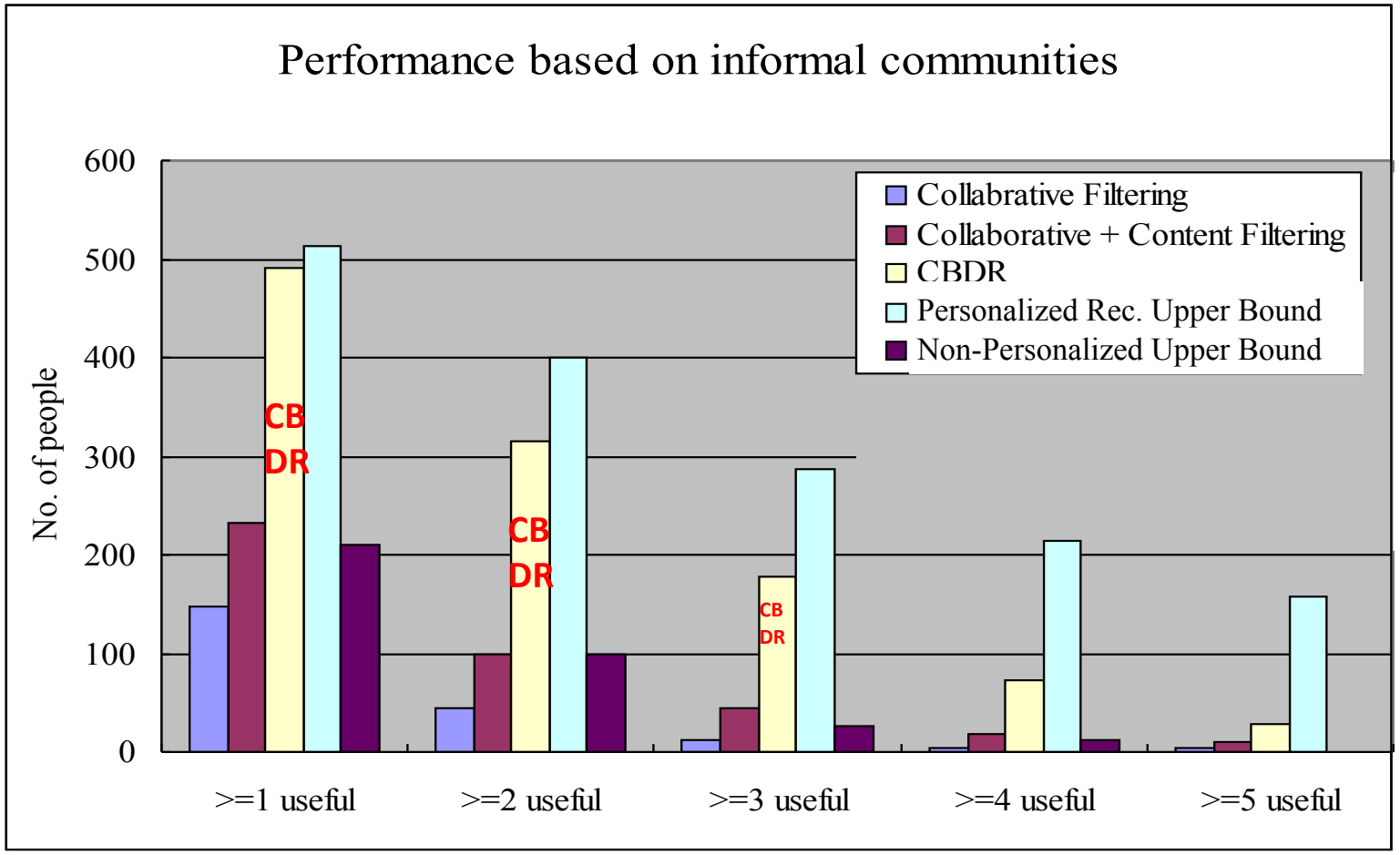
- Integrated Practitioner Portal, KnowledgeView, Media Library, Lotus Connections, and Learning@IBM and for a personalized ranking

Improving Recommendation Quality by Graph Community Analytics

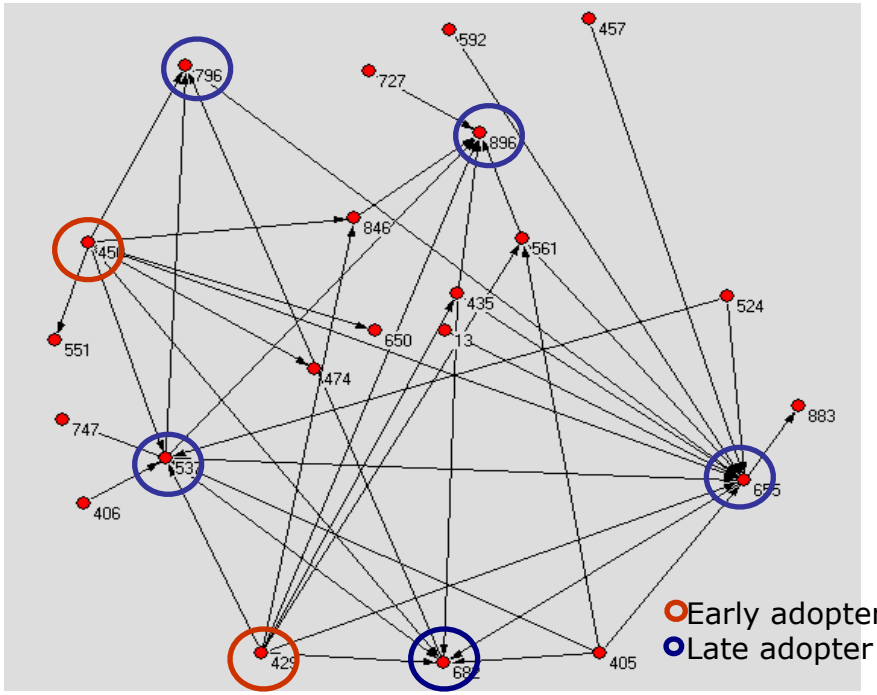
Graph Communities

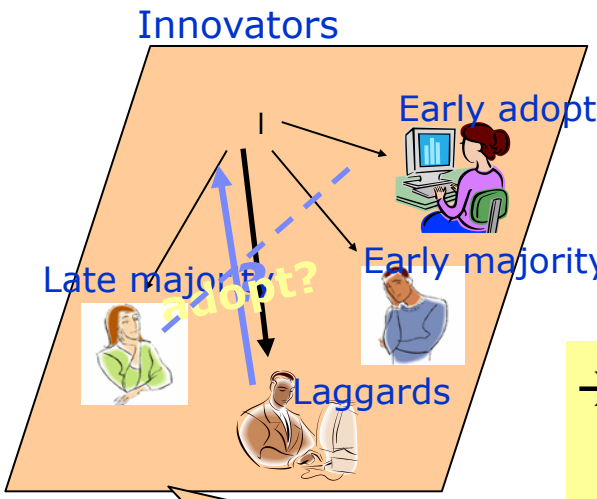
– A 3rd party Knowledge Repository: 30K users and 20K documents.
Study the most active 697 users who have at least 20 download in a year.

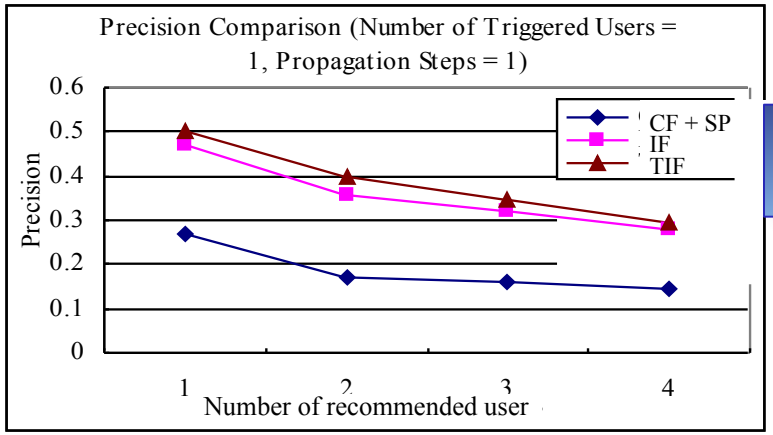
– Results: beyond Collaborative Filtering: (1) Collaborative + Content Filtering (53% improvement); (2) CBDR: Collaborative + Content Filtering + Graph Community Analytics (259% accuracy improvement over collaborative filtering)

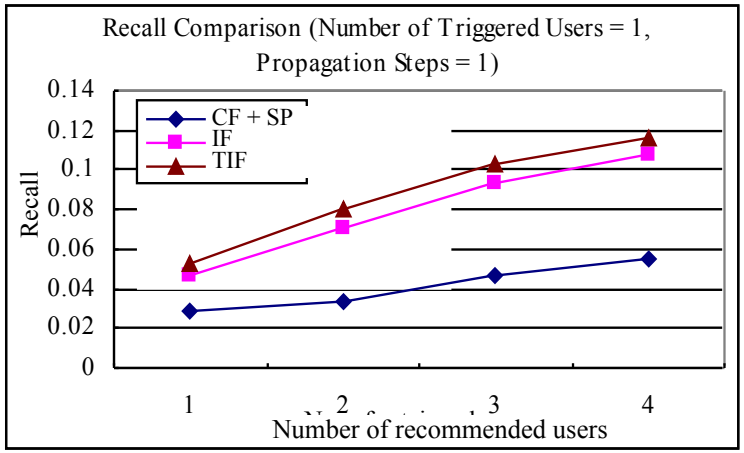


Use Case 3: Recommendation for Commerce









Network Info Flow

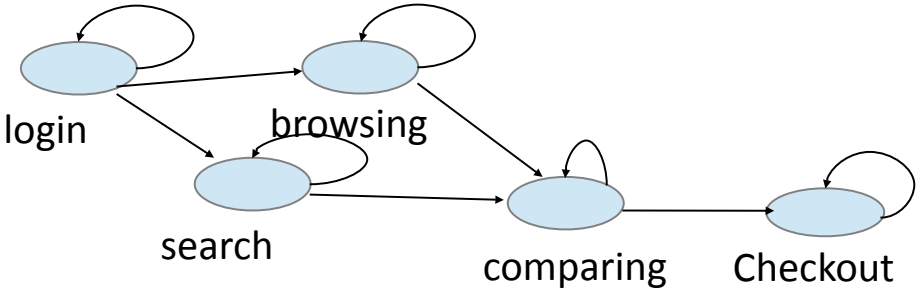
Tests:
– 1 month
– 586 new docs
– 1,170 users

IF: Graphical Information Flow Model
TIF: Joint Topic Detection + Information Flow Model

→ Comparing to Collaborative Filtering (CF) + Similar People
Precision: IF is 91% better, TIF is 108% better
Recall: IF is 87% better, TIF is 113% better

Customer Behavior Sequence Analytics

Markov Network | Latent Network | Bayesian Network

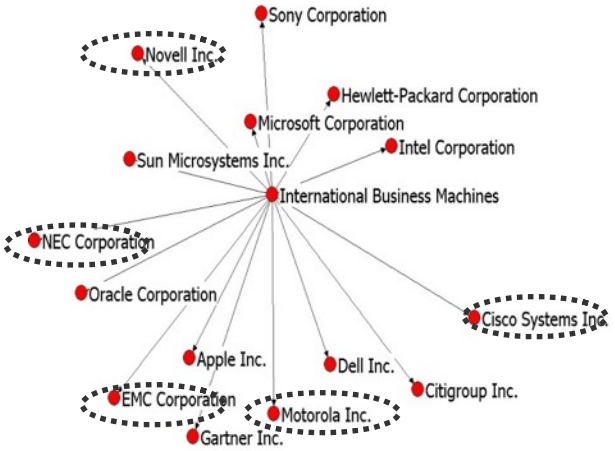


- Behavior Pattern Detection
- Help Needed Detection

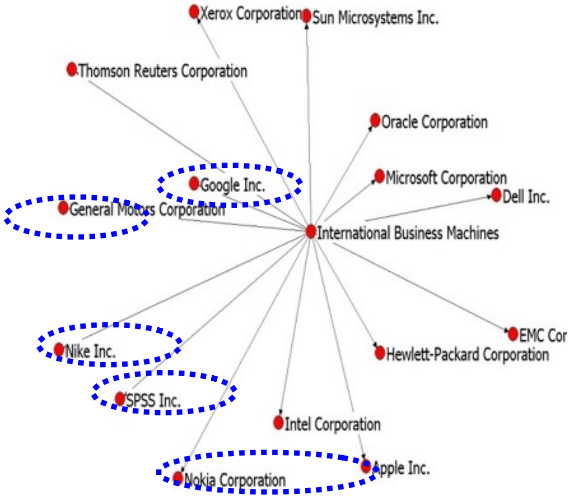
Use Case 4: Graph Analytics for Financial Analysis

Goal: *Injecting Network Graph Effects for Financial Analysis. Estimating company performance considering correlated companies, network properties and evolutions, causal parameter analysis, etc.*

- IBM 2003



- IBM 2009

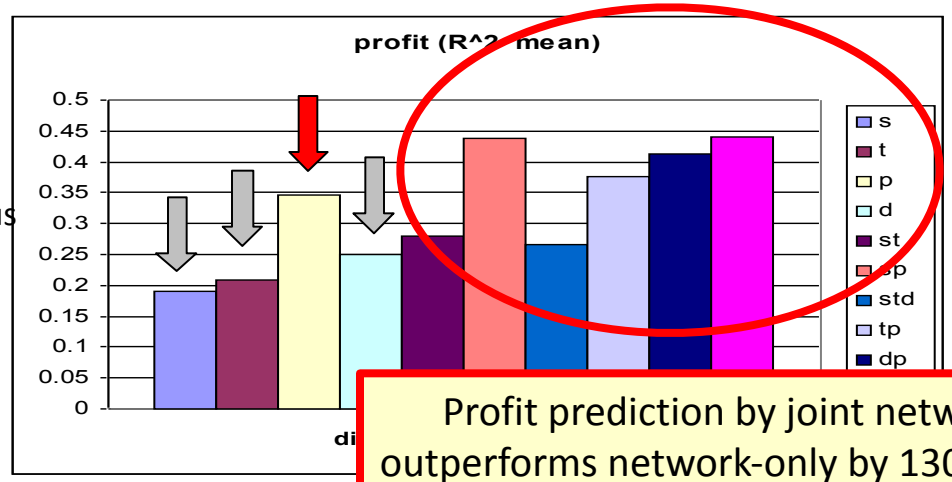


- Data Source:
  - Relationships among 7594 companies, data mining from NYT 1981 ~ 2009

Targets: 20 Fortune companies' normalized Profits

Goal: Learn from previous 5 years, and predict next year

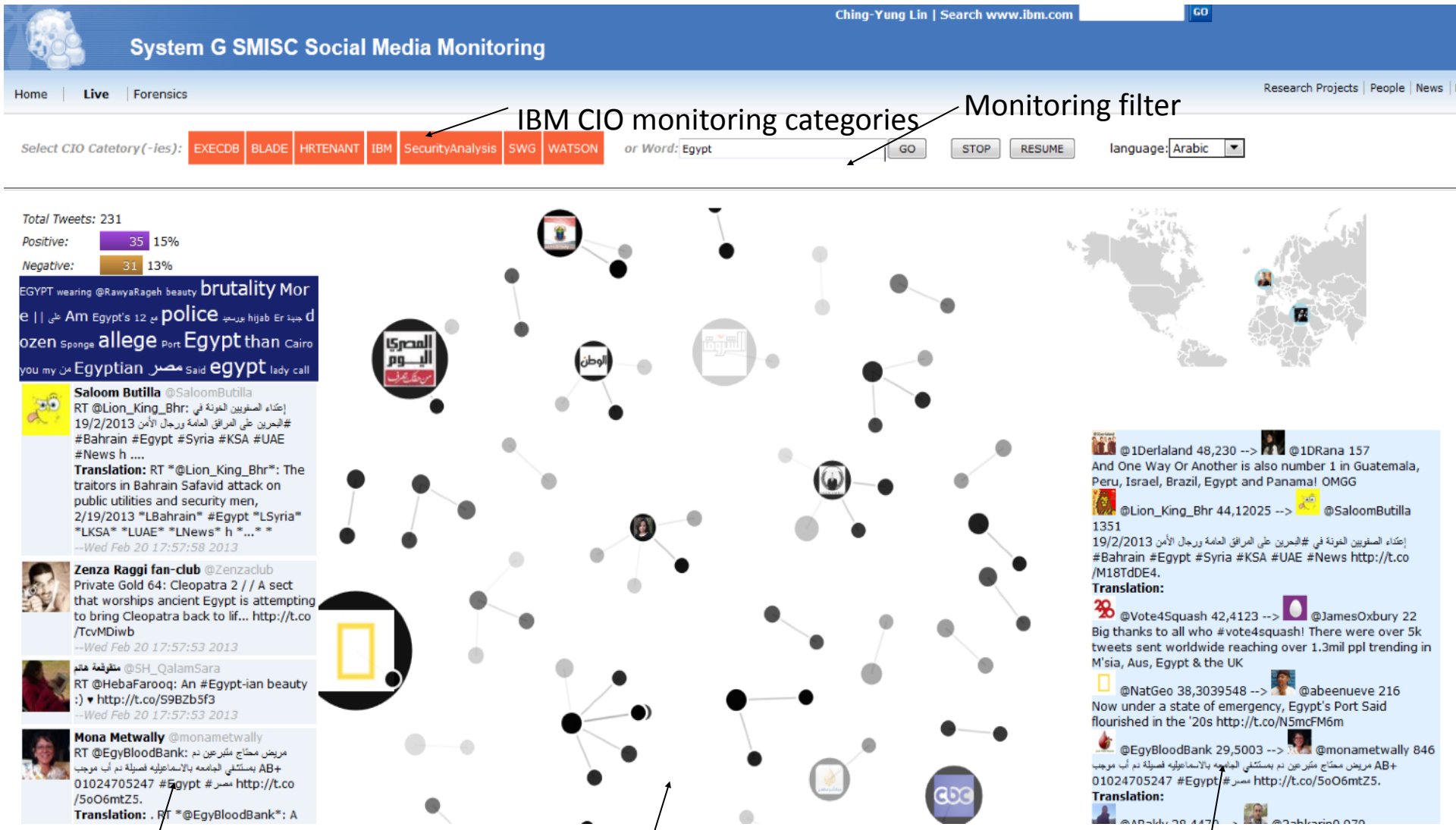
Model: Support Vector Regression (RBF kernel)



Network feature:
s (current year network feature),
t (temporal network feature),
d (delta value of network feature)
Financial feature:
p (historical profits and revenues)

Profit prediction by joint network and financial analysis outperforms network-only by 130% and financial-only by 33%.

Use Case 5: Social Media Monitoring



IBM System G Social Media Solution Research Tasks

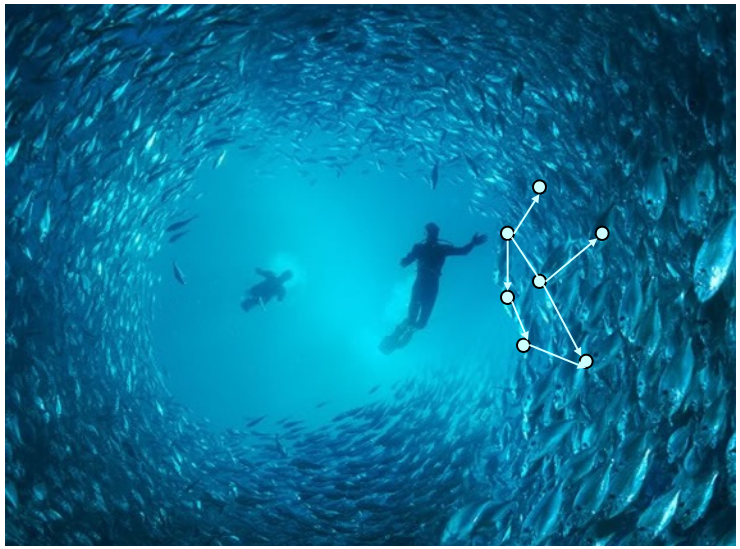
Thrust 1. Modeling Information Dissemination:
Task 1.1. Computational Modeling of User Dynamic Behavior
Task 1.2. Computational Models of Trust and Social Capital
Task 1.3. Information Morphing Modeling
Task 1.4. Persuasiveness of Memes
Task 1.5. The Observability of Social Systems
Task 1.6. Culture-Dependent Social Media Modeling
Task 1.7. Dynamics of Influence in Social Networks
Task 1.8. Understanding the Optimal Immunization Policy
Task 1.9. Modeling and Identification of Campaign Target Audience
Task 1.10. Modeling and Predicting Competing Memes

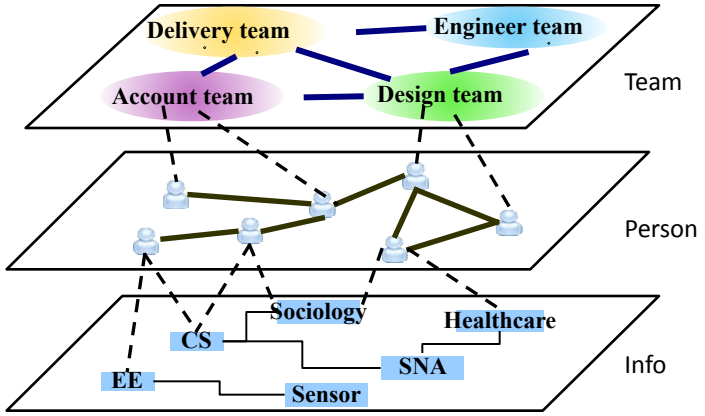
Thrust 2. Detecting and Tracking Information Dissemination:
Task 2.1. Real-Time and Large-Scale Social Media Mining
Task 2.2. Role and Function Discovery
Task 2.3. Detecting Malicious Users and Malware Propagation
Task 2.4. Emergent Topic Detection and Tracking
Task 2.5. Detecting Evolution History and Authenticity of Multimedia Memes
Task 2.6. Synchronistic Social Media Information and Social Proof Opinion Mining
Task 2.7. Community Detection and Tracking
Task 2.8. Interplay Across Multiple-Networks
Task 2.9: Assessing Affective Impact of Multi-Modal Social Media

Thrust 3. Affecting Information Dissemination:
Task 3.1. Crowd-sourcing Evidence Gathering to Formulate Counter-messaging Objectives
Task 3.2. Delivery and Evaluation of a Counter-messaging Campaign
Task 3.3. Optimal Target People Selection
Task 3.4. Automated Generation of Counter Messaging
Task 3.5. User Interfaces for Semi-Automatic Counter Messaging
Task 3.6. Controlling the Dynamics of Influence in Social Networks
Task 3.7. Influencing the Outcome of Competing Memes and Counter Messaging

Columbia University

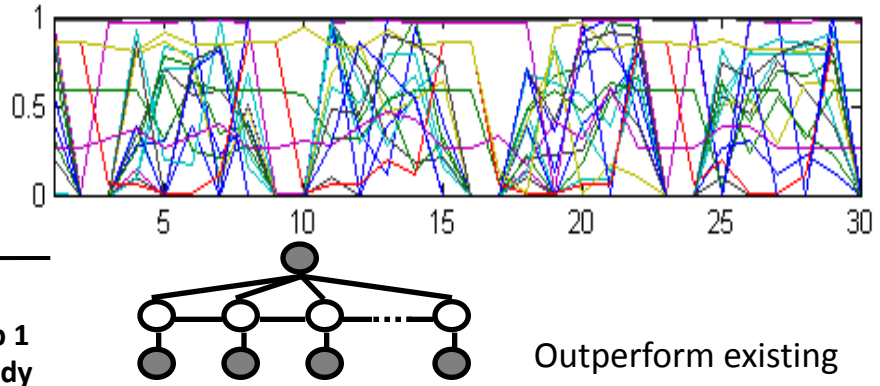
Heterogeneous Synchronicity Networks Predict Performance





Outperform existing approaches by up to 18% (SDM 13)

One-class HCRF to detect temporal anomalies



Detected as top 1 anomaly in Sandy Tweets

Outperform existing approaches by up to 180% (IJCAI 13)

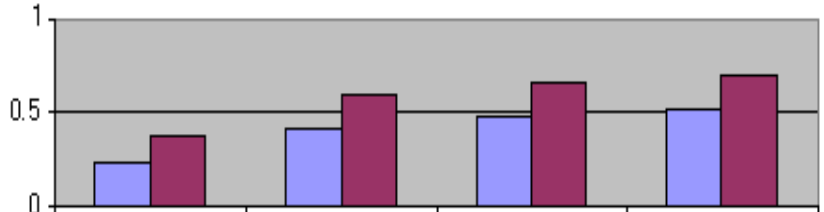
- **Motivation:**
  - –Info morph: new links keep emerging to give new meaning to existing phrases
- **Approach:**
  - –Compare characteristics of meta-paths between nodes in heterogeneous networks

Peace West King from ***Chongqing fell from power***, still need to ***sing red songs***?

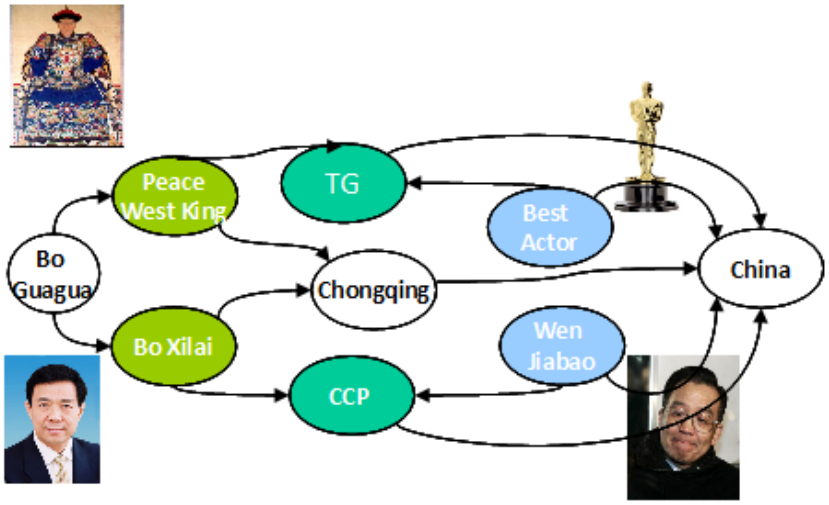
- ***Bo Xilai*** led ***Chongqing*** city leaders and 40 district and county party and government leaders to ***sing red songs***.

Entity morph resolution accuracy

(ACL 2013)



	Acc@1	Acc@5	Acc@10	Acc@20
NLP	0.234	0.416	0.477	0.519
NLP+Graph	0.379	0.594	0.659	0.701



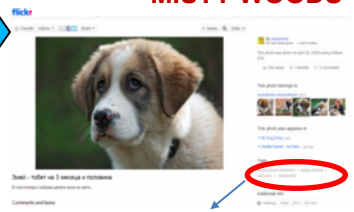
$$\sum_{i=1}^{N} p_m(x_i) \log \frac{p_m(x_i)}{p_e(x_i)} + p_e(x_i) \log \frac{p_e(x_i)}{p_m(x_i)}$$

Visual Sentiment and Semantic Analysis

COLUMBIA UNIVERSITY

First work in the literature on automatic visual sentiment analysis

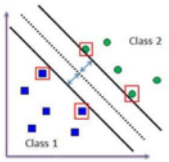
***"For content to go viral, it needs to be emotional,"* Dan Jones, 2012**



Training from 6 million tags

Select Adj-Noun Pairs

Build Sentiment Ontology



Train Classifiers

Performance Filtering

SentiBank (1200 Detectors)

Sentiment Prediction

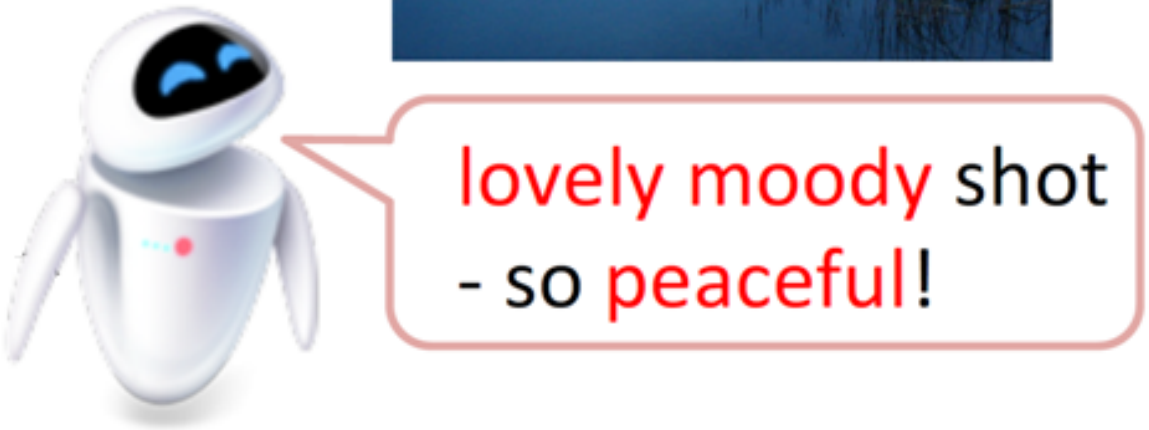
Detection results of "lonely dog" (80% accuracy, 4 out of 5 correct)

Detection results of "crazy car" (100% accuracy, 5 out of 5 correct)

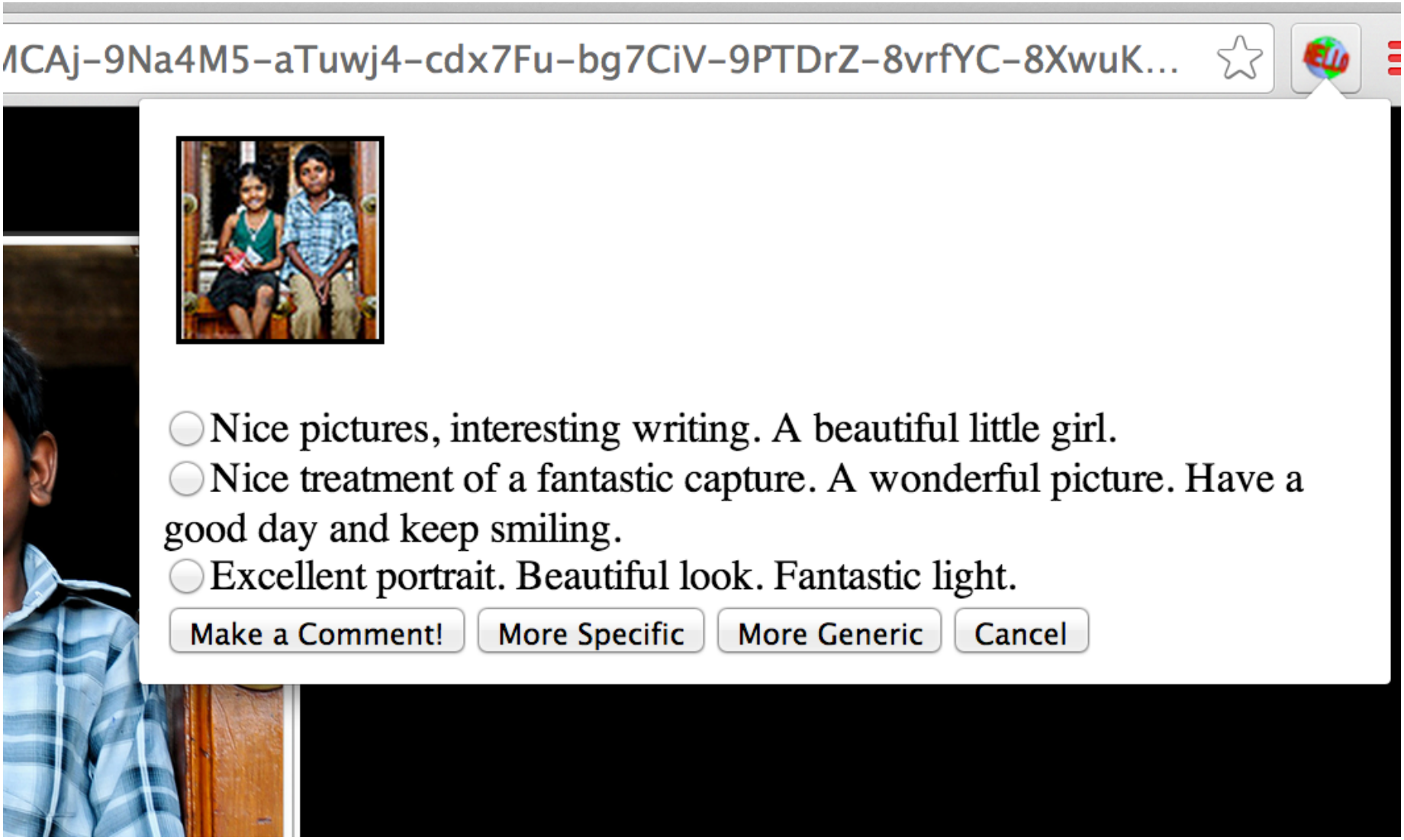
Experiment on Sentiment Detection Accuracy on Twitter

Text	0.43
Visual	0.70
T+V	0.72

Cognitive Feeling Detection on Images



Automatic Comments on Images



Measuring Human Essential Traits in Social Media

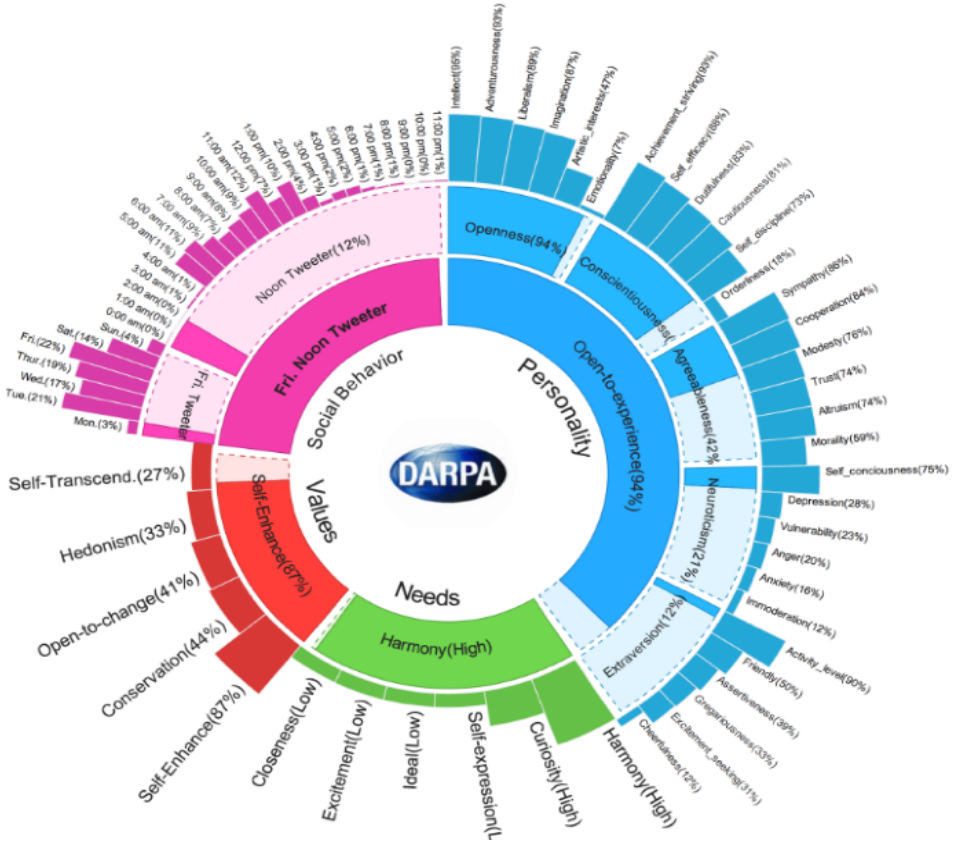
– **Personality:** Mapping personal/organizational social media postings to scores of BIG 5 Personality (*Openness, Conscientiousness, Extraversion, Agreeableness, and Neurocism*)

– **Needs:** Mapping personal/organizational social media postings to scores of *Harmony, Curiousity, Self-expression, Ideal, Excitement, and Closeness*.

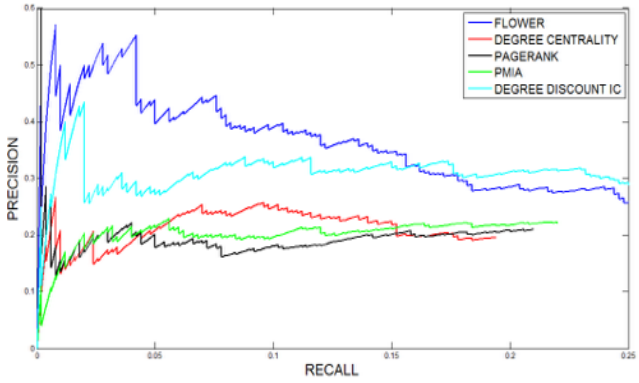
– **Values:** Mapping personal/organizational social media postings to scores of *Self-Enhance. Conservation, Open-to-Change, Hedonism, and Self-Transcend*.

– **Trustingness and Trustworthness:** Deriving from *interaction and propagation* history between the user and his followers and the people he follows.

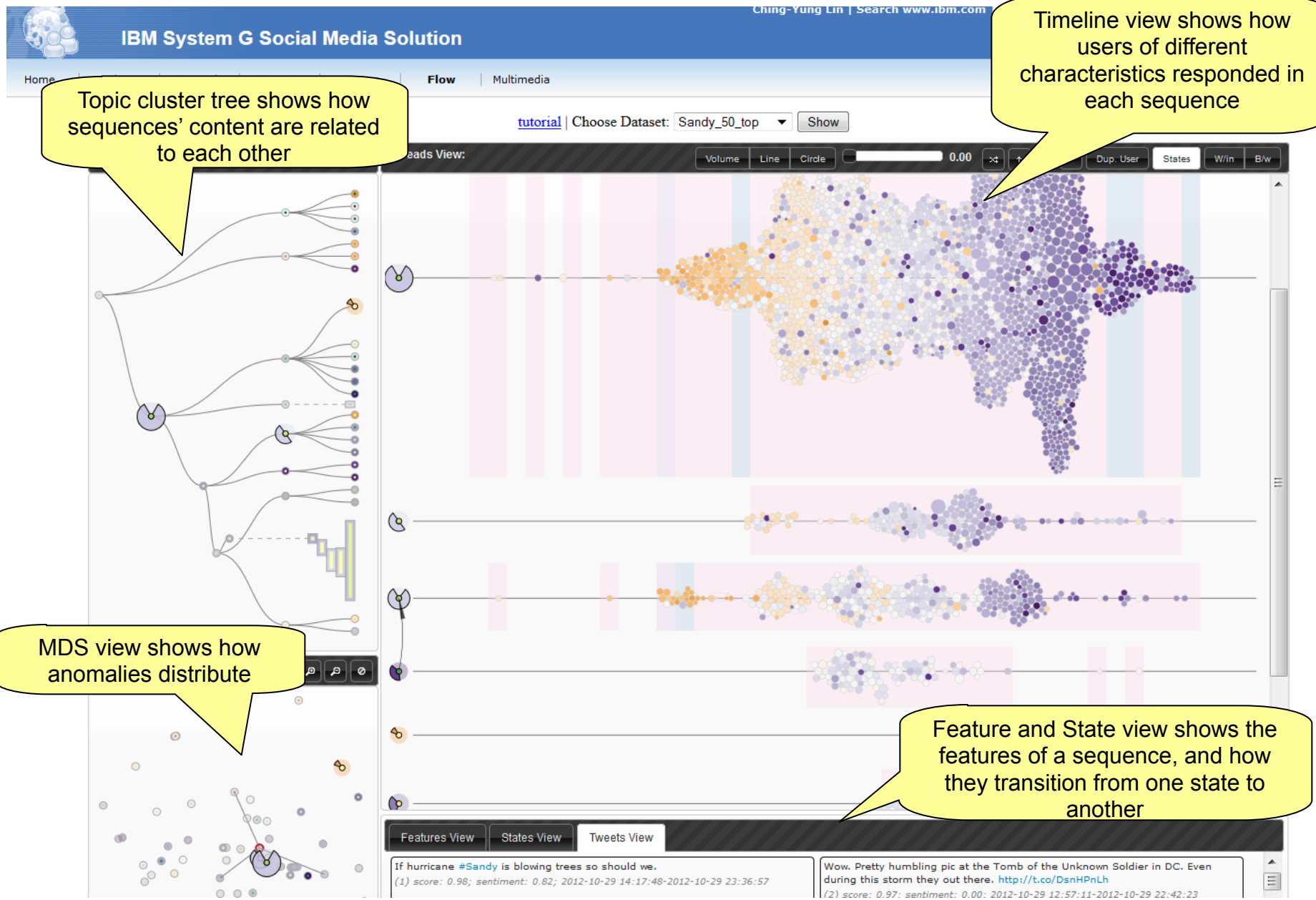
– **Influence:** Total *attention* received by user as leader across all discovered flows.



Precision-Recall performance of predicting info propagation by different features
(Our proposed influence index: FLOWER)



Flow Analytics - I



Topic cluster tree shows how sequences' content are related to each other

Timeline view shows how users of different characteristics responded in each sequence

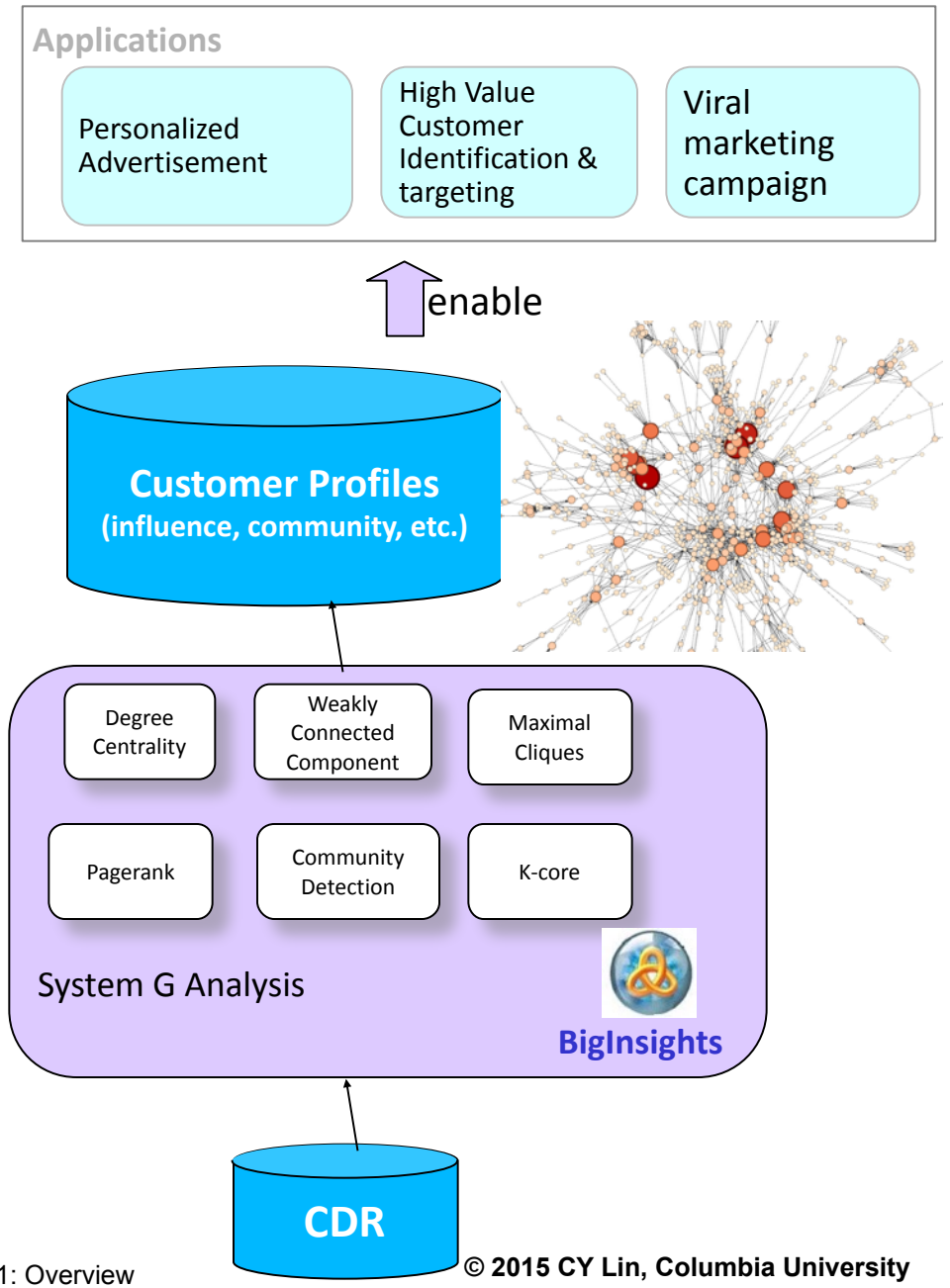
MDS view shows how anomalies distribute

Feature and State view shows the features of a sequence, and how they transition from one state to another

Use Case 6: Customer Social Analysis for Telco

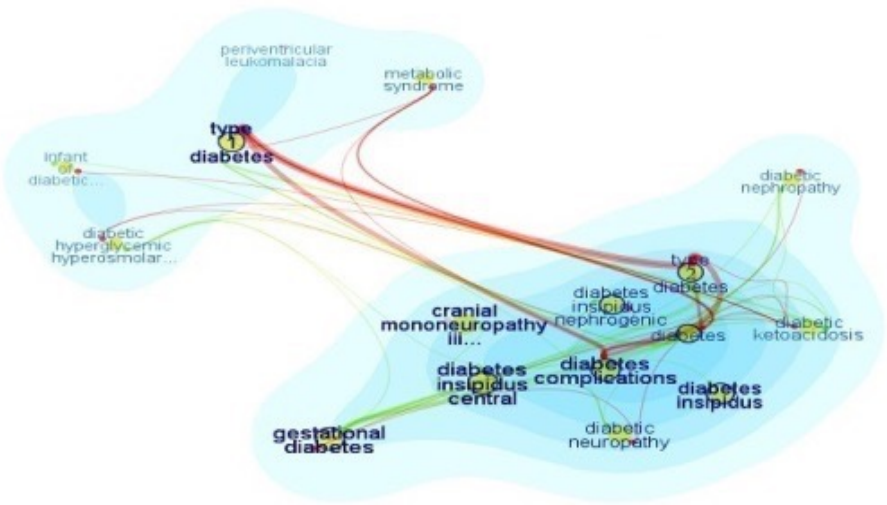
Goal: Extract customer social network behaviors to enable Call Detail Records (CDRs) data monetization for Telco.

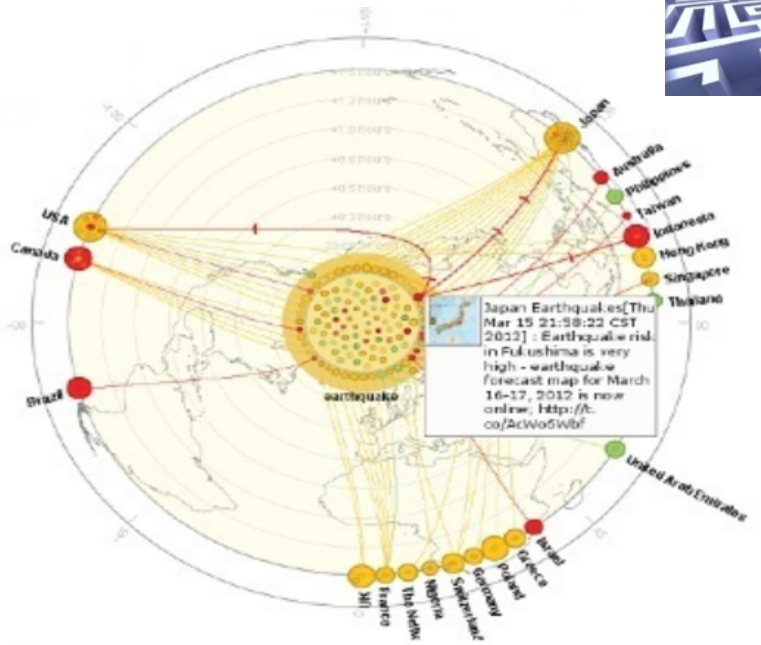
- Applications based on the extracted social profiles
  - Personalized advertisement (beyond the scope of traditional campaign in Telco)
  - High value customer identification and targeting
  - Viral marketing campaign
- Approach
  - Construct social graphs from CDRs based on {caller, callee, call time, call duration}
  - Extract customer social features (e.g. influence, communities, etc.) from the constructed social graph as customer social profiles
  - Build analytics applications (e.g. personalized advertisement) based on the extracted customer social profiles



PoCs with Chinese and Indian Telecomm companies

Category 2: Data Exploration





Enhancing:

Vivisimo

CÚRAM SOFTWARE

Huge Network Visualization | Network Propagation | I2 3D Network Visualization | Geo Network Visualization | Graphical Model Visualization

Communities | Graph Search | Network Info Flow | Bayesian Networks

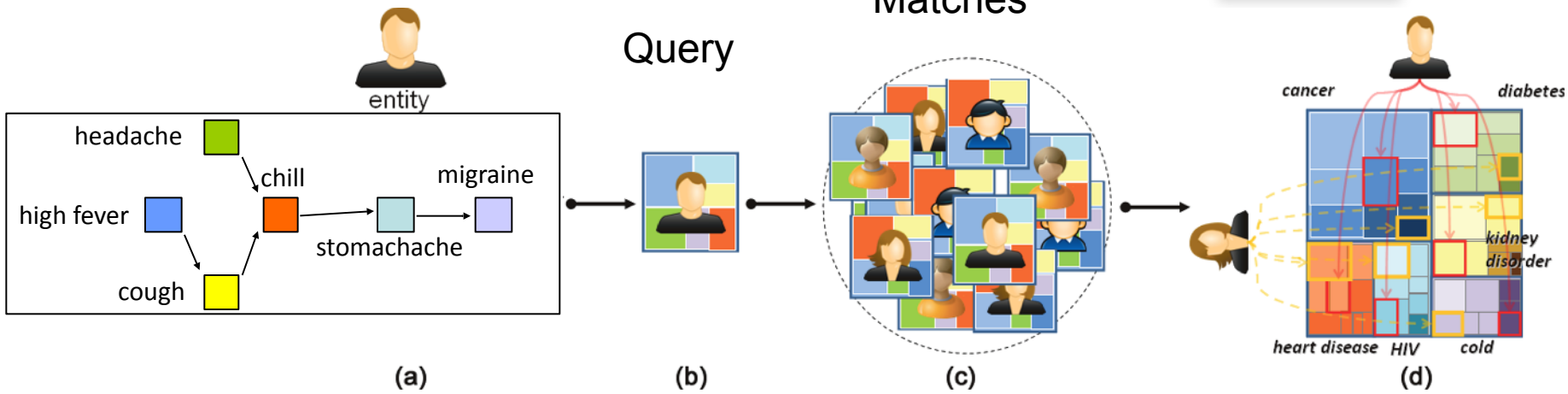
Centralities | Graph Query | Shortest Paths | Latent Net Inference

Ego Net Features | Graph Matching | Graph Sampling | Markov Networks

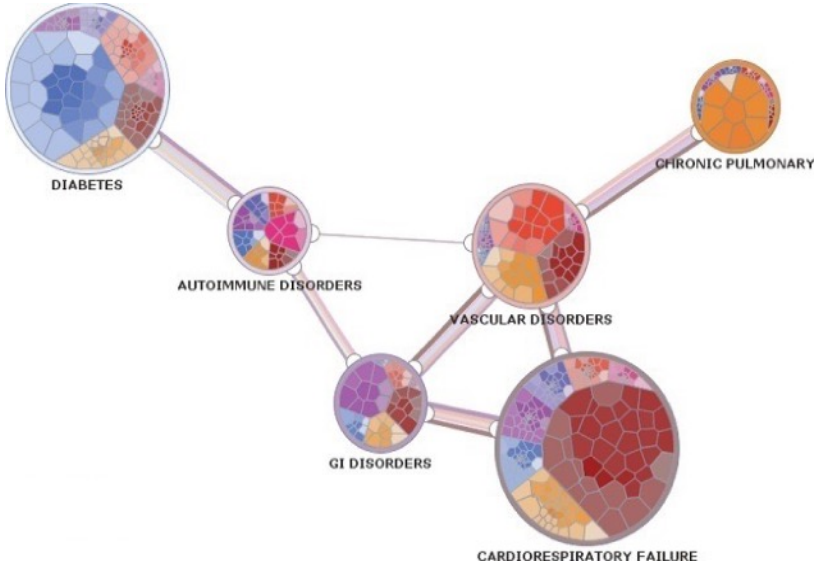
Middleware and Database

Use Case 7: Graph Analytics and Visualization for Watson

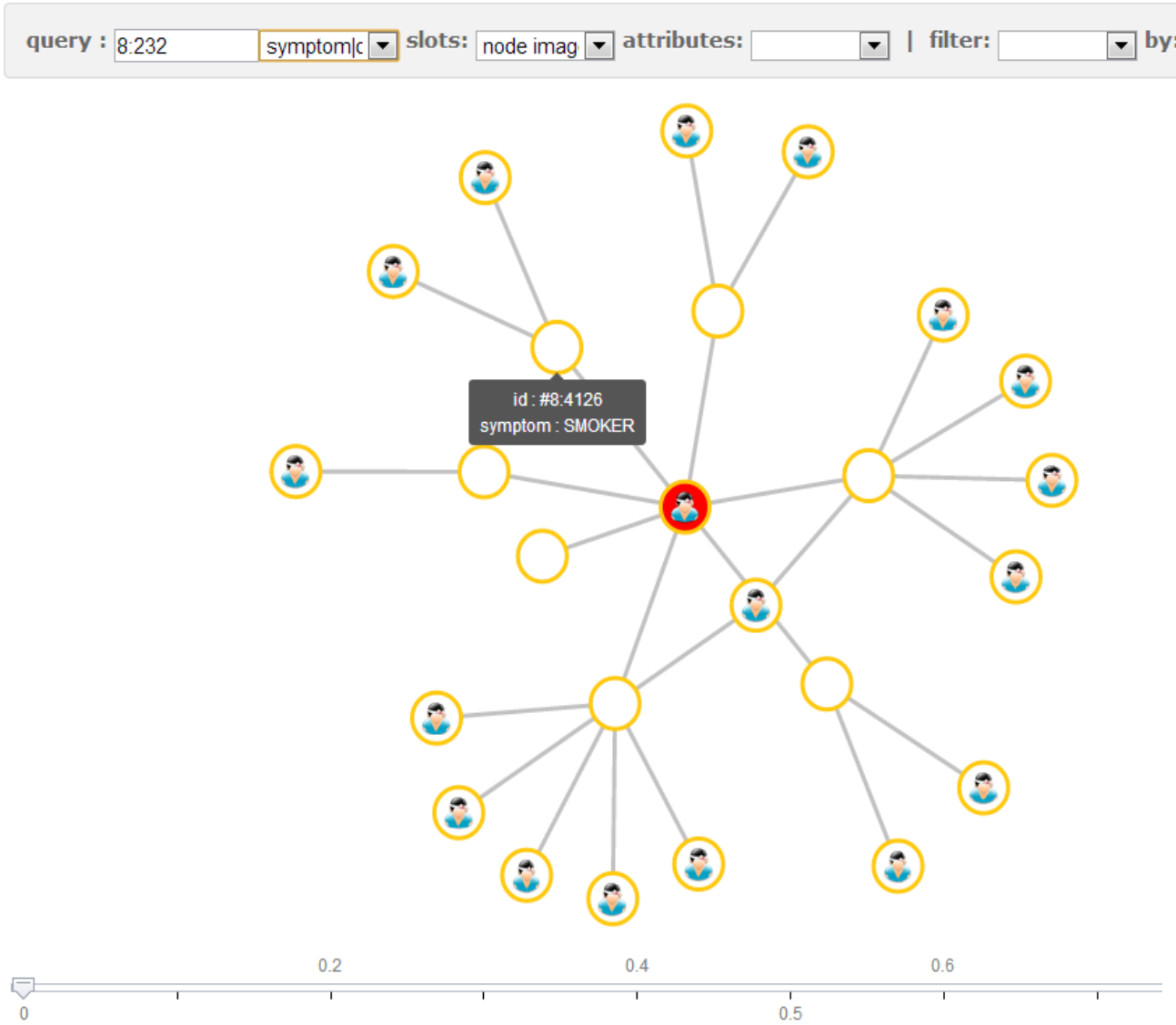
Graph Matching

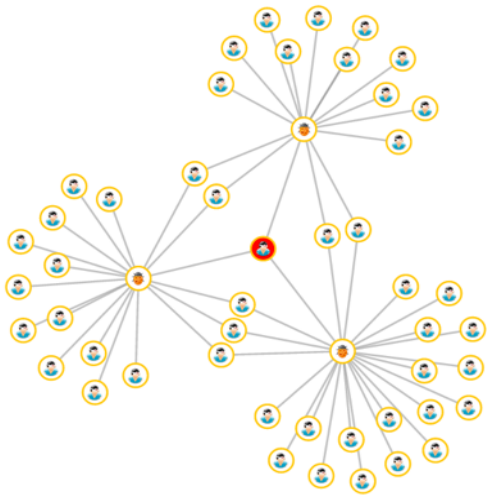


Graph Communities



Graph Analytics for Watson

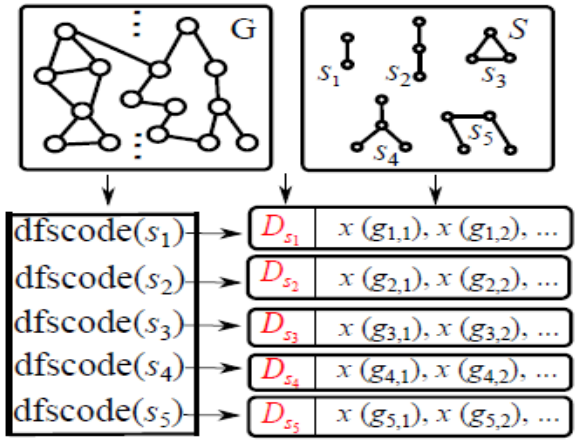




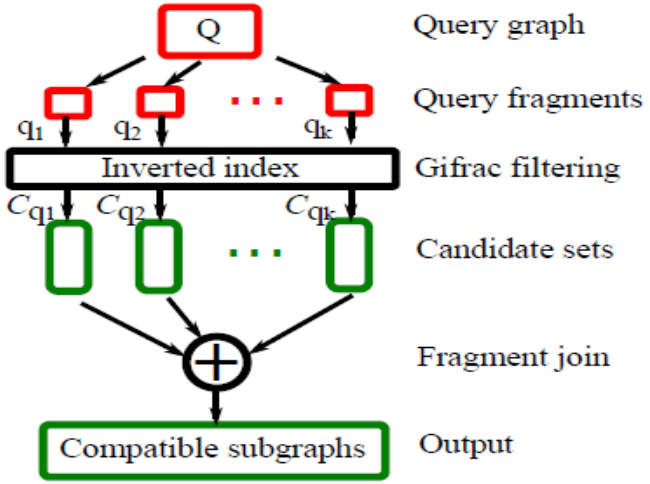
Fast Graph Matching Algorithm

- Data: (CAIDA) 26.5K nodes and 106.8K edges
- Index construction: 13-20 times faster than the prior state-of-the-art
- Query time: close to UpdAll (upper bound) and ~8x faster than UpdNo and NaiveGrid

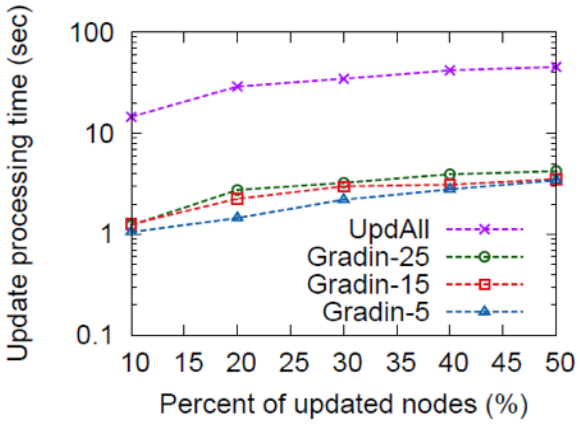
Graph Matching



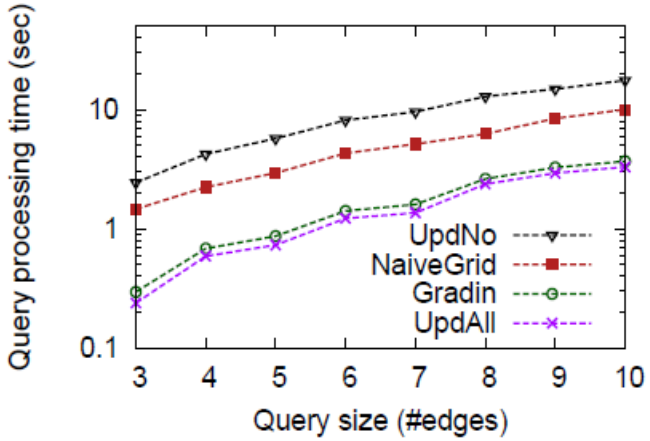
(a) Offline index building



(b) Online query processing

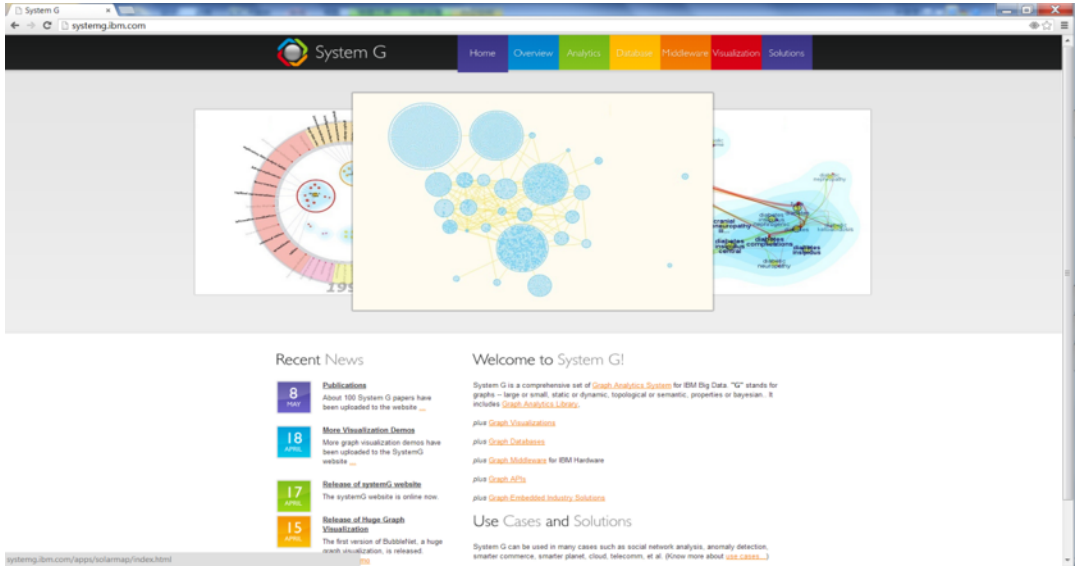


Indexing time

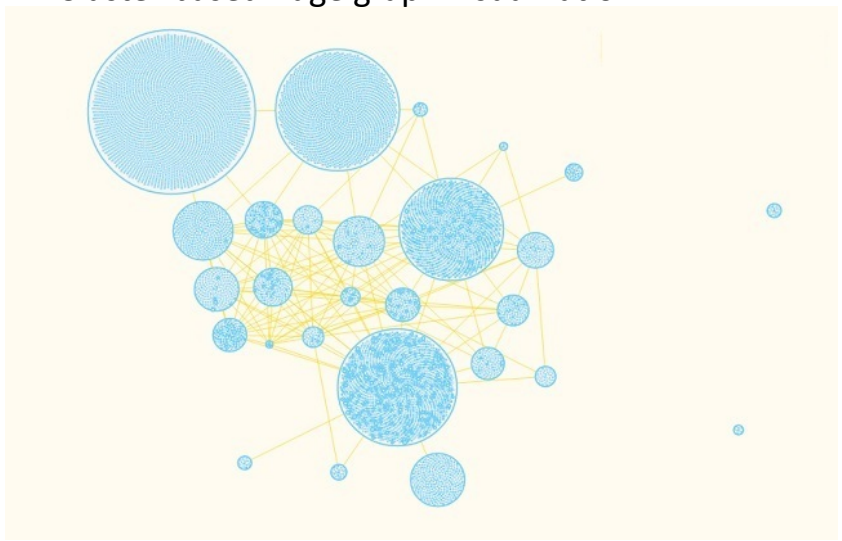


Query processing time

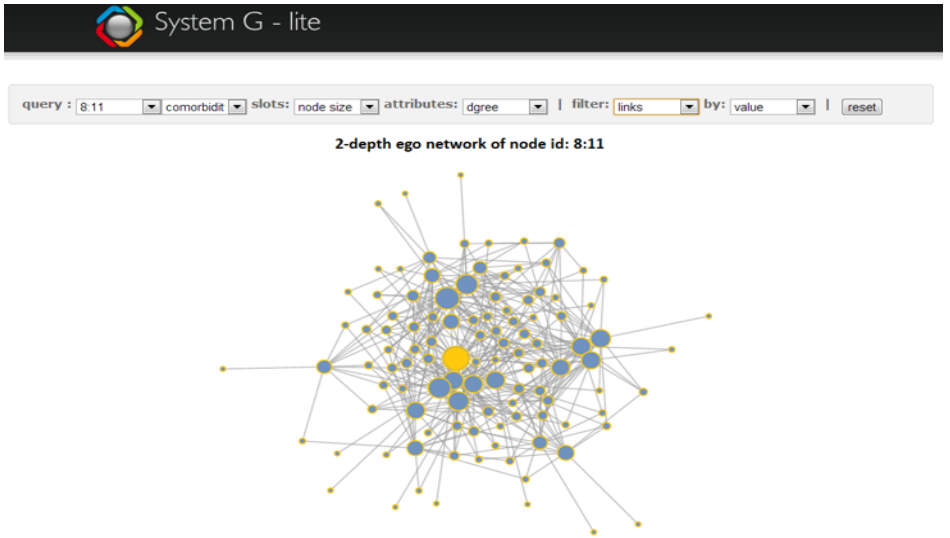
User Case 8: Visualization for Navigation and Exploration



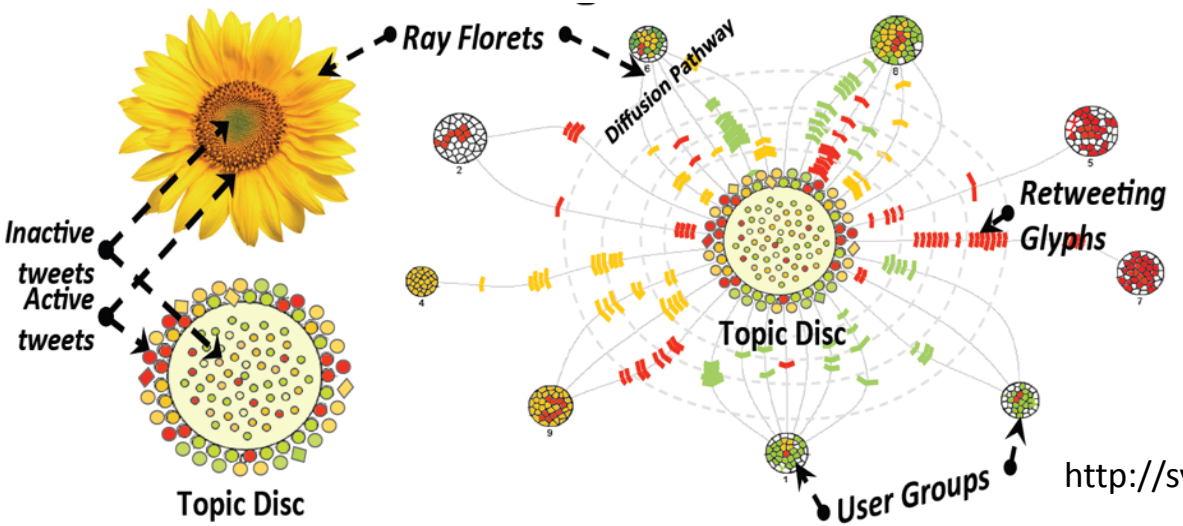
Cluster based huge graph visualization



Query based huge graph visualization



Visualizing Information Diffusion and Divergence

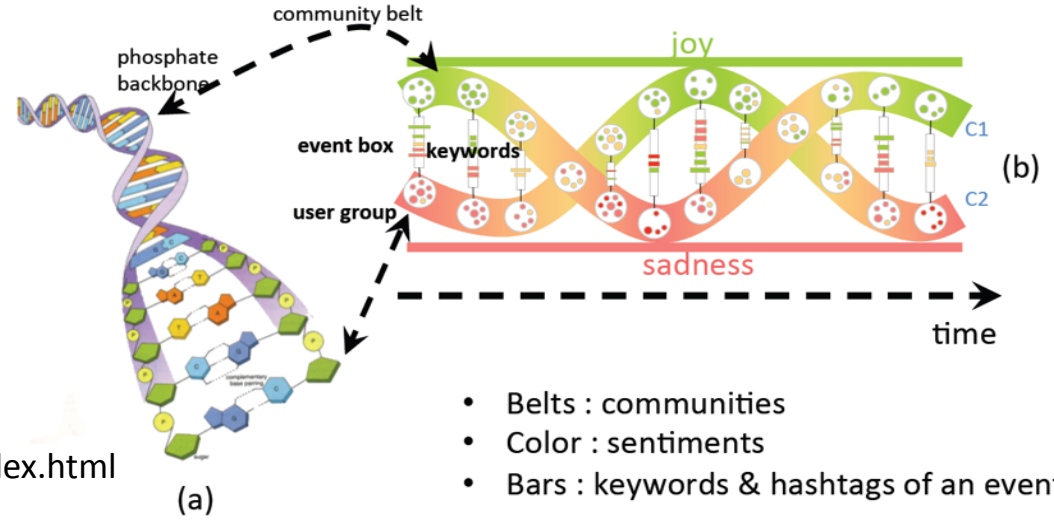


Whisper : Tracing the information diffusion in Social Media

http://systemg.ibm.com/apps/whisper/index.html

SocialHelix: Visualizaiton of Sentiment Divergence in Social Media

http://systemg.ibm.com/apps/socialhelix/index.html

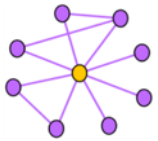


Use Case 9: Graph Search

Graph Search

existing search engine

query



Info-Socio networks

index

ranking

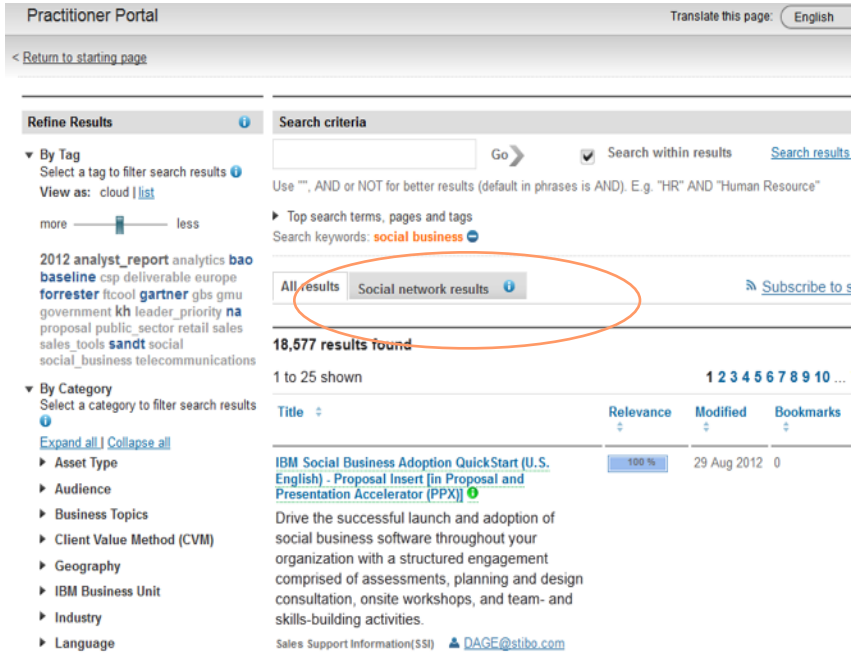
re-ranking

Improved search results

Interest / social network based content recommendations

Graph analysis

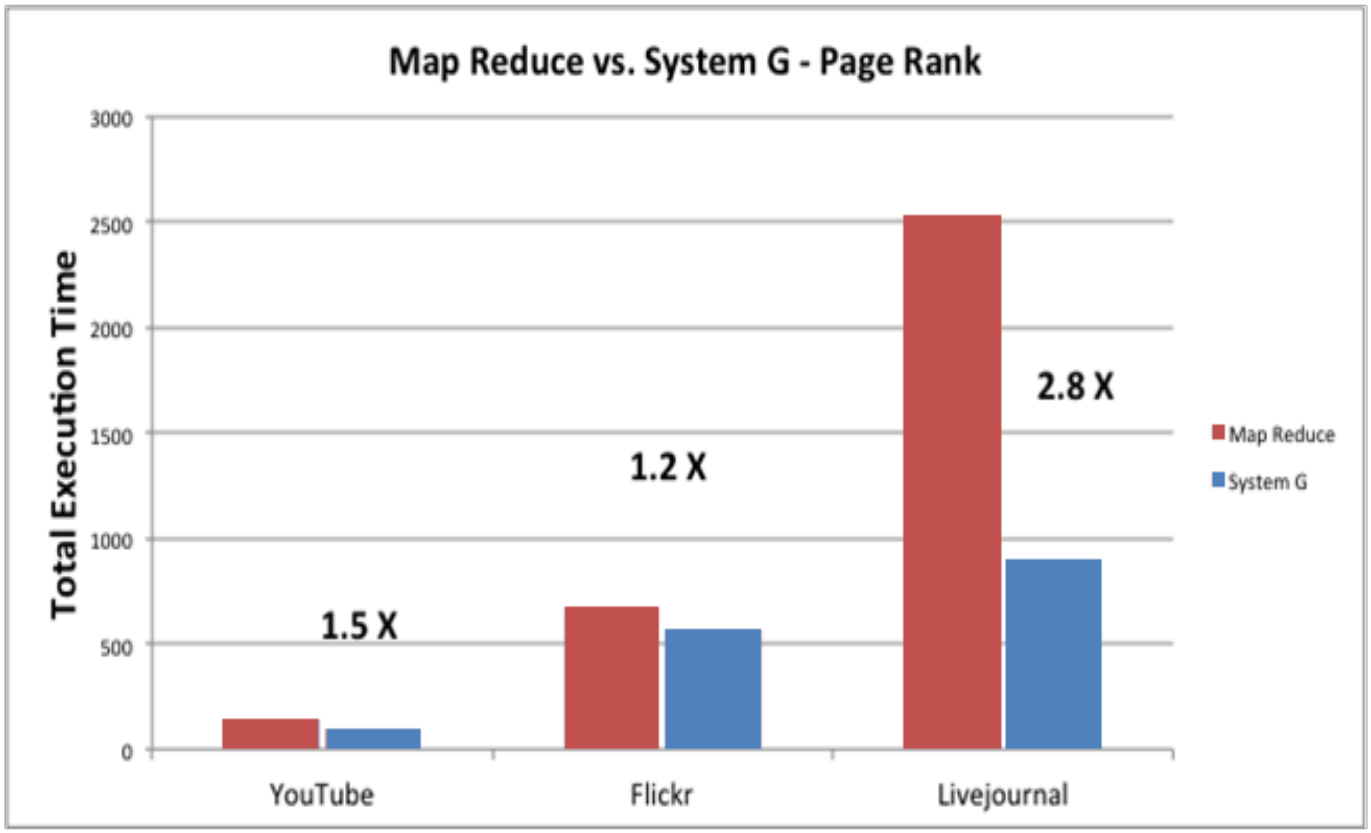
query context



Graph DB and Analytics Co-Processing

Centrailities

- Improving Offline Search Indexing speed



YouTube: 6M Edges
Flickr: 24M Edges
LiveJournal: 72M Edges

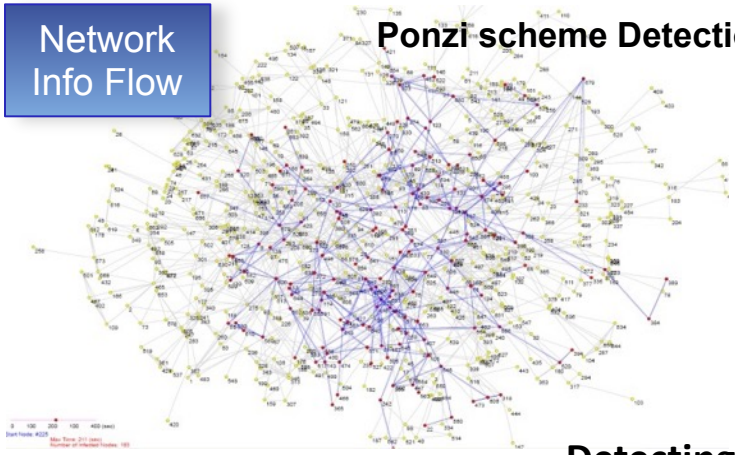
System G MapReduce

Execution Time in seconds.

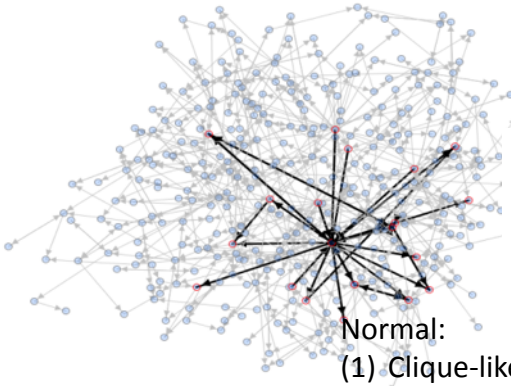
Category 3: Security

Network Info Flow

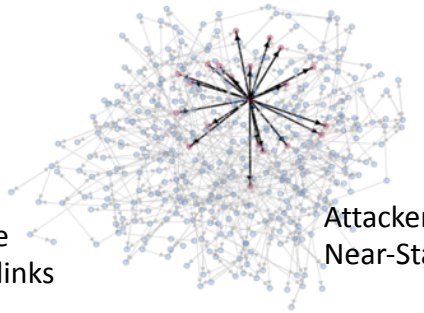
Ponzi scheme Detection



Ego Net Features

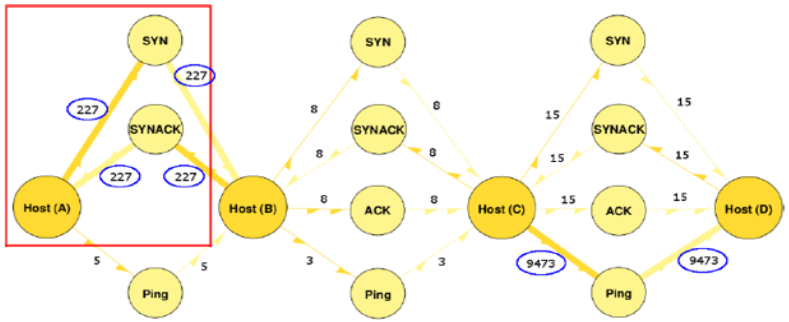


Normal:
(1) Clique-like
(2) Two-way links

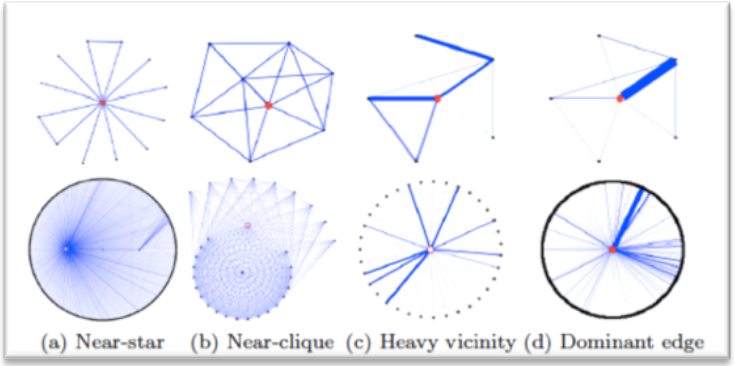


Attacker:
Near-Star

Detecting DoS attack



(a) Single large graph representing TCP SYN and ICMP PING network traffic, with two Denial of Service (DoS) attacks taking place.



(a) Near-star (b) Near-clique (c) Heavy vicinity (d) Dominant edge

Graph Visualizations

Communities	Graph Search	Network Info Flow	Bayesian Networks
Centralities	Graph Query	Shortest Paths	Latent Net Inference
Ego Net Features	Graph Matching	Graph Sampling	Markov Networks

Middleware and Database

Use Case 10: Anomaly Detection at Multiple Scales

Based on President Executive Order 13587

Goal: System for Detecting and Predicting Abnormal Behaviors in Organization, through large-scale social network & cognitive analytics and data mining, to decrease insider threats such as espionage, sabotage, colleague-shooting, suicide, etc.

"Enterprise Information Leakage Impacted economy and jobs" Feb 2013

"What's emerged is a multibillion dollar detective industry"
npr Jan 10, 2013

Emails
Instant Messaging
Web Access
Executed Processes
Printing
Copying
Log On/Off

→ **Social sensors** | **Click streams capturer** | **Feed subscription** | **Database access**

→ ***Graph analysis*** | ***Behavior analysis*** | ***Semantics analysis*** | ***Psychological analysis***

→ Multimodality Analysis → Detection, Prediction & Exploration Interface

Infrastructure + ~ 70 Analytics

Story – Espionage Example

(1)Personal stress:

(1)Gender identity confusion

(2)Family change (termination of a stable relationship)

(2)Job stress:

– Dissatisfaction with work

- Job roles and location (sent to Iraq)
- long work hours (14/7)

(1)Unstable Mental Status:

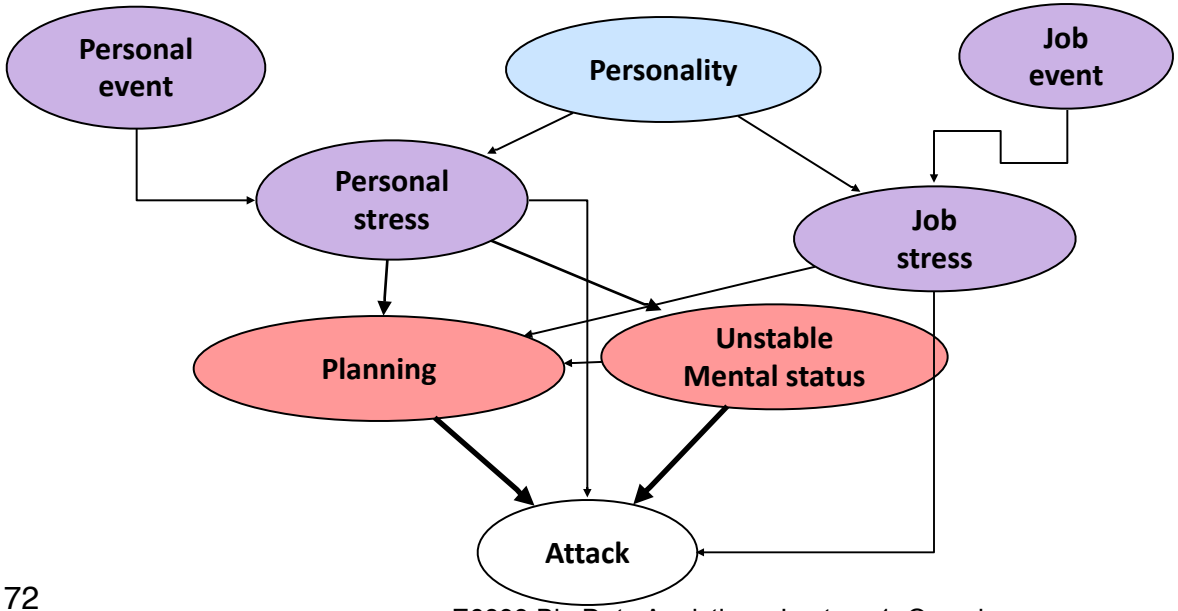
(1)Fight with colleagues, write complaining emails to colleagues

(2)Emotional collapse in workspace (crying, violence against objects)

(3)Large number of unhappy Facebook posts (work-related and emotional)

(2)Planning:

– Online chat with a hacker confiding his first attempt of leaking the information

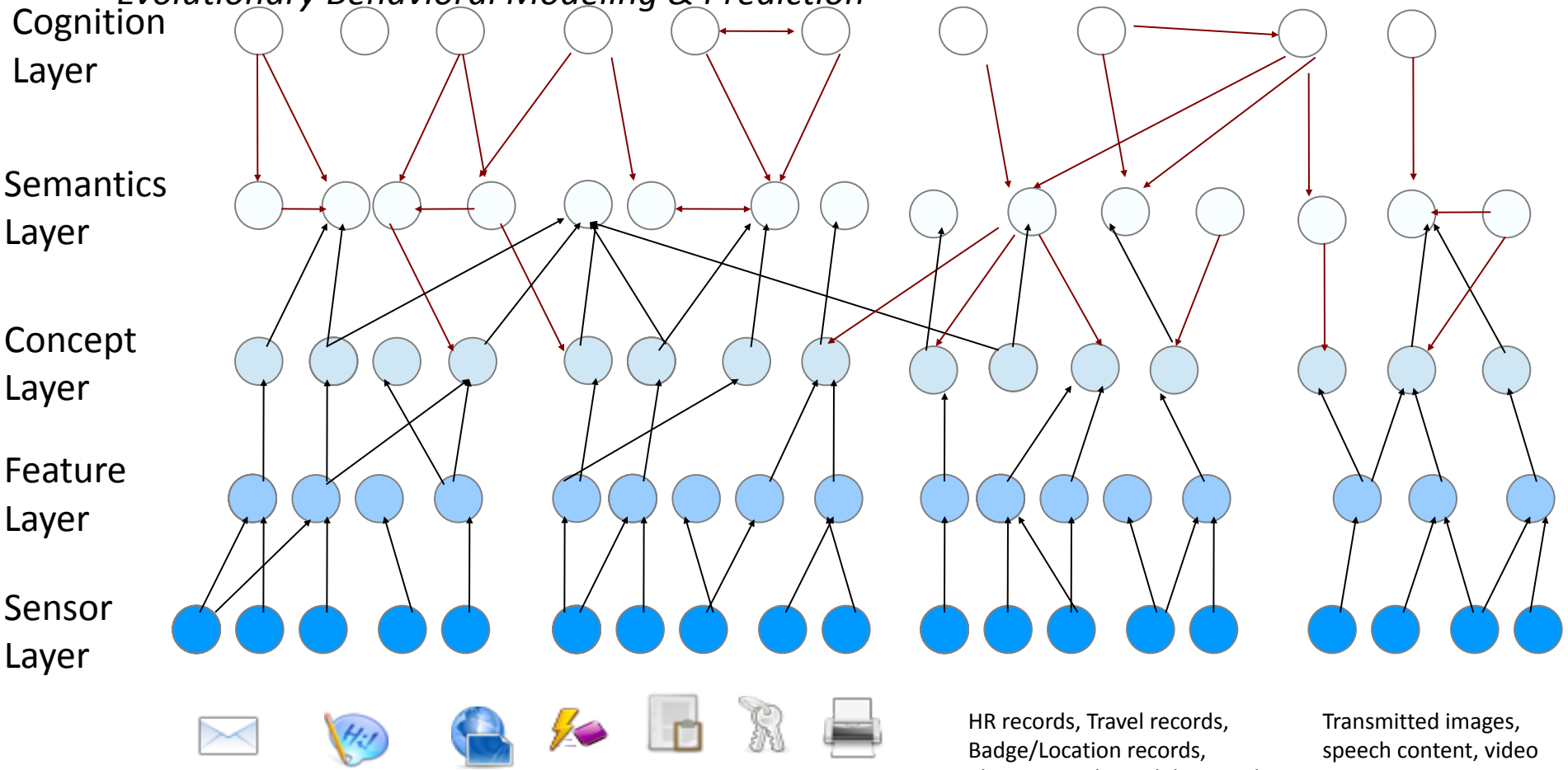


(1) Attack:

– Brought music CD to work and downloaded/ copied documents onto it with his own account

Multi-Modality Multi-Layer Understanding of Human

- *Mapping Espionage, Sabotage, and Fraud Use Cases into Five Layers of Classifiers*
- *Structure Learning*
- *Evolutionary Behavioral Modeling & Prediction*



HR records, Travel records, Badge/Location records, Phone records, Mobile records

Transmitted images, speech content, video content

Available existing data

future additions?

● : observations ○ : hidden states

Example of Graphical Analytics and Provenance

Columbia University

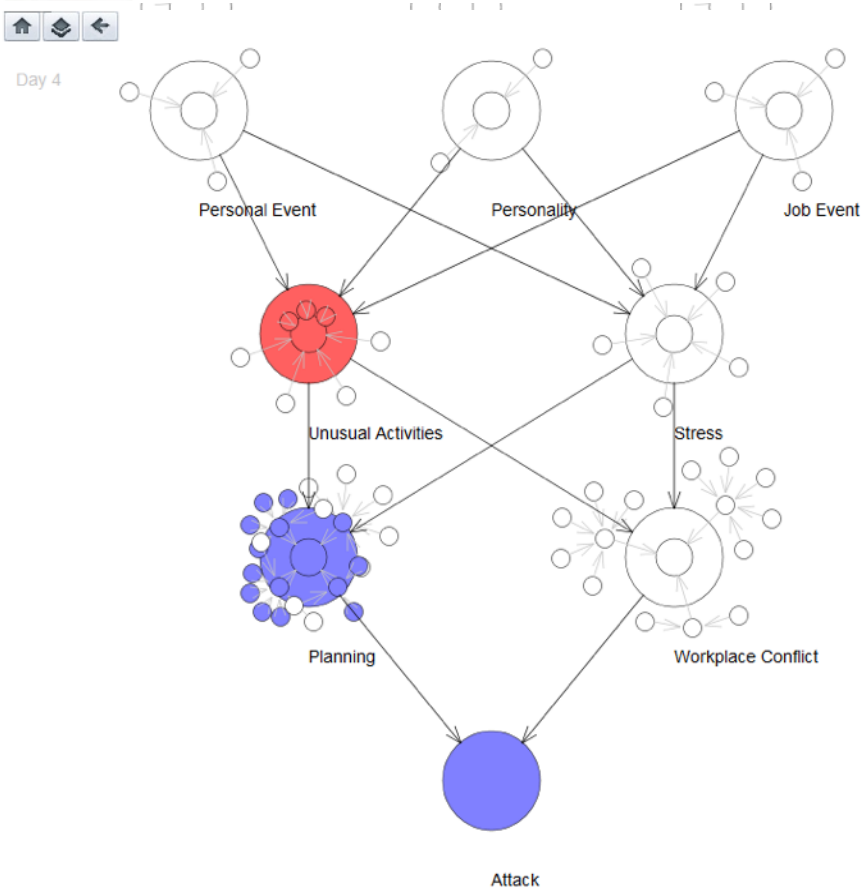
Markov Network | Latent Network | Bayesian Network

IBM Anomaly Detection at Multiple Scales (ADAMS) Analytics

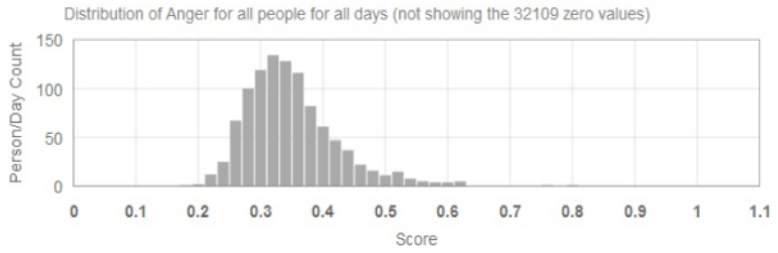
Search: GO

Sam Chang
Security Specialist
IT Department
samchang@company.com

Timeline: start stop



Email (Anger)



Top Person/Days -- Anger, group Self

Userid	Date	Anger
0A40E96890D1ED5E62F9C7F19191108D	2012-07-18	.81
7B131181E78AF8C08F3A9E605E58227B	2012-07-17	.77
41C50A4433E2CC2C34E6DCDFD1290C3F	2012-07-10	.63
369730CC2965FD97E8435A4365AF6FF6	2012-07-17	.63
2FF547A39E2D3E4D0B5DC6ACB1165441	2012-07-27	.62
6826DFDB7FFE74364C4FF7C58089E795	2012-07-10	.62
CBD7C1659A41C74998837310639E2817	2012-07-24	.62
C00A0A9DB436F130DCC5671D2936CD45	2012-07-13	.62
9C2568C8AF6809EAAAAC53E7B267AB00	2012-07-10	.62
215291F411748EDD54E2AA43966615A8	2012-07-24	.61
BCE7365D13A8396290BFB4CCB1D9DE36	2012-07-25	.60

Evaluations on the Real-World Data in Vegas Lab (Oct 2013)

Columbia University

- Each month, 3 cases were inserted (1 abnormal person per case) in the real data.
- Each performer system retrieved top abnormal people out of the 5,500 people per month.
- This chart showed where the 3 IBM systems (Sabotage, Espionage, and Fraud) ranked the abnormal person in each case. "All" is a combined rank list of the 3 systems. (Oct 2013 review on 12/12 ~ 03/13 data)

		Sabotage	Espionage	Fraud	All
Dec	Sabotage (Scenario 12)	4	241	1667	9
	Espionage (Scenario 8)	981	1	120	1
	Fraud (Scenario 13)	1526	454	1	2
Jan	Fraud (Scenario 13)	4230	3367	1	2
	Espionage (Scenario 14)	11	44	574	30
	Fraud (Scenario 5)	4230	1462	3	8
Feb	Espionage (Scenario 14)	1936	73	232	203
	Espionage (Scenario 4)	4101	9	803	26
	Sabotage (Scenario 15)	65	4101	654	181
Mar	Sabotage (Scenario 16)	1	1690	294	1
	Fraud (Scenario 5))	1544	9	5	10
	Espionage (Scenario 4)	4325	11	46	27

12. **Layoff Logic Bomb:** An engineer is worried about rumors of impending layoffs feels that he needs some kind of an "insurance policy", in case he gets laid-off or fired. He creates a "logic bomb" which will delete all files from a number of company Linux systems in five days, unless he resets the timer before then.

13. **Outsourcer's Apprentice:** (http://www.bbc.co.uk/news/technology-21043693) A software developer outsources his job to China and spends his workdays surfing the web. Most surfing occurs on a second laptop. He pays just a small fraction of his salary to a Chinese company to do his job. The developer provides his VPN credentials to the company and enabling Terminal Services on his workstation. The Chinese consulting firm sends the developer PayPal invoices.

8. **Anomalous Encryption:** A Subject wishes to pass sensitive information to a foreign government in exchange for that government setting him up with his own business. Subject researches NSA monitoring capabilities, generates a long random passphrase and then tests encrypting and mails data to personal account. The subject encrypts documents and emails the key.

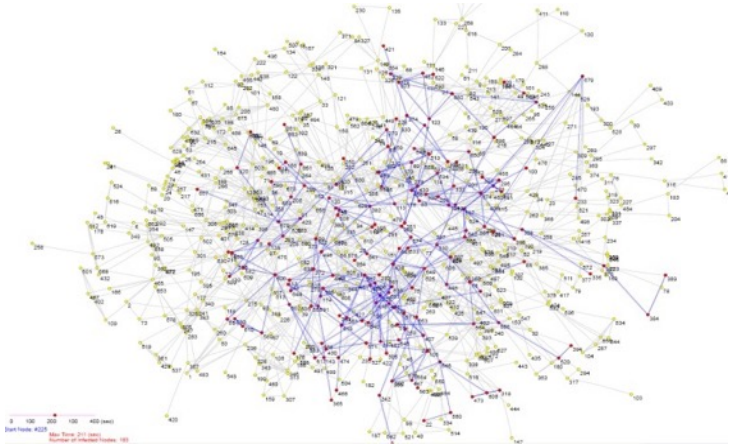
Promising results. IBM's system successfully caught the bad guys of the 12 cases: 4 as Top #1, 3 in Top #2-#5, 2 in Top #6-#20, 1 in Top #21-#50, and 2 in Top #51-#100. Performer 2 did not report results. Performer 3 reported: 3 of the 12 cases Top #50-#100, 6 cases Top #101-#500, and 3 cases beyond Top #501.

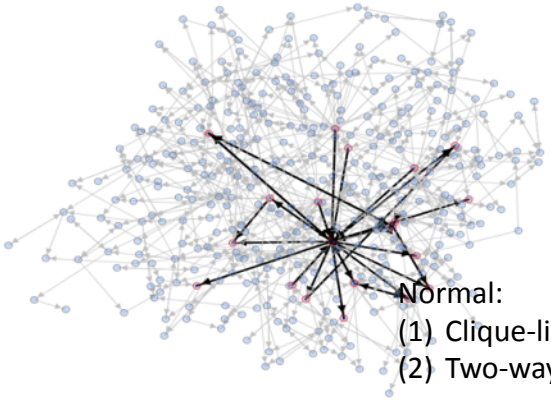
Use Case 11: Fraud Detection for Bank

Network Info Flow

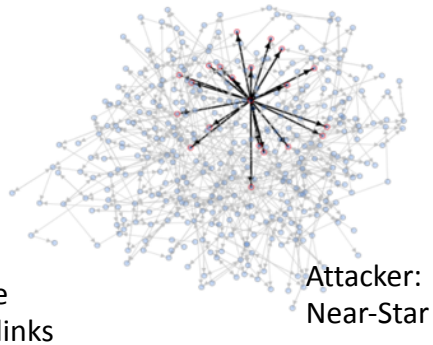
Ego Net Features

Ponzi scheme Detection

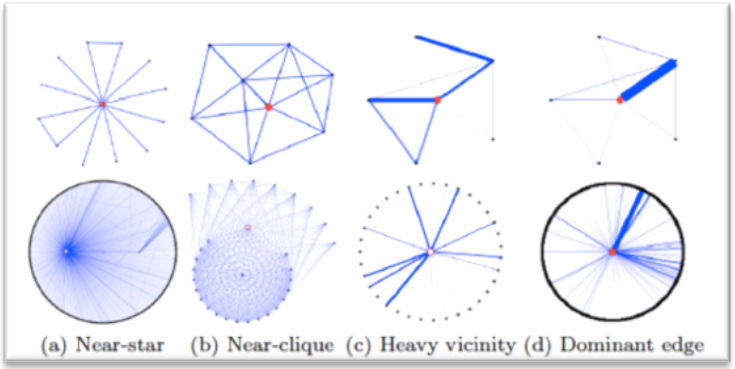




Normal:
(1) Clique-like
(2) Two-way links



Attacker:
Near-Star

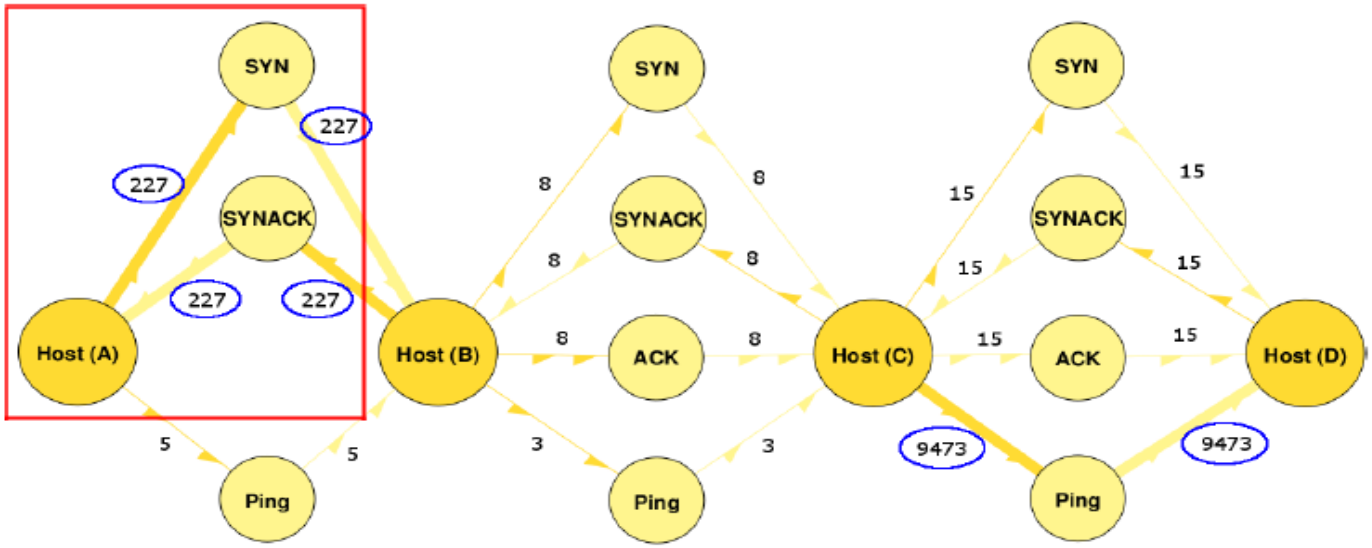


Use Case 12: Detecting Cyber Attacks

Network Info Flow

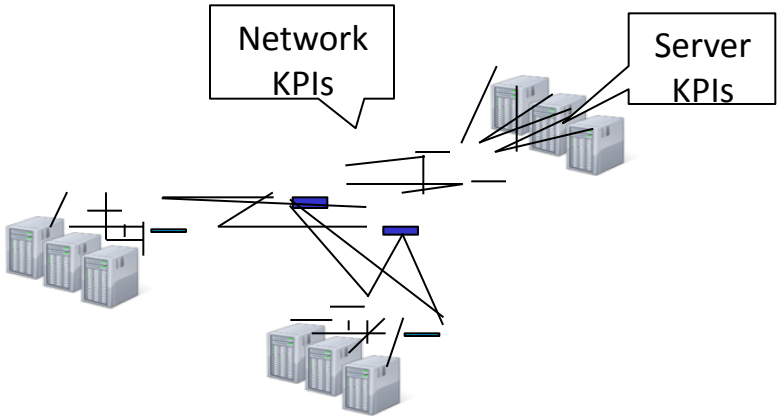
Ego Net Features

Detecting DoS attack



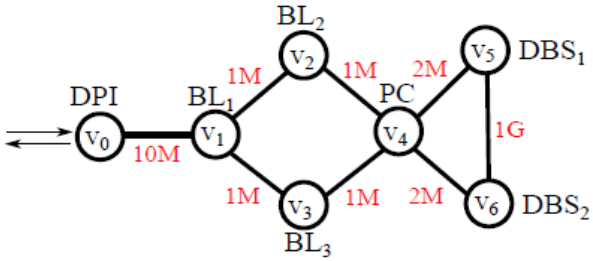
(a) Single large graph representing TCP SYN and ICMP PING network traffic, with two Denial of Service (DoS) attacks taking place.

Category 4: Operations Analysis



Cloud Service Placement

DPI - *Deep Package Inspector* BL - *Business Logic*
PC- *Package classifier* DBS - *DB Server*



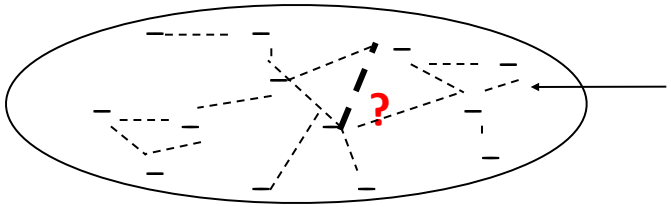
Memory requirements	
V_0	8G
V_1	2.5G
V_2	2G
V_3	2G
V_4	12G
V_5	20G
V_6	32G

Graph Matching

Bayesian Network

KPI time series (e.g., server performance/load, network performance/load)

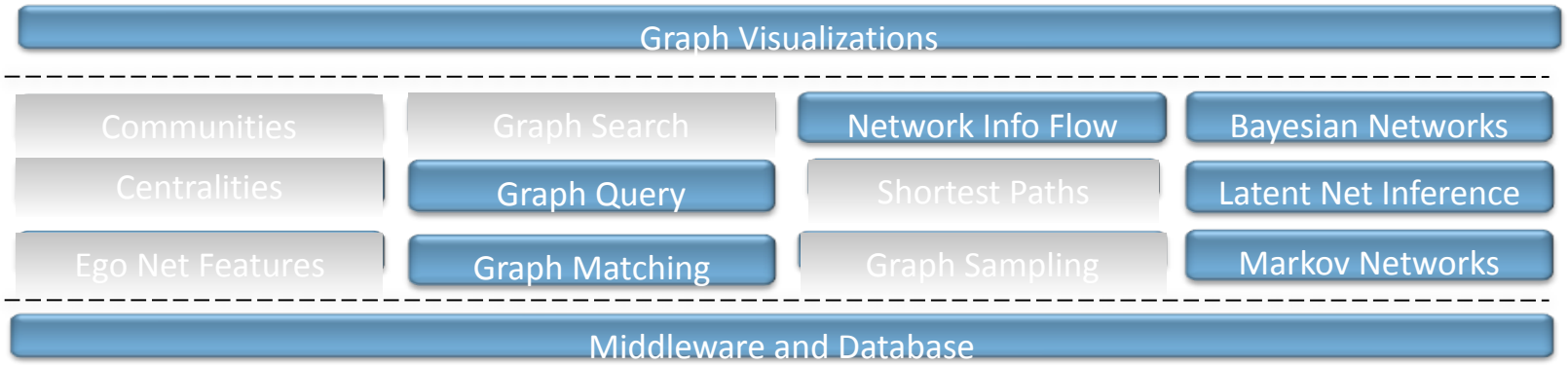
Causality analyzer



Varying over tim

– KPI (a time series)

--- (potential) pairwise relationship (e.g., causality)



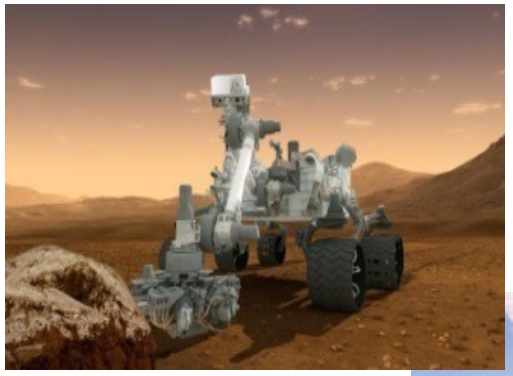
Use Case 13: Smarter *another* Planet

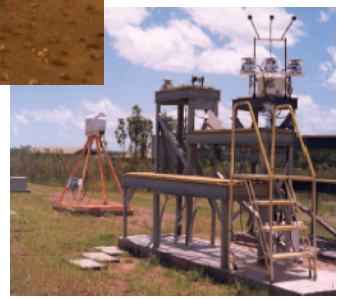
Columbia University

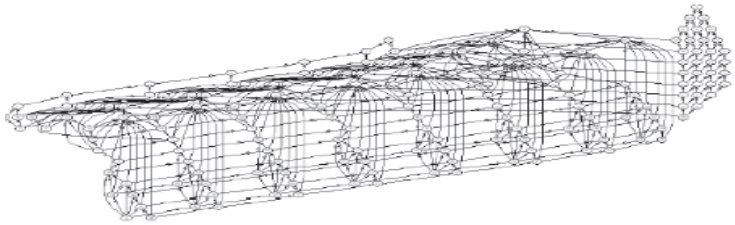
Bayesian Network

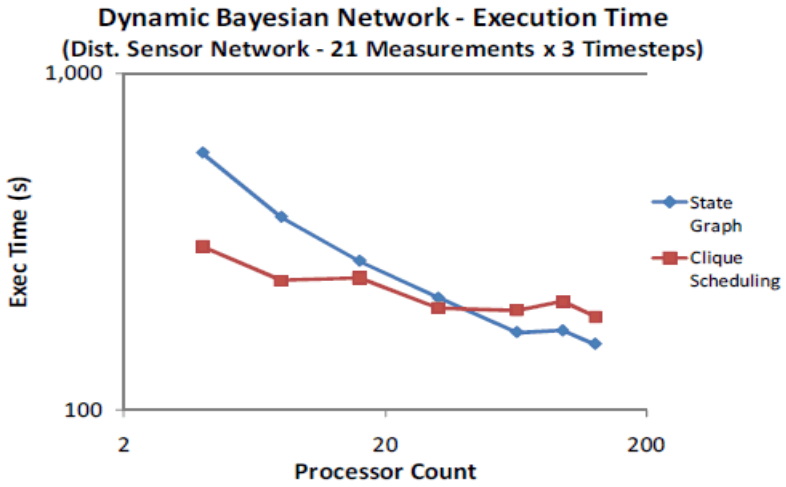
Goal: Atmospheric Radiation Measurement (ARM) climate research facility provides *24x7 continuous field observations* of cloud, aerosol and radiative processes. **Graphical models** can automate the validation with improvement efficiency and performance.

Approach: BN is built to represent the dependence among sensors and replicated across timesteps. BN parameters are learned from over *15 years* of ARM climate data to support distributed climate sensor validation. Inference validates sensors in the connected instruments.









Bayesian Network

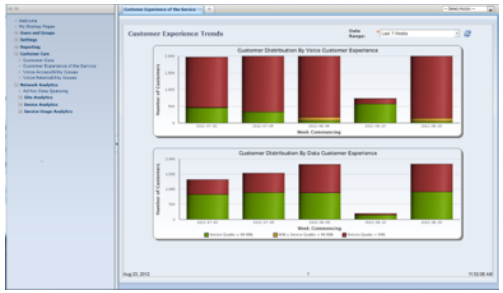
* 3 timesteps * 63 variables
* 3.9 avg states * 4.0 avg indegree
* 16,858 CPT entries

Junction Tree

* 67 cliques
* 873,064 PT entries in cliques

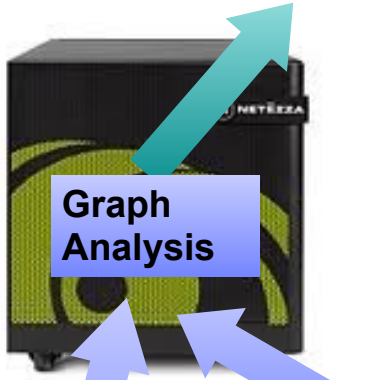
Use Case 14: Cellular Network Analytics in Telco Operation

Goal: Efficiently and uniquely identify *internal* state of Cellular/Telco networks (e.g., performance and load of network elements/links) using probes between monitors placed at selected network elements & endhosts

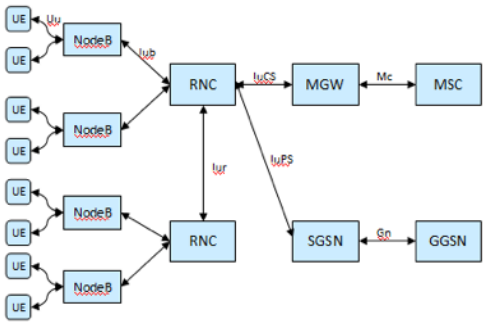


Network load level report

- Applied Graph Analytics to telco network analytics based on CDRs (call detail records): estimate traffic load on CSP network with low monitoring overhead
  - (1)CDRs, already collected for billing purposes, contain information about voice/data calls
  - (2)Traditional NMS* and EMS** typically lack of end-to-end visibility and topology across vendors
  - (3)Employ graph algorithms to analyze network elements which are not reported by the usage data from CDR information
- Approach
  - Cellular network comprises a hierarchy of network elements
  - Map CDR onto network topology and infer load on each network element using graph analysis
  - Estimate network load and localize potential problems



Network topology

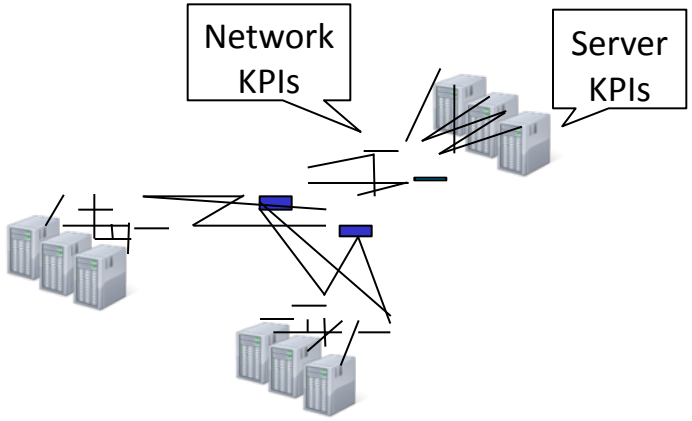


CDR

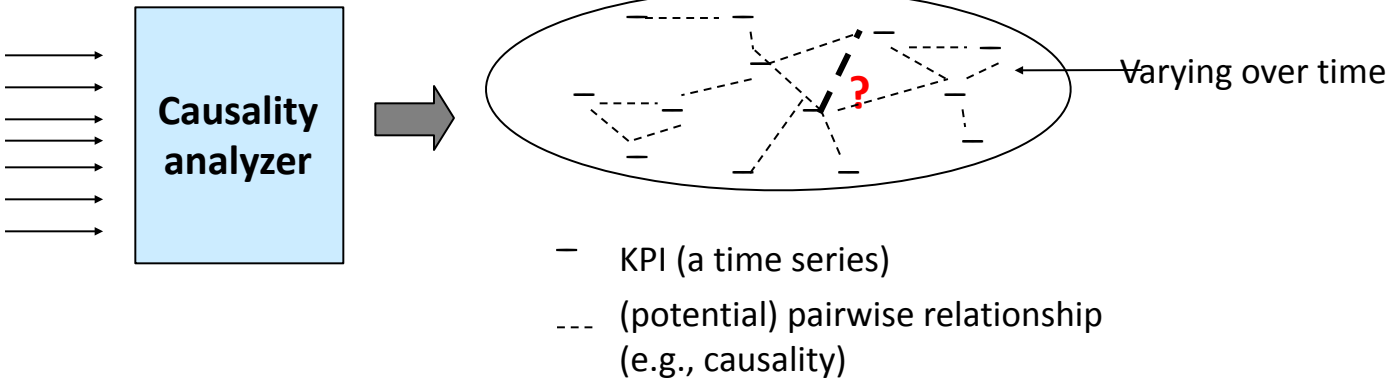
Use Case 15: Monitoring Large Cloud

Goal: *M*onitoring technology that can track the time-varying state (e.g., causality relationships between KPIs) of a large Cloud when the processing power of monitoring system cannot keep up with the scale of the system & the rate of change

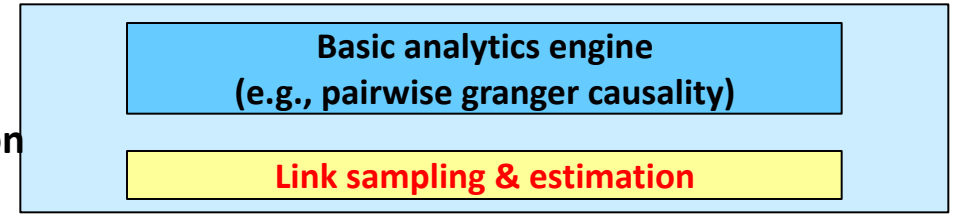
- *Causality relationships (e.g., Granger causality) are crucial in performance monitoring & root cause analysis*
- *Challenge: easy to test pairwise relationship, but hard to test multi-variate relationship (e.g., a large number of KPIs)*



KPI time series (e.g., server performance/ load, network performance/load)



Our approach: Probabilistic monitoring via sampling & estimation



Select KPI pairs (sampling)→ Test link existence → Estimate unsampled links based on history → Overall graph

Category 5: Data Warehouse Augmentation

(1)System G currently has 4 supported graph db backends:

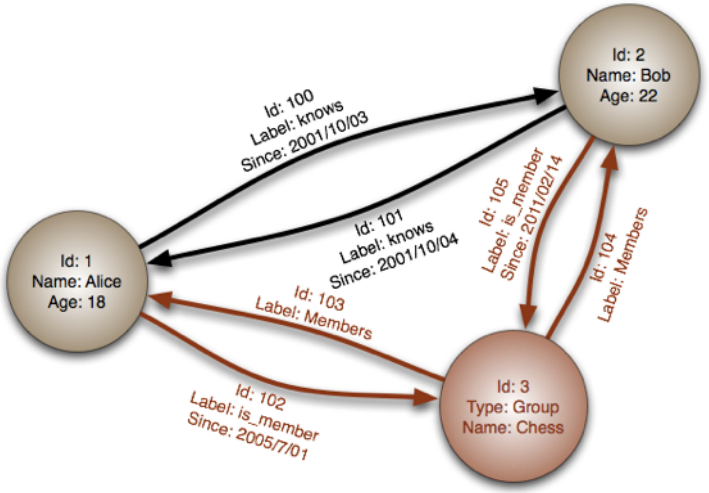
(1) A relational based architecture (DB2RDF) for enterprise specific graph query based workloads.

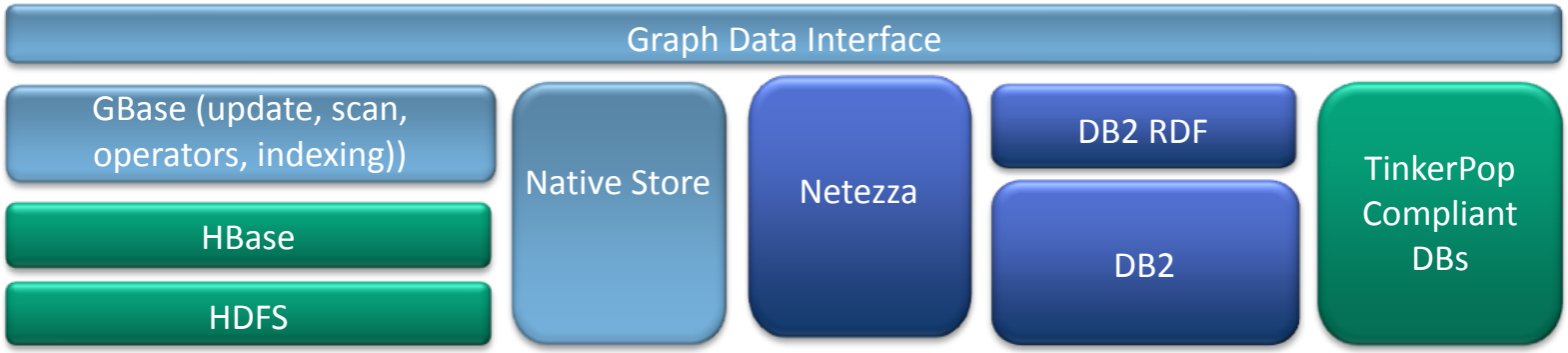
(2) A HBase based architecture, with Hadoop support for graph analytic workloads.

(3) A Native Store which is not a full database, but is optimized for storing and retrieving graphs

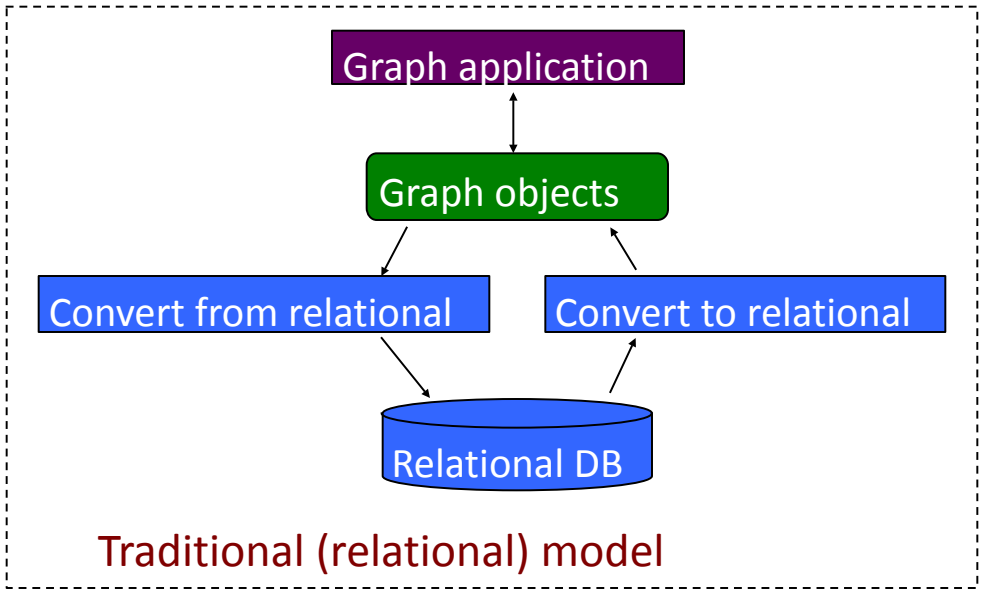
(4) Compliant with open source Graph databases that can be accessed through TinkerPop API (e.g., Neo4j, Titan).

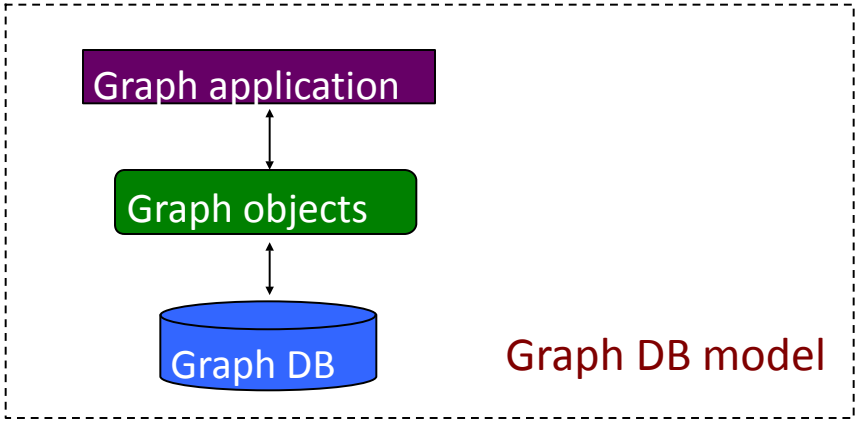
- System G creates API to allow Analytics, Middleware & Visualization to be swappable with different DB options.
- Netezza implements were started but not finished yet.





Use Case 16: Code Life Cycle Improvement





- Advantages of working directly with graph DB for graph applications
  - (1) Smaller and simpler code
  - (2) Flexible schema → easy schema evolution
  - (3) Code is easier and faster to write, debug and manage
  - (4) Code and Data is easier to transfer and maintain

Graph Query in DB2RDF

- Novel mechanisms to store sparse data in RDBMS (SIGMOD 2013 paper)
- 4-6 times better than other open source graph stores on 4 benchmarks
- Only store to handle all queries correctly
- Scalability tested up to 2.3 billion triples on real datasets (Uniprot). Worst performance was ~180 s for 2 queries, 2 queries took ~100 s, 14/31 query performance was under a second, others were under ~10 s. Worst performing queries had huge result sets (~100M)

Rational Jazz workload, single query

Systems	Average (secs)	Standard Dev.	Geometric mean	Min	Max	#Queries
Jena TDB	5.7	13.8	.06	.001	56.6	29/29
Virtuoso	3.9	8.6	.26	.003	39.7	25/29
DB2RDF	1.0	1.6	.27	.004	5.0	29/29

LUBM benchmark workload, single query

Systems	Average (secs)	Standard Dev.	Geometric mean	Min	Max	#Queries
Jena TDB	35.1	51.1	.29	.002	149.8	12/12
Sesame	164.7	328.9	.37	.001	658.0	4/12
Virtuoso	16.8	28.4	.19	.001	83.3	12/12
RDF-3X	2.8	4.7	.08	.001	12.9	11/12
DB2RDF	6.9	12.8	.14	.003	33.7	12/12

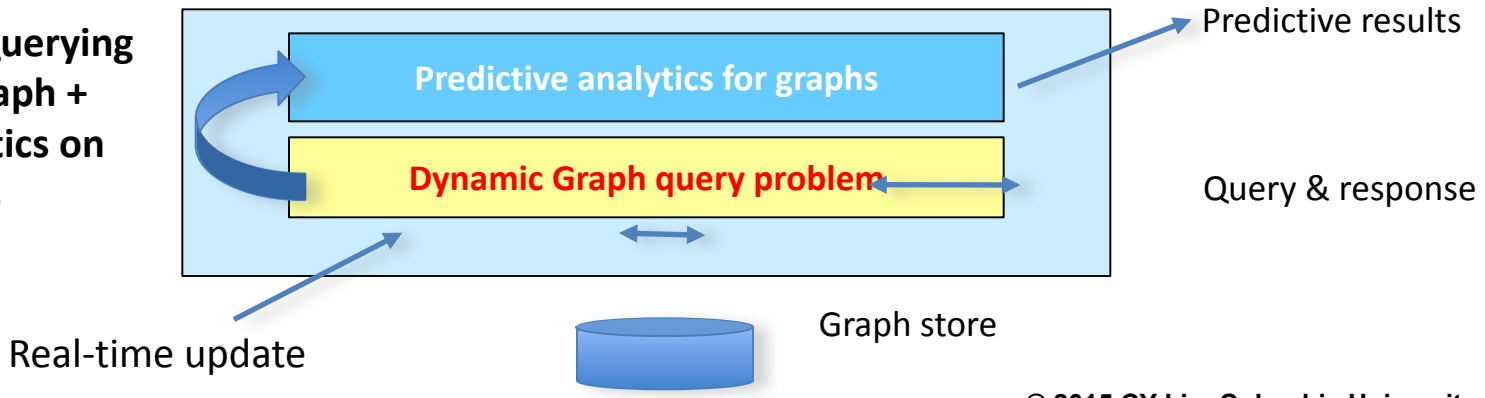
Use Case 17: Smart Navigation Utilizing Real-time Road Information

Goal: *Enable unprecedented level of accuracy in **traffic scheduling** (for a fleet of transportation vehicles) and navigation of individual cars utilizing the **dynamic real-time information** of changing road condition and predictive analysis on the data*

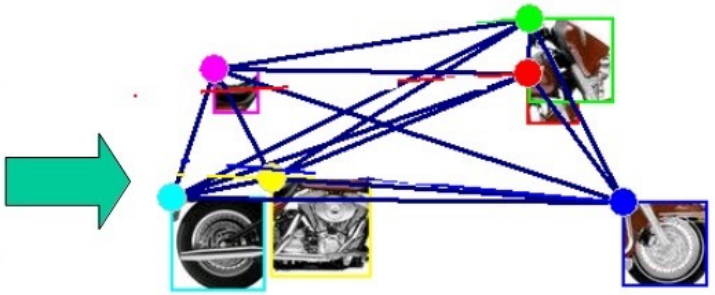
- *Dynamic graph algorithms implemented in System G provide **highly efficient graph query computation** (e.g. shorted path computation) on time-varying graphs (order of magnitudes improvement over existing solutions)*

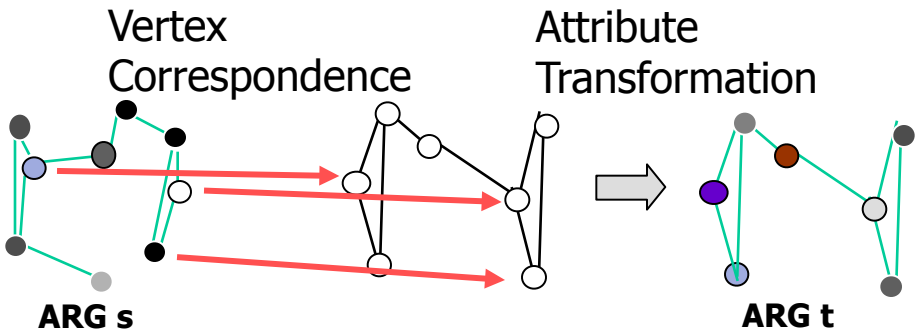
- *High-throughput **real-time predictive analytics** on graph makes it possible to estimate the future traffic condition on the route to make sure that the decision taken now is optimal overall*

Our approach: Querying over dynamic graph + predictive analytics on graph properties



Use Case 18: Graph Analysis for Image and Video Analysis





Use Case 19: Graph Matching for Genomic Medicine

- Ongoing discussions

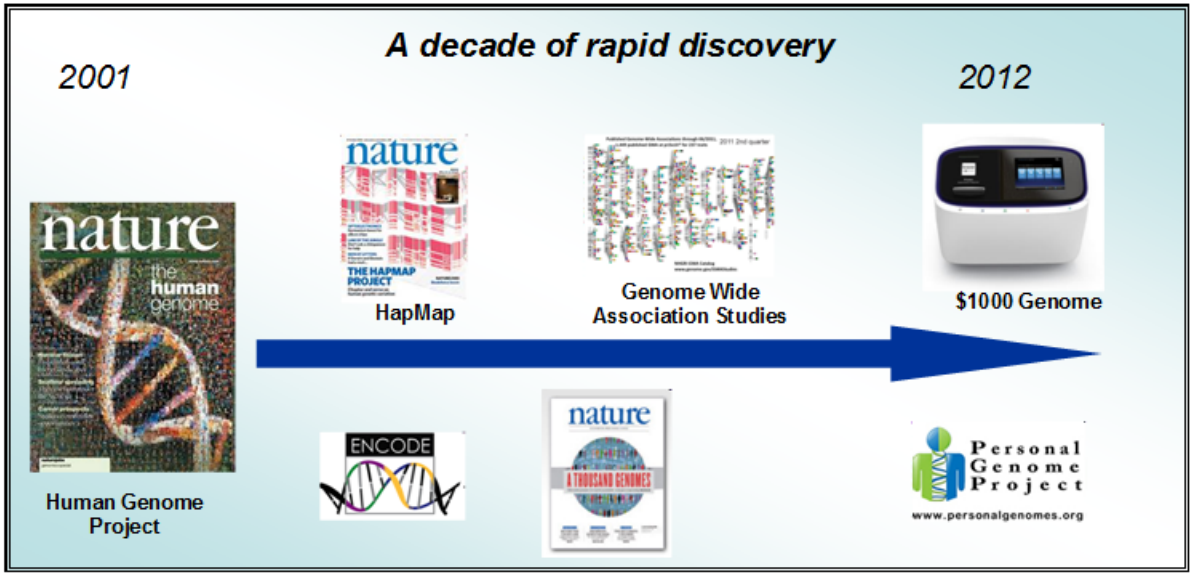
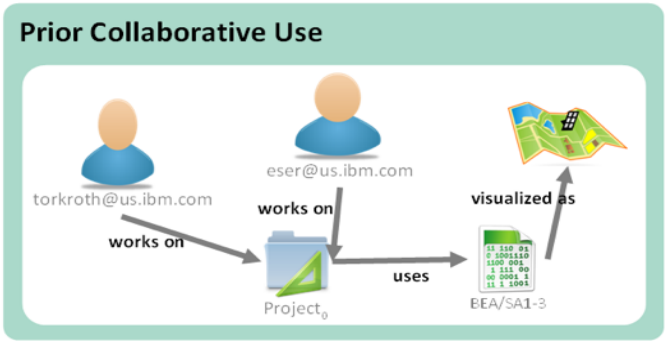
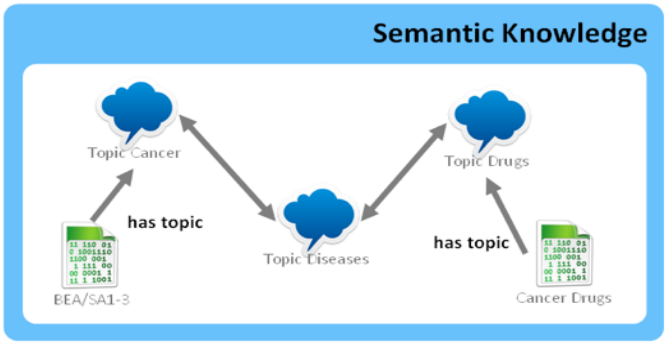
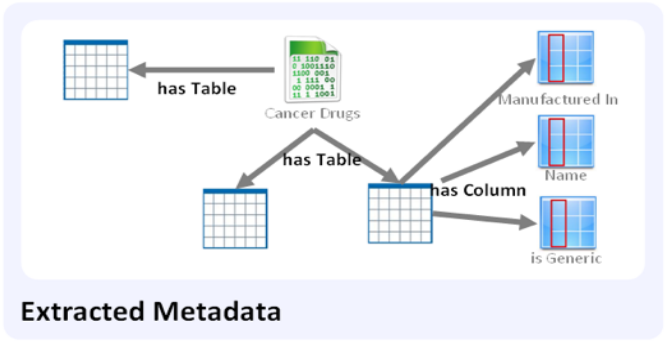


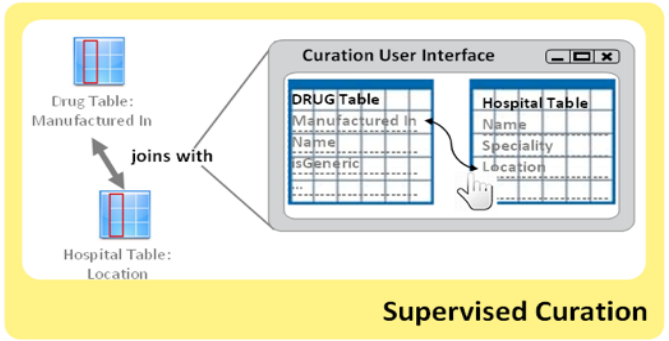
Figure 1: Since the Human Genome Project, various projects have started to reveal the mysteries of genomes and the $1000 Genome is almost reality.

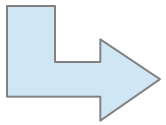
Use Case 20: Data Curation for Enterprise Data Management

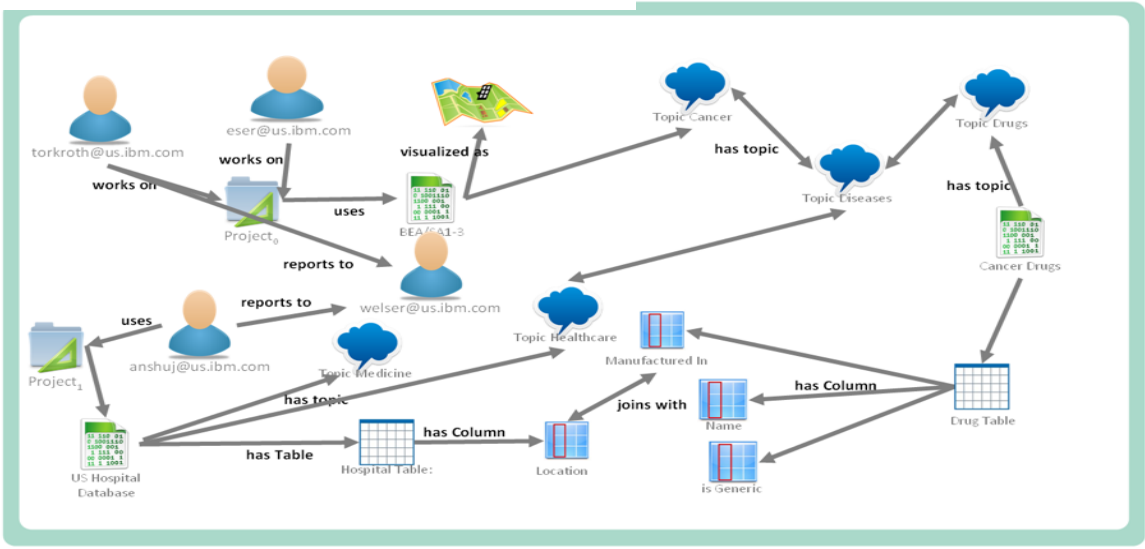




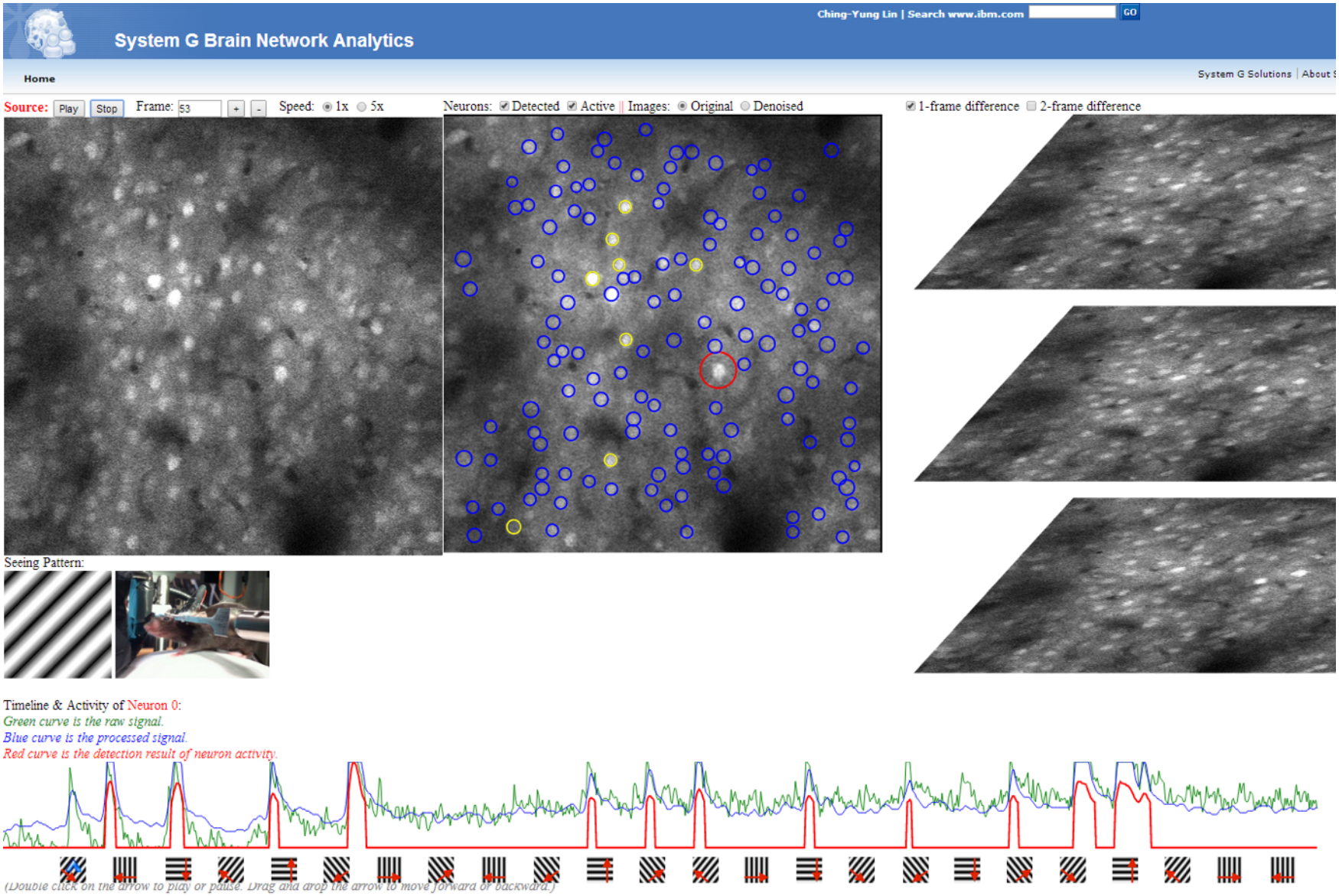








Use Case 21: Understanding Brain Network



Use Case 22: Planet Security

- Big Data on Large-Scale Sky Monitoring

Questions?

Sign List

Name (Last, First)	UNI	Department	Degree (yr)	Prior School or Company