Introduction to Big Data Analytics

Chap 1 – Overview of Big Data Analytics

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School of Data Science, Fudan University

Something about the course

1. 10% class, 30% about the project, 60% final exam.
2. TA: Yibin Sheng (wechat: syb3181, syb3181@gmail.com, 14210240021@fudan.edu.cn)
3. Office hours: Wednesday afternoon 4:15-6:00pm, Zibin building N210
4. Homepage: http://yanweifu.github.io/courses/Data_analytics/index.html

1. Every three weeks one component: linux_shell, OS, Spark, GPU computing, etc.
2. We will also do some tutorial.
3. may invite friends from industry to talk about their commercial systems for Big data analysis;
4. Pre-required course: nope.

Academic Integrity (学术诚信)

- **Academic integrity** is the moral code or ethical policy of academia. This includes values such as avoidance of cheating or plagiarism; maintenance of academic standards; honesty and rigor in research and academic publishing. (https://en.wikipedia.org/wiki/Academic_integrity)
- No cheating and plagiarism,
  - How to define *Plagiarism*? We follow ACM Policy on Plagiarism.
  - 抄袭和被抄袭双方的成绩都将被取消.
  - 作业、报告、期末论文的署名原则：署你名字的工作必须由自己完成；允许讨论，但作业必须独立完成，并在作业中列出所有参与讨论的人。不允许其他任何形式的合作——尤其是与已经完成作业的同学"讨论"。
  - 这是学术底线。

Define Plagiarism

Plagiarism manifests itself in a variety of forms, including

1. Verbatim copying, near-verbatim copying, or purposely paraphrasing portions of another author's paper;
2. Copying elements of another author's paper, such as equations or illustrations that are not common knowledge, or copying or purposely paraphrasing sentences without citing the source;
3. and Verbatim copying of portions of another author's paper with citing but not clearly differentiating what text has been copied (e.g., not applying quotation marks correctly) and/or not citing the source correctly.
4. Self-plagiarism is a related issue. In this document we define self-plagiarism as the verbatim or near-verbatim reuse of significant portions of one's own copyrighted work without citing the original source[2]. Note that self-plagiarism does not apply to publications based on the author's own previously copyrighted work (e.g., appearing in a conference proceedings) where an explicit reference is made to the prior publication[3]

1. Something about OS and linux shell. We need to know how to use linux do some simple preprocessing and data analysis on single machine;
2. Something about cloud computing and Spark;
3. Something about other advanced Big Data Analytics.

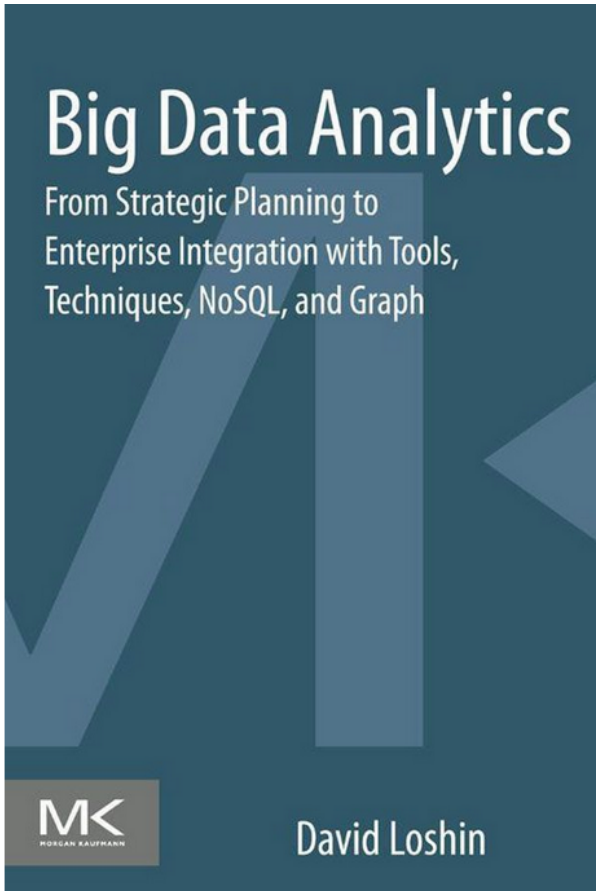
Enjoy

Yes, we need to know OS, linux commands and other stuffy, before really learning Spark; but not that difficulty.

Some jokes

- 我找不到普通家庭也需要计算机的理由。 —Ken Olsen, co-founder of DEC Corp.
- 很多人预测1996年互联网产业将大规模增长。但我的预测是1996年互联网产业由于增长过于快速，将像超新星一样爆炸后而走向崩溃。 — Robert Metcalfe, co-founder of 3Com
- 全球垃圾邮件问题将在今后两年内得到解决。—Bill Gates, MS.
- 电视节目的流行时间不会超过半年，公众每晚会面对着一个小盒子，他们将对此感到厌倦。—Darryl Zanuck, 20 Century Fox
- 苹果已死。— Nathan Myhrvold, CTO of Microsoft
- 我觉得全球市场大概只需要5台计算机。—Thomas Watson, CEO of IBM

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

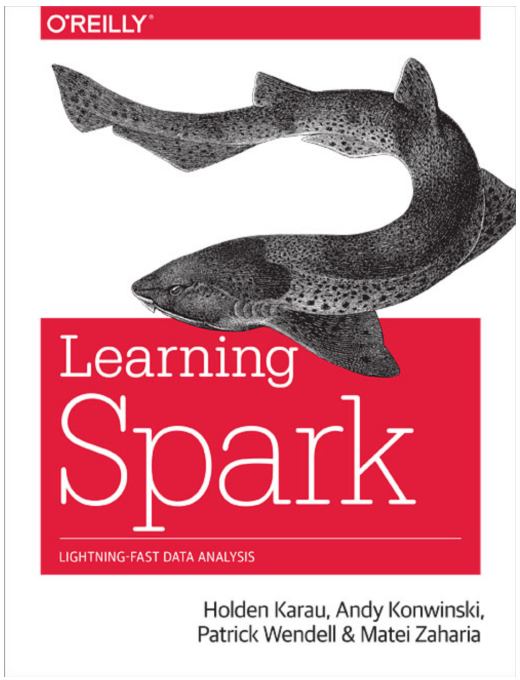
Chapter 8: Developing Big Data Applications

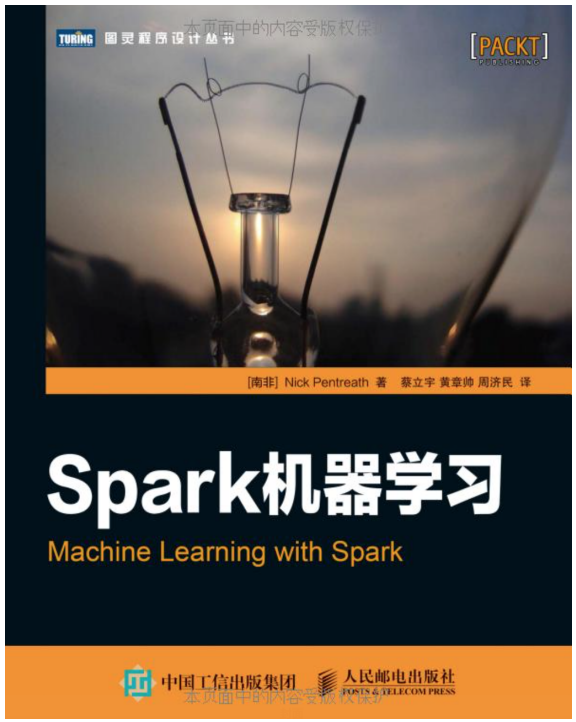
Chapter 9: NoSQL Data Management for Big Data

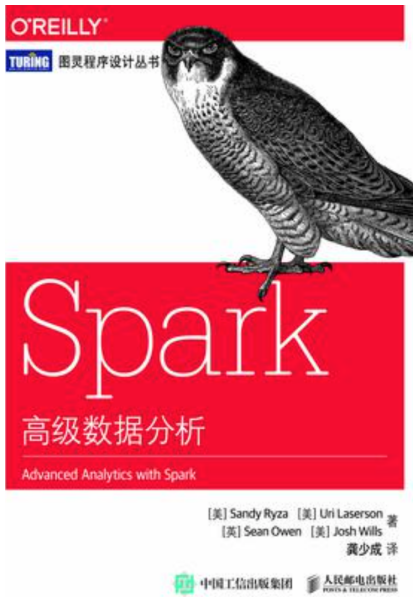
Chapter 10: Using Graph Analytics for Big Data

Chapter 11: Developing the Big Data Roadmap

References


O'REILLY
Learning
Spark
LIGHTNING-FAST DATA ANALYSIS
Holden Karau, Andy Konwinski,
Patrick Wendell & Matei Zaharia


TURING 图灵程序设计丛书
[PACKT]
[南非] Nick Pentreath 著 蔡立宇 黄章帅 周济民 译
Spark机器学习
Machine Learning with Spark
中国工信出版集团
人民邮电出版社


O'REILLY
TURING 图灵程序设计丛书
Spark
高级数据分析
Advanced Analytics with Spark
[美] Sandy Ryza [美] Uri Laserson
[美] Sean Owen [美] Josh Wills 著
龚少成 译
中国工信出版集团
人民邮电出版社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BLUE


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((FOR ONE WELCOME OUR NEW COMPUTER OVERLORDS)
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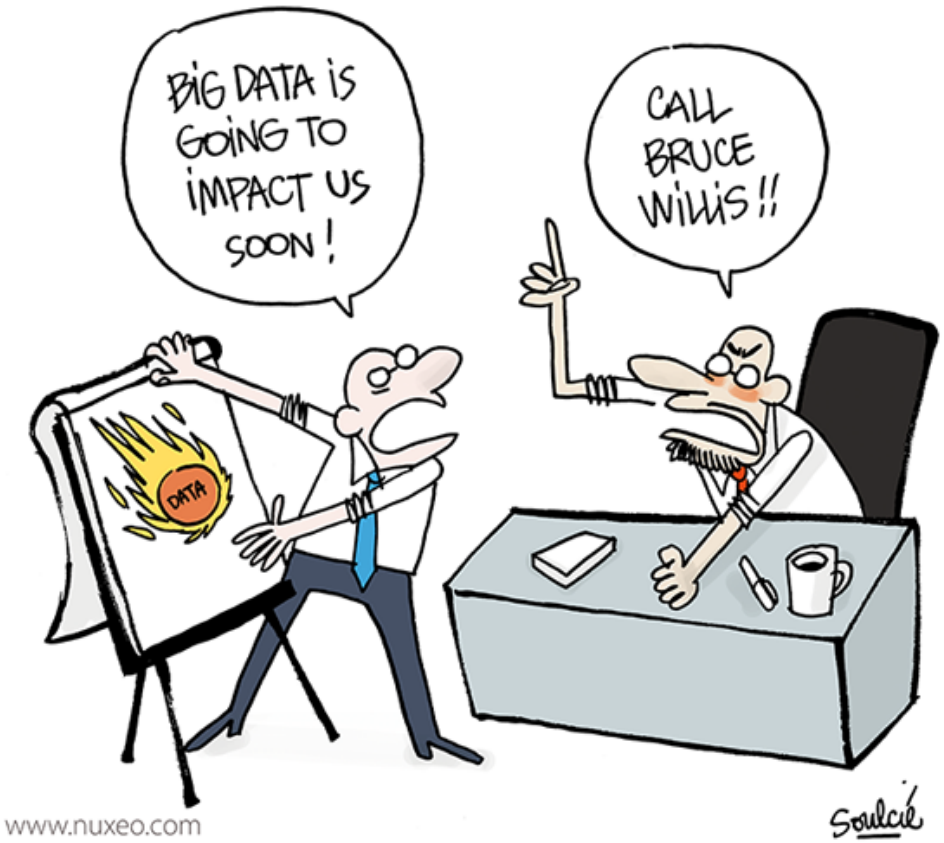
$77,147
Who is Bram Stoker?
$ 17,973
$21,600
WHO IS BRAM STOKER?
$5600


ALPHAGO
01:59:50
LEE SEDOL
AlphaGo
Lee Sedol

Big Data

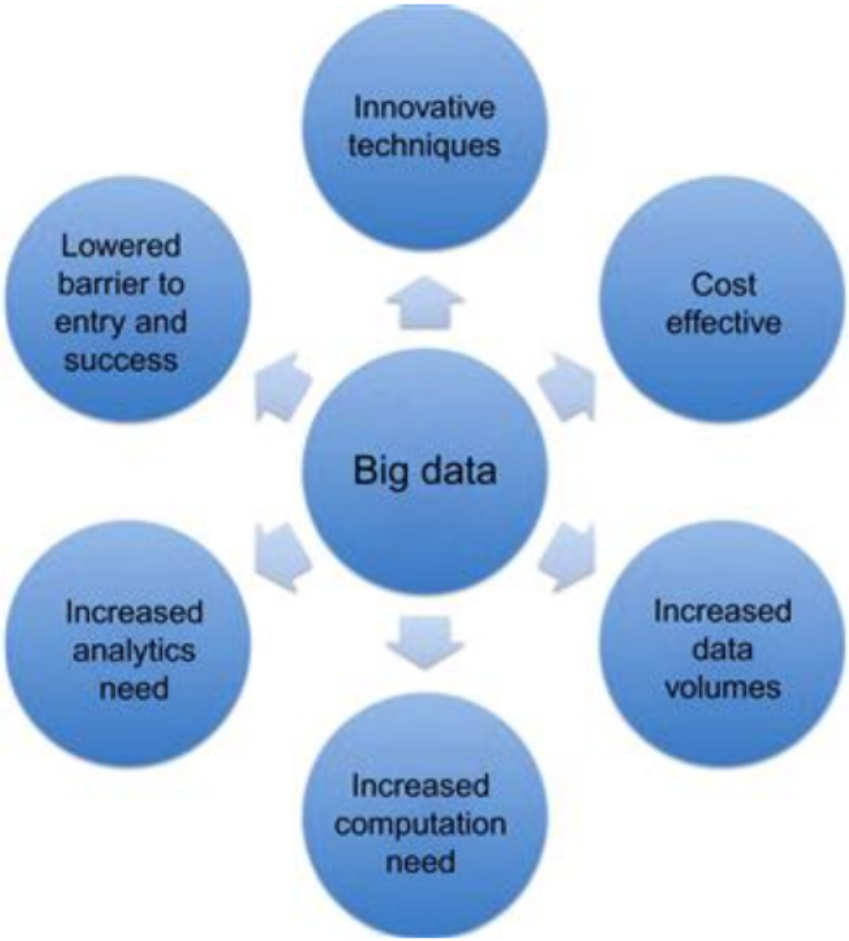

BIG DATA is GOING TO IMPACT US SOON!
CALL BRUCE WILLIS!!
DATA
www.nuxeo.com
Soulcié

"*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

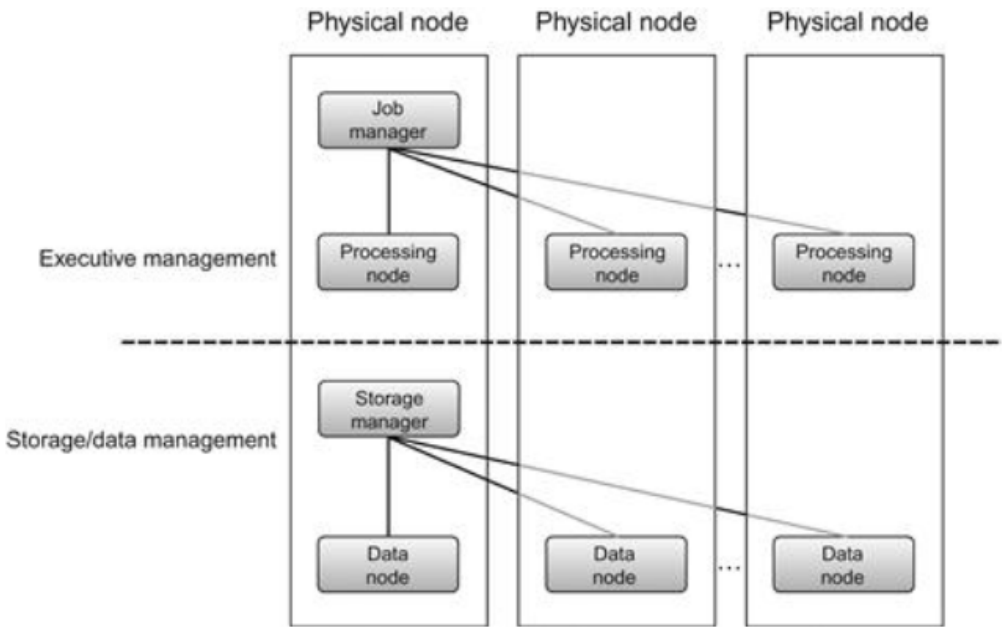
What made Big Data needed?



"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

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

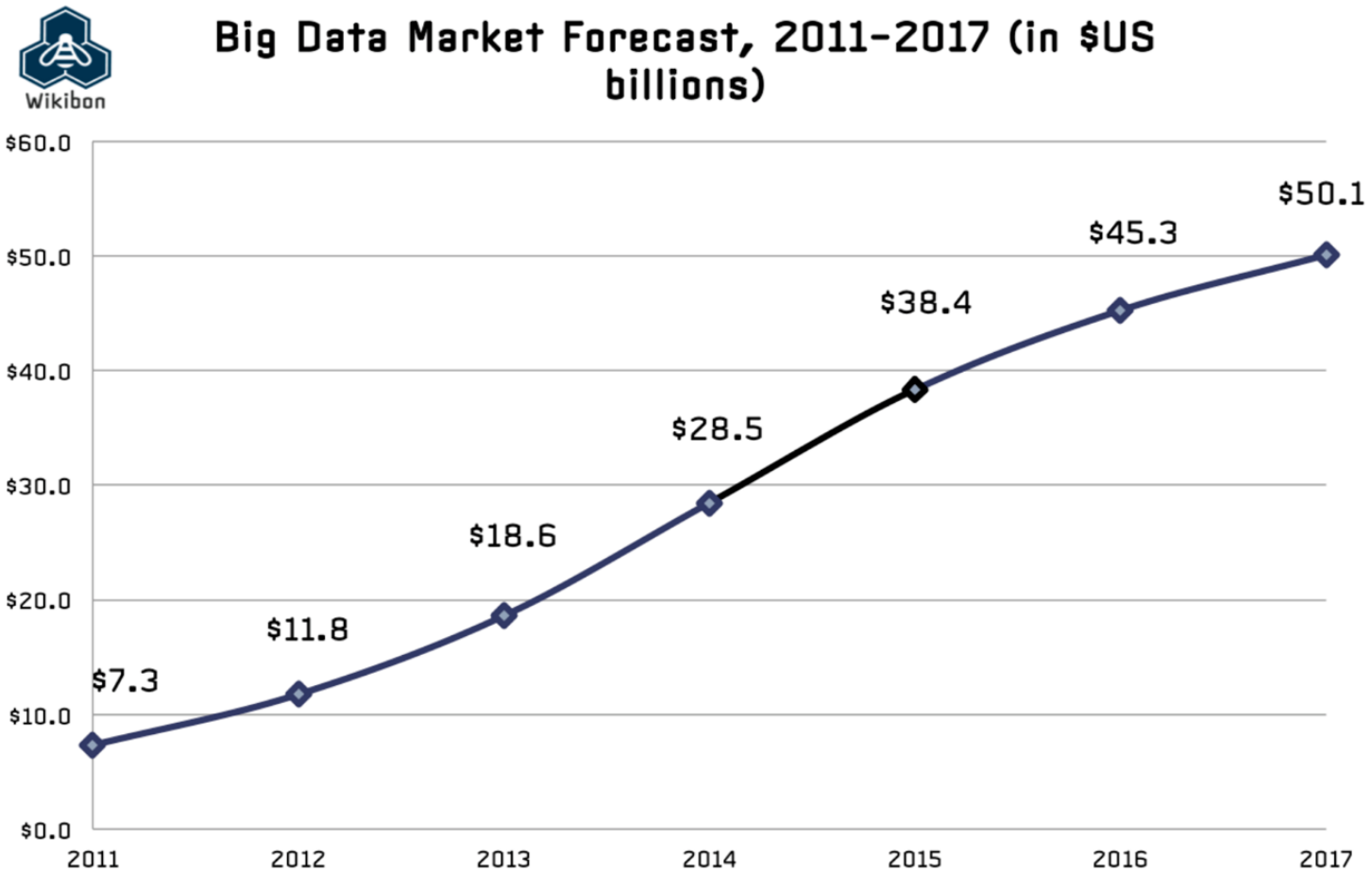
Operations Analysis

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 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

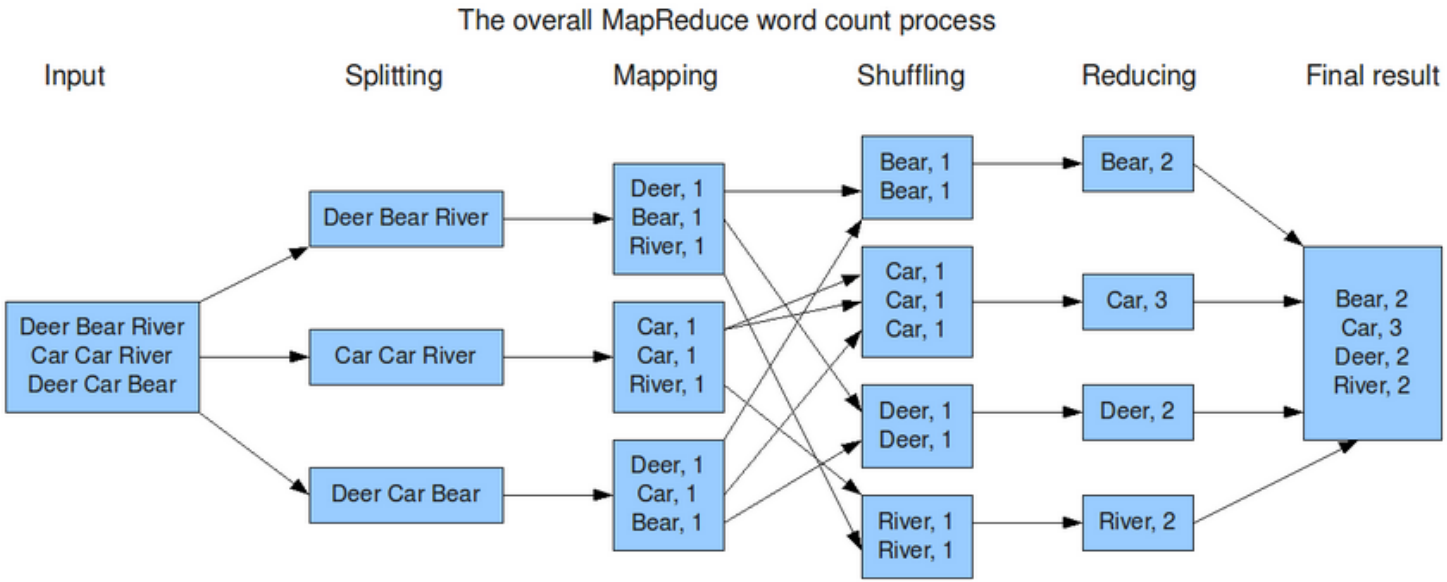
Sapphirine Big Data Analytics Open Source Applications

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

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

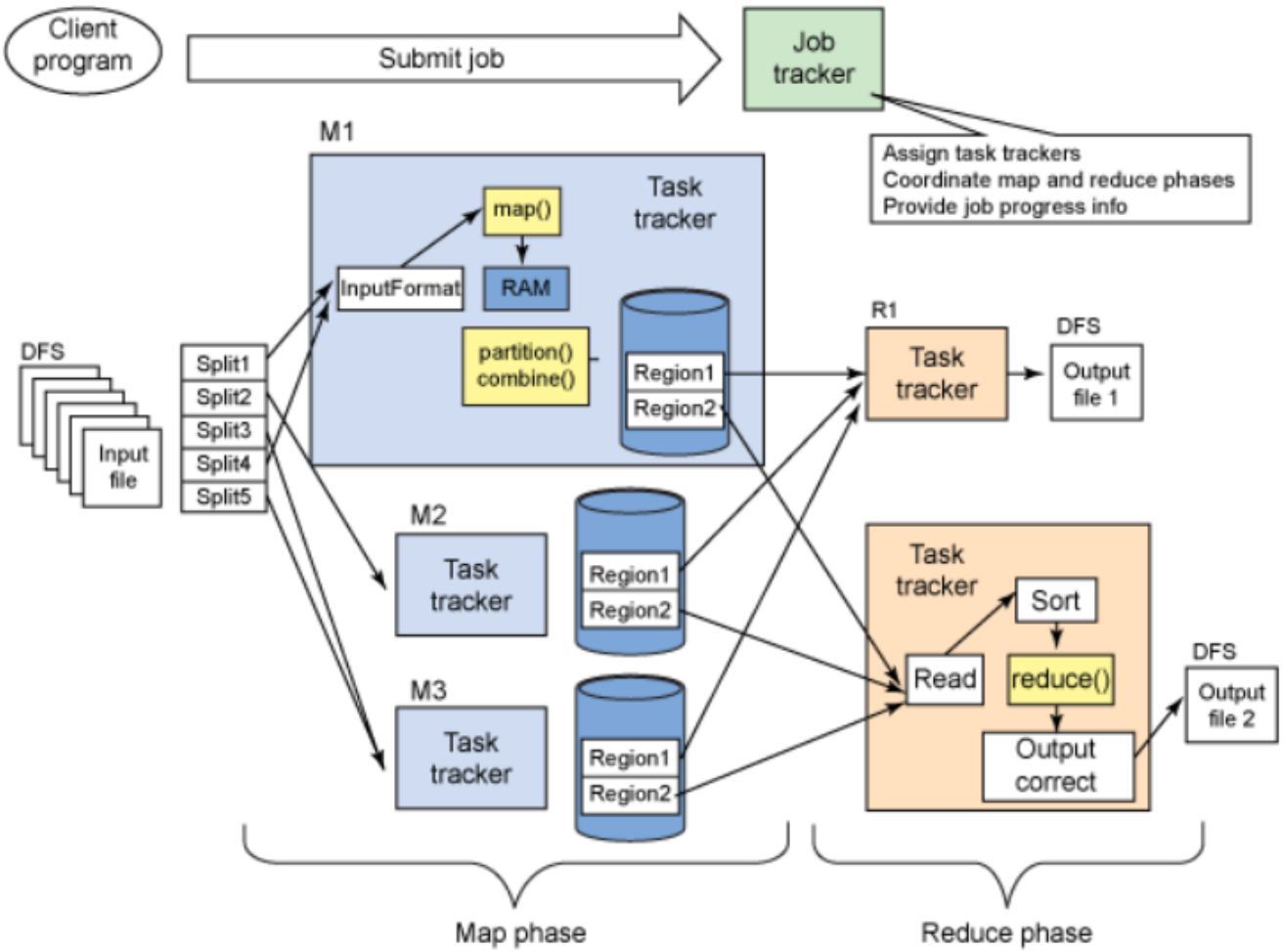
Crowdsourcing of our collective effort!!

MapReduce example



http://www.alex-hanna.com

MapReduce Data Flow



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

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:

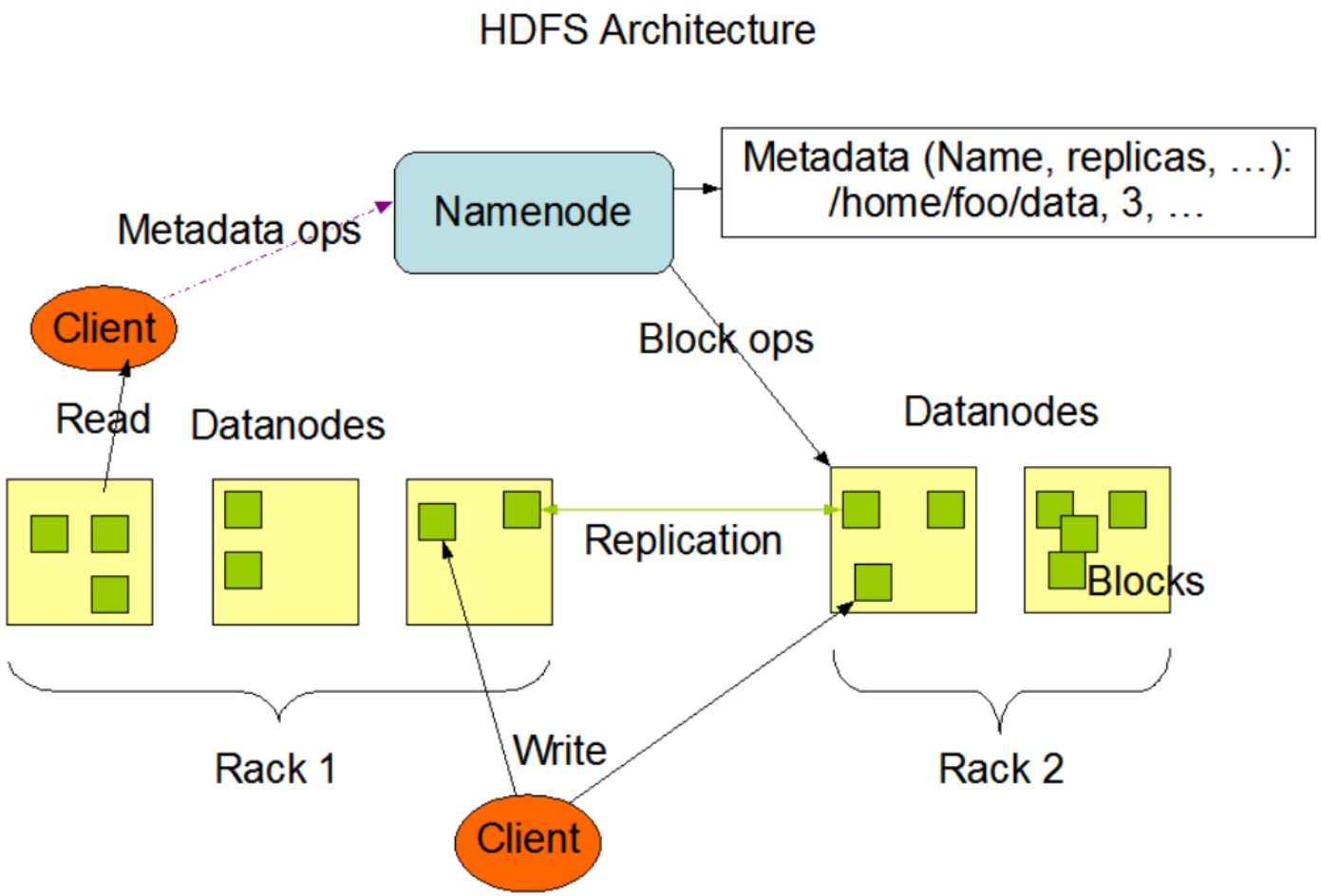
- **Hadoop Common**: The common utilities that support the other Hadoop modules.
- **Hadoop Distributed File System (HDFS™)**: A distributed file system that provides high-throughput access to application data.
- **Hadoop YARN**: A framework for job scheduling and cluster resource management.
- **Hadoop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



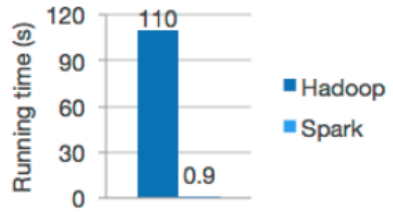
http://hortonworks.com/hadoop/hdfs/

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.

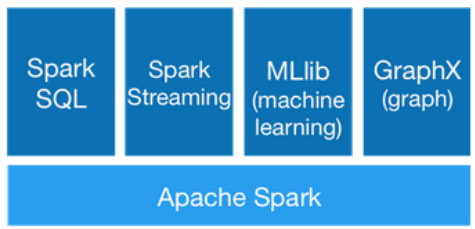
```
file = spark.textFile("hdfs://...")

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

Word count in Spark's Python API

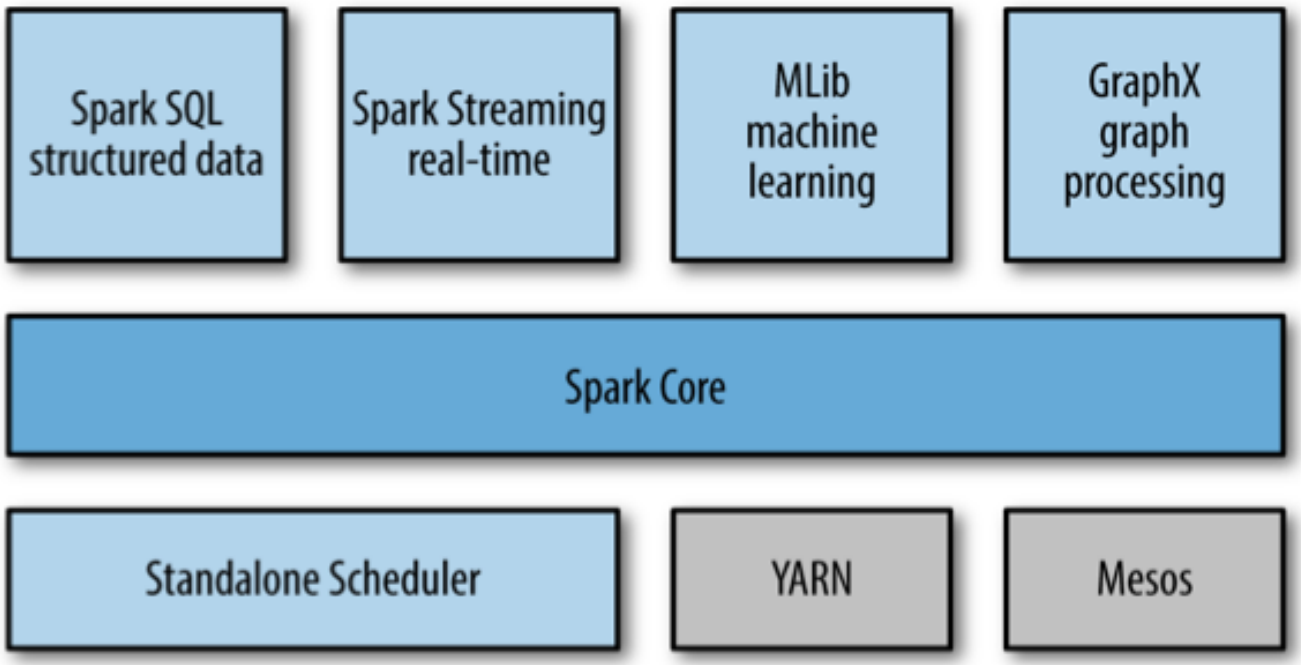
Generality

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.



Spark Stack


Spark SQL
structured data
Spark Streaming
real-time
MLib
machine
learning
GraphX
graph
processing
Spark Core
Standalone Scheduler
YARN
Mesos

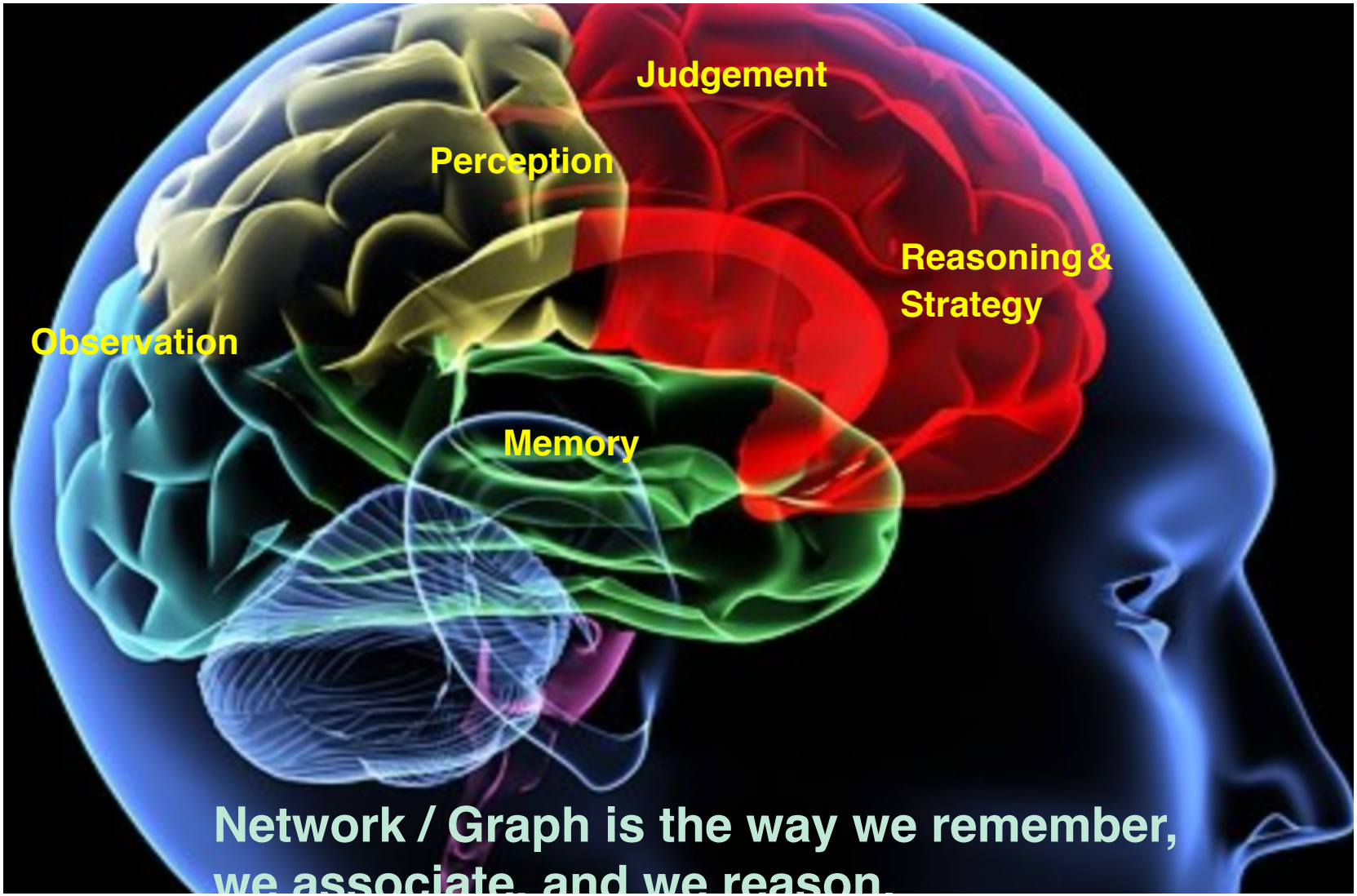
Spark Core

Basic functionality of Spark, including components for:

- Task Scheduling
- Memory Management
- Fault Recovery
- Interacting with Storage Systems
- and more

Home to the API that defines resilient distributed datasets (RDDs) - Spark's main programming abstraction.

RDD represents a collection of items distributed across many compute nodes that can be manipulated in parallel.

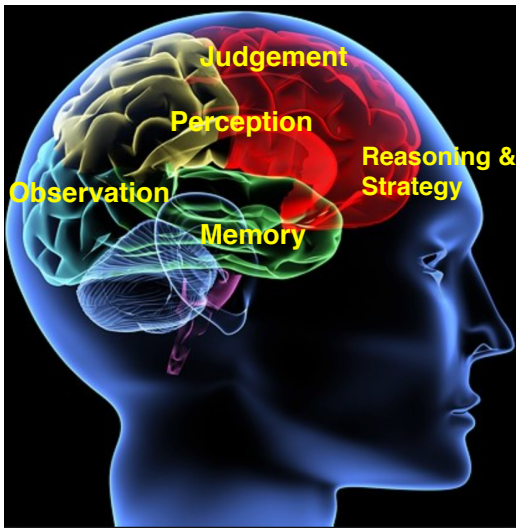

Judgement
Perception
Reasoning &
Strategy
Observation
Memory
Network / Graph is the way we remember,
we associate, and we reason.

http://spark.apache.org/docs/latest/quick-start.html

Now is the Appendix.

Linked Big Data — IBM System G

System G — Graph Computing for Machine Intelligence



"IBM System G": a brand name approved by HQ — April 2014.

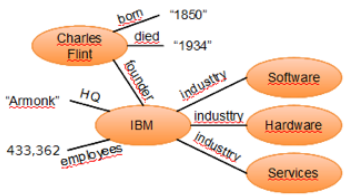
Based on 30+ graph-related projects; 150+ papers; ~40 patents; ~10 best paper awards; ~$25M Research funding

IBM System G

Connecting the Dots and Reasoning Big Data

http://systemg.research.ibm.com

Graph Database



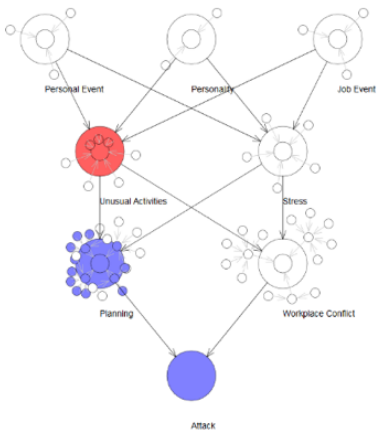
subject	predicate	object
Charles Flint	born	"1850"
Charles Flint	died	"1934"
Charles Flint	founder	IBM
IBM	HQ	"Armonk"
IBM	employees	433,362
IBM	industry	Software
IBM	industry	Hardware
IBM	industry	Services

Memory

Graph Analytics

Relationship, Perception &

Graphical Models



Machine Reasoning & Deep Learning

System G Tools — Building Blocks for Cognitive Solutions

- **Graph Middleware**:
  - Parallel Prog. Lib.
  - Power Optimization
  - GPU Optimization
- **Graph Analytics**:
  - Topological Analysis
  - Matching and Search
  - Path and Flow
- **Spatiotemporal Analytics:**
  - Spatiotemporal Mining
  - Spatiotemporal Indexing
- **Graph Database**:
  - Native Store
  - GBase
- **Graph Visualization:**
  - Multivariate Graph
  - Dynamic Graph
  - Big Graph

- **Machine Learning Classifiers:**
  - Deep Learning Tools
  - Visual and Text Sentiment Tools
  - Anomaly Detection Tools
- **Mobile Cognition:**
  - iOS Cognition Tools
  - Robot Cognition Tools

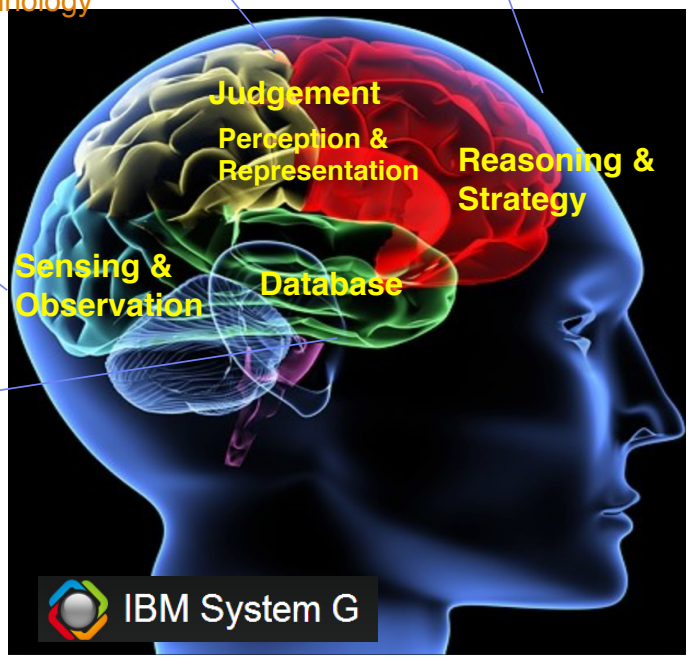
- **Machine Reasoning:**
  - Bayesian Networks
  - Game Theory Tools
  - Multimodal Analysis Platform

4 Machine Reasoning Technology

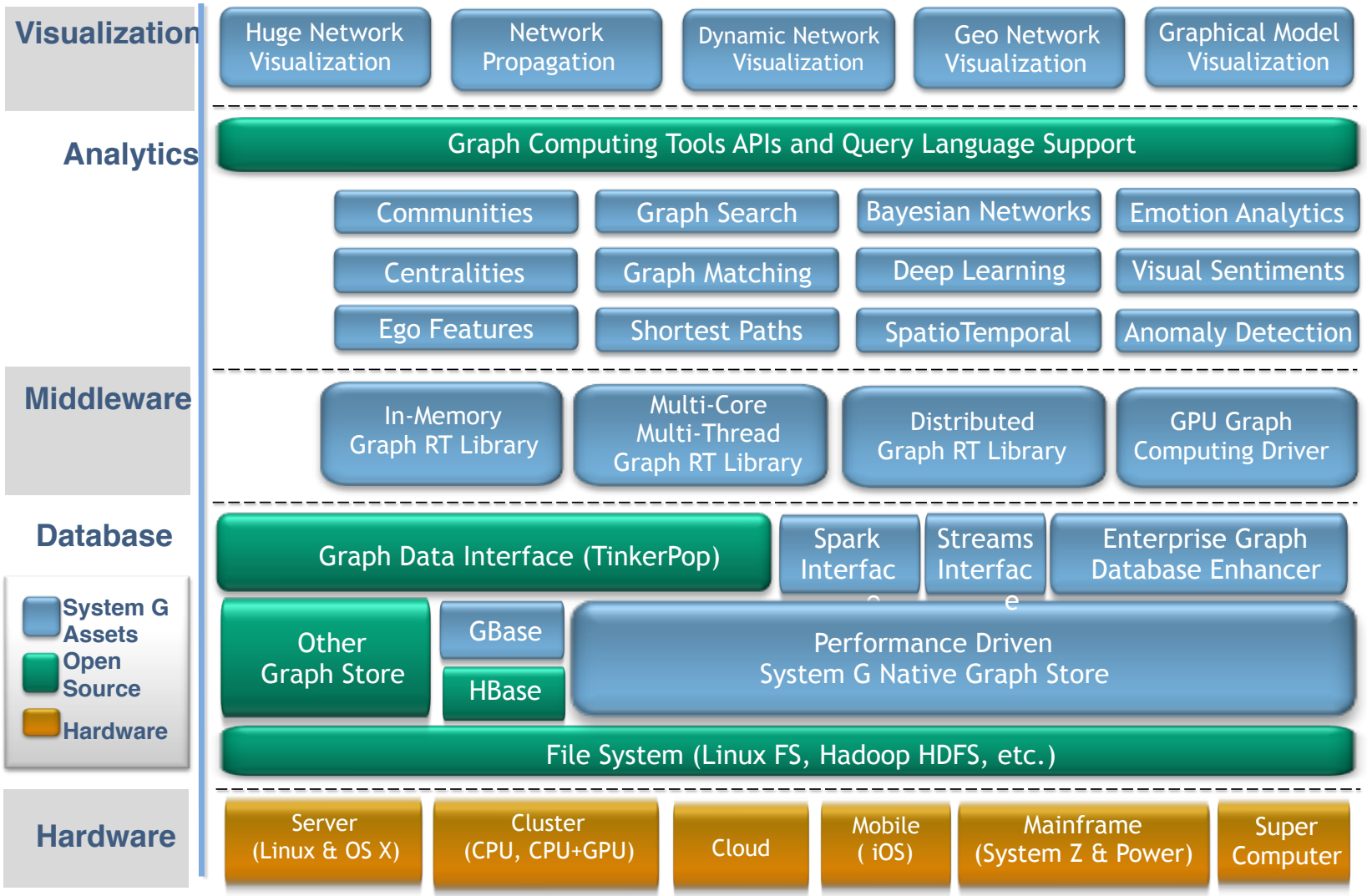
3 Machine Judgment Technology

2 Network Analysis Technology

1 Graph Database Technology



IBM System G Graph Tools



System G Solutions

- **Enterprise Social Solution v3.9.0 (SmallBlue)**
- **Insider Threat Solution v1.5.0 (ADAMS)**
- **Social Media Solution v2.0.0 (SMISC)**
- **Surveillance Insight v1.0.1**
- **Graph Tools v1.5.0**
- **Mobile Vision v0.5**
- **Mobile Security Solution**
- **Non-Performing Loans Solution**
- **Anti-Money Laundering Solution**
- **Investment Advisory Solution**

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

Financial Anomaly Detection

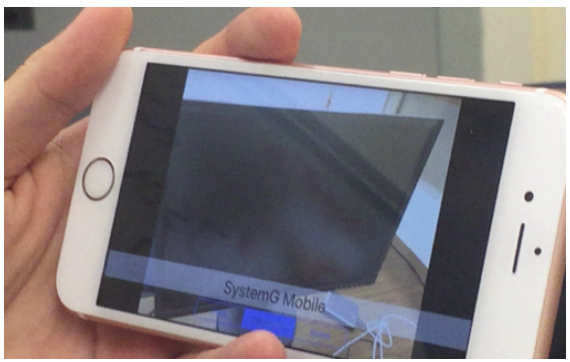
Model validation	*Entity process*	*Social net analysis*	**Analytic Engines**			*Predictive analysis*	*Peer group analysis*	*Sim. what/if analysis*
AML	**Anti-fraud**	**Non-Performing Loans**	**ABC**	**Trade Surveillance**	**PRG**	**Control room**	**Employee compliance**	**GRC**
Transaction monitoring	Internal fraud	Payment screening	Gifts & entertainment	Communication monitoring	Position disclosure	Conflict management	Employee trading	Risk assessment
Client screening	External fraud	List management	Bus dev consultants	Digital surveillance		List management	G&E	Control backtesting
CRE (list rating)	Unauthorized trading		Hiring practices	Information barrier monitoring		Research clearance	Annual attestations	Monitor testing
List management				Market abuse			Business interests	Regulatory charge

Alerting Engine	**Anomaly Detection**	**Machine Learning**	**Case Mgmt,& Workflow**
Natural Language Proc	**Text Analytics**	**Sentiment Analytics**	**Discover, Search & Export**
Cognitive Reasoning	**Data Lake**	**Entity/Link Analytics**	**Visualization / UI**

Mobile Cognition — Enabling AI right on the Edge

- Created novel graph computing and deep learning framework on iOS devices and NAOqi robots including:
  - generic object recognition, event recognition, face recognition, visual sentiment recognition, and document recognition
  - graph database
- Prototype summer 2016 and first version release 3Q2016

IBM System G



Novel Deep Learning works that Speed Up image computation utilizing the GPUs on iOS devices: 195x or 1657x faster

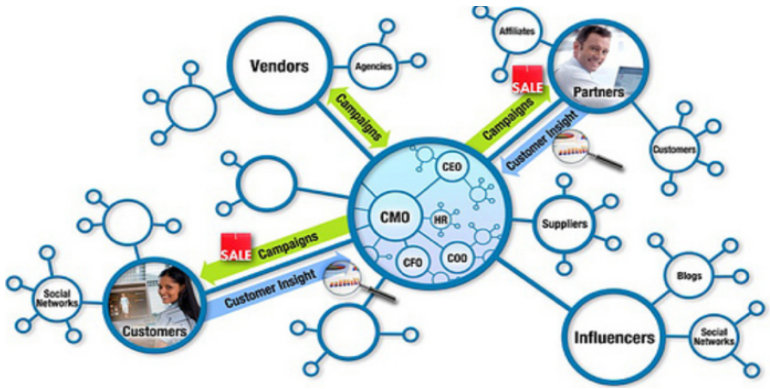
	iPad Pro	iPhone 6s
Classification rate (on ~1000 classes)	~13 frames/sec	~7 frames/sec

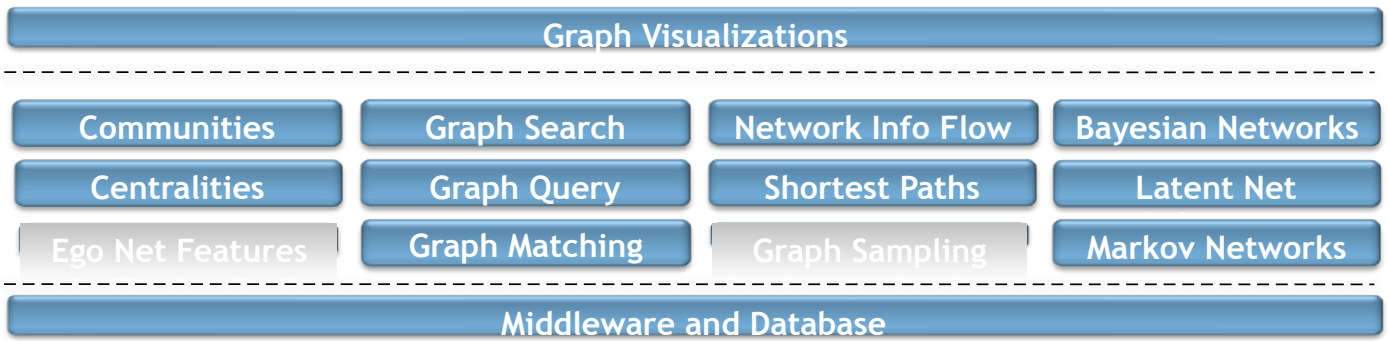
Task 1. Market Data Analysis and Investment Targets

Task 2. Advanced Dynamic 'Know Your Customer'

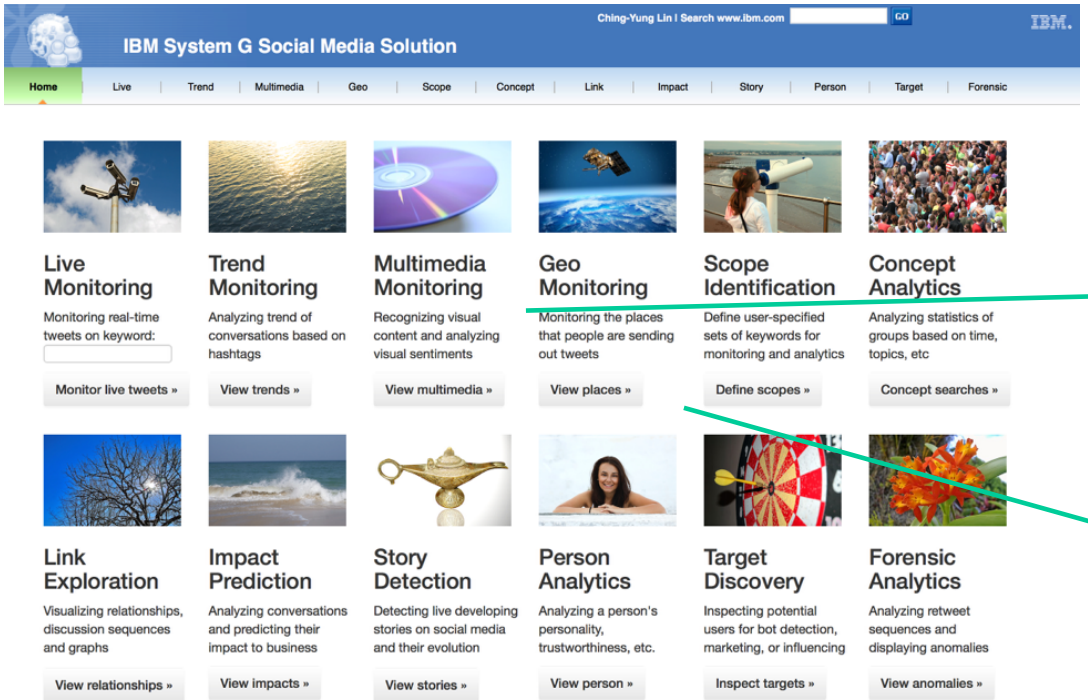
Task 3. Optimized Personalized Investment Strategy

Task 4. Bank-Customer Interaction Strategy





Social Media Solution



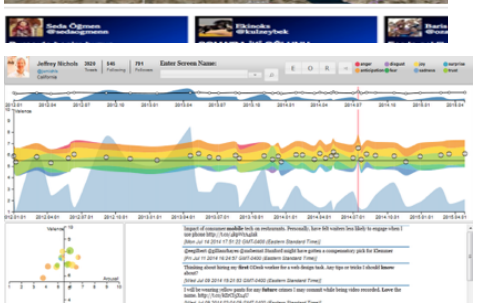
Sun Jan 25 02:00:04 +0000 2015 GMT

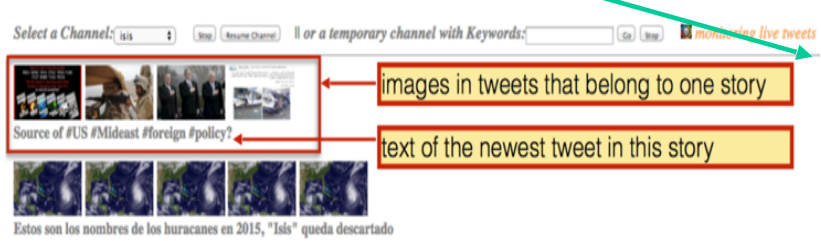
RT @IraqLiveUpdate: Pics - Large convoy of KH heading to undisclosed location (3 of 3) #Iraq http://t.co/l47ZjPkmsC

Retweet Count: *3*
Follower Count: *207*
Tweet Sender Location: *N/A*

Automatic Tagging: *deadly_attack, horizontal_text, excellent_book, annoying_reflection, busy_bridge*

Visual Sentiment Detection: ***Negative***





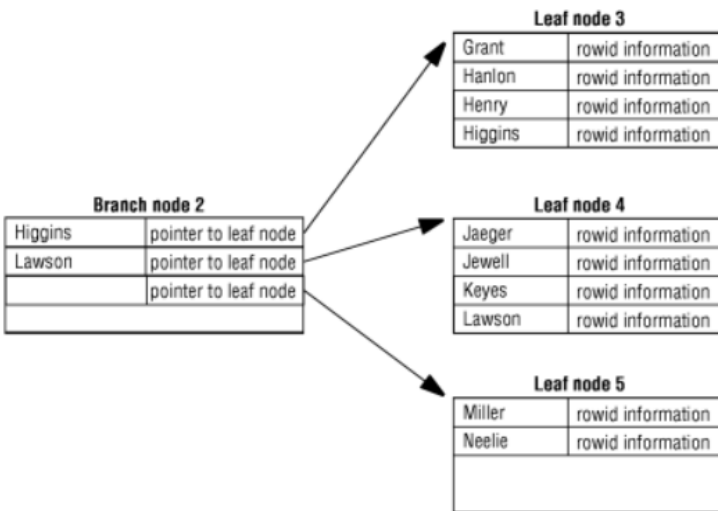
- Key-Value Store
- Document Store
- Tabular Store
- Object Database
- Graph Database (property graphs, RDF graphs)

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.

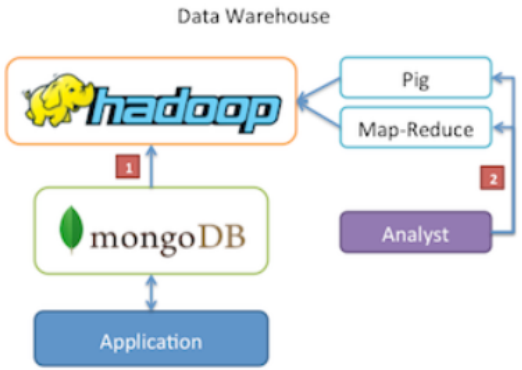
"Big Data Analytics", David Loshin, 2013



IBM Informix K-V store

Example Application: Spatio-Temporal Analys

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.

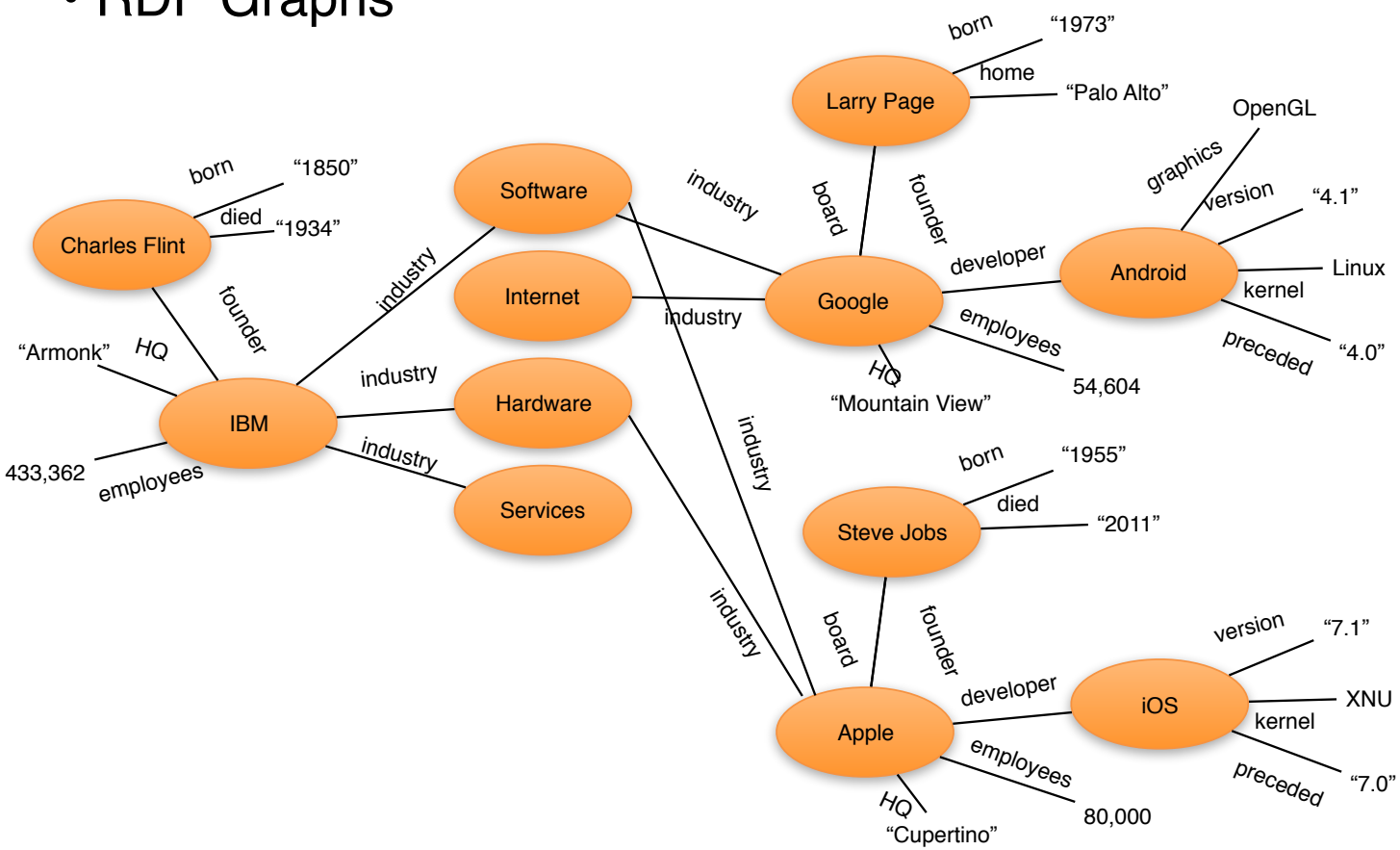
Relational data model

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.

- Property Graphs
- RDF Graphs

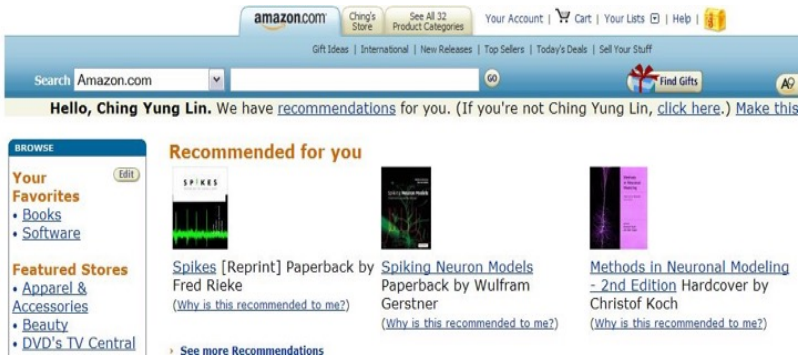


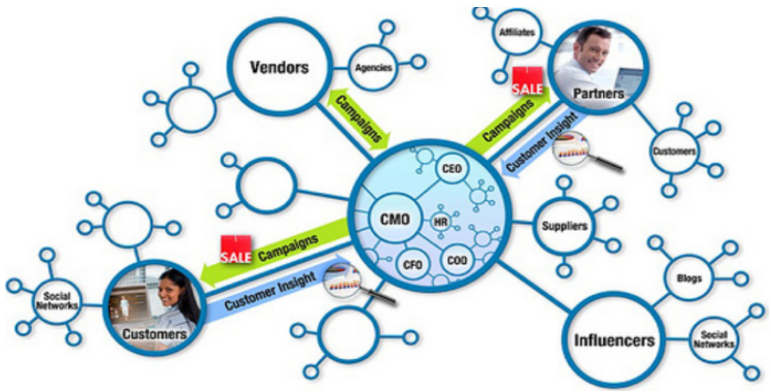
Big Data Analytics Example Use Cases

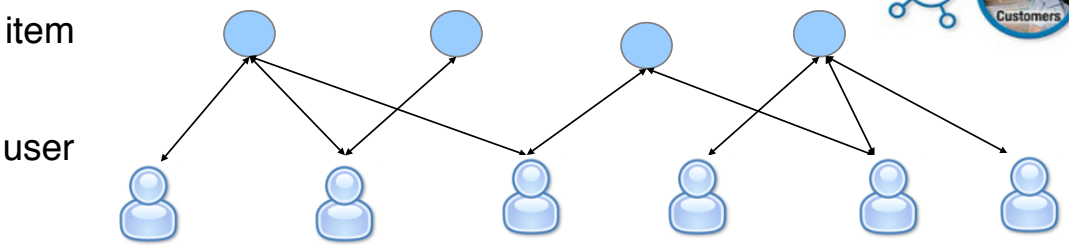
1. Expertise Location
2. Recommendation
3. Commerce
4. Financial Analysis
5. Social Media Monitoring
6. Telco Customer Analysis
7. Watson
8. Data Exploration and Visualization
9. Personalized Search
10. Anomaly Detection (Espionage, Sabotage, etc.)
11. Fraud Detection
12. Cybersecurity
13. Sensor Monitoring (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: 360^{o} View

Recommendation



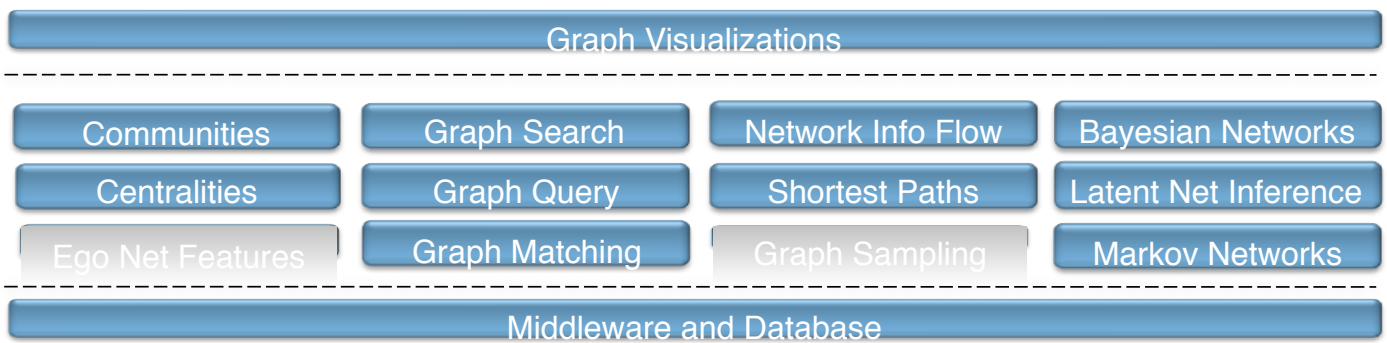




Enhancing:

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

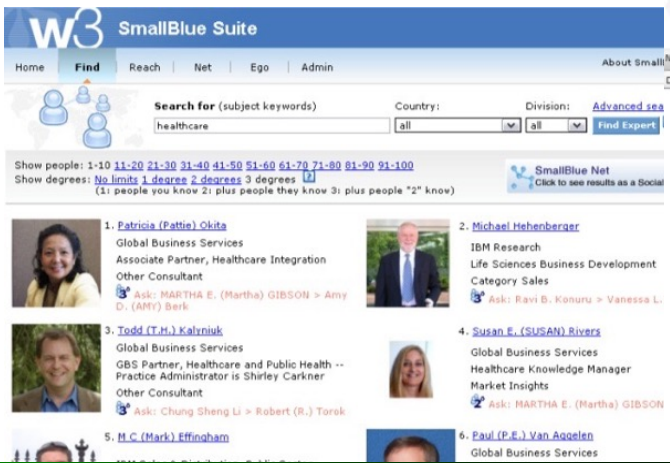
1,000,000+ Lotus Connections (blogs, file sharing, bookmark) data

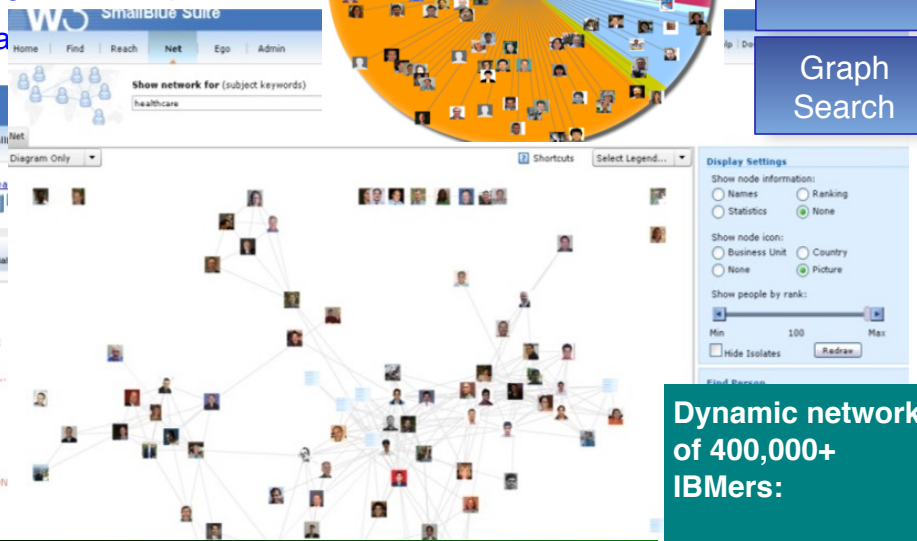
200,000 people's consulting project & earning da

Shortest Paths

Centralities

Graph Search





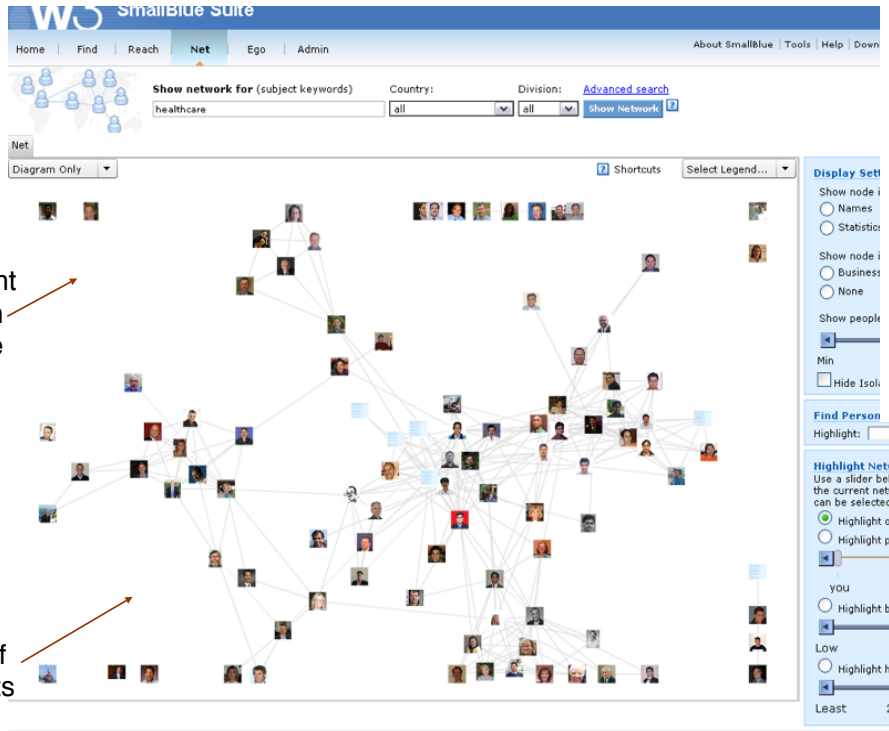
Dynamic networks of 400,000+ IBMers:

Shortest Paths
Social Capital
Bridges
Hubs
Expertise Search
Graph Search

– 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
– 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

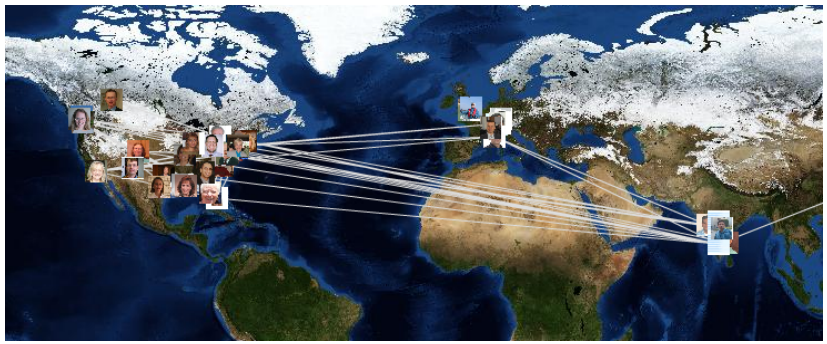
- Search for the most knowledgeable colleagues within organization or my 3-degree network for who knows topic XYZ (or within a country, a division, a job role, or any group/community)
- Based on IBM HR requirements, adding the 'sponsored search' for business department needs
- IBM HR gives a list of 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.

My shortest path to Susan

As a user, you can only see their public information. Private info is used internally to rank expertise but private data can never be exposed.

Click a name to see their profile (SmallBlue Reach)

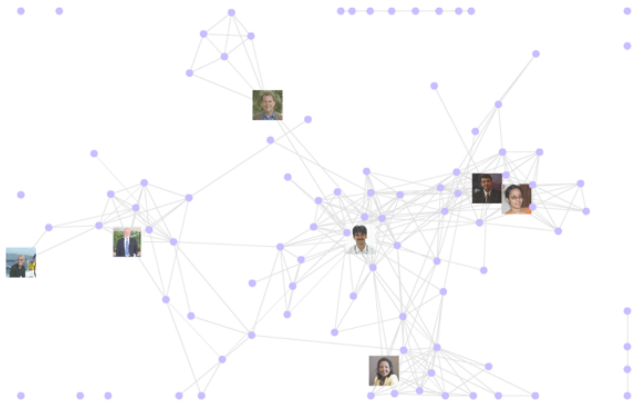
Visualize social roles of individuals in company



Example: Healthcare experts in the world

Example: Healthcare experts in the U.S.

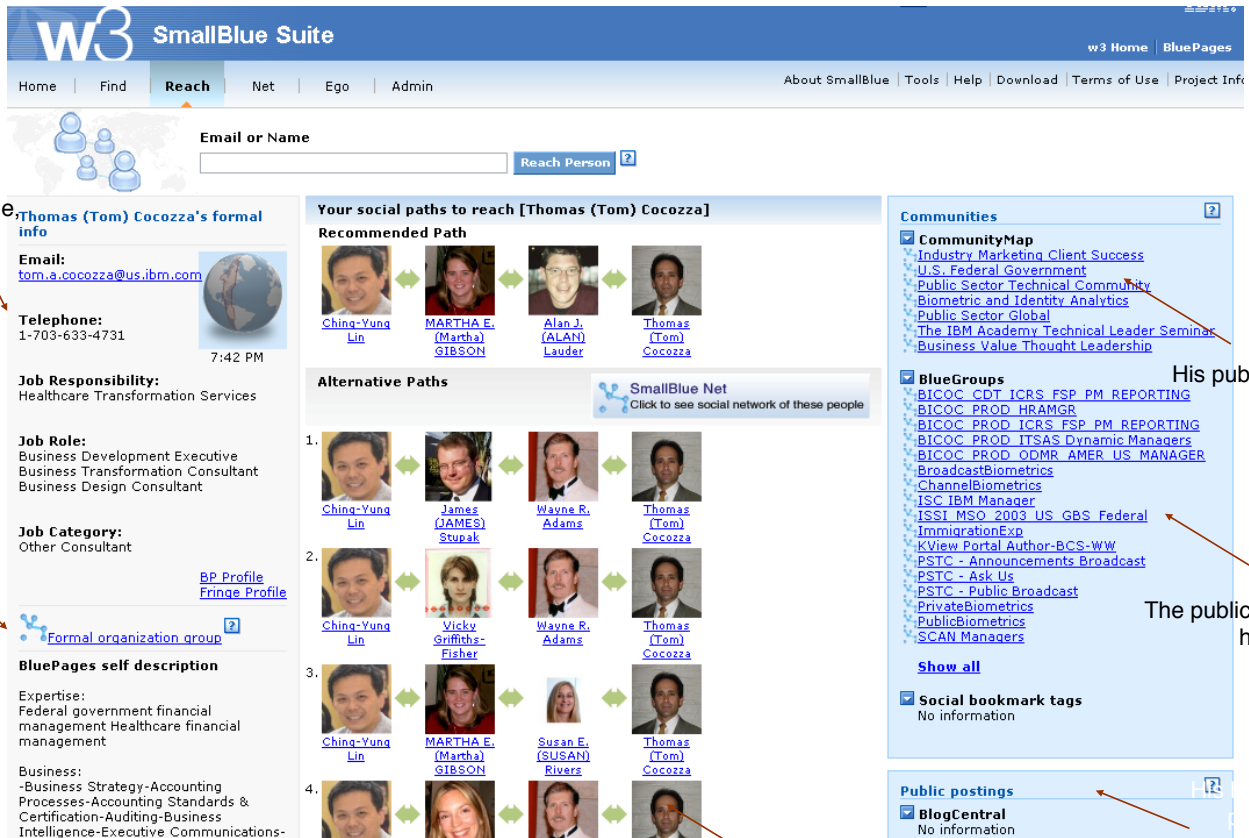
Connections between different divisions



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

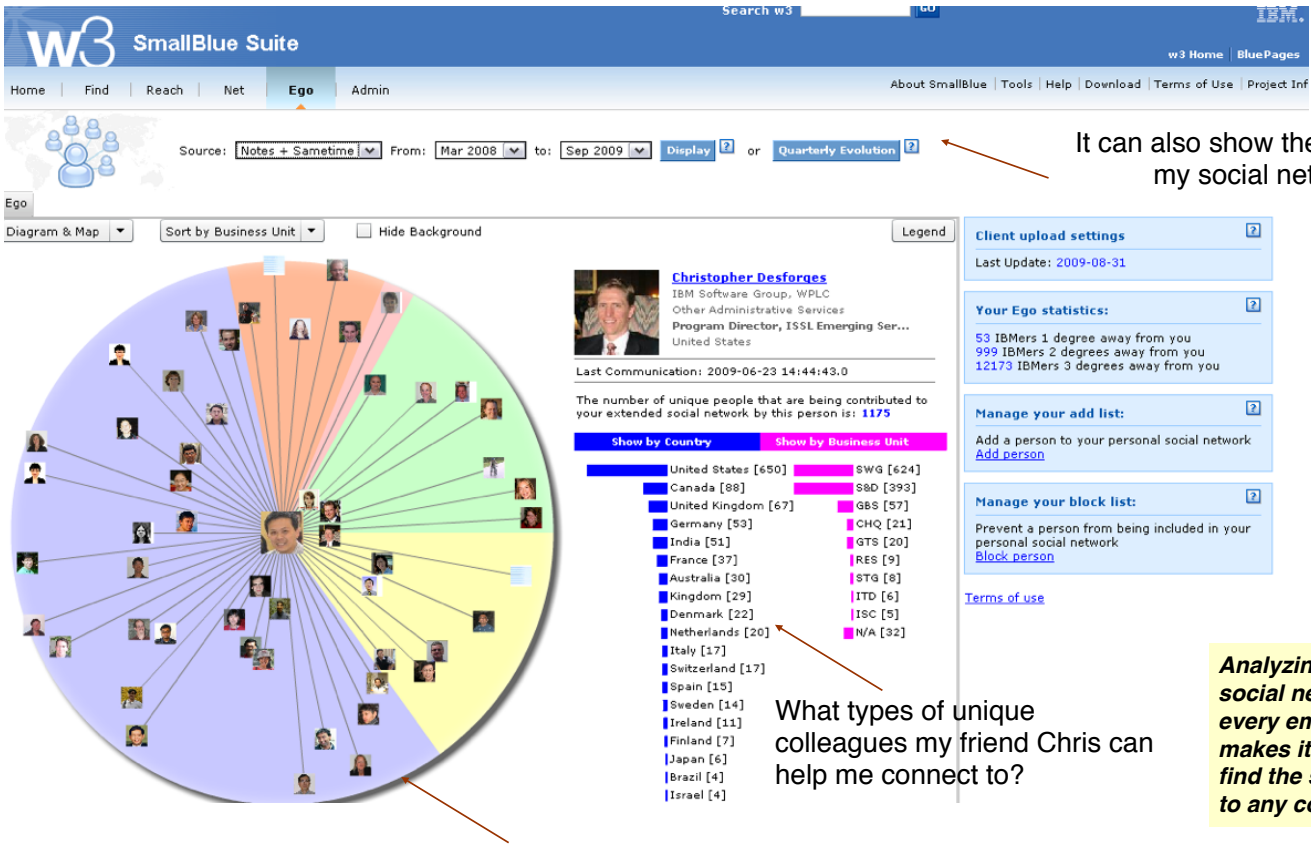
His public communities

The public interest groups he is in

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?

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

Evolutionalry personal social network

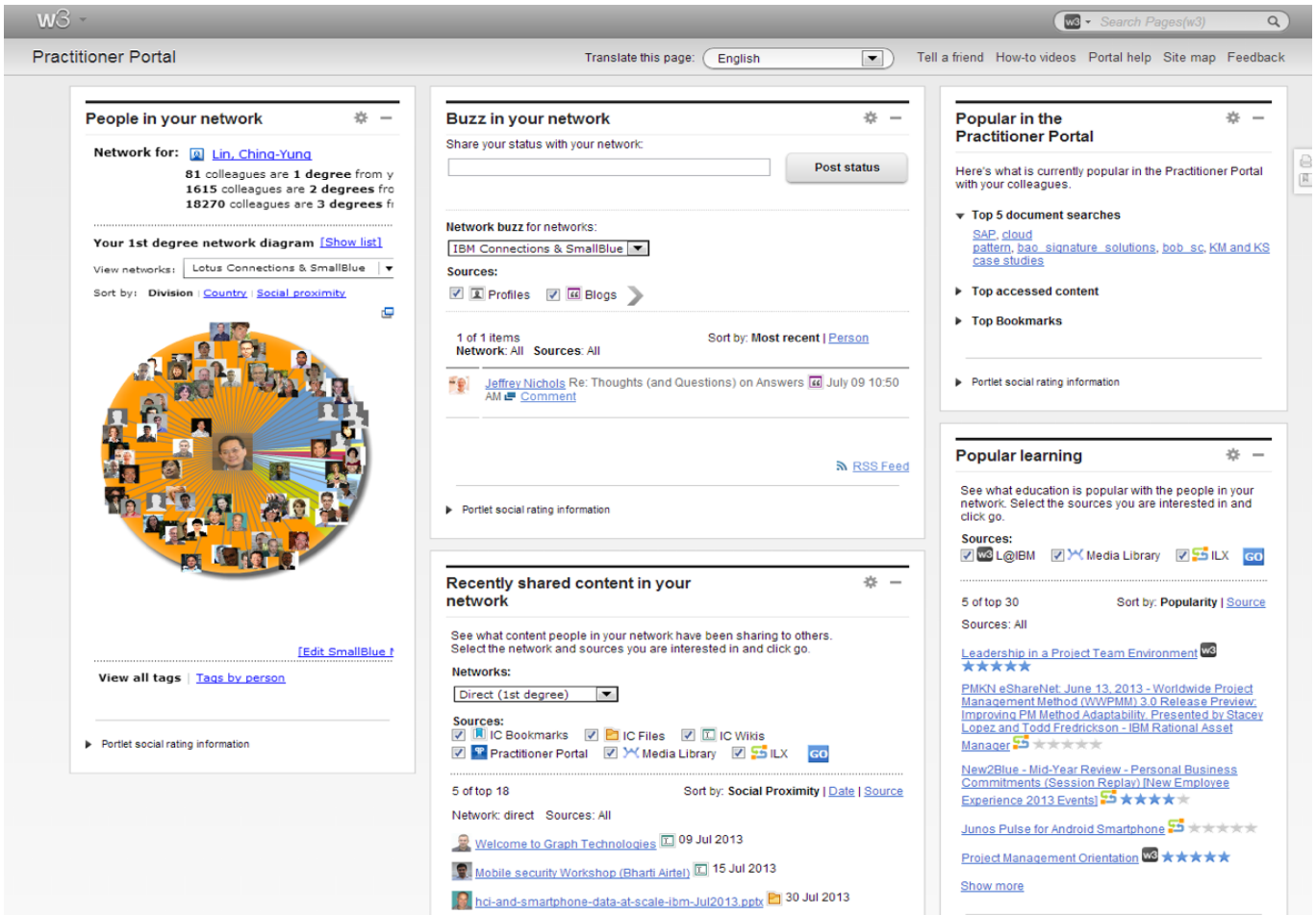
Network Value Analysis – First Large-Scale Economical Social Network Study

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



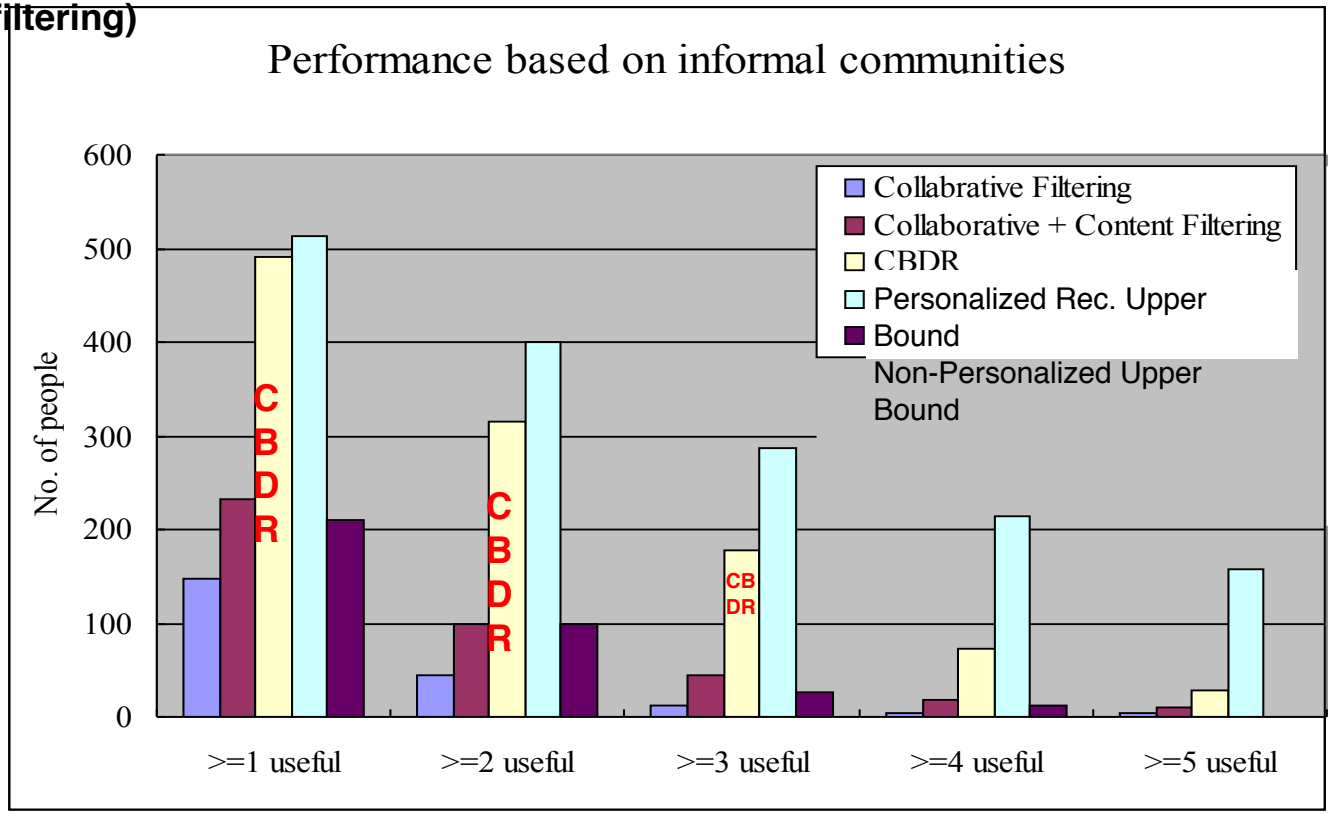
- Integrated Practitioner Portal, KnowledgeView, Media Library, Lotus Connections, and Learning@IBM and for a personalized ranking

Improving Recommendation Quality by Graph Community Analytics

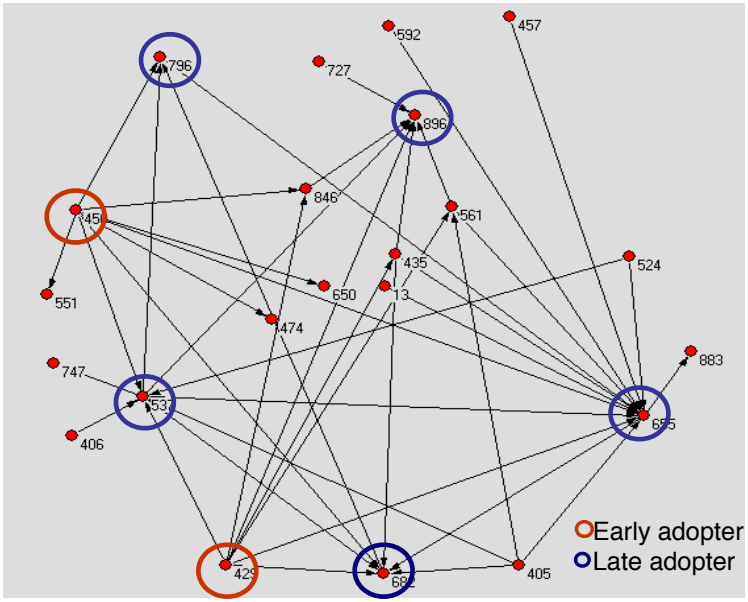
Graph Communities

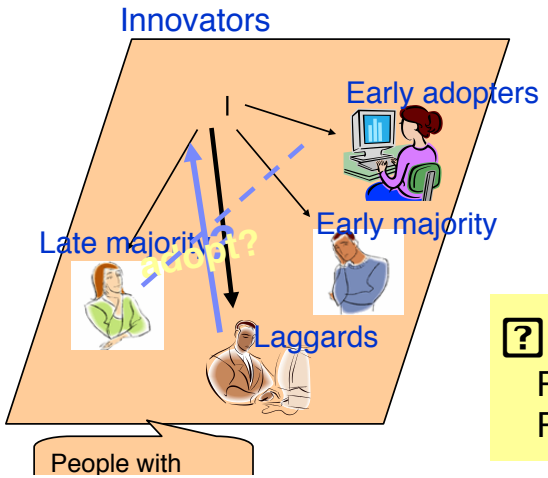
– A 3rd party Knowledge Repository: 30K users and 20K documents.
Study the most active 697 users who have at least 20 download in a year.

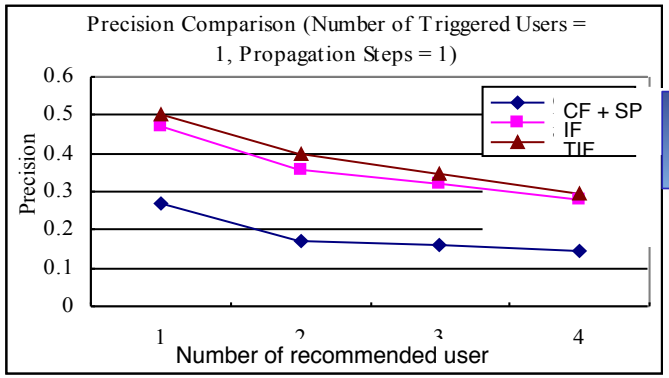
– **Results: beyond Collaborative Filtering: (1) Collaborative + Content Filtering (53% improvement); (2) CBDR: Collaborative + Content Filtering + Graph Community Analytics (259% accuracy improvement over collaborative filtering)**

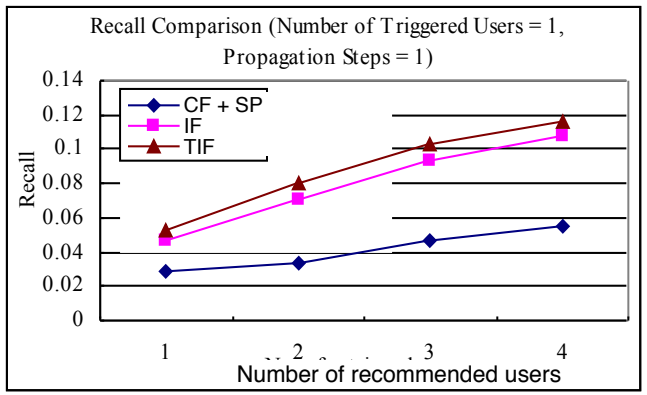


Use Case 3: Recommendation for Commerce









Network Info Flow

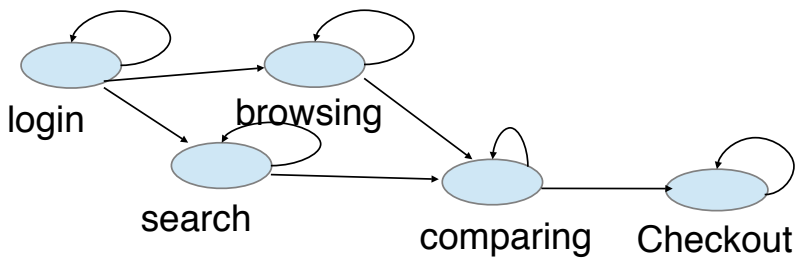
Tests:
– 1 month
– 586 new docs
– 1,170 users

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

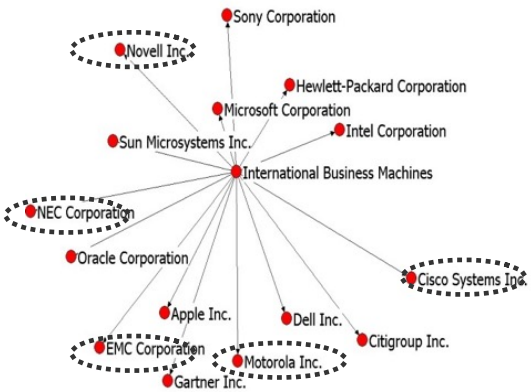


- Behavior Pattern Detection
- Help Needed Detection

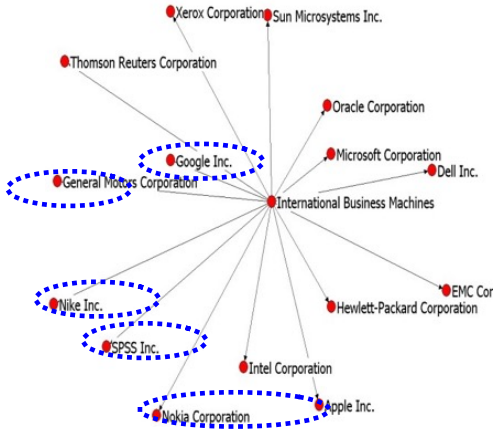
Use Case 4: Graph Analytics for Financial Analysis

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

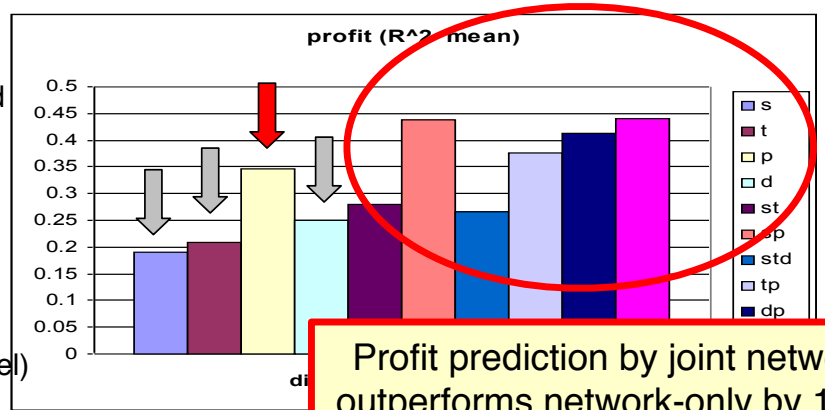


- Data Source:
  - Relationships among 7594 companies, data mining from NYT 1981 ~ 2009

Targets: 20 Fortune companies' normalized Profits

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

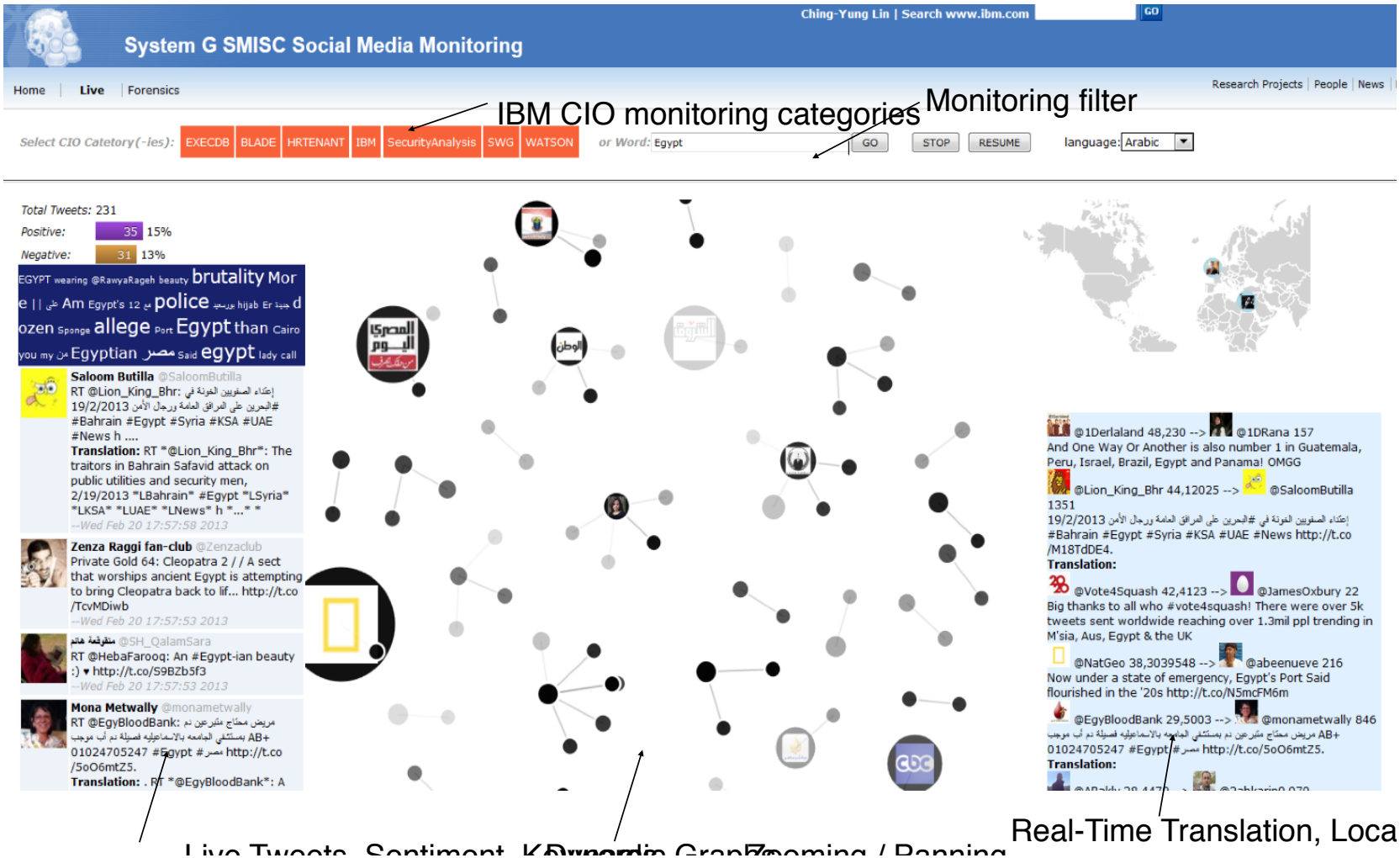
Model: Support Vector Regression (RBF kernel)



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

Use Case 5: Social Media Monitoring



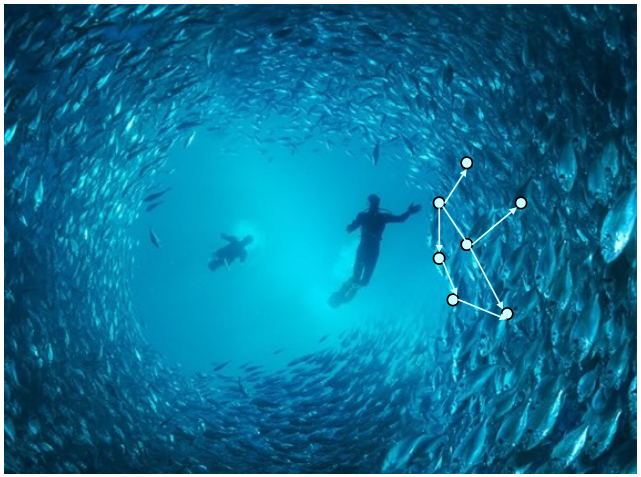
IBM System G Social Media Solution Research Tasks

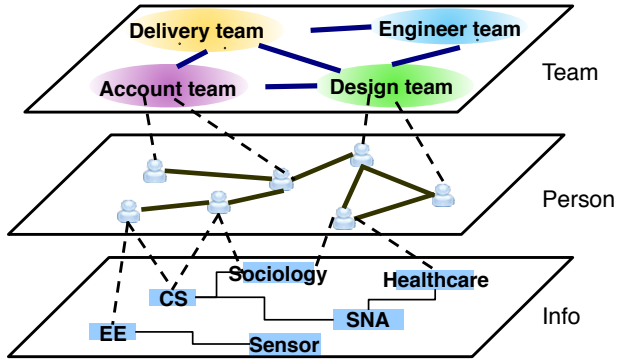
Thrust 1. Modeling Information Dissemination:
Task 1.1. Computational Modeling of User Dynamic Behavior
Task 1.2. Computational Models of Trust and Social Capital
Task 1.3. Information Morphing Modeling
Task 1.4. Persuasiveness of Memes
Task 1.5. The Observability of Social Systems
Task 1.6. Culture-Dependent 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

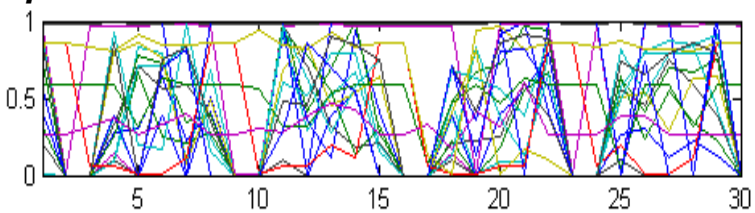
Heterogeneous Synchronicity Networks Predict Performance

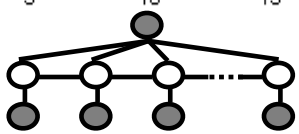




Outperform existing approaches by up to 18% (SDM 13)

One-class HCRF to detect temporal anomalies





Detected as top 1 anomaly in Sandy Tweets

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

Dynamics of Information Graphs in Social Media

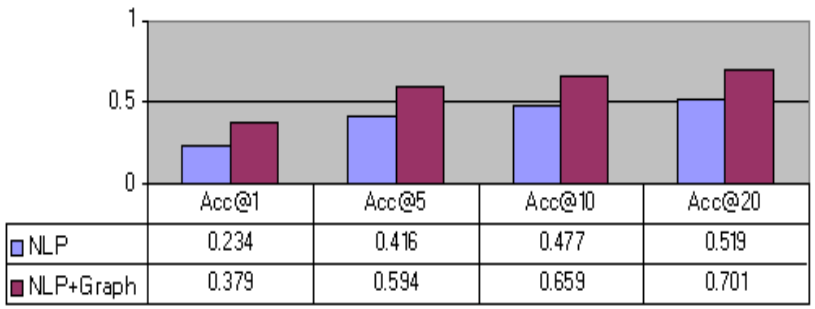
- **Motivation:**
  - –Info morph: new links keep emerging to give new meaning to existing phrases
- **Approach:**
  - –Compare characteristics of meta-paths between nodes in heterogeneous networks

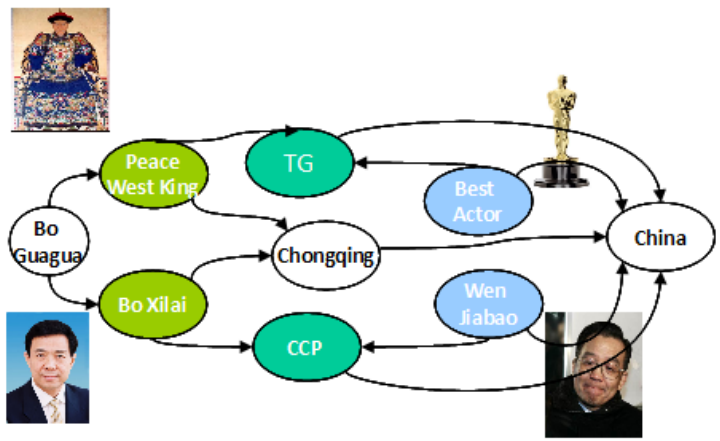
Peace West King from ***Chongqing fell from power***, still need to ***sing red songs***?

中国日報 CHINA DAILY
THE NATIONAL ENGLISH LANGUAGE NEWSPAPER

- ***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)



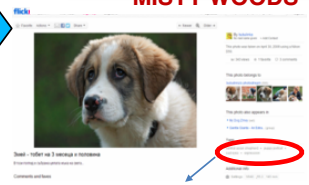


$$\sum_{i=1}^{N} p_m(x_i) \log \frac{p_m(x_i)}{p_e(x_i)} + p_e(x_i) \log \frac{p_e(x_i)}{p_m(x_i)}$$

Visual Sentiment and Semantic Analysis

First work in the literature on automatic visual sentiment analysis

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

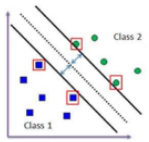


Training from 6 million tags

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)

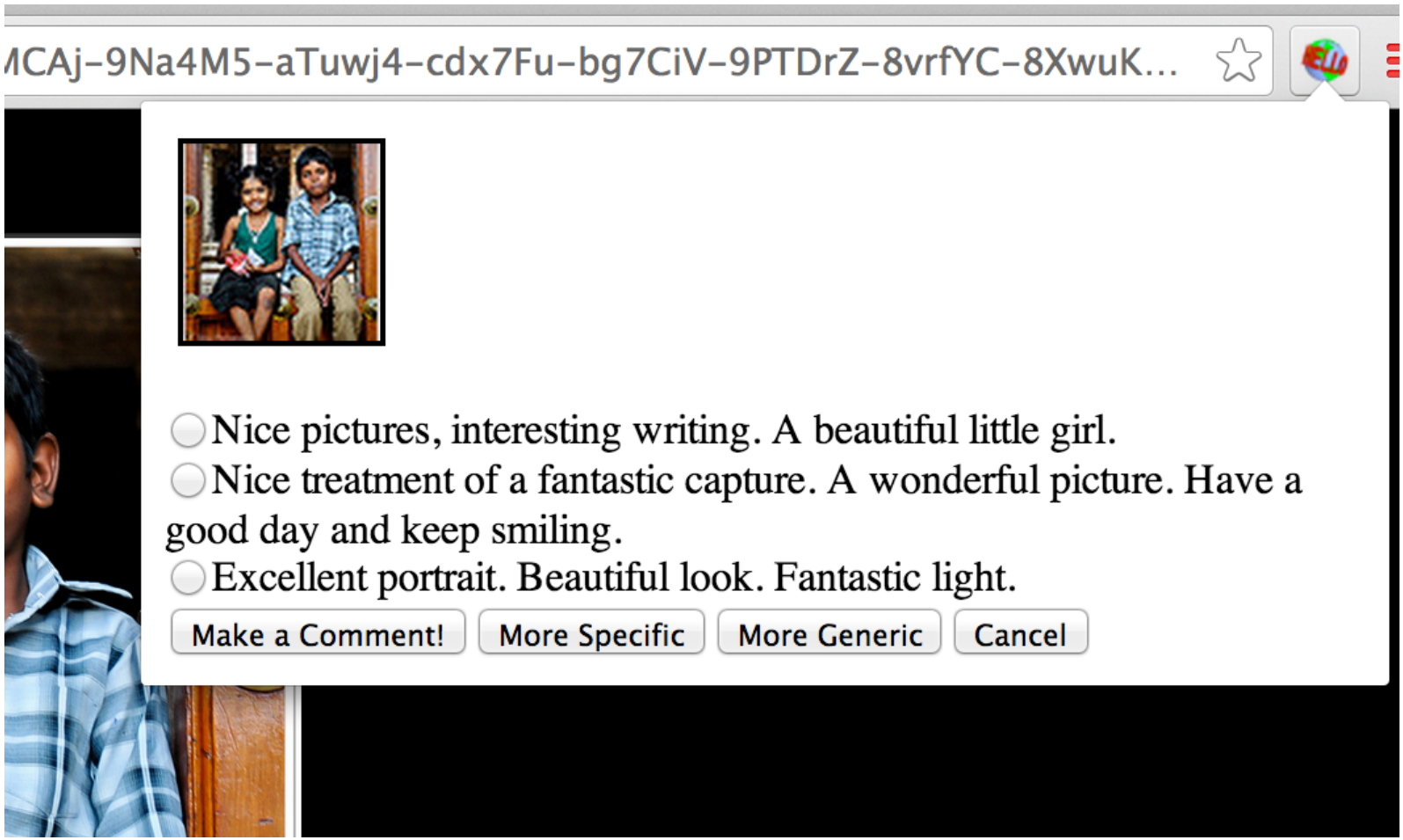
Detection results of "crazy car" (100% accuracy, 5 out of 5 correct)

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

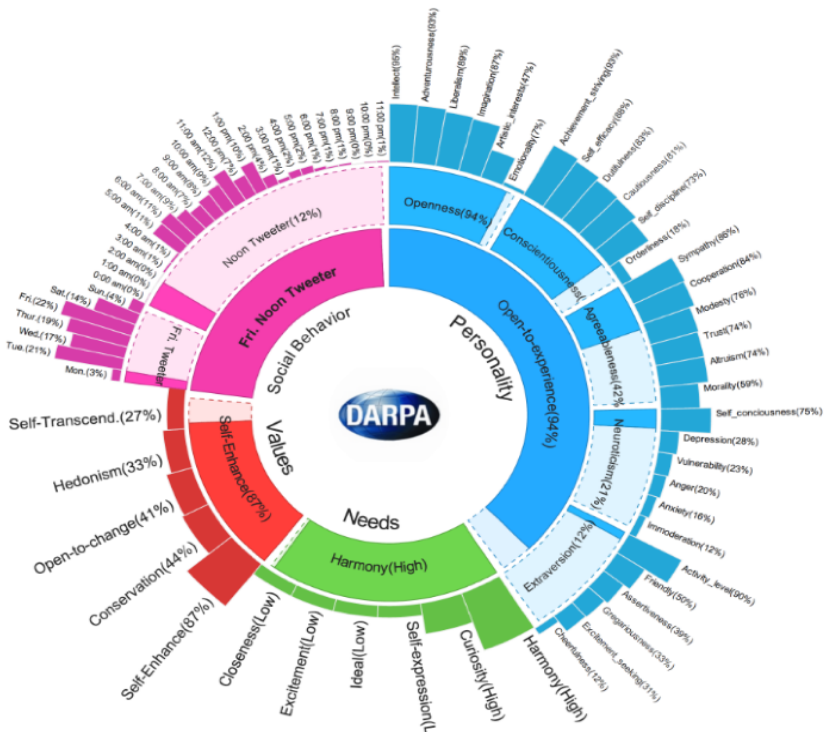
– **Personality:** Mapping personal/ organizational social media postings to scores of BIG 5 Personality (*Openness, Conscientiousness, Extraversion, Agreeableness, and Neurocism*)

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

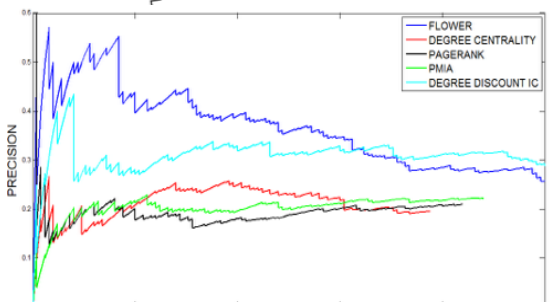
– **Values:** Mapping personal/organizational social media postings to scores of *Self-Enhance. Conservation, Open-to-Change, Hedonism, and Self-Transcend*.

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

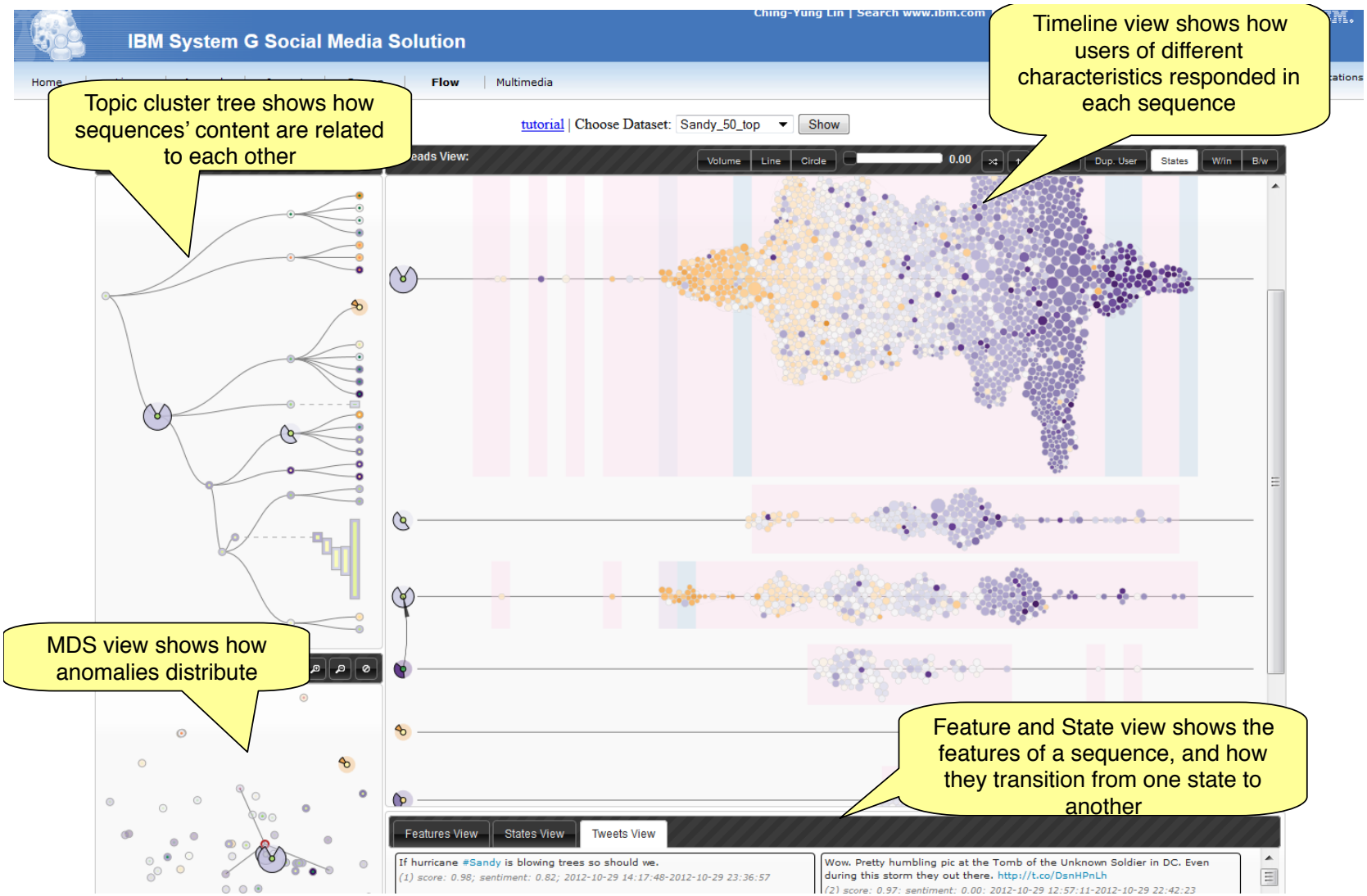
– **Influence:** Total *attention* received by user as leader across all discovered flows.



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



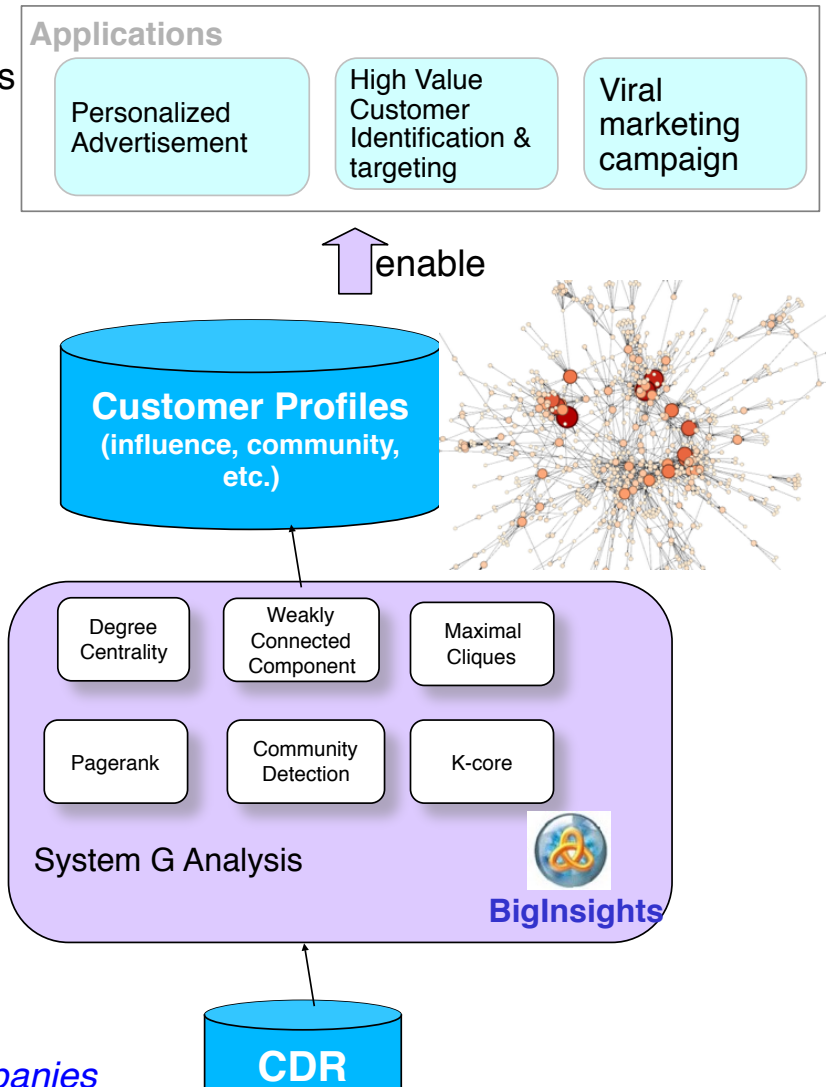
Flow Analytics - I



Use Case 6: Customer Social Analysis for Telco

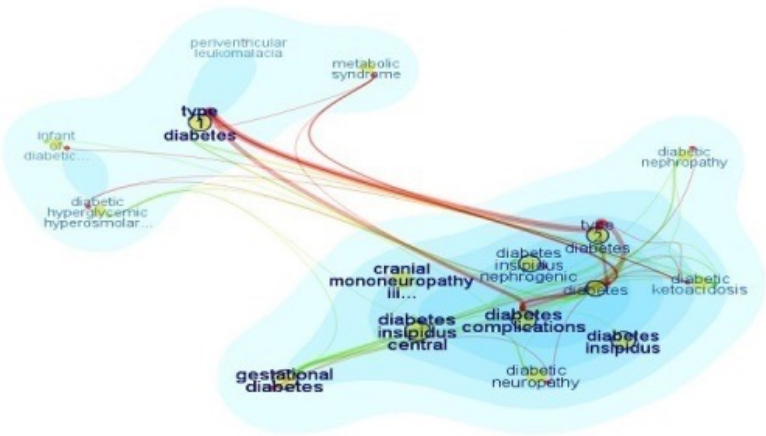
Goal: Extract customer social network behaviors to enable Call Detail Records (CDRs) data monetization for Telco.

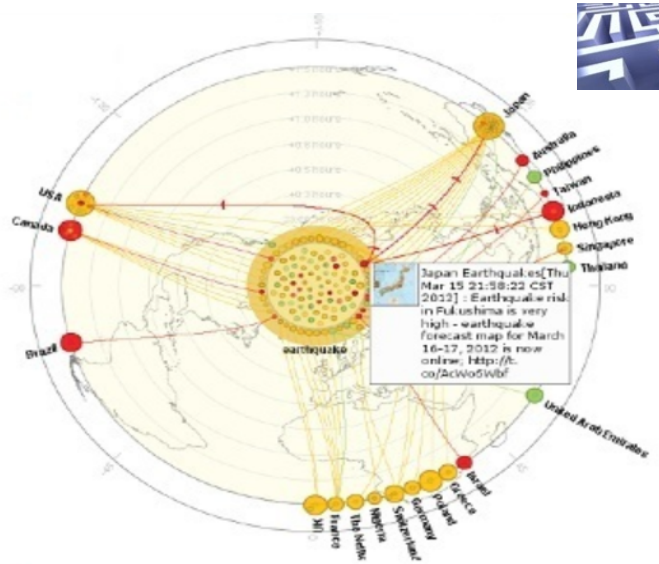
- Applications based on the extracted social profiles
  - Personalized advertisement (beyond the scope of traditional campaign in Telco)
  - High value customer identification and targeting
  - Viral marketing campaign
- Approach
  - Construct social graphs from CDRs based on {caller, callee, call time, 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:

Vivísimo

CÚRAM SOFTWARE

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

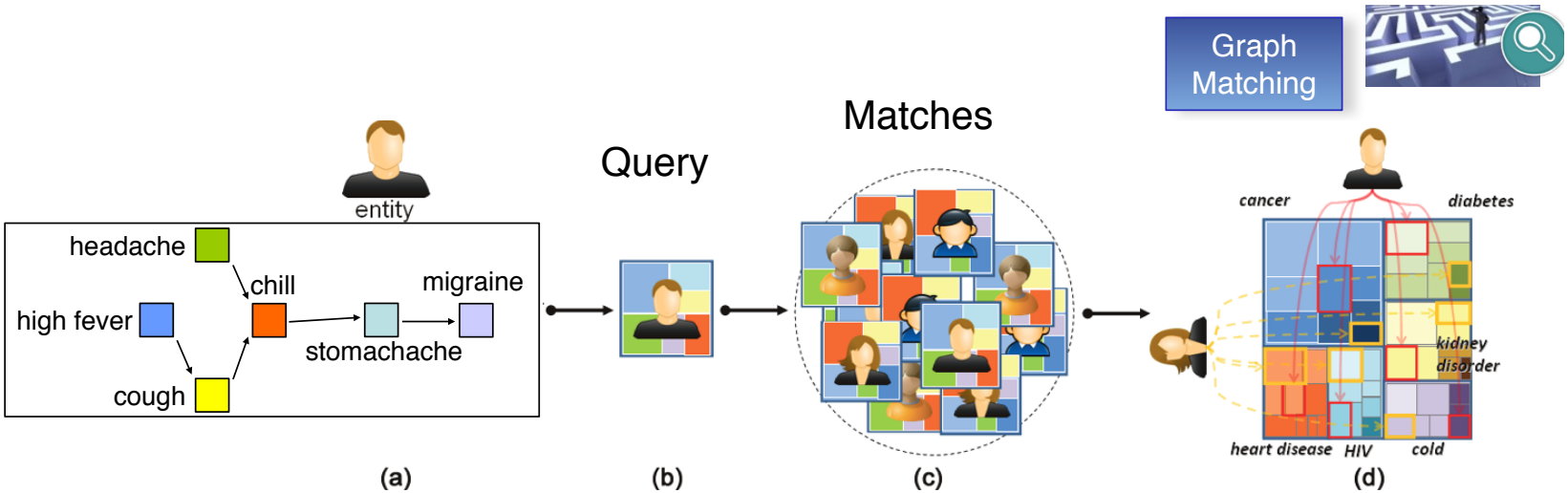
Communities | Graph Search | Network Info Flow | Bayesian Networks

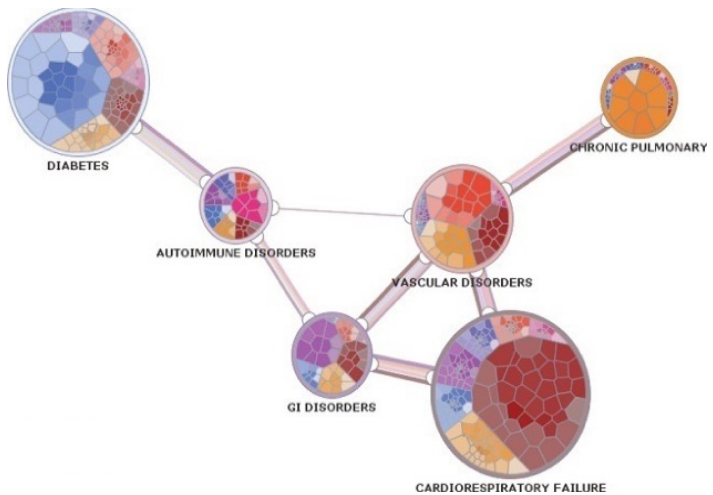
Centralities | Graph Query | Shortest Paths | Latent Net Inference

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

Middleware and Database

Use Case 7: Graph Analytics and Visualization for Watson

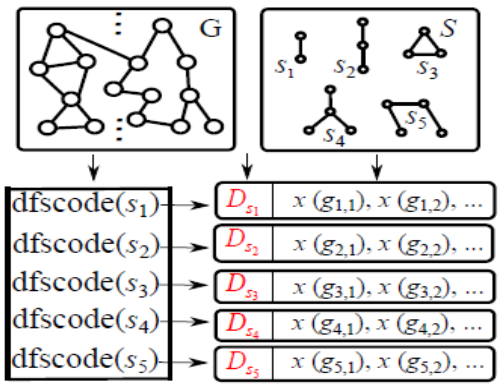




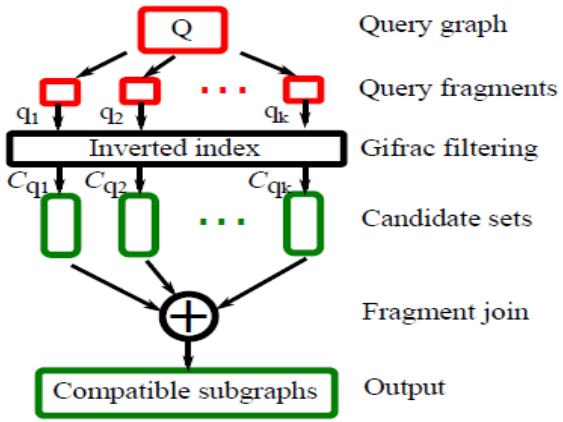
Fast Graph Matching Algorithm

- 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

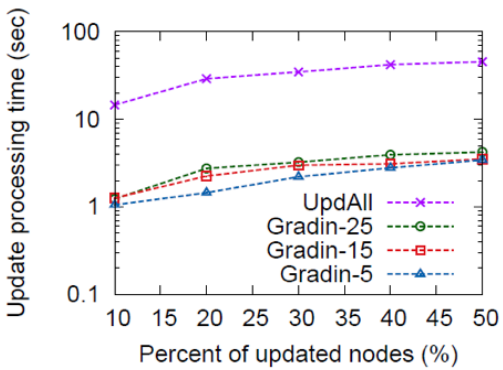
Graph Matching



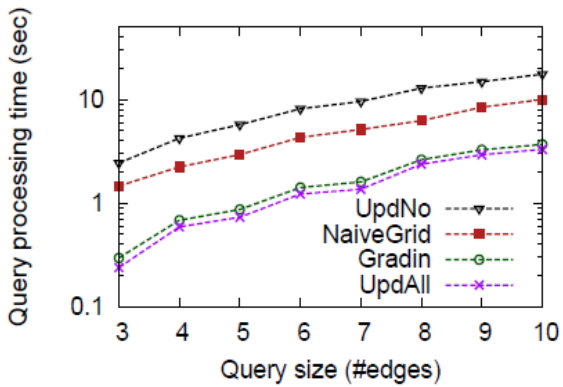
(a) Offline index building



(b) Online query processing

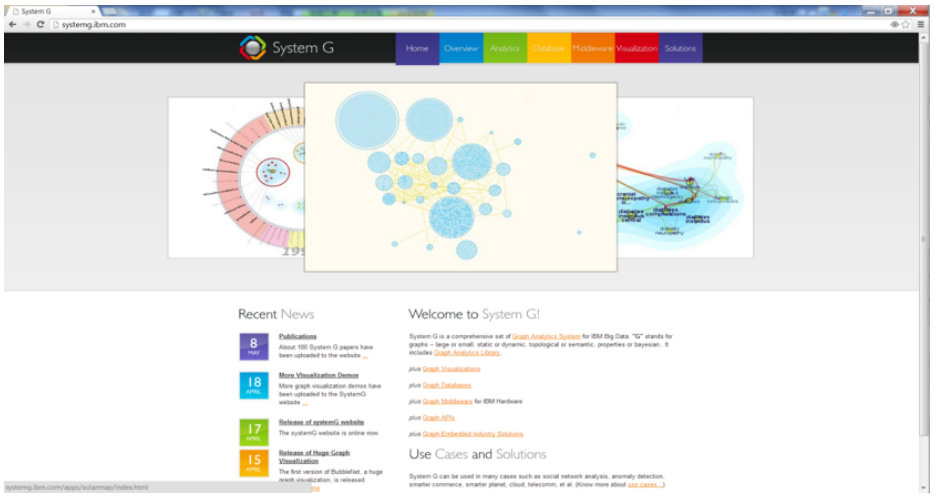


Indexing time

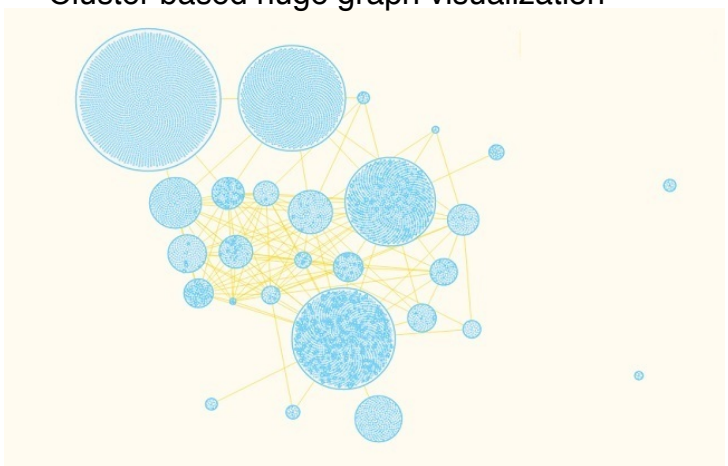


Query processing time

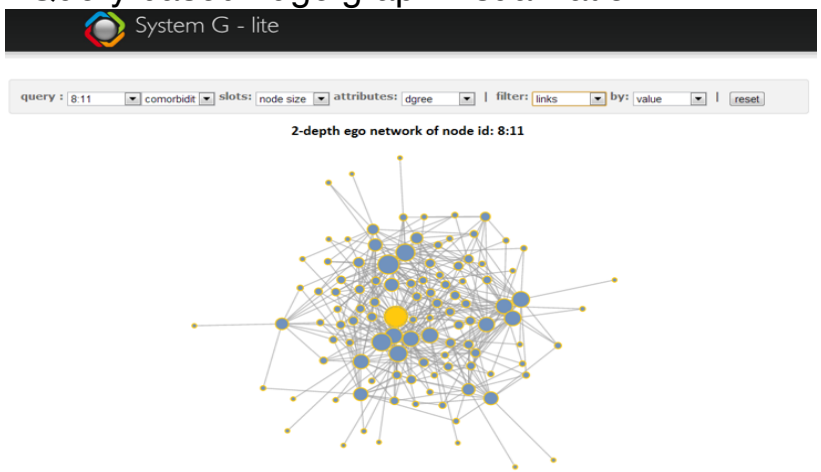
User Case 8: Visualization for Navigation and Exploration



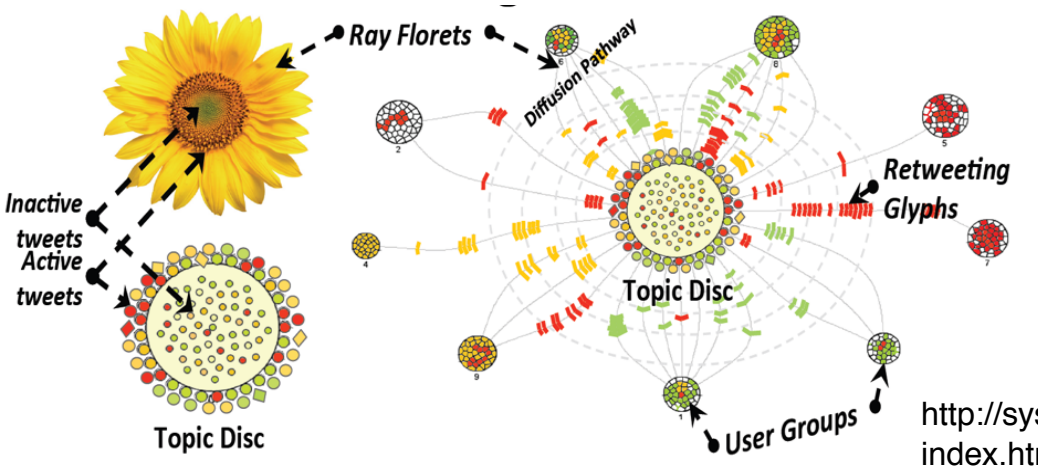
Cluster based huge graph visualization



Query based huge graph visualization



Visualizing Information Diffusion and Divergence

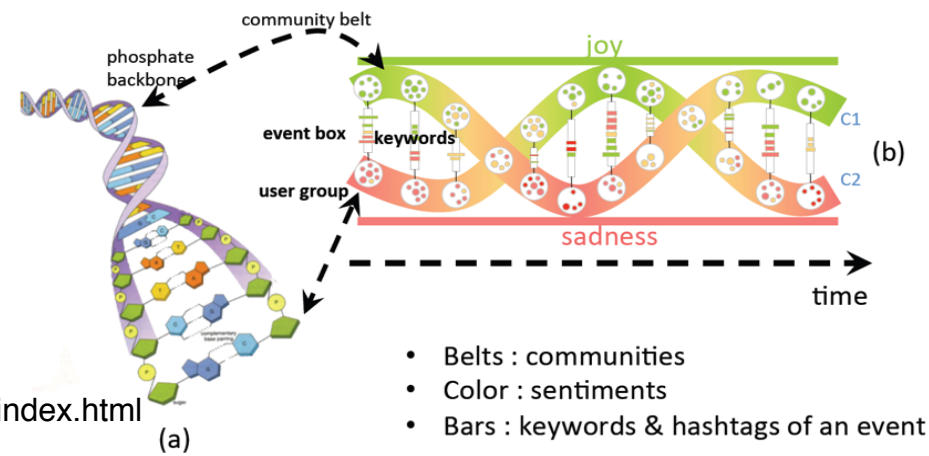


Whisper : Tracing the information diffusion in Social Media

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

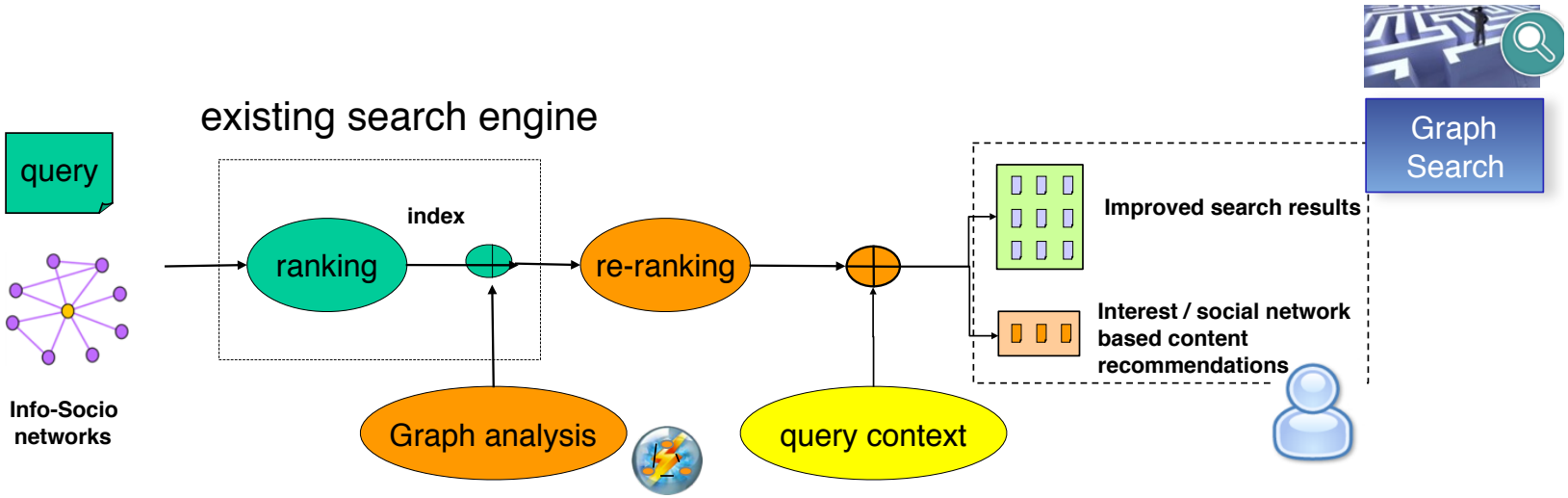
SocialHelix: Visualizaiton of Sentiment Divergence in Social Media

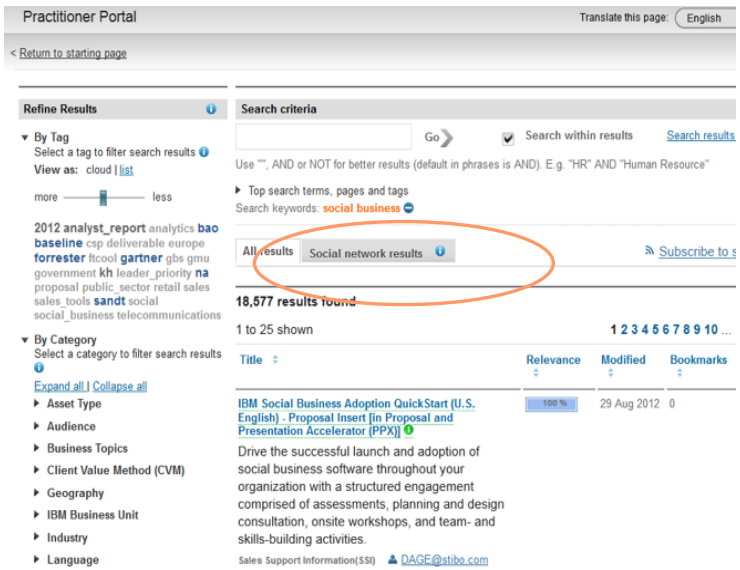
http://systemg.ibm.com/apps/socialhelix/index.html



- Belts : communities
- Color : sentiments
- Bars : keywords & hashtags of an event

Use Case 9: Graph Search

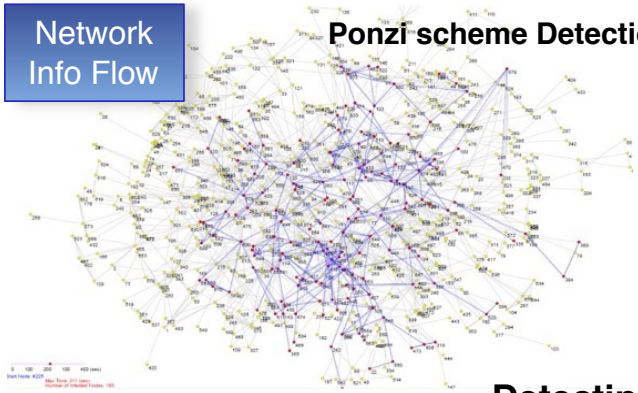




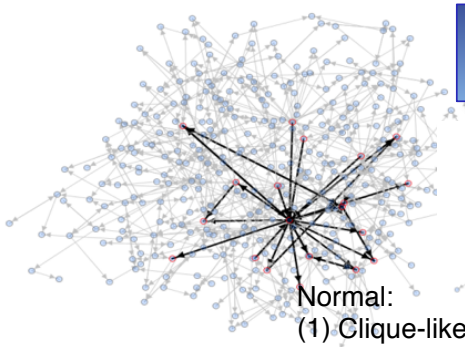
Category 3: Security

Network Info Flow

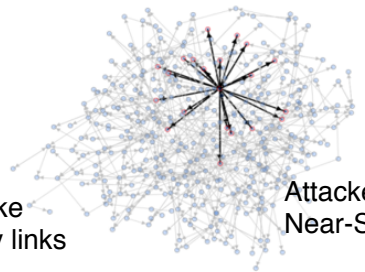
Ponzi scheme Detection



Ego Net Features

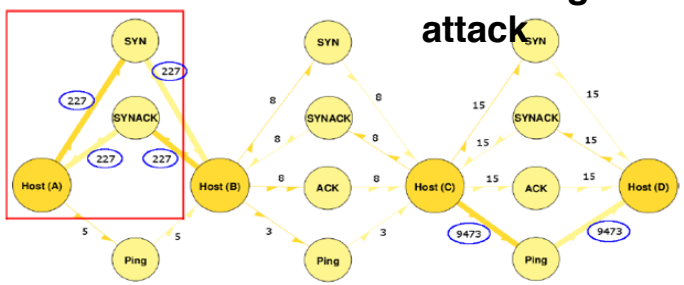


Normal:
(1) Clique-like
(2) Two-way links

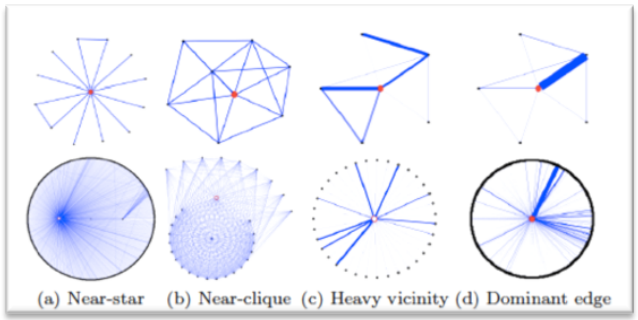


Attacker:
Near-Star

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

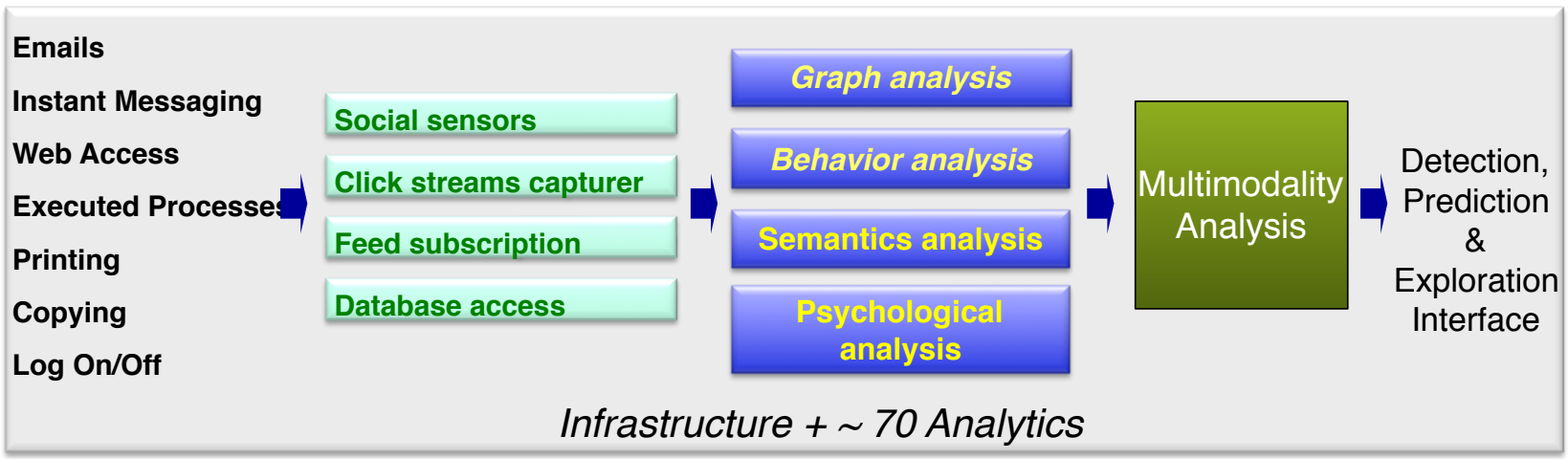
Use Case 10: Anomaly Detection at Multiple Scales

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



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:

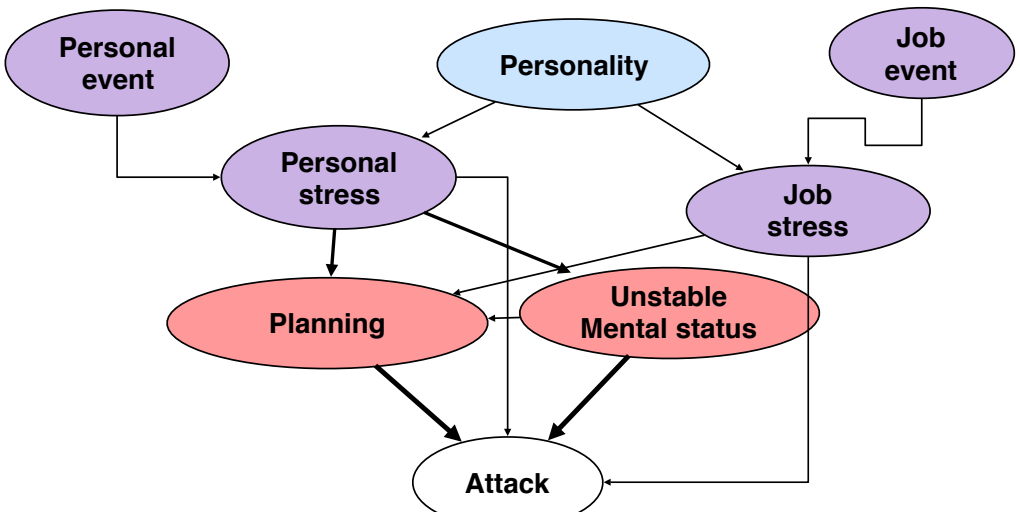
(1)Fight with colleagues, write complaining emails to colleagues

(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

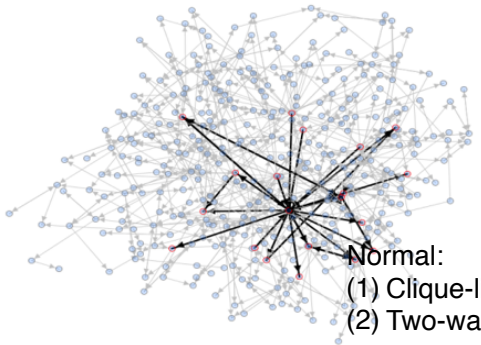
- *Mapping Espionage, Sabotage, and Fraud Use Cases into Five Layers of Classifiers*
- *Structure Learning*
- *Evolutionary Behavioral Modeling & Prediction*

Use Case 11: Fraud Detection for Bank

Network Info Flow

Ego Net Features

Ponzi scheme Detection



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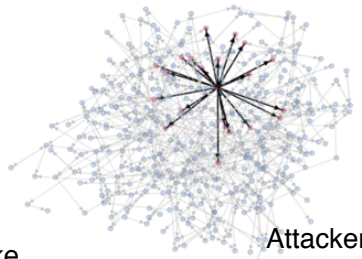
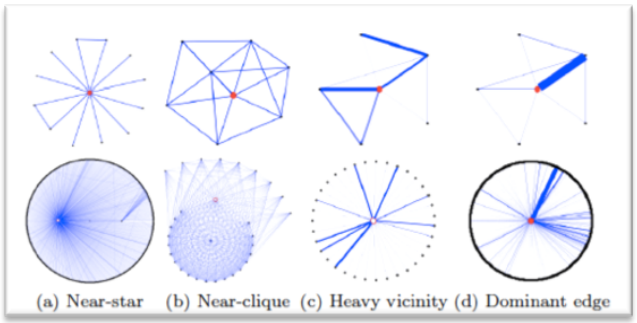


Attacker:
Near-Star

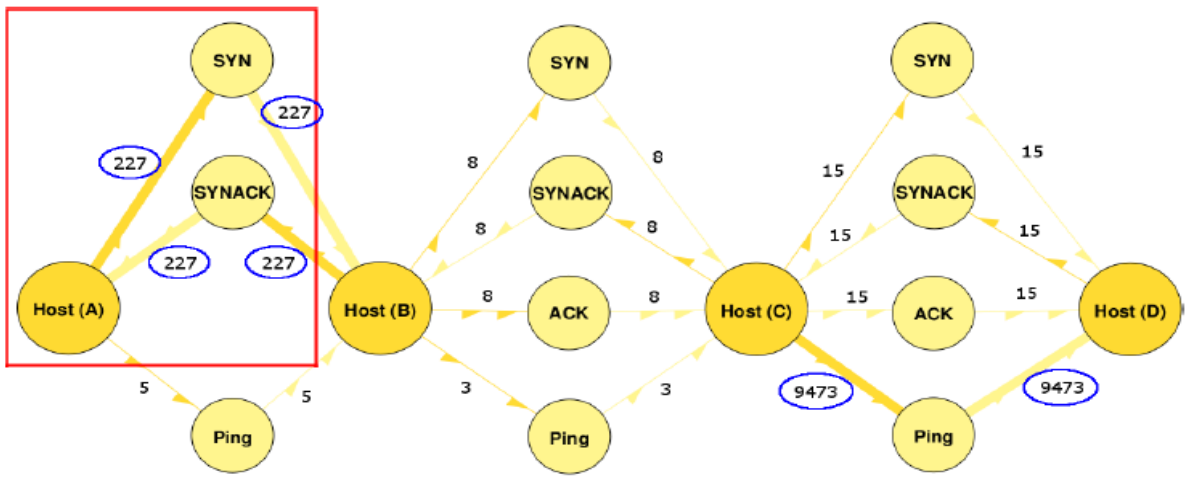


Use Case 12: Detecting Cyber Attacks

Network Info Flow

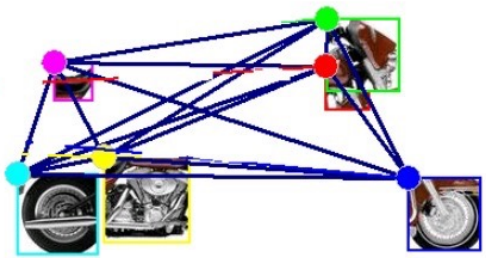
Ego Net Features

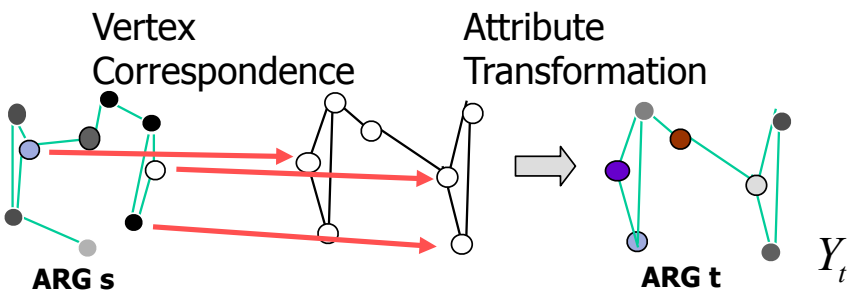
Detecting DoS attack



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

Use Case 13: Graph Analysis for Image and Video Analysis





Use Case 14: Planet Security

- Big Data on Large-Scale Sky Monitoring