

Big Data Analytics Lecture 1

Yilu Zhou, PhD
Associate Professor
Gabelli School of Business
Fordham University

^{*} Some slides are adopted from Professor Kunpeng Zhang's Big Data course @UMD

Yilu Zhou 周轶璐



Research Interest: Big Data, Data Science, Business Intelligence, Natural Language Processing, Machine Learning, Multilingual Knowledge Management.

FORDHAM UNIVERSITY

Associate Professor

Information Systems

2013



Assistant Professor of Information Systems

2006



Artificial Intelligence Laboratory

2001



Computer Science



About this class

- This class is covers
 - (1) introduction to the Big Data problem
 - current challenges, trends, and applications
 - (2) algorithms for Big Data analysis
- mining and learning algorithms that have been developed specifically to deal with large datasets
 - (3) technologies for Big Data management

Big Data technology and tools, special consideration made to the Map-Reduce paradigm and the Hadoop ecosystem.



About this class

- This class is NOT
 - a machine learning or data mining course
 - a programming course (however, you need to know basic programming with Python and some basic commands in Linux

Syllabus



Class Overview

- Introduction to Hadoop and MapReduce programming
- Hadoop overview
 - Framework / architecture
- Cloud computing (Amazon AWS)
- Data management
 - Hbase, hive, pig, sqoop, kafka



Class Overview -cont'd

Data analytics

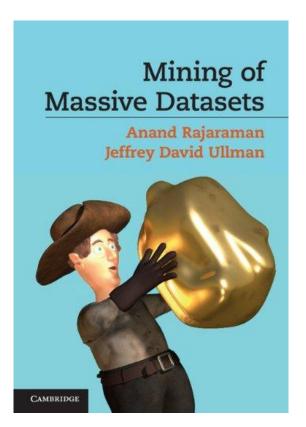
- Association rule mining
- Clustering
- Recommender system
- Topic modeling
- Social network analysis
- Spark

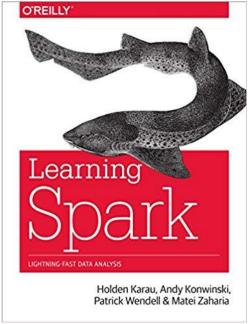
Algorithm level (not just the terminology)

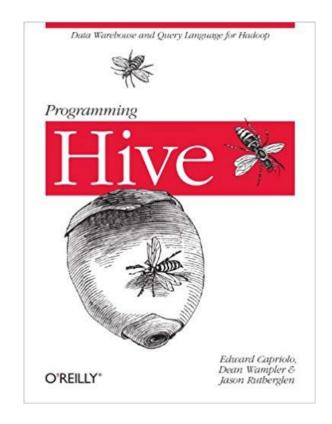


Textbooks

Recommend you read the following books:









Data-Intensive Text Processing with MapReduce

Jimmy Lin Chris Dyer

SYNTHESIS LECTURES ON HUMAN LANGUAGE TECHNOLOGIES

Graeme Hirst, Series Editor



How It All Fits Together

High dim. data

> Locality sensitive hashing

Clustering

Dimensional ity reduction

Graph data

PageRank, SimRank

Community Detection

Spam Detection Infinite data

data streams

Web advertising

Queries on streams

kNN

Machine learning

SVM

Decision Trees

Perceptron,

Apps

Recommen der systems

Association Rules

Duplicate document detection

J. Leskovec, A. Rajaraman, J. Ullman: Mining of Massive

Datasets, http://www.mmds.org



Labs

Configuration and installation of Hadoop

Data management (HQL)

Spark practice

ML practices (multiple!)



Assignments

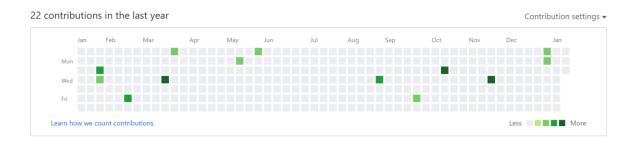
- 4 assignments (all of them require programming)
 - Basic MapReduce programming
 - Data management
 - Frequent Itemset Mining
 - K-Means
 - Recommendation System
 - Topic Models
 - Social network analysis

create github account

Two of these topics



Start to use GitHub



 Goal: to have at least 4 commits by the end of the semester



For MSBA: use it as your extended resume



Project

- 1. **Proposal presentation.** Maximum 6 PPT pages of project proposal, dataset, business problem, data processing, models and (optional) expected outcomes.
- 2. **Final Presentation.** There will be 1 presentation during the last class in the semester, major results are expected during the presentation.
- 3. **Report.** Maximum 15-page report (single-space, 12-point font) highlighting consisting on the traditional sections of introduction, motivation, method, results, and conclusion.
- 5. **Confidential peer-evaluation form**. You will evaluate the contribution of each of your group members.



Big Data Overview



Why Big Data?

- Science
- Engineering
- Business
 - In 2012, the Obama administration announced the Big Data Research and Development Initiative 84 different big data programs spread across six departments.
 - Walmart handles more than 1 million customer transactions every hour, which is imported into databases estimated to contain more than 2.5 petabytes of data.
 - Facebook handles 40 billion photos from its user base.
 - Falcon Credit Card Fraud Detection System protects 2.1 billion active accounts worldwide.
- Healthcare

• ...

The U.S. could face a shortage by 2018 of 140,000 to 190,000 people with "deep analytical talent" and of 1.5 million people capable of analyzing data in ways that enable business decisions. (McKinsey & Co)



Big data is everywhere...



processed about 24 petabytes of data per day in 2009.



transfers about 30 petabytes of data through its networks each day.

As of January 2013, Facebook users had uploaded over 240 billion photos, with 350 million new photos every day.

facebook

S3: 449B objects, peak 290k request/second (7/2011)
1T objects (6/2012)





By 2012, LHC collision data was being produced at approximately 25 petabytes per year.

Twitter now sends and receives as many as 200 million "tweets" every day.



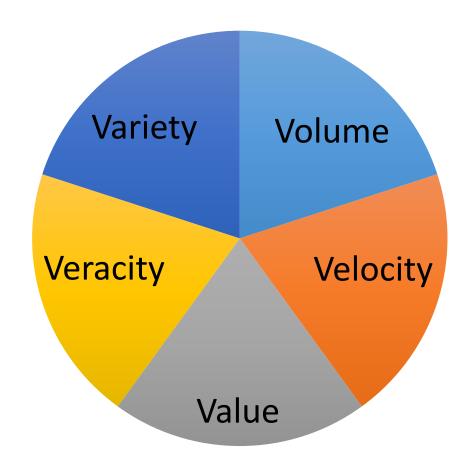
150 PB on 50k+ servers running 15k apps (6/2011)





5 Vs of Big Data

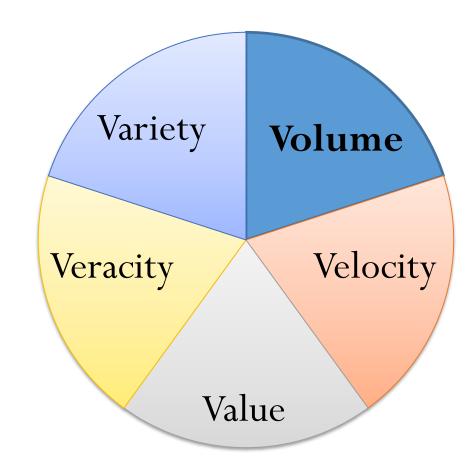
To get better understanding of what big data is, it is often described using 5 Vs.





We see increasing volume of data, that grow at exponential rates

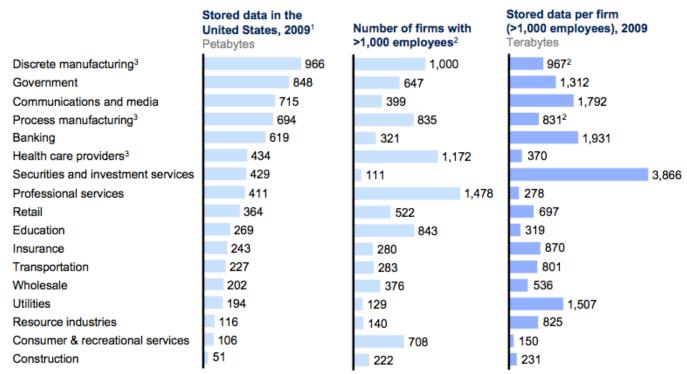
Volume refers to the vast amount of data generated every second. We are not talking about Terabytes but Zettabytes or Brontobytes. If we take all the data generated in the world between the beginning of time and 2008, the same amount of data will soon be generated every minute. This makes most data sets too large to store and analyze using traditional database technology. New big data tools use distributed systems so we can store and analyze data across databases that are dotted around everywhere in the world.





Big data is more prevalent than you think

Companies in all sectors have at least 100 terabytes of stored data in the United States; many have more than 1 petabyte



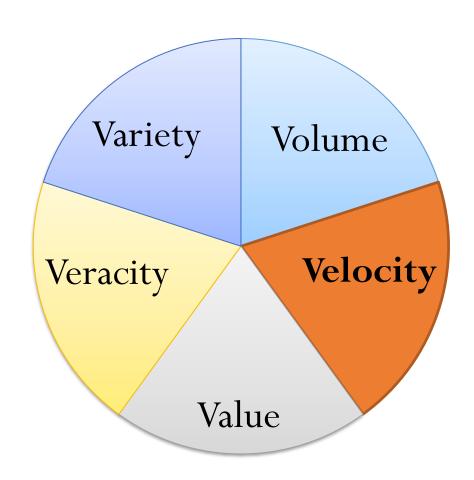
- 1 Storage data by sector derived from IDC.
- 2 Firm data split into sectors, when needed, using employment
- 3 The particularly large number of firms in manufacturing and health care provider sectors make the available storage per company much smaller.

SOURCE: IDC; US Bureau of Labor Statistics; McKinsey Global Institute analysis



We see increasing velocity (or speed) at which data changes, travels, or increases

Velocity refers to the speed at which new data is generated and the speed at which data moves around. Just think of social media messages going viral in seconds. Technology now allows us to analyze the data while it is being generated (sometimes referred to as it inmemory analytics), without ever putting into databases.

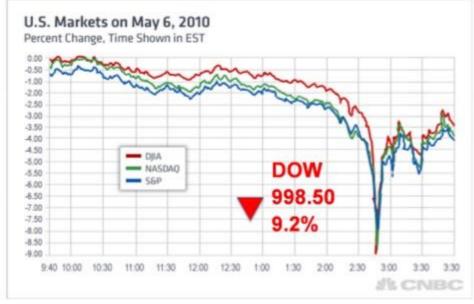




Stream Data and Real Time Data



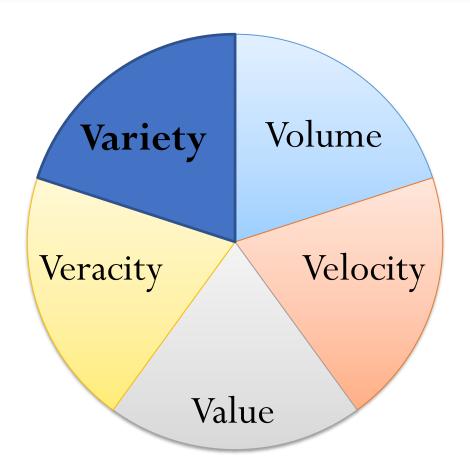
Big Data - Velocity Example





We see increasing variety of data types

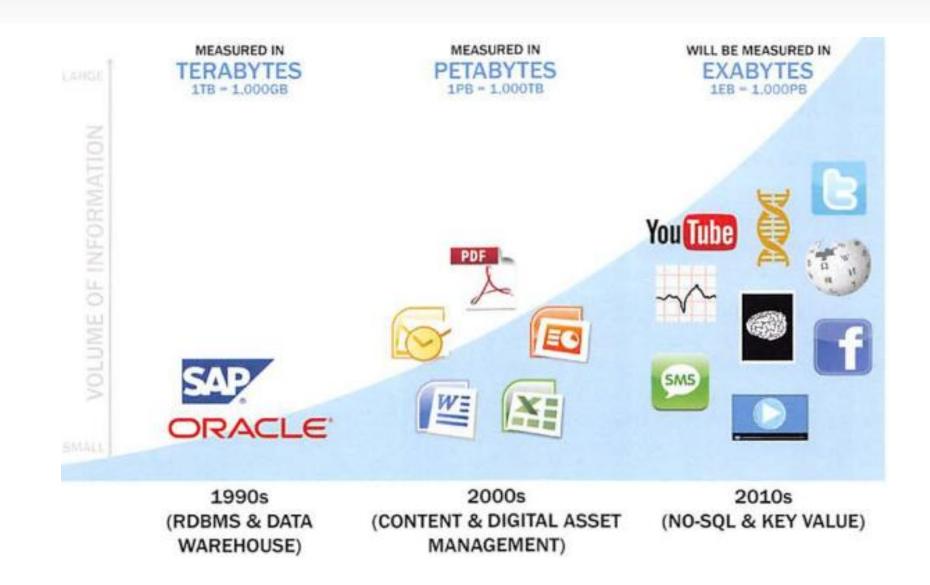
Variety refers to the different types of data we can now use. In the past we only focused on structured data that neatly fitted into tables or relational databases, such as financial data. In fact, 80% of world's data is unstructured (text, images, video, voice, etc.). With big data technology we can now analyze and bring together data of different types such as messages, social media conversations, photos, sensor data, video or voice recordings.



BUDT 758 21

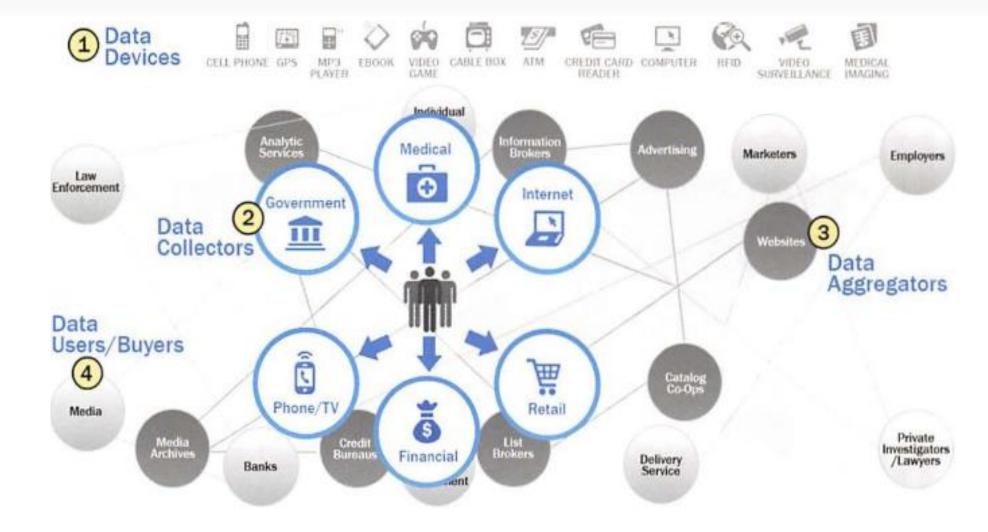


Data Evolution & Rise of Big Data Sources





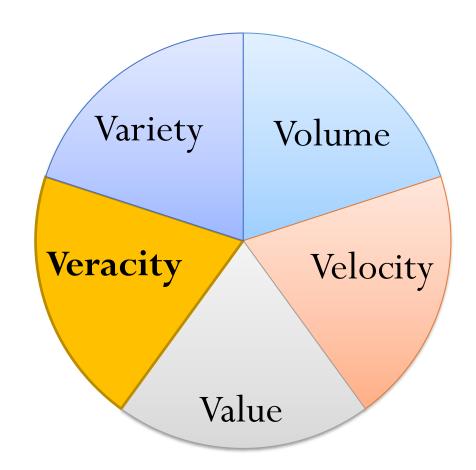
Emerging Big Data Ecosystem





We see increasing veracity (or accuracy) of data

Veracity refers to messiness or trustworthiness of data. With many forms of big data quality and accuracy are less controllable (just think Twitter posts with hash tags, abbreviations, typos and colloquial speech as well as the reliability and accuracy of content) but technology now allows us to work with this type of data.



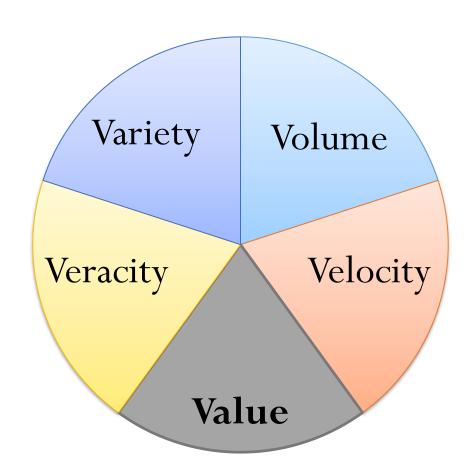


Value – the most important V of all

There is another V to take into account when looking at big data: **Value**.

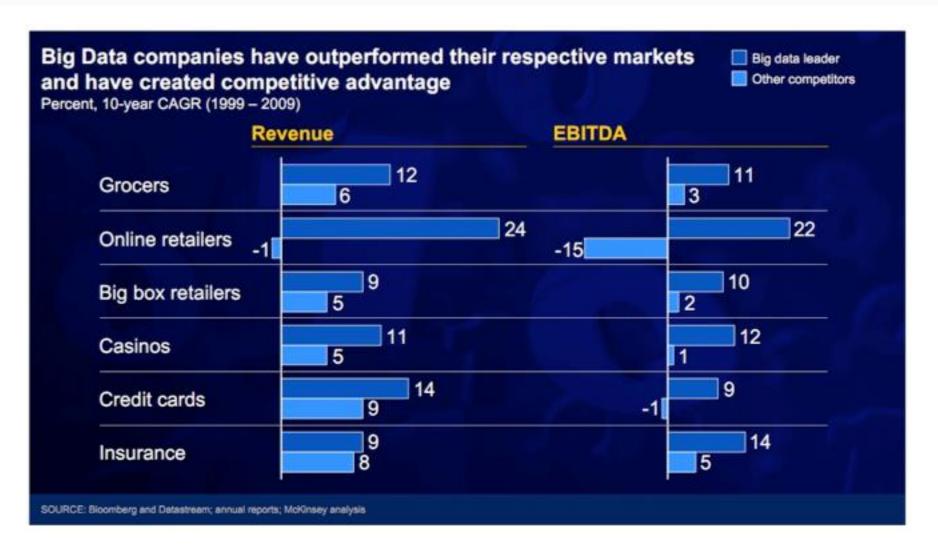
Having access to big data is no good unless we can turn it into value.

Companies are starting to generate amazing value from their big data.





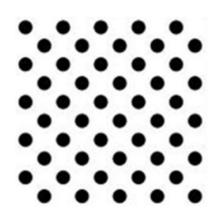
Competitive advantages gained through big data



To Summarize



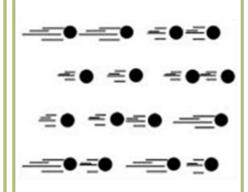
Volume



Data at Rest

Terabytes to
Exabytes of existing
data to process

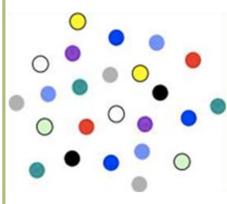
Velocity



Data in Motion

Streaming data, requiring milliseconds to seconds to respond

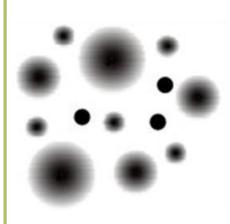
Variety



Data in Many Forms

Structured, unstructured, text, multimedia,...

Veracity



Data in Doubt

Uncertainty due to data inconsistency & incompleteness, ambiguities, latency, deception, model approximations

Value



Data into Money

Business models can be associated to the data

27



Obama for America 2012

April 2011: Campaign formed in Chicago

Nov. 2012: 800 offices, 4k staff, 40k volunteers







Source:

Matthew J. H. Rattigan matt@edgeflip.com

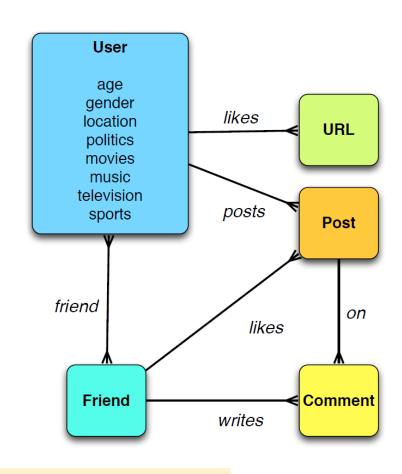
~4000 OFA ~400 Chicago HQ ~40 Analytics



Facebook



Facebook allows for much richer targeting, based on individual user preferences.



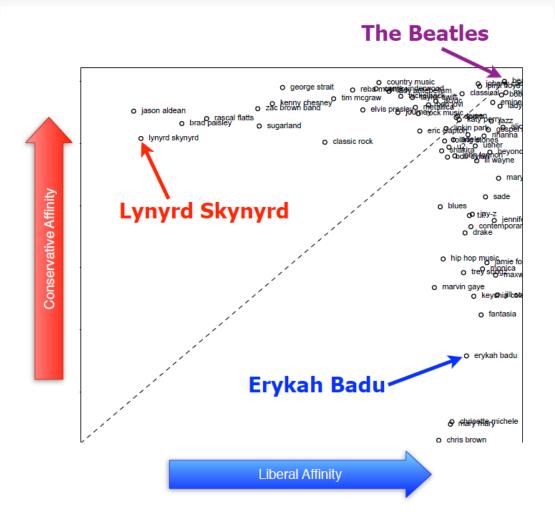
Source:



What you like tells me who you are



What music you like tells me who you are

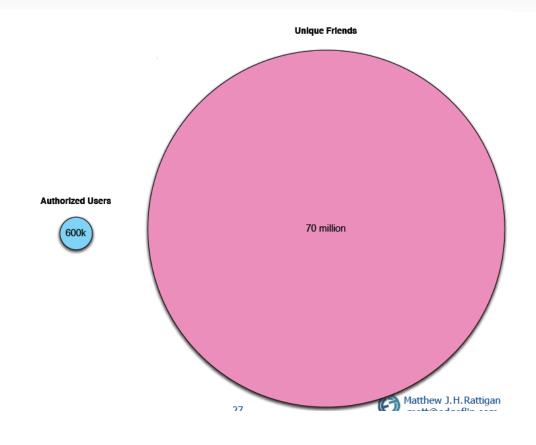


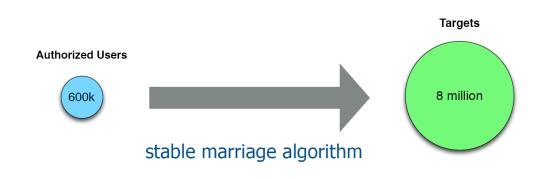
Source:





Target sharing





Too many

Target

Source:





Usage example of big data



- Predictive modeling
- mybarackobama.com
- Drive traffic to other campaign sites
 - Facebook page (33 million "likes")
 - YouTube channel (240,000 subscribers and 246 million page views).
- Every single night, the team ran 66,000 computer simulations.



- Data mining for individualized ad targeting
- Orca big-data app
- YouTube channel (23,700 subscribers and 26 million page views)



Applications, data, and corresponding commonly used analytical techniques



1. E-Commerce and marketing intelligence

Applications

- Recommender systems
- Social media monitoring and analysis
- Crowd-sourcing systems

Data

- Search and user logs
- Customer transaction records
- Customer generated content



Data characteristics

• Structured web-based, user-generated content, rich network information, unstructured informal customer opinions

Analytics

- Association rule mining
- Database segmentation and clustering
- Anomaly detection similar to classification but classification needs balance firs
- Graph mining
- Social network analysis
- Text and web analytics
- Sentiment and affect analysis

Impacts

 Long-tail marketing, targeted and personalized recommendation, increased sale and customer satisfaction



2. E-Government and Politics 2.0

Applications

- Ubiquitous government services
- Equal access and public services
- Citizen engagement and participation
- Political campaign and e-polling

Data

- Government information and services
- Rules and regulations
- Citizen feedback and comments



Data characteristics

• Fragmented information sources and legacy systems, rich textual content, unstructured informal citizen conversations

Analytics

- Information integration
- Content and text analytics
- Government information semantic services and ontologies
- Social media monitoring and analysis
- Social network analysis
- Sentiment and affect Analysis

Impacts

• Transforming governments, empowering citizens, improving transparency, participation, and equality



3. Science & Technology

Applications

- S&T innovation
- Hypothesis testing
- Knowledge discovery

Data

- S&T instruments and system generated data
- Sensor and network content



Data characteristics

 High-throughput instrument-based data collection, fine-grained multiple-modality and large-scale records, S&T specific data formats

Analytics

 S&T based domain-specific mathematical and analytical models

Impacts

• S&T advances, scientific impact



4. Smart Health and Wellbeing

Applications

- Human and plant genomics
- Healthcare decision support
- Patient community analysis

Data

- Genomics and sequence data
- Electronic medical records (EMR) app,
- Health and patient social media

app,patient like me



Data characteristics

• Disparate but highly linked content, person-specific content, and ethics issues

Analytics

- Genomics and sequence analysis and visualization
- EHR association mining and clustering
- Health social media monitoring and analysis
- Health text analytics
- Health ontologies
- Patient network analysis
- Adverse drug side-effect analysis
- Privacy-preserving data mining

Impacts

• Improved healthcare quality, improved long-term care, patient empowerment



5. Security and Public Safety

Applications

- Crime analysis
- Computational criminology
- Terrorism informatics
- Open-source intelligence
- Cyber security

Data

- Criminal records
- Crime maps
- Criminal networks
- News and web contents
- Terrorism incident databases
- Viruses, cyber attacks, and botnets



Data characteristics

 Personal identity information, incomplete and deceptive content, rich group and network information, multilingual content

Analytics

- Criminal association rule mining and clustering
- Criminal network analysis
- Spatial-temporal analysis and visualization
- Multilingual text analytics
- Sentiment and affect analysis
- Cyber attacks analysis and attribution

Impacts

Improved public safety and security

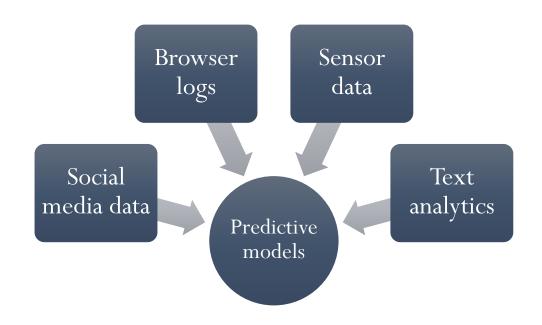


Typical applications in big data



1. Understanding and targeting customers

- Big data is used to better understand customers and their behaviors and preferences.
 - O Target: very accurately predict when one of their customers will expect a baby
 - Wal-Mart can predict what products will sell
 - Car insurance companies understand how well their customers actually drive
 - Obama use big data analytics to win 2012 presidential election campaign





2. Understanding and optimizing business processes

- Retailers are able to optimize their stock based on predictions generated from social media data, web search trends, and weather forecasts;
- Geographic positioning and radio frequency identification sensors are used to track goods or delivery vehicles and optimize routes by integrating live traffic data, etc.



- The Jawbone armband collects data on our calorie consumption, activity levels, and our sleep patterns and analyze such volumes of data to bring entirely new insights that it can feed back to individual users;
- Most online dating sites apply big data tools and algorithms to find us the most appropriate matches.



4. Improving healthcare and public health

- Big data techniques are already being used to monitor babies in a specialist premature and sick baby unit;
- Big data analytics allow us to monitor and predict the developments of epidemics and disease outbreaks;
- By recording and analyzing every heart beat and breathing pattern of every baby, infections can be predicted 24 hours before any physical symptoms appear.



5. Improving sports performance

- Use video analytics to track the performance of every player;
- Use sensor technology in sports equipment to allow us to get feedback on games;
- Use smart technology to track athletes outside of the sporting environment: nutrition, sleep, and social media conversation.



6. Improving science and research

• CERN, the Swiss nuclear physics lab with its Large Hadron Collider, the world's largest and most powerful particle accelerator is using thousands of computers distributed across 150 data centers worldwide to unlock the secrets of our universe by analyzing its 30 petabytes of data.





7. Optimizing machine and device performance

- Google self-driving car: the Toyota Prius is fitted with cameras, GPS, powerful computers and sensors to safely drive without the intervention of human beings;
- Big data tools are also used to optimize energy grids using data from smart meters.





8. Improving security and law enforcement

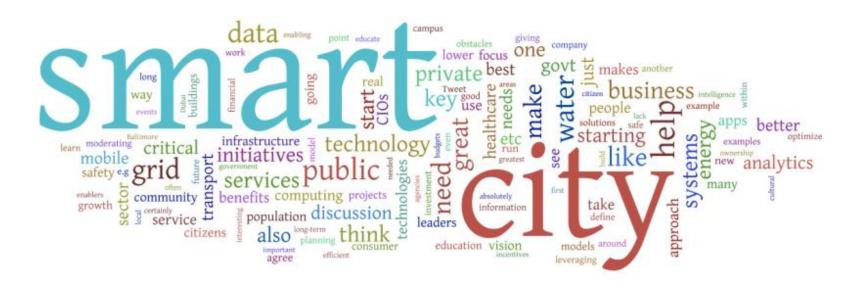
- National Security Agency (NSA) in the U.S. uses big data analytics to foil terrorist plots (and maybe spy on us);
- Police forces use big data tools to catch criminals and even predict criminal activity;
- Credit card companies use big data to detect fraudulent transactions.

fraud detect is important



9. Improving and optimizing cities and countries

• Smart cities optimize traffic flows based on real time traffic information as well as social media and weather data.



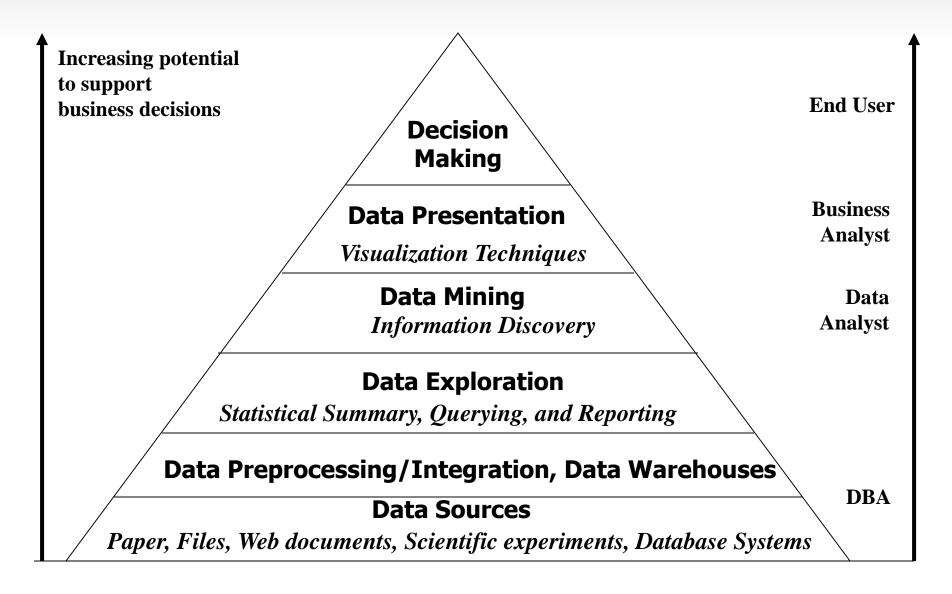


10. Financial trading

• The majority of equity trading now takes place via data algorithms that increasingly take into account signals from social media networks and news websites to make, buy and sell decisions in split seconds (High-Frequency Trading, HFT).

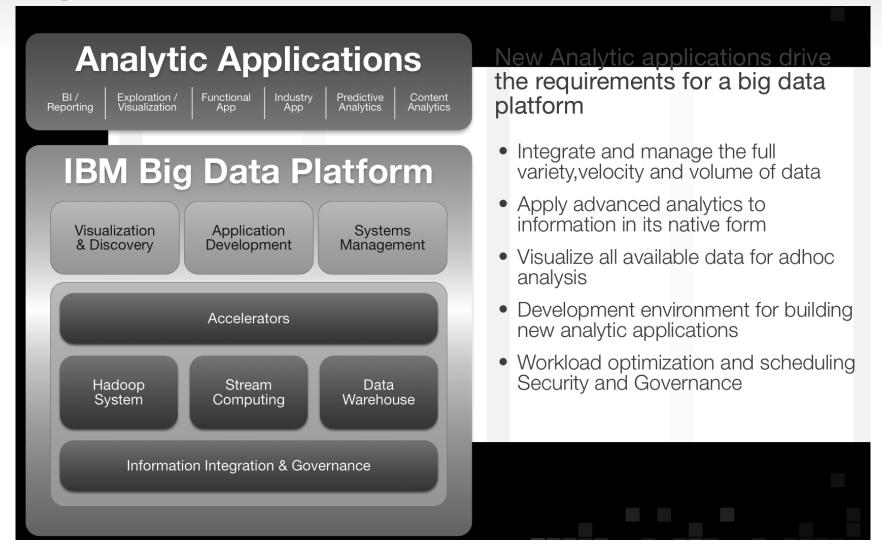


Data Mining in Business Intelligence





Big Data Platforms





Amazon EC2

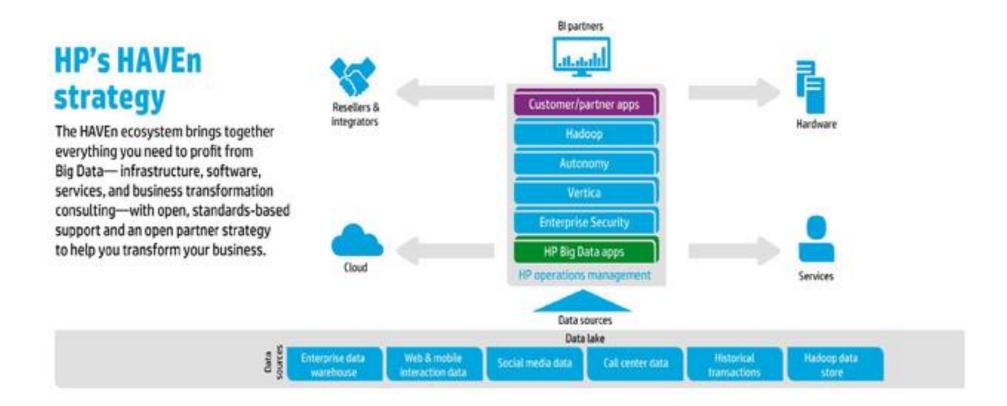
- Elastic MapReduce
- DynamoDB





HP HAVEn

HAVEn Brings Together Everything you Need to Profit from Big Data





Using Hadoop

- Java language
- High-level languages on top of Hadoop
 - Hive (Facebook)
 - A data warehouse system for Hadoop that facilitates easy data summarization, ad-hoc queries, and the analysis of large datasets stored in Hadoop compatible file systems
 - Provides a mechanism to project structure onto this data and query the data using a SQL-like language called HiveQL
 - It also allows traditional map/reduce programmers to plug in their custom mappers and reducers when it is inconvenient or inefficient to express this logic in HiveQL



Pig (Yahoo)

 A platform for analyzing large data sets that consists of a high-level language for expressing data analysis programs, coupled with infrastructure for evaluating these programs

Jaql (IBM)

 Primarily a query language for JavaScript Object Notation (JSON), but supports more than just JSON. It allows you to process both structured and nontraditional data



Big data analysis pipelines



- Data acquisition and recording
 - Filters: not discard useful data and not store irrelevant data
 - Metadata: describe what data is recorded and how it is recorded and measured
 - Data provenance: data quality



- Information extraction and cleaning
 - Raw data in different formats
 - Inaccurate data due to many reasons



- Data integration, aggregation, and representation
 - Database techniques: NoSQL DB



- Query processing, data modeling, and analysis
 - Data mining techniques
 - Statistical modeling
 - Query, indexing, searching techniques



- Interpretation
 - Report
 - Visualization



Review of Data Mining Concepts



Terminologies

- Dataset
 - Training set
 - Testing set
 - Validating set
- Data representation
 - Feature vector
- TF/IDF

$$\operatorname{idf}(\mathsf{this},D) = \log \frac{N}{|\{d \in D : t \in d\}|}$$

$$\begin{aligned} &\text{tf(example}, d_2) = 3 \\ &\text{idf(example}, D) = \log \frac{2}{1} \approx 0.3010 \end{aligned}$$

 $tfidf(example, d_2) = tf(example, d_2) \times idf(example, D) = 3 \times 0.3010 \approx 0.9030$

Document 1

Term	Term Count
this	1
is	1
a	2
sample	1

Document 2

Term	Term Count
this	1
is	1
another	2
example	3



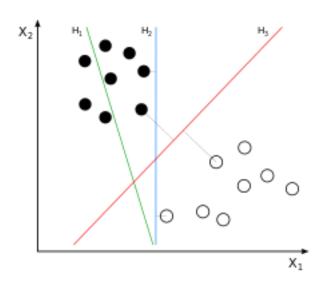
Supervised Learning

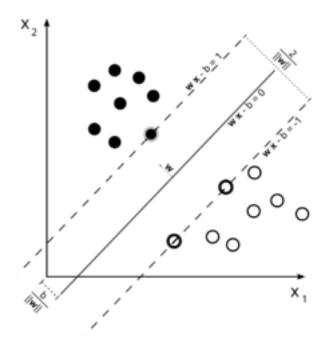
- Regression
 - Linear regression
 - Logistic regression
- Naïve Bayes
 - Strong independence assumption
- K-nearest neighboring (KNN)
- Decision Tree
 - C4.5
 - Can handle both numerical and categorical features
 - Missing values

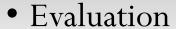


Support Vector Machine

• Find a hyper-plane to maximize the functional margin.







- Accuracy
- Precision-recall

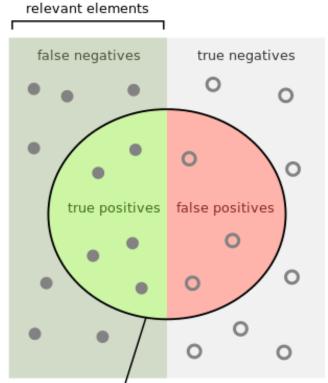
$$\begin{aligned} & precision = \frac{|\{relevant\ documents\} \cap \{retrieved\ documents\}|}{|\{retrieved\ documents\}|} \\ & recall = \frac{|\{relevant\ documents\} \cap \{retrieved\ documents\}|}{|\{relevant\ documents\}|} \end{aligned}$$

• F1 score

$$F = 2 \cdot \frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}}$$

- Over fitting
 - Cross-validation
 - Regularization: L1/L2-norm
 - Early stopping
 - Pruning







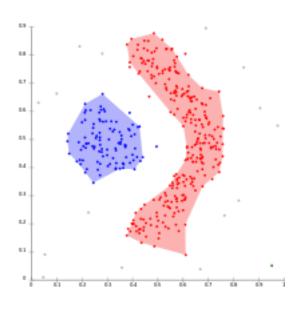
selected elements



Unsupervised Learning

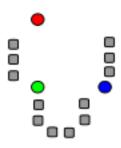
- Clustering
 - K-means
 - Spectral clustering
 - Hierarchical clustering
 - Density-based clustering (DBSCAN)
- Distance metric
 - Euclidean
 - Manhanttan
 - Cosine

•

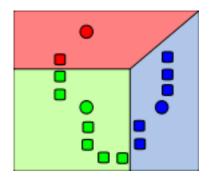




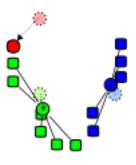
K-Means



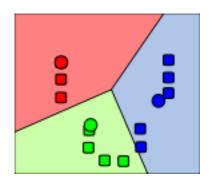
1) k initial "means" (in this case k=3) are randomly generated within the data domain (shown in color).



2) k clusters are created by associating every observation with the nearest mean. The partitions here represent the Voronoi diagram generated by the means.



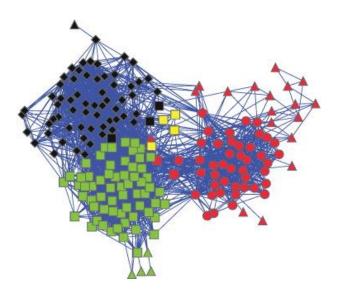
3) The centroid of each of the k clusters becomes the new mean.



4) Steps 2 and 3 are repeated until convergence has been reached.



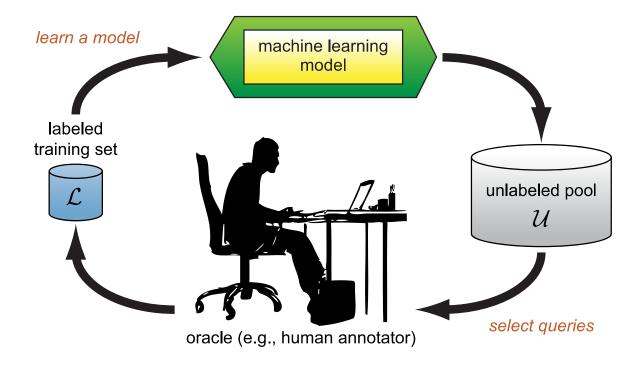
- Association rule mining (market basket analysis)
 - $\bullet \{x,y\} =>\{z\}$
 - $\{x,y,z\} = > \{u,v\}$
 - •
- Graph-based community detection
 - Modularity maximization-based
 - Networks with high modularity have dense connections between the nodes within modules but sparse connections between nodes in different modules.





Semi-supervised learning

• Active learning



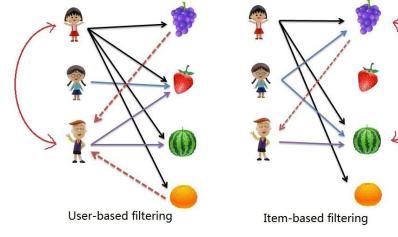


Recommender Systems

- User-based collaborative filtering
- Item-based collaborative filtering

• Sparse matrix completion

Netflix problem





Graphical Models: Topic Modeling

Topics

0.04 gene dna 0.02 genetic 0.01

life 0.02 0.01 evolve organism 0.01

brain 0.04 0.02 neuron 0.01 nerve

0.02 data number 0.02 computer 0.01

Documents

Topic proportions and assignments

Seeking Life's Bare (Genetic) Necessities

Haemophilus

genome 1703 gares

COLD SPRING HARBOR, NEW YORKsurvive? Last week at the genome meeting here, 8 two genome researchers with radically different approaches presented complementary views of the basic genes needed for life. sus answer may be more than just One research team, using computer analyses to compare known genomes, concluded that today's organisms can be sustained with just 250 genes, and that the earliest life forms required a mere 128 genes. The

other researcher mapped genes in a simple parasite and estimated that for this organism. 800 genes are plenty to do the job—but that anything short of 100 wouldn't be enough.

Although the numbers don't match precisely, those predictions



"are not all that far apart," especially in How many genes does an organism need to comparison to the 75,000 genes in the huan genome, notes Siv Andersson University in er. But coming up with sequenced. "It may be a way of organi any newly sequenced genome," explains

Arcady Mushegian, a computational molecular biologist at the National Center for Biotechnology Information (VCBI) in Bethesda, Maryland, Comparing



Stripping down. Computer analysis yields an estimate of the minimum modern and ancient genomes.

SCIENCE • VOL. 272 • 24 MAY 1996





Questions?