

Data science

The Big Data challenge

ELENA BARALIS

POLITECNICO DI TORINO

Big data hype?

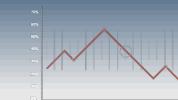
The image is a high-resolution word cloud centered on the theme of big data. The word 'big data' is the largest and most central word. Surrounding it are numerous other terms related to technology, business, and data management. The words are rendered in various sizes and orientations, creating a dynamic and interconnected visual representation of the concepts involved in big data analysis and its applications.

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Emergency management



UNMANNED AERIAL VEHICLES



HISTORICAL DATA



SEASONAL
WEATHER FORECAST



SOCIAL MEDIA
DATA STREAMS



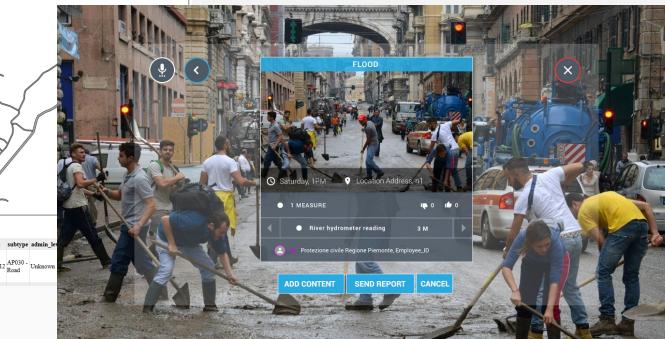
Improving Resilience to Emergencies
Through Advanced Cyber Technologies

 i REACT

Emergency management



FIRST RESPONDERS AND
DECISION MAKERS



CITIZENS



Improving Resilience to Emergencies
Through Advanced Cyber Technologies

 iREACT

User engagement

2005



2013

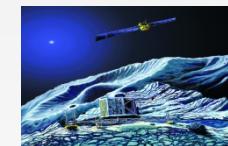


Who generates big data?

- User Generated Content (Web & Mobile)
 - E.g., Facebook, Instagram, Yelp, TripAdvisor, Twitter, YouTube

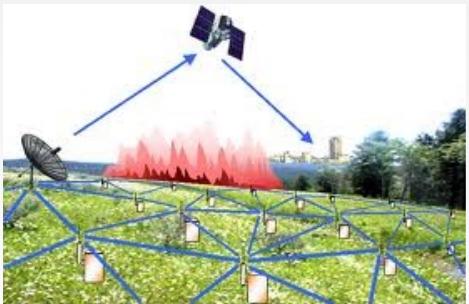


- Health and scientific computing



Who generates big data?

- ❑ Log files
- ❑ Web server log files, machine syslog files
- ❑ Internet Of Things
- ❑ Sensor networks, RFID, smart meters



What is big data?



- Many different definitions

“Data whose scale, diversity and complexity require new architectures, techniques, algorithms and analytics to manage it and extract value and hidden knowledge from it”

What is big data?



- Many different definitions

*“Data whose **scale**, **diversity** and **complexity** require new architectures, techniques, algorithms and analytics to manage it and extract value and hidden knowledge from it”*

What is big data?



- Many different definitions

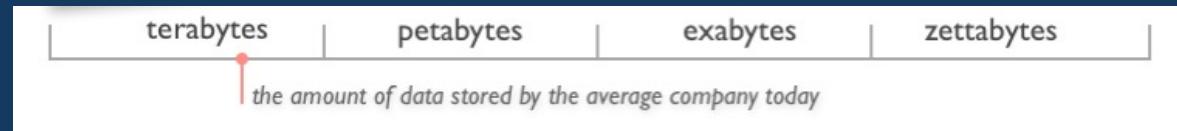
*“Data whose scale, diversity and complexity require new **architectures**, **techniques**, **algorithms** and **analytics** to manage it and extract value and hidden knowledge from it”*

What is big data?



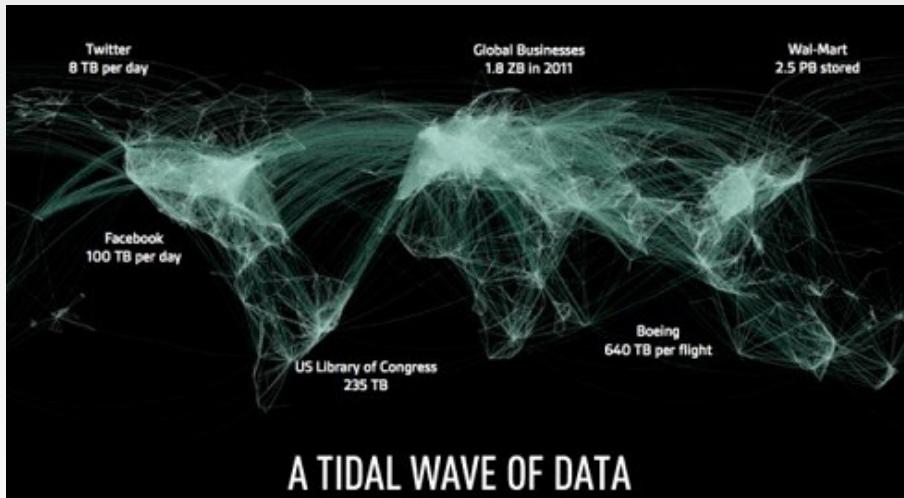
- Many different definitions

*“Data whose scale, diversity and complexity require new architectures, techniques, algorithms and analytics to manage it and extract **value** and hidden **knowledge** from it”*

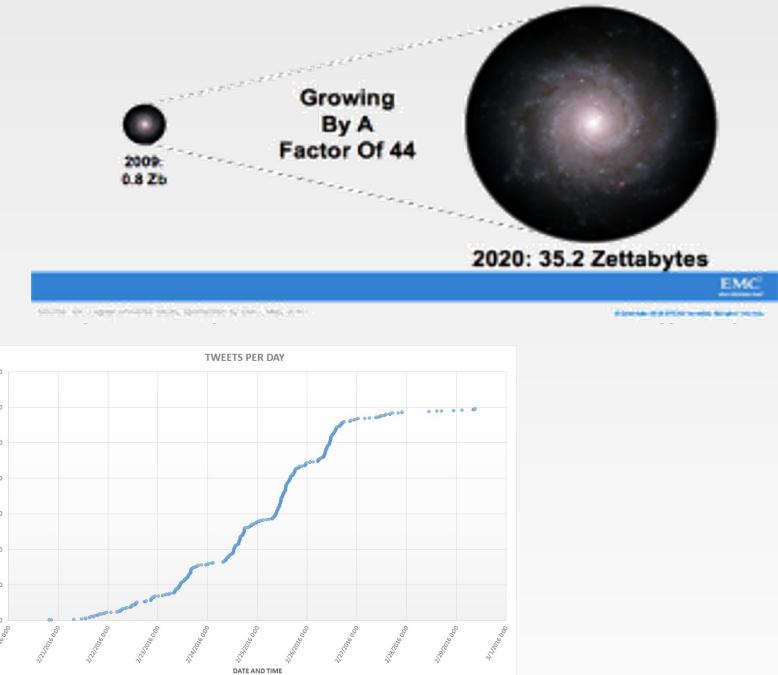


The Vs of big data: Volume

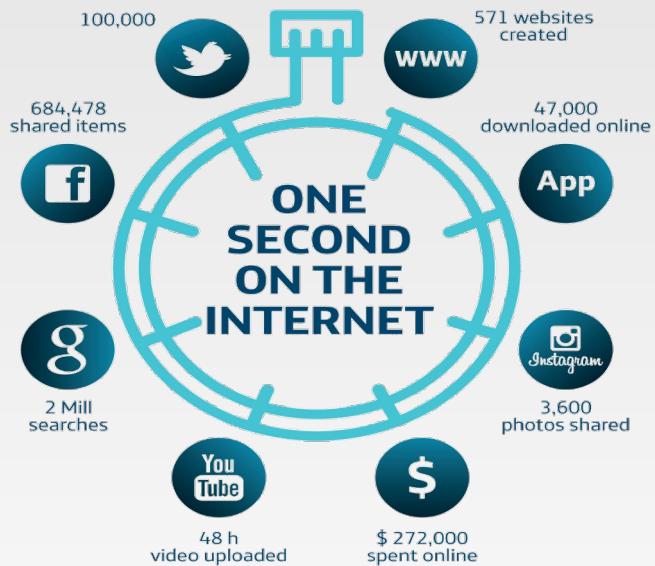
- Data volume increases exponentially over time
- 44x increase from 2009 to 2020
 - Digital data 35 ZB in 2020



The Digital Universe 2009-2020



On the Internet...

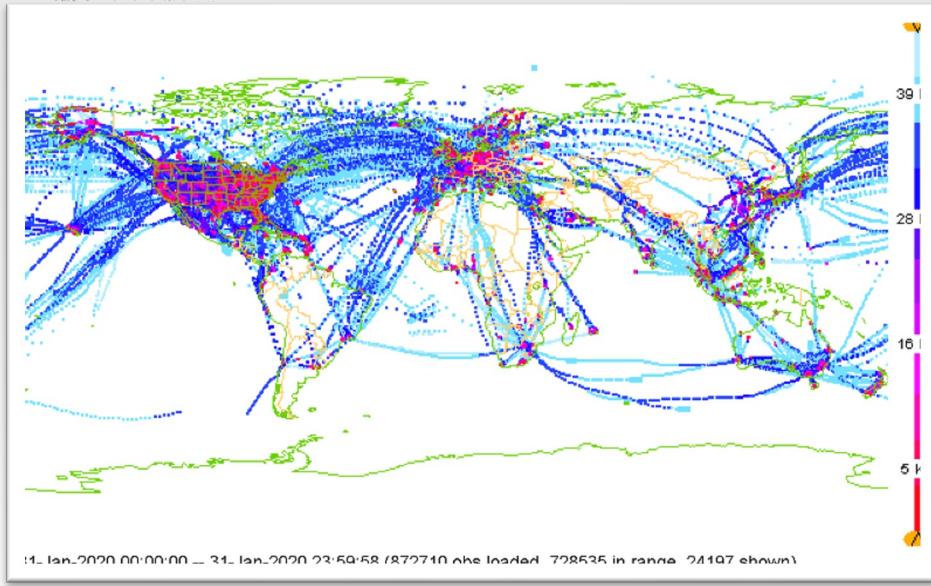


- <http://www.internetlivestats.com/>

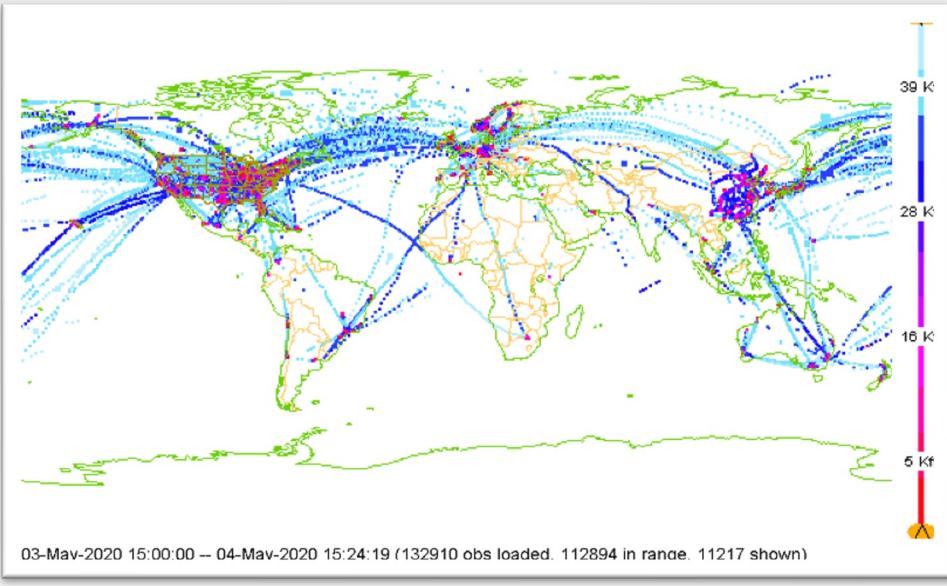
Weather forecast



January 2020

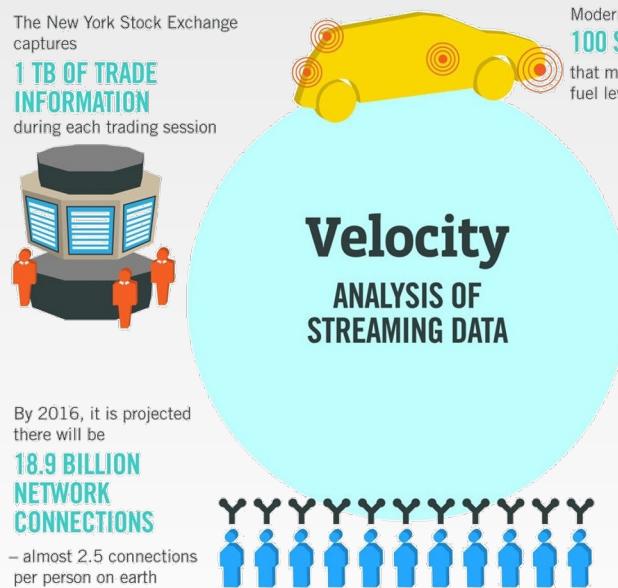


May 2020

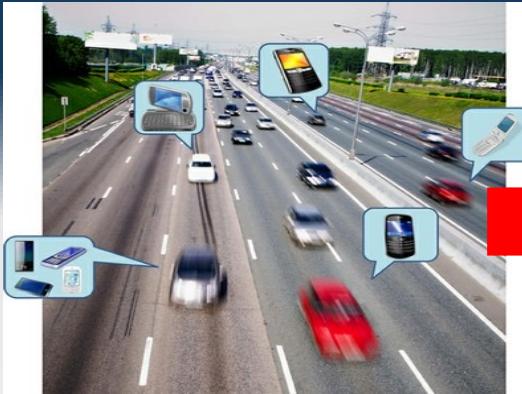


The Vs of big data: Velocity

- Fast data generation rate
- Streaming data
- Very fast data processing to ensure timeliness



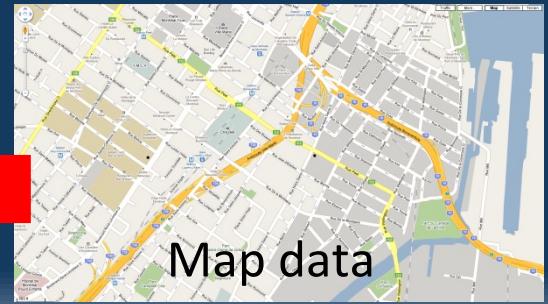
(Near) Real time processing



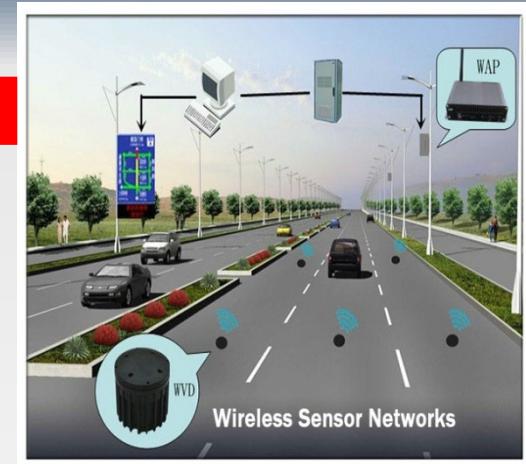
Crowdsourcing



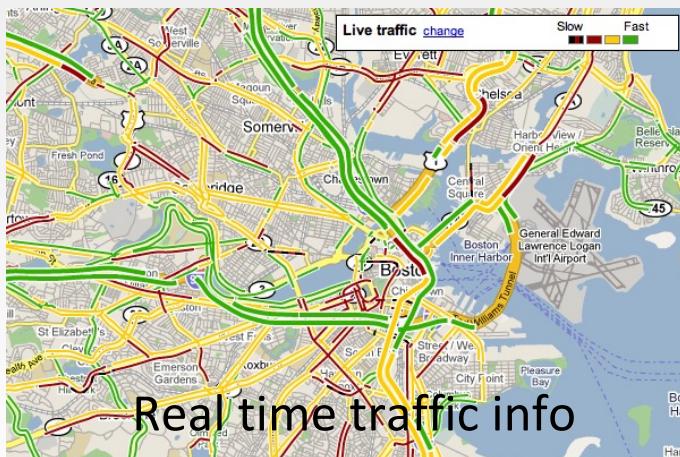
Computing



Map data



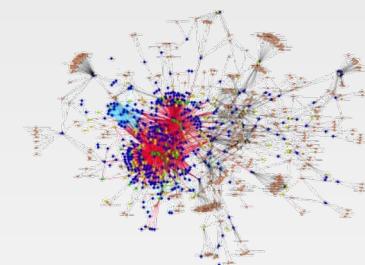
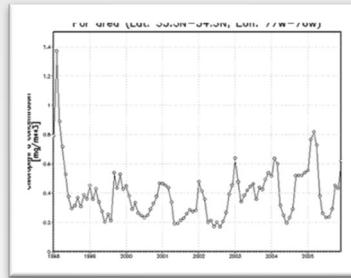
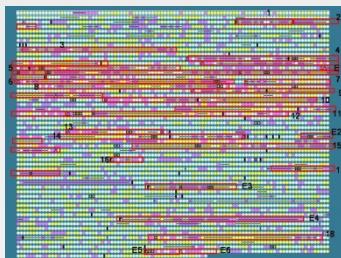
Sensing



Real time traffic info

The Vs of big data: Variety

- ❑ Various formats, types and structures
- ❑ Numerical data, image data, audio, video, text, time series



- ❑ A single application may generate many different formats

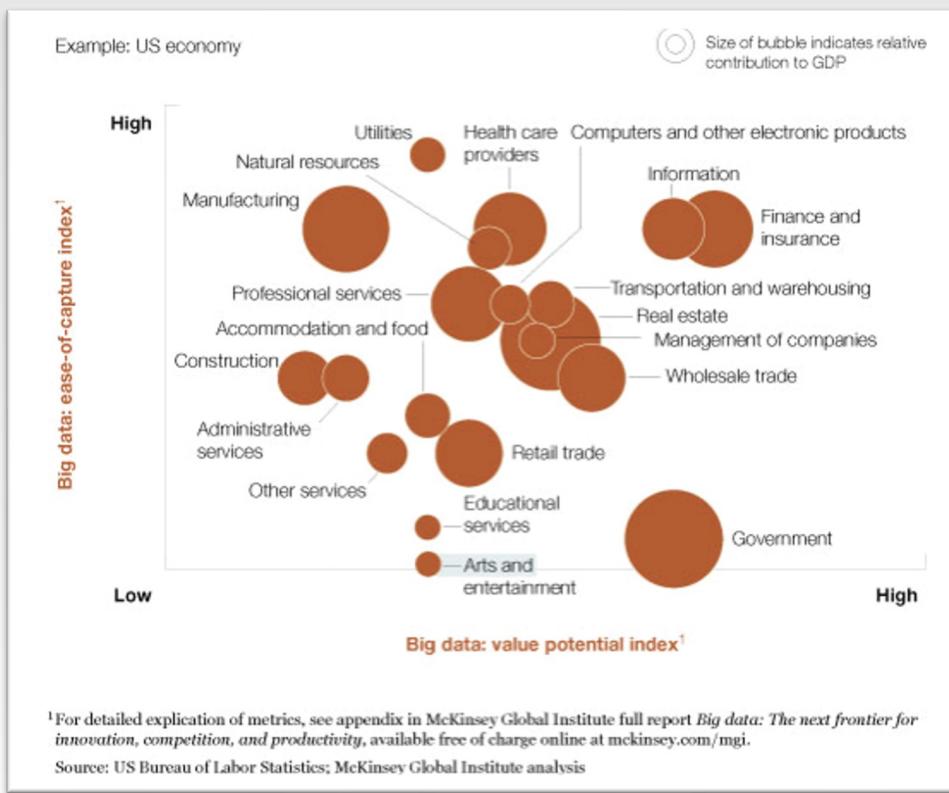
The Vs of big data: Veracity

□ Data quality



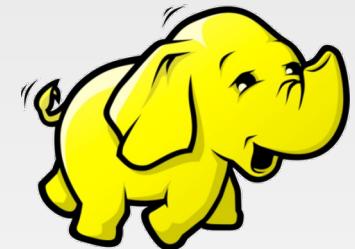
The most important V: Value

□ Translate data into business advantage



Big data challenges

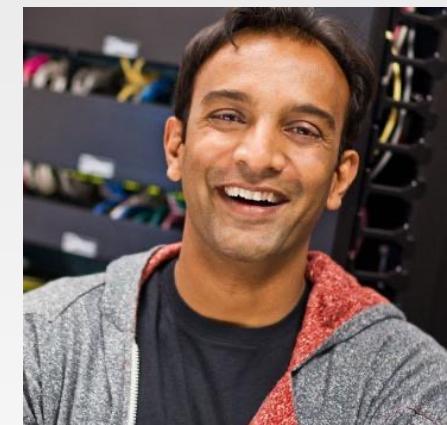
- ❑ Technology & infrastructure
 - ❑ New architectures, programming paradigms and techniques
Transfer the processing power to the data
- ❑ Apache Hadoop/Spark ecosystem
- ❑ Data management & analysis
- ❑ New emphasis on “data”



→ ***Data science***

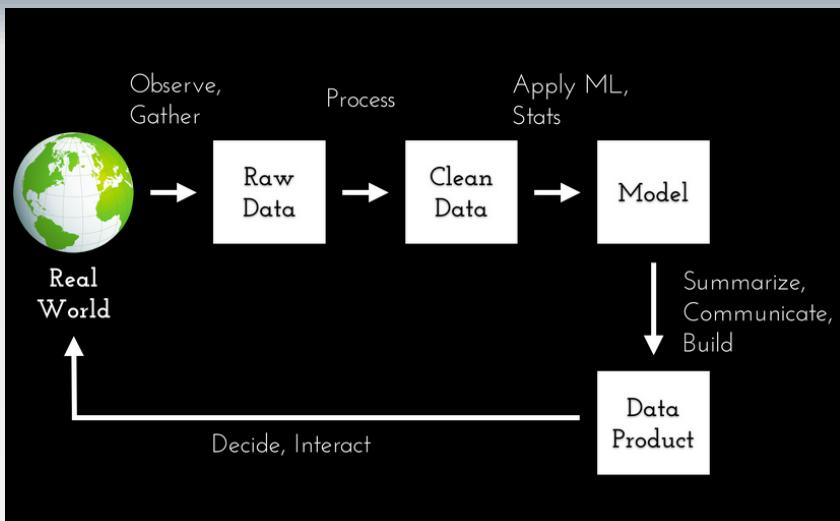
Data science

“Extracting meaning from very large quantities of data”

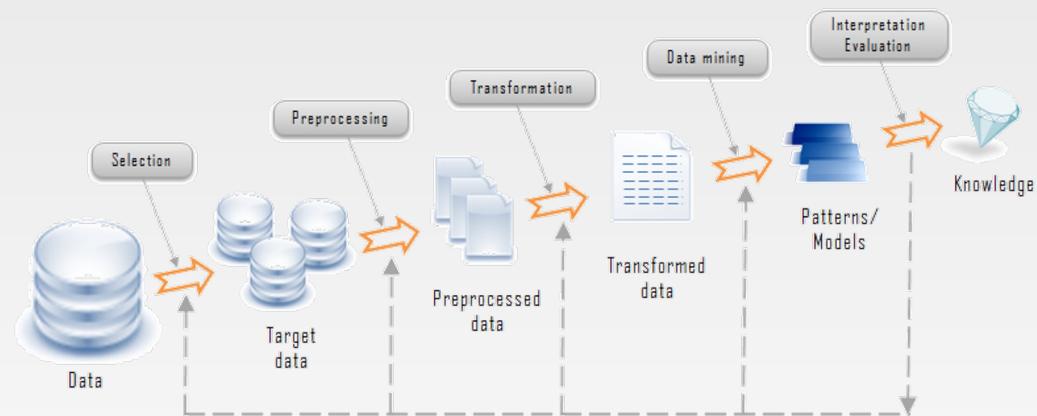


D.J. Patil coined the word *data scientist*

The data science process



AKA *KDD* process
Knowledge Discovery in Databases



Generation

Acquisition

Storage

Analysis

Generation

- ❑ Passive recording
 - ❑ Typically structured data
 - ❑ Bank trading transactions, shopping records, government sector archives
- ❑ Active generation
 - ❑ Semistructured or unstructured data
 - ❑ User-generated content, e.g., social networks
- ❑ Automatic production
 - ❑ Location-aware, context-dependent, highly mobile data
 - ❑ Sensor-based Internet-enabled devices (IoT)



Acquisition

❑ Collection

- ❑ Pull-based, e.g., web crawler
- ❑ Push-based, e.g., video surveillance, click stream

❑ Transmission

- ❑ Transfer to data center over high capacity links

❑ Preprocessing

- ❑ Integration, cleaning, redundancy elimination



Storage

❑ Storage infrastructure

- ❑ Storage technology, e.g., HDD, SSD
- ❑ Networking architecture, e.g., DAS, NAS, SAN

❑ Data management

- ❑ File systems (HDFS), key-value stores (Memcached), column-oriented databases (Cassandra), document databases (MongoDB)

❑ Programming models

- ❑ Map reduce, stream processing, graph processing



Analysis

❑ Objectives

- ❑ Descriptive analytics, predictive analytics, prescriptive analytics

❑ Methods

- ❑ Statistical analysis, machine learning and data mining, text mining, network and graph data mining

- ❑ Association analysis, classification and regression, clustering

❑ Diverse domains call for customized techniques



Machine learning and data mining

❑ Non trivial extraction of

- ❑ implicit
- ❑ previously unknown
- ❑ potentially useful

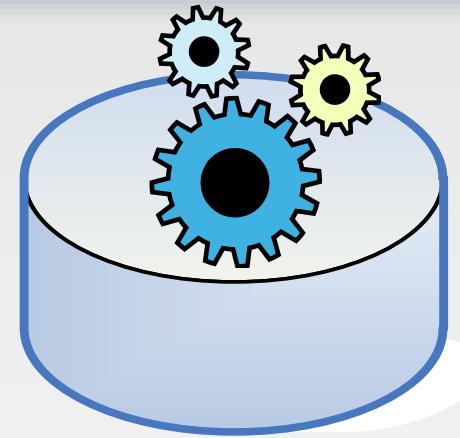
information from available data

❑ Extraction is automatic

- ❑ performed by appropriate algorithms

❑ Extracted information is represented by means of abstract models

- ❑ denoted as *pattern*



Example: profiling

- ❑ Consumer behavior in e-commerce sites
 - ❑ Selected products, requested information, ...
- ❑ Search engines and portals
 - ❑ Query keywords, searched topics and objects
- ❑ Social network data
 - ❑ Profiles (Facebook, Instagram, ...)
 - ❑ Dynamic data: posts on blogs, FB, tweets
- ❑ Maps and georeferenced data
 - ❑ Localization, interesting locations for users



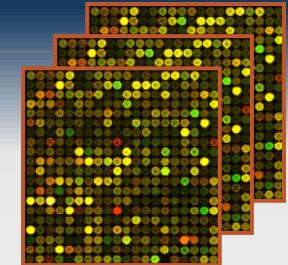
Example: profiling

- ❑ User/service profiling
 - ❑ Recommendation systems, advertisements
- ❑ Market basket analysis
 - ❑ Correlated objects for cross selling
 - ❑ User registration, fidelity cards
- ❑ Context-aware data analysis
 - ❑ Integration of different dimensions
 - ❑ E.g., location, time of the day, user interest
- ❑ Text mining
 - ❑ Brand reputation, sentiment analysis, topic trends

Example: biological data

□ Microarray

- expression level of genes in a cellular tissue
- various types (mRNA, DNA)



□ Patient clinical records

- personal and demographic data
- exam results

□ Textual data in public collections

- heterogeneous formats, different objectives
- scientific literature (PUBMed)
- ontologies (Gene Ontology)

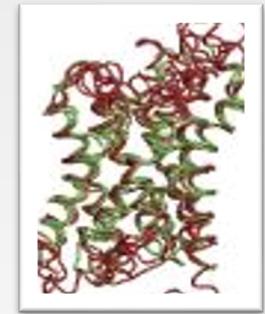
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| IMAGE:76 | TNFSF13 | -0.52 | -4.06 | -0.29 | 0.71 | 1.03 | -0.67 | 0.22 | -0.09 |
| IMAGE:36 | LOC93343 | -0.25 | -4.08 | 0.06 | 0.13 | 0.08 | 0.06 | -0.08 | -0.05 |
| IMAGE:23 | ITGA4 in | -1.375 | -1.605 | 0.155 | -0.015 | 0.035 | -0.035 | 0.505 | -0.865 |



Biological analysis objectives

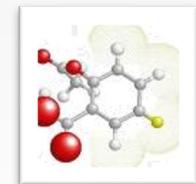
□ Clinical analysis

- detecting the causes of a pathology
 - monitoring the effect of a therapy
- ⇒ diagnosis improvement and definition of new specific therapies



□ Bio-discovery

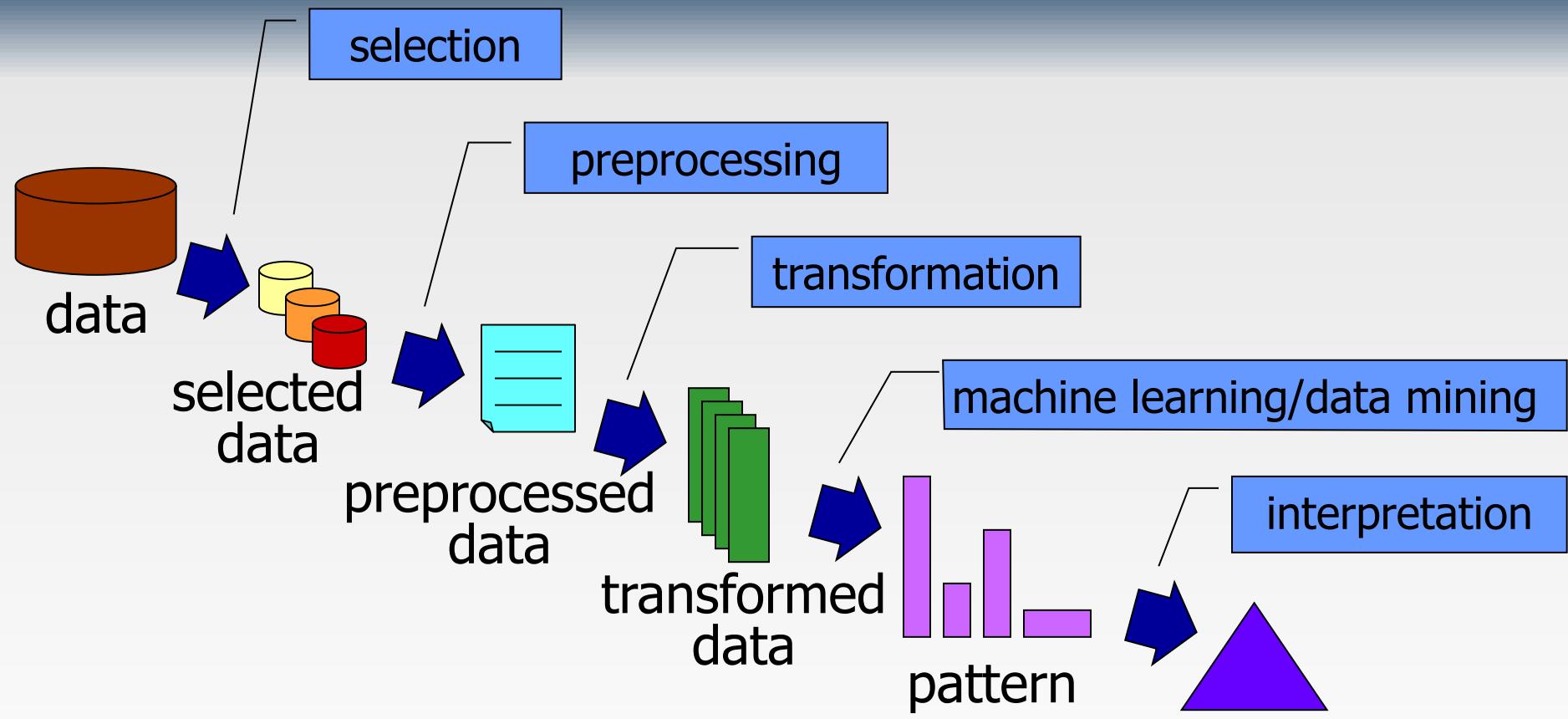
- gene network discovery
- analysis of multifactorial genetic pathologies



□ Pharmacogenomics

- lab design of new drugs for genic therapies

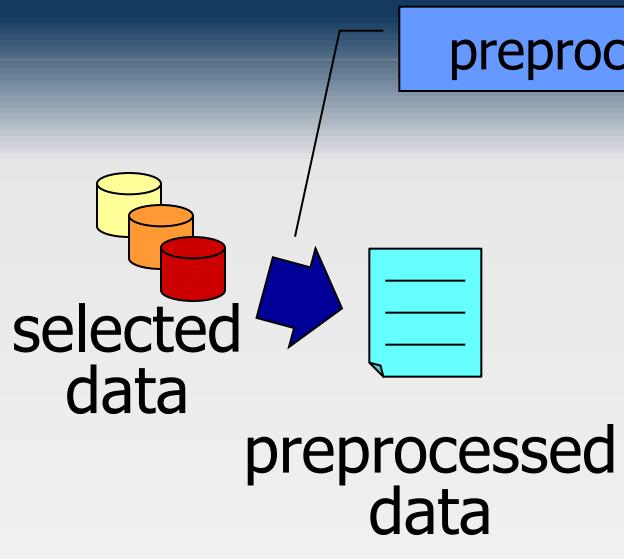
Knowledge Discovery Process



KDD = Knowledge Discovery from Data

knowledge

Preprocessing



data cleaning

- reduces the effect of noise
- identifies or removes outliers
- solves inconsistencies

data integration

- reconciles data extracted from different sources
- integrates metadata
- identifies and solves data value conflicts
- manages redundancy

Real world data is “dirty”

Without good quality data, no good quality pattern

A word from practitioners

- ❑ At least 80-90% of their work involves not machine learning, but
 - ❑ Working with experts to understand the domain, assumptions, questions
 - ❑ Trying to catalog and make sense of the data sources
 - ❑ Wrangling, extracting, and integrating the data
 - ❑ Cleaning the wrangled data

Association rules

❑ Objective

- ❑ extraction of frequent correlations or pattern from a transactional database

Tickets at a supermarket counter

| TID | Items |
|-----|----------------------------|
| 1 | Bread, Coke, Milk |
| 2 | Beer, Bread |
| 3 | Beer, Coke, Diapers, Milk |
| 4 | Beer, Bread, Diapers, Milk |
| 5 | Coke, Diapers, Milk |
| ... | ... |



■ Association rule

$\text{diapers} \Rightarrow \text{beer}$

- 2% of transactions contains both items
- 30% of transactions containing diapers also contain beer

Association rules

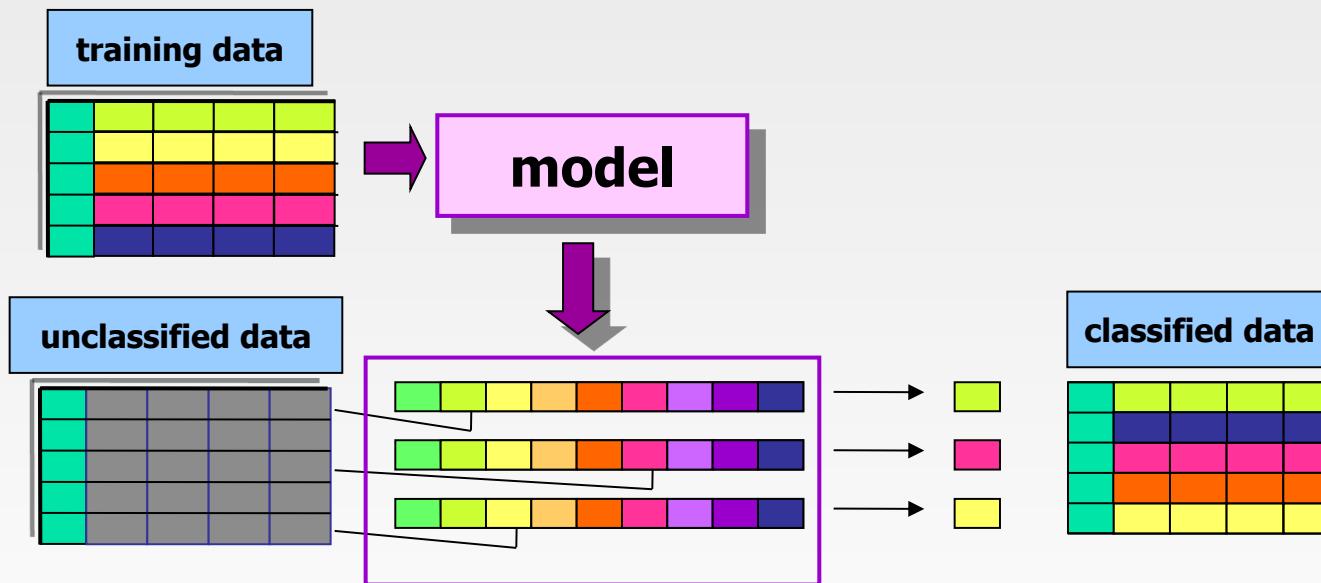
The collage includes:

- A cartoon illustration of a shop window titled "CUSTOMERS WHO BOUGHT THIS ITEM:" showing a woman looking at a display of bananas, with "ALSO BOUGHT:" items like carrots and bread below.
- A screenshot of an e-commerce product page for three Oxford dictionaries, showing a "Frequently Bought Together" section with a "Price For All Three: £9.00" offer.
- A screenshot of a Netflix homepage showing recommended TV shows and movies.
- A wire shopping basket filled with various fruits and vegetables.
- A screenshot of a LinkedIn job search results page titled "Jobs You May Be Interested In" with entries for Senior Data Analyst, Data Scientist, and Computer Scientist roles.

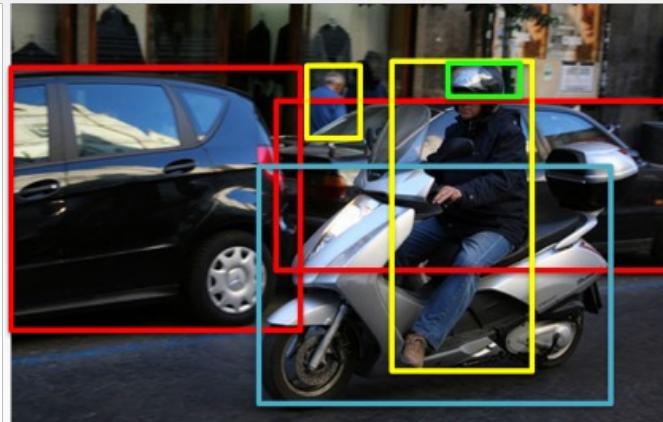
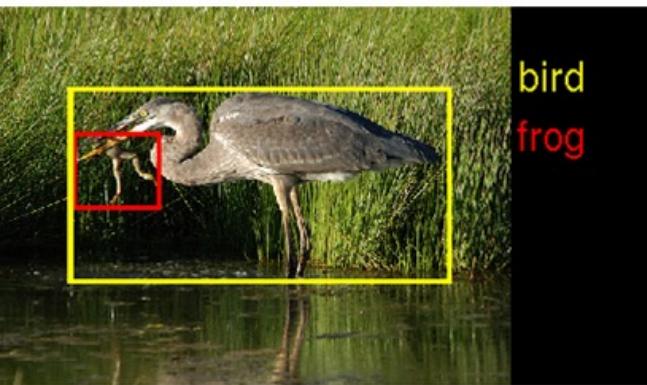
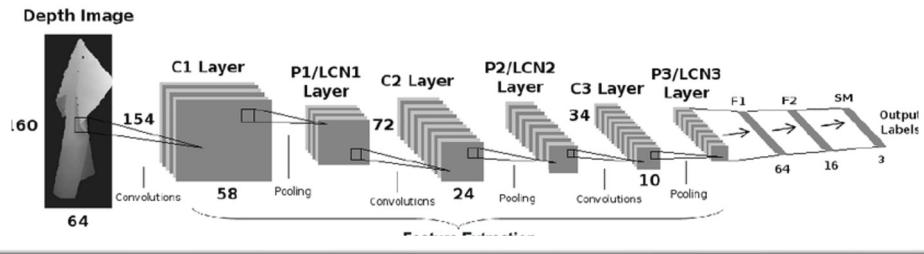
Classification

❑ Objectives

- ❑ prediction of a class label
- ❑ definition of an interpretable model of a given phenomenon



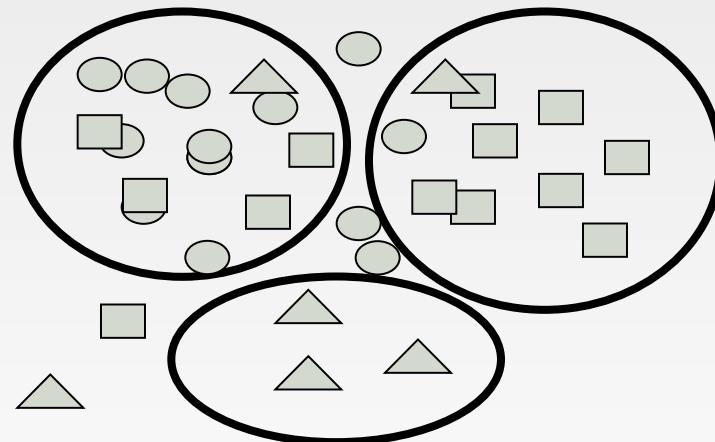
Classification



Person
Car
Motorcycle
Helmet

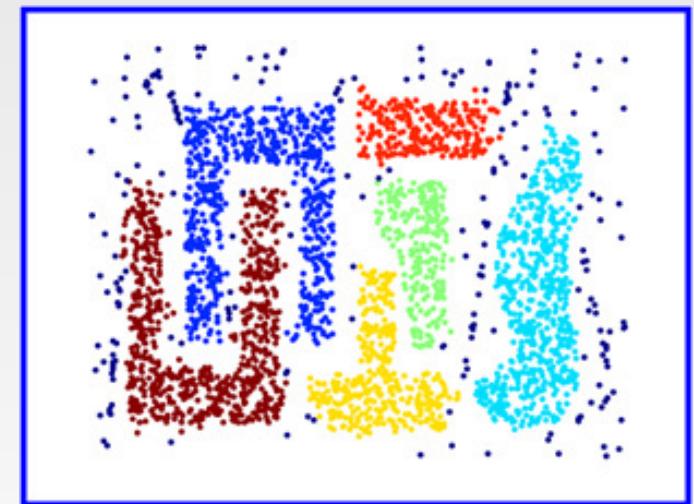
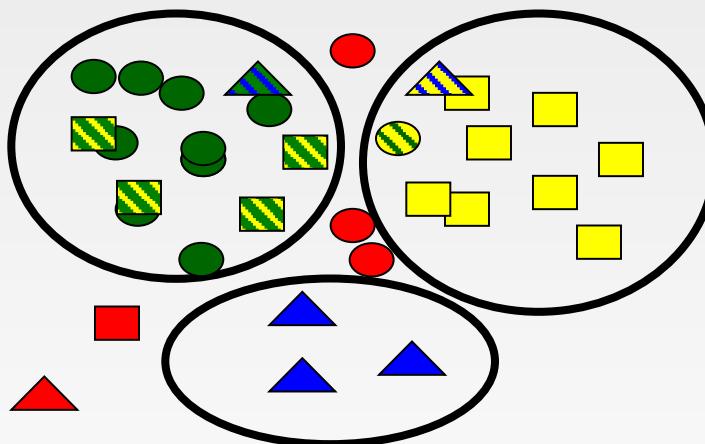
Clustering

- ❑ Objectives
 - ❑ detecting groups of similar data objects
 - ❑ identifying exceptions and outliers

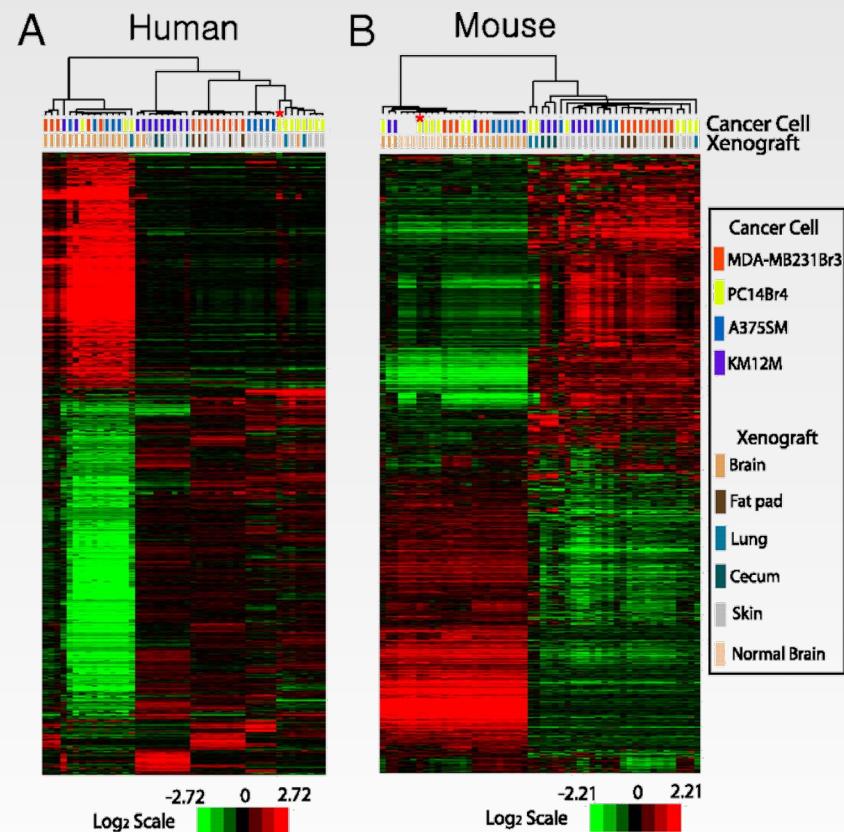


Clustering

- ❑ Objectives
 - ❑ detecting groups of similar data objects
 - ❑ identifying exceptions and outliers



Clustering



Other data mining techniques

Sequence mining

- ❑ ordering criteria on analyzed data are taken into account
 - ❑ example: motif detection in proteins



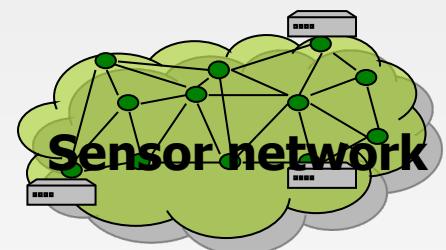
 Time series and geospatial data

- ❑ temporal and spatial information are considered
 - ❑ example: sensor network data



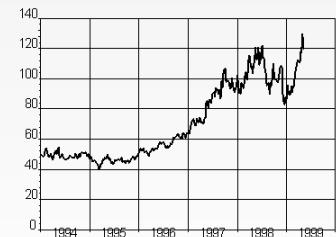
Regression

- ❑ prediction of a continuous value
 - ❑ example: prediction of stock quotes



Outlier detection

- example: intrusion detection in network traffic analysis



The data science process

- ❑ What *question* are you answering?
- ❑ What is the right *scope* of the project?
- ❑ What *data* will you use?
- ❑ What *techniques* are you going to try?
- ❑ How will you *evaluate* your result?
- ❑ What *maintenance* will be required?

The data science recipe

- ❑ Different ingredients needed
 - ❑ Data expert
 - ❑ Data processing, data structures
 - ❑ Data analyst
 - ❑ Data mining, statistics, machine learning
 - ❑ Visualization expert
 - ❑ Visual art design, storytelling skills
 - ❑ Domain expert
 - ❑ Provide understanding of the application domain
 - ❑ Business expert
 - ❑ Data driven decisions, new business models



MODERN DATA SCIENTIST

Data Scientist, the sexiest job of 21st century requires a mixture of multidisciplinary skills ranging from an intersection of mathematics, statistics, computer science, communication and business. Finding a data scientist is hard. Finding people who understand who a data scientist is, is equally hard. So here is a little cheat sheet on who the modern data scientist really is.

MATH & STATISTICS

- ★ Machine learning
- ★ Statistical modeling
- ★ Experiment design
- ★ Bayesian inference
- ★ Supervised learning: decision trees, random forests, logistic regression
- ★ Unsupervised learning: clustering, dimensionality reduction
- ★ Optimization: gradient descent and variants

PROGRAMMING & DATABASE

- ★ Computer science fundamentals
- ★ Scripting languages e.g. Python
- ★ Statistical computing package e.g. R
- ★ Databases SQL and NoSQL
- ★ Relational algebra
- ★ Parallel databases and parallel query processing
- ★ MapReduce concepts
- ★ Hadoop and Hive/Pig
- ★ Custom reducers
- ★ Experience with xaaS like AWS

DOMAIN KNOWLEDGE & SOFT SKILLS

- ★ Passionate about the business
- ★ Curious about data
- ★ Influence without authority
- ★ Hacker mindset
- ★ Problem solver
- ★ Strategic, proactive, creative, innovative and collaborative

COMMUNICATION & VISUALIZATION

- ★ Able to engage with senior management
- ★ Story telling skills
- ★ Tractable data-driven insights into decisions and actions
- ★ Visual art design
- ★ R packages like ggplot or lattice
- ★ Knowledge of any of visualization tools e.g. Tableau, T3.js, Tableau

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Marketing DISTILLERY

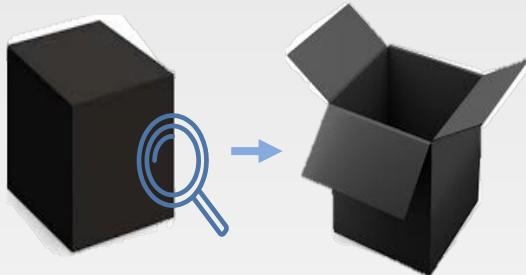
Open issues

- ❑ Social impact of analysis is very important
- ❑ Interpretability and transparency of the analysis process
- ❑ Bias in algorithms and data
- ❑ Privacy preservation



Interpretability in machine learning

“The ability to explain or to present in understandable terms to a human”



Open the black box



Trade-off Accuracy-Interpretability

- ❑ **Model explanation:** global understanding of how a model works
- ❑ **Prediction explanation:** local understanding of why a prediction is made
- ❑ **Interpretable feature selection:** incorporating interpretability-based criteria into the model design

Interpretability

- ❑ Learned decision rule in pneumonia patients dataset from USA hospital
history of asthma → lower chance of dying from pneumonia
- ❑ MD consider asthma as a serious risk factor for people who get pneumonia
- ❑ Analysis
 - ❑ asthmatics probably notice earlier the symptoms of pneumonia
 - ❑ a healthcare professional is going to provide earlier pneumonia diagnosis
 - ❑ as high-risk patients, they're going to get high-quality treatment sooner than other people
- ➡ asthmatics actually have almost half the chance of dying of non-asthmatics
- ❑ Using a neural network, this model issue would *never* have been uncovered

Algorithmic and data bias

- ❑ Task: predict likelihood of an individual committing a future crime
 - ❑ Risk scores used by US criminal justice system
 - ❑ Scores computed from
 - ❑ Questions answered by the defendants
 - ❑ Information pulled by criminal records
 - ❑ Race was not among the questions
 - ❑ ... however other items may be correlated (e.g., poverty, joblessness)
 - ❑ Software product flagged black defendants as future criminals more frequently than white defendants
- ➡ Training data was biased by a larger black defendant population

Privacy

STRAVA LABS Projects Blog Developers Strava.com Careers

Global Heatmap

Heatmap Color

IRAQ

AFGHANISTAN

https://www.theguardian.com/world/2018/jan/28/fitness-tracking-app-gives-away-location-of-secret-us-army-bases

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Fitness tracking app Strava gives away location of secret US army bases

Data about exercise routes shared online by soldiers can be used to pinpoint overseas facilities

Latest: Strava suggests military users 'opt out' of heatmap as row deepens

51 GMT

BBC Mark News Sport Weather iPlayer TV Radio

Strava released their global heatmap.
13 trillion GPS points from their users

Fitness app Strava lights up staff at military bases

29 January 2018

f t m Share



The movements of soldiers within Bagram air base - the largest US military facility in Afghanistan

Security concerns have been raised after a fitness tracking firm showed the exercise routes of military personnel in bases around the world.

Open issues

- Social impact of analysis is very important
 - Interpretability and transparency of the analysis process
 - Privacy preservation
- Many technical issues are not solved
 - Scalability to *huge* data volumes
 - Data dimensionality
 - Complex data structures, heterogeneous data formats
 - Data quality
 - Streaming data