

Data science

The Big Data challenge

ELENA BARALIS

POLITECNICO DI TORINO

Big data hype?



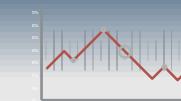
Emergency management



EARTH OBSERVATIONS



UNMANNED AERIAL VEHICLES



HISTORICAL DATA



SEASONAL
WEATHER FORECAST



SOCIAL MEDIA
DATA STREAMS



Improving Resilience to Emergencies
Through Advanced Cyber Technologies

 IREACT

Emergency management



Improving Resilience to Emergencies
Through Advanced Cyber Technologies

 iREACT

User engagement

2005



2013

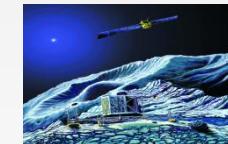


Who generates big data?

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

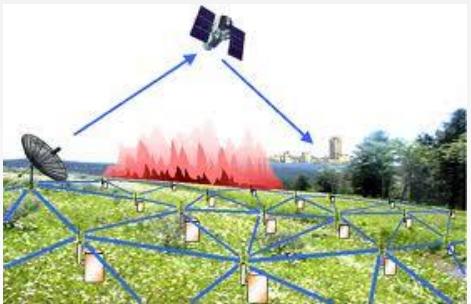


- Health and scientific computing



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

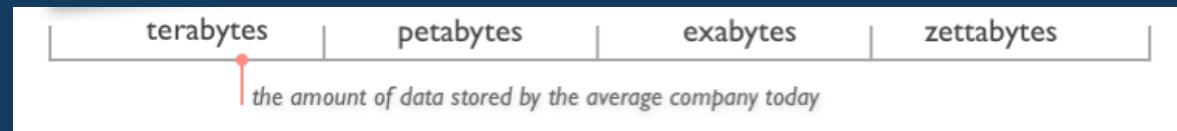
*“Data whose scale, diversity and complexity require new **architectures**, **techniques**, **algorithms** and **analytics** to manage it and extract value and hidden knowledge from it”*

What is big data?



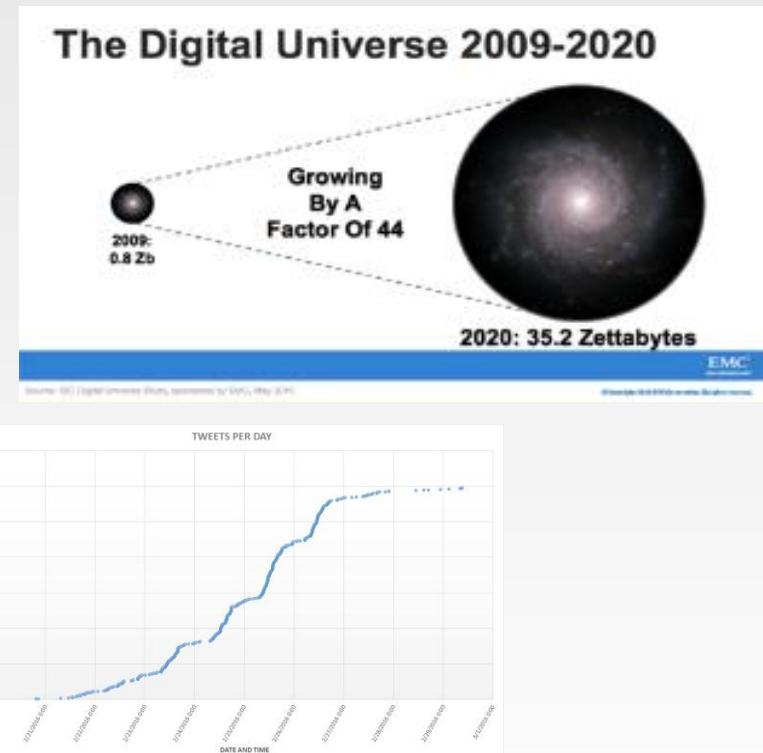
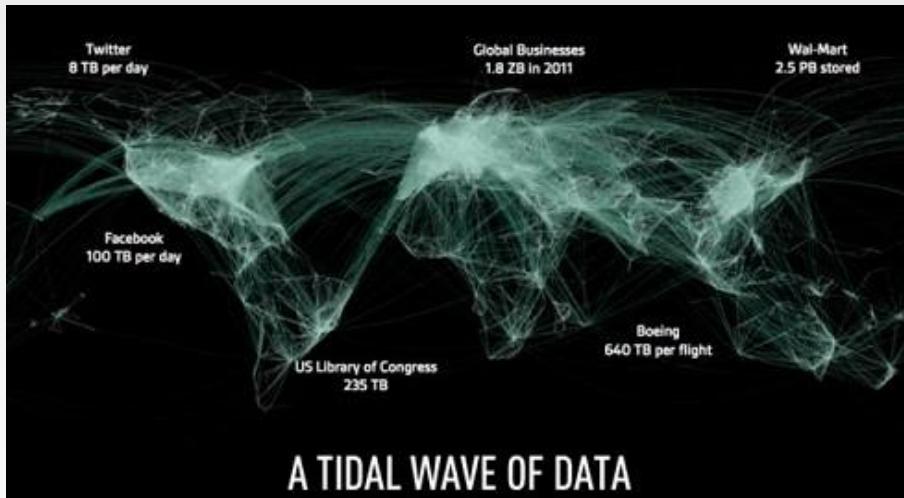
- Many different definitions

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

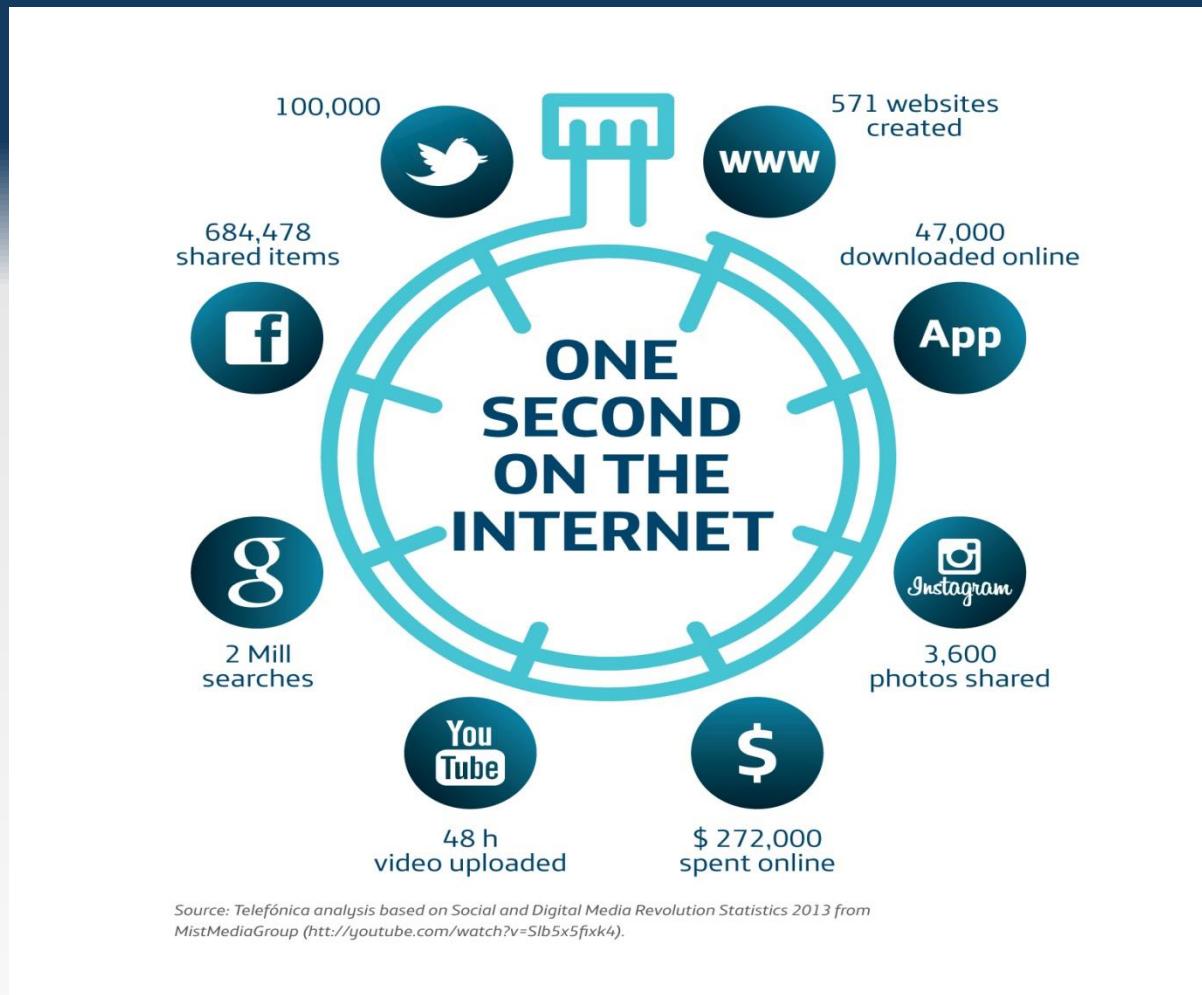


The Vs of big data: Volume

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



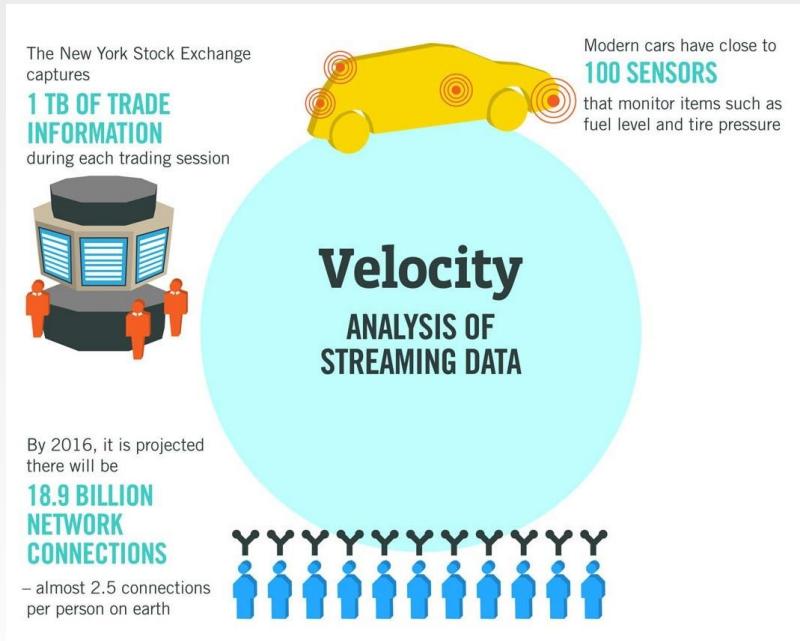
On the Internet...



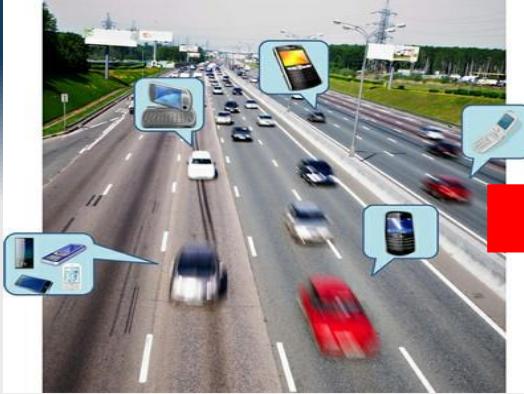
- <http://www.internetlivestats.com/>

The Vs of big data: Velocity

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



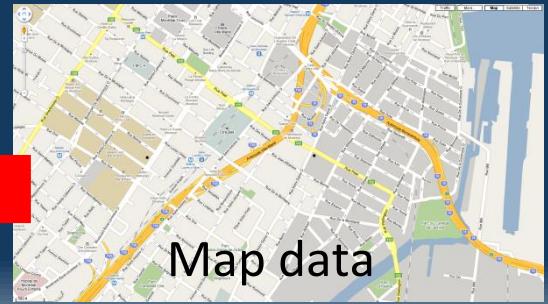
(Near) Real time processing



Crowdsourcing



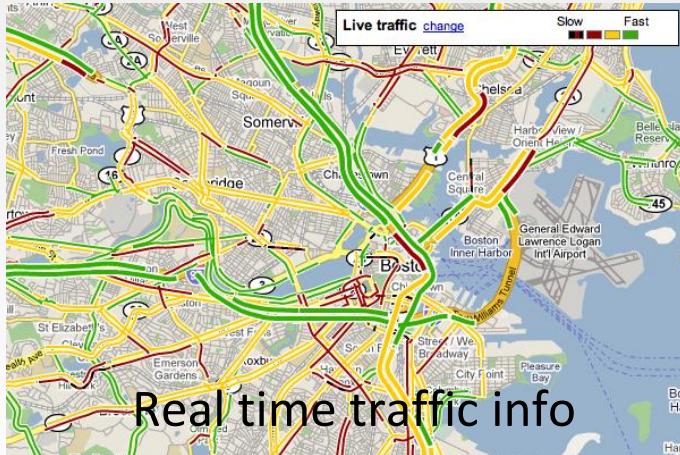
Computing



Map data



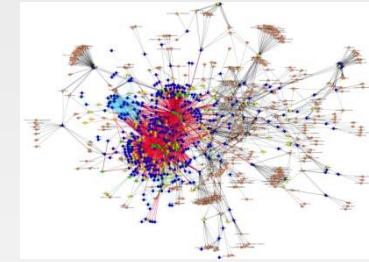
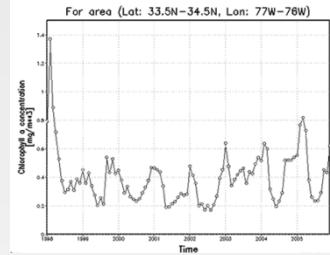
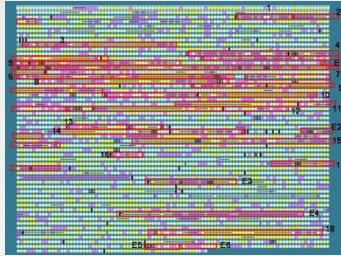
Sensing



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

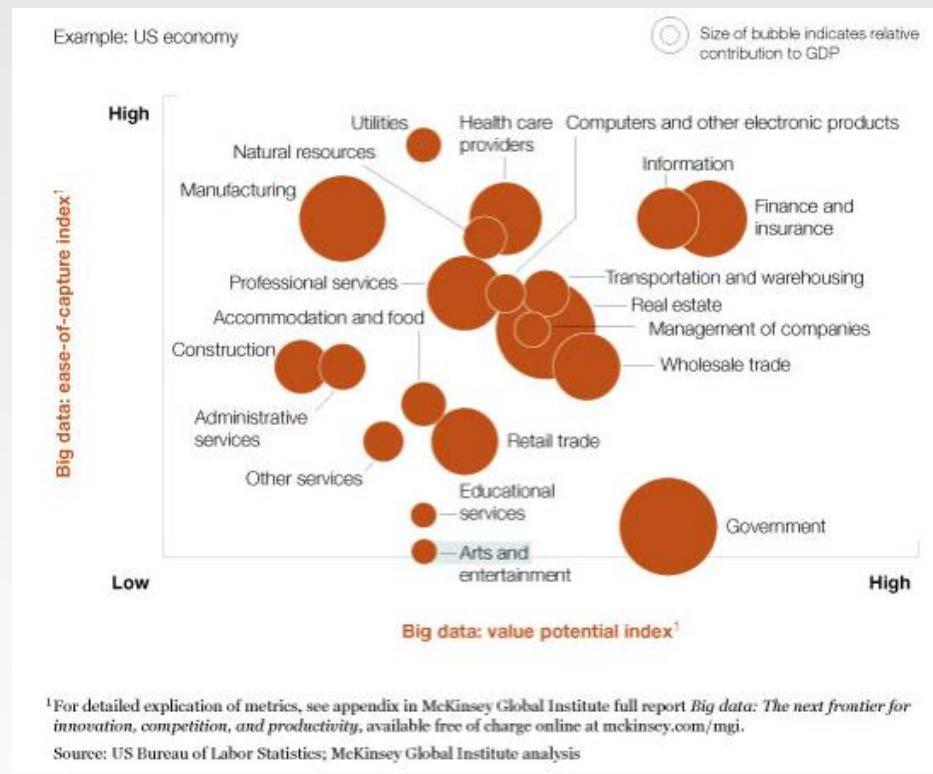
The Vs of big data: Veracity

□ Data quality



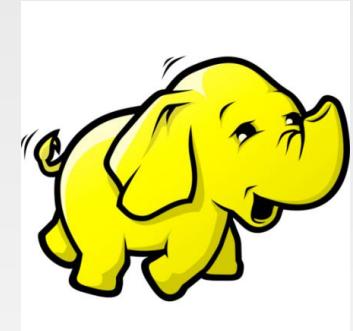
The most important V: Value

- Translate data into business advantage



Big data challenges

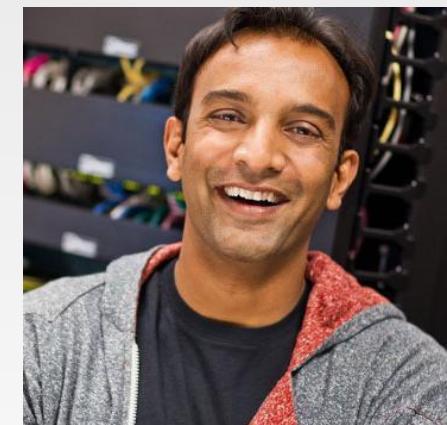
- ❑ Technology & infrastructure
 - ❑ New architectures, programming paradigms and techniques
Transfer the processing power to the data
- ❑ Apache Hadoop/Spark ecosystem
- ❑ Data management & analysis
- ❑ New emphasis on “data”



→ ***Data science***

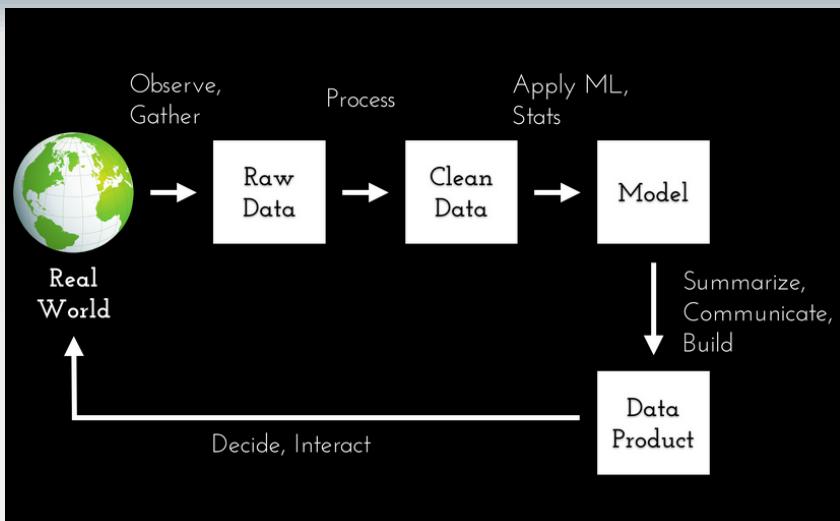
Data science

“Extracting meaning from very large quantities of data”

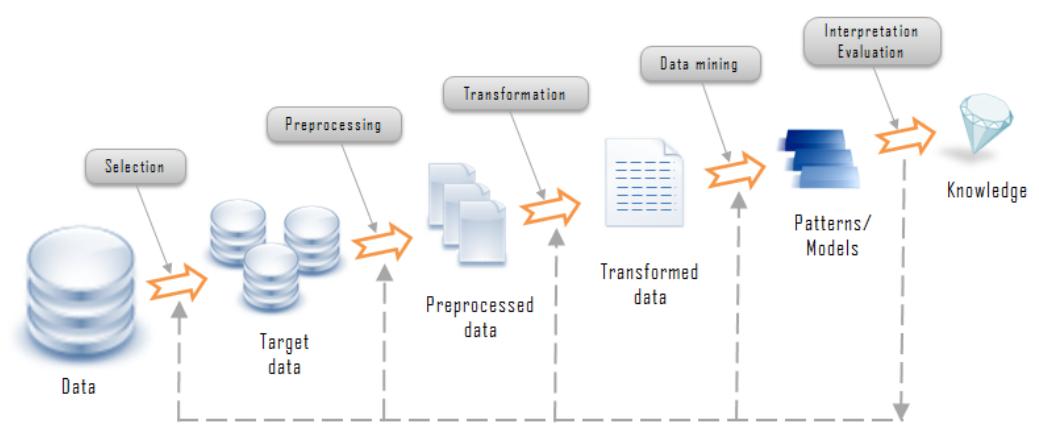


D.J. Patil coined the word *data scientist*

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, data mining, text mining, network and graph data mining
- ❑ Association analysis, classification and regression, clustering

❑ Diverse domains call for customized techniques



Data mining

❑ Non trivial extraction of

- ❑ implicit
- ❑ previously unknown
- ❑ potentially useful

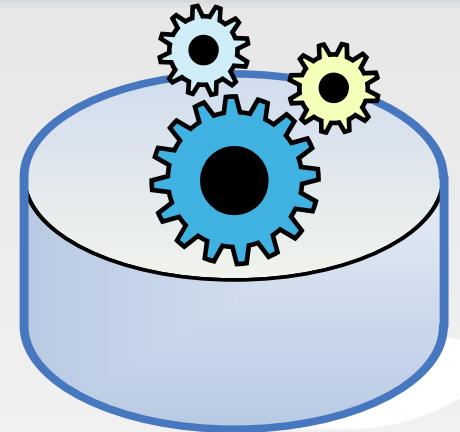
information from available data

❑ 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

- ❑ Facebook, google+ profiles



- ❑ Dynamic data: posts on blogs, FB, tweets



- ❑ Maps and georeferenced data

- ❑ Localization, interesting locations for users



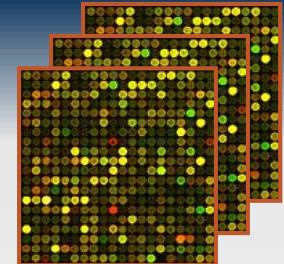
Google Maps

Example: profiling

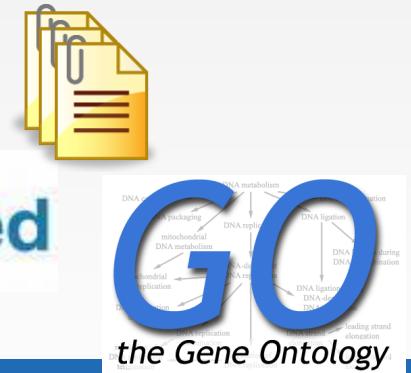
- ❑ User/service profiling
 - ❑ Recommendation systems, advertisements
- ❑ Market basket analysis
 - ❑ Correlated objects for cross selling
 - ❑ User registration, fidelity cards
- ❑ Context-aware data analysis
 - ❑ Integration of different dimensions
 - ❑ E.g., location, time of the day, user interest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



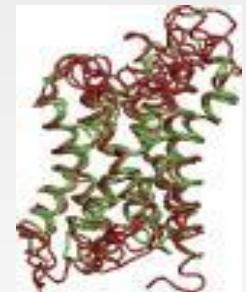
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IMAGE:74	ISG20 in	-1.02	-2.34	1.44	0.57	-0.13	0.12	0.34	-0.51
IMAGE:76	TNFSF13	-0.52	-4.06	-0.29	0.71	1.03	-0.67	0.22	-0.09
IMAGE:36	LOC93343	-0.25	-4.08	0.06	0.13	0.08	0.06	-0.08	-0.05
IMAGE:23	ITGA4 in	-1.375	-1.605	0.155	-0.015	0.035	-0.035	0.505	-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

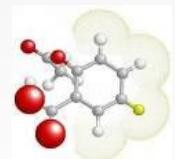


□ Bio-discovery

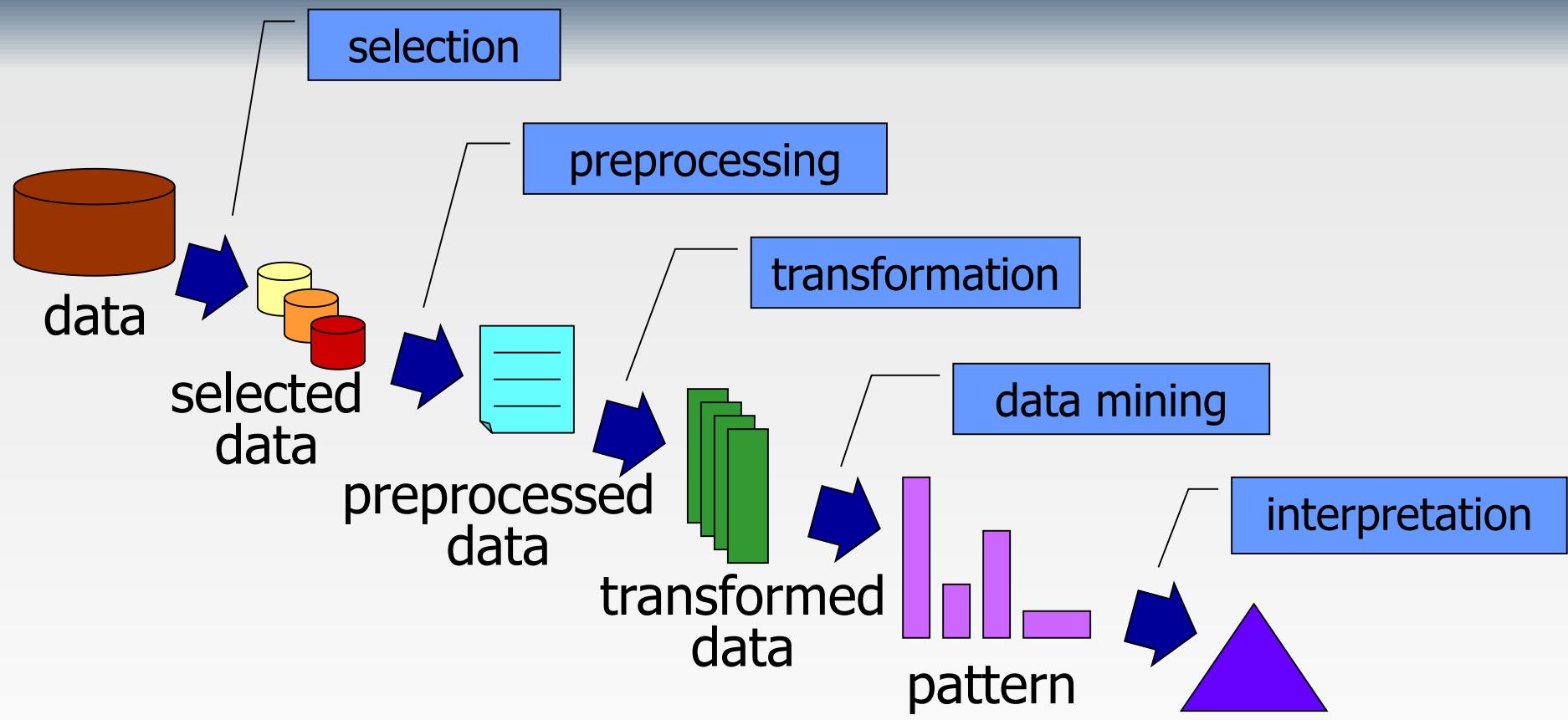
- gene network discovery
- analysis of multifactorial genetic pathologies

□ Pharmacogenomics

- lab design of new drugs for genic therapies



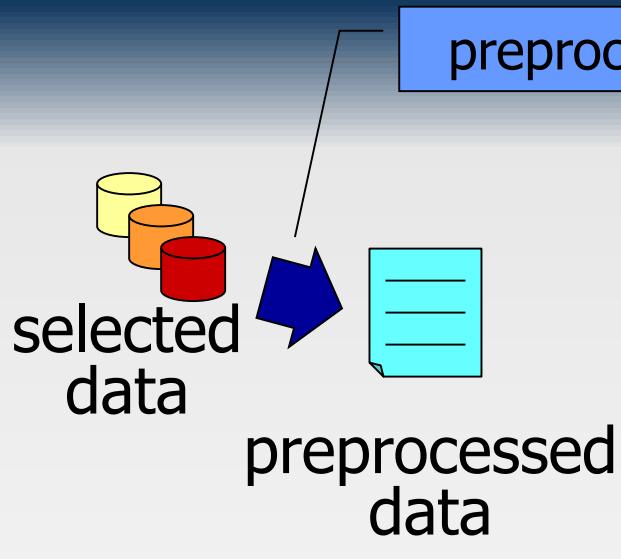
Knowledge Discovery Process



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

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



Frequently Bought Together



+

+

Price For All Three: £9.00

Add all three to Basket

Show availability and delivery details

- This item:** Paperback Oxford English Dictionary by Oxford Dictionaries Paperback £3.00
- Oxford Paperback Thesaurus by Oxford Dictionaries Paperback £3.00
- Oxford Essential French Dictionary by Oxford Dictionaries Paperback £3.00

Jobs You May Be Interested In

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Senior Data Analyst Job

Thomson Reuters - Bangalore, KA



Data Scientist/ Senior Data Scientist

HeadHonchos.com - Bangalore - IN



Hiring Computer Scientist (Java) for...

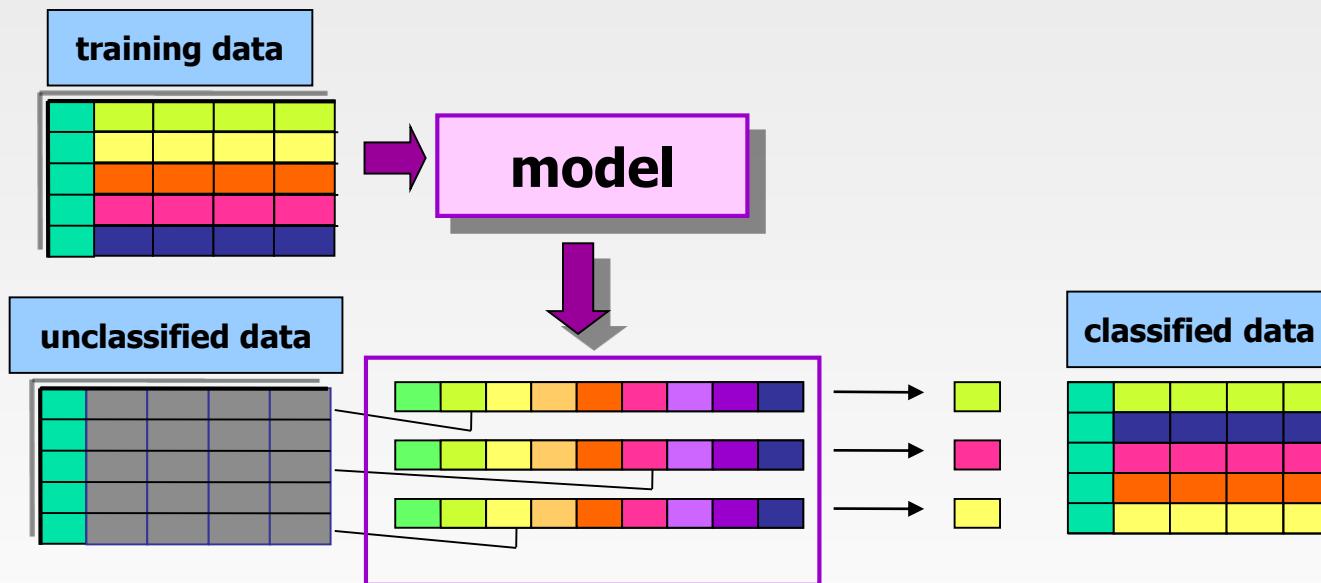
Adobe - Noida



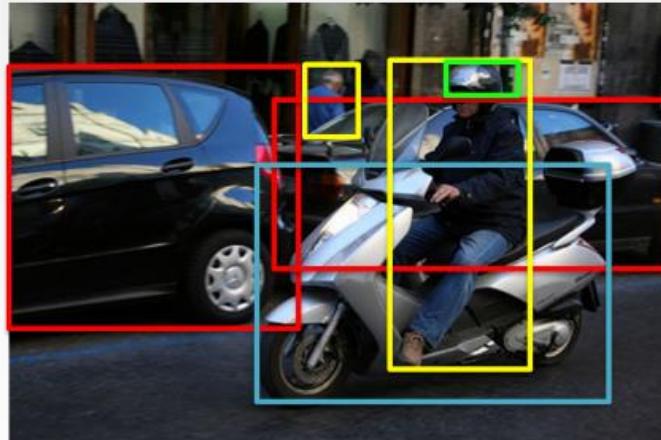
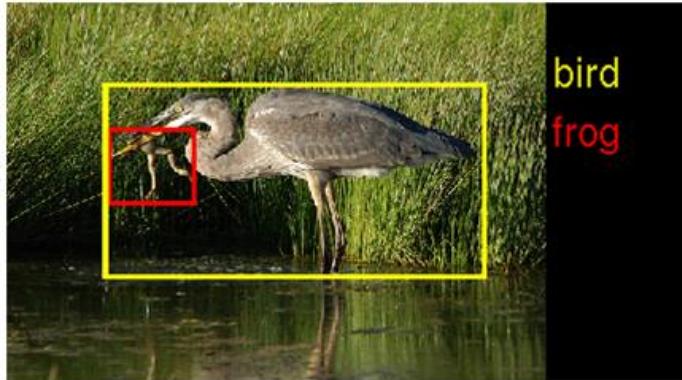
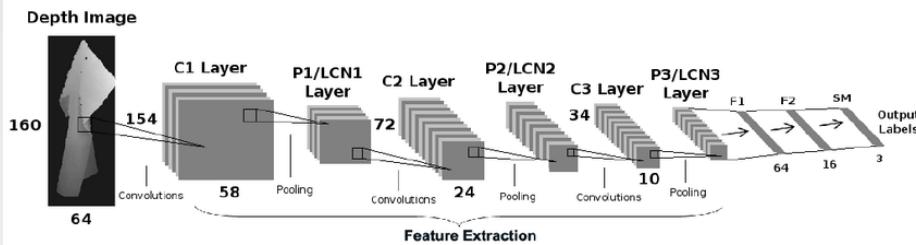
Classification

❑ Objectives

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



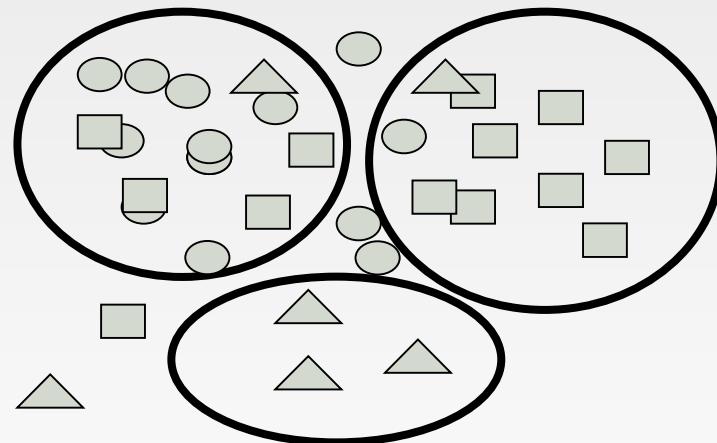
Classification



Person
Car
Motorcycle
Helmet

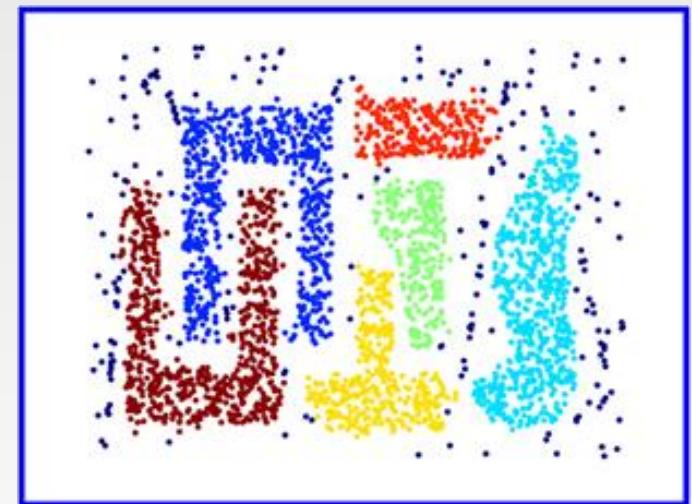
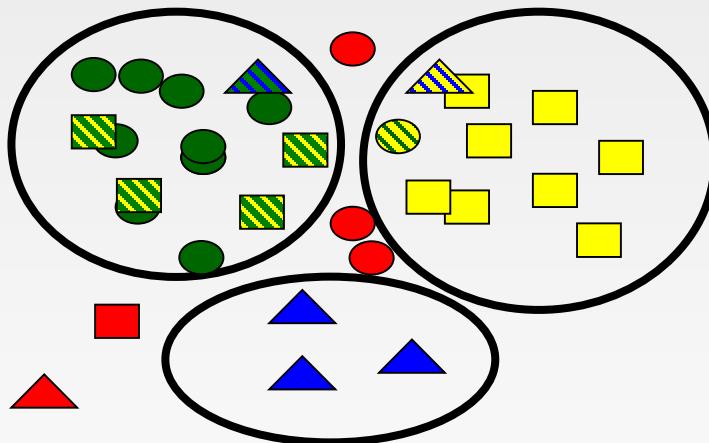
Clustering

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

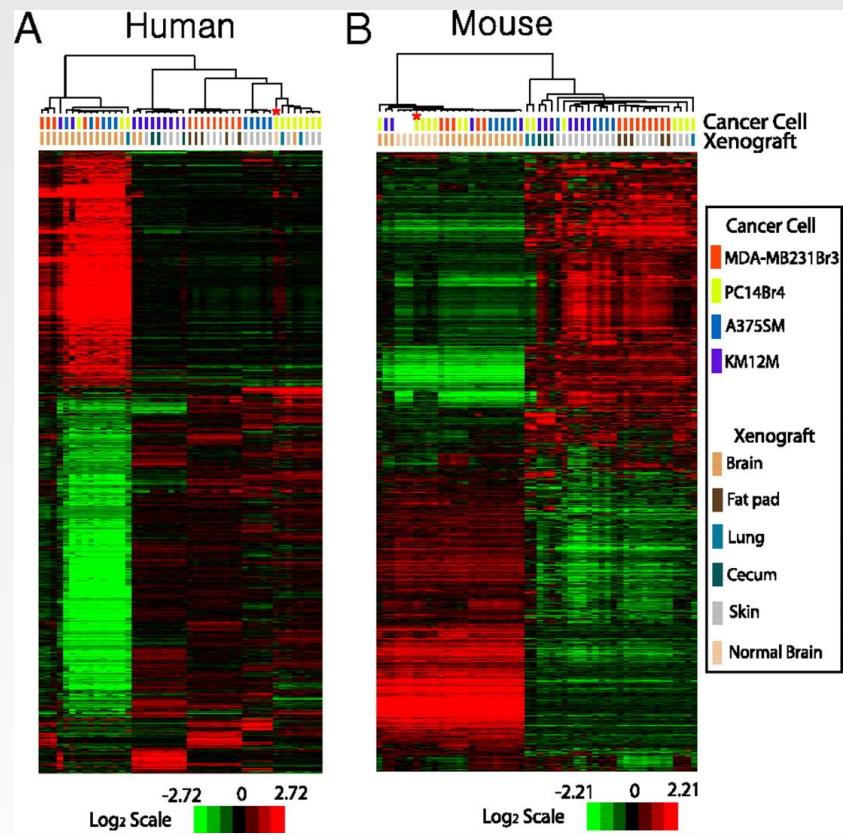
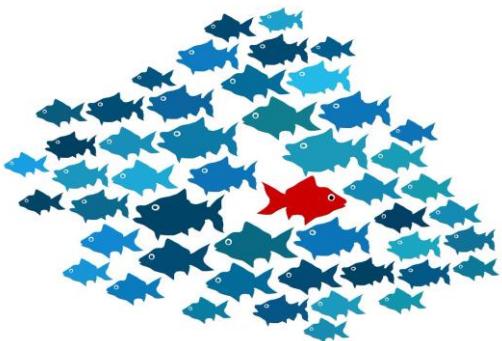


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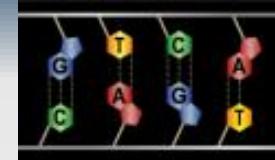
Clustering



Other data mining techniques

□ Sequence mining

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



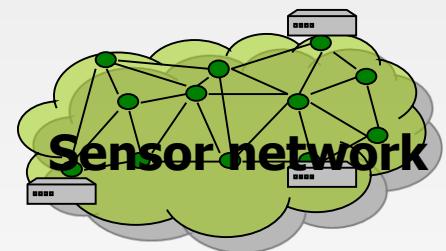
□ Time series and geospatial data

- 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 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 language 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 tools 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
- ★ Translate data-driven insights into decisions and actions
- ★ Visual art design
- ★ R packages like ggplot or lattice
- ★ Knowledge of any visualization tools e.g. Tableau, T3.js, D3.js

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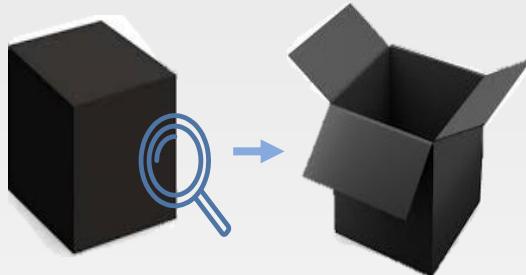
Marketing DISTILLERY

Open issues

- ❑ Social impact of analysis is very important
- ❑ Interpretability and transparency of the analysis process
- ❑ 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

Privacy

STRAVA LABS

Projects Blog Développers 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

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

Technology

Fitness app Strava lights up staff at military bases

29 January 2018



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