Data Science

Opportunities and Risks

Patrick Valduriez











Data versus Information

Data

- Elementary definition of a fact
 - E.g. temperature, exam grade, account balance, message, photo, transaction, etc.
- Can be complex
 - E.g. a satellite image
- Can also be very simple, and taken in isolation, not very useful
- But the integration with other data becomes useful

Les données en question

PAR
Stéphane Grumbach
Patrick Valduriez

NIVEAU DE LECTURE
Facile • • • • 31/03/2016

Au cœur de la connaissance et de l'information, les données ont peu à peu pris une importance qui nous dépasse. Mais qu'entend-on exactement par données ? Quels sont les enjeux autour de leur gestion ou de leur analyse ? Quels impacts sur la société ?



Une donnée est la description élémentaire d'une réalité ou d'un fait, comme par exemple un

Information

- Obtained by interpretation and analysis of data to yield sense in a given context
- Can be very useful to understand the world
 - E.g. climate evolution, ranking of a student, etc.

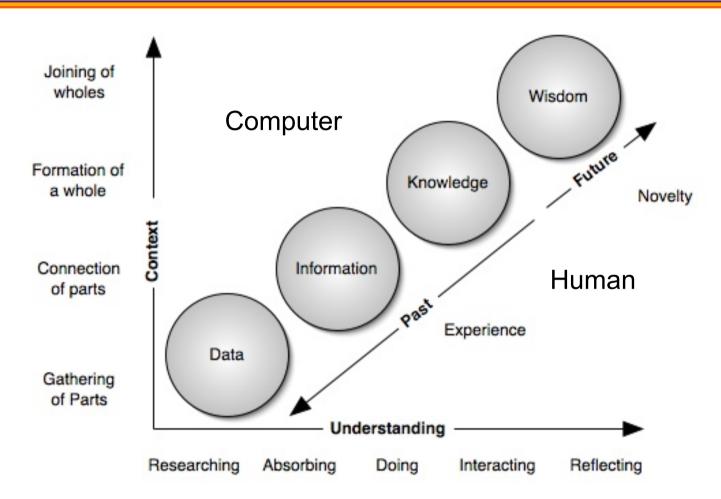
Data and Algorithm

"Content without method leads to fantasy, method without content to empty sophistry."

Johann Wolfgang von Goethe (Maxims and Reflections, 1892)

- The better the datasets, the better the machine learning algorithms
- Milestones
 - 1997: IBM Deep Blue defeats Chess world champion Garry Kasparov
 - Negascout planning algorithm (1983)
 - Dataset of 700 thousands of chess games (1991)
 - 2016: Google Alphago defeats Go master Lee Sedol (4-1)
 - Monte Carlo method based algorithm (from the 1940's) and neural network
 - Dataset of 30 millions of go moves

The Continuum of Understanding



- The more the data, the better the understanding
 - If we (humans) do a good job

Outline

- 1. Data science
- 2. The good, the bad and the ugly
- 3. Technologies for data science
- 4. HPC & big data analysis
- 5. Opportunities and risks

Data Science



Data Science: definition

Data science

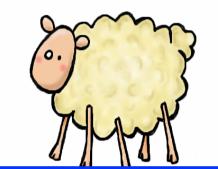
- The science of making sense of data
- The use of data management, statistics and machine learning, visualization and human-computer interactions to collect, clean, integrate, process, analyze and visualize big data
- Ultimate goal: create data products and data services

Data scientist

- Strong skills in statistics, data analysis and machine learning
- AND strong knowledge of the business domain, to interpret the analysis results and draw meaningful conclusions

Data Science: definition

Hard to find data scientists!



New training programs all over the world

Should we all be teaching "Intro to Data Science" instead of "Intro to Databases"?

ACM SIGMOD panel 2014

Big Data: what is it?

A buzz word!

- With different meanings depending on your perspective
 - E.g. 10 terabytes is big for an OLTP system, but small for a web search engine
- A definition (Wikipedia)
 - Consists of data sets that grow so large that they become awkward to work with using on-hand data management tools
 - But size is only one dimension of the problem
- How big is big?
 - Moving target: terabyte (10¹² bytes), petabyte (10¹⁵ bytes), exabyte (10¹⁸), zetabyte (10²¹)
 - Landmarks in DBMS products
 - 1980: Teradata database machine
 - 2010: Oracle Exadata database machine

Why Big Data Today?

- Overwhelming amounts of data
 - Exponential growth, generated by all kinds of programs, networks and devices
 - E.g. Web 2.0 (social networks, etc.), mobile devices, computer simulations, satellites, radiotelescopes, sensors, etc.
- Increasing storage capacity
 - Storage capacity has doubled every 3 years since 1980 with prices steadily going down
 - 1 Gigabyte (HDD): \$400K in 1980, \$10K in 1990, \$1K in 1995, \$10 in 2000, \$0.02 in 2015
- Very useful in a digital world!
 - Massive data => high-value information and knowledge

Big Data Dimensions: the V's

Volume

- Refers to massive amounts of data
- Makes it hard to store and manage

Velocity

- Continuous data streams are being produced
- Makes it hard to process online

Variety

- Different data formats, different semantics, uncertain data, multiscale data, etc.
- Makes it hard to integrate

Other V's

- Validity: is the data correct and accurate?
- Veracity: are the results meaningful?
- Volatility: how long do you need to store this data?

Big Data Analytics (BDA)

- Objective: find useful information and discover knowledge in data
 - Typical uses: forecasting, decision making, research, science, ...
 - Techniques: data analysis, data mining, machine learning, ...
- Why is this hard?
 - Low information density (unlike in corporate data)
 - Like searching for needles in a haystack
 - External data from various sources
 - Hard to verify and assess, hard to integrate
 - Different structures
 - Unstructured text, semi-structured document, key/value, table, array, graph, stream, time series, etc.
 - Hard to integrate
 - Simple machine learning models don't work
 - See next: "When big data goes bad" stories

Some BDA Killer Apps

- Social network analysis
 - Modeling, simulation, visualization of large-scale networks
- Online fraud detection across massive databases
 - Applicable in many domains (e-commerce, banking, telephony, etc.)
- National security
 - Signal intelligence, cyber analytics
- Real-time processing and analysis of raw data from high-throughput scientific instruments
 - E.g. to detect changing external conditions
- Health care/medical science
 - Drug design, personalized medicine

Example: data-intensive science











Observation

Experimentation



Processing Integration Analysis Search



Data
Information
Knowledge



Example: data-intensive science

The problem

"Scientists are spending most of their time manipulating, organizing, finding and moving data, instead of researching. And it's going to get worse"

The Office Science Data Management Challenge (USA DoE 2004)

In bioinformatics, the time to deal with data can be well above 50% (IBC annual review 2017)

Data Science the good, the bad and the ugly



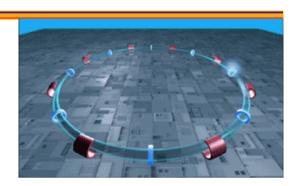
The good: Higgs Boson @ CERN

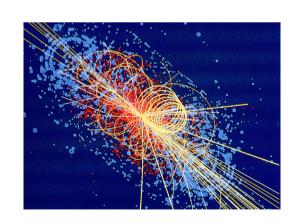
LHC (Large Hadron Collider)

- Instrument to study the properties of fundamental particules in physics
- Produces 15 petabytes / year
- Made available through the LHC Computing Grid to several computing centers, e.g. CC-IN2P3, Lyon
- Up to 200,000 simultaneous analyses



- 2012: CERN announces that it had discovered a particle that was probably a Higgs boson particle as predicted by the Standard Model of particle physics
- 2014: CERN confirms the discovery





The good: Google Sponsored Search Links

- Google Adwords and Adsense programs
 - Revenue around \$50 billion/year from marketing
 - The user defines its maximum cost-per-click bid (max. CPC bid), the most she's willing to pay for a click on her ad
- Sponsored search uses an auction
 - A pure competition for marketers trying to win access to consumers, i.e. a competition for models of consumers – their likelihood of responding to the ad – and of determining the right bid for the item
- There are around 30 billion search requests a month, perhaps a trillion events of history between search providers

When Big Data goes bad



November 5, 2013: 1:00 PM ET













How the models underlying today's supercomputing prowess are costing us its success.

By Joshua Klein



The Bad



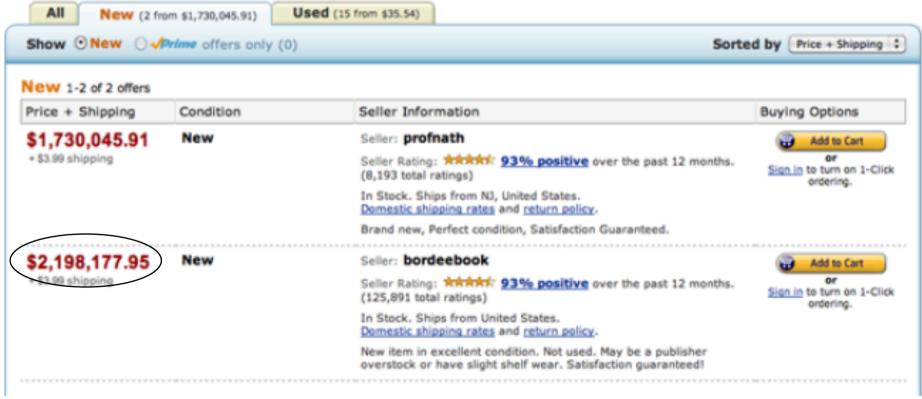
The Making of a Fly: The Genetics of Animal Design (Paperback) by Peter A. Lawrence

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Always pay through Amazon.com's Shopping Cart or 1-Click.

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Price at a Glance List \$70.00 Price: Used: from \$35.54 New: from \$1,730,045.91 Have one to sell? Sell yours here



The Bad

Excerpts:

What had happened was that two automated programs, one run by seller "bordeebook" and one by seller "profnath," were engaged in an iterative and incremental bidding war.

Once a day profnath would raise their price to *x* times bordeebook's listed price. Several hours later, bordeebook would increase their price to *y* times profnath's latest amount.

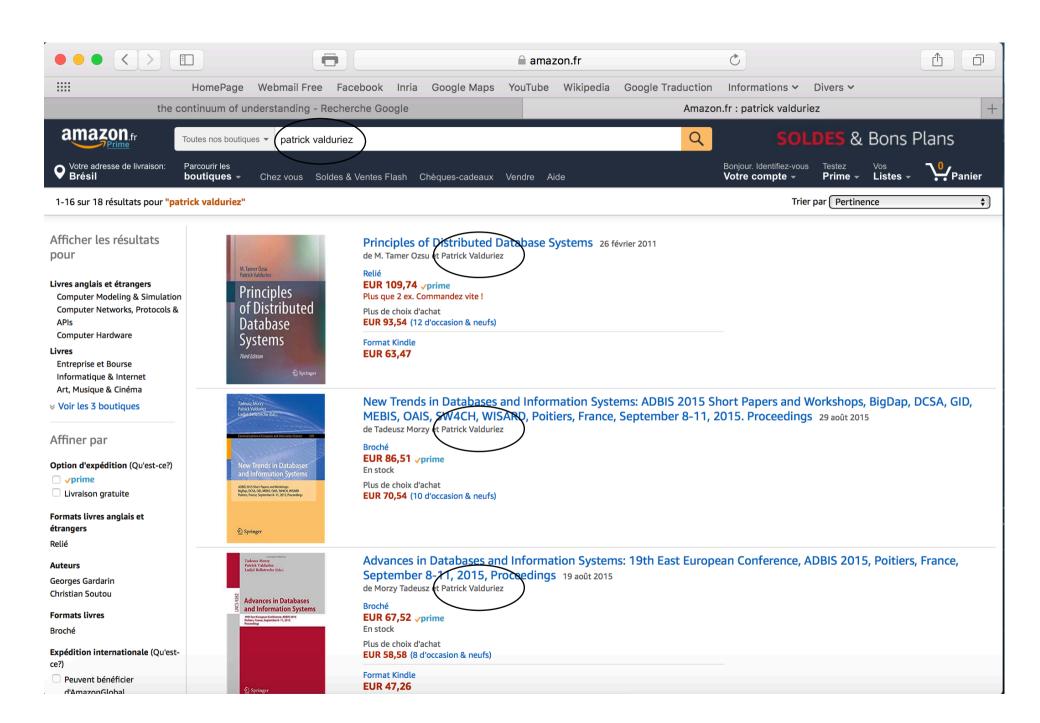
The Bad

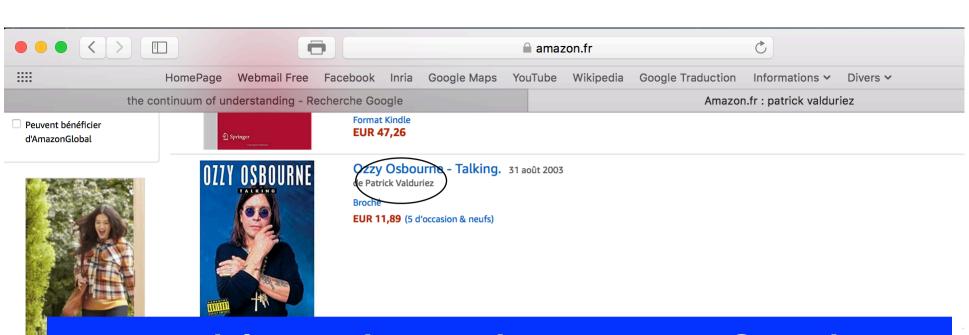
Excerpts:

What had happened was that two automated programs, one run by seller "bordeebook" and one by

Problem: over simplified models, but reality is complex!

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Problem: how do I get it fixed?

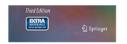
amazon prime

Essayez aratuitement Amazon Prime pendant 30 jours

Livraison en 1 jour ouvré sur des millions d'articles

Essayer maintenant .

Commentaires sur la publicité



EUR 232,52 (3 d'occasion & neufs)



Ozzy Osbourns, Fucking Mad. Die Story zu seinen Songs. 30 juin 2003 le Patrick Valduriez

EUR 9.99 (5 d'occasion & neufs)

Objects: Concepts and **Applications**

Object Technology 1 avril 1997 de Mokrane Bouzeghoub et Georges Gardarin

FUR 3.67 (5 d'occasion & neufs)





A tiny company in Worcester, Mass., has paid the ultimate price for posting offensive T-shirts for sale online.

Fierce public backlash brought down Solid Gold Bomb, which made headlines in March for offering shirts that said "Keep Calm and Rape a Lot." The company closed its doors last week and let go its remaining three employees.



Excerpts:

Solid Gold Bomb, the company that made the shirt, wasn't necessarily aware that it was even selling it. Solid Gold Bomb's business isn't in artfully designing T-shirts. Instead, it writes code that takes libraries of words that slot into popular phrases (such as "Keep Calm and Carry On," which enjoyed a brief mimetic popularity online) to make derivations that get dropped onto a template of a T-shirt and automatically get posted as an Amazon item for sale.

Their mistake was overlooking a single word in a list of 4,000 or so others.

Excerpts:

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Problem: context-independent model, but context does matter!

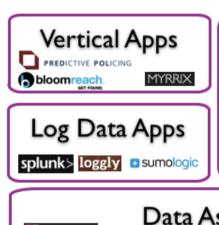
template of a 1-shirt and automatically get posted as an Amazon item for sale.

Their mistake was overlooking a single word in a list of 4,000 or so others.

Technologies



Data Science Landscape



















Data Processing Frameworks









NoSQL Databases

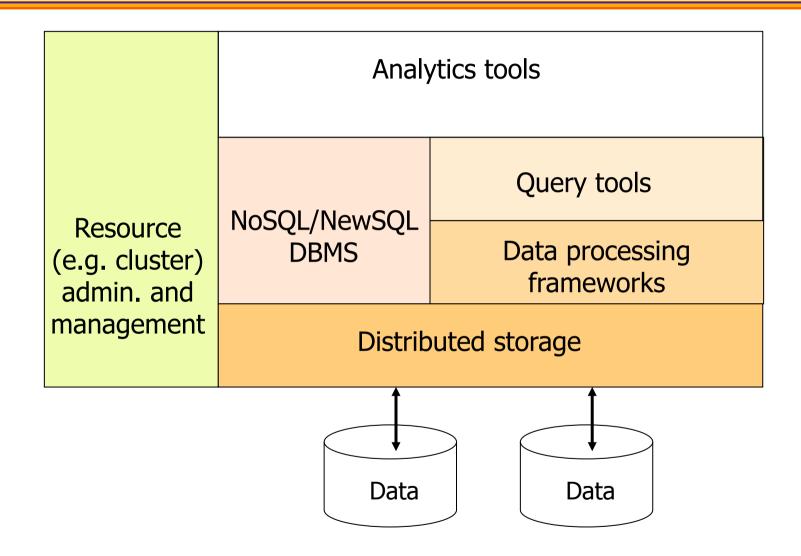




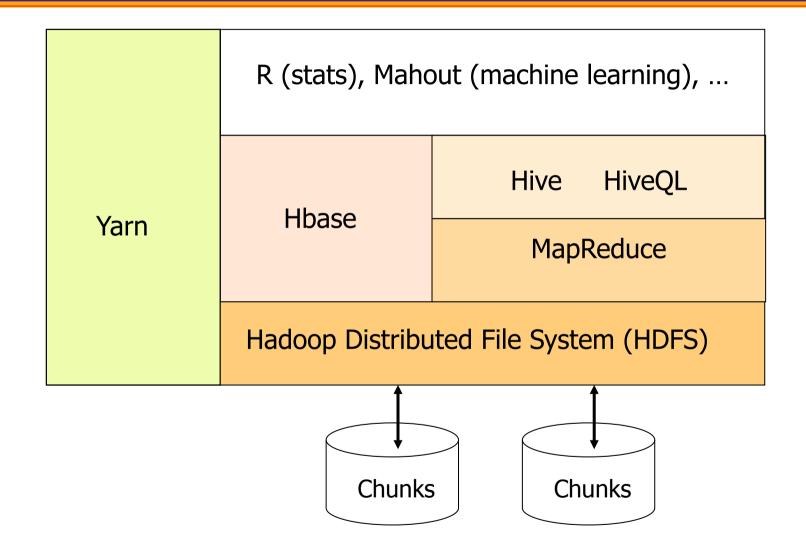
Data Science Landscape



A New Software Stack



Hadoop Architecture

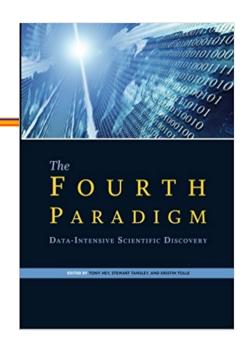


HPC & Big Data Analysis



Context: data-intensive science

- Modern science such as astronomy, biology and computational engineering must deal with overwhelming amounts of data
 - Generated by sensors, scientific instruments or simulation



- Increasingly, scientific breakthroughs will be powered by advanced computing capabilities that help researchers manipulate and explore these massive datasets
- Requires the integration of two paradigms
 - High-performance computing (HPC)
 - From high-end supercomputers to compute clusters
 - Data-intensive scalable computing (DISC)
 - Hadoop, Spark, Pregel, Giraph, NoSQL, NewSQL

HPC versus DISC

Dimensions	НРС	DISC
Focus	Compute-centric	Data-centric
Applications	Science, engineering	Web, business
Target	Simulation	Data management, data analysis
Objectives	High-performance	Scalability, fault-tolerance, availability, cost-performance
Programming models	Low-level (MPI, OpenMP) Operator libraries	High-level operators (Map, Reduce, Filter,)
Programming languages	C, C++	Java, Python, Scala
Parallel architectures	Shared-disk and specific hardware	Shared-nothing clusters of commodity hardware

Approaches



Postprocessing analysis

- Performs analysis after simulation, e.g. by loosely coupling a supercomputer and a DISC cluster (possibly in the cloud)
- Simple, non intrusive but is restricted to batch analysis

In-situ analysis

- Runs on the same compute resources as the simulation, e.g. a supercomputer
- Intrusive, but makes it easy to perform interactive analysis

In-transit analysis

- Offloads analysis to a separate partition of compute resources, e.g. using a single cluster with both compute nodes and data nodes
- Less intrusive than in-situ, but requires careful synchronization of simulation and analysis

SciDISC

Scientific data analysis using Data-Intensive Scalable Computing

Project coordinators: Marta Mattoso & Patrick Valduriez
Inria – Brazil Associated Team
2017 - 2019











Opportunities and Risks



Opportunities



- Cost reduction (vs. traditional data warehousing)
 - New open source technologies (Hadoop, Spark, etc.)
 - Cloud services
- Faster, better decision making
 - Realtime data processing (e.g. online fraud detection)
 - Data crowdsourcing to produce timely, precise data
- Better knowledge discovery
 - Virtuous circle between machine learning and big data
- New data products and services
 - Two-sided markets (Uber, Airbnb, Leboncoin, etc.)
 - Digital health, digital agriculture, etc.

Risks



Data security

The bigger your data, the bigger the target it presents to attackers

Data privacy

 Personal data can be misused by people who have responsibility for analytics, and may violate data protection laws

Cost

- Data collection, aggregation, storage, analysis, and reporting
- Data security and privacy

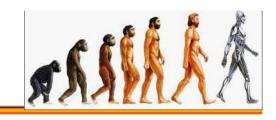
Bad analytics

- Oversimplified or wrong models (see "when big data goes bad")
- Misinterpreting the patterns shown by the data and drawing wrong conclusions

Bad data

 Many projects start off wrong by collecting irrelevant, out of date, or erroneous data

Impact on Homo Sapiens



- More and more intelligent tools
 - Self-driving cars, autonomous robots, digital assistants, drones, terminators, ...



- Responsibility in case of problem (failure, collateral damage, ...)
- Towards a job-less society
- Freedom and privacy



- Human enhancement through natural or artificial means
- Questions
 - The end of natural selection
 - A new human species
 - Immortality, e.g. replacing a dead person by an AI







Thanks

