Data Mining for the XXI Century: Real-Time Data Mining

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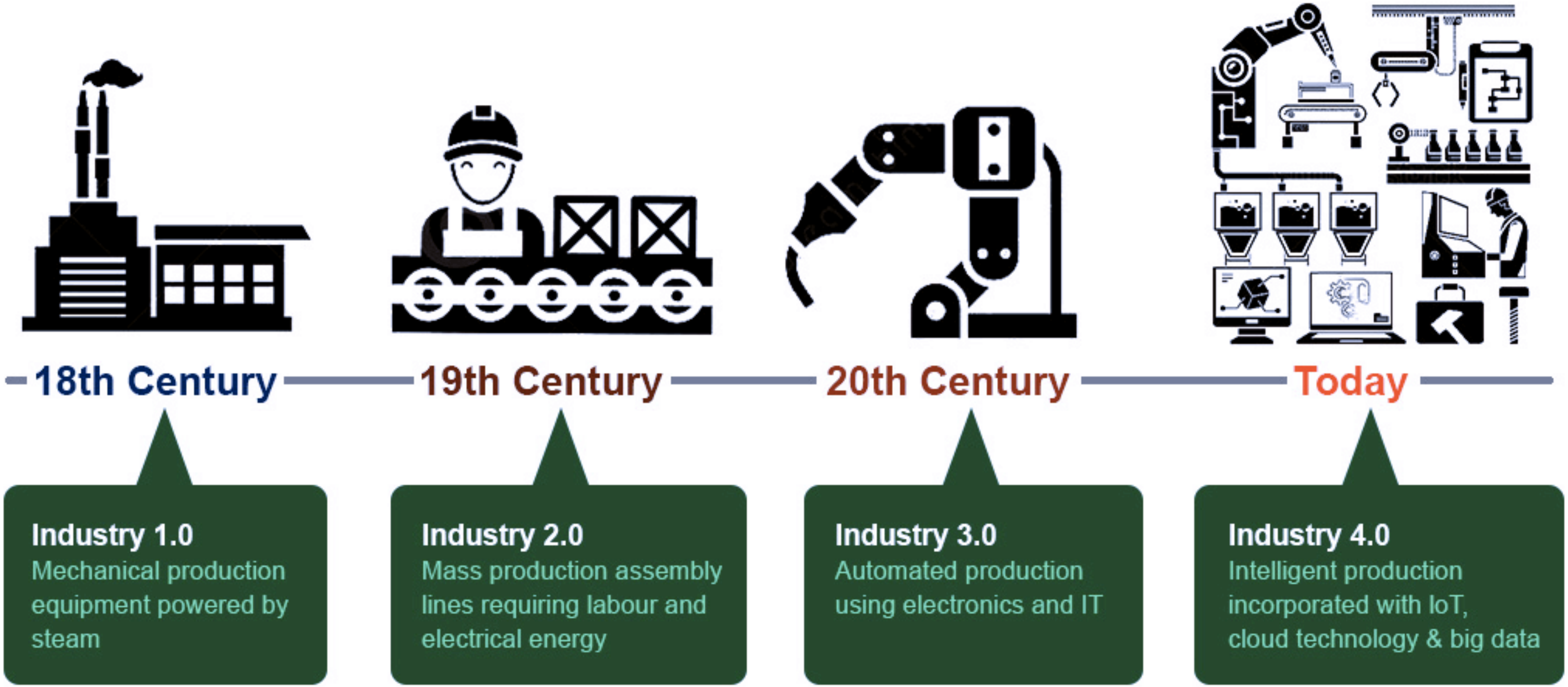
ULB
Brussels, March 2019

Motivation


18th Century
19th Century
20th Century
Today
Industry 1.0
Mechanical production equipment powered by steam
Industry 2.0
Mass production assembly lines requiring labour and electrical energy
Industry 3.0
Automated production using electronics and IT
Industry 4.0
Intelligent production incorporated with IoT, cloud technology & big data

Industry 4.0

We have machines that collect, process, and send information to other machines

Motivation

Global Future Report™ January 15th, 2001

10 Emerging Technologies That Will Change the World

© Dr. Terry J. van der Werff, CMC

MIT's Technology Review has identified 10 emerging areas of technology that will soon have a profound impact on the economy and how we live and work.

Regular readers of *Global Future Report*™ know I am a sucker for lists of things that matter. I even write lists of my own, e.g. my "Ten Tips for Harnessing the Future" or the four forces converging to alter global telecommunications in "Calling the Future."

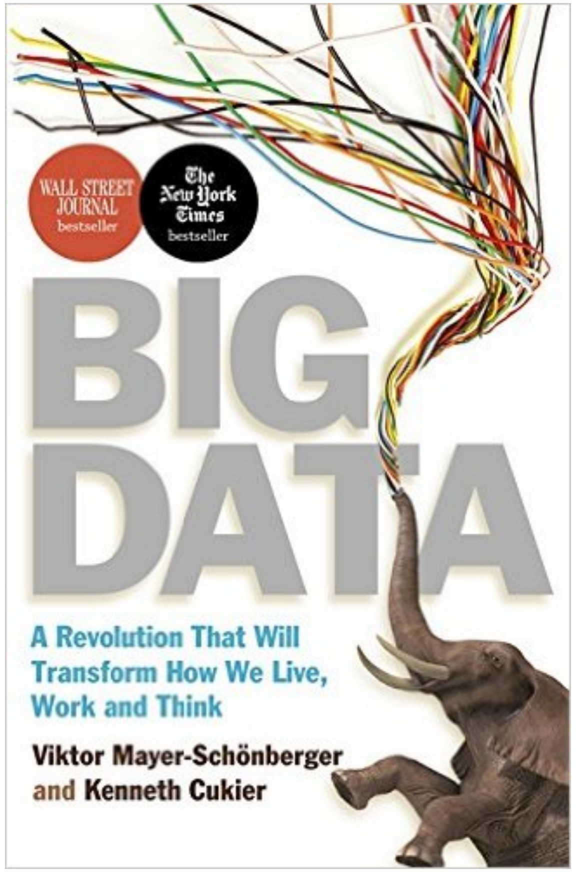
To launch the New Millennium the January/February issue of *Technology Review*, MIT's magazine of innovation, focuses on "The Technology Review Ten" - "10 emerging areas of technology that will soon have a profound impact on the economy and how we live and work." For each, one innovator's work is highlighted.

Drum roll, please! The ten emerging technologies that will change the world are:

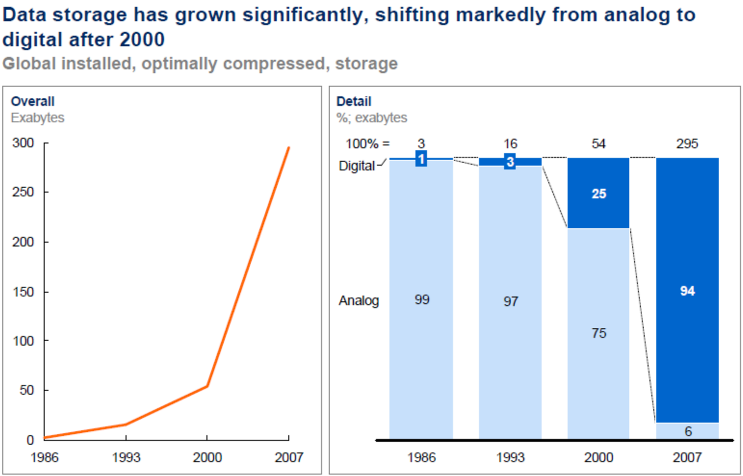
- **Brain-Machine Interfaces** - In essence, researchers try both to understand how the brain works and to use this knowledge to implant electrodes in specific parts of the brain to permit control of computers, robotic arms, or other artificial devices designed to restore lost sensory and motor functions.
- **Flexible Transistors** - Silicon does not bend readily, so a new class of hybrid materials are being developed that marry the speed of inorganic compounds with the flexibility of organic polymers. They have the advantage of being able to be dissolved and printed onto paper or plastic as if they were ink particles.
- **Data Mining** - Ever get an e-mail from amazon.com suggesting a book that relates to an earlier one you ordered from them? You have been the subject of data mining, which is nothing more than the extraction of meaningful information and patterns from huge data sets.

Motivation


McKinsey Global Institute
June 2011
Big data: The next frontier for innovation, competition, and productivity

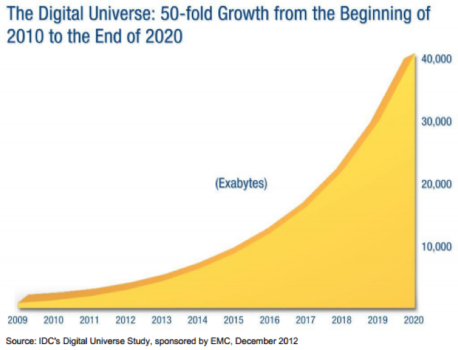

WALL STREET JOURNAL bestseller
The New York Times bestseller
BIG DATA
A Revolution That Will Transform How We Live, Work and Think
Viktor Mayer-Schönberger and Kenneth Cukier

We are living in a world of digital data ...



NOTE: Numbers may not sum due to rounding.
SOURCE: Hilbert and López, "The world's technological capacity to store, communicate, and compute information," *Science*, 2011

The Growth of Digital Data...



Memory unit	Size	Binary size
kilobyte (kB/KB)	10^3	2^{10}
megabyte (MB)	10^6	2^{20}
gigabyte (GB)	10^9	2^{30}
terabyte (TB)	10^{12}	2^{40}
petabyte (PB)	10^{15}	2^{50}
exabyte (EB)	10^{18}	2^{60}
zettabyte (ZB)	10^{21}	2^{70}
yottabyte (YB)	10^{24}	2^{80}

Big Data

A brief history of big data, the Noam Chomsky way

CNBC

Text Size

Published: Saturday, 23 Nov 2013 | 7:00 AM ET

By: Eric Rosenbaum | CNBC.com

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Noam Chomsky

The latest news from the fast-evolving world of the ***Data Economy****:*

For those familiar with Noam Chomsky, the pioneering linguist whose theory of recursion seeks to find the universal in all human languages, you probably also know that Chomsky often has not-so-nice things to say about the U.S. government, and has also made a career of finding the universal

Big data is a step forward, but our problems are not lack of access to data, but understanding them. Big data is very useful if I want to find out something without going to the library, but I have to understand it, and that's the problem.

Tools: time ago ...

Tools seemed quite powerful

Tools Problems

Algorithmic Aspects of Big Data, Nikhil Bansal, (TU Eindhoven)

Tools: nowadays ...

Last few years

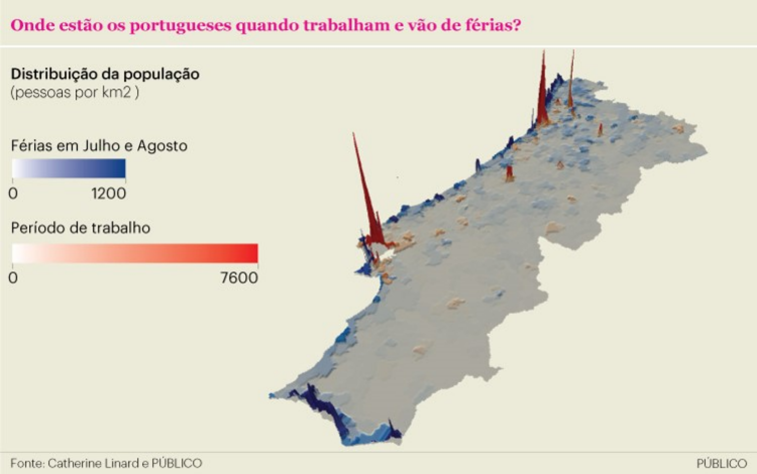
The Model has Changed ...

- **The Model of Generating/Consuming Data has Changed**

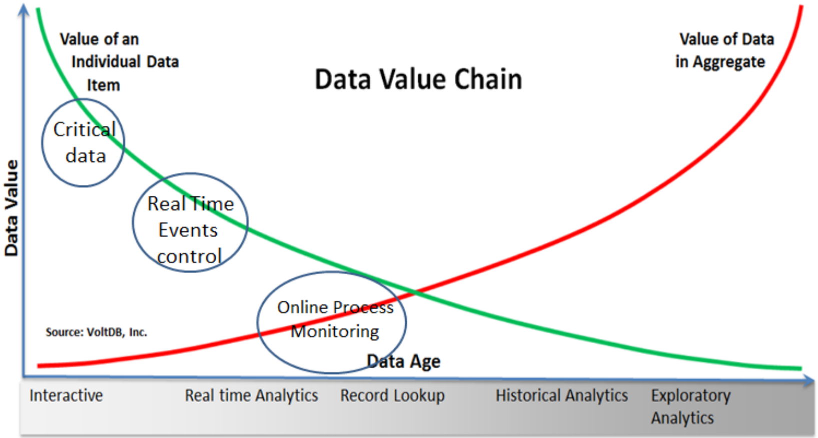
Old Model: Few companies are generating data, all others are consuming data

New Model: all of us are generating data, and all of us are consuming data

An Illustrative Example: Real-time Census ...



The Value of Information ...



A World in Movement

- The new characteristics of data:
  - **Time and space**: The objects of analysis exist in time and space. Often they are able to move.
  - **Dynamic environment**: The objects exist in a dynamic and evolving environment.
  - **Information processing capability**: The objects have limited information processing capabilities
  - **Locality**: The objects know only their local spatio-temporal environment;
  - **Distributed Environment**: Objects will be able to exchange information with other objects.
- Main Goal:
  - **Real-Time Analysis**: decision models have to evolve in correspondence with the evolving environment.

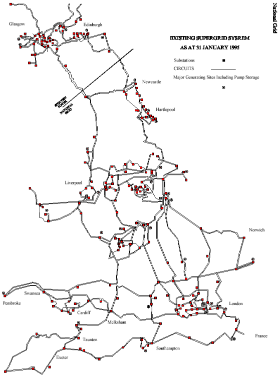
The Challenges of Real Time Data Mining

These characteristics imply:

- Switch from **one-shot learning** to continuously learning **dynamic models** that evolve over time.
- In this context, *finite training sets, static models, and stationary distributions* will have to be completely thought anew.
- Computational resources are finite. Algorithms will have to use *limited computational resources* (in terms of computations, memory, space and time, communications).

Outline

Scenario



Electrical power Network: Sensors all around network monitor measurements of interest.

Scenario

- Sensors produce continuous flow of data at high speed:
  - Send information at different time scales;
  - Act in adversary conditions: they are prone to noise, weather conditions, battery conditions, etc;
- Huge number of Sensors, variable along time
- Geographic distribution:
  - The topology of the network and the position of the sensors are known.

Illustrative Learning Tasks:

- Cluster Analysis
  - Identification of Profiles: Urban, Rural, Industrial, etc.
- Predictive Analysis
  - Predict the value measured by each sensor for different time horizons.
  - Prediction of peaks on the demand.
- Monitoring Evolution
  - Change Detection
    - Detect changes in the behavior of sensors;
    - Detect Failures and Abnormal Activities;
  - Extreme Values, Anomalies and Outliers Detection
    - Identification of **critical points** in load evolution;

Standard Approach:

This problem has been addressed time ago:

Strategy

- Select a finite sample
- Generate a static model (cluster structure, neural nets, Kalman filters, Wavelets, etc)
- Very good performance in next month!
- Six months later: Retrain everything!

Standard Approach:

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What is the Problem?

The world is not static!
Things change over time.

The Data Stream Phenomenon

- Highly detailed, automatic, rapid data feeds.
  - Internet: traffic logs, user queries, email, financial,
  - Telecommunications: phone calls, sms,
  - Astronomical surveys: optical, radio,.
  - Sensor networks: many more *observation points* ...
- Most of these data will never be seen by a human!
- Need for near-real time analysis of data feeds.
- Monitoring, intrusion, anomalous activity Classification, Prediction, Complex correlations, Detect outliers, extreme events, etc

Data Streams

Continuous flow of data generated at **high-speed** in **Dynamic**, **Time-changing** environments.

The usual approaches for *querying*, *clustering* and *prediction* use **batch procedures** cannot cope with this streaming setting.

Machine Learning algorithms assume:

- Instances are independent and generated at random according to some probability distribution $\mathcal{D}$.
- It is required that $\mathcal{D}$ is stationary

Practice: *finite* training sets, *static* models.

Data Streams

We need to maintain **Decision models** in **real time**.
Decision Models must be capable of:

- **incorporating** new information at the speed data arrives;
- **detecting** changes and **adapting** the decision models to the most recent information.
- **forgetting** outdated information;

Unbounded training sets, dynamic models.

Outline

Clustering Time Series Data Streams

Goal: Continuously maintain a clustering structure from evolving time series data streams.

- Ability to Incorporate new Information;
- Process new Information at the rate it is available.
- Ability to Detect and React to *changes* in the Cluster's Structure.

Clustering of *variables* (sensors) not examples!
The standard technique of transposing the working-matrix does not work: transpose is a blocking operator!

Online Divisive-Agglomerative Clustering

Online Divisive-Agglomerative Clustering, Rodrigues & Gama, 2008

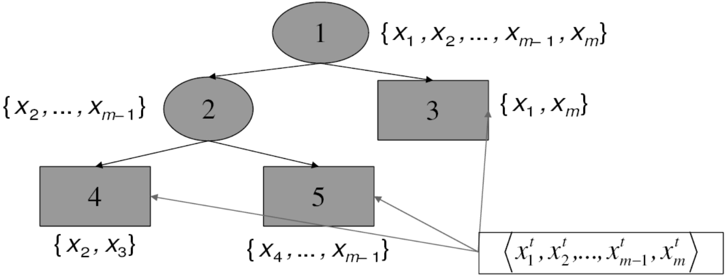
Goal: Continuously maintain a hierarchical cluster's structure from evolving time series data streams.

- Performs hierarchical clustering
- Continuously monitor the evolution of **clusters' diameters**
- Two Operators:
  - Splitting: expand the structure
    more data, more detailed clusters
  - Merge: contract the structure
    reacting to changes.
- Split and merge criteria are supported by a confidence level given by the **Hoeffding bounds**.

Feeding ODAC

Each example is processed once.
Only sufficient statistics **at leaves** are updated.
Sufficient Statistics: a triangular matrix of the correlations between variables in a leaf.

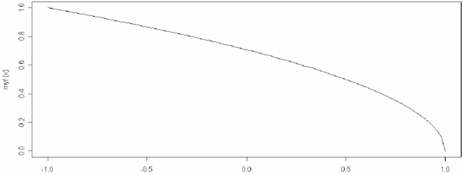
Released when a leaf expands to a node.



$$C_1 = \{x_2, x_3\}, C_2 = \{x_4, \ldots, x_{m-1}\}, C_3 = \{x_1, x_m\}$$

Similarity Distance

Distance between time Series: $rnomc(a, b) = \sqrt{\frac{1-corr(a,b)}{2}}$
where $corr(a, b)$ is the Pearson Correlation coefficient:
$corr(a, b) = \frac{P - \frac{AB}{n}}{\sqrt{A_2 - \frac{A^2}{n}}\sqrt{B_2 - \frac{B^2}{n}}}$
The *sufficient statistics* needed to compute the correlation are easily updated at each time step:
$A = \sum a_i,\ B = \sum b_i,\ A_2 = \sum a_i^2,\ B_2 = \sum b_i^2,\ P = \sum a_i b_i$

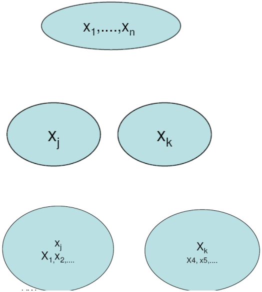


The Splitting Operator: Expanding a Leaf

Step 1 Find Pivots:
$x_j, x_k : d(x_j, x_k) > d(a, b)$
$\forall a, b \neq j, k$

Step 2 If Splitting Criteria applies:
Generate two new clusters.

Step 3 Each new cluster attract nearest variables.



Splitting a Leaf

The base Idea

A small sample can often be enough to choose a near optimal decision
(*Mining High-Speed Data Streams*, P. Domingos, G. Hulten; KDD00)

- Collect sufficient statistics from a small set of examples
- Estimate the merit of each alternative

How large should be the sample?

- **The wrong idea:** Fixed sized, defined *apriori* without looking for the data;
- **The right idea:** Choose the sample size that allow to differentiate between the alternatives.

Splitting Criteria

Expanding a leaf: How large should be the sample?

Let

- $d_1 = d(a, b)$ the farthest distance
- d_2 the second farthest distance

Question:

Is d_1 a stable option?

what if we observe more examples?

Hoeffding bound:

Split if $d_1 - d_2 > \epsilon$ with $\epsilon = \sqrt{\frac{R^2 ln(1/\delta)}{2n}}$

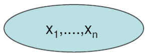
where R is the range of the random variable; δ is a user confidence level, and n is the number of observed data points.

Hoeffding bound

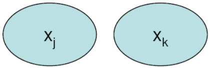
- Suppose we have made n independent observations of a random variable r whose range is R.
- The Hoeffding bound states that:
  - With probability $1 - \delta$
  - The true mean of r is in the range $\overline{r} \pm \epsilon$ where $\epsilon = \sqrt{\frac{R^2 ln(1/\delta)}{2n}}$
- Independent of the probability distribution generating the examples.

The Expand Operator: Expanding a Leaf

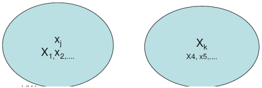
Step 1 Find Pivots:
$x_j, x_k : d(x_j, x_k) > d(a, b)$
$\forall a, b \neq j, k$



Step 2 If the Hoeffding bound applies:
Generate two new clusters.

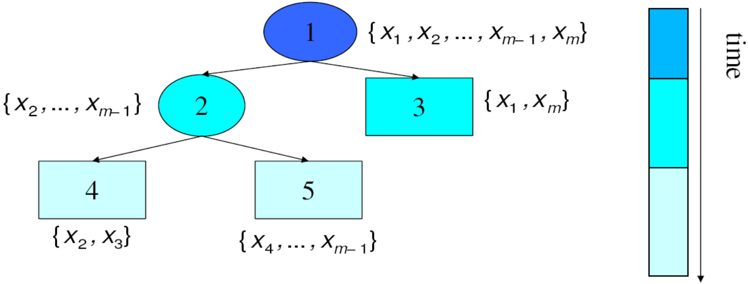


Step 3 Each new cluster attract nearest variables.



Multi-Time-Windows

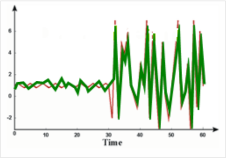
A multi-window system: each node (and leaves) receive examples from different time-windows.



The Merge Operator: Change Detection

Time Series Concept Drift:

- Time evolving time-series
- Changes in the distribution generating the observations.
- Clustering Concept Drift
  - Changes in the way time series correlate with each other
  - Change in the cluster Structure.

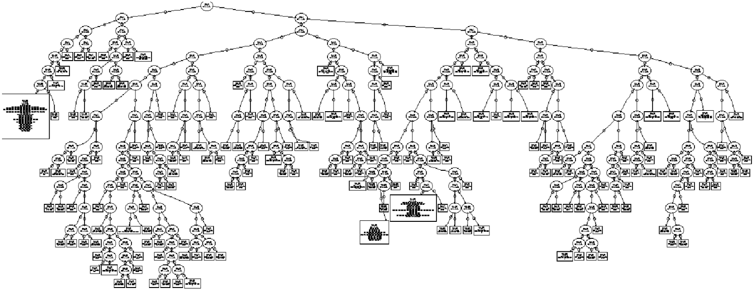


The Merge Operator: Change Detection

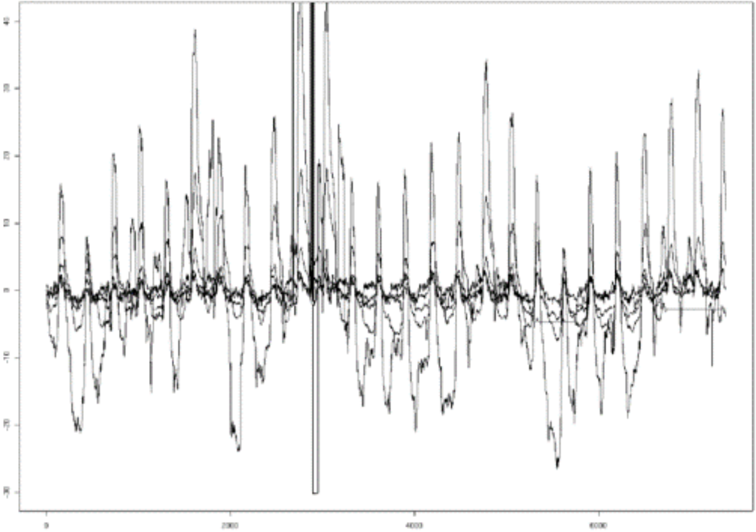
The Splitting Criteria guarantees that cluster's diameters monotonically decrease.

- Assume Clusters: c_j with descendants c_k and c_s.
- If $diameter(c_k) - diameter(c_j) > \epsilon$ OR $diameter(c_s) - diameter(c_j) > \epsilon$
  - Change in the correlation structure!
  - Merge clusters c_k and c_s into c_j.

The Electrical Load Demand Problem



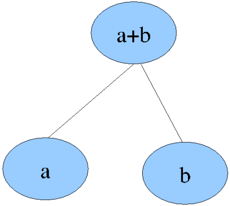
The Electrical Load Demand Problem



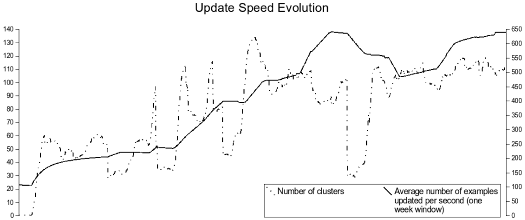
Properties of ODAC

- For stationary data the cluster's diameters monotonically decrease.
- **Constant update time/memory consumption** with respect to the number of examples!
- Every time a **split** is reported
  - the **time** to process the next example **decreases**, and
  - the **space** used by the new leaves is **less than** that used by the parent.

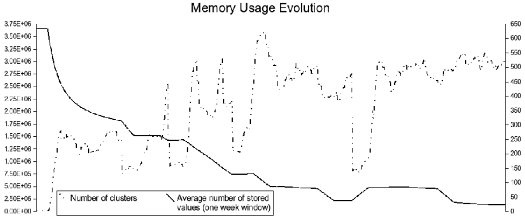
$$(a+b)^2 > a^2 + b^2$$



Evolution of Processing Speed



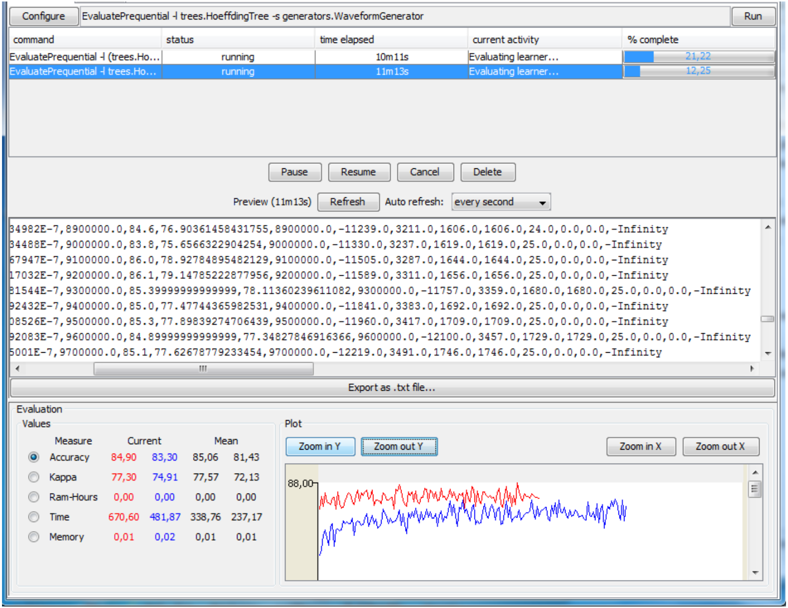
Evolution of Memory Usage



Hoeffding Algorithms

- Classification:
  Mining high-speed data streams, P. Domingos, G. Hulten, KDD, 2000
- Regression:
  Learning model trees from evolving data streams; Ikonomovska, Gama, Dzeroski; Data Min. Knowl. Discov. 2011
- Decision Rules:
  Learning Decision Rules from Data Streams, J. Gama, P. Kosina; IJCAI 2011
- Regression Rules
  E. Almeida, C. Ferreira, J. Gama: Adaptive Model Rules from Data Streams. ECML/PKDD 2013
- Clustering:
  Hierarchical Clustering of Time-Series Data Streams. Rodrigues, Gama, IEEE TKDE 20(5): 615-627 (2008)
- Multiple Models:
  Ensembles of Restricted Hoeffding Trees. Bifet, Frank, Holmes, Pfahringer; ACM TIST; 2012
  J. Duarte, J. Gama, Ensembles of Adaptive Model Rules from High-Speed Data Streams. BigMine 2014.
- ...

Massive Online Analysis



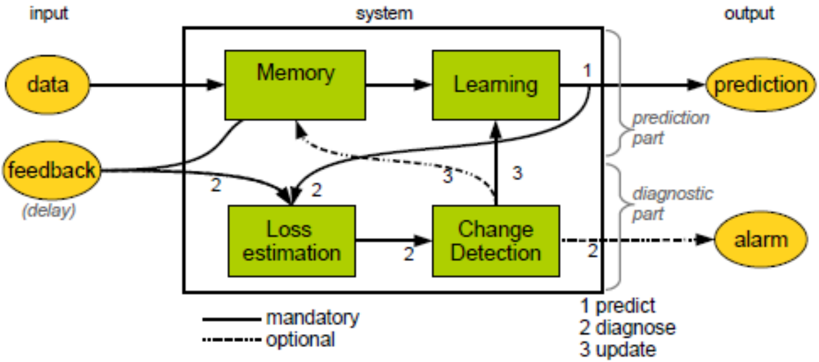
Hoeffding Algorithms: Analysis

The number of examples required to expand a node only depends on the Hoeffding bound.

- Low variance models:
  Stable decisions with statistical support.
- Low overfiting:
  Examples are processed only once.
- No need for pruning;
  Decisions with statistical support;
- **Convergence**: Hoeffding Algorithms becomes asymptotically close to that of a batch learner. The expected disagreement is δ/p; where p is the probability that an example fall into a leaf.

Outline

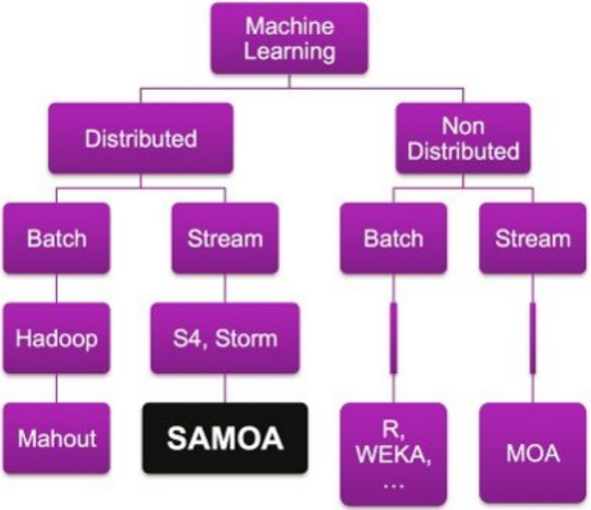
A Generic Model for Adaptive Learning Algorithms



A generic schema for an online adaptive learning algorithm.

(*A survey on concept drift adaptation*, J.Gama et al, ACM-CSUR 2014)

New Tools Emerge



Lessons Learned

Learning from data streams:

- Learning is not *one-shot*: is an evolving process;
- We need to monitor the learning process;
- Opens the possibility to reasoning about the learning

Reasoning about the Learning Process

Intelligent systems must:

- be able to adapt continuously to **changing environmental conditions** and evolving user habits and needs.
- be capable of **predictive self-diagnosis**.

The development of such self-configuring, self-optimizing, and self-repairing systems is a major scientific and engineering challenge.

Real-time learning: An existential pleasure!

Thank you!