Introduction to Machine Learning

Introduction

Andres Mendez-Vazquez

February 4, 2019

Outline

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Data is being produced in great quantities

After all our business is about

Big Data

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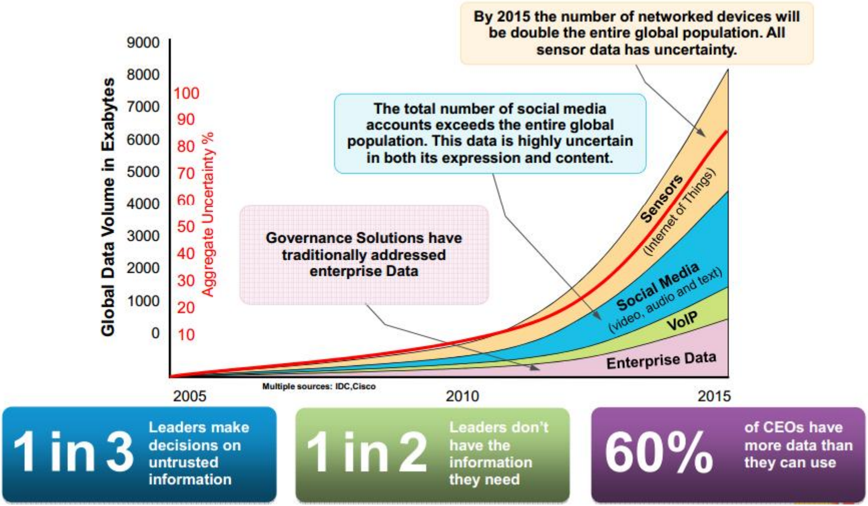
By 2015 the number of networked devices will be double the entire global population. All sensor data has uncertainty.
The total number of social media accounts exceeds the entire global population. This data is highly uncertain in both its expression and content.
Governance Solutions have traditionally addressed enterprise Data
Global Data Volume in Exabytes
9000
8000
7000
6000
5000
4000
3000
2000
1000
0
Aggregate Uncertainty %
100
90
80
70
60
50
40
30
20
10
Sensors
(Internet of Things)
Social Media
(video, audio and text)
VoIP
Enterprise Data
Multiple sources: IDC,Cisco
2005
2010
2015
1 in 3
Leaders make decisions on untrusted information
1 in 2
Leaders don't have the information they need
60%
of CEOs have more data than they can use

VOLUME

VOLUMES of Information

- Terabyte(10^{12} bits),
- Petabyte(10^{15} bits),
- UP!!!

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2. Transactions
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Cautionary Tale

What constitutes truly “high” volume varies by industry and even geography!!!

- Simply look at the DNA data for a cellular cycle.

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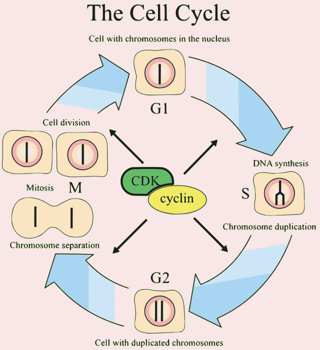

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When looking at the Structure of the Information, we have:

- **Variety** like there is not tomorrow:
  - It is structured, semi-structured and unstructured

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Count-Min Sketch Algorithm

Invented by

Charikar, Chen and Farch-Colton in 2004

With Properties

Space Used	Error Probability	Error
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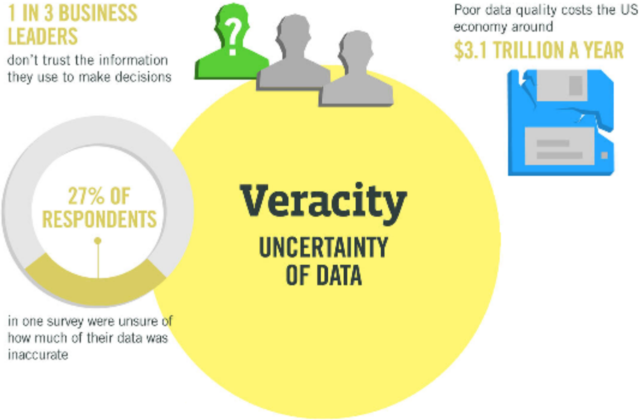
1 IN 3 BUSINESS LEADERS
don't trust the information they use to make decisions
27% OF RESPONDENTS
in one survey were unsure of how much of their data was inaccurate
Veracity
UNCERTAINTY OF DATA
Poor data quality costs the US economy around
$3.1 TRILLION A YEAR

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It refers to

Messiness or Trustworthiness of the data

- The Completeness on the Data
- The Representation of such Data
- etc!!!

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Given all these things

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Complexity goes through the roof!!!

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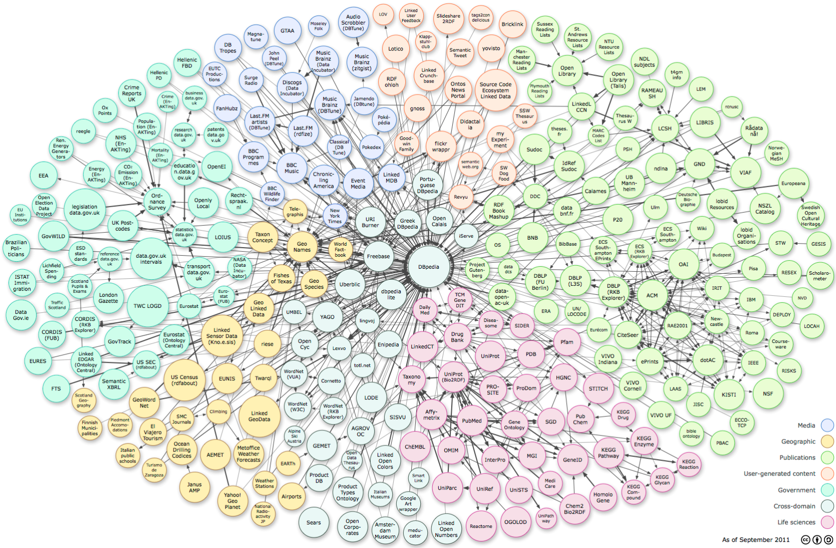
Example: Linking open-data community project



Cautionary Tale about Complexity

Something Notable

- In 1880 the USA made a Census of the Population in different aspects:
    - Population
    - Mortality
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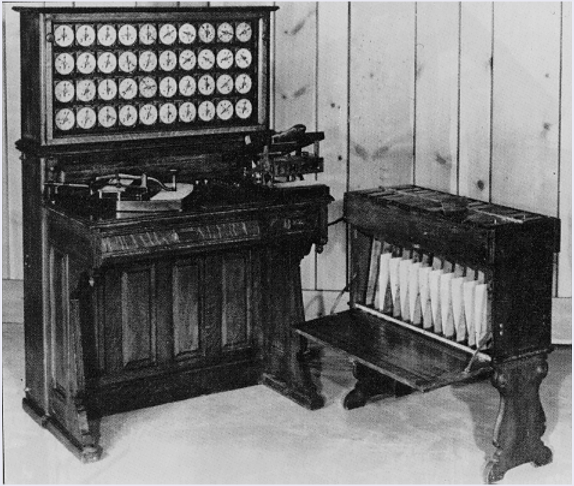
The Tabulator Machine

Thus, Hollering came with the following machine (Circa 1890)!!!



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It was basically a sorter and counter

- Using punching cards as memories.
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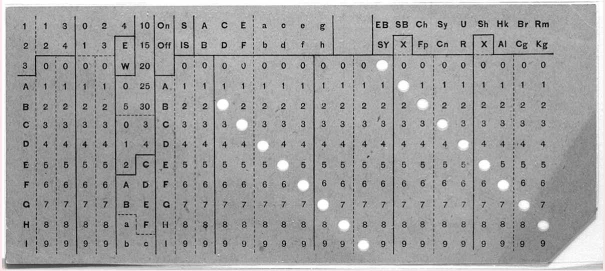

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Nevertheless in 1837

Babbage's Difference engine was

- The First General Computer!!!
- Turing-complete!!!
- **Way more complex than the tabulator!!! 53 years earlier!!!**

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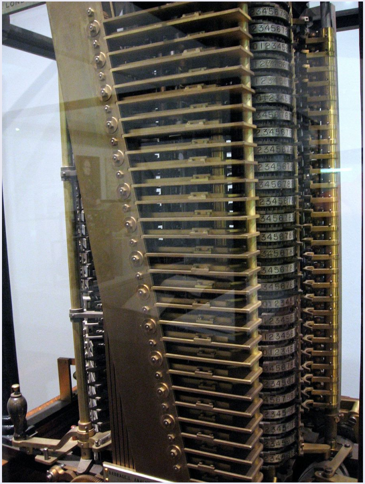
Complexity is highly **DEPENDANT** on the way data is handled and represented



Outline

Data is Everywhere!

Lots of data is being collected and warehoused

- Web data, e-commerce
- Purchases at department/ grocery stores
- Bank/Credit Card transactions
- Social Network
- etc

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A Ocean of Data

- How many data in the world?
  - 800 Terabytes, 2000
  - 160 Exabytes, 2006
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  - 35 Zettabytes by 2020

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So Big Data without Analytic Tools is basically...

"A Great!!! I am storing a bunch of data, so what?"

You require to have some way to get insights on such data sets

You need

- Algorithms to find those insights that are useful
- You need to apply them in the Large Data Set context

Here, it comes the Darling

Machine Learning!!! The Darling of Computer Science!!!

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Basically

- Inputs and their desired outputs are given $\left\{(x_i, y_i)_{i=1}^{N}\right\}$
- Then, the goal is to learn a general rule that maps inputs to outputs

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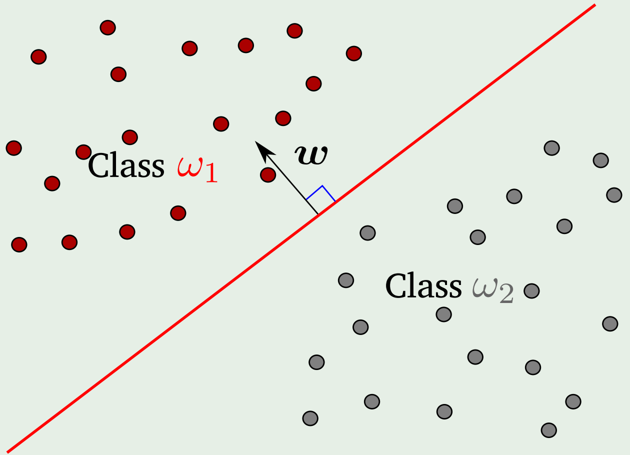
Classifying two classes in $\mathbb{R}^2$

Using a simple straight line



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Unsupervised Learning

Basically

No labels are given to the learning algorithm, leaving it on its own to find structure in its input.

$$SSE = \sum_{k=1}^{K} \sum_{x_i \in C_k} dist(x_i, c_k)^2$$

- Similarities

$$dist(x, y) = \|x - y\|_2 = \sqrt{(x - y)^T (x - y)}$$

- etc

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Therefore, it is necessary to find the clusters of Data

- Using Cost Functions

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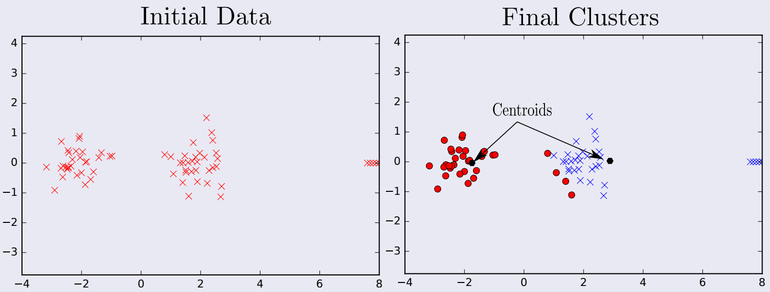
Example

K-Means



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Other Main Areas are...

Semi-Supervised Learning

There is a training set with some (often many) of the target outputs missing.

- The Program receives rewards and punishments given its actions
- Those inputs allows the Program to learn by reinforcement

- Experience is gained by exploiting meta-knowledge extracted
  - Thus, Learning Bias must be chosen dynamically

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There is a training set with some (often many) of the target outputs missing.

Reinforcement Learning

- The Program interacts with a dynamic environment to perform a certain goal.
- The Program receives rewards and punishments given its actions.
- Those inputs allows the Program to learn by reinforcement.

- Experience is gained by exploiting meta-knowledge extracted
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2. *Feature Extraction/Feature Generation*
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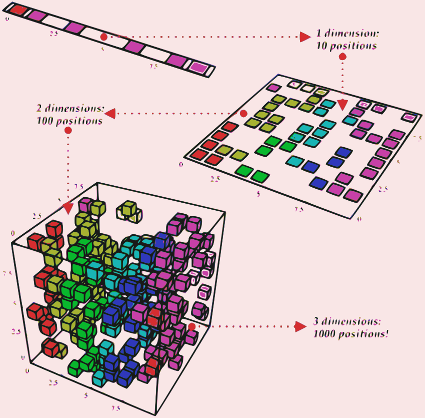

What can be done?

Hypothesis Testing to discriminate good features

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\begin{aligned}
H_1 &: \Delta\mu = \mu_1 - \mu_2 \neq 0 \\
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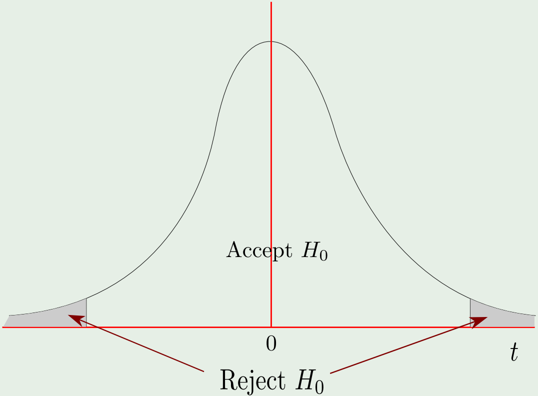

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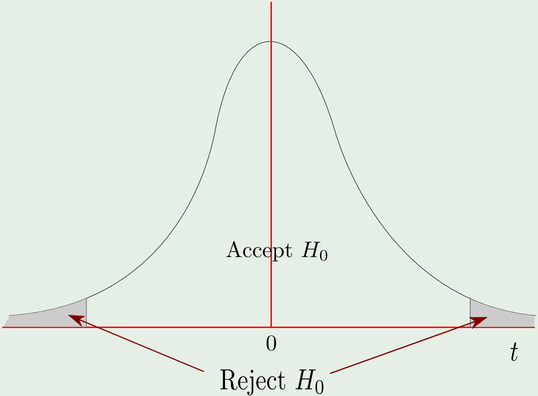

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Using Measures for Class Separability

- Between-class scatter matrix:

$$S_b = \sum_{i=1}^{M} P_i \left(\boldsymbol{\mu}_i - \boldsymbol{\mu}_0\right)\left(\boldsymbol{\mu}_i - \boldsymbol{\mu}_0\right)^T \tag{1}$$

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Examples of Clustering Algorithms

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   1. Fuzzy C-means
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What do we want from classification?

1. To Learn the pattern that relates $f(\boldsymbol{x}) \Longleftrightarrow y$ from the training set $\{(\boldsymbol{x}_i, y_i)\}_{i=1}^{n}$.
2. To generalize new samples i.e. given a new sample $\boldsymbol{x}'$, $f(\boldsymbol{x}')$ gets the correct label.

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The previous Controlled Over-fitting

We have a problem

Bias–Variance Trade-Off

Intuition - Bias

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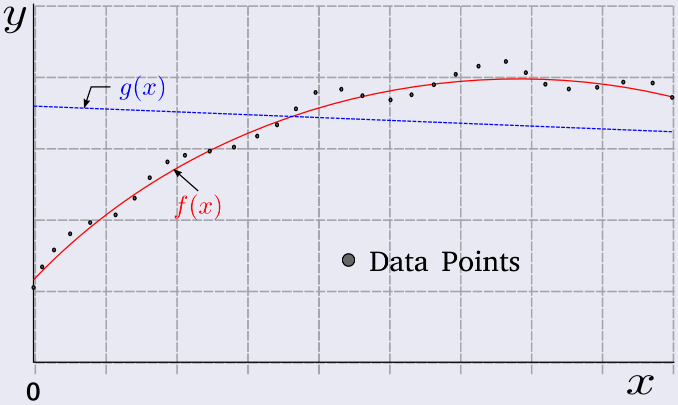
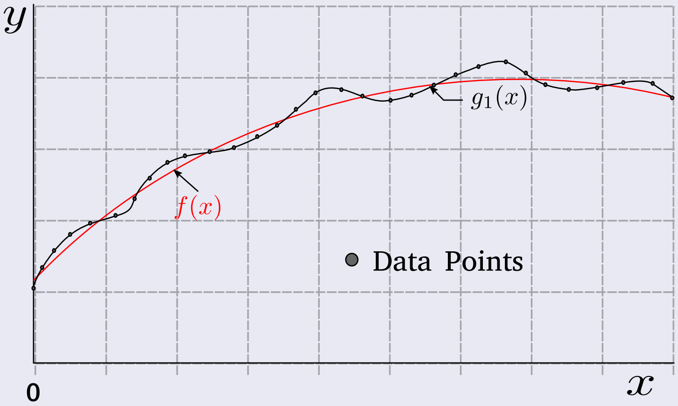


A the Other Hand

The Variance



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Validation Error and Training Error

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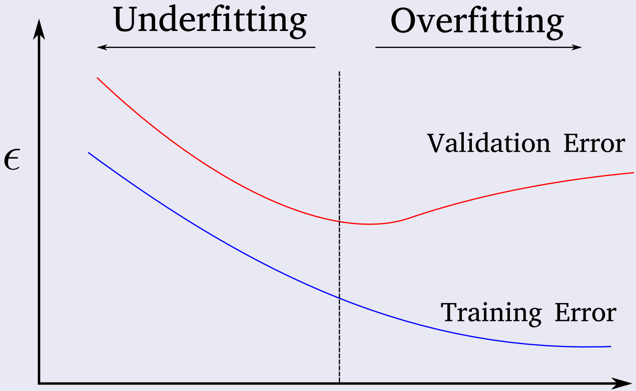

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