Introduction to Machine Learning
Introduction

Andres Mendez-Vazquez

January 7, 2023

Outline

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Data is being produced in great quantities

After all our business is about

Large Data

Definition

Large Data are sets that are large and complex that requiere processing for getting insights.

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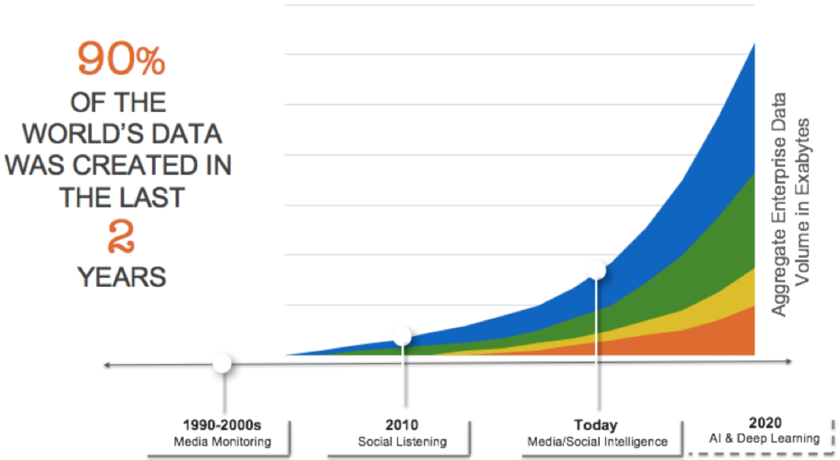
90%
OF THE
WORLD'S DATA
WAS CREATED IN
THE LAST
2
YEARS
Aggregate Enterprise Data
Volume in Exabytes
1990-2000s
Media Monitoring
2010
Social Listening
Today
Media/Social Intelligence
2020
AI & Deep Learning

VOLUME

VOLUMES of Information

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

Examples of these Volumes are

1. Records
2. Transactions
3. Web Searches
4. etc

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VARIETY

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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

Question

- Do you have some examples of such structures in Information?

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It refers to

- The **SPEED** at which the data is being generated.
- The **SPEED** at which the data moves around

Problem: Latency

- There is a **LAG TIME** between capture or generation, and when it is available!!!

It can be catastrophic

- Detecting fraudulent activities
- Detecting when sale and buy shares
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For Example

Imagine that I have a stream of $m = 10^{30}$ integers with Ranges in $[1, ..., 10^8]$

Now, somebody ask you to find the most frequent item!!!

A naive algorithm

1. Take hash table with a counter.
2. Then, put numbers in the hash table.

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Which problems we have?

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There is the

Count-Min Sketch Algorithm

Invented by

Charikar, Chen and Farch-Colton in 2004

With Properties

Space Used	Error Probability	Error
$O\left(\frac{1}{\epsilon}\log\left(\frac{1}{\delta}\right)\cdot(\log m+\log n)\right)$	δ	ϵ

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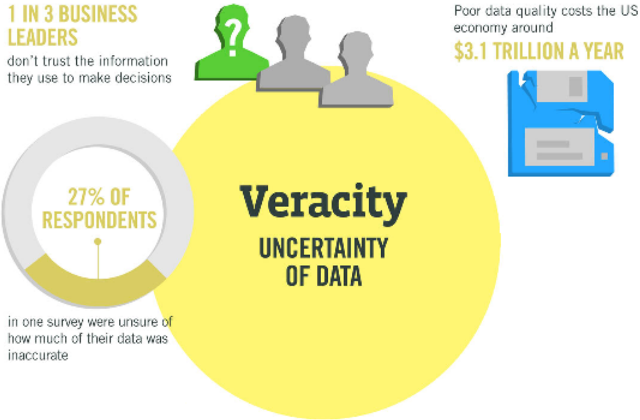
1 IN 3 BUSINESS LEADERS
don't trust the information they use to make decisions
Poor data quality costs the US economy around
$3.1 TRILLION A YEAR
27% OF RESPONDENTS
in one survey were unsure of how much of their data was inaccurate
Veracity
UNCERTAINTY OF DATA

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It refers to

Messiness or Trustworthiness of the data

However, some people claim

"The volumes often make up for the lack of quality or accuracy"

I say, it depends on

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

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Given all these things

- It is necessary to correlate and share data across entities.
- It is necessary to link, match and transform data.

With this...

Complexity goes through the roof!!!

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Cautionary Tale about Complexity

Something Notable

- In 1880 the USA made a Census of the Population in different aspects:
  - Population
  - Mortality
  - Agriculture
  - Manufacturing

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Once data was collected it took 7 years to say something!!!

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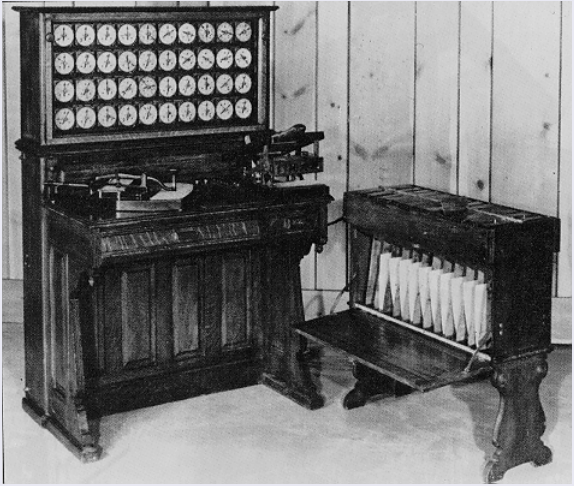
The Tabulator Machine

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



Hollering Tabulating Machine

It was basically a sorter and counter

- Using punching cards as memories.
- And Mercury Sensors.

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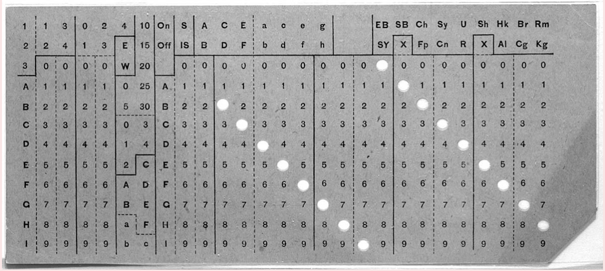

It was FAST!!!

It took only!!!

2 years!!!

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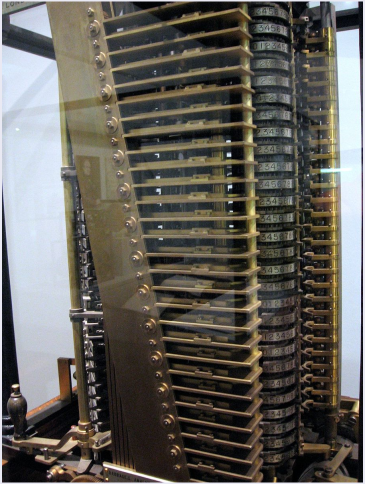
Complexity is highly DEPENDANT on the way data is handled and represented



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

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- Machine learning is the subfield of computer science that, according to Arthur Samuel, gives
  - "***computers the ability to learn without being explicitly programmed.***"

Therefore

- Learning Algorithms are devised to learn the input data

Examples

- Artificial Neural Network (ANN)
- Support Vector Machine (SVM)
- Expectation-Maximization (EM)

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Supervised Learning

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

$$f : X \to Y \text{ with } f(x_i) = y_i + \epsilon$$

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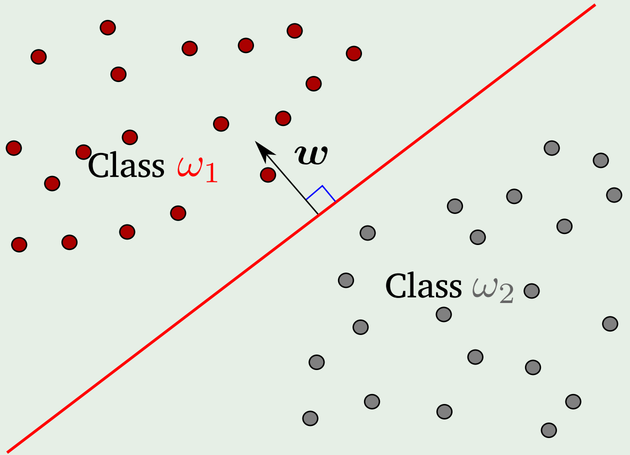
Classifying two classes in $\mathbb{R}^2$

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.

Therefore, it is necessary to find the clusters of Data

- Using Cost Functions

$$SSE = \sum_{k=1}^{K} \sum_{x \in c_k} dist\left(\mathbf{x}, \mathbf{v}_k\right)^2$$

- Similarities

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

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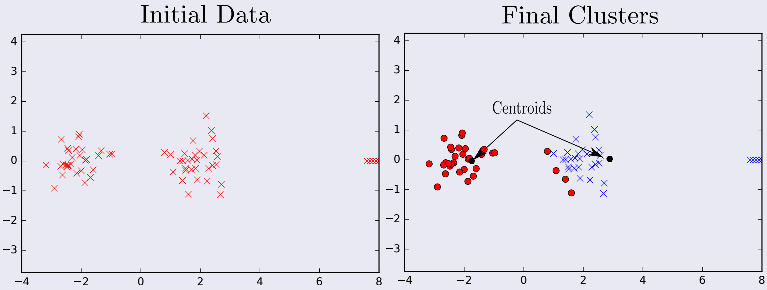
K-Means



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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.

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.

Meta Learning

- The system must include a learning subsystem, which adapts with experience.
- Experience is gained by exploiting meta knowledge extracted.
  - Thus, Learning Bias must be chosen dynamically.

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Machine Learning Process

Process

1. ***Preprocessing***
2. ***Feature Extraction/Feature Generation***
3. ***Clustering $\approx$ Class Identification $\approx$ Unsupervised Learning***
4. ***Classification $\approx$ Supervised Learning***

Then

- We need to process a lot of data...!!!

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- Given a set of measurements, the goal is to discover compact and informative representations of the obtained data.

Examples

1. The Karhunen–Loève transform $\approx$ Principal Component Analysis
   1. Popular for feature generation and Dimensionality Reduction
2. The Singular Value Decomposition
   1. Used for Dimensionality Reduction

Feature Extraction

Definition

- Process to transform high-dimensional data into low-dimensional ones for improving accuracy, understanding, or removing noises.

Why?

- **Curse of dimensionality:** Complexity grows exponentially in volume by adding extra dimensions.

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Curse of Dimensionality

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- Which **features** should be used for the classifier?

The Curse of Dimensionality!!!

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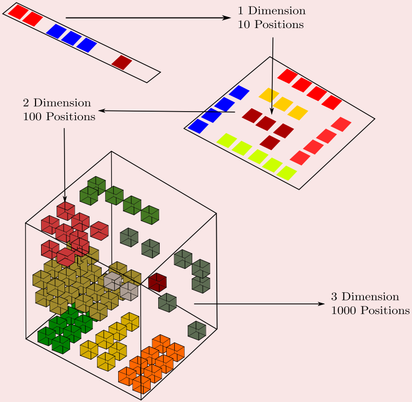

What can be done?

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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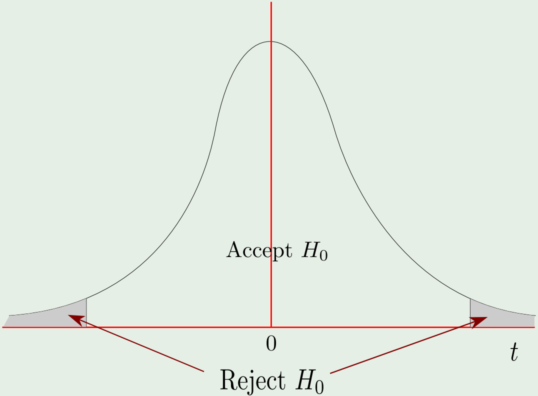

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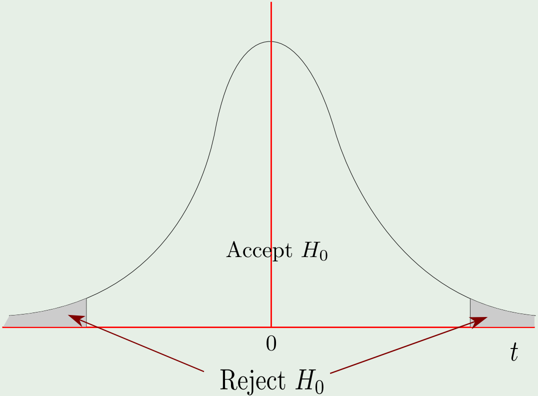

What can be done?

Using Measures for Class Separability

- Between-class scatter matrix:

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

Where

- $\boldsymbol{\mu}_0$ is the global mean vector, $\boldsymbol{\mu}_0 = \sum_{i=1}^{M} P_i \boldsymbol{\mu}_i$.
- $\boldsymbol{\mu}_i$ the median of class ω_i.
- $P_i \cong \frac{n_i}{N}$.

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Feature Subset Selection

- Examples:
  - Filter Approach
    - All combinations of features are used together with a separability measure.
  - Wrapper Approach:
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Clustering

Definition

Grouping unlabeled data into clusters, for the purpose of inference of hidden structures or information.

Using, for example

Dissimilarity measures

- Angle : Inner product, . . .
- Non-metric : Rank, Intensity, . . .
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Examples of Clustering Algorithms

Clustering

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   1. K-means
2. Clustering Based in Cost Functions
   1. Fuzzy C-means
   2. Possibilistic
3. Hierarchical Clustering
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Classification

Definition

- A procedure dividing data into the given set of categories based on the training set in a supervised way.

What do we want from classification?

1. To Learn the pattern that relates $f(x) \Longleftrightarrow y$ from the training set $\{(x_i, y_i)\}_{i=1}^{n}$.
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The previous Controlled Over-fitting

We have a problem

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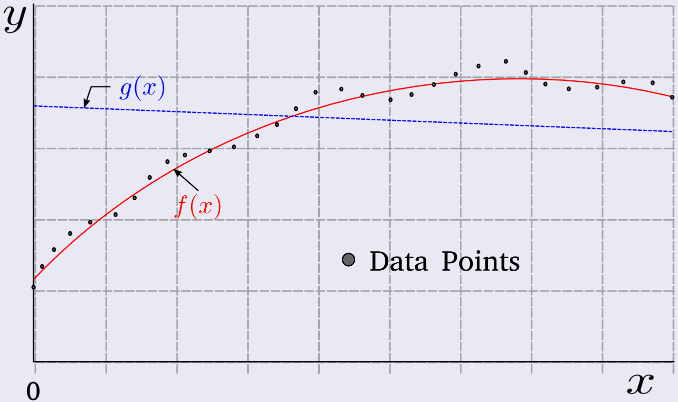
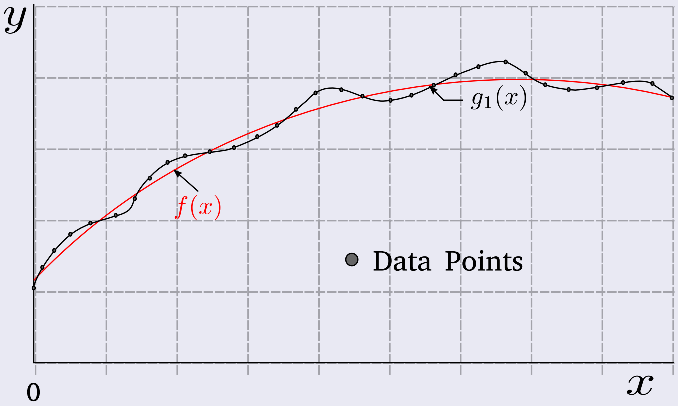


A the Other Hand

The Variance



Possible Solution

Validation Error and Training Error

- Two Data Sets are used:
  - One for validation
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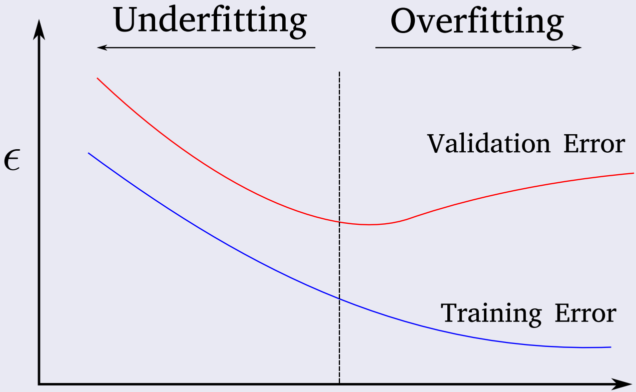

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Examples of Classification Algorithms

Many Possible Algorithms

- Linear Classifiers: Perceptron
- Probability Classifiers: Naive Bayes
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