Introduction to Machine Learning
Introduction

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April 26, 2019

Outline

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cinvestav

Data is being produced in great quantities

After all our business is about

Big Data

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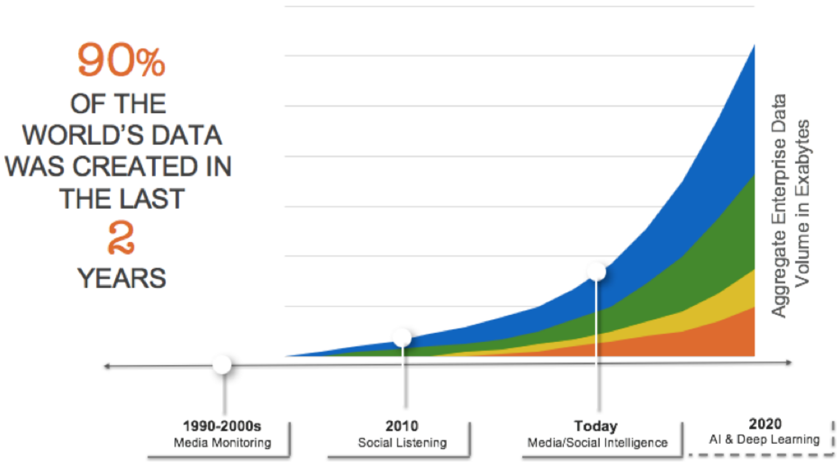
cinvestav
Unidad Guadalajara

VOLUME


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

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VOLUMES of Information

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However

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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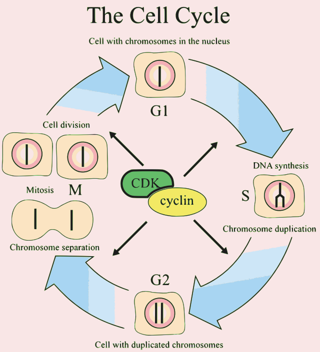

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- **Variety** like there is not tomorrow:
  - It is structured, semi-structured and unstructured

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Count-Min Sketch Algorithm

Invented by

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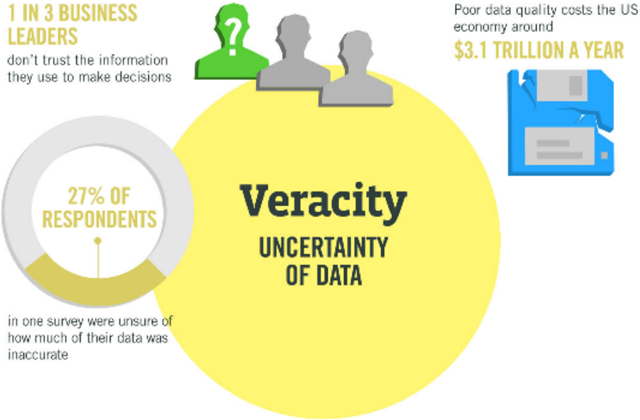

1 IN 3 BUSINESS LEADERS
don't trust the information they use to make decisions
Poor data quality costs the US economy around
$3.1 TRILLION A YEAR
27% OF RESPONDENTS
in one survey were unsure of how much of their data was inaccurate
Veracity
UNCERTAINTY OF DATA

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Messiness or Trustworthiness of the data

- The Completeness on the Data
- The Representation of such Data
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Complexity goes through the roof!!!

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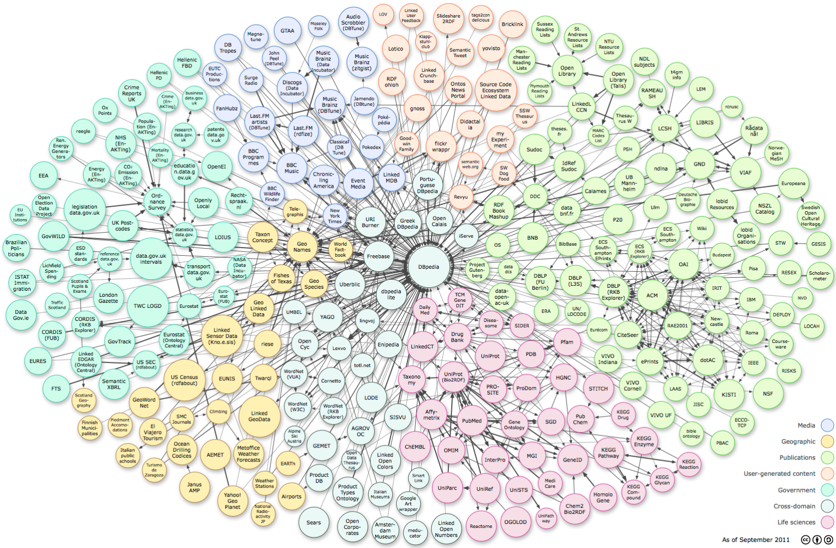
Example: Linking open-data community project



Cautionary Tale about Complexity

Something Notable

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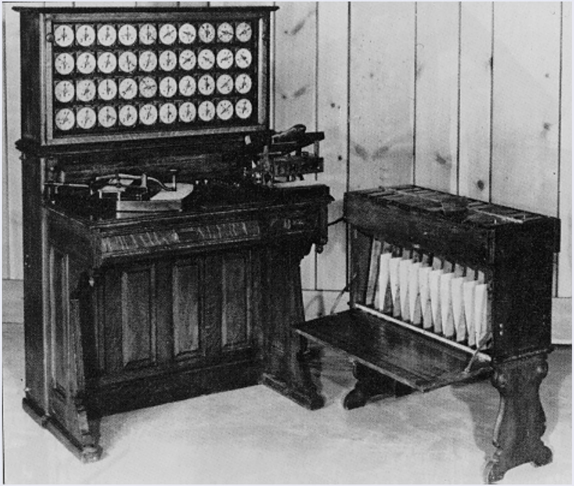
The Tabulator Machine

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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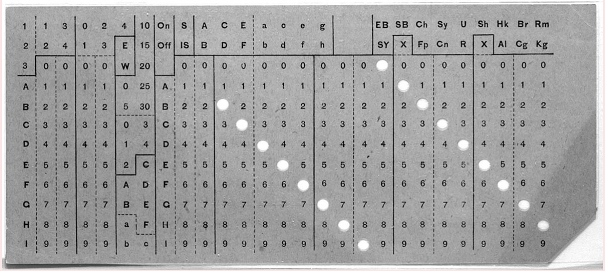

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Nevertheless in 1837

Babbage's Difference engine was

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

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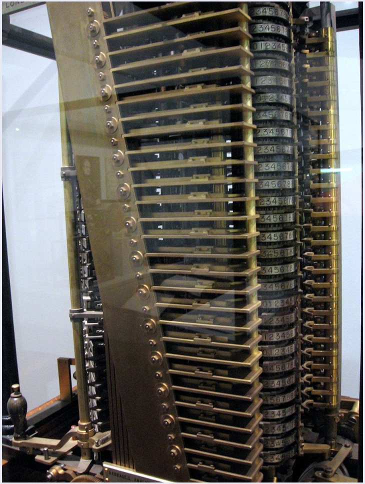
Complexity is highly **DEPENDANT** on the way data is handled and represented



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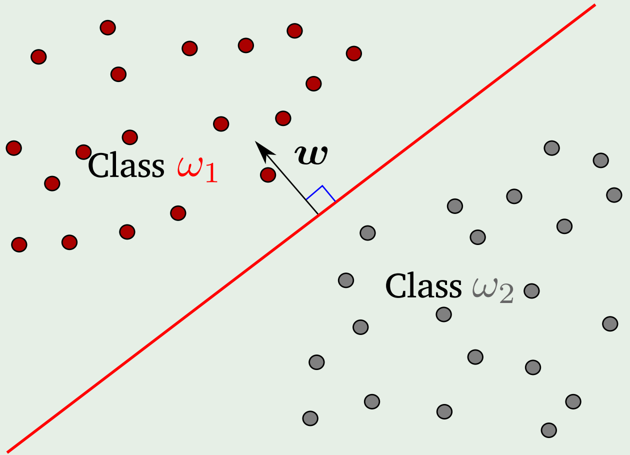
Classifying two classes in $\mathbb{R}^2$

Using a simple straight line



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- Similarities

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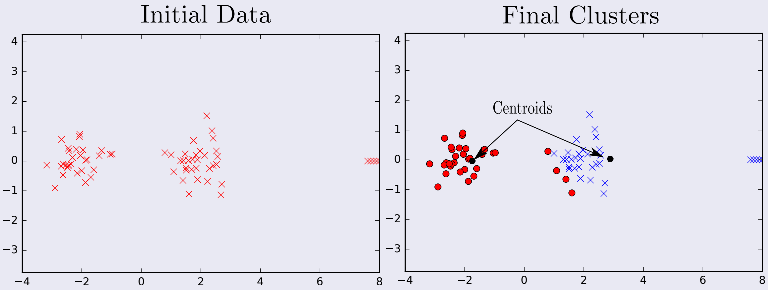
K-Means



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- The Program receives rewards and punishments given its actions
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- Experience is gained by exploiting meta-knowledge extracted
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Feature Extraction

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

Why?

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Feature Extraction

Definition

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Outline

Curse of Dimensionality

Question

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

The Curse of Dimensionality!!!

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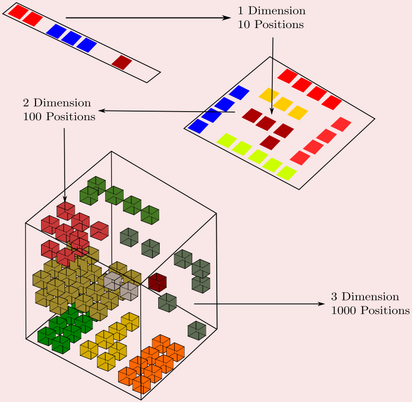

What can be done?

Hypothesis Testing to discriminate good features

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H_1 &: \Delta\mu = \mu_1 - \mu_2 \neq 0 \\
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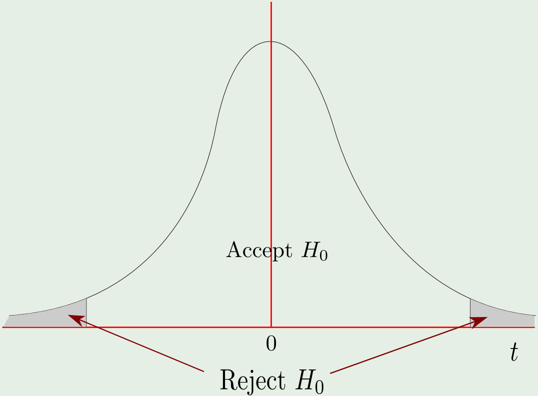

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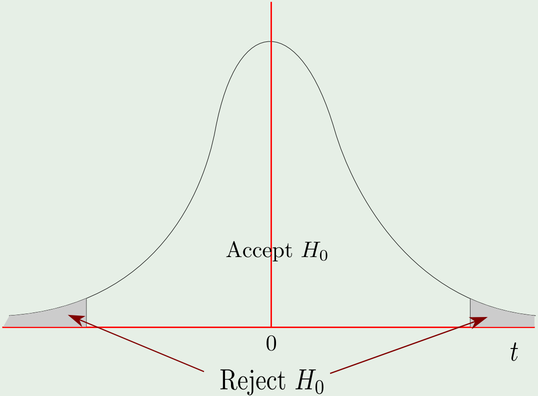

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Using Measures for Class Separability

- Between-class scatter matrix:

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

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Where

- $\boldsymbol{\mu}_0$ is the global mean vector, $\boldsymbol{\mu}_0 = \sum_{i=1}^{M} P_i \boldsymbol{\mu}_i$.
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    - All combinations of features are used together with a separability measure.
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Definition

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

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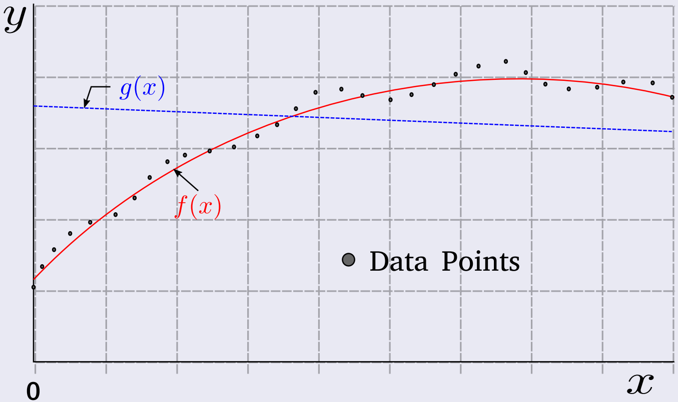
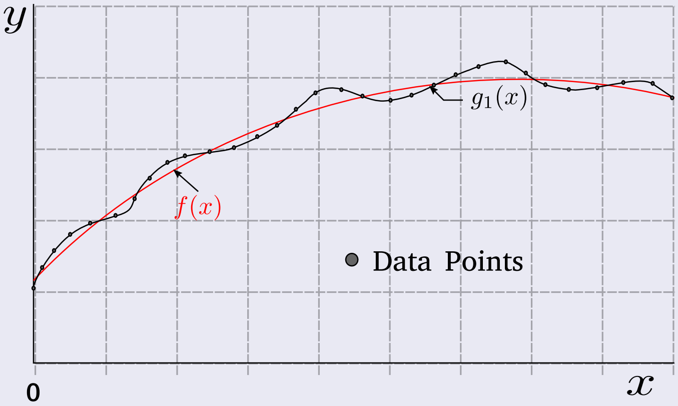


A the Other Hand

The Variance



Possible Solution

Validation Error and Training Error

- Two Data Sets are used:
  - One for validation
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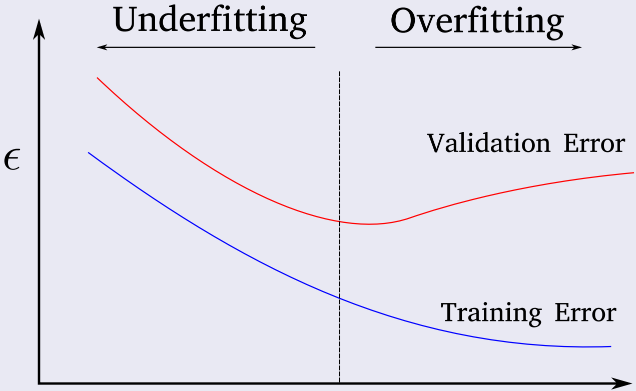

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Many Possible Algorithms

- Linear Classifiers: Perceptron
- Probability Classifiers: Naive Bayes
- Kernel Methods Classifiers : Support Vector Machines
- Non-Linear Classifiers: Artificial Neural Networks
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cinvestav
Unidad Guadalajara

Projects

Possible topic are:

- Oil exploration detection.
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- Page Ranking - Improving over the Google Matrix
- Influence Maximization in Social Networks.
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