SD201: Big Data Mining

Mauro Sozio, Tiphaine Viard

About the course

Pedagogical Team

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Goals of the course

Data Mining: glossary & definitions

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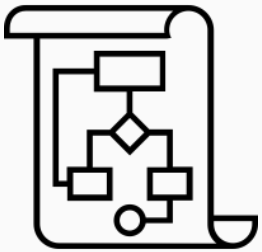
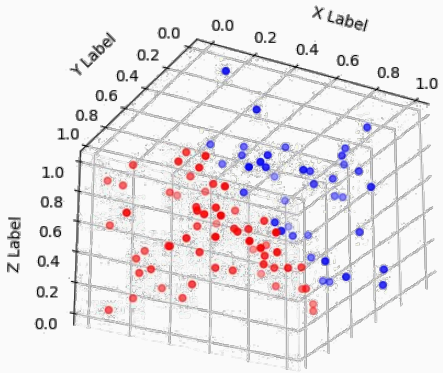


Algorithms & limits



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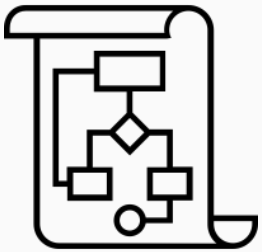

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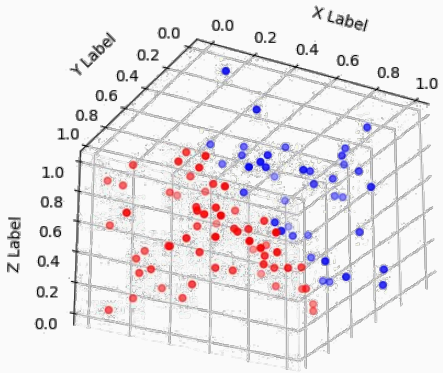

Practical experience with datasets

```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import scipy.stats as stats
```

Calendar

07/09	Telecom	Lesson
21/09	Telecom	Lesson
30/09	Telecom	Lab
07/10	Telecom	Lesson
12/10	Telecom	Lab
19/10	Telecom	Lesson
26/10	Telecom	Lab
09/11	Telecom	Lab/project

We will try to maintain a presence online. Documents related to the course will be here.

`https://ecampus.paris-saclay.fr/course/view.php?id=30869`

Grades

There will be a project. It will be graded.

Project goal : **explore and analyse a real-world dataset**

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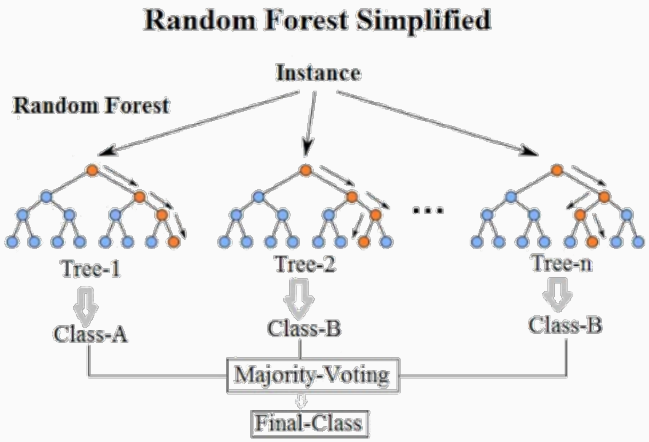
The grade will be on the project (75%) and your reviews of the project (25%).

Content of the course

Introduction to Data Mining

Big Data / Generalities / Features / Data Cleaning / Evaluation



Random forest

Decision Tree / Random forest / Algorithm / Ensemble methods

07/10 Lesson

Clustering

Definition / Goal / Hierarchical / DBSCAN /
K-Means ++

12/10: Lab on clustering

19/10 Lesson

Frequent itemsets

Definition / Goal / Apriori / Better algorithms

26/10: Lab on frequent itemsets

Project

Project : goals and calendar

In groups (4 students), explore, analyse a real-word dataset.

Answer a scientific question on this dataset.

Calendar :

- November 11 : initial project submission
- November 15 : review assignment
- November 21 : reviews submission deadline
- November 22 : access to your reviews
- November 30 : final project + review response submission

Due to timing constraints with the scolarité, there can be no deadline extensions

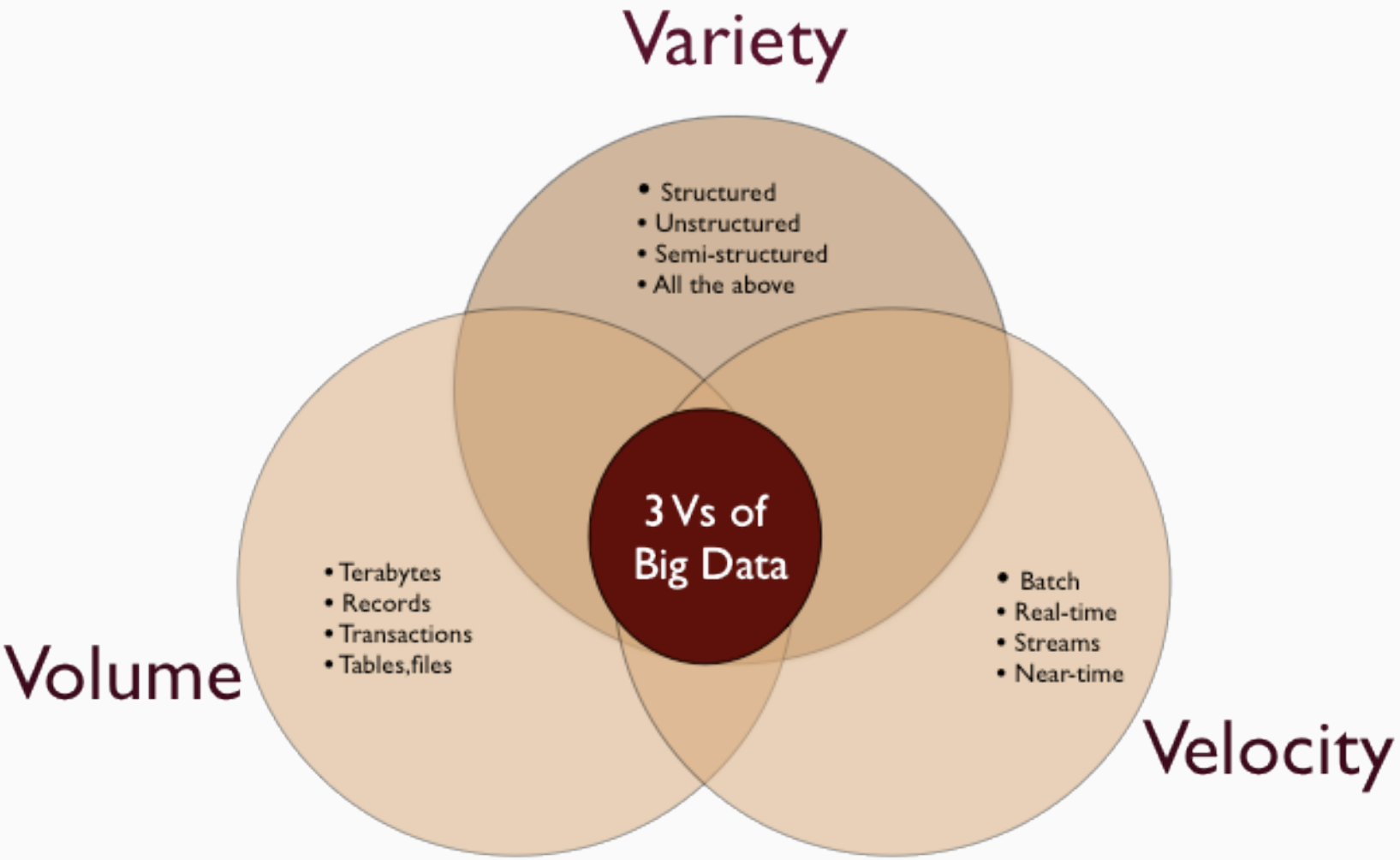
What is Big Data?

From Wikipedia

"Big data" is a field that treats ways to analyze, systematically extract information from, or otherwise deal with data sets that are too large or complex to be dealt with by traditional data-processing application software.

– Wikipedia @ 09/09/2019

The three Vs



source Wikipedia

Big Data depends on the

CONTEXT.

Controversy of Big Data

- All data is BIG now
- Hype to sell Hadoop based systems
- Ethical concerns about accessibility
- Limited access to Big Data creates new digital divides
- Statistical Significance:

> *When the number of variables grows, the number of fake correlations also grows Leinweber: S&P 500 stock index correlated with butter production in Bangladesh*

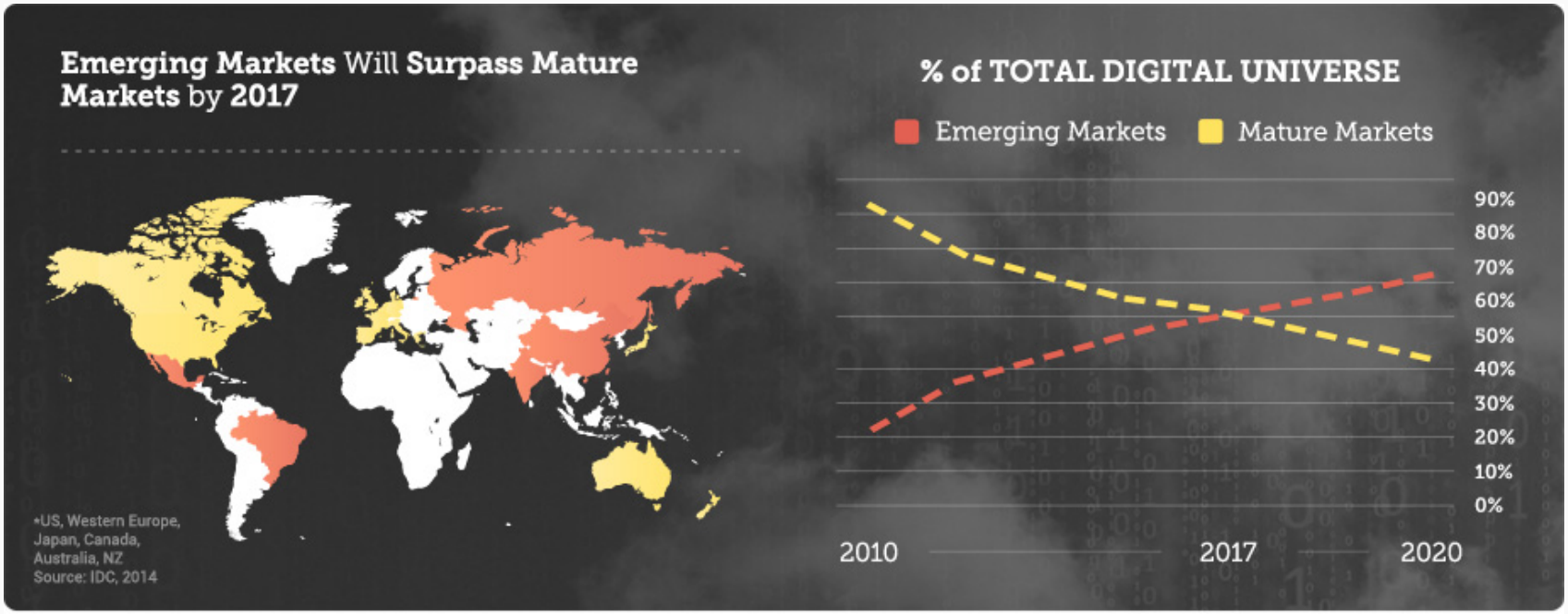
The six Vs?

- Volume
- Variety
- Velocity
- Value
- Variability
- Veracity

Digital Universe

source EMC Digital Universe

Digital Universe



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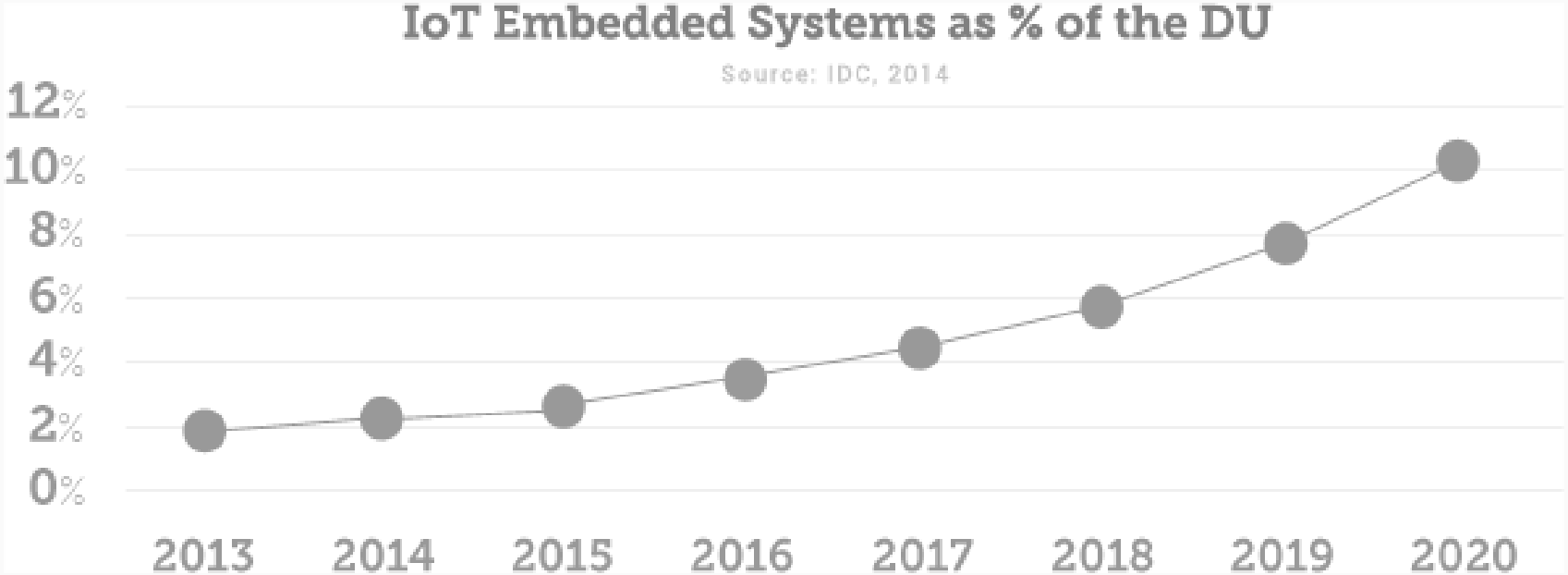

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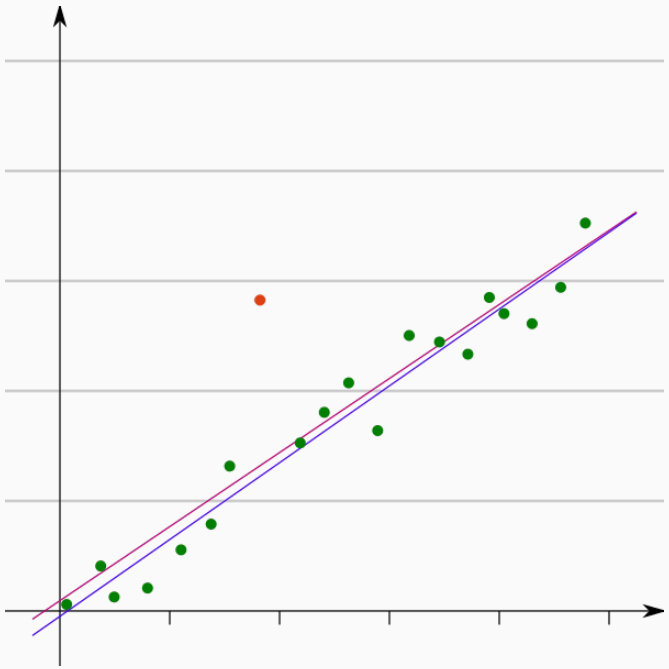
Data Mining: the six classes of common tasks

Anomaly detection (outlier/change/deviation detection)

The identification of unusual data records, that might be interesting or data errors that require further investigation.



A website collects which IPs are trying to log in. They can try to detect which IPs have a high failure rate to block them (and prevent brute force guessing).

Association rule learning (dependency modeling)

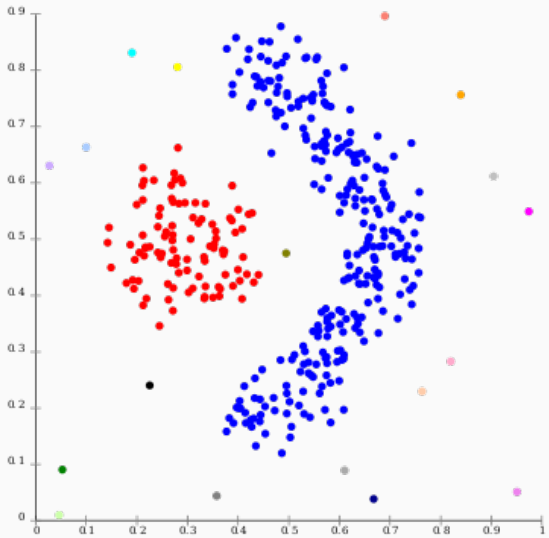
Search for relationships between variables.

$$X \wedge Y \Rightarrow Z$$

A supermarket might gather data on customer purchasing habits. Using association rule learning, the supermarket can determine which products are frequently bought together and use this information for marketing purposes. This is sometimes referred to as market basket analysis.

Clustering

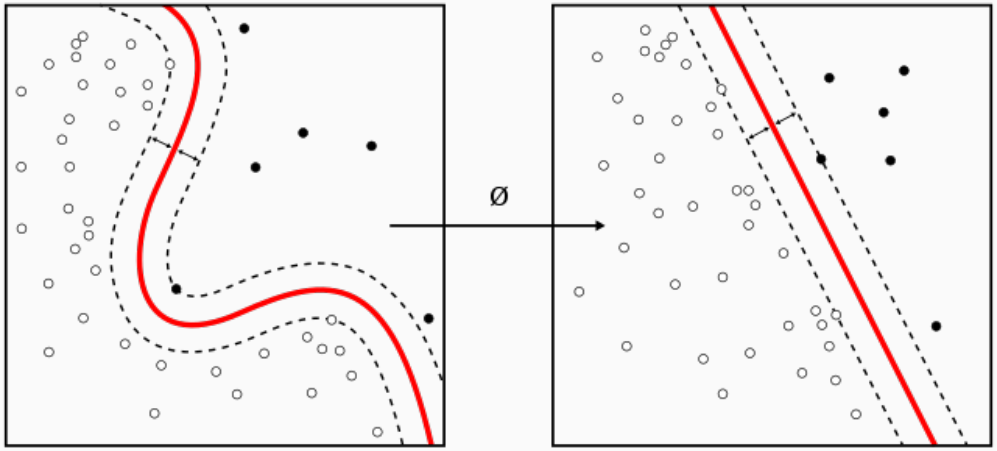
Discover groups and structures in the data that are in some way or another "similar", without using known structures in the data.



Automatically create categories for collections of items (e.g. music records or movies)

Classification

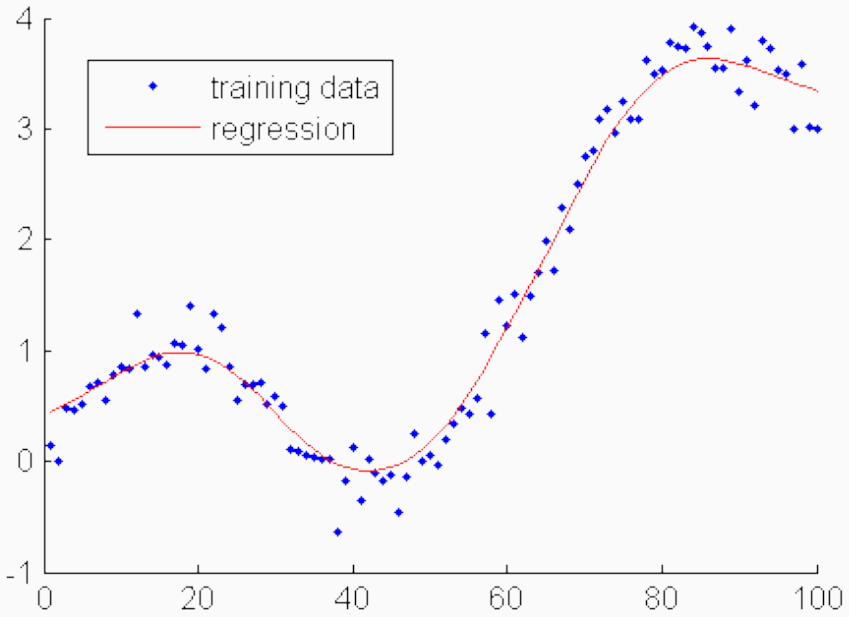
Generalize known structures to apply to new data.



An e-mail program might attempt to classify an e-mail as "legitimate" or as "spam".

Regression

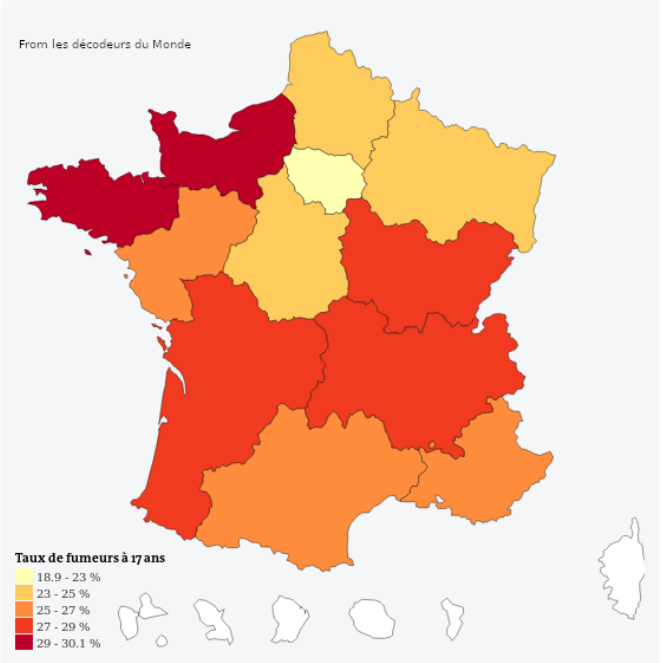
Find a function which models the data with the least error that is, for estimating the relationships among data or datasets.



Predict electricity consumption using: weather forecasts, TV program, day of the week, etc.

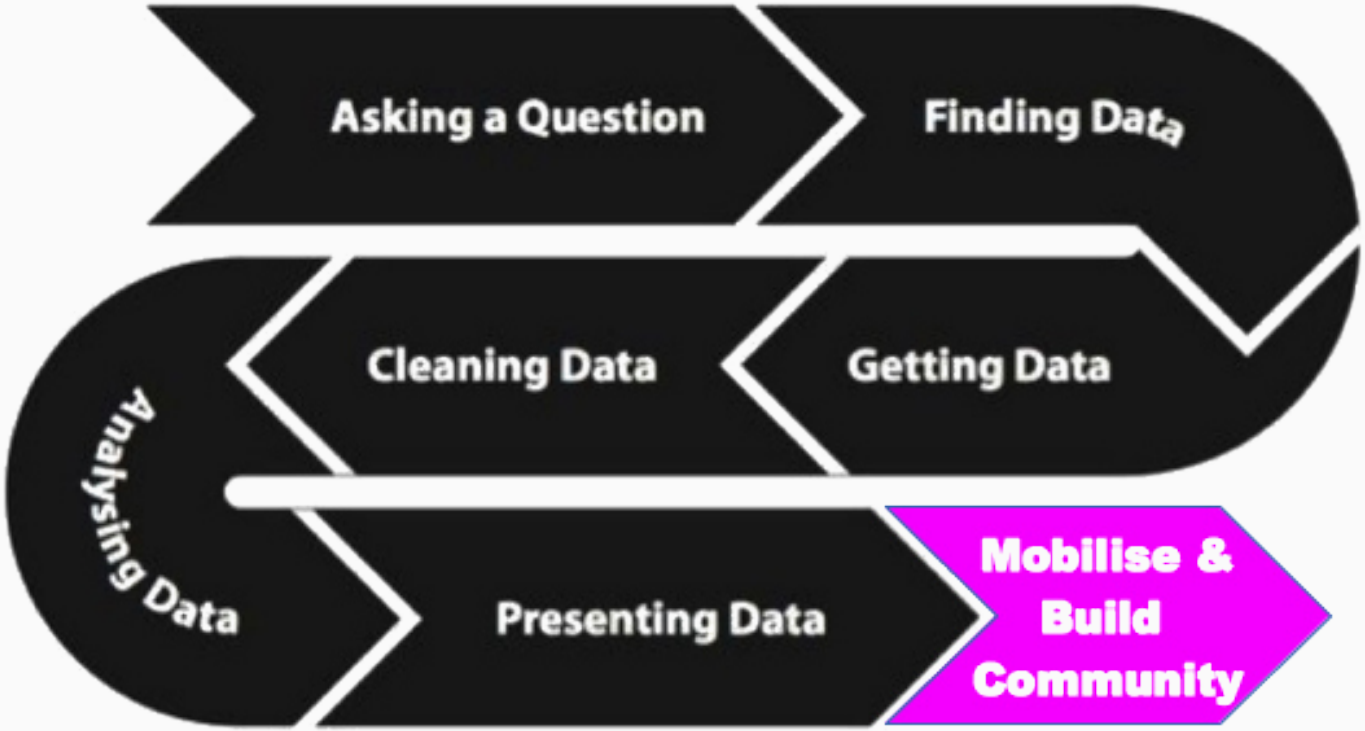
Summarization

Provide a more compact representation of the data set, including visualization and report generation.



Generalities of Data Mining

A Data Mining Pipeline



http://www.fabriders.net/data-literacy-update/

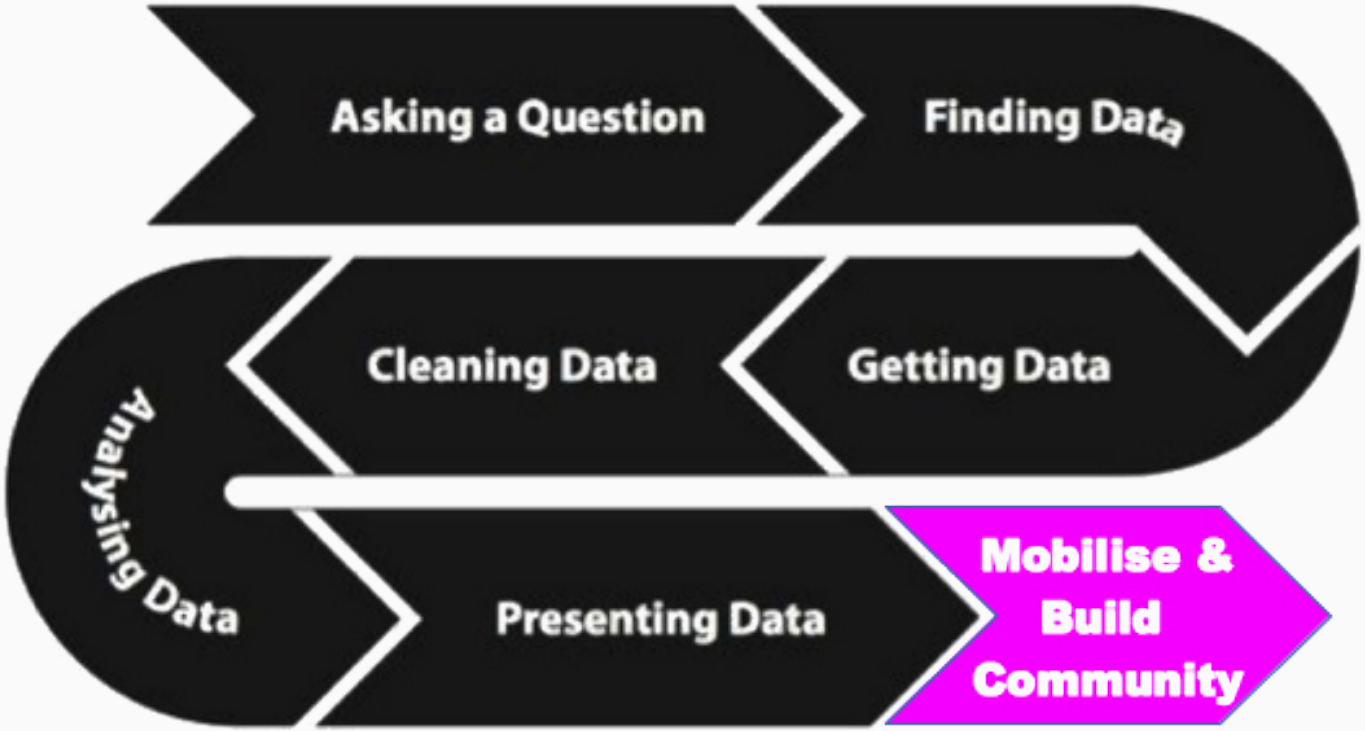
Data, Like Oil, Needs to be Refined to be Useful

– *Hal Varian*

The ability to take data—to be able to understand it, to process it, to extract value from it, to visualize it, to communicate it—that's going to be a hugely important skill in the next decades.

– *Hal Varian*

Data Mining is not only about analyzing!



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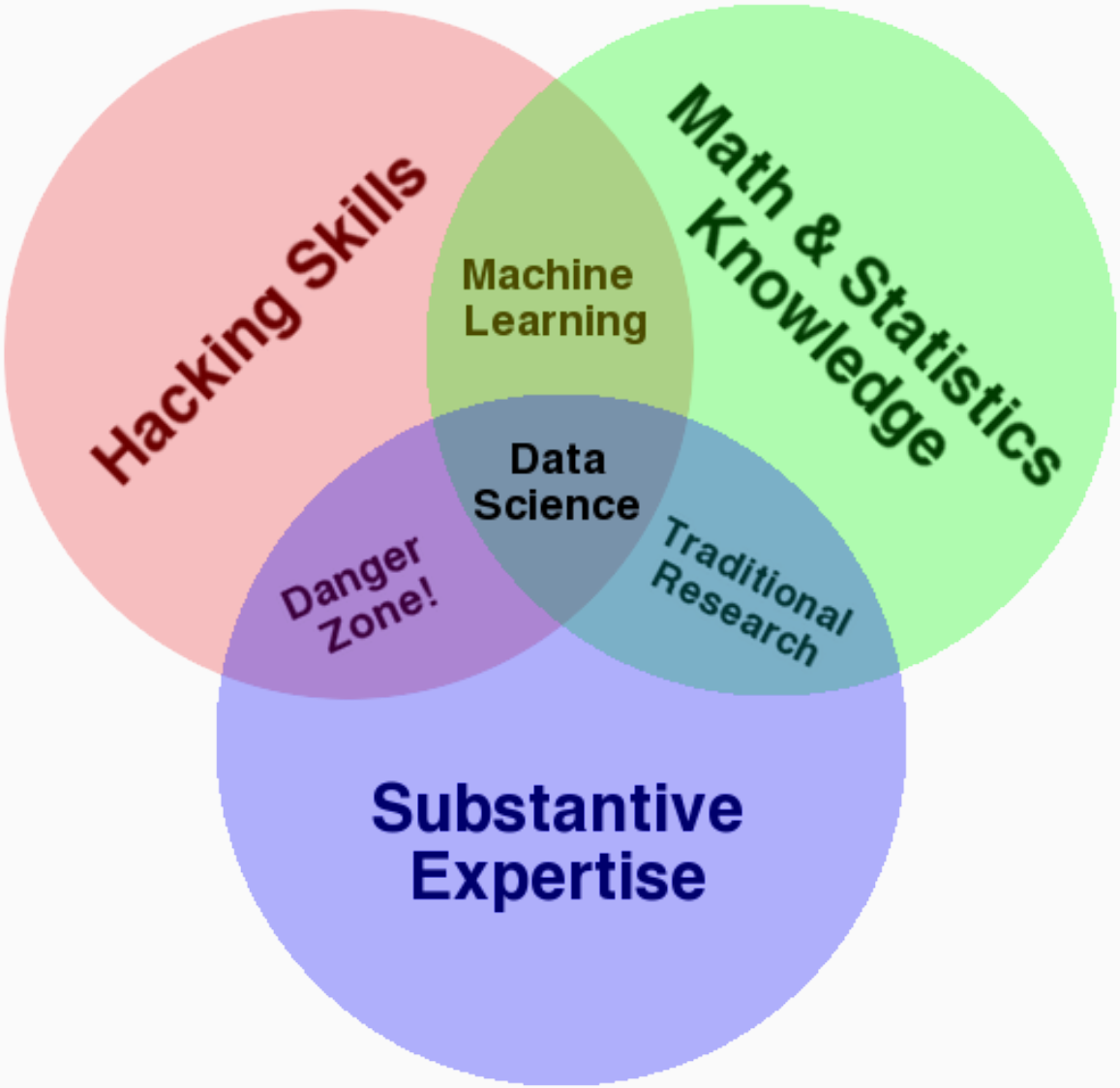

Machine Learning/Data Mining Applications

- Business Analytics
  - Is this costumer credit-worthy?
  - Is a costumer willing to respond to an email?
  - Do costumers divide in similar groups?
  - How much a costumer is going to spend next semester?
- World Wide Web
- Financial Analytics
- Internet of Things
- Image Recognition, Speech
- ..

Features

The Data Mining Process

- Data collection
- Data Preprocesing
  - Feature extraction
  - Data cleaning
  - Feature selection and transformation
- Analytical processing and algorithms
- Data Postprocesing

Multidimensional Data

- Example:

Competitor Name	Swim	Cycle	Run	Total
John T	13:04	24:15	18:34	55:53
Norman P	8:00	22:45	23:02	53:47
Alex K	14:00	28:00	n/a	n/a
Sarah H	9:22	21:10	24:03	54:35

Triathlon results

- Example or Instance
  - data point, transaction, entity, tuple, object, or feature-vector
- Attribute or Feature
  - field, dimension

Instance Types

- Dense
  - red, white, Barcelona, 3, up
  - red, red, Barcelona, 4, down
  - black, white, Paris, 2, up
  - red, green, Paris, 3, down
- Sparse
  - 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0
  - 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0
  - 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0
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Attribute Type

- Numerical
  - 0, 1, 3.43, 2.34, 4.23
- Categorical or Discrete
  - +, -
  - red, green, black
  - yes, no
  - up, down
  - Barcelona, Paris, London, New York
- Text Data: vector-space representation
  - The cat is black
- Binary: Categorical or Numerical

Exercise EDF scenario

You are working at EDF and you want to predict the energy consumption for tomorrow. What features do you use?

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Note

The same data can be presented in different manners!

Example: a timestamp vs (year,day in the year, hour, minute)

Feature Extraction

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- Sensor data (time series): Wavelets or Fourier Transforms
- Image Data: histograms or visual words
- Web logs: multidimensional data
- Network traffic: specific features as network protocol, bytes transferred
- Text Data: remove stop words, stem data, multidimensional data

Data Cleaning

Data Cleaning

- Handling missing entries
  - Eliminate entries with a missing value
  - Estimate missing values
  - Algorithms can handle missing values
- Handling incorrect entries
  - Duplicate detection and inconsistency detection
  - Domain knowledge
  - Data-centric methods
- Scaling and normalization
  - Standardization: for instance i, attribute j:

$$z_i^j = \frac{x_i^j - \mu_j}{\sigma_j}$$

  - Normalization:

$$y_i^j = \frac{x_i^j - \min_j}{\max_j - \min j}$$

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  - Equi-width ranges
  - Equi-log ranges
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- Time Series to Discrete Sequence Data
  - SAX: equi-depth discretization after window-based averaging

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  - SAX: equi-depth discretization after window-based averaging
- Time Series to Numeric Data
  - Discrete Wavelet Transform
  - Discrete Fourier Transform

Term Frequency-Inverse Document Frequency

- Term frequency
  - Boolean "frequencies"
    - $tf(t, d) = 1$ if t occurs in d and 0 otherwise;
  - Logarithmically scaled frequency
    - $tf(t, d) = 1 + log(f_{t,d})$, or zero if $f_{t,d}$ is zero;
  - Augmented frequency,

$$\mathrm{tf}(t, d) = 0.5 + 0.5 \cdot \frac{f_{t,d}}{\max\{f_{t',d} : t' \in d\}}$$

- Inverse document frequency

$$\mathrm{idf}(t, D) = \log \frac{|D|}{|\{d \in D : t \in d\}|}$$

- Term frequency-inverse document frequency

$$\mathrm{tfidf}(t, d, D) = \mathrm{tf}(t, d) \cdot \mathrm{idf}(t, D)$$

Feature conversion exercise

"What is the cure for Tuberculosis?" (in context of search engine)

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Predicting the next position of a car given the last positions?

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Predicting disease from noisy input (body temperature, etc.)

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Recognizing authors through their unique style?

Feature selection and transformation

- Sampling for Static Data
  - Sampling with Replacement
  - Sampling without Replacement: no duplicates
  - Biased Sampling
  - Stratified Sampling
- Reservoir Sampling for Data Streams
  - Given a data stream, choose k items with the same probability, storing only k elements in memory.

Reservoir Sampling

```
1  for every item i in the first k items of the stream
2        do store item i in the reservoir
3  n = k
4  for every item i in the stream after the first k items of the stream
5        do select a random number r between 1 and n
6           if r ≤ k
7              then replace item r in the reservoir with item i
8           n = n + 1
```

Algorithm Reservoir Sampling

Reservoir Sampling proof

- For all $i > k$, i^{th} element chosen with probability $\frac{k}{i}$
- For all $j \geq k$ is chosen to be replaced with probability $\frac{1}{k} \cdot \frac{k}{i}$
- At the end, each element of the population has probability $\frac{k}{n}$ to be in the reservoir [out of scope, by induction]

Reservoir Sampling has complexity $\mathcal{O}(n)$

- *Algorithm L*, and runs in $\mathcal{O}(k(1 + \log \frac{n}{k}))$
- This is optimal

Feature selection and transformation

- Feature Subset Selection
  - Supervised feature selection
  - Unsupervised feature selection
  - Biased Sampling
  - Stratified Sampling
- Dimensionality reduction with axis rotation
  - Principal Component Analysis
  - Singular Value Decomposition
  - Latent Semantic Analysis

Principal Component Analysis

- Goal: **Principal component analysis** computes the most meaningful basis to re-express a noisy, garbled data set. The hope is that this new basis will filter out the noise and reveal hidden dynamics

More on that in a later course!

Feature selection is an important step

- Simplification of models

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- Shorten training phase

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- Simplification of models
- Shorten training phase
- Avoids the curse of dimensionality
- Reduce overfitting

Analytical processing and algorithms

- Attribute/Column Relationships
  - **Classification** : predict value of a discrete attribute
  - **Regression**: predict value of a numeric attribute
- Instance/Row Relationships
  - **Clustering**: determine subsets of rows, in which the values in the corresponding columns are similar
  - **Outlier Detection**: determine the rows that are very different from the other rows

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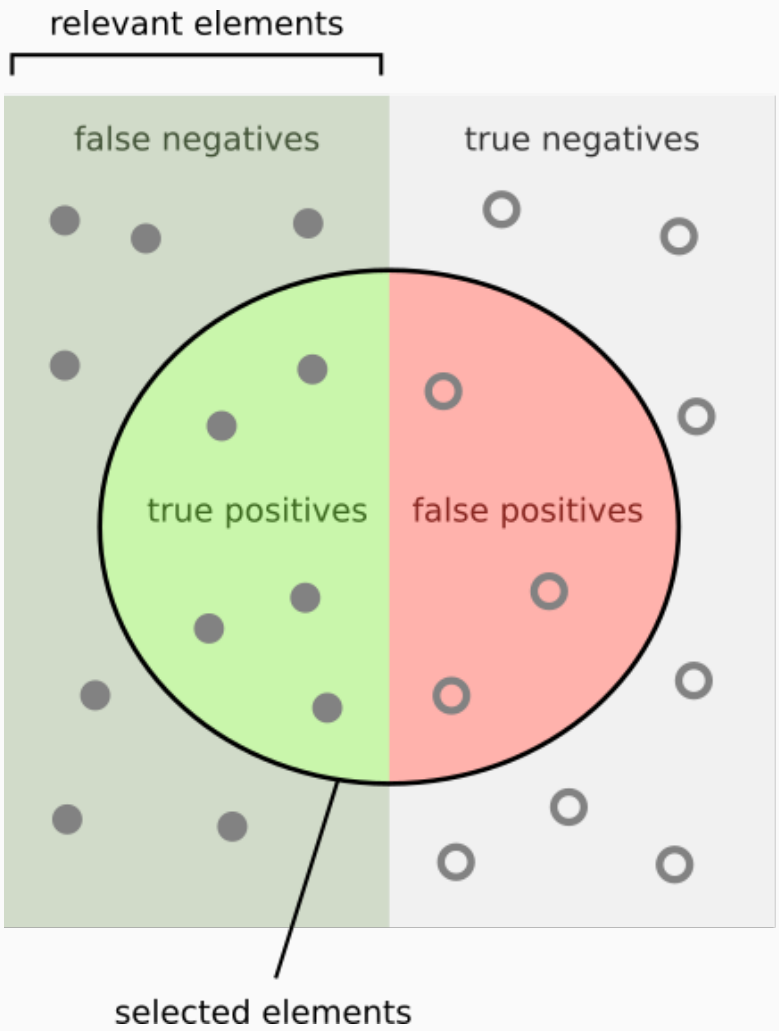
Big Data Scalability

- Distributed Systems:
  - Hardware: Hadoop cluster
  - Software: MapReduce, Spark, Flink, Storm
- Streaming Algorithms
  - Single pass over the data
  - Concept Drift

Classifier evaluation

Precision and recall



How many selected items are relevant?

$$\text{Precision} = \frac{\text{true positives}}{\text{selected elements}}$$

How many relevant items are selected?

$$\text{Recall} = \frac{\text{true positives}}{\text{relevant elements}}$$

wikipedia

What are the most important in these situations

What should be prioritized (true negative, false positive, true positive?) in these situations:

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- Medical test (pregnancy / cancer / 50-50-cure)

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What should be prioritized (true negative, false positive, true positive?) in these situations:

- "You might like this movie" recommendation
- Medical test (pregnancy / cancer / 50-50-cure)
- Danger prediction (pedestrian detection / hurricane alert)

Parameterized models

Most classification models come with a parameter that can be tuned between **precision** and **recall**.

Example: set of predictions with some "score".

Item	*A*	*B*	*C*	*D*	*E*	*F*	*G*	*H*	*I*	*J*
Prediction Score	97	91	85	75	63	51	42	32	18	7
Reality	1	1	0	1	1	0	0	1	0	0

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What are the precision and recall if we put the threshold at 50%?

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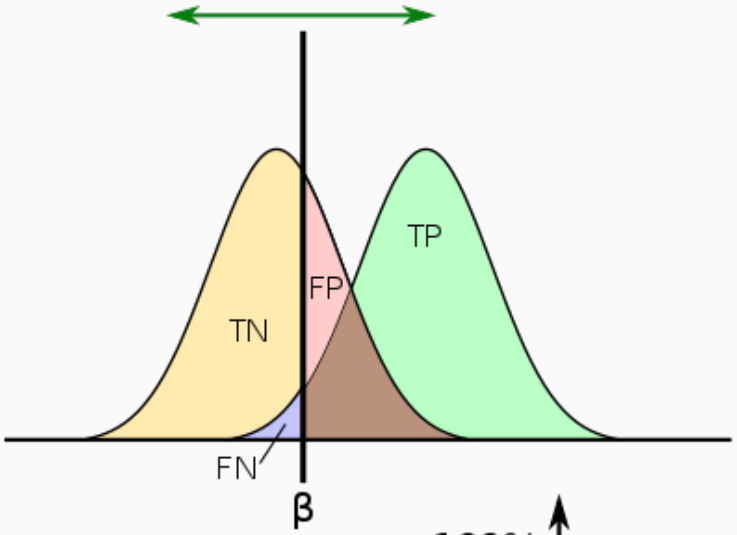
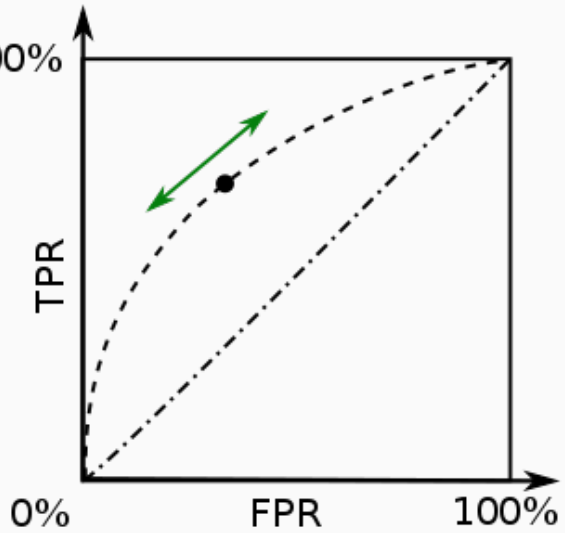
What are the precision and recall if we put the threshold at 50%? 30% ?80% ?

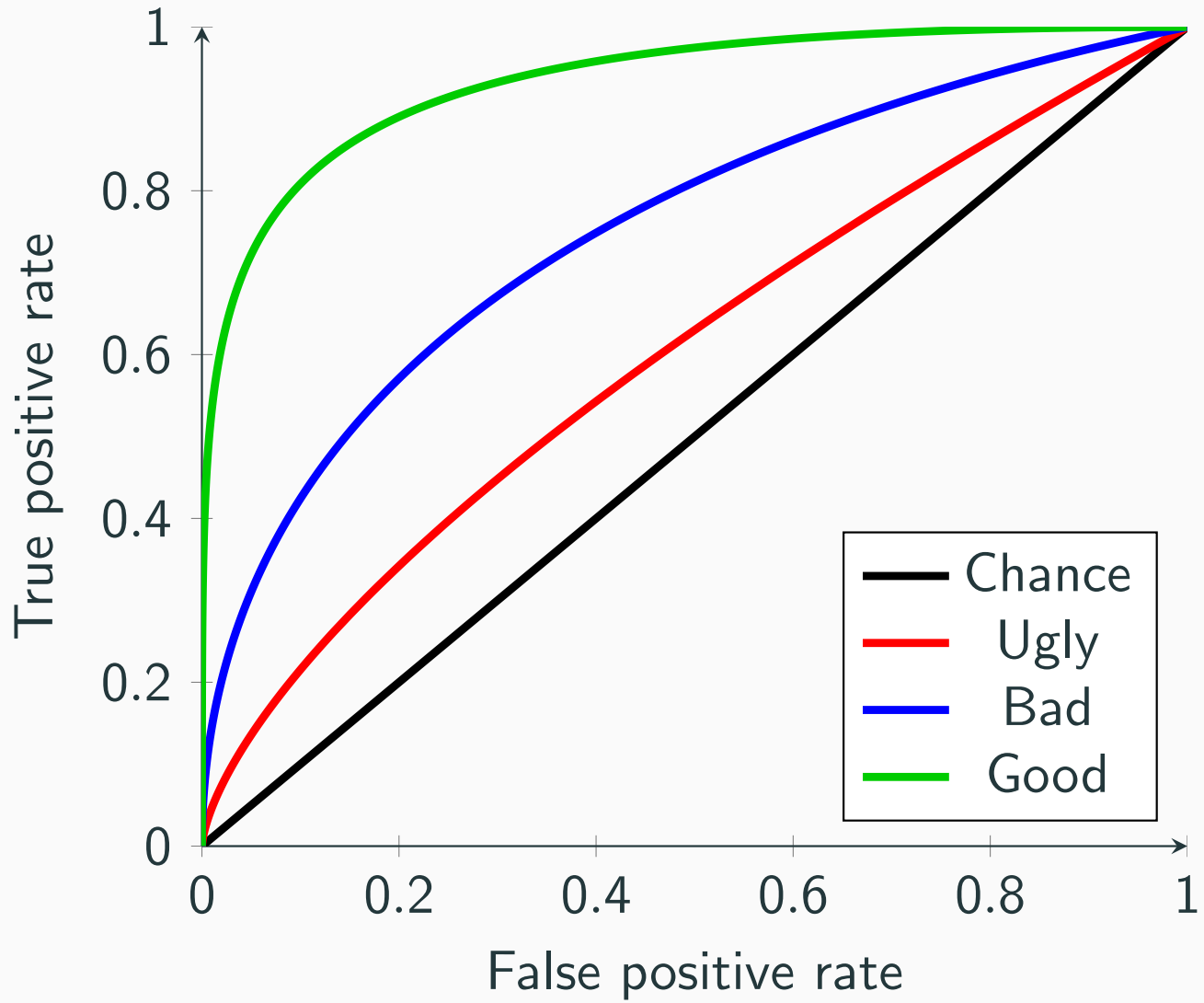
Comparing two models: ROC curves



TP	FP
FN	TN



Comparing two models: ROC curves



Evaluation

1. Error estimation: *Hold-out or Cross-Validation*
2. Evaluation performance measures: *Accuracy or κ-statistic*
3. Statistical significance validation: *MacNemar or Nemenyi test*

Error Estimation

Data available for testing

- Holdout an independent test set
- Apply the current decision model to the test set
- The loss estimated in the holdout is an unbiased estimator

Not enough data available for testing

- Divide dataset in 10 folds
- Repeat 10 times: use one fold for testing and the rest for training

	Predicted Class+	Predicted Class-	Total
Correct Class+	75	8	83
Correct Class-	7	10	17
Total	82	18	100

Simple confusion matrix example

2. Evaluation performance measures

	Predicted Class+	Predicted Class-	Total
Correct Class+	tp	fn	tp+fn
Correct Class-	fp	tn	fp+tn
Total	tp+fp	fn+tn	N

Simple confusion matrix example

- Precision $= \frac{tp}{tp+fp}$
- Recall $= \frac{tp}{tp+fn}$
- Accuracy $= \frac{tp+tn}{total}$
- $F_1 = 2 \cdot \frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}}$

	Predicted Class+	Predicted Class-	Total
Correct Class+	75	8	83
Correct Class-	7	10	17
Total	82	18	100

Simple confusion matrix example

- Accuracy $= \frac{75}{100} + \frac{10}{100} = \frac{75}{83}\frac{83}{100} + \frac{10}{17}\frac{17}{100} = 85\%$

  Others:
- Arithmetic mean $= (\frac{75}{83} + \frac{10}{17})/2 = 74.59\%$
- Geometric mean $= \sqrt{\frac{75}{83}\frac{10}{17}} = 72.90\%$

	Predicted Class+	Predicted Class-	Total
Correct Class+	75	8	83
Correct Class-	7	10	17
Total	82	18	100

Simple confusion matrix example

	Predicted Class+	Predicted Class-	Total
Correct Class+	0.689	0.141	83
Correct Class-	0.141	0.028	17
Total	82	18	100

Confusion matrix for chance predictor

Kappa Statistic

- p_0: classifier's prequential accuracy
- p_c: probability that a chance classifier makes a correct prediction.
- κ statistic

$$\kappa = \frac{p_0 - p_c}{1 - p_c}$$

- $\kappa = 1$ if the classifier is always correct
- $\kappa = 0$ if the predictions coincide with the correct ones as often as those of the chance classifier

Matthews correlation coefficient (MCC)

$$\frac{tp \times tn - fp \times fn}{\sqrt{(tp + fp)(tp + fn)(tn + fp)(tn + fn)}}$$

	Predicted Class+	Predicted Class-	Total
Correct Class+	tp	fn	tp+fn
Correct Class-	fp	tn	fp+tn
Total	tp+fp	fn+tn	N

Simple confusion matrix example

AUC Area under the curve

A ROC space is defined by FPR and TPR (recall)

- FPR $= \frac{fp}{fp+tp}$
- TPR $= \frac{tp}{tp+fn}$

Comparing two models: Accuracy

	Classifier A **correct**	Classifier B wrong
Classifier A **correct**	Both	A only
Classifier B wrong	B only	Both

Statistical significance validation (2 Classifiers)

	Classifier A Class+	Classifier A Class-	Total
Classifier B Class+	c	a	c+a
Classifier B Class-	b	d	b+d
Total	c+b	a+d	a+b+c+d

$$M = |a - b - 1|^2/(a + b)$$

The test follows the χ^2 distribution. At 0.99 confidence it rejects the null hypothesis (the performances are equal) if $M > 6.635$.

Statistical significance validation (> 2 Classifiers)

2 classifiers are performing differently if the corresponding average ranks differ by at least the critical difference

$$CD = q_\alpha \sqrt{\frac{k(k+1)}{6N}}$$

- k is the number of learners, N is the number of datasets,
- critical values q_α are based on the Studentized range statistic divided by $\sqrt{2}$.

Statistical significance validation (> 2 Classifiers)

Two classifiers are performing differently if the corresponding average ranks differ by at least the critical difference

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# classifiers	2	3	4	5	6	7
$q_{0.05}$	1.960	2.343	2.569	2.728	2.850	2.949
$q_{0.10}$	1.645	2.052	2.291	2.459	2.589	2.693

Critical values for the Nemenyi test