Computational Social Science: exploration

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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, 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, 0, 1, 0, 0, 1, 0, 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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- 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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- 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

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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

Reservoir Sampling

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

Algorithm Reservoir Sampling

- 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

- 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!

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- 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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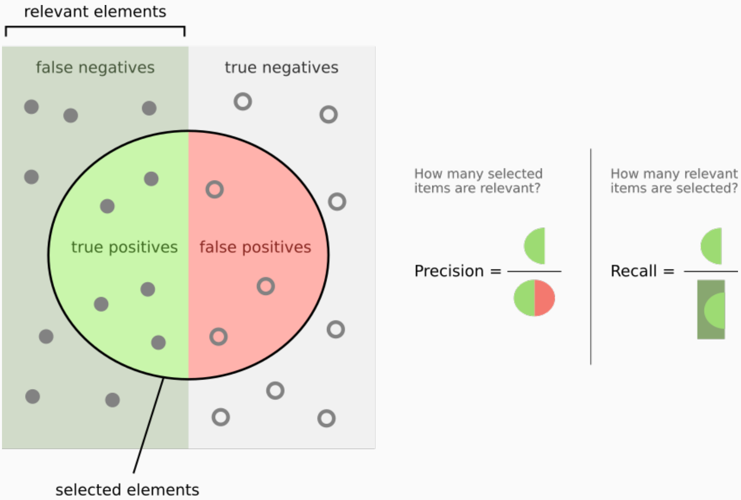
Big Data Scalability

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

Classifier evaluation

Precision and recall



wikipedia

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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% ?

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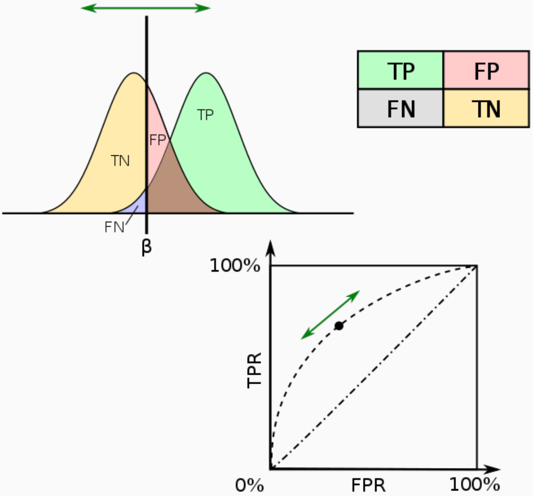
What are the precision and recall if we put the threshold at 50%? 30% ?80% ?

Comparing two models: ROC curves



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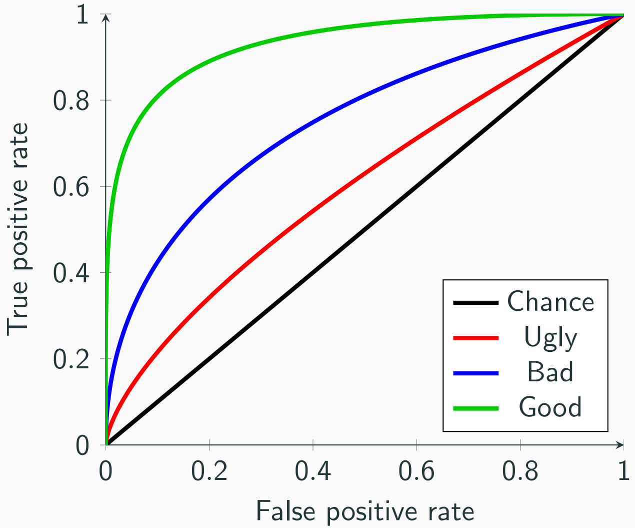

Evaluation

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 $= \frac{tp+tn}{total}$
- $F_1 = 2 \cdot \frac{\text{precision}\cdot\text{recall}}{\text{precision}+\text{recall}}$

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- 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
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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 $\sqrt{2}$.

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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