Recap

- Probability theory
  - Probability: Fraction of positive over all possible events
  - Conditional probability: Restrict the space of possible events
- Naive Bayes
  - Probability-based classification algorithm
  - Assumes feature independence (therefore: “naive”)
  - Still used in many applications
    - E.g., spam classification

UNIVERSITÄT
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Machine Learning 2: Evaluation

VL Sprachliche Informationsverarbeitung

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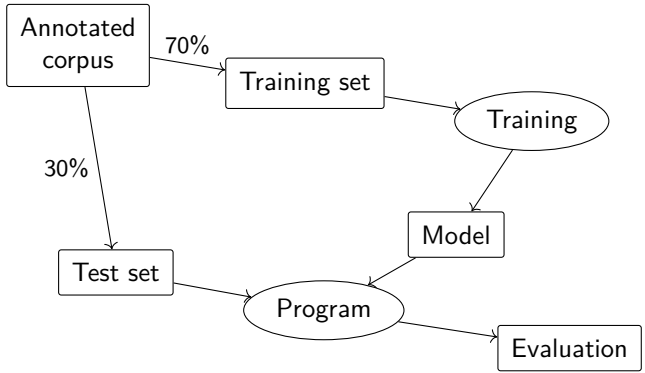
Training and Testing

- Goal: Apply the model on new data (and estimate its performance then)
- The program cannot have seen the data, so that it is a realistic test



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- What could be problems with this metric?

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- How exactly do we evaluate? How do we measure how good predictions are?

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- Linguistic expression: sentences, phrases, documents
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- Linguistic expression: sentences, phrases, documents
  - In this example: Documents
- Classification task: Instances are sorted into previously known categories
- Data set: 100 documents that have labels
  - I.e., we know the result to expect

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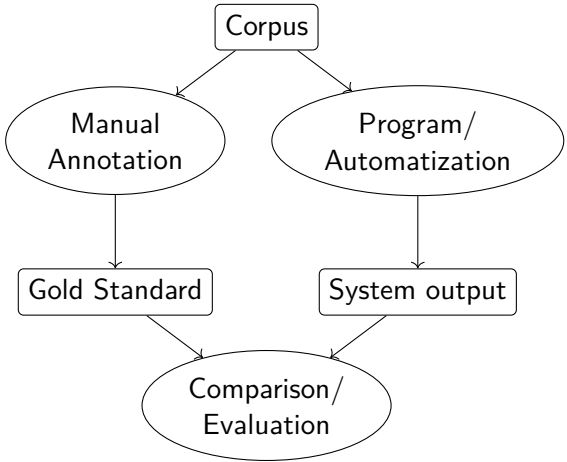
  - ⊕ Realistic evaluation (if it's a realistic application)
- Pre-defined reference data set
  - ⊖ Not always available, expensive, time-consuming
  - ⊕ Most reliable, easiest to reproduce
  - ML systems need annotated data anyway

Experiments



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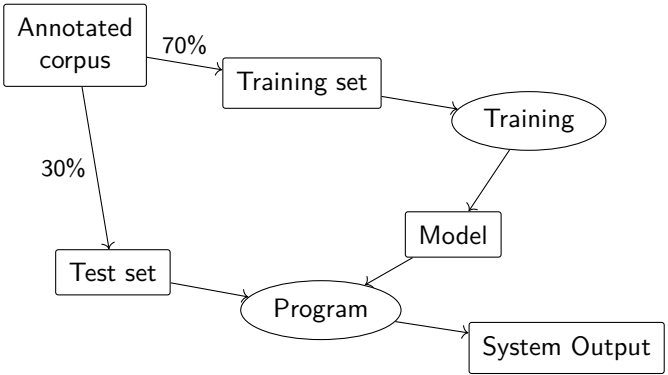

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Example (Sentiment Analysis)

- Gold standard: `[1, 0, -1, -1]`
- System output: `[1, -1, 1, 0]`
- (positive: 1, neutral: 0, negative: -1)

Evaluation

Accuracy and Error Rate

- Accuracy
  - Percentage of correctly classified instances
  - Example above
    - $A = \frac{1}{4} = 0.25 = 25\%$
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    - $E = \frac{3}{4} = 0.75 = 75\%$
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  - Percentage of *incorrectly* classified instances
  - Example above
    - $E = \frac{3}{4} = 0.75 = 75\%$
  - "the lower the better"
- $A + E = 1$, $E = 1 - A$ and $A = 1 - E$

Accuracy and Error Rate

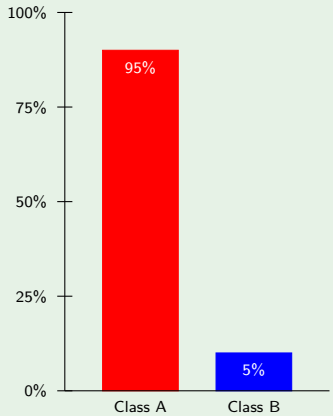
Examples

- `G = [1, 0, 1], S = [0, 0, 1]`
  - $A = \frac{1}{3}$
- `G = ["f", "m", "u", "m", "f"], S = ["m", "f", "u", "m", "f"]`
  - $E = \frac{2}{5}$

(We don't need the original data for evaluation, we are just comparing gold standard classes with system output.)

Pitfalls

Example (Uneven Distributions)



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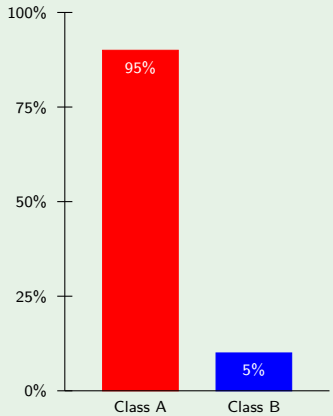

- What's the accuracy if the system assigns all items to category A?

Pitfalls

Example (Multiple Classes)

↓ System / Gold →	A	B	C
A			
B			
C			

Table: Confusion Matrix

- What's the accuracy of the system?

Per Class Evaluation

- Accuracy gives us an overall score
- But we want to know more details:
  - Some classes are more important for applications
  - Error analysis!
- We want to evaluate per class (i.e., per polarity)

Sentiment Analysis

Different Kinds of Errors

Polarity	Document
positive	Awesome movie!
neutral	Great start, boring afterwards. Very good acting.
negative	Boring as hell
...	...

Table: Gold Standard

Sentiment Analysis

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Table: Gold Standard

Variant	Output
GS	1, 0, -1, 1, 1, 0, -1, 1
Program 1	1, 0, -1, 1, 1, 0, 1, 1
Program 2	1, 0, -1, 1, -1, 0, -1, 1

Sentiment Analysis

Different Kinds of Errors

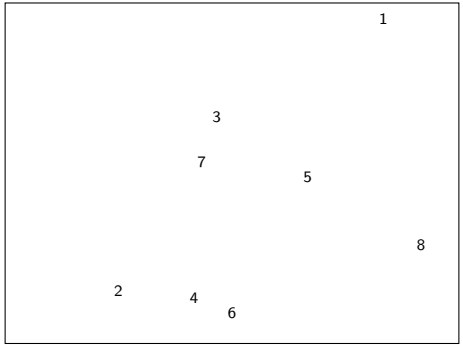

Figure: Visual representation of errors, focussing on -1 class

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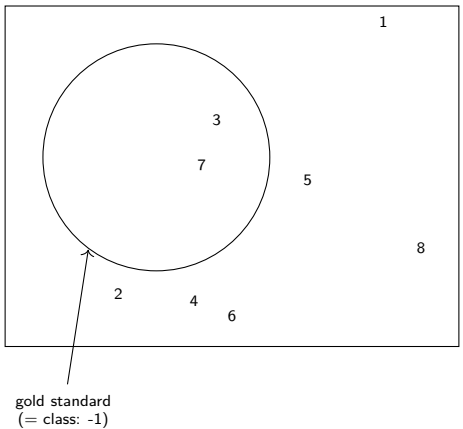

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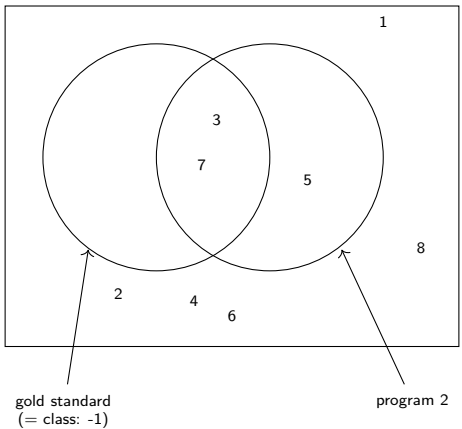

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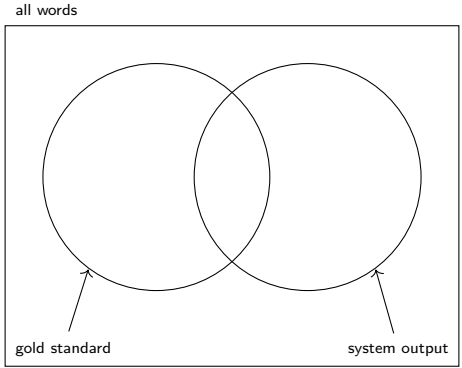

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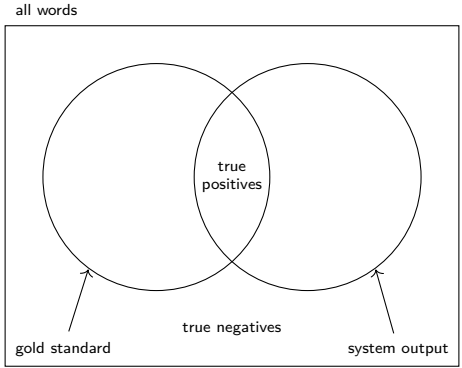

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true negative (tn) Correctly classified as not target category

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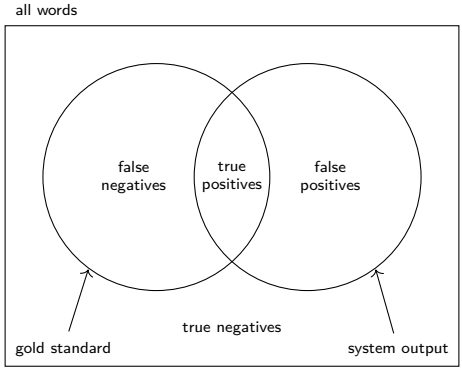

true positive (tp) Correctly classified as target category

true negative (tn) Correctly classified as not target category

false positive (fp) Incorrectly classified as target category

false negative (fn) Incorrectly classified as not target category

Accuracy, revisited

Accuracy: Percentage of correctly classified instances

$$A = \frac{tp + tn}{tp + tn + fp + fn}$$

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Error rate: Percentage of incorrectly classified instances

$$E = \frac{fp + fn}{tp + tn + fp + fn}$$

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$$\text{Recall} \quad R = \frac{tp}{tp + fn}$$

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- Precision
  - Denominator: $tp + fp$
  - Number of things that the system labelled as target category (correct and incorrect)
- Recall
  - Denominator: $tp + fn$
  - Number of things that the gold standard contained as target category (what the system should have found)

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Importance/Weighting

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Example (Test performance in a pandemic)

- Individual health: Mistakenly being in quarantine is a severe limitation, and might have economic consequences
- Public health: Find more infections, even if it means a few people are mistakenly put in quarantine

F-Score

- Sometimes, it is convenient to combine precision and recall into a single number
- F-Score is common way to do that
  (it's a fancy way of averaging)
  - β can be used to weight precision and recall differently
  - $\beta = 1$ means equal weighting
- F-Measure corresponds to the harmonic mean

$$F_\beta = (1 + \beta^2)\frac{PR}{\beta^2 P + R}$$

$$F_1 = 2\frac{PR}{P + R}$$

Baseline

A simple solution to the problem

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- How well can the task be solved without investing (a lot of) time and work?
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- Baselines are used for comparison in experiments
- 'Real' algorithms should be able to beat the baseline, i.e., achieve higher accuracy
- Baselines have obvious shortcomings, are not expected to work every time
  - Although, sometimes they work surprisingly well

Baseline

Group Exercises

What are reasonable baselines for these tasks?

- Detecting nouns in German texts
- Detecting sentence boundaries
- Detecting fake news
- Detecting the gender of dramatic characters (18-19th century)
- Predict the pos tag of the word after a determiner
- Given a corpus consisting of 'the Universal Declaration of Human Rights', 'Lord of the Rings' and the minutes of the European Parliament. Predict the origin of a random sentence.

Majority Baseline

- Select the most frequent category
- Works well in un-even data distributions
- Can be hard to beat
  - E.g. word sense disambiguation

Precision and Recall

Thresholds

- Sometimes, we have a single parameter that directly controls P and R
  E.g., a threshold for document similarity
  - Lower threshold: More documents are included ⇒ Higher recall, at the cost of precision
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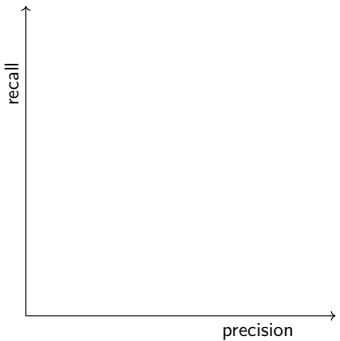

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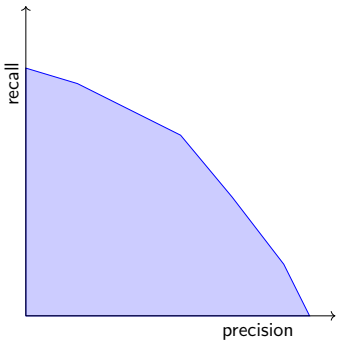

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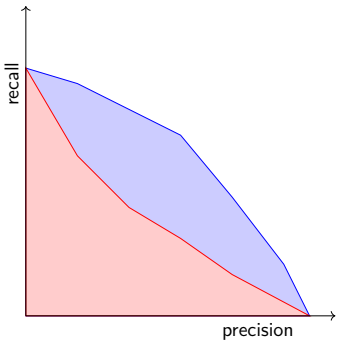

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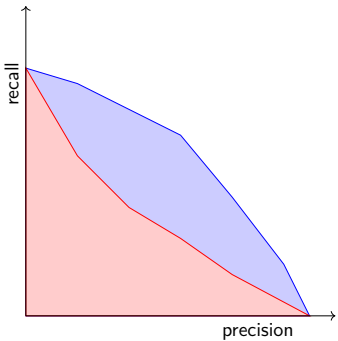

- AUC(blue) > AUC(red):
  Blue system better

References I