Introduction to Text Mining

Part IV: Basics of Empirical Methods

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Basics of Empirical Research: Learning Objectives

Concepts

- The need for annotated text corpora
- Standard evaluation measures in text mining
- The most relevant basics from statistics
- The notion of empirical methods

Methods

- Development and evaluation of approaches on text corpora
- Selection of the right evaluation measure for a task
- Measuring of effectiveness in text mining
- The study of hypotheses with significance tests

Outline of the Course

What Are Empirical Methods?

Empirical Methods

What is an empirical method?

- A quantitative method based on numbers and statistics.
- Studies a question on behaviors or phenomena by analyzing data.
- Derives knowledge from experience rather than from theory or belief.

Quantitative vs. qualitative methods

- Quantitative. Characterized by objective measurements.
- Qualitative. Emphasize the understanding of human experience.

Descriptive and inferential statistics

- Descriptive. Methods for summarizing and comprehending a sample or distribution of values. Used to describe phenomena.

  4.5, 5, 6, 6.5, 6.5, 7, 7, 7, 7.5, 8 $\rightarrow$ mean M = 6.5

- Inferential. Methods for drawing conclusions based on values. Used to generalize inferences beyond a given sample.

  The average number is significantly higher than 5.

Empirical Methods

Research Questions

A good research question (Bartos, 1992)

- Asks about the relationship between two or more variables.
- Is testable, i.e., it is possible to collect data to answer the question.
- Is stated clearly, in the form of a question.
- Does not pose an ethical or moral problem for implementation.
- Is specific and restricted in scope.
- Identifies exactly what is to be solved.

Example of a poorly formulated question

"How effective is tokenization using hand-crafted decision trees?"

Example of a well-formulated question

"What accuracy does the hand-crafted decision-tree tokenizer from 'Introduction to Text Mining' achieve on the test set of the English CoNLL-2003 corpus (as opposed to a tokenizer that simply splits at every whitespace)?"

Empirical Methods

Text Mining and Empirical Methods

Text mining (recap)

- Aims to infer structured output information from unstructured texts.
- Uses rule-based or statistical approaches for this purpose.
- The output information produced is not always be correct.

Empirical methods in text mining

All detailed below.

- Corpus linguistics. Approaches are developed and evaluated on text collections called *corpora*.
- Evaluation measures. The quality of an approach needs to be evaluated, especially of its *effectiveness*.
- Experiments. The quality is empirically evaluated on test corpora and compared to alternative approaches.
- Hypothesis testing. Methods are used to statistically "proof" the quality.

Corpus Linguistics

Corpus Linguistics

What is corpus linguistics?

- The study of language as expressed in principled collections of natural language texts, called *text corpora*.

  For spoken language, also other corpora exist, of course.
- Aims to derive knowledge and rules from real-world text.
- Covers both manual and automatic analysis of text.

Main techniques

- Annotation. Adding annotations to a text or span of text.
- Abstraction. Mapping of annotated texts to a theory-based model.
- Analysis. Developing and evaluating methods based on a corpus.

Need for text corpora

- Without a corpus, it's hard to develop a strong approach — and impossible to reliably evaluate it.

"It's not the one who has the best algorithm that wins.
It's who has the most data."

Text Corpora

What is a text corpus?

- A collection of real-world texts with known properties, compiled to study a language problem.

  Examples: 200,000 product reviews for sentiment analysis, 1000 news articles for part-of-speech tagging, ...

- The texts in a corpus are often annotated, at least for the problem to be studied.

  Examples: Sentiment polarity of a full text, part-of-speech tags of each token, ...

Corpora in text mining

- Text mining approaches are developed and evaluated on text corpora.
- Usually, the corpora contain annotations of the output information type to be inferred.

Annotations

What is an annotation?

- An annotation marks a text or a span of text as representing meta-information of a specific type.
- Can also be used to specify relations between other annotations.
- The types are specified by an annotation scheme.

Time entity **Organization entity**

" 2014 ad revenues of Google are going to reach

Reference **Time entity**

$20B. The search company was founded in '98.

Founded relation

Reference **Time entity**

Its IPO followed in 2004. [...] "

Topic: "Google revenues" **Genre:** "News article"

Annotations

Ground Truth vs. Automatic Annotation

Manual annotation

- The annotations of a text corpus are usually created manually.
- To assess the quality of manual annotations, inter-annotator agreement is computed based on texts annotated multiple times.

  Standard chance-corrected measures: Cohen's κ, Fleiss' κ, Krippendorff's α, ...

Ground-truth annotations

- Manual annotations are assumed to be correct, called the *ground truth*.
- Text mining usually learns from ground-truth annotations.

Automatic annotation

- Technically, text mining algorithms can be seen as just adding annotations of certain types to a processed text.
- The automatic process usually aims to mimic the manual process.

Annotations

Three Ways of Obtaining Ground-Truth Annotations

Expert annotation

- Experts for the task at hand (or for linguistics, ...) manually annotate each corpus text.
- Usually achieves the best results, but often time and cost-intensive.

Crowd-based annotation

- Instead of experts, crowdsourcing is used to create manual annotation.
- Common platforms: `http://mturk.com`, `http://upwork.com`, ...
- Access to many lay annotators (cheap) or semi-experts (not too cheap).
- Distant coordination overhead; results for complex tasks unreliable.

Distant supervision

- Annotations are (semi-) automatically derived from existing metadata.
- Examples: Sentiment from user ratings, entity relations from databases
- Enables large corpora, but annotations may be noisy.

Text Corpora

Example: ArguAna TripAdvisor Corpus * (Wachsmuth et al., 2014)

Compilation

- 2100 manually annotated hotel reviews, 300 each out of 7 locations.
- 420 each with user overall rating 1–5.
- Additional 196,865 not manually-annotated reviews.

title: *great* **location**, *bad* **service** **sentiment score:** 2 of 5

body: *stayed at the darling harbour holiday inn.* *The* **location** *was great, right there at China town, restaurants everywhere, the monorail station is also nearby.* *Paddy's market is like 2 mins walk.* **Rooms** *were however very small.* *We were given the 1st floor* **rooms**, *and we were right under the monorail track,* *however* **noise** *was not a problem.* **Service** *is terrible.* **Staffs** *at the* **front desk** *were impatient,* *I made an enquiry about* **internet access** *from the* **room** *and the person on the phone was rude and unhelpful.* *Very shocking and unpleasant encounter.*

Annotation

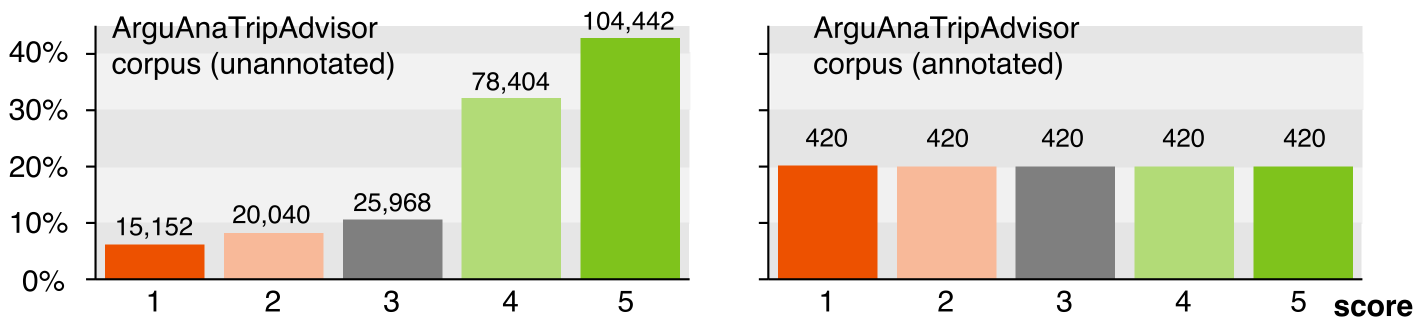
- Manual annotations. Clause-level sentiment polarity, hotel aspects.
- Distant supervision. Review-level sentiment scores from overall ratings (analog for other user ratings).

Text Corpora

Representativeness

Representativeness

- A corpus is representative for an output information type C, if it includes the full range of variability of texts with respect to C.
- Important for generalization, because the given corpus governs what can be learned about the associated domain.



Representative vs. balanced distributions

- Evaluation. The distribution of texts over the values of C should be representative for the real distribution.
- Development. A balanced distribution, where all values are evenly represented, may be favorable (particularly for machine learning).

Evaluation Measures

Evaluation Measures

Evaluation measures in text mining

- An evaluation measure quantifies the quality of an approach on a given task and corpus.
- Approaches can be ranked with respect to an evaluation measure.
- Quality is assessed in terms of *effectiveness* or *efficiency*.

Effectiveness

- The extent to which the output information of an approach is correct.
- Measures. Accuracy, precision, recall, ... (see below).
- High effectiveness is the primary goal of any text mining approach.

Efficiency

- The costs of an approach in terms of the consumption of time.
- Measures. Overall run-time, mean run-time per unit, training time, ...
- Space efficiency (i.e., memory consumption) may play a role, too.

  Efficiency is beyond the scope of this course.

Evaluation Measures

Effectiveness

What is effectiveness?

- The effectiveness of a text mining approach is the extent to which its output information is correct.

Evaluation of classification effectiveness

- All tasks where instances of an output information type C are to be inferred can be evaluated as a binary classification task.
- Check for each candidate instance whether the decision of an approach to infer the instance or not matches the ground truth.

Evaluation of regression effectiveness

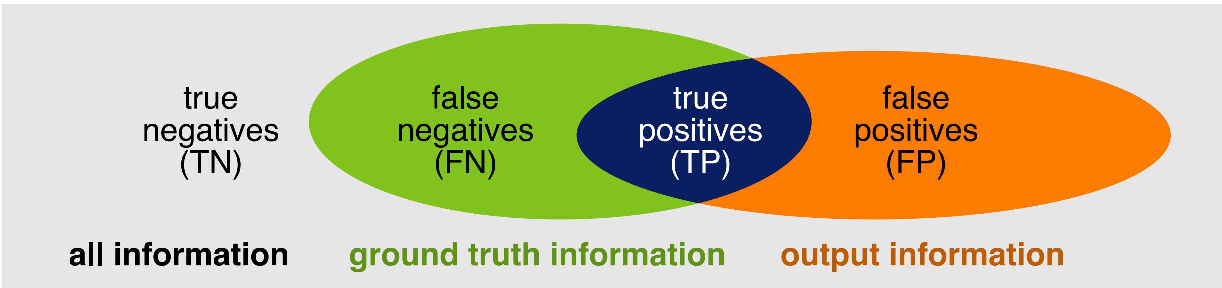
- In tasks where numeric values have to be predicted, the regression error is usually evaluated.
- Check for each value predicted for an instance by an approach how different the value is from instance's ground-truth value.

Classification Effectiveness

Instance Types

Instance types of a text mining approach in a task

- Positives. The output information instances the approach has inferred.
- Negatives. All other possible instances.



Instance types in the evaluation of the task

- True positive (TP). A positive that belongs to the ground truth.
- True negative (TN). A negative that does not belong to the ground truth.
- False negative (FN). A negative that belongs to the ground truth.
- False positive (FP). A positive that does not belong to the ground truth.

Classification Effectiveness

Evaluation based on the Instance Types

Example: Sentiment analysis

- Assume the sentiment of comments to videos is labeled as "positive", "negative", or "neutral".
  Don't confuse these labels with the instance types above!

Which of the following approaches is better?

- Approach 1. Classifies the first 70 of 100 comments correctly.
- Approach 2. Classifies the last 80 of the same 100 comments correctly.

Which dataset appears to be "easier"?

- Dataset 1. 800 out of 900 comments classified correctly.
- Dataset 2. 500 out of 600 comments classified correctly.

True vs. false instances

- A straightforward way to answer these questions is to compare the ratios of true instances under all instances.

Accuracy

Accuracy

- The accuracy A is a measure of the correctness of an approach.
- How many classification decisions are correct?

$$A = \frac{|TP| + |TN|}{|TP| + |TN| + |FP| + |FN|}$$

When to use accuracy?

- Accuracy is adequate when all classes are of similar importance.
- For instance, this holds for text classification tasks, such as sentiment analysis and part-of-speech tagging.

“The”/DT “man”/NN “sighed”/VBD “.”/. “It”/PRP “'s”/VBZ “raining”/VBG ...

- Also, accuracy may make sense where virtually every span of a text needs to be annotated, e.g., in sentence splitting.

“The man sighed. _ It’s raining cats and dogs, he felt.”

Classification Effectiveness

Limitations of Accuracy

Example: Spam detection

- Assume 5% of the mails that your mail server lets through are spam.
- What accuracy does a spam detector have that always predicts "no spam" for these mails?

When *not* to use accuracy?

- In tasks where the positive class is rare, high accuracy can be achieved by simply inferring no information.

  5% spam $\rightarrow$ 95% accuracy by always predicting "no spam"

- This includes tasks where the correct output information covers only portions of text, such as in entity recognition.

  "Apple rocks." $\rightarrow$ Negatives: "A", "Ap", "App", "Appl", "Apple ", "Apple r", ...

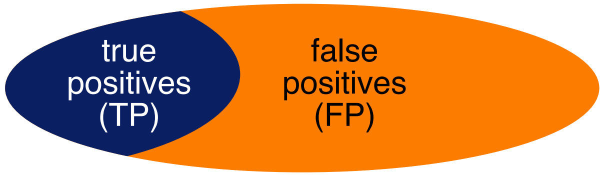
- Accuracy is inadequate when true negatives are of low importance.

Precision and Recall

Precision

- The precision P is a measure of the exactness of an approach.
- P answers: How many of the found instances are correct?

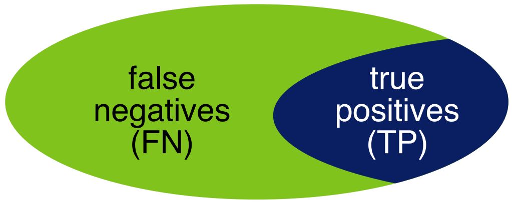
$$P = \frac{|TP|}{|TP| + |FP|}$$



Recall

- The recall R is a measure of the completeness of an approach.
- R answers: How many of the correct instances have been found?

$$R = \frac{|TP|}{|TP| + |FN|}$$



Observation

- True negatives not included in formulas.

Precision and Recall

Implications

Example: Spam detection (revisited)

- Assume 5% of the mails that your mail server lets through are spam.
- What precision and recall does the “always no spam” detector have for detecting spam?

Idea of precision and recall

- Put the focus on a specific class (here: “spam”).
- The typical case is that the true negatives are irrelevant.
- If multiple classes are important, precision and recall can be computed for each class.

Example: Spam detection (a last time)

- What precision and recall does an “always spam” detector have?

$P = 0.05 \qquad R = 1.0$

Precision and Recall

Interplay between Precision and Recall

Perfect precision and recall

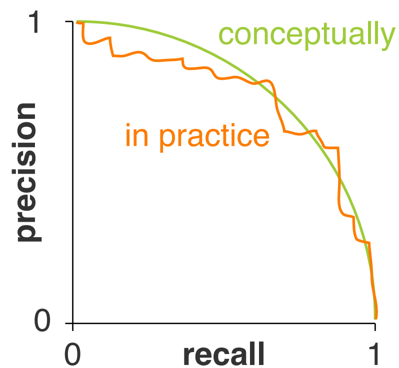
- A recall of 1.0 is mostly trivial; just assume every instance to be a TP.
  Only hard if there are too many instances, or if finding them is already a challenge.
- A precision of 1.0 is a bit more complicated; need to find at least one TP.

Precision vs. recall

- What is more important depends on the application.
- Usually, both precision and recall are to be maximized.

Trade-off between precision and recall

- The more true positives should be found, the more likely it is to choose also false instances.
- This leads to a typical *precision-recall curve*.



F_1-Score

What is better?

- A precision of 0.51 and a recall of 0.51 (option a).
- A precision of 0.07 and a recall of 0.95 (option b).
- Often, a single effectiveness value is desired.

Problem with the mean

- In the above example, the mean would be the same for both options.
- But 93% of the found instances are wrong for option b.

F_1-score (aka F_1-measure)

- The F_1-score is the harmonic mean of precision and recall.
- F_1 favors balanced over imbalanced precision and recall values.

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

Option a: $F_1 = 0.51$, option b: $F_1 = 0.13$.

F_1-Score

Generalization *

F_β-Score

- The 1 in the F_1-score in fact denotes a weighting factor.
- The general weighted harmonic mean is the F_β-score:

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

Problem with the weighting

- $\beta > 1$ give more weight to precision, $\beta < 1$ gives more weight to recall.
- It is unclear how to interpret a particular choice of β.
- Therefore, nearly always $\beta = 1$ is used in practice.

F_1-Score

Issue in Tasks with Boundary Detection

Boundary errors

- A common error in tasks where text spans need to be annotated is to choose a (slightly) wrong boundary of the span.

Entities: "First Bank of Chicago stated..." vs. "First Bank of Chicago stated..."

Sentences: "Max asked: 'What's up?'" vs. "Max asked: 'What's up?'"

Issue with boundary errors

- Boundary errors leads to both an FP and an FN.
- Identifying nothing as a positive would increase the F_1-score.

How to deal with boundary errors

- Different accounts for the issue have been proposed, but the standard F_1 is still used in most evaluations.
- A relaxed evaluation is to consider some character overlap (e.g., >50%) instead of exact boundaries.

Micro-Averaging and Macro-Averaging

Evaluation of multi-class tasks

- In general, each class in a multi-class task can be evaluated binarily.
- Accuracy can be computed for any number k of classes.
- Other results need to be combined with micro- or macro-averaging.

Micro-averaged precision (recall and F$_1$-score analog)

- Micro-averaging takes into account the number of instances per class, so larger classes get more importance.

$$Micro\text{-}P \;=\; \frac{|TP_1| + \ldots + |TP_k|}{|TP_1| + \ldots + |TP_k| \quad + \quad |FP_1| + \ldots + |FP_k|}$$

Macro-averaged precision (recall and F$_1$-score analog)

- Macro-averaging computes the mean result over all classes, so each class gets the same importance.

$$Macro\text{-}P \;=\; \frac{P_1 + \ldots + P_k}{k}$$

Micro-Averaging and Macro-Averaging

Confusion Matrix

Confusion matrix

- Each row refers to the ground-truth instances of one of k classes.
- Each column refers to the classified instances of one class.
- The cell values illustrate the correct and incorrect classifications of a given approach.

Ground truth	**Classified as**			
	Class a	Class b	...	Class k
Class a	$\lvert TP_a \rvert$	$\lvert FP_b \cap FN_a \rvert$	...	$\lvert FP_k \cap FN_a \rvert$
Class b	$\lvert FP_a \cap FN_b \rvert$	$\lvert TP_b \rvert$	...	$\lvert FP_k \cap FN_b \rvert$
...	...	...	...	...
Class k	$\lvert FP_a \cap FN_k \rvert$	$\lvert FP_b \cap FN_k \rvert$	...	$\lvert TP_k \rvert$

Confusion matrixes for what?

- Used to analyze errors, to see which classes are confused with which.
- Contains all values for computing micro- and macro-averaged results.

Micro-Averaging and Macro-Averaging

Computation

Example: Evidence classification

- Assume an approach that classifies candidate evidence statements as being an “anecdote”, “statistics”, “testimony”, or “none”.

Confusion matrix of the results

Ground-truth	Classified as			
	Anecdote	Statistics	Testimony	none
Anecdote	199	5	35	183
Statistics	17	29	0	27
Testimony	30	1	123	71
None	118	7	36	1455

Total		Precision
TP	FP	per class
199	165	0.55
29	13	0.69
123	71	0.63
1455	281	0.84

Micro- vs. macro-averaged precision (recall and F_1-score analog)

- $Micro{-}P = \frac{199+29+123+1455}{199+29+123+1455+165+13+71+281} = 0.77$
- $Macro{-}P = \frac{0.55+0.69+0.63+0.84}{4} = 0.68$

Regression Effectiveness

Regression task

- A regression task requires to predict numeric values for instances from a (usually but not necessarily predefined) continuous scale.
- Examples. Automatic essay grading, review rating prediction, ...

Example: Automatic essay grading

- Given a set of n student essays, automatically assign each essay i a score $y_i \in \{1, ..., 4\}$.

  The 4-point scale is the default in today's grading systems.

Regression errors

- In many regression tasks, it is unlikely to predict the exact values of instances. Therefore, accuracy is not the primary measure.
- The focus is on the mean error of predicted values $Y = (y_1, \ldots, y_n)$ compared to ground-truth values $\hat{Y} = (\hat{y}_1, \ldots, \hat{y}_n)$.

Regression Effectiveness

Types of Regression Errors

Mean absolute error (MAE)

- The MAE is the mean difference of predicted to ground-truth values.
- It is robust to outliers, i.e., it does not treat them specially.

$$MAE \;=\; \frac{1}{n} \cdot \sum_{i=1}^{n} |y_i - \hat{y}_i|$$

Mean squared error (MSE)

- The MSE is the mean squared difference of predicted to ground-truth values.
- It is specifically sensitive to outliers.

$$MSE \;=\; \frac{1}{n} \cdot \sum_{i=1}^{n} (y_i - \hat{y}_i)^2$$

- Sometimes, also the root mean squared error (RMSE) is computed, defined as $RMSE = \sqrt{MSE}$.

Regression Effectiveness

Computation

Example: Automatic essay grading (revisited)

- Assume we have three automatic essay grading approaches applied to 10 essays resulting in the following scores.

	Essay										Regression error	
Approach	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**MAE**	**MSE**
Approach 1	2.6	2.6	2.6	2.6	2.6	2.6	2.6	2.6	2.6	2.6	0.88	1.04
Approach 2	1.0	3.2	2.0	2.1	3.0	3.1	2.8	3.1	1.2	4.0	0.55	1.28
Approach 3	1.5	2.0	1.5	2.5	2.0	2.7	3.3	3.5	3.2	3.6	0.58	0.40
Ground truth	1	1	2	2	3	3	3	3	4	4	0.00	0.00

Which approach is best?

- Approach 1 trivially always predicts the mean $\rightarrow$ useless in practice.
- Approach 2 has a better MAE than approach 3, but fails with its MSE.
- Whether MAE or MSE is more important, depends on the application.

  In essay grading, outliers are particularly problematic.

Evaluation of Effectiveness

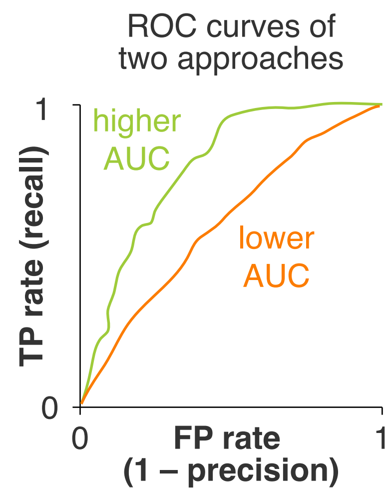
Other Measures *

Notice

- Accuracy, precision, recall, F_1-score, and mean absolute/squared error are the standard effectiveness measures.
- There are several other measures useful in particular settings.

Selection of other measures

- Error rate. Simply 1 – accuracy.
- Labeled attachment score. Proportion of fully correctly classified tokens in syntactic parsing.
- Precision@k. Precision within the top k results of a ranking problem (also recall@k is used where it makes sense).
- Area under curve (AUC). Expected proportion of positives ranked before a negative, based on the receiver-operating characteristic (ROC) curve.



Empirical Experiments

Empirical Experiments

Empirical experiments in text mining

- An empirical experiment tests a hypothesis based on observations.
- The focus is here on effectiveness evaluation in text mining.

Intrinsic vs. extrinsic effectiveness evaluation

- Intrinsic. The effectiveness of an approach is directly evaluated on the task it is made for.

  "What accuracy does a part-speech tagger *A* have on the dataset *D*?"

- Extrinsic. The effectiveness of an approach is evaluated by measuring how effective its output is in a *downstream task*.

  "Does the ouput of *A* improve sentiment analysis on *D'*?"

Corpus-based experiments vs. user studies

- We consider the empirical evaluation of approaches on corpora here.
- A whole different branch of experiments is related to *user studies*.

  Not covered in this course.

Datasets

What is a dataset?

- A sub-corpus of a corpus that is compiled and used for developing and/or evaluating approaches to specific tasks.

Development and evaluation based on datasets

1. An approach is developed based on a set of training instances.
2. The approach is applied to a set of test instances.
3. The output of the approach is compared to the ground-truth of the test instances using evaluation measures.
4. Steps 1–3 may be iteratively repeated to improve the approach.

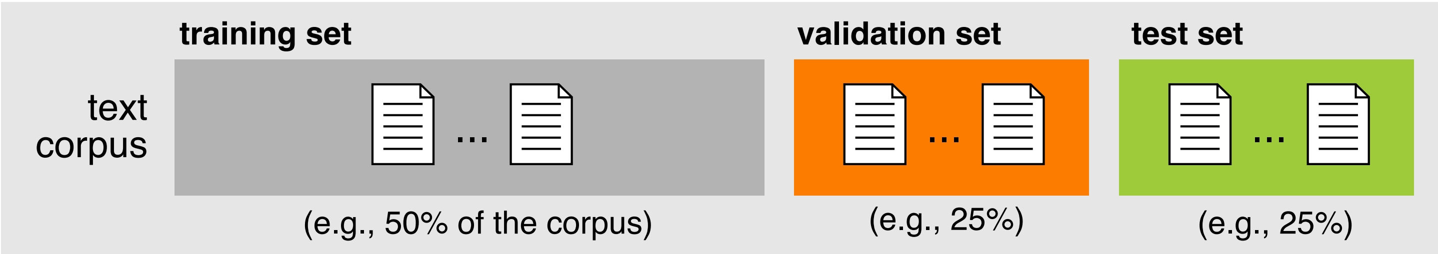
Corpus splitting

- The split of a corpus into datasets should represent the task well.

  Out of scope here. Example: No overlap of instances from one text in different sets.
- The way a corpus is split implies how to evaluate.
- Main evaluation types. *Training, validation, and test* vs. *cross-validation*.

Types of Evaluation

Training, Validation, and Test



Training set

- Known instances used to develop or statistically learn an approach.
- The training set may be analyzed manually and automatically.

Validation set (aka development set)

- Unknown test instances used to iteratively evaluate an approach.
- The approach is optimized on (and adapts to) the validation set.

Test set (aka held-out set)

- Unknown test instances used for the final evaluation of an approach.
- The test set represents unseen data.

Types of Evaluation

Cross-Validation

(Stratified) n-fold cross-validation

- A corpus is split into n dataset folds of equal size, usually $n = 10$.
  The split is done *stratified*, i.e., the target variable distribution is stable across folds.
- n runs. The evaluation results are averaged over n runs.
- i-th run. The i-th fold is used for evaluation (validation). All other folds are used for development (training).

Pros and cons of cross-validation

- Often preferred when data is small, as more data is given for training.
- Cross-validation avoids potential bias in a corpus split.
- Random splitting often makes the task easier, due to corpus bias.

Types of Evaluation

Variations

Repeated cross-validation

- Often, cross-validation is repeated multiple times with different folds.
- This way, coincidental effects of random splitting are accounted for.

Leave-one-out validation

- Cross-validation where n equals the number of instances.
- This way, any potential bias in the splitting is avoided.
- But even more data is given for training, which makes a task easier.

Cross-validation + test set

- When doing cross-validation, a held-out test set is still important.
- Otherwise, repeated development will overfit to the splitting.

Comparison

Example: Evidence classification (revisited)

- Assume an evidence classification approach obtains an accuracy of 60% on a given test set, how good is this?

Selected factors that influence effectiveness

- The number of classes and their distribution in the training set.
- The class distribution in the test set.
- The heterogeneity of the test set.
- The similarity between training and test set.
- The representativeness of the test set.
- The complexity of the task.

Observation

- Some factors can be controlled or quantified, but not all.
- To assess the quality of an approach, we need *comparison*.

Comparison

Upper Bounds and Lower Bounds

Why comparing?

- A new approach is seen as useful if it is better than other approaches, usually measured in terms of effectiveness.
- Approaches may be compared to a *gold standard* and to *baselines*.

Gold standard (upper bound)

- The gold standard represents the best possible result on a given task.
- For many tasks, the effectiveness that humans achieve is seen as best.
- For simplicity, the gold standard is often equated with the ground truth in a corpus. This means: perfect effectiveness.

Baseline (lower bound)

- A baseline is an alternative approach that has been proposed before or that can easily be realized.
- A new approach should be better than all baselines.

Comparison

Types of Baselines

Trivial baselines

- Approaches that can easily be derived from a given task or dataset.
- Used to evaluate whether a new approach achieves anything.

Standard baselines

- Approaches that are often used for related tasks.
- Used to evaluate how hard a task is.

Sub-approaches

- Sub-approaches of a new approach.
- Used to analyze the impact of the different parts of an approach.

State of the art

- The best published approaches for the addressed task (if available).
- Used to verify whether a new approach is best.

Comparison

Exemplary Baselines

Example: Evidence classification (revisited)

- Assume an evidence classification approach obtains an accuracy of 60% on a given test set, how good is this?

Exemplary dataset and task parameters (Al-Khatib et al., 2016)

• Four classes.	"anecdote",	"statistics",	"testimony",	"none" (majority)
• Test distribution.	18%	3%	10%	69%

Potential baselines

- Trivial. Random guessing achieves an accuracy of 25%.
- Trivial. Always predicting the majority achieves 69%.
- Standard. Using the distribution of word {1, 2, 3}-grams achieves 76%.
- State of the art. The best published value is 78%. (Al-Khatib et al., 2017)

Comparison
Implications

When does comparison work?

- Variations of a task may affect its complexity.
- The same task may have different complexity on different datasets.
- Only in *exactly* the same experiment setting, two approaches can be compared reasonably.

Example: Evidence classification (a last time)

- Assume evidence classification approach A obtains an accuracy of 79%, and approach B 78% in exactly the same setting.
- Is A better than B?

How to know that some effectiveness is better?

- Effectiveness differences may be coincidence.
- The significance of differences can be "proven" statistically.

Hypothesis Testing

Statistics

Variable

- An entity that can take on different quantitative or qualitative values.
  A variable thereby represents a distribution of values.

- Independent. A variable X that is expected to affect another variable.
- Dependent. A variable Y that is expected to be affected by others.
  Other types not in the focus here: Confounders, mediators, moderators, ...

Possible causes $X_1, \ldots, X_k \quad \rightarrow \quad$ Effect Y

Scales of variables

- Nominal. Values that represent discrete, separate categories.
- Ordinal. Values that can be ordered/ranked by what is better.
- Interval. Values whose difference can be measured.
- Ratio. Interval values that have a "true zero".
  A true zero indicates the absence of what is represented by a variable.

Interval vs. ratio scale test

- Only for ratios, it is right to say that a value is twice as high as another.

Statistics

Variables and Scales

What is independent, what is dependent?

"Does our sentiment analysis approach achieve higher accuracy with features based on part-of-speech tags than without them?"

Independent: features based on part-of-speech tags
Dependent: accuracy

What type of scale?

1. Celsius temperature
2. Exam grades
3. Phone prices
4. Colors
5. Text length

1. Interval 2. Ordinal 3. Ratio 4. Nominal 5. Ratio

Descriptive Statistics

What is descriptive statistics?

- Measures for summarizing (samples $\tilde{X}$ of) distributions of values X.
- Used to describe phenomena.

Measures of central tendency

- Mean. The arithmetic average M of a sample of values $\tilde{X}$ of size n.
  M is used for a sample, μ for the whole distribution.

$$M = \frac{1}{n} \sum_{i=1}^{n} \tilde{X}_i$$

- Median. The middle value Mdn of the ordered values in a sample.
  Even size: The value halfway between the two middle values.

$$Mdn = (\tilde{X}_{\lfloor \frac{n+1}{2} \rfloor} + \tilde{X}_{\lceil \frac{n+1}{2} \rceil}) \;/\; 2$$

- Mode. The value Md with the greatest frequency in a sample.

Descriptive Statistics

Central Tendency and its Disperson

When to use what tendency measure?

- Mean. For (rather) symmetrical distributions of interval/ratio values.
- Median. For ordinal values and skewed interval/ratio distributions.
- Mode. For nominal values.

Measures of dispersion

- Range. The distance r between minimum and maximum.

$$r = \tilde{X}_{max} - \tilde{X}_{min}$$

- Variance. The mean s^2 of all values' squared differences to the mean.

  s is used for a sample, σ for the whole distribution.

$$\text{biased}: \; s^2 = \frac{1}{n}\sum_{i=1}^{n}(\tilde{X}_i - M)^2 \qquad \text{unbiased}: \; s^2 = \frac{1}{n-1}\sum_{i=1}^{n}(\tilde{X}_i - M)^2$$

- Standard deviation. The square root s of the variance.

$$s = \sqrt{s^2}$$

Descriptive Statistics

Bias and Example

Biased vs. unbiased variance

- The biased variance formula tends to underestimate the real variance of the distribution.
- For samples, the unbiased variance formula is used in statistics.

  The division by $n-1$ instead of n corrects for the small sample size.

Example for an ordered sample of 10 values

$$\tilde{X} = (1, 3, 3, 3, 5, 6, 6, 7, 10, 15)$$

$$M = \frac{1}{10}\sum_{i=1}^{10}\tilde{X}_i = 5.9$$

$$Mdn = (\tilde{X}_4 + \tilde{X}_5)\ /\ 2 = 5.5$$

$$Md = 3$$

$$r = \tilde{X}_{10} - \tilde{X}_1 = 14$$

$$s^2 = \frac{1}{9}\sum_{i=1}^{10}(\tilde{X}_i - M)^2 \approx 15.97$$

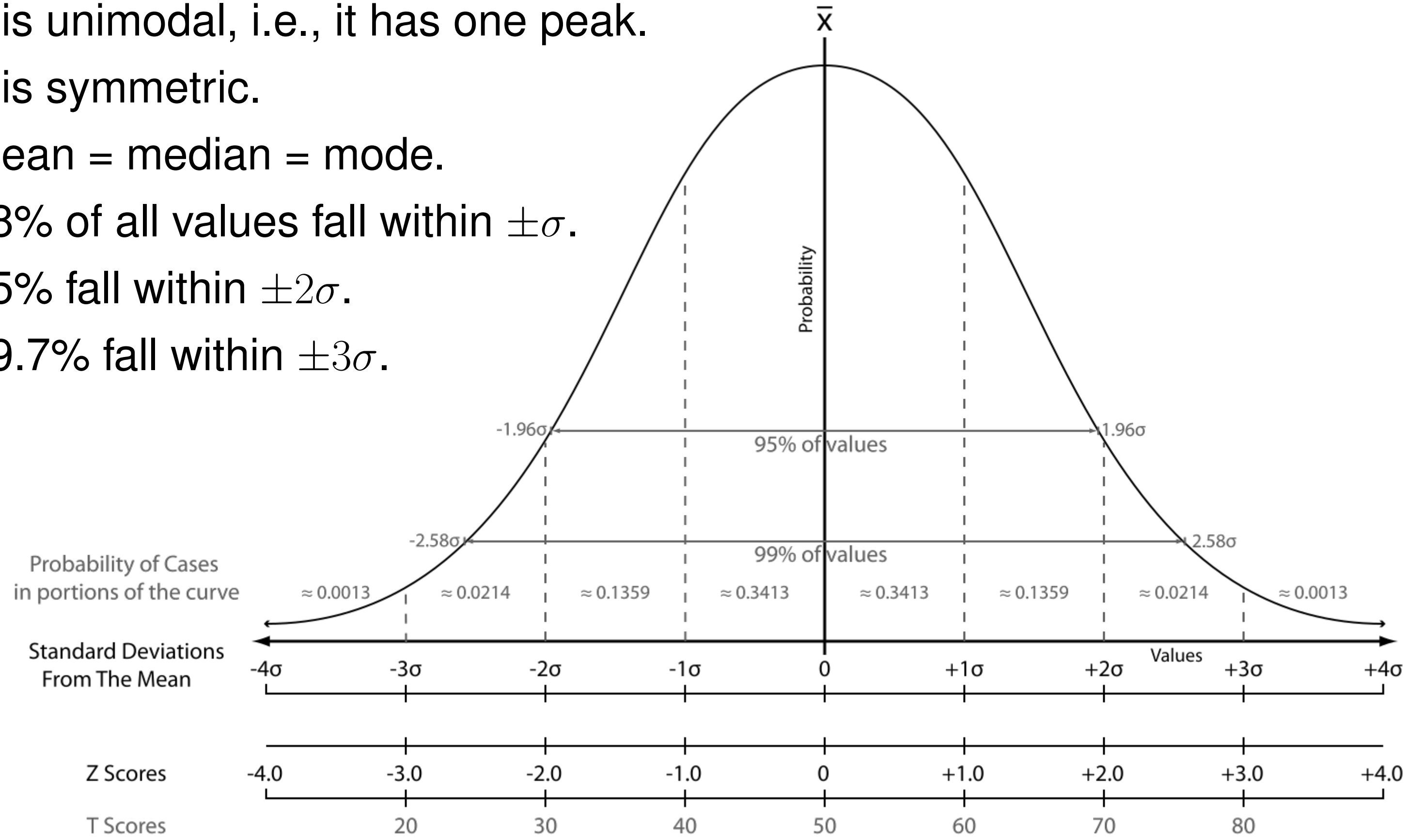
$$s = \sqrt{s^2} \approx 4.00$$

Descriptive Statistics

Normal Distribution

Normal distribution (aka Gaussian distribution)

- The frequency distribution that follows a normal curve.
- It is unimodal, i.e., it has one peak.
- It is symmetric.
- Mean = median = mode.
- 68% of all values fall within $\pm\sigma$.
- 95% fall within $\pm 2\sigma$.
- 99.7% fall within $\pm 3\sigma$.



Descriptive Statistics

Standard Scores

Standard score

- Indicates how many standard deviations a value is away from the mean of a distribution X.

z-score

- Indicates the precise location of a value X_i within a distibution X.

  Positive if above the mean, negative otherwise.

$$z = \frac{X_i - \mu}{\sigma} \quad \text{approximated as} \quad z = \frac{\tilde{X}_i - M}{s}$$

t-score

- Transforms a value $\tilde{X}_i$ from a sample of size n into a standardized comparable form.

  Usually used for small samples with less than 30 values.

$$t = \frac{\tilde{X}_i - M}{s/\sqrt{n}}$$

Inferential Statistics

What is inferential statistics?

- Procedures that help study *hypotheses* based on values.
- Used to make inferences about a distribution beyond a given sample.

Two competing hypotheses

- Research hypothesis (H). Prediction about how a change in variables will cause changes in other variables.

  "There is a statistically significant difference between the RMSE of our approach and the RMSE reported by Persing et al. (2015)."

- Null hypothesis (H_0). Antithesis to H.

  "There is *no* statistically significant difference between the RMSE of our approach and the RMSE reported by Persing et al. (2015)."

- If H_0 is true, then any results observed in an experiment that support H are due to chance or sampling error.

Inferential Statistics

Hypotheses

Two types of hypotheses

- Non-directional. Specifies only that any difference is expected.
  Indicates that a *two-tailed test* needs to be conducted.

  "There is a statistically significant difference between the RMSE of our approach and the RMSE reported by Persing et al. (2015)."

- Directional. Specifies the direction of an expected difference.
  Indicates that a *one-tailed test* needs to be conducted.

  "The RMSE of our approach is statistically significantly lower than the RMSE reported by Persing et al. (2015)."

A good hypothesis (Bartos, 1992)

- Is founded in a problem statement and supported by research.
- Is testable, i.e., it is possible to collect data to study the hypothesis.
- States an expected relationship between variables.
- Is phrased as simply and concisely as possible.

Hypothesis Testing

Hypothesis test (aka statistical significance test)

- A statistical procedure that determines how likely it is that the results of an experiment are due to chance (or sampling error).
- Tests whether a null hypothesis H_0 can be rejected (and hence, H can be accepted) at some chosen *significance level*.

Significance level α

- The accepted risk (in terms of a probability) that H_0 is wrongly rejected.

  Usually, α is set to 0.05 (default) or to 0.01.
- A choice of α = 0.05 means that there is no more than 5% chance that a potential rejection of H_0 is wrong.

  In other words, with $\geq$ 95% confidence a potential rejection is correct.

p-value

- The likelihood (in terms of a probability) that results are due to chance.
- If $p \leq \alpha$, H_0 is rejected. The results are seen as statistically significant.
- If $p > \alpha$, H_0 cannot be rejected.

Hypothesis Testing

Effect size *

Statistical significance vs. effect size

- Significance does not state how large a difference is.
- The effect size describes the magnitude of the difference.

Effect size measure Cohen's d

- The effect size is usually computed based on the standard deviations:

$$d = \frac{M_1 - M_2}{\sqrt{\frac{s_1 + s_2}{2}}}$$

- Small effect: $d \geq$ 0.2, medium effect: $d \geq$ 0.5, large effect: $d \geq$ 0.8.

Notice

- The focus is largely on significance in text mining (and in this course).

Hypothesis Testing

Testing a Hypothesis

Four steps of hypothesis testing

1. Hypothesis. State H and H_0.
2. Significance level. Choose α (always *before* the test!).
3. Testing. Carry out an appropriate hypothesis test to get the p-value.
4. Decision. Depending on α and p, reject H_0 or fail to reject it.

Hypothesis Testing

What Test to Choose

Hypothesis tests

- Different tests exist that make different assumptions about the data.
- A significance test needs to be chosen that fits the data.

Parametric vs. non-parametric tests

- Parametric. More powerful and precise, i.e., it is more likely to detect a significant effect when one truly exists.
- Non-parametric. Fewer assumptions and, thus, more often applicable.

Parametric test	Non-parametric correspondent
Independent t-test	Mann-Whitney Test
Dependent and one-sample t-test	Wilcoxon Signed-Rank Test
One way, between group ANOVA	Kruskal-Wallis
One way, repeated measures ANOVA	Friedman Test
Factorial ANOVA	–
MANOVA	–
Pearson	Spearman, Kendall's τ, χ^2
Bivariate regression	–

Hypothesis Testing

Assumptions

Assumptions of all significance tests

- Sampling. The sample is a random sample from the distribution.
  Notice: In text mining, each "instance" of a sample usually consists of multiple texts.
- Values. The values within each variable are independent.

Assumption of all parametric tests

- Scale. The dependent variable has an interval or ratio scale.
- Distribution. The given distributions are normally distributed.
  Tested by checking histograms or by using normality tests, e.g., the Shapiro-Wilk test.
- Variance. Distributions that are compared have the same variances.
  Tested using Levene's Test, Bartlett's test, or scatterplots and Box's M.

Test-specific assumptions

- In addition, specific tests may have specific assumptions.
- Depending on which are met, an appropriate test is chosen.

The Student's t-Test

What is the student's t-test?

- A parametric statistical significance test for small samples ($\sim n \leq$ 30).
- Computes a t-*score* from which significance can be derived.
- Types. Independent t-test, one-sample t-test, dependent t-test.

The term *student* was simply used as a pseudonym by the inventor.

Test-specific assumptions

- The independent variable has a nominal scale.
- t-tests are robust over moderate violations of the normality assumption.

One-tailed vs. two-tailed

- One-tailed. Test whether one value is higher or lower than another one.
- Two-tailed. Test whether two values are different from each other.

One sample vs. paired samples

- One sample. A sample mean is compared to a known value.
- Paired samples. Two sample means are compared to each other.

The Student's t-Test

t-Score

t-distribution

- Variation of the normal distribution for small sample sizes.
- Dependent on the *degrees of freedom (DoF)* in an experiment.

  Put simply, DoF is the number of potential variations in the computation of a value.
- Statistics tools, such as *R*, can compute t-distributions.
- Otherwise, tables exist with the significance confidences of t-values.

  https://en.wikipedia.org/wiki/Student%27s_t-distribution

	95%	**97.5%**	**99%**	**99.5%**	**99.9%**	**99.95%**	*One-tailed*
DoF	**90%**	**95%**	**98%**	**99%**	**99.8%**	**99.9%**	*Two-tailed*
3	2.353	3.182	4.541	5.841	10.21	12.92	
4	2.132	2.776	3.747	4.604	7.173	8.610	
...	...	...	...	...	...	...	

How to use the table

- Compare t-score with value at given DoF and α ($=1-$ confidence).
- If t-score > value, then H_0 can be rejected. Otherwise not.

The Student's t-Test

One-Sample t-Test

One-sample t-test

- Compares the mean M of a sample $\tilde{X}$ of size n from a distribution X to a known distribution mean μ.
- $n-1$ degrees of freedom (since the n-th value is implied by M).

Example research question

- "Does our essay grader improve over the best result reported so far?"

  H_0. "The RMSE of our approach is not statistically significantly lower than the RMSE reported by Persing et al. (2015)."

Process

1. Compute the mean M of all sample values $\tilde{X}$.
2. Compute the variance: $s^2 = \frac{1}{n-1} \sum_{i=1}^{n} (\tilde{X}_i - M)^2$
3. Compute the standard deviation of the distribution of means: $s_M = \sqrt{\frac{s^2}{n}}$

   Also called *standard error*. Division by n normalizes into the t-distribution.
4. Compute the t-score: $t = \frac{M-\mu}{S_M}$

The Student's t-Test

Dependent t-Test

Dependent t-test (aka paired-sample test)

- Compares two samples $\tilde{X}, \tilde{X}'$ of size n from the same distribution X, taken at different *times* (i.e., they may have changed in between).
- $n - 1$ degrees of freedom.

Example research question

- "Does adding POS tags improve our sentiment analysis approach?"

H_0. "The accuracy of our approach is not statistically significantly higher with POS tags than without POS tags."

Process

1. Compute each difference $\Delta_i = \tilde{X}_i - \tilde{X}'_i$ between the paired samples.
2. Compute the mean M of all differences Δ.
3. Compute the variance: $s^2 = \frac{1}{n-1} \sum_{i=1}^{n} (\Delta_i - M)^2$
4. Compute the standard error: $s_M = \sqrt{\frac{s^2}{n}}$
5. Compute the t-score: $t = \frac{M-0}{S_M} = \frac{M}{S_M}$

The Student's t-Test

Independent t-Test

Independent t-test

- Compares two independent samples $\tilde{X}, \tilde{X}'$ of size n from the same distribution X.
- $2 \cdot (n-1) = 2n-2$ degrees of freedom.

Example research question

- "Are the predicted essay grades different from the gold standard?"

H_0. "There is no statistically significant difference between the gold standard scores and the scores predicted by the approach."

Process

1. Compute the means M, M' of all sample values of $\tilde{X}, \tilde{X}'$.
2. Compute the variances: $s_1^2 = \sum_{i=1}^{n} \frac{(\tilde{X}_i - M)^2}{n-1}$, $\quad s_2^2 = \sum_{i=1}^{n} \frac{(\tilde{X}'_i - M')^2}{n-1}$
3. Compute the standard error: $S_M = \sqrt{\frac{s_1^2 + s_2^2}{2}} \cdot \sqrt{\frac{2}{n}}$
4. Compute the t-score: $t = \frac{M - M'}{S_M}$

The Student's t-Test

Example: One-Tailed One-Sample t-Test

"The essay grading approach achieves a lower RMSE than 0.244"

1. State hypotheses and define significance level.

   H: RMSE $- 0.244 < 0$ $\quad H_0$: RMSE $- 0.244 \geq 0$ $\quad \alpha = 0.05$

2. Given a sample (say, $n = 5$), compute RMSE values.

   $$\tilde{X} = (0.226, 0.213, 0.200, 0.268, 0.225)$$

3. Compute sample mean, variance, and standard error.

   $$M = \frac{1}{5} \cdot (0.226 + 0.213 + 0.200 + 0.268 + 0.225) = 0.226$$

   $$s^2 = \frac{(0.226-0.226)^2 + (0.213-0.226)^2 + (0.200-0.226)^2 + (0.268-0.226)^2 + (0.225-0.226)^2}{4} = 0.00065$$

   $$s_M = \sqrt{\frac{0.00065}{5}} = 0.0114$$

4. Compute t-score and make decision.

   $t = \frac{0.244-0.226}{0.0114} = 1.579$ $\quad$ 4 DoFs $\quad$ critical t-value from table is 2.132.

   $\rightarrow \quad 1.579 < 2.132$, so H_0 cannot be rejected.

The Student's t-Test

Alternatives

What to do if the t-test assumptions are not met?

- Test-specific assumption. Find other parametric test that is applicable.
- Assumptions of parametric tests. Find applicable non-parametric test.
  A common case is that the given values are not normally distributed.
- Assumptions of all significance tests. Hypotheses cannot be tested.

Example: Wilcoxon Signed-Rank Test *

- Non-parametric alternative to dependent t-test, for small sample sizes.
- Requires randomly chosen, independent paired samples, dependent variable with interval or ratio scale.
- Does not require a normal distribution.
- Computes a z-score based on a ranking of the differences of the pairs.
  The value can also be checked against a reference table.

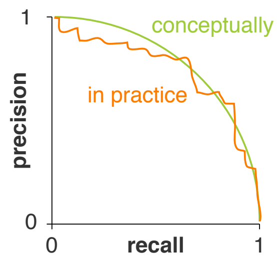
Conclusion

Summary

Empirical methods

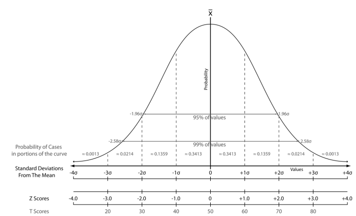
- Text mining uses empirical methods for linguistic tasks.
- An annotated text corpus represents the data of a task.
- Approaches are developed and evaluated on corpora.

Evaluation measures



- Text mining is usually evaluated for its effectiveness.
- Measures: Accuracy, precision, recall, F_1-score, ...
- Effectiveness is measured in experiments on datasets.

Comparison



- Need to compare approaches to reasonable baselines.
- Descriptive and inferential statistics play a role.
- Significance tests check whether a result is better.

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