Computational Argumentation – Part II

Basics of Natural Language Processing

Henning Wachsmuth

henningw@upb.de

PADERBORN UNIVERSITY

Learning goals

- **Concepts**
  - Basics from linguistics, statistics, and machine learning

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- **Methods**
  - How to develop and evaluate data-driven algorithms
  - Standard techniques used in machine learning
  - Types of analyses used in computational linguistics

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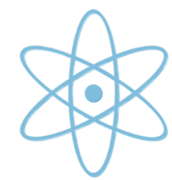
- **Associated research fields**
  - Computational linguistics



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- **Within this course**
  - Concepts and methods this course builds upon

- **Disclaimer**
  - The basics selected here are all but complete and only revisited high-level.
    For a more comprehensive overview, see e.g. the slides of my bachelor‘s course ”Introduction to Text Mining“.

Outline

I. Introduction to computational argumentation

II. Basics of natural language processing

- **a) Introduction**
- b) Linguistics
- c) Empirical methods
- d) Tasks and techniques
- e) Rule-based NLP
- f) Statistical NLP
- g) Conclusion

III. Basics of argumentation

IV. Argument acquisition

V. Argument mining

VI. Argument assessment

VII. Argument generation

VIII. Applications of computational argumentation

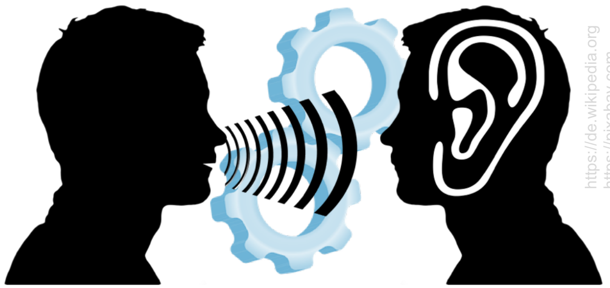
IX. Conclusion

Natural language processing (recap)

- **Natural language processing (NLP)** (Tsujii, 2011)
  - Algorithms for understanding and generating speech and human-readable text
  - From natural language to structured information, and vice versa

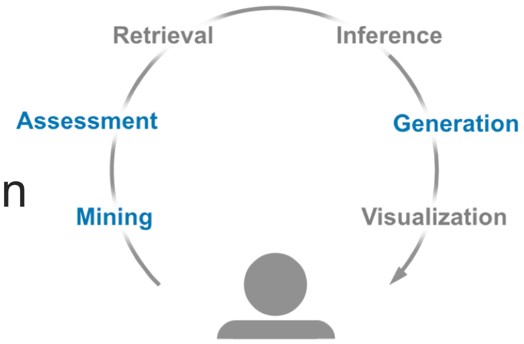
Analysis
Synthesis

- **Computational linguistics** (see http://www.aclweb.org)
  - Intersection of computer science and linguistics
  - Technologies for natural language processing
  - Models to explain linguistic phenomena, based on knowledge and statistics



- **Main NLP stages in computational argumentation**
  - Mining arguments and their relations from text
  - Assessing properties of arguments and argumentation
  - Generating arguments and argumentative text

  In most applications, not all stages/tasks are needed.



Evolution of natural language processing (NLP)

- **Selected milestones from industry**
  - February 2011. IBM’s Watson wins Jeopardy
    https://www.youtube.com/watch?v=P18EdAKuC1U
  - October 2011. Apple‘s Siri starts on the iPhone
    https://www.youtube.com/watch?v=gUdVie_bRQo
  - August 2014. Microsoft Skype translates conversations in real time
    https://www.youtube.com/watch?v=RuAp92wW9bg
  - May 2018. Google Assistant does phone call appointments
    https://www.youtube.com/watch?v=pKVppdt_-B4
  - June 2018. IBM Debater competes in classical debates
    https://www.youtube.com/watch?v=UeF_N1r91RQ
- **Observations**
  - All applications need to ”understand“ language → linguistics needed
  - None of these applications works perfectly → empirical methods needed

Next section: Linguistics

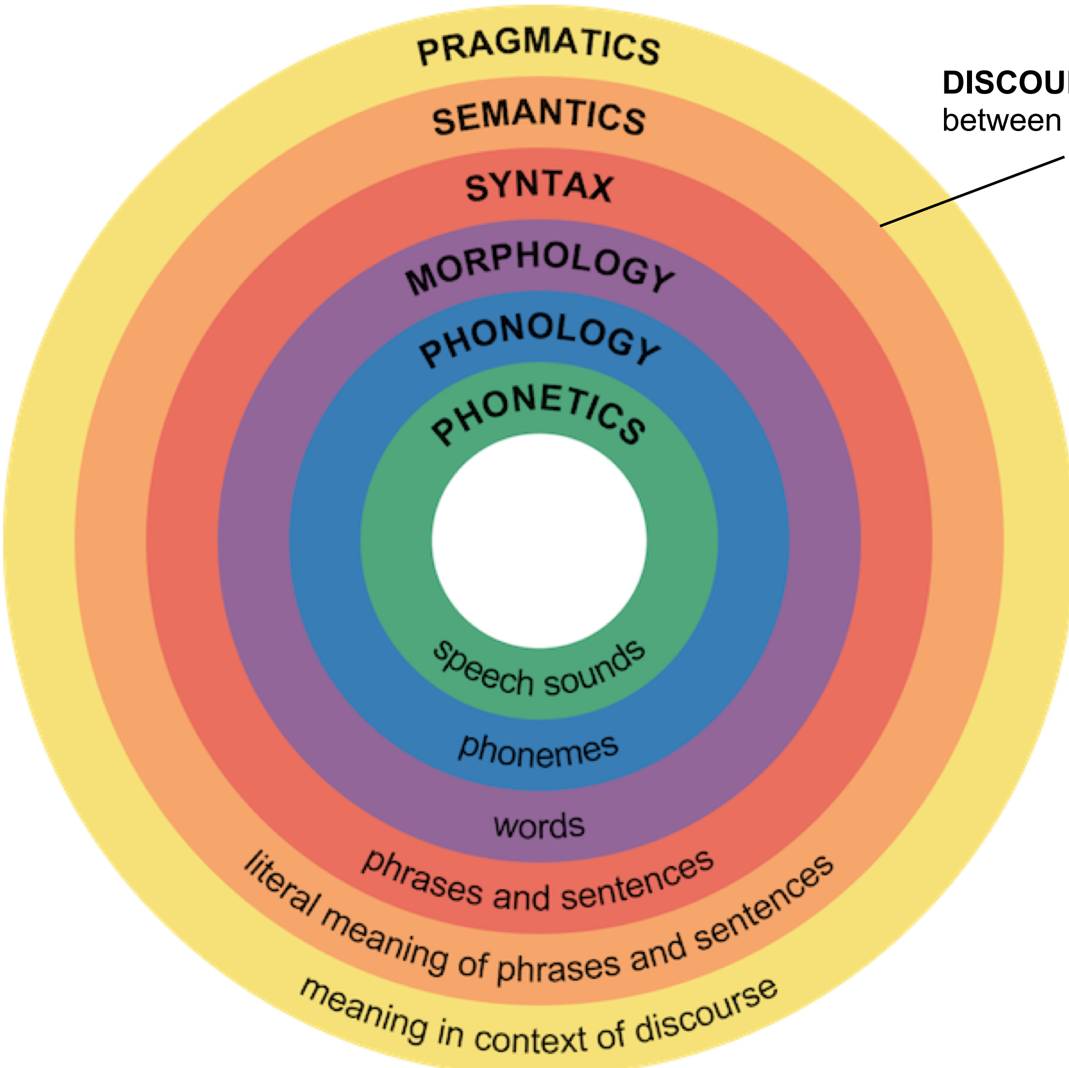
What is linguistics?

- **Linguistics**
  - The study of spoken and written natural language in terms of the analysis of form, meaning, and context.

- **Levels of spoken language only**
  - Phonetics. The physical aspects of speech sounds.
  - Phonology. The linguistic sounds of a particular language.

- **Levels of spoken and written language**
  - Morphology. The senseful components of words and wordforms.
  - Syntax. The structural relationships between words, usually within a sentence (or a similar utterance).
  - Semantics. The meaning of single words and compositions of words.
  - Discourse. Linguistic units larger than a single sentence, such as paragraphs or complete documents.
  - Pragmatics. How language is used to accomplish goals.

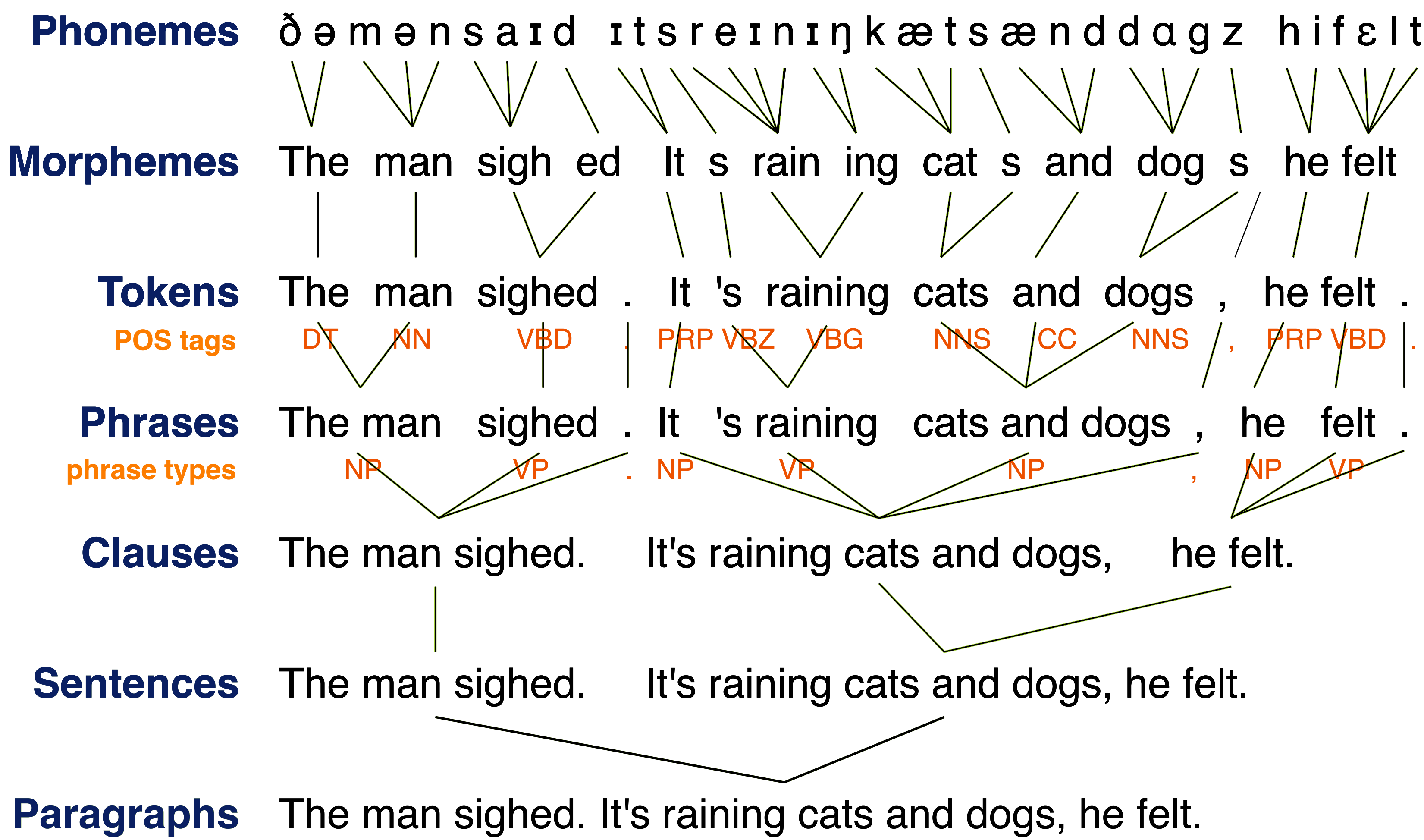
Levels of language analysis



DISCOURSE is on the boundary between semantics and pragmatics.

https://en.wikipedia.org

Linguistic text units



Main morphological concepts

- **Word**
  - The smallest unit of language that is to be uttered in isolation.
    Example: ”cats“ and ”ran“ in ”cats ran.“
- **Lemma**
  - The dictionary form of a word.
    Example: ”cat“ for ”cats“, ”run“ for ”ran“
- **Wordform**
  - The fully inflected surface form of a lemma as it appears in a text.
    Example: ”cats“ for ”cats“, ”ran“ for ”ran“
- **Stem**
  - The part of a word(form) that never changes.
    Example: ”cat“ for ”cats“, ”ran“ for ”ran“
- **Token**
  - The smallest text unit in NLP: A wordform, number, symbol, or similar.
    Example: ”cats“, ”ran“, and ”.“ in ”cats ran.“ (whitespaces are usually not considered as tokens)

Main syntactic concepts

- **Part-of-speech (POS)**
  - The lexical category (or word class) of a word.
  - Abstract classes. Nouns, verbs, adjectives, adverbs, prepositions, ...
  - POS tags. NN (single nouns), NNS (plural nouns), NNP (proper nouns), ...
- **Phrases**
  - A contiguous sequence of related words, functioning as a single meaning unit.
  - Phrases often contain nested phrases.
  - Types. Noun phrase (NP), verb phrase (VP), prepositional phrase (PP).
    Sometimes also adjectival phrase (AP) and adverbial phrase (AdvP).
- **Clause**
  - The smallest grammatical unit that can express a complete proposition.
  - Types. Main clause and subordinate clause.
- **Sentence**
  - A grammatically independent linguistic unit consisting of one or more words.

Main semantic concepts

- **Lexical semantics**
  - The meaning of words and multi-word expressions.
    Different senses of a word, the roles of predicate arguments, ...

- **Compositional semantics**
  - The meaning of the composition of words in phrases, sentences, and similar.
    Relations, scopes of operators, and much more.

- **Entities**
  - An object from the real world.
  - Named entities. Persons, locations, organizations, products, ...
    For example, ”Jun.-Prof. Dr. Henning Wachsmuth”, “Paderborn”, “Paderborn University”
  - Numeric entities. Values, quantities, ranges, periods, dates, ...
    For example, “in this year”, “2018-10-18”, “$ 100 000”, “60-68 44”

- **Relations**
  - Semantic. Relations between entities, e.g., organization *founded in* period.
  - Temporal. Relations describing courses of events, e.g., as in news reports.

Main discourse and pragmatics concepts

- **Discourse (structure)**
  - Linguistic utterances larger than a sentence, e.g., paragraphs or entire texts.
    Usually monological. Dialogical discourse often referred to as *dialogue*.
  - Discourse segments. Building block of a discourse in terms of linguistic units.
  - Coherence relations. Semantic or pragmatic relations between segments.

- **Coreference**
  - Two or more expressions in a text that refer to the same thing.
  - Types. Pronouns in anaphora and cataphora, coreferring noun phrases, ...
    Examples: "**Apple** is based in Cupertino. **The company** is actually called **Apple Inc.**, and **they** make hardware."

- **Speech acts**
  - Linguistic utterances with a performative function.

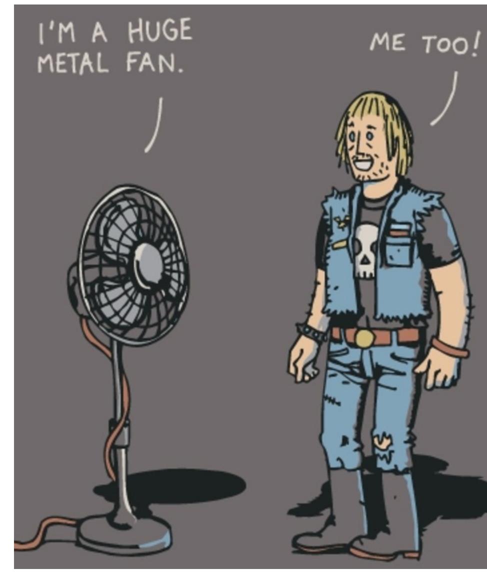
- **Communicative goals**
  - Specific functions of passages within a discourse.
  - Specific effects intended to be achieved by an untterance.

more details in the lecture on basics of argumentation

What makes language understanding hard?

- **Ambiguity**
  - The fundamental challenge of NLP is that language is ambiguous.

- **Ambiguity is pervasive**
  - Phonetic. ”wreck a nice beach”
  - Word sense. ”I went to the bank”.
  - Part of speech. ”I made her duck.”
  - Attachment. ”I saw a kid with a telescope.”
  - Coordination. ”If you love money problems show up.“
  - Scope of quantifiers. ”I didn’t buy a car.”
  - Speech act. “Have you emptied the dishwasher?”



- **Other challenges**
  - World knowledge. ”Trump must rethink capital punishment”
  - Domain dependency. ”Read the book!”
  - Language dependency. ”Bad”

  ... and many more

(Felbo et al., EMNLP 2017)

Is written language enough?

- **What‘s the purpose of this sentence?**
  - ”I never said she stole my money.“

- **Possible interpretations**
  - I never said she stole my money.
    Someone else said it, but I didn’t.
  - I never said she stole my money.
    I simply didn’t ever say it.
  - I never said she stole my money.
    I might have implied it in some way. But I never explicitly said it.
  - I never said she stole my money.
    I said someone took it. But I didn’t say it was her.
  - I never said she stole my money.
    I just said she probably borrowed it.
  - I never said she stole my money.
    I said she stole someone else’s money.
  - I never said she stole my money.
    But not my money.

Next section: Empirical methods

Development and evaluation in NLP

- **Development and evaluation**
  - NLP algorithms are developed based on *text corpora*.
  - The output of NLP algorithms is rarely free of errors, which is why it is usually evaluated empirically in comparison to ground-truth annotations.

- **Evaluation criteria**
  - Effectiveness. The extent to which the output of an algorithm is correct.
  - Efficiency. The consumption of time (or space) of an algorithm on an input.
  - Robustness. The extent to which an algorithm remains effective (or efficient) across different inputs, often in terms of textual domains.

- **Evaluation measures**
  - Quantify the quality of an algorithm on a specific task and text corpus.
  - Algorithms can be ranked with respect to an evaluation measure.
  - Different measures are useful depending on the task.

Annotated text corpora

- **Text corpus (and datasets)**
  - A collection of real-world texts with known properties, compiled to study a language problem.
  - The texts are often *annotated* with meta-information.
  - Corpora are usually split into datasets for developing (training) and/or evaluating (testing) an algorithm.

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- **Annotations**
  - Marks a text or span of text as representing meta-information of a specific type.
  - Also used to specify relations between different annotations.

Time entity / Organization entity

“ 2014 ad revenues of Google are going to reach

Reference / Time entity

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

Reference / Time entity / Founded relation

Its IPO followed in 2004 . […] “

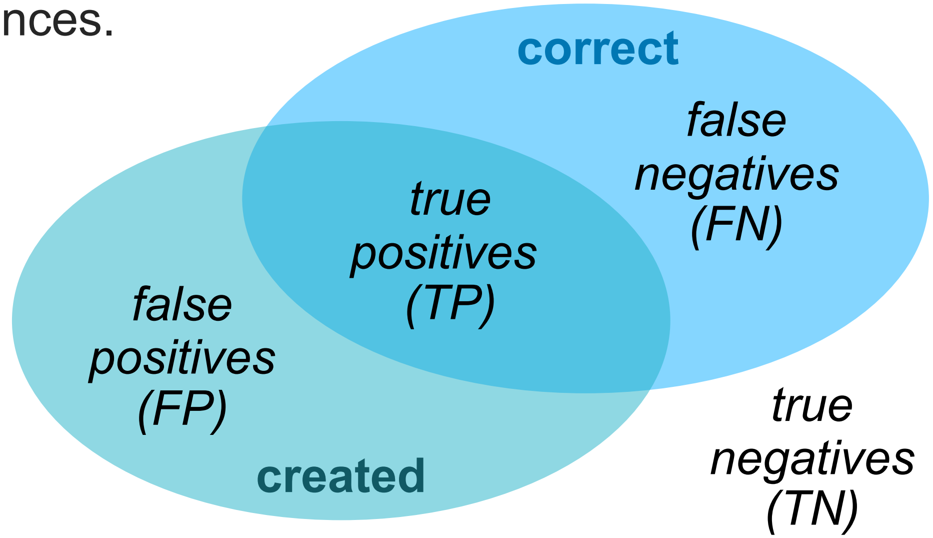
Topic: ”Google revenues“ Genre: ”News article“

- **Types of annotations**
  - Ground-truth. Manual annotations, often created by experts.
  - Automatic. NLP algorithms add annotations to texts.

more details in the part on acquisition

Evaluation of effectiveness in classification tasks

- **Instances in classification tasks**
  - Positives. The output instances (annotations) an algorithm has created.
  - Negatives. All other possible instances.



- **Accuracy**
  - Used if positives and negatives are similarly important.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

- **Precision, recall, and F_1-score**
  - Used if positives are in the focus.

$$Precision\ (P) = \frac{TP}{TP + FP} \qquad Recall\ (R) = \frac{TP}{TP + FN} \qquad F_1\text{-score} = \frac{2 \cdot P \cdot R}{P + R}$$

  - In multi-class tasks, *micro*- and *macro-averaged* values can be computed.

Evaluation of effectiveness in regression tasks

- **Instances in regression tasks**
  - In regression tasks, algorithms predict values y_i from a real-valued scale.
  - The numeric difference to the ground-truth values y_i^* is usually in the focus.

- **Mean absolute error (MAE)**
  - Used if outliers require no special treatment.

$$MAE = \frac{1}{n} \cdot \sum_{i=1}^{n} |y_i - y_i^*|$$

- **Mean squared error (MSE)**
  - Used if outliers are considered particularly problematic.

$$MSE = \frac{1}{n} \cdot \sum_{i=1}^{n} (y_i - y_i^*)^2$$

- **Root mean squared error (RMSE)**
  - Just a different way of quantifying the squared error, $RMSE = \sqrt{MSE}$

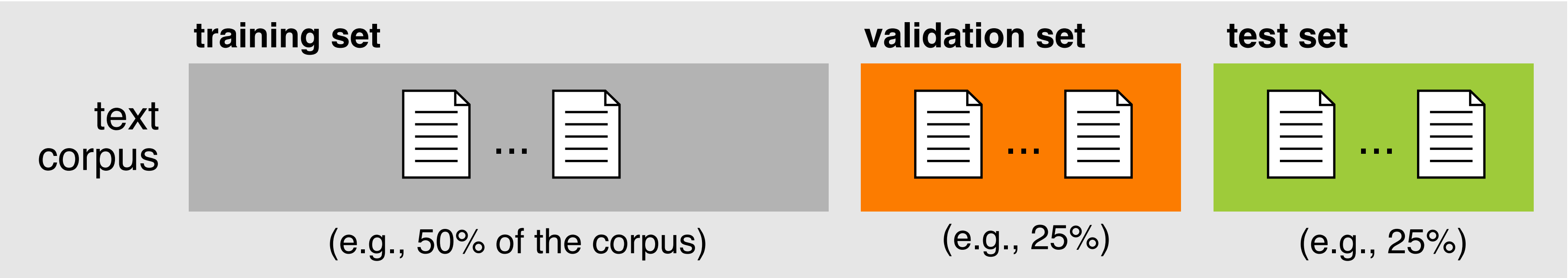
Dataset preparation

- **Dataset preparation**
  - Text corpora usually contain annotations for the task to be studied.
  - Not always, these annotations match with the task instances required for development and evaluation.

- **Creation of task instances**
  - Particularly, ”negative” instances often need to be created for learning.
    Example: ”[Jaguar]$_{ORG}$ is named after the animal *jaguar*.”
  - Also, annotations may have to be mapped to other task instances.
    Example: Ratings 1–2 → ”negative”, 3 → ignore, 4–5 → ”positive”

- **Balancing of datasets**
  - A balanced distribution of target classes in the training set is often preferable.
  - Undersampling. Removal of instances from majority classes.
  - Oversampling. Addition of instances from minority classes.
  - In machine learning, an alternative is to weight classes inverse to their size.

Training, validation, and test set



- **Training set**
  - Known instances used to develop or statistically learn an algorithm.
  - The training set may be analyzed manually and automatically.
- **Validation set (aka development set)**
  - Unknown test instances used to iteratively evaluate an algorithm.
  - The algorithm is optimized towards and adapts to the validation set.
- **Test set (aka held-out set)**
  - Unknown test instances used for the final evaluation of an algorithm.
  - The test set represents unseen data.

Cross-validation

- **(Stratified) *n*-fold cross-validation**
  - Randomly split a corpus into *n* datasets of equal size, usually *n = 10.*
  - The development and evaluation consist of *n* runs. The evaluation results are averaged over all *n* runs.
  - In the *i*-th run, the *i*-th fold is used for evaluation (testing). 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.

Comparison

- **Need for comparison**
  - It is unclear how good a measured effectiveness result in a given task is.
  - Comparison against lower (and upper) bounds is needed.
- **Baseline (lower bound)**
  - An alternative approach proposed before or can be developed easily.
  - A new algorithm aims to be better than all baselines.
- **Types of baselines**
  - Trivial. An approach that can easily be derived from a given task or dataset.
  - Standard. An approach that is often used for related tasks.
  - Sub-approach. A sub-part of a new approach.
  - State of the art. The best published approach for the addressed task.
- **Gold standard (upper bound)**
  - The best possible result in a given task, often what humans would achieve.
  - Often equated with the ground-truth annotations in a corpus.

Empirical research and variables

- **Empirical methods**
  - Quantitative methods based on numbers and statistics.
  - Study questions on behaviors and phenomena by analyzing data.
  - Asks about the relationships between variables.

- **Variable**
  - An entity that can take on different numeric or non-numeric values.
  - Independent. A variable *X* that is expected to affect another variable.
  - Dependent. A variable *Y* that is expected to be effected by others.
  - Other. Confounders, mediators, moderators, ...

- **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 an absolute zero.

Descriptive statistics

- **Descriptive statistics**
  - Measures for summarizing and comprehending distributions of values.
  - Used to describe phenomena.

- **Measures of central tendency**
  - Mean. The arithmetic average of a sample from a distribution of values.
    For (rather) symmetrical distributions of interval/ratio values.
  - Median. The middle value of the ordered values in a sample.
    For ordinal values and skewed interval/ratio distributions.
  - Mode. The value with the greatest frequency in a sample.
    For nominal values.

- **Measures of dispersion**
  - Range. The distance between minimum and maximum in a sample.
  - Variance. The mean squared difference between each value and the mean.
  - Standard deviation. The square root of the variance.

Inferential statistics

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

- **Two competing hypothesis**
  - Research hypothesis (H). Prediction about how some inpedendent variables will affect a dependent variable.
  - Null hypothesis (H_0). Antithesis to H.

> *"The accuracy of our approach is not higher with POS tags than without."*

- **Hypothesis test (aka statistical significance test)**
  - A statistical procedure which determines the probability (p-value) that results supporting H are due to chance (or sampling error).
  - Significance given, if p is $\leq$ a significance level α (usually 0.05 or 0.01).

- **Steps in a hypothesis test**
  - State H and H_0, choose α.
  - Compute p-value with an adequate test. Decide whether H_0 can be rejected.

Hypothesis tests

- **How to choose an adequate test?**
  - All tests require a random sample and independent values of variables.
  - Parametric vs. non-parametric. Parametric tests make it easier to find significance but do not always apply.

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
Pearson	Spearman, Kendall's τ , χ^2

- **Prerequisites of parametric tests**
  - The dependent variable needs to have an interval or ratio scale.
  - The distributions needs to be normal.
  - The compared distributions need to have the same variances.

  Besides, different tests have different specific prerequisites.

Next section: Tasks and techniques

Common text analyses

- **Lexical and syntactic**
  - Tokenization
  - Sentence splitting
  - Paragraph detection

  - Stemming
  - Lemmatization
  - Part-of-speech tagging

  - Similarity computation
  - Spelling correction
  - Phrase chunking

  - Dependency parsing
  - Constituency parsing

  ... and some more

- **Semantic and pragmatic**
  - Attribute extraction
  - Numeric entity recognition
  - Named entity recognition

  - Reference resolution
  - Entity relation extraction
  - Temporal relation extraction

  - Topic detection
  - Authorship attribution
  - Sentiment analysis

  - Discourse parsing
  - Spam detection

  ... and many many more

Example task: Information extraction

- **Information extraction**
  - The mining of entities, their attributes, relations between entities, and events the entities participate in from natural language text.
  - The output is structured information that can, e.g., be stored in databases.

- **Example task**
  - Extraction of the founding dates of companies

Time entity — Organization entity

“ 2014 ad revenues of Google are going to reach

Reference — Time entity

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

Reference — Time entity — Founded relation

Its IPO followed in 2004 . [...] “

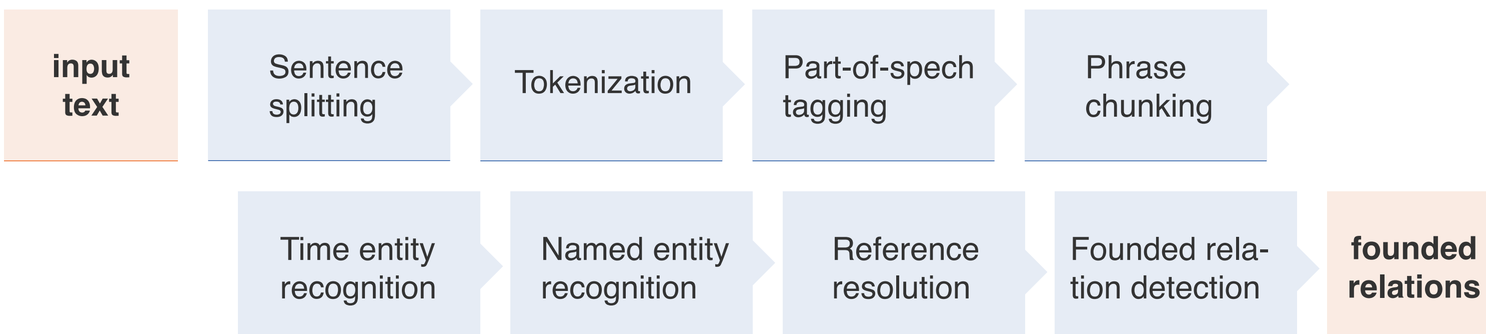
Output: Founded("Google", 1998)

- **Typical text analysis steps**
  1. Lexical and syntactic preprocessing
  2. Named and numeric entity recognition
  3. Reference resolution
  4. Entity relation extraction

Text analysis pipelines and alternatives

- **Text analysis pipeline**
  - The standard way to tackle an NLP task is with a pipeline that sequentially applies a set of algorithms to the input texts.
  - The output of one algorithm is the input to the next.

- **Example pipeline**
  - Extraction of the founding dates of companies



- **Alternatives**
  - Joint model. Realizes multiple analysis steps at the same time.
  - Neural network. Often works on the raw input text.

Dimensions of NLP tasks

- **Types of tasks**
  - Classification. Each input instance is assigned a predefined class label.
  - Regression. Each input instance is assigned a numeric value.
  - Clustering. A set of input instances is grouped into not-predefined classes.

  ... and some others

- **Types of approaches**
  - Supervised. Training instances with known output used in development.
  - Unsupervised. No output labels/values used in development.

  ... and some others

- **Types of techniques**
  - Rule-based. Analysis based on manually encoded expert knowledge.
    Knowledge includes rules, lexicons, grammars, ...
  - Feature-based. Analysis based on statistical patterns in text features.
    The text features used are encoded manually or semi-automatically.
  - Neural. Analysis based on statistical patterns in self-learned functions.
    Neural networks automatically learn and represent complex functions (often called *deep learning*).

Overview of rule-based and statistical techniques

- **Rule-based techniques**
  - (Hand-crafted) decision trees. Analyze text in a series of if-then-else rules.
  - Lexicon matching. Match text spans with terms from a lexicon.
  - Regular expressions. Extract text spans that follow sequential patterns.
  - Probabilistic context-free grammars. Parse hierarchical structures of spans.

  ... among others

- **Statistical (machine learning) techniques**
  - Categorization. Assign a label to a text or span of text.
  - Sequence labeling. Assign a label to each span in a sequence of spans.
  - Scoring. Predict a score (or other numeric value) for a text or span of text.
  - Clustering. Find possibly overlapping groups of similar texts.

  ... among others

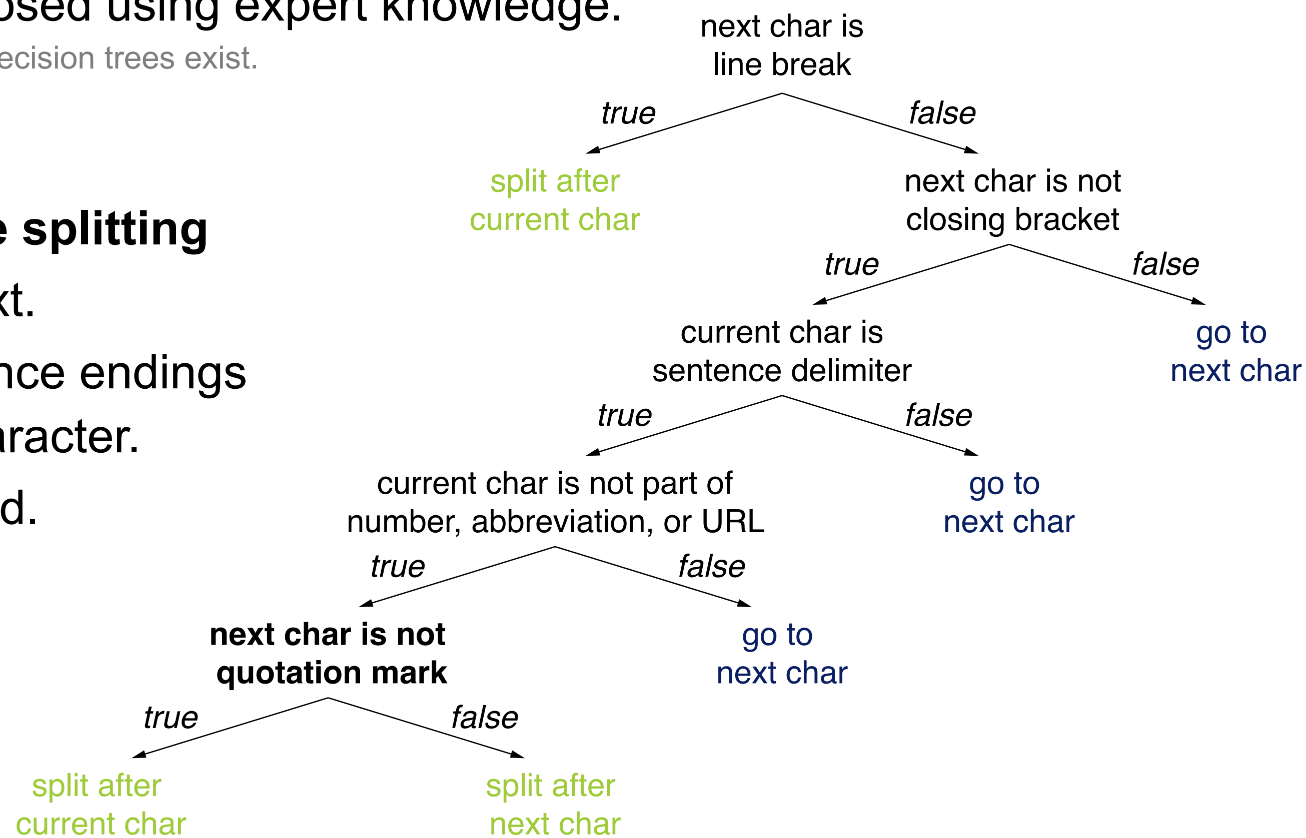
- **Rules vs. statistics**
  - Rule-based techniques are often easier to control and explain.
  - Statistical techniques are often more effective.

Next section: Rule-based NLP

NLP using decision trees

- **(Hand-crafted) Decision trees**
  - The representation of a series of if-then-else decision rules.
  - Inner nodes are decision criteria, leafs the final outcomes in a task.
  - Rules are composed using expert knowledge.
    Also, machine-learned decision trees exist.

- **Example: Sentence splitting**
  - Given a plain text.
  - Check for sentence endings character by character.
  - Split and proceed.



NLP using lexicons

- **Several types of lexicons**
  - Terms. Term lists, language lexicons, vocabularies
  - + Definitions. Dictionaries, glossaries, thesauri
  - + Structured information. Gazetters, frequency lists, confidence lexicons
- **Use cases of lexicons**
  - A given lexicon can be used to find all term occurrences in a text.
  - The existence of a given term in a lexicon can be checked.
  - The density or distribution of a vocabulary in a text can be measured.
- **Example: Attribute extraction**
  - Given a training set where attributes are annotated.
  - Compute confidence of each term, i.e., how often it is annotated as attribute.
  - Consider terms with confidence above a certain threshold as attributes.

Attribute	Confidence
minibar	1.00
towels	0.97
wi-fi	0.83
front desk	0.74
alcohol	0.5
waiter	0.4
buffet	0.21
people	0.01

NLP using regular expressions

- **Regular expression (regex)**
  - A representation of a regular grammar.
  - Combines characters and meta-characters to generalize over language structures.
  - Used in NLP mainly to match text spans that follow clear sequential patterns.

- **Types of patterns in regexes**
  - Disjunctions. Alternative options, such as `([Ww]oodchuck|[Gg]roundhog)`.
  - Negation+choice. Restrictions and arbitrary parts, such as `[^A-Z]` or `19..`.
  - Repetitions. Parts that are optional and/or may appear multiple times, such as `woo(oo)?dchuck`, `woo(oo)*dchuck`, or `woo(oo)+dchuck`.

- **Example**
  - `(0?[1-9]|[10-31])\.(0?[1-9]|[10-12])\.(19|20)[0-9][0-9]`
    matches German dates, such as 8.5.1945 or 30.04.2020.

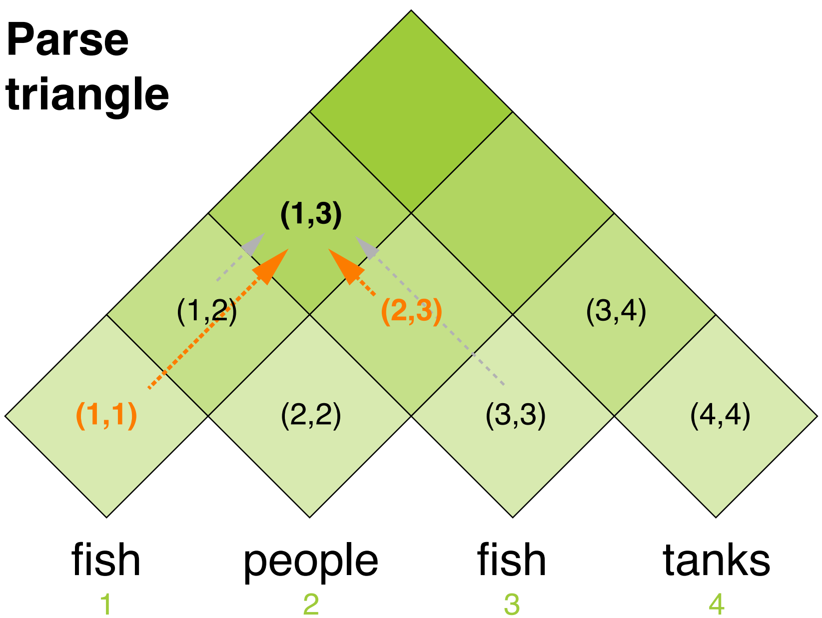
NLP using probabilistic context-free grammars

- **Probabilistic context-free grammar (PCFG)**
  - A CFG where each rule is assigned a probability.
  - Used in NLP mainly to parse sentence structure.
  - The goal is to find the most likely parse tree.

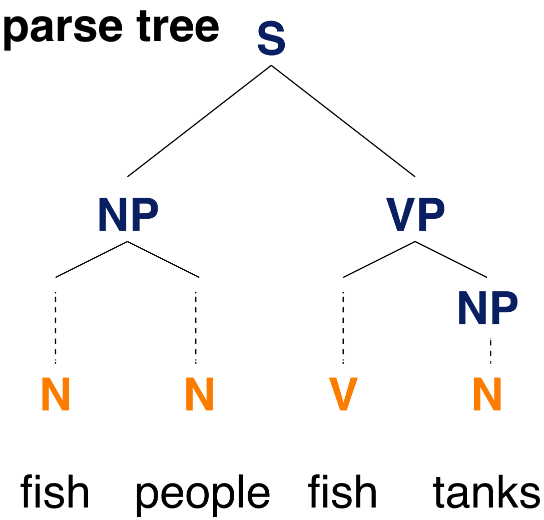
Rule	Probability
S → NP VP	1.0
VP → V NP	0.6
VP → V NP PP	0.4
...	...
V → fish	0.6
V → tanks	0.3

- **Example: Constituency parsing**
  - Use dynamic programming to iteratively compute the most likely parse tree.

Parse triangle



Most likely parse tree



Next section: Statistical NLP

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Machine learning in NLP

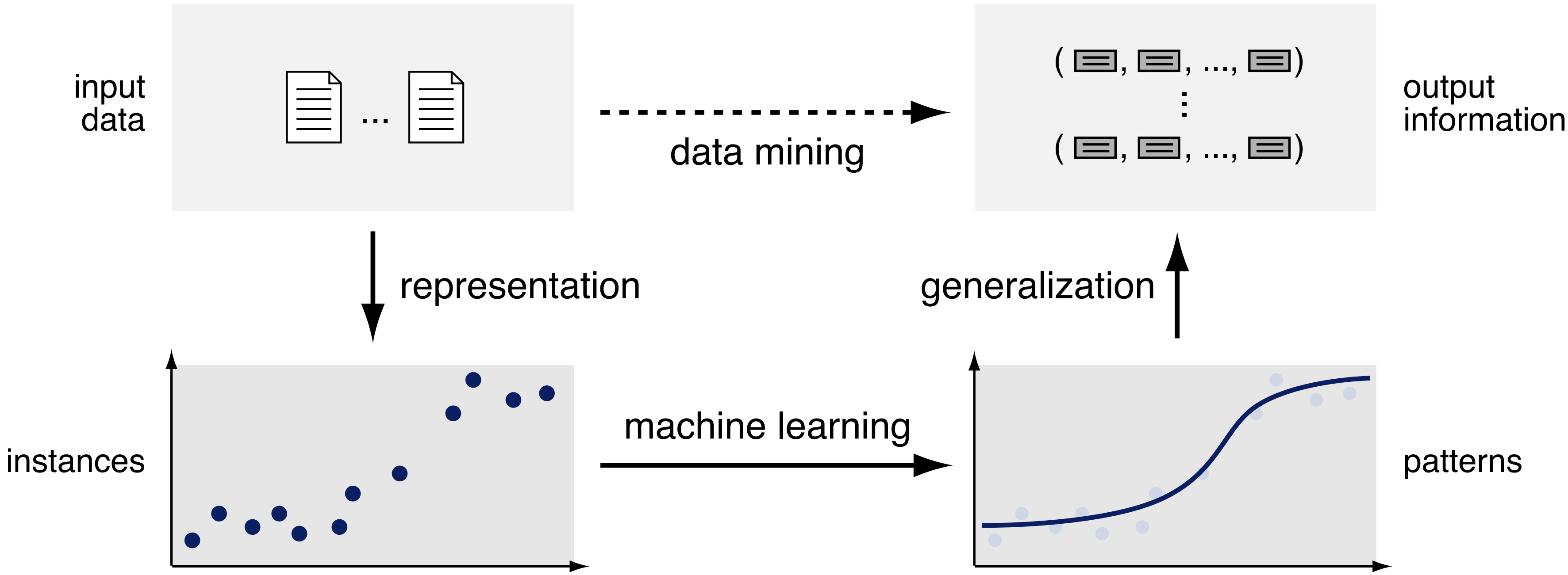
- **Machine learning**
  - The ability of an algorithm to learn without being explicitly programmed.
  - An algorithm learns from experience wrt. a task and a performance measure, if its performance on the task increases with the experience.
  - Aims at tasks where a target function γ that maps input to output is unknown.
  - A model *y* is learned that approximates γ.

- **Typical output in NLP**
  - Text labels, such as topic, genre, and sentiment.
  - Span annotations, such as tokens and entities.
  - Span classifications, such as part-of-speech tags and entity types.
  - Relations between annotations, such as entity relations.

- **Two-way relationship**
  - The output information of NLP serves as the input to machine learning.
  - Many NLP algorithms rely on machine learning to produce output information.

Data mining

- **Data mining vs. machine learning**
  - Data mining puts the output into the view, machine learning the method.



- **Text mining: NLP for data mining purposes**
  - Input data. A text corpus, i.e., a collection of texts to be processed.
  - Output information. Annotations of the texts.

Representation

- **Feature**
  - A feature x denotes any measurable property of an input.
    Example: The relative frequency of a particular word in a text.
- **Feature value**
  - The value of a feature of a given input, usually real-valued and normalized.
    Example: The feature representing ”is“ would have the value 0.5 for the sentence ”is is a word“.
- **Feature type**
  - A set of features that conceptually belong together.
    Example: The relative frequency of each known word in a text (this is often called ”bag-of-words“).
- **Feature vector**
  - A vector $\mathbf{x}^{(i)} = (x_1^{(i)}, \ldots, x_m^{(i)})$ where each $x_j^{(i)}$ is the value of one feature x_j.
    Example: For two feature types with k and l features respectively, $\mathbf{x}^{(i)}$ would contain m = k+l values.
- **Feature-based vs. neural representations**
  - In feature-based learning, each instance is represented as a feature vector.
  - In neural learning, features are not represented explicitly anymore.

Feature determination and computation

- **How to determine the set of features in a vector**

1. Specify (using expert knowledge) what feature types to consider.
   (a) token 1-grams ("bag-of-words")
   (b) text length in # tokens and # sentences

2. Where needed, process training set to get counts of candidate features.
   (a) "the" → 4242, "a" → 2424, . . . , "engineeeering" → 1
   (b) not needed

3. Keep only features whose counts lie within some defined thresholds.
   (a) "the", "a", . . . , ~~"engineeeering"~~

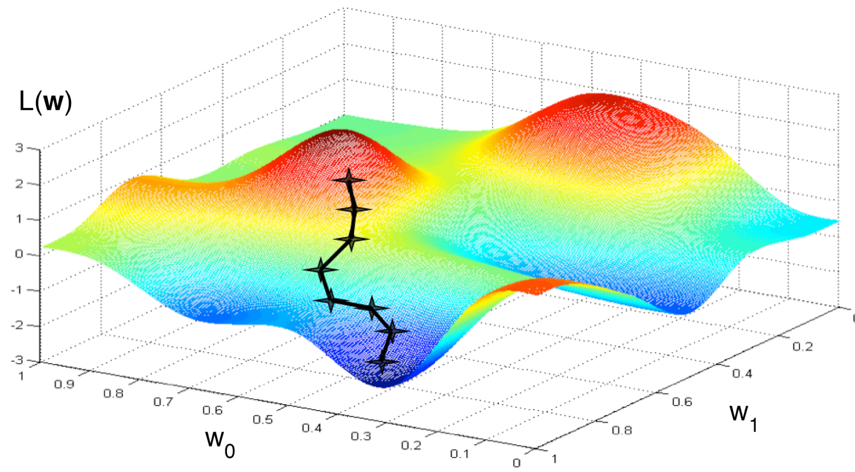
- **How to compute the values for each feature**

1. Compute value of each feature in a vector for a given input text.
   (a) "the" → 6, "a" → 7, …
   (b) # tokens → 50, # sentences → 10

2. Normalize feature values.
   (a) "the" → 0.12, "a" → 0.14, …
   (b) # tokens → 0.42, # sentences → 0.5

Machine learning

- **Machine learning process**
  - A learning algorithm explores several candidate models *y*.
  - Each *y* assigns one weight w_j to each feature x_j.
  - *y* is evaluated on training data against a cost function *L*.
  - Based on the result, the weights are adapted to obtain the next model.
  - The adaptation relies on an optimization procedure.



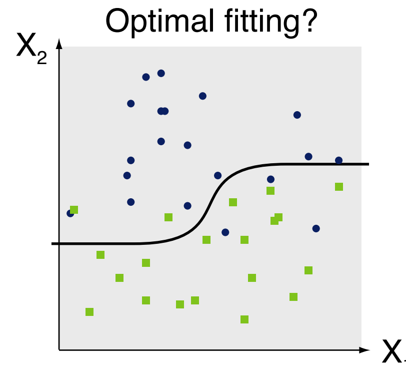
Ng (2018)

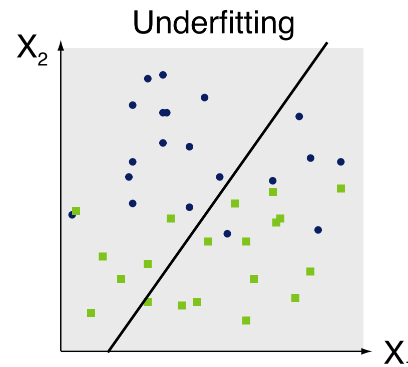
- **Common optimization procedures**
  - Batch gradient descent. In each step, *y* is adapted to all training instances.
  - Stochastic gradient descent. Adapts *y* iteratively to each single instance.

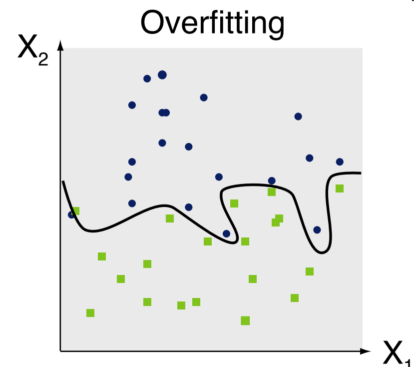
- **Hyperparameters**
  - Many learning algorithms have parameters that are not optimized in training.
  - They need to be optimized against a validation set.

Generalization

- **Fitting**
  - To generalize well, y should approximate the complexity of the unknown function γ based on the training data.
- **Underfitting (too high bias)**
  - The model generalizes too much, not capturing certain relevant properties.
- **Overfitting (too high variance)**
  - The model captures too many irrelevant properties of the input data.
- **Regularization**
  - To avoid overfitting, the use of complex functions can be penalized.
  - A term is added to the cost function that forces feature weights to be small.

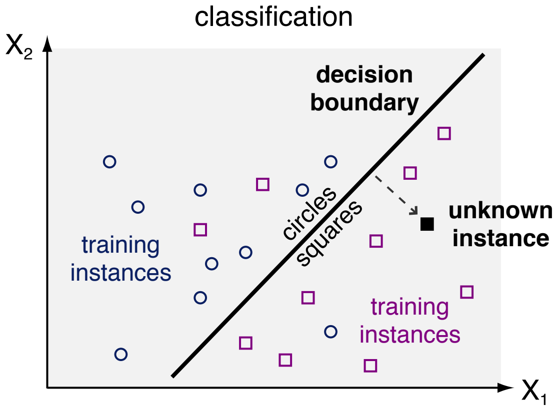




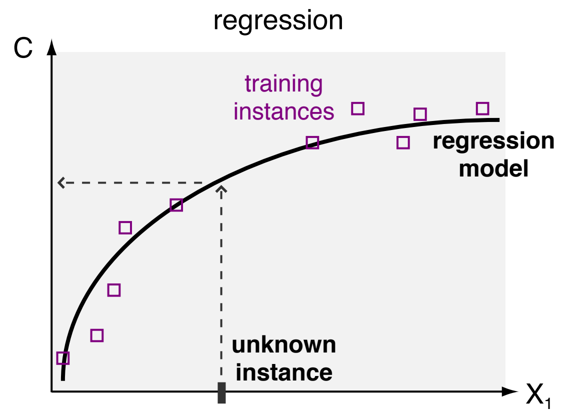


Supervised learning

- **Supervised (machine) learning**
  - A learning algorithm derives a model *y* from known training data, i.e., pairs of instances $x^{(i)}$ and the associated output information $y^{(i)}$.
  - *y* can then predict output information for unknown data.



- **Classification**
  - Assign an instance to the most likely class of a set of predefined classes.
  - A decision boundary *y* is learned that decides the class of unknown instances.



- **Regression**
  - Assign an instance to the most likely value of a continuous target variable.
  - A regression function *y* is learned that decides the value of unknown instances.

Classification and regression algorithms

- **Selected classification algorithms**
  - Naïve Bayes. Predicts classes based on conditional probabilities.
  - Support vector machine. Maximizes the margin between classes.
  - Decision tree. Sequentially compares instances on single features.
  - Random forest. Majority voting based on several decision trees.
  - Neural network. Learns complex functions on feature combinations.

  ... among many others

- **Selected regression algorithms**
  - Linear regression. Predict output values using a learned linear function.
  - Support vector regression. Maximize the flatness of a regression model.
  - Neural network. As above

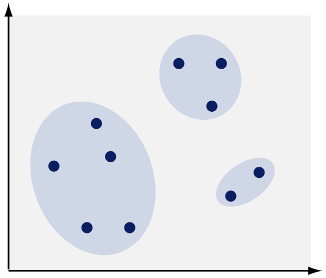
  ... among many others

- **Ensemble methods**
  - Meta-algorithms that combine multiple classifiers/regressors.

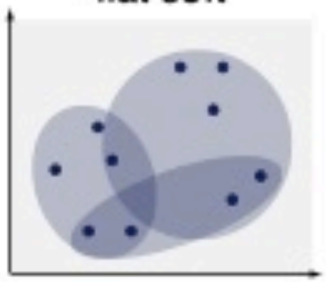
Unsupervised learning

- **Unsupervised (machine) learning**
  - A model *y* is derived from instances without output information.
  - The model reveals the organization and association of data.
- **Clustering**
  - The grouping of a set of instances into a possibly but not necessarily predefined number of classes.
  - The meaning of a class is usually unknown in advance.
- **Hard vs. soft clusters**
  - Hard. Each instance belongs to a single cluster.
  - Soft. Instances belong to each cluster with a certain weight.
- **Flat vs. hierarchical clustering**
  - Flat. Group instances into a set of independent clusters.
  - Hierarchical. Create a binary clustering tree over all instances.

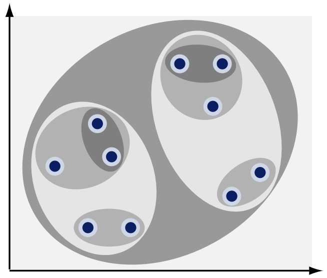
flat hard



flat soft



hierarchical



Clustering algorithms

- **Selected flat hard clustering algorithms**
  - k-means. Iteratively create *k* instance clusters based on distance to centroids.
  - DBSCAN. Cluster instances into regions of similar density.
- **Selected flat soft clustering algorithms**
  - Fuzzy k-means. Variation of *k*-means where clusters may overlap.
  - LDA (topic modeling). Represent clusters by their most common features.
- **Selected hierarchical clustering algorithms**
  - Agglomerative. Incrementally merge closest clusters, starting from instances.
  - MinCut. Split clusters based on their minimum cut, starting from one cluster.
- **Methods to find the best number of clusters**
  - Elbow criterion. Find *k* that maximizes cost reduction.
  - Silhouette analysis. Find *k* that maximizes distances between clusters (and balances their size).

Similarity measures

- **Similarity measure**
  - A real-valued function that quantifies how similar two instances of the same concept are (between 0 and 1).
  - Distance measures can be used as (inverse) similarity measures.

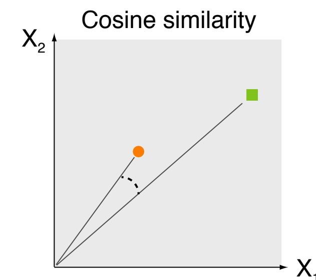
- **Selected use cases in NLP**
  - Clustering
  - Spelling correction
  - Retrieval of relevant web pages or related documents
  - Paraphrase, (near-) duplicate, or plagiarism detection

- **Text similarity measures**
  - Vector-based measures. Mainly, for similarities between feature vectors.
  - Edit distance. For spelling similarities.
  - Thesaurus methods. For synonymy-related similarities.
  - Distributional similarity. For similarities in the contextual usage.

Vector-based similarity (and distance) measures

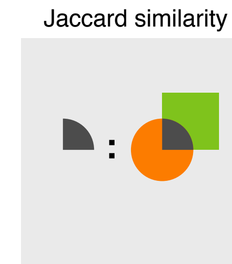
- **Cosine similarity** (aka cosine score)

$$cosine(\mathbf{x}^{(1)}, \mathbf{x}^{(2)}) = \frac{\mathbf{x}^{(1)} \cdot \mathbf{x}^{(2)}}{||\mathbf{x}^{(1)}|| \cdot ||\mathbf{x}^{(2)}||} = \frac{\sum_{i=1}^{m} x_i^{(1)} \cdot x_i^{(2)}}{\sqrt{\sum_{i=1}^{m} x_i^{(1)^2}} \cdot \sqrt{\sum_{i=1}^{m} x_i^{(2)^2}}}$$



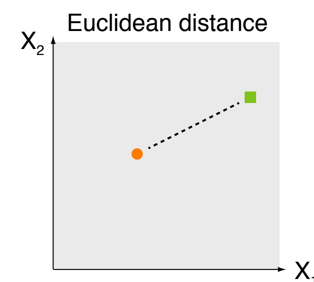
- **Jaccard similarity coefficient** (aka Jaccard index)

$$jaccard(\mathbf{x}^{(1)}, \mathbf{x}^{(2)}) = \frac{|\mathbf{x}^{(1)} \cap \mathbf{x}^{(2)}|}{|\mathbf{x}^{(1)} \cup \mathbf{x}^{(2)}|} = \frac{|\mathbf{x}^{(1)} \cap \mathbf{x}^{(2)}|}{|\mathbf{x}^{(1)}| + |\mathbf{x}^{(2)}| - |\mathbf{x}^{(1)} \cap \mathbf{x}^{(2)}|}$$



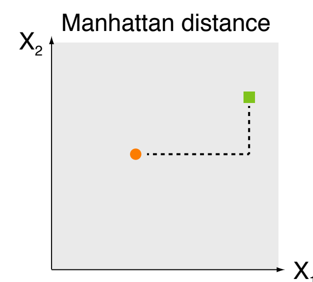
- **Euclidean distance**

$$euclidean(\mathbf{x}^{(1)}, \mathbf{x}^{(2)}) = \sqrt{\sum_{i=1}^{m} |x_i^{(1)} - x_i^{(2)}|^2}$$



- **Manhattan distance** (aka city block distance)

$$manhattan(\mathbf{x}^{(1)}, \mathbf{x}^{(2)}) = \sum_{i=1}^{m} |x_i^{(1)} - x_i^{(2)}|$$

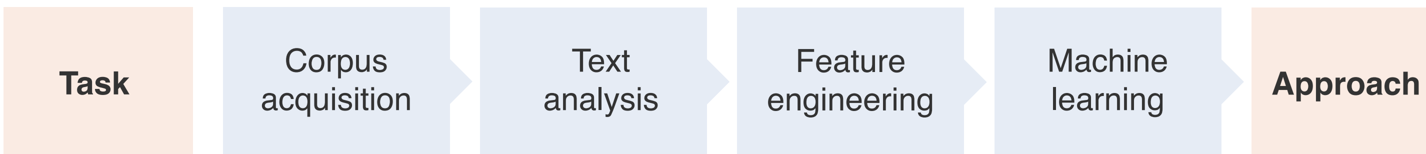


Other learning types and variations

- **Sequence labeling**
  - Classifies each instance in a sequence of instances, exploiting information about dependencies between instances.
- **Semi-supervised learning**
  - Derive patterns from little training data, then find similar patterns in unannotated data to get more training data.
- **Reinforcement learning**
  - Learn, adapt, or optimize a behavior in order to maximize some benefit, based on feedback provided by the environment.
- **Recommender systems**
  - Predict missing values of entities based on values of similar entities.
- **One-class classification and outlier detection**
  - Learn to classify, having only a representative sample of one class.

Development and evaluation of a learning approach

- **Machine learning in NLP**
  - Machine learning serves as a technique to approach a given task.
  - A suitable learning algorithm from a library is chosen and applied.

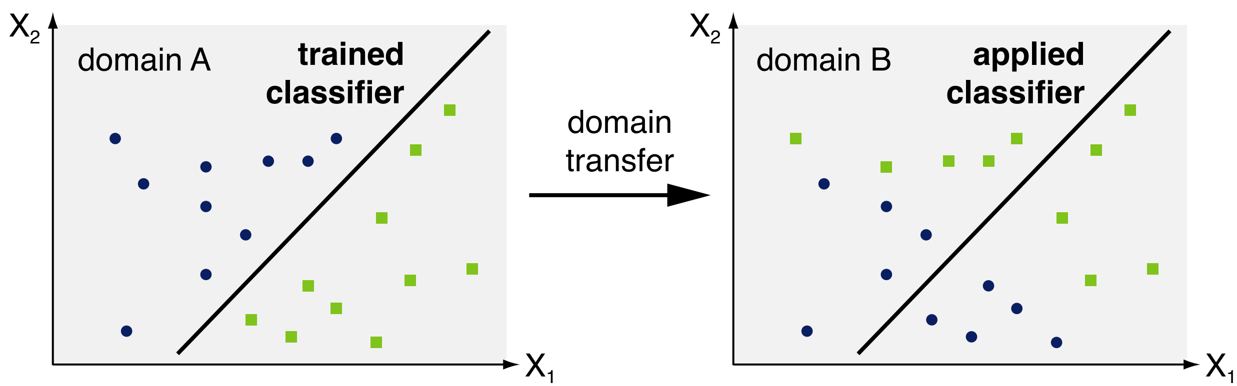


- **Process steps**
  - Corpus acquisition. Acquire a corpus (and datasets) suitable to study the task.
  - Text analysis. Preprocess all instances with existing NLP algorithms, in order to obtain information that can be used in features.
  - Feature engineering. Identify helpful features on training set, compute feature vectors for each instance on all datasets.
  - Machine learning. Train algorithm on training set and evaluate on validation set, optimize hyperparameters. Finally, evaluate on test set.

Domain dependency

- **Domain**
  - A set of texts that share certain properties.
  - Can refer to a topic, genre, style, or similar — or combinations.
  - Texts from the same domain often have a similar feature distribution.

- **Domain dependency**
  - Many algorithm work better in the domain of training texts than in others.



  - The same feature values result in different output information.
  - Different features are discriminative regarding the target variable.
    Example: ”Read the book” in book reviews vs. movie reviews... vs. hotel reviews?

Next section: Conclusion

I. Introduction to computational argumentation
II. Basics of natural language processing
III. Basics of argumentation
IV. Argument acquisition
V. Argument mining
VI. Argument assessment
VII. Argument generation
VIII. Applications of computational argumentation
IX. Conclusion

a) Introduction
b) Linguistics
c) Empirical methods
d) Tasks and techniques
e) Rule-based NLP
f) Statistical NLP
g) Conclusion

What makes NLP hard?

- **Effectiveness challenges**
  - Ambiguity of natural language.
  - Missing context and world knowledge.
  - Accumulation of errors through the text analysis process.
  - Lack of sufficient data for development.

- **Efficiency challenges**
  - Large amounts of data may need to be processed, possibly repeatedly.
  - Complex, space-intensive models may be learned.
  - Often, several time-intensive text analyses are needed.

- **Robustness challenges**
  - Datasets for training may be biased.
  - Many text characteristics are domain-specific.
  - Learned algorithms often capture too much variance (i.e., they overfit).

Approaches to NLP challenges

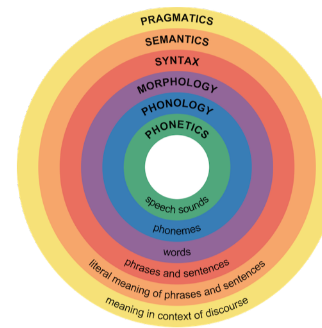
- **How to improve effectiveness?**
  - Joint inference may reduce/avoid error propagation.
  - Different algorithms work well for different amounts of data.
  - Sometimes, data can be extended easily.
  - Redundancy can be exploited in large-scale situations.
  - Combinations of statistical and rule-based approaches often do the trick.

- **How to improve efficiency?**
  - Resort to simpler algorithms
  - Filtering of relevant information and scheduling in pipelines.
  - Scale-out and parallelization of text analysis processes.

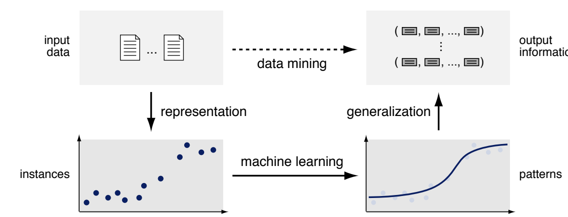
- **How to improve robustness?**
  - Use of heterogenous datasets in training.
  - Resort to domain-independent features.
  - Adaptation of algorithms based on sample from target domain.

Conclusion

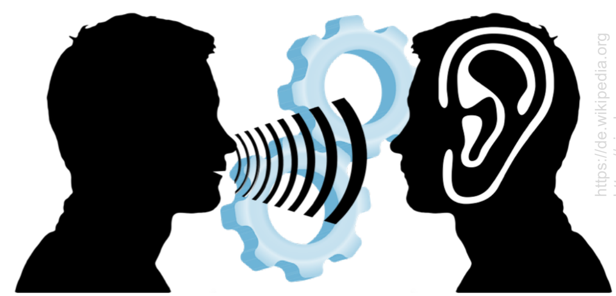
- **Basics of natural language processing (NLP)**
  - Linguistic knowledge from phonetics to pragmatics.
  - Empirical methods for development and evaluation.
  - Rule-based and statistical (machine-learned) algorithms.



- **How to approach NLP tasks?**
  - Start from annotated text corpora.
  - Develop algorithms that use rules or learn patterns.
  - Evaluate quality of their output empirically.



- **Goals of NLP**
  - Technology that can process natural language.
  - Empirical explanations of linguistic phenomena.
  - Solutions to problems from the real world.



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