Information Management: Natural Language Processing

Summary
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November 8, 2023

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Contents

1 Introduction

Natural Language Processing is all about:

- Interpreting (creating information)
- Linking (supporting knowledge acquisition)
- Analyzing
- Verifying

1.1 Language and Knowledge Processing

- The World Wide Web grows about by 25 PB per day.
- Most of this data is unstructured.

1.1.1 Implicit Information

- Data always contains *implicit data*.
- Example: Nearly every supermarket stores information about each transaction. This data includes lots of implicit information:
  - products rarely sold
  - products often bought together
  - ...
- Language and knowledge processing is about making this implicit information explicit.

1.1.2 Text- and Data-Mining

- **Data Mining:** Exploring and analyzing large amount of data automatically to discover meaningful patterns.
  - Machine learning
  - Distributed systems, Databases
  - Data modeling and pattern recognition
  - Software engineering
- **Text Mining:** Exploring and analyzing large amount of *text* automatically to discover meaningful patterns.
  - Natural Language Processing.

1.1.3 Examples

Recommender Systems

Given A set of items and background information about users, items, ...

Goal Present the user with a subset of items that use user will like.

Machine Learning (ML)

Given Task, experience, performance feedback

Goal Perform a task well, improving it with experience

- A fundamental method for many text and data mining tasks.

Document Classification

Given Document, set of Topics

Goal Find a topic in the given set of topics that describes the given document.

Machine Translation (MT)

Given A text in a language.

Goal Output a text in another language with the same meaning as the given text.

Speech Processing

Automatic Speech Recognition

Given Recorded voice.

Goal Find the transcript of the given recording.

Speech Synthesis

Given Written text (transcript).

Goal Find the corresponding acoustic signals for the given text.

Information Retrieval (IR)

Given A document collection and a query.

Goal Find a subset of the documents which is maximally relevant to the query.

Information Extraction (IE)

Given A document collection.

Goal Extract structured knowledge (like entities, events, relationships, . . .).

Question Answering

Given A natural language question and knowledge sources.

Goal Generate an answer for the question based on the knowledge sources.

Automatic Summarization

Given A document collection.

Goal Find a smaller text that summarizes the documents.

- Variations
  - Single- vs. Multi-document summarization
  - Abstractive vs. Extractive summarization
  - Indicative vs. Informative summarization
  - General vs. Query-focused summarization

Sentiment Analysis and Opinion-Mining

Given A text.

Goal Separate subjective/objective opinions from objective statements; distinguish positive/negative statements; identify specific opinions and opinion targets

Intelligent Computer-Assisted Language Learning (ICALL)

Given Learning and a learning goal.

Goal Assist the learning with intelligent tools.

1.2 Major Scientific Challenges

1.2.1 Ambiguity

See chapter 3.

The sentence “pretty little girl’s school” can refer to:

- Very small girl going to school.
- Beautiful girl going to school.
- Very small school the girl goes to.
- Beautiful school the girl goes to.

1.2.2 Underspecification and Vagueness

"Alice is pretty little."

- height(Alice, x)
- $x = 0 \lor x = 3$ is very unlikely.
- $x = 1.6m$ is more likely.

"He usually does other things before dinner."

- Who is "he"?
- What are these "other things"?
- What does "before dinner" mean? One hour or ten days? When is dinner time?
- …

1.2.3 Scientific Data

See chapter 4.

Most of the NLP methods require data for

- training,
- development and
- evaluation.

It is often hard and expensive to obtain high-quality data, for both researchers and companies.

For example: Find a data set with more than a million examples for good/bad arguments.

1.2.4 System Evaluation

- Intrinsic evaluation
  - Test the method in isolation by comparing the actual output with the expected output (the so-called gold standard).
- Extrinsic evaluation
  - Test the method in use by embedding it into a larger system or experimental setup (e.g. a user study).

2 Natural Language Text

Alphabet $\Sigma = \{A, B, C, \cdots, a, b, c, \cdots, 0, 1, \cdots\}$

Characters $s' \in \Sigma$

String $s = s_1 \cdots s_n \in \Sigma^*$

Message A string that follows a grammar.

Data An exchanged message that is not yet interpreted.

Text Written coherent data of a language.

Coherence Coherence is what makes a text semantically meaningful and connects the ideas arranged in a text.

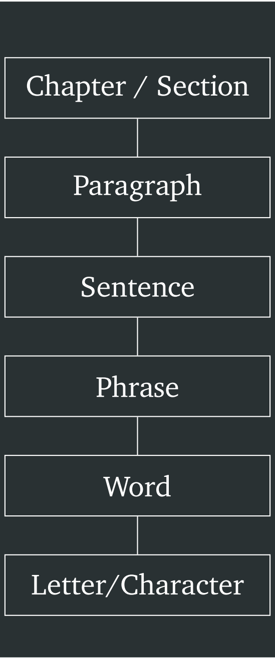
2.1 Scripts and Language

- Script
  - Defines the symbol set Σ.
  - *Alphabetic* scripts: Latin, Greek, Cyrillic, . . .
  - *Logographic* or syllabic: Hanzi (Chinese), Kanji, Katakana, . . .
  - Consonant-Based (*Abjab*): Arabic, Hebrew, . . .
  - Segment-based (*Abugida*): Devanagari, Tibetan, Indic, . . .
  - Writing direction: left-to-right, right-to-left, top-to-bottom, bottom-to-top, . . .
- Language
  - Determines the grammar and the vocabulary.
  - Examples: English, German, Japanese, Spain, . . .

2.2 Properties of Text

- **Text type/Genre:** textbook, scientific paper, news item, social media post, . . .
- **Register:** language variety (dialect, jargon, formal, . . .)
- **Style:** how the text is written (e.g. funny, political, scientific, . . .)
- **Domain/topic:** biology, information science, education, spacecrafts, . . .
- **Time** of writing as languages change during time

2.2.1 Structure



2.3 Examples of electronic Text Formats

- Mostly unstructured
  - Plain text
- Semi-structured
  - Hypertext markup language (HTML)
  - Extensible markup language (XML)
- XML-based formats
  - Open document format (ODT)
  - Word files (DOCX)
- Binary content
  - Word files (DOC)
- Mixed text and binary content
  - Rich text (RTF)
  - Portable document format (PDF)

2.3.1 Text in relational Databases

- It is also possible to store large amount data in a relational database.
- `CHAR`(n) and `VARCHAR`(n) can only store up to n characters with typically $n \leq 4000 \cdots 8000$.
- A lot more text with more or less arbitrary length can be saved using:

- Binary large objects (BLOBs)
- Character large objects (CLOBs)

- The size limit for these data types are mostly infinite with ranging from 2 GB to more that 128 TB.
- But in most DBs it is not possible to do sorting/group and comparing is limited to the most basic (`=`, `BETWEEN`, ...).

2.4 Character Encoding

- As databases can only store 1s and 0s a character encoding is needed:

$$\text{enc} : \Sigma^* \to \{0,1\}^* \qquad \text{(Encoding)}$$
$$\text{dec} : \{0,1\}^* \to \Sigma^* \qquad \text{(Decoding)}$$

- Typically each character is mapped onto a bit mask using a character set $\Psi : \Sigma \to \{0,1\}^*$, so a text $T = c_1 \cdots c_n \in \Sigma^*$ is encoding as enc$(T) = \Psi(c_1) \cdots \Psi(c_n)$
- There are several base categories of encoding:
  - **Single byte**
    Each character corresponds to a single byte (8 Bit).
  - **Multi byte**
    Each character corresponds to a fixed number of bytes.
  - **Variable-length**
    The bit length of each character might change depending on the character.
  - **Escape-code-based**
    Switch between different character sets using escape codes.

2.4.1 Encoding Issues in Software and Databases

- Key question when working with text: Which encoding does the text use?
- Key question when programming: Default encoding of source files? Default encoding of string types? Default encoding when reading/writing a file?
- Key questions when working with databases: Default encoding of a table? Default encoding of the database connection?
- Example Issues
  - String length of variable-length encodings
  - String operations
  - String searching
  - Sort strings alphabetically

Sorting

- **Order of Characters**
  - Latin script: A < B < … < Y < Z
  - Chinese: How to sort? By number of strokes?
- **Case**
  - Binary sort: A < B < … < a < b < …
  - Alternatives: A = a < B vs. A < a < B
  - Turkish: `istanbul` = `iSTANBUL`
  - German: `istanbul` = `ISTANBUL`
- **Transliteration**
  - Greek: $\alpha < \beta < \gamma < \delta$
  - German: a < b < g??? < d
- **Equivalent Characters**
  - German (dictionary, DIN 5007-1): n < o = ö < p
  - Finnish: n < o < p < … < z < ä < ö
- **Diacritics**
  - e < é < f vs. e = é < f
  - French: côte < coté
  - English: coté < côte
- **Character Combinations**
  - German (phonebook, DIN 5007-2): n < o [ö = oe] < p
  - Spanish (traditional): ce < cu < ch < da
  - Danish: z < æ < œ = ø = ö < å

Collation Framework

The collation…

- is the definition of a sort order,
- is available for multiple language, e.g. German and
- there are variants for sorting, e.g. lexical, phone book, traditional vs. modern, …

2.4.2 Example Encodings

ASCII

See https://www.asciitable.com.

Unicode

- The idea was to define one character set that covers all characters observed in the world including:
  - logographic languages
  - fantasy languages
  - currency symbols
  - emoji characters
  - ...
- Unicode 14.0 defines 144,697 characters, 159 writing systems and 3633 emojis.
- Each character has 4 bytes with currently 21 significant bits.

Architecture

- Overall count of 1,114,112 code points ranging from `0x000000` to `0x10FFFF`.
- The notation is `U+ppxxxx`.
- `pp` subdivides the code into 17 planes (from `0x00` to `0x10`).
- The plane $\texttt{pp} = 0$ is called the *Basic Multilingual Plane* (BMP) and contains the most commonly used characters:
  - Latin, Greek, Cyrillic
  - Arabic, Hebrew
  - Most of the Chinese, Japanese and Korean languages (CJK)
  - ...
- Other planes are:

Plane 1	Supplementary Multilingual Plane (SMP) Historic languages
Plane 2	(Supplementary Ideographic Plane) (SIP) Extensions for Chinese, Japanese, Korean
Plane 3-13	Empty
Plane 14	Supplementary Special-purpose Plane (SSP) Control characters (e.g. language tags)
Plane 15-16	Supplementary Private Use Area (PUA-A/B) Reserved for private characters of a certain font

UTF-32/UCS-4

- Each character is encoded with exactly 4 bytes.
- Directly corresponds to Unicode.
- Disadvantages:

  - Wastes disk space and memory, 4 times the size of ISO 8859-1.
  - This might yield to longer processing times.

UCS-2

- Each character is encoded with exactly 2 bytes.
- Directly corresponds to the Unicode BMP.

UTF-16

- Each character is encoded with 2 to 4 bytes.
- Directly corresponds to the Unicode BMP.
- Divides characters of supplementary planes into a so-called high and low surrogate.
- Surrogates: Subtract `0x10000` and divide into upper/lower 10 bits.

UTF-8

- Each character is encoded with 1 to 4 bytes.
- Directly corresponds to ASCII.
- Non-ASCII characters use additional bytes.
- Theoretically it is possible to extend the code to 6 bytes.

3 Linguistic Preprocessing

3.1 Segmention

`The | dwarfs | loved | her | dearly`

3.1.1 Tokenization

- The task of *tokenization* is to segment an input stream into an ordered sequence of tokens.
- Most of the time, *tokens* correspond to inflected word forms.
- The system for segmenting the input stream is called *tokenizer*.
- Naive approach: split on whitespaces.
  - This leads to multiple problems, for instance with the following sentence:
    Mr. Sherwood said, reaction to Sea Containers' proposal has been "very positive."
  - Splitting on whitespaces gives the following false tokens:
    - `said,`
    - `"very`
    - `positive."`
  - Thus, splitting on whitespaces is not a solution.

Ambiguities

- Periods
  - In most cases, a period represents a sentence termination $\implies$ separate tokens.
  - But sometimes, it is part of a token:
    - abbreviations (e.g. `e.g.`)
    - Ordinal numbers (e.g. `21.`), fractions (e.g. `12.34`)
    - references to resource locators (e.g. `www.twitter.com`)
- Comma
  - Part of numbers (e.g. `1,234`) $\implies$ part of token.
- Whitespace
  - Part of numbers (e.g. `1 234`) $\implies$ part of token.

- Single Quote
  - In some cases, it is an enclosing quote (e.g. `“You asked ’why’,” he said.`) ⟹ separate tokens.
  - In contractions or elisions (e.g. `don’t`, `James’ book`) ⟹ should it be a part of the token or a separate token?
- Dash
  - In most cases, it is part of a token (e.g. `part-time job`).
  - But it may be part of ranges (e.g. `see page 100-102`) ⟹ may be separate tokens.
- Colon
  - In most cases, it is a sentence delimiter ⟹ separate tokens.
  - But it may be part of expressions (e.g. `12:30`) ⟹ part of a token.
- And many, many other ambiguities…

3.1.2 Segmention in other Languages

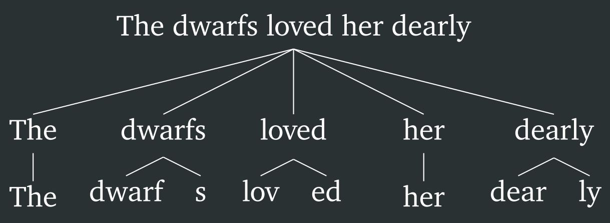
- In Chinese, there are no spaces.
- Beyond that, sentences may have completely different meanings when splitting on the wrong position. Chinese is context-sensitive.

3.1.3 Software

- **Stanford CoreNLP and Word Segmenter** (Java)
- **OpenNLP Tokenizer** (Java)
- **LanguageTool Segmenter** (Java)
- **DKPro Core** (Java)
- **Natural Language Processing Toolkit (NLTK)** (Python)

3.2 Morphology

- Morphology is about how single words are composed and is the study of word forms and word formation.
- Single words are composed of morphemes.
- *Morphemes* are the smallest unit a word can be split into.
- For instance:



3.2.1 Bases and Affixes

- Free morpheme
  - Morphemes that can appear in isolation.
  - Example: Both words “cat” and “cats” can appear in isolation.
- Bound morpheme, affix
  - Morphemes that can not appear in isolation, like the suffix “-s” in “cats”.
  - These are often used for inflection (plural, 3rd person singular, past, . . .).
- Bases, stems
  - The minimal free morpheme of a word is called the *stem* of the word.
  - These stems carry the main meaning of the word.
  - Example: The stem of “cats” is “cat”.

Types of Affixes

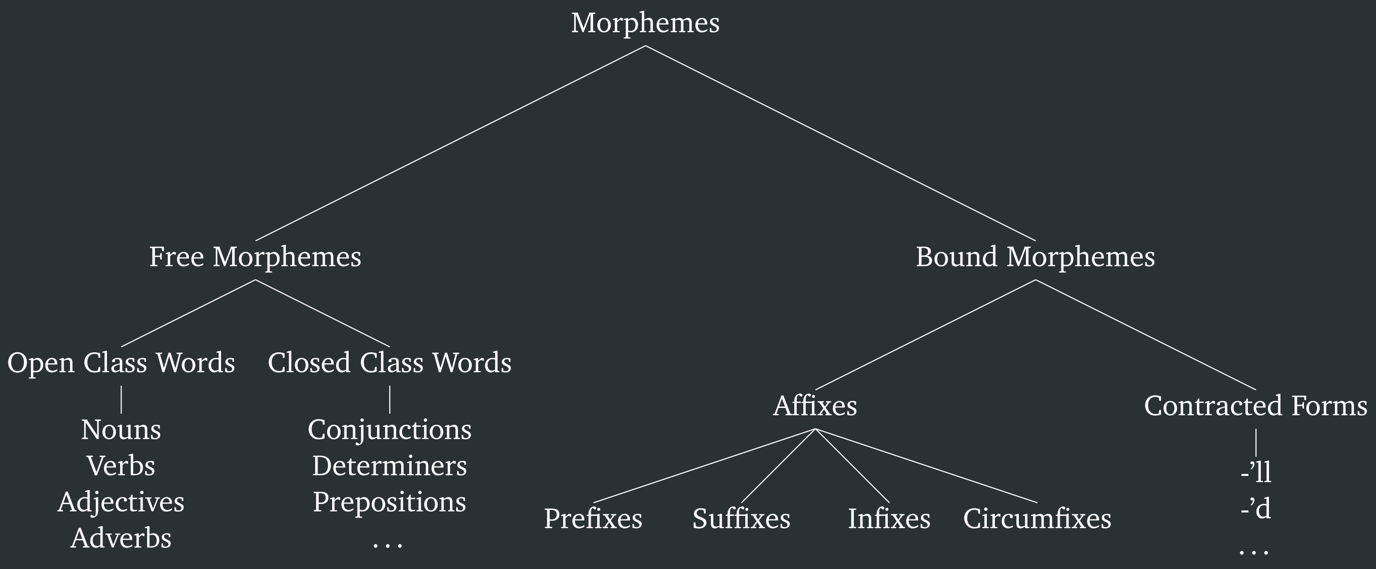
Suffix Appears after the base.
Example: “cat + s”

Prefix Appears before in the base.
Example: “un + true”

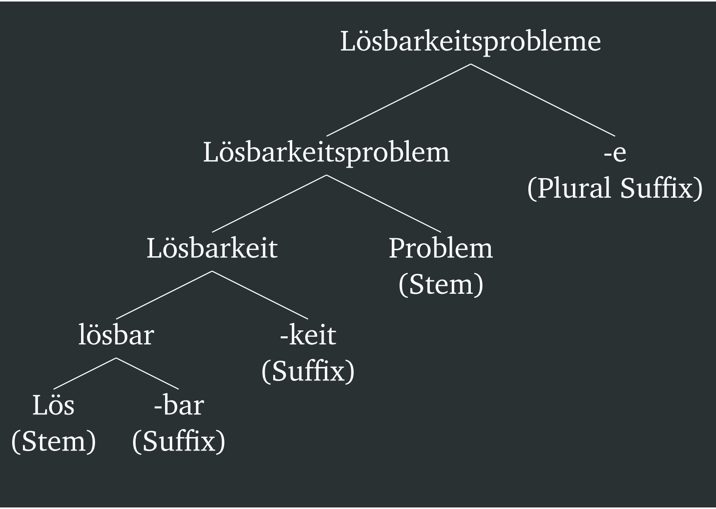
Infix Appears inside the base.
Example: “fan + bloody + tastic”

Circumfix Appears around (on both sides of) the base.
Example: “ge + sag + t”

3.2.2 Classification of Morphemes



Morphological Analysis



3.2.3 Word Formation

Derivation Forming new words from a free morpheme and an affix.

Conversion Also called *zero derivation*; Forming new words by changing the meaning of a word an affix, for example by modifying the stem.
Example: to talk → a talk; to host a party → the host; . . .

Composition Also called *compounding*; Forming new words by combining multiple free morphemes and linking elements.

Decompounding

- Splitting compounds into the creating parts.
- Example: "Bücherregale" → Bücher + Regale
- This may be complicated as splitting on different positions may lead to different meanings:
  - Kulturteilen → Kultur + teilen
  - Kulturteilen → Kult + urteilen

3.2.4 Morphology in other Languages

- In Turkish, only affixes are combined to form complete words.
- This is extremely hard to split.

3.2.5 Morphological Normalization

Normalizing a word is about to find a single canonical representation of a word. This gives multiple approaches:

- Stemming
- Lemmatization
- Morphological analysis

Stemming

- Algorithmic approach to bring any word in its stemmed form.
- Words with the same morphological family should end up in similar stems.
- Stemming does not differentiate between stemming and derivation.
- The stemmed results may not be genuine word forms!
- Examples (Porter's Stemmer):

Original		**Stemmed Word**
visible	→	visibl
visibility	→	visibl
vision	→	vision
visionary	→	visionari
visioner	→	vision
visual	→	visual

Errors

Under-stemming The stemmer does not transform related word to the same stem.

- adhere → adher
- adhesion → adhes

Over-stemming The stemmer can not distinguish between actual different words.

- appendicitis → append
- append → append

Ambiguity: Homographs

- There are words that have different meanings, like:
  - Saw - The singular form of the noun "saw".
  - Saw - The past form of the present verb "see".
- It is not possible to handle these cases with stemming only, the word category (noun, verb, adverb, . . .) also has to be identified.

Lemmatization

- "Undo" the inflection changes and determine the actual base form.
- This typically requires information about the part of speech:
  - Verb: left → leave saw → see
  - Noun: left → left saw → saw
- Lemmatization has to deal with irregular forms:

- sing, sang, sung → sing
- indices → index
- Bäume → Baum

Stemming, Lemmatization, Morphological Analysis

Original	**Stemmed**	**Lemmatized**	Analysis
visibilities	visibl	visibility	+PL
adhere	adher	adhere	
adhesion	adhes	adhesion	
appendicitis	append	appendicitis	+PL
oxen	oxen	ox	+PL
indices	indic	index	+PL
swum	swum	swim	+PP

3.2.6 Software

- **Stanford CoreNLP** (Java)
- **SMOR Morphological Analysis for German**
- **Language Tool Lemmatizer** (Java)
- **DKPro Core** (Java)
- **Natural Language Processing Toolkit (NLTK)** (Python)

3.3 Syntax

- The *Syntax* refers to the way multiple words are arranged together.
- There are infinite way to form word together to make up a sentence.
- Humans can understand most sentences they never heard before.

3.3.1 Part of Speech Tagging (POS Tagging)

- POS tagging is the process of assigning each word of a text its lexical class:

$$\underbrace{\text{The}}_{\text{Determiner}} \quad \underbrace{\text{dwarfs}}_{\text{Noun}} \quad \underbrace{\text{loved}}_{\text{Verb}} \quad \underbrace{\text{her}}_{\text{Pronoun}} \quad \underbrace{\text{dearly}}_{\text{Adjective}}$$

Parts of Speech

- The most commonly used word classes are:

N Noun

V	Verb
ADJ	Adjective
ADV	Adverb
P	Preposition
PRO	Pronoun,
DET	Determiner

- These so-called *tagsets* differ for every language and may be really fine-grained or rough.
- Common tagset sizes:
  - English: 139
  - Czech: 970
  - Estonian: 476
  - Hungarian: 401
  - Romanian: 486
  - Slovene: 1033
- Data that is POS-tagged provides valuable information about:
  - the word formation → lemmatization, morphological analysis
  - a word and its possible neighbors → language models
  - the correct pronunciation → speech synthesis
  - its intended sense → word sense disambiguation
  - the meaning of a sentence → shallow parsing
- Example:

Word	**Lemmatized**	**POS-Tag**
the	the	+DET
girl	girl	+NOUN
kissed	kiss	+VPAST
the	the	+DET
boy	boy	+NOUN
on	on	+PREP
the	the	+DET
cheek	cheek	+NOUN

Example Tagsets

- Penn Treebank Tagset: http://www.clips.ua.ac.be/pages/mbsp-tags
- Stuttgart-Tübingen Tagset: http://www.ims.uni-stuttgart.de/forschung/ressourcen/lexika/TagSets/stts-table.html

Ambiguity

- Often one word may have multiple possibilities for the POS-tag:
  - The back door is open. → ADJ
  - Peter has a scan on his back. → NOUN
  - She tried to win the voters back. → ADVERB
  - He promised to back the bill. → VERB

Approaches to POS Tagging

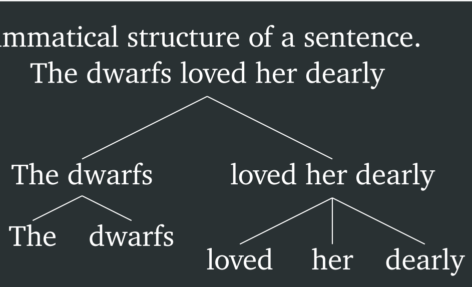
- Rule-based Tagging
  - Create a dictionary word form → POS tags.
  - Then apply or automatically learn transformation rules to improve accuracy.
  - For yet unknown words, use the most frequent POS tag (e.g. NOUN).
- Probabilistic Tagging
  - Estimate the probability that a word has a specific tag → assign the tag with the highest probability.
  - Probabilities are learned from manually labeled data.

Software

- **Stanford CoreNLP** (Java)
- **TreeTagger**
- **Mate Tools** (Java)
- **DKPro Core** (Java)
- **Natural Language Processing Toolkit (NLTK)** (Python)

3.3.2 Parsing

Parsing is about determining the grammatical structure of a sentence.



Phrase Structure Grammars

- The *phase structure grammar* is about representing a sentence by decomposing it into its constituents.
- A *constituent* is a group of words that behaves like a single unit. In phrase structure grammars, these are mostly phrases.
  Tests are used to identify constituents:
  - Example: The dog ate a cookie.
  - *Substitution:* The dog ate it.
  - *Movement:* A cookie was eaten by the dog.
  - *Coordination:* The dog ate a cookie and a sausage.
  - *Question:* What did the dog eat? A cookie.

Phrase Types

Noun Phrase (NP) Noun as head.
Example: "the black cat"; "a cat on the mat"

Prepositional Phrase (PP) Preposition as head.
Example: "in love"; "over the rainbow"

Verb Phrase (VP) Verb as head.
Example: "eat cheese"; "jump up and down"

Adjectival Phrase (AP) Adjective as head.
Example: "full of toys"; "fraught with guilt"

Adverbial Phrase (AdbP) Adverb as head.
Example: "dearly"; "very carefully"

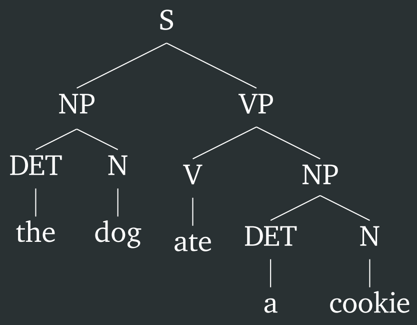
- The *phrase head* determines the syntactical type of the sentence.
- A *grammatical modifier* is an optional element of a phrase.
  - "Modifies" the meaning (e.g. "the ball" vs. "the red ball").
  - A *premodifier* appears in front of the head.
  - A *postmodifier* appears after the head.
  - These are often adjectives, adverbs, prepositional phrases, …

Phrase Parsing

- For a given sentence, check if it can be generated by a given grammar.
- Sentences that can be generated by a grammar are called *grammatical sentences*.
- *Ungrammatical sentences* are unacceptable/uninterpretable with respect to the grammar.

- Even more important than that can it be generated by a grammar is, how can it be generated? That is, how can a sentence be decomposed into phrases.
- This step produces a *parse tree*.

Parse Tree The following is the parse tree for the sentence “the dog ate a cookie”.



Alternative Notations

- Bracket notation:

$$[_{\text{S}}\ [_{\text{NP}}\ [_{\text{DET}}\ \text{the}]\ [_{N}\ \text{dog}]]\ [_{\text{VP}}\ [_{\text{V}}\ \text{ate}]\ [_{\text{NP}}\ [_{\text{DET}}\ \text{a}]\ [_{\text{N}}\ \text{cookie}]]]]$$

- Parenthesized notation:

```
(S
    (NP
        (DET the)
        (N dog) )
    (VP
        (V ate)
        (NP
            (DET a)
            (N cookie) ) ) )
```

Context-Free Grammars (CFG)

Context-free grammar $G = (T, N, S, R)$ with:

- Terminals T,
- Non-terminals N,
- Start symbol S and
- production rules R with elements in the form $X \rightarrow \gamma$, where $X \in N$ and $\gamma \in (T \cup N)^*$.

The grammar G generates language $L(G)$.

Syntactical Ambiguity

Sometimes a sentence has more than one valid syntactical structure.

- **Attachment Ambiguity:** A constituent can be added to the parse tree at different locations. Example:

  - "I shot an elephant in my pants."

    $\overset{A?}{\Longrightarrow}$ VP $\rightarrow$ VP NP $\Longrightarrow$ $\underbrace{\text{I shot}}_{\text{VP}}\underbrace{\text{an elephant in my pants.}}_{\text{NP}}$

    $\overset{B?}{\Longrightarrow}$ VP $\rightarrow$ NP NP $\Longrightarrow$ $\underbrace{\text{I shot an elephant}}_{\text{NP}}\underbrace{\text{in my pants.}}_{\text{NP}}$

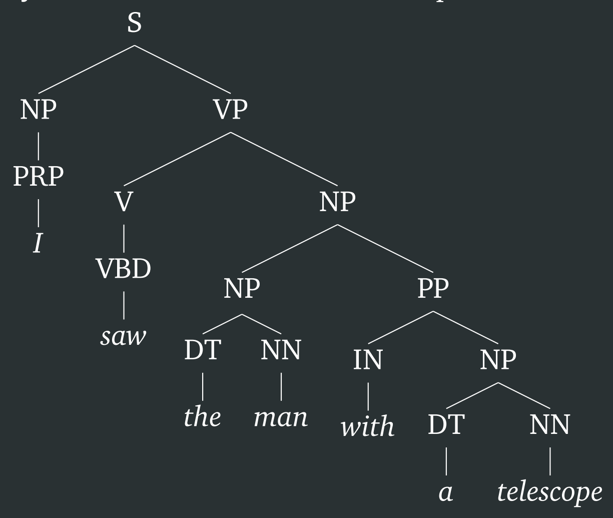
- **Coordination Ambiguity:** Varying scope of the conjunction.
  Example:
  - "Black cats and dogs like to play."

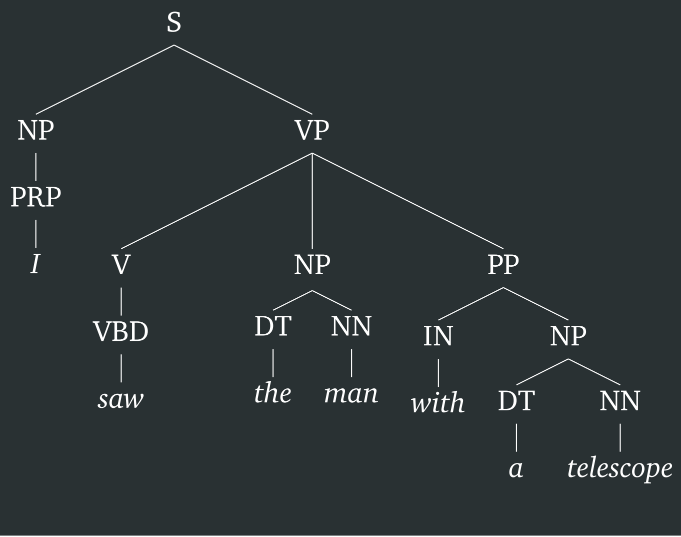
    $\overset{A?}{\Longrightarrow}$ NP $\rightarrow$ AP VP $\underbrace{\text{Black cats and dogs}}_{\text{AP}}\underbrace{\text{like to play.}}_{\text{VP}}$

    $\overset{B?}{\Longrightarrow}$ NP $\rightarrow$ AP NP VP $\underbrace{\text{Black cats}}_{\text{AP}}\underbrace{\text{and dogs}}_{\text{NP}}\underbrace{\text{like to play.}}_{\text{VP}}$

- **Garden path sentence:** A grammatical sentence where it is not possible to apply obvious grammatical rules.
  - "The old man the boat."

Example: Attachment Ambiguity "I saw the man with a telescope."





Dependency Grammar

- A *dependency grammar* is a different kind of syntactic representation.
- Not based on phrases but on binary relations between words:

$$\textit{grammatical-function}(\textbf{head}, \underline{\text{dependent}})$$

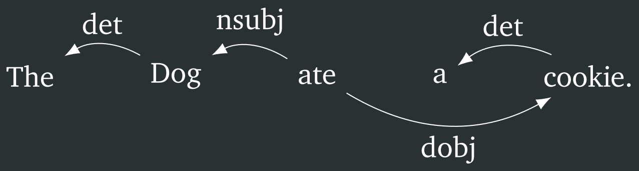
- Examples:
  - Subject: "Sue **watched** the man at the next table."
  - Direct Object: "Sue **watched** the man at the next table."
  - Determiner: "Sue watched the **man** at the next table."
  - ...
- Abstract from word order.

Example "The dog ate a cookie."

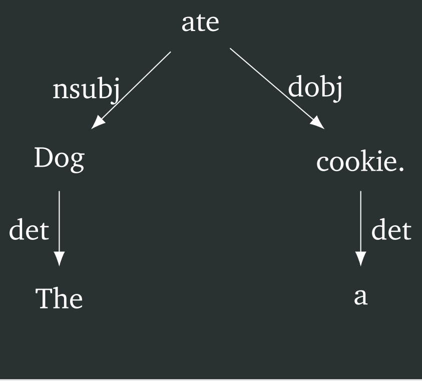
- Textual notation:

```
det(dog, The)
nsubj(ate, dog)
root(ROOT, ate)
det(cookie, a)
dobj(ate, cookie)
```

- Line notation:



- Tree notation:



Software

- **Stanford Parser** (Java, PHP, Python, Ruby)
- **Berkeley Parser** (Java)
- **Mate Tools** (Java)
- **DKPro Core** (Java)
- **Natural Language Processing Toolkit (NLTK)** (Python)

3.4 Semantic

- *Semantics* is the study of meaning.
- *Lexical Semantics* is the study of the meaning of lexical terms (e.g. word).
- *Structure Semantics* is the study of the relationships between the meaning of lexical items in a larger context (e.g. phrases, sentences, documents).

3.4.1 Ambiguity

- Lexical Ambiguity: “He hit the ball with a bat.”
  1. Bat could refer to the animal or
  2. Bat could refer to a baseball racket.
- Syntactical Ambiguity: “If you love money problems show up.”
  1. If you love, money problems show up.
  2. If you love money, problems show up.
  3. If you love money problems, show up.
- Syntactic and lexical ambiguity: “Time flies like an arrow.”
  1. Time moves quickly.
  2. Measure the speed of flies the same way as the speed of an arrow.

3. Measure the speed of flies like an arrow would.
4. Measure the speed of flies that behave/look/. . . like an arrow.
5. The insect type “time flies” enjoy a single arrow (like “fruit flies like a banana”).
6. Each of the “time flies” individually enjoys a different arrow.
7. A concrete object (e.g. Time magazine) travels through the air in an arrow-like manner.
8. . . .

3.4.2 Word Sense Disambiguation

- *Word sense disambiguation* is about to remove the the ambiguity by putting the single words into the context of the sentence/text/. . . and using background information.

4 Text Corpora, Lexical Resources and Knowledge Bases

4.1 Text Corpora

- A *Text Corpus* is collection of text used to train or evaluate a system.
- Examples:
  - Brown Corpus: 500 texts, 15 genres, ≈ 1 mio. words
  - Wall Street Journal Campus: news, ≈ 30 mio. words
  - British National Corpus: balanced among genres, ≈ 100 mio. words
  - WaCKy Corpora: large web corpora in multiple language
- A *Parallel Corpora* is a corpora with their documents translated into two or more languages.
  - Ideally it is sentence-aligned.
  - Used for machine translation or cross-lingual information retrieval.
  - Examples:
    - Canadian Hansard
    - EuroParl
- A (good) corpus provides information about:
  - real usage examples,
  - a view on what is common and typical (e.g. count frequencies),
  - a comprehensive and balanced view on language (if the corpus was constructed correspondingly),
  - recent changes in a language (if the corpus is continuously updated) and
  - a basis for reproducible experimental results.

4.1.1 Parameters of a Corpus

- Language (Monolingual, Multilingual, Parallel)
- Communication (Written, Spoken, Mix)
- Size
- Annotations
- Static ↔ Dynamic

- Genre/Text Type (news, novels, social media text, personal conversations, . . .)
- Domain/Topic (education, biology, information science, . . .)
- Time of Compilation/Creation Time

4.1.2 Content of a Corpus

Corpus Annotation

- *Corpus Annotations* are enrichments of a corpus with various types of information.
- Annotations can be done on different levels, e.g.:
  - Word: part of speech, lemma, sense
    These require segmentation of the document texts into parts.
  - Phrase: named entities, multi-word expressions
  - Sentence: sentence boundaries, syntactic tree
  - Discourse: co-referential chains, discourse segments

Frequencies

- **Collocations:** Sequence of words that occur together usually often.
- **Distributional Hypothesis:** Word in the same context might have similar meanings.

4.1.3 Distributional Hypothesis

- Main idea:

  > "You shall know a word by the company it keeps" (Firth, 1957: p. 11)

- Words that occur in the same contexts have similar meanings
- She adores green paint.
  - verbs expressing admiration: adores, loves, likes, . . .
  - colors: green, blue, red, . . .
- Word sense disambiguation
- Word space models: Compute word or text similarity
  - "cab – van" is more similar than "cab – database"
- It is important for:
  - Document classification/clustering
  - Information retrieval
  - Question answering (find similar questions)
  - Paraphrasing assistance
  - Word embeddings and deep learning

4.1.4 Corpus Creation

1. Retrieve and store original documents.
2. Convert these document to plain text.
3. Segment the documents into chapters, sentences, phrases, words, . . .
4. Create manual and/or automatic annotations.
5. Store all data in a reusable format.
6. Analyze and use the corpus.

Important: Store all intermediate results and document the steps for reproducible results.

Storing Annotations

There are two main ways to store annotations:

1. Inline Annotations
   - The annotations are directly added to the text.
   - This changes the format of the original.
2. Stand-off Annotations
   - The annotations are stored in a separate file.
   - This leaves the original file as is, but the annotation data has to be restored.

4.1.5 Corpus Query Languages

- The standard operations in SQL are exact and substring matches.
- But with complex corpus queries, it should be possible to find things like:
  - All words with 6 letters starting with A or K that end with a vowel.
  - Sentences containing two words at any position.
  - . . .
- Possible solutions:
  - SQL functions
  - Pattern matching and regular expressions
  - Corpus Query Processor (CQP) language

4.1.6 Example Corpora

Treebanks: Penn Treebank

- Mostly based on Wall Street Journal text.
- Annotations: POS, syntactic parse tree

Brown Corpus: POS-Tagged Text

- Inline POS-tags.

Corpora in Relational Databases

- Example: Leibniz Corpus Collection

XML Corpora: British National Corpus

- Stored in XML.

Getting Corpora

- Major organizations:
  - Linguistic Data Consortium
  - European Language Resources Association
- Freely accessible corpora:
  - Oxford Text Archive
  - Electronic Text Archive
  - Project Gutenberg
  - Leibniz Corpora Collection
  - NLTK Corpora
  - Institut für Deutsche Sprache

4.2 Lexical Resources and Knowledge Bases

Types of lexical resources:

- Dictionaries
- Encyclopedias
- Thesauri
- Wordnets
- ...

4.2.1 Lexical Resources ↔ Corpora

Corpus	Lexical Resource
Collected from real-world text/speech.	Derived from corpora (aggregated view).
Contains multiple occurrences of a lemma.	A lemma usually only occurs once.
Frequent phenomena occur more often.	Rare and frequent phenomena are treated equally.
Show how language is used	Describes how language is used.
Provides typical context and frequencies.	Provide meta information (e.g. sense definition)

4.2.2 Meaning, Lexical Ambiguity, Synonymy

- A single lexical entry may have multiple meanings.
- The meanings described in a dictionary are called *word senses*.
- Example:
  - The word “bat” could either refer
  - to a racket or
  - to an animal.
- Vice versa, the same sense may have multiple associated words (synonyms).

4.2.3 Relation Types

Relation Type	Description	Relations	Example
synonymy	same meaning	antonym of antonymy	stack is synonym of pile
antonymy	opposite meaning	antonym of synonymy	rich is antonym of poor
hypernymy	broader meaning	antonym of hyponymy	vehicle is hypernym of car
hyponymy	narrower meaning	antonym of hypernym	taxi is hyponym of car
co-hypernymy	same hypernym	hypernym, synonym	cat and dog are co-hyponyms of pet
troponymy	“hyponymy for verbs”	related to hypernymy	(to) nap is troponym of (to) sleep
holonymy	X is the whole of Y	antonym of meronymy	car is holonym of door
meronymy	X is a part of Y	antonym of holonymy	door is meornym of car
seeAlso	related meaning		bread and baker are related

4.2.4 Wordnets

- Princeton WordNet
- GermaNet
- EuroWordNet

5 Information Retrieval

5.1 Overview

- *Information Retrieval* is about retrieving information from unstructured data best matching a given query.
- Exemplary scenarios:
  - Web search
  - E-Mail search
  - Search in knowledge base or wiki
  - ...

5.1.1 Basic Concepts

- *Information Need*, also called *intent*, is the state of a person requiring information for solving a problem.
- The system-interpretable information need is formulated as a *Query*, e.g. the keywords entered into a search engine.
- The *Relevance* is about how relevant a particular document is to a particular query. The task of IR is to retrieve the most relevant documents.

5.1.2 IR Engine vs. DBMS

- The DBMS relies on structure in the data (tables, columns, ...).
- An IR engine works with unstructured data like text.
- Thus, an IR engine supports more complex finding operations like “documents in which word1 is next to word2”.
- `LIKE`-Queries in DBMS require linear searches on the text and full table scans $\implies$ inefficient.

5.1.3 Core Challenges in IR

- **Number of result:** There are millions of documents in the web, what are the relevant ones?
- **Relevance:** Some results may be better than others, how to separate them?
- **Intent:** The user may not use an ideal query for their information need, how to find what the user wants rather than what the user says he wants?
- **Lexical gap:** Searching for “get rid of mice” should lead to documents about mouse traps.
- **Ambiguity:** Mouse may be an animal or an input device, how to separate?

5.1.4 IR Activities

- *Indexing:* Create a simple document representation to enhance search.
- *Searching:* Interpret the query and return matching documents, sorted by relevance, ranked by results, improved by user feedback, ...

5.2 Boolean Retrieval

- *Boolean Retrieval* is the most simple retrieval model.
- One document is considered to be a *set of words* with no duplicates.
- Searching for documents be like:
  - contains a word,
  - does not contain a word,
  - contains word1 and word2,
  - contains word1 or word2

5.2.1 Term-Document Matrix

Whether a word is contained in a document can be represented as a 1, not containing as a 0. This leads to the following matrix (as an example), the so-called *Term-Document Matrix*:

Term t	Webshop deadfall traps	Wikipedia: mouse-traps	Webshop live-capture traps 1	Wikipedia: traps	tips to get rid of rodents	Webshop live-capture traps 2	bear hunting overview
`mouse`	1	1	1	0	0	0	0
`trap`	1	1	1	1	0	1	0
`not`	1	0	1	0	0	0	0
`hurt`	0	1	1	0	1	0	0
`dead`	1	0	0	1	0	0	0
`alive`	0	0	0	1	1	1	0
`bear`	0	0	0	0	0	0	1
`rodent`	0	1	0	0	1	1	0

- One column represents one document and one row represents one term.
- As said above, a 1 means the term is in the document, a 0 means the term is not.
- When searching for a term, say $(\text{mouse} \vee \text{rodent}) \wedge \neg\text{hurt}$, the searching can be processed using bit-wise

logic:

$$\begin{aligned} & (\text{mouse} \vee \text{rodent}) \wedge \neg\text{hurt} \\ \simeq\ & (\texttt{1110000} \vee \texttt{0100110}) \wedge \neg\texttt{0110100} \\ =\ & \texttt{1110110} \wedge \texttt{1001011} \\ =\ & \texttt{1000010} \\ \simeq\ & \{\text{Webshop deadfall traps}, \text{Webshop live-capture traps 2}\} \end{aligned}$$

- The result bit pattern, `1000010`, refers to the documents to select: “Webshop deadfall traps” and “Webshop live-capture traps 2”.

Scaling, Inverted Matrix

- Saving the matrix as described above would lead to high memory usages to save lots of 0s.
- There must be a better way to save the data.
- Idea: Just save the 1s.
- This can be done using an *Inverted Index*:
  - Each document is assigned a number (say from d1 to d7 for the example above).
  - Then, each term is assigned a set of document numbers the term appears in.
  - Using this technique, one the appearances of a word are saved rather than saving a bunch of “does not appear in”, “does not appear in”, “does not appear in”, ...

Webshop deadfall traps	Wikipedia: mousetraps	Webshop live-capture traps 1	Wikipedia: traps	tips to get rid of rodents	Webshop live-capture traps 2	bear hunting overview
d1	d2	d3	d4	d5	d6	d7

`mouse`	d1	d2	d3		
`trap`	d1	d2	d3	d4	d6
`not`	d1	d3			
`hurt`	d2	d3	d5		
`dead`	d1	d4			
`alive`	d4	d5	d6		
`bear`	d1				
`rodent`	d2	d5	d6		

5.3 Vector Space Model

5.3.1 Boolean Search Issues

1. **Syntax Needed**

- The user has to write Boolean expressions.
- This is nearly impossible for the average user and time-consuming for the expert user.
- **Solution:** use keyword-bases search instead (e.g. mouse trap $\simeq$ mouse $\wedge$ trap).

2. **"Feast or Famine"**
   - Boolean queries often give either too few (≈ 0) or too many ($\gg 1000$) results.
   - Neither of these is useful.
   - **Solution:** Ranked retrieval.

5.3.2 Ranked Retrieval

- In the Boolean retrieval, a term was either in a document or not.
- But a document containing one word multiple times may be more relevant that a document containing the term a single time.
- Idea: Sort (rank) the results by relevance.
- Often, the best 10 results are the most relevant. Others can be discarded.
- This solves the "feast or famine"-problem.

Time-Document Matrix Weights

- Instead of weighing the matrix components as 1 or 0, each field can be assigned the *Term Frequency*, the occurrence count of a word.
- That way, the matrix is weighted and can distinguish between not-so-relevant and relevant results.

Term t	Webshop deadfall traps	Wikipedia: mouse-traps	Webshop live-capture traps 1	Wikipedia: traps	tips to get rid of rodents	Webshop live-capture traps 2	bear hunting overview
`mouse`	12	53	3	0	0	0	0
`trap`	5	11	34	10	0	8	0
`not`	231	0	53	0	0	0	0
`hurt`	0	1	22	0	2	0	0
`dead`	50	0	0	3	0	0	0
`alive`	0	0	0	5	7	3	0
`bear`	0	0	0	0	0	0	32
`rodent`	0	45	0	0	3	5	0

5.3.3 Set of Words, Bag of Words

- Set of Words
  - Disregards word order, grammar, meaning, ...
  - A document either contains a term or not.
  - Each term is assumed to occur only once or never.
- Bag of Words
  - Disregards word order, grammar, meaning, ...
  - A token may occur multiple times in a document.
  - The term frequency (TF) function represents the occurrence counts.

5.3.4 Vector Space Model (VSM)

- Each document in the TD-matrix can be represented as an n-dimensional vector, where n is the number of terms.
- This puts the TD-matrix into a vector space which then allows to apply linear algebra operations.

Example *In this example, the dimension of the VCM is reduced to 2 to ease the visualization, a 8-dimensional vector space is kinda complicated to visualize.*

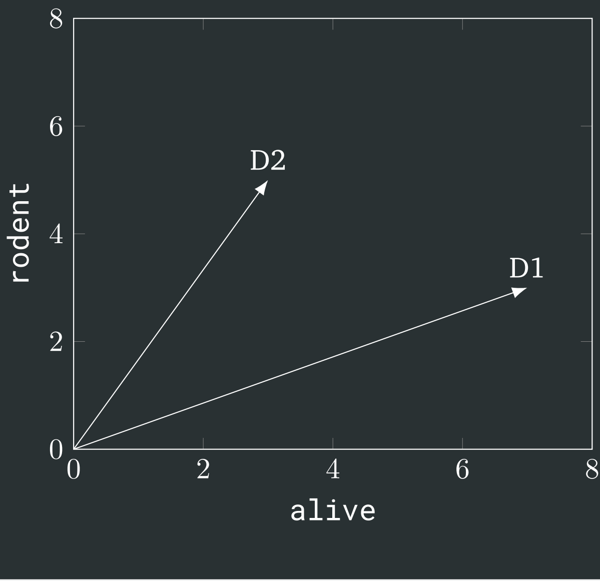
Given the following TD-matrix (reduced to 2 dimensions as explained):

Term t	tips to get rid of rodents (D1)	Webshop live-capture traps 2 (D2)
`alive`	7	3
`rodent`	3	5

So, the documents D1 and D2 can be represented using vectors:

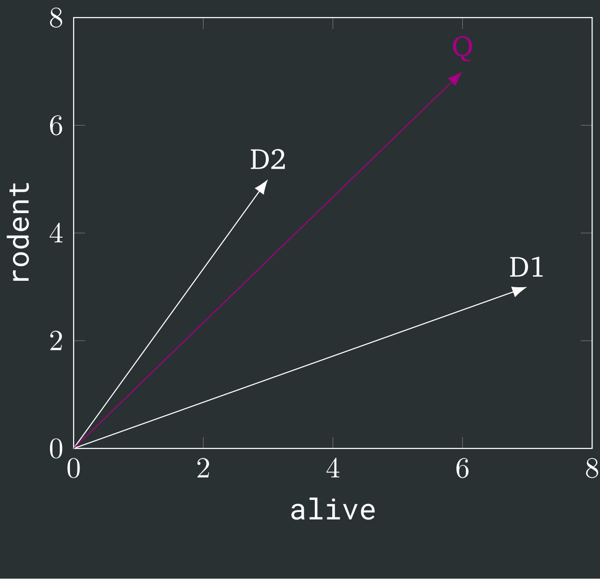
$$\text{D1} = \begin{bmatrix} 7 \\ 3 \end{bmatrix}, \qquad \text{D2} = \begin{bmatrix} 3 \\ 5 \end{bmatrix}$$

In a two-dimensional vector space, this gives the following graph:



5.3.5 Search the VSM

Given the above vector space, it is possible to trace out a query Q in the vector space:



Vector Similarity

- To find results in the VSM, the similarity between the vectors has to be calculated.
- The first approach might be to use the **Euclidean Similarity**, which is to calculate the distance between the query vector and every other vector:

  $$\text{Similarity}(D, Q) = |Q - D|$$

  Problem: The distance differs depending on how often a keyword is entered into the query.
- The much better approach is not measure the angle between the query vector and every other vector:

  $$\text{Similarity}(D, Q) = \frac{\langle Q \mid D \rangle}{|Q| \cdot |D|}$$

- Example:
  - $q = (0; 5; 0; 1; 0)$
  - $v = (0; 2; 3; 2; 1)$

$$\text{sim}(q, v) = \frac{0 \cdot 0 + 5 \cdot 2 + 0 \cdot 3 + 1 \cdot 2 + 0 \cdot 1}{\sqrt{0^2 + 5^2 + 0^2 + 1^2 + 0^2} \cdot \sqrt{0^2 + 2^2 + 3^2 + 2^2 + 1^2}} = \frac{12}{\sqrt{26} \cdot \sqrt{18}} \approx 0.55$$

5.3.6 Vector Weights

- Let $v = (w_{t_1}, \cdots, w_{t_n})$ be the vector for the document d with terms t_1 to t_n.
- Let $\text{tf}_d(t)$ be the occurrence count of t in d, the *Term Frequency*.

Binary

$$w_t = \begin{cases} 1 & t \in d \\ 0 & \text{otherwise} \end{cases}$$

- Discussion: Isn't there a relevance difference between documents with one occurrence and a document with thousand occurrences?

Term Frequencies

$$w_t = \begin{cases} \text{tf}_d(t) & t \in d \\ 0 & \text{otherwise} \end{cases}$$

- Discussion: Is a document containing the search term 1000 times really 100 times more relevant than a document containing the search term 10 times?

Normalized Term Frequencies

$$w_t = \begin{cases} \log_{10}(\text{tf}_d(t)) + 1 & t \in d \\ 0 & \text{otherwise} \end{cases}$$

- Discussion: Determiners occur very often, but are not really relevant. Words occurring rarely over a set of document would be useful.
- Example: the, a and am appear very often and are probably not as important as paint, colour, mouse, …

Document Frequency Let $\text{df}(t)$ be the count of documents containing the term t, the *Document Frequency*.

$$w_t = \begin{cases} f(\log_{10}(\text{tf}_d(t)) + 1, \text{df}(t)) & t \in d \\ 0 & \text{otherwise} \end{cases}$$

with some function $f(\cdot, \cdot)$.

- Discussion; TF should be maximized, DF should be minimized $\implies$ hard to perform on a single output number.

Inverse Document Frequency

Let $\mathrm{idf}(t) := \log_{10}\left(\frac{|D|}{\mathrm{df(t)}}\right)$ be the *Inverse Document Frequency* with the document set D.

$$w_t = \begin{cases} f(\log_{10}(\mathrm{tf}_d(t)) + 1, \mathrm{idf}(t)) & t \in d \\ 0 & \text{otherwise} \end{cases}$$

with some function $f(\cdot, \cdot)$.

Concrete Vector Weights: TF.IDF

$$w_t = \begin{cases} (\log_{10}(\mathrm{tf}_d(t)) + 1) \cdot \mathrm{idf}(t) & t \in d \\ 0 & \text{otherwise} \end{cases}$$

Of course, other normalization strategies are also possible, like:

$$w_t = \begin{cases} \mathrm{tf}_d(t) \cdot \mathrm{idf}(t) & t \in d \\ 0 & \text{otherwise} \end{cases}$$

5.3.7 VSM Retrieval: Example

Term t	Webshop deadfall traps	Wikipedia: mouse-traps	Webshop live-capture traps 1	Wiki-pedia: traps	tips to get rid of rodents	Webshop live-capture traps 2	bear hunting overview	Query Q
`mouse`	12	53	3	0	0	0	0	1
`trap`	5	11	34	10	0	8	0	1
`not`	231	0	53	0	0	0	0	1
`hurt`	0	1	22	0	2	0	0	1
`dead`	50	0	0	3	0	0	0	0
`alive`	0	0	0	5	7	3	0	0
`bear`	0	0	0	0	0	0	32	0
`rodent`	0	45	0	0	3	5	0	0
$\|d\|$	237	70	67	12	8	9	6	2
$\mathrm{sim}(D, Q)$	0.52	0.46	0.84	0.42	0.13	0.44	0	

5.4 Information Retrieval Evaluation

- The evaluation of a retrieval system is extremely important to check how good the retrieval system really is.
- The basic measurements are:
  - *Precision* - The fraction of the retrieved documents that are relevant to the user's information need.

$$P = \frac{|\text{Retrieved} \cap \text{Relevant}|}{|\text{Retrieved}|} = \frac{|\text{True Positives}|}{|\text{True Positives}| + |\text{False Positives}|}$$

- *Recall* - The fraction of the relevant documents if the collection that are retrieved.

$$R = \frac{|\text{Retrieved} \cap \text{Relevant}|}{|\text{Relevant}|} = \frac{|\text{True Positives}|}{|\text{True Positives}| + |\text{False Negatives}|}$$

- Confusion Matrix

	Relevant	Irrelevant	Σ
Retrieved	TP = 2	FP = 1	3
Not Retrieved	FN = 3	TN = ??	
Σ	5		

5.4.1 F_1 Score

The F_1-score is the weighted average of precision and recall:

$$F_1 = \frac{2PR}{P+R} \qquad \text{(Harmonic Mean of } P \text{ and } R\text{)}$$

Generalization: F_β Score

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

5.4.2 Cutoff and Precision at Rank

$$\text{P@R} = \frac{\#\text{Relevant Documents before } R}{R} \qquad \text{(Precision at Rank)}$$

6 Information Extraction and Classification

6.1 Information Extraction (IE)

Given A document collection.

Goal Extract structured knowledge, entities, facts, ...

6.1.1 Information Retrieval vs. Information Extraction

- *Information Retrieval* finds documents that are relevant to a query.
  - Output: List of relevant documents.
  - A lot less difficult than IE, as “only” documents have to be found.
  - Domain-independent.
  - Query types are usually unconstrained (can contain any keyword).
  - Faster.
  - Less effective as the user wants answers, not documents.
- *Information Extraction* extracts structured information from an unstructured document.
  - Output: Set of structured facts extracted from documents.
  - Much more difficult than IR (has to do IR first and then extract facts).
  - Often domain-dependent.
  - Pre-defined query types (e.g. SQL).
  - Slower.
  - More effective as the user wants answers and gets answers.

6.2 Entity Recognition

6.2.1 Entity Types

Commonly used entity types:

Type	**Examples**
ORGANIZATION	TU Darmstadt, TU Dresden
PERSON	Angela Merkel, Goethe
LOCATION	Darmstadt, Rhein, Luisenplatz
DATE	10.09.2018
TIME	10:00
MONEY	250 Euros
PERCENT	43%
FACILITY	London Bridge, Karo5
. . .	. . .

The definition of the concrete used entity types highly depends on the domain and on the task.

6.2.2 Challenges

- Entity vs. Non-Entity
  Example: Mobile Phone vs. Mobile, Alabama
- Coverage Issues
  Example: It is impossible to create a list of all persons, locations, ...
- Variation
  Example: John Smith vs. Mr. Smith, John vs. Mr. J. Smith
- Ambiguity
  Example: Darmstadt (German vs. US city)
- Time Dependency
  Example: The president of the TU Darmstadt (Prömel, Wörner, . . .).
- Multi-word Expressions; The boundaries are often not clear.
  Example: Carlo und Karin Giersch-Stiftung an der TU Darmstadt
- Metonymy
  - A figure of speech in which an entity is not called by its name but by the name of any property intimately associated with it.
  - Examples:
    - Darmstadt won by a penalty goal in the last minute of the game.
      (Darmstadt does not refer to the city, but to the SV Darmstadt 98.)
    - She only reads Goethe and Schiller.
      (Refers to books of Goethe and Schiller, not their personalities.)

6.2.3 Approaches

List Lookup

- Recognize only entities that are stored in a list.
- For locations, these lists are called *gazetteers*.

- **Advantages**
  - Simple
  - Fast
  - Easy to adapt to a different domain
- **Disadvantages**
  - Lists have to be collected and maintained
  - Cannot deal with name variants and abbreviations
  - Cannot resolve ambiguity

Rule-based Methods

- Most often, the rules are regular expressions.
- But: Extremely Labor-intensive.
  - It is easy to get a fairly good performance (e.g. 50% correct).
  - But it is incredible hard to get a good performance (e.g. > 70% correct).
  - It is very expensive to maintain and to adapt to new domains, tasks and languages.

6.2.4 Next Steps After Information Extraction

- After we extracted all these facts, what shall we do with this information?
- We save it in a knowledge base

Knowledge Bases

- A knowledge base is a special kind of database for knowledge management. A knowledge base provides a means for information to be collected, organized, shared, searched and utilized.
- Collection of facts, which can be stored as SPO Triples (Subject, Predicate, Object)
- Example: "Leonard Nimoy was an actor who played the character Spock in the science-fiction movie Star Trek"

Subject	**Predicate**	**Object**
(LeonardNimoy,	profession,	Actor)
(LeonardNimoy,	starredIn,	StarTrek)
(LeonardNimoy,	played,	Spock)
(Spock	characterIn,	StarTrek)
(StarTrek	genre,	ScienceFiction)

- SPO Triples can be combined to form a graph

Nodes	Entities (all subjects and objects)
Directed edges	predicates

- This graph is called a **Knowledge Graph (KG)**

Knowledge Base Construction Methods

- **Curated approaches**
  - Triples are created manually by a closed group of experts
  - (+) High quality
  - (-) Low scalability
- **Collaborative approaches**
  - Triples are created manially by an open group of volunteers
  - Examples: Freebase, Wikipedia, Wikidata
  - (+) Better scalability
  - (-) Still limited
- **Automated semi-structured approaches**
  - Triples are extracted automatically from semi-structured text
    - Infoboxes in Wikipedia
    - hand-crafted rules, learned rules or regular expressions
  - Examples: YAGO, DBPedia
  - (+) Large knowledge graphs
  - (-) Still cover only a small fraction of the Web
- **Automated unstructured approaches**
  - Triples are extracted automatically from unstructured text
  - Machine learning and natural language processing (NLP) techniques
  - Examples: NELL, Knowledge Vault
  - (+) huge knowledge graphs: “read the web”

6.3 Supervised vs. Probabilistic Machine Learning

- Supervised Machine Learning
  - Core Idea: Create a dataset and let the machine learn rules or statistical models to label unseen data.
- Corpus-based Probabilistic Methods
  - Core Idea: Estimate the probability for certain language structures based in large corpora.

6.3.1 Classification

- **Classification** is the task if choosing the correct **class label** for a given input (=instance) based in its features
- Examples:

  - Email spam classification
  - Categorizing news articles by topic

- **Classification variants**
  - binary (2 classes) vs multi-class classification (>2 classes)
  - multi-class problem can be decomposed using binary classifiers
  - single-label vs. multi-label classification, each instance may be assigned one vs. multiple class labels
  - sequence classification, a sequence of instances are jointly classified

6.3.2 General (Supervised) ML Workflow

1. Obtain training, development, test data
2. Represent the input (e.g., using features)
3. Select an algorithm and train the model
4. Evaluate the results; perform the task

Split the Data

- If possible: use separate datasets for development, testing and evaluation
- If not: divide one large dataset in three parts

Training Set Trains the model

Test Set Analyze errors, select features and optimize parameters on it

Evaluation Set Test on held-out data and evaluate how well the algorithm works, dont optimize on it