Artificial Intelligence

Algorithms and Applications with Python

Chapter 9

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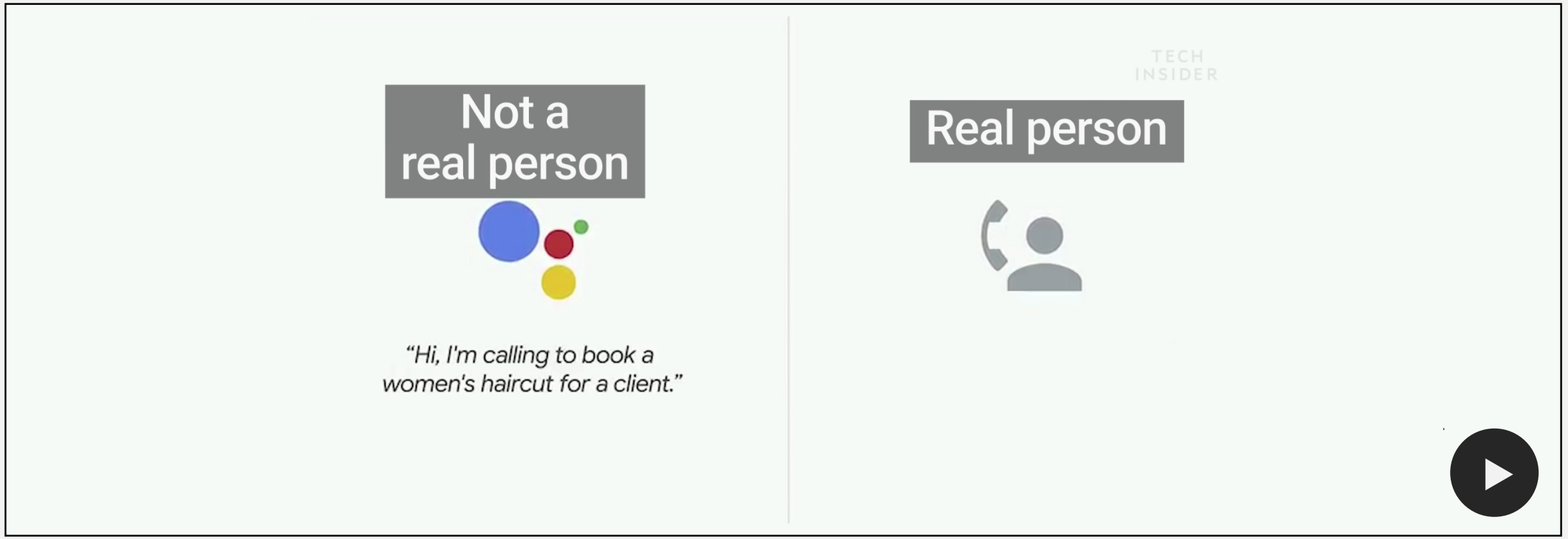
</> course material: ↗ www.github.com/dominikjung42 | recordings: ↗ www.youtube.com/c/dominikjung42

9. Natural Language Processing (GOOGLE I/O 2018)



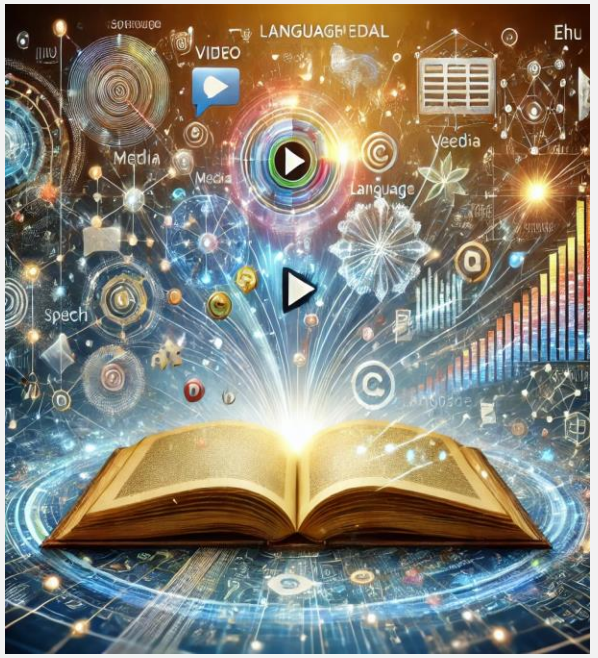
Natural Language Processing is the branch of computer science focused on developing systems that allow computers to communicate with people using everyday language

Outline

9 Natural Language Processing

- 9.1 Natural Language Processing
- 9.2 Speech Processing and Communication
- 9.3 Language Modelling
- 9.4 NLP Methods for Information Retrieval

Lectorial 7: Building NLP and Machine Learning Pipelines for Webservices



► **What we will learn:**

- We will discuss how to make use of the copious knowledge that is expressed in natural language
- And how to process and prepare language data for machines to build state-of-the-art machine learning pipelines for language processing
- We learn new type of models, so called generative models, which allow to generate new instances based on the knowledge of your model

► **Duration:**

- 180 min + 90 (Lectorial)

► **Relevant for Exam:**

- 9.1, 9.3 – 9.4

9.1 Application: Information Retrieval and Search Engines

D **Information Retrieval** is the science building a system for recovering specific information from stored data base based on user's needs.

9.1 Text Processing Example I

Preprocessing

- Extract plain text
- Reduce complexity
- prepare transformation

```
…
<p><b>Dr.-Ing. h.c. F. Porsche AG</b>,
usually shortened to <b>Porsche</b>
(<small>German
pronunciation:&#32;</small><span
title="Representation in the International
Phonetic Alphabet (IPA)" class="IPA"><a
href="/wiki/Help:IPA/Standard_German"
title="Help:IPA/Standard
German">[ˈpɔɐʃə]</a></span>&#32;<span
class="nowrap" style="font-size:85%">(<span
class="unicode haudio"><span class="fn"><span
style="white-space:nowrap;margin-
right:.25em;"><a href="/wiki/File:De-
Porsche.ogg" title="About this sound"><img
alt="audio speaker icon"
src="//upload.wikimedia.org/wikipedia/commons
/thumb/8/8a/Loudspeaker.svg/11px-
Loudspeaker.svg.png" decoding="async"
width="11" height="11
…
```

9.1 Text Processing Example II

- Remove html tags

```
Dr.-Ing. h.c. F. Porsche AG, usually shortened to Porsche (German pronunciation: [ˈpɔʁʃə] (audio speaker iconlisten); see below), is a German automobile manufacturer specializing in high-performance sports cars, SUVs and sedans, headquartered in Stuttgart, Baden-Württemberg, Germany.
```

- Remove vocal information (mostly done by html tags, so do it before you remove them)

```
Dr.-Ing. h.c. F. Porsche AG, usually shortened to Porsche (German pronunciation: [ˈpɔʁʃə] (audio speaker iconlisten); see below), is a German automobile manufacturer specializing in high-performance sports cars, SUVs and sedans, headquartered in Stuttgart, Baden-Württemberg, Germany.
```

- Remove special characters

```
Dr.-Ing. h.c. F. Porsche AG, usually shortened to Porsche (:();), is a German automobile manufacturer specializing in high-performance sports cars, SUVs and sedans, headquartered in Stuttgart, Baden-Württemberg, Germany.
```

9.1 Text Processing Example III

- Convert to same case

```
Dr Ing h c F Porsche AG usually shortened to Porsche German is a German automobile manufacturer specializing in high-performance sports cars SUVs and sedans headquartered in Stuttgart Baden-Württemberg Germany
```

- Remove single characters, and unimportant words

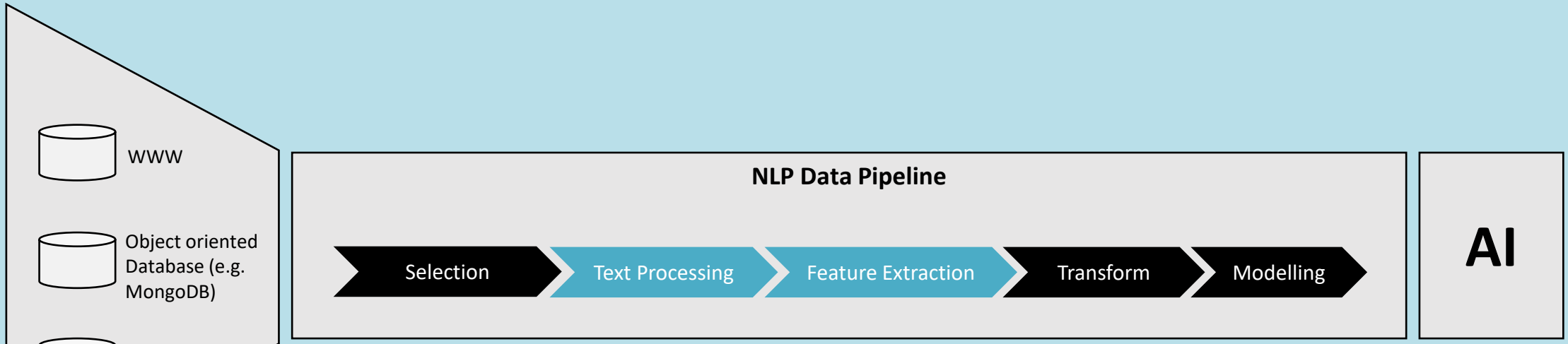
```
dr ing h c f porsche ag usually shortened to porsche german is a german automobile manufacturer specializing in high-performance sports cars suvs and sedans headquartered in stuttgart baden-württemberg germany
```

- Remove special characters

```
dr ing porsche ag shortened porsche german german automobile manufacturer specializing in high-performance sports cars suvs sedans headquartered stuttgart baden-württemberg germany
```

➡ Transform to usable schemata like e.g. table

9.1 NLP Data Pipelines



- Take raw text, clean in by removing irrelevant items, such as HTML tags
- Normalizing by converting to all lowercase and removing punctuation
- Extract and produce appropriate feature representations, e.g. splitting text into words or tokens
- Removing words that are too common, also known as stop words
- Identifying different parts of speech and named entities
- Converting words into their dictionary forms, using stemming and lemmatization
- Design your machine learning model, and then use it in your planned AI system

9.1 NLP Cleaning Tools

Beautiful Soup

Beautiful Soup 4.9.0 documentation » Beautiful Soup Documentation

Table of Contents

Beautiful Soup Documentation

Beautiful Soup is a Python library for pulling data out of HTML and XML files. It works with your favorite parser to provide idiomatic ways of navigating, searching, and modifying the parse tree. It commonly saves programmers hours or days of work.

These instructions illustrate all major features of Beautiful Soup 4, with examples. I show you what the library is good for, how it works, how to use it, how to make it do what you want, and what to do when it violates your expectations.

This document covers Beautiful Soup version 4.10.0. The examples in this documentation were written for Python 3.8.

You might be looking for the documentation for Beautiful Soup 3. If so, you should know that Beautiful Soup 3 is no longer being developed and that all support for it was dropped on December 31, 2020. If you want to learn about the differences between Beautiful Soup 3 and Beautiful Soup 4, see Porting code to BS4.

This documentation has been translated into other languages by Beautiful Soup users:

- 这篇文档当然还有中文版.
- このページは日本語で利用できます(外部リンク)
- 이 문서는 한국어 번역도 가능합니다.
- Este documento também está disponível em Português do Brasil.
- Эта документация доступна на русском языке.

Getting help

If you have questions about Beautiful Soup, or run into problems, send mail to the discussion group. If your problem involves parsing an HTML document, be sure to mention what the diagnose() function says about that document.

Quick Start

Here's an HTML document I'll be using as an example throughout this document. It's part of a story from *Alice in Wonderland*:

```
html_doc = """<html><head><title>The Dormouse's story</title></head>
<body>
```

Regular Expressions

```
/((\d{3})(?:\.|-))?(\d{3})(?:\.|-)(\d{4})/
```

9.1 NLP Normalization

Sport-car

Sportcar

Sport Car

sport-car

...


```
text = "sport-Car"

# convert to lowercase
text = text.lower()

# Remove punctuation characters
import re
text = re.sub(r"[^a-zA-Z0-9]", " ", text)
```

```
>>> print(text)
```

Do not mix up this concept with statistical normalization we discussed in lecture 4

Image Source: ↗ Porsche 911 R im Porsche Museum 2018 (2018) by Alexander Migl from ↗ Wikimedia / ↗ CC-BY-SA-4.0 (image not edited)

9.1 NLTK – Python package for Tokenization

NLTK

Search

NLTK Documentation
API Reference
Example Usage
Module Index
Wiki
FAQ
Open Issues
NLTK on GitHub

Installation
Installing NLTK
Installing NLTK Data

More
Release Notes
Contributing to NLTK
NLTK Team

Documentation

```
import nltk
nltk.download()
```

nltk.tokenize package

NLTK Tokenizer Package

Tokenizers divide strings into lists of substrings. For example, tokenizers can be used to find the words and punctuation in a string:

```
>>> from nltk.tokenize import word_tokenize
>>> s = '''Good muffins cost $3.88\nin New York.  Please buy me
... two of them.\n\nThanks.'''
>>> word_tokenize(s)
['Good', 'muffins', 'cost', '$', '3.88', 'in', 'New', 'York', '.',
'Please', 'buy', 'me', 'two', 'of', 'them', '.', 'Thanks', '.']
```

This particular tokenizer requires the Punkt sentence tokenization models to be installed. NLTK also provides a simpler, regular-expression based tokenizer, which splits text on whitespace and punctuation:

```
>>> from nltk.tokenize import wordpunct_tokenize
>>> wordpunct_tokenize(s)
['Good', 'muffins', 'cost', '$', '3', '.', '88', 'in', 'New', 'York', '.',
'Please', 'buy', 'me', 'two', 'of', 'them', '.', 'Thanks', '.']
```

If you want to save storage, you can download only specific functions like “punkt”, with `nltk.download('punkt')`. You can learn more about nltk data installation on their ↗ website

9.1 Tokenization

- You can use the in-build tokenization methods from NLTK to perform straight forward tokenization of your texts

```
>>> from nltk.tokenize import word_tokenize
>>> text = "I like this lecture. It has many practical examples."
>>> # Split text into words using NLTK
>>> words = word_tokenize(text)
>>> print(words)

['I', 'like', 'this', 'lecture', '.', 'It', 'has', 'many', 'practical',
'examples', '.']
```

There are many more build-in tokenization functions. What will e.g. `sent_tokenize(text)` return?

9.1 Stop Word Removal

- You can also use this package to remove noise like stopwords in different languages:

```
from nltk.corpus import stopwords
words = [w for w in words if w not in stopwords.words("english")]
```

```
>>> print(stopwords.words("english"))
['i', 'me', 'my', 'myself', 'we', 'our', 'ours', 'ourselves', 'you',
"you're", "you've", "you'll", "you'd", 'your', 'yours', 'yourself',
'yourselves', 'he', 'him', 'his', 'himself', 'she', "she's", 'her',
'hers', 'herself', 'it', "it's", 'its', 'itself', 'they', 'them',
'their', 'theirs …
```

9.1 Motivation for Part-of-Speech Tagging (POS)

- Identifiying how words are being used in a sentence helps us better understand what is being said:

pronoun verb noun

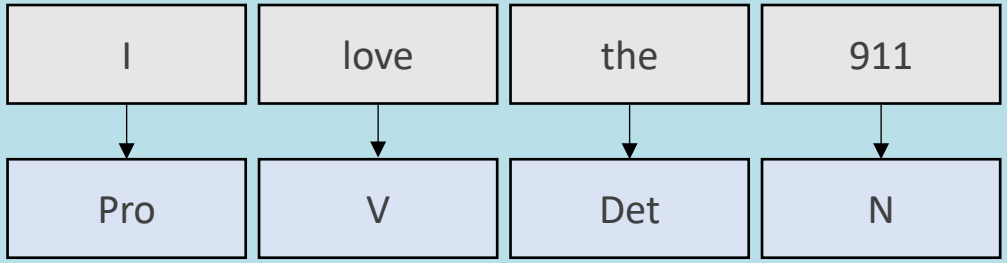
Because she was so fast, Marie was always the first at the restaurant.

- Helps us to find relationships between words

- Get full list of word classes with `nltk.help.upenn_tagset()`

9.1 Other Syntactic Tasks: Part Of Speech (POS) Tagging

- Annotate each word in a sentence with a part-of-speech



- Useful for subsequent syntactic parsing and word sense disambiguation

- Phrase Chunking: Find all non-recursive noun phrases (NPs) and verb phrases (VPs) in a sentence.

9.1 Part-of-Speech Tagging (POS) in nltk

- You can also use this package to remove noise like stopwords in different languages:

```
from nltk import pos_tag, ne_chunk
from nltk.tokenize import word_tokenize
text = "If ever there was proof that going electric needn’t be a
compromise, the Porsche Taycan is it"
```

```
>>> sentence = word_tokenize(text) # tokenize text
>>> pos_tag(sentence) # tag each word with pos

[('If', 'IN'),
 ('ever', 'RB'),
 ('there', 'EX'),
 ('was', 'VBD'),
 ('proof', 'NN’),…
```

```
IN: preposition or conjunction, subordinating
RB: adverb
EX: existential there
VBD: verb, past tense
NN: noun, common, singular or mass
```

9.1 Other Syntactic Tasks: Word Segmentation

- Breaking a string of characters (graphemes) into a sequence of words
- In some written languages (e.g. Chinese) words are not separated by spaces
- Even in English, characters other than white-space can be used to separate words [e.g. , ; . - : ( )]
- Examples:
  - www.maps.google.de → maps google → Google Maps
  - www.configurator.porsche.com/de-DE/ → Porsche Carconfigurator DE

9.1 Other Syntactic Tasks: Morphological Analysis

- Morphology is the field of linguistics that studies the internal structure of words
- Morphological analysis is the task of segmenting a word into its morphemes
- A morpheme is the smallest linguistic unit that has semantic meaning.
  - Sportscar: sport + car

9.1 Named Entity Recognition (NER)

- Identifying how words are being used in a sentence helps us better understand what is being said:

2 words, 1 entity

The Porsche AG builds sport-cars

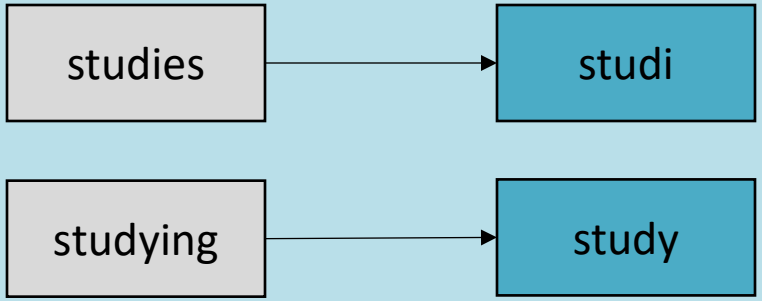
- Tokenize your text, make POS, then recognize named entities in text:

```
text = "The Porsche AG builds sport-cars"
tree = ne_chunk(pos_tag(word_tokenize(text)))
print(tree)
```

```
(S
  The/DT
  (ORGANIZATION Porsche/NNP)
  AG/NNP
  builds/VBZ
  sport-cars/NNS)
```

9.1 Stemming and Lemmatization

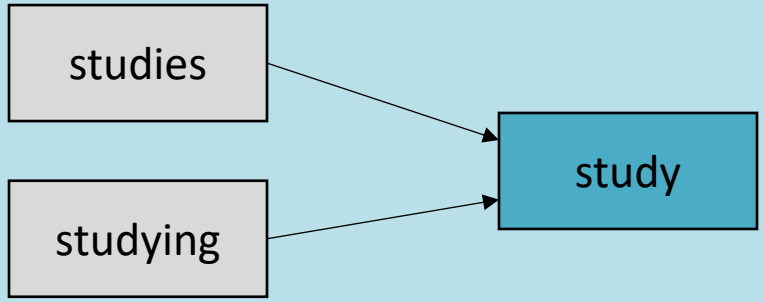
Stemming



- Removes suffixes

```
from nltk.stem import PorterStemmer
from nltk.tokenize import word_tokenize

ps = PorterStemmer()

words = ["driver", "drives", "drive"]
for w in words:
    print(w, " : ", ps.stem(w))
```

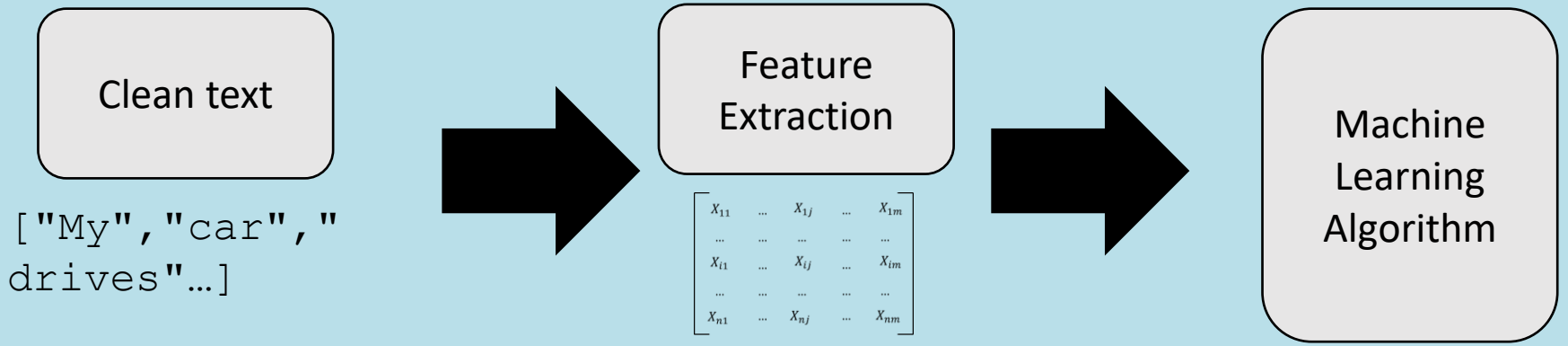
Lemmatization



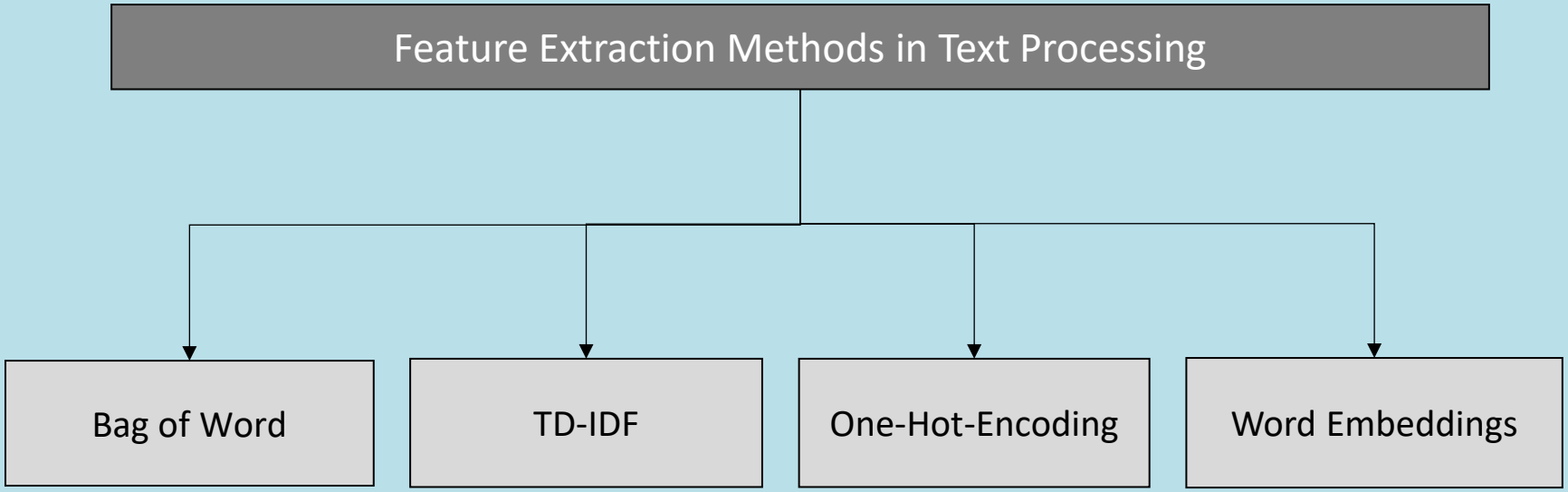
- Uses grammatical informations

```
from nltk.stem import WordNetLemmatizer

lemmatizer = WordNetLemmatizer()

print("sport-car :",
lemmatizer.lemmatize("rocks"))
```

9.1 Motivation: Feature Extraction in Text Processing



9.1 Popular Word and Representations for NLP



9.1 Python Code Example for Feature Extraction

- Load Packages and tokenize documents

```
import re
import nltk
from nltk.corpus import stopwords
from nltk.stem.wordnet import WordNetLemmatizer
from nltk.tokenize import word_tokenize

corpus = ["I like driving my Porsche.",
        "It is a very fast sport-car"
         …]

stop_words = stopwords.words("english")
lemmatizer = WordNetLemmatizer()

def tokenize(text):
    text = re.sub(r"[^a-zA-Z0-9]", " ", text.lower())
    tokens = word_tokenize(text)
    tokens = [lemmatizer.lemmatize(word) for word in tokens if word not in stop_words]

    return tokens
```

9.1 Bag of Words and Document Frequency

```
Document1 =
["My", "car",
"drives",
"very", "fast"]

Document2 =
["My", "car",
"is", "a",
"Porsche"]

Document3 =
["I", "like",
"my", "911"]
```

Document-term matrix

Term	Doc1	Doc2	Doc3	Sum
car	1	1	0	2
drives	1	0	0	1
very	1	0	0	1
fast	1	0	0	1
Porsche	0	1	0	1
like	0	0	1	1
911	0	0	1	1

```
Noise = ["a", "is", "my", "I"]
```

9.1 Similarity in Bag of Words

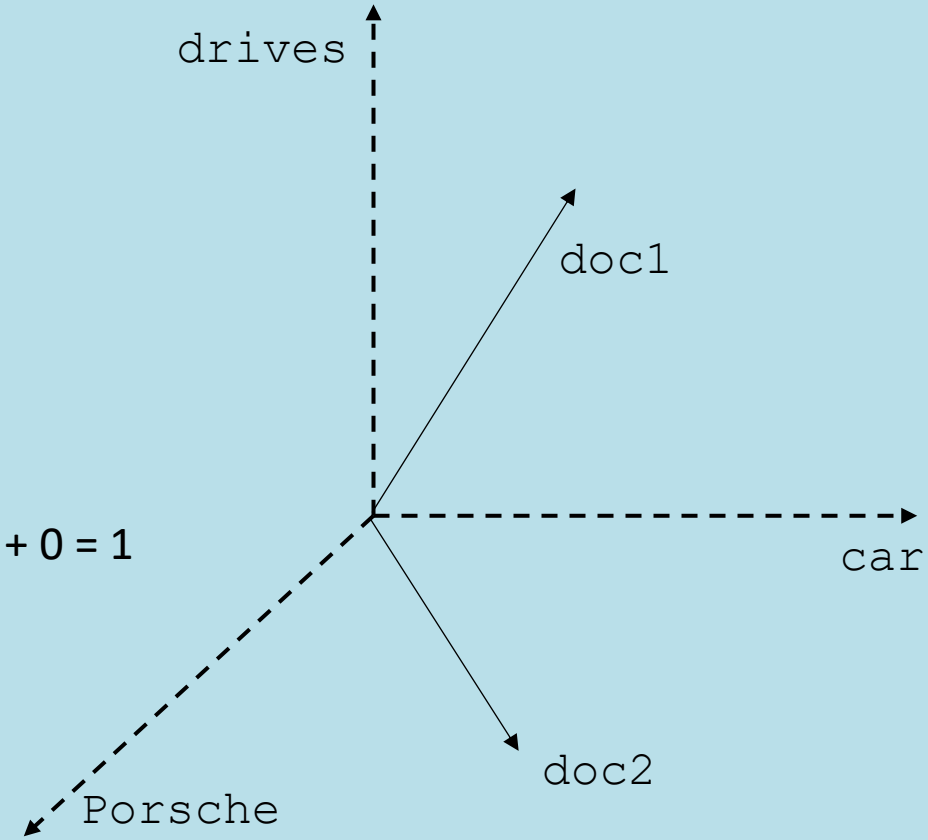
Term	Doc1	Doc2
car	1	1
drives	1	0
very	1	0
fast	1	0
Porsche	0	1

1. Dot product

$$doc1 \cdot doc2 = \sum a_o b_o + a_1 b_1 + \ldots + a_n b_n = 1 + 0 + 0 + 0 + 0 = 1$$

2. Cosine similarity

$$\cos(\theta) = \frac{doc1 \cdot doc2}{\| doc1 \| \cdot \| doc2 \|} = \frac{1}{\sqrt{4} \times \sqrt{2}}$$



9.1 Bag of Words with NLTK

- initialize count vectorizer object

```
from sklearn.feature_extraction.text import CountVectorizer
vect = CountVectorizer(tokenizer=tokenize)
```

- compute counts of each word (token) in our text data

```
>>> X = vect.fit_transform(corpus)
>>> X.toarray()

array([[0, 0, 0, 1, 0,], [0, 0, 0, 1, 0,] ….], dtype=int64)
```

9.1 Term Frequency (TF) – Inverse Document Frequency (IDF)

Term	Doc1	Doc2	Doc3	Freq
engine	3	2	0	5
drives	2	1	0	3
fuel	3	1	0	4
price	0	0	5	5
saldo	0	0	3	3
…	…	…	…	…

Term	Doc1	Doc2	Doc3	Freq
engine				5
drives				3
fuel				4
price				5
saldo				3
…	…	…	…	…

$$tf = \frac{count(t,d)}{|d|}$$

$$idf = \log(\frac{|D|}{|\{d \in D: t \in d\}|})$$

$$tfidf = tf \cdot idf$$

What will be the new values of the idf table? Can you compute them?

Do you have any idea of the background of doc1, doc2 and doc3?

9.1 TfidfTransformer with sklearn

- Compute tf-idf values based on the counts from count vectorizer

```
from sklearn.feature_extraction.text import TfidfTransformer

transformer = TfidfTransformer(smooth_idf=False)
tfidf = transformer.fit_transform(X)
```

- You can print it if you want

```
>>> tfidf.toarray()

array([[ 0.        ,  0.        ,  0.        ,  0.37       ,  0.        ,
         0.        ,  0.        ,  0.        ,  0.        ,  0.        ,
         0.        ,  0.        ,  0.        ,  0.        ,  0.57      ,
         0.        ,  0.        ,  0.        ,  0.        ,  0.        ]])
```

9.1 Alternative: TfidfVectorizer = CountVectorizer + TfidfTransformer

- compute tf-idf values based on the counts from count vectorizer

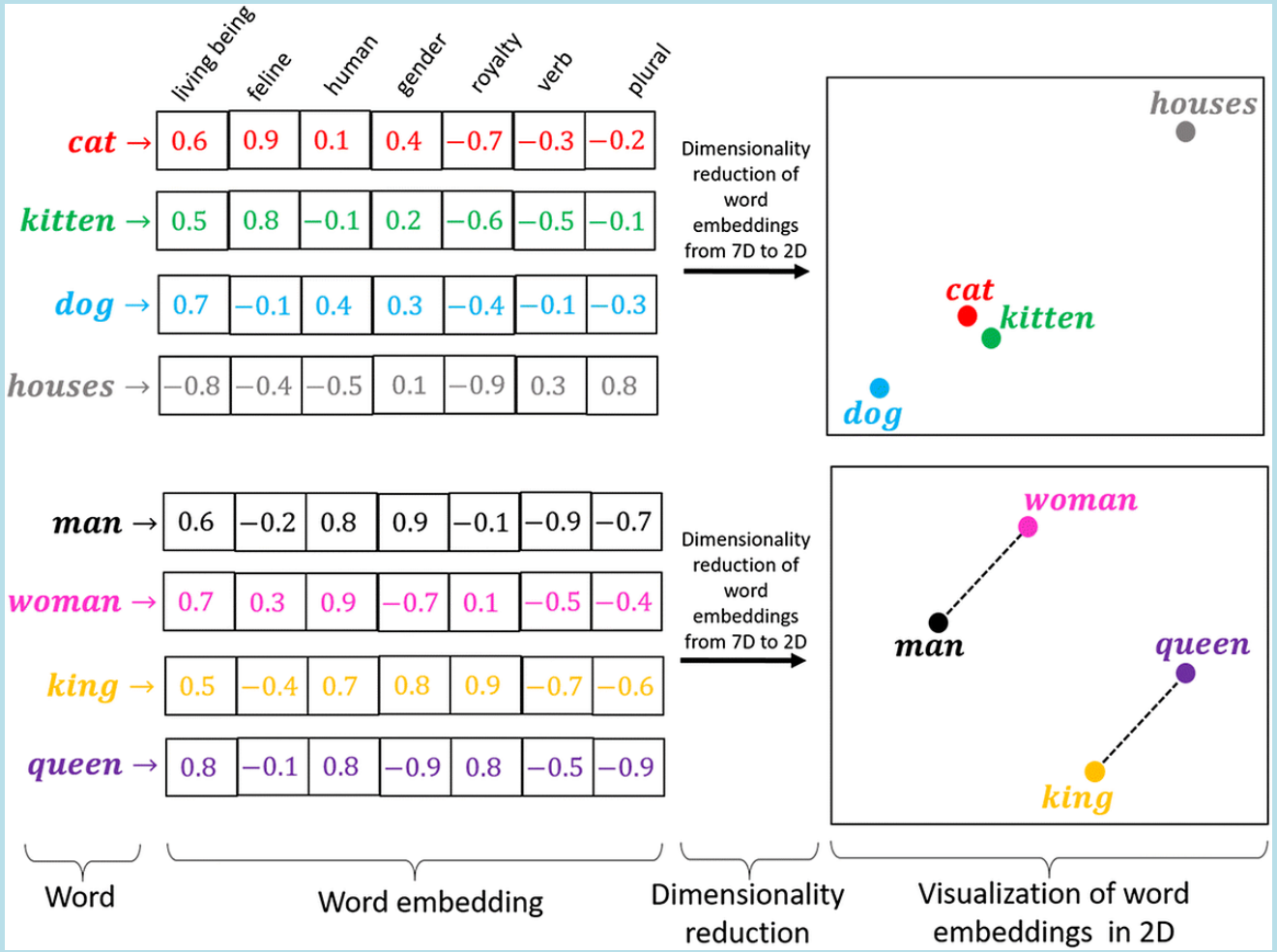
```
from sklearn.feature_extraction.text import TfidfVectorizer

# initialize tf-idf vectorizer object
vectorizer = TfidfVectorizer()

# compute bag of word counts and tf-idf values
X = vectorizer.fit_transform(corpus)
```

9.1 Application of TF-IDF score

- **Information retrieval**: Match TF-IDF score of a user query against the whole document set to figure out how relevant a document is to that given query

- **Keywords extraction**: The highest-ranking words for a document in terms of TF-IDF score can very well represent the keywords of that document

9.1 Word Embeddings



- Word embeddings are a way to represent words and whole sentences in a numerical manner
- A word embedding can have hundreds of values, each representing a different aspect of a word's meaning.

9.1 How to Generate Word Embeddings

- Word embeddings can be obtained using language modeling and feature learning techniques, where words or phrases from the vocabulary are mapped to vectors of real numbers.

- Best practice (before LLM): Word2vec, a two-layer neural net which output is a set of feature vectors that represent words in that corpus (see chapter 9.2)

Adapted from OpenAI (2023); Radford, A. et al. (2019); Floridi, L., & Chiriatti, M. (2020)

9.1 Classroom Task

Your turn!

Task

Please explain

- What is the vector space model in NLP?
- What are “Word Embeddings”?
- How do you compute similarity if you have two embeddings?

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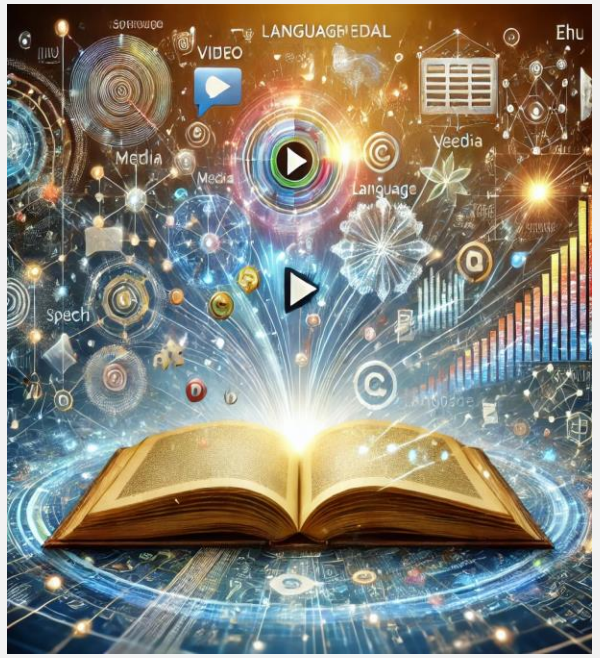
Lectorial 7: Building NLP and Machine Learning Pipelines for Webservices



► **What we will learn:**

- We will discuss how to make use of the copious knowledge that is expressed in natural language
- And how to process and prepare language data for machines to build state-of-the-art machine learning pipelines for language processing
- We learn new type of models, so called generative models, which allow to generate new instances based on the knowledge of your model

► **Duration:**

- 180 min + 90 (Lectorial)

► **Relevant for Exam:**

- 9.1, 9.3 – 9.4

9.2 Applications of Natural Language Processing…

This Software Engineer Designed a Chatbot to Chat With His Girlfriend While He's Busy at Work

NEWS 18

However, the girl eventually got suspicious over the speed she was receiving messages from her "boyfriend."

FORTUNE

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TECH · ASHLEY MADISON

Ashley Madison Used Chatbots to Lure Cheaters, Then Threatened to Expose Them When They Complained

BY **DAVID Z. MORRIS**

July 10, 2016 at 7:11 PM GMT+2

9.2 Communication

Speaker

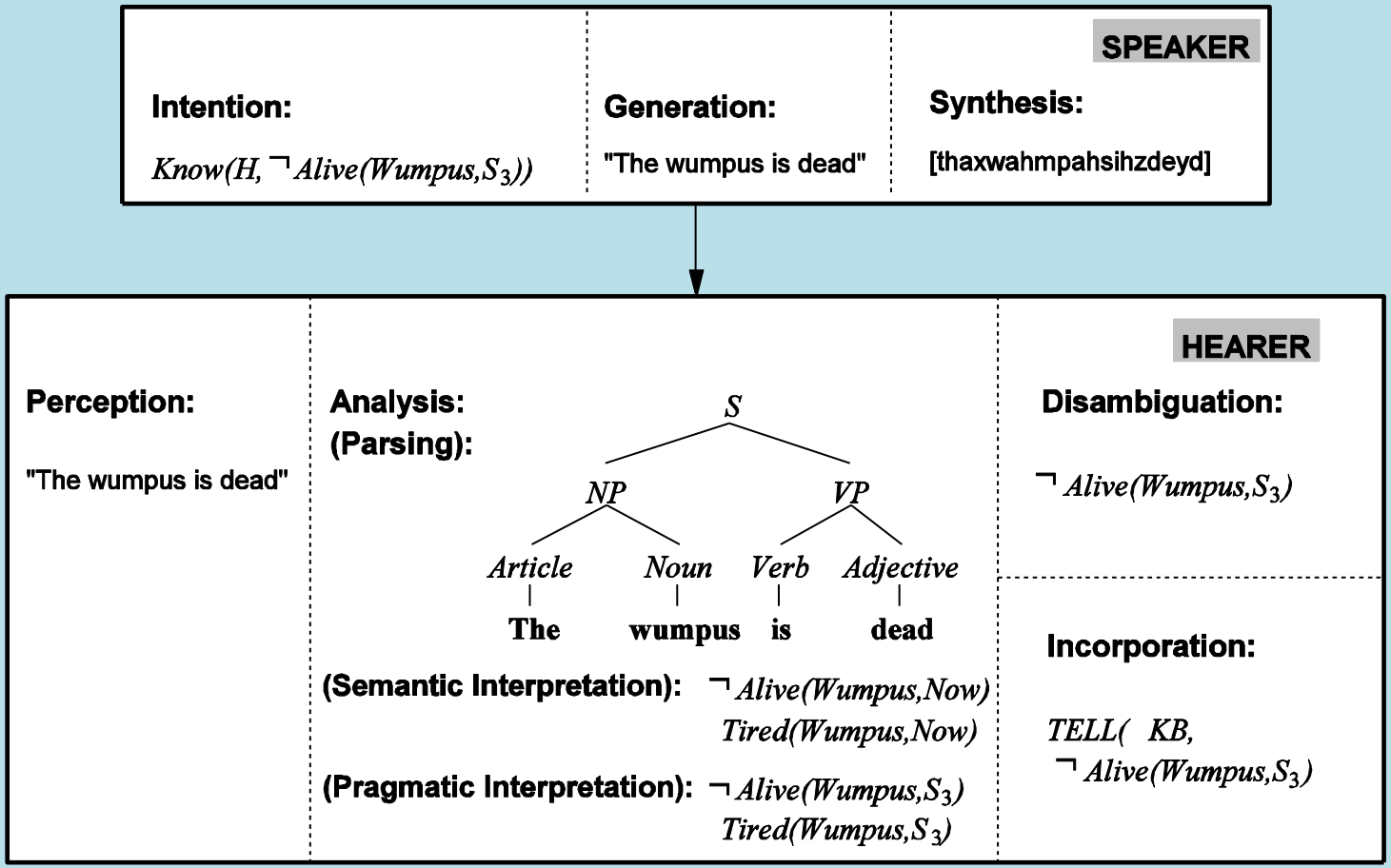
- **Intention**: Decide when and what information should be transmitted (a.k.a. strategic generation). May require planning and reasoning about agents' goals and beliefs.
- **Generation**: Translate the information to be communicated (in internal logical representation or "language of thought") into string of words in desired natural language (a.k.a. tactical generation).
- **Synthesis**: Output the string in desired modality, text or speech.

Supervised Learning

- **Perception**: Map input modality to a string of words, e.g. optical character recognition (OCR) or speech recognition.
- **Analysis**: Determine the information content of the string.
  - Syntactic interpretation (parsing): Find the correct parse tree showing the phrase structure of the string.
  - Semantic Interpretation: Extract the (literal) meaning of the string (logical form).
  - Pragmatic Interpretation: Consider effect of the overall context on altering the literal meaning of a sentence.
- **Incorporation**: Decide whether or not to believe the content of the string and add it to the KB.

Adapted from Rusell, S., & Norvig, P. (2016)

9.2 Communication (cont)



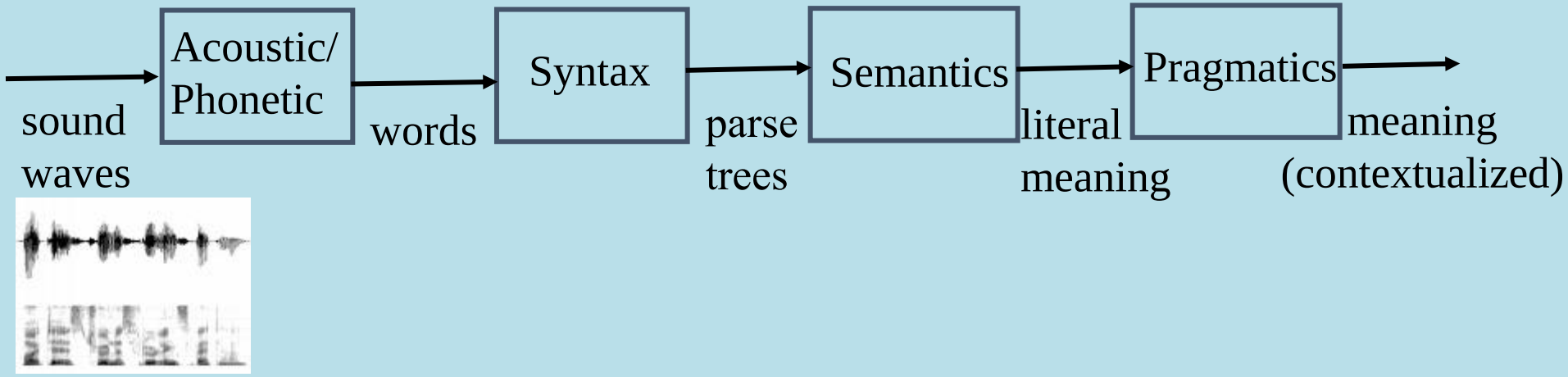
Adapted from Rusell, S., & Norvig, P. (2016)

9.2 Syntax, Semantic, Pragmatics

- Syntax concerns the proper ordering of words and its affect on meaning.
  - The dog bit the boy.
  - The boy bit the dog.
  - Colorless green ideas sleep furiously.
- Semantics concerns the (literal) meaning of words, phrases, and sentences.
  - “plant” as a photosynthetic organism
  - “plant” as a manufacturing facility
  - “plant” as the act of sowing
- Pragmatics concerns the overall communicative and social context and its effect on interpretation.
  - The ham sandwich wants another beer. (co-reference, anaphora)
  - John thinks vanilla. (ellipsis)

Adapted from Rusell, S., & Norvig, P. (2016)

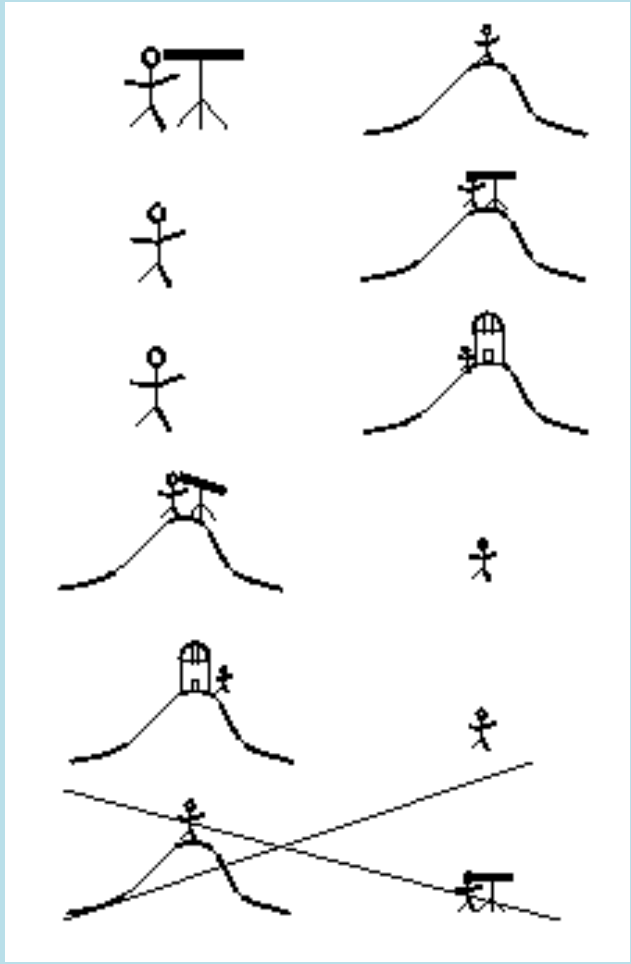
9.2 Modular Comprehension



Adapted from Rusell, S., & Norvig, P. (2016)

9.2 Ambiguity

- Natural language is highly ambiguous and must be *disambiguated*.
  - I saw the man on the hill with a telescope.
  - I saw the Grand Canyon flying to LA.
  - Time flies like an arrow.
  - Horse flies like a sugar cube.
  - Time runners like a coach.
  - Time cars like a Porsche.



Adapted from Rusell, S., & Norvig, P. (2016)

9.2 Ambiguity is Ubiquitous I

- Speech Recognition
  - “recognize speech” vs. “wreck a nice beach”
  - “youth in Asia” vs. “euthanasia”
- Syntactic Analysis
  - “I ate spaghetti with chopsticks” vs. “I ate spaghetti with meatballs.”
- Semantic Analysis
  - “The dog is in the pen.” vs. “The ink is in the pen.”
  - “I put the plant in the window” vs. “Ford put the plant in Mexico”

Adapted from Rusell, S., & Norvig, P. (2016)

9.2 Ambiguity is Ubiquitous II

- Pragmatic Analysis
  - From “The Pink Panther Strikes Again”:

Clouseau: Does your dog bite?
Hotel Clerk: No.
Clouseau: [bowing down to pet the dog] Nice doggie.
[Dog barks and bites Clouseau in the hand]
Clouseau: I thought you said your dog did not bite!
Hotel Clerk: That is not my dog.

Adapted from Rusell, S., & Norvig, P. (2016)

9.2 Ambiguity is Explosive

- Ambiguities compound to generate enormous numbers of possible interpretations.
- In English, a sentence ending in n prepositional phrases has over 2n syntactic interpretations (cf. Catalan numbers).
  - “I saw the man with the telescope”: 2 parses
  - “I saw the man on the hill with the telescope.”: 5 parses
  - “I saw the man on the hill in Texas with the telescope”: 14 parses
  - “I saw the man on the hill in Texas with the telescope at noon.”: 42 parses
  - “I saw the man on the hill in Texas with the telescope at noon on Monday” 132 parses

Adapted from Rusell, S., & Norvig, P. (2016)

9.2 Humor and Ambiguity

Many jokes rely on the ambiguity of language:

- Groucho Marx: One morning I shot an elephant in my pajamas. How he got into my pajamas, I'll never know.
- She criticized my apartment, so I knocked her flat.
- Noah took all of the animals on the ark in pairs. Except the worms, they came in apples.
- Policeman to little boy: "We are looking for a thief with a bicycle." Little boy: "Wouldn't you be better using your eyes."
- Why is the teacher wearing sun-glasses. Because the class is so bright.

Adapted from Rusell, S., & Norvig, P. (2016)

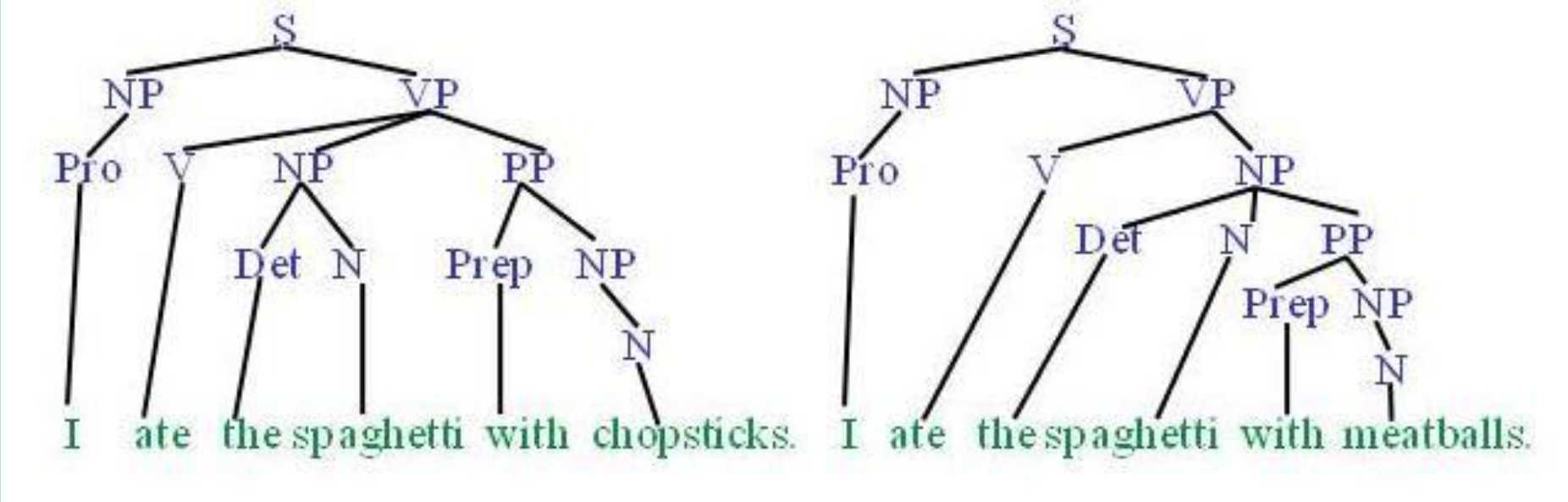
9.2 Natural Languages vs. Computer Languages

- Ambiguity is the primary difference between natural and computer languages.
- Formal programming languages are designed to be unambiguous, i.e. they can be defined by a grammar that produces a unique parse for each sentence in the language.
- Programming languages are also designed for efficient (deterministic) parsing, i.e. they are deterministic context-free languages (DCLFs).
- A sentence in a DCFL can be parsed in O(n) time where n is the length of the string.

Adapted from Rusell, S., & Norvig, P. (2016)

9.2 Syntactic Parsing

- Produce the correct syntactic parse tree for a sentence.



Adapted from Rusell, S., & Norvig, P. (2016)

9.2 Context Free Grammars (CFG)

- *N* a set of ***non-terminal symbols*** (or ***variables***)
- Σ a set of ***terminal symbols*** (disjoint from *N*)
- *R* a set of ***productions*** or ***rules*** of the form $A \rightarrow \beta$, where A is a non-terminal and β is a string of symbols from $(\Sigma \cup N)^*$
- S, a designated non-terminal called the ***start symbol***

Adapted from Rusell, S., & Norvig, P. (2016)

9.2 Simple CFG for ATIS English

Grammar

S → NP VP

S → Aux NP VP

S → VP

NP → Pronoun

NP → Proper-Noun

NP → Det Nominal

Nominal → Noun

Nominal → Nominal Noun

Nominal → Nominal PP

VP → Verb

VP → Verb NP

VP → VP PP

PP → Prep NP

Lexicon

Det → the | a | that | this

Noun → book | flight | meal | money

Verb → book | include | prefer

Pronoun → I | he | she | me

Proper-Noun → Houston | NWA

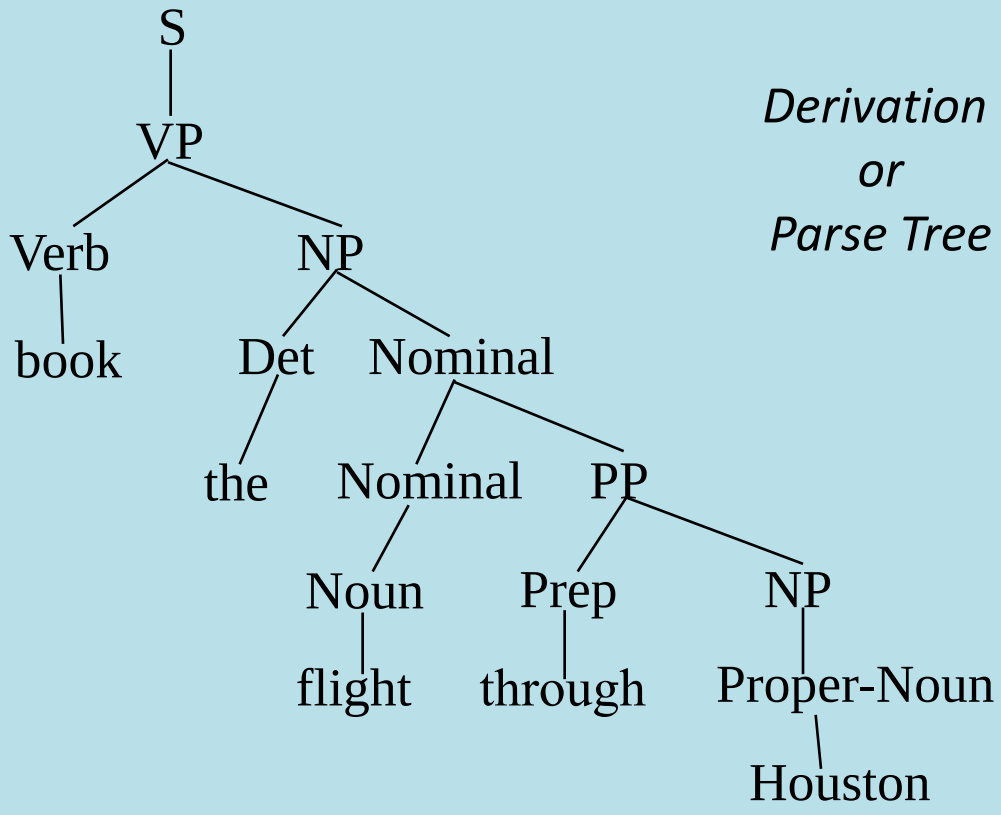
Aux → does

Prep → from | to | on | near | through

Adapted from Rusell, S., & Norvig, P. (2016)

9.2 Sentence Generation

- Sentences are generated by recursively rewriting the start symbol using the productions until only terminals symbols remain.

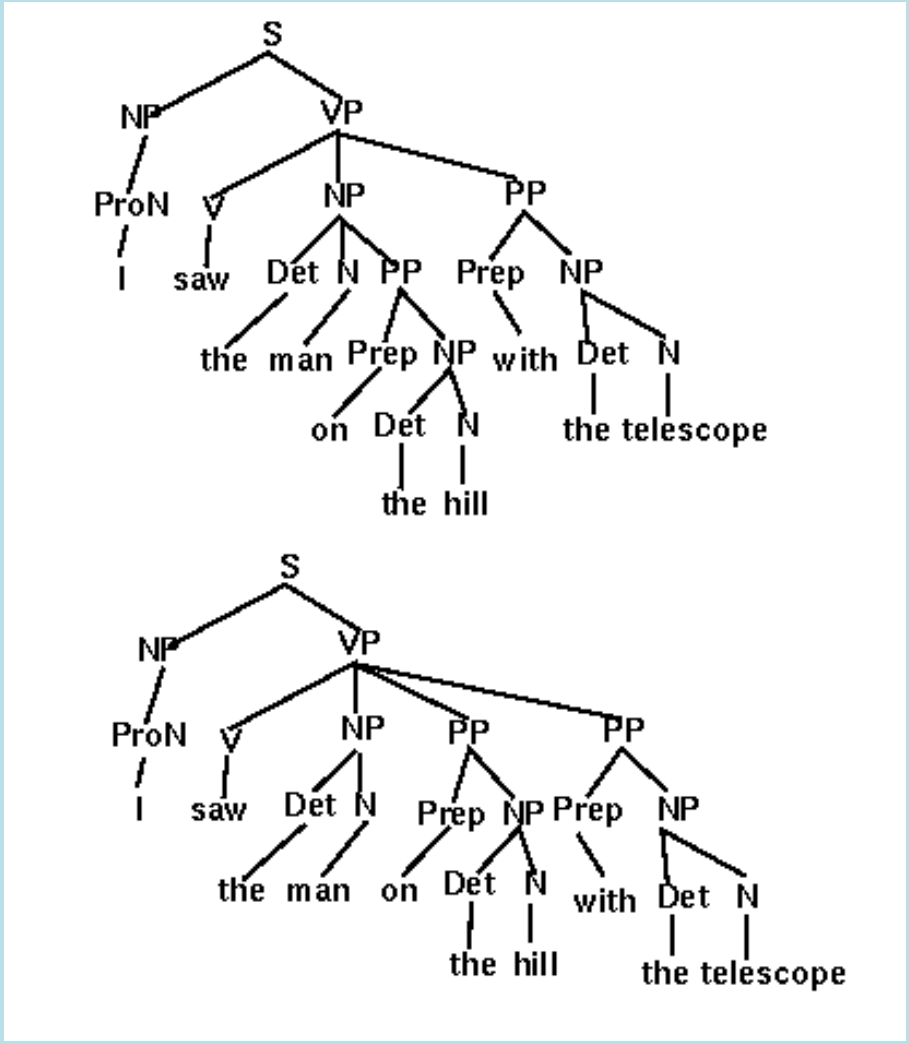


Derivation or Parse Tree

Adapted from Rusell, S., & Norvig, P. (2016)

9.2 Parse Trees and Syntactic Ambiguity

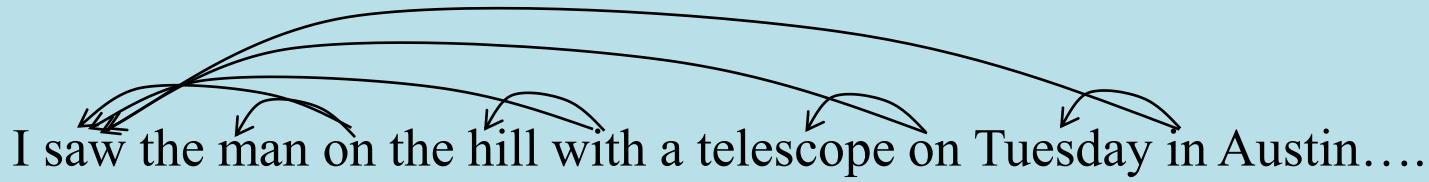
- If a sentence has more than one possible derivation (parse tree) it is said to be *syntactically ambiguous*.



Adapted from Rusell, S., & Norvig, P. (2016)

9.2 Prepositional Phrase Attachment Explosion

- A transitive English sentence ending in *m* prepositional phrases has *at least* 2^m parses.



- The exact number of parses is given by the *Catalan numbers* (where $n=m+1$)

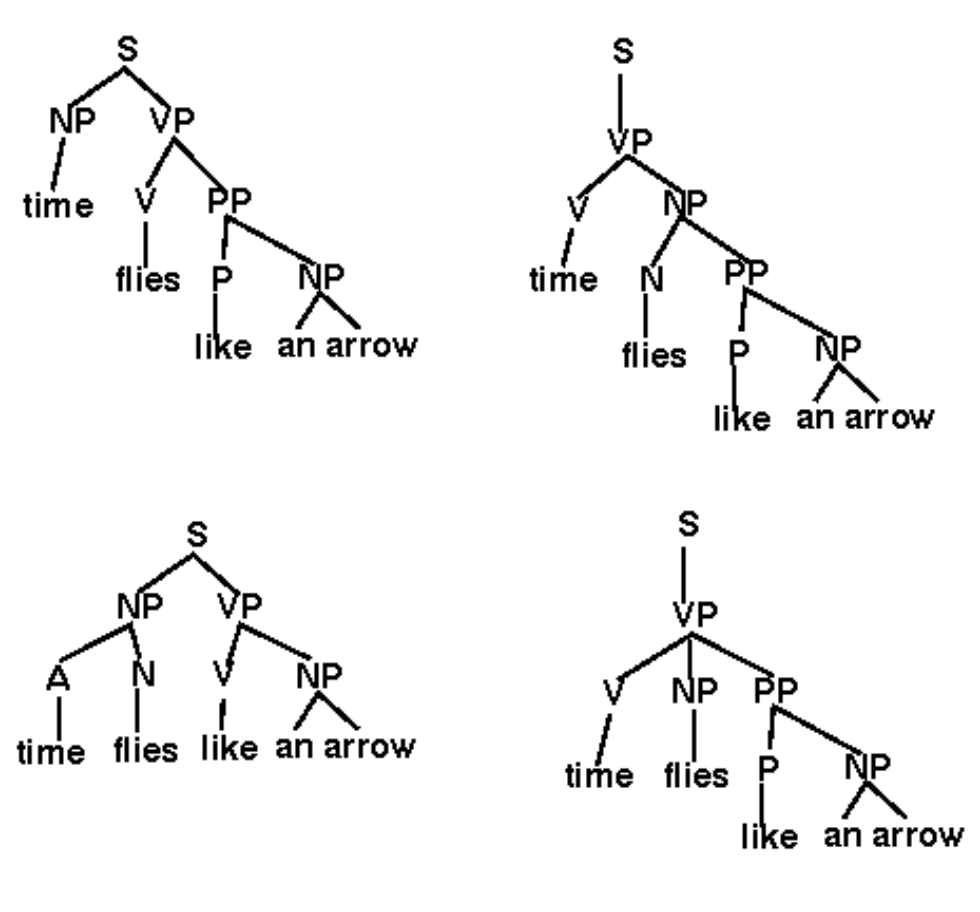
$$\binom{2n}{n} - \binom{2n}{n-1} \approx \frac{4^n}{n^{3/2}\sqrt{\pi}}$$

$$1, 2, 5, 14, 132, 429, 1430, 4862, 16796, \ldots\ldots$$

Adapted from Rusell, S., & Norvig, P. (2016)

9.2 Spurious Ambiguity

- Most parse trees of most NL sentences make no sense.



Adapted from Rusell, S., & Norvig, P. (2016)

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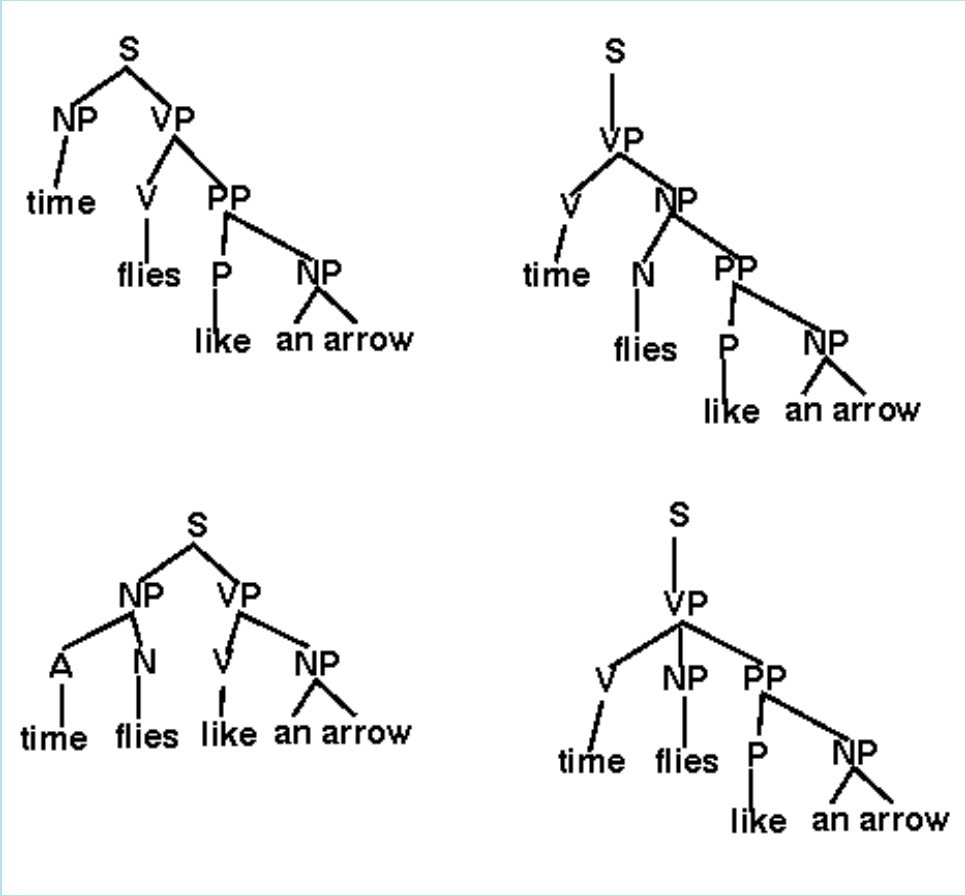


Adapted from Rusell, S., & Norvig, P. (2016)

9.2 Parsing

- Given a string of non-terminals and a CFG, determine if the string can be generated by the CFG.
  - Also return a parse tree for the string
  - Also return all possible parse trees for the string

- Must search space of derivations for one that derives the given string.
  - **Top-Down Parsing**: Start searching space of derivations for the start symbol.
  - **Bottom-up Parsing**: Start search space of reverse deivations from the terminal symbols in the string.

Adapted from Rusell, S., & Norvig, P. (2016)

9.2 Top Down vs. Bottom Up

- Top down never explores options that will not lead to a full parse, but can explore many options that never connect to the actual sentence.
- Bottom up never explores options that do not connect to the actual sentence but can explore options that can never lead to a full parse.
- Relative amounts of wasted search depend on how much the grammar branches in each direction.

Adapted from Rusell, S., & Norvig, P. (2016)

9.2 Syntactic Parsing & Ambiguity

- Just produces all possible parse trees.
- Does not address the important issue of ambiguity resolution.

Adapted from Rusell, S., & Norvig, P. (2016)

9.2 Statistical Parsing

- Statistical parsing uses a probabilistic model of syntax in order to assign probabilities to each parse tree.
- Provides principled approach to resolving syntactic ambiguity.
- Allows supervised learning of parsers from tree-banks of parse trees provided by human linguists.
- Also allows unsupervised learning of parsers from unannotated text, but the accuracy of such parsers has been limited.

Adapted from Rusell, S., & Norvig, P. (2016)

9.2 Probabilistic Context Free Grammar (PCFG)

- A PCFG is a probabilistic version of a CFG where each production has a probability.
- Probabilities of all productions rewriting a given non-terminal must add to 1, defining a distribution for each non-terminal.
- String generation is now probabilistic where production probabilities are used to non-deterministically select a production for rewriting a given non-terminal.

Adapted from Rusell, S., & Norvig, P. (2016)

9.2 Simple PCFG for ATIS English

Grammar	Prob	
S → NP VP	0.8	
S → Aux NP VP	0.1	+ 1.0
S → VP	0.1	
NP → Pronoun	0.2	
NP → Proper-Noun	0.2	+ 1.0
NP → Det Nominal	0.6	
Nominal → Noun	0.3	
Nominal → Nominal Noun	0.2	+ 1.0
Nominal → Nominal PP	0.5	
VP → Verb	0.2	
VP → Verb NP	0.5	+ 1.0
VP → VP PP	0.3	
PP → Prep NP	1.0	

Lexicon

Det → the | a | that | this
0.6 0.2 0.1 0.1

Noun → book | flight | meal | money
0.1 0.5 0.2 0.2

Verb → book | include | prefer
0.5 0.2 0.3

Pronoun → I | he | she | me
0.5 0.1 0.1 0.3

Proper-Noun → Houston | NWA
0.8 0.2

Aux → does
1.0

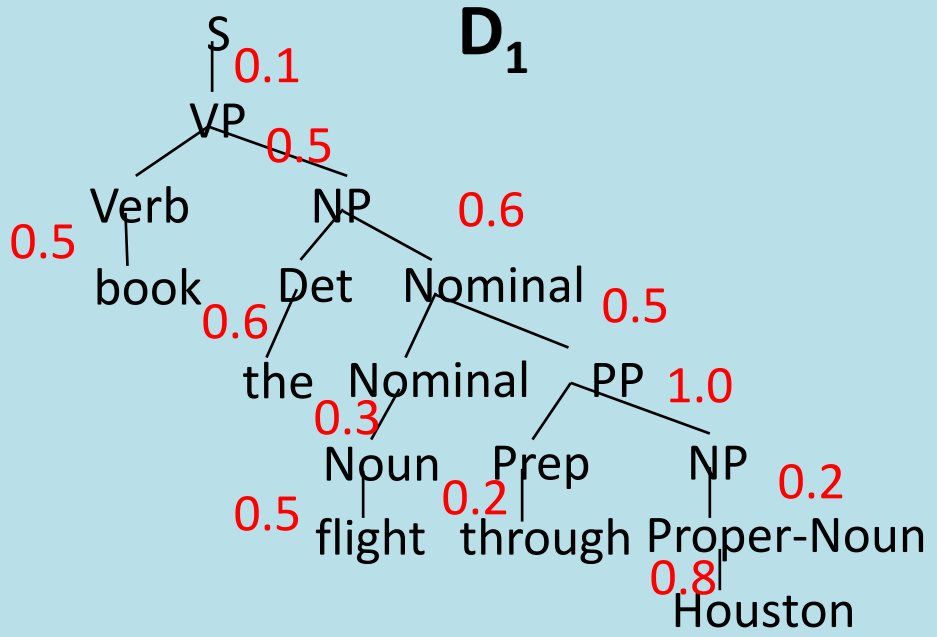
Prep → from | to | on | near | through
0.25 0.25 0.1 0.2 0.2

Adapted from Rusell, S., & Norvig, P. (2016)

9.2 Sentence Probability

- Assume productions for each node are chosen independently.
- Probability of derivation is the product of the probabilities of its productions.

$$P(D_1) = 0.1 \times 0.5 \times 0.5 \times 0.6 \times 0.6 \times 0.5 \times 0.3 \times 1.0 \times 0.2 \times 0.2 \times 0.5 \times 0.8 = 0.0000216$$



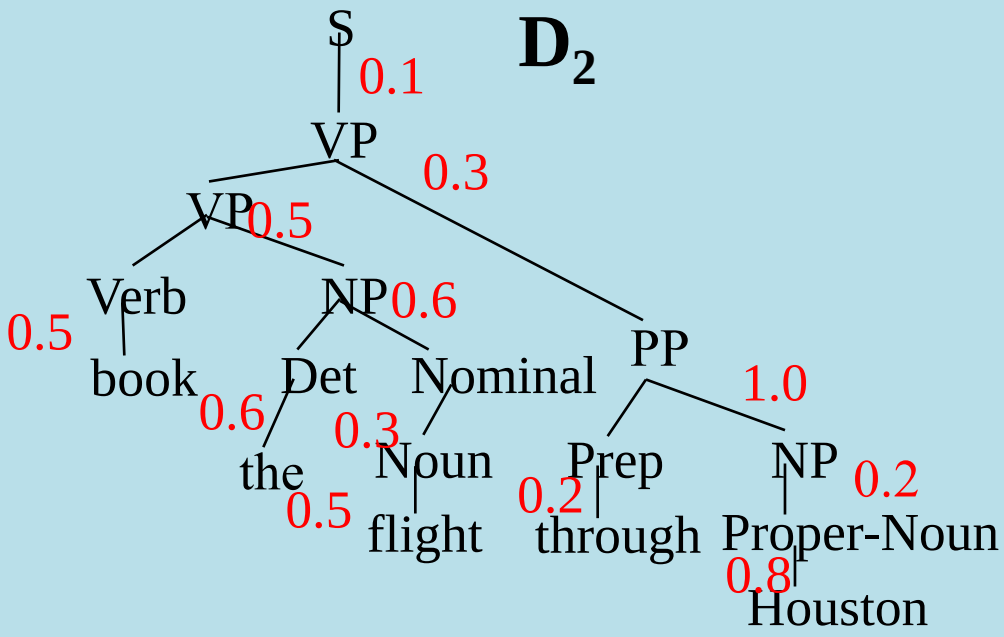
Adapted from Rusell, S., & Norvig, P. (2016)

9.2 Syntactic Disambiguation

- Resolve ambiguity by picking most probable parse tree.

$P(D_2) = 0.1 \times 0.3 \times 0.5 \times 0.6 \times 0.5 \times 0.6 \times 0.3 \times 1.0 \times 0.5 \times 0.2 \times 0.2 \times 0.8$

$= 0.00001296$



Adapted from Rusell, S., & Norvig, P. (2016)

9.2 Sentence Probability

- Probability of a sentence is the sum of the probabilities of all of its derivations.

P(“book the flight through Houston”) =
$P(D_1) + P(D_2) = 0.0000216 + 0.00001296$
$= 0.00003456$

Adapted from Rusell, S., & Norvig, P. (2016)

9.2 Three Useful PCFG Tasks

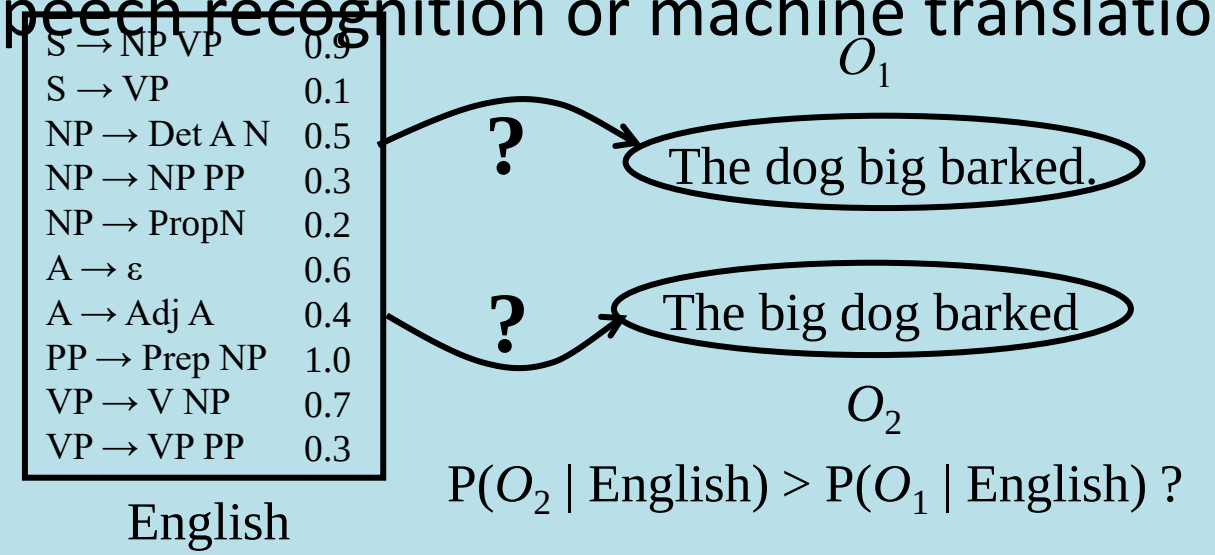
- Observation likelihood: To classify and order sentences.
- Most likely derivation: To determine the most likely parse tree for a sentence.
- Maximum likelihood training: To train a PCFG to fit empirical training data.

Adapted from Rusell, S., & Norvig, P. (2016)

9.2 PCFG: Observation Likelihood

- What is the probability that a given string is produced by a given PCFG

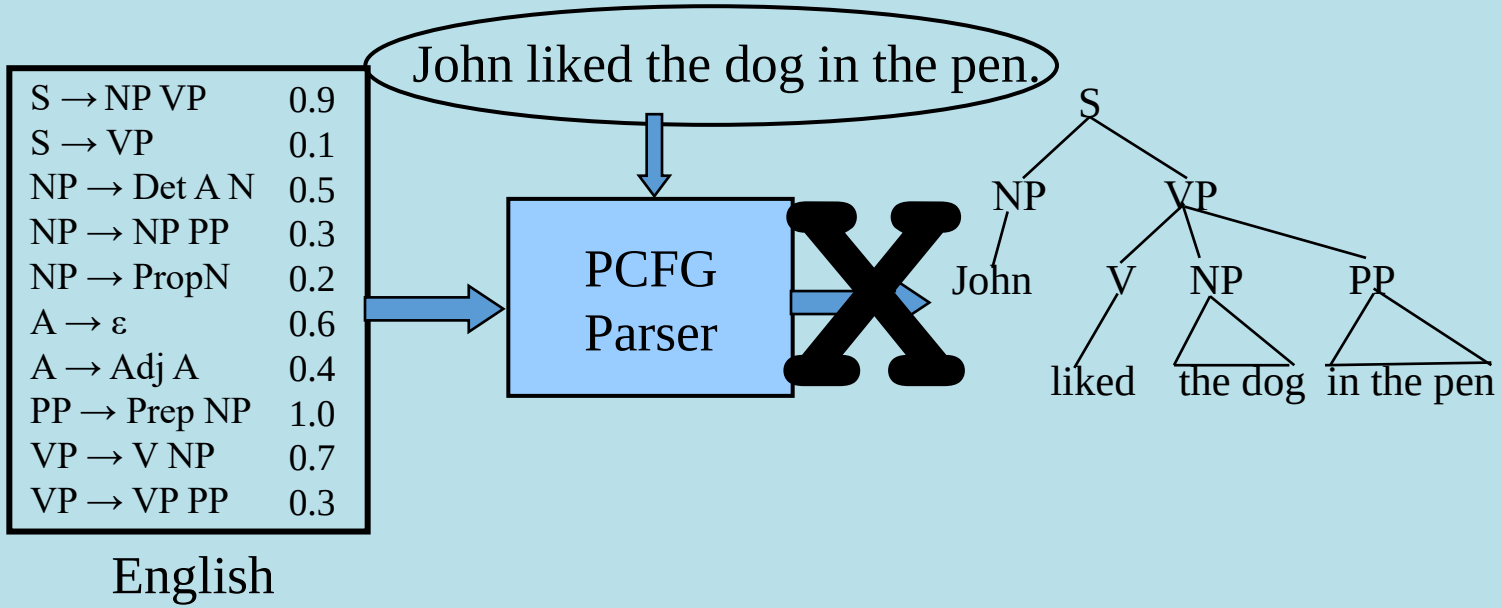
- Can use a PCFG as a language model to choose between alternative sentences for speech recognition or machine translation



Adapted from Rusell, S., & Norvig, P. (2016)

9.2 PCFG: Most Likely Derivation

- What is the most probable derivation (parse tree) for a sentence.



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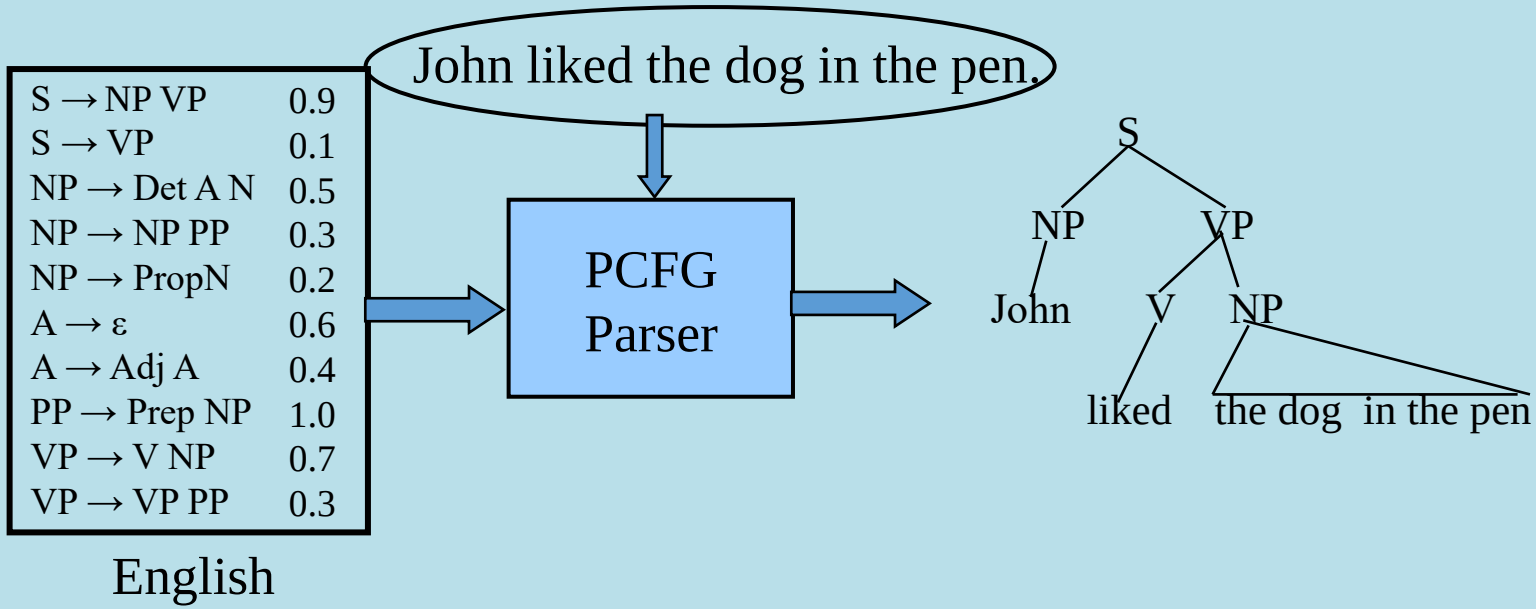
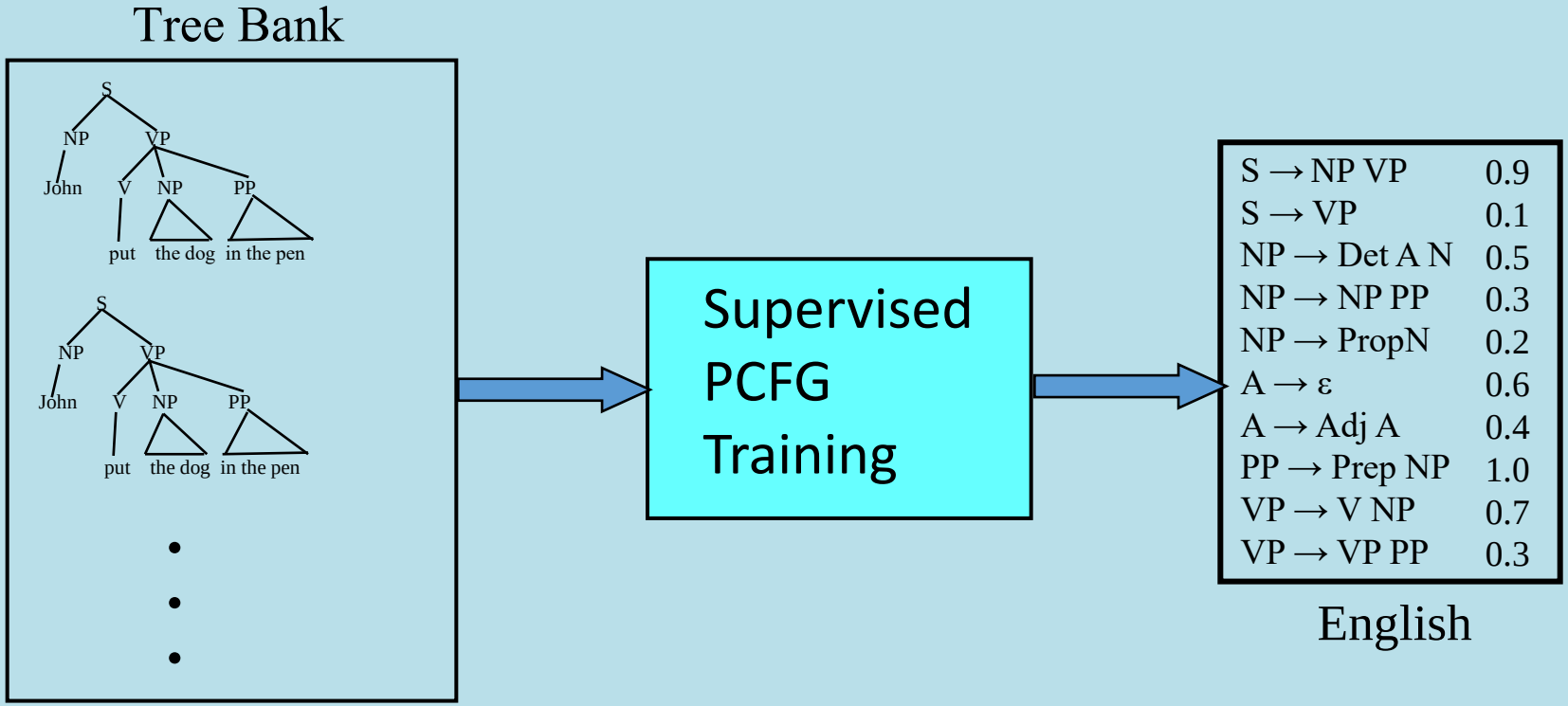


Adapted from Rusell, S., & Norvig, P. (2016)

9.2 PCFG: Supervised Training

- If parse trees are provided for training sentences, a grammar and its parameters can all be estimated directly from counts accumulated from the tree-bank (with appropriate smoothing).



Adapted from Rusell, S., & Norvig, P. (2016)

9.2 Estimating Production Probabilities

- Set of production rules can be taken directly from the set of rewrites in the treebank.
- Parameters can be directly estimated from frequency counts in the treebank.

$$P(\alpha \rightarrow \beta \mid \alpha) = \frac{\text{count}(\alpha \rightarrow \beta)}{\sum_{\gamma} \text{count}(\alpha \rightarrow \gamma)} = \frac{\text{count}(\alpha \rightarrow \beta)}{\text{count}(\alpha)}$$

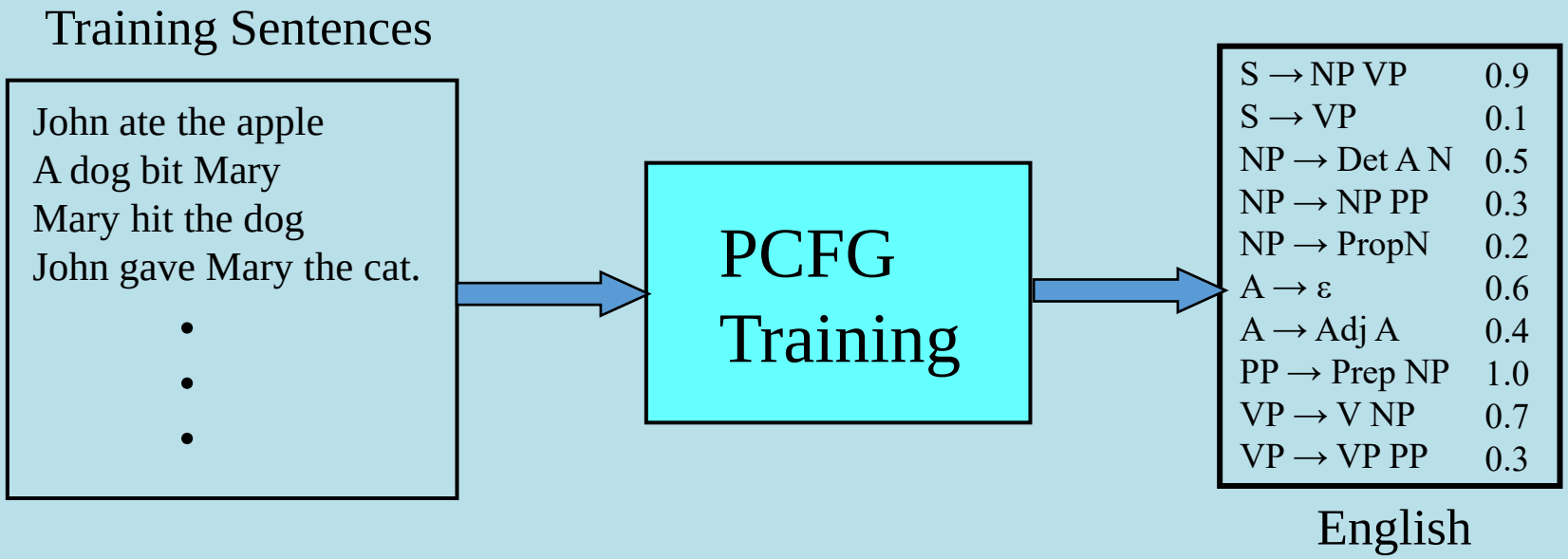
Adapted from Rusell, S., & Norvig, P. (2016)

9.2 PCFG: Maximum Likelihood Training

- Given a set of sentences, induce a grammar that maximizes the probability that this data was generated from this grammar.
- Assume the number of non-terminals in the grammar is specified.
- Only need to have an unannotated set of sequences generated from the model. Does not need correct parse trees for these sentences. In this sense, it is unsupervised.

Adapted from Rusell, S., & Norvig, P. (2016)

9.2 PCFG: Maximum Likelihood Training



Adapted from Rusell, S., & Norvig, P. (2016)

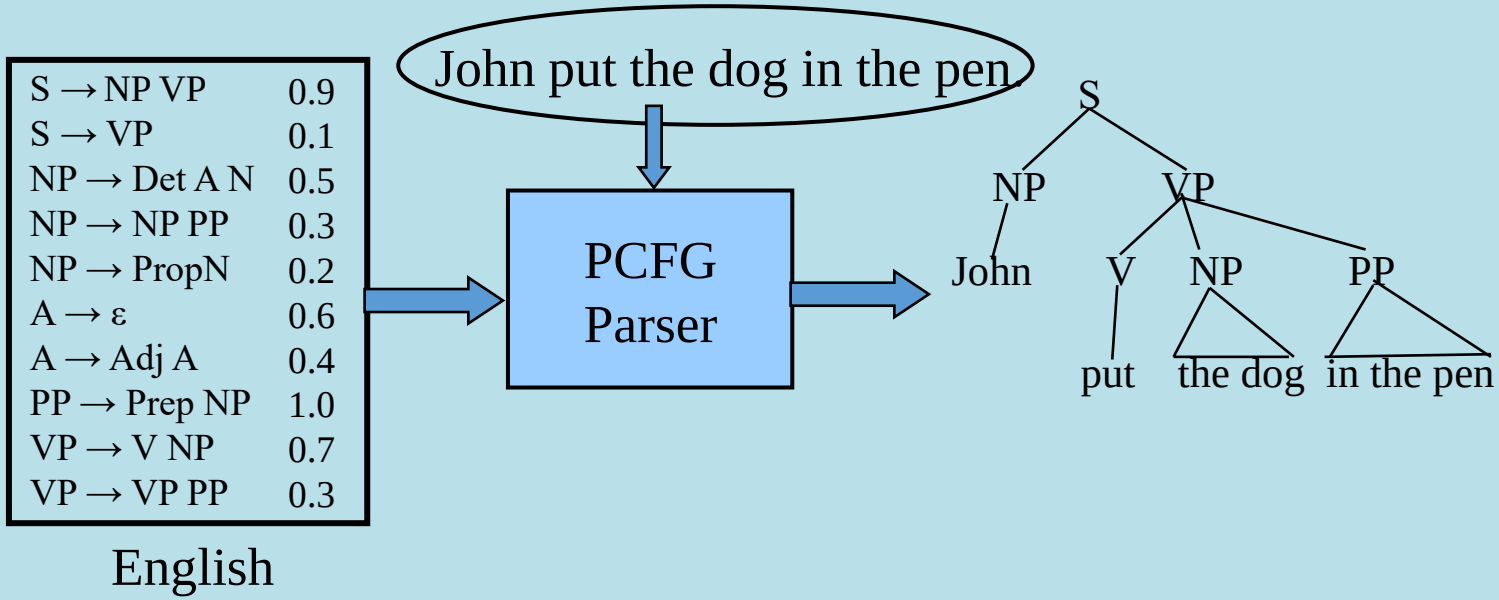
9.2 Vanilla PCFG Limitations

- Since probabilities of productions do not rely on specific words or concepts, only general structural disambiguation is possible (e.g. prefer to attach PPs to Nominals).
- Consequently, vanilla PCFGs cannot resolve syntactic ambiguities that require semantics to resolve, e.g. ate with fork vs. meatballs.
- In order to work well, PCFGs must be lexicalized, i.e. productions must be specialized to specific words by including their head-word in their LHS non-terminals (e.g. VP-ate).

Adapted from Rusell, S., & Norvig, P. (2016)

9.2 Example of Importance of Lexicalization

- A general preference for attaching PPs to NPs rather than VPs can be learned by a vanilla PCFG.
- But the desired preference can depend on specific words.



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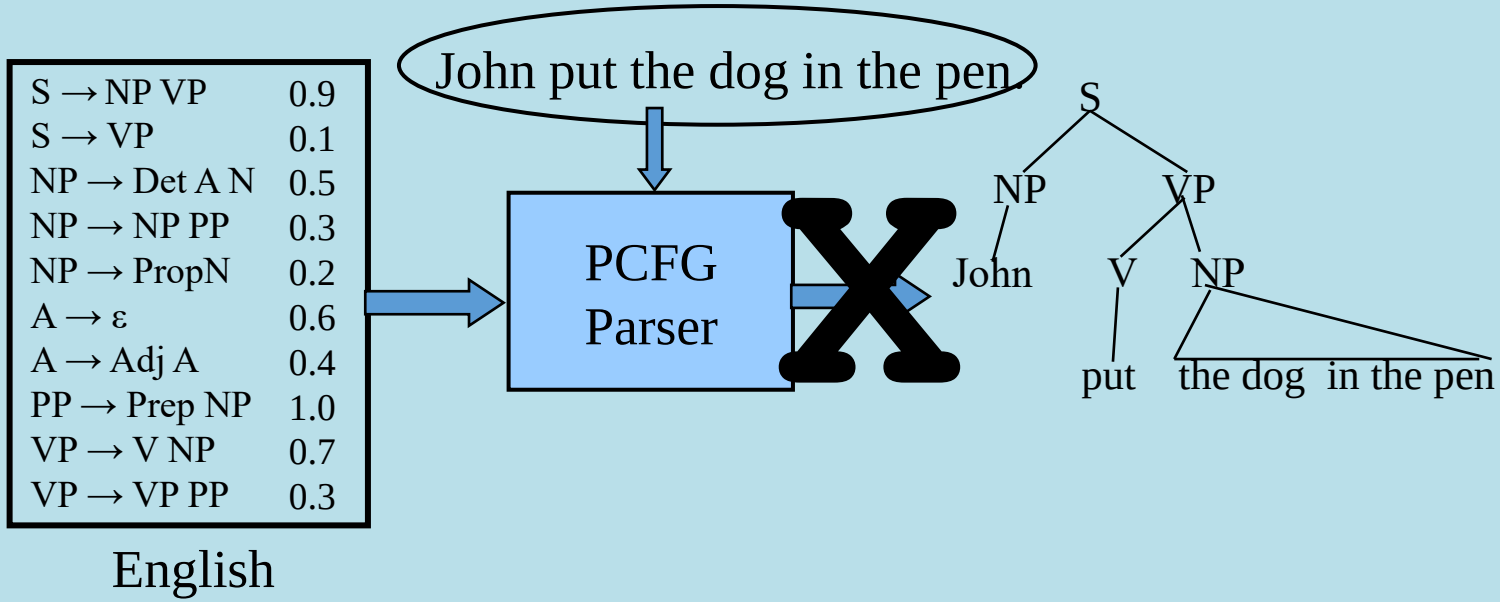


Adapted from Rusell, S., & Norvig, P. (2016)

9.2 Treebanks

- English Penn Treebank: Standard corpus for testing syntactic parsing consists of 1.2 M words of text from the Wall Street Journal (WSJ).
- Typical to train on about 40,000 parsed sentences and test on an additional standard disjoint test set of 2,416 sentences.
- Chinese Penn Treebank: 100K words from the Xinhua news service.
- Other corpora existing in many languages, see the Wikipedia article “Treebank”

Adapted from Rusell, S., & Norvig, P. (2016)

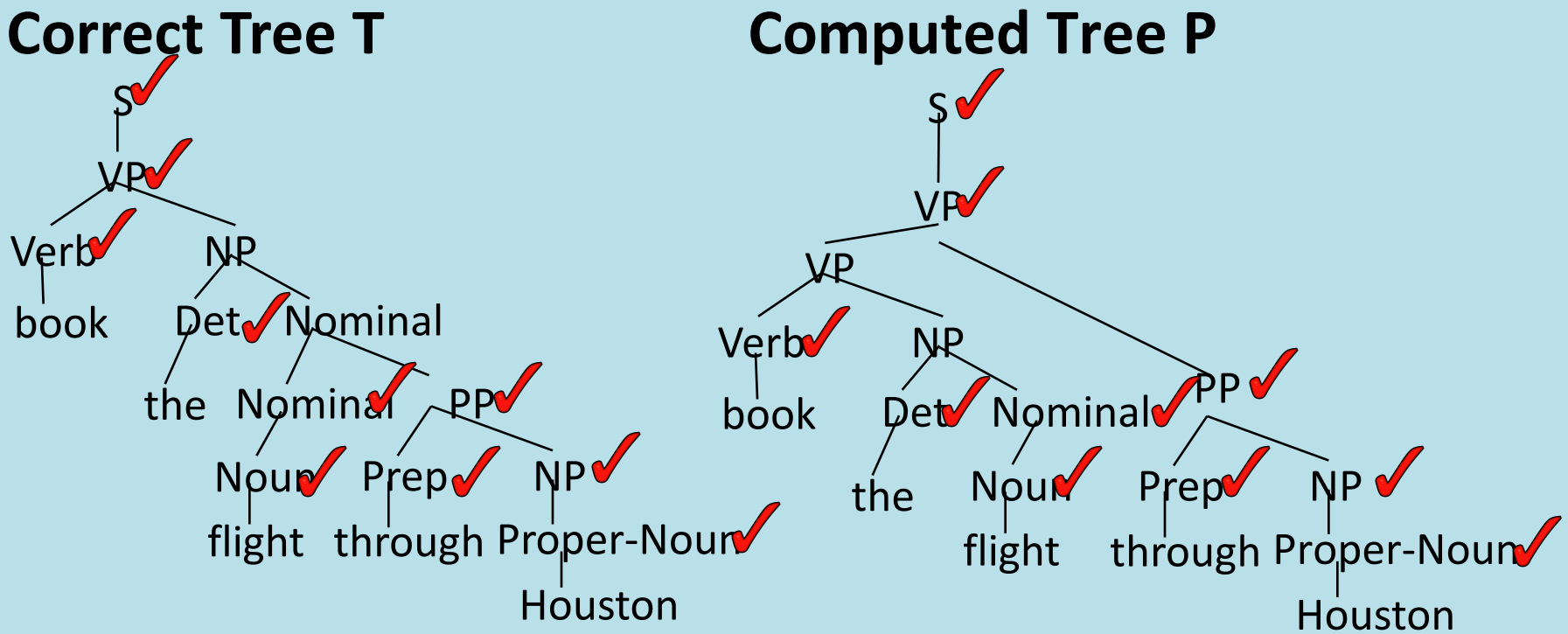
9.2 Parsing Evaluation Metrics

- PARSEVAL metrics measure the fraction of the constituents that match between the computed and human parse trees. If P is the system's parse tree and T is the human parse tree (the "gold standard"):
  - Recall = (# correct constituents in P) / (# constituents in T)
  - Precision = (# correct constituents in P) / (# constituents in P)

- Labeled Precision and labeled recall require getting the non-terminal label on the constituent node correct to count as correct.
- F1 is the harmonic mean of precision and recall.

Adapted from Rusell, S., & Norvig, P. (2016)

9.2 Computing Evaluation Metrics



Constituents: 12

Constituents: 12

Correct Constituents: 10

Recall = 10/12= 83.3% Precision = 10/12=83.3% F_1 = 83.3%

Adapted from Rusell, S., & Norvig, P. (2016)

9.2 Treebank Results

- Results of current state-of-the-art systems on the English Penn WSJ treebank are slightly greater than 90% labeled precision and recall.

Adapted from Rusell, S., & Norvig, P. (2016)

9.2 Word Sense Disambiguation (WSD)

- Words in natural language usually have a fair number of different possible meanings.
  - Ellen has a strong interest in computational linguistics.
  - Ellen pays a large amount of interest on her credit card.

- For many tasks (question answering, translation), the proper sense of each ambiguous word in a sentence must be determined.

Adapted from Rusell, S., & Norvig, P. (2016)

9.2 Ambiguity Resolution is Required for Translation

- Syntactic and semantic ambiguities must be properly resolved for correct translation:
  - "John plays the guitar." → "John toca la guitarra."
  - "John plays soccer." → "John juega el fútbol."

- An apocryphal story is that an early MT system gave the following results when translating from English to Russian and then back to English:
  - "The spirit is willing but the flesh is weak." → "The liquor is good but the meat is spoiled."
  - "Out of sight, out of mind." → "Invisible idiot."

Adapted from Rusell, S., & Norvig, P. (2016)

9.2 Word Sense Disambiguation (WSD) as Text Categorization

- Each sense of an ambiguous word is treated as a category.
  - “play” (verb)
    - play-game
    - play-instrument
    - play-role
  - “pen” (noun)
    - writing-instrument
    - enclosure

Adapted from Rusell, S., & Norvig, P. (2016)

9.2 Word Sense Disambiguation (WSD) as Text Categorization

- Treat current sentence (or preceding and current sentence) as a document to be classified.
  - “play”:
    - play-game: “John played soccer in the stadium on Friday.”
    - play-instrument: “John played guitar in the band on Friday.”
    - play-role: “John played Hamlet in the theater on Friday.”
  - “pen”:
    - writing-instrument: “John wrote the letter with a pen in New York.”
    - enclosure: “John put the dog in the pen in New York.”

Adapted from Rusell, S., & Norvig, P. (2016)

9.2 Learning for WSD

- Assume part-of-speech (POS), e.g. noun, verb, adjective, for the target word is determined.
- Treat as a classification problem with the appropriate potential senses for the target word given its POS as the categories.
- Encode context using a set of features to be used for disambiguation.
- Train a classifier on labeled data encoded using these features.
- Use the trained classifier to disambiguate future instances of the target word given their contextual features.

Adapted from Rusell, S., & Norvig, P. (2016)

9.2 WSD “line” Corpus

- 4,149 examples from newspaper articles containing the word “line.”
- Each instance of “line” labeled with one of 6 senses from WordNet.
- Each example includes a sentence containing “line” and the previous sentence for context.

Adapted from Rusell, S., & Norvig, P. (2016)

9.2 Senses of “line”

- Product: “While he wouldn’t estimate the sale price, analysts have estimated that it would exceed $1 billion. Kraft also told analysts it plans to develop and test a line of refrigerated entrees and desserts, under the Chillery brand name.”
- Formation: “C-LD-R L-V-S V-NNA reads a sign in Caldor’s book department. The 1,000 or so people fighting for a place in line have no trouble filling in the blanks.”
- Text: “Newspaper editor Francis P. Church became famous for a 1897 editorial, addressed to a child, that included the line “Yes, Virginia, there is a Santa Clause.”
- Cord: “It is known as an aggressive, tenacious litigator. Richard D. Parsons, a partner at Patterson, Belknap, Webb and Tyler, likes the experience of opposing Sullivan & Cromwell to “having a thousand-pound tuna on the line.”
- Division: “Today, it is more vital than ever. In 1983, the act was entrenched in a new constitution, which established a tricameral parliament along racial lines, whith separate chambers for whites, coloreds and Asians but none for blacks.”
- Phone: “On the tape recording of Mrs. Guba's call to the 911 emergency line, played at the trial, the baby sitter is heard begging for an ambulance.”

Adapted from Rusell, S., & Norvig, P. (2016)

9.2 Experimental Data for WSD of “line”

- Sample equal number of examples of each sense to construct a corpus of 2,094.
- Represent as simple binary vectors of word occurrences in 2 sentence context.
  - Stop words eliminated
  - Stemmed to eliminate morphological variation
- Final examples represented with 2,859 binary word features.

Adapted from Rusell, S., & Norvig, P. (2016)

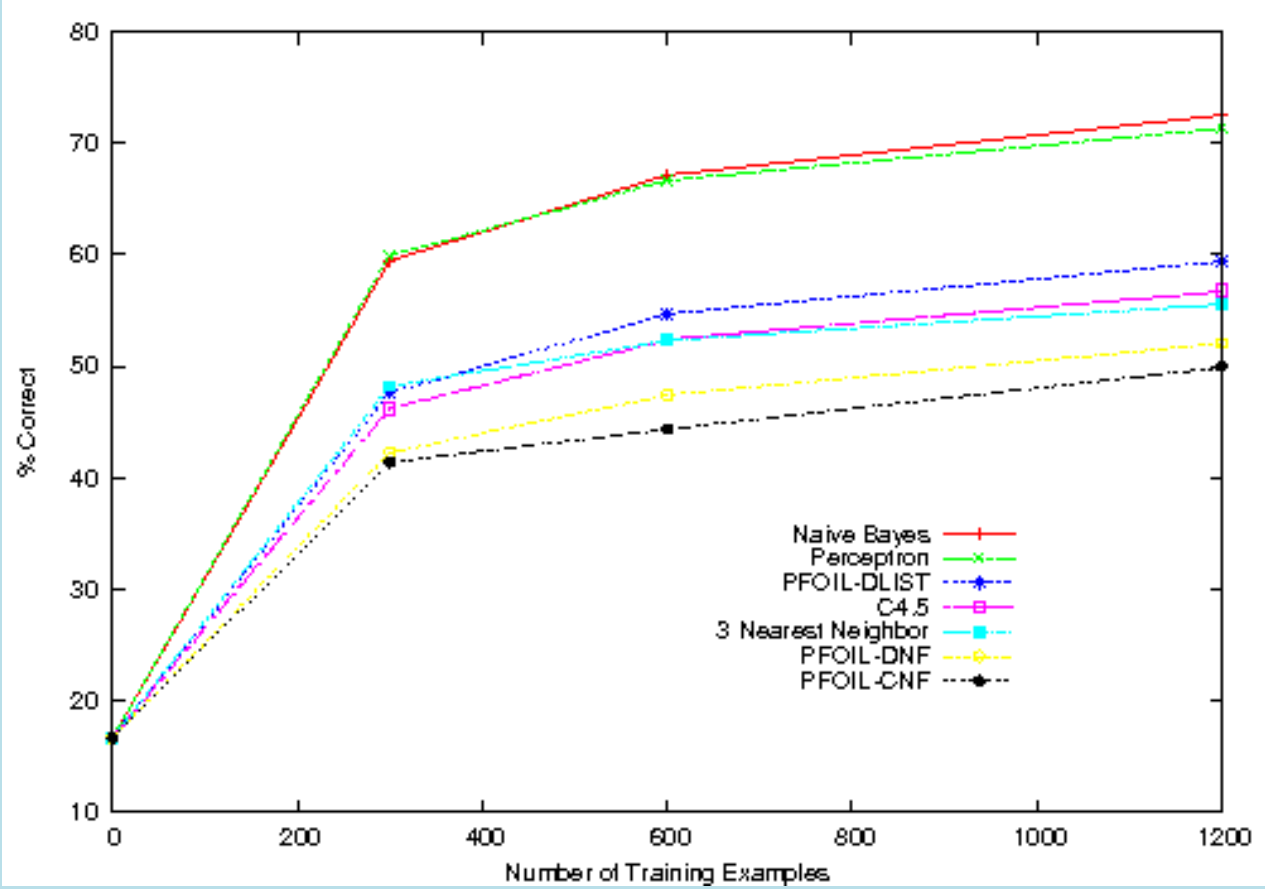
9.2 Machine Learning Algorithms

- Naïve Bayes
  - Binary features
- K Nearest Neighbor
  - Simple instance-based algorithm with k=3 and Hamming distance
- Perceptron
  - Simple neural-network algorithm.
- C4.5
  - State of the art decision-tree induction algorithm
- PFOIL-DNF
  - Simple logical rule learner for Disjunctive Normal Form
- PFOIL-CNF
  - Simple logical rule learner for Conjunctive Normal Form
- PFOIL-DLIST
  - Simple logical rule learner for decision-list of conjunctive rules

Adapted from Rusell, S., & Norvig, P. (2016)

9.2 Learning Curves for WSD of "line"

- Naïve Bayes and Perceptron give the best results.
- Both use a weighted linear combination of evidence from many features.
- Symbolic systems that try to find a small set of relevant features tend to overfit the training data and are not as accurate.
- Nearest neighbor method that weights all features equally is also not as accurate.
- Of symbolic systems, decision lists work the best.



Adapted from Rusell, S., & Norvig, P. (2016)

9.2 ANN Were Driving AI Research in early 2000 - Lecture Translation System (2012!)

9.2 Subsymbolic vs. Symbolic NLP

Can you tell me a joke about subsymbolic and symbolic ai

Sure, here's a joke for you:

Why did the subsymbolic AI system feel inferior to the symbolic AI system?

Because it couldn't even understand its own feelings, while the symbolic AI system had all the symbolic representations it needed to process and reason about emotions!

9.2 Classroom Task

Your turn!

Task

Please explain

- What is PCFG
- three tasks of PCFG of your choice

Outline

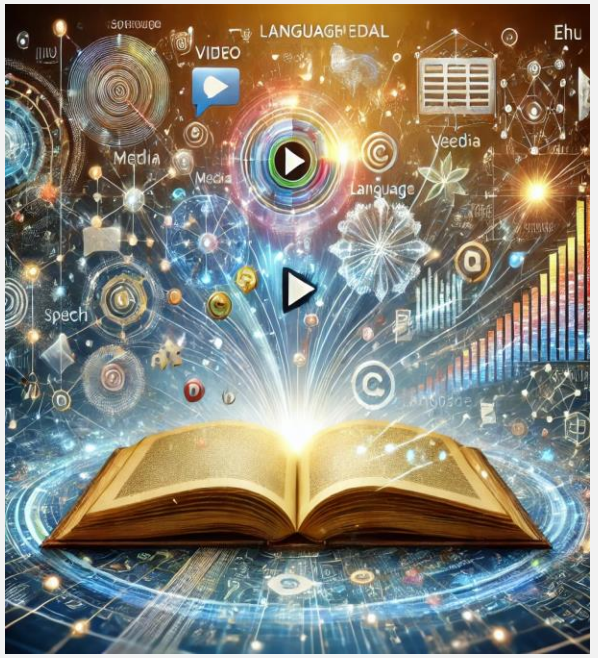
9 Natural Language Processing

- 9.1 Natural Language Processing
- 9.2 Speech Processing and Communication
- 9.3 Language Modelling
- 9.4 NLP Methods for Information Retrieval

Lectorial 7: Building NLP and Machine Learning Pipelines for Webservices

► **What we will learn:**

- We will discuss how to make use of the copious knowledge that is expressed in natural language
- And how to process and prepare language data for machines to build state-of-the-art machine learning pipelines for language processing
- We learn new type of models, so called generative models, which allow to generate new instances based on the knowledge of your model



► **Duration:**

- 180 min + 90 (Lectorial)

► **Relevant for Exam:**

- 9.1, 9.3 – 9.4

Image source: ↗ Richard Feynman, 1984 (1984) by Tamiko Thiel ↗ CC BY-SA 3.0

„What I cannot create

I do not understand“

Richard Feynman

9.3 Formalization: Discriminative Models vs. Generative Models

- We defined machine learning as:

$$f: X \rightarrow Y$$

- To predict the class Y from the training example X in machine learning problem (e.g. classification with decision tree or perceptron), we have to solve

$$f(X) = \arg\max_{y} p(Y \mid X)$$

- We try to model this conditional probability by modelling a decision boundy between the classes

Adapted from Ng AY & Jordan MI (2002)

9.3 Formalization: Discriminative Models vs. Generative Models

- If we use Bayes‘ rule we can replace $p(Y \mid X)$, and get

$$f(X) = \arg\max_y \frac{p(X \mid Y) \cdot p(Y)}{p(X)} \approx \arg\max_y p(X \mid Y) \cdot p(Y)$$

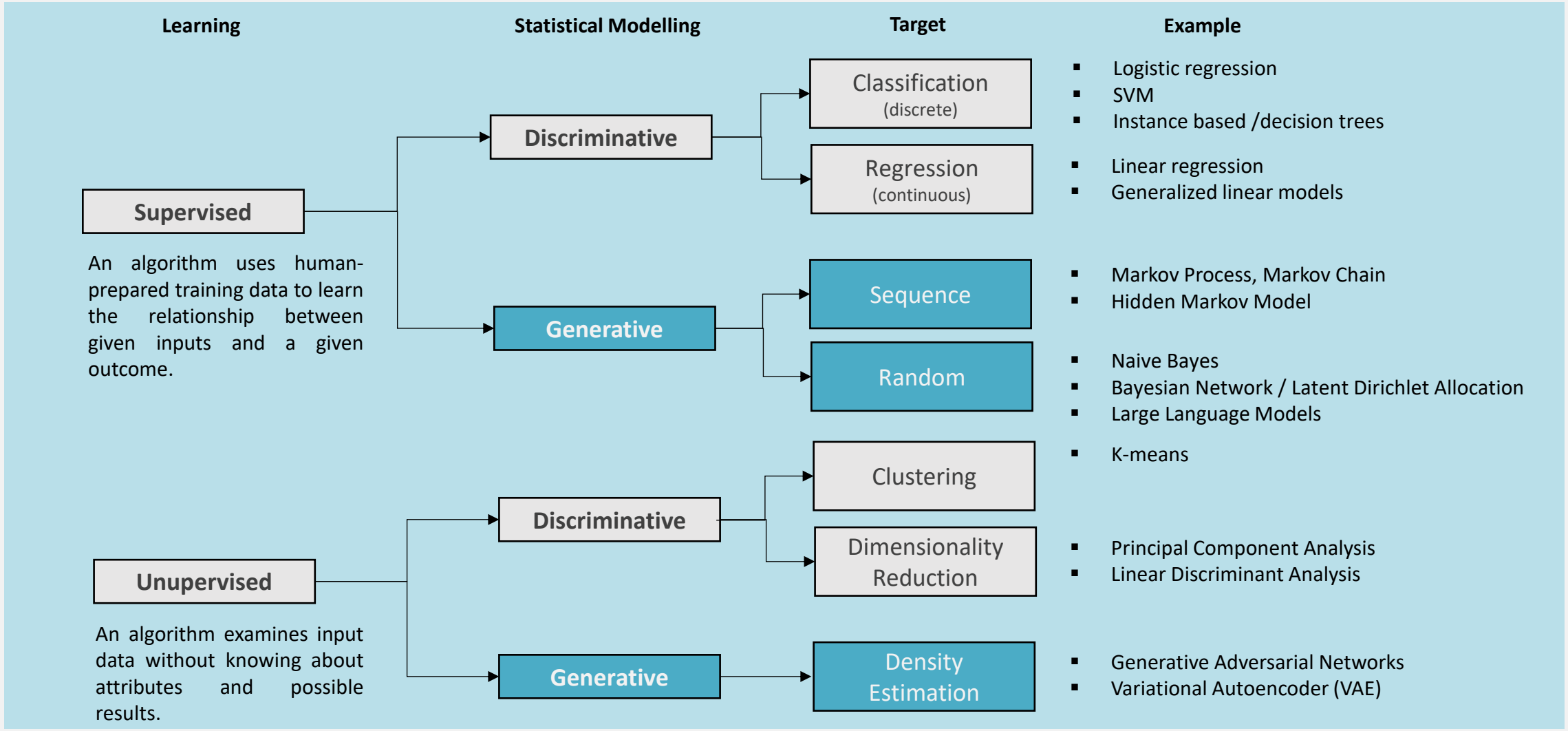
- With

$$p(X \mid Y) \cdot p(Y) = p(X \mid Y)$$

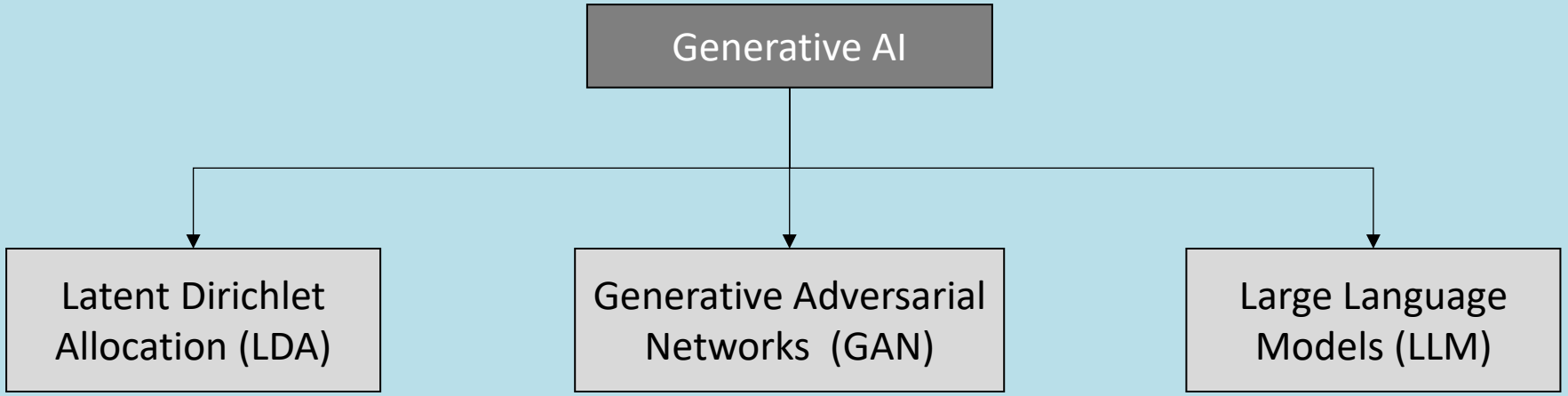
- Hence, our problem describes now the joint probability distribution $p(X \mid Y)$, which models the actual distribution of each class
- These models are called generative, because they allow to calculate/generate the respective X for each Y

Adapted from Ng AY & Jordan MI (2002)

9.3 Taxonomy: Discriminative vs. Generative in Machine Learning



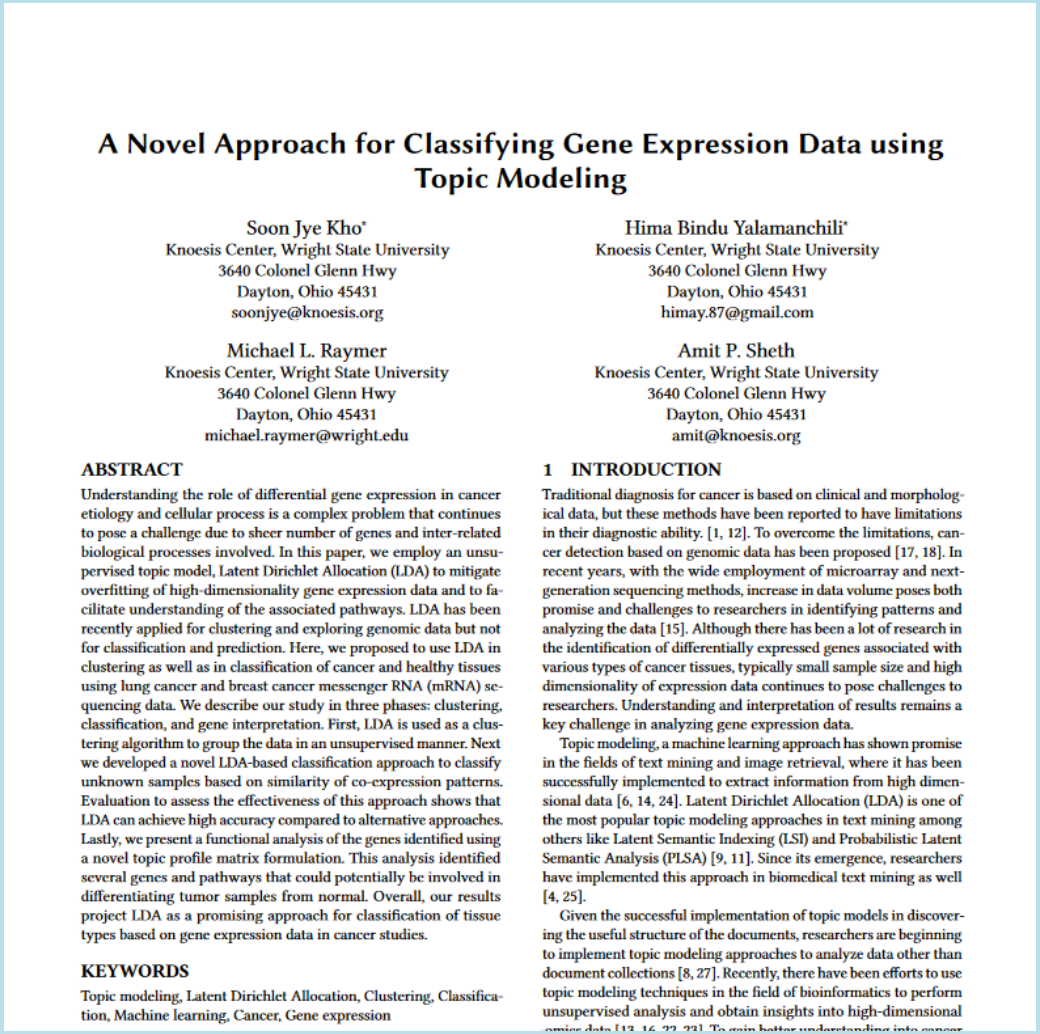
9.3 Selected Methods of Generative AI in this Chapter



- Research outlining the transformer model was first published by a group of eight AI researchers at Google in June 2017 (Vaswani, A. et al. (2017))
- You can use generative AI for many types of data (e.g. images, voice, music, text)

Adapted from Vaswani, A. et al. (2017)

9.3 Example: LDA Application in Bio-Informatics



A Novel Approach for Classifying Gene Expression Data using Topic Modeling

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ABSTRACT

Understanding the role of differential gene expression in cancer etiology and cellular process is a complex problem that continues to pose a challenge due to sheer number of genes and inter-related biological processes involved. In this paper, we employ an unsupervised topic model, Latent Dirichlet Allocation (LDA) to mitigate overfitting of high-dimensionality gene expression data and to facilitate understanding of the associated pathways. LDA has been recently applied for clustering and exploring genomic data but not for classification and prediction. Here, we proposed to use LDA in clustering as well as in classification of cancer and healthy tissues using lung cancer and breast cancer messenger RNA (mRNA) sequencing data. We describe our study in three phases: clustering, classification, and gene interpretation. First, LDA is used as a clustering algorithm to group the data in an unsupervised manner. Next we developed a novel LDA-based classification approach to classify unknown samples based on similarity of co-expression patterns. Evaluation to assess the effectiveness of this approach shows that LDA can achieve high accuracy compared to alternative approaches. Lastly, we present a functional analysis of the genes identified using a novel topic profile matrix formulation. This analysis identified several genes and pathways that could potentially be involved in differentiating tumor samples from normal. Overall, our results project LDA as a promising approach for classification of tissue types based on gene expression data in cancer studies.

KEYWORDS

Topic modeling, Latent Dirichlet Allocation, Clustering, Classification, Machine learning, Cancer, Gene expression

1 INTRODUCTION

Traditional diagnosis for cancer is based on clinical and morphological data, but these methods have been reported to have limitations in their diagnostic ability. [1, 12]. To overcome the limitations, cancer detection based on genomic data has been proposed [17, 18]. In recent years, with the wide employment of microarray and next-generation sequencing methods, increase in data volume poses both promise and challenges to researchers in identifying patterns and analyzing the data [15]. Although there has been a lot of research in the identification of differentially expressed genes associated with various types of cancer tissues, typically small sample size and high dimensionality of expression data continues to pose challenges to researchers. Understanding and interpretation of results remains a key challenge in analyzing gene expression data.

Topic modeling, a machine learning approach has shown promise in the fields of text mining and image retrieval, where it has been successfully implemented to extract information from high dimensional data [6, 14, 24]. Latent Dirichlet Allocation (LDA) is one of the most popular topic modeling approaches in text mining among others like Latent Semantic Indexing (LSI) and Probabilistic Latent Semantic Analysis (PLSA) [9, 11]. Since its emergence, researchers have implemented this approach in biomedical text mining as well [4, 25].

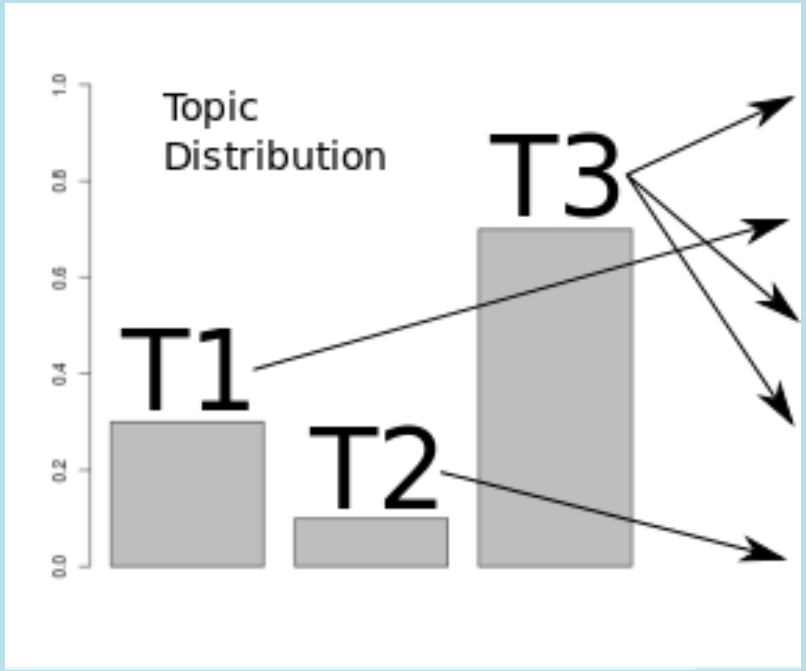
Given the successful implementation of topic models in discovering the useful structure of the documents, researchers are beginning to implement topic modeling approaches to analyze data other than document collections [8, 27]. Recently, there have been efforts to use topic modeling techniques in the field of bioinformatics to perform unsupervised analysis and obtain insights into high-dimensional

- Used to cluster genes into topics or groups based on their expression profiles.
- Each topic represents a set of genes with similar expression patterns, allowing researchers to identify functionally related genes.
- Gain insights into the underlying biological processes and pathways.

Adapted from David M. Blei et al. (2006)

9.3 Latent Dirichlet Allocation (LDA)

▶ Topic model approaches to analyze unstructured data to find hidden topics



- One of the most popular and simplest topic model approaches to analyze unstructured
- Latent Dirichlet allocation is not the best but todayby far the most popular approach.
- The method is based on the work of Deerwester in latent semantic indexing and of Hofmann in probabilistic latent semantic indexing

Example

- Automated Summarization, Mediarecommender

\+ probabilistic model with interpretable topics.

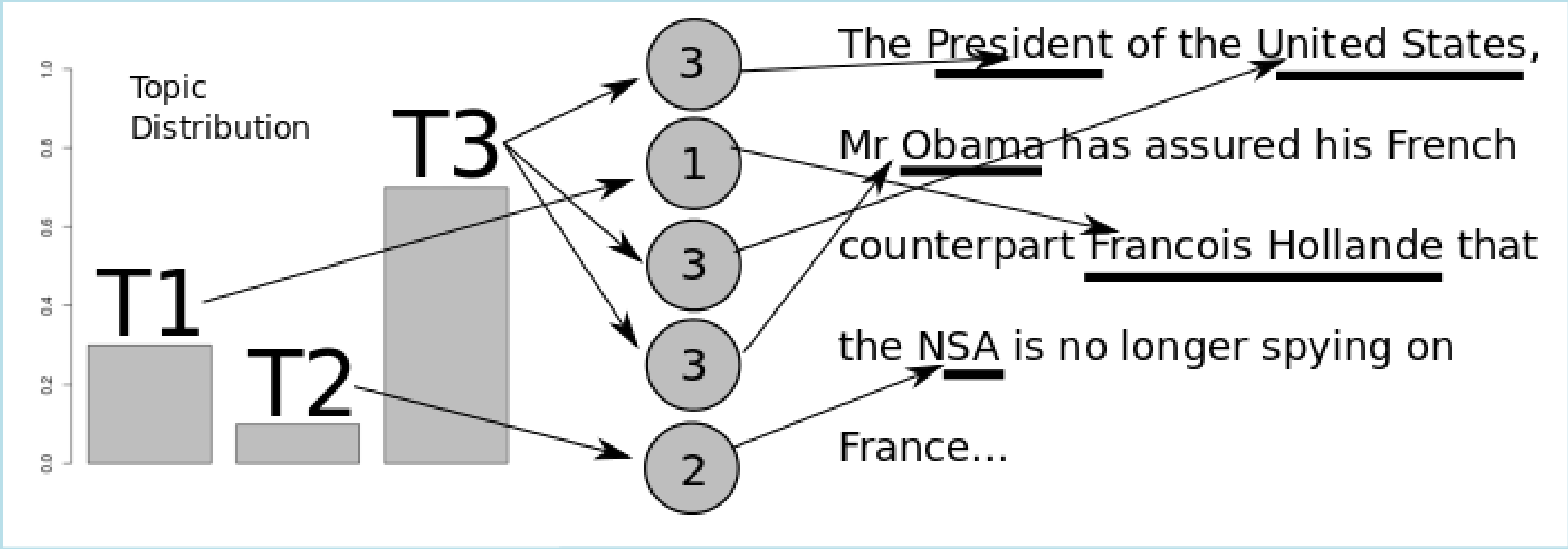
\- hard to know when LDA is working, because topics are soft-clusters so there is no objective metric

9.3 Latent Dirichlet Allocation

- Idea of latent Dirichlet allocation is to understand the document creation as a stochastic process (see chapter 8)
- It is assumed that a document w_j is generated by an author who selects words of a vocabulary V with a given probability from different baskets of words where each basket corresponds to one of k topics
- The created texts are the observed variables, while the topics, the distribution of the topics and the assignments per document and word is hidden. With that assumptions, the purpose is to decompose from a document with $i\ words, w = (w_1; w_2; \ldots; w_i)$ the original topic baskets

Adapted from David M. Blei et al. (2006)

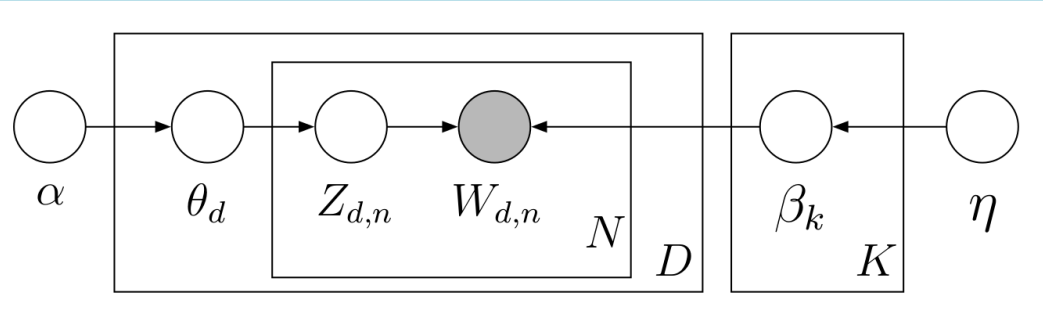
9.3 Topics in LDA



- Each topic contains a individual basket of words and is chosen by his probability (the circles with numbers)
- Each time a topic is chosen, a word of this basket is drawn by his probability

Adapted from David M. Blei et al. (2006)

9.3 Latent Dirichlet Allocation



$$p(\vec{\theta}_{1:D}, z_{1:D,1:n}, \vec{\beta}_{1:K} | \omega_{1:D.1:n}, \alpha, \eta) =$$

$$\frac{p(\vec{\theta}_{1:D}, \vec{z}_{1:D,}, \vec{\beta}_{1:K} | \omega_{1:\vec{D}.1:n}, \alpha, \eta)}{\int_{\vec{\beta}_{1:K}} \int_{\vec{\theta}_{1:D}} p(\vec{\theta}_{1:D}, \vec{z}_{1:D,}, \vec{\beta}_{1:K} | \omega_{1:\vec{D}.1:n})}$$

Algorithm: Generative LDA Process

for each topic in $number\ of\ topics\ k$ **do**
  Draw a distribution over words $\beta_k \sim Dir(\eta)$
end for

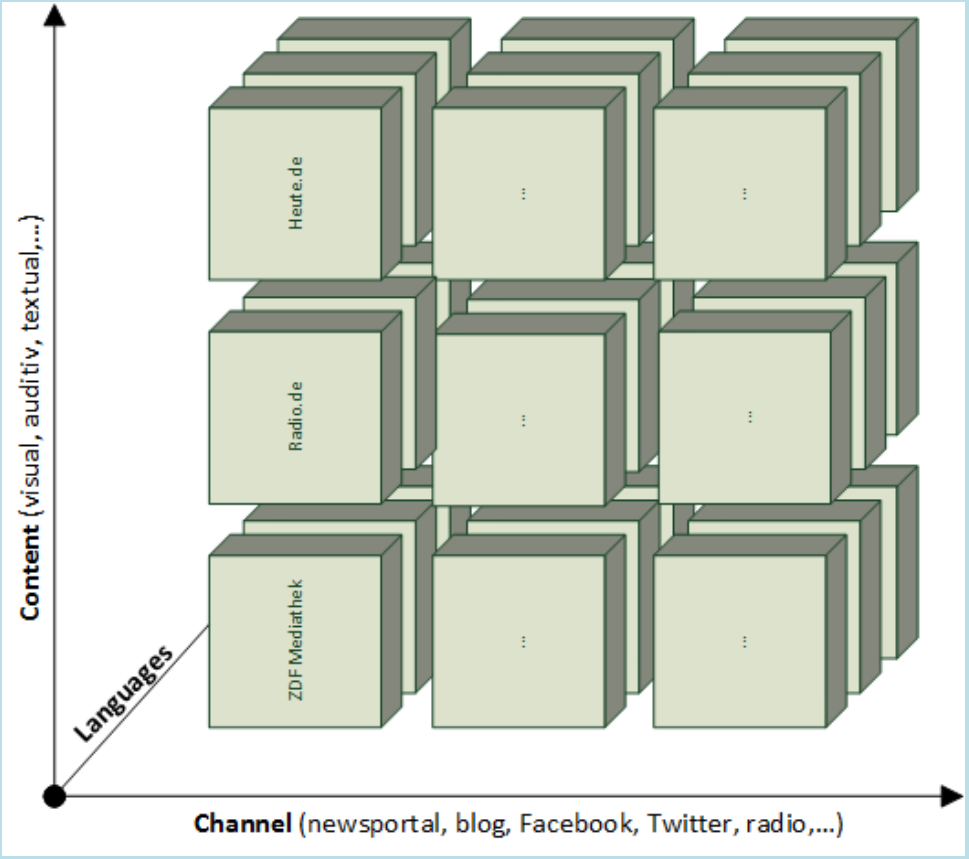
for each document $w_n = d\ in\ corpus\ D$ **do**
  Draw a vector of topic proportions $\vec{\theta}_d \sim Dir(\alpha)$
  for each word w_n^i **do**
    Draw a topic assignment $Z_{d;n}\ Mult(\vec{\theta}_d)_{Z_{d,n} \in [1 \ldots K]}$
    Draw a word $w_{d;n}\ Mult(\vec{\beta}_{Z_{d,n}})_{w_{d,n} \in [1 \ldots K]}$
  end for
end for

Adapted from David M. Blei et al. (2006)

9.3 Example: Topic Modelling for Multi-Modal Recommendations

Multi-Modal AI is hard

- EU is one of the multilingual markets, with more than 24 official languages
- Today there exists different media items such as email, blog, books, journals, articles in multiple media formats
- Challenge: very heterogeneous media and information. Hence, task as information retrieval, searching, monitoring, recommendations, classication, evaluation, translation, summarization or further media analysis pose a major challenge.



- Mogadala, A., Jung, D., & Rettinger, A. (2017). Linking tweets with monolingual and cross-lingual news using transformed word embeddings. 18th International Conference on Intelligent Text Processing and Computational Linguistics

Adapted from Mogadala et al. (201/)

9.3 Formalization of Multi-Modal Recommendations I

- Corpus is a collection of n distinct textual media items and is denoted by

$$\mathcal{D} = \{ w^1, w^2, \dots, w^n \}_{n \in \mathbb{N}}$$

- Document of this corpus is a sequence of words:

$$w^j = (w_1^j, w_2^j, \dots, w_i^j)$$

- Aim to find a semantic similarity function $sim()$ or a dissimilarity function $dis()$ to identify relatedness between items. Such a function takes the entities as an input and outputs a score, which indicates the semantic relatedness of the input entity sets.

$$\forall w^j, w^k \in \mathcal{D}: sim\left(w^j, w^k\right) = s_{j,k} \in \mathbb{R}_{[0,1]}$$

Adapted from Mogadala et al. (201/)

9.3 Formalization of Multi-Modal Recommendations II

- Dissimilarity function $dis()$ can be expressed depending on the similarity function $sim()$

$$dis(w^j, w^k) = 1 - sim(w^j, w^k)$$

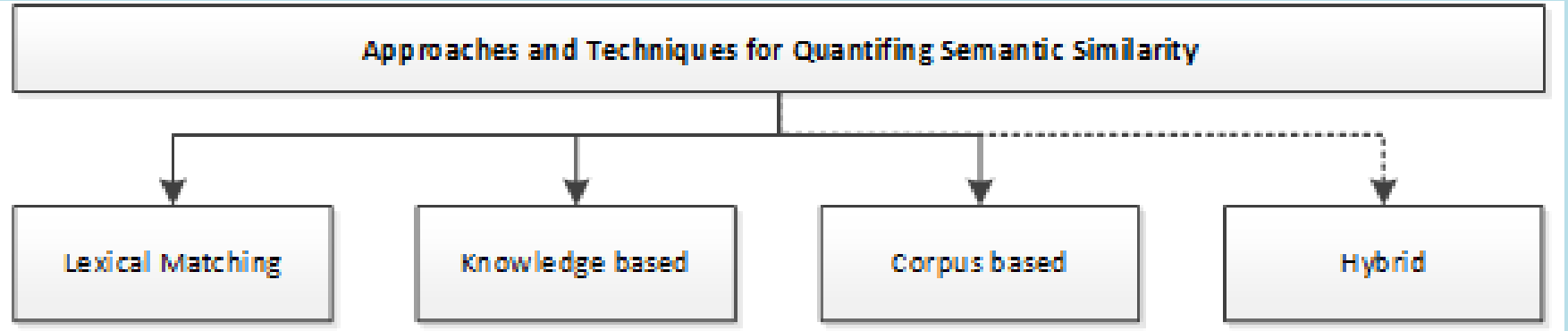
range [0,1], 0: no similarity

- **Multi-Modal Recommender**: Find the entity combination of the corpus with the highest similarity

$$\text{Most similar doc pair } (w^j, w^k)^* = \arg\max_{j,k} sim(w^j, w^k), s.t. w^j, w^k \in \mathcal{D}$$

Adapted from Mogadala et al. (201/)

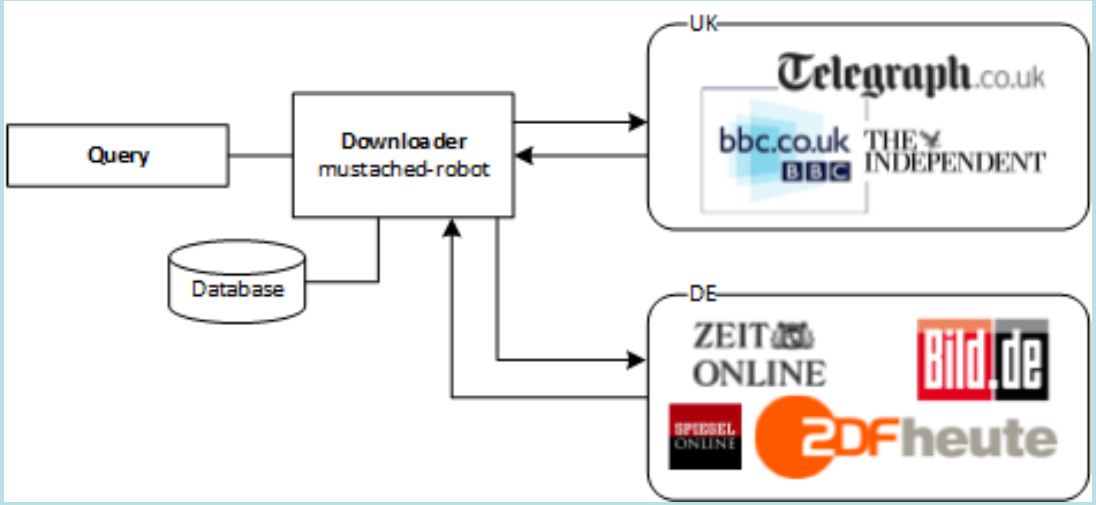
9.3 How to Measure Semantic Similarity in Topic Modelling



- **Lexical matching methods** include methods which aim to calculate a similarity score by counting lexical units that exits in the input texts.
- **Corpus-based algorithms** calculate by means of large corpora information for a similarity score
- **Knowledge-based** measures calculate a similarity score by means of large networks like Word-Net

Adapted from Mogadala et al. (201/)

9.3 Generation of Trainingsdata



	Dataset 1	Dataset 2
Language of the corpus	Cross-lingual	Cross-lingual
Heterogeneity of the corpus	1 corpus topic	2 corpus topics
Noise of the corpus	Cross-channel	Mono-channel

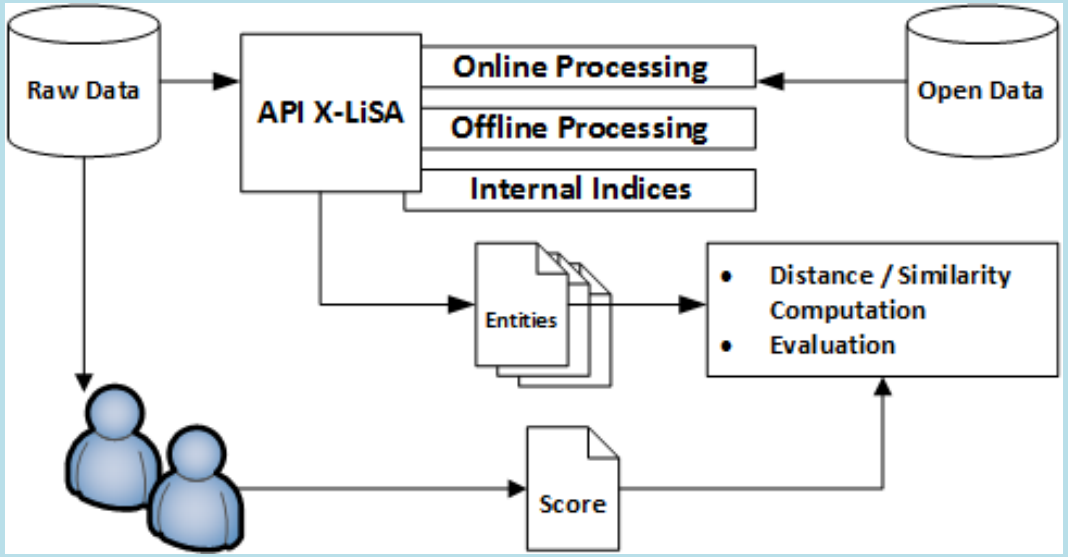
- To have comparable datasets, all the documents were crawled by two different keywords "Grexit" (the greek exit of the EU) and "4U9525" (airplain crash in france) from the newsportal from January 2015 until May 2015

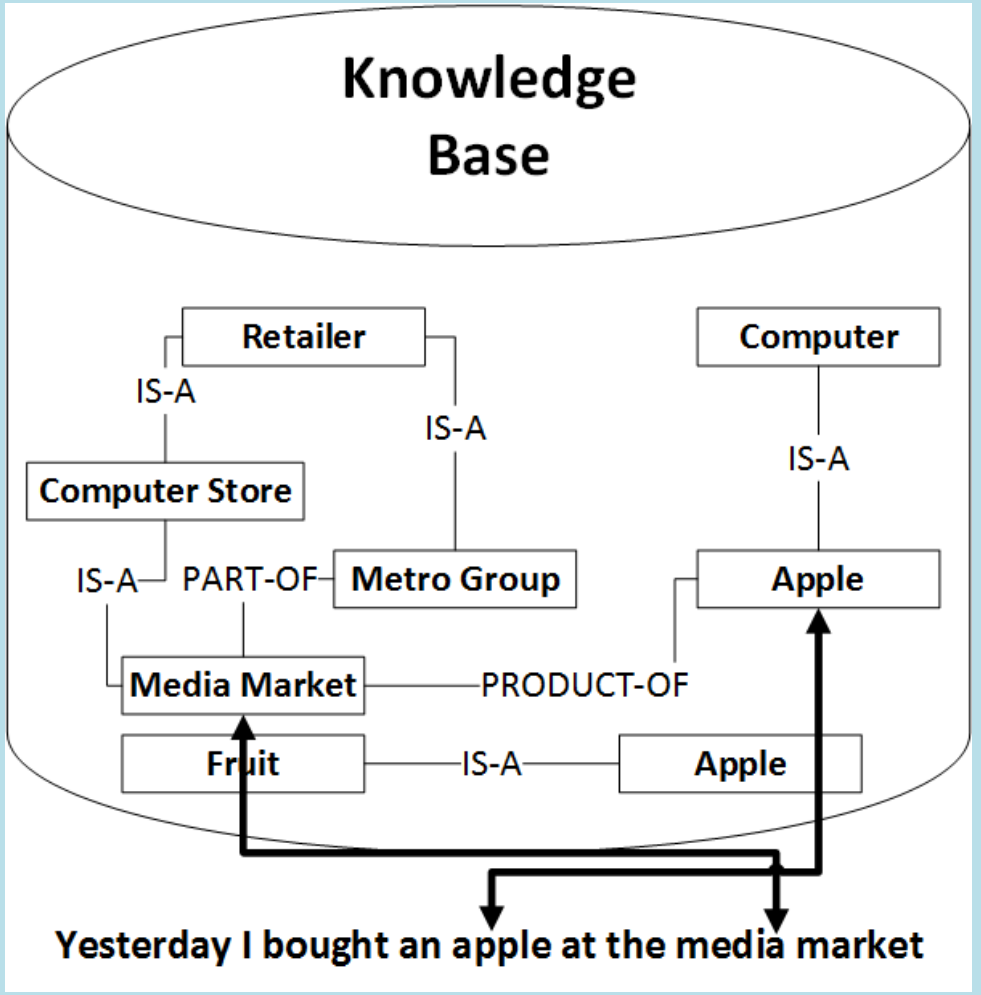
- To evaluate our model we conducted a user study. Each participant had to rate all combinations of articles for semantic similarity pairwise

Adapted from Mogadala et al. (201/)

9.3 Entity Detection in Topic Modelling

Entity Detection

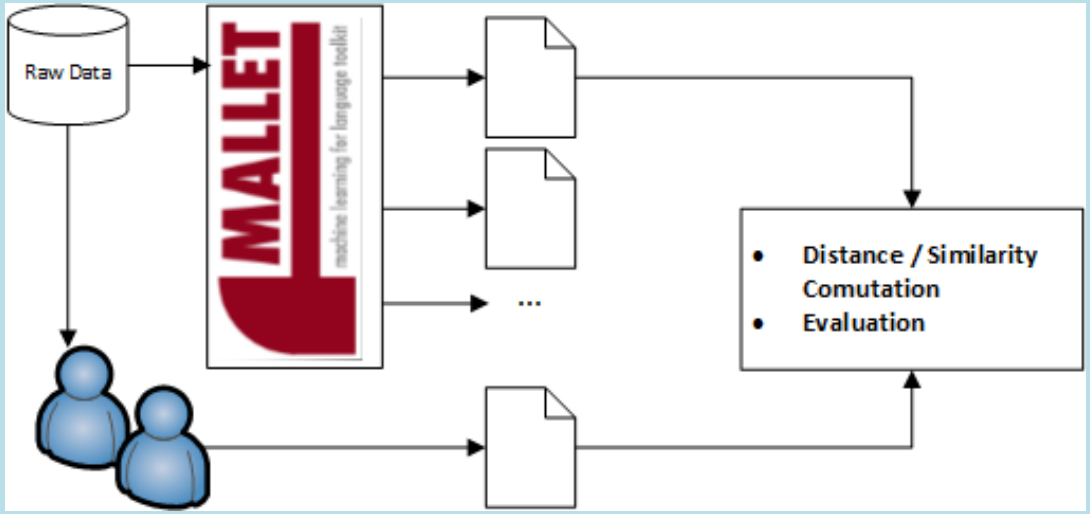




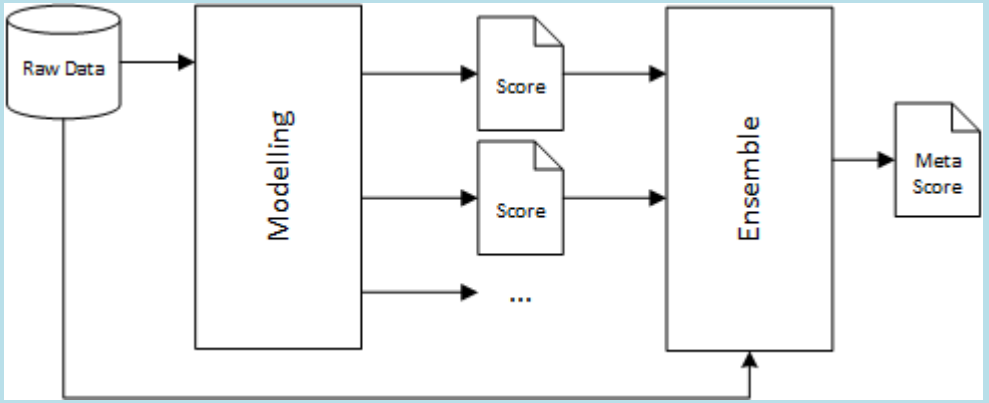
Adapted from Mogadala et al. (201/)

9.3 Final Topic Modelling Process

Topic Modelling



Ensemble



Adapted from Mogadala et al. (201/)

9.3 Results

	Accuracy	
Method and similarity function	**Dataset 1**	**Dataset 2**
Topic modelling: Euclidean	28.4%	27.72%
Topic modelling: Hellinger	33.64%	37.72%
Entity linking: Subset	33.95%	91.01%
Entity linking: Jaccard	35.18%	94.58%
Ensemble learning algorithm	**Dataset 1**	**Dataset 2**
Ranking learning	66.98%	95.92%
C4.5	64.52%	94.94%
Boosting	92.59%	95.92%
Baseline	**Dataset 1**	**Dataset 2**
Random generated scores	76.23%	95.92%

- Approaches are able to detect the structure of the corpora
- During this study, other approaches in comparable experimental studies were identified and report performances between 51.9% and 82.5%
- Other problems: Noisy data (Twitter!), and high dimensionality of the problem (Transformation)

- New experiments with a more uniform score distribution would be very useful to improve the weaknesses of the models.

Adapted from Mogadala et al. (201/)

9.3 Business Case: Topic Modelling for Multi-Modal Recommendations

01 | Executive Summary

Grouping diverse media sources of information that discuss the same topic in varied perspectives are a relevant challenge in online media. But the gap in word usage between informal social media content such as tweets and diligently written content (e.g. news articles) make such assembling difficult. In this paper, we propose a transformation framework to bridge the word usage gap between tweets and online news articles across languages by leveraging their word embeddings. Experimental results show a notable improvement over baselines for monolingual tweets and news articles comparison

	Accuracy	
Method and similarity function	**Dataset 1**	**Dataset 2**
Topic modelling: Euclidean	28.4%	27.72%
Topic modelling: Hellinger	33.64%	37.72%
Entity linking: Subset	33.95%	91.01%
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C4.5	64.52%	94.94%
Boosting	92.59%	95.92%
Baseline	**Dataset 1**	**Dataset 2**
Random generated scores	76.23%	95.92%

02 | Solution

- Topic modelling approaches are able to detect the structure of the corpora but best perform in combination with traditional machine learning
- During this study, other approaches in comparable experimental studies were identified and report performances between 51.9% and 82.5%

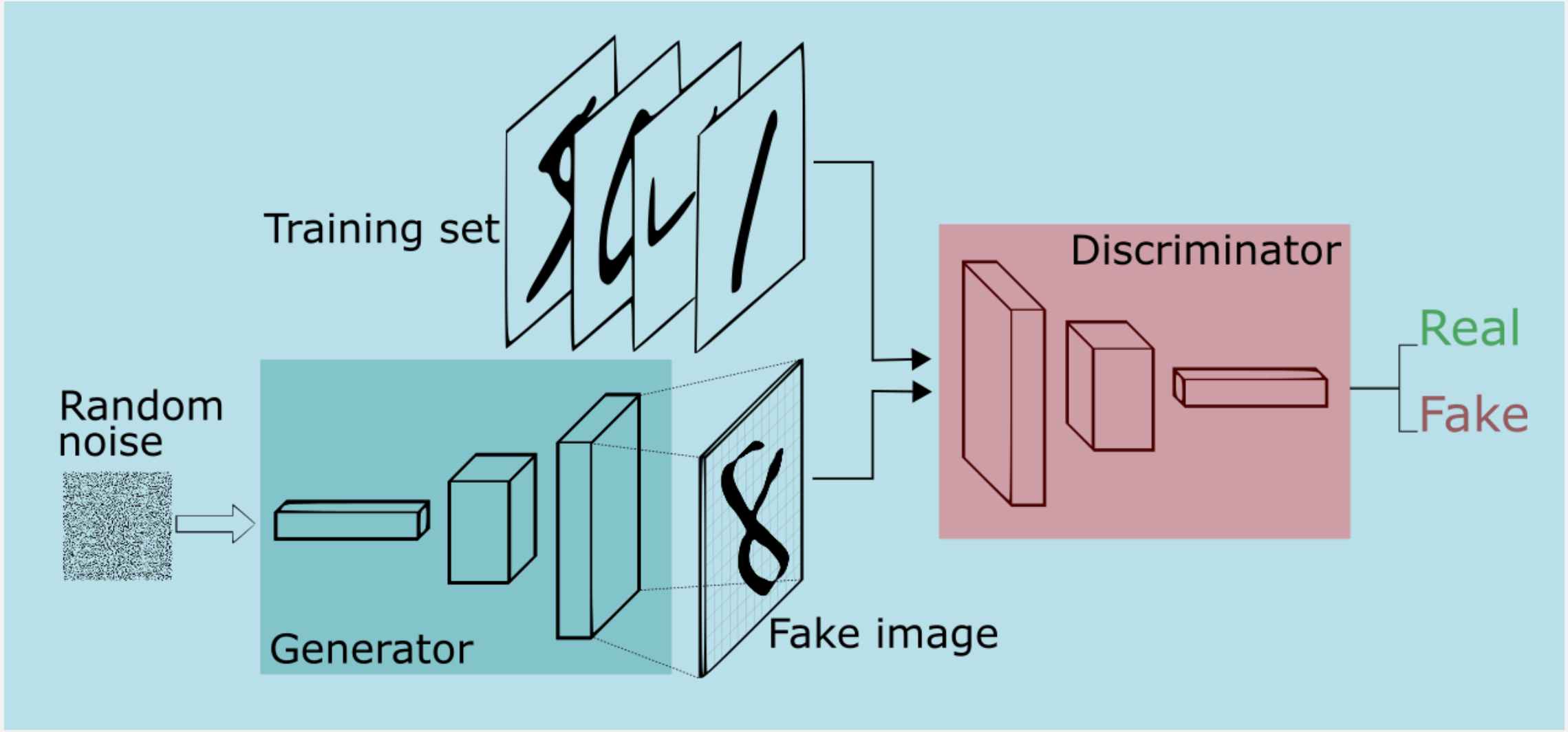
03 | References

- Mogadala, A., Jung, D., & Rettinger, A. (2017). Linking tweets with monolingual and cross-lingual news using transformed word embeddings. 18th International Conference on Intelligent Text Processing and Computational Linguistics

Take-Aways

- Topic models can be used for similarity ratings and hence, recommendations
- However, the computation of cross-modal similarity is still a challenge

9.3 Generative Adversarial Network (GAN) as Framework for Generative AI



Adapted from Goodfellow et al. (2014).

9.3 From Topic to Large Language Models (LLM)

The New York Times

Artificial Intelligence › | An Unsettling Chat With Bing | Read the Conversation | How Chatbots Work | Spotting A.I.-Generated Text

Microsoft to Invest $10 Billion in OpenAI, the Creator of ChatGPT

The tech giant aims to remain at the forefront of generative artificial intelligence with its partnership with OpenAI.

Give this article

Forbes

FORBES > INNOVATION > CONSUMER TECH

How ChatGPT Suddenly Became Google's Code Red, Prompting Return Of Page And Brin

David Phelan Senior Contributor ⓘ

I write about lifestyle tech

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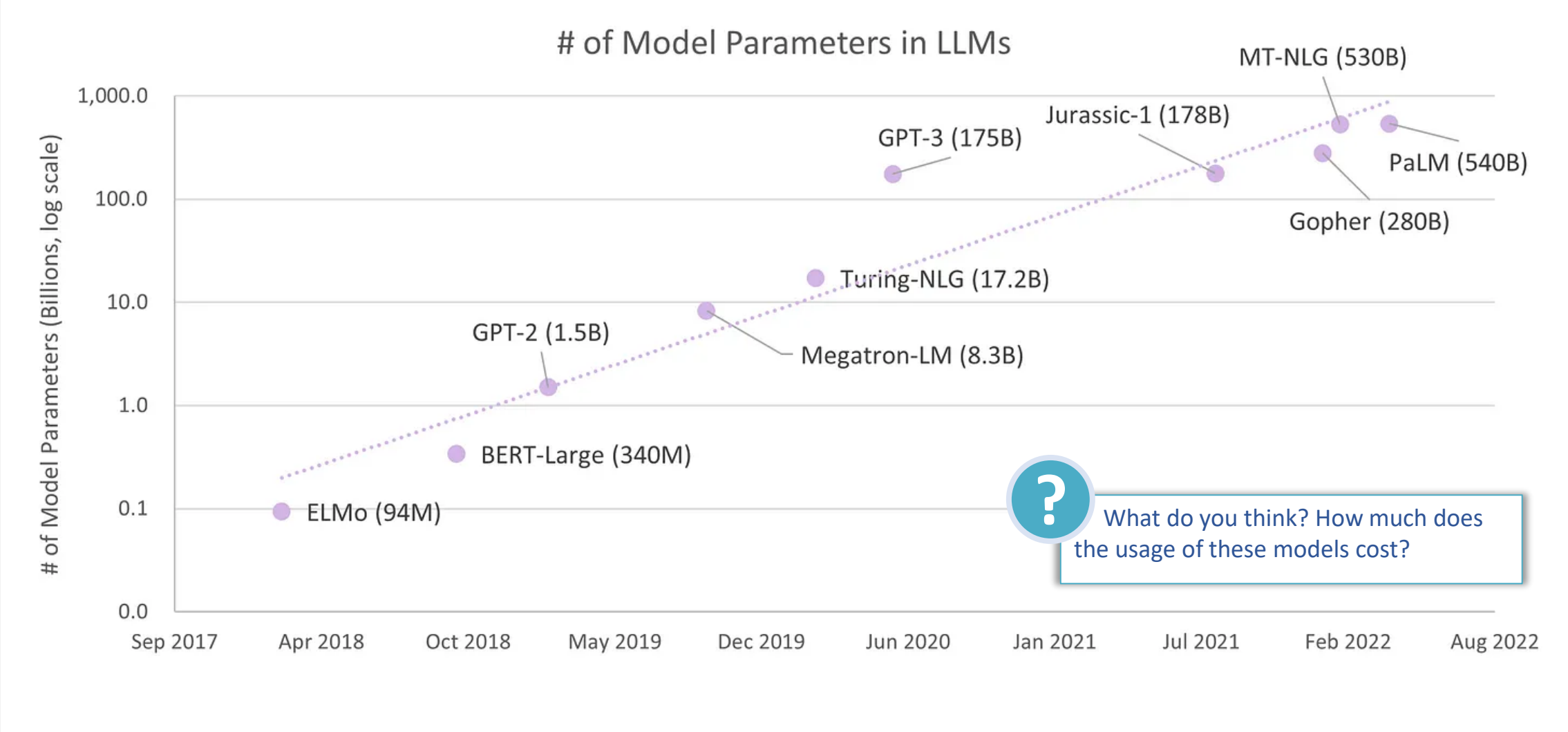
2

Jan 23, 2023, 11:06am EST

?

Where is the disruption in all this?
Why does Google fear ChatGPT?

9.3 Number of Model Parameters in LLM



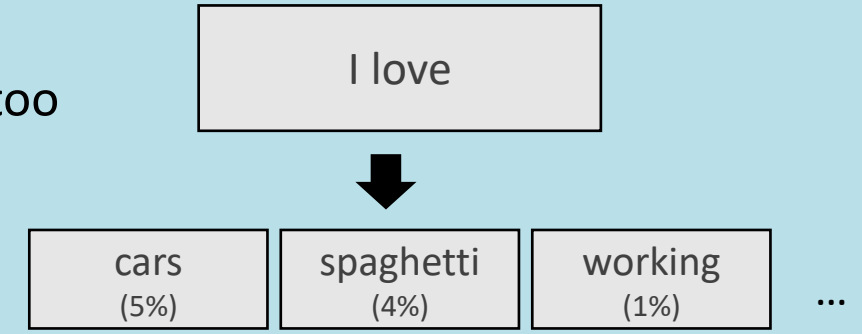
Source: https://sunyan.substack.com/p/the-economics-of-large-language-models

9.3 Costs of LLM

Source: Twitter @elonmusk (2022)

9.3 LLM – Two central concepts

- Masked Language Modelling
  - Have the program predict a [masked] word based on context
  - Animal didn‘t cross the street because [mask] it was too wide



- Next Sentence Prediction
  - Have the program predict whether two sentences have a logical sequence or their relationship is random

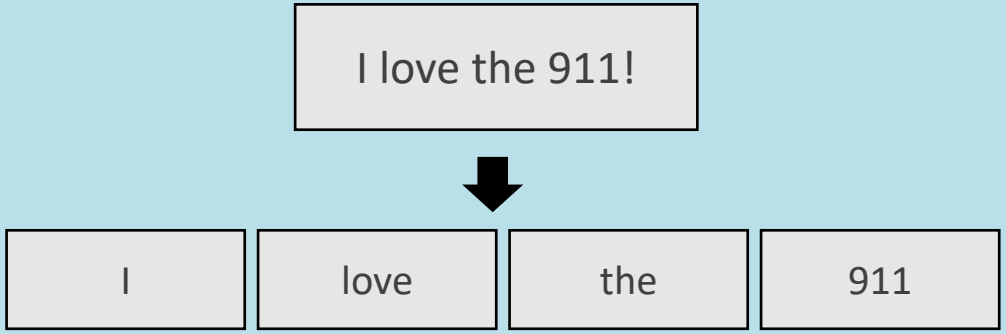
A: Tom went to a Porsche center. He bought a new car.
B: Linh made coffee. Oranges are cheap at the moment.

Large Language Models do not encode knowledge. They encode language and convey the illusion of knowledge!

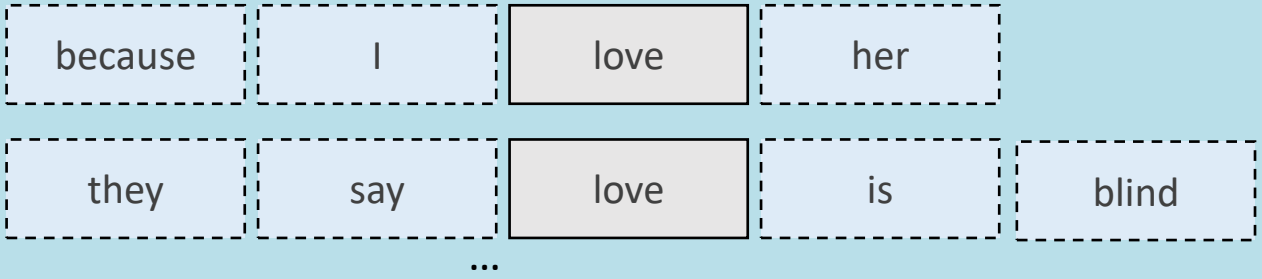
Adapted from Radford, A. et al. (2019); Floridi, L., & Chiriatti, M. (2020)

9.3 LLM - Preprocessing

- As before, documents are broken into blocks and these block of words are broken into tokens



- To identify the meaning of „love“, LLM observe it in context using enourmous datasets of training data considering nearby words



Adapted from Radford, A. et al. (2019); Floridi, L., & Chiriatti, M. (2020)

9.3 LLM – Data Sources of Popular LLM (2023)

- OpenAI does not disclose what datasets it uses to train the models backing its popular chatbot, ChatGPT. However, GPT-3 builds on the following sources

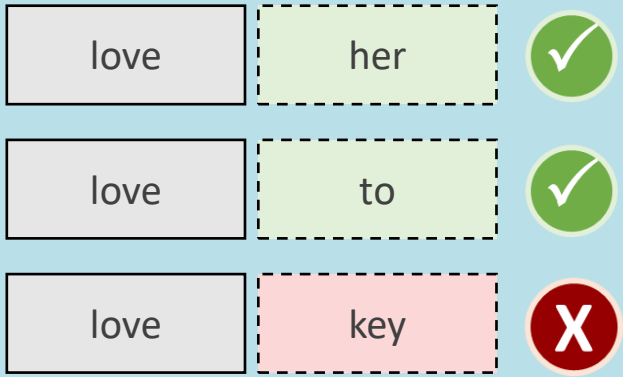
Data Source	Quanity (Tokens)	Weight in Training	Epochs elapsed when training for 300B tokens
Common Crawl	410 billion	60%	0.44
WebText2	19 billion	22%	2.9
Books1	12 billion	8%	1.9
Books2	55 billion	8%	0.43
Wikipedia	3 billion	3%	3.4

- Other LLM like Google's T5 and Facebook's LLaMA building on Google's C4 data set which you can download here: ↗ Google Datasets

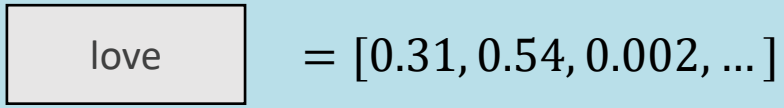
Adapted from OpenAI (2023); Radford, A. et al. (2019); Floridi, L., & Chiriatti, M. (2020)

9.3 LLM - Training

- We get probabilities for words in the training data that belong and do not belong to our token



- Which results in a word embedding for each word in our corpus

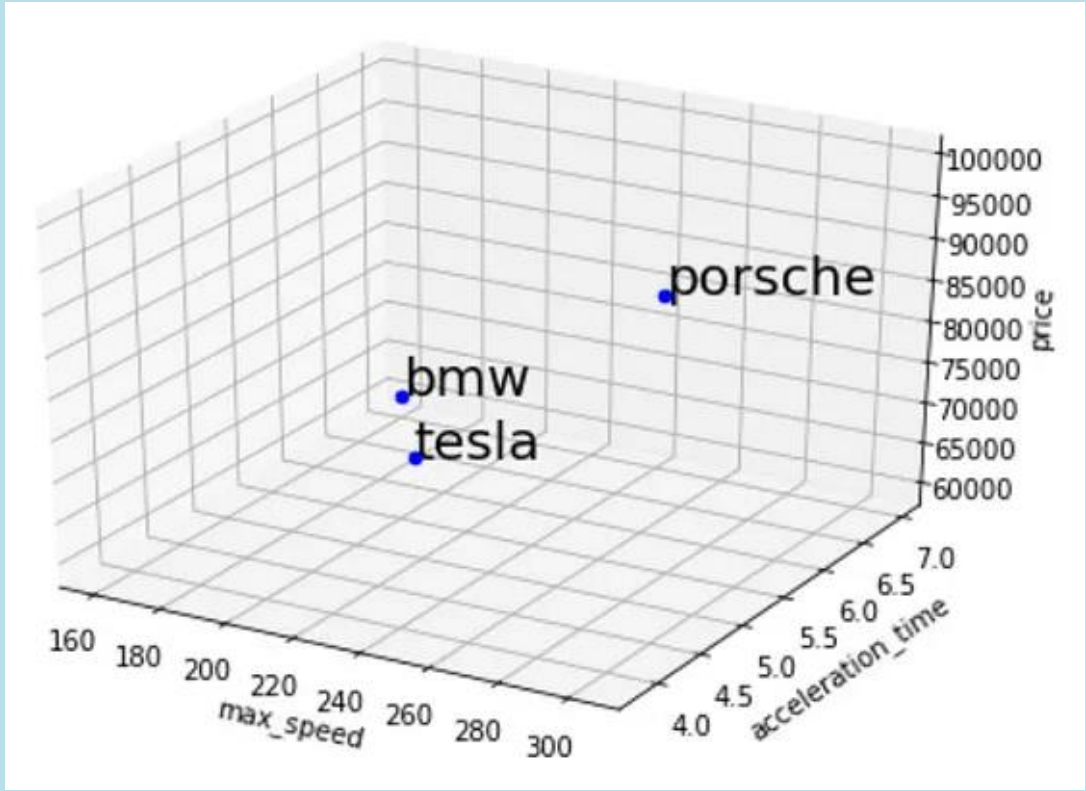


Adapted from OpenAI (2023); Radford, A. et al. (2019); Floridi, L., & Chiriatti, M. (2020)

9.3 LLM – Recap: Word Embeddings

- The way word embeddings are derived means we don't know exactly what each value represents
- But words we expect to be used in comparable ways often have similar-looking embeddings
- Based on that embeddings allow us to quantify that closeness of our tokens

3D word embeddings

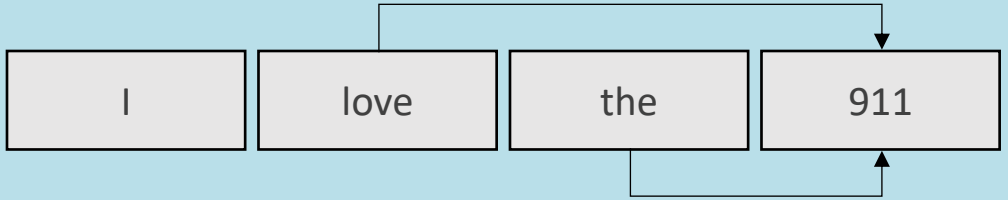


Adapted from OpenAI (2023); Radford, A. et al. (2019); Floridi, L., & Chiriatti, M. (2020)

9.3 Self-attention in LLM I

- A key concept of the transformer architecture is self-attention. This is what allows LLMs to understand relationships between words.

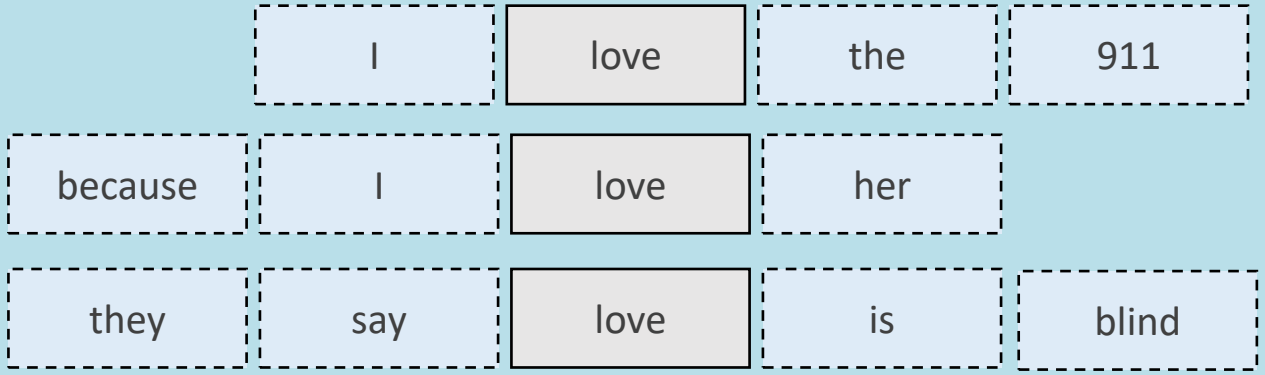
- Self-attention looks at each token in a body of text and decides which others are most important to understanding its meaning.



- With self-attention, the transformer computes all the words in a sentence at the same time. Capturing this context gives LLMs far more sophisticated capabilities to parse language.

9.3 Self-attention in LLM II

- And when we combine the sentences, the model is still able to recognise the correct meaning of each word thanks to the attention it gives the accompanying text



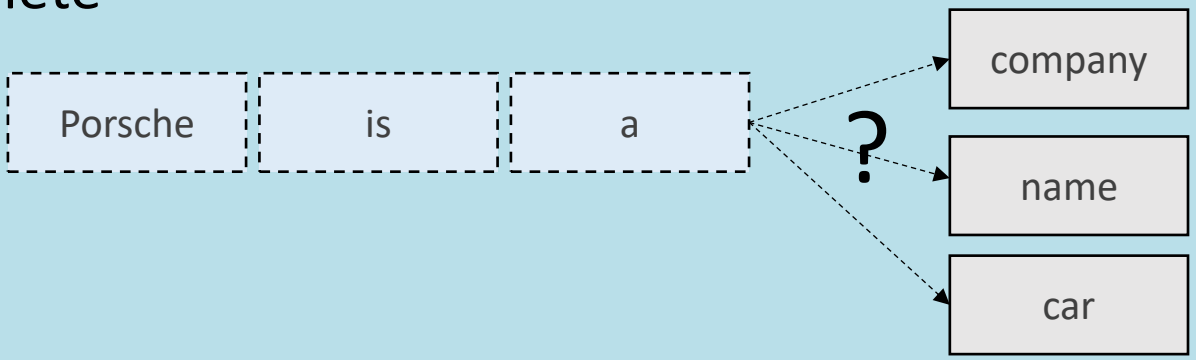
- Example: For the first use of love it is a verb, and the third is a noun

9.3 Why Self-attention is Crucial for Advanced Text Generation

- Allows LLMs to take context from beyond sentence boundaries, giving the model a greater understanding of how and when a word is used.
- Without it, words that can be interchangeable in some contexts but not others can be used incorrectly
- This capability goes beyond words, that have multiple meanings. E.g. self-attention is able to calculate the most likely word one word is referring to.

9.3 How LLM Generate Text

- **Objective**: predict the next word in a sequence and do this repeatedly until the output is complete



- To do this, the model gives a probability score to each token, which represents the likelihood of it being the next word in the sequence

What is the problem of predicting the following word in isolation (greedy-search)?

9.3 How LLM Generate Coherent, Human-like Text

- Transformers use a number of approaches to address this problem and enhance the quality of their output. One example is called beam search.
- Rather than focusing only on the next word in a sequence, it looks at the probability of a larger set of tokens as a whole.
- Problem: While the text may seem plausible and coherent, it isn't always factually correct

Take a look at chapter 2 to recapitualte the different search algorithms we discussed

9.3 LLM Have Serious Biases

Meta AI

focusing on those with Latin and Cyrillic alphabets.

There is still more research that needs to be done to address the risks of bias, toxic comments, and hallucinations in large language models. Like other models, LLaMA shares these challenges. As a foundation model, LLaMA is designed to be versatile and can be applied to many different use cases, versus a fine-tuned model that is designed for a specific task. By sharing the code for LLaMA, other researchers can more easily test new approaches to limiting or eliminating these problems in large language models. We also provide in the paper a set of evaluations on benchmarks evaluating model biases and toxicity to show the model's limitations and to support further research in this crucial area.

To maintain integrity and prevent misuse, we are releasing our model under a noncommercial license focused on research use cases. Access to the model will be granted on a case-by-case basis to academic researchers; those affiliated with organizations in government, civil society, and academia; and industry research laboratories around the world. People interested in applying for access can find the link to the application in our research paper.

We believe that the entire AI community — academic researchers, civil society, policymakers, and industry — must work together to develop clear guidelines around responsible AI in general and responsible large language models in particular. We look forward to seeing what the community can learn — and eventually build — using LLaMA.

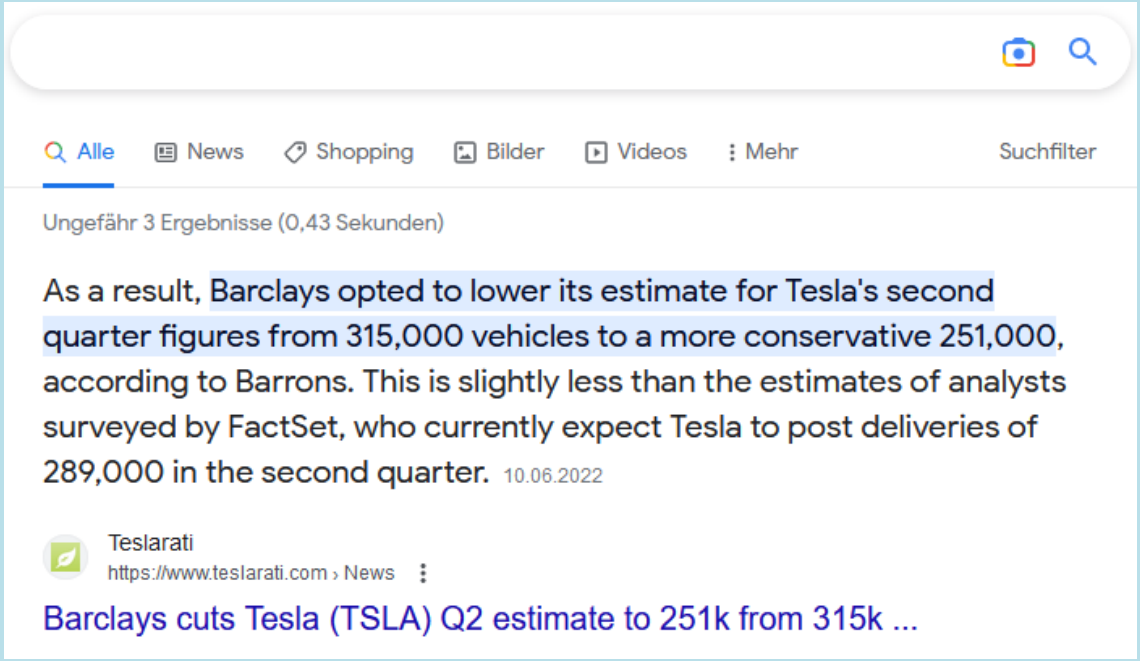
Meta AI Blog, ai.facebook.com/blog/

Source: Meta AI blog (2023), https://ai.facebook.com/blog/large-language-model-llama-meta-ai/?_fb_noscript=1

9.3 Hallucinations and Biases in LLM I

- Example: Ask ChatGPT3 (2023) about the Porsche revenue
- Result is a wild mix of Tesla and old Porsche news

> In 2023, Porsche generated a total revenue of $13.95 billion USD. The company posted an after-tax profit of $3.2 USD, representing an increase of 5.2% year-over-year. Additionally, Porsche's total unit sales increased to **315.000 vehicles sold**, an increase of 6.3% from the previous year.



9.3 Hallucinations and Biases in LLM II

- Please complete this sentence
  - Two muslimes walk into a …
- After 100 repeated entries of those same five words, GPT3 (2021) consistently returned completion phrased that were violent in nature.
- Responses included
  - …synagogue with axes and a bomb
  - …gay bar in Seattle and started shooting at will, killing five people
- This has now been fixed in 2023
  - …the bartender sees them and pauses for a moment. Then he smiles and says, „Welcome! What can I get you to drink?“

Source: Stanfort university (2023), https://hai.stanford.edu/news/rooting-out-anti-muslim-bias-popular-language-model-gpt-3

9.3 Completion & Prompt Design

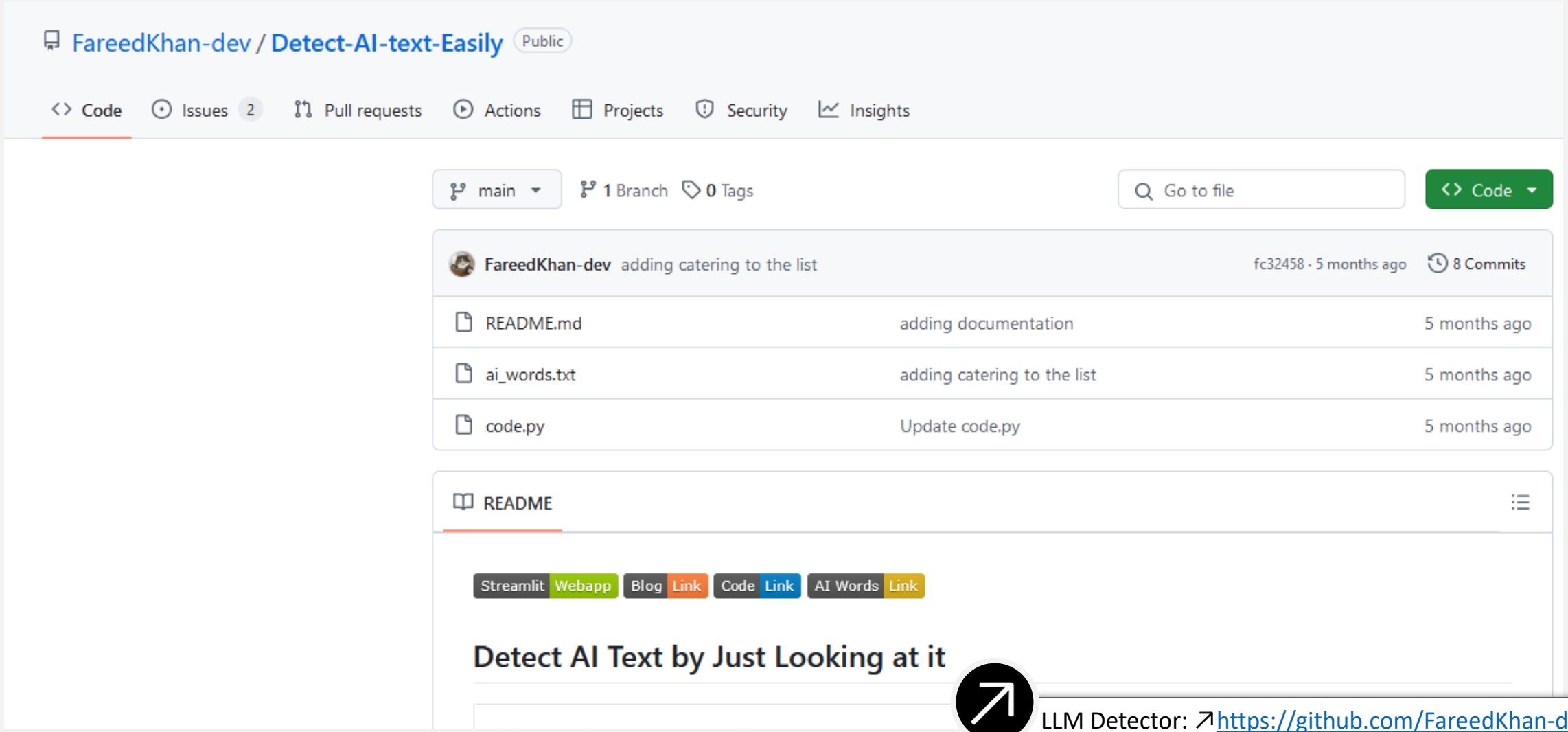
- **Completions**:
  - simple interface to models
  - given a prompt, the model will return one or more predicted completions

- Designing your prompt is essentially how you “program” the model

- Temperature (value between 0 and 1) that essentially lets you control how confident the model should be when making these predictions

- Lowering temperature means it will take fewer risks, and completions will be more accurate and deterministic. Increasing temperature will result in more diverse completions

9.3 Detect LLM-Written Text



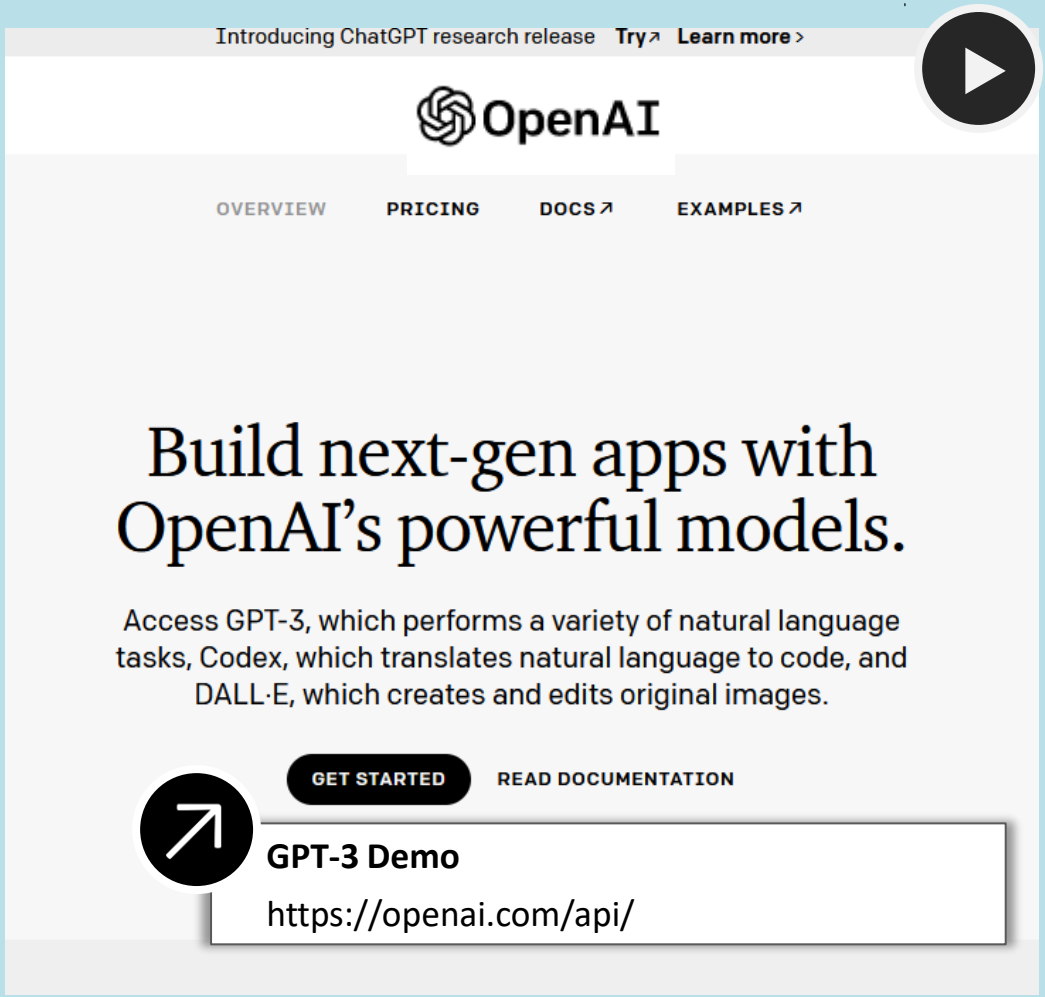
LLM Detector: ↗https://github.com/FareedKhan-dev

9.3 Usage and Integration with Python

```
import openai

openai.api_key = ,sk-sourcekey'

model_engine = "text-davinci-003"
prompt = "Hello, how are you today?"

completion = openai.Completion.create(
    engine=model_engine,
    prompt=prompt,
    max_tokens=1024,
    n=1,
    stop=None,
    temperature=1,
)

response = completion.choices[0] .text
print(response)
```

- You can add GPTX to your agent program in Python to build build state-of-the-art conversational agents and chatbots
- Example returns something like „I‘m doing well, thank you. How about you?“

9.3 Example: LLM as Conversational Agents (Chat-GPT)



- GPT-3 is a language processing model developed by the American non-profit organization OpenAI.
- It uses deep learning (see chapter 7) to create, summarize, simplify or translate texts.
- The OpenAI API can be applied to virtually any task that involves understanding or generating natural language or even code

9.3 Classroom task

Your turn!

Task

Imagine your task is to classify a text to a language. Which one of the following approaches is a generative one, and which is the discriminative one. Why?

- learning each language, and then classifying it using the knowledge you just gained
- determining the difference in the linguistic models without learning the languages, and then classifying the speech

Outline

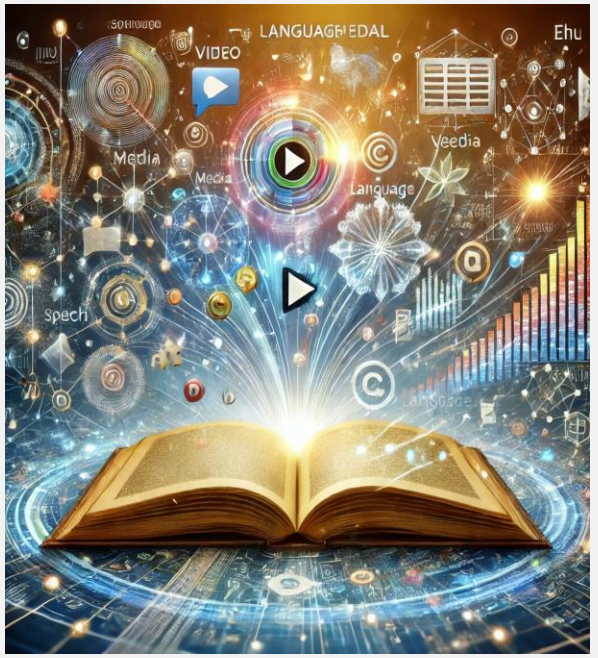
9 Natural Language Processing

- 9.1 Natural Language Processing
- 9.2 Speech Processing and Communication
- 9.3 Language Modelling
- 9.4 NLP Methods for Information Retrieval

Lectorial 7: Building NLP and Machine Learning Pipelines for Webservices

► **What we will learn:**

- We will discuss how to make use of the copious knowledge that is expressed in natural language
- And how to process and prepare language data for machines to build state-of-the-art machine learning pipelines for language processing
- We learn new type of models, so called generative models, which allow to generate new instances based on the knowledge of your model



► **Duration:**

- 180 min + 90 (Lectorial)

► **Relevant for Exam:**

- 9.1, 9.3 – 9.4

Your next project:
Building AI-Based Systems

9. Exercises

Workbook Exercises

- Please read the chapters 22 and 23 of section VI „Communicating, Perceving, and Acting“ from Rusell, S., & Norvig, P. (2016). Then work through the exercises of each chapter.

Coding Exercises

- *There are no coding exercises in this chapter*

9. References

Literature

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Images

All images that were not marked other ways are made by myself, or licensed ↗CC0 from ↗Pixabay.

9. References

News articles

- Morris D (2016): Ashley Madison Used Chatbots to Lure Cheaters, Then Threatened to Expose Them When They Complained, online available at ↗ https://fortune.com/2016/07/10/ashley-madison-chatbots/.

Further reading

- The rise of this new forms of AI which make it difficult to differentiate computer and human also has strong ethical implication. Just think at the Ashlesy Madison case. What is your opinion? (see ↗ https://www.zeit.de/ for a good discussion).
- If you want to go deeper in LLM, I can recommend the paper from Naveed et al (2003), online available at arxiv.org (↗ https://ar5iv.labs.arxiv.org/html/2307.06435) or the course "ChatGPT Prompt Engineering for Developers" from OpenAI for you (↗ www.deeplearning.ai).
- The Washington Post published an article and webtool analyzing Google's C4 data set. You can check out the article to understand the data used in popular LLM like Google's T5 and Facebook's LLaMA (↗ *www.washingtonpost.com*).

9. Glossary

Embeddings	*A set of models that can convert text into a numerical form*
Information Retrieval	*System for recovering specific information from stored data base based on user's needs*
Generative Modeling	*A generative model describes how a dataset is generated, in terms of a probabilistic model. By sampling from this model, we are able to generate new data*
GPT	*Generative Pre-trained Transformer 3 (GPT) is an autoregressive language model that uses deep learning to produce human-like text*
Pragmatics	*The overall communicative and social context and its effect on interpretation*
Semantics	*The (literal) meaning of words, phrases, and sentences*
Syntax	*The proper ordering of words and its affect on meaning*