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| **Computing**

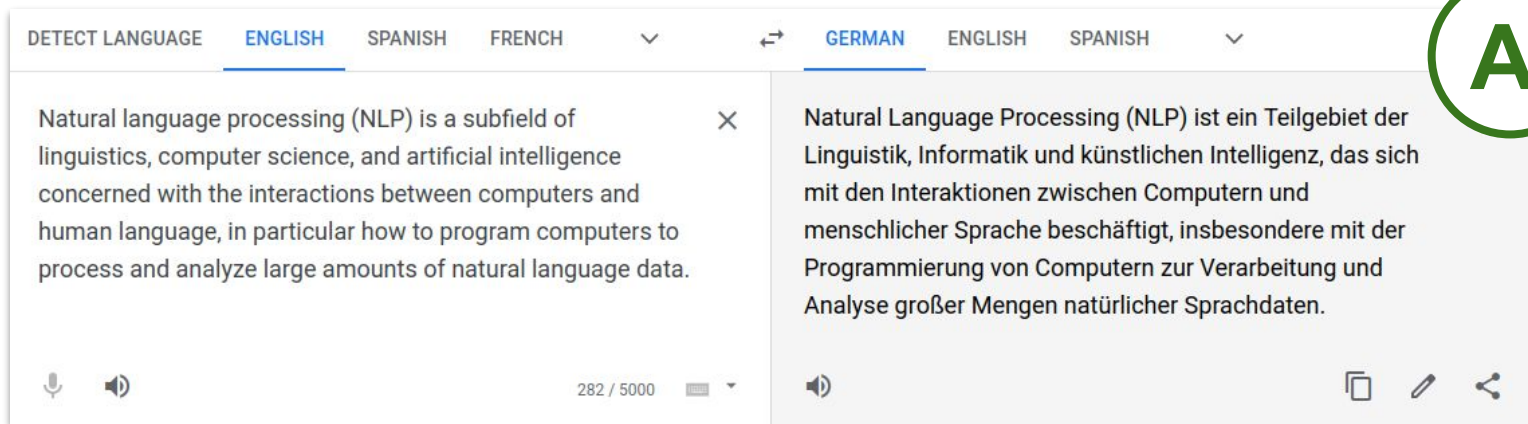
Natural Language Processing: Foundations

Section 1 — NLP in Everyday Life

NLP Applications

- NLP application in almost daily use
 - Machine translation
 - Conversational agents (e.g., chat bots)
 - Text summarization
 - Text generation (e.g., autocomplete)
- Applications powered by NLP
 - Social media
 - Search engines
 - Writing assistants (e.g., grammar checking)

Machine Translation



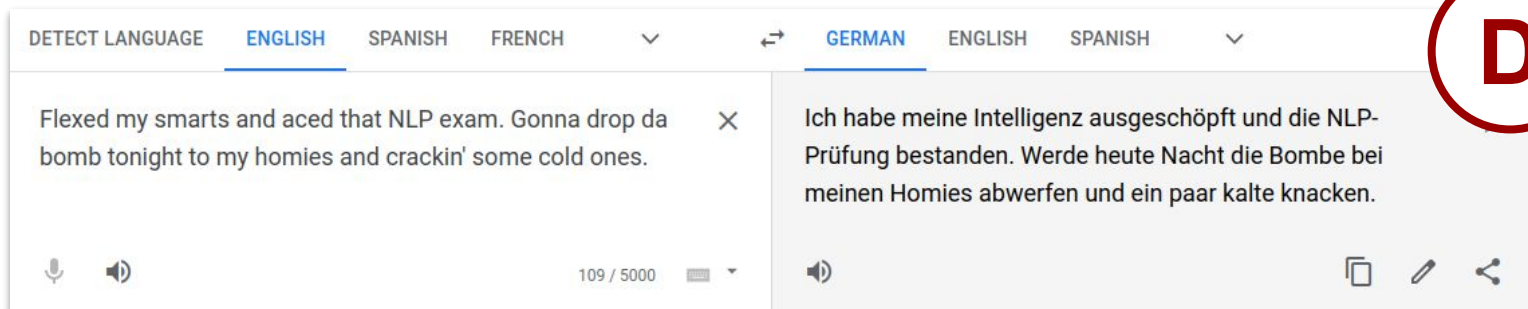
DETECT LANGUAGE ENGLISH SPANISH FRENCH ▼ ↔ GERMAN ENGLISH SPANISH ▼

Natural language processing (NLP) is a subfield of linguistics, computer science, and artificial intelligence concerned with the interactions between computers and human language, in particular how to program computers to process and analyze large amounts of natural language data.

Natural Language Processing (NLP) ist ein Teilgebiet der Linguistik, Informatik und künstlichen Intelligenz, das sich mit den Interaktionen zwischen Computern und menschlicher Sprache beschäftigt, insbesondere mit der Programmierung von Computern zur Verarbeitung und Analyse großer Mengen natürlicher Sprachdaten.

282 / 5000

A-



DETECT LANGUAGE ENGLISH SPANISH FRENCH ▼ ↔ GERMAN ENGLISH SPANISH ▼

Flexed my smarts and aced that NLP exam. Gonna drop da bomb tonight to my homies and crackin' some cold ones.

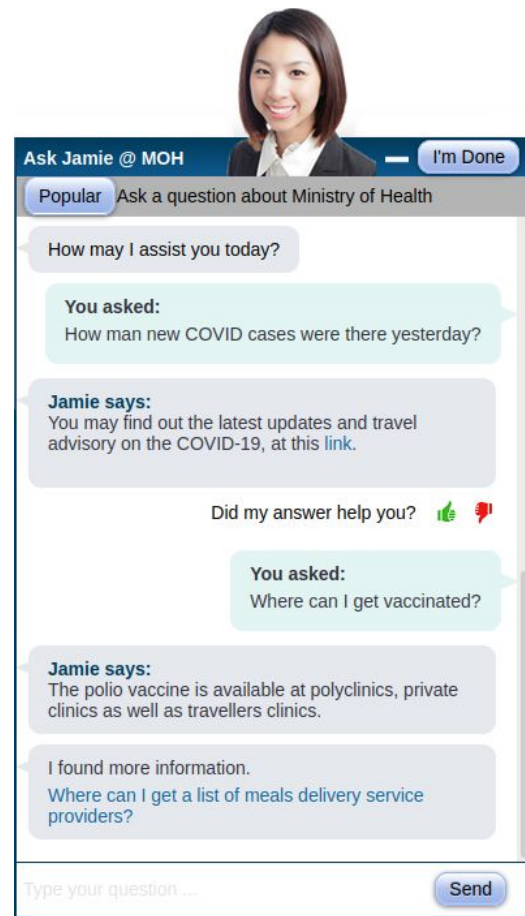
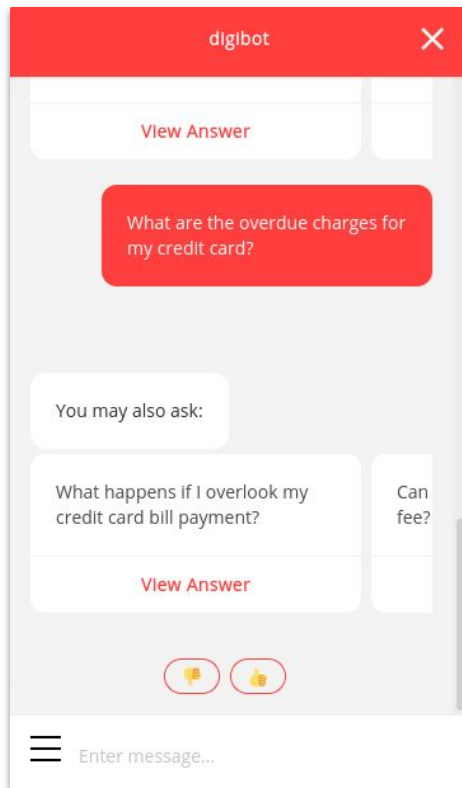
Ich habe meine Intelligenz ausgeschöpft und die NLP-Prüfung bestanden. Werde heute Nacht die Bombe bei meinen Homies abwerfen und ein paar kalte knacken.

109 / 5000

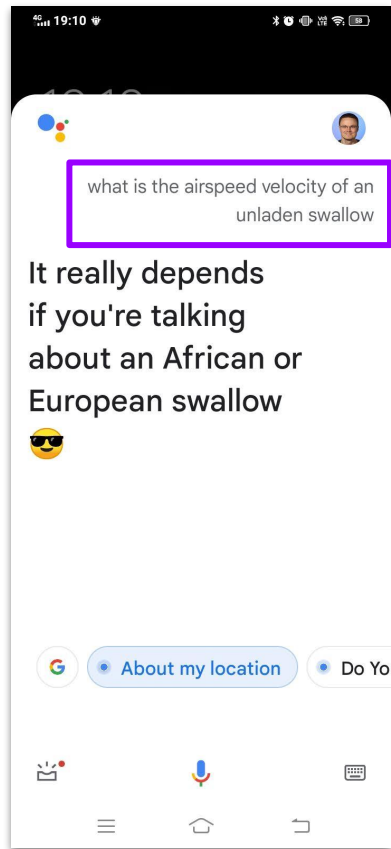
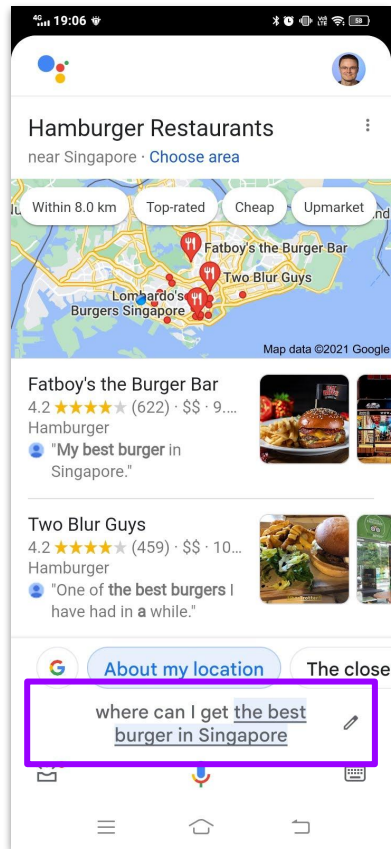
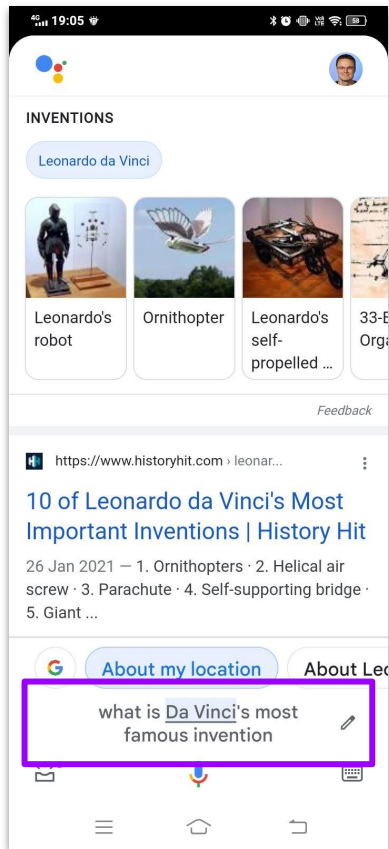
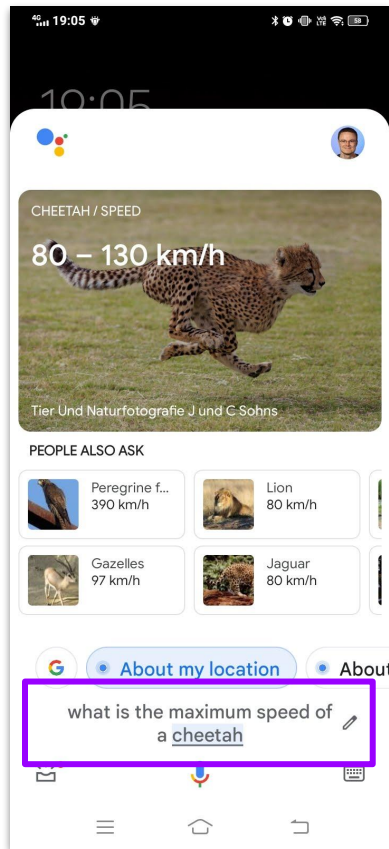
D

Conversational Agents

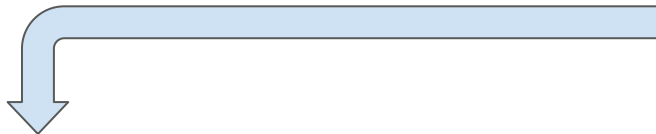
- Conversational agents
 - core components
 - Speech recognition
 - Language analysis
 - Dialogue processing
 - Information retrieval
 - Text-to-Speech



Conversational Agents — Question Answering



Text Summarization



Google's cloud unit looked into using artificial intelligence to help a financial firm decide whom to lend money to. It turned down the client's idea after weeks of internal discussions, deeming the project too ethically dicey. Google has also blocked new AI features analysing emotions, fearing cultural insensitivity. Microsoft restricted software mimicking voices and IBM rejected a client request for an advanced facial-recognition system.

Money and mind control: Big Tech slams ethics brakes on AI

PUBLISHED SEP 14, 2021, 5:00 PM SGT



SAN FRANCISCO (REUTERS) - In September last year, Google's cloud unit looked into using artificial intelligence (AI) to help a financial firm decide whom to lend money to.

It turned down the client's idea after weeks of internal discussions, deeming the project too ethically dicey because the AI technology could perpetuate biases like those around race and gender.

Since early last year, Google has also blocked new AI features analysing emotions, fearing cultural insensitivity, while Microsoft restricted software mimicking voices and IBM rejected a client request for an advanced facial-recognition system.

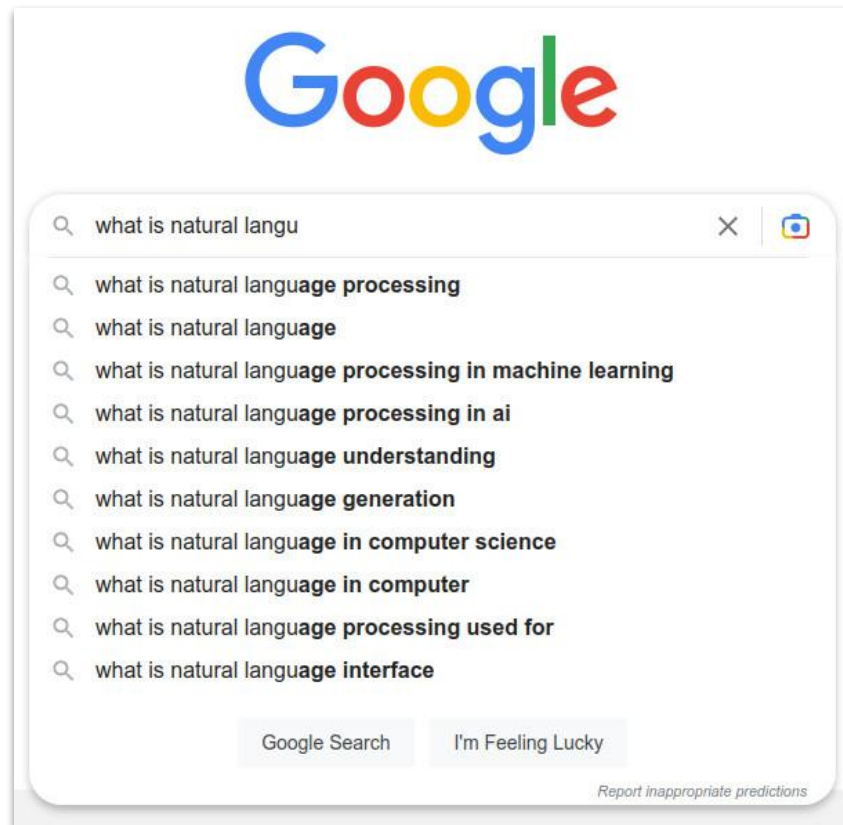
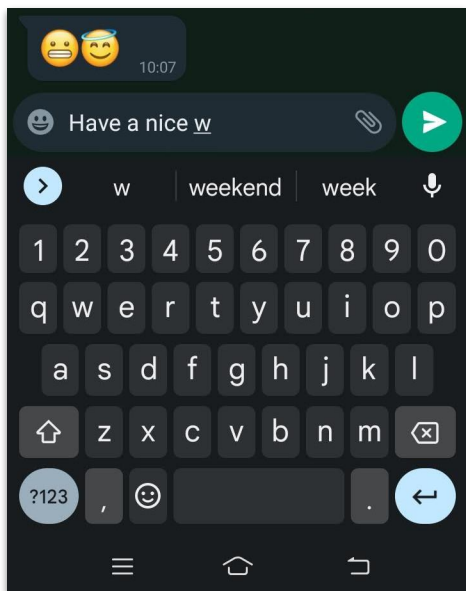
All these technologies were curbed by panels of executives or other leaders, according to interviews with AI ethics chiefs at the three US technology giants.

Reported here for the first time, their vetoes and the deliberations that led to them reflect a nascent industry-wide drive to balance the pursuit of lucrative AI systems with a greater consideration of social responsibility.

"There are opportunities and harms, and our job is to maximise opportunities and minimise harms," said Ms

Text Generation

- Example: Autocomplete
 - Given the first words of a sentence, predict the next most likely word



Text Generation

- Example: Image Captioning

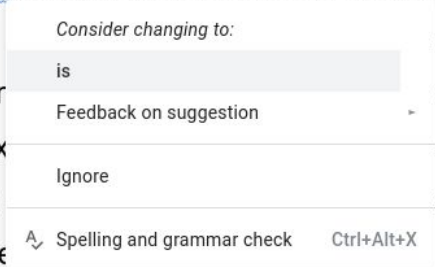


→ *"A man riding a red bicycle."*

Other Applications

- Spelling correction
- Document clustering
- Document classification, e.g.:
 - Spam detection
 - Sentiment analysis
 - Authorship attribution

Natural language processing (NLP) is a subfield of linguistics, computer science, and artificial intelligence concerned with the interactions between computers and human language, in particular how to program computers to process and analyze large amounts of natural language data. The goal is a computer capable of "understanding" the contents of documents, identifying the contextual nuances of the language within them, and then accurately extracting requested information. NLP is contained in the documents themselves and can be used to analyze the documents themselves.





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Natural Language Processing: Foundations

Section 1 — What is Language? What is NLP?

What is Natural Language?

- Natural Language

- Means of communicating thoughts, feelings, opinions, ideas, etc.
- Not formal, yet systematic: rules can emerge which were not previously defined
(this includes that many rules can be bent until reaching a breaking point)
- Characteristics: ambiguous, redundant, changing, unbounded, imprecise, etc.

- Text / Writing

- Visual representation of verbal communication (i.e., Natural Language)
- Writing system: agreed meaning behind the sets of characters that make up a text
(most importantly: letters, digits, punctuation, white space characters: spaces, tabs, new lines, etc.)

Core Building Blocks of (Written) Language

Character

- Basic symbol of written language
(letter, numeral, punctuation mark, etc.)

r, e, a, c, t, i, o, n

Morpheme
(1..n characters)

- Smallest meaning-bearing
unit in a language

re-act-ion

Word
(1..n morphemes)

- Single independent unit of
language that can be represented

reaction

Phrase
(1..n words)

- Group of words expressing a
particular idea or meaning

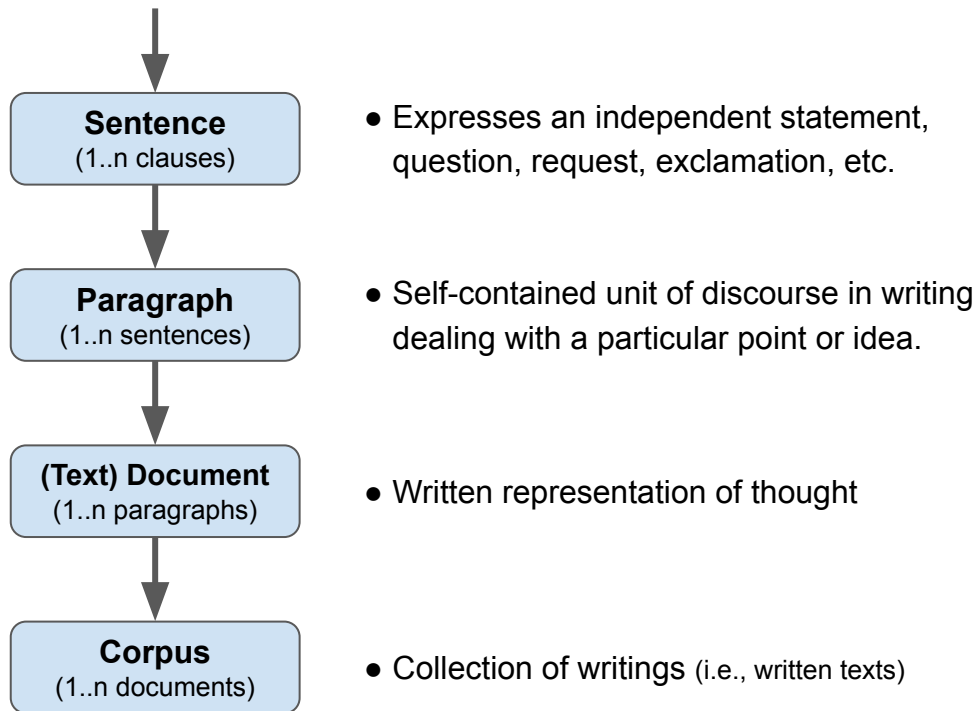
his quick reaction

Clause
(1..n phrases)

- Phrase with a subject and verb

his quick reaction saved him

Core Building Blocks of (Written) Language



His quick reaction saved him from the oncoming traffic.

Bob lost control of his car. His quick reaction saved him from the oncoming traffic. Luckily nobody was hurt and the damage to the car was minimal.

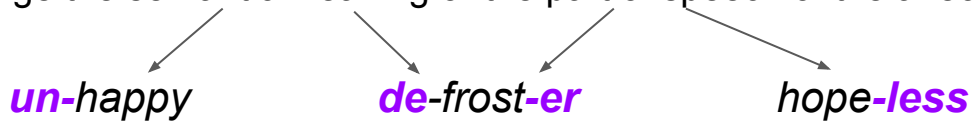
Morphemes

- Morpheme

- Smallest meaning-bearing unit in a language → word = 1..n morphemes

- Example: Prefixes & Suffixes

- Change the semantic meaning or the part of speech of the affected word



- Assign a particular grammatical property to that word (e.g., tense, number, possession, comparison)

walk-ed *elephant-s* *Bob-'s* *fast-er*

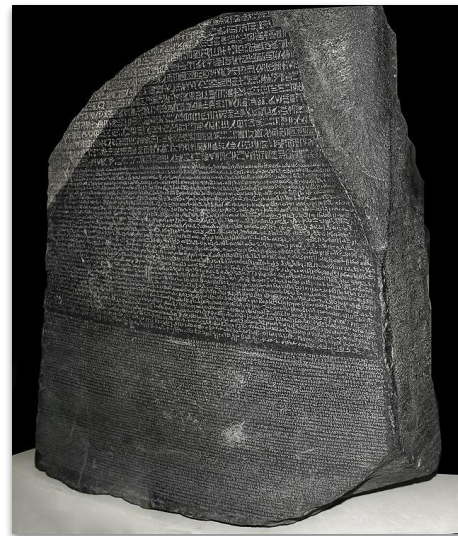
Examples

	Prefix	Prefix	Stem	Suffix	Suffix	Suffix
<i>dogs</i>			<i>dog</i>	<i>-s</i>		
<i>walked</i>			<i>walk</i>	<i>-ed</i>		
<i>imperfection</i>		<i>im-</i>	<i>perfect</i>	<i>-ion</i>		
<i>hopelessness</i>			<i>hope</i>	<i>-less</i>	<i>-ness</i>	
<i>undesirability</i>		<i>un-</i>	<i>desire</i>	<i>-able</i>	<i>-ity</i>	
<i>unpremeditated</i>	<i>un-</i>	<i>pre-</i>	<i>mediate</i>	<i>-ed</i>		
<i>antidisestablishmentarianism</i>	<i>anti-</i>	<i>dis-</i>	<i>establish</i>	<i>-ment</i>	<i>-arian</i>	<i>-ism</i>

Examples with multiple stems: *daydream-ing*, *paycheck-s*, *skydive-er*

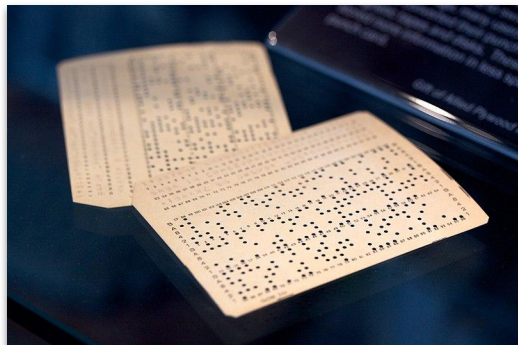
Using Language Before ~1950

- Verbal communication between *people*
 - Day-to-day conversations
 - Oral history
- Written communication for *people*
 - Stone tablets, scrolls, books, etc.
 - Permanent record of written language



Since 1950: Communication with Machines

~50s-70s



Basic symbolic languages
(e.g., punch cards)

~80s



Formal languages
(e.g., programming languages)

Today



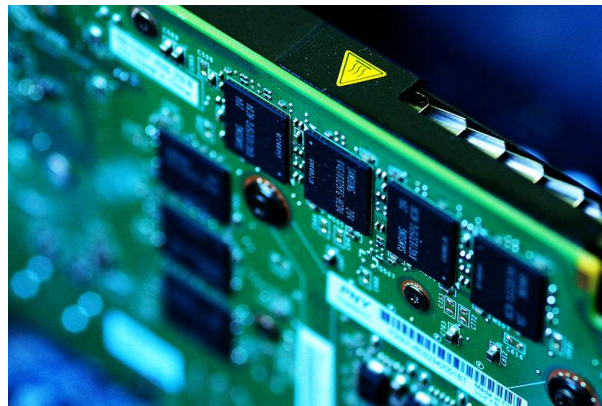
Natural language
(e.g., conversational agents / chatbots)

Communication with Machines

Humans



Machines



Natural
Language

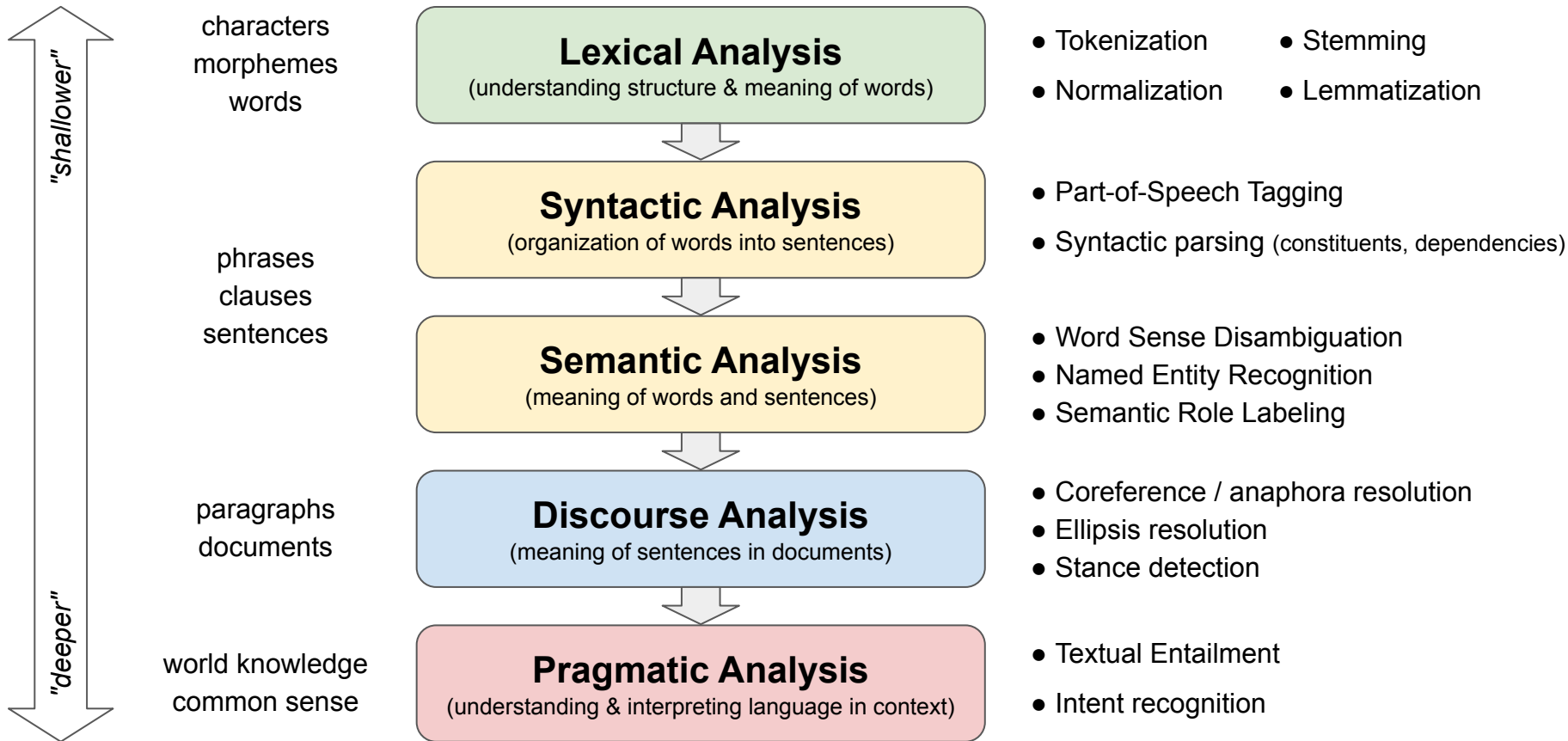
Analysis

Generation

\mathcal{R}

Some abstract internal
representation / model of
language and the world

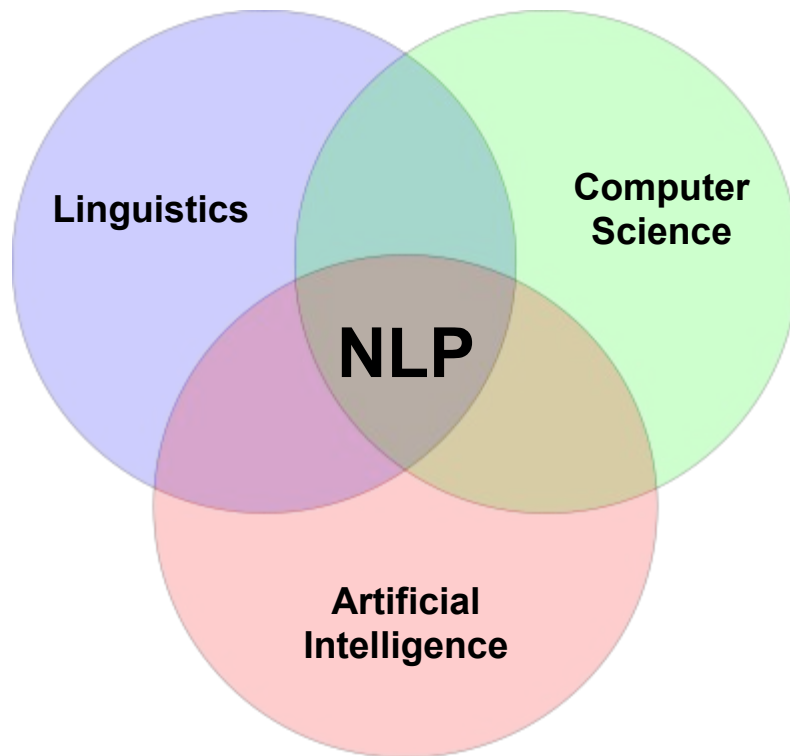
NLP in One Slide



What is NLP? — The Big Picture

Human Language

- Speech
- Writing



Algorithms, e.g.:

- Indexing / search
- Pattern matching

Machine Learning
Deep Learning



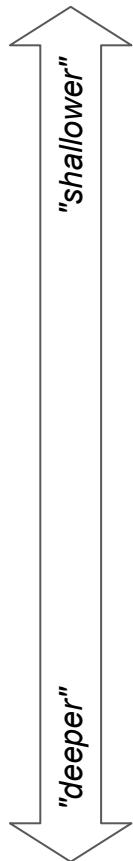
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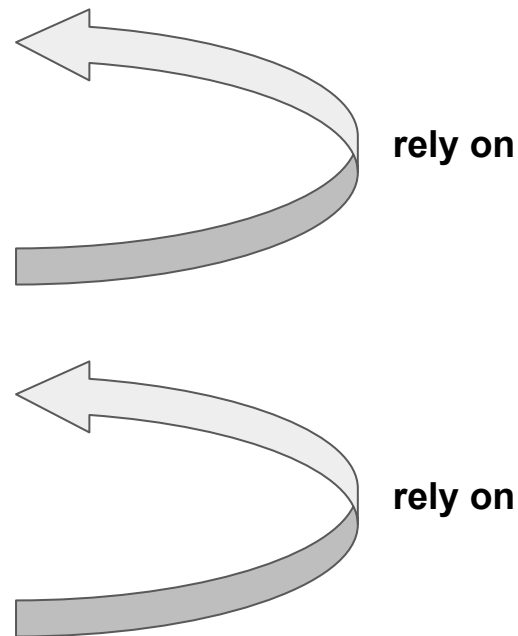
Natural Language Processing: Foundations

Section 1 — Important NLP Tasks

Important NLP Tasks



- Lower-level tasks, e.g.:
 - Text preprocessing
(e.g., tokenization, normalization)
 - Part-of-Speech Tagging
- Mid-level tasks, e.g.:
 - Word Sense Disambiguation
 - Named Entity Recognition
- Higher-level tasks, e.g.:
 - Coreference / anaphora resolution
 - Intent recognition



Lexical Analysis — Tokenization

- Tokenization

- Splitting a sentence or text into meaningful / useful units
- Different levels of granularity applied in practice

character-
based

S	h	e	'	s	d	r	i	v	i	n	g	f	a	s	t	e	r	t	h	a	n	a	l	l	o	w	e	d	.
---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---

subword-
based

She	's	driv	ing	fast	er	than	allow	ed	.
-----	----	------	-----	------	----	------	-------	----	---

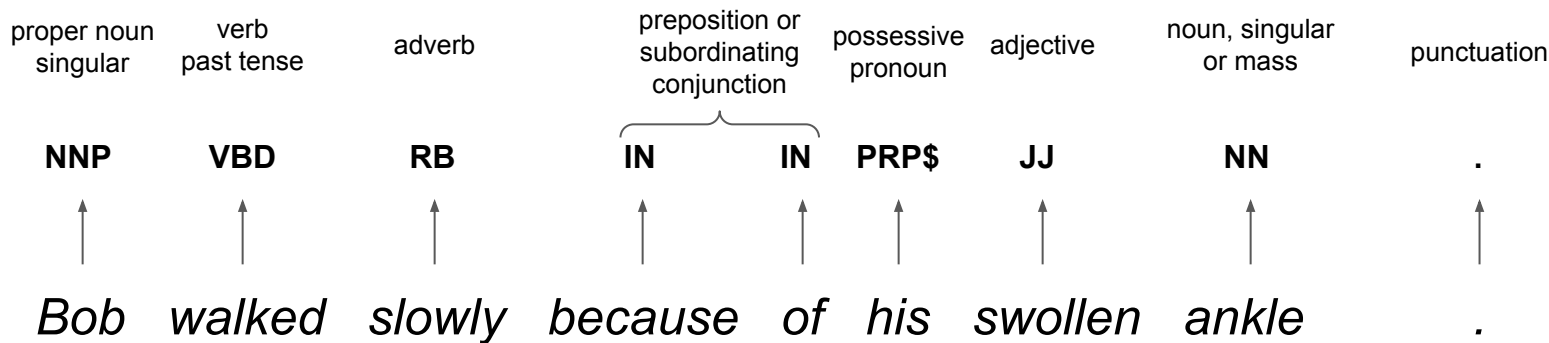
word-
based

She's	driving	faster	than	allowed	.
-------	---------	--------	------	---------	---

Syntactic Analysis — Part-of-Speech Tagging

- Part-of-Speech (POS) tagging

- Labeling each word in a text corresponding to a part of speech
- Basic POS tags: noun, verb, article, adjective, preposition, pronoun, adverb, conjunction, interjection

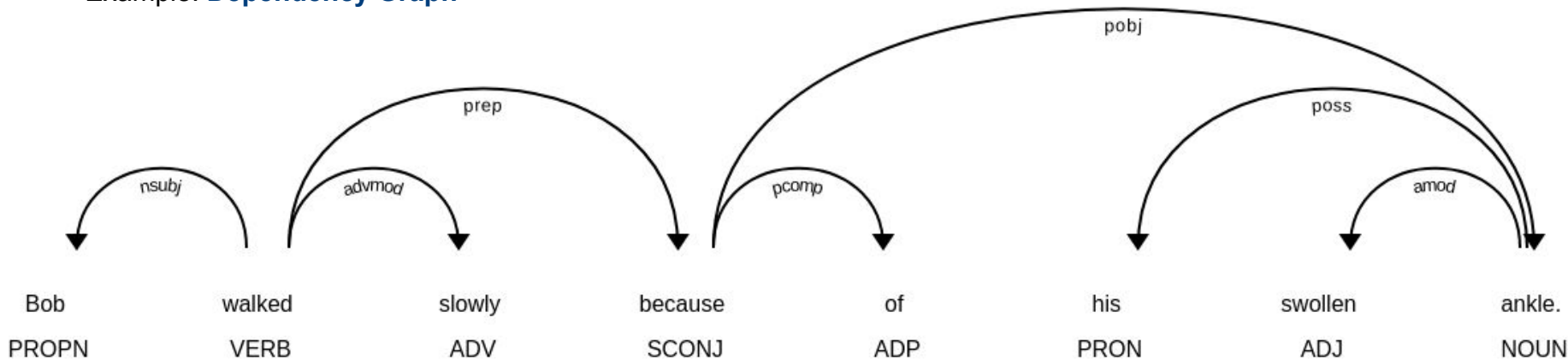


Syntactic Analysis — Syntactic Parsing

- Dependency parsing

- Analyze the grammatical structure in a sentence
- Find related words & the type of the relationship between them

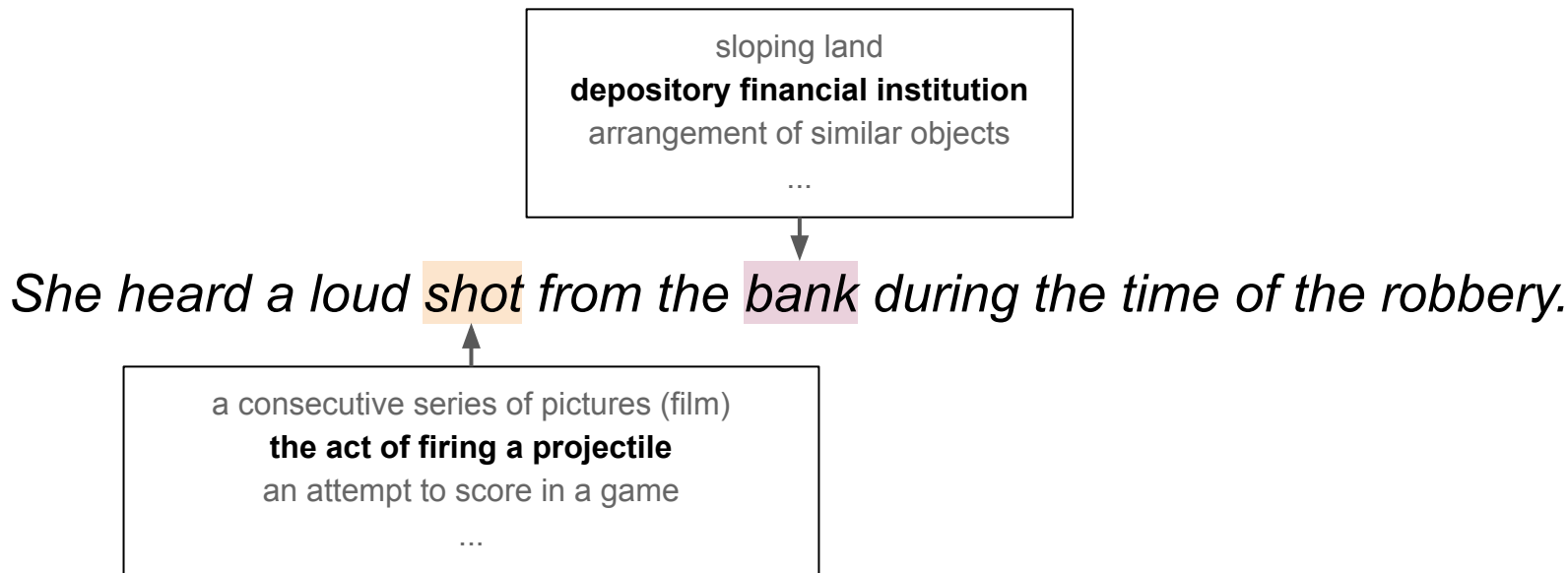
Example: **Dependency Graph**



Semantic Analysis — Word Sense Disambiguation

- Word Sense Disambiguation (WSD)

- Identification of the right **sense** of a word among all possible senses
- Semantic ambiguity: many words have multiples meanings (i.e., senses)



Semantic Analysis — Named Entity Recognition

- Named Entity Recognition (NER)
 - Identification of **named entities**: terms that represent real-world objects
 - Examples: persons, locations, organizations, time, money, etc.

PERSON

ORGANIZATION

LOCATION

MONEY

Chris booked a *Singapore Airlines* flight to *Germany* for *S\$1,200*.

Semantic Analysis — Semantic Role Labeling

- Semantic Role Labeling (SRL)
 - Identification of the semantic roles of these words or phrases in sentences
 - Express semantic roles as predicate-argument structures

Who

did **What** to **Whom**

What exactly

at **When**

The teacher sent the class the assignment last week.

Discourse Analysis — Coreference Resolution

- Coreference Resolution

- Identification of expressions that refer to the same entity in a text
- Entities can be referred to by named entities, noun phrases, pronouns, etc.

Mr Smith didn't see *the car*. Then *it* hit *him*.



Mr Smith didn't see *the car*. Then *the car* hit *Mr Smith*.

Discourse Analysis — Ellipsis Resolution

- Ellipsis Resolution

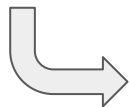
- Inference of ellipses using the surrounding context
- **Ellipsis**: omission of a word or phrases in sentence

He studied at NUS, his brother at NTU.



*He studied at NUS, his brother **studied** at NTU.*

She's very funny. Her sister is not.



*She's very funny. Her sister is not **very funny**.*

Pragmatic Analysis — Textual Entailment

- Textual Entailment

- Determining the inference relation between two short, ordered texts
- Given a text t and hypothesis h , " t entails h " ($t \Rightarrow h$)
 - someone reading t would infer that h is most likely true

t: *A mixed choir is performing at the National Day parade.*

h: *The anthem is sung by a group of men and women.*

} **$t \Rightarrow h$**

Required world knowledge:

- Mixed choir: male and female members
- Singing a song is a performance
- "anthem" typically refers to "national anthem"

Pragmatic Analysis — Intent Recognition

- Intent Recognition

- Classification of an utterance based on what the speaker/writer is trying to achieve
- Core component of sophisticated chatbots

"I'm hungry!"

Additional context:

- The writer is vegetarian
- The writer is near VivoCity
- It's 1pm: lunch time
- ...

→ **Intent:**
Writer is looking
for a place to eat

→ **Action:**
Search for vegetarian restaurants in
and around VivoCity that are open.



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Natural Language Processing: Foundations

Section 1 — What makes NLP so Hard?

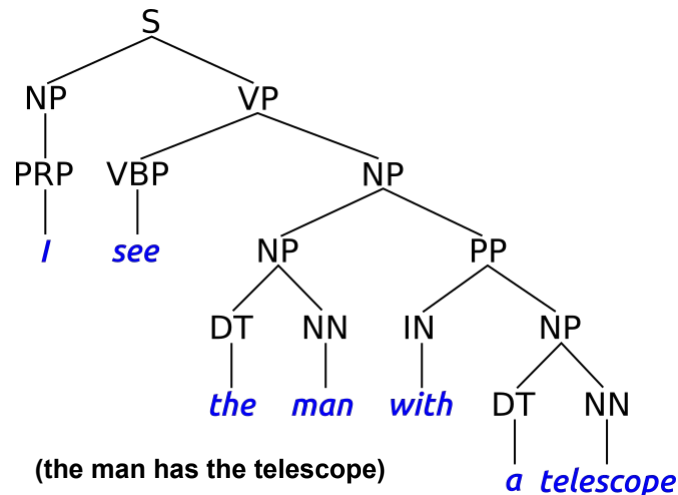
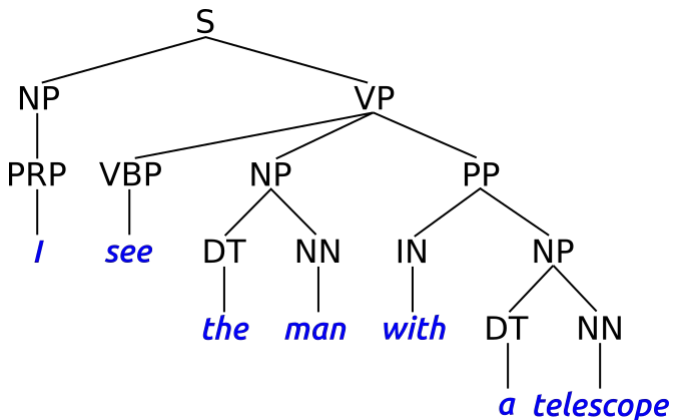
What Makes NLP so Hard?

Challenges of Language → Challenges of NLP

- ambiguous
- redundant
- changing
- unbounded
- imprecise
- expressive
- sparse
- variable
- "large-scale"
- ...

Ambiguity

- Ambiguity at different levels, e.g.:
 - Word senses: *bank* (financial institute or edge of river?), *cancer* (disease or zodiac sign?)
 - Part of Speech: *run* (verb or noun?), *fast* (verb or noun or adjective or adverb?)
 - Syntactic structure: "*I see the man with a telescope*" → affects semantics!



Ambiguity

- Anaphoric ambiguity

- Ambiguous resolution of anaphora / coreferences (without additional context)

Alice and Sarah went for dinner. ^{???}She invited ^{???}her.

Who is "she" and "her" referring to?

Useful context: It was Sarah's birthday.

The box didn't fit in the car because ^{???}it was too big.

vs.

The box didn't fit in the car because ^{???}it was too small.

What is "it" referring to?

Resolution requires the understanding of

- Objects can contain other objects
- Physical size of objects
- Physical limitations due to size

Ambiguity

- Winograd Schema (Challenge)

- A pair of sentences differing in only one or two words and containing an ambiguity that is resolved in opposite ways
- Resolution requires the use of world knowledge & reasoning

- Example

???

I poured water from the bottle into the cup until it was full.

vs.

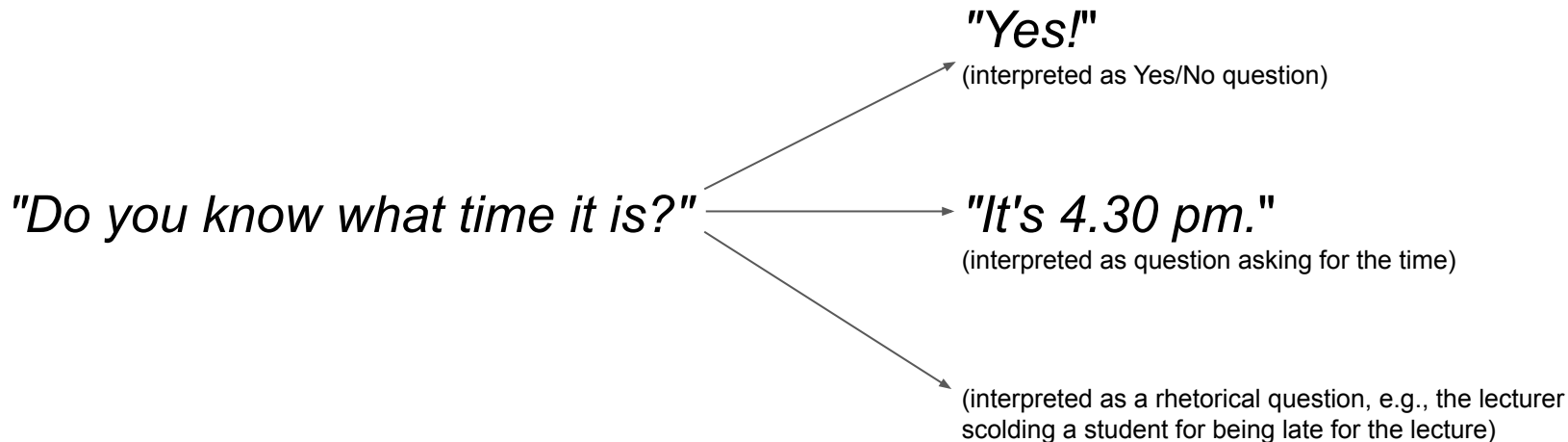
???

I poured water from the bottle into the cup until it was empty.

Ambiguity

- Pragmatic Ambiguity

- Unclear semantics if context is unknown



Expressivity

- In general, the same meaning can be expressed with different forms

Alice gave Bob the book. **vs.** *Alice gave the book to Bob.*

This burger is very delicious. **vs.** *This burger is a banger!*

Please stop talking and pay close attention to what I want to tell you! **vs.** *Shut up and listen to me!*

Expressivity

- Idioms

*It's **raining cats and dogs** today.*

*He was **over the moon** to see her.*

- Neologisms

- May be added to the dictionary over time

***selfie**, **retweet**, **photobomb**, **staycation**, **binge-watching**, **crowdfunding**, **adulting**, **chillax**, **noob**, **kudos**, etc.*

- Literary devices, e.g:

- Humor
- Sarcasm
- Irony
- Satire
- Exaggeration

"Oh yeah...studying NLP 24/7 is reeeally my favorite way to spend a weekend!"

Variation

- No one-size-fits-all NLP solutions

- Difference in underlying task

- (tokenizing, stemming, syntax parsing, part-of-speech tagging, entity recognizing, etc.)

- ~6.500 languages and ~150 language families

- (different phonetics/phonology, morphology, syntax, grammar)

- Different domains: news articles, social media, scientific papers, ancient literature, etc.

- (particularly: different vocabularies, formal vs. informal language (e.g., slang), narrative vs. dialogue)

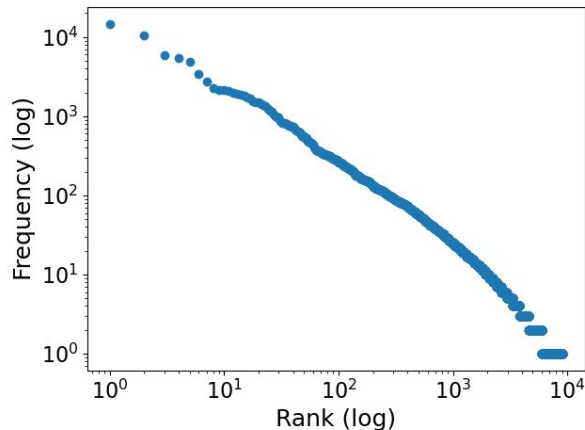
- Cultural differences and biases

- (example: *"I'm over 40 and live alone."* — perceived sentiment affected by cultural background)

Sparsity

- Sparsity in text corpora

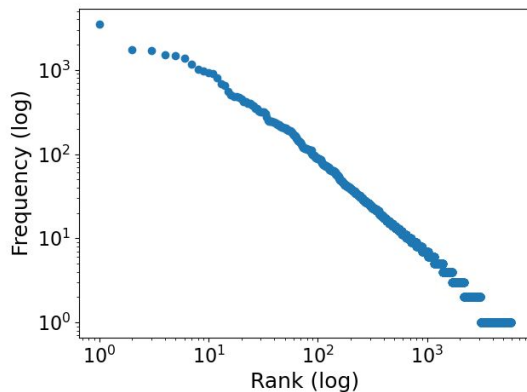
- Word frequencies inversely proportional to their rank → Zipf's Law
- Example: "*On the Origin of Species*"
(Charles Darwin, 1859; 212k+ words)



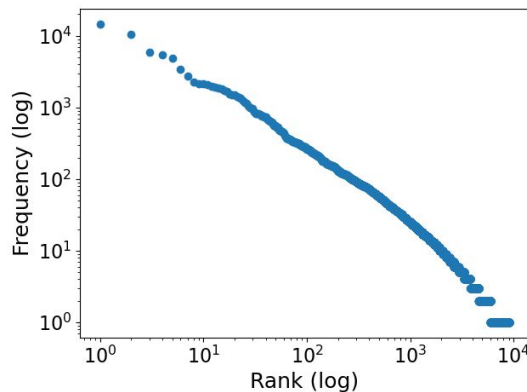
Rank	Word	Freq.
1	<i>the</i>	14,767
2	<i>of</i>	10567
3	<i>and</i>	5920
4	<i>in</i>	5477
5	<i>to</i>	4837
6	<i>a</i>	3460
7	<i>that</i>	2764
8	<i>as</i>	2242
9	<i>have</i>	2121
10	<i>be</i>	2116
...
101	<i>mr</i>	263
102	<i>parts</i>	260
103	<i>often</i>	260
104	<i>period</i>	259
105	<i>common</i>	256
...
1001	<i>increasing</i>	25
1002	<i>expected</i>	25
1003	<i>egg</i>	25
1004	<i>fly</i>	25
1005	<i>aquatic</i>	25
...

Sparsity

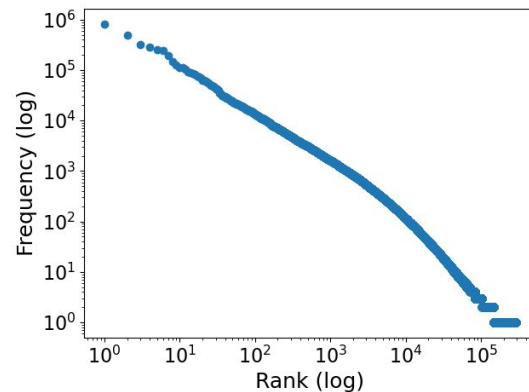
The Hound of the Baskervilles (63k+ words)



On the Origin of Species (212k+ words)



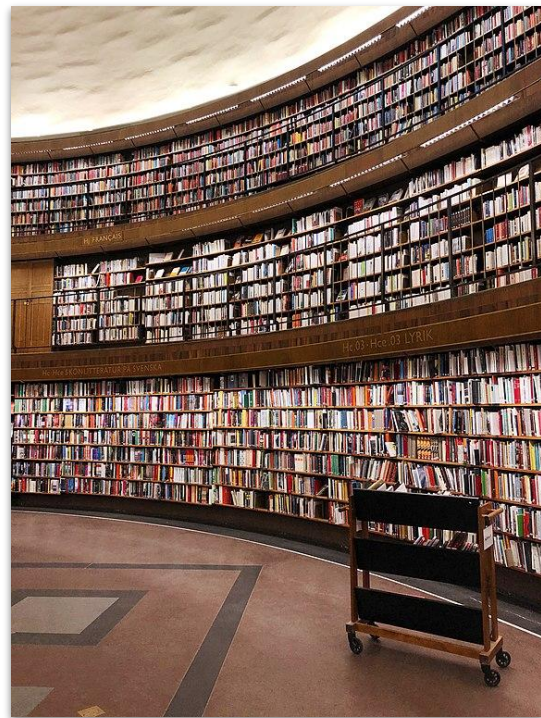
100MB Wikipedia dump (14.4M+ words)



→ Regardless of size and domain of a corpus, there will be a lot of infrequent words!

Scale

- ~6,500 languages and ~150 language families
- Number of words (e.g., in English)
 - Dictionary: ~470,000
 - Web corpus: > 1,000,000



Source: Wiki Commons (CC0 1.0): [Stockholm Public Library](#)

Unmodeled Representation

- The meaning / interpretation of a sentence often depends on:
 - The current context or situation
 - Shared understanding about the world
- } → How to capture this in \mathcal{R} ?

"I killed all the children."

Serial killer or **Linux administrator**?

"I slipped and fell hard on the floor."

Arguably a negative sentiment, but **WHY**?



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Natural Language Processing: Foundations

Section 1 — When NLP Goes Wrong

NLP — Ethical Questions & Challenges

- "Could" vs. "Should" — e.g.:

- **Should** we build a classifier to identify social media user if they suffer from depression based on their posts?
- **Should** we organize users news feed based on their interests and likings to maximize user engagement?
- **Should** we build chatbots that can perfectly mimic humans?

"If you torture the data long enough, it will confess to anything"

(Ronald Coase; 1981 — paraphrased)

"With great power comes great responsibility!"

(Spider-Man's Uncle Ben)

- Fundamental challenges in NLP

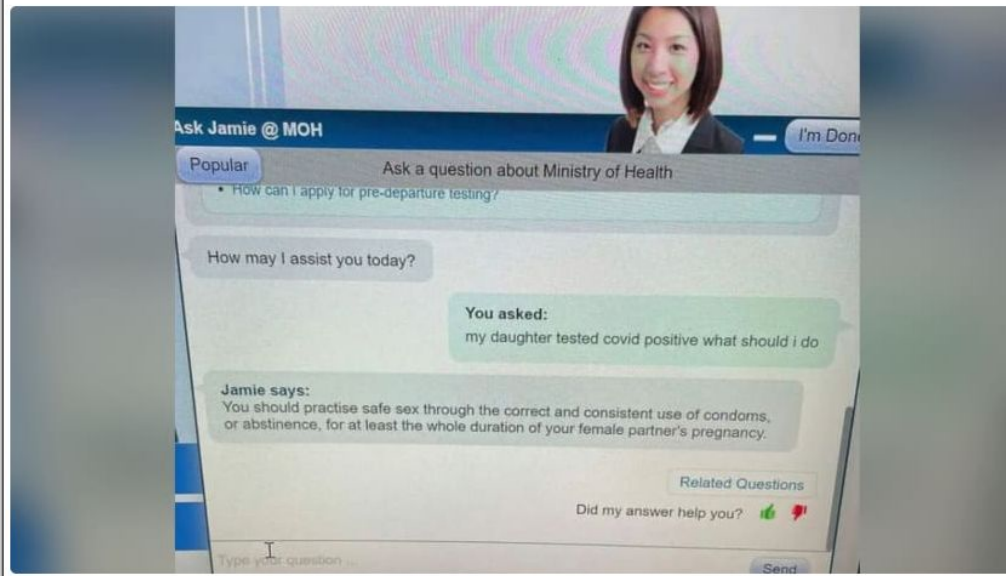
- Most NLP techniques rely on statistical models
(never 100% correct and often difficult to quantify errors)
- Most NLP techniques learn from data
(Is the data representative? Is the data biased?)

*"Your scientists were so preoccupied with whether they **could**, they didn't stop to think if they **should**."*

(Ian Malcolm; Jurassic Park, 1991)

NLP in the Press — For the Wrong Reasons

MOH temporarily disables Ask Jamie chatbot after 'misaligned replies'



Afifah Darke

05 Oct 2021 02:11PM

(Updated: 05 Oct 2021 02:17PM)



NLP in the Press — For the Wrong Reasons

College Kid's Fake, AI-Generated Blog Fooled Tens of Thousands

Microsoft terminates its Tay AI chatbot after she turns into a Nazi

OpenAI Shuts Down GPT-3 Bot Used To Emulate Dead Fiancée

Not spam: estimated cost of 'false positive' junk mail amounts to more than €19.4 billion in Europe alone

Artificial intelligence has a problem with grammar

Why chatbots still suck in 2021

AI tools that companies use to scan resumes are stopping 27 million people finding new jobs, a Harvard report says

Facebook's data on you runs deeper than your therapist's notes

Our computers are sexist towards male and female politicians

AI Wrote Better Phishing Emails Than Humans in a Recent Test



NUS
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| **Computing**

Natural Language Processing: Foundations

Section 1 — The Big Picture

What is NLP? — The Big Picture

- NLP as machine learning

- Symbolic, probabilistic, and connectionist ML have found their way into NLP
- Good ML needs bias and assumptions → NLP: linguistic theory & representations

- NLP as linguistics

- NLP must contend with NL data as found in the world
- NLP \approx computational linguistics
- Linguists now use tools that originated from NLP!

What is NLP? — The Big Picture

Fields with Connections to NLP

- Cognitive Science
- Information Theory
- Data Science
- Political Science
- Psychology
- Economics
- Education
- Ethics

"Language shapes the way we think, and determines what we can think about."

Benjamin Lee Whorf

"Knowledge of languages is the doorway to wisdom."

Roger Bacon

"Language is the road map of a culture. It tells you where its people come from and where they are going."

Rita Mae Brown

"We should learn languages because language is the only thing worth knowing even poorly."

Kató Lomb

Desiderata of NLP Models

- What makes good NLP?

- Sensitivity to a wide range of phenomena and constraints in language
- Generality across languages, modalities, genres, styles
- Strong formal guarantees (e.g., convergence, statistical efficiency, consistency)
- High accuracy when judged against expert annotations or test data
- Computational efficiency during training and testing (construction and production)
- Explainable to human users → transparency
- Ethical considerations

In practice, often conflicting goals
(e.g., accuracy vs explainability)

NLP is Changing

- Increases in computing power
 - Deep Learning = matrix operations → Game changer: GPUs
- The rise of the Web, then the social web
 - More "food" for data hungry algorithms
 - User generated content = informal, natural, lively text
- Advances in machine learning
 - Continuously growing model zoo (LSTM/GRU, CNN, VAE, Transformers, etc.)
- Advances in understanding of language in social context

Course Meta Topics

- Linguistic Issues

- What is the range of language phenomena?
- What are the knowledge sources that let us disambiguate?
- What representations are appropriate?
- How do you know what to model and what not to model?

- Statistical Modeling Methods

- Increasingly complex model structures
- Learning and parameter estimation
- Efficient inference: dynamic programming, search
- Deep neural networks for NLP: LSTM, CNN, Seq2seq

Section 1 — Summary

- Main takeaway messages

NLP is important!

- Communication with machines and not only with other people
- NLP-powered applications more and more commonplace
- More on more written language will be generated by machines

NLP is challenging!

- NLP is challenging because Natural Language is challenging
- Natural Language is ambiguous, redundant, changing, unbounded, imprecise, expressive, etc.
- NLP methods need to be flexible, robust, efficient, accurate, etc.

NLP is interdisciplinary!

- NLP covers many fields
- Main fields: linguistics and computer science
- Many connected fields (e.g., ethics, psychology, education)