ESKWELABS

Eskwelabs x Shopee Code League

Bash Yumol

Introduction

Who am I?

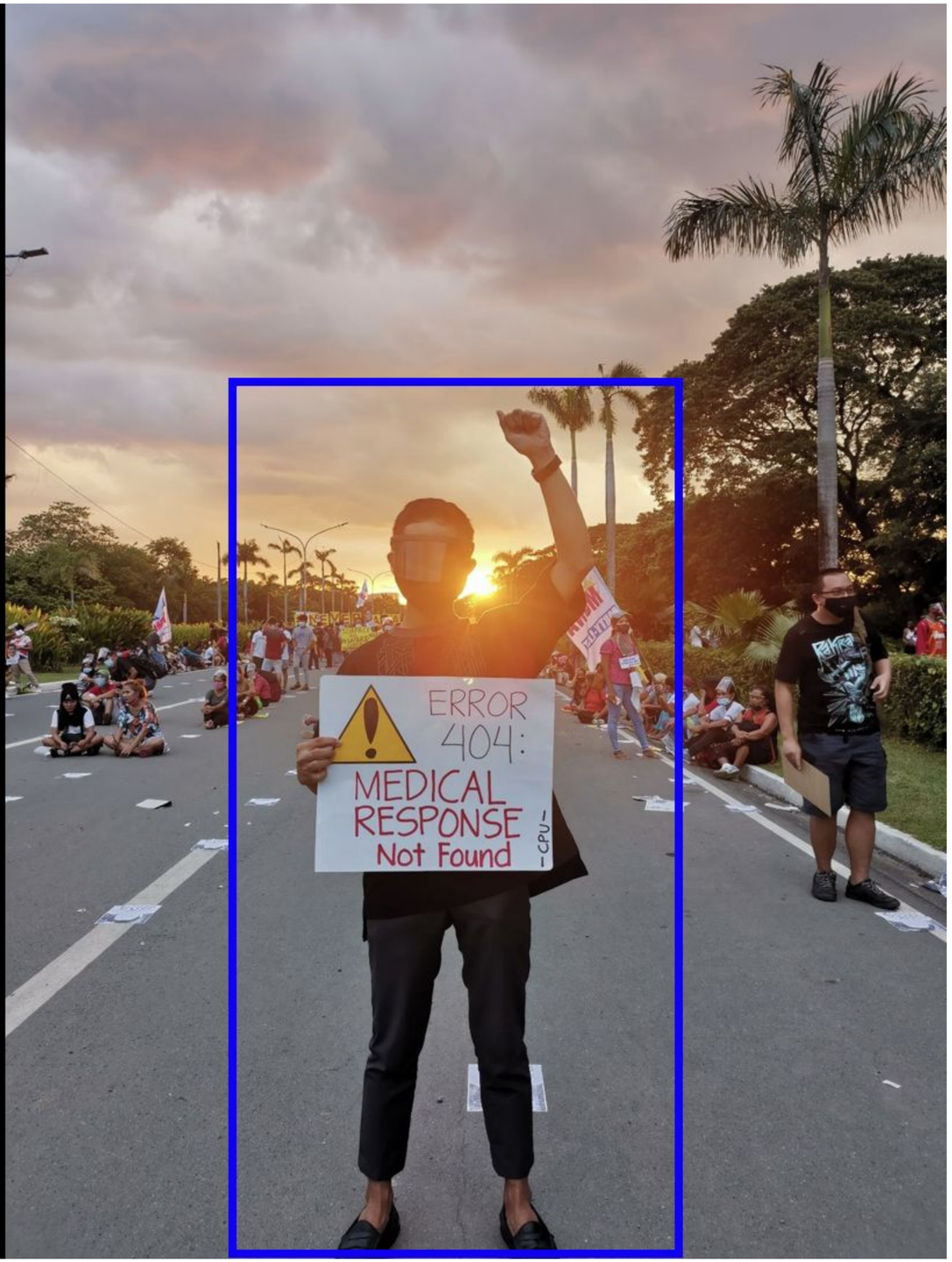
Name: Albert 'Bash' Yumol

Lives: Manila Philippines

Interests: Physics, AI, Big Data,
Cryptography, IoT, Activism

Occupation: Data Scientist and AI Consultant, EdTech

Connect: https://www.linkedin.com/in/albertyumol/
https://github.com/albertyumol
https://albertyumol.github.io/



Mission

Eskwelabs is an online data upskilling school based in the Philippines driving social mobility in the future of work.

We build data skills for workers and teams through mentor-led project-based upskilling.

For Individuals

90% job placement within 90 days
50% increase in income

Source: Job outcome survey reported by students from Cohort I-III, Eskwelabs Data Science program.

For Companies

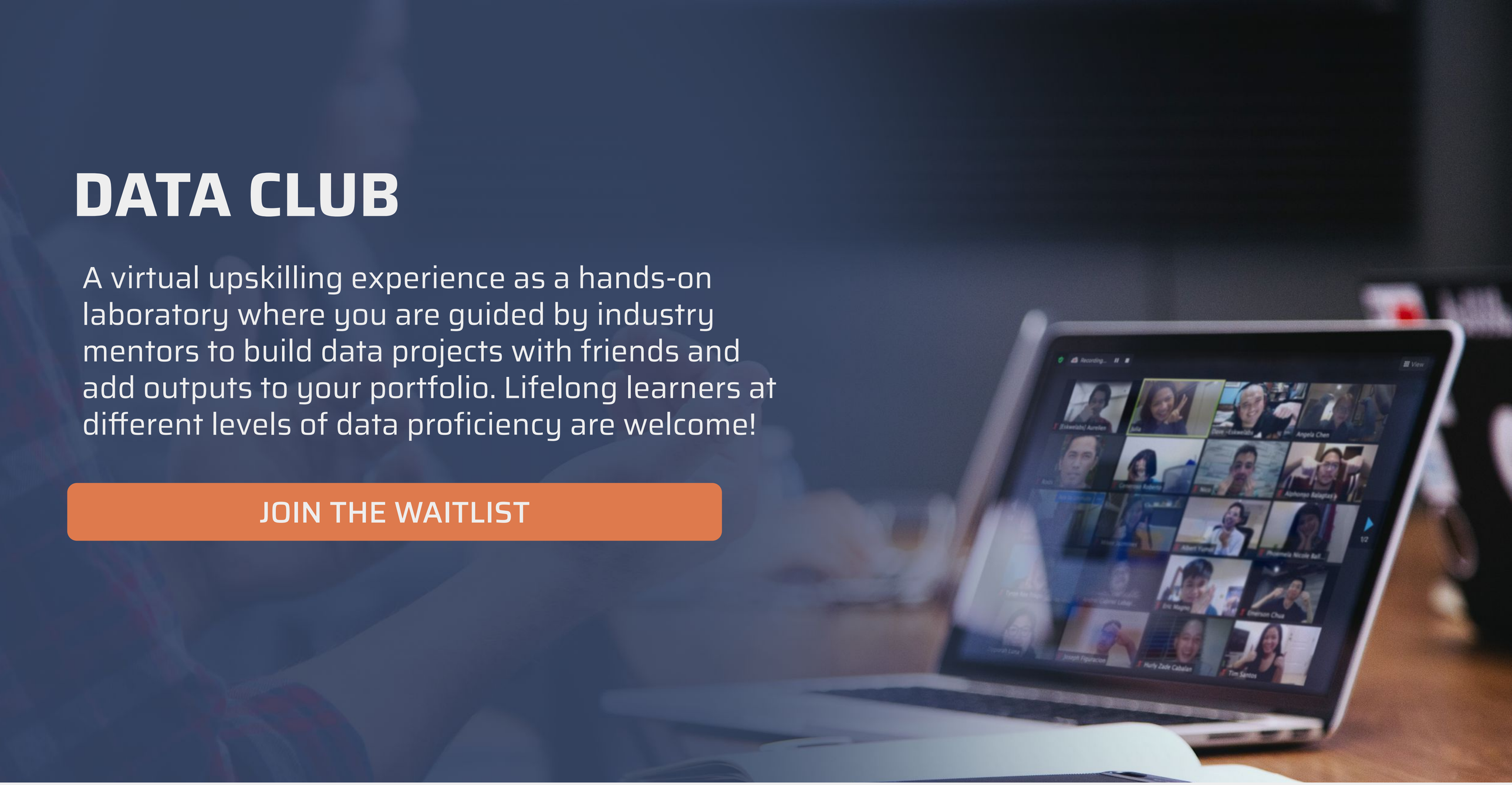
Build or buy talent
Pivot to mid to high-value work

TaskUs
UnionBank
pwc
MSCI
Uber
InterContinental Hotels & Resorts
Shopee
kumu
The World Bank
AboitizPower

DATA CLUB

A virtual upskilling experience as a hands-on laboratory where you are guided by industry mentors to build data projects with friends and add outputs to your portfolio. Lifelong learners at different levels of data proficiency are welcome!

JOIN THE WAITLIST



SPRINT TOPICS

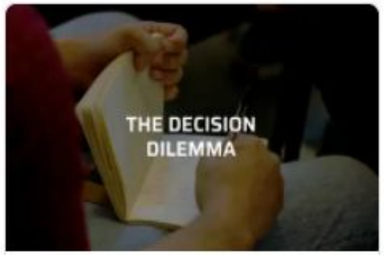
www.eskwelabs.com/data-club

Interactive Data Visualization with PowerBI

Learn how to turn visualization into insights with one of the most powerful tools for data analysis - PowerBI - while building a beautiful, and interactive dashboard to track the latest pandemic developments.

Beginner | No Code | PowerBI

READ MORE →



What-If Analysis and Optimization with Solver in Excel

Make better everyday and business decisions using Excel Solver that optimize allocation of resources.

Beginner | No Code

READ MORE →

Create Exploratory Data Analysis in Python

Tell a story through data on how far the world has progressed on the UN's Global Goals, a universal call to action to end poverty, protect the planet, and ensure that all people enjoy peace and prosperity by 2030.

Data for Good | Beginner | Python

READ MORE →

Save Time by Automating Work in Excel

Ever wonder how some people manage to get their work done faster? Their secret is working smart by using Excel VBA to automate repeatable tasks.

Beginner | No Code

READ MORE →

Introduction to Object Recognition

Learn the foundations of computer vision and implement your own object detection algorithm and identify an object of your choice.

Intermediate | Python

READ MORE →

The Rise of BTS

Create a bar chart race using Python to visualize how music artist popularity changed over time.

Beginner | Python | Data Viz

READ MORE →

Design Data Strategy for a Fast Food Restaurant

Help craft the data strategy for your favourite fast food chain by understanding how data can serve business goals.

Beginner | No Code

READ MORE →

Data meets Don Draper - Customer Segmentation Analysis

The digital economy means customers are online. Help a creative ad agency target the right audiences with digital marketing.

Beginner | No Code | SQL

READ MORE →

Start

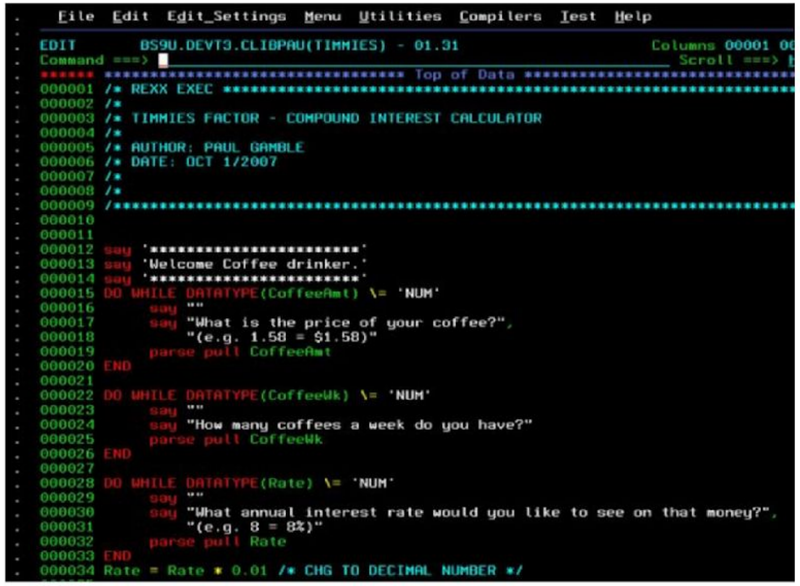
Objectives

Natural Language Processing

a branch of artificial intelligence that helps machine understand and respond to human language.

Communication With Machines

~50-70s



~80s

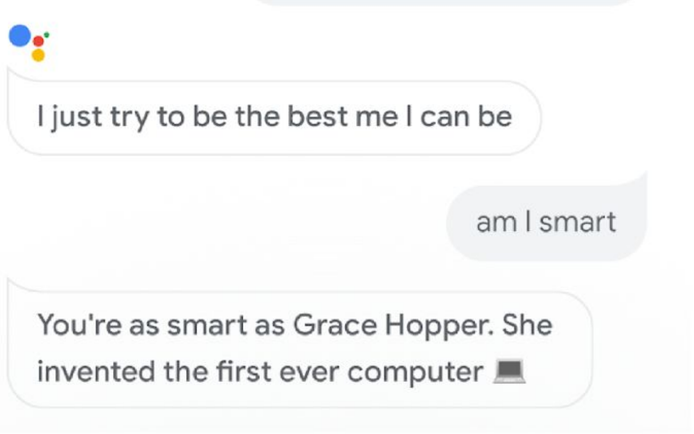
today

Conversational Agents

Conversational agents contain:

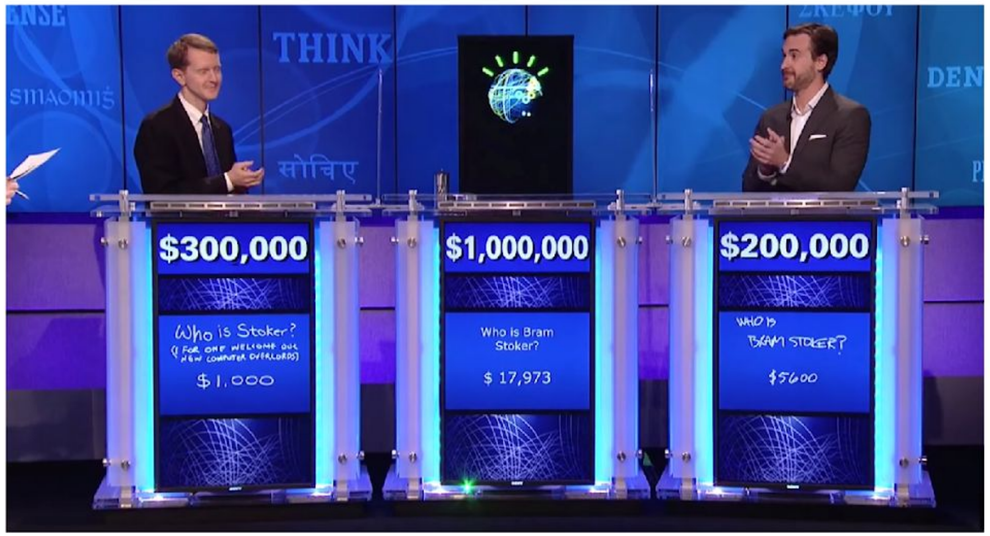
- Speech recognition
- Language analysis
- Dialogue processing
- Information retrieval
- Text to speech

works with the Google Assistant



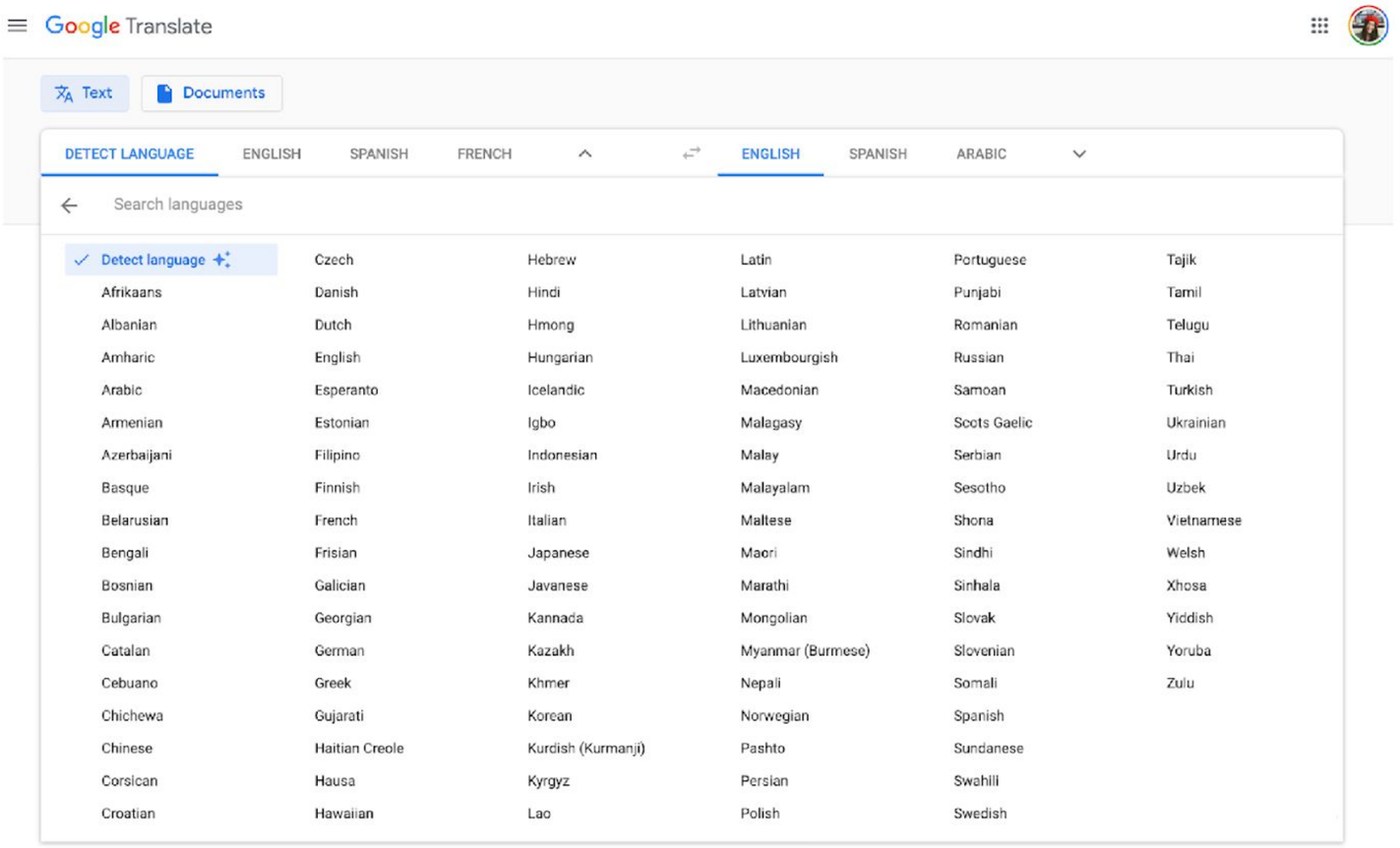

In early 2011, an IBM computing system named Watson
competed against the world's best Jeopardy! champions.

Question Answering



- What does “divergent” mean?
- What year was Abraham Lincoln born?
- How many states were in the United States that year?
- How much Chinese silk was exported to England in the end of the 18th century?
- What do scientists think about the ethics of human cloning?

Machine Translation



Natural Language Processing

Applications

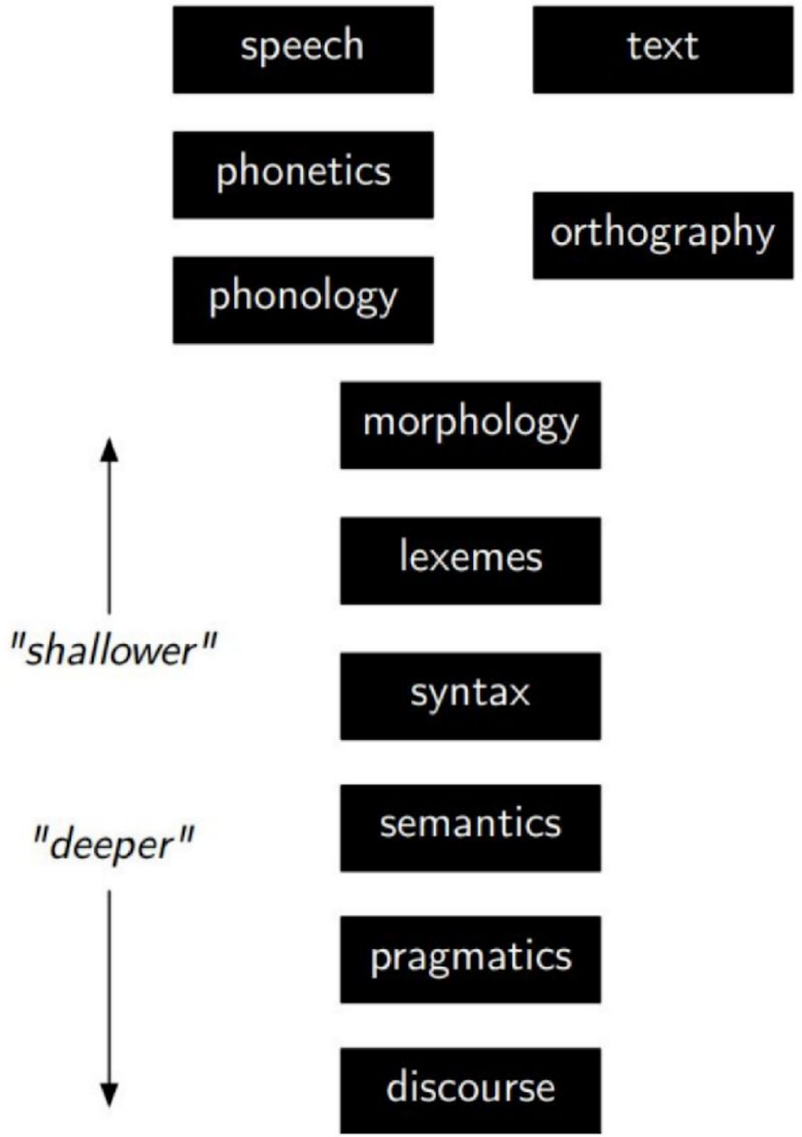
- Machine Translation
- Information Retrieval
- Question Answering
- Dialogue Systems
- Information Extraction
- Summarization
- Sentiment Analysis
- ...

Core Technologies

- Language modeling
- Part-of-speech tagging
- Syntactic parsing
- Named-entity recognition
- Word sense disambiguation
- Semantic role labeling
- ...

NLP lies at the intersection of computational linguistics and machine learning.

Level Of Linguistic Knowledge



Phonetics, Phonology

- Pronunciation Modeling

SOUNDS	Th	i	a	si	e	n

Words

- Language Modeling
- Tokenization
- Spelling correction

WORDS This is a simple sentence

Morphology

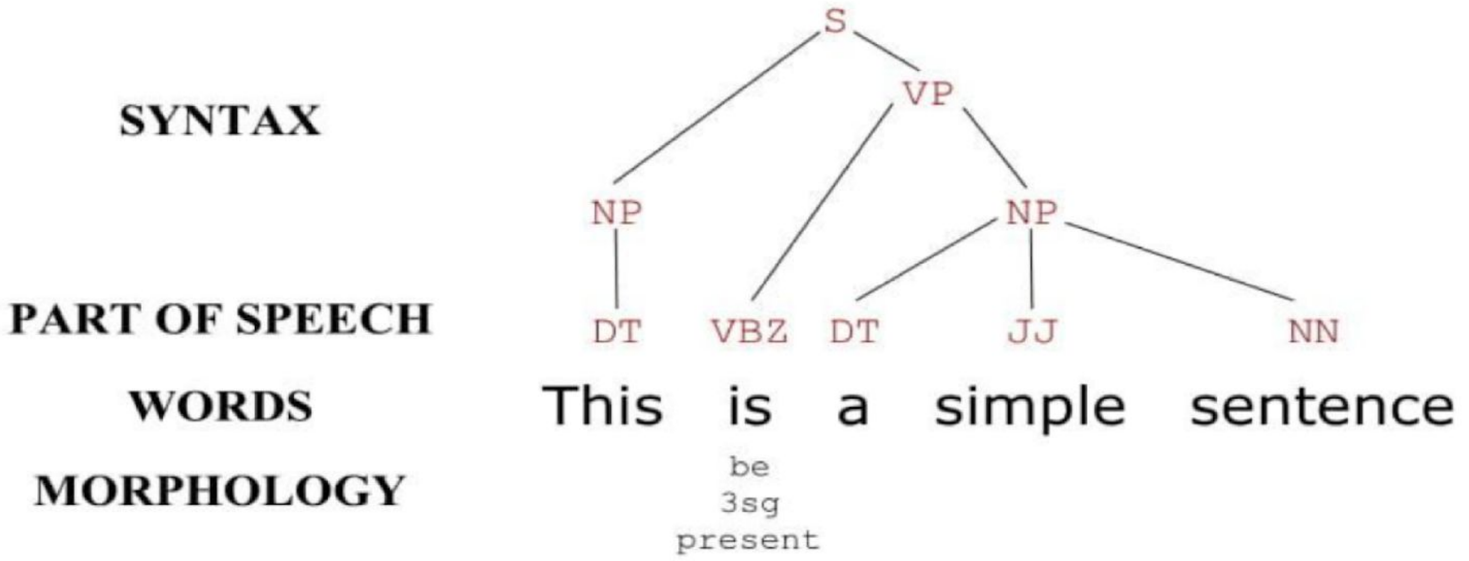
- Morphology analysis
- Tokenization
- Lemmatization

Part of Speech

- Part of speech tagging

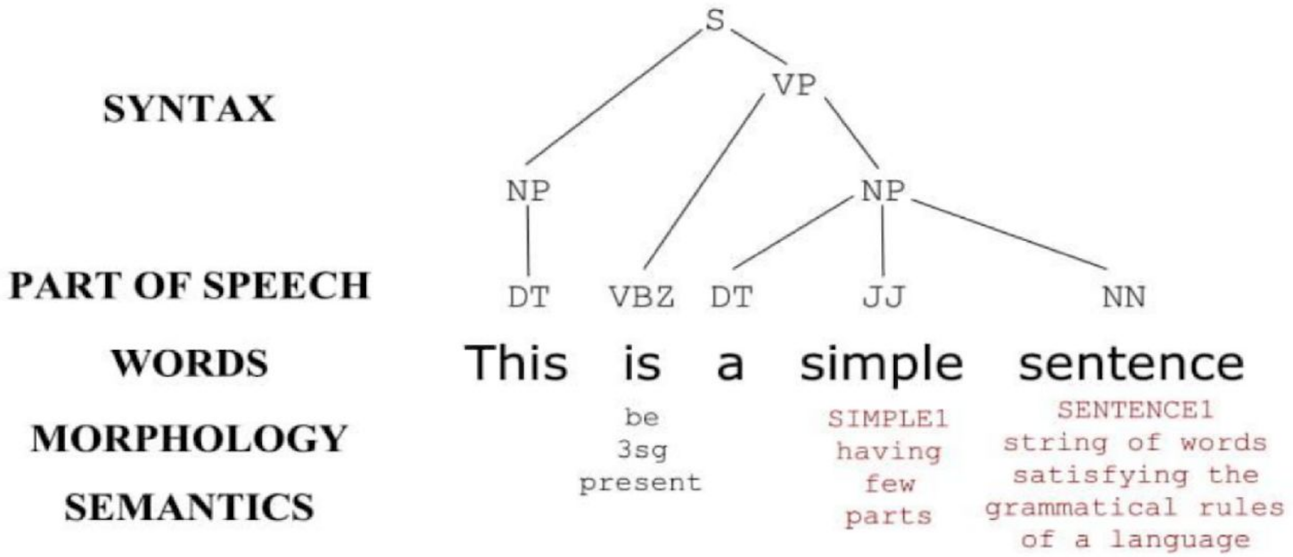
Syntax

- Syntactic parsing

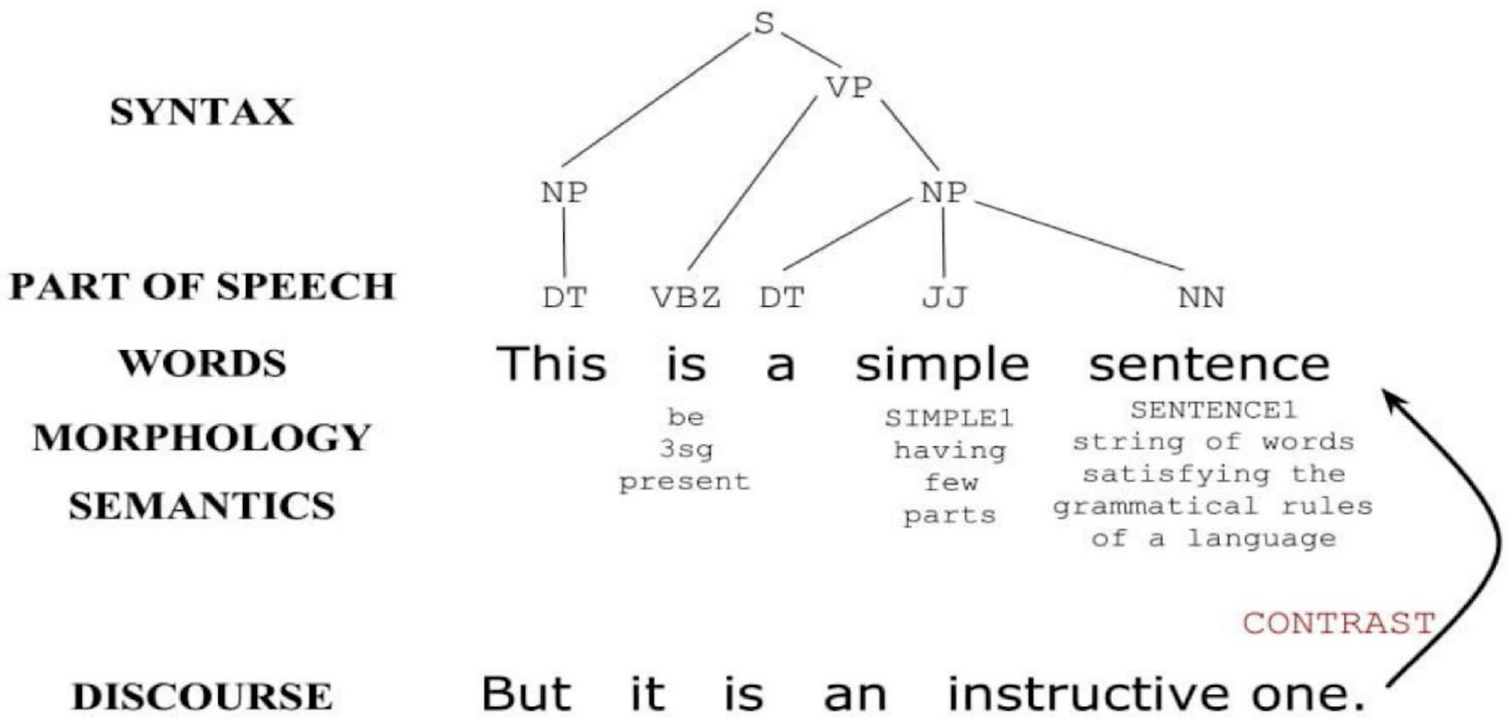


Semantics

- Named entity recognition
- Word sense disambiguation
- Semantic role labeling



Discourse


SYNTAX
PART OF SPEECH
WORDS
MORPHOLOGY
SEMANTICS
DISCOURSE
S
VP
NP
NP
DT
VBZ
DT
JJ
NN
This
is
a
simple
sentence
be
3sg
present
SIMPLE1
having
few
parts
SENTENCE1
string of words
satisfying the
grammatical rules
of a language
CONTRAST
But
it
is
an
instructive one.

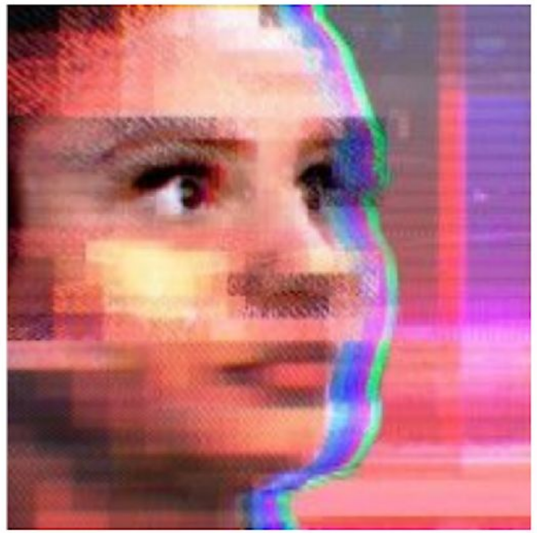
Where Are We Now?

Where Are We Now?

Baseline mutual information model (Li et al. 2015)
A: Where are you going? (1) B: I'm going to the restroom. (2) A: See you later. (3) B: See you later. (4) A: See you later. (5) B: See you later. (6) ... ...
A: how old are you? (1) B: I'm 16. (2) A: 16? (3) B: I don't know what you are talking about. (4) A: You don't know what you are saying. (5) B: I don't know what you are talking about . (6) A: You don't know what you are saying. (7) ...

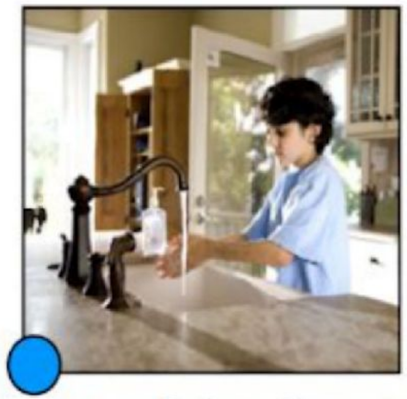
VS

Where Are We Now?



https://www.theverge.com/2016/3/24/11297050/tay-microsoft-chatbot-racist

woman cooking



man fixing faucet

Zhao, J., Wang, T., Yatskar, M., Ordonez, V and Chang, M.-W. (2017) Men Also Like Shopping: Reducing Gender Bias Amplification using Corpus-level Constraint. EMNLP

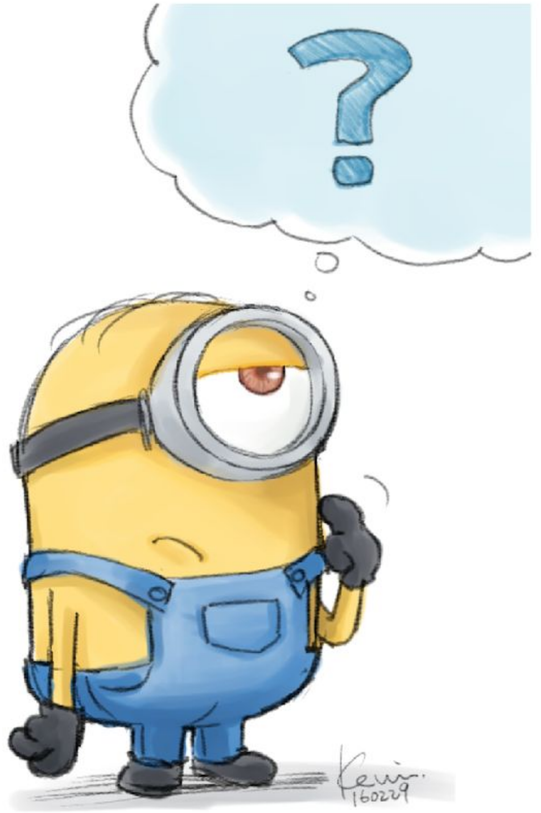
How can computers understand language?

Mapping words and numbers with word embedding

```
the 0.0897 0.0160 -0.0571 0.0405 -0.0696  ...
and -0.0314 0.0149 -0.0205 0.0557 0.0205  ...
of -0.0063 -0.0253 -0.0338 0.0178 -0.0966 ...
to 0.0495 0.0411 0.0041 0.0309 -0.0044    ...
in -0.0234 -0.0268 -0.0838 0.0386 -0.0321 ...
```

Why NLP is Hard?

1. Ambiguity
2. Scale
3. Sparsity
4. Variation
5. Expressivity
6. Unmodeled Variables
7. Unknown representations



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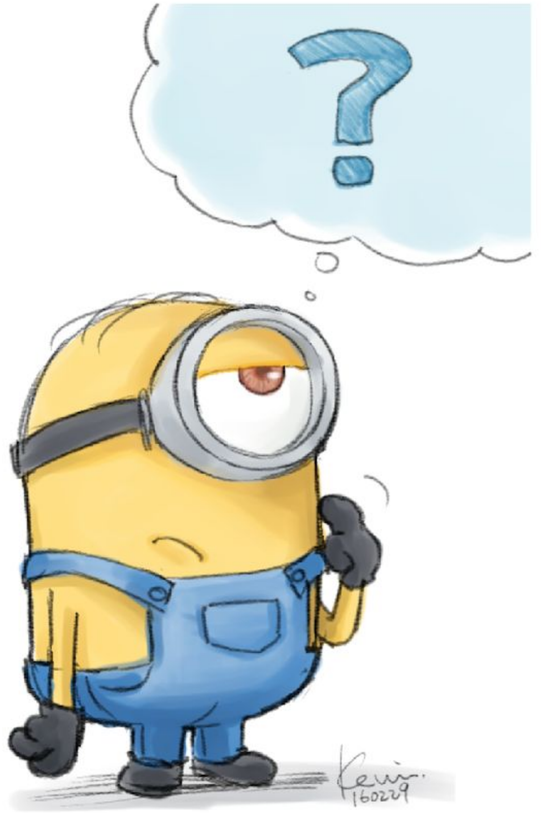
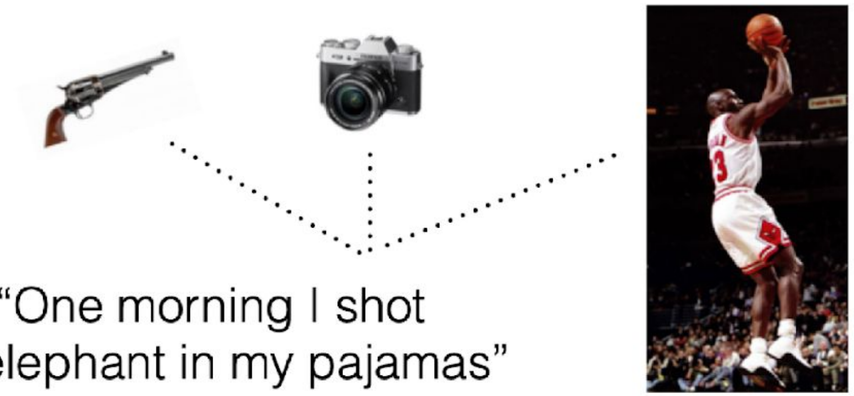


Ambiguity

- Ambiguity at multiple levels
  - Word senses: **bank** (finance or river ?)
  - Part of speech: **chair** (noun or verb ?)
  - Syntactic structure: **I can see a man with a telescope**
  - Multiple: **I made her duck**



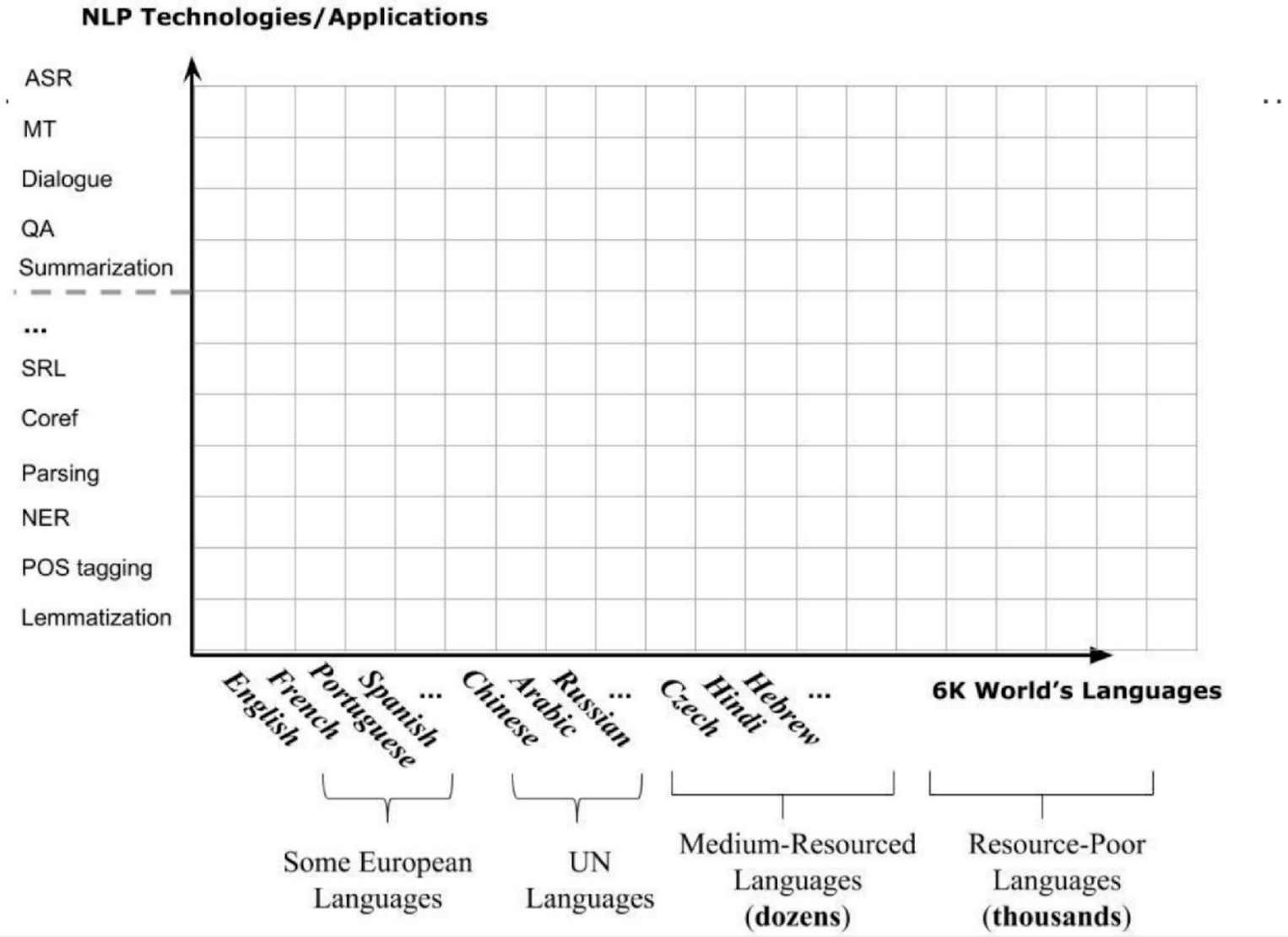
"One morning I shot
an elephant in my pajamas"

I made her duck

[SLP2 ch. 1]

- I cooked waterfowl for her
- I cooked waterfowl belonging to her
- I created the (plaster?) duck she owns
- I caused her to quickly lower her head or body
- …

Ambiguity and Scale



The Challenges of "Words"

- Segmenting text into words
- Morphological variation
- Words with multiple meanings: bank, mean
- Domain-specific meanings: latex
- Multiword expressions: make a decision, take out, make up

Part of Speech Tagging

ikr smh he asked fir yo last name

so he can add u on fb lolololol

Part of Speech Tagging

I know, right	shake my head			for	your		
ikr	smh	he	asked	fir	yo	last	name

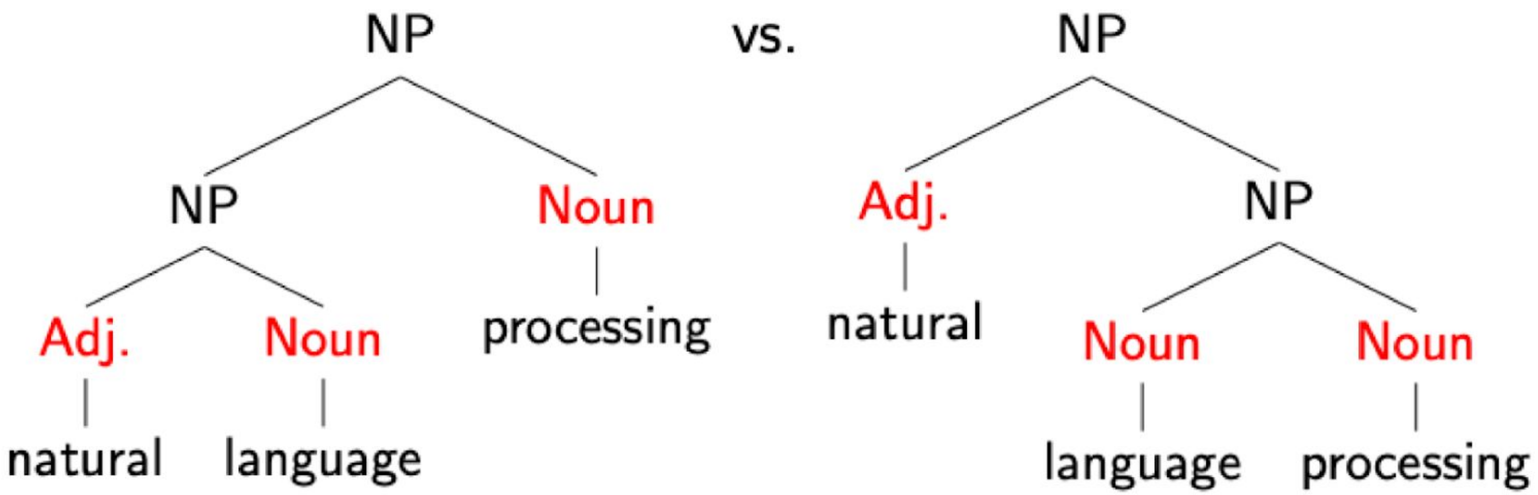
				you		Facebook	laugh out loud
so	he	can	add	u	on	fb	lolololol

Part of Speech Tagging

I know, right	shake my head			for	your		
ikr	smh	he	asked	fir	yo	last	name
!	G	O	V	P	D	A	N
interjection	acronym	pronoun	verb	prep.	det.	adj.	noun

				you		Facebook	laugh out loud
so	he	can	add	u	on	fb	lololol
P	O	V	V	O	P	∧	!
preposition						proper noun	

Syntax


NP
NP
Noun
Adj.
Noun
processing
natural
language
vs.
NP
Adj.
NP
natural
Noun
Noun
language
processing

Morphology + Syntax

A ship-shipping ship, shipping shipping-ships

Semantics

- Every fifteen minutes a woman in this country gives birth.

Semantics

- Every fifteen minutes a woman in this country gives birth. Our job is to find this woman, and stop her!

– Groucho Marx

Syntax + Semantics

- We saw the woman with the telescope wrapped in paper.

Syntax + Semantics

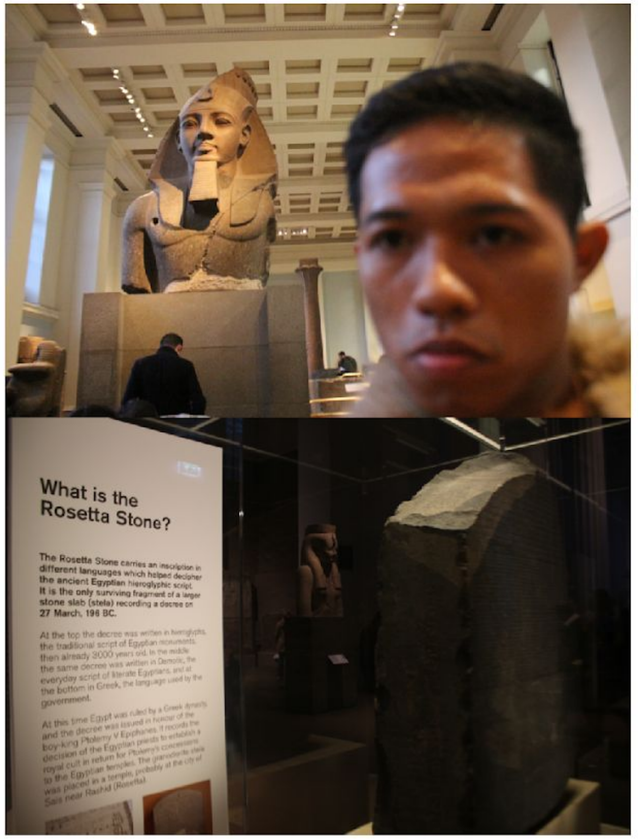
- We saw the woman with the telescope wrapped in paper.
  - Who has the telescope?
  - Who or what is wrapped in paper?
  - An even of perception, or an assault?

Dealing with Ambiguity

- How can we model ambiguity?
  - Non-probabilistic methods (CKY parsers for syntax) return all possible analyses
  - Probabilistic models (HMMs for POS tagging, PCFGs for syntax) and algorithms (Viterbi, probabilistic CKY) return the best possible analyses, i.e., the most probable one
- But the "best" analysis is only good if our probabilities are accurate. Where do they come from?

Corpora

- A corpus is a collection of text
  - Often annotated in some way
  - Sometimes just lots of text
- Examples
  - Penn Treebank: 1M words of parsed WSJ
  - Canadian Hansards: 10M+ words of French/English sentences
  - Yelp reviews
  - The Web!



Statistical NLP

- Like most other parts of AI, NLP is dominated by statistical methods
  - Typically more robust than rule-based methods
  - Relevant statistics/probabilities are learned from data
  - Normally requires lots of data about any particular phenomenon

Why NLP is Hard?

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5. Expressivity
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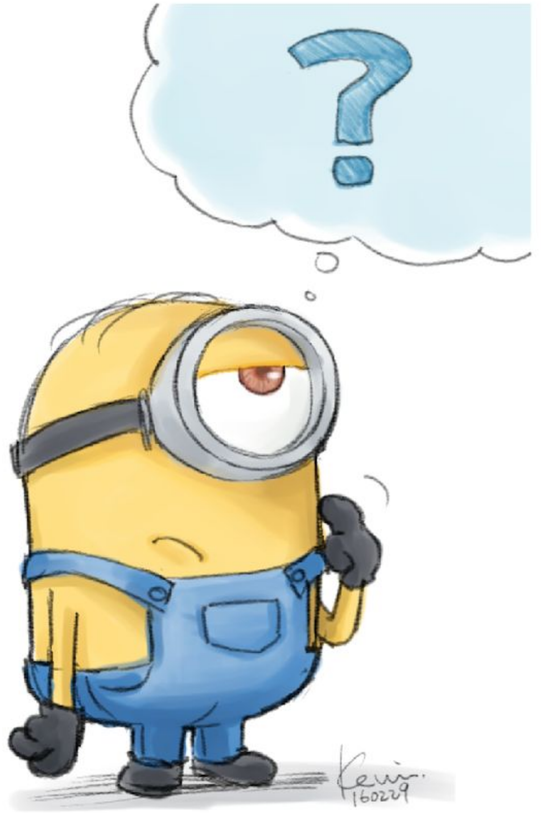


Sparsity

- Sparse data due to Zipf's Law
- Example: the frequency of different words in a large text corpus

any word

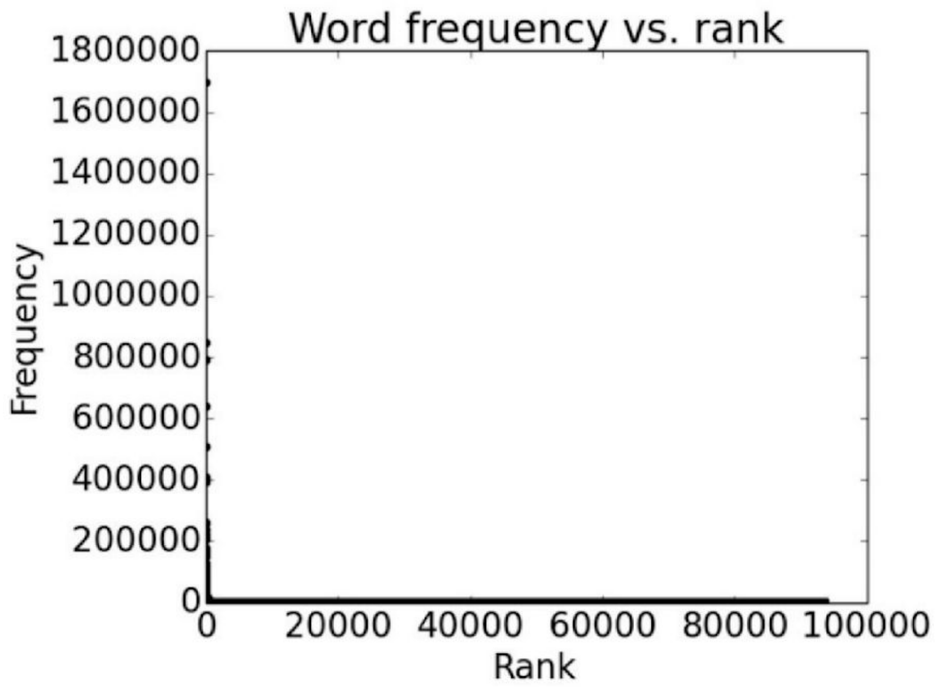
Frequency	Token
1,698,599	the
849,256	of
793,731	to
640,257	and
508,560	in
407,638	that
400,467	is
394,778	a
263,040	I

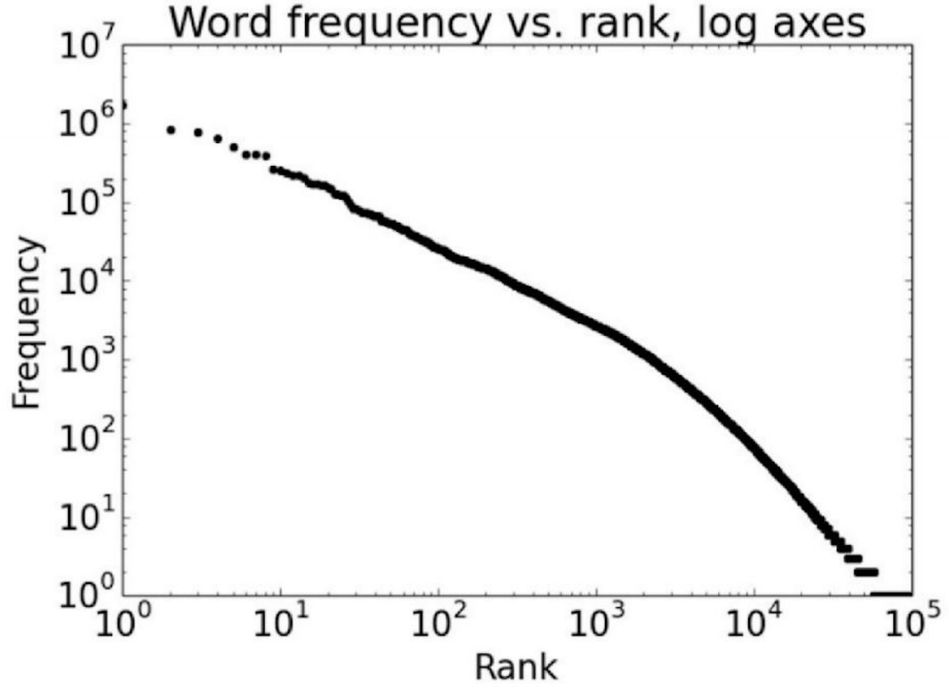
nouns

Frequency	Token
124,598	European
104,325	Mr
92,195	Commission
66,781	President
62,867	Parliament
57,804	Union
53,683	report
53,547	Council
45,842	States

Sparsity

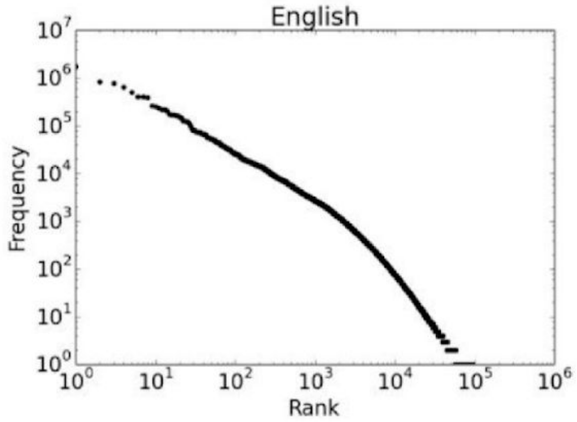
- Order words by frequency. What is the frequency of nth ranked word?

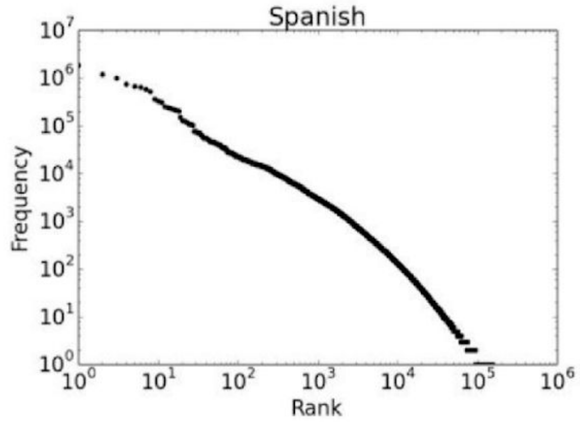


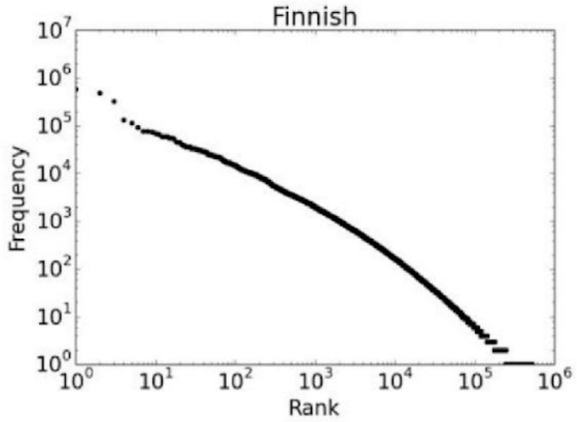


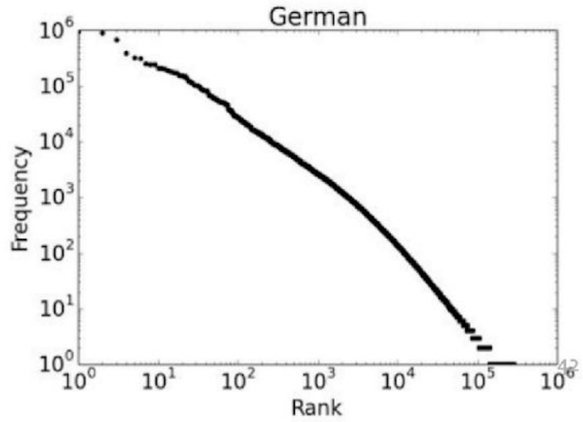
Sparsity

- Regardless of how large our corpus is, there will be a lot of infrequent words
- This means we need to find clever ways to estimate probabilities for things we have rarely or never seen









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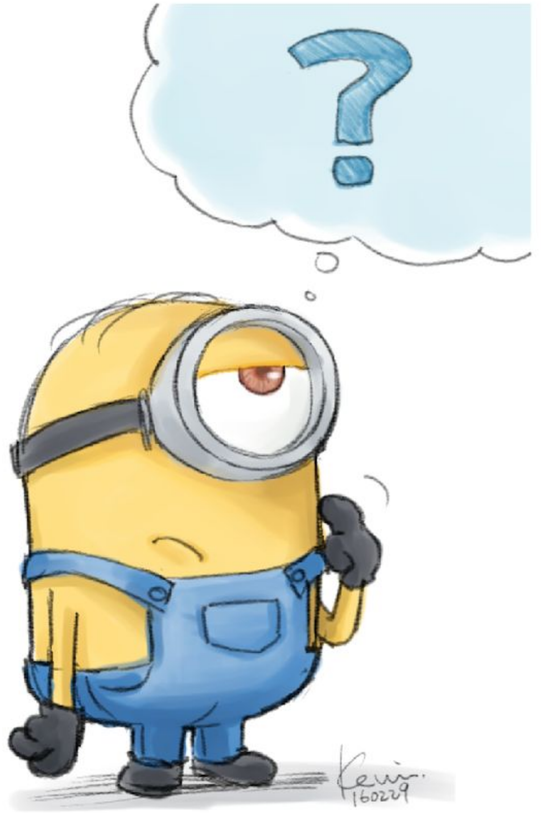
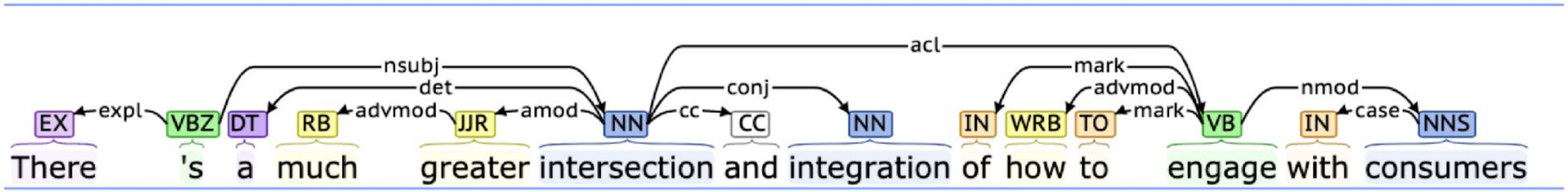


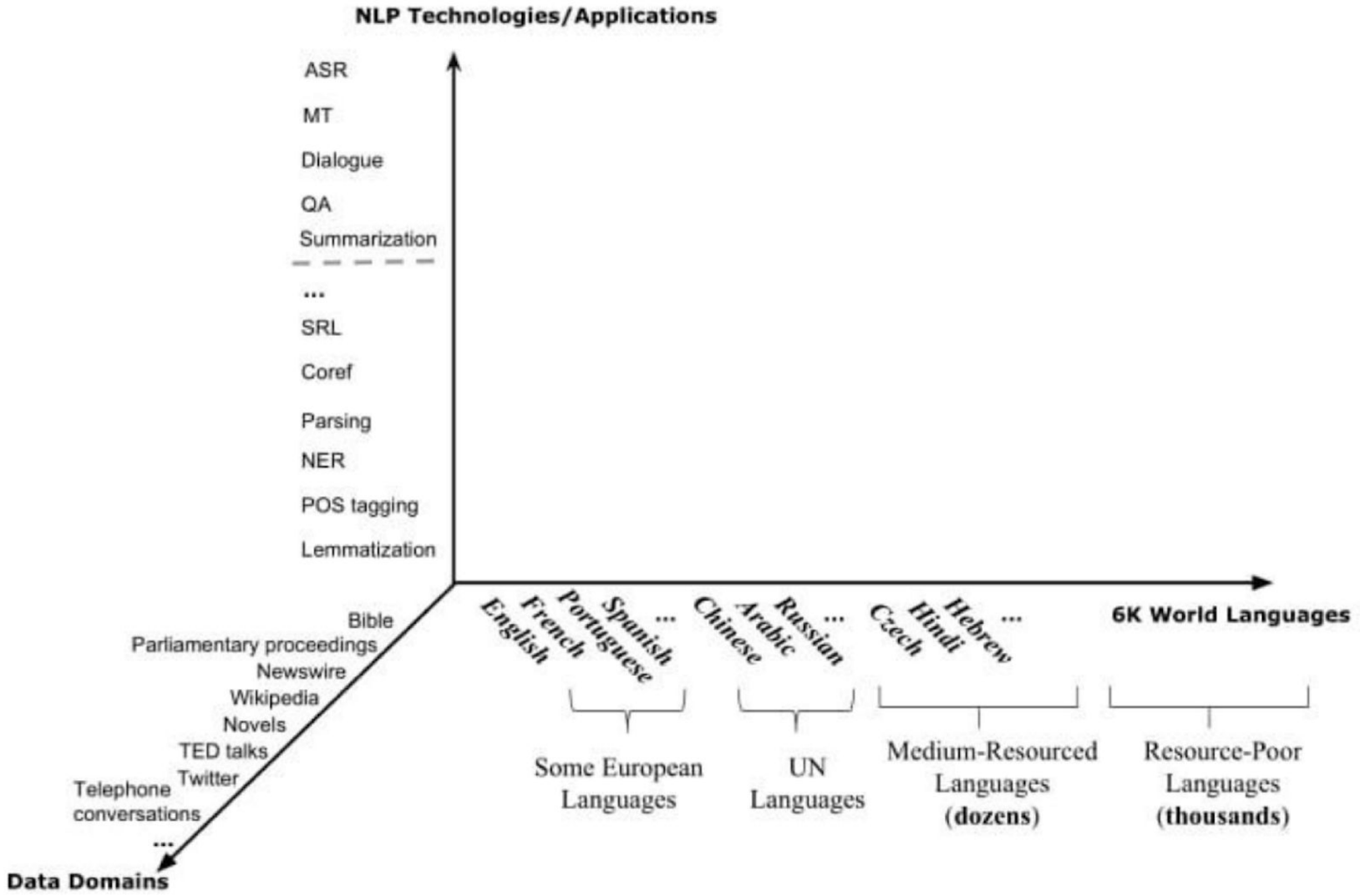
Variation

- Suppose we train a part of speech tagger or a parser on the Wall Street Journal



- What will happen if we try to use this tagger/parser for social media?
  - *"ikr smh he asked fir yo last name so he can add u on fb lolololol"*

Variation


NLP Technologies/Applications
ASR
MT
Dialogue
QA
Summarization
...
SRL
Coref
Parsing
NER
POS tagging
Lemmatization
Bible
Parliamentary proceedings
Newswire
Wikipedia
Novels
TED talks
Twitter
Telephone conversations
...
Data Domains
English
French
Portuguese
Spanish
...
Chinese
Arabic
Russian
...
Czech
Hindi
Hebrew
...
6K World Languages
Some European Languages
UN Languages
Medium-Resourced Languages (dozens)
Resource-Poor Languages (thousands)

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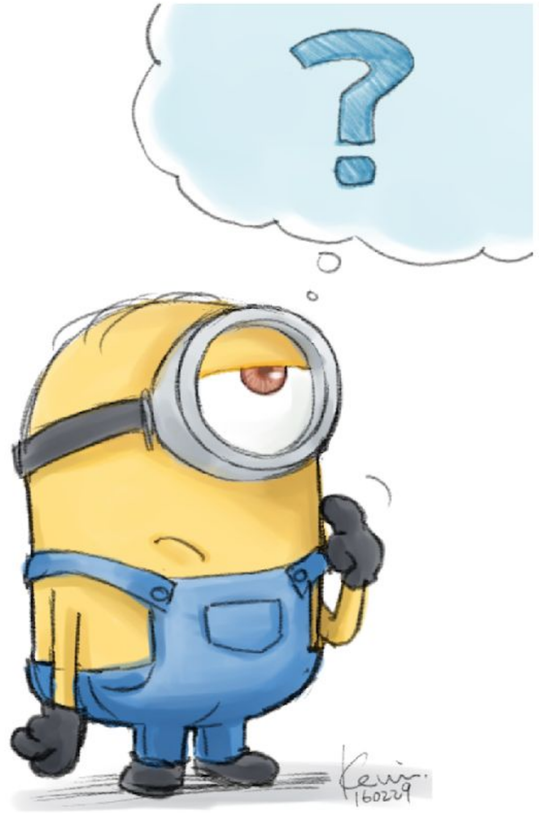
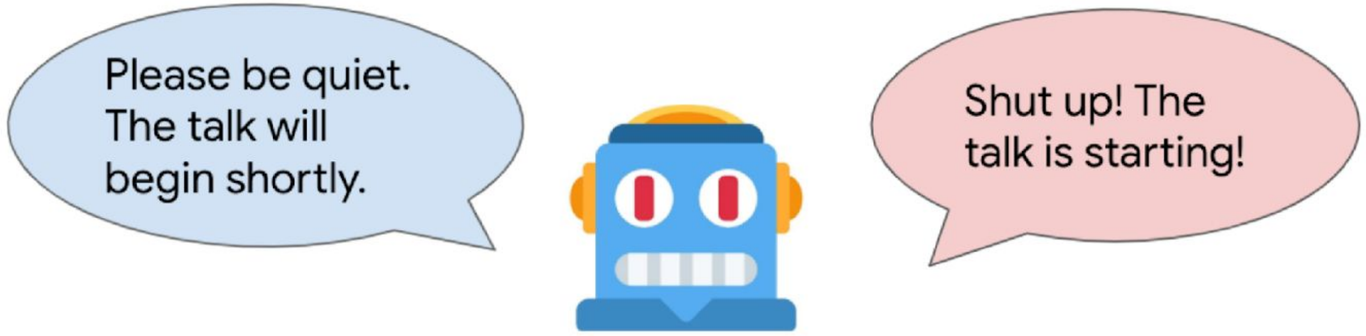


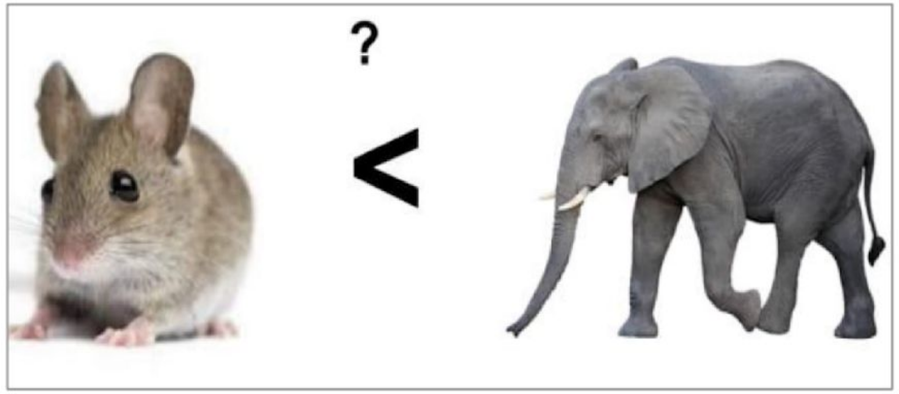
Expressivity

- Not only can one form have different meanings (ambiguity) but the same meaning can be expressed with different forms:
  - *She gave the book to Tom* vs. *She gave Tom the book*
  - *Some kids popped by* vs. *A few children visited*
  - *Is that window still open?* vs. *Please close the window*



Unmodeled Variables

"Drink this milk"



World knowledge

I dropped the glass on the floor and it broke

I dropped the hammer on the glass and it broke

Unmodeled Representation

Very difficult to capture what is $\mathcal{R}$, since we don't even know how to represent the knowledge a human has/needs:

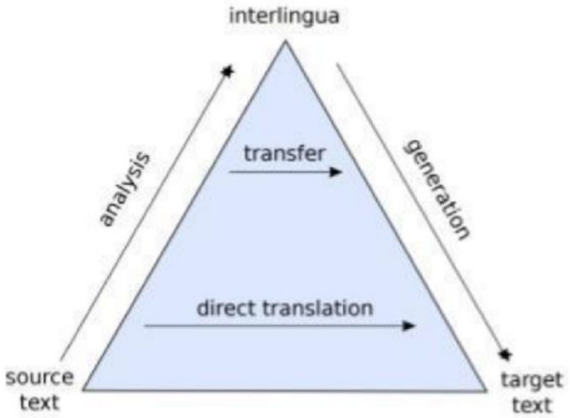
- What is the "meaning" of a word or sentence?
- How to model context?
- Other general knowledge?

Desiderate for NLP Models

- Sensitivity to a wide range of phenomena and constraints in human 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
- Ethical

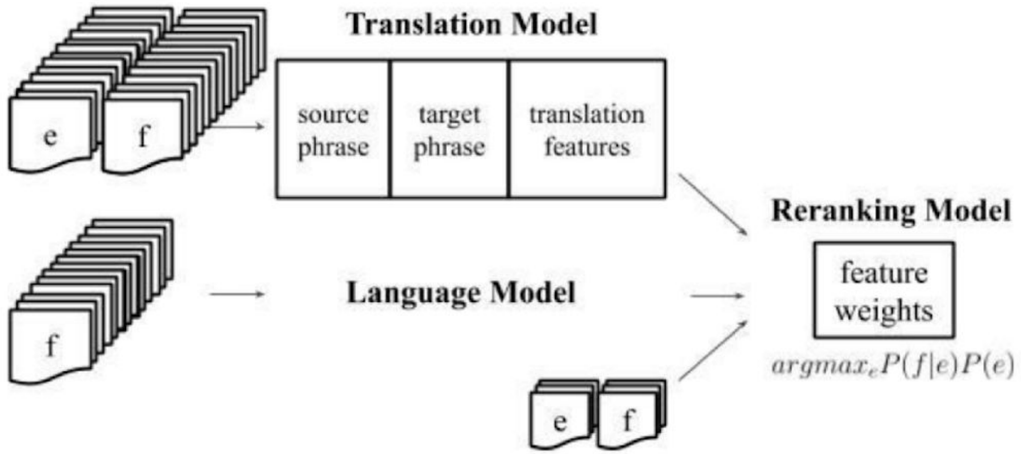
Symbolic and Probabilistic NLP

Logic-based/Rule-based NLP



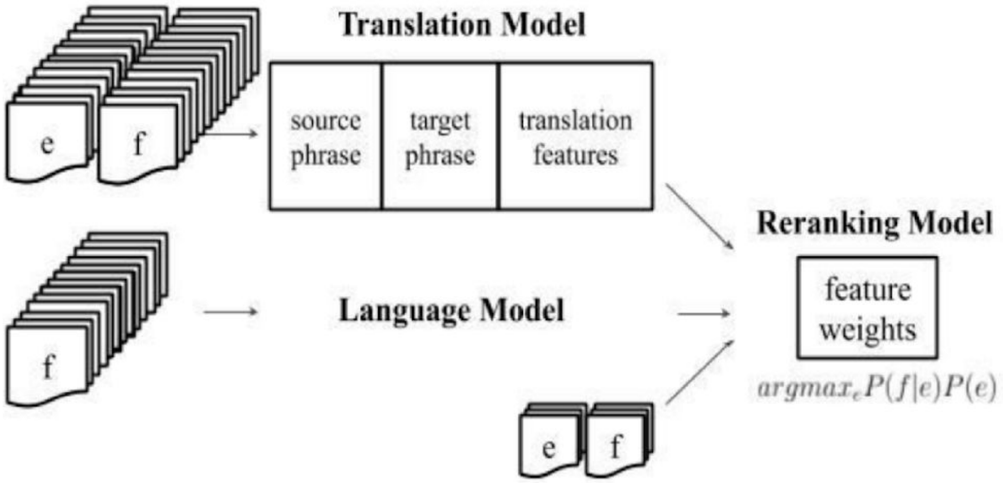
~90s

Statistical NLP



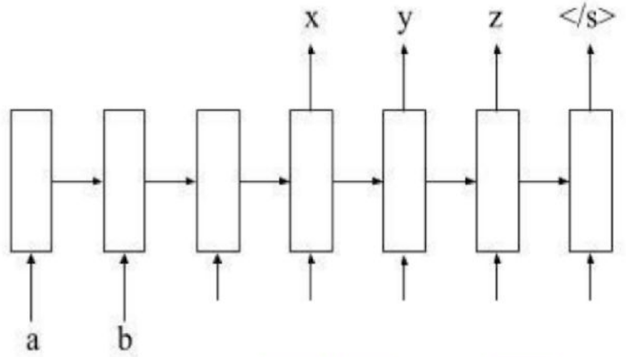
Probabilistic and Connectionist NLP

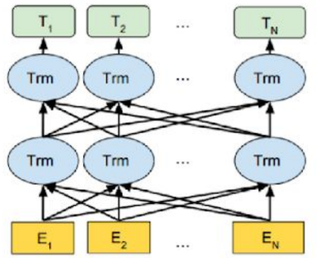
Engineered Features/Representations



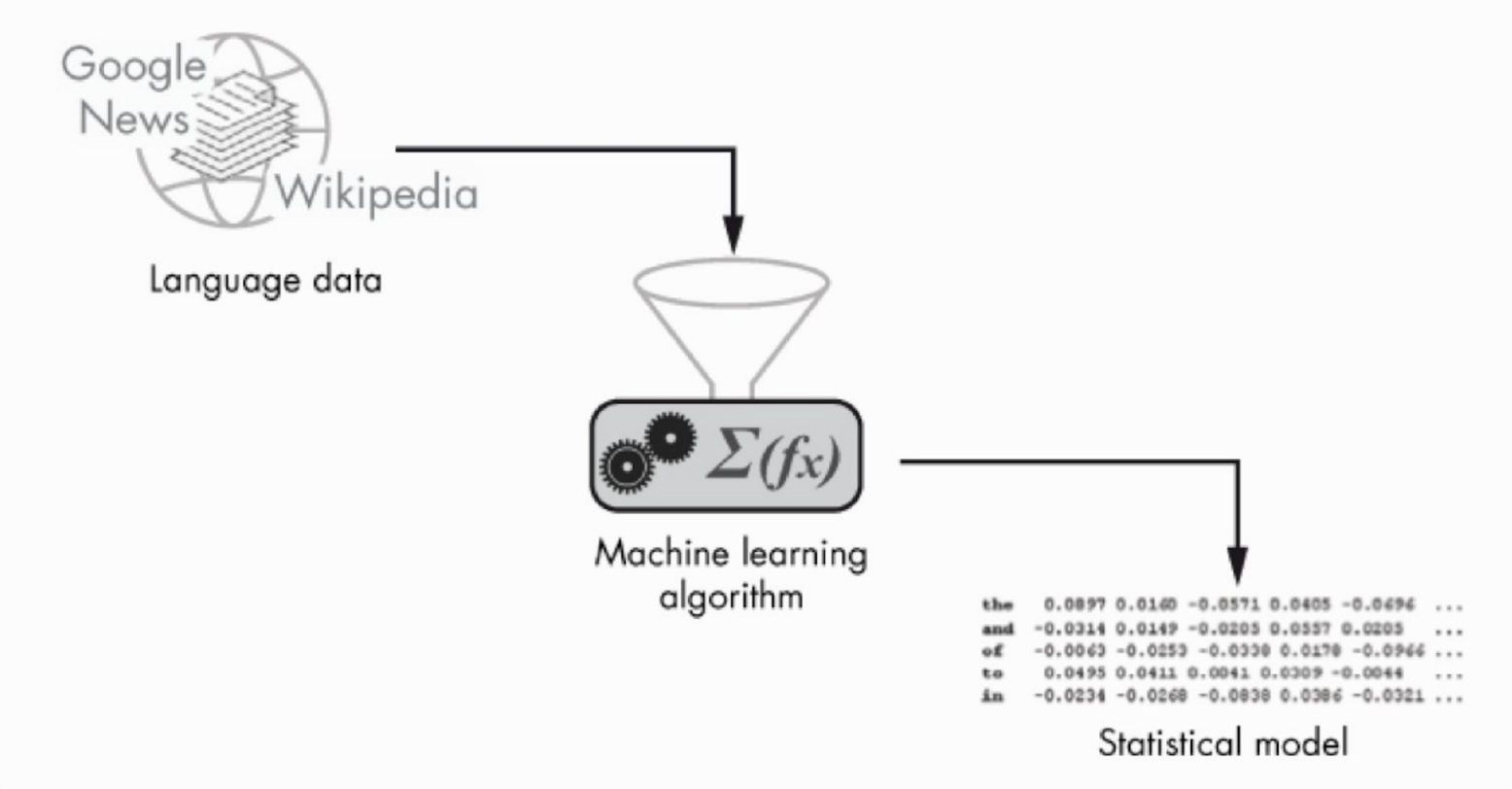
~mid 2010s

Learned Features/Representations

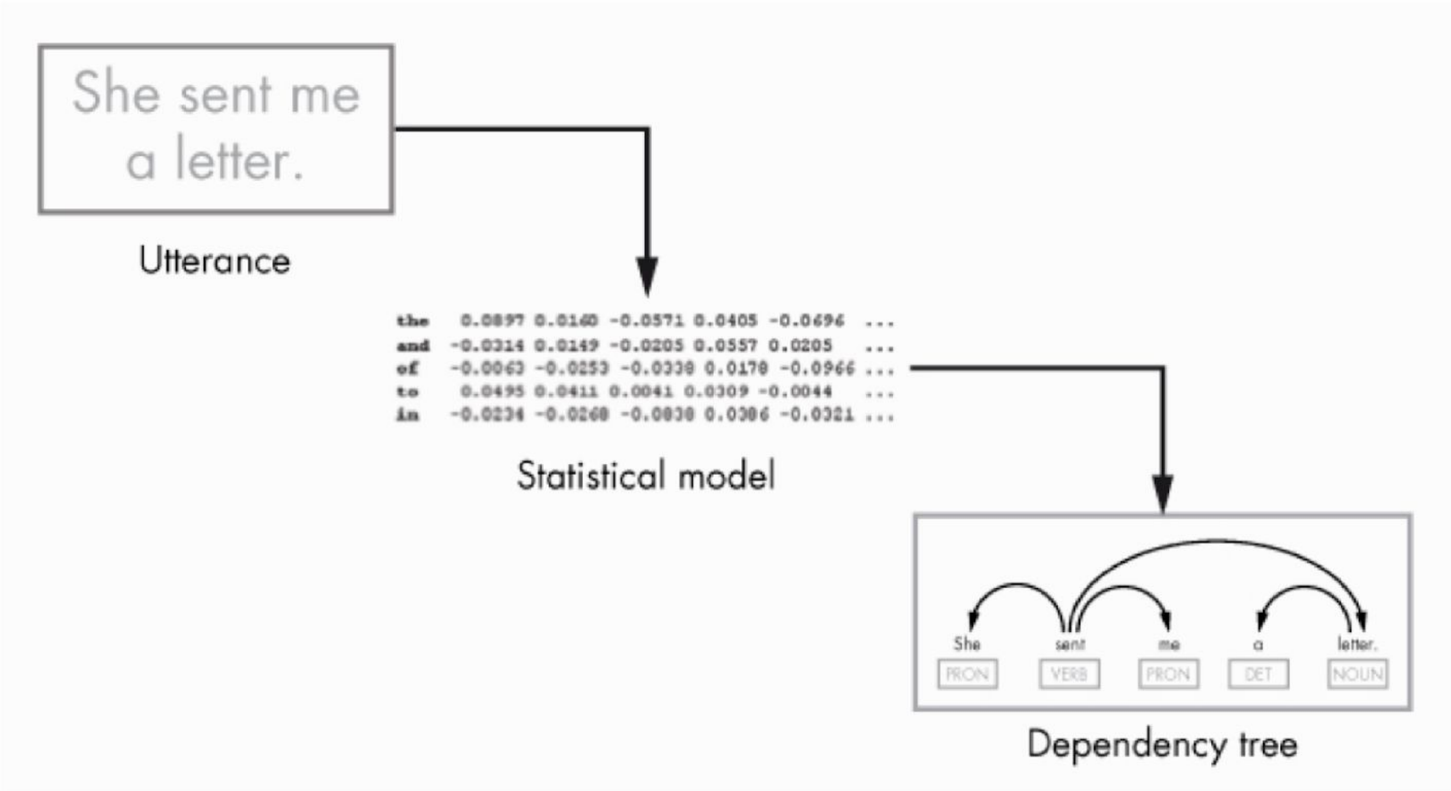




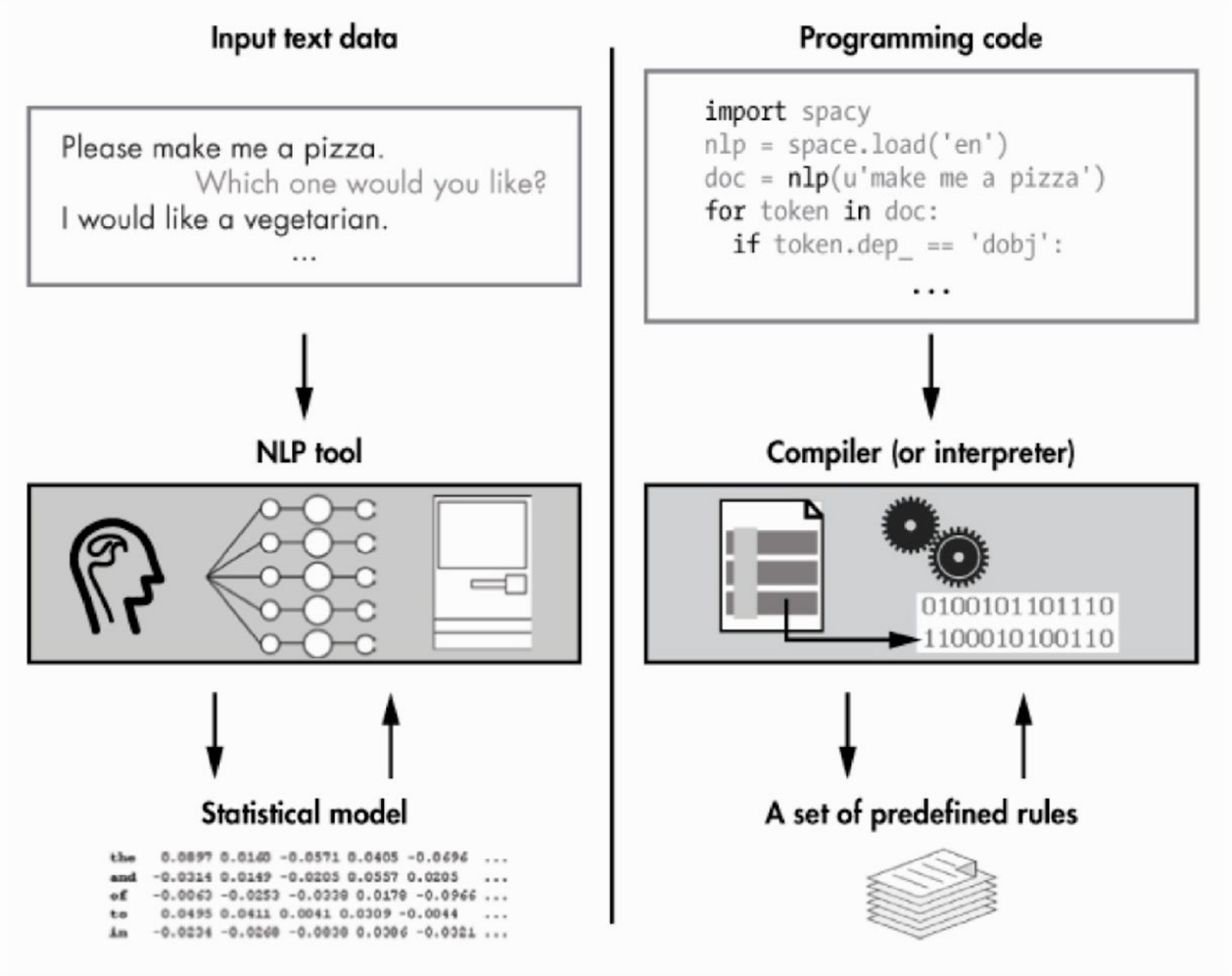
Machine Learning Pipeline for NLP



Machine Learning uses Statistical Models

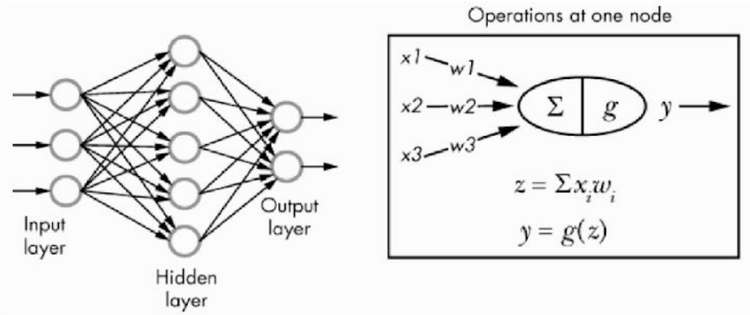


Machine Learning vs Standard Programming



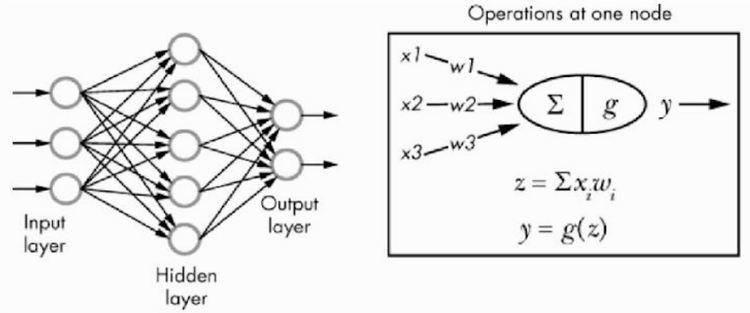
State-of-the-Art

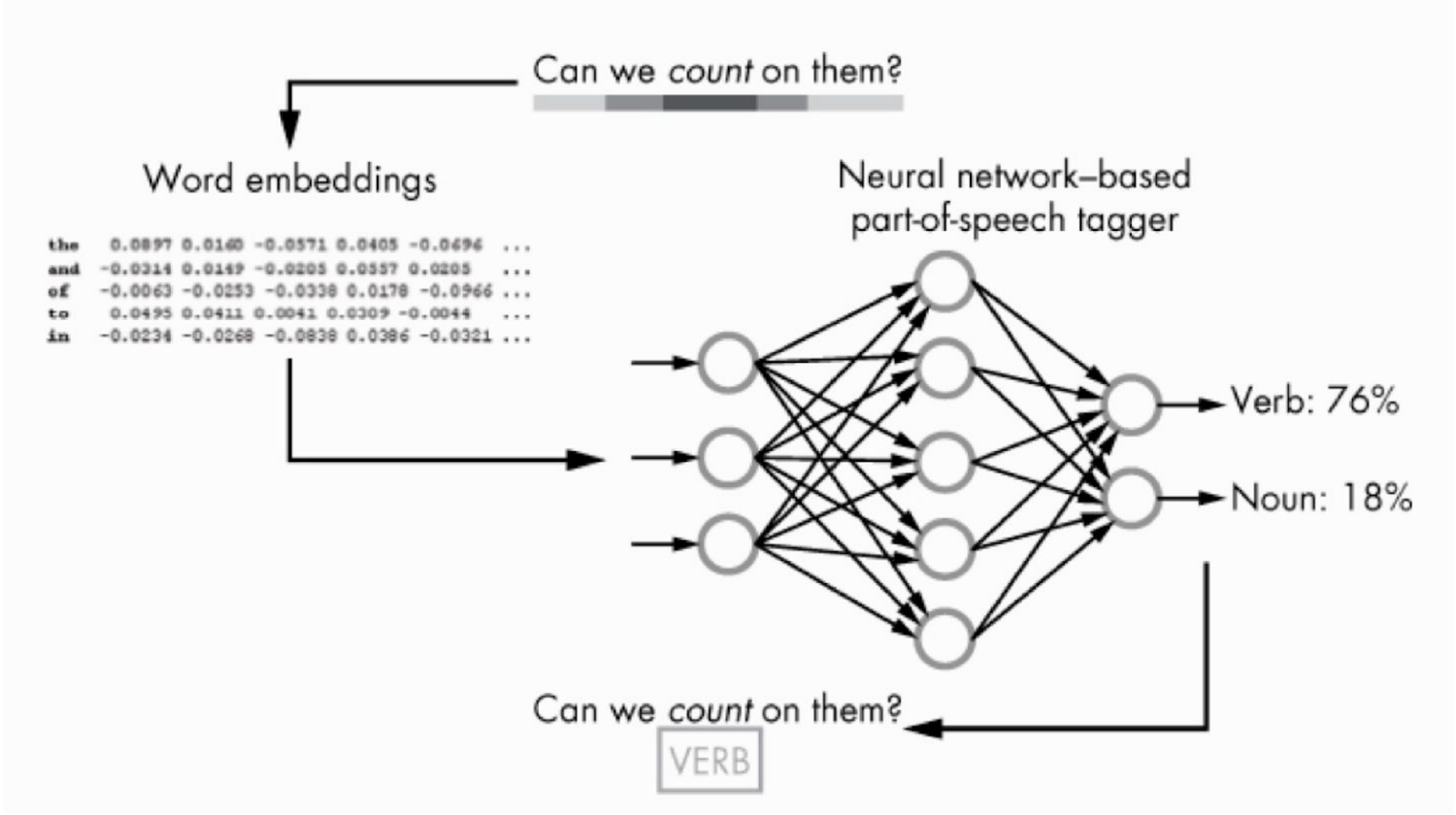
Neural Networks



State-of-the-Art

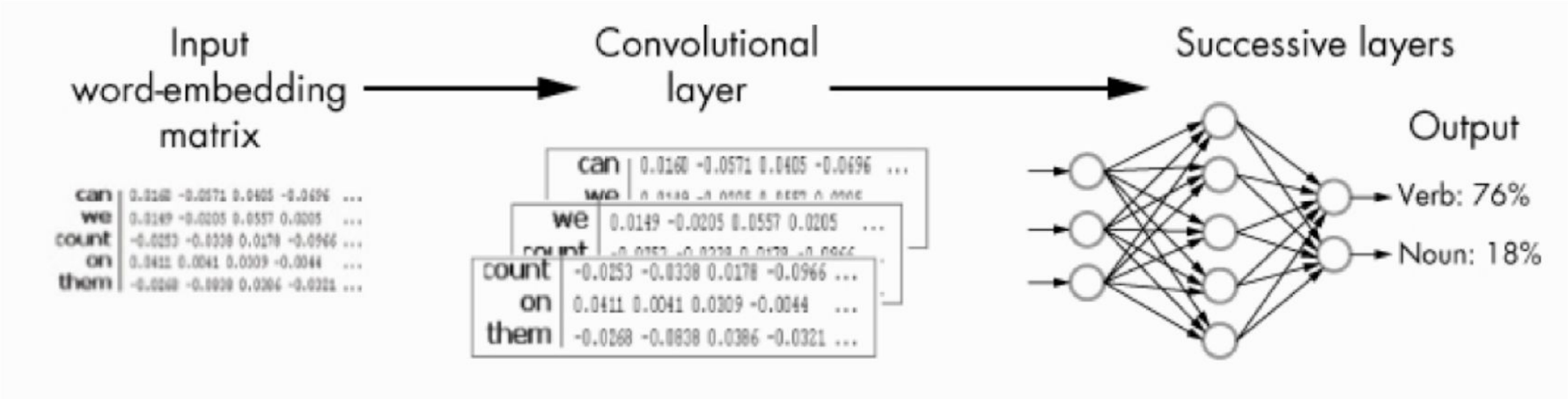
Neural Networks





State-of-the-Art

Neural Networks



NLP vs. Linguistics

- NLP must contend with NL data as found in the world
- NLP ≈ computational linguistics
- Linguistics has begun to use tools originating in NLP!

Fields with Connections to NLP

- Machine learning
- Linguistics (including psycho-, socio-, descriptive, and theoretical)
- Cognitive science
- Information theory
- Logic
- Data science
- Political science
- Psychology
- Economics
- Education

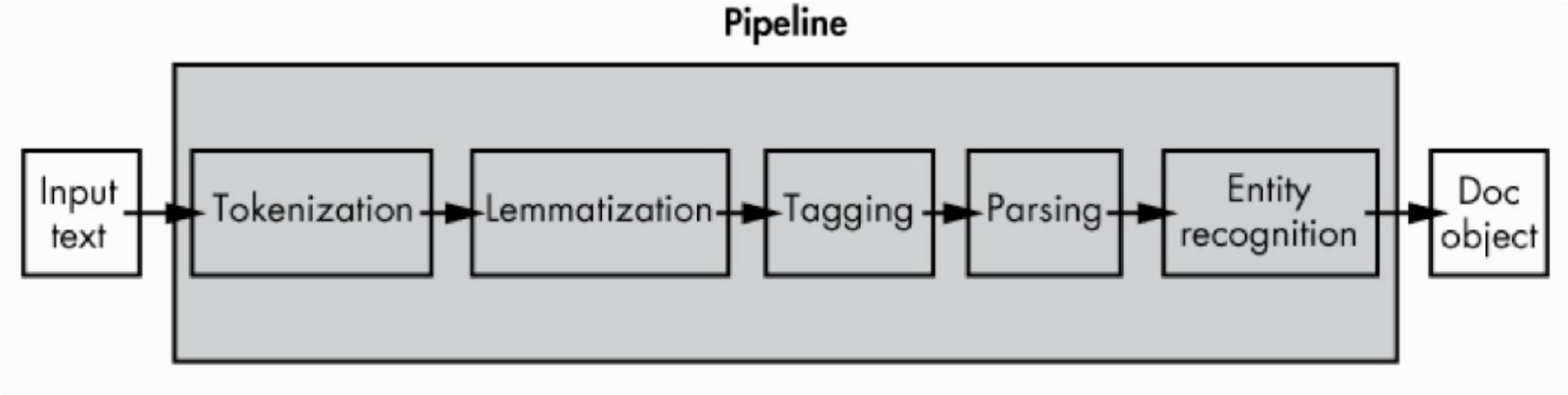
Today's Applications

- Conversational agents
- Information extraction and question answering
- Machine translation
- Opinion and sentiment analysis
- Social media analysis
- Visual understanding
- Essay evaluation
- Mining legal, medical, or scholarly literature

Factors Changing NLP Landscape

1. Increases in computing power
2. The rise of the web, then the social web
3. Advances in machine learning
4. Advances in understanding of language in social context

Basic NLP Operations with SpaCy



Code Time

References

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Natural Language Processing with Python and Spacy: Yuli Vasiliev

THANK YOU!

Q & A

ESKWELABS