## Natural Language Processing Introduction to NLP

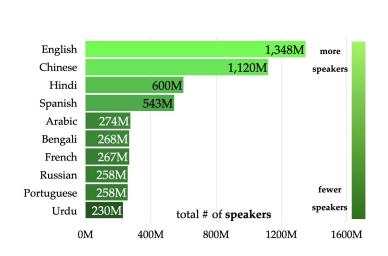
Sofia Serrano sofias6@cs.washington.edu

Credit to Yulia Tsvetkov and Noah Smith for slides

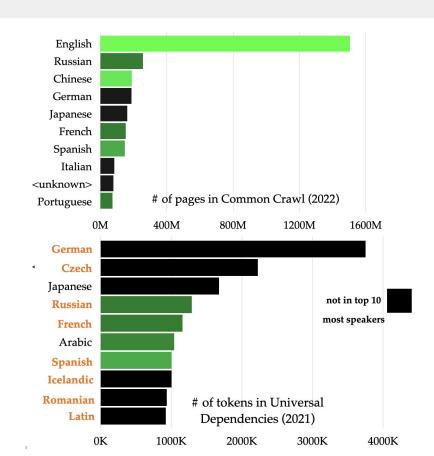
#### **Announcements**

- Academic Integrity Form is out on Canvas
- A1 is out on GitLab
  - Don't see it? Reply to this thread on Ed with your NetID: https://edstem.org/us/courses/32306/discussion/2365366
- Access to lecture recordings
  - No @cs.washington.edu google account? Click through to (request) access any lecture recording sooner rather than later so that we can give you access
- Make sure you can access the course machines
  - o (if connecting from off campus) Run Husky OnNet VPN OR first ssh into an attu machine
  - o ssh yourNetID@nlpg00.cs.washington.edu (nlpg00-nlpg03)
  - O Not working?
    - Not a CSE major/no CSE account? Email <u>ugrad-adviser@cs.washington.edu</u> to request a CSE account (include your student ID number in the email) and CC Sofia
    - Still not working? Reply to this thread on Ed so that we can help troubleshoot: https://edstem.org/us/courses/32306/discussion/2368995

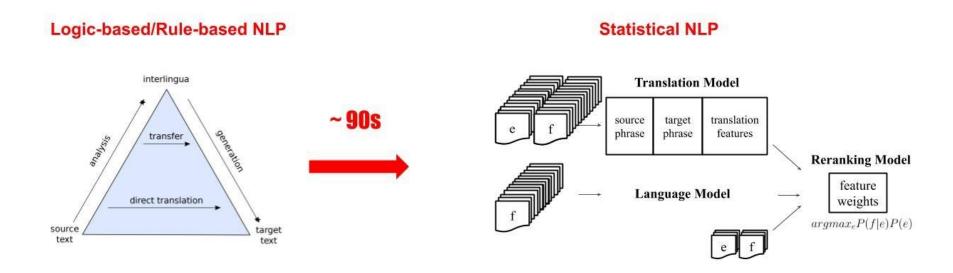
#### Following up on a question from last lecture



Credit to **Phoebe Mulcaire** for figures

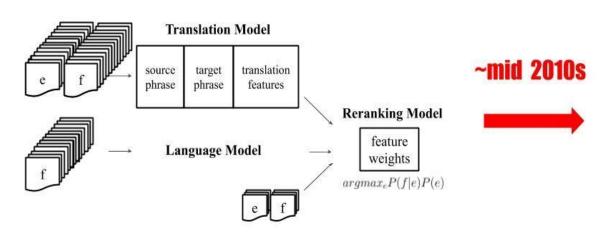


#### Symbolic and Probabilistic NLP

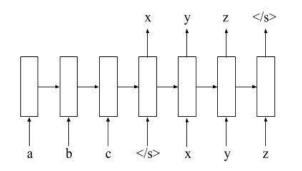


#### **Probabilistic and Connectionist NLP**

#### Engineered Features/Representations



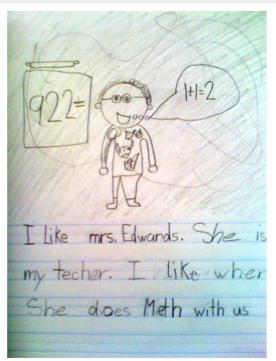
#### **Learned Features/Representations**



## Linguistic Background

## What does it mean to "know" a language?







(Thanks Canadian Internet Registration Authority!)

Last login: Mon Jan 9 08:08:57 2023 from 97.1 [sofias6@attu8 ~]\$ wc myfile.txt

What do we need to "tell" a computer program so that it knows more English than wc or a dictionary, maybe even as much as a three-year-old, for example?

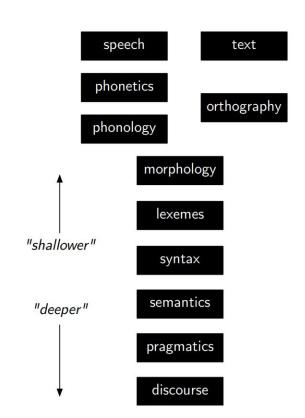
## What does an NLP system need to 'know'?

Language consists of many levels of structure

Humans fluently integrate all of these in producing/understanding language

Ideally, so would a computer!

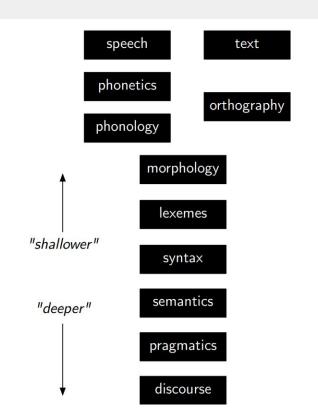
## Levels of linguistic knowledge



## Speech, phonetics, phonology



This is a simple sentence . / ðis iz ə 'simpl 'sɛntəns /.



## Orthography

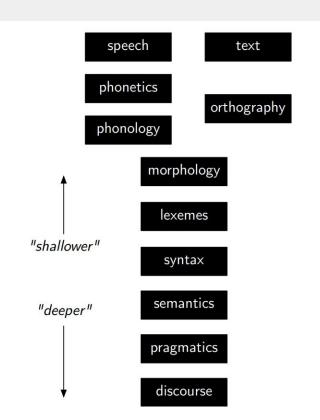
هذه جملة بسيطة

đây là một câu đơn giản

यह एक साधारण वाक्य है

This is a simple sentence.

/ ŏis iz ə 'simpl 'sɛntəns /.



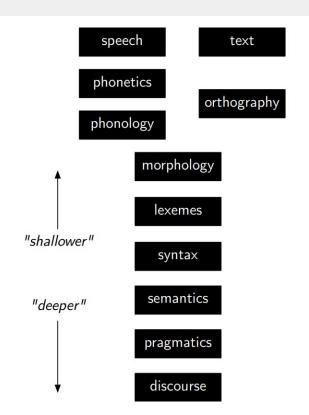
### Words, morphology

- Morphological analysis
- Tokenization
- Lemmatization

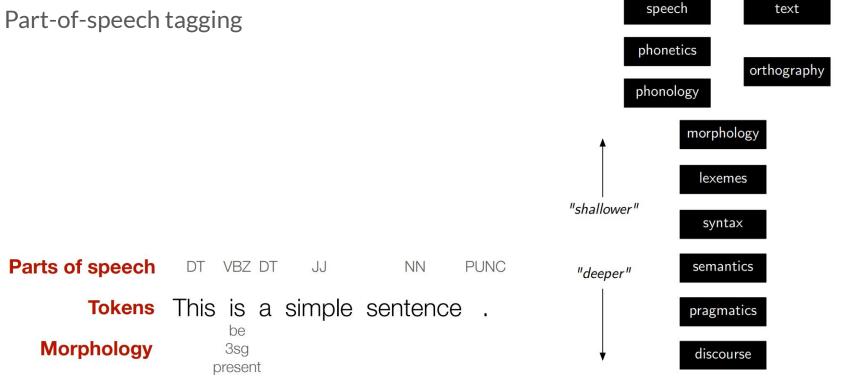
Tokens This is a simple sentence.

Morphology

3sg
present

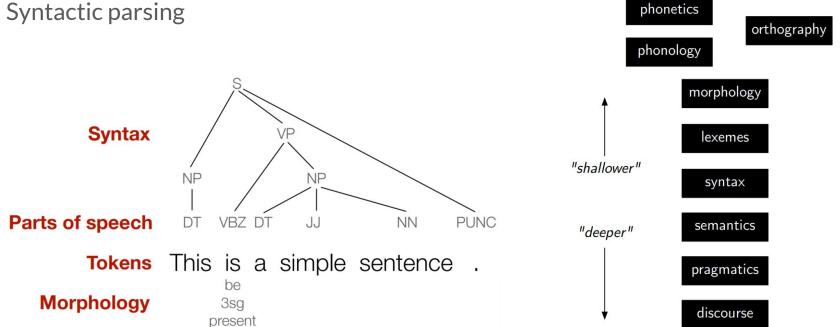


### **Syntax**



#### **Syntax**

- Part-of-speech tagging
- Syntactic parsing

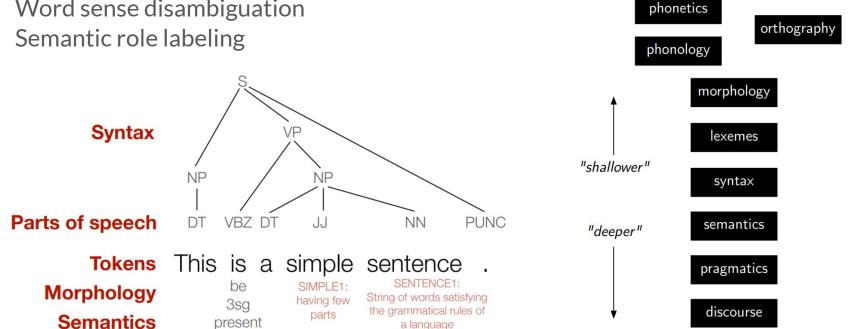


speech

text

#### **Semantics**

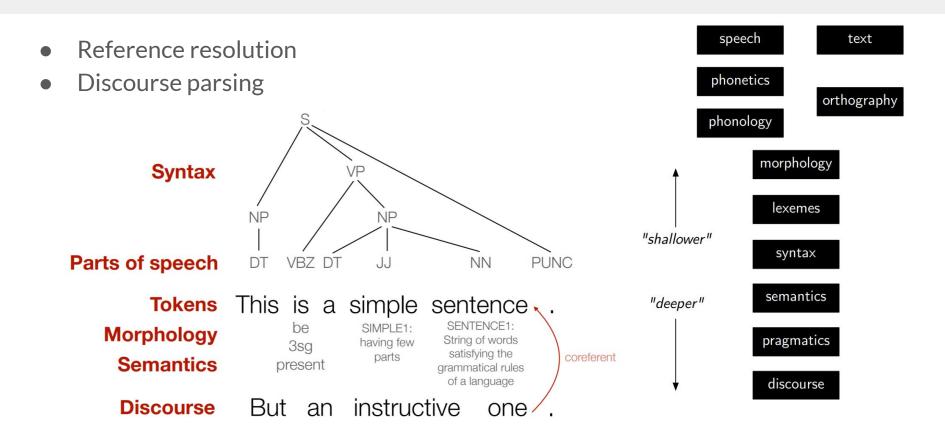
- Named entity recognition
- Word sense disambiguation



speech

text

#### **Discourse**



# Linguistic challenges we'll need to deal with in designing NLP systems

### What are some challenges for NLP systems?

- 1. Ambiguity
- 2. Variation
- 3. Sparsity
- 4. Expressivity
- 5. Unmodeled variables
- 6. Unknown representation  $\mathcal{R}$

## **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 saw her duck





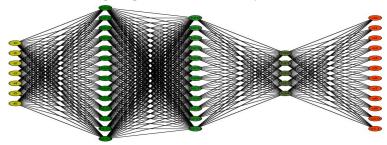






#### **Dealing with ambiguity**

- How can we model ambiguity and choose the correct analysis in context?
  - o non-probabilistic methods (FSMs for morphology, CKY parsers for syntax) return *all possible* analyses.
  - o probabilistic models (HMMs for part-of-speech tagging, PCFGs for syntax) and algorithms (Viterbi, probabilistic CKY) return *the best possible analysis*, i.e., the most probable one according to the model
  - Neural networks, pretrained language models now provide end-to-end solutions



• 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 aligned French / English sentences
  - Yelp reviews
  - The Web: billions of words of who knows what



### What are some challenges for NLP systems?

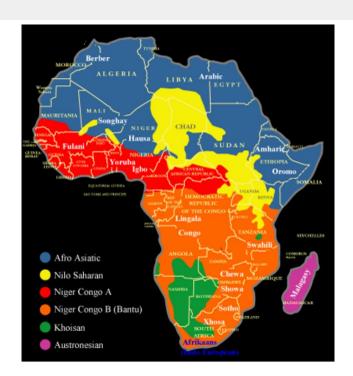
- 1. Ambiguity
- 2. Variation
- 3. Sparsity
- 4. Expressivity
- 5. Unmodeled variables
- 6. Unknown representation  $\mathcal{R}$

#### Scale

- ~7K languages
- Thousands of language varieties



Englishes



Africa is a continent with a very high linguistic diversity: there are an estimated 1.5-2K African languages from 6 language families. 1.33 billion people

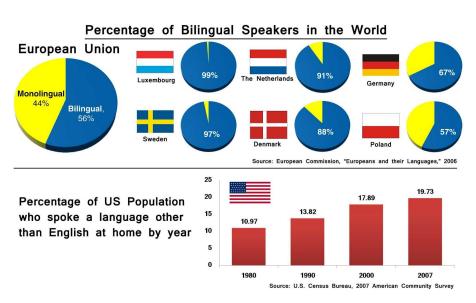
#### NLP beyond English

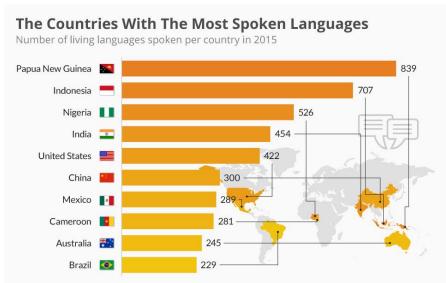
- ~7,000 languages
- thousands of language varieties



2

#### Most of the world today is multilingual





Source: US Census Bureau

Source: Ethnologue

#### Semantic analysis

- Every language represents the world in a different way
  - For example, it could depend on cultural or historical conditions







- Russian has very few words for colors, Japanese has hundreds
- Multiword expressions, e.g. happy as a clam, it's raining cats and dogs or wake up and metaphors, e.g. love is a journey are very different across languages

27

#### **Tokenization**

WORDS

这是一个简单的句子

This is a simple sentence

זה משפט פשוט

#### **Tokenization + disambiguation**

in tea her daughter

בתה

in tea בתה in the tea בהתה that in tea שבתה that in the tea שבהתה and that in the tea

ושבתה

most of the vowels unspecified

and her saturday ו+שבת+ה and that in tea ו+ש+ב+תה and that her daughter ו+ש+בת+ה

- · most of the vowels unspecified
- particles, prepositions, the definite article, conjunctions attach to the words which follow them
- · tokenization is highly ambiguous

#### Tokenization + morphological analysis

Quechua

#### Much'ananayakapushasqakupuniñataqsunamá

Much'a -na -naya -ka -pu -sha -sqa -ku -puni -ña -taq -suna -má

"So they really always have been kissing each other then"

```
Much'a to kiss
       expresses obligation, lost in translation
       expresses desire
-naya
-ka
       diminutive
       reflexive (kiss *eachother*)
-pu
       progressive (kiss*ing*)
-sha
       declaring something the speaker has not personally witnessed
-sqa
       3rd person plural (they kiss)
-ku
       definitive (really*)
-puni
       alwavs
-ña
-tag
       statement of contrast (...then)
       expressing uncertainty (So...)
-suna
       expressing that the speaker is surprised
-má
```

30

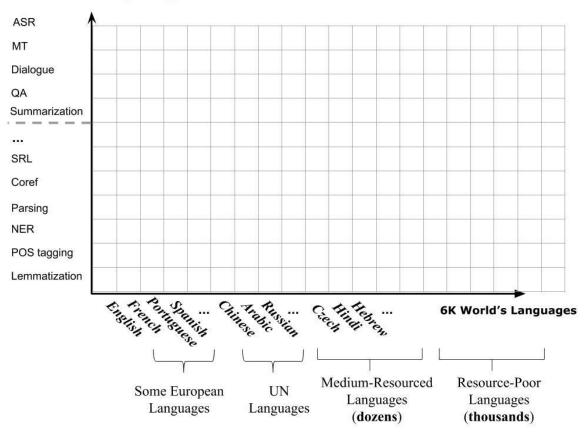
### Tokenization + morphological analysis

German



Infektionsschutzmaßnahmenverordnung

#### **NLP Technologies/Applications**



#### Linguistic variation

Non-standard language, emojis, hashtags, names

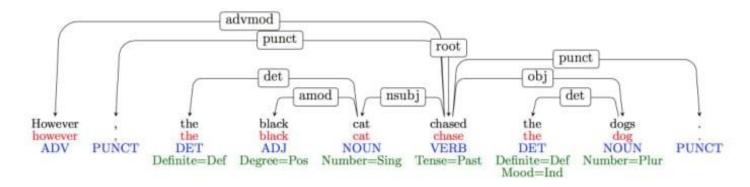


chowdownwithchan #crab and #pork #xiaolongbao at @dintaifungusa... where else? Note the cute little crab indicator in the 2nd pic

22

#### **Variation**

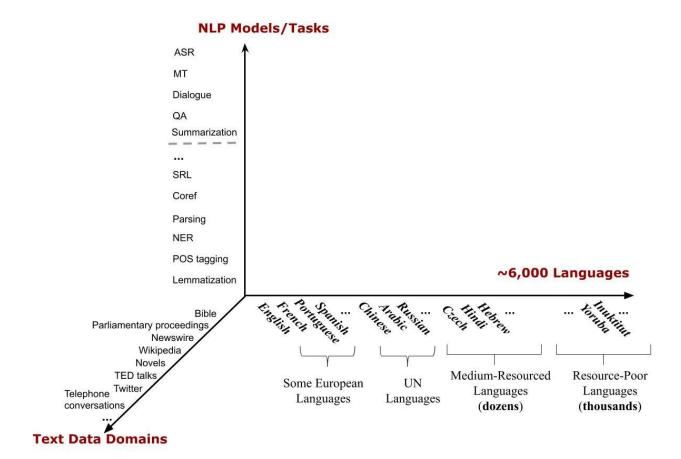
Suppose we train a part of speech tagger or a parser on the Wall Street Journal



What will happen if we try to use this tagger/parser for social media??

@\_rkpntrnte hindi ko alam babe eh, absent ako kanina I'm sick rn hahaha 😌 🙌

34



## What are some challenges for NLP systems?

- 1. Ambiguity
- 2. Variation
- 3. Sparsity
- 4. Expressivity
- 5. Unmodeled variables
- 6. Unknown representation  $\mathcal{R}$

### **Sparsity**

#### Sparse data due to Zipf's Law

- To illustrate, let's look at the frequencies of different words in a large text corpus
- Assume "word" is a string of letters separated by spaces

#### **Word Counts**

Most frequent words in the English Europarl corpus (out of 24m word tokens)

any word			nouns		
Frequency	Token	Freq	uency	Token	
1,698,599	the	12	4,598	European	
849,256	of	10	4,325	Mr	
793,731	to	9	2,195	Commission	
640,257	and	6	6,781	President	
508,560	in	6	2,867	Parliament	
407,638	that	5	7,804	Union	
400,467	is	5	3,683	report	
394,778	a	5	3,547	Council	
263,040	I	4	5,842	States	

#### **Word Counts**

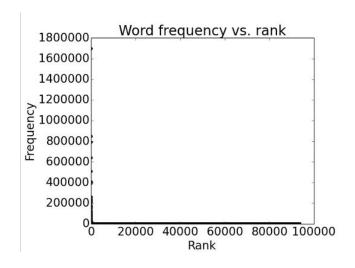
But also, out of 93,638 distinct words (word types), 36,231 occur only once.

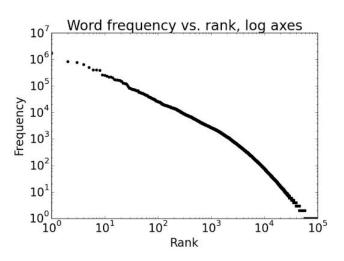
#### Examples:

- cornflakes, mathematicians, fuzziness, jumbling
- pseudo-rapporteur, lobby-ridden, perfunctorily,
- Lycketoft, UNCITRAL, H-0695
- policyfor, Commissioneris, 145.95, 27a

## Plotting word frequencies

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





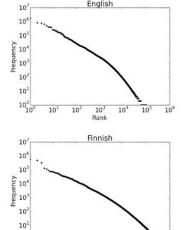
### Zipf's Law

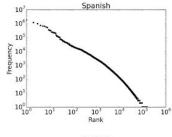
#### **Implications**

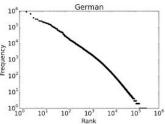
 Regardless of how large our corpus is, there will be a lot of infrequent (and zero-frequency!) words

This means we need to find clever ways to estimate probabilities for things we

have rarely or never seen







## What are some challenges for NLP systems?

- 1. Ambiguity
- 2. Variation
- 3. Sparsity
- 4. Expressivity
- 5. Unmodeled variables
- 6. Unknown representation  $\mathcal{R}$

## **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

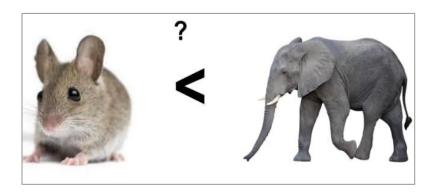
## What are some challenges for NLP systems?

- 1. Ambiguity
- 2. Variation
- 3. Sparsity
- 4. Expressivity
- 5. Unmodeled variables
- 6. Unknown representation  $\mathcal{R}$

#### **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

## What are some challenges for NLP systems?

- 1. Ambiguity
- 2. Variation
- 3. Sparsity
- 4. Expressivity
- 5. Unmodeled variables
- 6. Unknown representation  $\mathcal{R}$

### Unknown representation

- Very difficult to decide on a representation  $\mathcal{R}$ , 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?

#### **Desiderata for NLP models**

- Sensitivity to a wide range of phenomena and constraints in human language
- Generality across languages, modalities, genres, styles
- Computational efficiency at construction time and runtime
- Strong formal guarantees (e.g., convergence, statistical efficiency, consistency)
- High accuracy when judged against expert annotations and/or test data specific to a particular task
- Explainable to human users
- Ethical

### **Next class**

• Text classification

# Questions?