Speech and Natural Language Processing

#1. Introduction

Emmanuel Dupoux & Benoît Sagot

Plan E/B

- Exemple d'une application 'end to end': assistant vocal - 10 min
- Le langage: une introduction éclair

  + Problèmes transversaux (ambiguité, variation, longue traine) - 40 min
- Décortiquer un assistant vocal, étape par étape

  + Algorithmes principaux (search, dnn) - 40 min
- Principales autres applications (commande vocale, fouille de donnée, traduction, résumé, analyse de texte, HN; renseignement/militaire) - 10 min
- Current landscape (IA/NLP/Speech; universités, industries) - 10 min
- Course outline (roadmap) - 5min
- Logistics (where, when, what, TDs, gradings) - 5 min

The vocal assistant (myth & reality) - 10min

SF

A brief history

Current systems

Capabilities & limits

Introduction:
Chatting with a computer?

Dialogue systems in films

Dave: Open the pod bay doors, HAL.
HAL: I'm sorry Dave, I'm afraid I can't do that.

(2001: A Space Odyssey, 1968)

Theodore: Do you talk to someone else while we're talking?
Samantha: Yes.
Theodore: Are you talking with someone else right now? People, OS, whatever...
Samantha: Yeah.
Theodore: How many others?
Samantha: 8,316.
Theodore: Are you in love with anybody else?
Samantha: Why do you ask that?
Theodore: I do not know. Are you?
Samantha: I've been thinking about how to talk to you about this.
Theodore: How many others?
Samantha: 641.

(Her, 2013)

Dialogue systems in real life

- ELIZA program (Weizenbaum, 1966)
  - early natural language processing system capable of carrying on a limited form of conversation
  - makes use of pattern-matching to process the input and translate it into suitable outputs
  - **ELIZA doesn't need to *know* anything to mimic a psychotherapist**
- Loebner Prize competition, since 1991
  - An event has attempted to put various computer programs to the Turing test

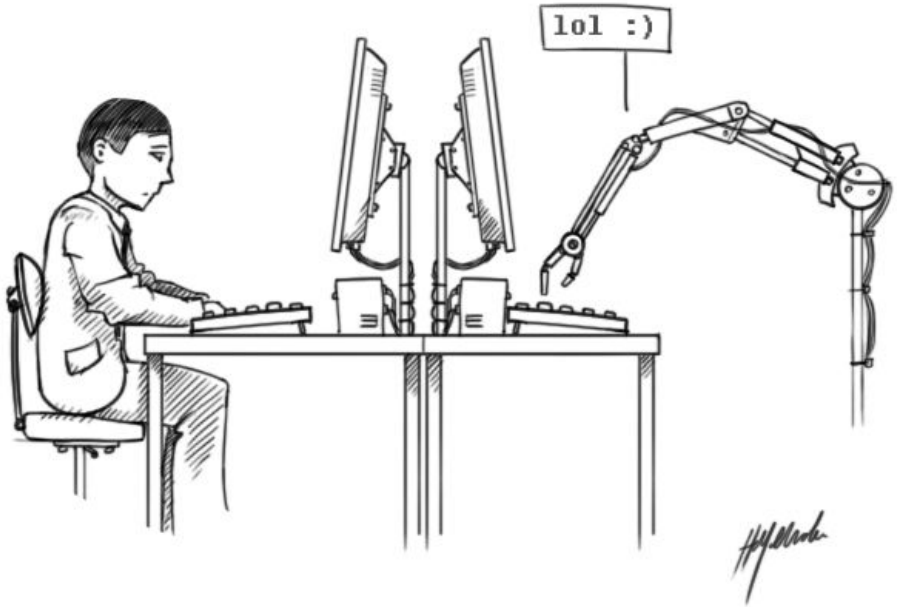
User1: You are like my father in some ways.
ELIZA1: WHAT RESEMBLANCE DO YOU SEE
User2: You are not very aggressive but I think you don't want me to notice that.
ELIZA2: WHAT MAKES YOU THINK I AM NOT AGGRESSIVE
User3: You don't argue with me.
ELIZA3: WHY DO YOU THINK I DON'T ARGUE WITH YOU
User4: You are afraid of me.
ELIZA4: DOES IT PLEASE YOU TO BELIEVE I AM AFRAID OF YOU

Turing’s test (1950)

To which extent can a machine simulate the linguistic behaviour of a human?

However:

- Not a test of intelligence (humans are not always intelligent, machine’s intelligence is often not very human)
- Some behaviours are easy to reproduce
- Some behaviours can fool the human because of his/her attemps (spelling errors…)
- Results can be influenced by the human communicating with the machine



Today’s chatbots and virtual assistants

A new generation of chatbots

- M (Facebook), ~~Tay~~ et Zo (Microsoft), Siri (Apple), Alexa (Amazon)…

Major limits:

- The machine learning component can be fooled/perverted
- Level of understanding and appropriateness of reaction
- Language variety is a major issue

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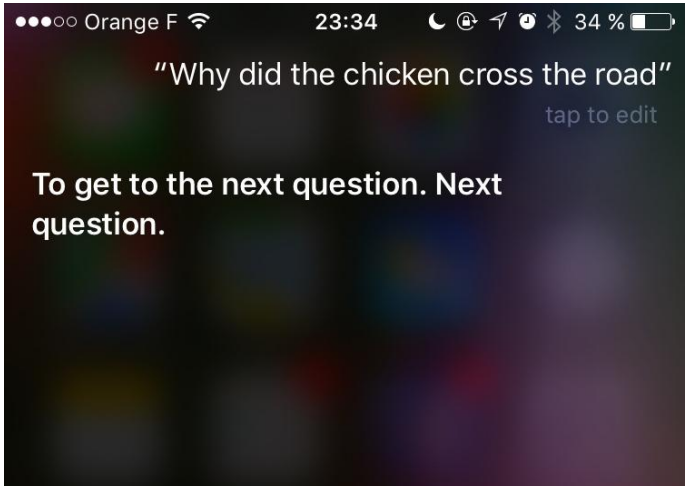

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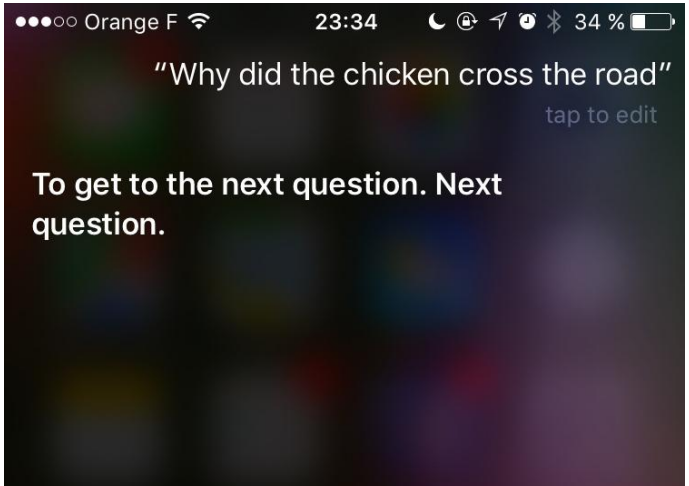

Dialogue systems in real life

SIRI (Apple): a limited intelligence personal assistant

- CALO project (DARPA)+ SRI international
- capabilities:
  - make restaurant reservations,
  - send emails, tweets, take notes,
  - check sports news and stats, weather forecast
  - search web and dictionaries,
  - set up alarms, reminders and meetings
  - check traffic provide directions, check movies
  - open apps
  - pre-recorded funny answers
- limitations:
  - no linking between apps (reserve a restaurant based on agenda availabilities)
  - no discourse processing 'Tell Bill he's going to have to leave without me' -> email: He's going to have to leave without me.

- other systems:
  - www.wolframalpha
  - Microsoft Cortana
  - Amazon echo
  - Google now/Home

What is language (a brief overview) - 40 min

Main components: phonetics/phono; morpho/syntax; semantics/pragmatics

Variations and universals

Formal tools (automata, formal languages)

(voir les slides dans scratch -- imported slides on language,... 151→ 30 max)

A very quick introduction to linguistics

Sentence-level analysis

Phonological level

International Phonetic Alphabet

[aɪ pʰiː eɪ]

Sentence-level analysis

Phonological level

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[aɪ pʰiː eɪ]

Graphemic level

enough, cough, draught, although, brought, through, thorough, hiccough

Analysis in context

Sentence-level analysis

Morphological level

brav+itude, bio+terror-isme/-iste, skype+(e)r

mang-er-i-ons = MANGER+cond+1pl

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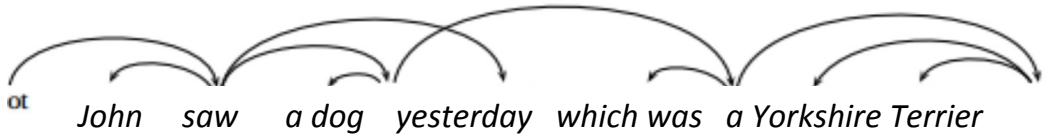
Syntactic level



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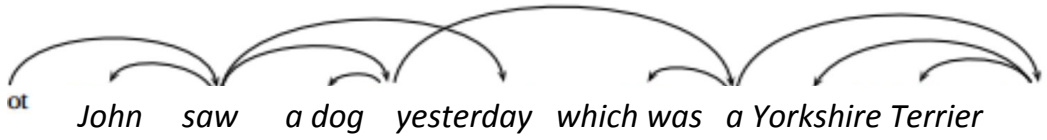
Semantic level

The landlord$_{SPEAKER}$ has not yet **REPLIED**$^{Communication\_response}$ in writing$_{MEDIUM}$ to the tenant$_{ADRESSEE}$ objecting the proposed alterations$_{MESSAGE}$.*DNI*$_{TRIGGER}$

Syntactic level



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Analysis in context

Sentence-level analysis

Linguistic context

— *You know what? John gave Peter a Christmas present yesterday*
— *Wow, was **he** surprised? What was **it** like?*
— *Surprisingly good. **He** spent quite a bit on it.*

Semantic level

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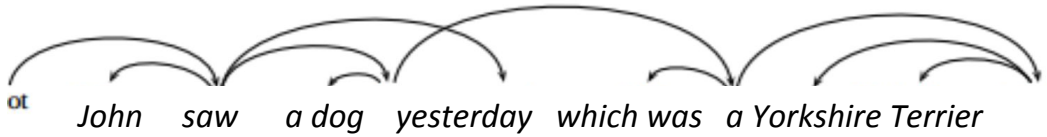

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Analysis in context

Extra-linguistic context

*Found **him** in the street inside a bag. I think **he** is happy with his new life*

http://9gag.com/gag/azVnEwp/found-him-in-the-street-inside-a-bag-i-think-he-is-happy-with-his-new-life

Linguistic context

— *You know what? John gave Peter a Christmas present yesterday*
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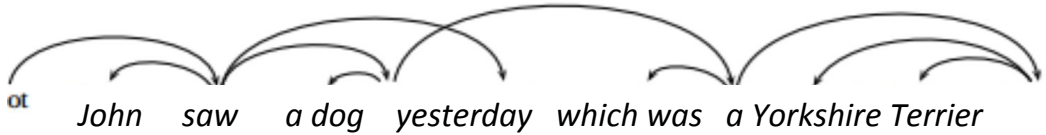
Sentence-level analysis

Syntactic level



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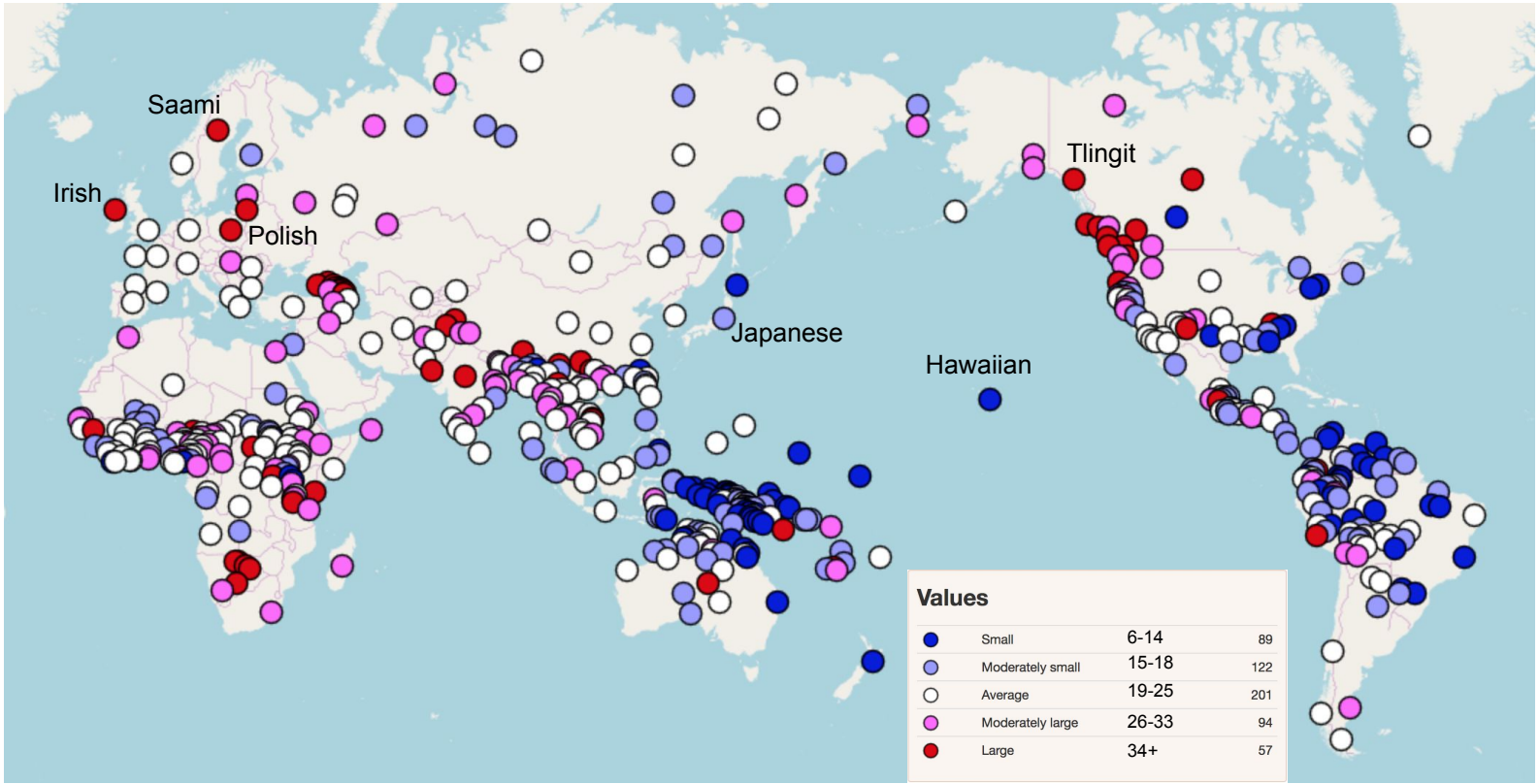
The 4 major challenges of language processing

- Language **diversity**
- Language **variation**
- Language **ambiguity**
- Language **sparsity**

Language diversity

Phonological diversity



Phonological diversity

Central Rotokas	Bilabial	Alveolar	Velar
Voiceless	p	t	k
Voiced	b ~ β	d ~ ɾ	g ~ ɣ

Ubykh		Labial		Alveolar			Postalveolar					Velar				Uvular					Glottal
							laminal closed		laminal		apical										
		plain	phar.	plain	lab.	lat.	plain	lab.	plain	lab.		pal.	plain	lab.	phar.	pal.	plain	lab.	phar.	phar. & lab.	
Plosive	voiceless	p	pˤ	t	tʷ							kʲ	k	kʷ		qʲ	q	qʷ	qˤ	qˤʷ	
	voiced	b	bˤ	d	dʷ							gʲ	g	gʷ							
	ejective	pʼ	pˤʼ	tʼ	tʷʼ							kʲʼ	kʼ	kʷʼ		qʲʼ	qʼ	qʷʼ	qˤʼ	qˤʷʼ	
Affricate	voiceless			t͡s			t͡ʃ		t͡ɕ	t͡ɕʷ	ʈ͡ʂ										
	voiced			d͡z			d͡ʒ		d͡ʑ	d͡ʑʷ	ɖ͡ʐ										
	ejective			t͡sʼ			t͡ʃʼ		t͡ɕʼ	t͡ɕʷʼ	ʈ͡ʂʼ										
Fricative	voiceless	f		s		ɬ	ʃ	ʃʷ	ɕ	ɕʷ	ʂ		x			χʲ	χ	χʷ	χˤ	χˤʷ	h
	voiced	v	vˤ	z			ʒ	ʒʷ	ʑ	ʑʷ	ʐ		ɣ			ʁʲ	ʁ	ʁʷ	ʁˤ	ʁˤʷ	
	ejective					ɬʼ															
Nasal		m	mˤ	n																	
Approximant						l						j		w	wˤ						
Trill				r																	

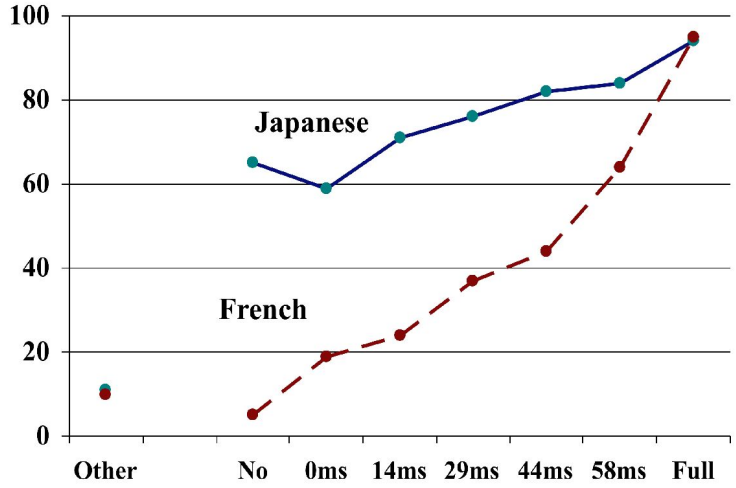
Phonological diversity

Syllables are formed of phoneme sequences

In most languages, some syllables are valid, some are not

Japanese: only V, CV, VN, CVN allowed

> phonological adaptation of borrowings:
sphinx > /sufiNkusu/
Christmas > /kurisumasu/



/ebzo/ → /ebuzo/

Phonological diversity

Different vowel/consonant frequencies and cluster usage:

Georgian /gvbrdɣvnis/ ‘he's plucking us’

Nuxalk *clhp’xwlhtlhplhhskwts’* /xɬpʼχʷɬtʰɬpʰɬːskʷʰt͡s’
‘he had had [in his possession] a bunchberry plant’

Hawaiian *He aha kēia?* ‘What is it?’

Morphological diversity

- Analytic and isolating languages
    - Each word carries exactly one meaning
    - Ex.: Chinese /wɔ mən tan tçin lə/ (1st_pers PLUR play piano PAST) ‘we played the piano’

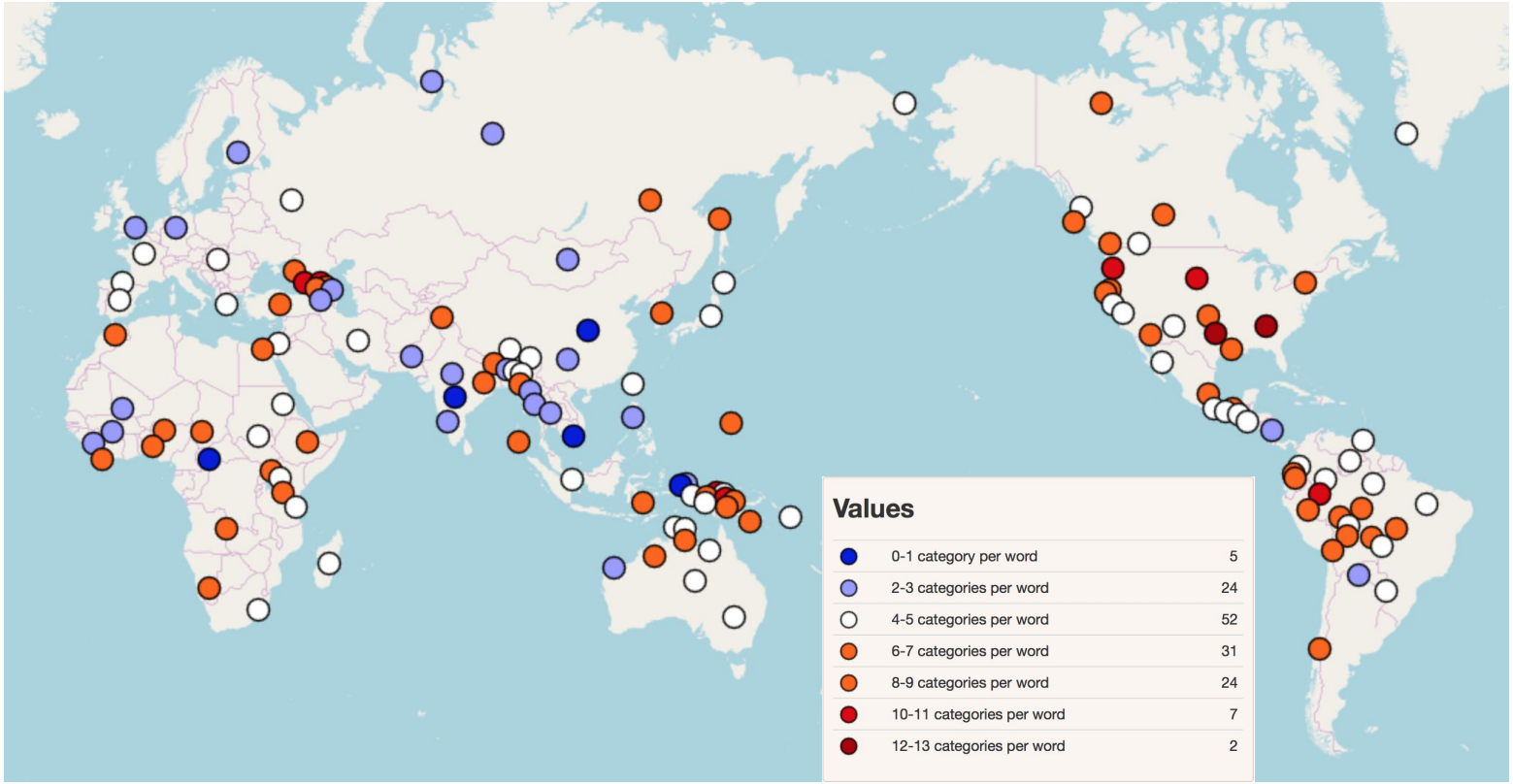
- Synthetic languages
    - Agglutinative
        - Each word can have several morphs, each carrying one meaning
        - Ex.: Turkish *el-ler-imiz-in* (hand-pl-poss1pl-genitive) ‘of our hands’
    - Fusional
        - Each word can have several morphs, each carrying one or more meanings, of which (generally) only one lexical morph (ex.: inflectional morphology, i.e. conjugation, declension…)
        - Ex.: Latin *rexistis* /rek-s-is-tis/ (rule-perf-perf-perf.2sg) ‘you$_{PLUR}$ ruled’
    - Polysynthetic
        - Each word can have several lexical or grammatical morphs
        - Ex.: Island Halkomelem (Salish) *hwpulqwitth’a’ustum*
          (locative-ghost/death(?)-blanket/cloth-face-transitive-passive)
          ‘to be adversely affected by a spirit entering the body through the face’

Morphological diversity

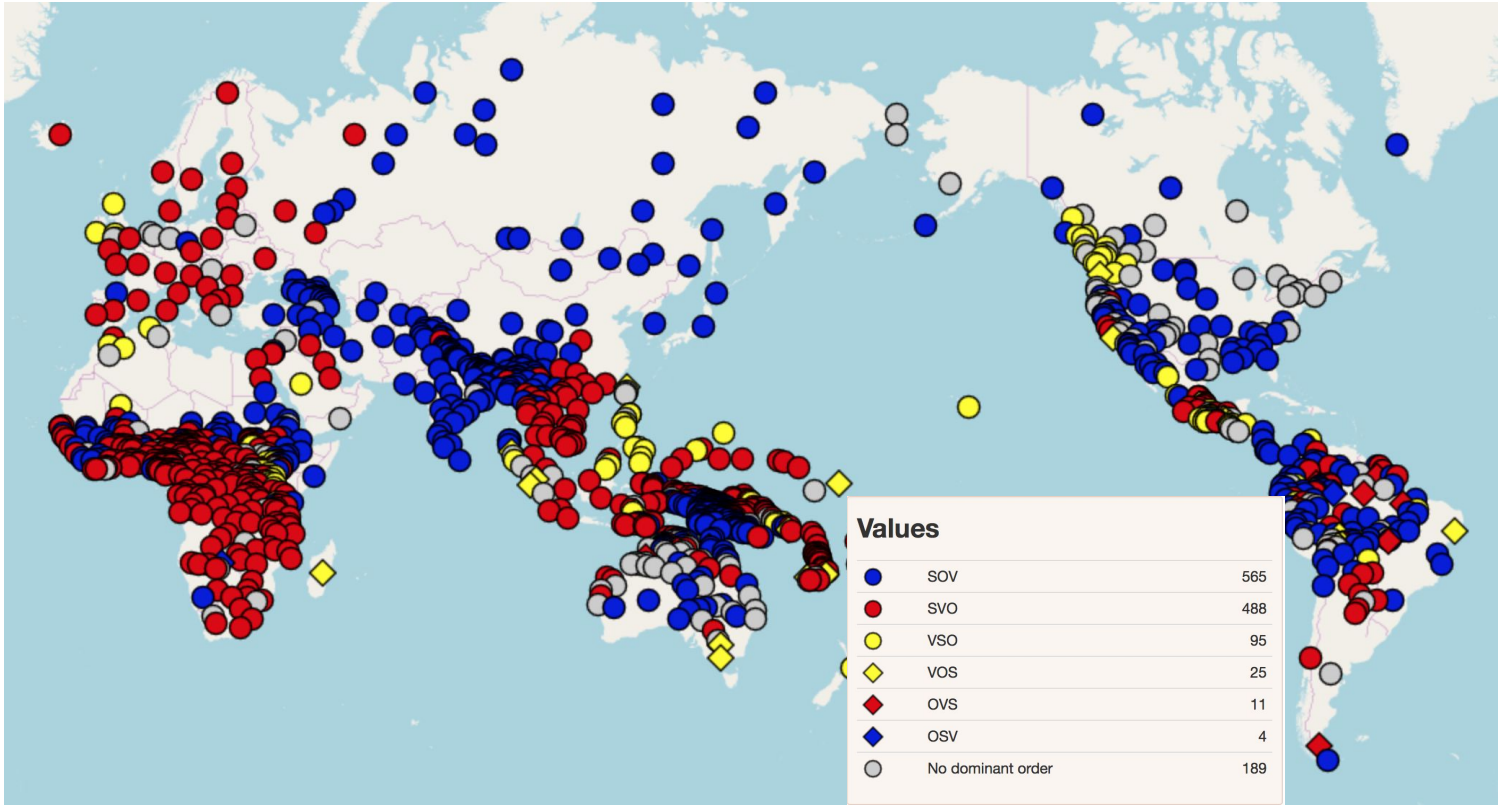
Most languages show elements of different morphological types

- Ex.: English!
  - *the boy will play with the dog*
  - *John's cat eats mice*
  - *antidisestablishmentarianism* (derivational morphology)
- Other example: creating words or word-like sequences from sentences
  - French: *je-m'en-foutisme*
  - English: *You know, I can't take all this let's-be-faithful-and-never-look-at-another-person routine, because it just doesn't work* (The Boys in the Band, 1970)

Morphological diversity



Syntactic diversity



Syntactic diversity

Levels of configurationality

- Free word order (often with very rich morphological marking)
  - Ex.: Warlpiri
- Relatively free word order
  - Often with rich morphological marking
  - And discontinuous constituents
  - Ex.: Polish ‘John went to the cinema’

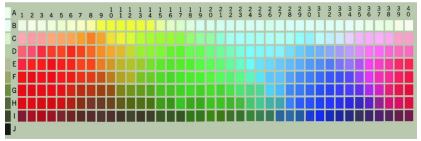
Jaś poszedł do kina.
Poszedł Jaś do kina.
Jaś do kina poszedł.
Poszedł do kina Jaś.
Do kina Jaś poszedł.
Do kina poszedł Jaś.

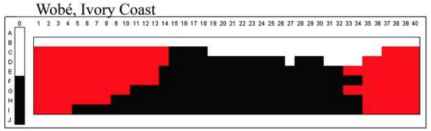
- Constrained word order (“configurational”)
  - Ex.: English, Chinese
  - Often with limited or no morphological marking
  - Discontinuous constituents are rare

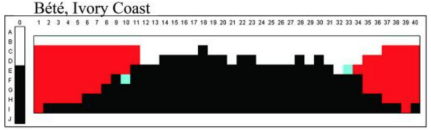
Semantic diversity

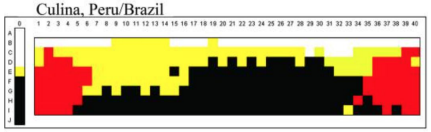
Words (fuzzily) partition the semantic space

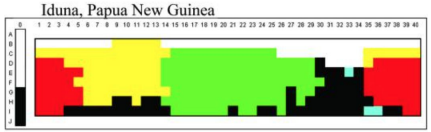
Partitions can differ from one language to another

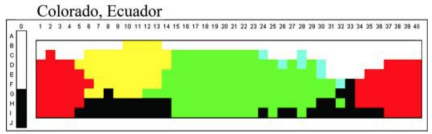


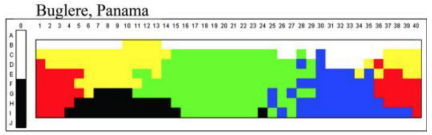


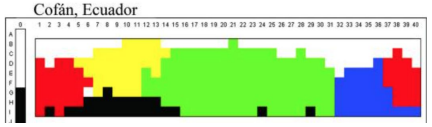


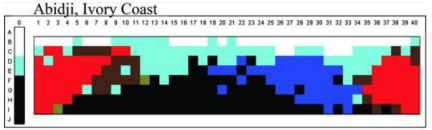


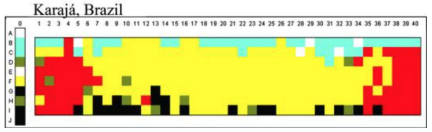


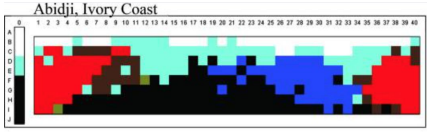


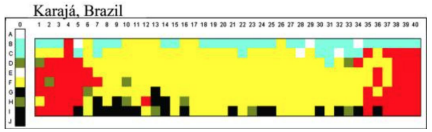












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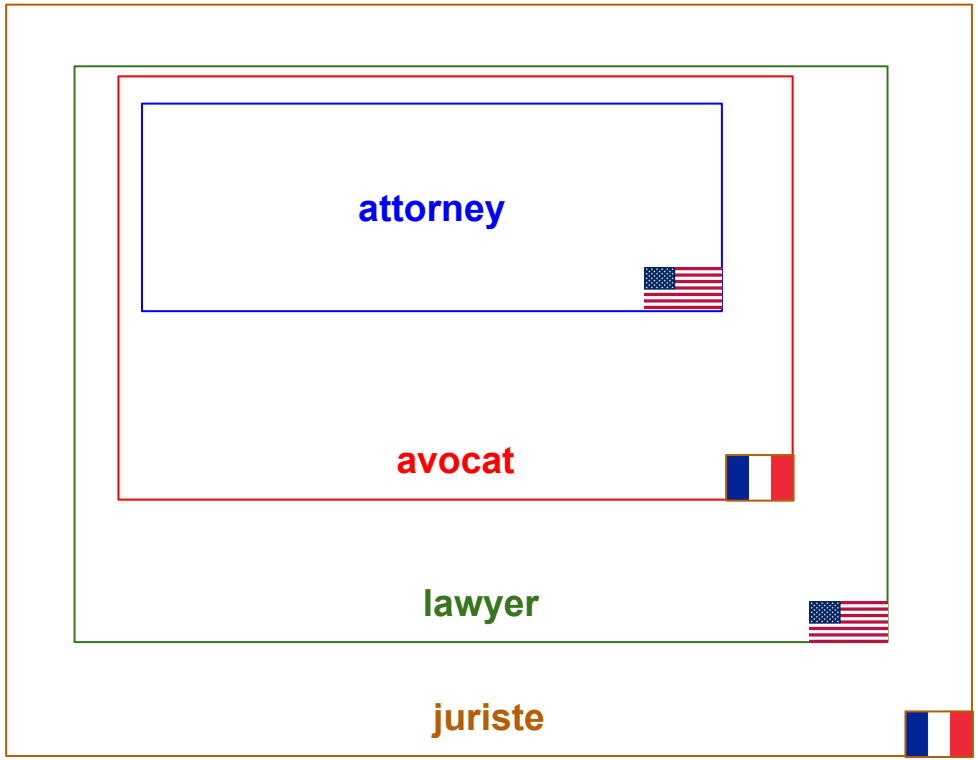
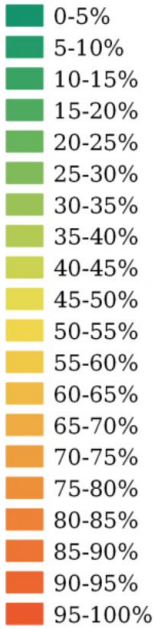
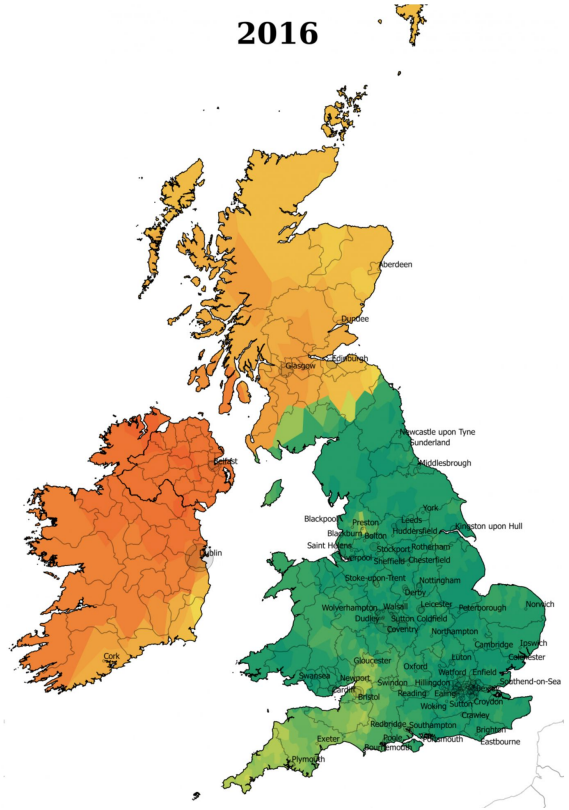


Language variation

Phonetic and phonological variation

Do you pronounce the “r” in “arm” ?

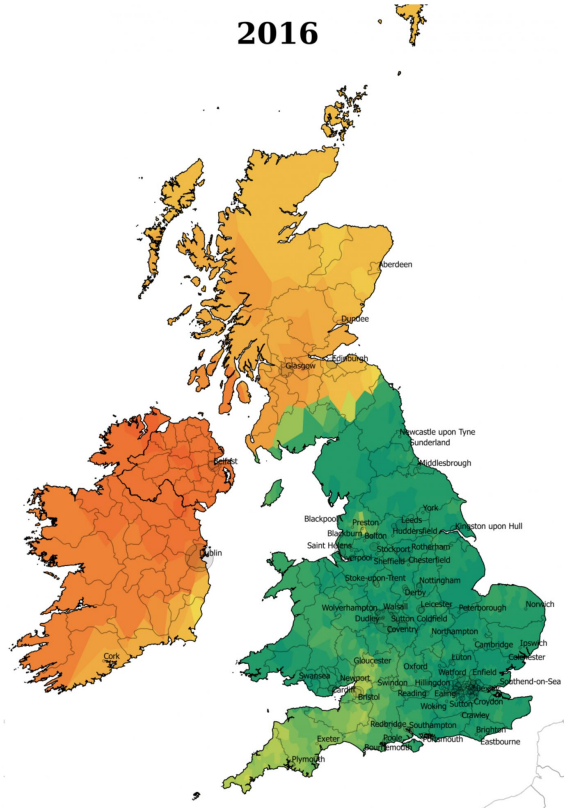


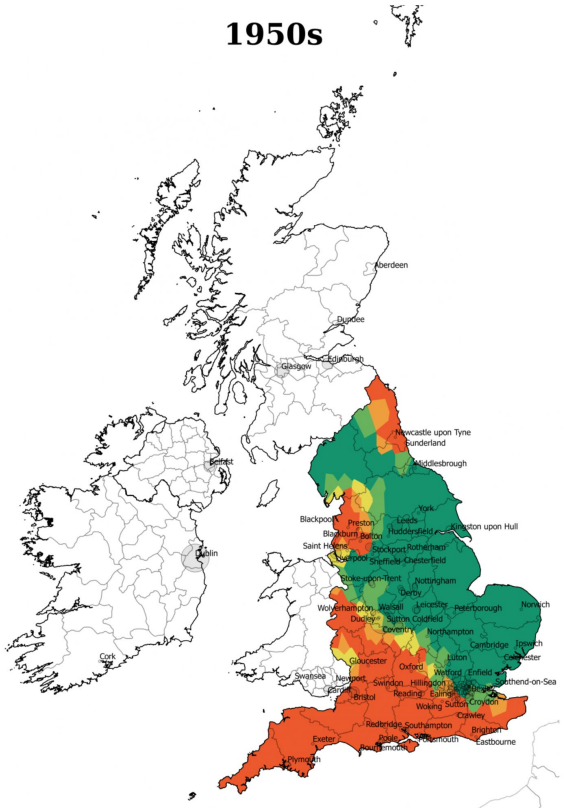


Phonetic and phonological variation

Do you pronounce the “r” in “arm” ?

- 0-5%
- 5-10%
- 10-15%
- 15-20%
- 20-25%
- 25-30%
- 30-35%
- 35-40%
- 40-45%
- 45-50%
- 50-55%
- 55-60%
- 60-65%
- 65-70%
- 70-75%
- 75-80%
- 80-85%
- 85-90%
- 90-95%
- 95-100%





Spelling “variation”

anagement maagement maanagement
maangement magagement magement
mamagement mamangement manaagement manaement
managaement manageement manageemnt managegment
managemaent managemant managememt managemen managemenet
managementt managemet managemetn managemnent managemnet
managemnt managemrnt managemt managenent managenment managent
managerment managhement managmeent managmement managment managnment
manament manamgement mananement manangment manasgement
manegement manegment mangaement mangagement mangagment
mangament mangement manggement mangment
mangmt menagement mgmt mgnt
mnagement mngmnt mngmt

Sociolinguistic variation

Interpreting tweets produced by Chicago gang members

Tweet	Label	Youth Interpretation
If We see a opp Fuck it We Gne smoke em 😈	Aggression (Threat)	he mean like if he see opp he go kill him opp mean like the people he dont like
Dnt get caught on Dat 800 block lame ass Lil niggas Betta take Dat Shyt on stony spot	Aggression (Insult)	he saying them lil nigga better not get caught on the 800 block or they go kill them so he tell them if they wanna live they better stay on stony
Young niggas still getting shot babies still dying 🙏	Loss	he mean like teen keep die and babys and kid keep die

Blevins et al. 2016

Sociolinguistic variation

T'as vu il l'a bien cherché wsh #AperoChezRicard

> +10000, shah!

> tabuz, lavé rien fé

> ki ca ? le mec ou son chien ?

> Wtf is wrong with him ? #PETA4EVER

> ki ca ? le chien ?

> looool

Sociolinguistic variation

T'as vu il l'a bien cherché wsh #AperoChezRicard
> +10000, shah!
> tabuz, lavé rien fé
> ki ca ? le mec ou son chien ?
> Wtf is wrong with him ? #PETA4EVER
> ki ca ? le chien ?
> looool

BING translation:
You saw coming it #AperoChezRicard wsh
> +10000, shah!
> tabuz, washed anything fe
> Ki ca? the guy or his dog?
> WTF is wrong with him? #PETA4EVER
> Ki ca? the dog?
> looool

Diachronic variation

Li reis Marsilie esteit en Sarraguce.
Alez en est en un verger suz l'umbre;
Sur un perrun de marbre bloi se culchet,
Envirun lui plus de vint milie humes.
Il en apelet e ses dux e ses cuntes:
« Oëz, seignurs, quel pecchet nus encumbret :
Li emper[er]es Carles de France dulce
En cest païs nos est venuz cunfundre.
Jo nen ai ost qui bataille li dunne,
Ne n'ai tel gent ki la sue derumpet.
Cunseilez mei cume mi savie hume,
Si m(e) guarisez e de mort et de hunte. »
N'i ad paien ki un sul mot respundet,
Fors Blancandrins de Castel de Valfunde.

Chanson de Roland (XIth century)

Hwæt! Wé Gárdena in géardagum
þéodcyninga þrym gefrúnon·
hú ðá æþelingas ellen fremedon.
Oft Scyld Scéfing sceaþena þréatum
monegum maégþum meodosetla oftéah·
egsode Eorle syððan aérest wearð
féasceaft funden hé þæs frófre gebád·
wéox under wolcnum· weorðmyndum þáh
oð þæt him aéghwylc þára ymbsittendra
ofer hronráde hýran scolde,
gomban gyldan· þæt wæs gód cyning.

Beowulf (Xth century)

Language ambiguity

Lexical ambiguity: homonymy

Homophony: same pronunciation, different words (and often spelling)

- Ex.: English *weather, wether, whether* / French: *vers, verre, ver, vert, vair*
- More extreme case = oronyms. Cf. English *ice cream* vs. *I scream*
- Even more extreme case = holoryms

  Étonnamment monotone et lasse
  Est ton âme en mon automne, hélas !

  (Louise de Vilmorin)

Homography: same spelling, different words (and sometimes pronunciation)

- Ex.: French *les poules du couvent couvent*
  English *if you have not read this book yet, read it!*

Segmentation ambiguity

Segmentation in elementary linguistic units

- *Bob* | *a* | *mangé* | *une* | ***pomme de terre***
- *Bob* | *,* | *sculpteur* | *,* | *a* | *fabriqué* | *une* | ***pomme* | *de* | *terre cuite***

=> distinction between **tokens** and **forms**

Token = typographic unit (*pomme de terre* is always 3 tokens)

Form (wordform) = linguistic unit (*pomme de terre* can be 1 or 3 forms)

Amalgams = several forms in one token (French *aux*, English *don't*)

Can be ambiguous! French *des* (1 token) can be *de + les* (2 forms) or *des* (1 form)

There are complex cases. Cf. French *à l' instar du* = *à_l'_instar_de + le*

Morphological ambiguity

Lemma = equivalence class of forms belonging to a same morphological paradigm

A lemma is often represented by one of its forms, the “citation form”

- Example: for a verb, the infinitive (French) or its 1st pers. prs. ind. (Latin, Greek)

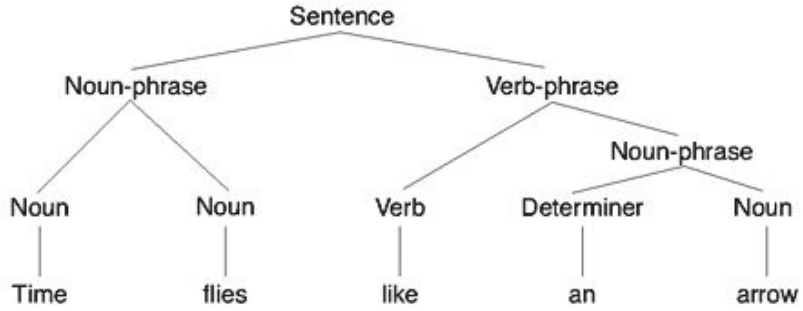
Lemmatisation = associate each form in a sentence with its lemma

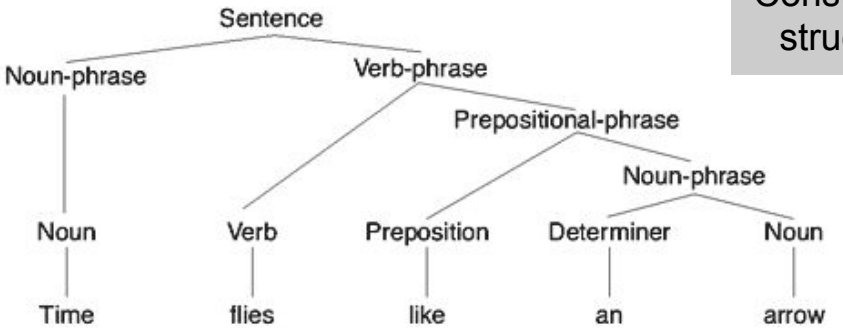
Morphological analysis = associate each form in a sentence with its lemma AND morphological tags

- Example: *mangerons* = MANGER(v)+ind.fut.1pl

Syntactic ambiguity

Time flies like an arrow



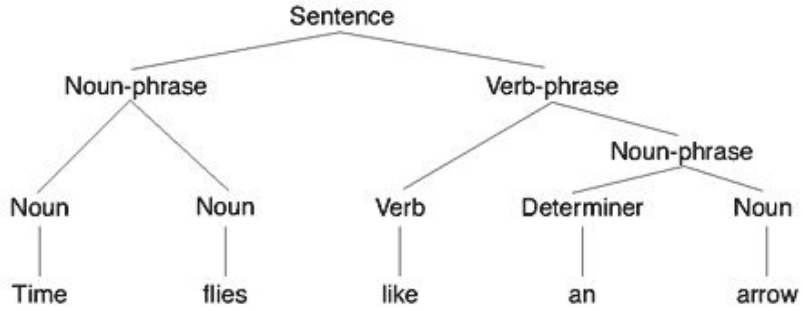


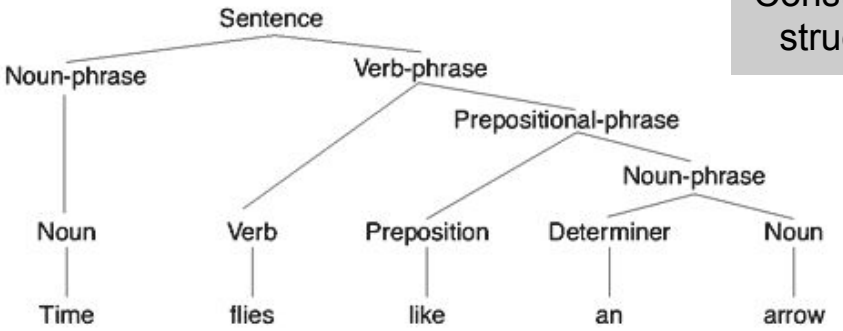
Constituency structures

Syntactic ambiguity

Time flies like an arrow

Cf. *Fruit flies like a banana*

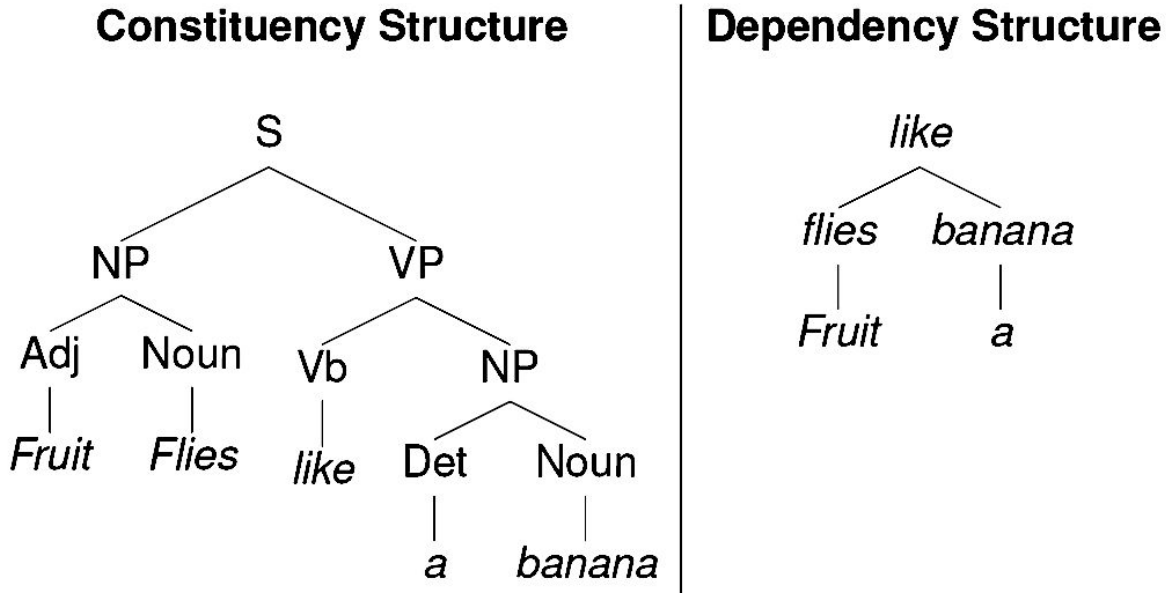




Constituency structures

A bit of terminology

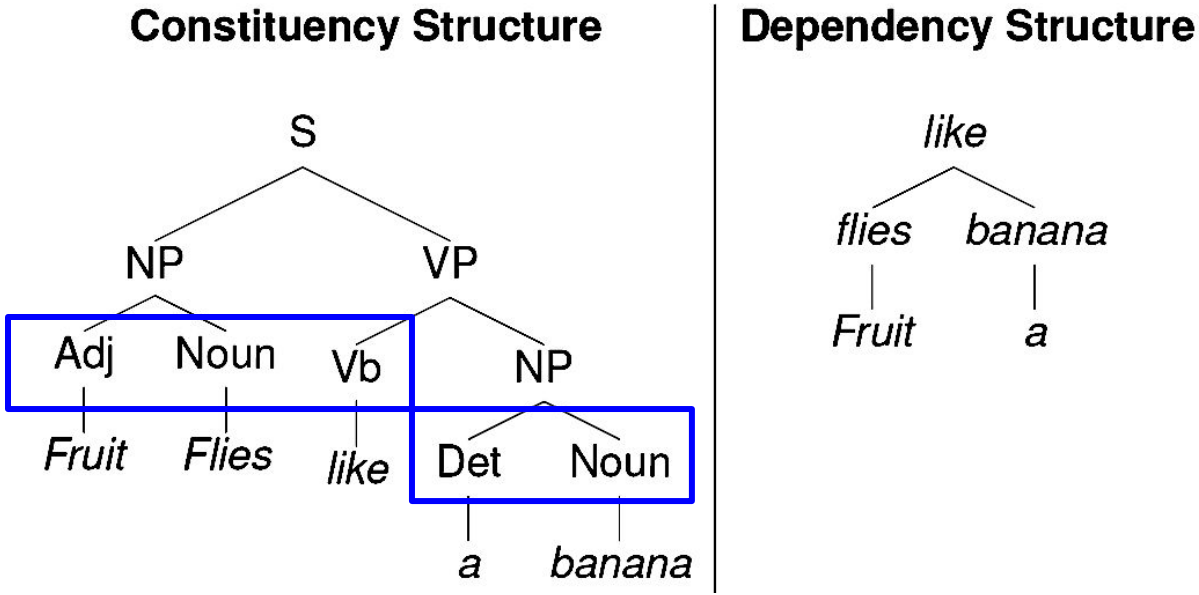
Fruit flies like a banana



A bit of terminology

Fruit flies like a banana

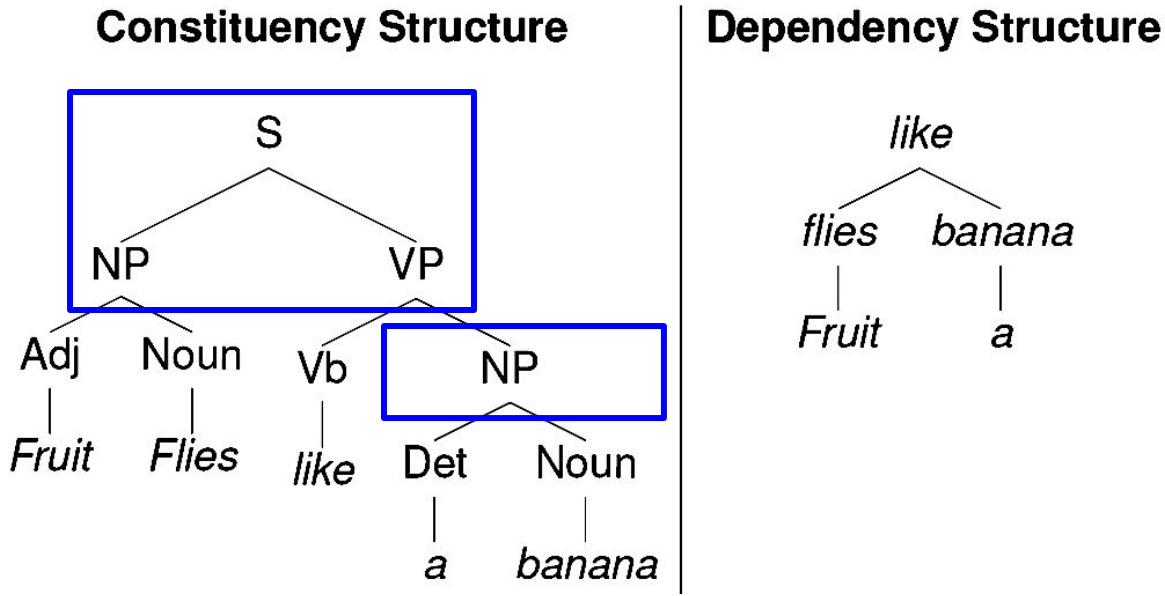
Parts-of-speech
(PoS)



A bit of terminology

Fruit flies like a banana

Phrases (or constituents)

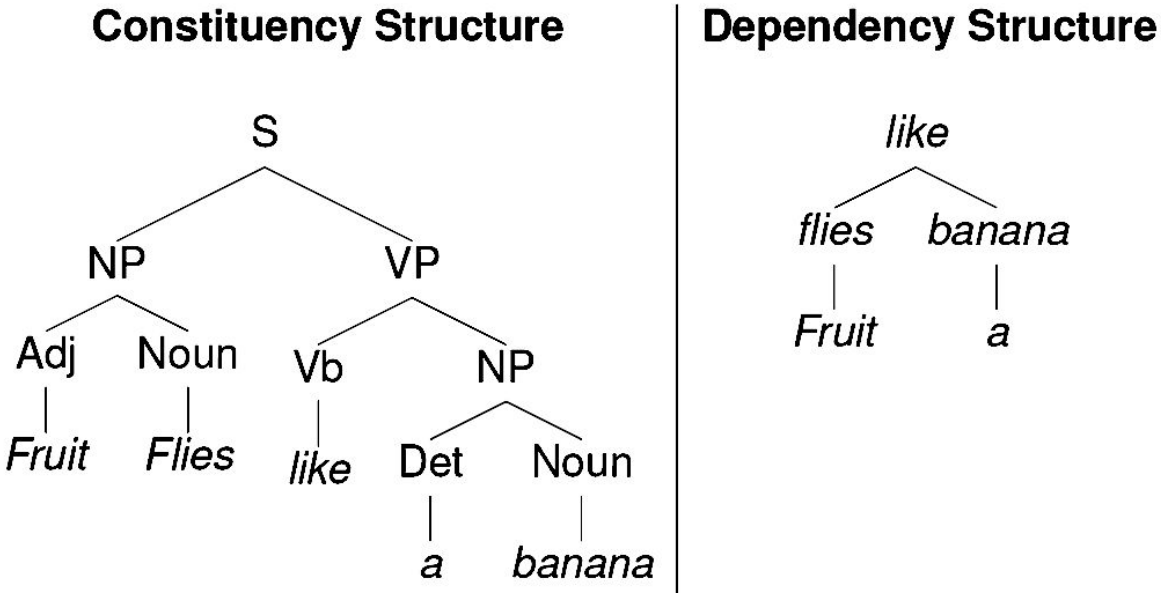


A bit of terminology

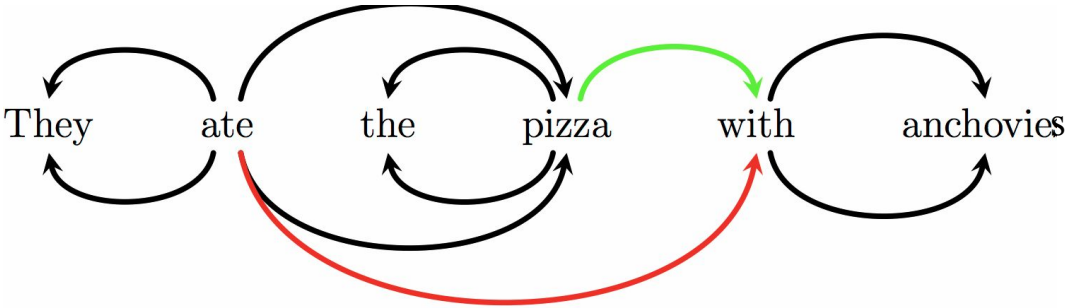
Fruit flies like a banana

Automatic syntactic analysis = parsing

- Constituency parsing
- Dependency parsing



Syntactic ambiguity: PP attachment



Garden-path sentences

The cotton clothing is usually made of grows in Mississippi

Until the police arrest the drug dealers control the street

Mary gave the child the dog bit a bandaid

The girl told the story cried

The dog that I had really loved bones

The old man the boat

The raft floated down the river sank

We painted the wall with cracks

Garden-path sentences

(The cotton (clothing is usually made of)) grows in Mississippi

(Until the police arrest) (the drug dealers control the street)

Mary gave (the child (the dog bit)) (a bandaid)

(The girl (told the story)) cried

(The dog that I had) really loved bones

(The old) man (the boat)

(The raft (floated down the river)) sank

We painted (the wall with cracks)

Semantic ambiguity: polysemy

Hyponymy: man (vs. animals) ⊃ man (vs. woman) ⊃ man (vs. boy)

Metaphor: mole (the animal) > mole (a spy)

Object/color: cherry (the fruit) > cherry (as a color, cf. *I like your cherry shirt*)

Object/Informational content: book (the object) // book (its content)

Object/Collective abstract: tramway (vehicle) // tramway (means of transportation)

Tree or plant/Material/fruit/vegetable it produces: cotton (plant) > cotton (material)

Animal/Its (edible) flesh: rabbit (animal) > rabbit (meat)

Semantic ambiguity

Named entities:

- Detection
- Linking

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The Free Encyclopedia

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Featured content
Current events
Random article
Donate to Wikipedia
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Interaction
Help
About Wikipedia
Community portal
Recent changes
Contact page

Tools
What links here
Related changes
Upload file
Special pages
Permanent link
Page information
Wikidata item
Cite this page

Michael Jordan (disambiguation)

From Wikipedia, the free encyclopedia

Michael Jordan (born 1963) is an American basketball player.

Michael Jordan or **Mike Jordan** may also refer to:

Contents [hide]
1 People
1.1 Sports
1.2 Other people
2 Other uses
3 See also

People [edit]

Sports [edit]

- Michael Jordan (footballer) (born 1986), English goalkeeper (Arsenal, Chesterfield, Lewes)
- Mike Jordan (racing driver) (born 1958), English racing driver
- Mike Jordan (baseball, born 1863) (1863–1940), baseball player
- Michael Jordan (American football) (born 1992), American football cornerback
- Michael-Hakim Jordan (born 1977), American professional basketball player
- Michal Jordán (born 1990), Czech ice hockey player

Other people [edit]

- Michael B. Jordan (born 1987), American actor
- Michael Jordan (insolvency baron) (born 1931), English businessman
- Michael Jordan (Irish politician), Irish Farmers' Party TD from Wexford, 1927–1932
- Michael I. Jordan (born 1956), American researcher in machine learning and artificial intelligence
- Michael H. Jordan (1936–2010), American executive for CBS, PepsiCo, Westinghouse
- Michael Jordan (mycologist), English mycologist

Multiple ambiguity

- Most or all tasks in speech and language processing can be viewed as resolving **ambiguity** at one of the levels of signal or linguistic structure.
- The spoken sentence, *I made her duck,* has five different meanings.
  - (1) I cooked waterfowl for her.
  - (2) I cooked waterfowl belonging to her.
  - (3) I created the (plaster?) duck she owns.
  - (4) I caused her to quickly lower her head or body.
  - (5) I waved my magic wand and turned her into undifferentiated waterfowl.

Multiple ambiguity

- These different meanings are caused by multiple ambiguities.
  - PoS: *duck* can be a verb or a noun, while *her* can be a dative pronoun or a possessive pronoun -> part-of-speech tagging
  - Polysemy: the word *make* can mean *create* or *cook* -> word sense disambiguation
  - Syntactic ambiguity: the verb *make* is syntactically ambiguous in that it can be transitive (2), or it can be ditransitive (5). Moreover, *make* can take a direct object and a verb (4), meaning that the object (*her*) got caused to perform the verbal action (*duck*) -> parsing
  - In a spoken sentence, phonological ambiguity (homophones) is also present; the first word could have been *eye* or the second word *maid*.

Language sparsity

Corpora

Corpus = body of text stored in a machine-readable form

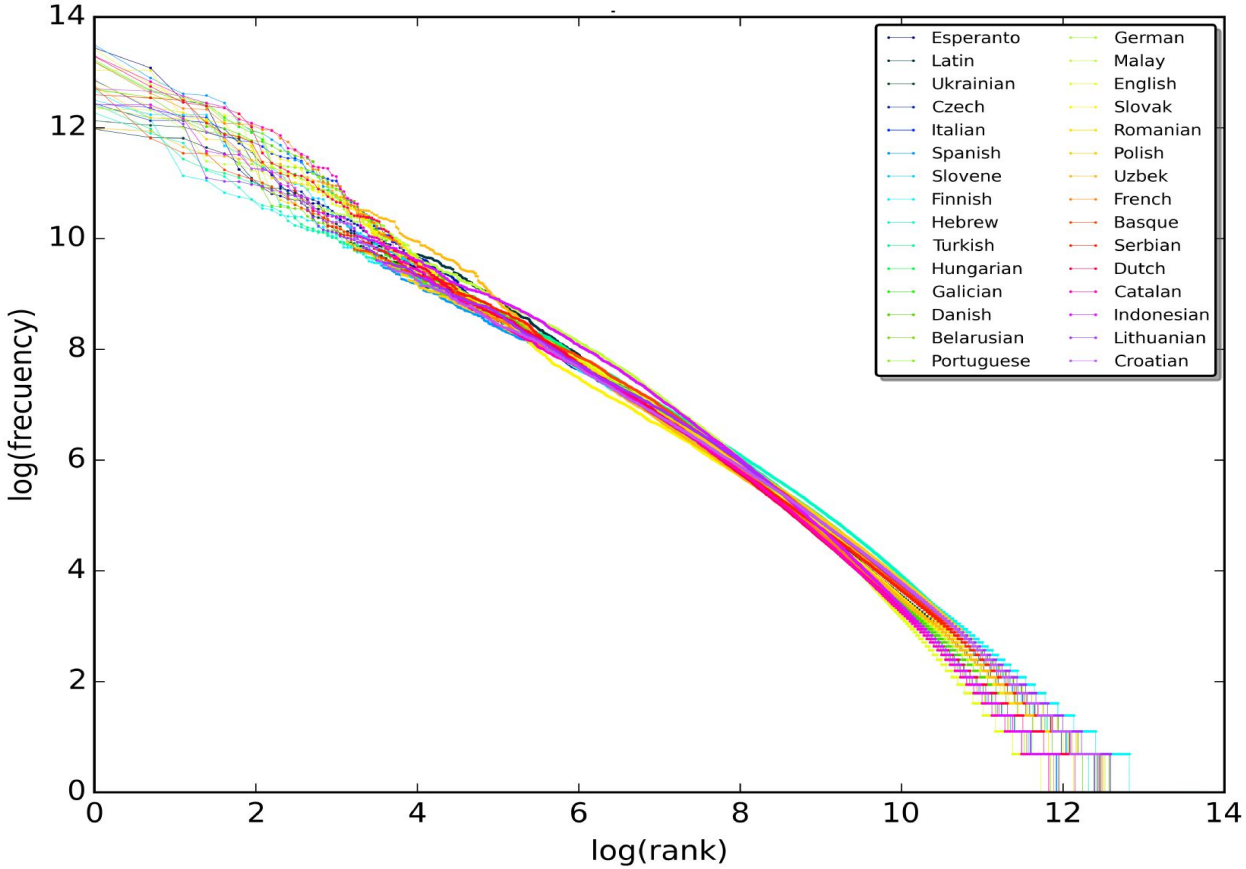
Corpora can be annotated, for serving as training, development or test data

- Morphosyntactically-annotated corpora
- Treebanks (syntactically-annotated)
- Semantically disambiguated corpora
- etc.

Zipf's law

A plot of the rank versus frequency for the first 10 million words in 30 Wikipedias

(source: Wikipedia; data: dumps from Oct 2015)



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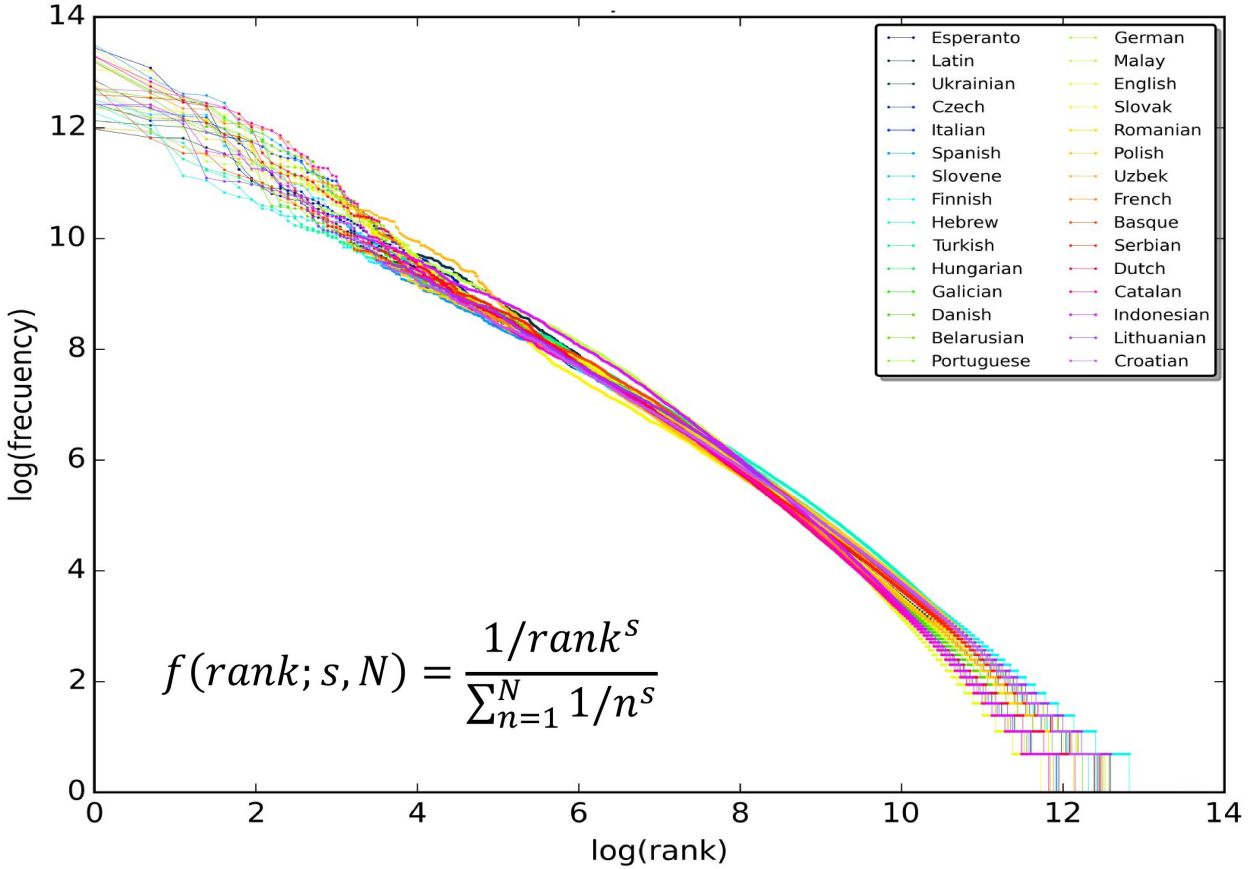
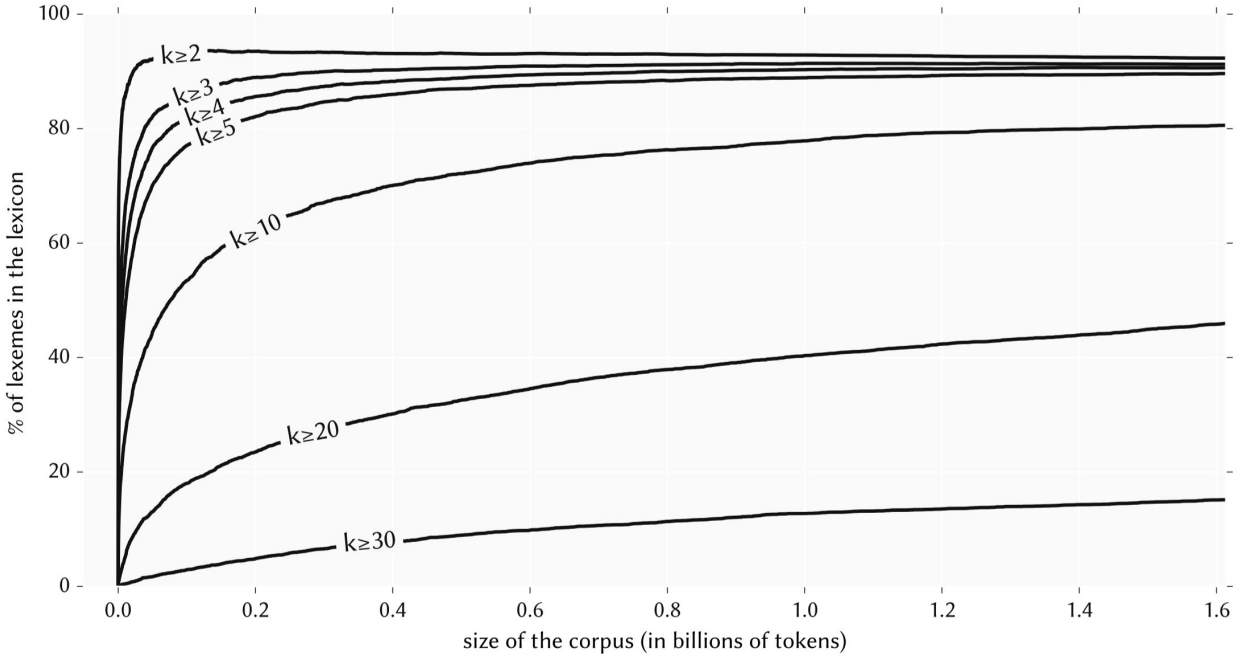


Zipf’s law

In language data, many phenomena follow a zipfian distribution

Heaps’s law

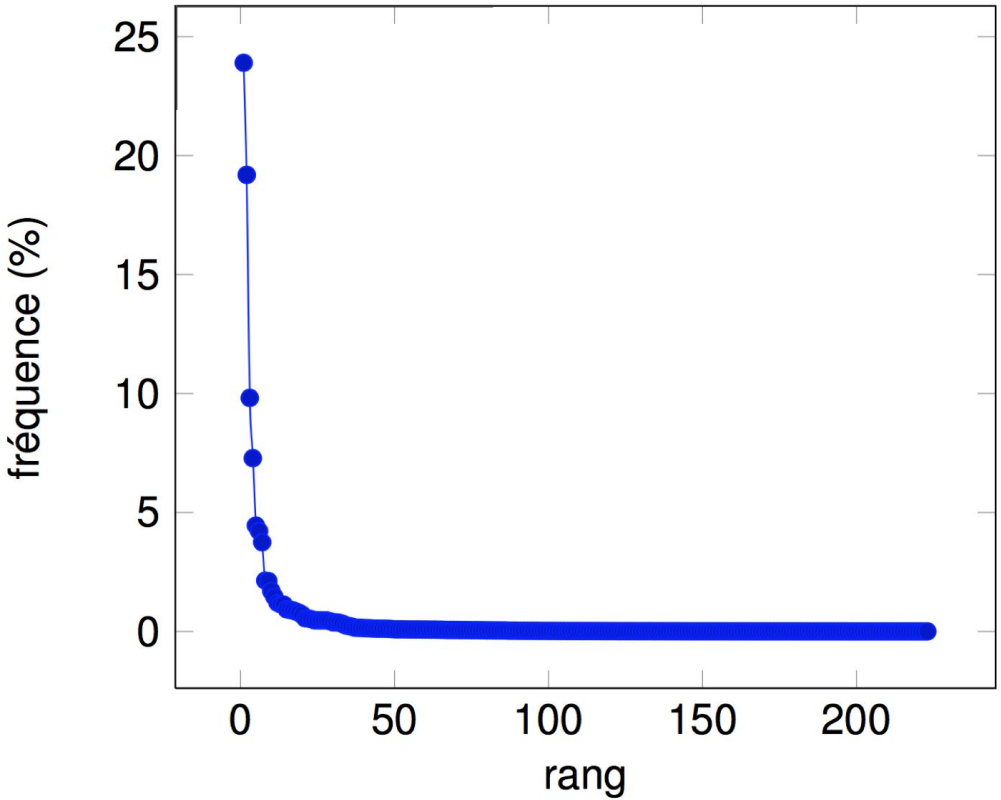
Example: proportion of lemmas (known to a pre-defined lexicon) attested in at least *k* inflected forms as a function of vocabulary size in a large web-based corpus of French (FrWaC) for various values of *k*



Zipf’s law

In language data, many phenomena follow a zipfian distribution

Example: frequency of syntactic constructions in an automatically parsed 500M-word corpus



Deconstructing Siri - 30 min

ASR

Paralinguistics

NLU

Dialog

Generation&Synthesis

Deconstructing Siri

The personal assistant

“Trouve moi un resto Grec près d’ici”

Amazon Alexa,
Google Home,
Baidu Raven, etc

Such systems can

- Identify the talker
- Recognize the words
- Understand the query
- Respond orally

Such systems can

- **Identify the talker**
- Recognize the words
- Understand the query
- Respond orally

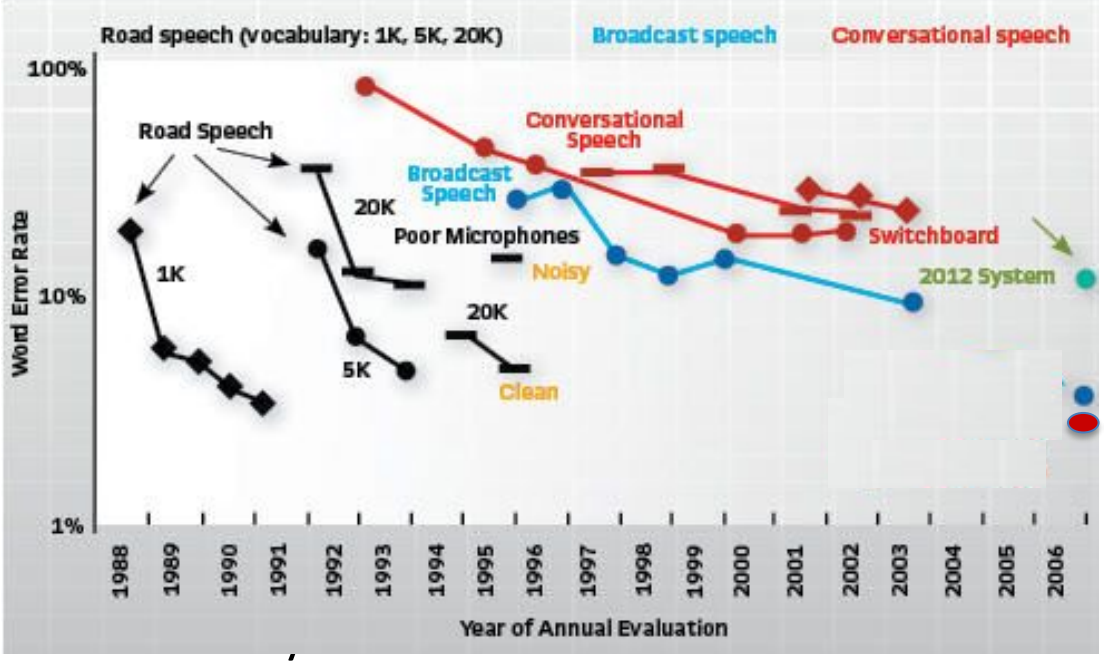
TALKER:
Emmanuel
Dupoux

performance:
better than human
(for long
utterances)

Such systems can

- Identify the talker
- **Recognize the words (speech to text)**
- Understand the query
- Respond orally

performance: roughly like humans



MSR 2016: 5.9%

MSR 2017: 5.1%

- **<u>Recognize the words (speech to text)</u>**
- Understand the query
- Respond orally

Trouve moi un resto Grec près d ici

performance: roughly like humans (not for casual or noisy)

Such systems can

- Identify the talker
- Recognize the words
- **Understand the query**
- Respond orally

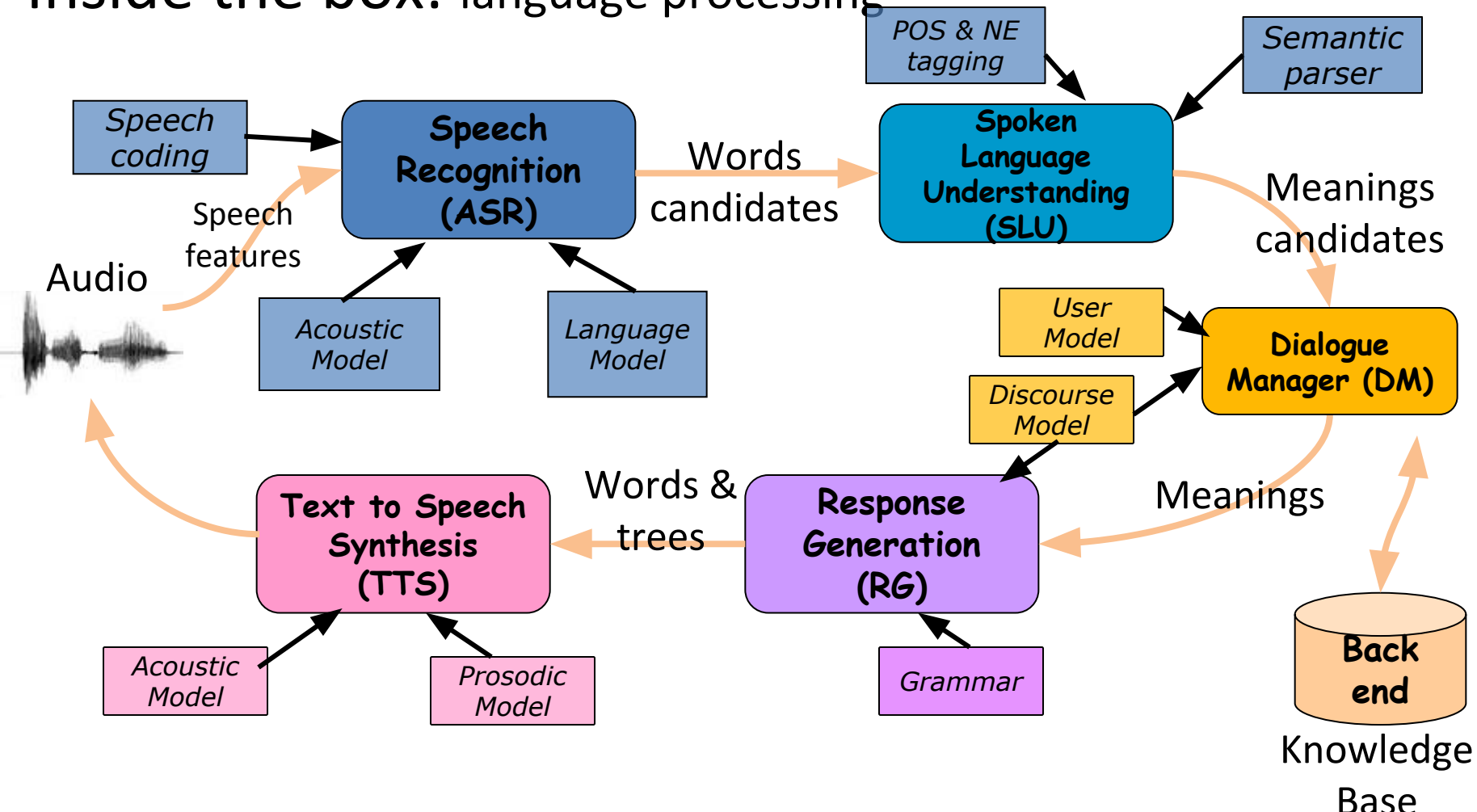
performance: only for simple requests

Such systems can

- Identify the talker
- Recognize the words
- Understand the query
- **Respond orally**

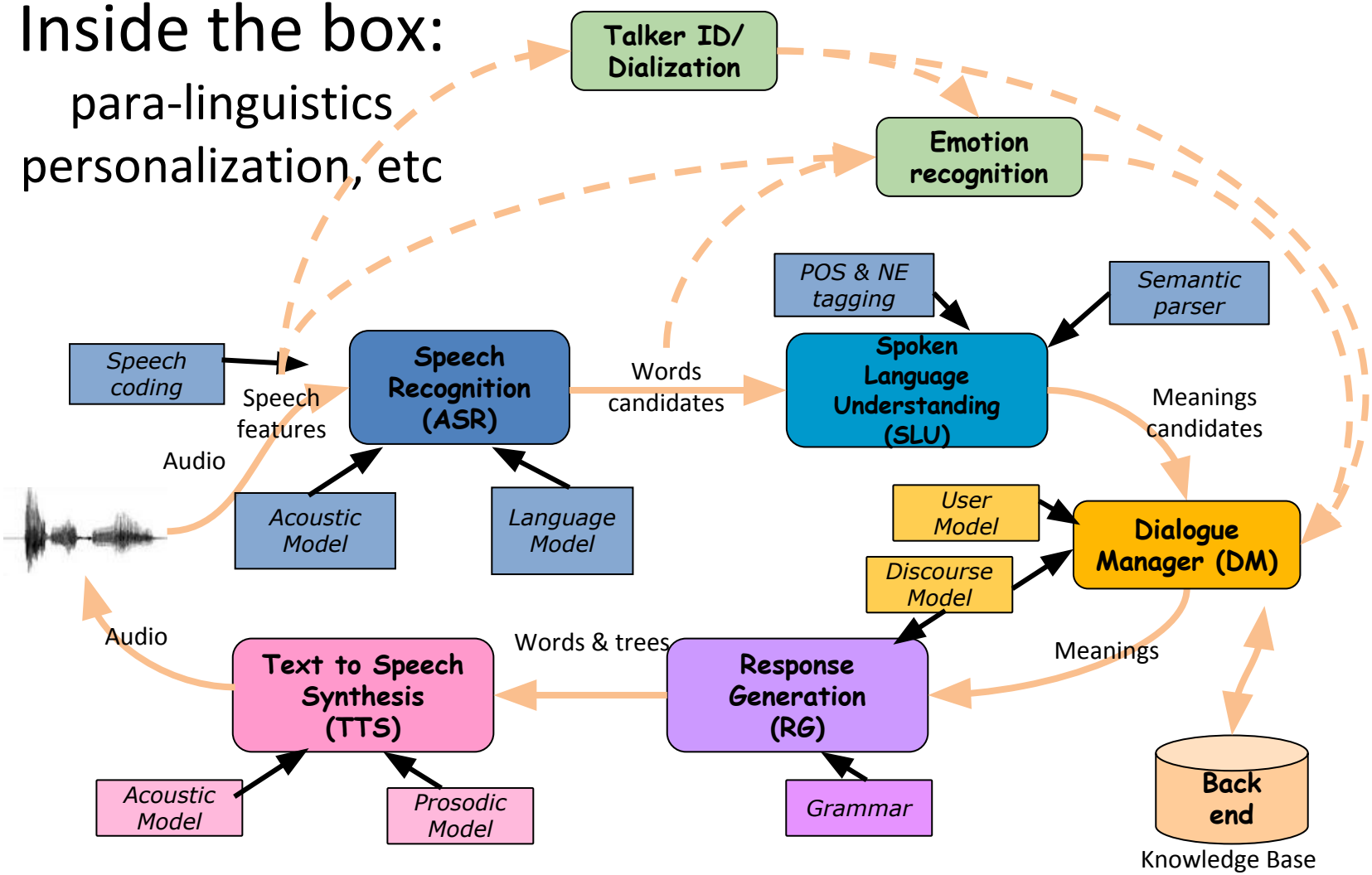
performance: close to natural speech (not emotional speech)

Inside the box: language processing



Inside the box:

para-linguistics
personalization, etc



Main algorithms (that address these problems) -20 min

Modular approach

Symbolic approaches

Probabilistic framework

Search algorithms

End-to-end training

Algorithms and methods for speech and language processing

Computational approaches to NLP over time

Symbolic approaches

- **Computational expertise:**
Formal grammars (algebraic grammars, mildly context-sensitive grammars, polynomial languages…), parsing algorithms, dynamic programming

- **Comp. linguistics expertise:**
Formal and descriptive linguistics, grammar engineering, development of lexical resources

Computational approaches to NLP over time

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Statistical approaches

- **Computational expertise:** (statistical) machine learning, supervised, semi-supervised and non-supervised (PCFG, CRF, MEMM, discriminative algorithms…), hybrid approaches
- **Comp. linguistics expertise:** development of annotated corpora (training dataset), development of lexical resources

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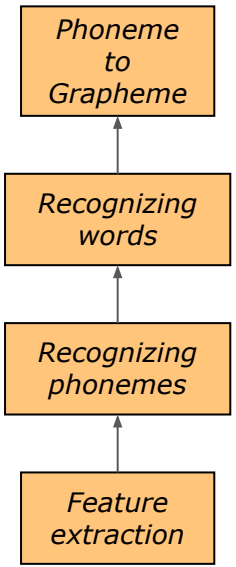
- **Comp. linguistics expertise:** development of annotated corpora (training dataset), development of lexical resources

Neural approaches

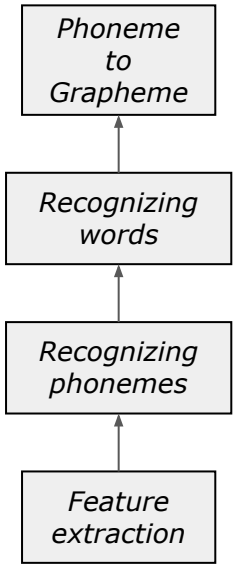
- **Comp. expertise:** neural networks, deep learning, end-to-end training
- **Comp. ling. exp.:** same as for statistical approaches

Hand engineered system



Problems :
- Labor intensive
- Brittle (early errors catastrophic)

Hand engineered system



Probabilistic system

Acoustic model

Langage model

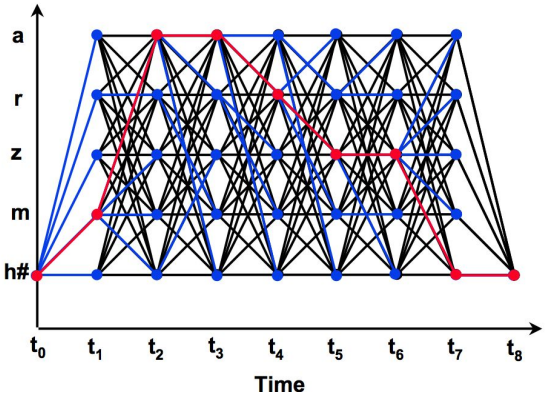
$$P(W|X) \sim P(X|W).P(W)$$

Decoding :

$$W = \text{argmax}_W \, P(X|W).P(W)$$

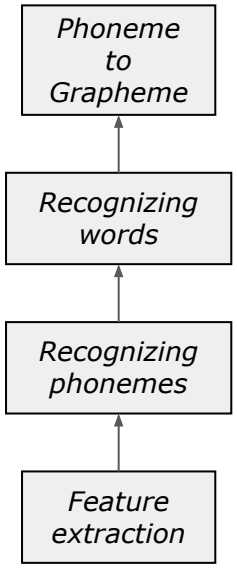
Algorithms: State search space

Dynamic programming

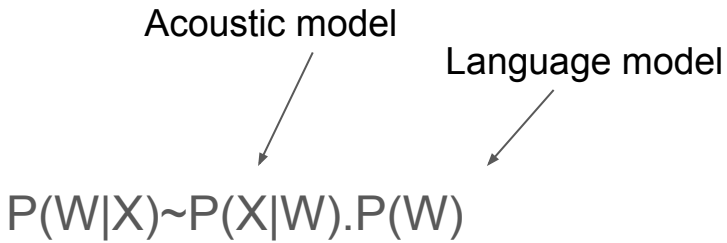


Advantage: robust to error

Hand engineered system



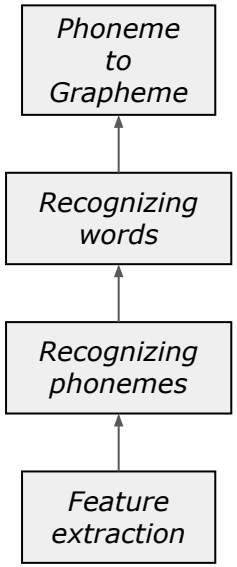
Probabilistic system



Learning the probabilities

Algorithms: EM, ..
Problem: Lots of annotated data

Hand engineered system



Probabilistic system

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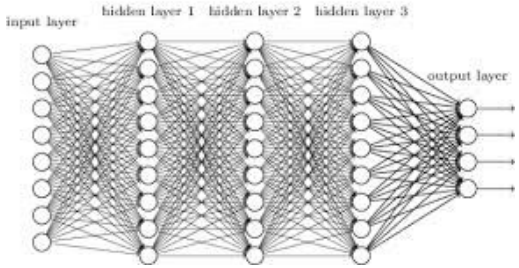
Langage model

$$P(W|X) \sim P(X|W).P(W)$$

Deep learning systems



Decoding:

Distributed intermediate representations

Probabilistic interpretation of final layer

Learning:

Stochastic Gradient Descent

Advantage: more robust

Problem: even more annotated data

Main applications -10min

Assistant (already seen)

Information retrieval

Translation & summarization

etc

Applications of speech and language processing

Current landscape - 10 min

A brief history of the interaction between IA, NLP/CL and Speech processing.

Academia (USA: Stanford, MIT, CMU, JHU, ..; Asia: NAIST, …; Europe: …)

Industry (GAFA)

Government (US: DARPA, IARPA, more than NSF / Europe/France: national funding agencies (ANR), EC)

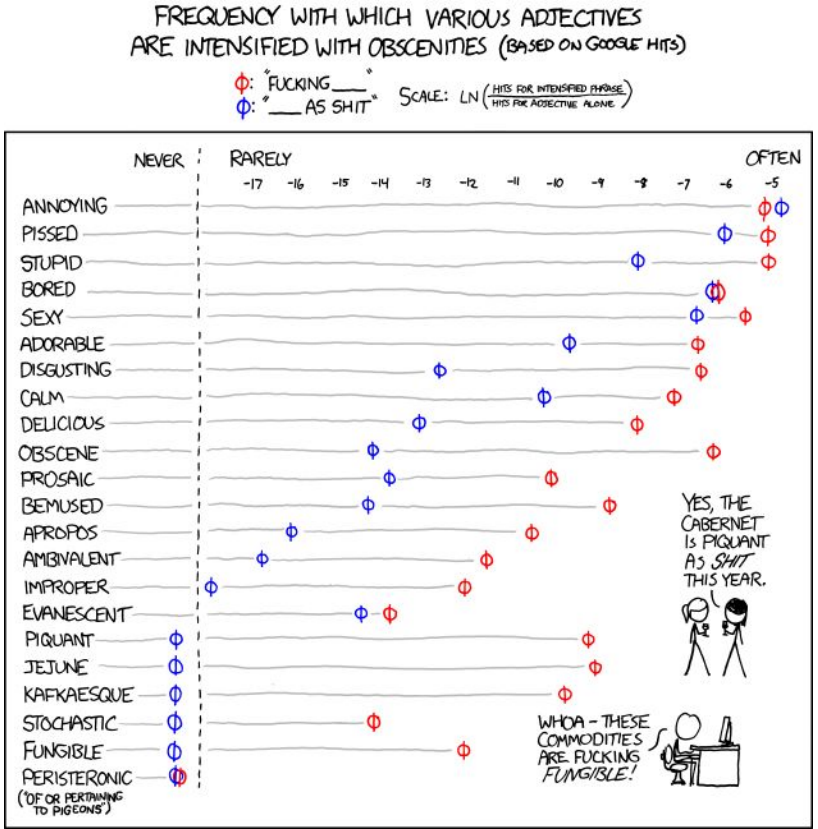
Applications

- Information extraction, information retrieval, text mining (ex.: opinion surveys)
- Text generation, text simplification, automatic summarisation
- Spelling correction (writing aid, post-OCR, normalisation of noisy/non-canonical texts)
- Machine translation, computer-aided translation
- Chatbots, conversational agents, question answering systems
- Medical applications (early diagnosis, language-based medical monitoring…)
- **Applications in linguistics** (modelling languages and their evolution, sociolinguistic studies…)
- **Digital humanities** (exploitation of text documents, for instance in historical research)

Academic applications: comp. linguistics

Examples

- Language modelling (synchronic, diachronic), with a number of approaches: formal, corpus-based, simulation-based, psycholinguistics, neurolinguistics
- Sociolinguistics



xkcd.com

Academic applications: digital humanities

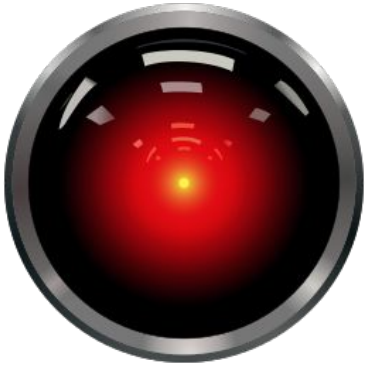
Examples

- Exploitation of textual data for research in other domains (history, philology…)
- Computational epigraphy
  (in collaboration with image processing specialists)

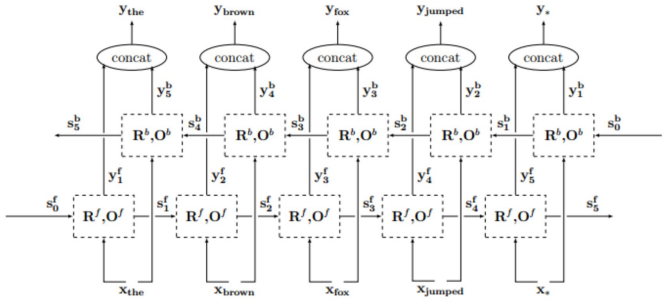
Speech and language processing today

NLP and AI

- NLP is one of the areas within “old” AI
  - AI = computationally simulate human behaviours requiring intelligence
  - Among them: understanding, producing and transforming speech / language



- One of the areas taking advantage of the “new” AI
  - In particular: deep learning
  - *confusion between objectives and means*



NLP and AI

- Neural approaches have resulted in major improvements, esp. in:
  - Machine translation
  - Semantic analysis
- However,
  - Technically complex approaches (training times…)
  - It is difficult to “correct” a neural model
  - Often require huge amounts of training data
  - Models are dependent to the characteristics of training data

What is still really hard?

- **Many languages are more difficult to process than English**
  - Low-resource languages (Turkish, Romanian, Icelandic, Inuktikut…)
  - Morphologically rich languages (Czech, Finnish, Basque, Inuktikut…)
  - For machine translation: very divergeant language pairs (Russian<->Chinese)
- **A number of tasks are really difficult**
  - Semantics / pragmatics
  - How can we represent meaning?
  - How can we represent world knowledge?
- **New and/or difficult types of data**
  - Noisy textual data
  - Data in context
  - Spontaneous dialogue

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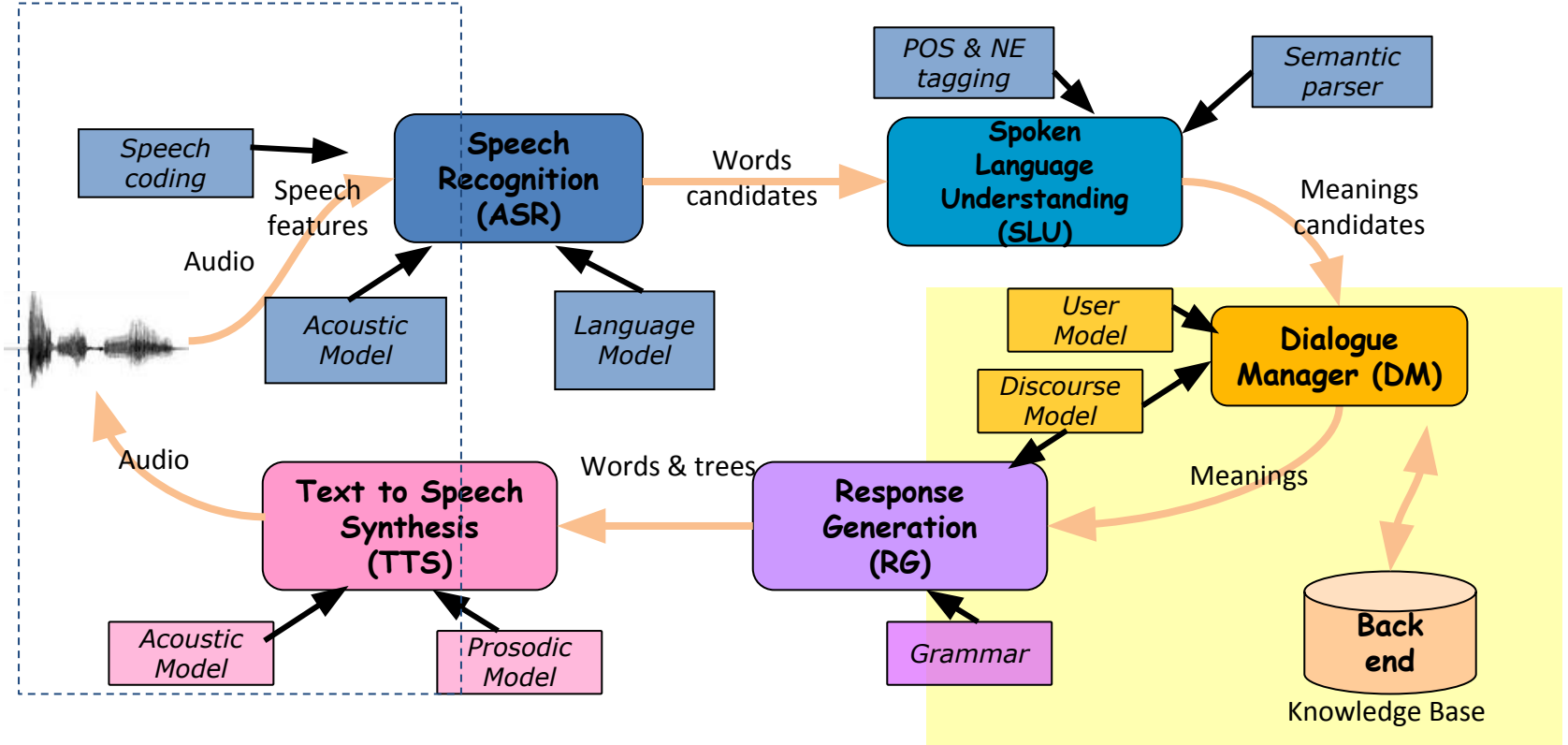
This course

Course roadmap

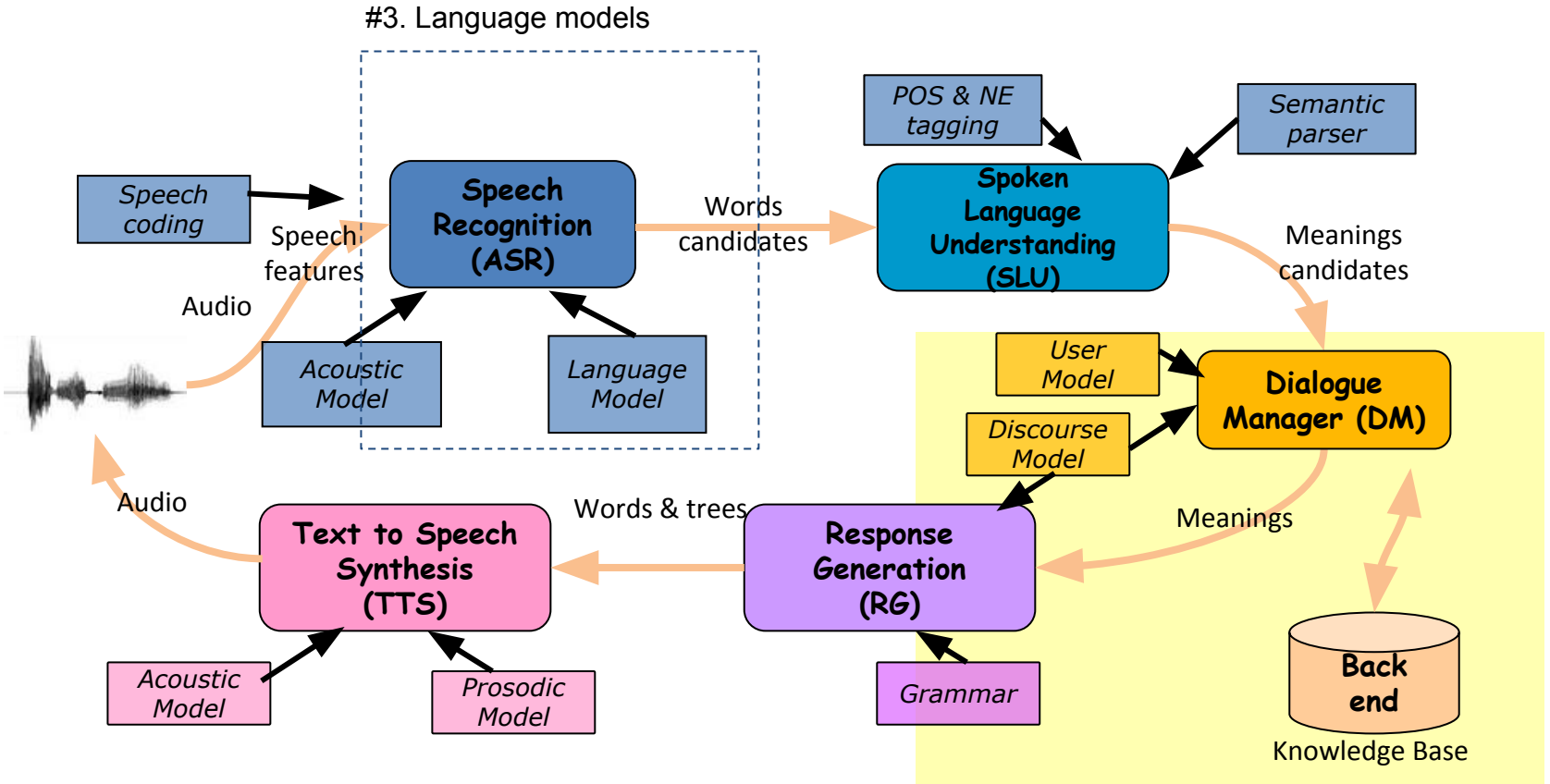
1. Introduction to speech and language processing
2. Acoustic modeling
3. Language modeling
4. Language Processing in the wild: Word embeddings and noisy texts
5. Formal Grammars and Syntax
6. Parsing
7. Lost in translation
8. Conclusion: Open questions and hot topics

Course roadmap

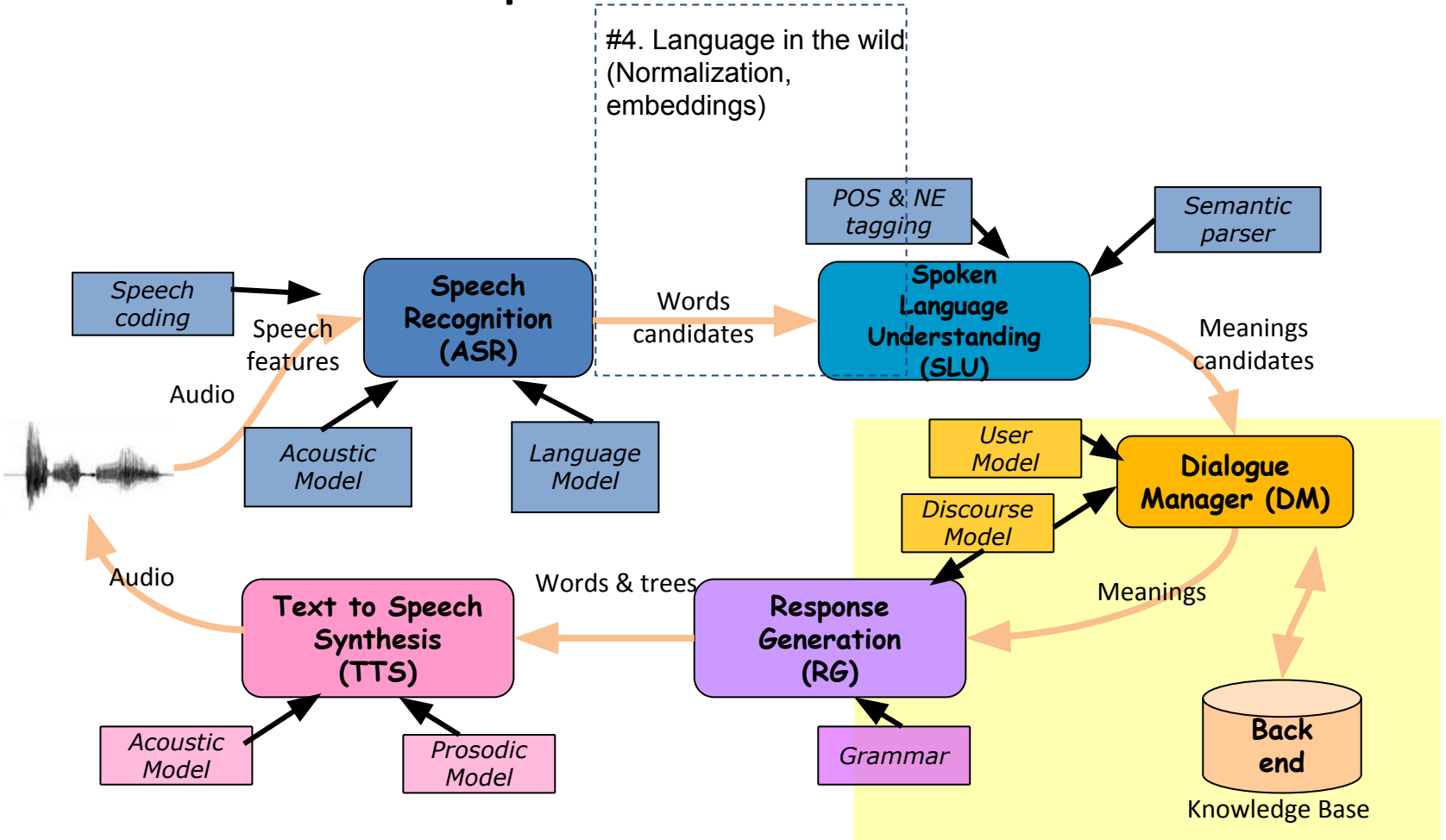
#2. Speech features & Acoustic models



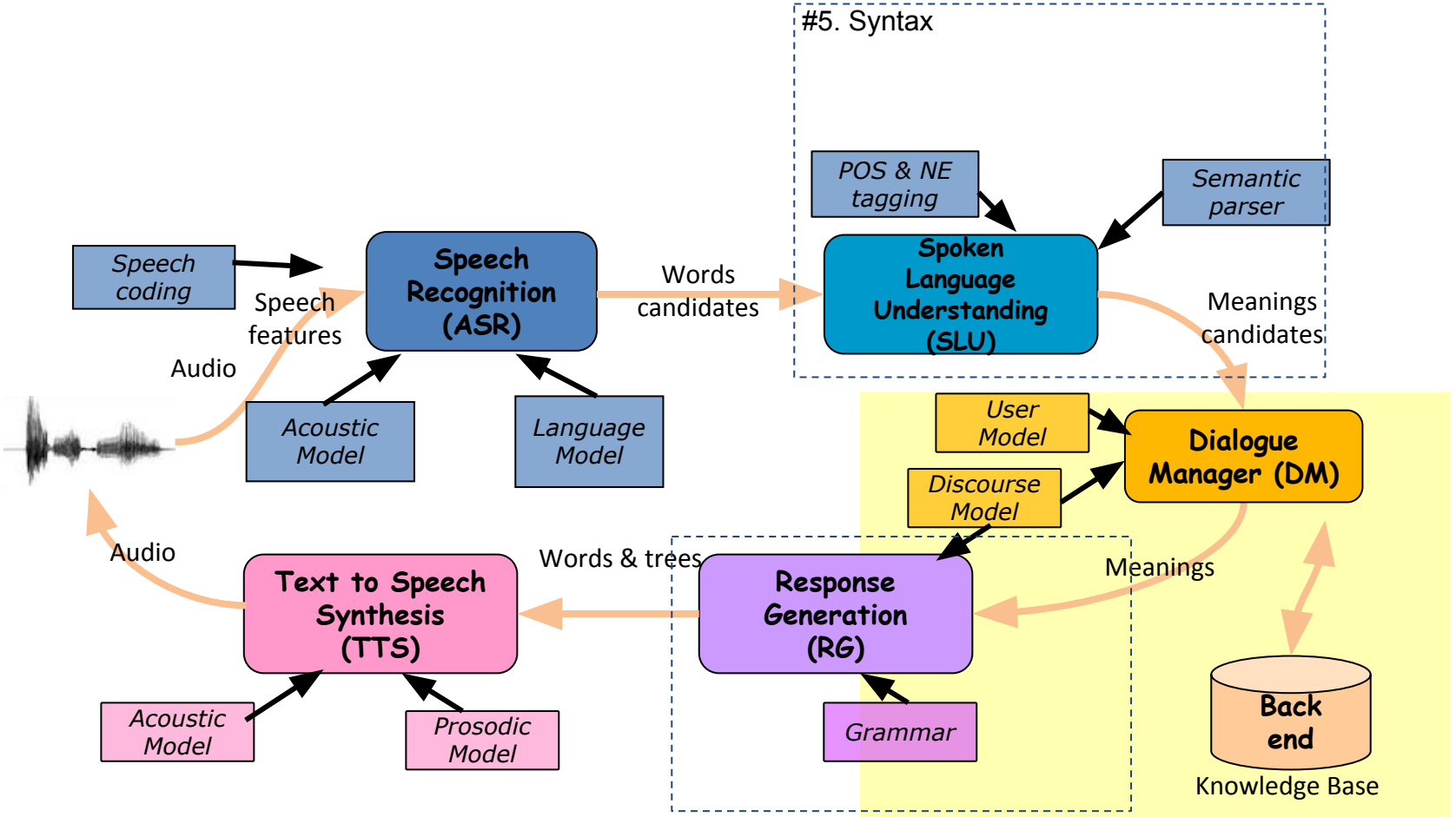
Course roadmap



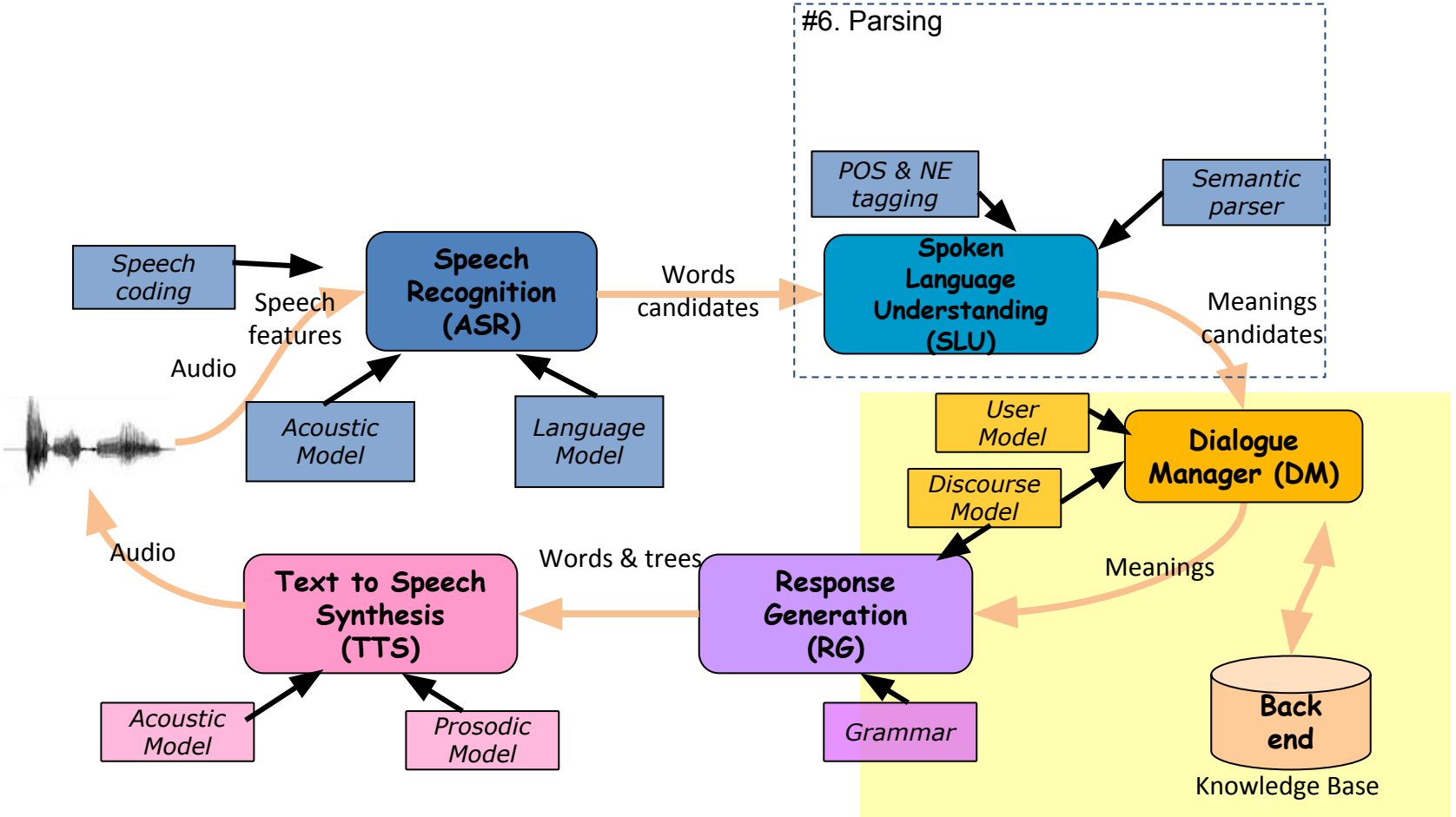
Course roadmap



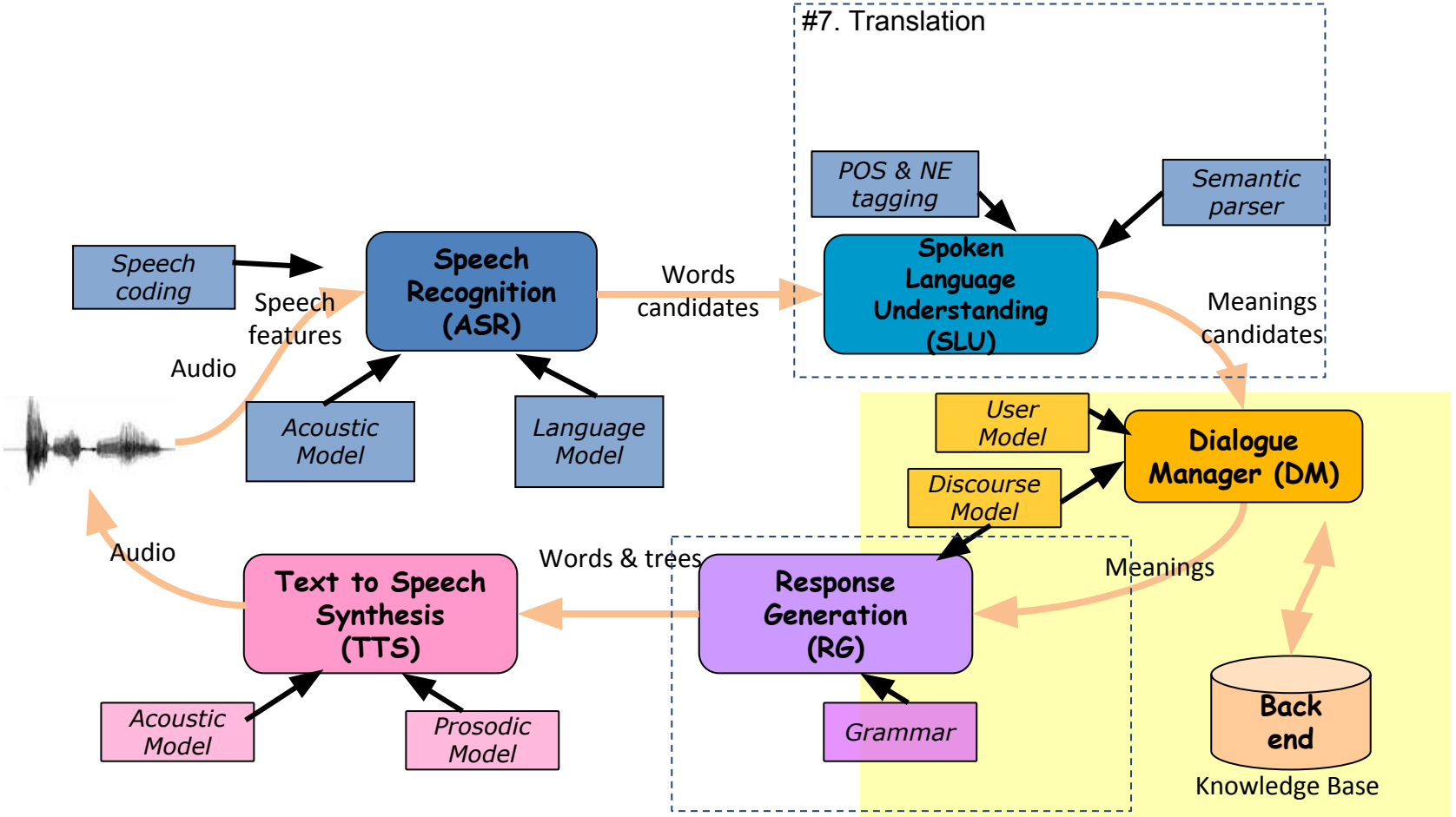
Course roadmap



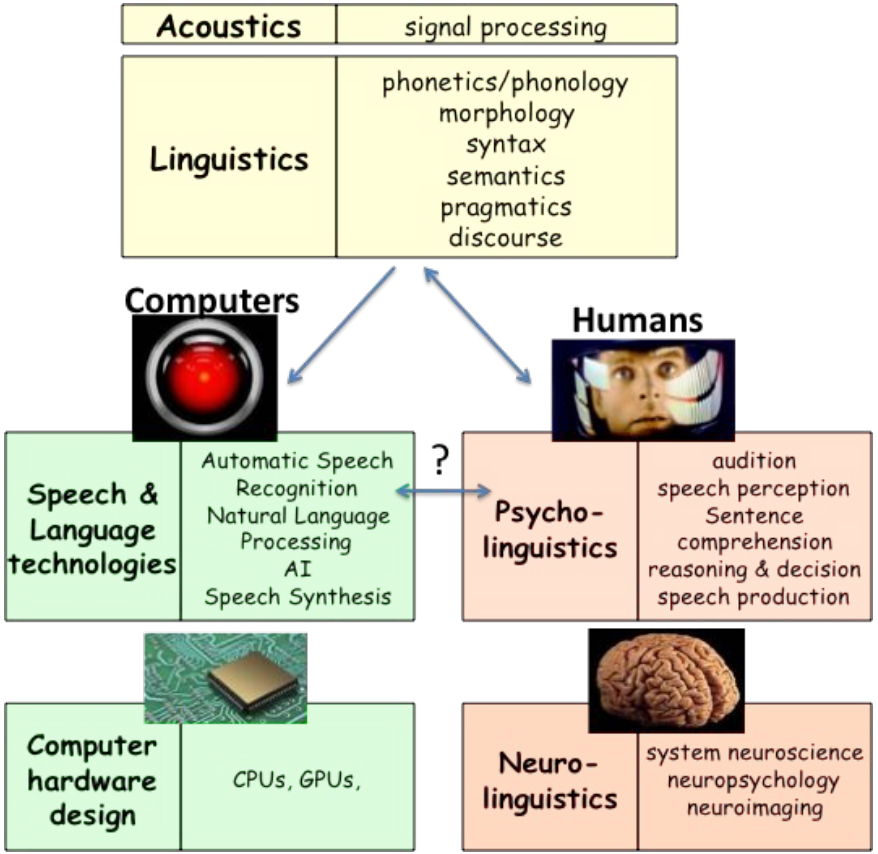
Course roadmap



Course roadmap



#8. New directions, challenges



Course logistics

#1: Intro (Sagot & Dupoux)

#2: ASR1 (Dupoux & Zeghidour)**

#3: ASR2 (Dupoux, Zeghidour, Riad)**

#4: NLP1 (Sagot)**

#5: NLP2 (Sagot)**

#6: NLP3 (Sagot)*

#7: Translation (Guest: Schwenk)

#8: Conclusion (Sagot & Dupoux)

- 4**+1* TDs & Assignments
  - 75% note
  - Bring your computer. Install virtual box
  - Notés entre 0 et 3.
- On-line Quizz
  - 25% note

On-line Quizz

https://pollev.com/emmanueldupo031

Screen name: Your name

Question (you can only click once):

Are personal assistants at home raising ethical issues regarding data privacy?

1. Yes
2. No
3. Don’t know