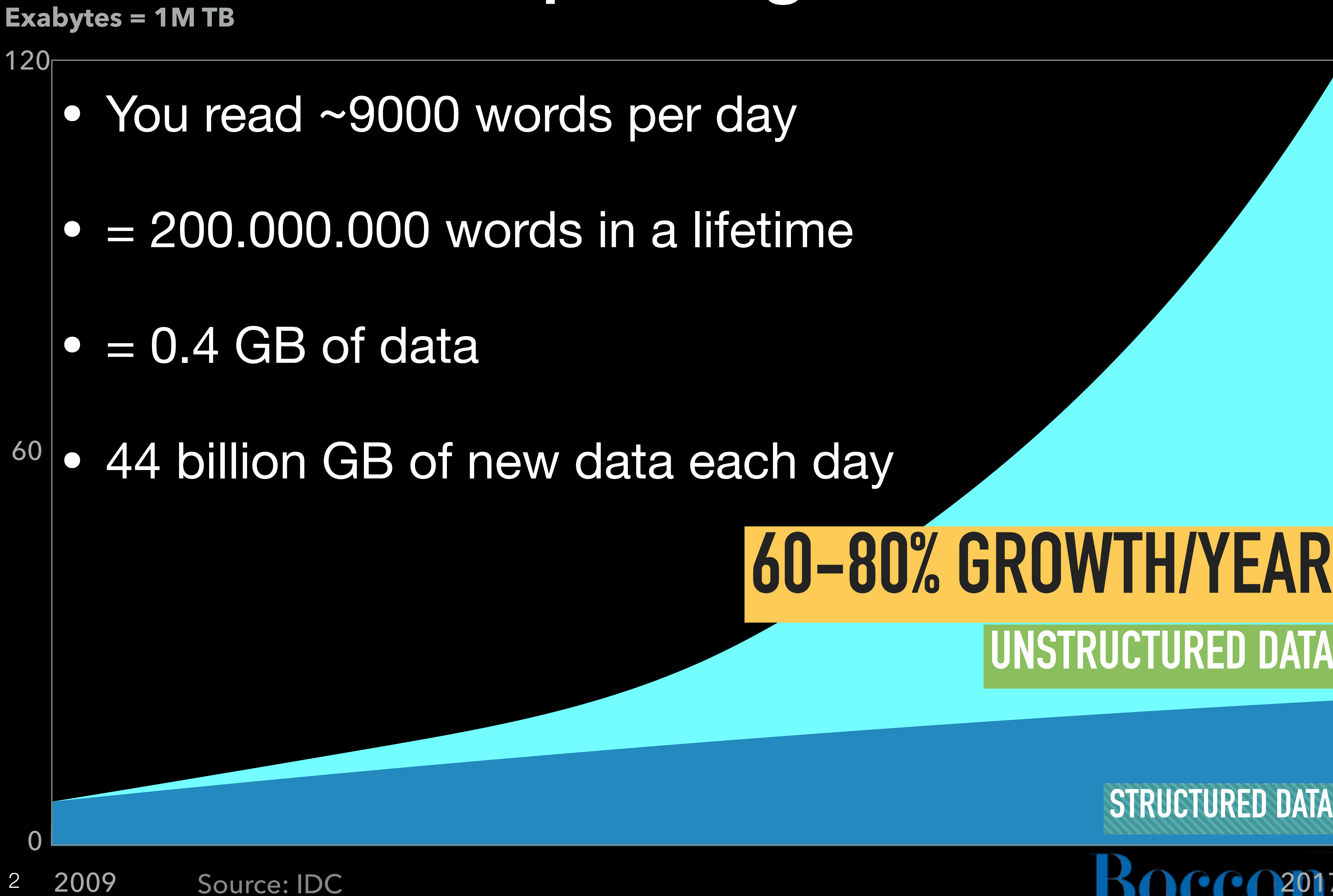
Let's start!

Today's Goals

- Understand where NLP comes from
- Learn about the different steps of preprocessing
- Understand the use of
  - parts of speech,
  - parsing, and
  - named entities

Text is an exploding data source

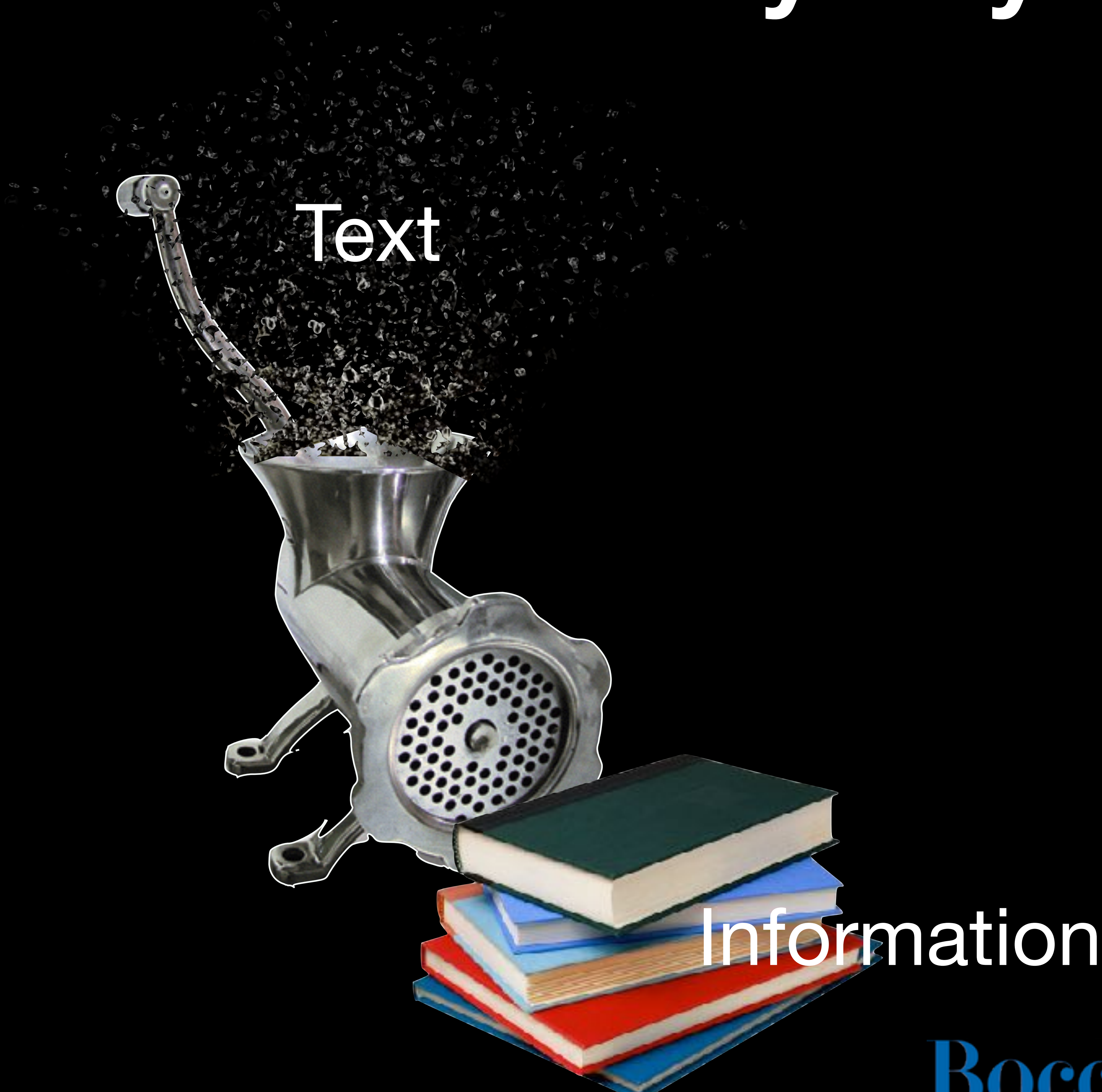
- You read ~9000 words per day
- = 200.000.000 words in a lifetime
- = 0.4 GB of data
- 44 billion GB of new data each day



NLP is booming

 Source: Tractica

So, what's NLP anyway?



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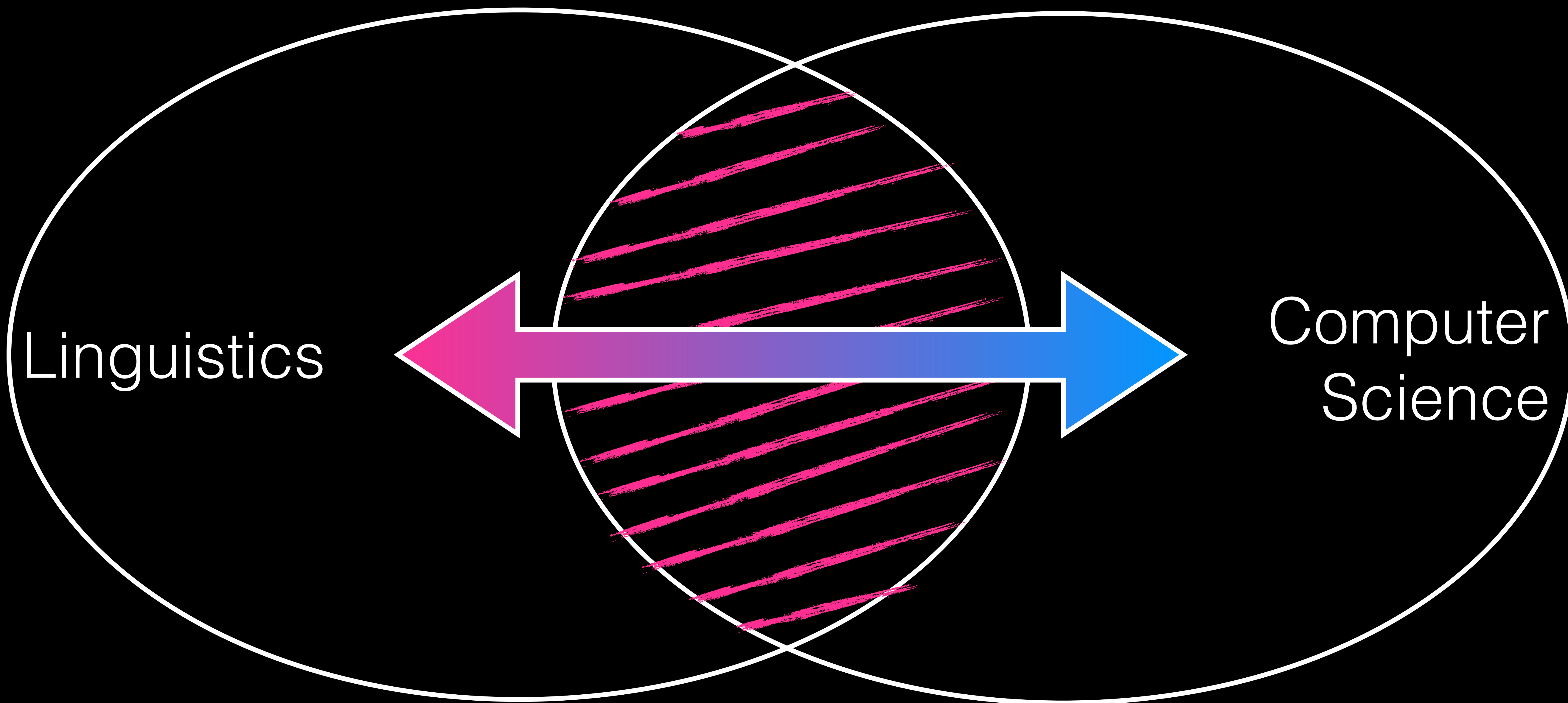
The two sides of NLP



informed linguistic hypotheses large-scale statistical analysis

A very Brief History of NLP

Symbolic Processing

Handwritten rules and logic

for input,

output,

and processing

Epoch 1

Statistical revolution

Statistical NLP

Engineered input

Defined output,

Automatic processing

Epoch 2

Deep learning

Deep Learning for NLP

Defined input and output,

Learned representations

end-to-end processing

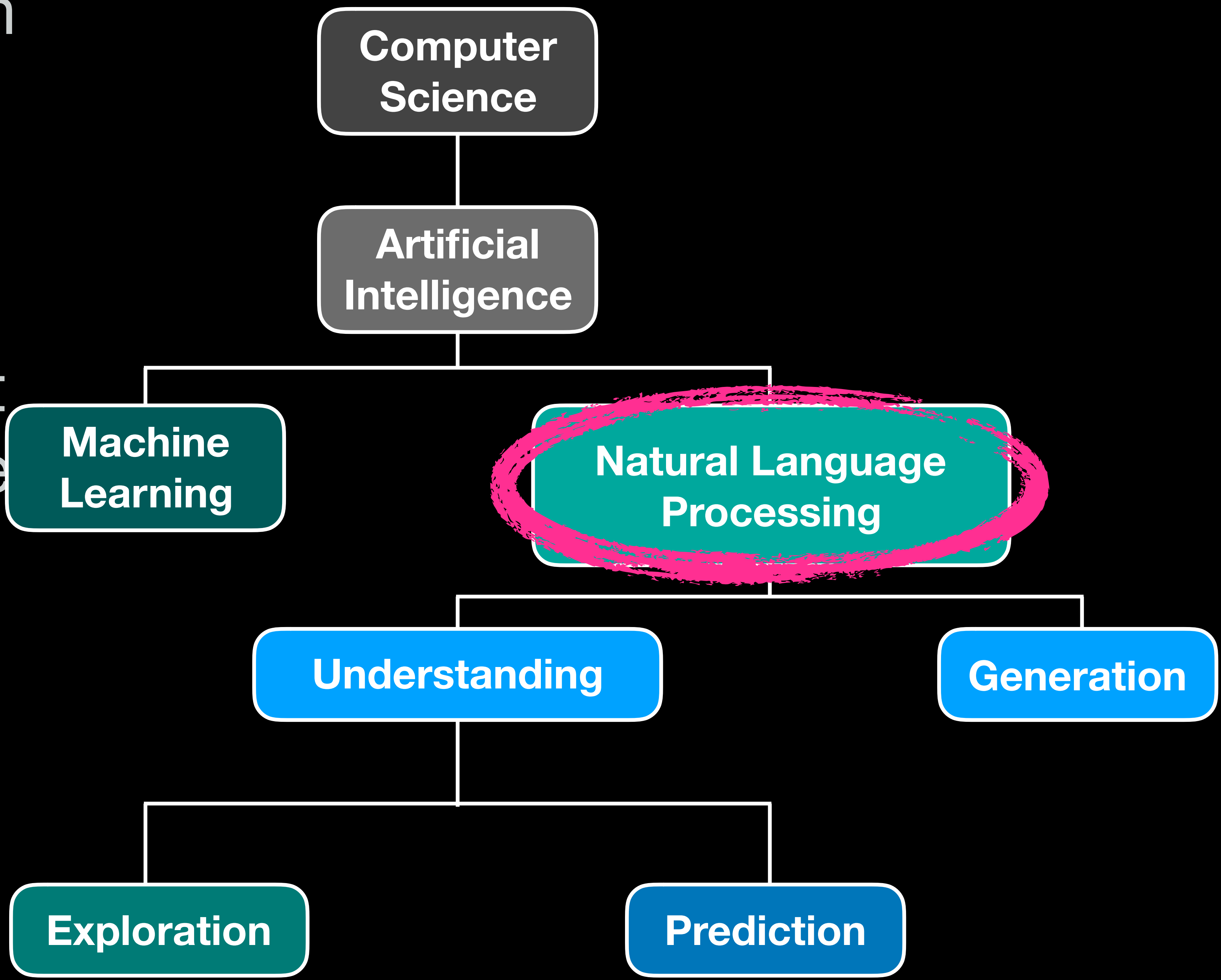
Epoch 3

approx. 1980s

2015

Structure of NLP

- Extract information from text: topics, trends
- Classify text sentiment, content type, author profile
- Generate text: translations, automated responses



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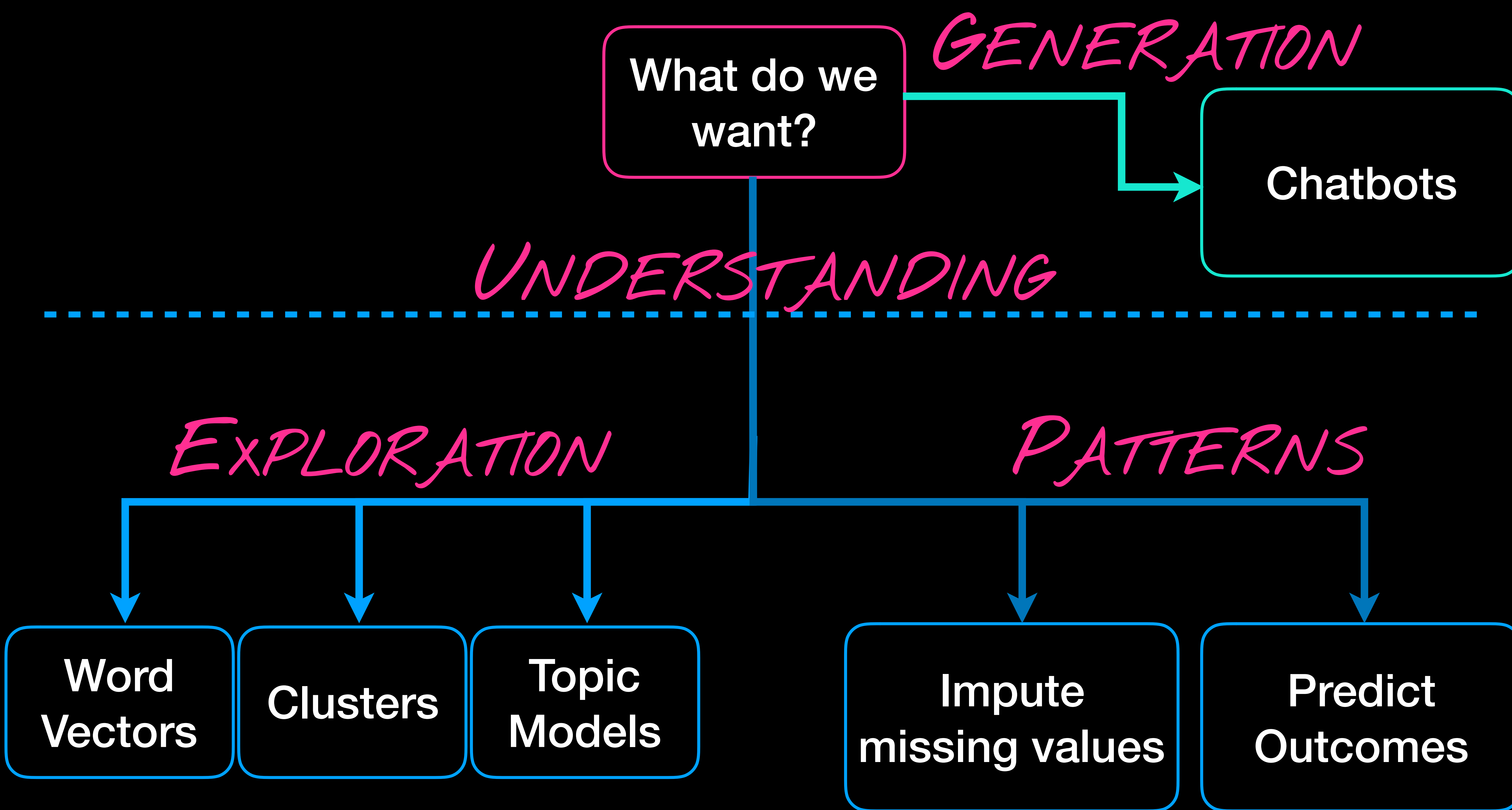
Two Uses of NLP



Linguistic Analysis

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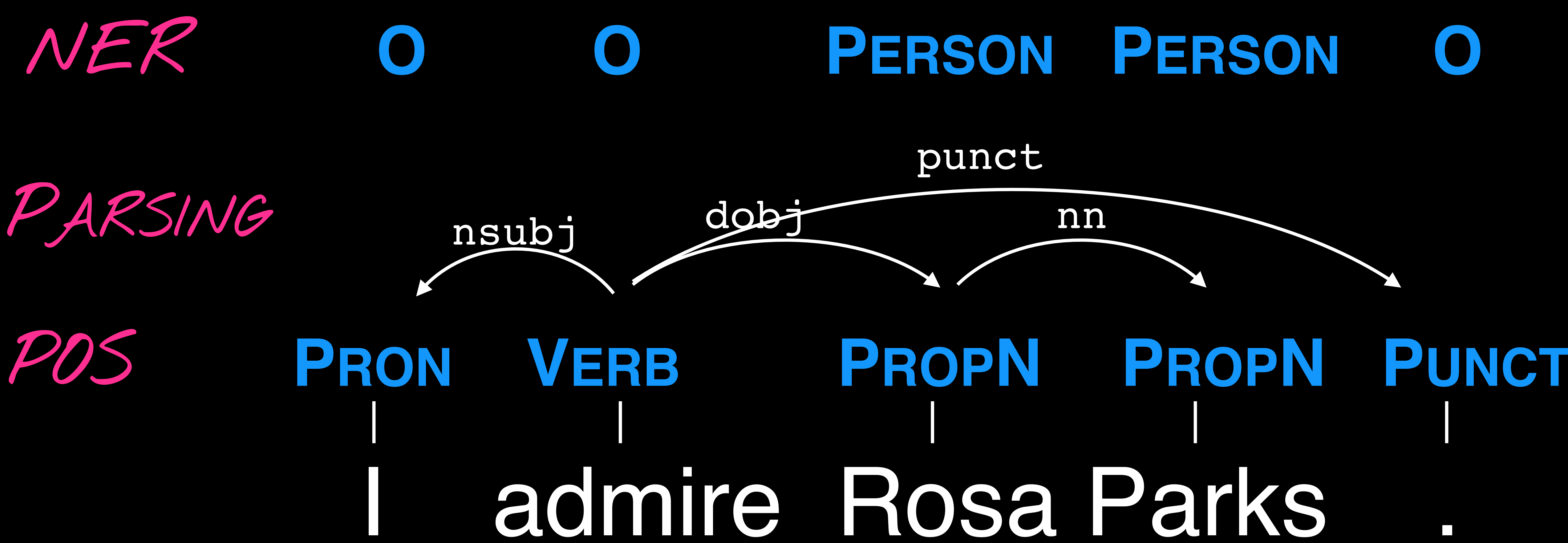
Examples of Analysis



Pre-processing

Pre-processing steps

```
<div id="text">I've been in New York
in 2011, but didn’t like it. I
preferred Los Angeles.</div>
```

GOAL: MINIMIZE VARIATION

Pre-processing steps

- Remove formatting (e.g. HTML)
- Segment sentences
- Tokenize words
- Normalize words
    - numbers
    - lemmas vs. stems
- Remove unwanted words
    - stopwords
    - content words (use POS tagging!)
- join collocations

```
I've been in New York in
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```


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```
i 've been in new york
in 0000 , but did n't
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i preferred los
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0000 , but do not like
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i prefer los angeles .
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```
i new york 0000 , like .

i prefer los angeles .
```


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```
new york 0000 like

prefer los angeles
```

CONTENT = (NOUN, VERB, NUM)

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```
new_york 0000 like

prefer los_angeles
```


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Pre-processing steps

<div id="text">I've been in New York in 2011, but didn’t like it. I preferred Los Angeles.</div>

MINIMIMAL VARIATION

"BAG OF WORDS"

new_york 0000 like

prefer los_angeles

Parts of Speech

POS tagging

Grassfed highland Chianina beef with handcut fries and seasonal micro greens 29,–

Rich, **tender**, **golden-brown** beef with **crisp** fries and **tender** greens 18,–

Savory beef with **delicious** fries and **tasty** salad 12,–

ADJs = price?

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POS tagging

POS

PRON	VERB	PROPN	PROPN	PUNCT
I	admire	Rosa	Parks	.

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POS tagging

Open class words	Closed class words	Other
ADJ adjectives: *awesome, red*	**ADP** adpositions: *over, before*	**PUNCT** punctuation marks: *!, ?, –*
ADV adverbs: *quietly, where, never*	**AUX** auxiliary/modal verbs: *have* (been), *could* (do), *will* (change)	**SYM** symbols: *%, $, :)*
INTJ interjections: *ouch, shhh*	**CCONJ** coordinating conjunctions: *and, or, but*	**X** other: *pffffrt*
NOUN nouns: *book, war*	**DET** determiners: *a, they, which*	
PROPN proper nouns: *Rosa, Twitter*	**NUM** numbers. Exactly what you would think it is...	
VERB full verbs: (she) *codes*, (they) *submitted*	**PART** particles: *'s*	
	PRON pronouns: *you, her, myself*	
	SCONJ subordinating conjunctions: *since, if, that*	

POS tagging

show `{VERB, NOUN}`

PART show

show

PRON show

show

show

DET show

show

ADJ show

Structured prediction: depends on the POS of a previous word

Parsing

Dependency Parsing

Facebook eventually **acquire**d **WhatsApp** after hard negotiations. → **acquire(Facebook, WhatsApp)**

WhatsApp was **acquire**d by **Facebook**. → **acquire(Facebook, WhatsApp)**

Facebook subsidiary **WhatsApp** to acquire new look. → **acquire(WhatsApp,** look**)**

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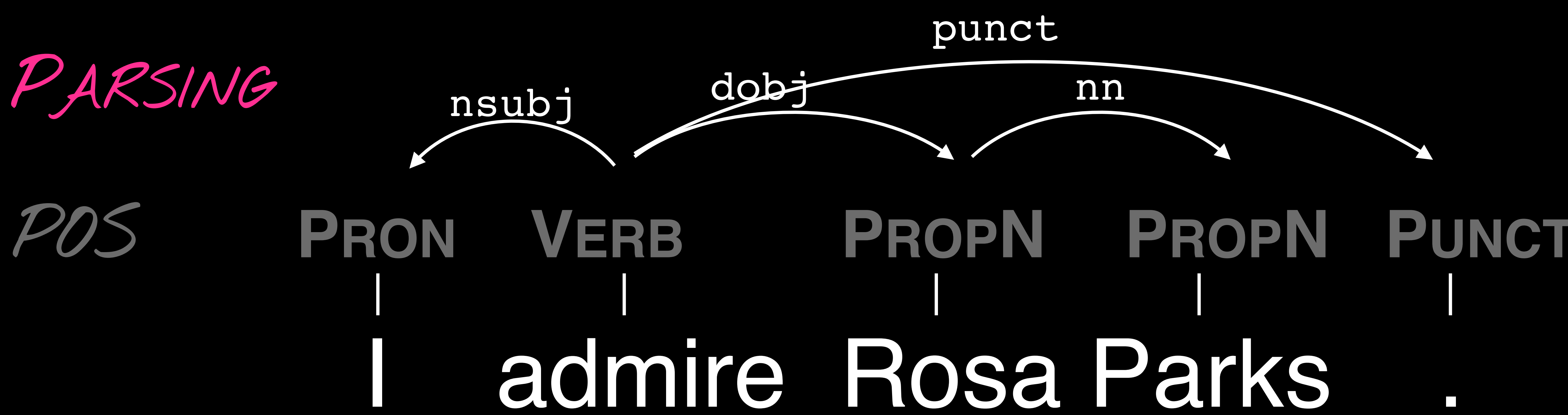
Dependency Parsing



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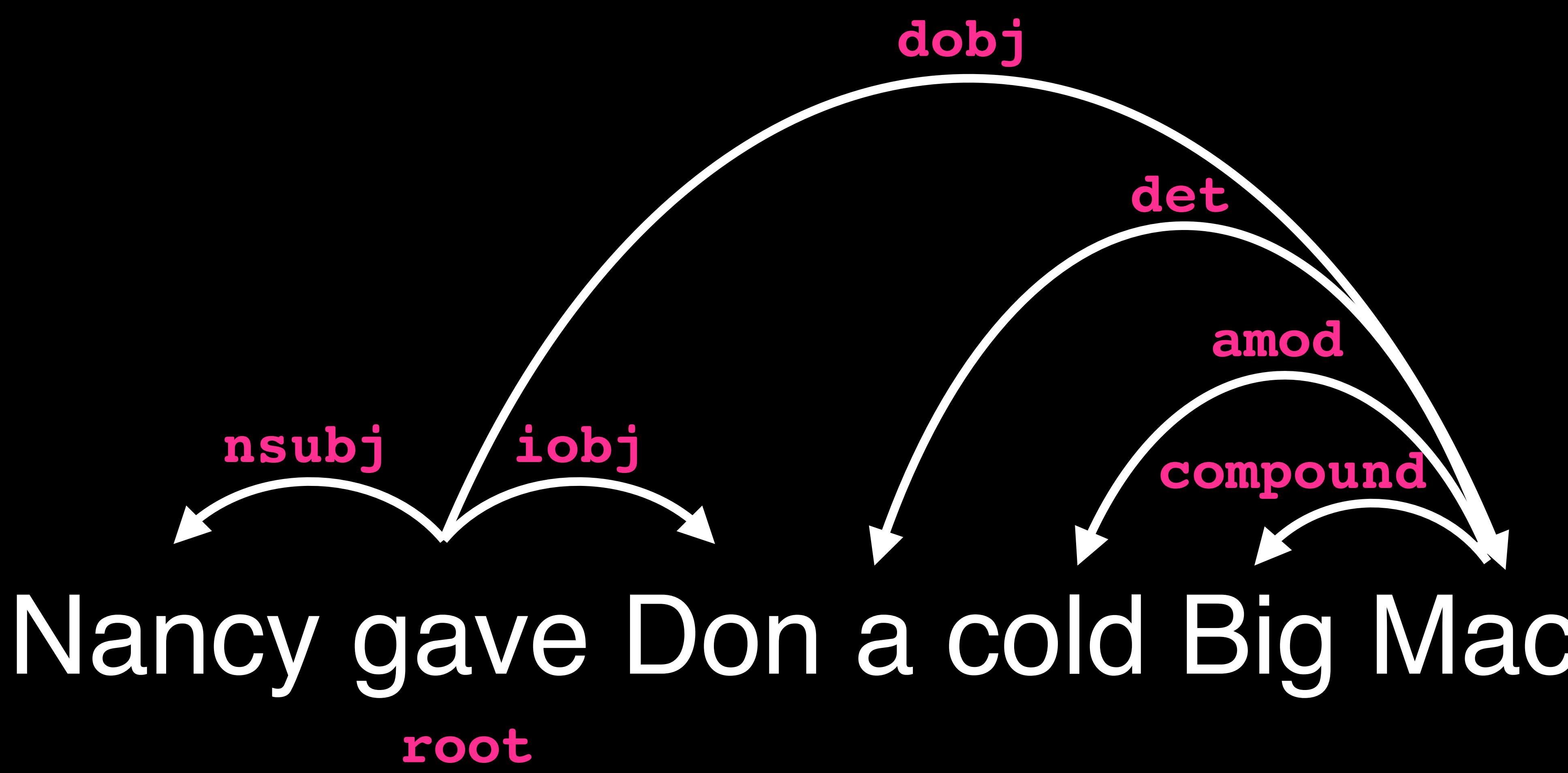
Dependency Parsing

acl: adjectival clause
advcl: adverbial clause modifier
advmod: adverbial modifier
amod: adjectival modifier
appos: appositional modifier
aux: auxiliary
case: case marking
cc: coordinating conjunction
ccomp: clausal complement
clf: classifier
compound: compound
conj: conjunct
cop: copula
csubj: clausal subject
dep: unspecified dependency
det: determiner
discourse: discourse element
dislocated: dislocated elements
dobj: direct object
expl: expletive
fixed: fixed multiword expression
flat: flat multiword expression
goeswith: goes with
iobj: indirect object
list: list
mark: marker
nmod: nominal modifier
nsubj: nominal subject
nummod: numeric modifier
obl: oblique nominal
orphan: orphan
parataxis: parataxis
punct: punctuation
reparandum: overridden disfluency
root: root
vocative: vocative
xcomp: open clausal complement



Named Entities

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Named Entities

Places:

```
{'Ada',
 'Antigone',
 'Belgrade',
 'Berlin',
 'Constitución',
 'Danube',
 'Florence',
 'France',
 'Mikser',
 'Rome',
 'Santa Cruz',
 'Savamala',
 'Schlachtensee',
 'Serbia',
 'Spain',
 'Tezga',
 'Ville',
 'Wannsee'}
```


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Named Entities

NER	O	O	B-PERSON	I-PERSON	O
POS	PRON	VERB	PROPN	PROPN	PUNCT
	I	admire	Rosa	Parks	.

Named Entities

NE	Example
PERSON	
NORP (Nationality OR Religious or Political group)	
FAC (facility)	
ORG (organization)	
GPE (GeoPolitical Entity)	
LOC (locations, such as seas or mountains)	
PRODUCT	
EVENT (in sports, politics, history, etc.)	
WORK_OF_ART	
LAW	
LANGUAGE	
DATE	
TIME	
PERCENT	
MONEY	
QUANTITY	
ORDINAL	
CARDINAL (numbers)	

Wrapping up

Take Home Points

- NLP is a subfield of AI, using ML on linguistic problems to **explore**, **predict**, and **generate** text
- **Preprocessing** removes noise and unwanted variation
- Parts of speech (**POS**) denote a word's grammatical *category*
- **Parsing** denotes a word's grammatical *function*
- **Named entities** categorize a noun's semantic type

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