CS 4650: Natural Language Processing

Alan Ritter

Administrivia

- Course website: https://aritter.github.io/CS-7650-sp22/

- Piazza and Gradescope: links on the course website
  - We will do our best to answer questions within 24 hours (or Monday for questions asked over the weekend).

- TA Office hours:
  - See spreadsheet

Instructor

Alan Ritter

alan.ritter@cc.gatech.edu

Teaching Assistants

Ashutosh Baheti

abaheti95@gatech.edu

Raj Sanjay Shah

rajsanjayshah@gatech.edu

Vinay Sammangi

vsammangi3@gatech.edu

COVID-19

Georgia Tech

Stamps Health Services

About | Coronavirus | Health Services | For Students | For Employees | Patient Portal

Covid-19 Institute Operations Updates

The most current status updates from around Georgia Tech.

Latest Updates

June 30, 2022 — Covid-19 Operations Update

Masking Guidance

The University System of Georgia encourages people to wear masks

CDC Centers for Disease Control and Prevention
CDC 24/7: Saving Lives, Protecting People™

COVID-19 County Check

Find community levels and prevention steps by county. Data updated weekly.

Select a Location (all fields required)

Georgia | Fulton County | Go

< Start Over

Medium

In **Fulton County, Georgia**, community level is **Medium**.

- If you are at high risk for severe illness, talk to your healthcare provider about whether you need to wear a mask and take other precautions
- Stay up to date with COVID-19 vaccines
- Get tested if you have symptoms

People may choose to mask at any time. People with symptoms, a positive test, or exposure to someone with COVID-19 should wear a mask.

If you are immunocompromised, learn more about how to protect yourself.

Find out more about the COVID-19 situation in **Fulton County, Georgia** with COVID-19 Data Tracker.

August 18, 2022

COVID-19

Georgia Tech

Stamps Health Services

About | Coronavirus | Health Services | For Students | For Employees | Patient Portal

Covid-19 Institute Operations Updates

The most current status updates from around Georgia Tech.

Latest Updates

June 30, 2022 — Covid-19 Operations Update

Masking Guidance

The University System of Georgia encourages people to wear masks

CDC Centers for Disease Control and Prevention
CDC 24/7: Saving Lives, Protecting People™

COVID-19 County Check

Find community levels and prevention steps by county. Data updated weekly.

Select a Location (all fields required)

Georgia | Fulton County | Go

< Start Over

Medium

In **Fulton County, Georgia**, community level is **Medium**.

- If you are at high risk for severe illness, talk to your healthcare provider about whether you need to wear a mask and take other precautions
- Stay up to date with COVID-19 vaccines
- Get tested if you have symptoms

People may choose to mask at any time. People with symptoms, a positive test, or exposure to someone with COVID-19 should wear a mask.

If you are immunocompromised, learn more about how to protect yourself.

Find out more about the COVID-19 situation in **Fulton County, Georgia** with COVID-19 Data Tracker.

August 18, 2022

You are encouraged to wear a mask while in this class.

Prerequisites

- Probability
- Linear Algebra
- Multivariable Calculus
- Programming / Python experience
- Prior exposure to machine learning very helpful but not required

Prerequisites

- Probability
- Linear Algebra
- Multivariable Calculus
- Programming / Python experience
- Prior exposure to machine learning very helpful but not required

There will be a lot of math and programming!

Coursework

- 4 Programming Projects (fairly substantial implementation effort)
  - Logistic Regression
  - Text classification
  - Named entity recognition (BiLSTM-CNN-CRF)
  - Neural chatbot (Seq2Seq with attention)

Coursework

- 4 Programming Projects (fairly substantial implementation effort)
  - Logistic Regression
  - Text classification
  - Named entity recognition (BiLSTM-CNN-CRF)
  - Neural chatbot (Seq2Seq with attention)
- 2 written assignments + midterm exam
  - Mostly math problems related to ML / NLP

Coursework

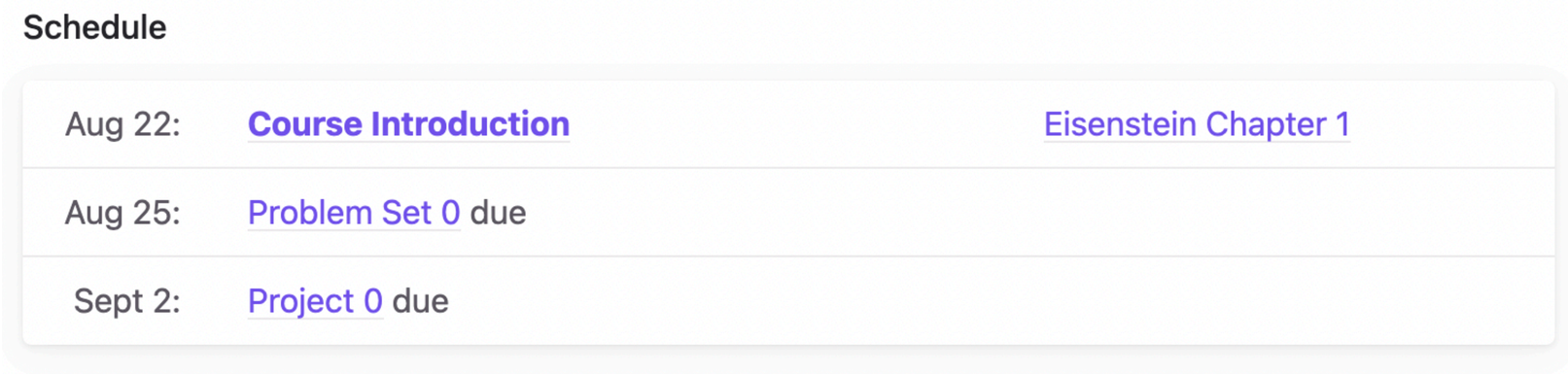
- 4 Programming Projects (fairly substantial implementation effort)
  - Logistic Regression
  - Text classification
  - Named entity recognition (BiLSTM-CNN-CRF)
  - Neural chatbot (Seq2Seq with attention)
- 2 written assignments + midterm exam
  - Mostly math problems related to ML / NLP
- Final project (details on course website, will discuss later)

Coursework

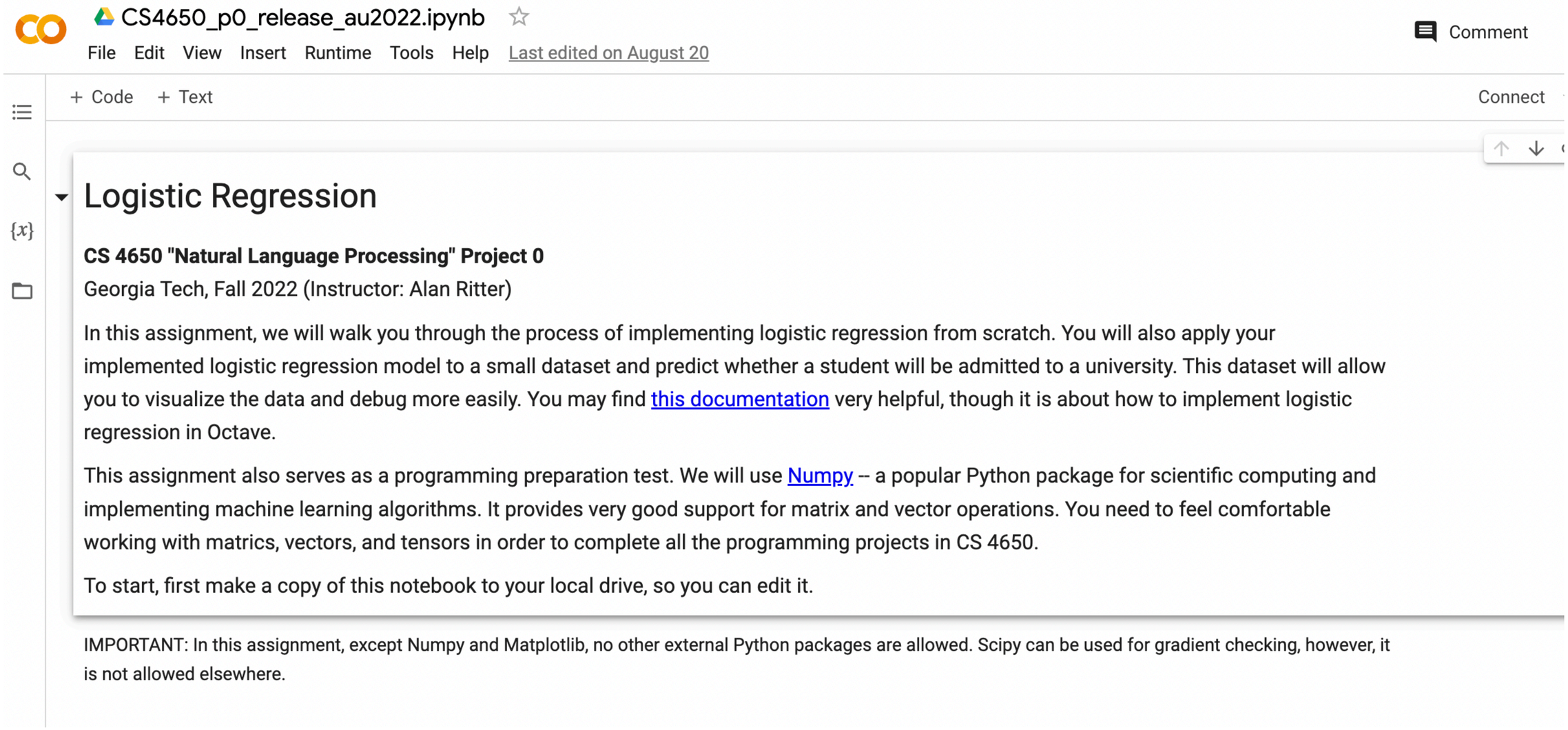
- 4 Programming Projects (fairly substantial implementation effort)
  - Logistic Regression
  - Text classification
  - Named entity recognition (BiLSTM-CNN-CRF)
  - Neural chatbot (Seq2Seq with attention)
- 2 written assignments + midterm exam
  - Mostly math problems related to ML / NLP
- Final project (details on course website, will discuss later)
- Problem Set 0 (background review) is out now and **due Thursday**.

Problem Set 1 (Background Review)

- Due this Thursday.
- Background review on probability, linear algebra, calculus.
- **Waitlisted students:** please submit PS1 by Friday if you plan to enroll in the course.
  - We can't predict whether or not you will get in, as this depends on other students dropping the class…
- Submit on Gradescope



Project 0 is also out (please look!)

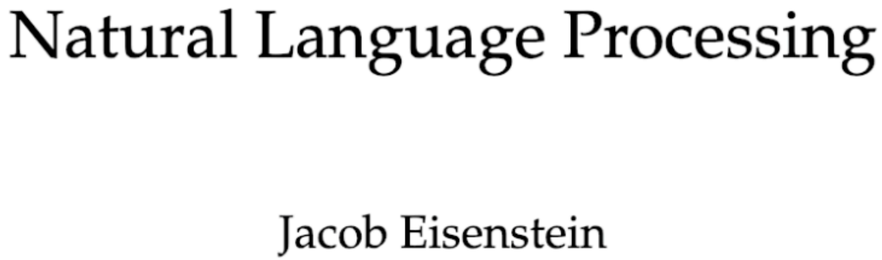


Free Textbooks! 😊

- 2 really awesome free textbooks available
  - There will be assigned readings from both
  - Both freely available online

Speech and Language Processing (3rd ed. draft)

Dan Jurafsky and James H. Martin



Not free: GPUs 😢

- Modern NLP methods require non-trivial computation
  - Training neural networks with many parameters can take a long time (it is a very good idea to start working on the assignments early!)
    - This is a big part of modern NLP methods. It is important to get experience training these networks.
  - You want to use GPUs
  - Google Colab: has free GPUs, but with some big limitations that will make the assignments very difficult to complete.
  - The programming projects are designed with Colab in mind
  - Colab Pro subscription ($10/month). This is highly recommended once we start working with PyTorch.

What’s the goal of NLP?

What’s the goal of NLP?

- Be able to solve problems that require deep understanding of text

What’s the goal of NLP?

- Be able to solve problems that require deep understanding of text
- Example: dialogue systems

What’s the goal of NLP?

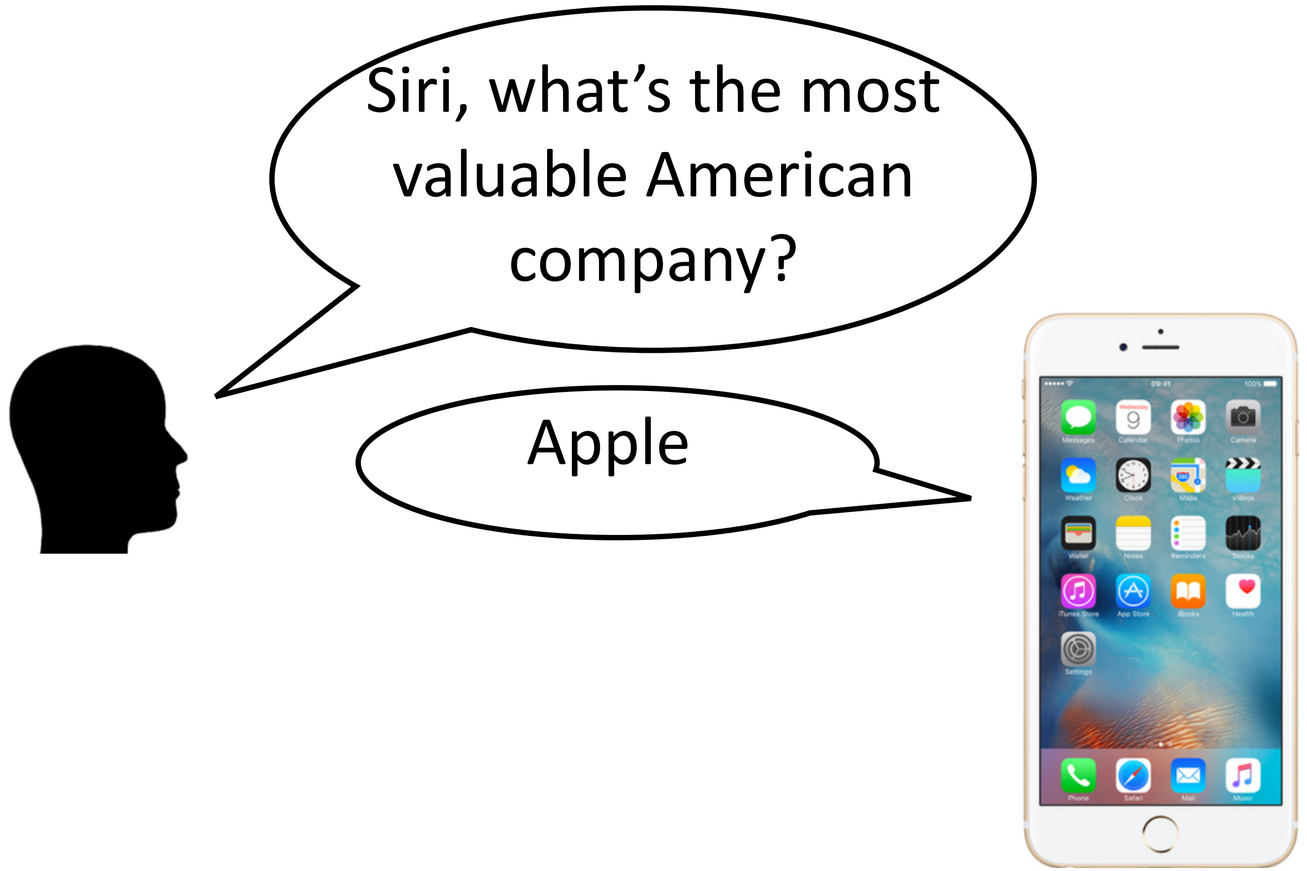
- Be able to solve problems that require deep understanding of text
- Example: dialogue systems

What’s the goal of NLP?

- Be able to solve problems that require deep understanding of text
- Example: dialogue systems

What's the goal of NLP?

- Be able to solve problems that require deep understanding of text
- Example: dialogue systems

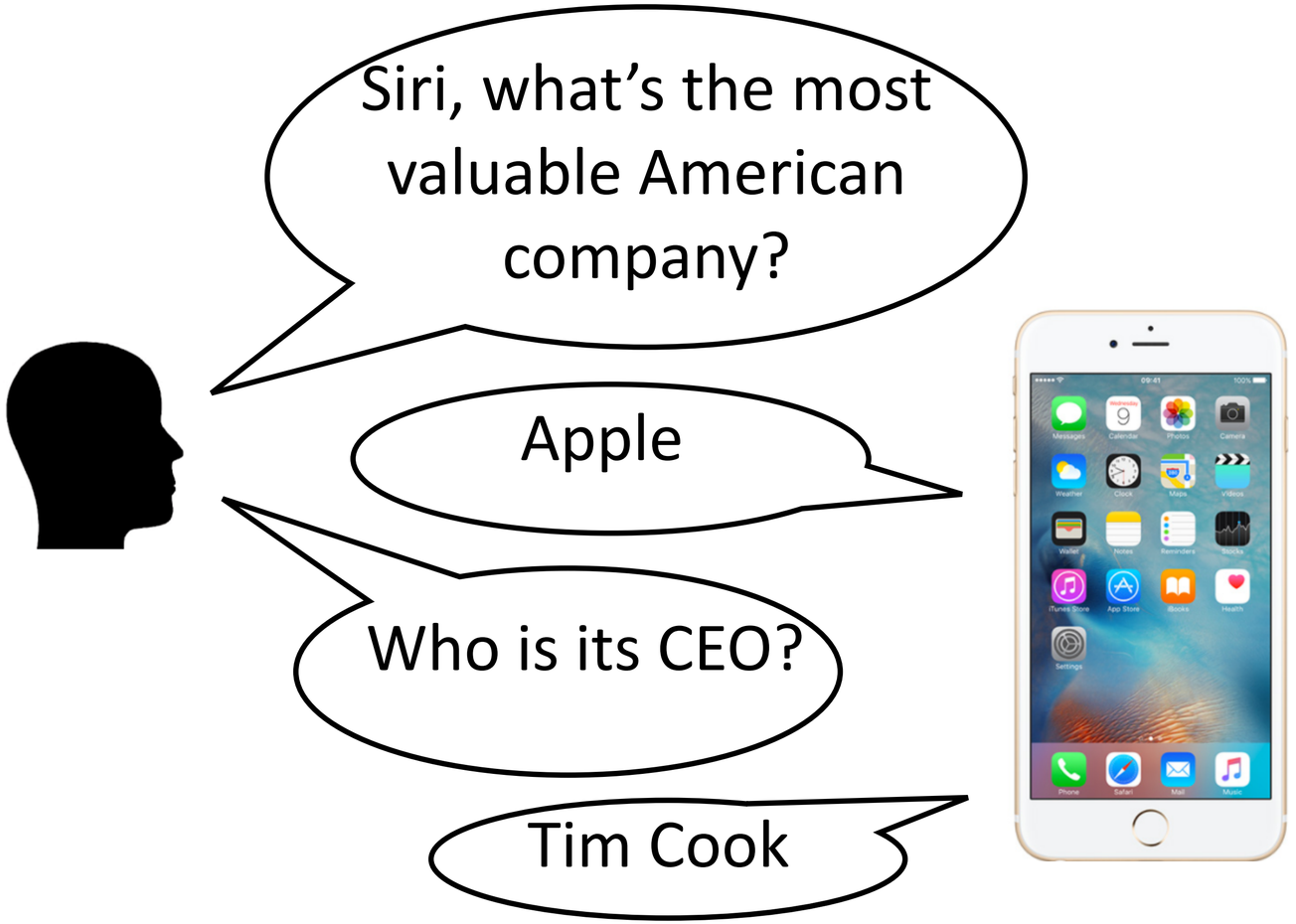


What's the goal of NLP?

- Be able to solve problems that require deep understanding of text
- Example: dialogue systems

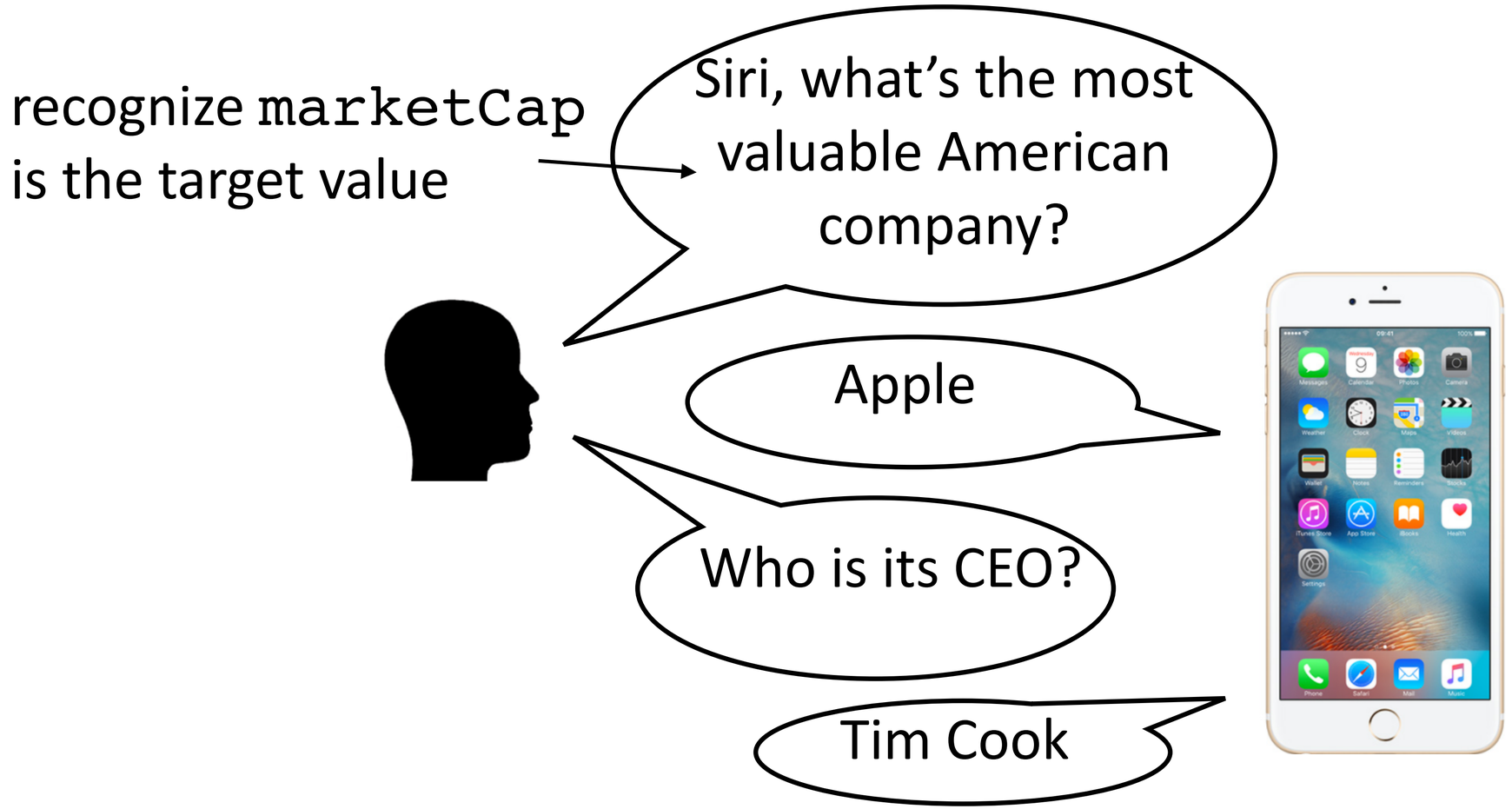
What's the goal of NLP?

- Be able to solve problems that require deep understanding of text
- Example: dialogue systems



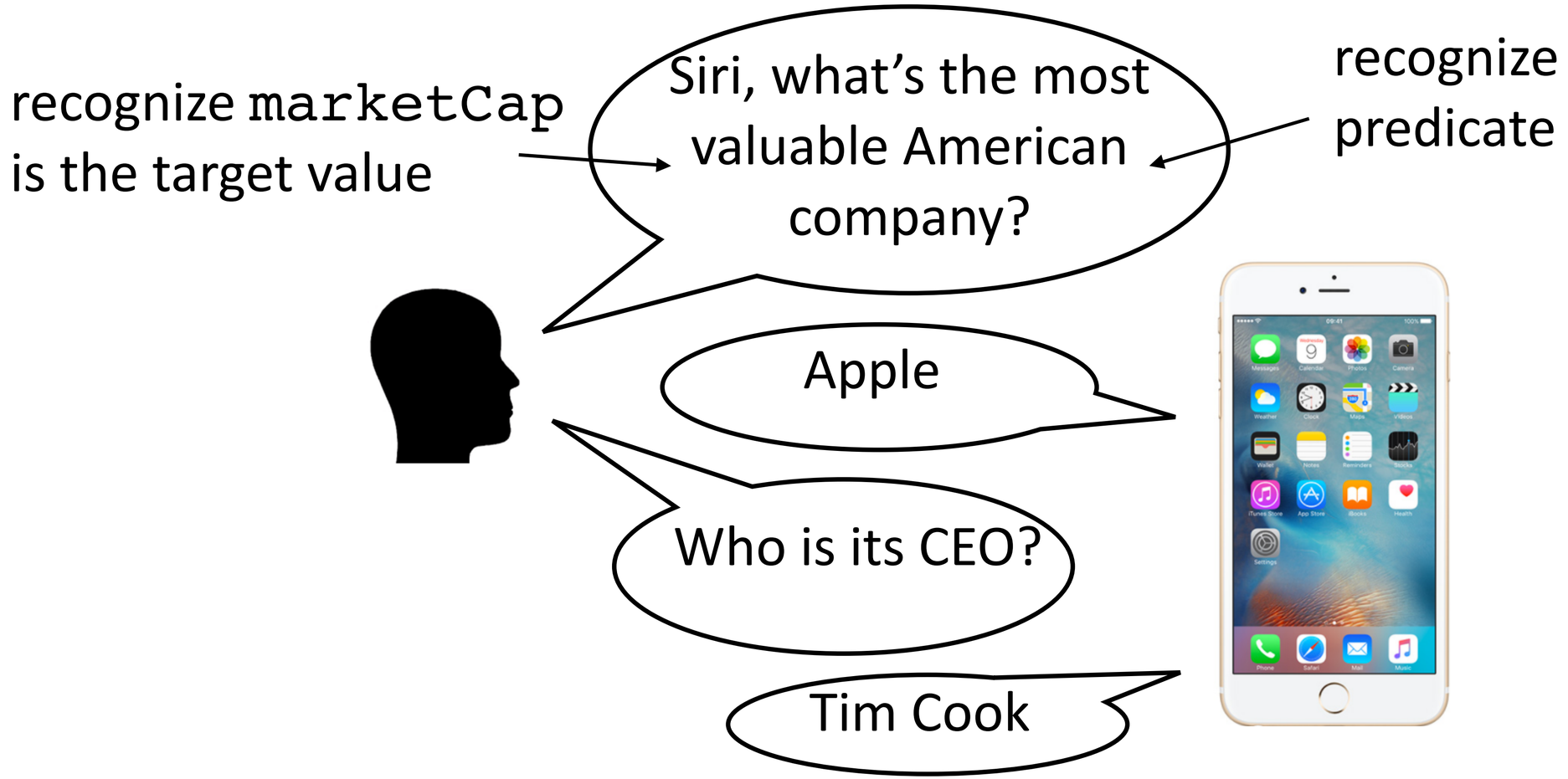
What's the goal of NLP?

- Be able to solve problems that require deep understanding of text
- Example: dialogue systems



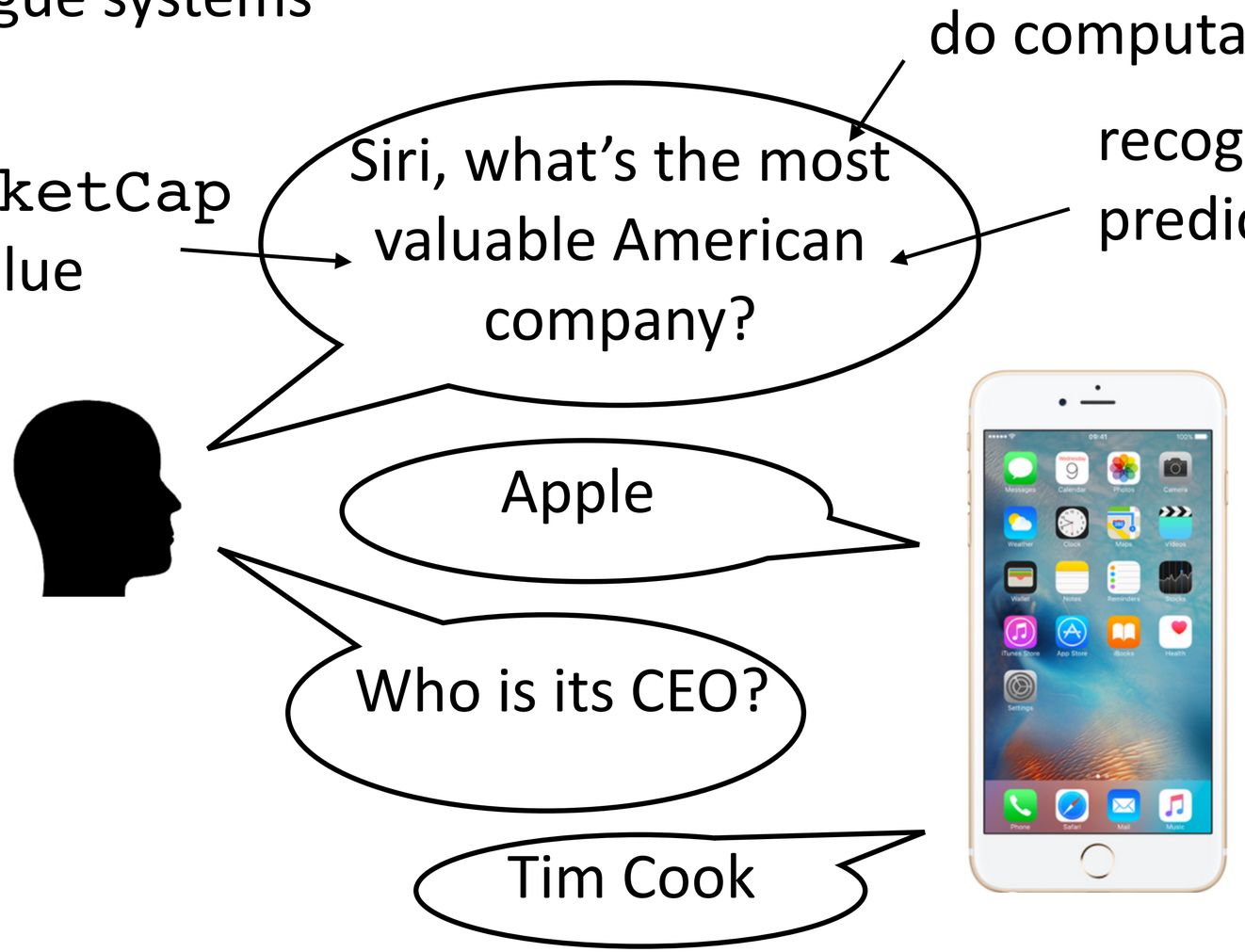
What's the goal of NLP?

- Be able to solve problems that require deep understanding of text
- Example: dialogue systems



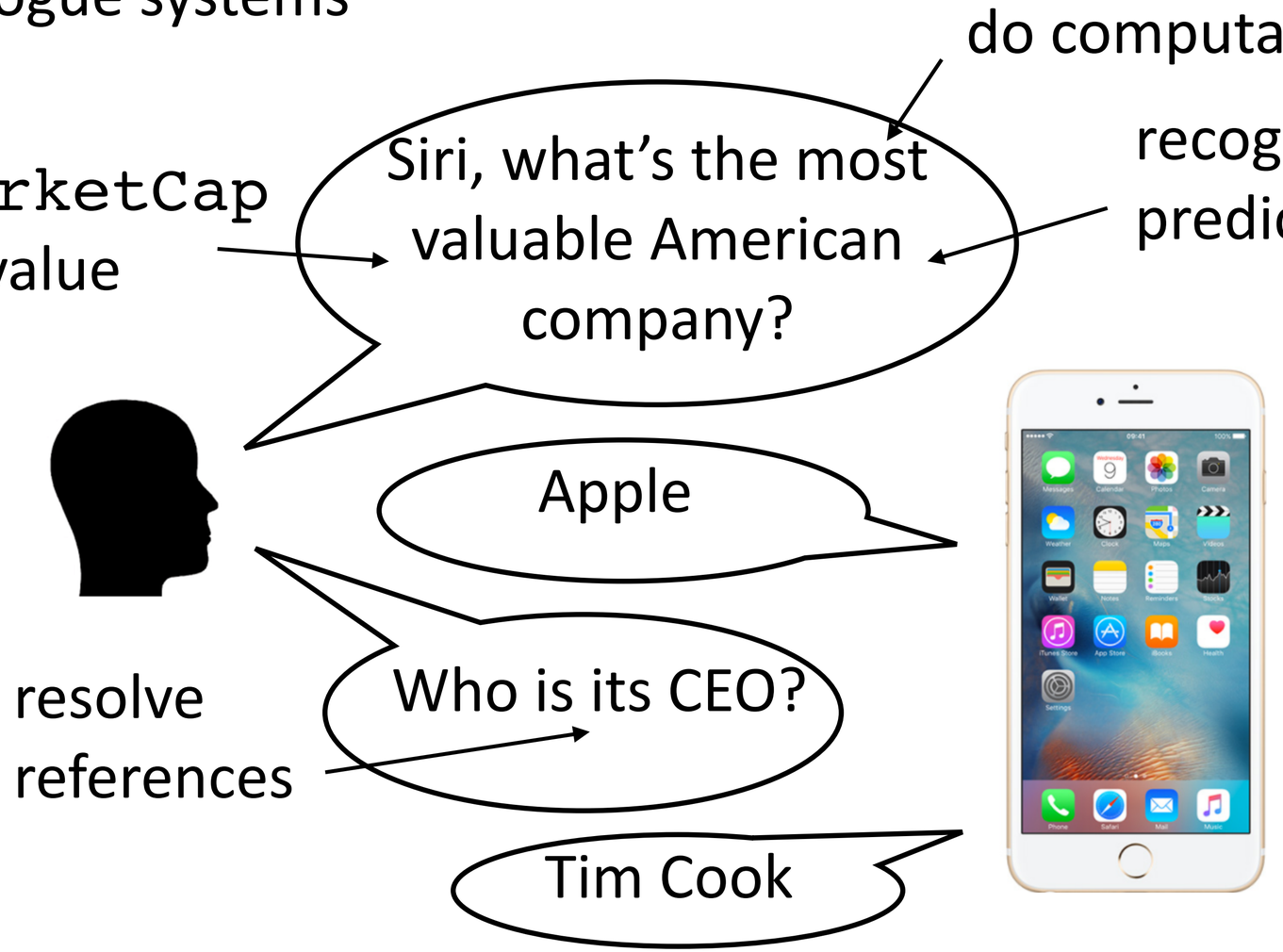
What's the goal of NLP?

- Be able to solve problems that require deep understanding of text
- Example: dialogue systems



What's the goal of NLP?

- Be able to solve problems that require deep understanding of text
- Example: dialogue systems



Automatic Summarization

Automatic Summarization

POLITICS

Google Critic Ousted From Think Tank Funded by the Tech Giant

WASHINGTON — In the hours after European antitrust regulators levied a record $2.7 billion fine against Google in late June, an influential Washington think tank learned what can happen when a tech giant that shapes public policy debates with its enormous wealth is criticized.

• • •

But not long after one of New America's scholars posted a statement on the think tank's website praising the European Union's penalty against Google, Mr. Schmidt, who had been chairman of New America until 2016, communicated his displeasure with the statement to the group's president, Anne-Marie Slaughter, according to the scholar.

• • •

Ms. Slaughter told Mr. Lynn that "the time has come for Open Markets and New America to part ways," according to an email from Ms. Slaughter to Mr. Lynn. The email suggested that the entire Open Markets team — nearly 10 full-time employees and unpaid fellows — would be exiled from New America.

Automatic Summarization

POLITICS

Google Critic Ousted From Think Tank Funded by the Tech Giant

WASHINGTON — In the hours after European antitrust regulators levied a record $2.7 billion fine against Google in late June, an influential Washington think tank learned what can happen when a tech giant that shapes public policy debates with its enormous wealth is criticized.

• • •

But not long after one of New America's scholars posted a statement on the think tank's website praising the European Union's penalty against Google, Mr. Schmidt, who had been chairman of New America until 2016, communicated his displeasure with the statement to the group's president, Anne-Marie Slaughter, according to the scholar.

• • •

Ms. Slaughter told Mr. Lynn that "the time has come for Open Markets and New America to part ways," according to an email from Ms. Slaughter to Mr. Lynn. The email suggested that the entire Open Markets team — nearly 10 full-time employees and unpaid fellows — would be exiled from New America.

One of New America's writers posted a statement critical of Google. Eric Schmidt, Google's CEO, was displeased.

The writer and his team were dismissed.

Automatic Summarization

POLITICS

Google Critic Ousted From Think Tank Funded by the Tech Giant

WASHINGTON — In the hours after European antitrust regulators levied a record $2.7 billion fine against Google in late June, an influential Washington think tank learned what can happen when a tech giant that shapes public policy debates with its enormous wealth is criticized.

• • •

But not long after one of New America's scholars posted a statement on the think tank's website praising the European Union's penalty against Google, Mr. Schmidt, who had been chairman of New America until 2016, communicated his displeasure with the statement to the group's president, Anne-Marie Slaughter, according to the scholar.

• • •

Ms. Slaughter told Mr. Lynn that "the time has come for Open Markets and New America to part ways," according to an email from Ms. Slaughter to Mr. Lynn. The email suggested that the entire Open Markets team — nearly 10 full-time employees and unpaid fellows — would be exiled from New America.

compress
text

One of New America's writers posted a statement critical of Google. Eric Schmidt, Google's CEO, was displeased.

The writer and his team were dismissed.

Automatic Summarization

POLITICS

Google Critic Ousted From Think Tank Funded by the Tech Giant

WASHINGTON — In the hours after European antitrust regulators levied a record $2.7 billion fine against Google in late June, an influential Washington think tank learned what can happen when a tech giant that shapes public policy debates with its enormous wealth is criticized.

• • •

But not long after one of New America's scholars posted a statement on the think tank's website praising the European Union's penalty against Google, Mr. Schmidt, who had been chairman of New America until 2016, communicated his displeasure with the statement to the group's president, Anne-Marie Slaughter, according to the scholar.

• • •

Ms. Slaughter told Mr. Lynn that "the time has come for Open Markets and New America to part ways," according to an email from Ms. Slaughter to Mr. Lynn. The email suggested that the entire Open Markets team — nearly 10 full-time employees and unpaid fellows — would be exiled from New America.

compress text

provide missing context

One of New America's writers posted a statement critical of Google. Eric Schmidt, Google's CEO, was displeased.

The writer and his team were dismissed.

Automatic Summarization

POLITICS

Google Critic Ousted From Think Tank Funded by the Tech Giant

WASHINGTON — In the hours after European antitrust regulators levied a record $2.7 billion fine against Google in late June, an influential Washington think tank learned what can happen when a tech giant that shapes public policy debates with its enormous wealth is criticized.

• • •

But not long after one of New America's scholars posted a statement on the think tank's website praising the European Union's penalty against Google, Mr. Schmidt, who had been chairman of New America until 2016, communicated his displeasure with the statement to the group's president, Anne-Marie Slaughter, according to the scholar.

• • •

Ms. Slaughter told Mr. Lynn that "the time has come for Open Markets and New America to part ways," according to an email from Ms. Slaughter to Mr. Lynn. The email suggested that the entire Open Markets team — nearly 10 full-time employees and unpaid fellows — would be exiled from New America.

compress text

provide missing context

One of New America's writers posted a statement critical of Google. Eric Schmidt, Google's CEO, was displeased.

The writer and his team were dismissed.

paraphrase to provide clarity

Machine Translation

People's Daily, August 30, 2017

Machine Translation

People's Daily, August 30, 2017

Machine Translation

People's Daily, August 30, 2017

Trump Pope family watch a hundred years a year in the White House balcony

Machine Translation

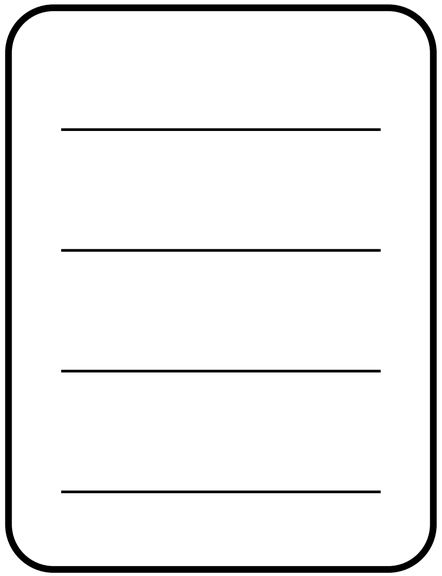
People's Daily, August 30, 2017

Trump Pope family watch a hundred years a year in the White House balcony

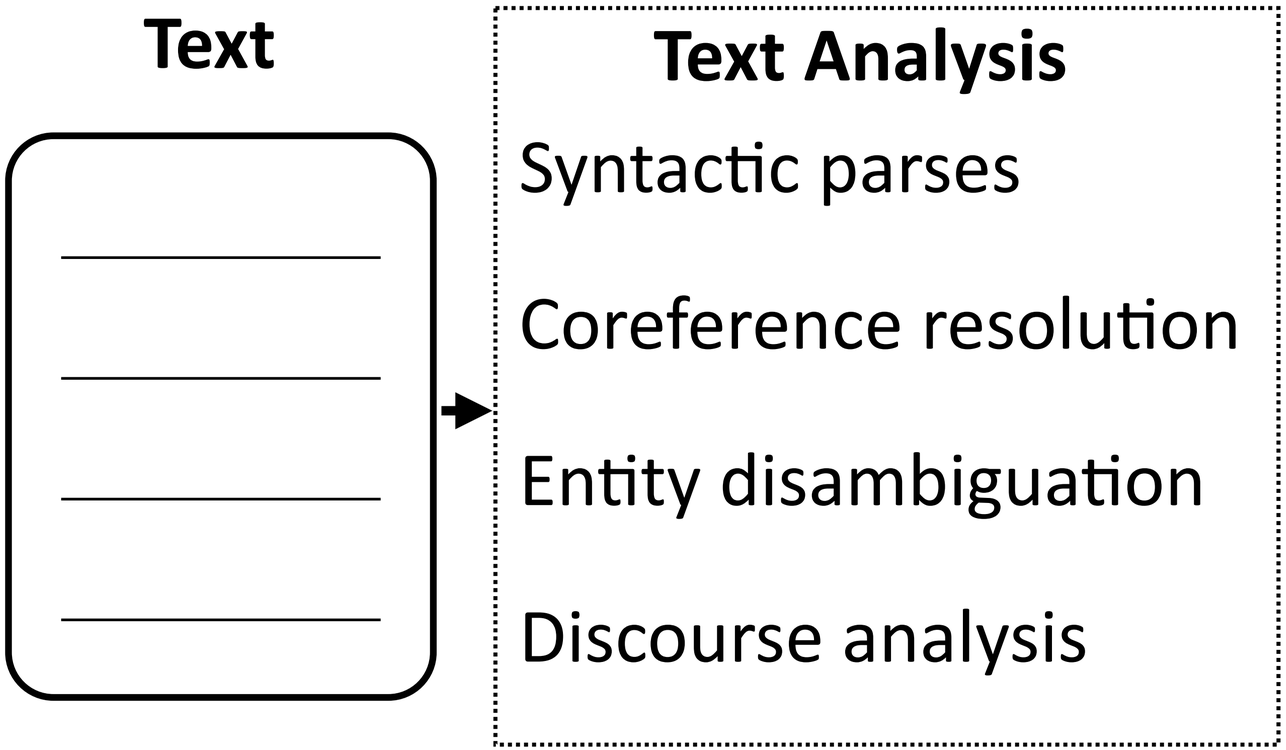
NLP Analysis Pipeline

NLP Analysis Pipeline

Text



NLP Analysis Pipeline



NLP Analysis Pipeline

Text

Text Analysis

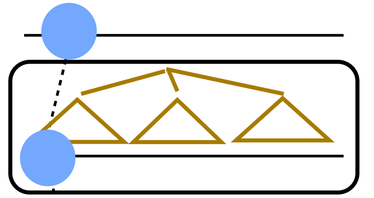
Syntactic parses

Coreference resolution

Entity disambiguation

Discourse analysis

Annotations



NLP Analysis Pipeline

Text

Text Analysis

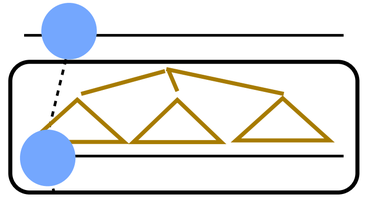
Syntactic parses

Coreference resolution

Entity disambiguation

Discourse analysis

Annotations



Applications

NLP Analysis Pipeline

Text

Text Analysis

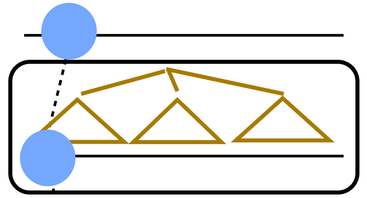
Syntactic parses

Coreference resolution

Entity disambiguation

Discourse analysis

Annotations



Applications

Summarize

NLP Analysis Pipeline

Text

Text Analysis

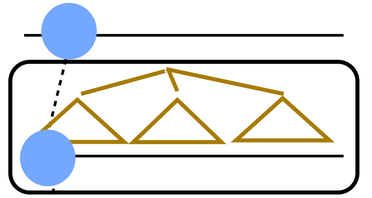
Syntactic parses

Coreference resolution

Entity disambiguation

Discourse analysis

Annotations



Applications

Summarize

Extract information

NLP Analysis Pipeline

Text

Text Analysis

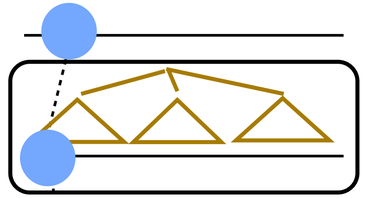
Syntactic parses

Coreference resolution

Entity disambiguation

Discourse analysis

Annotations



Applications

Summarize

Extract information

Answer questions

NLP Analysis Pipeline

Text

Text Analysis

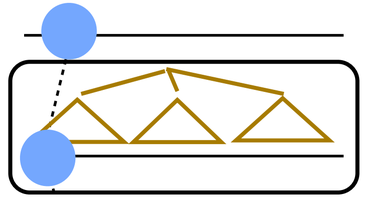
Syntactic parses

Coreference resolution

Entity disambiguation

Discourse analysis

Annotations



Applications

Summarize

Extract information

Answer questions

Identify sentiment

NLP Analysis Pipeline

Text

Text Analysis

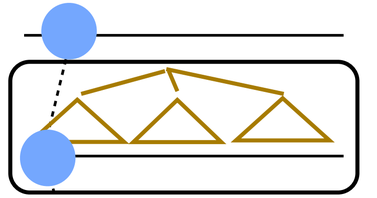
Syntactic parses

Coreference resolution

Entity disambiguation

Discourse analysis

Annotations



Applications

Summarize

Extract information

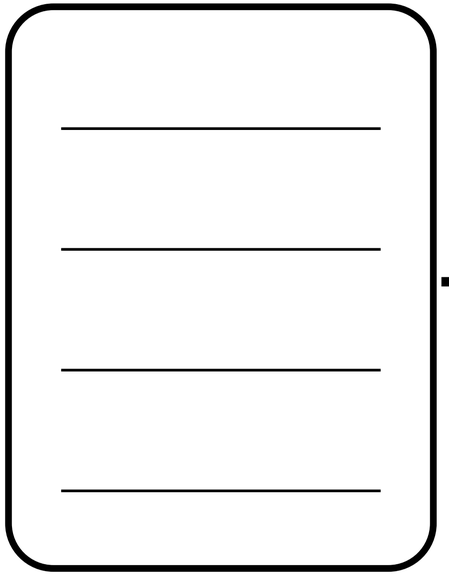
Answer questions

Identify sentiment

Translate

NLP Analysis Pipeline

Text



Text Analysis

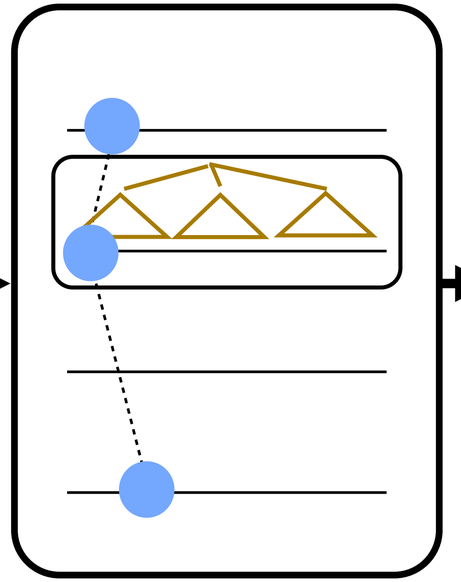
Syntactic parses

Coreference resolution

Entity disambiguation

Discourse analysis

Annotations



Applications

Summarize

Extract information

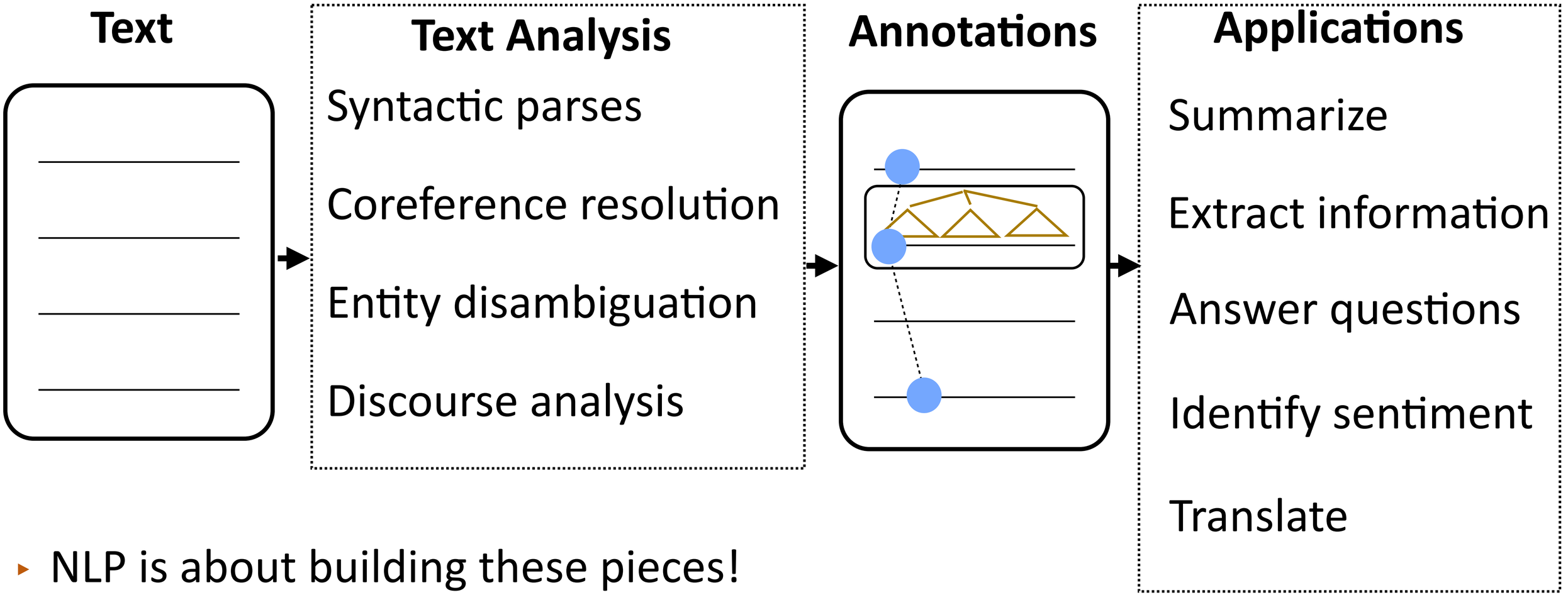
Answer questions

Identify sentiment

Translate

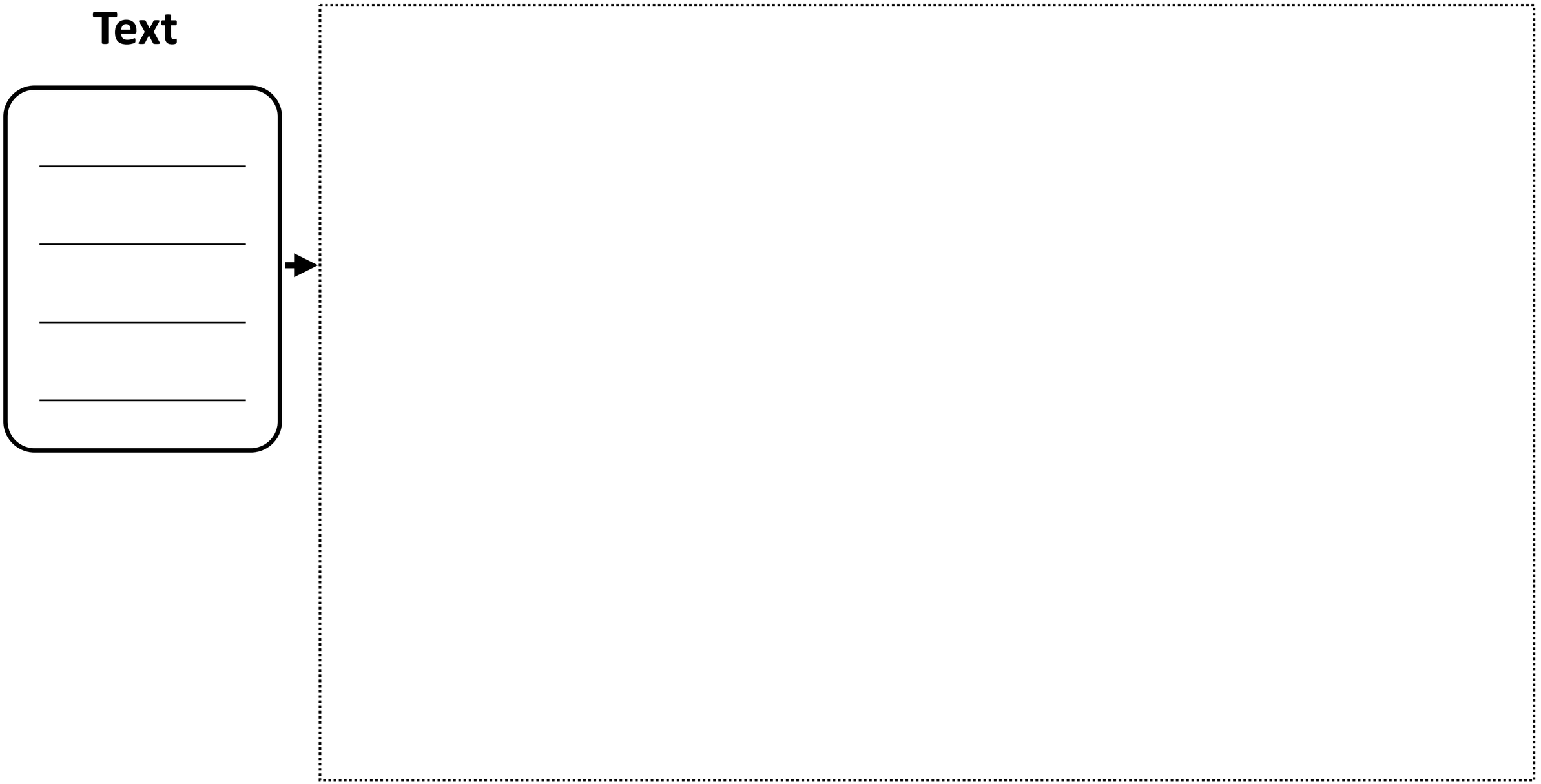
- NLP is about building these pieces!

NLP Analysis Pipeline



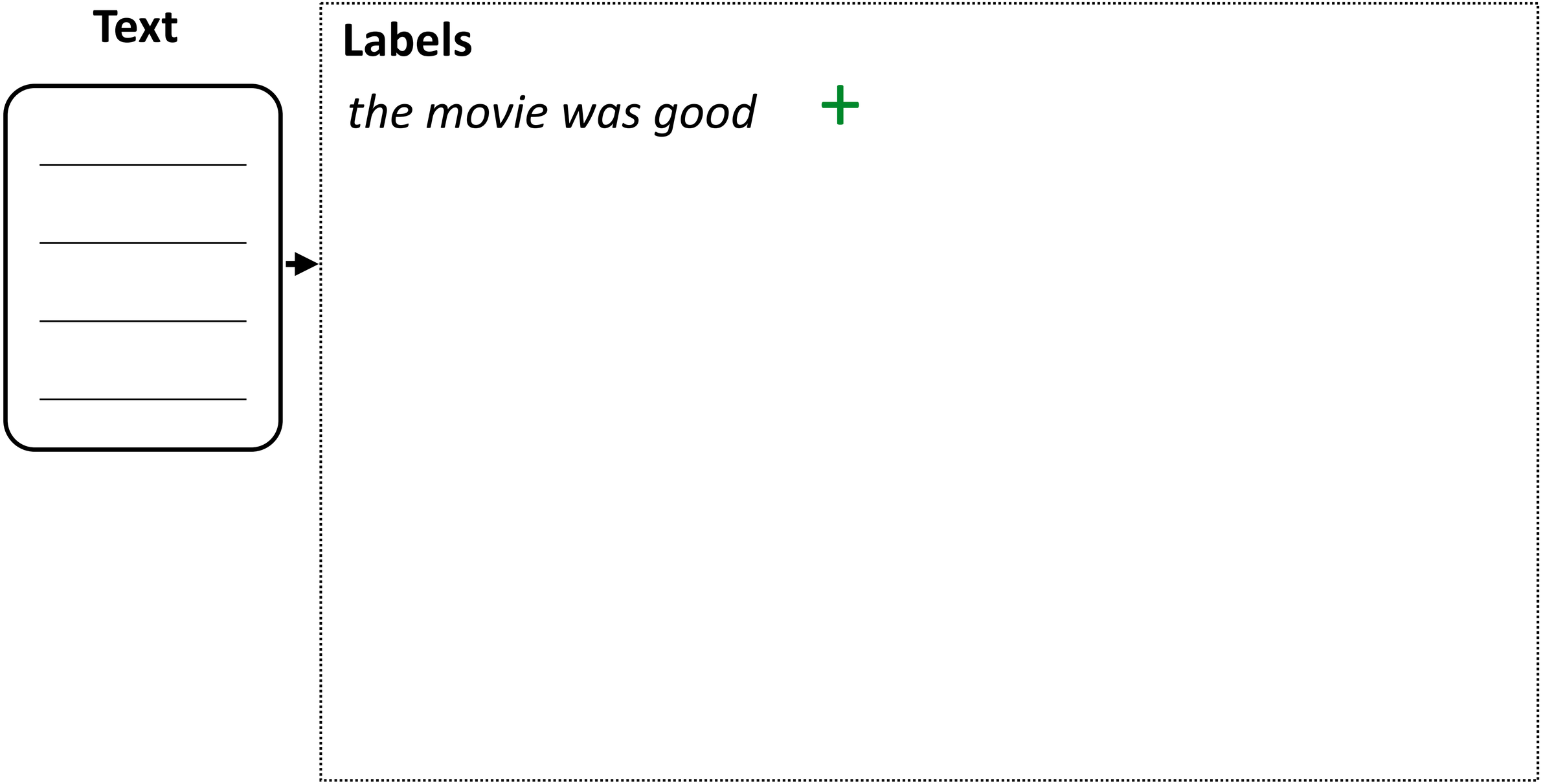
- NLP is about building these pieces!
- All of these components are modeled with statistical approaches trained with machine learning

How do we represent language?



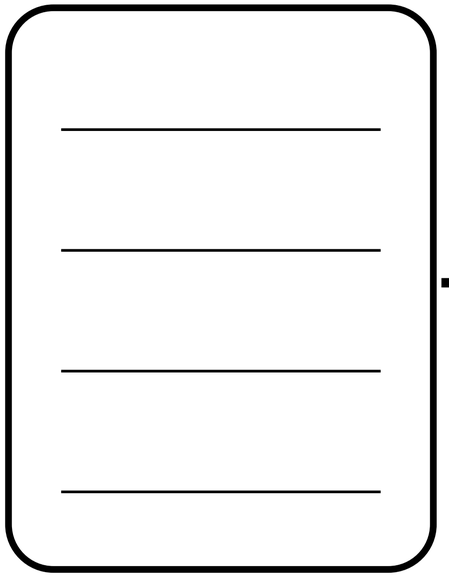
How do we represent language?

How do we represent language?



How do we represent language?

Text



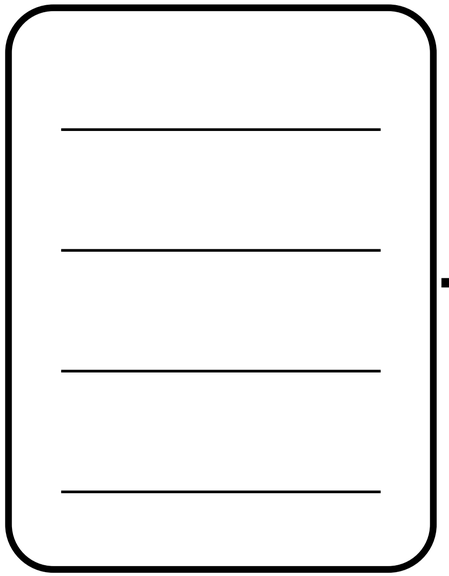
Labels

the movie was good +

Beyoncé had one of the best videos of all time **subjective**

How do we represent language?

Text



Labels

the movie was good +

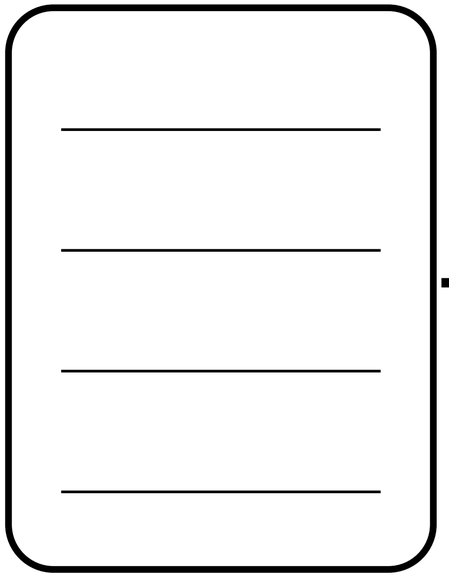
Beyoncé had one of the best videos of all time **subjective**

Sequences/tags

PERSON *Tom Cruise* *stars in the new* **MOVIE** *Mission Impossible* *film*

How do we represent language?

Text



Labels

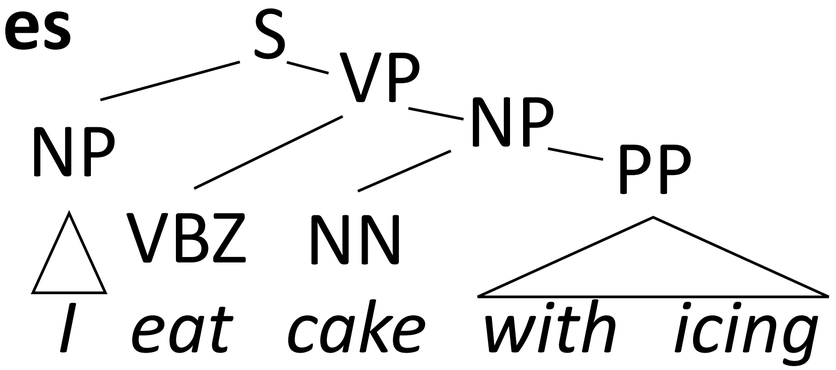
the movie was good +

Beyoncé had one of the best videos of all time **subjective**

Sequences/tags

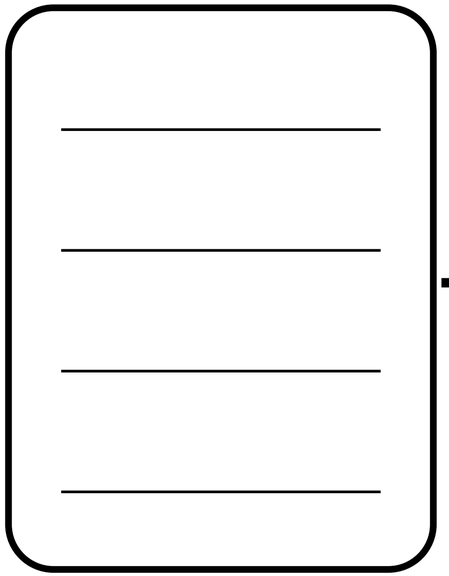
PERSON *Tom Cruise* *stars in the new* **MOVIE** *Mission Impossible* *film*

Trees



How do we represent language?

Text



Labels

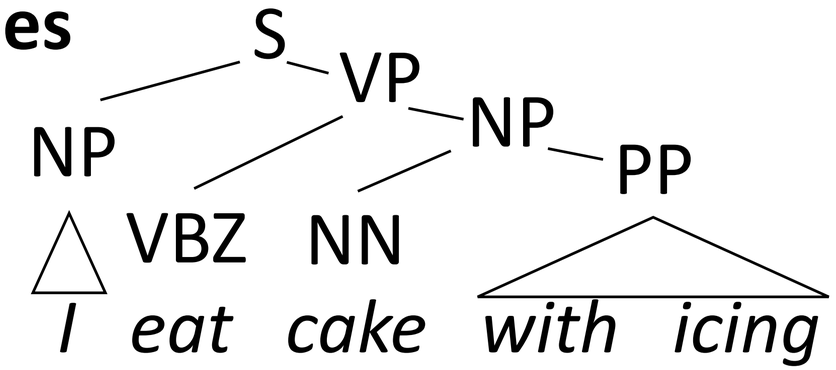
the movie was good +

Beyoncé had one of the best videos of all time **subjective**

Sequences/tags

PERSON *Tom Cruise* *stars in the new* **MOVIE** *Mission Impossible* *film*

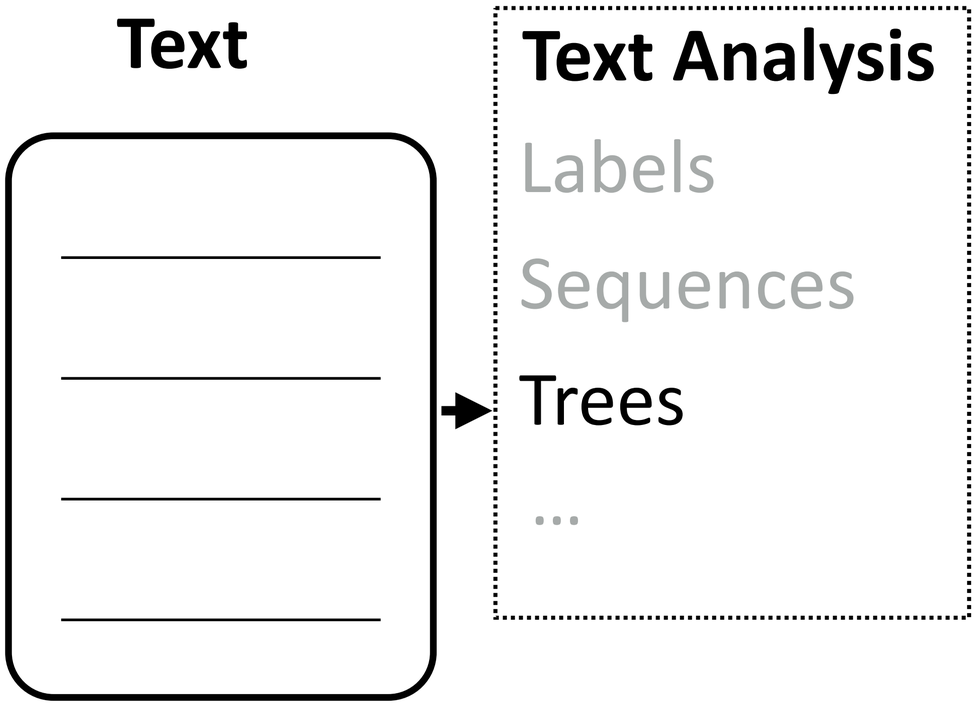
Trees



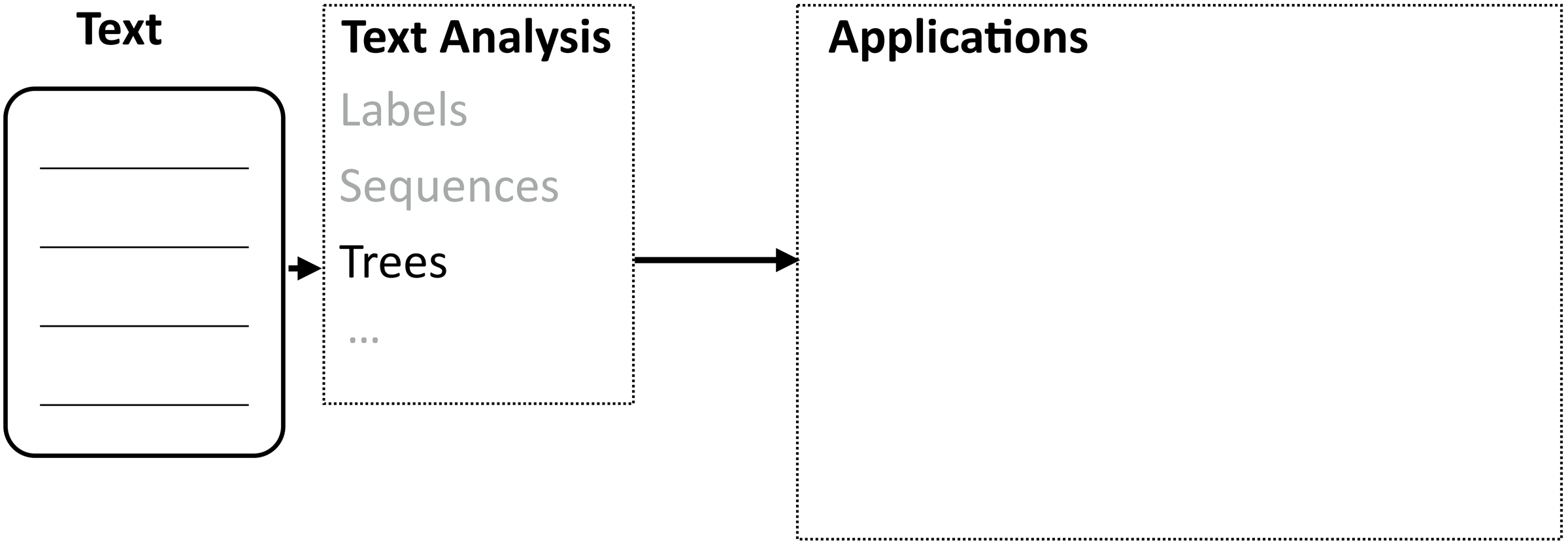
$\lambda x.\ flight(x) \wedge dest(x)=Miami$

flights to Miami

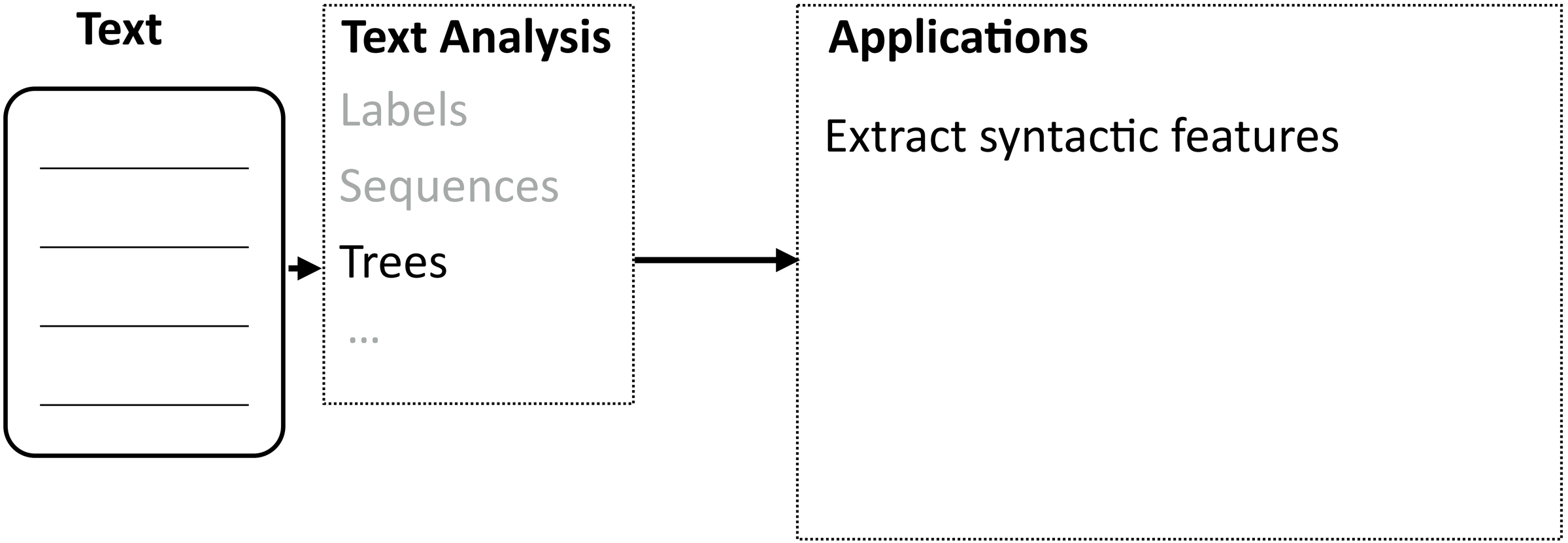
How do we use these representations?



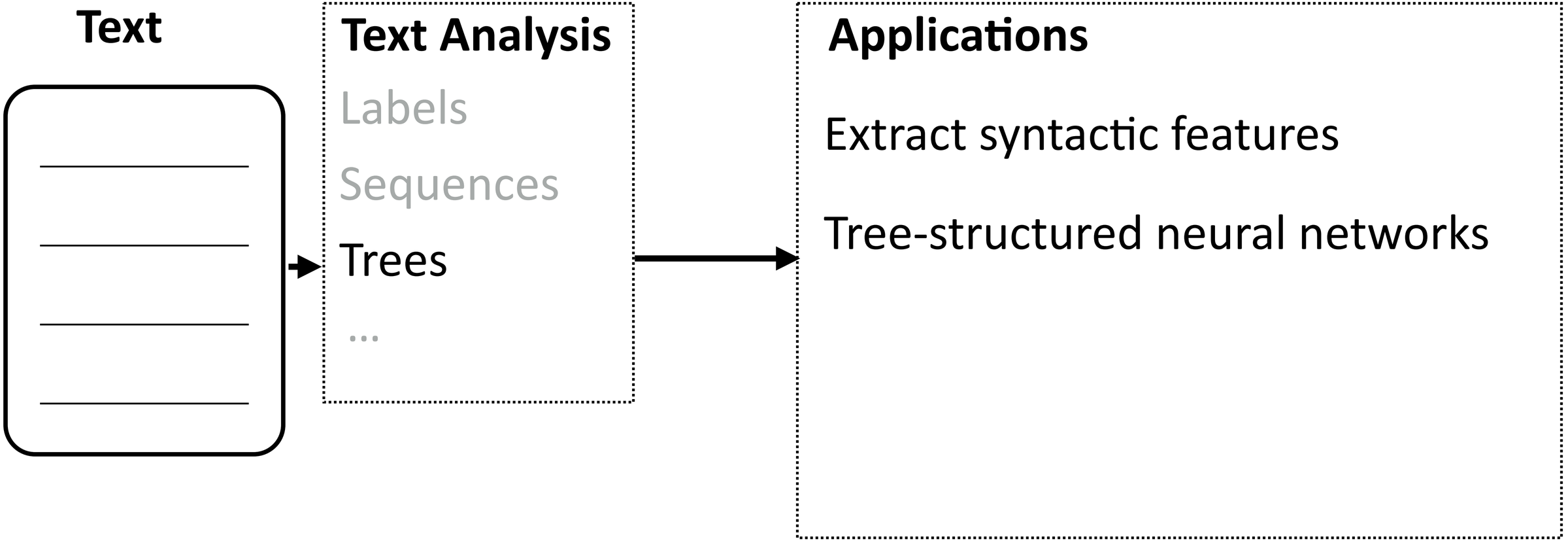
How do we use these representations?



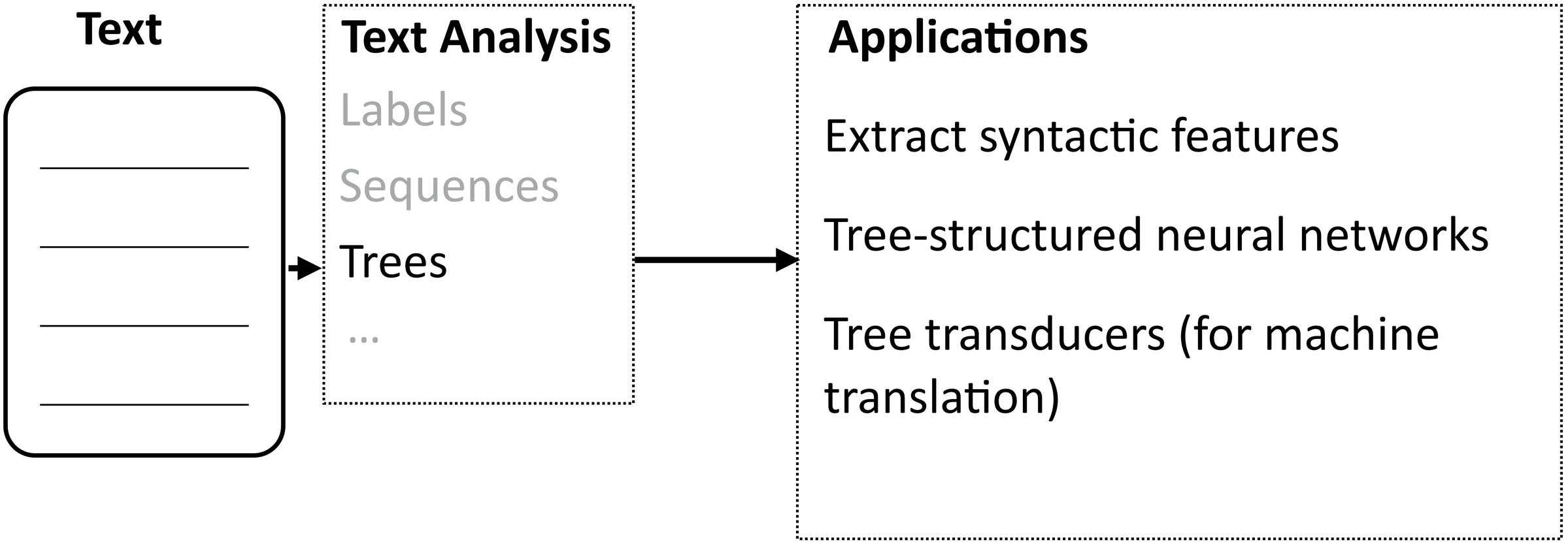
How do we use these representations?



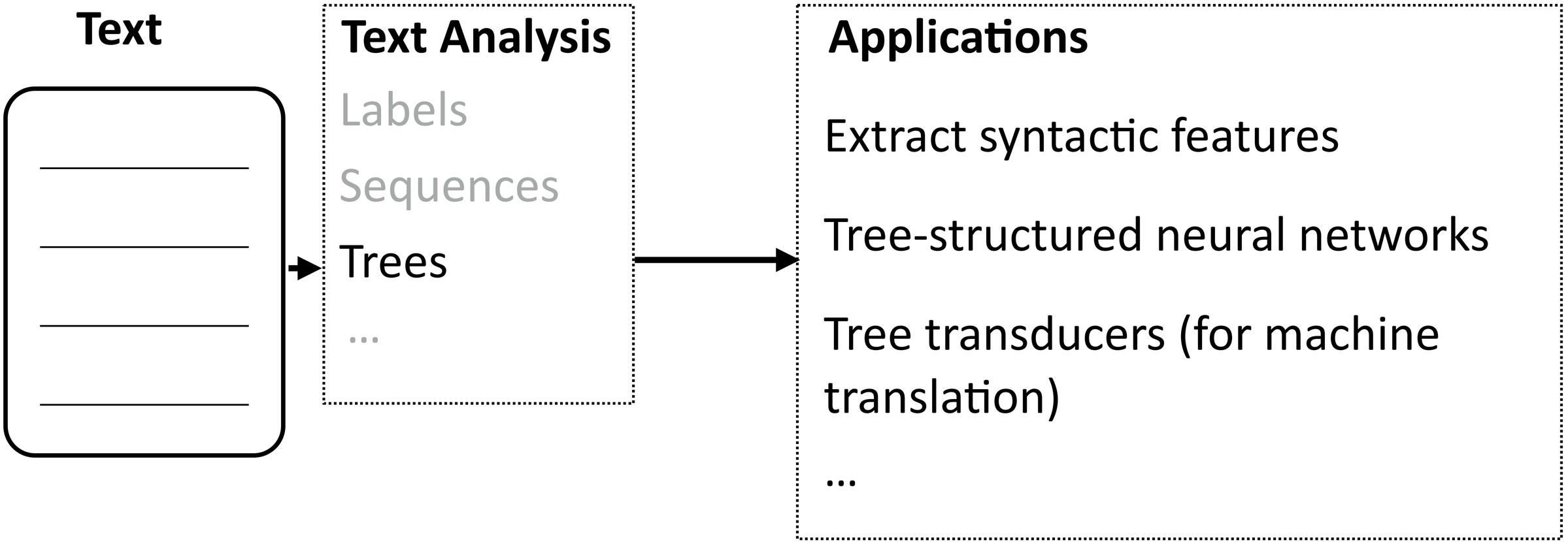
How do we use these representations?



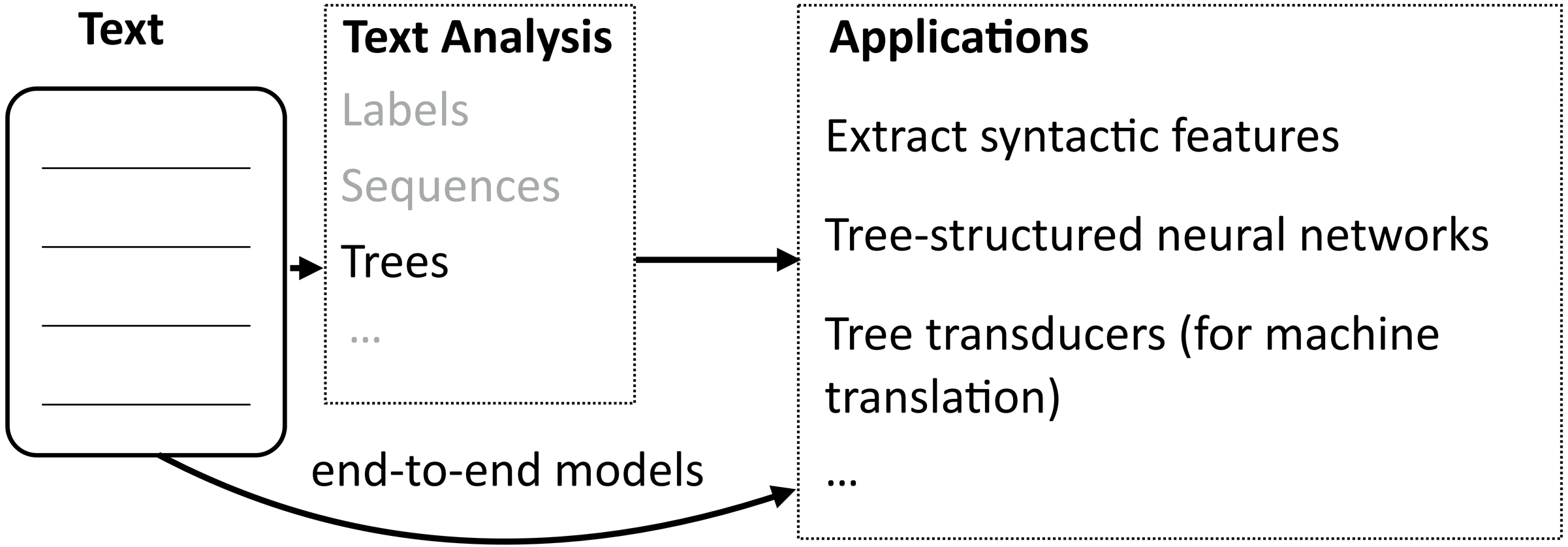
How do we use these representations?



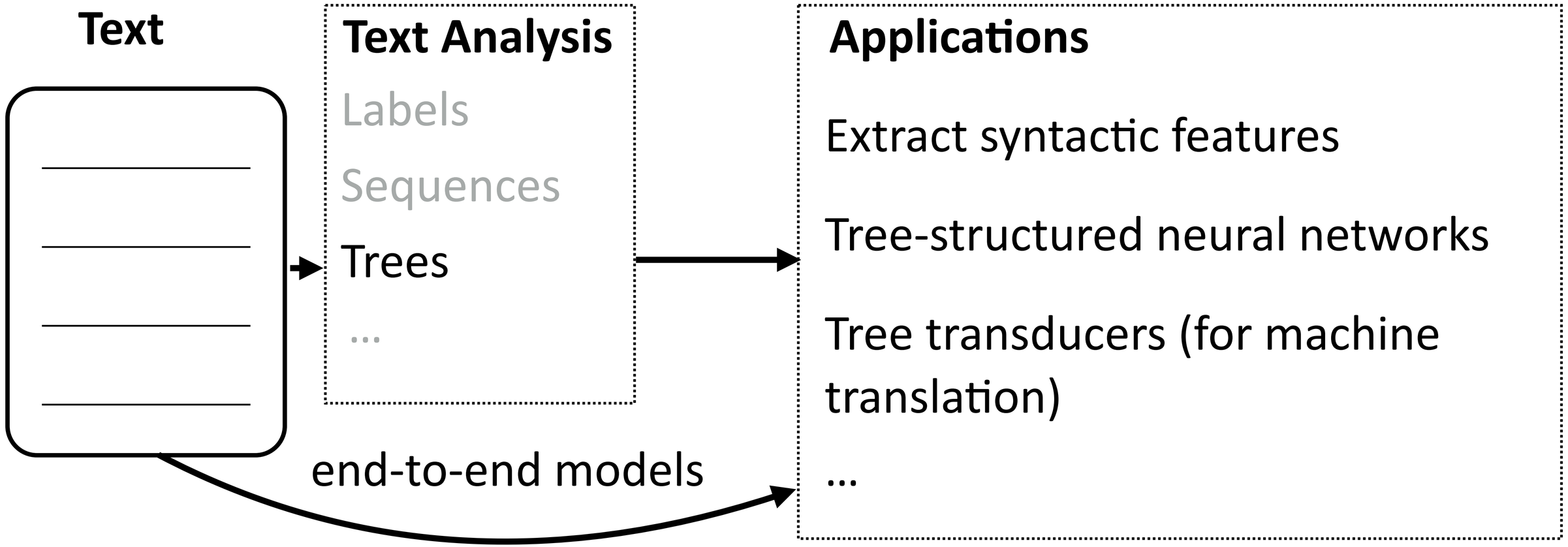
How do we use these representations?



How do we use these representations?

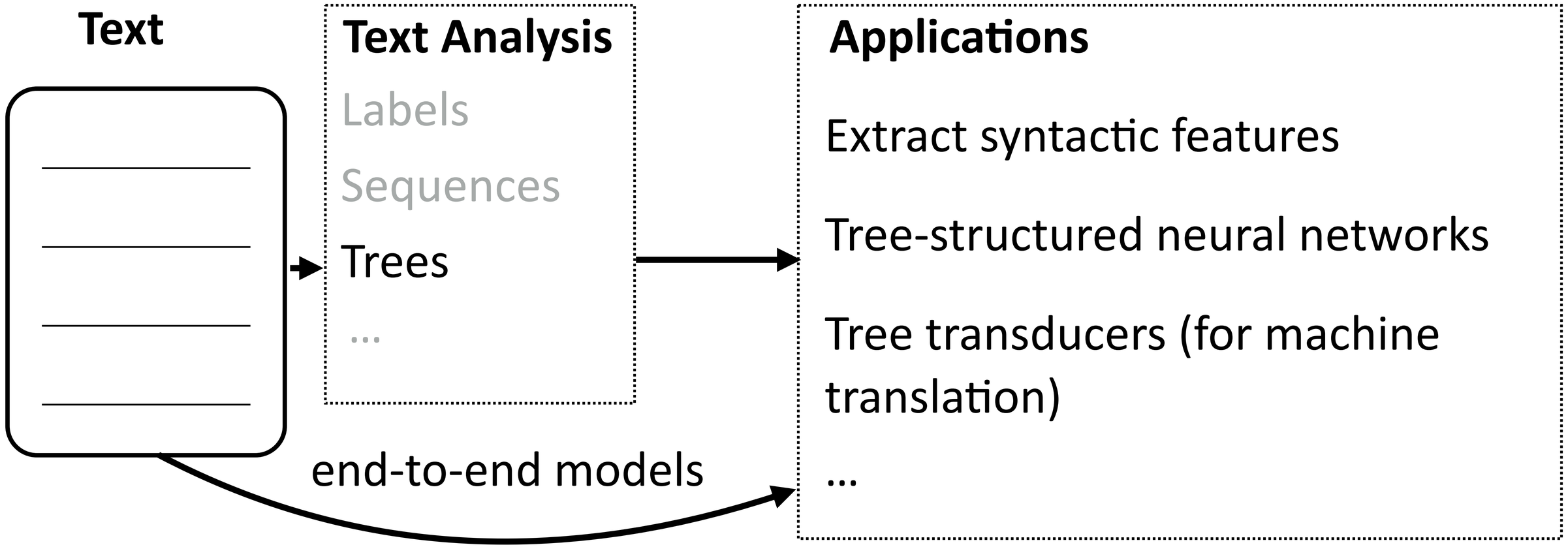


How do we use these representations?



- Main question: What representations do we need for language? What do we want to know about it?

How do we use these representations?



- Main question: What representations do we need for language? What do we want to know about it?
- Boils down to: what ambiguities do we need to resolve?

Why is language hard?

(and how can we handle that?)

Language is Ambiguous!

- Hector Levesque (2011): “Winograd schema challenge” (named after Terry Winograd, the creator of SHRDLU)

Language is Ambiguous!

- Hector Levesque (2011): “Winograd schema challenge” (named after Terry Winograd, the creator of SHRDLU)

The city council refused the demonstrators a permit because they _____ violence

Language is Ambiguous!

- Hector Levesque (2011): “Winograd schema challenge” (named after Terry Winograd, the creator of SHRDLU)

The city council refused the demonstrators a permit because they _____ violence

Language is Ambiguous!

- Hector Levesque (2011): “Winograd schema challenge” (named after Terry Winograd, the creator of SHRDLU)

they advocated

The city council refused the demonstrators a permit because they _____ violence

Language is Ambiguous!

- Hector Levesque (2011): “Winograd schema challenge” (named after Terry Winograd, the creator of SHRDLU)

The city council refused the demonstrators a permit because they _____ violence

they advocated

Language is Ambiguous!

- Hector Levesque (2011): “Winograd schema challenge” (named after Terry Winograd, the creator of SHRDLU)

The city council refused the demonstrators a permit because they _____ violence

they advocated

they feared

Language is Ambiguous!

- Hector Levesque (2011): “Winograd schema challenge” (named after Terry Winograd, the creator of SHRDLU)

The city council refused the demonstrators a permit because they _____ violence

they advocated

they feared

Language is Ambiguous!

- Hector Levesque (2011): “Winograd schema challenge” (named after Terry Winograd, the creator of SHRDLU)

The city council refused the demonstrators a permit because they _____ violence

they advocated

they feared

- This is so complicated that it’s an AI challenge problem! (AI-complete)

Language is Ambiguous!

- Hector Levesque (2011): “Winograd schema challenge” (named after Terry Winograd, the creator of SHRDLU)

The city council refused the demonstrators a permit because they _____ violence

they advocated

they feared

- This is so complicated that it’s an AI challenge problem! (AI-complete)
- Referential/semantic ambiguity

Language is Ambiguous!

slide credit: Dan Klein

Language is Ambiguous!

- Ambiguous News Headlines:

slide credit: Dan Klein

Language is Ambiguous!

- Ambiguous News Headlines:
  - Teacher Strikes Idle Kids

slide credit: Dan Klein

Language is Ambiguous!

- Ambiguous News Headlines:
  - Teacher Strikes Idle Kids
  - Hospitals Sued by 7 Foot Doctors

slide credit: Dan Klein

Language is Ambiguous!

- Ambiguous News Headlines:
  - Teacher Strikes Idle Kids
  - Hospitals Sued by 7 Foot Doctors
  - Ban on Nude Dancing on Governor’s Desk

slide credit: Dan Klein

Language is Ambiguous!

- Ambiguous News Headlines:
  - Teacher Strikes Idle Kids
  - Hospitals Sued by 7 Foot Doctors
  - Ban on Nude Dancing on Governor’s Desk
  - Iraqi Head Seeks Arms

slide credit: Dan Klein

Language is Ambiguous!

- Ambiguous News Headlines:
  - Teacher Strikes Idle Kids
  - Hospitals Sued by 7 Foot Doctors
  - Ban on Nude Dancing on Governor’s Desk
  - Iraqi Head Seeks Arms
  - Stolen Painting Found by Tree

slide credit: Dan Klein

Language is Ambiguous!

- Ambiguous News Headlines:
  - Teacher Strikes Idle Kids
  - Hospitals Sued by 7 Foot Doctors
  - Ban on Nude Dancing on Governor’s Desk
  - Iraqi Head Seeks Arms
  - Stolen Painting Found by Tree
  - Kids Make Nutritious Snacks

slide credit: Dan Klein

Language is Ambiguous!

- Ambiguous News Headlines:
  - Teacher Strikes Idle Kids
  - Hospitals Sued by 7 Foot Doctors
  - Ban on Nude Dancing on Governor’s Desk
  - Iraqi Head Seeks Arms
  - Stolen Painting Found by Tree
  - Kids Make Nutritious Snacks
  - Local HS Dropouts Cut in Half

slide credit: Dan Klein

Language is Ambiguous!

- Ambiguous News Headlines:
  - Teacher Strikes Idle Kids
  - Hospitals Sued by 7 Foot Doctors
  - Ban on Nude Dancing on Governor's Desk
  - Iraqi Head Seeks Arms
  - Stolen Painting Found by Tree
  - Kids Make Nutritious Snacks
  - Local HS Dropouts Cut in Half
- Syntactic/semantic ambiguity: parsing needed to resolve these, but need context to figure out which parse is correct

slide credit: Dan Klein

Language is **Really** Ambiguous!

- There aren’t just one or two possibilities which are resolved pragmatically

Language is **Really** Ambiguous!

- There aren't just one or two possibilities which are resolved pragmatically

il fait vraiment beau 

Language is **Really** Ambiguous!

- There aren't just one or two possibilities which are resolved pragmatically

It is really nice out

il fait vraiment beau ⟶

Language is **Really** Ambiguous!

- There aren't just one or two possibilities which are resolved pragmatically

il fait vraiment beau ⟶ It is really nice out

il fait vraiment beau ⟶ It's really nice

Language is **Really** Ambiguous!

- There aren't just one or two possibilities which are resolved pragmatically

il fait vraiment beau ⟶

It is really nice out

It's really nice

The weather is beautiful

Language is **Really** Ambiguous!

- There aren't just one or two possibilities which are resolved pragmatically

il fait vraiment beau ⟶

It is really nice out

It's really nice

The weather is beautiful

It is really beautiful outside

Language is **Really** Ambiguous!

- There aren't just one or two possibilities which are resolved pragmatically

il fait vraiment beau ⟶

It is really nice out

It's really nice

The weather is beautiful

It is really beautiful outside

He makes truly beautiful

Language is **Really** Ambiguous!

- There aren't just one or two possibilities which are resolved pragmatically

il fait vraiment beau ⟶

It is really nice out

It's really nice

The weather is beautiful

It is really beautiful outside

He makes truly beautiful

He makes truly boyfriend

Language is **Really** Ambiguous!

- There aren't just one or two possibilities which are resolved pragmatically

il fait vraiment beau ⟶

It is really nice out

It's really nice

The weather is beautiful

It is really beautiful outside

He makes truly beautiful

He makes truly boyfriend

It fact actually handsome

Language is **Really** Ambiguous!

- There aren't just one or two possibilities which are resolved pragmatically

il fait vraiment beau ⟶

It is really nice out

It's really nice

The weather is beautiful

It is really beautiful outside

He makes truly beautiful

He makes truly boyfriend

It fact actually handsome

- Combinatorially many possibilities, many you won't even register as ambiguities, but systems still have to resolve them

What do we need to understand language?

- Lots of data!

SOURCE	Cela constituerait une solution transitoire qui permettrait de conduire à terme à une charte à valeur contraignante.
HUMAN	That would be an interim solution which would make it possible to work towards a binding charter in the long term .
1x DATA	[this] [constituerait] [assistance] [transitoire] [who] [permettrait] [licences] [to] [terme] [to] [a] [charter] [to] [value] [contraignante] [.]
10x DATA	[it] [would] [a solution] [transitional] [which] [would] [of] [lead] [to] [term] [to a] [charter] [to] [value] [binding] [.]
100x DATA	[this] [would be] [a transitional solution] [which would] [lead to] [a charter] [legally binding] [.]
1000x DATA	[that would be] [a transitional solution] [which would] [eventually lead to] [a binding charter] [.]

slide credit: Dan Klein

What do we need to understand language?

- World knowledge: have access to information beyond the training data

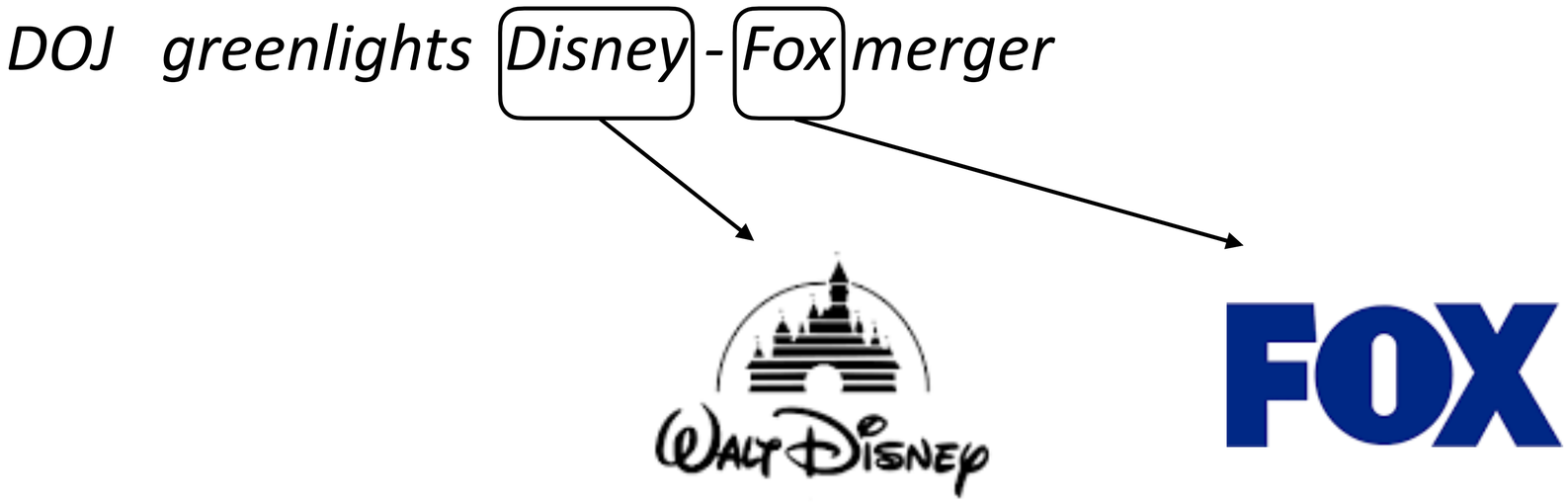
What do we need to understand language?

- World knowledge: have access to information beyond the training data

DOJ greenlights Disney - Fox merger

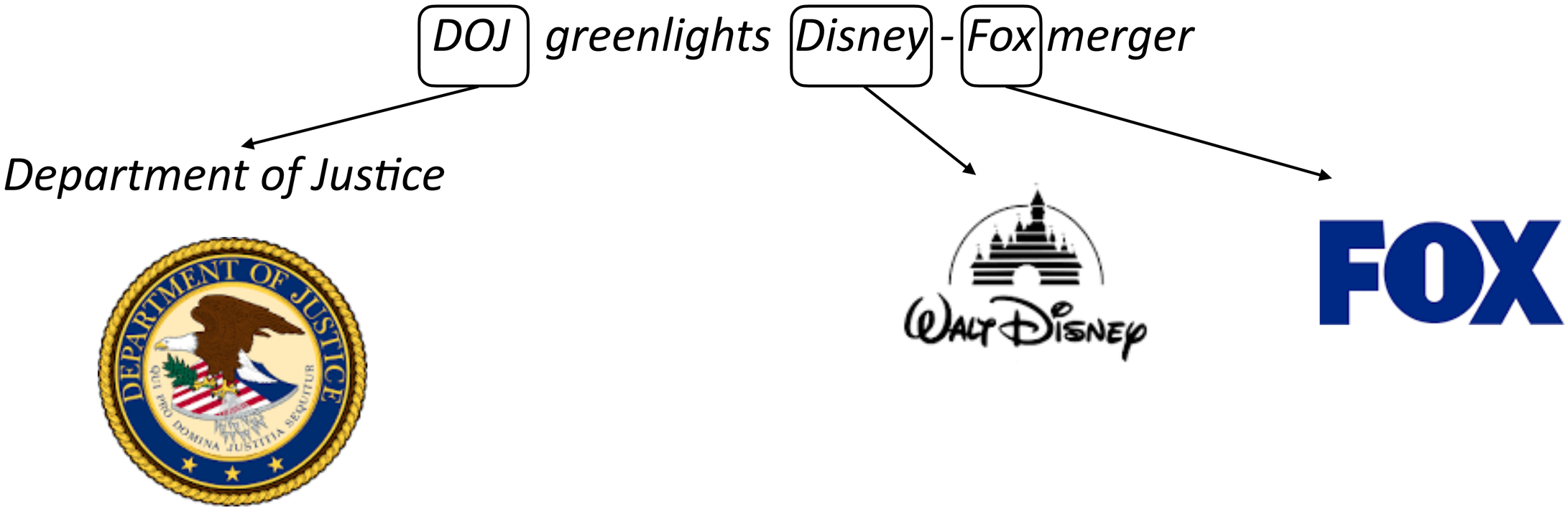
What do we need to understand language?

- World knowledge: have access to information beyond the training data



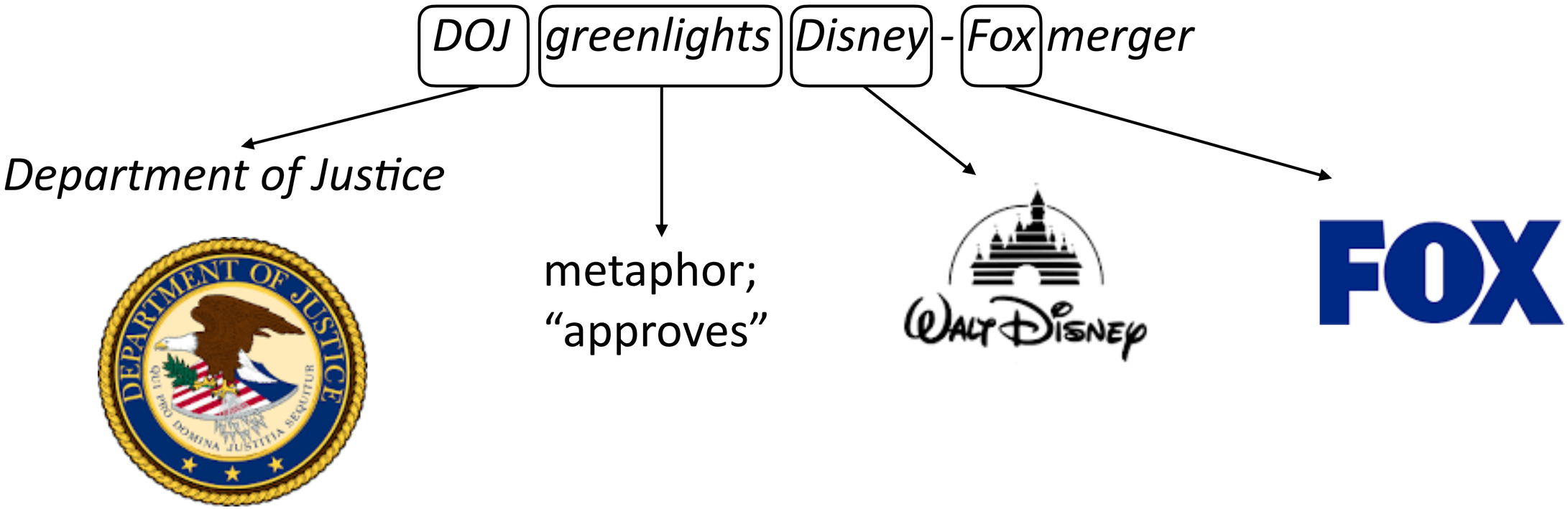
What do we need to understand language?

- World knowledge: have access to information beyond the training data



What do we need to understand language?

- World knowledge: have access to information beyond the training data



What do we need to understand language?

- World knowledge: have access to information beyond the training data

DOJ *greenlights* *Disney* - *Fox* *merger*

Department of Justice

metaphor;
"approves"

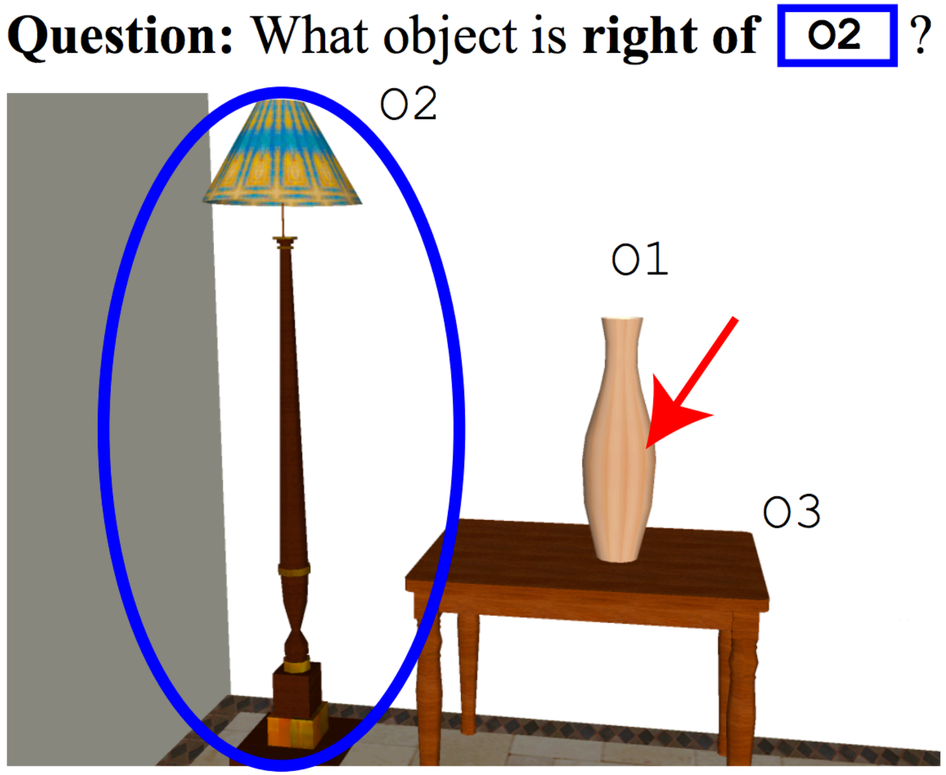
- What is a green light? How do we understand what "green lighting" does?

What do we need to understand language?

- Grounding: learn what fundamental concepts actually mean in a data-driven way

What do we need to understand language?

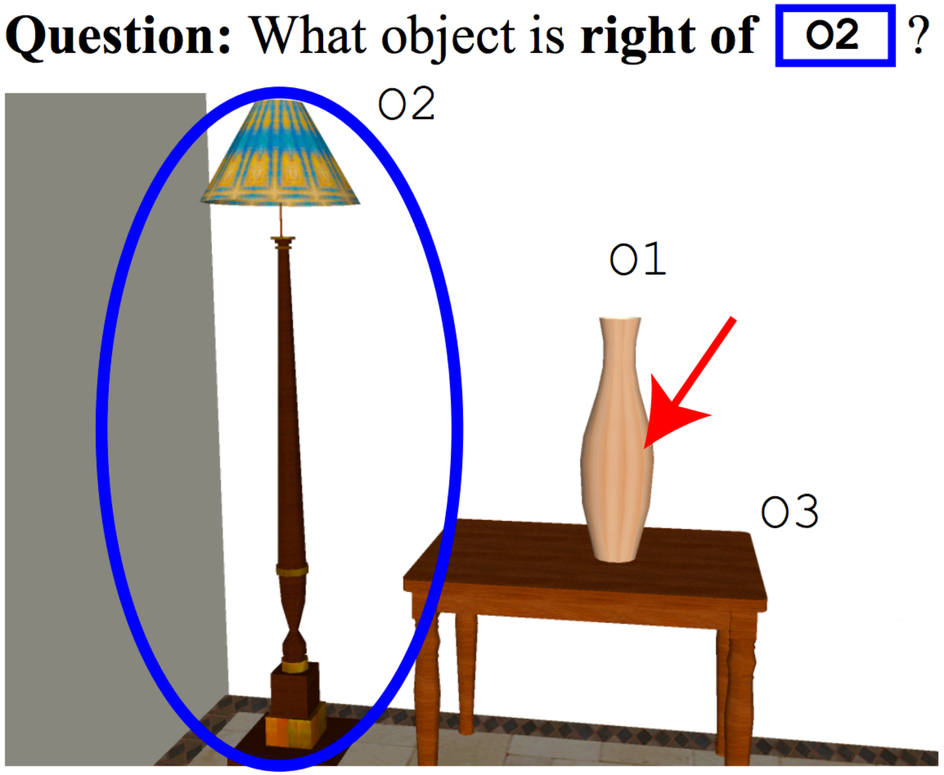
- Grounding: learn what fundamental concepts actually mean in a data-driven way



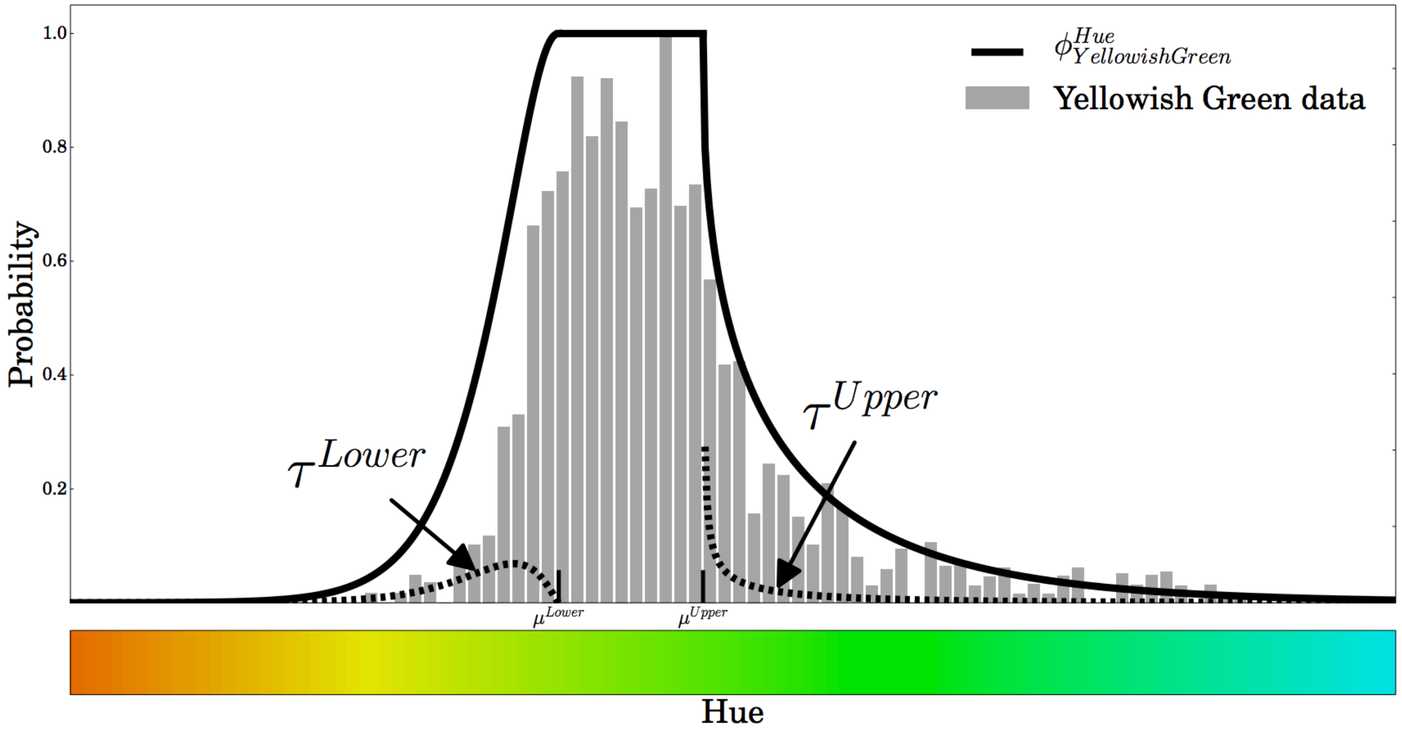
Golland et al. (2010)

What do we need to understand language?

- Grounding: learn what fundamental concepts actually mean in a data-driven way



Golland et al. (2010)



McMahan and Stone (2015)

What do we need to understand language?

- Linguistic structure

Centering Theory
Grosz et al. (1995)

What do we need to understand language?

- Linguistic structure
- …but computers probably won't understand language the same way humans do

Centering Theory
Grosz et al. (1995)

What do we need to understand language?

- Linguistic structure
- …but computers probably won't understand language the same way humans do
- However, linguistics tells us what phenomena we need to be able to deal with and gives us hints about how language works

Centering Theory
Grosz et al. (1995)

What do we need to understand language?

- Linguistic structure
- …but computers probably won't understand language the same way humans do
- However, linguistics tells us what phenomena we need to be able to deal with and gives us hints about how language works

a. John has been having a lot of trouble arranging his vacation.

b. He cannot find anyone to take over his responsibilities. (he = John)
C_b = John; C_f = {John}

c. He called up Mike yesterday to work out a plan. (he = John)
C_b = John; C_f = {John, Mike} (CONTINUE)

d. Mike has annoyed him a lot recently.
C_b = John; C_f = {Mike, John} (RETAIN)

e. He called John at 5 AM on Friday last week. (he = Mike)
C_b = Mike; C_f = {Mike, John} (SHIFT)

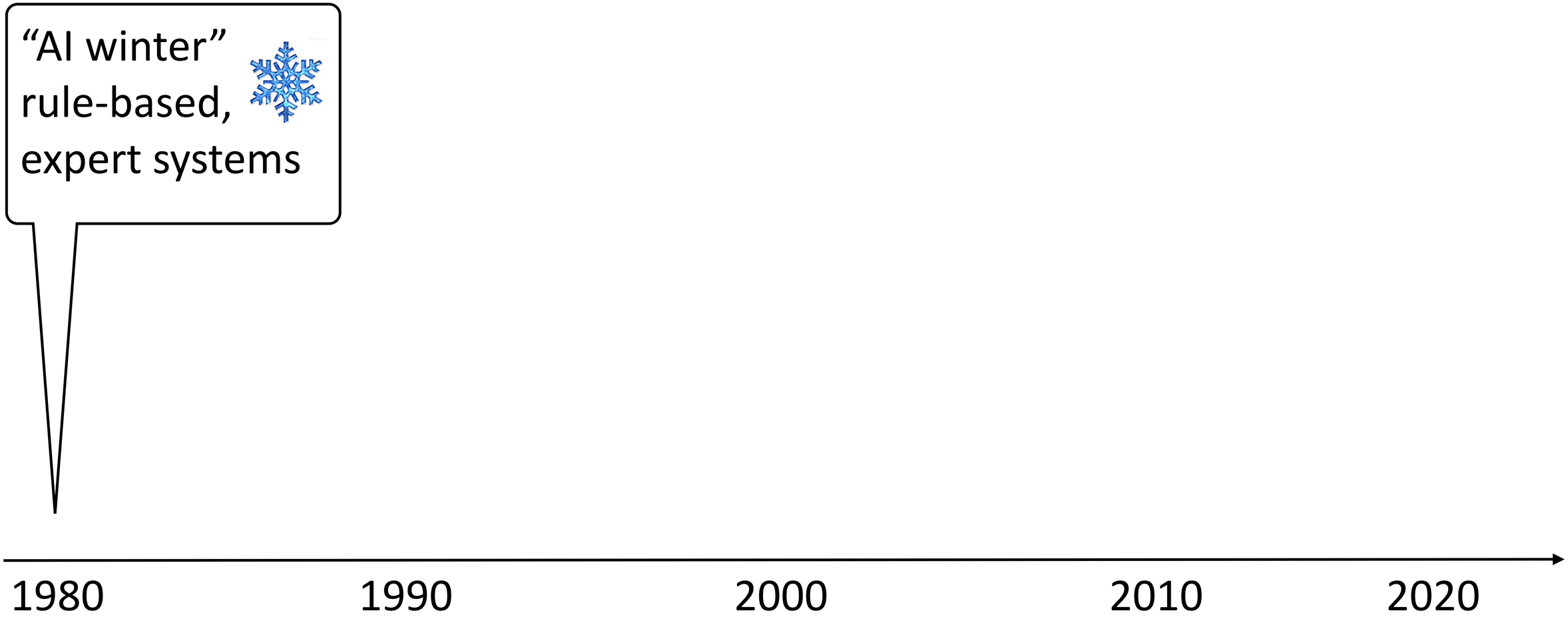
Centering Theory
Grosz et al. (1995)

What techniques do we use?

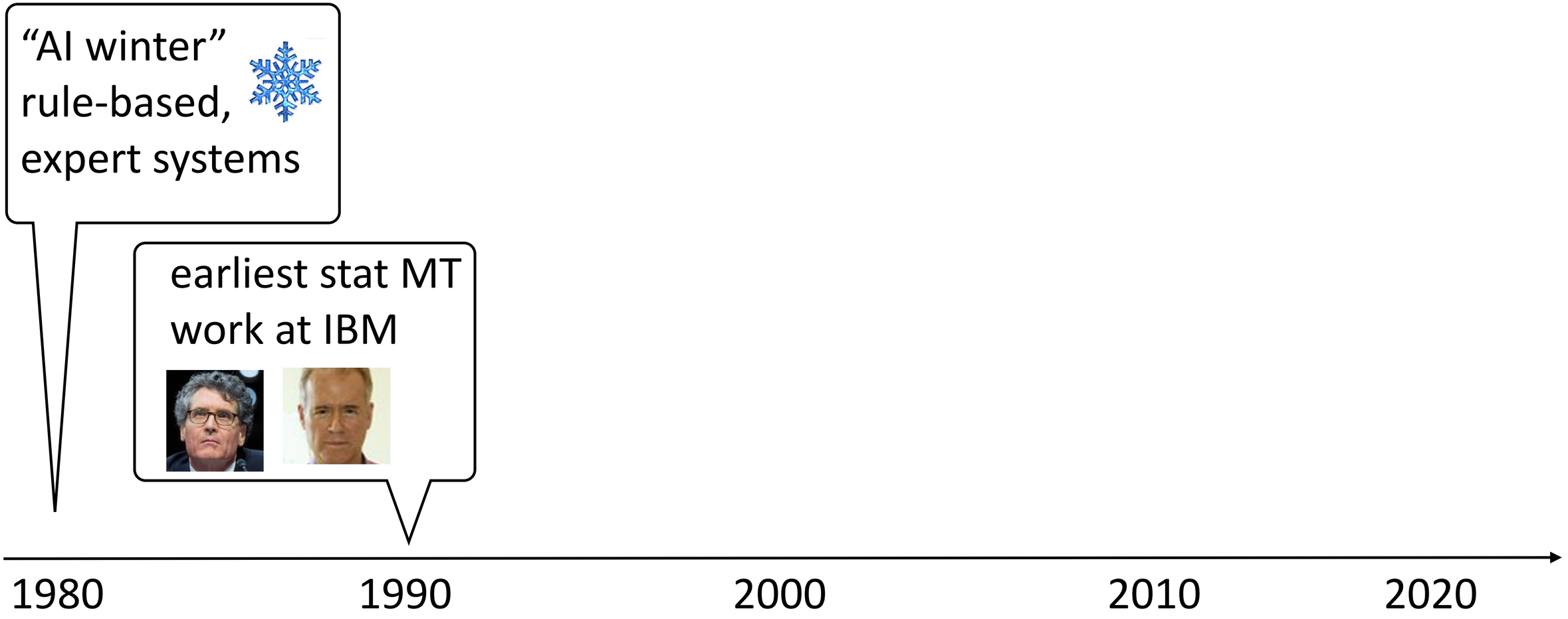
(to combine data, knowledge, linguistics, etc.)

A brief history of (modern) NLP

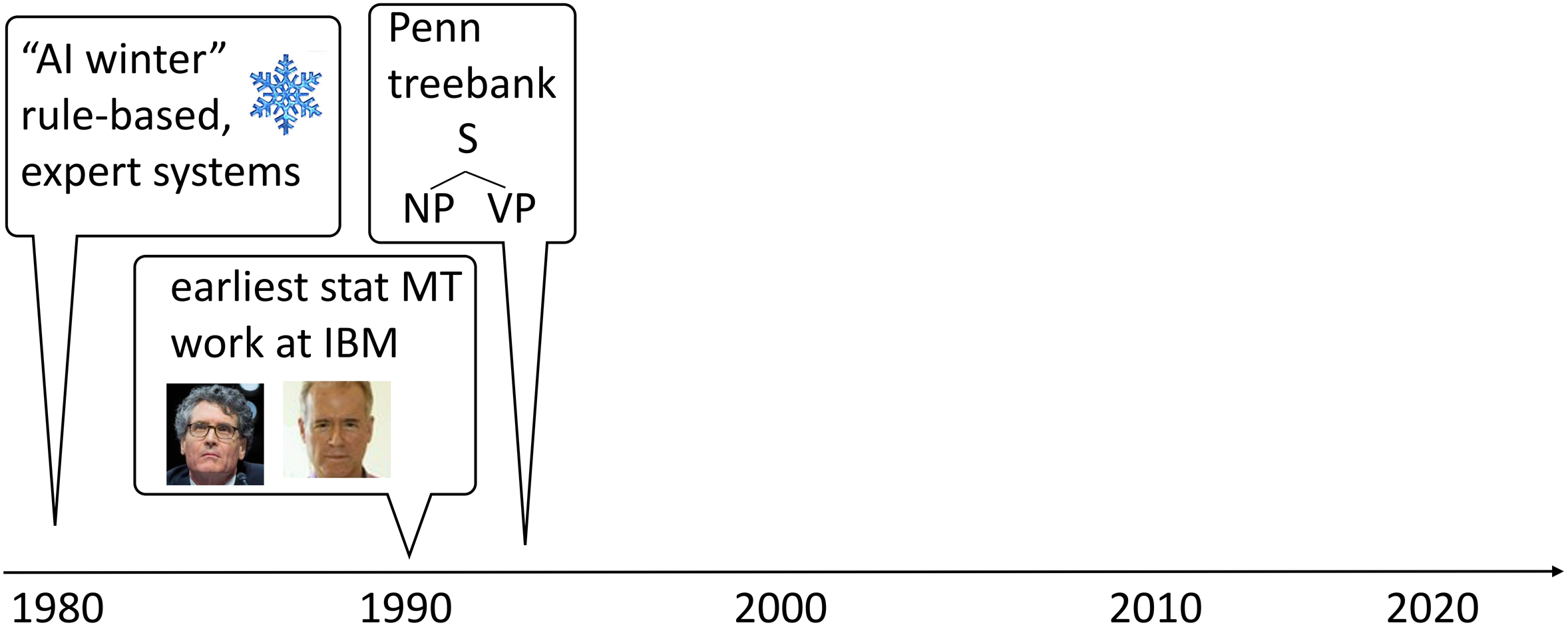
A brief history of (modern) NLP



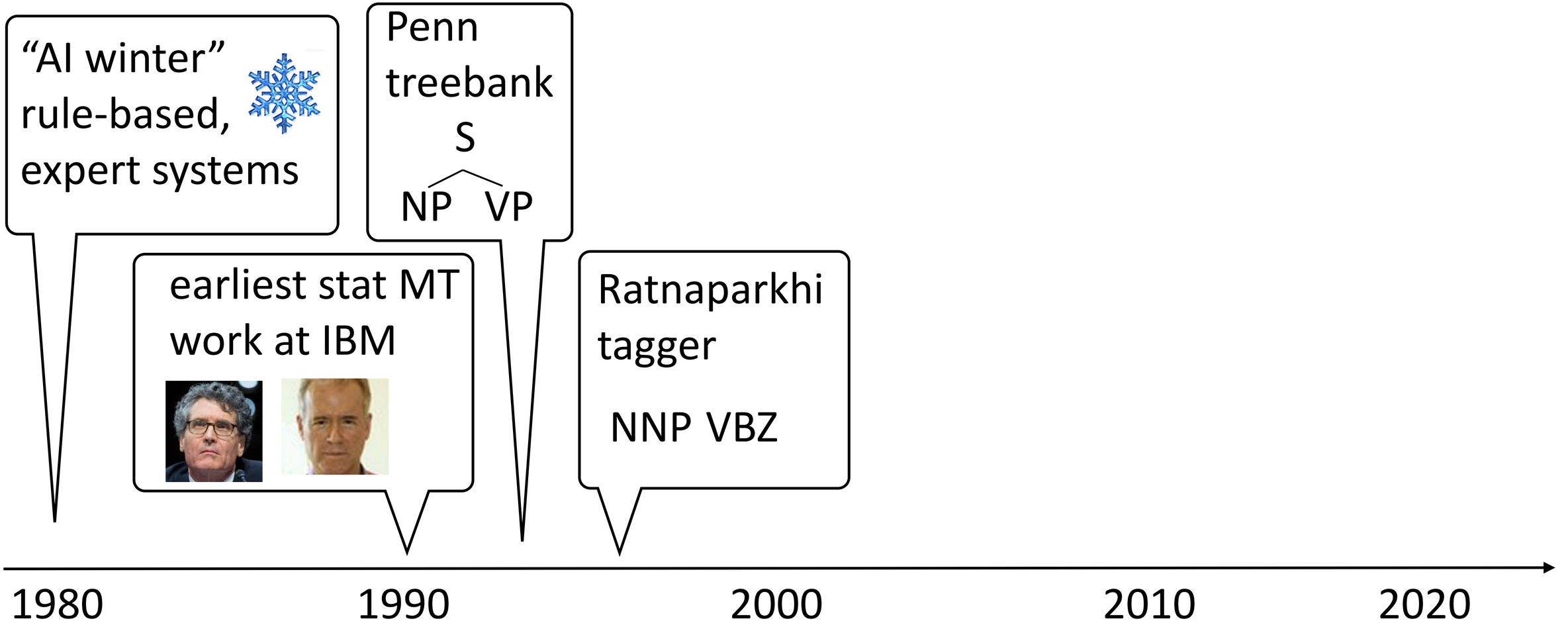
A brief history of (modern) NLP



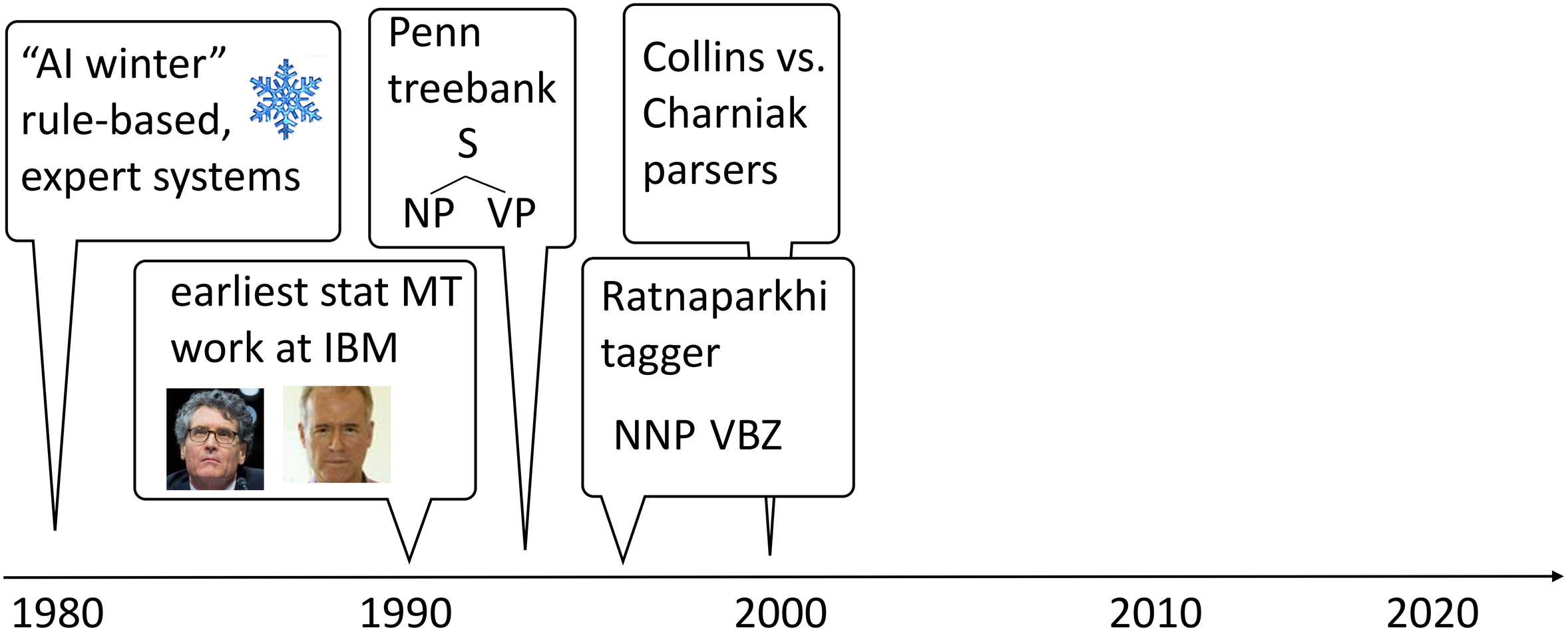
A brief history of (modern) NLP



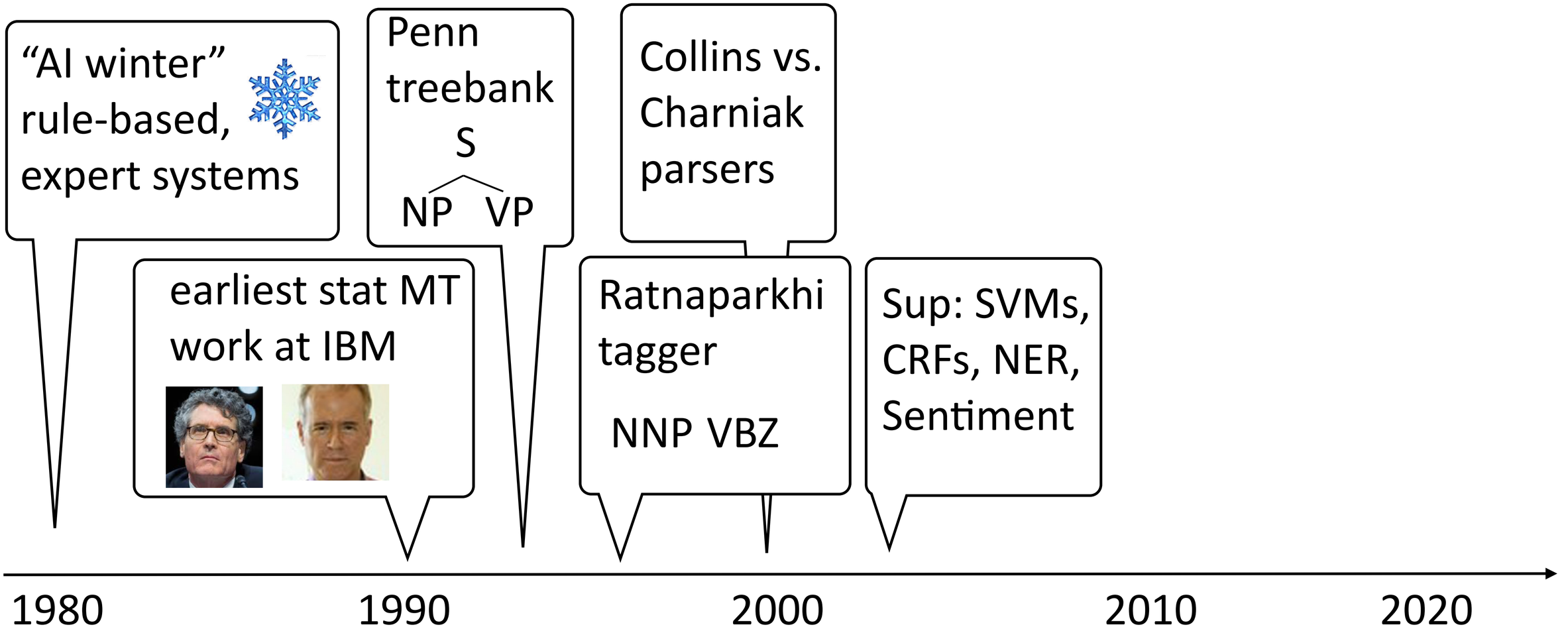
A brief history of (modern) NLP



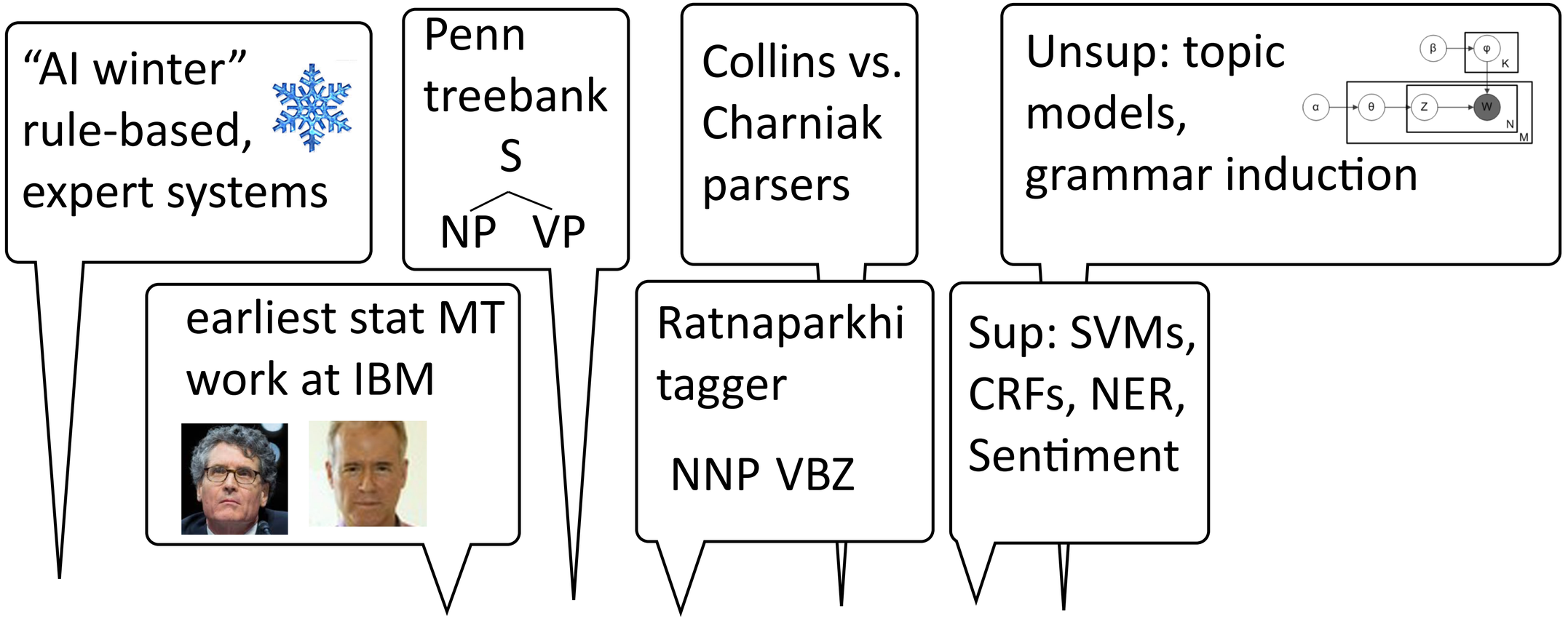
A brief history of (modern) NLP



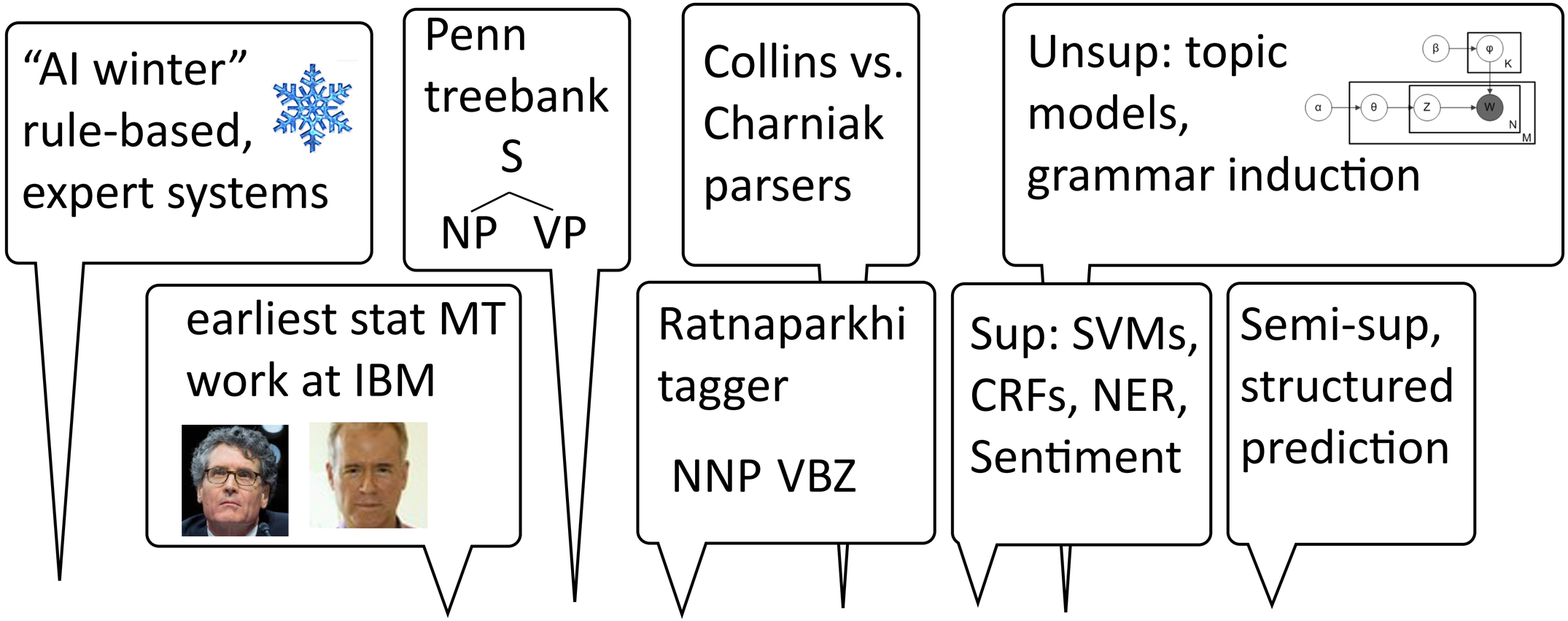
A brief history of (modern) NLP



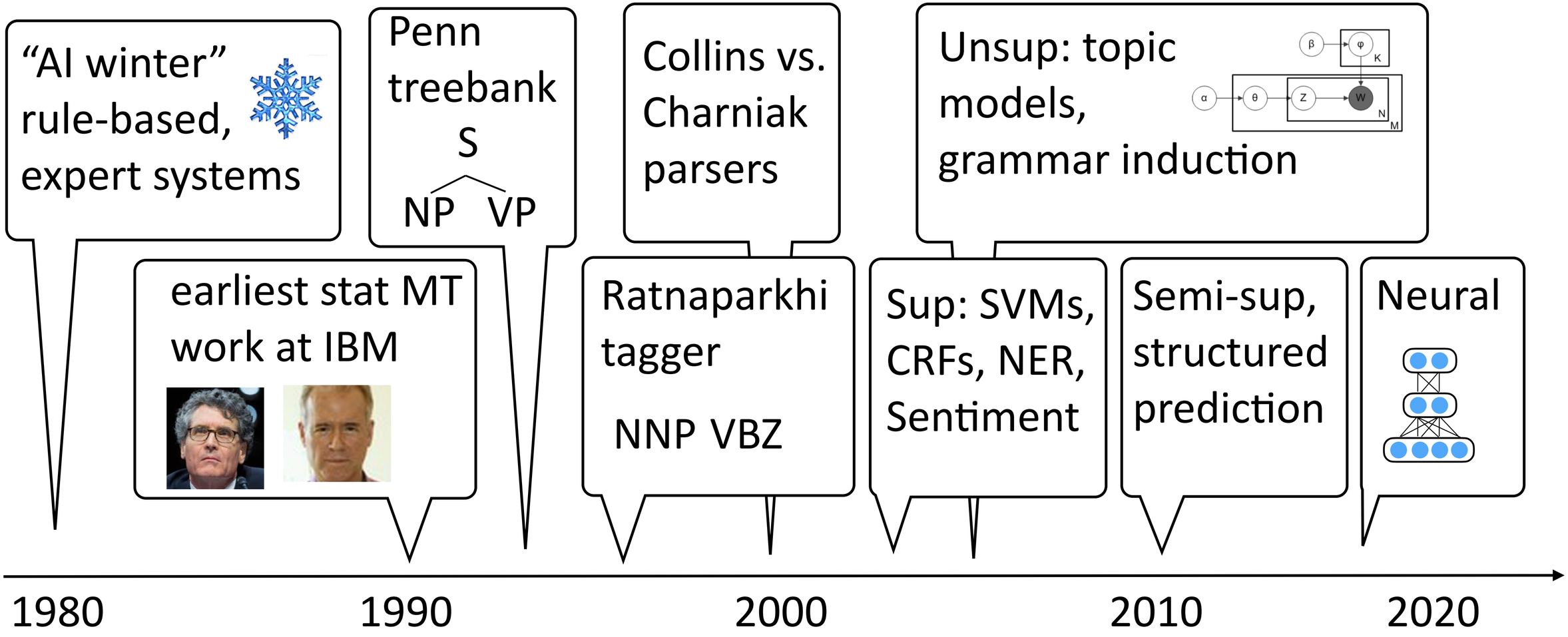
A brief history of (modern) NLP



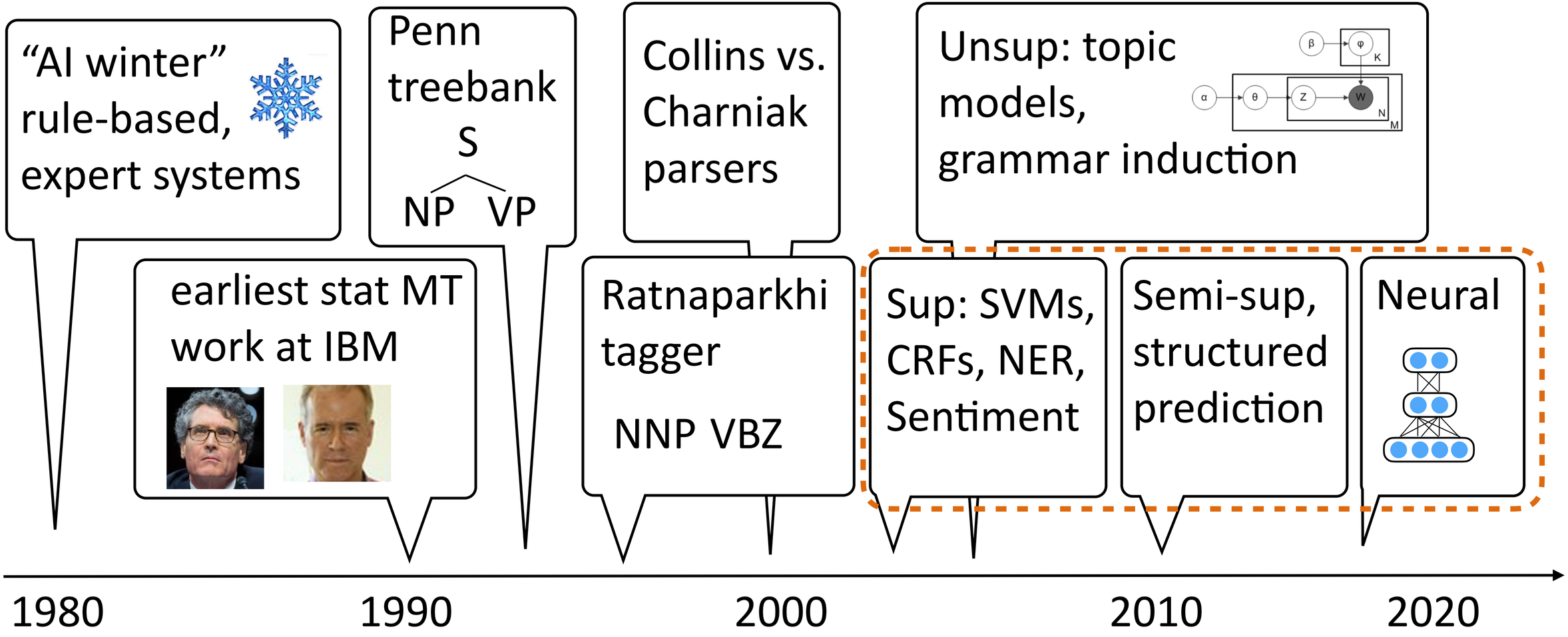
A brief history of (modern) NLP



A brief history of (modern) NLP



A brief history of (modern) NLP



Structured Prediction

“Learning a Part-of-Speech Tagger from Two Hours of Annotation”
Garrette and Baldridge (2013)

Structured Prediction

- All of these techniques are data-driven! Some data is naturally occurring, but may need to label

"Learning a Part-of-Speech Tagger from Two Hours of Annotation"
Garrette and Baldridge (2013)

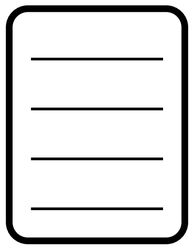
Structured Prediction

- All of these techniques are data-driven! Some data is naturally occurring, but may need to label
- Supervised techniques work well on very little data

“Learning a Part-of-Speech Tagger from Two Hours of Annotation”
Garrette and Baldridge (2013)

Structured Prediction

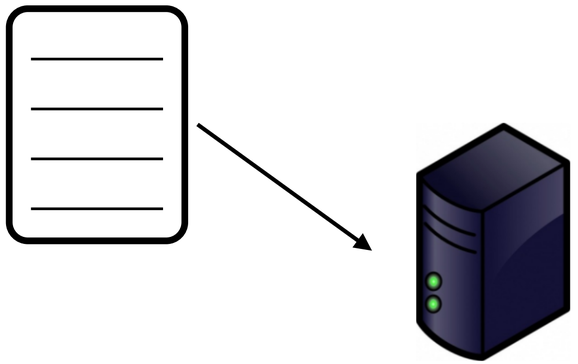
- All of these techniques are data-driven! Some data is naturally occurring, but may need to label
- Supervised techniques work well on very little data



“Learning a Part-of-Speech Tagger from Two Hours of Annotation”
Garrette and Baldridge (2013)

Structured Prediction

- All of these techniques are data-driven! Some data is naturally occurring, but may need to label
- Supervised techniques work well on very little data

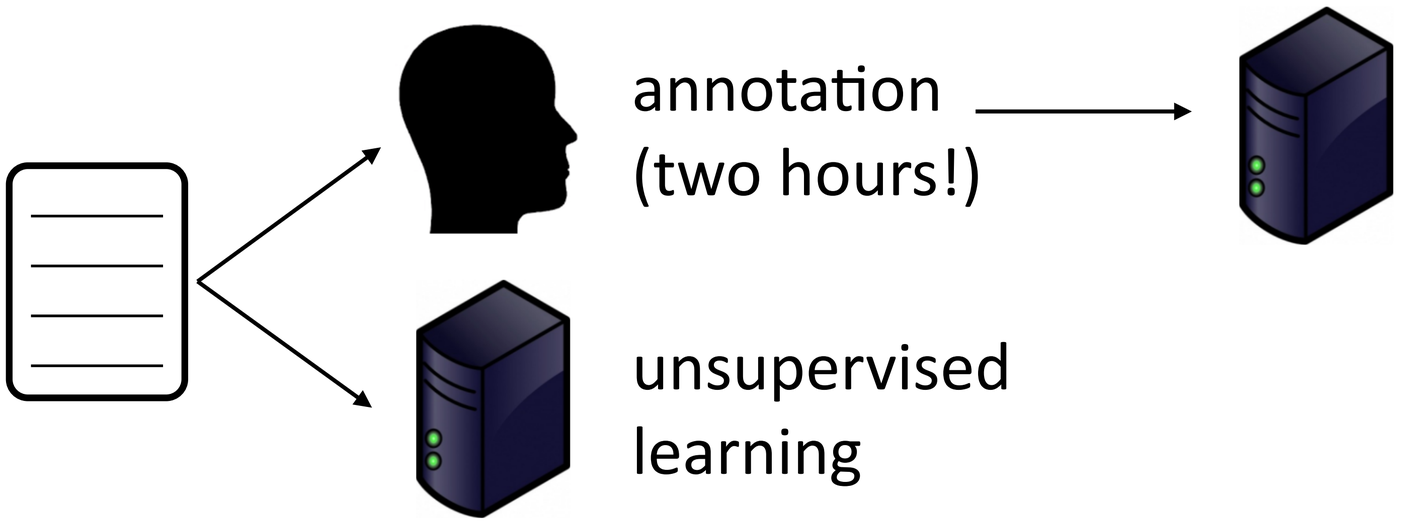


unsupervised learning

"Learning a Part-of-Speech Tagger from Two Hours of Annotation"
Garrette and Baldridge (2013)

Structured Prediction

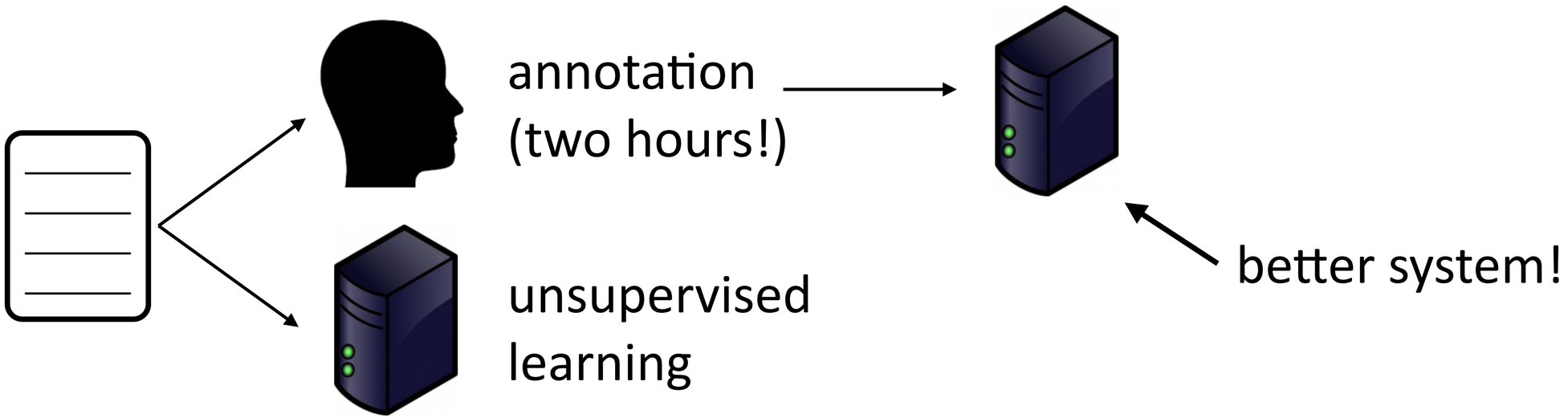
- All of these techniques are data-driven! Some data is naturally occurring, but may need to label
- Supervised techniques work well on very little data



"Learning a Part-of-Speech Tagger from Two Hours of Annotation"
Garrette and Baldridge (2013)

Structured Prediction

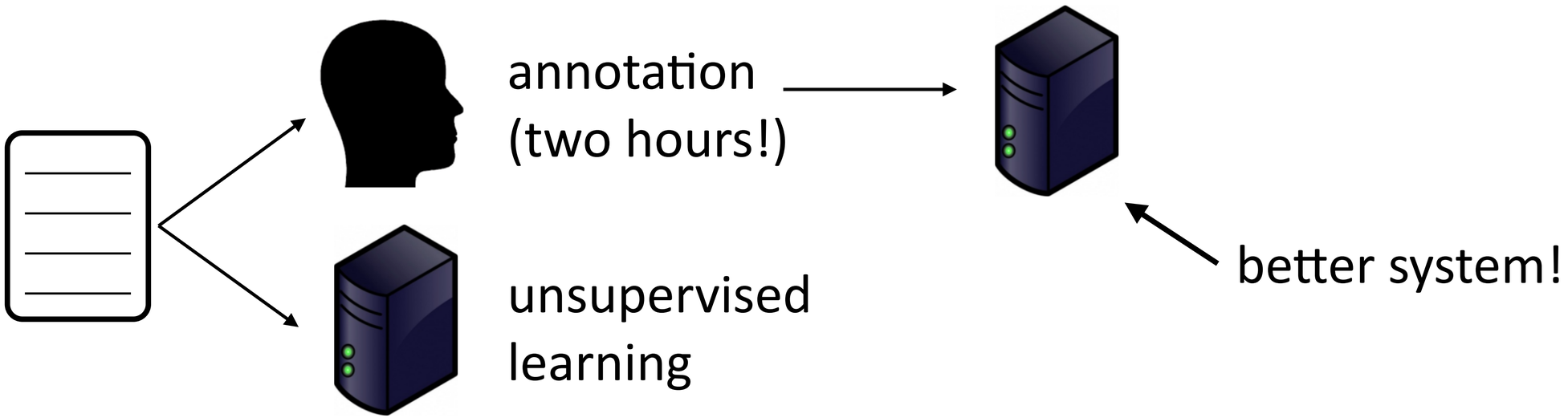
- All of these techniques are data-driven! Some data is naturally occurring, but may need to label
- Supervised techniques work well on very little data



"Learning a Part-of-Speech Tagger from Two Hours of Annotation"
Garrette and Baldridge (2013)

Structured Prediction

- All of these techniques are data-driven! Some data is naturally occurring, but may need to label
- Supervised techniques work well on very little data



- Even neural nets can do pretty well!

"Learning a Part-of-Speech Tagger from Two Hours of Annotation"
Garrette and Baldridge (2013)

Pretraining

- Language modeling: predict the next word in a text $P(w_i|w_1, \ldots, w_{i-1})$

P(*w* | I want to go to) = 0.01 Hawai'i

0.005 LA

0.0001 class

: use this model for other purposes

P(*w* | the acting was horrible, I think the movie was) = 0.1 bad

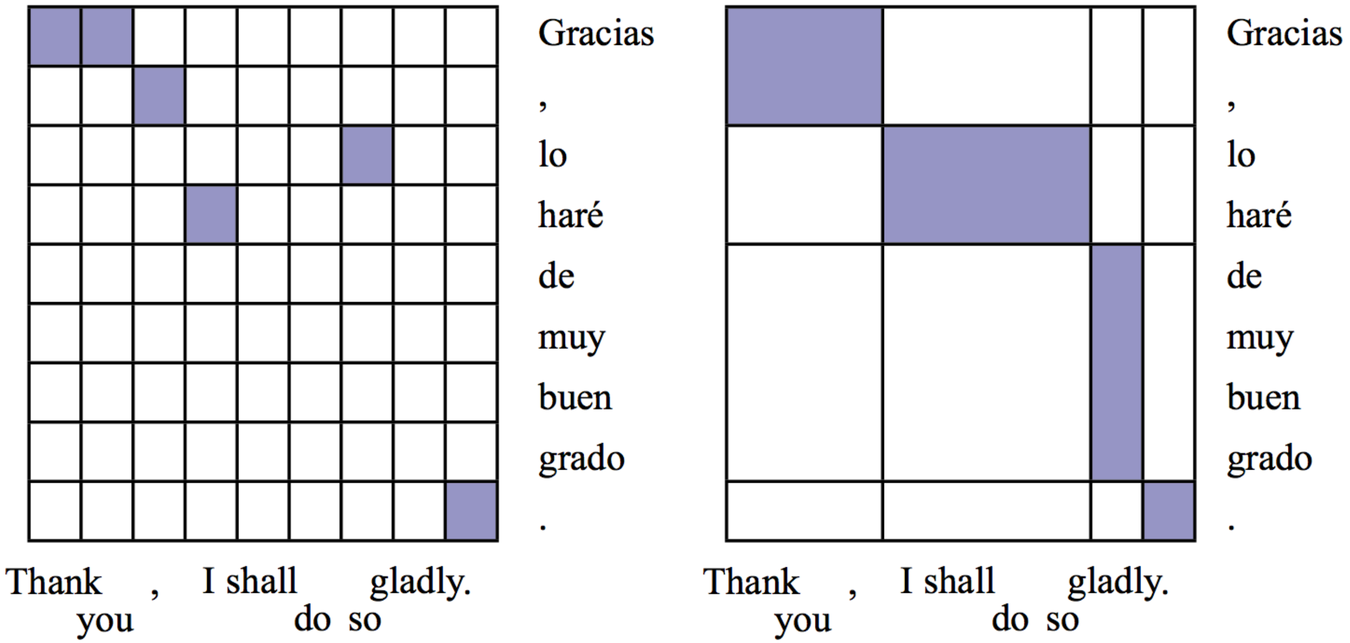
0.001 good

- Model understands some sentiment?

- Train a neural network to do language modeling on massive unlabeled text, fine-tune it to do {tagging, sentiment, question answering, …}

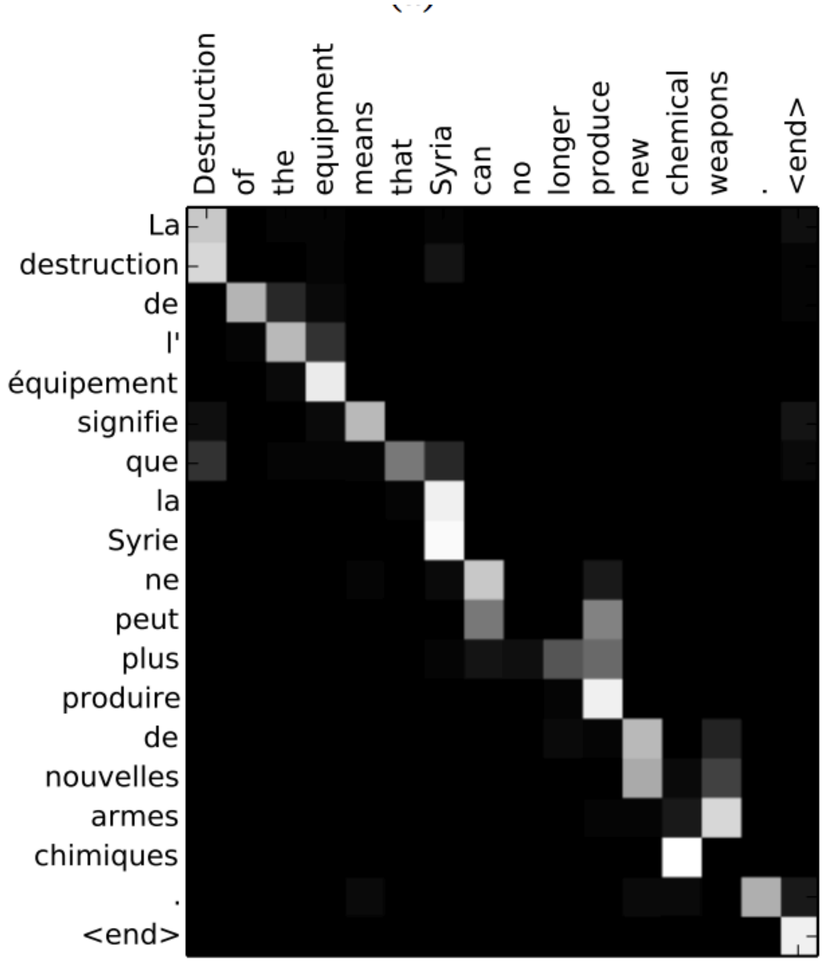
Peters et al. (2018), Devlin et al. (2019)

Less Manual Structure?



(a) example word alignment (b) example phrase alignment

DeNero et al. (2008)



Bahdanau et al. (2014)

Does manual structure have a place?

Does manual structure have a place?

- Neural nets don’t always work out of domain!

Does manual structure have a place?

- Neural nets don't always work out of domain!

- Coreference: rule-based systems are still about as good as deep learning out-of-domain

Does manual structure have a place?

- Neural nets don't always work out of domain!
- Coreference: rule-based systems are still about as good as deep learning out-of-domain

	CoNLL Avg. F_1
Newswire	
rule-based	55.60
berkeley	61.24
cort	63.37
deep-coref [conll]	65.39
deep-coref [lea]	65.60
Wikipedia	
rule-based	51.77
berkeley	51.01
cort	49.94
deep-coref [conll]	52.65
deep-coref [lea]	53.14
deep-coref$^-$	51.01

Moosavi and Strube (2017)

Does manual structure have a place?

- Neural nets don't always work out of domain!
- Coreference: rule-based systems are still about as good as deep learning out-of-domain
- LORELEI: transition point below which phrase-based systems are better

	CoNLL Avg. F_1
Newswire	
rule-based	55.60
berkeley	61.24
cort	63.37
deep-coref [conll]	65.39
deep-coref [lea]	65.60
Wikipedia	
rule-based	51.77
berkeley	51.01
cort	49.94
deep-coref [conll]	52.65
deep-coref [lea]	53.14
deep-coref^{-}	51.01

Moosavi and Strube (2017)

Does manual structure have a place?

- Neural nets don't always work out of domain!
- Coreference: rule-based systems are still about as good as deep learning out-of-domain
- LORELEI: transition point below which phrase-based systems are better
- Why is this? Inductive bias!

	CoNLL Avg. F_1
Newswire	
rule-based	55.60
berkeley	61.24
cort	63.37
deep-coref [conll]	65.39
deep-coref [lea]	65.60
Wikipedia	
rule-based	51.77
berkeley	51.01
cort	49.94
deep-coref [conll]	52.65
deep-coref [lea]	53.14
deep-coref^{-}	51.01

Moosavi and Strube (2017)

Does manual structure have a place?

- Neural nets don't always work out of domain!
- Coreference: rule-based systems are still about as good as deep learning out-of-domain
- LORELEI: transition point below which phrase-based systems are better
- Why is this? Inductive bias!
- Can multi-task learning help?

	CoNLL Avg. F_1
Newswire	
rule-based	55.60
berkeley	61.24
cort	63.37
deep-coref [conll]	65.39
deep-coref [lea]	65.60
Wikipedia	
rule-based	51.77
berkeley	51.01
cort	49.94
deep-coref [conll]	52.65
deep-coref [lea]	53.14
deep-coref^{-}	51.01

Moosavi and Strube (2017)

Does manual structure have a place?

Trump Pope family watch a hundred years a year in the White House balcony

Does manual structure have a place?

Trump Pope family watch a hundred years a year in the White House balcony

- Maybe manual structure would help…

Where are we?

Where are we?

- NLP consists of: analyzing and building representations for text, solving problems involving text

Where are we?

- NLP consists of: analyzing and building representations for text, solving problems involving text
- These problems are hard because language is ambiguous, requires drawing on data, knowledge, and linguistics to solve

Where are we?

- NLP consists of: analyzing and building representations for text, solving problems involving text
- These problems are hard because language is ambiguous, requires drawing on data, knowledge, and linguistics to solve
- Knowing which techniques to use requires understanding dataset size, problem complexity, and a lot of tricks!

Where are we?

- NLP consists of: analyzing and building representations for text, solving problems involving text
- These problems are hard because language is ambiguous, requires drawing on data, knowledge, and linguistics to solve
- Knowing which techniques to use requires understanding dataset size, problem complexity, and a lot of tricks!
- NLP encompasses all of these things

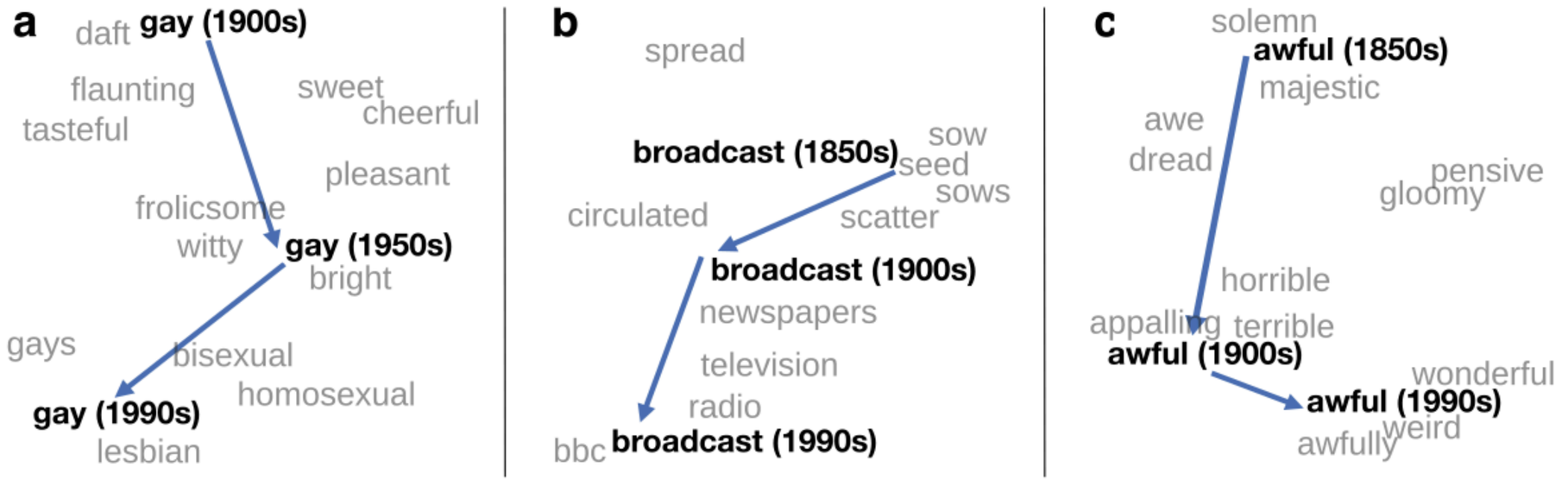
NLP vs. Computational Linguistics

- NLP: build systems that deal with language data
- CL: use computational tools to study language

Hamilton et al. (2016)

NLP vs. Computational Linguistics

- NLP: build systems that deal with language data
- CL: use computational tools to study language



Hamilton et al. (2016)

NLP vs. Computational Linguistics

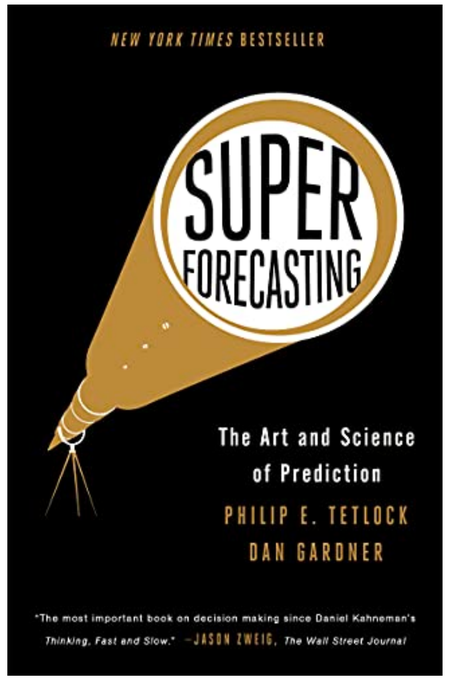
- Computational tools for other purposes: literary theory, political science, computational social science…

Zong, Ritter, Hovy (2020)

NLP vs. Computational Linguistics

- Computational tools for other purposes: literary theory, political science, computational social science…

Is it possible to predict a forecaster's skill based on their text justifications?



Question: Will Kim Jong Un visit Seoul before 1 October 2019?
Estimated Chance: 5%
Forecast Justification: No North Korean leader has stepped foot in Seoul since the partition of the Koreas at the end of the Korean War. . . .

Figure 1: A sample prediction made by a user in response to a question posted by *the Economist*.

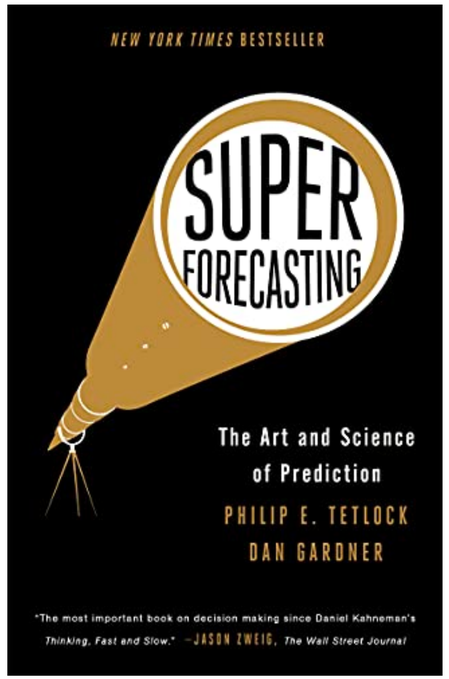
	K	100	200	300	500	1000
LR	Bag-of-ngrams	69.5	74.2	72.5	69.2	64.8
Neural	CNN	71.5	75.0	72.0	69.6	64.0
	BERT-base	74.5	77.3	74.3	69.7	65.1

Zong, Ritter, Hovy (2020)

NLP vs. Computational Linguistics

- Computational tools for other purposes: literary theory, political science, computational social science…

Is it possible to predict a forecaster's skill based on their text justifications?



Question: Will Kim Jong Un visit Seoul before 1 October 2019?
Estimated Chance: 5%
Forecast Justification: No North Korean leader has stepped foot in Seoul since the partition of the Koreas at the end of the Korean War. . . .

Figure 1: A sample prediction made by a user in response to a question posted by *the Economist*.

	K	100	200	300	500	1000
LR	Bag-of-ngrams	69.5	74.2	72.5	69.2	64.8
Neural	CNN	71.5	75.0	72.0	69.6	64.0
	BERT-base	74.5	77.3	74.3	69.7	65.1

Yes!

All accuracies are well above 50% random baseline

Zong, Ritter, Hovy (2020)

Course Goals

Course Goals

- Cover fundamental machine learning techniques used in NLP

Course Goals

- Cover fundamental machine learning techniques used in NLP
- Understand how to look at language data and approach linguistic phenomena

Course Goals

- Cover fundamental machine learning techniques used in NLP
- Understand how to look at language data and approach linguistic phenomena
- Know about modern NLP methods: what is the state-of-the-art in 2022?

Course Goals

- Cover fundamental machine learning techniques used in NLP
- Understand how to look at language data and approach linguistic phenomena
- Know about modern NLP methods: what is the state-of-the-art in 2022?
- Make you a “producer” rather than a “consumer” of NLP tools

Course Goals

- Cover fundamental machine learning techniques used in NLP
- Understand how to look at language data and approach linguistic phenomena
- Know about modern NLP methods: what is the state-of-the-art in 2022?
- Make you a “producer” rather than a “consumer” of NLP tools
  - The assignments should teach you what you need to know to understand nearly any modern NLP system.

Assignments

- 4 Programming Assignments
  - Implementation-oriented
  - ~2 weeks per assignment

Assignments

- 4 Programming Assignments
  - Implementation-oriented
  - ~2 weeks per assignment

These projects require understanding of the concepts, ability to write performant code, and ability to think about how to debug complex systems. **They are challenging, so start early!**

Final Project

- Final project (20%)
  - Groups of 3-4 recommended. 1 is possible, but will require more work.
  - 4 page report + final project presentation.