

CS 7650: 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/Tuesday for questions asked over the weekend).
- ▶ TA Office hours:
 - ▶ See spreadsheet

Instructor



[Alan Ritter](#)

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Teaching Assistants

Jan Vijay Singh

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Xurui Zhang

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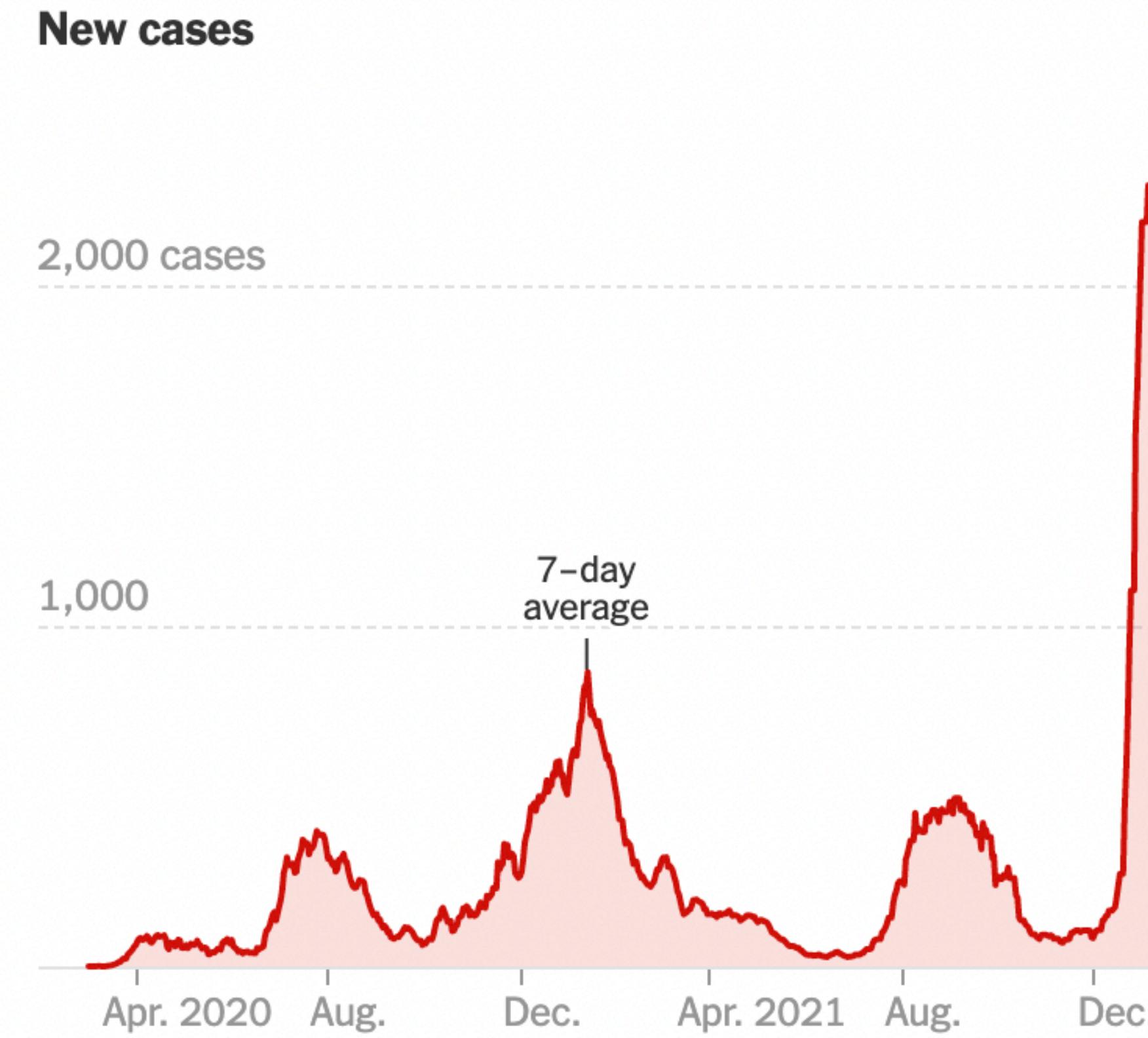
COVID-19

The New York Times



Fulton County, Ga.

Unvaccinated people in Fulton County are at an extremely high risk for Covid-19 infections. The average number of new cases in Fulton County was **2,253** yesterday, **about the same** as the day before. Because of high spread, **the C.D.C. recommends that even vaccinated people wear masks here.** Since January 2020, at least **1 in 6** people who live in Fulton County have been infected, and at least **1 in 561** people have died.



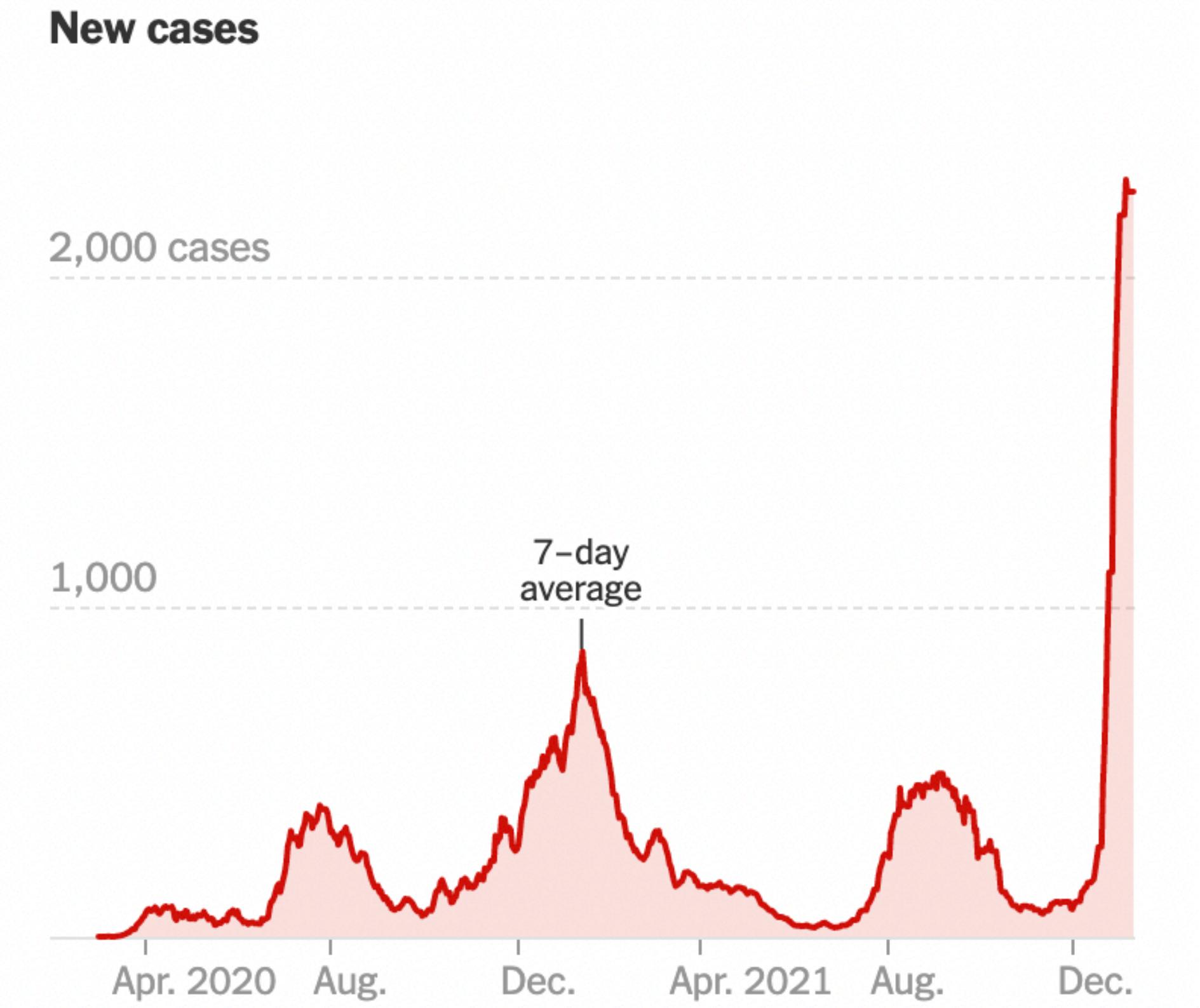
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Please wear a mask while you are in this class!

Prerequisites

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

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There will be a lot of math and programming!

S

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

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- ▶ Final project (details on course website, will discuss later)
- ▶ Problem Set 1 (background review) is out now on Gradescope (due Jan 14)

Problem Set 1 (Background Review)

- ▶ Due Jan 14 (this Friday).
- ▶ 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

Schedule		
Jan 10:	Course Introduction	Eisenstein Chapter 1
Jan 12:	Machine Learning	Eisenstein 2.0-2.5, 4.1,4.3-4.5
Jan 13:	Problem Set 1 due	
Jan 17:	MLK Holiday	
TBD:	Project 1	

Project 1 is also out (please look!)

The screenshot shows a Jupyter Notebook interface with the following details:

- Title:** TextClassification_release.ipynb
- Toolbar:** File, Edit, View, Insert, Runtime, Tools, Help. Last saved at January 8.
- Code Cell:** Contains Python code for licensing and attribution:

```
# Licensing Information: You are free to use or extend this project for
# educational purposes provided that (1) you do not distribute or publish
# solutions, (2) you retain this notice, and (3) you provide clear
# attribution to The Georgia Institute of Technology, including a link to https://aritter.github.io/CS-7650/
#
# Attribution Information: This assignment was developed at The Georgia Institute of Technology
# by Alan Ritter (alan.ritter@cc.gatech.edu)
```
- Section Header:** Project #1: Text Classification
- Description:** In this assignment, you will implement the perceptron algorithm, and a simple, but competitive neural bag-of-words model, as described in [this paper](#) for text classification. You will train your models on a (provided) dataset of positive and negative movie reviews and report accuracy on a test set.
- Note:** In this notebook, we provide you with starter code to read in the data and evaluate the performance of your models. After completing the instructions below, please follow the instructions at the end to submit your notebook and other files to Gradescope.
- Reminder:** Make sure to make a copy of this notebook, so your changes are saved.

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Free Textbooks!

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

Natural Language Processing

Speech and Language Processing (3rd ed. draft)

[Dan Jurafsky](#) and [James H. Martin](#)

Jacob Eisenstein

Programming Projects: Computation

- ▶ 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!)
 - ▶ You probably want to use a GPU
 - ▶ Google Colab: free GPUs (some limitations)
 - ▶ The programming projects are designed with Colab in mind
 - ▶ Colab Pro subscription (\$10/month). This is highly recommended once we start working with PyTorch.



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

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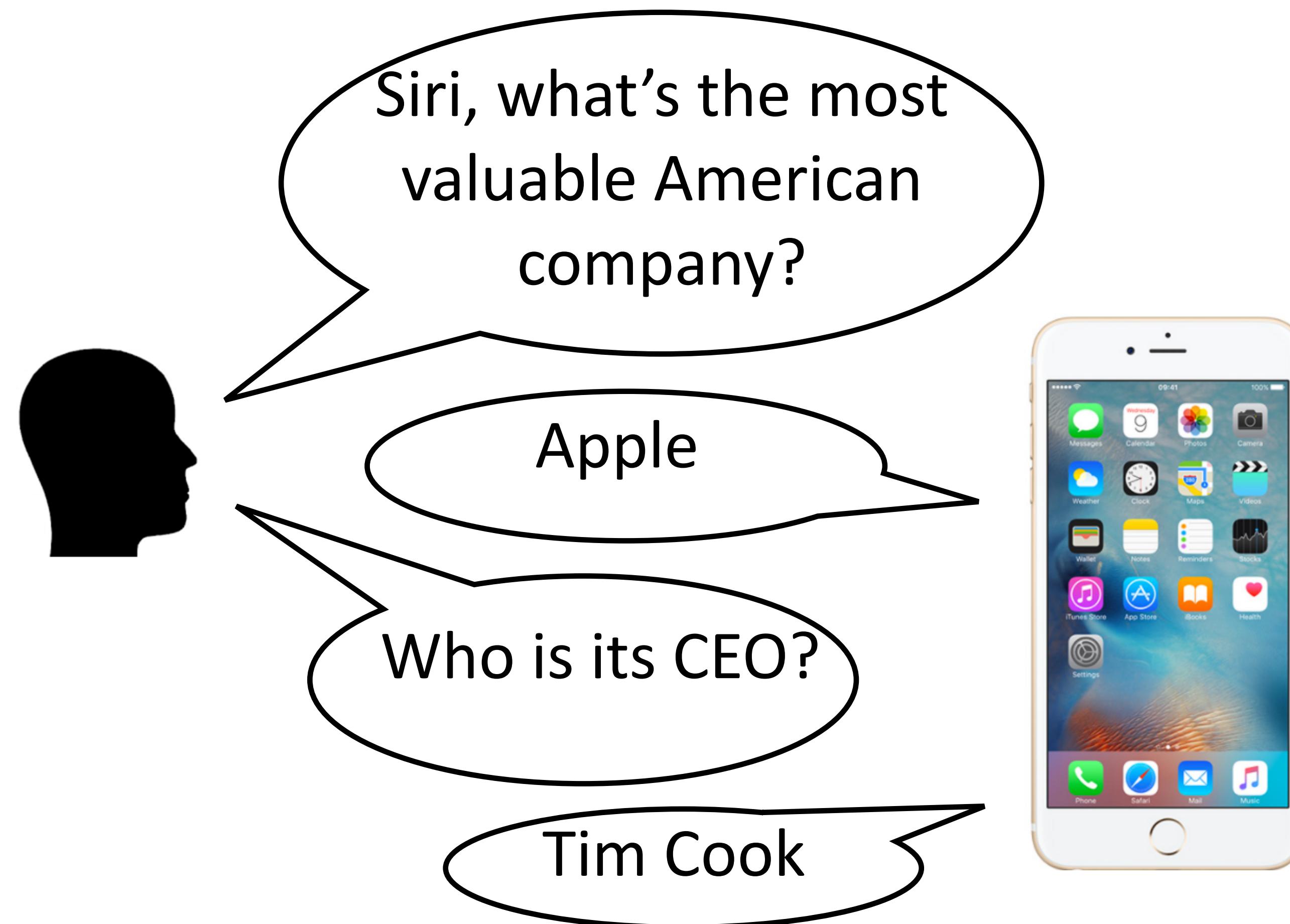
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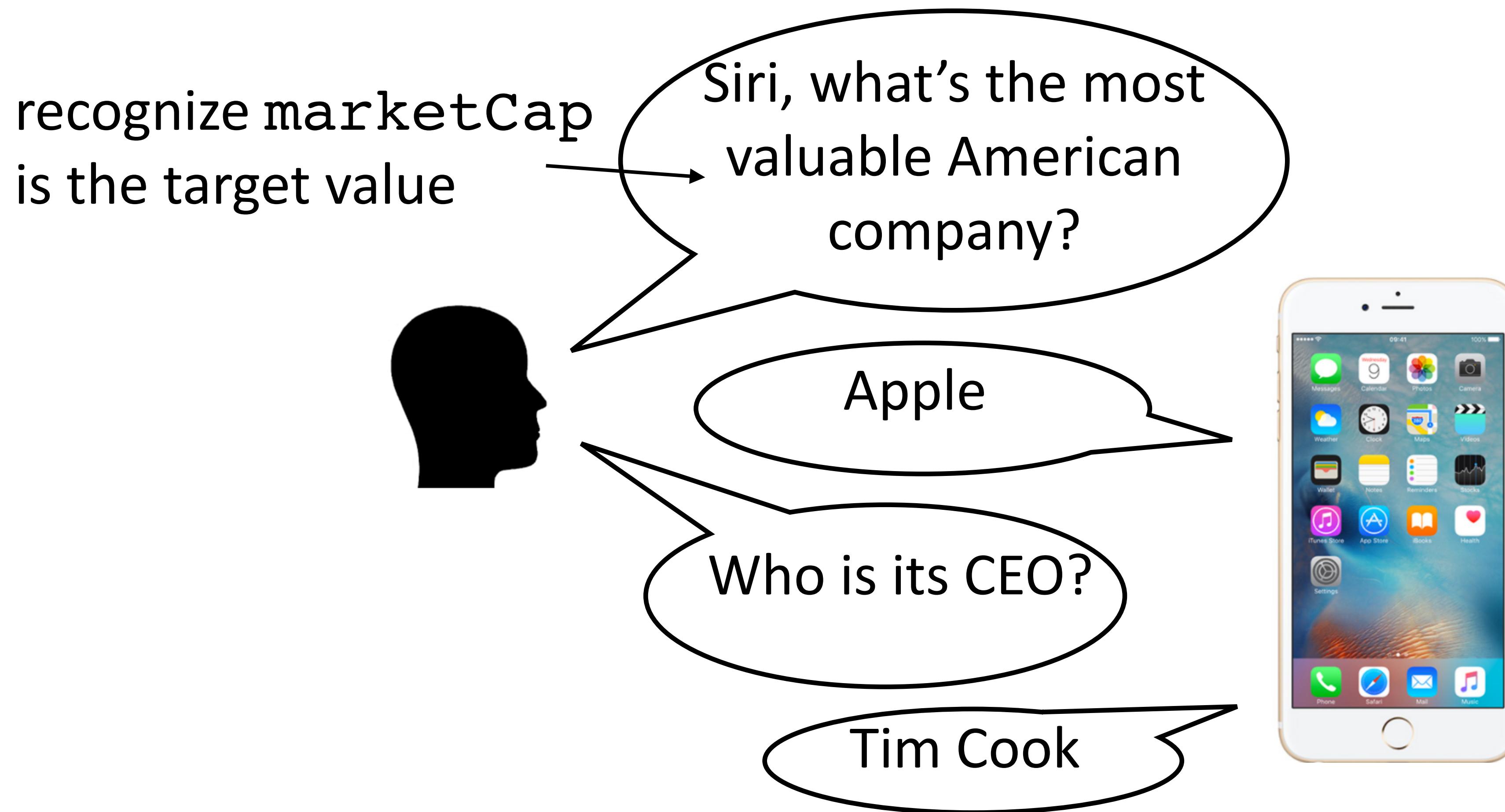
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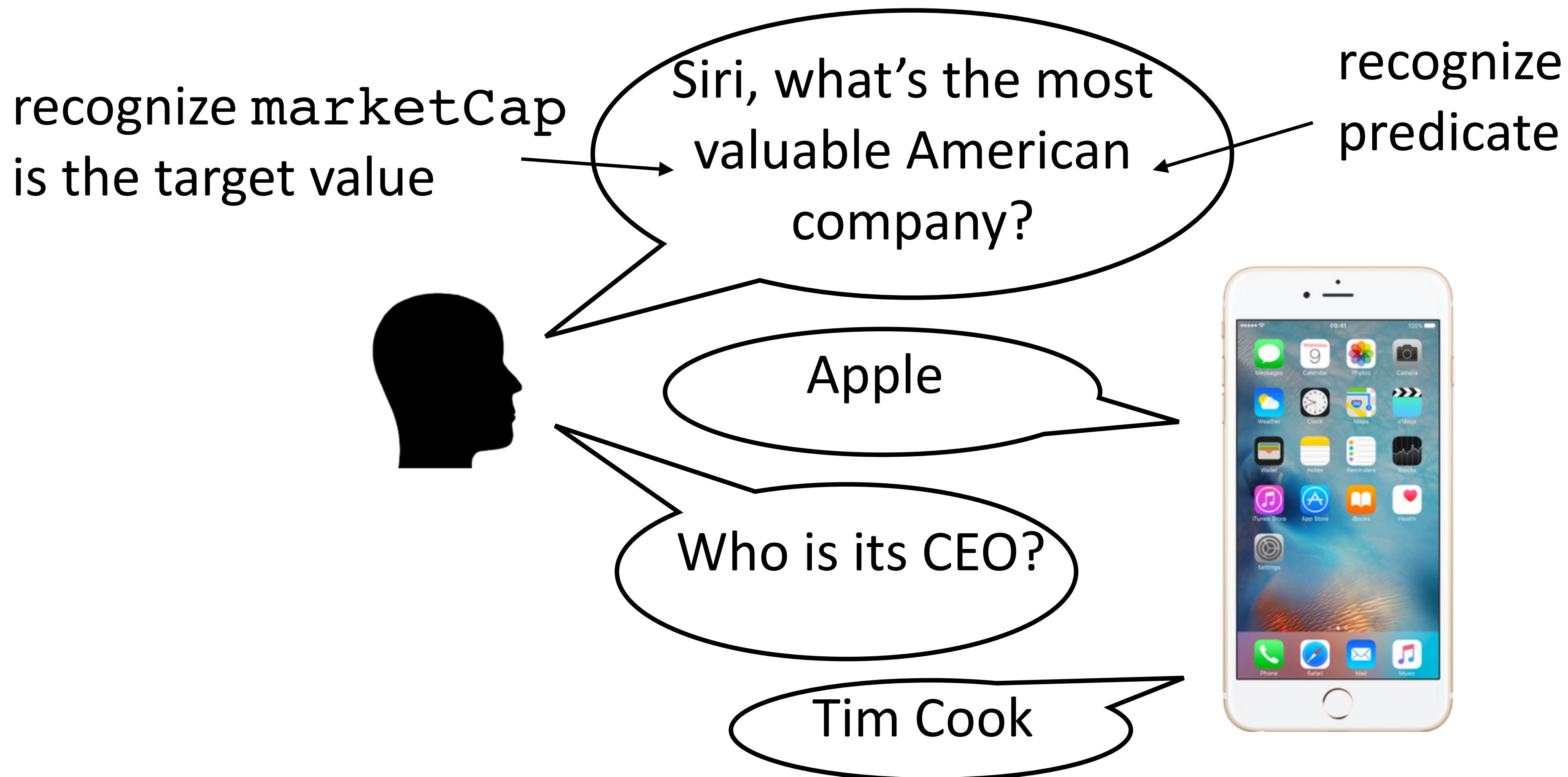
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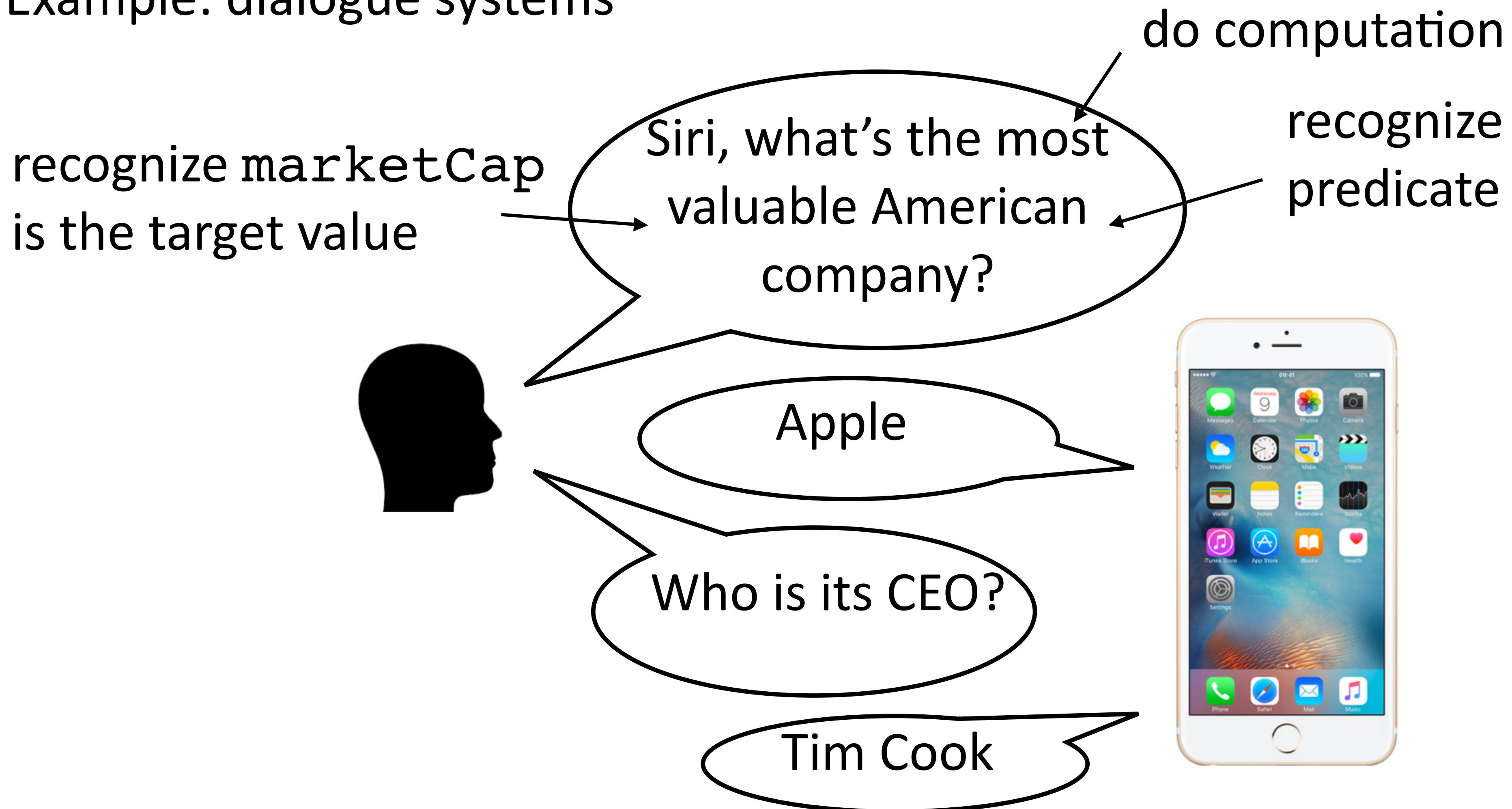
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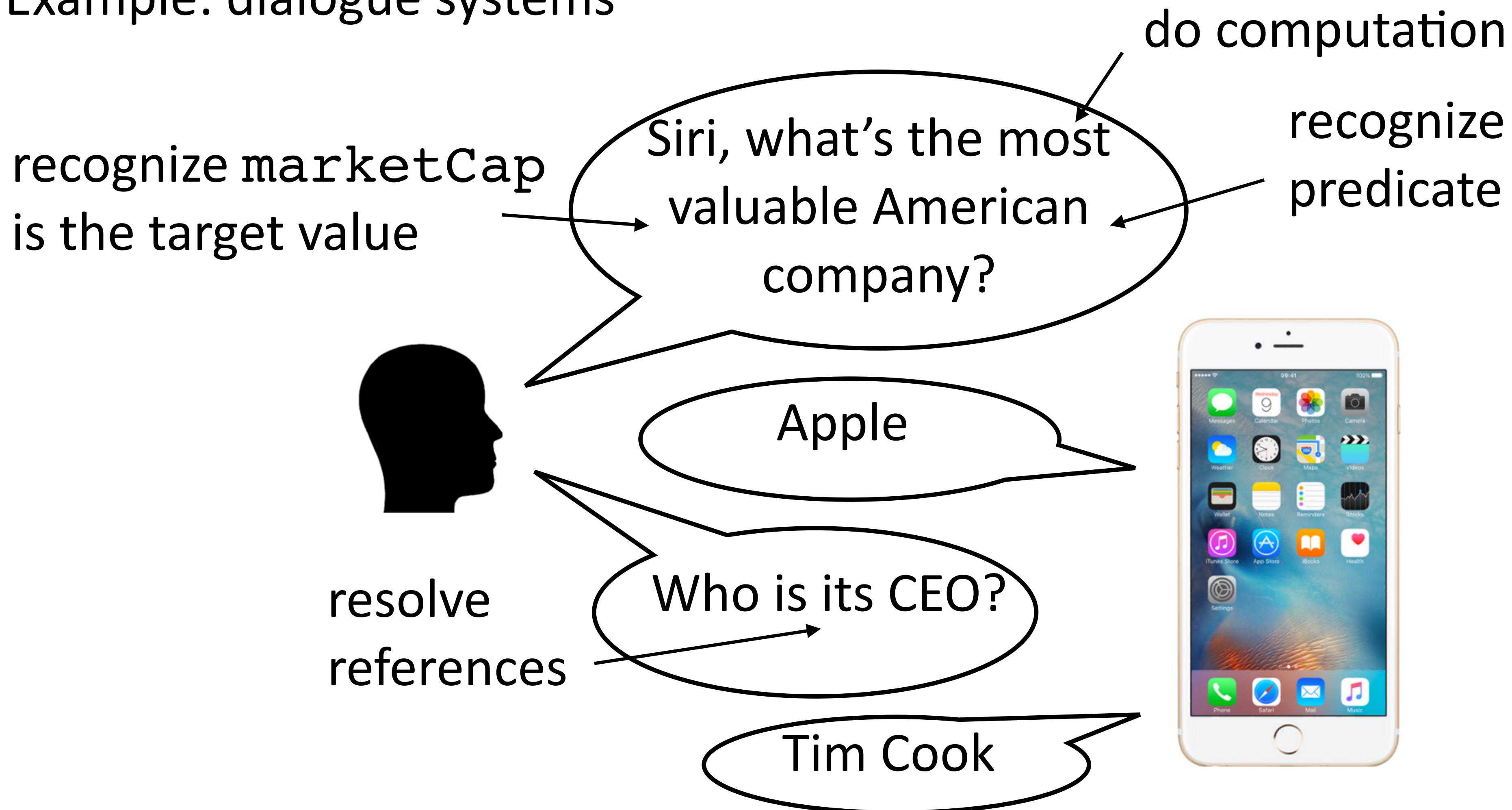
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Automatic Summarization

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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.

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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.

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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.

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paraphrase to provide clarity

Machine Translation



< 2/8

特朗普偕家人在白宫阳台观看百年一遇日全食

>

People's Daily, August 30, 2017

Machine Translation



A photograph of a woman with blonde hair, wearing a black sleeveless dress and 3D glasses, looking upwards. She is standing next to a man in a dark suit. The background is a plain wall.

Translate

English French Spanish Chinese - detected ▾

特朗普偕家人在白宫阳台观看百年一遇日全食

2/8 特朗普偕家人在白宫阳台观看百年一遇日全食

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

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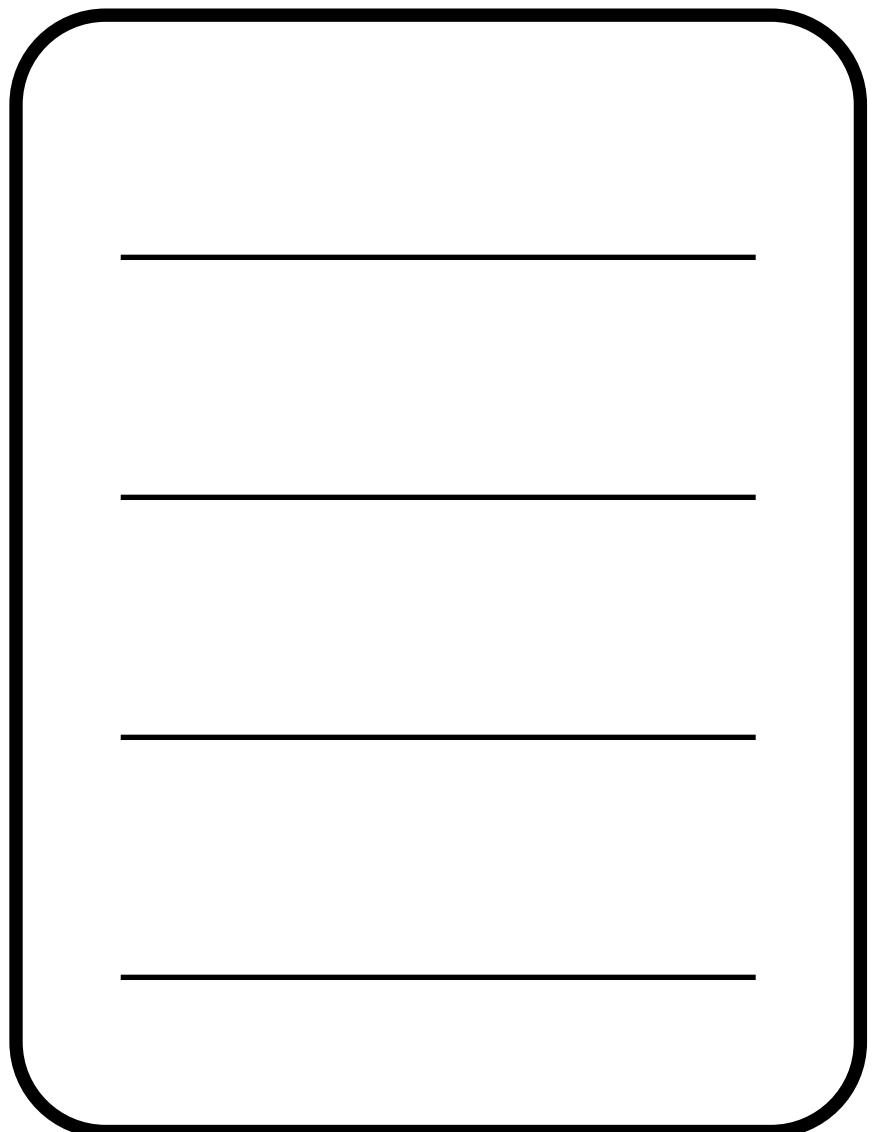


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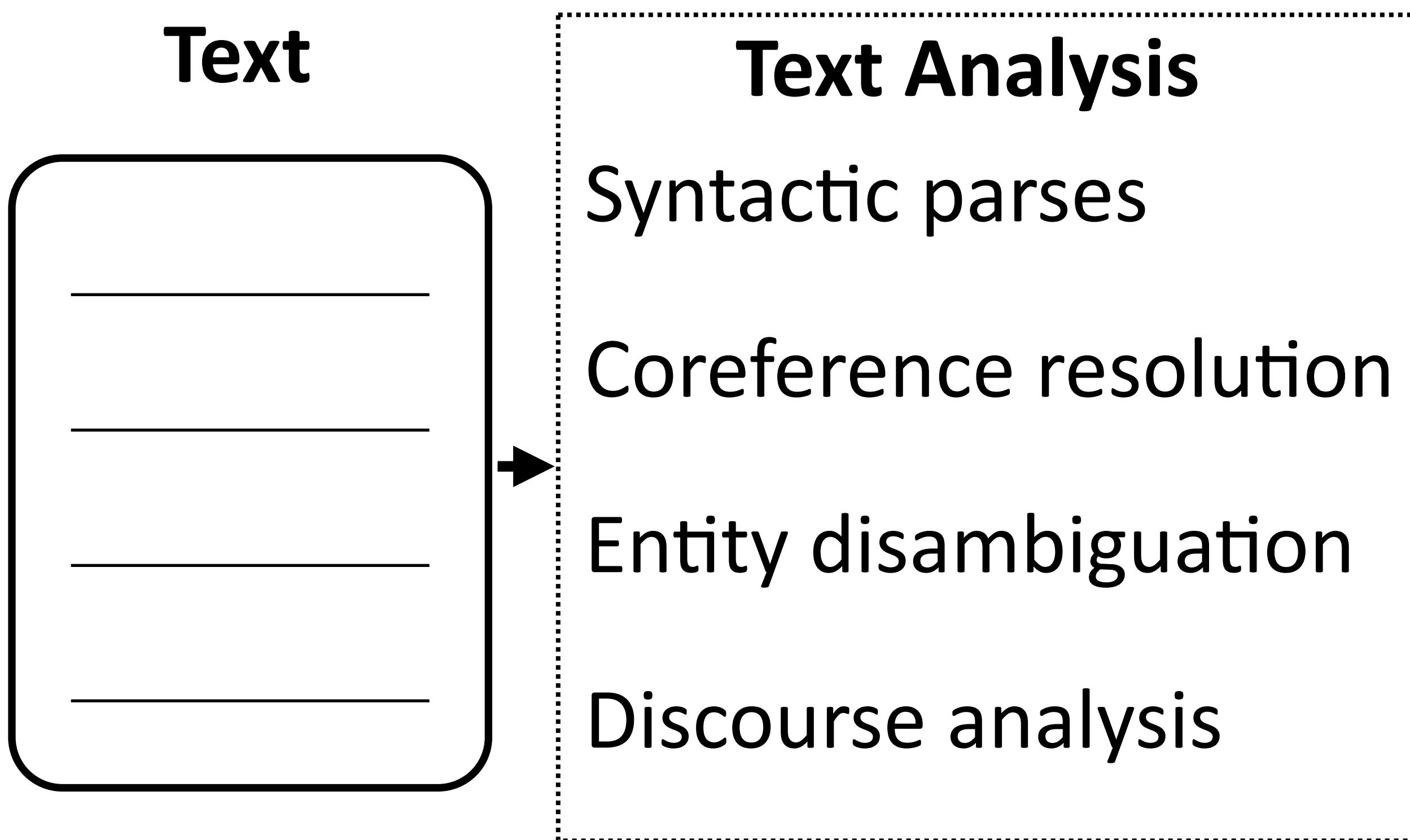
NLP Analysis Pipeline

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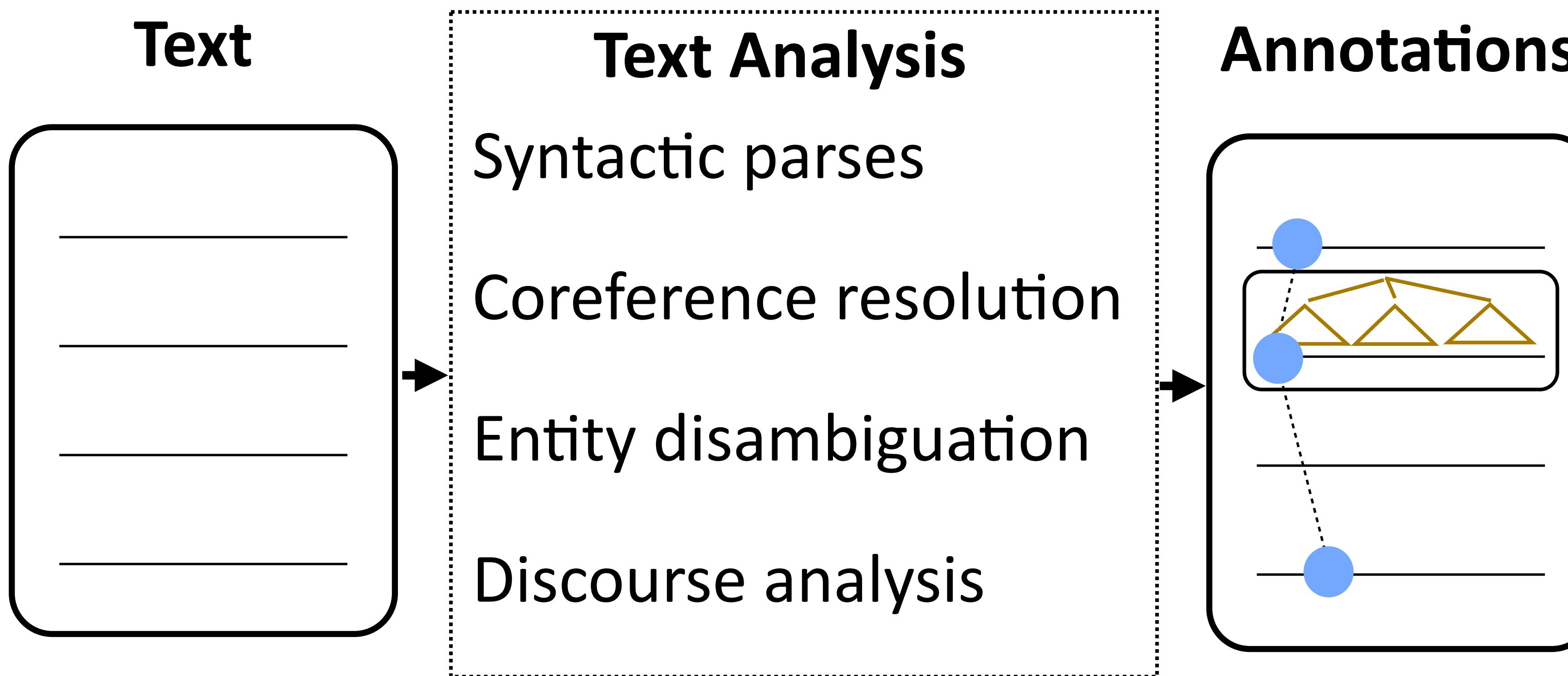
Text



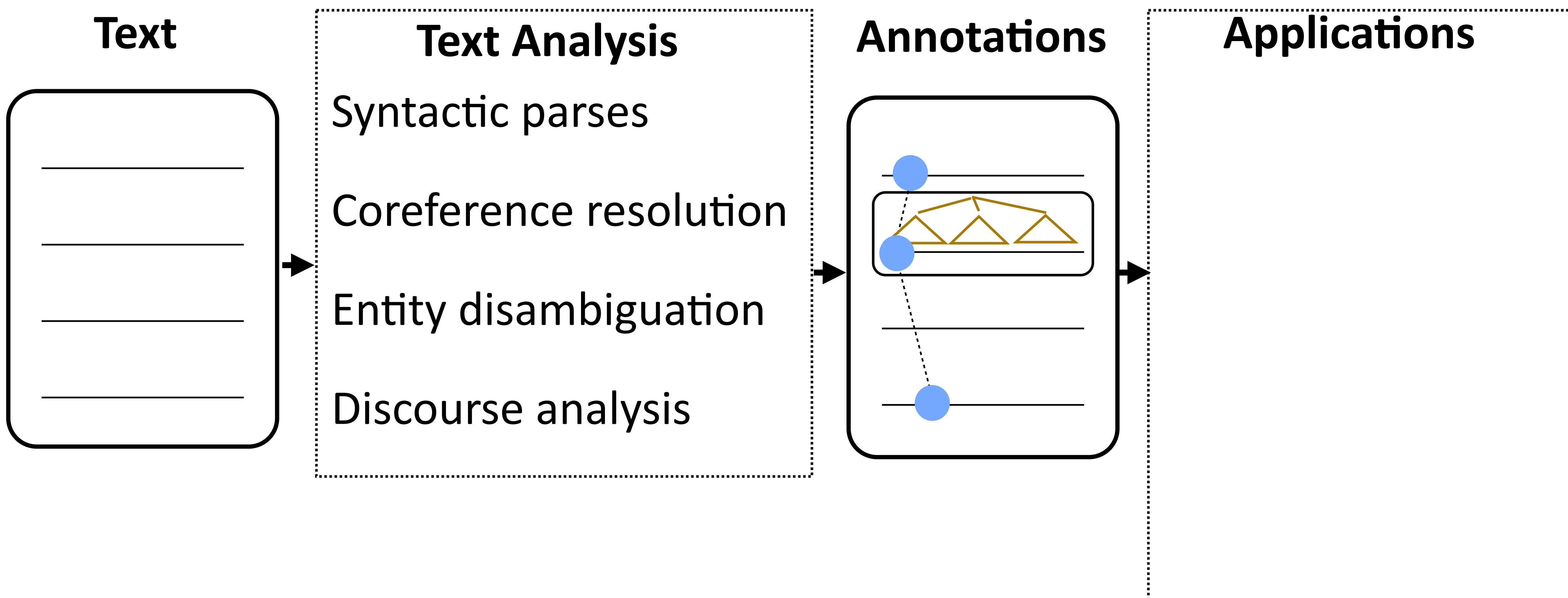
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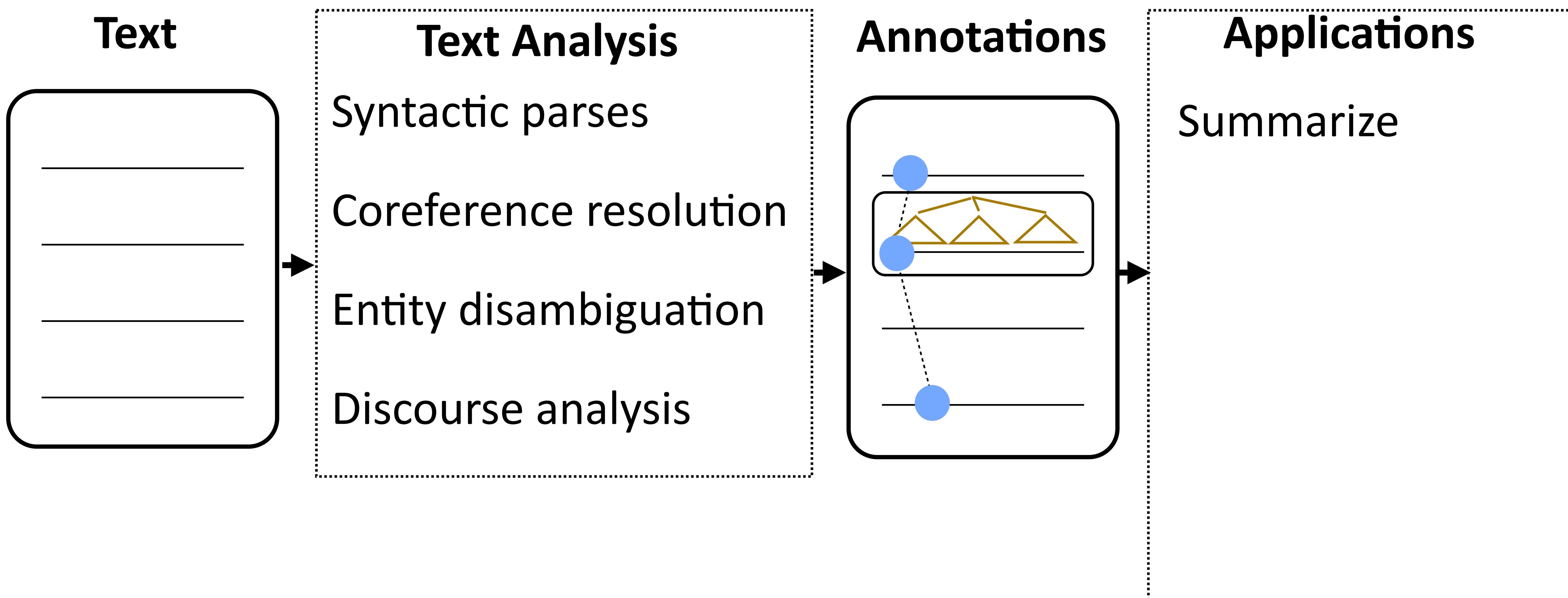
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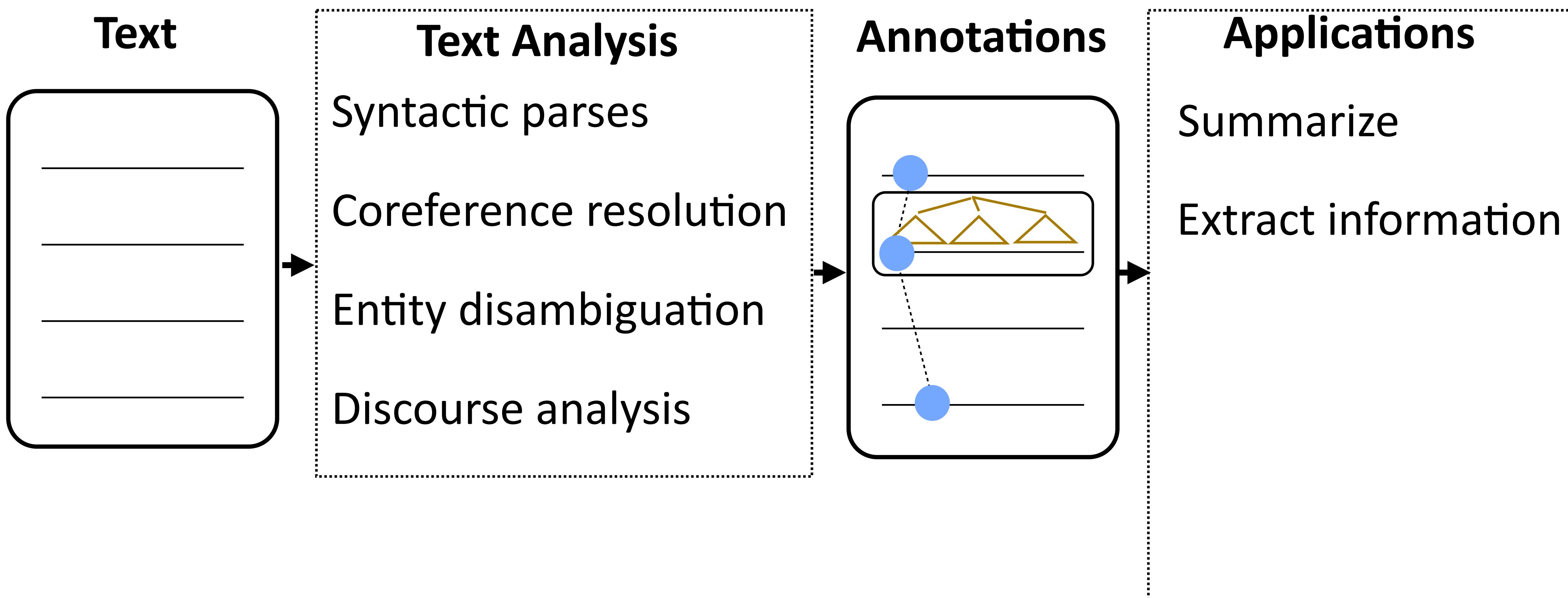
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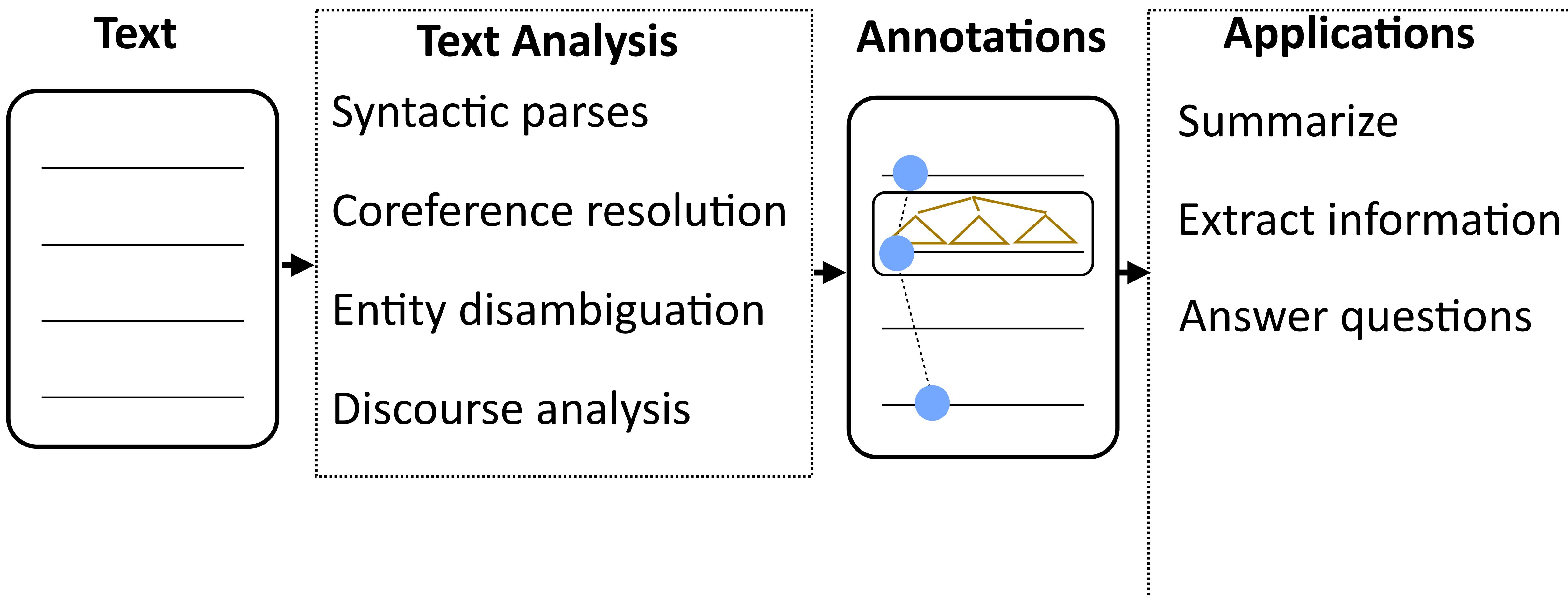
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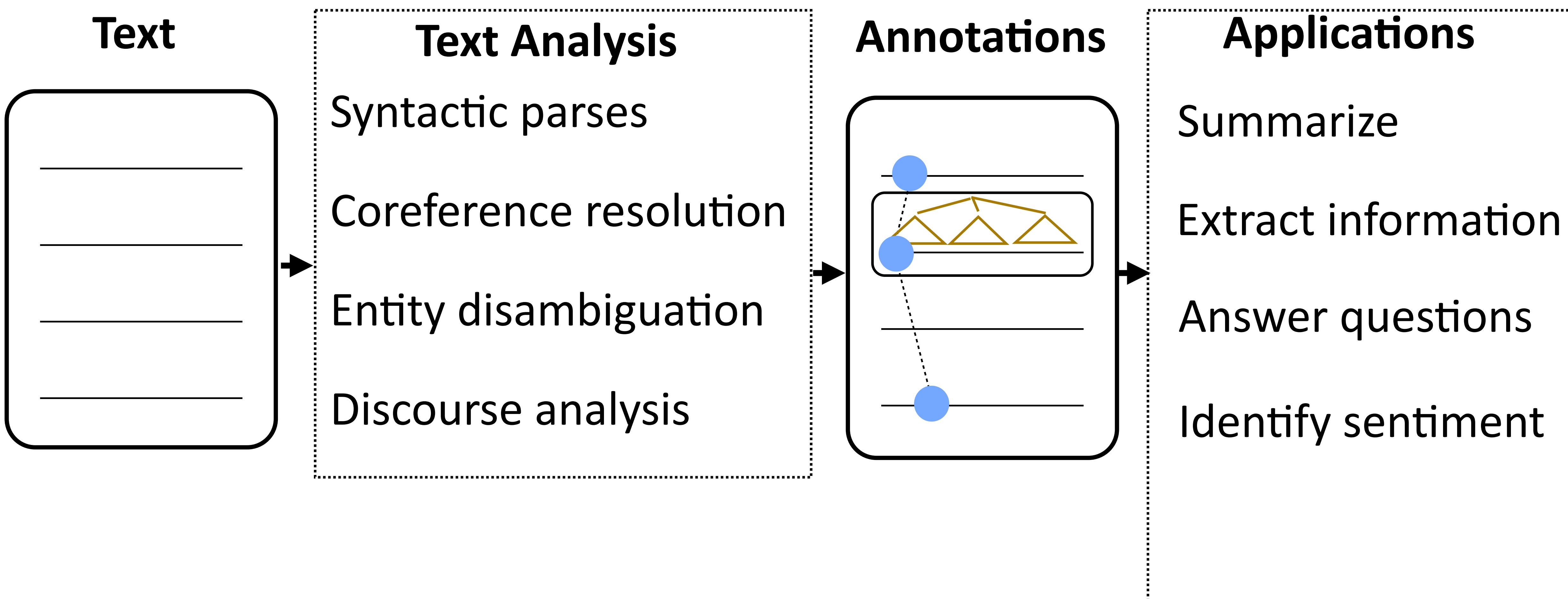
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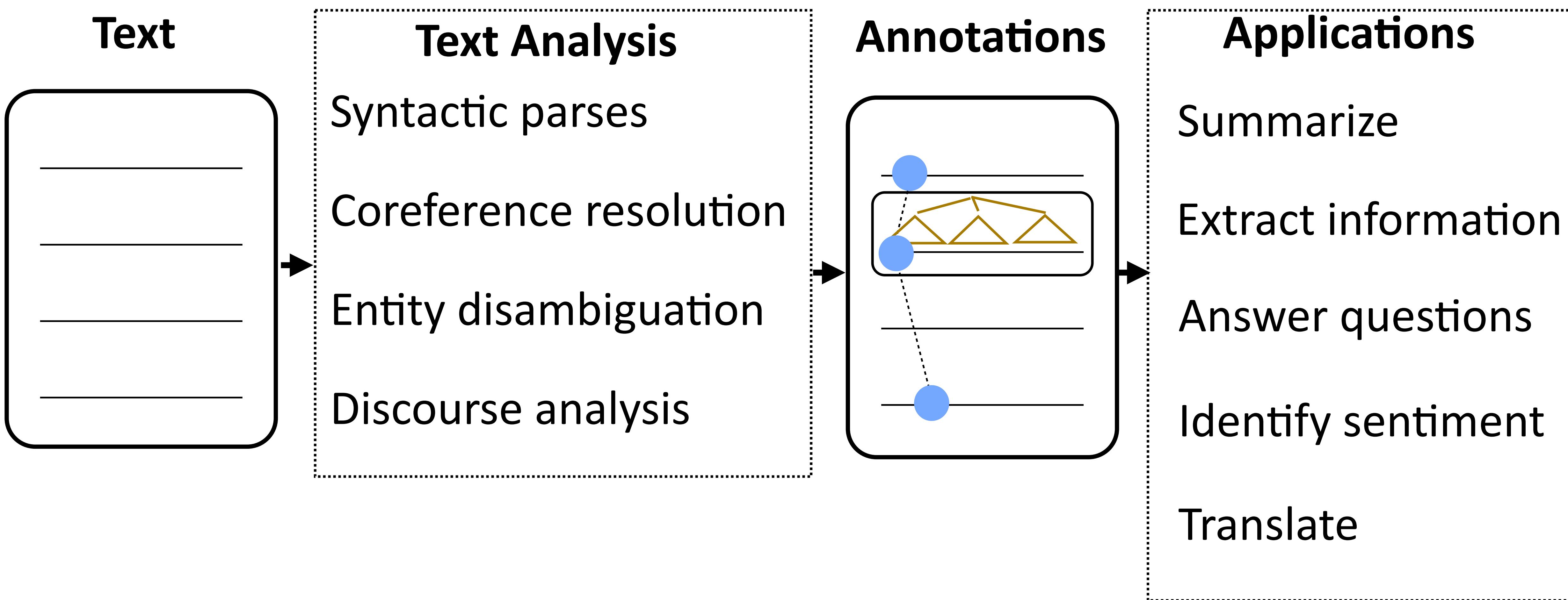
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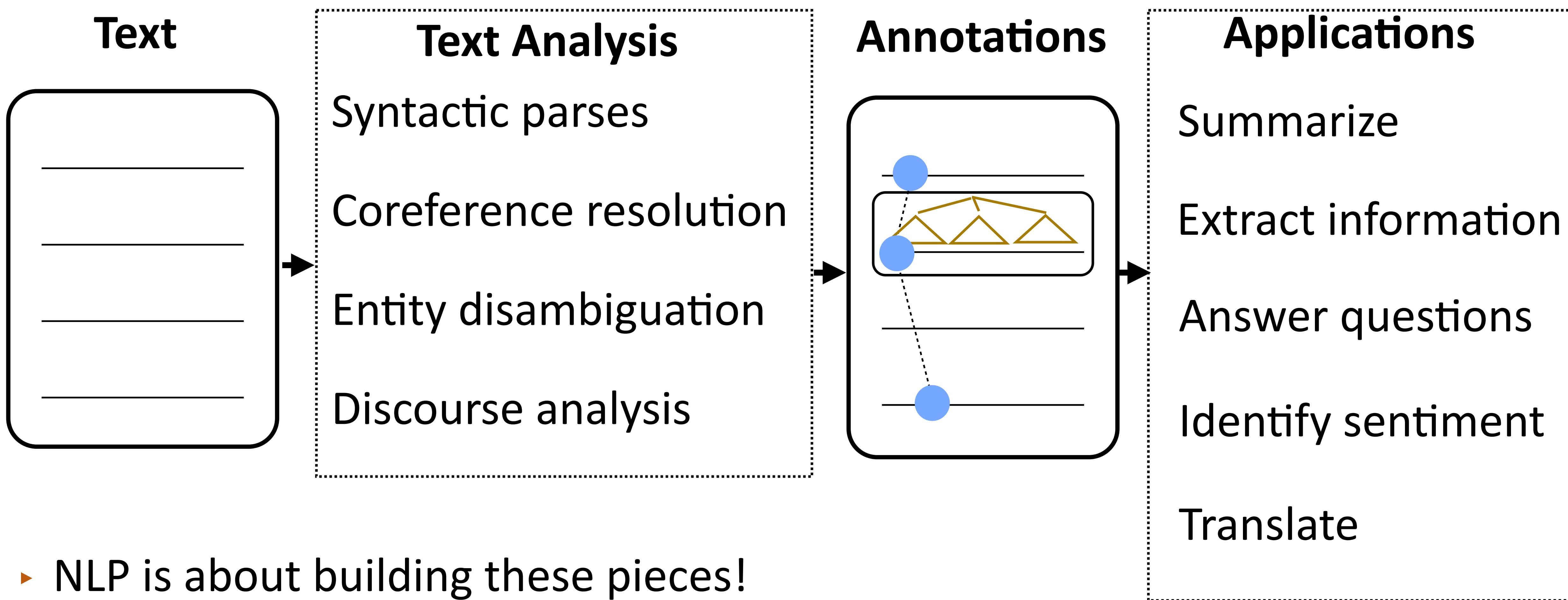
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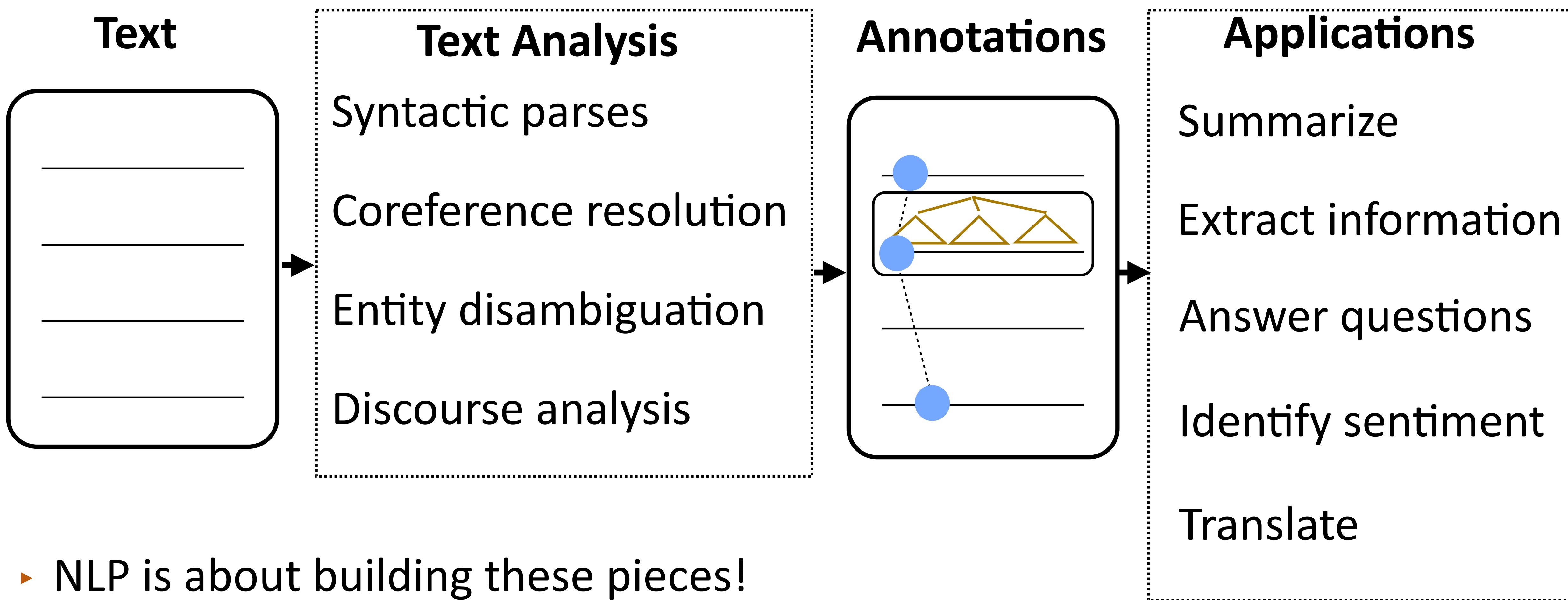
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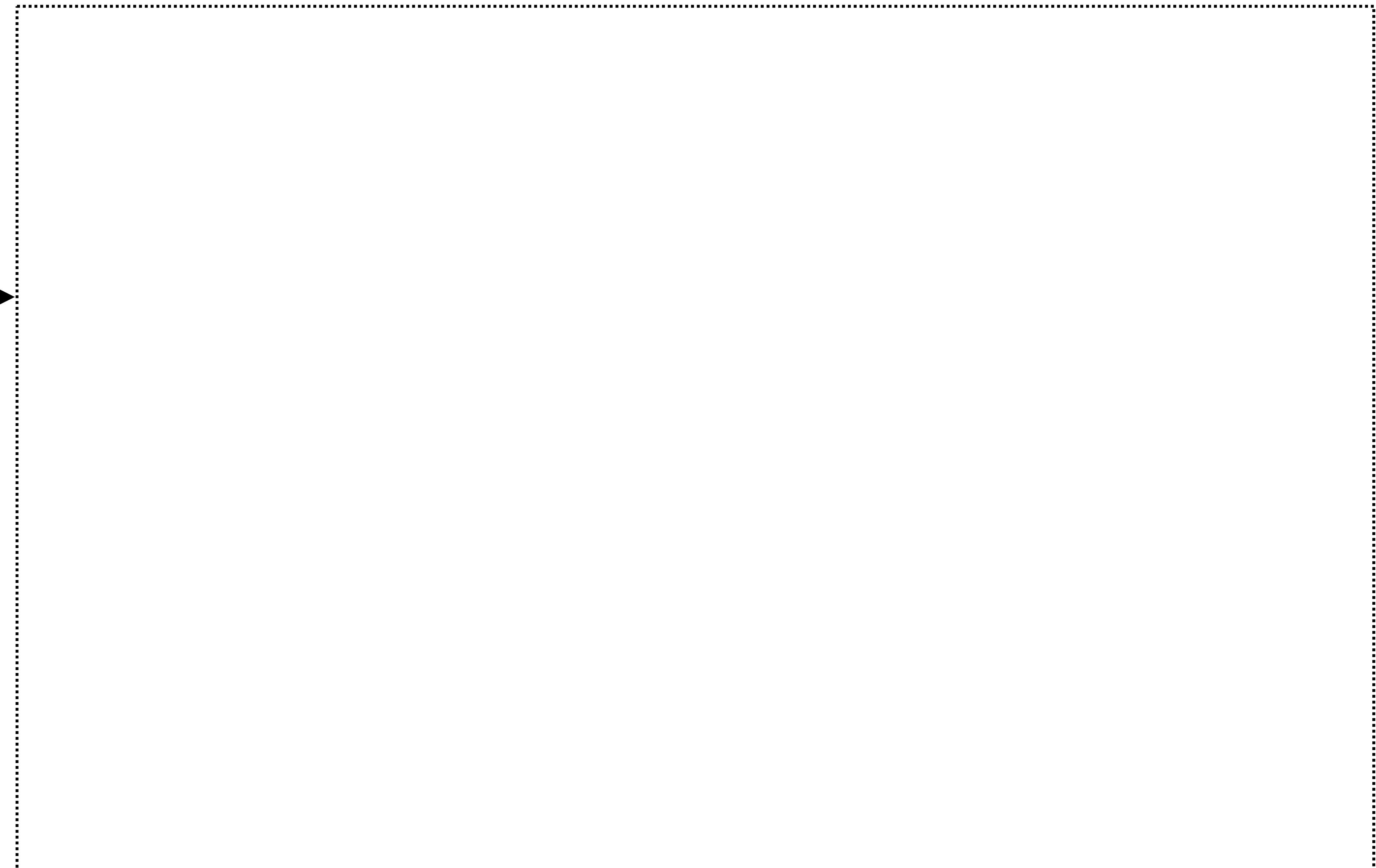
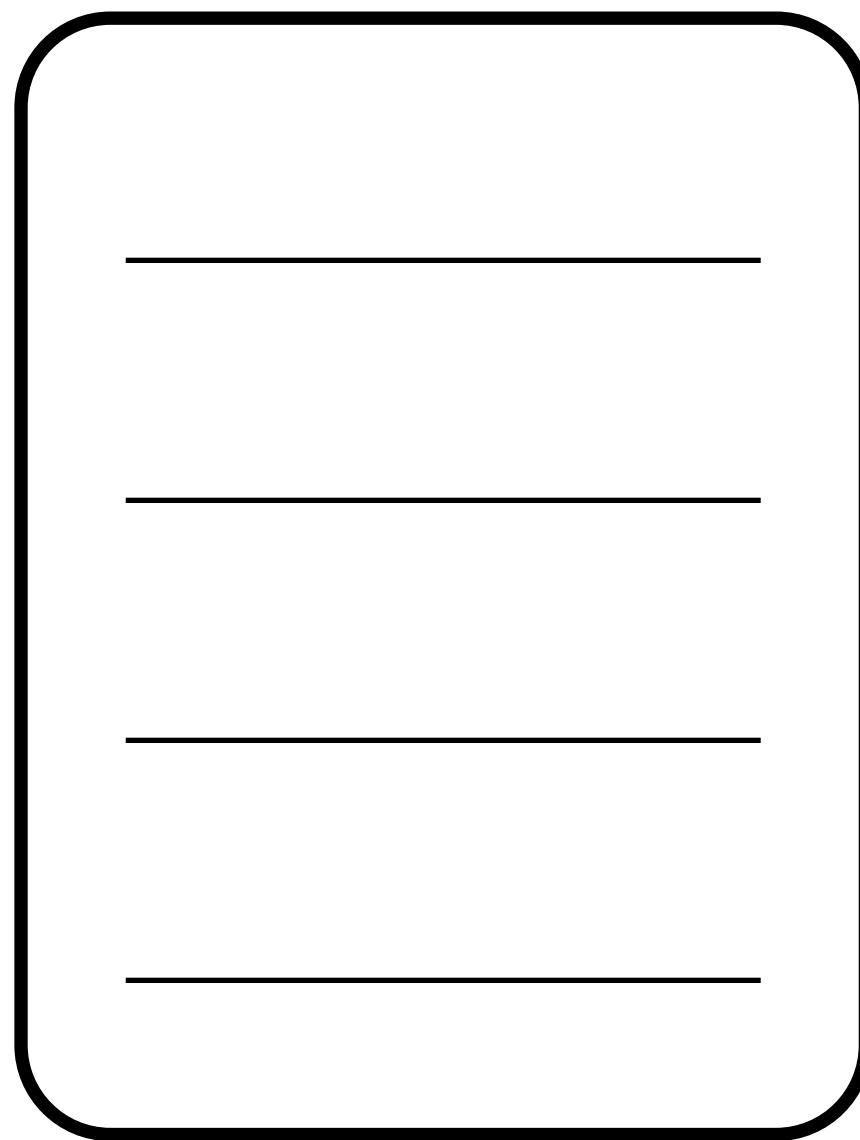
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- ▶ NLP is about building these pieces!
- ▶ All of these components are modeled with statistical approaches trained with machine learning

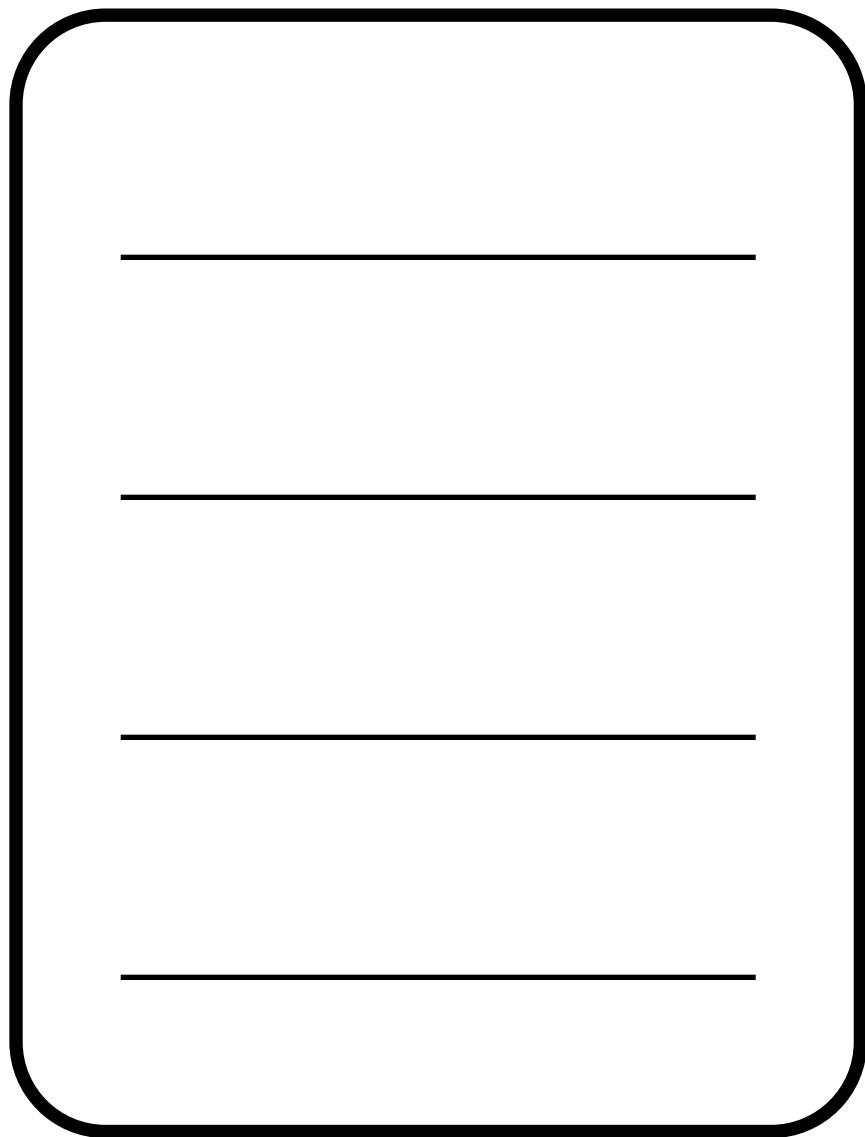
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Text



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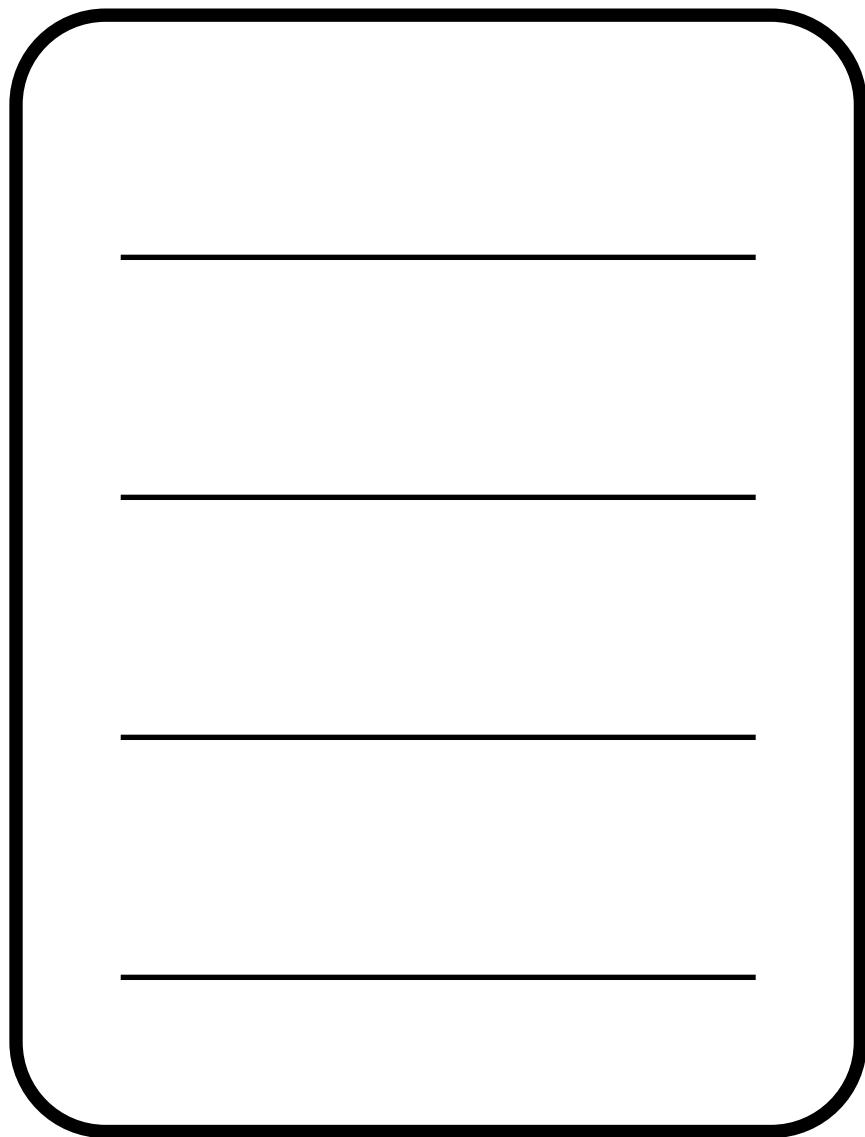


Labels



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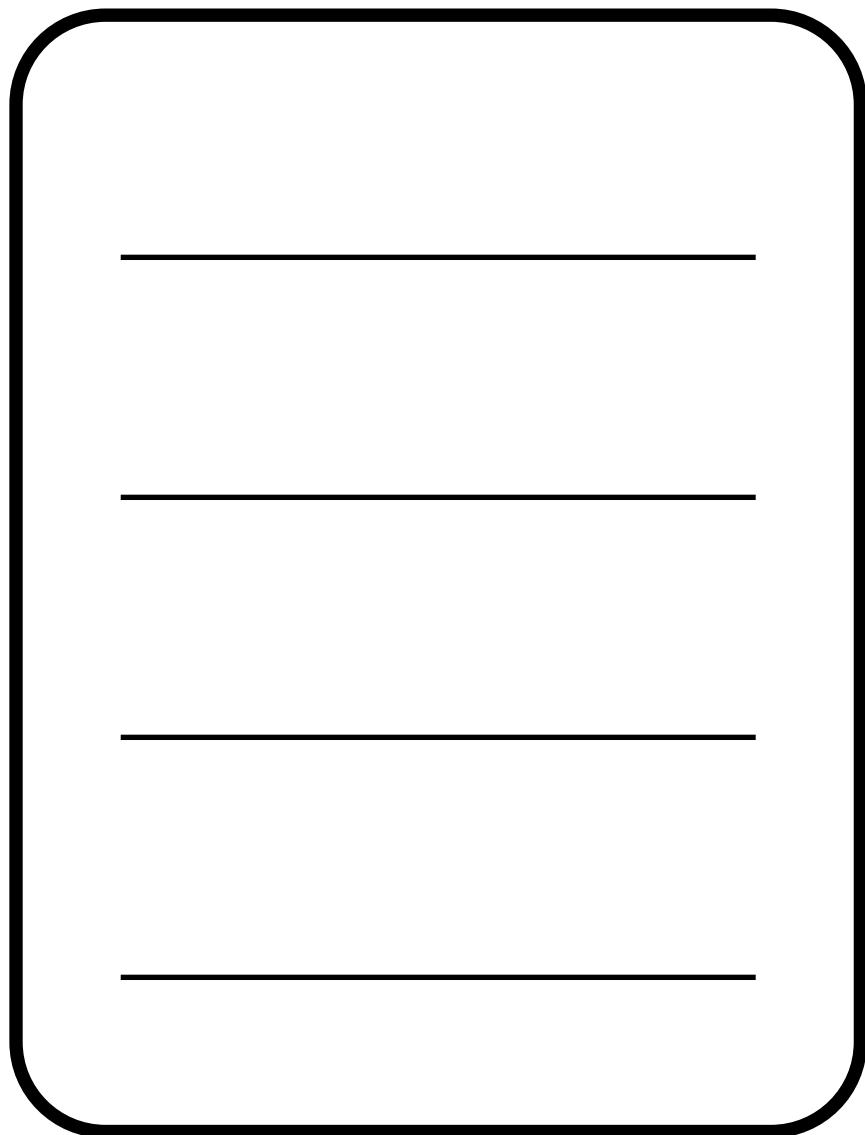


Labels

the movie was good +

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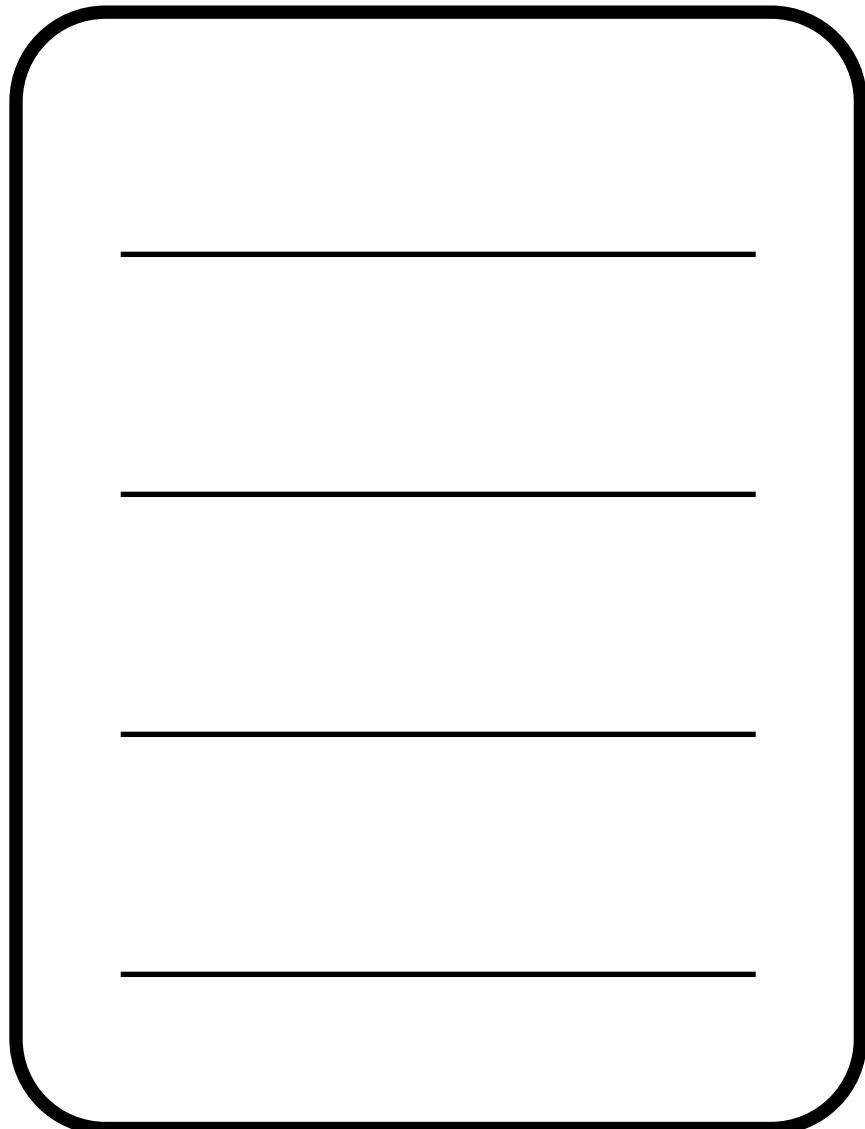
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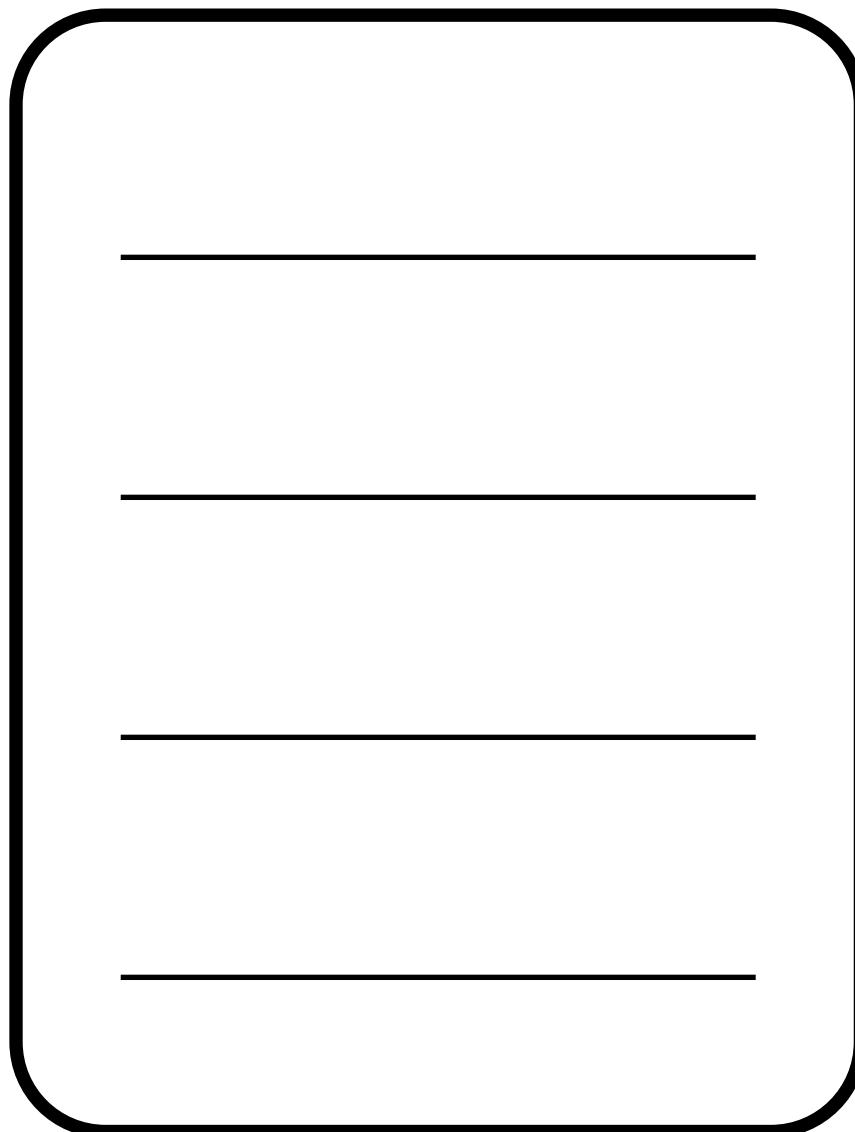
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Tom Cruise stars in the new Mission Impossible film

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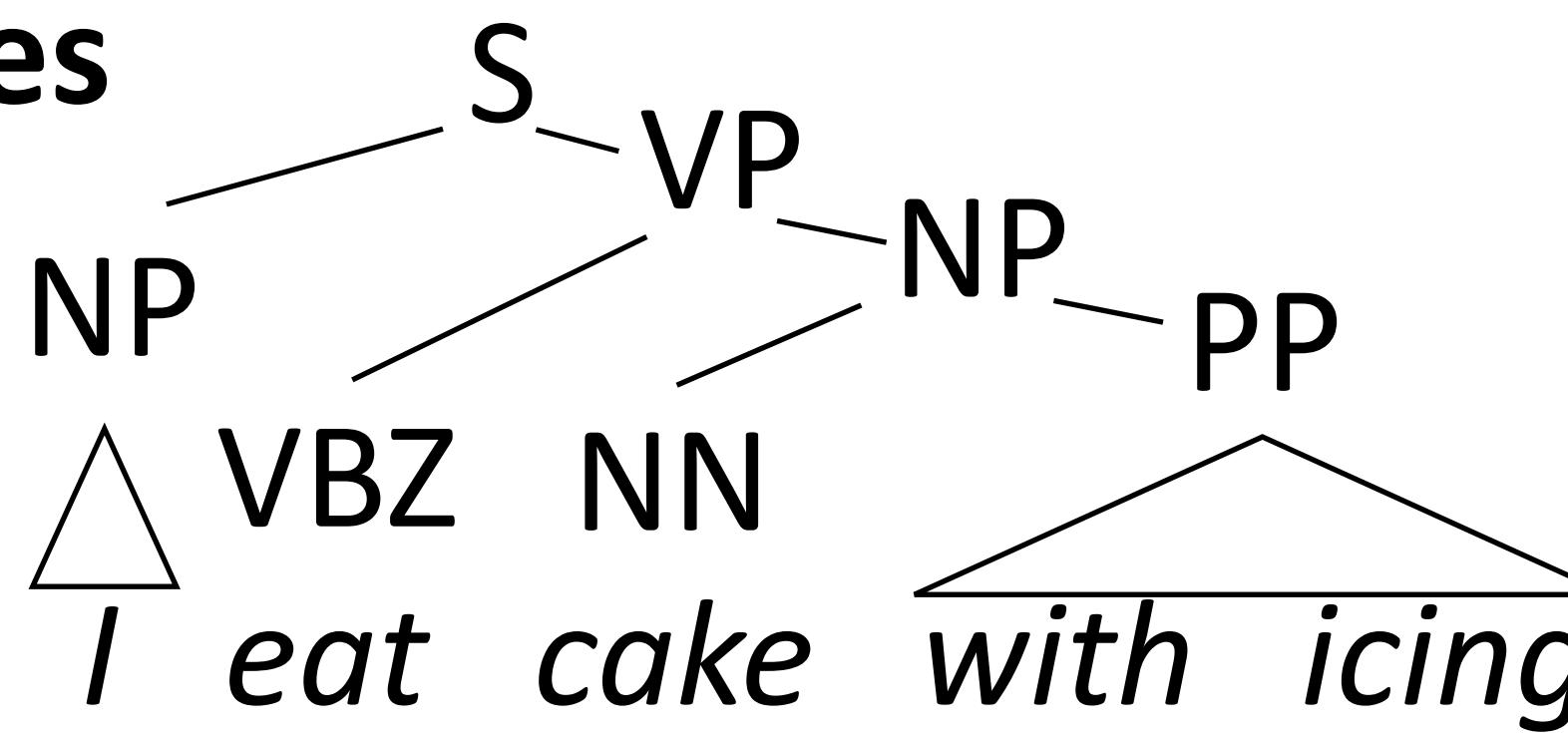
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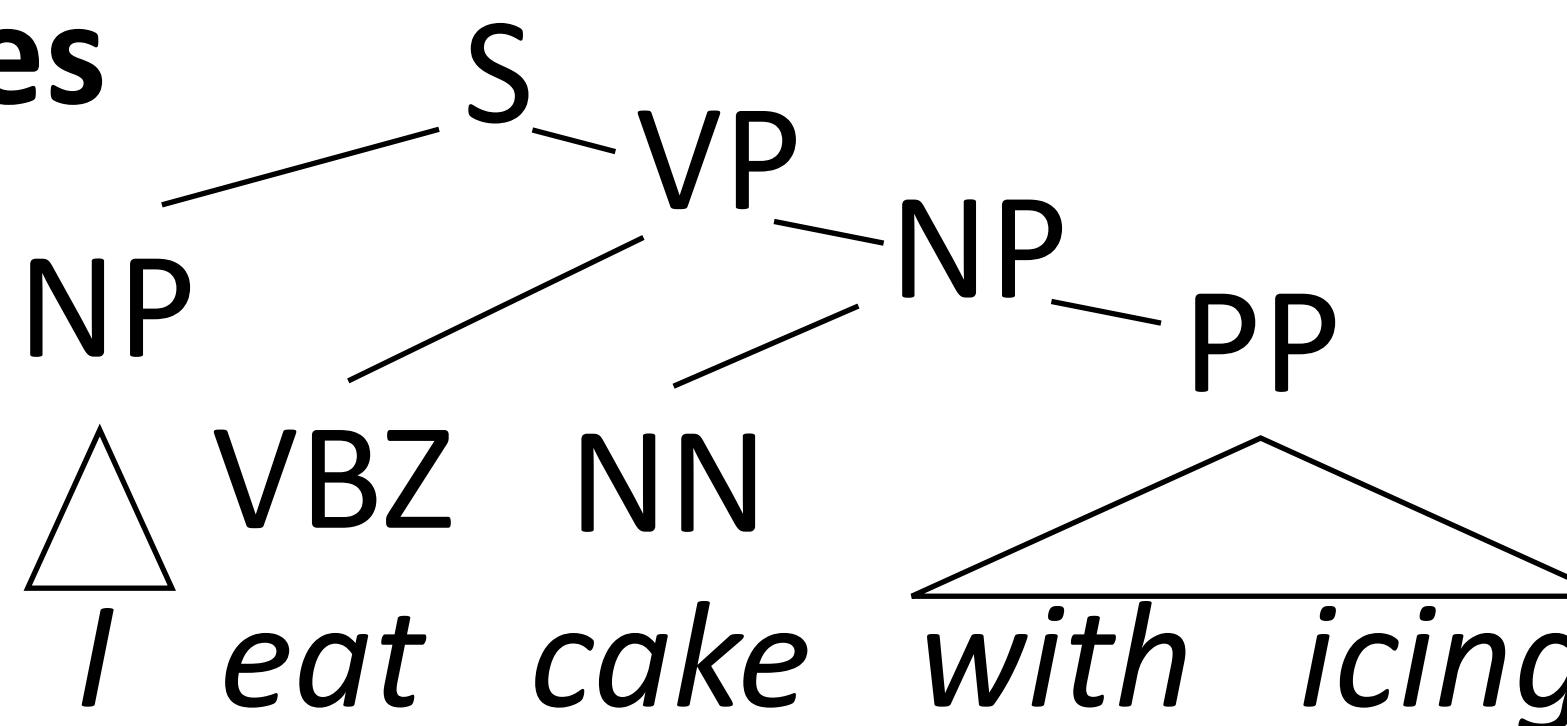
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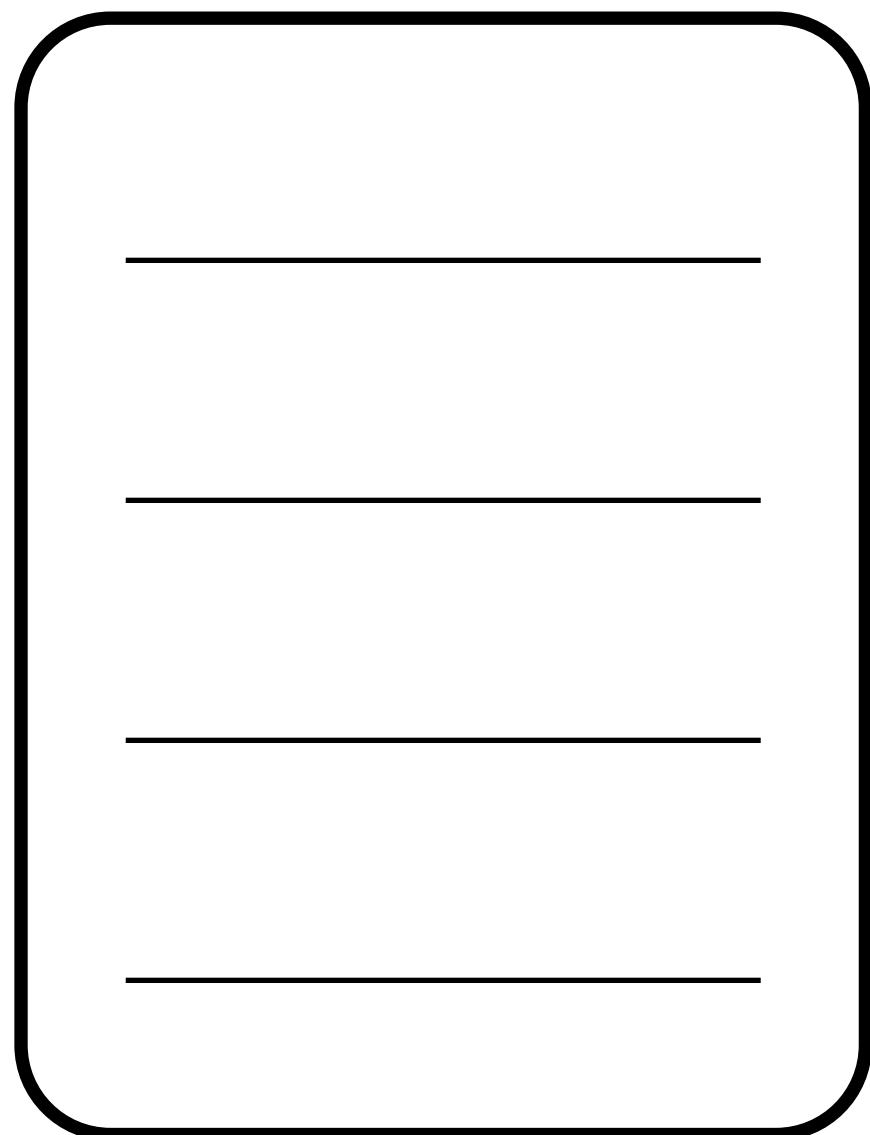
Trees



$\lambda x. \text{flight}(x) \wedge \text{dest}(x) = \text{Miami}$
flights to Miami

How do we use these representations?

Text



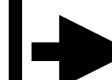
Text Analysis

Labels

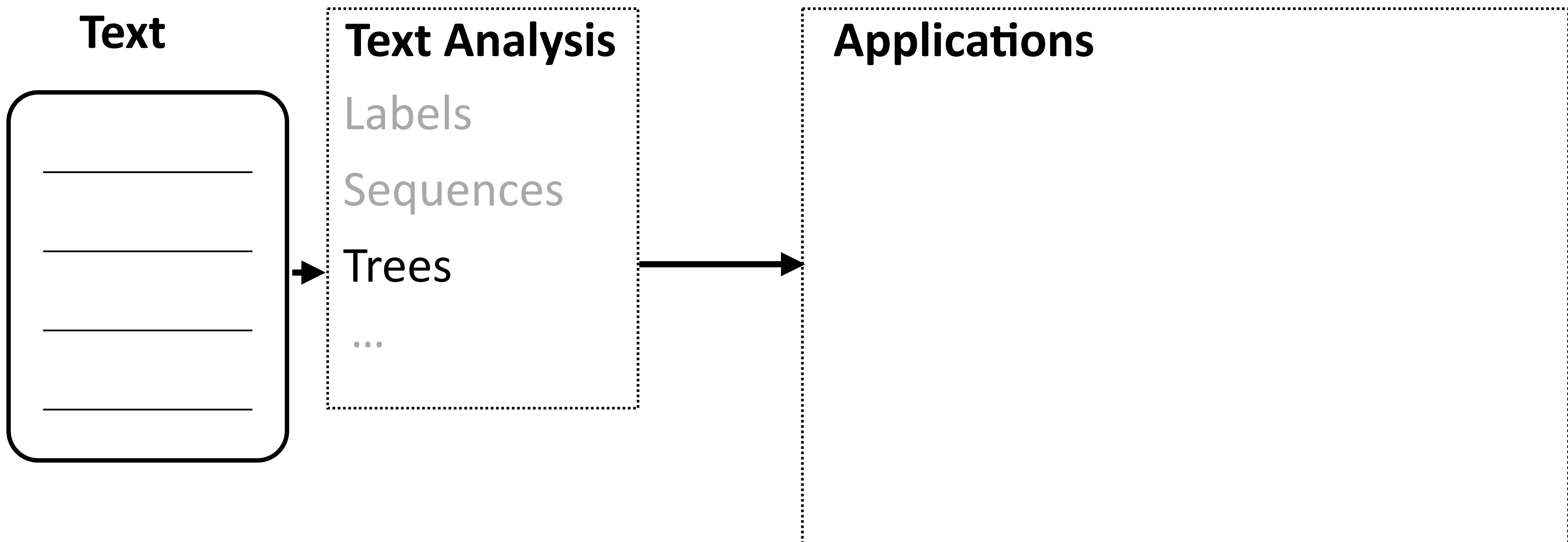
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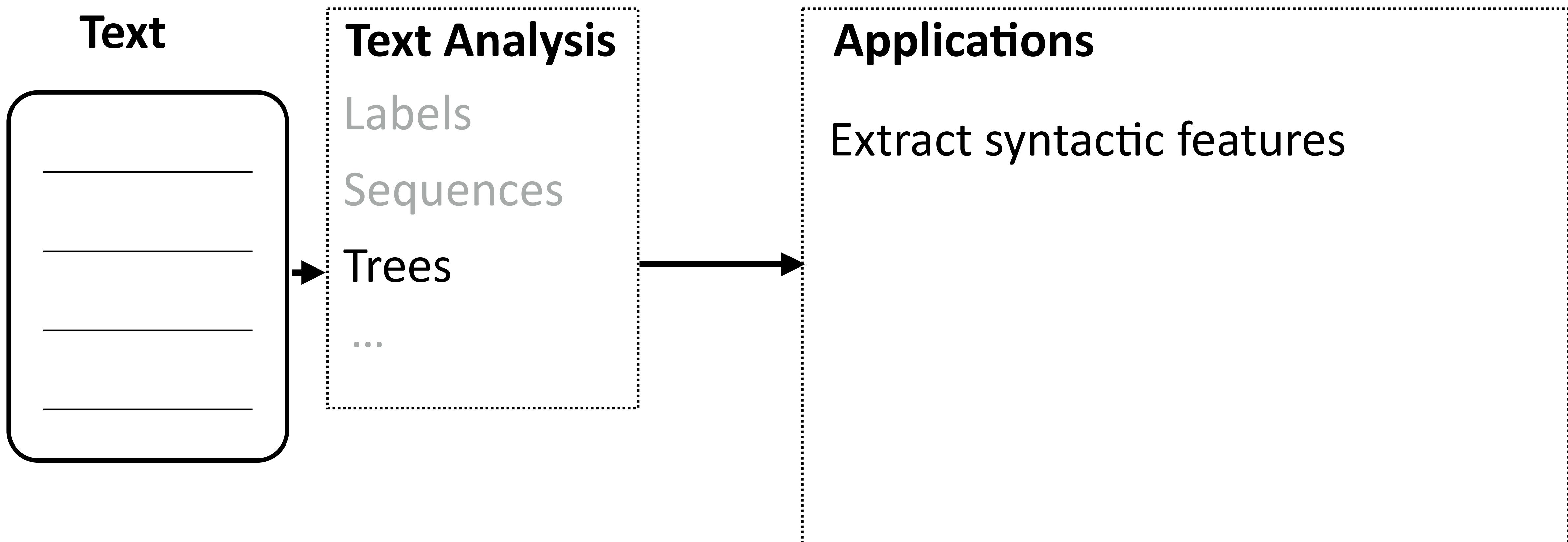
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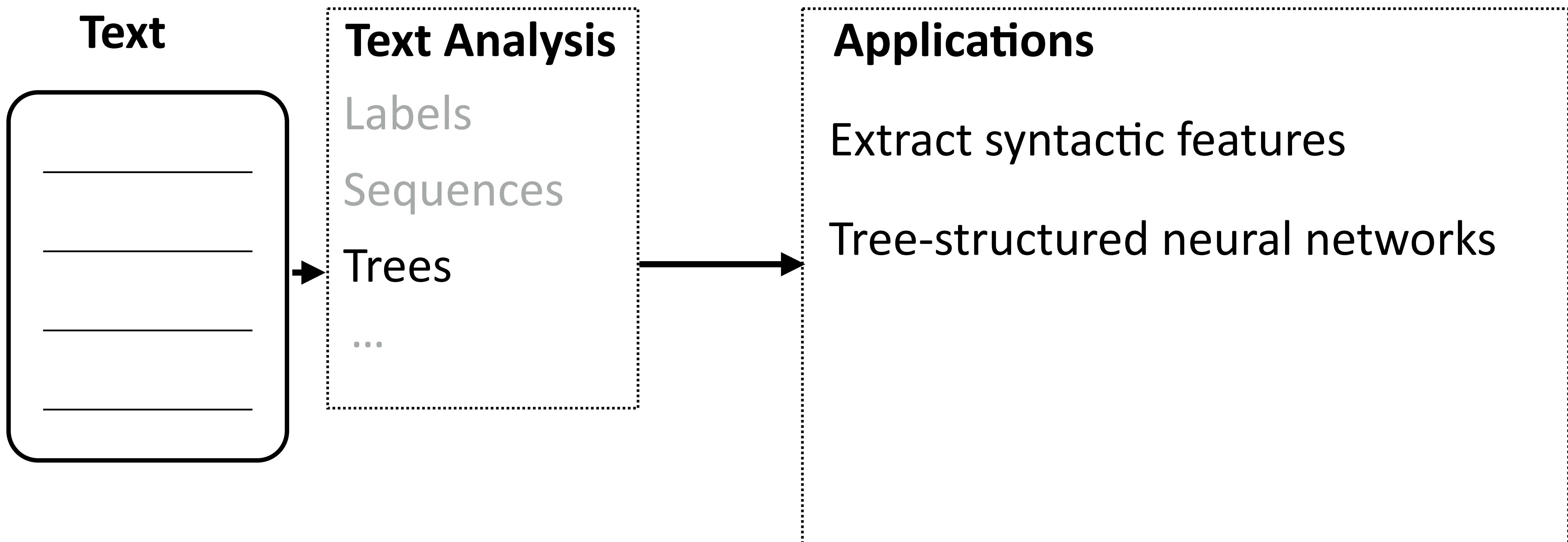
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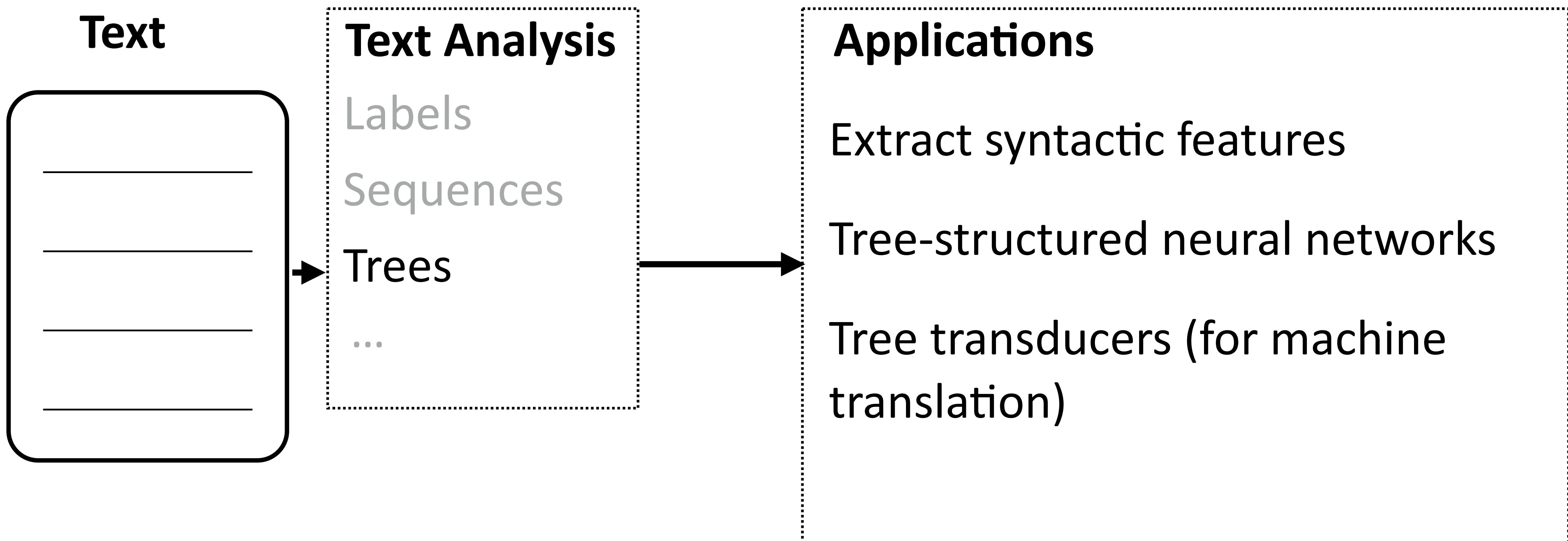
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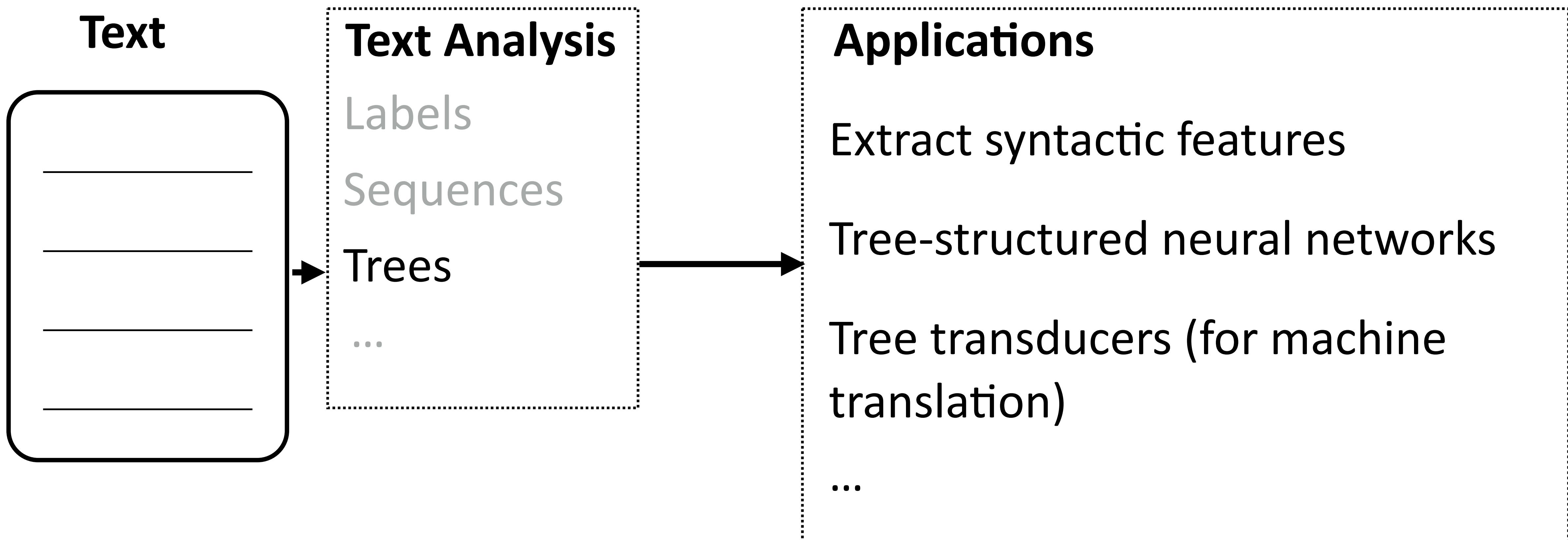
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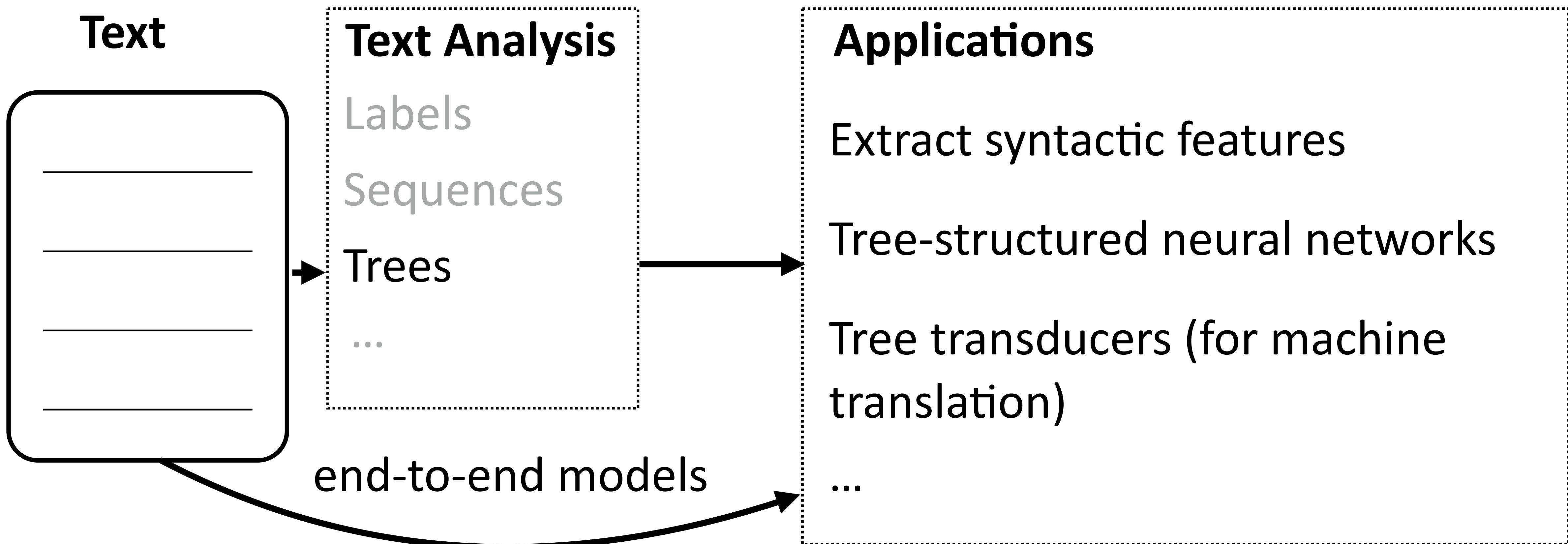
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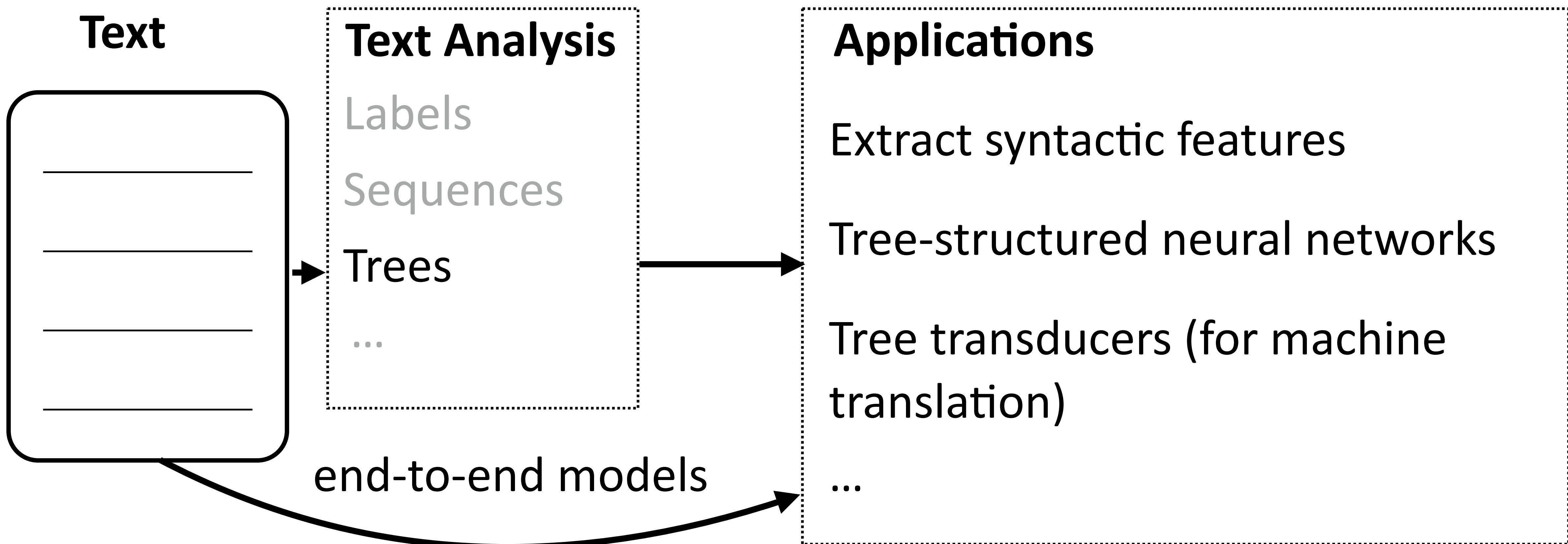
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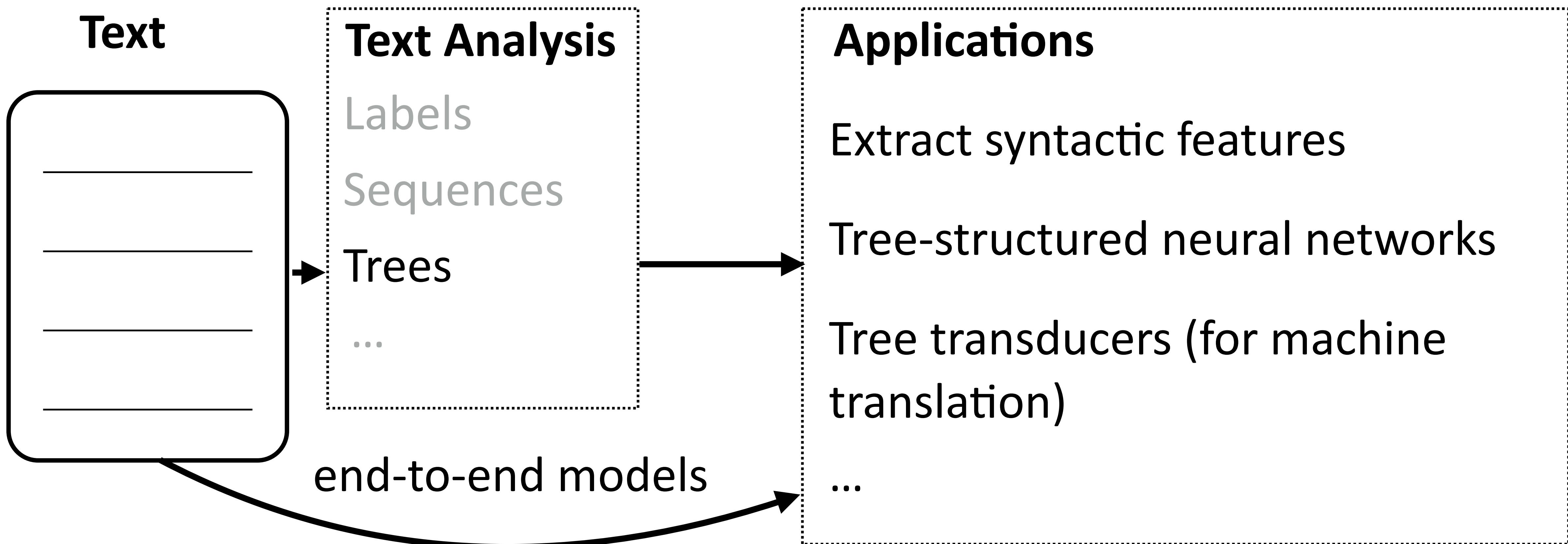


How do we use these representations?



- ▶ 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)

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

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

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they feared

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

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- ▶ Syntactic/semantic ambiguity: parsing needed to resolve these, but need context to figure out which parse is correct

Language is Really Ambiguous!

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

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It is really nice out

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It is really nice out
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It fact actually handsome

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il fait vraiment beau



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- ▶ 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] [.]

What do we need to understand language?

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

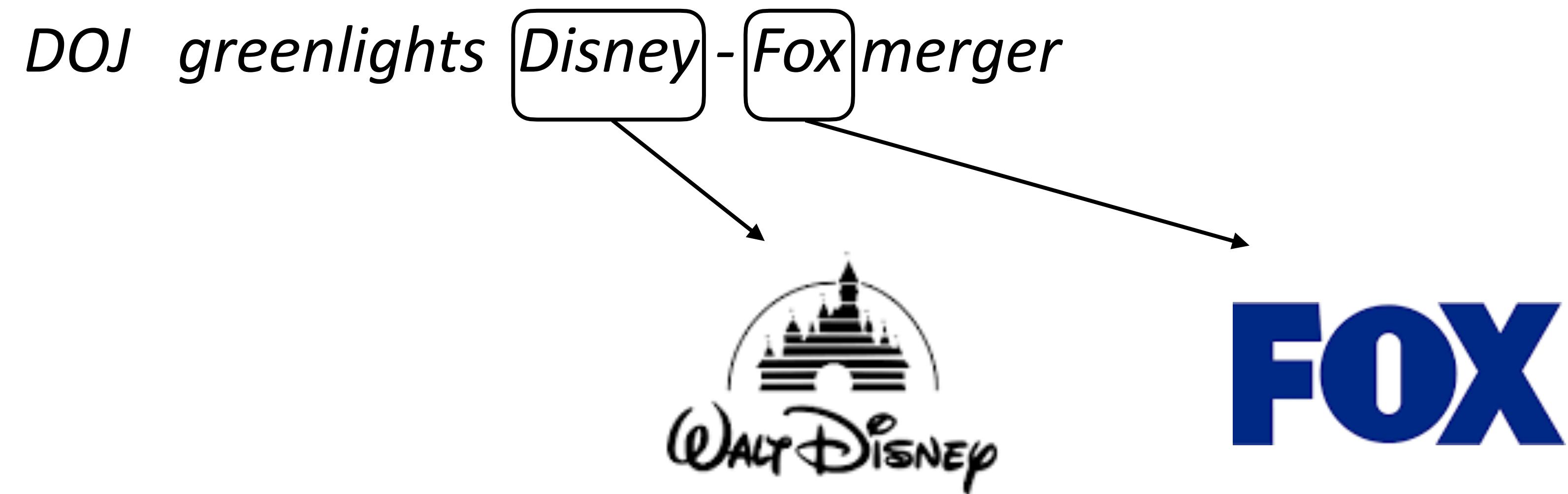
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DOJ greenlights Disney - Fox merger

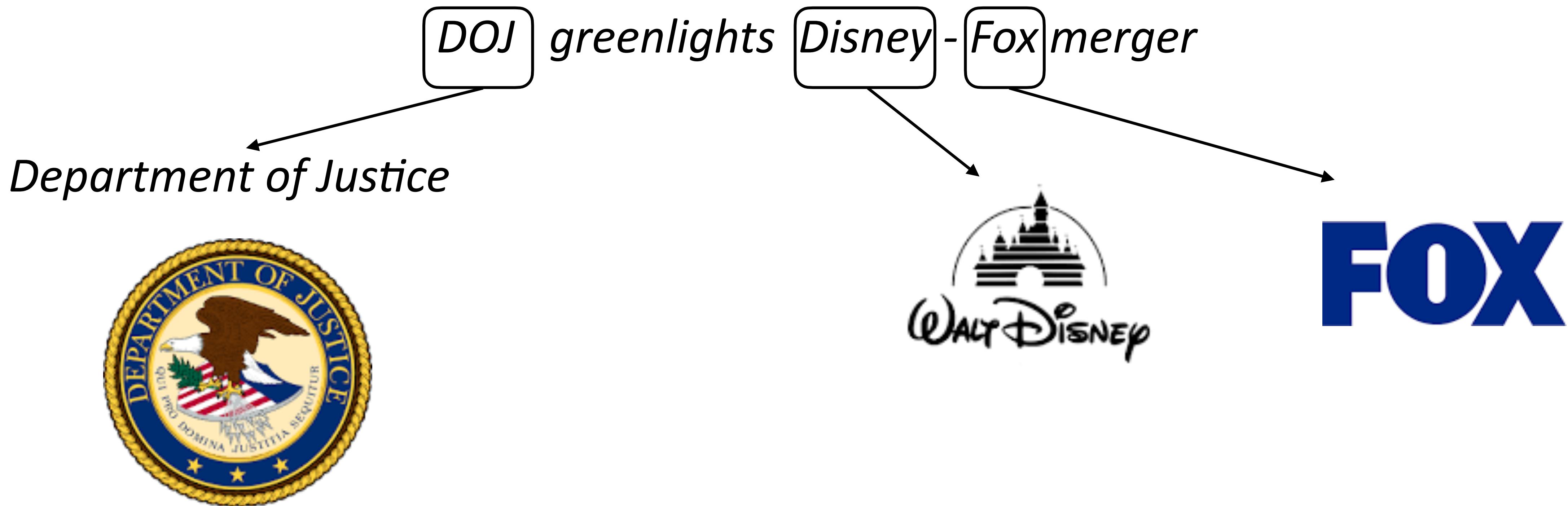
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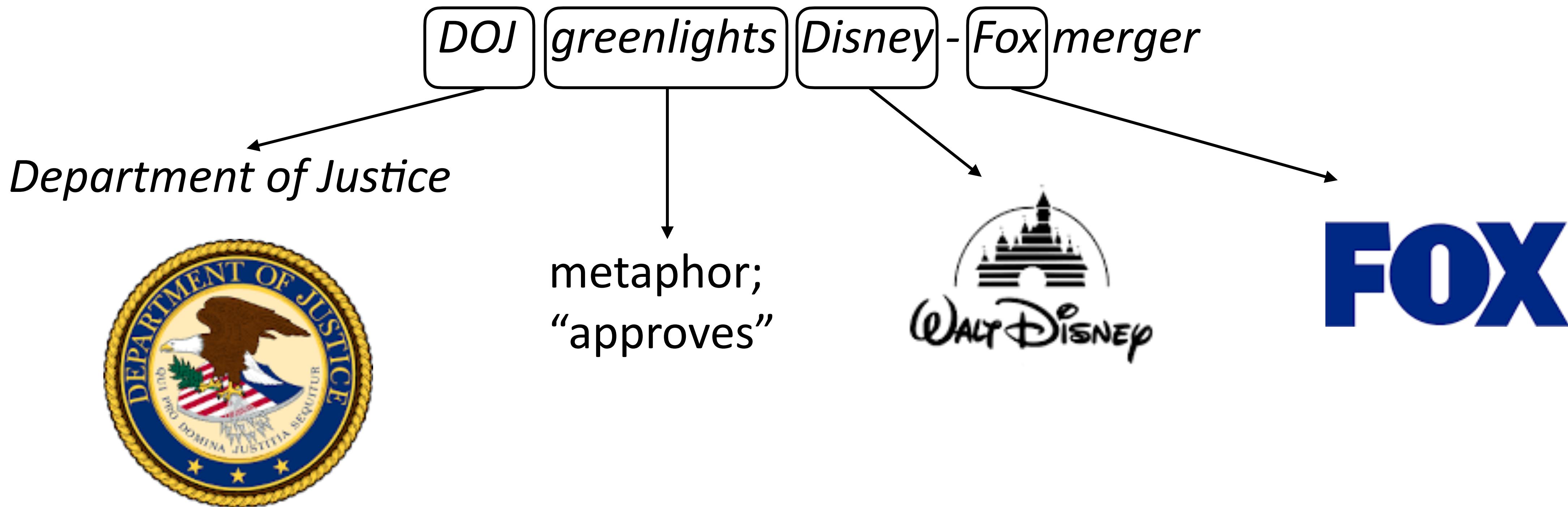
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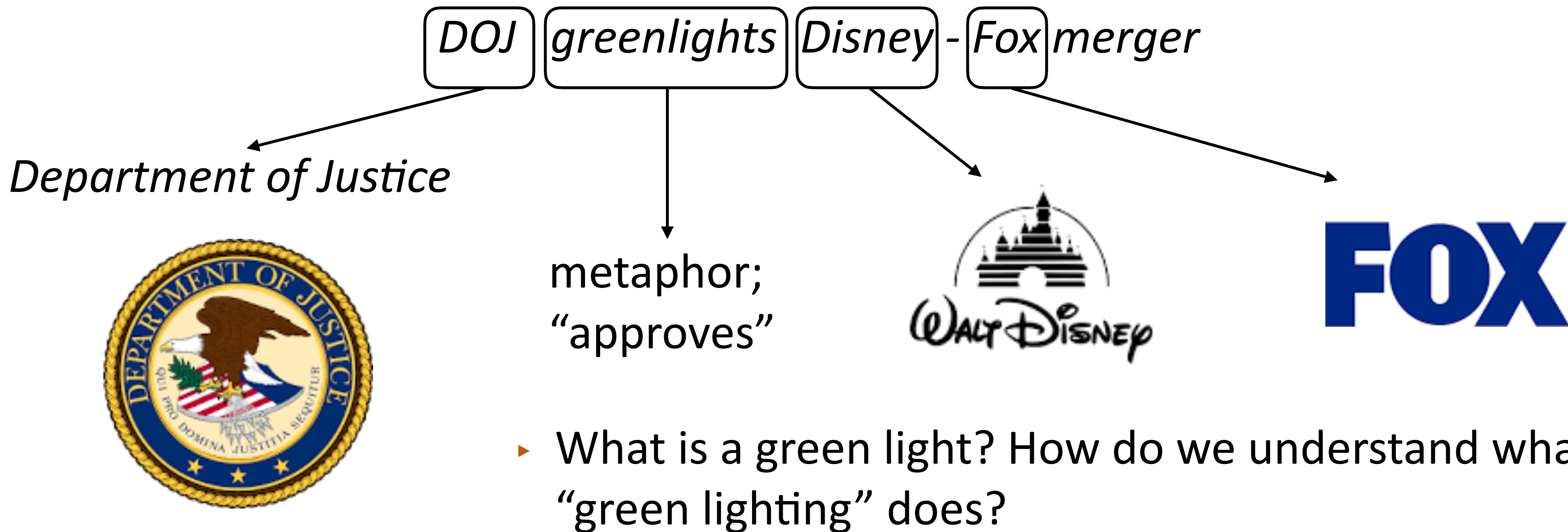
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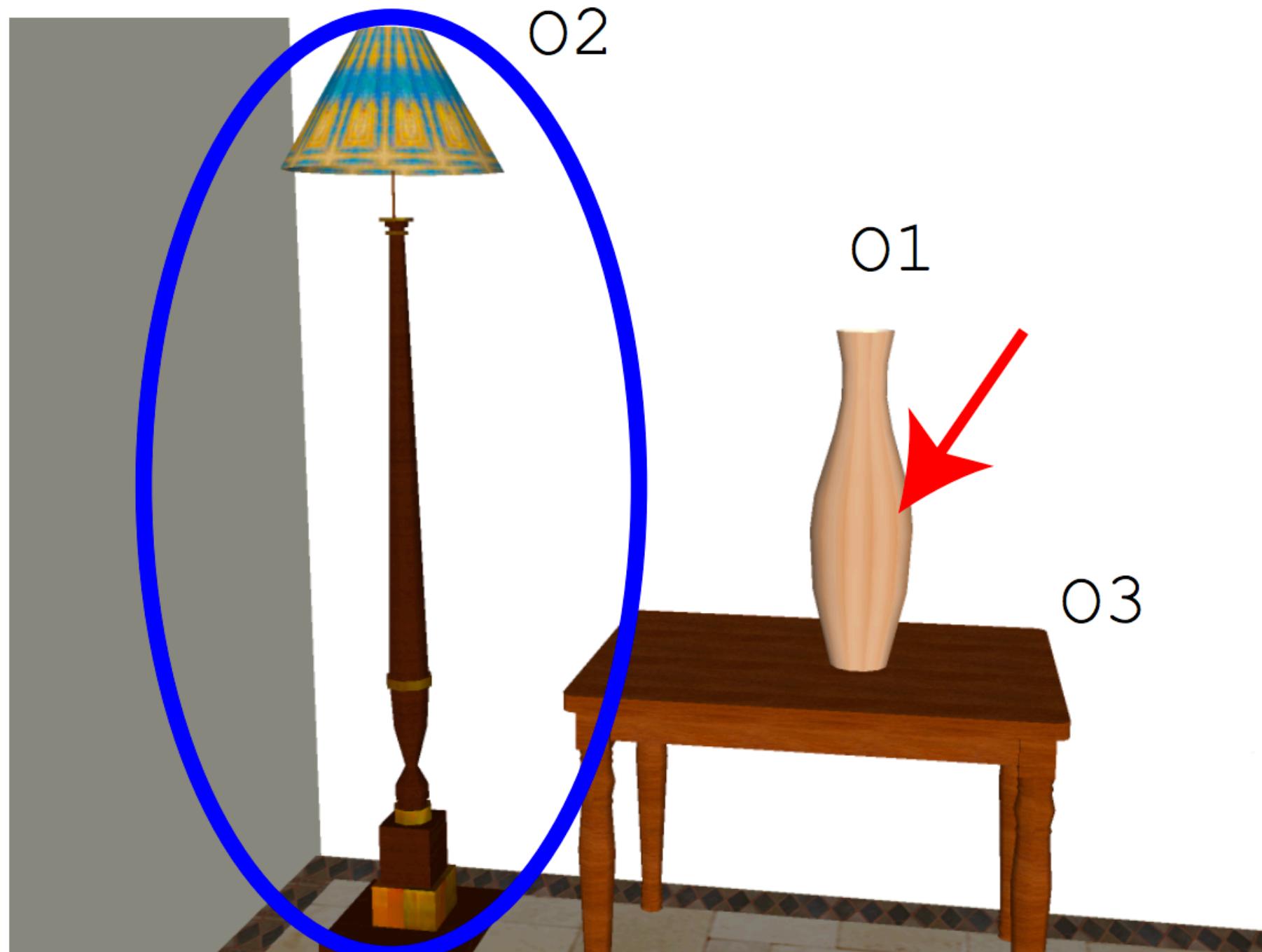
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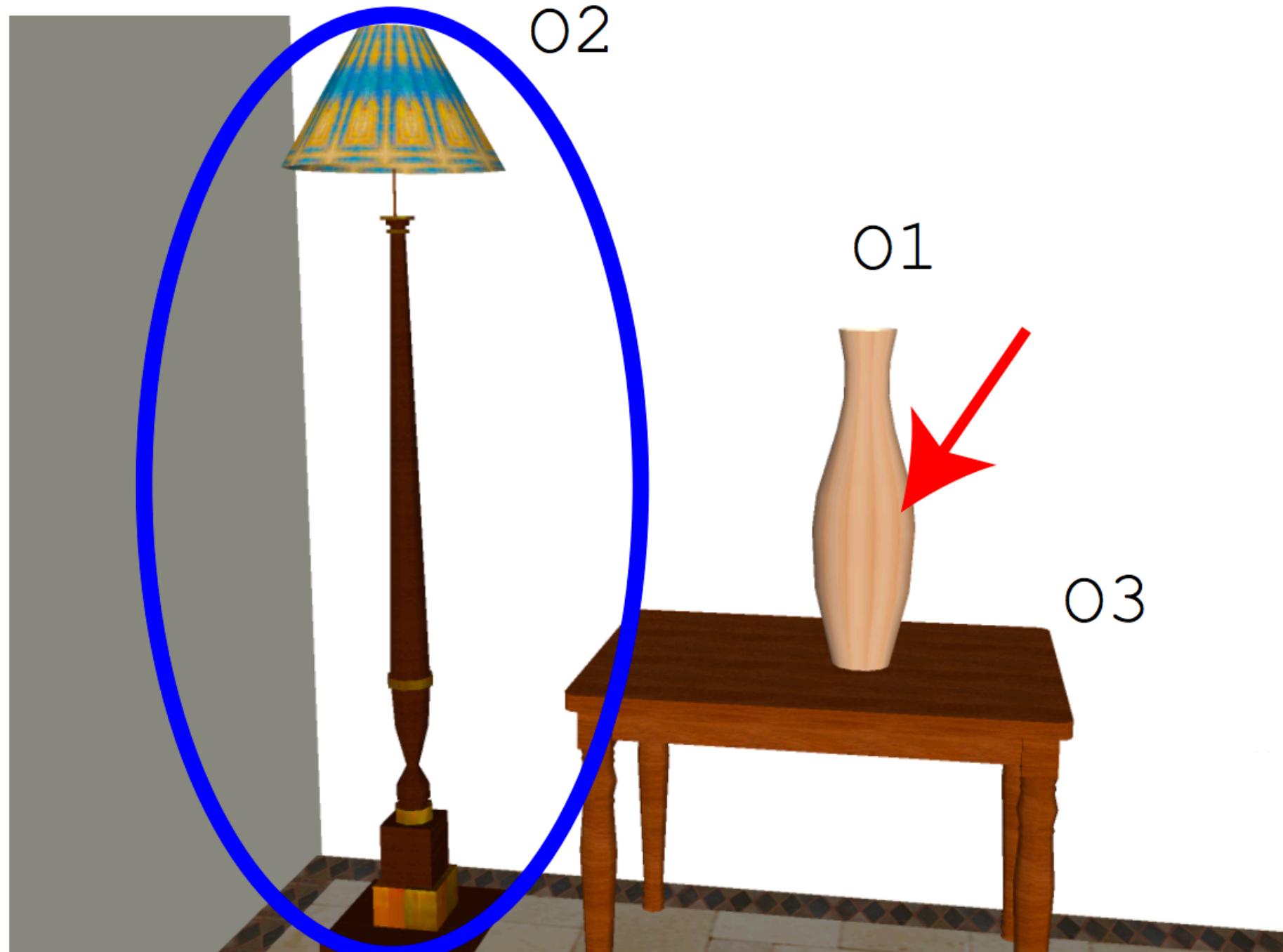


Golland et al. (2010)

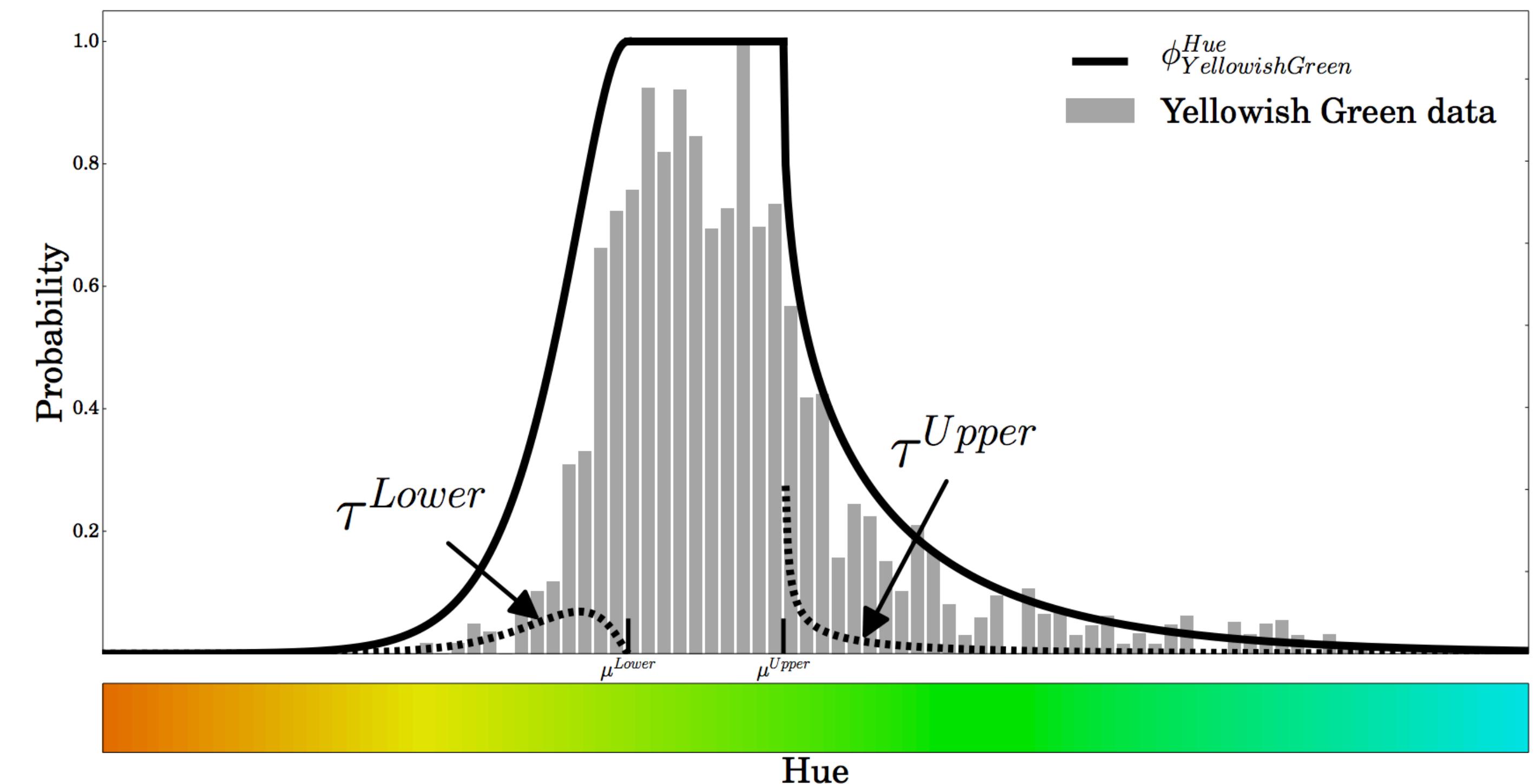
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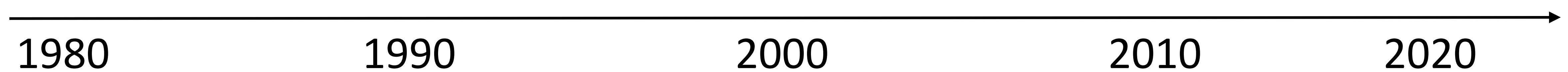
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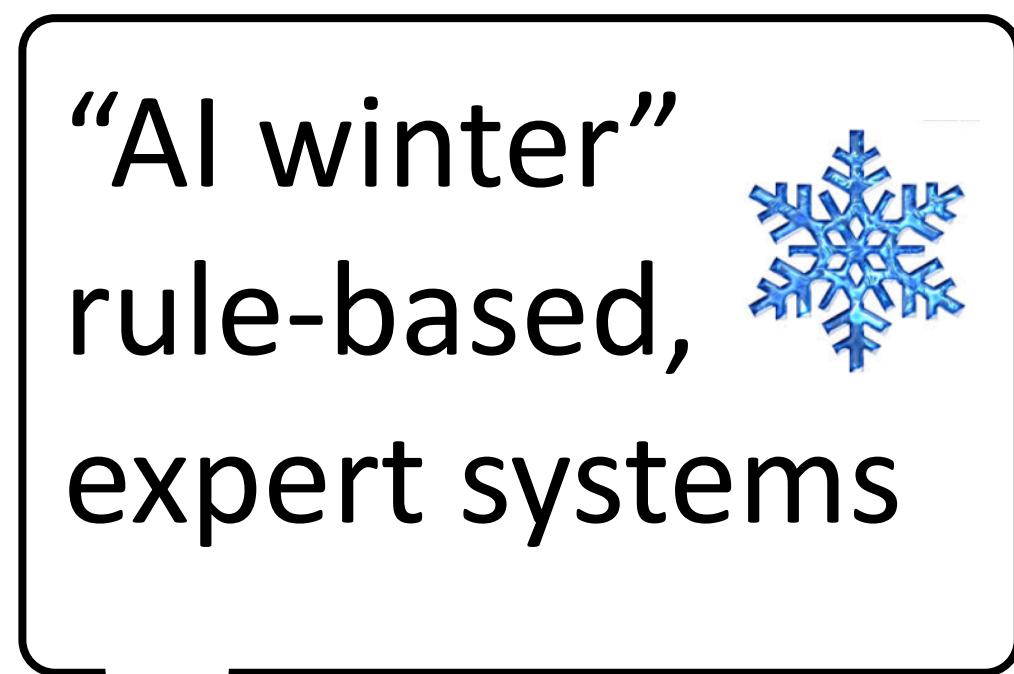
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 - a. John has been having a lot of trouble arranging his vacation.
 - b. He cannot find anyone to take over his responsibilities. (he = John)
 $C_b = \text{John}; C_f = \{\text{John}\}$
 - c. He called up Mike yesterday to work out a plan. (he = John)
 $C_b = \text{John}; C_f = \{\text{John}, \text{Mike}\}$ (CONTINUE)
 - d. Mike has annoyed him a lot recently.
 $C_b = \text{John}; C_f = \{\text{Mike}, \text{John}\}$ (RETAIN)
 - e. He called John at 5 AM on Friday last week. (he = Mike)
 $C_b = \text{Mike}; C_f = \{\text{Mike}, \text{John}\}$ (SHIFT)

What techniques do we use?
(to combine data, knowledge, linguistics, etc.)

A brief history of (modern) NLP



A brief history of (modern) NLP



1980

1990

2000

2010

2020

A brief history of (modern) NLP

“AI winter”
rule-based,
expert systems

earliest stat MT
work at IBM



1980

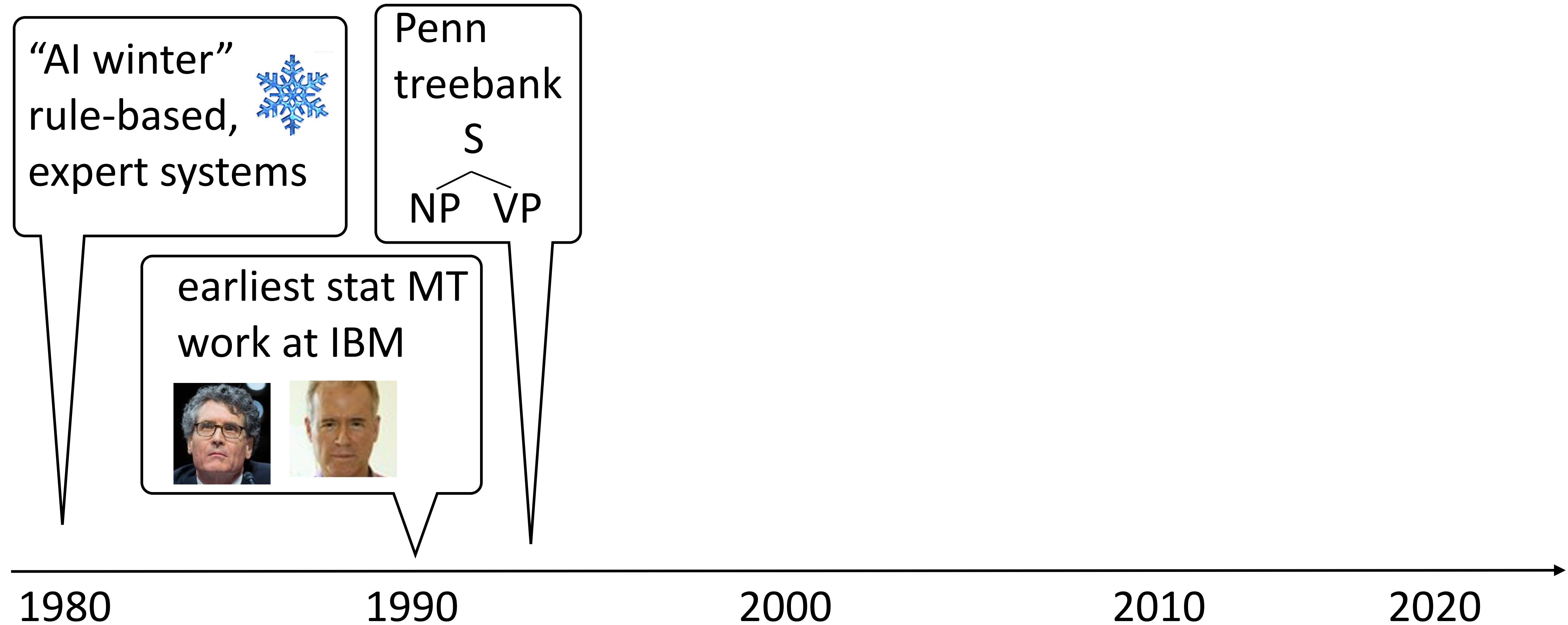
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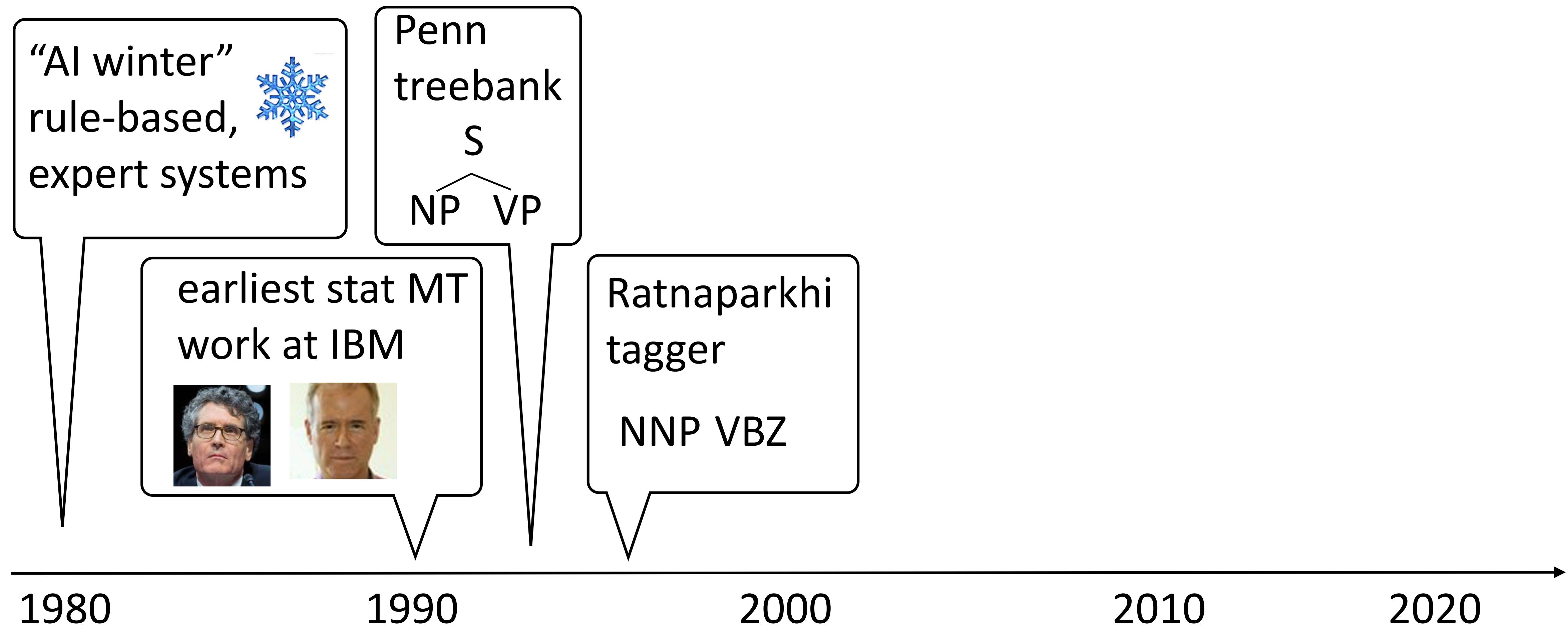
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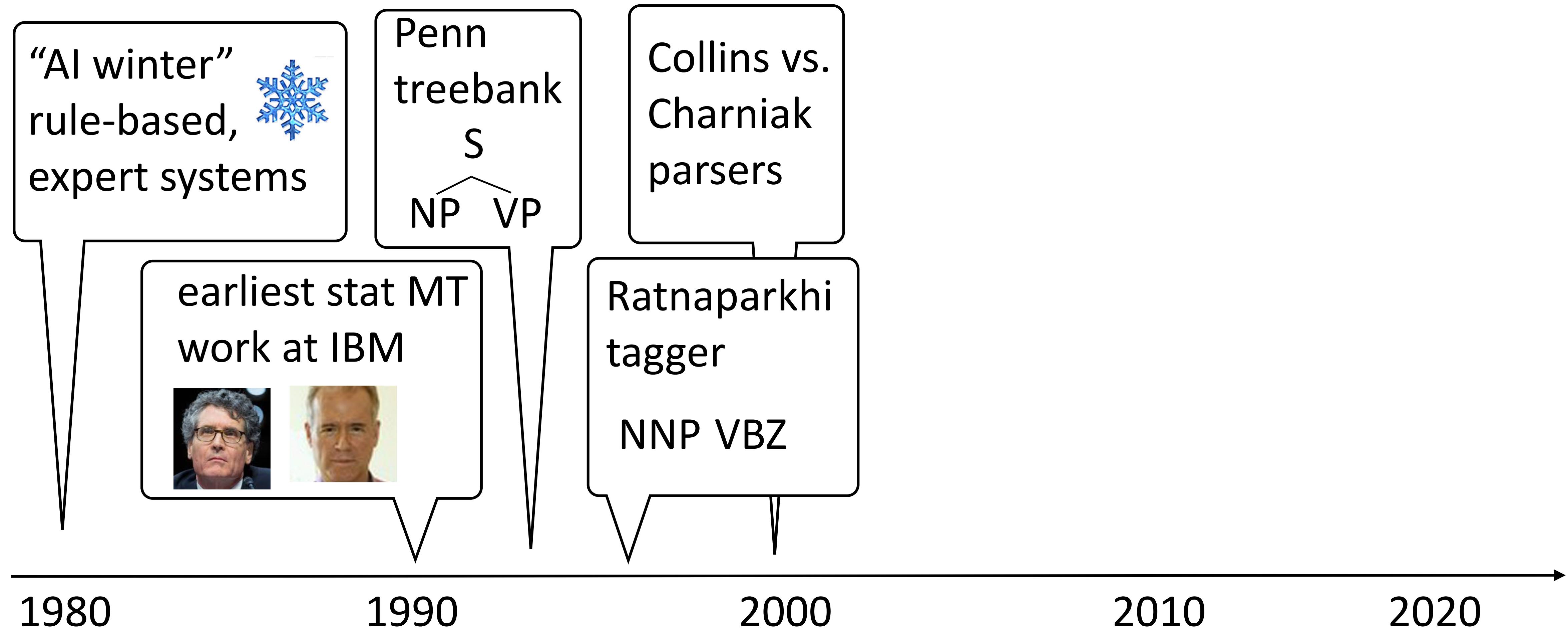
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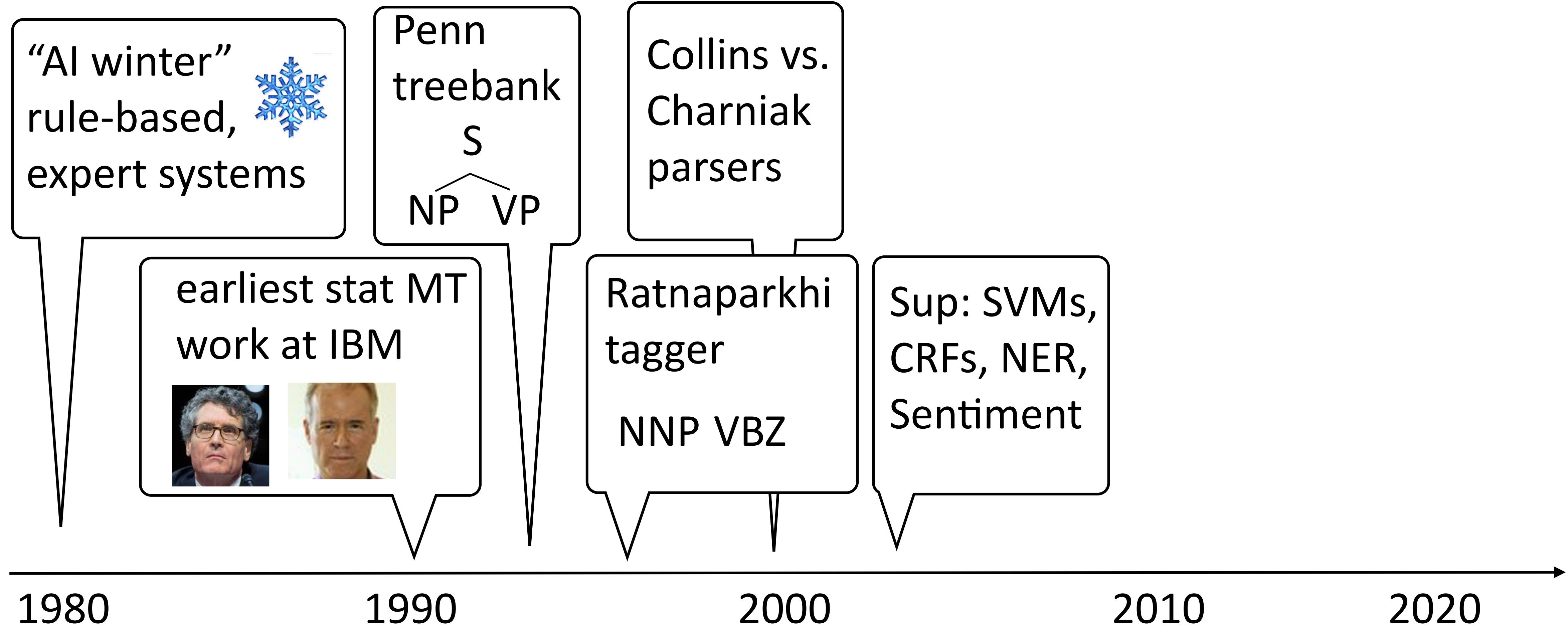
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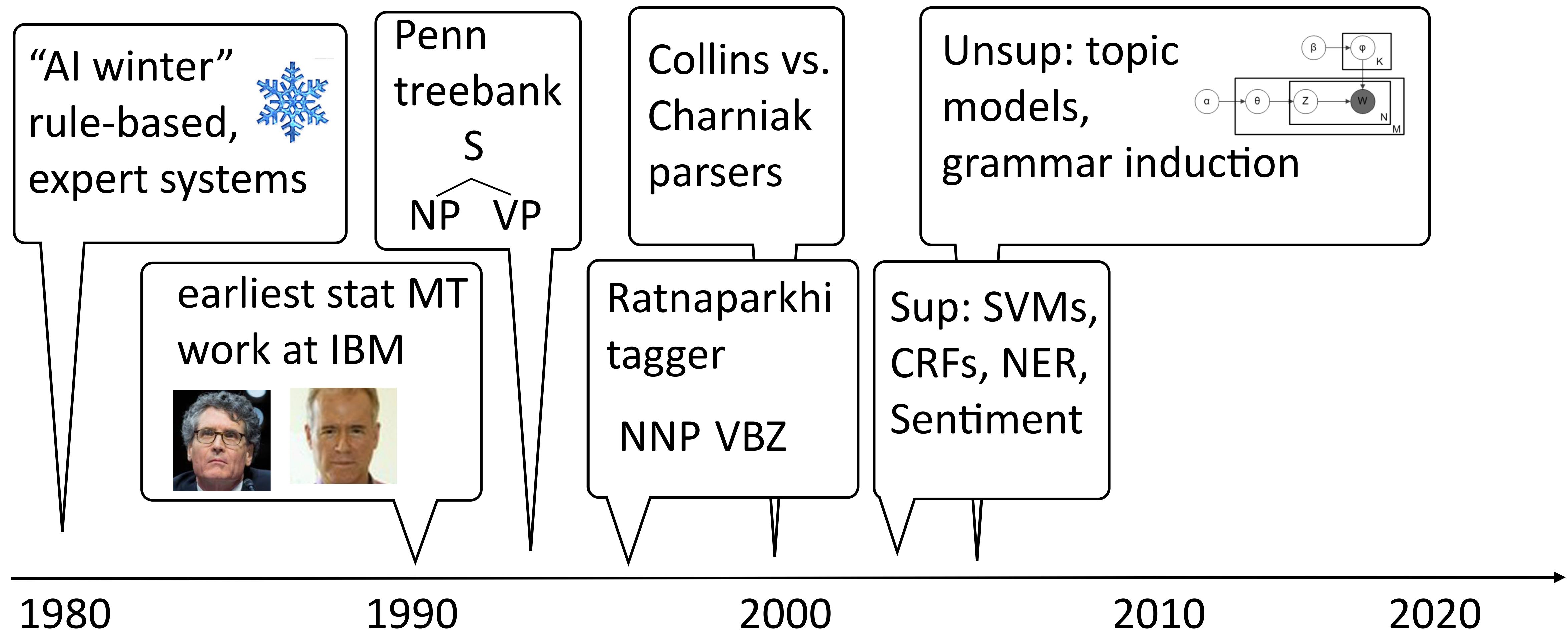
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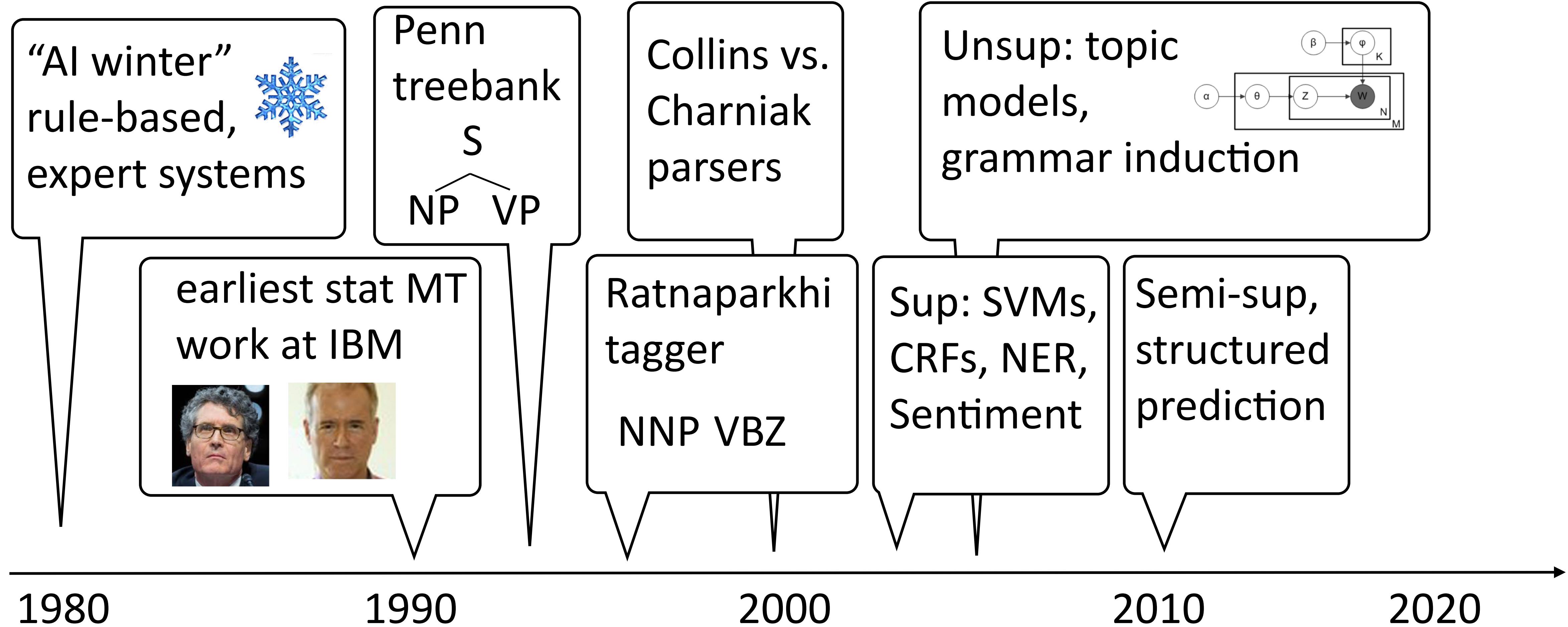
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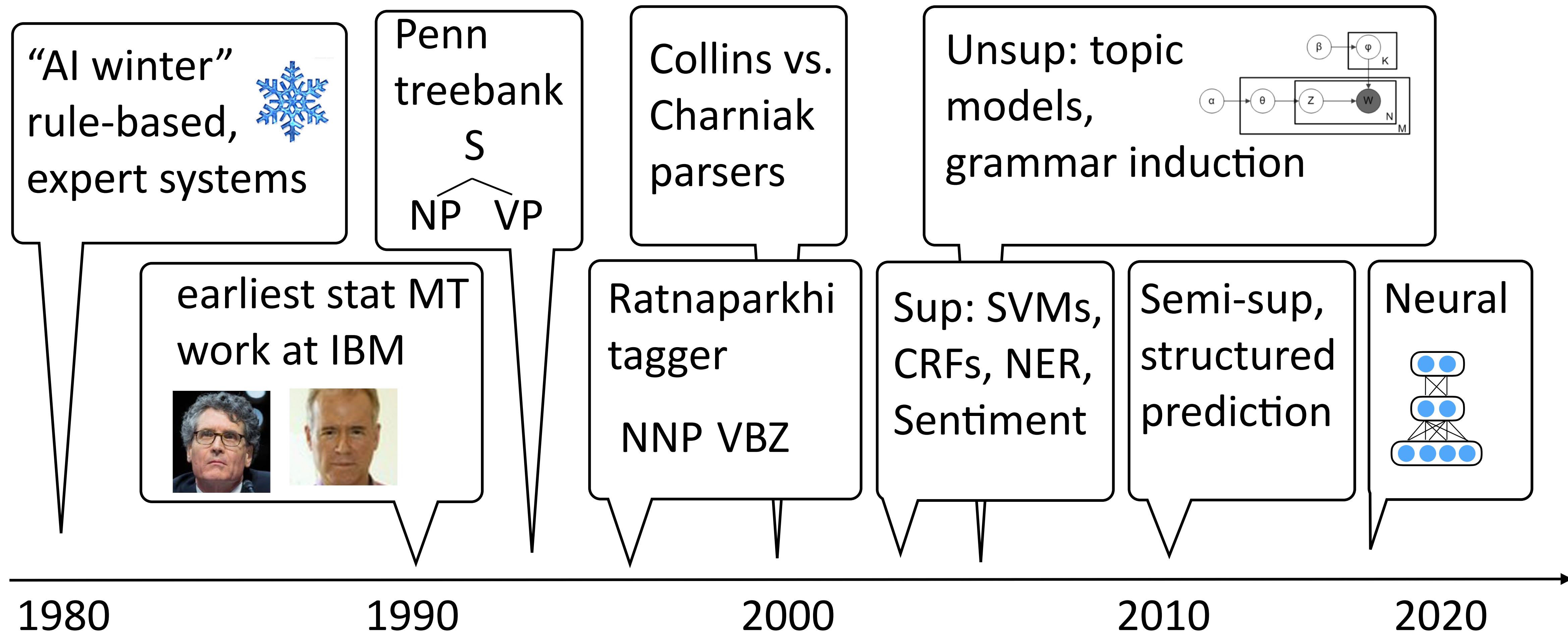
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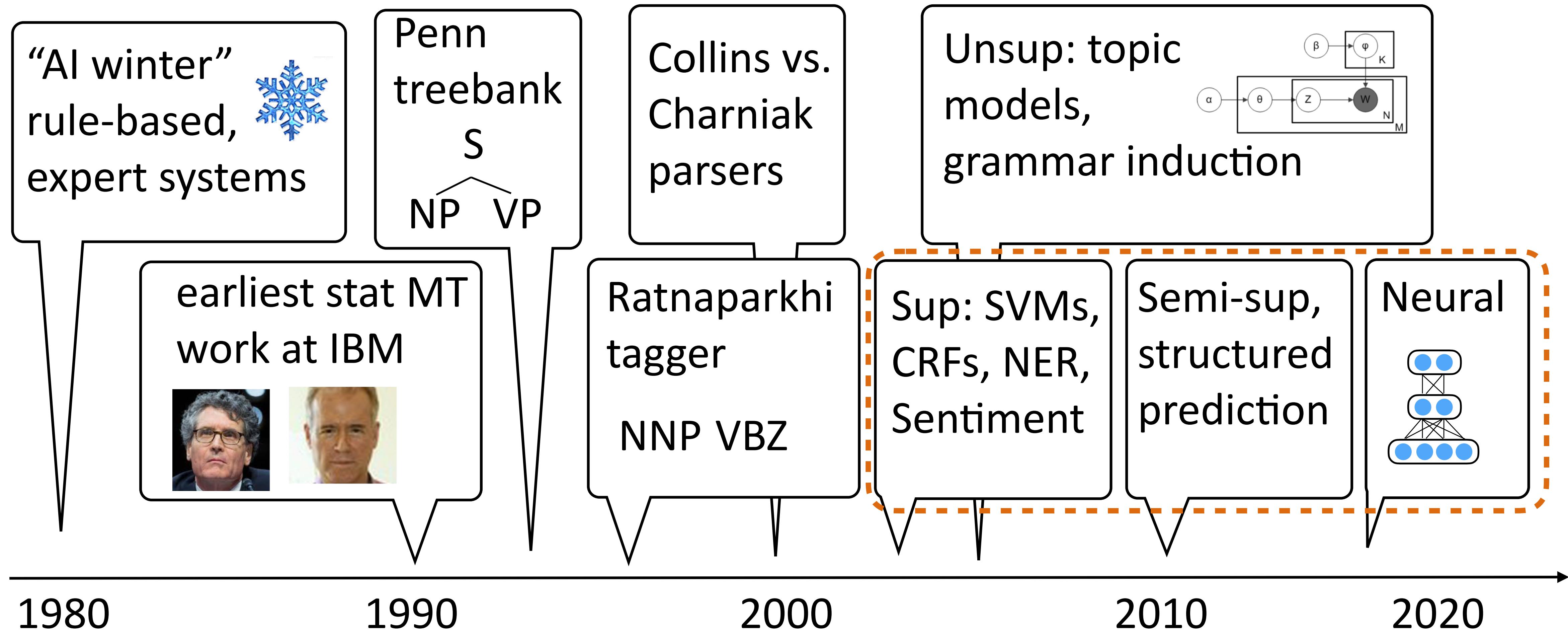
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Structured Prediction

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

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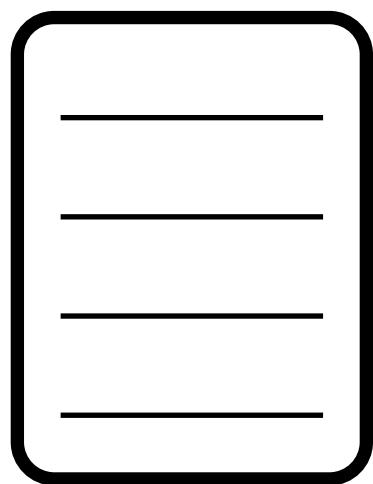
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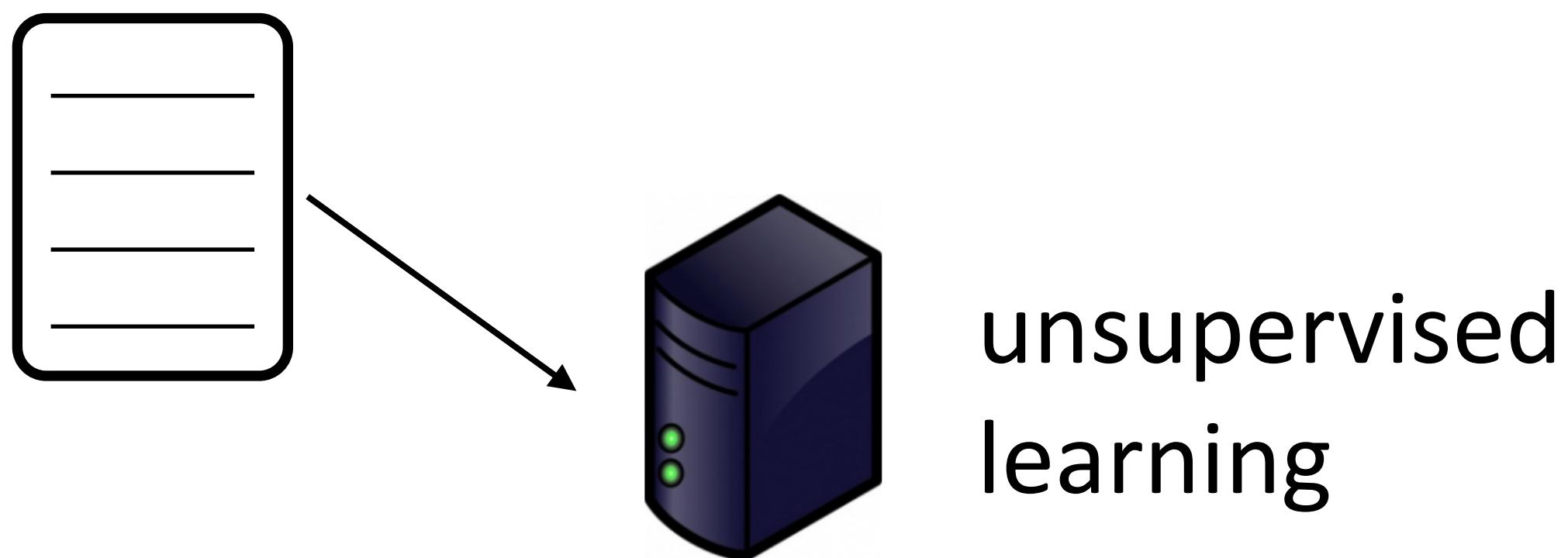
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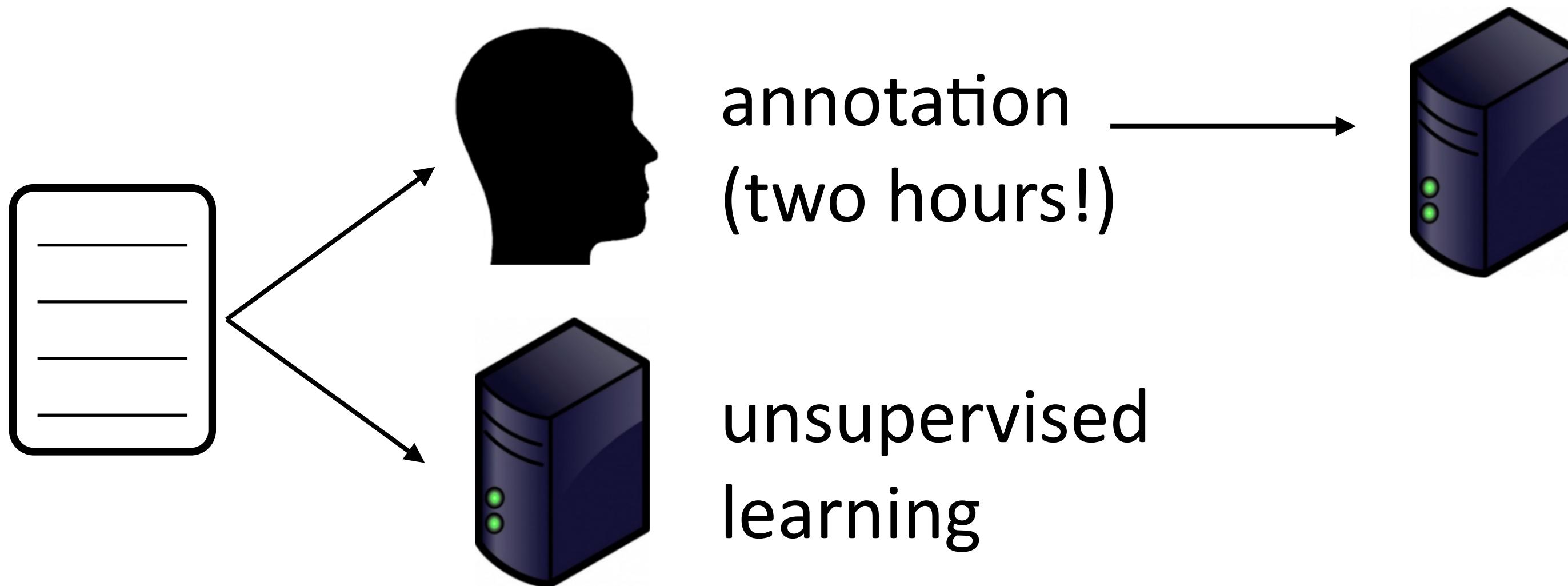
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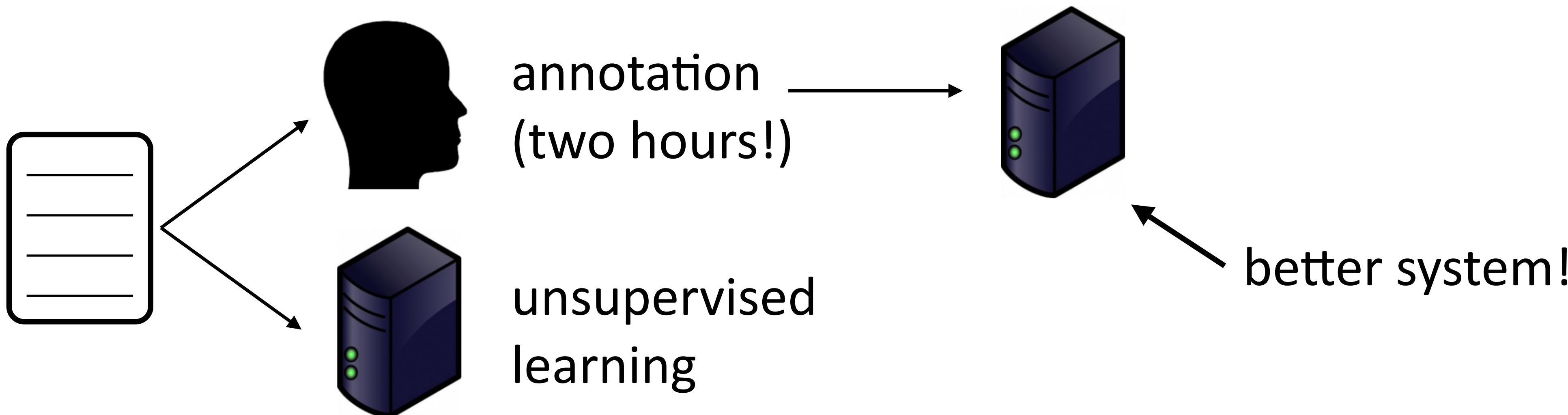
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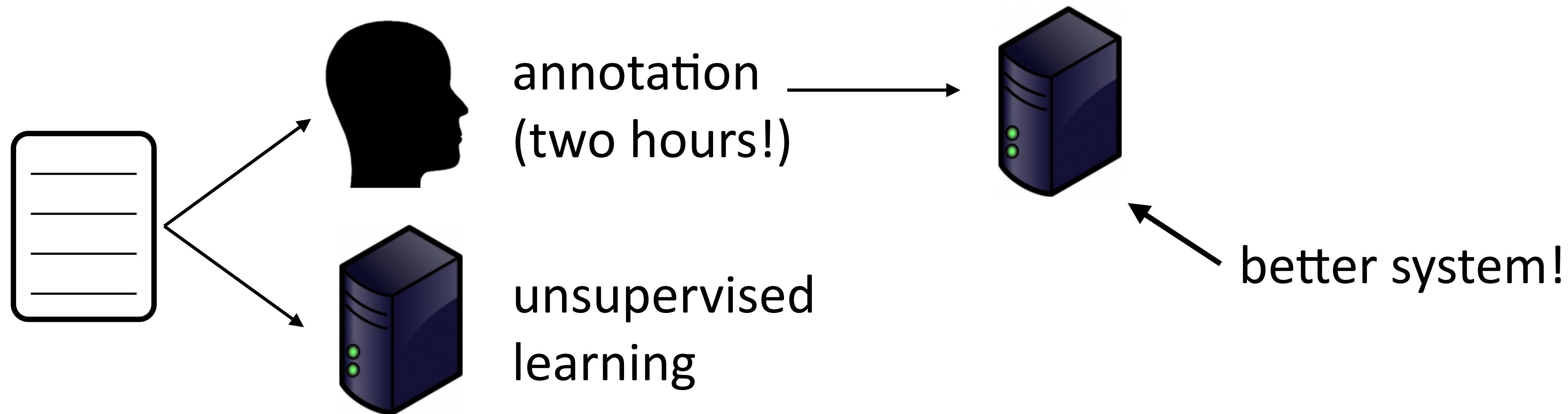
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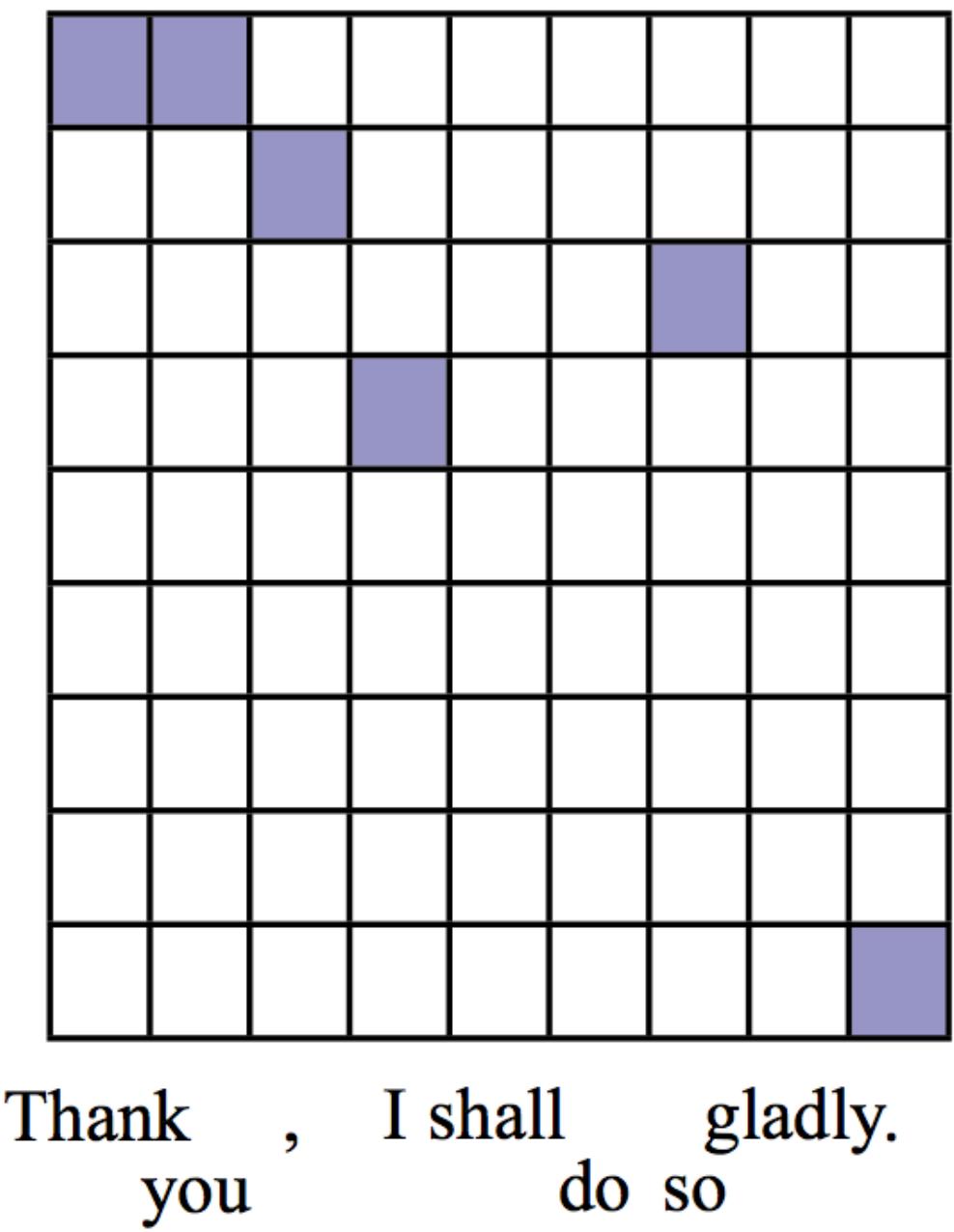
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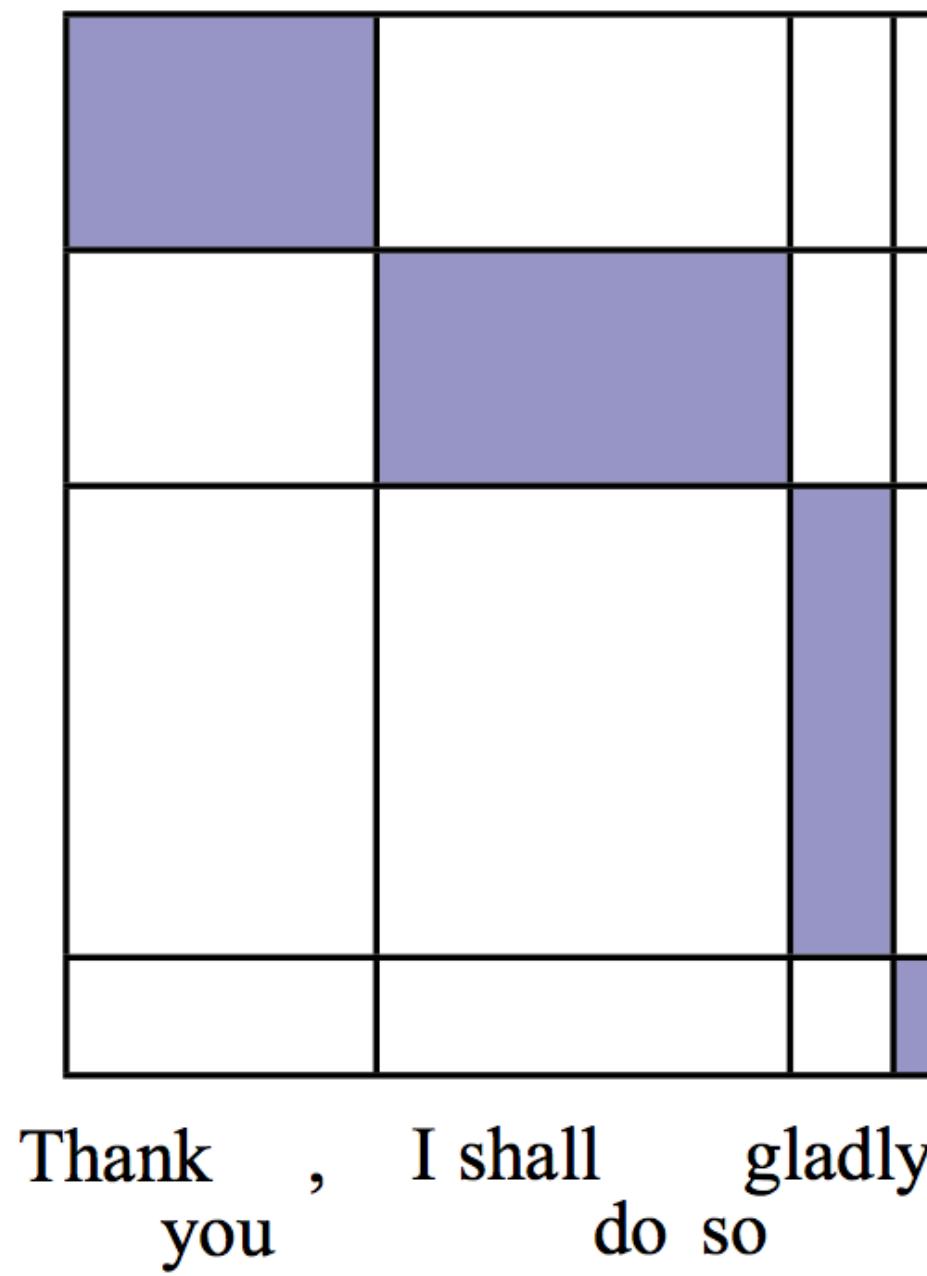
- ▶ Even neural nets can do pretty well!

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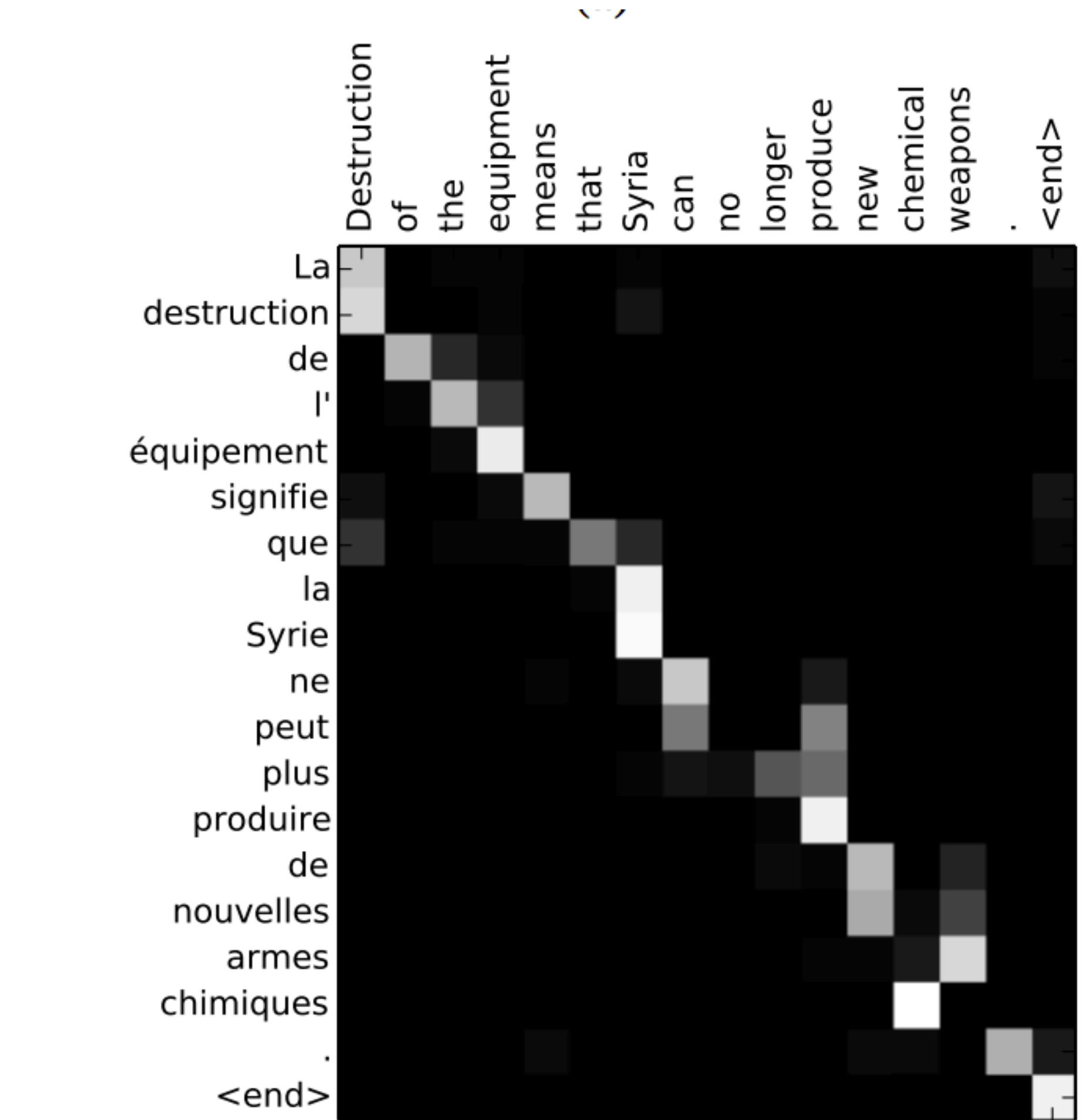
Less Manual Structure?



(a) example word alignment



(b) example phrase alignment



DeNero et al. (2008)

Bahdanau et al. (2014)

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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
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Moosavi and Strube (2017)

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- ▶ Can multi-task learning help?

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Moosavi and Strube (2017)

Does manual structure have a place?

Translate

English French Spanish Chinese - detected ▾

特朗普偕家人在白宫阳台观看百年一遇日全食 X

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...

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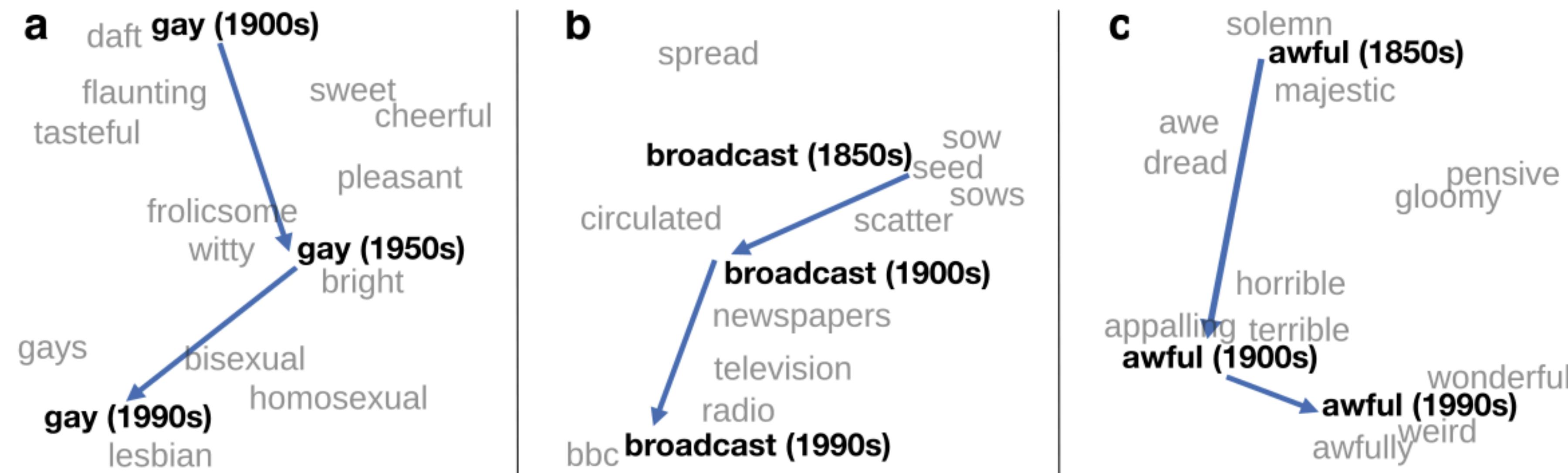
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- ▶ NLP encompasses all of these things

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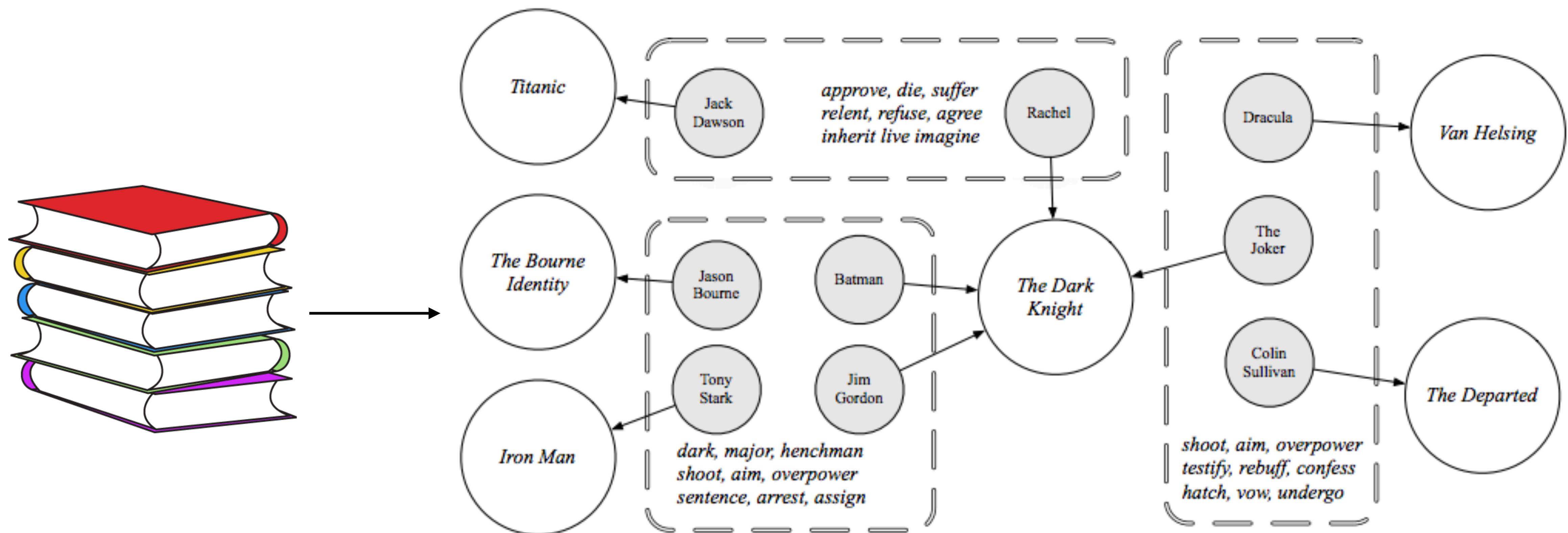


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- ▶ Make you a “producer” rather than a “consumer” of NLP tools
 - ▶ The three assignments should teach you what you need to know to understand nearly any system in the literature

Assignments

- ▶ 3 Programming Assignments
 - ▶ Implementation-oriented
 - ▶ ~2 weeks per assignment, 3 “slip days” for automatic extensions

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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 preferred, 1 is possible.
 - ▶ 4 page report + final project presentation.