

CS 4650: Natural Language Processing

Alan Ritter

Administrivia

- ▶ Course website:

<https://aritter.github.io/CS-4650-sp26/>

- ▶ 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).

▶ **Please Sign Yourself up for Piazza**

- ▶ TA Office hours:

- ▶ See spreadsheet

tinyurl.com/4650-office-hours-sp26

Instructor



Alan Ritter

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Teaching Assistants

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Prerequisites

- ▶ Probability/Statistics
- ▶ Linear Algebra
- ▶ Multivariable Calculus
- ▶ Programming / Python experience
- ▶ A prior Machine Learning course will be very helpful

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Coursework

- ▶ 4 Programming Projects (fairly substantial implementation effort)
 - ▶ Logistic Regression
 - ▶ Text classification
 - ▶ Sequence Labeling
 - ▶ Language Modeling

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- ▶ Final project
- ▶ Problem Set 0 (background review) is out now and **due Thursday**.

Final Project

- ▶ Final project (20%)
 - ▶ Groups of 3-4.
 - ▶ 1 is possible, but will require more work. Grading requirements are the same for individual projects.
 - ▶ 4 page report.
 - ▶ We will discuss more and have a “project kickoff” later in the semester.

Problem Set 0 (Background Review)

- ▶ Due this Thursday.
- ▶ Background review on probability, linear algebra, calculus.
- ▶ **Waitlisted students:** please submit PS0 by Thursday 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
 - ▶ If you don't have access to Gradescope, send the course staff a private message on Piazza, and we will give you the access code.

Project 0 is also out (please look!)



▼ Logistic Regression

CS 4650 "Natural Language Processing" Project 0

▼ 4. Gradient Computation [5 points]

Implement the gradient computations for logistic regression.

```
▶ def gradient_update(theta, X, y):
    """ The gradient update for logistic regression"""
    #####
    # Compute the gradient update #
    #####
    grad = None

    ## YOUR CODE HERE

    ## END YOUR CODE
```

Free Textbooks!



- ▶ 2 excellent textbooks for NLP
 - ▶ 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

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 will need to use GPUs to complete the programming assignments.
- ▶ Google Colab: has free GPUs, but with some big limitations that will make the assignments very difficult to complete.
- ▶ Another resource you have access to through this class is PACE/ICE

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Recommended

Colab Pro

\$9.99 per month

Colab Pro for Education

No cost for students and educators

✓ 100 compute units per month
Compute units expire after 90 days.
Purchase more as you need them.

✓ Faster GPUs
Upgrade to more powerful GPUs.

✓ More memory
Access our highest memory machines.

Outline of the Course

- Machine Learning Review (Naive Bayes, Log. Reg. SVMs, Neural Nets)
- Sequence Models (HMMs, CRFs)
- Word Embeddings
- Neural Networks in NLP (NBOW, RNNs, CNNs, Transformers)
- Machine Translation
- Pre-trained Transformers (e.g. BERT, BART, T5, GPT, Llama)
- Question Answering, Multilingual NLP, etc.

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- ▶ Cover fundamental machine learning techniques used in NLP
 - ▶ Deeper understanding of algorithms beyond “how to use ML/NLP libraries”.
- ▶ Know about modern NLP methods: what is the state-of-the-art in 2025?
- ▶ Make you a “producer” rather than a “consumer” of NLP tools

Programming Assignments

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

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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!**

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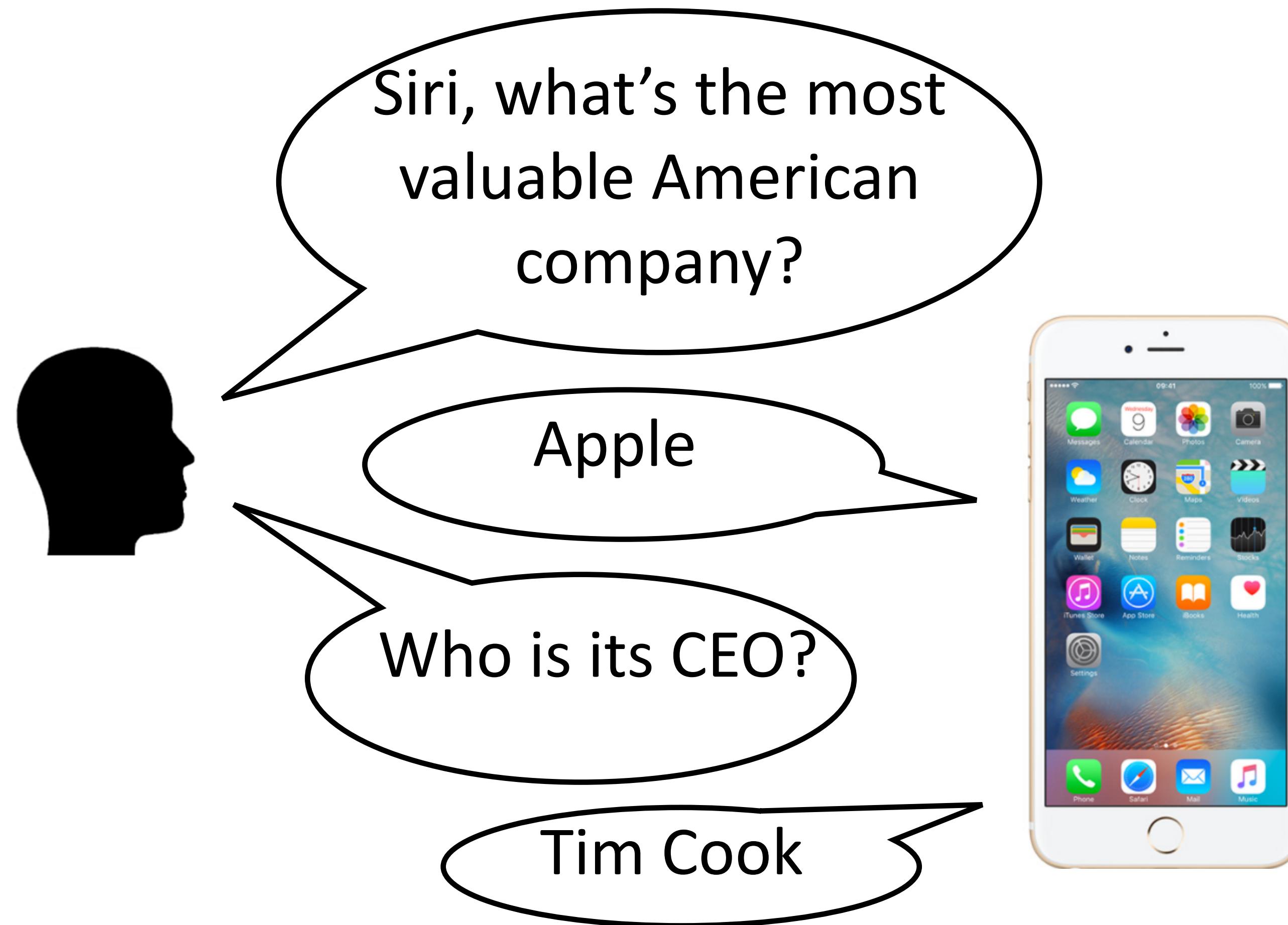
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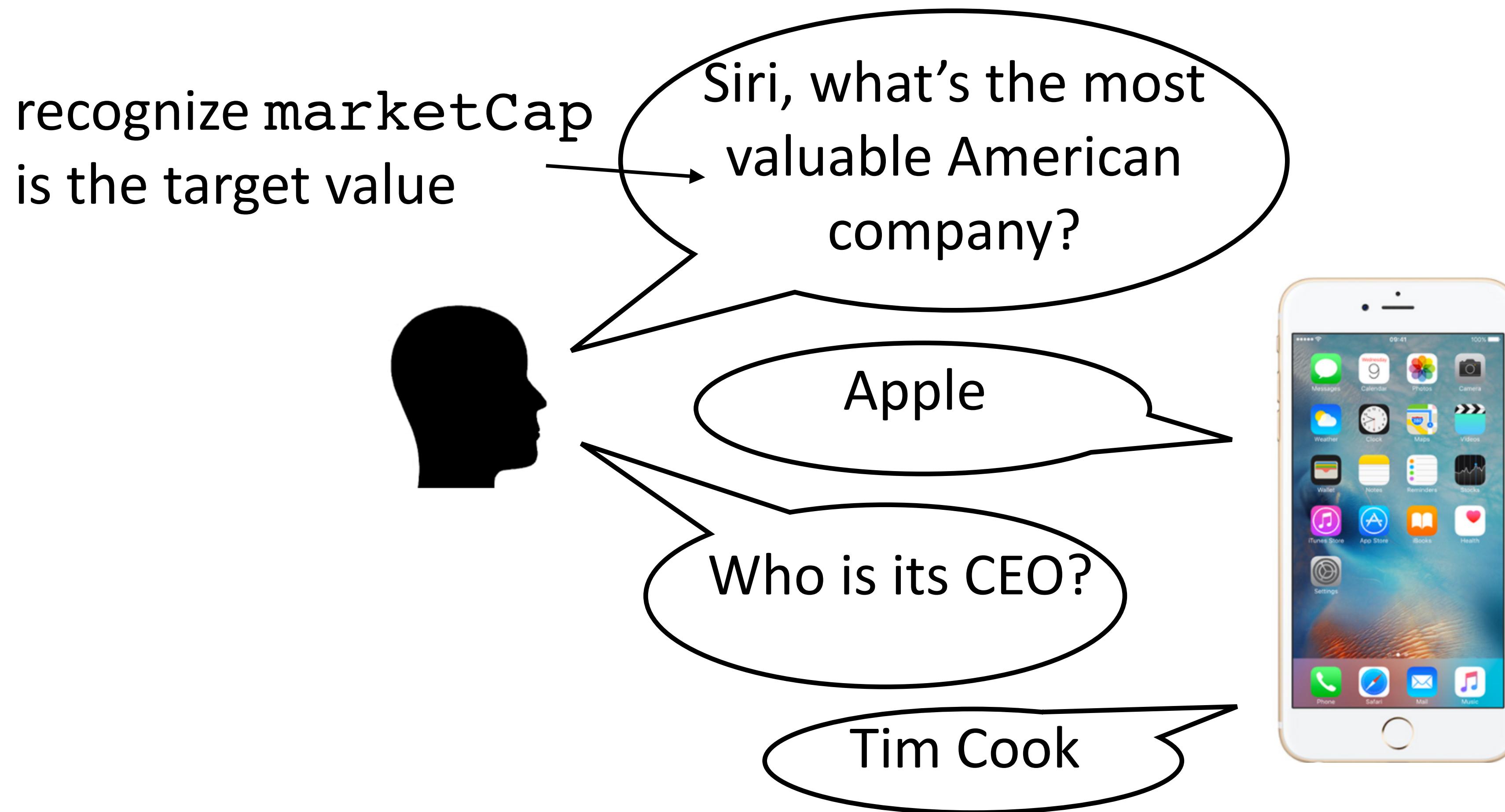
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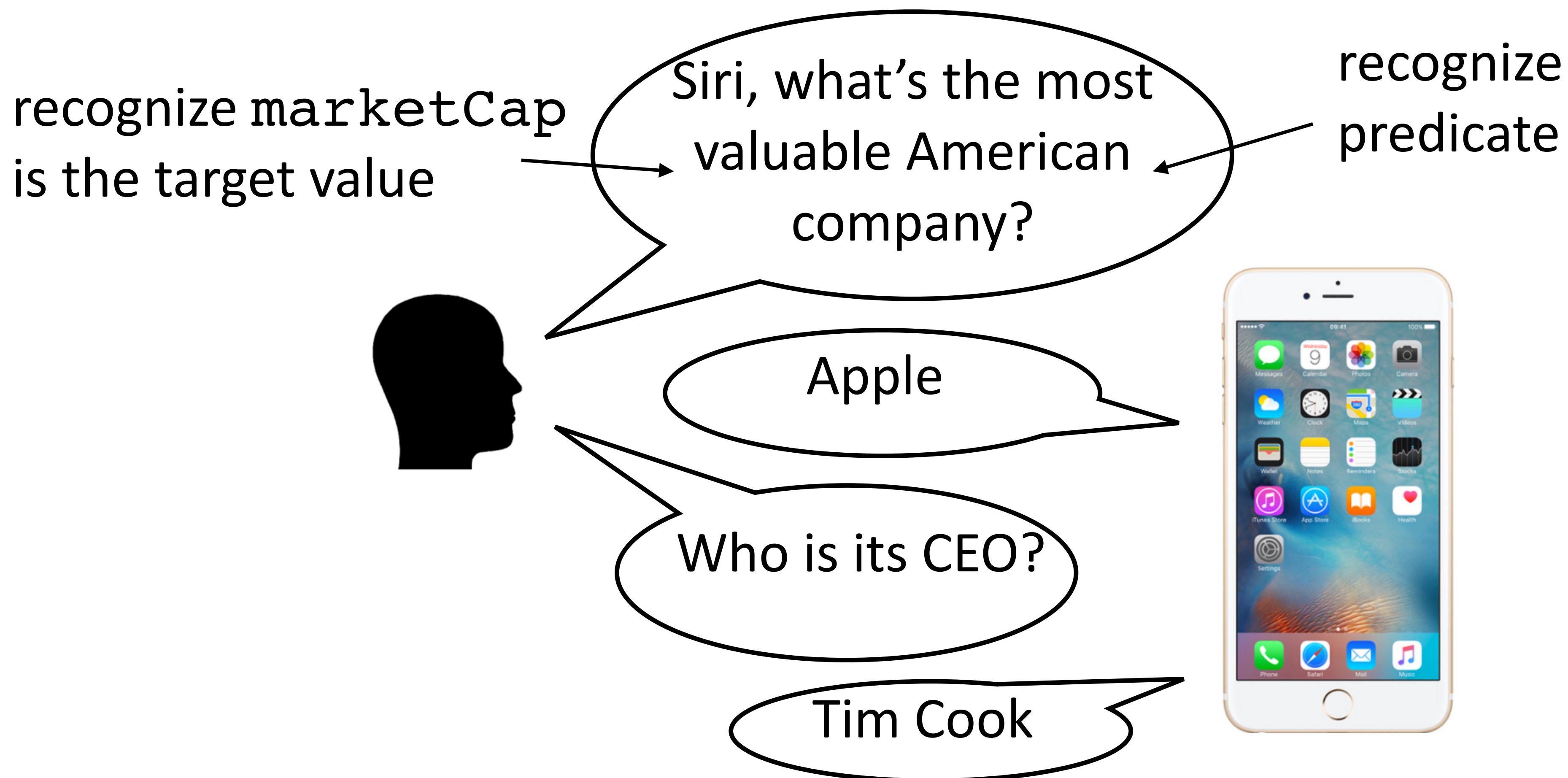
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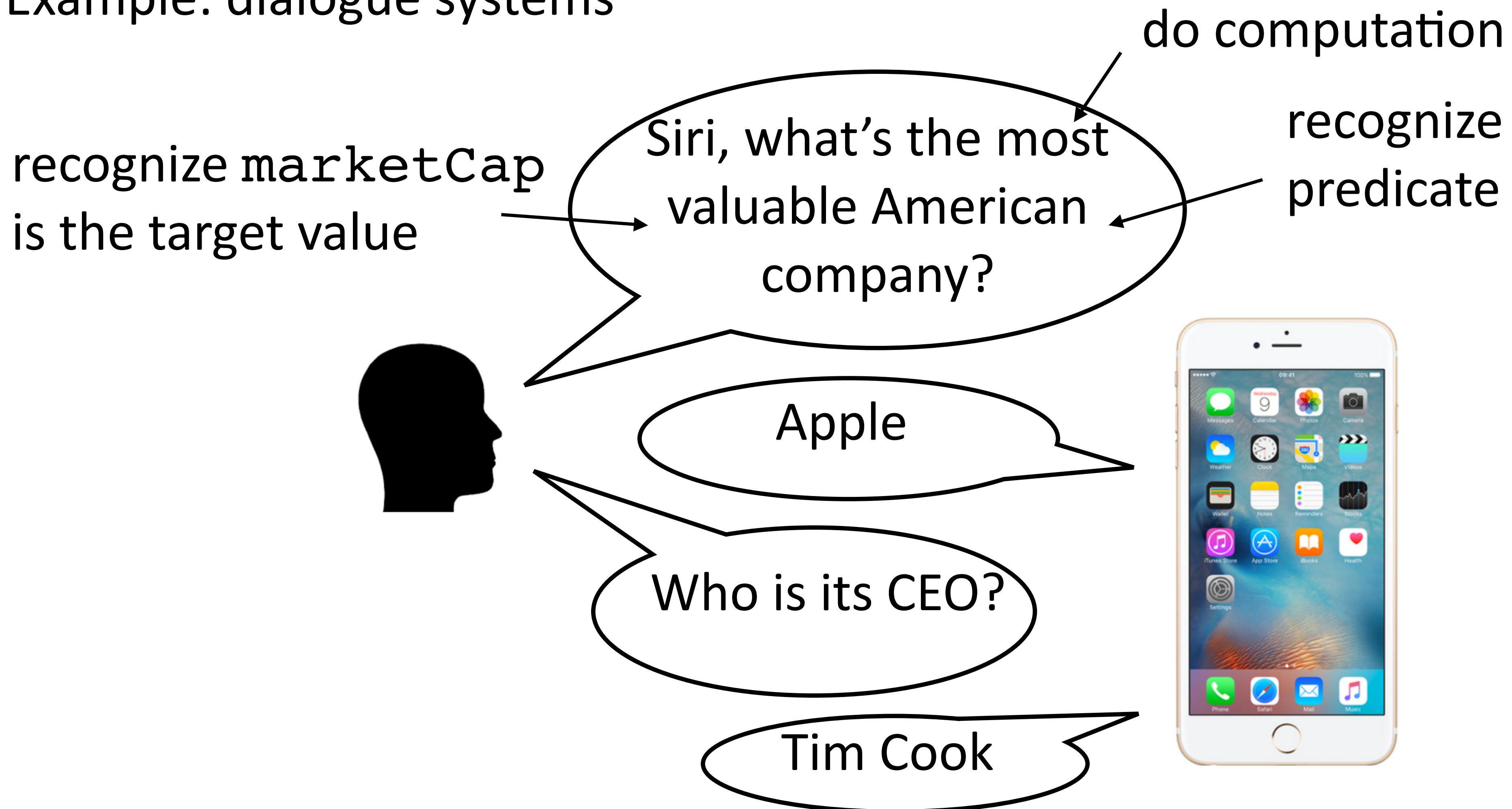
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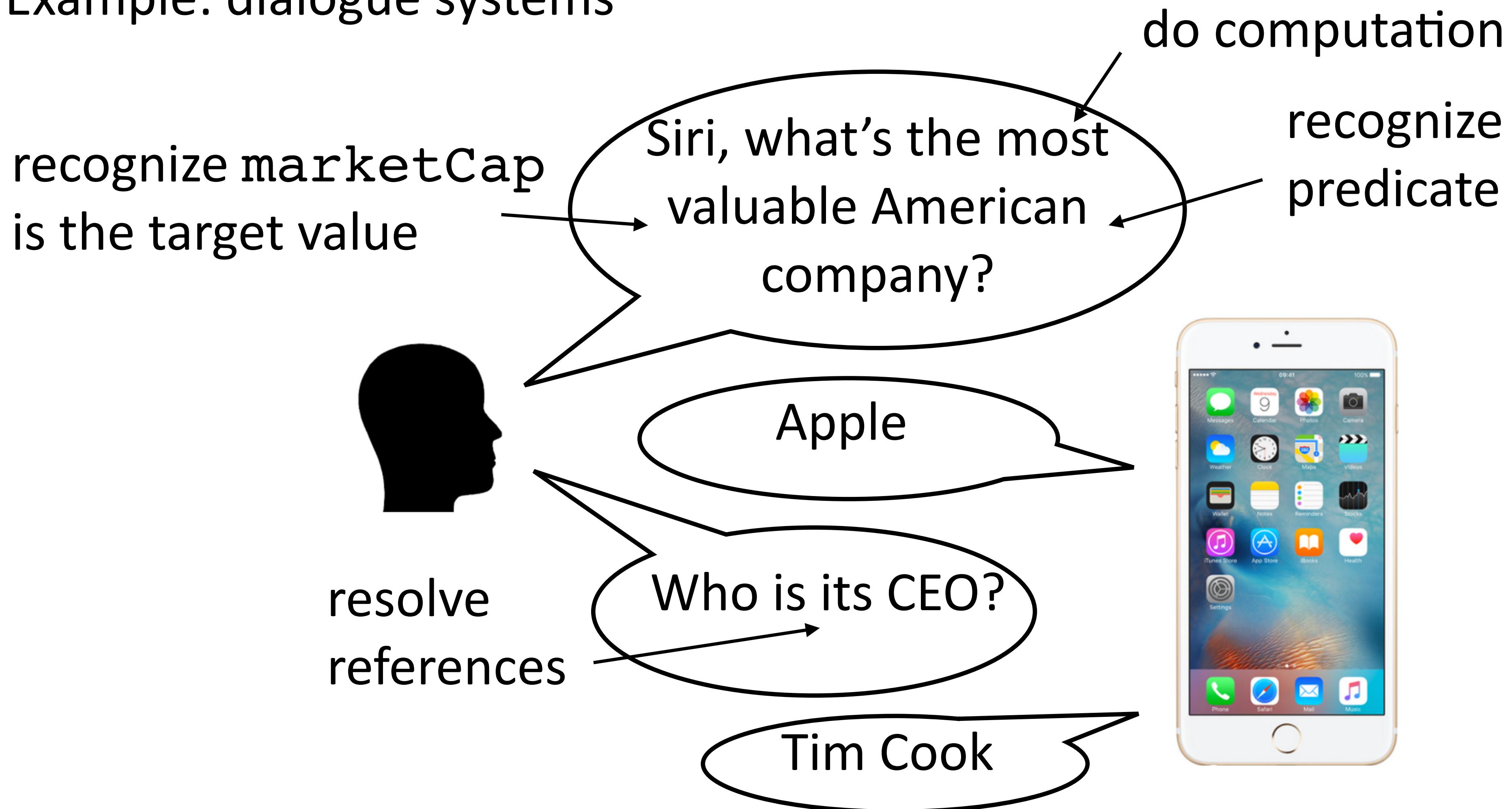
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paraphrase to provide clarity

Machine Translation



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Language Models



Translate this sentence to English: 中国和俄罗斯已在推进一种非正式的政治和经济联盟，共同对抗西方。现在，两国正在通过越来越具挑衅性的联合军事演习来加大双边军事合作。



The sentence translates to:

"China and Russia have been advancing an informal political and economic alliance to jointly oppose the West. Now, the two countries are increasing bilateral military cooperation through increasingly provocative joint military exercises."



Summarize this article in two sentences:



China and Russia have deepened their military cooperation, conducting joint exercises near Alaska and the South China Sea as part of a broader alignment against the United States. This collaboration underscores their shared intent to challenge U.S. dominance, with China also pursuing trade alliances and influence-building to counter American power.



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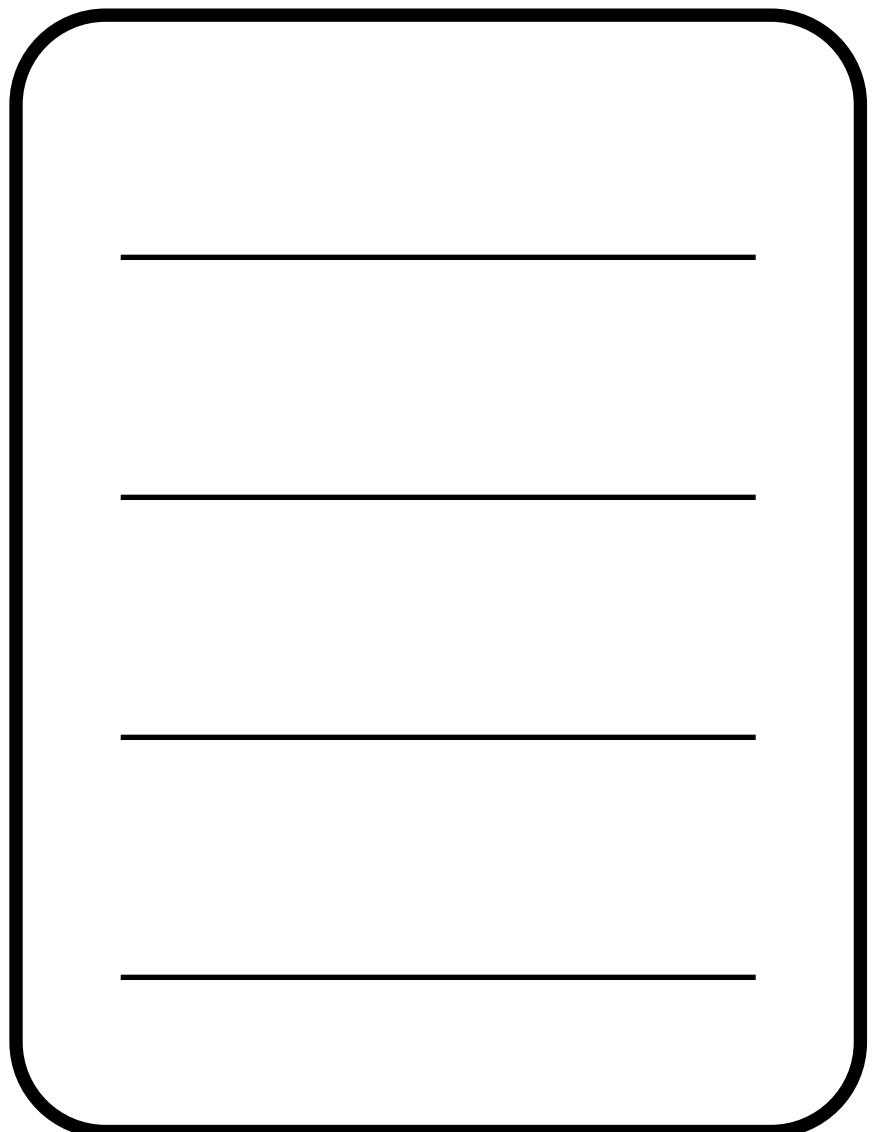
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- ▶ Still useful to think about capabilities in specific tasks / domains.

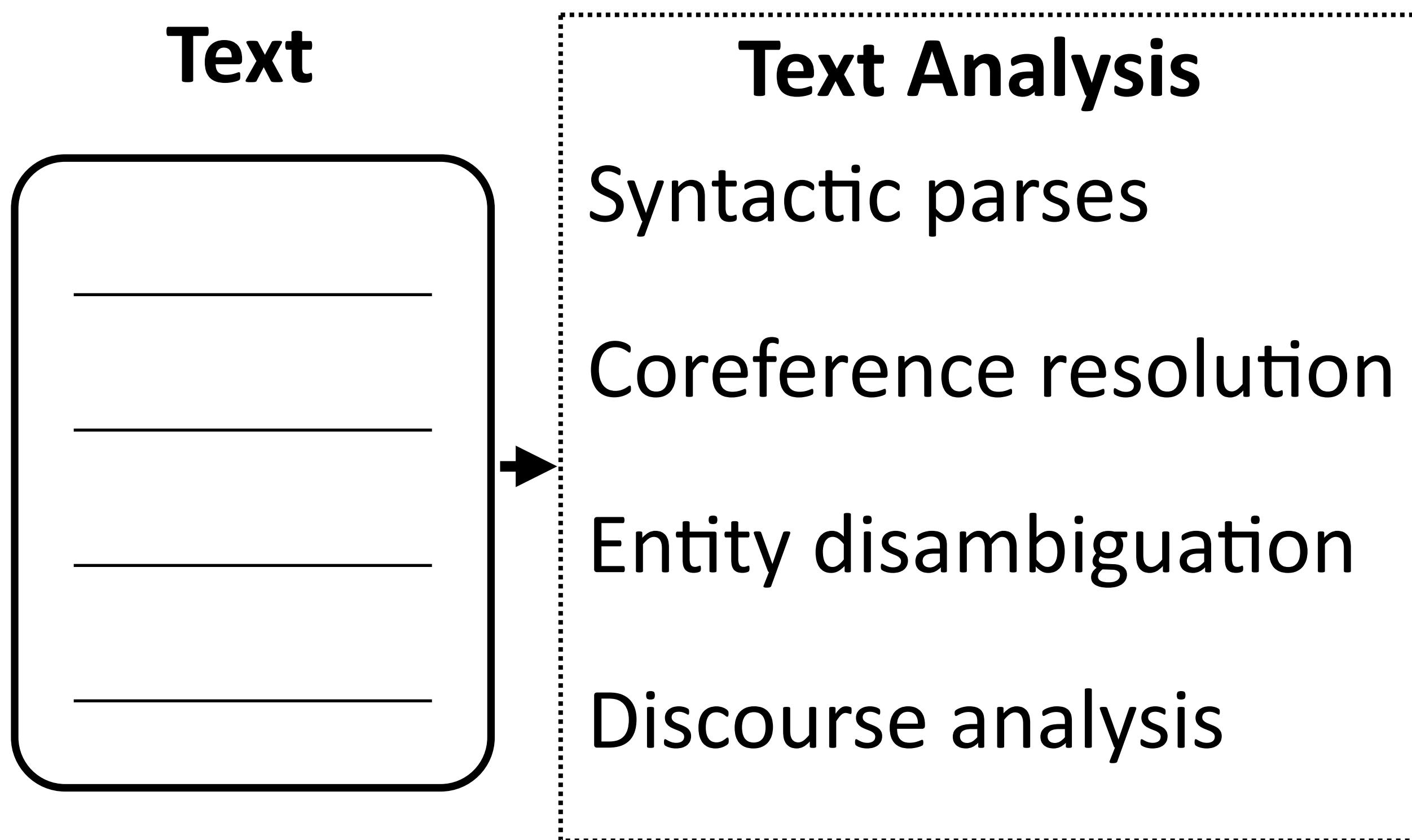
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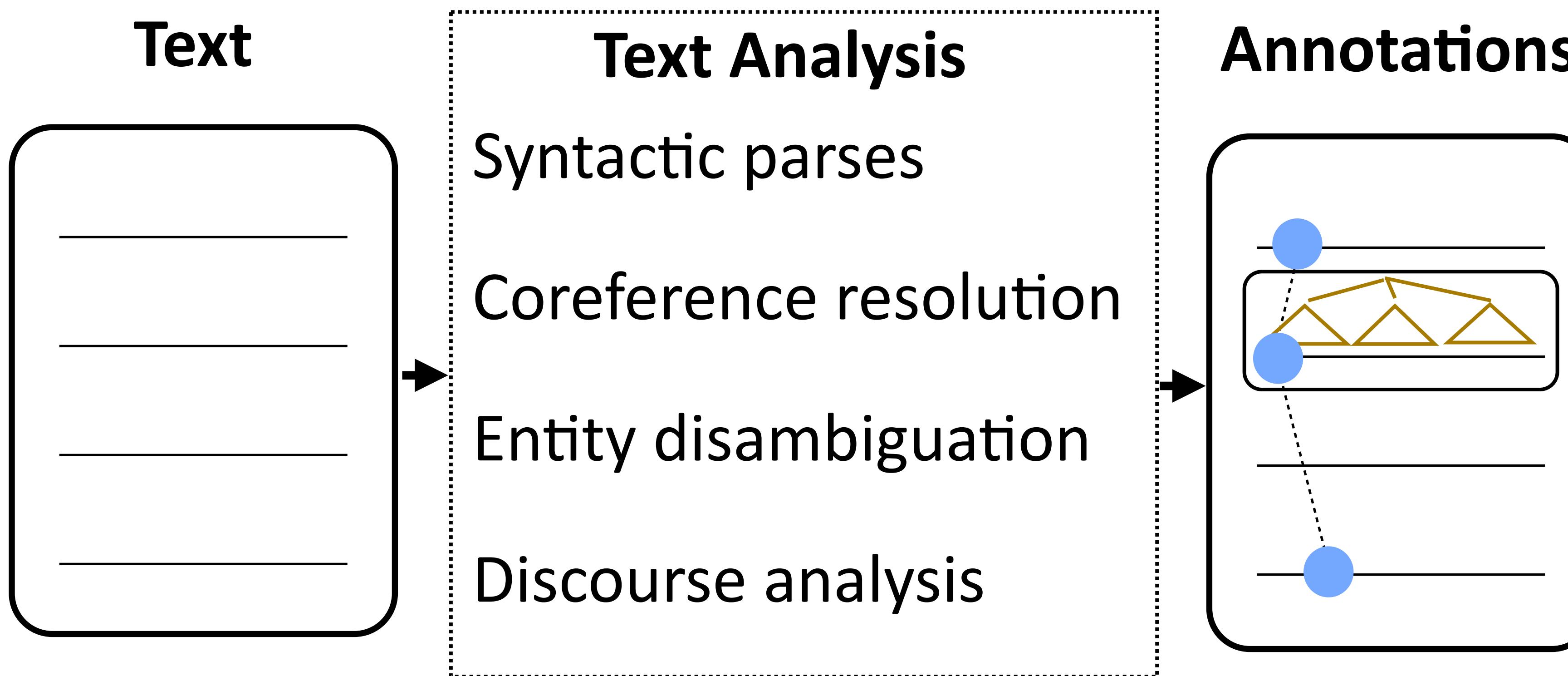
Text



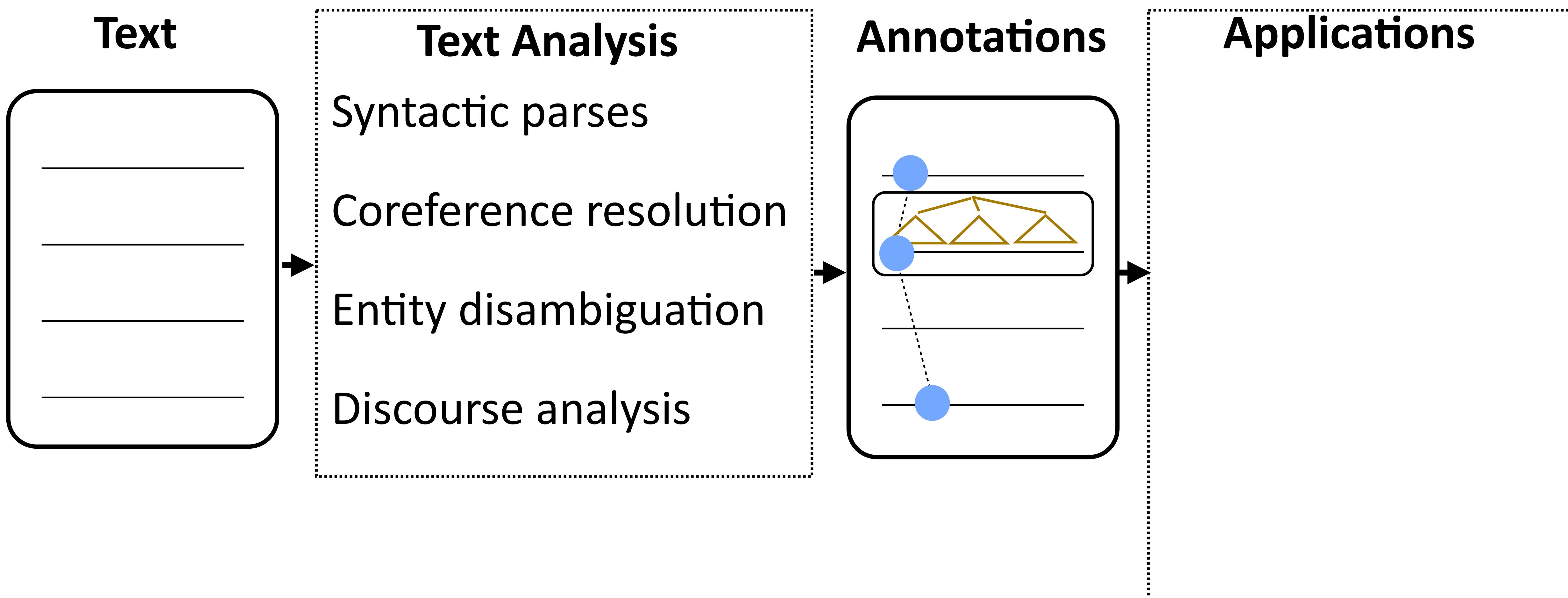
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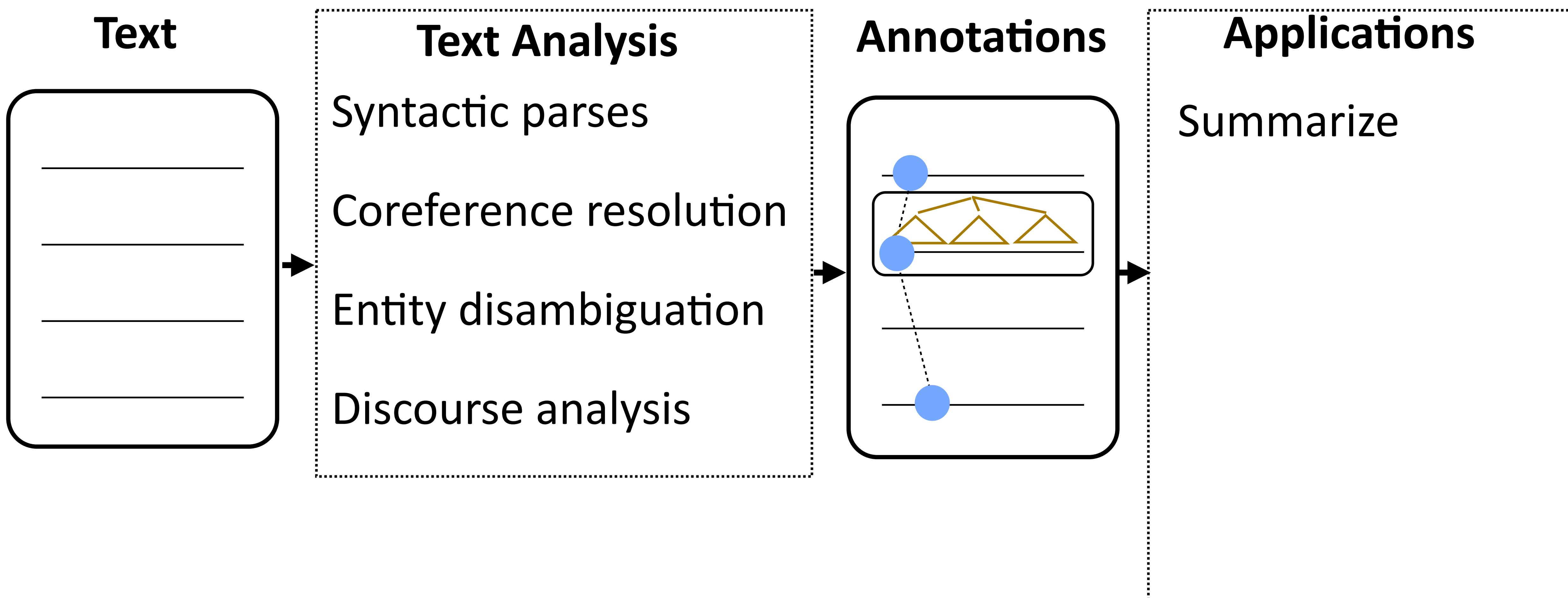
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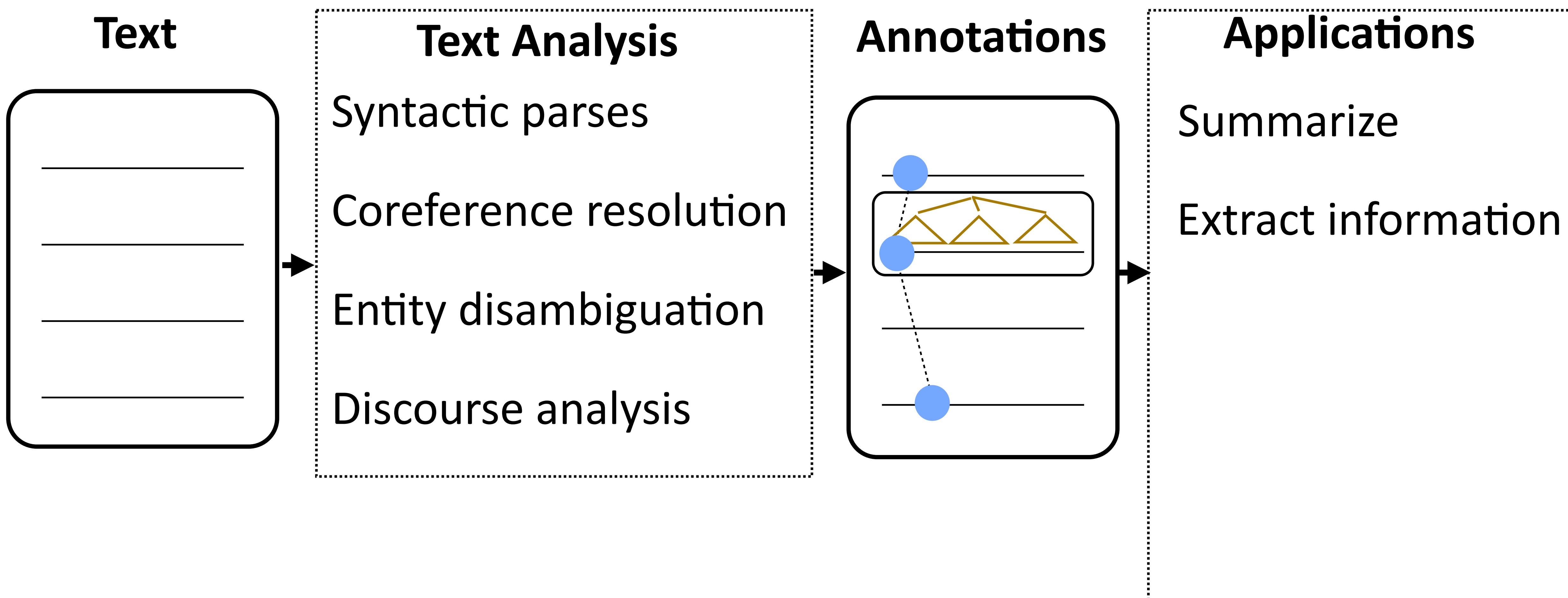
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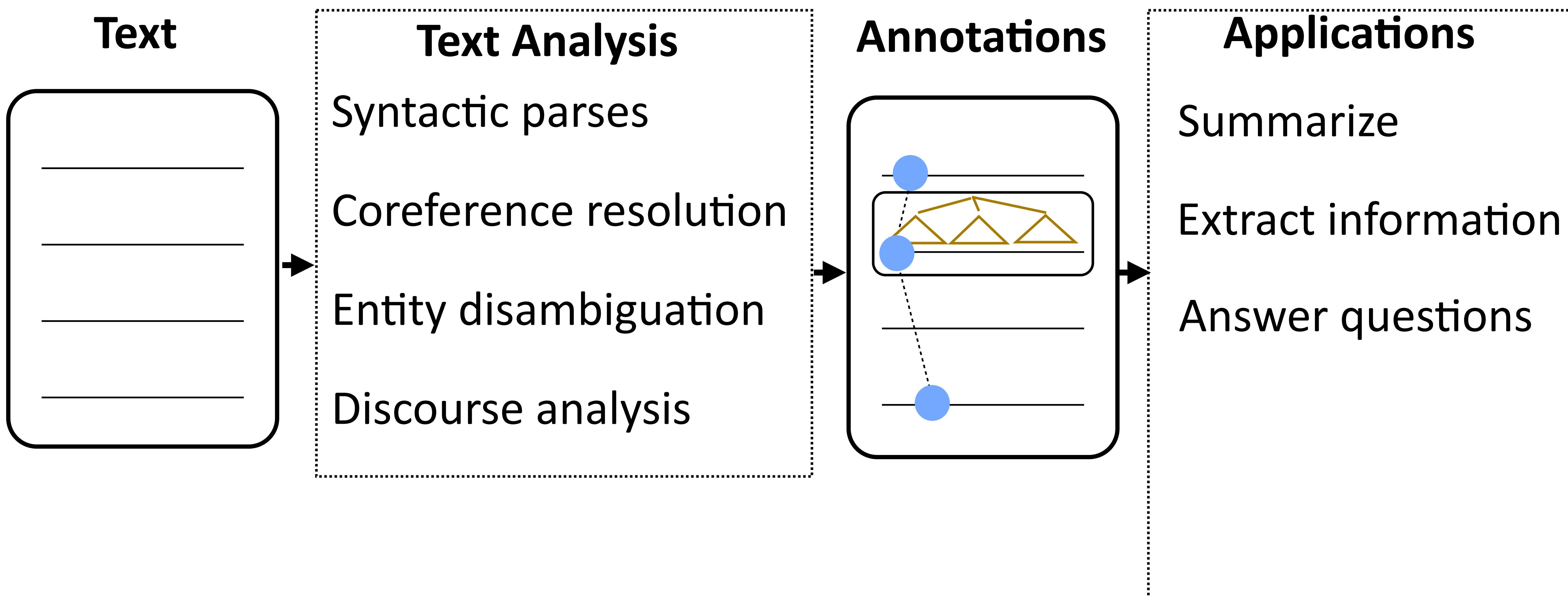
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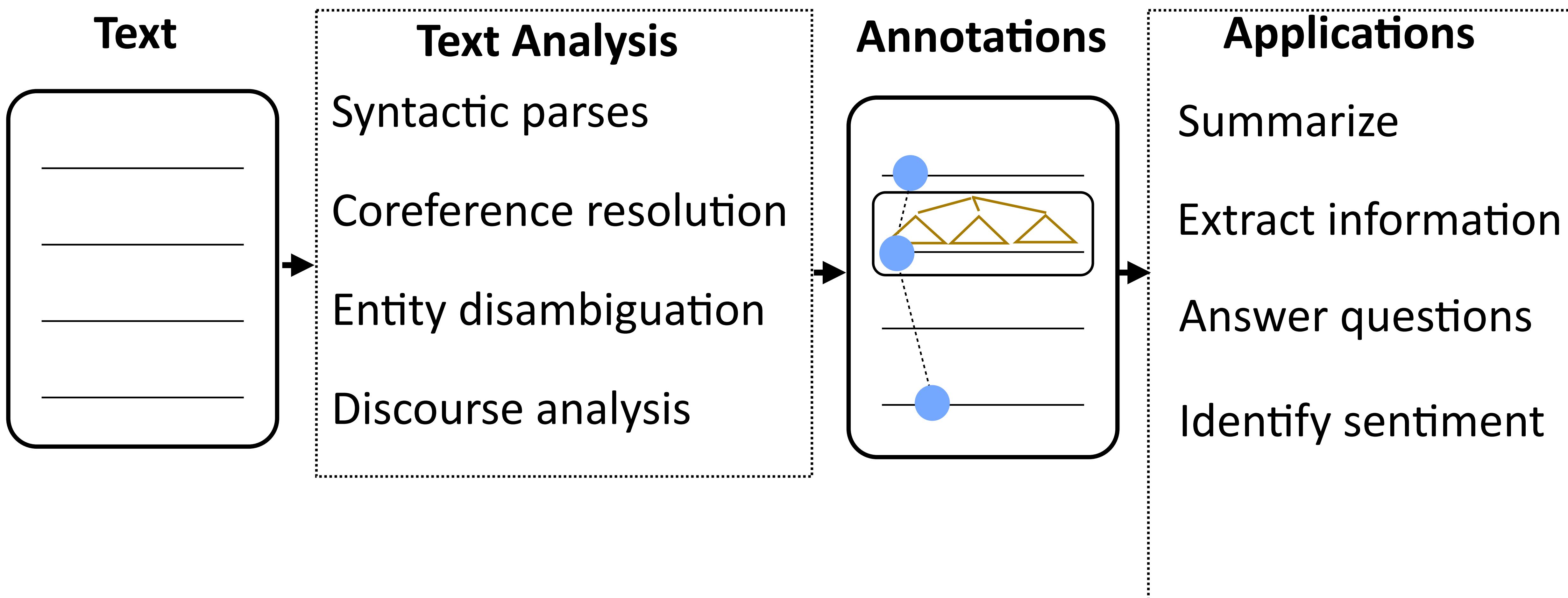
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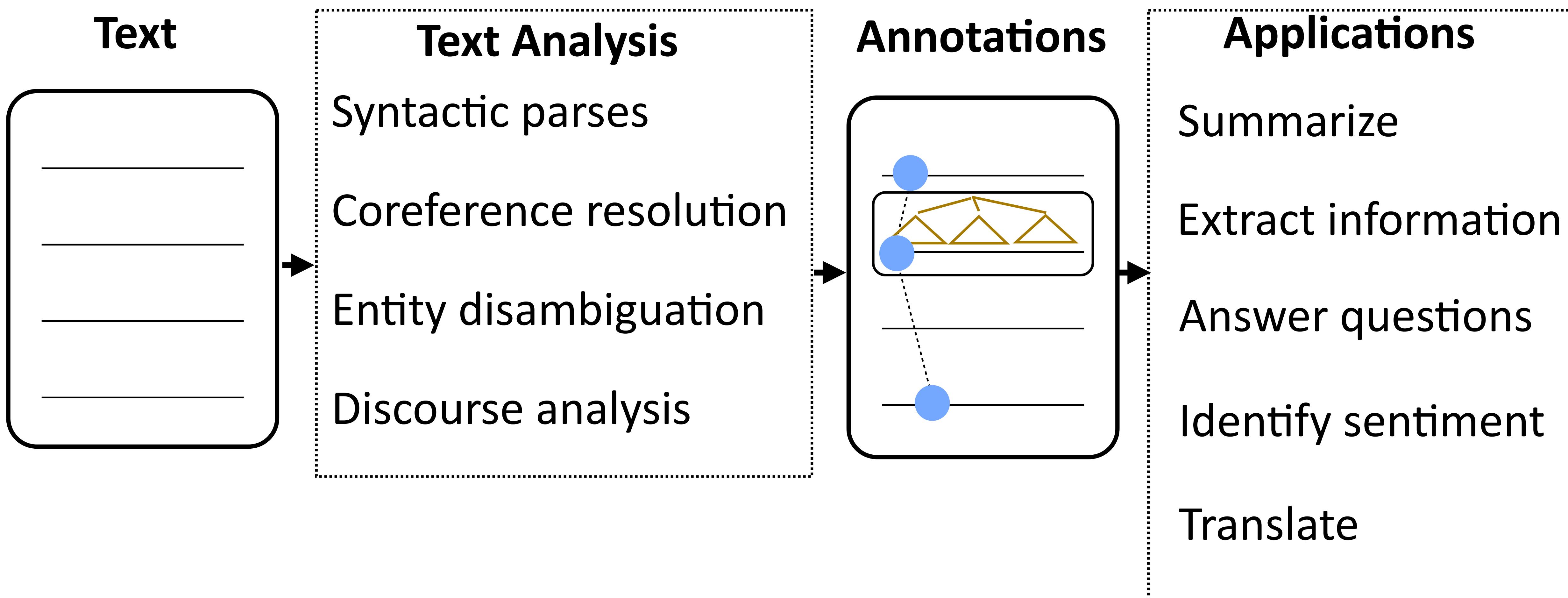
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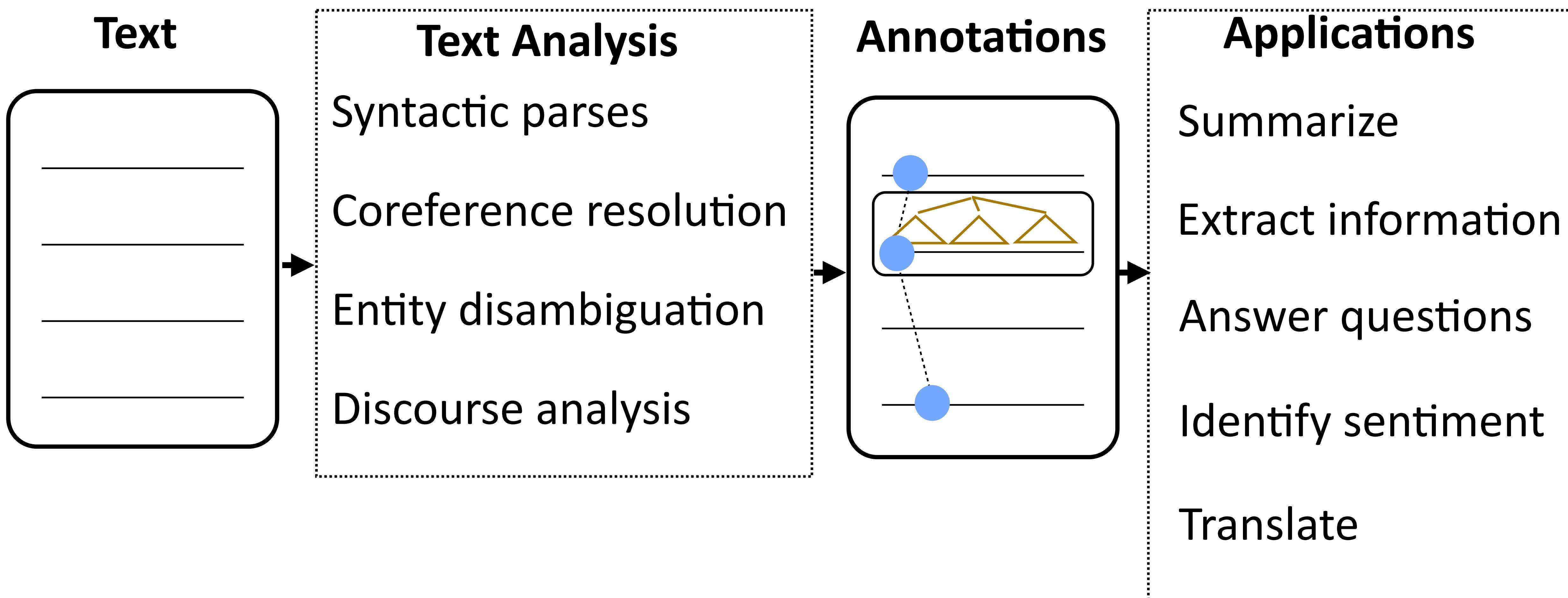
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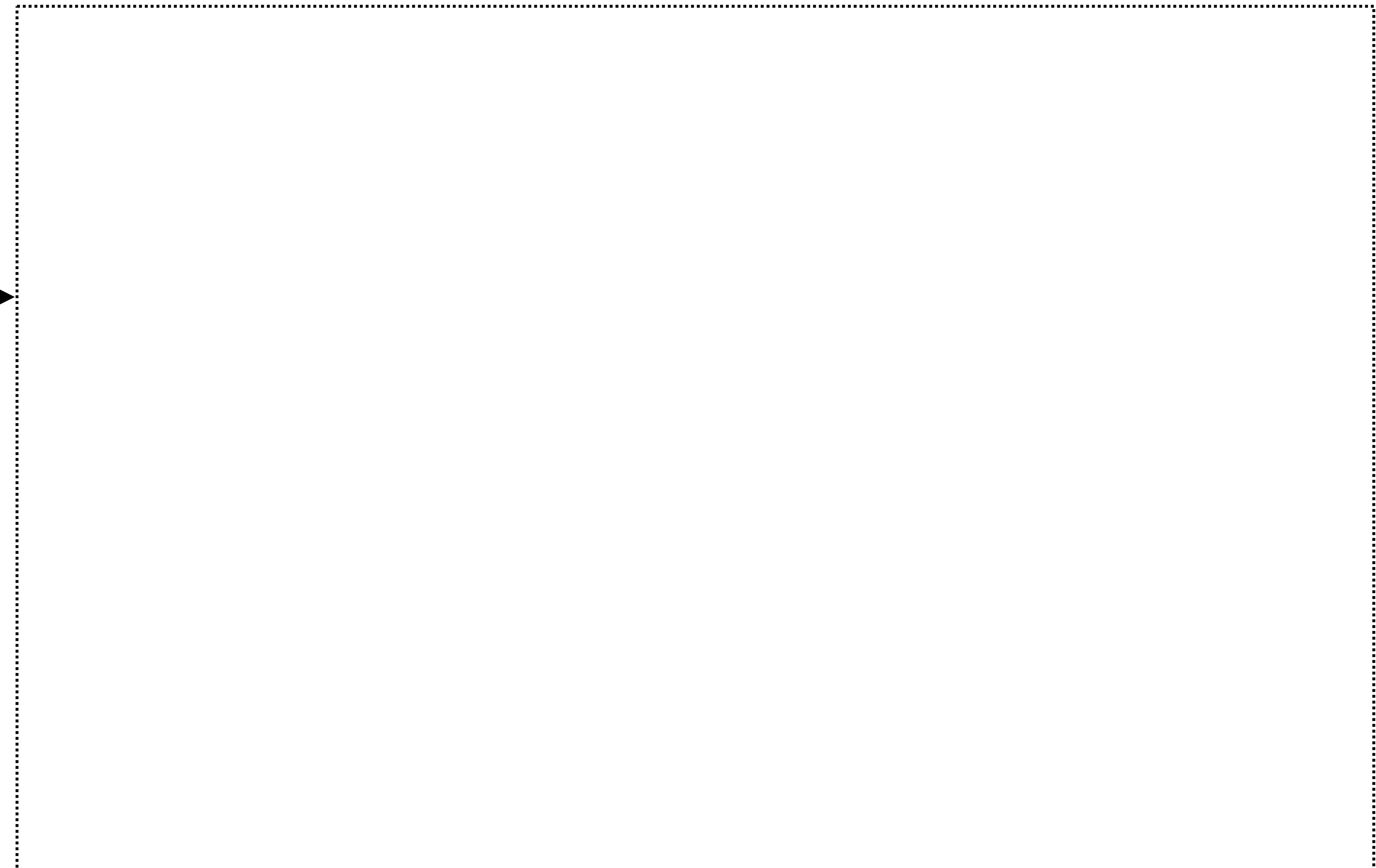
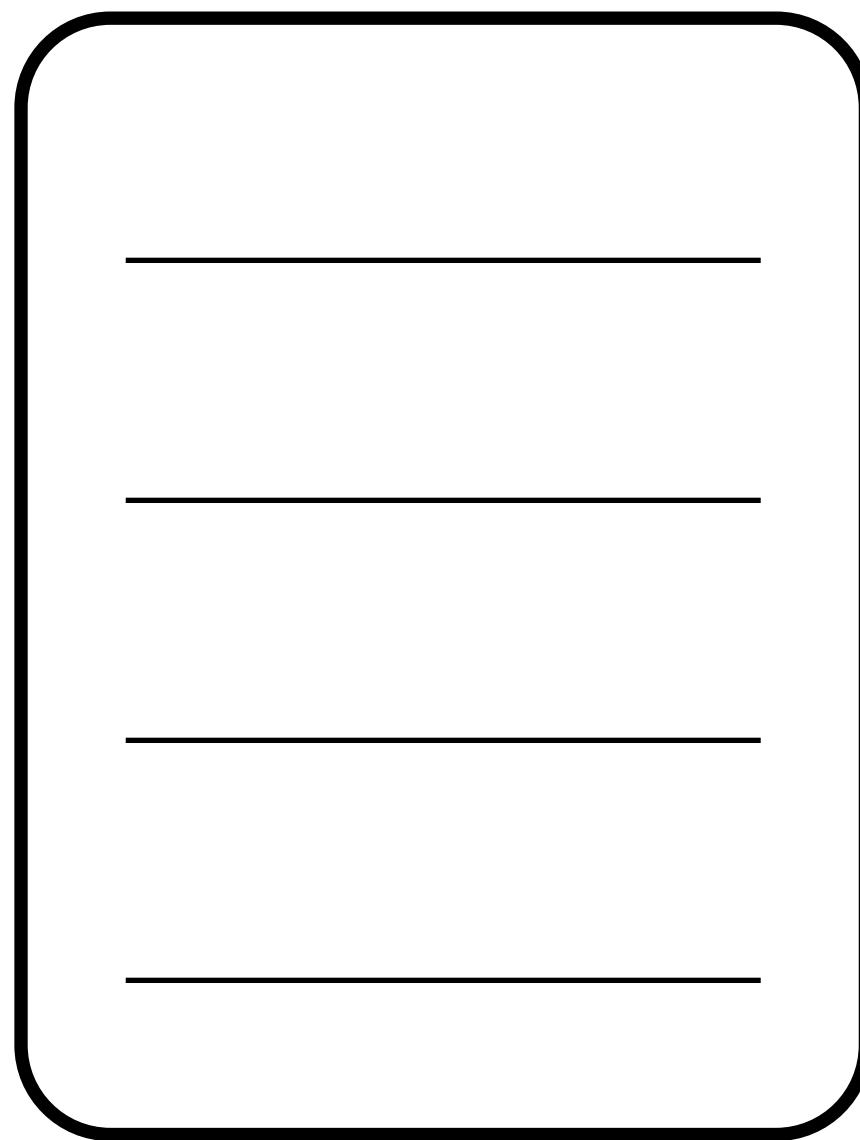
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- ▶ All of these components were modeled with statistical approaches trained with machine learning

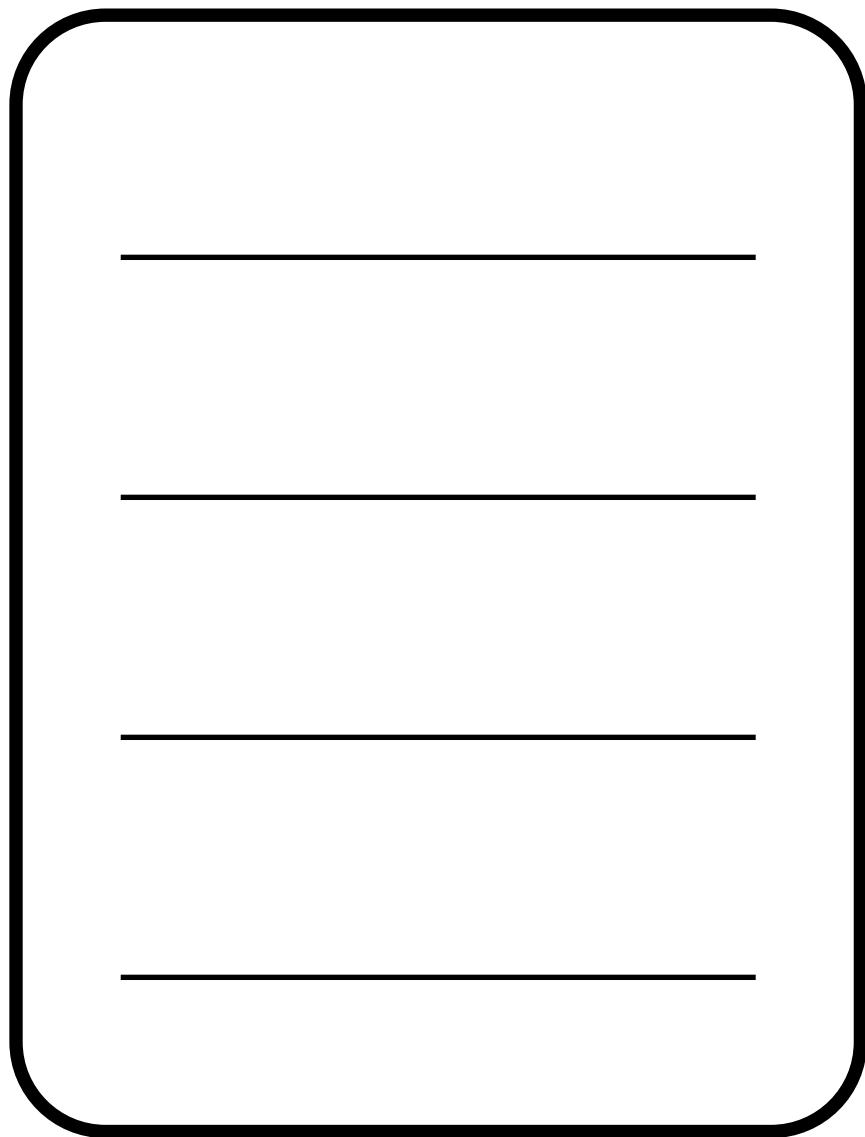
How do we represent language?

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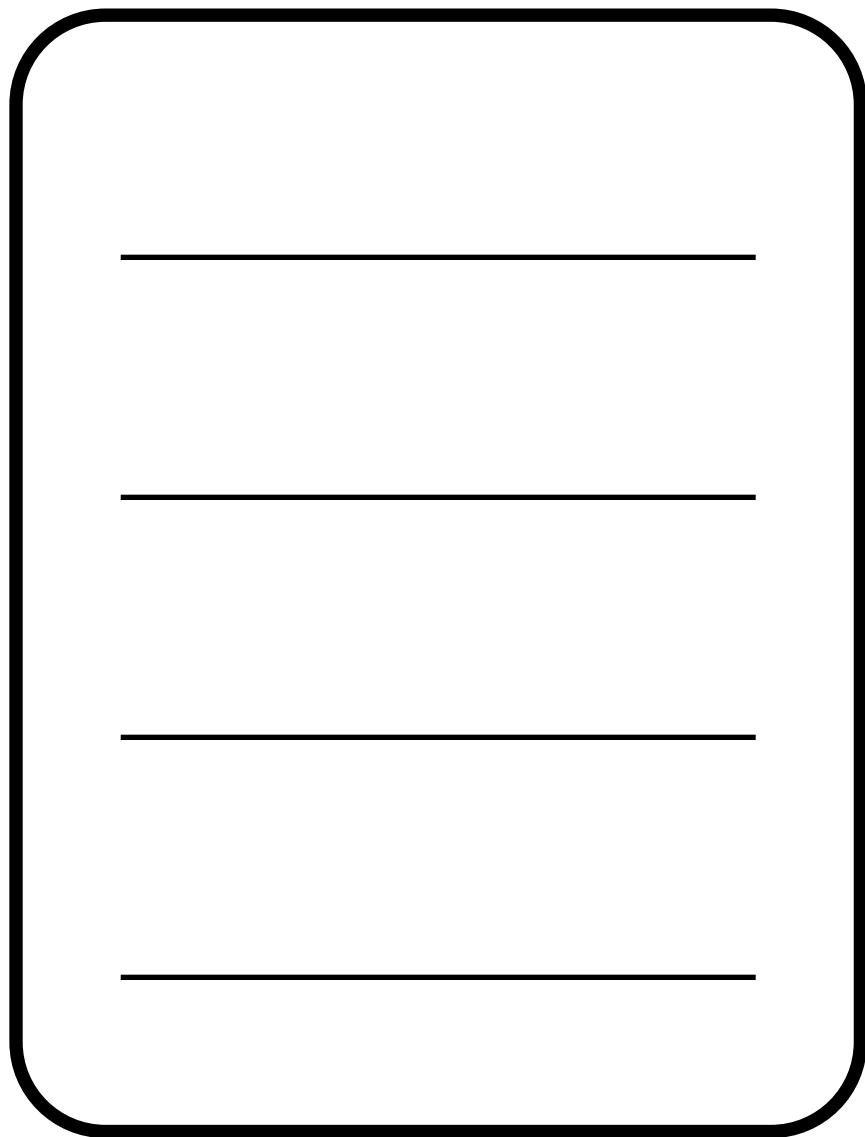


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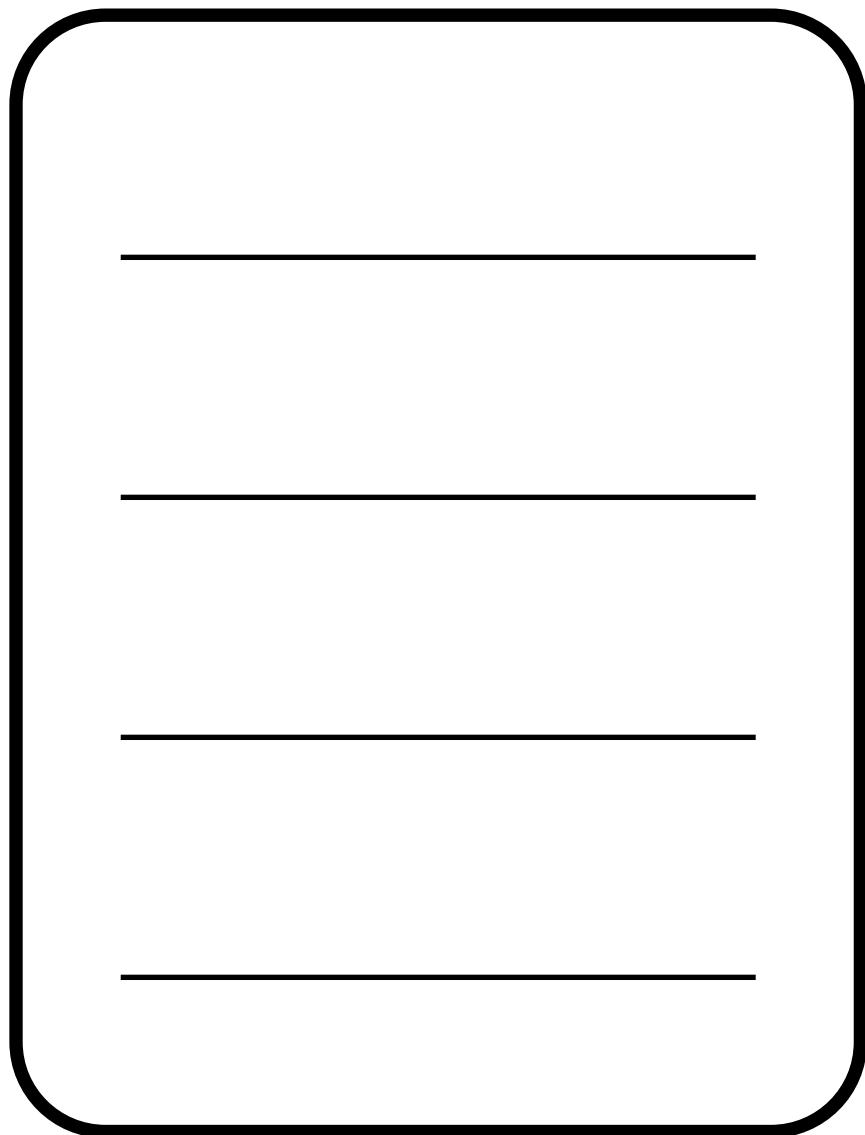


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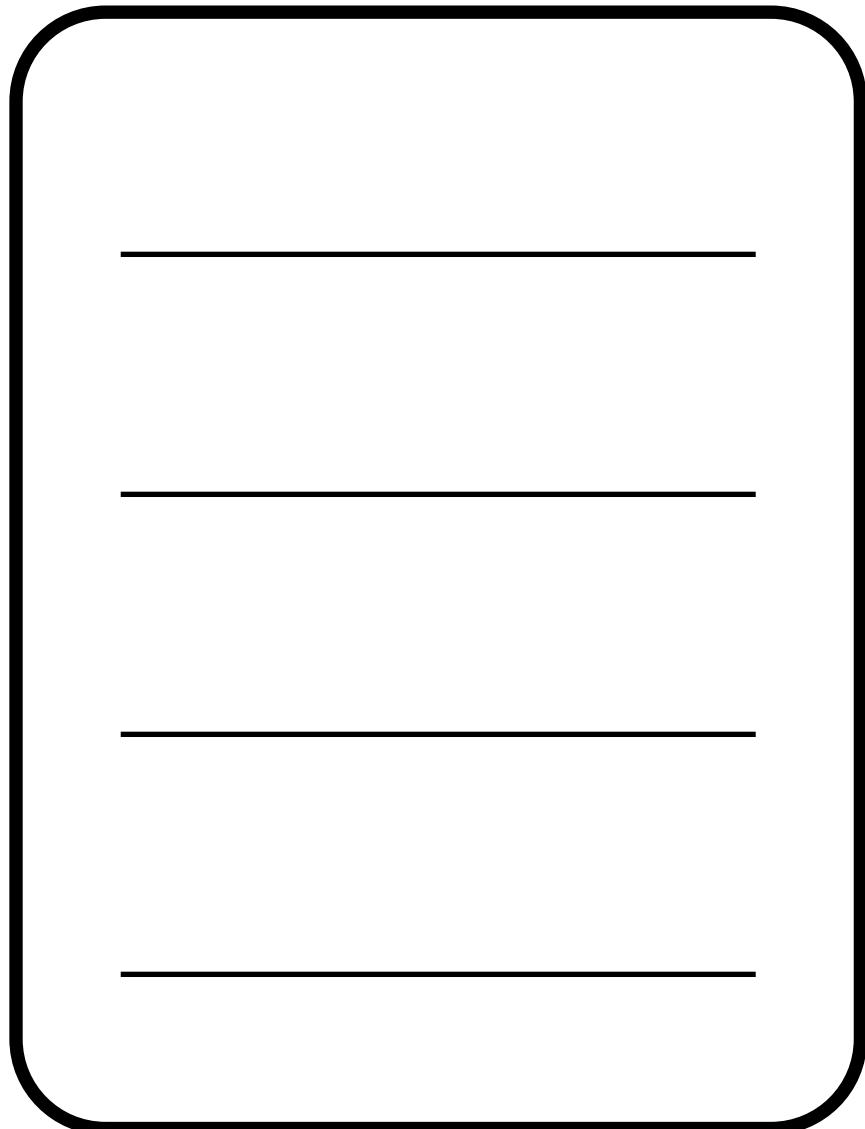
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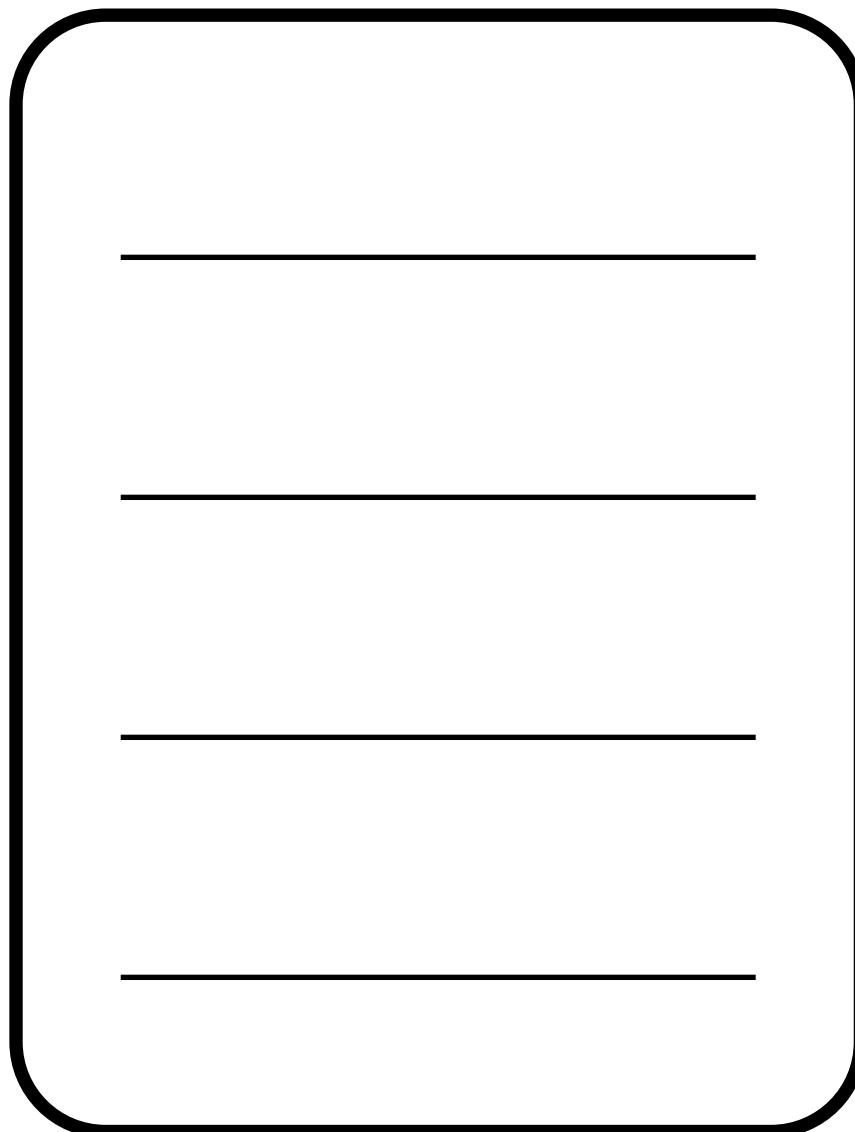
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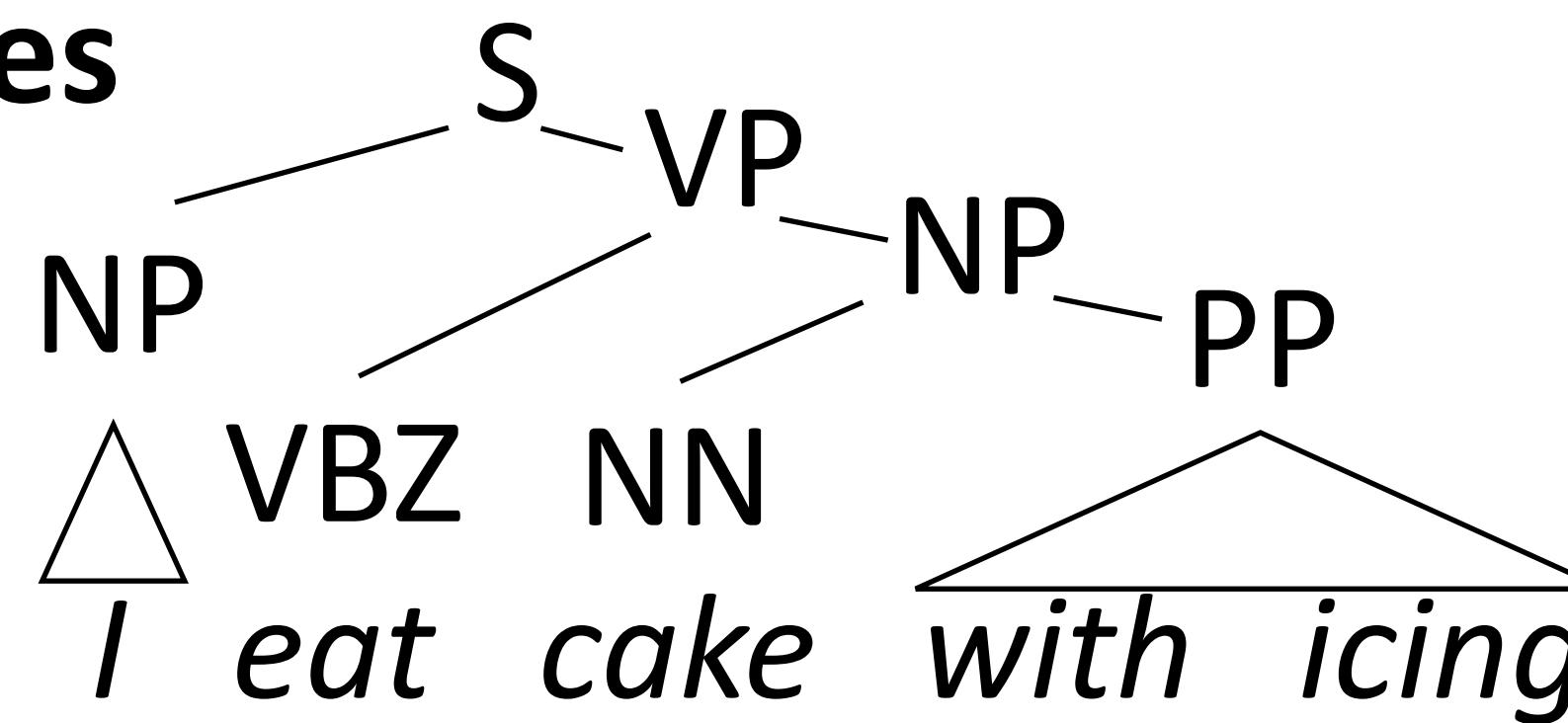
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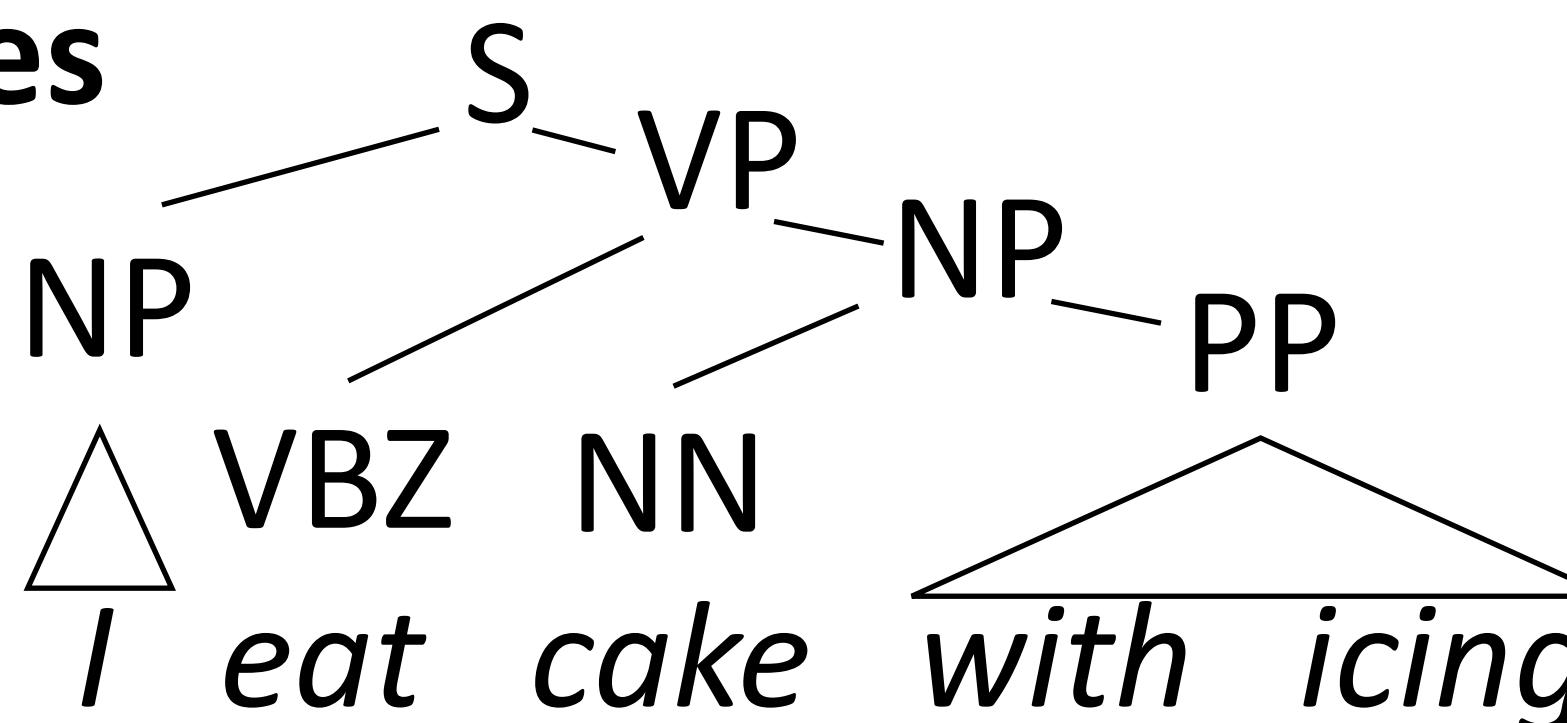
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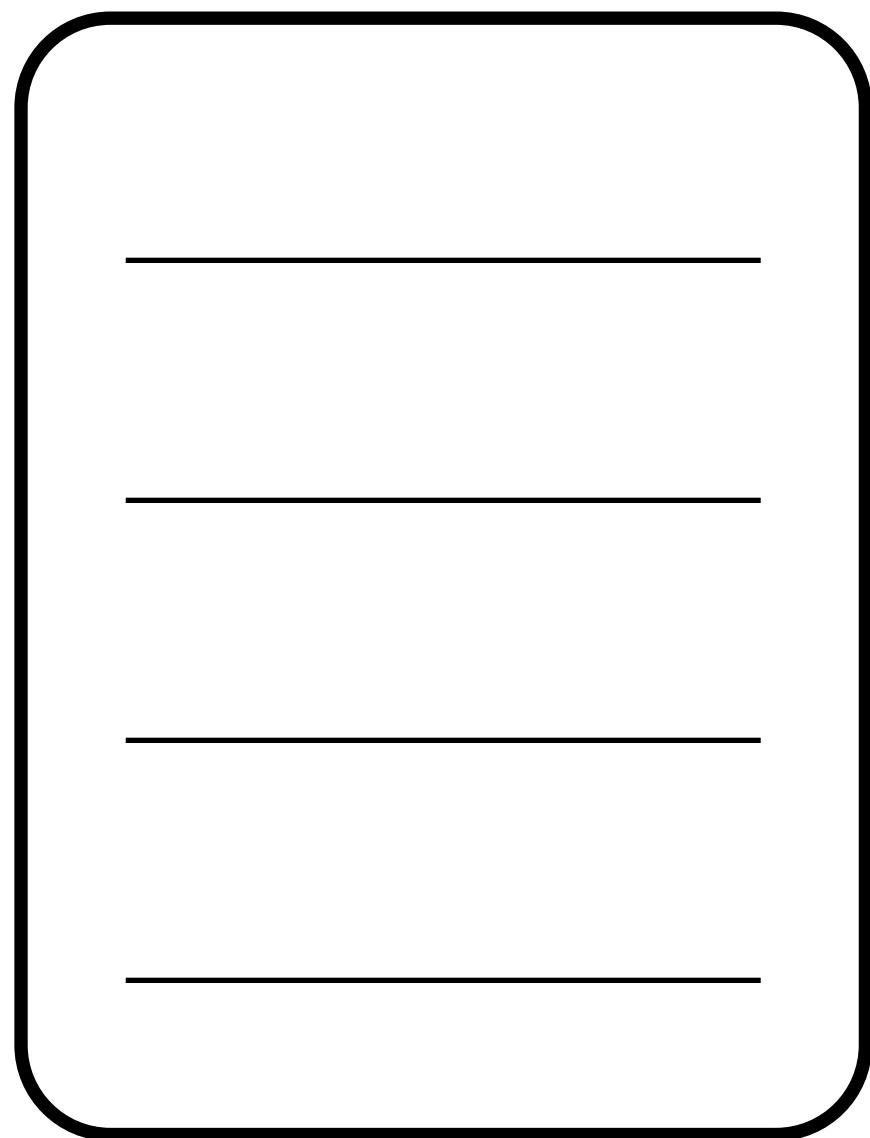
Trees



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

How do we use these representations?

Text



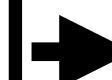
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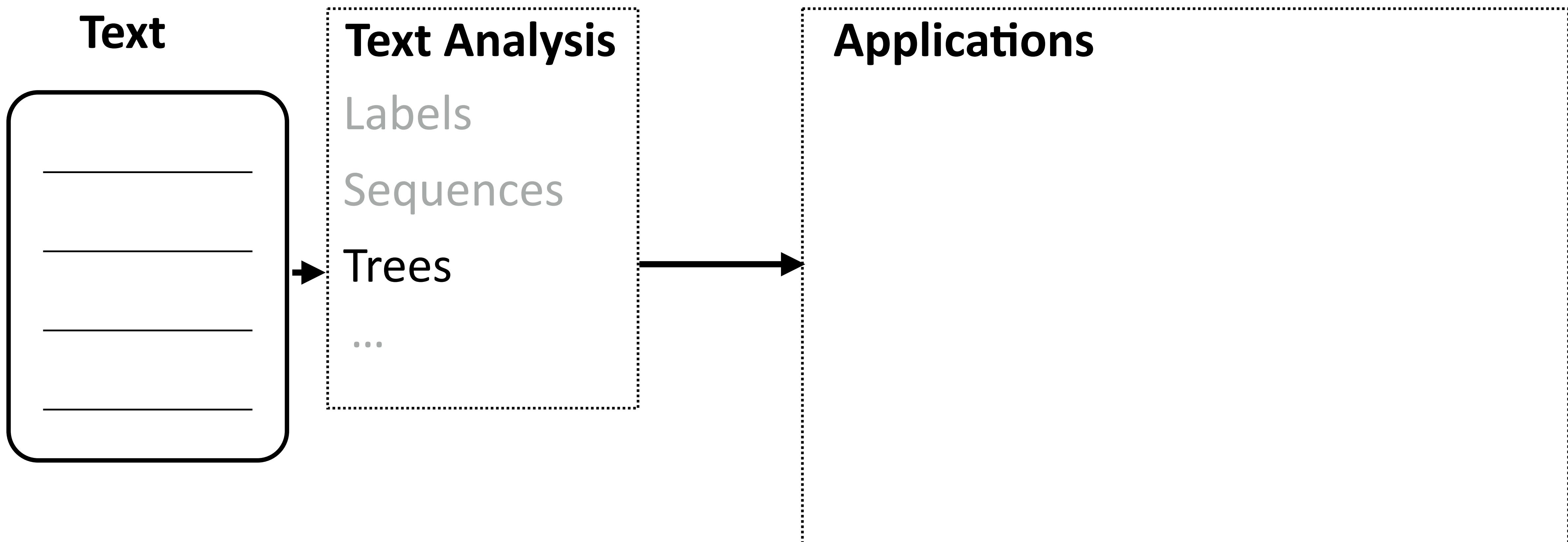
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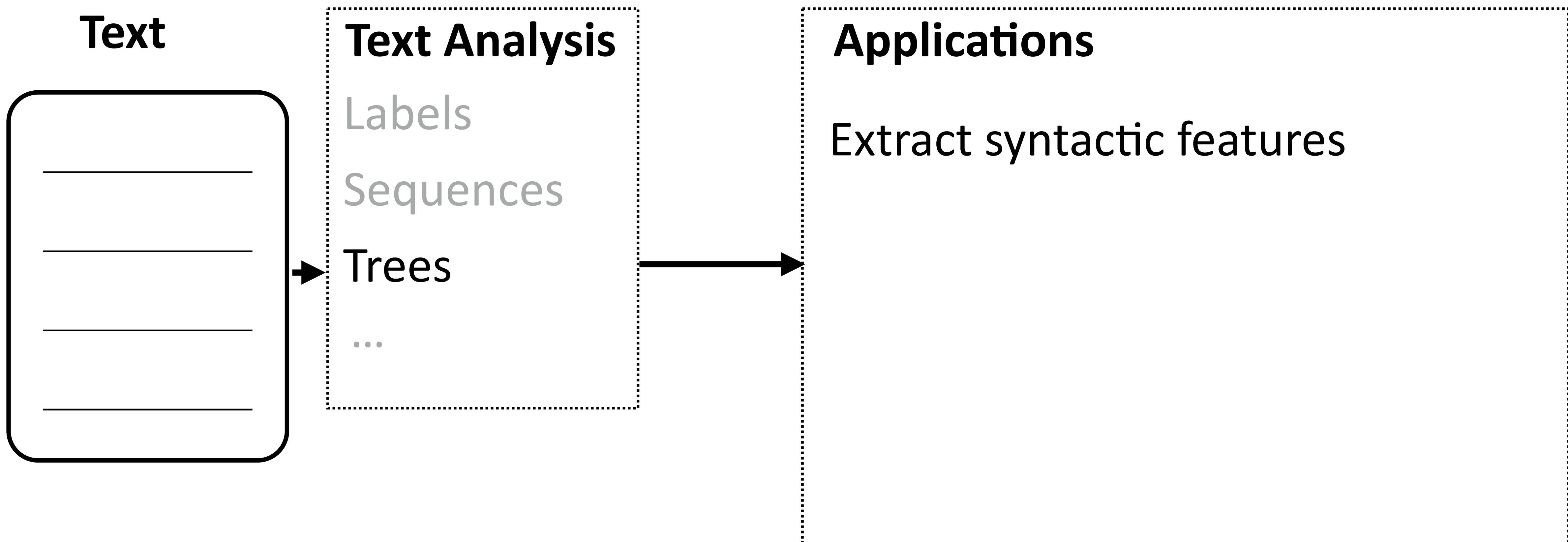
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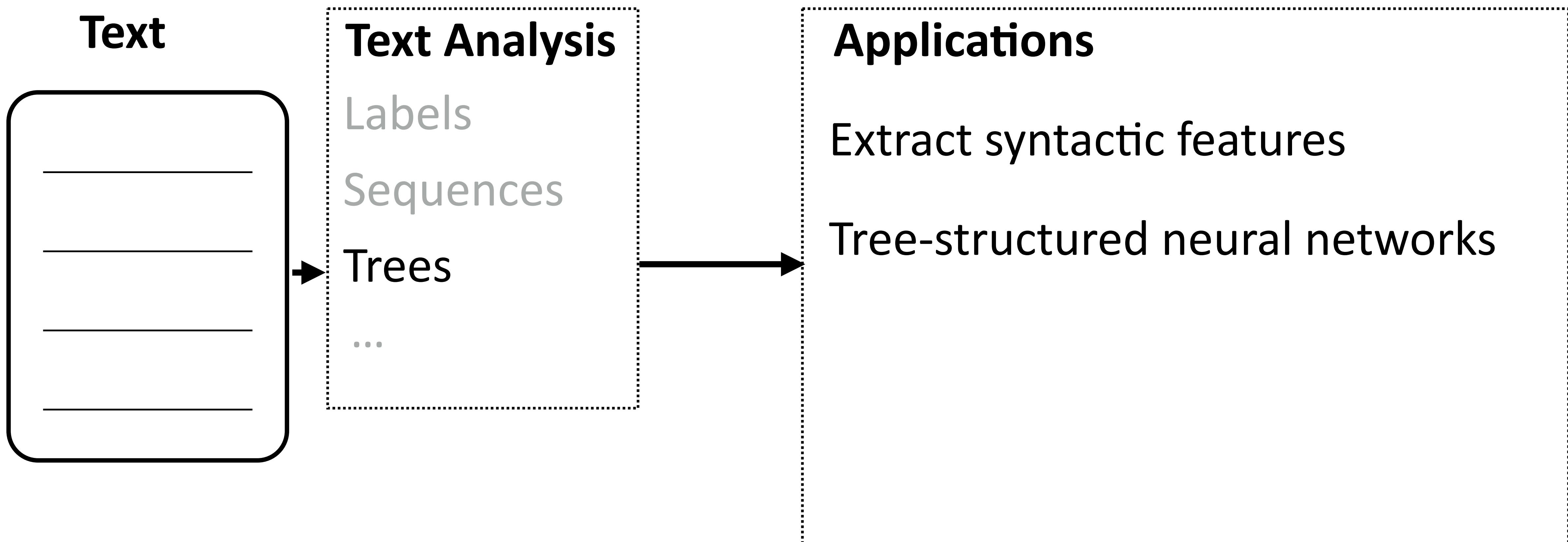
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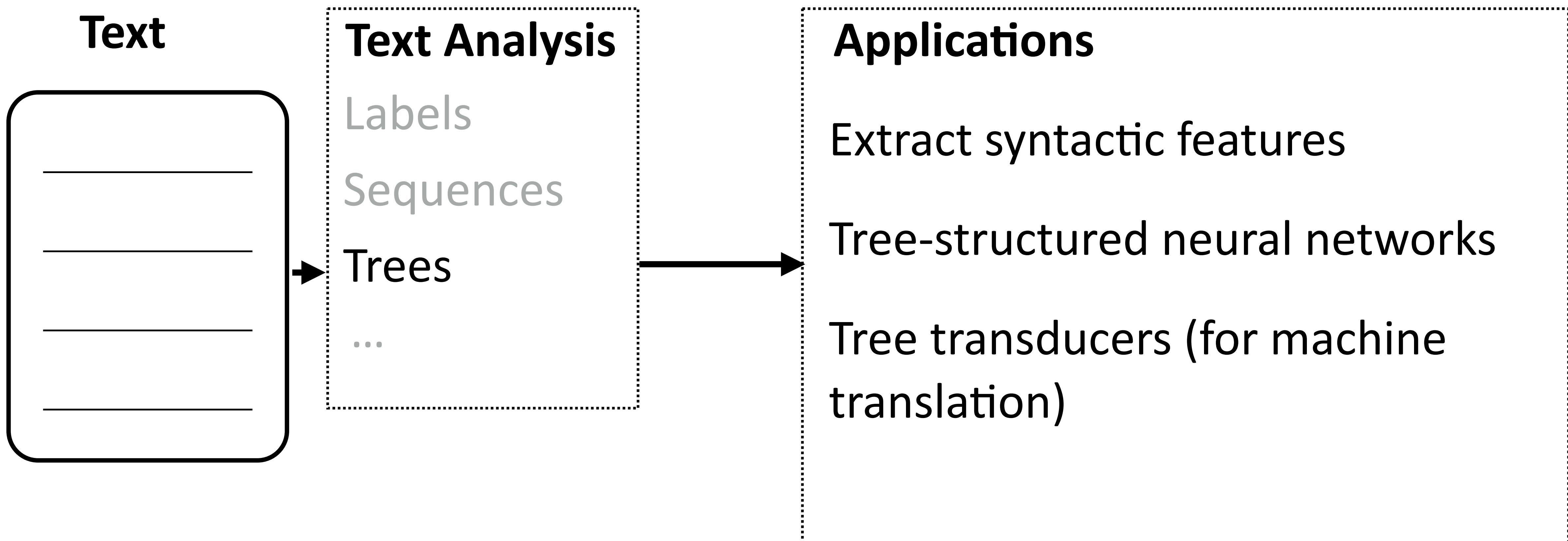
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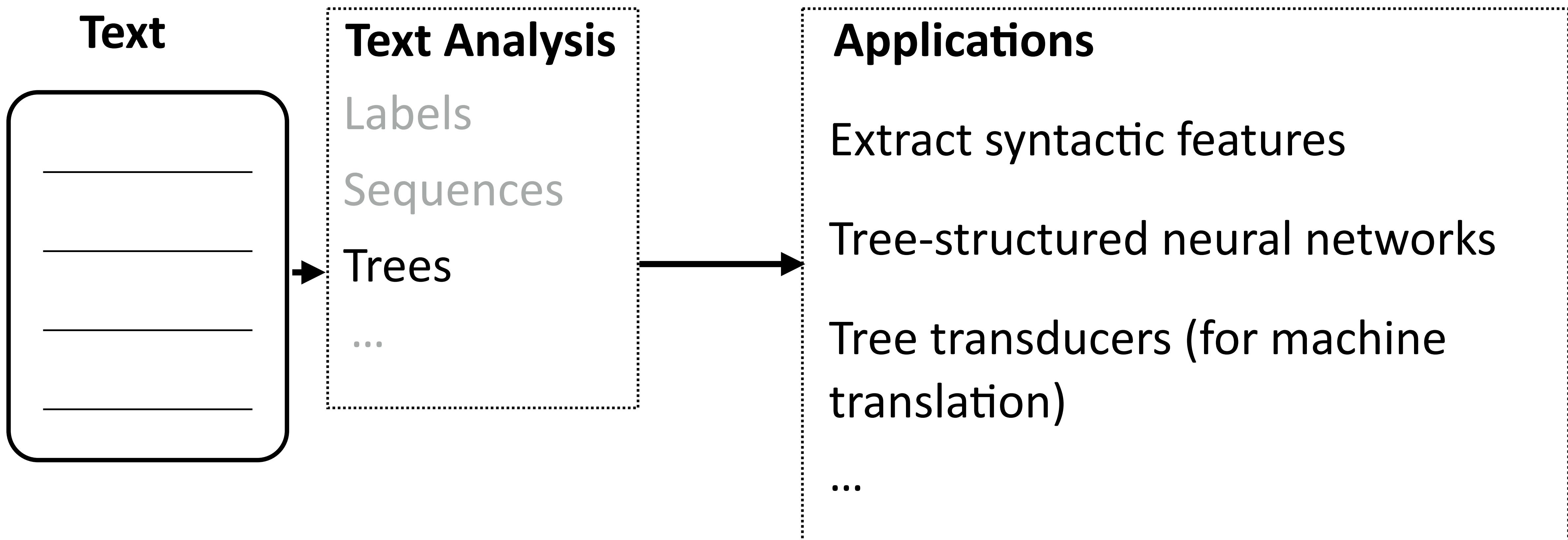
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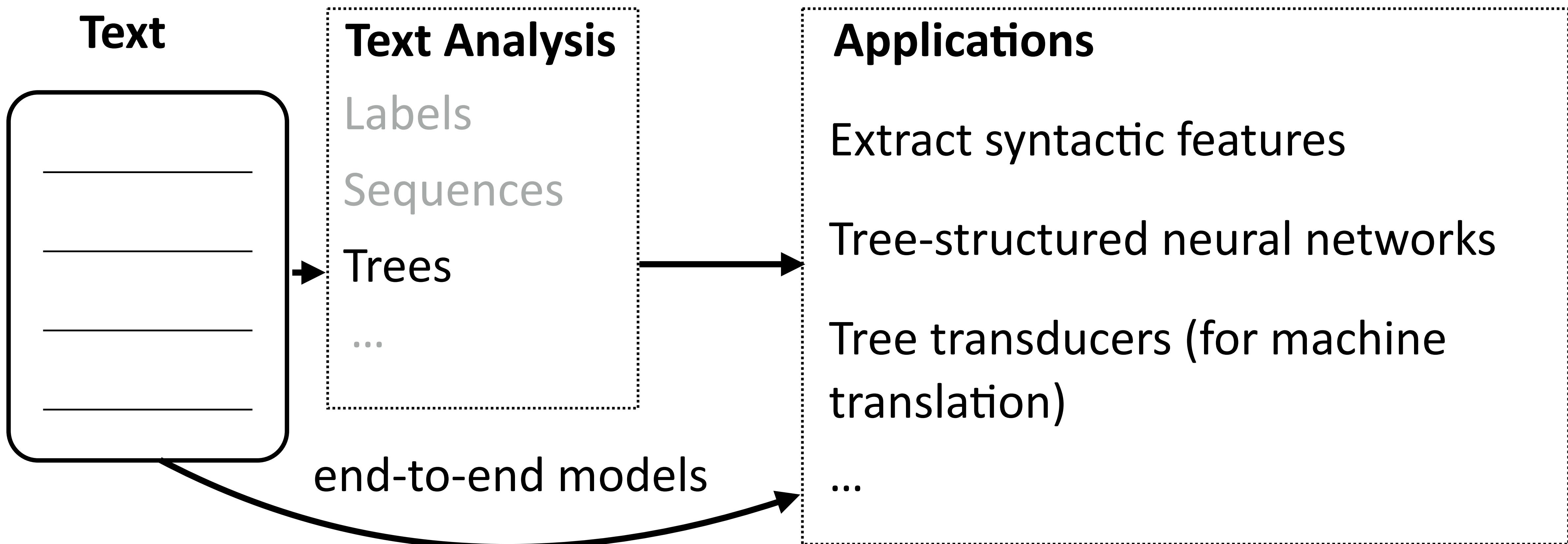
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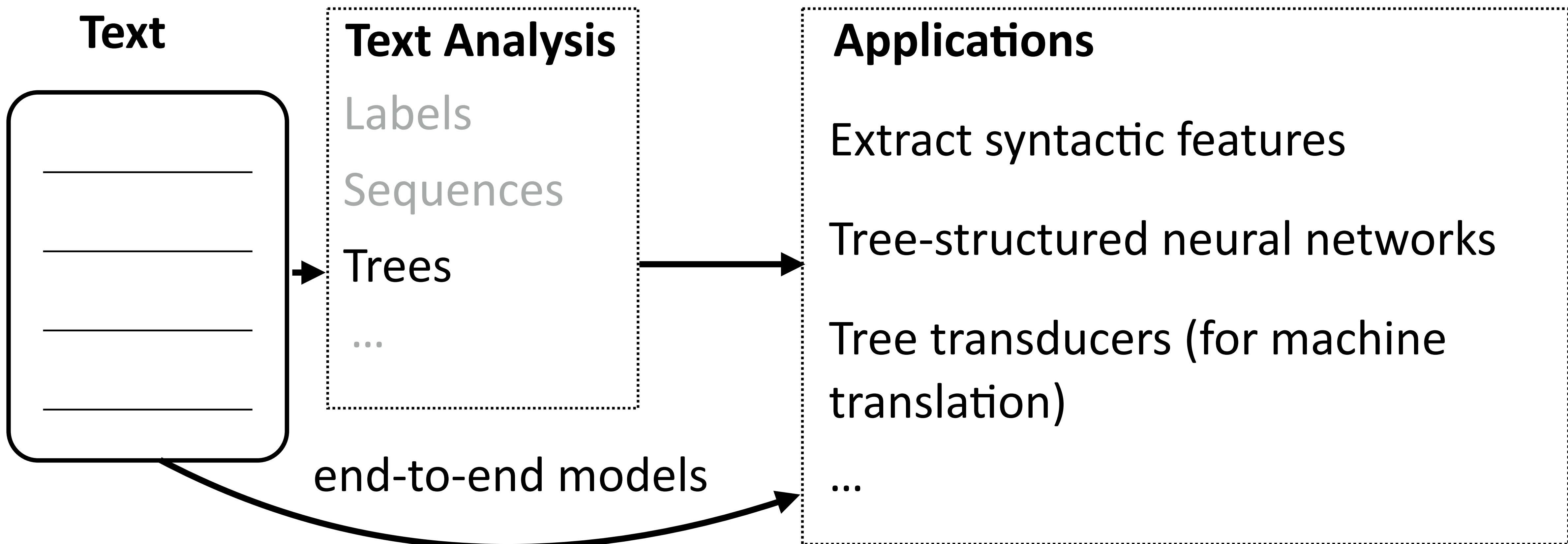
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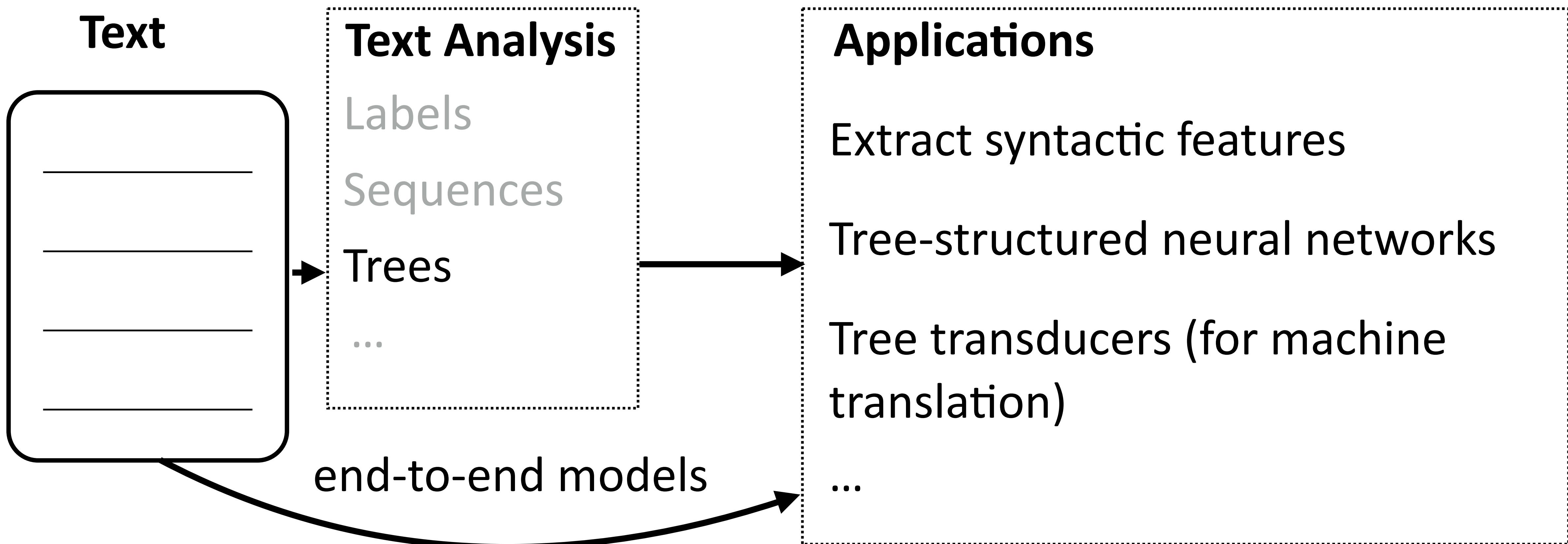


How do we use these representations?



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

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- ▶ 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?)

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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

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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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il fait vraiment beau 

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It is really nice out

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It is really nice out
It's really nice
The weather is beautiful

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It's really nice
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It is really beautiful outside

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It is really nice out
It's really nice
The weather is beautiful
It is really beautiful outside
He makes truly beautiful

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It is really nice out
It's really nice
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It is really beautiful outside
He makes truly beautiful
He makes truly boyfriend

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il fait vraiment beau



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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

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He makes truly beautiful
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It fact actually handsome

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

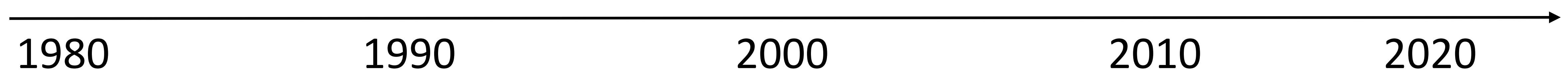
What do we need to understand language?

- ▶ Lots of data!

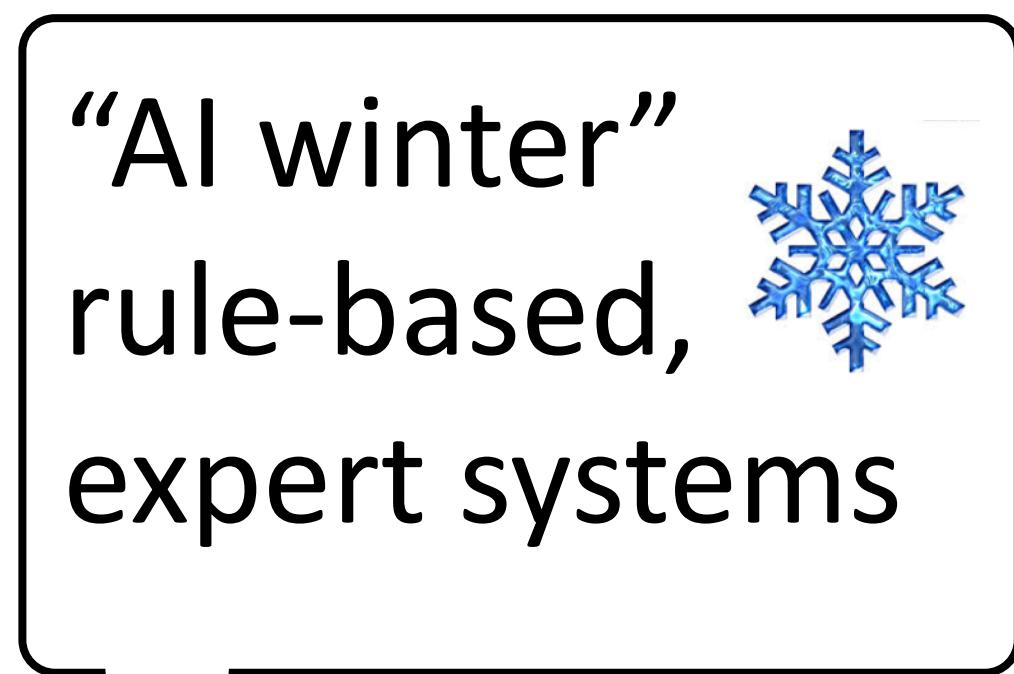
SOURCE	Cela constituerait une solution transitoire qui permettrait de conduire à terme à une charte à valeur contraignante.
HUMAN	That would be an interim solution which would make it possible to work towards a binding charter in the long term .
1x DATA	[this] [constituerait] [assistance] [transitoire] [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] [.]

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

A brief history of (modern) NLP



A brief history of (modern) NLP



1980

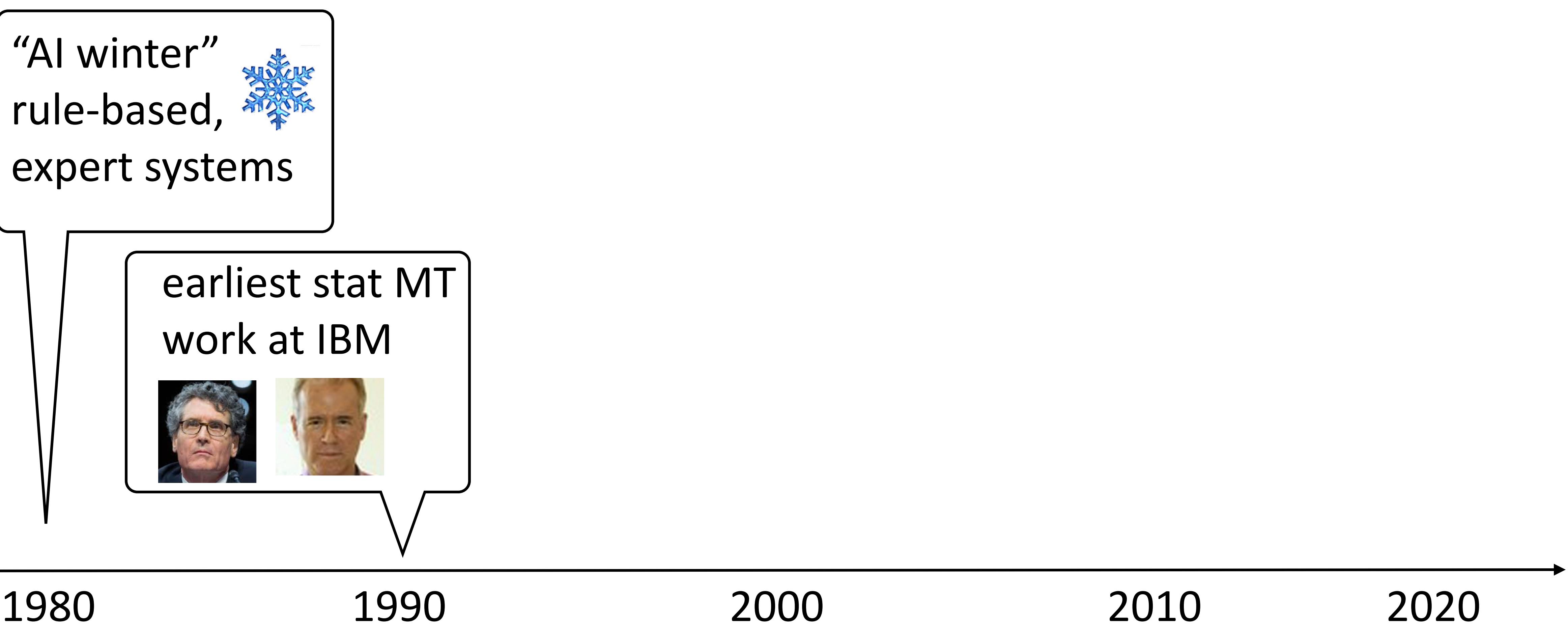
1990

2000

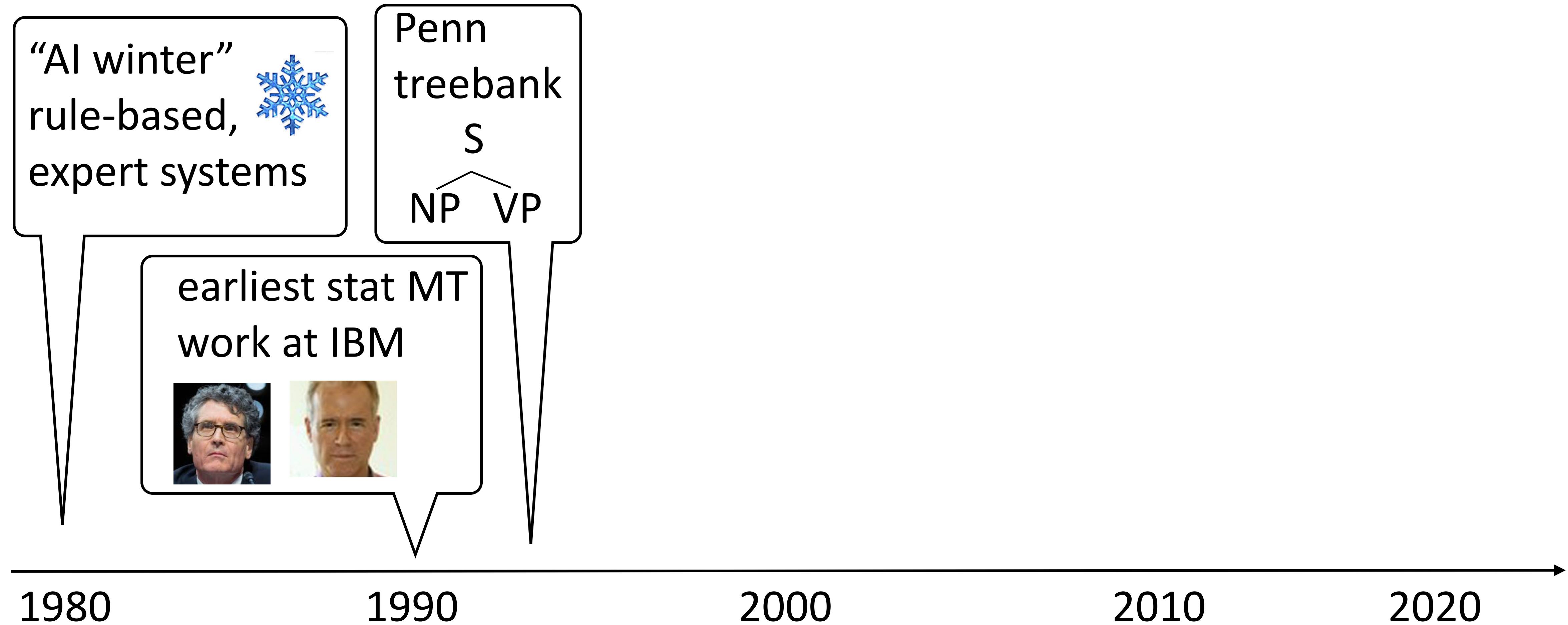
2010

2020

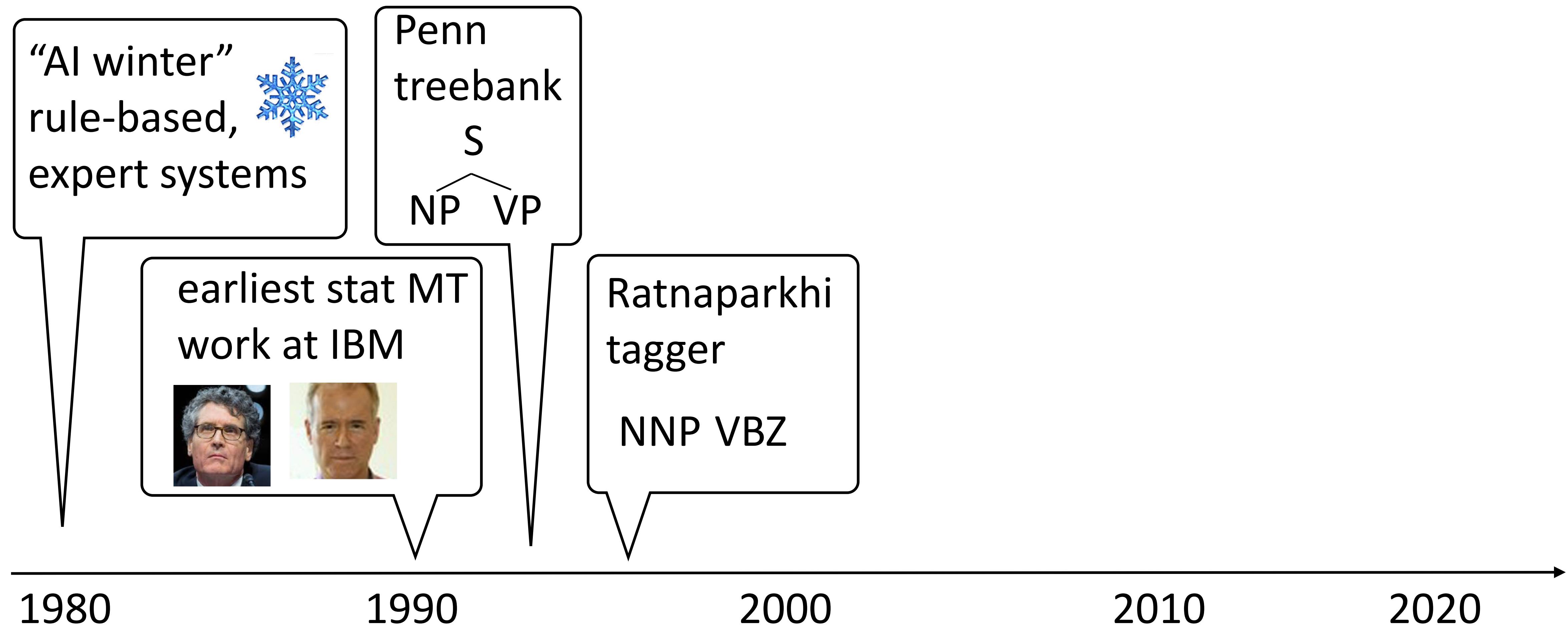
A brief history of (modern) NLP



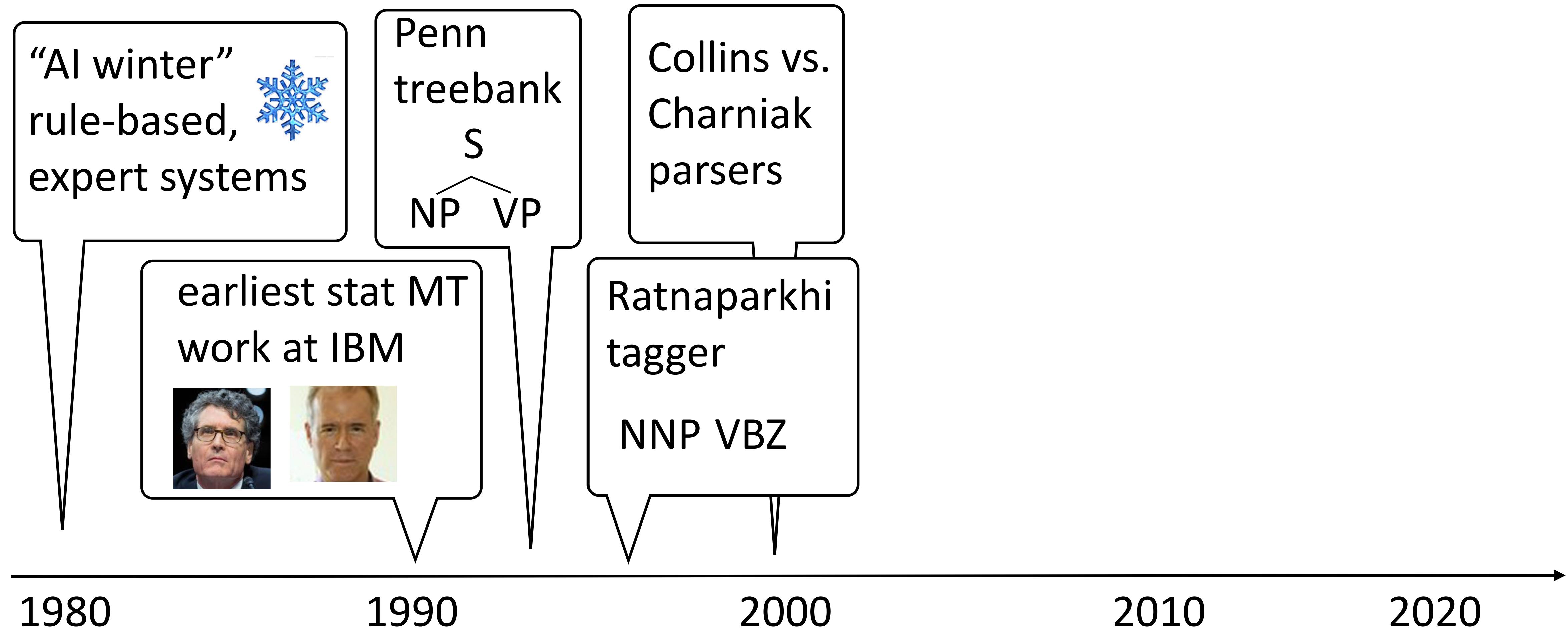
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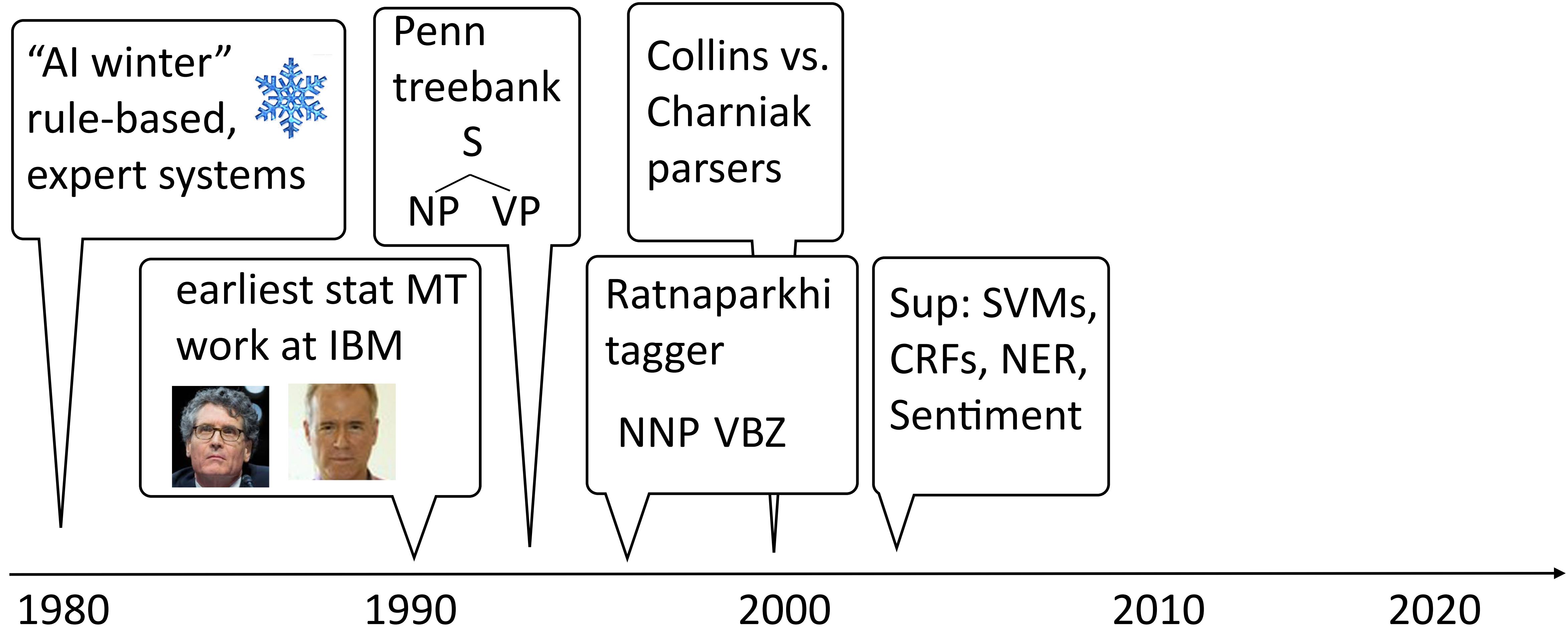
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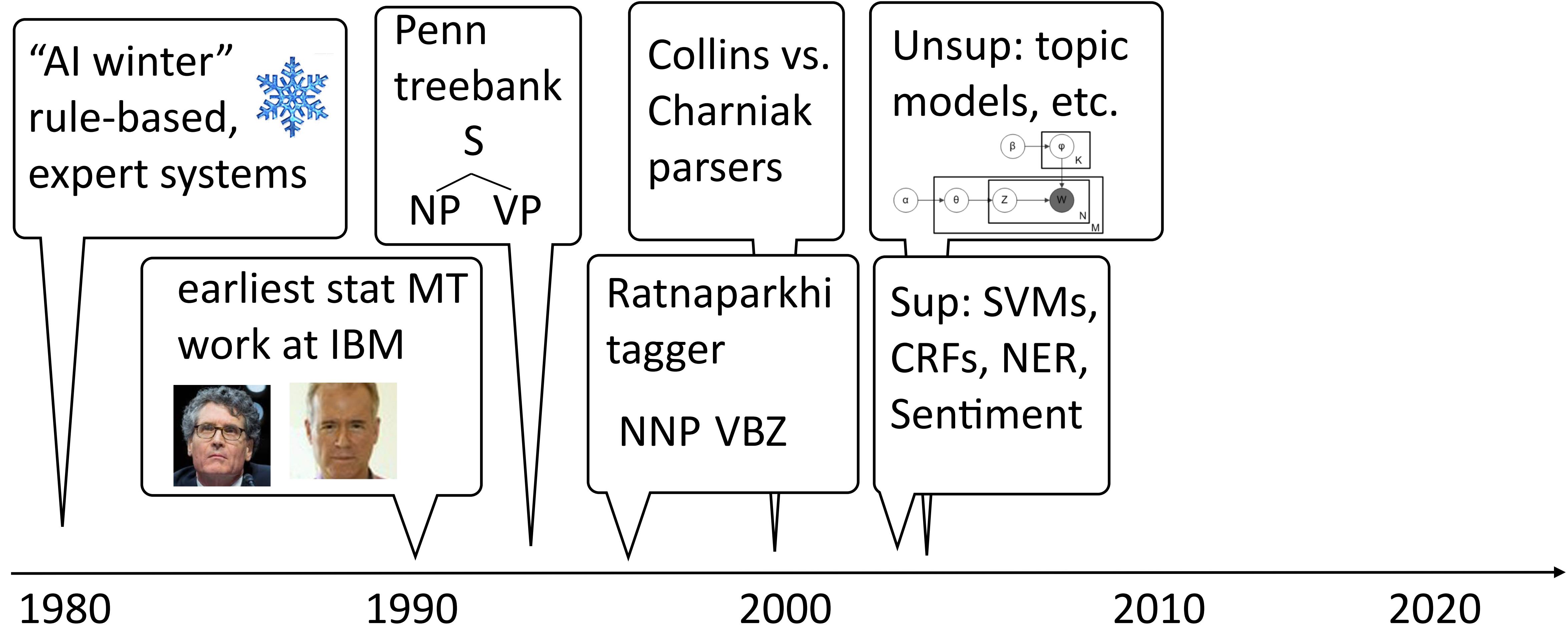
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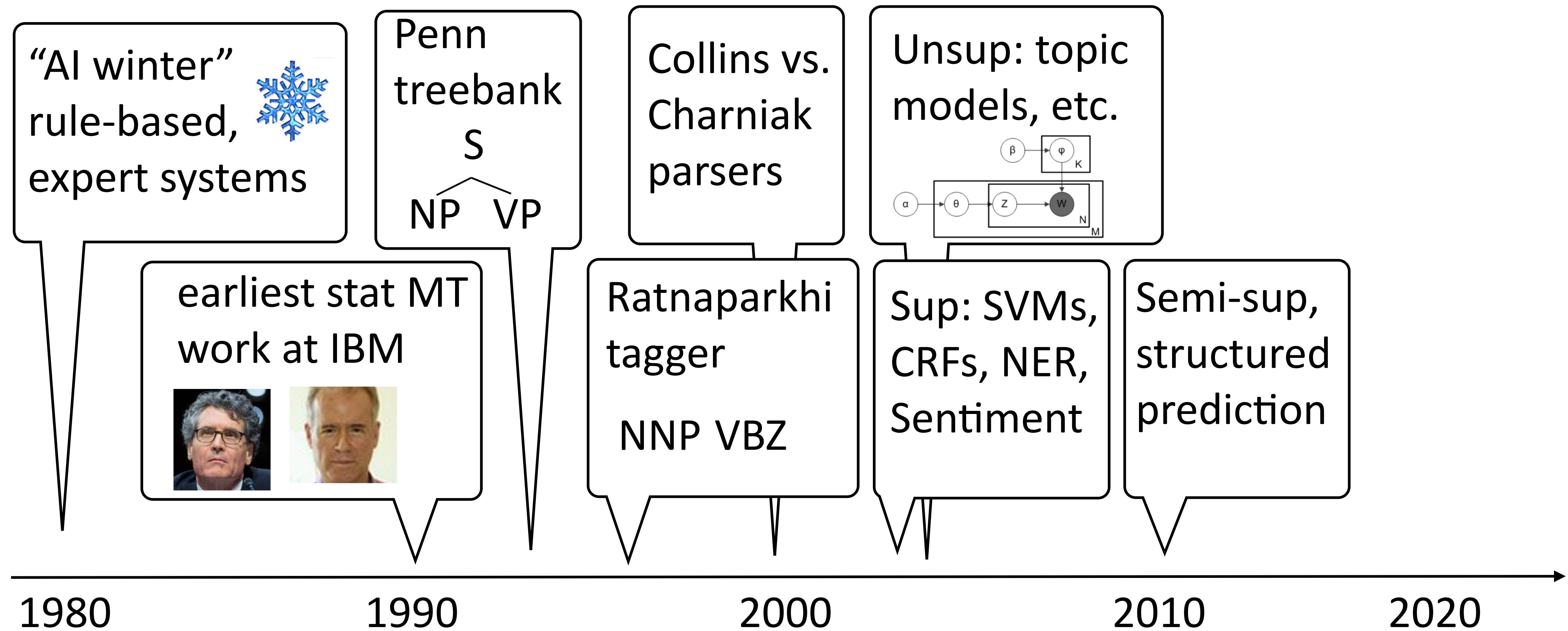
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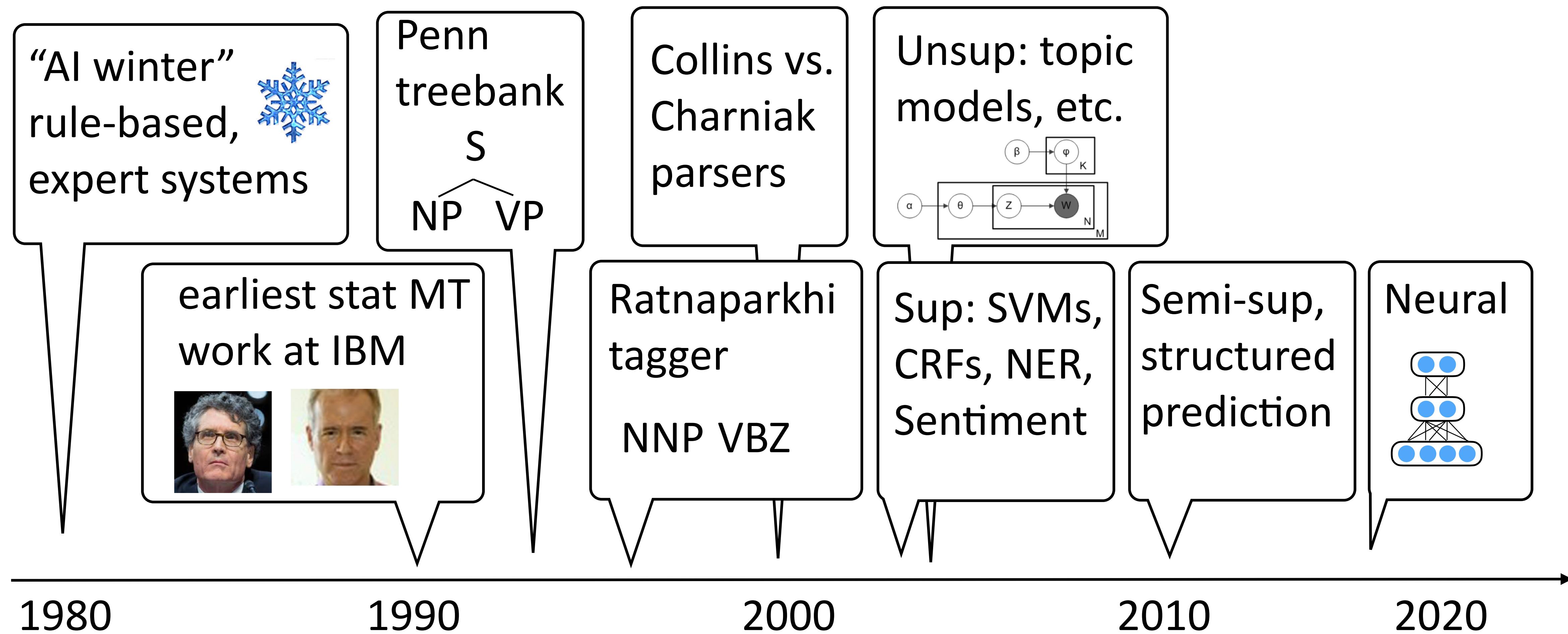
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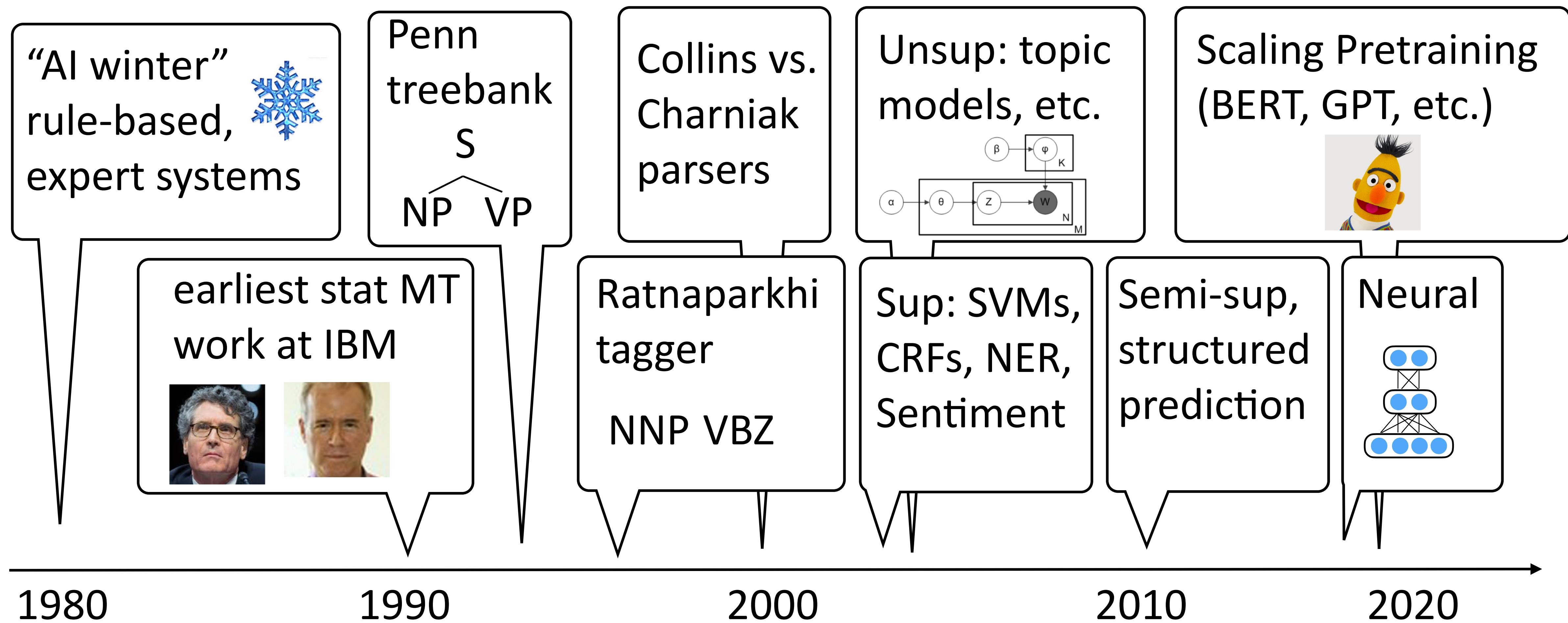
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How Much Training Data do we Need?

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

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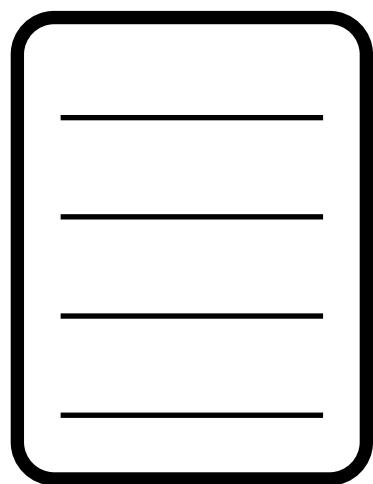
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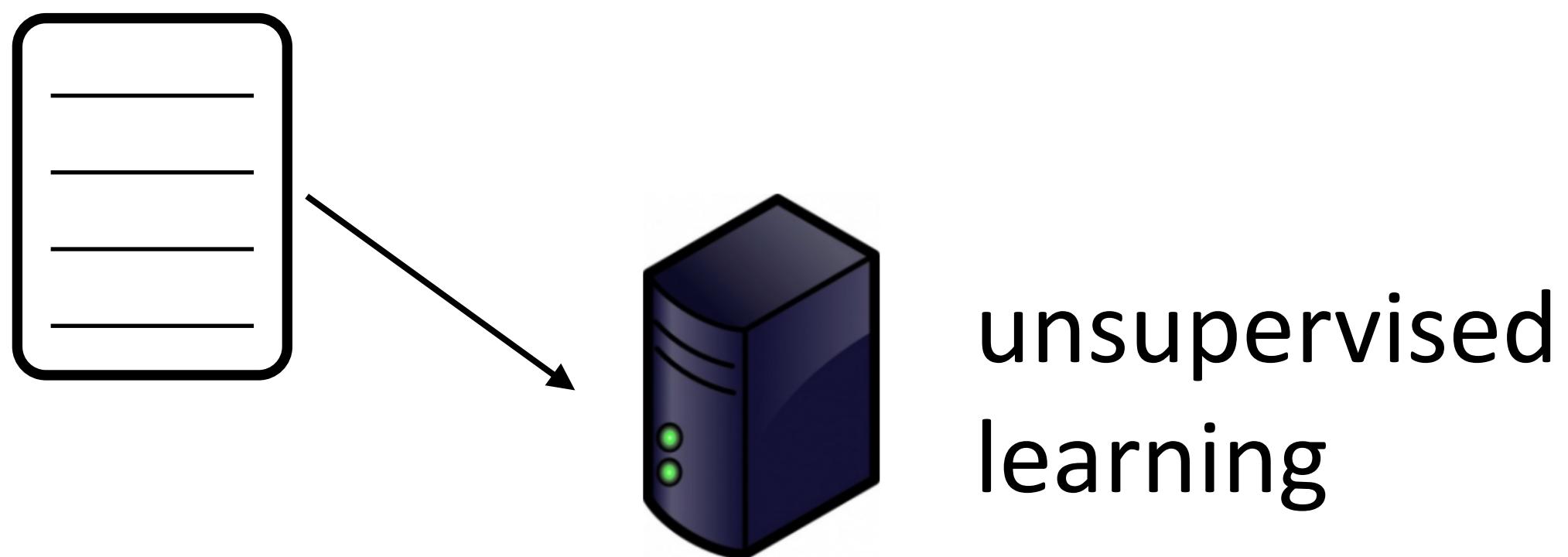
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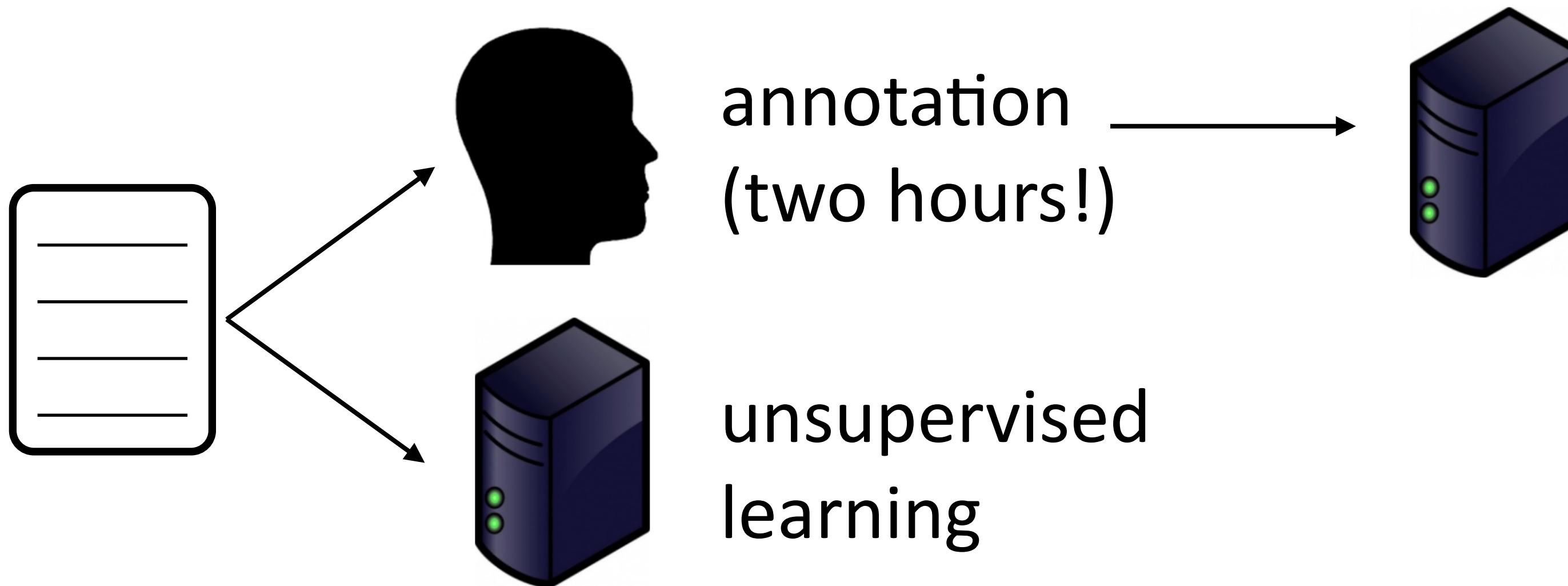
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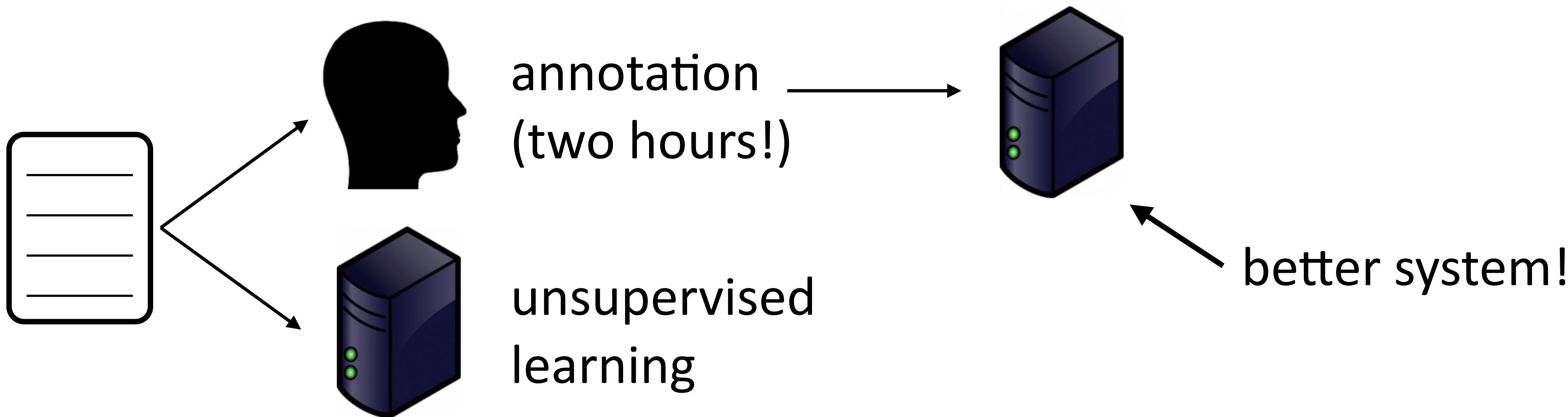
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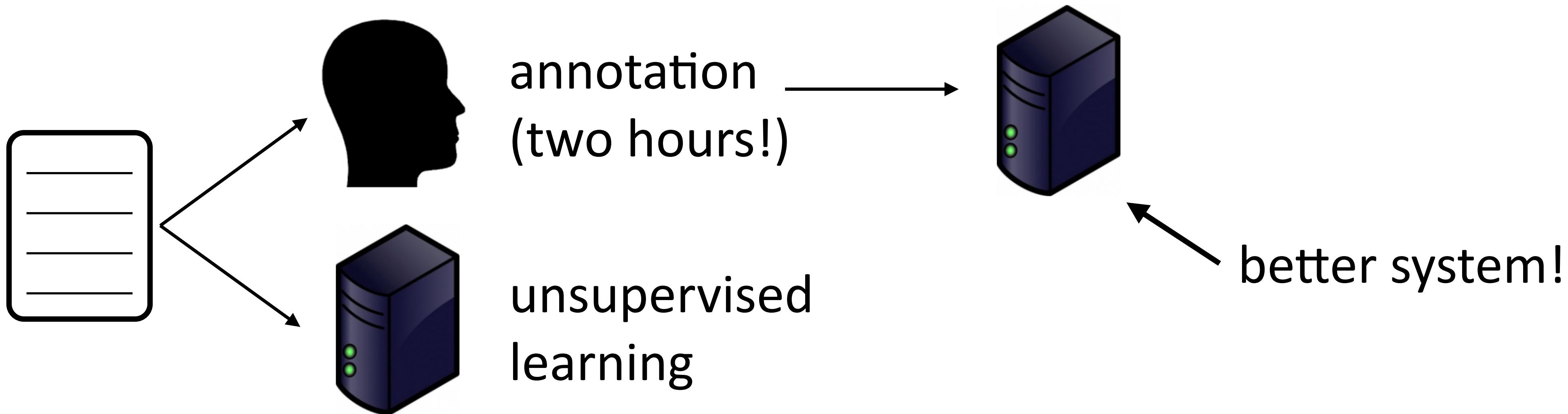
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- ▶ Even neural nets can do pretty well!

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Pretraining

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

$P(w | \text{I want to go to}) = 0.01 \text{ Hawai'i}$

0.005 LA

0.0001 class



: use this model for other purposes

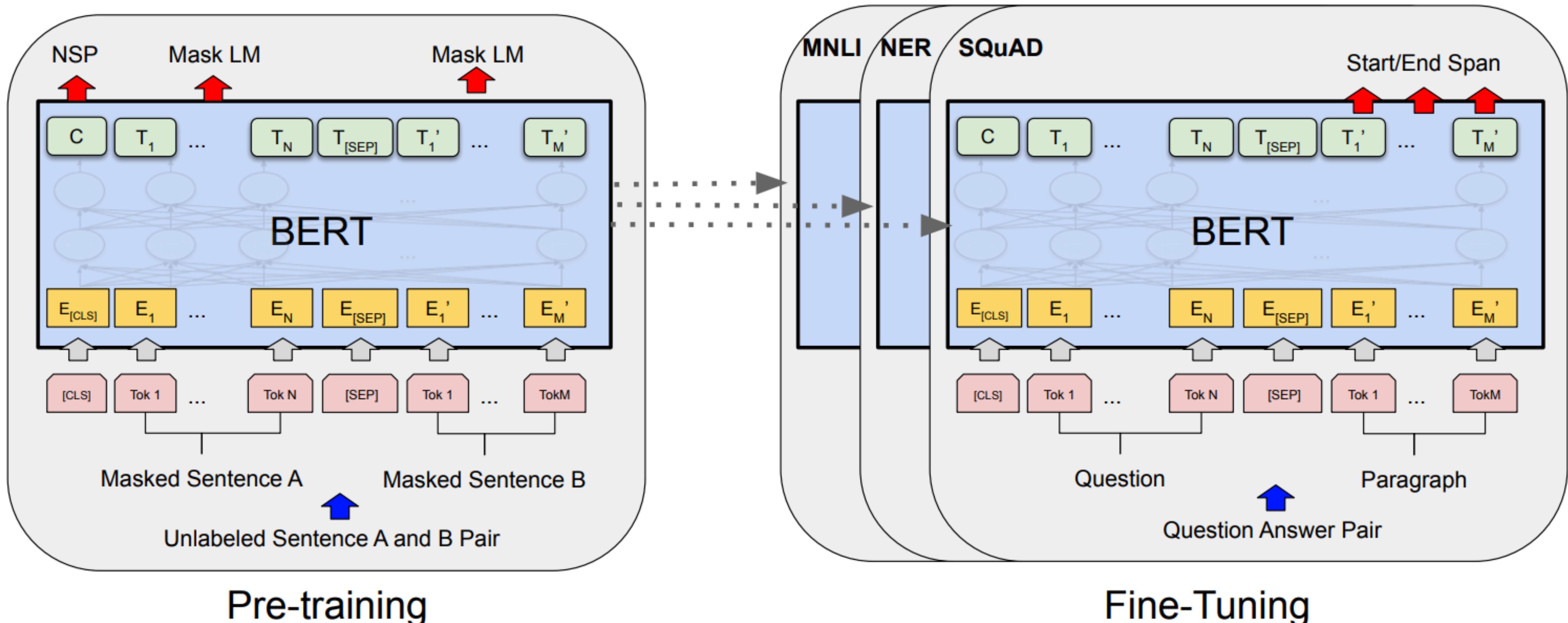
$P(w | \text{the acting was horrible, I think the movie was}) = 0.1 \text{ bad}$

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, ...}

BERT



Pre-training

- ▶ Key parts which we will study: (1) Transformer architecture; (2) what data is used (both for pre-training and fine-tuning)

Fine-Tuning

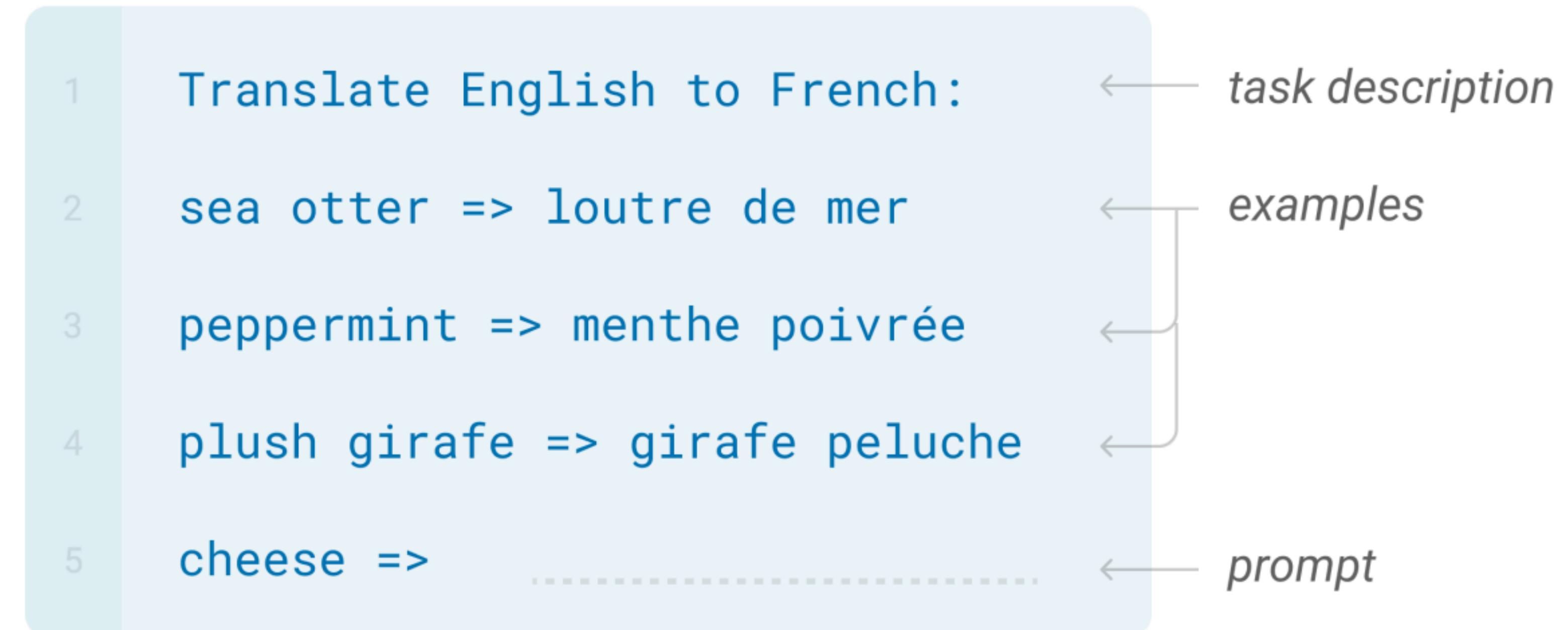
Devlin et al. (2019)

GPT and In-Context Learning

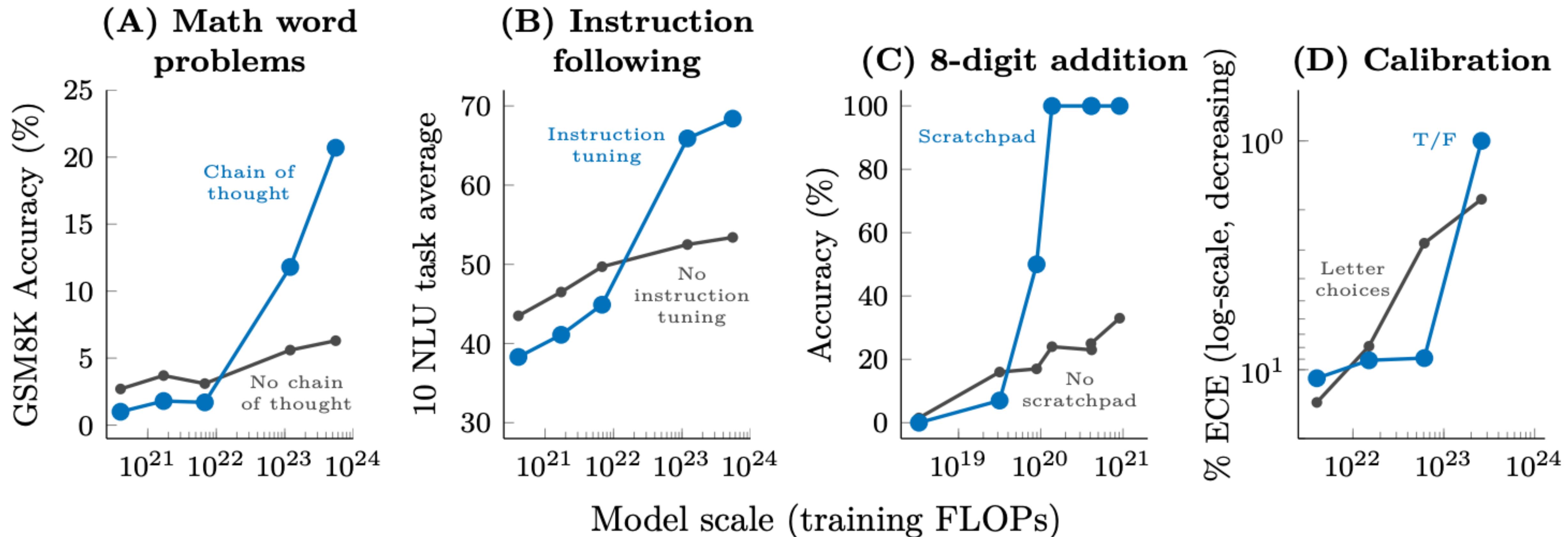
- ▶ Even more “extreme” setting: no gradient updates to model, instead large language models “learn” from examples in their context
- ▶ Many papers studying why this works. We will read some!

Few-shot

In addition to the task description, the model sees a few examples of the task. No gradient updates are performed.

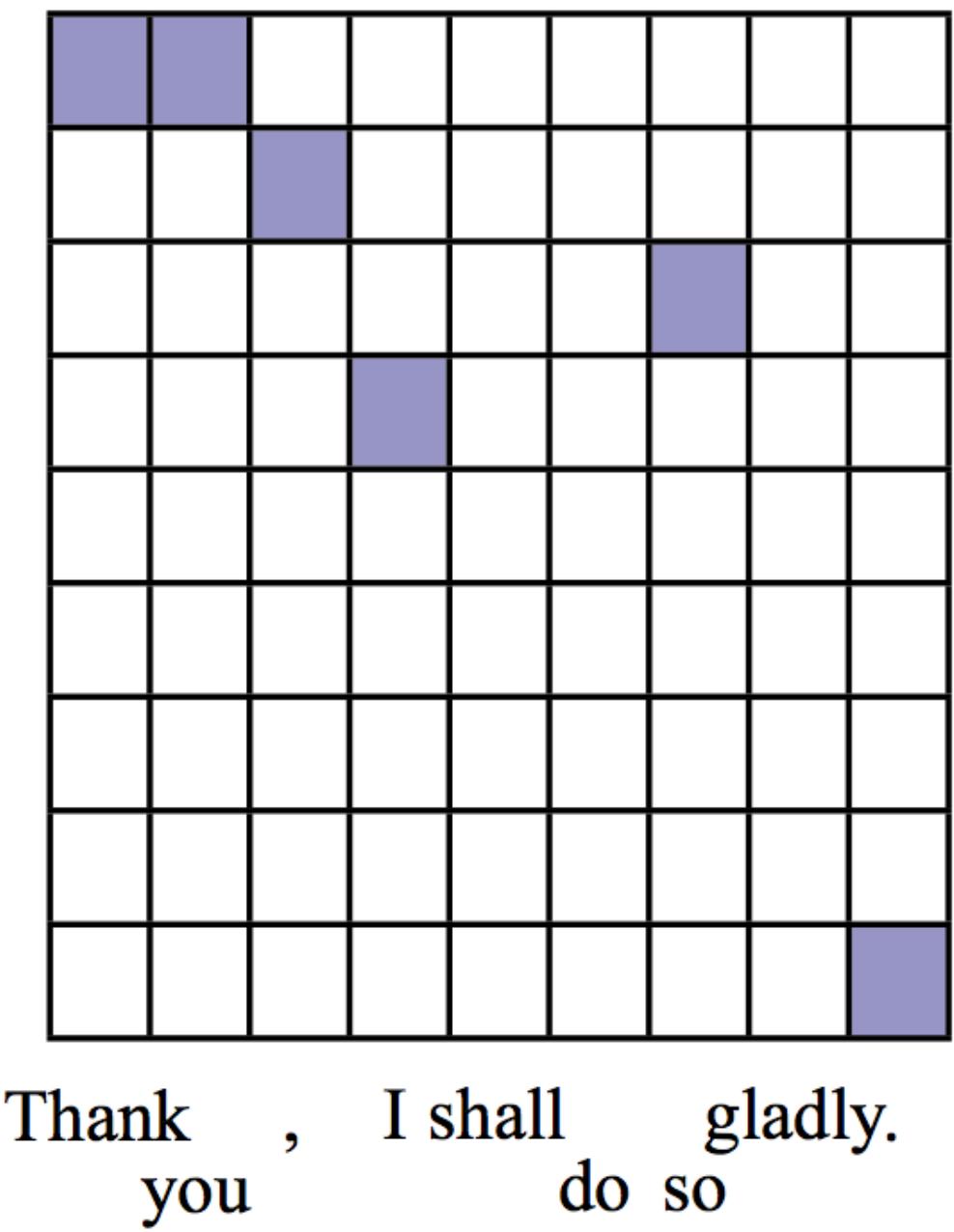


Scaling Laws

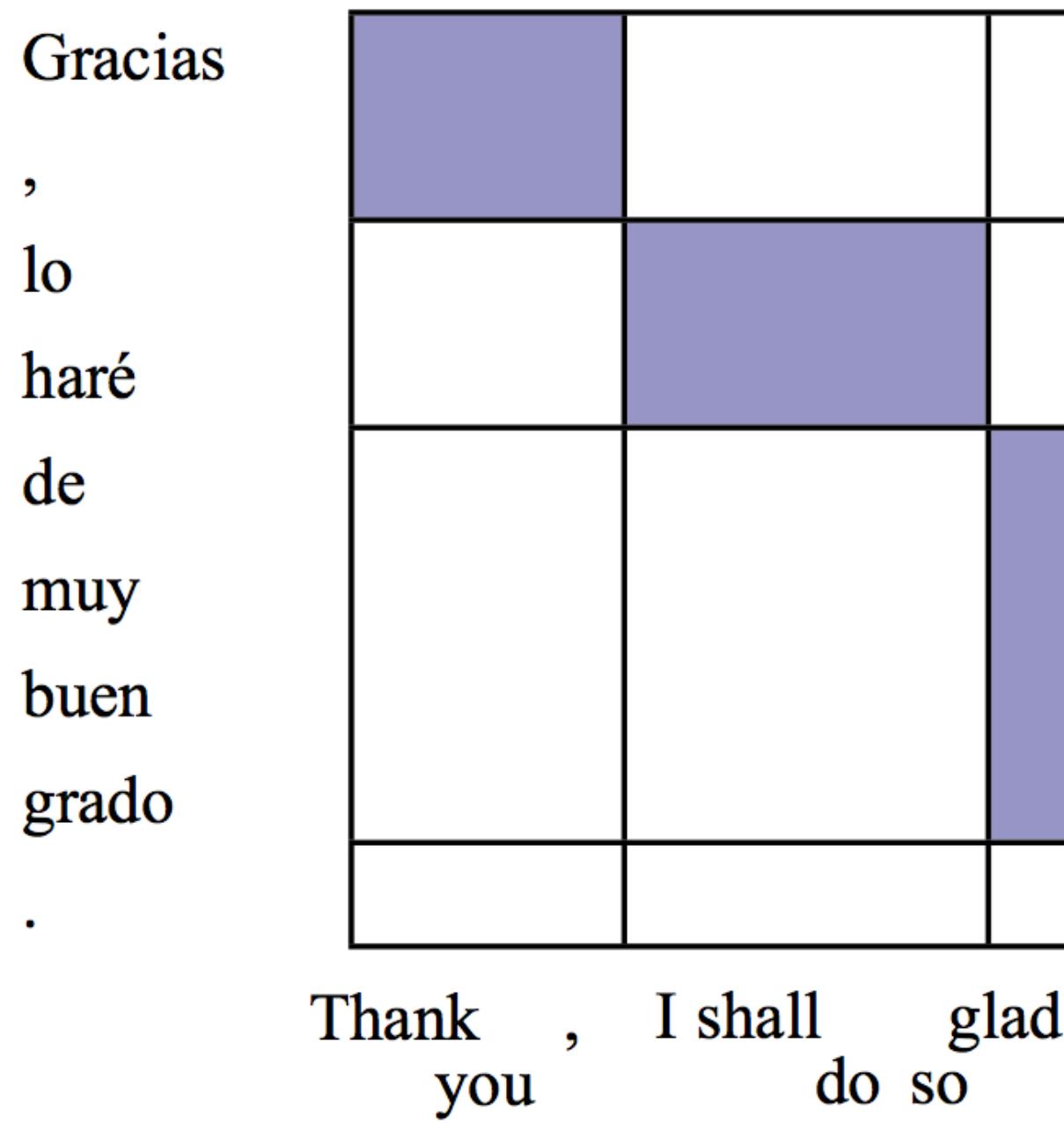


- ▶ Many of the ideas that are big in 2023 only make sense and only work because the models are so big!

Less Manual Structure?

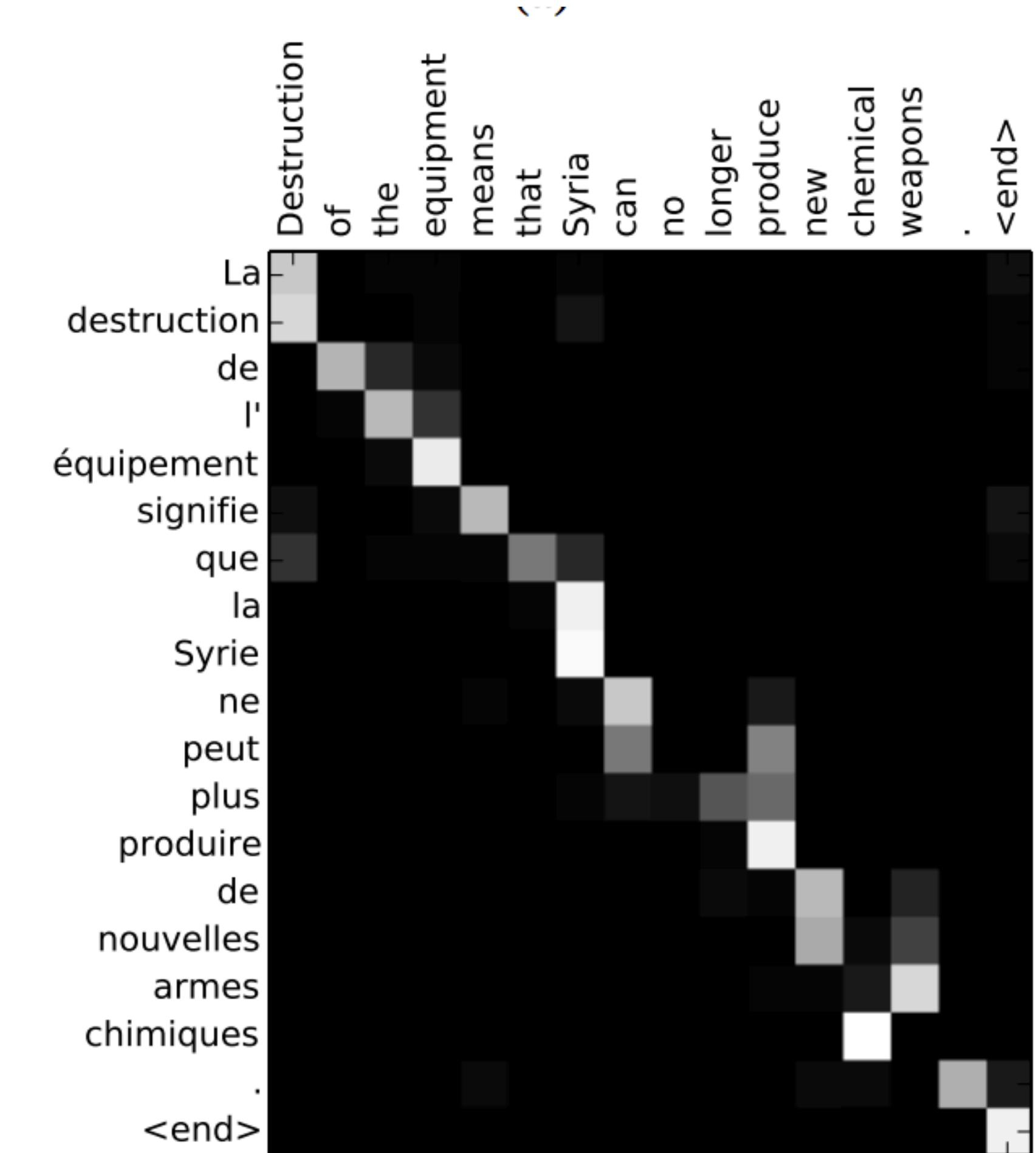


(a) example word alignment



(b) example phrase alignment

Gracias
,
lo
haré
de
muy
buen
grado
.



Where are we?

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- ▶ 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