

CS 4650: Natural Language Processing

Alan Ritter

Administrivia

- ▶ Course website:
 - <https://aritter.github.io/CS-4650-au24/>
- ▶ 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

<https://tinyurl.com/4650-TAs>

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

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 - ▶ Logistic Regression
 - ▶ Text classification
 - ▶ Sequence Labeling
 - ▶ Neural chatbot

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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

Georgia Tech, Fall 2023 (Instructor: Alan Ritter)

In this assignment, we will walk you through the process of implementing logistic regression from scratch. You will also apply your implemented logistic regression model to a small dataset and predict whether a student will be admitted to a university. This dataset will allow you to visualize the data and debug more easily. You may find [this documentation](#) very helpful (although it uses Octave rather than Python).

This assignment also serves as a programming preparation test. We will use [NumPy](#) -- a popular Python package for scientific computing and implementing machine learning algorithms. It provides very good support for matrix and vector operations. You need to feel comfortable working with matrices, vectors, and tensors in order to complete all the programming projects in CS 4650.

To start, first make a copy of this notebook to your local drive, so you can edit it.

▼ 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 #
    #####
```

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

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 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.
 - ▶ The programming projects are designed with Colab in mind
 - ▶ Colab Pro subscription (\$10/month). This is highly recommended once we start working with PyTorch.

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)
- Pre-trained Transformers (e.g. BERT, BART, T5, GPT)
- Machine Translation
- Dialogue
- Question Answering

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- ▶ Know about modern NLP methods: what is the state-of-the-art in 2023?
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 - ▶ The assignments should teach you what you need to know to understand nearly any modern NLP system.

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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 2023?
- ▶ Make you a “producer” rather than a “consumer” of NLP tools
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Assignments

- ▶ 3 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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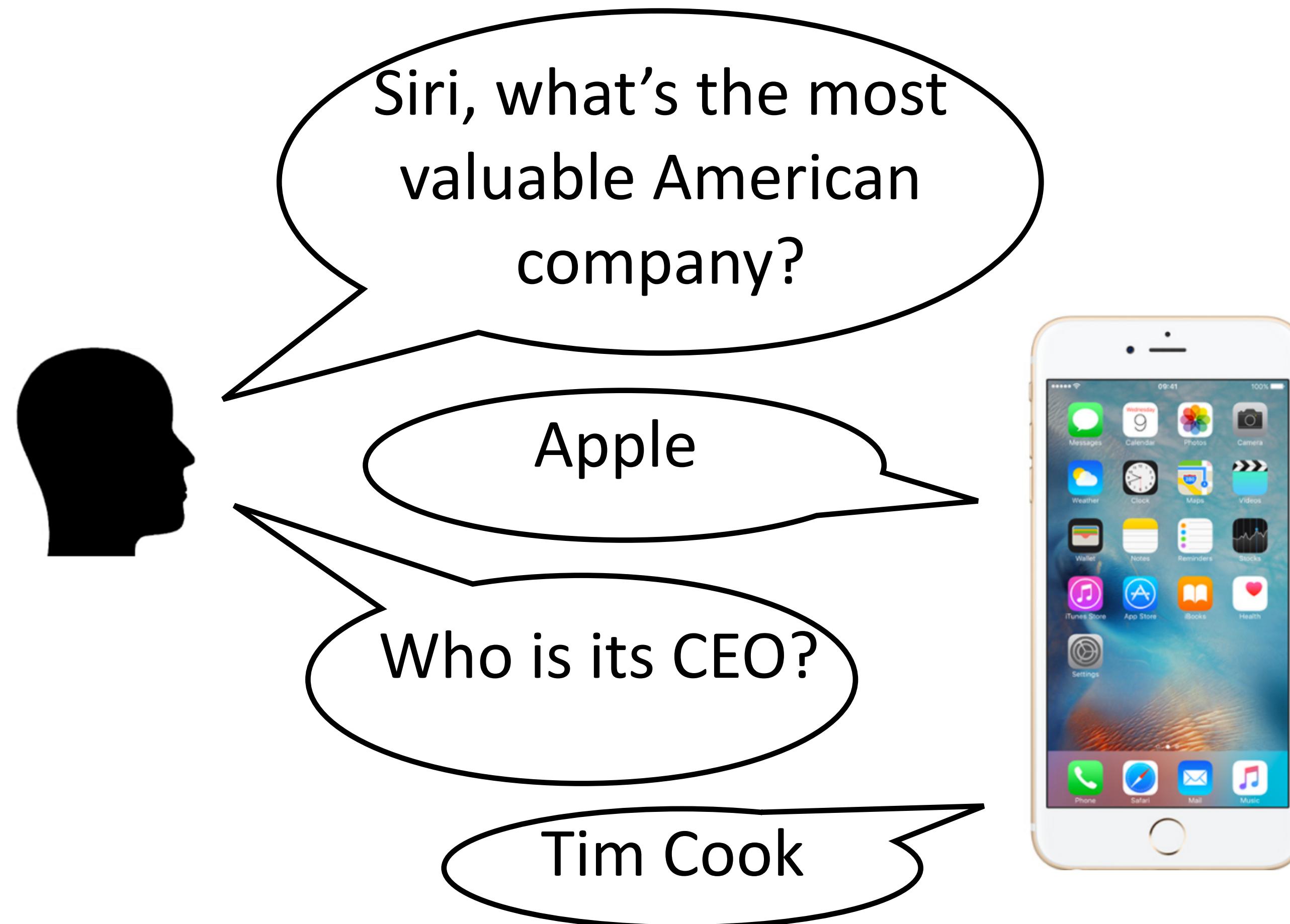
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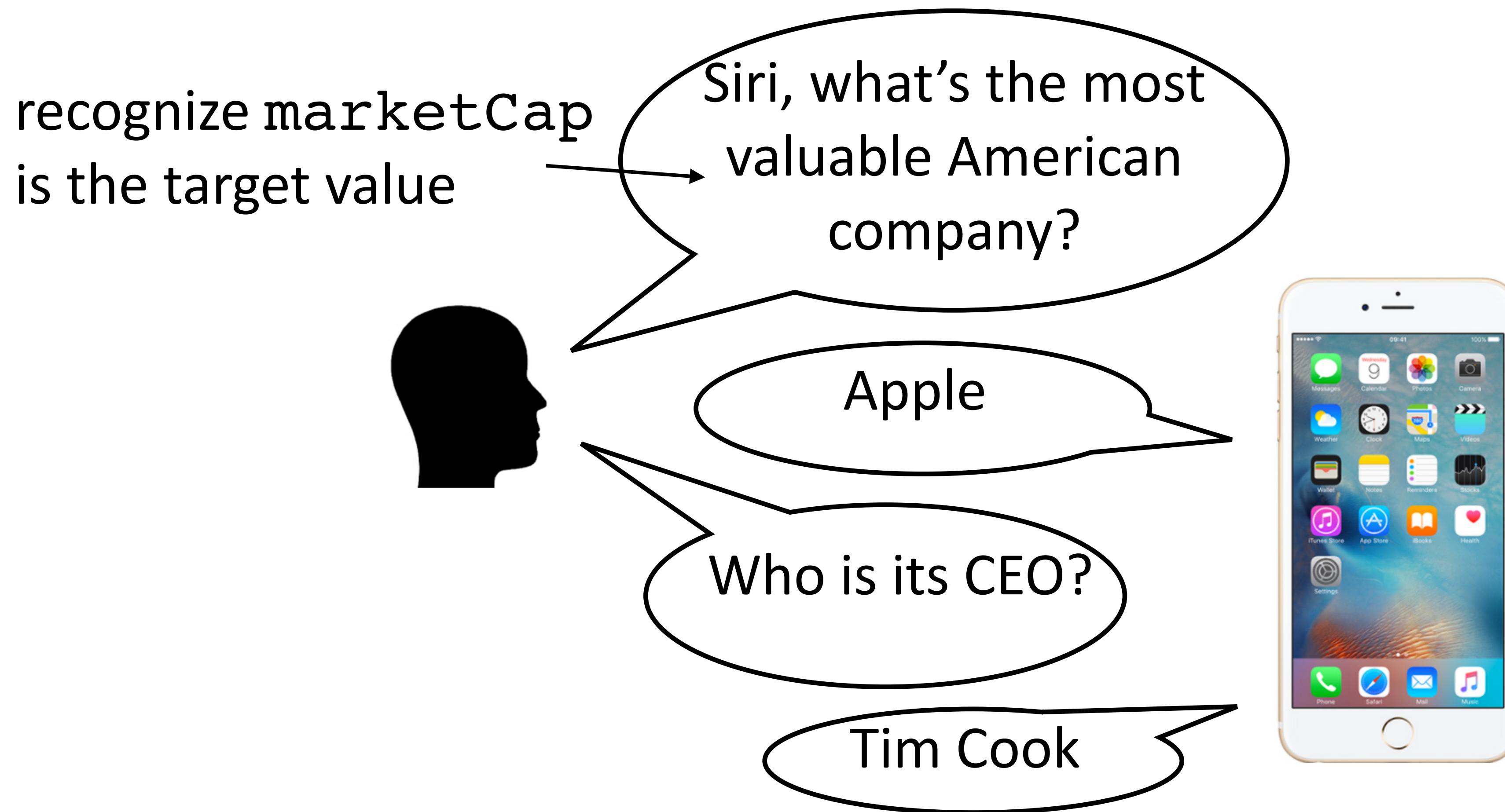
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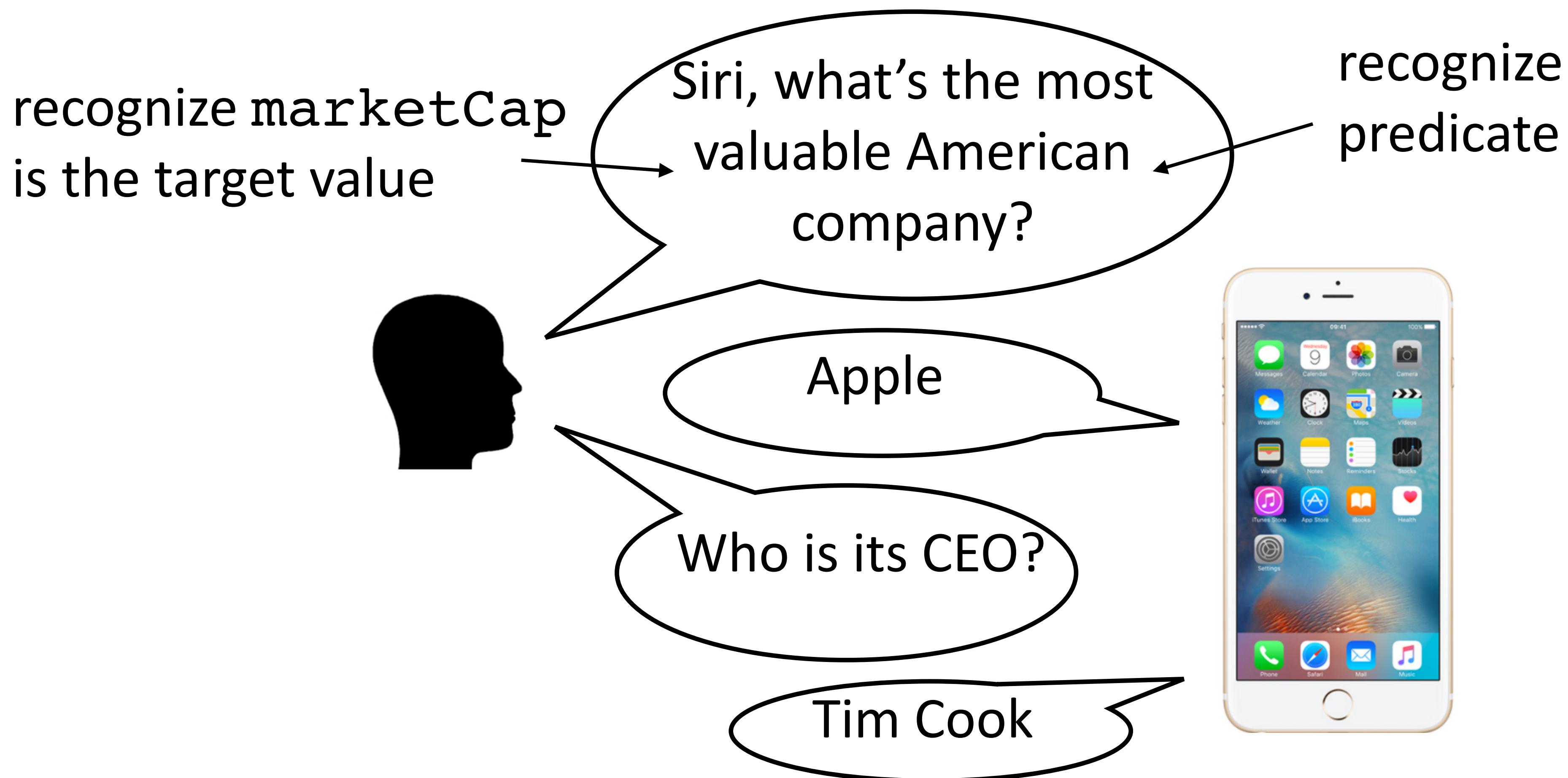
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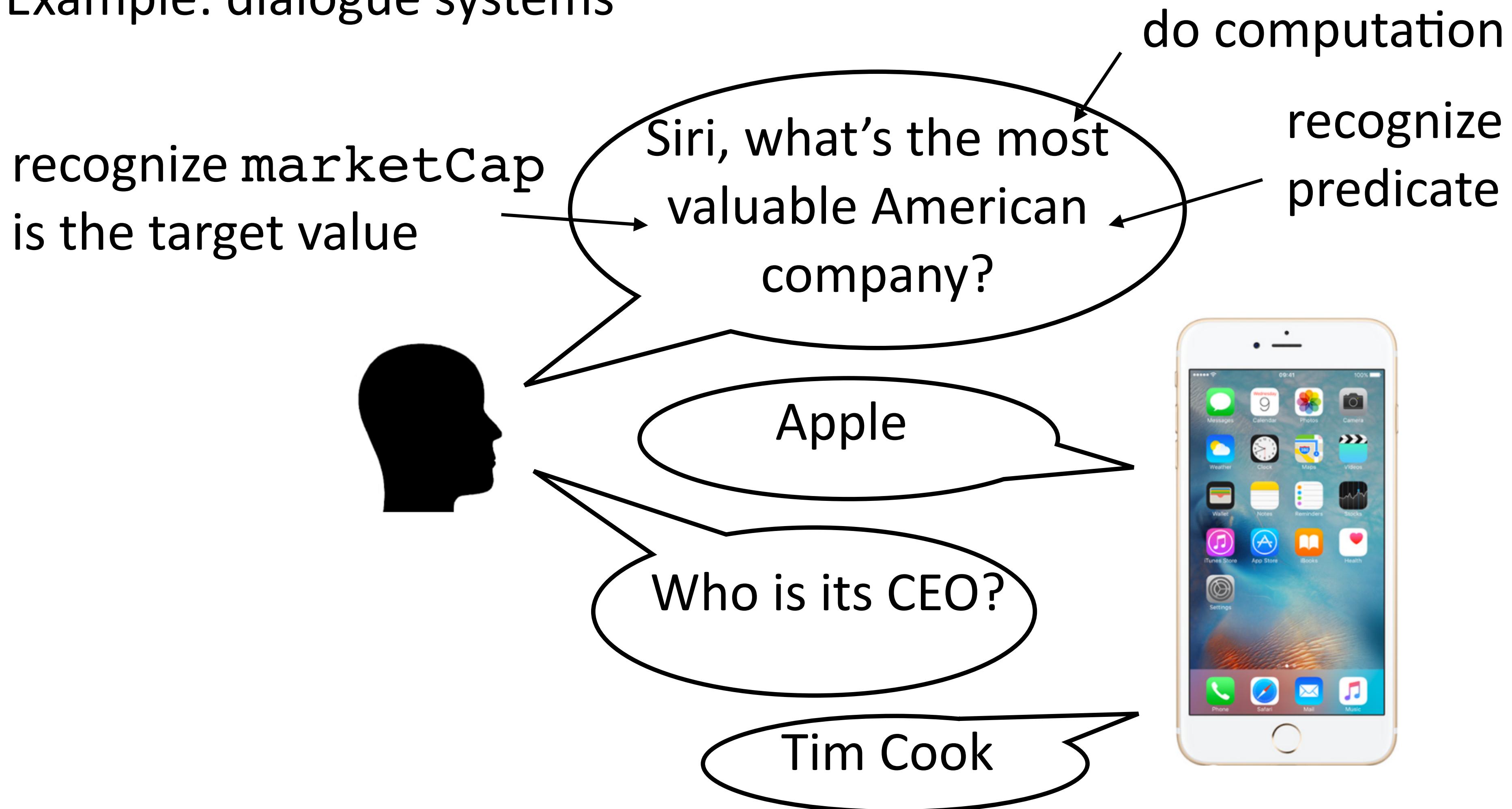
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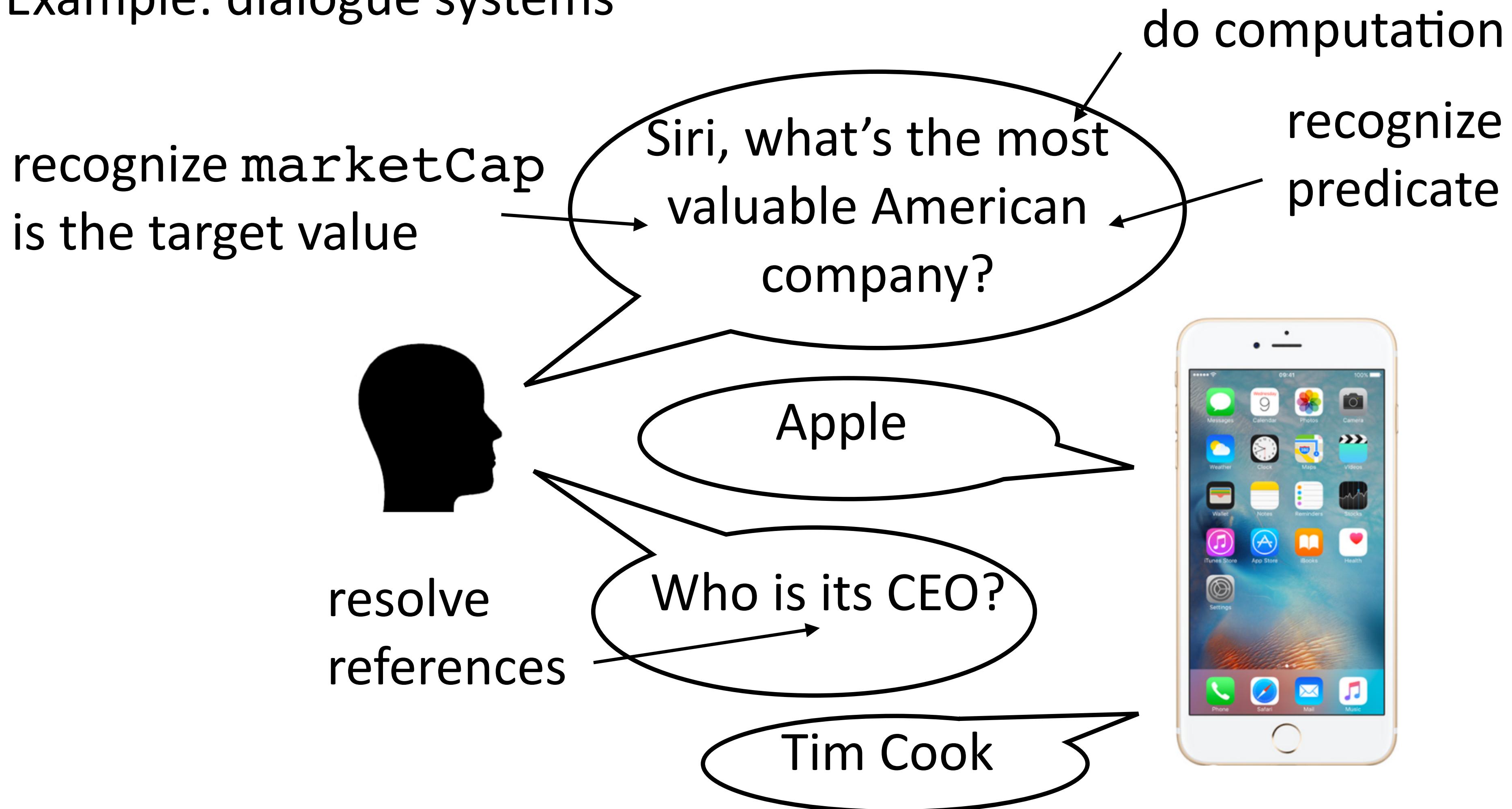
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paraphrase to provide clarity

Machine Translation



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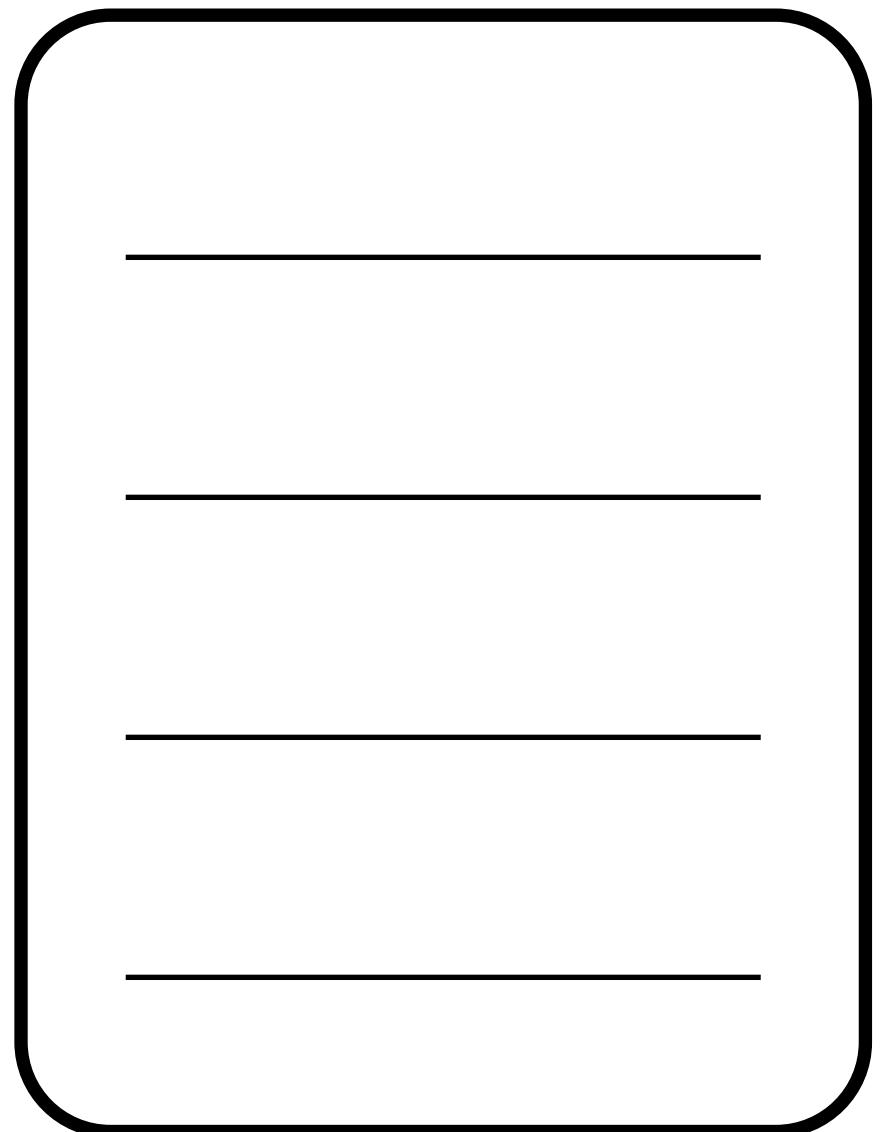
U.S. House speaker race ends as Republican lawmakers focus on spending, China



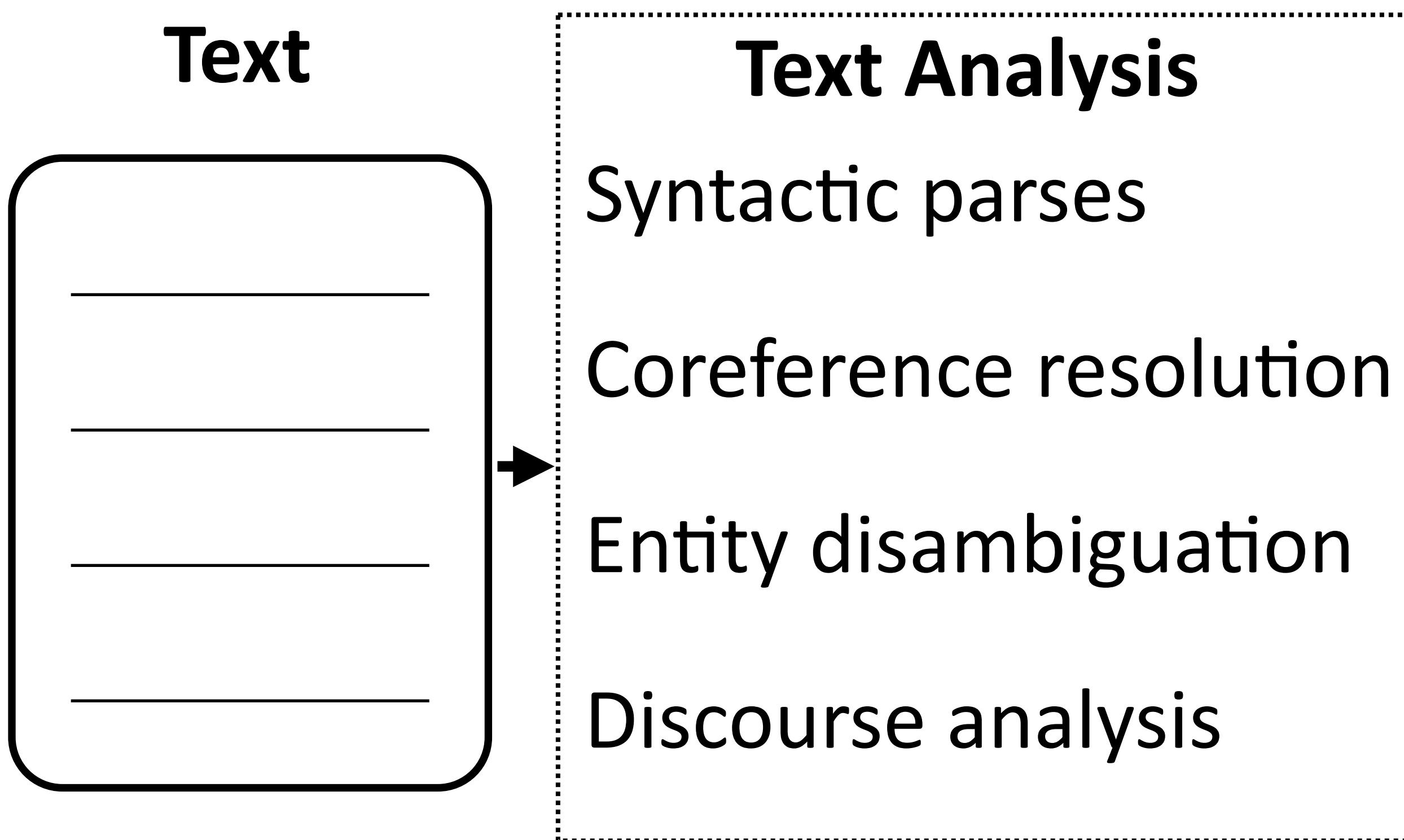
NLP Analysis Pipeline

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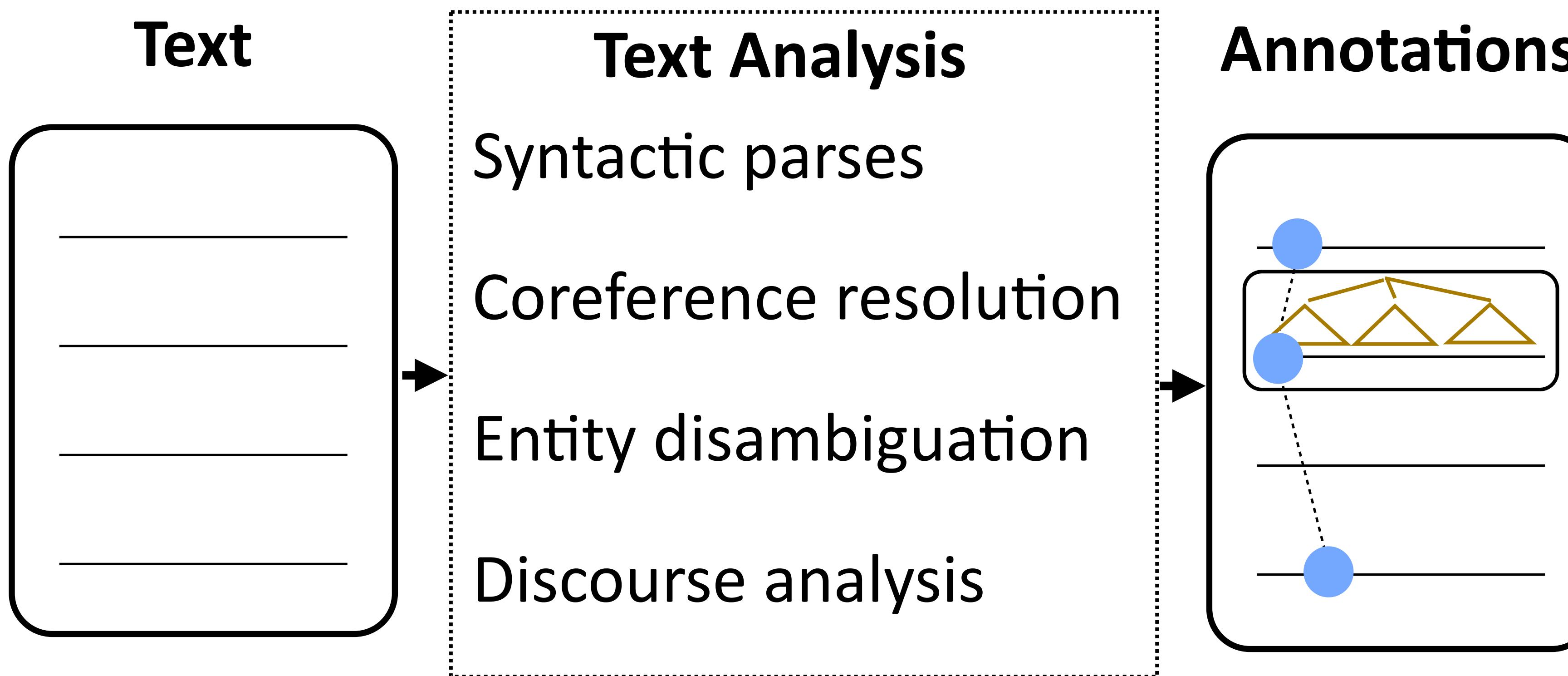
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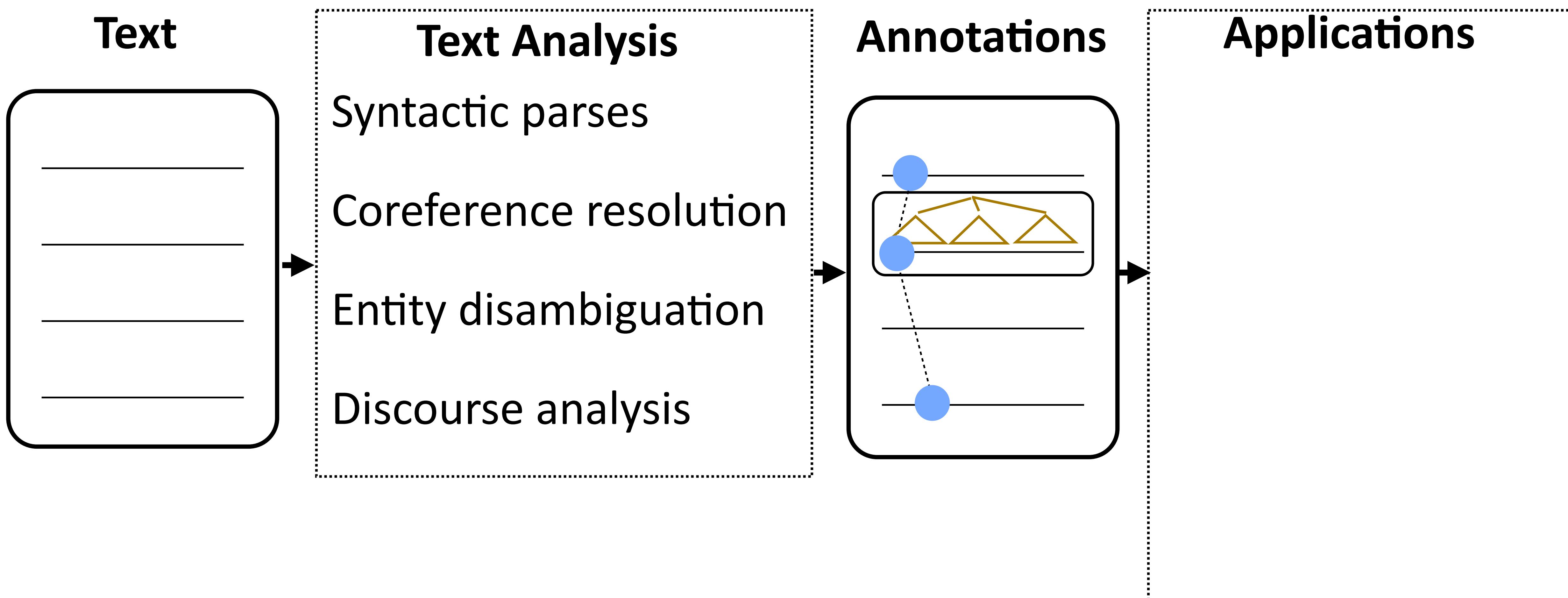
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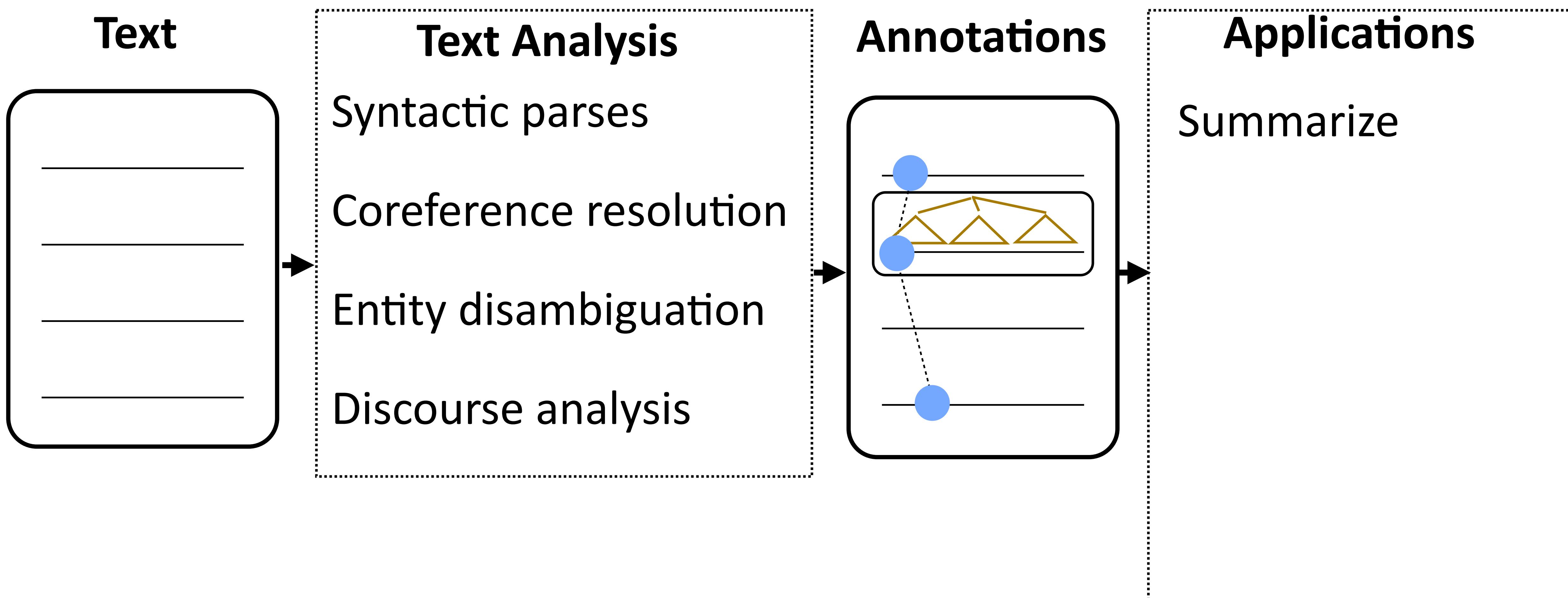
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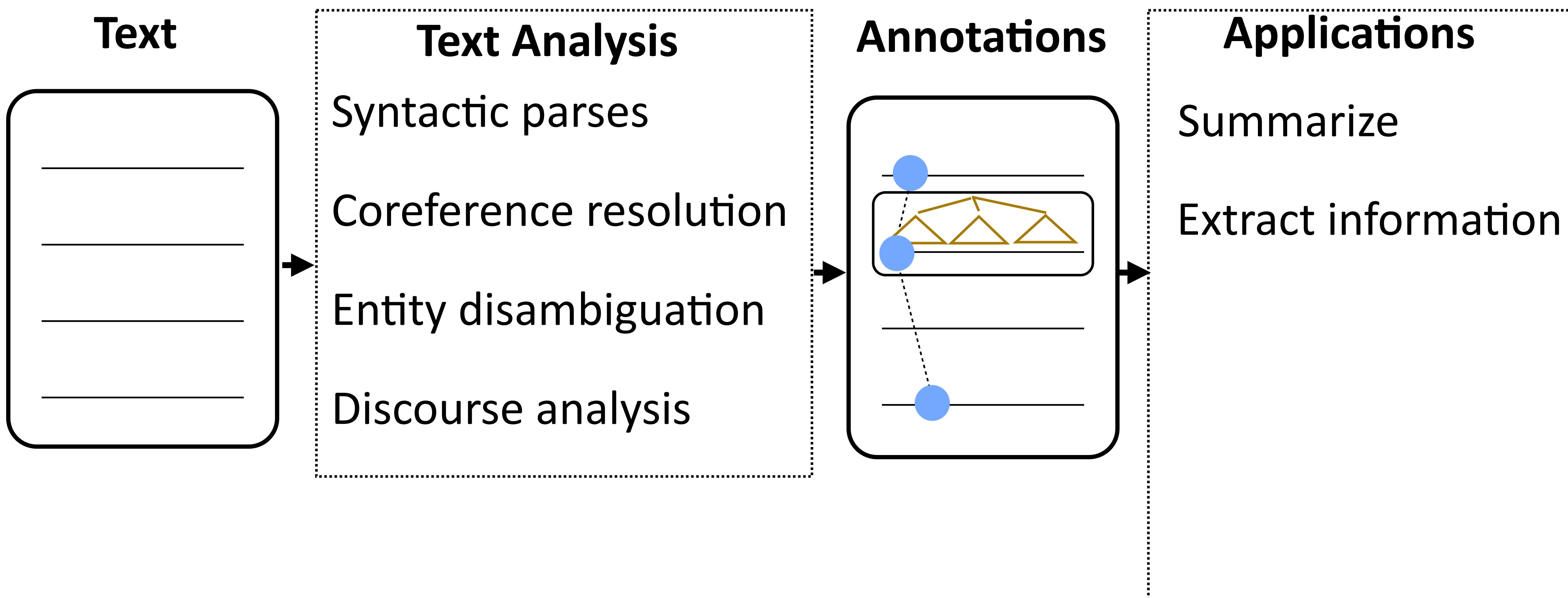
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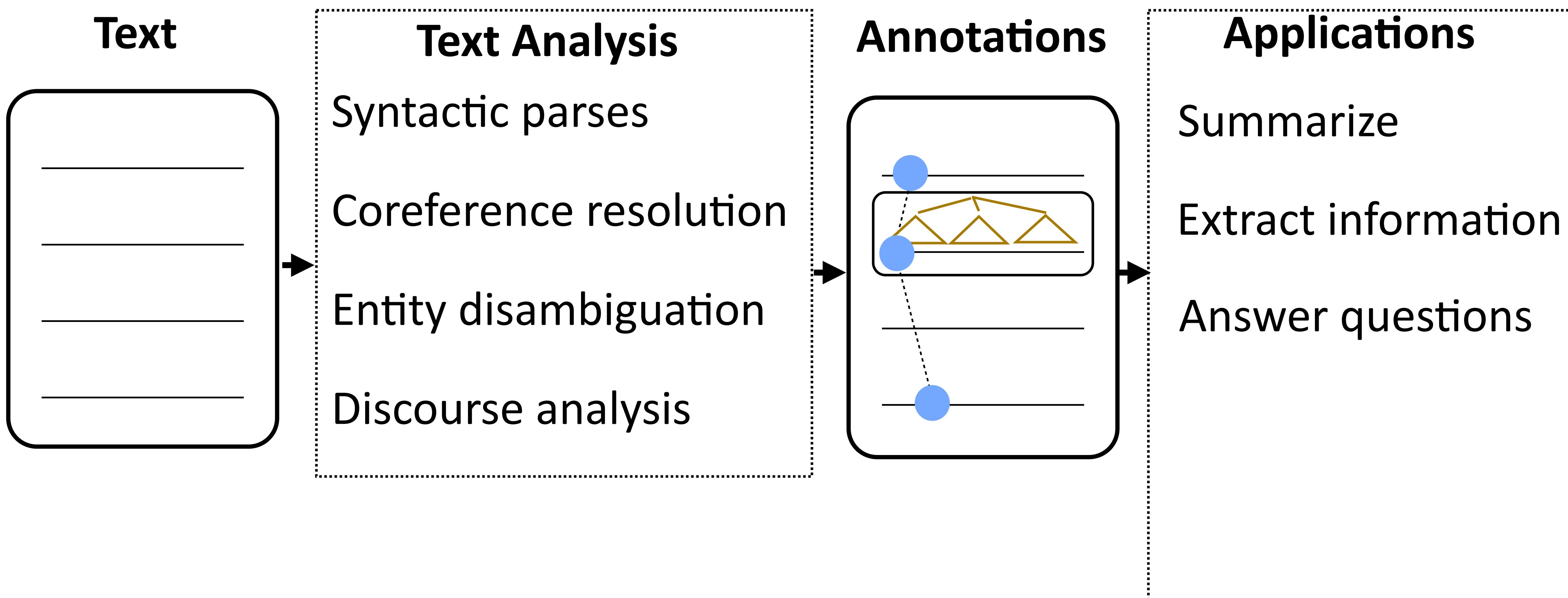
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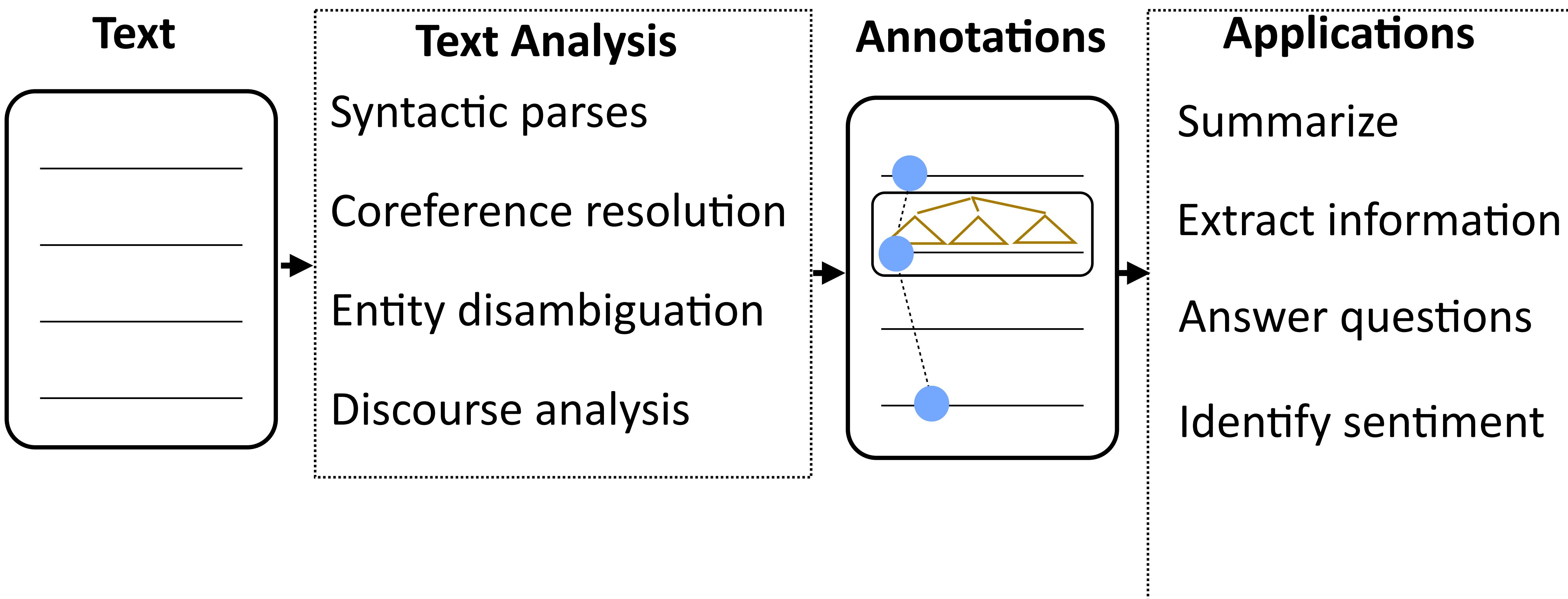
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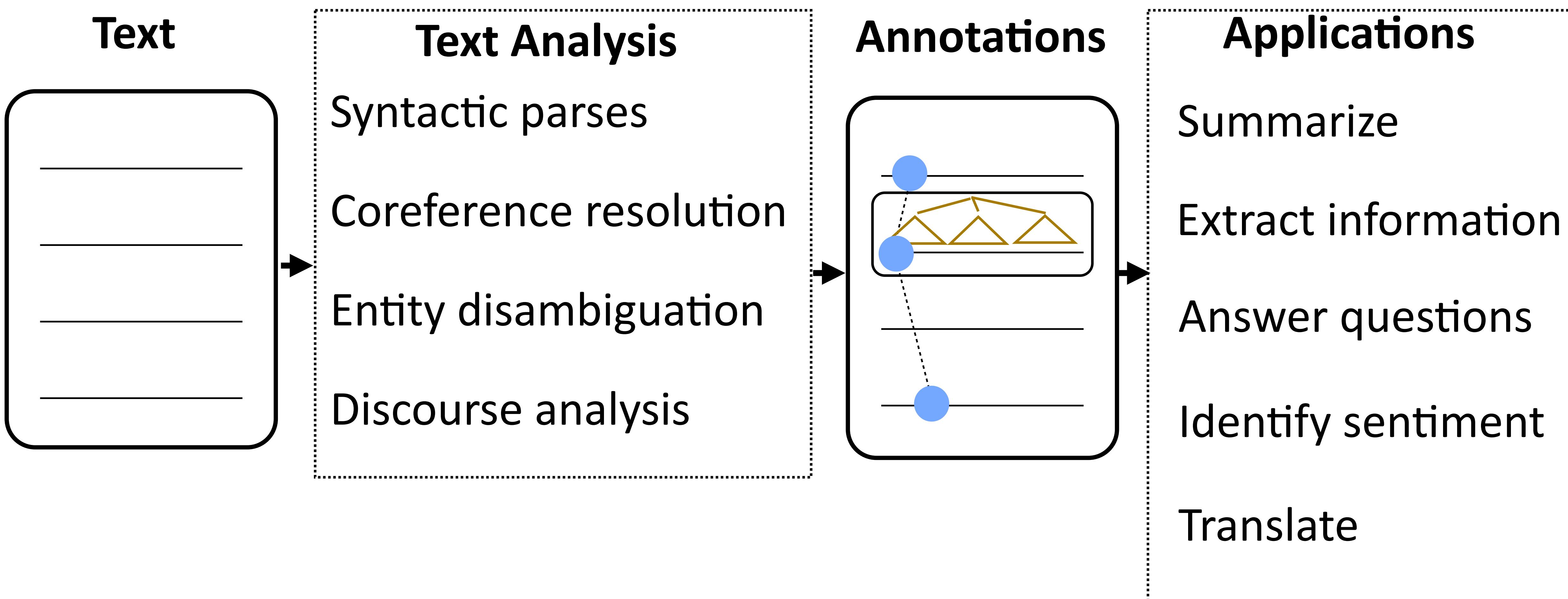
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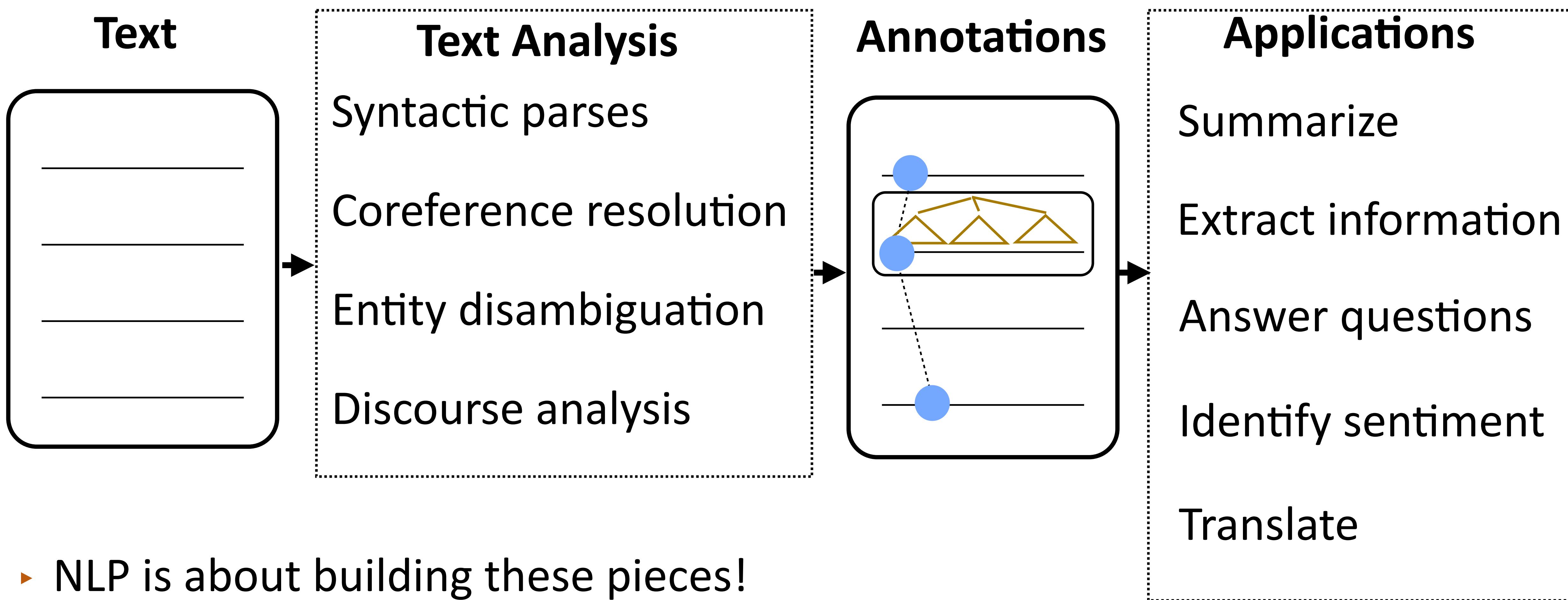
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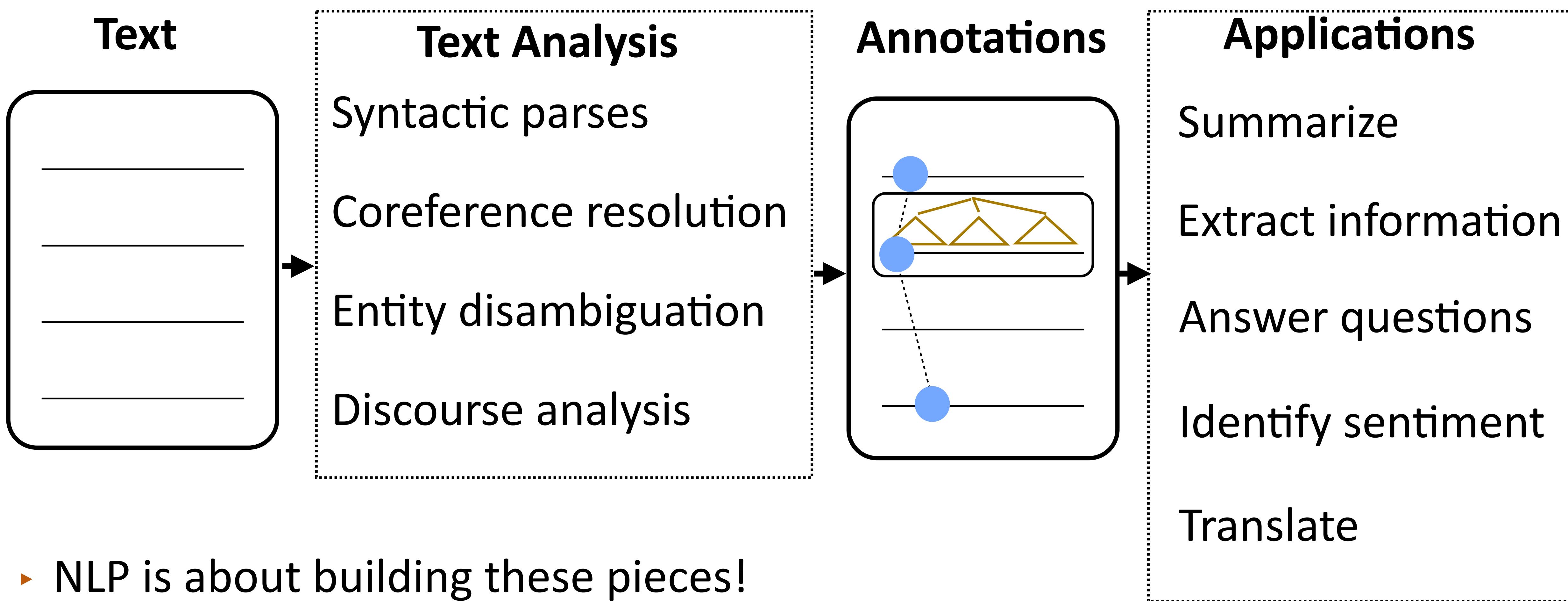
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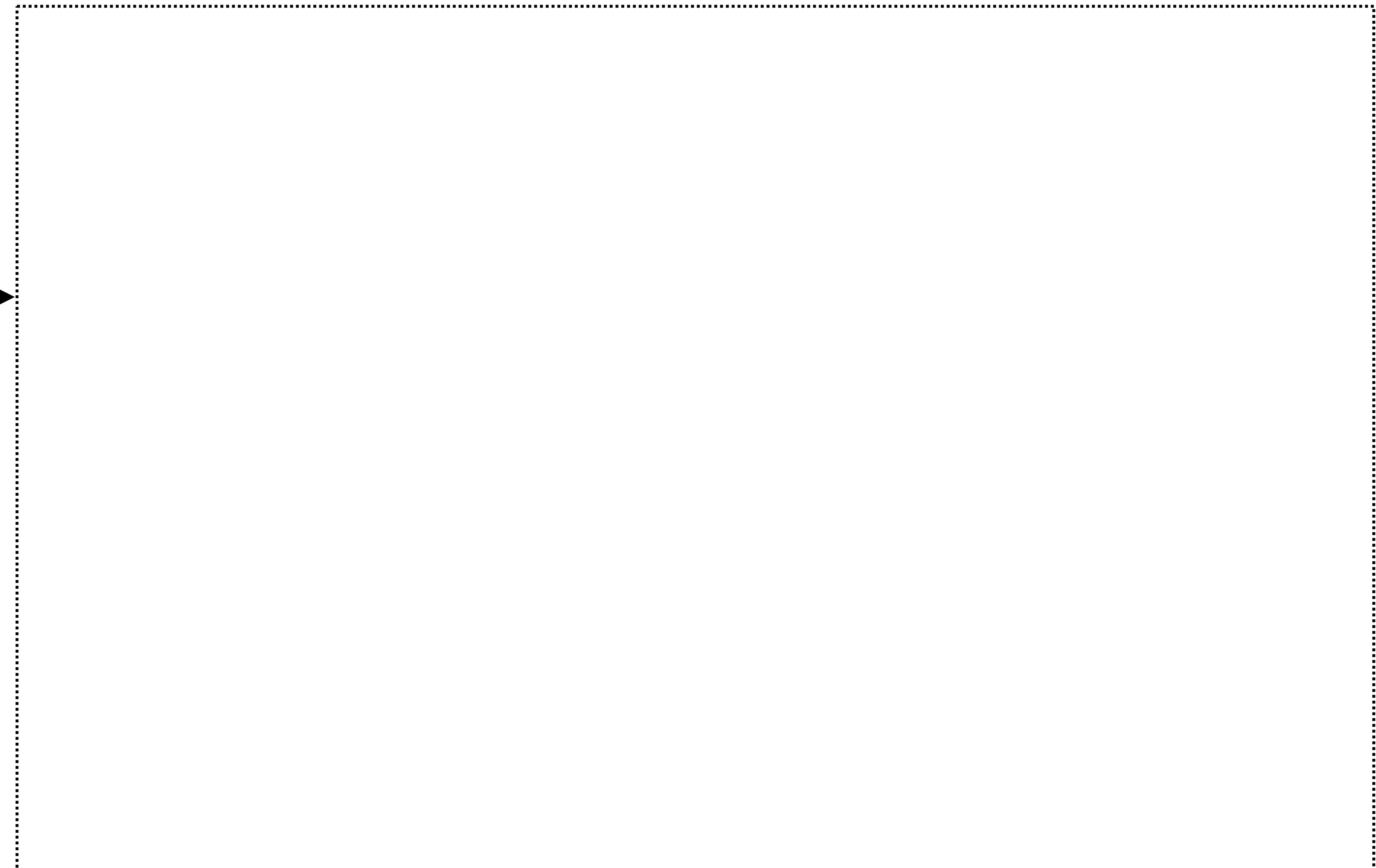
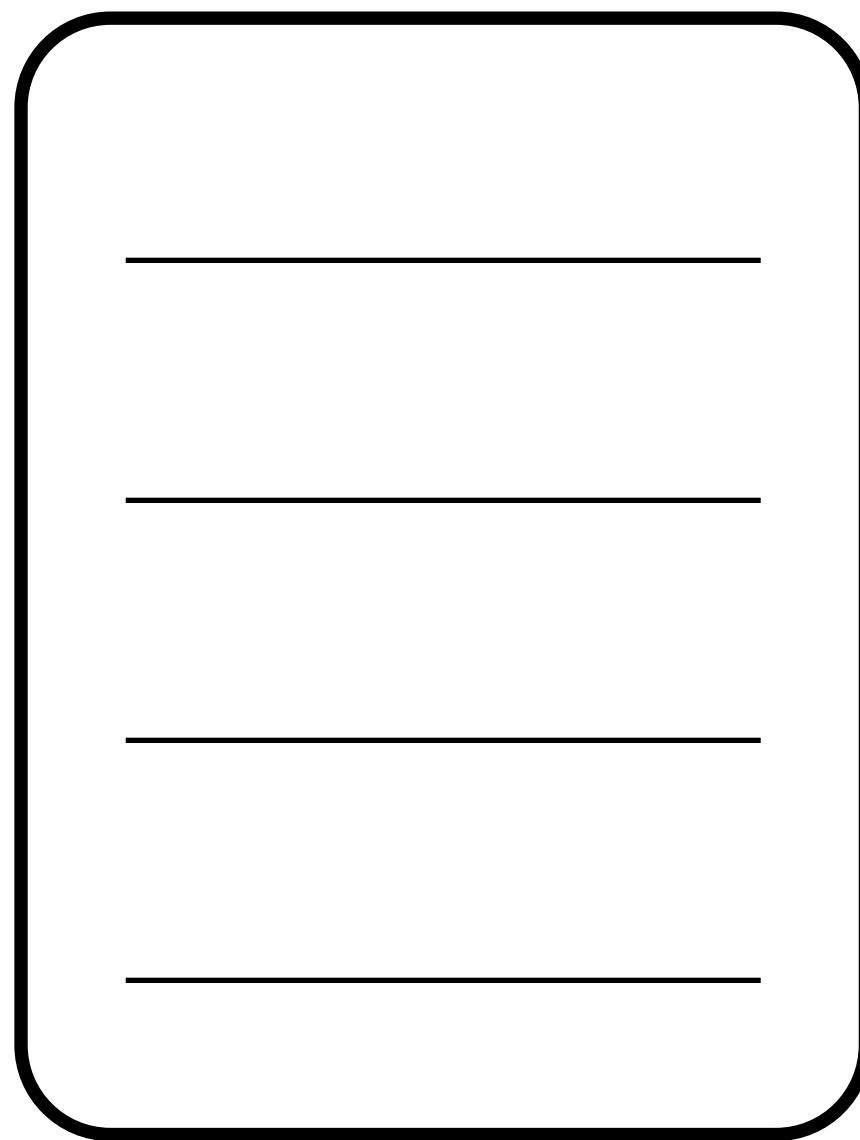
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- ▶ NLP is about building these pieces!
- ▶ All of these components are modeled with statistical approaches trained with machine learning

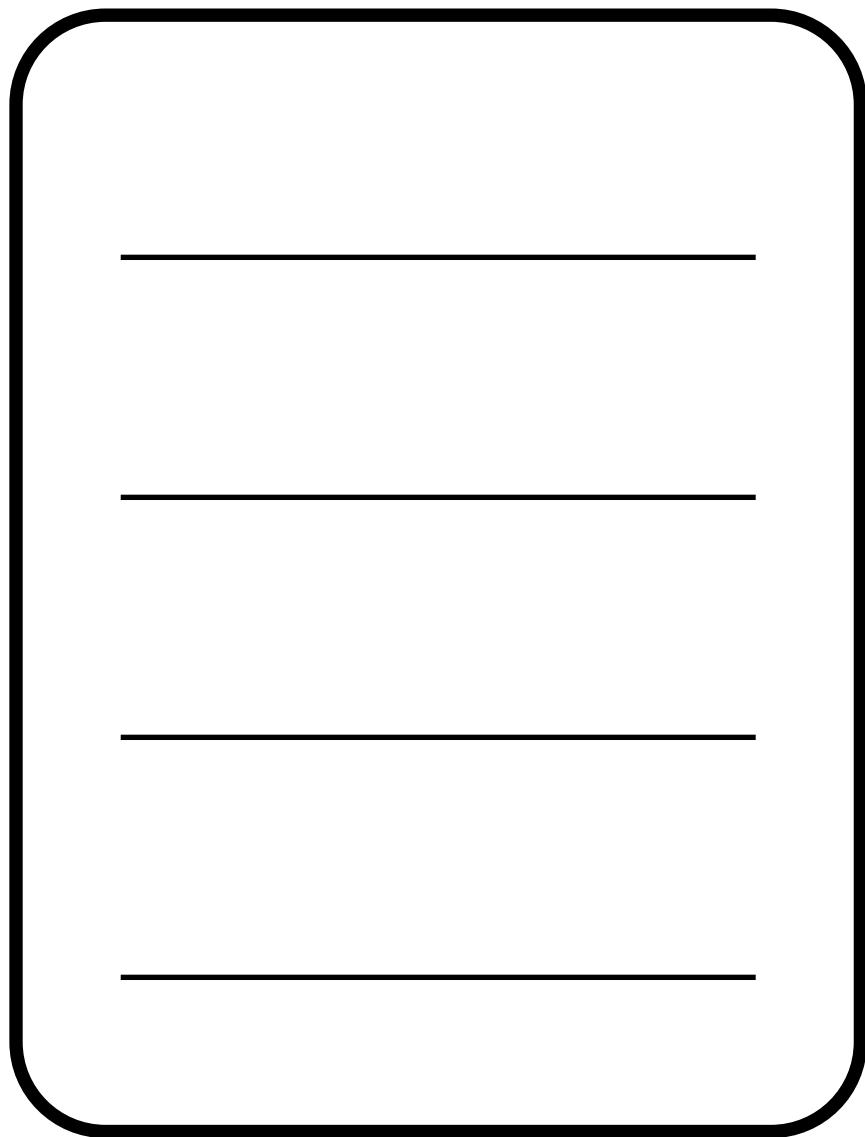
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Text



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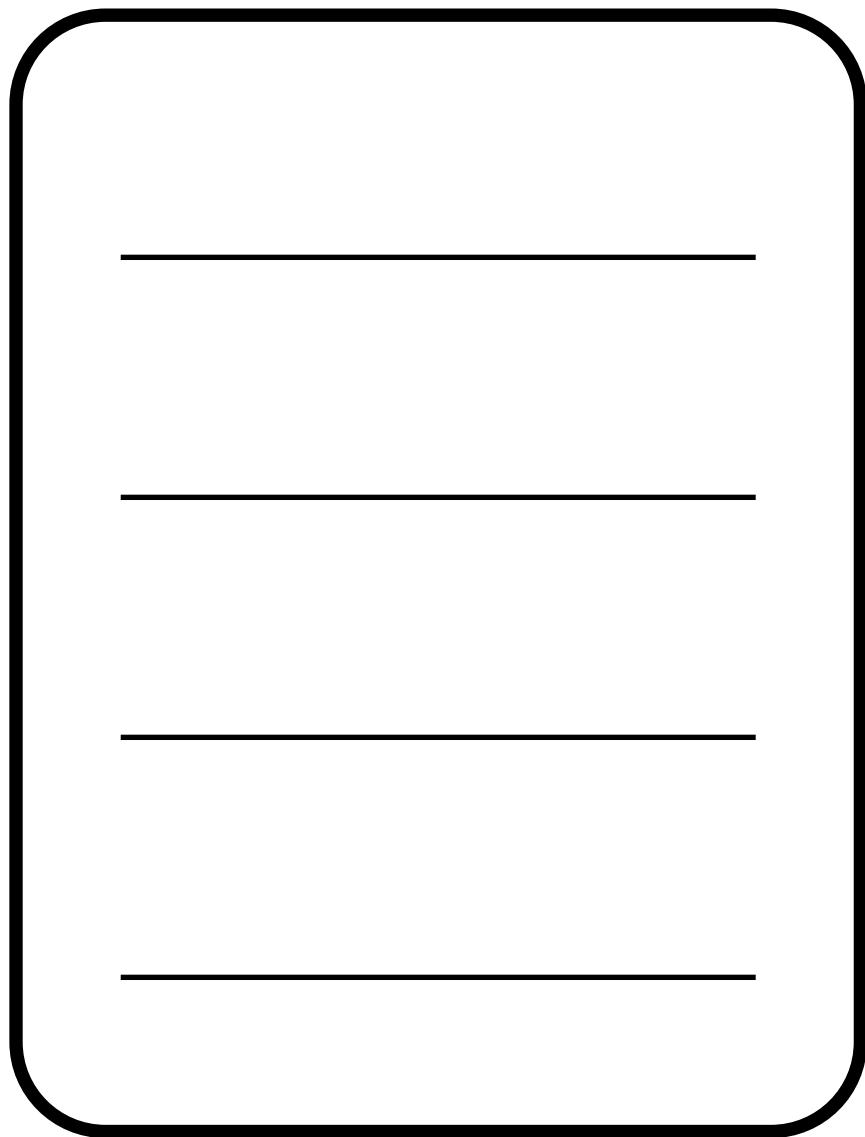


Labels



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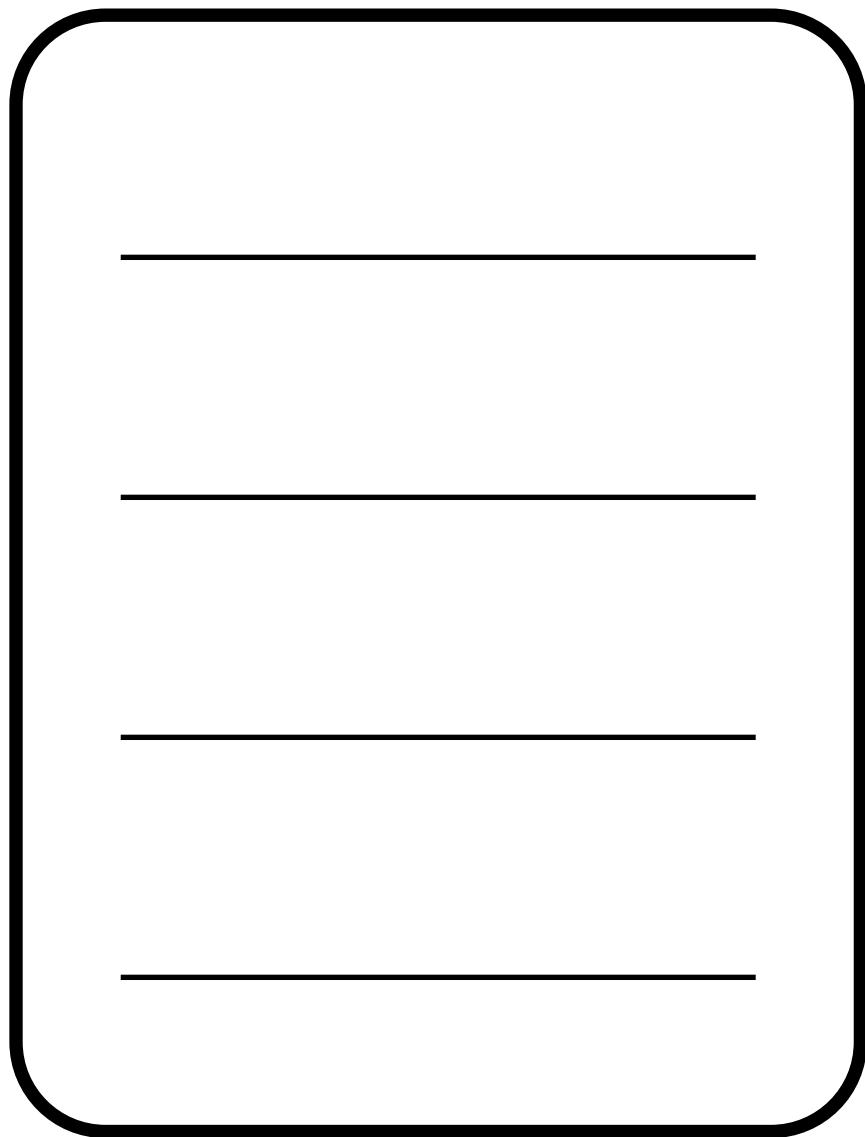


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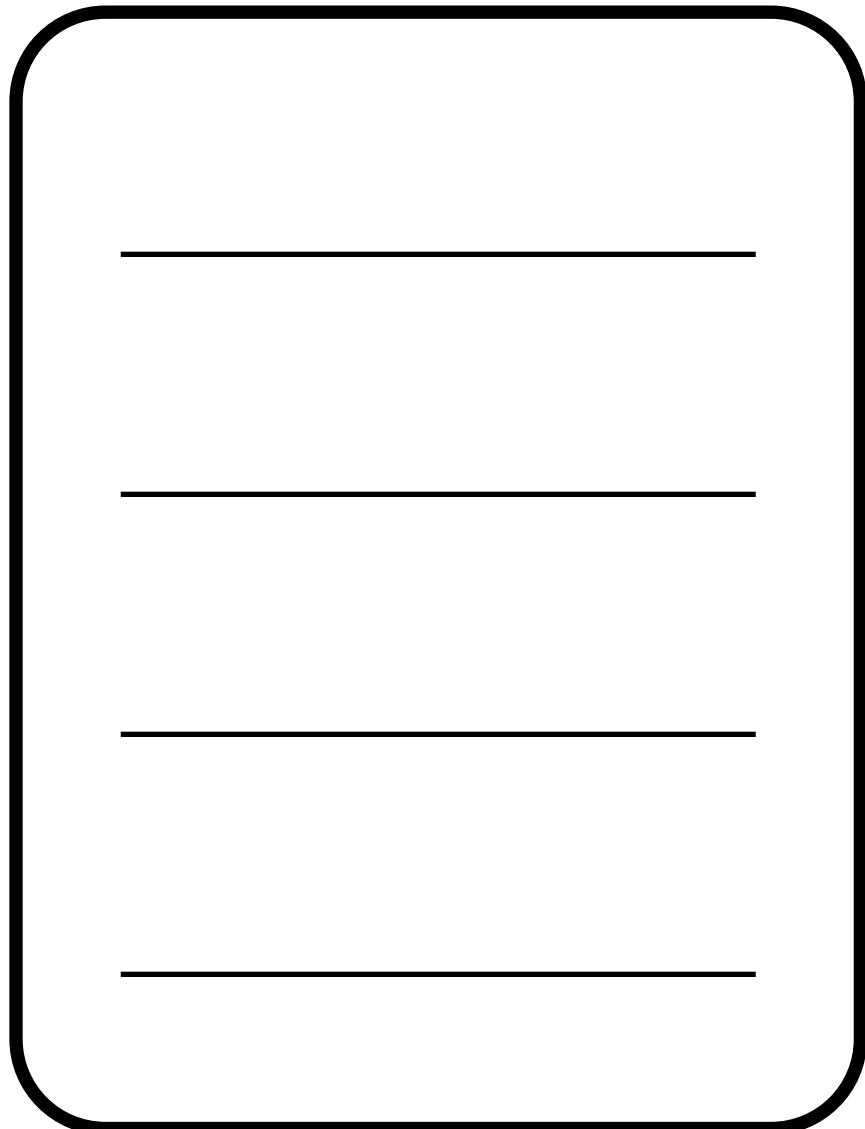
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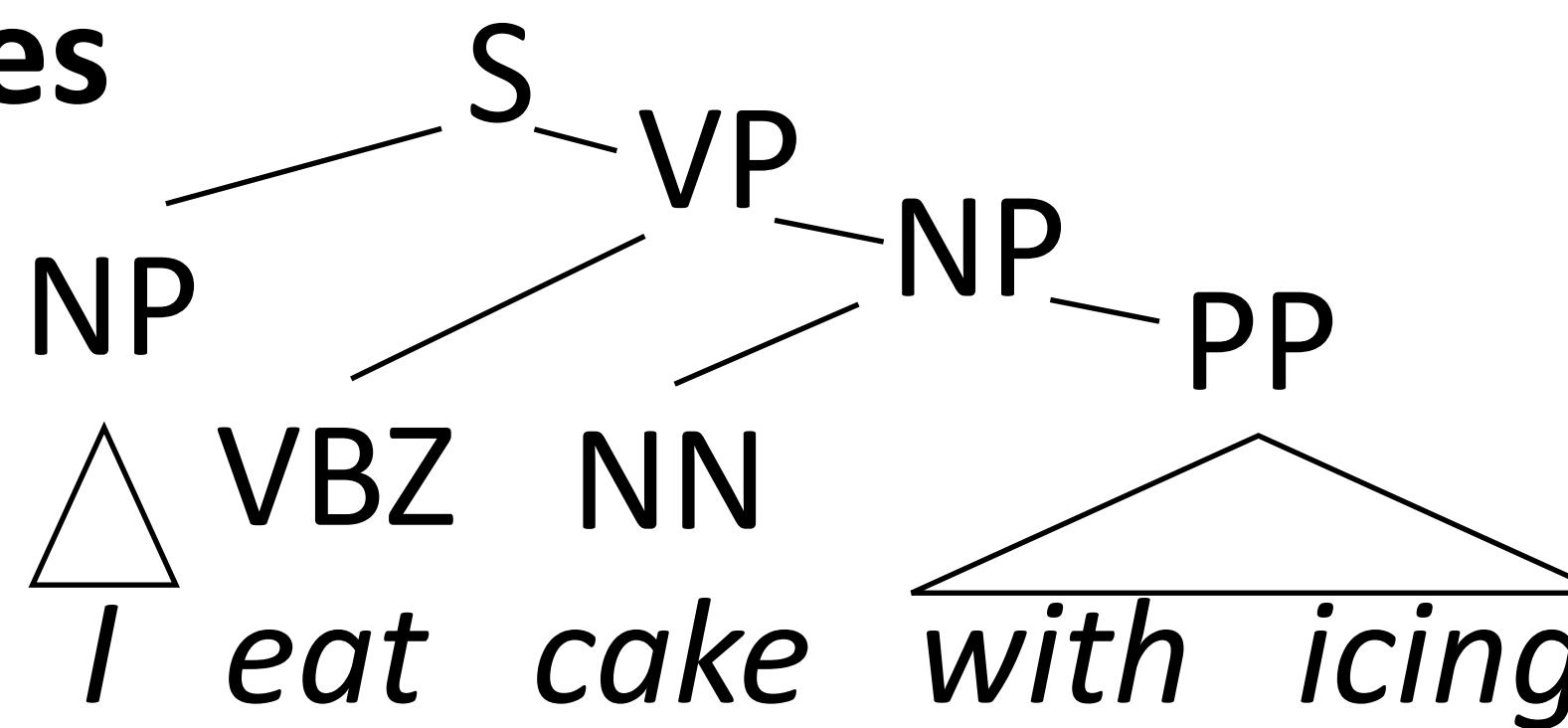
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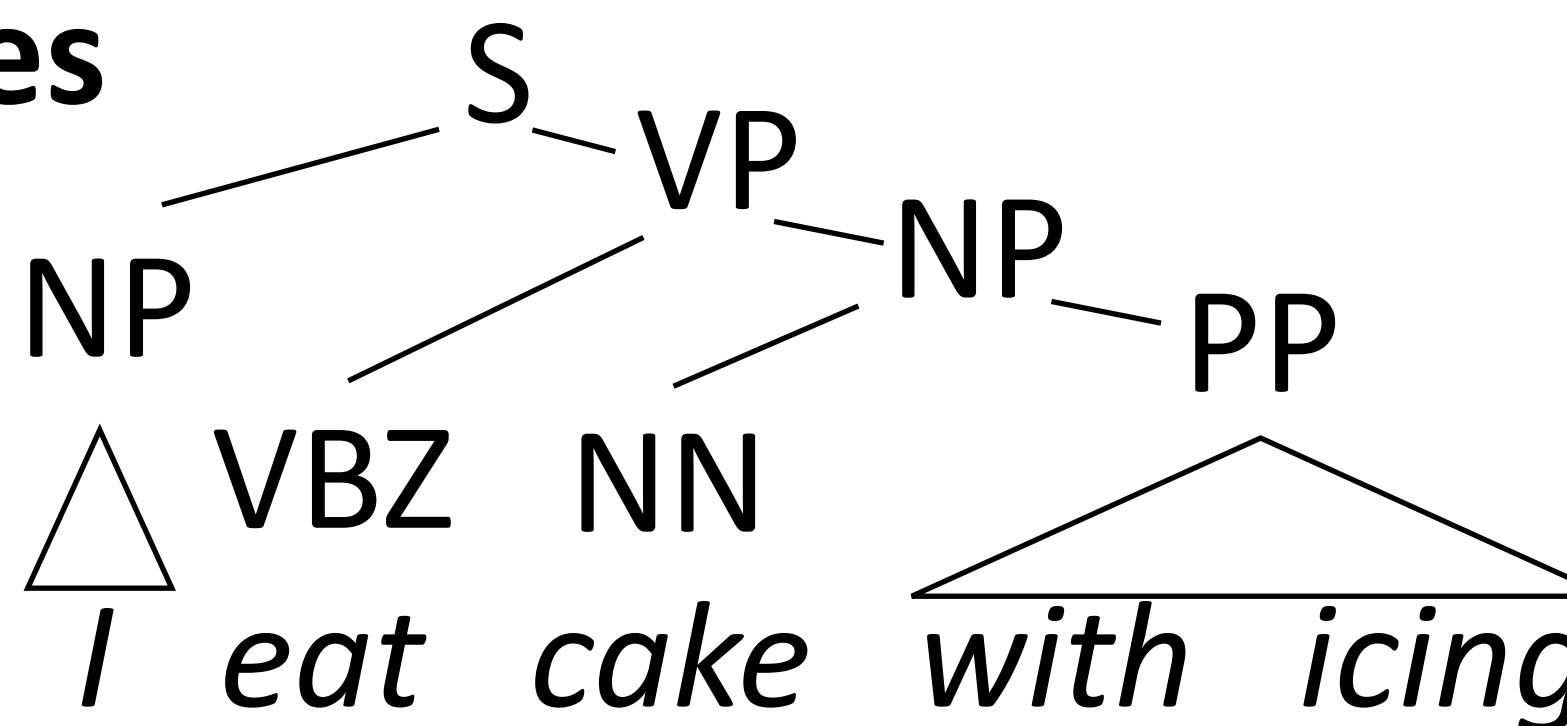
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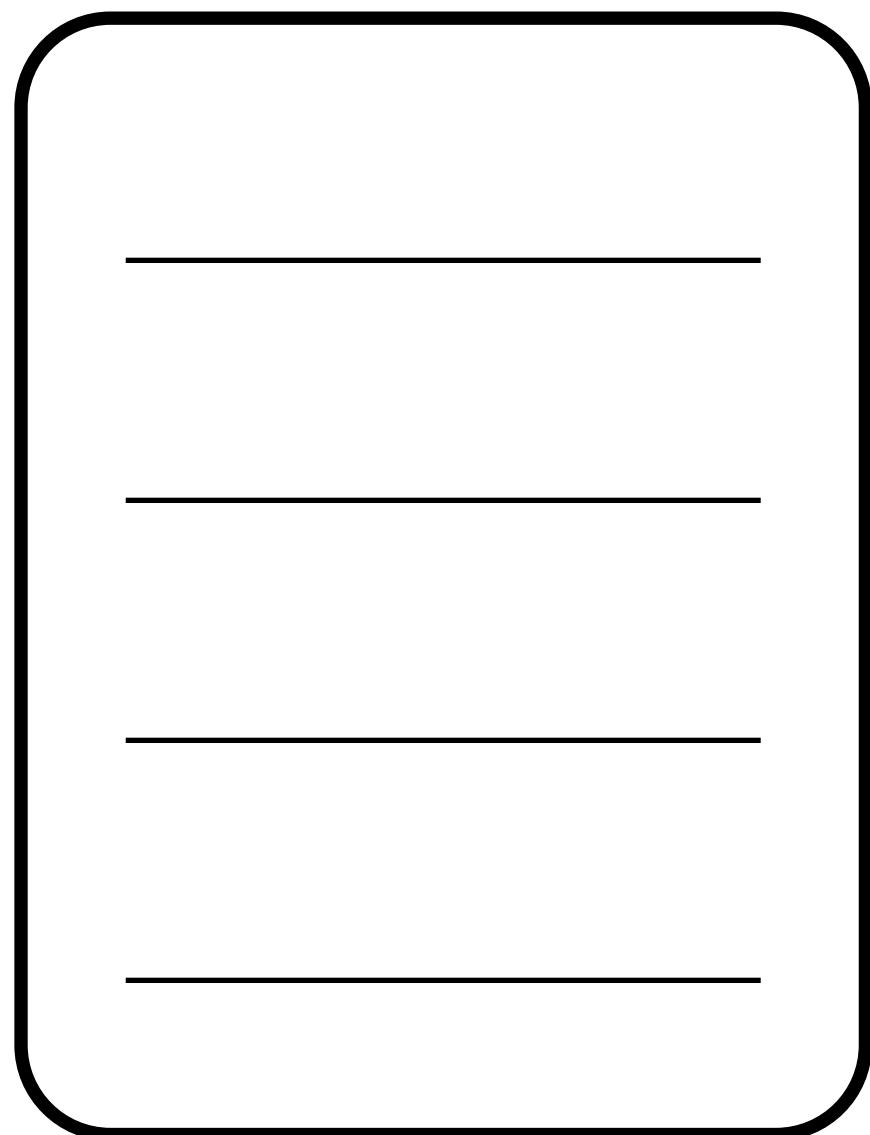
Trees



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

How do we use these representations?

Text



Text Analysis

Labels

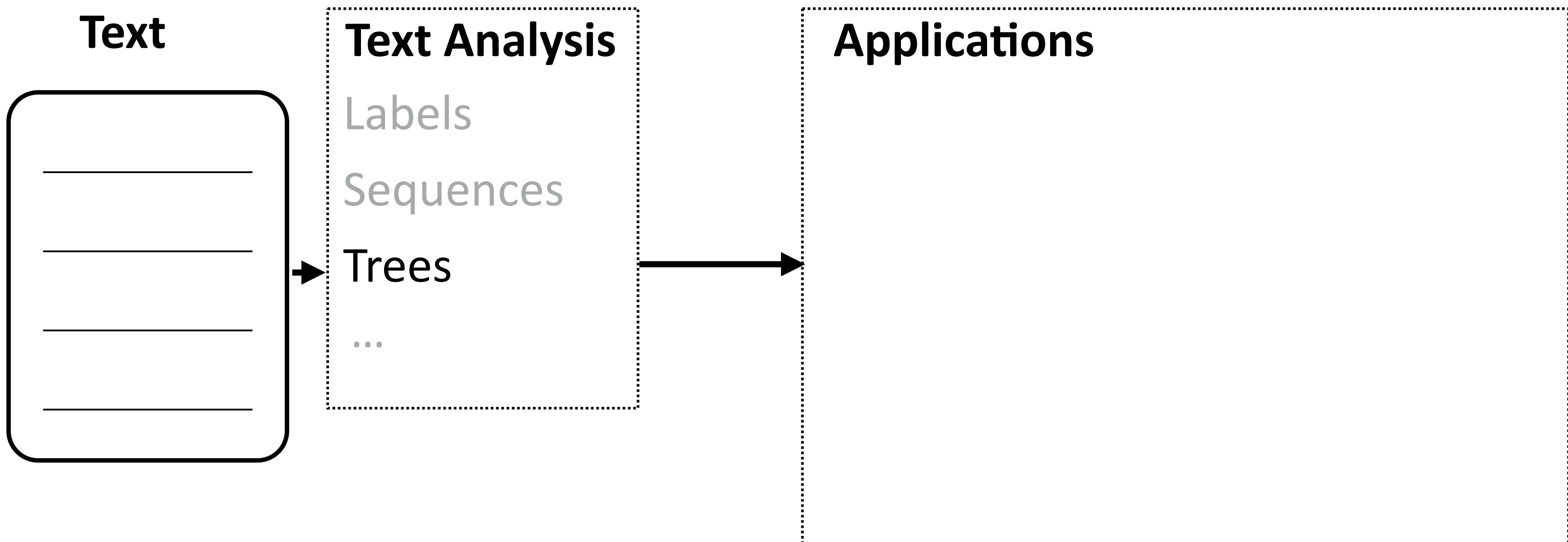
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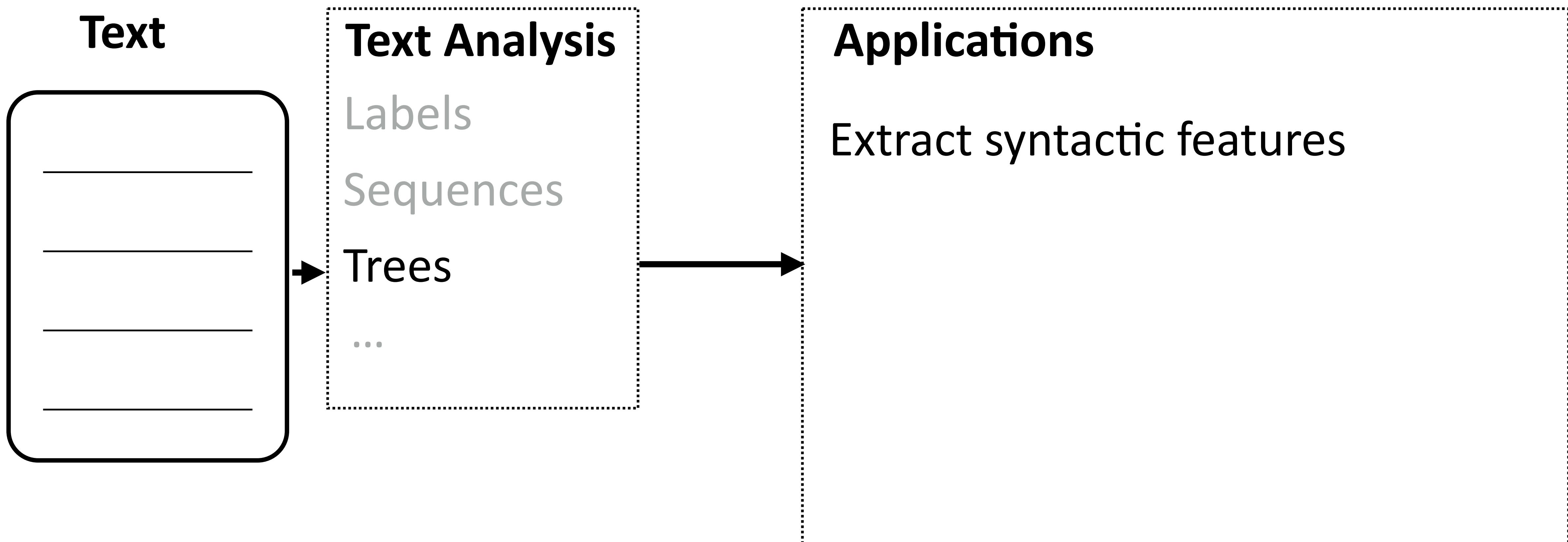
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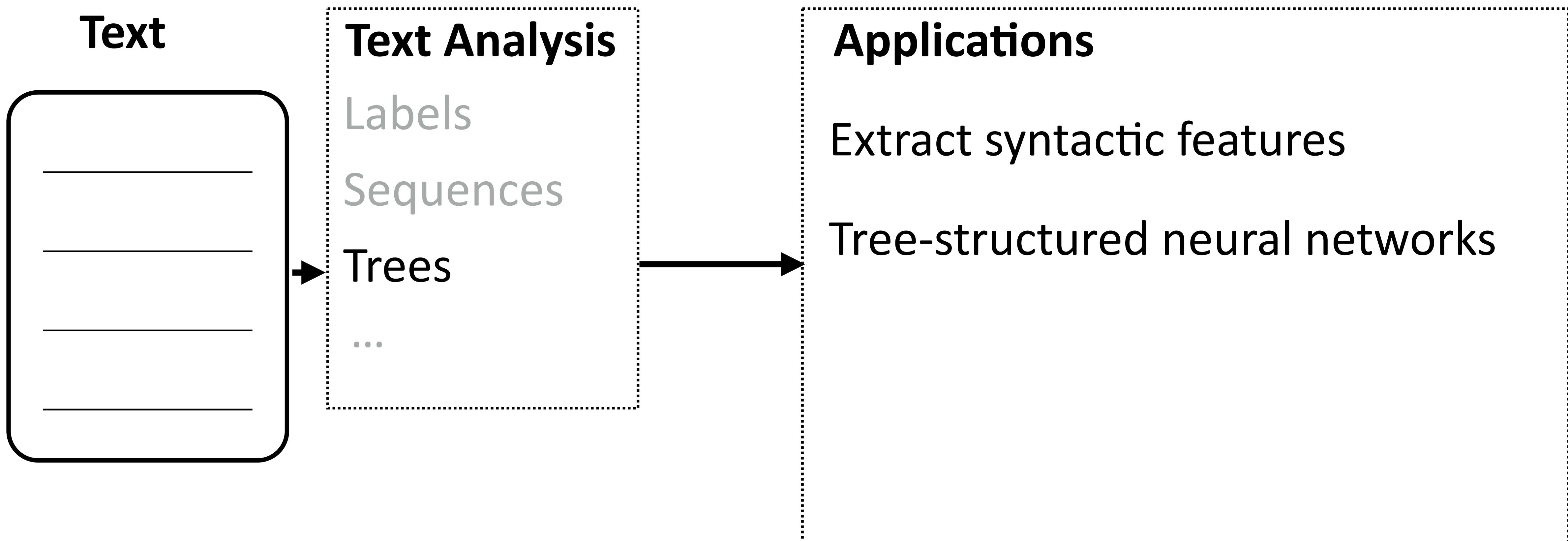
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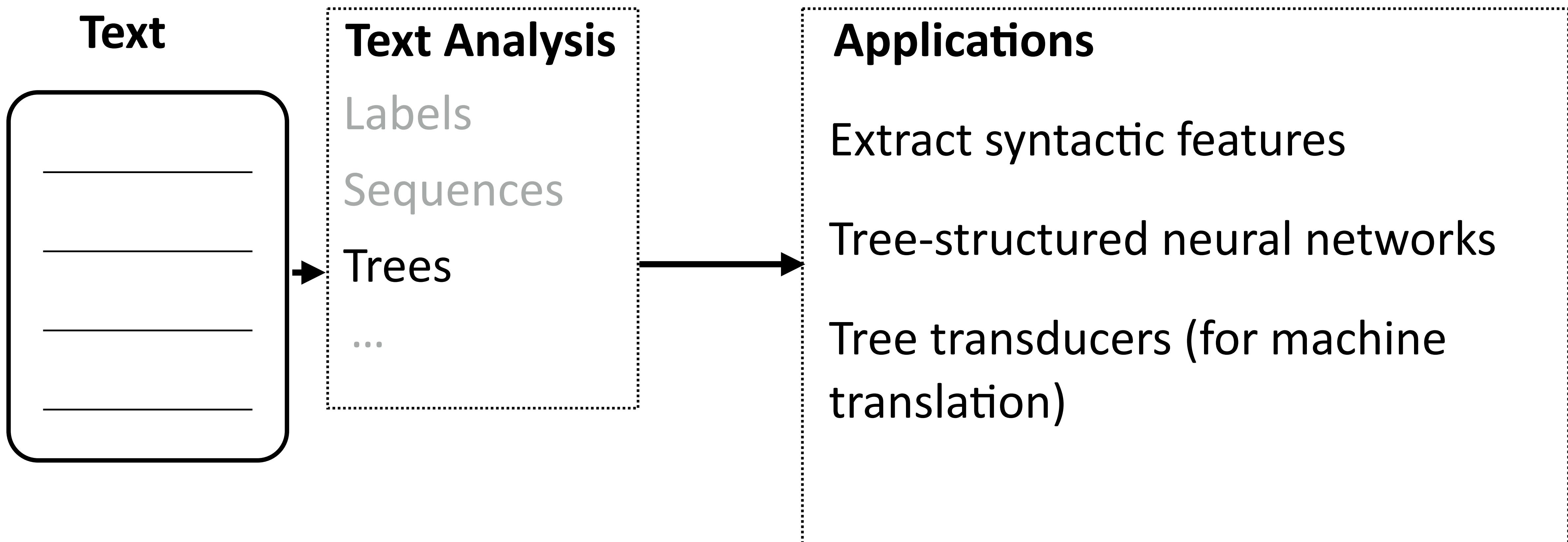
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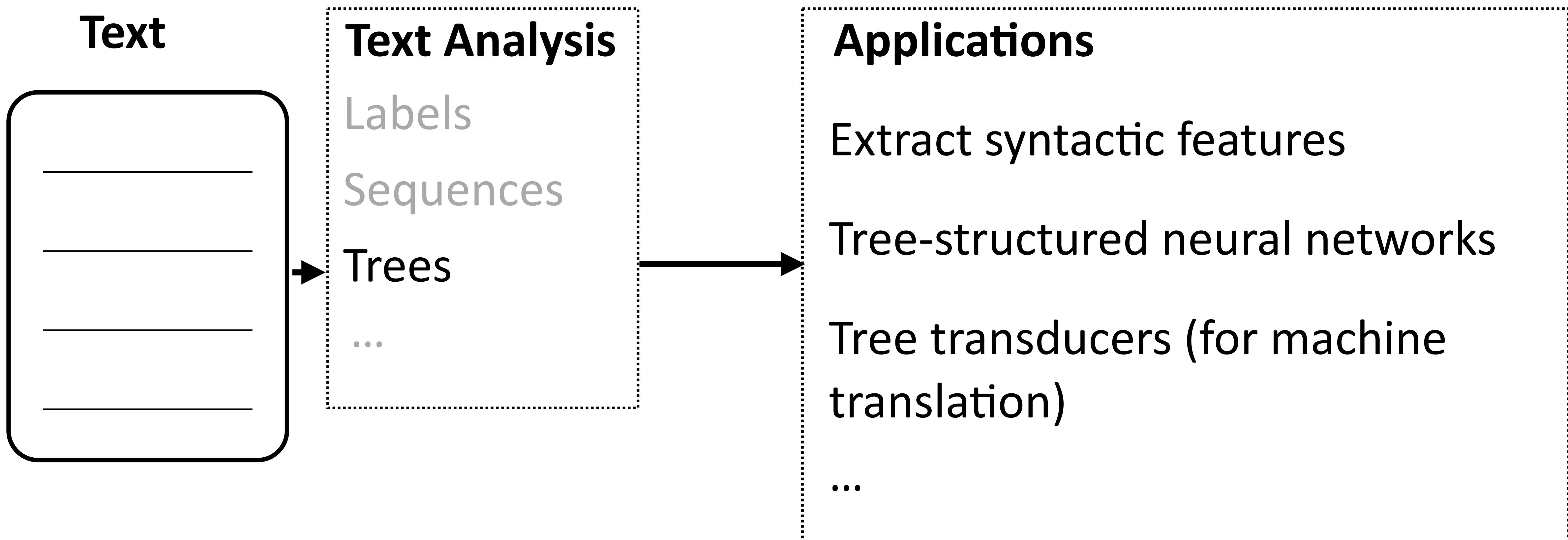
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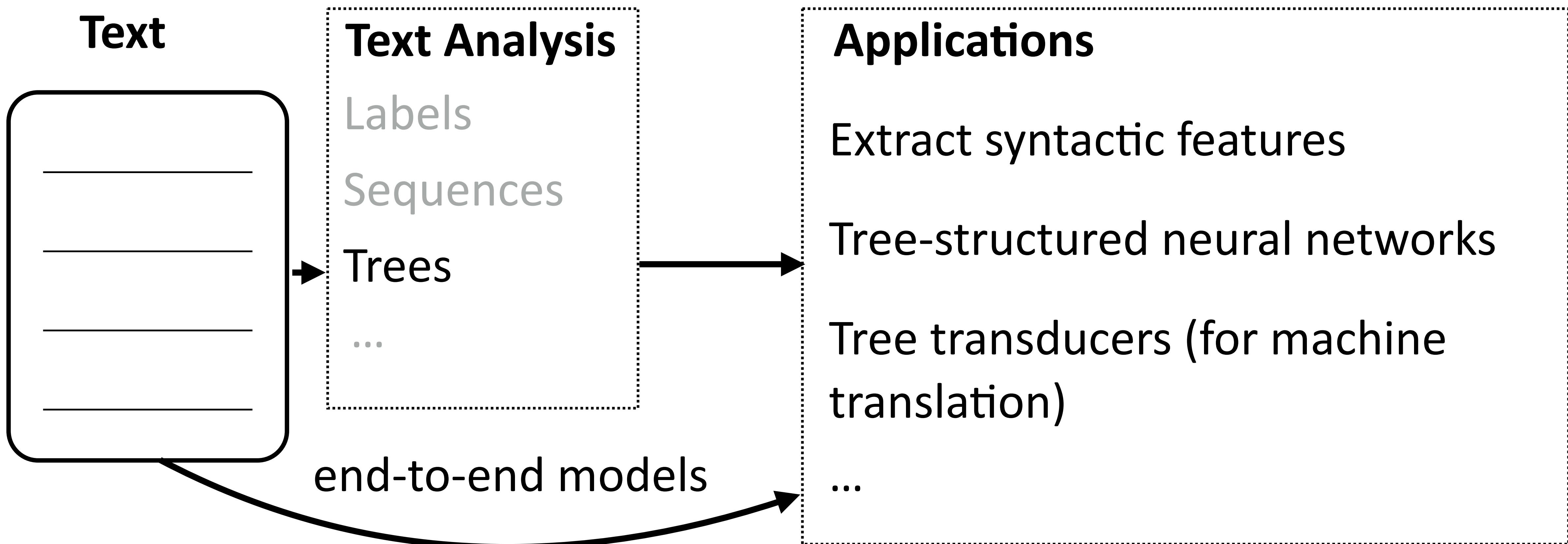
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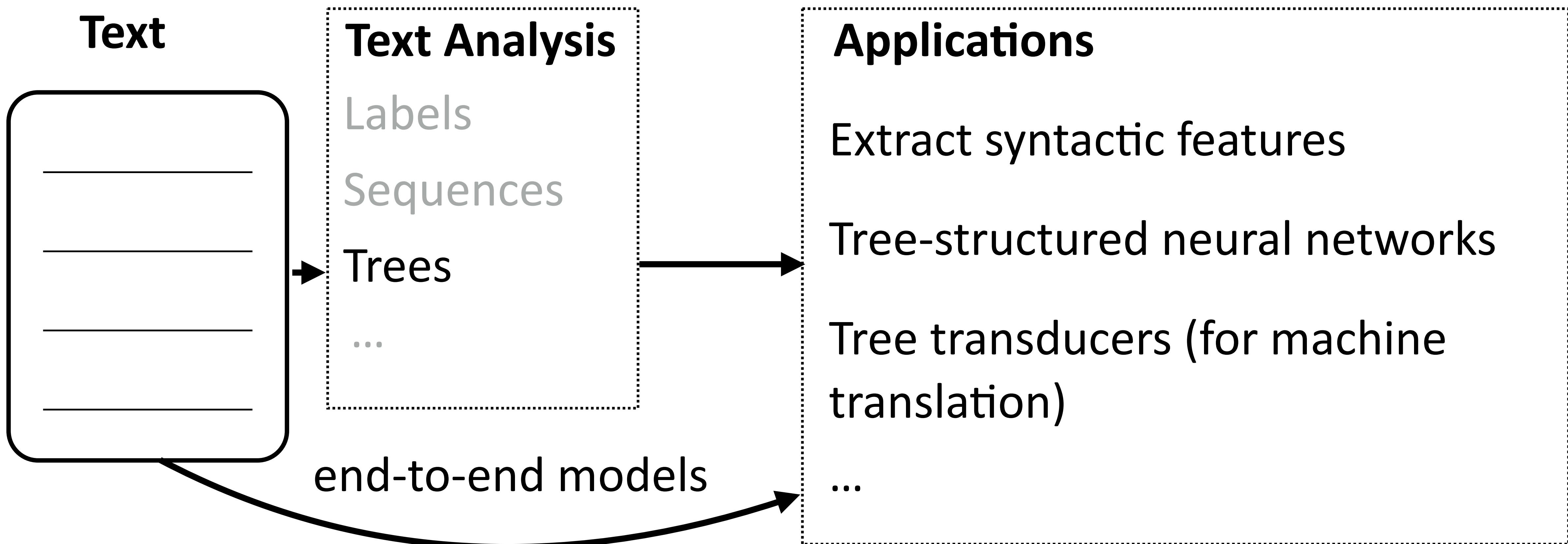
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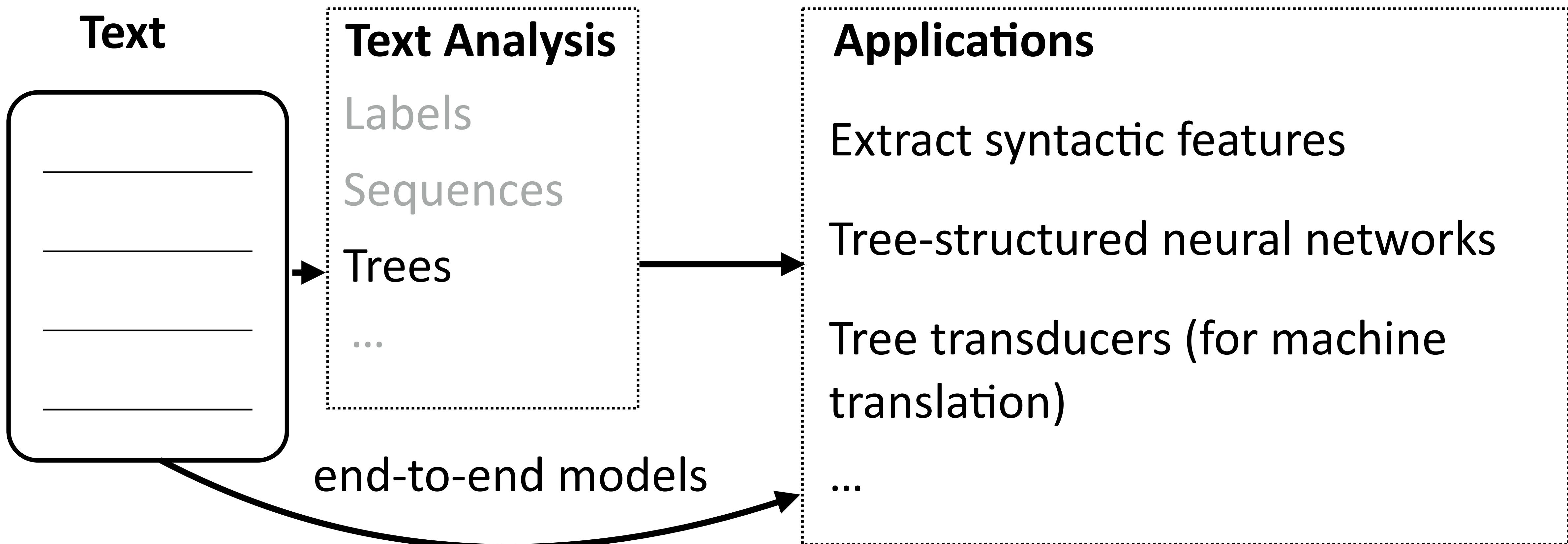


How do we use these representations?



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

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- ▶ Boils down to: what ambiguities do we need to resolve?

Why is language hard?
(and how can we handle that?)

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

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they advocated

they feared

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

Language is Ambiguous!

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- ▶ Ambiguous News Headlines:

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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

il fait vraiment beau



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

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il fait vraiment beau



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

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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
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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

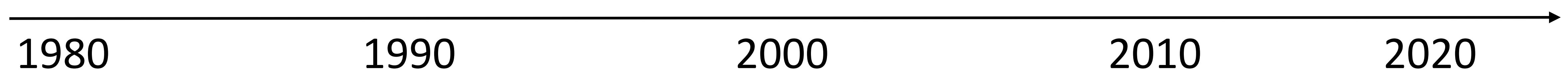
What do we need to understand language?

- ▶ Lots of data!

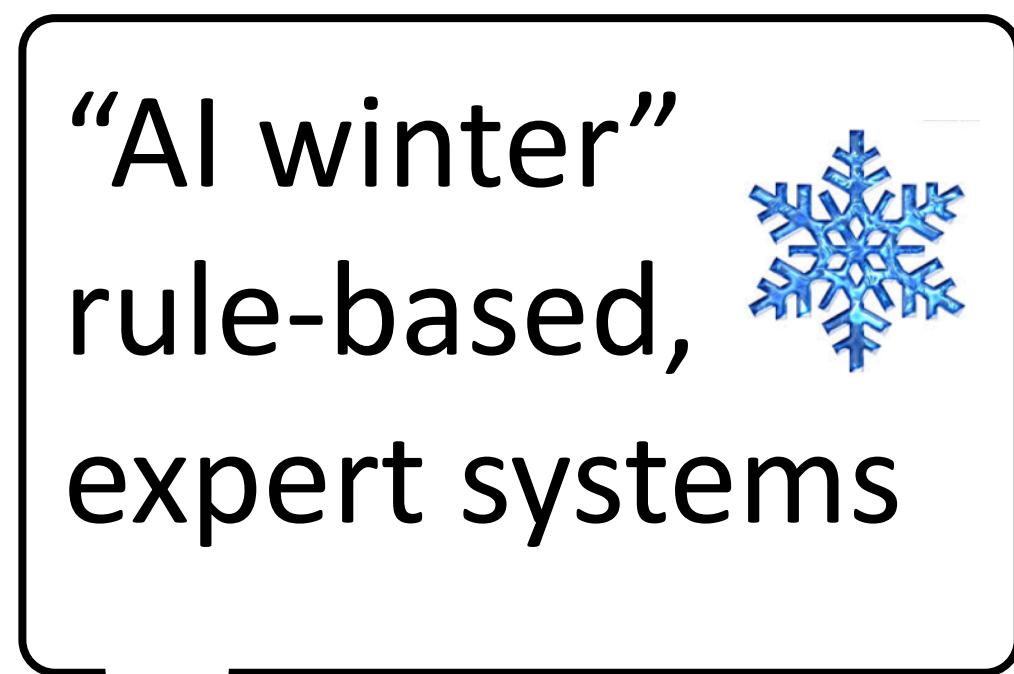
SOURCE	Cela constituerait une solution transitoire qui permettrait de conduire à terme à une charte à valeur contraignante.
HUMAN	That would be an interim solution which would make it possible to work towards a binding charter in the long term .
1x DATA	[this] [constituerait] [assistance] [transitoire]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

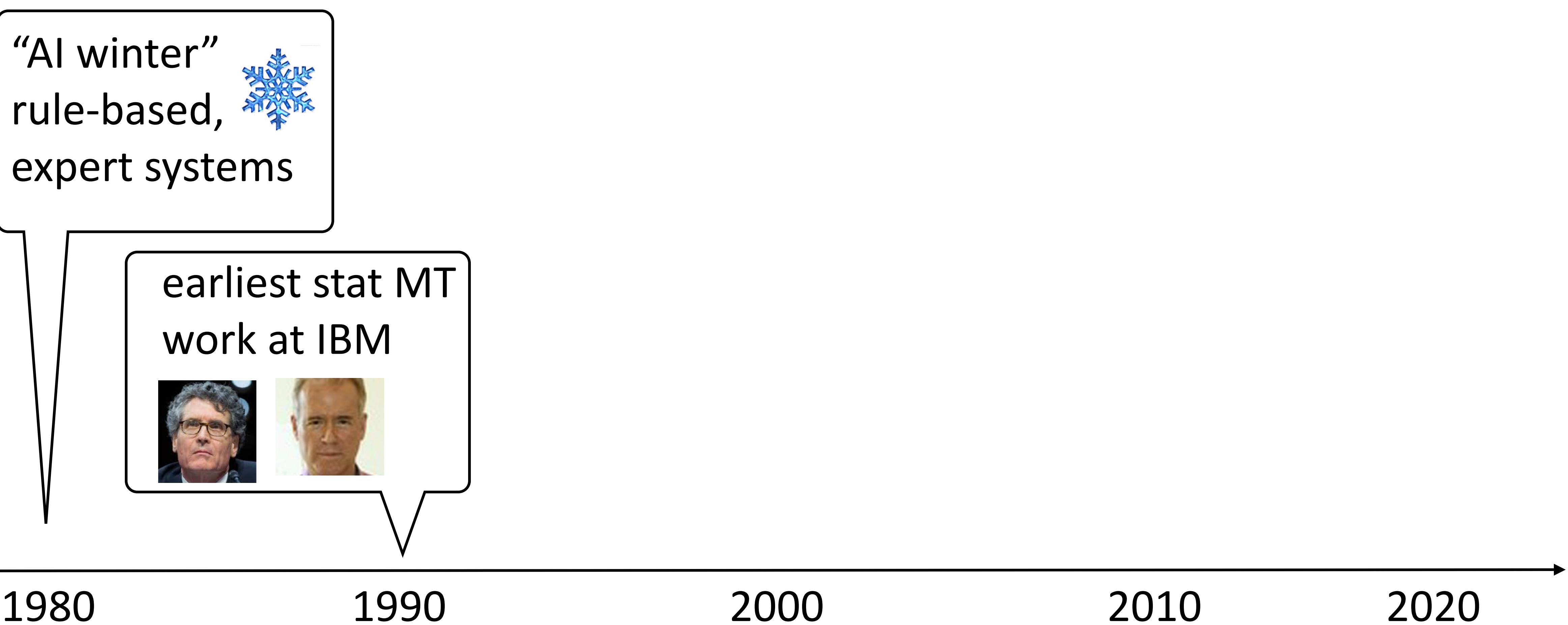
1990

2000

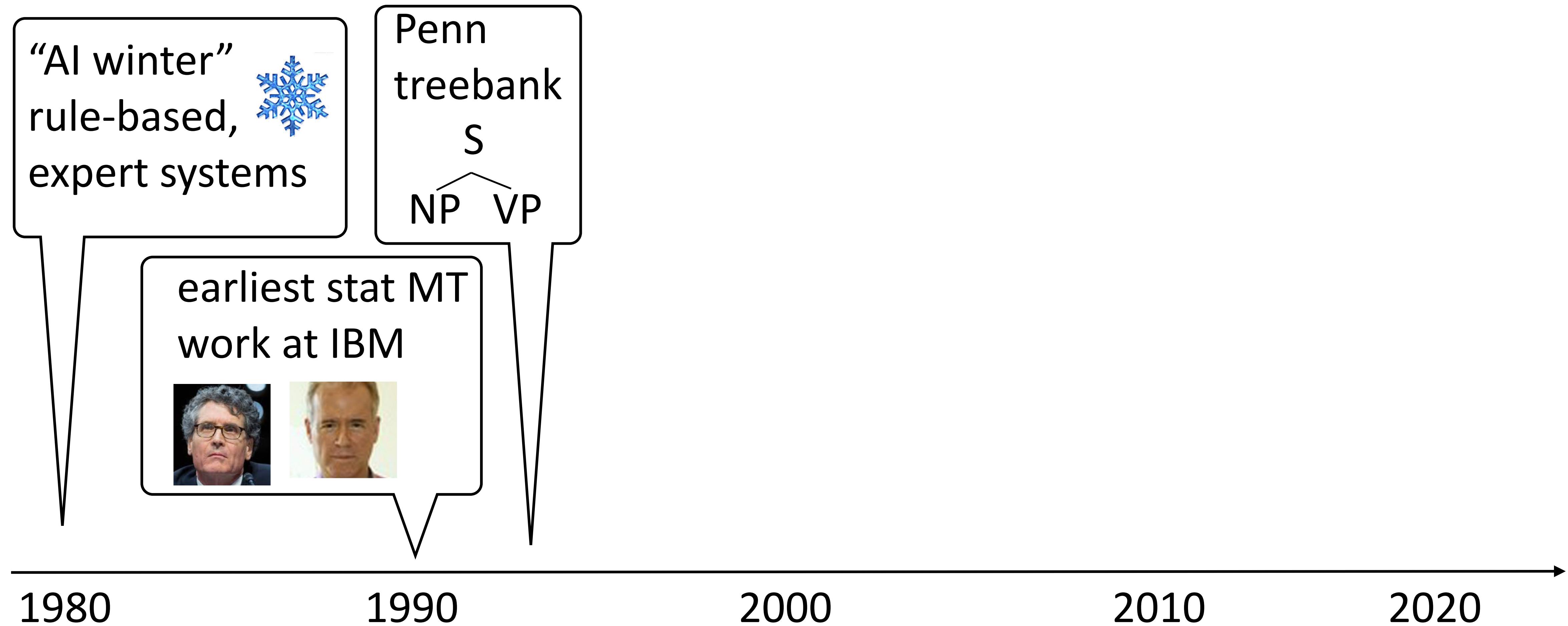
2010

2020

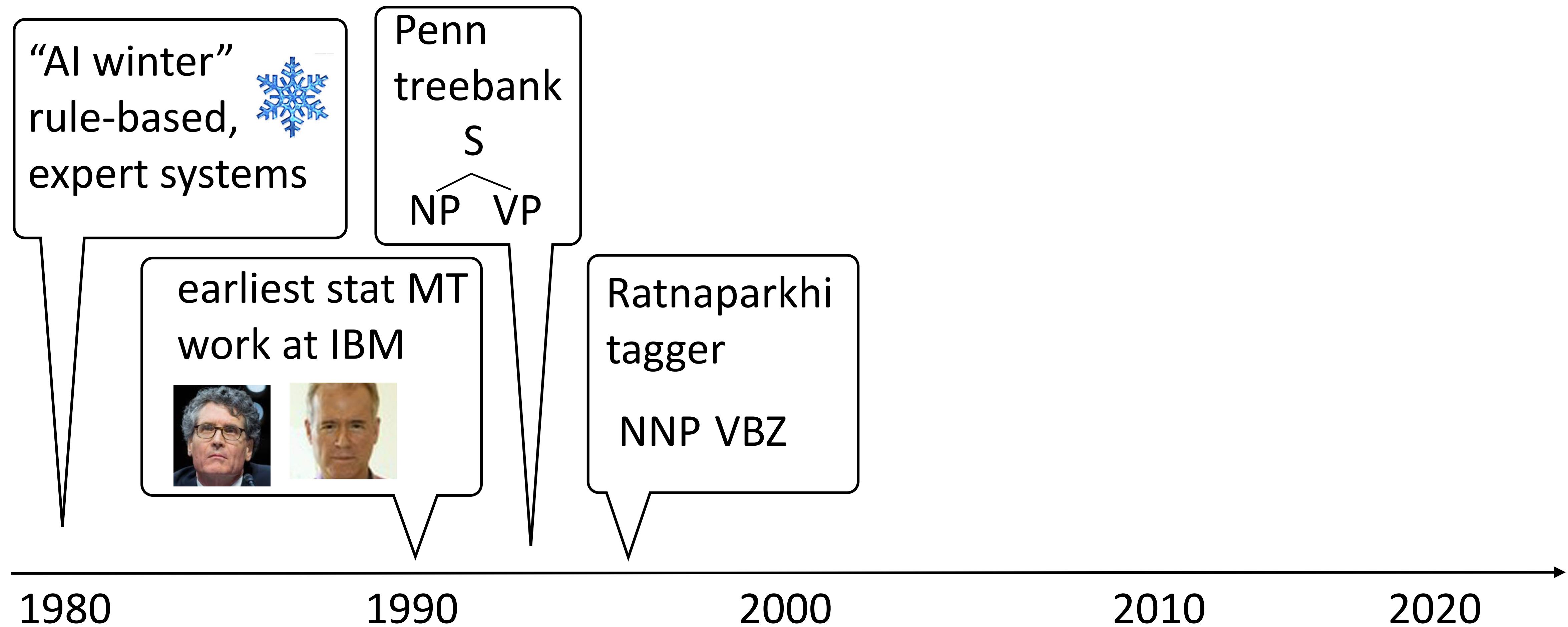
A brief history of (modern) NLP



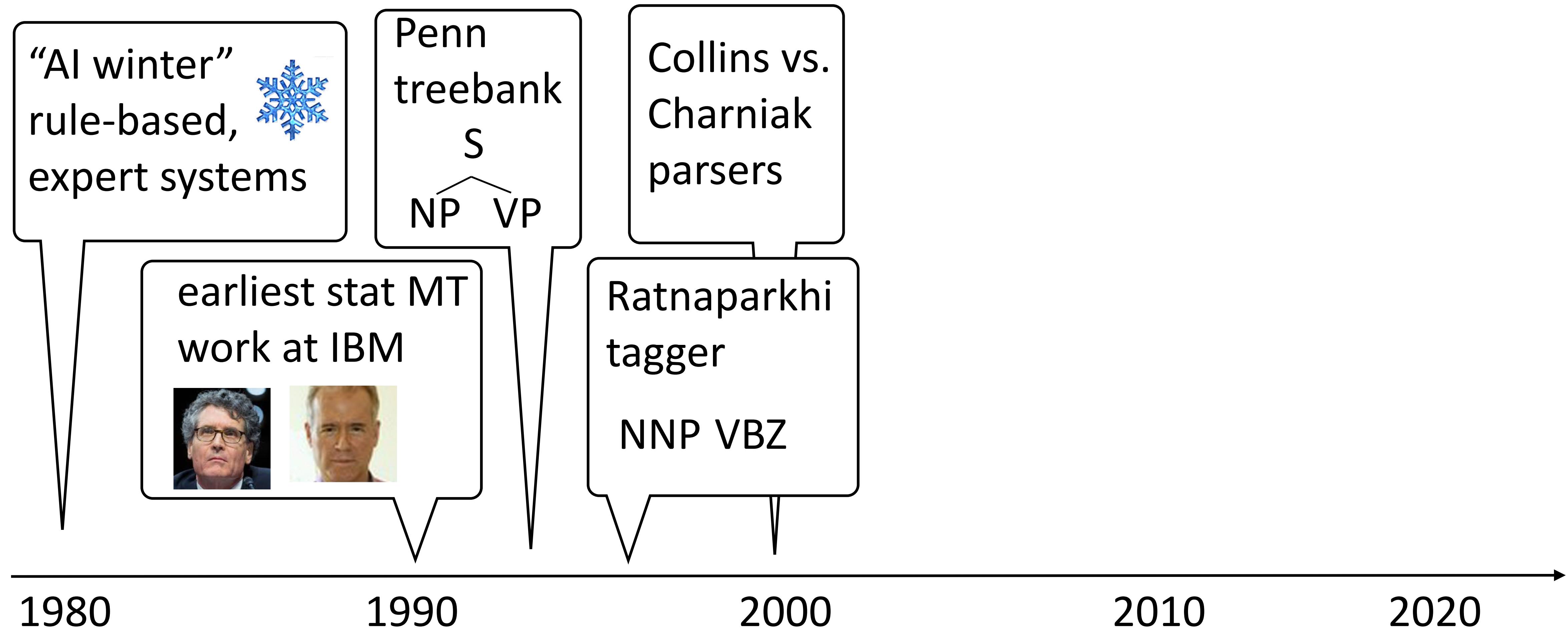
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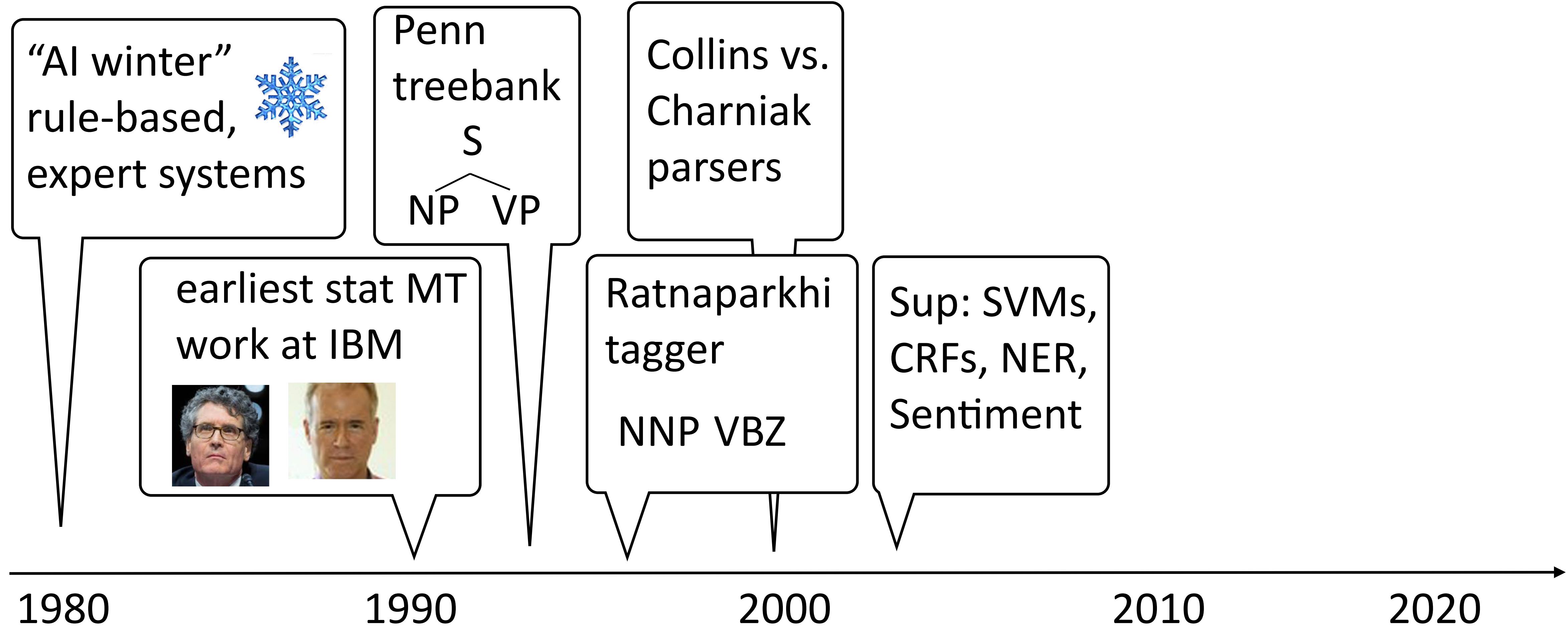
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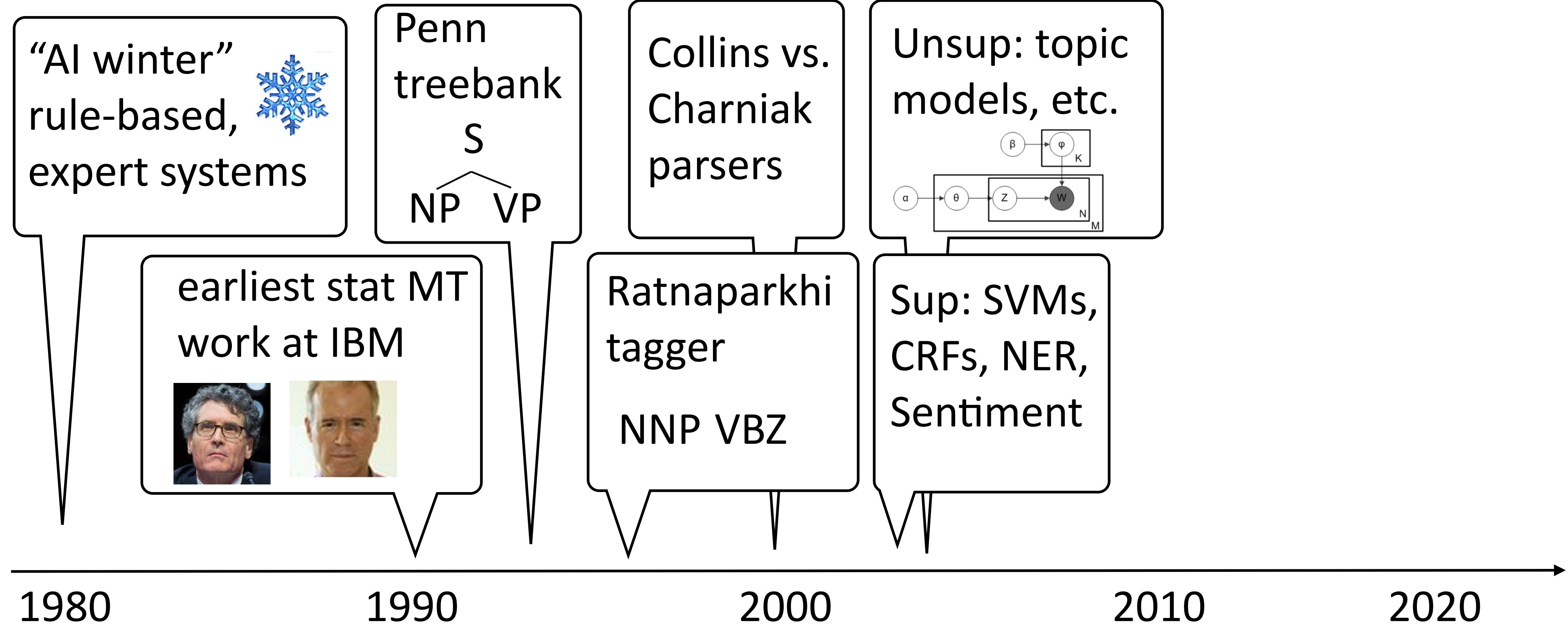
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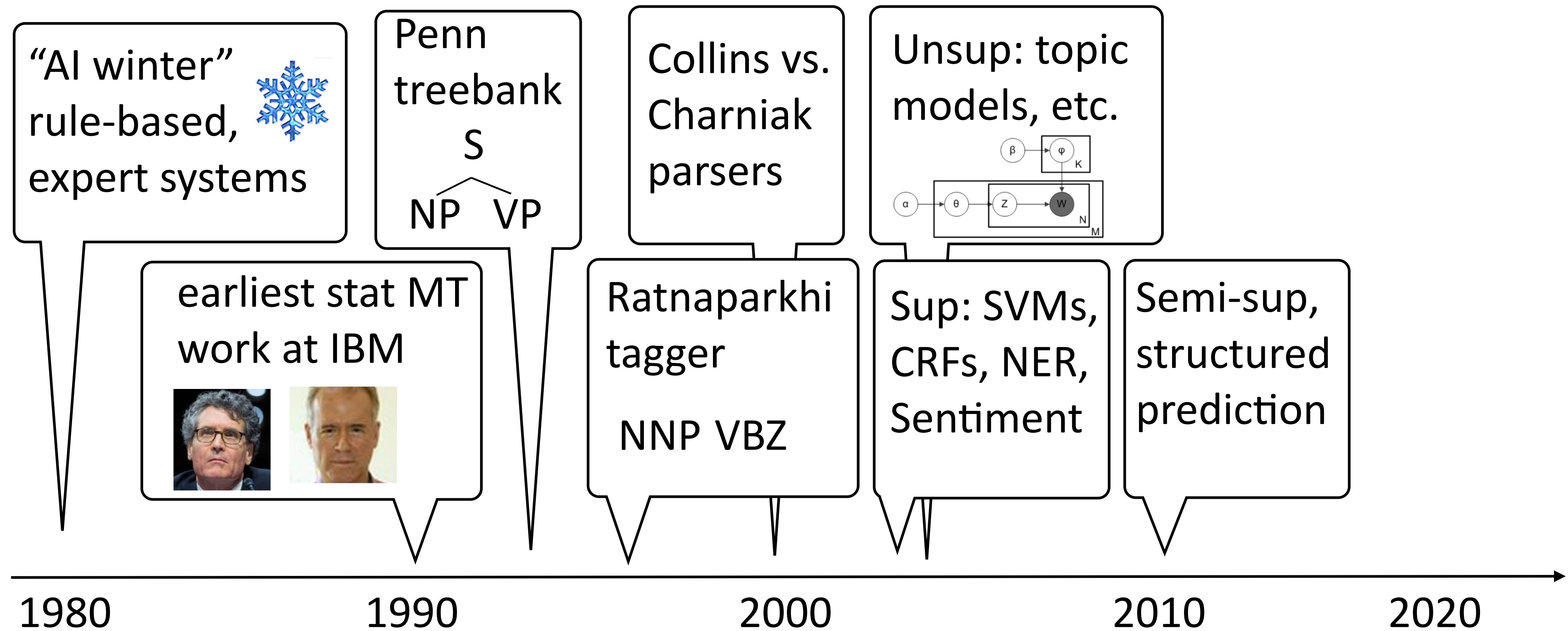
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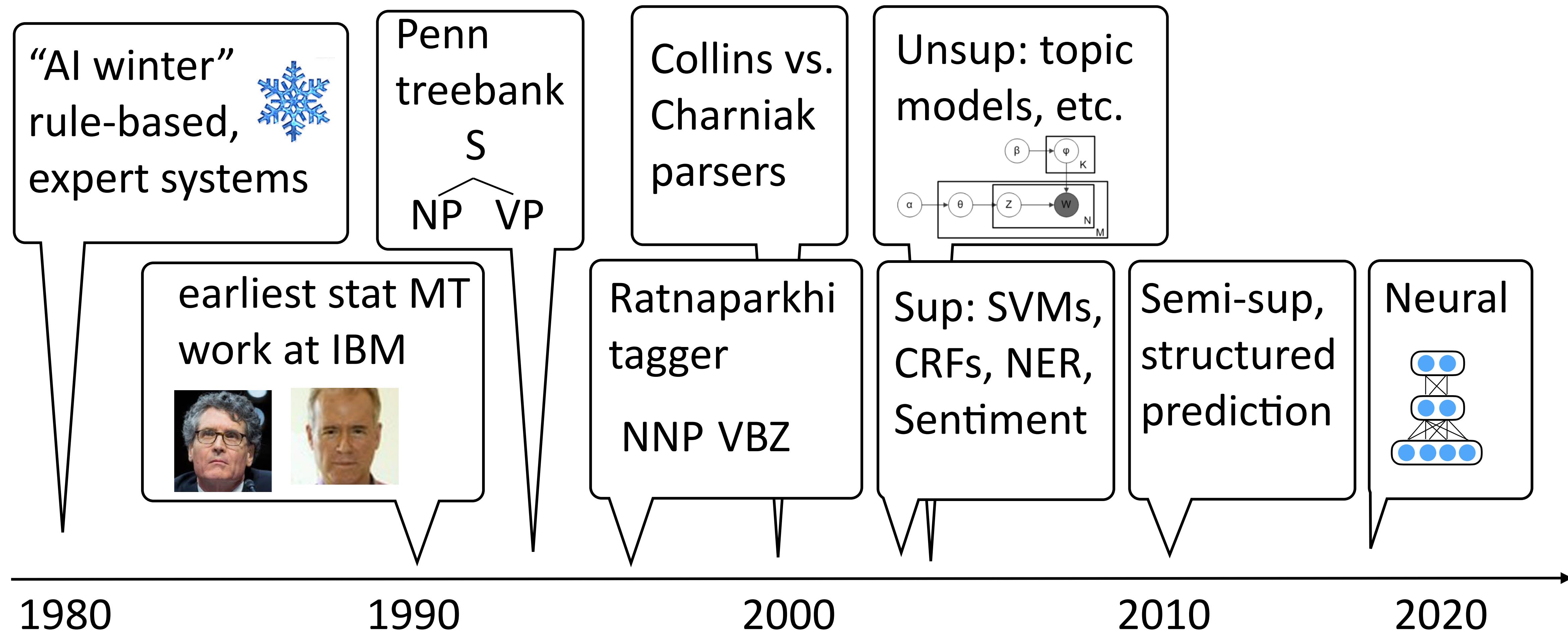
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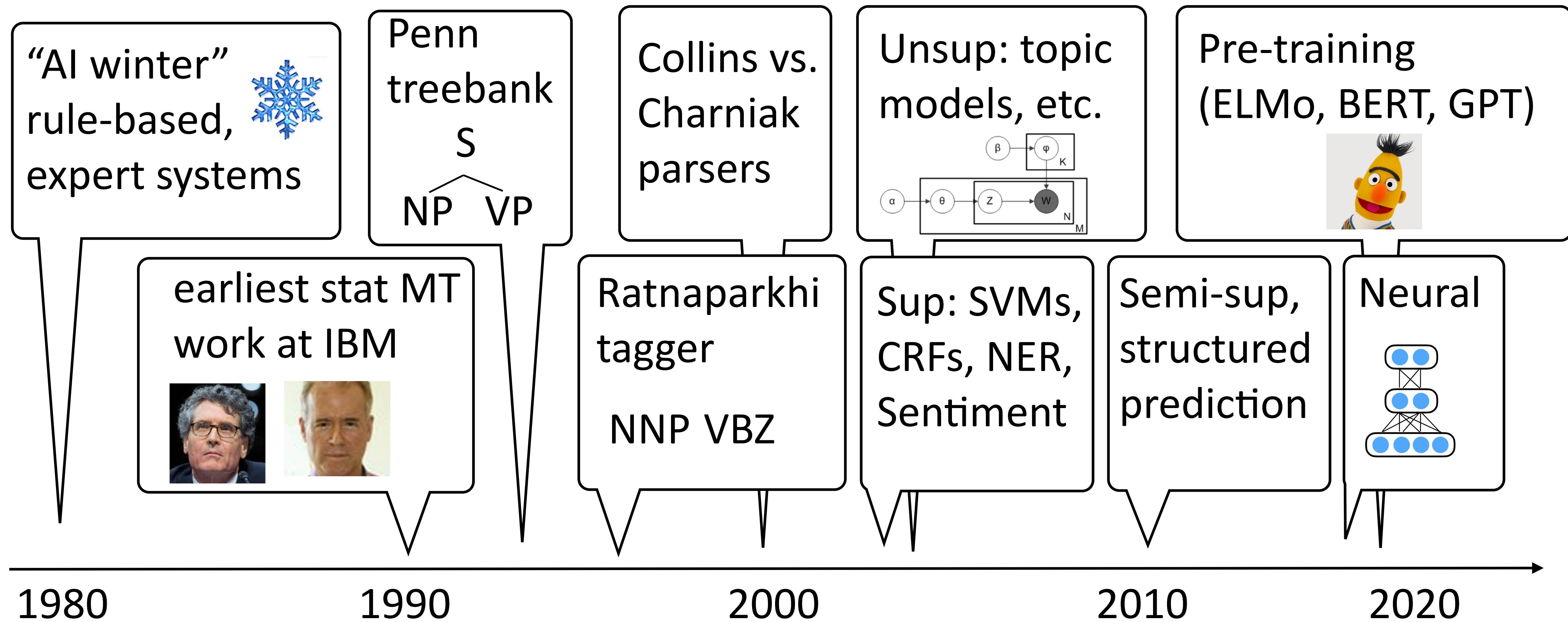
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How Much Training Data do we Need?

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

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

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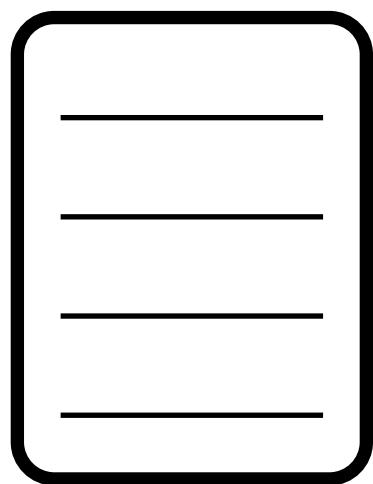
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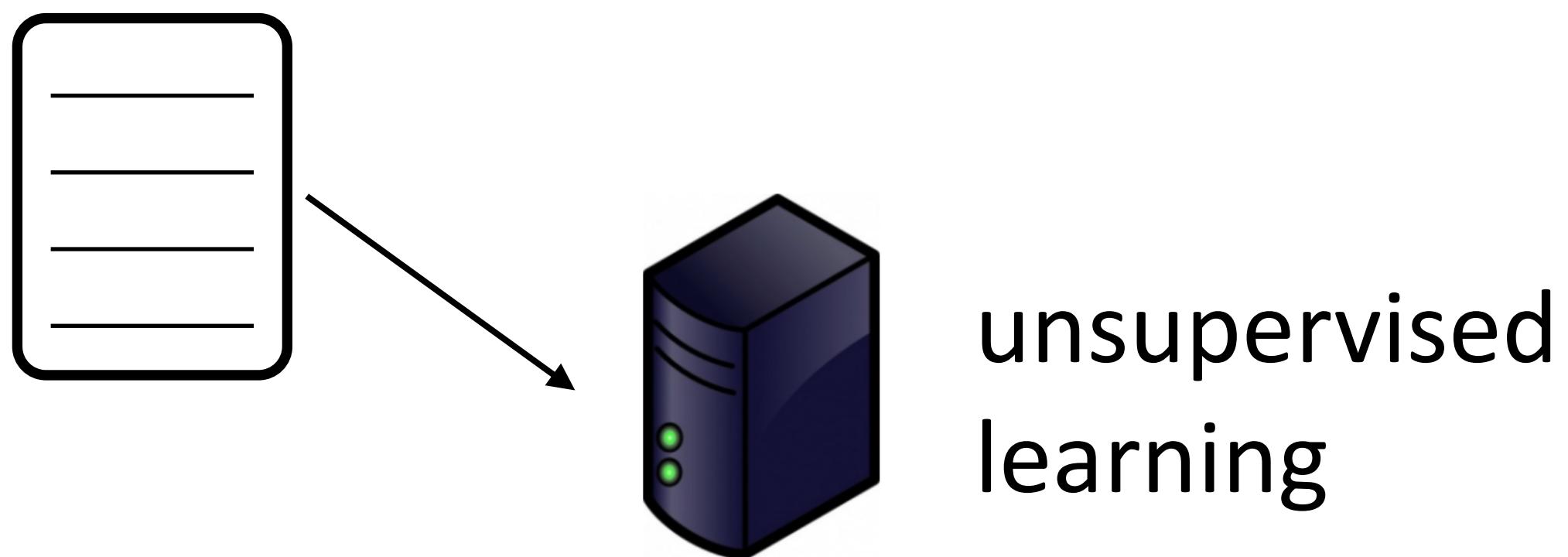
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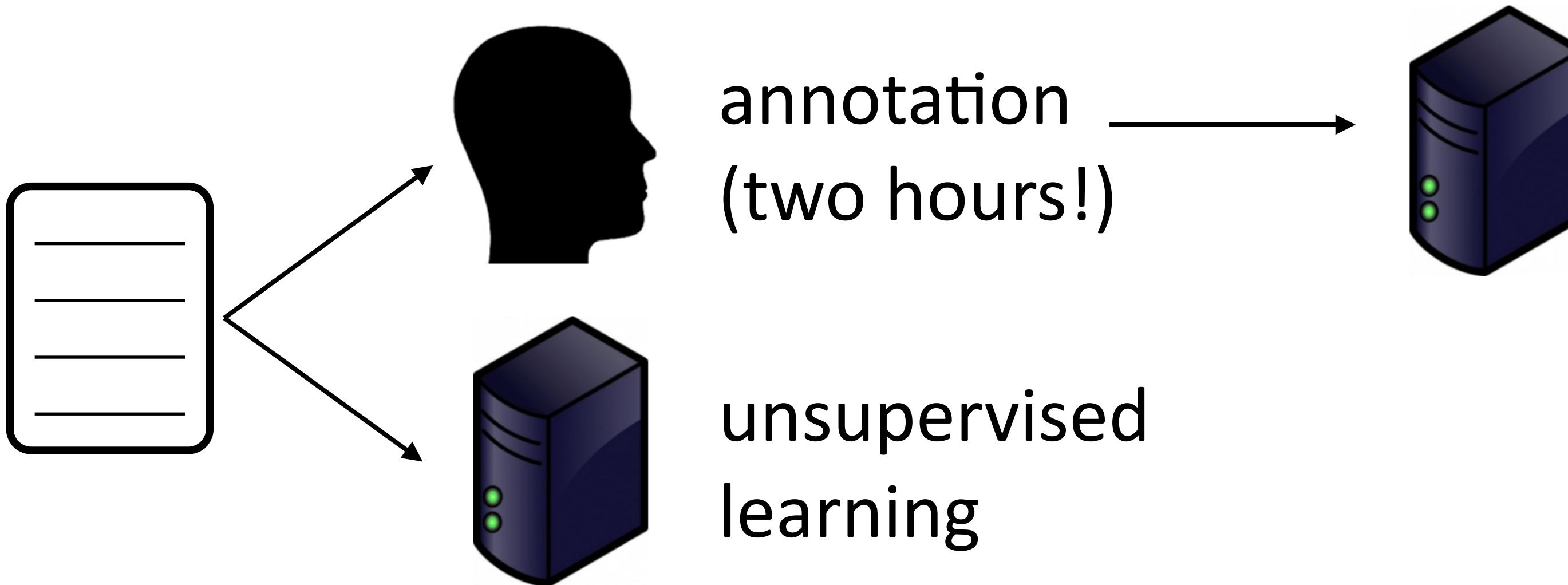
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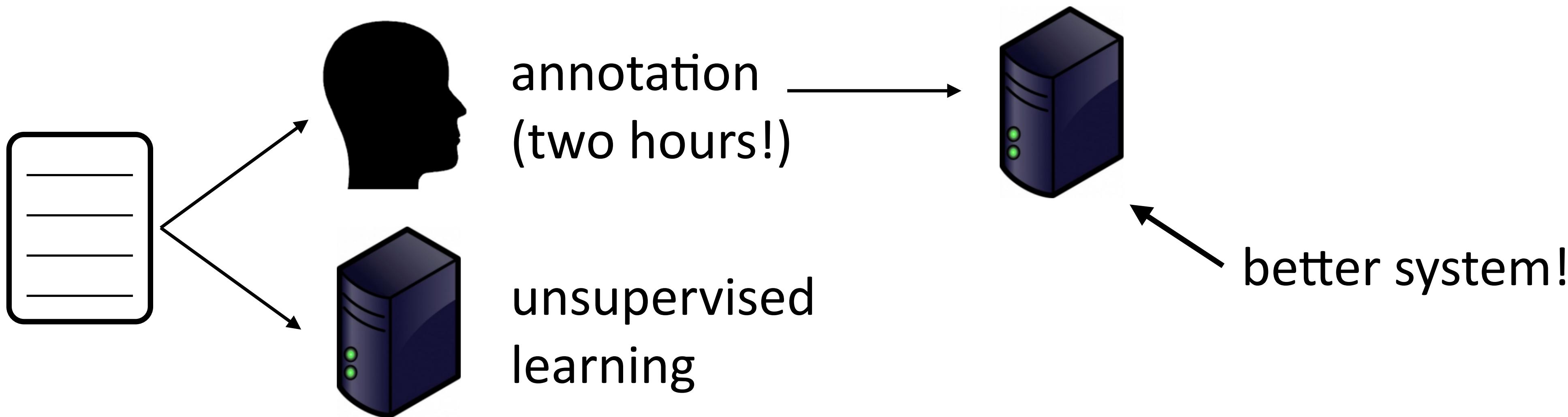
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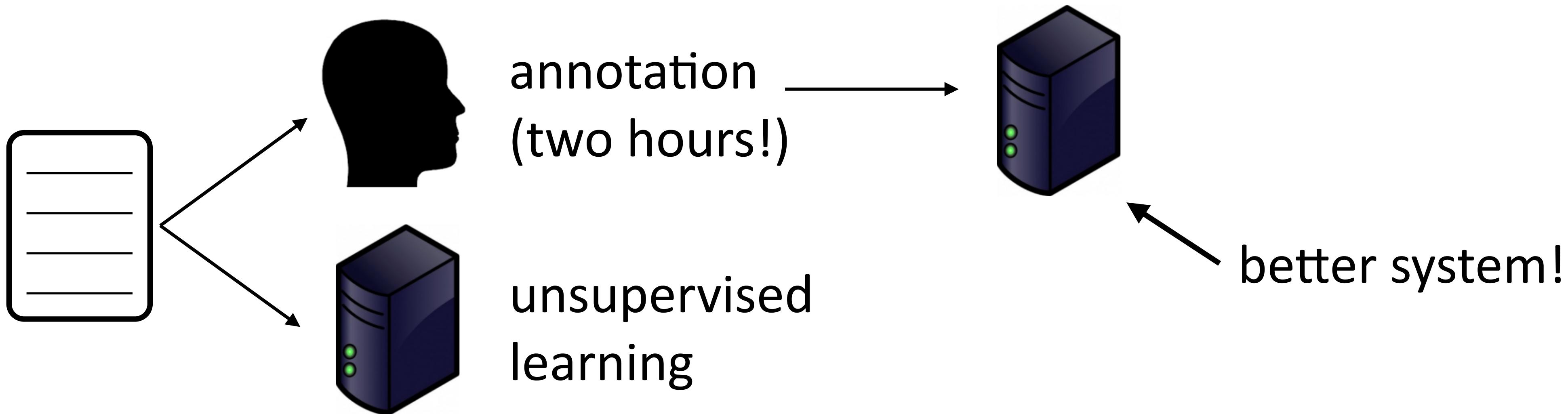
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- ▶ Even neural nets can do pretty well!

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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

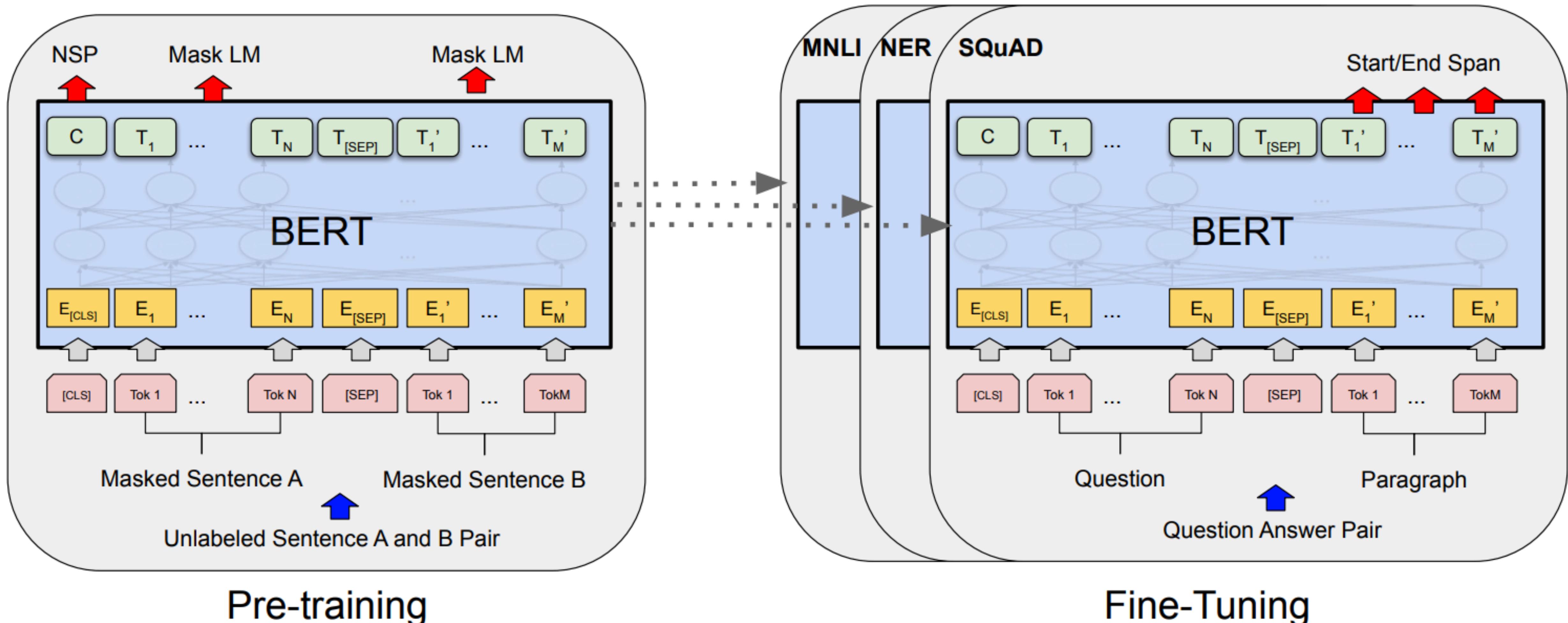
$P(w | \text{the acting was horrible, I think the movie was}) = 0.1 \text{ bad}$

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

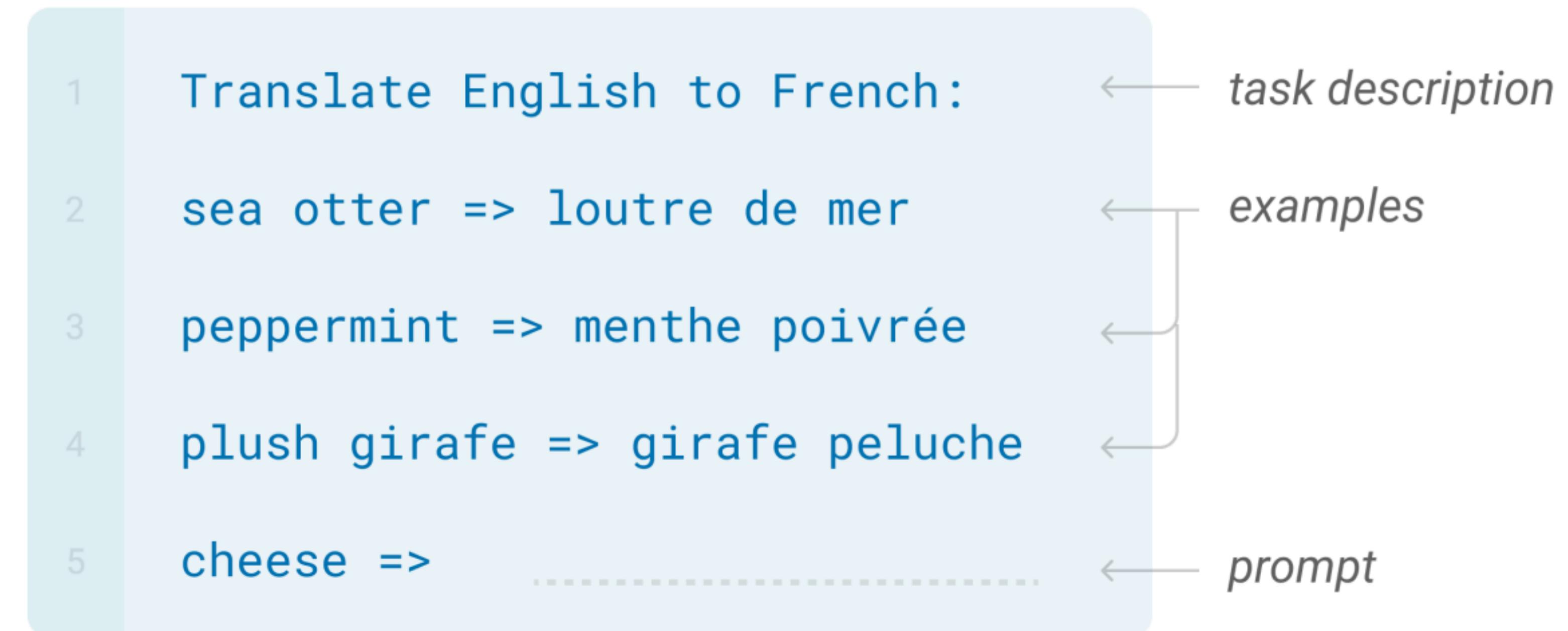
Devlin et al. (2019)

GPT and In-Context Learning

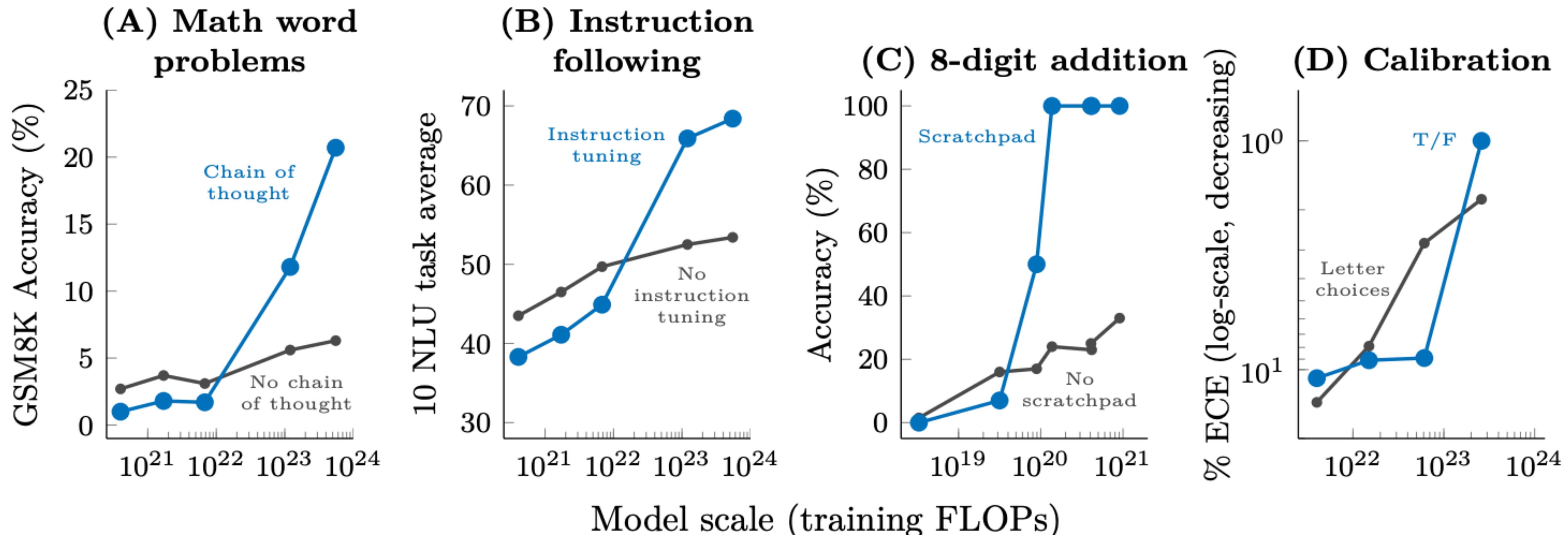
- ▶ Even more “extreme” setting: no gradient updates to model, instead large language models “learn” from examples in their context
- ▶ Many papers studying why this works. We will read some!

Few-shot

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

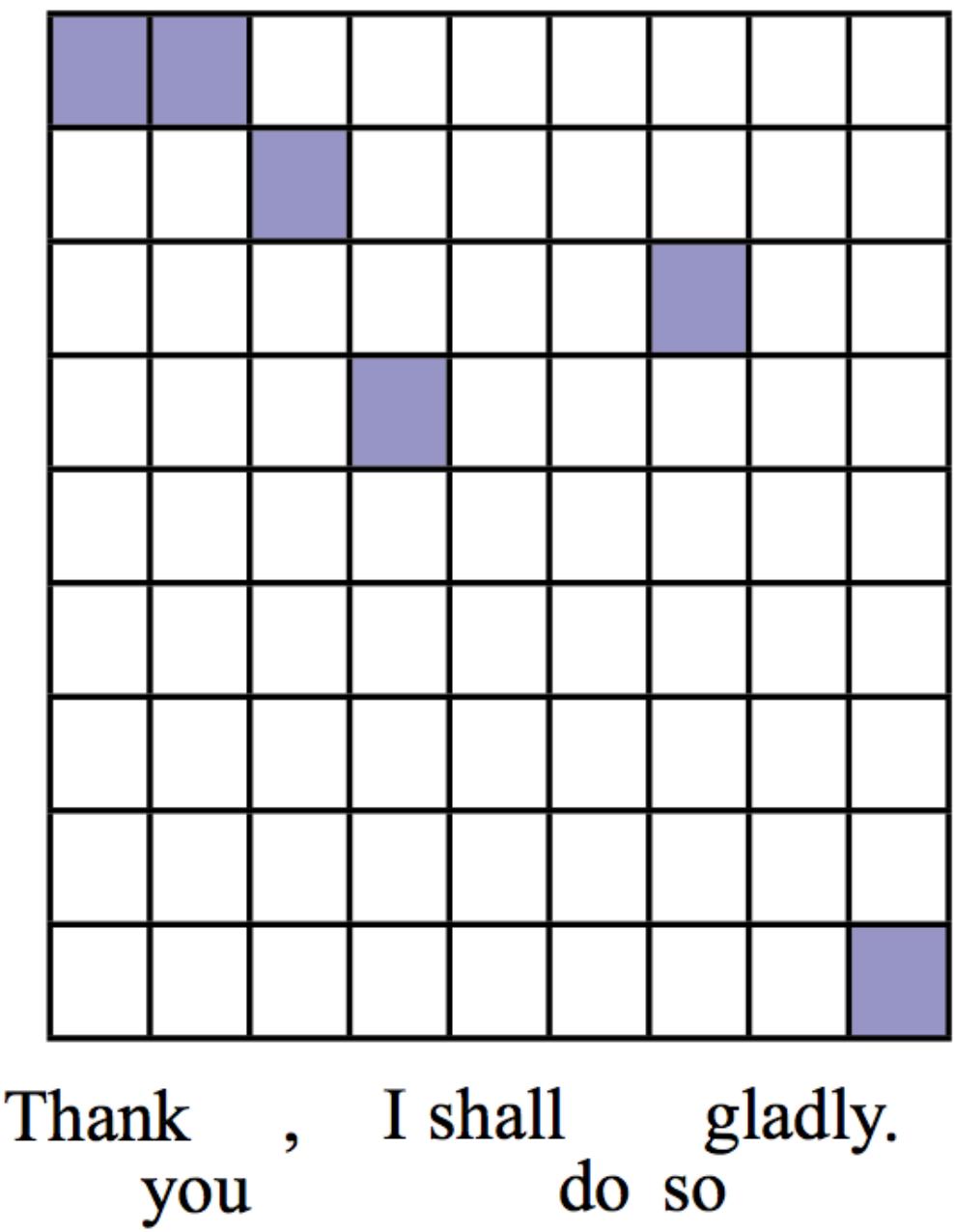


Scaling Laws

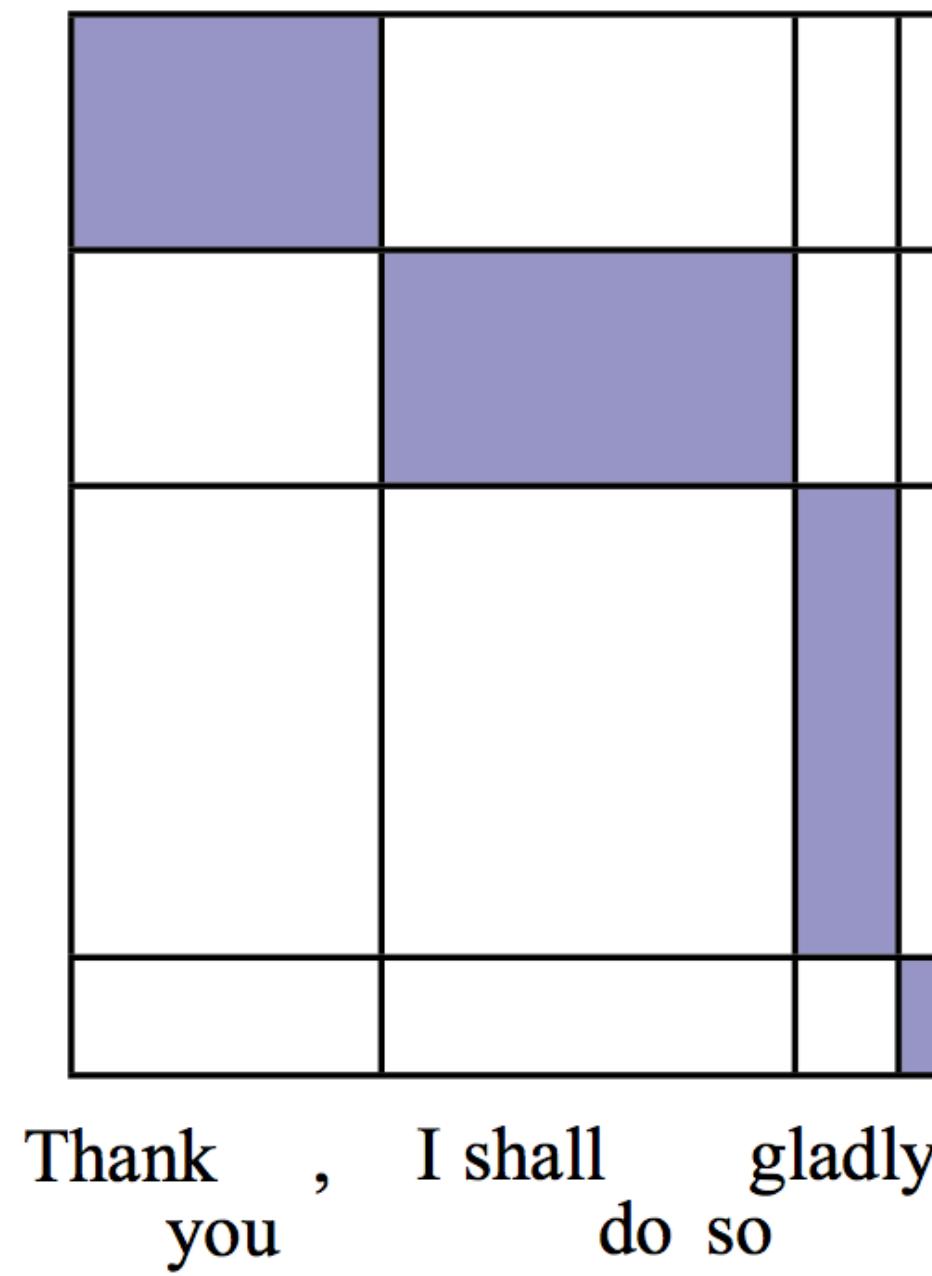


- ▶ Many of the ideas that are big in 2023 only make sense and only work because the models are so big!

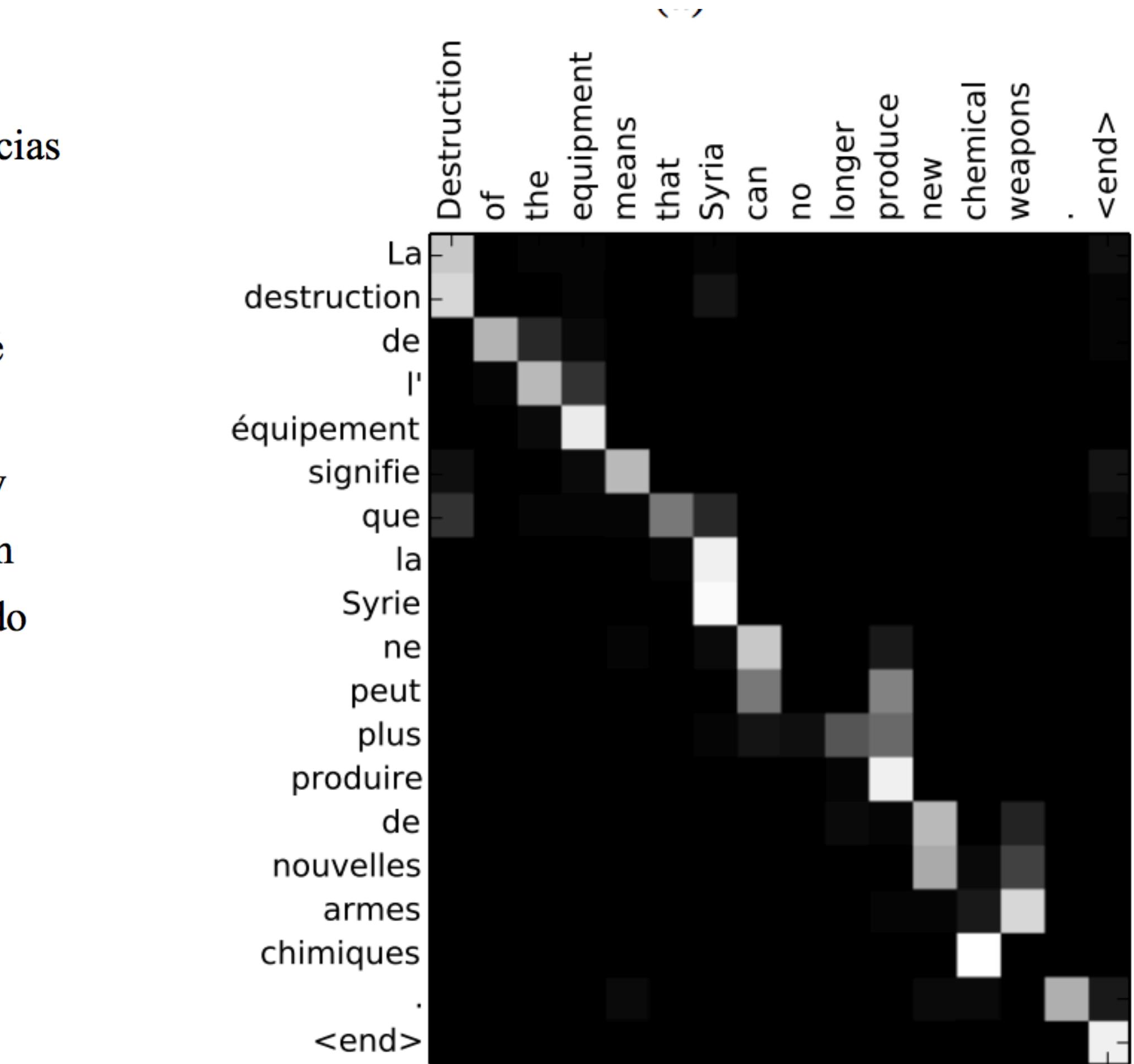
Less Manual Structure?



(a) example word alignment



(b) example phrase alignment



DeNero et al. (2008)

Bahdanau et al. (2014)

Does manual structure have a place?

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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)

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- ▶ Can multi-task learning help?

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- ▶ NLP encompasses all of these things