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
alan.ritter@cc.gatech.edu

Teaching Assistants

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jyu673@gatech.edu

Junmo Kang
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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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There will be a lot of math and programming!

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

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- Final project

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- 3 written assignments + midterm exam
  - Mostly math problems related to ML / NLP
- 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 matrics, 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

Speech and Language Processing **(3rd ed. draft)**

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

Natural Language Processing

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

Course Goals

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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 2024?
- Make you a “producer” rather than a “consumer” of NLP tools

Programming 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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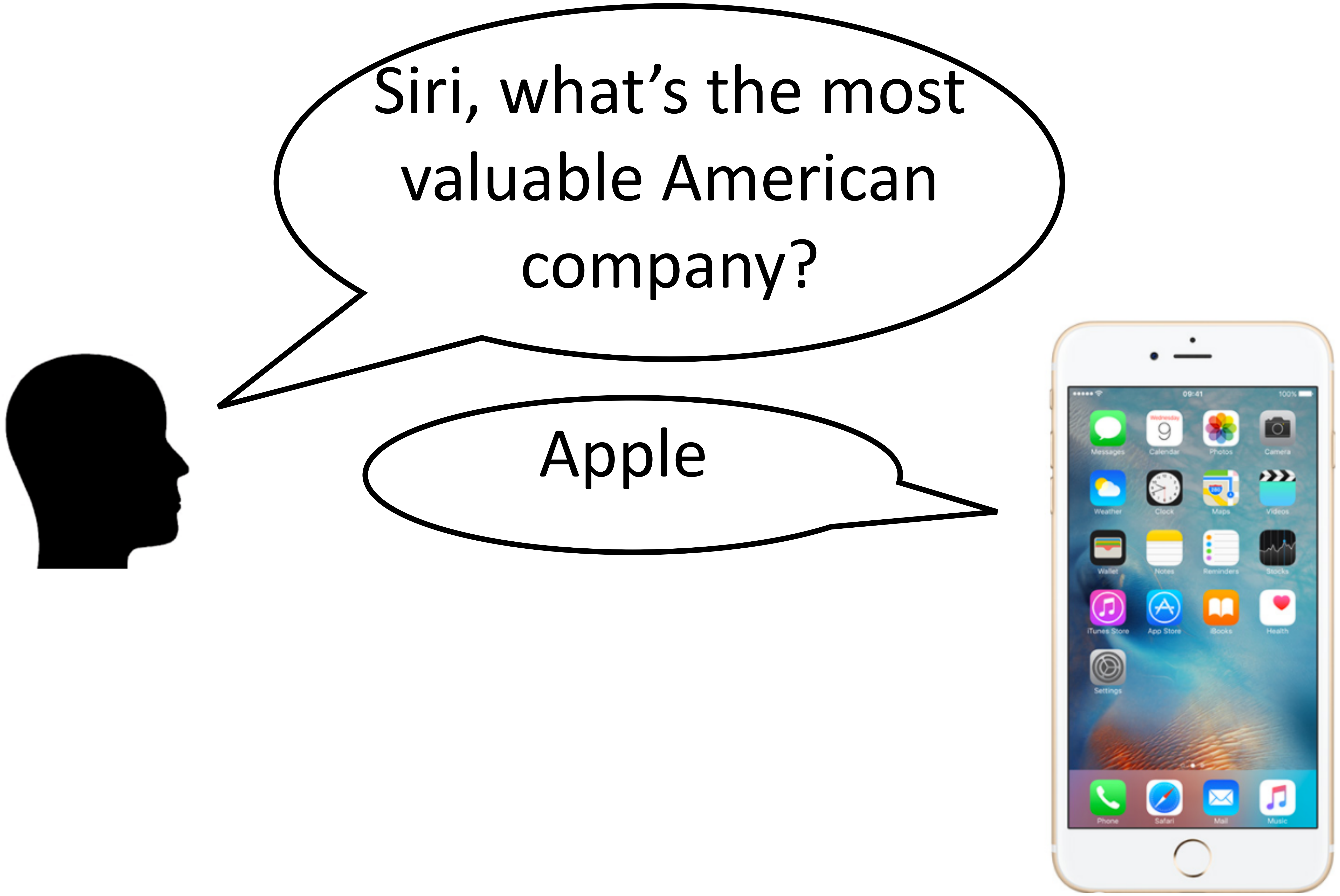

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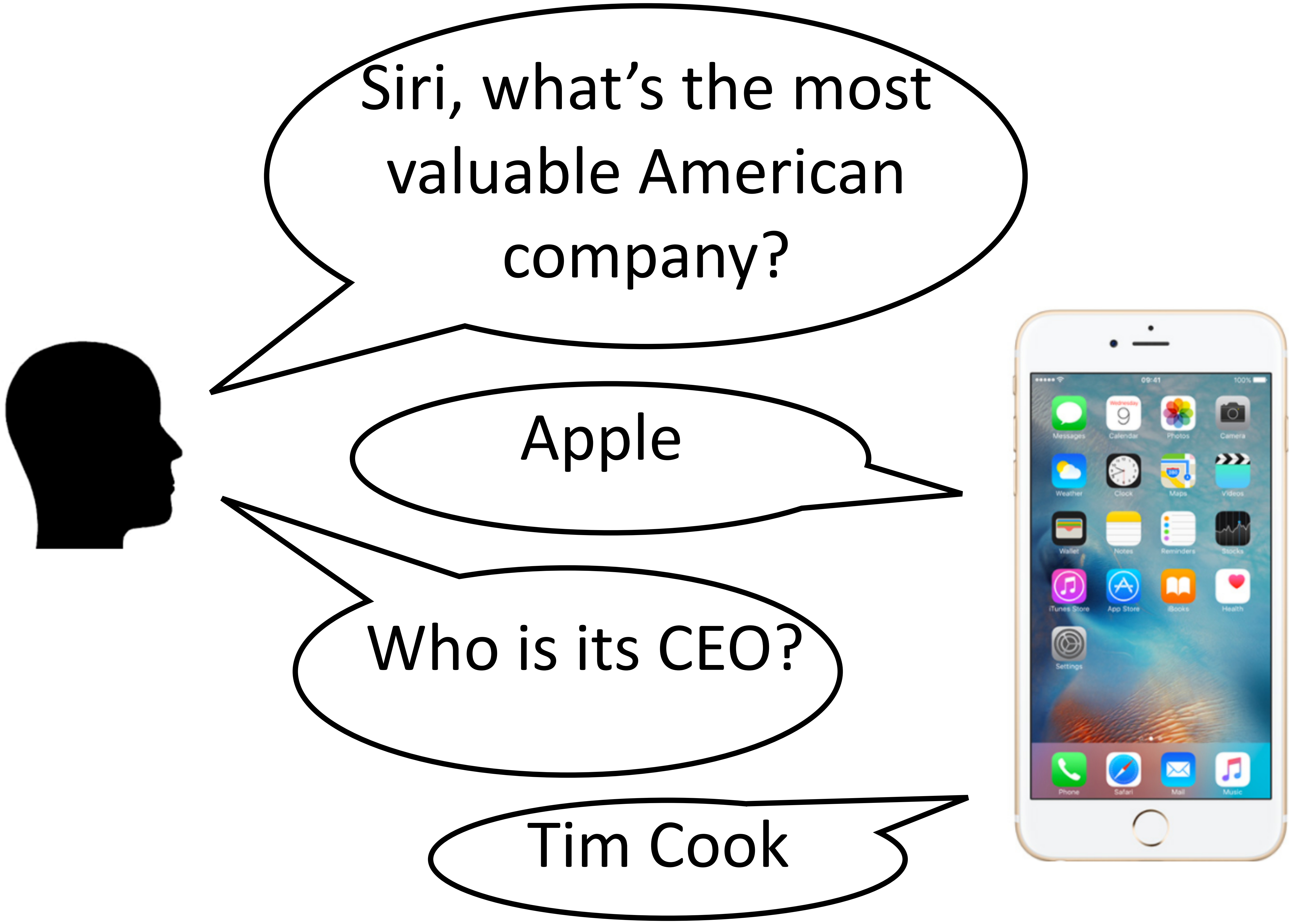

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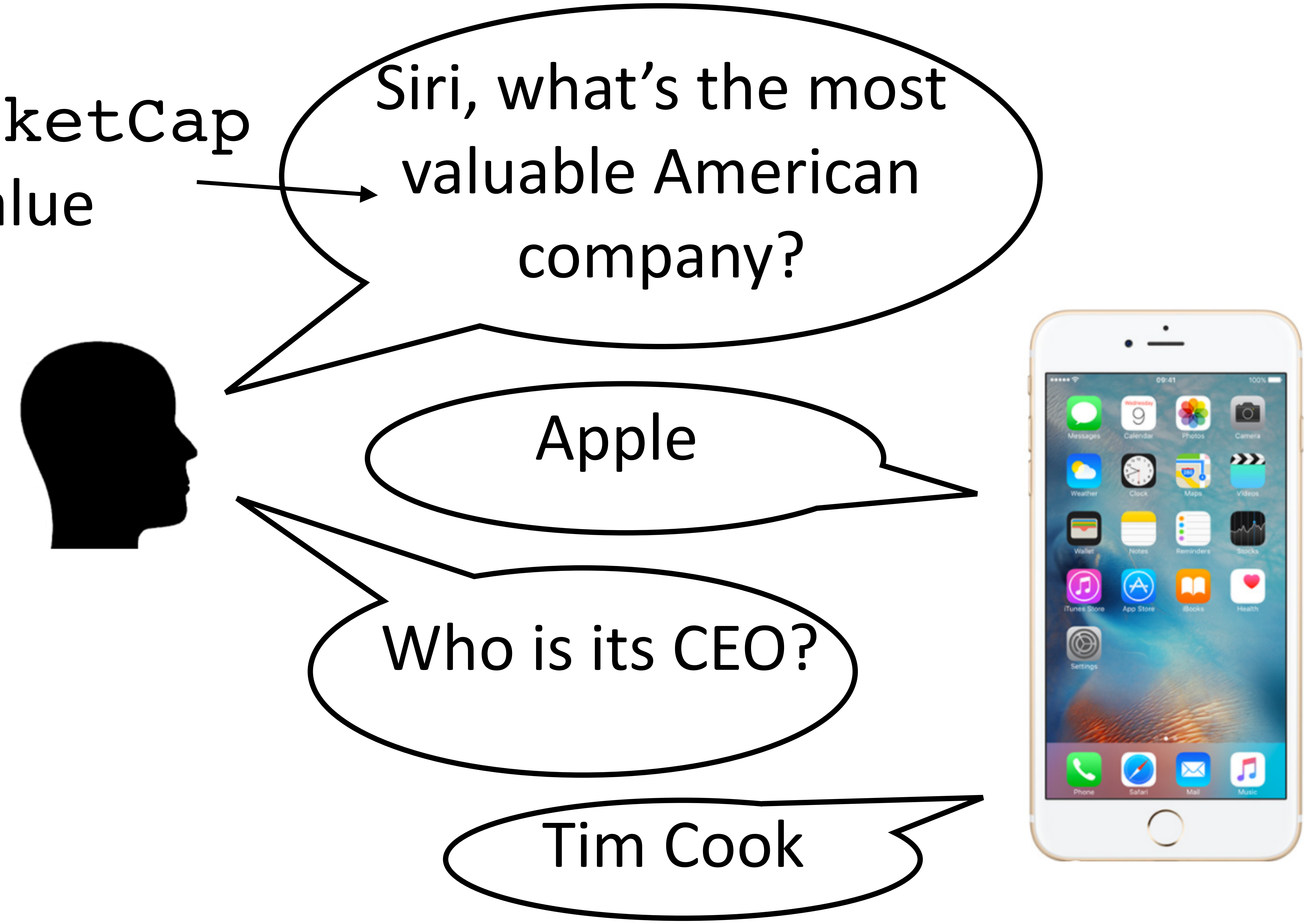
recognize `marketCap` is the target value



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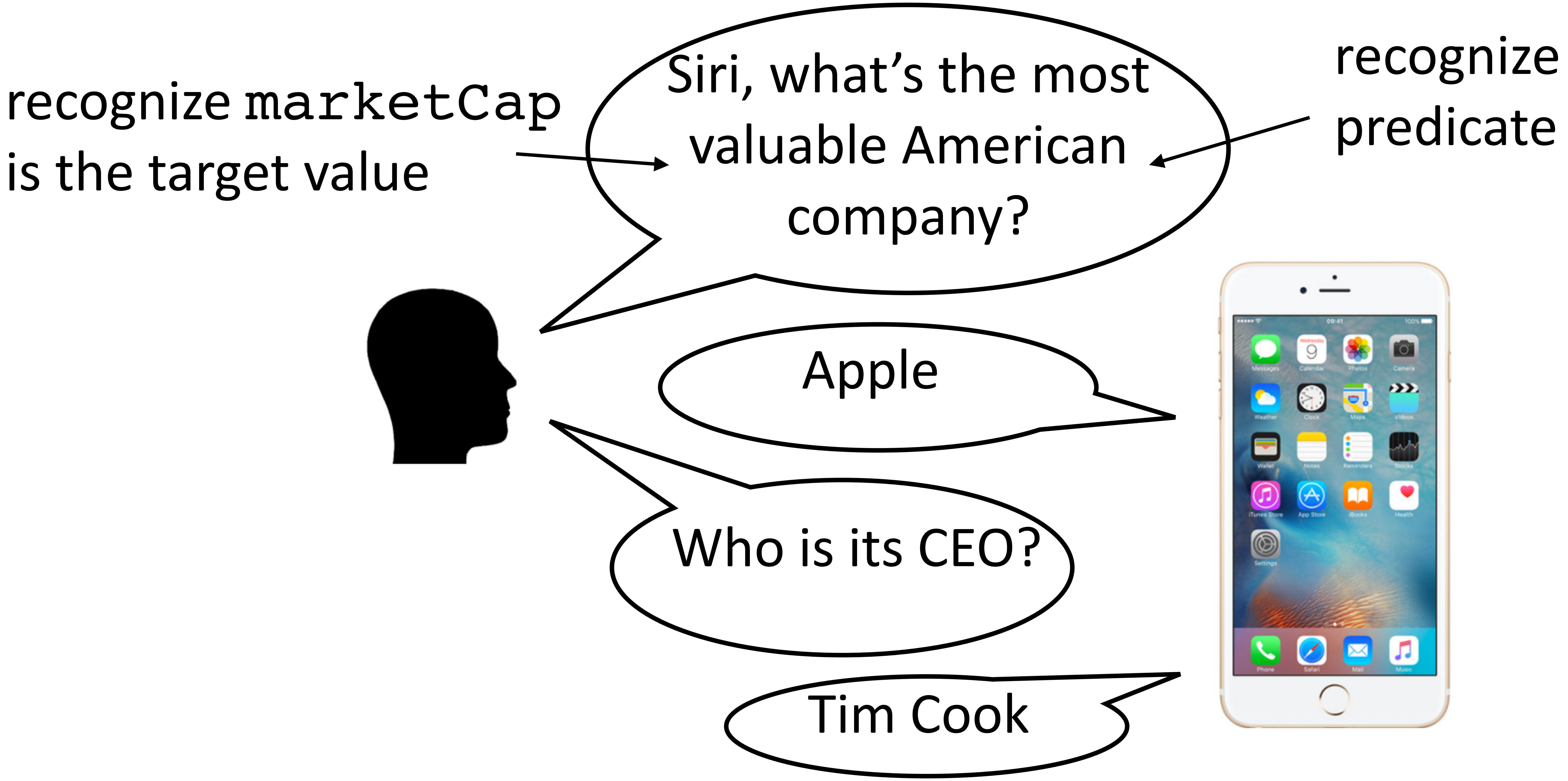

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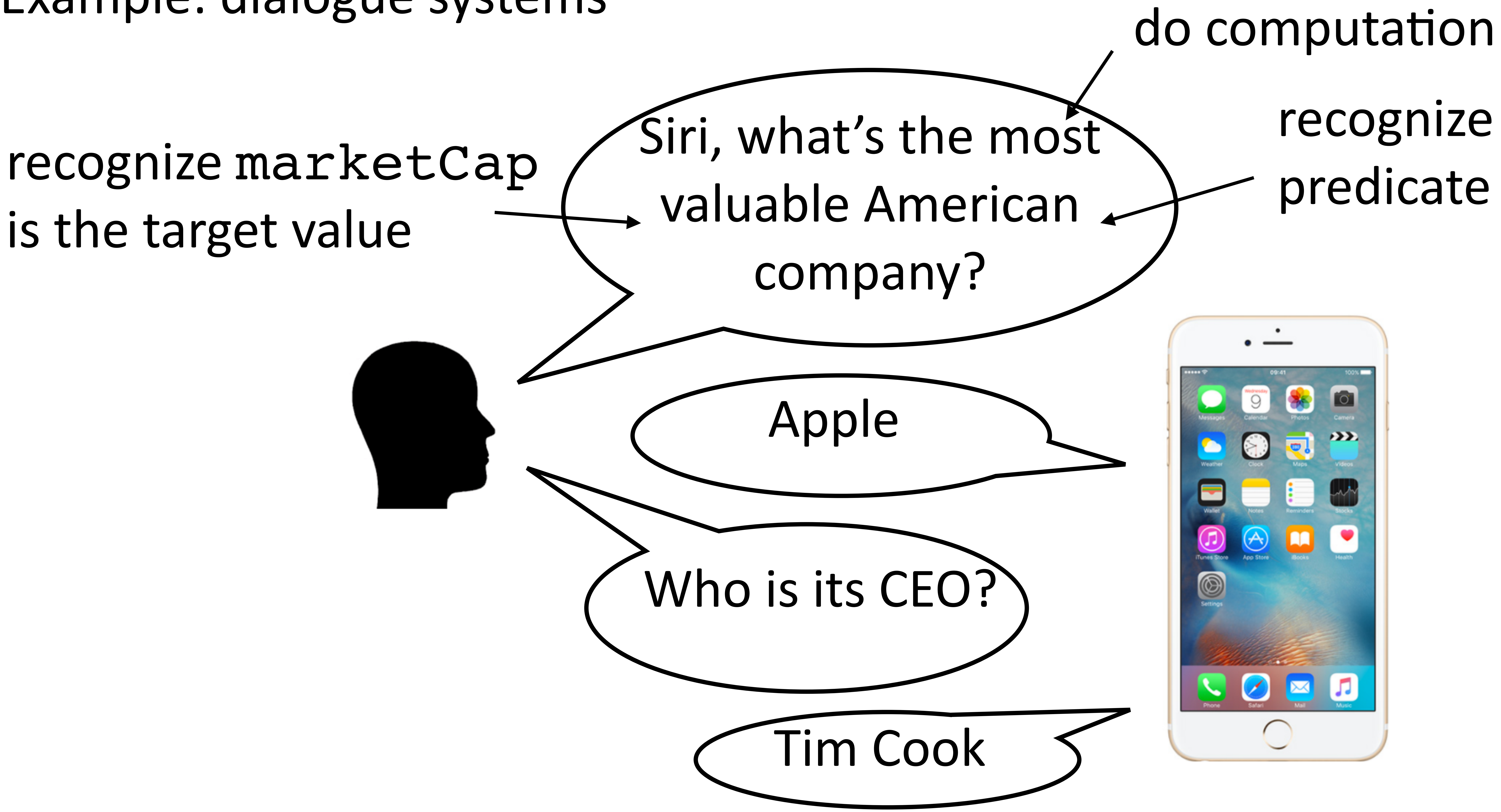

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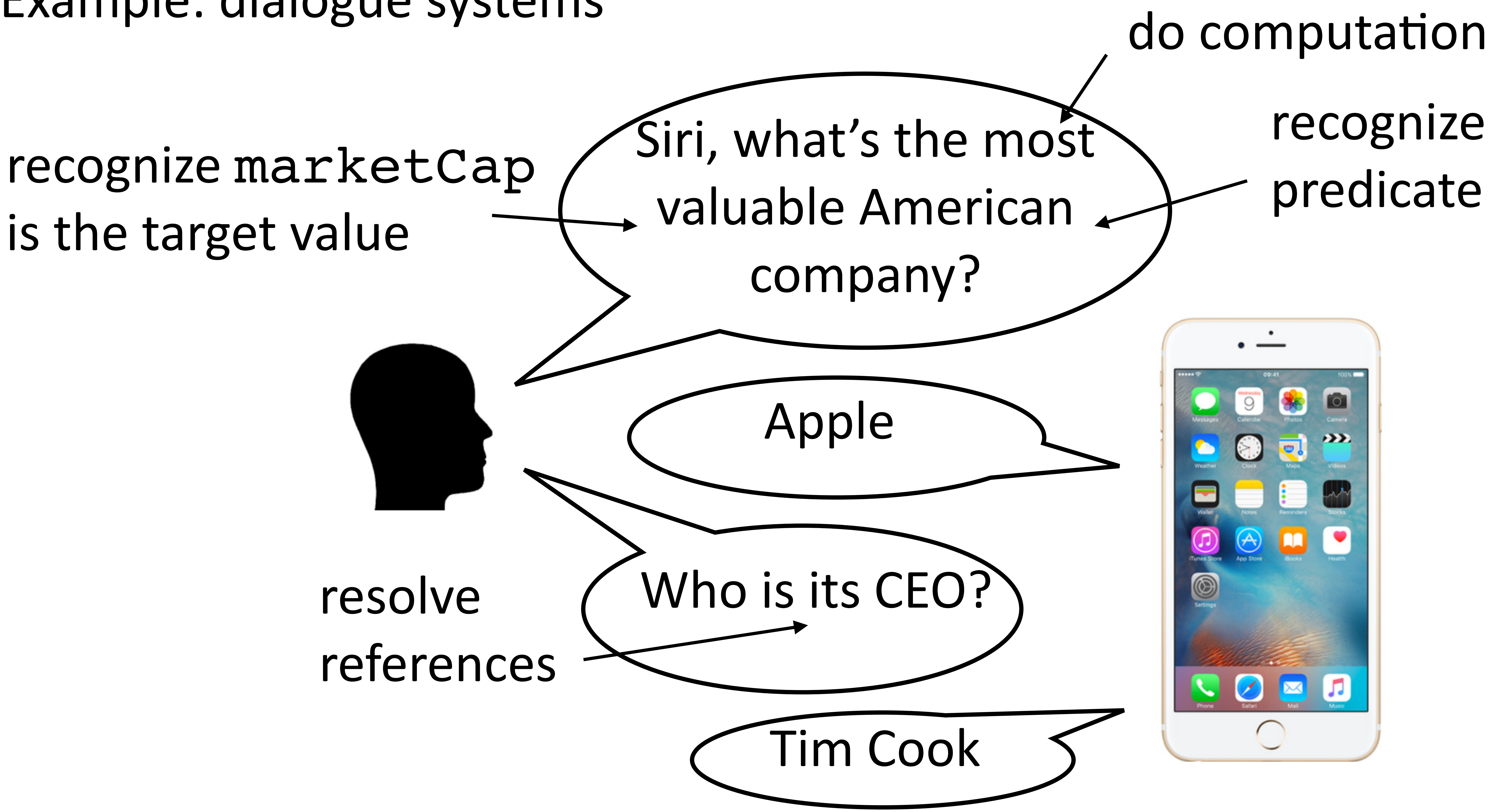

Automatic Summarization

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POLITICS

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paraphrase to provide clarity

Machine Translation

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- Working very well now for high-resource languages.
- Some language pairs more difficult (e.g. English-Chinese)
- Still a number of challenges (scaling up to thousands of languages, etc.)

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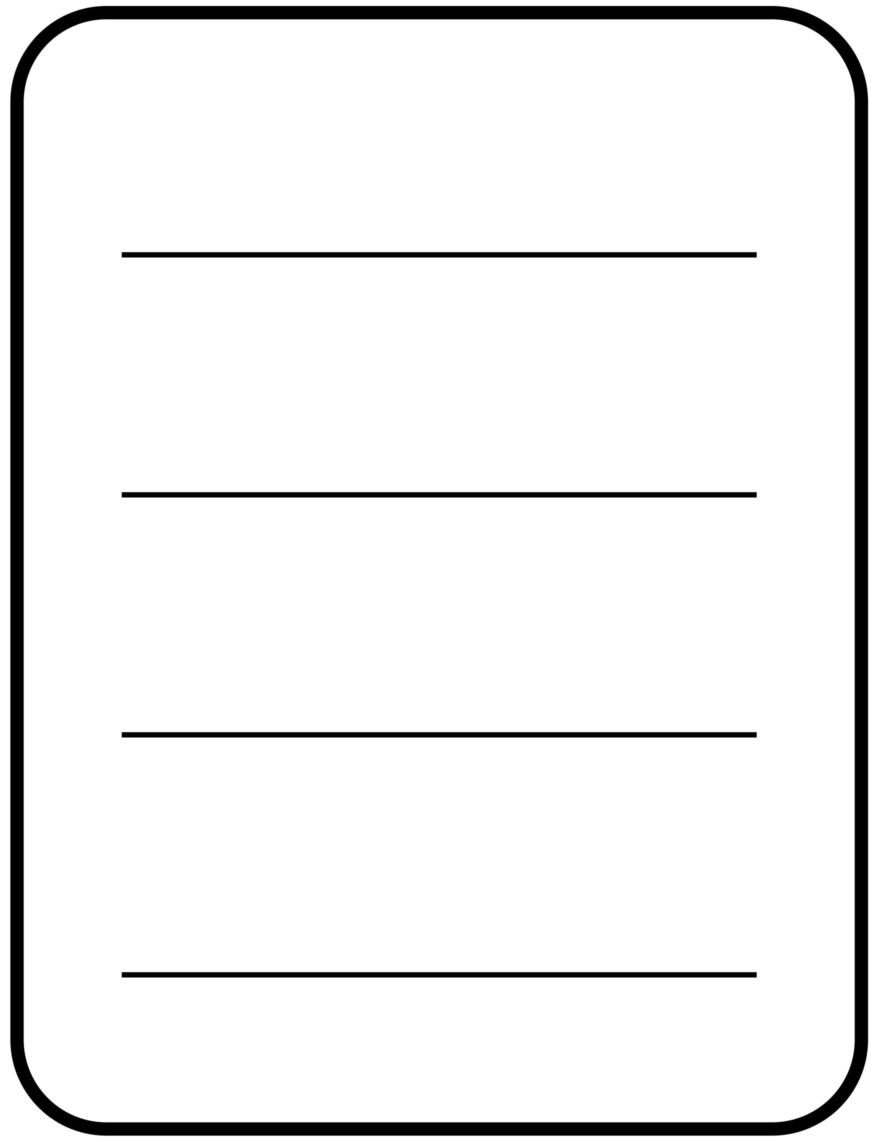

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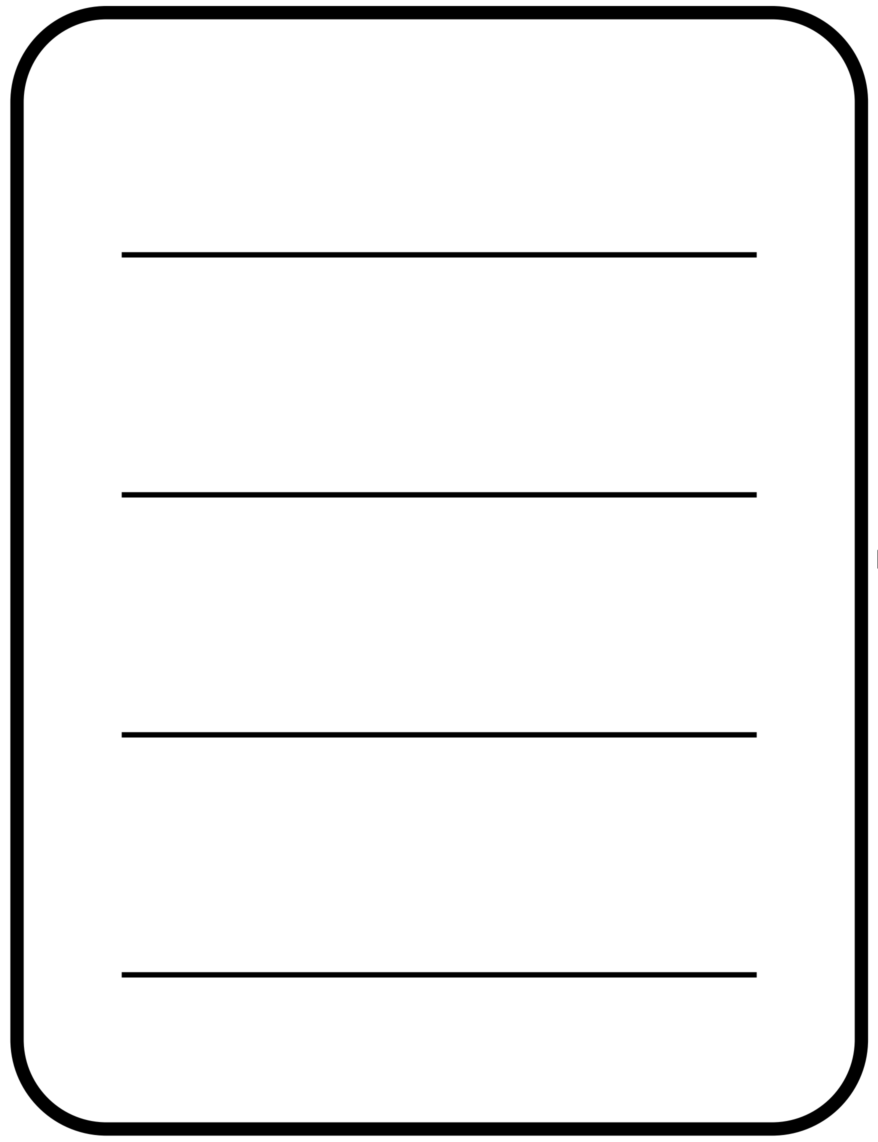

Text Analysis

Syntactic parses

Coreference resolution

Entity disambiguation

Discourse analysis

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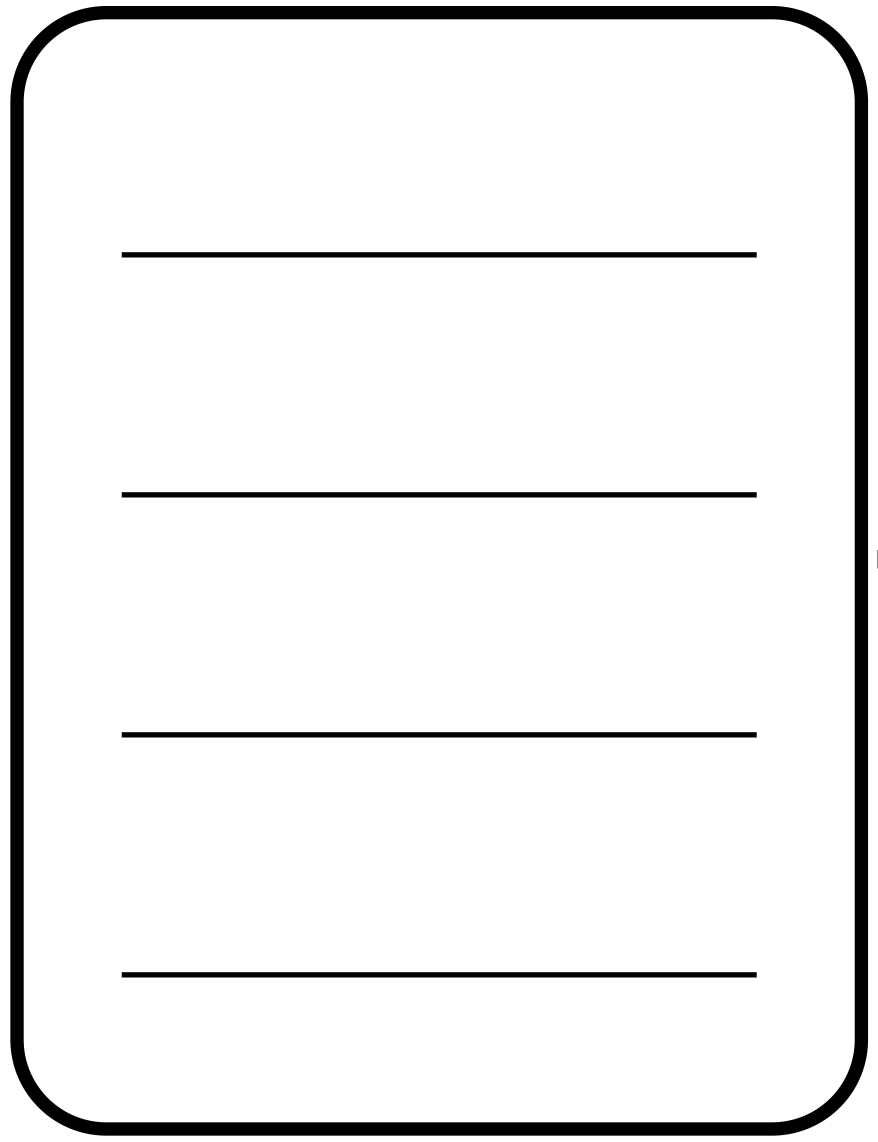

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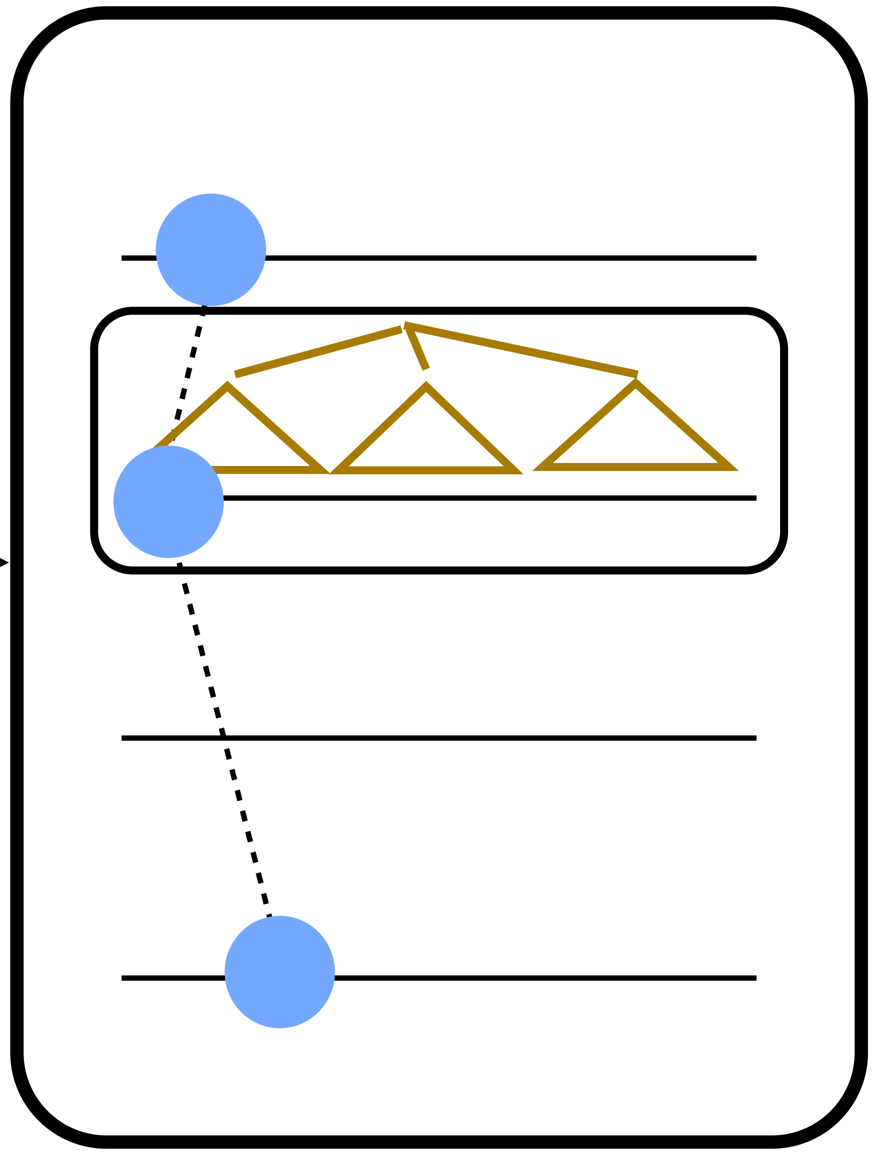

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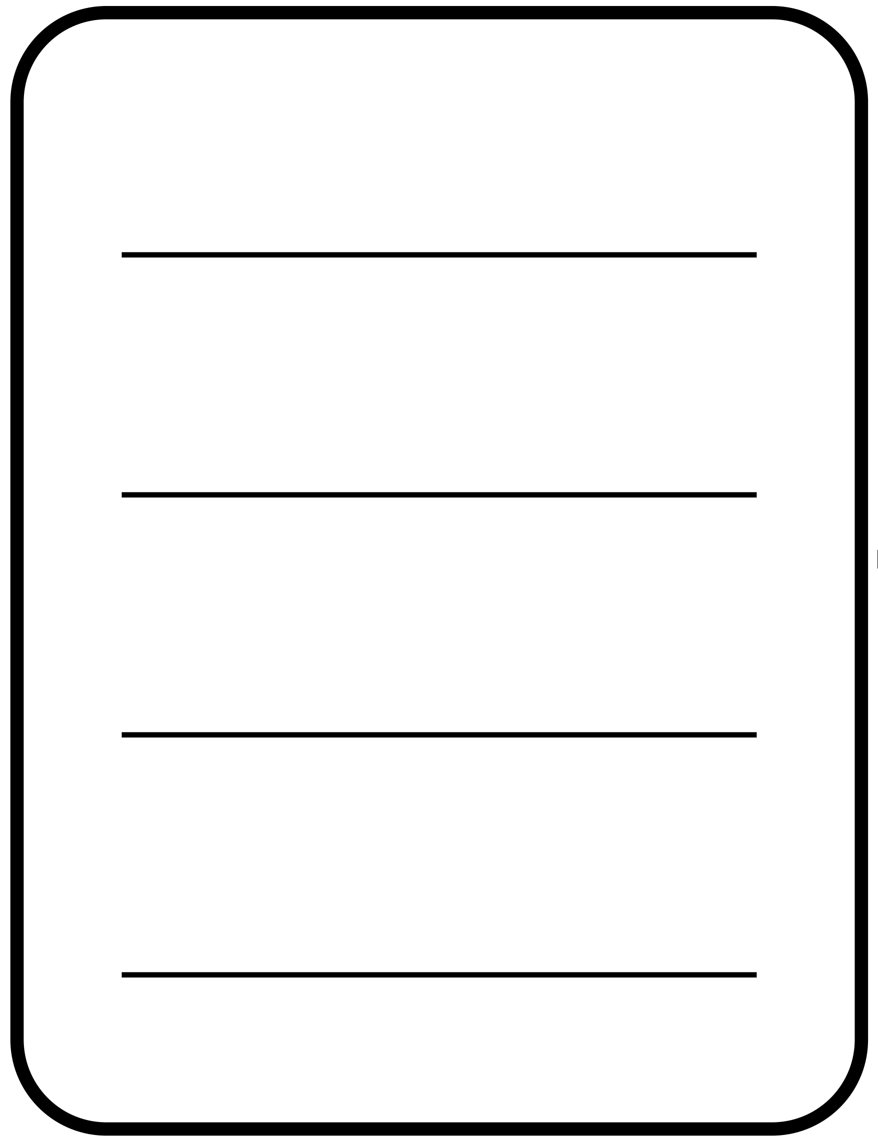

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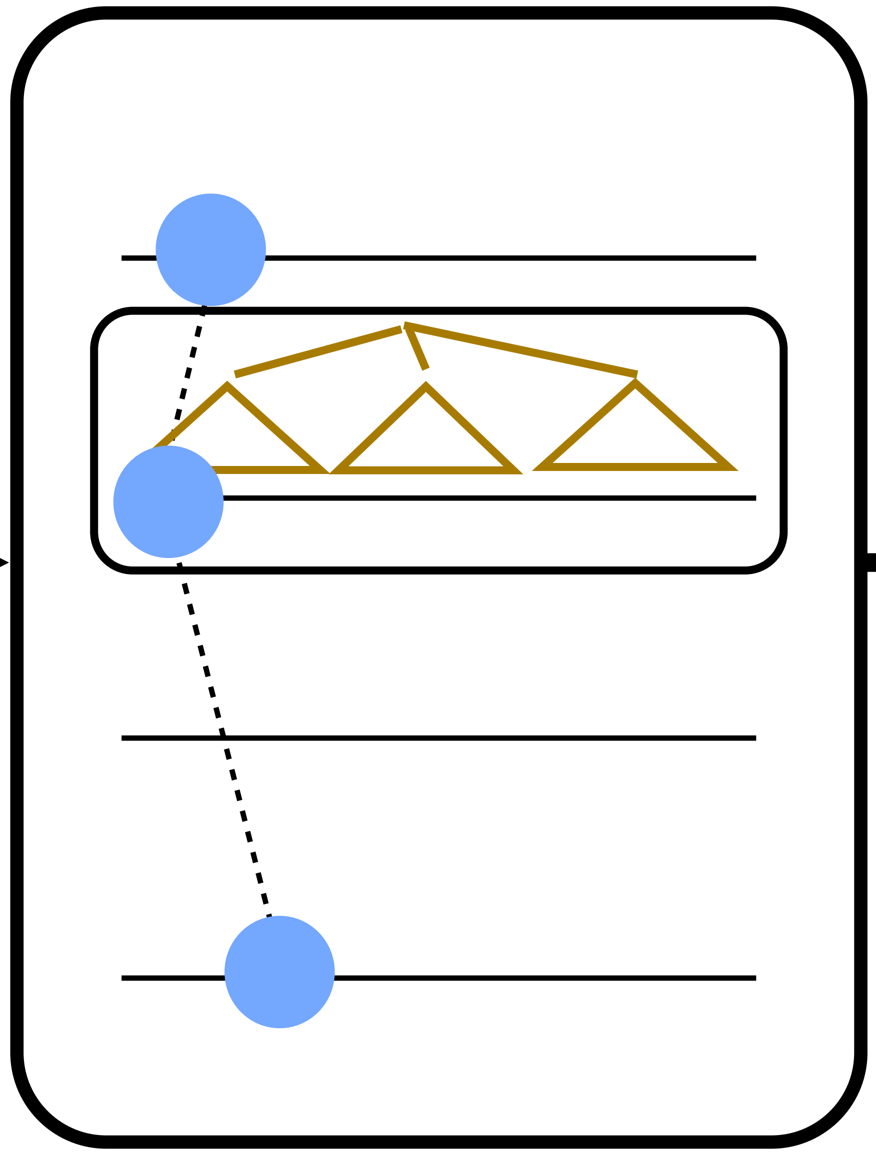

Applications

Traditional NLP Analysis Pipeline

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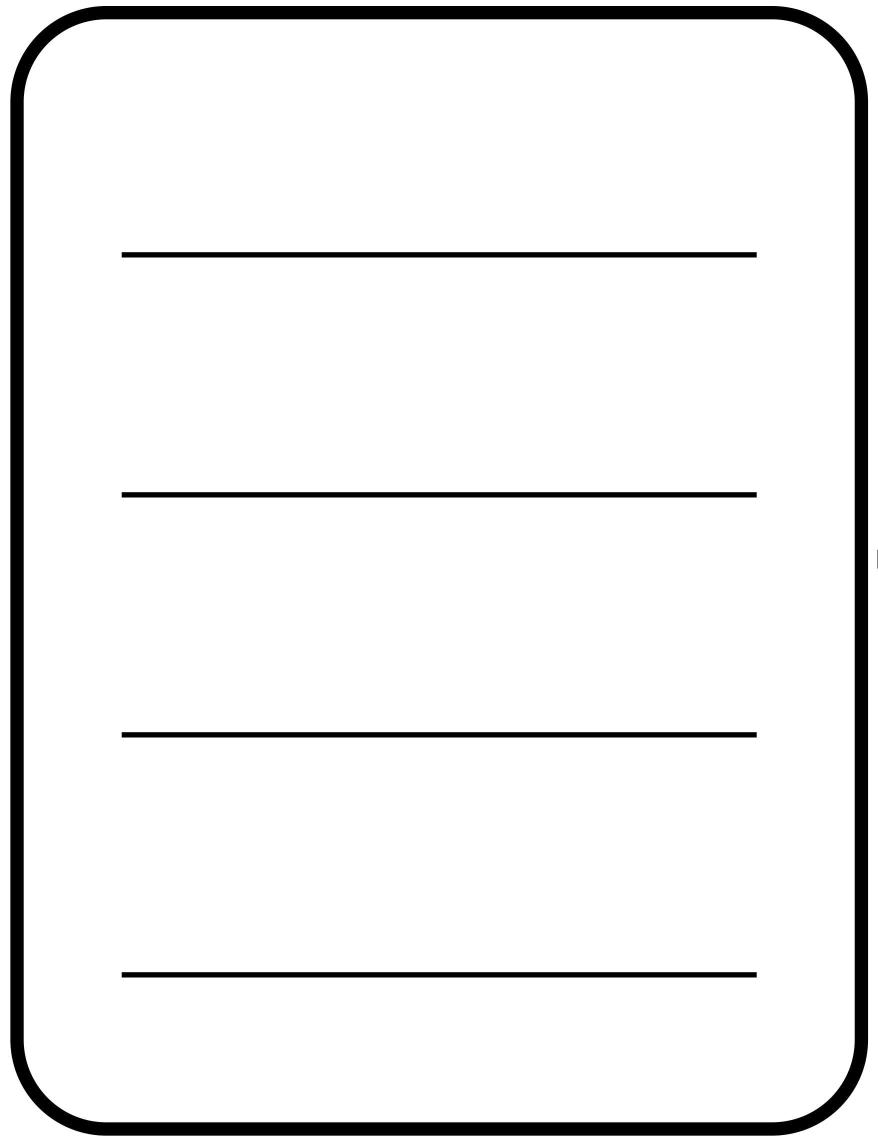

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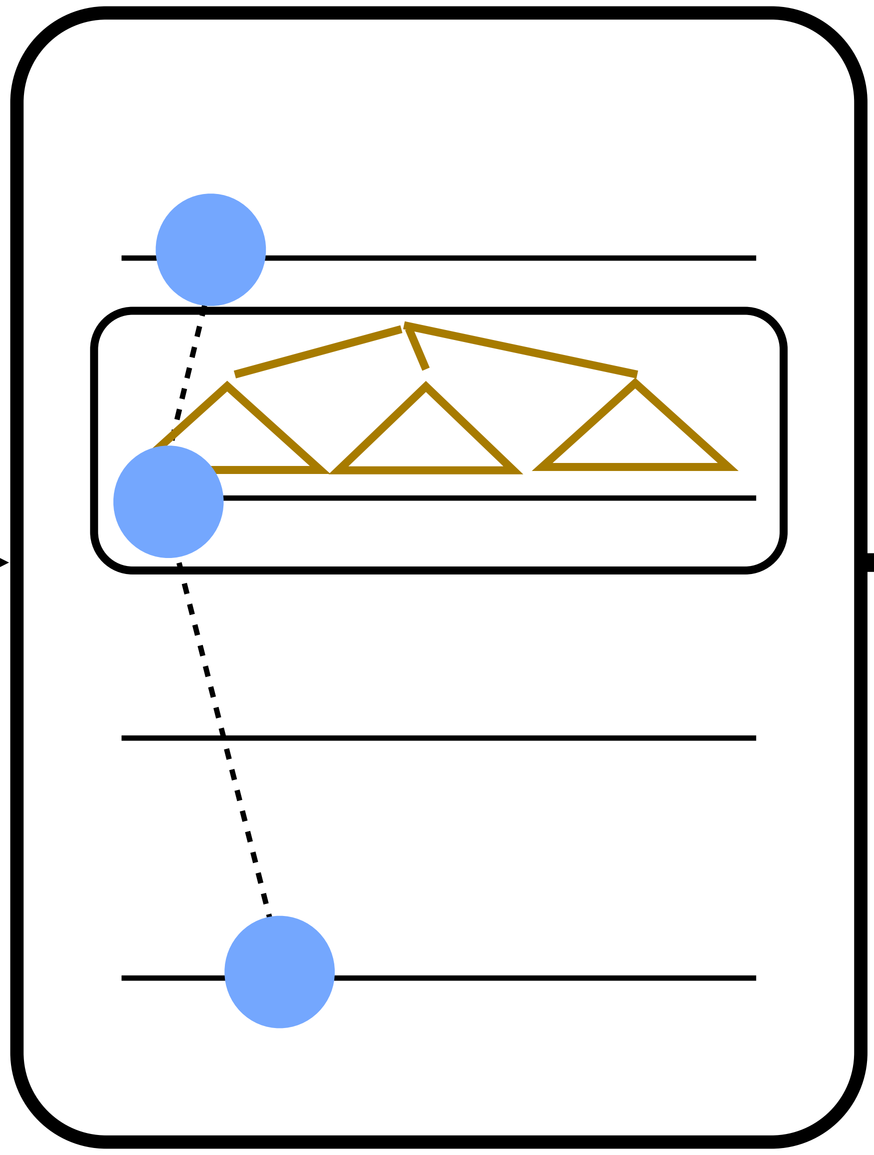

Applications

Summarize

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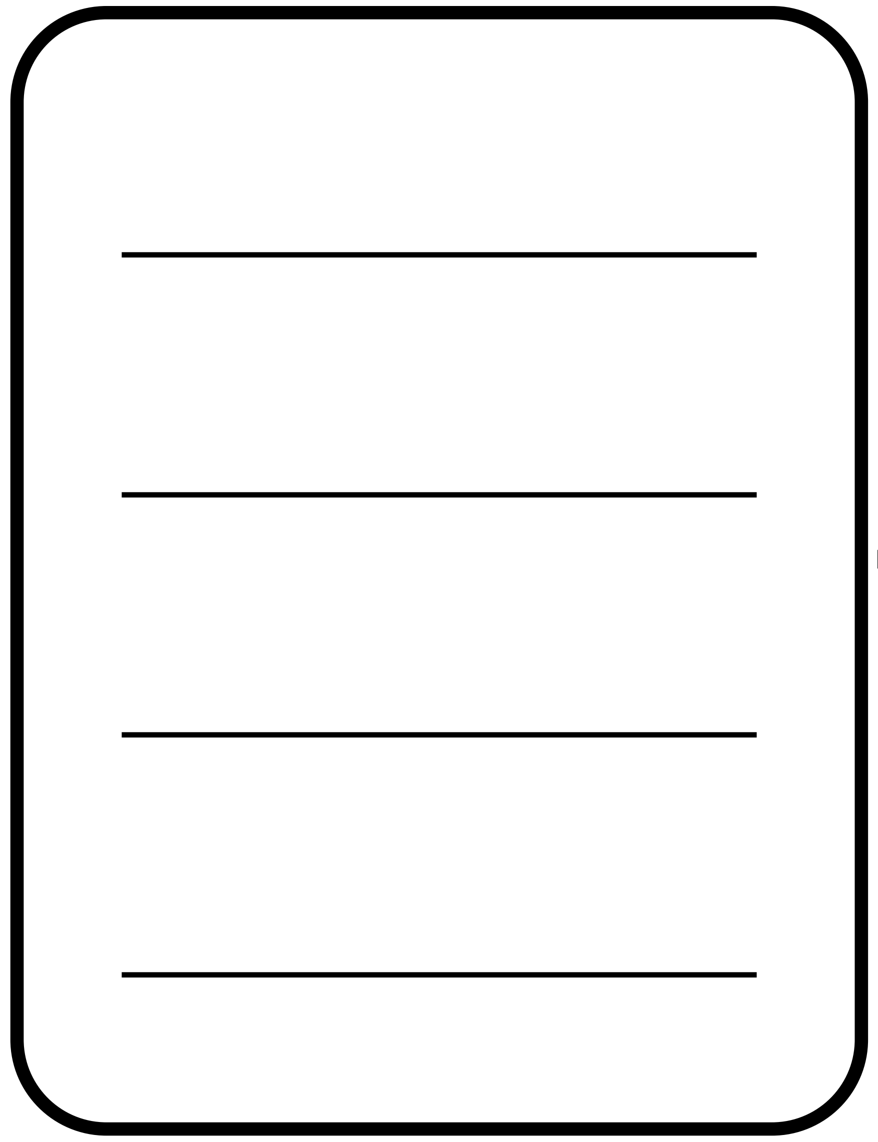

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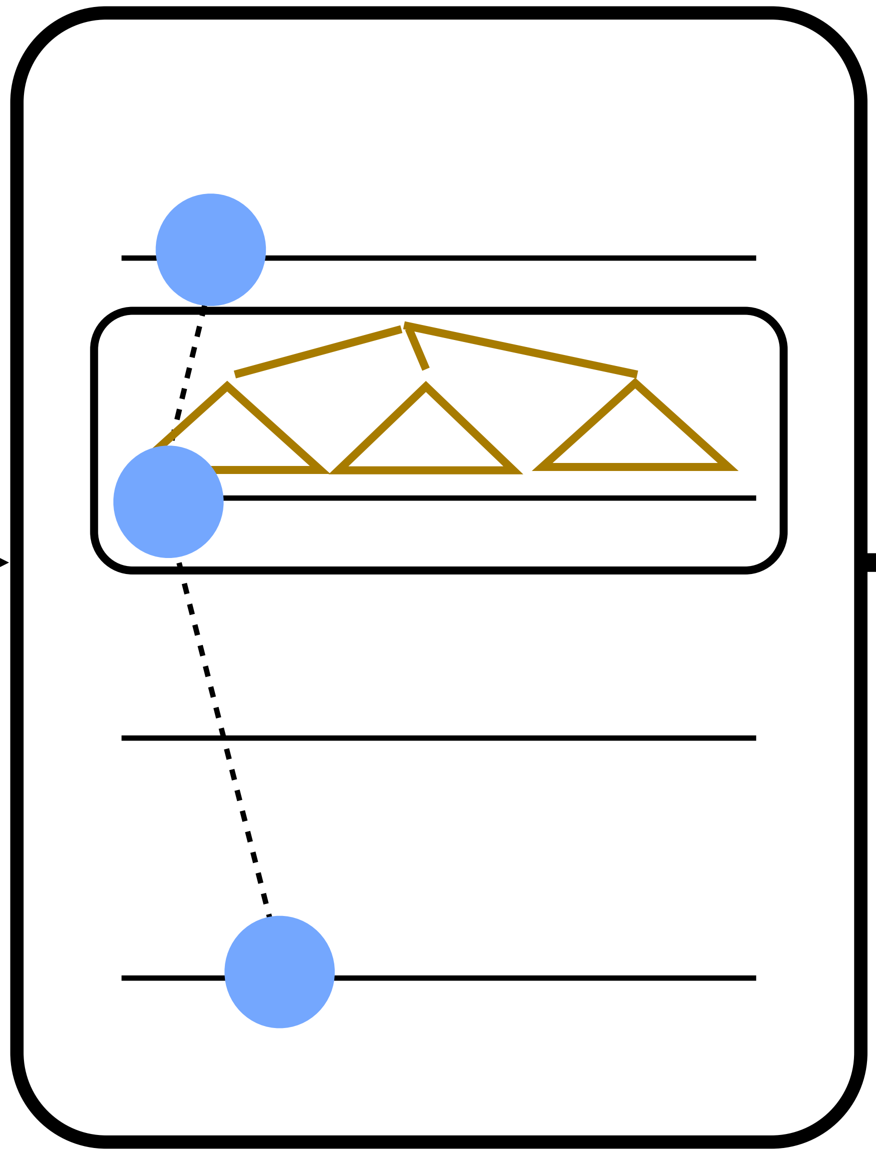


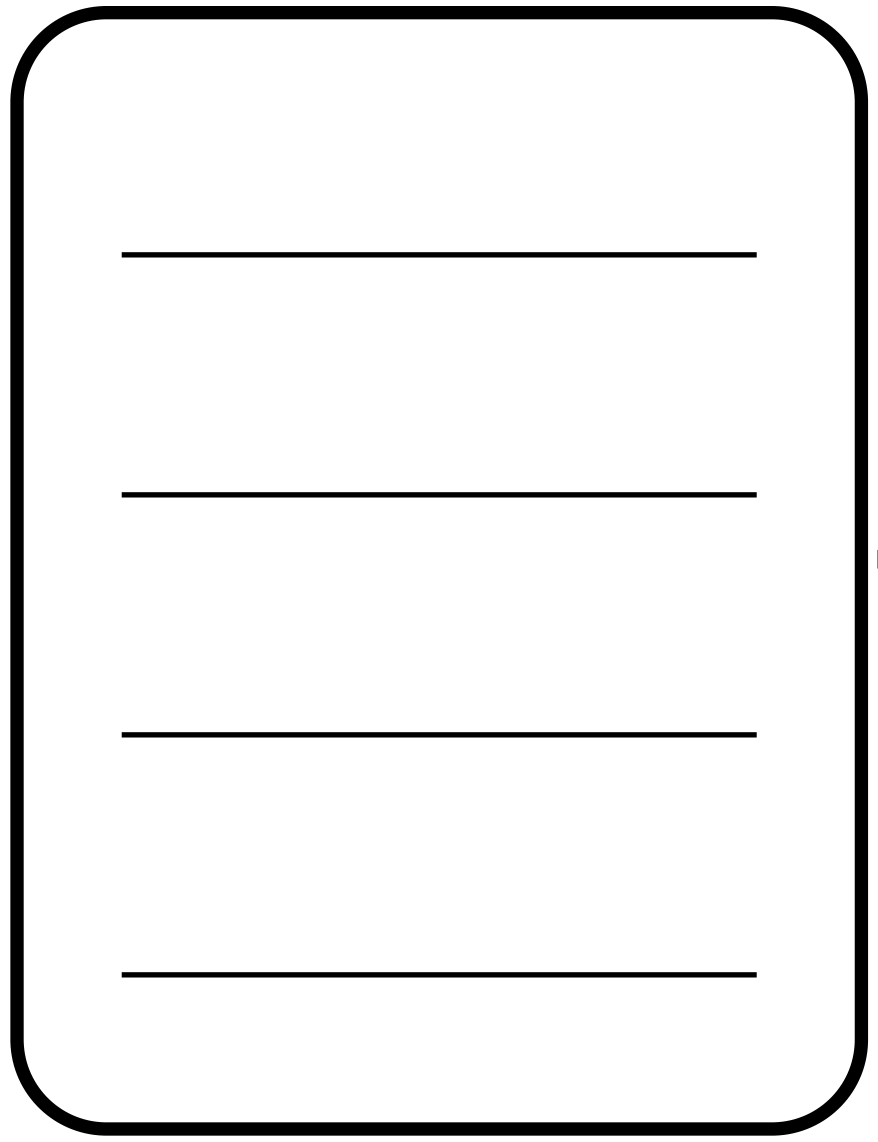
Applications

Summarize

Extract information

Traditional NLP Analysis Pipeline

Text



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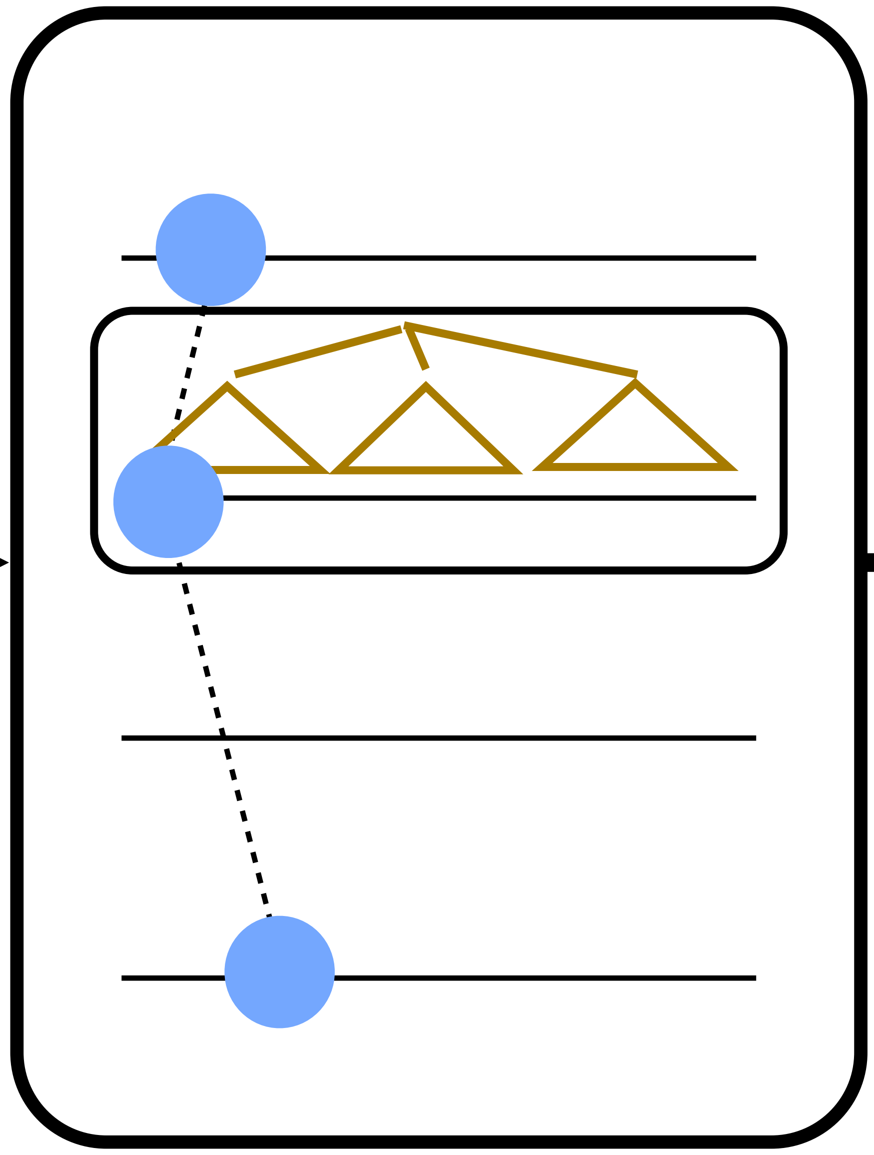


Applications

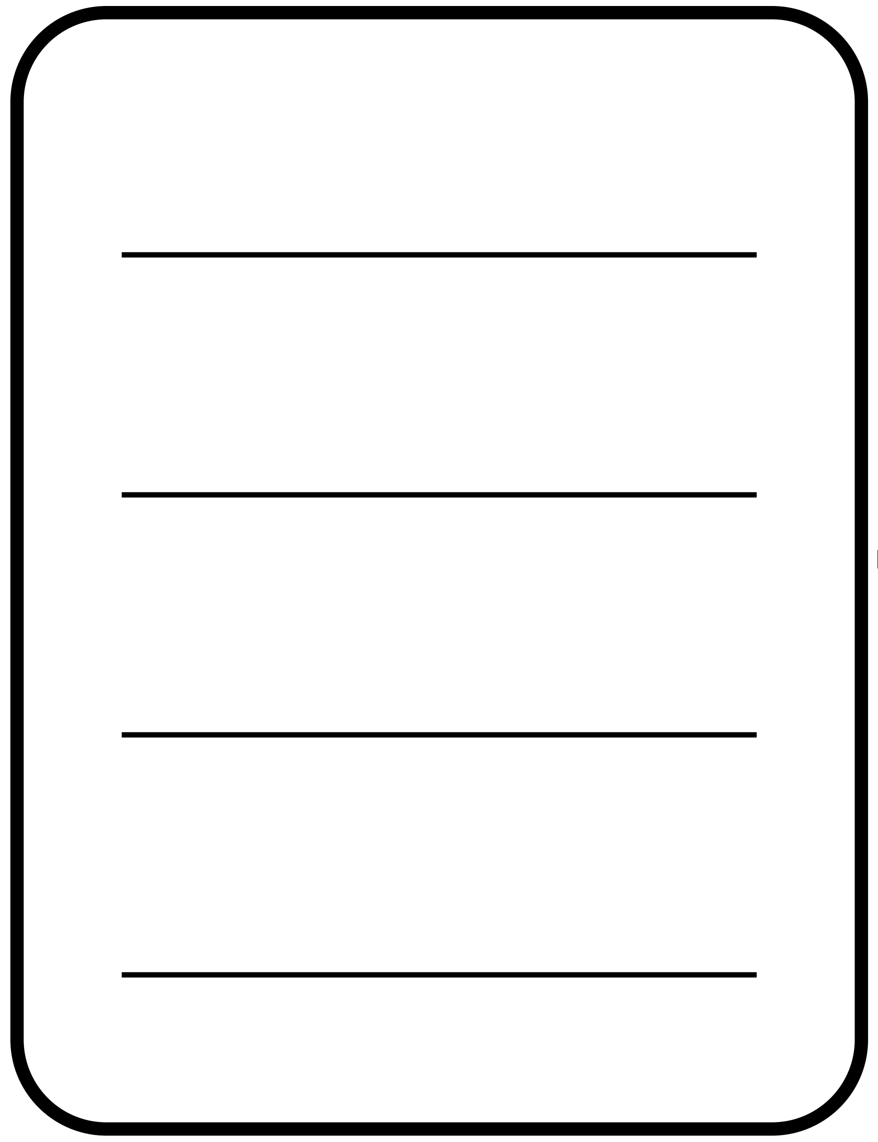
Summarize

Extract information

Answer questions

Traditional NLP Analysis Pipeline

Text



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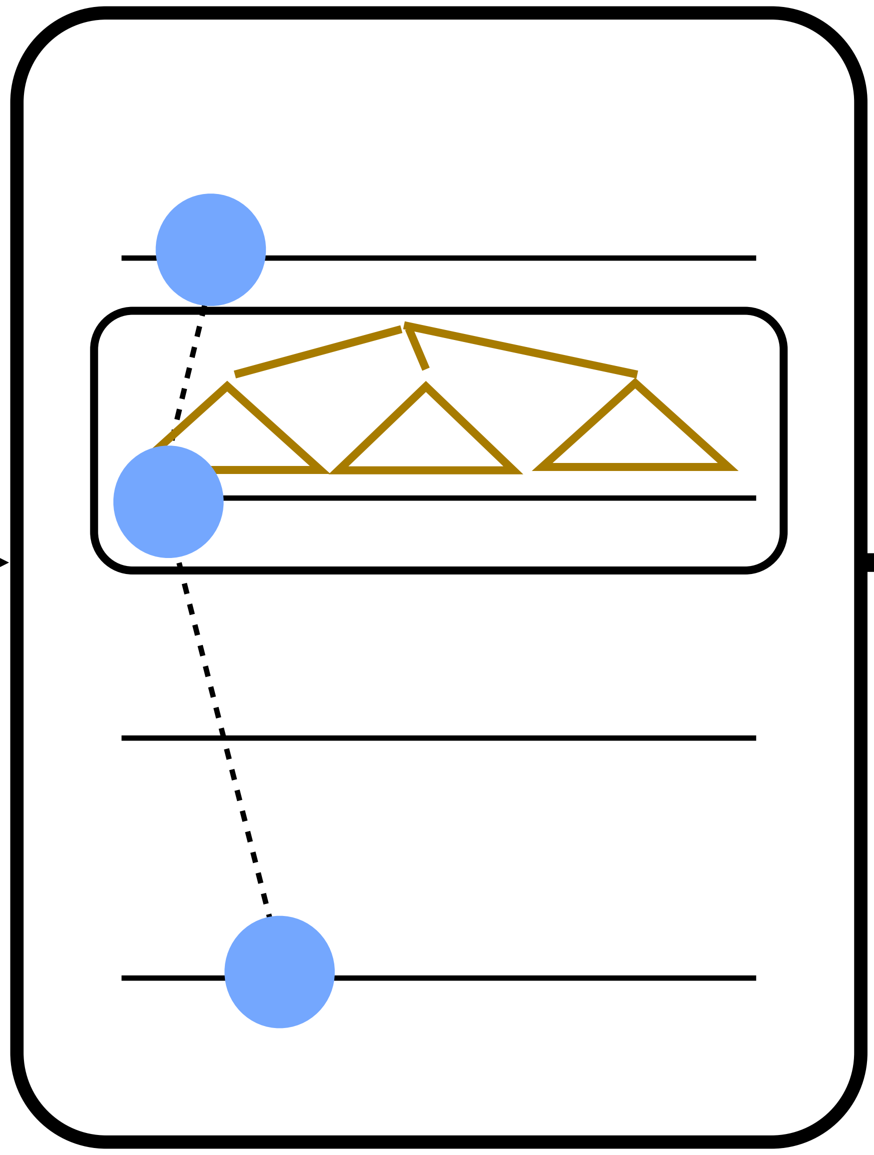


Applications

Summarize

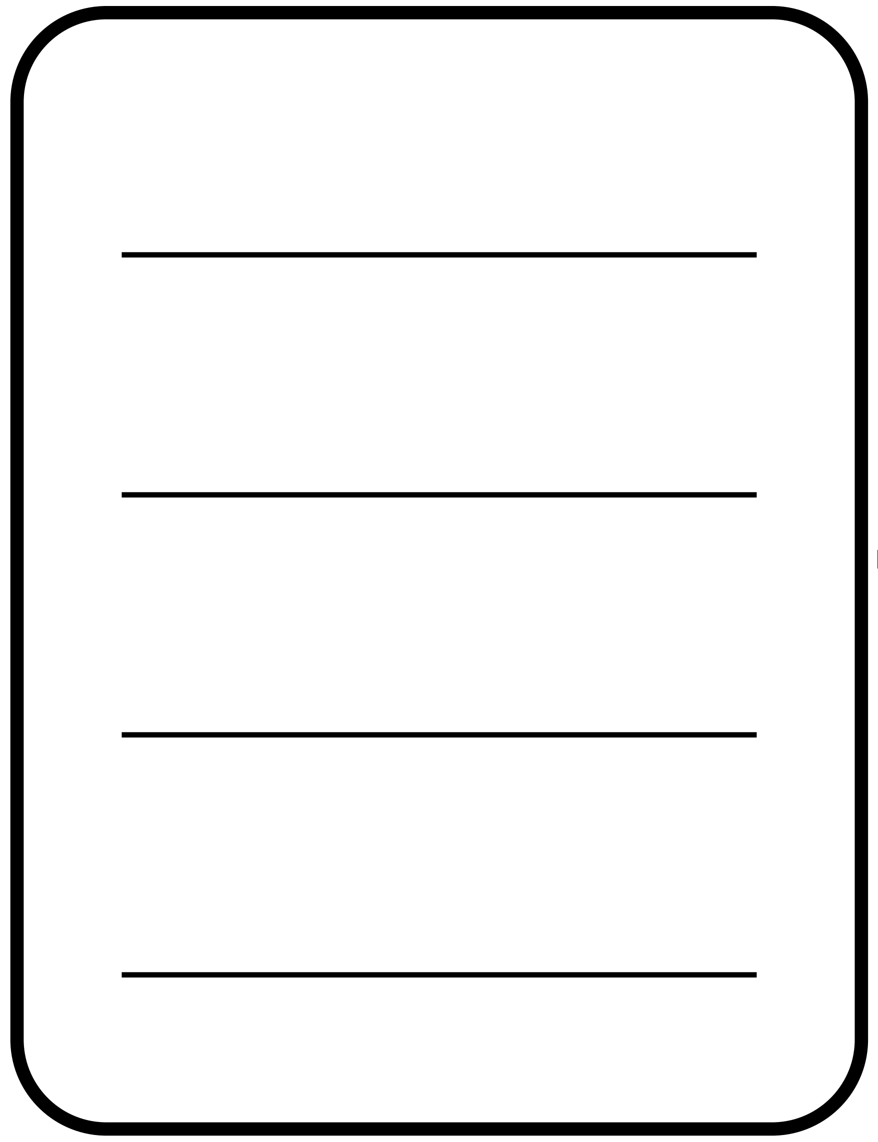
Extract information

Answer questions

Identify sentiment

Traditional NLP Analysis Pipeline

Text



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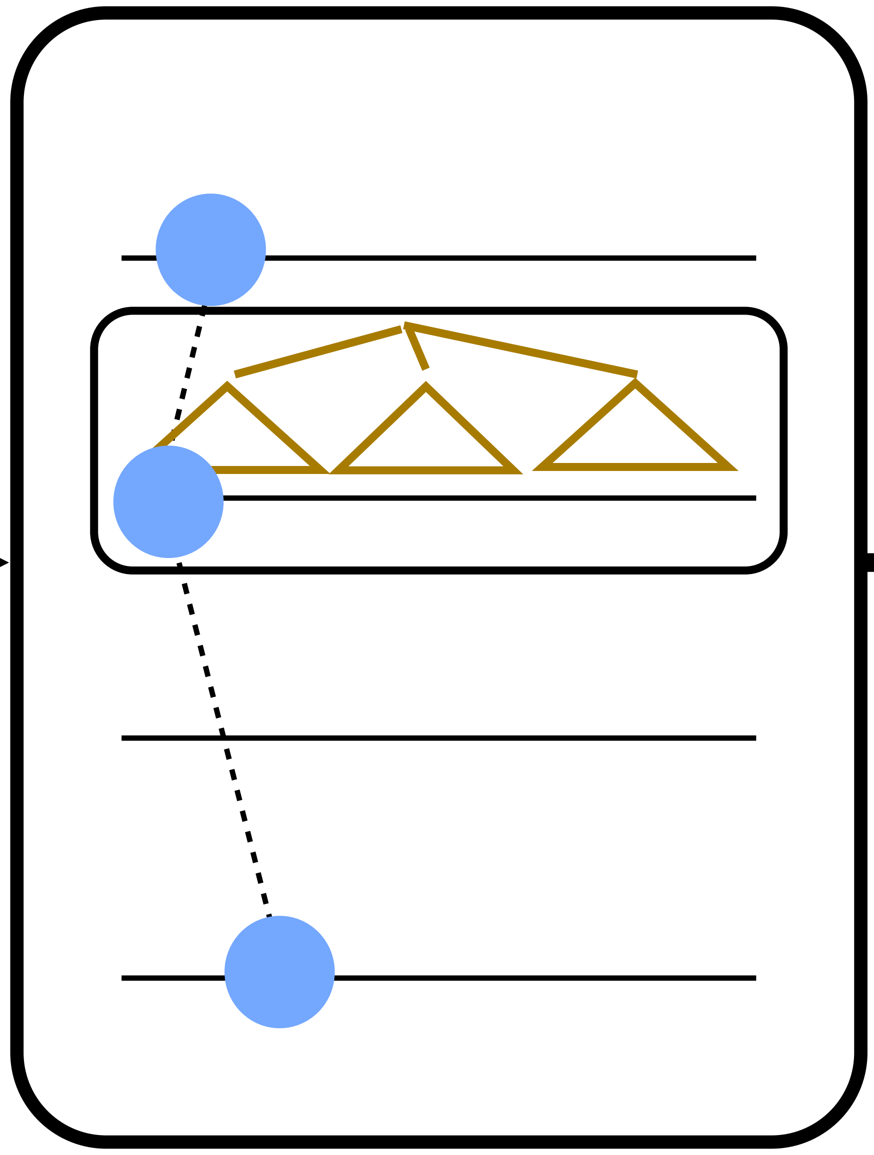


Applications

Summarize

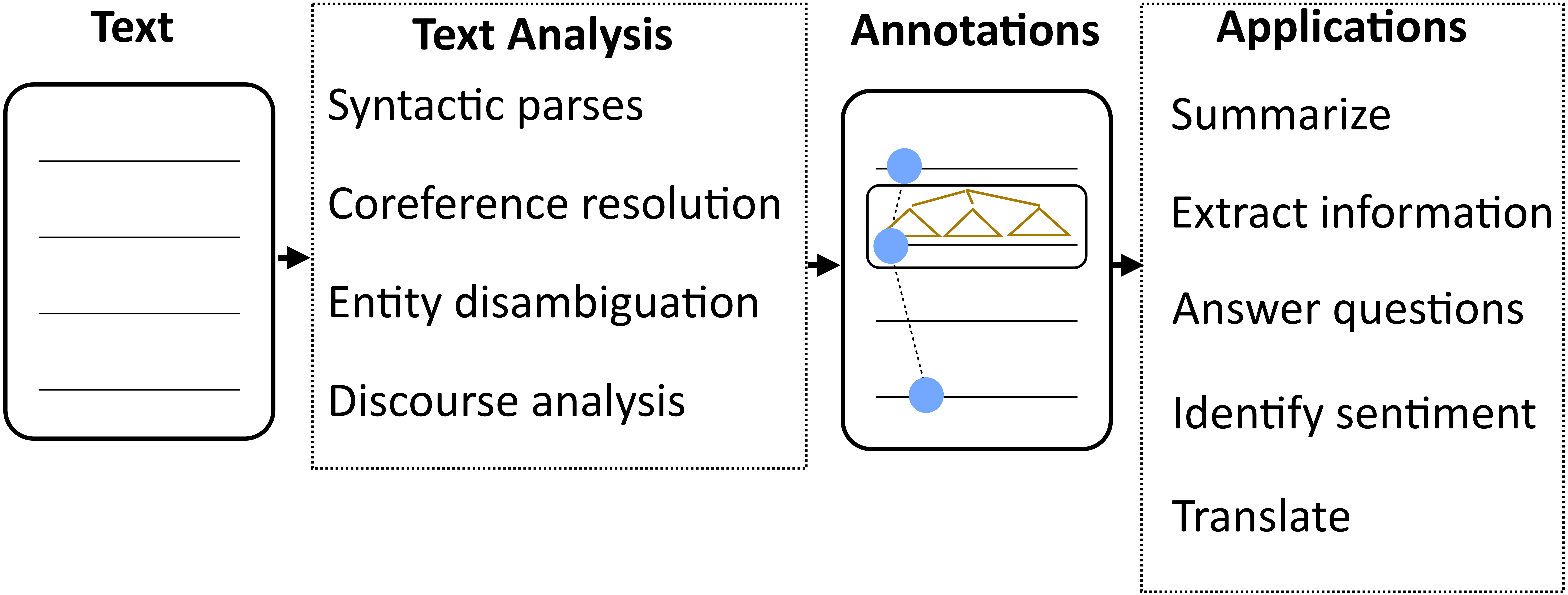
Extract information

Answer questions

Identify sentiment

Translate

Traditional NLP Analysis Pipeline



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

How do we represent language?

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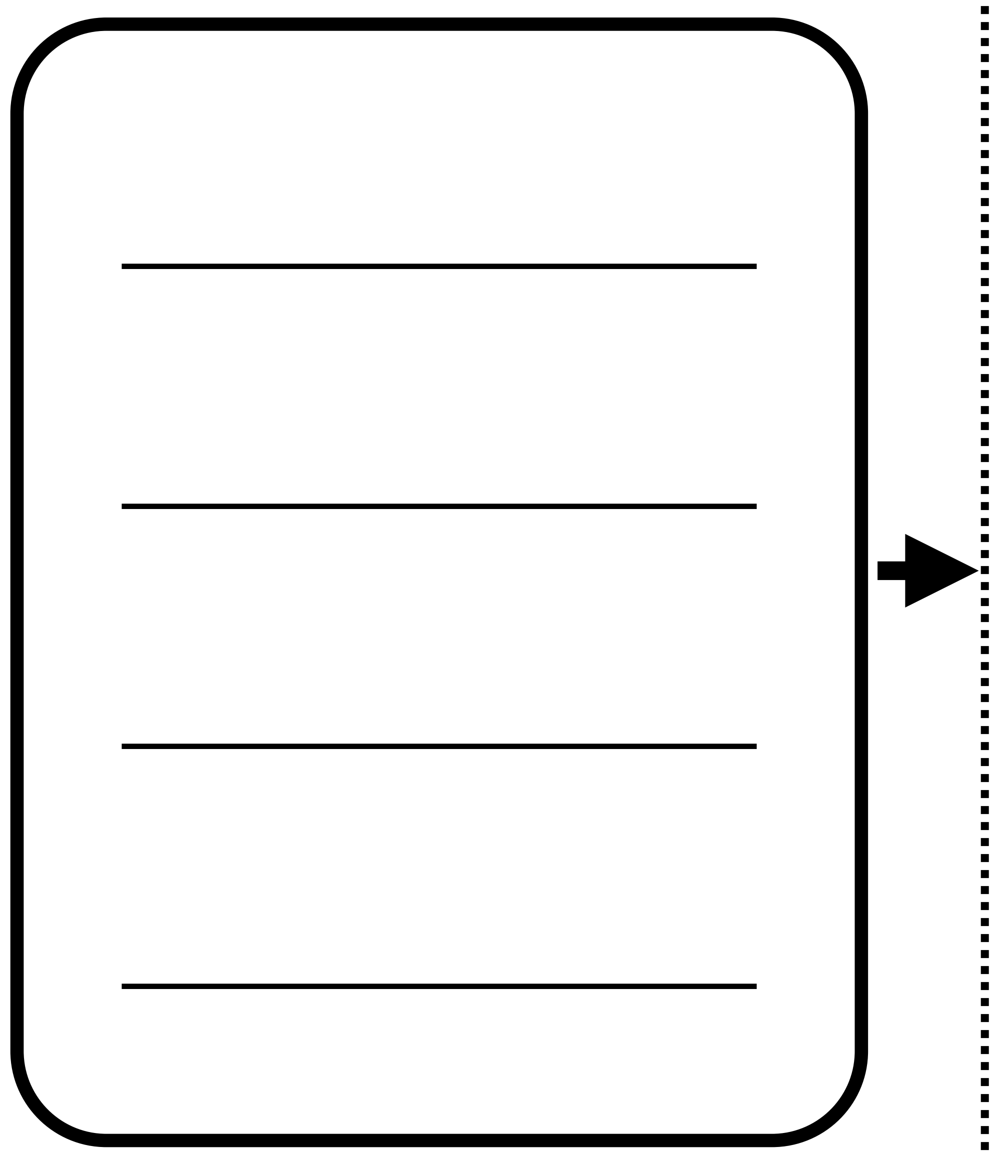

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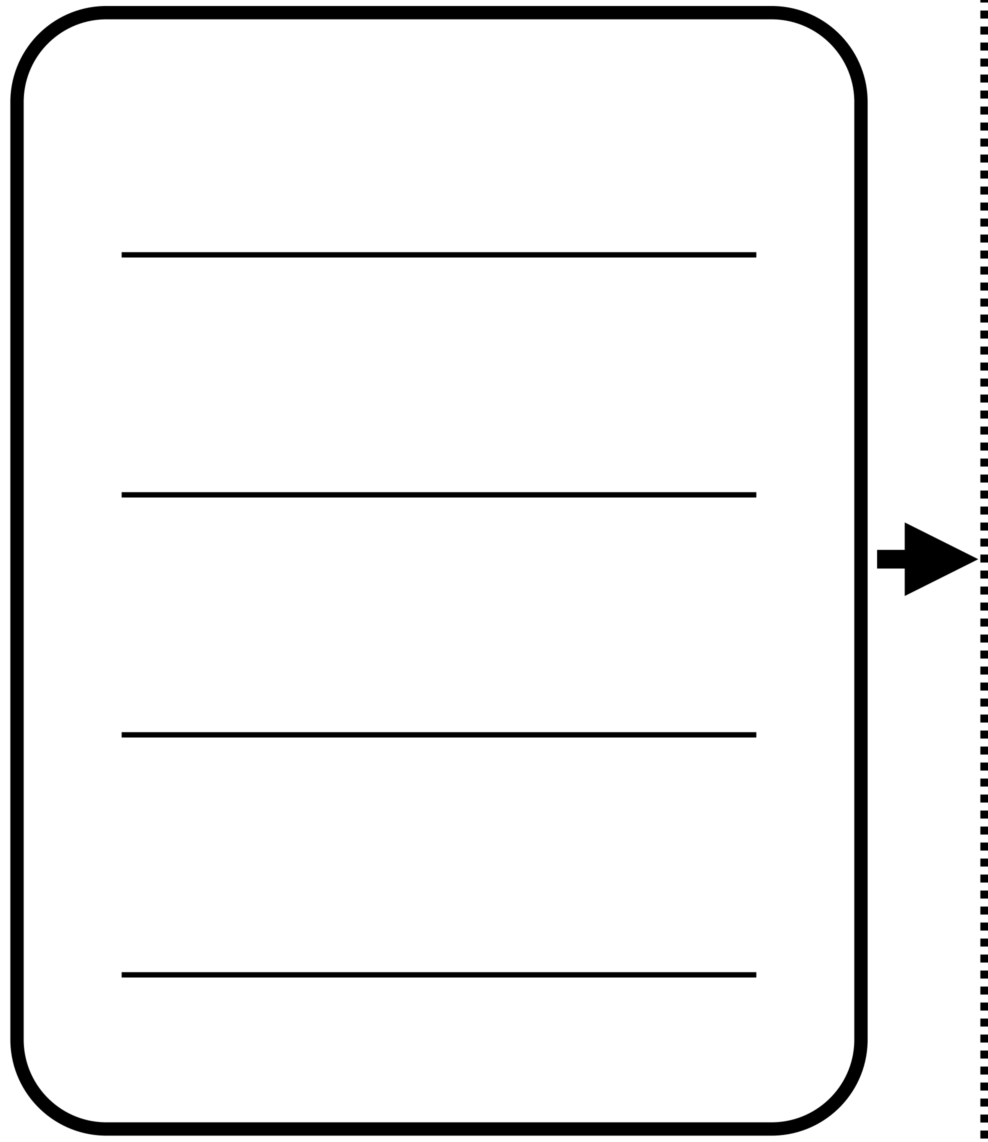

Labels

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Text

Labels

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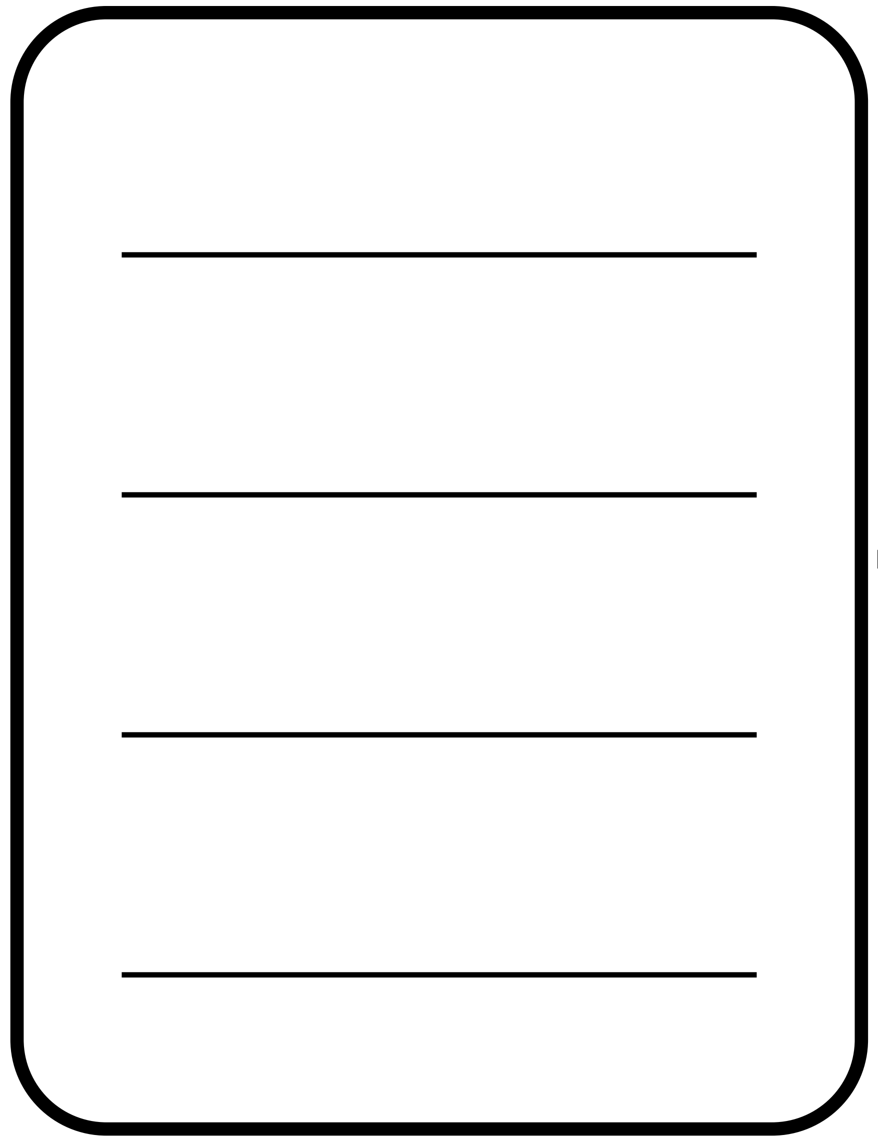

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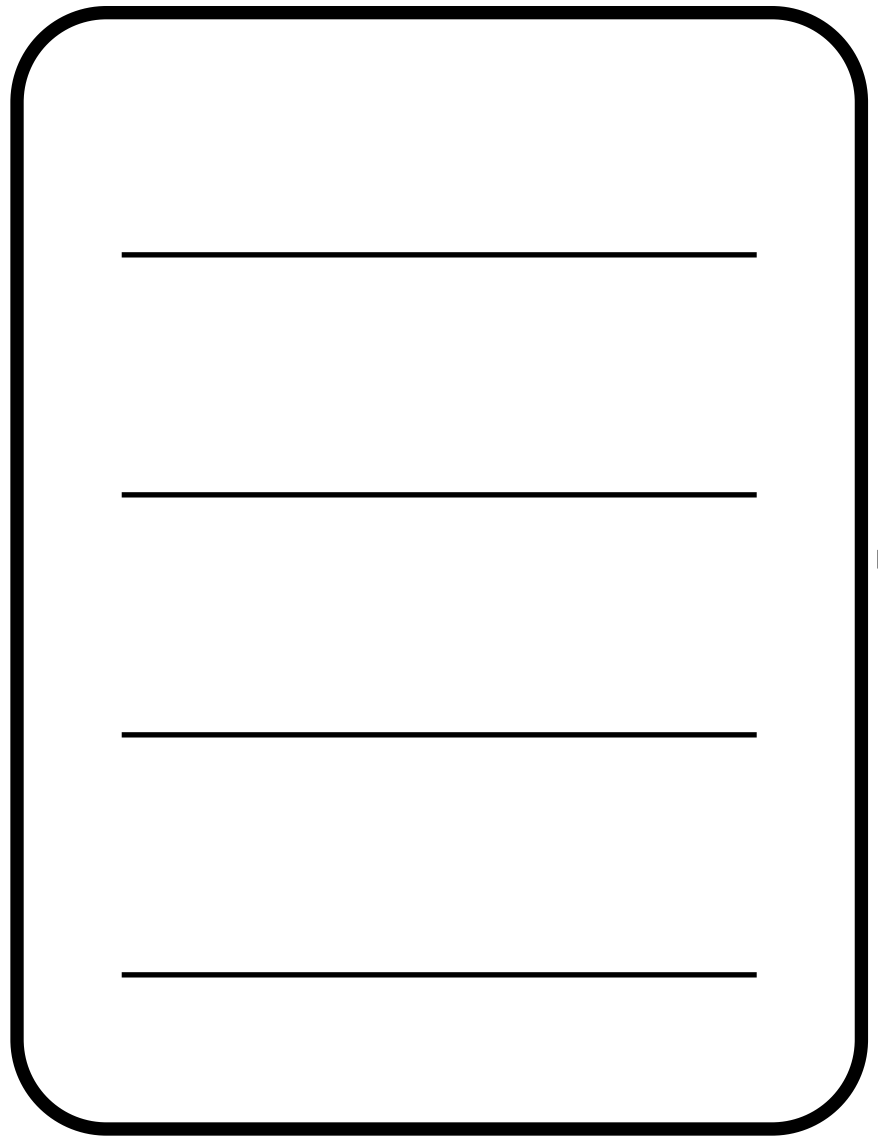

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Sequences/tags

PERSON **MOVIE**

Tom Cruise stars in the new Mission Impossible film

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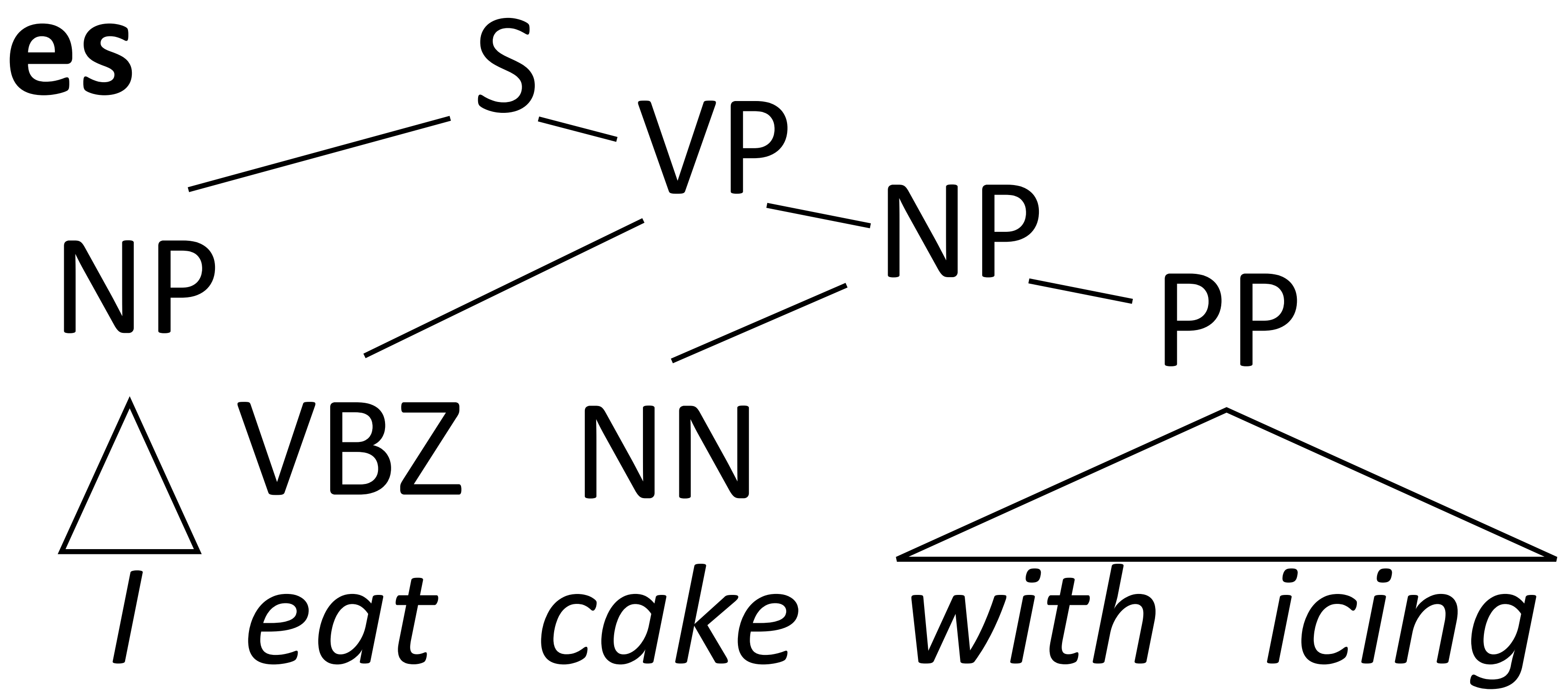
Sequences/tags

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

Trees



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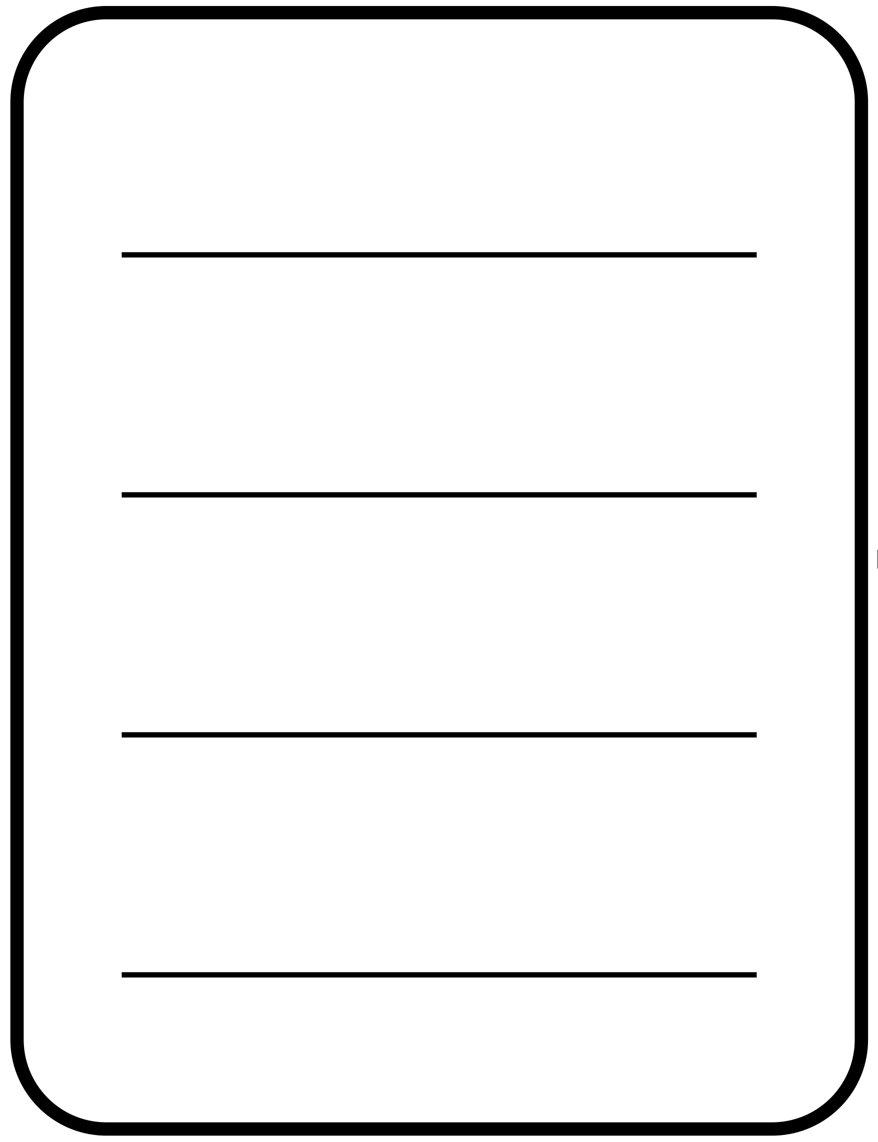

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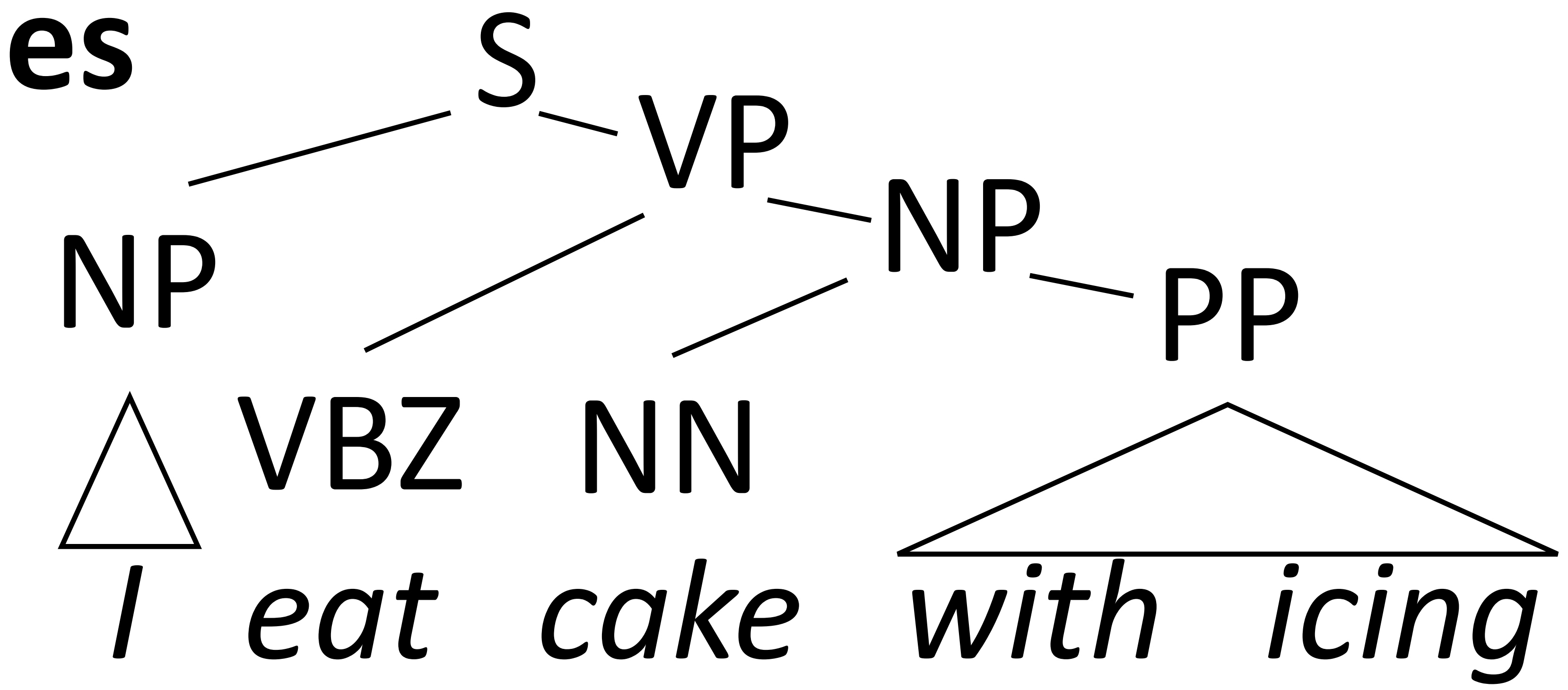
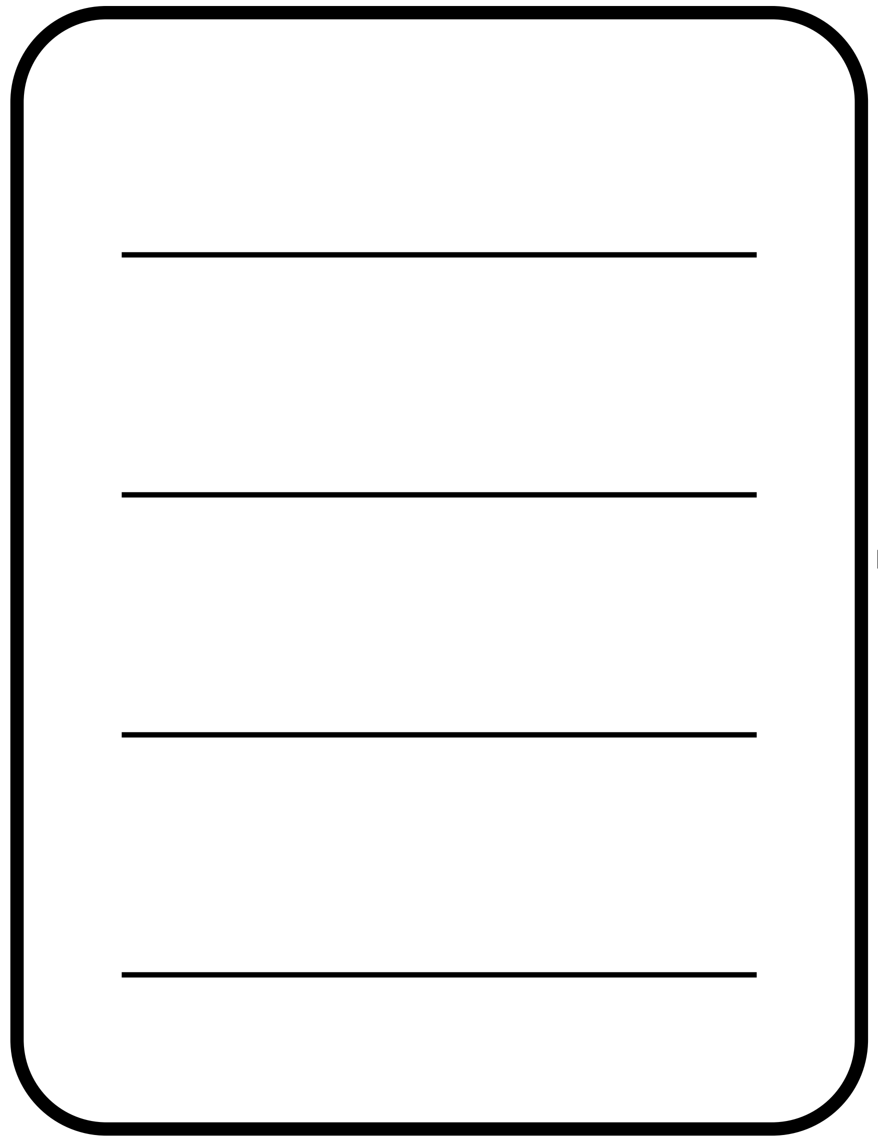


λx. flight(x) ∧ dest(x)=Miami

flights to Miami

How do we use these representations?

Text



Text Analysis

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…

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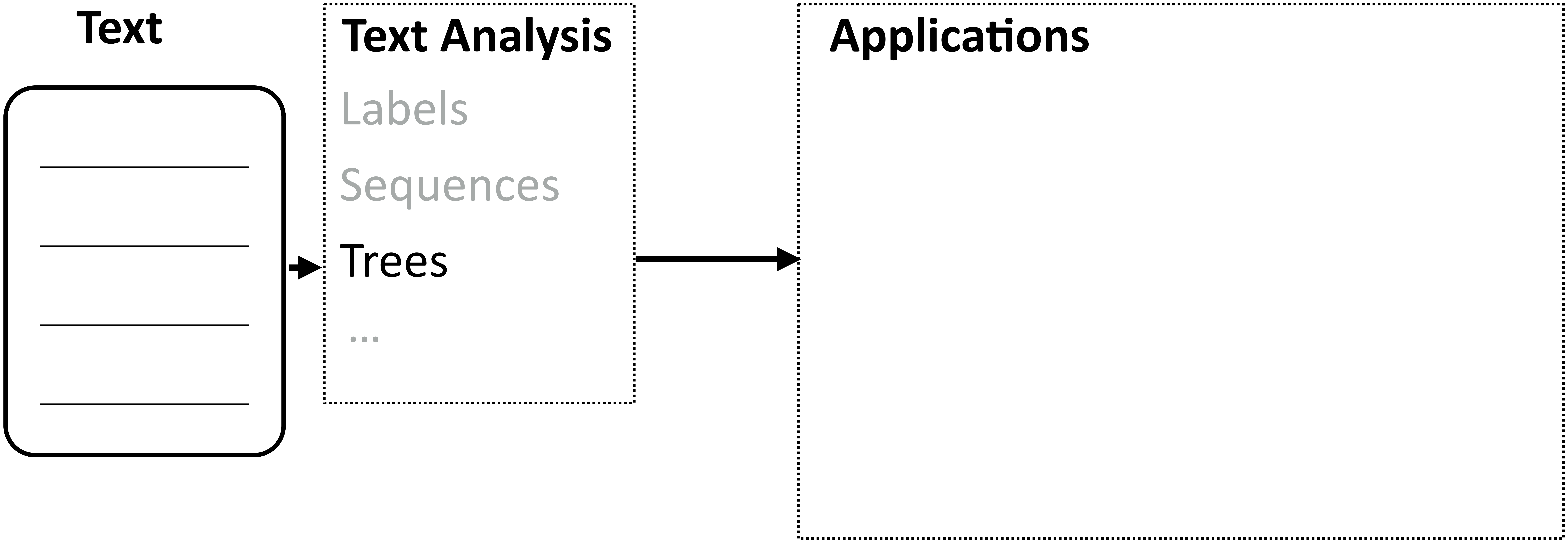

How do we use these representations?

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Text Analysis

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Applications

Extract syntactic features

How do we use these representations?

Text

Text Analysis

Labels

Sequences

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Applications

Extract syntactic features

Tree-structured neural networks

How do we use these representations?

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Trees

…

Applications

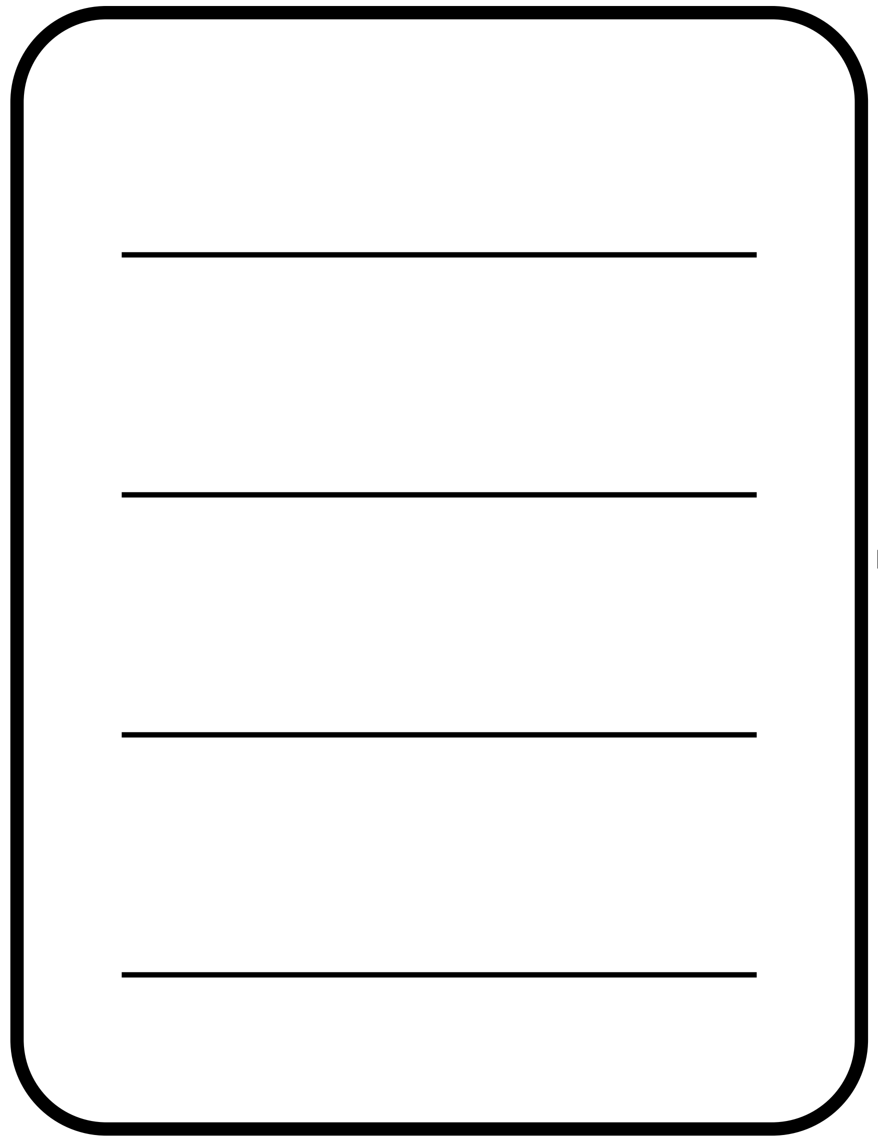
Extract syntactic features

Tree-structured neural networks

Tree transducers (for machine translation)

How do we use these representations?

Text



Text Analysis

Labels

Sequences

Trees

…

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How do we use these representations?

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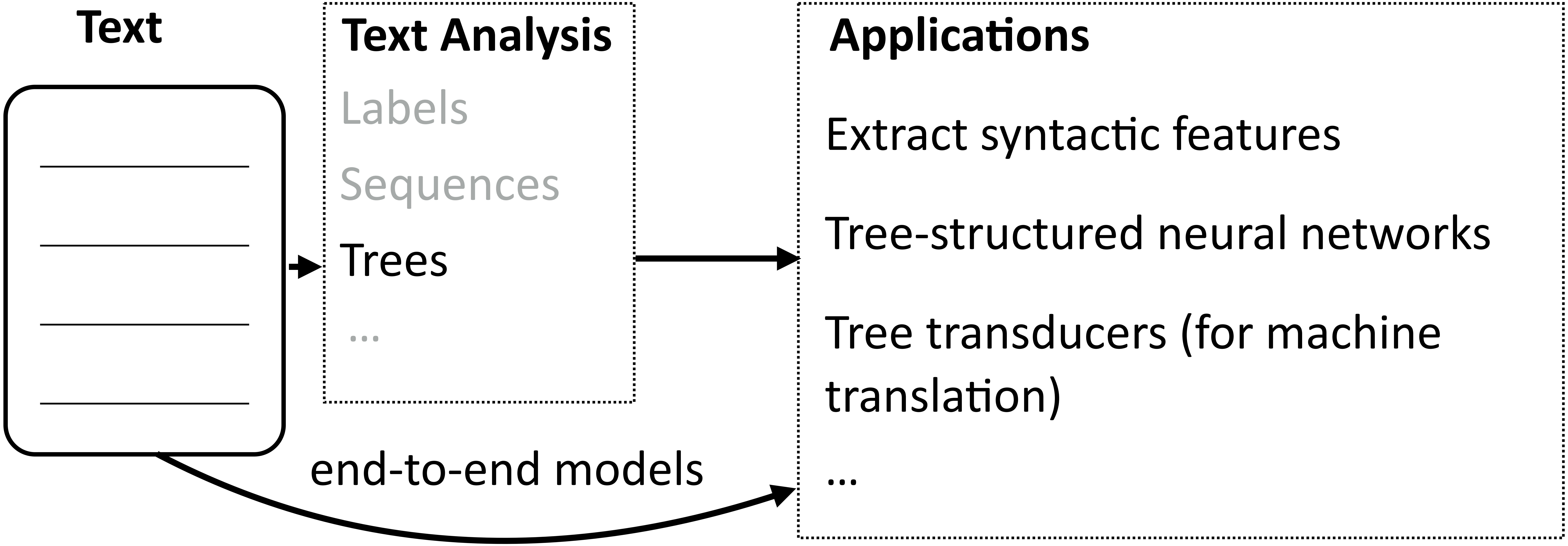
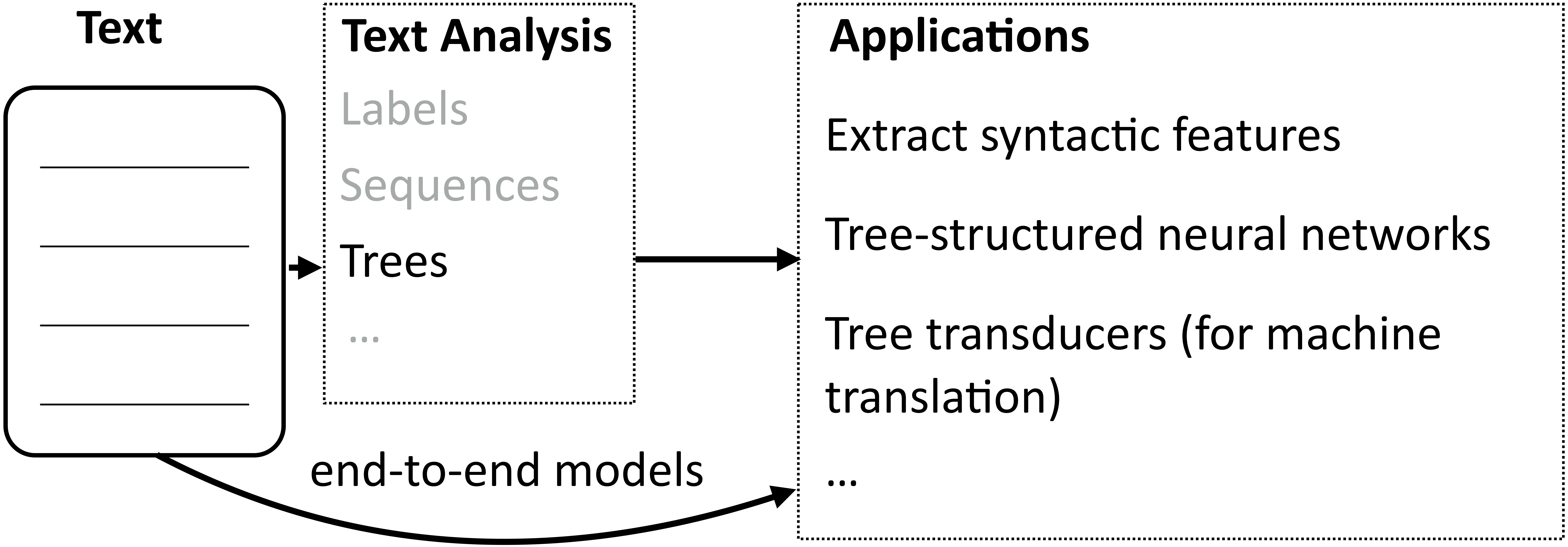
end-to-end models

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!

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

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slide credit: Dan Klein

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

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Language is **Really** Ambiguous!

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

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The weather is beautiful

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He makes truly beautiful

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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 →

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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

- 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 techniques do we use?

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

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1980 1990 2000 2010 2020

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rule-based,
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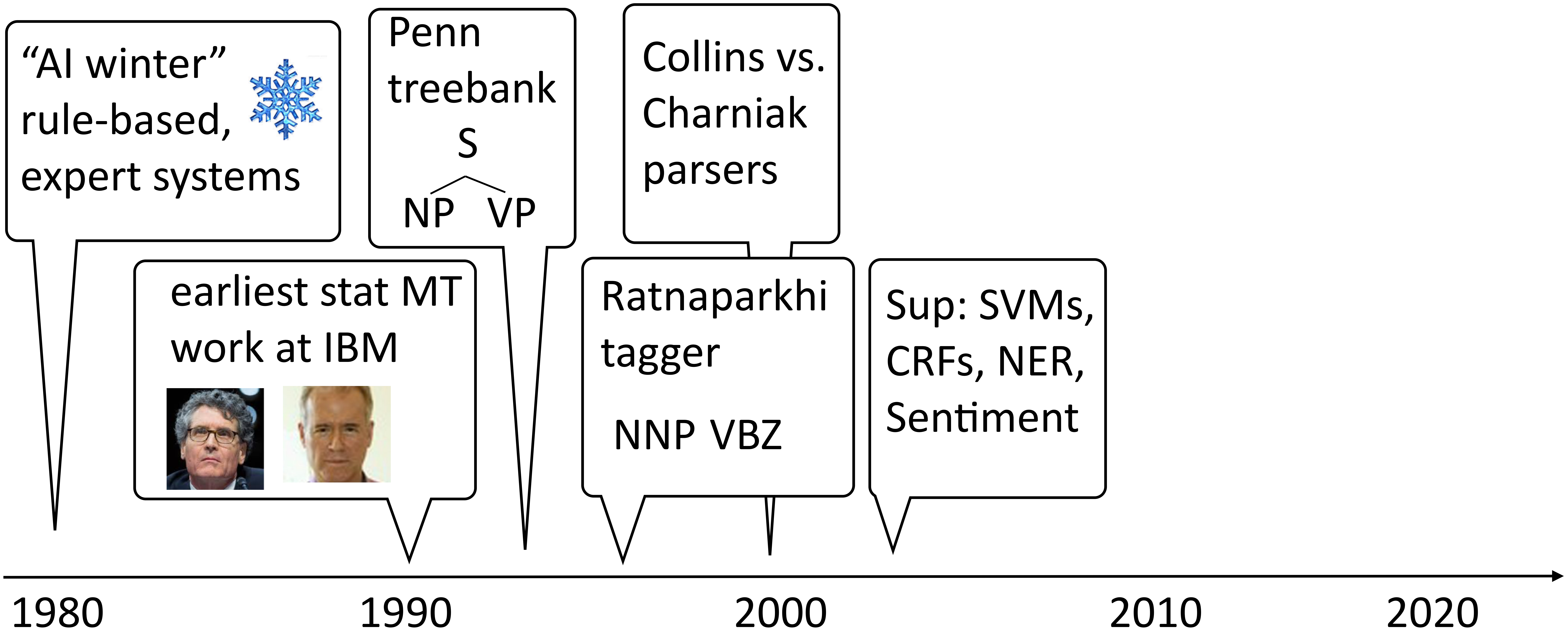

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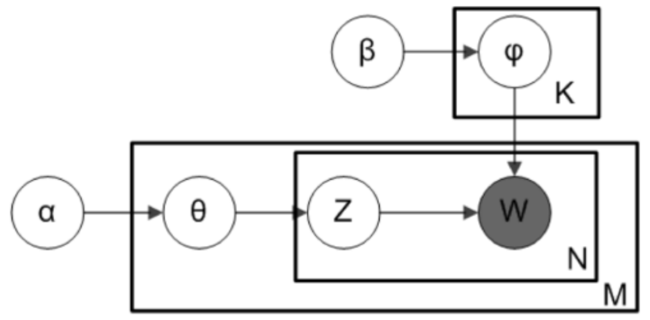
Unsup: topic
models, etc.



Sup: SVMs,
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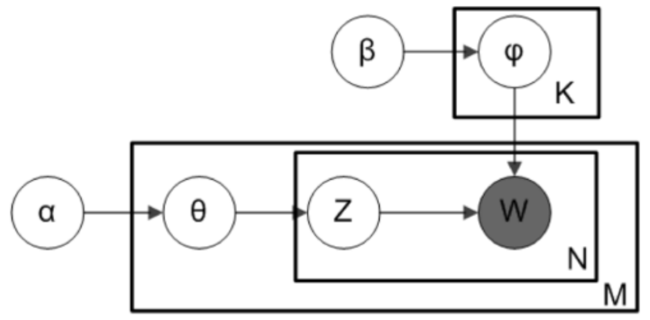

Semi-sup,
structured
prediction

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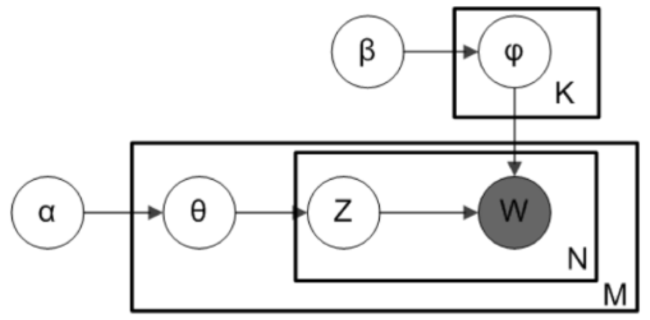

Semi-sup,
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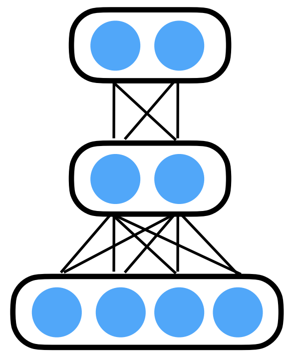
Neural



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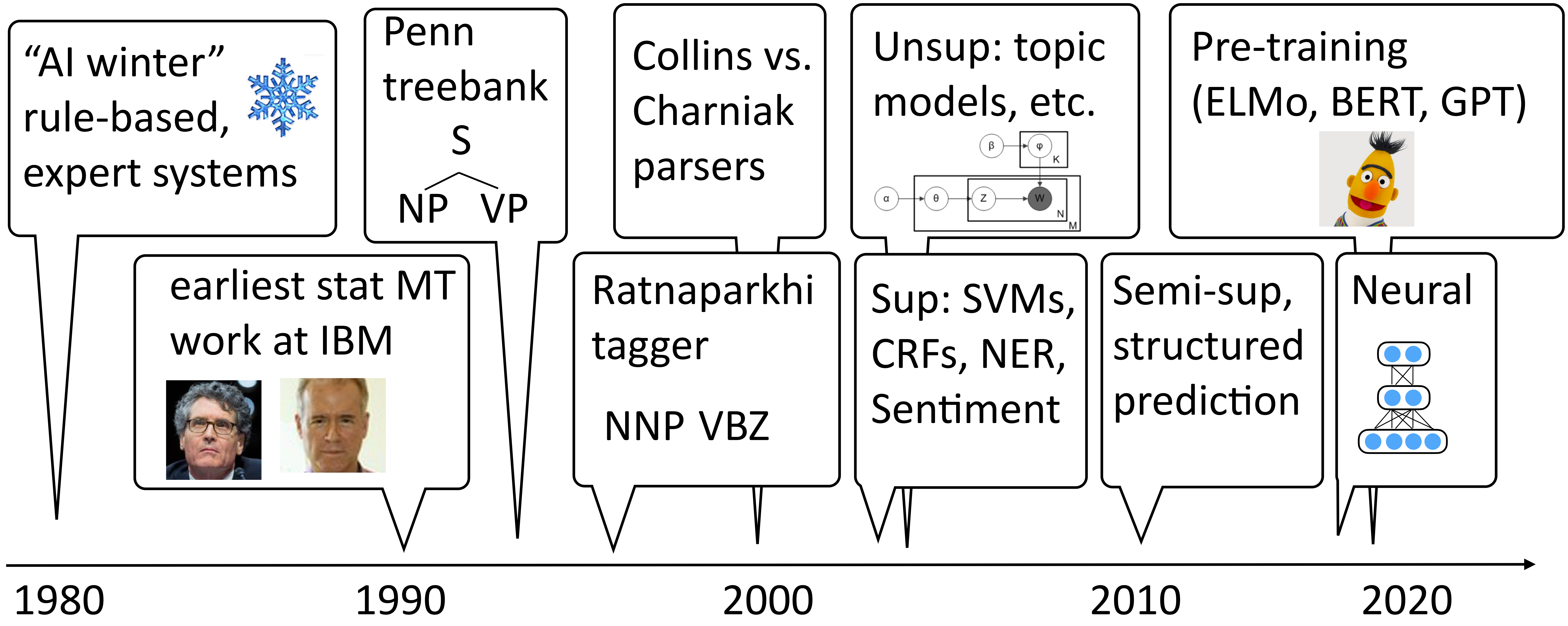

How Much Training Data do we Need?

"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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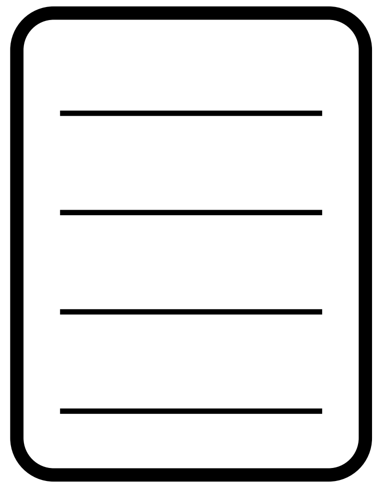

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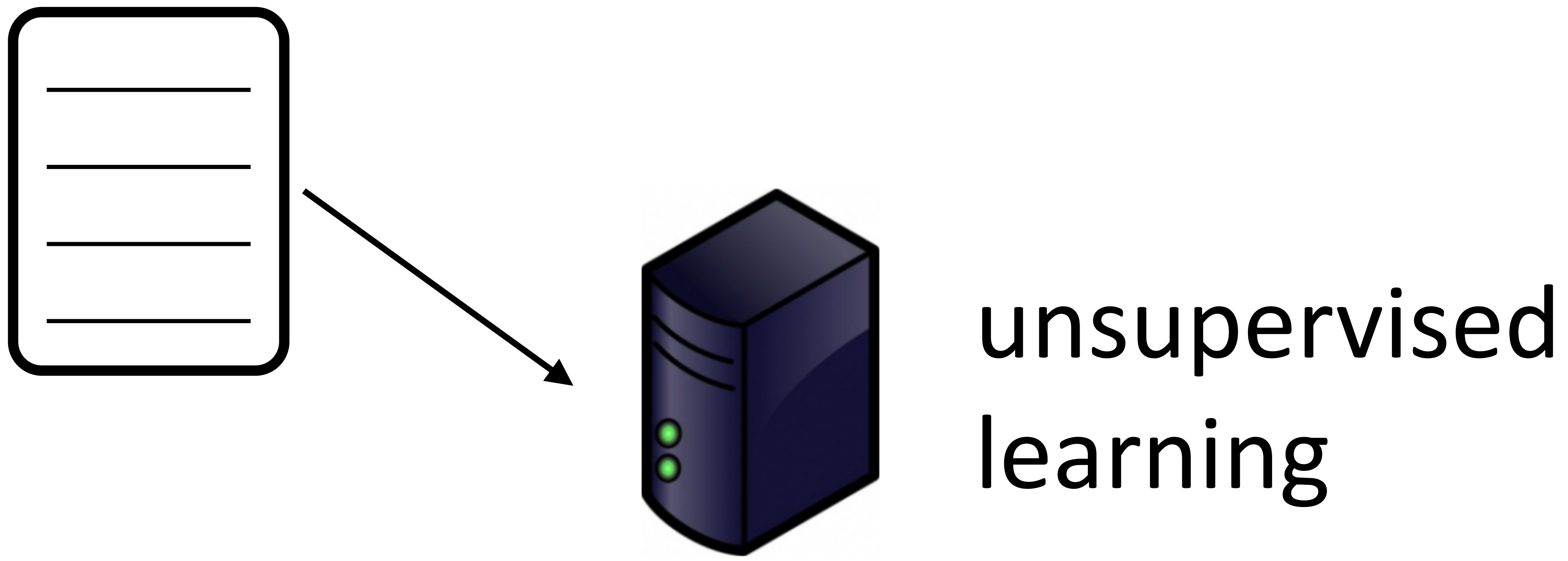

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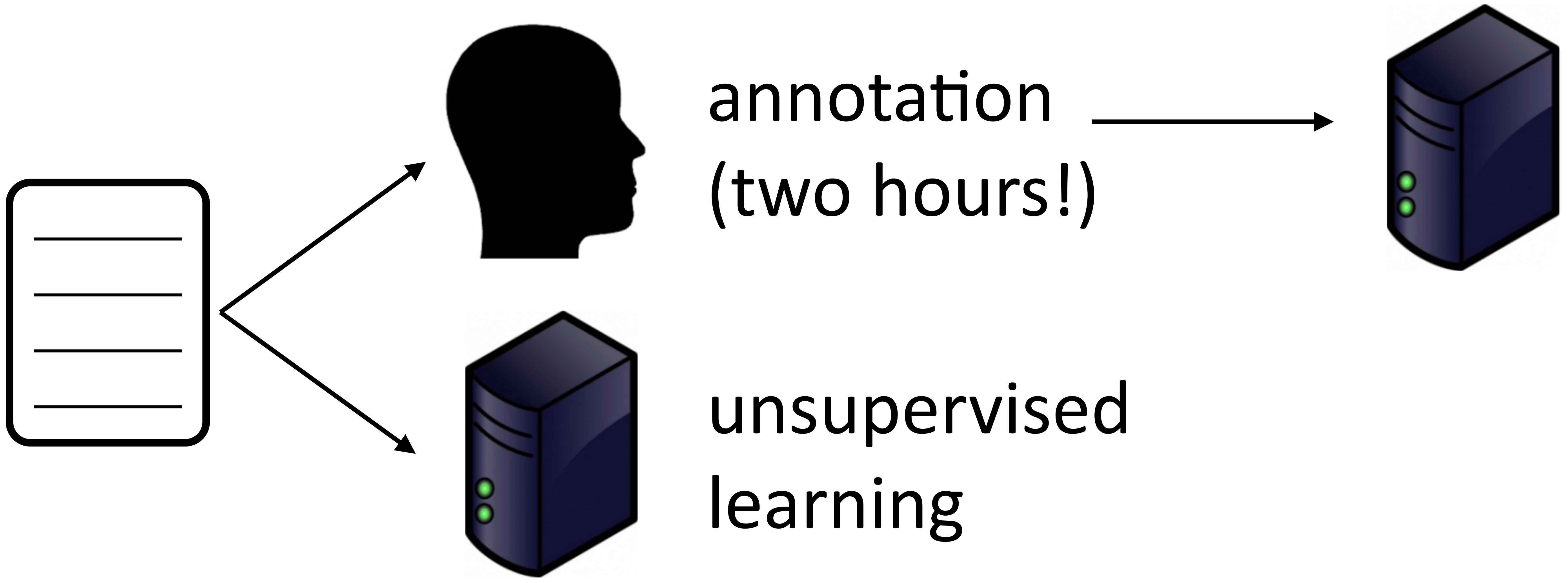

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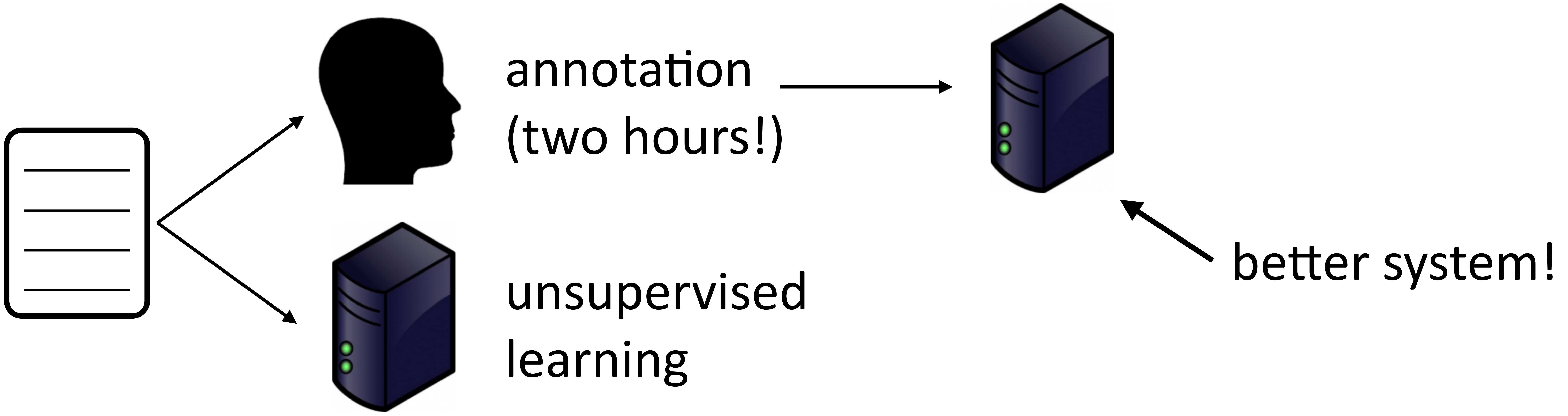

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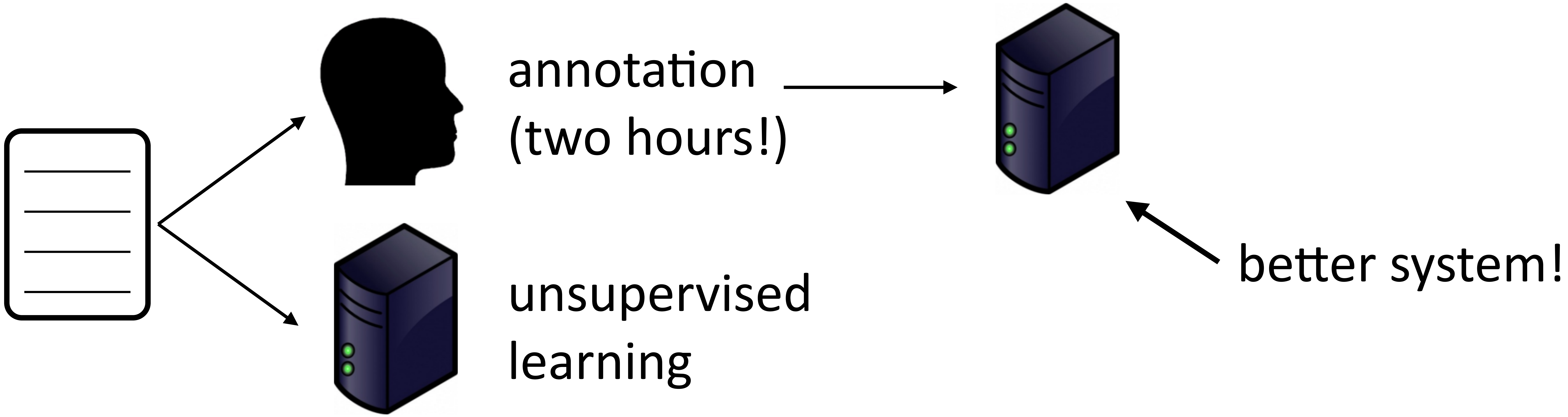

- Even neural nets can do pretty well!

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Pretraining

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

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

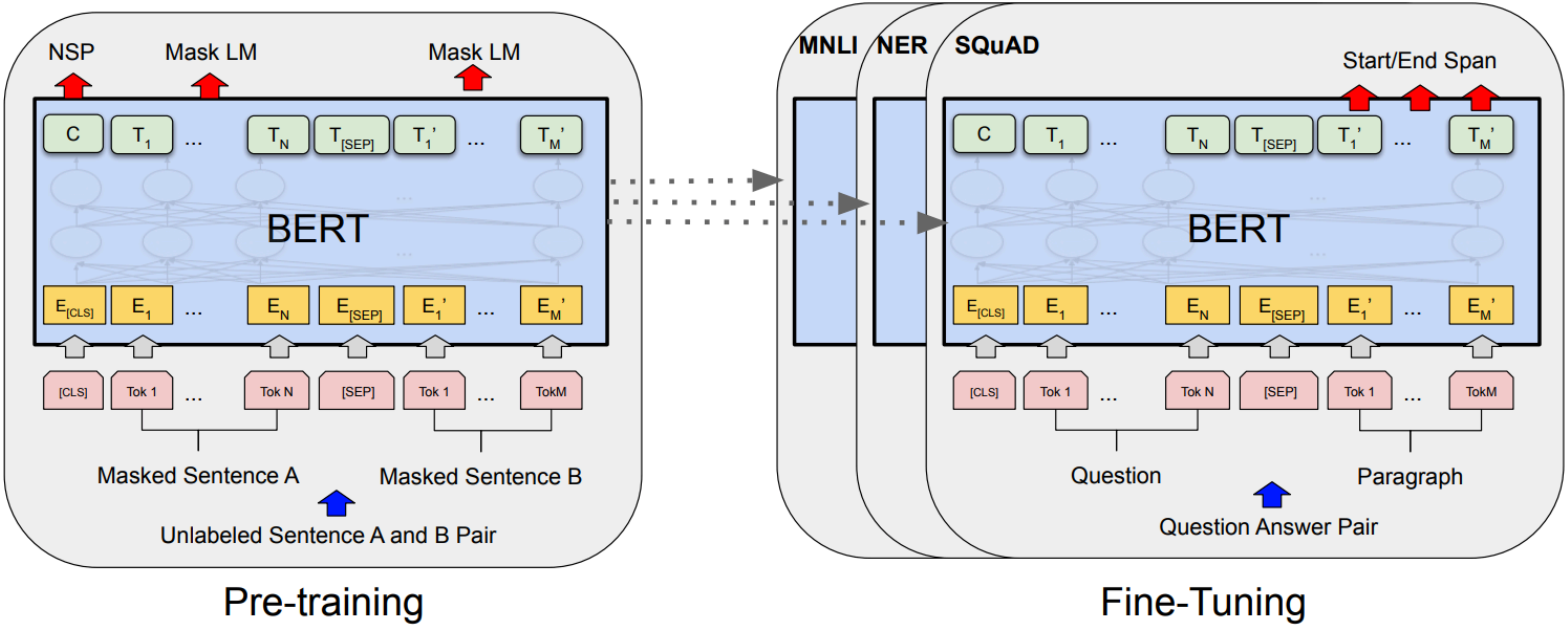
0.001 good

- 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)

BERT



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

Devlin et al. (2019)

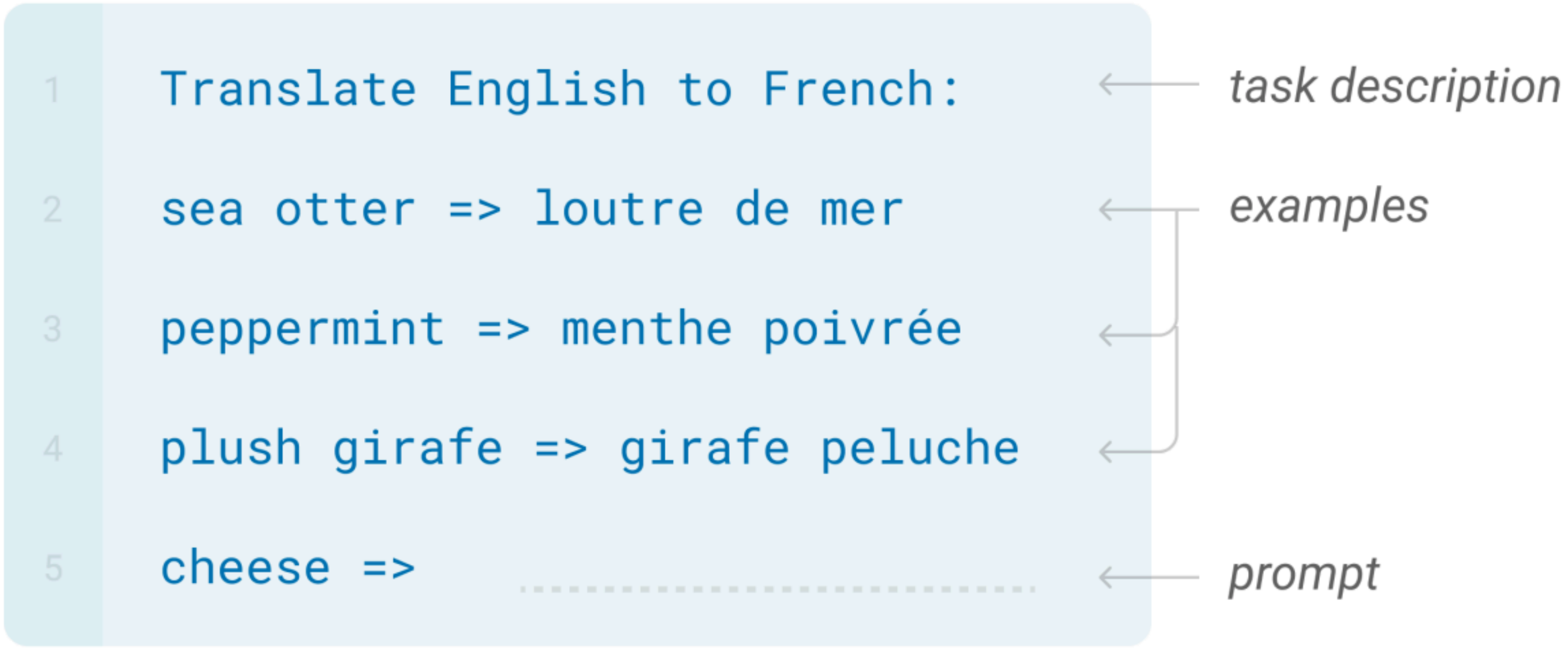
GPT and In-Context Learning

- 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!

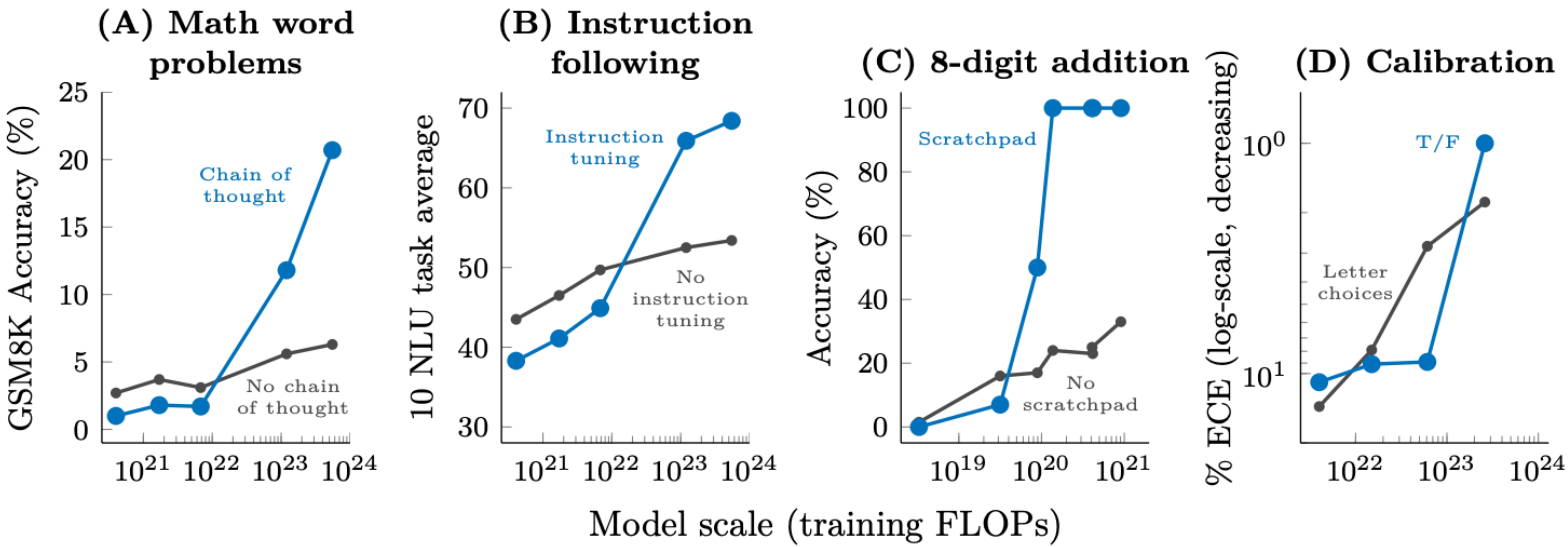
Few-shot

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



Brown et al. (2020)

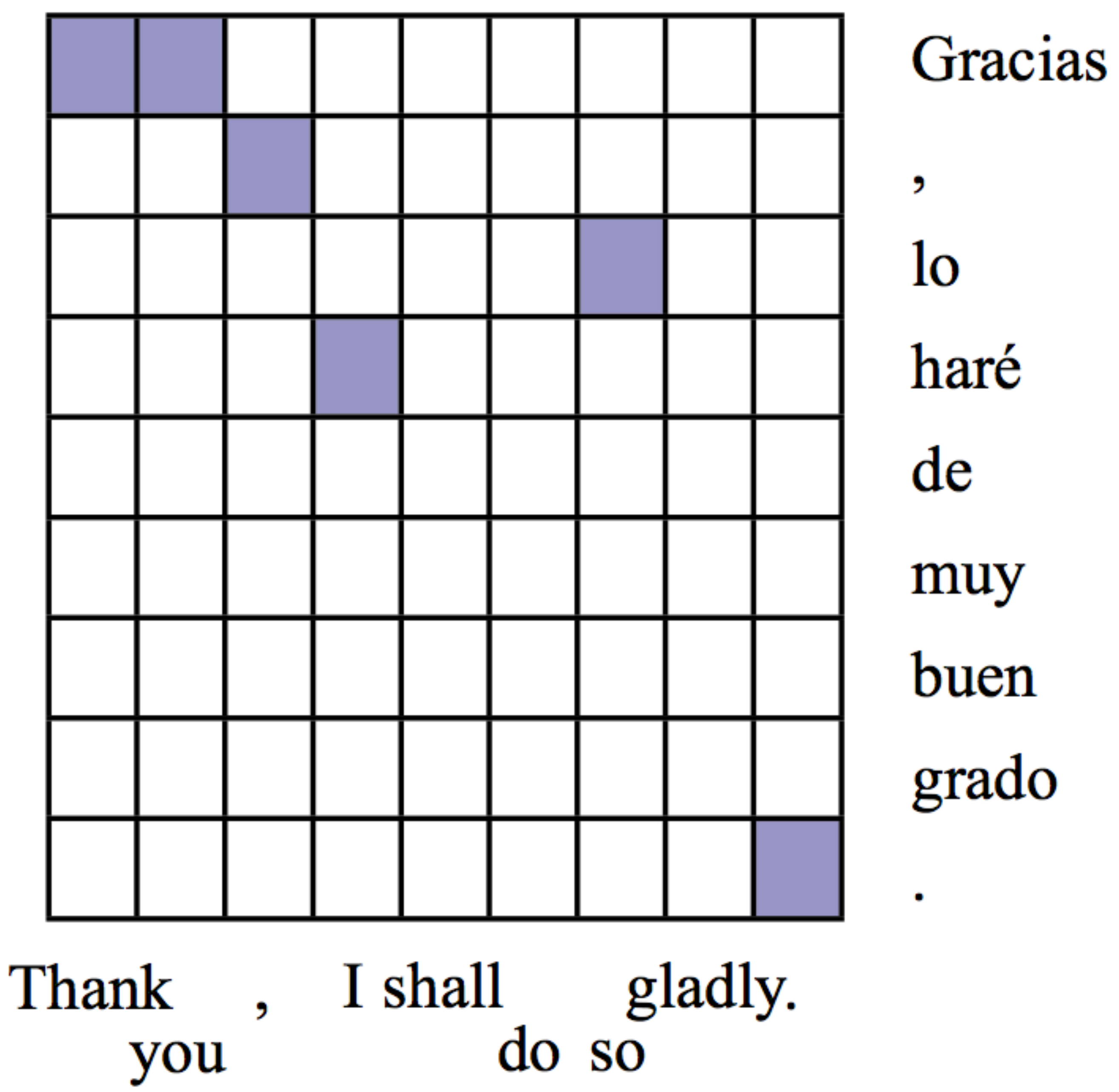
Scaling Laws



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

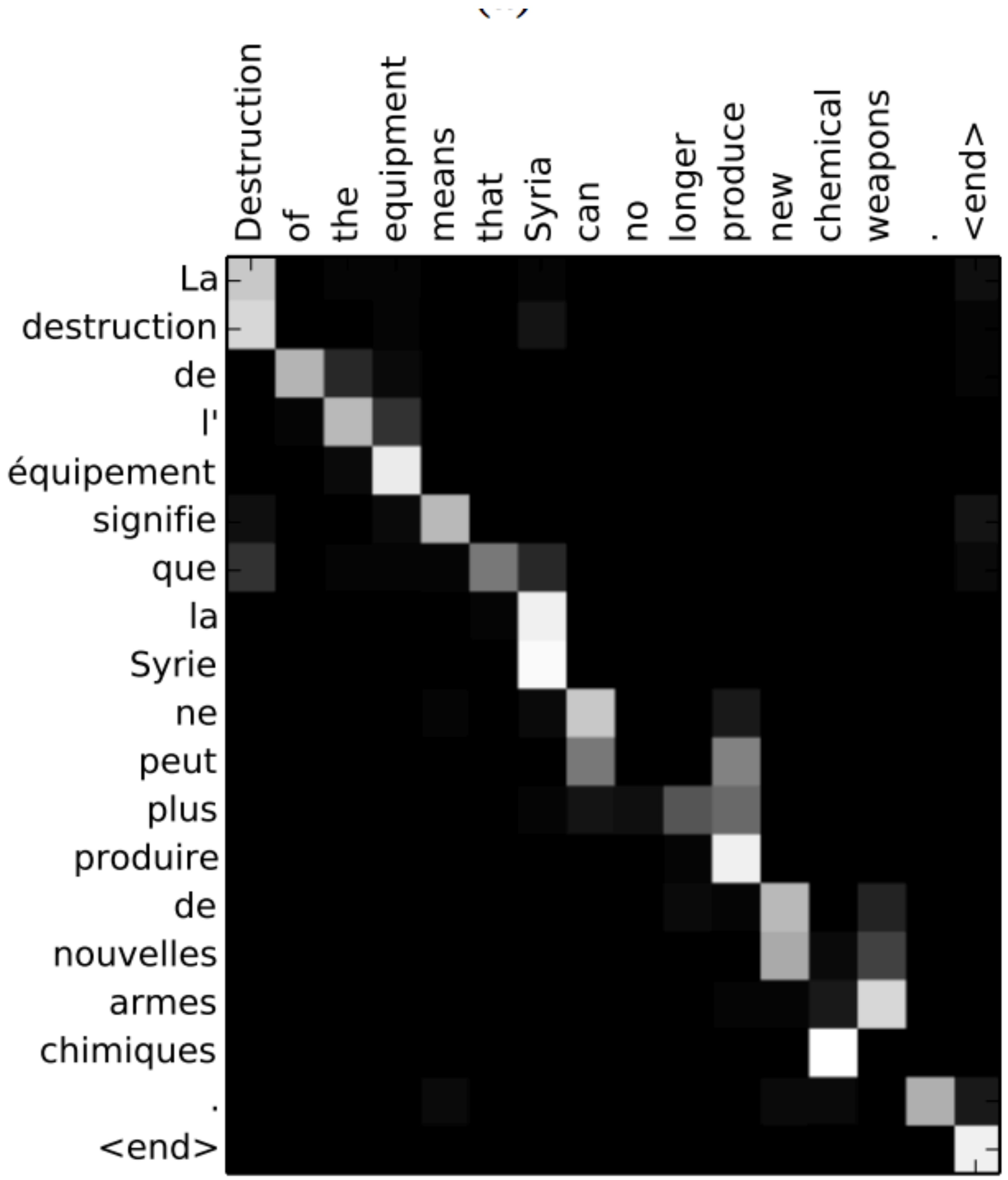
Kaplan et al. (2020), Jason Wei et al. (2022)

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
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