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 for questions asked over the weekend).
- TA Office hours:
  - See spreadsheet

https://tinyurl.com/7650-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 Machine Learning Course (otherwise this class will be a LOT more work)

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There will be a lot of math and programming!

Coursework

- 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

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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 recommended.
    - 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 1 (Background Review)

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

Project 1 is also out (please look!)

TextClassification_release_v2.ipynb

File Edit View Insert Runtime Tools Help All changes saved

+ Code + Text

```
# 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)
```

Project #1: Text Classification

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.

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.

Make sure to make a copy of this notebook, so your changes are saved.

Download the dataset

First you will need to download the IMDB dataset - to do this, simply run the cell below. We have prepared a small version of the ACL IMDB

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

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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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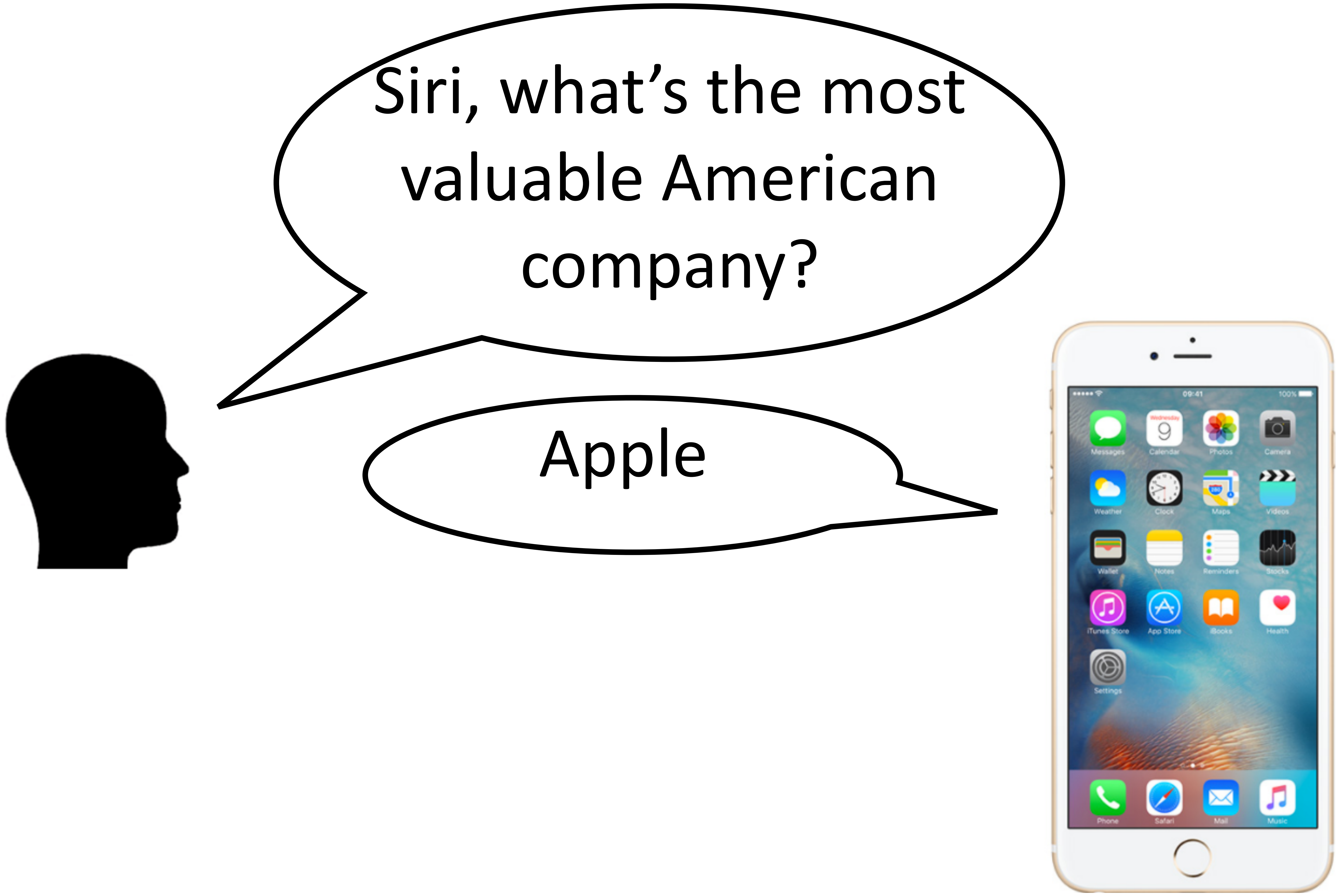

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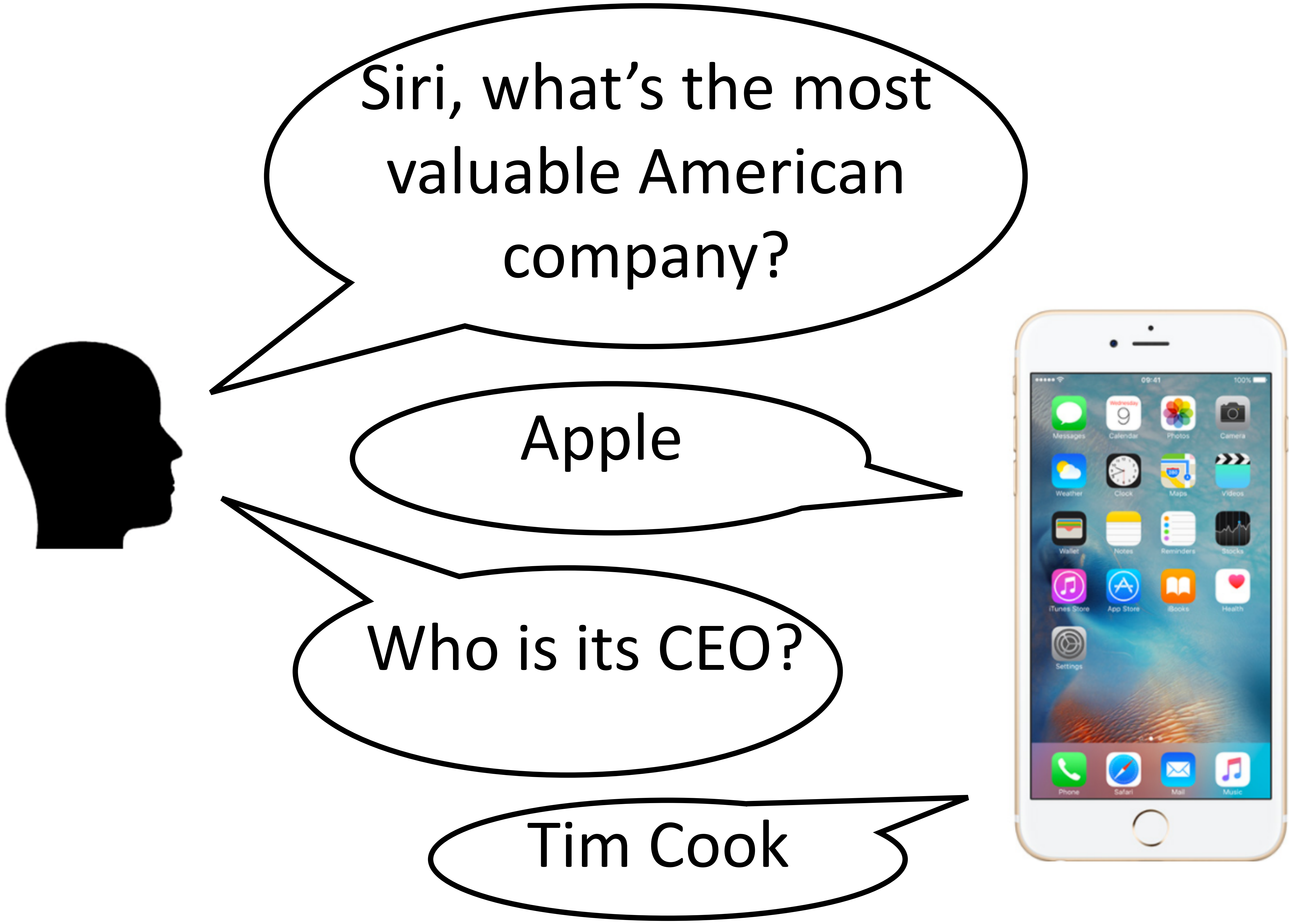

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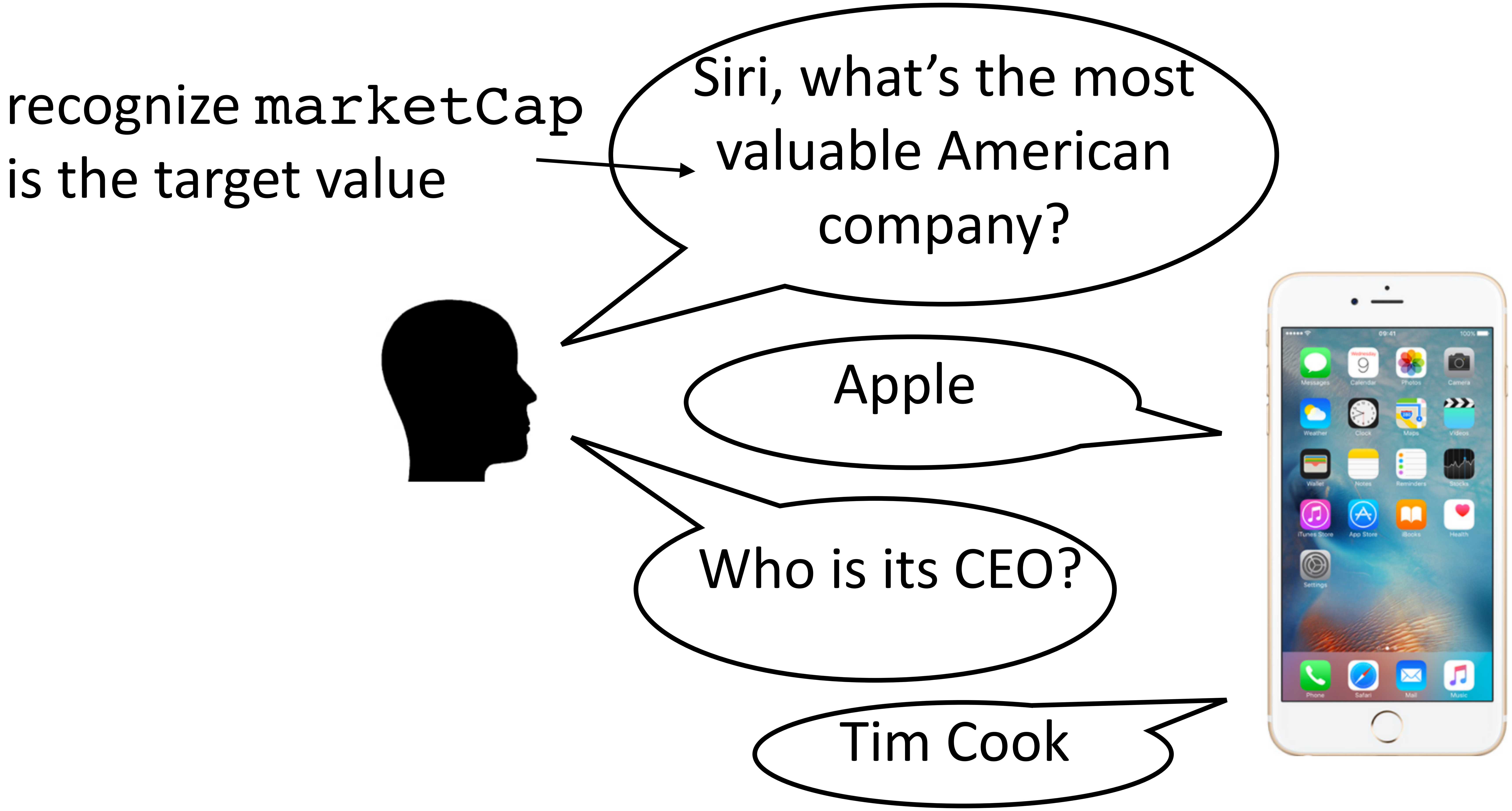

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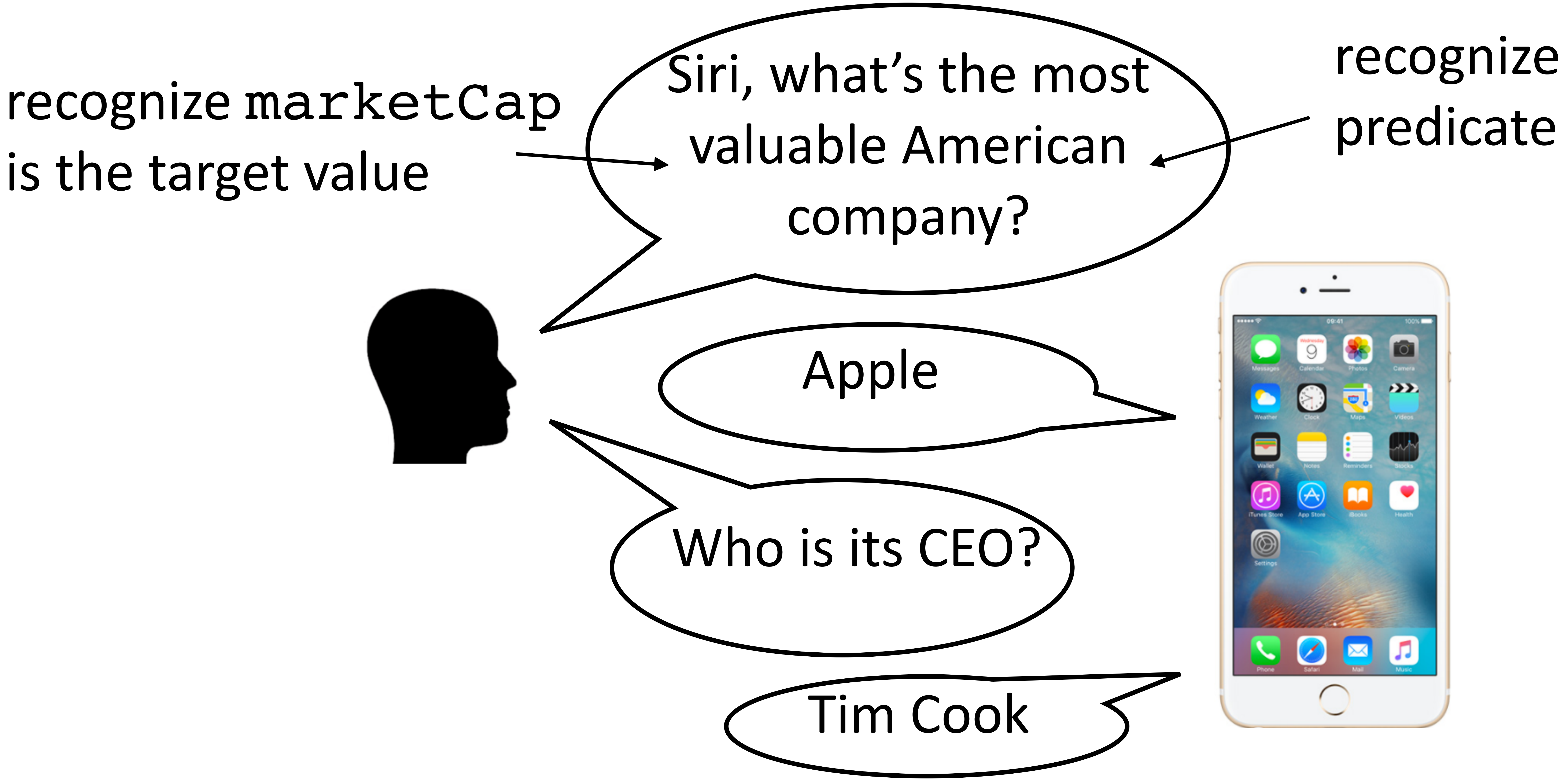

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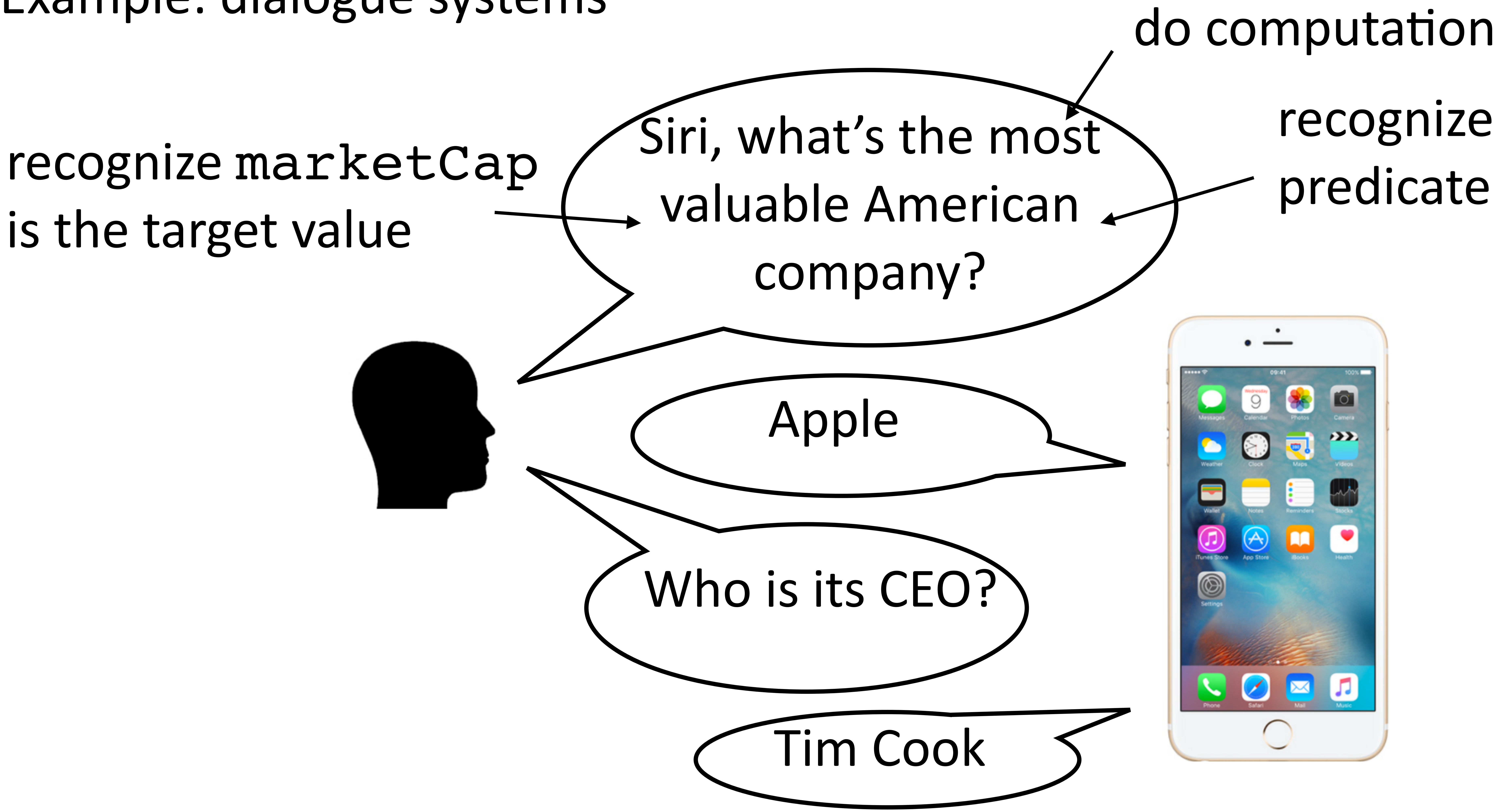

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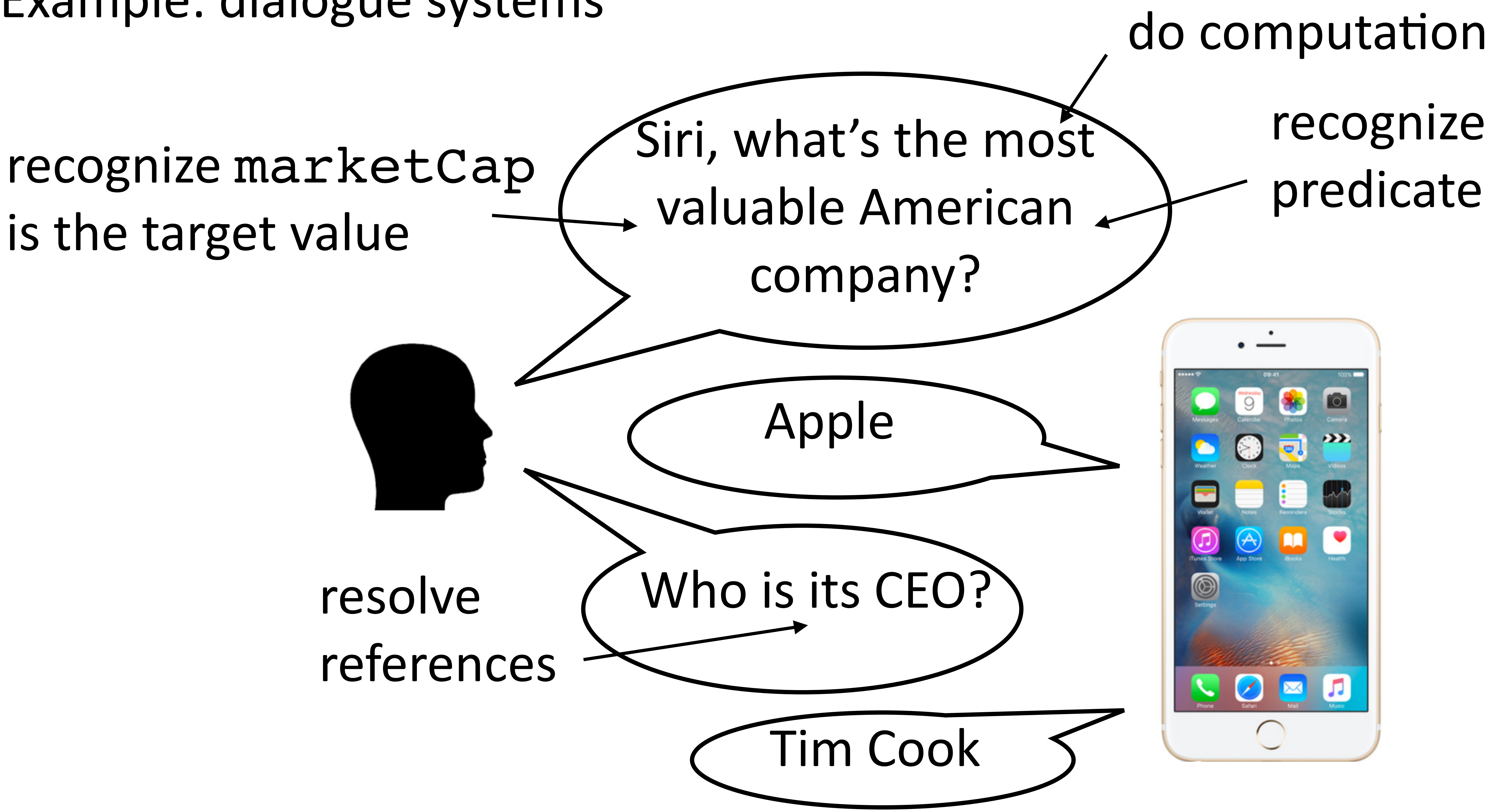

Automatic Summarization

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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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paraphrase to provide clarity

Machine Translation

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7 小时前

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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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NLP Analysis Pipeline

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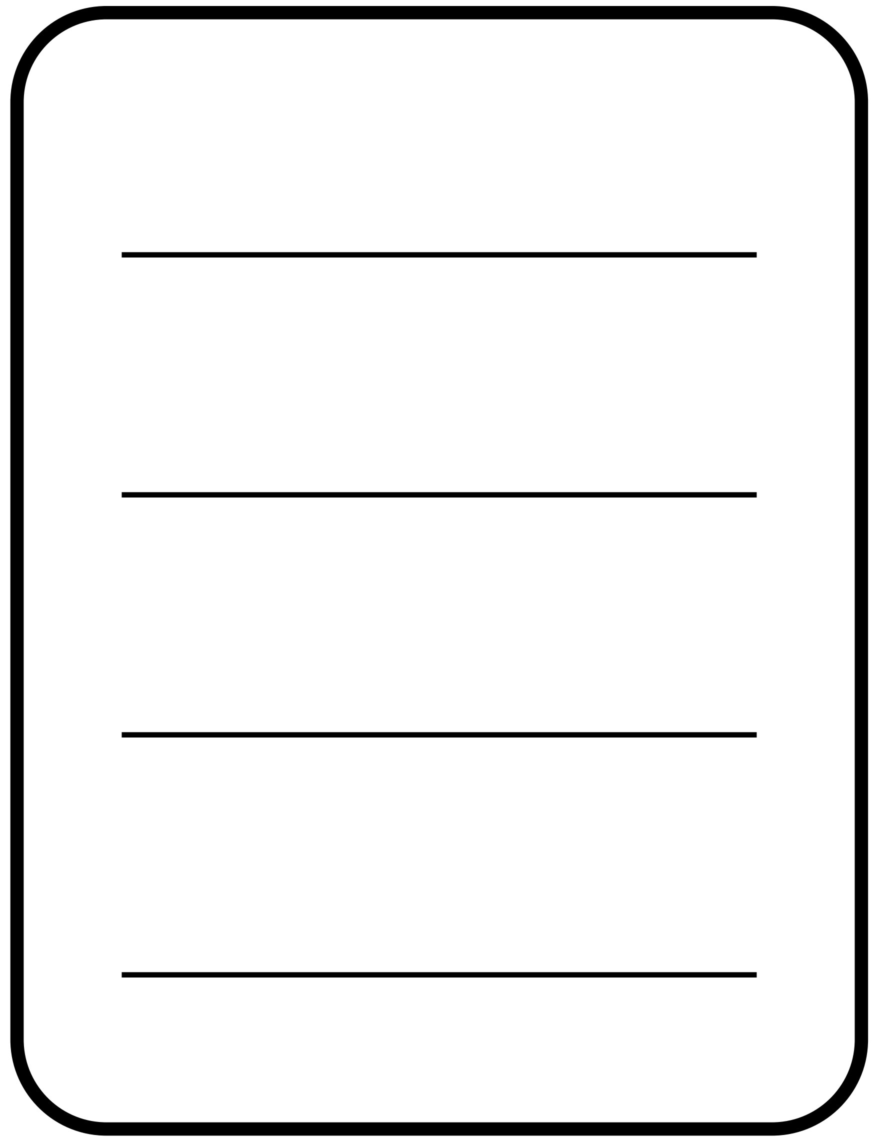

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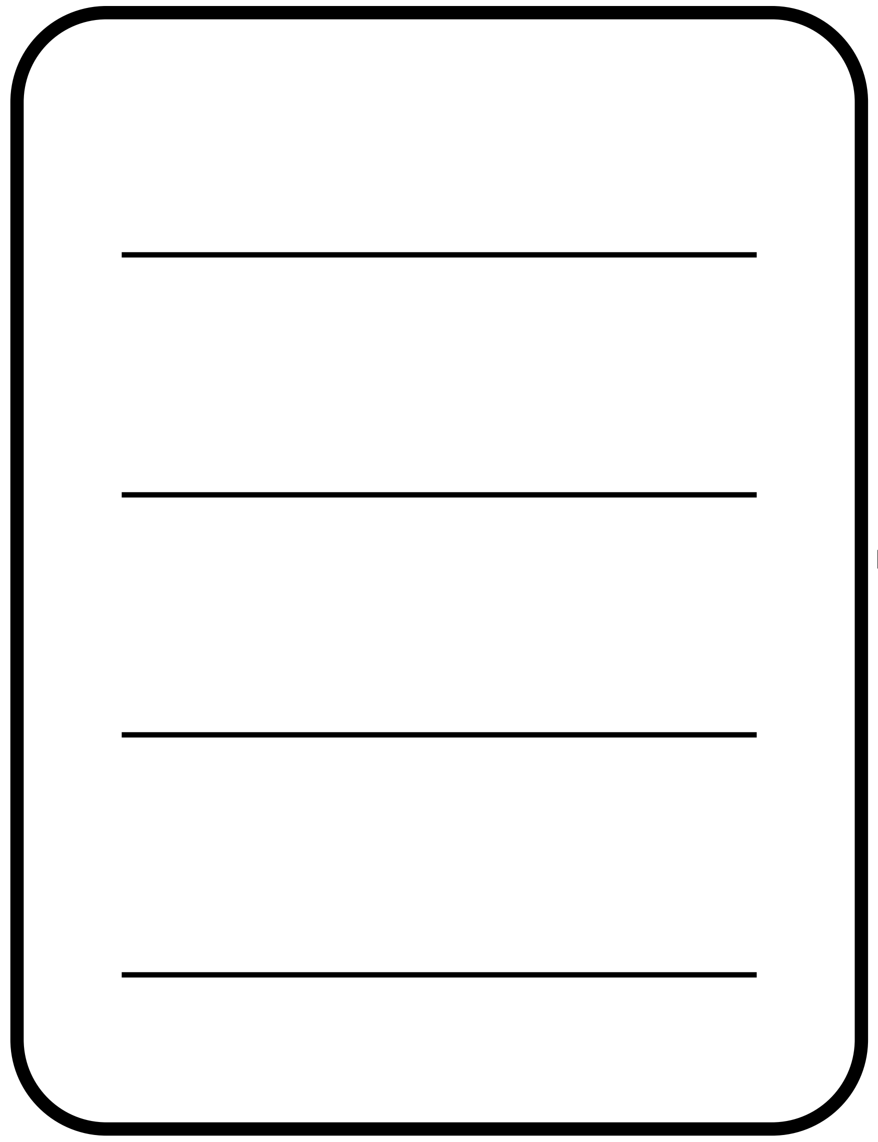

Text Analysis

Syntactic parses

Coreference resolution

Entity disambiguation

Discourse analysis

NLP Analysis Pipeline

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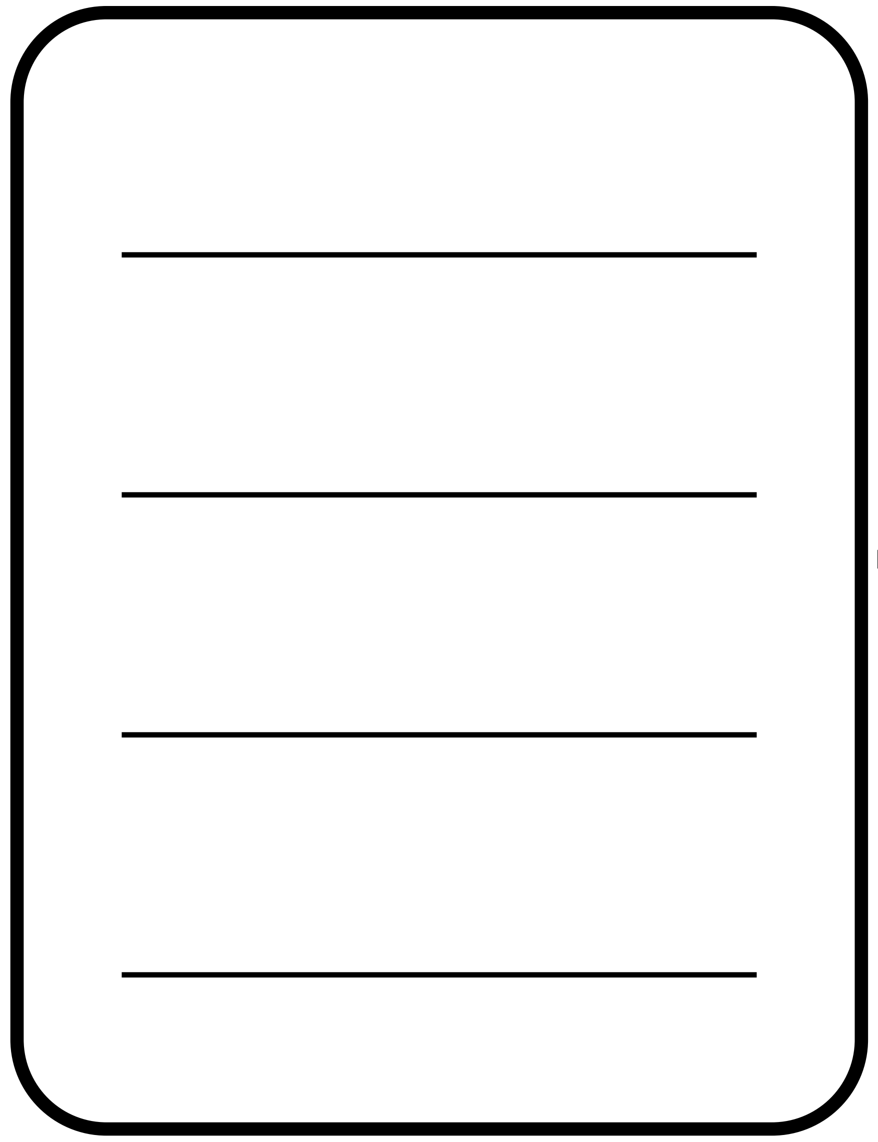

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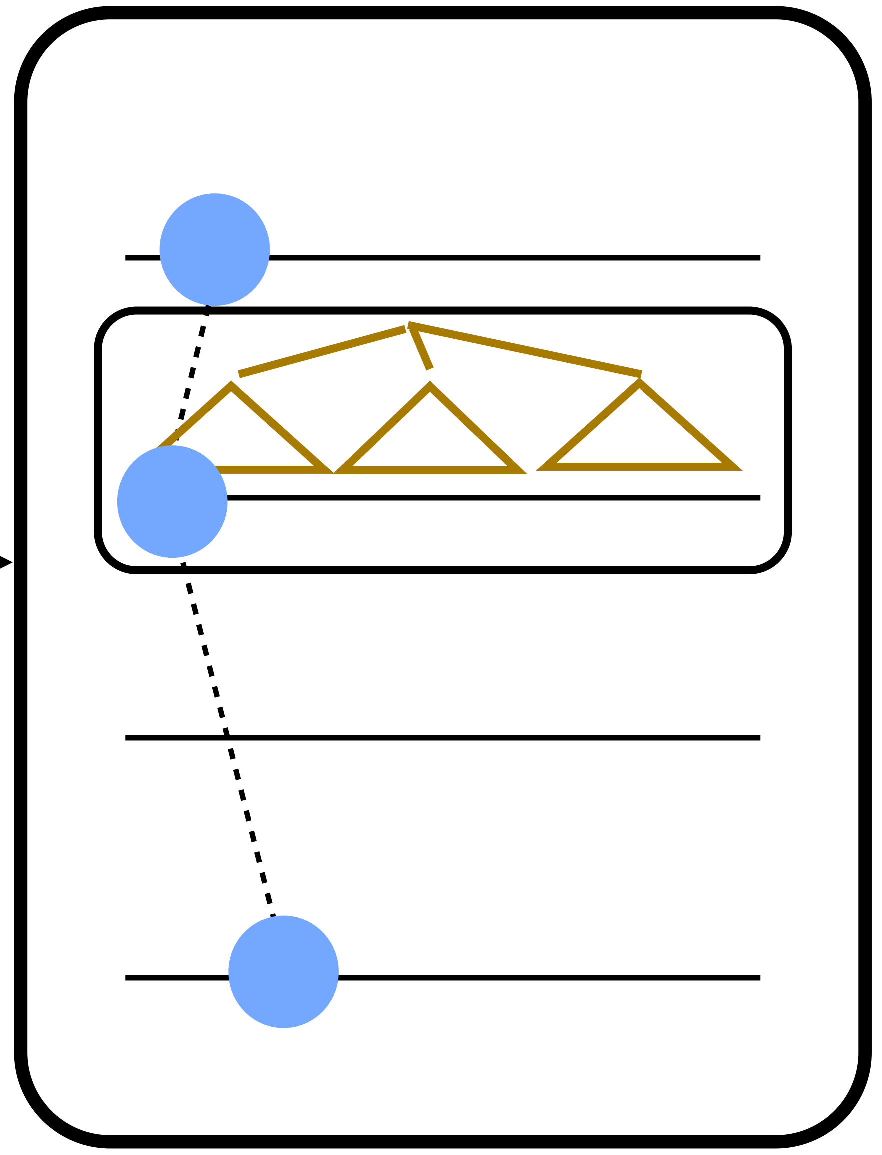

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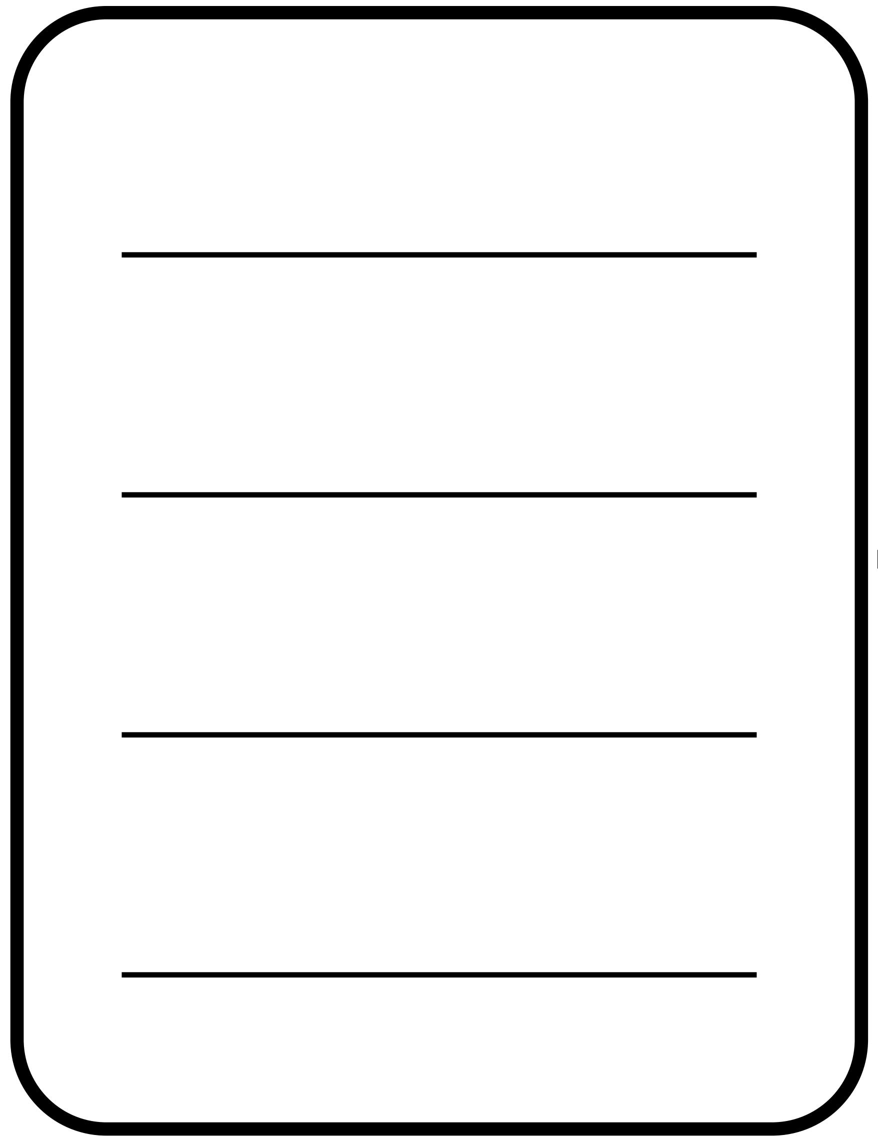

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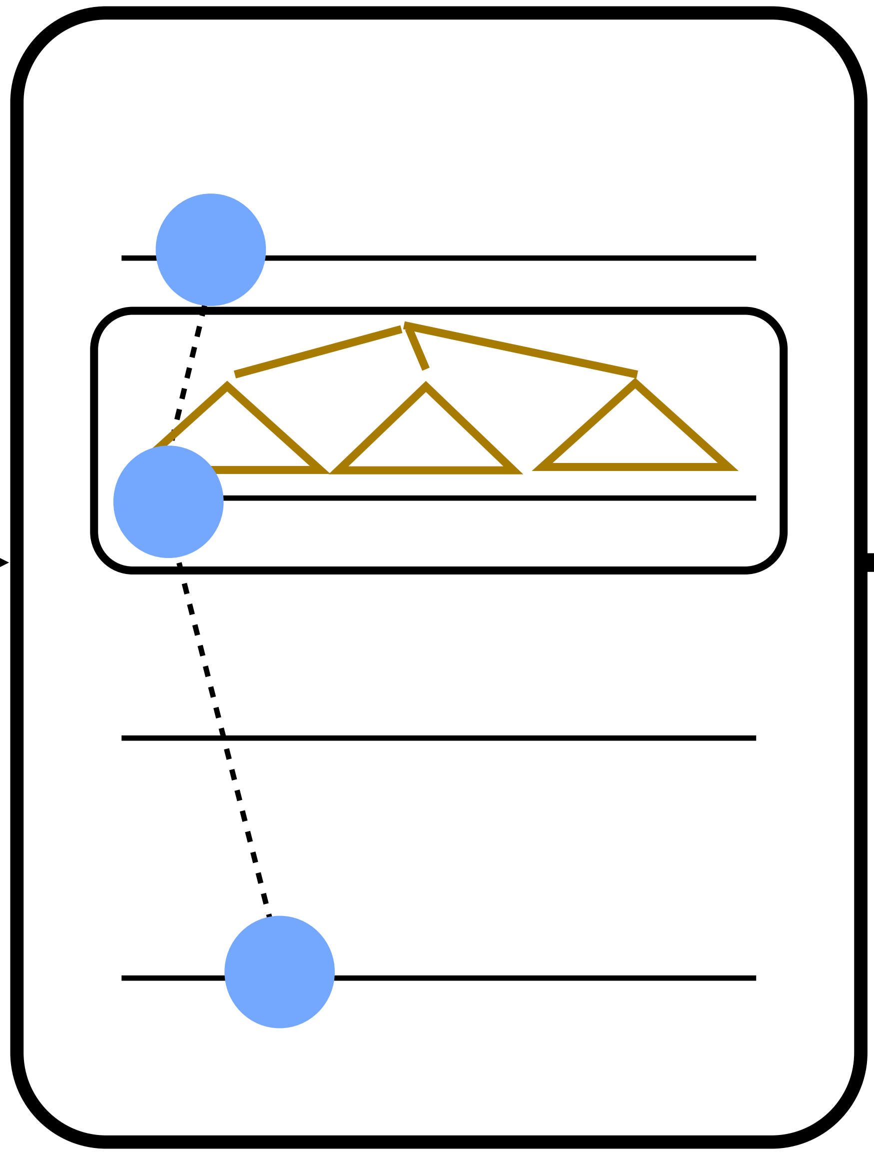

Applications

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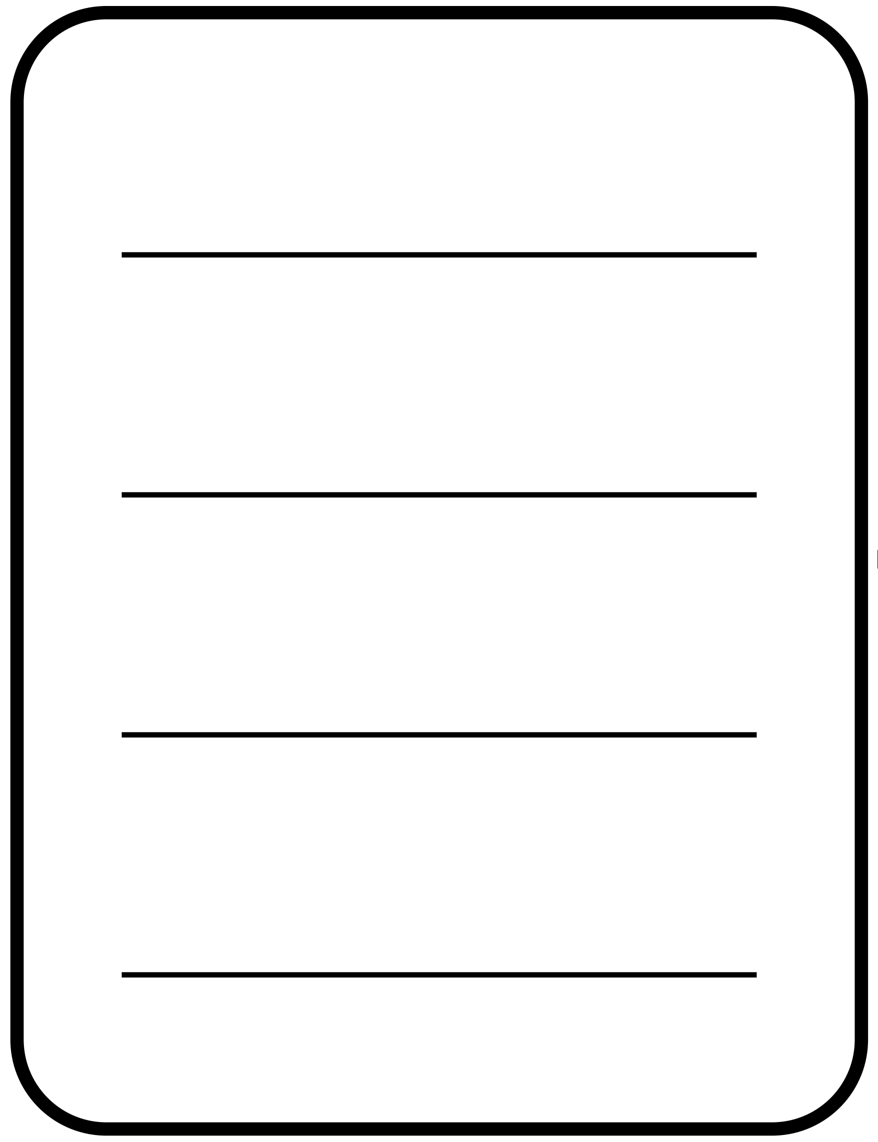

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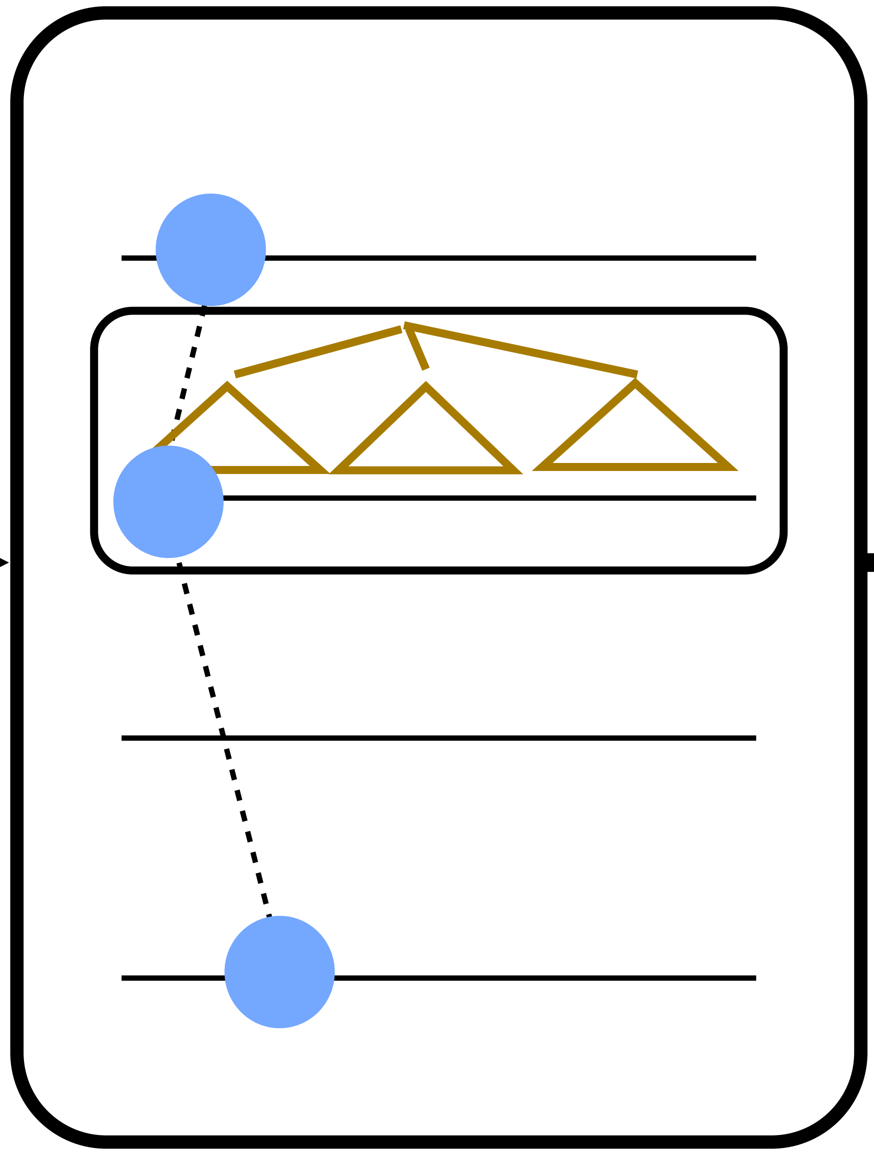

Applications

Summarize

NLP Analysis Pipeline

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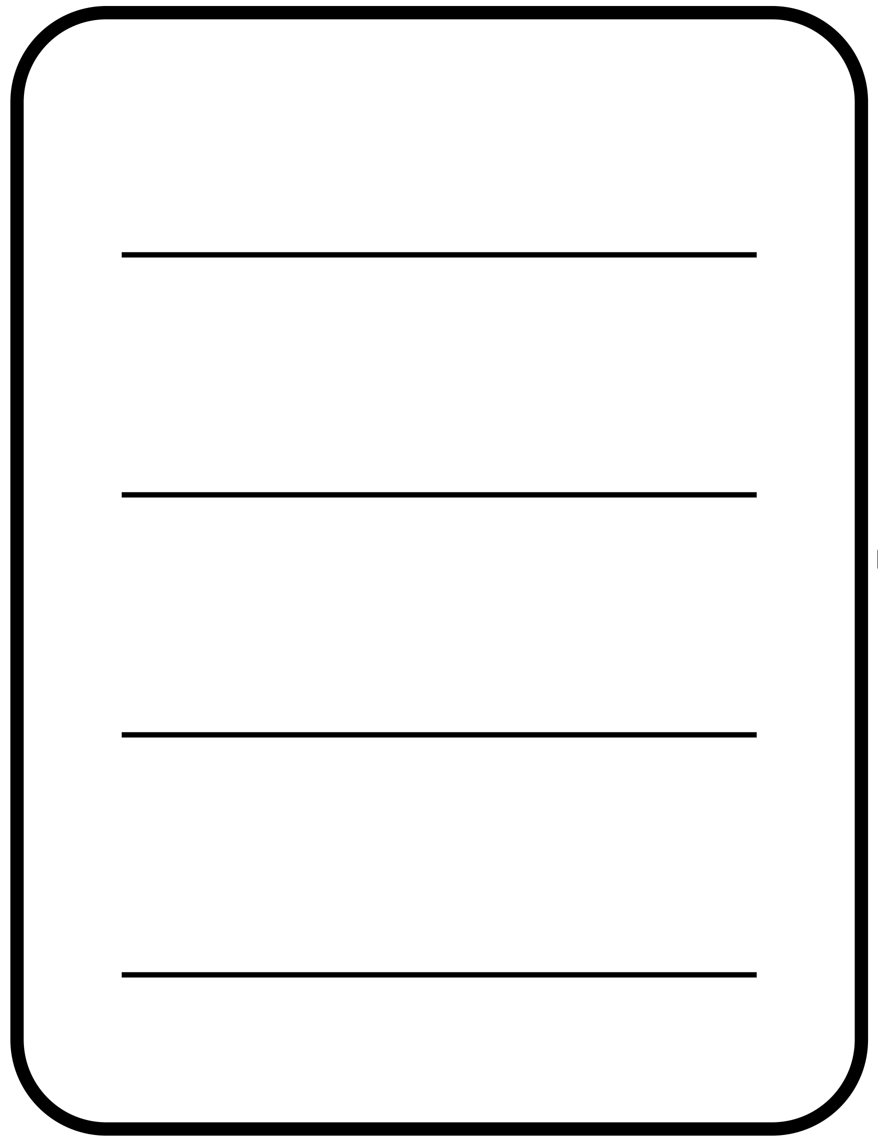

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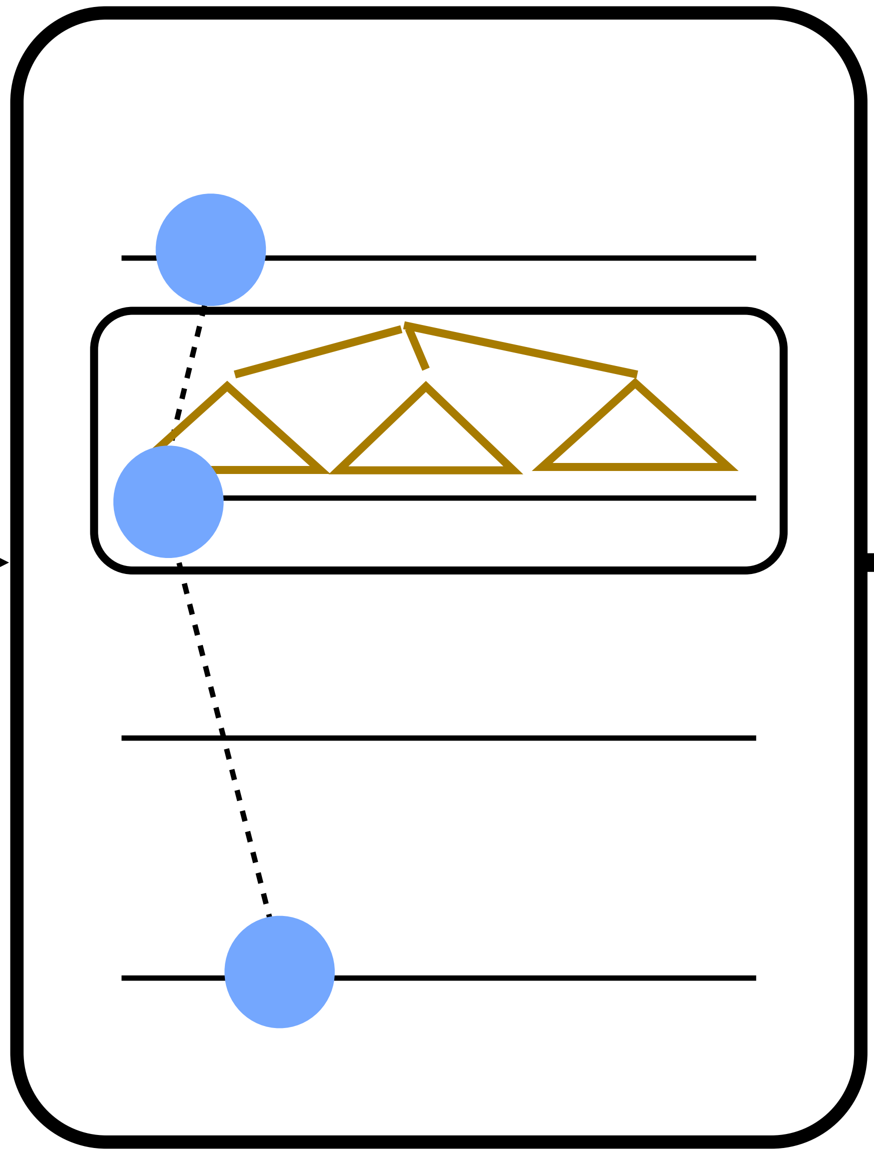

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Summarize

Extract information

NLP Analysis Pipeline

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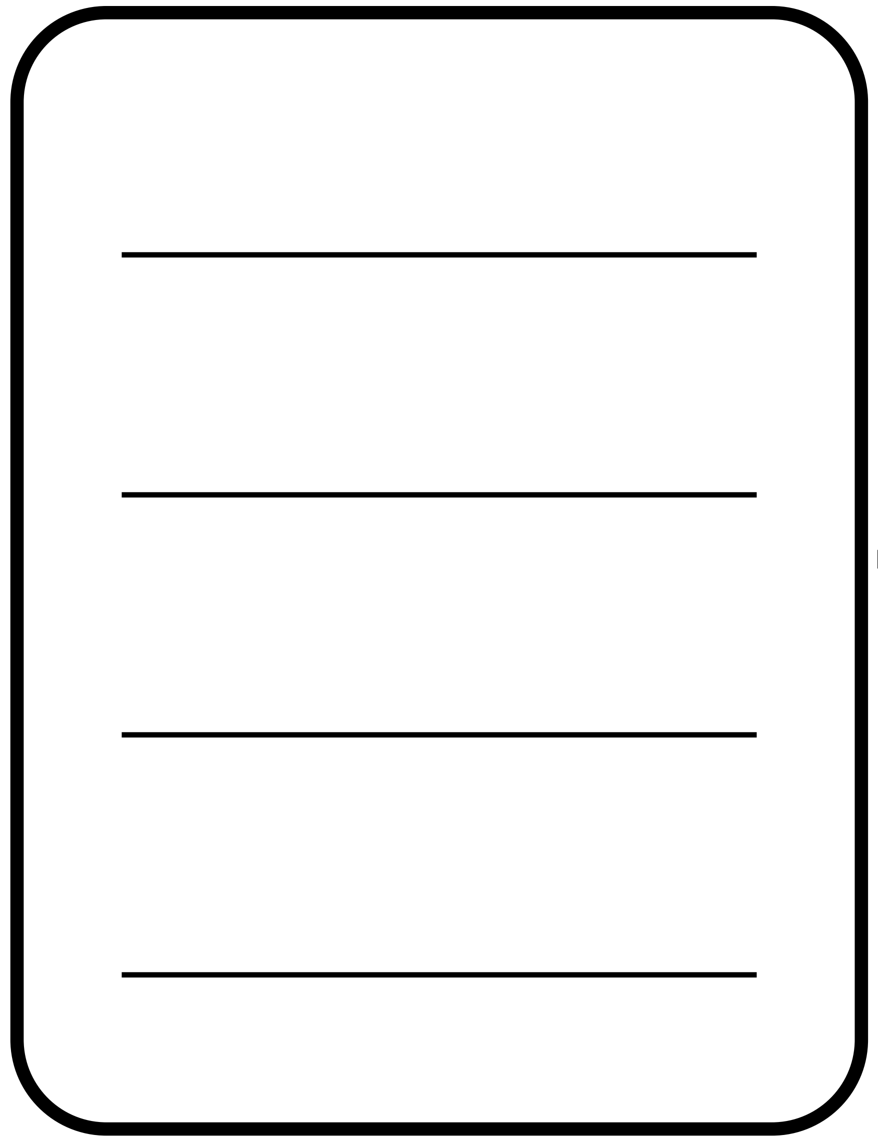

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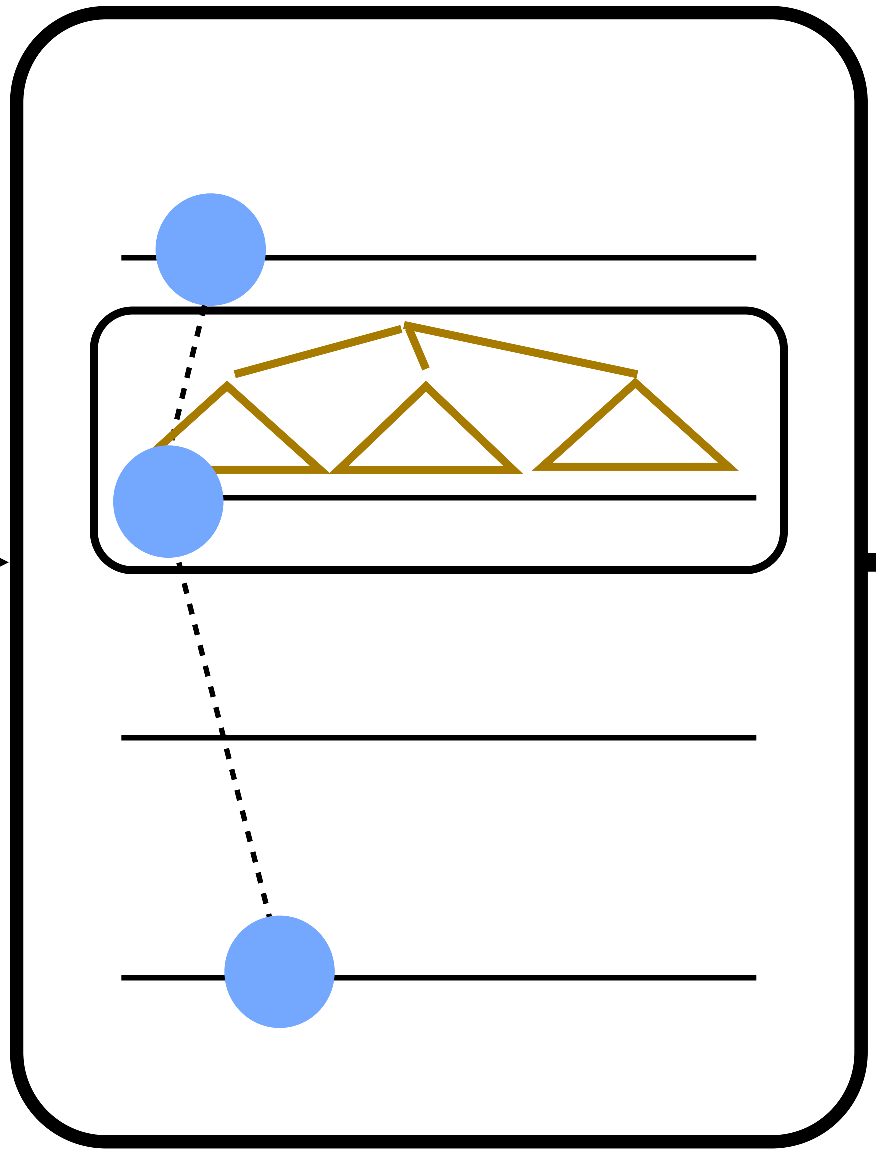

Applications

Summarize

Extract information

Answer questions

NLP Analysis Pipeline

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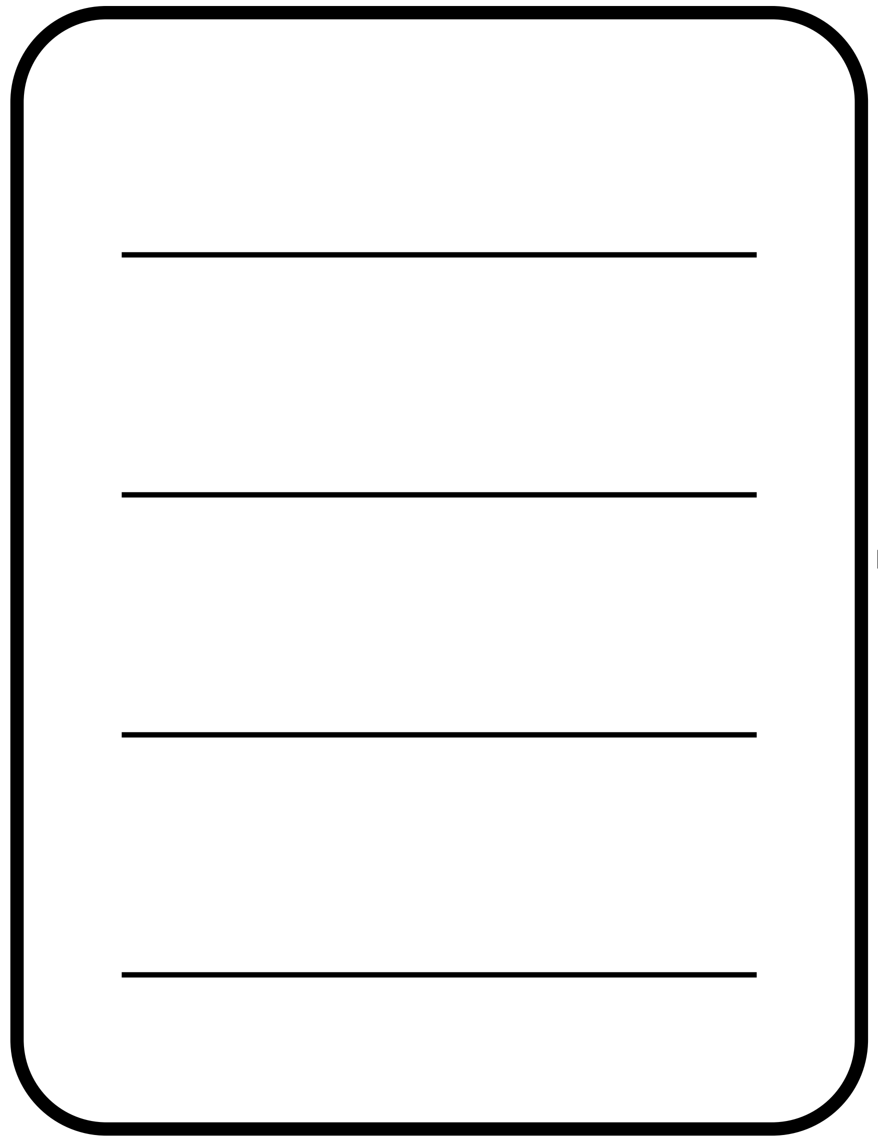

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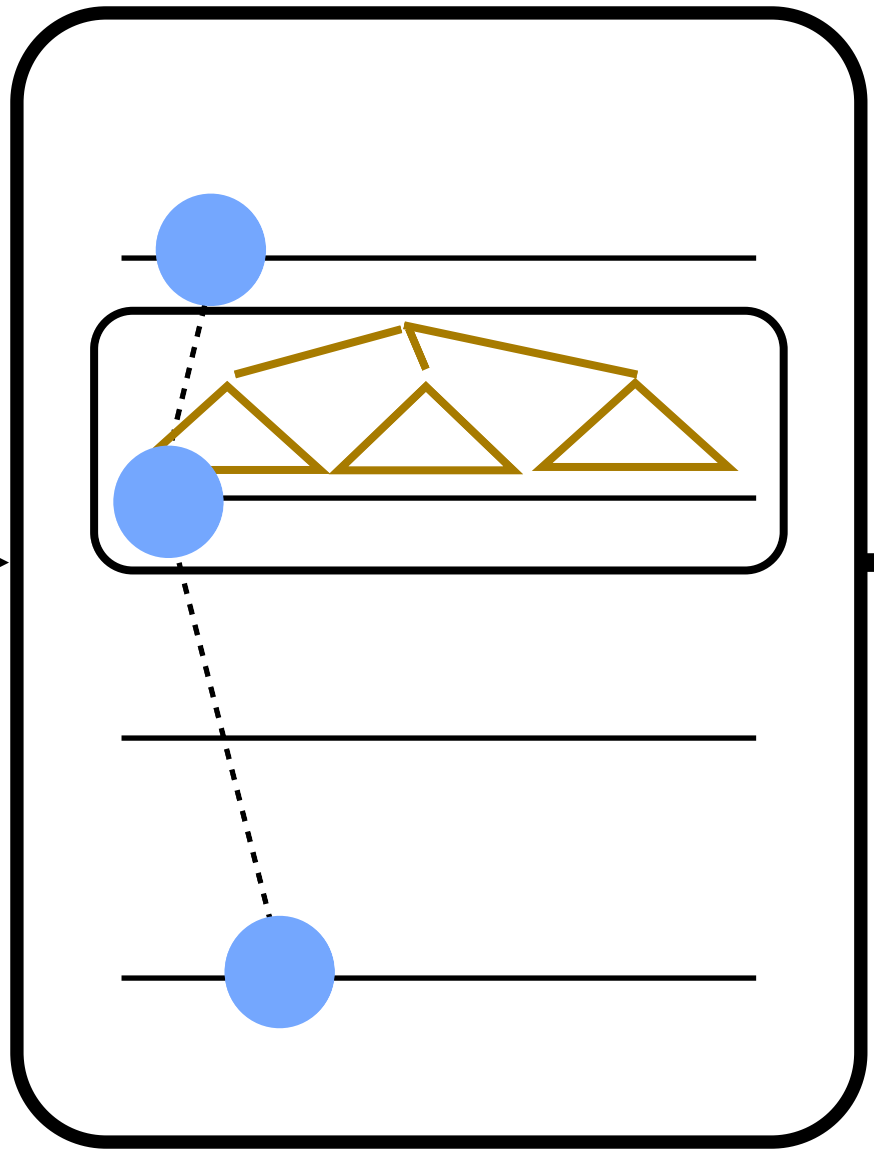

Applications

Summarize

Extract information

Answer questions

Identify sentiment

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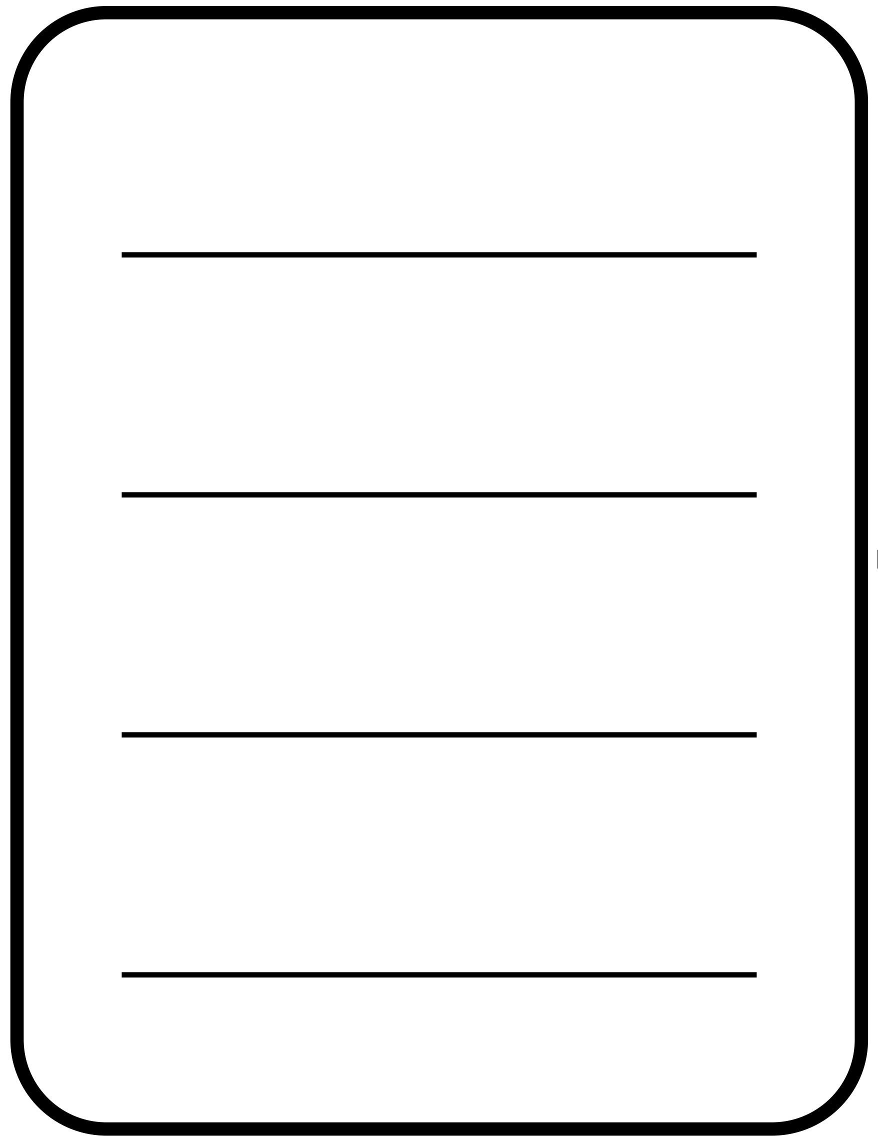

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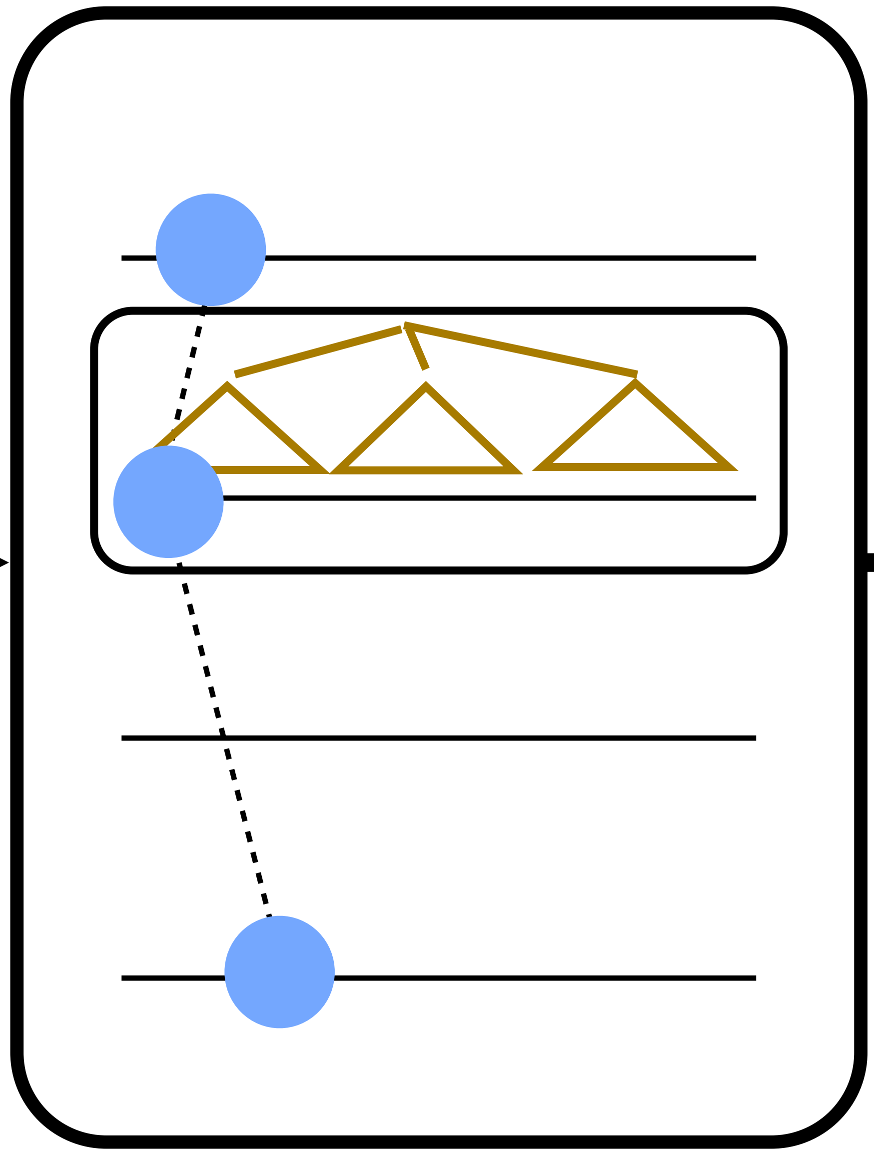

Applications

- Summarize
- Extract information
- Answer questions
- Identify sentiment
- Translate

NLP Analysis Pipeline

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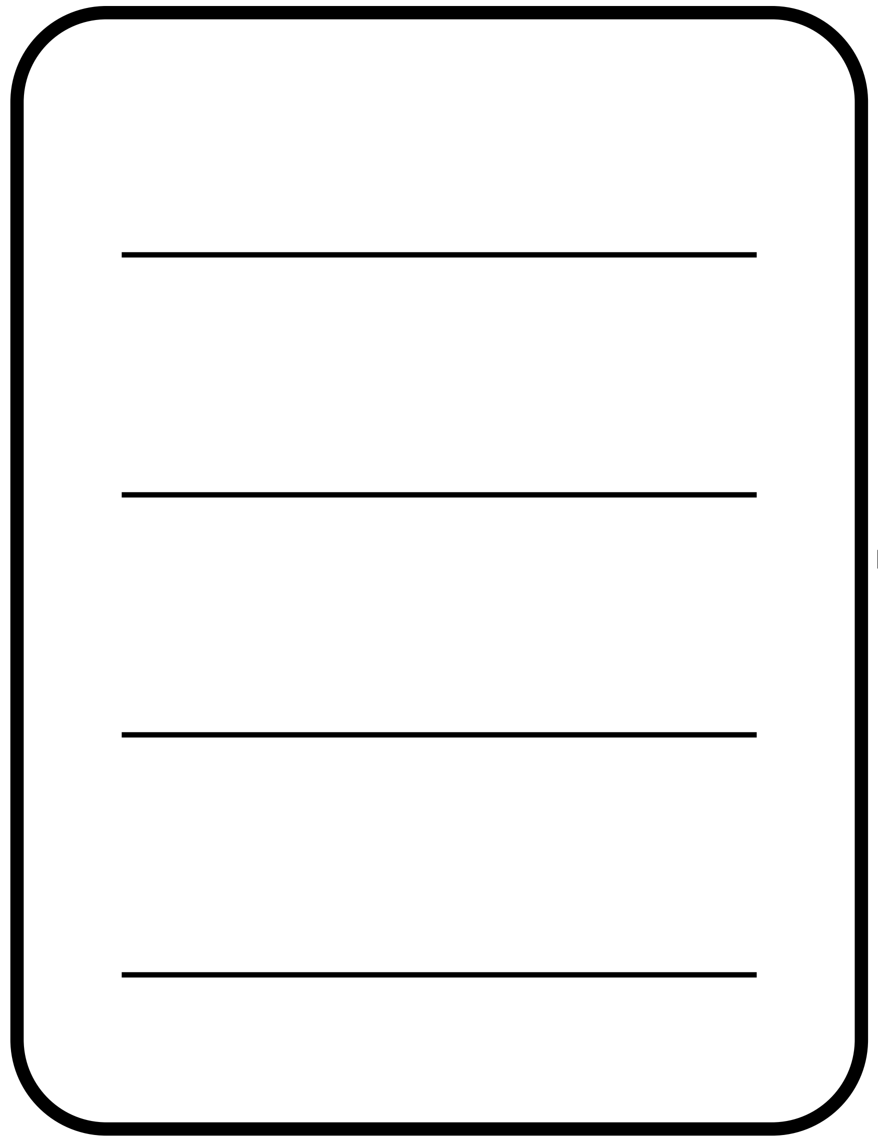

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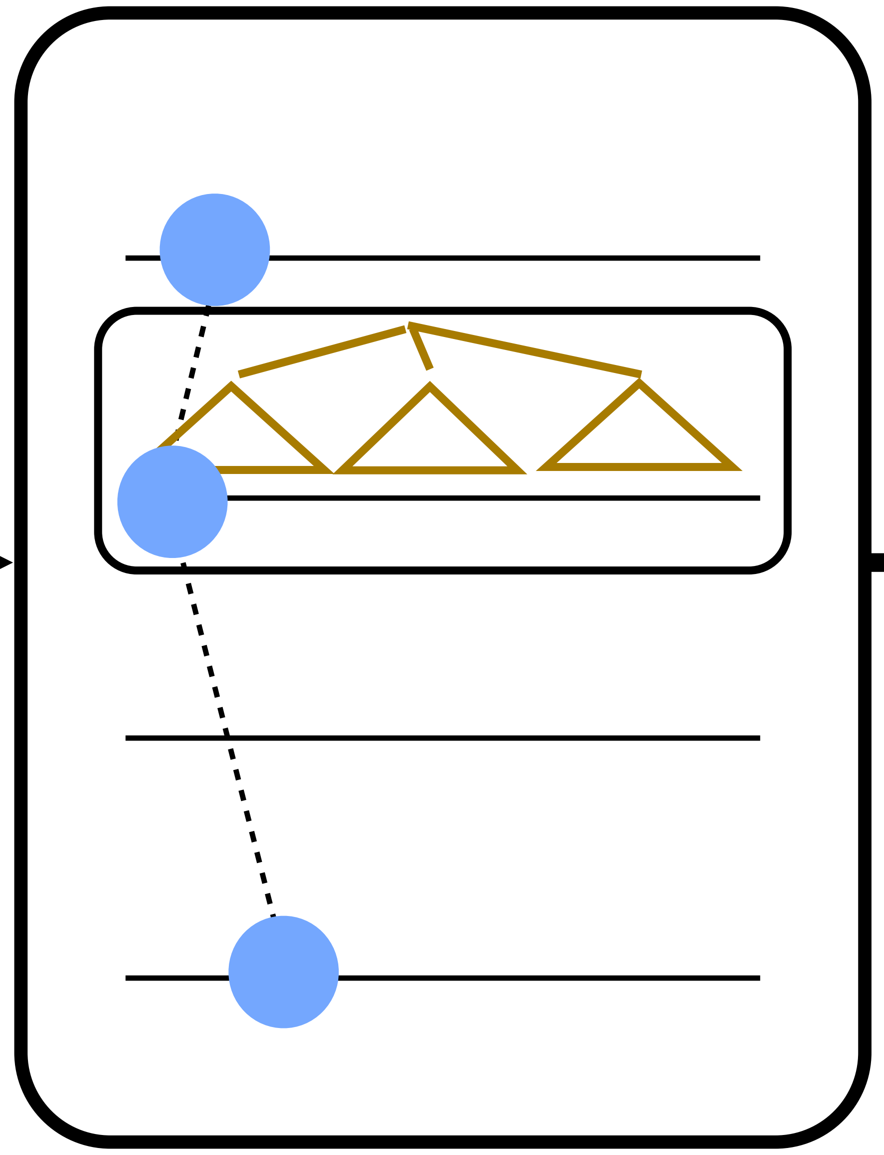

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- NLP is about building these pieces!

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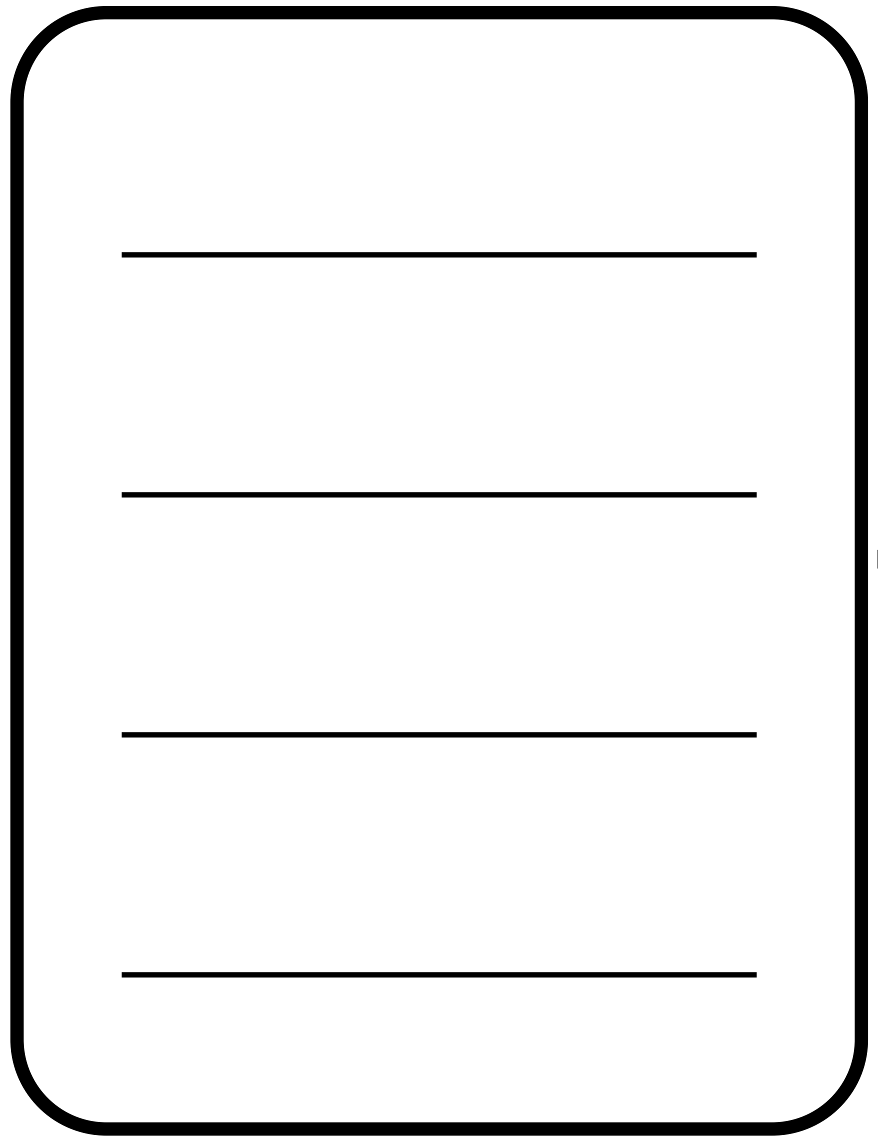

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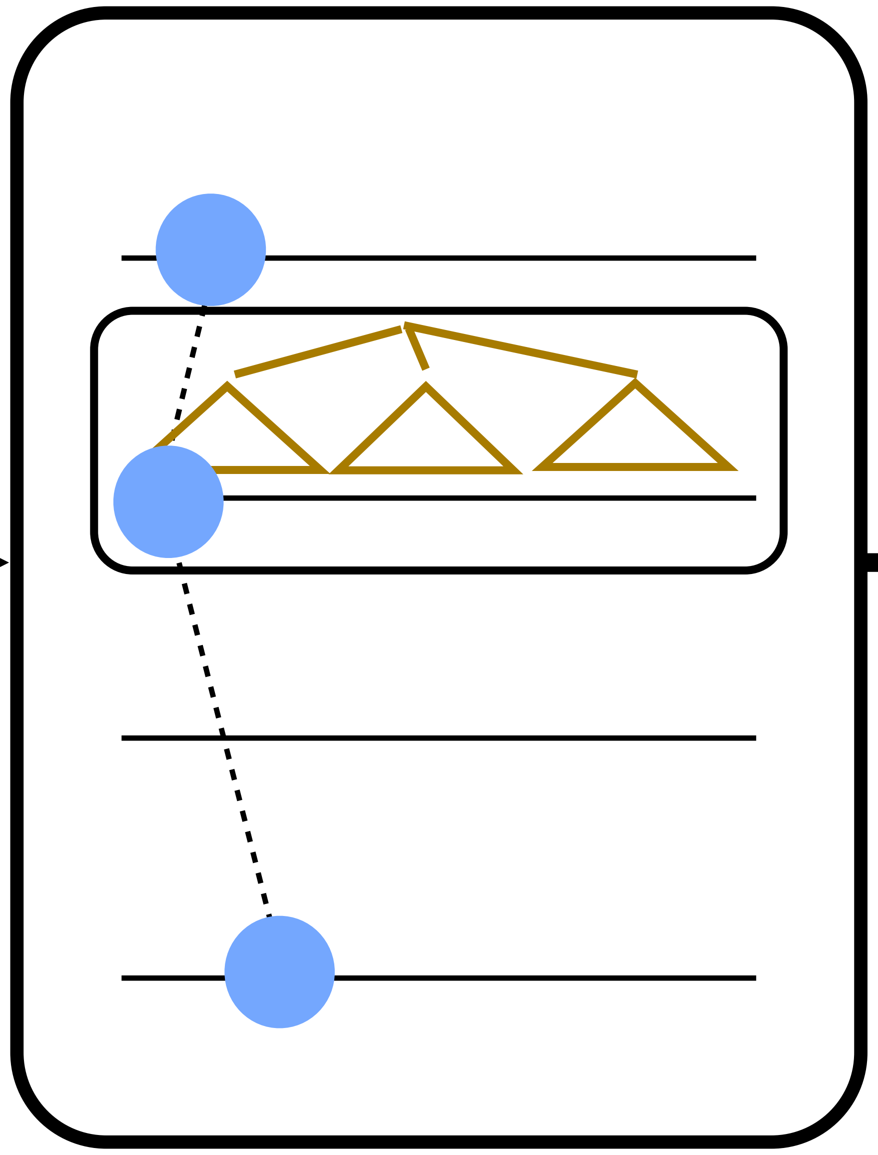

Applications

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

How do we represent language?

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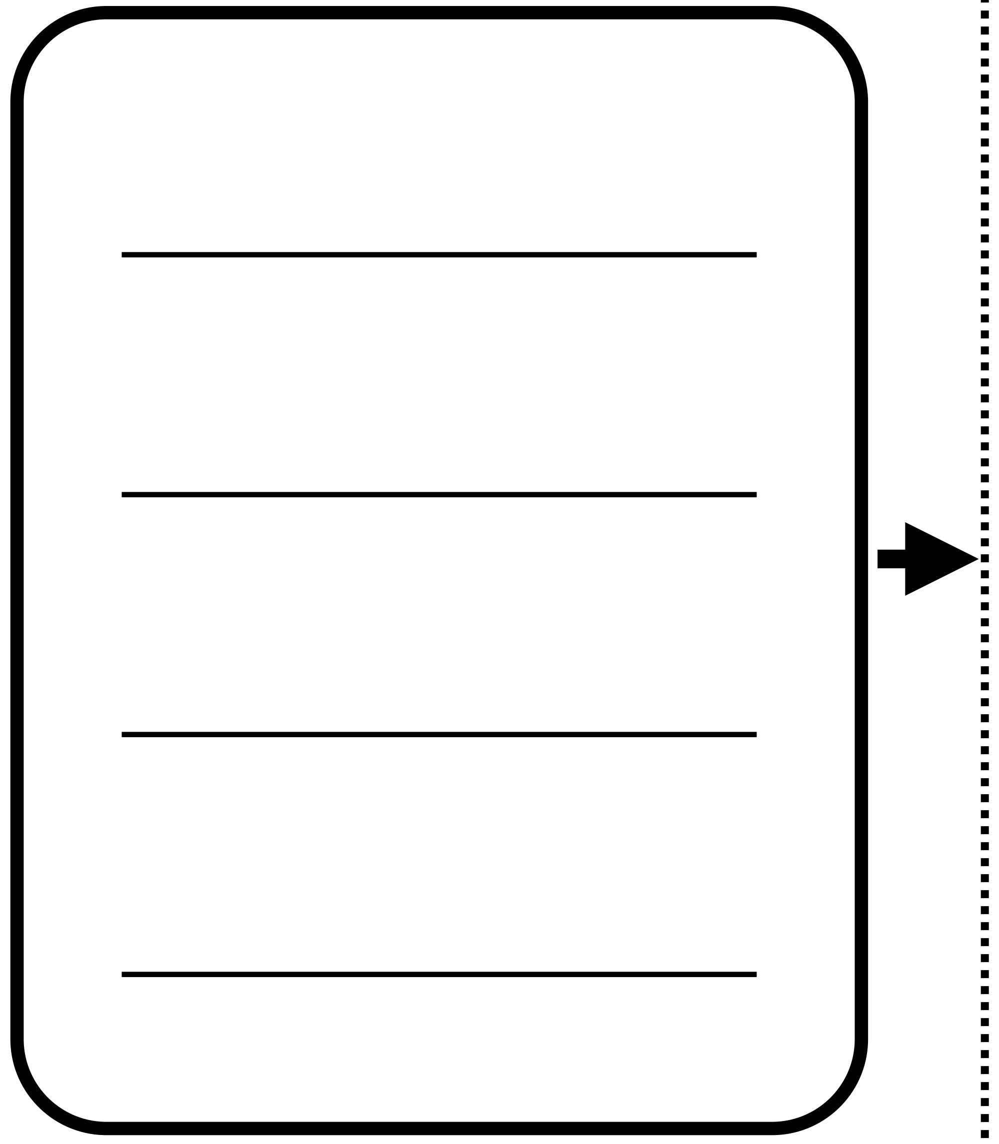

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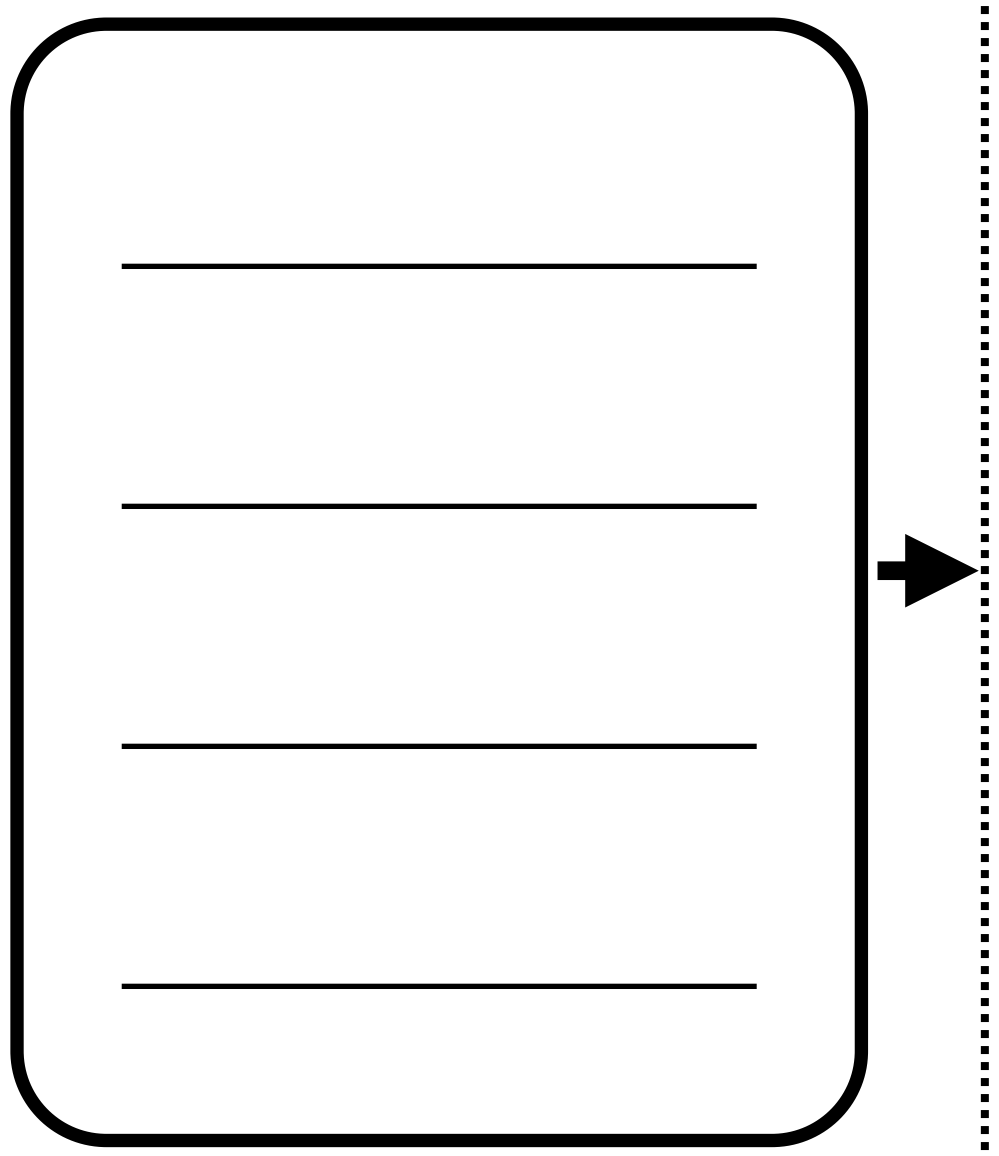

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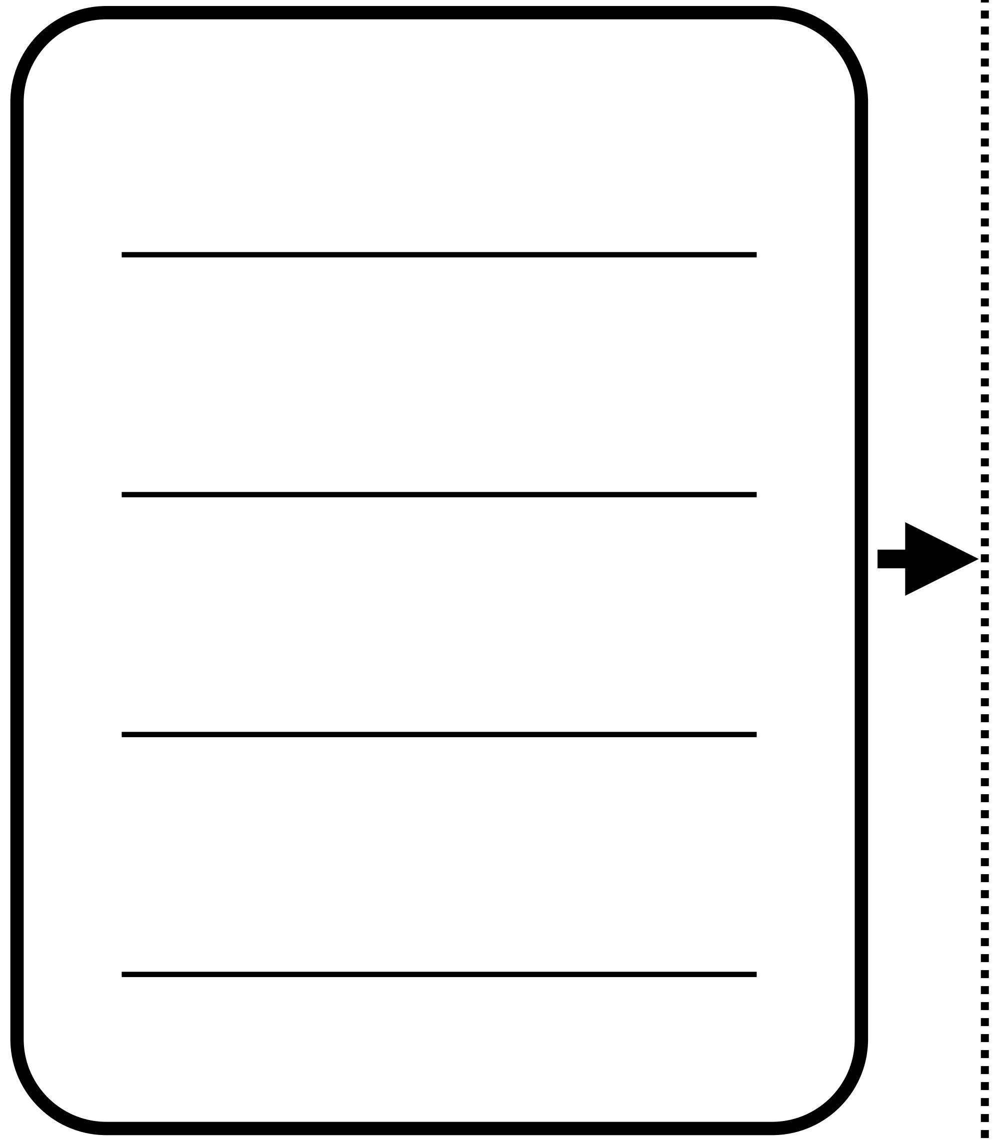

Labels

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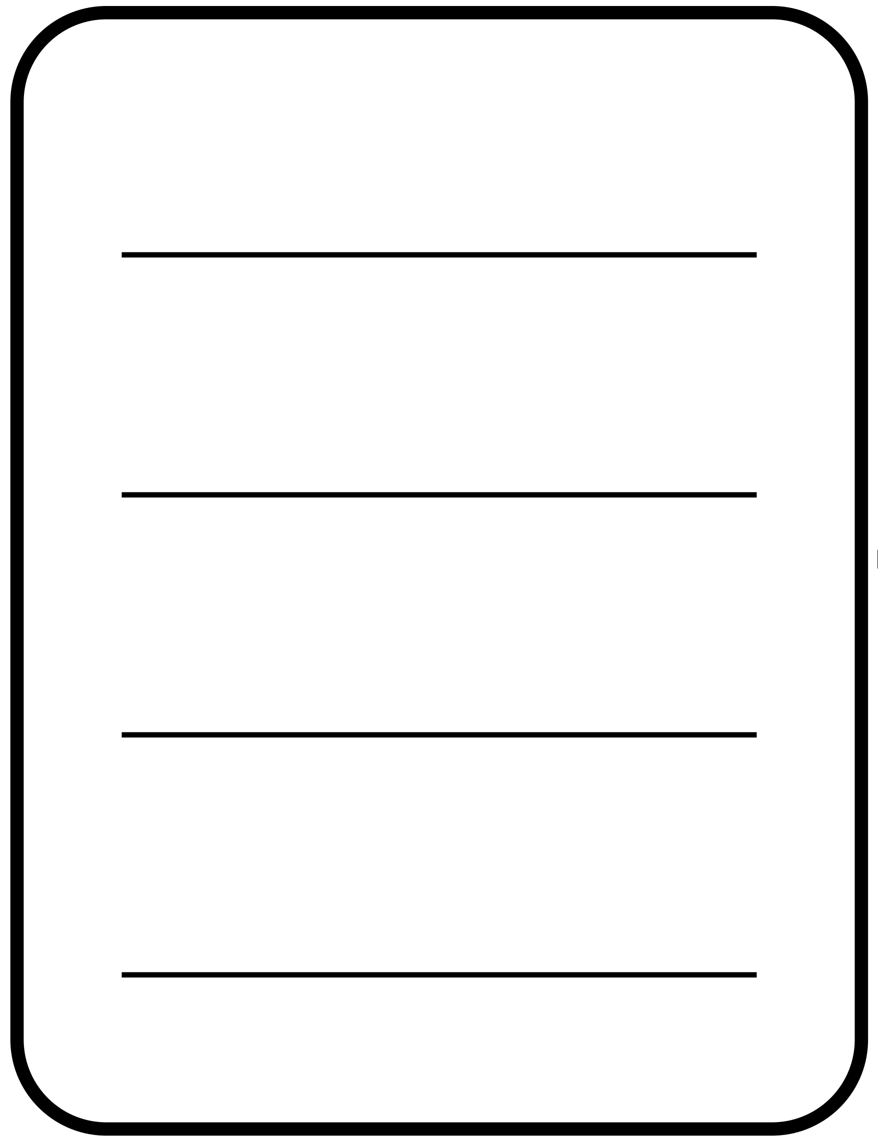

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Beyoncé had one of the best videos of all time **subjective**

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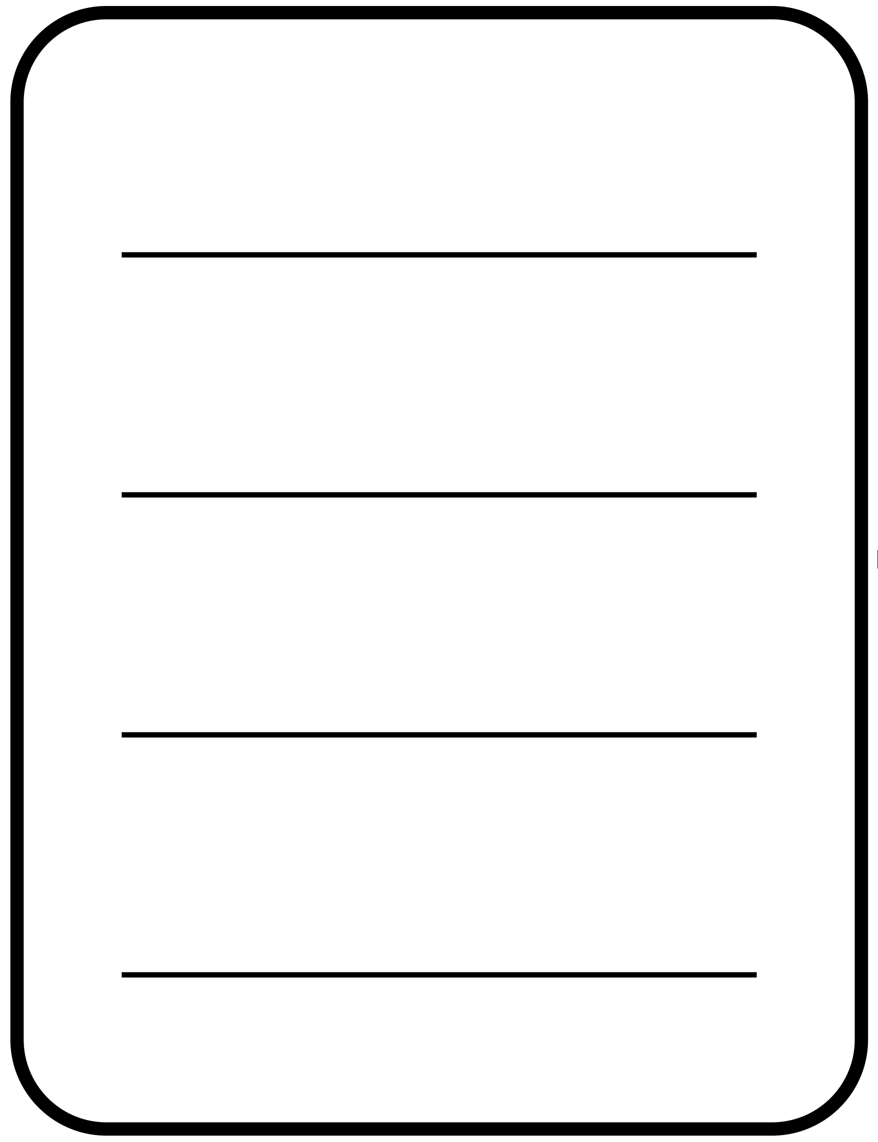

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Sequences/tags

PERSON **MOVIE**

Tom Cruise stars in the new Mission Impossible film

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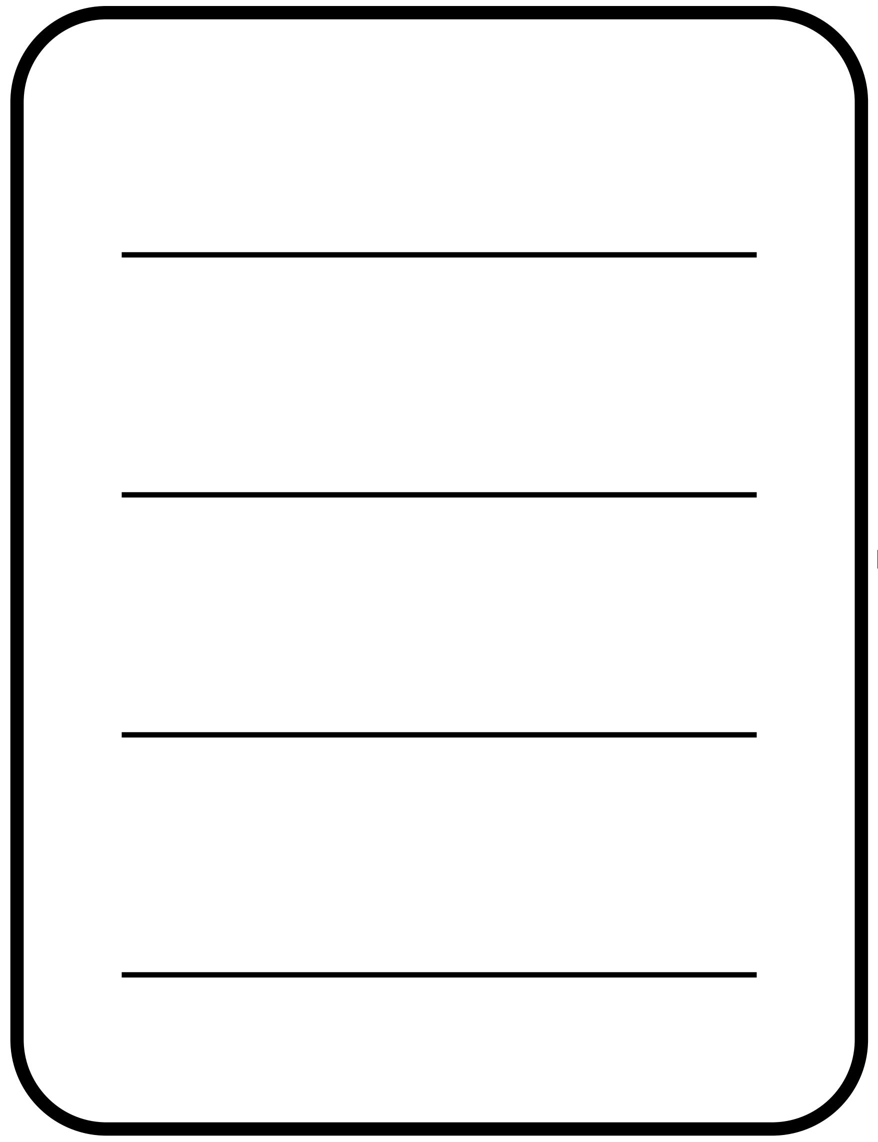

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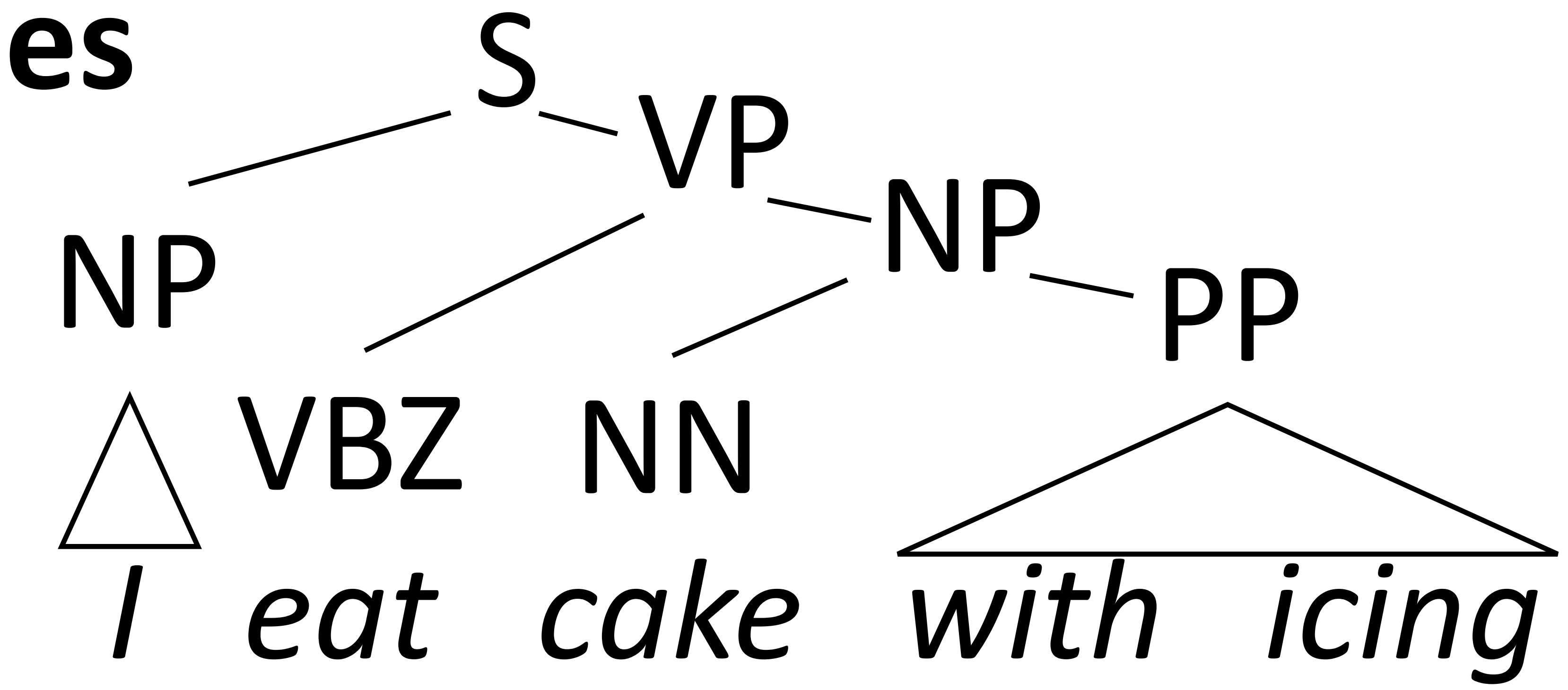
Beyoncé had one of the best videos of all time **subjective**

Sequences/tags

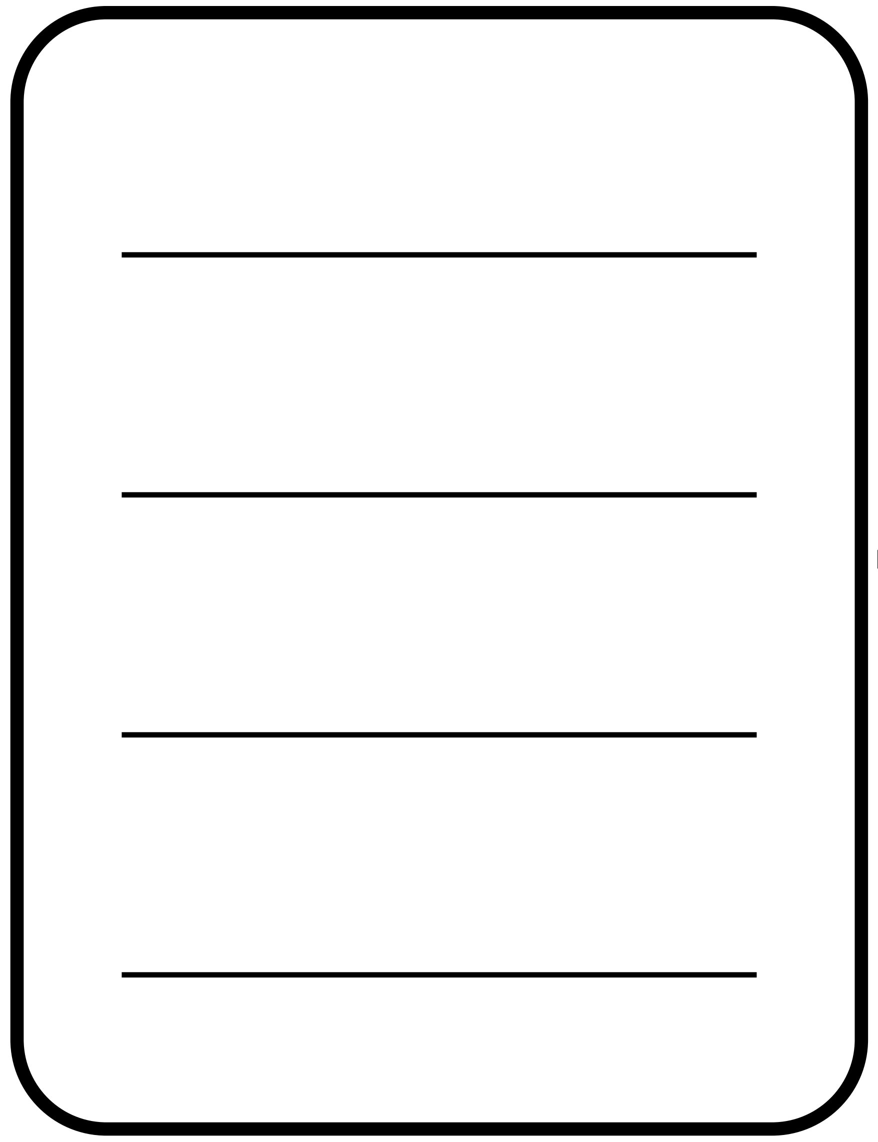
PERSON *Tom Cruise* *stars in the new* **MOVIE** *Mission Impossible* *film*

Trees



How do we represent language?

Text



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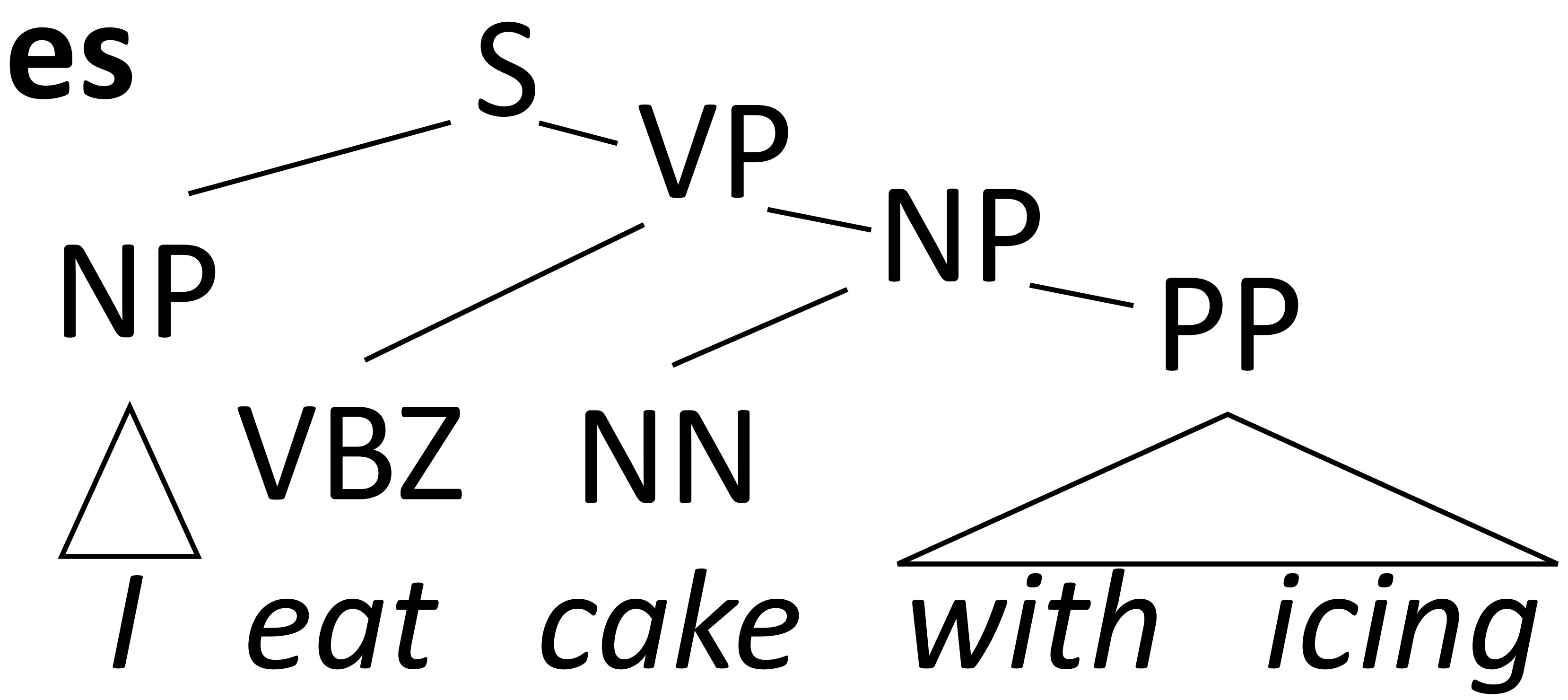
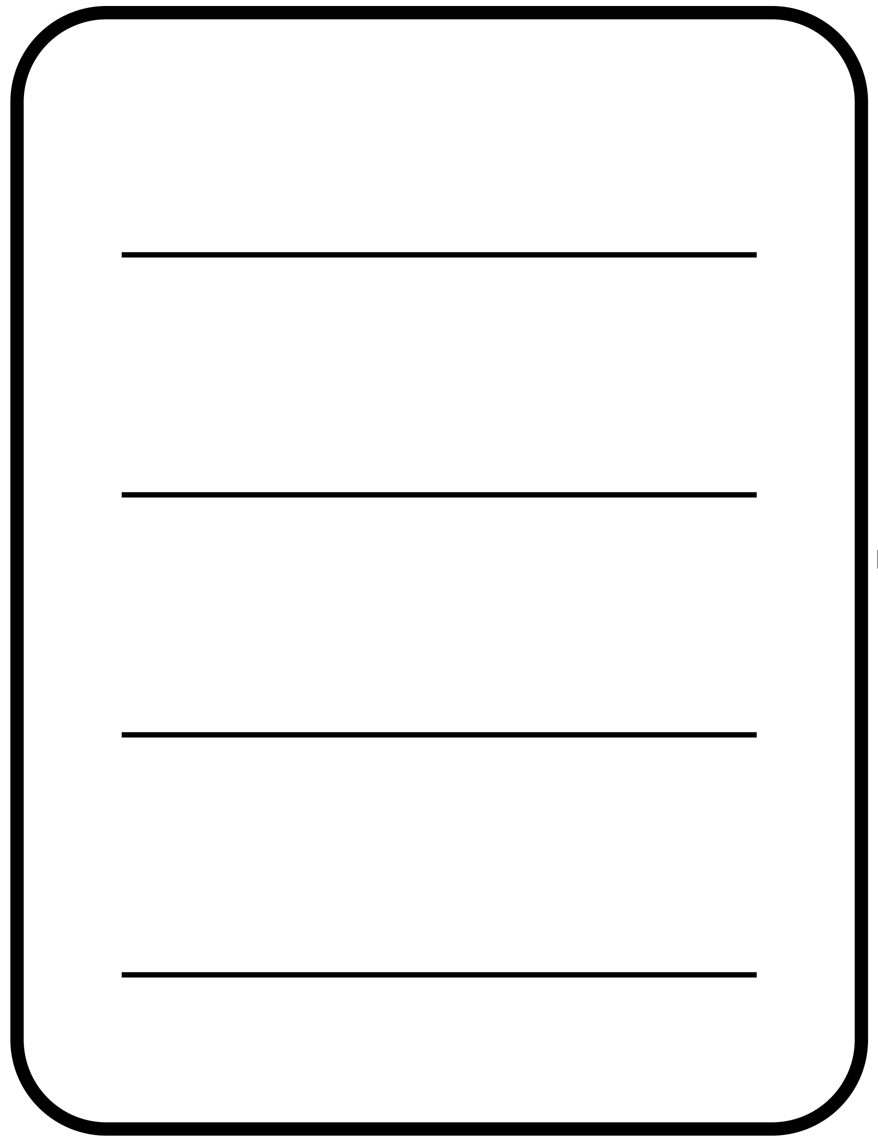


λx. flight(x) ∧ dest(x)=Miami

flights to Miami

How do we use these representations?

Text



Text Analysis

Labels

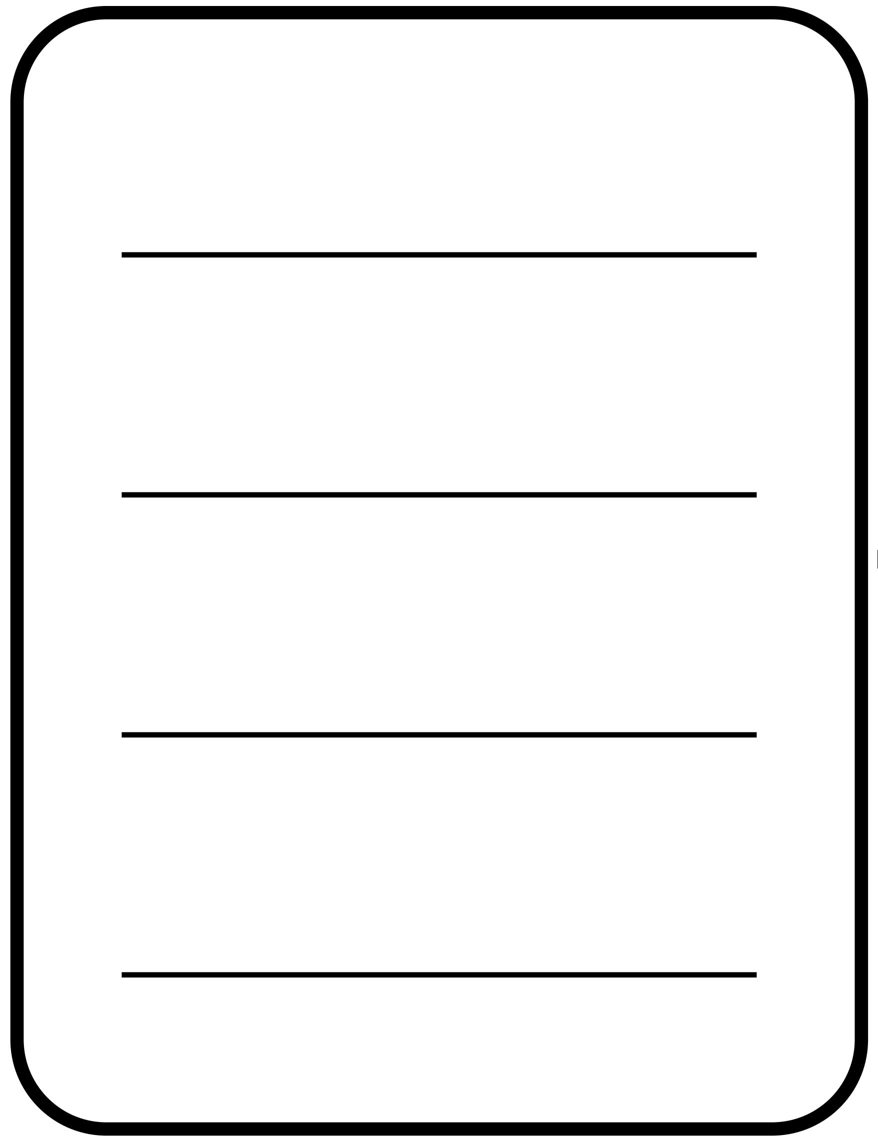
Sequences

Trees

…

How do we use these representations?

Text



Text Analysis

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Applications

How do we use these representations?

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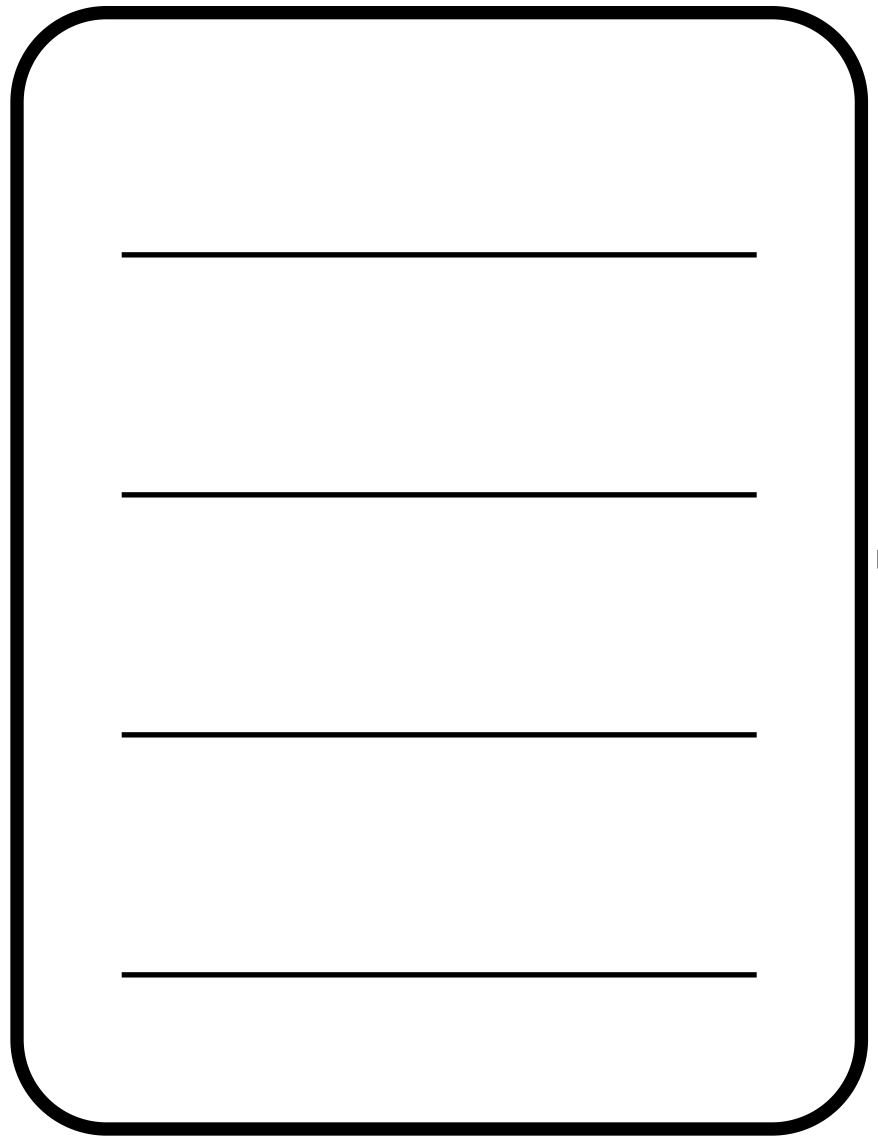

Text Analysis

Labels

Sequences

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…

Applications

Extract syntactic features

How do we use these representations?

Text

Text Analysis

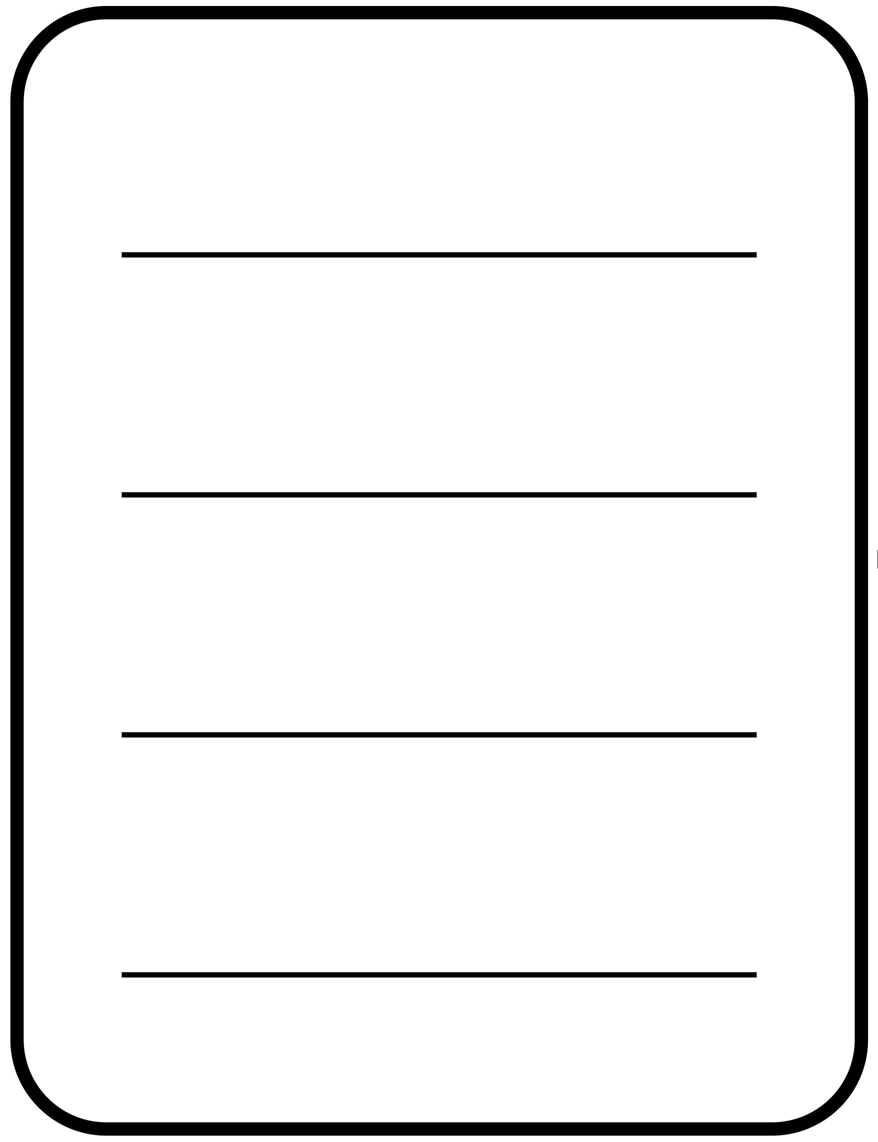
- Labels
- Sequences
- Trees
- …

Applications

- Extract syntactic features
- Tree-structured neural networks

How do we use these representations?

Text



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Tree transducers (for machine translation)

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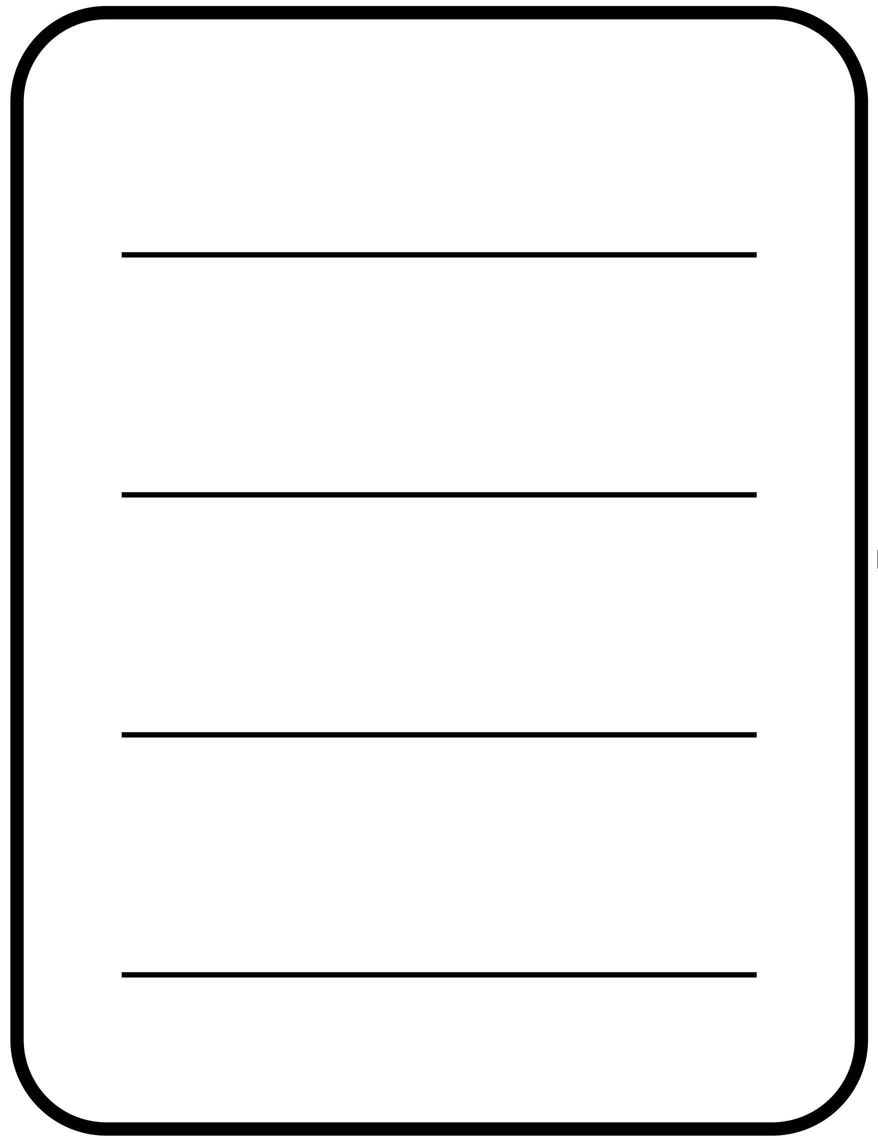

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How do we use these representations?

Text

Text Analysis

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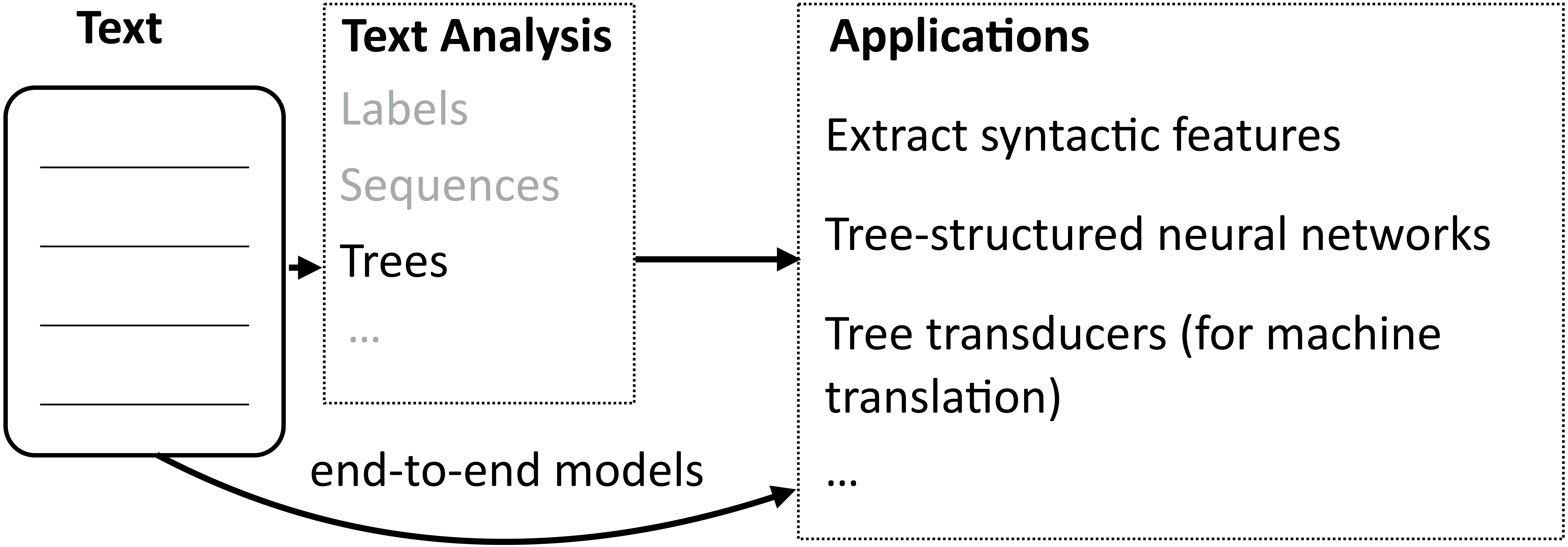
Tree transducers (for machine translation)

…

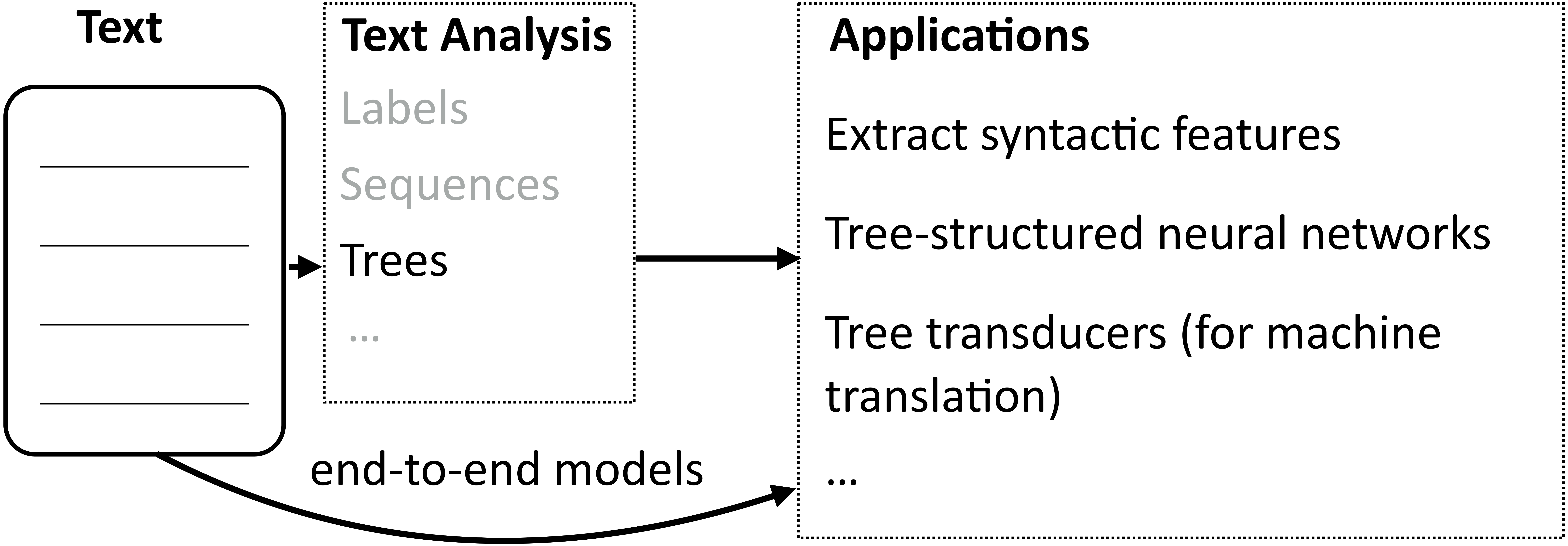
end-to-end models

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)

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they advocated

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they feared

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

Language is Ambiguous!

slide credit: Dan Klein

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- Ambiguous News Headlines:

slide credit: Dan Klein

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- Ambiguous News Headlines:
  - Teacher Strikes Idle Kids

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  - Local HS Dropouts Cut in Half
- Syntactic/semantic ambiguity: parsing needed to resolve these, but need context to figure out which parse is correct

slide credit: Dan Klein

Language is **Really** Ambiguous!

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

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il fait vraiment beau ⟶

Language is **Really** Ambiguous!

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

It is really nice out

il fait vraiment beau →

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il fait vraiment beau $\longrightarrow$ It is really nice out

It's really nice

Language is **Really** Ambiguous!

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il fait vraiment beau → It is really nice out

It's really nice

The weather is beautiful

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It is really beautiful outside

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The weather is beautiful

It is really beautiful outside

He makes truly beautiful

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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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il fait vraiment beau ⟶

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
It fact actually handsome

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

What do we need to understand language?

- Lots of data!

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

slide credit: Dan Klein

What do we need to understand language?

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

What do we need to understand language?

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

DOJ greenlights Disney - Fox merger

What do we need to understand language?

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Department of Justice

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metaphor;
"approves"

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

Department of Justice

metaphor;
“approves”

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

What techniques do we use?

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

A brief history of (modern) NLP

1980 1990 2000 2010 2020

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"AI winter"
rule-based,
expert systems

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Ratnaparkhi
tagger

NNP VBZ

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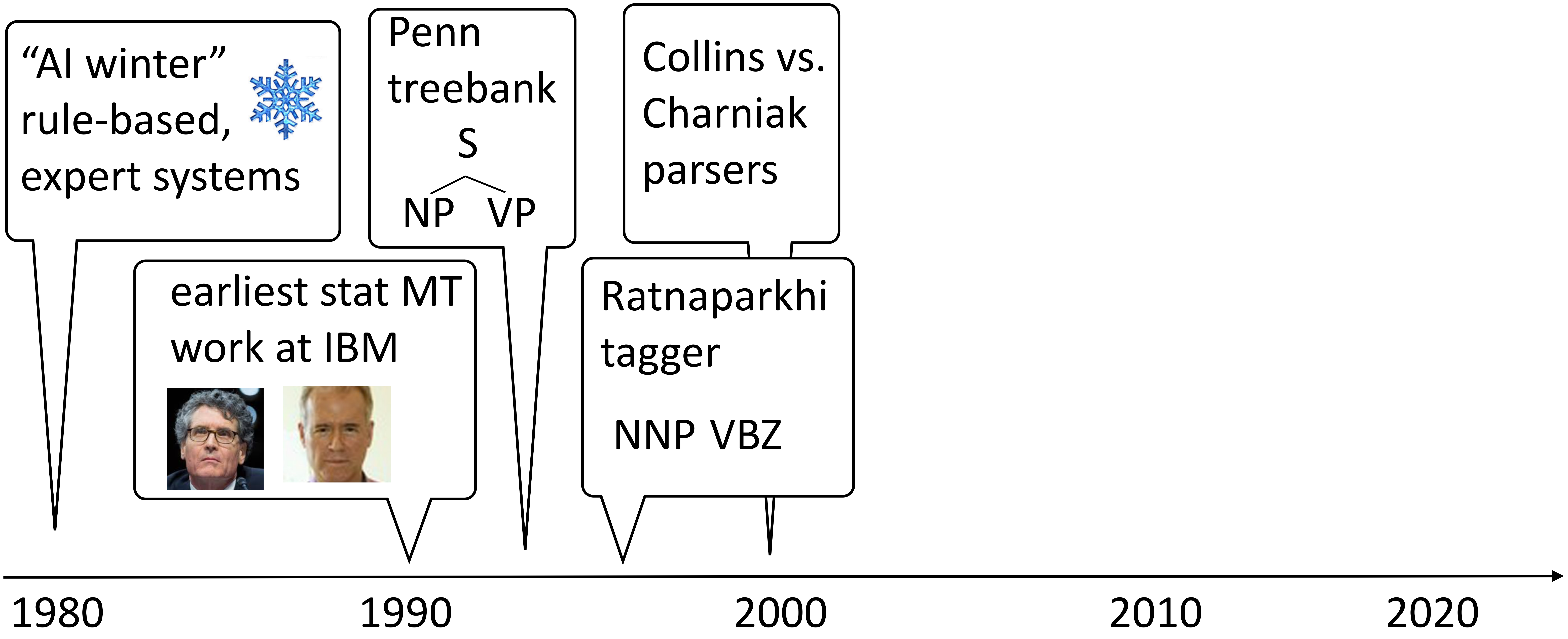

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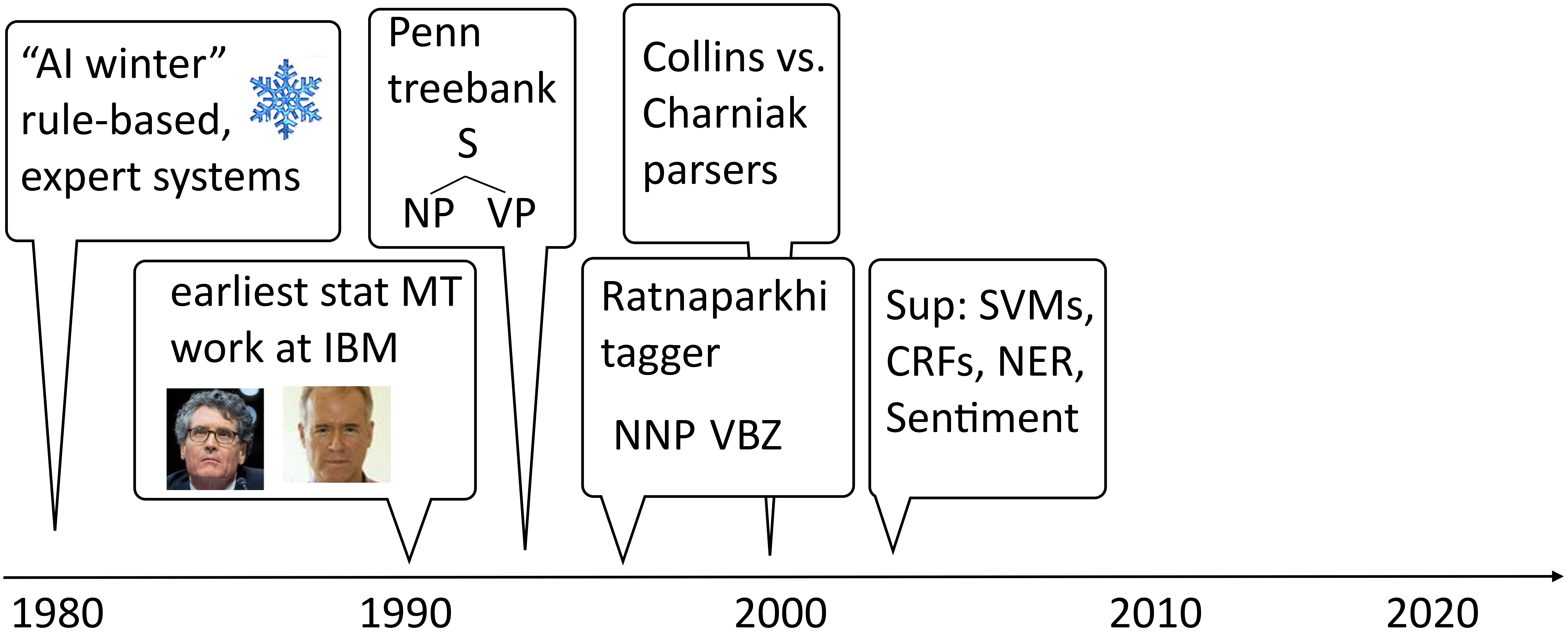

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Ratnaparkhi tagger

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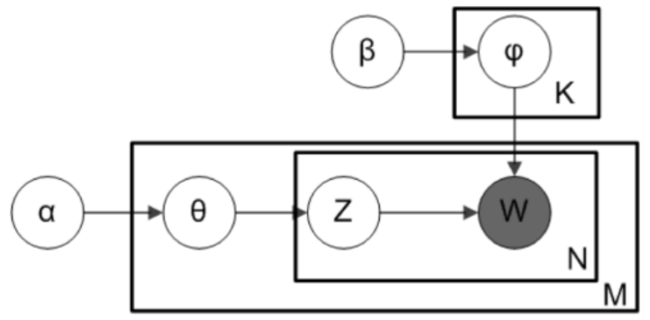
Collins vs. Charniak parsers

Unsup: topic models, etc.



Sup: SVMs, CRFs, NER, Sentiment

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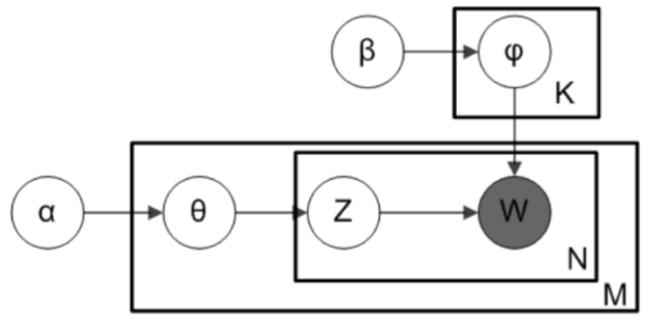

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Semi-sup,
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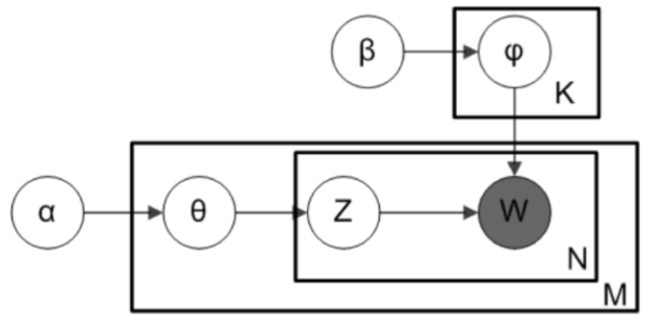

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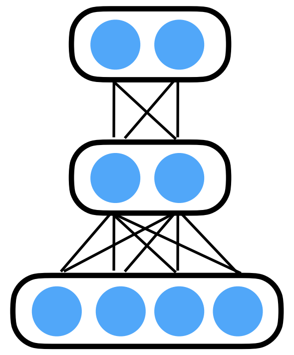
Semi-sup, structured prediction

Neural



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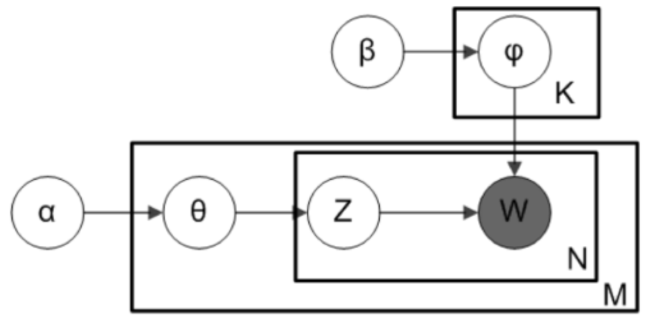

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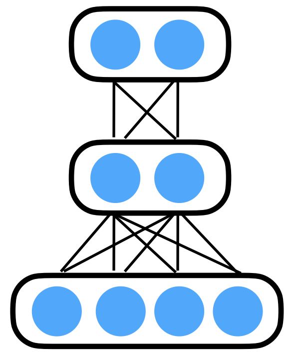

Pre-training
(ELMo, BERT, GPT)

1980 1990 2000 2010 2020

How Much Training Data do we Need?

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

How Much Training Data do we Need?

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

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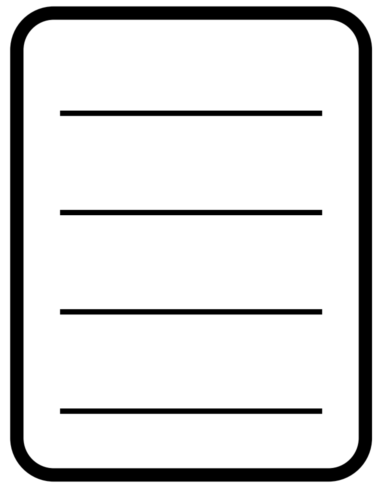

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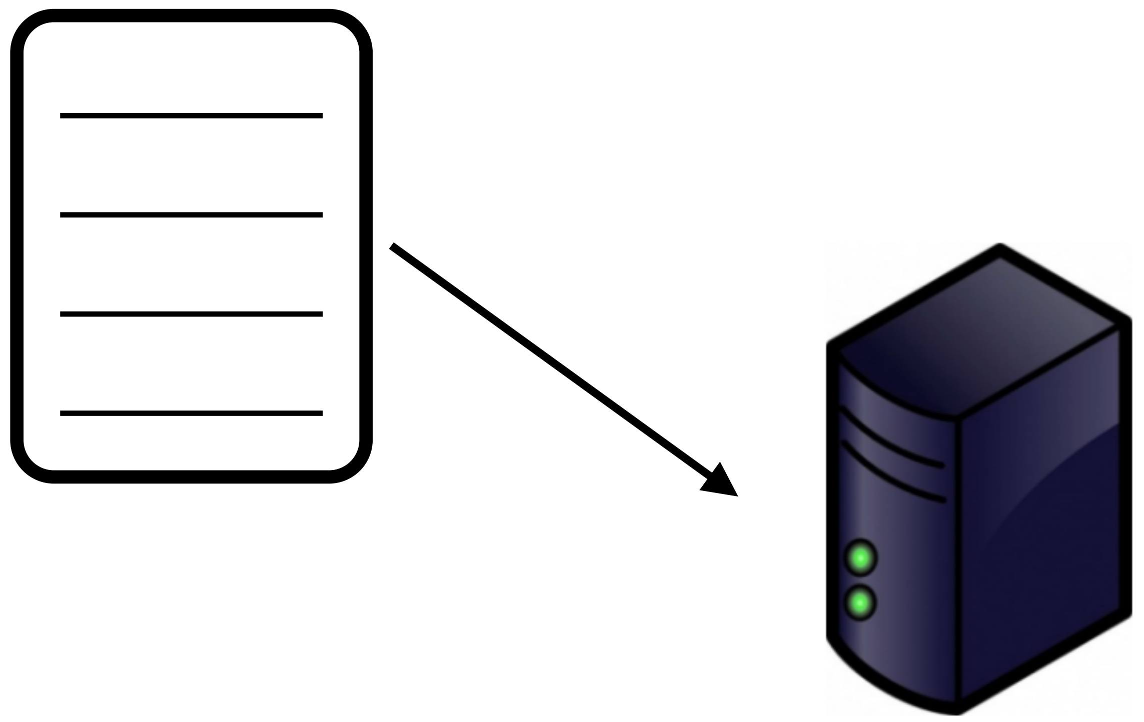

unsupervised learning

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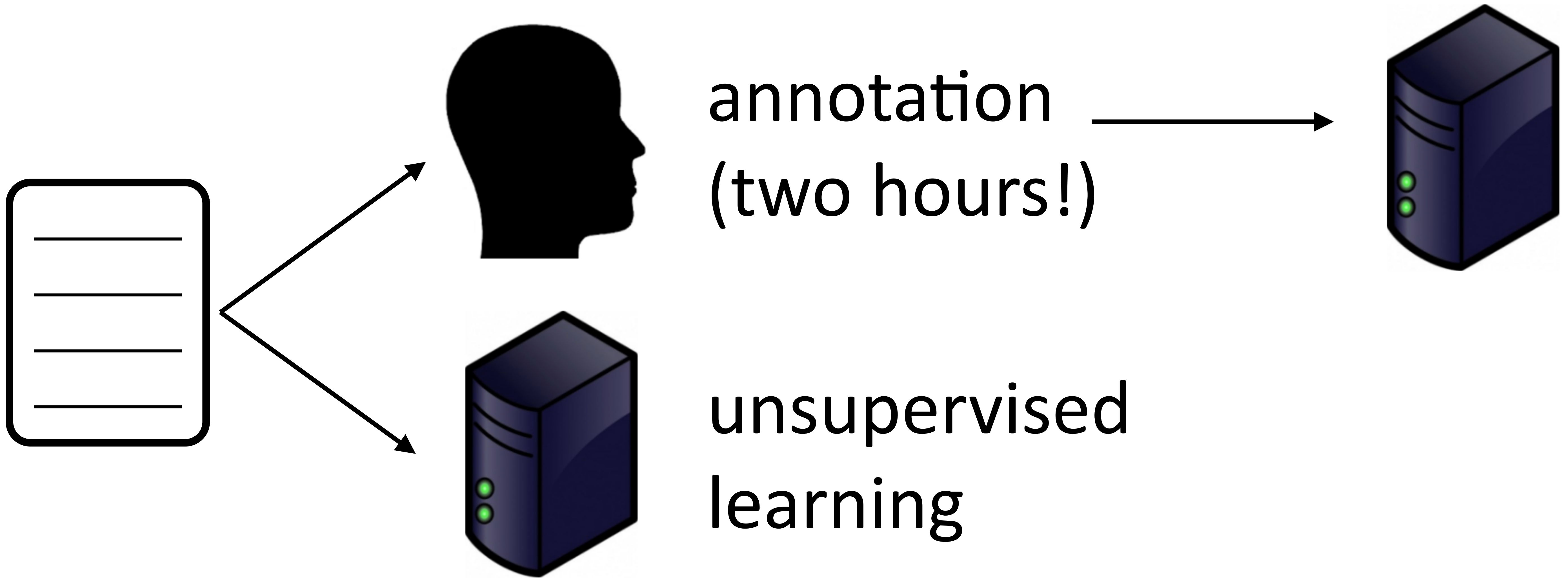

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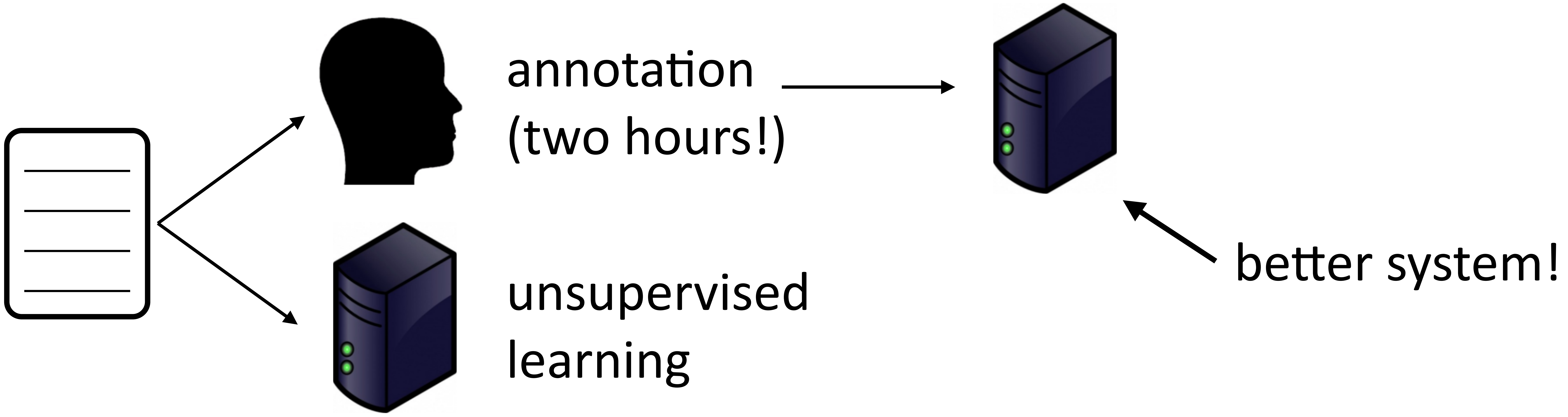

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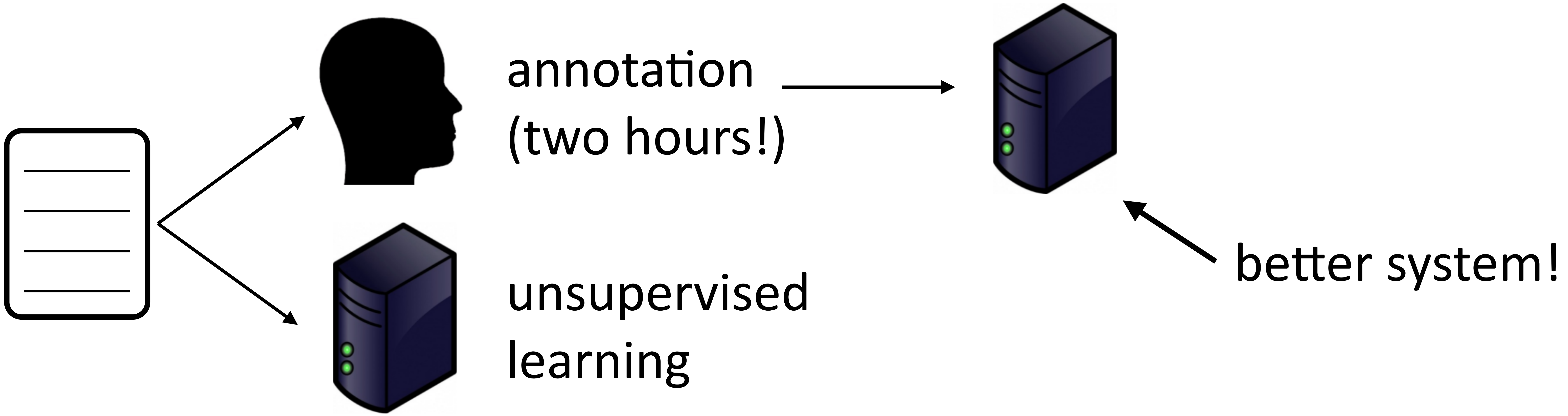

- Even neural nets can do pretty well!

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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

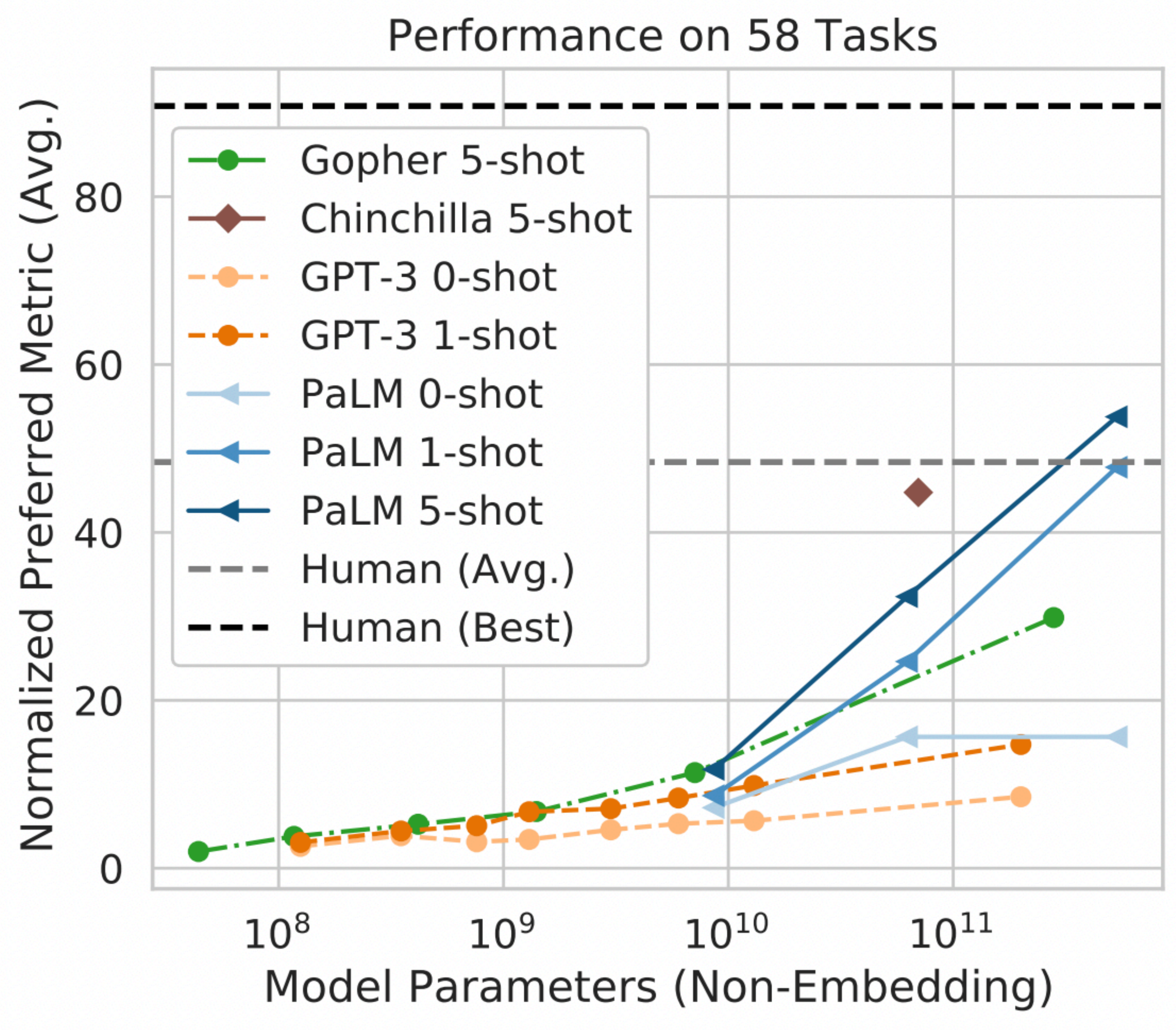
- Model understands some sentiment?

- 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)

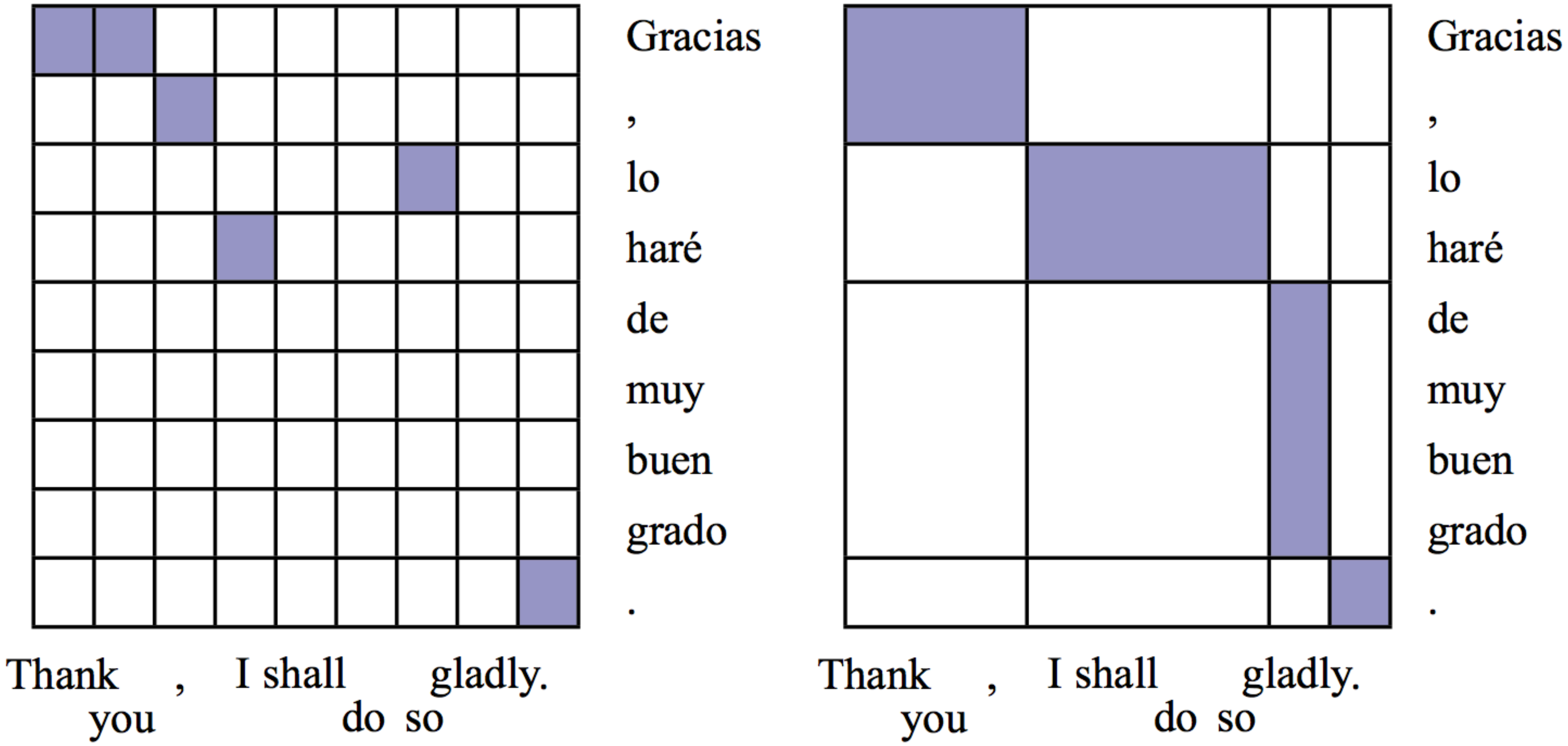
Large Language Models

- Google's PaLM: 540 billion parameter model
  - Trained on 780 billion tokens (~780 GB)
- GPT-3 / ChatGPT
  - https://chat.openai.com

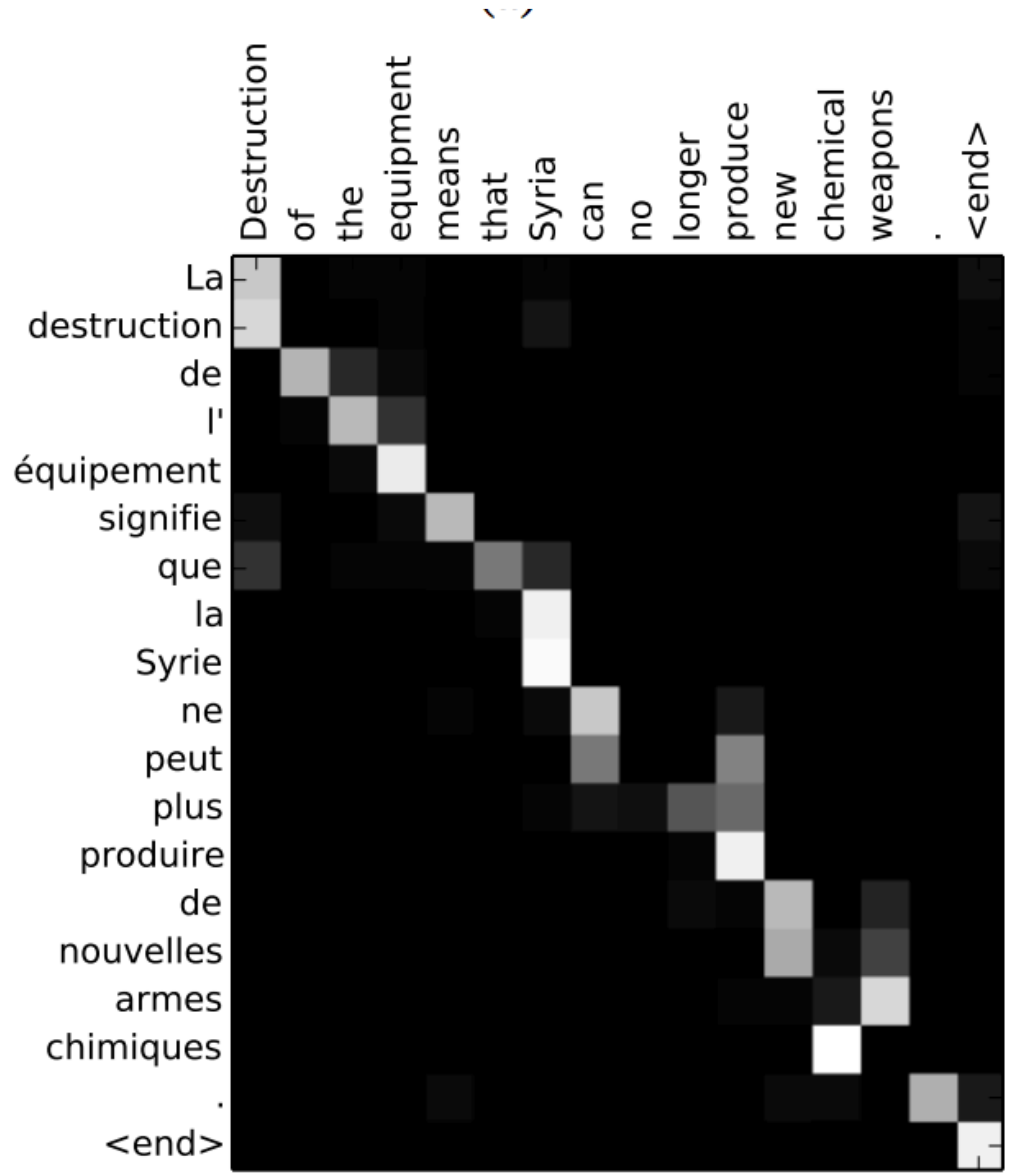


Chowdhery et al. (2022)

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

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

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

Moosavi and Strube (2017)

Does manual structure have a place?

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- LORELEI: transition point below which phrase-based systems are better

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- Why is this? Inductive bias!

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- LORELEI: transition point below which phrase-based systems are better
- Why is this? Inductive bias!
- Can multi-task learning help?

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

Moosavi and Strube (2017)

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- NLP encompasses all of these things