CS 7650: Natural Language Processing

Alan Ritter

(many slides from Greg Durrett)

Administrivia

- Course website: https://aritter.github.io/CS-7650/
- Piazza and Gradescope: links on the course website
  - We will do our best to make sure questions about the homework, etc. get answered within 24 hours
- TA Office hours:
  - See spreadsheet

Staff

Instructor

Alan Ritter
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Teaching Assistants

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William Braga
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Course Requirements

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

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There will be a lot of math and programming!

Coursework Plan

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

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- Final project (details on course website, will discuss later)
- Problem Set 1 (math review) is out now on Gradescope (due Jan 25)

Free Textbooks!

- 2 really awesome free textbooks available
  - 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

Programming Projects: Computation

- Modern NLP methods require non-trivial computation
  - Training neural networks with many parameters can take a long time (it is a very good idea to start working on the assignments early!)
  - You probably want to use a GPU
  - Google Colab: free GPUs (some limitations)
  - The programming projects are designed with Colab in mind

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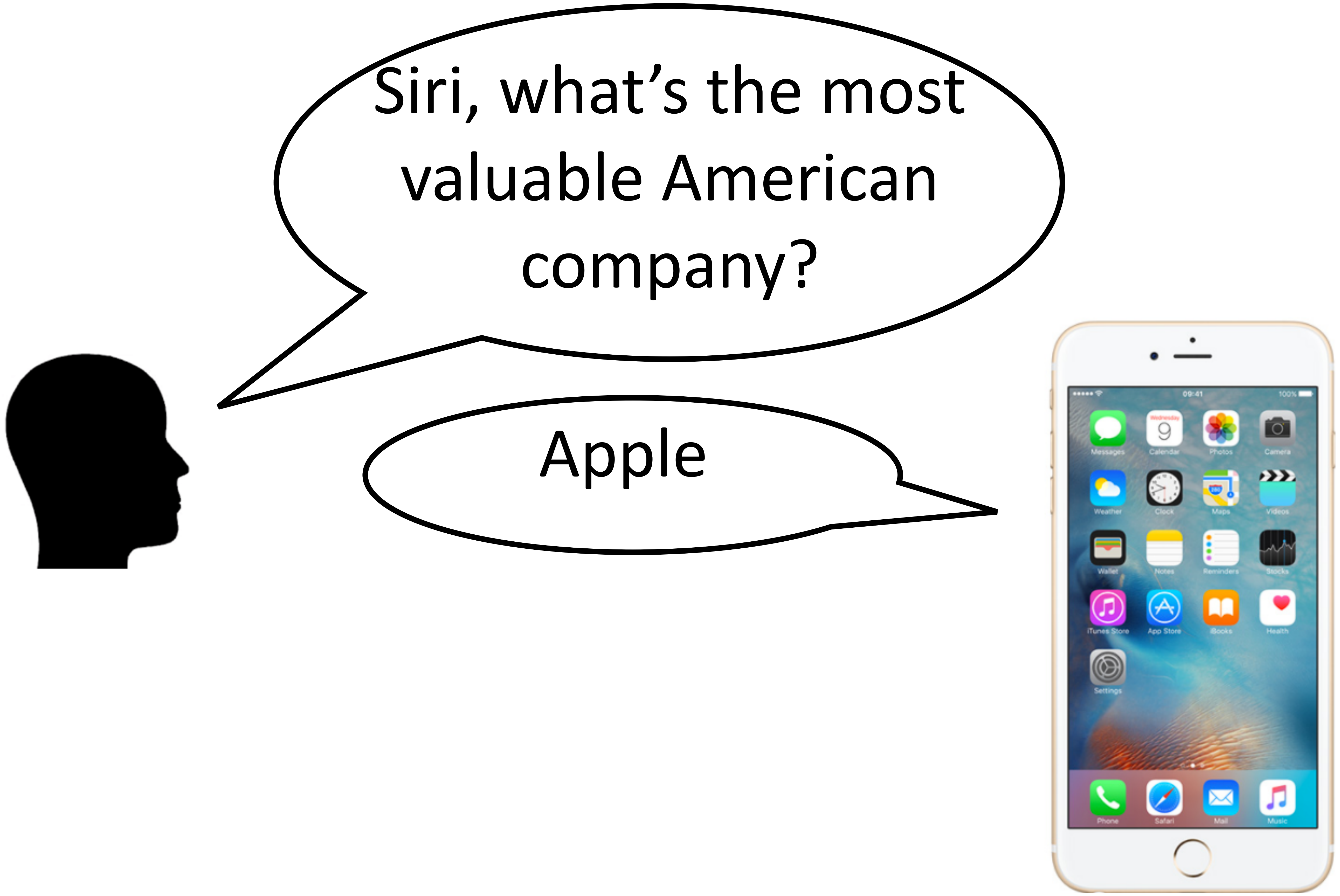

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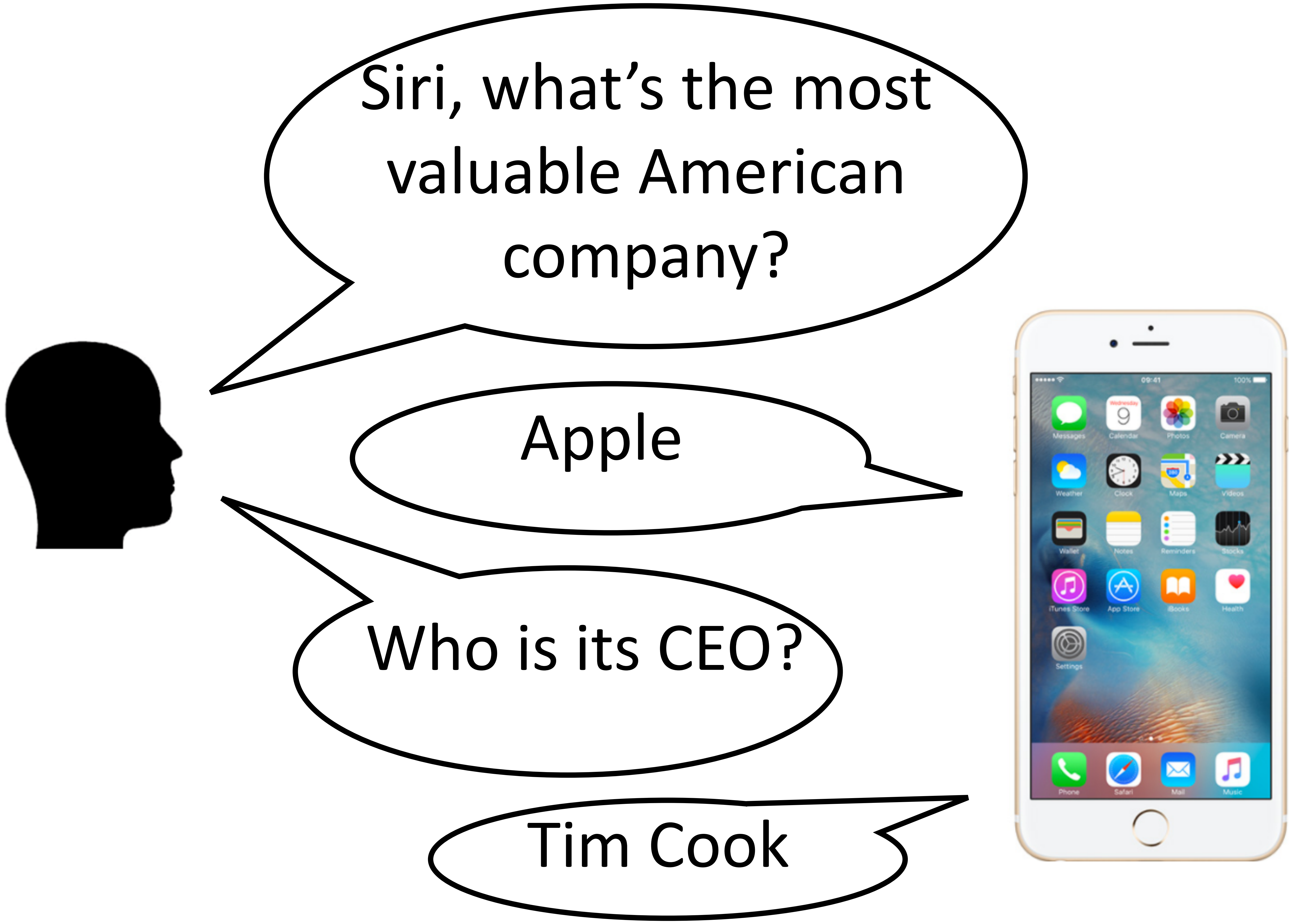

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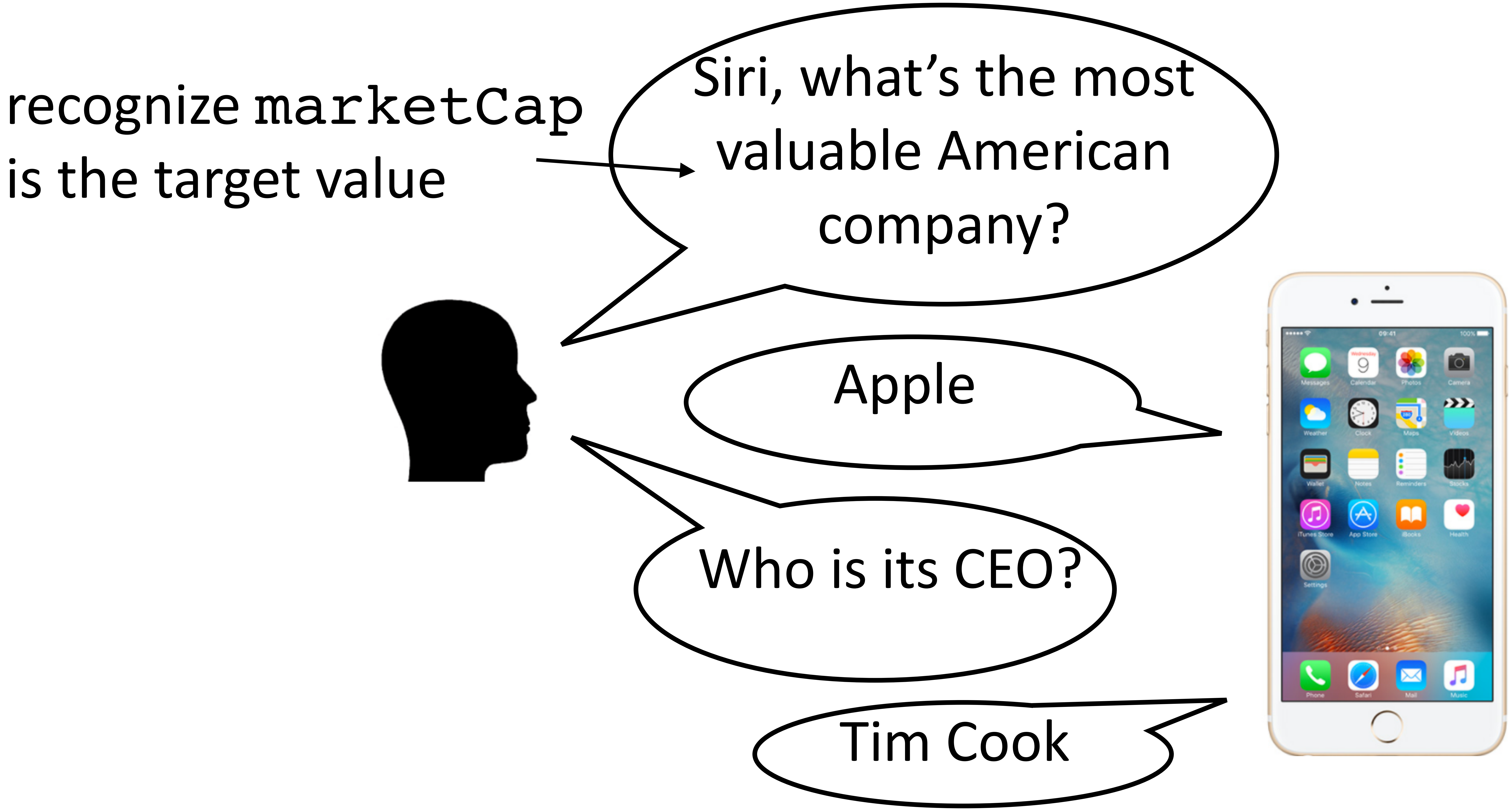

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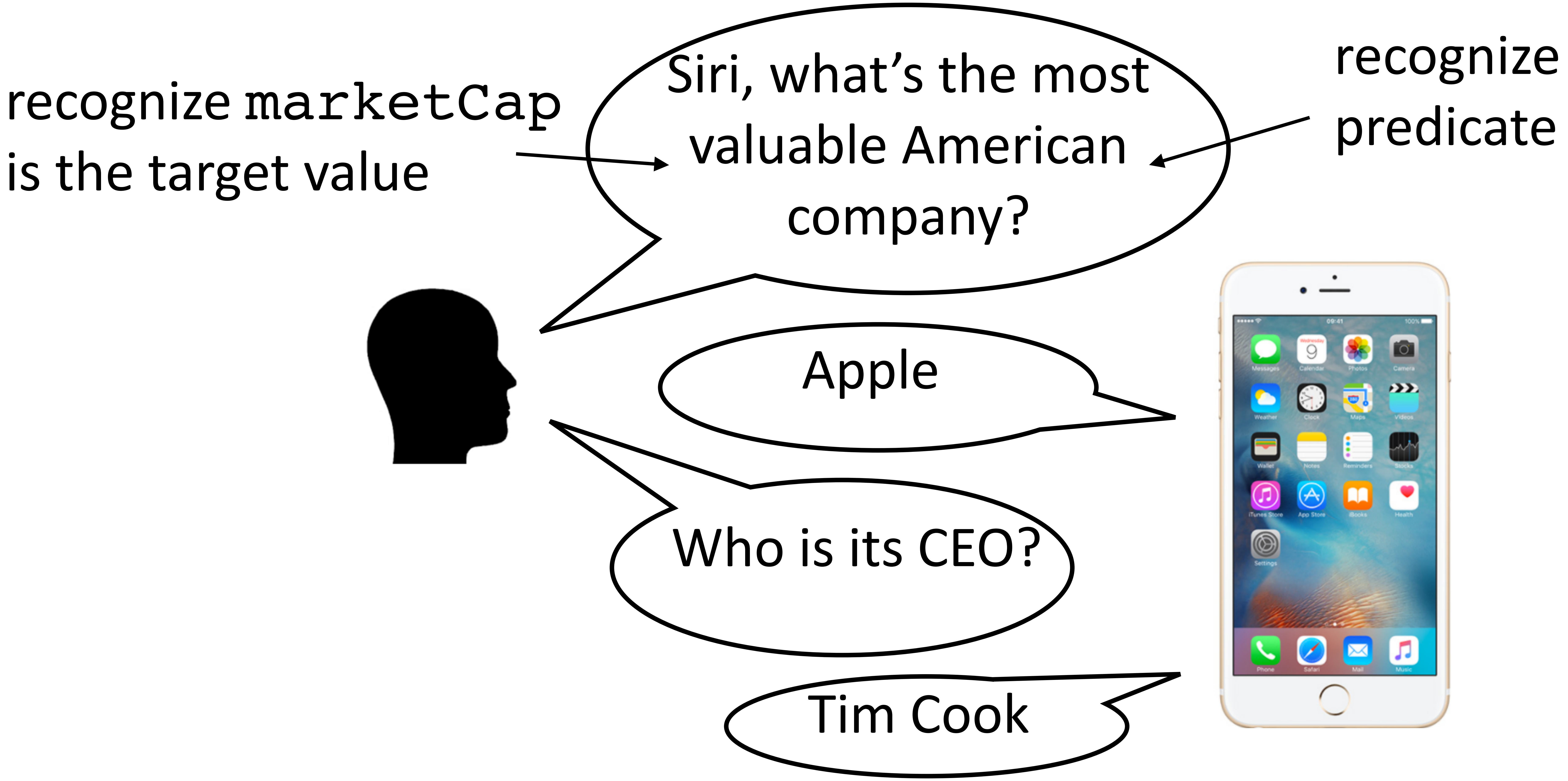

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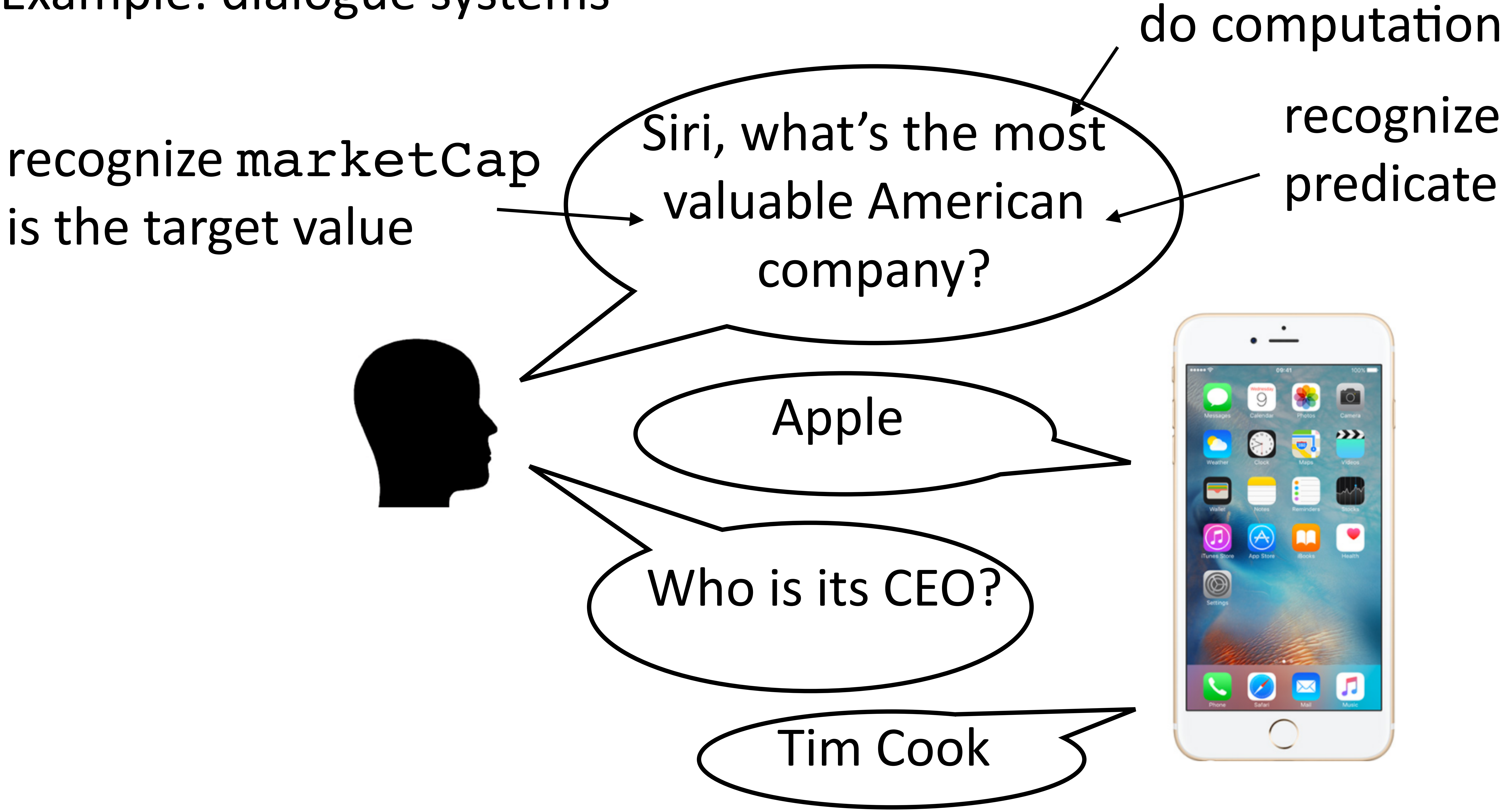

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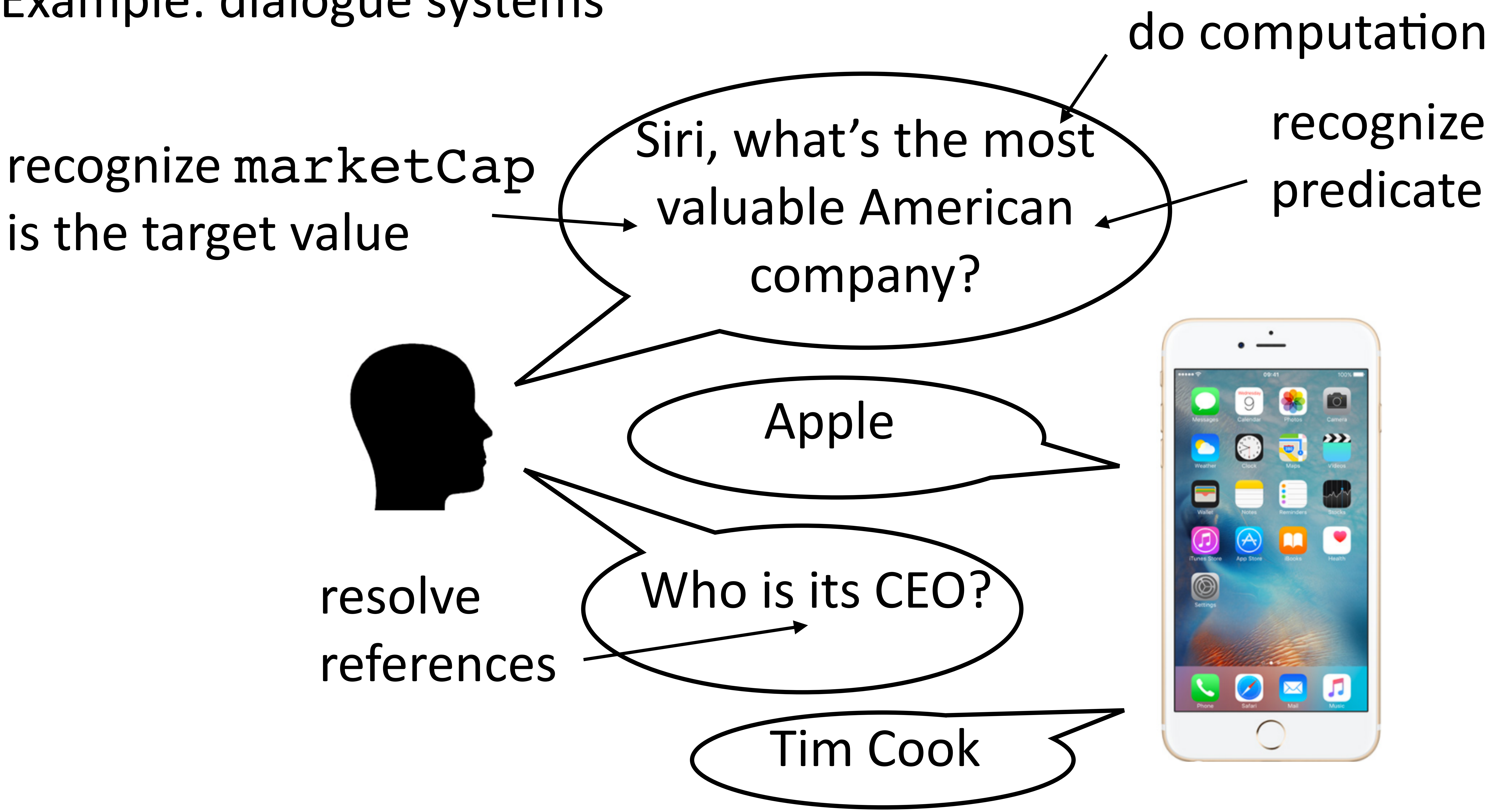

Automatic Summarization

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POLITICS

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paraphrase to provide clarity

Machine Translation

People’s Daily, August 30, 2017

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Translate

English | French | Spanish | Chinese - detected

特朗普偕家人在白宫阳台观看百年一遇日全食

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

Machine Translation

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NLP Analysis Pipeline

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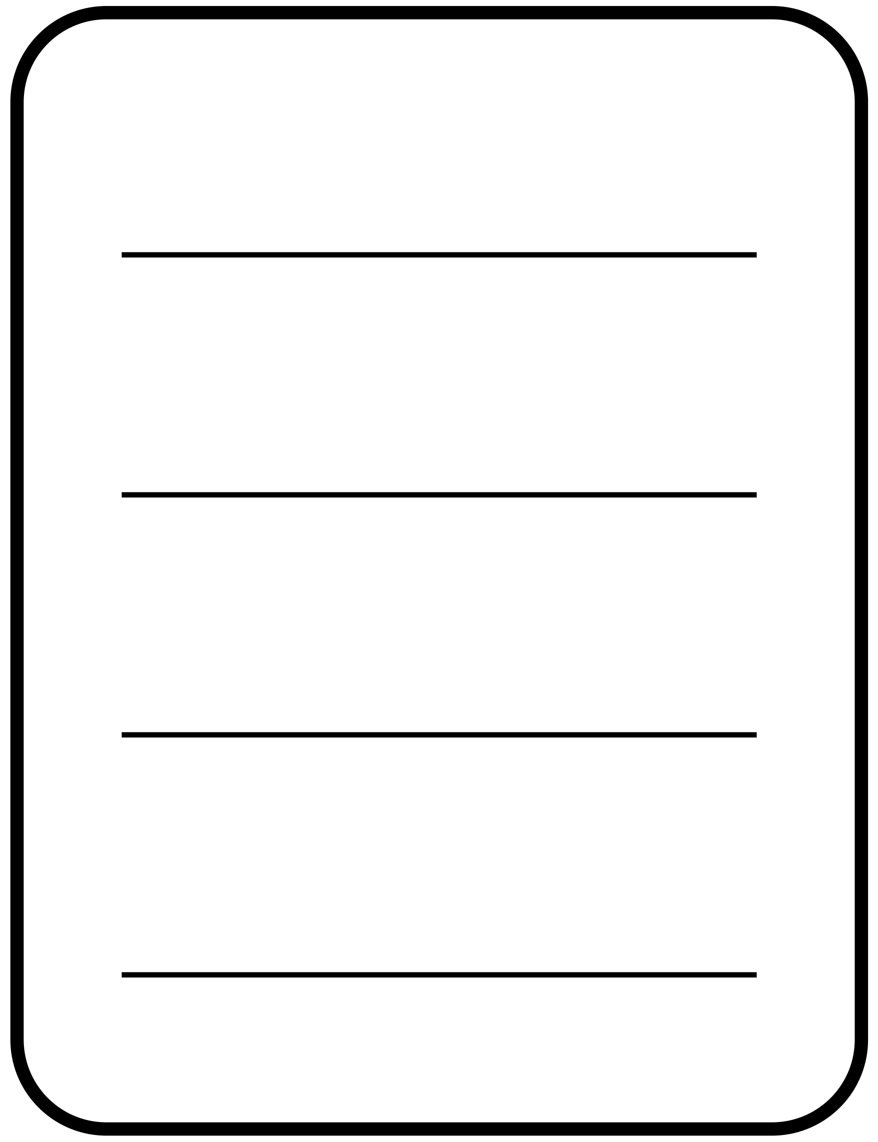

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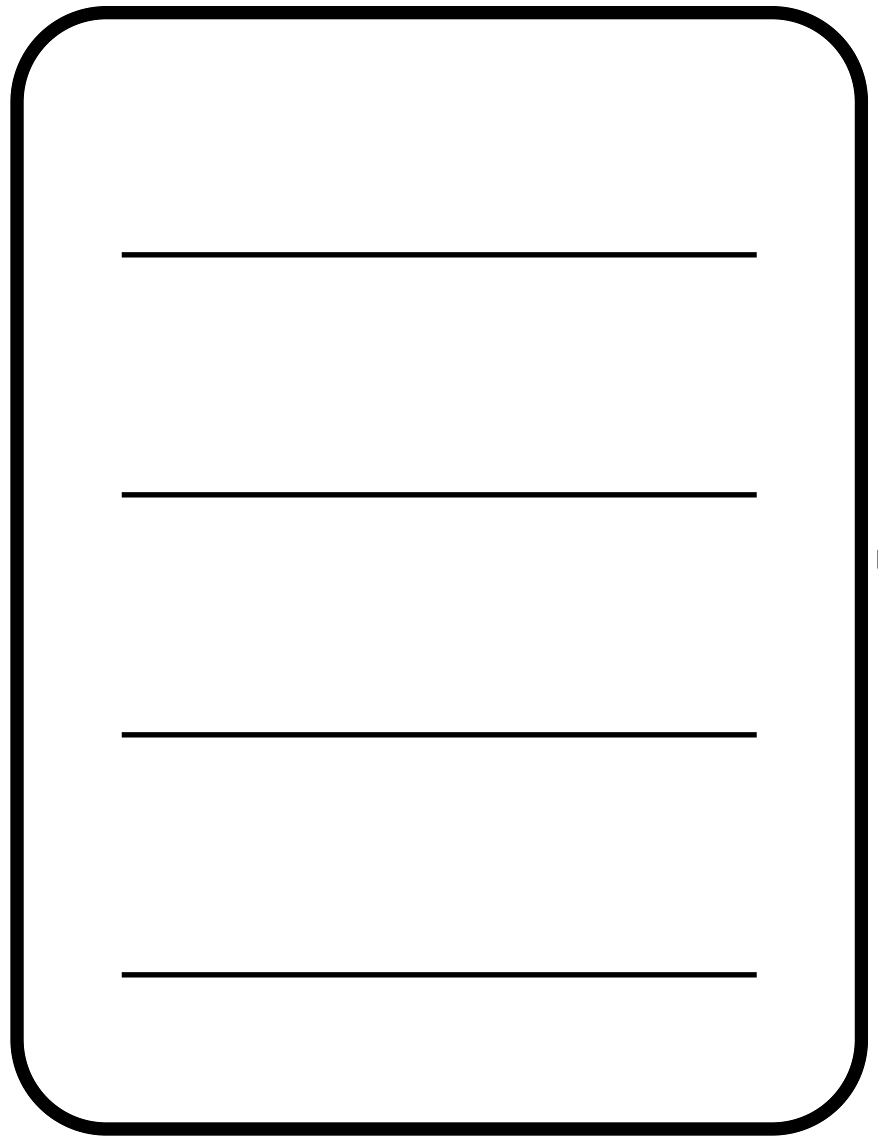

Text Analysis

Syntactic parses

Coreference resolution

Entity disambiguation

Discourse analysis

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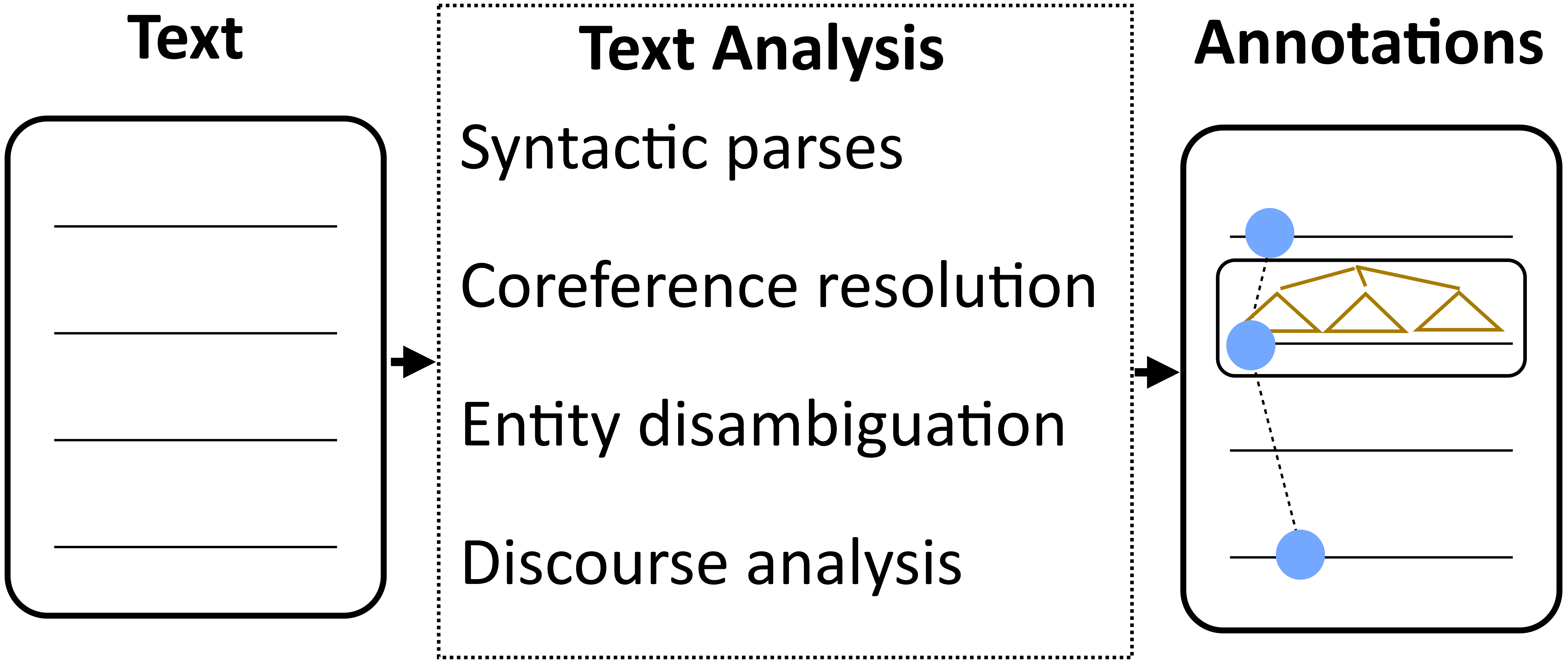

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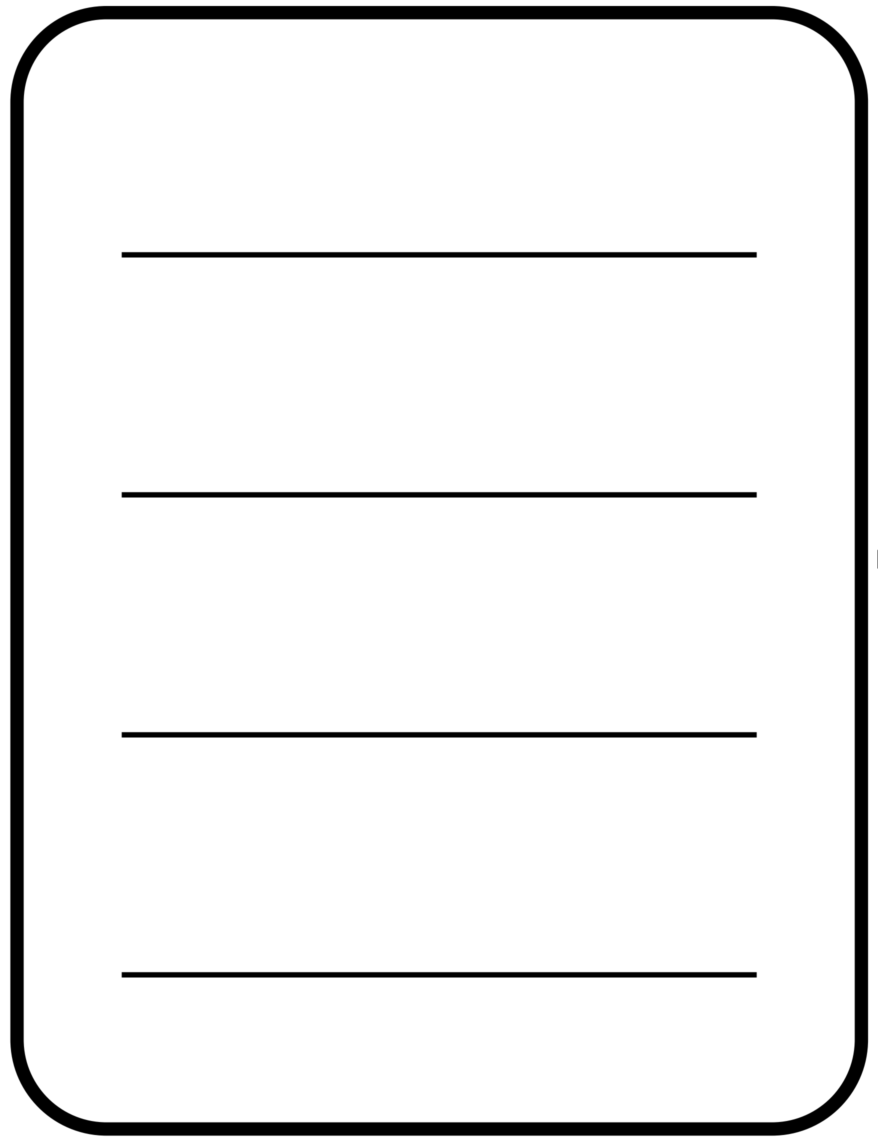

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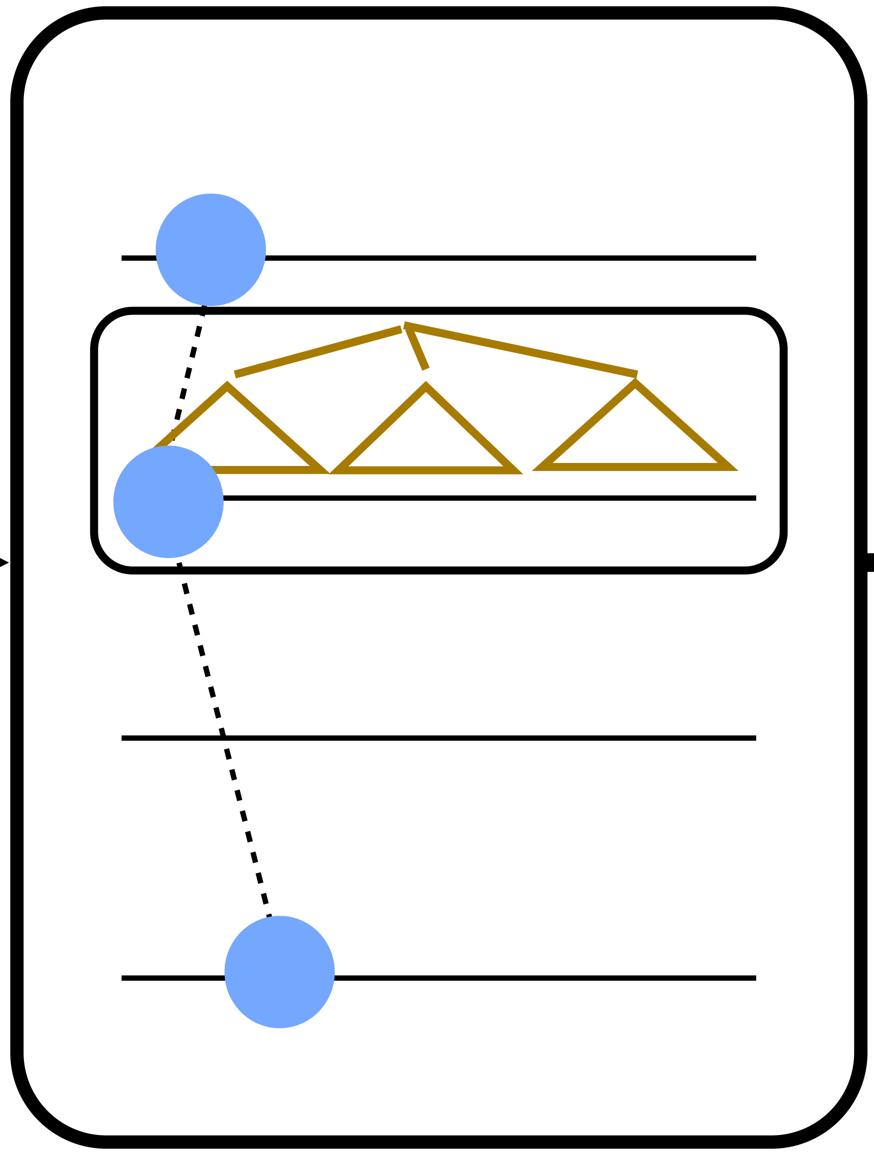

Applications

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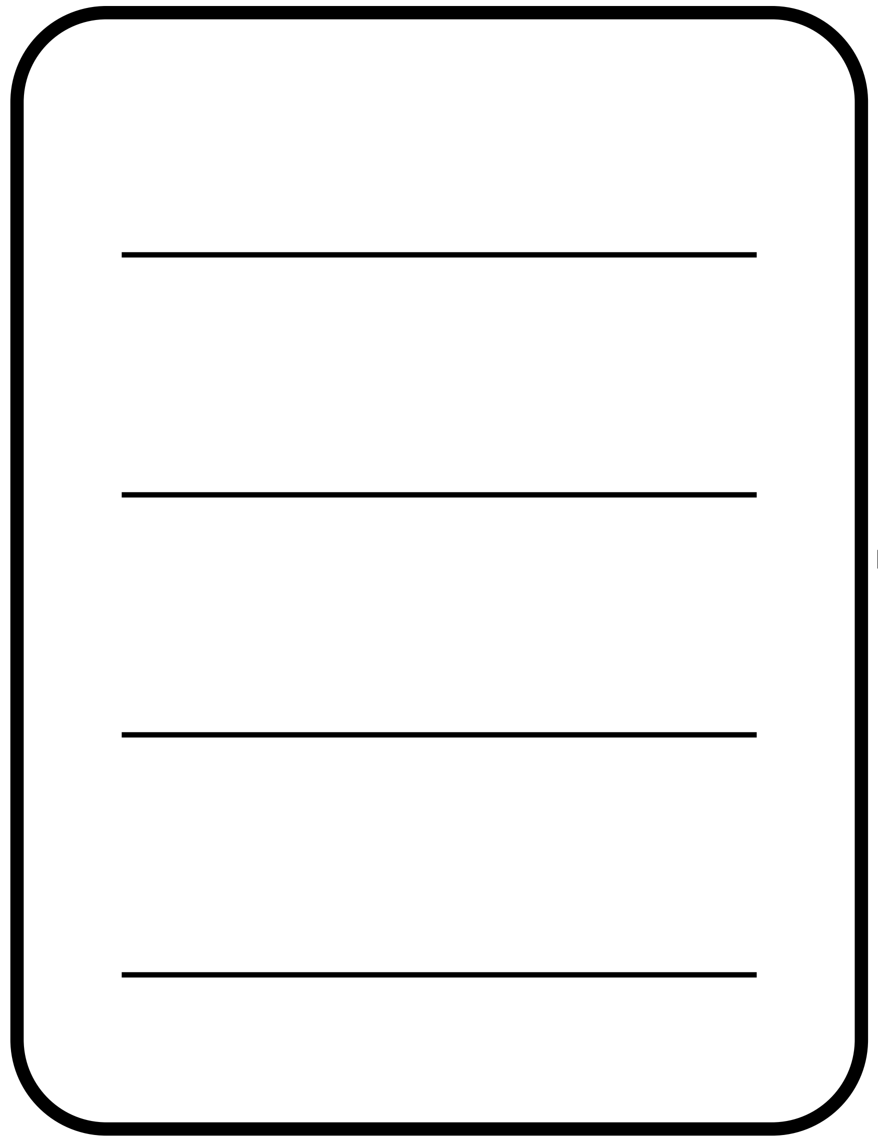

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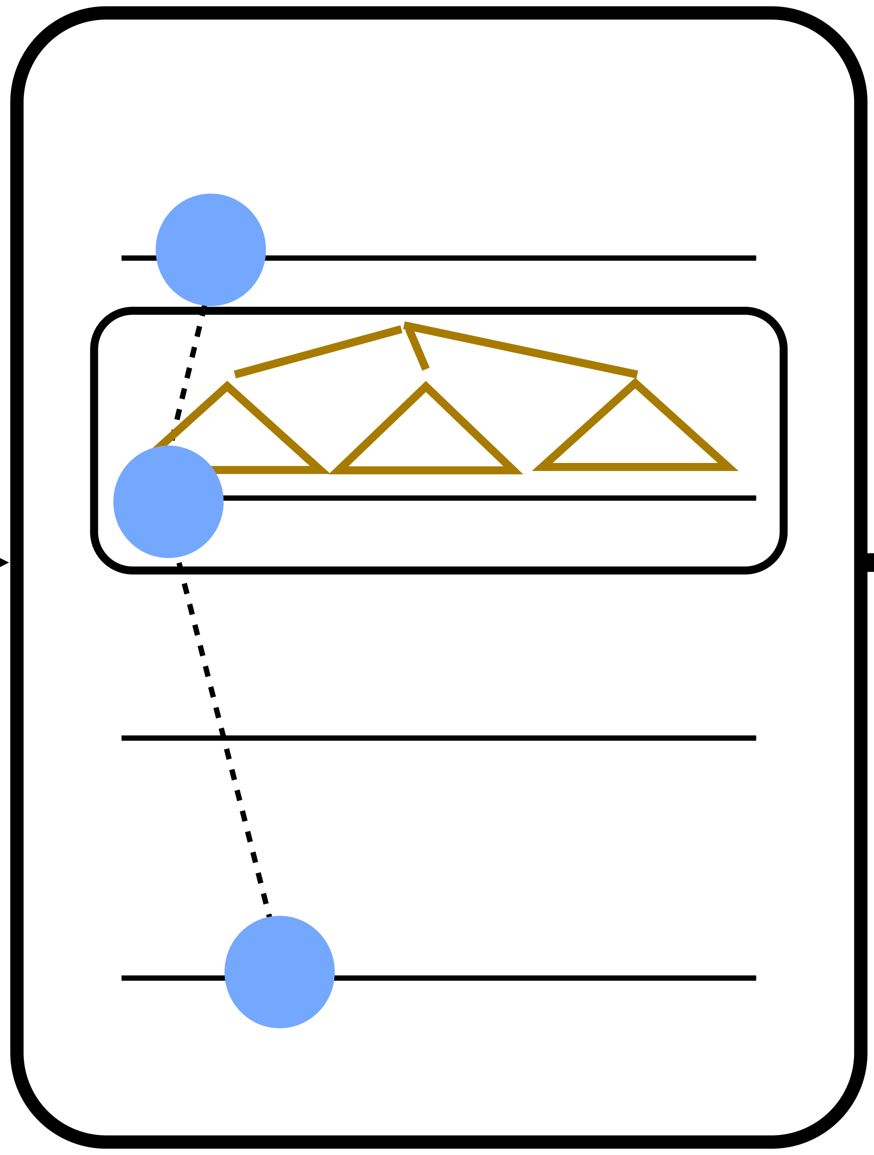

Applications

Summarize

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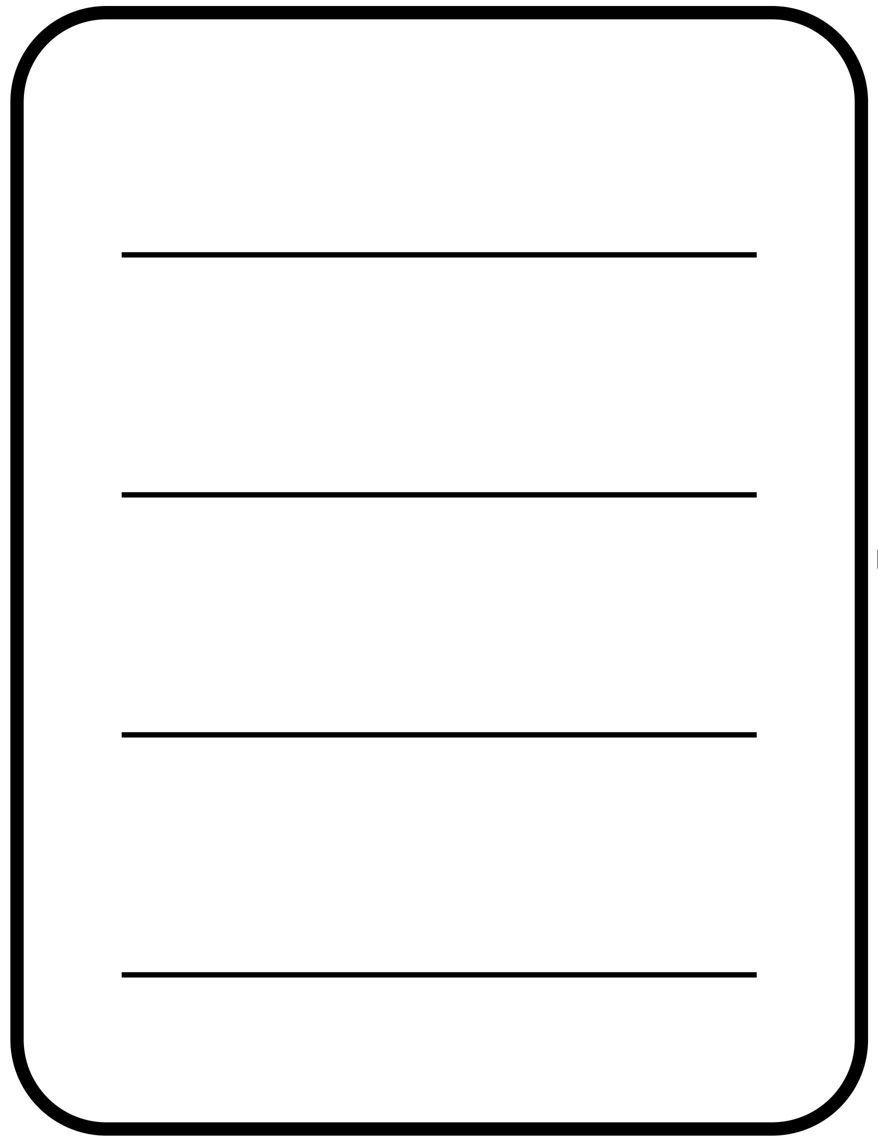

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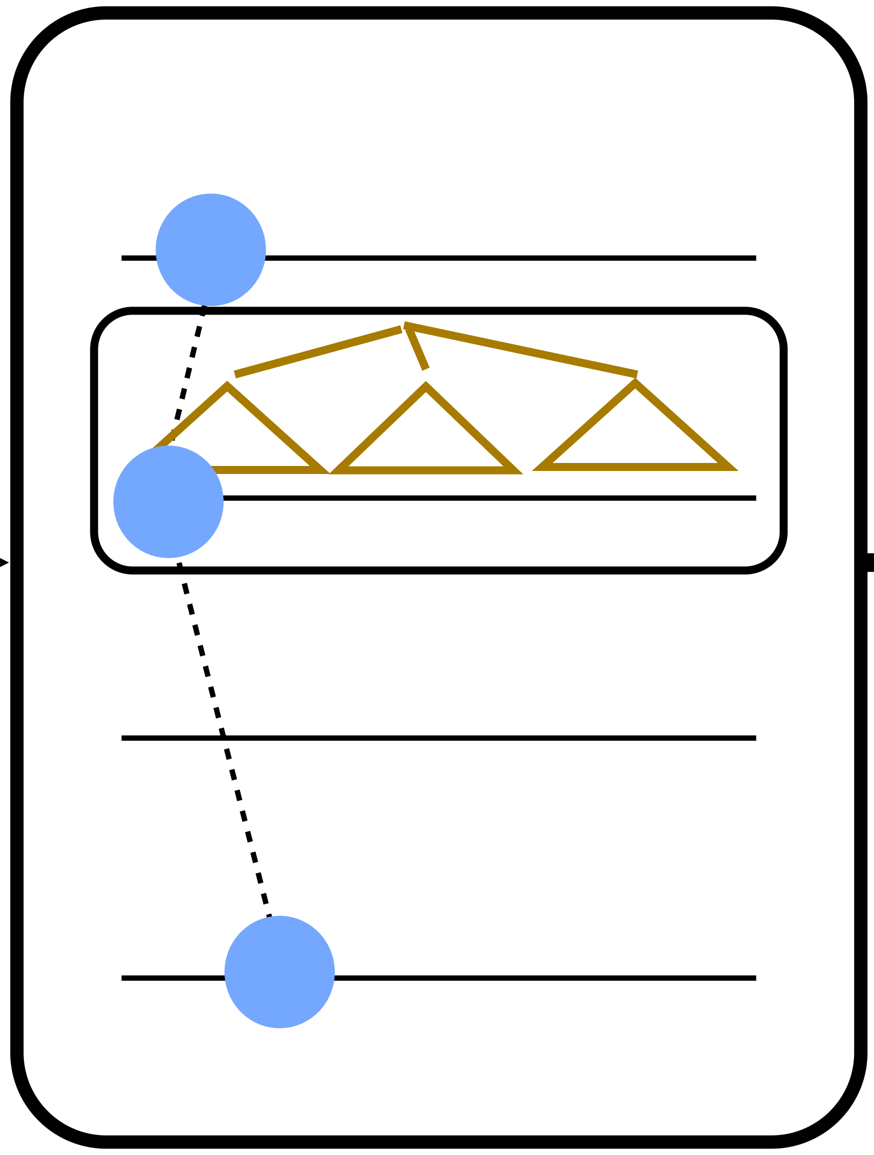

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Summarize

Extract information

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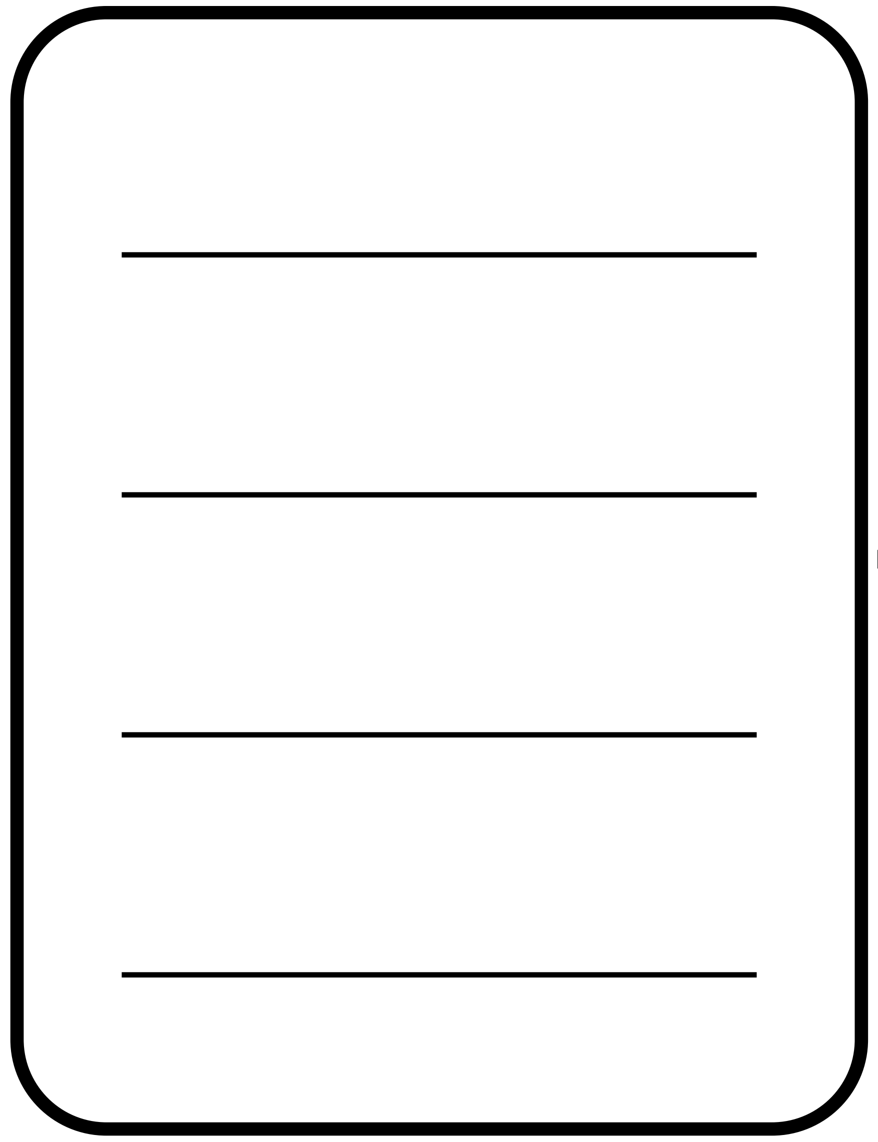

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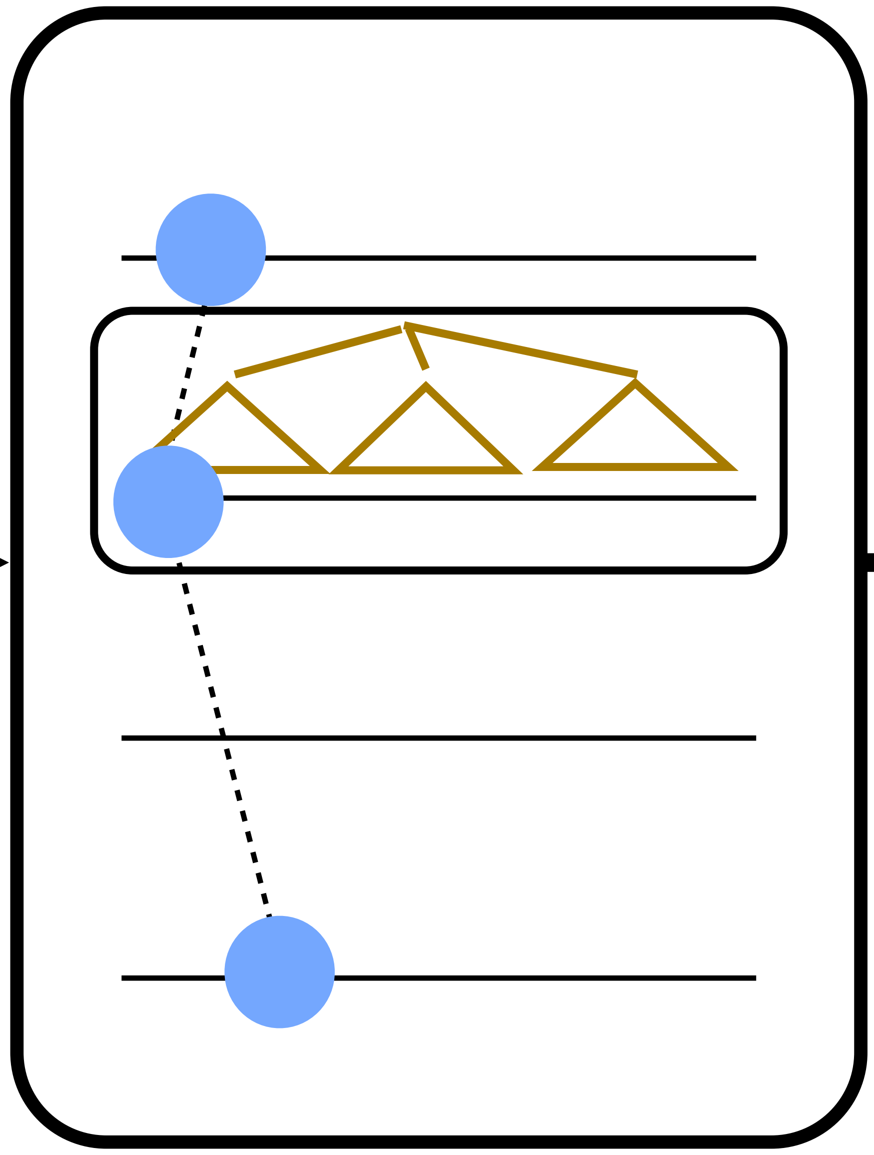

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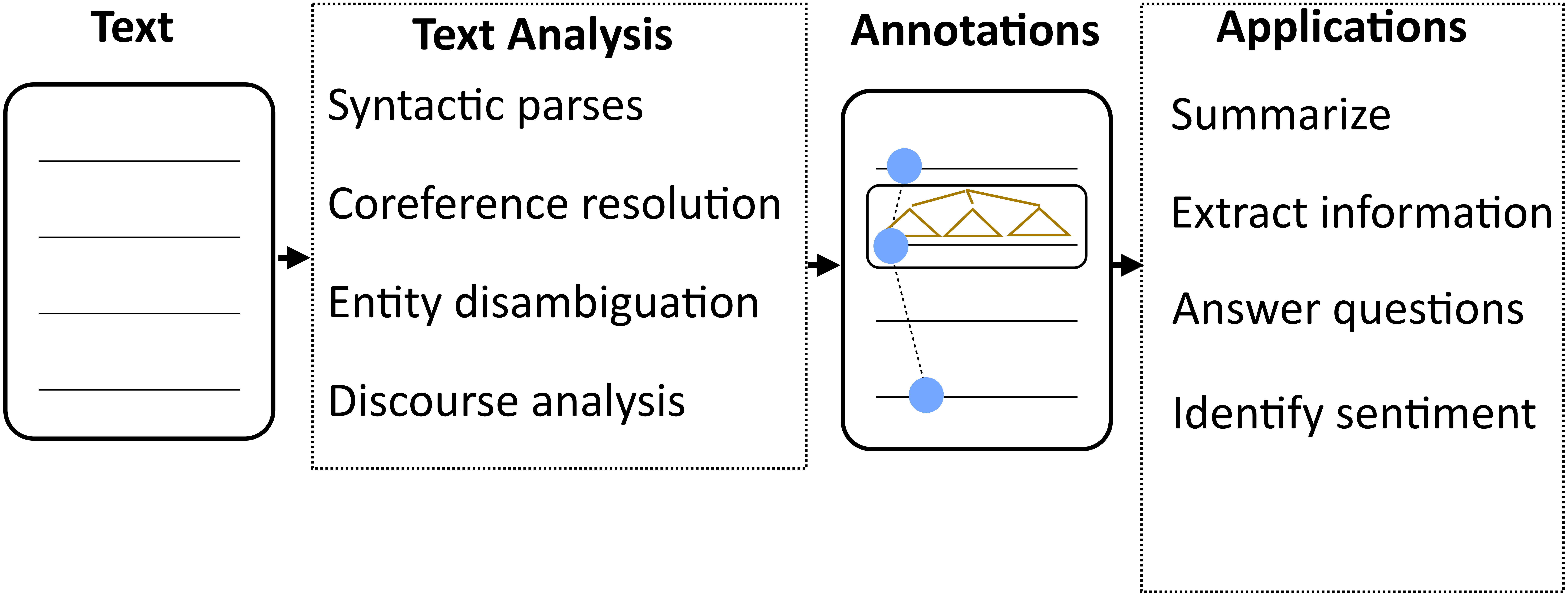

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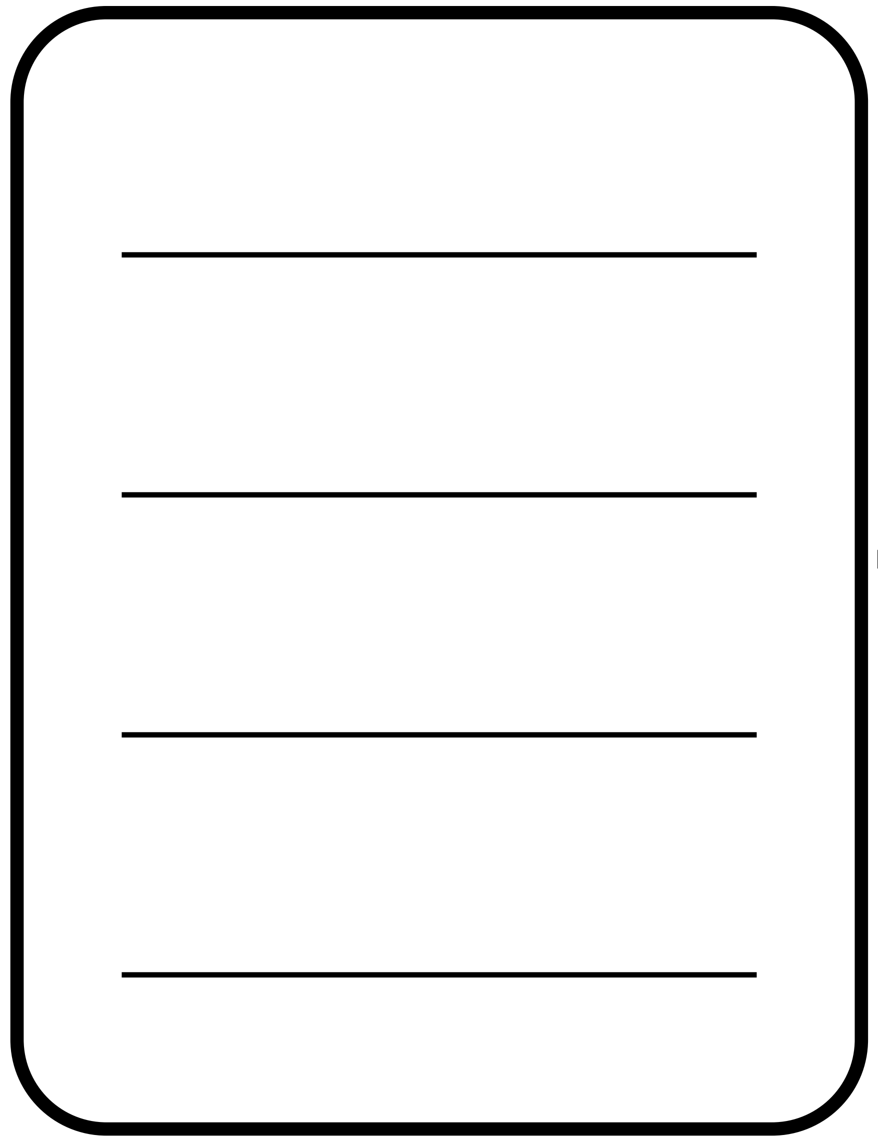

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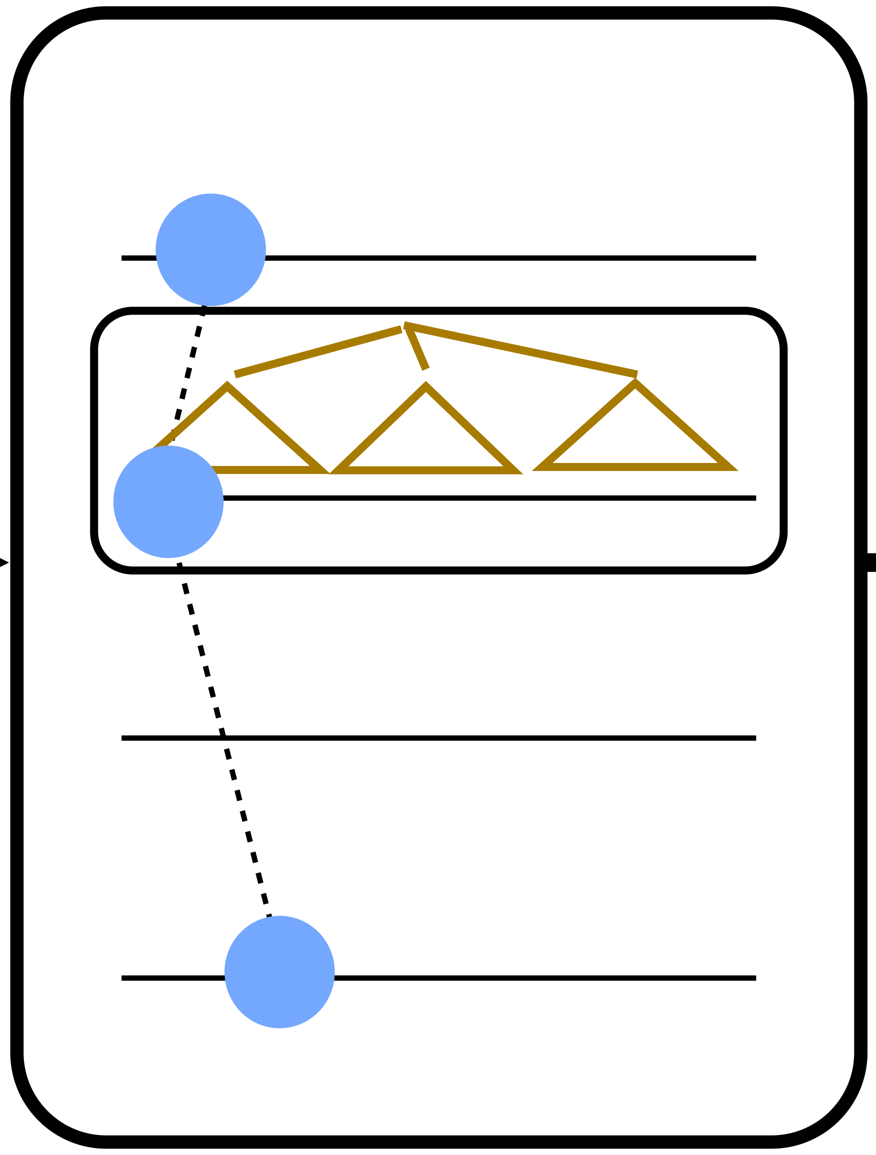

Applications

Summarize

Extract information

Answer questions

Identify sentiment

Translate

NLP Analysis Pipeline

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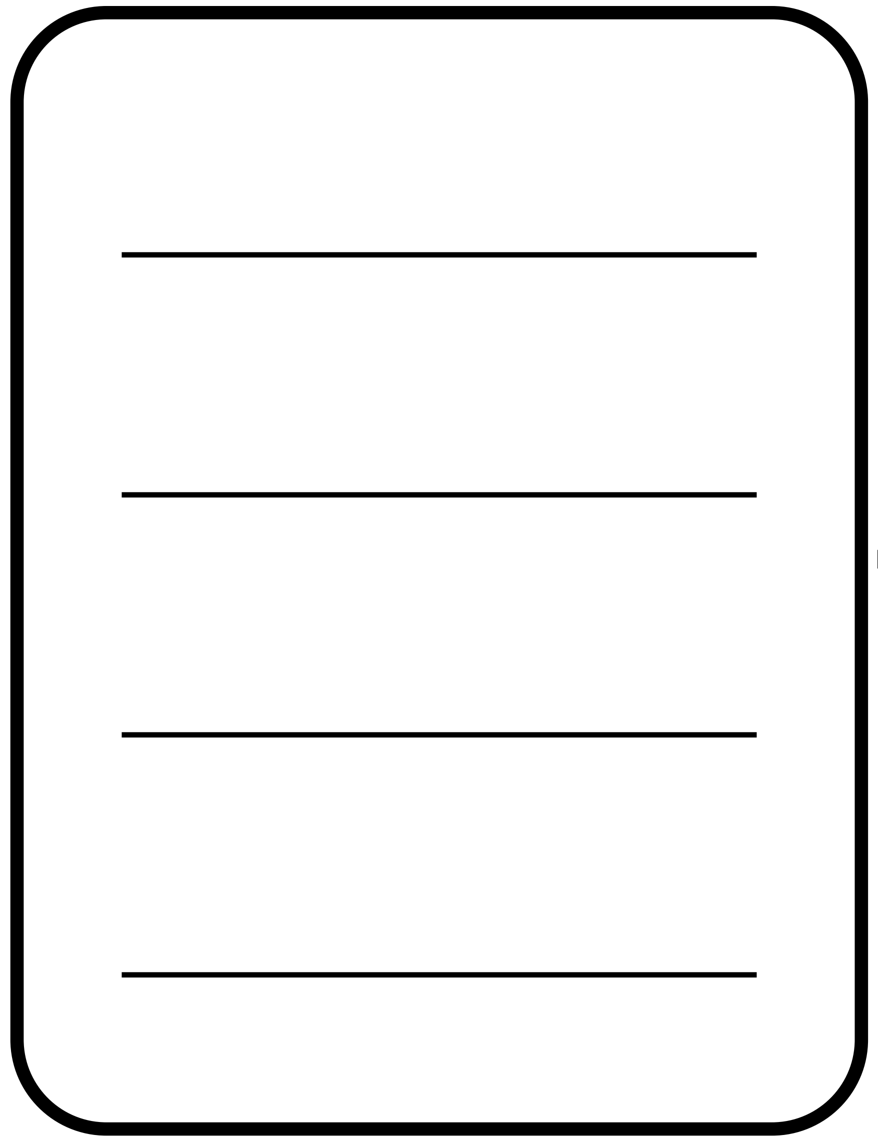

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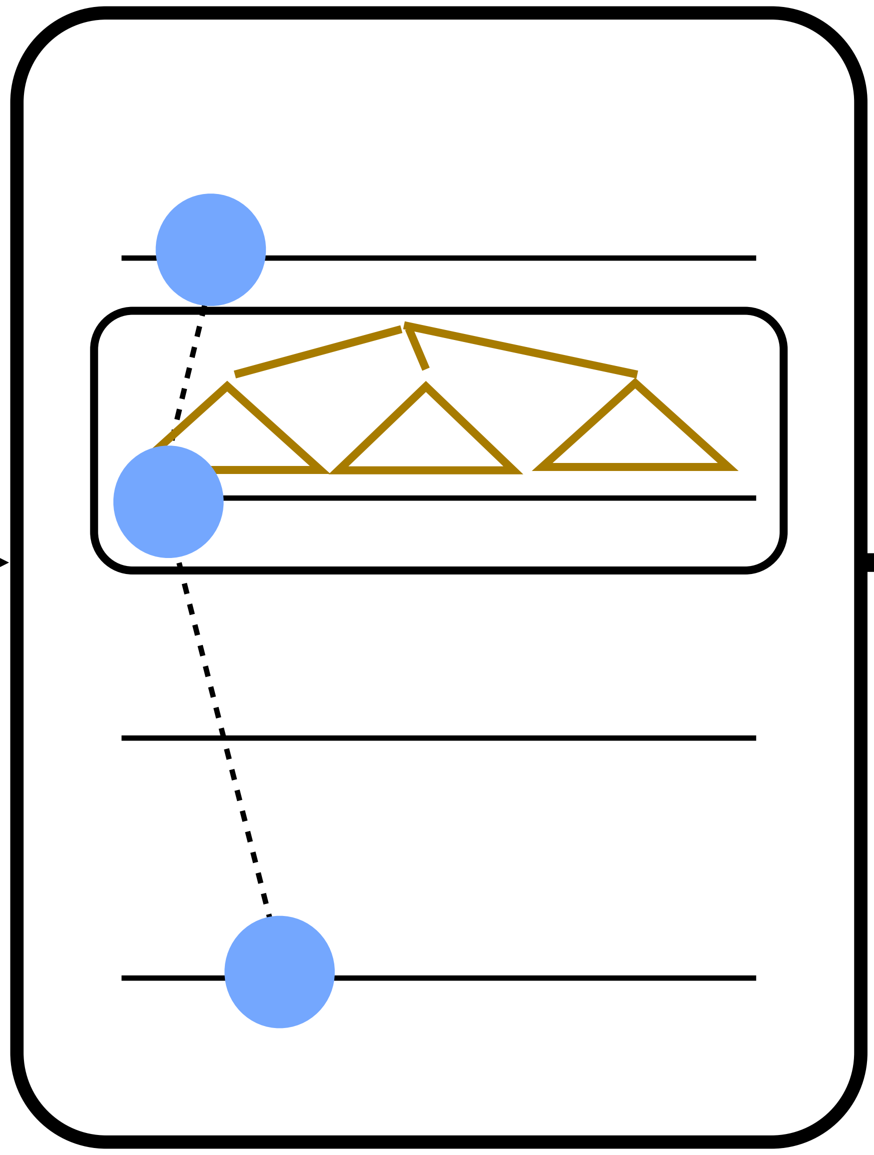

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- NLP is about building these pieces!

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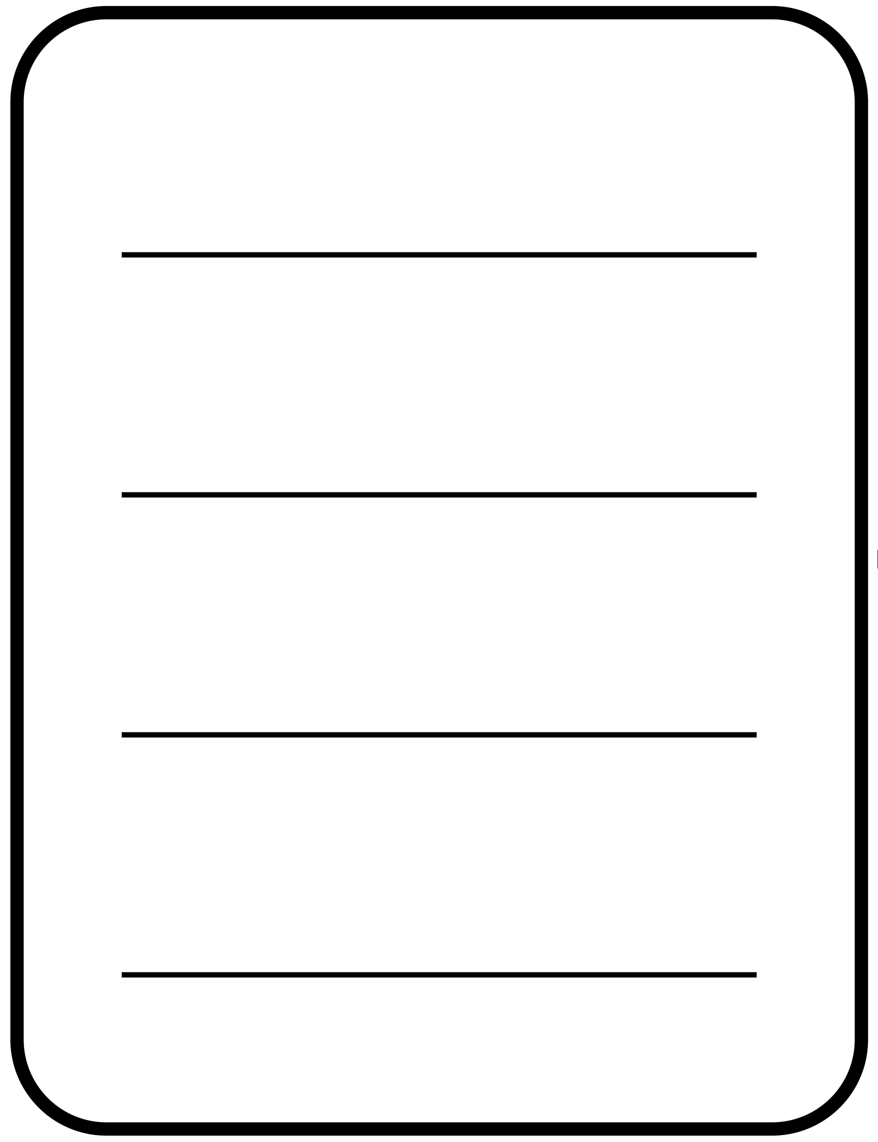

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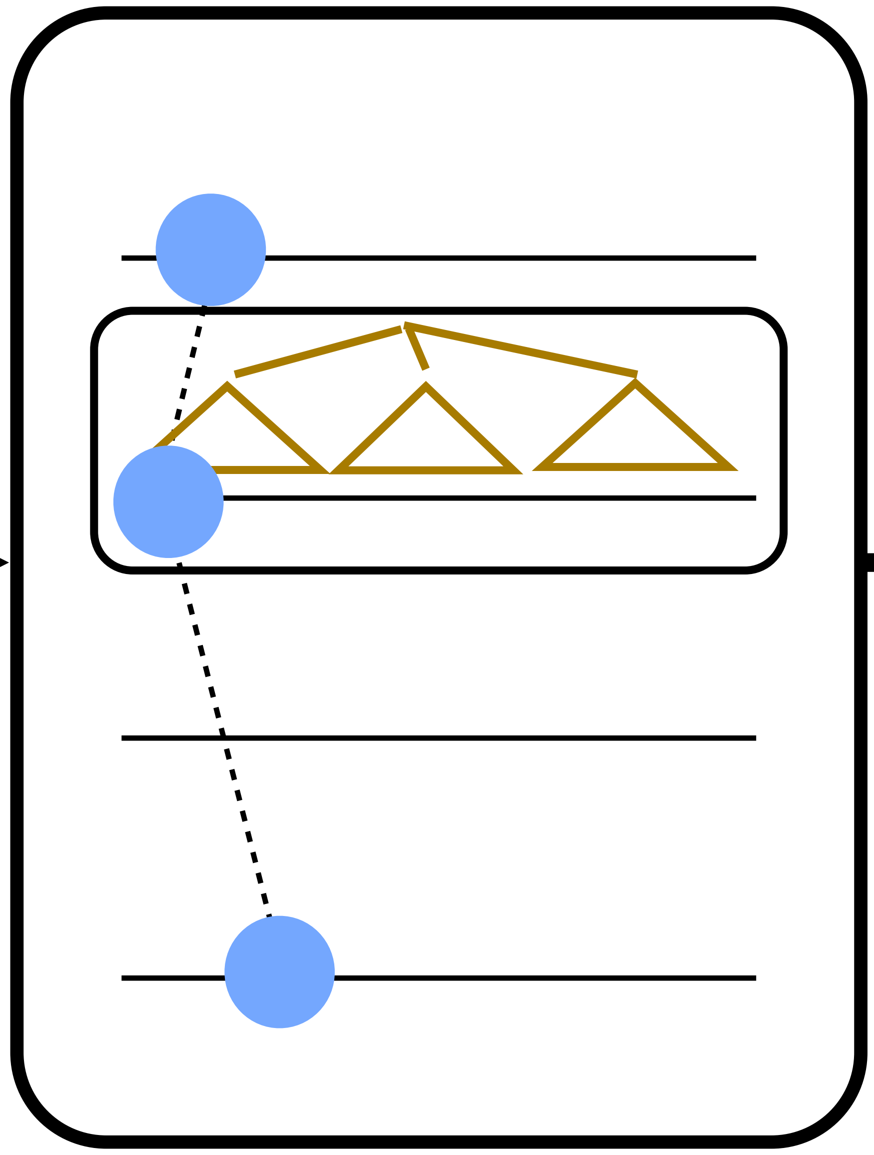

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- NLP is about building these pieces!
- All of these components are modeled with statistical approaches trained with machine learning

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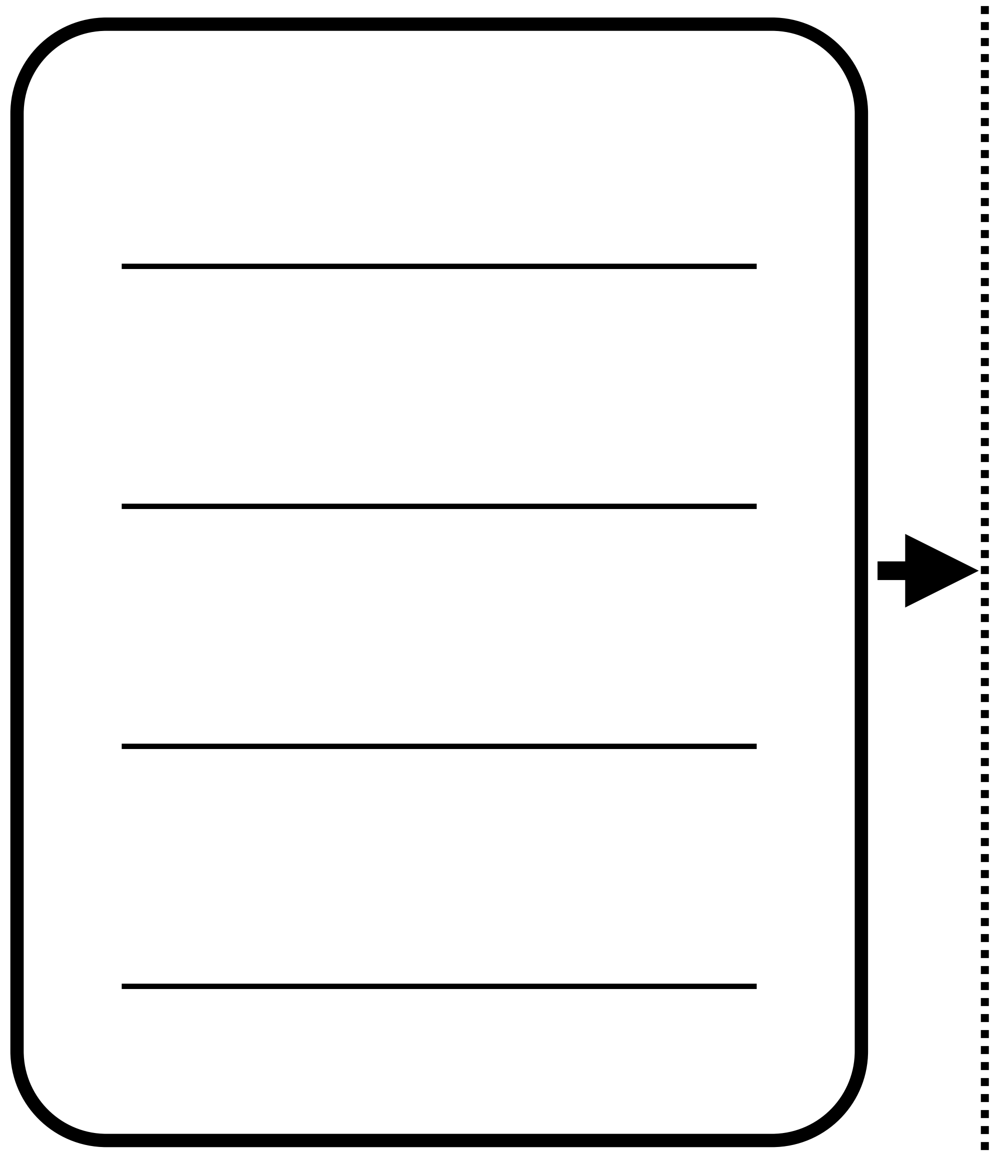

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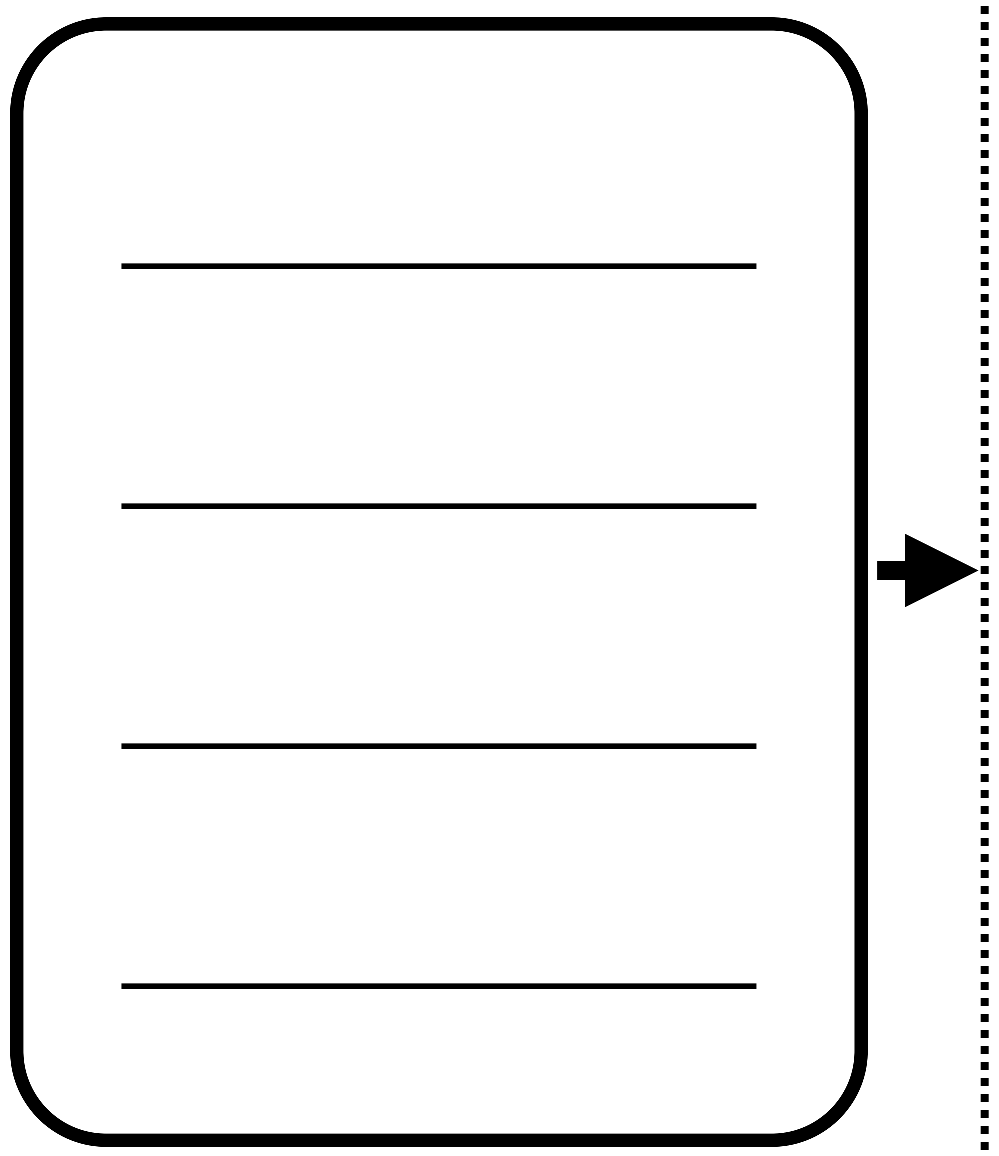

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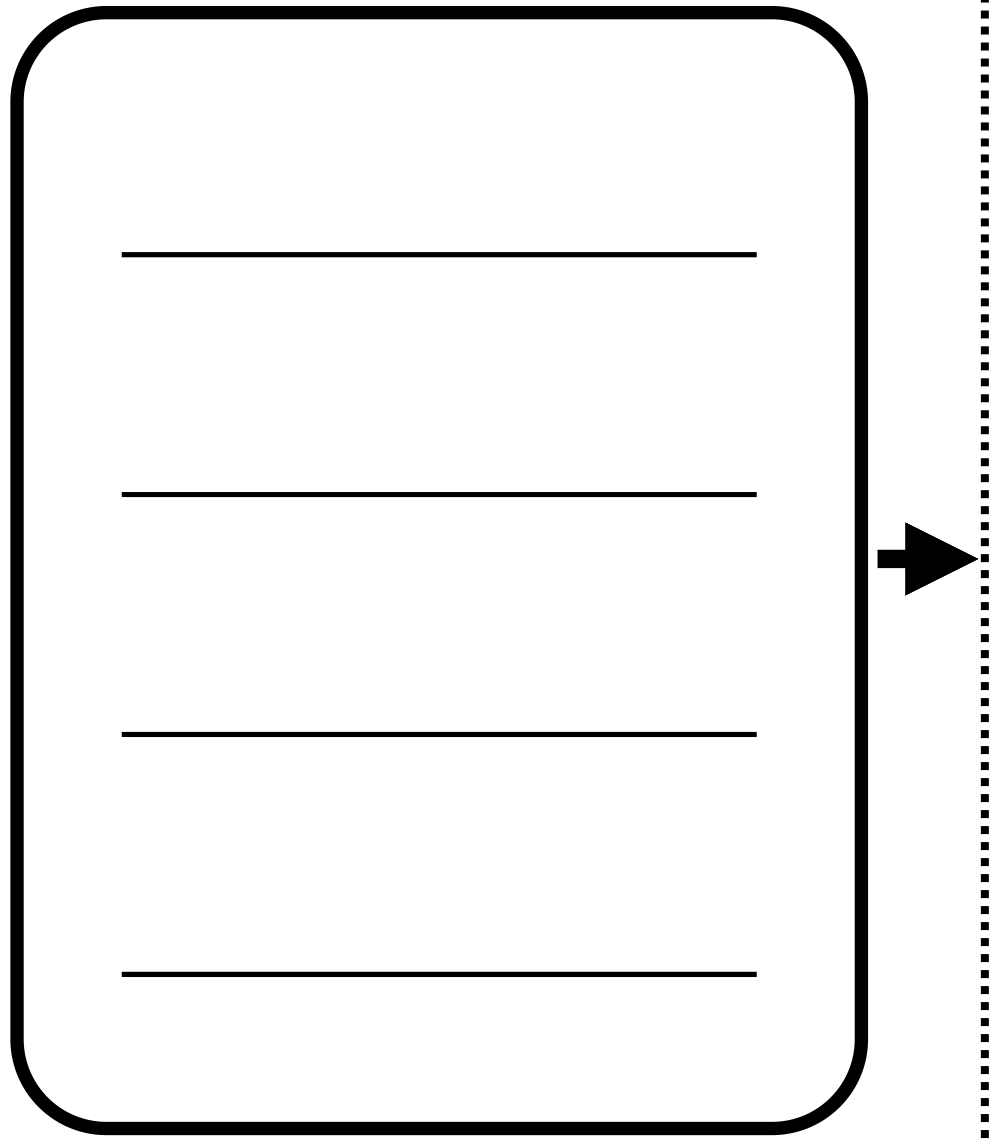

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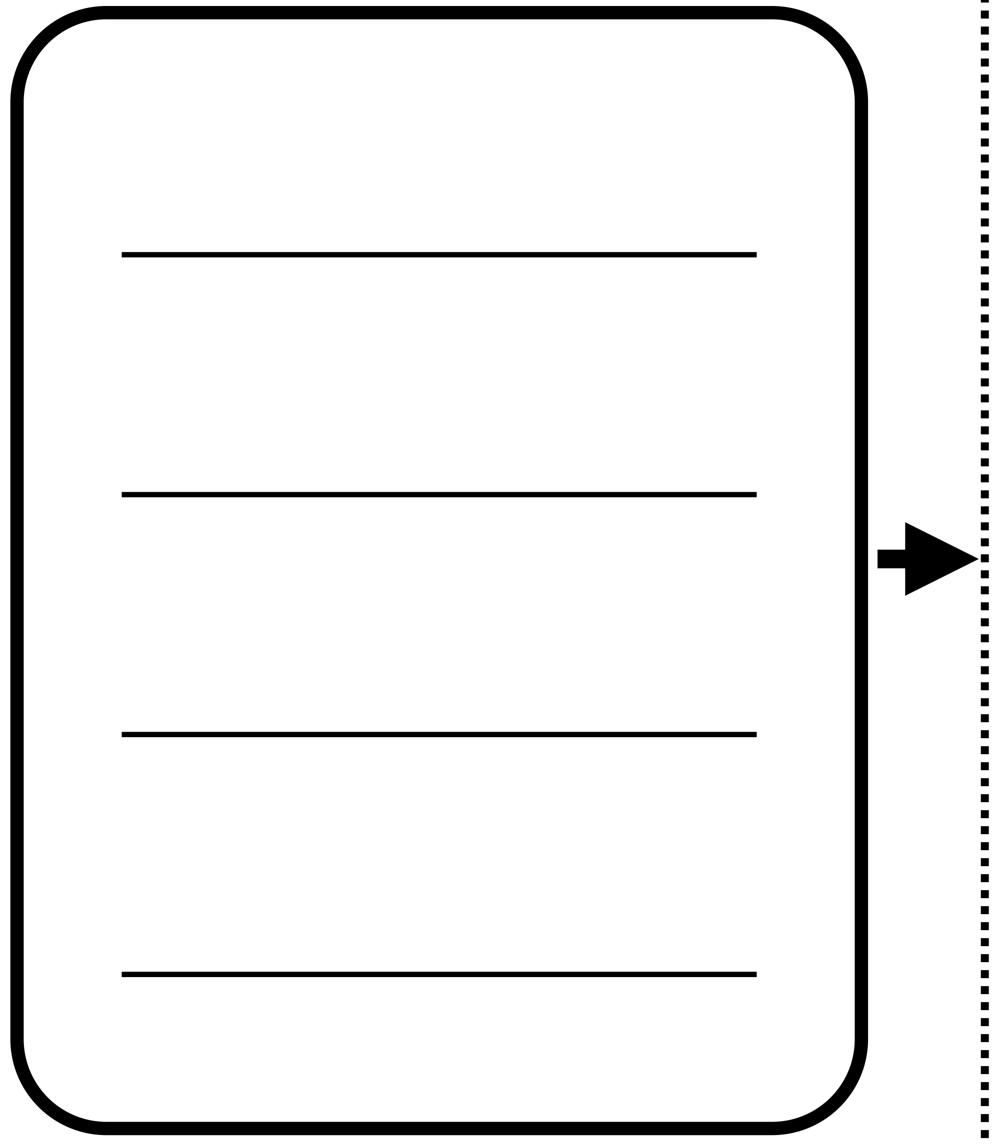

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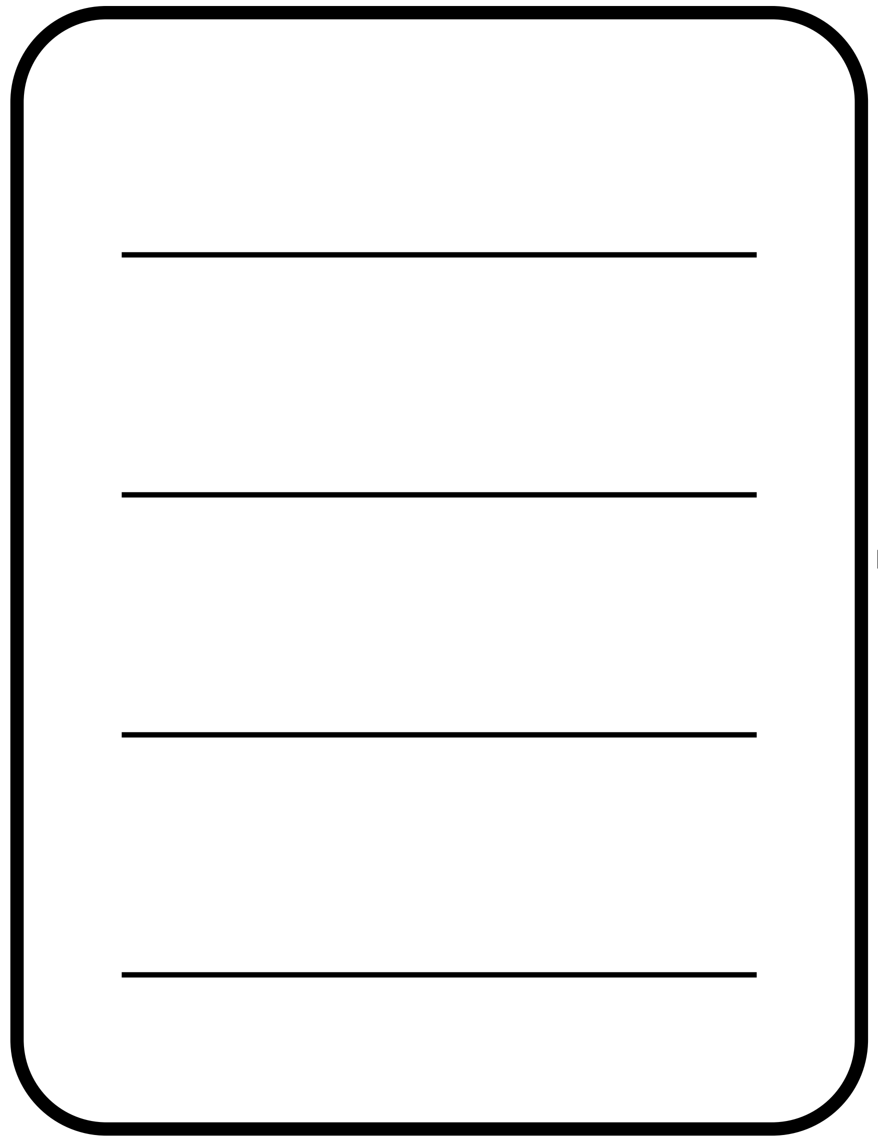

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Sequences/tags

PERSON		**MOVIE**	
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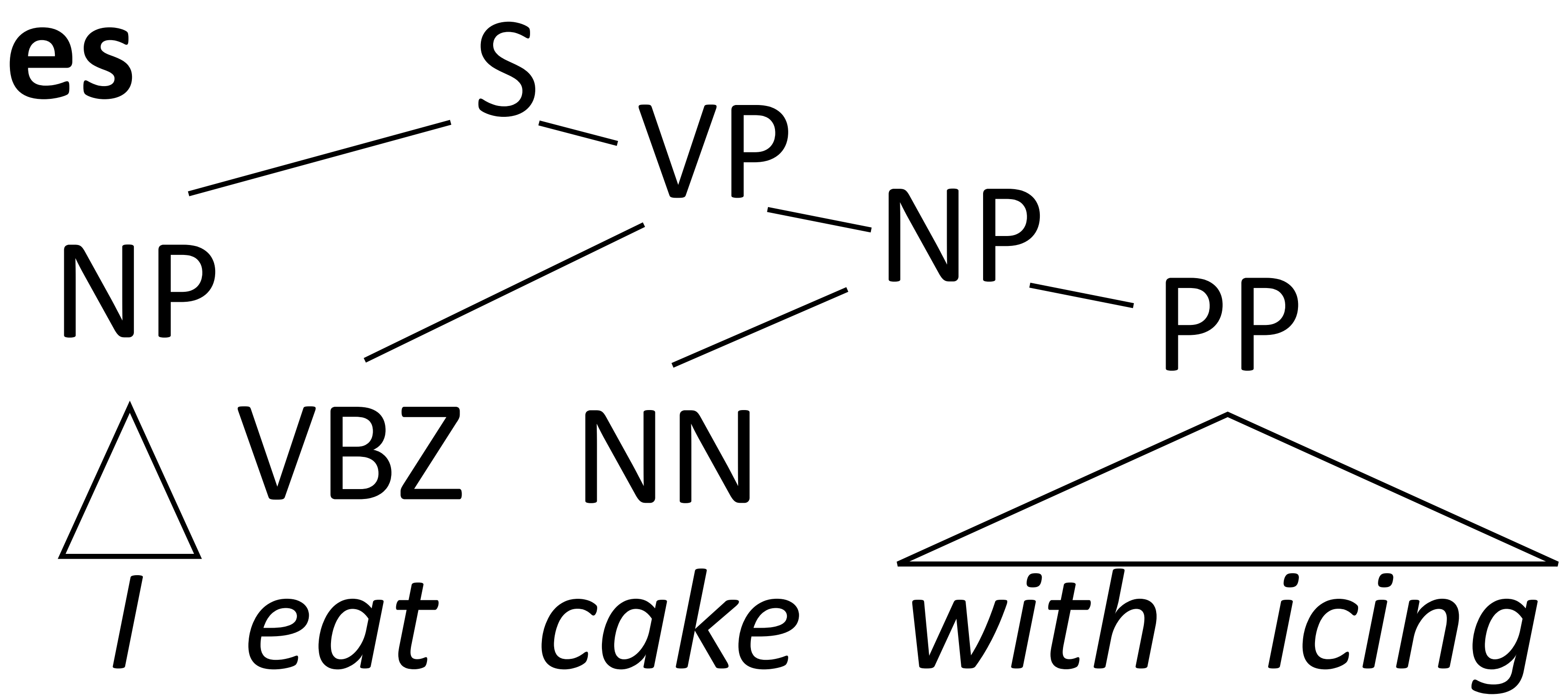
Trees



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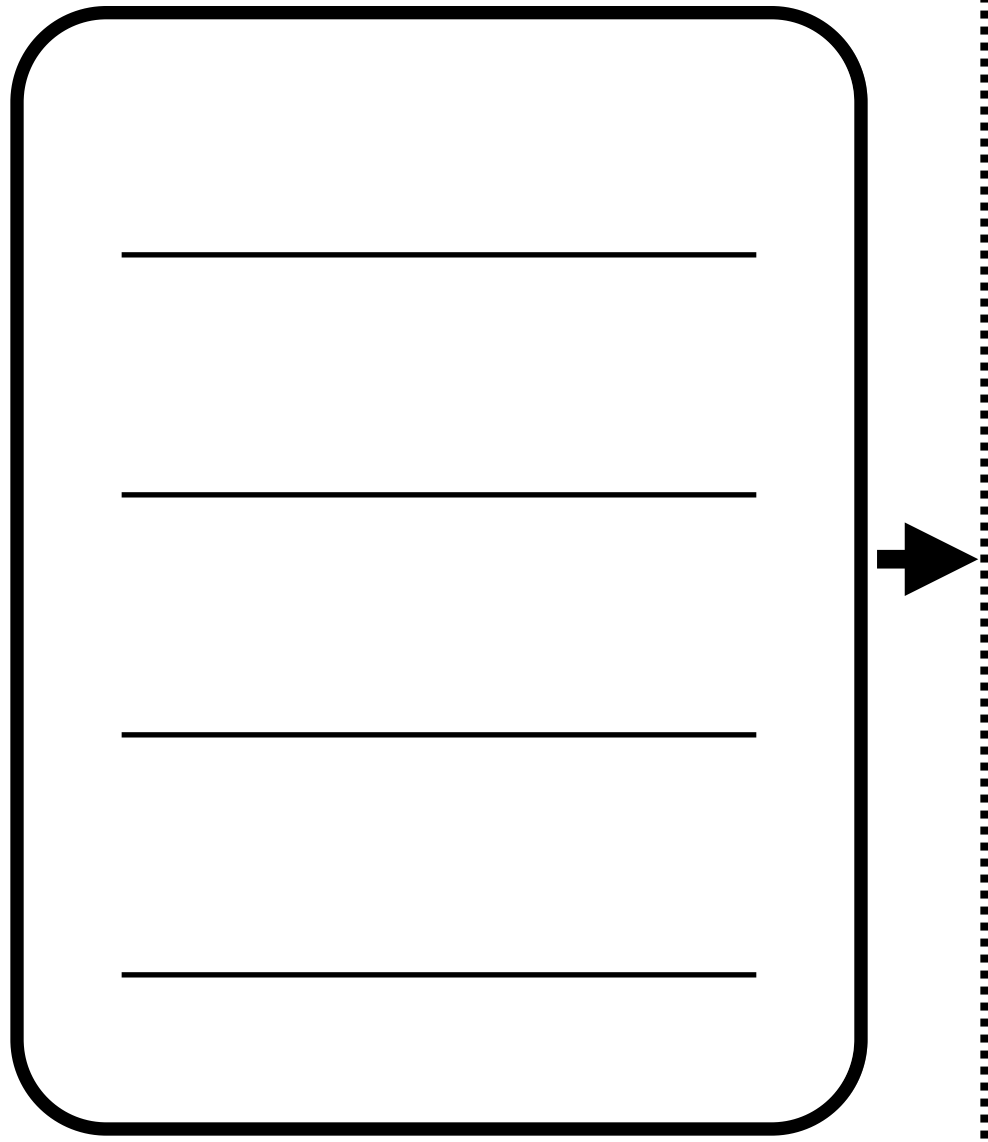

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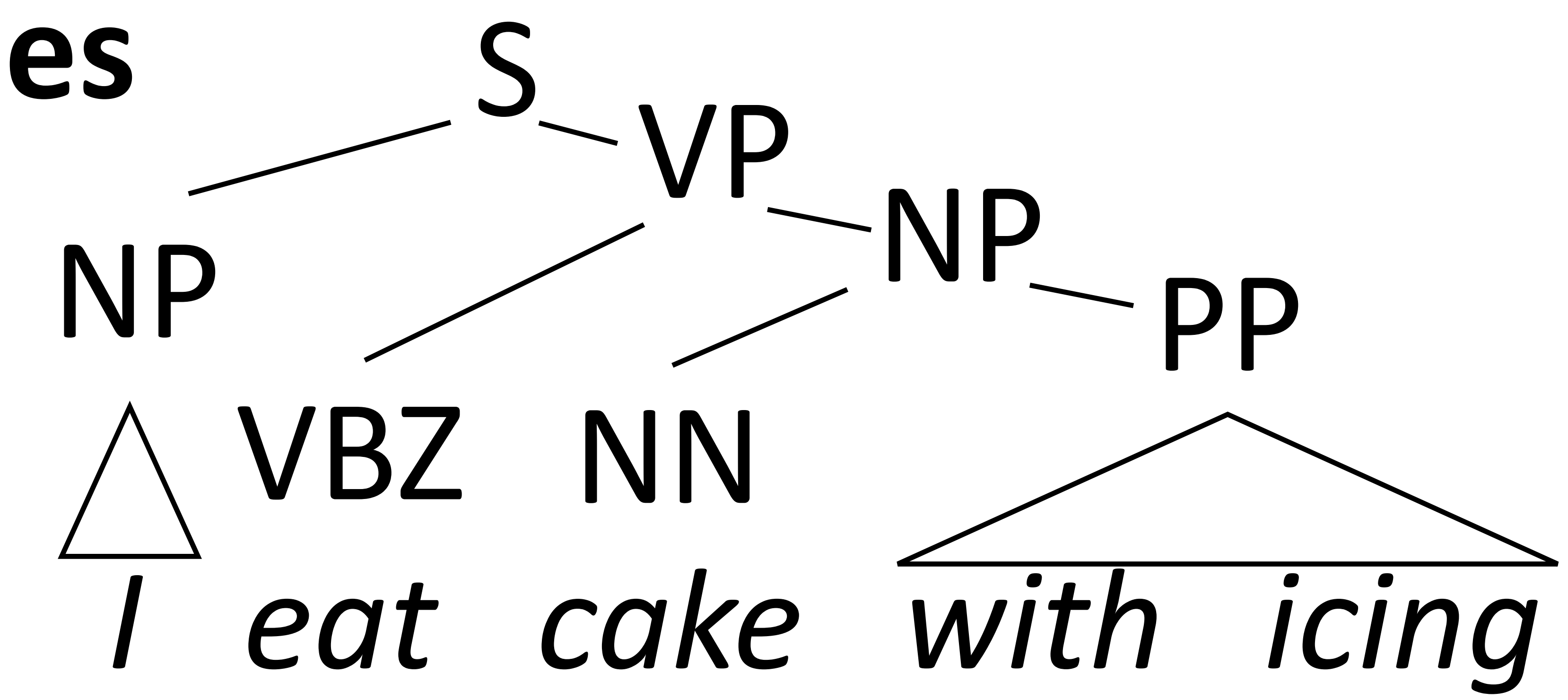
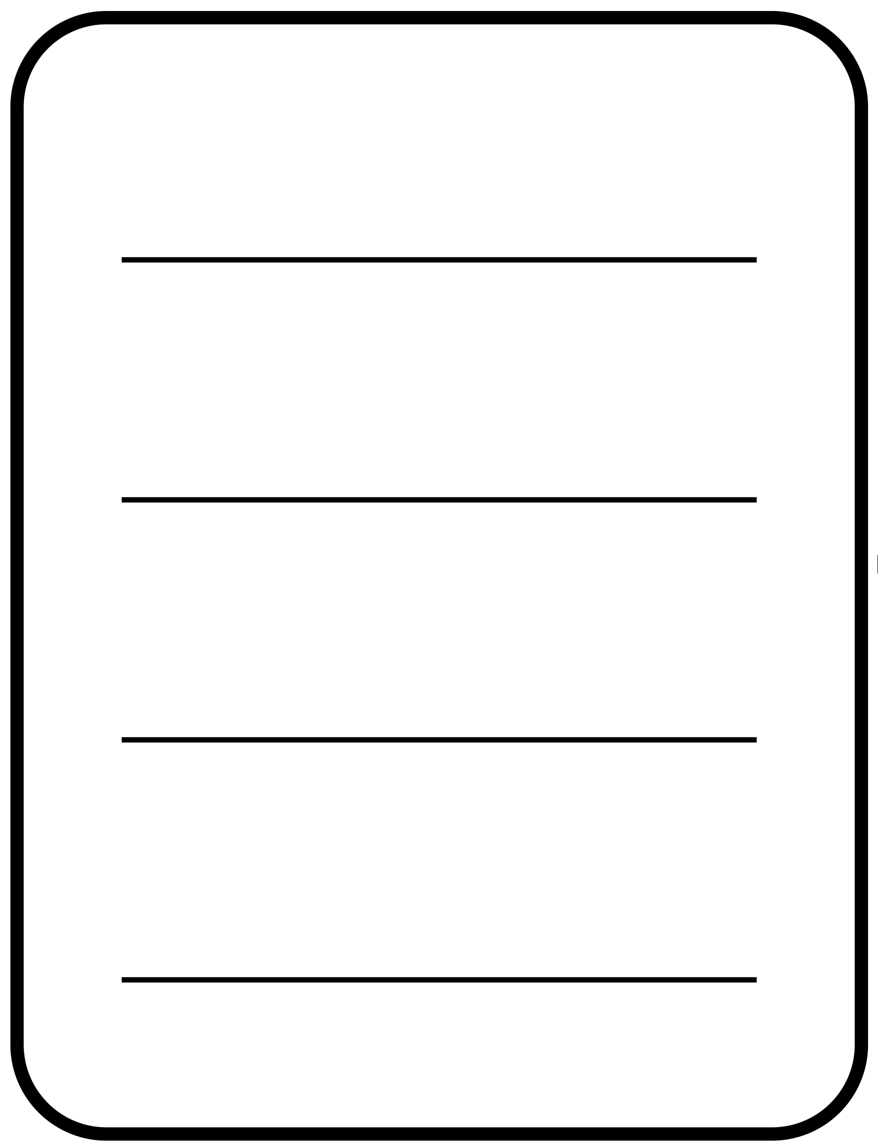


λx. flight(x) ∧ dest(x)=Miami

flights to Miami

How do we use these representations?

Text



Text Analysis

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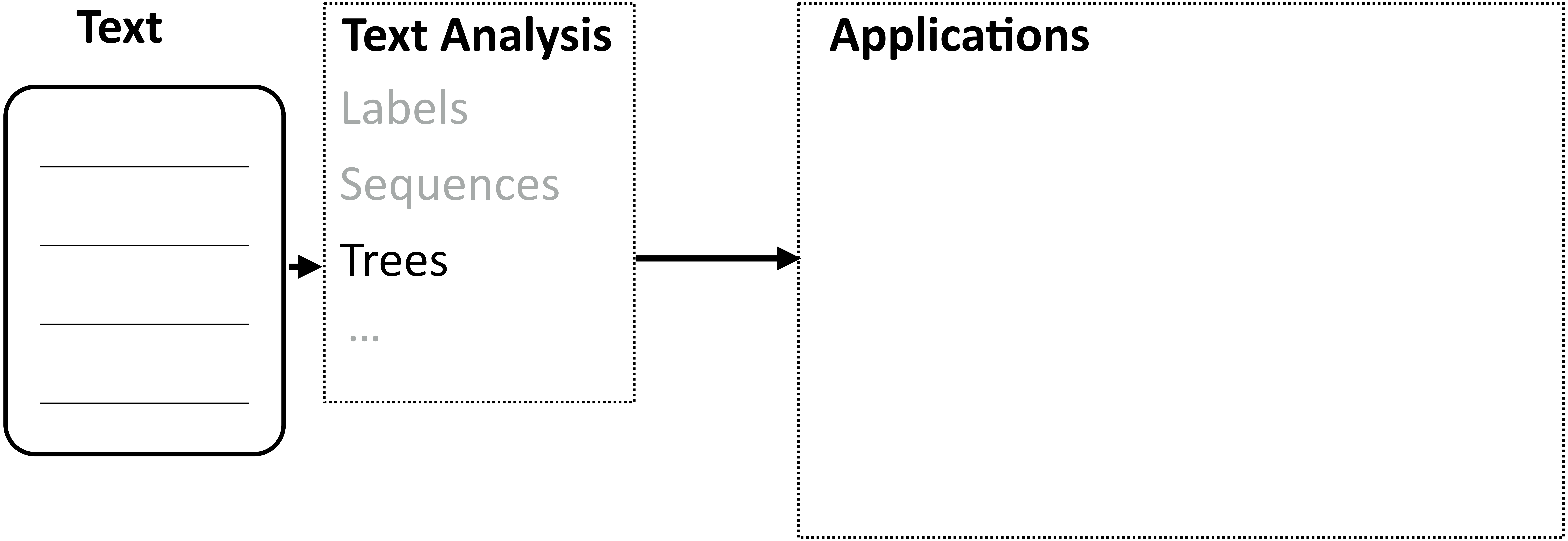

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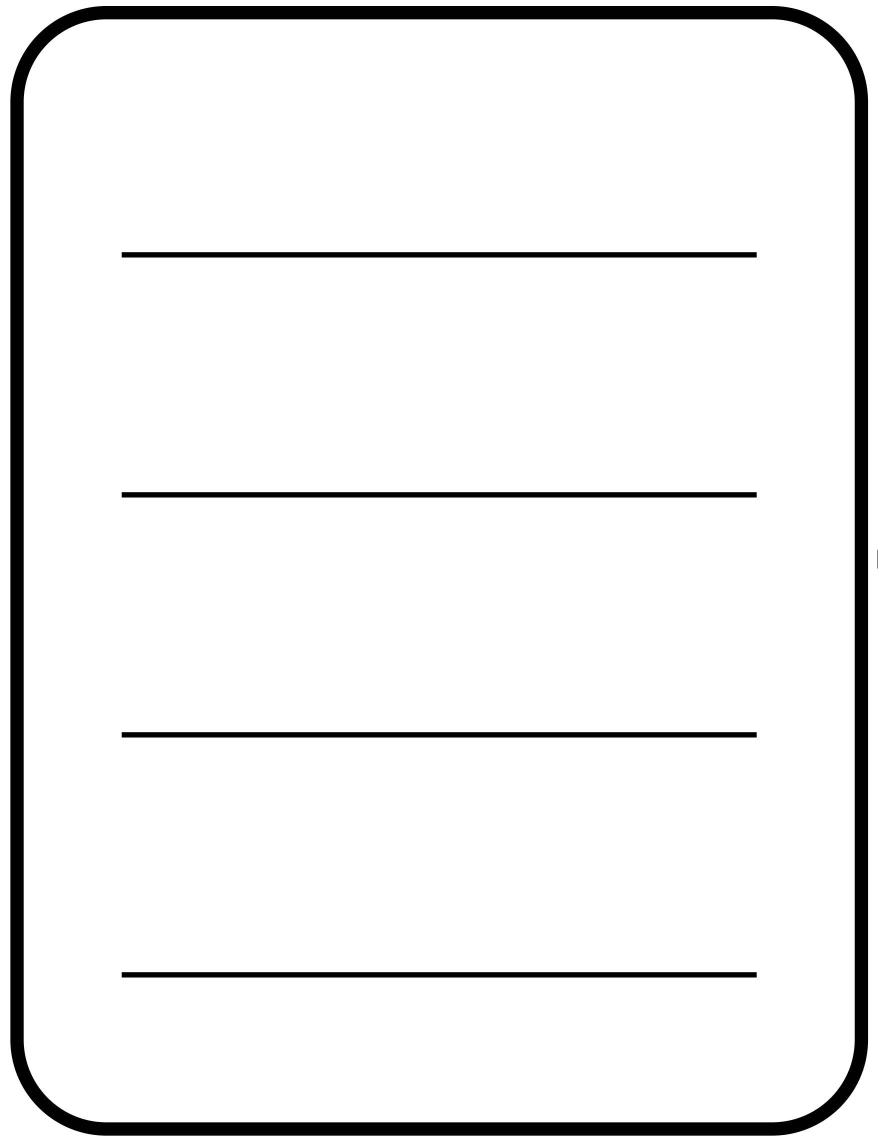

Text Analysis

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Applications

Extract syntactic features

How do we use these representations?

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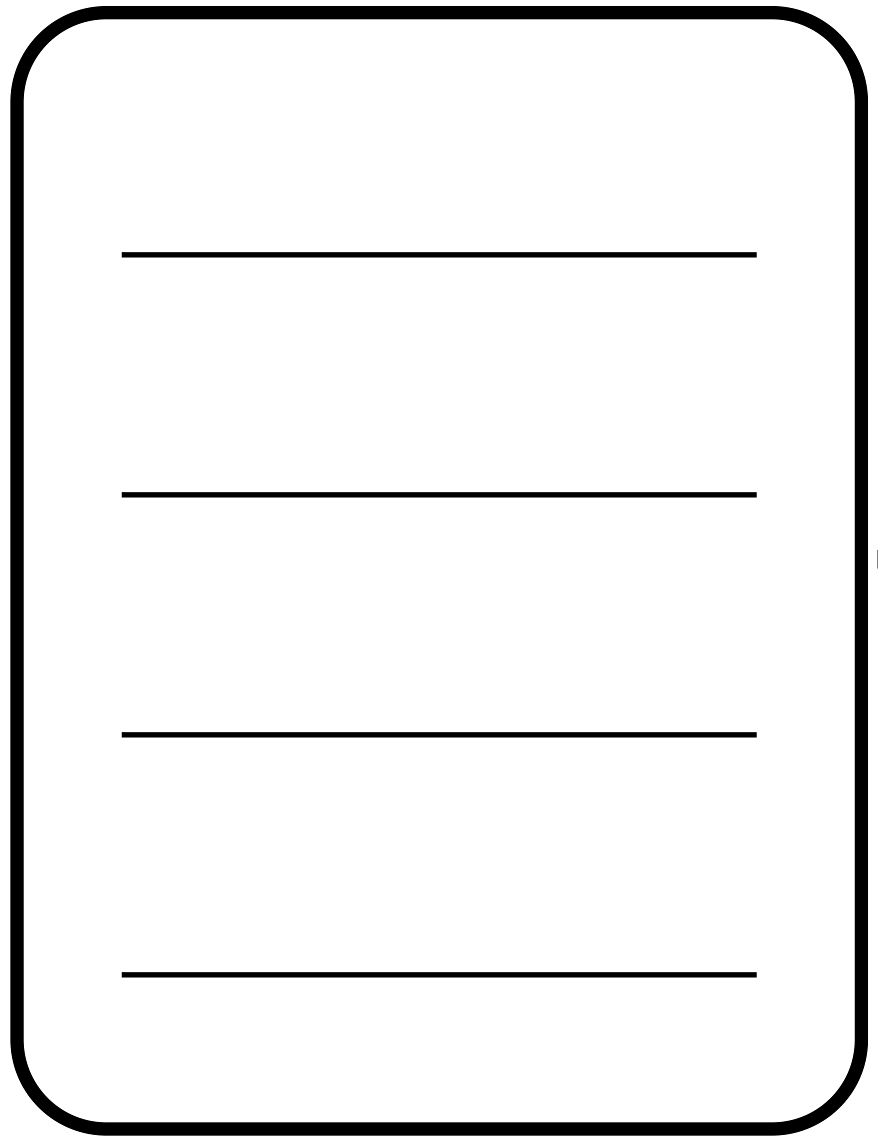

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Extract syntactic features

Tree-structured neural networks

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Text

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Tree-structured neural networks

Tree transducers (for machine translation)

How do we use these representations?

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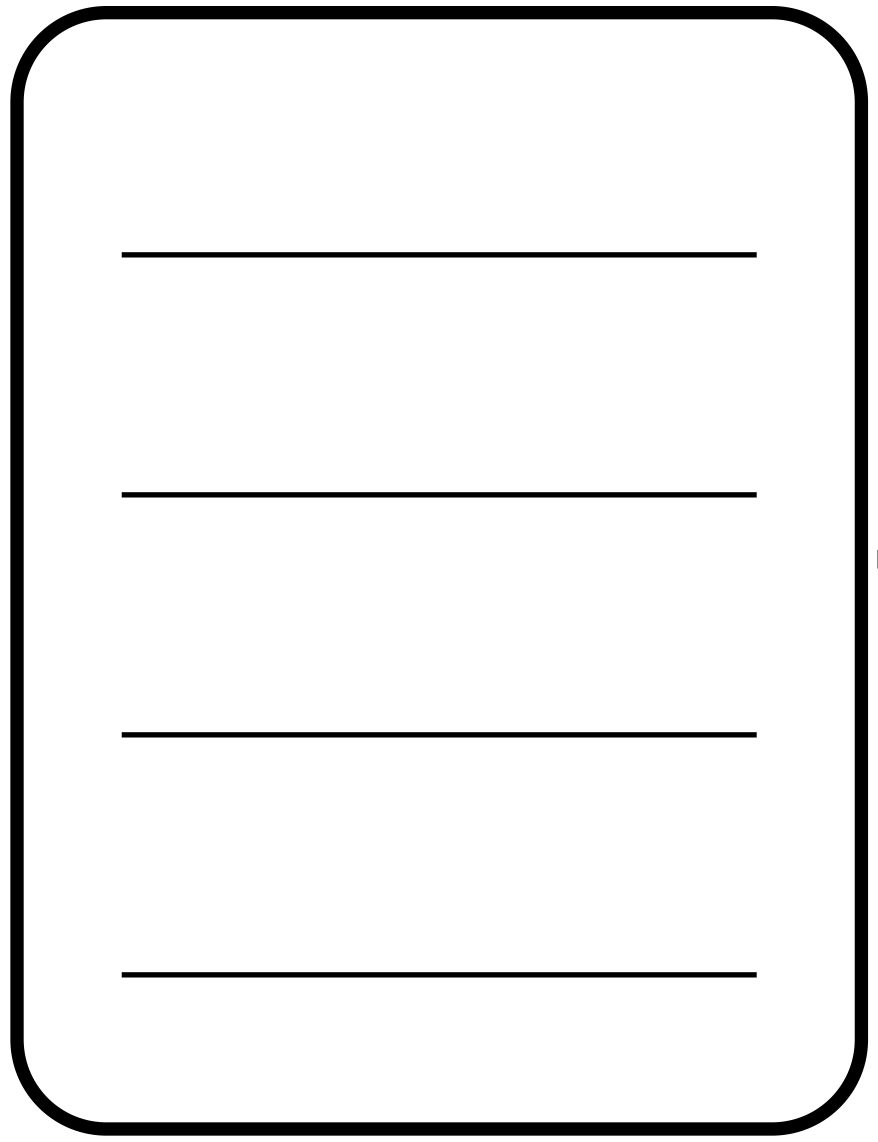

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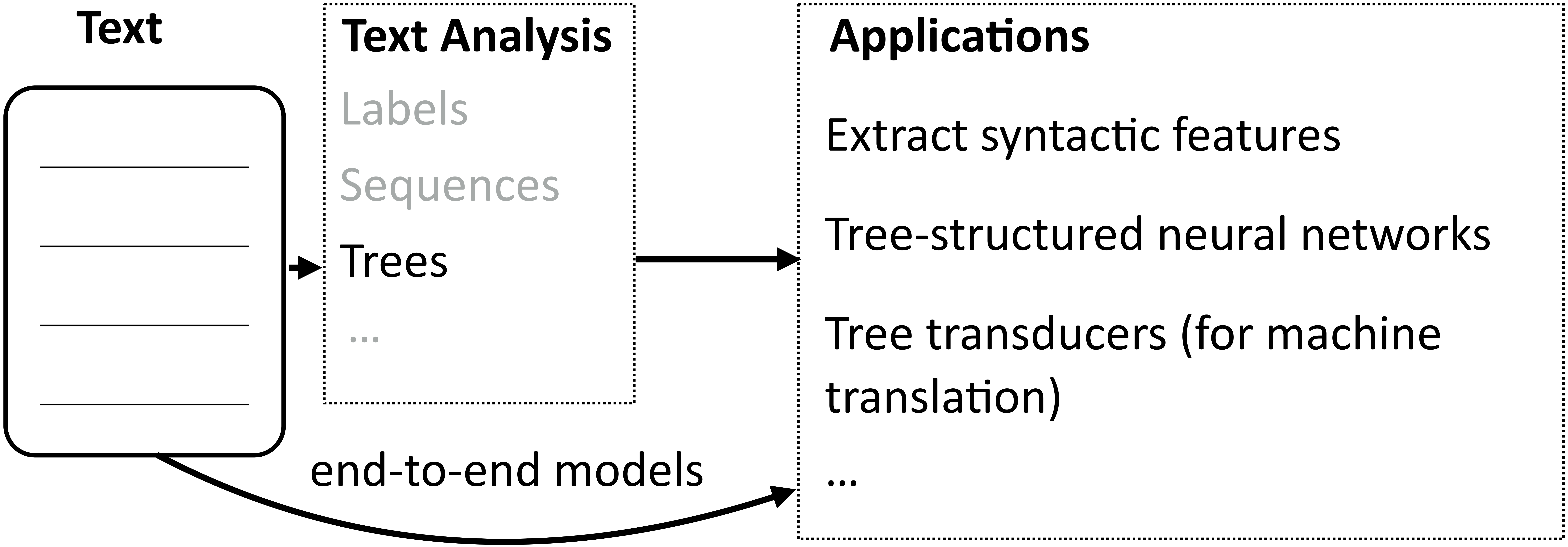
end-to-end models

How do we use these representations?



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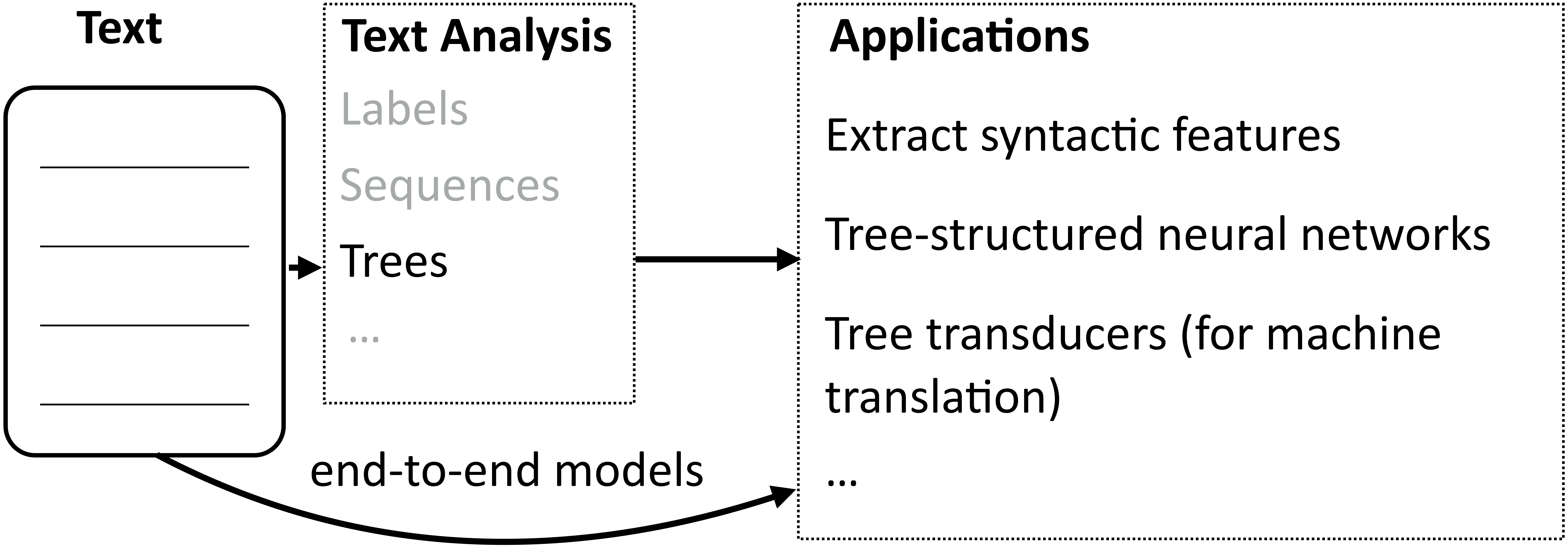
How do we use these representations?



- Main question: What representations do we need for language? What do we want to know about it?
- Boils down to: what ambiguities do we need to resolve?

Why is language hard?

(and how can we handle that?)

Language is Ambiguous!

- Hector Levesque (2011): "Winograd schema challenge" (named after Terry Winograd, the creator of SHRDLU)

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- Referential/semantic ambiguity

Language is Ambiguous!

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

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 ⟶

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

What do we need to understand language?

- Lots of data!

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

slide credit: Dan Klein

What do we need to understand language?

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

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DOJ greenlights Disney - Fox merger

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metaphor;
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DOJ *greenlights* *Disney* - *Fox* *merger*

Department of Justice

metaphor;
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- What is a green light? How do we understand what "green lighting" does?

What do we need to understand language?

- Grounding: learn what fundamental concepts actually mean in a data-driven way

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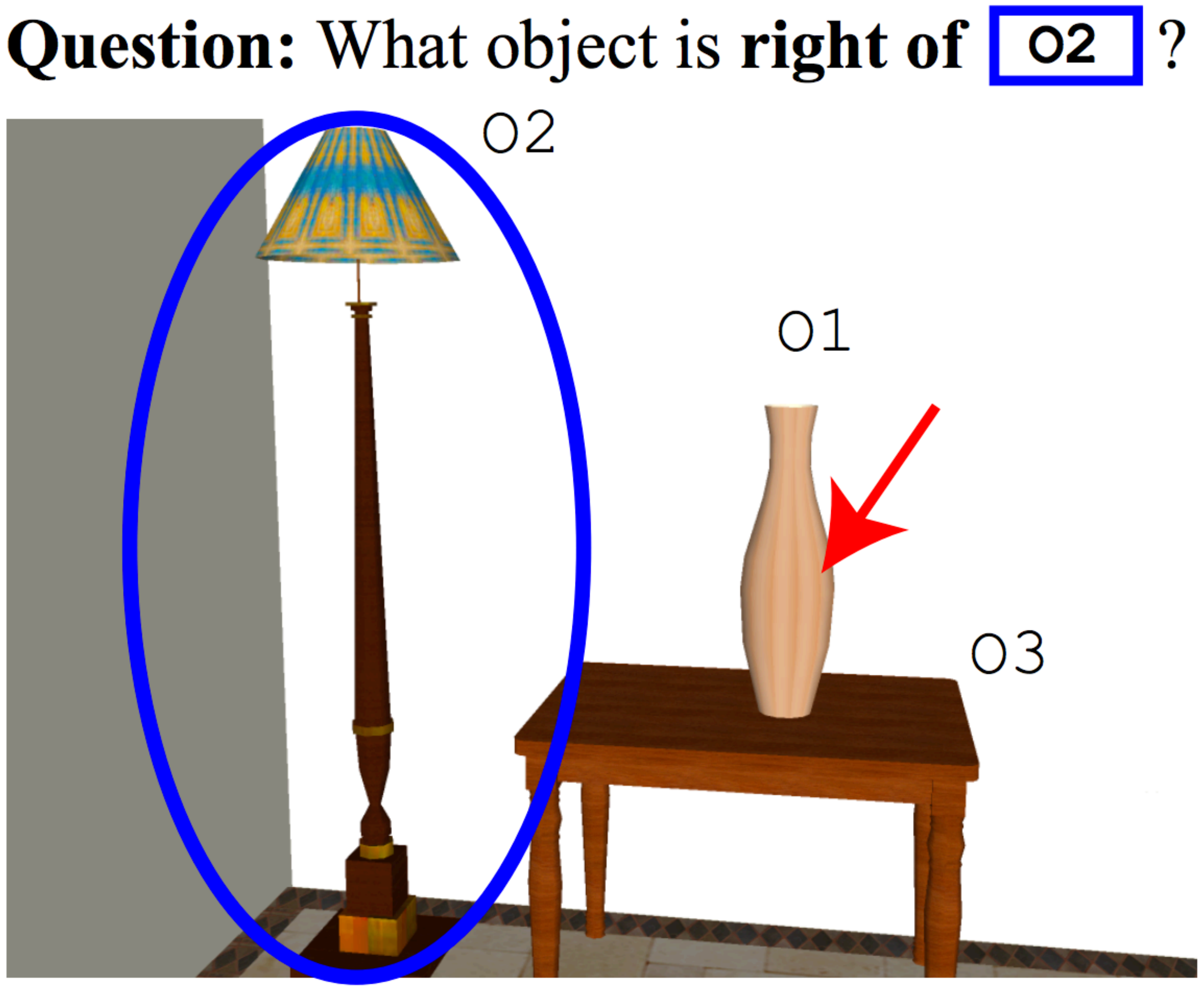

Golland et al. (2010)

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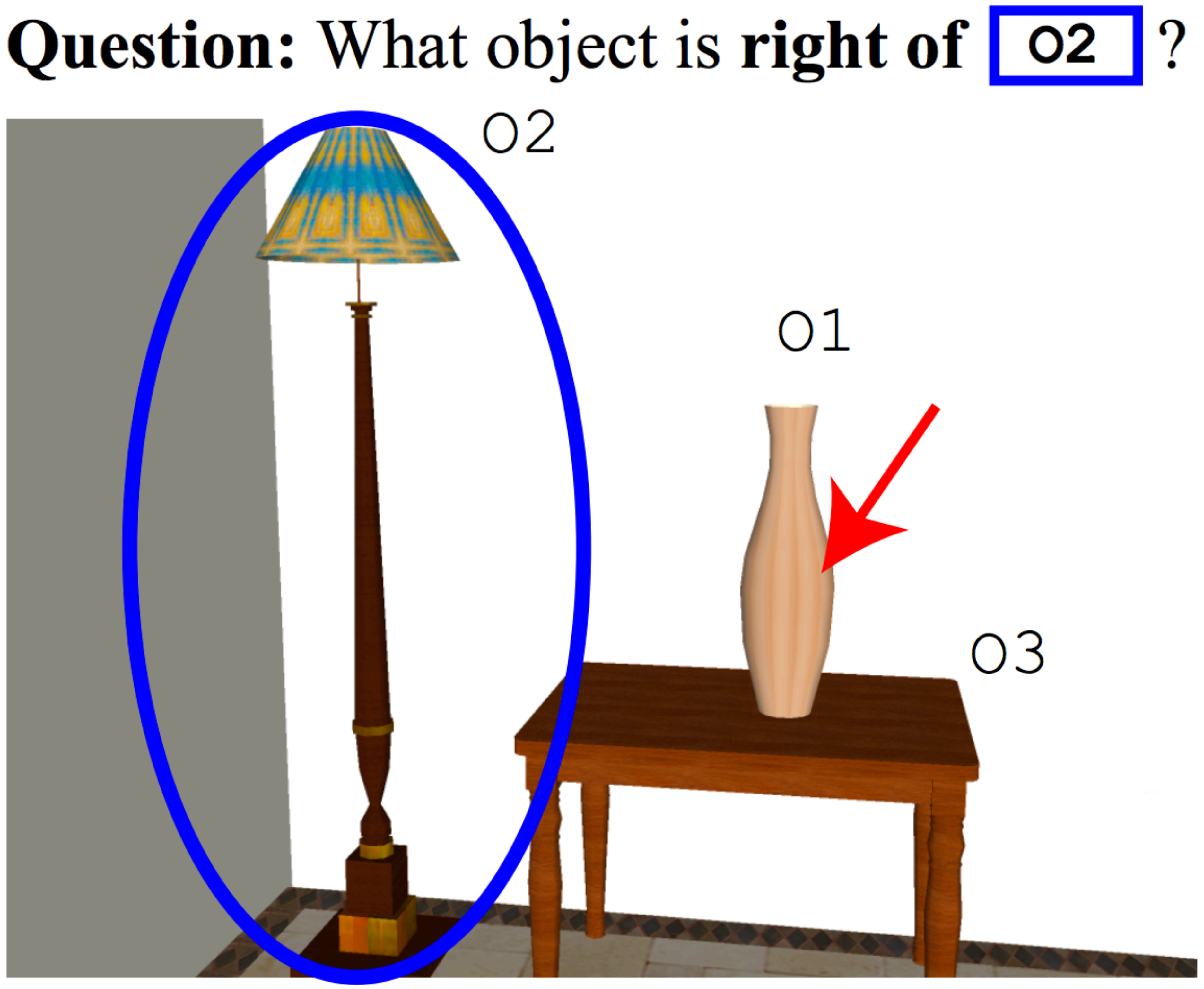

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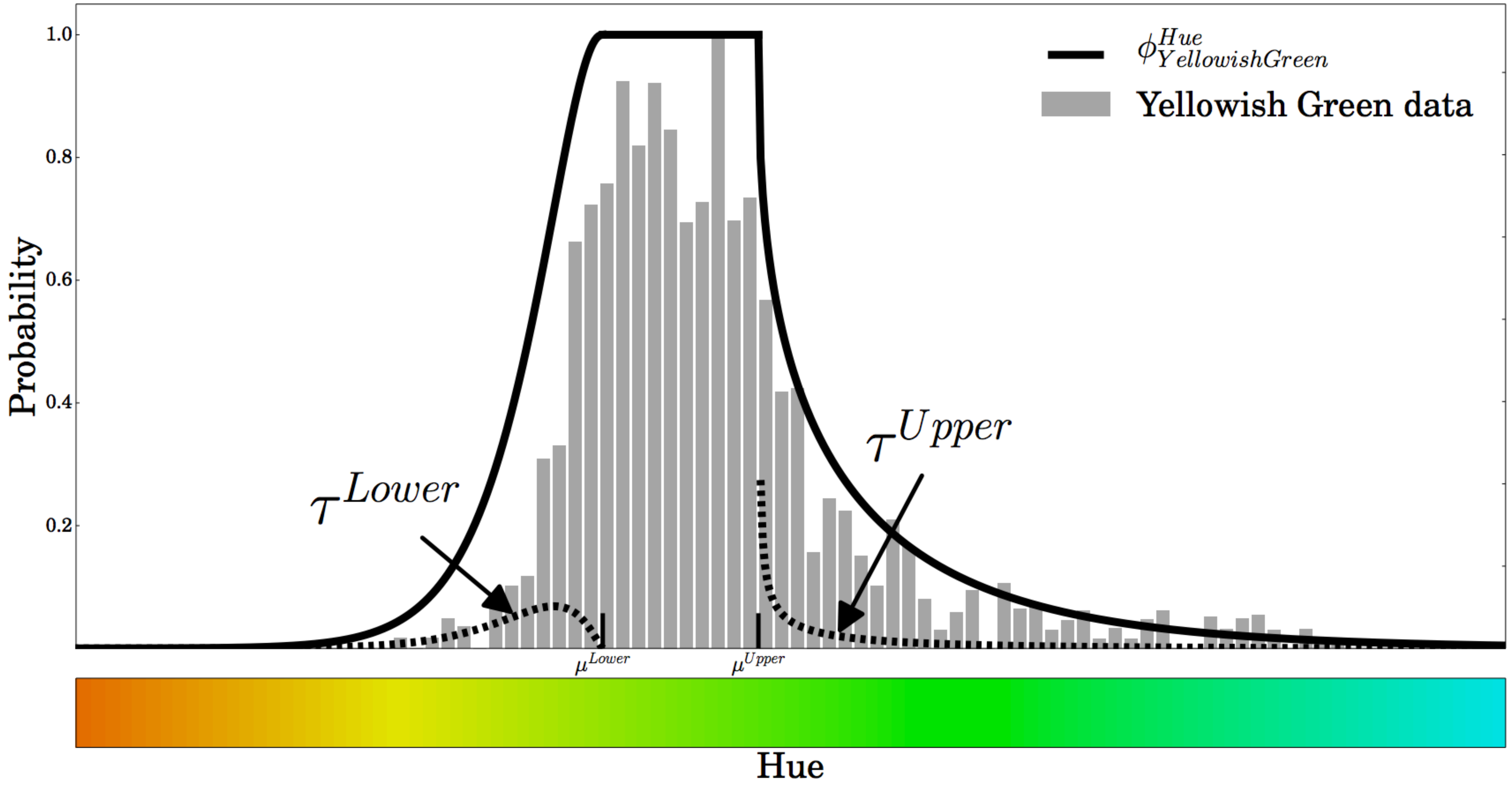

McMahan and Stone (2015)

What do we need to understand language?

- Linguistic structure

Centering Theory
Grosz et al. (1995)

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a. John has been having a lot of trouble arranging his vacation.

b. He cannot find anyone to take over his responsibilities. (he = John)
C_b = John; C_f = {John}

c. He called up Mike yesterday to work out a plan. (he = John)
C_b = John; C_f = {John, Mike} (CONTINUE)

d. Mike has annoyed him a lot recently.
C_b = John; C_f = {Mike, John} (RETAIN)

e. He called John at 5 AM on Friday last week. (he = Mike)
C_b = Mike; C_f = {Mike, John} (SHIFT)

Centering Theory
Grosz et al. (1995)

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,
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Unsup: topic
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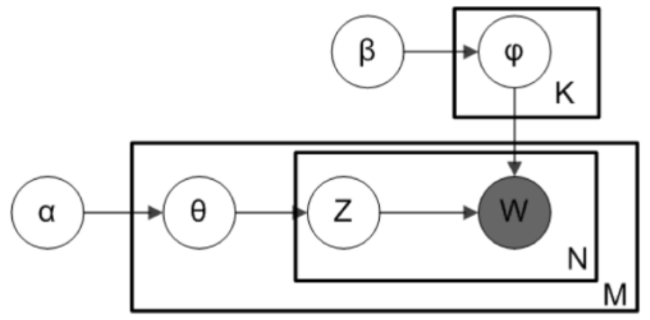

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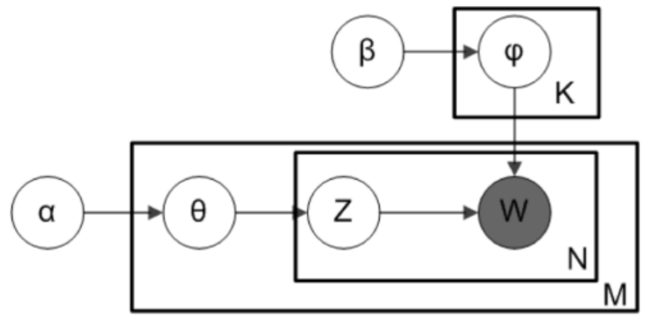

Semi-sup,
structured
prediction

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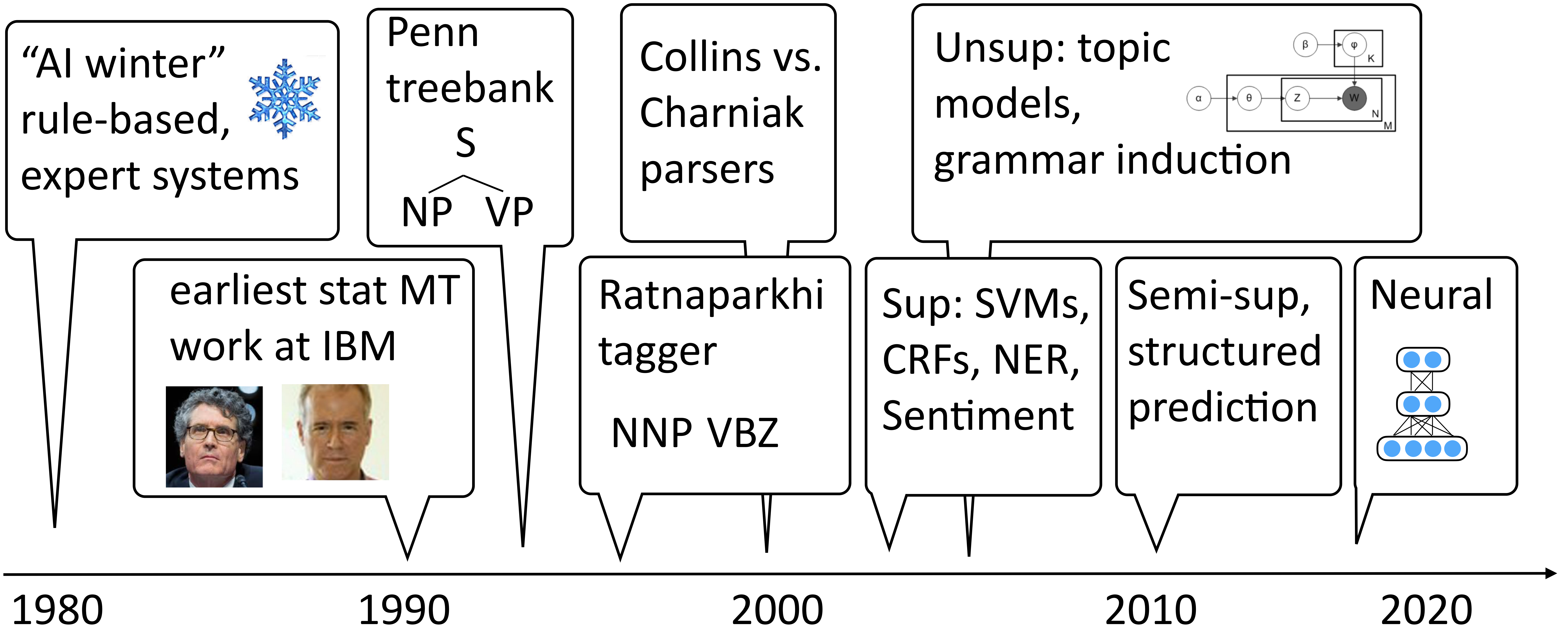

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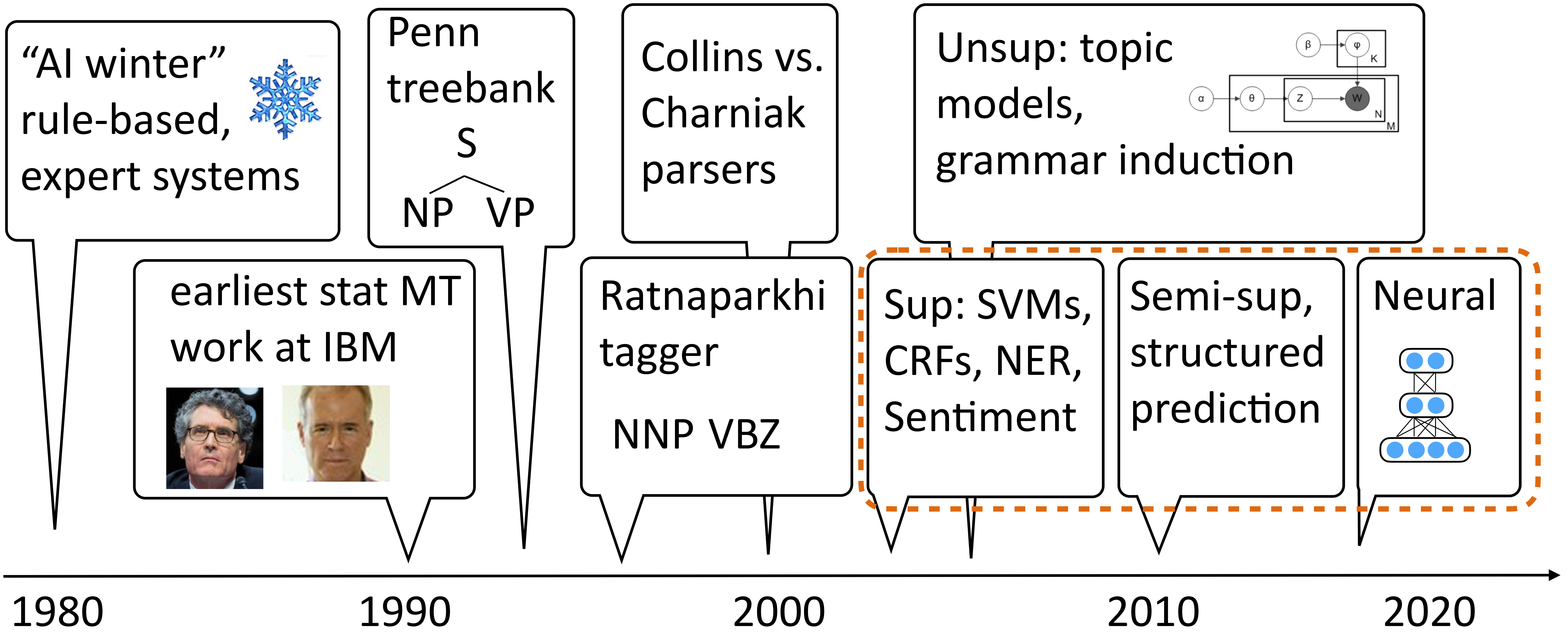

Structured Prediction

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

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

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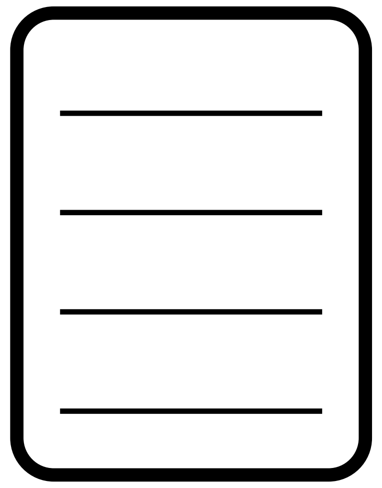

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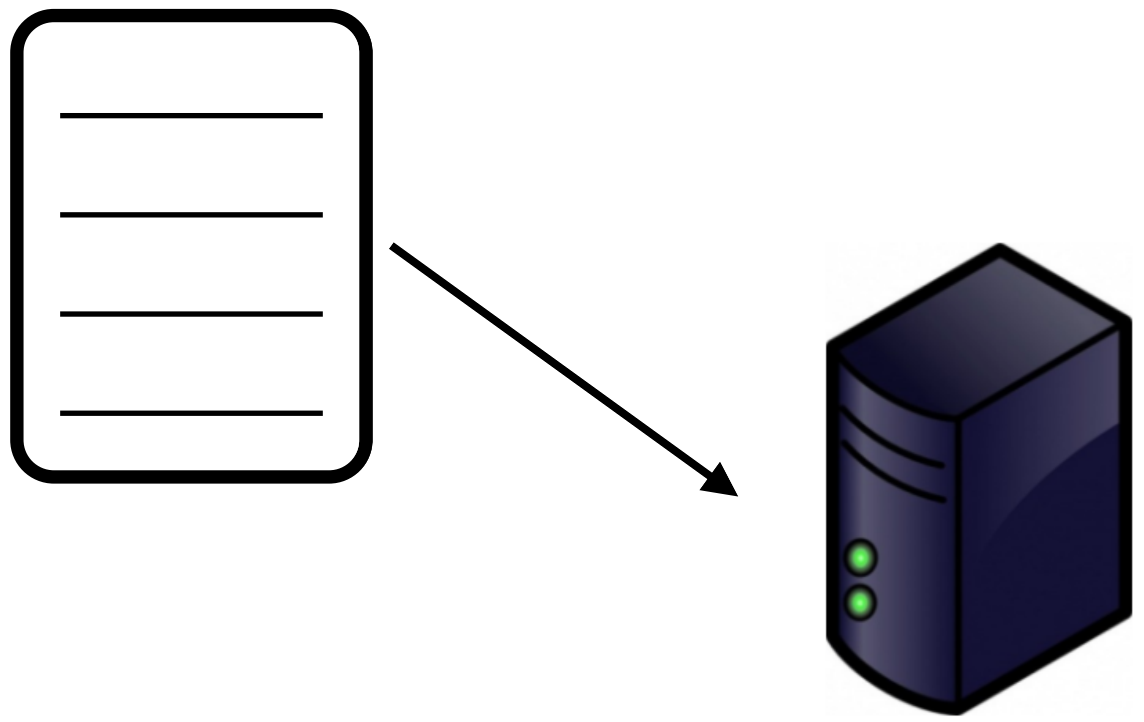

unsupervised learning

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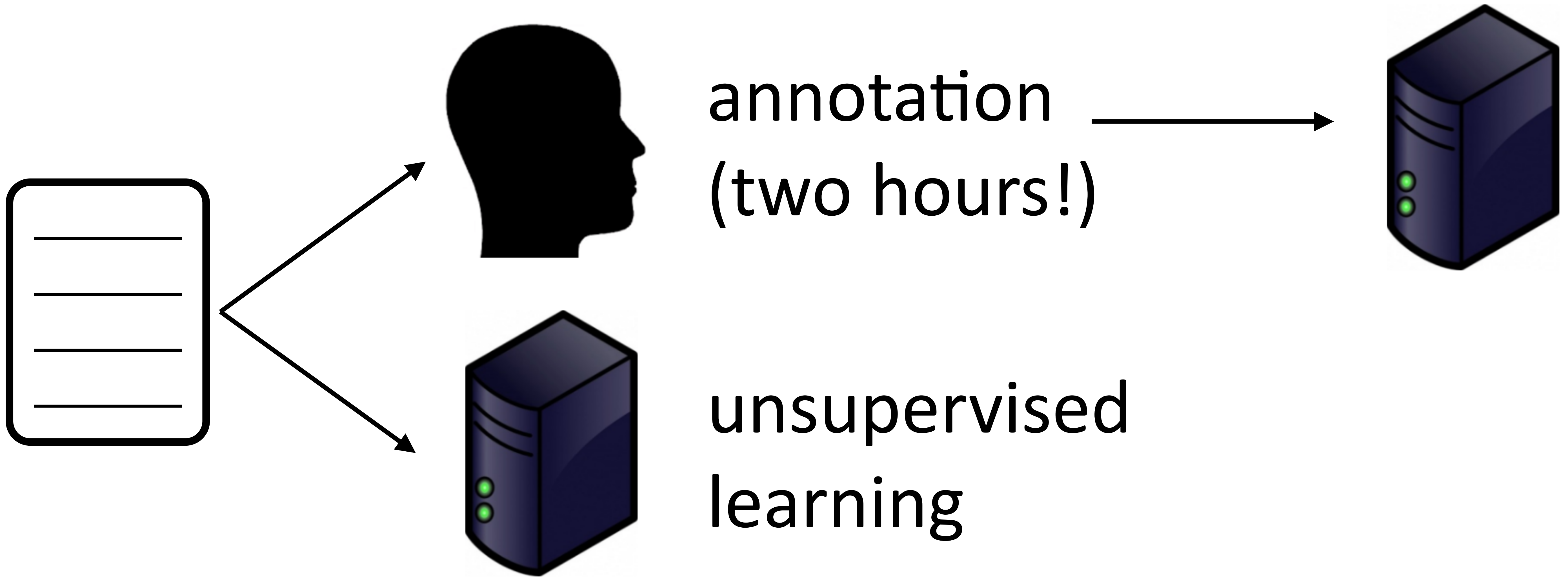

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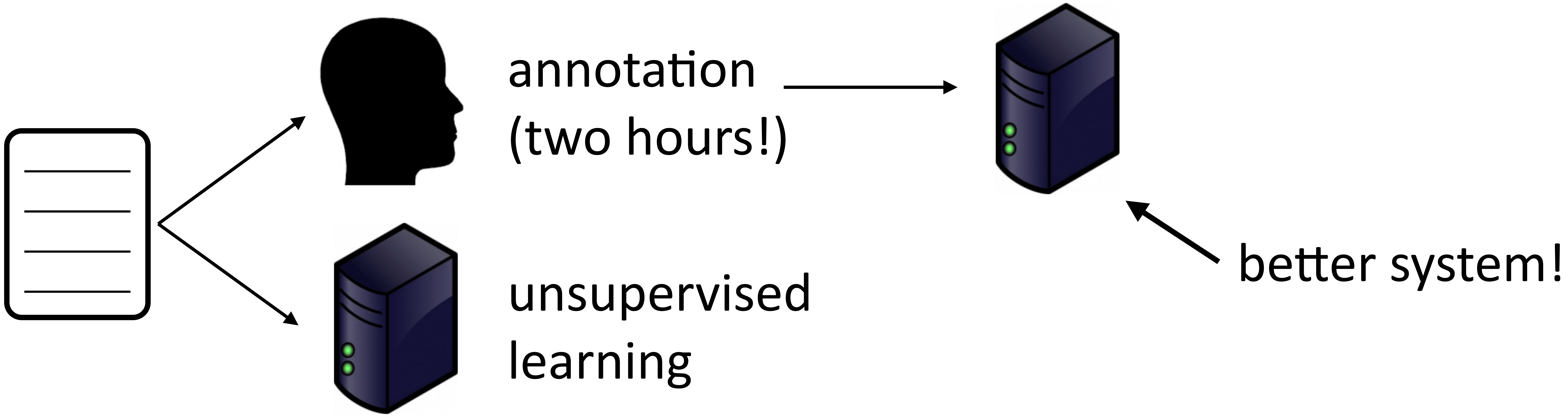

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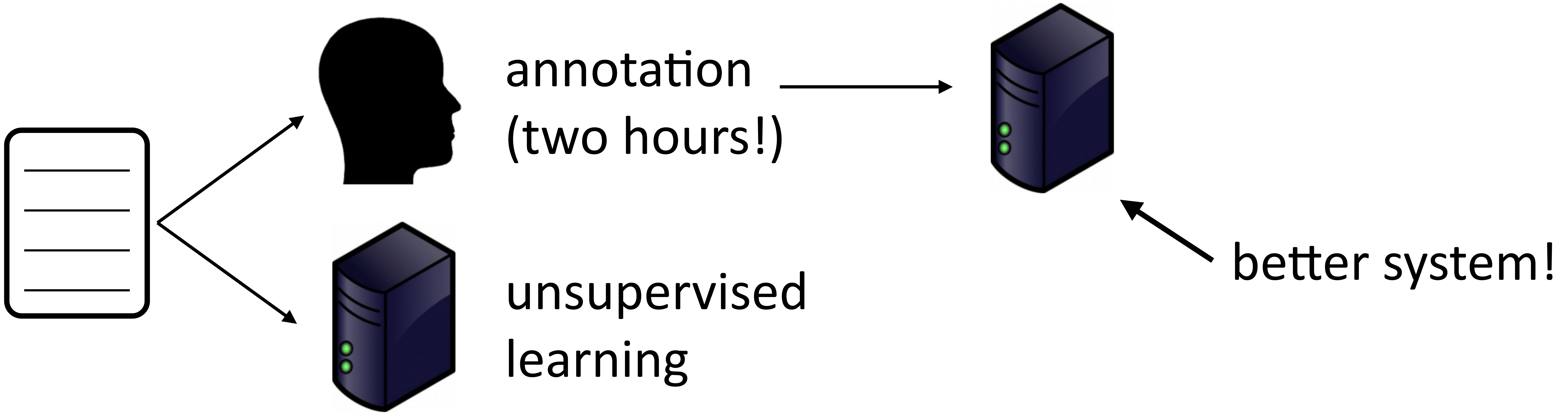

- Even neural nets can do pretty well!

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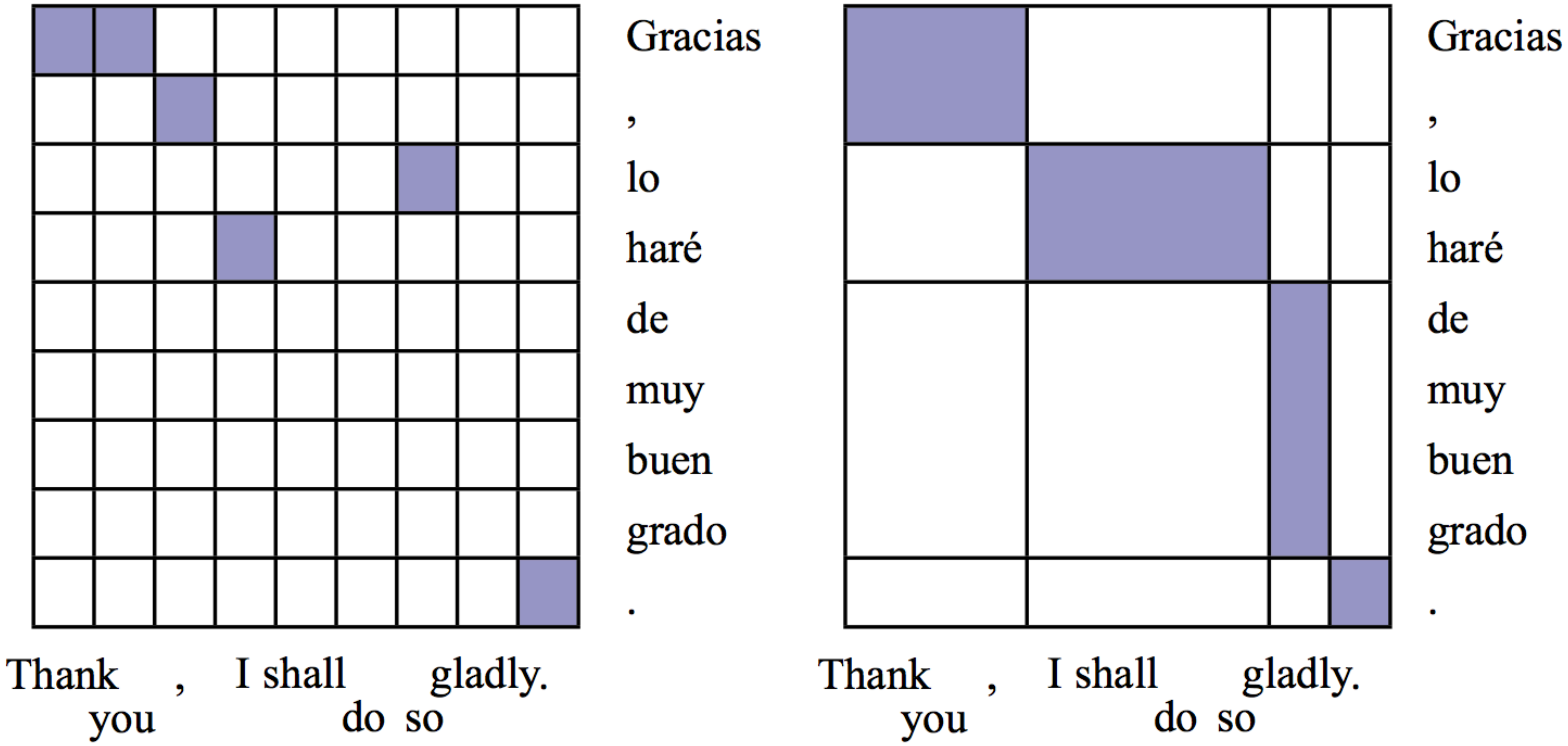
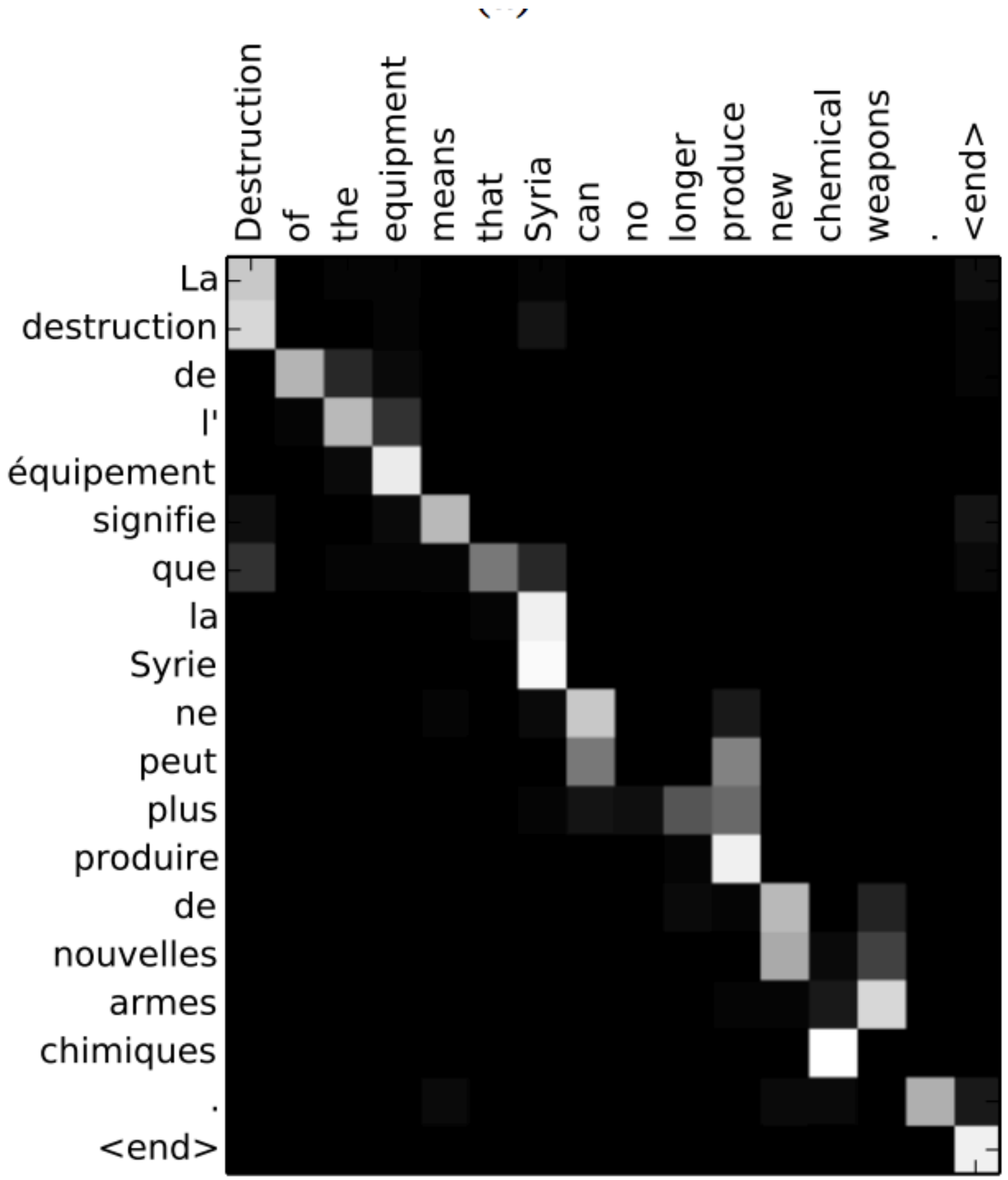
Less Manual Structure?



(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
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deep-coref^{-}	51.01

Moosavi and Strube (2017)

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- Can multi-task learning help?

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Does manual structure have a place?

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

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- Maybe manual structure would help…

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- NLP encompasses all of these things

NLP vs. Computational Linguistics

- NLP: build systems that deal with language data
- CL: use computational tools to study language

Hamilton et al. (2016)

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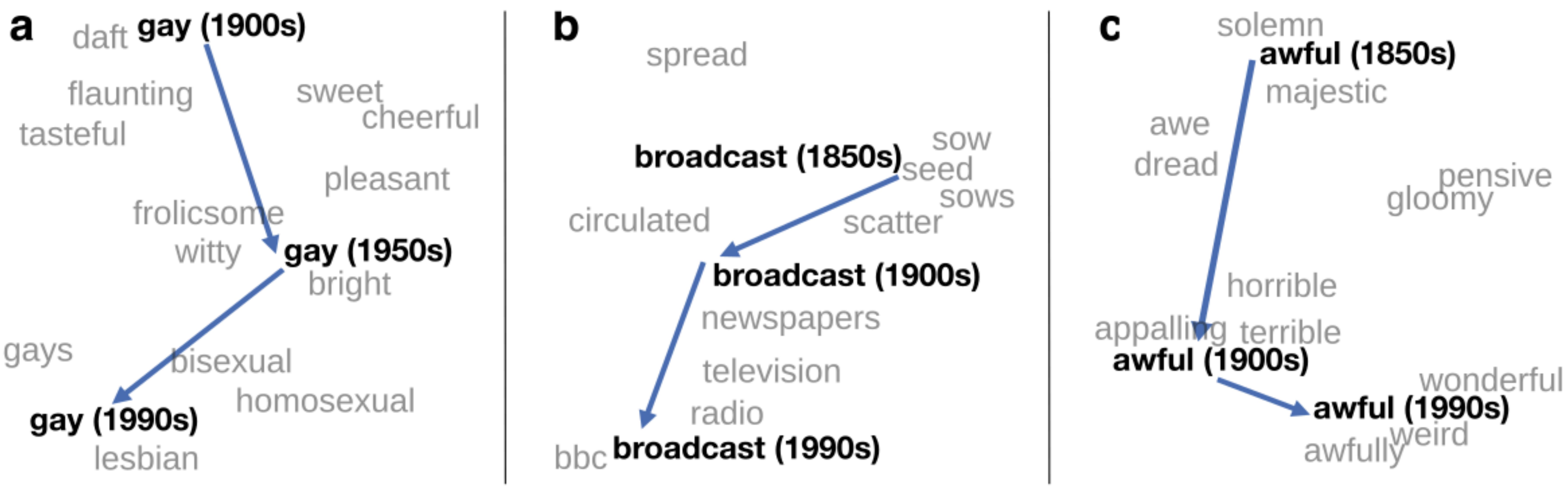

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NLP vs. Computational Linguistics

- Computational tools for other purposes: literary theory, political science…

Bamman, O'Connor, Smith (2013)

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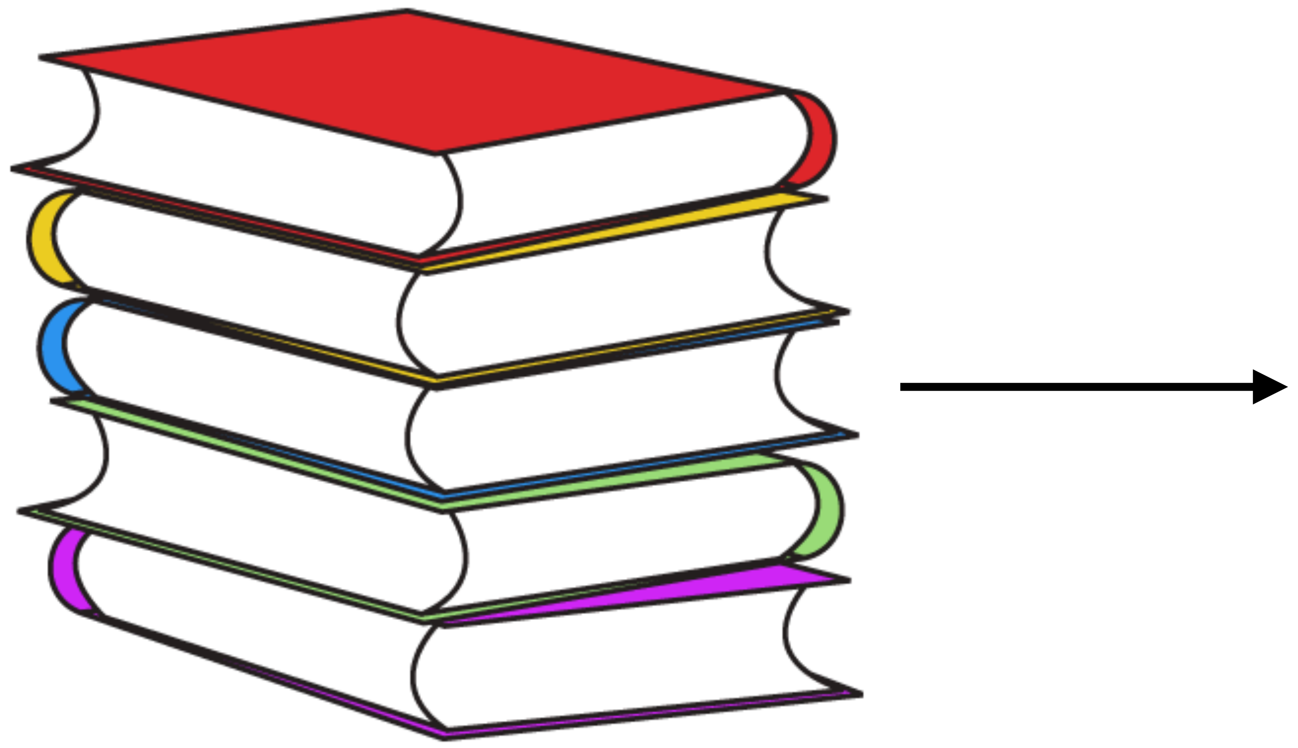

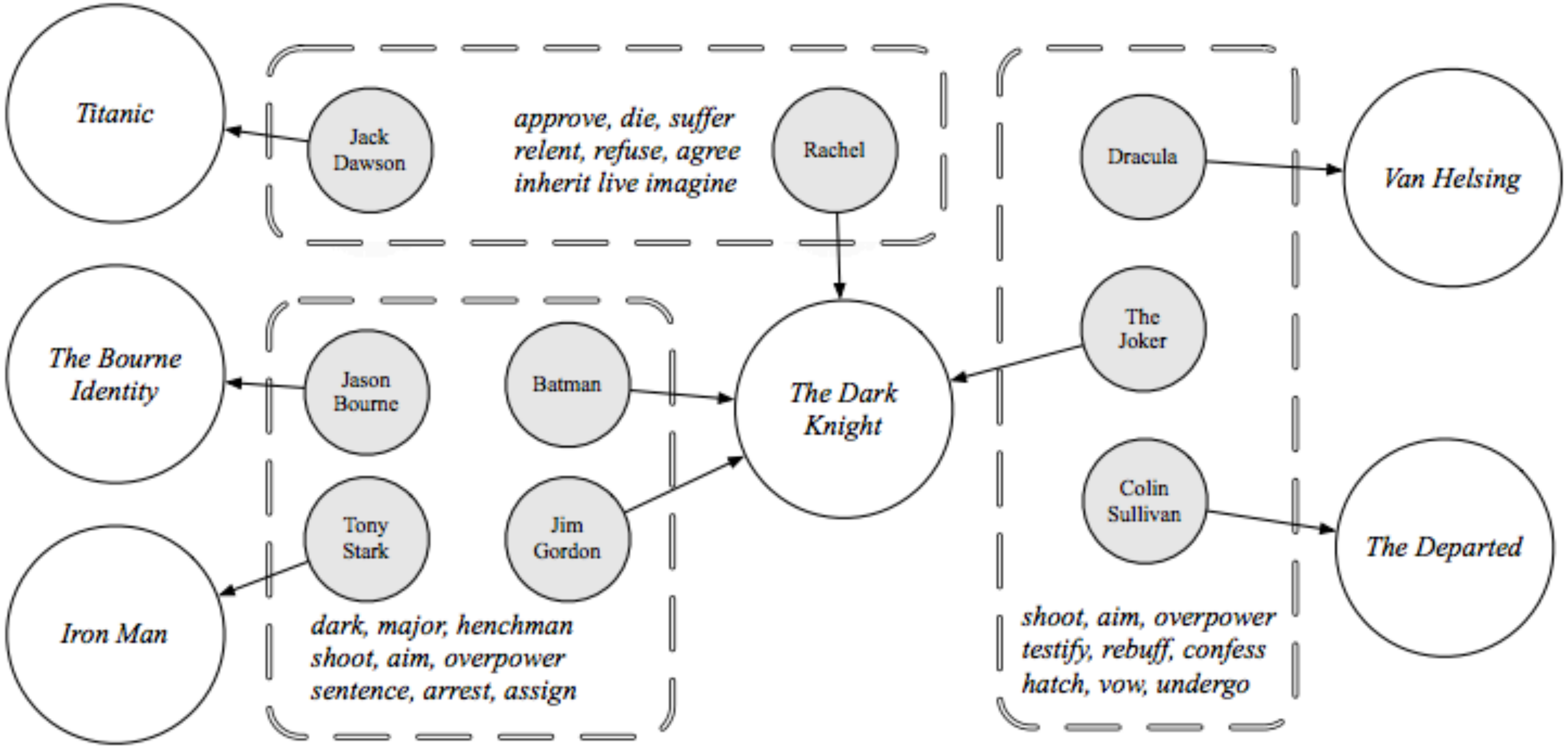

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  - The three assignments should teach you what you need to know to understand nearly any system in the literature

Assignments

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

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These projects require understanding of the concepts, ability to write performant code, and ability to think about how to debug complex systems. **They are challenging, so start early!**

Final Project

- Final project (20%)
  - Groups of 3-4 preferred, 1 is possible.
  - Good idea to talk to run your project idea by me in office hours or email.
  - 4 page report + final project presentation.

Gather.town Hangout