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

Instructor

Alan Ritter
alan.ritter@cc.gatech.edu

Teaching Assistants

Jan Vijay Singh
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Xurui Zhang
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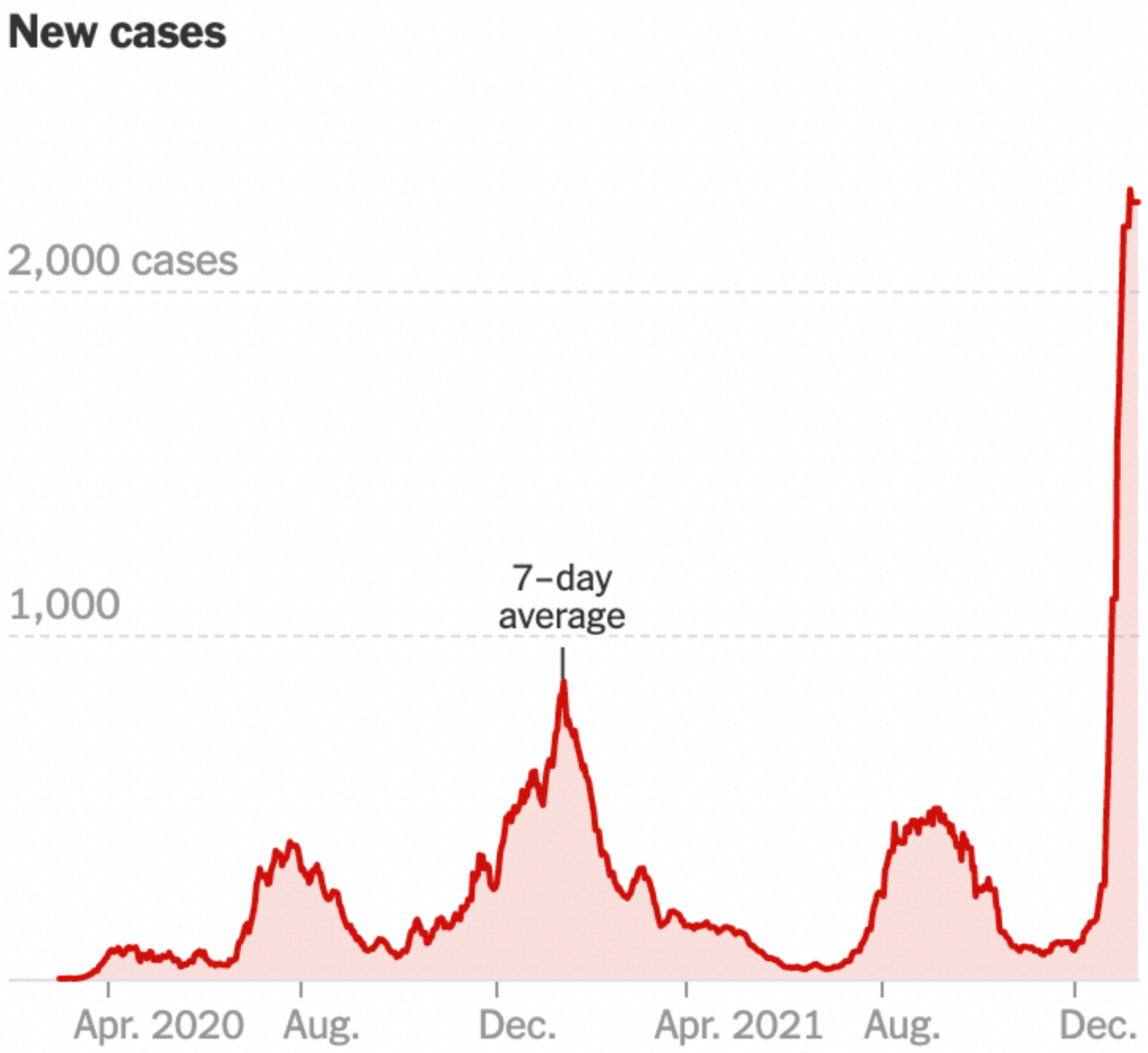
COVID-19

The New York Times

Fulton County, Ga.

Unvaccinated people in Fulton County are at an extremely high risk for Covid-19 infections. The average number of new cases in Fulton County was **2,253** yesterday, **about the same** as the day before. Because of high spread, the C.D.C. recommends that even vaccinated people wear masks here. Since January 2020, at least **1 in 6** people who live in Fulton County have been infected, and at least **1 in 561** people have died.



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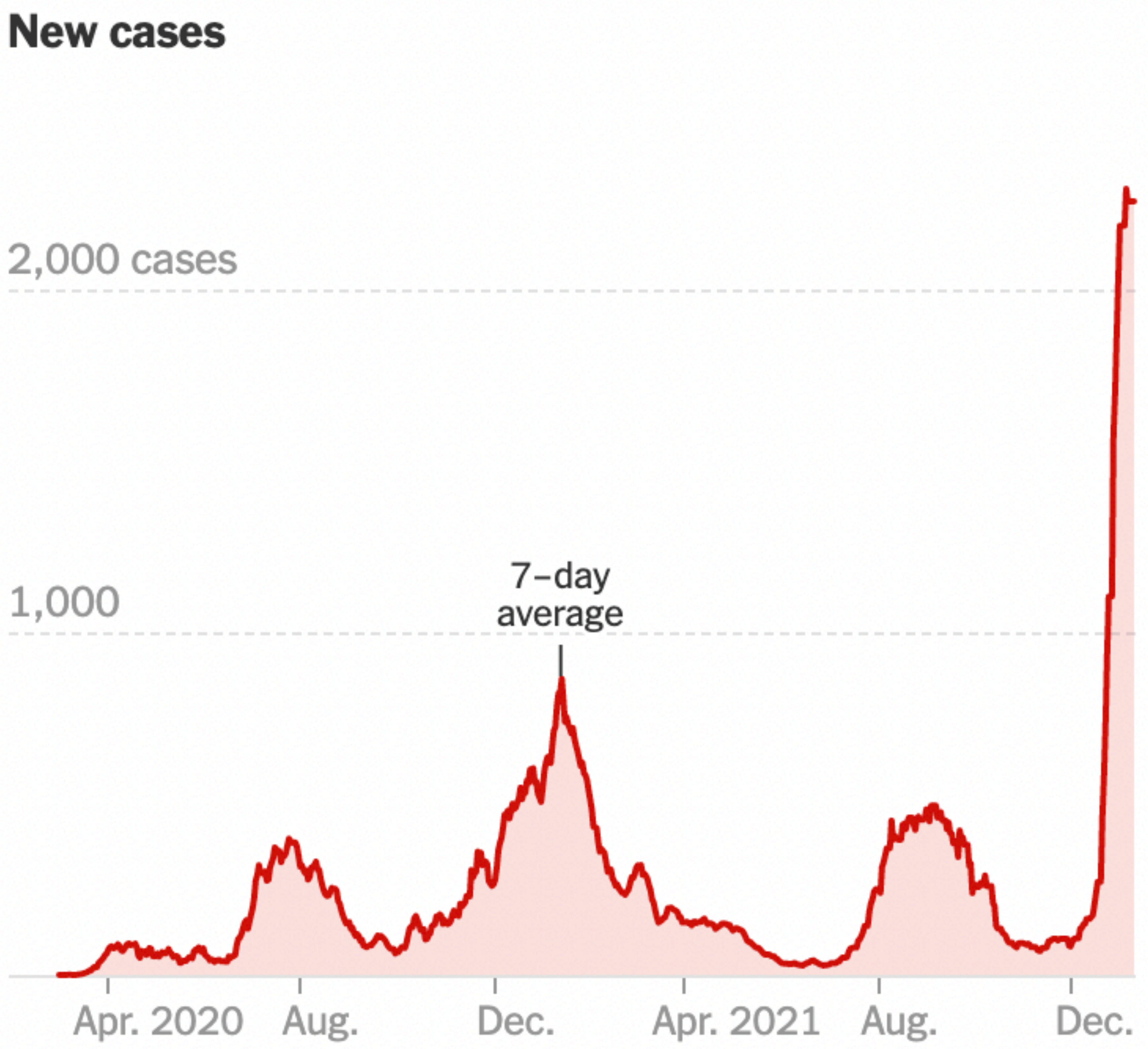

Please wear a mask while you are in this class!

Prerequisites

- 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!

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  - 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)

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- Final project (details on course website, will discuss later)
- Problem Set 1 (background review) is out now on Gradescope (due Jan 14)

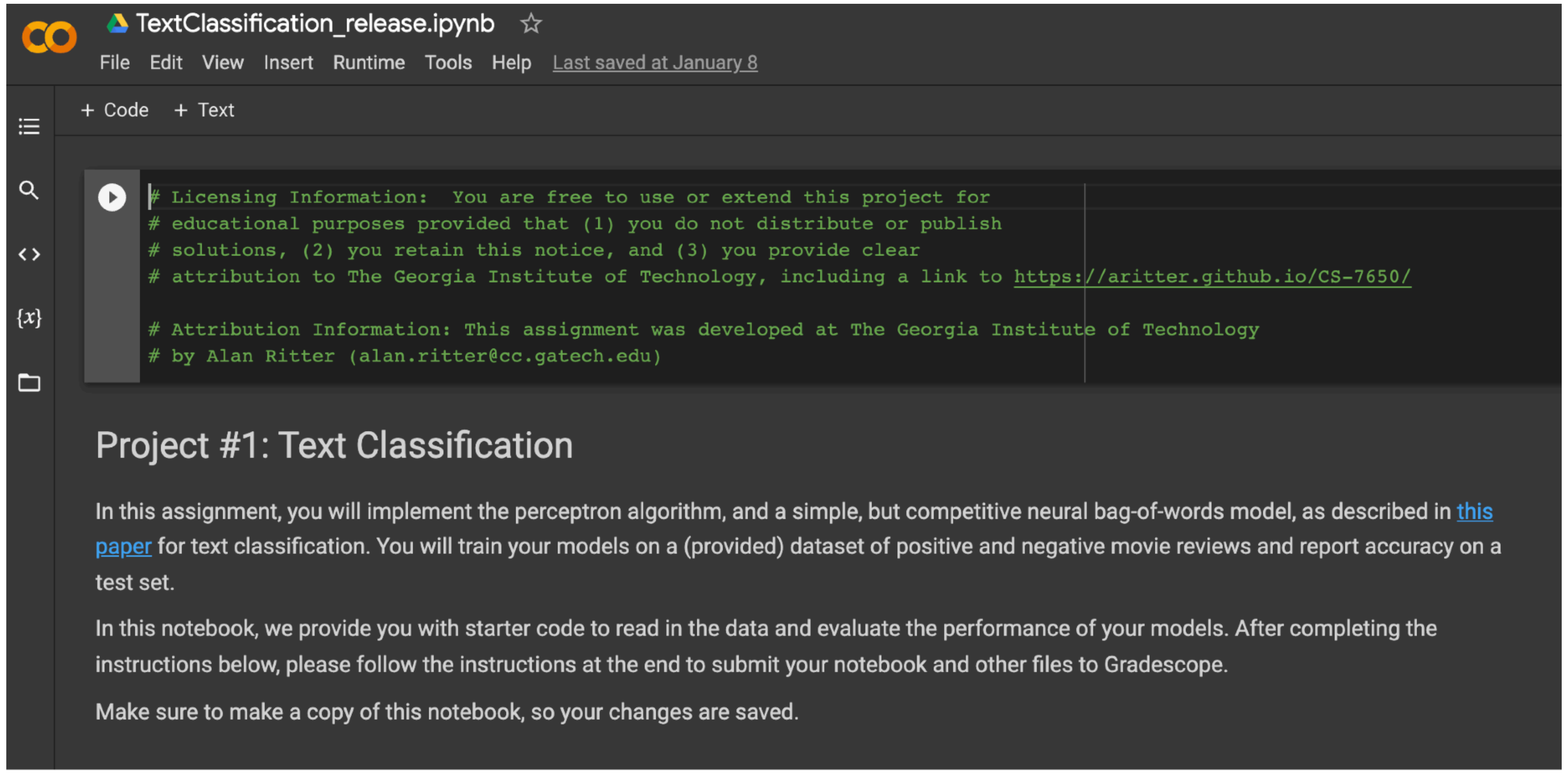
Problem Set 1 (Background Review)

- Due Jan 14 (this Friday).
- 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

Schedule

Jan 10:	**Course Introduction**	Eisenstein Chapter 1
Jan 12:	**Machine Learning**	Eisenstein 2.0-2.5, 4.1,4.3-4.5
Jan 13:	Problem Set 1 due	
Jan 17:	MLK Holiday	
TBD:	Project 1	

Project 1 is also out (please look!)



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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
  - Colab Pro subscription ($10/month). This is highly recommended once we start working with PyTorch.

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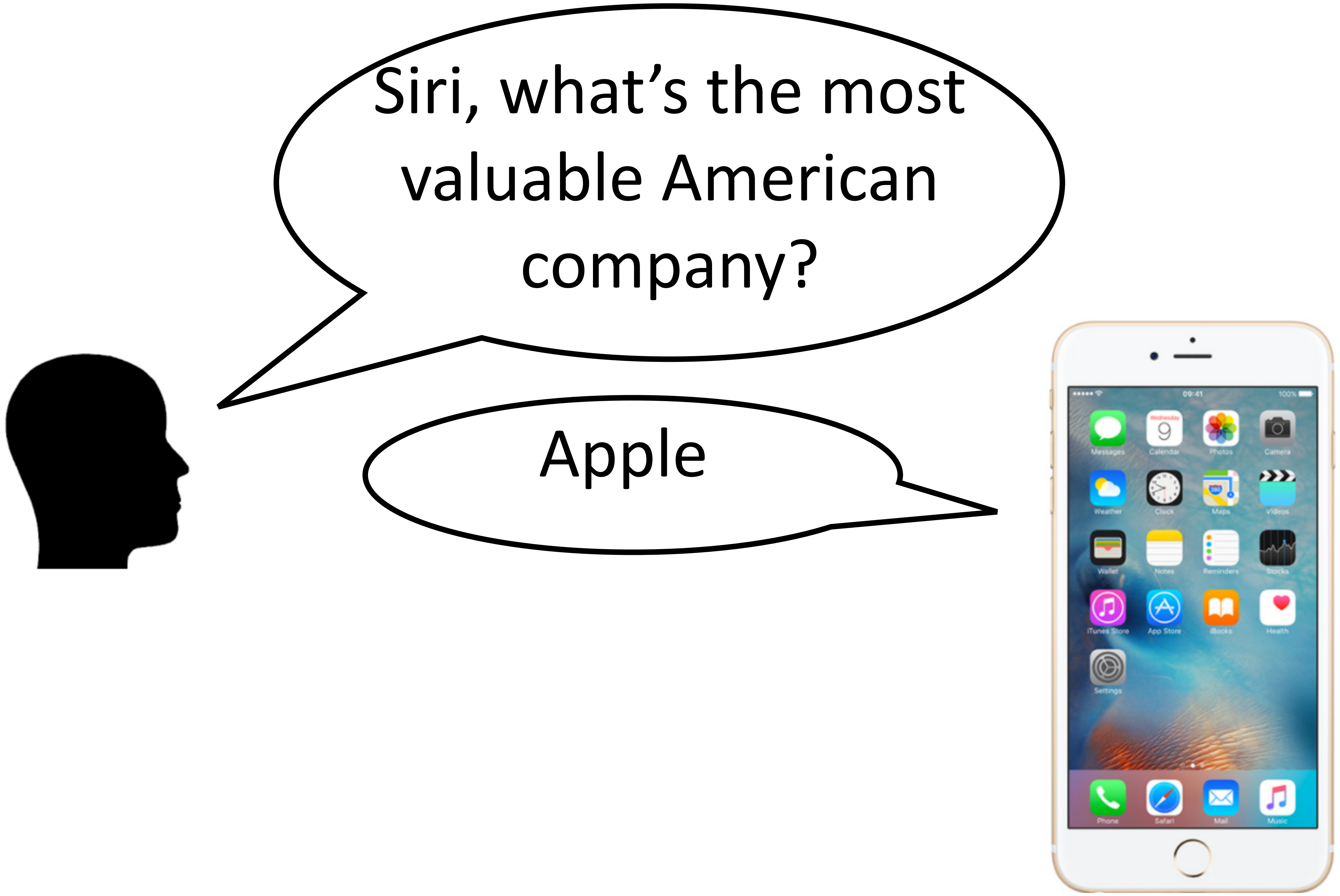

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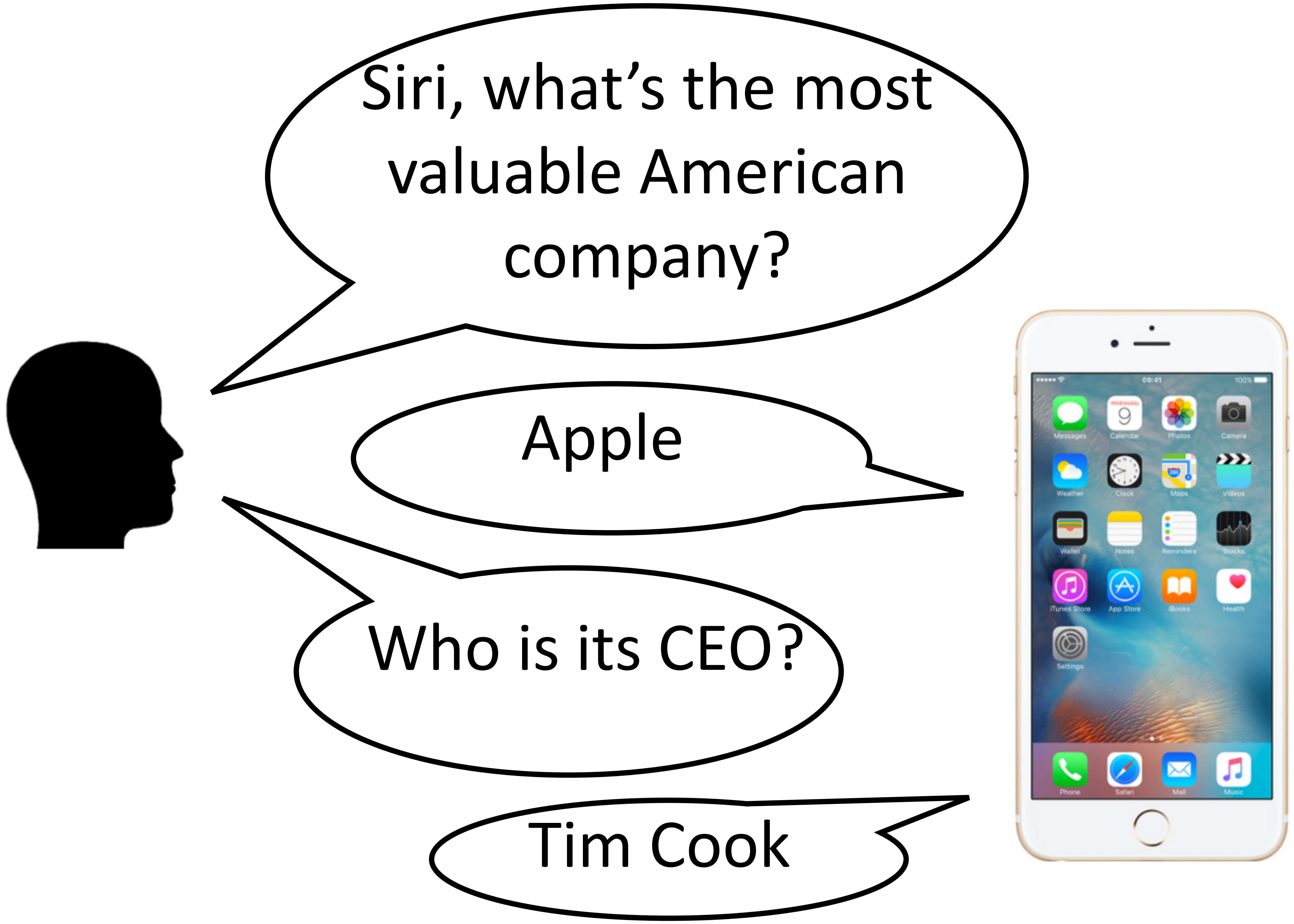

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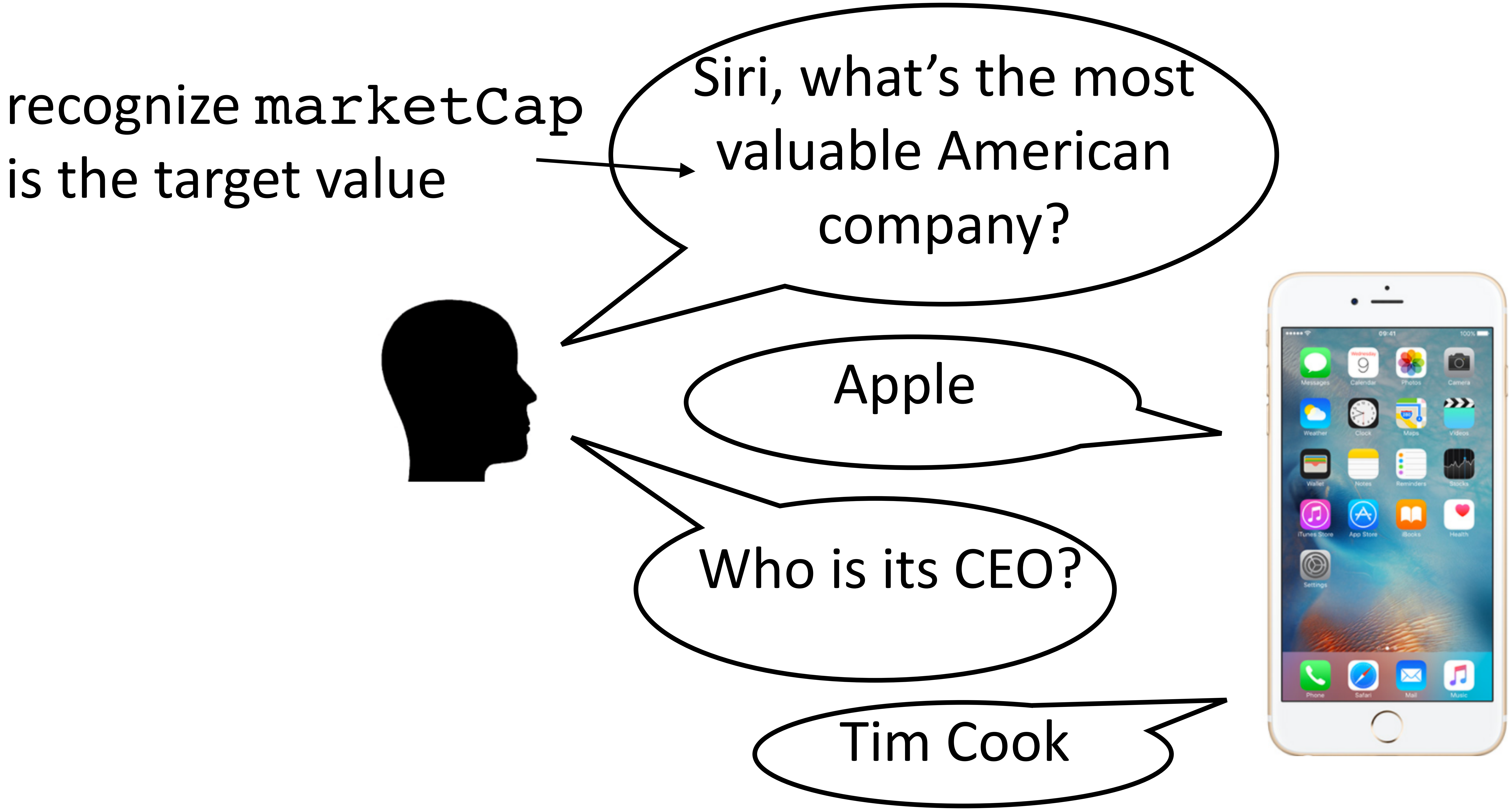

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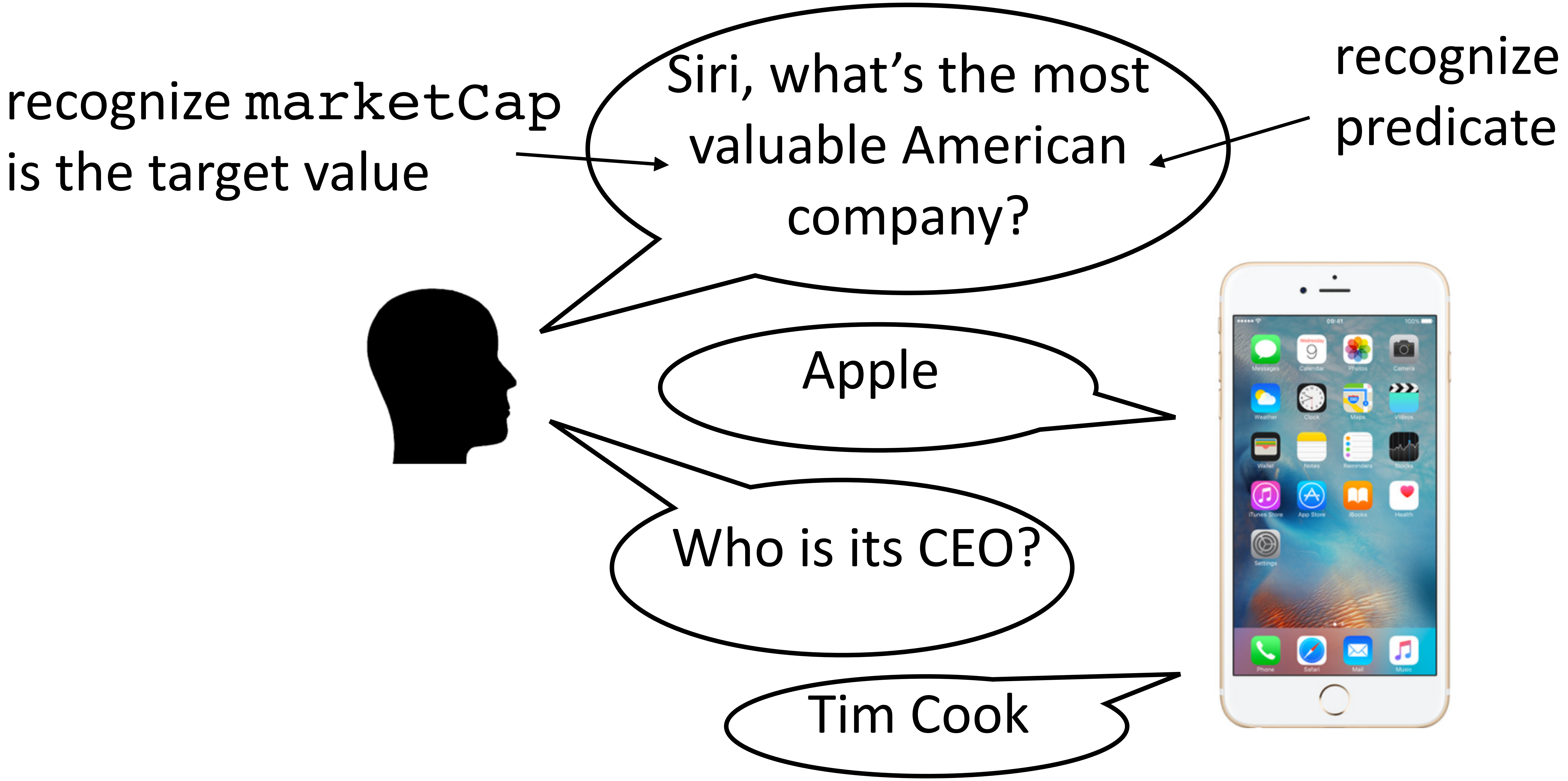

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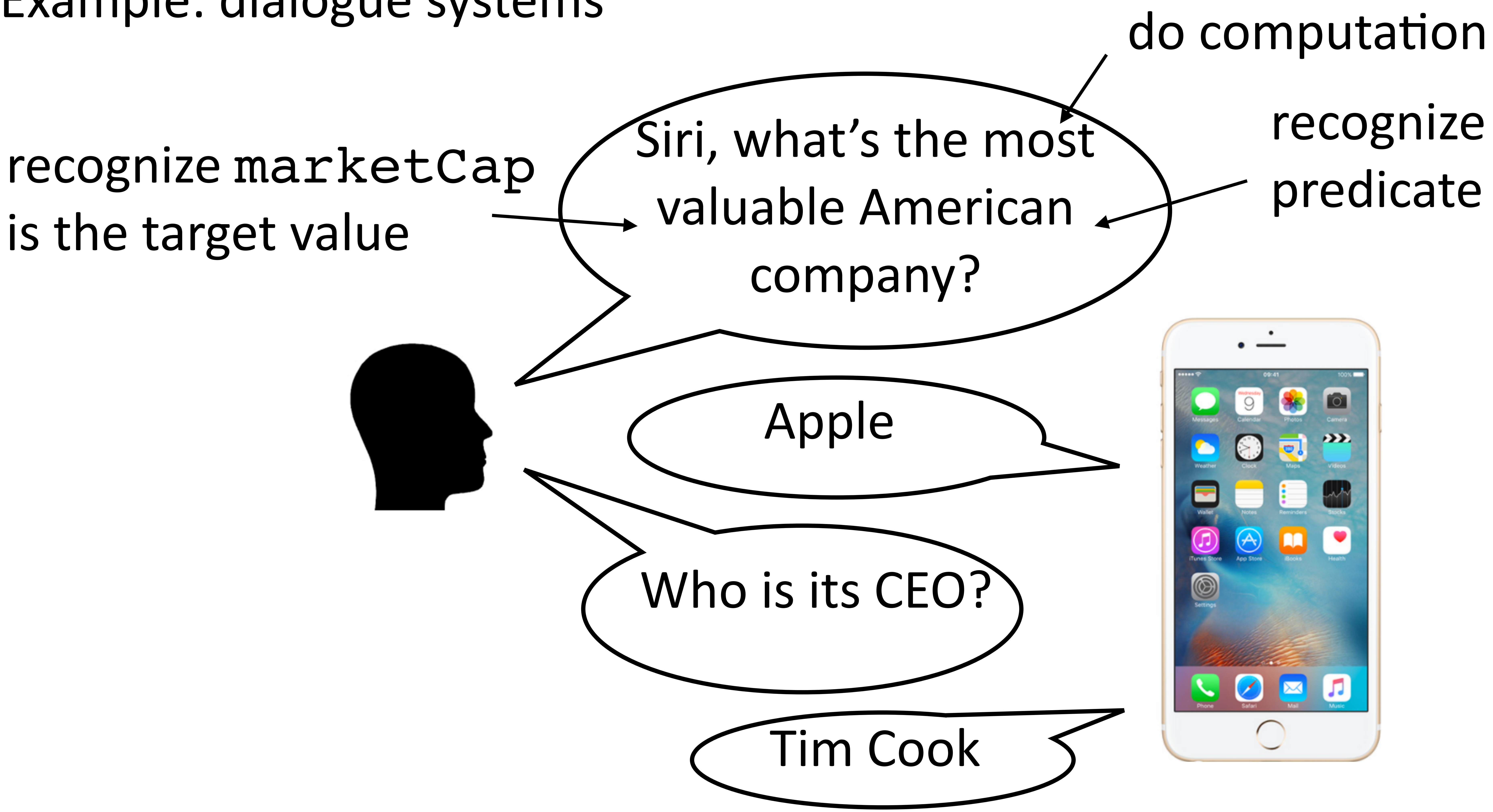

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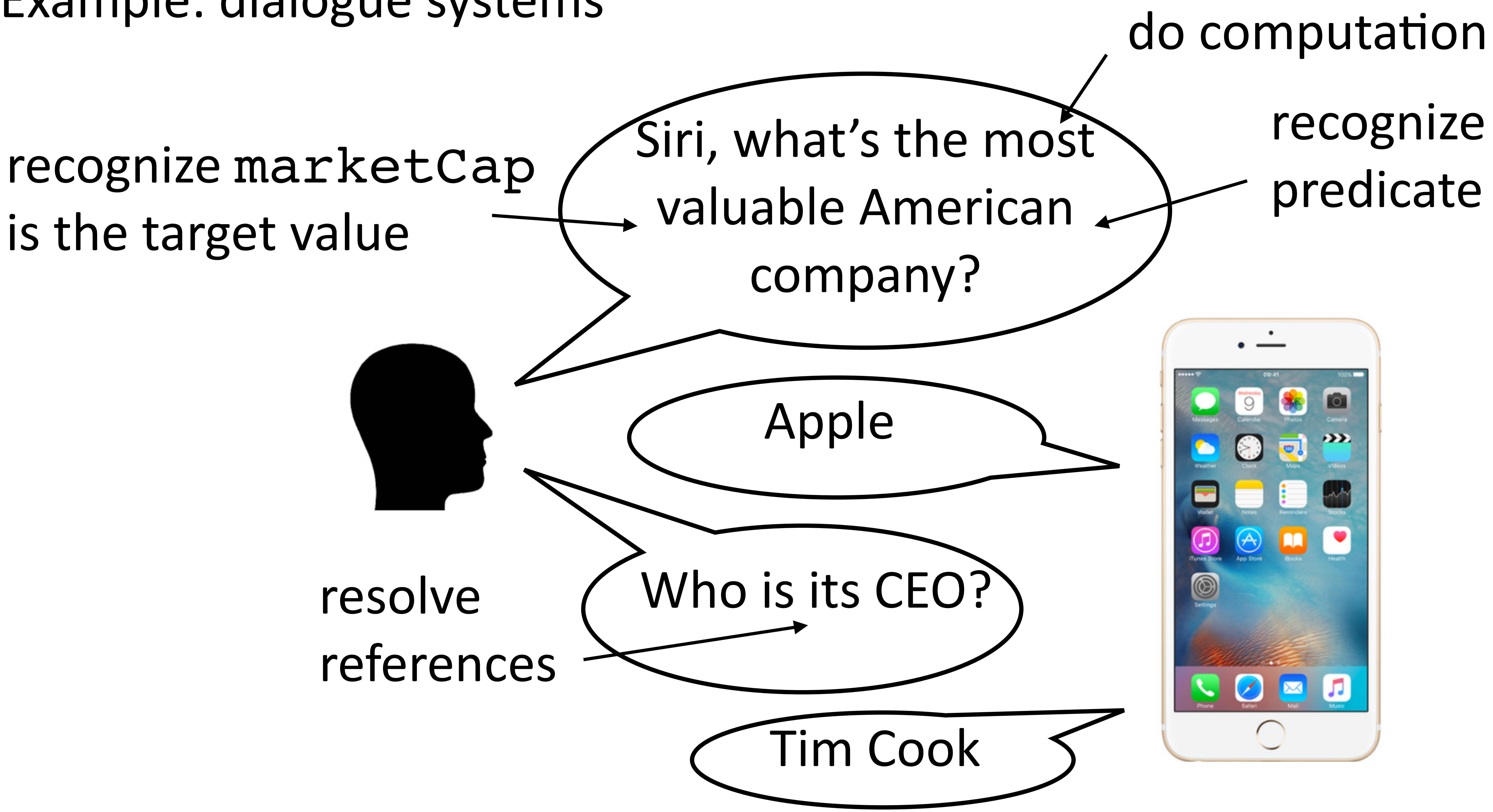

Automatic Summarization

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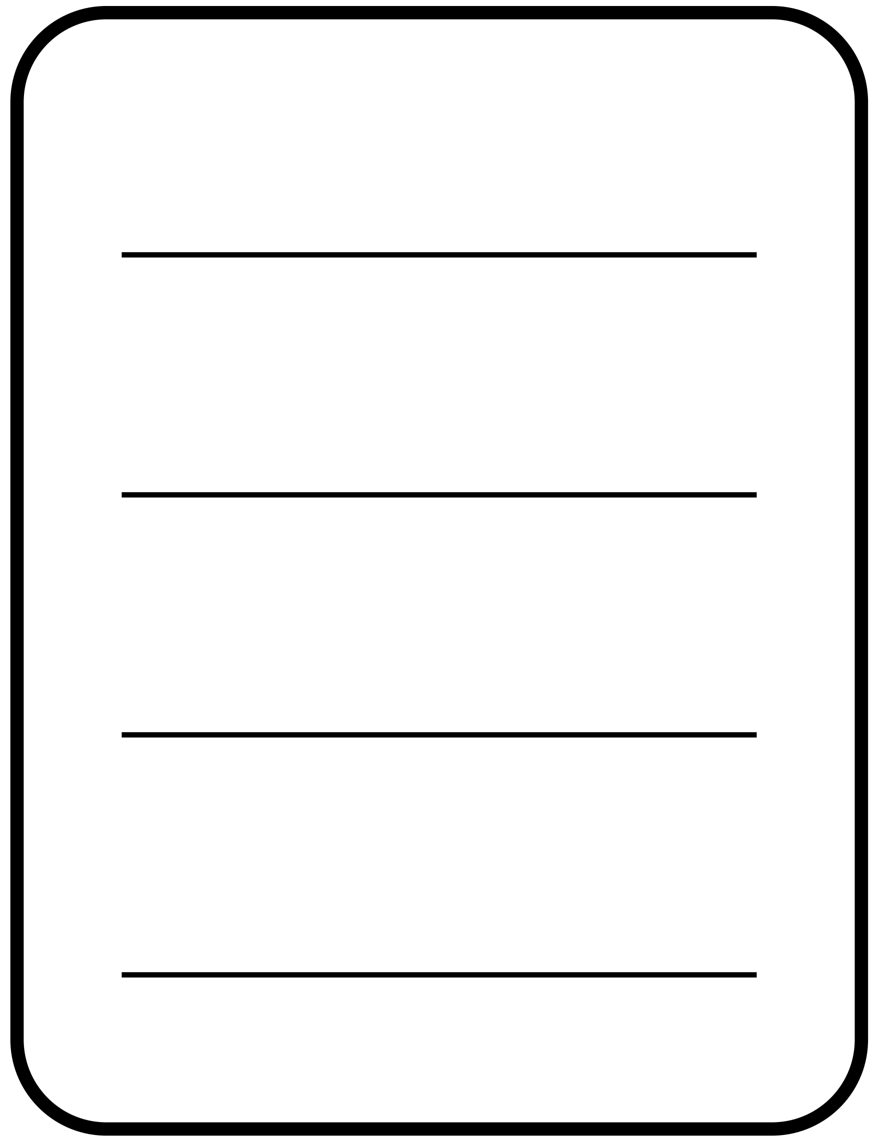

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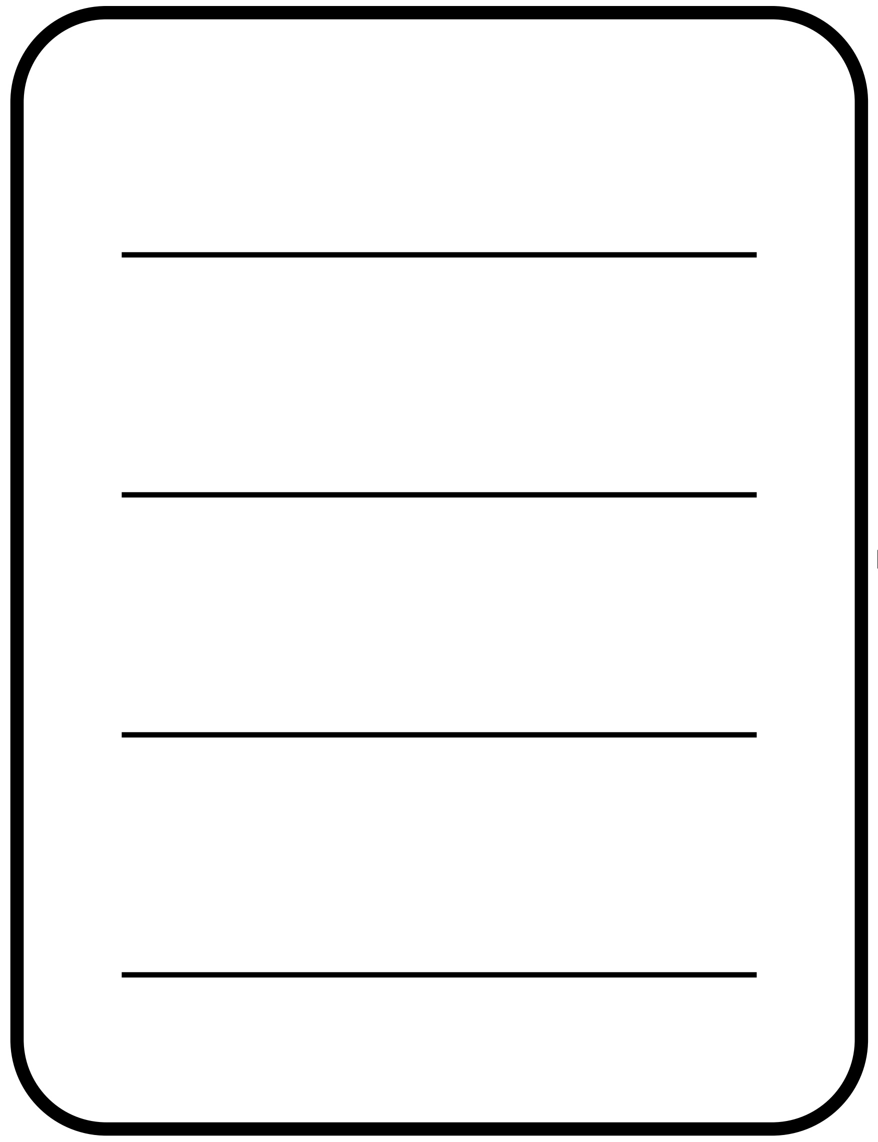

Text Analysis

Syntactic parses

Coreference resolution

Entity disambiguation

Discourse analysis

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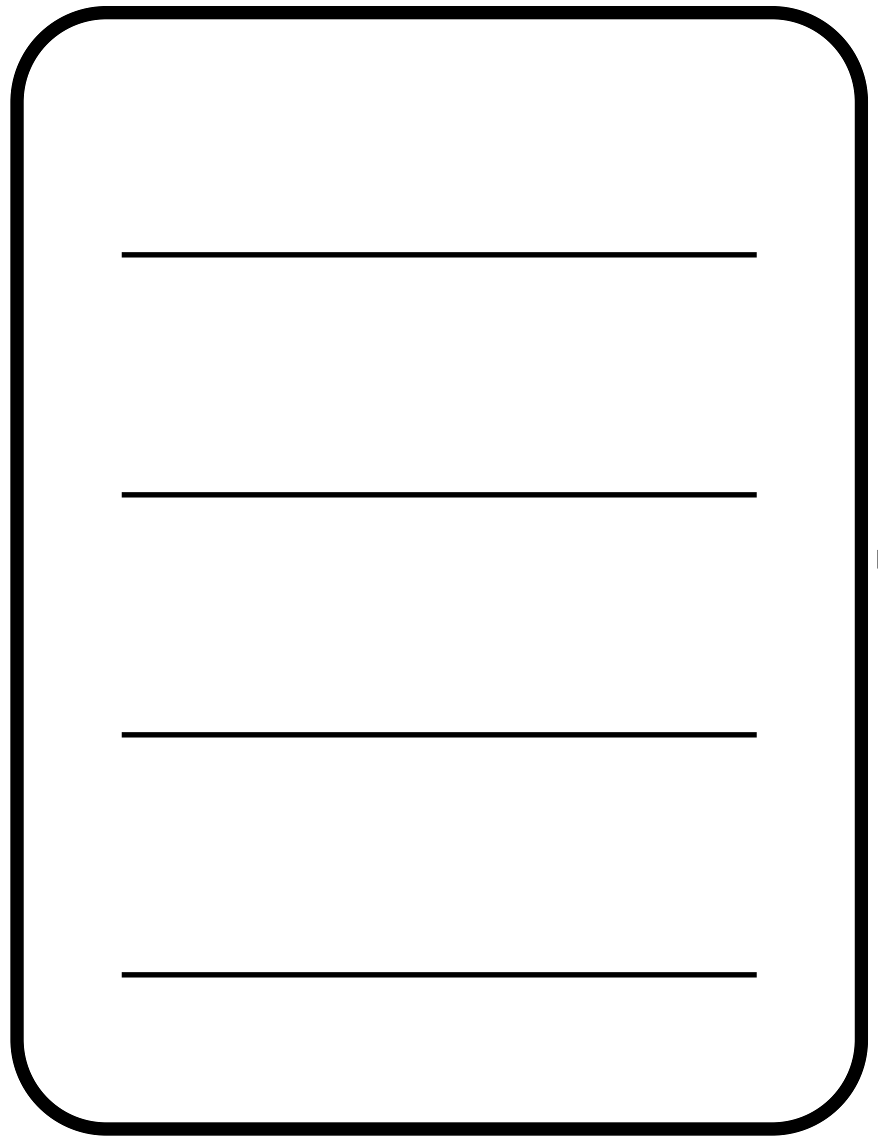

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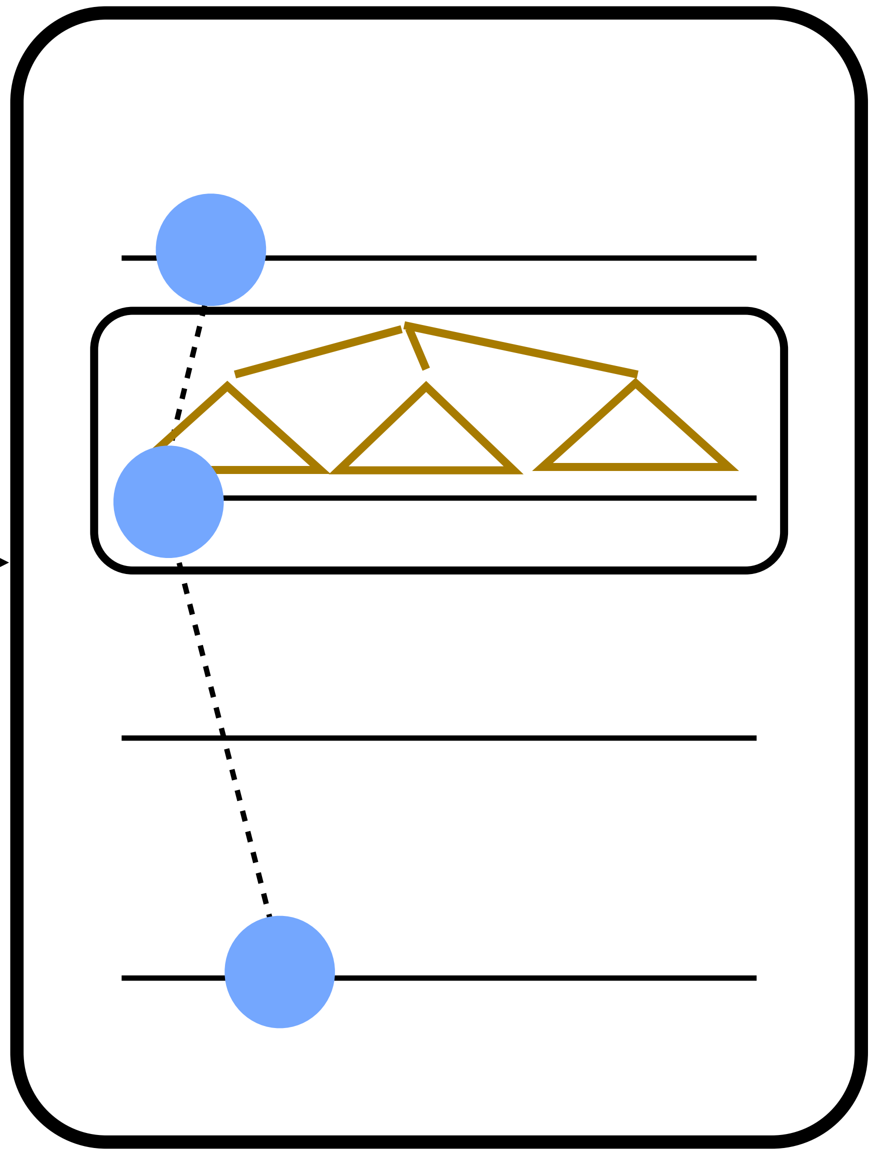

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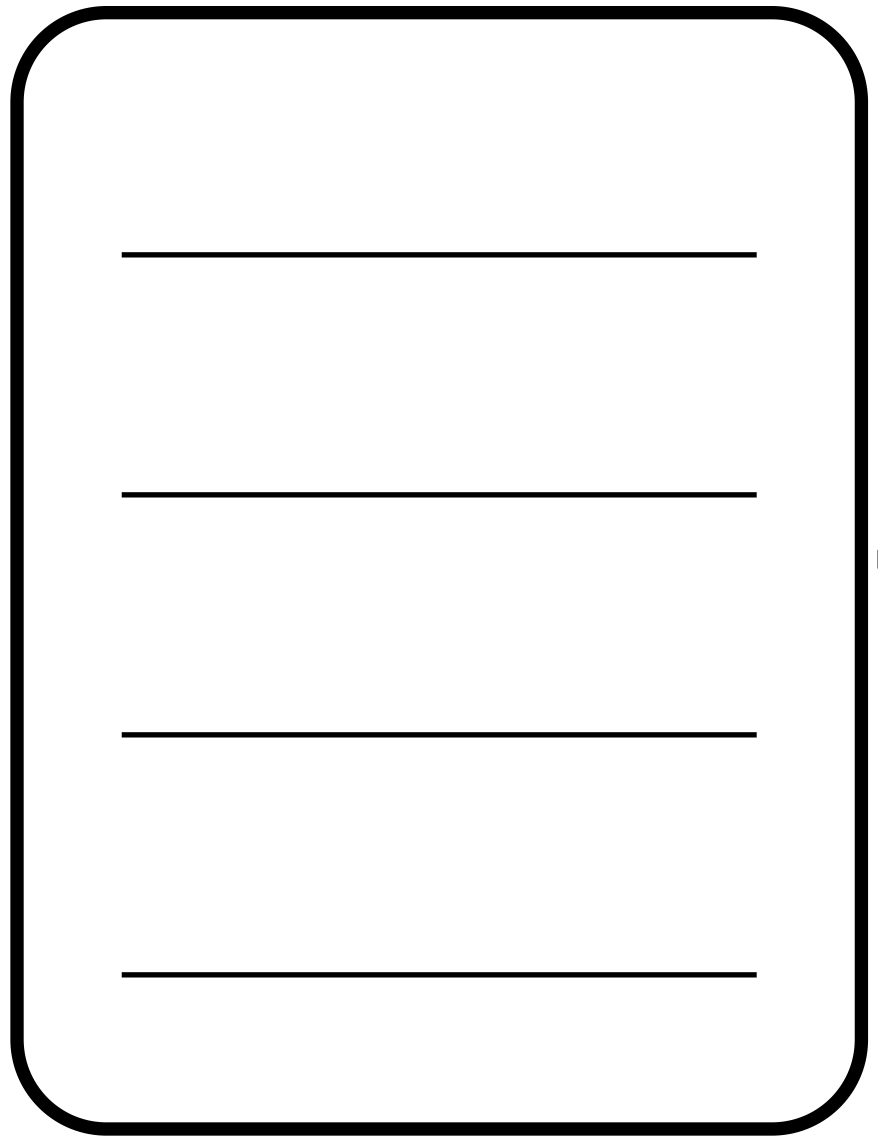

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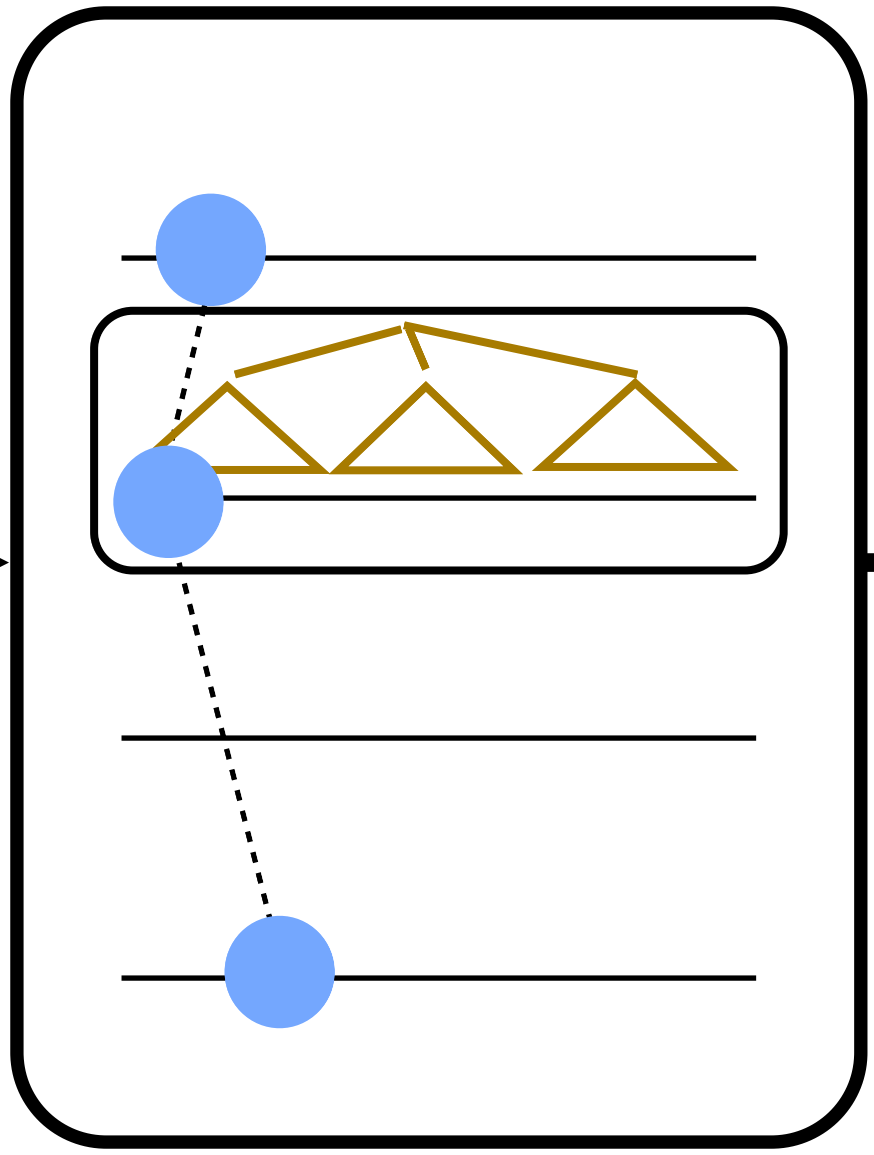

Applications

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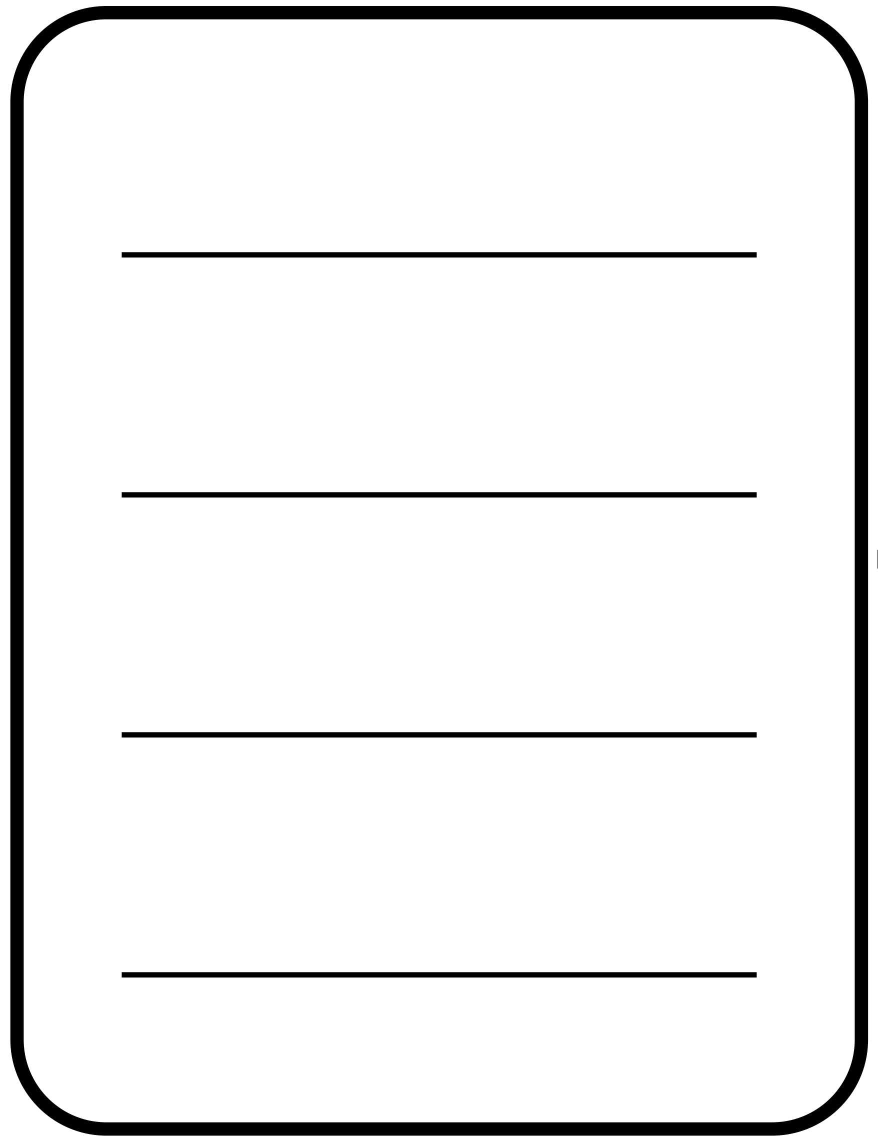

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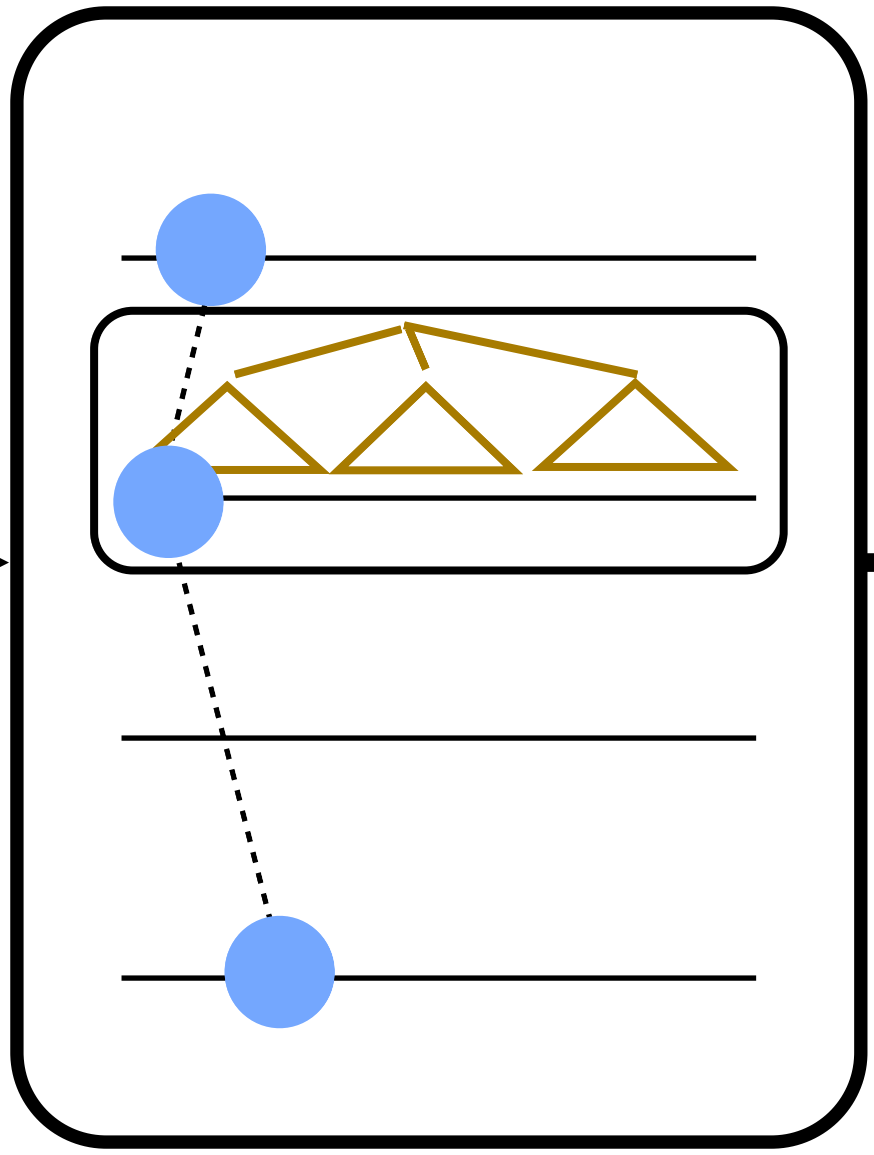

Applications

Summarize

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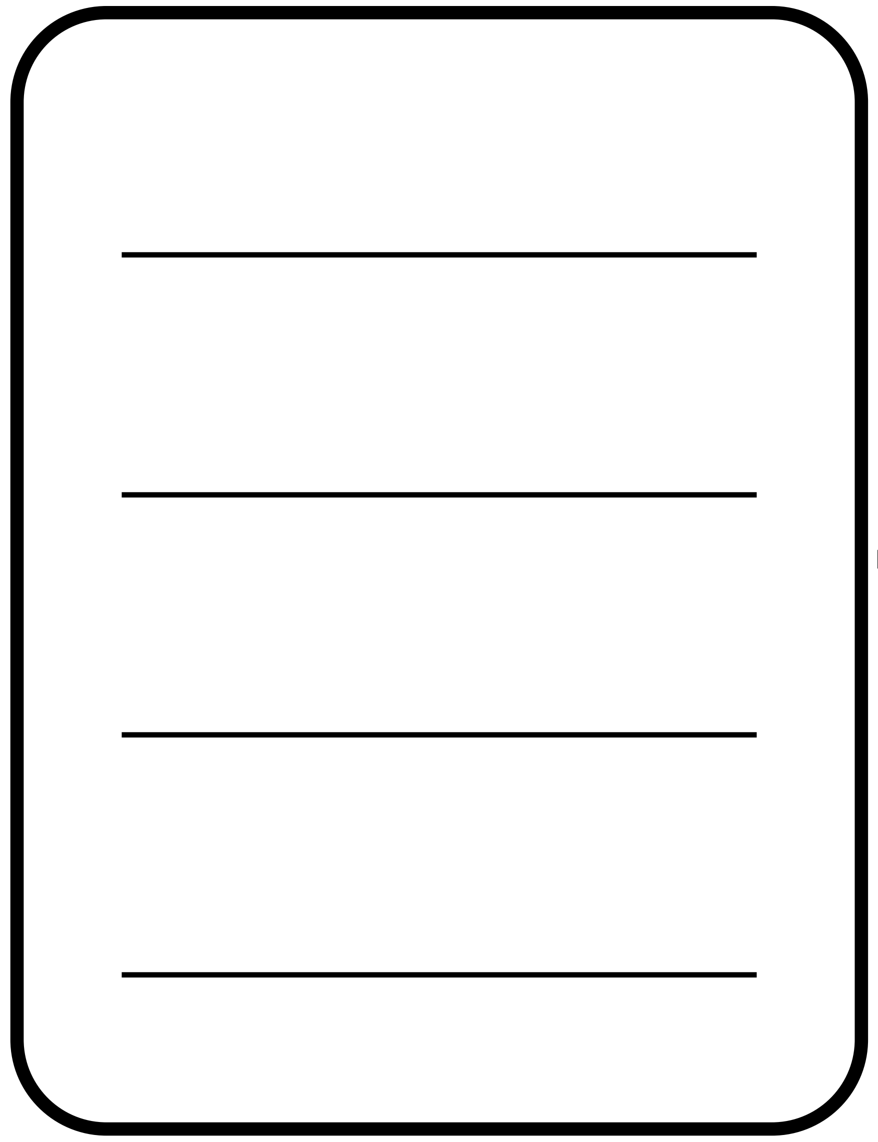

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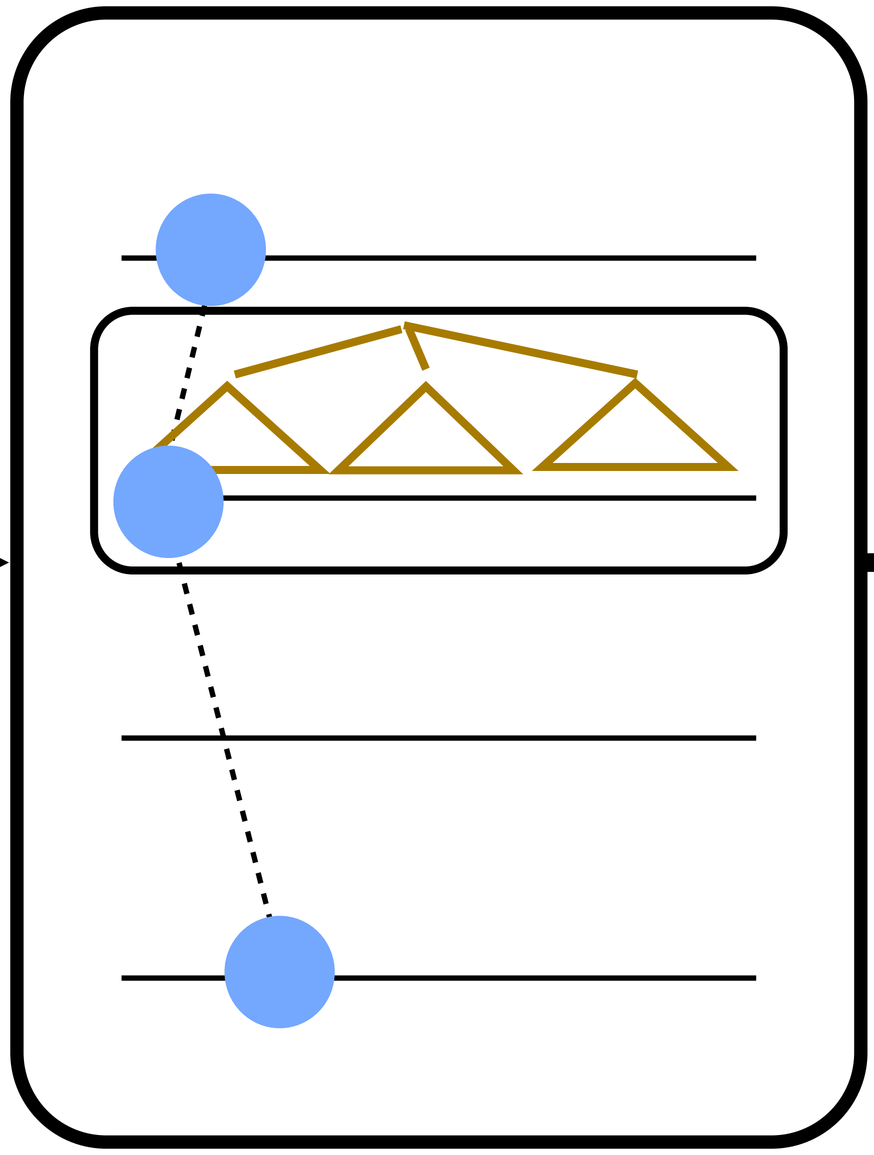

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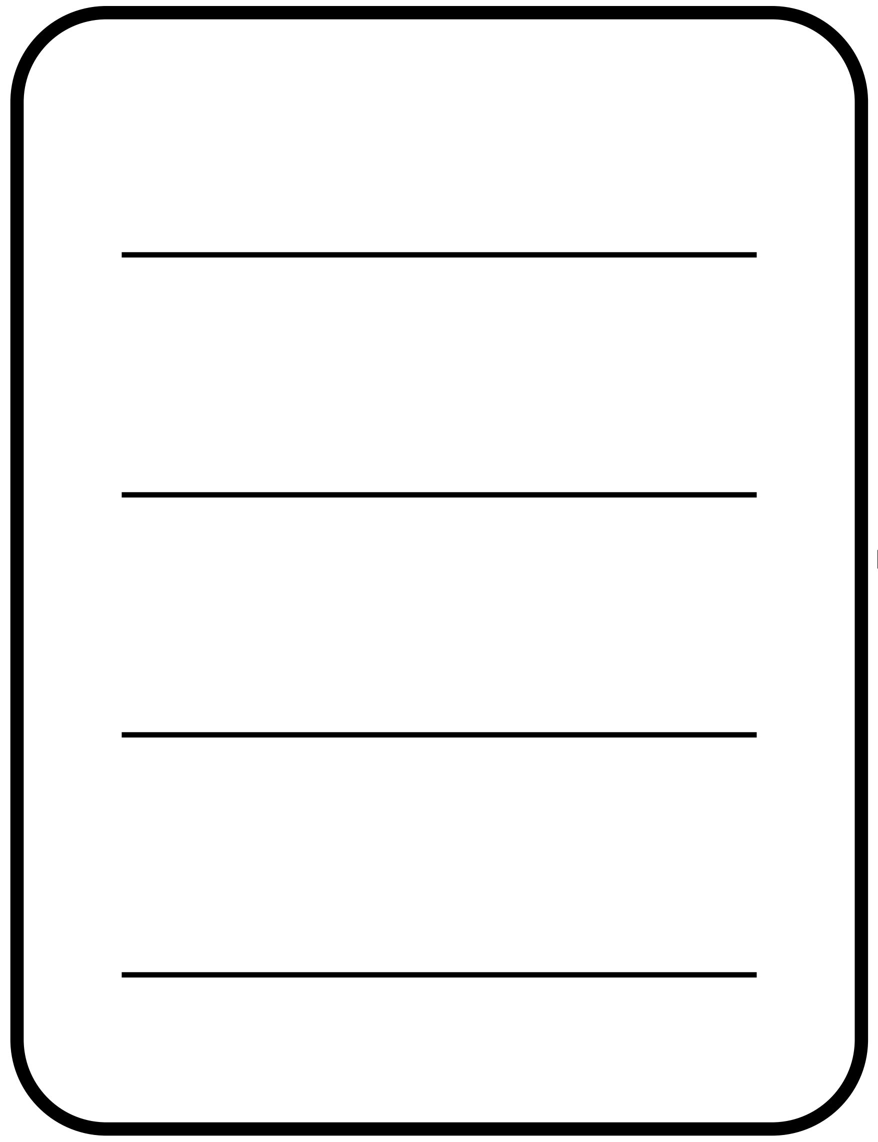

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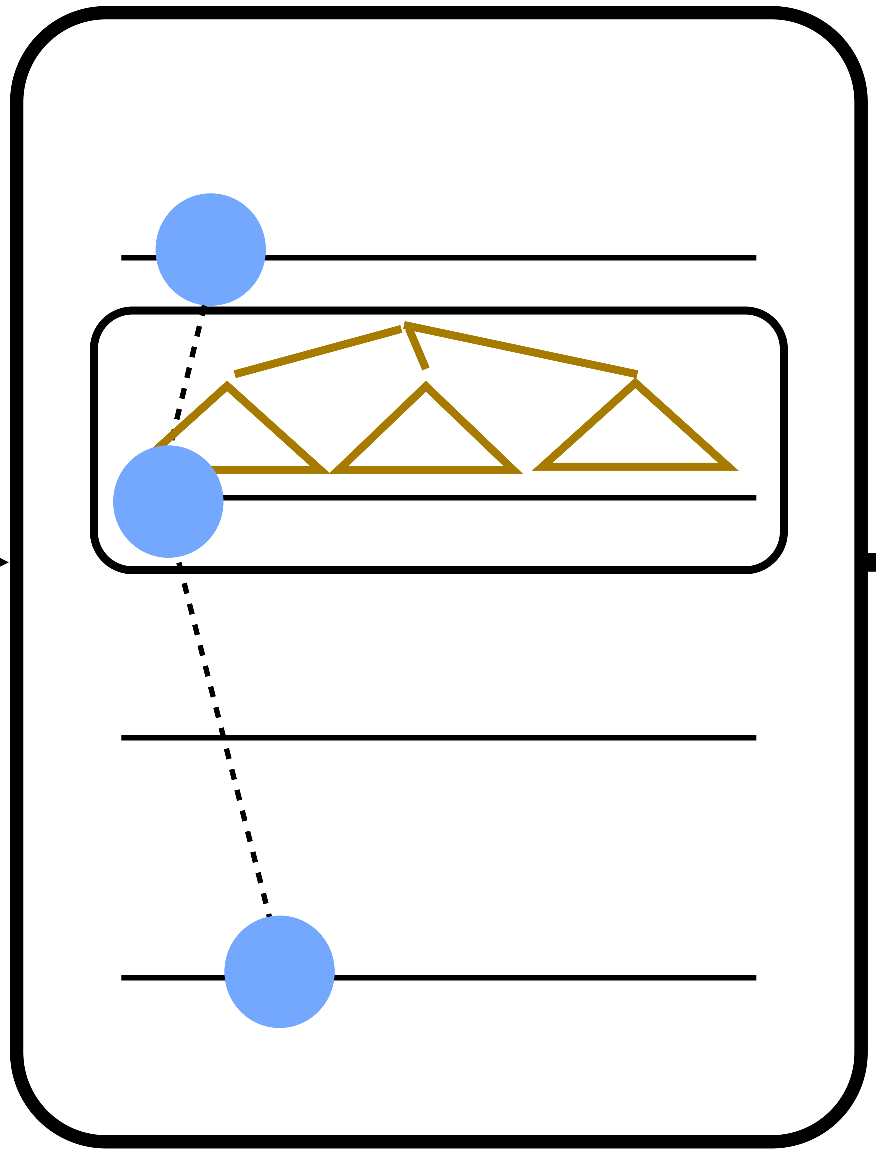

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Applications

Summarize

Extract information

Answer questions

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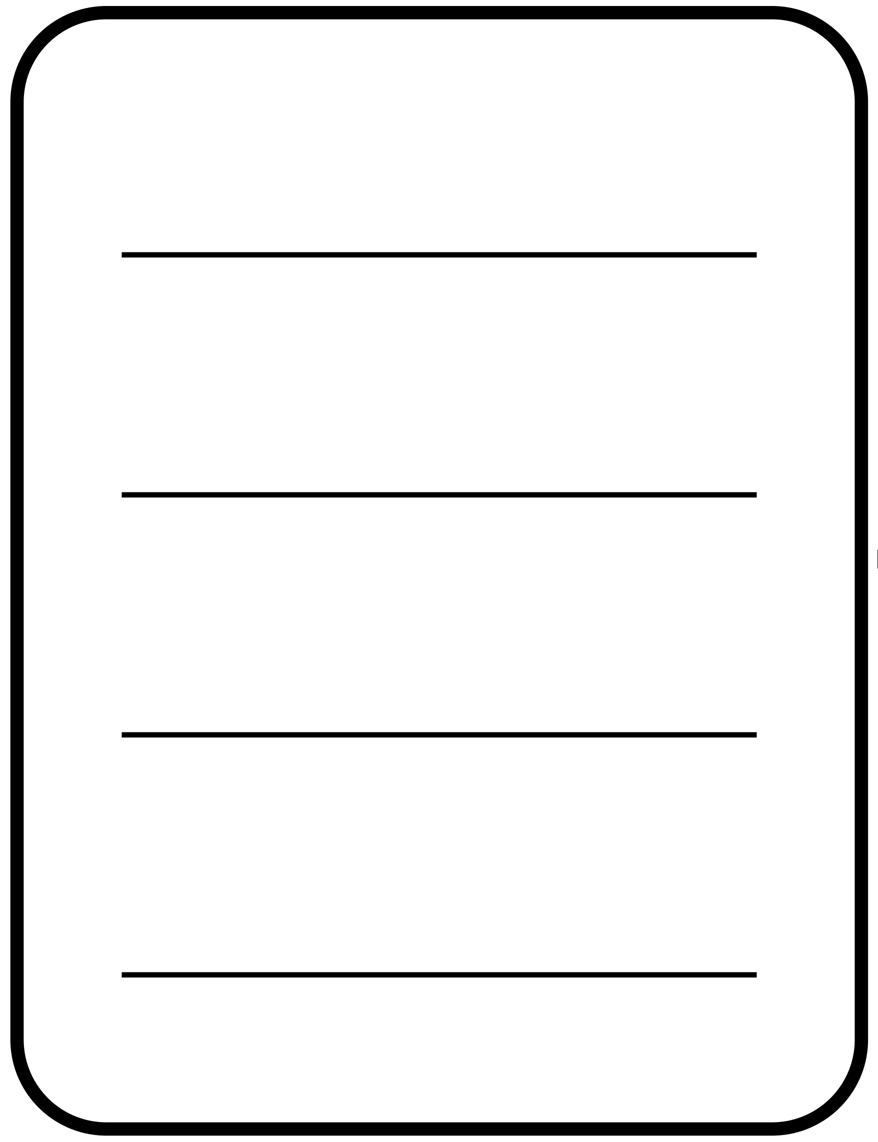

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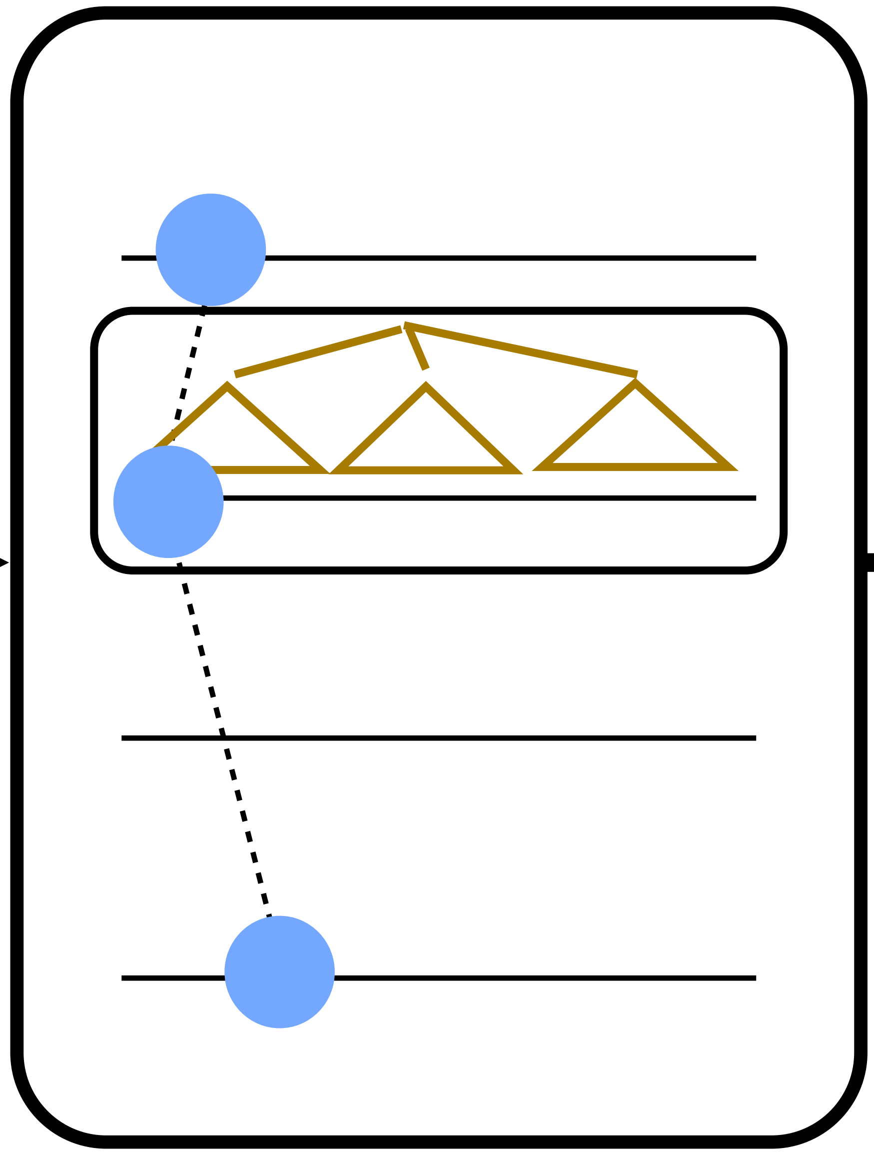

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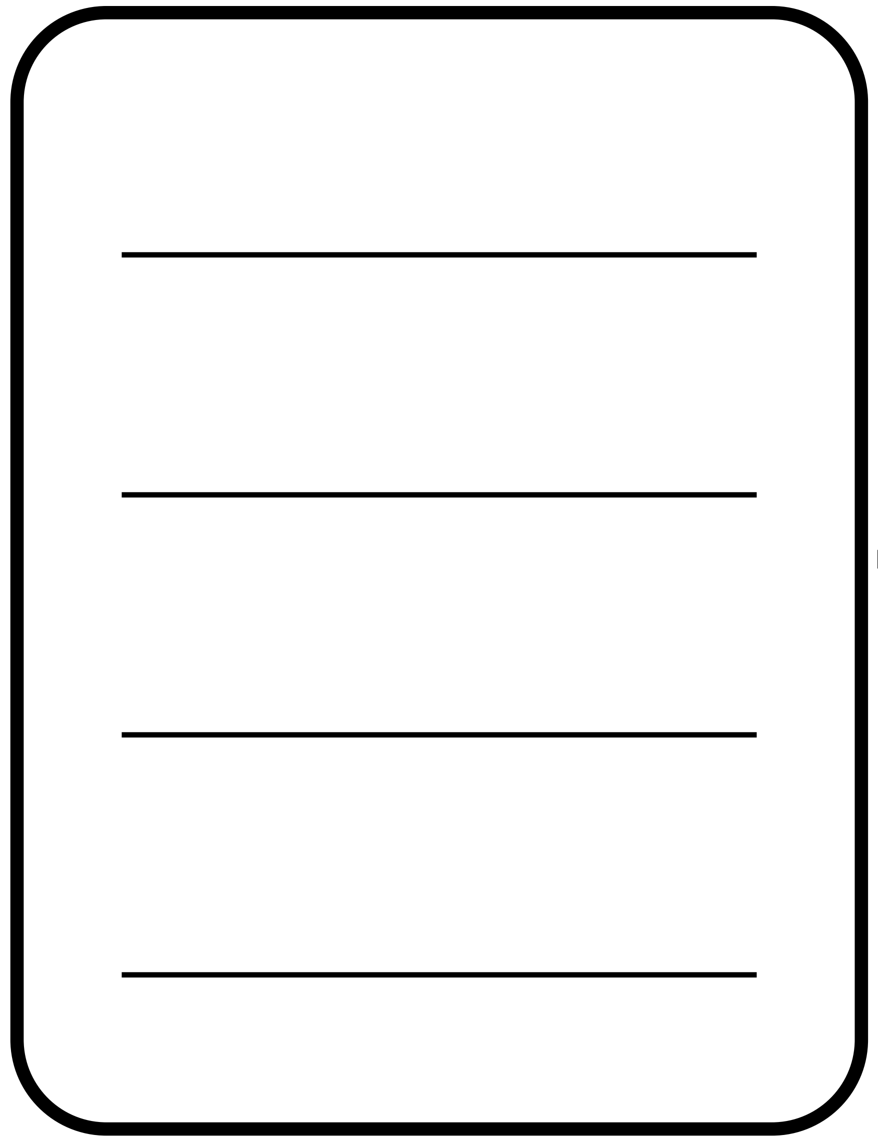

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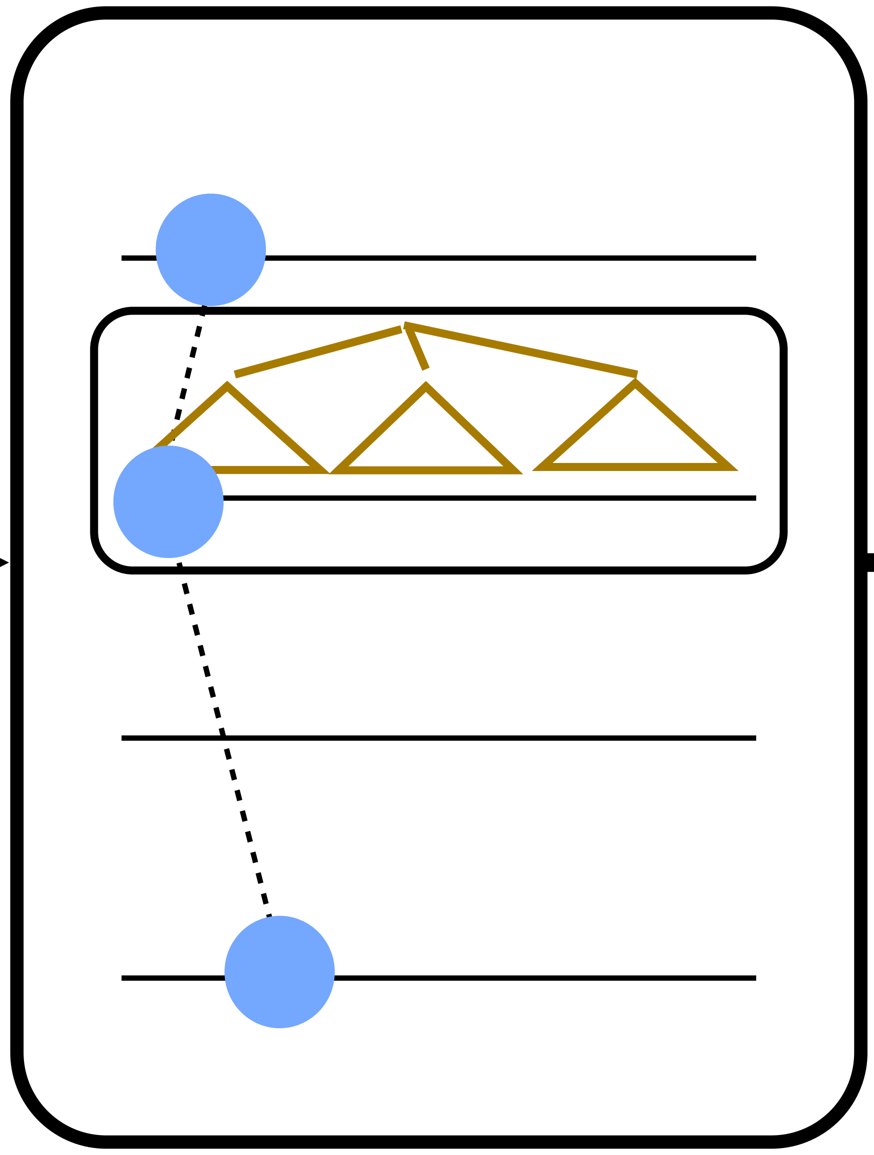

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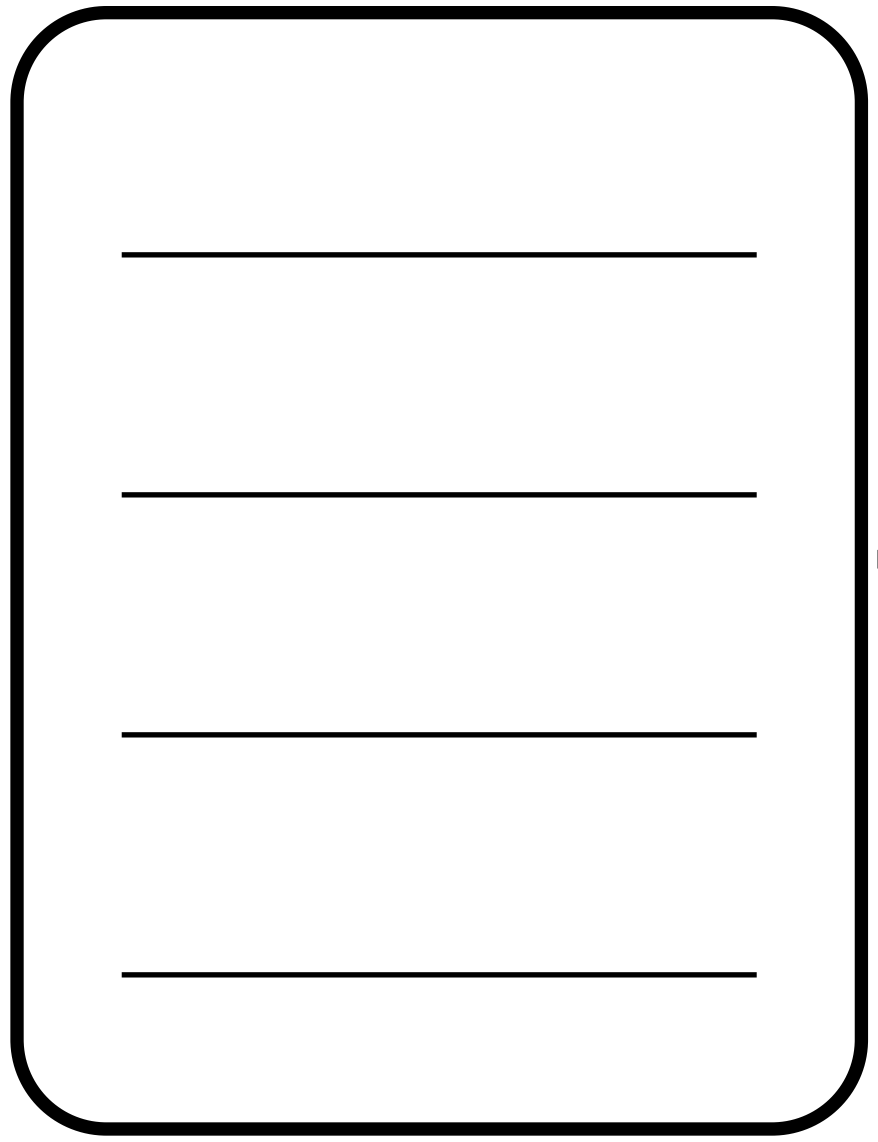

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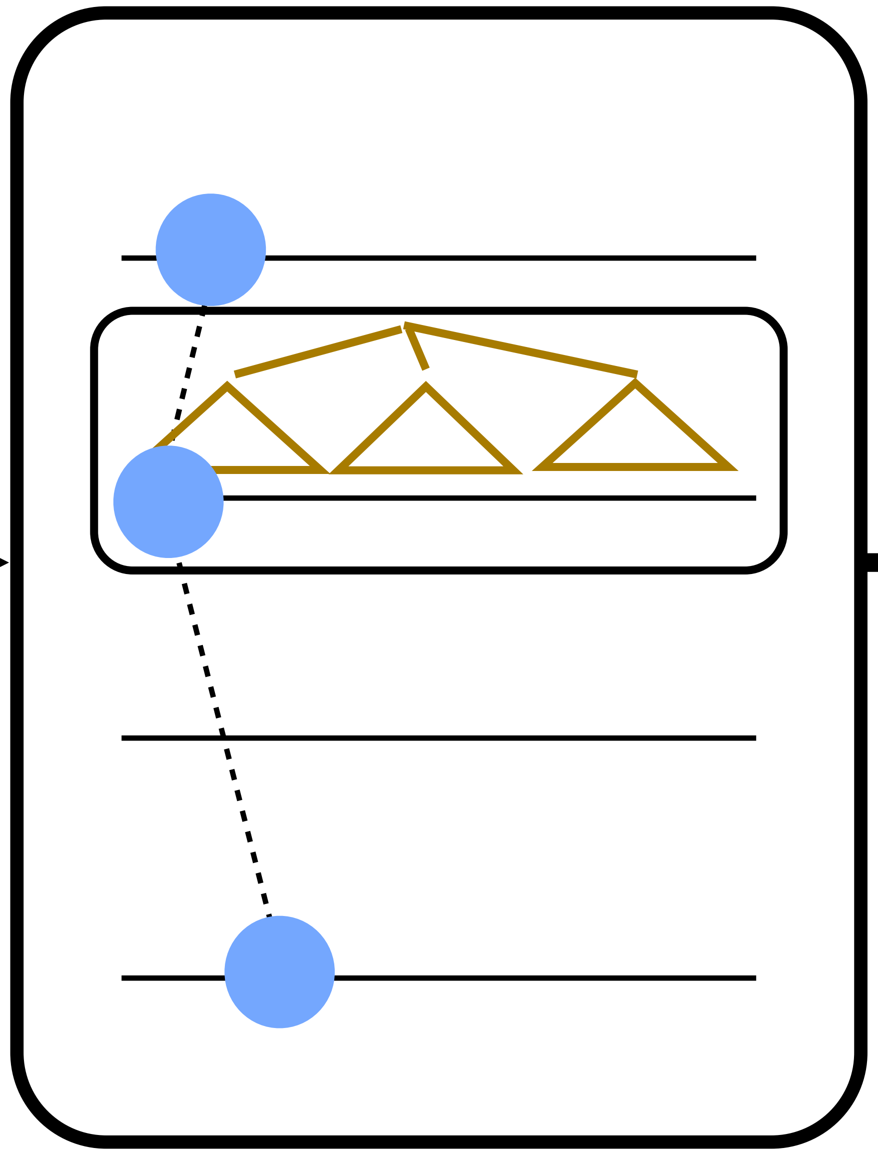

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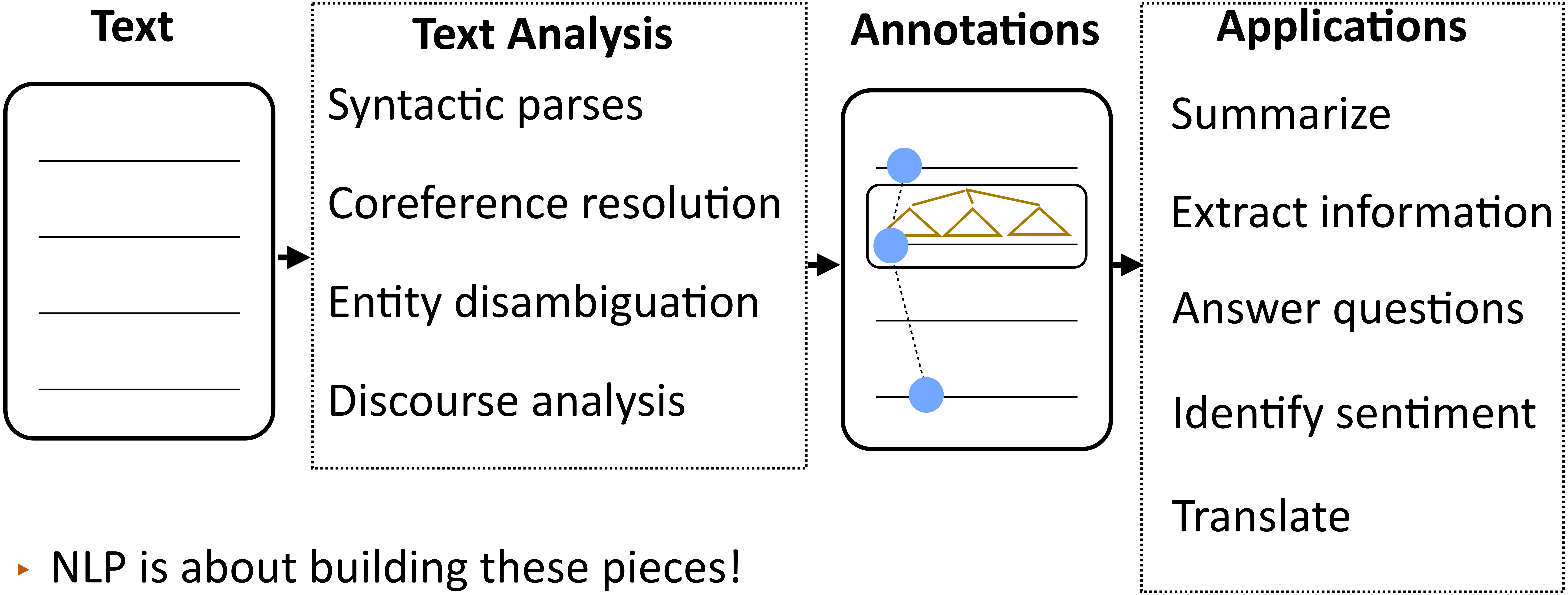
NLP Analysis Pipeline



- 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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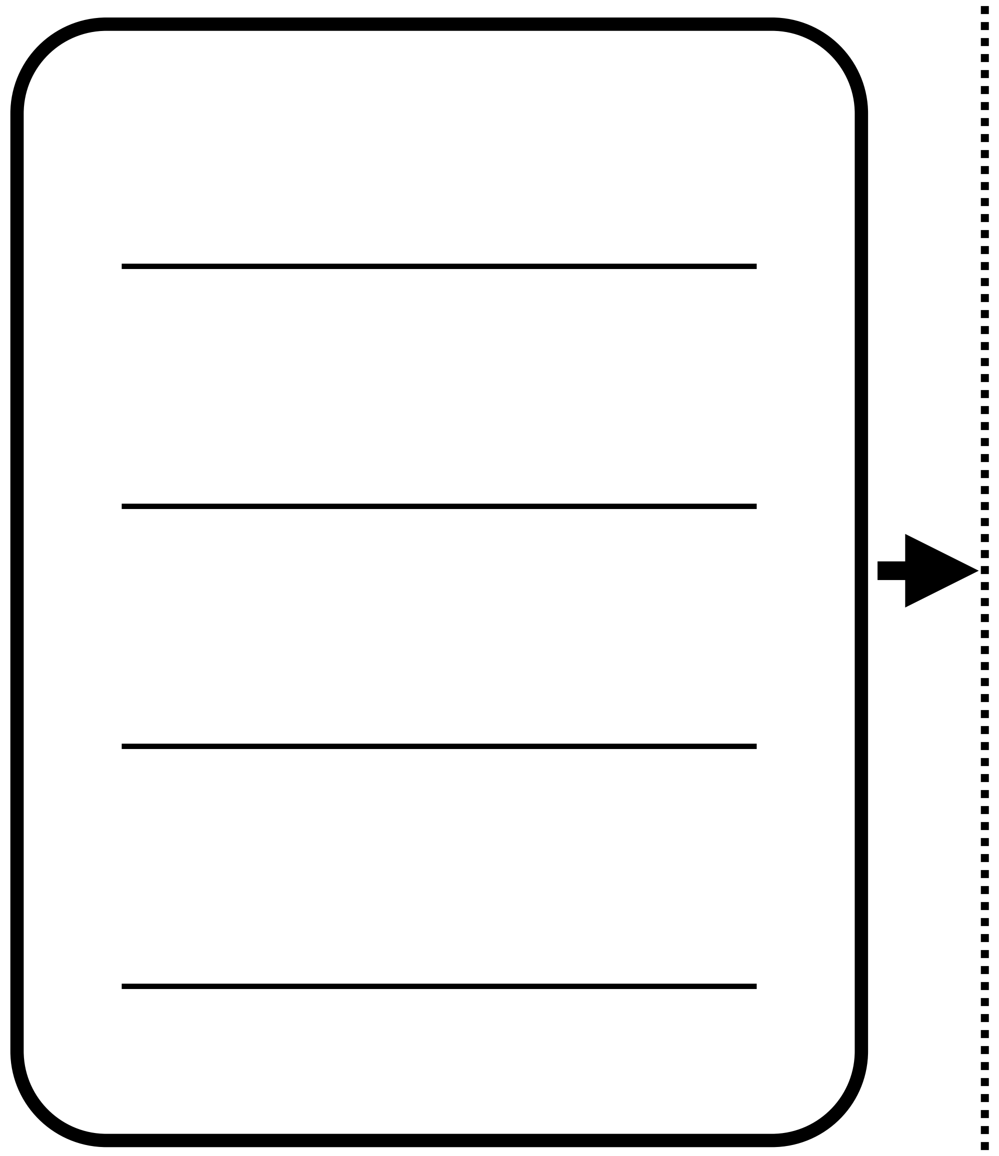

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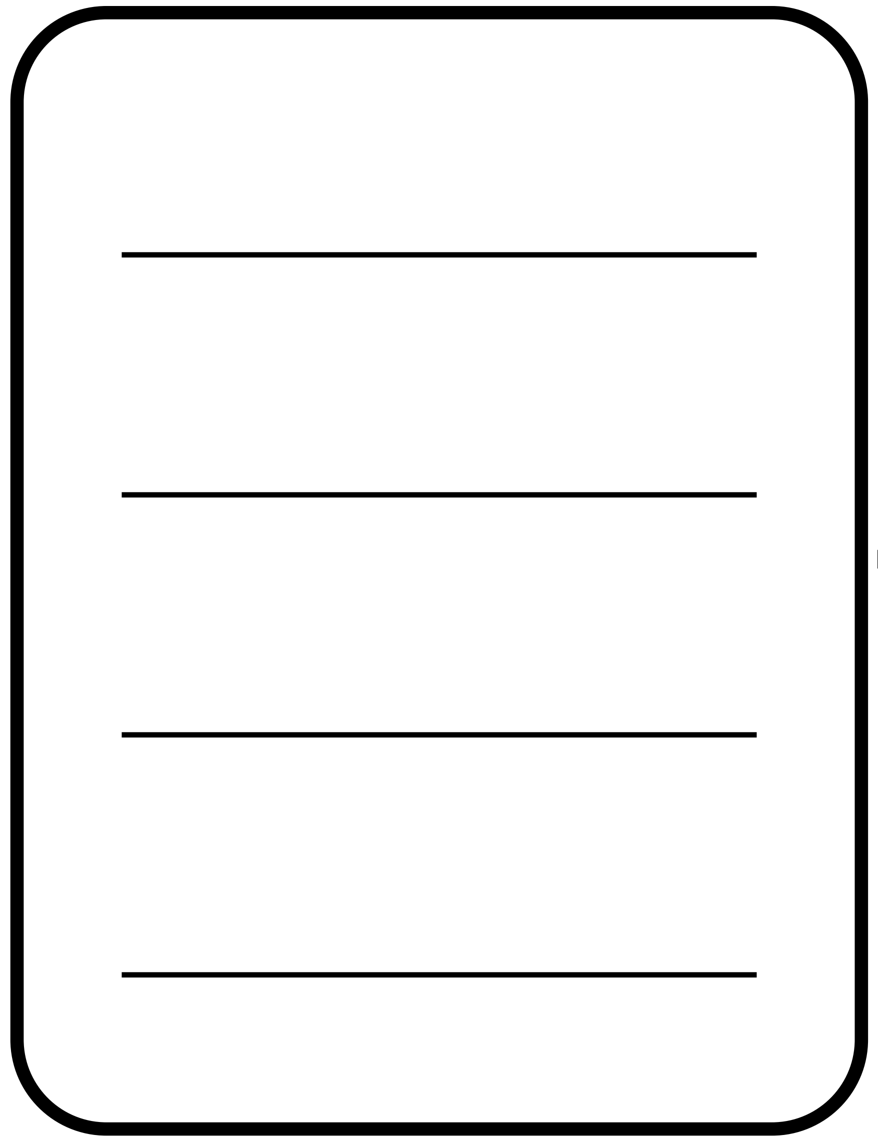

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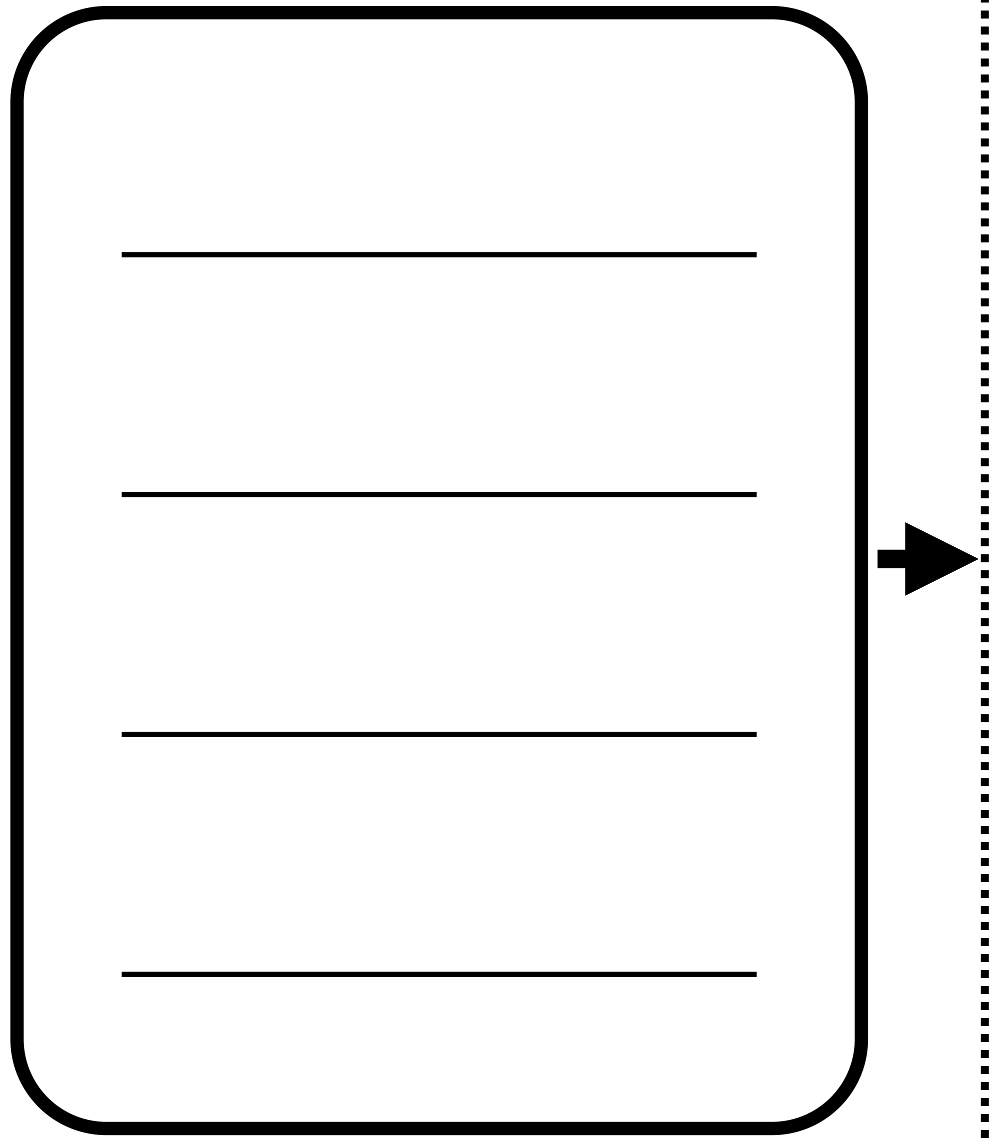

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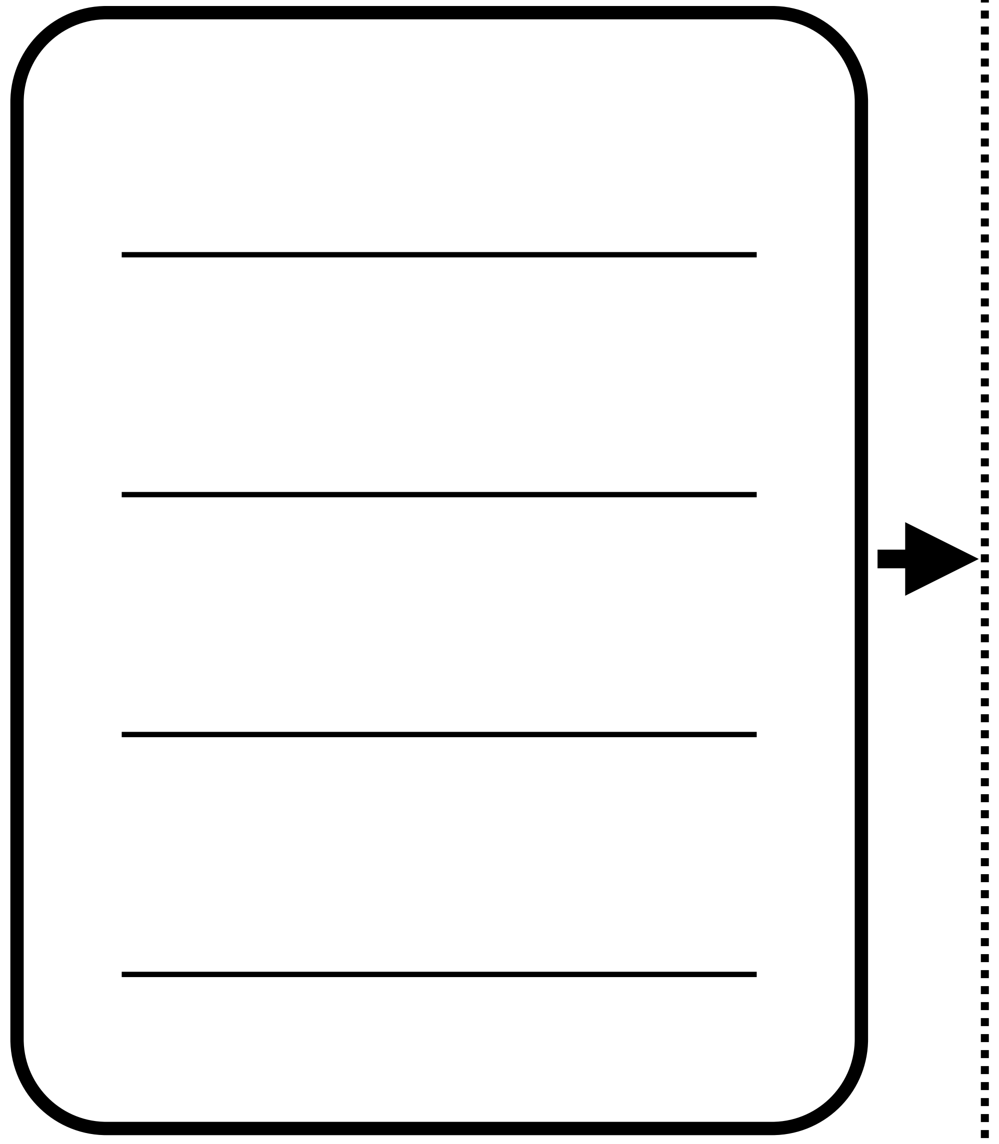

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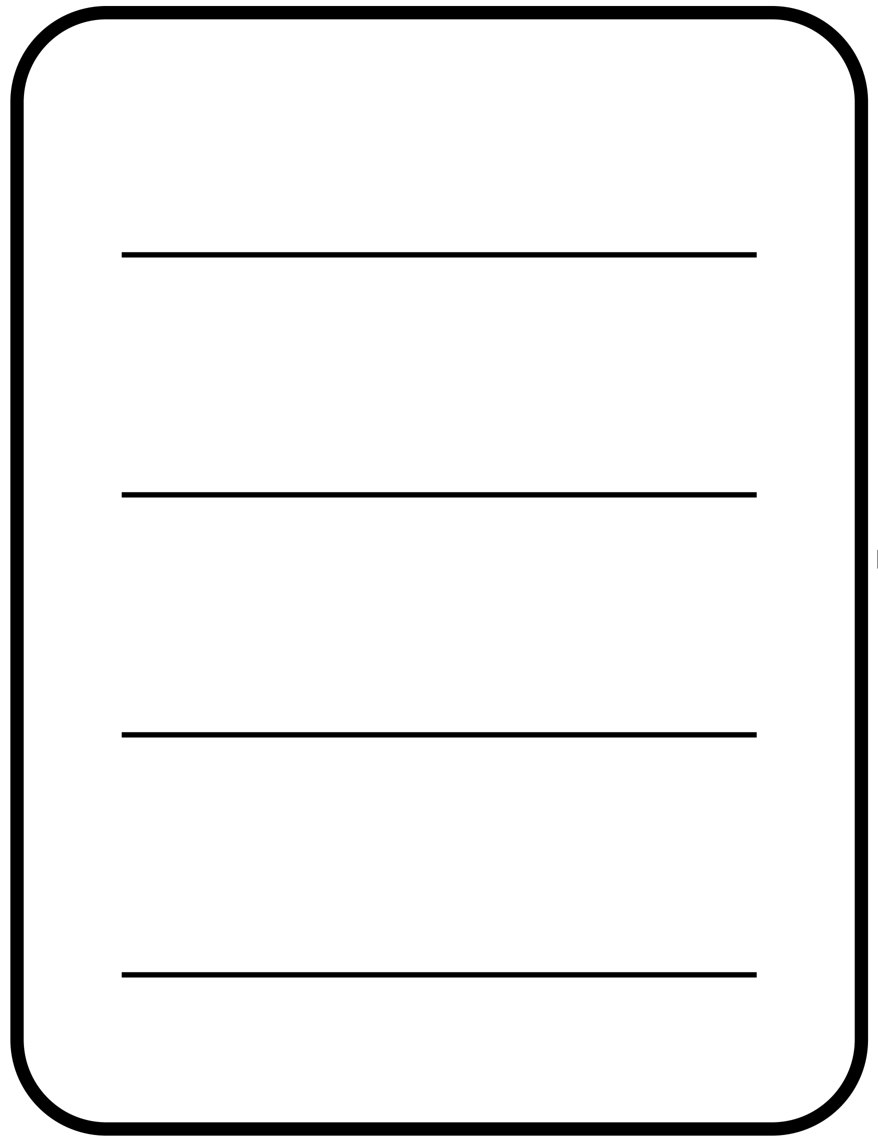

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Sequences/tags

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

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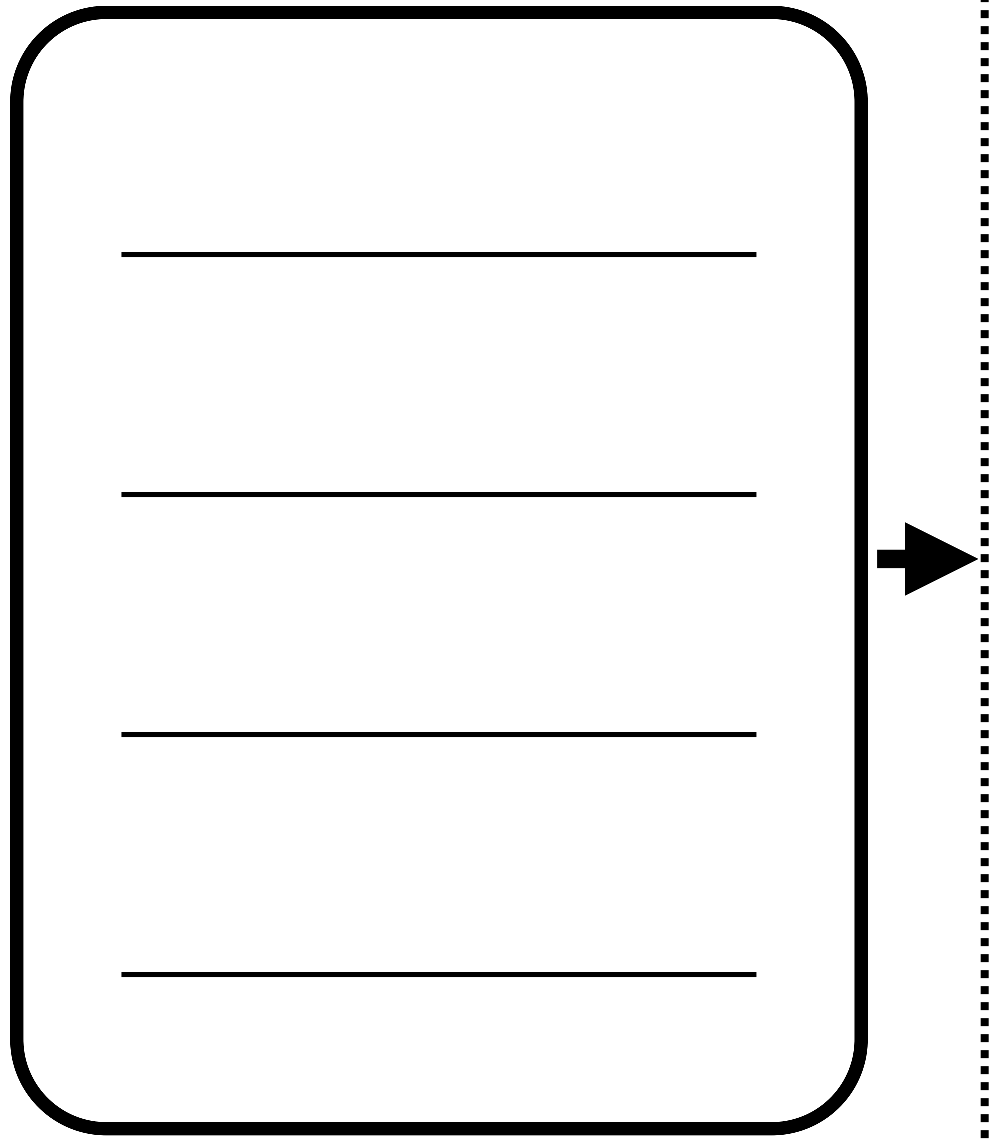

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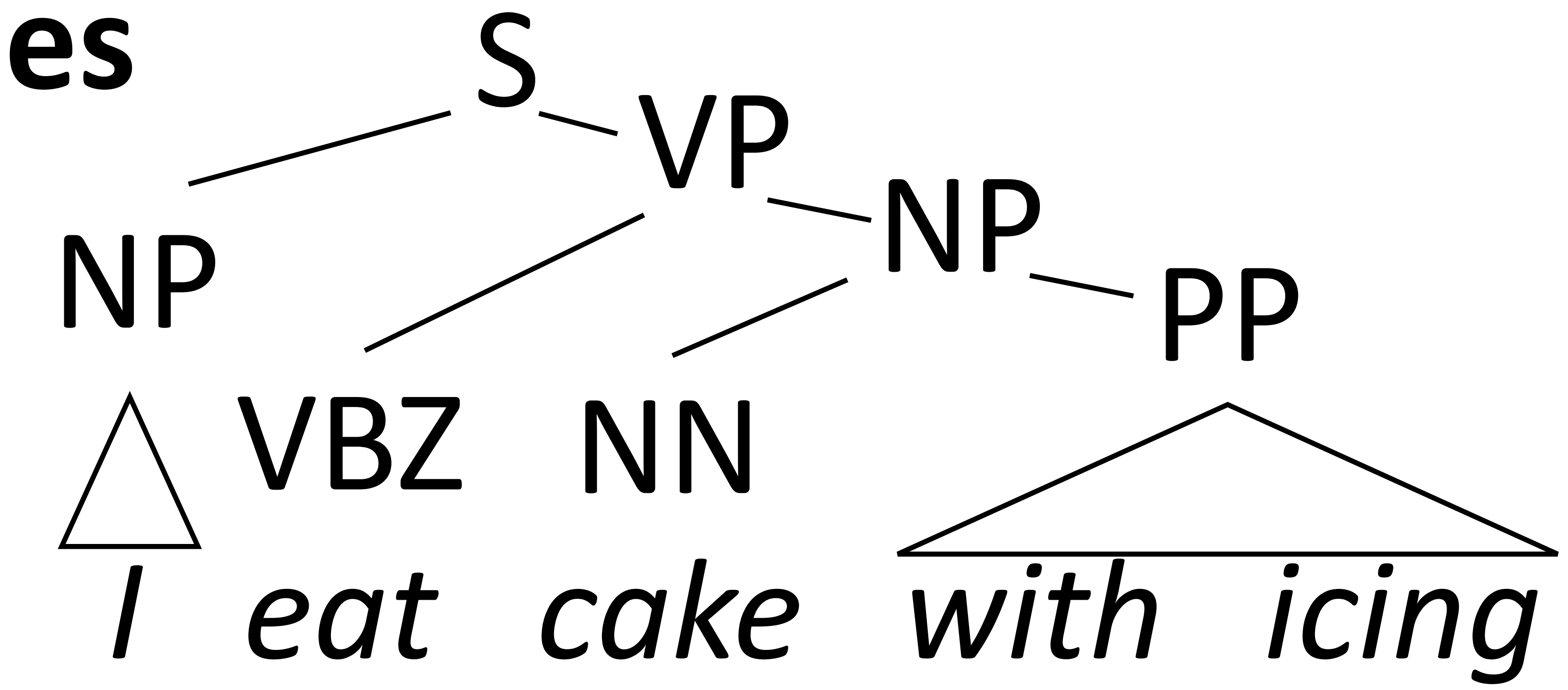

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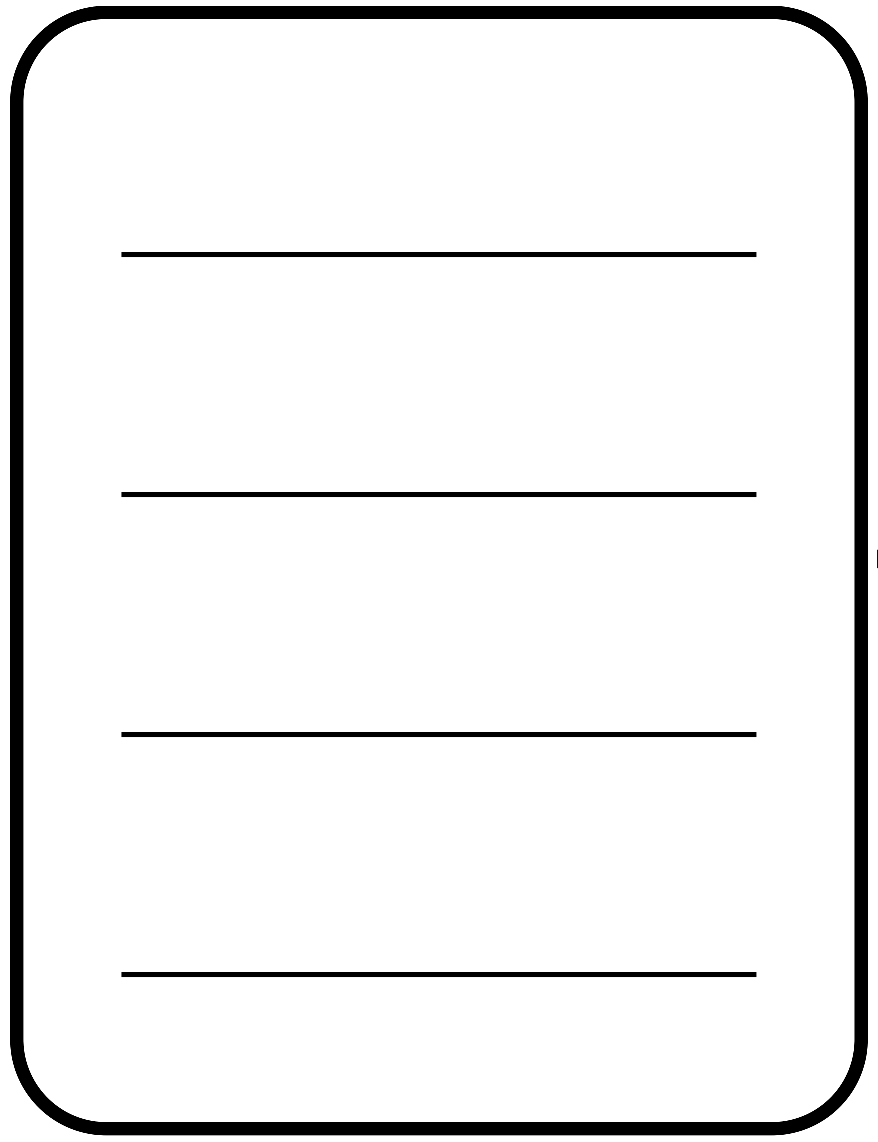

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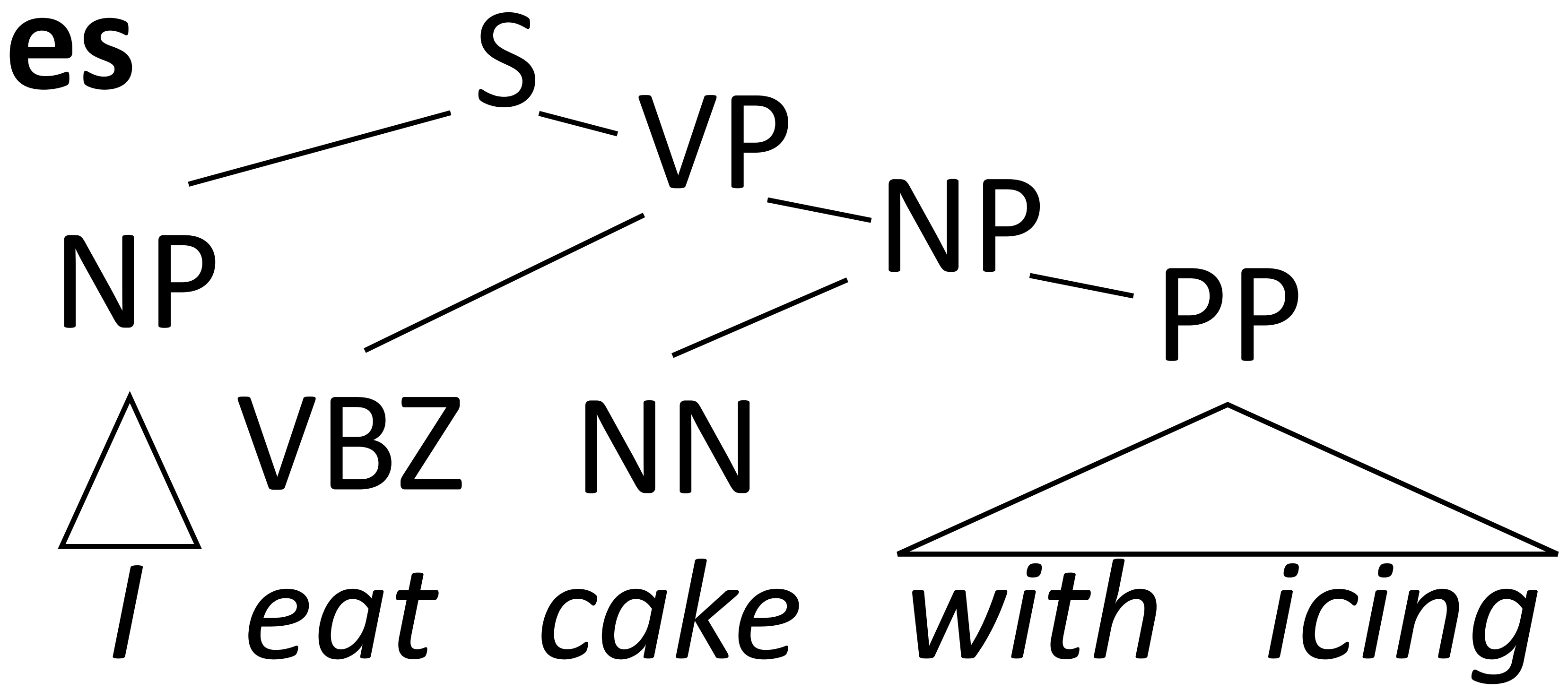

λx. flight(x) ∧ dest(x)=Miami

flights to Miami

How do we use these representations?

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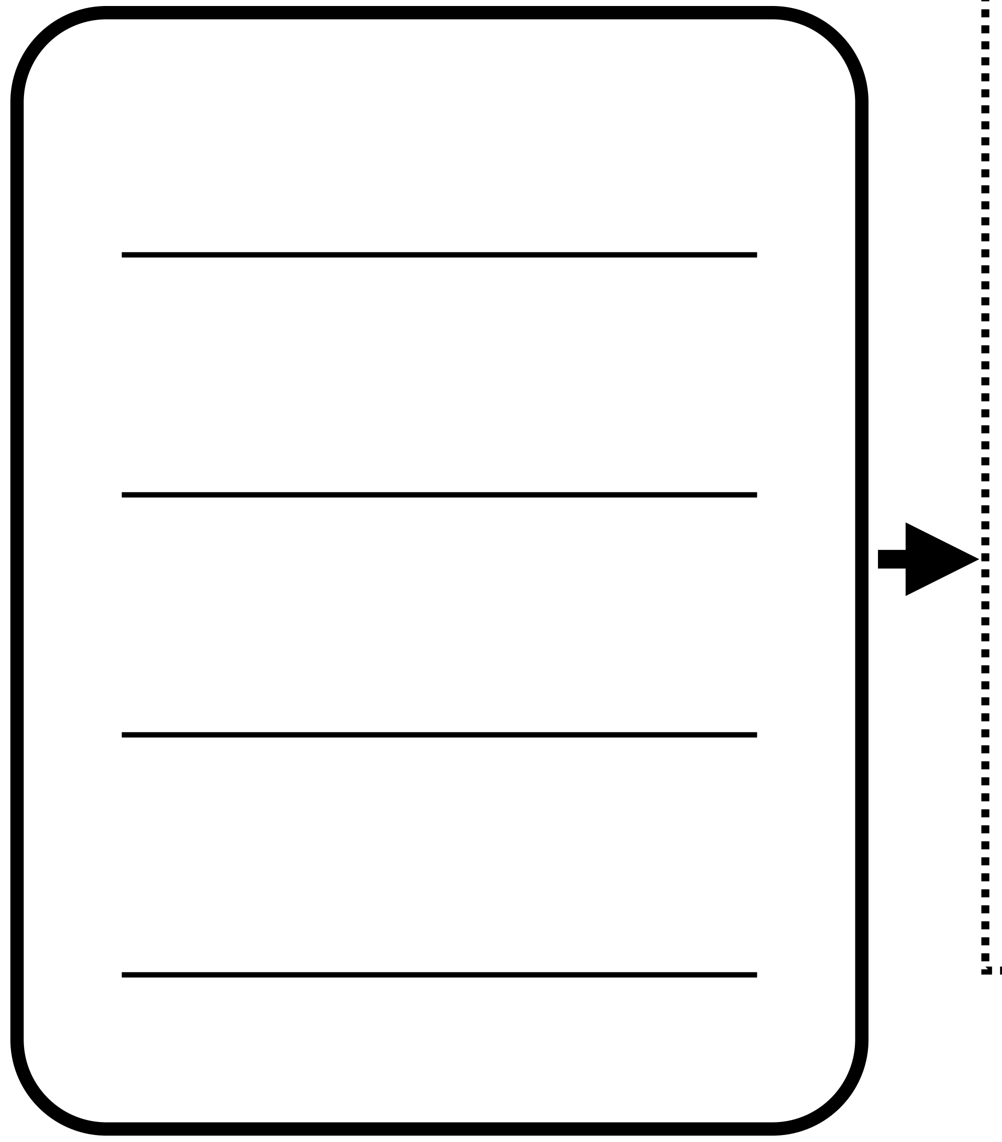

Text Analysis

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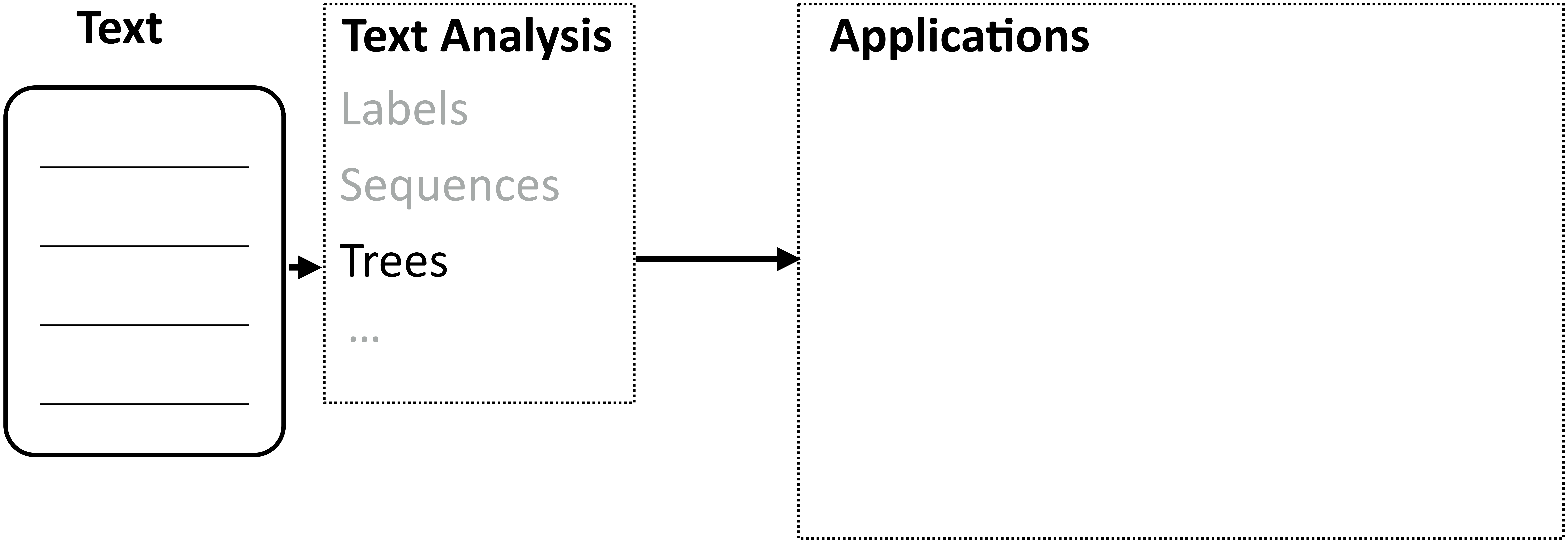

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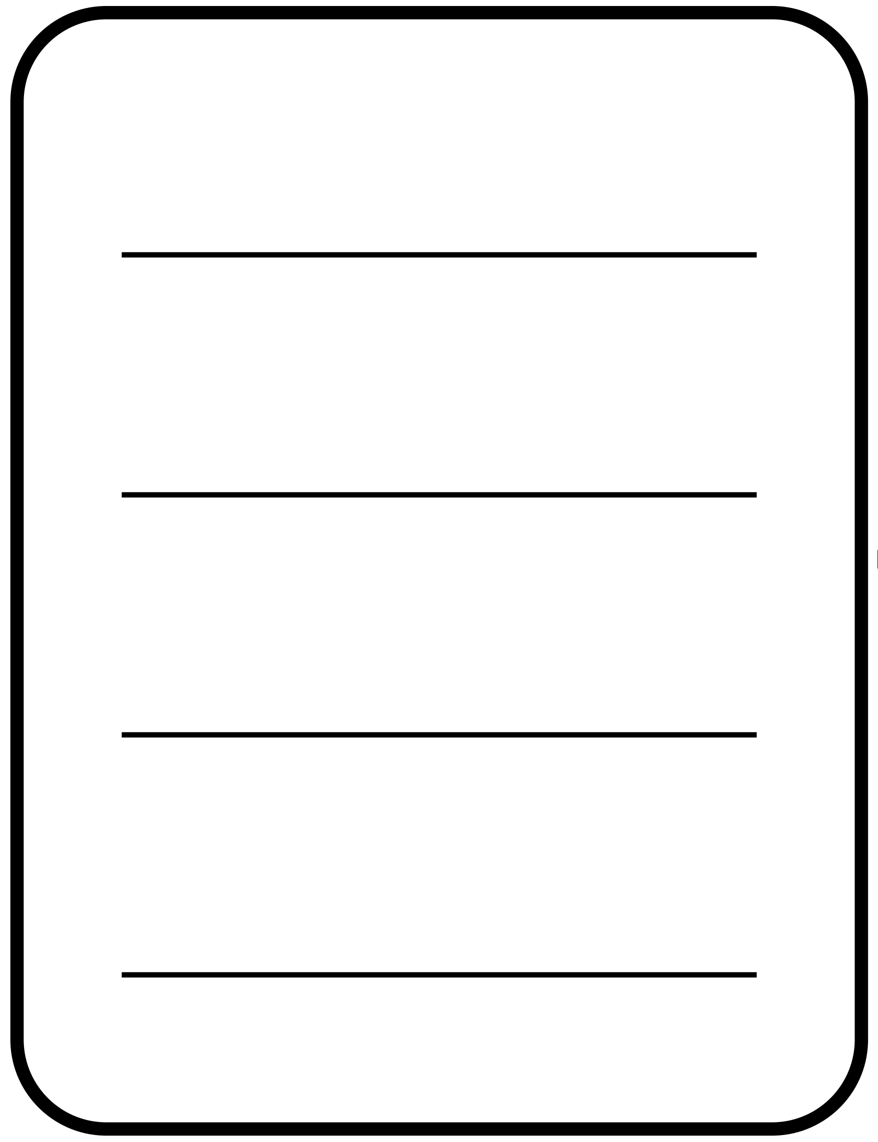

Text Analysis

Labels

Sequences

Trees

…

Applications

Extract syntactic features

How do we use these representations?

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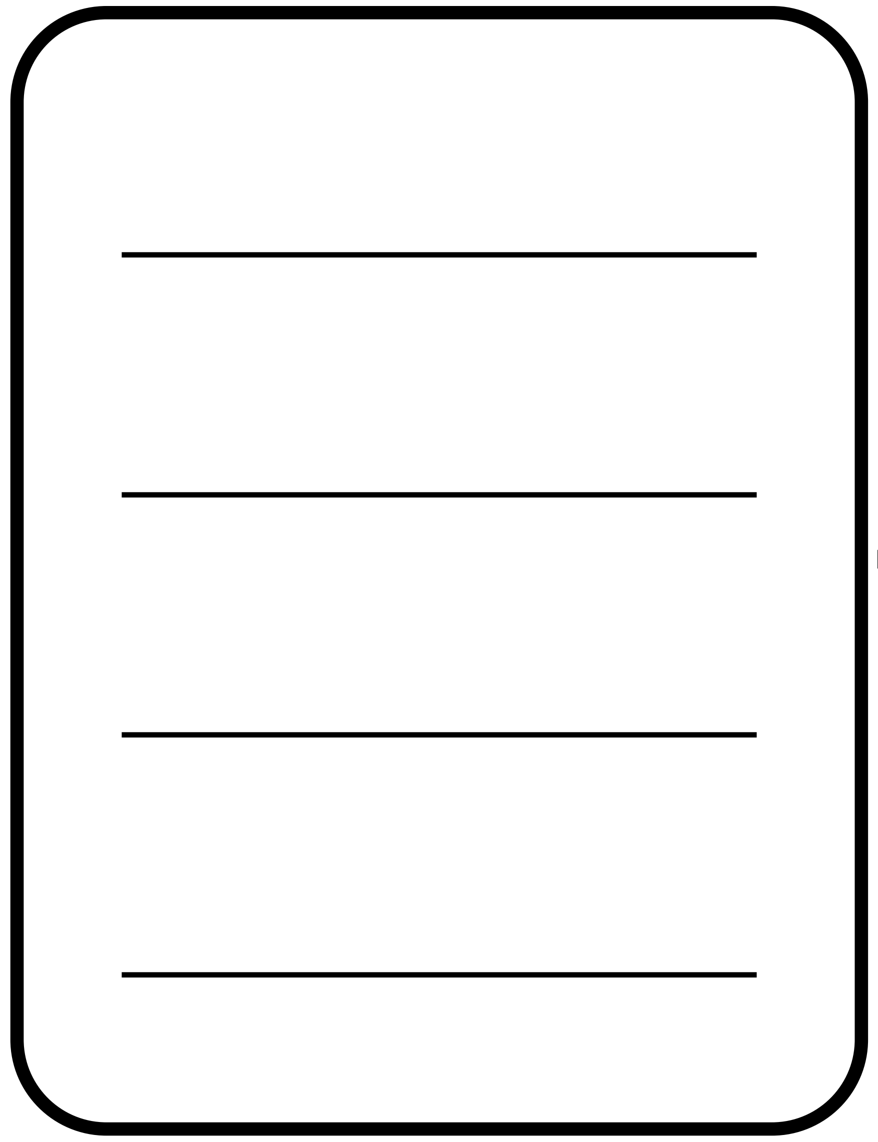

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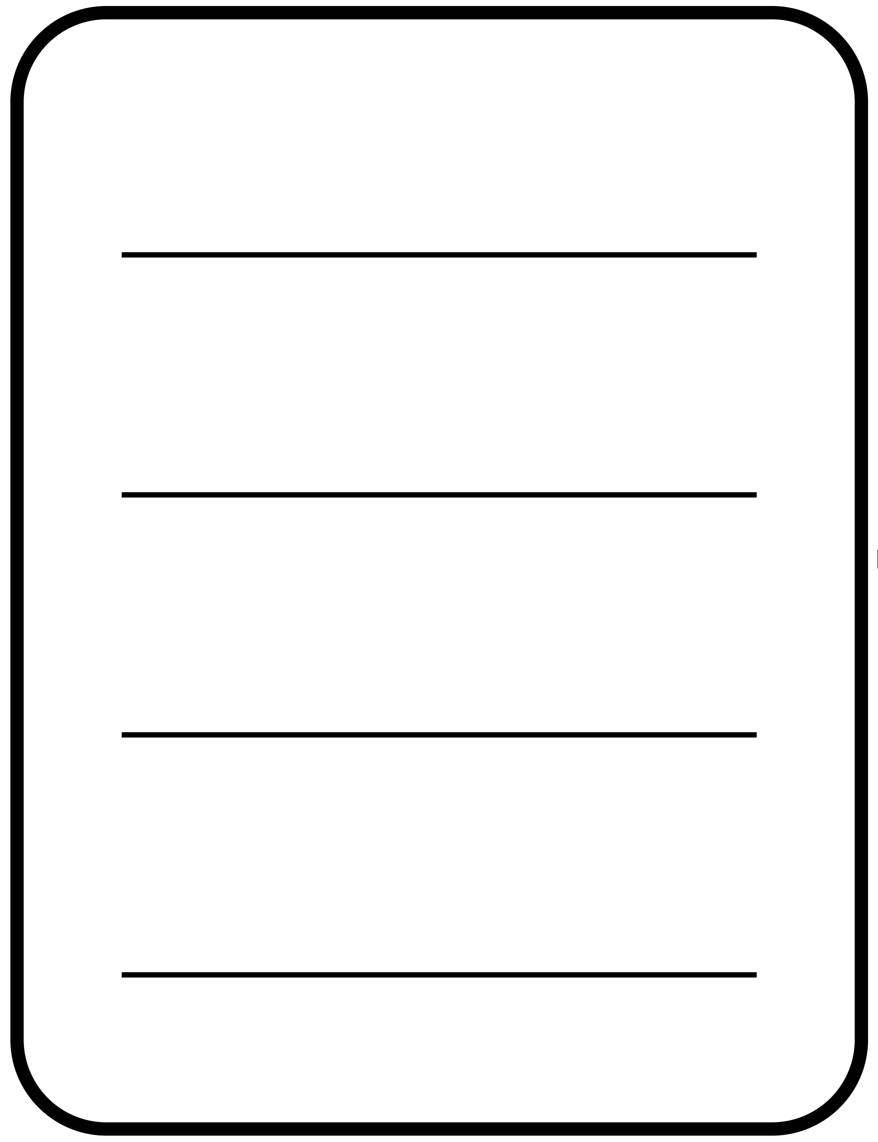

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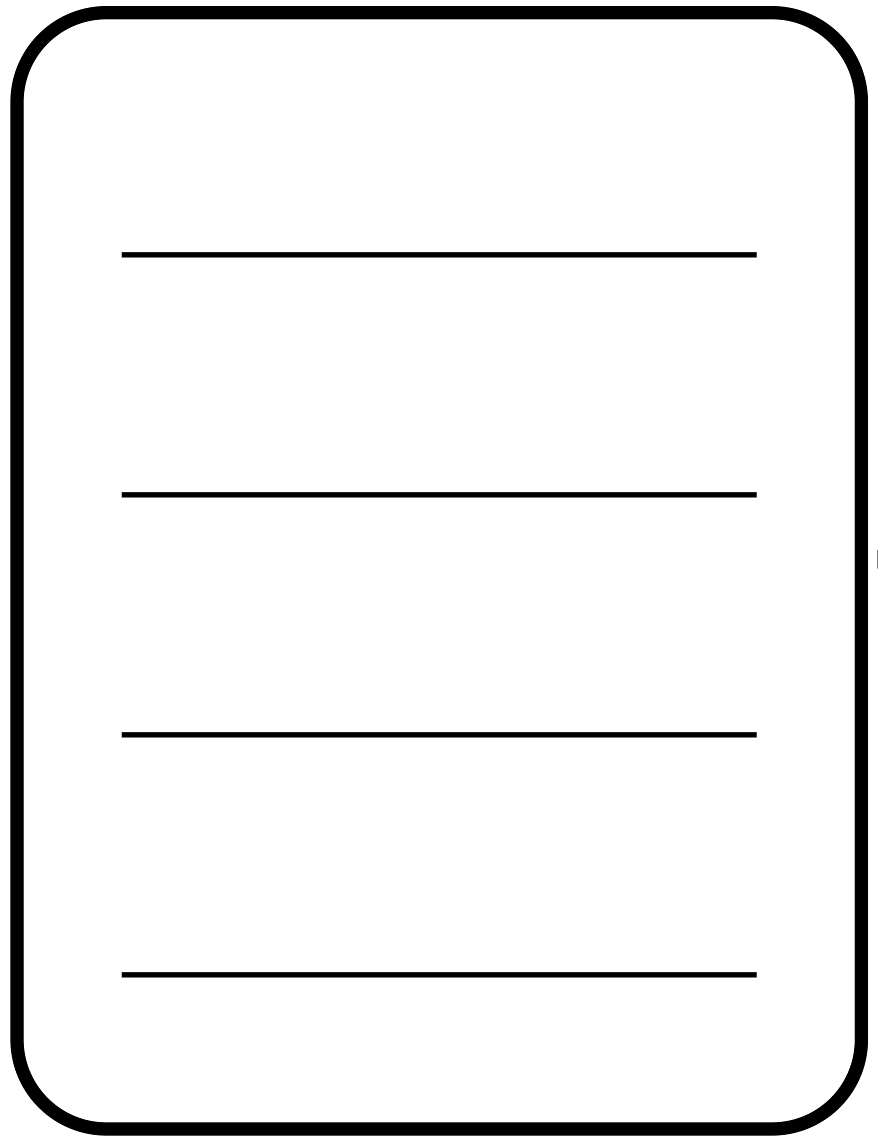

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How do we use these representations?

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end-to-end models

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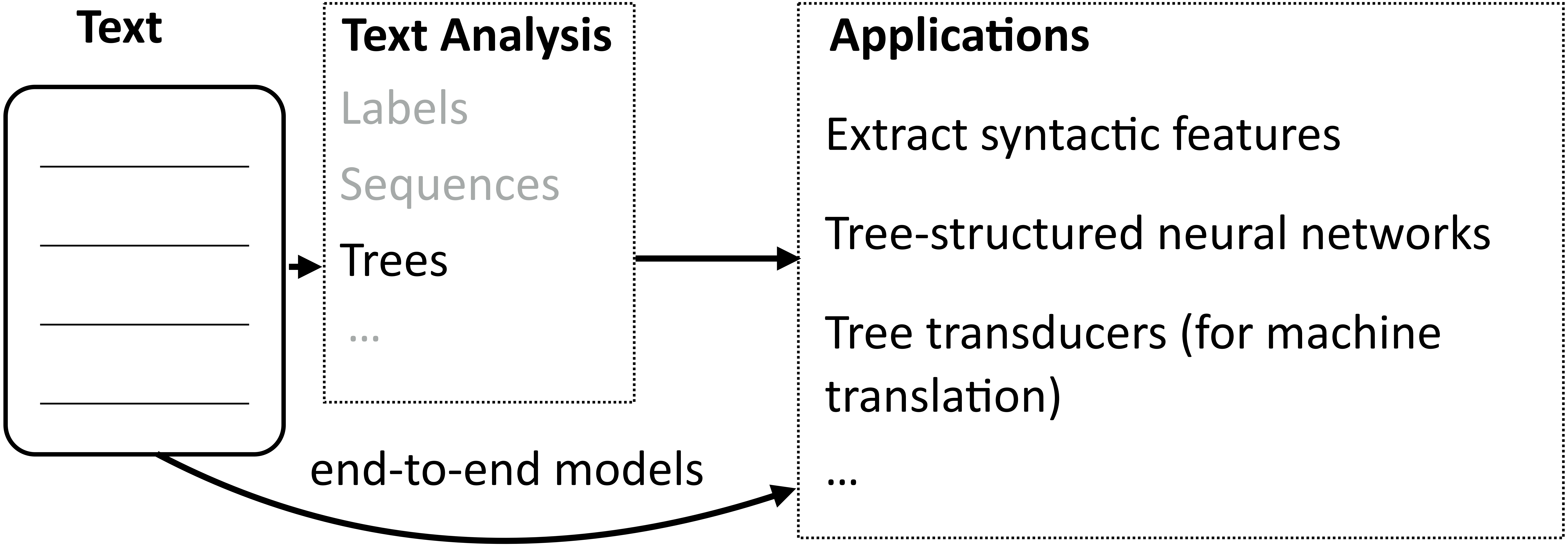
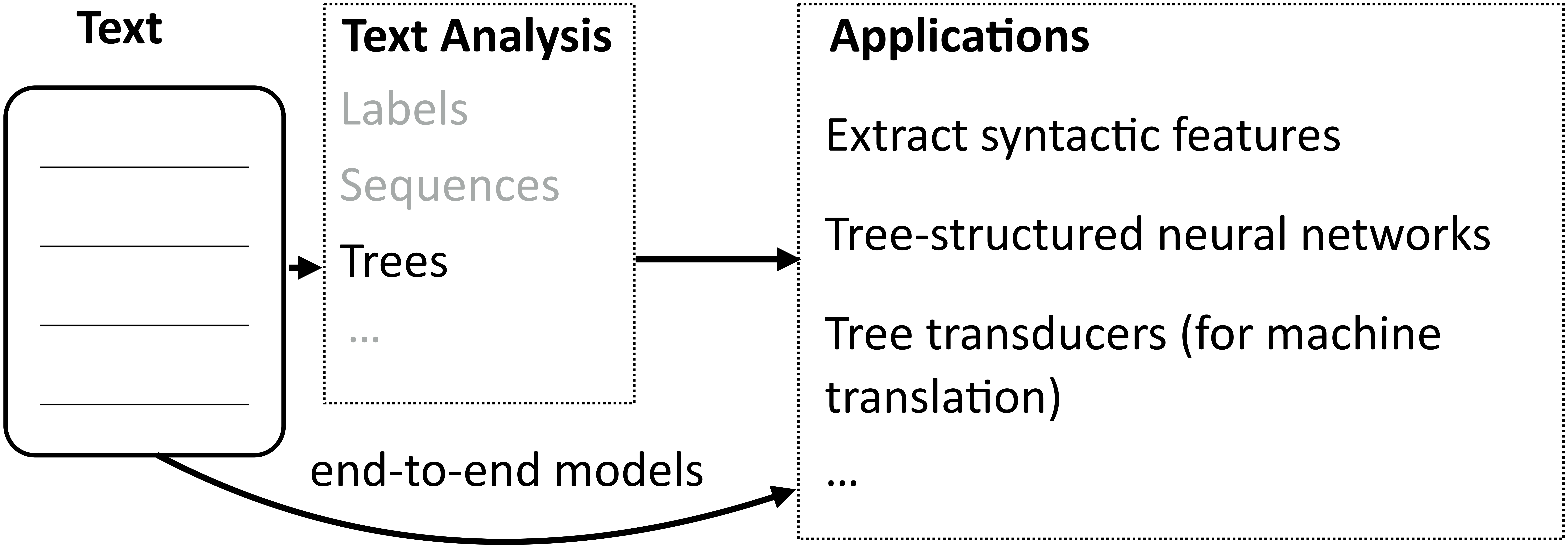


- Main question: What representations do we need for language? What do we want to know about it?

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!

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

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

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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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  - 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 →

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It is really nice out

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il fait vraiment beau $\longrightarrow$

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It's really nice

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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 nice out

It's really nice

The weather is beautiful

It is really beautiful outside

He makes truly beautiful

Language is **Really** Ambiguous!

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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

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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
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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?

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DOJ greenlights Disney - Fox merger

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metaphor;
“approves”

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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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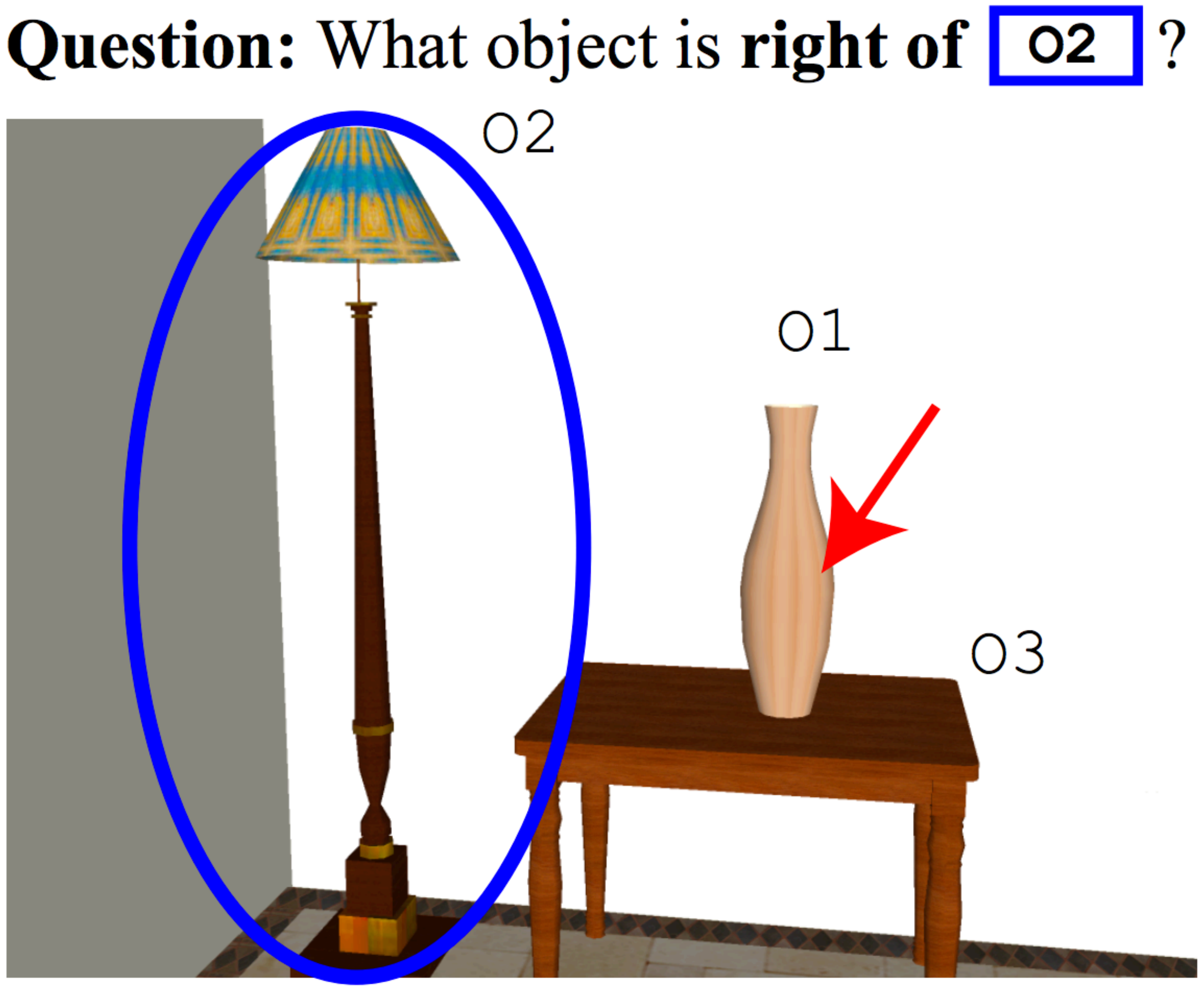

Golland et al. (2010)

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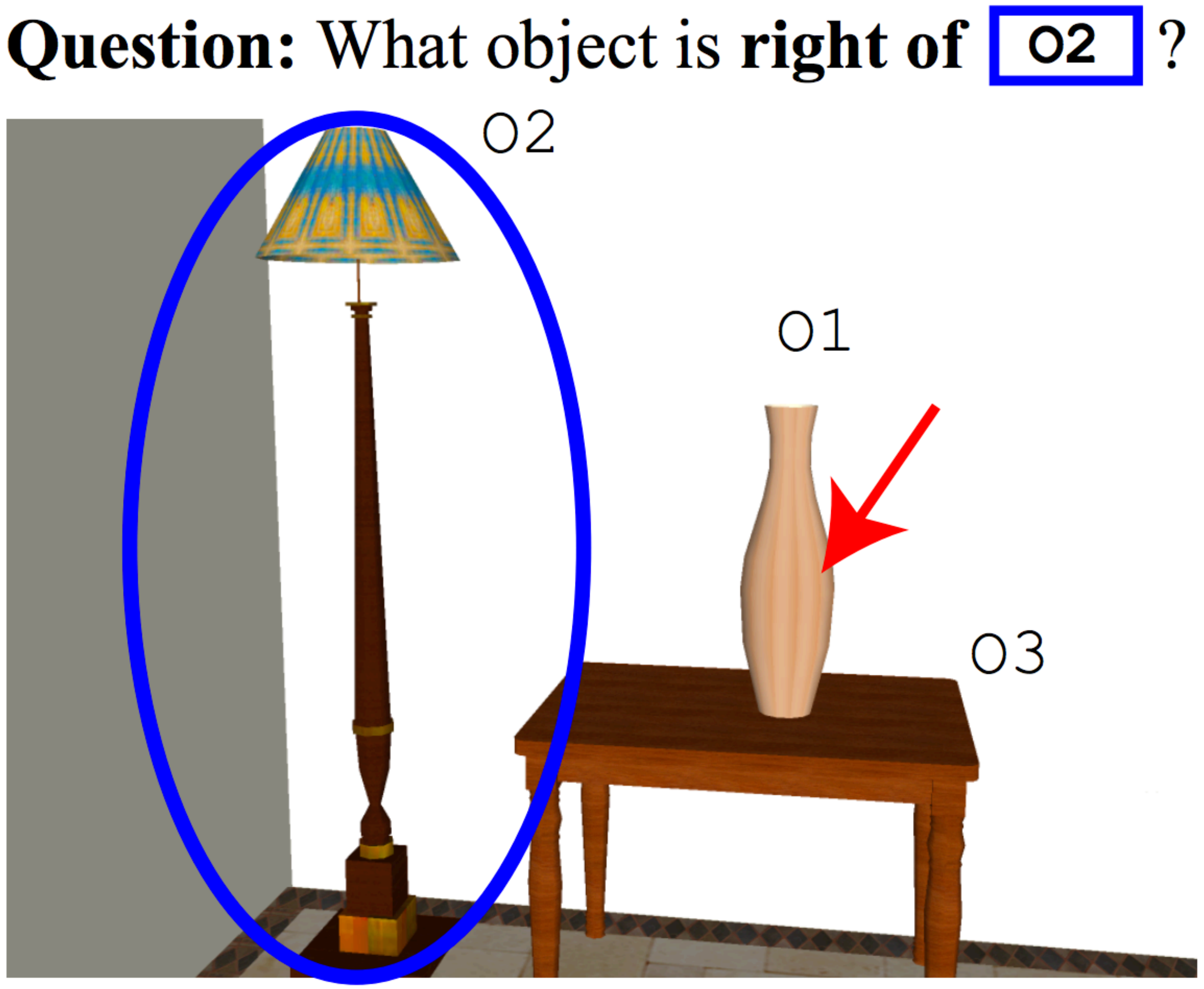

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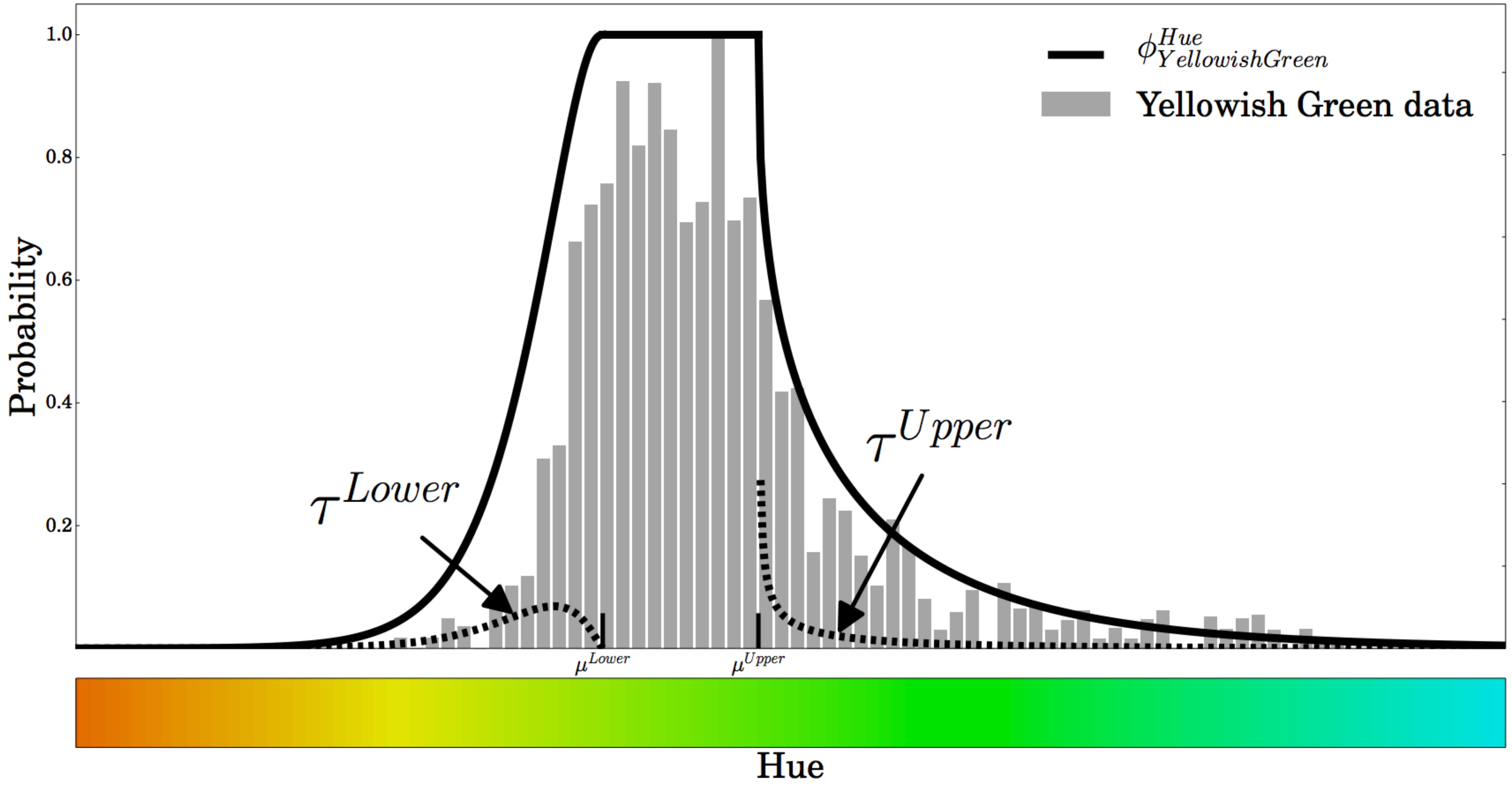

McMahan and Stone (2015)

What do we need to understand language?

- Linguistic structure

Centering Theory
Grosz et al. (1995)

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- …but computers probably won’t understand language the same way humans do

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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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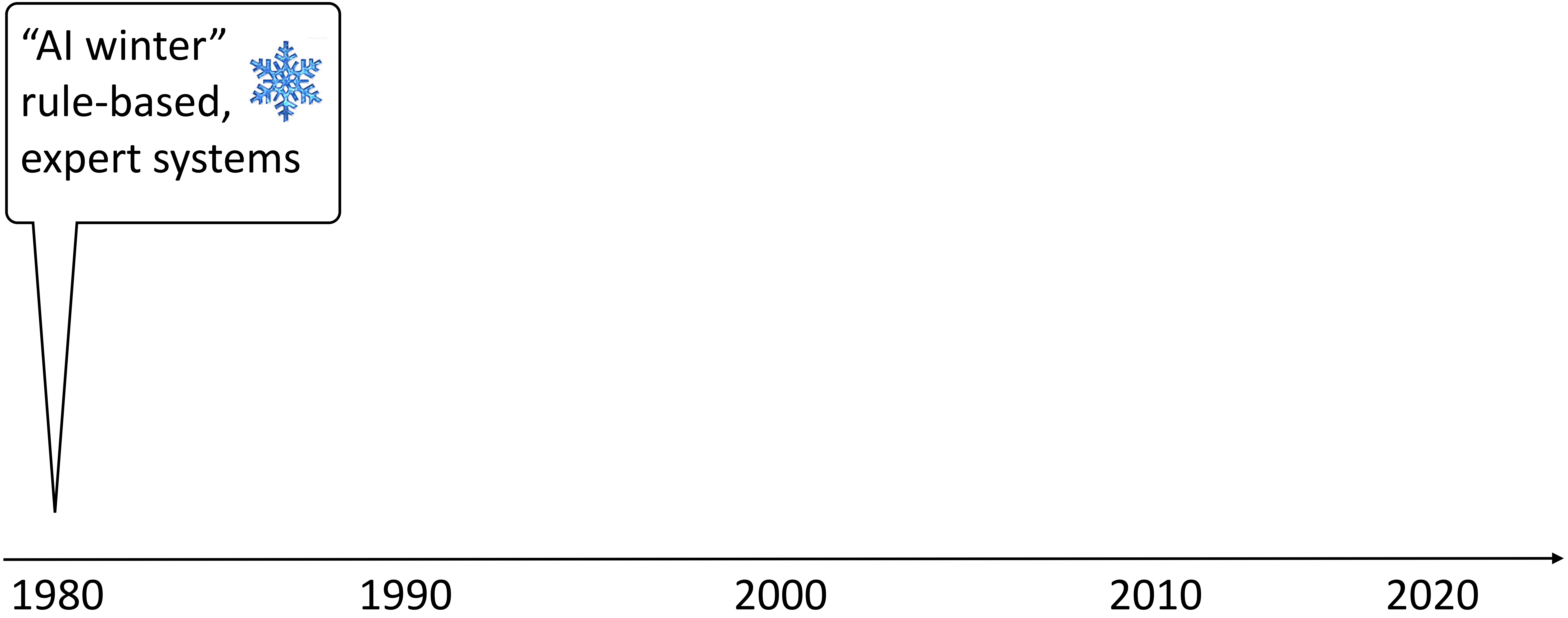

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“AI winter”
rule-based,
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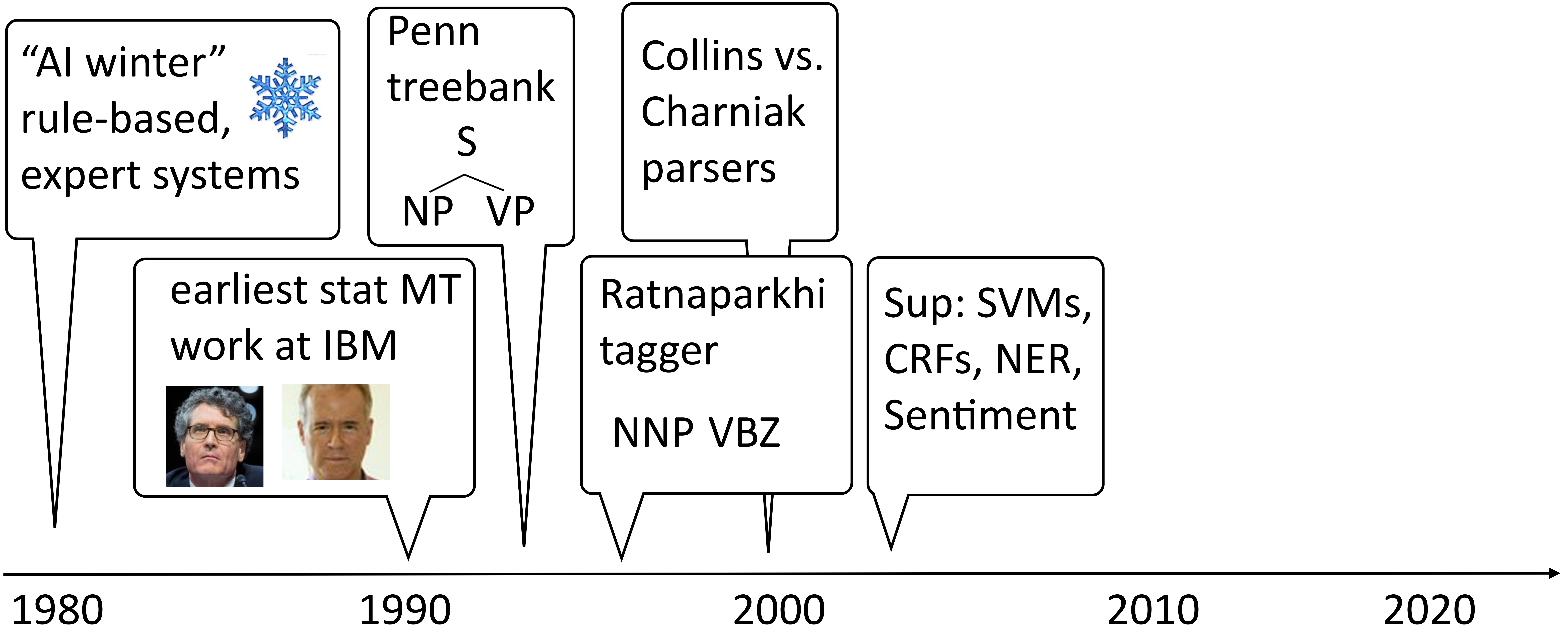

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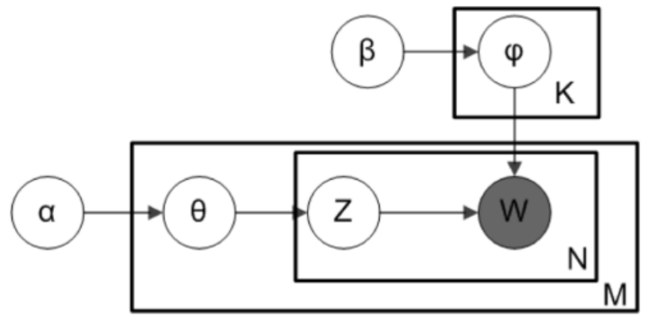
Sentiment

Unsup: topic
models,
grammar induction



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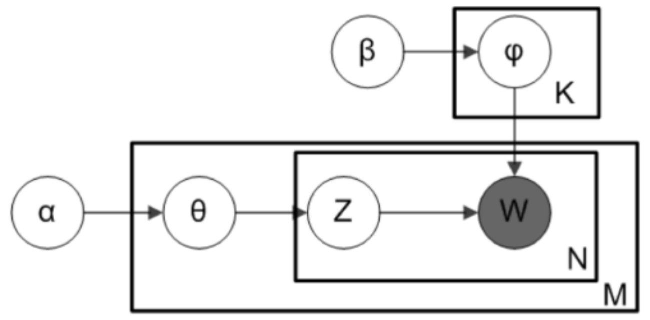

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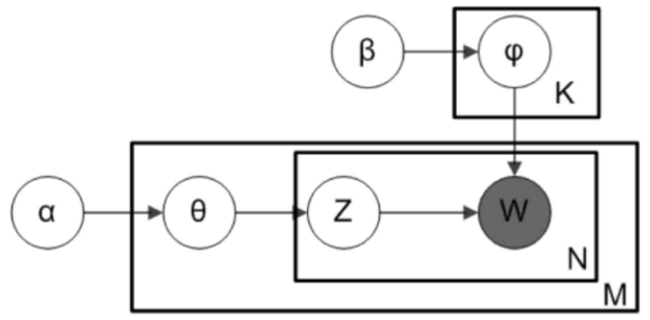

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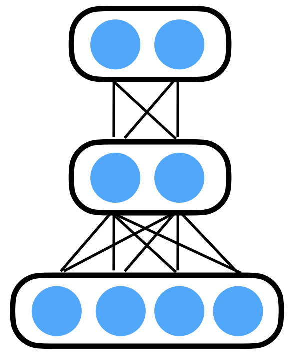

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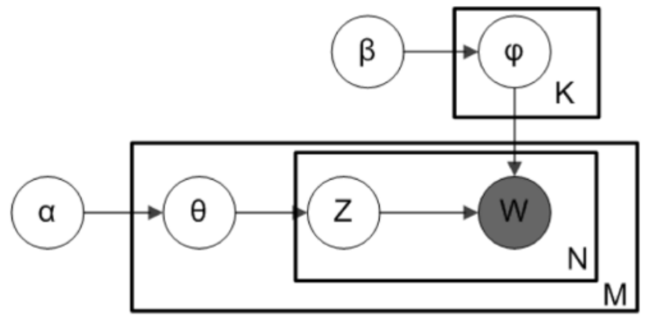

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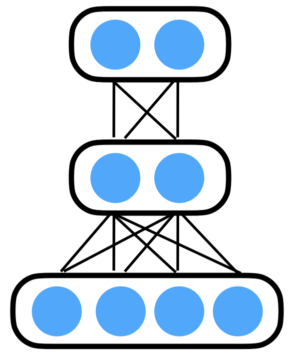

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Structured Prediction

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

Structured Prediction

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

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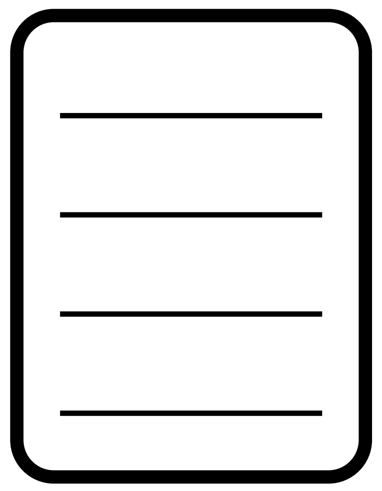

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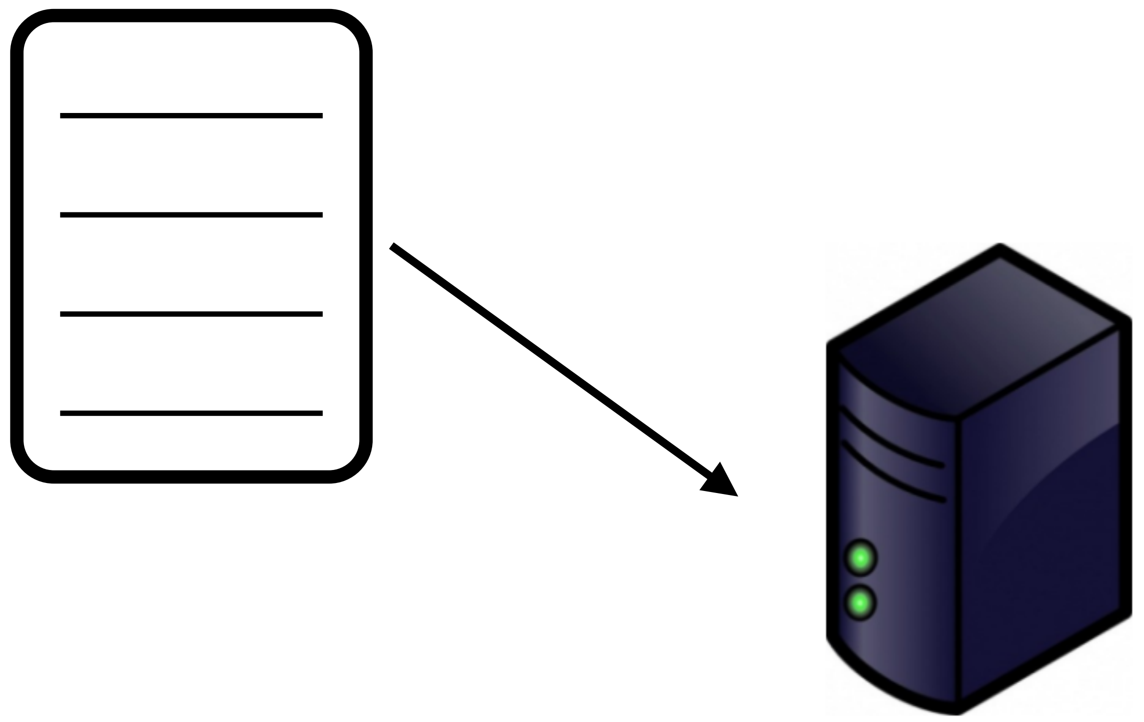

unsupervised learning

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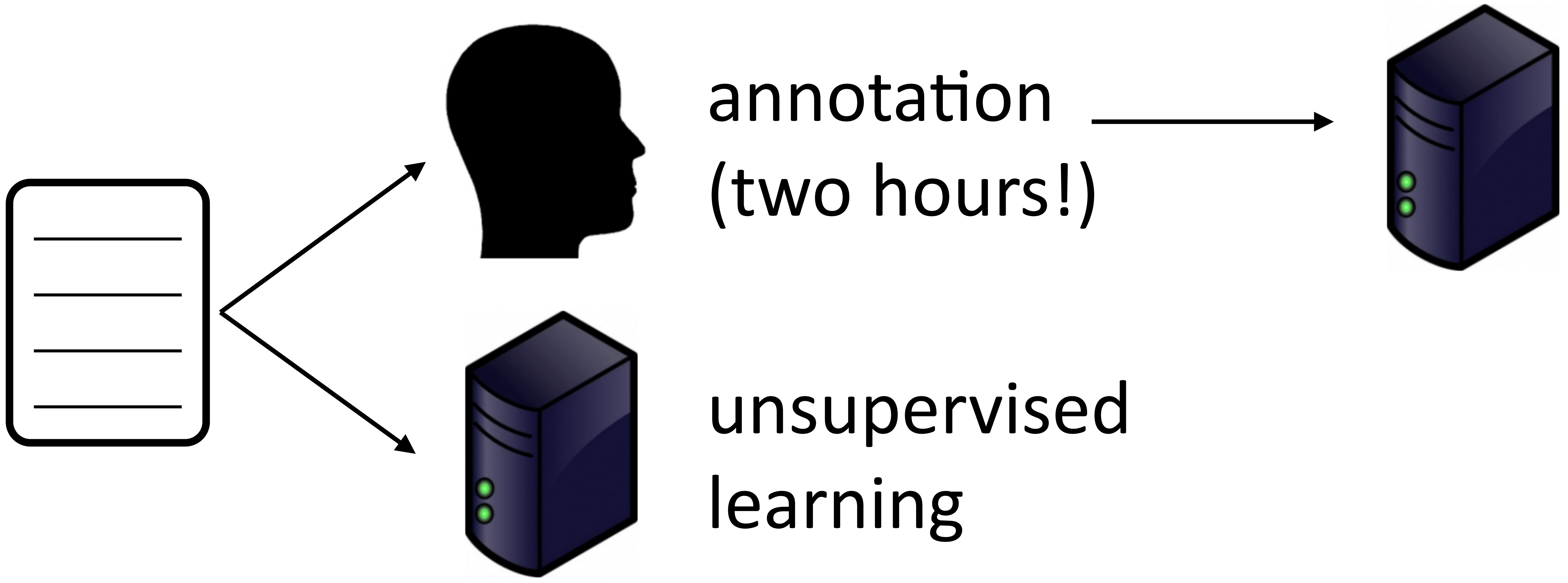

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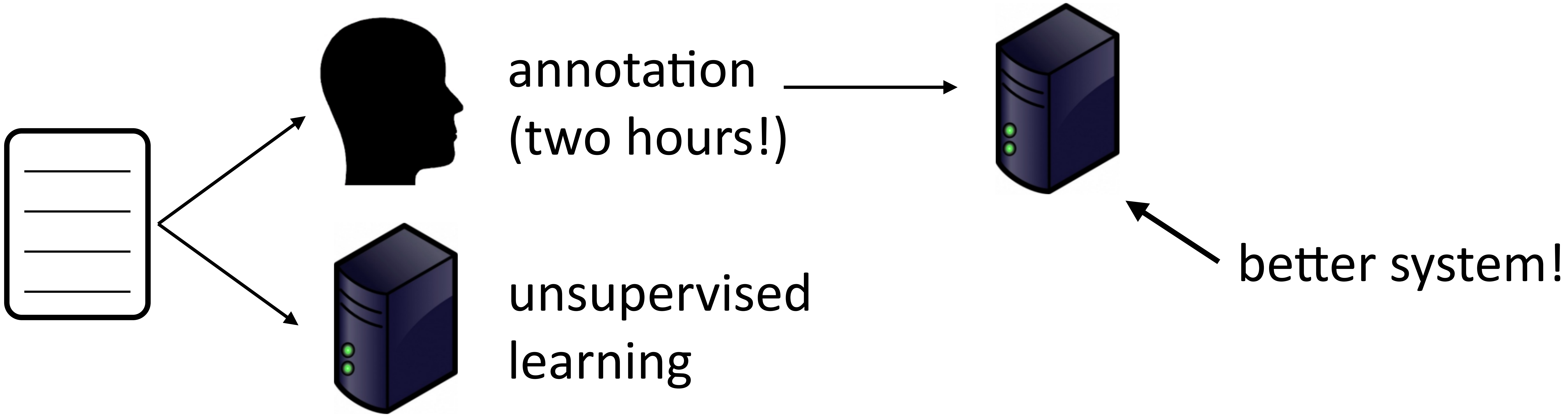

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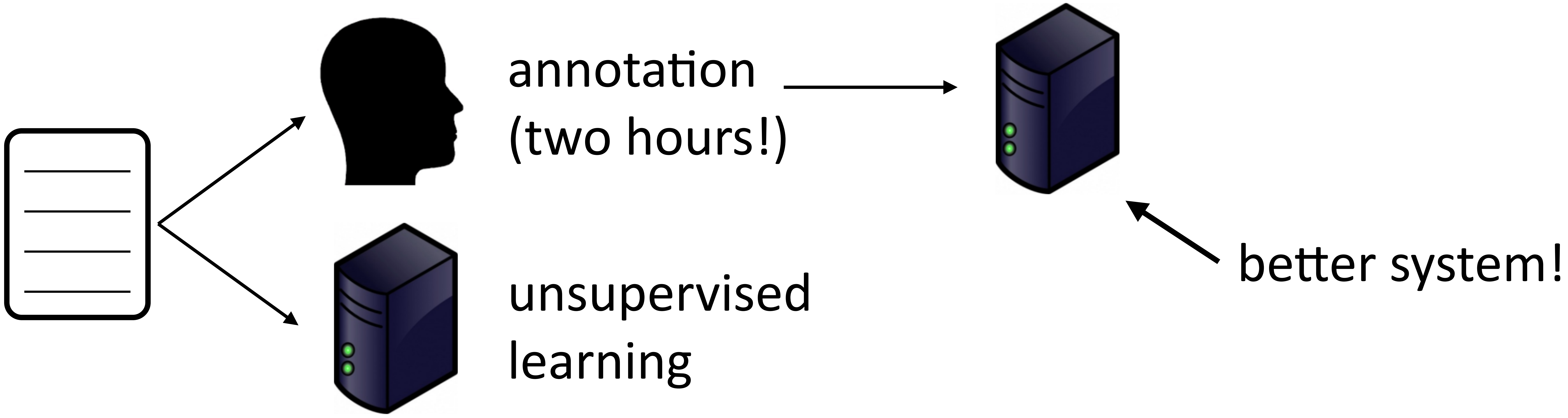

- Even neural nets can do pretty well!

"Learning a Part-of-Speech Tagger from Two Hours of Annotation"
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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

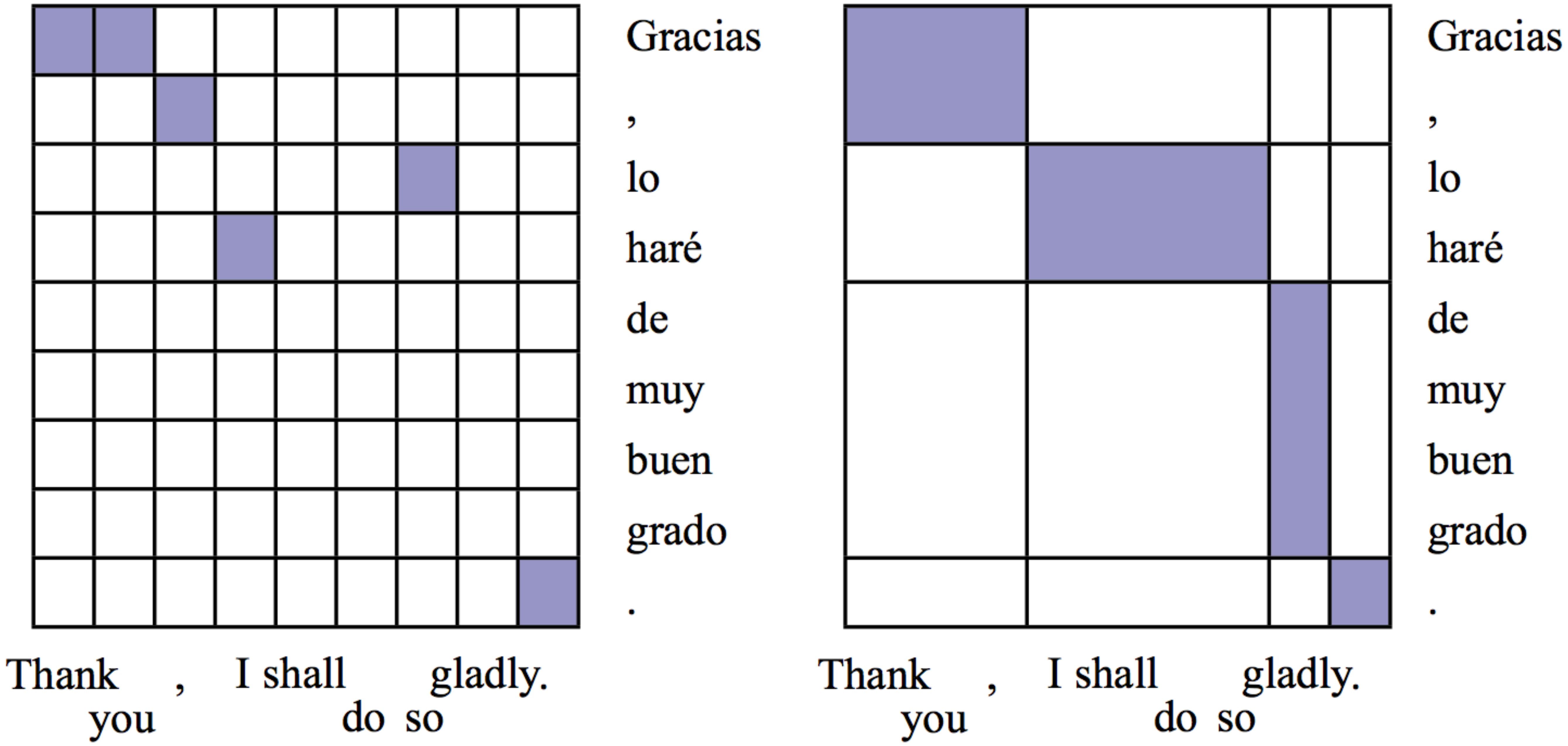
0.001 good

- Model understands some sentiment?

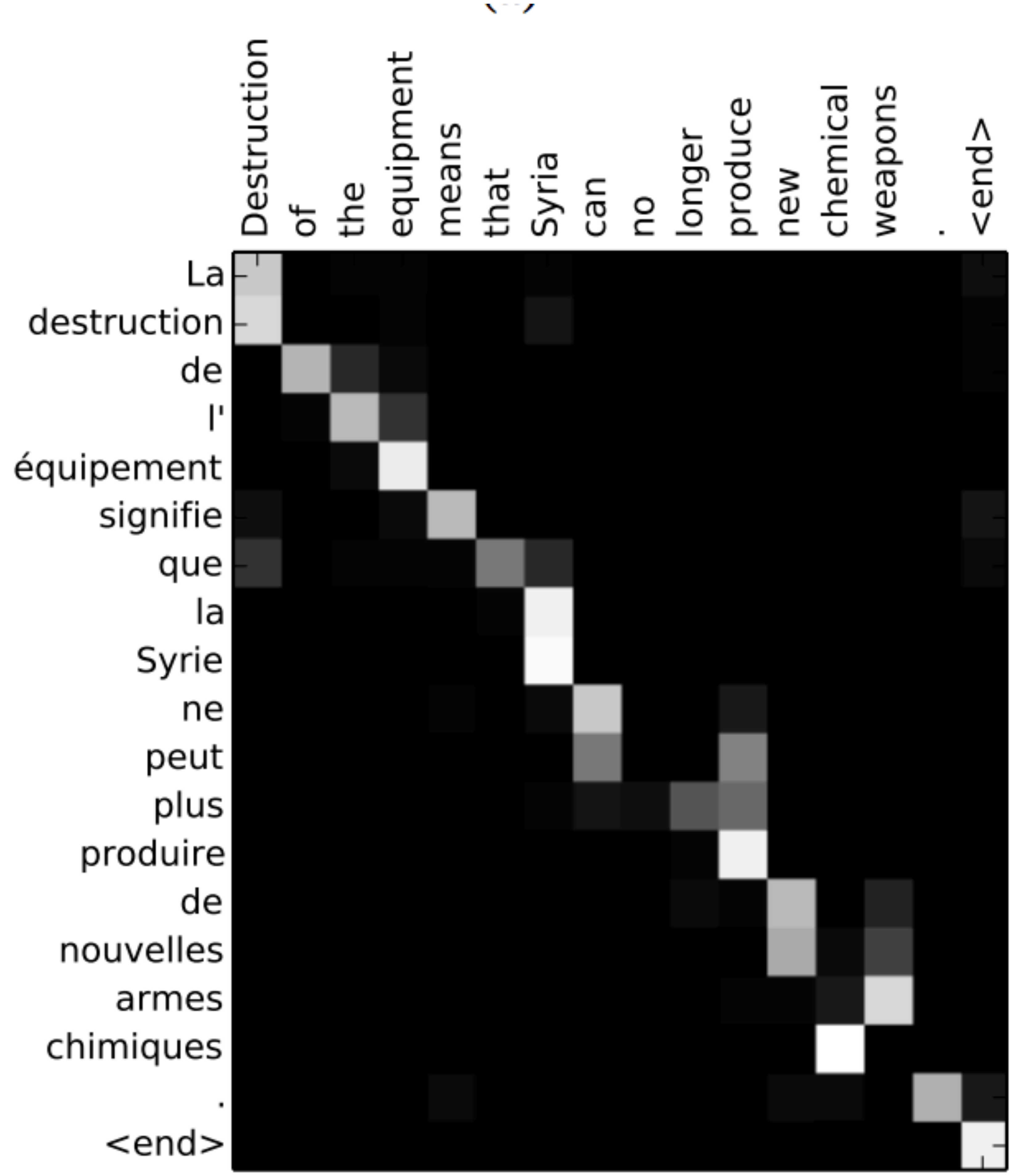
- Train a neural network to do language modeling on massive unlabeled text, fine-tune it to do {tagging, sentiment, question answering, ...}

Peters et al. (2018), Devlin et al. (2019)

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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	CoNLL Avg. F_1
Newswire	
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berkeley	61.24
cort	63.37
deep-coref [conll]	65.39
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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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- 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)

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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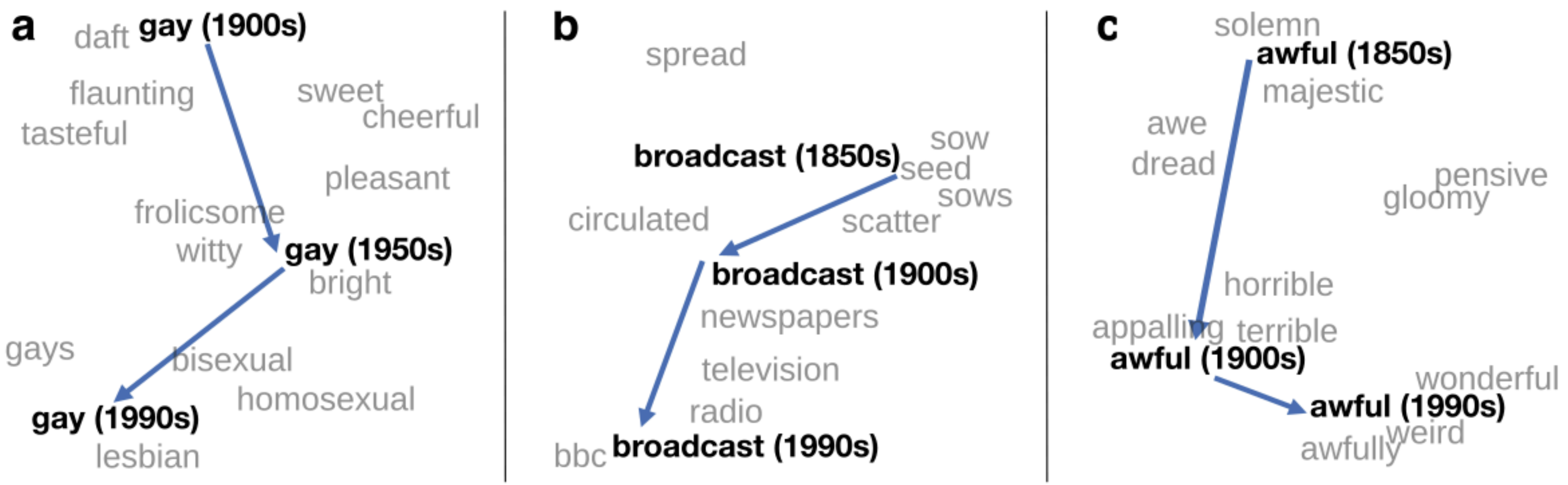

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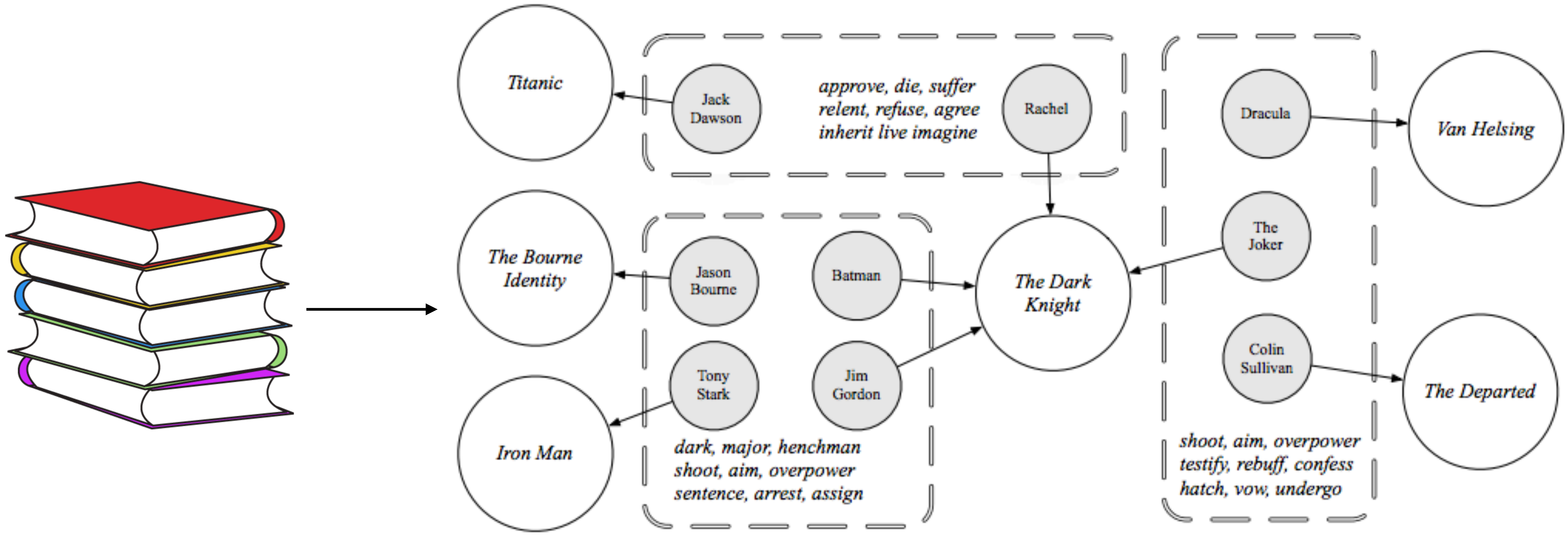

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- Make you a “producer” rather than a “consumer” of NLP tools
  - The three assignments should teach you what you need to know to understand nearly any system in the literature

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- 3 Programming Assignments
  - Implementation-oriented
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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.
  - 4 page report + final project presentation.