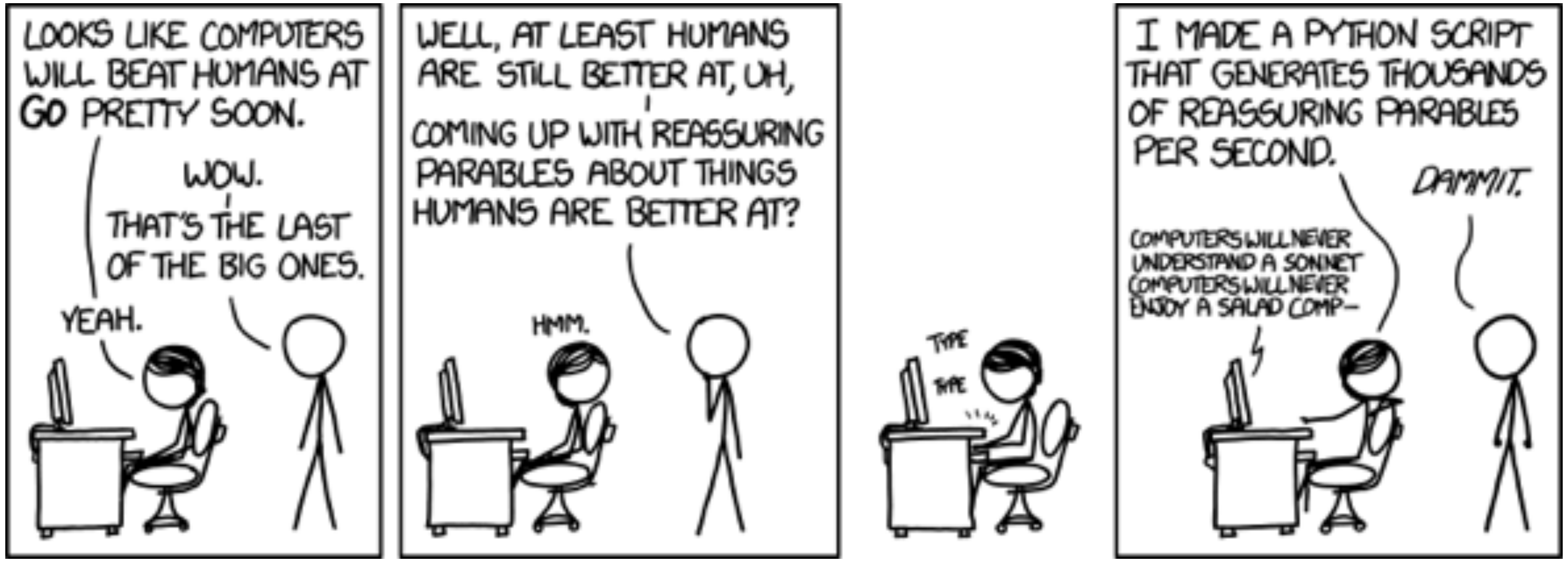
5525: Speech and Language Processing



Alan Ritter

(many slides from Greg Durrett)

Administrivia

- Course website: http://aritter.github.io/courses/5525_spring19.html
- Piazza: link on the course website
- My office hours: Friday 4-5pm DL 595
- TA: Ashutosh Baheti; Office hours: Wednesday 1-2pm, DL 574

Course Requirements

- Probability
- Linear Algebra
- 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!

Enrollment

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  - Please look at the assignment well before then

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  - Please look at the assignment well before then
  - If this seems like it’ll be challenging for you, come and talk to me (this is smaller-scale than the later assignments, which are smaller-scale than the final project)

Texts

- 2 great 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

What’s the goal of NLP?

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- Be able to solve problems that require deep understanding of text

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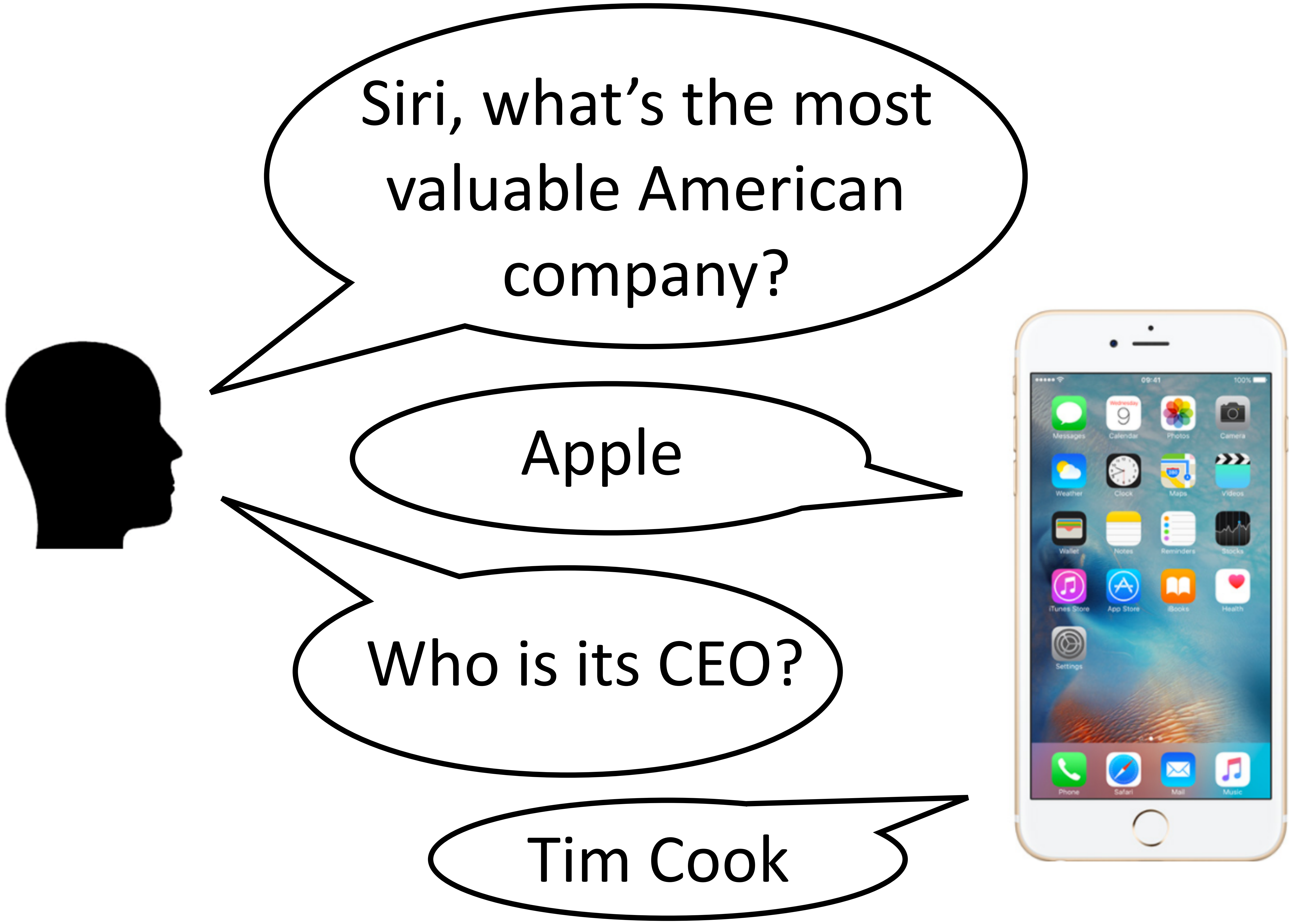

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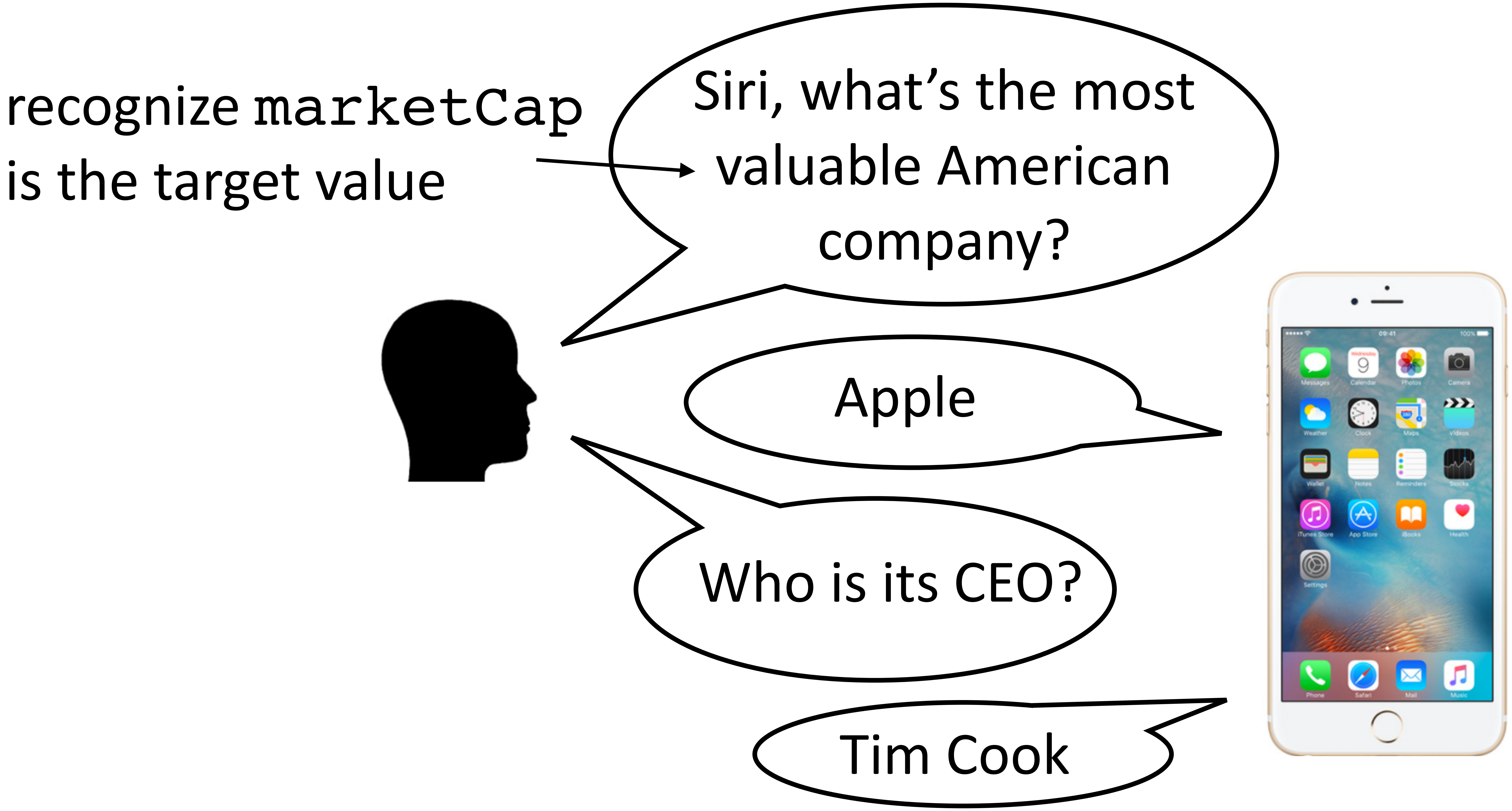

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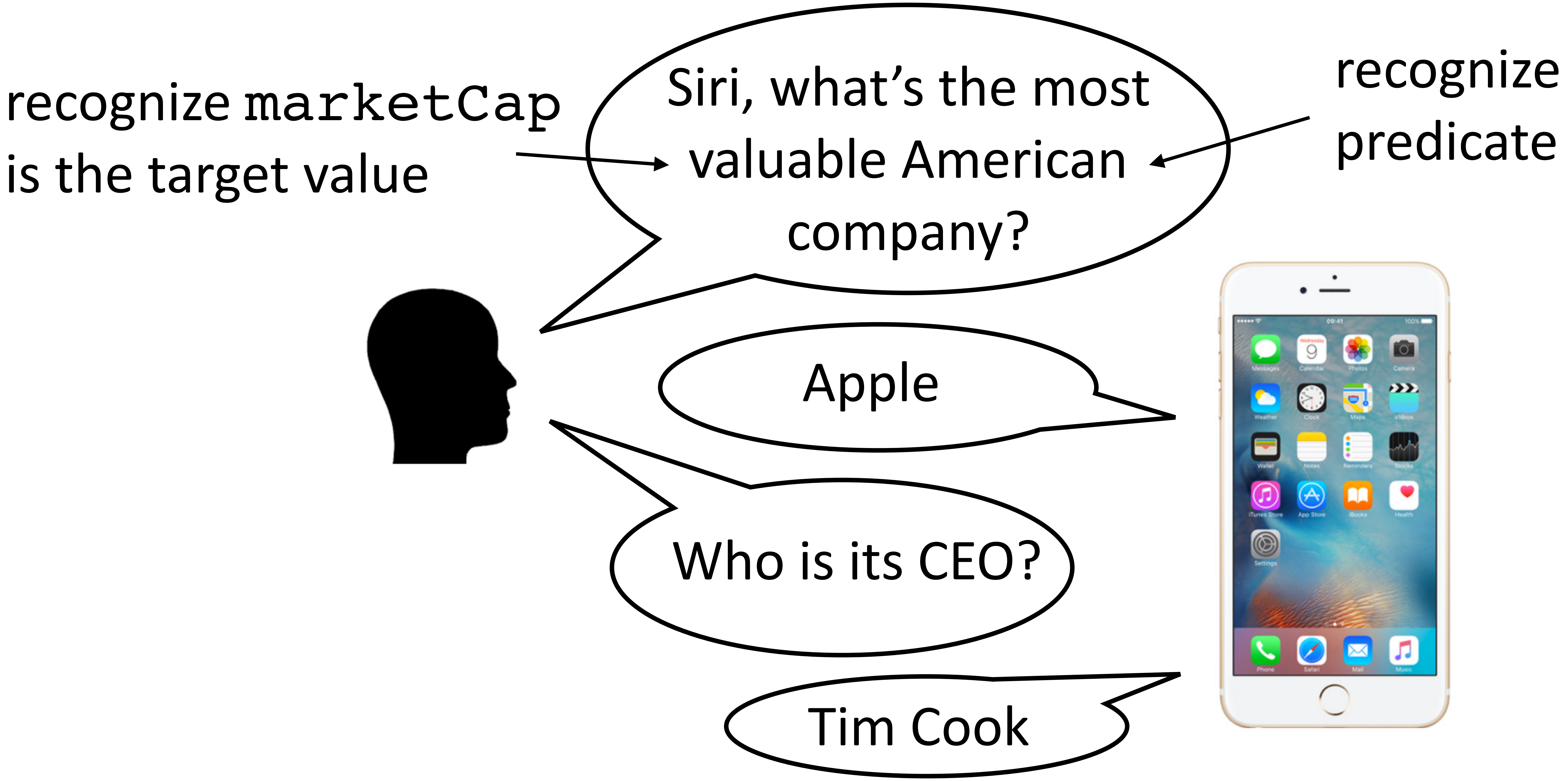

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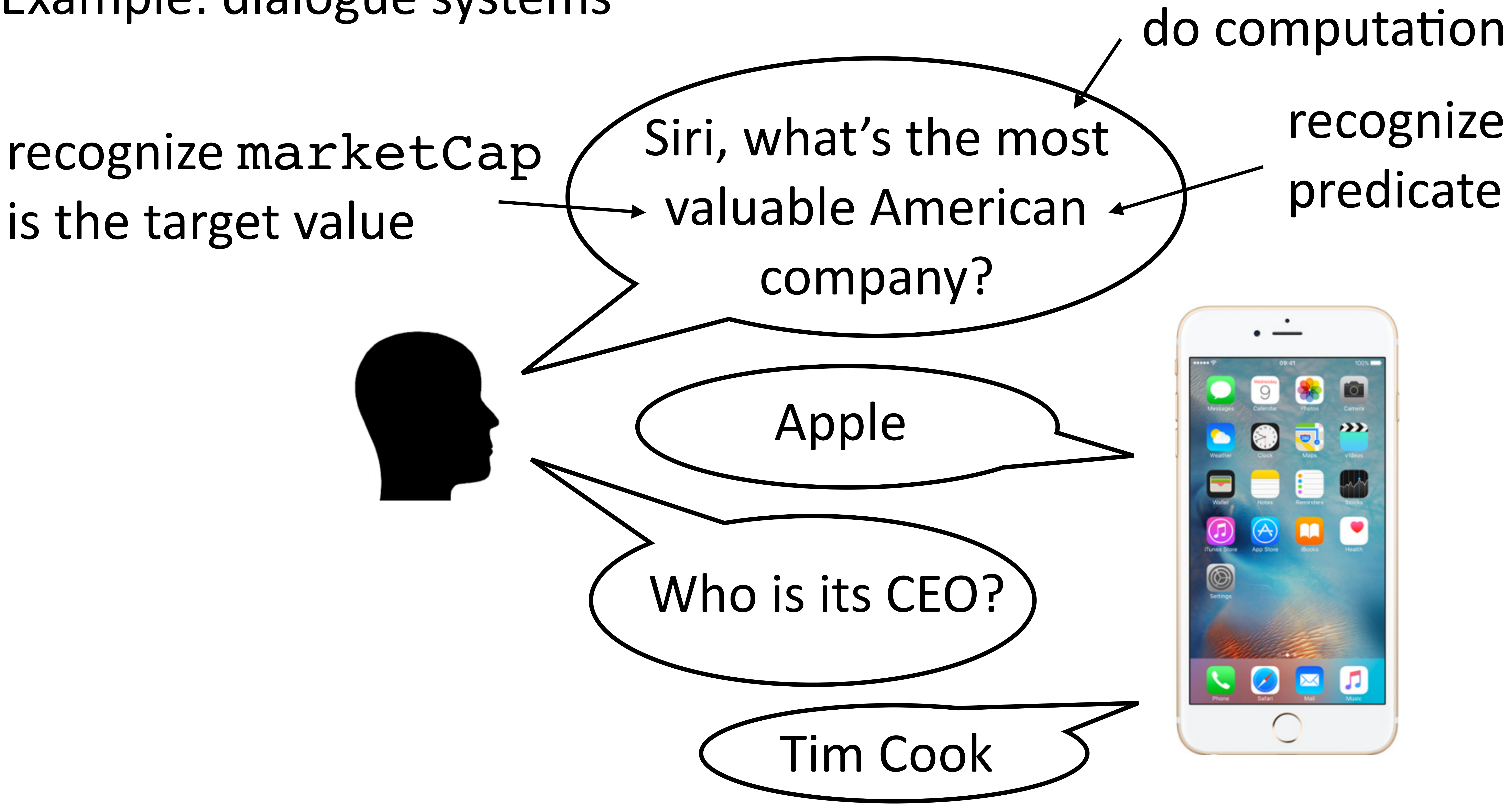

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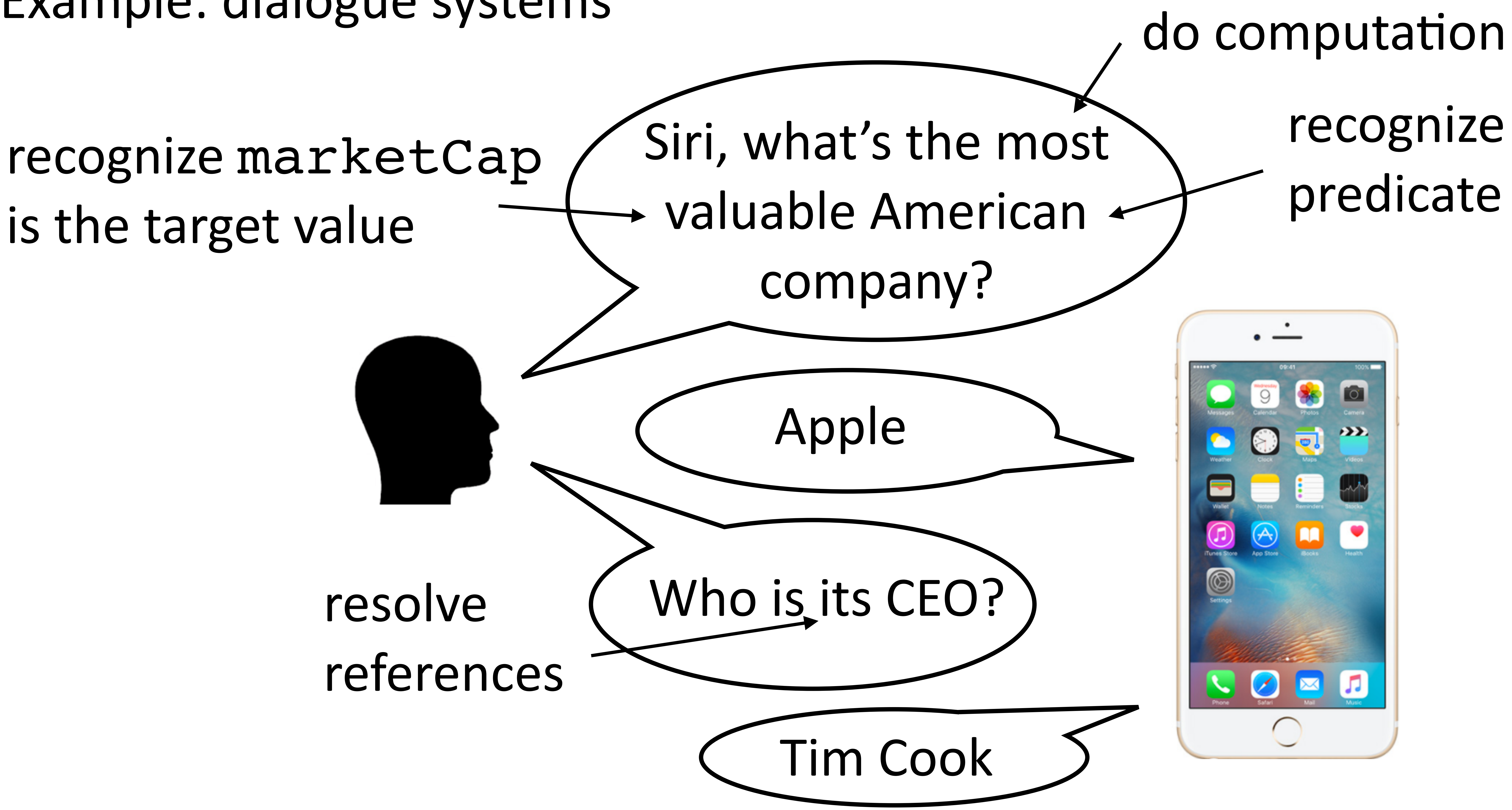

Automatic Summarization

Automatic Summarization

POLITICS

Google Critic Ousted From Think Tank Funded by the Tech Giant

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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paraphrase to provide clarity

Machine Translation

People’s Daily, August 30, 2017

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

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NLP Analysis Pipeline

NLP Analysis Pipeline

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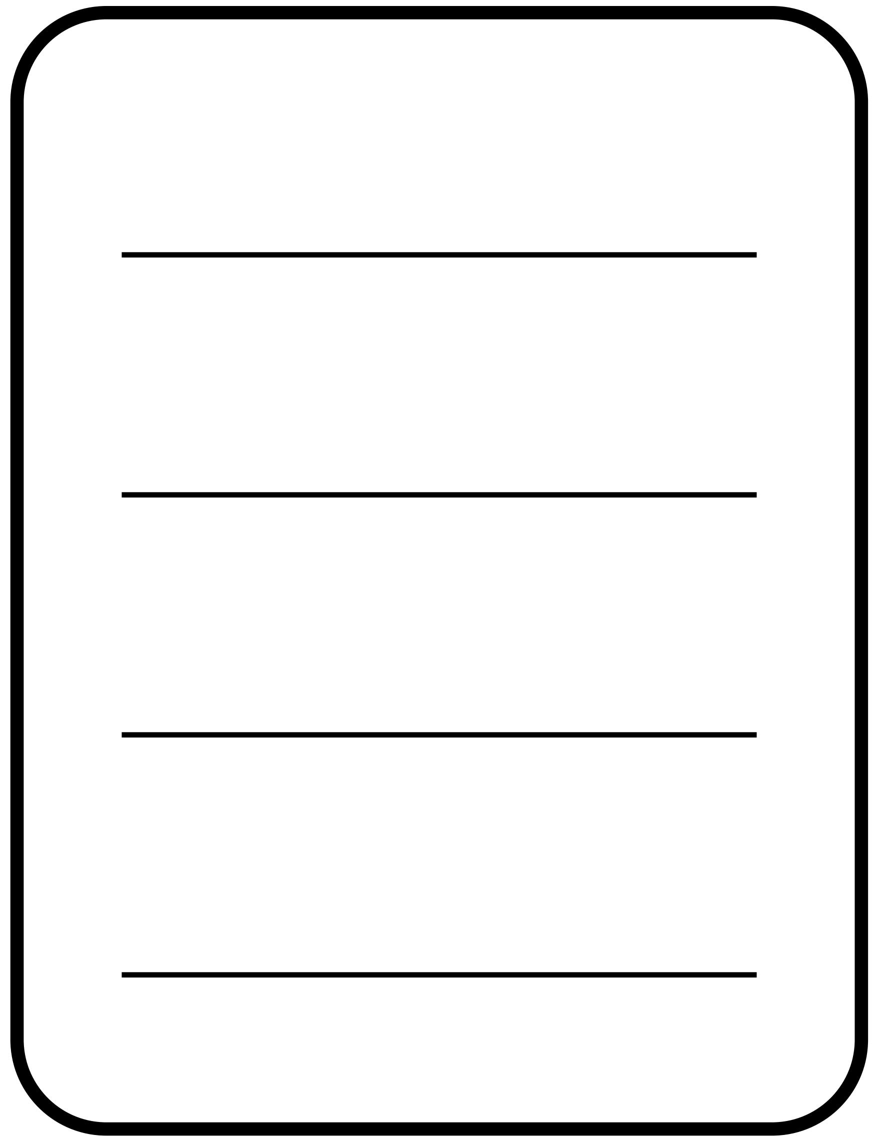

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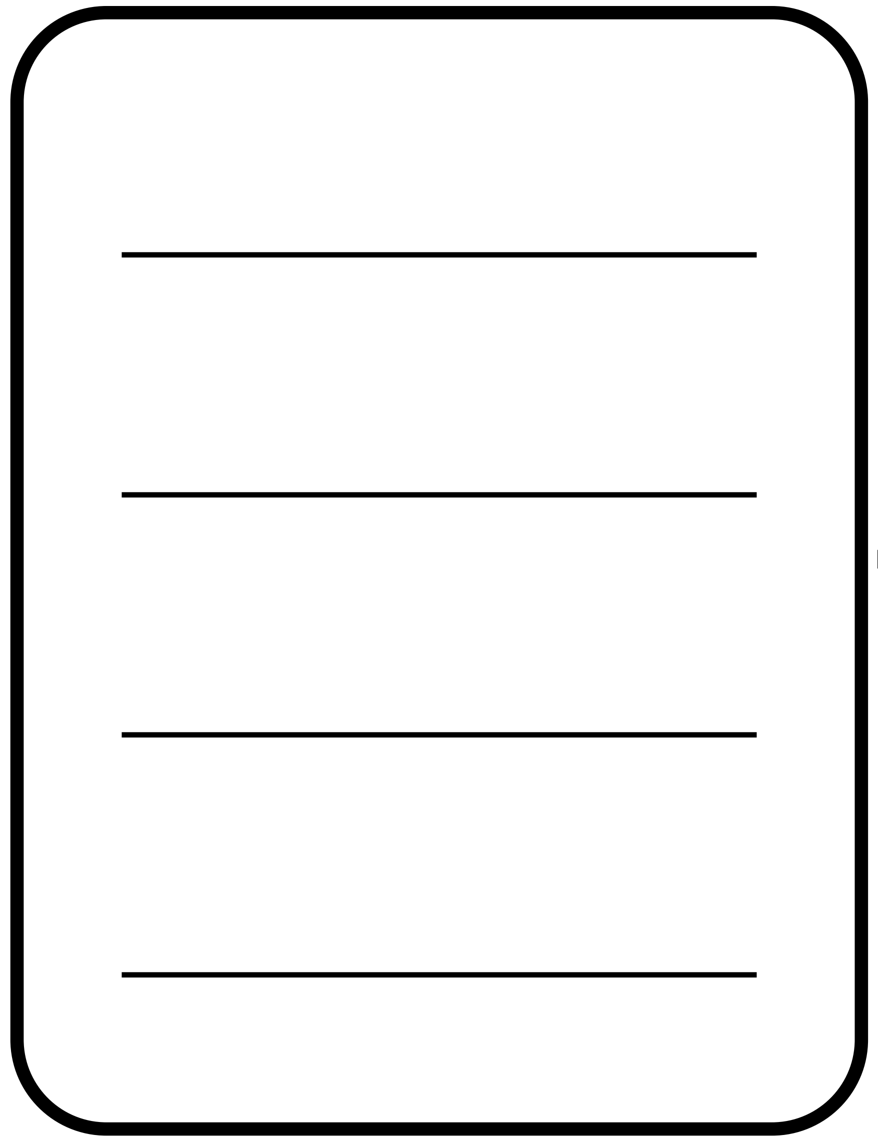

Text Analysis

Syntactic parses

Coreference resolution

Entity disambiguation

Discourse analysis

NLP Analysis Pipeline

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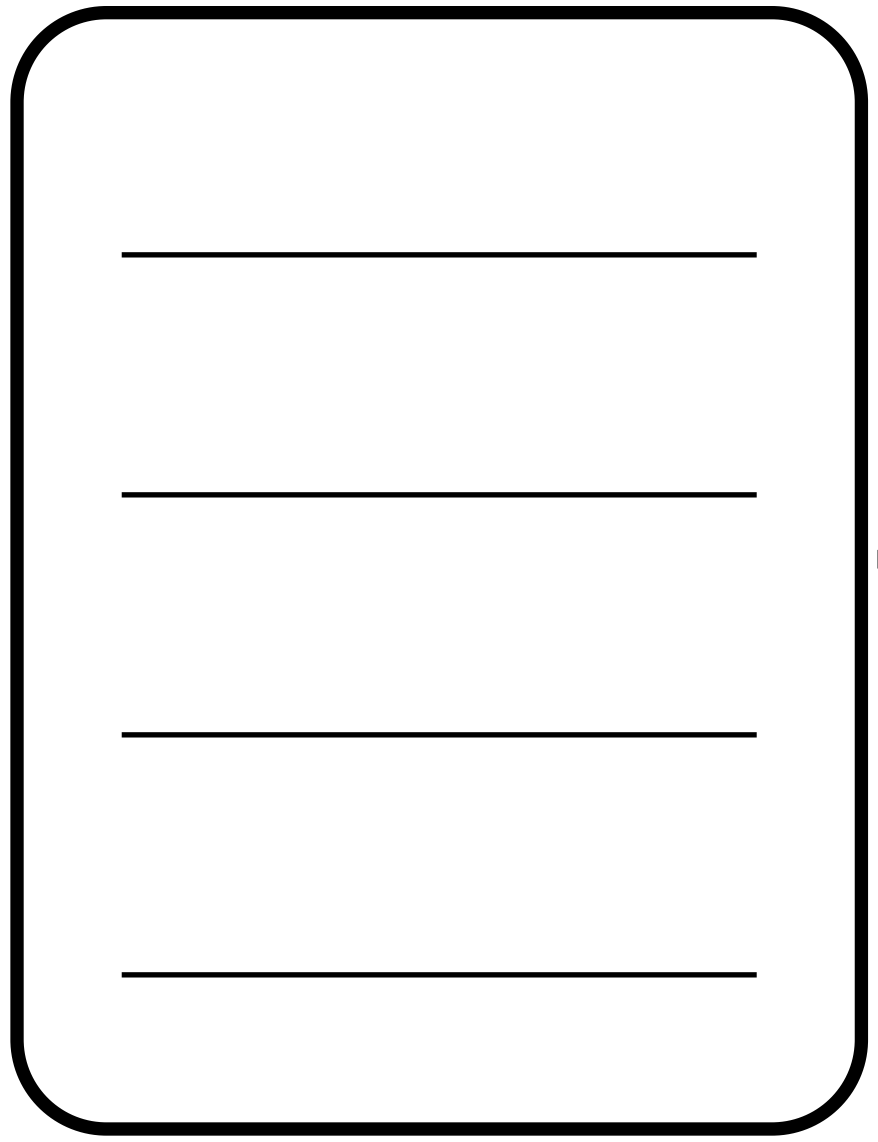

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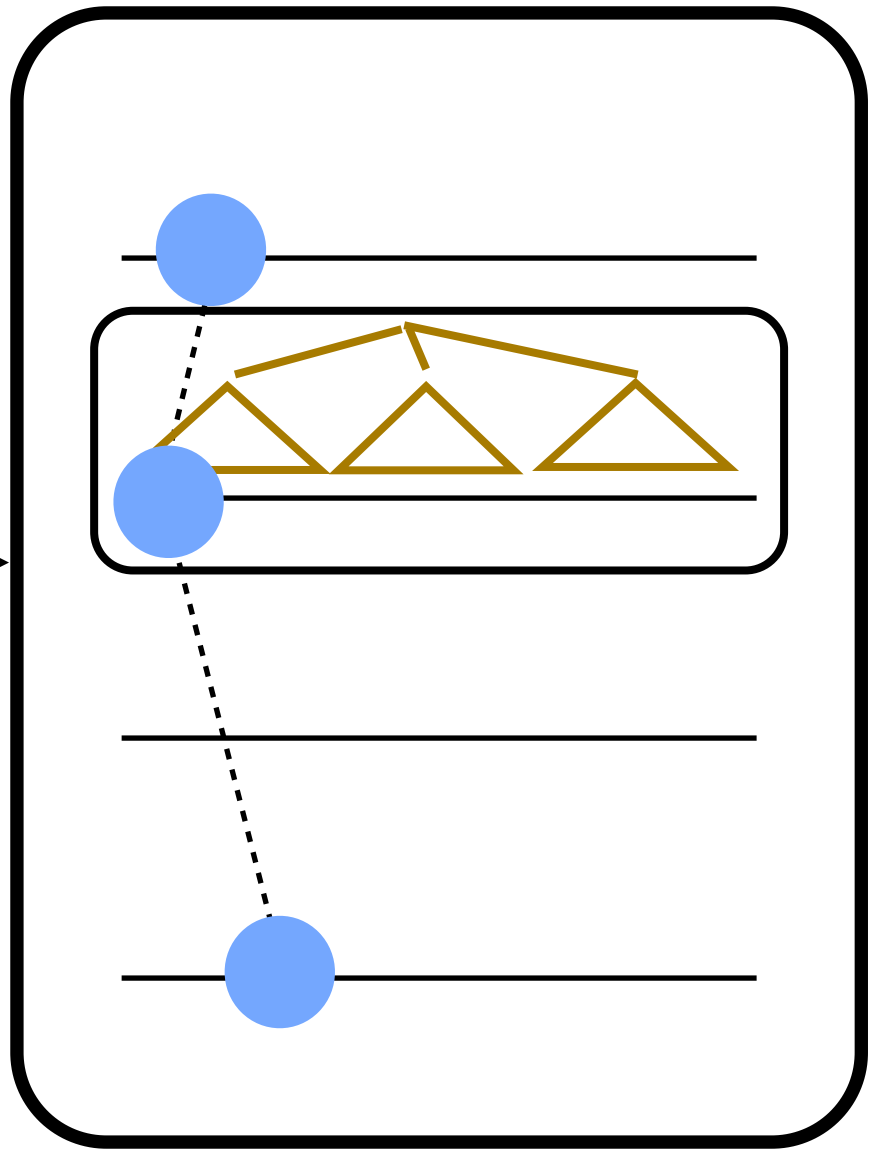

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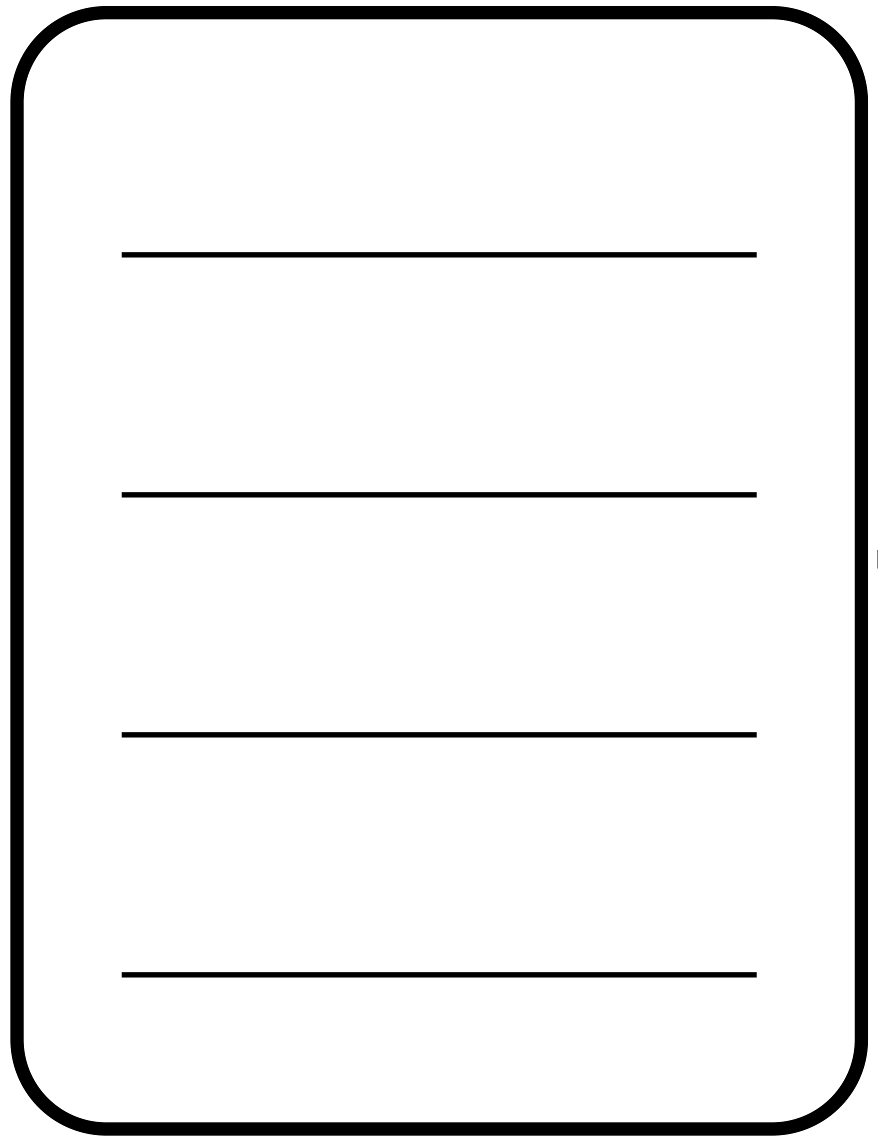

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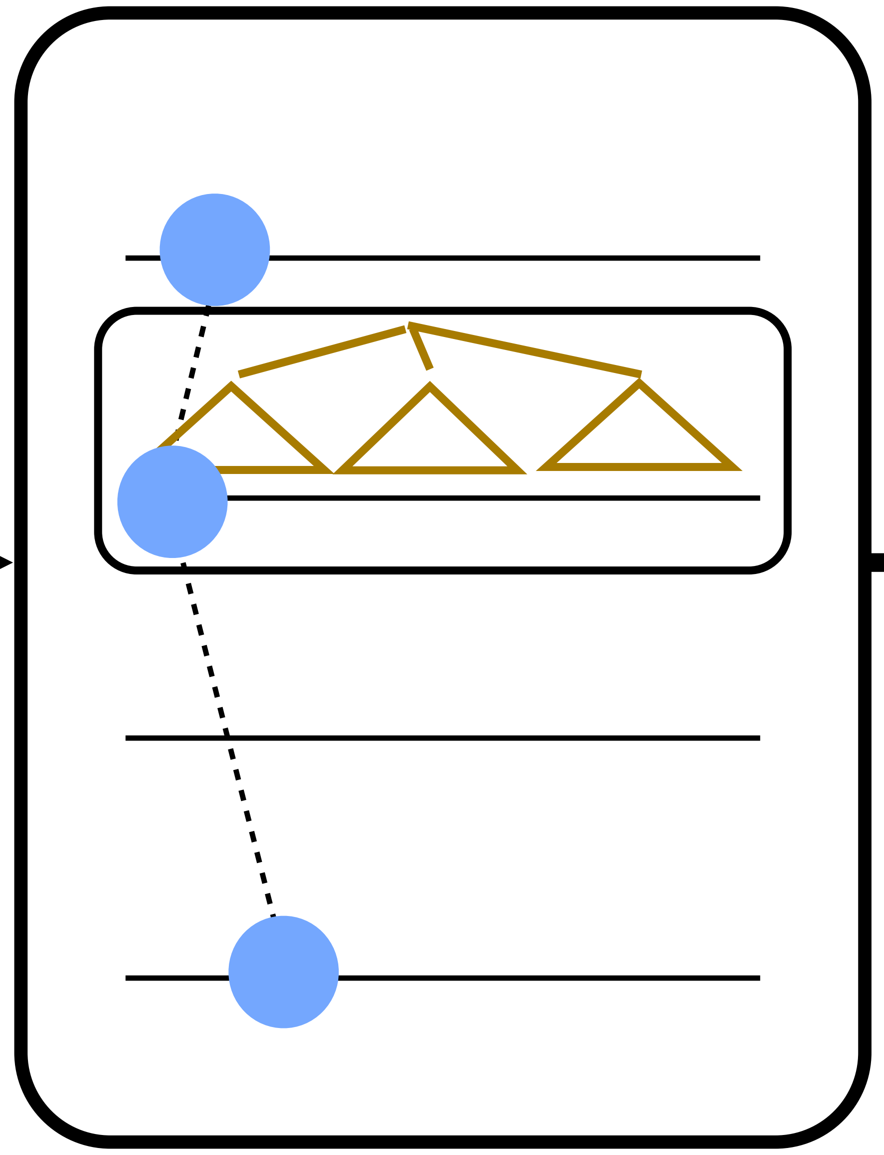
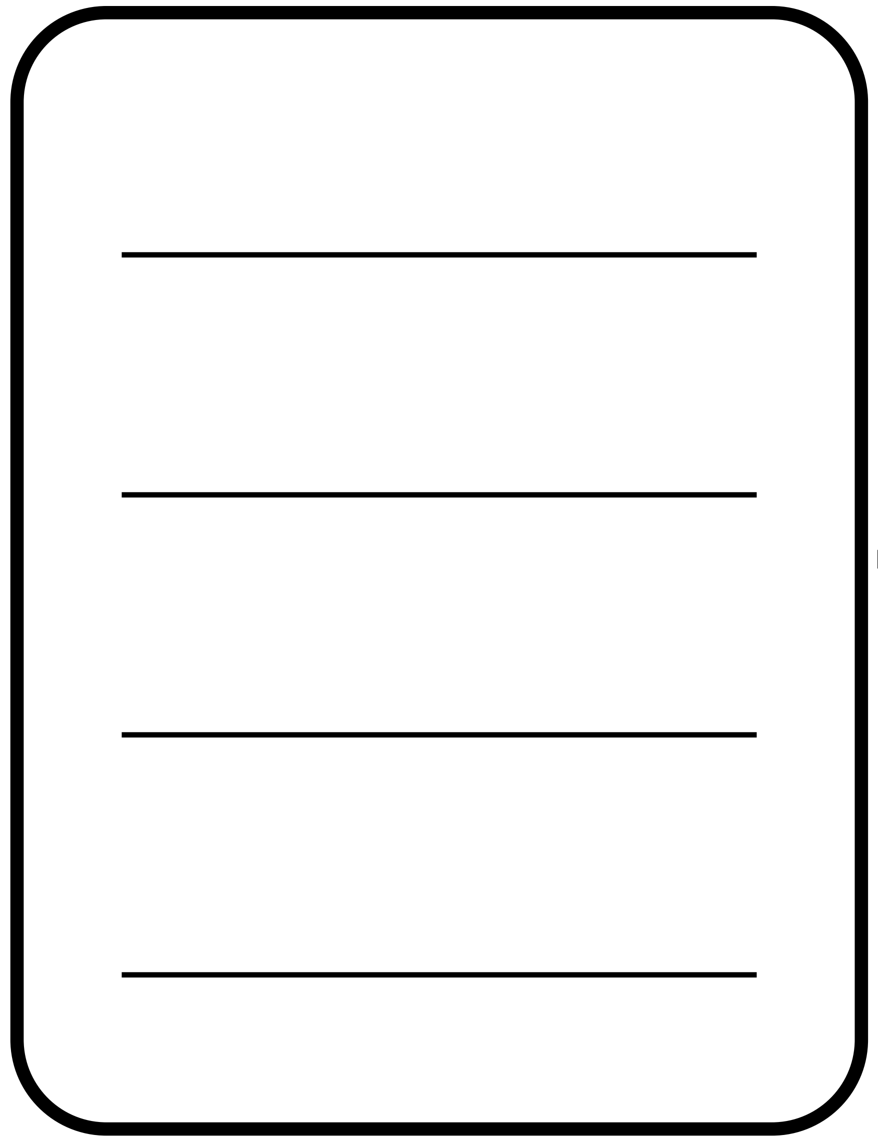


Applications

NLP Analysis Pipeline

Text



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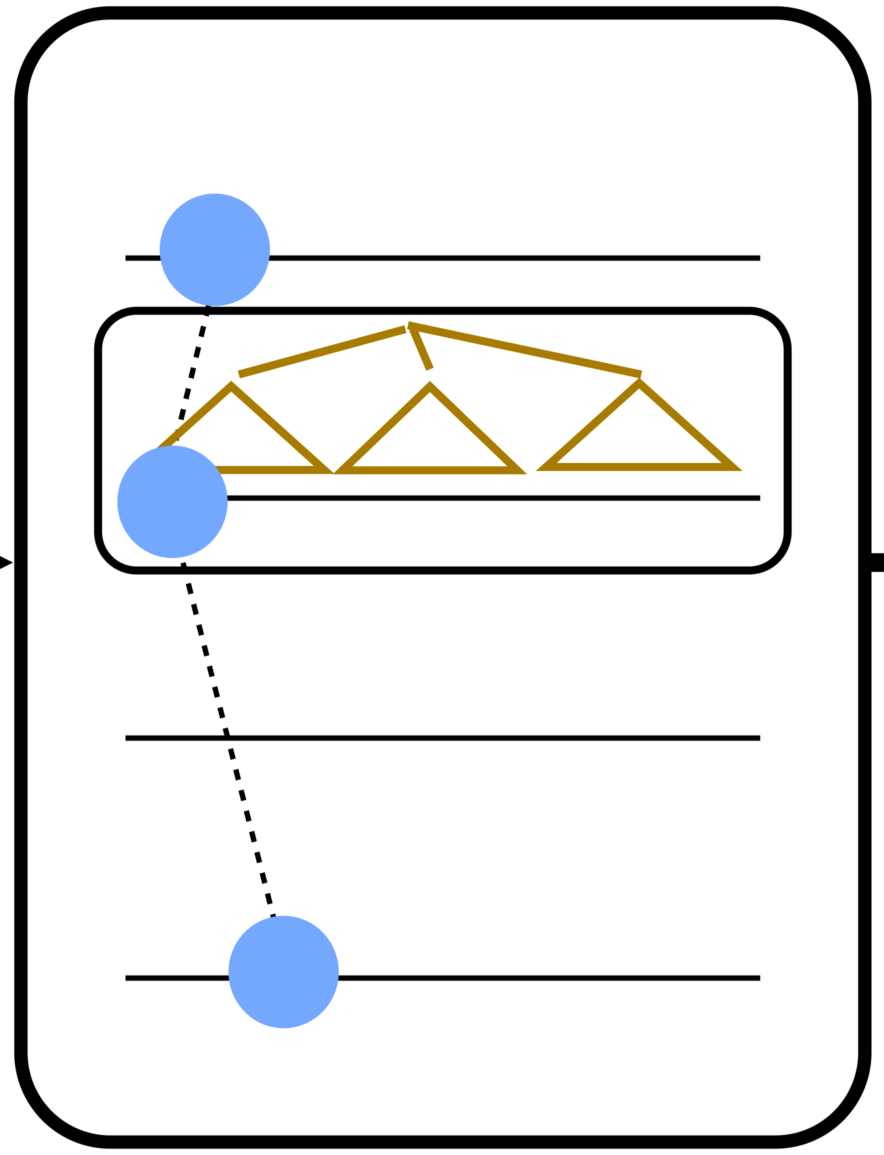
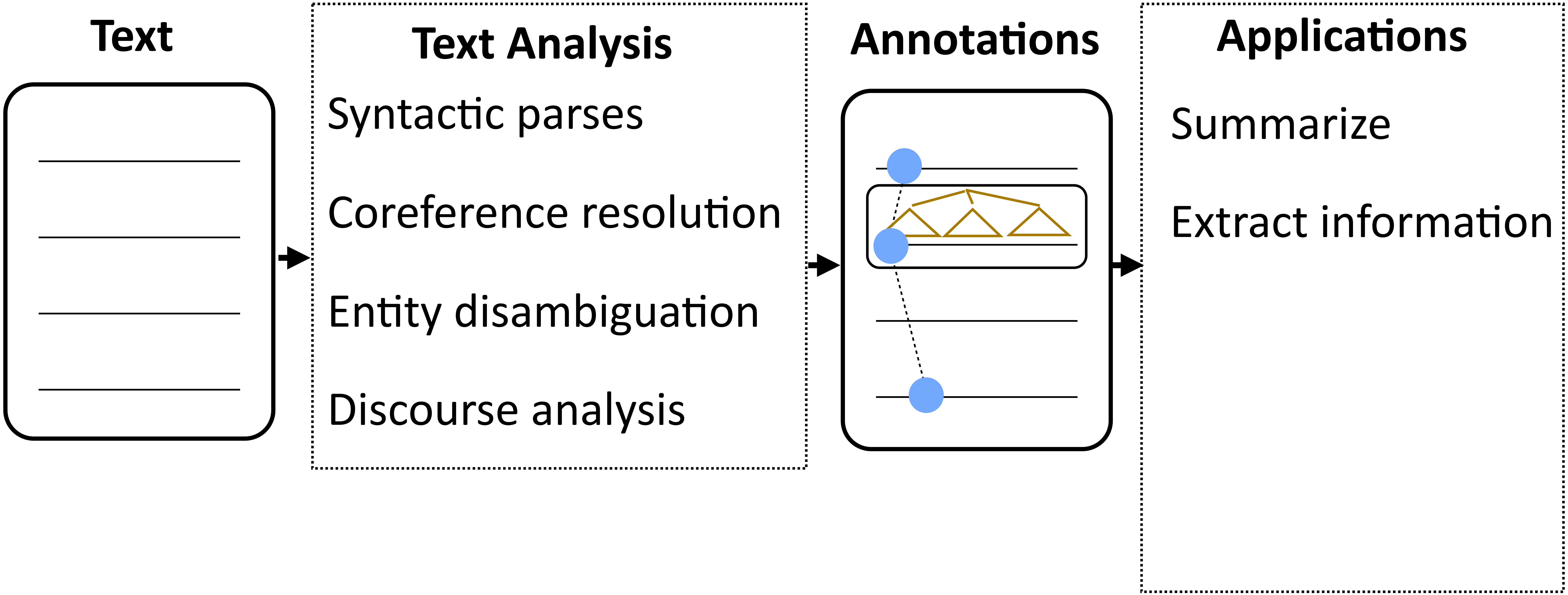


Applications

Summarize

NLP Analysis Pipeline



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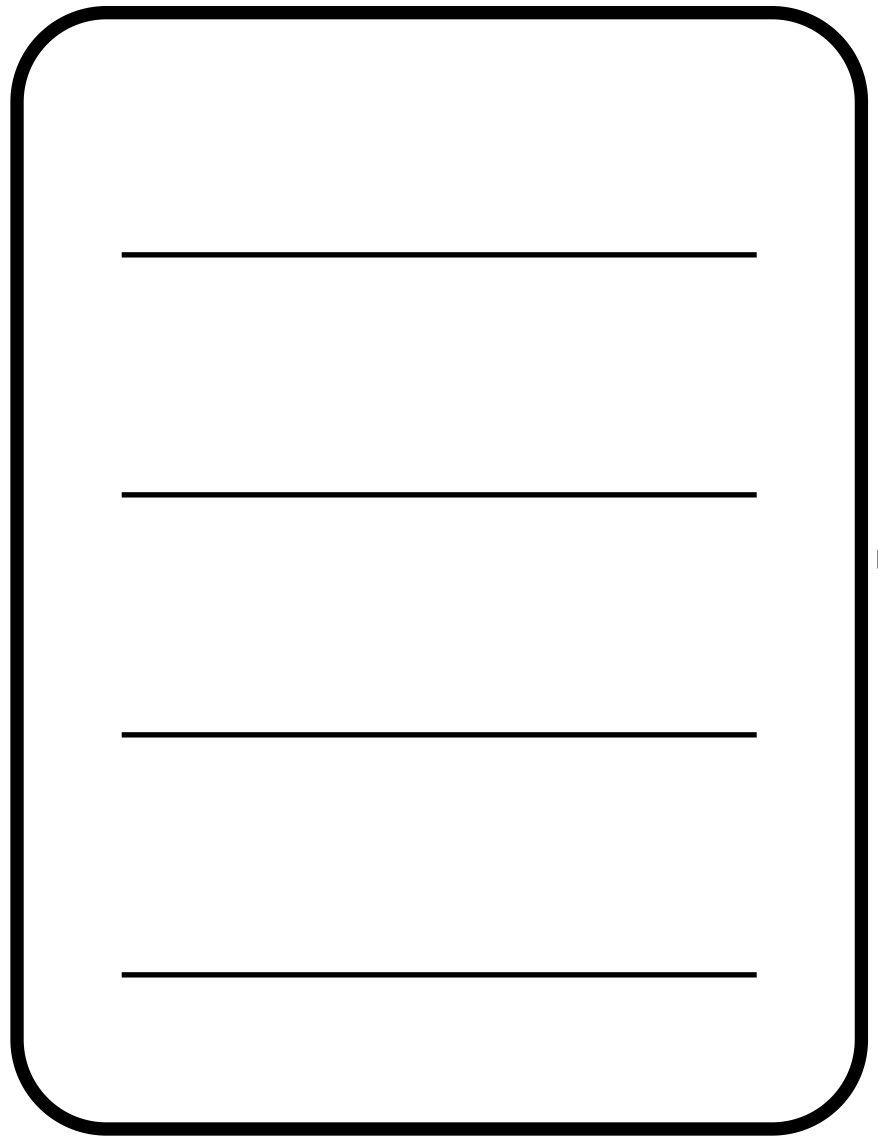

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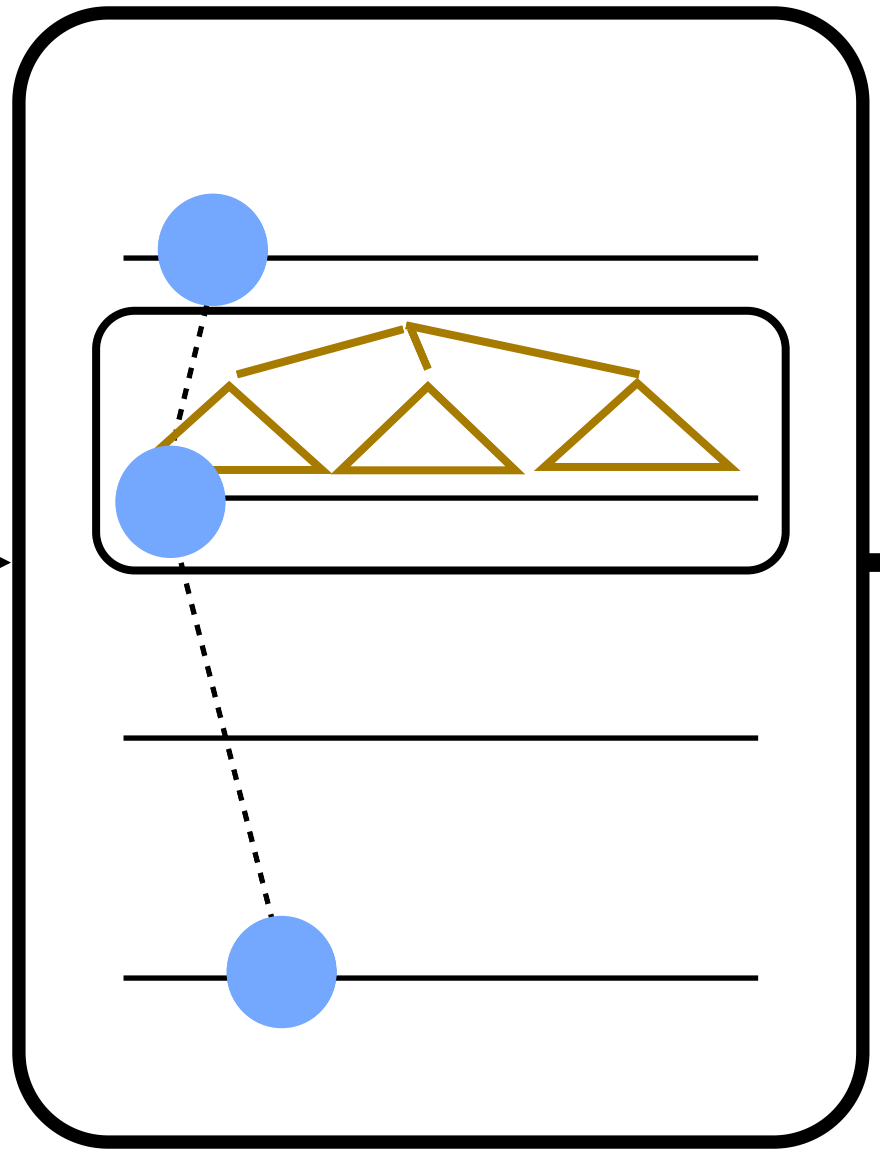


Applications

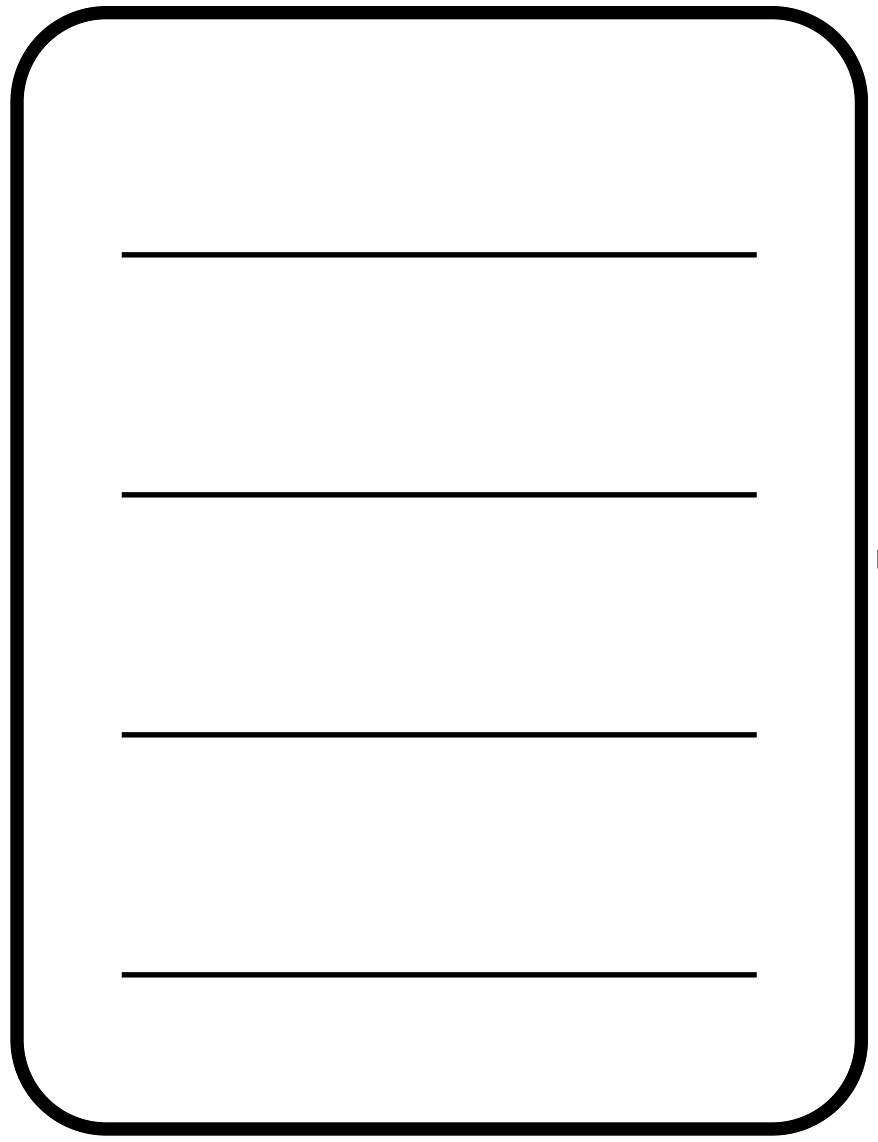
Summarize

Extract information

Answer questions

NLP Analysis Pipeline

Text



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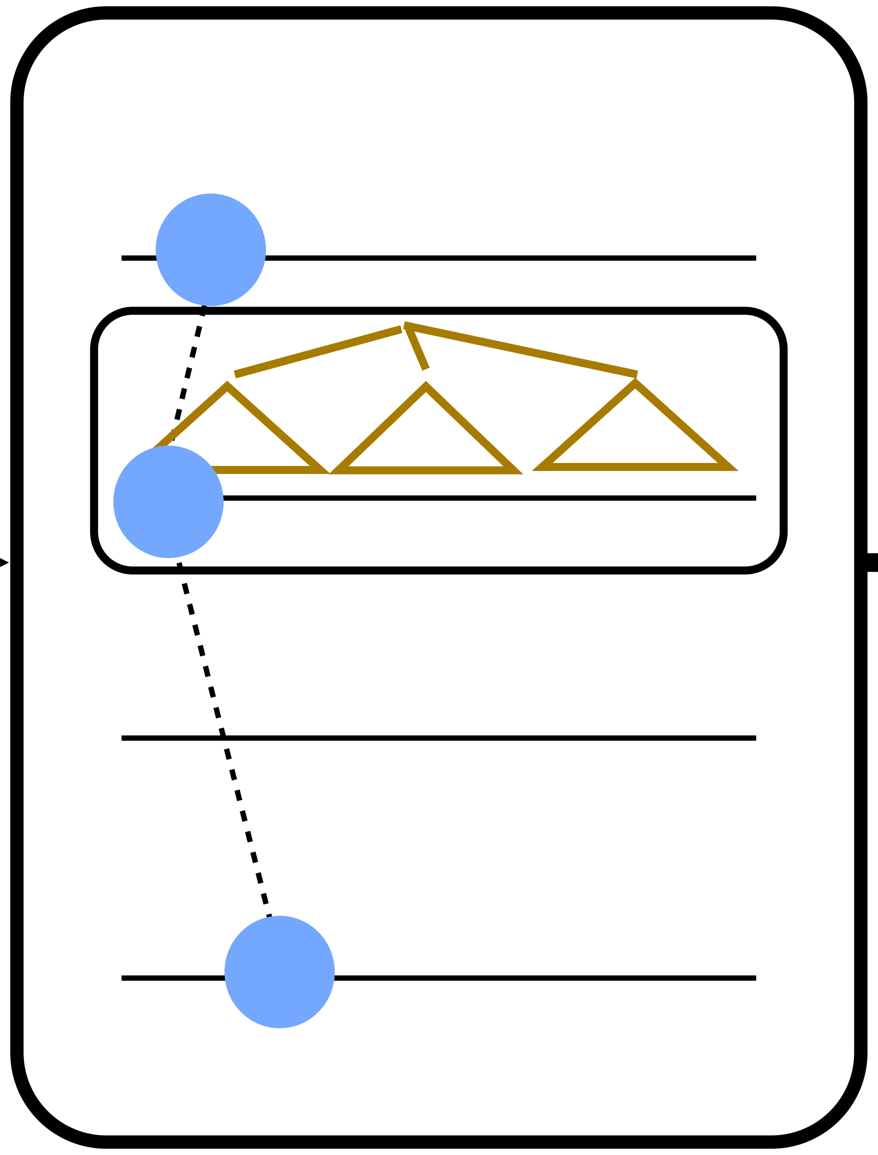


Applications

Summarize

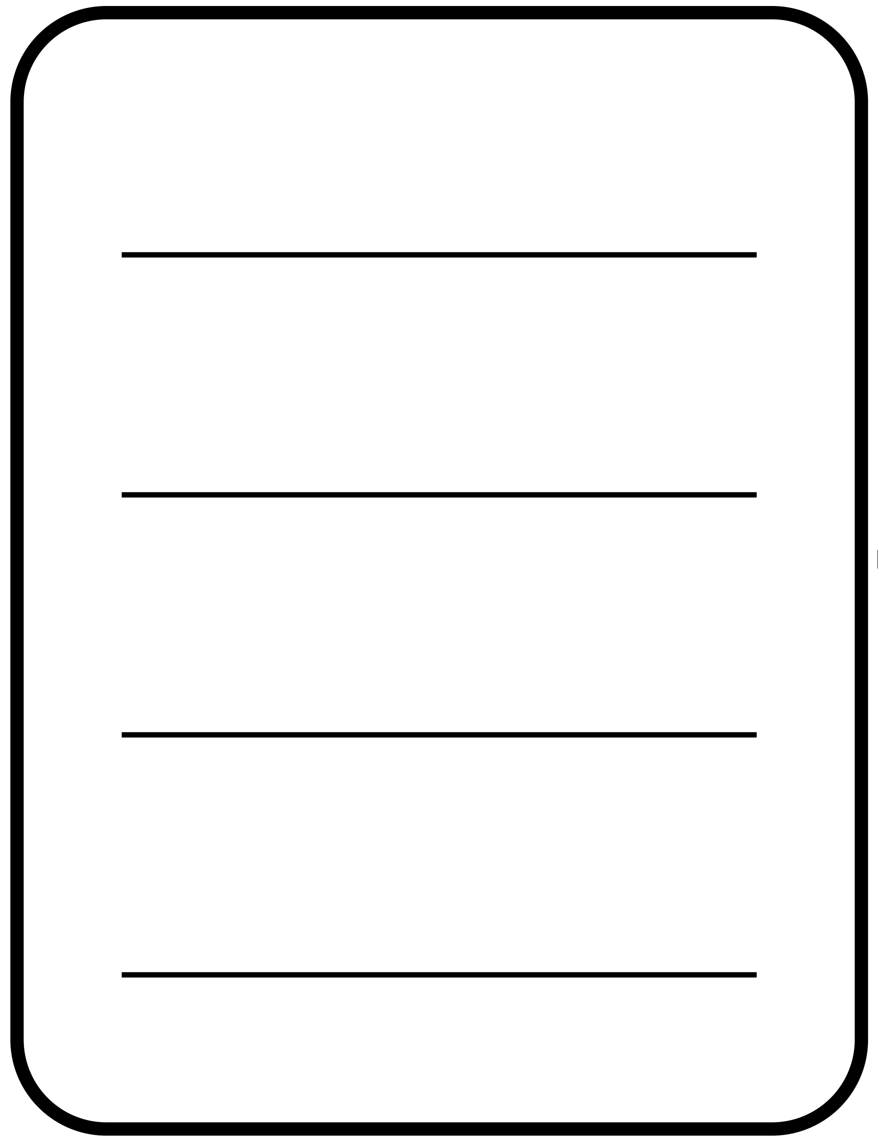
Extract information

Answer questions

Identify sentiment

NLP Analysis Pipeline

Text



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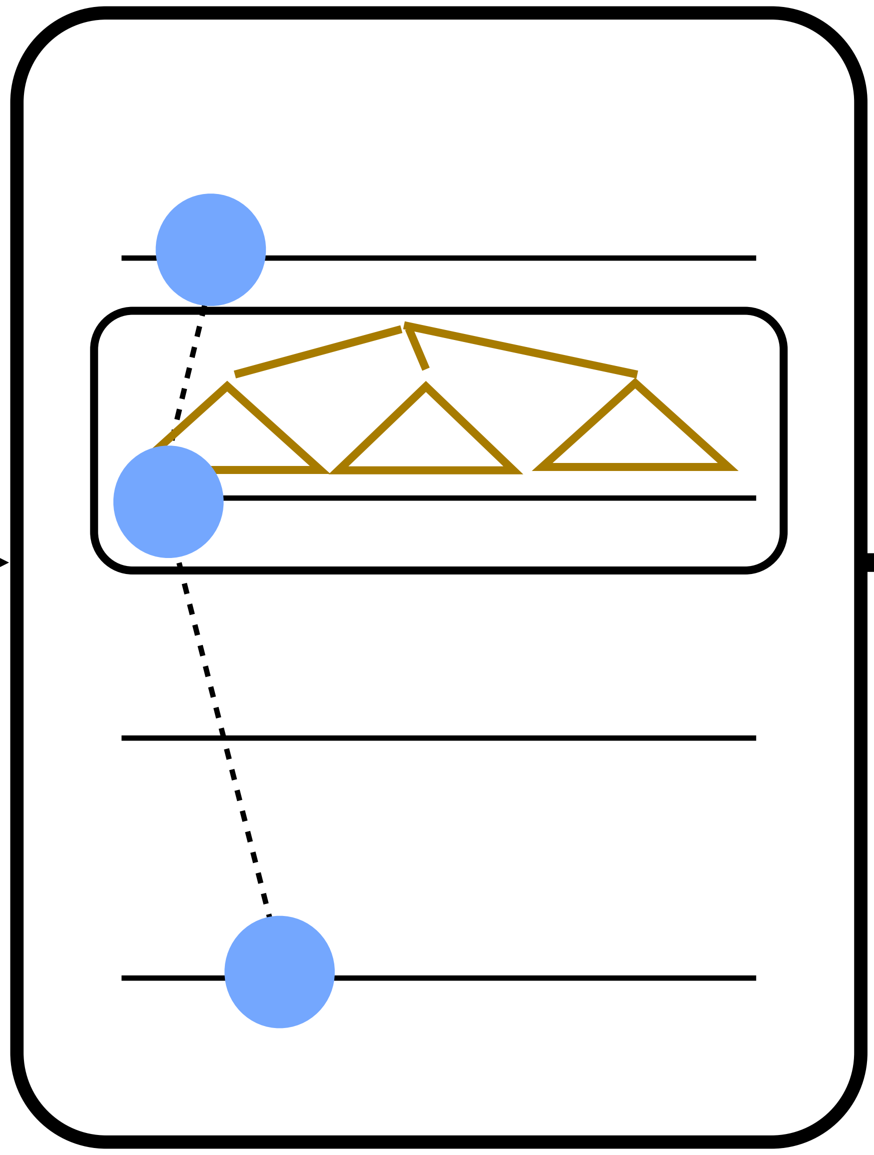

Applications

Summarize

Extract information

Answer questions

Identify sentiment

Translate

NLP Analysis Pipeline

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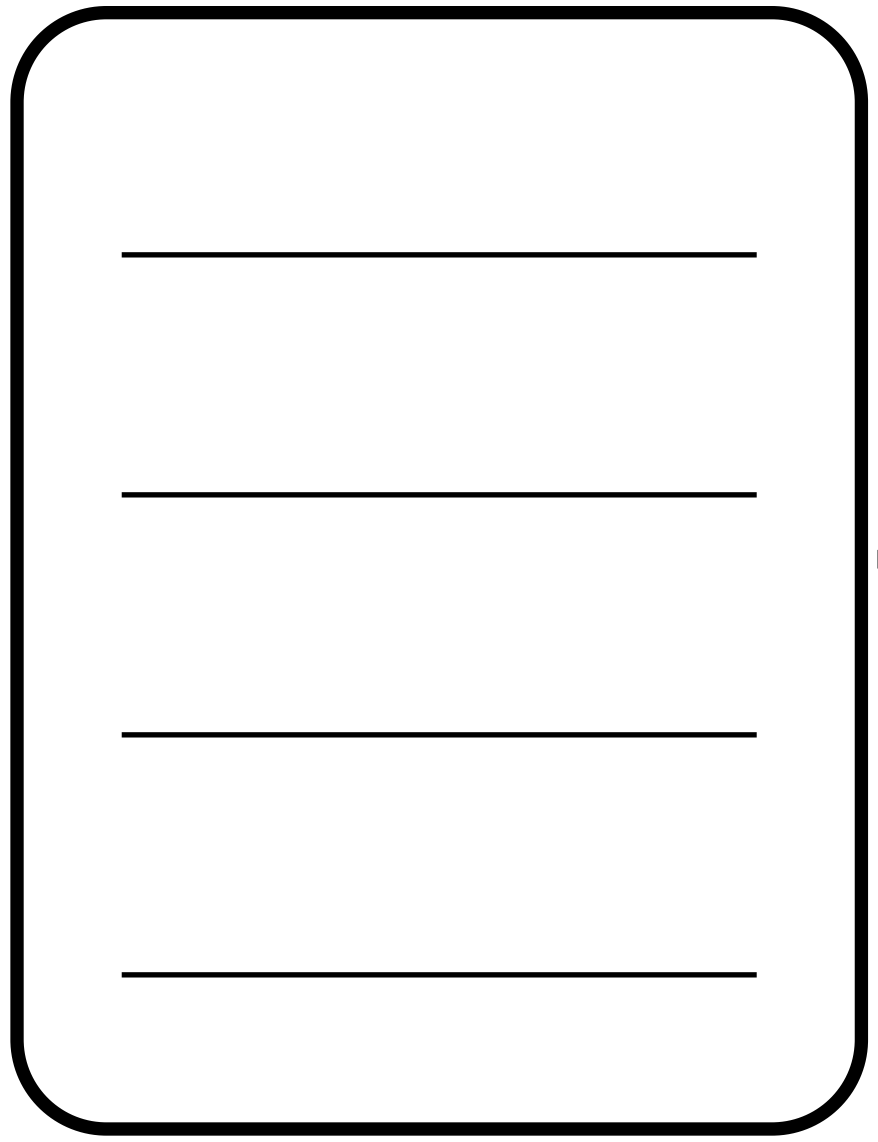

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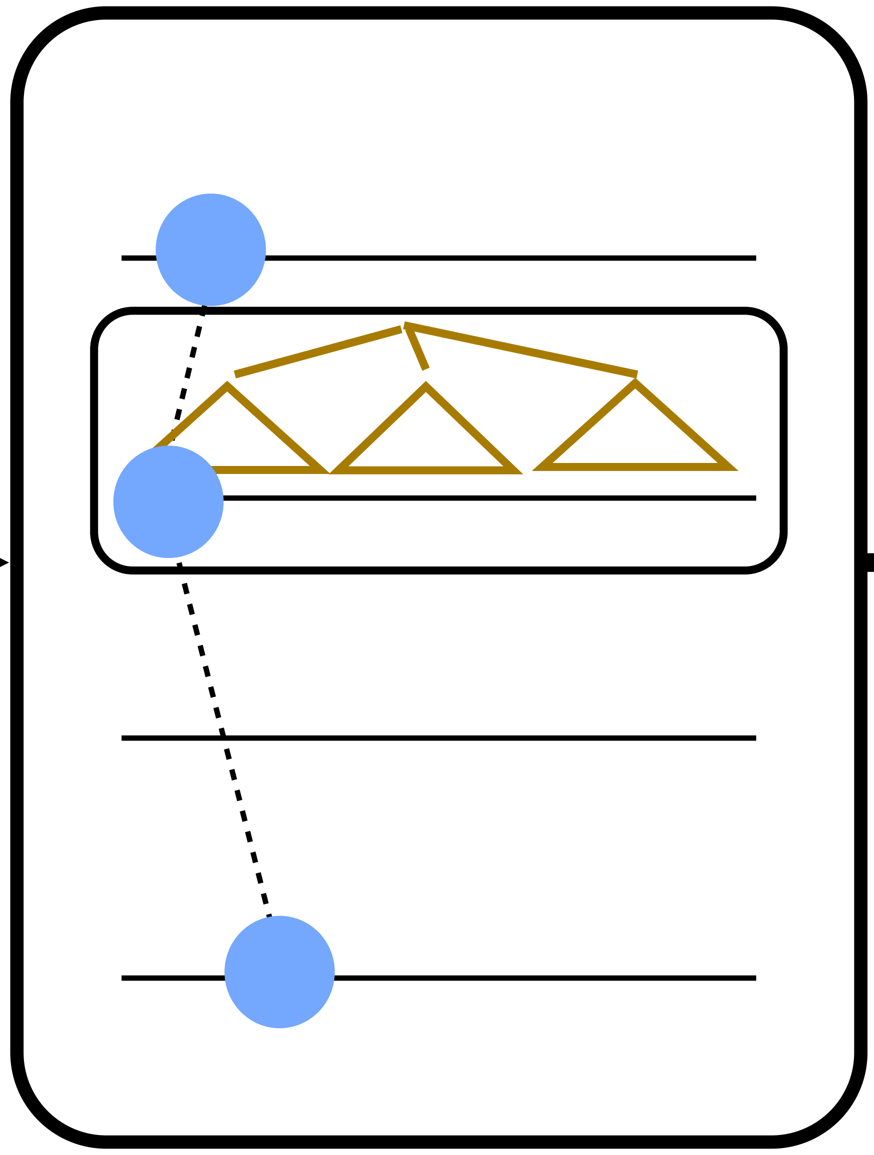

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Summarize

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- NLP is about building these pieces!

NLP Analysis Pipeline

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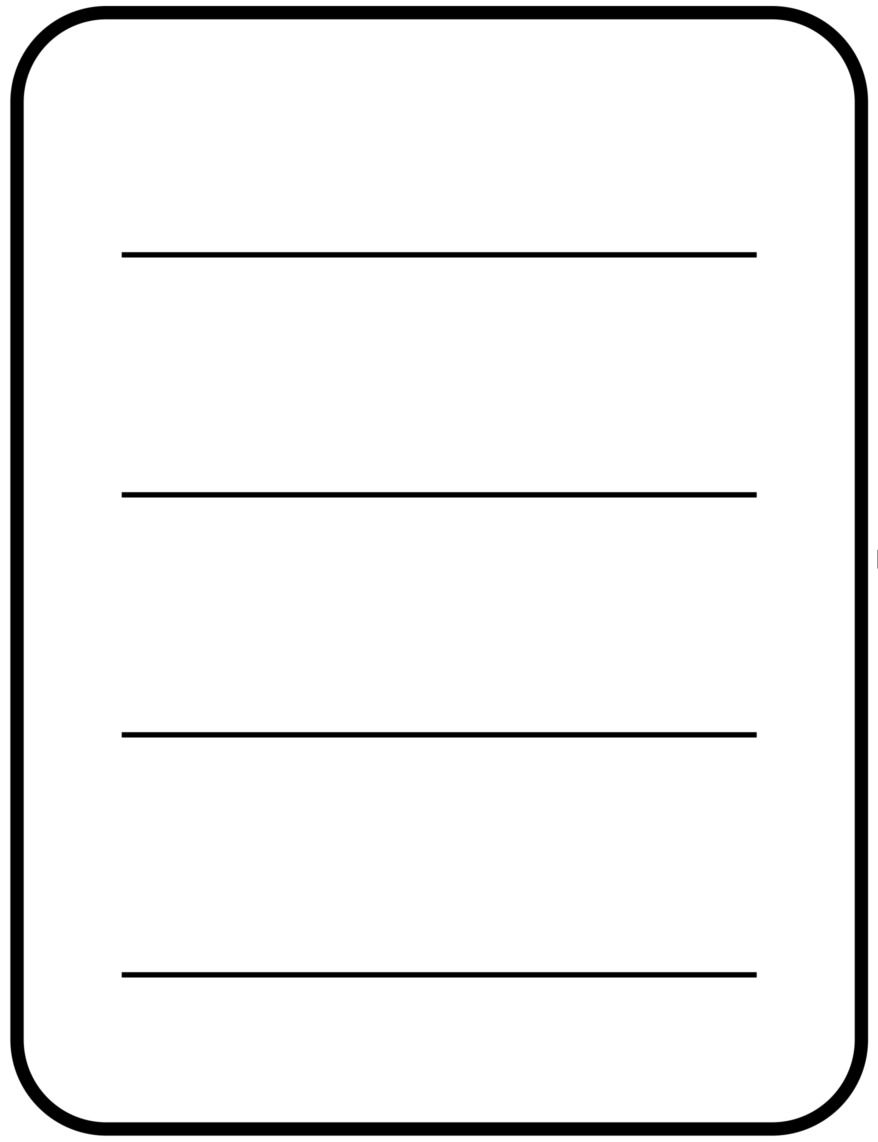

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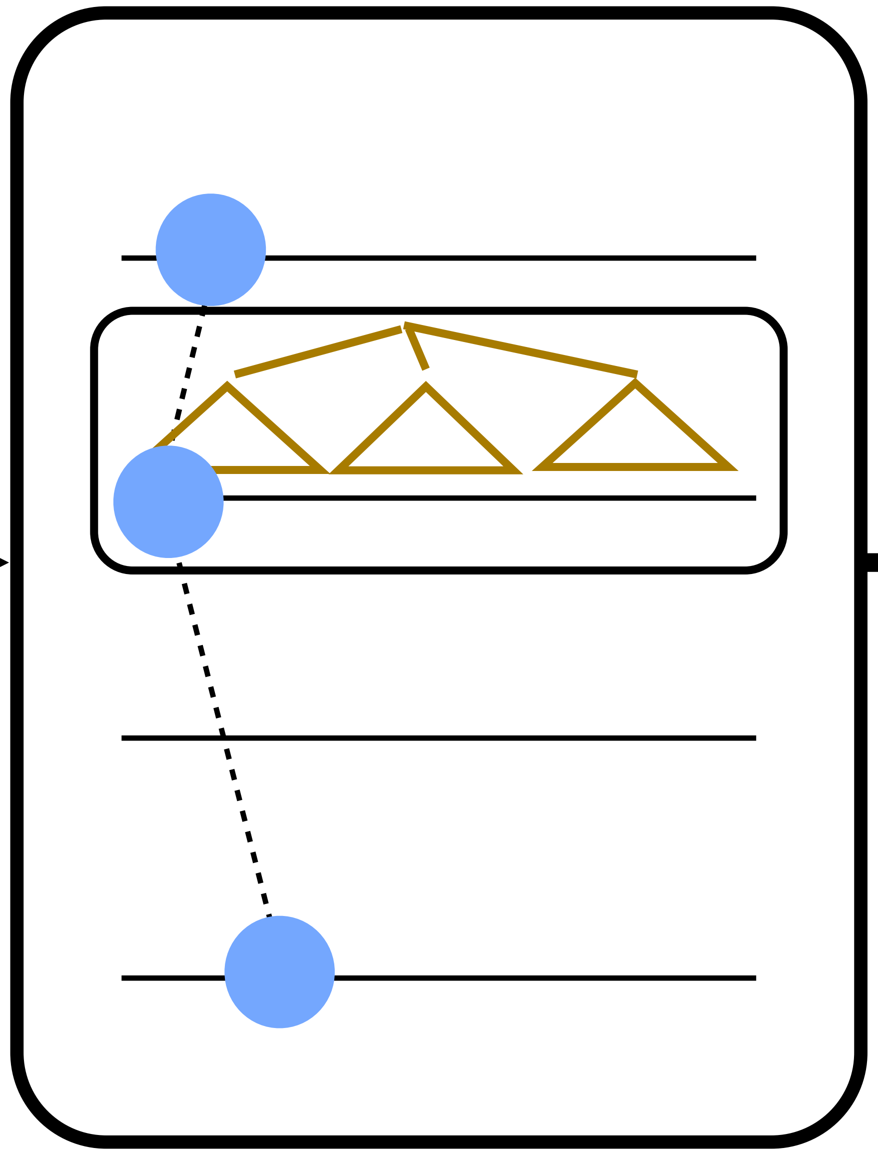

Applications

Summarize

Extract information

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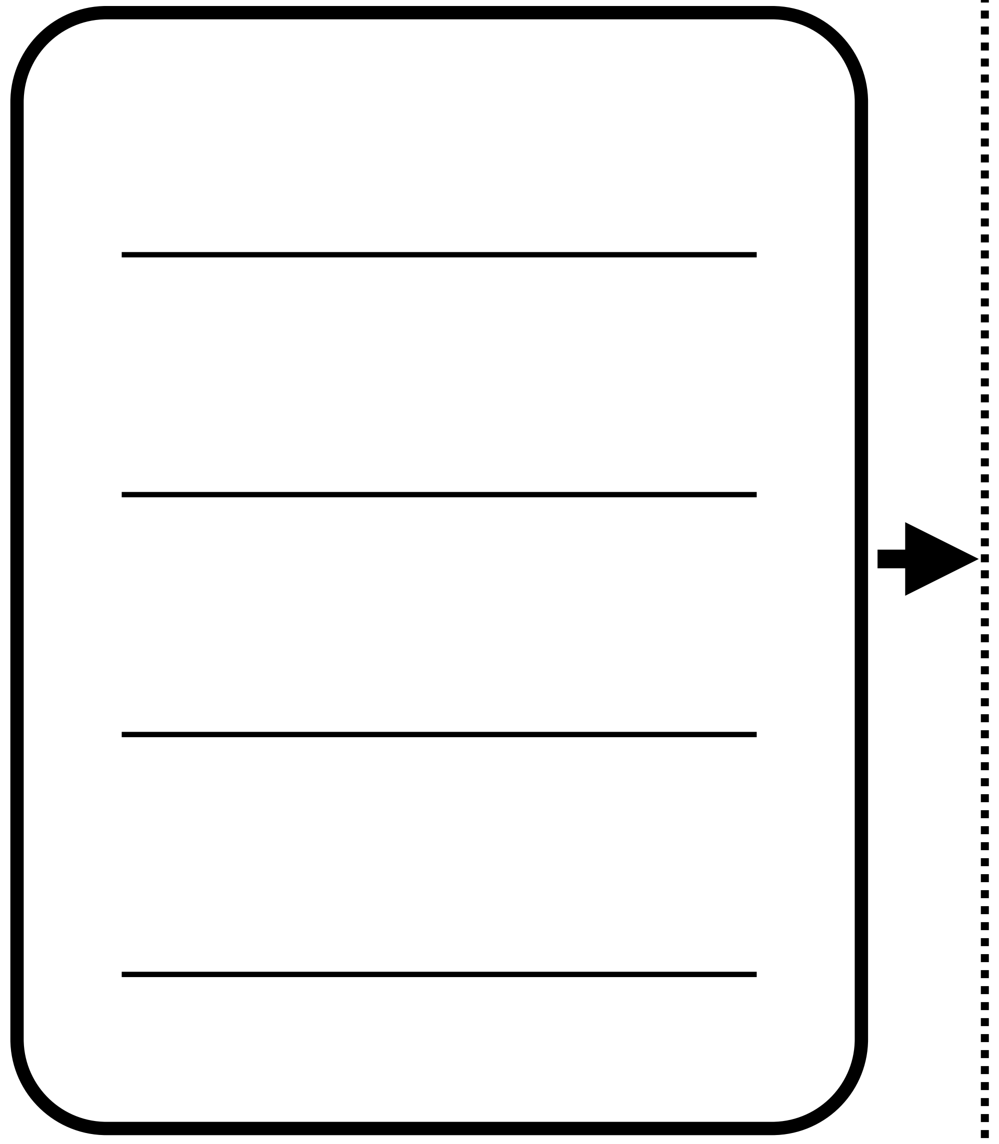
Translate

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

How do we represent language?

Text



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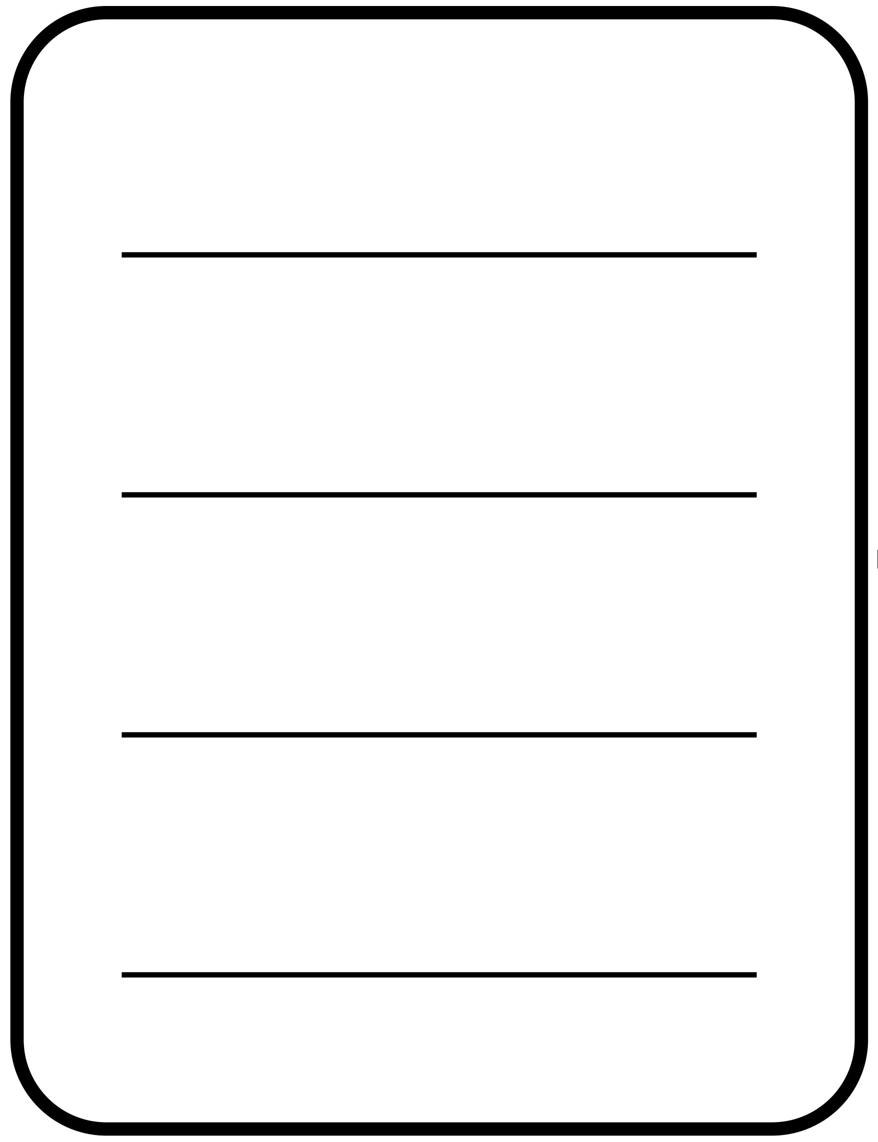

Labels

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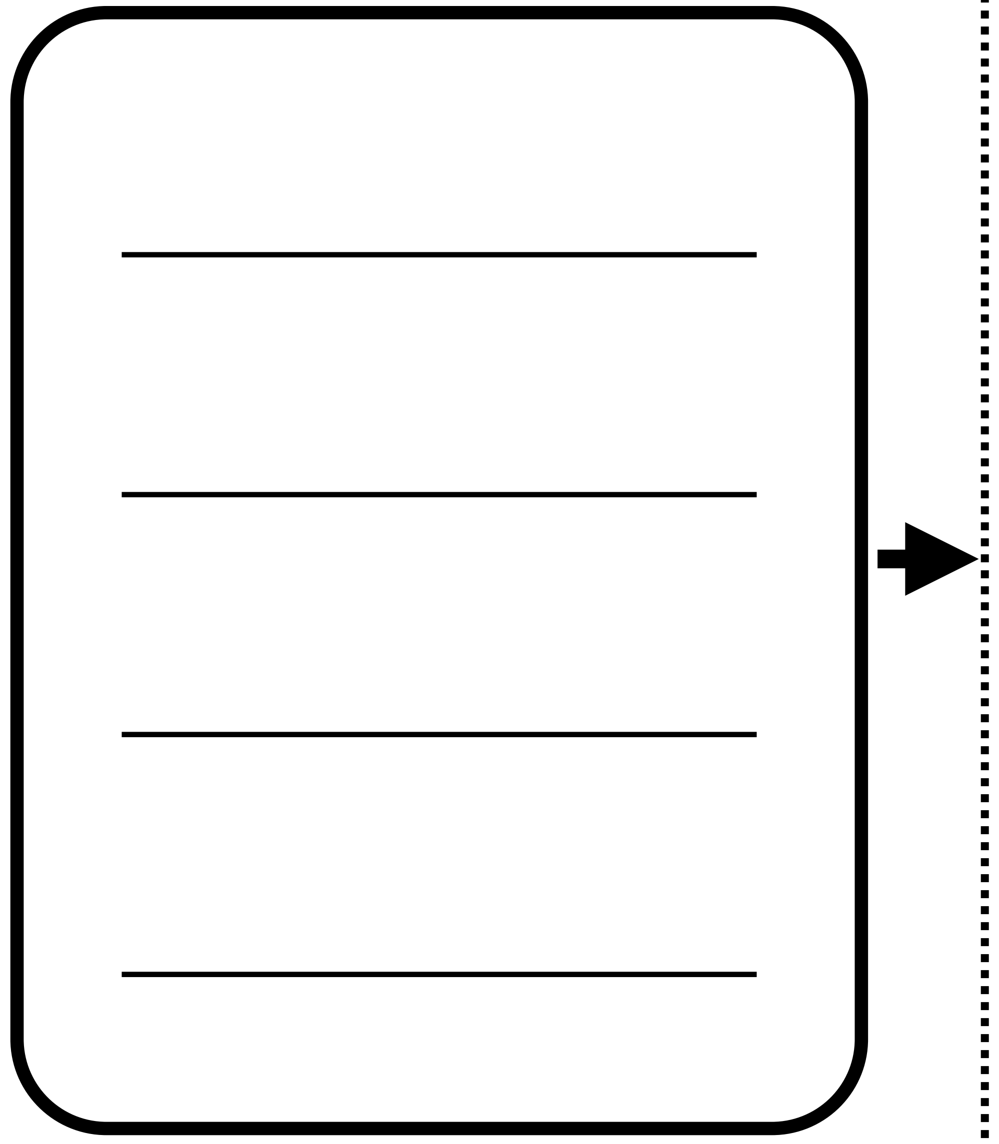

Labels

the movie was good +

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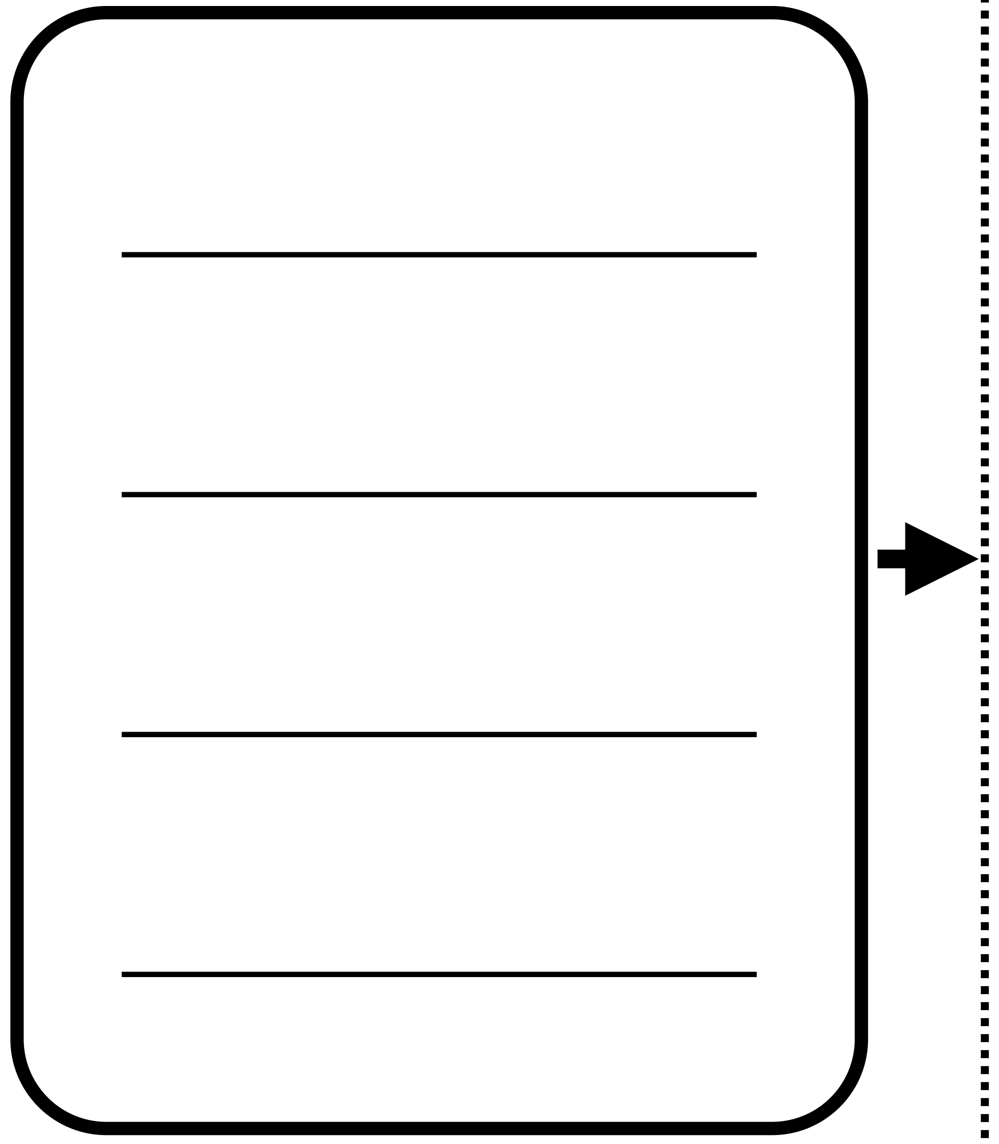

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Beyoncé had one of the best videos of all time **subjective**

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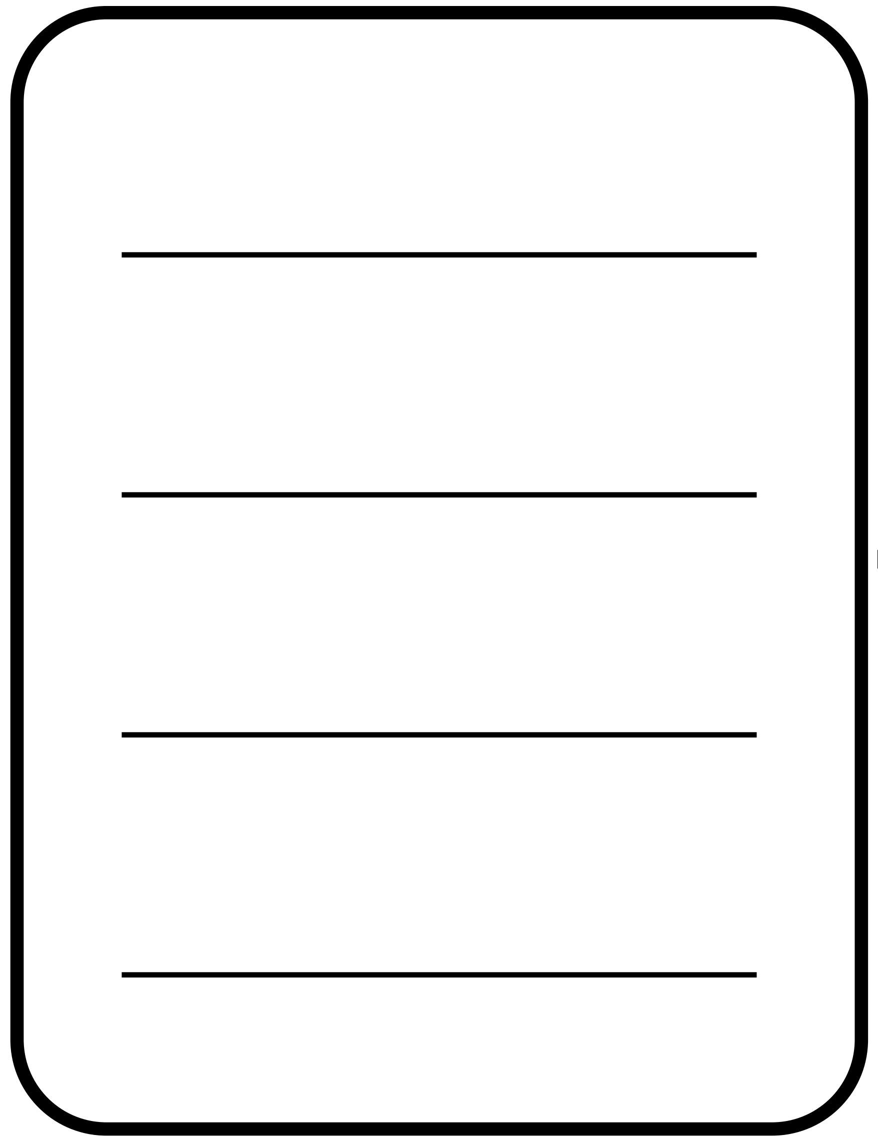

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Sequences/tags

PERSON **WORK_OF_ART**

Tom Cruise stars in the new Mission Impossible film

How do we represent language?

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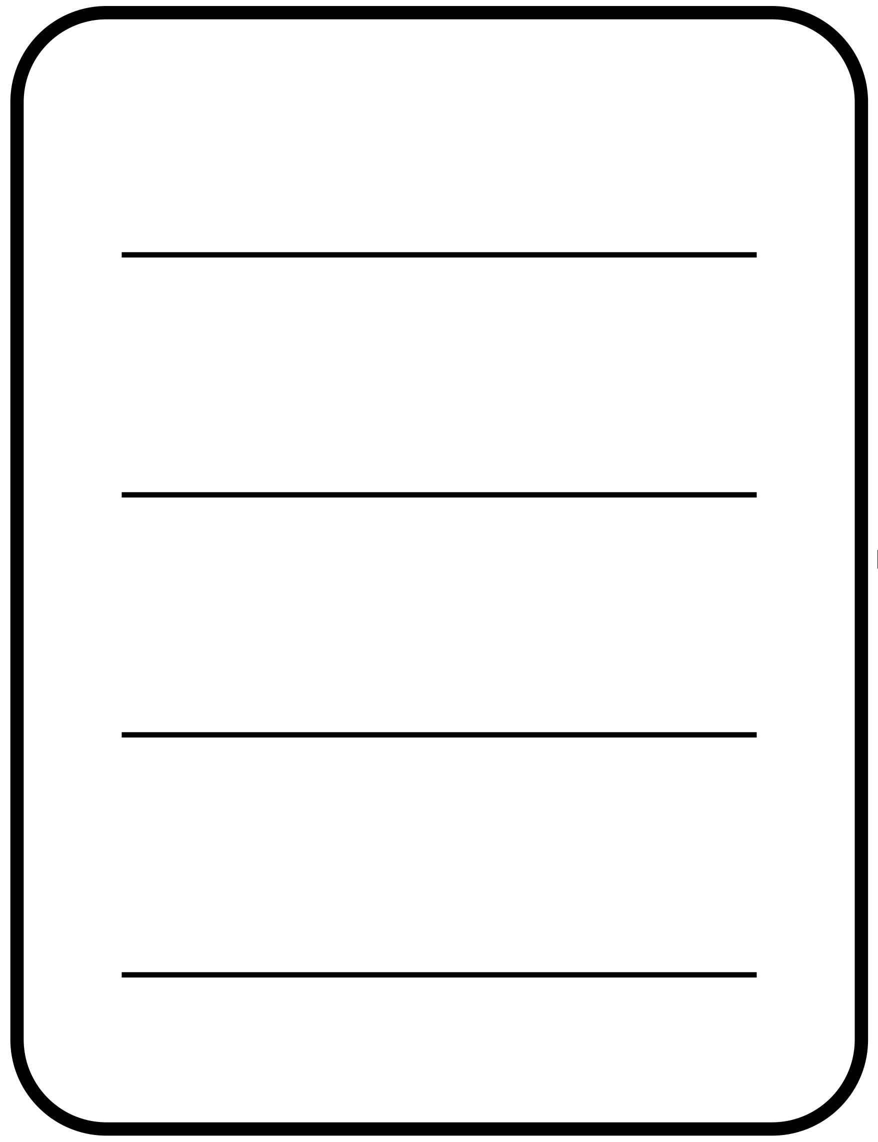

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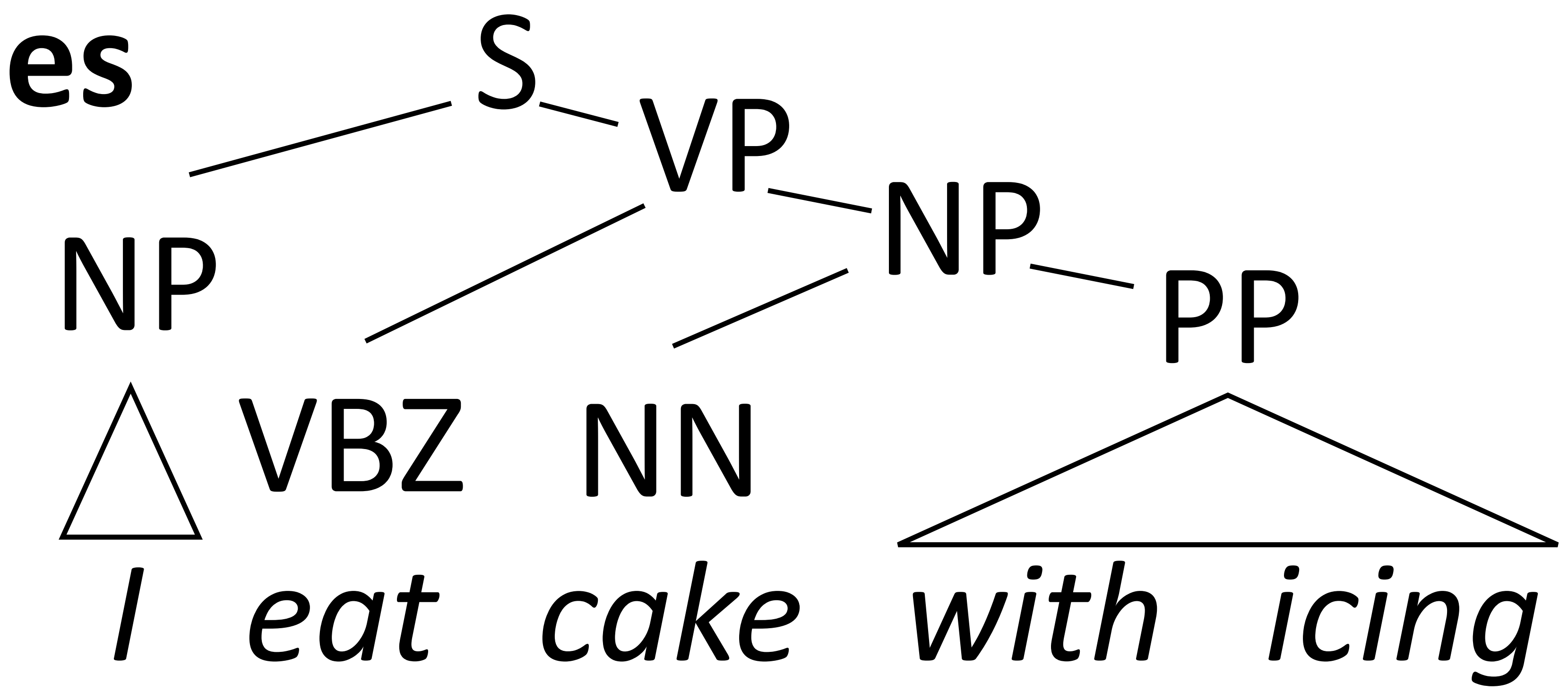
Trees



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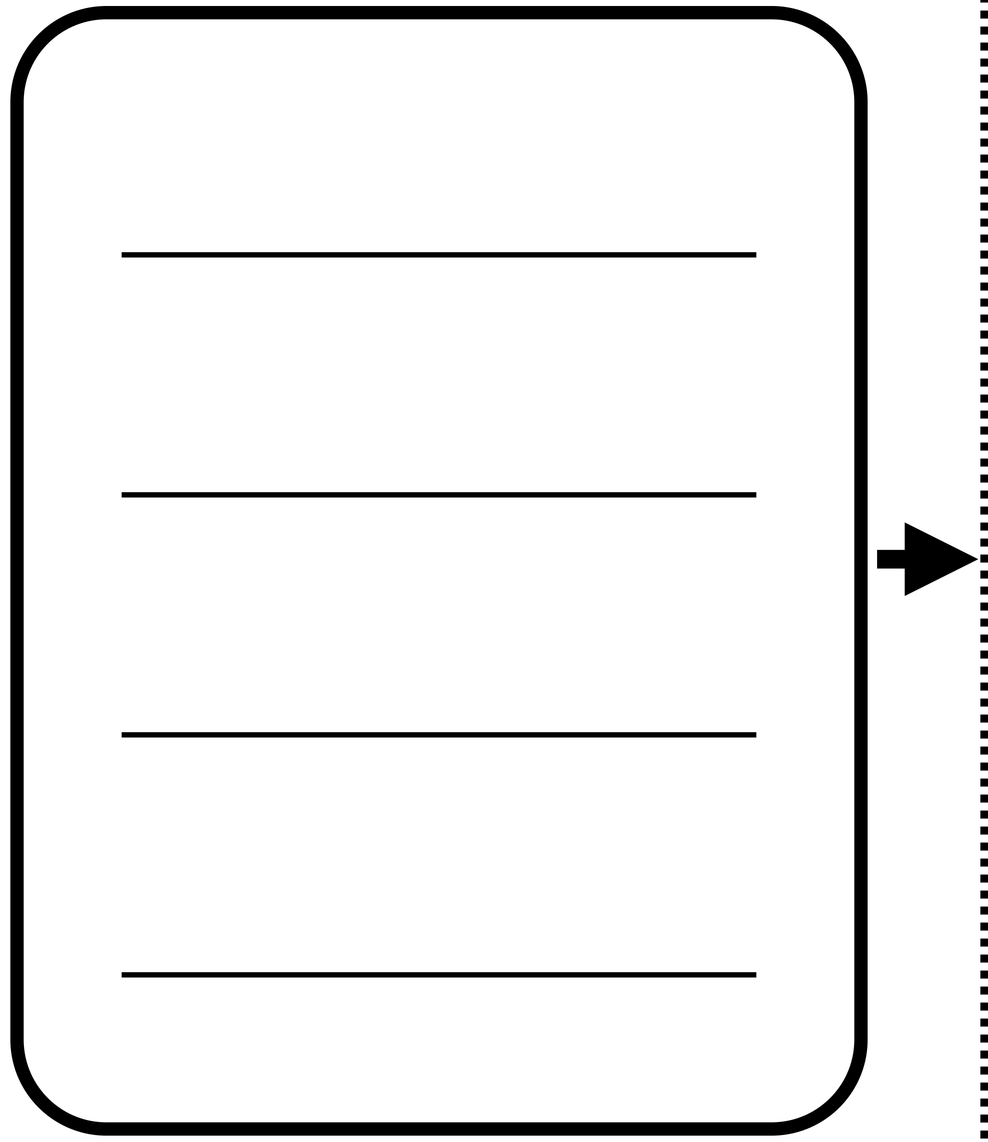

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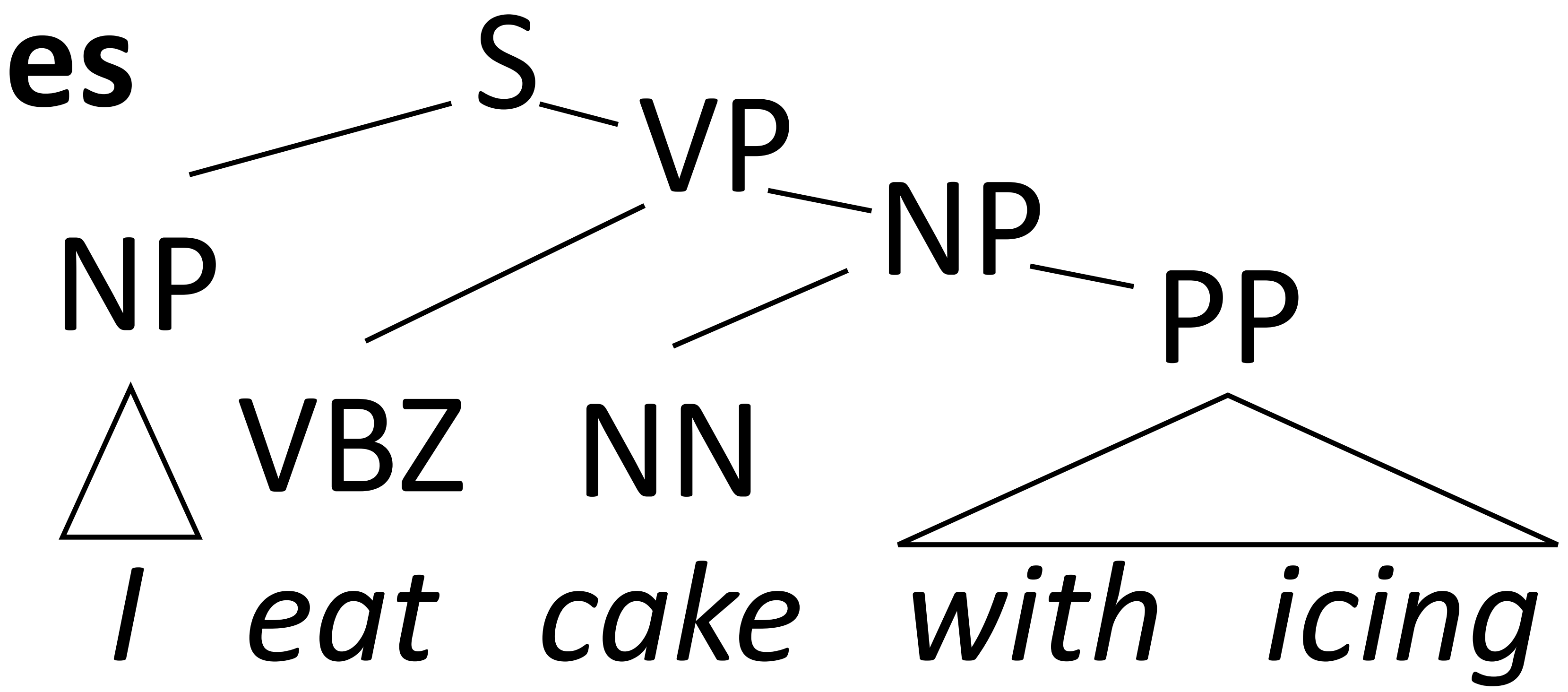
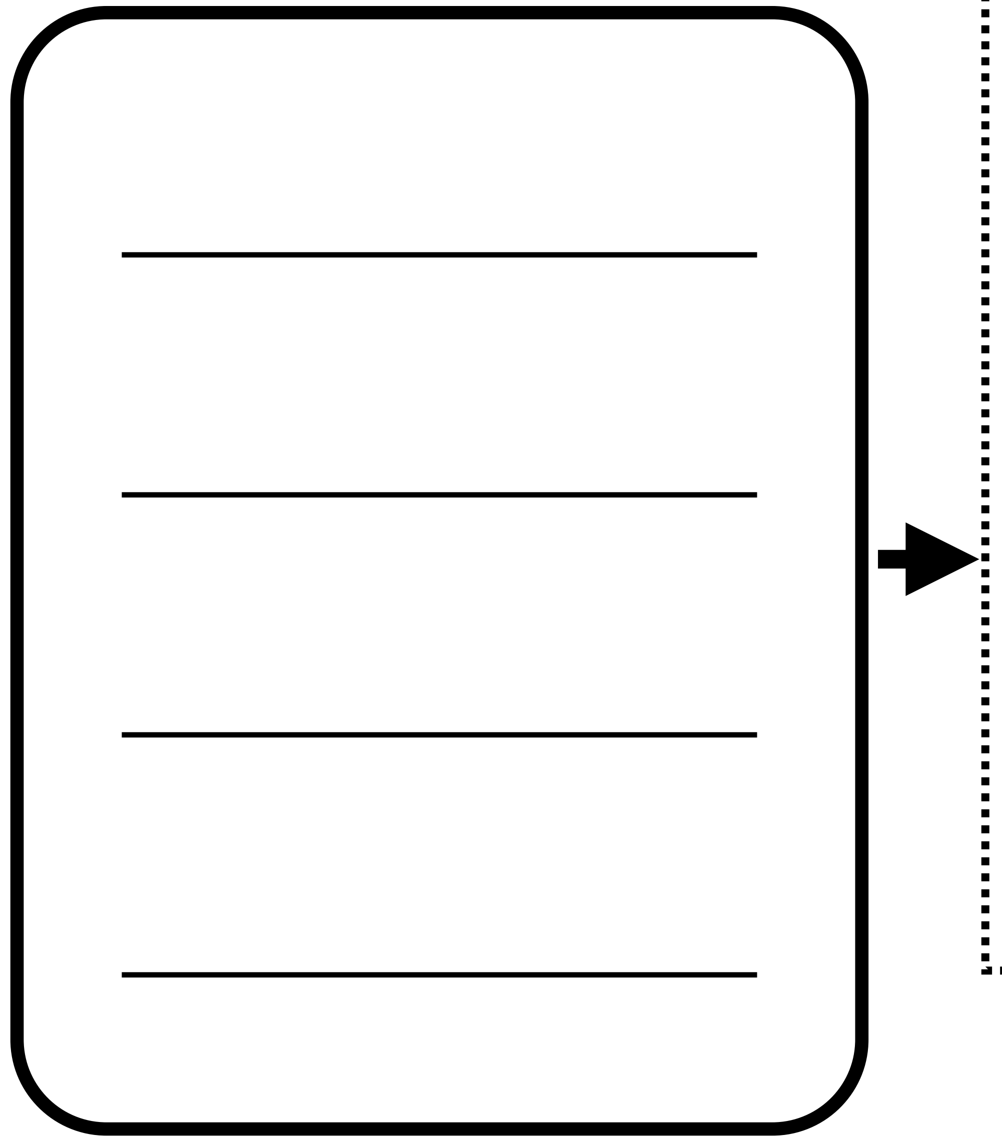


$\lambda x.\ flight(x) \wedge dest(x) = Miami$

flights to Miami

How do we use these representations?

Text



Text Analysis

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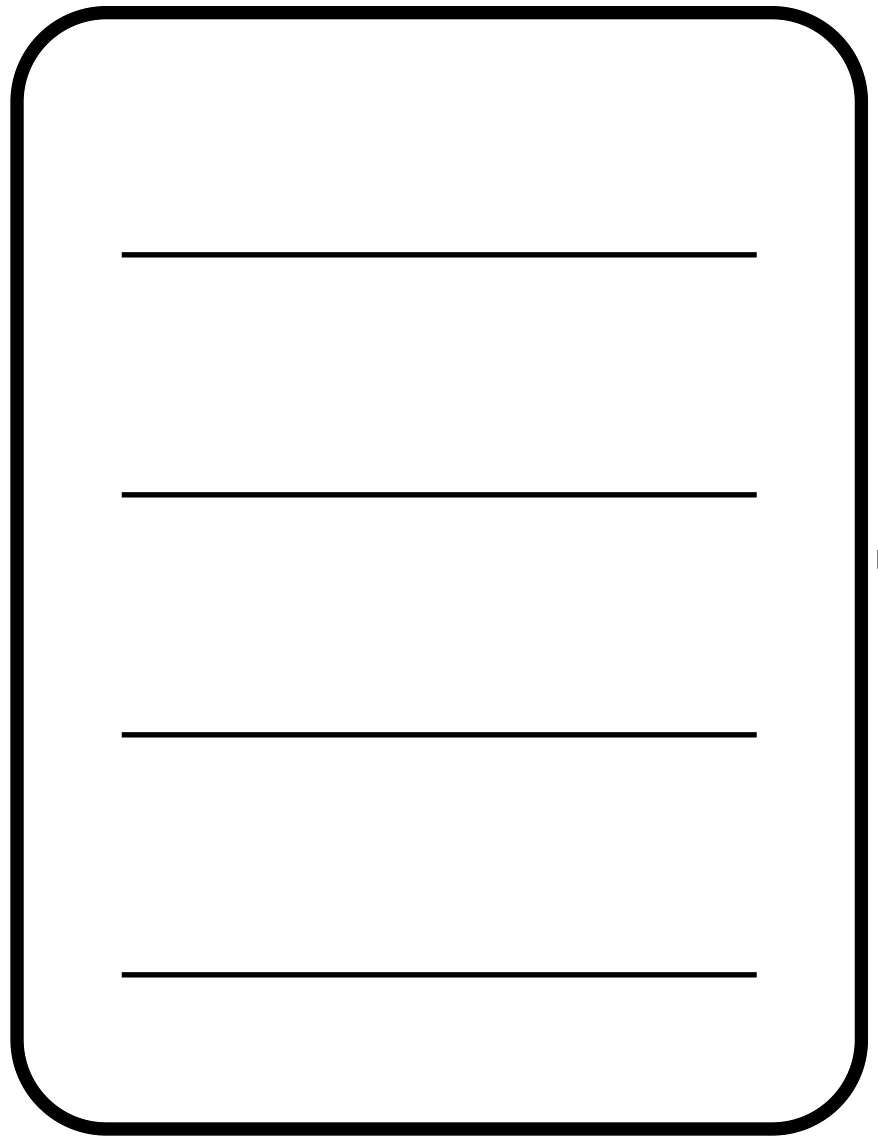

Text Analysis

Labels

Sequences

Trees

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Applications

How do we use these representations?

Text

Text Analysis

Labels

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…

Applications

Extract syntactic features

How do we use these representations?

Text

Text Analysis

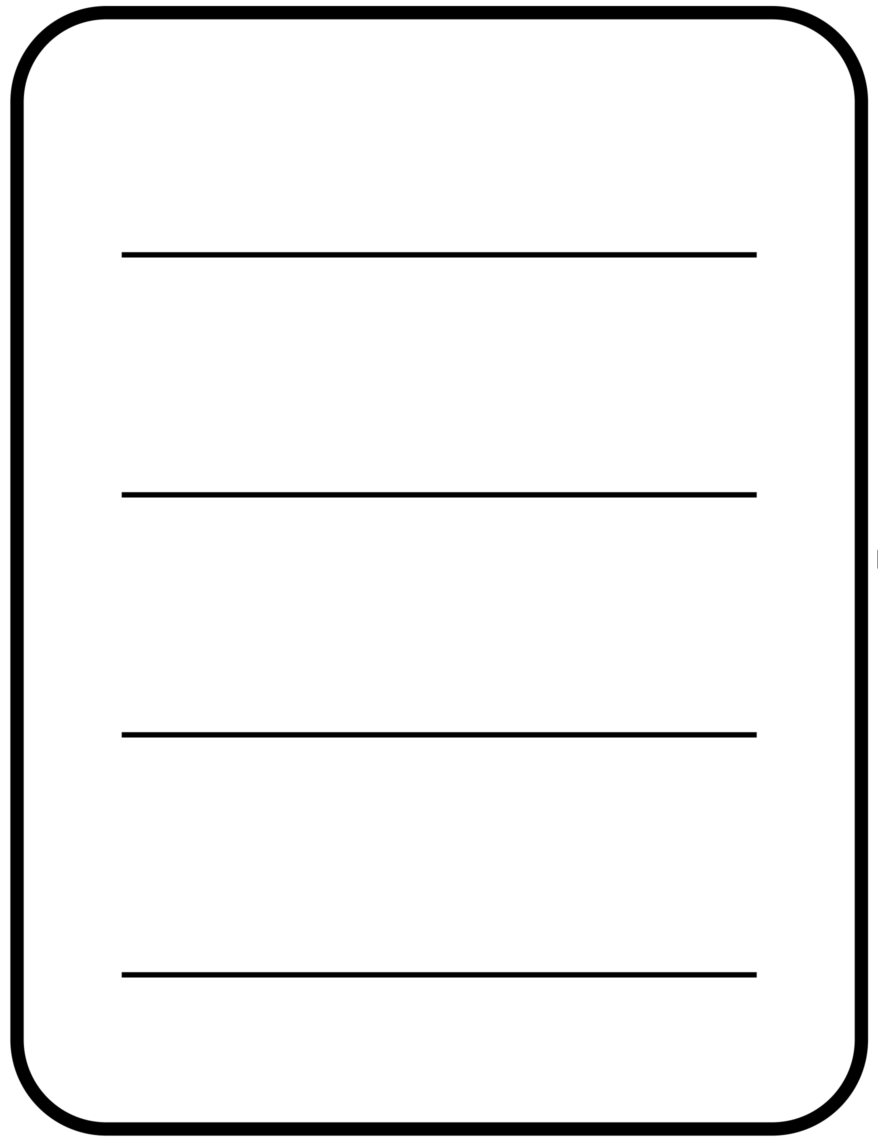
- Labels
- Sequences
- Trees
- …

Applications

- Extract syntactic features
- Tree-structured neural networks

How do we use these representations?

Text



Text Analysis

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Applications

Extract syntactic features

Tree-structured neural networks

Tree transducers (for machine translation)

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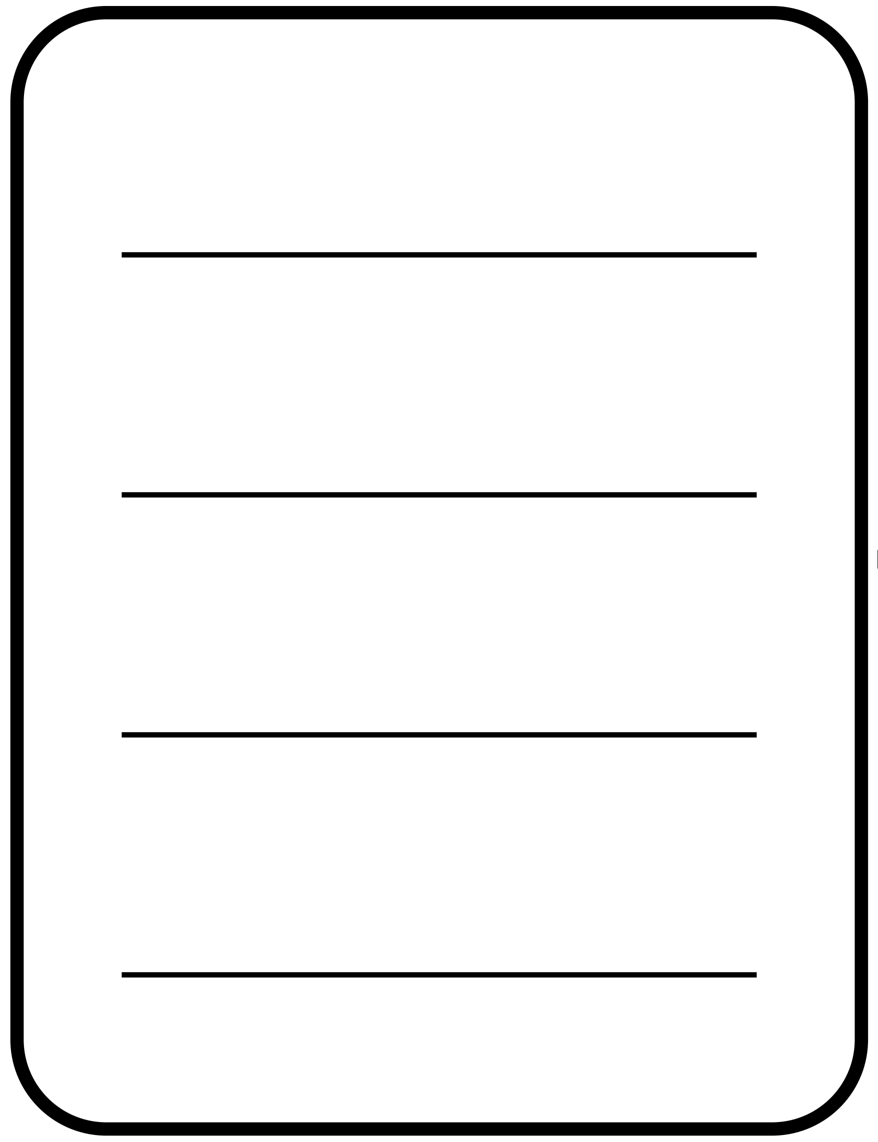

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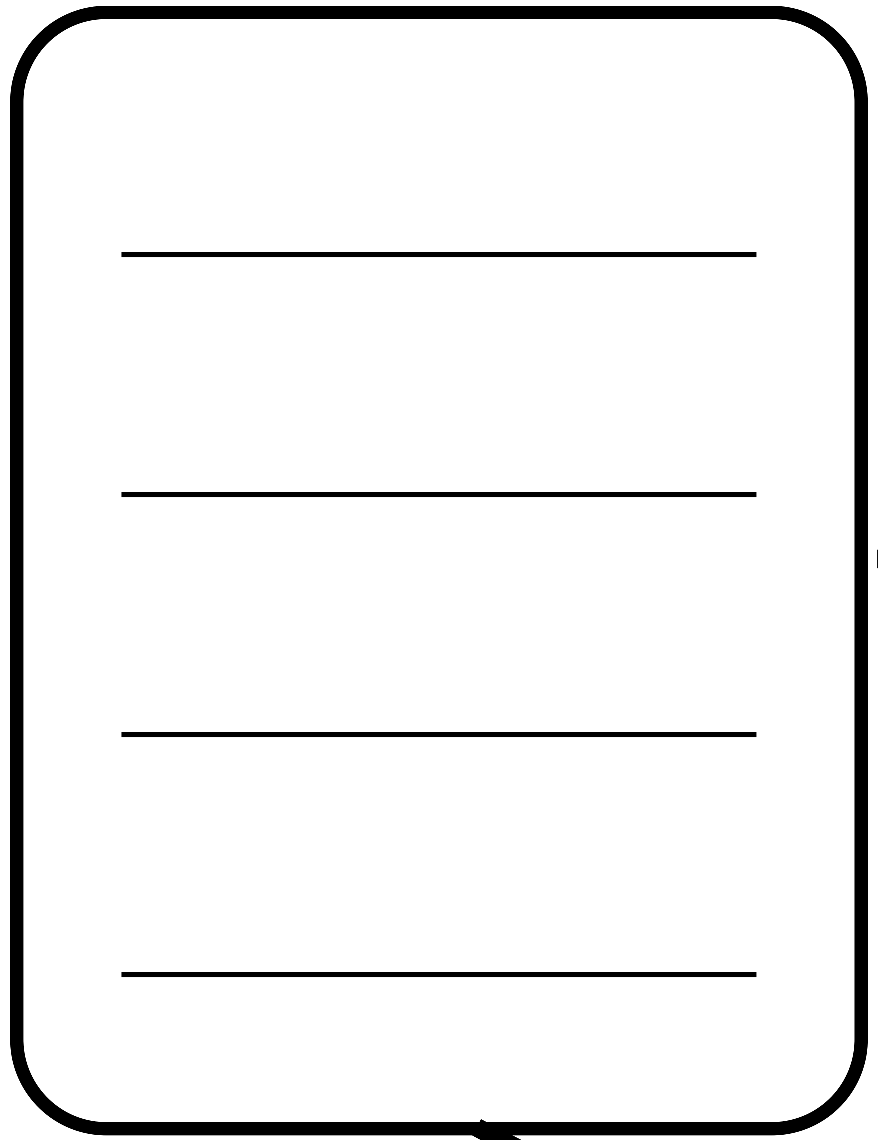

Text Analysis

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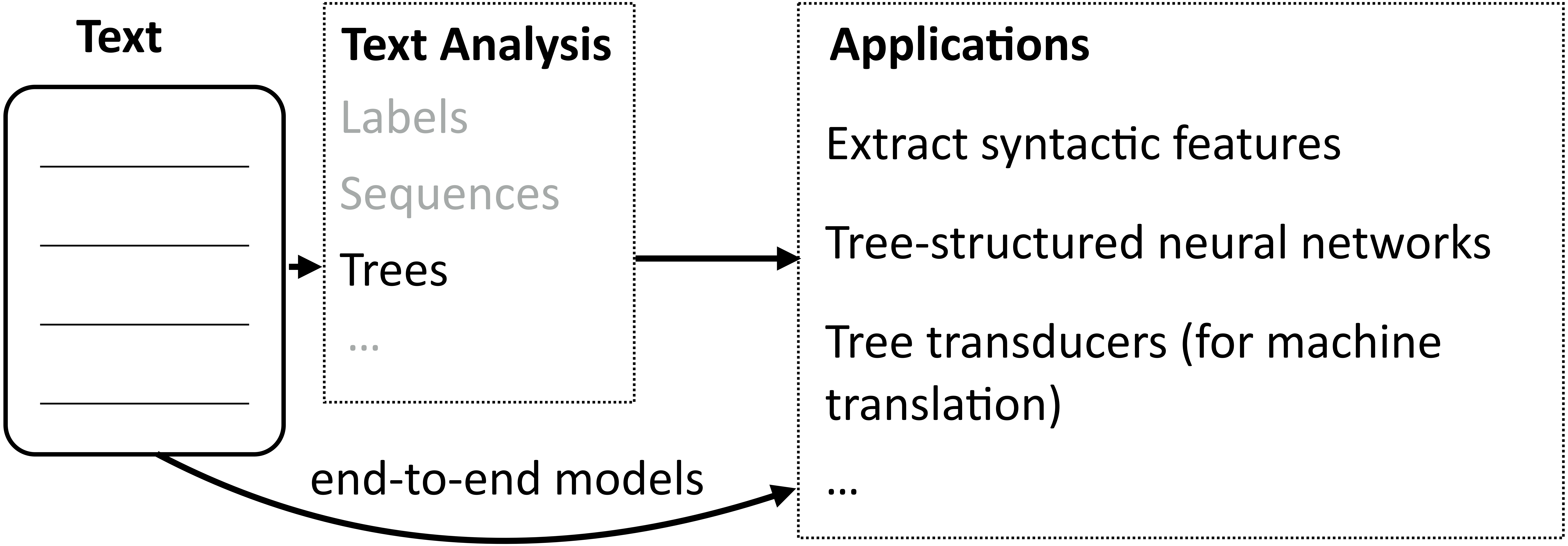
end-to-end models

How do we use these representations?



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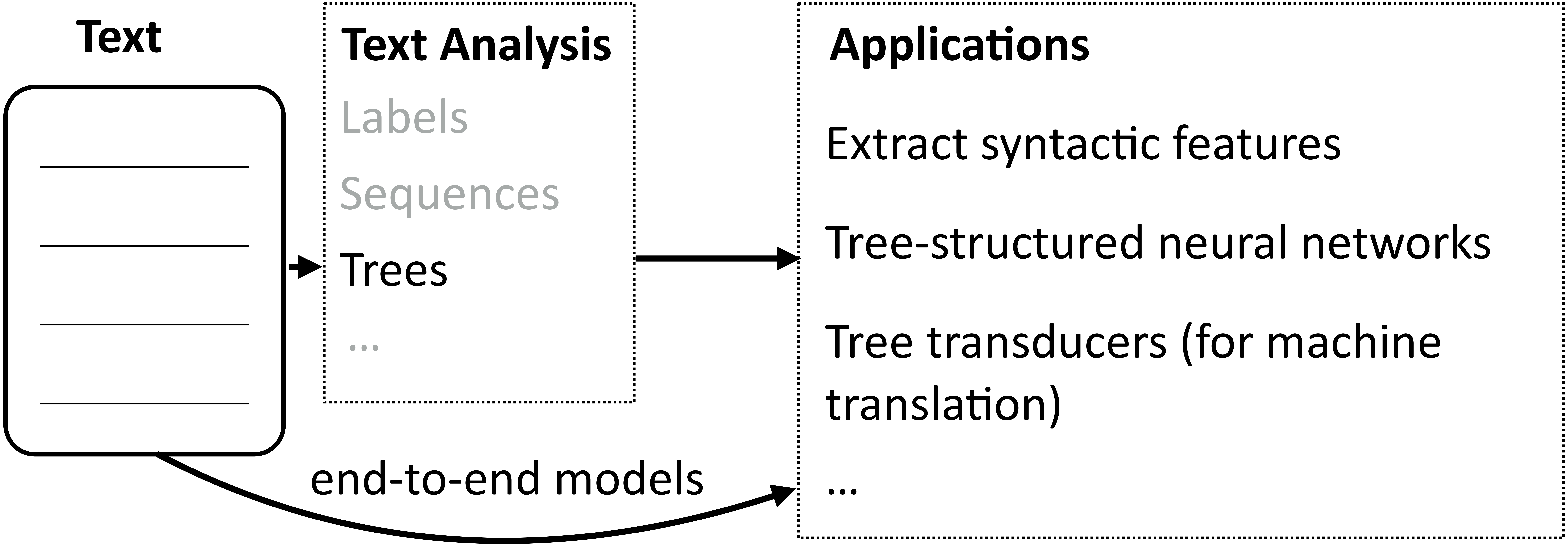
How do we use these representations?



- 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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The city council refused the demonstrators a permit because they ______ violence

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they advocated

The city council refused the demonstrators a permit because they _______ violence

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- Referential/semantic ambiguity

Language is Ambiguous!

slide credit: Dan Klein

Language is Ambiguous!

- Headlines

slide credit: Dan Klein

Language is Ambiguous!

- Headlines
  - Teacher Strikes Idle Kids

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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He makes truly beautiful

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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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Department of Justice

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metaphor;
“approves”

What do we need to understand language?

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

Department of Justice

metaphor;
“approves”

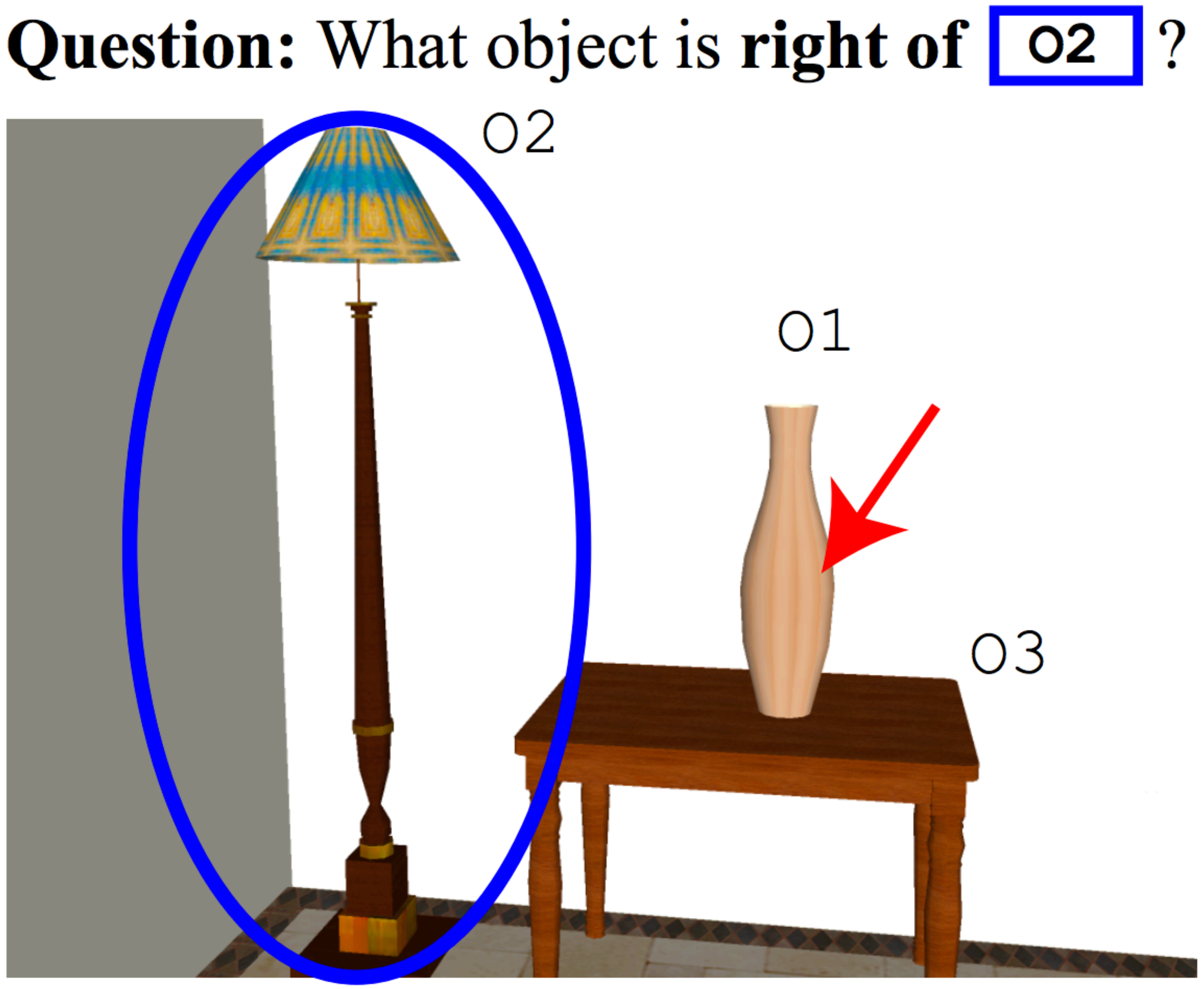
- What is a green light? How do we understand what “green lighting” does?

What do we need to understand language?

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

What do we need to understand language?

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



Golland et al. (2010)

What do we need to understand language?

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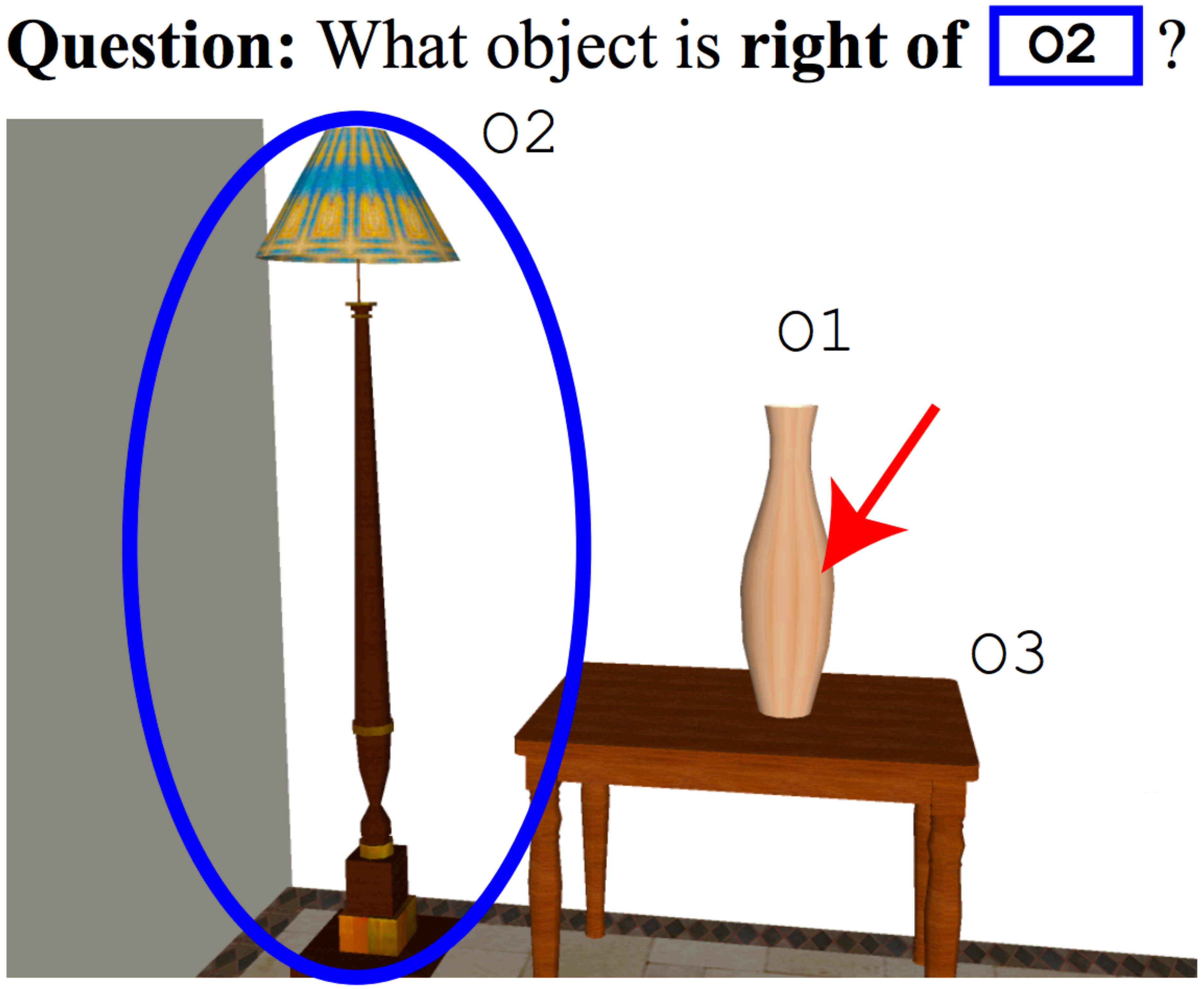

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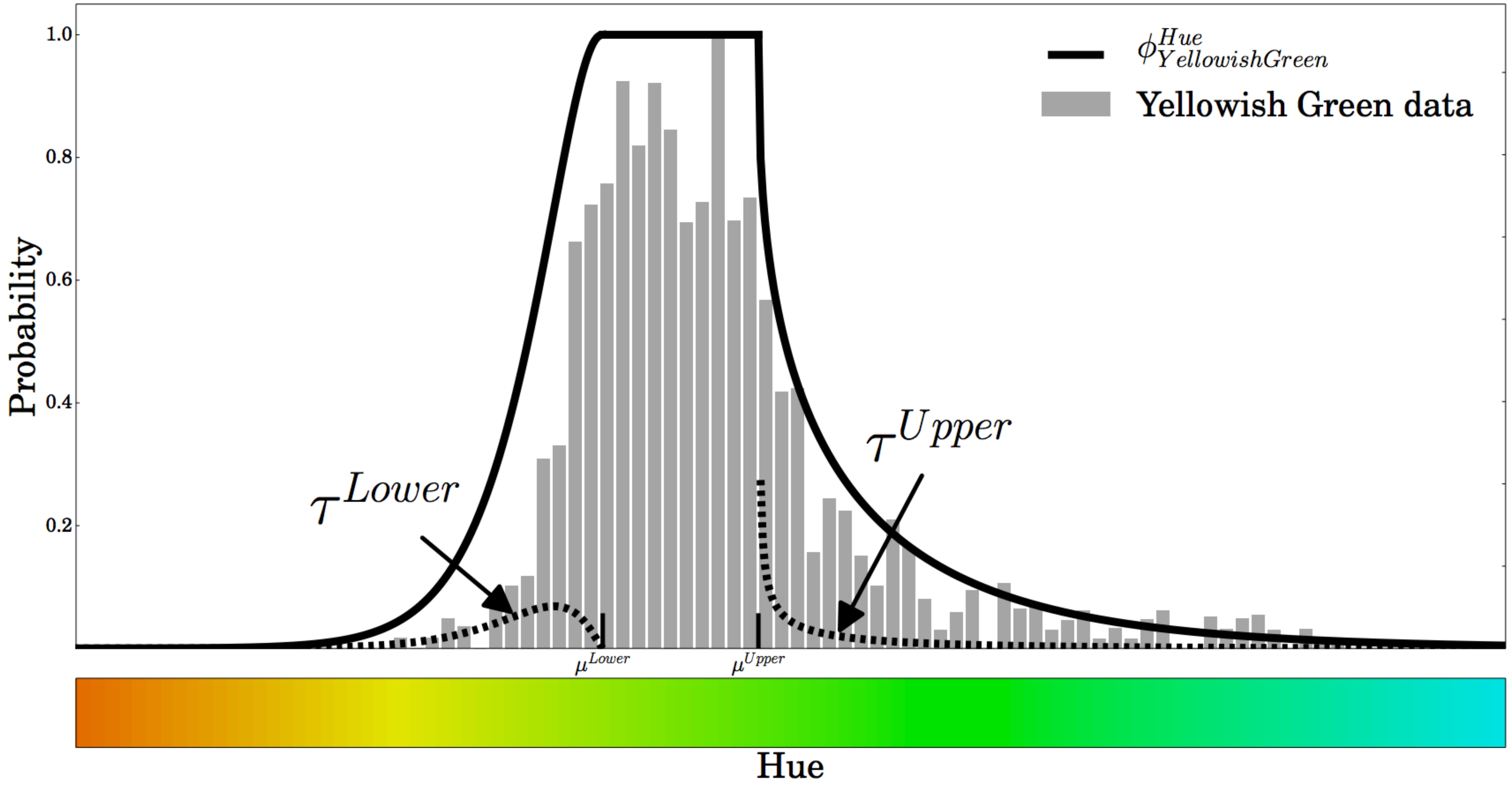

McMahan and Stone (2015)

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 2018

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“AI winter”
rule-based,
expert systems

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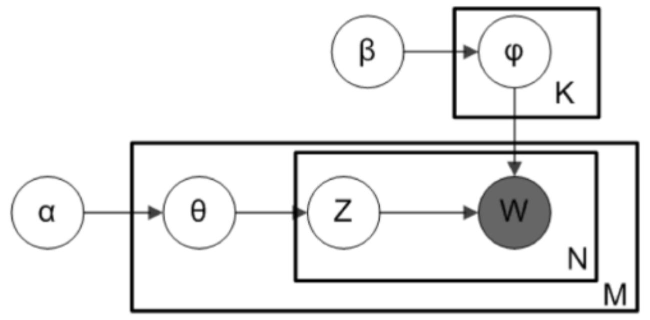
Unsup: topic models, grammar induction



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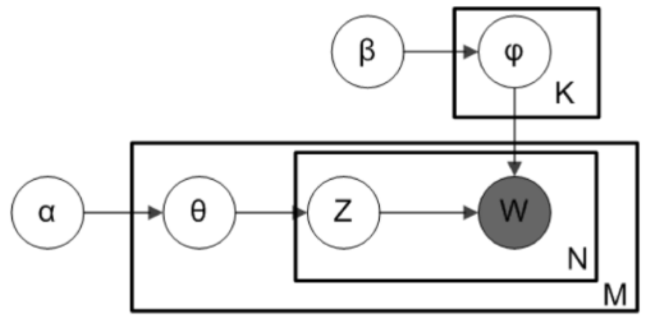

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Semi-sup,
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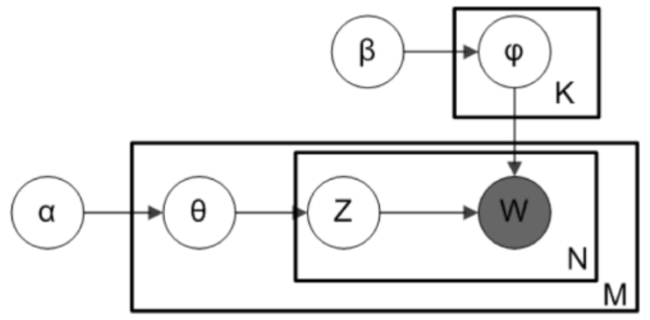

Sup: SVMs,
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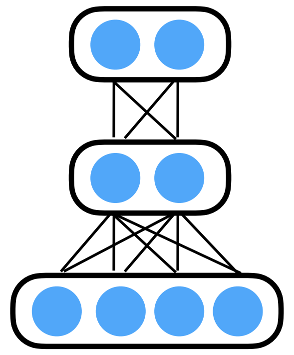
Neural



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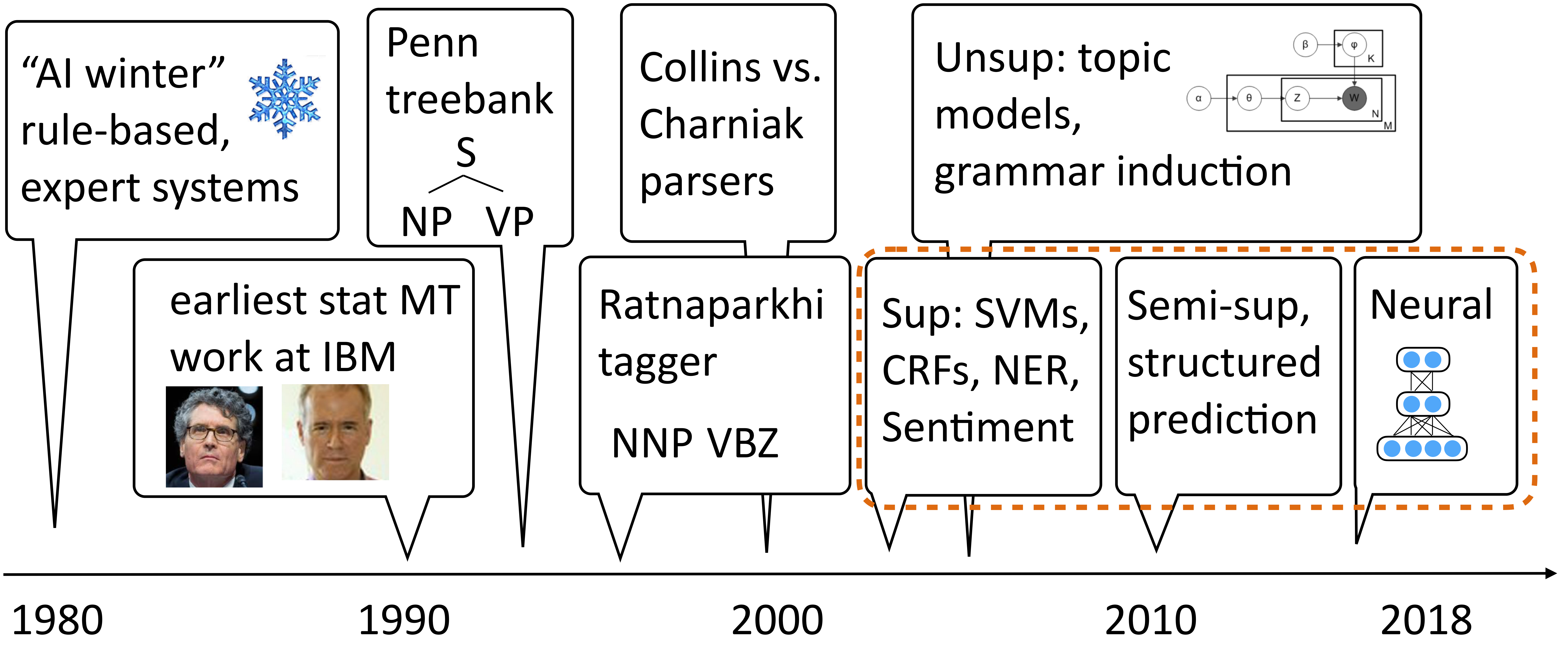

Structured Prediction

"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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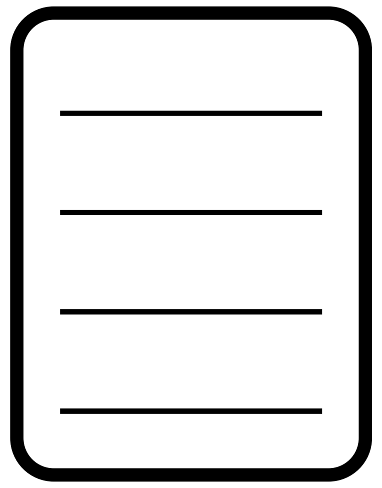

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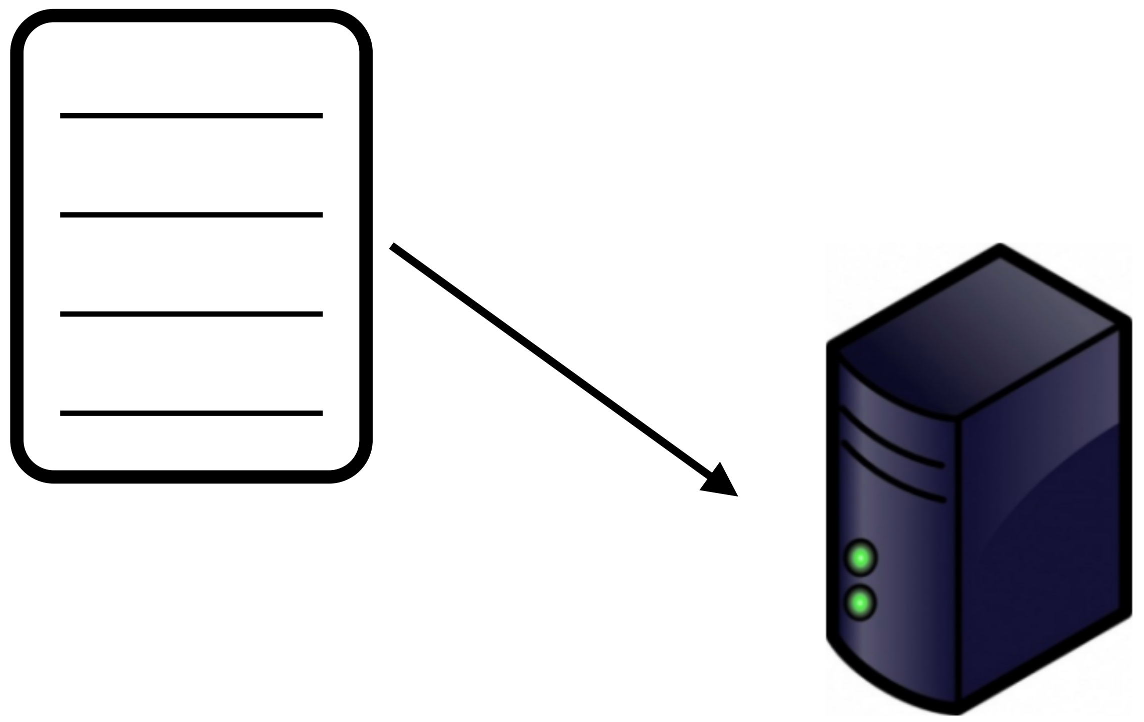

unsupervised learning

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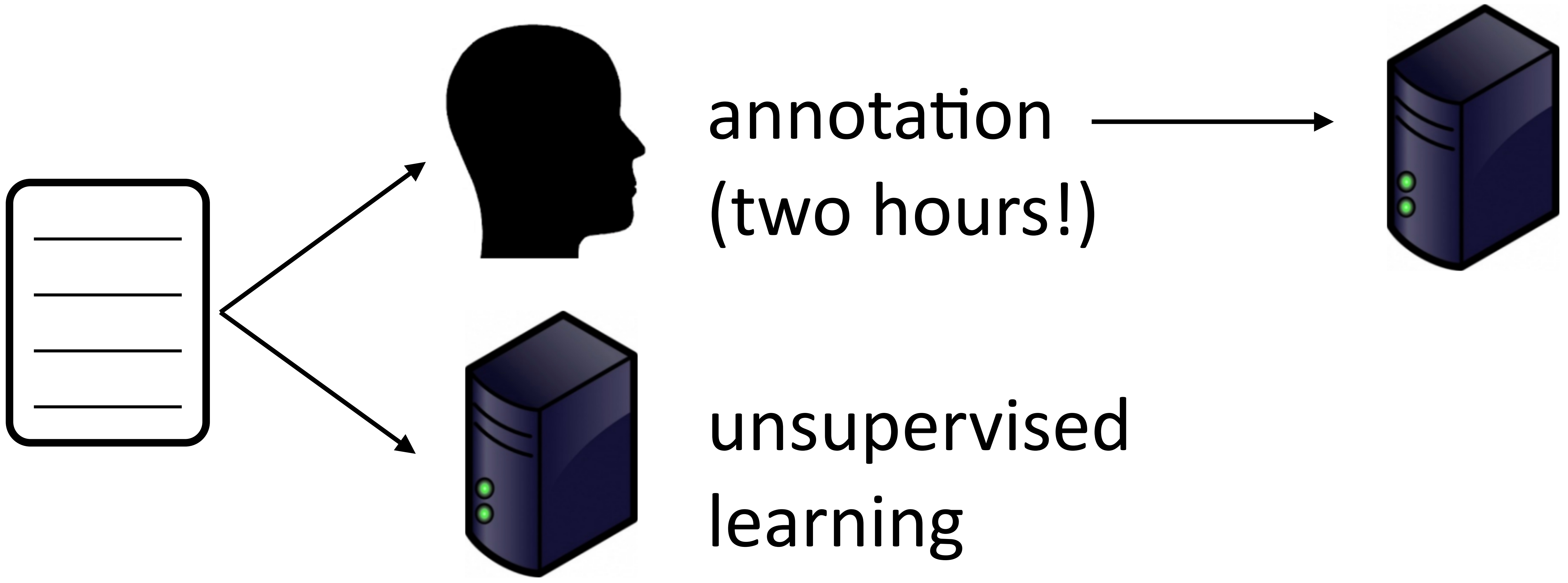

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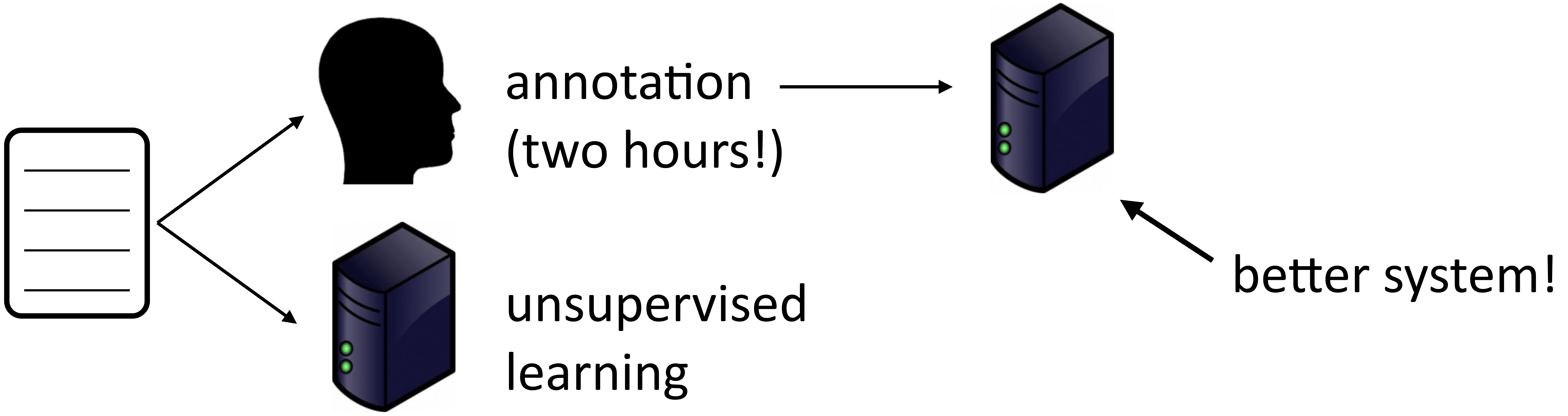

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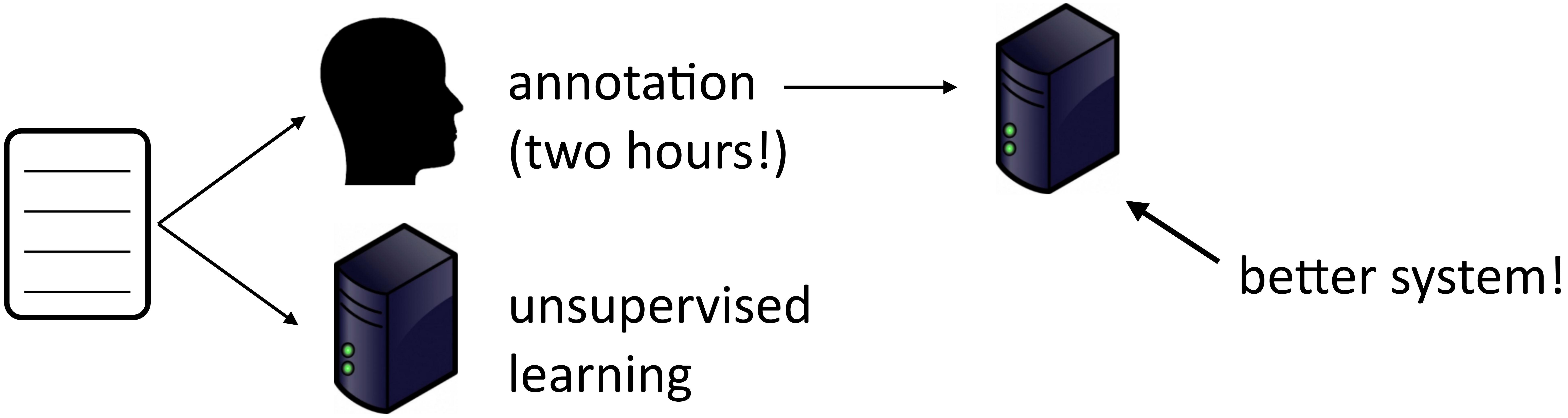

- Even neural nets can do pretty well!

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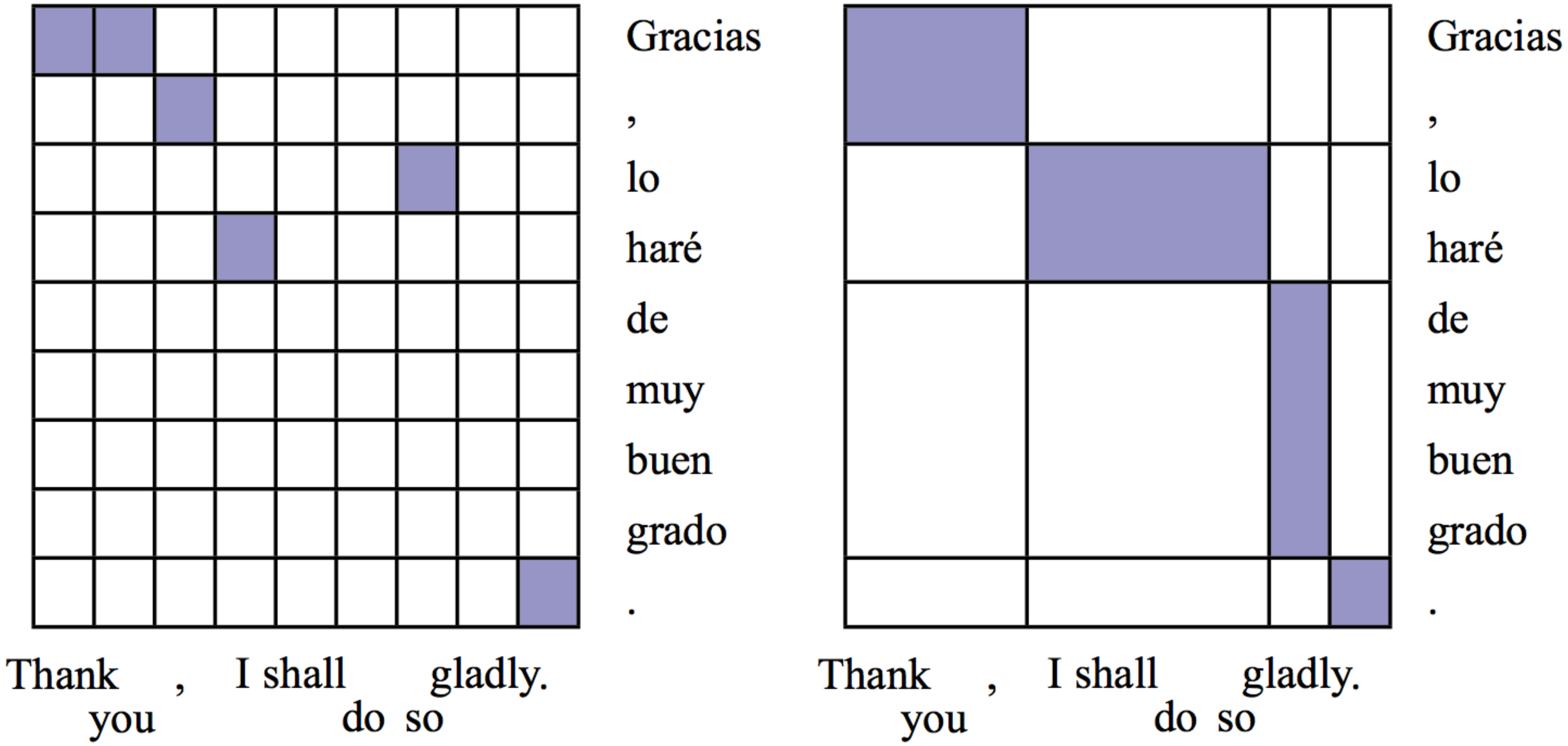
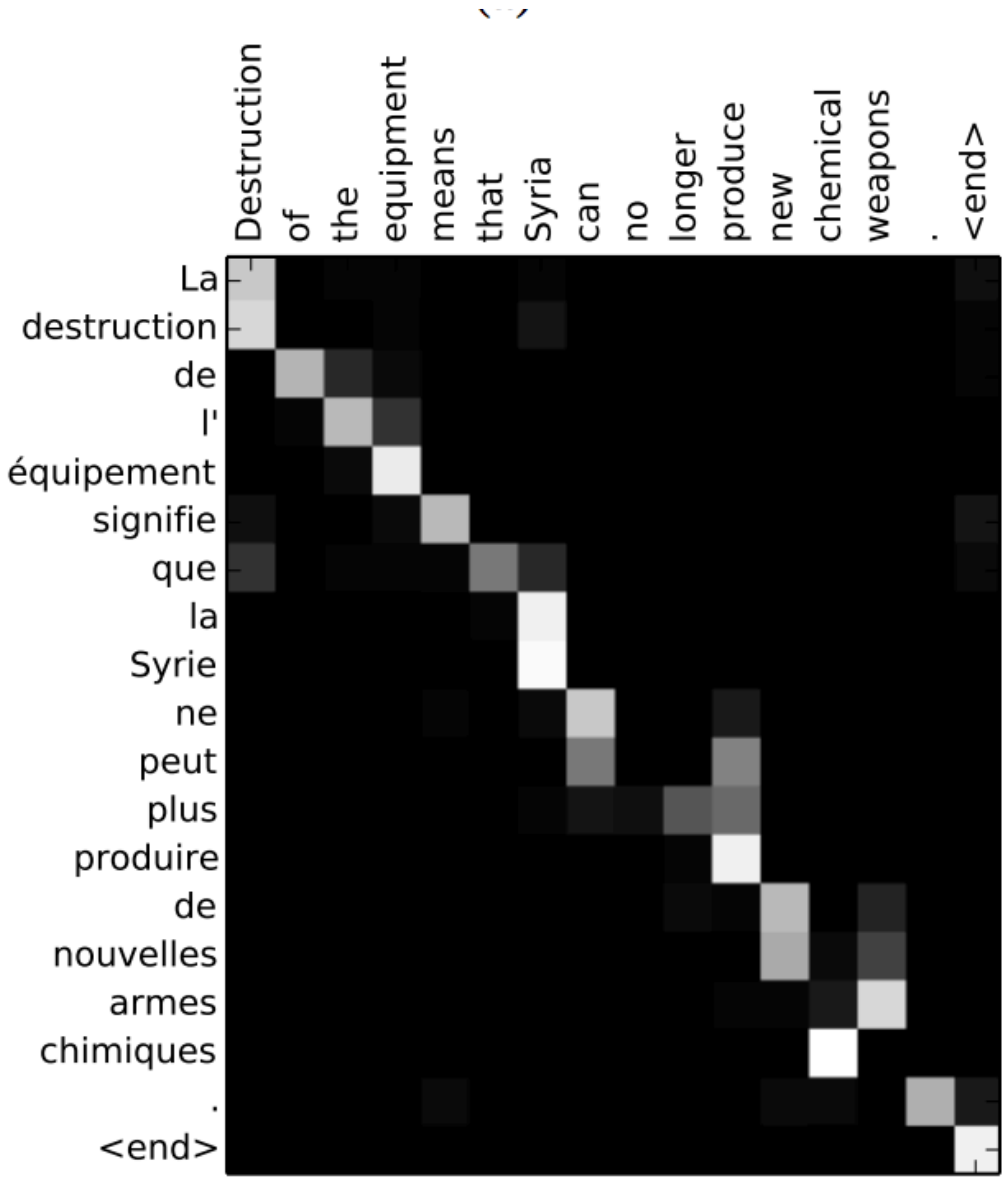
Less Manual Structure?



(a) example word alignment **(b) example phrase alignment**



DeNero et al. (2008)

Bahdanau et al. (2014)

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Newswire	
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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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Moosavi and Strube (2017)

Does manual structure have a place?

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

Does manual structure have a place?

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- Maybe manual structure would help…

Where are we?

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- NLP consists of: analyzing and building representations for text, solving problems involving text

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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)

NLP vs. Computational Linguistics

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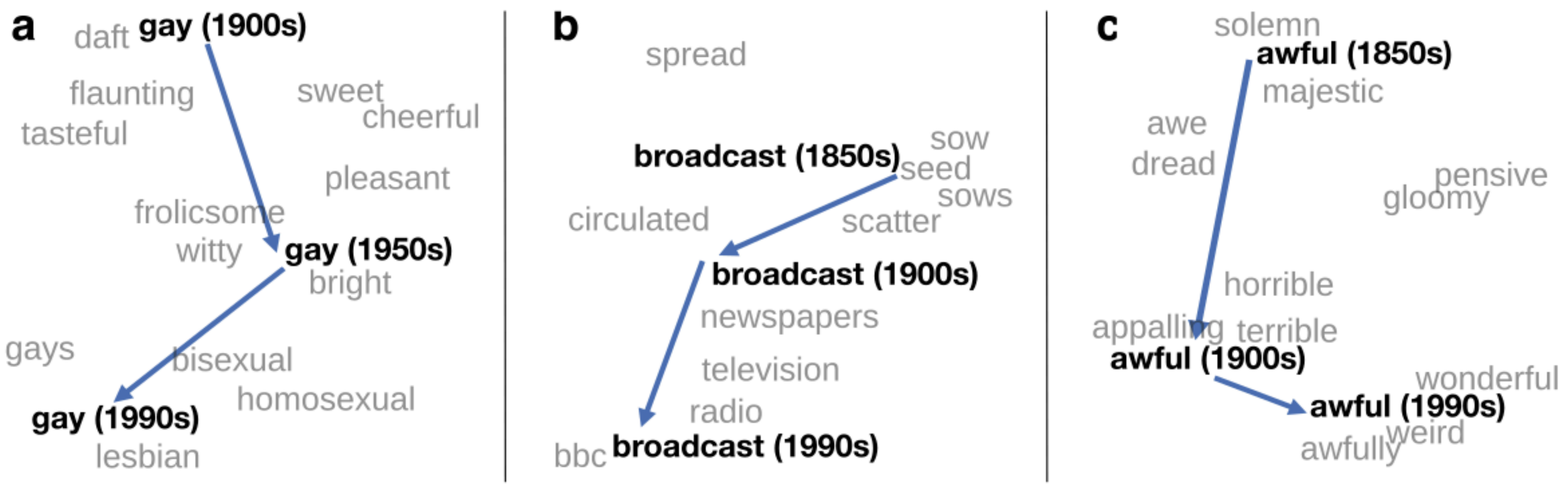

Hamilton et al. (2016)

NLP vs. Computational Linguistics

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

Bamman, O'Connor, Smith (2013)

NLP vs. Computational Linguistics

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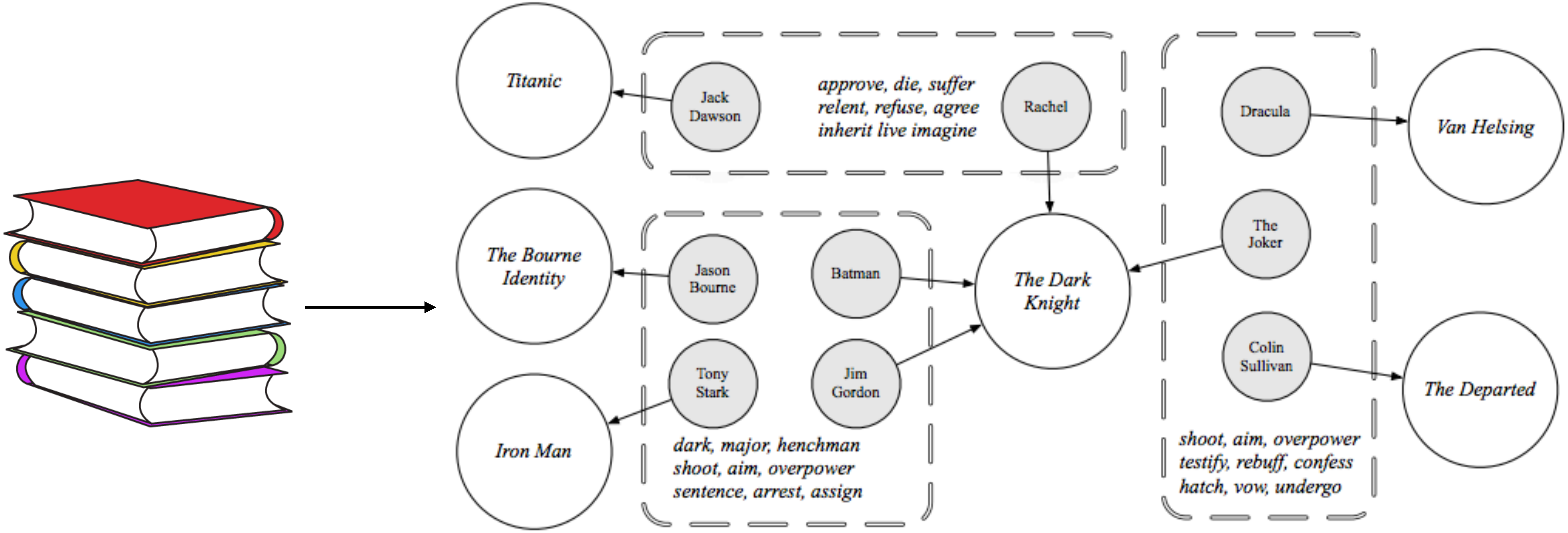

Bamman, O'Connor, Smith (2013)

Outline of the Course

Topics	Readings
Introduction [4pp]	
Binary classification	JM 6.1-6.3
Multiclass classification	JM 7, Structured SVM secs 1-2
Sequence models I: HMMs	JM 9, JM 10.4, Manning POS
Sequence models II: CRFs	Sutton CRFs 2.3, 2.6.1, Wallach CRFs tutorial, Illinois NER
Neural Nets I: FFNNs	Goldberg 1-4, 6, NLP with FFNNs, DANs
Neural Nets II: NN impl / word embeddings	Goldberg 5, word2vec, GloVe, Dropout
Neural Nets III: RNN and CNN encoders	Goldberg 9-11, Kim
Neural Nets IV: Neural CRFs	Collobert and Weston, Neural NER, Neural CRF parsing
Trees I: Constituency, PCFGs	JM 13.1-13.7, Structural, Lexicalized, State-split
Trees II: Dependency I	JM 14.1-14.4, Huang 1-2
Trees III: Dependency II	Parsey, Huang 2
Semantics I	
Semantics II / Seq2seq I	
Seq2seq II: Beam search, attention	Seq2seq, Attention, Luong Attention
Information Extraction / SRL	Distant supervision, RL for slot filling, TextRunner, ReVerb, NELL
Discourse and Coreference	
Machine Translation I: Phrase-based	HMM alignment, Pharaoh
Machine Translation II: Neural	
Applications I: Reading comprehension / MemNets	E2E Memory Networks, CBT, SQuAD, BiDAF
Applications II: Language grounding	
Applications III: Summarization	MMR, Gillick, Sentence compression, SummaRuNNER, Pointer
Applications IV: Dialogue	RNN chatbots, Diversity, Goal-oriented, Latent Intention, QA-as-dialogue
Unsupervised Learning	
NO CLASS (Thanksgiving)	
Multilinguality and morphology	
Wrapup	

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Sequence models I: HMMs	JM 9, JM 10.4, Manning POS
Sequence models II: CRFs	Sutton CRFs 2.3, 2.6.1, Wallach CRFs tutorial, Illinois NER
Neural Nets I: FFNNs	Goldberg 1-4, 6, NLP with FFNNs, DANs
Neural Nets II: NN impl / word embeddings	Goldberg 5, word2vec, GloVe, Dropout
Neural Nets III: RNN and CNN encoders	Goldberg 9-11, Kim
Neural Nets IV: Neural CRFs	Collobert and Weston, Neural NER, Neural CRF parsing
Trees I: Constituency, PCFGs	JM 13.1-13.7, Structural, Lexicalized, State-split
Trees II: Dependency I	JM 14.1-14.4, Huang 1-2
Trees III: Dependency II	Parsey, Huang 2
Semantics I	
Semantics II / Seq2seq I	
Seq2seq II: Beam search, attention	Seq2seq, Attention, Luong Attention
Information Extraction / SRL	Distant supervision, RL for slot filling, TextRunner, ReVerb, NELL
Discourse and Coreference	
Machine Translation I: Phrase-based	HMM alignment, Pharaoh
Machine Translation II: Neural	
Applications I: Reading comprehension / MemNets	E2E Memory Networks, CBT, SQuAD, BiDAF
Applications II: Language grounding	
Applications III: Summarization	MMR, Gillick, Sentence compression, SummaRuNNER, Pointer
Applications IV: Dialogue	RNN chatbots, Diversity, Goal-oriented, Latent Intention, QA-as-dialogue
Unsupervised Learning	
NO CLASS (Thanksgiving)	
Multilinguality and morphology	
Wrapup	

Outline of the Course

ML and structured prediction for NLP

Neural nets

Syntax/ semantics

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Applications: MT, IE, summarization, dialogue, etc.

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

Assignments

- 4 Homework Assignments
  - Implementation-oriented, with an open-ended component to each
  - Homework 1 (Naive Bayes for sentiment classification) is out NOW
  - ~2 weeks per assignment, 3 “slip days” for automatic extensions

Assignments

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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.