Natural Language Understanding with Indirect Supervision

Daniel Khashabi

Age of Big Data

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- Big data:
  - Over 56 billion pages
  - Over 500 million tweets are sent every day.
  - Over 4 million blog posts are published on the Internet every day.
- Deep learning:
  - 1.5 billion parameters [Radford et al. 2019]
  - Super-human performance [Devlin et al. 2018]

Troubling Observations

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- Brittleness with respect to small changes [K at al. 2016; Jia et al. 2017; Ribeiro et al. 2018; others]

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Context: *In the United States especially, several high-profile cases such as Debra LaFave, Pamela Rogers, and Mary Kay Letourneau have caused increased scrutiny on teacher misconduct.*

Question: *What has been the result of this publicity?*

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→ *"increased scrutiny on teacher misconduct"*

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Question: *~~What has~~ been the result of this publicity?* → *"increased scrutiny on teacher misconduct"*

What's → *"teacher misconduct"*

Scenarios with Little (no?) Supervision

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- Majority of our success has been on tasks w/ abundant **annotations.**
  - And tasks with little annotated data get the least attention.

- There will be settings where there is not “enough” direct supervision.
  - Unseen/unexpected scenarios.
  - Change of style, context, domain, etc.
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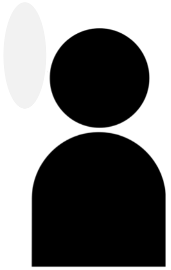
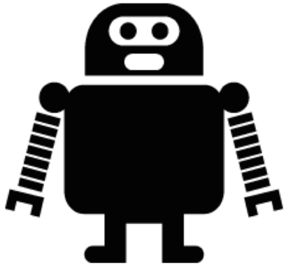
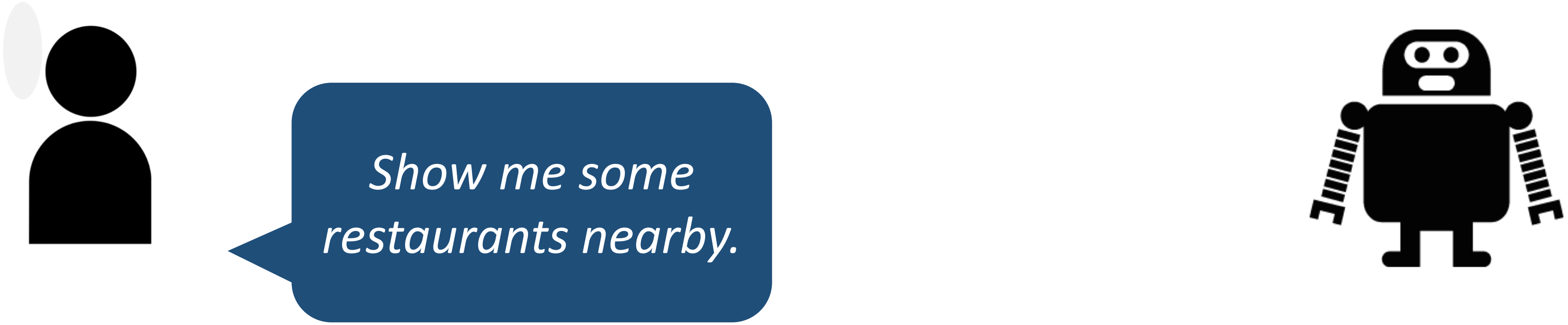
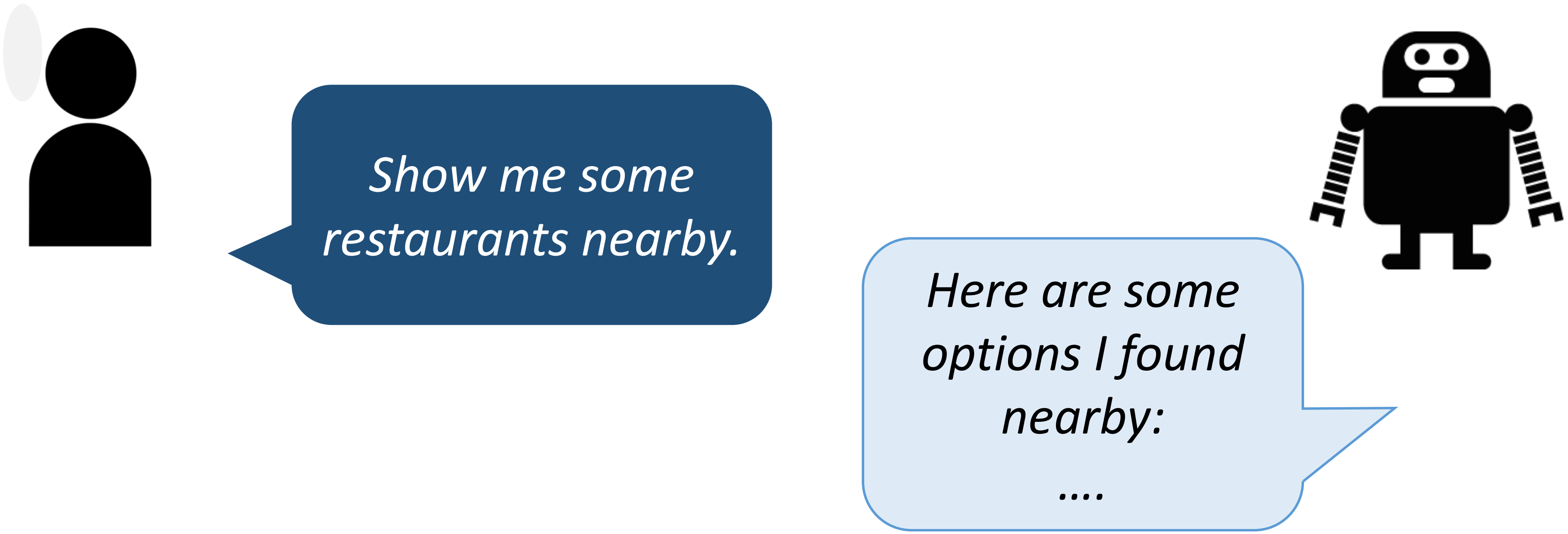





Show me some restaurants nearby.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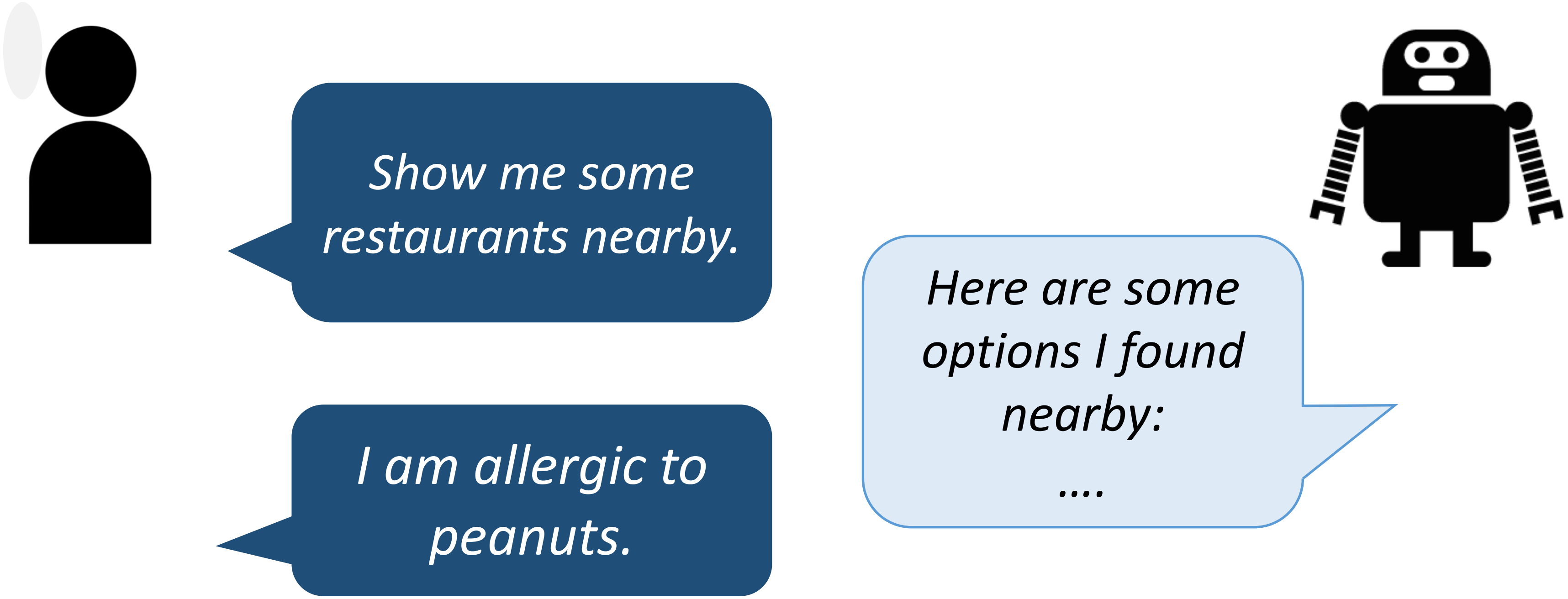
Show me some restaurants nearby.
I am allergic to peanuts.
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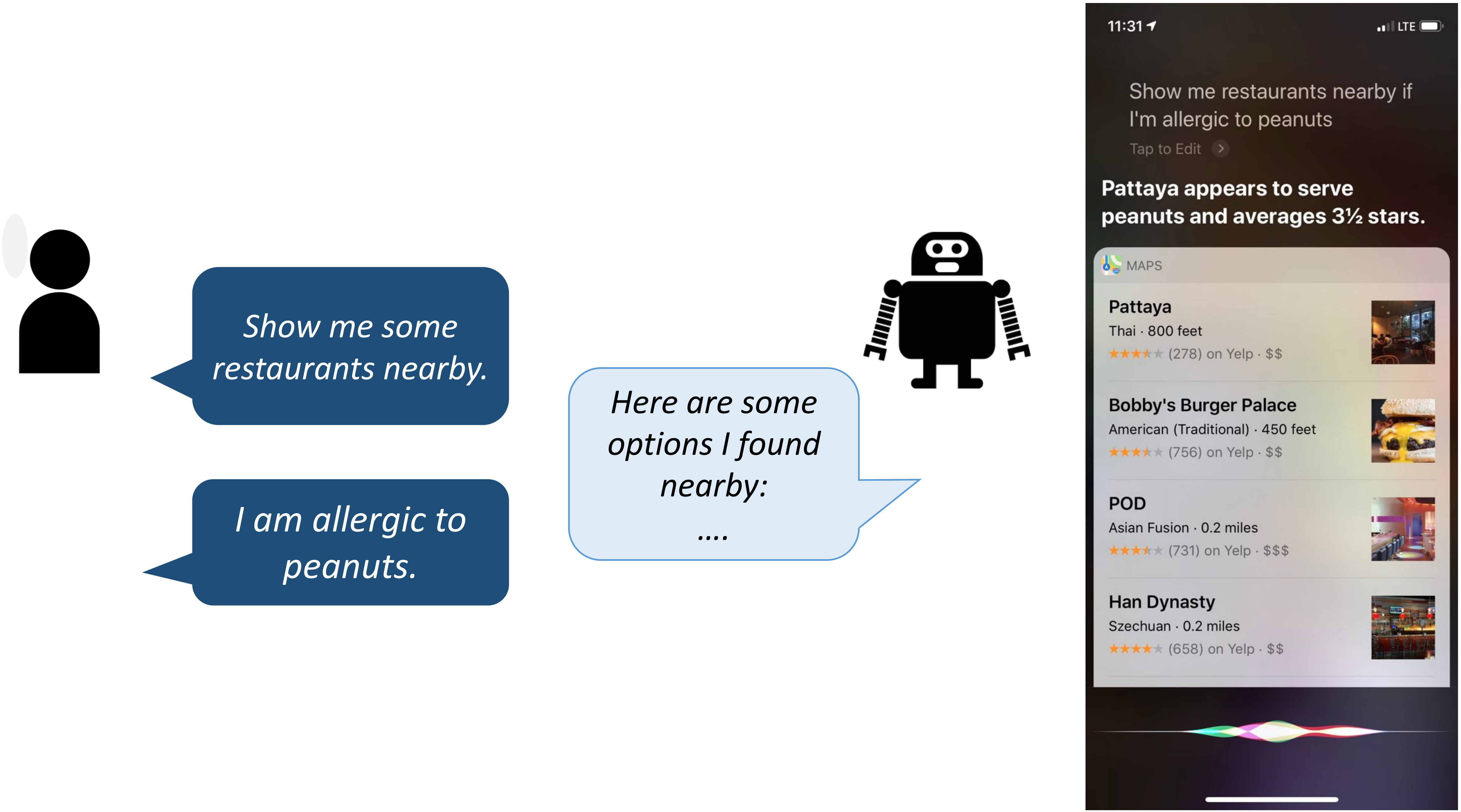

Show me some restaurants nearby.
I am allergic to peanuts.
Here are some options I found nearby:
....
11:31
LTE
Show me restaurants nearby if I'm allergic to peanuts
Tap to Edit
Pattaya appears to serve peanuts and averages 3½ stars.
MAPS
Pattaya
Thai · 800 feet
(278) on Yelp · $$
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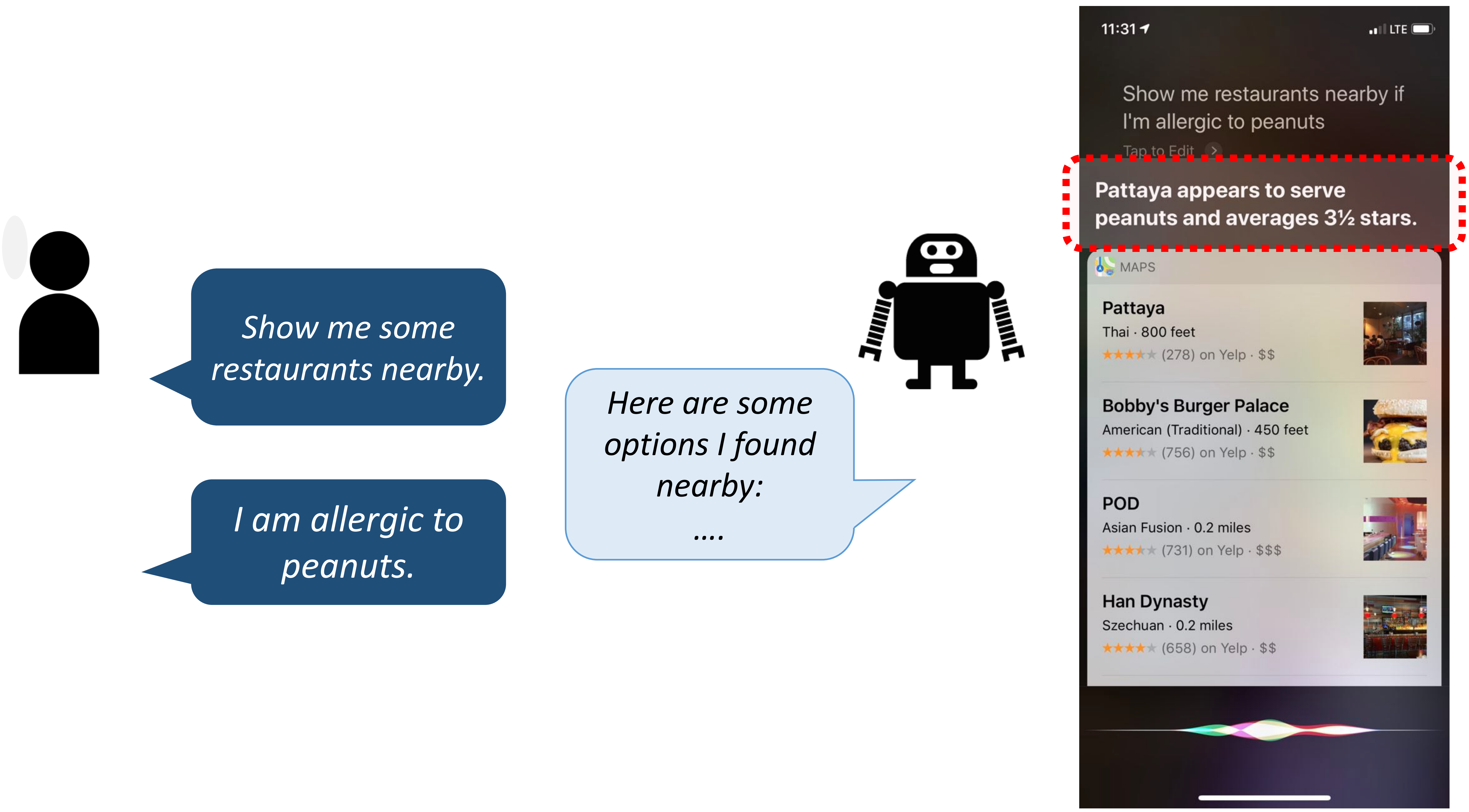
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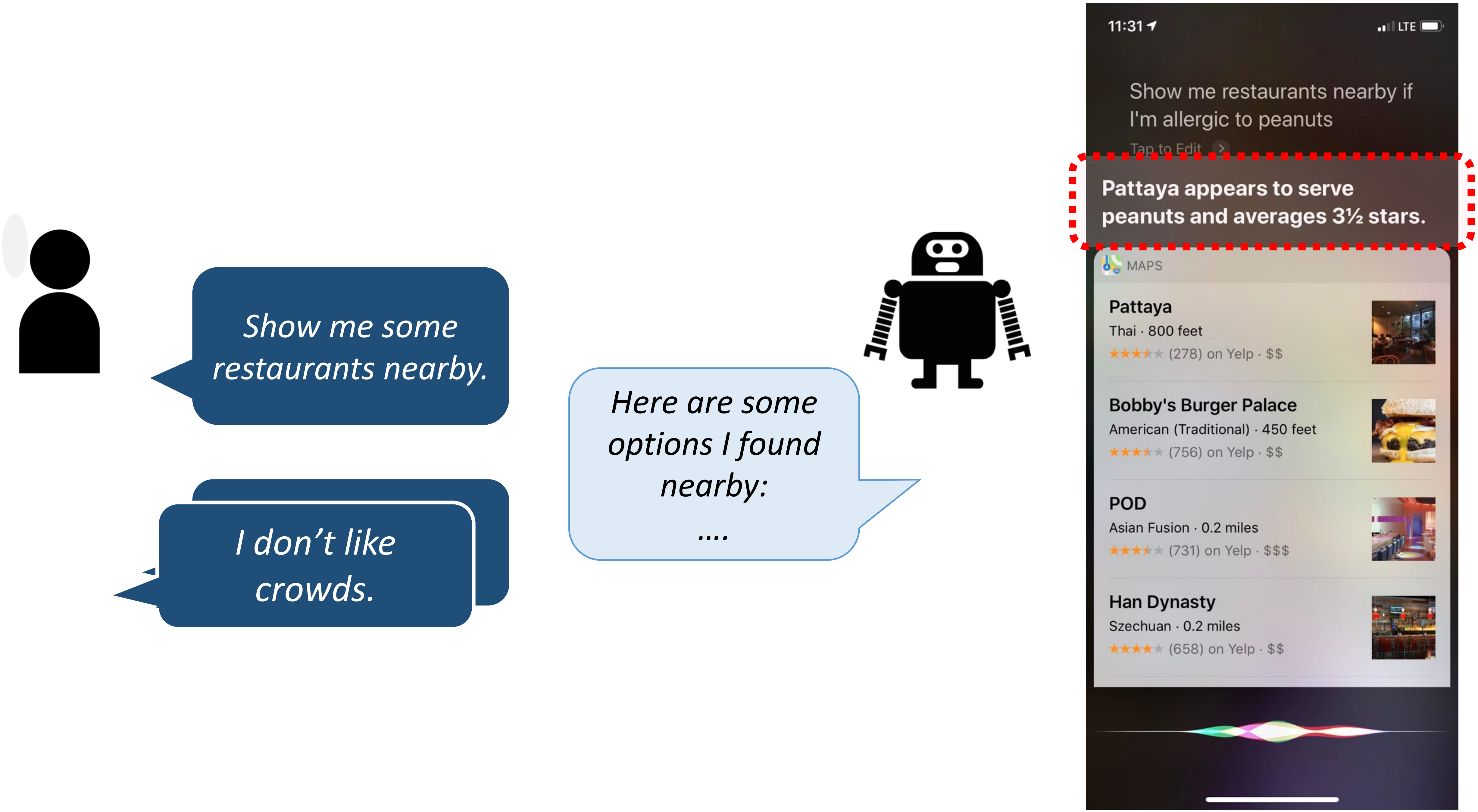

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I don't like crowds.
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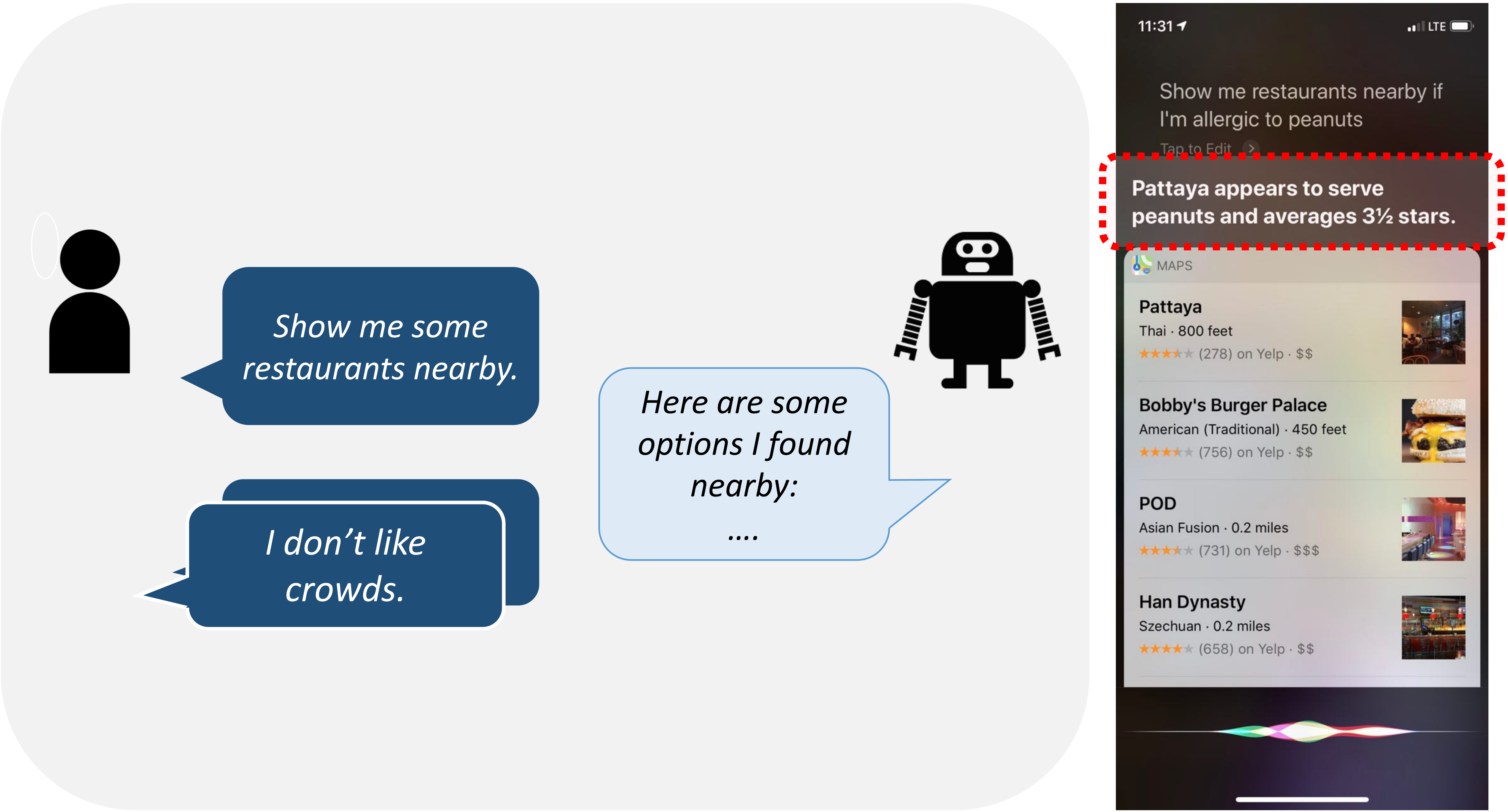
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- It's unlikely that we will have directly "annotated" data that cover **all** aspects of natural language understanding.

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- Weak signals can be amplified to produce higher quality signals.
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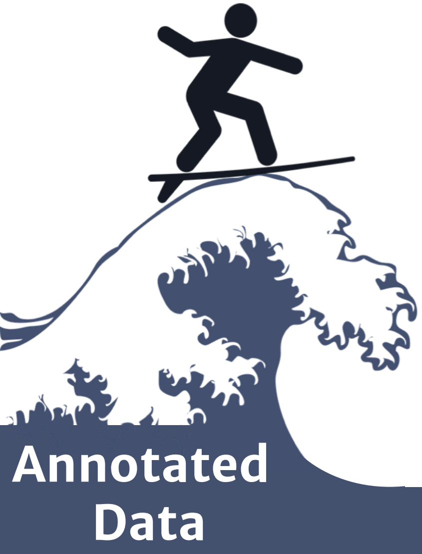
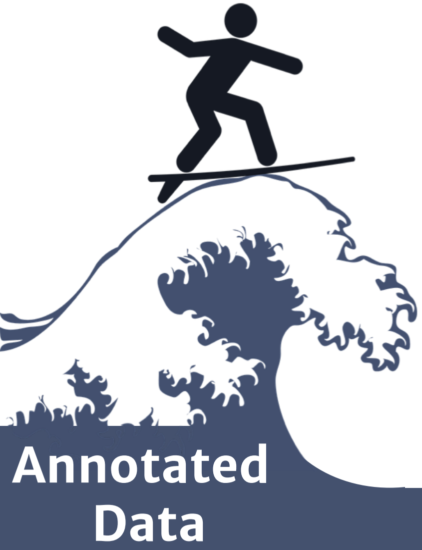

Annotated
Data



This talk

“Supervision” vs “Data”

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$$\{(\mathbf{x},\mathbf{y})\} \Rightarrow$$

( ,"spam")

( ,"ham")

( ,"spam")

⋮

Supervision
(direct annotations)

“Supervision” vs “Data”

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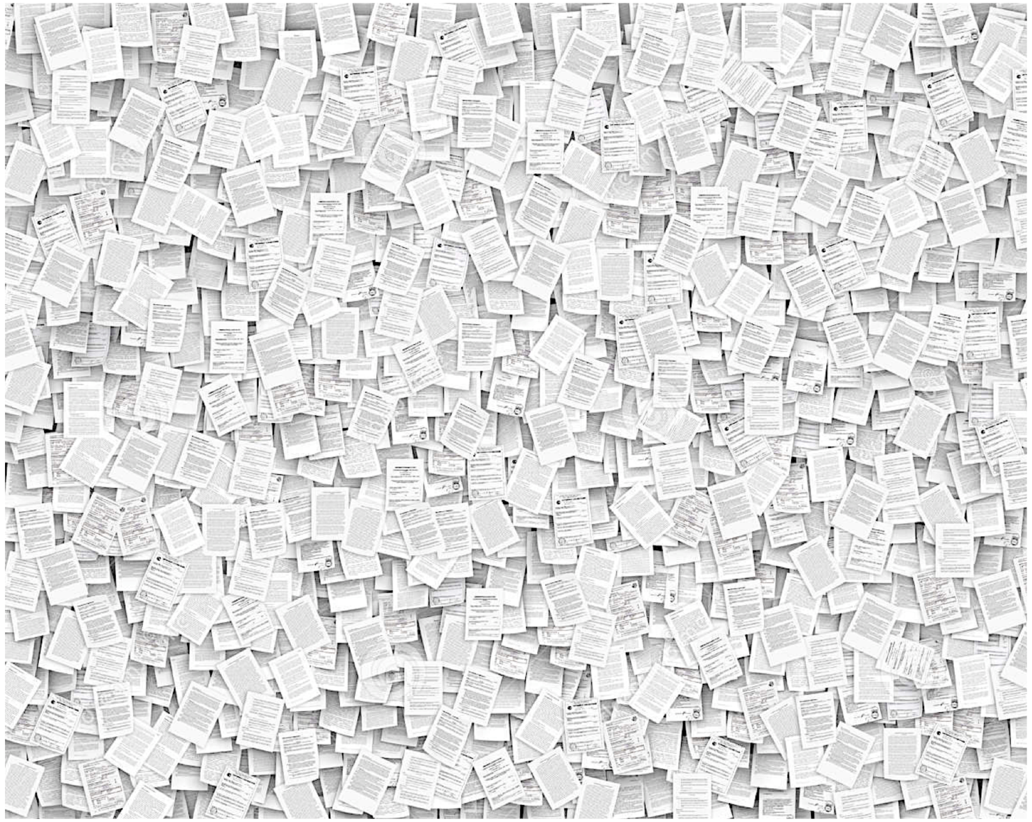

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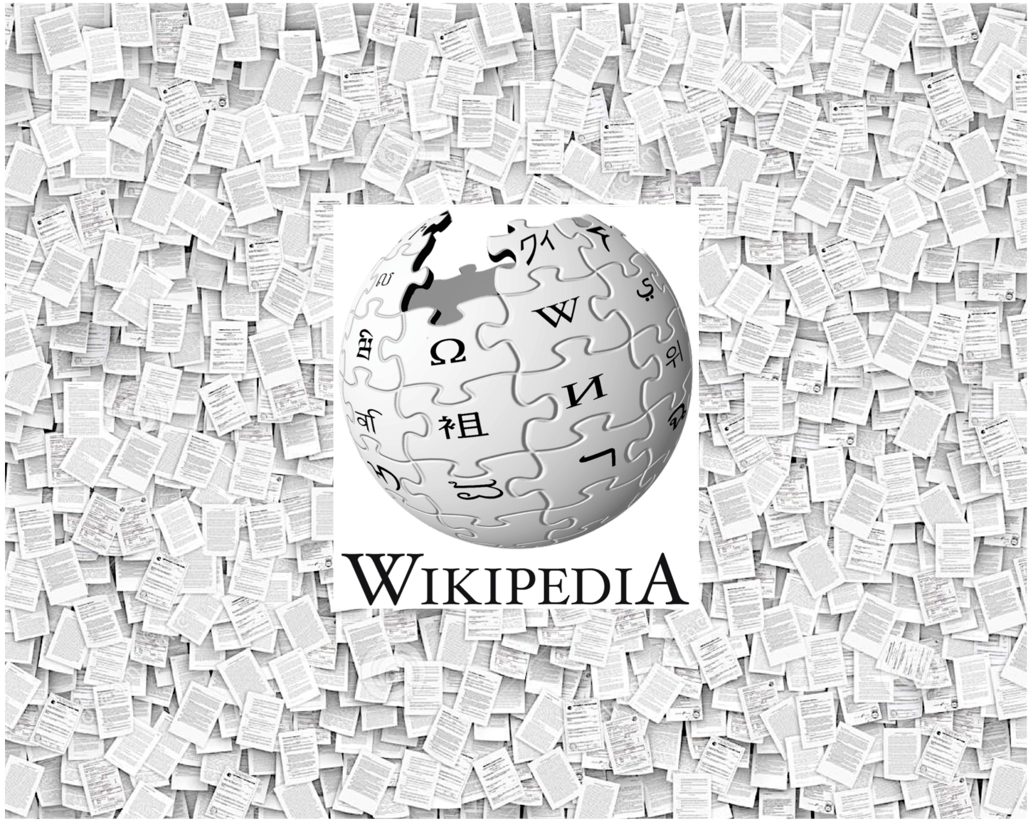

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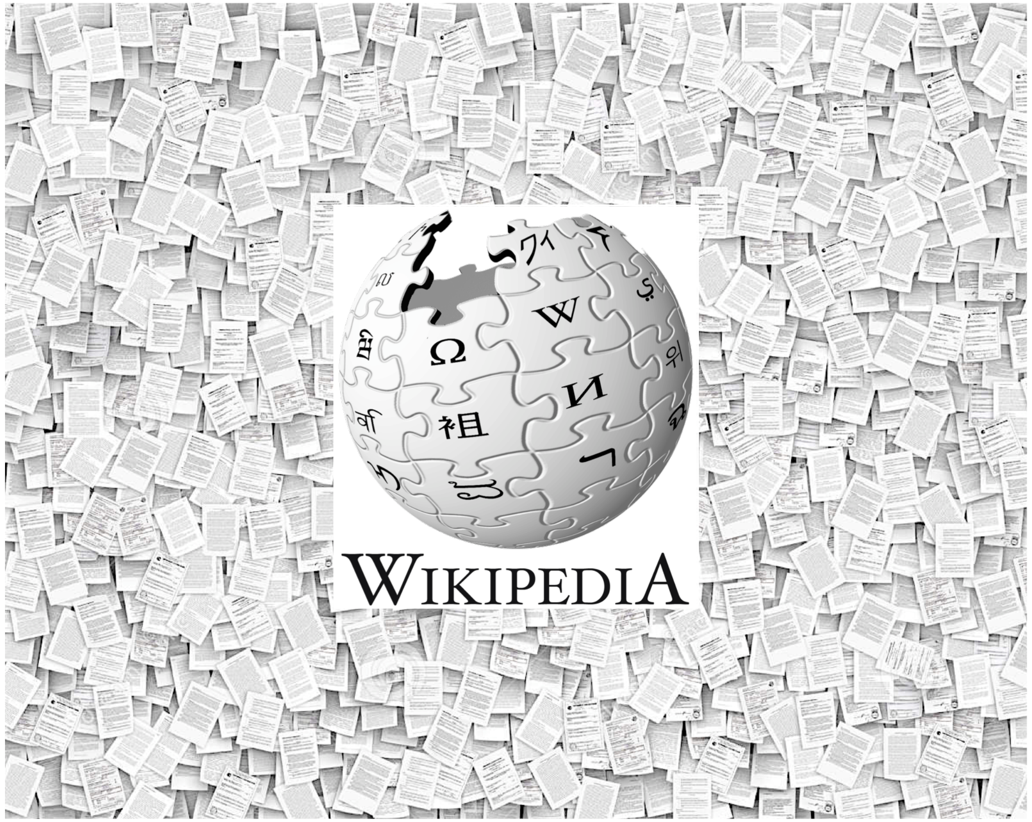

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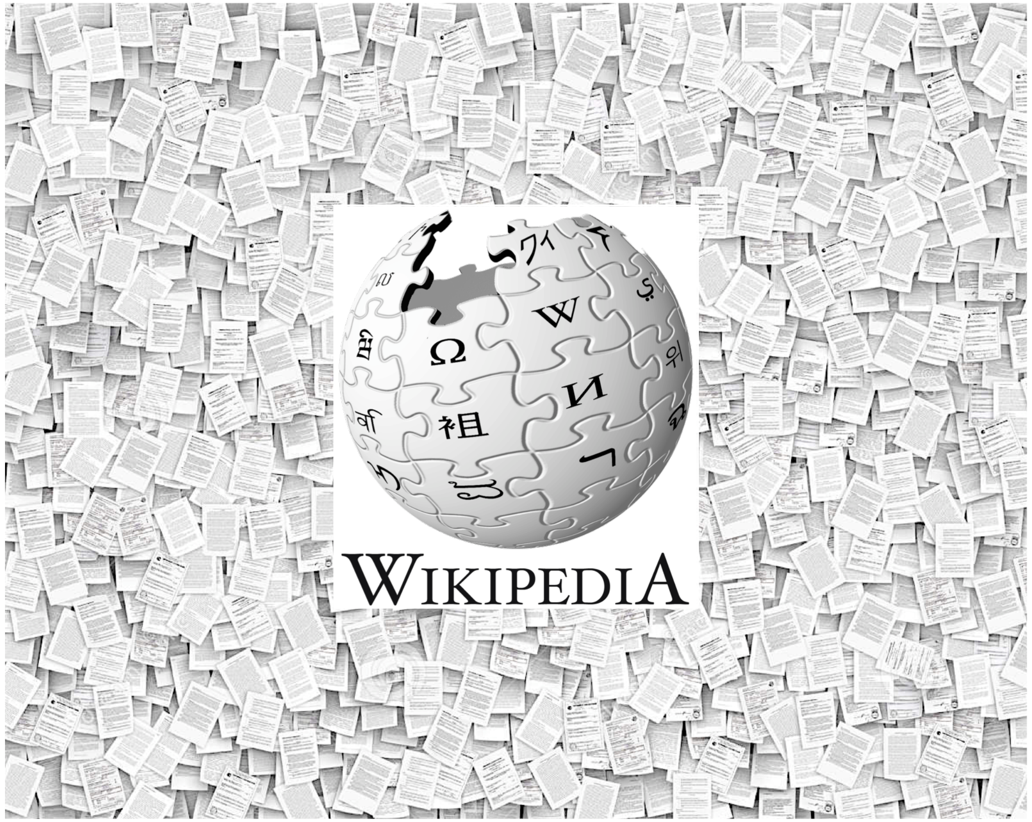

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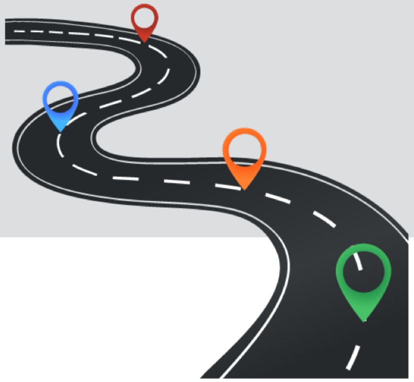

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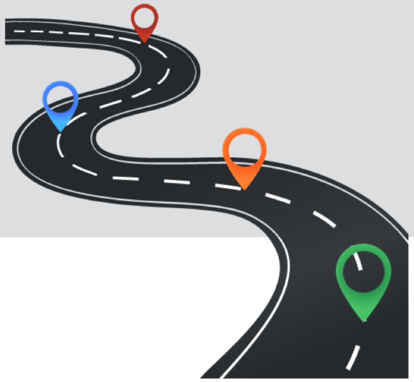

with minimal supervision

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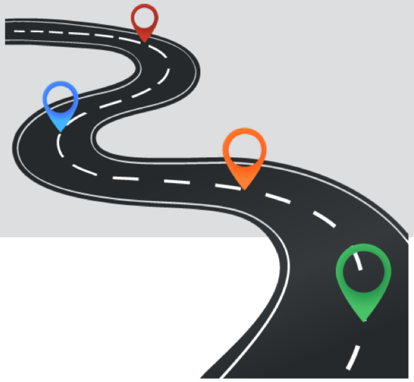

with minimal supervision

- Representations
- Wikipedia
- Structure of the problem
- Compositionality
- Other learned models
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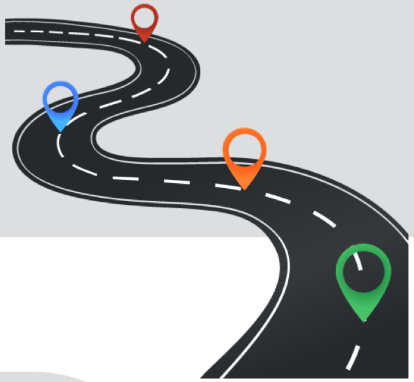

▣ Introduction

▢ Answering Questions

▢ Semantic Typing of Entities

▢ Future Work

with minimal supervision

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ANSWERING QUESTIONS *with minimal supervision*

K et al. Question Answering as Global Reasoning over Semantic Abstractions. AAAI 18.

K et al. Question Answering via Integer Programming over Semi-Structured Knowledge. IJCAI 16.

Clark, EKSTT**K**. Combining Retrieval, Statistics, and Inference to Answer Elementary Science Questions. AAAI 16.

Why Answering Questions?

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- The grand goal: *Natural Language Understanding (NLU).*
- Measuring progress by answering questions.
  - A system that is better at understanding language should have a higher chance of answering questions.
  - This has been used in the field for many years.
    [Winograd, 1972; Lehnert, 1977b; others]
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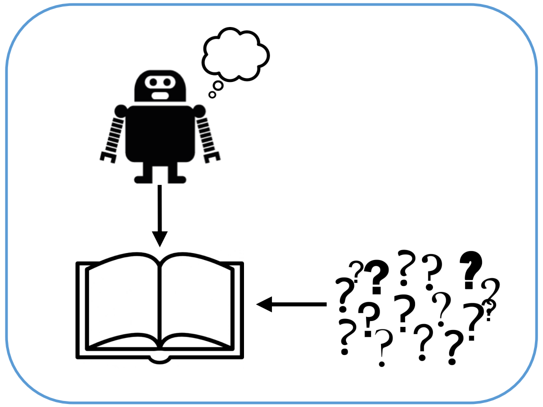

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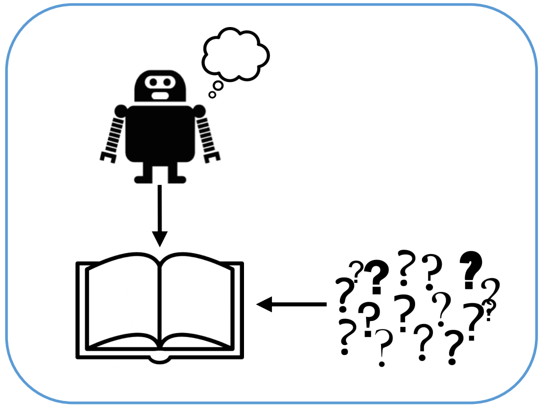

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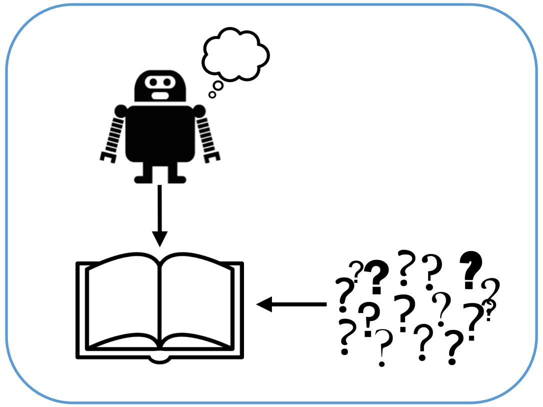

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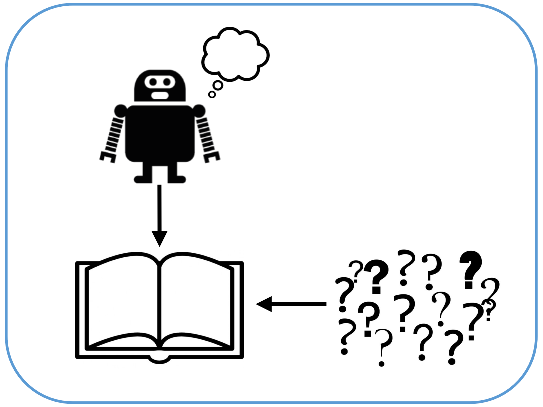

Answering Questions: The Setting

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Question: *A bear survives winters with what structure?*

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(A) big ears
(B) black nose
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Attached to each question is an **evidence paragraph**, potentially with the answer to the question.

Answering Questions: The Setting

- Standardized science exams. [Clark et al. 2015]
- Simple language; machines require the ability to use the knowledge and abstract over it.

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Evidence paragraph

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Evidence paragraph

… Polar bears, saved from the bitter cold by their thick fur coats, are among the animals in danger of extinction because of global warming and human activities. …

Linguistic Variability

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Evidence paragraph

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A given "meaning" can be phrased in many surface forms!

Linguistic Variability

Question: *A bear survives winters with what structure?* +

(A) big ears
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Evidence paragraph

Polar bears have white fur so that they can camouflage into their environment. Their coat is so well camouflaged in Arctic environments that it can sometimes pass as a snow drift. They have a thick layer of body fat, which keeps them warm while swimming, and a double-layered coat that insulates them from the cold Arctic air.

Polar bears, saved from the bitter cold by their thick fur coats, are among the animals in danger of extinction because of global warming and human activities. *Polar bears' lives depend wholly on the sea, their main source of food, and the place they spend most of their lives. But as the climate warms, that ice is melting, threatening polar bears. A common method of hunting by polar bears involves the bear keeping perfectly still by a seal's breathing hole, waiting for hours—or even days—for a seal to pop up for air.*

A Common Approach: Supervised Learning

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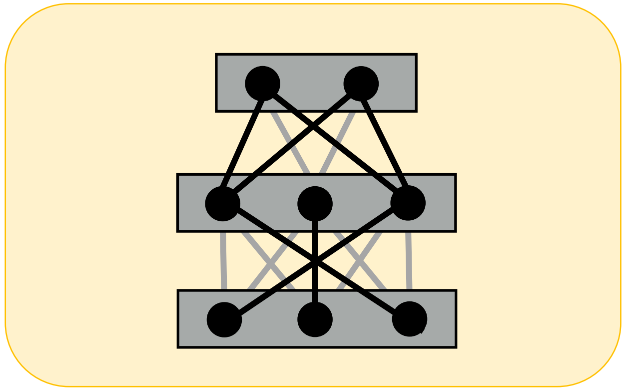

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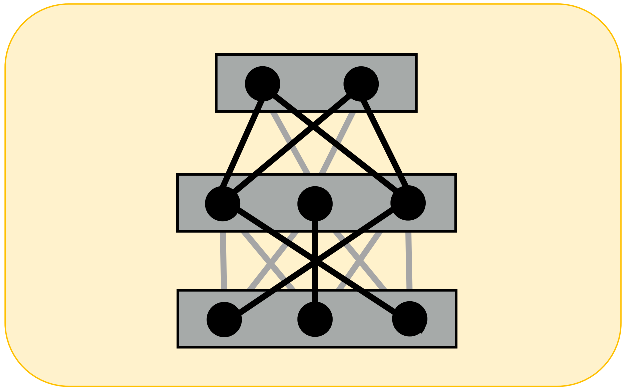

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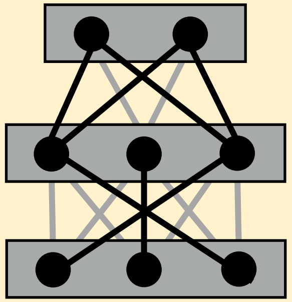

“thick fur coats”

A Common Approach: Supervised Learning

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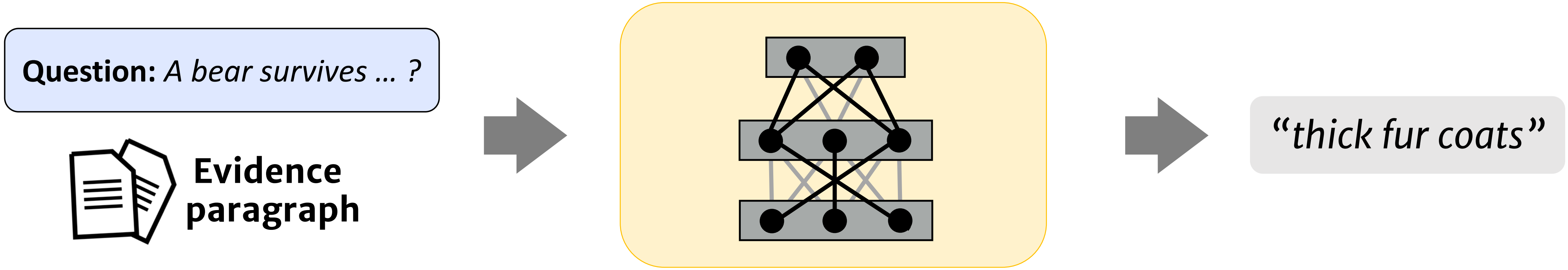

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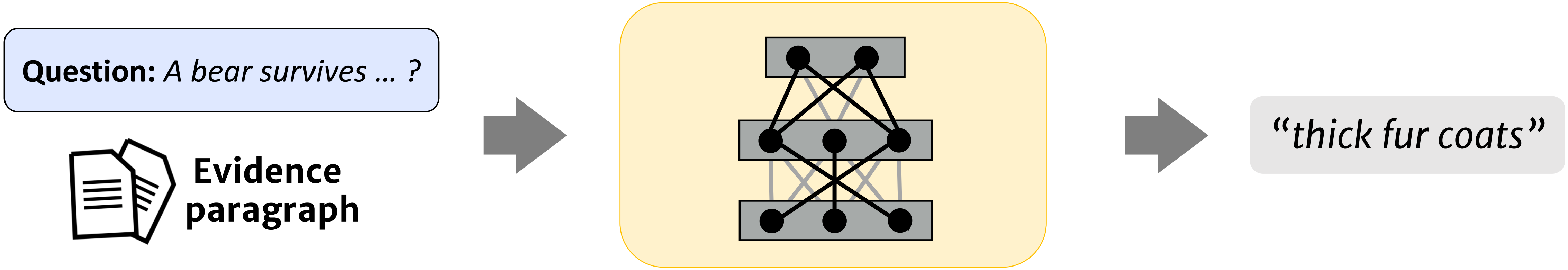

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[Fetched on March 26, 2019]

https://demo.allennlp.org

[Seo et al, 17, Gardner et al, 18]

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Predicted Answer

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Predicted Answer

- Can we "explain" the decision?
- Can we "fix" such behaviors?

[Fetched on March 26, 2019]
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Semi-Structured Inference: High-level View

Question Answering

as Global Reasoning

over Semi-Structured Knowledge

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Question Answering

Knowledge Representation
Structured,
yet flexible

Semi-Structured Inference: High-level View

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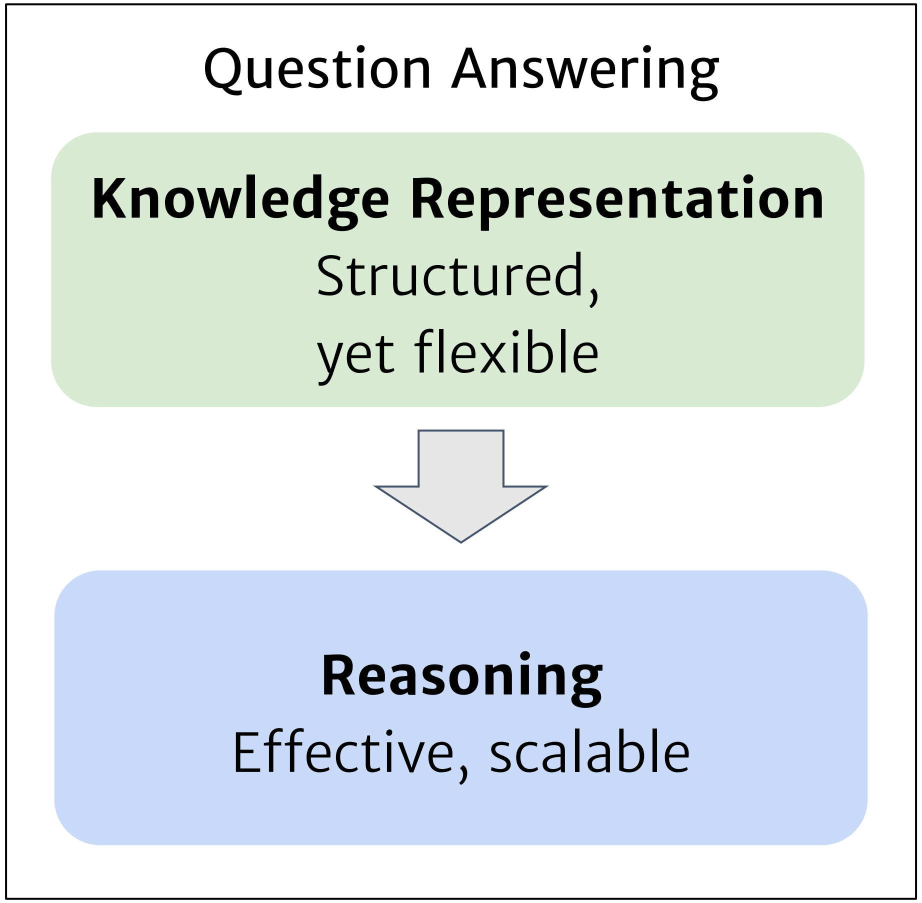

Language Understanding Phenomena

Question: *A bear survives winters with what structure?*

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(A) big ears
(B) black nose
(C) thick fur
(D) brown eyes

Evidence paragraph

*Polar bears, saved from the bitter cold **by** their thick fur coats, are among the animals in danger of extinction because of global warming and human activities.*

Language Understanding Phenomena

verb

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(D) brown eyes

Evidence paragraph

*Polar bears, saved from the bitter cold **by** their thick fur coats, are among the animals in danger of extinction because of global warming and human activities.*

Language Understanding Phenomena

verb

Question: *A bear survives winters with what structure?*

+

(A) big ears
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Evidence paragraph

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verb

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preposition

Evidence paragraph

*Polar bears, saved from the bitter cold **by** their thick fur coats, are among the animals in danger of extinction because of global warming and human activities.*

Language Understanding Phenomena

verb

Question: *A bear <u>survives</u> winters with what structure?*

+

(A) big ears
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comma

preposition

Evidence paragraph

Polar bears, <u>saved from</u> the bitter cold ***by*** *their thick fur coats, are among the animals in danger of extinction because of global warming and human activities.*

Language Understanding Phenomena

verb

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Polar bears, saved from the bitter cold by their thick fur coats, are among the animals in danger of extinction because of global warming and human activities.

QA is fundamentally a NLU problem

"Lifting" Meaning as Semantic Graphs

“Lifting” Meaning as Semantic Graphs

Evidence paragraph

... Polar bears, saved from the bitter cold by their thick fur coats, are among the animals in danger of extinction because of global warming and human activities.

“Lifting” Meaning as Semantic Graphs

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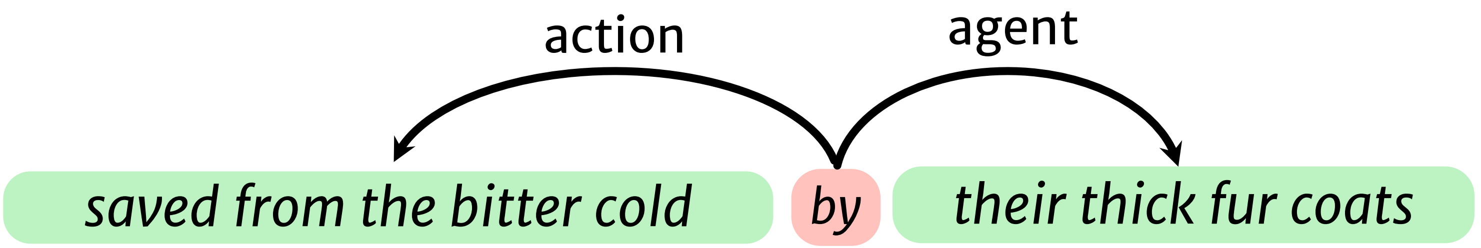

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"Lifting" Meaning as Semantic Graphs

action

agent

Agent of action

saved from the bitter cold *by* *their thick fur coats*

Evidence paragraph

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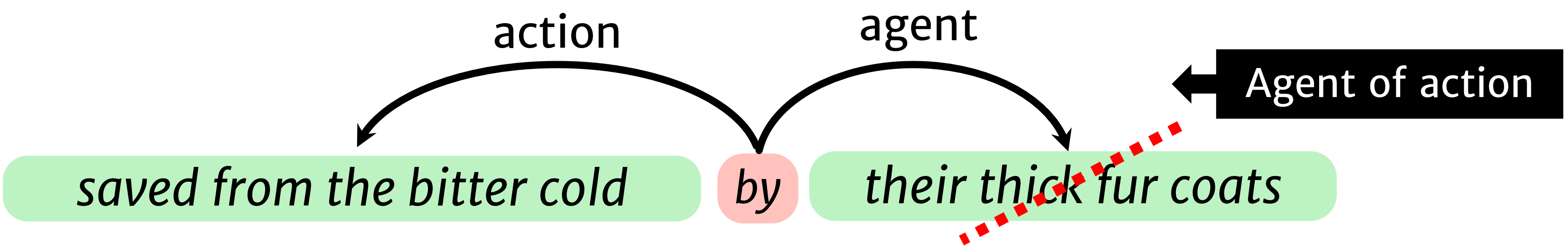

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Preposition Semantic Roles [Srikumar & Roth, 2013]

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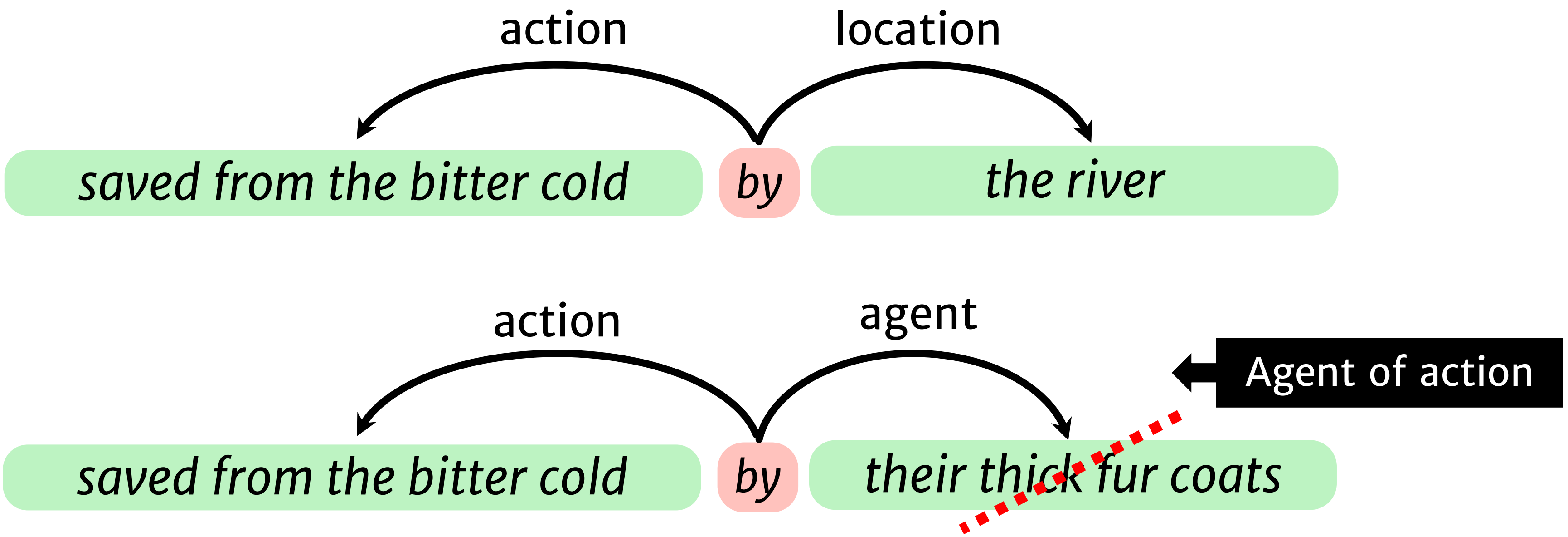

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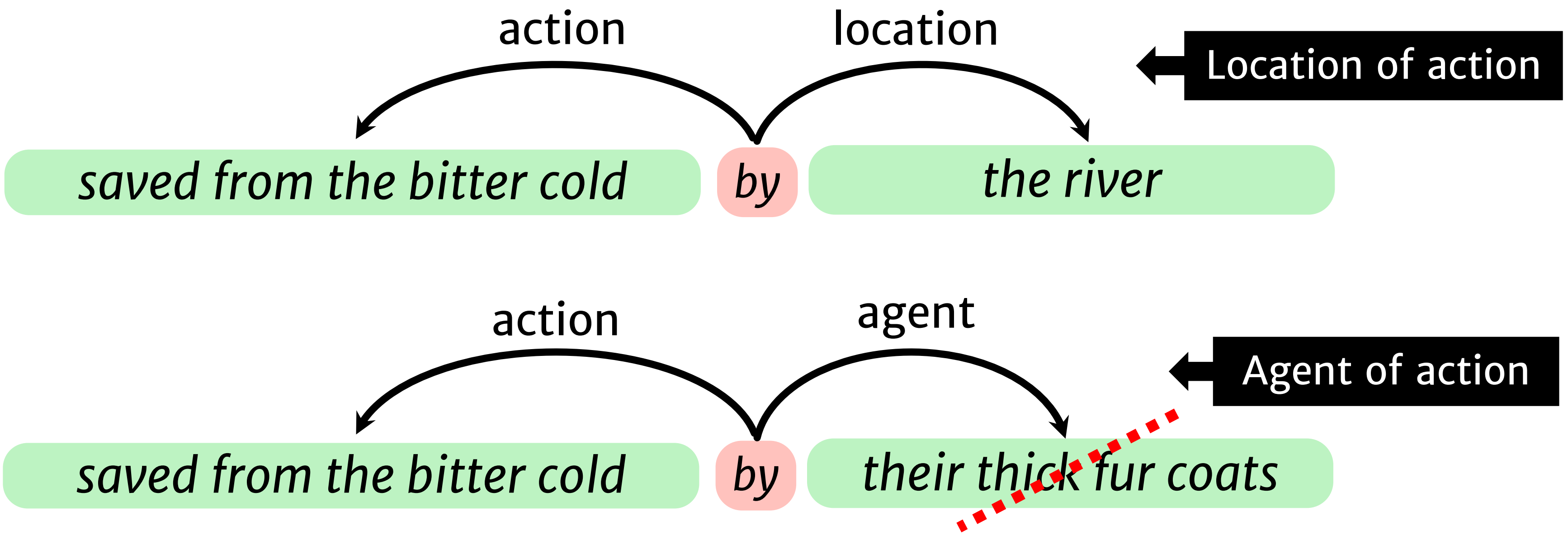

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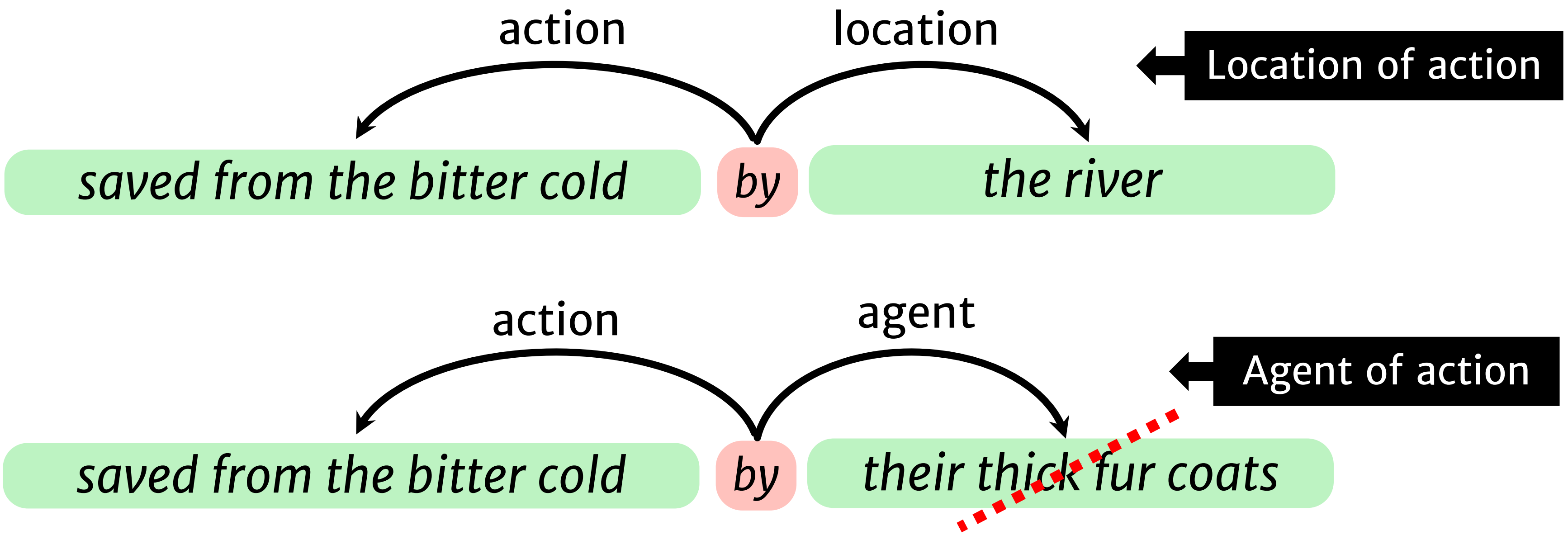
"Lifting" Meaning as Semantic Graphs

Oxford English Dictionary lists **<u>8</u>** primary meanings for "by".



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"Lifting" Meaning as Semantic Graphs

Oxford English Dictionary lists <u>**8**</u> primary meanings for "by".

Disambiguation!

action — location

saved from the bitter cold | *by* | *the river*

Location of action

action — agent

saved from the bitter cold | *by* | *their thick fur coats*

Agent of action

Evidence paragraph

... Polar bears, saved from the bitter cold by their thick fur coats, are among the animals in danger of extinction because of global warming and human activities.

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“Lifting” Meaning as Semantic Graphs

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Evidence paragraph

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"Lifting" Meaning as Semantic Graphs

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“Lifting” Meaning as Semantic Graphs

mention description

Polar bears , *saved from the bitter cold*

Evidence paragraph

... Polar bears , saved from the bitter cold by their thick fur coats, are among the animals in danger of extinction because of global warming and human activities.

"Lifting" Meaning as Semantic Graphs

mention   description

Polar bears , *saved from the bitter cold*

apposition structure

Evidence paragraph

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“Lifting” Meaning as Semantic Graphs

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a bear — survivor

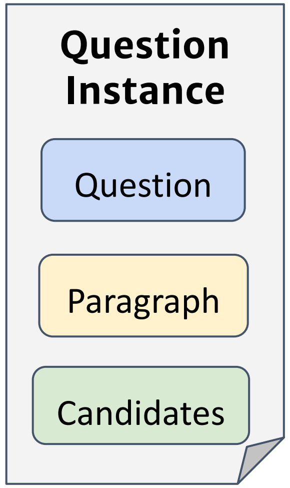
survive

a winter — adverse circumstance

what structure

live despite circumstance

Semantic Representations Altogether



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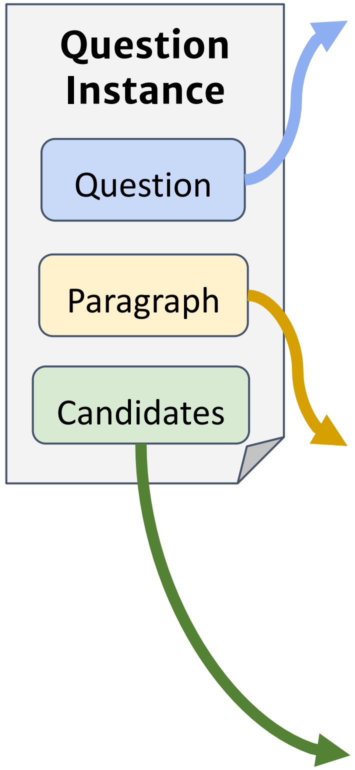

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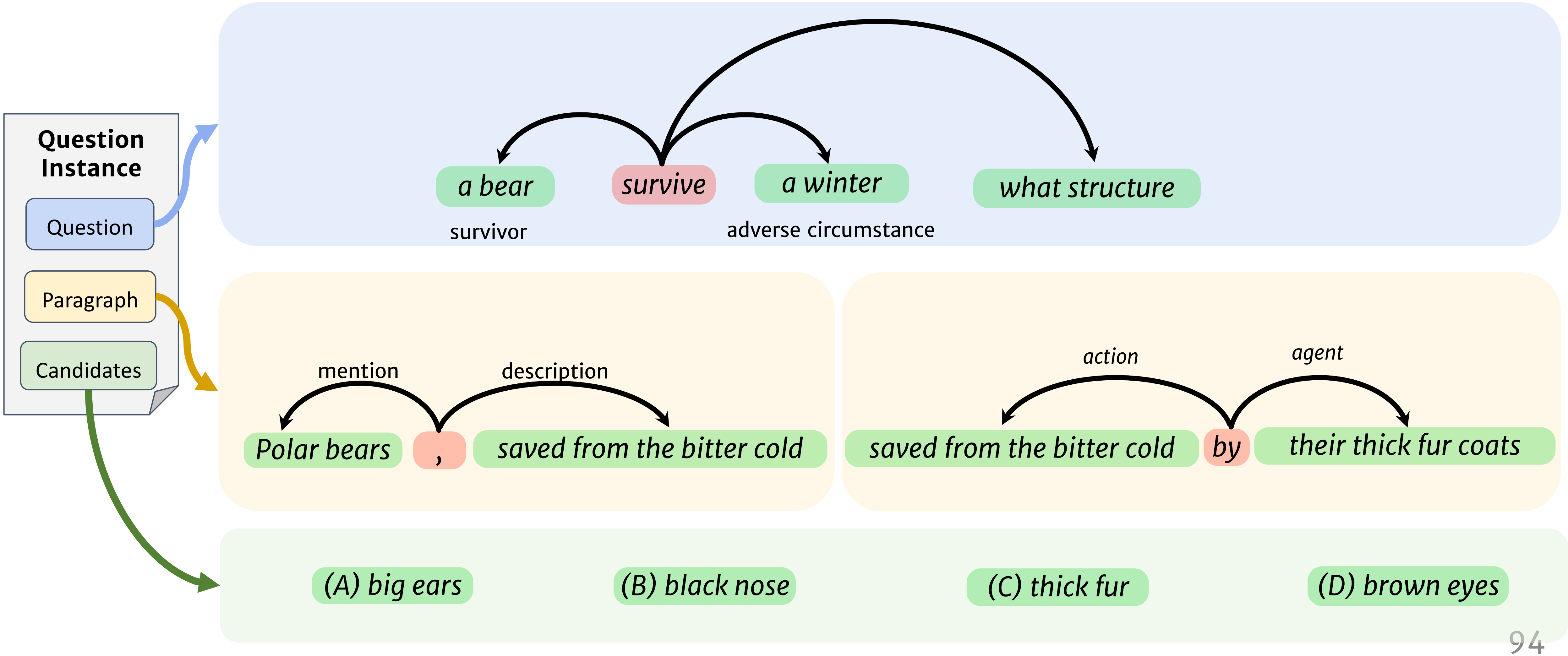
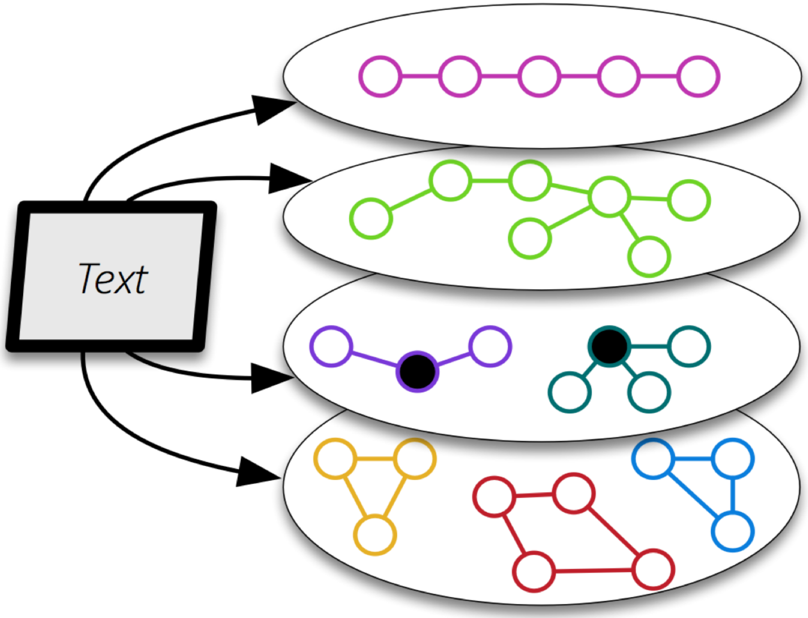


Collections of Semantic Graphs

- Create a unified representation of families of graphs



- Verb Semantic Roles [Punyakanok et al. 2008]
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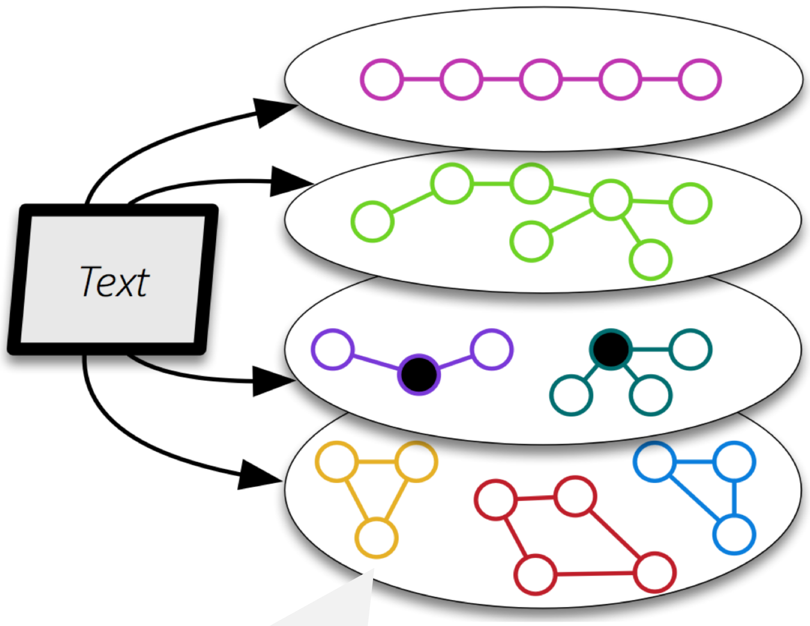

- Surface word
- Semantic labels
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- ...

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Collections of Semantic Graphs

available in our software pipeline.
K et al. LREC'18

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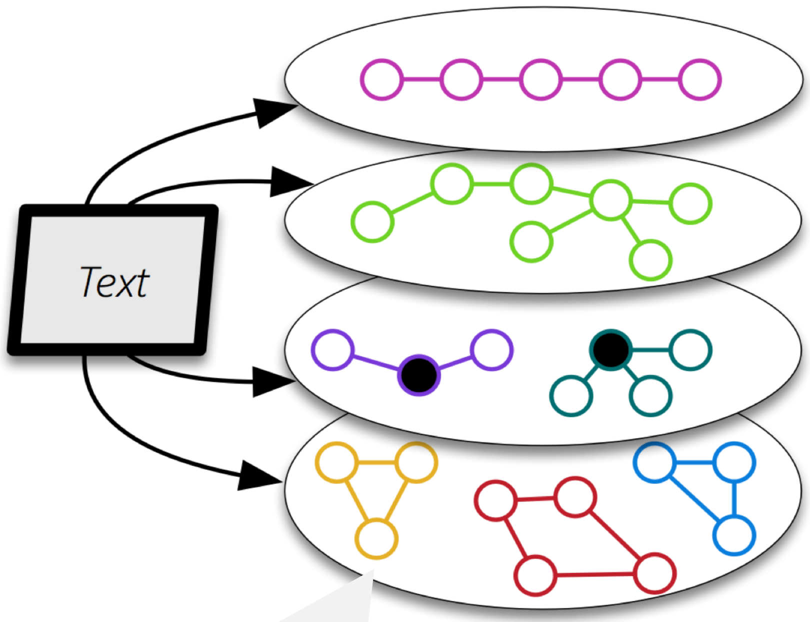

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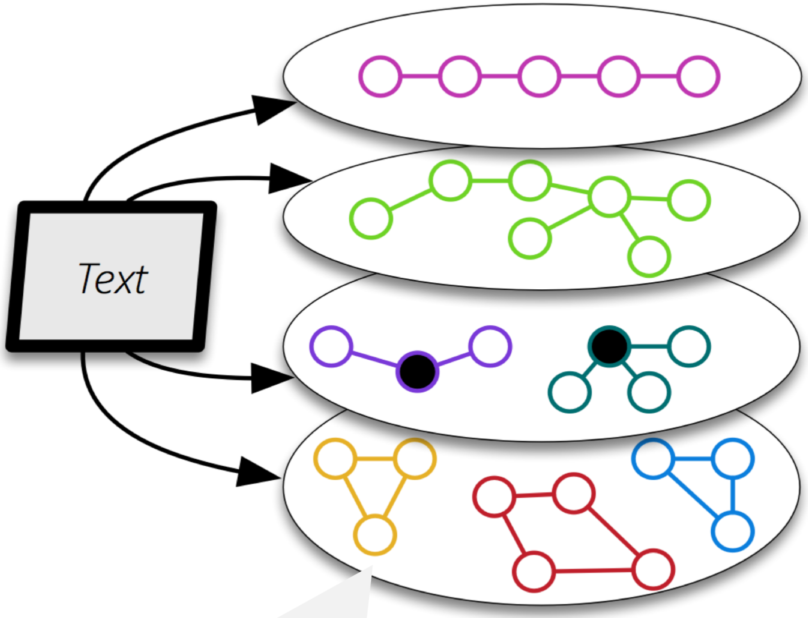

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Our representation is **not** QA-specific.
It reflects our understanding of the language

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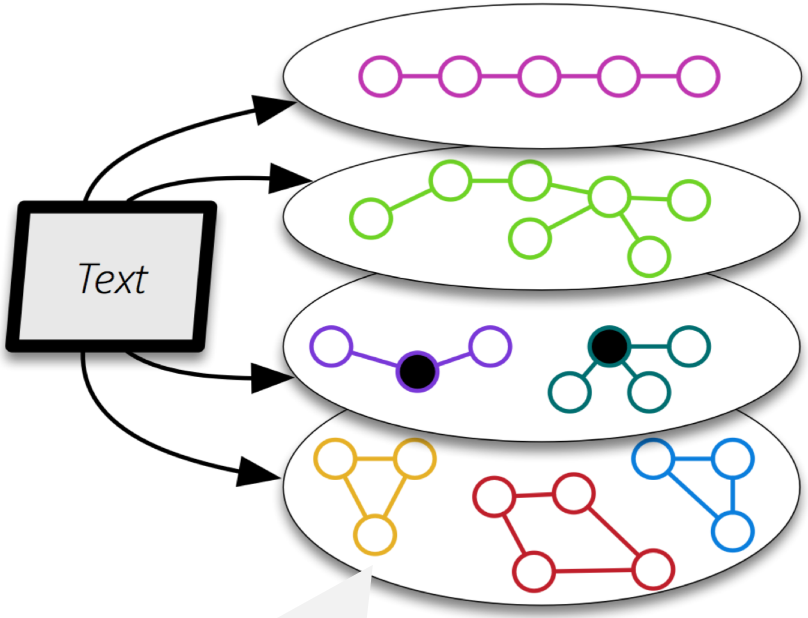

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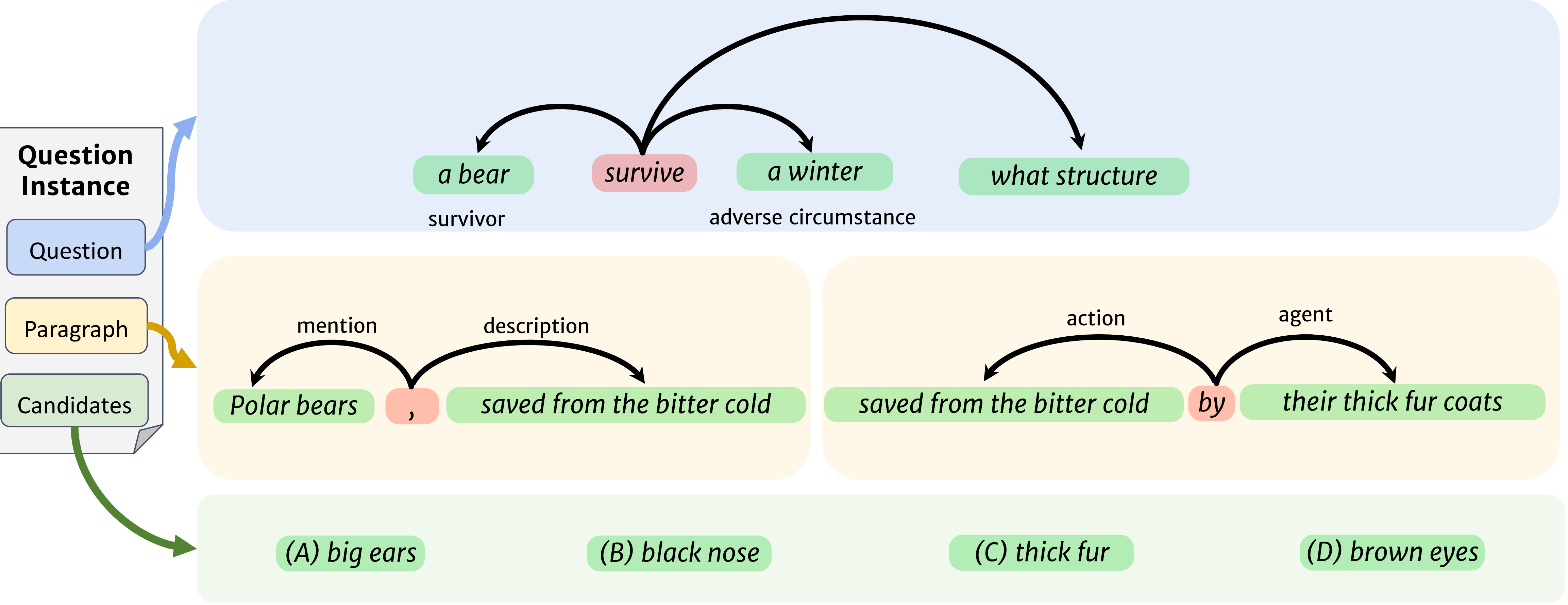
Consequently, we expect these representations to be useful for a range of tasks

Support Graph



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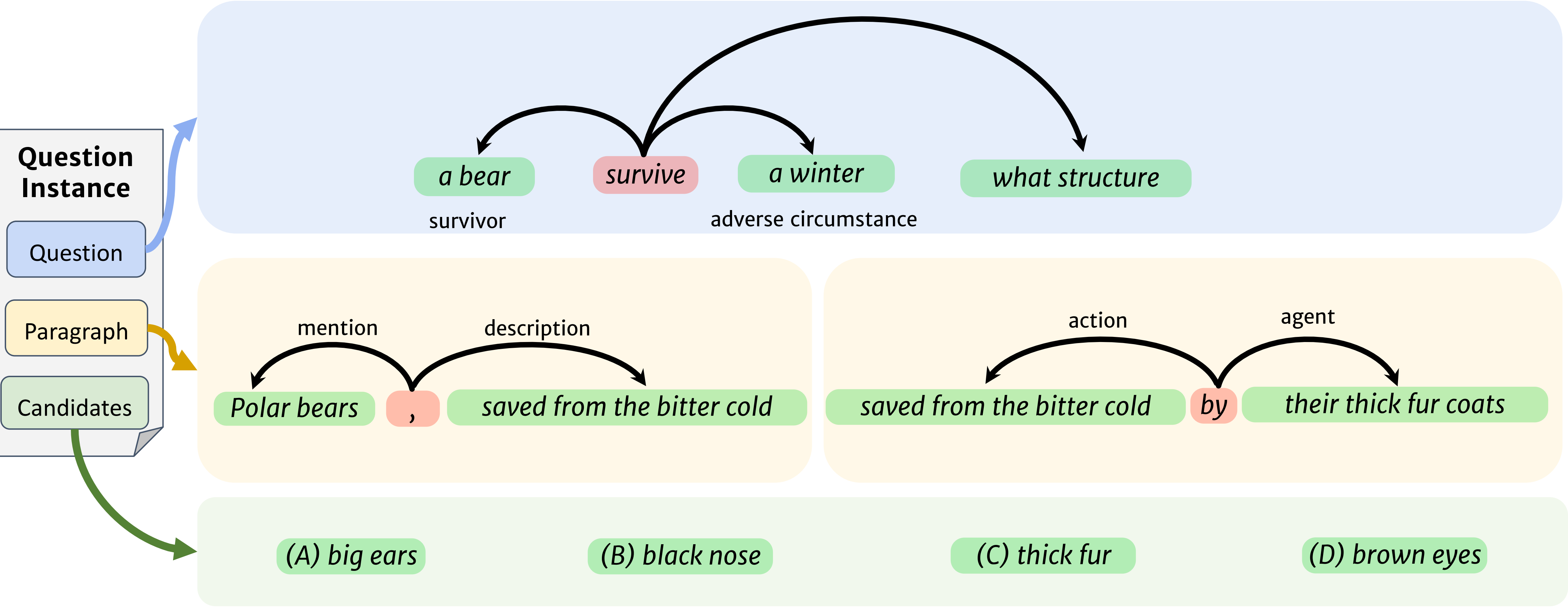
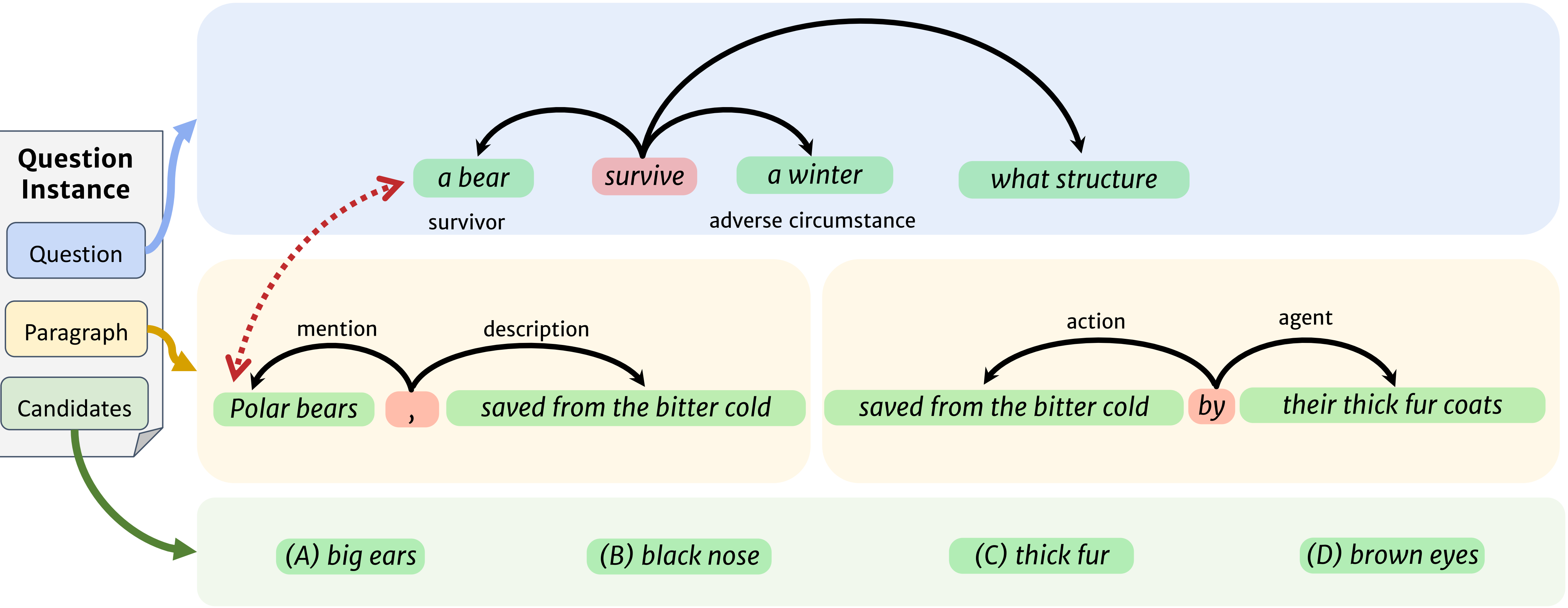


Search for the best **Support Graph** connecting the Question to an Answer through the knowledge graph.

Support Graph



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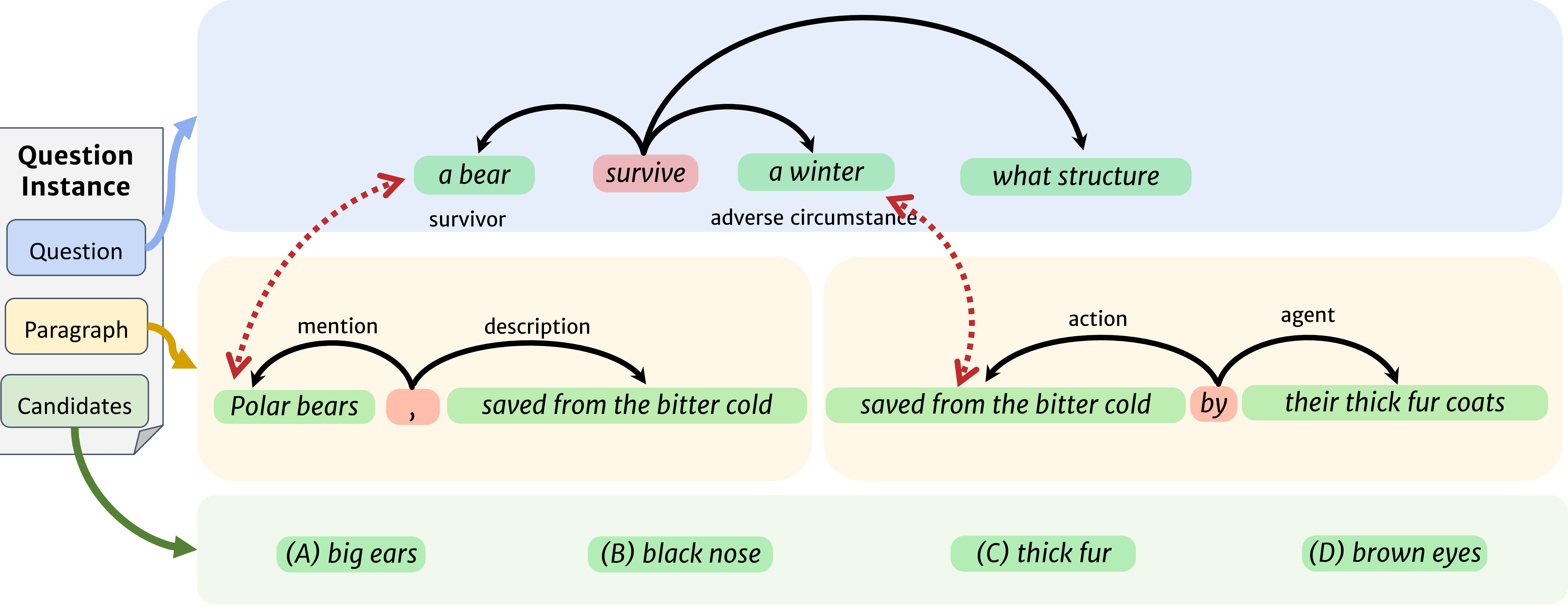

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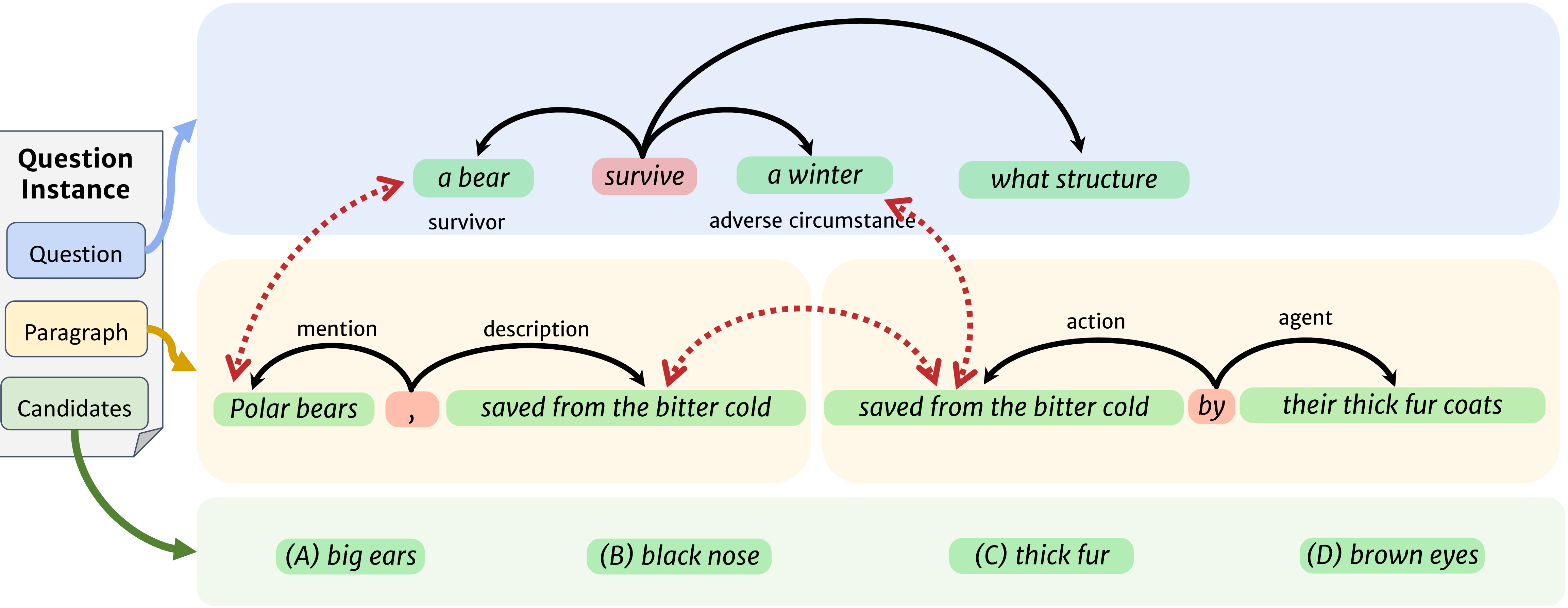

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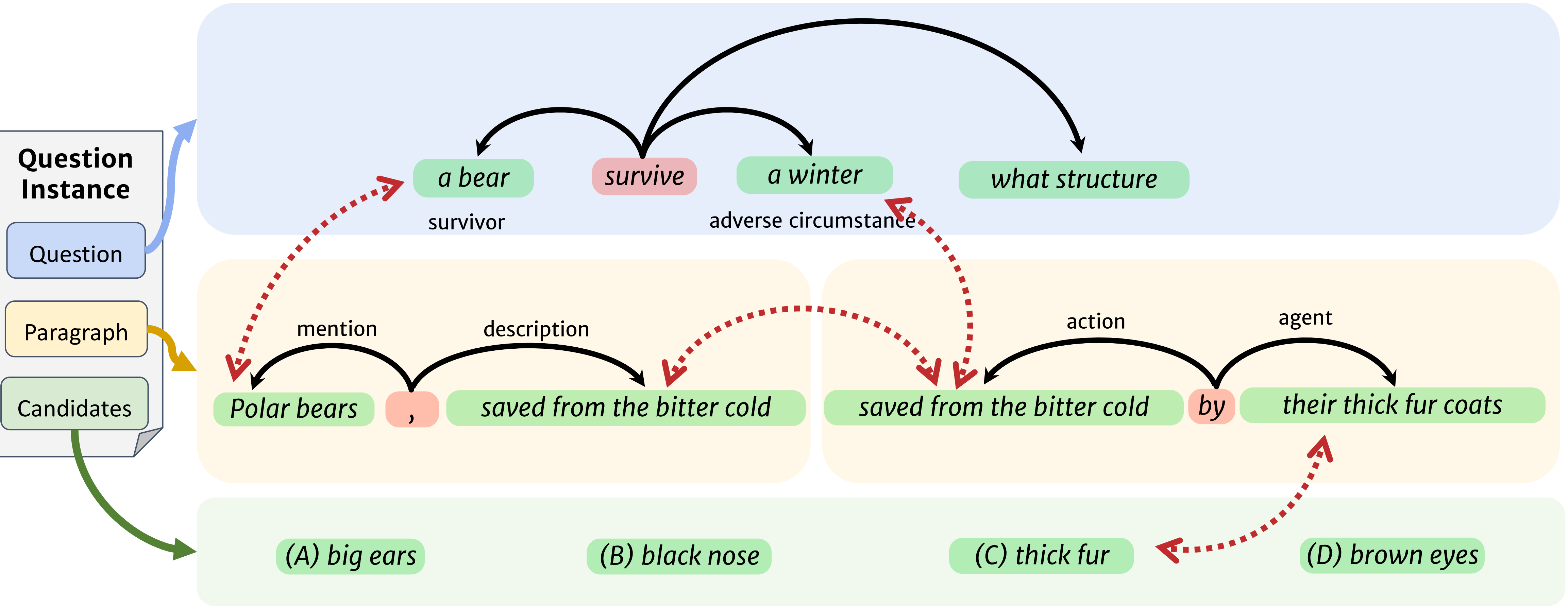

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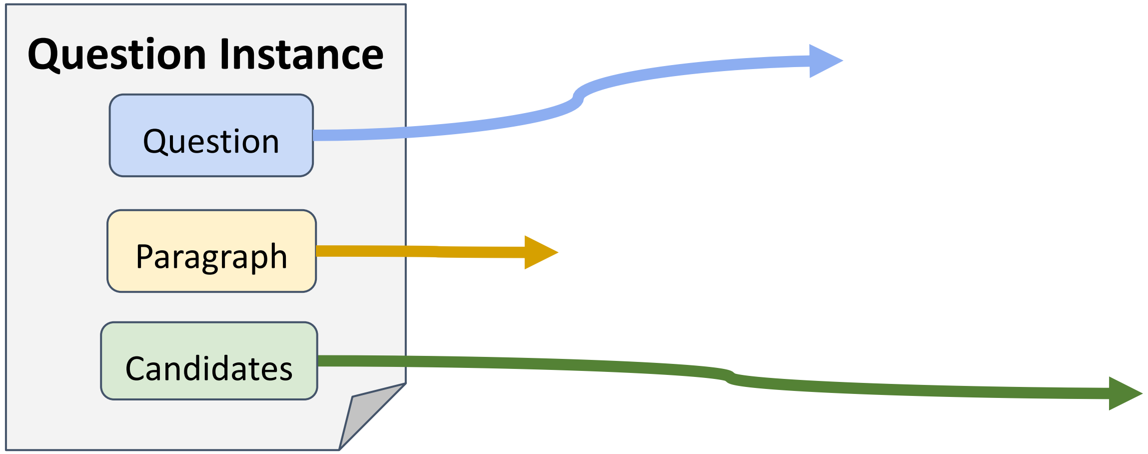
Reasoning With a Meaning Representation

- **Support Graph** creates potential alignments between various semantic abstractions.



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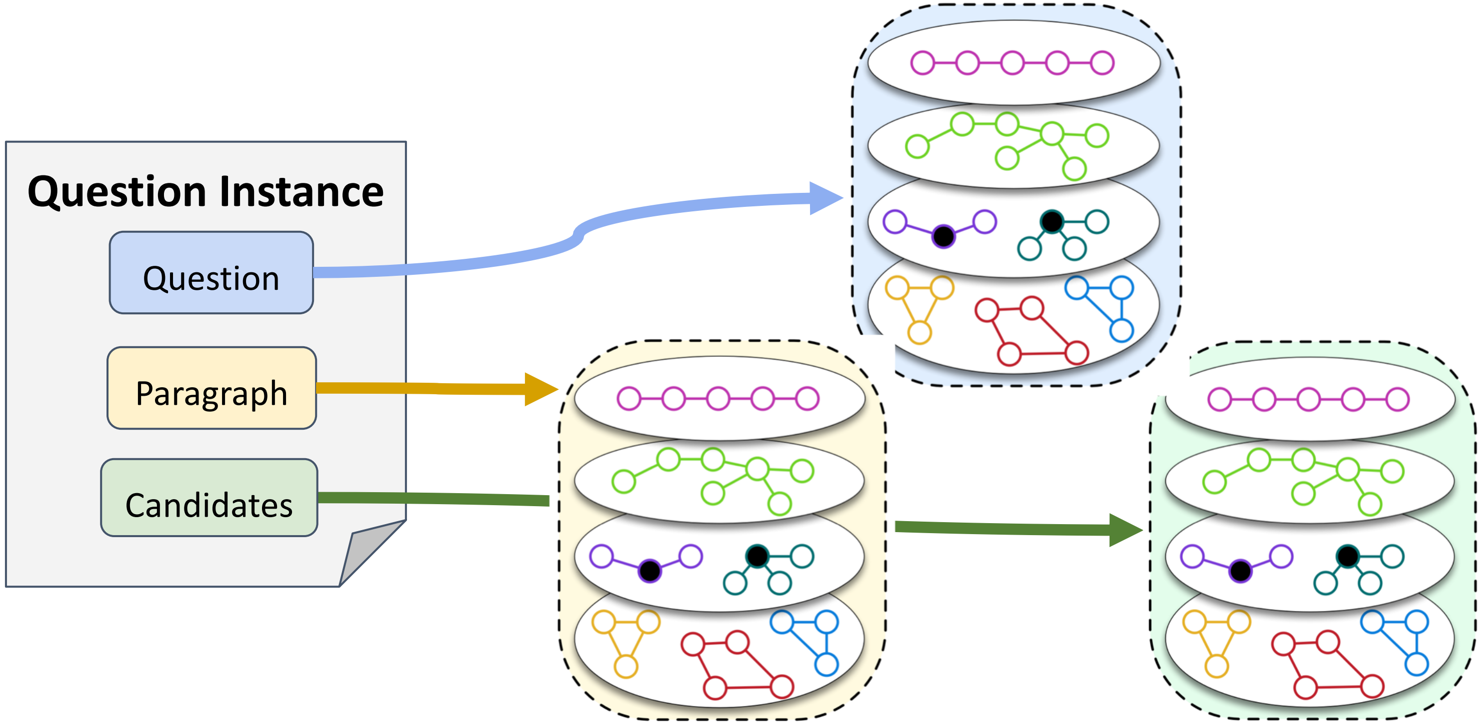

Edges reflect similarity / entailment

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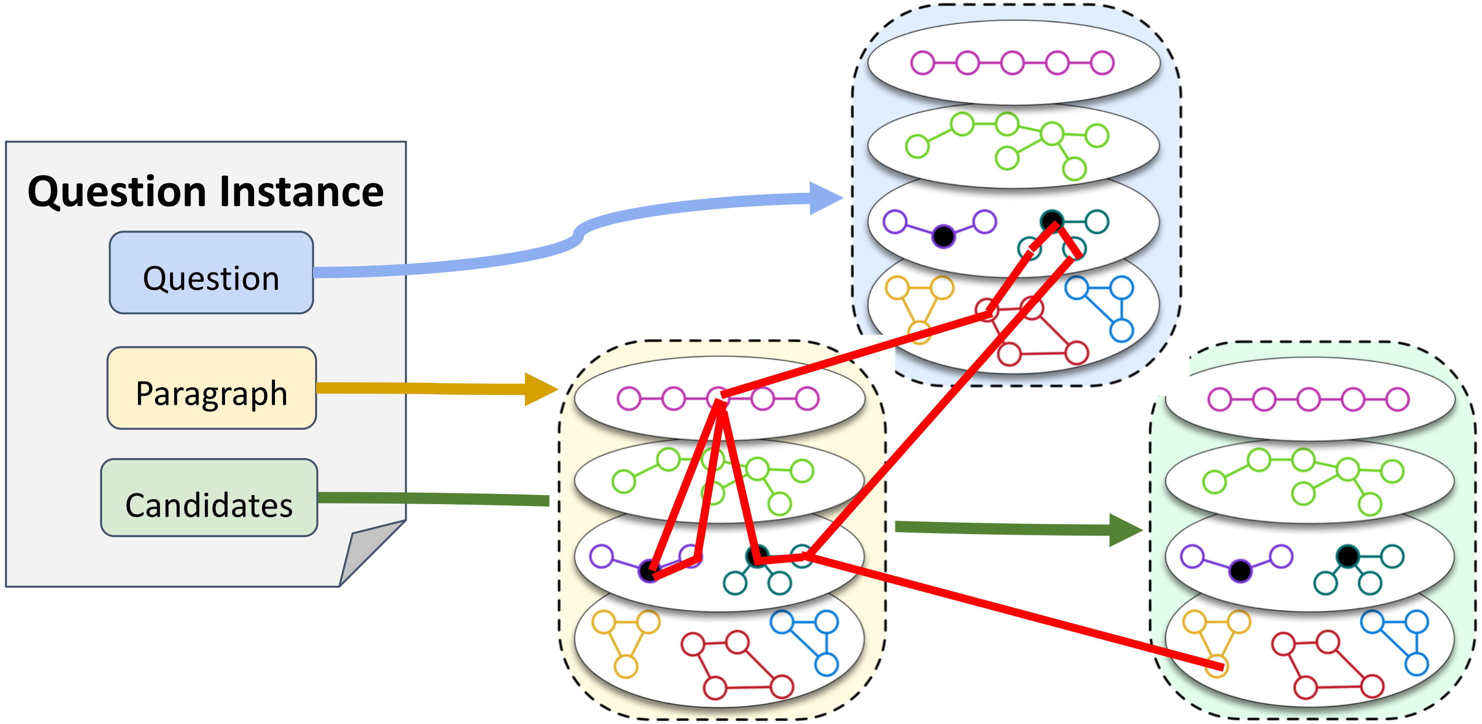

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QA Reasoning formulated as finding "best" explanation – subgraph connecting the Question to the Answers via the Knowledge

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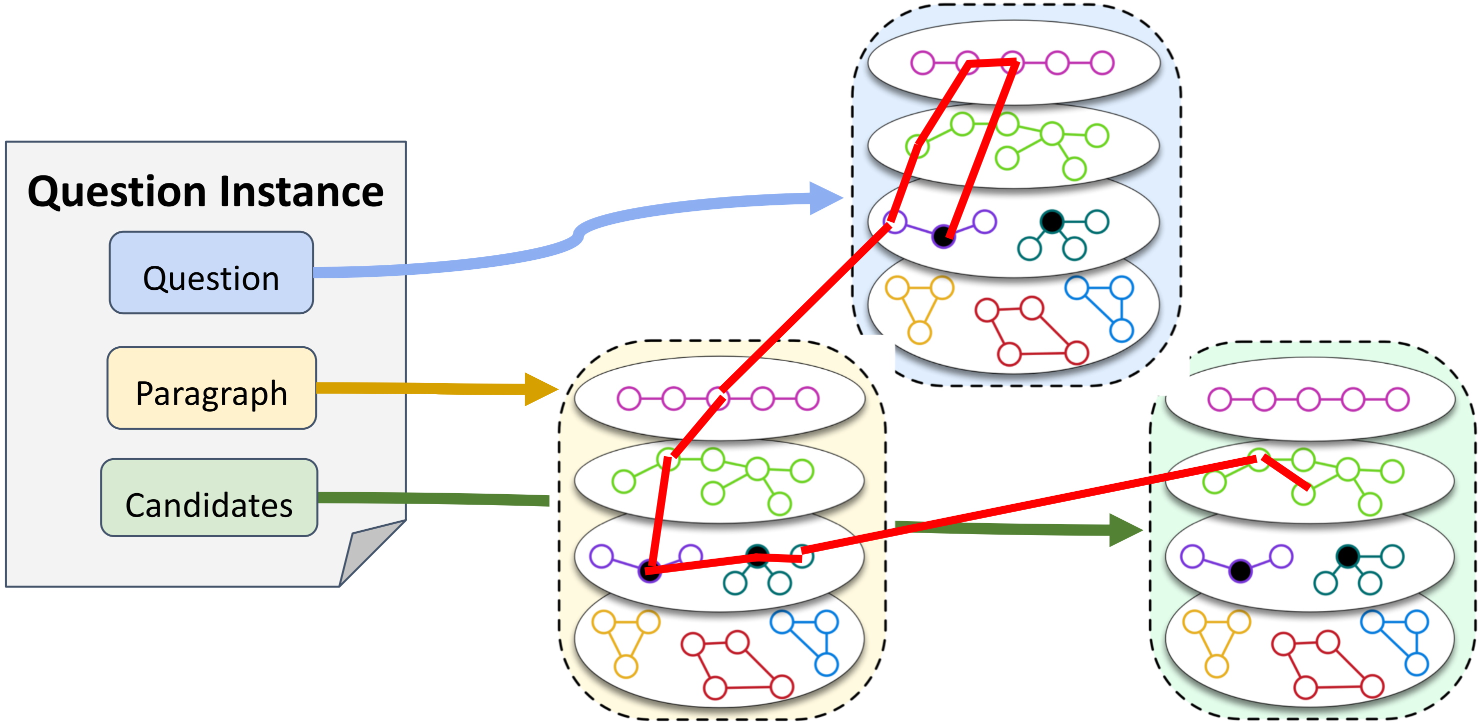

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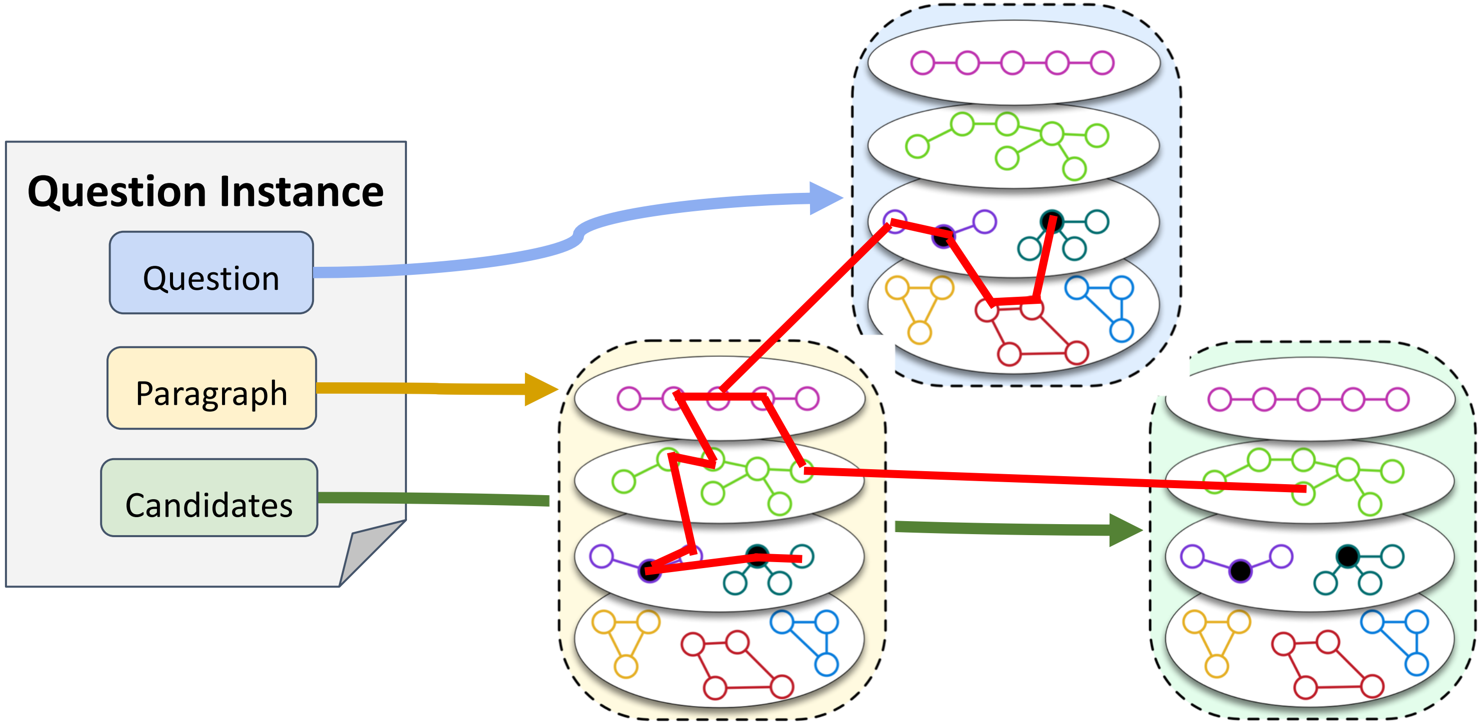

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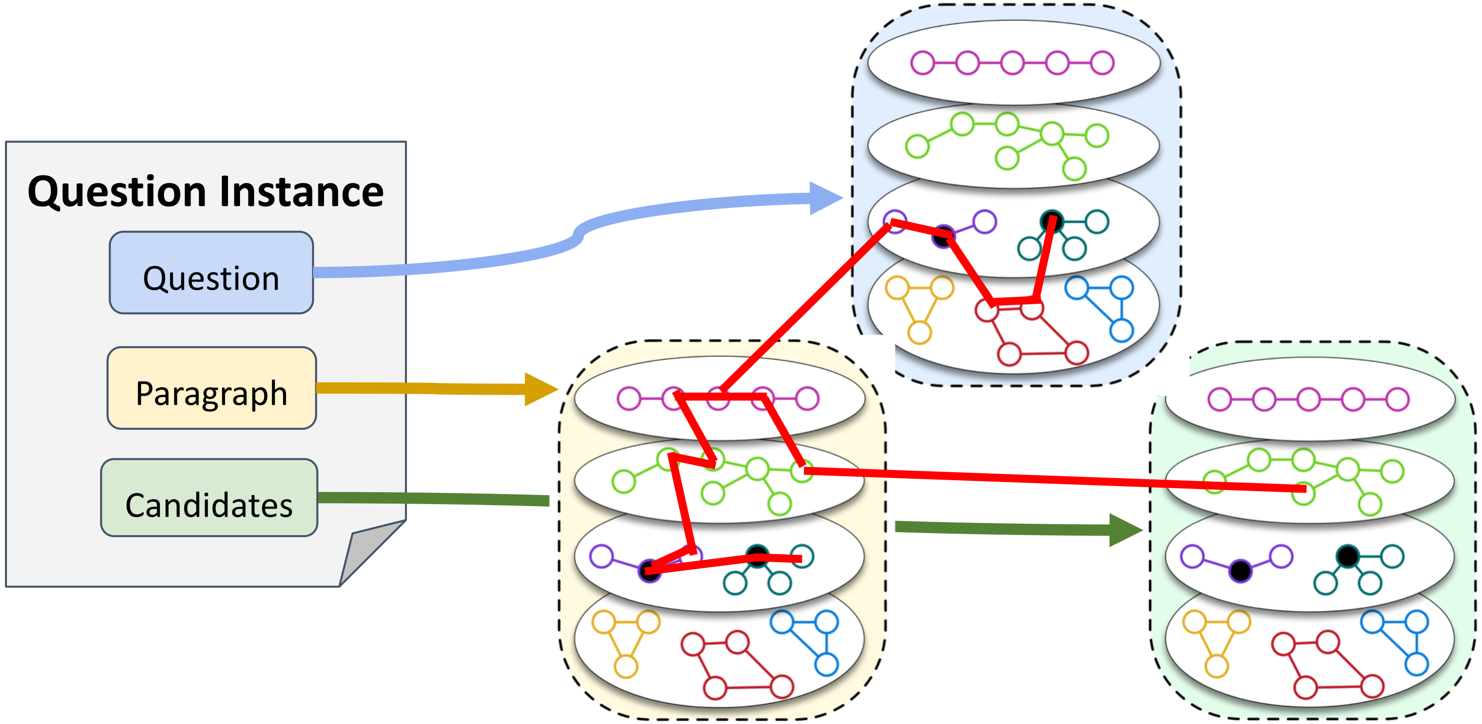

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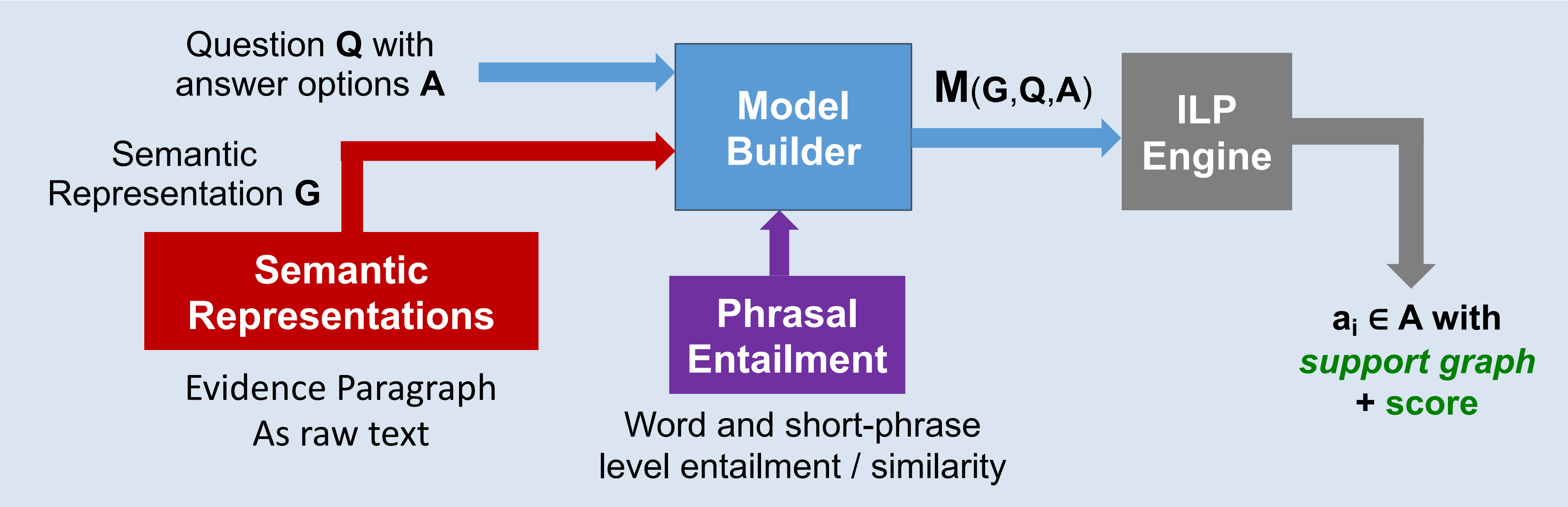
Abductive reasoning

[Peirce, 1883]

QA Reasoning formulated as finding "best" explanation – subgraph connecting the Question to the Answers via the Knowledge

Framework Overview

- A discrete **optimization** approach to QA for multiple-choice questions



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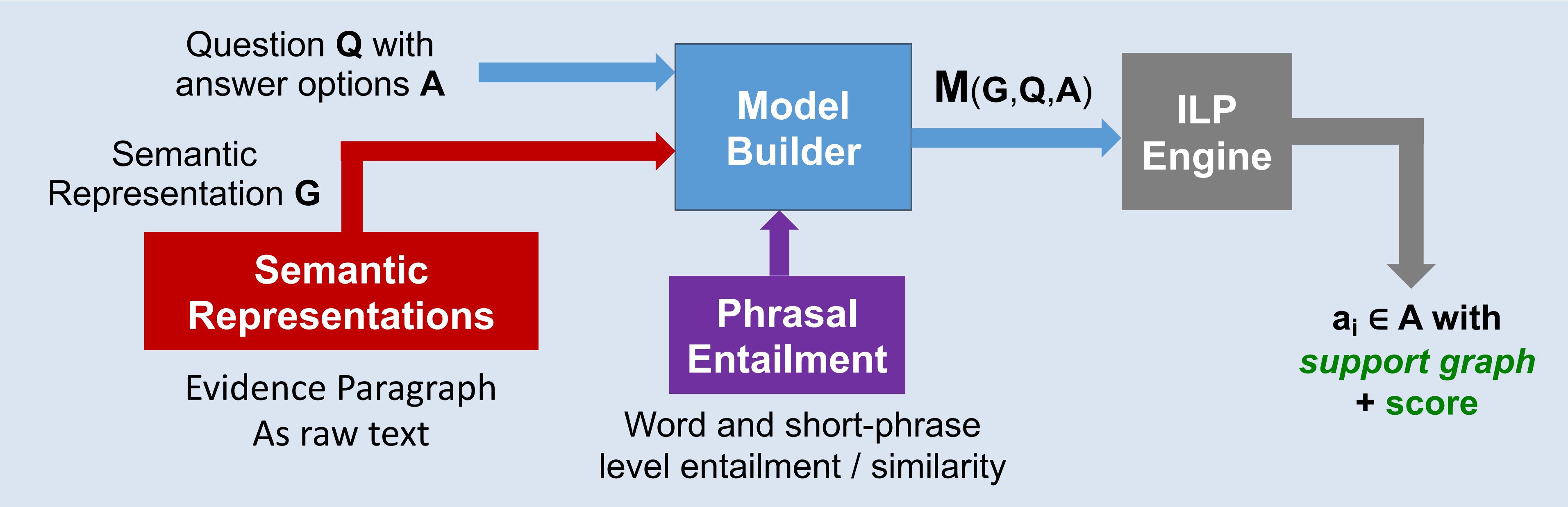

M(**G**,**Q**,**A**) ⟶

$$\max \sum_i c_i x_i \qquad \begin{cases} \sum_i a_{1i} x_i \leq b_1 \\ \quad \dots \\ \sum_i a_{ki} x_i \leq b_k \end{cases}$$

$$\forall\, x_i \in \mathbb{N} \cup \{0\}$$

Optimization using Integer Linear Program (**ILP**) formalism

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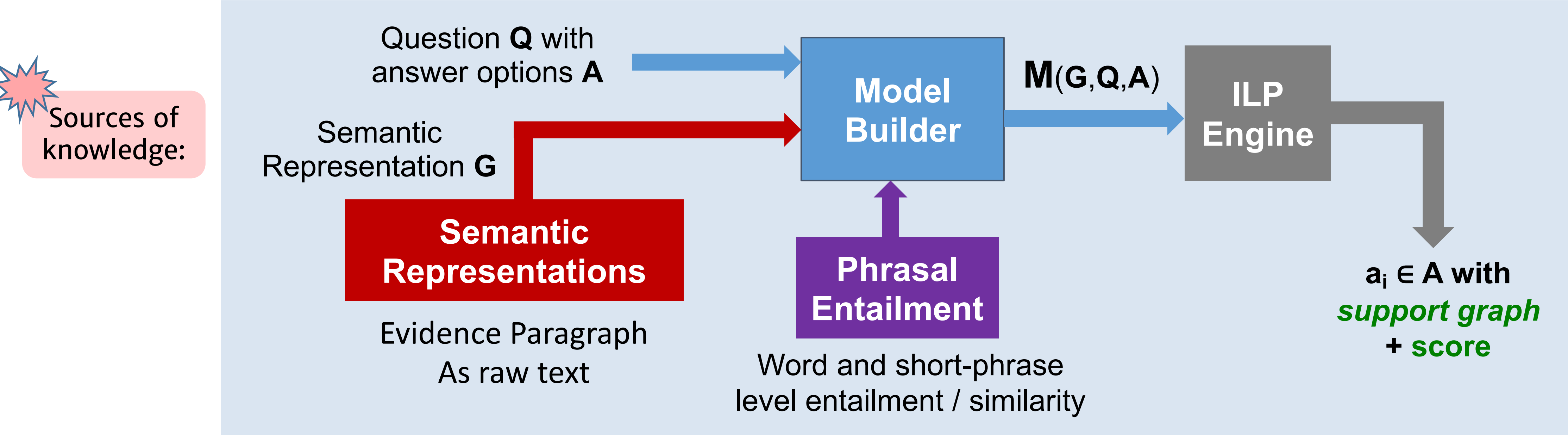

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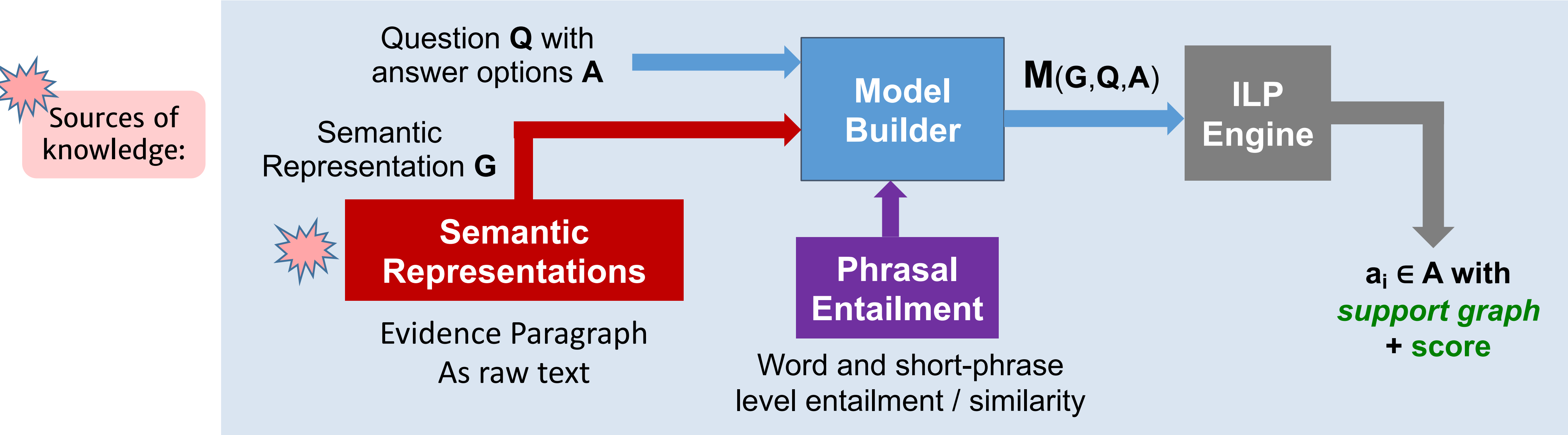

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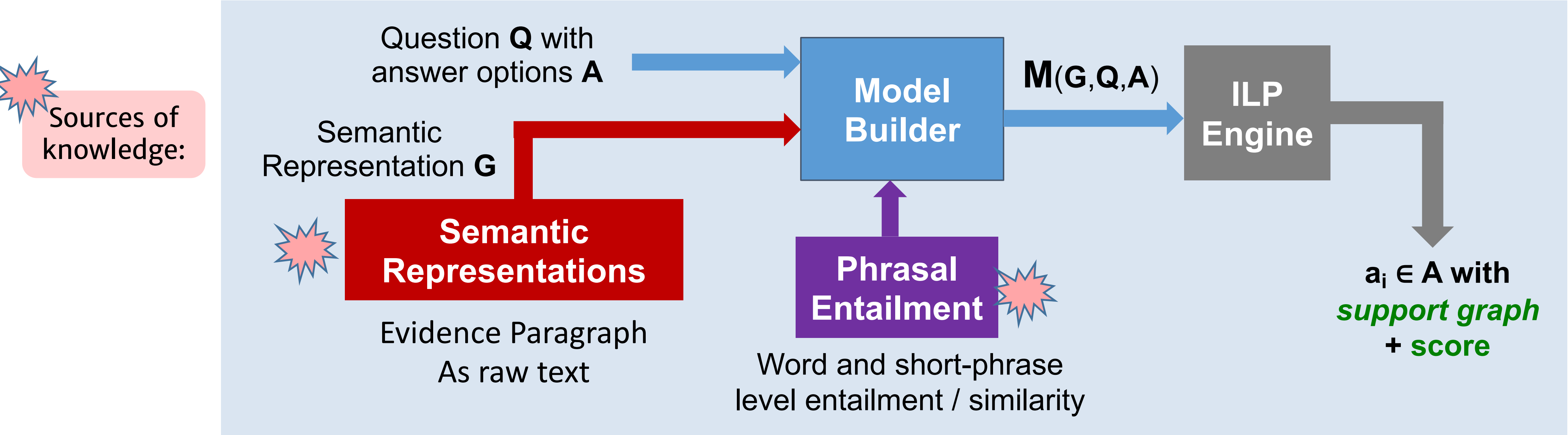

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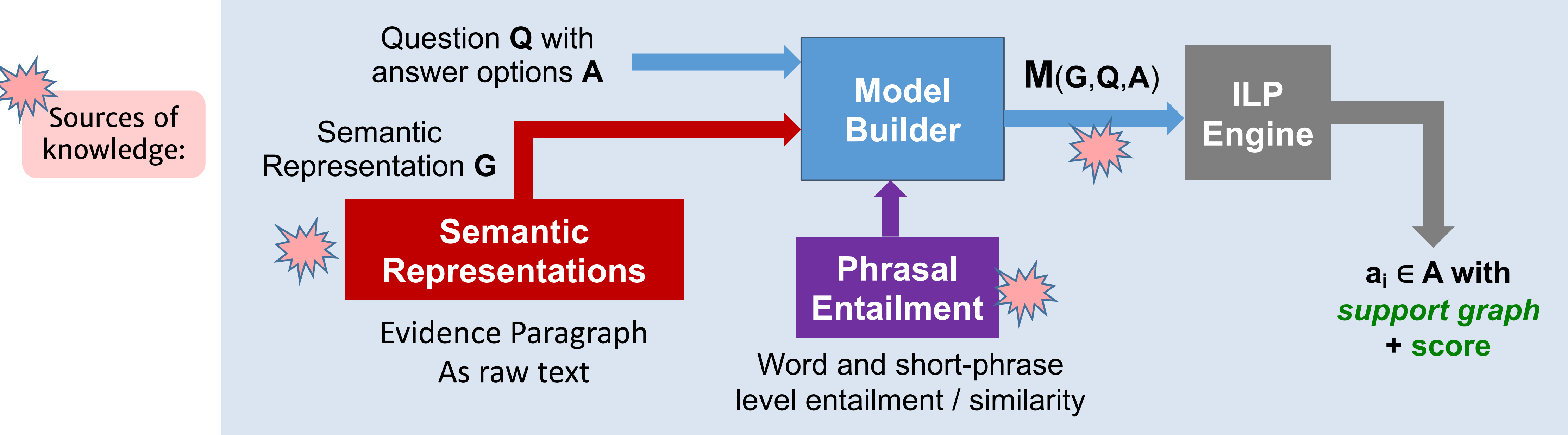

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Optimization using Integer Linear Program (**ILP**) formalism

ILP Model: Design Challenges

Goal: *Design ILP objective function, s.t. maximizing it subject to the constraints yields a "desirable" support graph*

Not so straightforward!

$$\max \sum_i c_i x_i \qquad \begin{cases} \sum_i a_{1i} x_i \leq b_1 \\ \quad \ldots \\ \sum_i a_{ki} x_i \leq b_k \end{cases}$$

$$\forall\, x_i \in \mathbb{N} \cup \{0\}$$

- Many possible "proof structures"
- Imperfect lexical "similarity" blackbox
- Partial or missing knowledge
- Question logic (negation, conjunction, comparison)
- Scalability of ILP solvers
- …

ILP Model: Some Details

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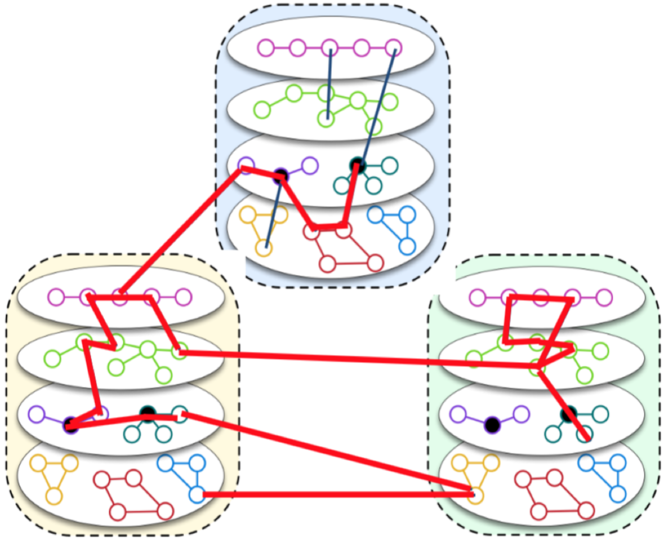

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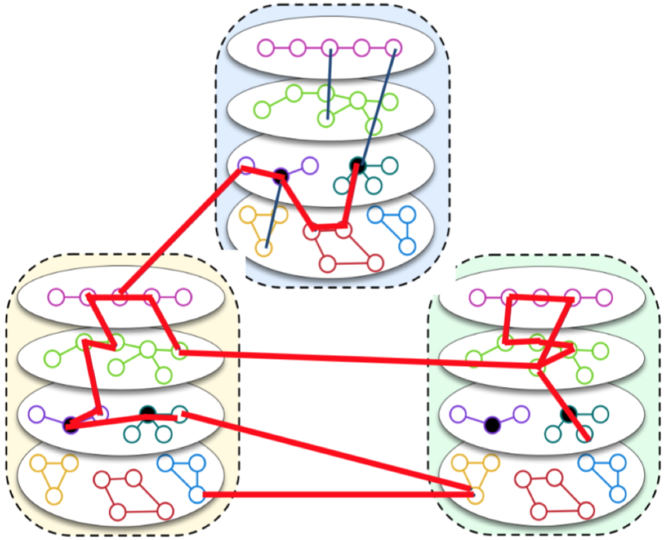

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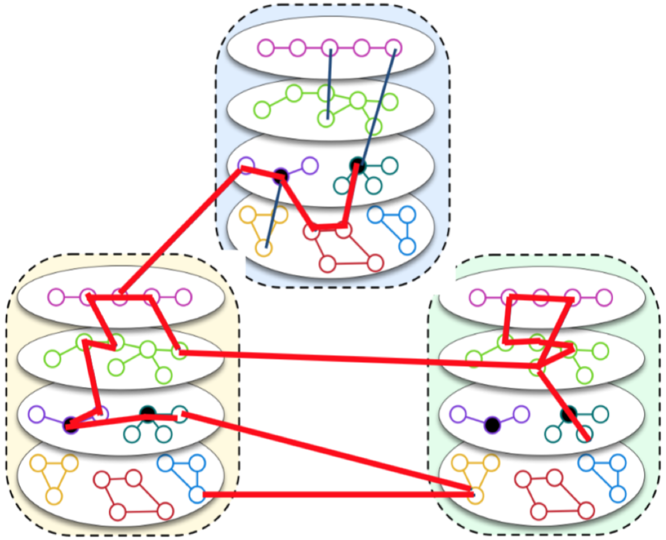

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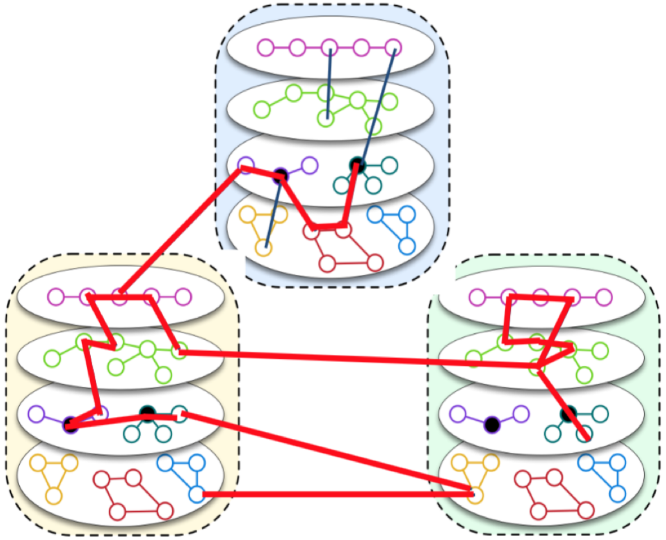

ILP Model: Some Details

Variables define the space of “support graphs”:

- Each variable corresponds to to a node or edge.
- *x=1* iff nodes / edges are part of the semantic graph.

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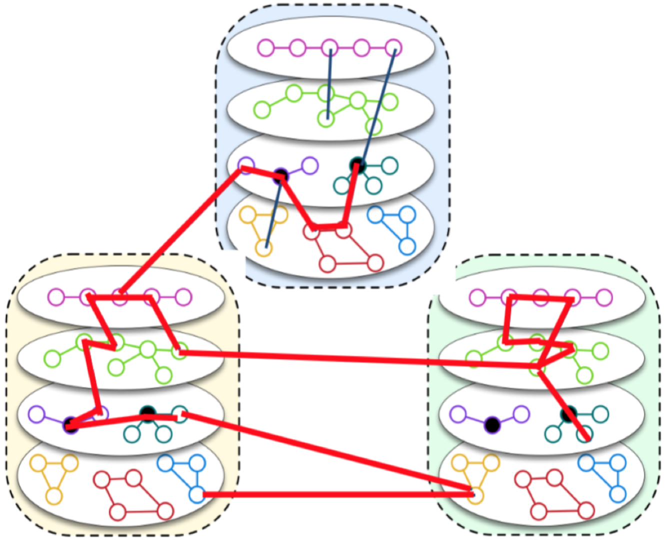

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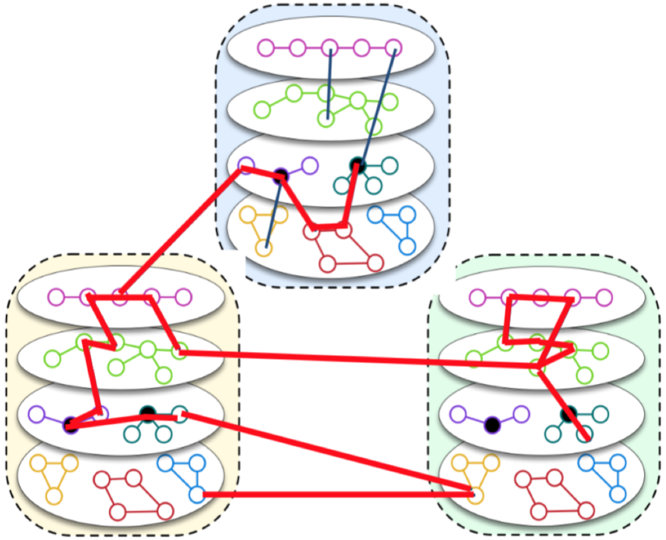

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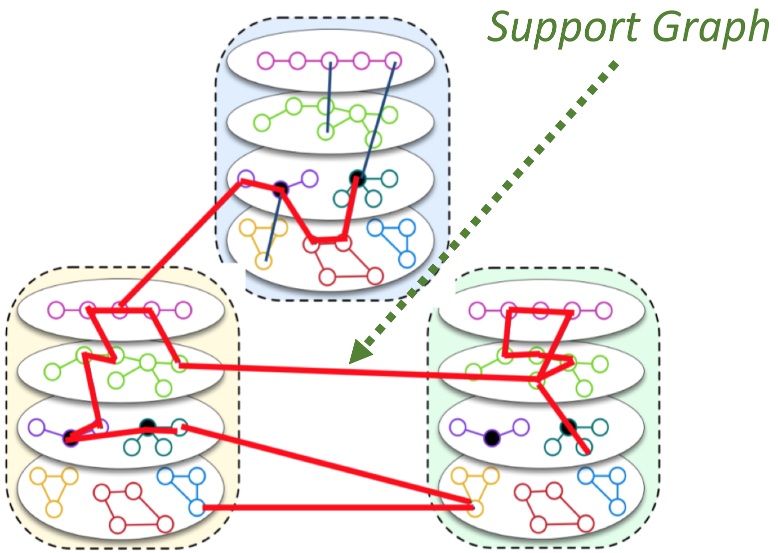

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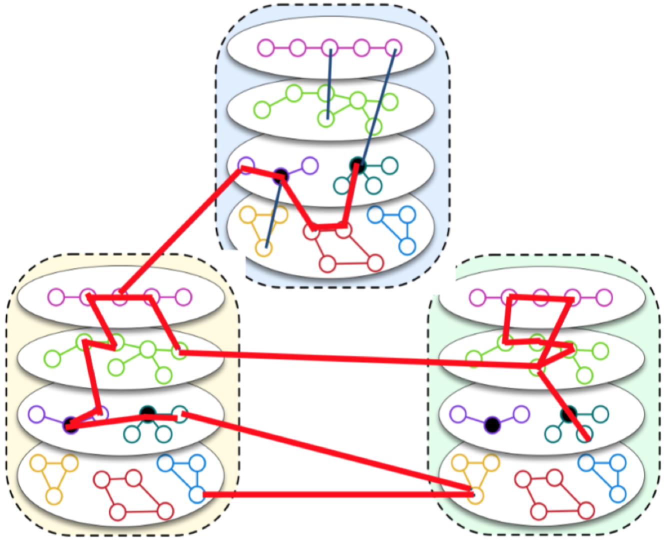

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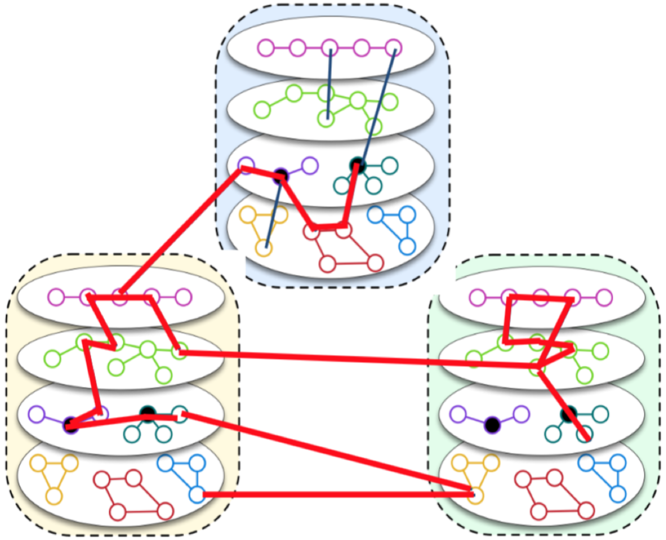

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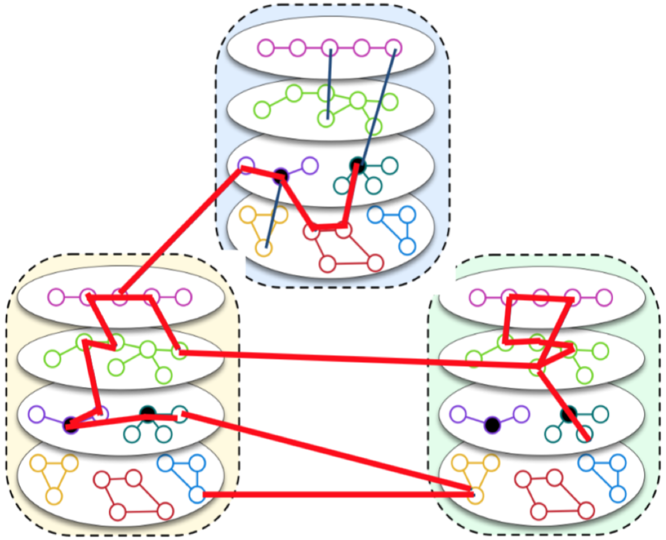

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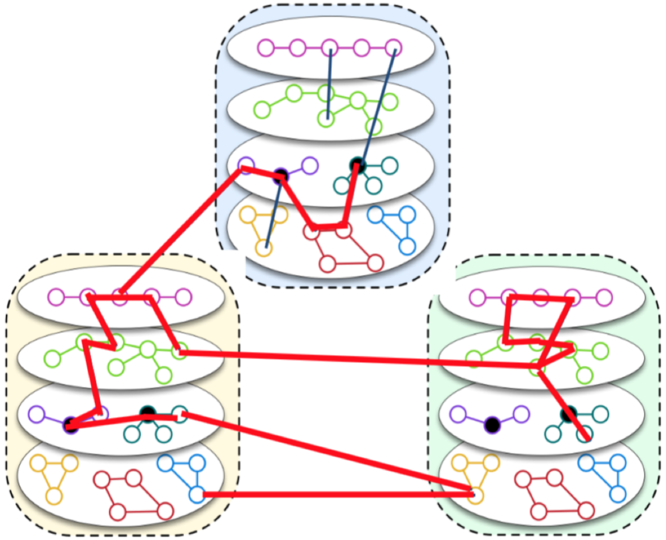

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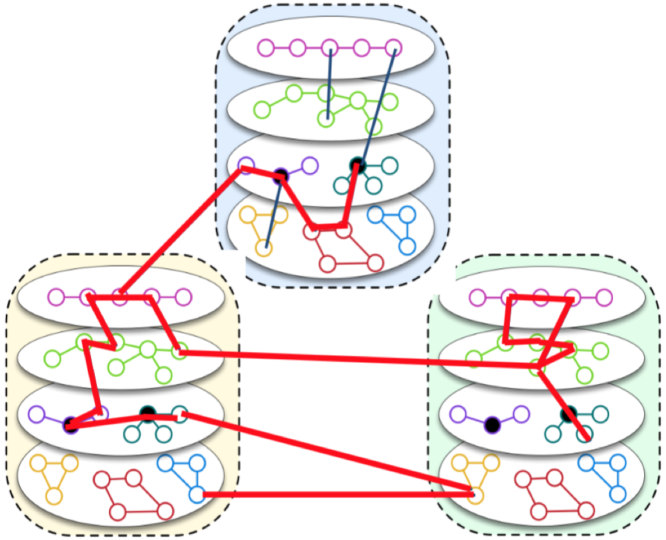

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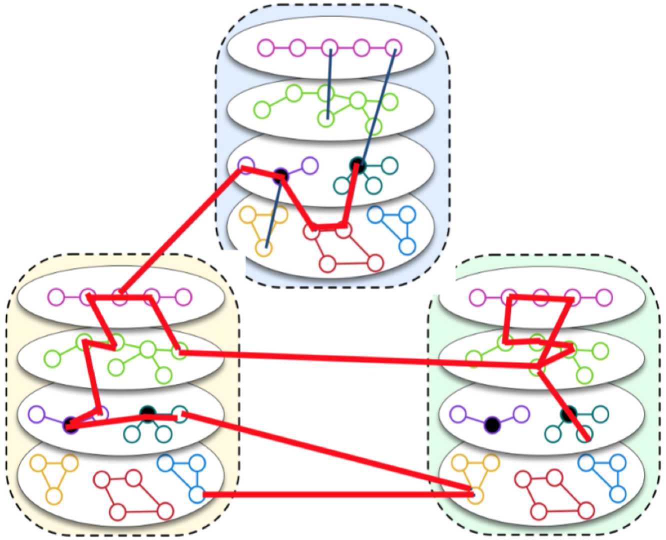
- **Semantic Constraints**
  - If using a predicate-argument graphs,
    - use at least predicate and argument



Evaluation: Notable Baselines

[Clark et al. AAAI'15]

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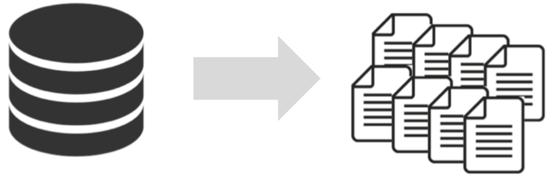

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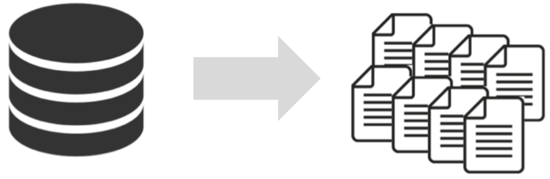

Inference over structure (TupleInf)

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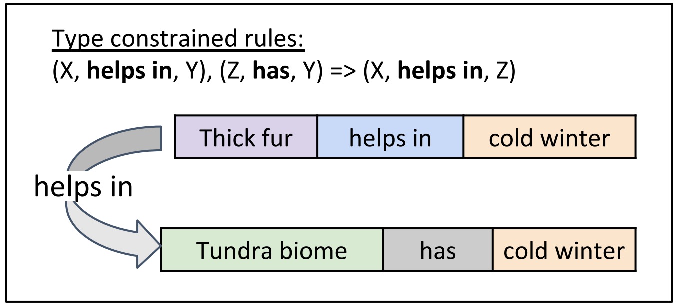
Inference over auto-generated short triples

And type-constrained rules



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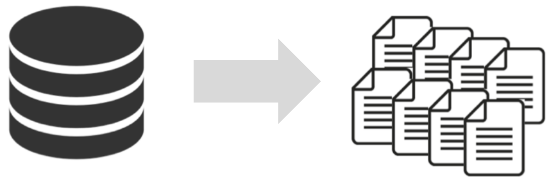

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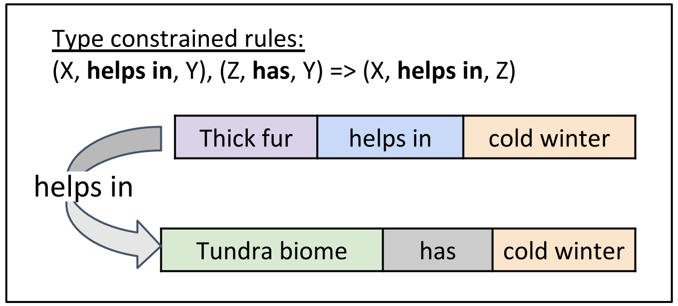
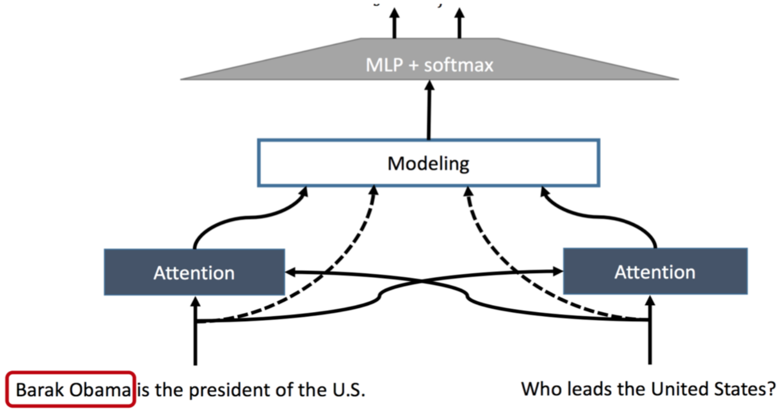


Neural Network (BiDAF)

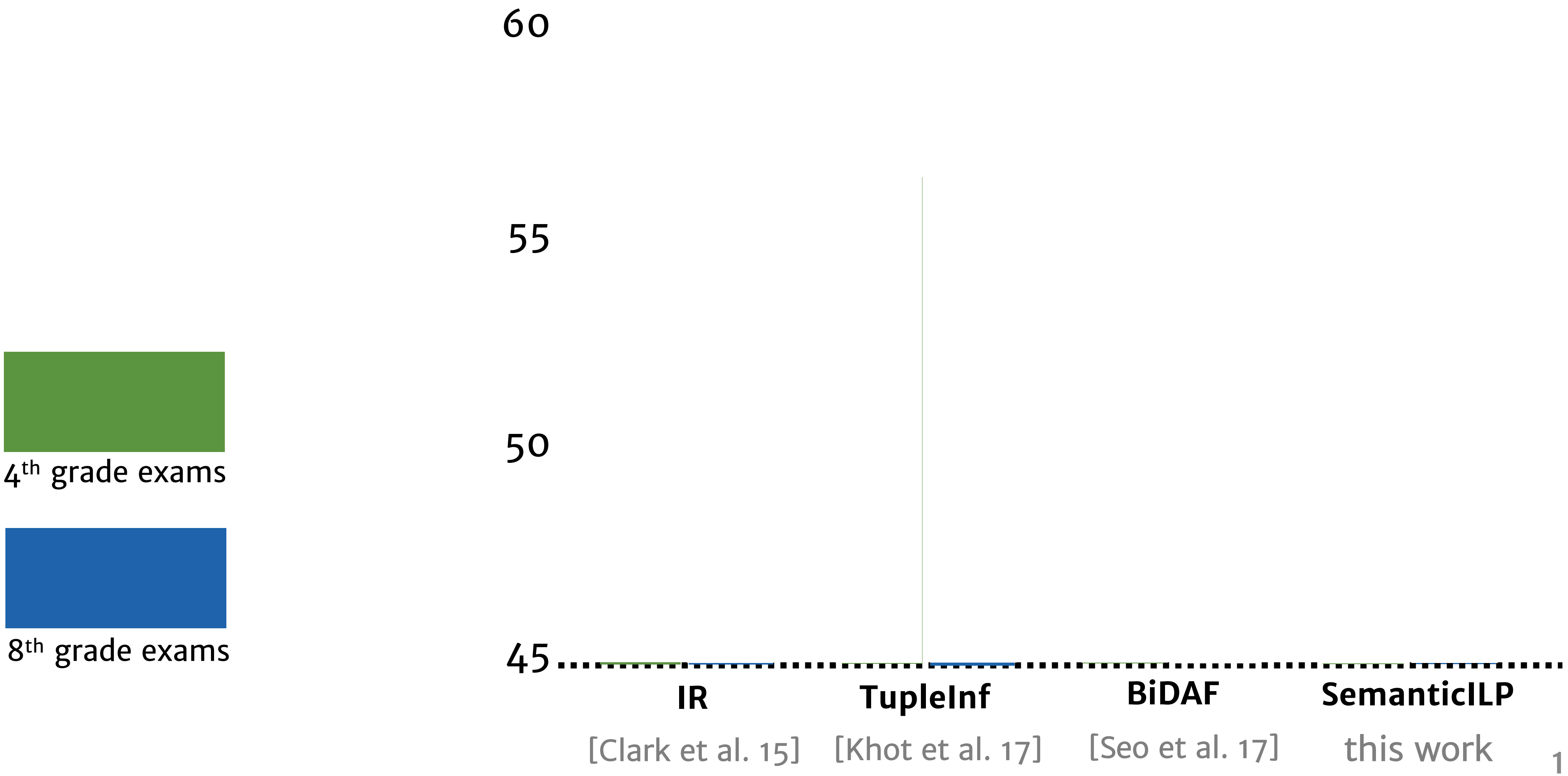
[Seo et al. ICLR'16]

Attention & LSTM

Extractive, i.e select a contiguous phrase in a given paragraph



Empirical results: Science Domain [ZKTR'18]



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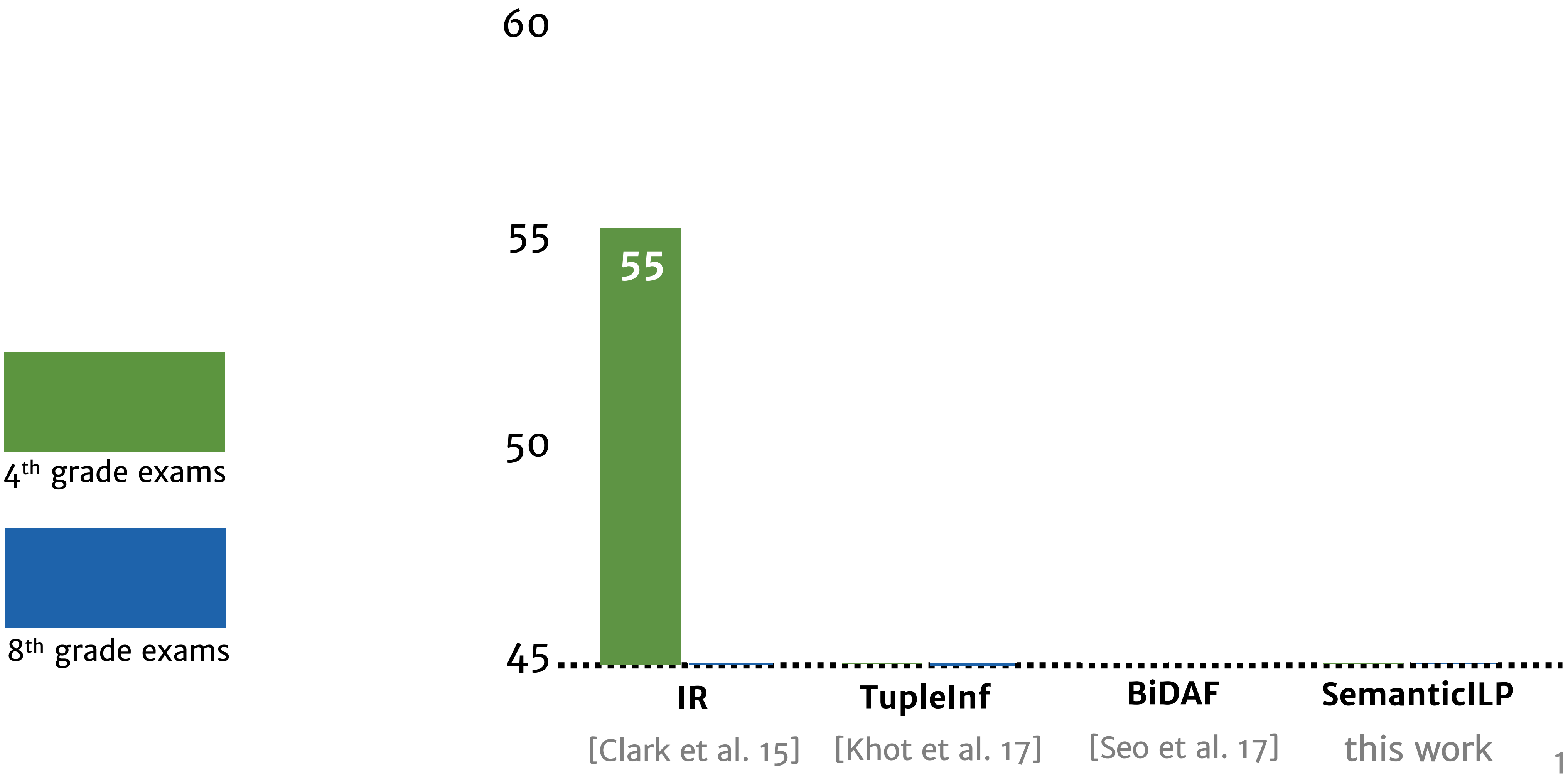

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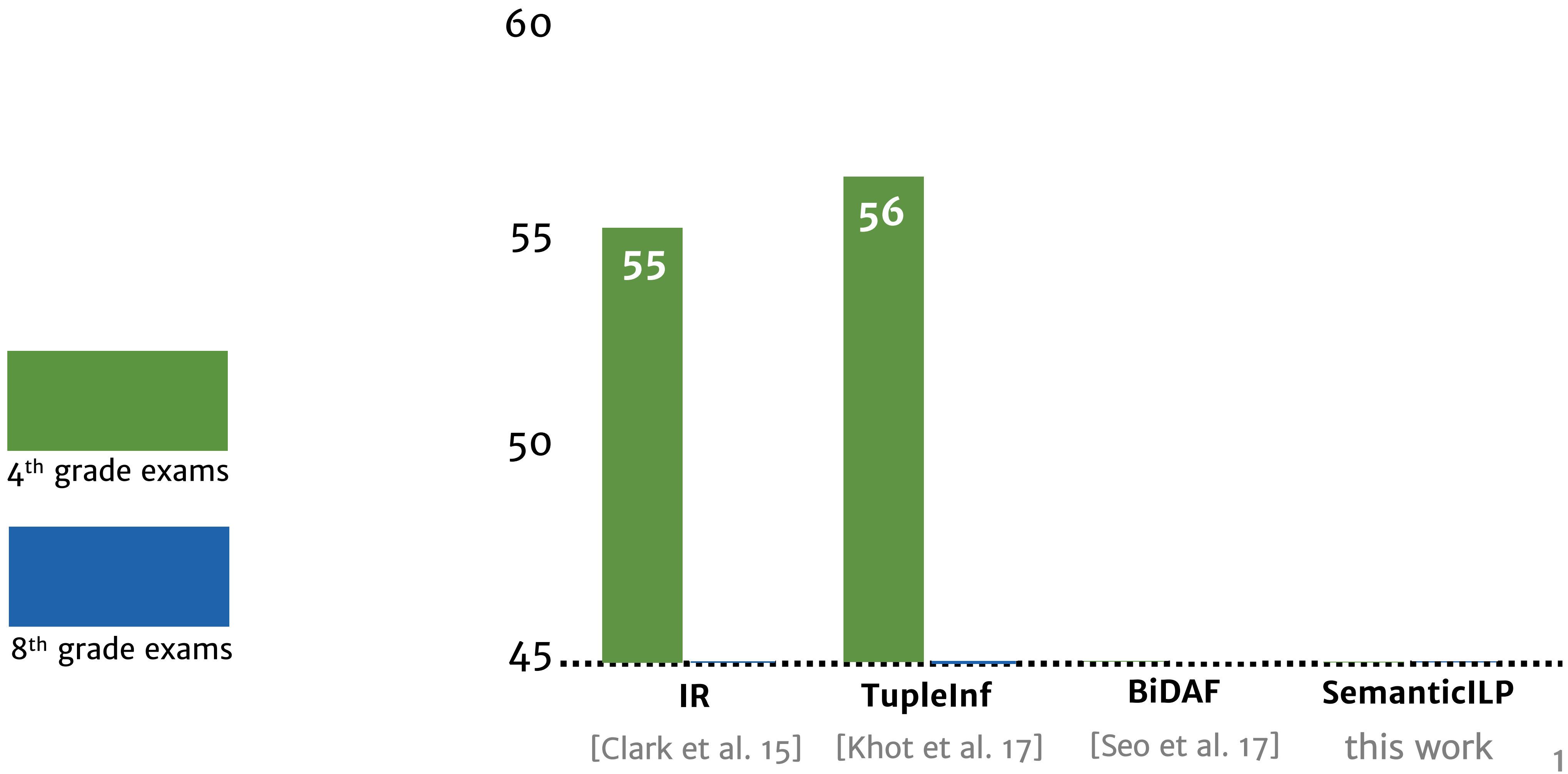

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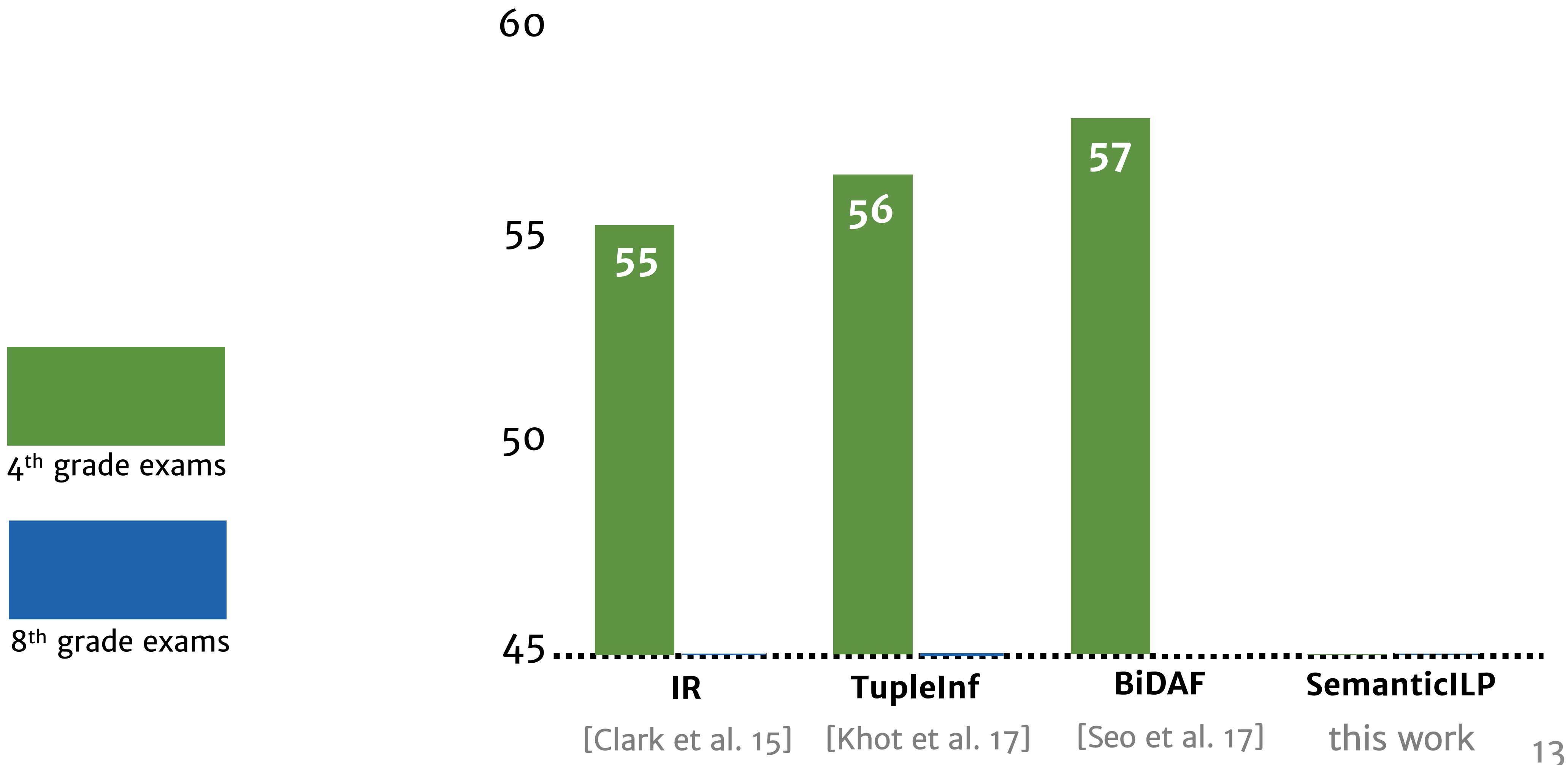

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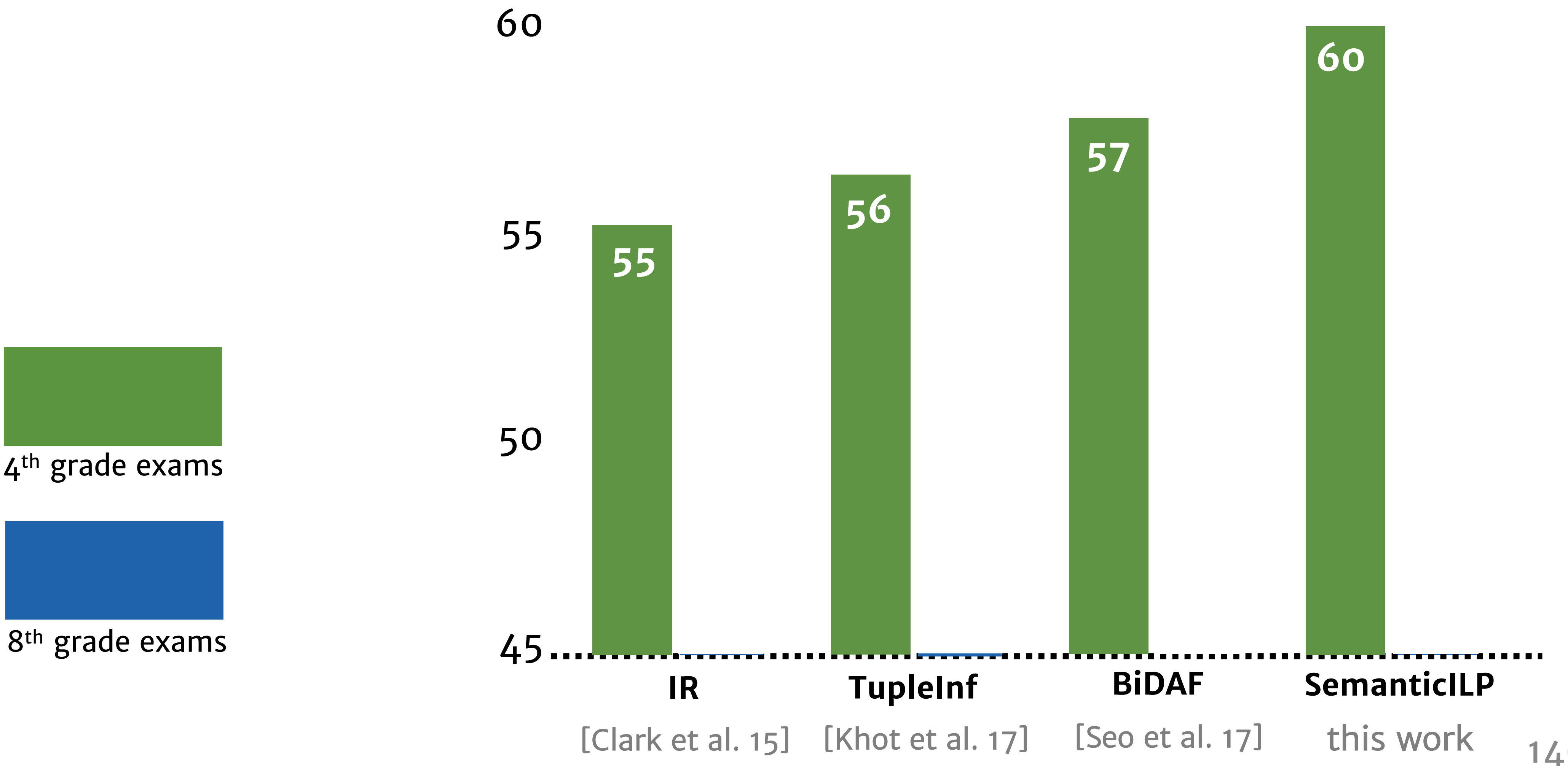

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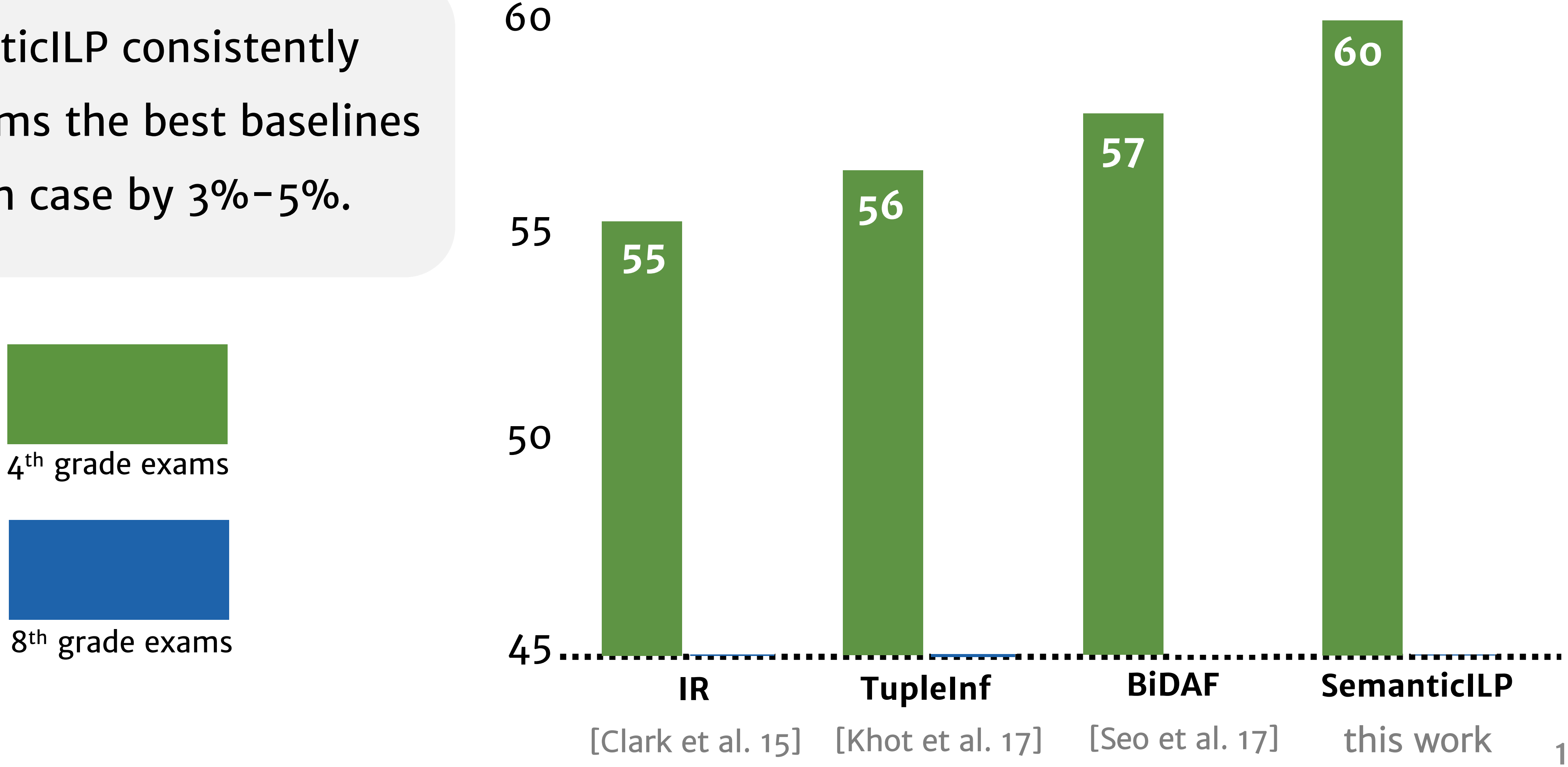
SemanticILP consistently outperforms the best baselines in each case by 3%-5%.



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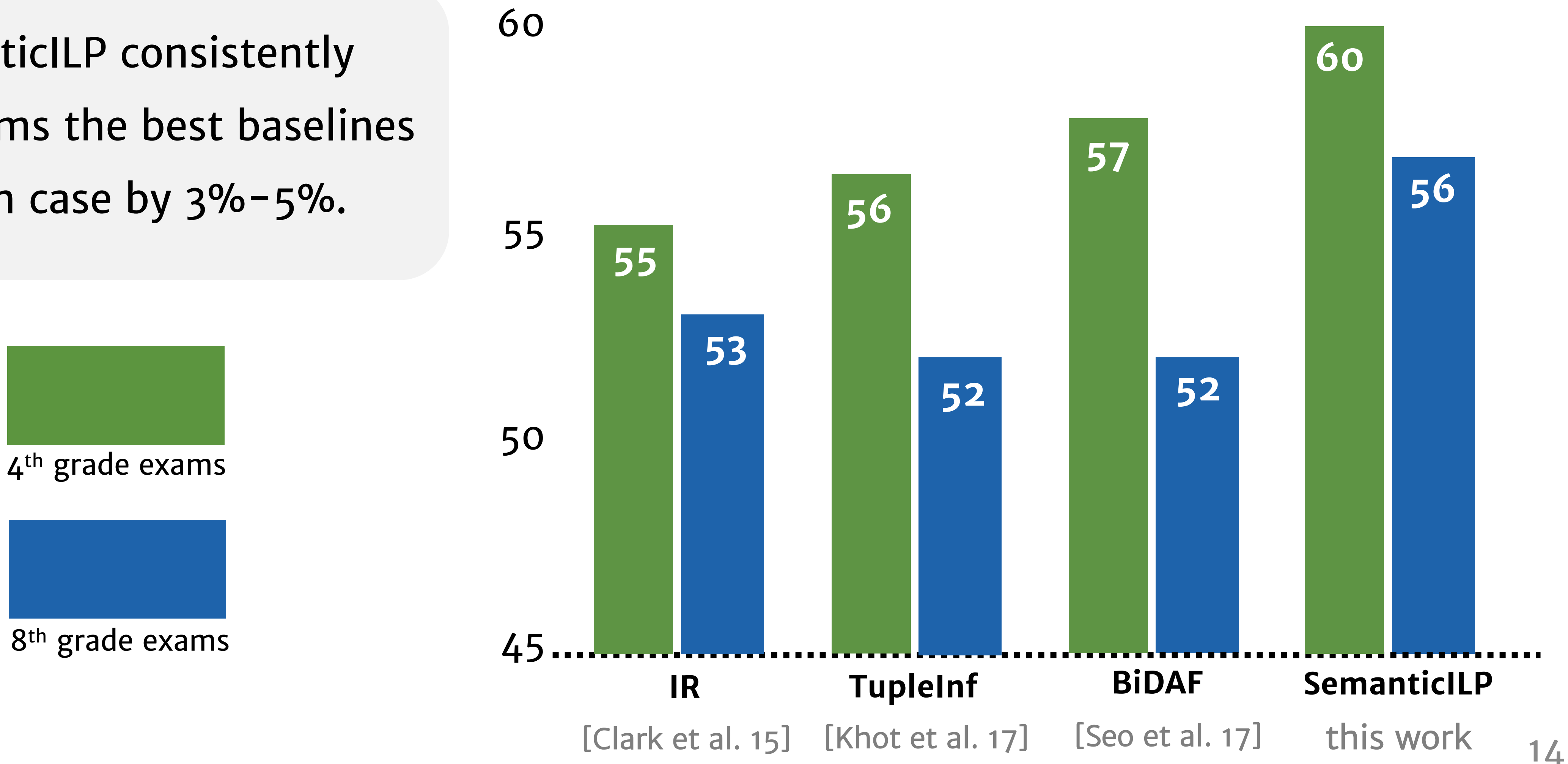

Answering Questions: Biology Exams

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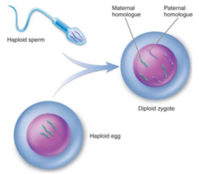

Question: *What does meiosis directly produce?*

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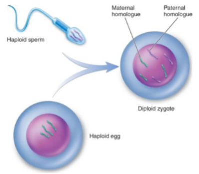

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Evidence paragraph

*… **Meiosis produces not gametes but haploid cells** that then divide by mitosis and give rise to either unicellular descendants or a haploid multicellular adult organism. Subsequently, the haploid organism carries out further mitoses, producing the cells that develop into gametes….*

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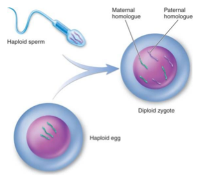
We use **the same** version of our systems across our datasets.



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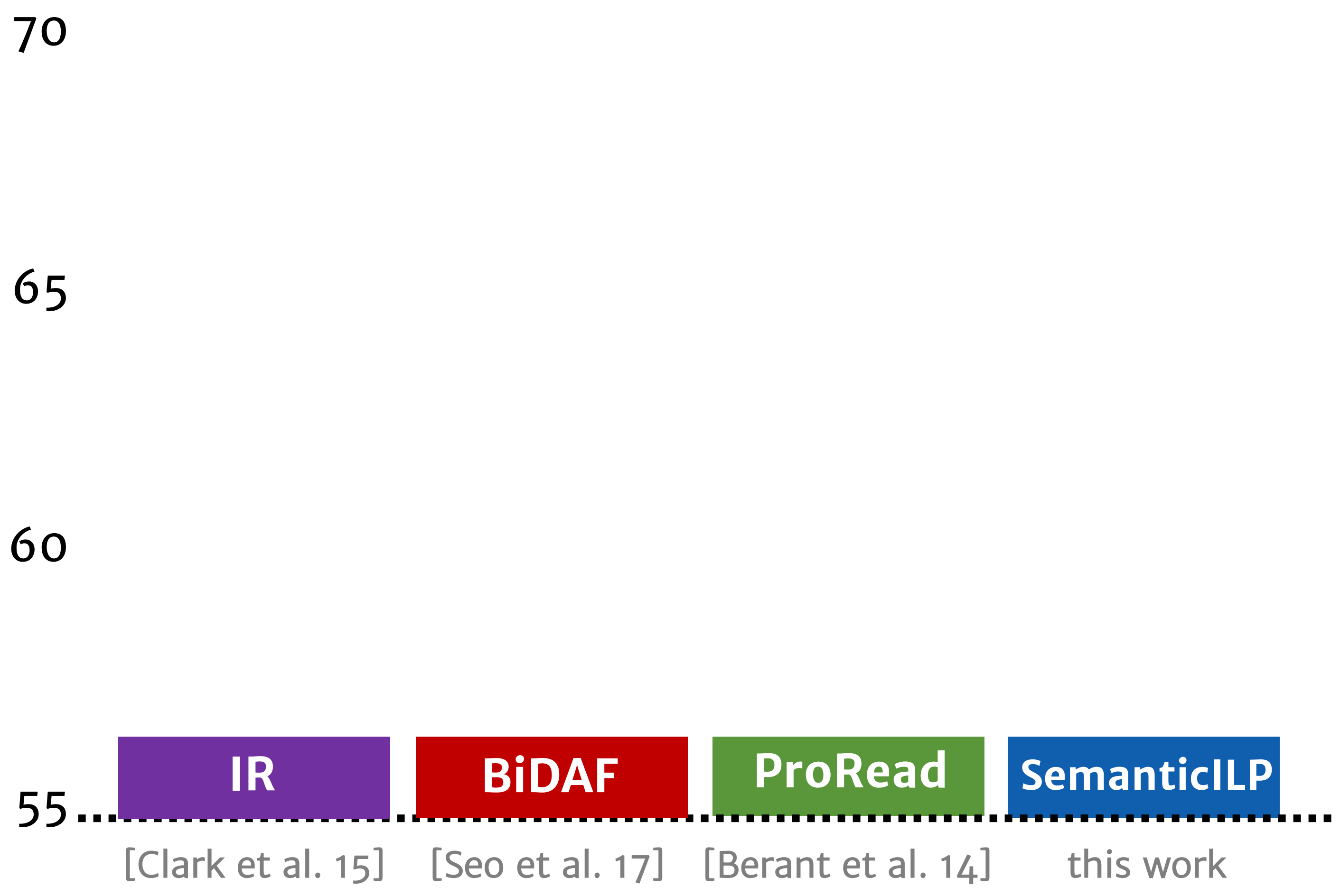

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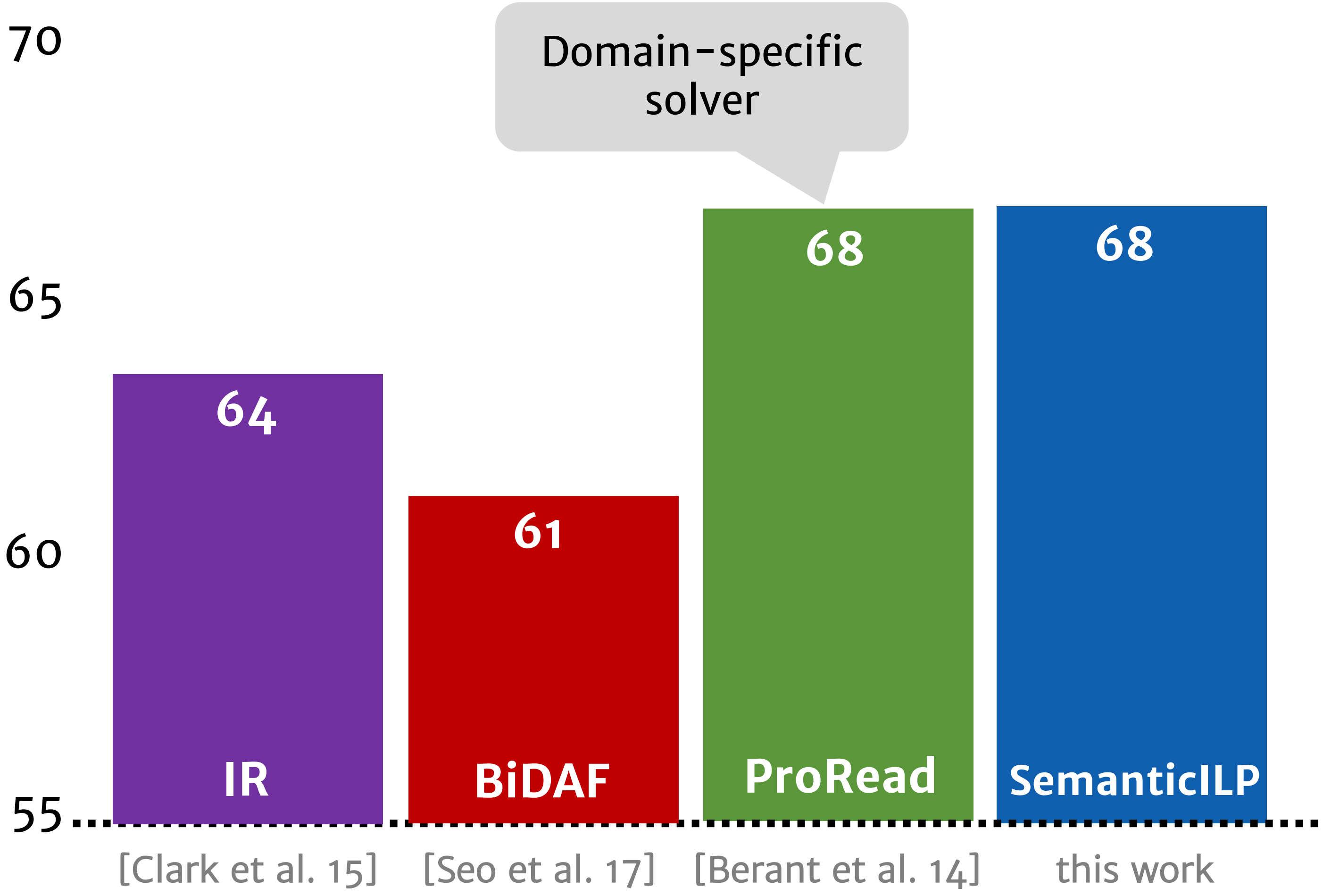
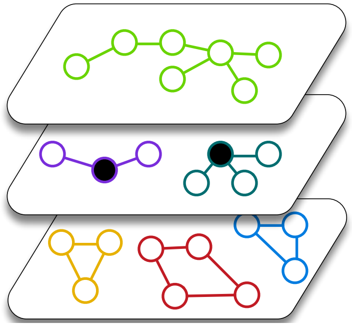
SemanticILP generalizes to a **different** domain and achieves on-par score with the best domain-specific system.



Lessons



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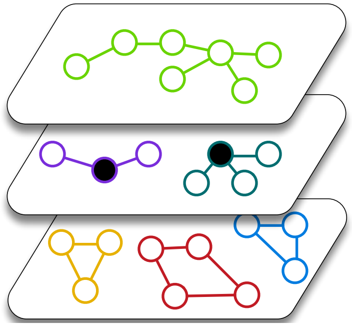

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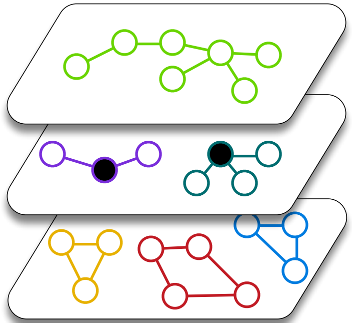

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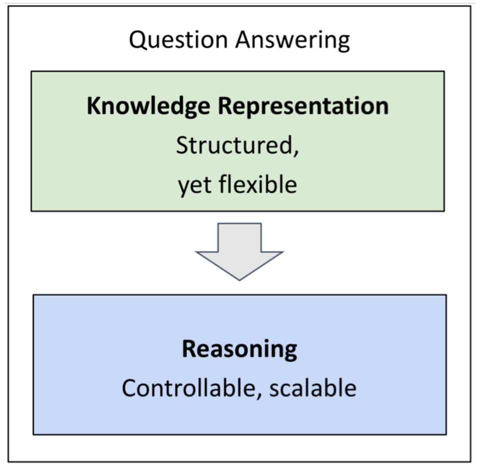

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ENTITY TYPING *with minimal supervision*

Zhou, **K** et al. Zero-Shot Open Entity Typing as Type-Compatible Grounding. EMNLP 18.
Fei, **K** et al. Illinois-Profiler: Knowledge Schemas at Scale. IJCAI (Cognitum) 15.

SEMANTIC TYPING OF ENTITIES

Label mentions with their semantic **types.**

*A handful of professors in the **CMU** **Department of Chemistry** are being recognized for their efforts and contributions to the scientific community.*

CMU:

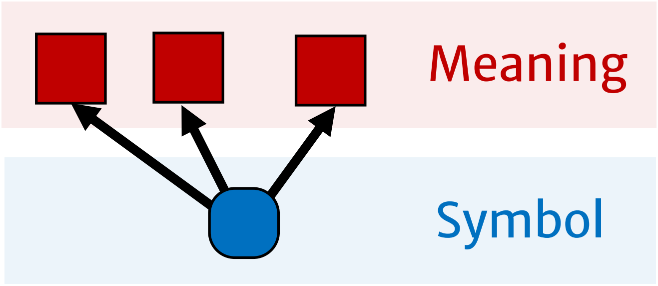
```
/organization
/organization/education_institution
```

Department of Chemistry:

```
/organization
/education
/education/department
```

Semantic Entity Typing: The Necessity (1)

- Dealing with ambiguity



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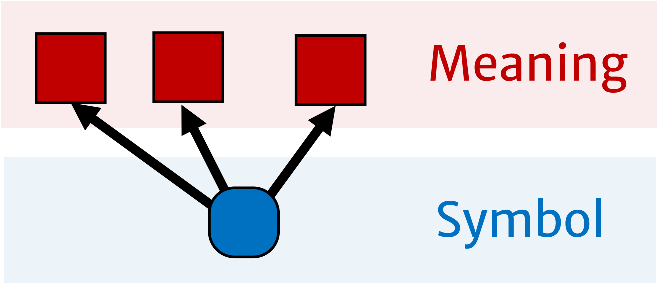

*Our break in **Paris** was quite memorable.*

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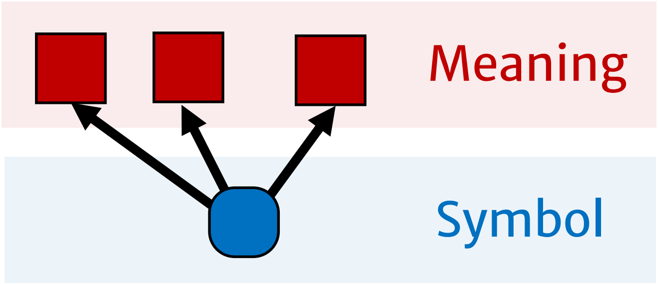

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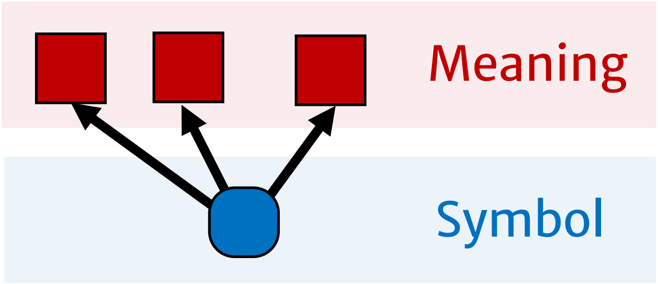

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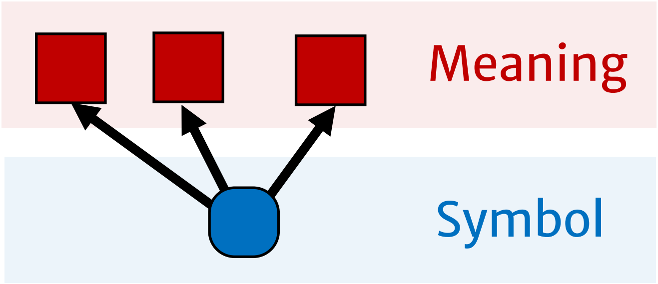

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`government`

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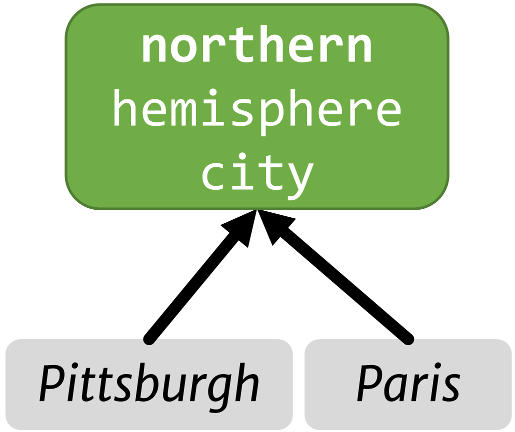

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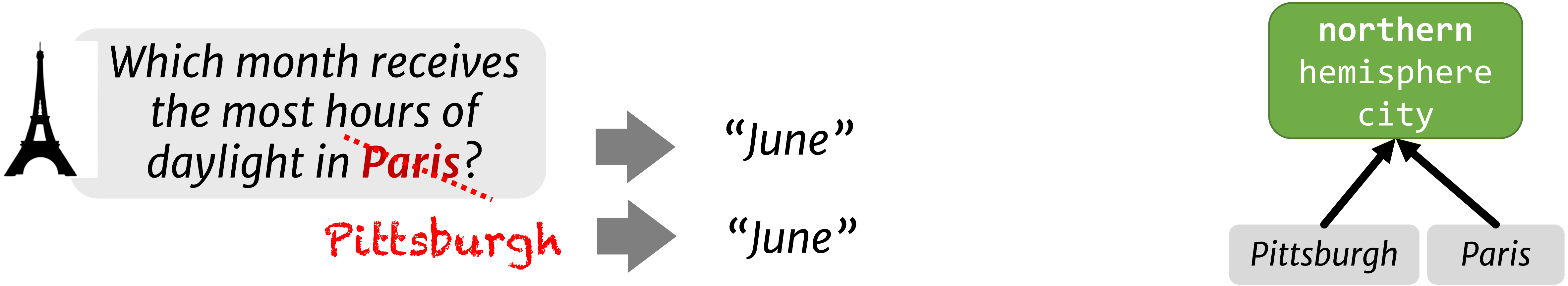

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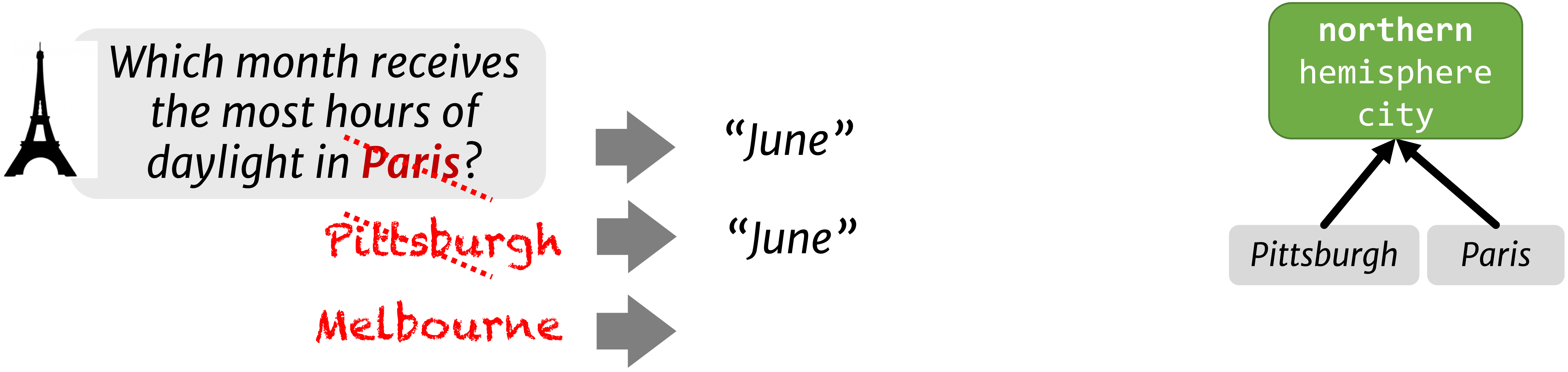

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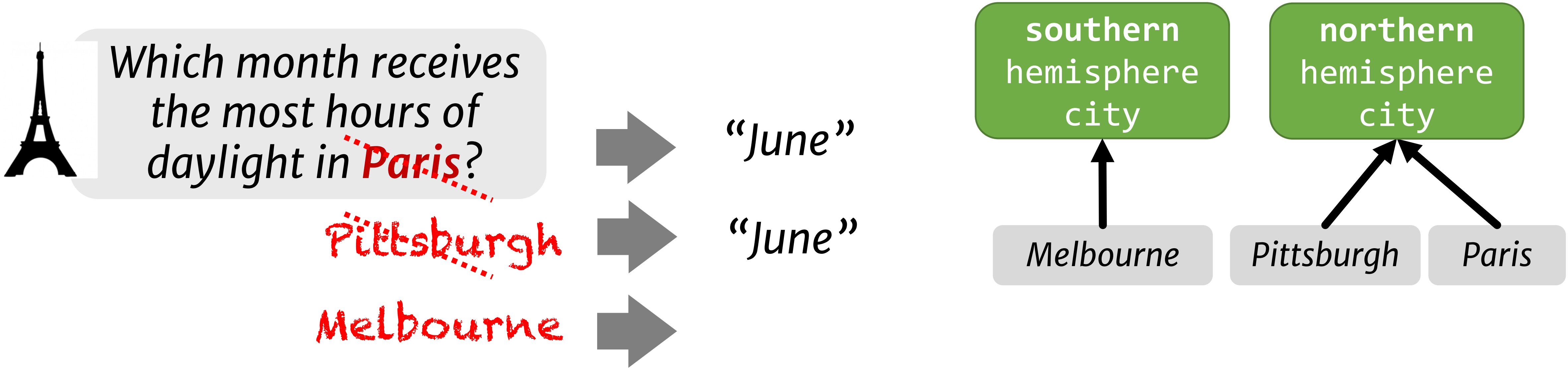

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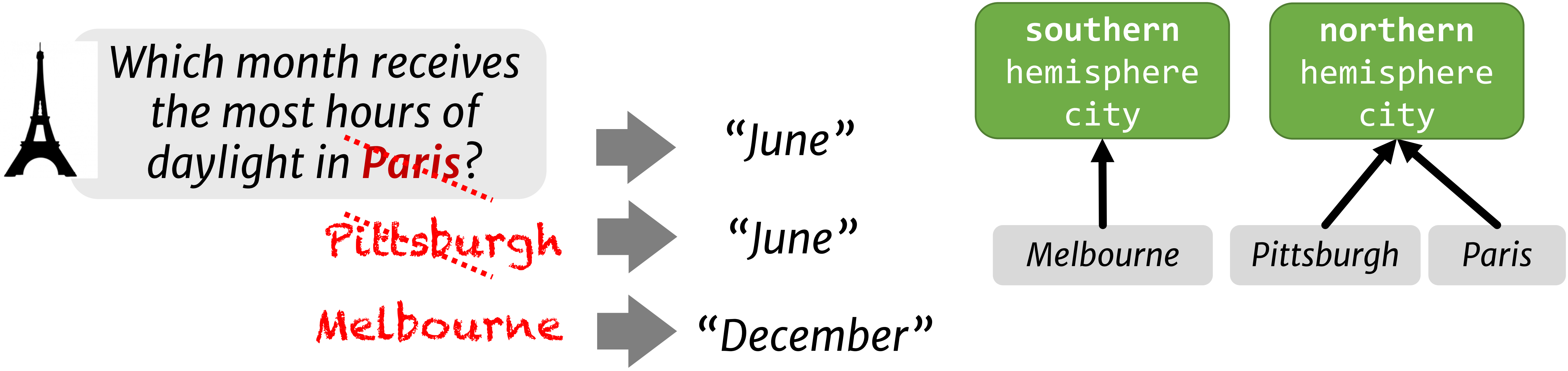

Entity Typing: Existing Work

- Multiple datasets for semantic typing

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Coarse Typing

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[Sang&Meulder,03] [Hovy,06]

CoNLL
4 types

OntoNotes
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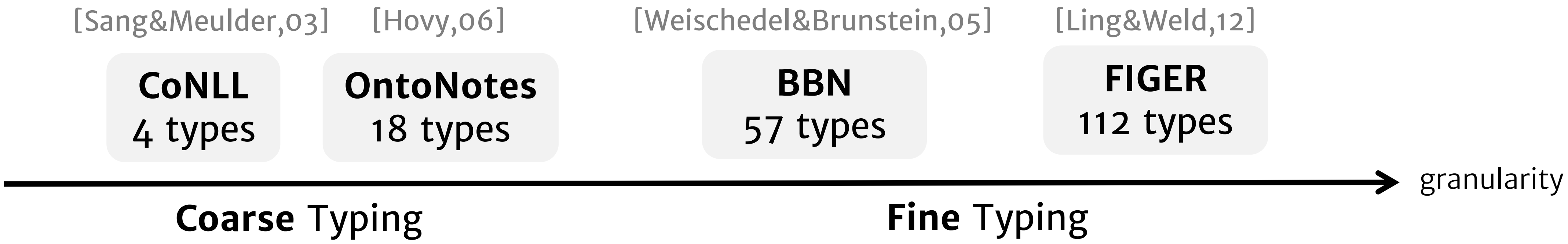

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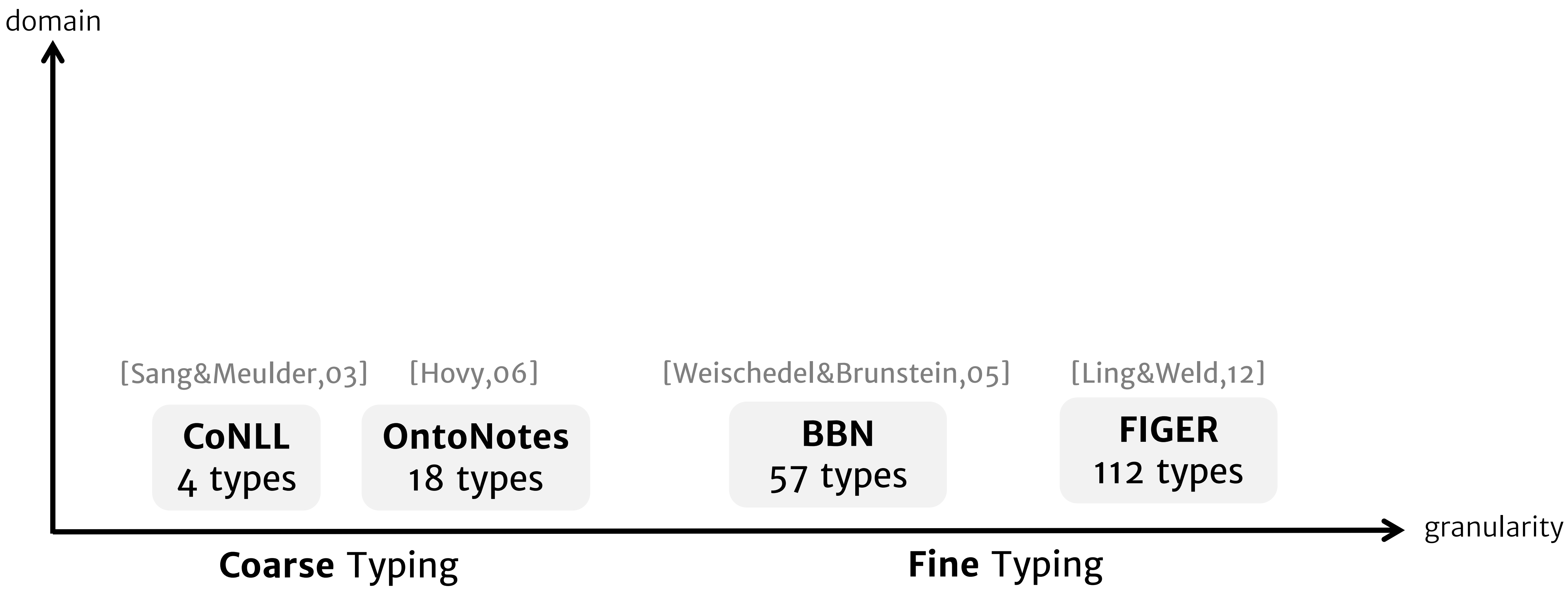

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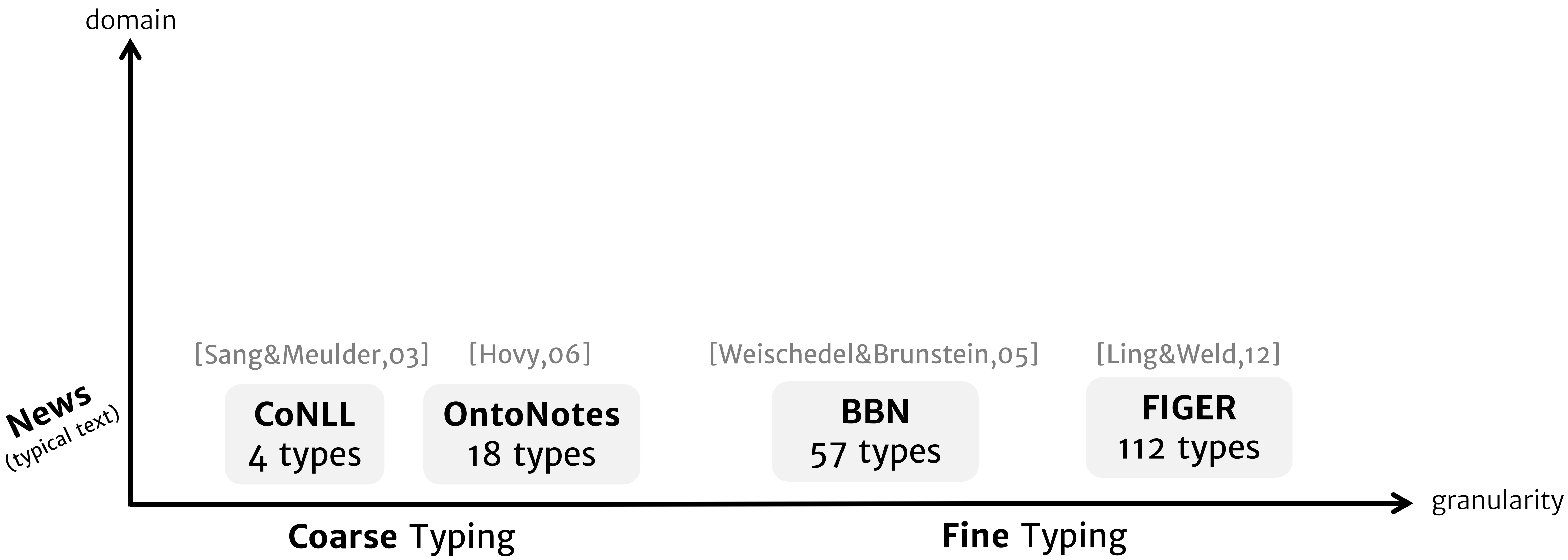

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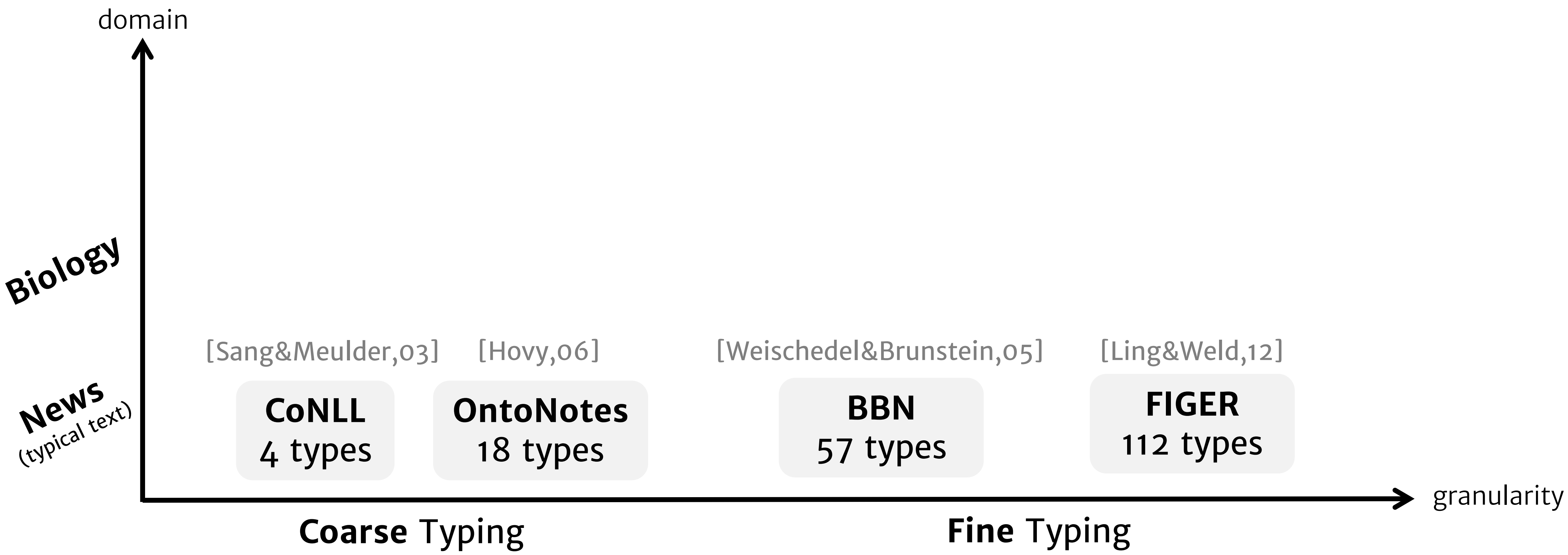

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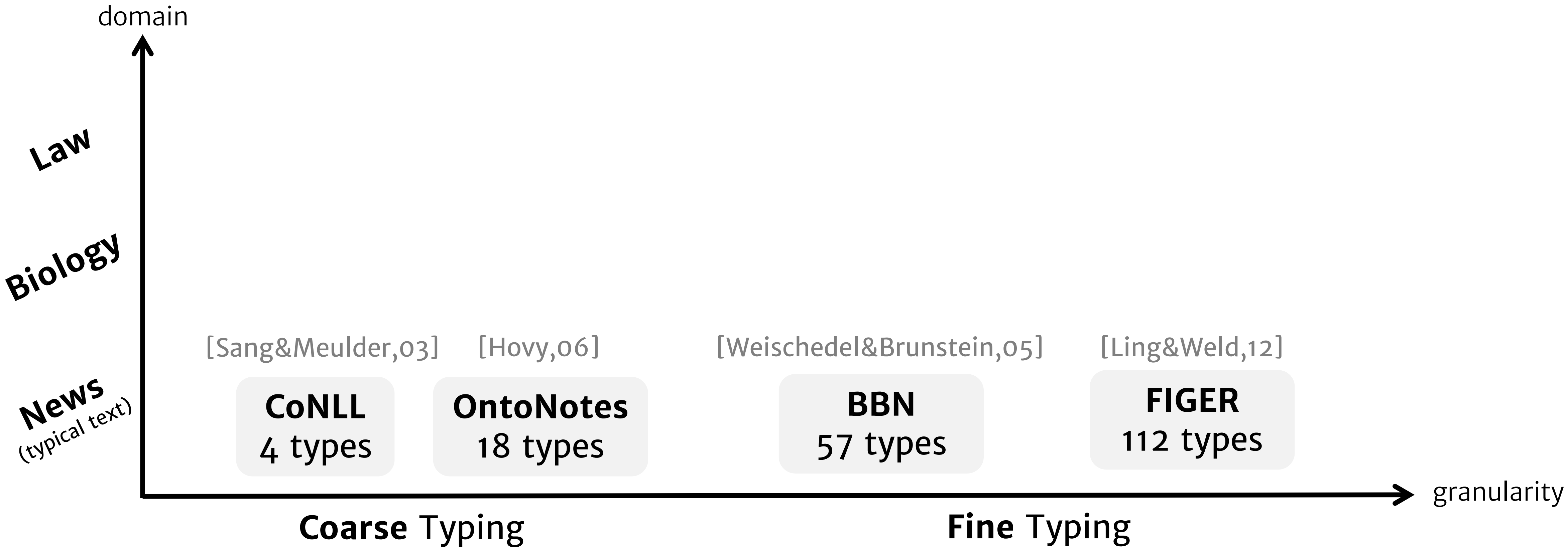

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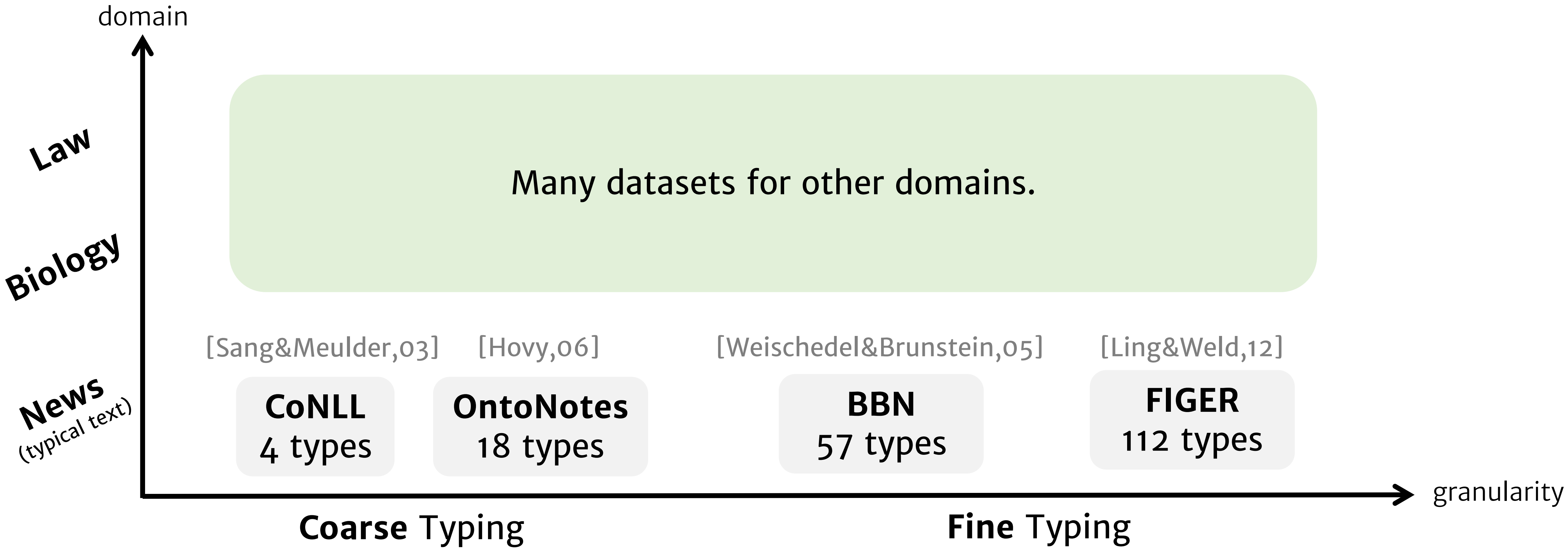

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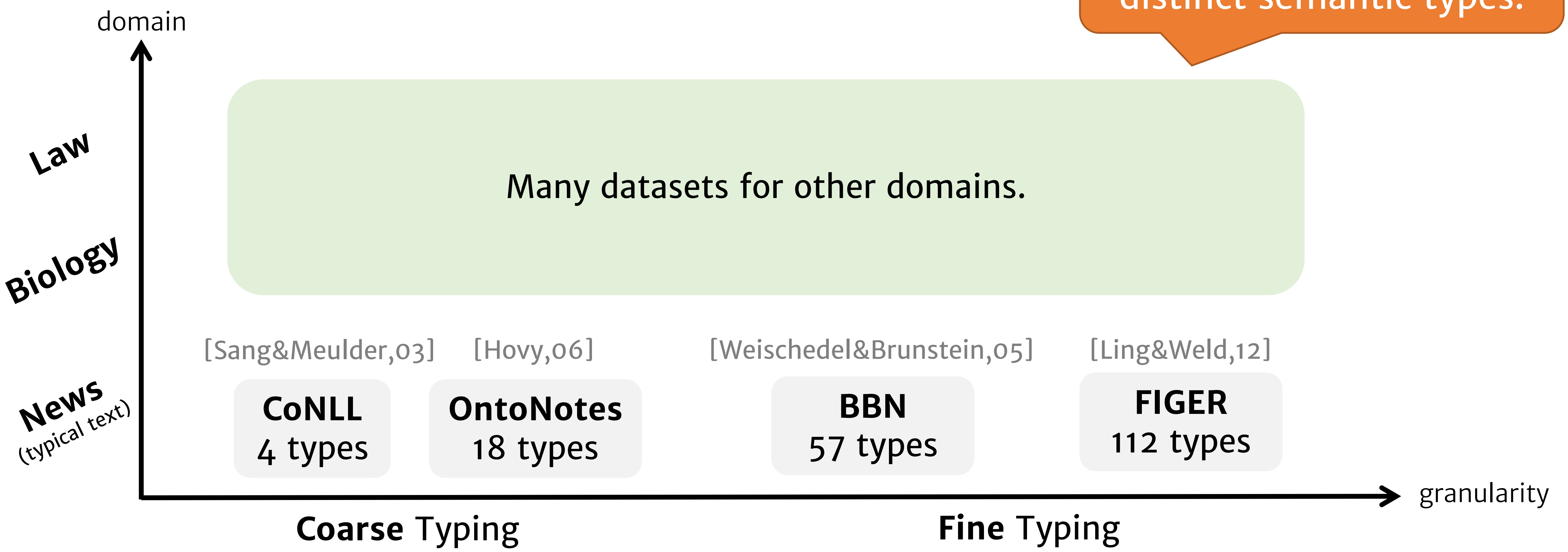
- Multiple datasets for semantic typing

Many datasets, each with distinct semantic types.



“Cheap” Typing with Wikipedia

A former Democrat, ***Bloomberg*** *switched his party registration in 2001.*

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Entity Linking

[Ratinov et al. 11]

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politician

businessman

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businessman

philanthropist

Not consistent with the context

A Common Approach: Supervised Learning

- **Input:** sentence, mention.
- **Output:** a set of types.

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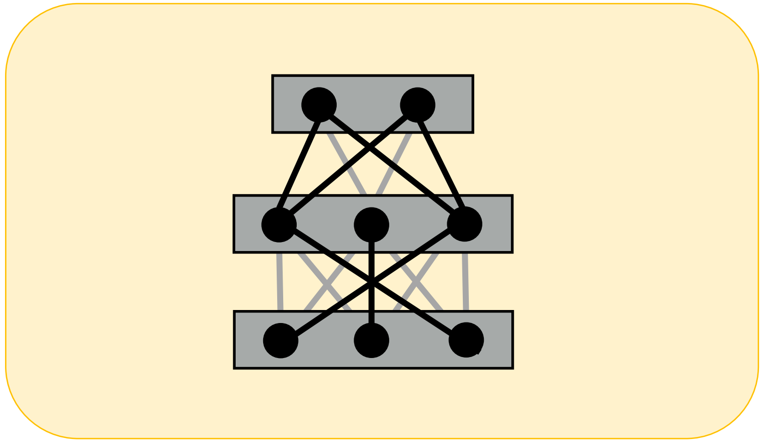

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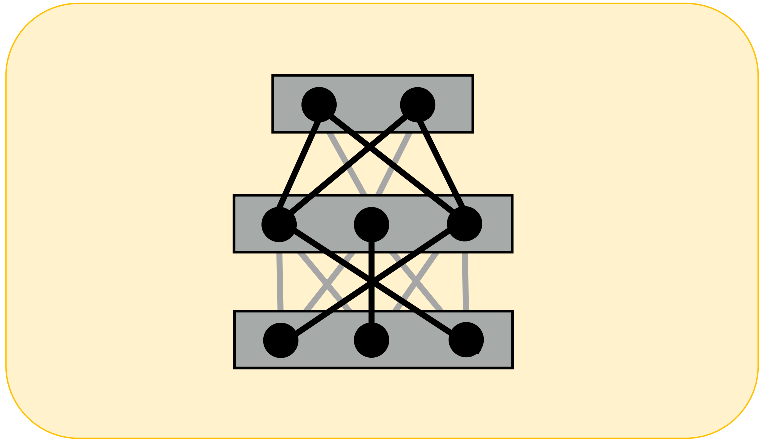

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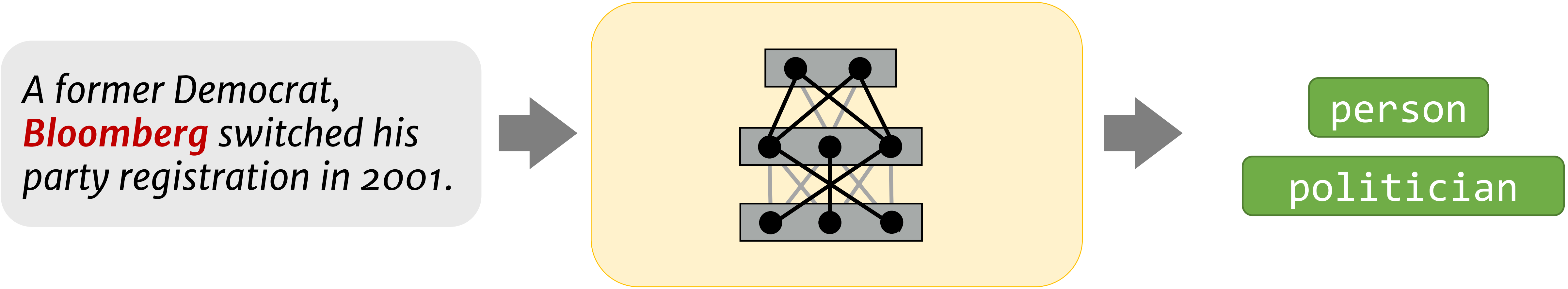

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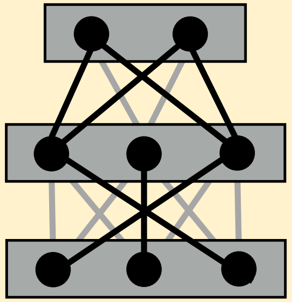

person

politician

Taxonomy is [indirectly] defined during the **training** time.

A Common Approach: Supervised Learning

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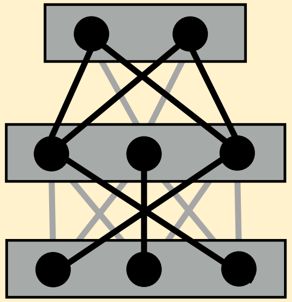

Zero-Shot Open Entity Typing

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Zero-Shot Open Entity Typing

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ZOE

(Zero-shot Open Entity Typing)

Zero-Shot Open Entity Typing

- **Input:** sentence, mention, **target taxonomy**.
- **Output:** a set of types (according to the target type taxonomy).

*A former Democrat, **Bloomberg** switched his party registration in 2001.*

ZOE
(Zero-shot Open Entity Typing)

Target Taxonomy

`person` `location` `organization`

Zero-Shot Open Entity Typing

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ZOE
(Zero-shot Open Entity Typing)

Target Taxonomy

person location
organization

Classifies into a **given taxonomy**

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Target Taxonomy

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location
organization

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ZOE
(Zero-shot Open Entity Typing)

Target Taxonomy

- person
  - politician
  - doctor
- org
  - hospital
  - hotel

Zero-Shot Open Entity Typing

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ZOE

(Zero-shot Open Entity Typing)

person

politician

Target Taxonomy

person → politician, doctor

org → hospital, hotel

Zero-Shot Open Entity Typing

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Open:
Classifies into a given taxonomy

ZOE
(Zero-shot Open Entity Typing)

person
politician

Target Taxonomy

person
politician
doctor
org
hospital
hotel

Zero-Shot Open Entity Typing

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ZOE

(Zero-shot Open Entity Typing)

person

politician

Open:
Classifies into a given taxonomy

Zero-shot:
no taxonomy-specific supervision

Target Taxonomy

- person
  - politician
  - doctor
- org
  - hospital
  - hotel

ZOE: Type-Compatible Grounding

- “Type” as conceptual container binding entities together.

ZOE: Type-Compatible Grounding

- "Type" as conceptual container binding entities together.

politician

ZOE: Type-Compatible Grounding

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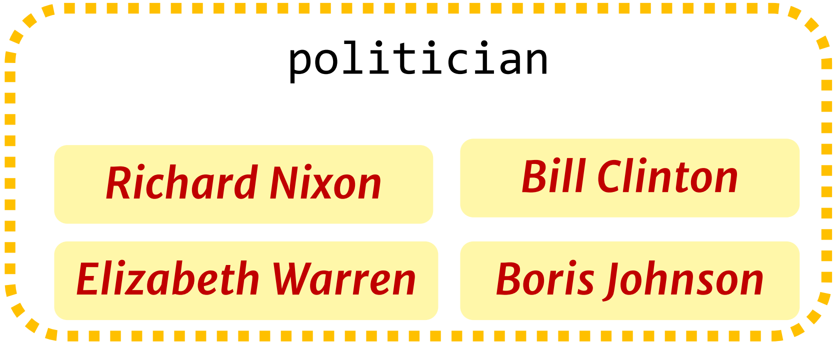

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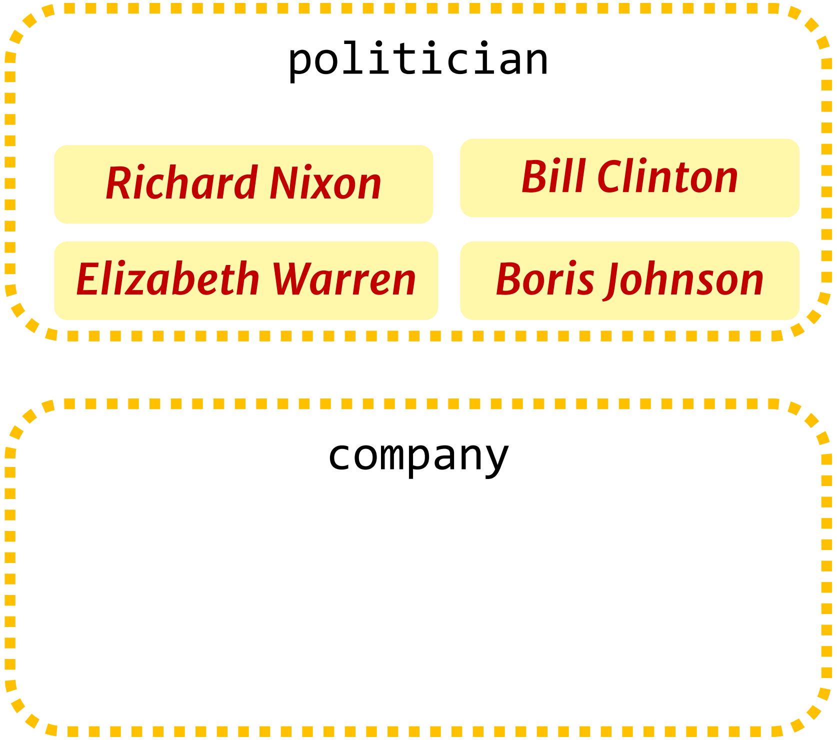

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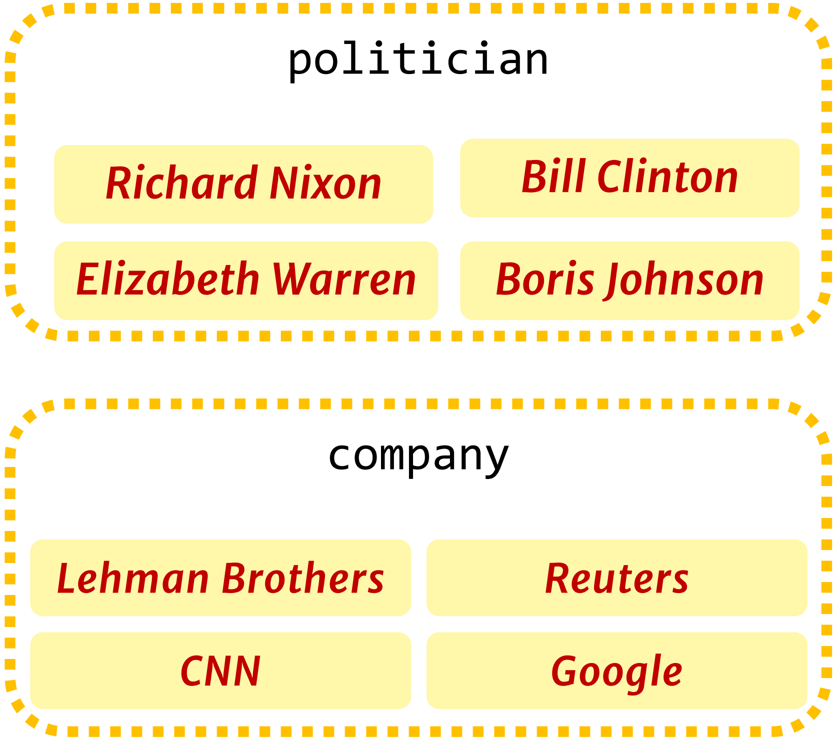

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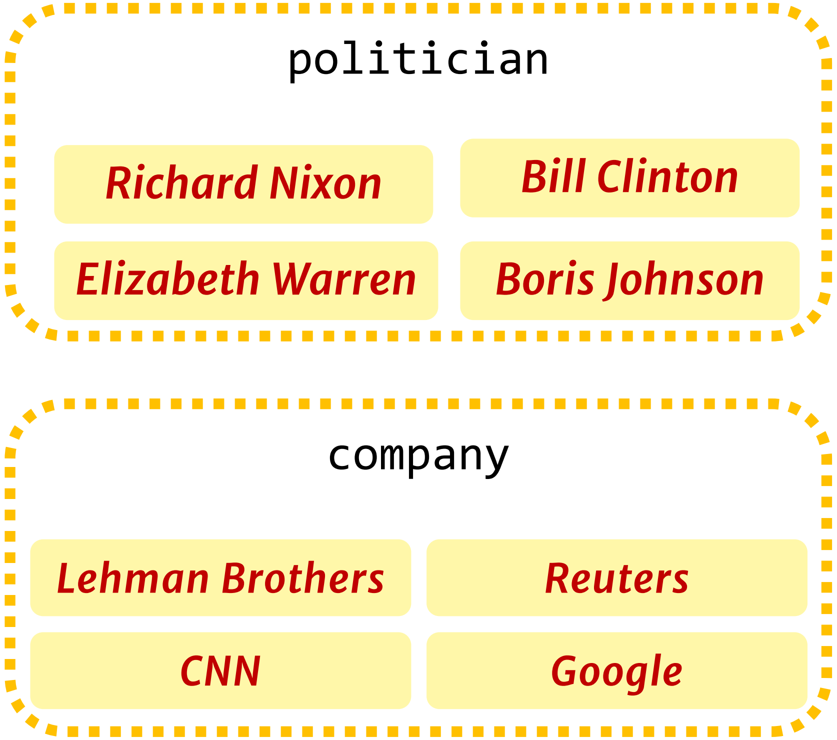

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Key idea: Determine the **type** of an input mention by finding entities in the **type defining set** that share a similar context

politician

Richard Nixon ***Bill Clinton***

Elizabeth Warren ***Boris Johnson***

company

Lehman Brothers ***Reuters***

CNN ***Google***

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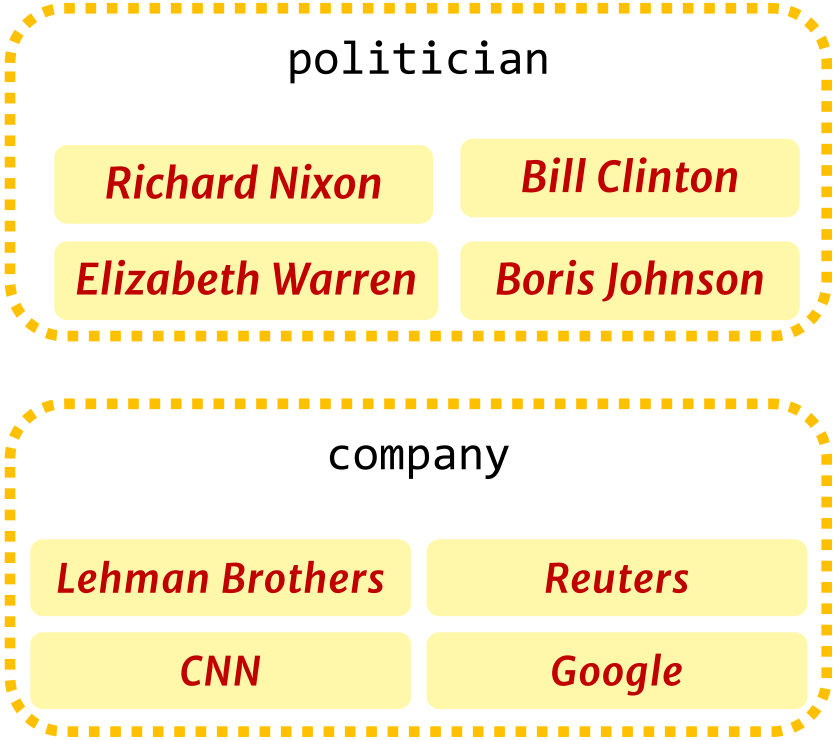

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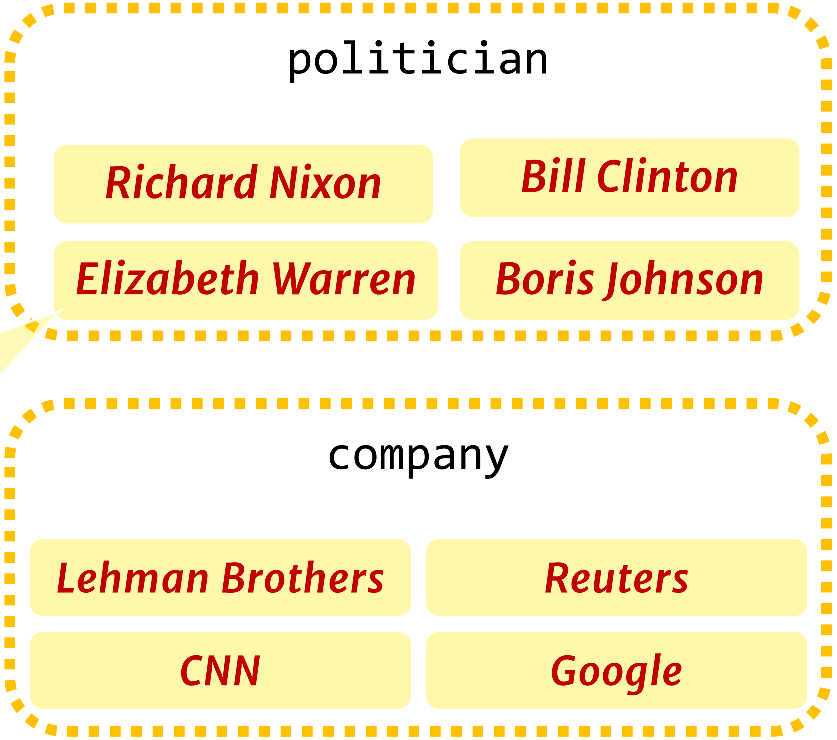

Different contexts where ***“Elizabeth Warren”*** is mentioned

WikiLinks [Singh et al. 12]

ZOE: Type-Compatible Grounding

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*A former Democrat, **Bloomberg** switched his party registration in 2001.*

***Warren** is a member of the Democratic Party, after switching party affiliation from the Republican Party in 1996.*

Different contexts where ***"Elizabeth Warren"*** is mentioned

WikiLinks [Singh et al. 12]

politician

Richard Nixon ***Bill Clinton***

Elizabeth Warren ***Boris Johnson***

company

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ELMo [Peters et al. 18]

Context-consistent

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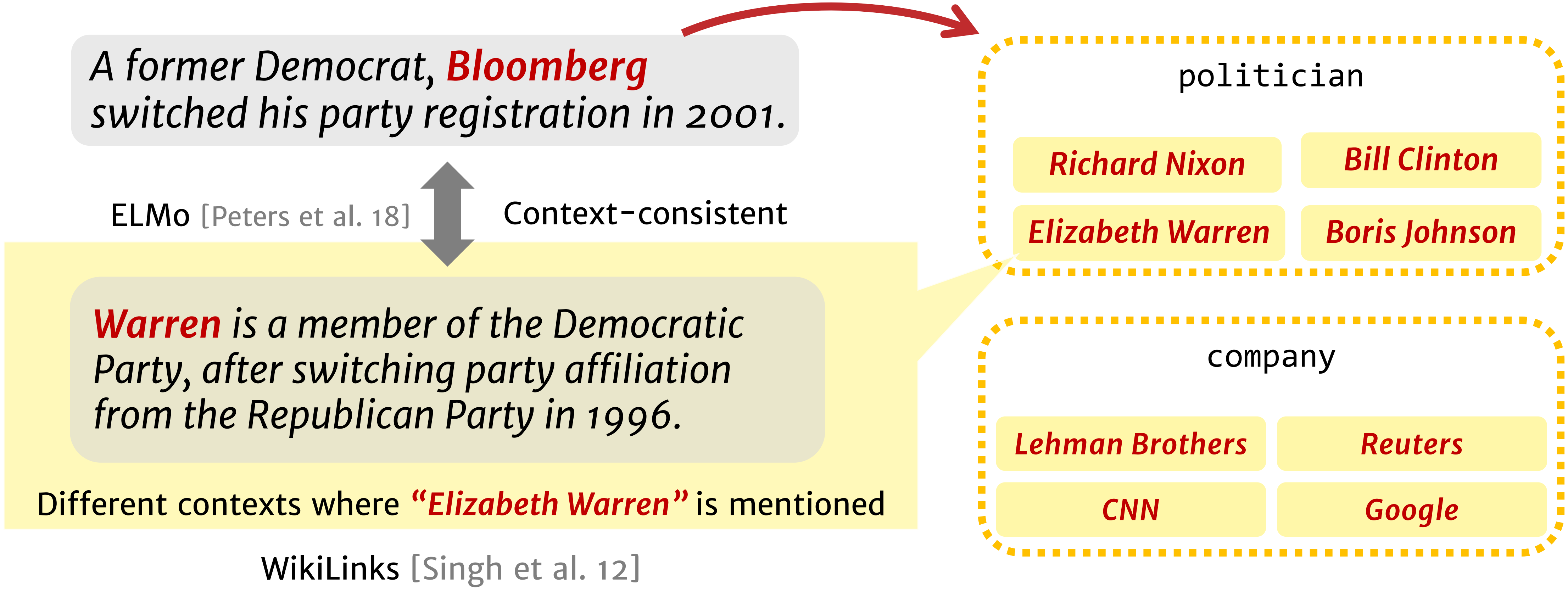

ZOE: Type-Compatible Grounding

- "Type" as conceptual container binding entities together.

*Since its founding, **Bloomberg** has made several acquisitions.*

politician

Richard Nixon | ***Bill Clinton***

Elizabeth Warren | ***Boris Johnson***

company

Lehman Brothers | ***Reuters***

Berkshire Hathaway | ***Enron***

ZOE: Type-Compatible Grounding

- "Type" as conceptual container binding entities together.

*Since its founding, **Bloomberg** has made several acquisitions.*

Different contexts where *"Berkshire Hathaway"* is mentioned

politician

Richard Nixon ***Bill Clinton***

Elizabeth Warren ***Boris Johnson***

company

Lehman Brothers ***Reuters***

Berkshire Hathaway ***Enron***

ZOE: Type-Compatible Grounding

- "Type" as conceptual container binding entities together.

*Since its founding, **Bloomberg** has made several acquisitions.*

__Berkshire Hathaway__ Berkshire Hathaway Inc has acquired a 25 billion rupees ($356 million) stake in the parent of digital payments company Paytm.

Different contexts where ***"Berkshire Hathaway"*** is mentioned

politician

Richard Nixon ***Bill Clinton***

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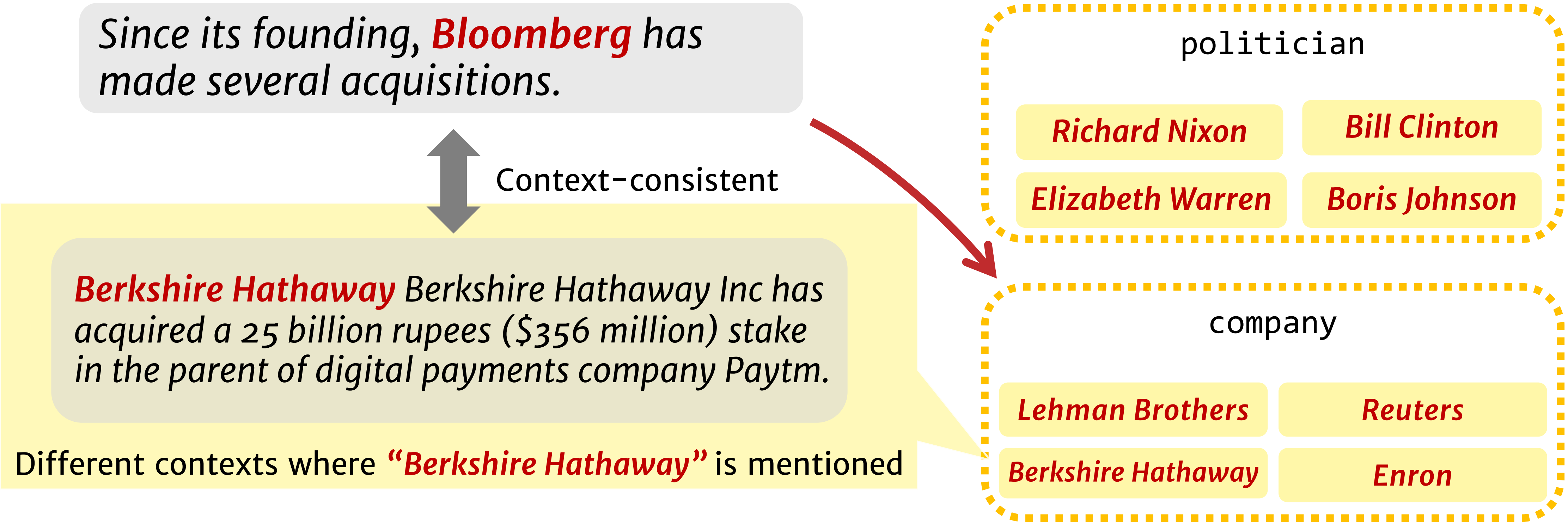

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Different contexts wh

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Context consistency allows us to determine good candidates for **type compatibility.**

Zero-Shot Open Typing: Big Picture

A mention & its context

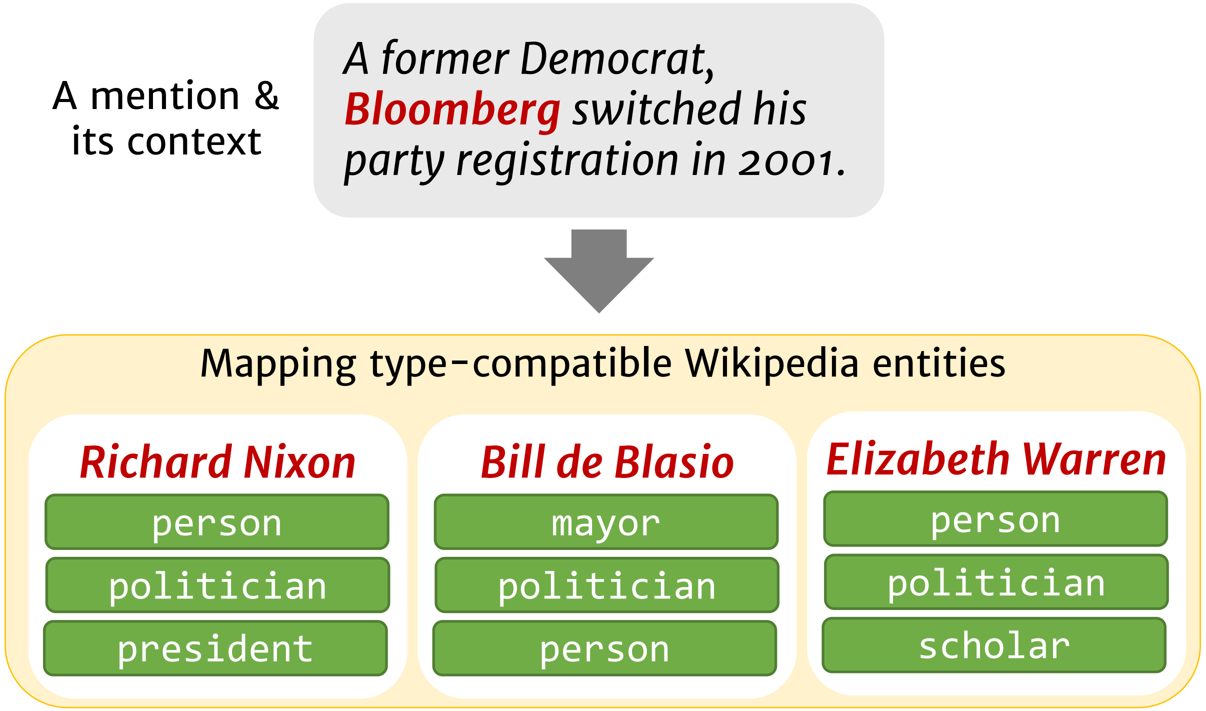
*A former Democrat, **Bloomberg** switched his party registration in 2001.*

High-level Algorithm:

1. Map the mention to **context-consistent** Wikipedia concepts

2. Rank candidate titles by **context-consistency** and infer the types according to the **type taxonomy**.

Zero-Shot Open Typing: Big Picture



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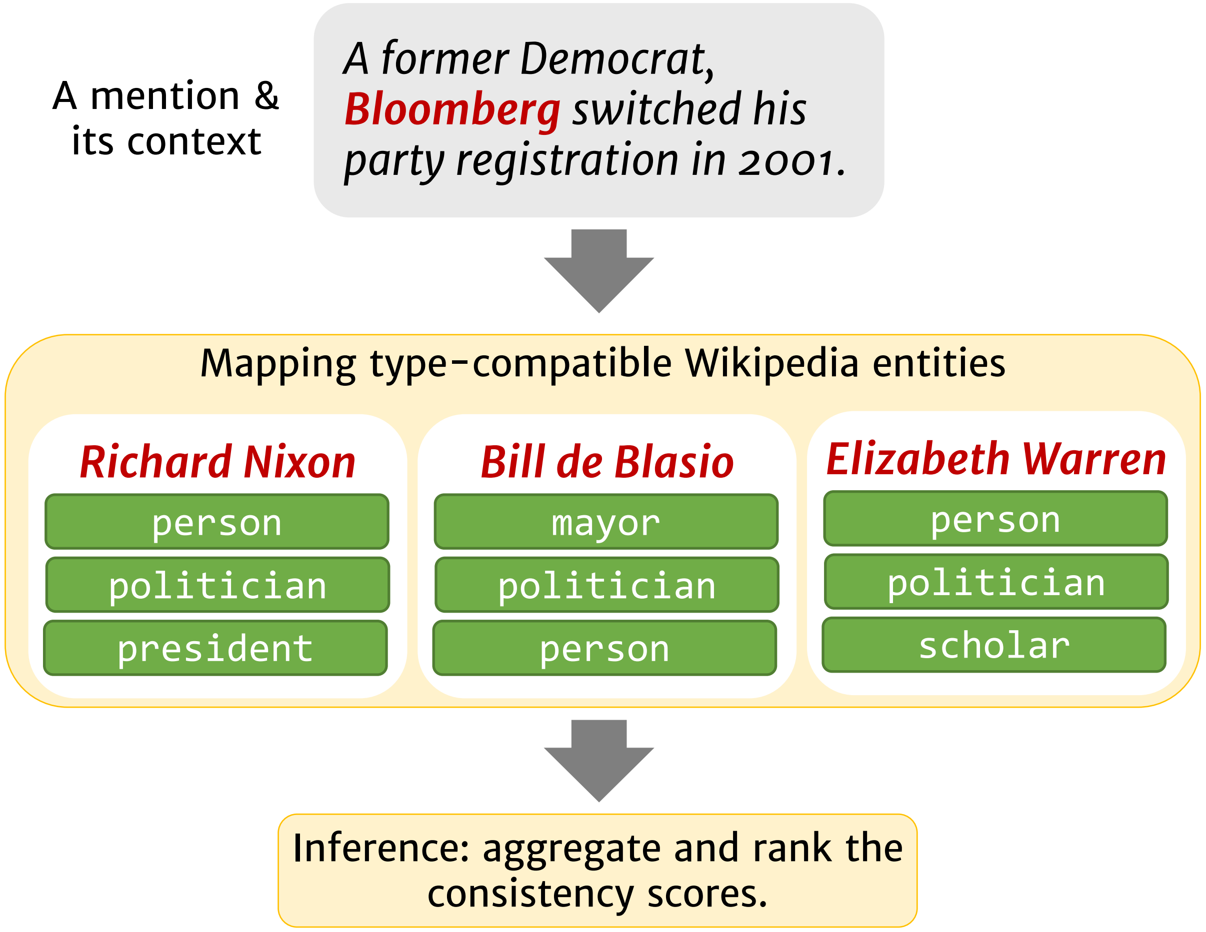

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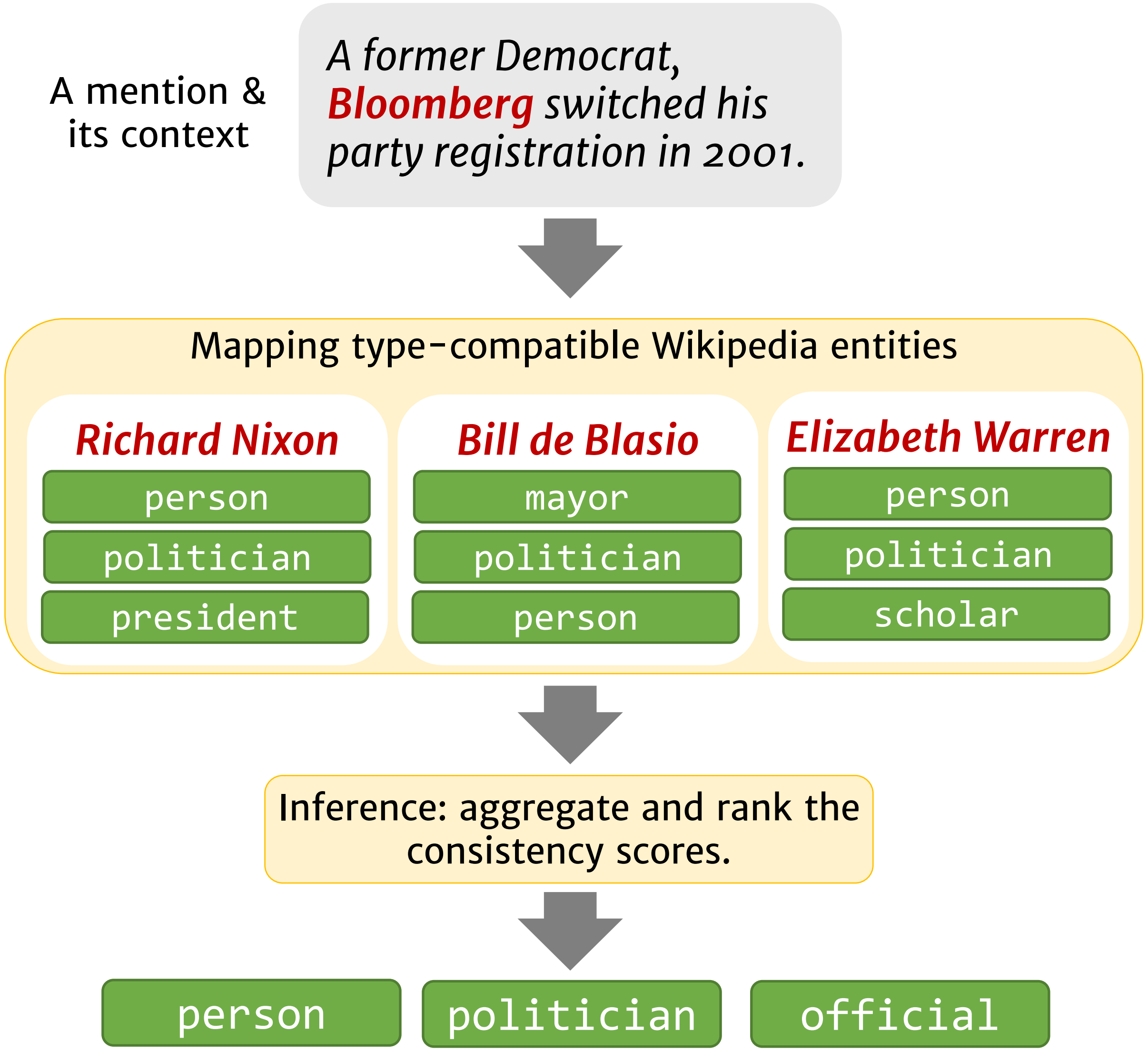

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Mapping type-compatible Wikipedia entities

Richard Nixon	***Bill de Blasio***	***Elizabeth Warren***
person	mayor	person
politician	politician	politician
president	person	scholar

Inference: aggregate and rank the consistency scores.

person | politician | official

Resources

Zero-Shot Open Typing: Big Picture

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Resources

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Freebase

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WikiLinks

[Singh et al. 12]

Contextualized Representations

[Peters et al.18]

Empirical Results: Fine-Typing [ZKTR18]

- Outperforms supervised system in cross-domain.

- Comparable results with supervised systems.

System	Trained on	Evaluated on		
		FIGER	BBN	Ontonotes

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AFET [Ren et al. 16]	FIGER			
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AFET [Ren et al. 16]	**BBN**	?	75	?
AAA [Abishek et al. 17]	**BBN**	?	79	?

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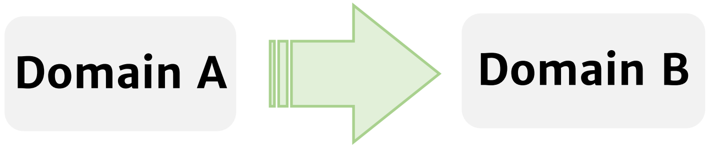
ZOE (this work)	-	71	75	61

Lessons

- Reformulating the task and using weak signals helps us reduce our dependence on direct "supervision".



- This type-aware approach leads to the ability to transfer across **domains & taxonomies.**

Beyond Supervision-rich “tasks”

- We will never have **enough annotated data** to train all the models for **all** the tasks.
    - Annotation for complex tasks is difficult, costly and sometimes impossible.

- We don’t even know what are “all the tasks”.

Beyond Supervision-rich “tasks”

- Two samples of research projects in an attempt to utilize hints in data to infer supervision signals:
  - Representation
  - Structure

- Not just two systems:
  - Initial steps towards a broader theory of using “incidental” signals.

[Roth, AAAI’17]

BIG PICTURE + LOOK AHEAD

Machine Learning,
Optimization &
applications

Natural Language Processing

Machine Learning, Optimization & applications

KSKCSSR. StartAI'18

KKCMSR. COLING'16

QK. NourIPS'15

KNJF. TIP'14

NKTNJ. SMC'11

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Natural Language Processing

Semantics

Semantic Role Labeling, Name Entities, Semantic Language models, Coreference, etc.

ZKCR. EMNLP'18
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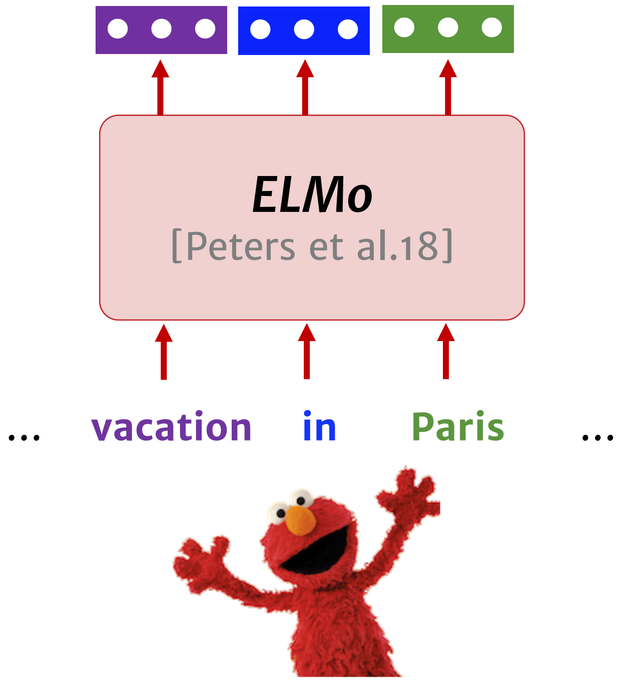
NLP tools/software

K et al. LREC'18
SCKKSVBWR. LREC'16

Beyond Supervision-rich "tasks"

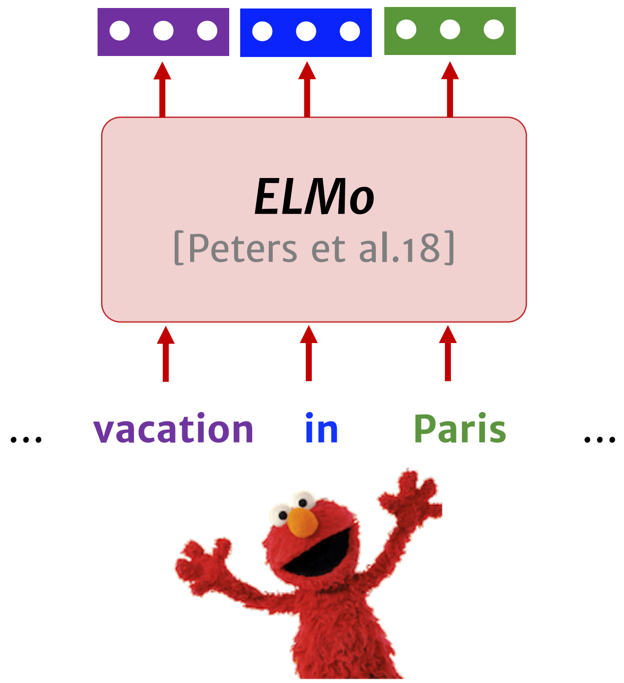
- A major shift in the field:
  - Being able to make use of massive loads of **unlabeled** data in the form of language models.
  - Compatible with the philosophy I advocated for here.



Other works:
[Devlin et al.18; Radford et al.18]

Language Models: Means to Access Knowledge

- They let you "query" for knowledge:



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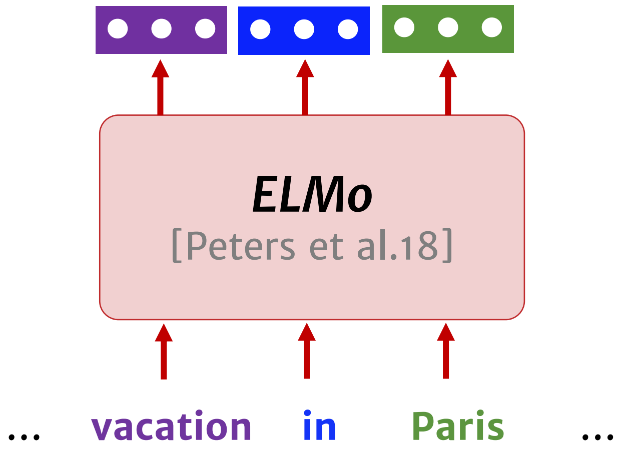

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Pittsburgh is the _____ –largest populated city in Pennsylvania.

Language Models: Means to Access Knowledge

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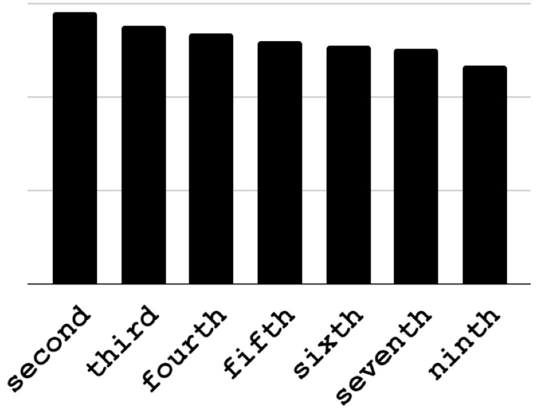

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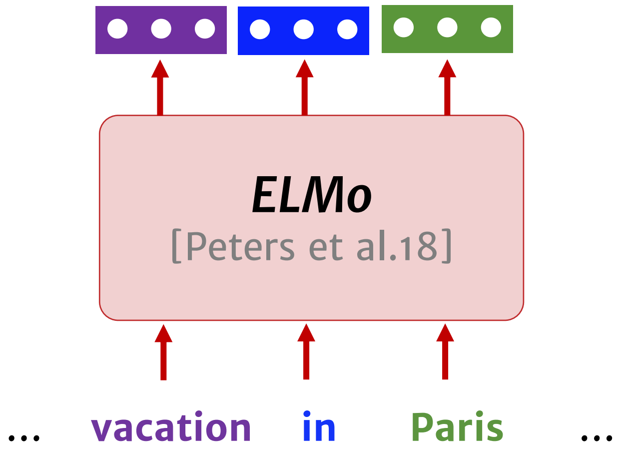

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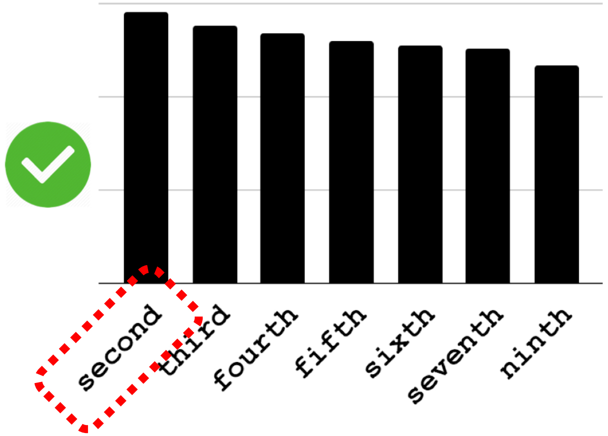

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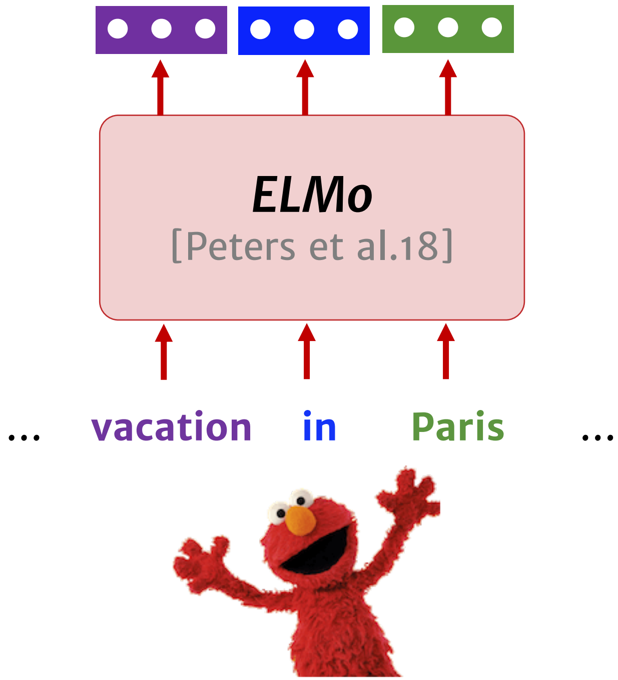

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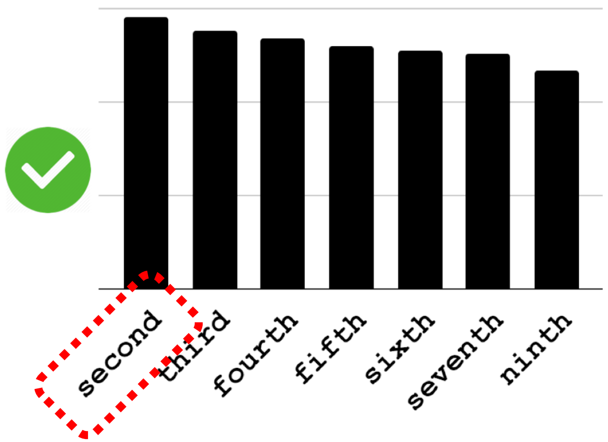
[Devlin et al.18; Radford et al.18]

Language Models: Means to Access Knowledge



Pittsburgh is the _____ -largest populated city in Pennsylvania.

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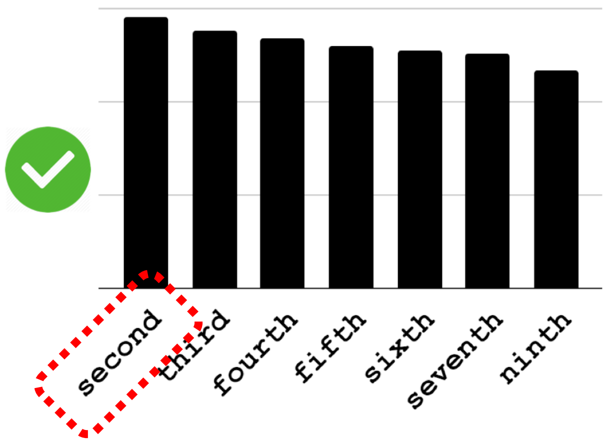

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  - What is the nature the knowledge that they have internalized?
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  - Access what is known and be able to solve bigger problems.

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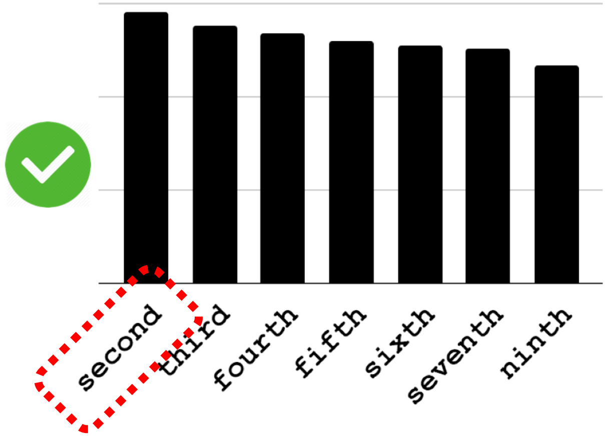

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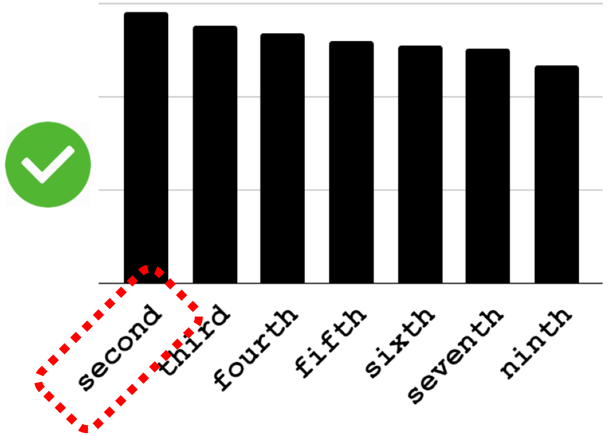

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Language Models: Biases

- What does this mean for the NLP systems built out of such systems?
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  - How can we automate the discovery of issues?
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Language Models: Biases

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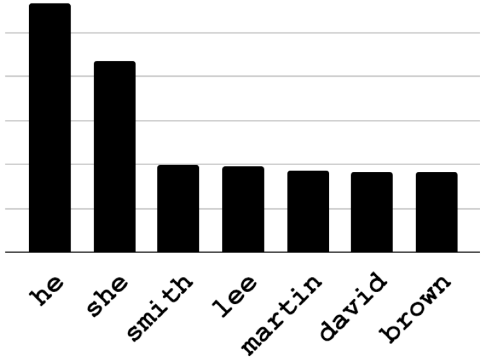

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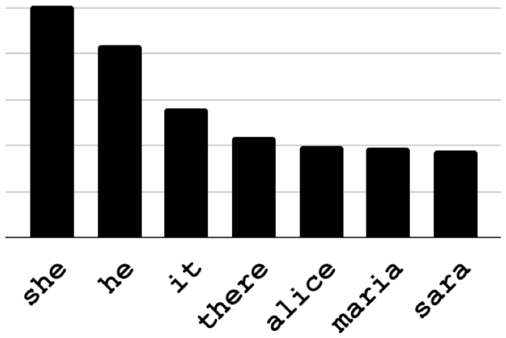

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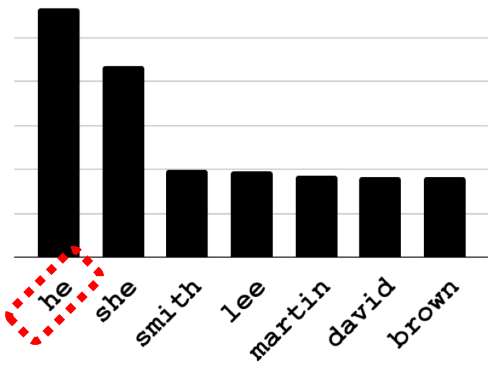

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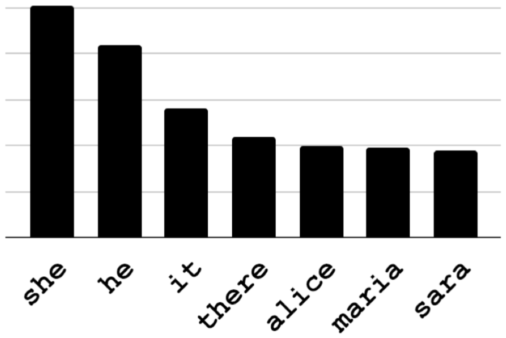

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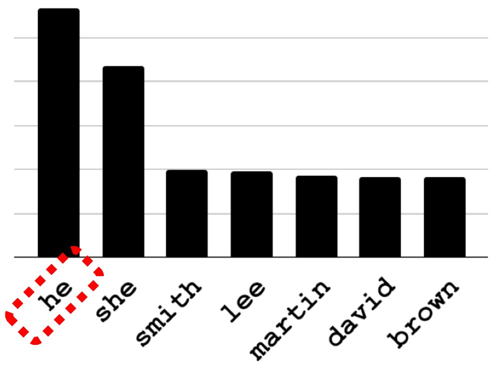

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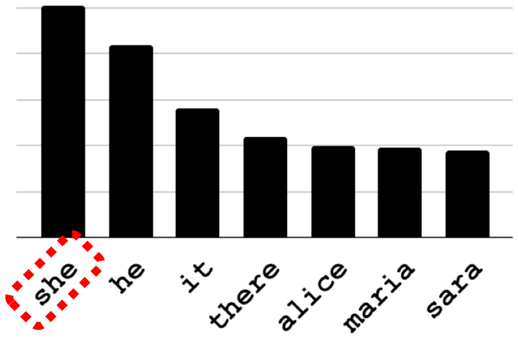

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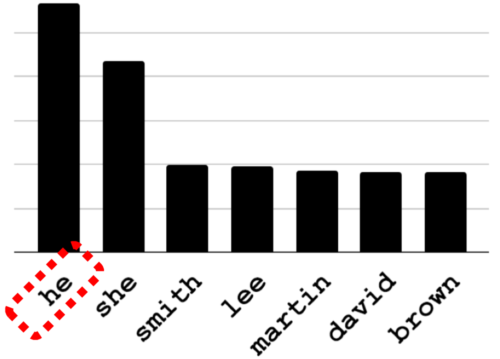

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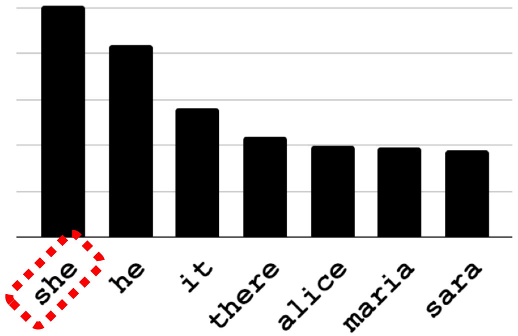
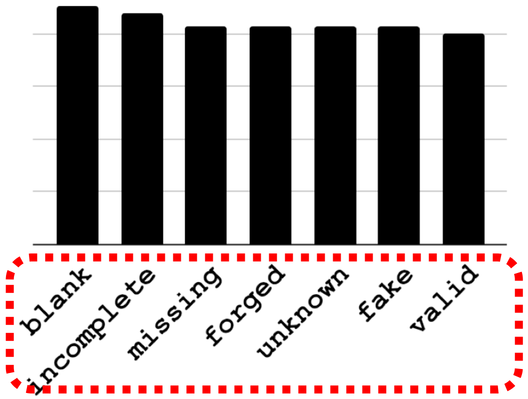


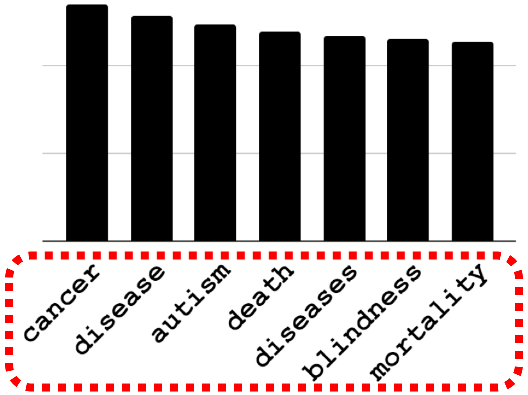
Bias

[May et al.19; Zhao et al.19]

Obama's birth certificate is ____.



Vaccines cause ____.



Conspiracy Theories

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Machine Learning, Optimization & applications

KSKCSSR. StartAI'18
KKCMSR. COLING'16
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KNJF. TIP'14
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Natural Language Processing

Semantics

Semantic Role Labeling, Name Entities, Semantic Language models, Coreference, etc.

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Learning & Inference

Question Answering, Textual Entailment, etc.

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Information Pollution

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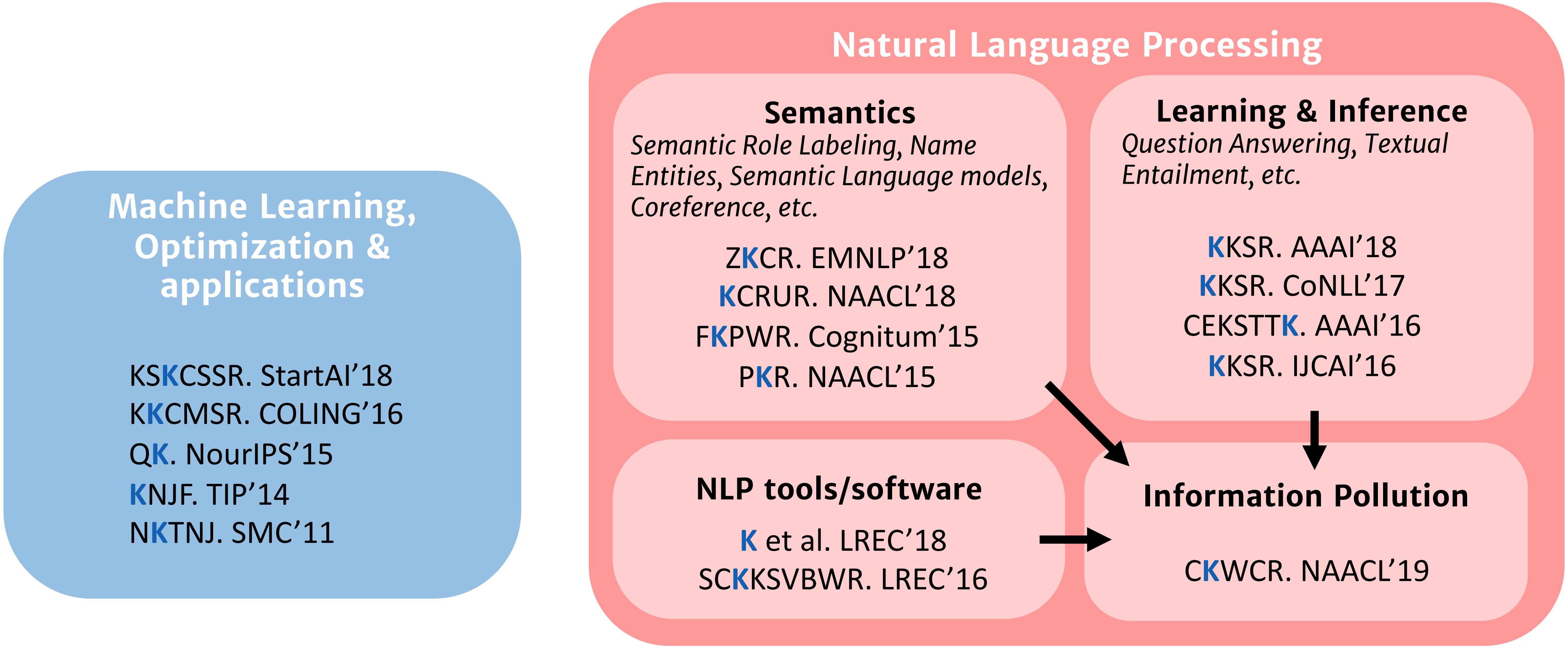
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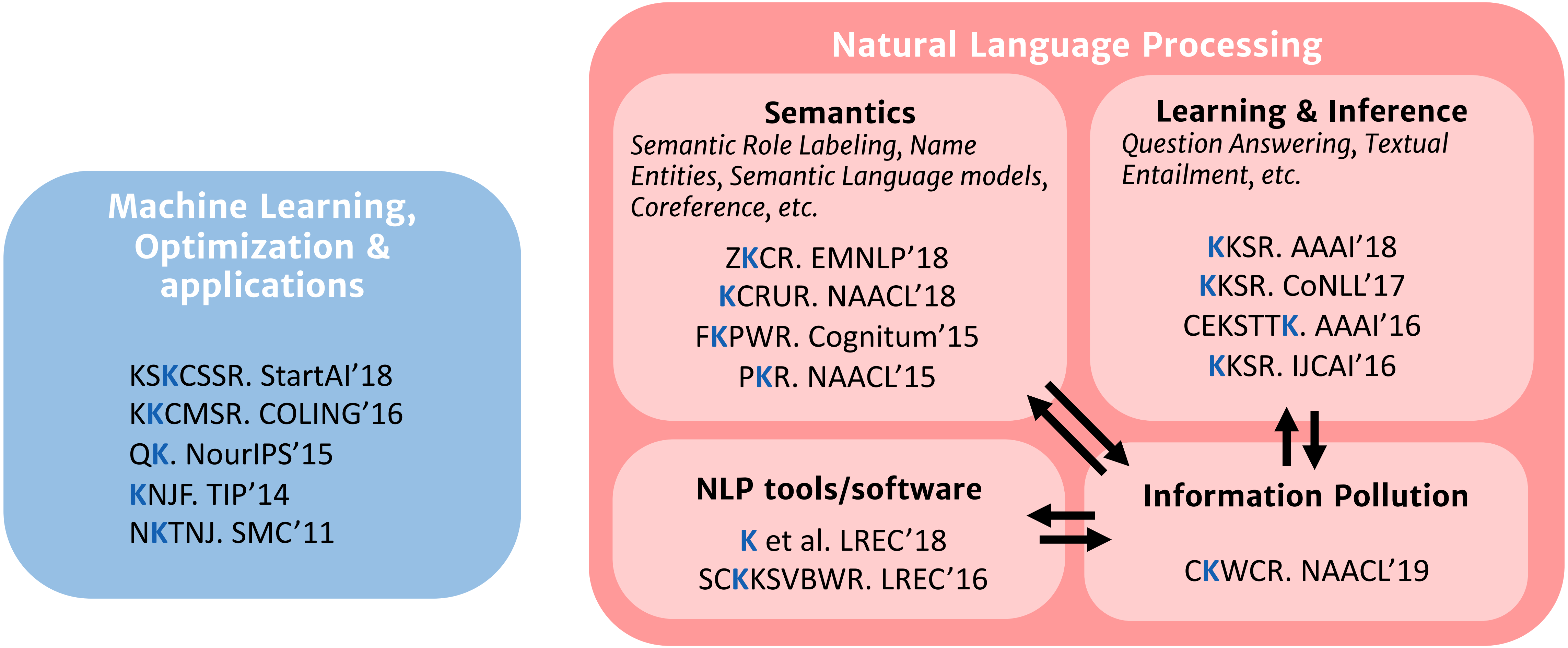
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> "The contamination of the information supply with irrelevant, redundant, unsolicited, incorrect, and otherwise low-value information."

[Levent Orman'15]

Information Pollution: Not Just Politics

- Medical Domain, Education, Public Policy, etc.
  - *"Best treatment for X;" "Side effects of X ."*

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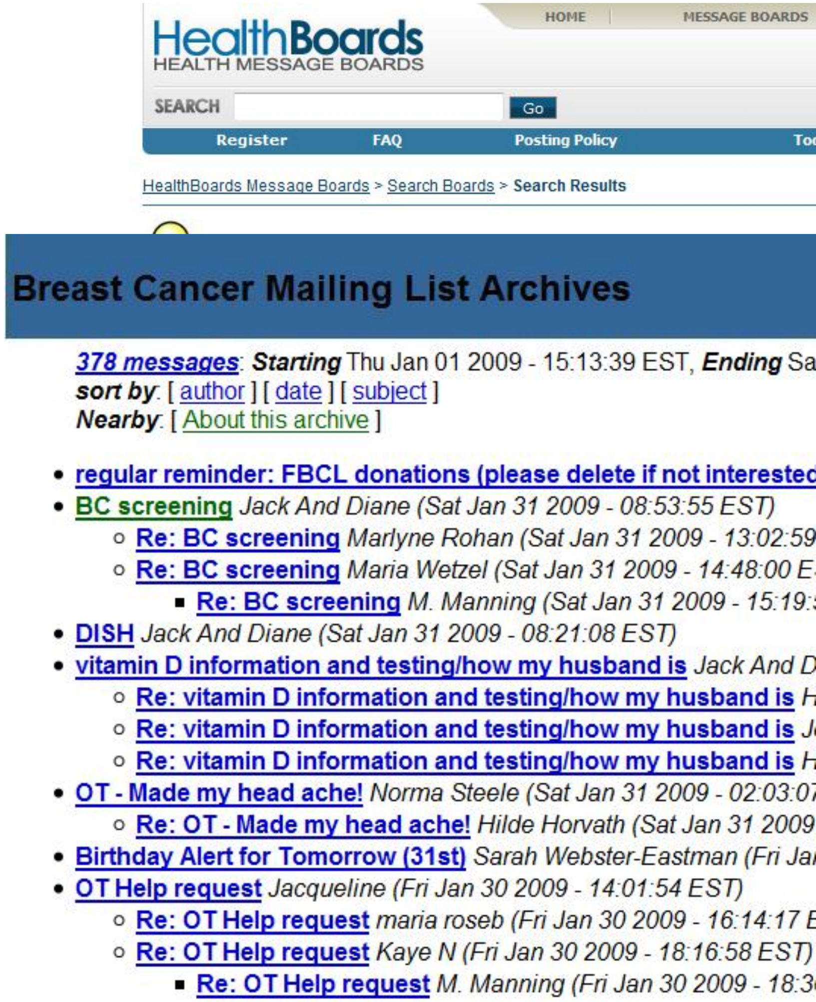

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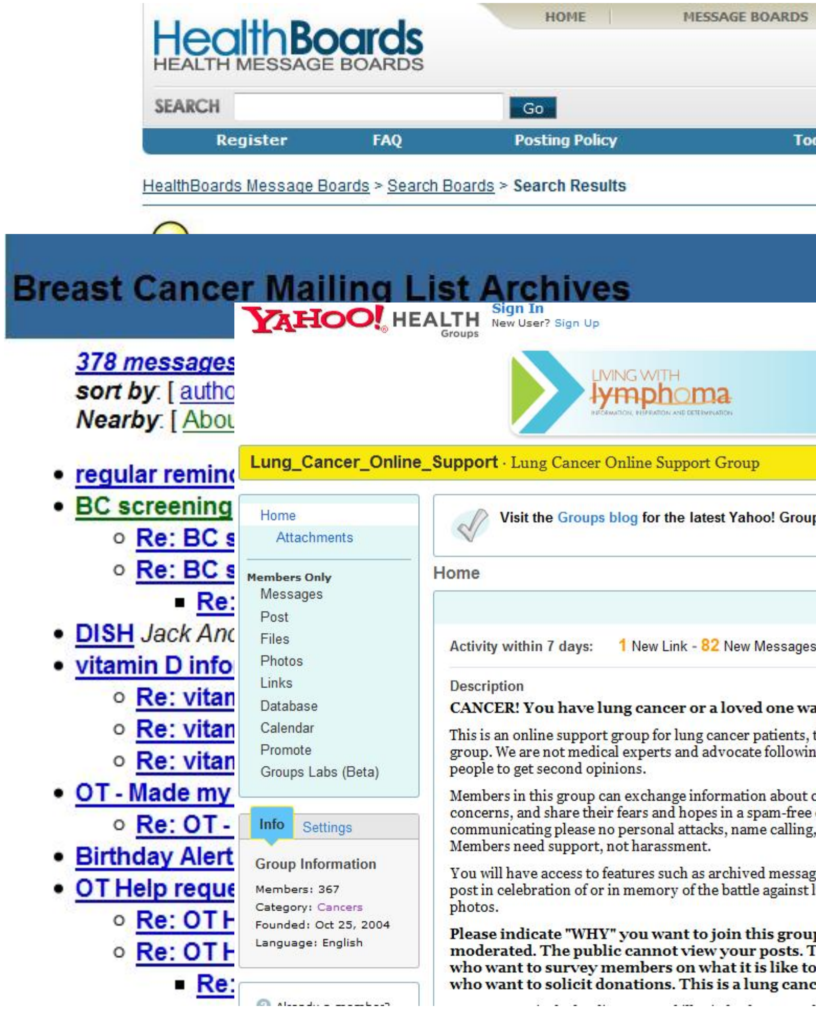

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- Are they consistent?
- Are they trustworthy?
- Are they written by someone with an agenda?

Information Pollution: Not Just Fact-Checking

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    - Possible answers are subject to situations, world views or background.
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Factual information (or lack of) is **not** really the core of the problem.

Information Pollution, as NLU Problems

Not only applications for NLP, but also drive the research in important directions.

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- **Understanding Sources**
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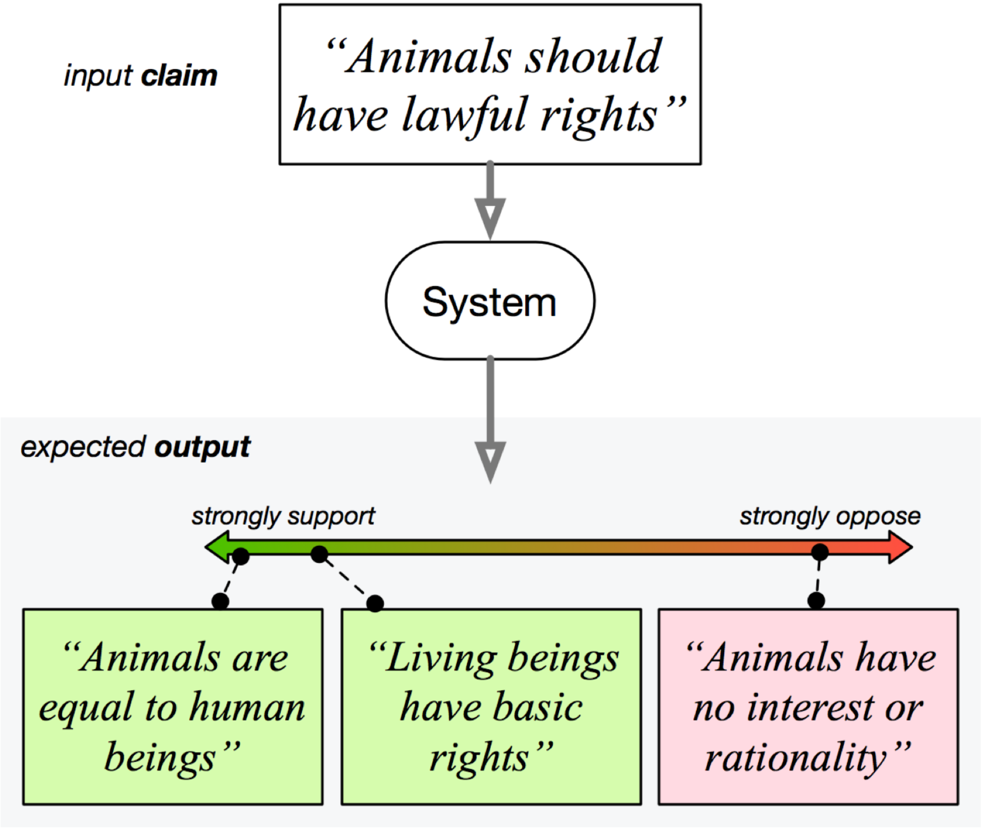

[Chen, **K**, et al. NAACL'19]

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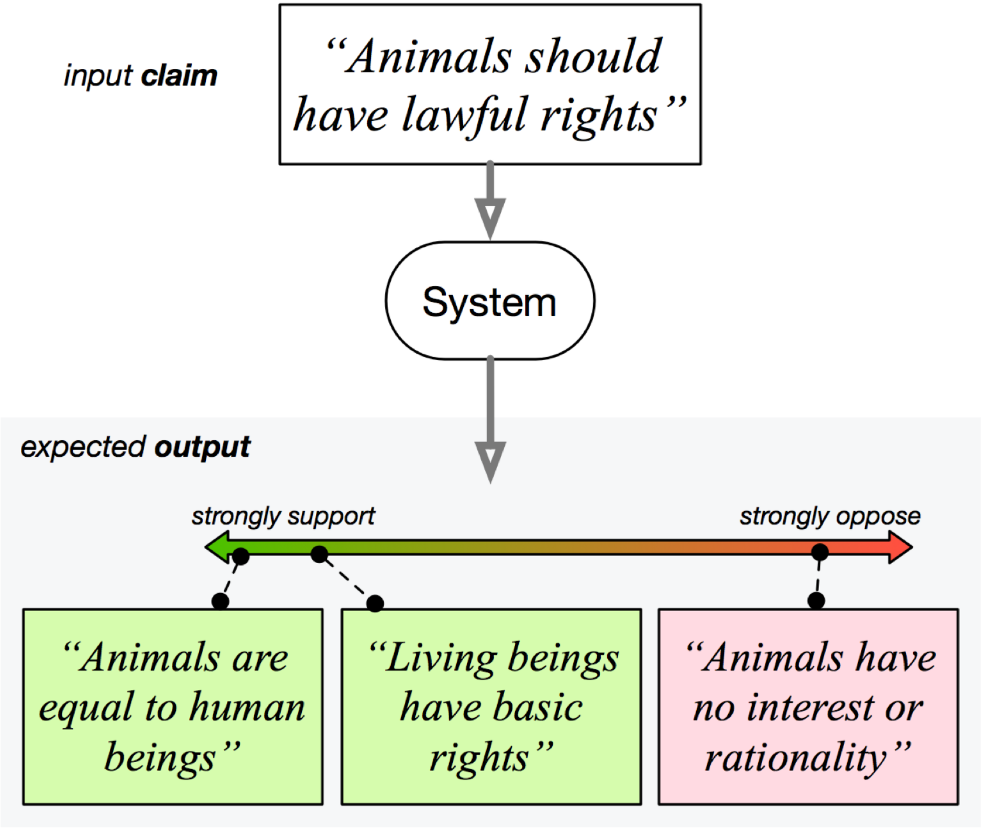

[Chen, K, et al. NAACL'19]

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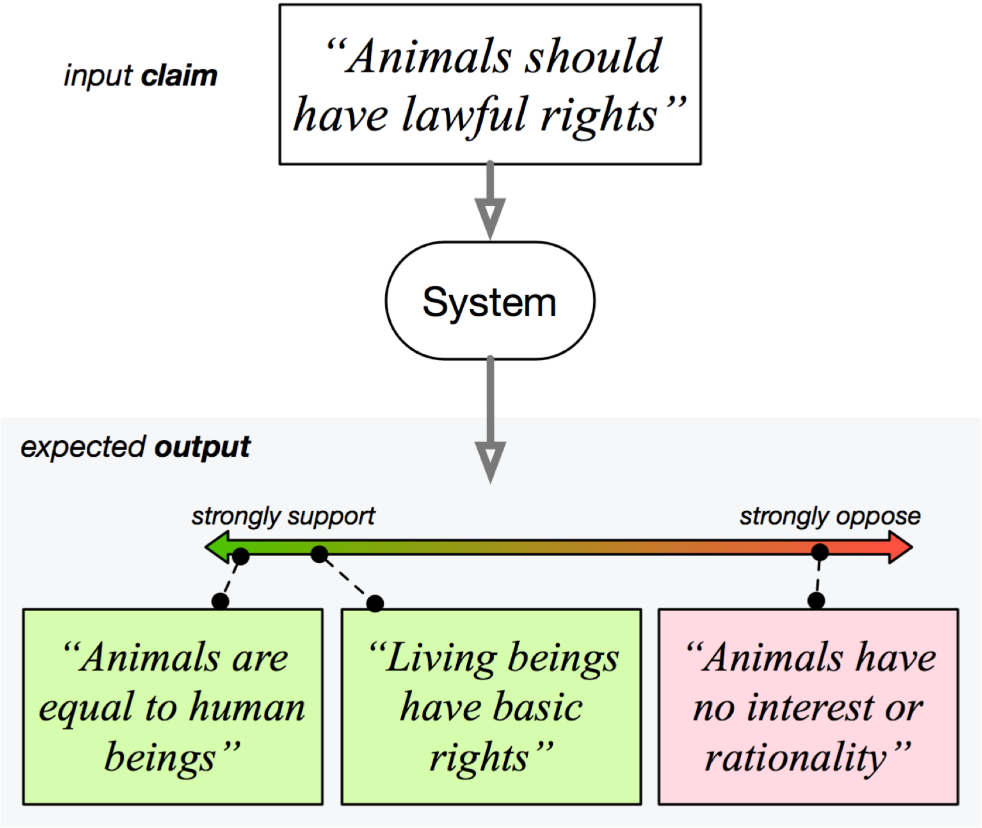

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Information Pollution: an NLU Challenge

- Suffering from this pollution is not a forgone conclusion.
- A computational model that will help us navigate the polluted world.
  - Natural Language Processing/Understanding + Algorithmic Components
  - Collaborative efforts involving experts from the social sciences, policy, and others.
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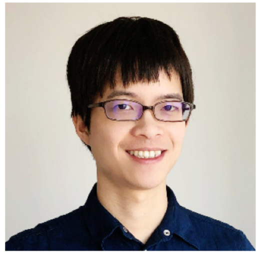

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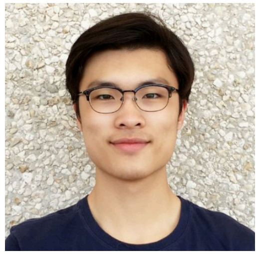

Ben Zhou
(UIUC → UPenn)

That’s it, folks!