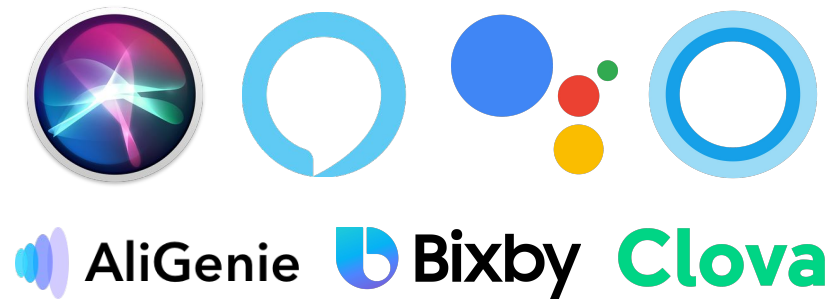


Natural Language Interfaces for Semi-Structured Web Pages

University Oral Examination

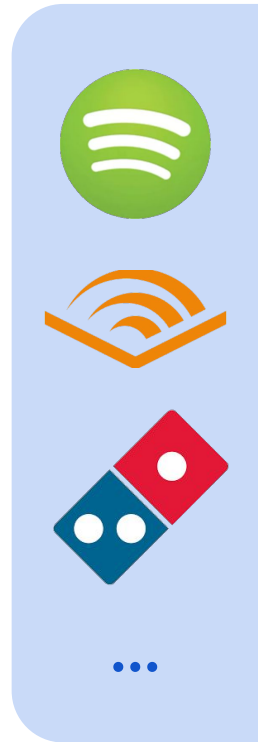
Ice Pasupat

Motivation



Motivation

environment

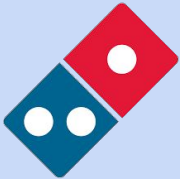


Motivation

utterance

Alexa, play Despacito

environment




Motivation

environment

utterance

Alexa, play Despacito

actions

 play(track=Despacito)



A vertical light blue panel on the right side of the slide, labeled 'environment'. It contains four icons: a green Spotify icon at the top, an orange book icon, a red and blue Domino's icon, and three blue dots at the bottom representing a menu.




Motivation

environment

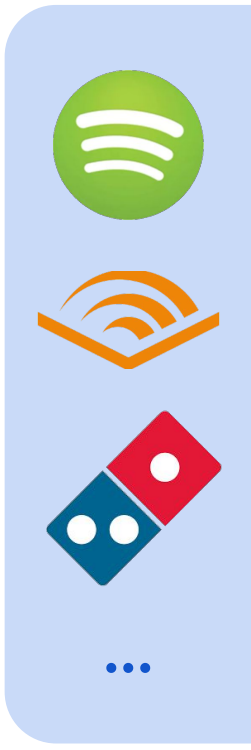
utterance

Alexa, play Despacito

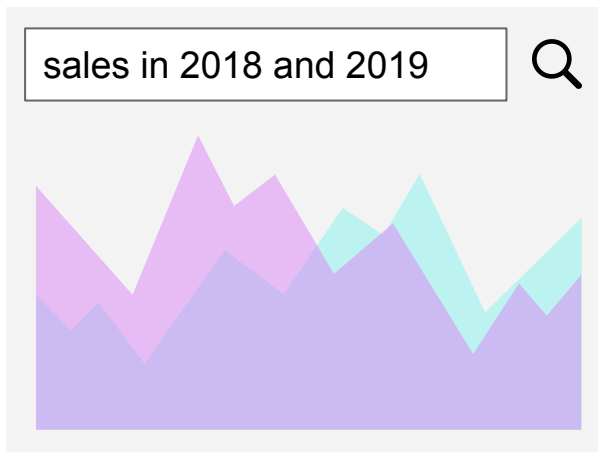
actions

 play(track=Despacito)

response

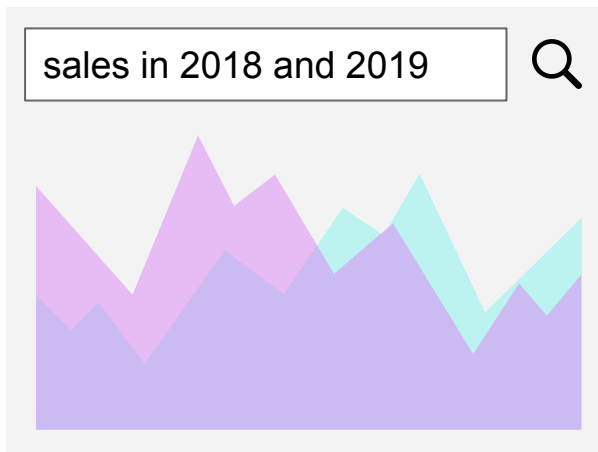


Motivation



natural language interface to database

Motivation



natural language interface to database



A search interface showing a search box with the text "barack obama's wife" and a magnifying glass icon. Below the search box is a search result for "Barack Obama / Wife". The result includes a profile picture of Michelle Obama, her name "Michelle Obama", and her birth year "m. 1992". Below the profile picture is a short biography: "Michelle LaVaughn Obama is an American lawyer, university administrator and writer, who was First Lady of the United States from 2009 to 2017. She is married to the 44th U.S. president, Barack Obama, and was the first African-American first lady. [Wikipedia](#)". At the bottom, there is a section "People also search for" with several small profile pictures and a "View 15+ more" link.

smart search engines

Motivation

Goal: Extend the capability of these systems along two axes:

- ▶
- ▶



Motivation

Goal: Extend the capability of these systems along two axes:

- ▶ Scope of the environment (**breadth**)
- ▶

How much is a Steak Burrito at Ray's Grill?



Motivation

Goal: Extend the capability of these systems along two axes:

- ▶ Scope of the environment (**breadth**)
- ▶

How much is a Steak Burrito at Ray's Grill?

?????



Motivation



semantic parsing on
databases



most virtual
assistants

database / apps
limited schema



Scope of the environment (**breadth**)

Motivation



semantic parsing on
databases



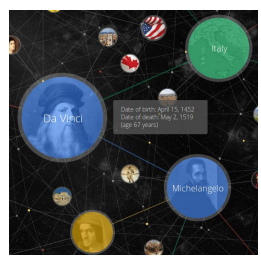
most virtual
assistants

database / apps
limited schema



semantic parsing on
knowledge bases

knowledge base
still limited schema



 **Freebase**[™]



Scope of the environment (**breadth**)

[Cai + Yates, 2013 / Berant et al., 2013 / Kwiatkowski et al., 2013 / Bordes et al., 2015 / ...]

Motivation

● semantic parsing on databases

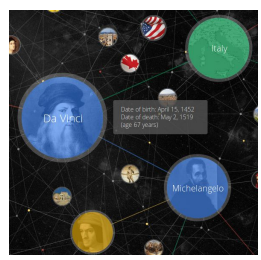
● most virtual assistants

database / apps limited schema



● semantic parsing on knowledge bases

knowledge base still limited schema



Freebase

● web scraping

web pages open schema



● question answering on paragraphs

● web search

any texts open schema

The Lacey Act of 1900 was the first federal law that regulated commercial animal markets. It prohibited interstate commerce of animals killed in violation of state game laws, and covered all fish and wildlife and their parts or products, as well as plants. Other legislation followed, including the Migratory Bird Conservation Act of 1929, a 1937 treaty prohibiting the hunting of right and gray whales, and the Bald Eagle Protection Act of 1940. These later laws had a low cost to society—the species were relatively rare—and little opposition was raised.^[9]

Scope of the environment (breadth)

[Robertson et al., 19xx / Hearst, 1992 / Richardson et al., 2013 / Rajpurkar et al., 2016 / ...]

Motivation

Goal: Extend the capability of these systems along two axes:

- ▶ Scope of the environment (**breadth**)
- ▶

How much is a Steak Burrito at Ray's Grill?

?????



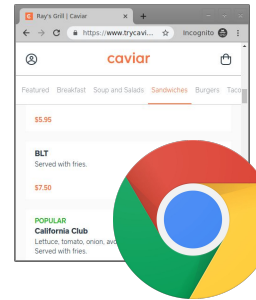
Motivation

Goal: Extend the capability of these systems along two axes:

- ▶ Scope of the environment (**breadth**)
- ▶

How much is a Steak Burrito at Ray's Grill?

\$8.50



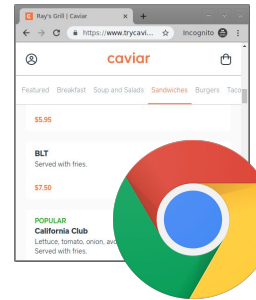
Motivation

Goal: Extend the capability of these systems along two axes:

- ▶ Scope of the environment (**breadth**)
- ▶ Task complexity (**depth**)

How much is a Steak Burrito at Ray's Grill?

\$8.50

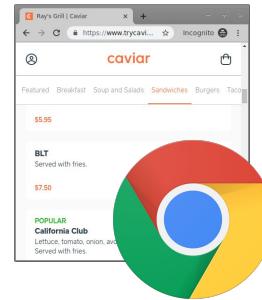


Motivation

Goal: Extend the capability of these systems along two axes:

- ▶ Scope of the environment (**breadth**)
- ▶ Task complexity (**depth**)

What's the cheapest burrito with chicken?



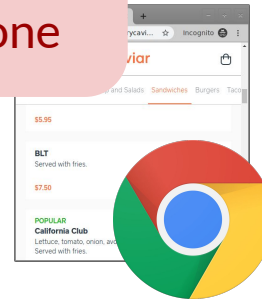
Motivation

Goal: Extend the capability of these systems along two axes:

- ▶ Scope of the environment (**breadth**)
- ▶ Task complexity (**depth**)

What's the cheapest burrito with chicken?

Step 1: Find burritos
Step 2: Filter for chicken
Step 3: Find the cheapest one



Motivation

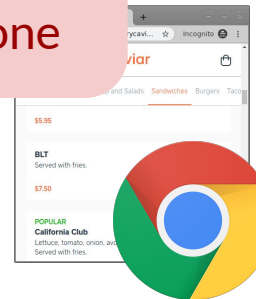
Goal: Extend the capability of these systems along two axes:

- ▶ Scope of the environment (**breadth**)
- ▶ Task complexity (**depth**)

What's the cheapest burrito with chicken?

Grilled Chicken Burrito
(\$6.95)

Step 1: Find burritos
Step 2: Filter for chicken
Step 3: Find the cheapest one



Motivation

Task Complexity (depth)



Find pages with
"burrito"

surface form
matching

Motivation

Task Complexity (depth)



How much is a
steak burrito?

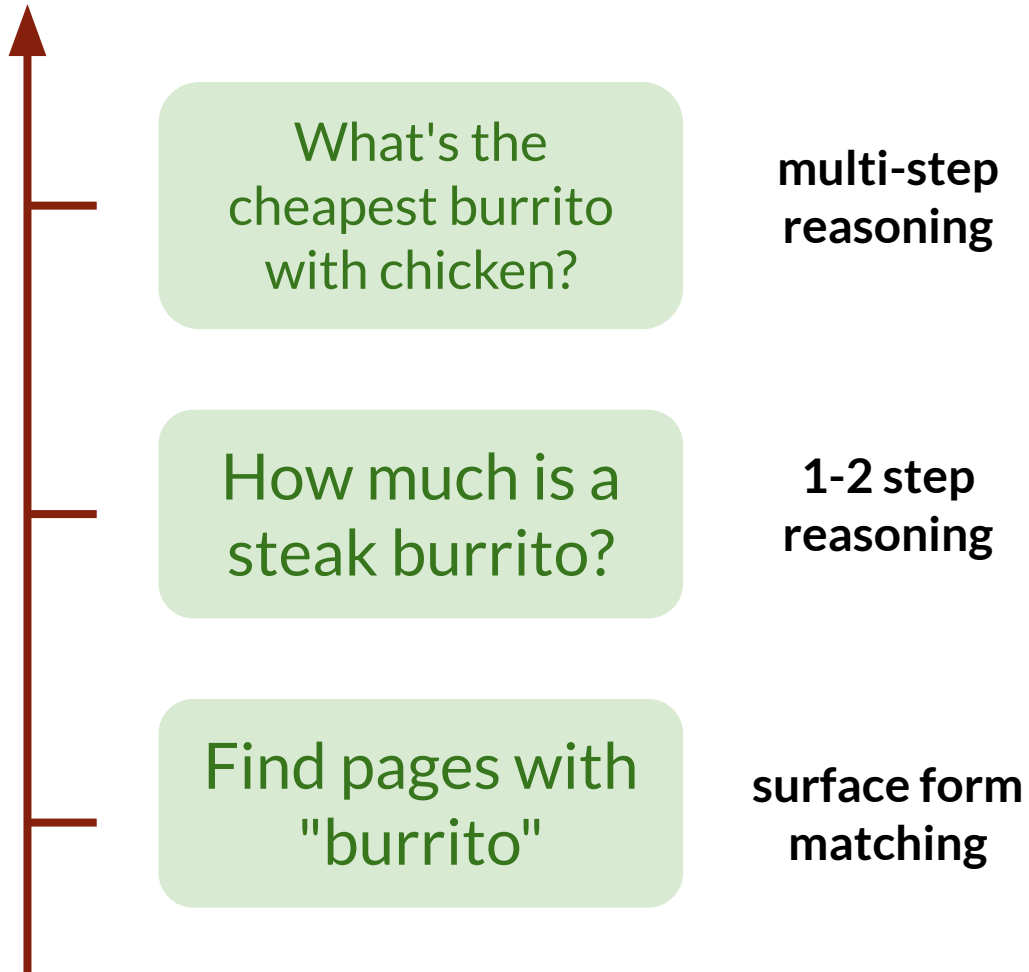
1-2 step
reasoning

Find pages with
"burrito"

surface form
matching

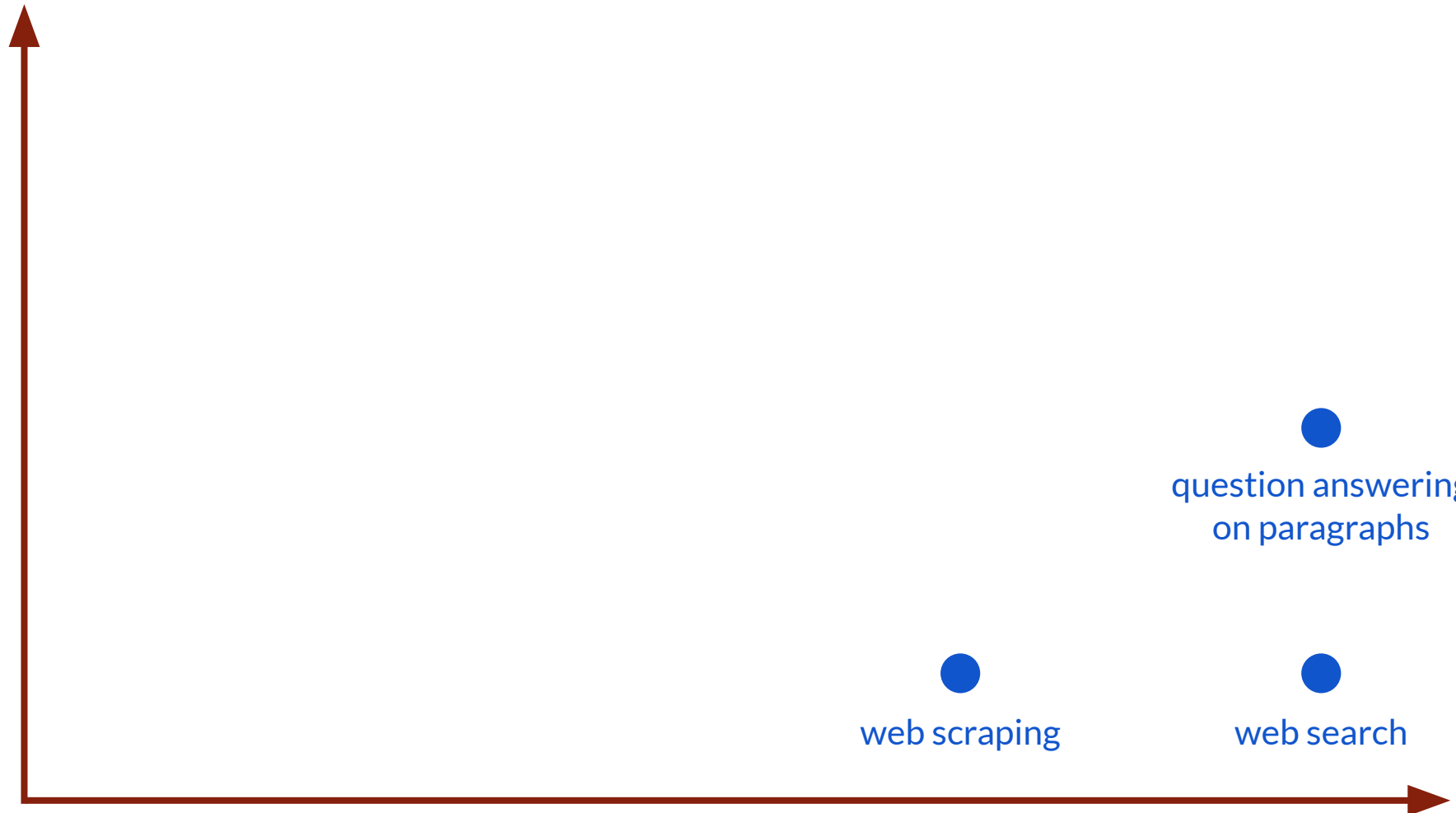
Motivation

Task Complexity (depth)



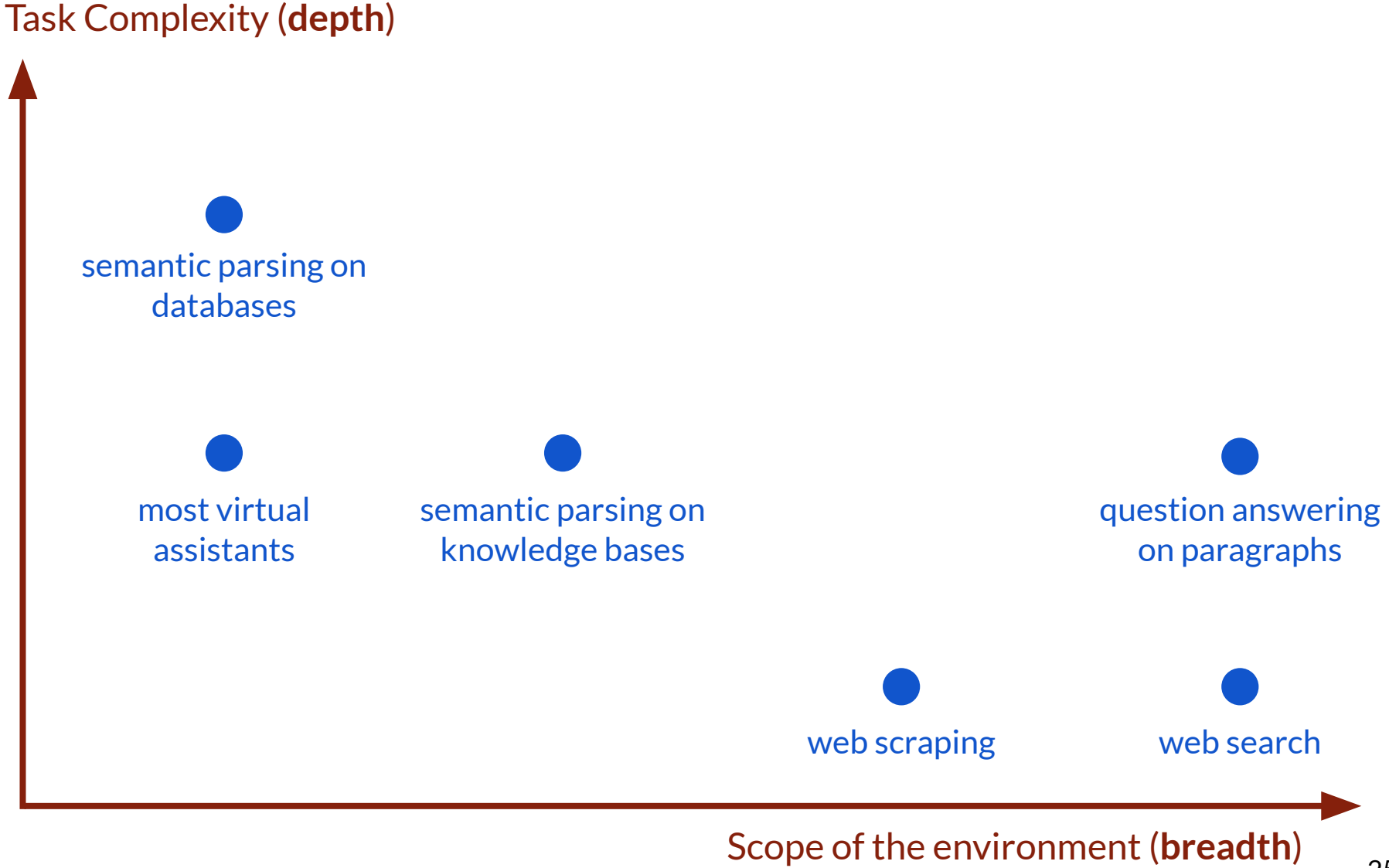
Motivation

Task Complexity (depth)

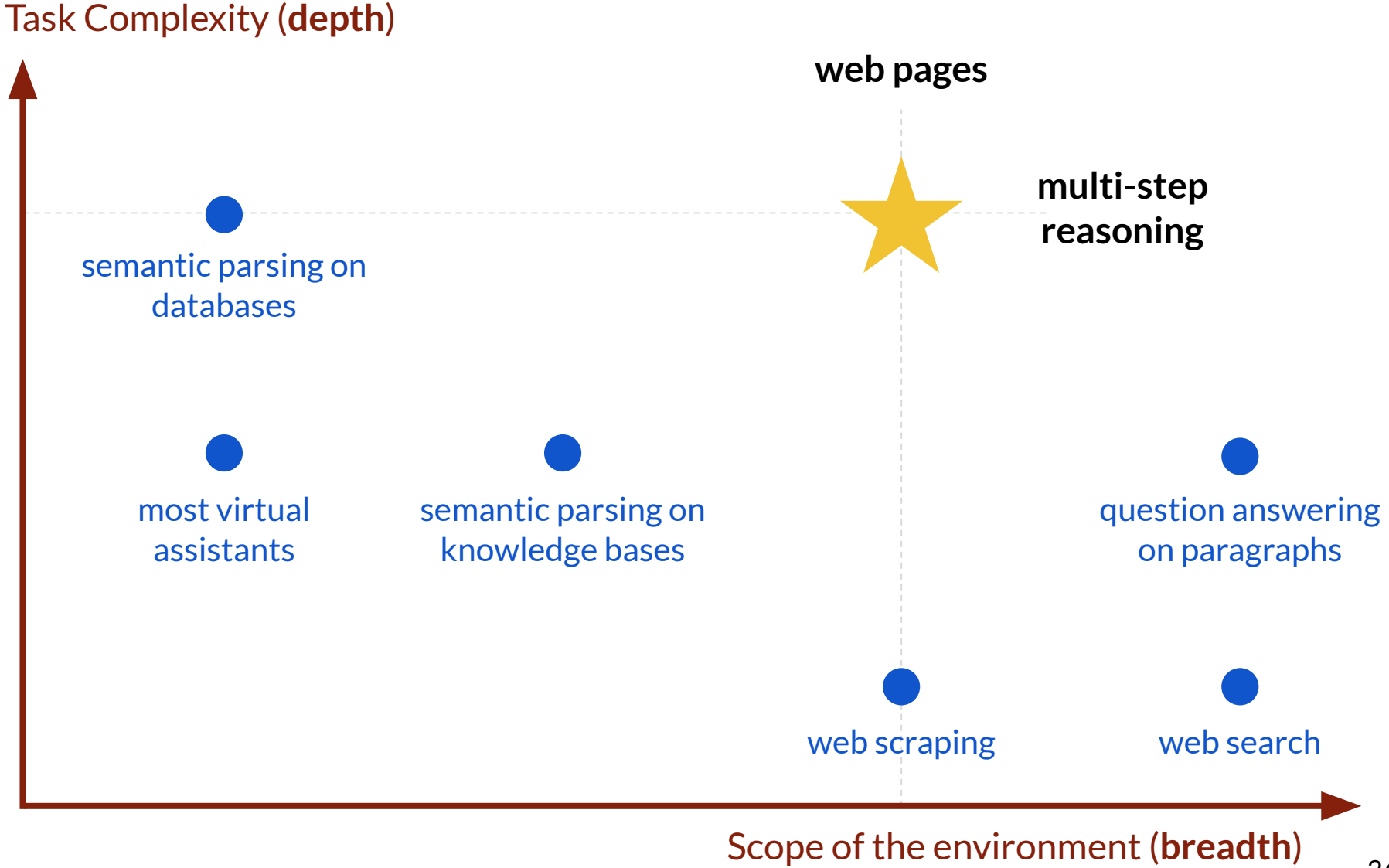


Scope of the environment (**breadth**)

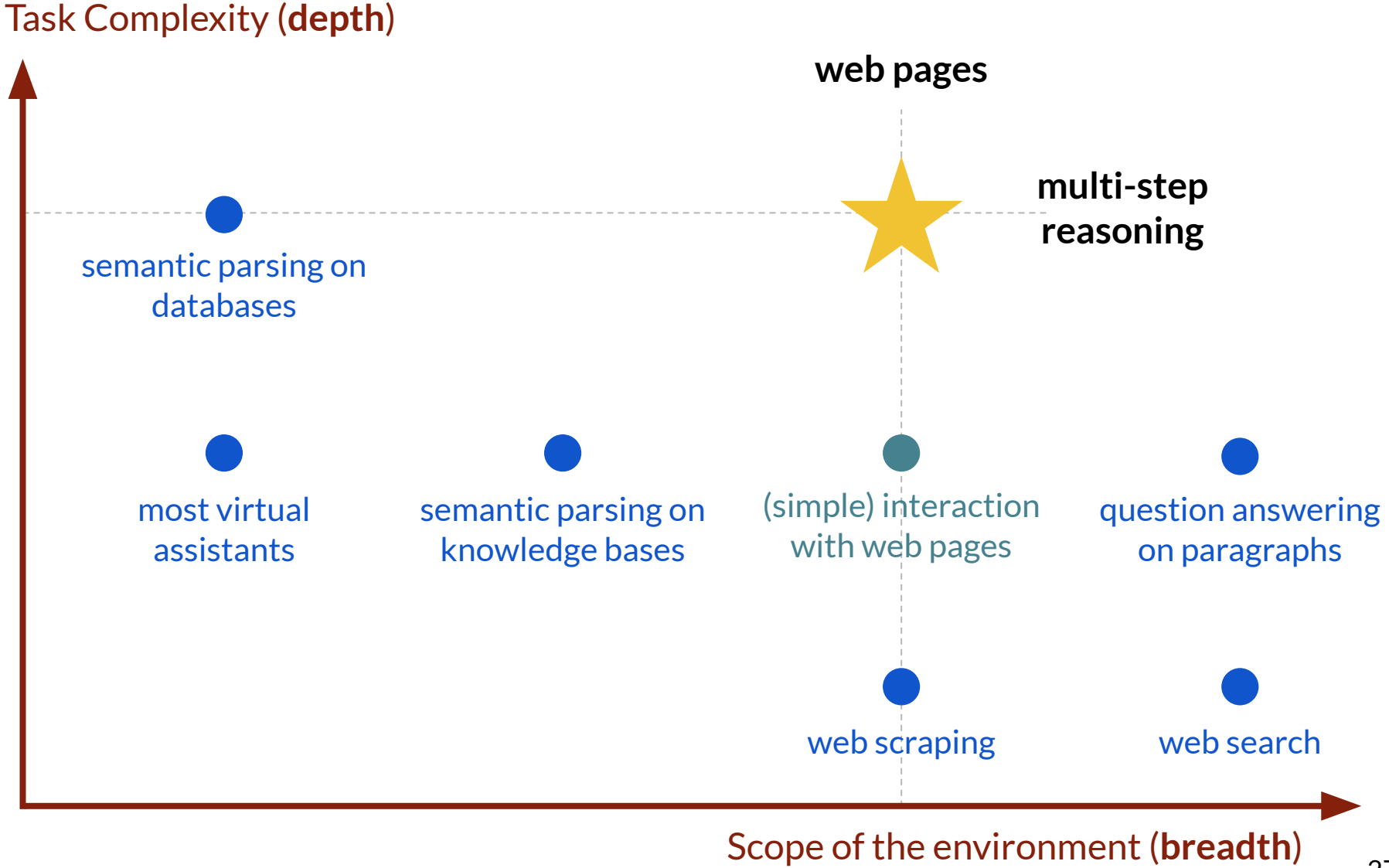
Motivation



Motivation



Motivation



Interacting with Web Pages

interact with HTML elements
based on the queries

follow on facebook

appleinsider



MacBook Pro: Chip upgrades,
better keyboard



Exclusive deals: Up to \$150 off
2019 iMacs



Follows us     Subscribe to get weekly updates, deals and more!

Tuesday, May 28, 2019

 2019 iPod touch: Everything you need to know

Apple has just updated the last remaining iPod, the iPod touch, for 2019 with an A10 Fusion processor and storage boost. Here is everything you need to know about Tuesday's release.



[P., Allan Jiang, Evan Liu, Kelvin Guu, Percy Liang, 2018]

Interacting with Web Pages

interact with HTML elements
based on the queries

follow on facebook

appleinsider



MacBook Pro: Chip upgrades,
better keyboard



Exclusive deals: Up to \$150 off
2019 iMacs



Follows u



Subscribe to get weekly updates, deals and more!

Tuesday, May 28, 2019

Video 2019 iPod touch: Everything you need to know

Apple has just updated the last remaining iPod, the iPod touch, for 2019 with an A10 Fusion processor and storage boost. Here is everything you need to know about Tuesday's release.



[P., Allan Jiang, Evan Liu, Kelvin Guu, Percy Liang, 2018]

Interacting with Web Pages

interact with HTML elements
based on the queries

follow on facebook

appleinsider

Home | Reviews | Deals | Price Guides | Follow Us | Tip Us | Forums | Podcast

MacBook Pro: Chip upgrades,
better keyboard



Exclusive deals: Up to \$150 off
2019 iMacs



Follows u



Subscribe to get weekly updates, deals and more!

Tuesday, May 28, 2019

Video 2019 iPod touch: Everything you need to know

Apple has just updated the last remaining iPod, the iPod touch, for 2019 with an A10 Fusion processor and storage boost. Here is everything you need to know about Tuesday's release.



[P., Allan Jiang, Evan Liu, Kelvin Guu, Percy Liang, 2018]

extracting a list of entities
from the web page

hiking trails in baltimore

EveryTrail

HOME | EXPLORE | MOBILE APPS | CREATE TRIP | MY EVERYTRAIL

Hiking near Baltimore, Maryland

Guides



Avalon Super Loop - Patapsco State Park

Patapsco State Park, Maryland, United States (7.5 miles away)

Difficult: 12.7 miles, Full day

lots of ruins, waterfalls, trains, and river views

Do the entire Avalon Patapsco state park in 1 day! This loop covers the majority of the Avalon area, with multiple ruins, waterfalls and other artifacts to find along the way. Starting at the parking lot, you hike up the road a ways to the Ridge trail sign. The next leg is the maintenance loop which has an old tractor to look at and some...



Patapsco Valley State Park - Hilton Area 8 Miles/Moderate

Catonsville, Maryland, United States (7.7 miles away)

Moderate: 7.8 miles, Half day

8 mile circuit hike including sections in the Avalon, Orange Grove and Glen Artney areas of PVSP.

[P. and Liang, 2014]

Interacting with Web Pages

interact with HTML elements
based on the queries

follow on facebook

appleinsider

Home | Reviews | Deals | Price Guides | Follow Us | Tip Us | Forums | Podcast

MacBook Pro: Chip upgrades,
better keyboard



Exclusive deals: Up to \$150 off
2019 iMacs



Follows u



Subscribe to get weekly updates, deals and more!

Tuesday, May 28, 2019

Video 2019 iPod touch: Everything you need to know

Apple has just updated the last remaining iPod, the iPod touch, for 2019 with an A10 Fusion processor and storage boost. Here is everything you need to know about Tuesday's release.



[P., Allan Jiang, Evan Liu, Kelvin Guu, Percy Liang, 2018]

extracting a list of entities
from the web page

hiking trails in baltimore

EveryTrail

HOME | EXPLORE | MOBILE APPS | CREATE TRIP | MY EVERYTRAIL

Hiking near Baltimore, Maryland

Guides



Avalon Super Loop - Patapsco State Park

Difficult: 12.7 miles, Full day
lots of ruins, waterfalls, trains, and river views

Do the entire Avalon Patapsco state park in 1 day! This loop covers the majority of the Avalon area, with multiple ruins, waterfalls and other artifacts to find along the way. Starting at the parking lot, you hike up the road a ways to the Ridge trail sign. The next leg is the maintenance loop which has an old old tractor to look at and some...



Patapsco Valley State Park - Hilton Area 8 Miles/Moderate

Moderate: 7.8 miles, Half day
8 mile circuit hike including sections in the Avalon, Orange Grove and Glen Artney areas of PVSP.

[P. and Liang, 2014]

Interacting with Web Pages

Structures such as tables have potential for **complex reasoning!**

Interacting with Web Pages

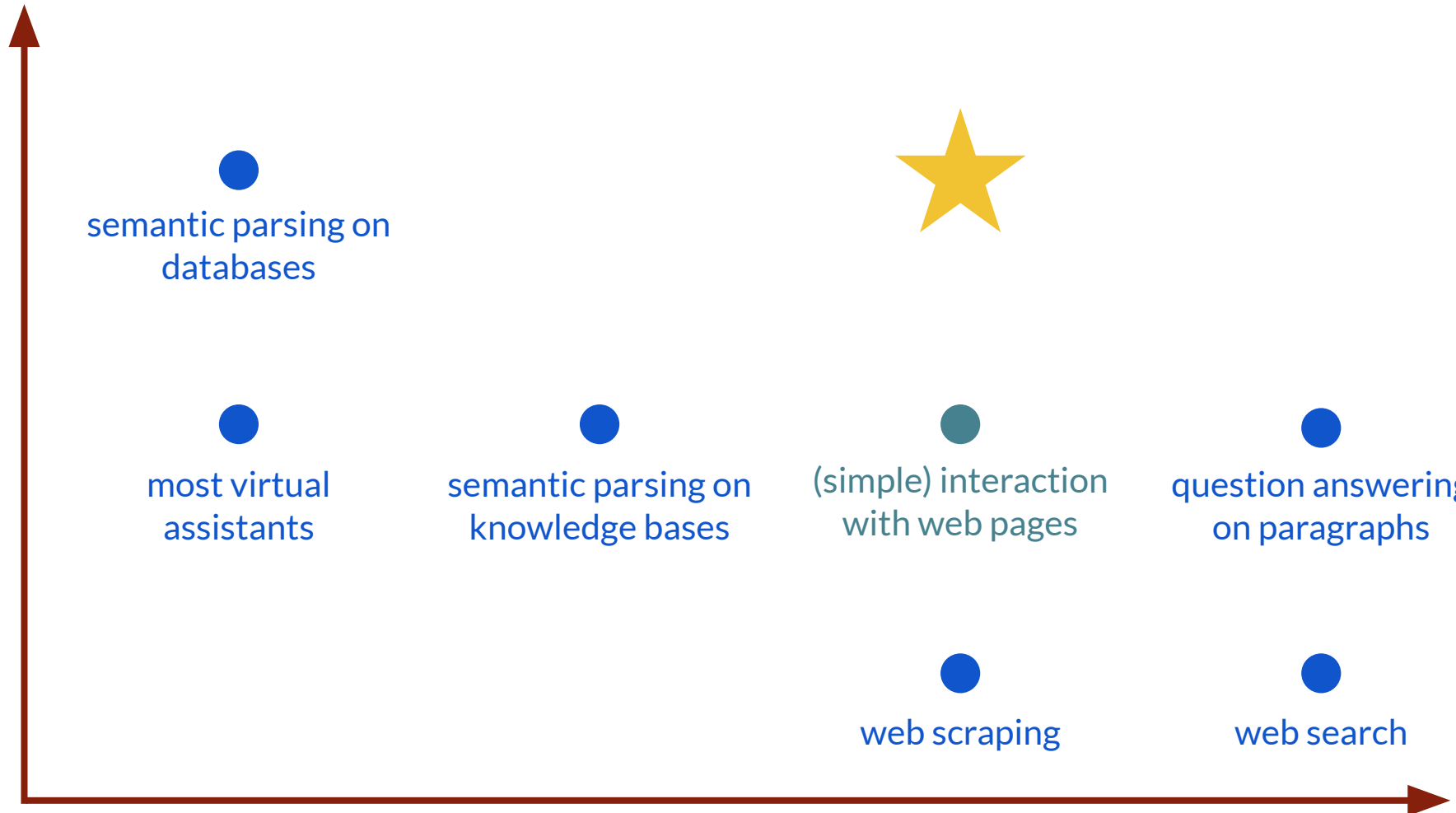
Structures such as tables have potential for **complex reasoning!**

list of hedge funds in new york

Rank ↕	Firm	Headquarters ↕
1	Bridgewater Associates	 Westport, CT
2	Man Group	 London
3	J.P. Morgan Asset Management	 New York
4	Brevan Howard Asset Management	 London
5	Och-Ziff Capital Management Group	 New York
6	Paulson & Co.	 New York
7	BlackRock Advisors	 New York

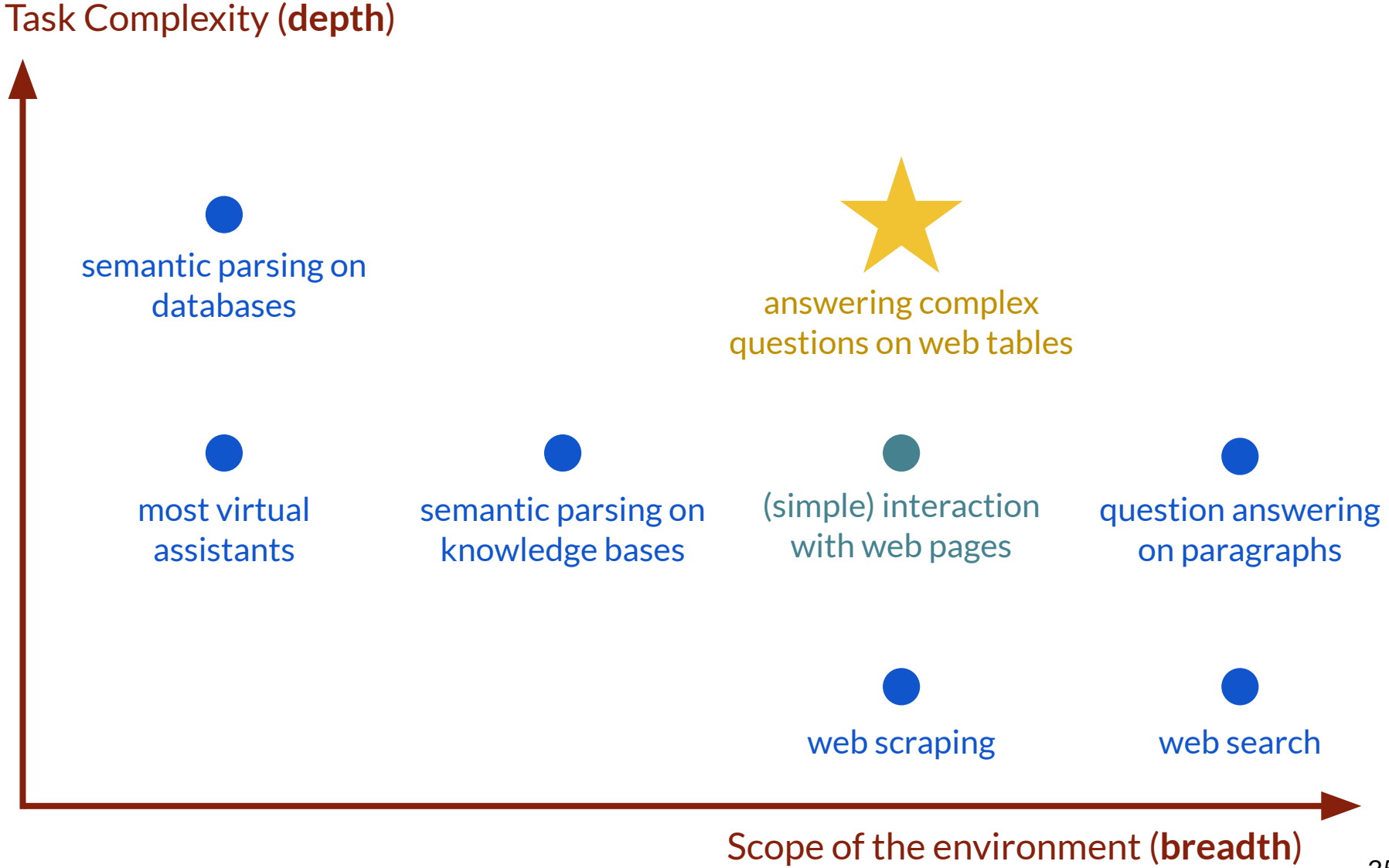
Motivation

Task Complexity (**depth**)



Scope of the environment (**breadth**)

Motivation



Outline

- ▶ Motivation
- ▶ **Task: Answering complex questions on web tables**
- ▶ Approach: Semantic parsing with distant supervision
- ▶ Improvement 1: Make it faster
- ▶ Improvement 2: Convert to direct supervision

Piotr Kędzia

Competition record

Year ↕	Competition ↕	Venue ↕	Position ↕	Event ↕	Notes ↕
Representing  Poland					
2001	World Youth Championships	Debrecen, Hungary	2nd	400 m	47.12
			1st	Medley relay	1:50.46
	European Junior Championships	Grosseto, Italy	1st	4x400 m relay	3:06.12
2003	European Junior Championships	Tampere, Finland	3rd	400 m	46.69
			2nd	4x400 m relay	3:08.62
2005	European U23 Championships	Erfurt, Germany	11th (sf)	400 m	46.62
			1st	4x400 m relay	3:04.41
	Universiade	Izmir, Turkey	7th	400 m	46.89
			1st	4x400 m relay	3:02.57
2006	World Indoor Championships	Moscow, Russia	2nd (h)	4x400 m relay	3:06.10
	European Championships	Gothenburg, Sweden	3rd	4x400 m relay	3:01.73
2007	European Indoor Championships	Birmingham, United Kingdom	3rd	4x400 m relay	3:08.14
	Universiade	Bangkok, Thailand	7th	400 m	46.85
			1st	4x400 m relay	3:02.05
2008	World Indoor Championships	Valencia, Spain	4th	4x400 m relay	3:08.76
	Olympic Games	Beijing, China	7th	4x400 m relay	3:00.32
2009	Universiade	Belgrade, Serbia	2nd	4x400 m relay	3:05.69

Piotr Kędzia

Competition record

Year ↕	Competition ↕	Venue ↕	Position ↕	Event ↕	Notes ↕
Representing  Poland					
2001	World Youth Championships	Debrecen, Hungary	2nd	400 m	47.12
			1st	Medley relay	1:50.46
	European Junior Championships	Grosseto, Italy	1st	4x400 m relay	3:06.12
2003	European Junior Championships	Tampere, Finland	3rd	400 m	46.69
			2nd	4x400 m relay	3:08.62
2005	European U23 Championships	Erfurt, Germany	11th (sf)	400 m	46.62
			1st	4x400 m relay	3:04.41
	Universiade	Izmir, Turkey	7th	400 m	46.89
			1st	4x400 m relay	3:02.57
2006	World Indoor Championships	Moscow, Russia	2nd (h)	4x400 m relay	3:06.10
	European Championships	Gothenburg, Sweden	3rd	4x400 m relay	3:01.73
2007	European Indoor Championships	Birmingham, United Kingdom	3rd	4x400 m relay	3:08.14
	Universiade	Bangkok, Thailand	7th	400 m	46.85
			1st	4x400 m relay	3:02.05
2008	World Indoor Championships	Valencia, Spain	4th	4x400 m relay	3:08.76
	Olympic Games	Beijing, China	7th	4x400 m relay	3:00.32
2009	Universiade	Belgrade, Serbia	2nd	4x400 m relay	3:05.69

In what city did Piotr's last 1st place finish occur?

WikiTableQuestions Dataset

A new dataset of Wikipedia tables, complex questions, and answers

- ▶ 22K examples
- ▶ 2K tables

WikiTableQuestions Dataset

Task Complexity (depth):

How long did it take this competitor to finish the 4x400 meter relay at Universiade in 2005?

Year ↕	Competition ↕	Venue ↕	Position ↕	Event ↕	Notes ↕
Representing  Poland					
2001	World Youth Championships	Debrecen, Hungary	2nd	400 m	47.12
			1st	Medley relay	1:50.46
	European Junior Championships	Grosseto, Italy	1st	4x400 m relay	3:06.12
2003	European Junior Championships	Tampere, Finland	3rd	400 m	46.69
			2nd	4x400 m relay	3:08.62
2005	European U23 Championships	Erfurt, Germany	11th (sf)	400 m	46.62
			1st	4x400 m relay	3:04.41
	Universiade	Izmir, Turkey	7th	400 m	46.89
			1st	4x400 m relay	3:02.57
2006	World Indoor Championships	Moscow, Russia	2nd (h)	4x400 m relay	3:06.10
	European Championships	Gothenburg, Sweden	3rd	4x400 m relay	3:01.73
2007	European Indoor Championships	Birmingham, United Kingdom	3rd	4x400 m relay	3:08.14
	Universiade	Bangkok, Thailand	7th	400 m	46.85
			1st	4x400 m relay	3:02.05
2008	World Indoor Championships	Valencia, Spain	4th	4x400 m relay	3:08.76
	Olympic Games	Beijing, China	7th	4x400 m relay	3:00.32
2009	Universiade	Belgrade, Serbia	2nd	4x400 m relay	3:05.69

WikiTableQuestions Dataset

Task Complexity (depth):

Year ↕	Competition ↕	Venue ↕	Position ↕	Event ↕	Notes ↕
Representing  Poland					
2001	World Youth Championships	Debrecen, Hungary	2nd	400 m	47.12
			1st	Medley relay	1:50.46
	European Junior Championships	Grosseto, Italy	1st	4x400 m relay	3:06.12
2003	European Junior Championships	Tampere, Finland	3rd	400 m	46.69
			2nd	4x400 m relay	3:08.62
2005	European U23 Championships	Erfurt, Germany	11th (sf)	400 m	46.62
			1st	4x400 m relay	3:04.41
	Universiade	Izmir, Turkey	7th	400 m	46.89
			1st	4x400 m relay	3:02.57
2006	World Indoor Championships	Moscow, Russia	2nd (h)	4x400 m relay	3:06.10
	European Championships	Gothenburg, Sweden	3rd	4x400 m relay	3:01.73
2007	European Indoor Championships	Birmingham, United Kingdom	3rd	4x400 m relay	3:08.14
	Universiade	Bangkok, Thailand	7th	400 m	46.85
			1st	4x400 m relay	3:02.05
2008	World Indoor Championships	Valencia, Spain	4th	4x400 m relay	3:08.76
	Olympic Games	Beijing, China	7th	4x400 m relay	3:00.32
2009	Universiade	Belgrade, Serbia	2nd	4x400 m relay	3:05.69

How long did it take this competitor to finish the 4x400 meter relay at Universiade in 2005?

Where was the competition held immediately before the one in Turkey?

WikiTableQuestions Dataset

Task Complexity (depth):

Year ↕	Competition ↕	Venue ↕	Position ↕	Event ↕	Notes ↕
Representing  Poland					
2001	World Youth Championships	Debrecen, Hungary	2nd	400 m	47.12
			1st	Medley relay	1:50.46
	European Junior Championships	Grosseto, Italy	1st	4x400 m relay	3:06.12
2003	European Junior Championships	Tampere, Finland	3rd	400 m	46.69
			2nd	4x400 m relay	3:08.62
2005	European U23 Championships	Erfurt, Germany	11th (sf)	400 m	46.62
			1st	4x400 m relay	3:04.41
	Universiade	Izmir, Turkey	7th	400 m	46.89
			1st	4x400 m relay	3:02.57
2006	World Indoor Championships	Moscow, Russia	2nd (h)	4x400 m relay	3:06.10
	European Championships	Gothenburg, Sweden	3rd	4x400 m relay	3:01.73
2007	European Indoor Championships	Birmingham, United Kingdom	3rd	4x400 m relay	3:08.14
	Universiade	Bangkok, Thailand	7th	400 m	46.85
			1st	4x400 m relay	3:02.05
2008	World Indoor Championships	Valencia, Spain	4th	4x400 m relay	3:08.76
	Olympic Games	Beijing, China	7th	4x400 m relay	3:00.32
2009	Universiade	Belgrade, Serbia	2nd	4x400 m relay	3:05.69

How long did it take this competitor to finish the 4x400 meter relay at Universiade in 2005?

Where was the competition held immediately before the one in Turkey?

How many times has this competitor placed 5th or better in competition?

WikiTableQuestions Dataset







Scope of the environment (breadth):

- Diverse data types: 4K different column headers among 2K tables

Year	Division	League	Regular Season	Playoffs	Open Cup	Avg. Attendance
2001	2	USL A-League	4th, Western	Quarterfinals	<i>Did not qualify</i>	7,169
2002	2	USL A-League	2nd, Pacific	1st Round	<i>Did not qualify</i>	6,260
2003	2	USL A-League	3rd, Pacific	<i>Did not qualify</i>	<i>Did not qualify</i>	5,871
2004	2	USL A-League	1st, Western	Quarterfinals	4th Round	5,628
2005	2	USL First Division	5th	Quarterfinals	4th Round	6,028
2006	2	USL First Division	11th	<i>Did not qualify</i>	3rd Round	5,575
2007	2	USL First Division	2nd	Semifinals	2nd Round	6,851
2008	2	USL First Division	11th	<i>Did not qualify</i>	1st Round	8,567
2009	2	USL First Division	1st	Semifinals	3rd Round	9,734
2010	2	USF D-2 Pro League	3rd, USL (3rd)	Quarterfinals	3rd Round	10,727

Year	Competition	Venue	Position	Event	Notes
Representing  Poland					
2001	World Youth Championships	Debrecen, Hungary	2nd	400 m	47.12
	European Junior Championships	Grosseto, Italy	1st	Medley relay	1:50.46
2002	World Junior Championships	Kingston, Jamaica	4th	4 × 400 m relay	3:06.25
	European Junior Championships	Tampere, Finland	3rd	400 m	46.69
2003	European U23 Championships	Erfurt, Germany	2nd	4 × 400 m relay	3:08.62
	Universiade	Izmir, Turkey	1st	400 m	46.62
2005	European U23 Championships	Erfurt, Germany	1st	4 × 400 m relay	3:04.41
	Universiade	Izmir, Turkey	7th	400 m	46.89
2006	World Indoor Championships	Moscow, Russia	2nd	4 × 400 m relay	3:02.57
	European Championships	Gothenburg, Sweden	3rd	4 × 400 m relay	3:06.10
2007	European Indoor Championships	Birmingham, United Kingdom	3rd	4 × 400 m relay	3:01.73
	Universiade	Bangkok, Thailand	7th	400 m	3:08.14
2008	World Indoor Championships	Valencia, Spain	1st	4 × 400 m relay	46.85
	Olympic Games	Beijing, China	4th	4 × 400 m relay	3:02.05
2009	Universiade	Belgrade, Serbia	6th	4 × 400 m relay	3:08.76
	Universiade	Belgrade, Serbia	2nd	4 × 400 m relay	3:00.32
2009	Universiade	Belgrade, Serbia	2nd	4 × 400 m relay	3:05.69

	Team	County	Wins	Years won
1	Two Mile House	Kildare	1	2018
	Kilanerlin-Ballyfad	Wexford	1	2017
	St. Colmcille's	Meath	1	2016
	Ratoath	Meath	1	2015
	Seán O'Mahonys	Louth	1	2014
	Geraldines	Louth	1	2013
	Monasterevin	Kildare	1	2012
	Éire Óg Greystones	Wicklow	1	2011
	Ballymore Eustace	Kildare	1	2010
	Maynooth	Kildare	1	2009
	Ballyroan Abbey	Laois	1	2008
	Fingal Ravens	Dublin	1	2007
	Confey	Kildare	1	2006
	Crettyard	Laois	1	2005
	Wolfe Tones	Meath	1	2004
Dundalk Gaels	Louth	1	2003	

Rank	City	Passengers	Ranking	Airline
1	 United States, Los Angeles	15,383	—	Alaska Airlines
2	 Canada, Calgary	9,279	—	Westjet
3	 Canada, Toronto	2,241	▲3	Sunwing Airlines
4	 United States, Houston	1,730	▲1	United Express
5	 United States, Minneapolis	1,279	▲1	Sun Country Airlines
6	 United States, Phoenix-Sky Harbor	821	▲2	American Airlines

Date	Opponent	Venue	Result	Attendance	Scorers	Notes
15 August 1987	Derby County	Away	0-1	17,204	—	
18 August 1987	Coventry City	Home	0-1	9,380	—	
22 August 1987	West Ham United	Home	2-2	8,073	Harford (2)	
29 August 1987	Chelsea	Away	0-3	16,075	—	
31 August 1987	Arsenal	Home	1-1	8,745	Wilson (pen)	
5 September 1987	Oxford United	Away	5-2	6,804	Breacker, Harford, Hill, Nwajobi, B. Stein	
12 September 1987	Everton	Home	2-1	8,124	Hill, B. Stein	
19 September 1987	Charlton Athletic	Away	0-1	5,002	—	
26 September 1987	Queens Park Rangers	Away	0-2	11,175	—	
3 October 1987	Manchester United	Home	1-1	9,137	Harford	
10 October 1987	Portsmouth	Away	1-3	12,391	Harford (pen)	
17 October 1987	Wimbledon	Home	2-0	7,018	B. Stein, Wilson	
24 October 1987	Liverpool	Home	0-1	11,997	—	
7 November 1987	Newcastle United	Home	4-0	7,638	Nwajobi, B. Stein, M. Stein (2)	
14 November 1987	Sheffield Wednesday	Away	2-0	16,960	Allinson, M. Stein	
21 November 1987	Tottenham Hotspur	Home	2-0	10,091	Allinson (2)	
5 December 1987	Norwich City	Home	1-2	7,002	B. Stein	
12 December 1987	Watford	Away	1-0	12,152	Foster	
18 December 1987	Southampton	Home	2-2	6,618	Harford, McDonough	
26 December 1987	Everton	Away	0-2	32,128	—	
28 December 1987	Charlton Athletic	Home	1-0	7,243	Wilson	
1 January 1988	Chelsea	Home	3-0	8,018	Harford, B. Stein, M. Stein	
2 January 1988	West Ham United	Away	1-1	16,716	M. Stein	
16 January 1988	Derby County	Home	1-0	7,175	McDonough	
6 February 1988	Oxford United	Home	7-4	8,063	Harford (2), McDonough, B. Stein, M. Stein (3)	
13 February 1988	Arsenal	Away	1-2	22,612	M. Stein	
5 March 1988	Wimbledon	Away	0-2	4,854	—	
15 March 1988	Coventry City	Away	0-4	13,711	—	
29 March 1988	Portsmouth	Home	4-1	6,740	B. Stein, M. Stein, Wilson, own goal	

WikiTableQuestions Dataset

Scope of the environment (breadth):

- ▶ Diverse data types: 4K different column headers among 2K tables
- ▶ Only ~20% can be answered by Freebase (a large knowledge base)

WikiTableQuestions Dataset

Scope of the environment (breadth):

- ▶ Diverse data types: 4K different column headers among 2K tables
- ▶ Only ~20% can be answered by Freebase (a large knowledge base)

We ensure that tables in the test set do not appear in the training data

- ▶ This tests the model's ability to generalize to unseen data schema

Outline

- ▶ Motivation
- ▶ Task: Answering complex questions on web tables
- ▶ **Approach: Semantic parsing with distant supervision**
- ▶ Improvement 1: Make it faster
- ▶ Improvement 2: Convert to direct supervision

Semantic Parsing

Idea: Parse the utterance into an executable **logical form**

Where did the last 1st place finish occur?

VenueOf.argmax(HasPosition.1st, Index)

Year	Venue	Position	Time
2003	Finland	1st	47.12
2005	Germany	5th	46.62
2007	Thailand	1st	53.13

Semantic Parsing

Idea: Parse the utterance into an executable **logical form**

Where did the last 1st place finish occur?

VenueOf.argmax(HasPosition.1st, Index)

Year	Venue	Position	Time
2003	Finland	1st	47.12
2005	Germany	5th	46.62
2007	Thailand	1st	53.13

Semantic Parsing

Idea: Parse the utterance into an executable **logical form**

Where did the last 1st place finish occur?

VenueOf.argmax(HasPosition.1st, Index)

Year	Venue	Position	Time
2003	Finland	1st	47.12
2005	Germany	5th	46.62
2007	Thailand	1st	53.13

Semantic Parsing

Idea: Parse the utterance into an executable **logical form**

Where did the last 1st place finish occur?

VenueOf.argmax(HasPosition.1st, Index)

Year	Venue	Position	Time
2003	Finland	1st	47.12
2005	Germany	5th	46.62
2007	Thailand	1st	53.13

Semantic Parsing

Idea: Parse the utterance into an executable **logical form**

Where did the last 1st place finish occur?

VenueOf.argmax(HasPosition.1st, Index)

Year	Venue	Position	Time
2003	Finland	1st	47.12
2005	Germany	5th	46.62
2007	Thailand	1st	53.13

Semantic Parsing

Idea: Parse the utterance into an executable **logical form**

Where did the last 1st place finish occur?

VenueOf.argmax(HasPosition.1st, Index)

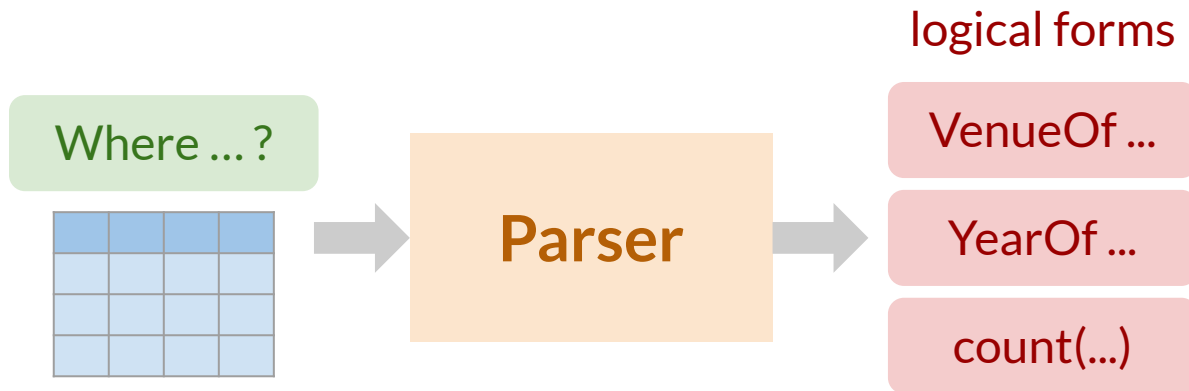
Year	Venue	Position	Time
2003	Finland	1st	47.12
2005	Germany	5th	46.62
2007	Thailand	1st	53.13

"denotation"

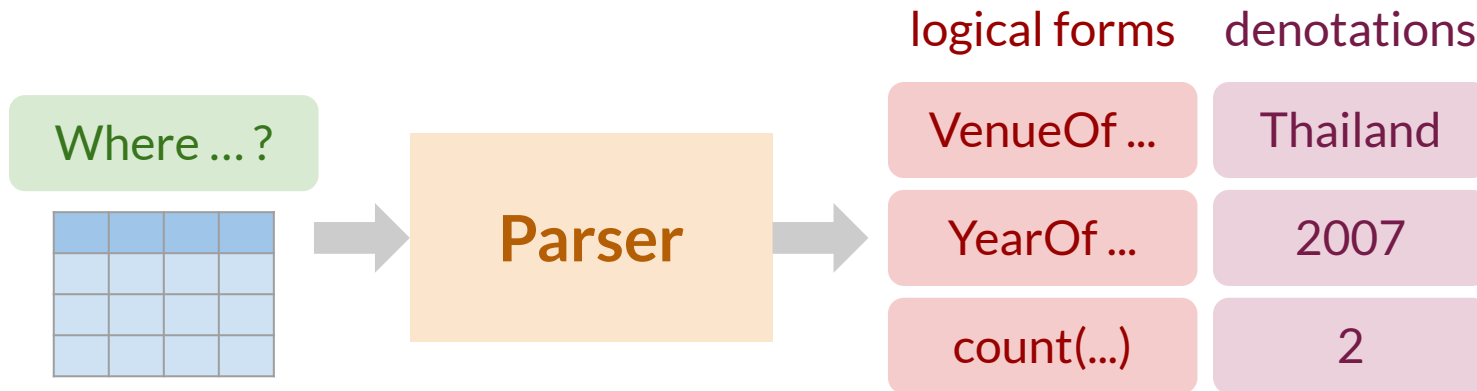
Prediction

Where ... ?

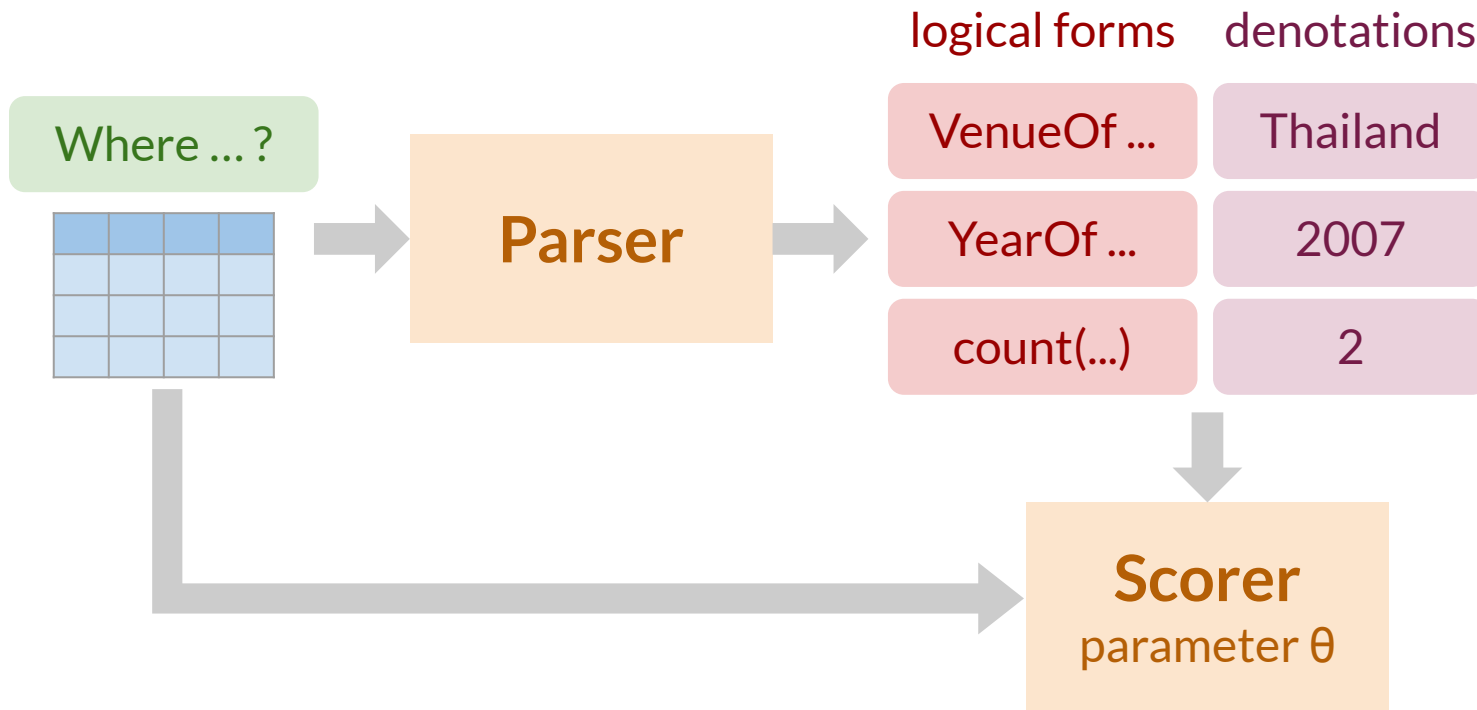
Prediction



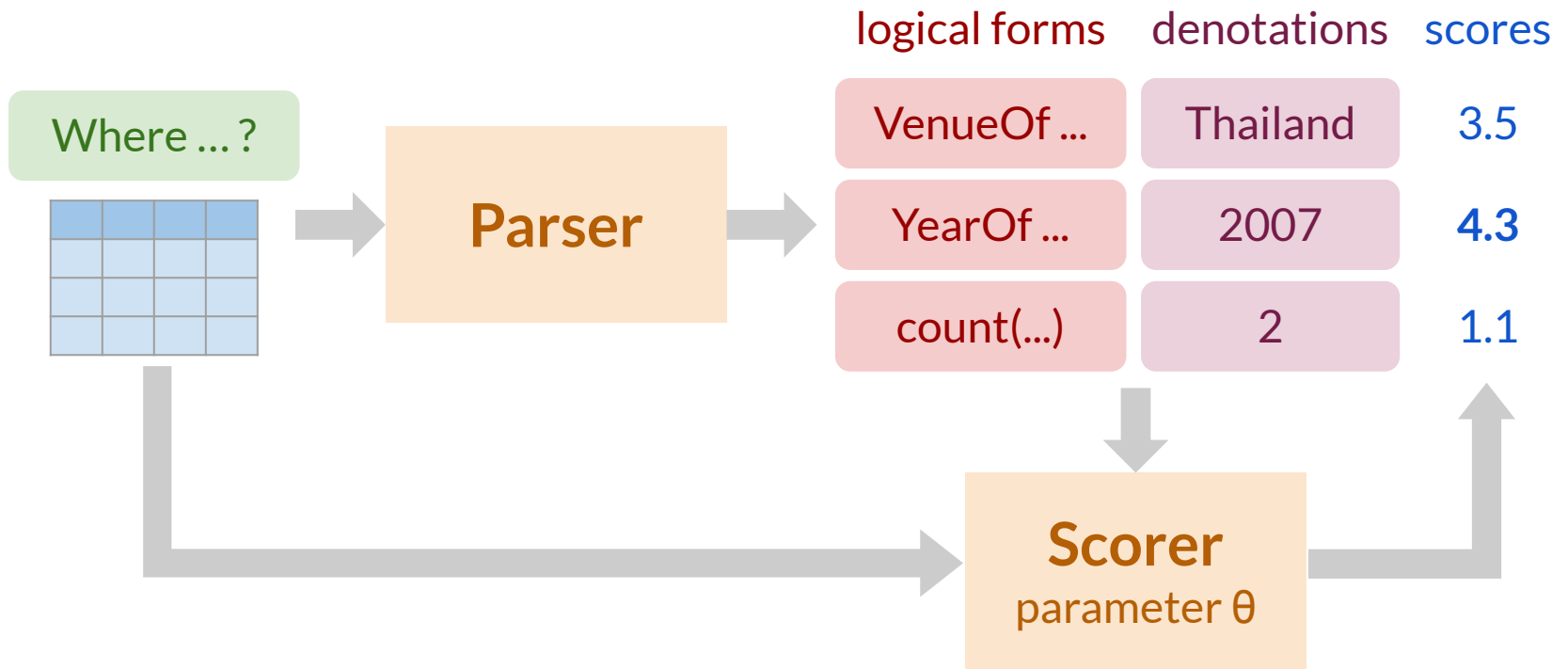
Prediction



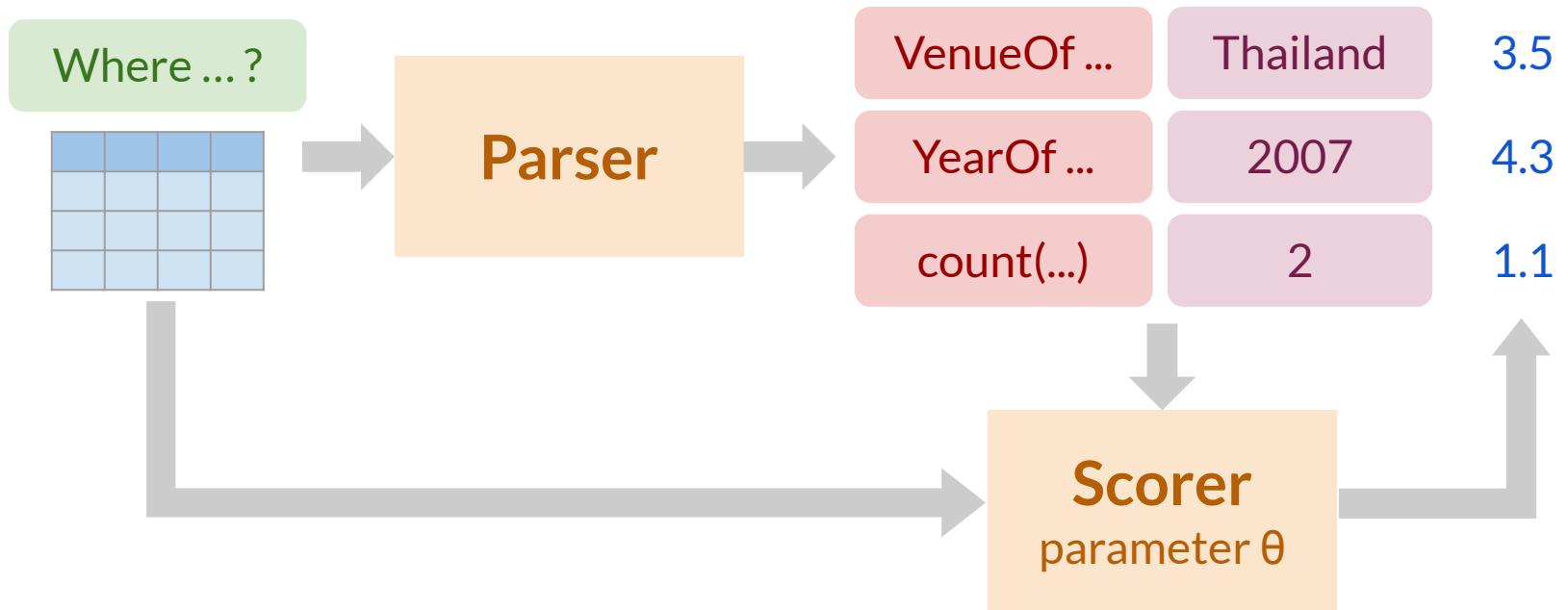
Prediction



Prediction



Learning from Denotations

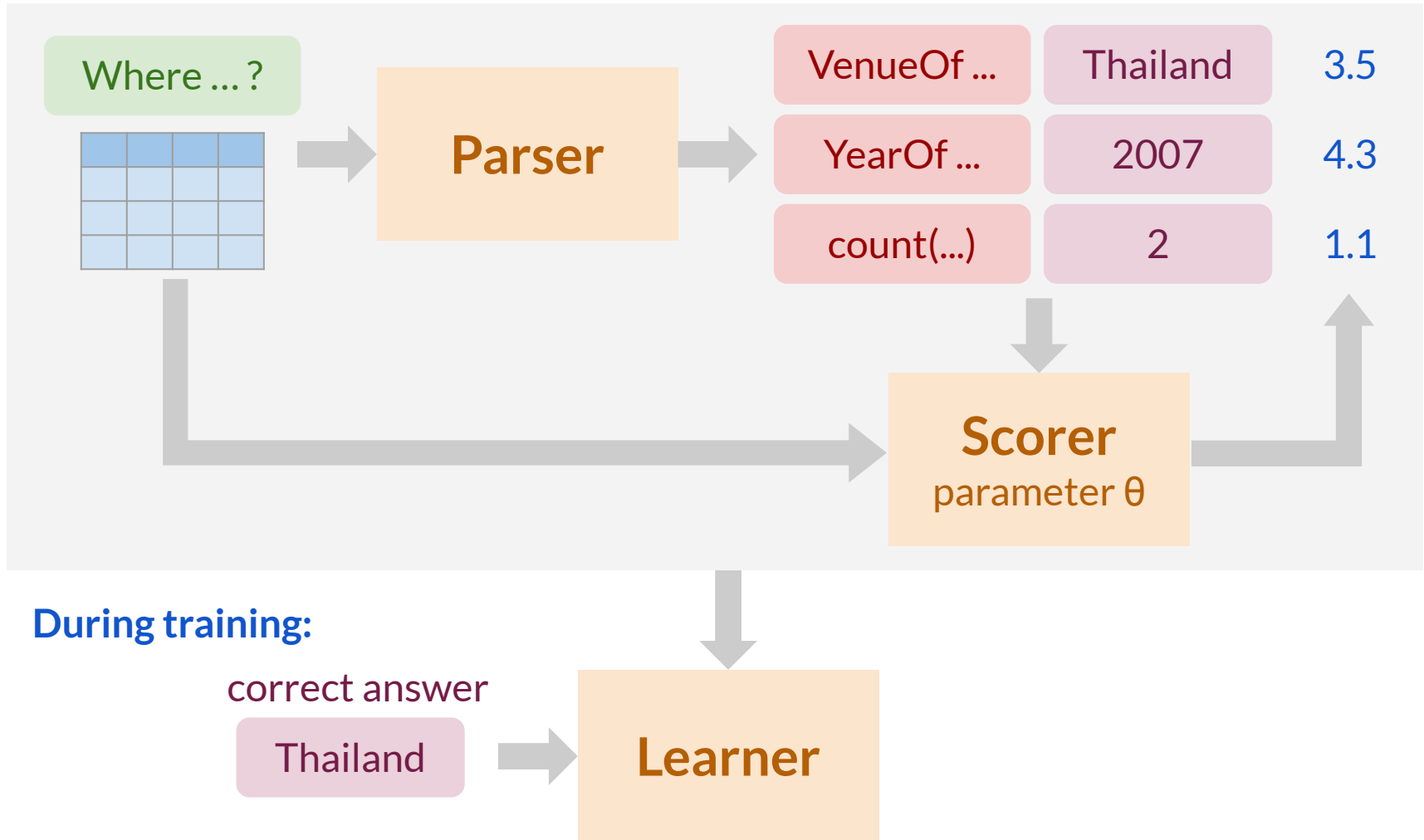


During training:

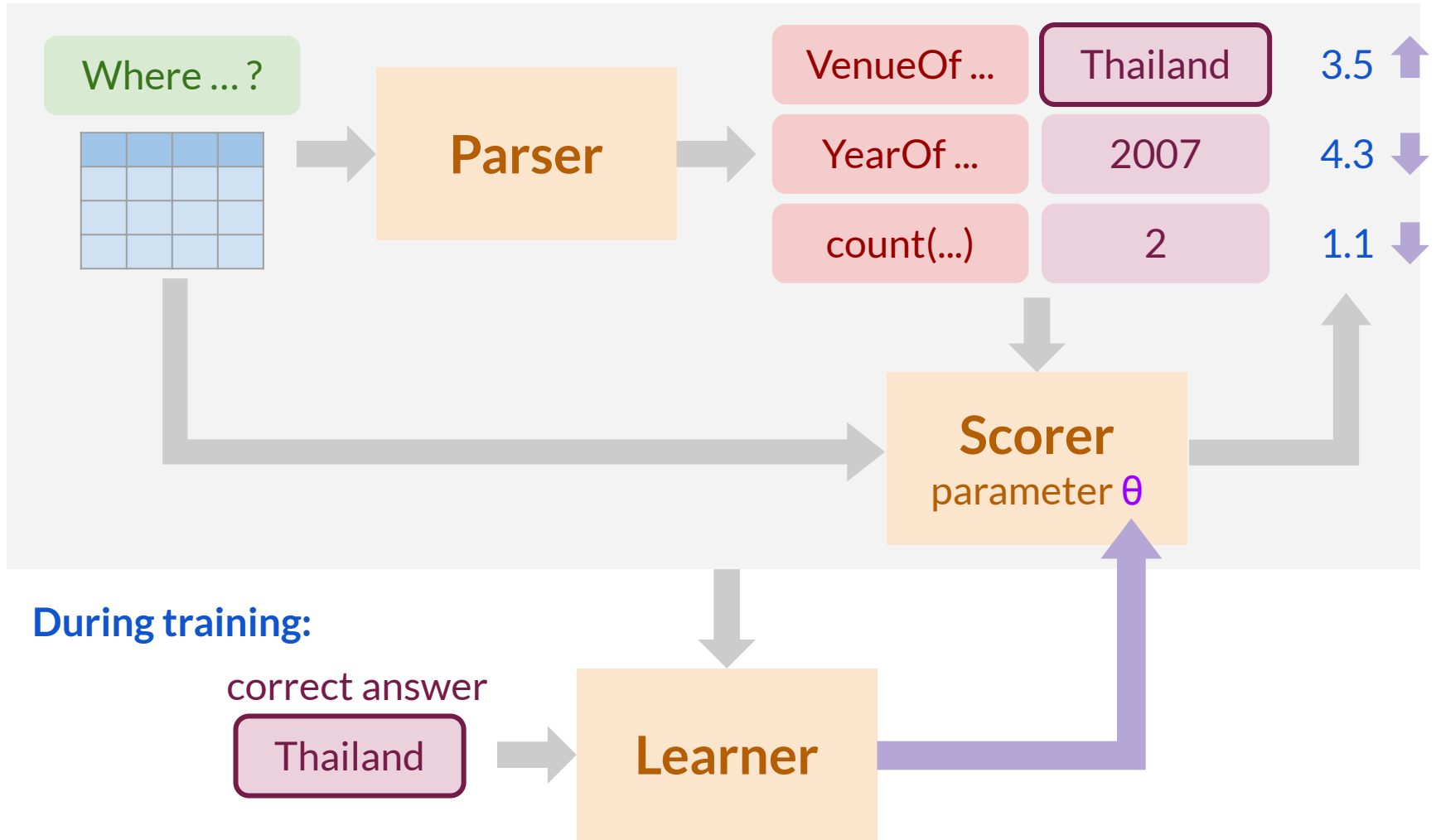
correct answer

Thailand

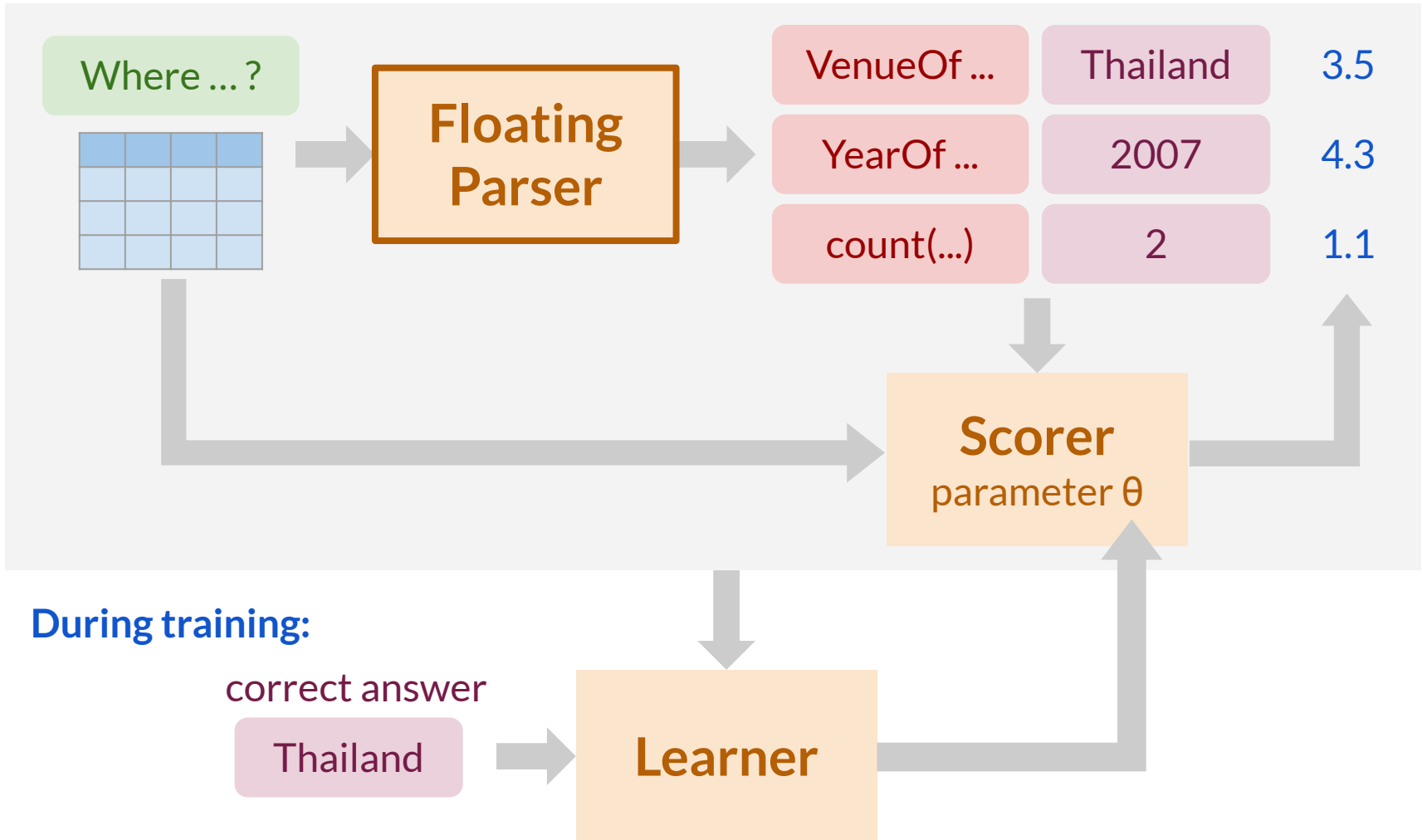
Learning from Denotations



Learning from Denotations



Parser



Parser

The parser **generates logical forms** from the utterance and table

VenueOf.argmax(HasPosition.1st, Index)

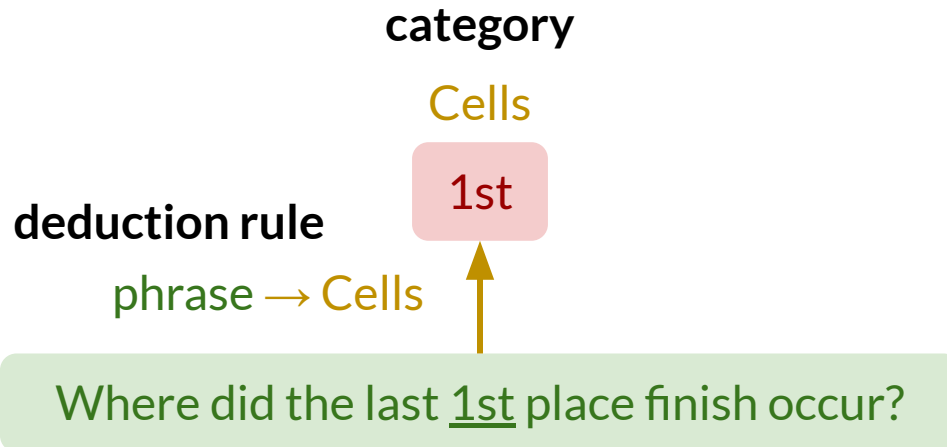
Year	Venue	Position	Time
2003	Finland	1st	47.12
2005	Germany	5th	46.62
2007	Thailand	1st	53.13

Where did the last 1st place finish occur?

Parser

The parser **generates logical forms** from the utterance and table

VenueOf.argmax(HasPosition.1st, Index)



Year	Venue	Position	Time
2003	Finland	1st	47.12
2005	Germany	5th	46.62
2007	Thailand	1st	53.13

Parser

The parser **generates logical forms** from the utterance and table

VenueOf.argmax(HasPosition.1st, Index)

Cells

1st

Col

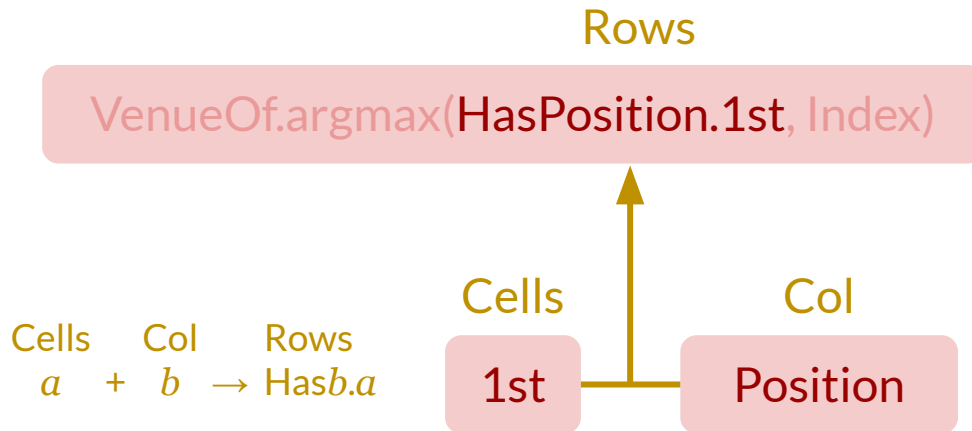
Position

Year	Venue	Position	Time
2003	Finland	1st	47.12
2005	Germany	5th	46.62
2007	Thailand	1st	53.13

Where did the last 1st place finish occur?

Parser

The parser **generates logical forms** from the utterance and table



Year	Venue	Position	Time
2003	Finland	1st	47.12
2005	Germany	5th	46.62
2007	Thailand	1st	53.13

Where did the last 1st place finish occur?

Parser

The parser **generates logical forms** from the utterance and table

VenueOf.argmax(HasPosition.1st, Index)

Venue

1st

Position

?????

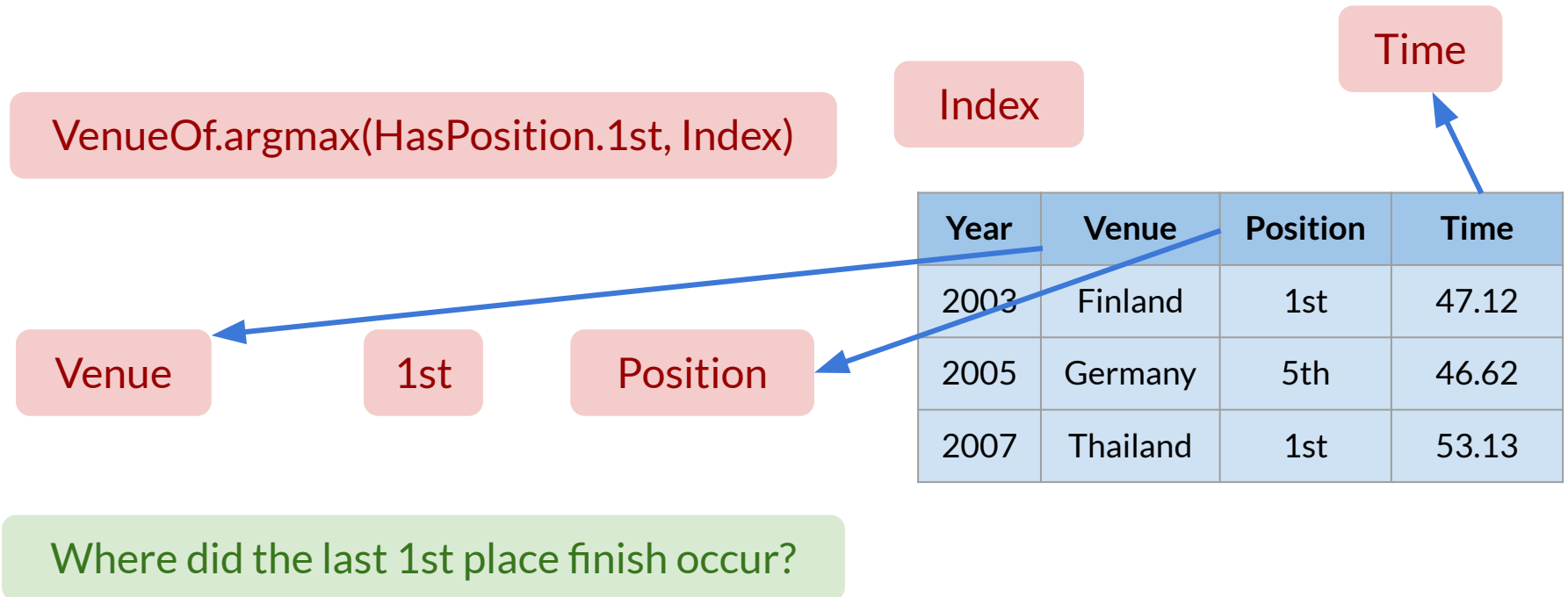
?????

Where did the last 1st place finish occur?

Year	Venue	Position	Time
2003	Finland	1st	47.12
2005	Germany	5th	46.62
2007	Thailand	1st	53.13

Floating Parser

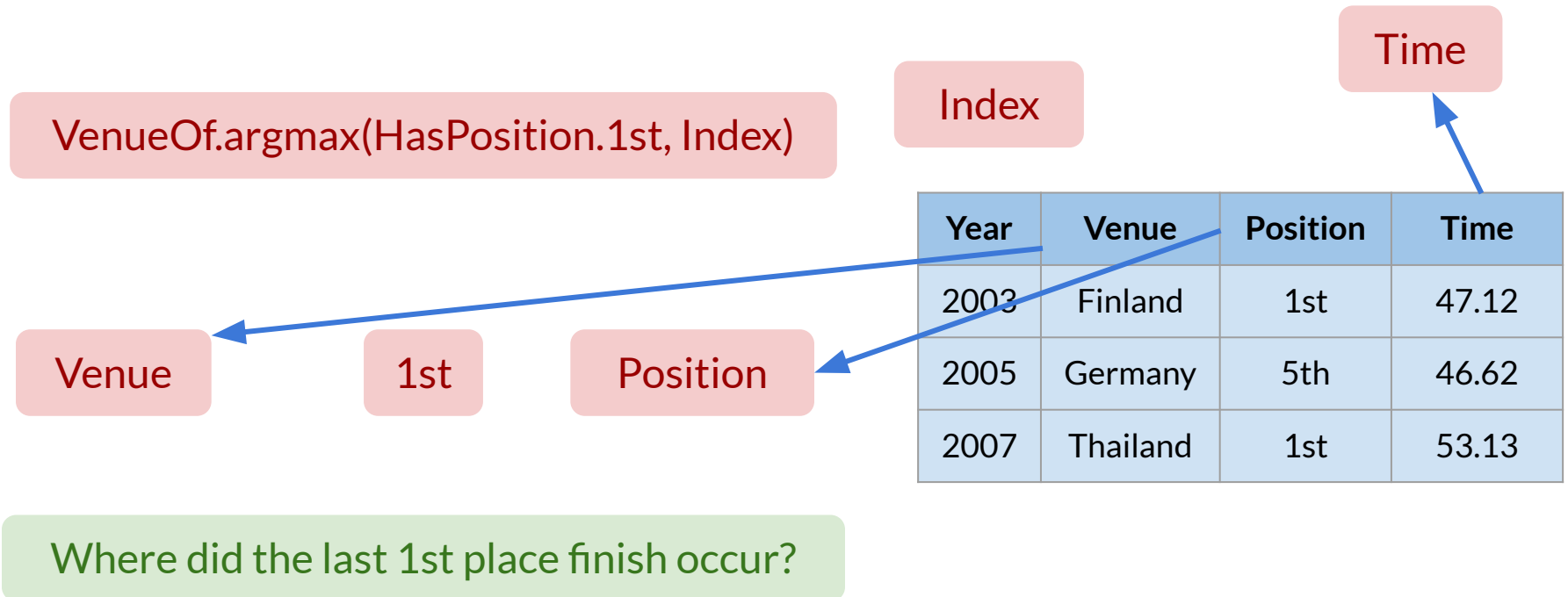
Allows LF parts to be **generated from other sources** than the utterance



Floating Parser

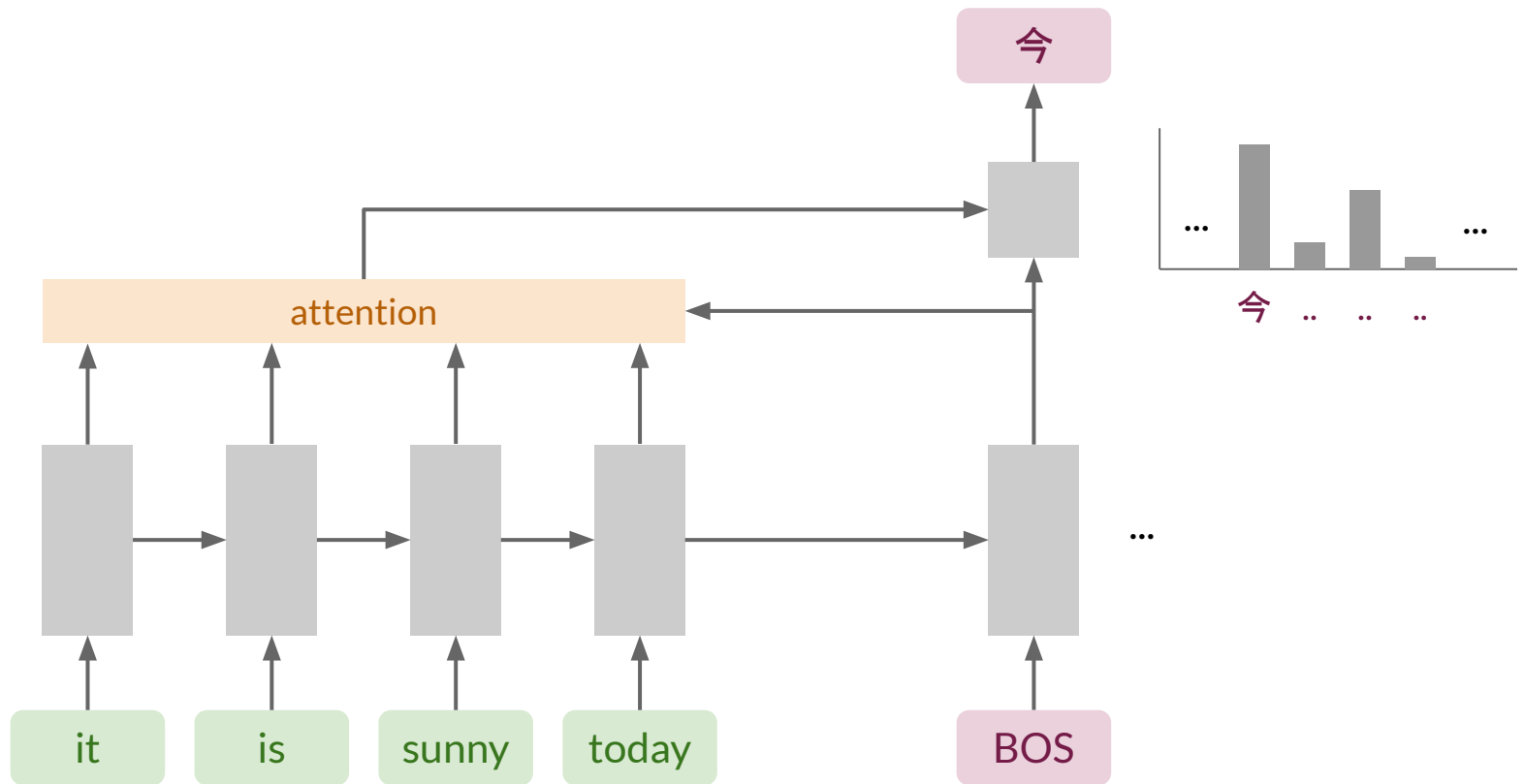
Allows LF parts to be **generated from other sources** than the utterance

The **scorer** is responsible for capturing the relationship between "Venue" and words in the utterance



Floating Parser

Most neural decoders today generate tokens in a floating fashion (with a soft guidance from attention)



Results

	Test Accuracy
Tiny rule set (cell lookup + counting)	24.3
Small rule set (sum, argmax, next/prev row, subtraction, etc.)	37.1
Large rule set (fuzzy string matching, advanced argmax, etc.)	42.7

Results

	Test Accuracy
Tiny rule set (cell lookup + counting)	24.3
Small rule set (sum, argmax, next/prev row, subtraction, etc.)	37.1
Large rule set (fuzzy string matching, advanced argmax, etc.)	42.7
Upper bound (Ice writes a logical form)	(84.0)

Results

	Test Accuracy	Runtime
Tiny rule set (cell lookup + counting)	24.3	
Small rule set (sum, argmax, next/prev row, subtraction, etc.)	37.1	~ 4 hours
Large rule set (fuzzy string matching, advanced argmax, etc.)	42.7	~ 11 hours
Upper bound (Ice writes a logical form)	(84.0)	

Slow runtime prevents us from increasing coverage!

Outline

- ▶ Motivation
- ▶ Task: Answering complex questions on web tables
- ▶ Approach: Semantic parsing with distant supervision
- ▶ **Improvement 1: Make it faster**
- ▶ Improvement 2: Convert to direct supervision

Using macros to make search faster

For each training example:

Who took office right after Uriah Forrest?

Using macros to make search faster

For each training example:

- ▶ Fetch previously processed examples with **similar utterances** (Levenshtein distance)

Who took office right after Uriah Forrest?

Who ranked right after Turkey?

NationOf.NextOf.HasNation.Turkey

Using macros to make search faster

For each training example:

- ▶ Fetch previously processed examples with **similar utterances** (Levenshtein distance)

Who took office right after Uriah Forrest?

macro

Column

Of.NextOf.Has

Column

Cell

.

Using macros to make search faster

For each training example:

- ▶ Fetch previously processed examples with **similar utterances**
- ▶ During search, try creating logical forms from **macros** found in those examples first

Who took office right after Uriah Forrest?

macro

Column Of.NextOf.Has Column . Cell

NameOf.NextOf.HasName.UriahForrest

BossOf.NextOf.HasBoss.UriahForrest

Using macros to make search faster

	Dev Accuracy	Time (ms/example)	
		Train	Predict
Large rule set	40.6	1117	1150
+ Macros	40.4	99	70

11× speedup!

16× speedup!

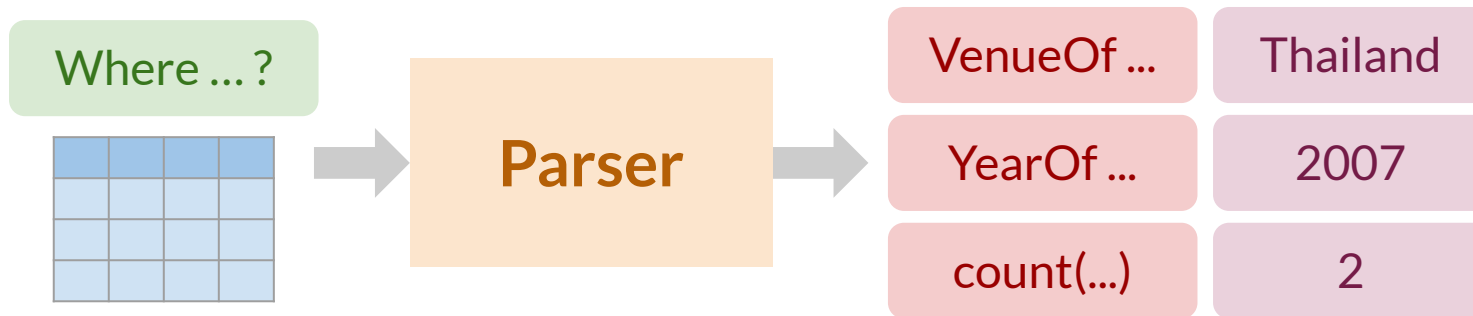
Using macros to make search faster

	Test Acc.	+Ensemble
Small rule set	37.1	-
Neural Programmer (Neelakantan et al., 2016)	34.2	37.7
Neural Multi-Step Reasoning (Haug et al., 2017)	34.8	38.7
Large rule set	42.7	-
+ Macros	43.7	-
Upper bound (Ice writes a logical form)	(84.0)	-

Outline

- ▶ Motivation
- ▶ Task: Answering complex questions on web tables
- ▶ Approach: Semantic parsing with distant supervision
- ▶ Improvement 1: Make it faster
- ▶ **Improvement 2: Convert to direct supervision**

Learning from Denotations

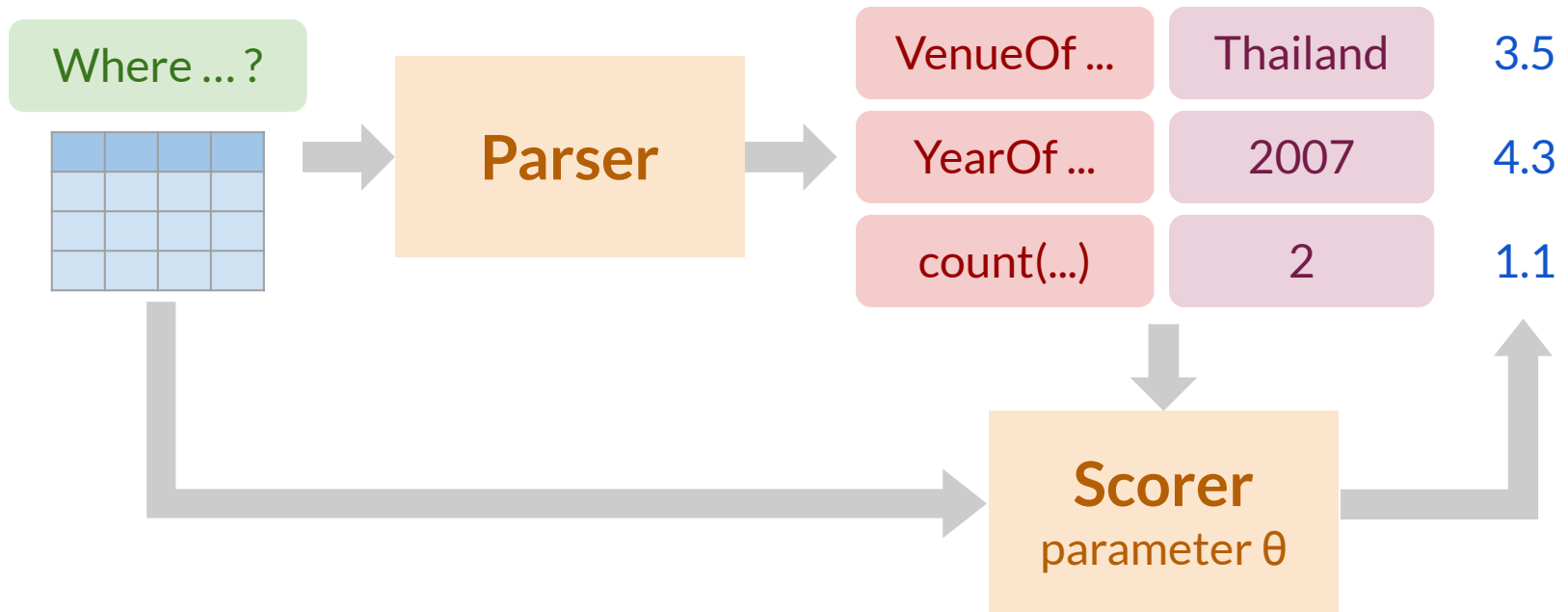


During training:

correct answer

Thailand

Learning from Denotations

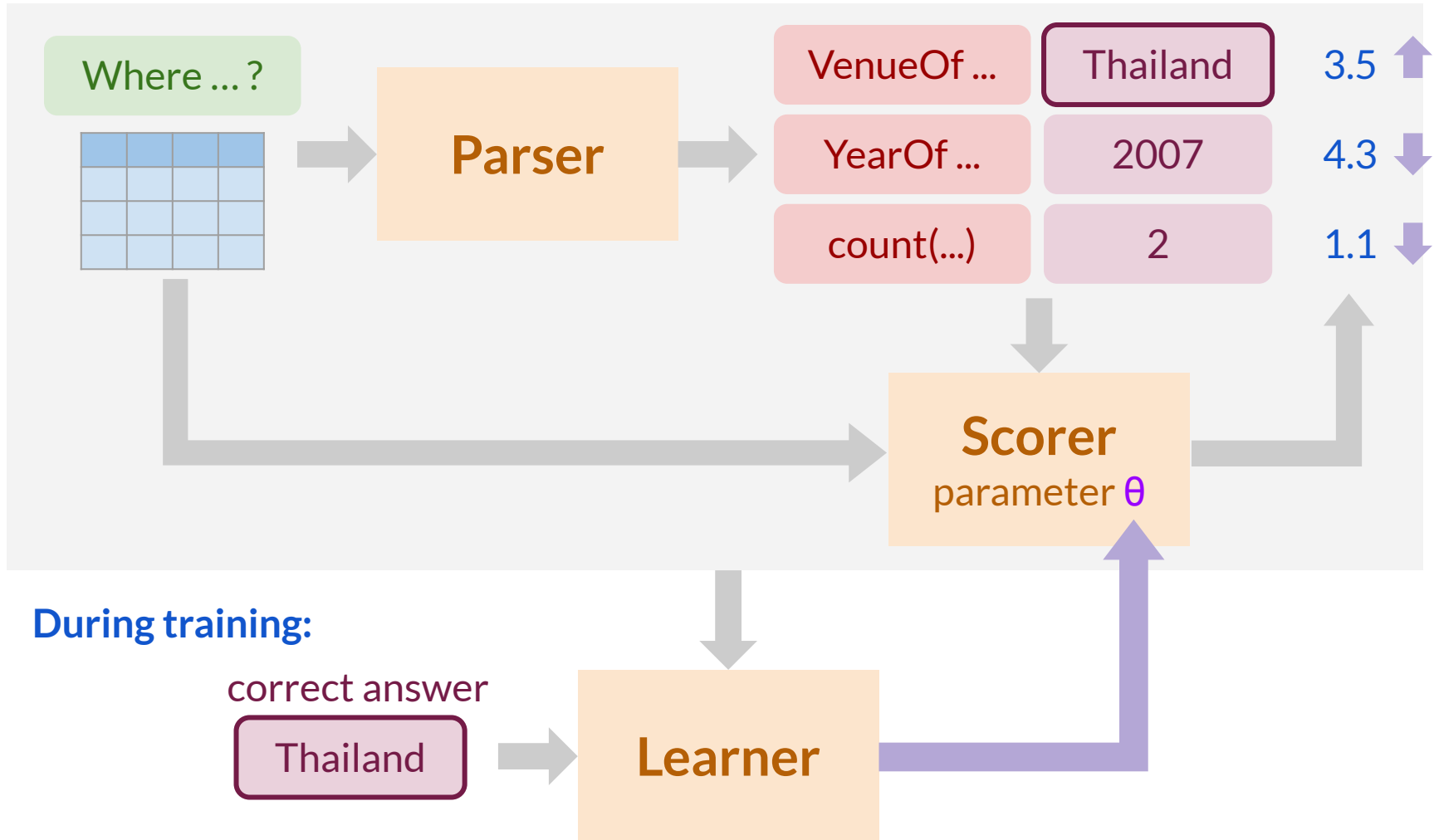


During training:

correct answer

Thailand

Learning from Denotations



Learning from Denotations

Pros:

- ▶ Collecting answers is easier than collecting LFs for each question
- ▶ The dataset is not tied to a specific LF formalism

Learning from Denotations

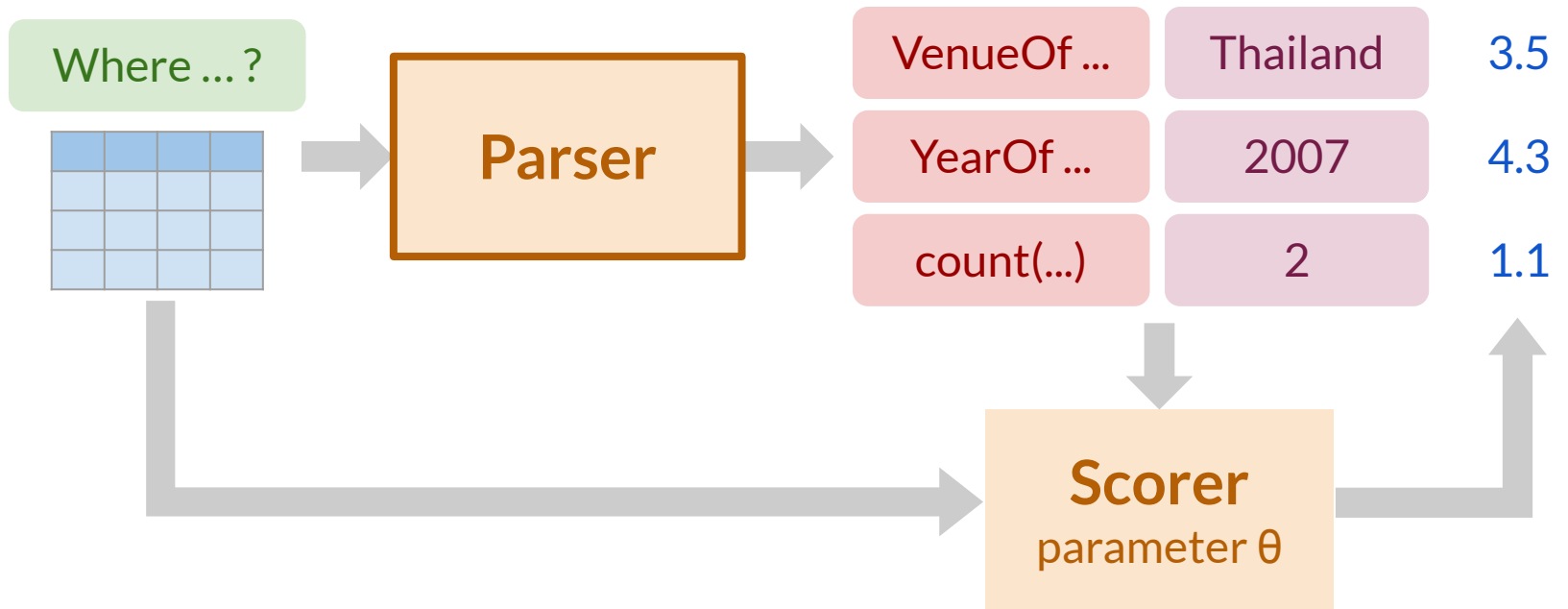
Pros:

- ▶ Collecting answers is easier than collecting LFs for each question
- ▶ The dataset is not tied to a specific LF formalism

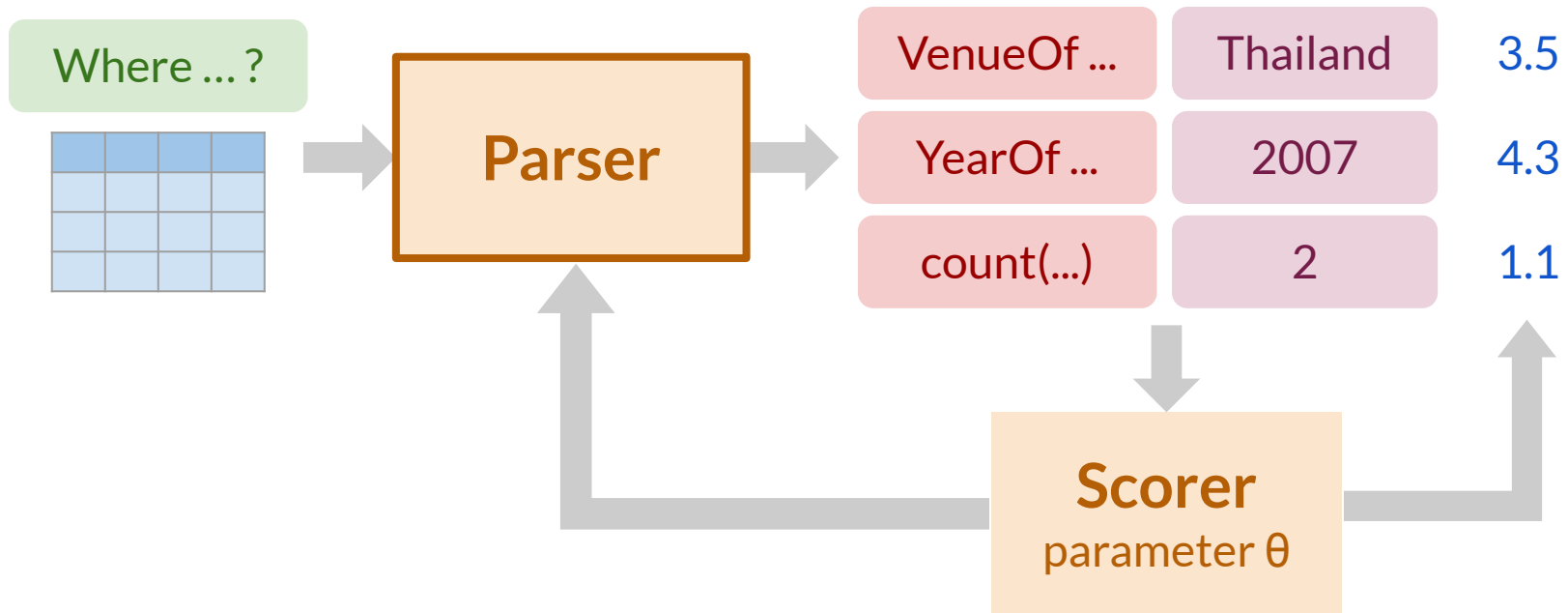
Cons:

- ▶ Need to do **search** (both at training and test time)
 - ▷ Slow (macros helped a bit)
 - ▷ **Two more problems during training: ...**

Search is Hard



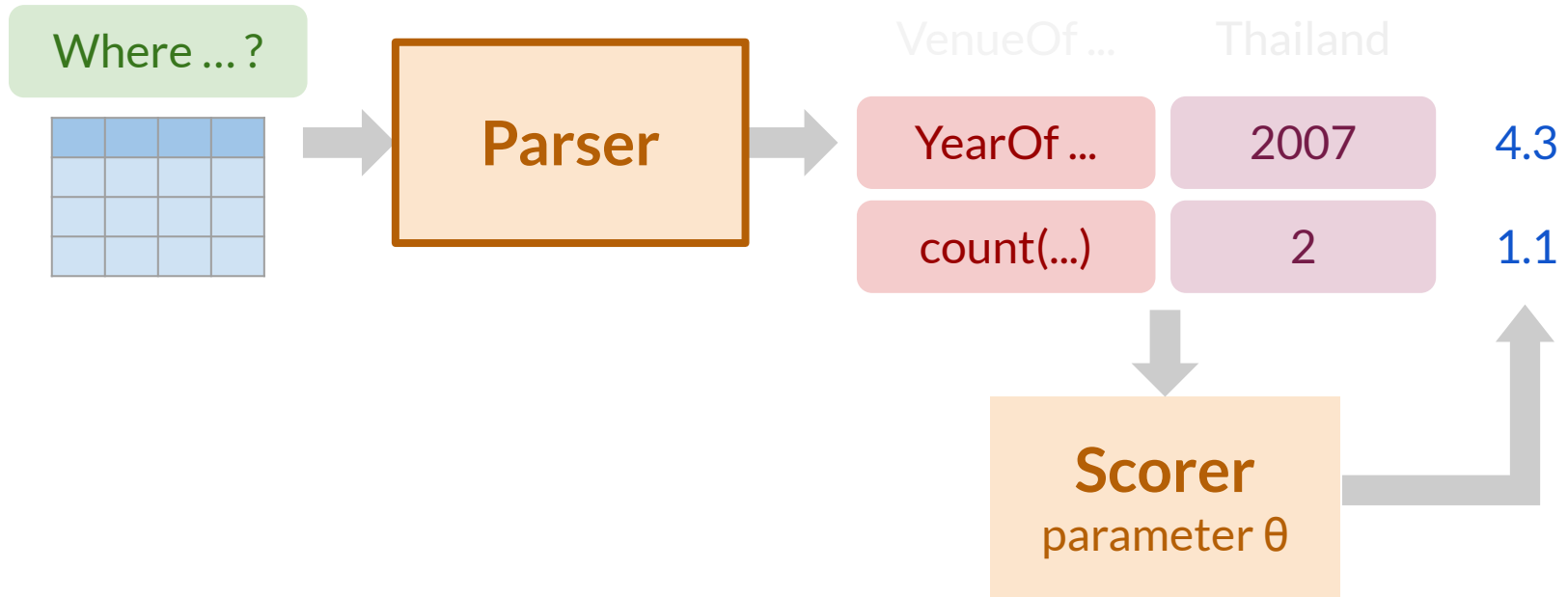
Search is Hard



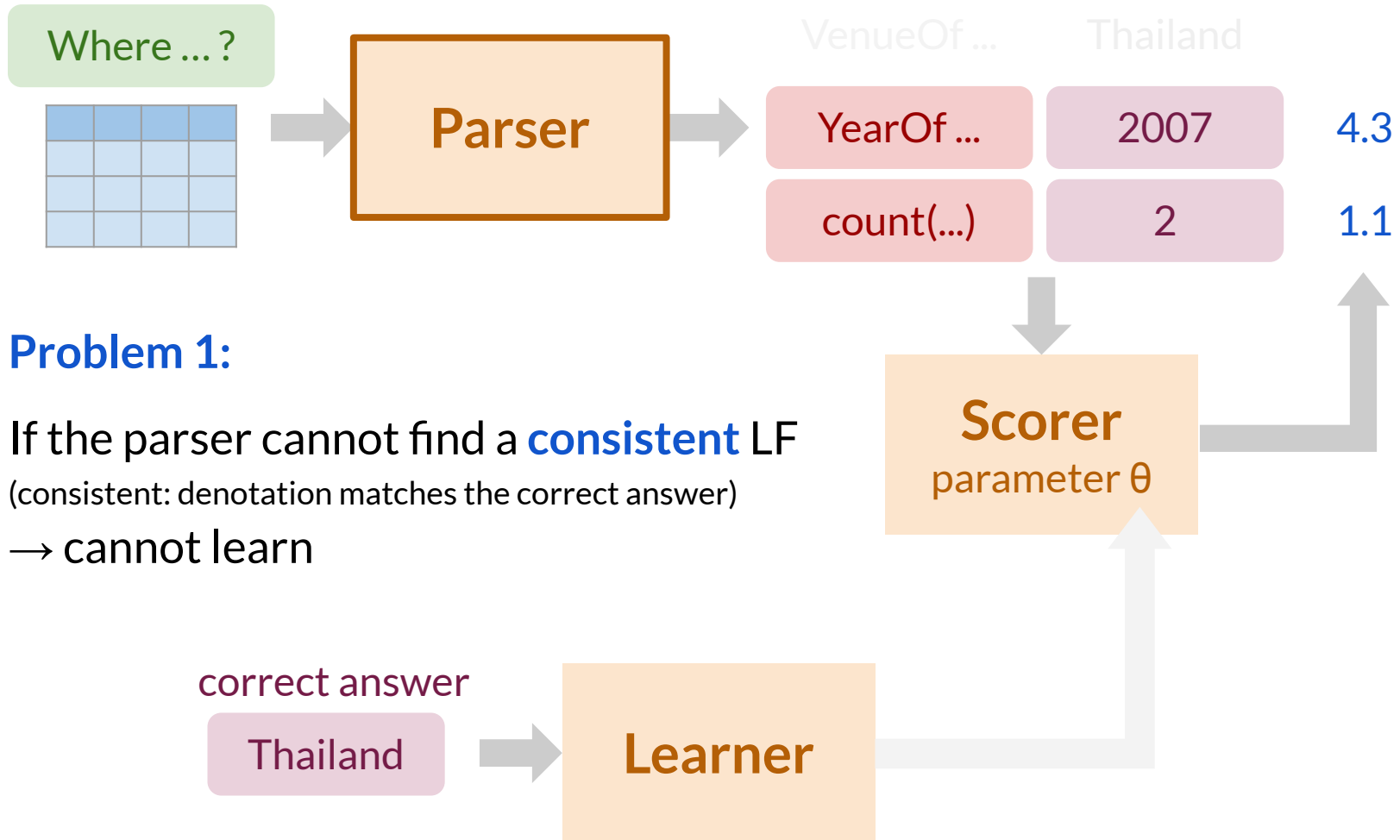
Parser uses **beam search** to make search tractible

- ▶ For each parsing state, only keep up to $B = 100$ highest-scoring partial LFs and **discard the rest**

Search is Hard



Search is Hard



Search is Hard

Some LFs are **spurious** (right for wrong reasons)

Where did the last 1st place finish occur?

VenueOf.argmax(HasPosition.1st, Index)

Year	Venue	Position	Time
2003	Finland	1st	47.12
2005	Germany	5th	46.62
2007	Thailand	1st	53.13

Search is Hard

Some LFs are **spurious** (right for wrong reasons)

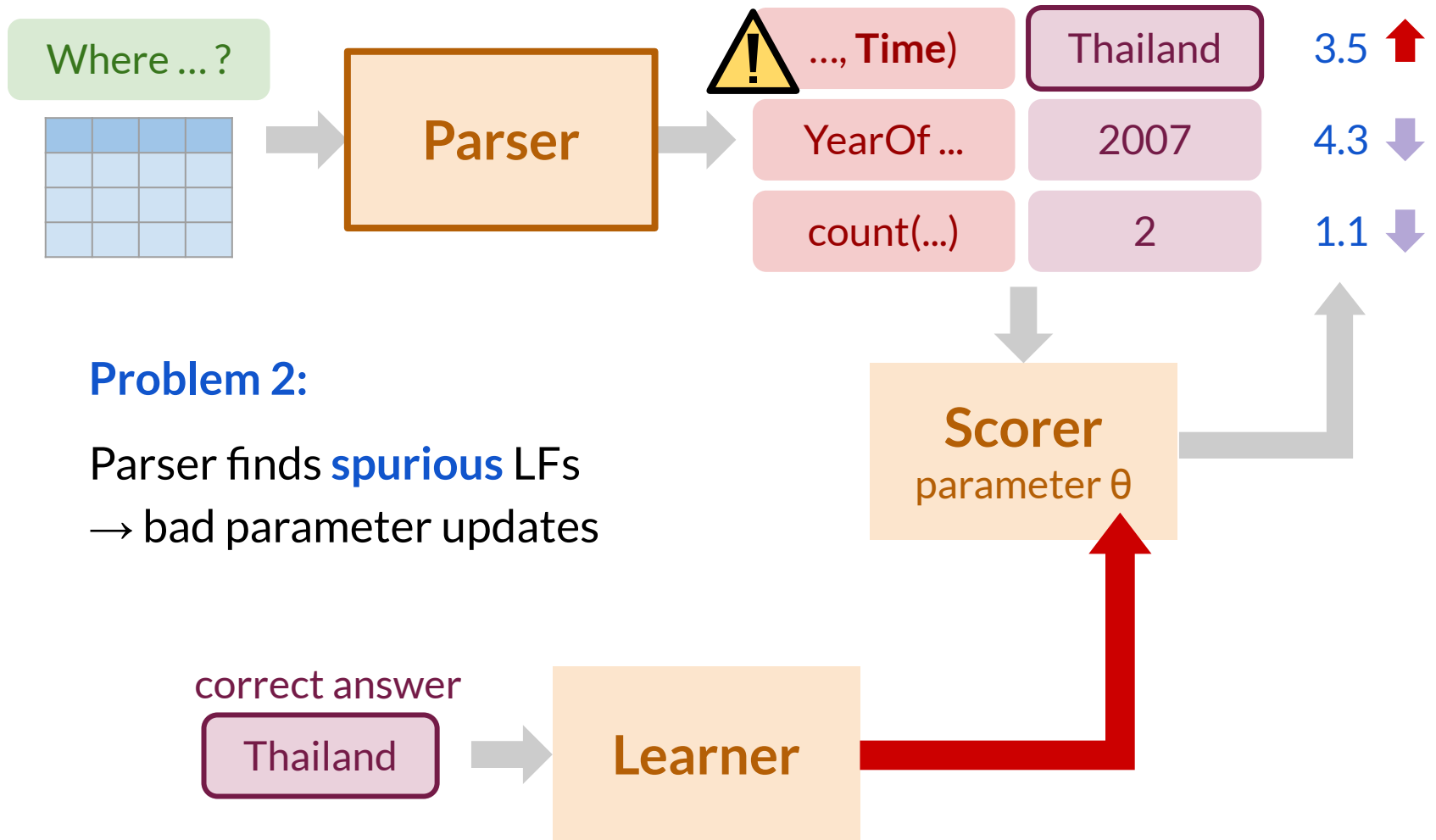
Where did the last 1st place finish occur?



VenueOf.argmax(HasPosition.1st, Time)

Year	Venue	Position	Time
2003	Finland	1st	47.12
2005	Germany	5th	46.62
2007	Thailand	1st	53.13

Search is Hard



Learning from Denotations

Pros:

- ▶ Collecting answers is easier than collecting LFs for each question
- ▶ The dataset is not tied to a specific LF formalism

Cons:

- ▶ Need to do **search**
 - ▷ Slow
 - ▷ Cannot find consistent LFs → cannot learn
 - ▷ Find spurious LFs → bad updates

Offline search

Let's avoid search during training altogether!

Offline search

Let's avoid search during training altogether!

- ▶ For each training example (utterance, table, **answer**), augment it with LFs

- ▶ Use (utterance, table, **LFs**) for **supervised training**

Offline search

Let's avoid search during training altogether!

- ▶ For each training example (utterance, table, answer), augment it with LFs
 - ▶
 - ▶
- ▶ Use (utterance, table, LFs) for supervised training

Offline search

Let's avoid search during training altogether!

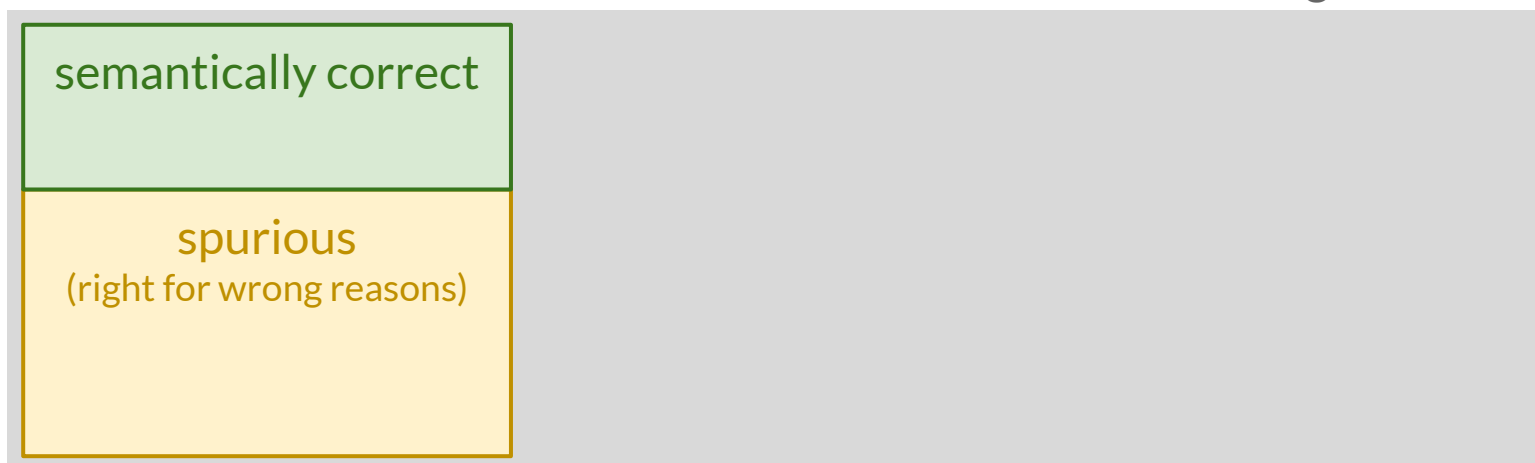
- ▶ For each training example (utterance, table, **answer**), augment it with LFs
 - ▷ **Enumerate** all LFs consistent with the **correct answer**
 - ▷
- ▶ Use (utterance, table, LFs) for supervised training



Offline search

Let's avoid search during training altogether!

- ▶ For each training example (utterance, table, answer), augment it with LFs
 - ▷ **Enumerate** all LFs consistent with the correct answer
 - ▷
- ▶ Use (utterance, table, LFs) for supervised training

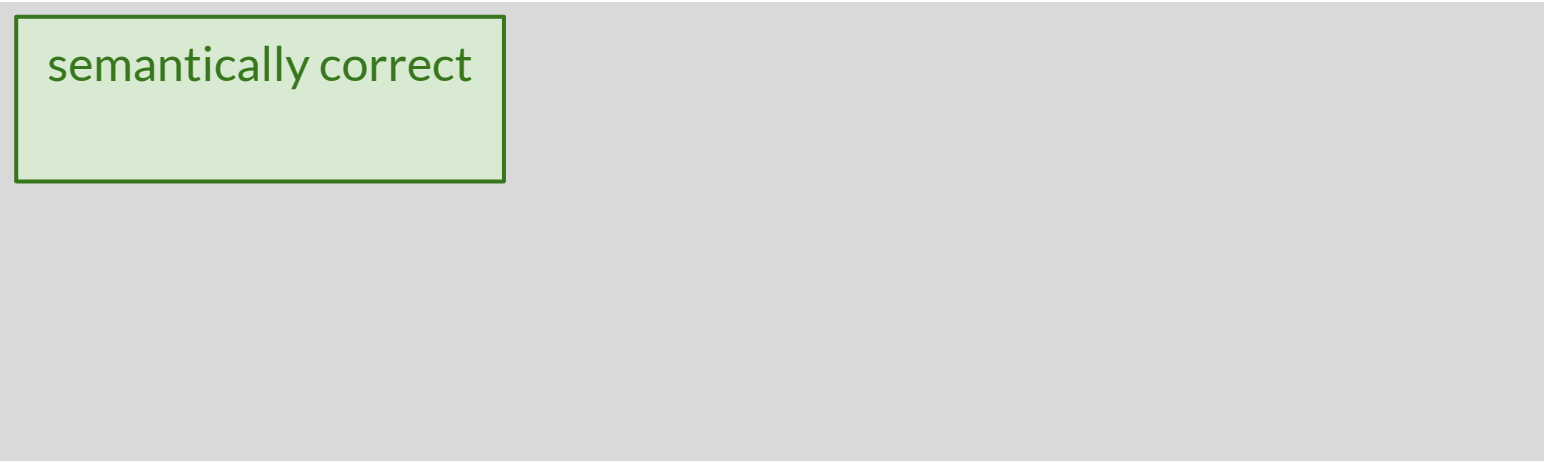


Offline search

Let's avoid search during training altogether!

- ▶ For each training example (utterance, table, answer), augment it with **semantically correct** LFs
 - ▷ **Enumerate** all LFs consistent with the correct answer
 - ▷ **Filter out** spurious LFs
- ▶ Use (utterance, table, LFs) for supervised training

all logical forms



semantically correct

Offline search

Let's avoid search during training altogether!

- ▶ For each training example (utterance, table, answer), augment it with **semantically correct LFs**
 - ▷ **Enumerate** all LFs consistent with the correct answer
 - ▷ **Filter out** spurious LFs
- ▶ Use (utterance, table, LFs) for supervised training



Enumerating consistent LFs

Beam search controls the search space, but can **discard crucial LF parts**
→ low coverage!

If we have access to the **correct answer**, is there a better way to control the search space?

Dynamic Programming on Denotations

Year	Venue	Position	Time
2003	Finland	1st	47.12
2005	Germany	5th	46.62
2007	Thailand	1st	53.13

Dynamic Programming on Denotations

HasIndex.2

HasPosition.5th

HasVenue.Germany

Year	Venue	Position	Time
2003	Finland	1st	47.12
2005	Germany	5th	46.62
2007	Thailand	1st	53.13

r_2

Dynamic Programming on Denotations

TimeOf. HasIndex.2

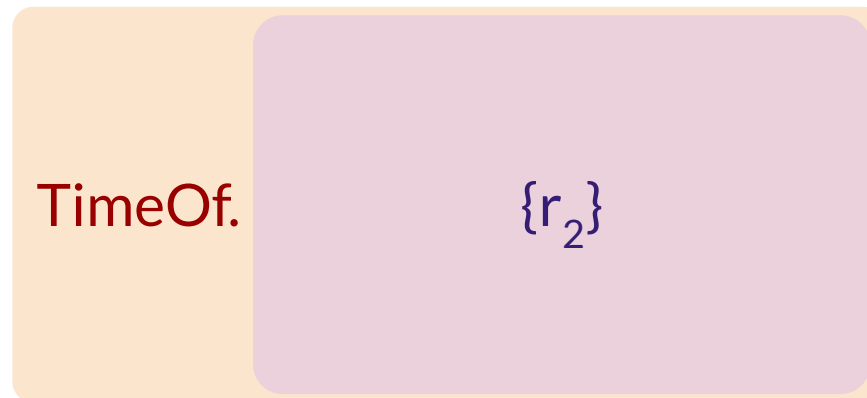
TimeOf. HasPosition.5th

TimeOf. HasVenue.Germany

Year	Venue	Position	Time
2003	Finland	1st	47.12
2005	Germany	5th	46.62
2007	Thailand	1st	53.13

Dynamic Programming on Denotations

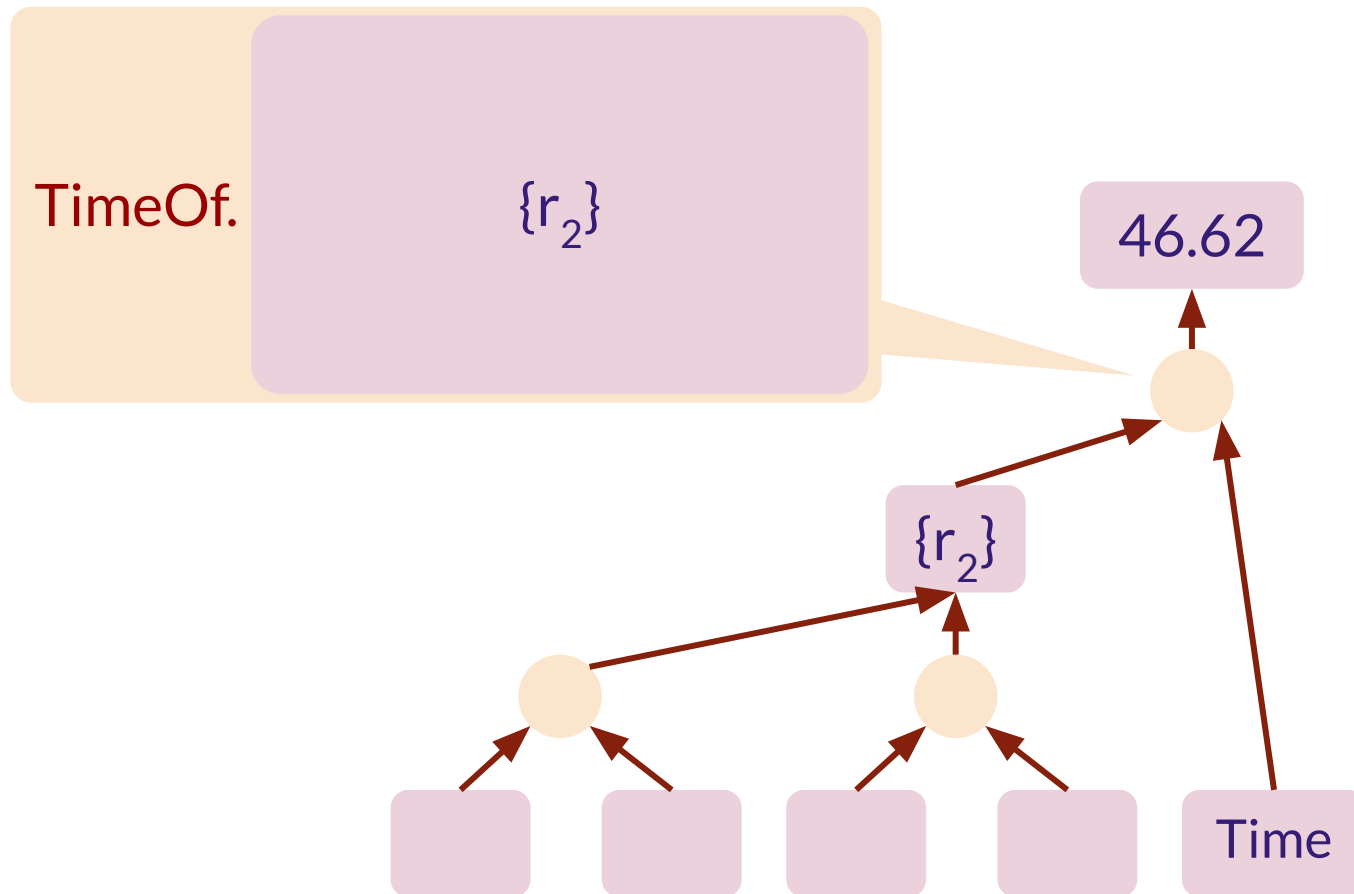
Group LFs with the same denotation together during search



Year	Venue	Position	Time
2003	Finland	1st	47.12
2005	Germany	5th	46.62
2007	Thailand	1st	53.13

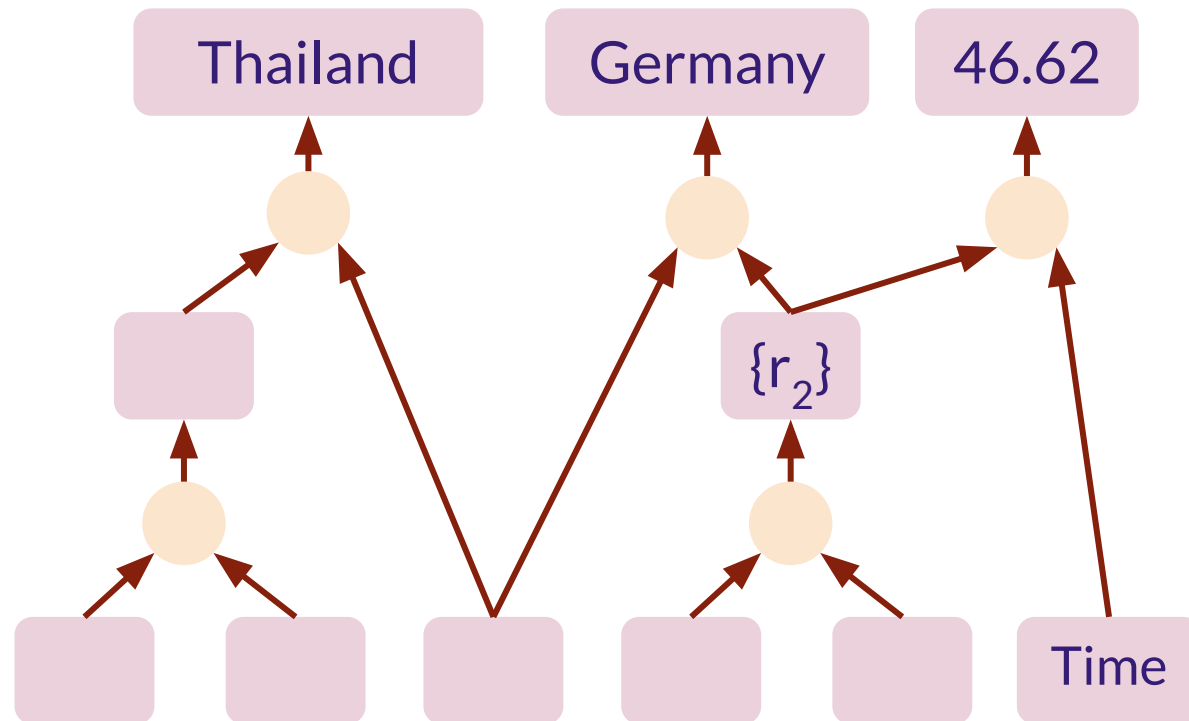
Dynamic Programming on Denotations

Phase 1: Group LFs with the same denotation together during search



Dynamic Programming on Denotations

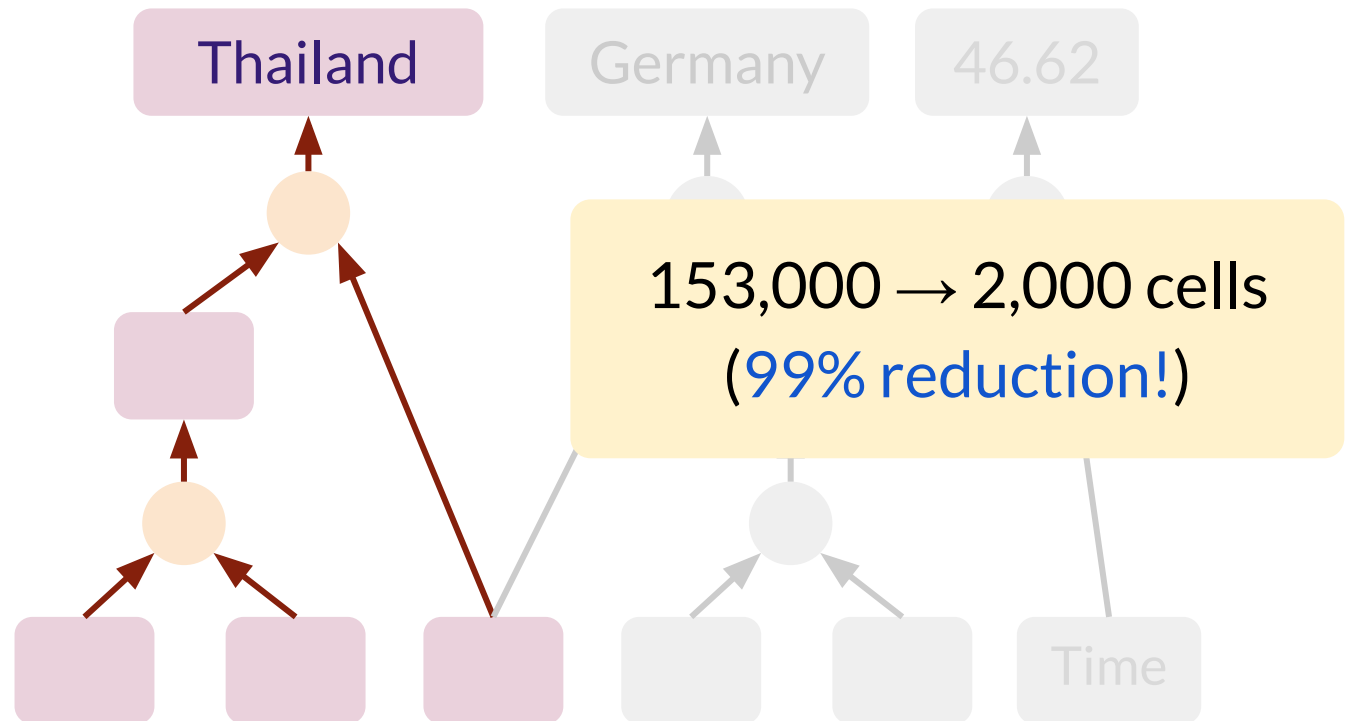
Phase 1: Group LFs with the same denotation together during search



Dynamic Programming on Denotations

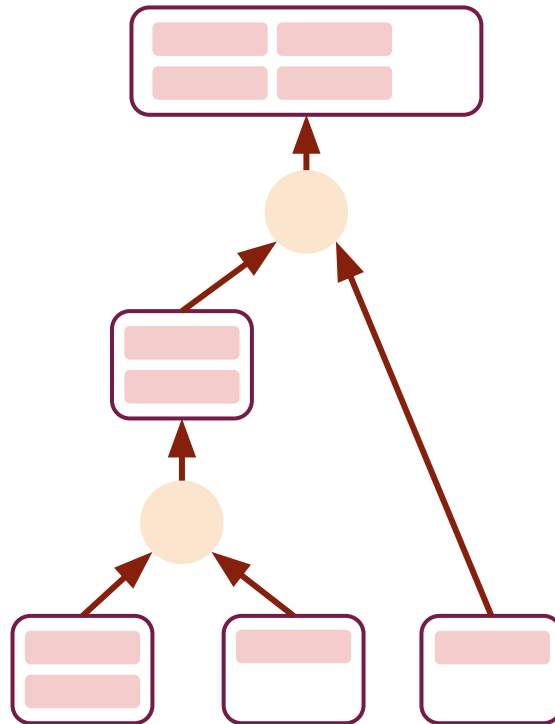
Phase 1: Group LFs with the same denotation together during search

- ▶ Remove paths that do not give the **correct answer**



Dynamic Programming on Denotations

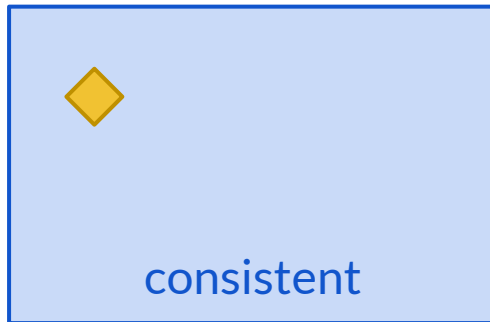
Phase 2: Search over LFs, but only on the paths found in Phase 1



Results

Testing coverage:

- ▶ Annotate each example with a semantically correct LF
- ▶ Test whether the algorithm can generate the annotated LF

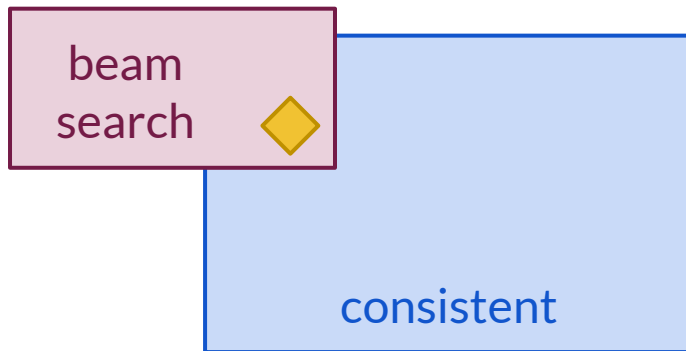


Note: Maximum success rate = 84.0% (% of examples with annotated LFs)

Results

Testing coverage:

- ▶ Annotate each example with a semantically correct LF
- ▶ Test whether the algorithm can generate the annotated LF



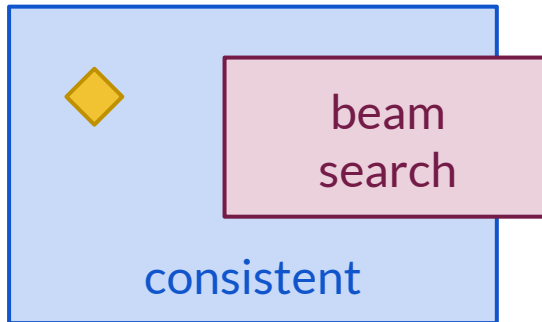
Success rate: 53.7%

Note: Maximum success rate = 84.0% (% of examples with annotated LFs)

Results

Testing coverage:

- ▶ Annotate each example with a semantically correct LF
- ▶ Test whether the algorithm can generate the annotated LF



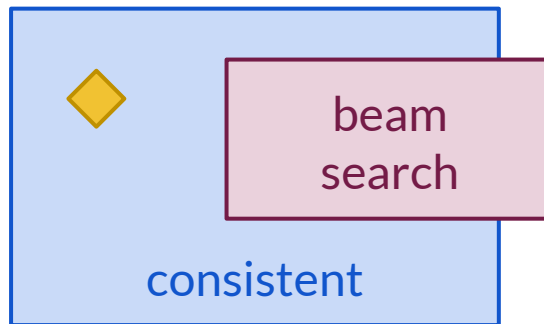
Success rate: 53.7%

Note: Maximum success rate = 84.0% (% of examples with annotated LFs)

Results

Testing coverage:

- ▶ Annotate each example with a semantically correct LF
- ▶ Test whether the algorithm can generate the annotated LF



Success rate: 53.7%



Success rate: 76.0%

Note: Maximum success rate = 84.0% (% of examples with annotated LFs)

Offline search

Let's avoid search during training altogether!

- ▶ For each training example (utterance, table, answer), augment it with **semantically correct LFs**
 - ▷ **Enumerate** all LFs consistent with the correct answer
 - ▷ **Filter out** spurious LFs
- ▶ Use (utterance, table, LFs) for supervised training



Offline search

Let's avoid search during training altogether!

- ▶ For each training example (utterance, table, answer), augment it with **semantically correct LFs**
 - ▷ **Enumerate** all LFs consistent with the correct answer
 - ▷ **Filter out** spurious LFs
- ▶ Use (utterance, table, LFs) for supervised training



Offline search

Let's avoid search during training altogether!

- ▶ For each training example (utterance, table, answer), augment it with **semantically correct LFs**
 - ▷ Enumerate all LFs consistent with the correct answer
 - ▷ **Filter out** spurious LFs
- ▶ Use (utterance, table, LFs) for supervised training



Filtering out Spurious LFs

Year	Venue	Position	Time
2003	Finland	1st	47.12
2005	Germany	5th	46.62
2007	Thailand	1st	53.13

Where did the last 1st place finish occur?

Human

Thailand

Correct LF

Thailand

Spurious LF

Thailand

Filtering out Spurious LFs

Year	Venue	Position	Time
2003	Germany	1st	53.13
2005	Finland	1st	47.12
2007	Thailand	5th	46.62

Randomize cells in each column

Where did the last 1st place finish occur?

Human

Finland

Correct LF

Finland

Spurious LF

Germany

Fictitious Tables

Generate **fictitious tables** and execute the logical forms on them

Original Table

LF 1	Thailand
LF 2	Thailand
LF 3	Thailand
LF 4	Thailand
LF 5	Thailand
Human	Thailand



Fictitious Tables

Generate **fictitious tables** and execute the logical forms on them

	Original Table	Fictitious Table 1
LF 1	Thailand	Finland
LF 2	Thailand	Thailand
LF 3	Thailand	Finland
LF 4	Thailand	Finland
LF 5	Thailand	Germany
Human	Thailand	Finland

Fictitious Tables




Generate **fictitious tables** and execute the logical forms on them

	Original Table	Fictitious Table 1
LF 1	Thailand	Finland
 LF 2	Thailand	Thailand
LF 3	Thailand	Finland
LF 4	Thailand	Finland
 LF 5	Thailand	Germany
Human	Thailand	Finland

Fictitious Tables

Generate **fictitious tables** and execute the logical forms on them

We also propose a way to select the **most informative** fictitious tables

	Original Table	Fictitious Table 1	Fictitious Table 2
LF 1	Thailand	Finland	Germany
 LF 2	Thailand	Thailand	Germany
 LF 3	Thailand	Finland	Thailand
LF 4	Thailand	Finland	Germany
 LF 5	Thailand	Germany	Finland
Human	Thailand	Finland	Germany

Fictitious Tables

Results:

- ▶ Accidentally pruned correct LFs in 20% of the examples
 - ▷ because randomizing cells can create nonsensical tables
- ▶ But for the remaining examples, pruned out 92.1% of spurious LFs

Fictitious Tables

Relax assumption: Only filter LFs disagreeing with humans > once


- ▶ Accidentally pruned correct LFs in ~~20%~~^{3%} of the examples
 - ▷ because randomizing cells can create nonsensical tables
- ▶ But for the remaining examples, pruned out ~~92.1%~~^{78%} of spurious LFs

Offline search

Let's avoid search during training altogether!

- ▶ For each training example (utterance, table, answer), augment it with **semantically correct** LFs
 - ▷ **Enumerate** all LFs consistent with the correct answer
 - ▷ **Filter out** spurious LFs
- ▶ Use (utterance, table, LFs) for supervised training

all logical forms



semantically correct

Offline search

Let's avoid search during training altogether!

- ▶ For each training example (utterance, table, answer), augment it with **semantically correct LFs**
 - ▷ Enumerate all LFs consistent with the correct answer
 - ▷ Filter out spurious LFs
- ▶ Use (utterance, table, LFs) for supervised training

all logical forms



semantically correct

Using macros to make search faster

	Test Acc.	+Ensemble
Small rule set	37.1	-
Neural Programmer (Neelakantan et al., 2016)	34.2	37.7
Neural Multi-Step Reasoning (Haug et al., 2017)	34.8	38.7
Large rule set	42.7	-
+ Macros	43.7	-

Krishnamurthy et al., 2017 uses 100 shortest LFs we generated to train a neural parser (top-down tree generation)

Using macros to make search faster

	Test Acc.	+Ensemble
Small rule set	37.1	-
Neural Programmer (Neelakantan et al., 2016)	34.2	37.7
Neural Multi-Step Reasoning (Haug et al., 2017)	34.8	38.7
Large rule set	42.7	-
+ Macros	43.7	-
Neural Parser trained on consistent LFs (DPD; no filtering)	36.3	

Krishnamurthy et al., 2017 uses 100 shortest LFs we generated to train a neural parser (top-down tree generation)

Using macros to make search faster

	Test Acc.	+Ensemble
Small rule set	37.1	-
Neural Programmer (Neelakantan et al., 2016)	34.2	37.7
Neural Multi-Step Reasoning (Haug et al., 2017)	34.8	38.7
Large rule set	42.7	-
+ Macros	43.7	-
Neural Parser trained on consistent LFs (DPD; no filtering)	36.3	
Neural Parser trained on correct LFs (DPD + filtering)	43.3	45.9

Krishnamurthy et al., 2017 uses 100 shortest LFs we generated to train a neural parser (top-down tree generation)

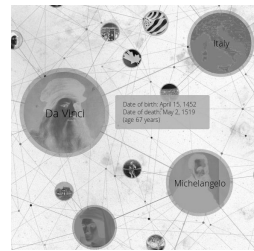
Summary

Task Complexity (depth)

database / apps

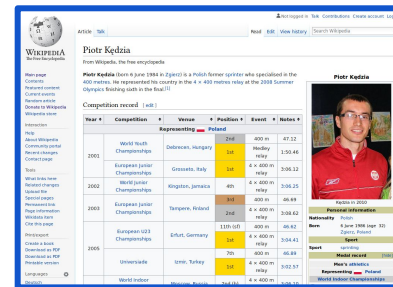


knowledge base



Freebase™

web pages



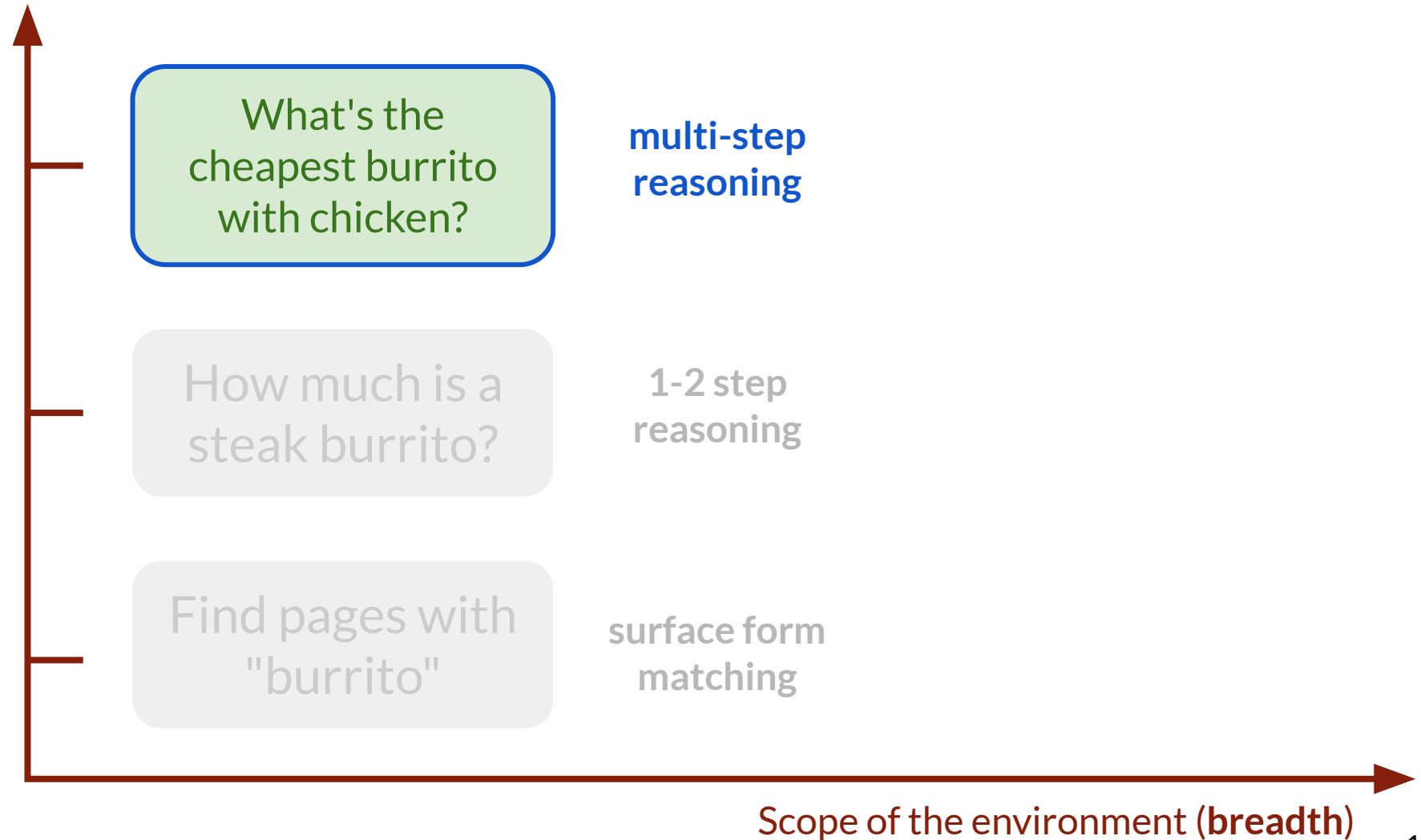
any texts

The Lacey Act of 1900 was the first federal law that regulated commercial animal markets. It prohibited interstate commerce of animals killed in violation of state game laws, and covered all fish and wildlife and their parts or products, as well as plants. Other legislation followed, including the Migratory Bird Conservation Act of 1929, a 1937 treaty prohibiting the hunting of right and gray whales, and the Bald Eagle Protection Act of 1940. These later laws had a low cost to society—the species were relatively rare—and little opposition was raised.^[9]

Scope of the environment (breadth)

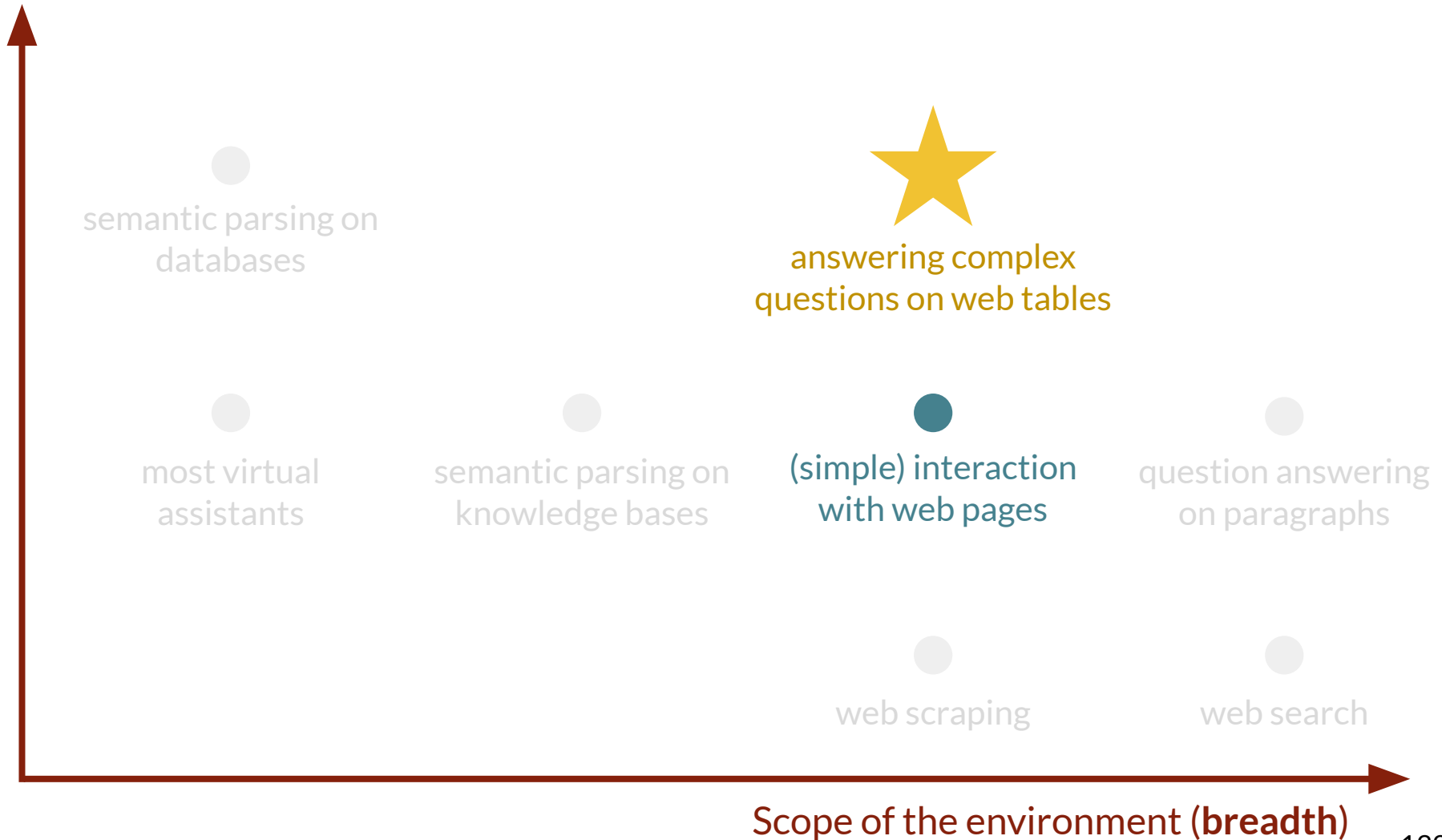
Summary

Task Complexity (**depth**)



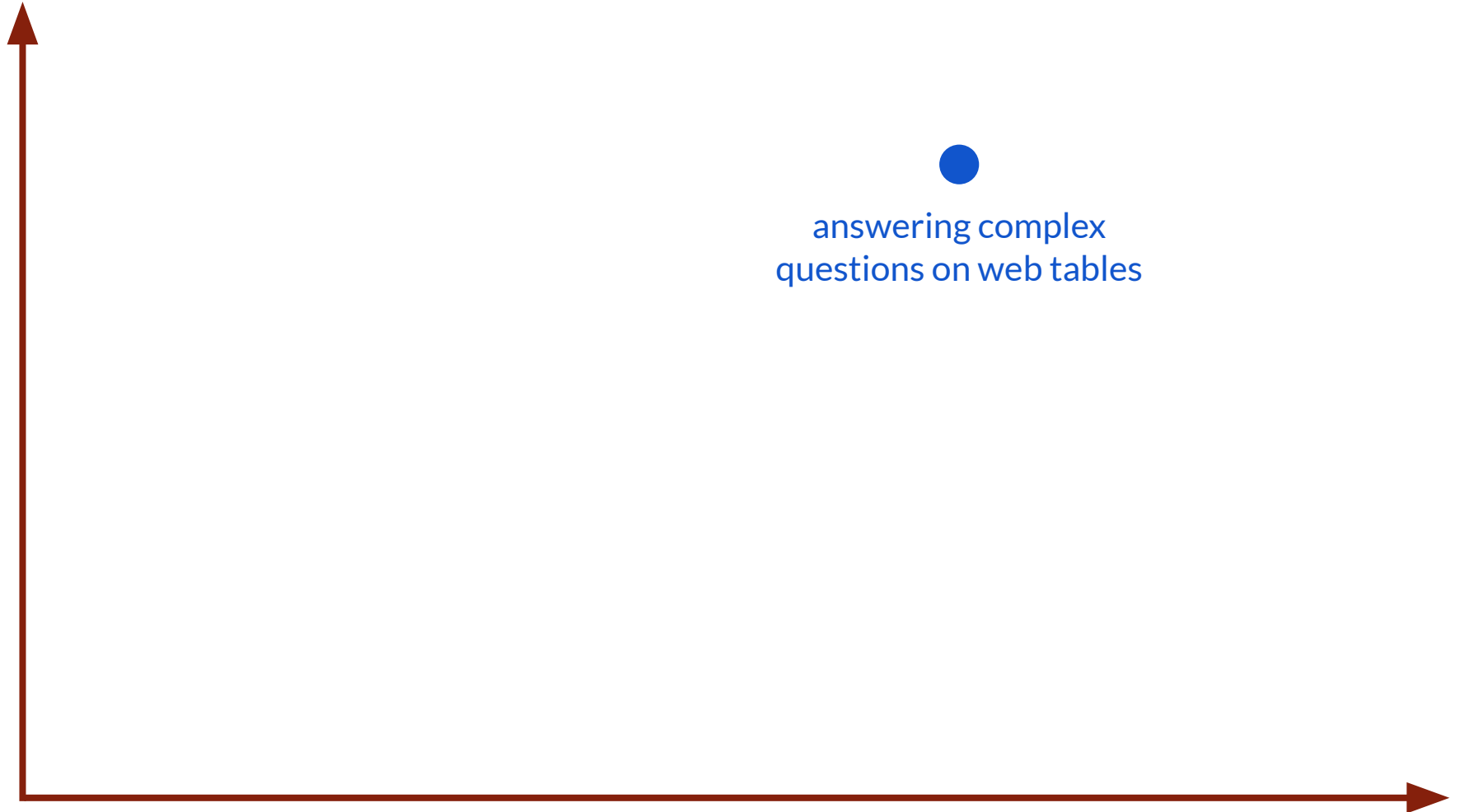
Summary

Task Complexity (**depth**)



Future Directions

Task Complexity (**depth**)




Scope of the environment (**breadth**)

Future Directions

Task Complexity (**depth**)

- ▶ Learn implicit columns
("What is?" → which column?)
- ▶ Detect if the question cannot be answered by the table
- ▶ More complex reasoning
(e.g., "consecutive")
- ▶ Better table understanding
($\cup \circ \square \circ$) \cap \perp \perp
- ▶ ...


answering complex
questions on web tables

Scope of the environment (**breadth**)

Future Directions

multi-step web interaction

answering complex questions on web tables

Task Complexity (depth)

The image shows a screenshot of the Alaska Airlines website's flight booking interface. At the top, there is a dark blue header with the Alaska logo and a home icon. Below the header, the main heading is "Book a flight". There are two radio buttons: "One-way" (selected) and "Use miles". Below this are input fields for "From" and "To", each with a clear (X) and search (+) icon. There are also "Depart" and "Return" date pickers with calendar icons. A "Number of passengers" section shows a minus button, the number "1", and a plus button, along with a "Child traveling alone?" checkbox. A "More search options" link is visible. At the bottom of the form is a green "FIND FLIGHTS" button. A footer contains links for "FAQ", "Full site", "Legal", "Privacy", and "Contact us".

Scope of the environment (breadth)

Future Directions

Task Complexity (depth)

multi-step web interaction

combine information from multiple sources

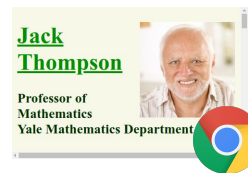
answering complex questions on web tables

gas station near Jack's office

which Jack?

office?

gas station?



Scope of the environment (breadth)

Thank you!