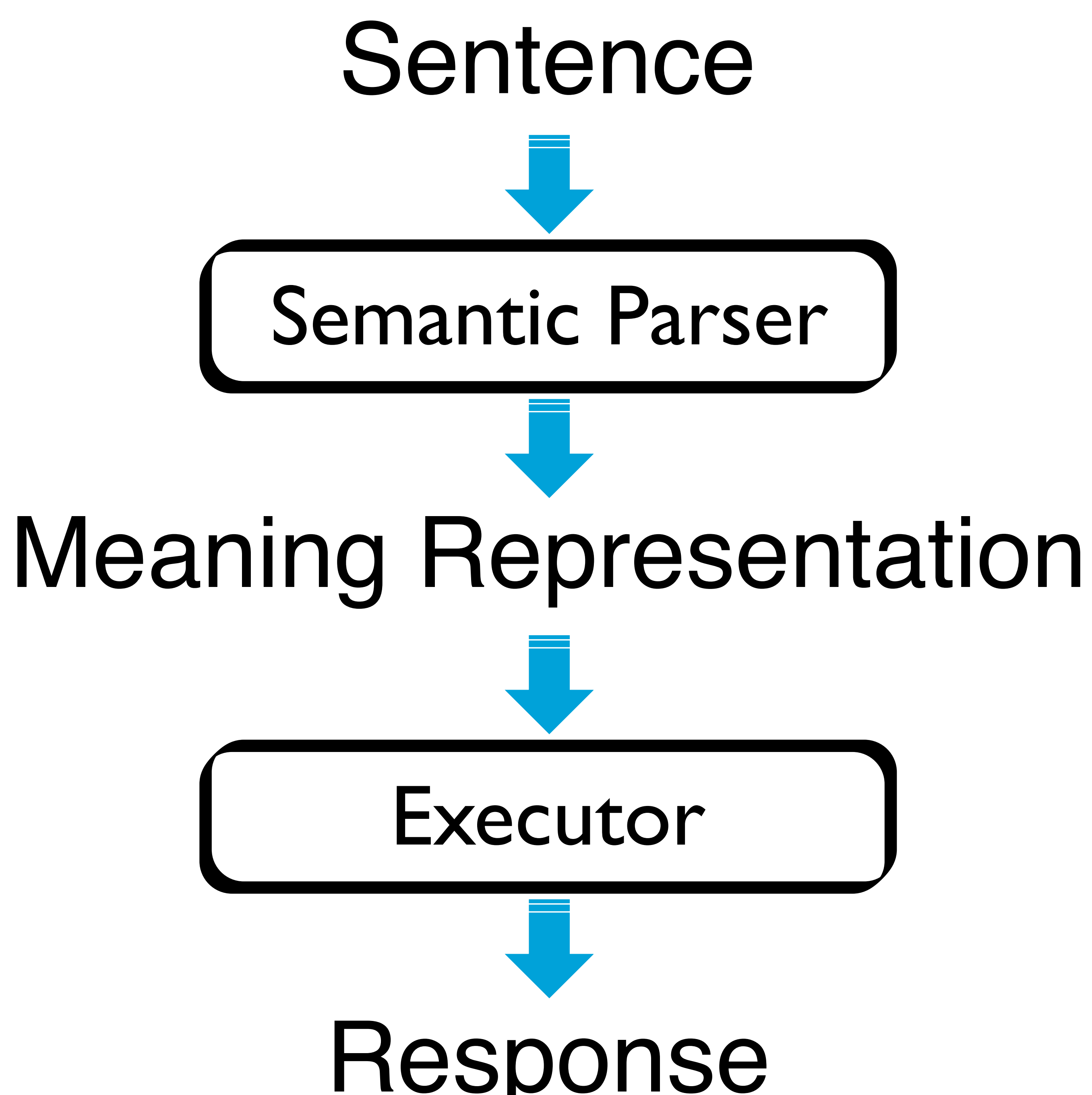
Neural Semantic Parsing

Pradeep Dasigi, Srini Iyer, Alane Suhr,
Matt Gardner, Luke Zettlemoyer

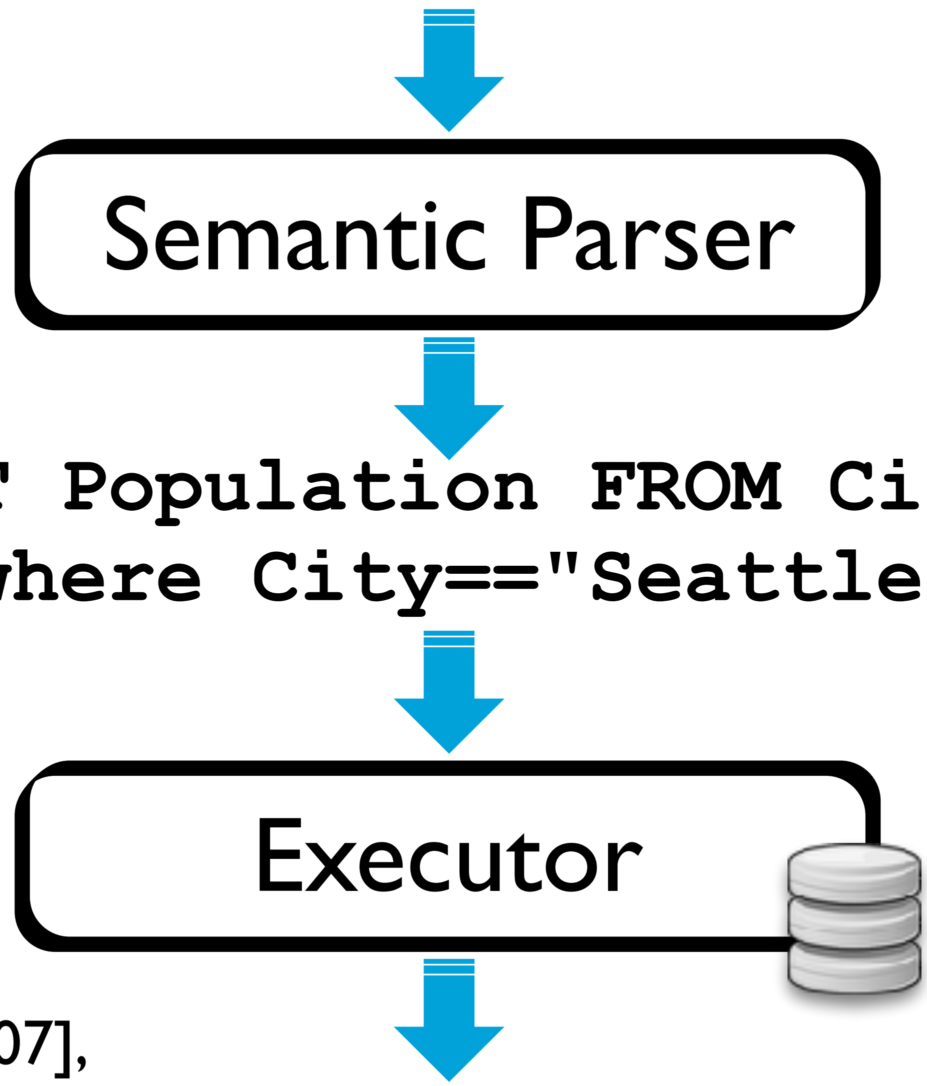
    

Semantic Parsing



Semantic Parsing: QA

How many people live in Seattle?




```
SELECT Population FROM CityData
where City=="Seattle";
```

620,778

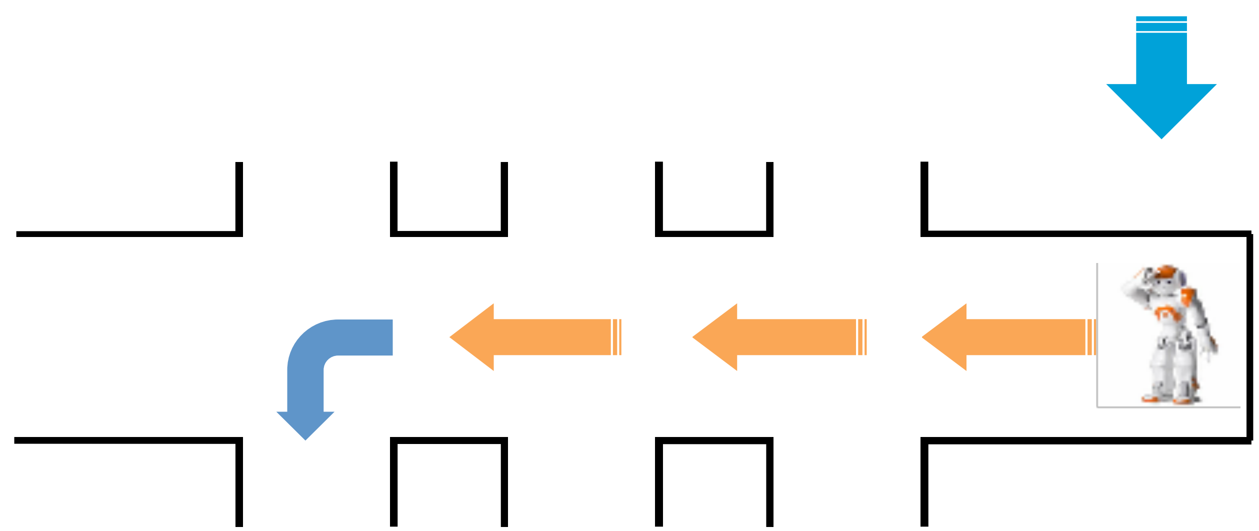
[Wong & Mooney 2007],
[Zettlemoyer & Collins 2005, 2007],
[Kwiatkowski et.al 2010, 2011],
[Liang et.al. 2011],[Berant et.al. 2013,2014],[Reddy et.al, 2014,2016],
[Dong and Lapata, 2016] .....

Semantic Parsing: Instructions

Go to the third junction and take a left

Semantic Parser

```
(do-seq(do-n-times 3
  (move-to forward-loc
    (do-until
      (junction current-loc
        (move-to forward-loc))))
  (turn-right))
```



[Chen & Mooney 2011]
[Matuszek et al 2012]
[Artzi & Zettlemoyer 2013]
[Mei et.al. 2015][Andreas et al, 2015]
[Fried at al, 2018] ....

Language to Meaning

More informative

Language to Meaning

Information Extraction

Recover information about pre-specified relations and entities

More informative

Example Task

Relation Extraction


The New York Times

OBAMA

RACIAL BARRIER FALLS IN DECISIVE VICTORY

Democrats in Congress Strengthen Grip

$$is\_a(OBAMA, PRESIDENT)$$

Language to Meaning

Broad-coverage
Semantics

Focus on specific
phenomena (e.g., AMR)

More informative

Example Task

Summarization

Obama wins election. Big party in Chicago. Romney a bit down, asks for some tea.

Language to Meaning

Example Task

Database Query

What states border Texas?

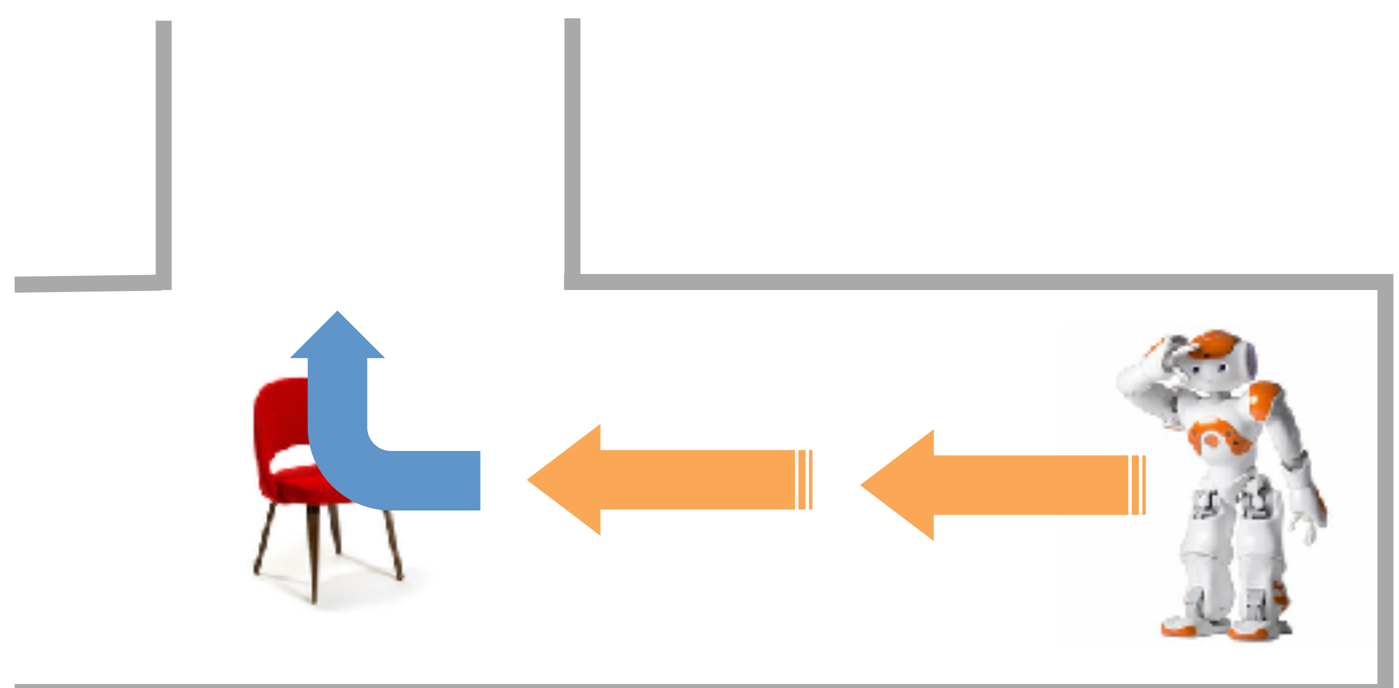
Oklahoma
New Mexico
Arkansas
Louisiana

Language to Meaning

Example Task

Instructing a Robot

at the chair,
turn right



Language to Meaning

<u>Complete</u> meaning is sufficient to complete the task

- Convert to database query to get the answer
- Allow a robot to do planning

Language to Meaning

at the chair, move forward three steps past the sofa

$$\lambda a.pre(a, \iota x.chair(x)) \wedge move(a) \wedge len(a, 3) \wedge$$
$$dir(a, forward) \wedge past(a, \iota y.sofa(y))$$

Language to Meaning

Semantic
Parsing

Recover **complete**
meaning
representation

More informative

at the chair, move forward three steps past the sofa

$$\lambda a.pre(a, \iota x.chair(x)) \wedge move(a) \wedge len(a,3) \wedge dir(a, forward) \wedge past(a, \iota y.sofa(y))$$

Language to Meaning

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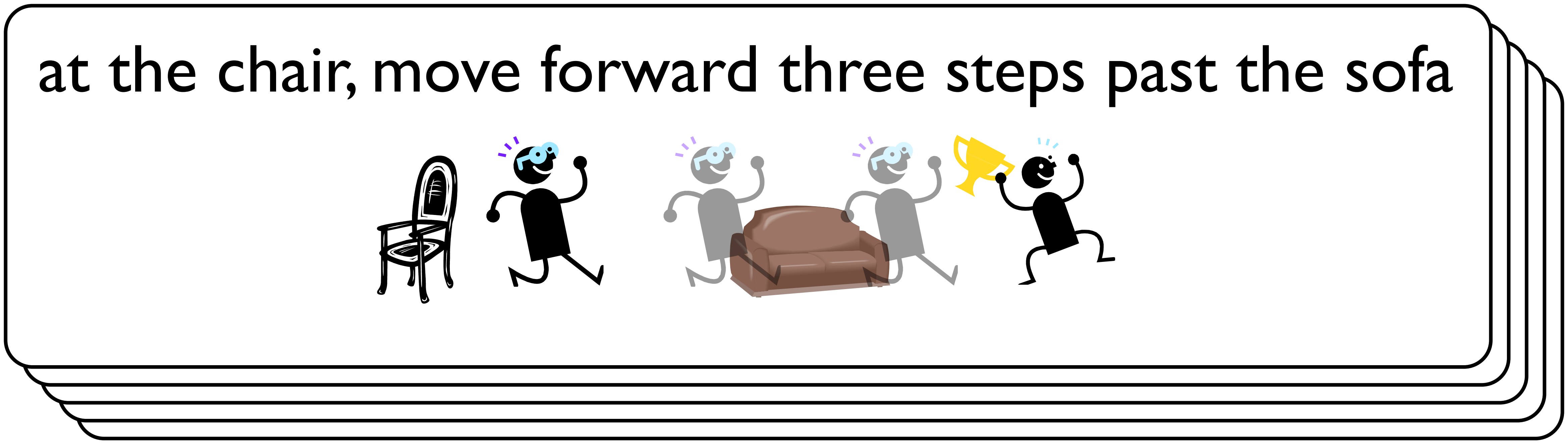
Learn

$$f : \text{sentence} \rightarrow \text{logical form}$$

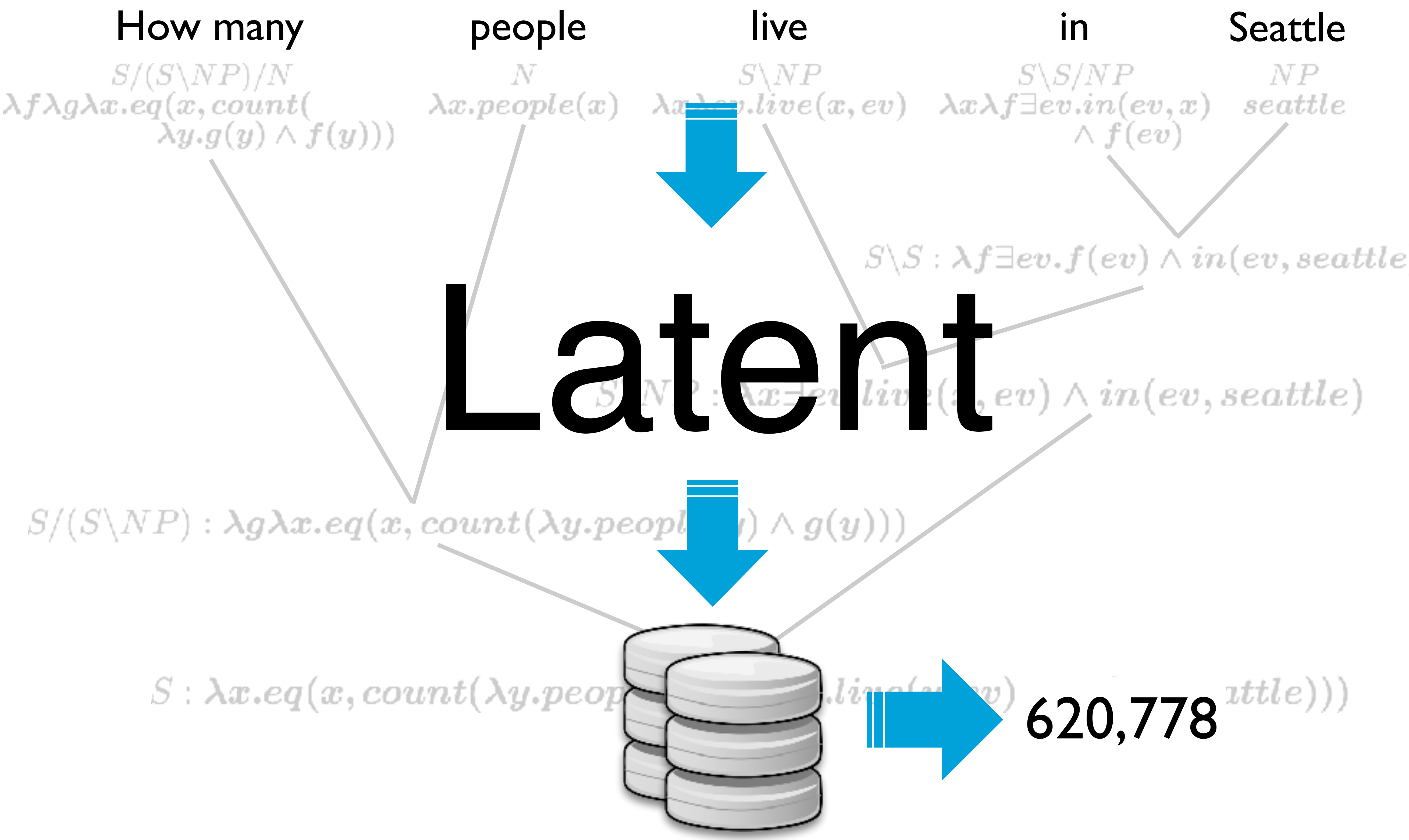
Language to Meaning



Learn

$$f : \text{sentence} \rightarrow \text{logical form}$$

Semantic Parsing: Complex Structure



CCG Semantic Parsing

$$\begin{array}{cccc}
\text{move} & \text{to} & \text{the} & \text{chair} \\
\hline
S & AP/NP & NP/N & N \\
\lambda a.move(a) & \lambda x.\lambda a.to(a,x) & \lambda f.\iota x.f(x) & \lambda x.chair(x)
\end{array}$$

$$\frac{\lambda f.\iota x.f(x) \quad \lambda x.chair(x)}{NP \quad \iota x.chair(x)} >$$

$$\frac{\lambda x.\lambda a.to(a,x) \quad \iota x.chair(x)}{AP \quad \lambda a.to(a, \iota x.chair(x))} >$$

$$\frac{AP \quad \lambda a.to(a, \iota x.chair(x))}{S\backslash S \quad \lambda f.\lambda a.f(a) \wedge to(a, \iota x.chair(x))}$$

$$\frac{\lambda a.move(a) \quad \lambda f.\lambda a.f(a) \wedge to(a, \iota x.chair(x))}{S \quad \lambda a.move(a) \wedge to(a, \iota x.chair(x))} >$$

[Zettlemoyer & Collins 2005, 2007]

CCG Semantic Parsing

move | to | the | chair

"The classic approach"

-Mark Johnson (~2016)

S

$\lambda a.move(a) \wedge to(a, \iota x.chair(x))$

[Zettlemoyer & Collins 2005, 2007]

CCG Semantic Parsing

move to the chair

- Complex discrete learning algorithms
- But, grammars hopefully generalize to unseen data well!
- Difficult to engineer: few people can do it and it takes a lot of time

$\lambda a.move(a) \wedge to(a, \iota x.chair(x))$

[Zettlemoyer & Collins 2005, 2007]

Enter seq2seq... (Dong & Lapata, 2016)

- Treat meaning as a string...
- Apply NMT
- Close to SOTA performance!!!
- Much easier to build (with toolkits)

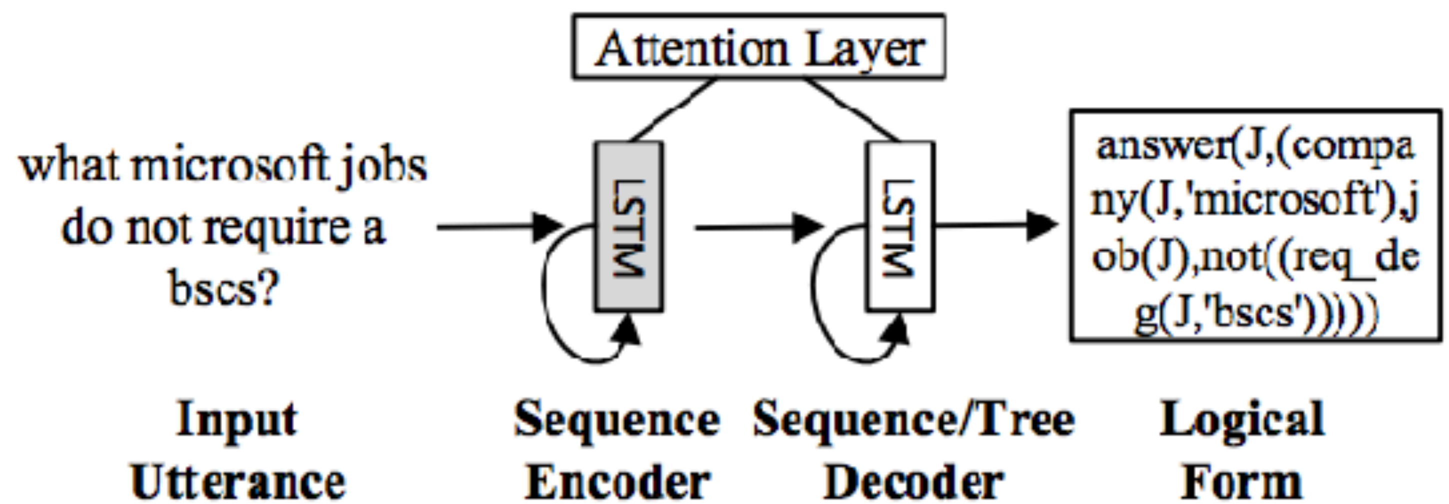
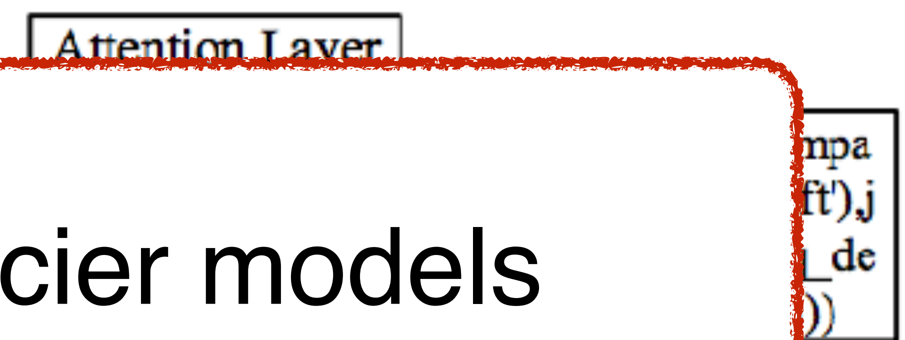


Figure 1: Input utterances and their logical forms are encoded and decoded with neural networks. An attention layer is used to learn soft alignments.

Enter seq2seq... (Dong & Lapata, 2016)

- Treat meaning as a st
- A
- C
  p
- Much easier to build (with toolkits)

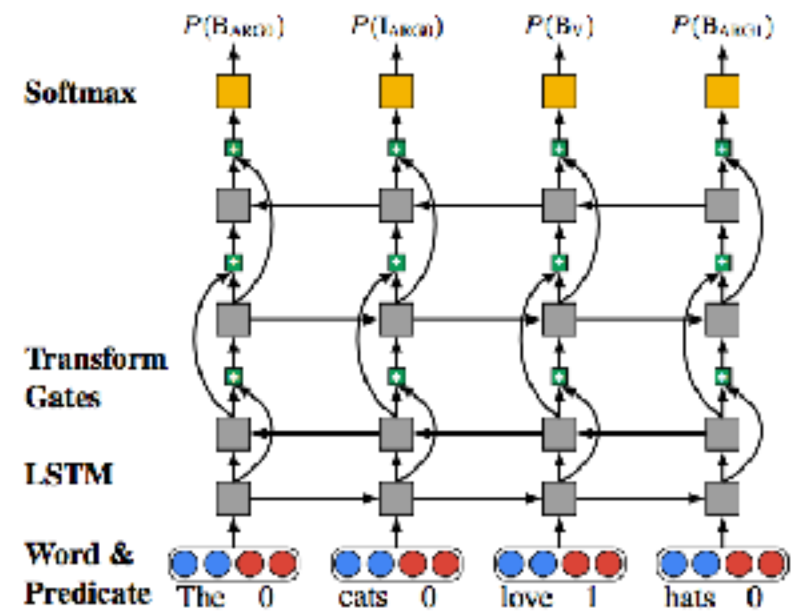


rms
rks.
An attention layer is used to learn soft alignments.

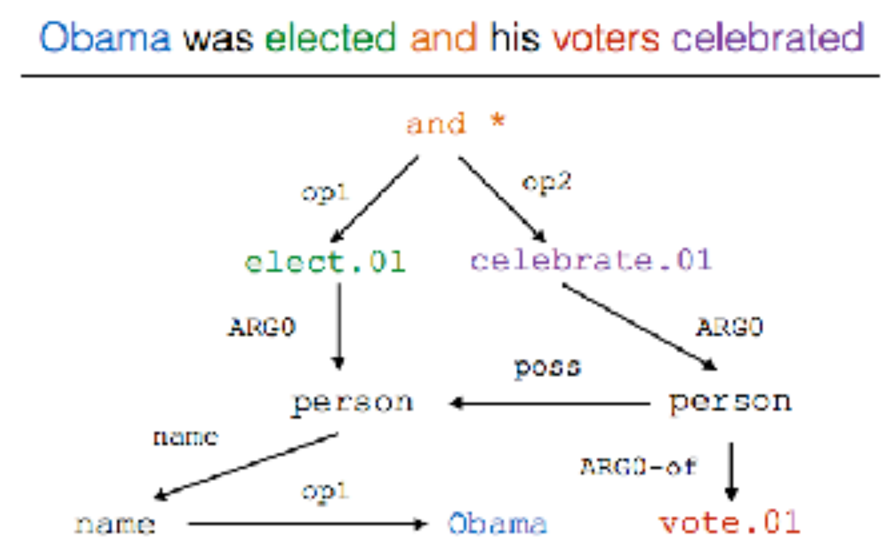
We will talk about lots of fancier models throughout this tutorial, but this was a ***very*** unexpected result... (at least for me...)

And, this wasn't an isolated event...

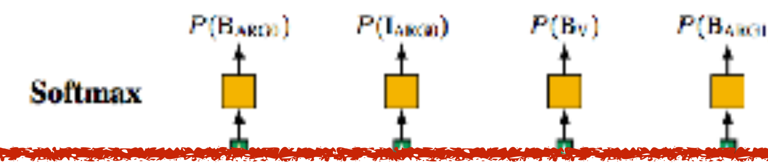
- CCGbank parsers for SRL
  (Lewis, He, Lee, et al ~2015)
  - Deep BIO Taggers work better! (Zhou and Xu, 2015)



- CCG AMR parsing
  (Artzi et al, 2015)
  - seq2seq performs better! (Konstas et al 2017)



And, this wasn't an isolated event...

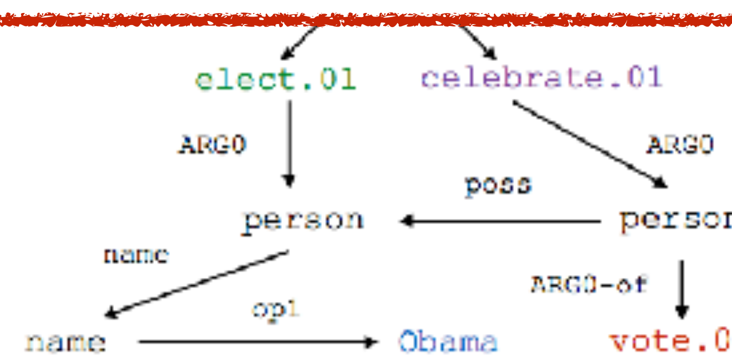


- CCGbank parsers for SRL
  (L
  -
- C

"What Now? Is NLP dead?"

-Mirella Lapata
(ACL 2017 Keynote)

- seq2seq performs better!
  (Konstas et al 2017)



This Tutorial: Neural Semantic Parsing

... or, carefully adding structure into seq2seq...

...while also studying lots of new problems...

- Part 1: Datasets

- Part 2: Models (e.g. seq2tree)

...break...

- Part 3: Language to Code
- Part 4: Language in Context

- Part 5: Building parsers (e.g. toolkits)