Grounded Semantics

Berkeley

N L P

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What does the world look like?

HAL'

$open'$

$\wedge$

$close'$

$Bowman'$

$podBayDoors'$

$\exists$

Today's plan

1. How do we relate language to a richer representation of the world?

2. How do we learn meanings without annotated logical forms?

Today's plan

Open the pod bay doors, HAL

↓

$$\mathrm{open}(\mathrm{HAL}, \mathrm{podBayDoors})$$

↓

Today's plan

Grounded

~~Formal~~ semantics:

How do we learn the relationship between text and ~~logical forms~~?

the world

Three approaches

1. Learning with hardcoded predicates

2. Jointly learning parsers and classifiers

3. Learning a policy directly

Hard-coded predicates

Don't forget:

the λ-calculus is a programming language!

```
final Entity HAL = ...
Entity podBayDoors = ...
void open(Entity opener, Entity opened) {
   ...
}
```

Hard-coded predicates

Given full supervision we can immediately execute output from our semantic parser.

```
final Entity HAL = ...
Entity podBayDoors = ...
void open(Entity opener, Entity opened) {
   ...
}
```

Hard-coded predicates

Open the pod bay doors, HAL

↓

`open(HAL, podBayDoors)`

↓

Distant supervision

Can we use the ability to execute predicted parses to learn with weaker supervision?

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Before:

Open the pod bay doors	observe text
`close(HAL, podBayDoors)`	predict LF
`open(HAL, podBayDoors)`	observe true LF
1.0	incur loss

Distant supervision

Can we use the ability to execute predicted parses to learn with weaker supervision?

Before:

Open the pod bay doors	observe text
`open(HAL, podBayDoors)`	predict LF
`open(HAL, podBayDoors)`	observe true LF
0.0	incur loss

Distant supervision

Can we use the ability to execute predicted parses to learn with weaker supervision?

Now:

Open the pod bay doors	observe text
`close(HAL, podBayDoors)`	predict LF
`doorsClosed = true`	predicted outcome
`doorsClosed = false`	desired outcome
1.0	incur loss

Distant supervision

Recall our previous training procedure.

Structured perceptron update:

$$\theta^{t+1} = \theta^t + \Phi(x, y) - \Phi(x, \hat{y})$$

where

$$\hat{y} = \arg\max_y \ \theta^\top \Phi(x, y)$$

Distant supervision

Now only supervision is an outcome z.

Structured perceptron update:

$$\theta^{t+1} = \theta^t + \Phi(x, \boxed{y^*}) - \Phi(x, \hat{y})$$

where

$$\hat{y} = \arg\max_{y} \ \theta^\top \Phi(x, y)$$

$$y^* = \arg\max_{y:\boxed{\mathrm{exec}(y)=z}} \ \theta^\top \Phi(x, y)$$

Distant supervision

close(HAL, podBayDoors) $\hat{y}$

open(HAL, podBayDoors) y^*

open(HAL, cockpitDoors)

make(HAL, sandwich, Dave)

…

smash(HAL, podBayDoors, filingCabinet) y^*

Distant supervision

Open the pod bay doors, HAL

↓

`open(HAL, podBayDoors)`

↑

What can we do with this?

Learn to answer questions given only (question, answer) pairs and a database of facts

[Liang et al. 2011 & various others]

Learn to follow directions given only (source, pairs) and a model environment

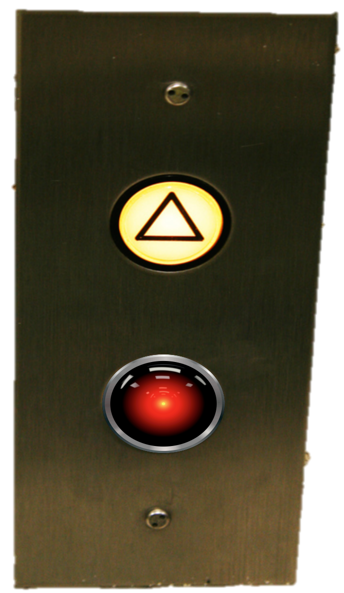
[Chen & Mooney 2011, Artzi & Zettlemoyer 2013]

Joint parsing and perception

What if the world doesn't look like a database underneath?

Open the elevator doors, HAL

What's a door?



Joint parsing and perception

What's a door?

$$f(podBayDoors) = \text{true}$$

door	podBayDoor, elevatorDoor1, cockpitDoor, …
window	bridgeWindow, bathroomWindow, …
isOpen	podBayDoor, bathroomWindow

Joint parsing and perception

What's a door?

$f\Bigg($  $\Bigg) = \text{true}$

Joint parsing and perception

What's a door?

$f\Big($  $\Big) = \text{true}$

Joint parsing and perception

What's a door?

$$f\left(\right) = \text{false}$$

Joint parsing and perception

Fixed inventory of functions

Joint parsing and perception

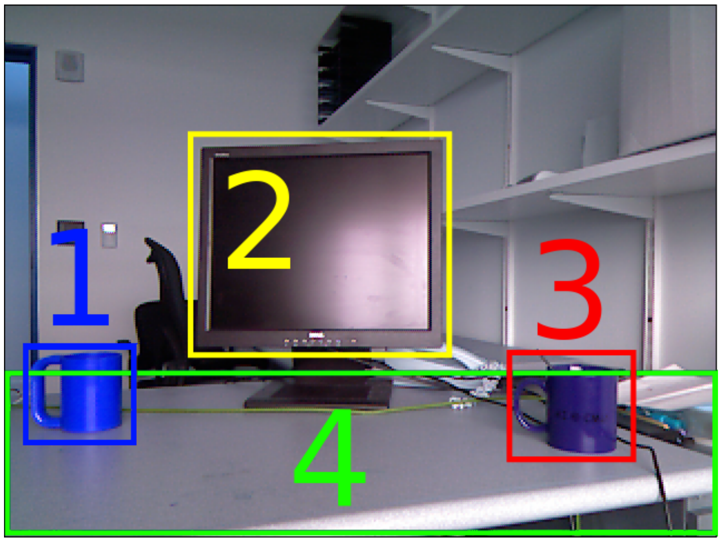
~~Fixed inventory of functions~~

One function per word

door door': Image $\mapsto$ Boolean

in in': (Image, Image) $\mapsto$ Boolean

Joint parsing and perception



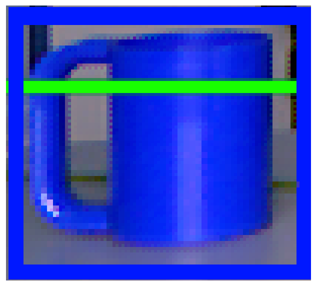
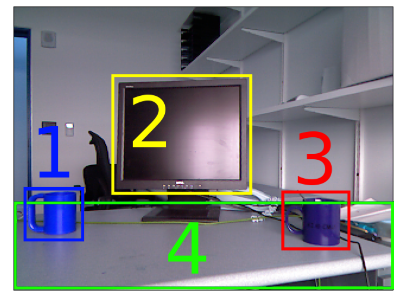
blue	1
mug	1, 3
on	(1,4), (2,4), (3,4)
table	4

blue mug on the table

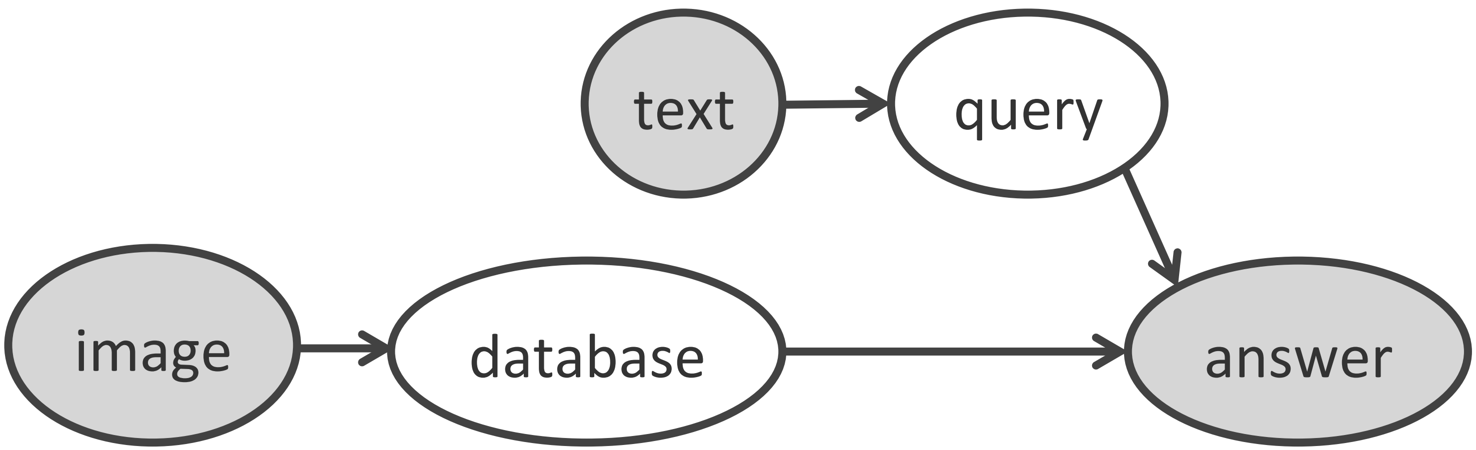
$$\lambda x.\exists y.blue(x) \wedge table(y) \wedge on(x, y)$$

[Krishnamurthy et al. 2013]

Joint parsing and perception

$p\Bigg($  $\Bigg|$ blue mug on the table , 

$\Bigg)$



Joint parsing and perception

Can even learn to compose these grounding functions:

a blue eye

a dark blue eye

a dark pastel blue eye

[Andreas et al. 2013]

The picture so far

Open the pod bay doors	observe text
`close(HAL, podBayDoors)`	predict LF
`doorsClosed = true`	predicted outcome
`doorsClosed = false`	desired outcome
1.0	incur loss

The picture so far

Open the pod bay doors	observe text
`doorsClosed = true`	predicted outcome
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Learning a conditional policy

~~Learn an intermediate meaning representation~~

$$\cancel{p(\mathrm{result}|\mathrm{text}) = \sum_{\mathrm{MR}} p(\mathrm{result}|\mathrm{MR})\; p(\mathrm{MR}|\mathrm{text})}$$

Learn $p(\mathrm{result}|\mathrm{text})$ directly

MDP refresher

- Set S of states
- Set A of actions
- Transition function $T : (S \times A) \rightarrow S$
- Reward function $R : (S \times A) \rightarrow \mathbb{R}$

Lots of algorithms for *learning* a policy
$\pi : S \rightarrow A$ given only black-box interaction

Reading as an MDP

Idea: augment base MDP state space with position in document.

Open the pod bay doors after making me a sandwich

```
{sandwich=true, doorOpen=true},
{sandwich=true, doorOpen=false},
...
```

{ sandwich=true, doorOpen=false
text=Open the pod bay doors ~~after making me a sandwich~~ }

Reading as an MDP

Now just want to pick

$f\left(\begin{array}{l}\texttt{sandwich=true, doorOpen=false} \\ \texttt{text=}\underline{\text{Open the pod bay doors }}\sout{\text{after making me a sandwich}}\end{array}\right) \in$

$$\{a_1, a_2, \ldots\}$$

maximizing reward.

Use your favorite policy learning technique!

[Vogel & Jurafsky 2010, Branavan et al. numerously]

Reading as an MDP

We get pragmatics for free: easy to learn that

Open the pod bay doors

I want you to open the pod bay doors

I'm ready to come inside now

prefer destination states with {doorOpen = true}

Reading as an MDP

But less clear how to handle composition (syntactic or semantic) in this framework:

Open the red door located between two small doors.

Need some way of handling structured action spaces that don't correspond to syntax.

What else is hard?

Event compositionality and coreference:

1. Before disassembling your iPhone, be sure it is powered off
2. Remove the two 3.6mm Pentalobe or Phillips #000 screws next to the dock connector
   …
27. Use the clear plastic pull tab to gently lift the battery out of the iPhone

…

59. De-route the digitizer and LCD cables through the steel inner frame, and remove the display from the iPhone
60. To reassemble your device, follow these instructions in reverse order.

Summary

- Grounding relates language to a model environment with more (or different) structure than formal calculus

- Lots of tools for using environment models to learn semantics without annotated logical forms

Question time