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:

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

where

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

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

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]

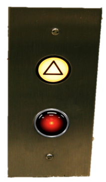
Learn to follow directions given only (source, pairs) and a model environment
[Chen & Mooney 2011, Artzi & Zettlemoyer 2013]

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?

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

Joint parsing and perception

What's a door?

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

Joint parsing and perception

What's a door?

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

Joint parsing and perception

Fixed inventory of functions

Joint parsing and perception

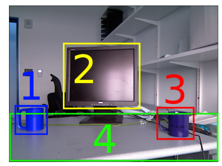
~~Fixed inventory of functions~~

One function per word

door door′: Image ⟼ Boolean

in in′: (Image, Image) ⟼ Boolean

Joint parsing and perception



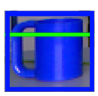
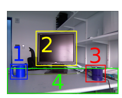
blue	1
mug	1, 3
on	(1,4), (2,4), (3,4)
table	4

blue mug on the table

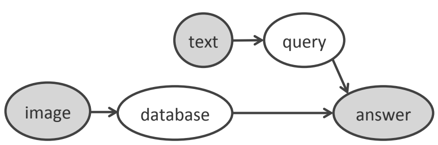
$\lambda x.\exists y.blue(x) \wedge table(y) \wedge on(x, y)$

[Krishnamurthy et al. 2013]

Joint parsing and perception

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

$\Big)$



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

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Learning a conditional policy

~~Learn an intermediate meaning representation~~
$$\cancel{p(\text{result}|\text{text}) = \sum_{\text{MR}} p(\text{result}|\text{MR})\ p(\text{MR}|\text{text})}$$

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

MDP refresher

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

Lots of algorithms for *learning* a policy
π : S → 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

$f($ sandwich=true, doorOpen=false
text=Open the pod bay doors ~~after making me a sandwich~~ $) \in$
$\{a_1, a_2, \ldots\}$

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