

Lecture 1: Course Introduction

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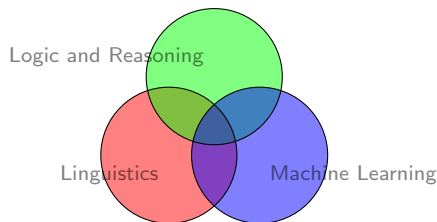
April 10, 2016

Weakly-Supervised Semantic Processing

- ▶ **Semantic Processing:** Formal and computational modeling of natural language meaning.
- ▶ **Weakly Supervised:** Machine learning methods and problems that involve partially annotated data.

Weakly-Supervised Semantic Processing

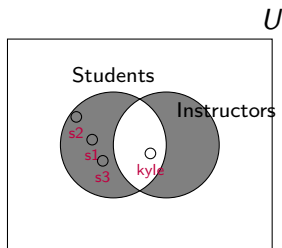
- ▶ **Semantic Processing:** Formal and computational modeling of natural language meaning.
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Formal Modeling of Natural Language Meaning

“I reject the contention that an important theoretical difference exists between formal and natural languages.” Montague (1970)

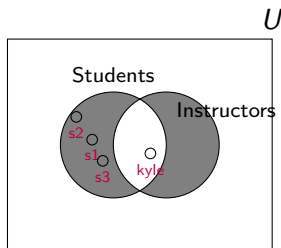
- ▶ **object-language** A student in the room is also an instructor.
- ▶ **meta-language** $\exists x. \text{Students}(x) \wedge \text{Instructors}(x)$



Formal Modeling of Natural Language Meaning

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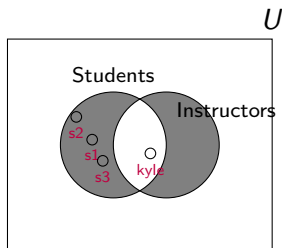
- ▶ **object-language** All instructors in the room are students.
- ▶ **meta-language** $\forall x. \text{Instructors}(x) \rightarrow \text{Students}(x)$



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- ▶ **object-language** Student instructors of this class.
- ▶ **meta-language** $\lambda x. \text{Instructors}(x) \wedge \text{Students}(x)$



Formal Modeling of Natural Language Meaning

Allows us to rigorously define the truth conditions of statements.

- ▶ **object-language** Student instructors of this class.
- ▶ **meta-language** $\lambda x. \text{Instructors}(x) \wedge \text{Students}(x)$

$(\lambda x. \text{Instructors}(x) \wedge \text{Students}(x))(\text{Kyle}) \rightarrow \text{True}$
 $(\lambda x. \text{Instructors}(x) \wedge \text{Students}(x))(\text{Prof. Kuhn}) \rightarrow \text{False}$
 $(\lambda x. \text{Instructors}(x) \wedge \text{Students}(x))(\text{Anna}) \rightarrow \text{False}$

Lambda Functions and Programming (Lisp)

```
(setf Students '(kyle mary anna john)) ;; Students  
(setf Instructors '(kyle))) ;; Instructors
```

```
((lambda (x)  
  (and  
    (member x Students)  
    (member x Instructors)))  
 'kyle)  
;; => True
```


Lambda Functions and Programming (Python)

```
Students = set(["Kyle","Mary","Anna","John"])
Instructors = set(["Kyle"])
```

```
Student_Instructors = lambda x :  
    (x in Students) and (x in Instructors)
```

```
Student_Instructors("Kyle")  
## => True  
Student_Instructors("Mary")  
## => False
```

Logic and Inference

Logic can be used for drawing new conclusions or reasoning with background knowledge.

- ▶ **object-language** All instructors in the room are students.
- ▶ **meta-language** $\forall x. \text{Instructor}(x) \rightarrow \text{Students}(x)$
 - \Rightarrow All **tall** instructors in the room are students.
 - \Rightarrow No instructors here are professors.
 - \Rightarrow Our instructor is a student.
 - \neg Our instructor is a professor.
 - \neg Our instructor is a **famous** professor.
 - ? Our instructor is a **brilliant** student.

Automated Reasoning: Cyc

Justification

Proof 1

Query: Who or what had a motive for the assassination of Hariri?





Answer: Syria

Because:

Detailed Justification:

- Syria had a motive for the assassination of Hariri
 - If
 - some intelligent agent opposes some policy,
 - and some other intelligent agent *VICTIM* is an advocate of that policy,
 - and some other intelligent agent *ADOPTER* is responsible for according with the policy,
 - and it is adopted by *ADOPTER* in some *ADOPT-TYPE*,
 - and some *ACT* prevents *VICTIM* from playing the role "key participants" in *ADOPT-TYPE*,

then that intelligent agent has a motive for *ACT*.

- Since 2000, Lebanon has been responsible for according with Lebanese economic reform. ¹
- Syria has opposed Lebanese economic reform since 2000. ¹
- Syria is an intelligent agent.
- The assassination of Hariri prevents Rafik Hariri from playing the role "key participants" in any adoption of economic reforms by Lebanon.
 - If something dies in some event, then that event prevents that thing from being a deliberate actor in any other event from that point on.
- The assassination of Hariri occurred on February 14, 2005. ²
- Rafik Hariri was killed during the assassination of Hariri. ²
- Adoption of economic reforms by Lebanon is a type of event.
- Rafik Hariri is an advocate of Lebanese economic reform.

Cyc thinks this might be true but can't prove it.

External Sources:

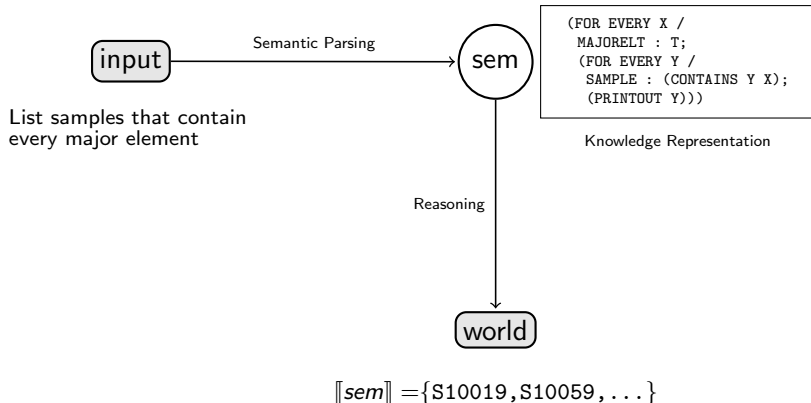
Dismiss

Options

- Confirm...
- Deny...
- Research...

Computational Modeling: The full picture

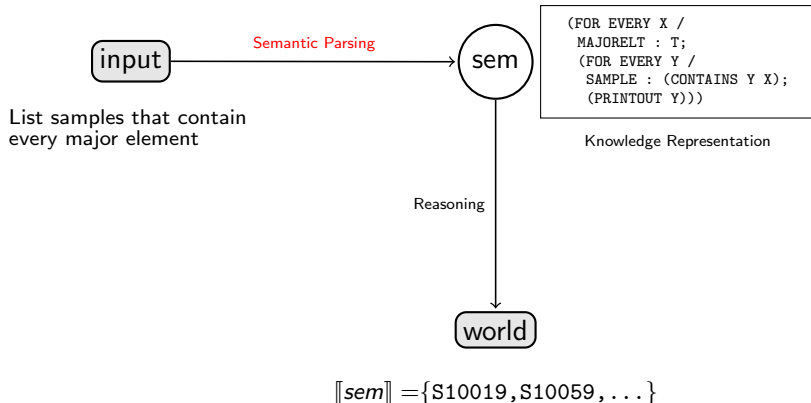
► Standard processing pipeline



Lunar QA system (Woods (1973))

Computational Modeling: The full picture

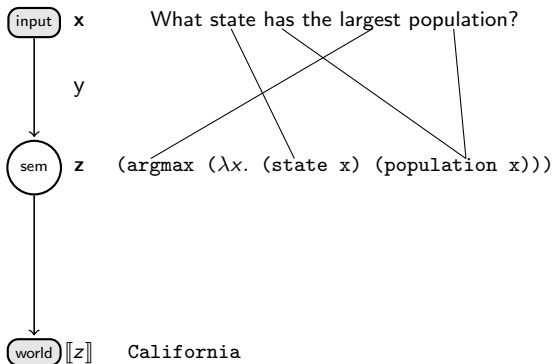
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Lunar QA system (Woods (1973))

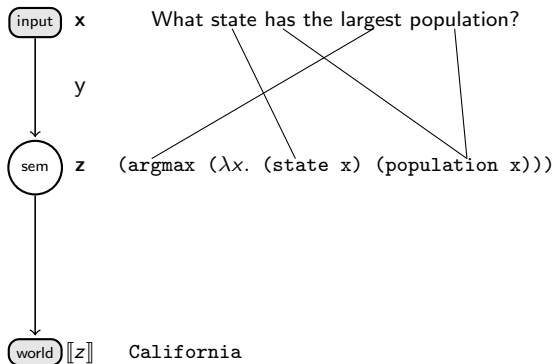
Semantic Parsing: Generating formal representations

- ▶ **Data-driven:** Given data, **learn** a function that can map any given input (x) to a meaning representation (z).
- ▶ What kind of data do we learn from?



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Supervision: Dataset D

Logical Forms: $D = \{(x_i, z_i)\}_{i=1}^N$

Task: learn (latent) y , **translation**

Zettlemoyer and Collins (2009)

Kwiatkowski et al. (2010)

Denotations: $D = \{(x_j, \llbracket z_j \rrbracket)\}_{j=1}^N$

Task: learn z, y , **program synthesis**

Liang et al. (2013)

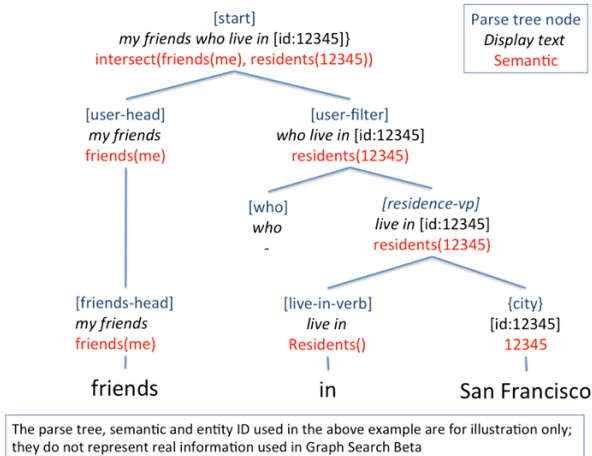
Berant et al. (2013)

Learning with Weak Supervision

- ▶ **Weak-Supervision:** Not all linguistic structure is annotated, learning is autonomous, learning cues are underspecified.
- ▶ **Techniques:** Statistical Machine Translation, Parsing, Structured Classification, Program Induction.

Applications

Applications: Facebook graph search



Applications: Smart Homes (KIT.ai)

PersonalIntel

Lightcast

Parsing

hey microwave please nuke this frozen chicken for me, let's say 4 minutes and 30 seconds

Grammar: microwave

Incremental: ☐

Parse

Parse Tree:

0	task	nuke
1	Optional(Literal("frozen"))	0 Literal("frozen") frozen
2	ZeroOrMore(food)	0 food 0 meat chicken
3	Optional(weight)	(Empty String)
goal	4 Optional(time)	0 time 0 And(number, Literal("minutes"), number, Literal("seconds"))
		0 number 4
		1 Literal("minutes") minutes
		2 number 30
		3 Literal("seconds") seconds

Applications: Open-domain Question-Answering (KITTT.ai)


Web Search Intelligence

Knowledge Base Intelligence

Intent-aware Intelligence

what to see and do in malta?

Answer



Malta

/travel/travel_destination/tourist_attractions (0.57)

Gozo 360° Multivision Show

Casa Rocca Piccola

Megalithic Temples of Malta

Manoel Theatre

The Armoury and the Maritime Museum

Fort Rinella

St. Paul's Catacombs

National Museum of Fine Arts, Malta

Dingli Cliffs

Organizational Matters

Goals

What this course is not:

- ▶ Not a semantics course.
- ▶ Not a pure machine learning or mathematics course.
- ▶ Not a programming course.

But:

- ▶ Will involve knowledge of linguistic semantics.
- ▶ Assumes machine learning and math knowledge.
- ▶ Requires basic programming and algorithmic knowledge.
- ▶ An ability to tie together all these different components.

Formal Requirements

- ▶ Weakly required and supplementary readings.
- ▶ Writing summaries for a subset of required readings.
- ▶ Give a presentation on a research paper.
- ▶ An in-depth term paper about a specific topic.

References I

- Berant, J., Chou, A., Frostig, R., and Liang, P. (2013). Semantic parsing on Freebase from question-answer pairs. In *in Proceedings of EMNLP-2013*, pages 1533–1544.
- Kwiatkowski, T., Zettlemoyer, L., Goldwater, S., and Steedman, M. (2010). Inducing probabilistic CCG grammars from logical form with higher-order unification. In *Proceedings of EMNLP-2010*, pages 1223–1233.
- Liang, P., Jordan, M. I., and Klein, D. (2013). Learning dependency-based compositional semantics. *Computational Linguistics*, 39(2):389–446.
- Montague, R. (1970). Universal grammar. *Theoria*, 36(3):373–398.
- Woods, W. A. (1973). Progress in natural language understanding: an application to lunar geology. In *Proceedings of the June 4–8, 1973, National Computer Conference and Exposition*, pages 441–450.
- Zelle, J. M. and Mooney, R. J. (1996). Learning to parse database queries using inductive logic programming. In *Proceedings of AAAI-1996*, pages 1050–1055.
- Zettlemoyer, L. S. and Collins, M. (2009). Learning context-dependent mappings from sentences to logical form. In *Proceedings of ACL-2009*, pages 976–984.