## Computational Semantics

Deep Processing for NLP Ling 571 February 6, 2017

### Roadmap

- Motivation: Dialog Systems
- Key challenges
- Meaning representation
  - Representational requirements
  - → First-order logic
    - Syntax & Semantics
  - Representing compositional meaning

## Dialogue Systems

User: What do I have on Thursday?

```
Parse:
```

```
    -□ (S
    -□ (Q-WH-Obj
    -□ (Whwd What)
    -□ (Aux do )
    -□ (NP (Pron I))
    -□ (VP/NP (V have)
    -□ (NP/NP *t*)
    -□ (PP (Prep on)
    -□ (NP (N Thursday))))))
```

## Dialogue Systems

- Parser:
  - → Yes, it's grammatical!
  - Here's the structure!
- System: Great, but what am I supposed to DO?!

Need to associate meaning with structure

## Dialogue Systems

```
    ── (Q-WH-Obj Action: check; cal: USER; Date:Thursday
    ── (Whwd What)
    ── (Aux do )
    ── (NP (Pron I)) Cal: USER
    ── (VP/NP (V have)
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## Natural Language

Syntax: Determine the structure of natural language input

Semantics: Determine the meaning of natural language input

### Tasks for Semantics

- Semantic interpretation required for many tasks
  - Answering questions
  - → Following instructions in a software manual
  - → Following a recipe
- Requires more than phonology, morphology, syntax
- Must link linguistic elements to world knowledge

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  - Some support Mubarak.
  - There was a confrontation between two groups.
  - Anti-government crowds are not Mubarak supporters.
  - Etc...

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    - 'kick the bucket'

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  - Developing techniques for semantic analysis, to convert NL strings to meaning representations
  - Developing methods for reasoning about these representations and performing inference from them

### **NLP Semantics Tasks**

- Tasks:
  - → Semantic similarity: words, texts
  - → Semantic role labeling
  - → Semantic analysis
  - → "Semantic parsing"
  - Recognizing textual entailment
  - Sentiment Analysis

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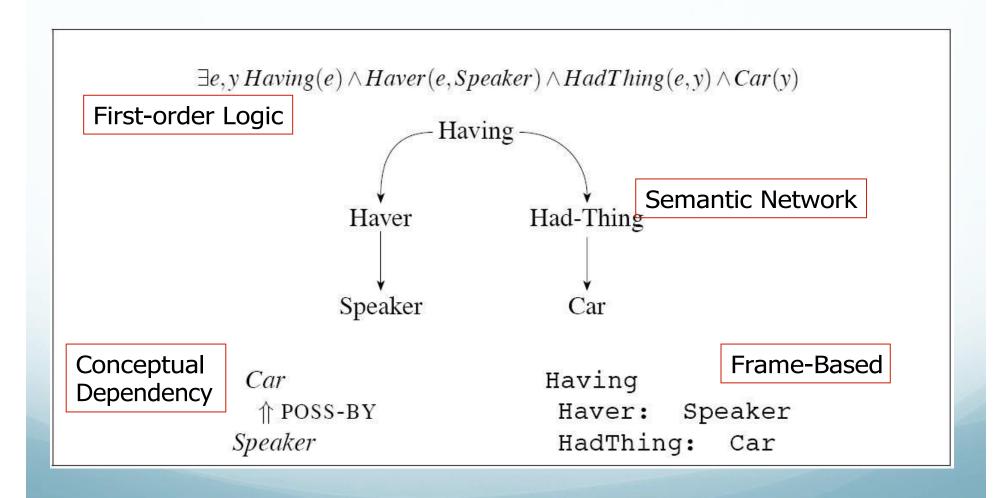
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### Effectively AI-complete

Need representation, reasoning, world model, etc

### Representing Meaning



- All consist of structures from set of symbols
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  - → Properties of objects
  - → Relations among objects
- Can be viewed as:
  - Representation of meaning of linguistic input
  - Representation of state of world
- Here we focus on literal meaning

- Verifiability
- Unambiguous representations
- Canonical Form
- Inference and Variables
- Expressiveness

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- Inference and Variables
  - ── Way to draw valid conclusions from semantics and KB
- Expressiveness
  - Represent any natural language utterance

# Meaning Structure of Language

- Human languages
  - → Display basic predicate-argument structure
  - Employ variables
  - Employ quantifiers
  - Exhibit a (partially) compositional semantics

- Represent concepts and relationships
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- Subcategorization frames indicate:
  - Number, Syntactic category, order of args

- Meaning representation:
  - Provides sound computational basis for verifiability, inference, expressiveness
- Supports determination of propositional truth
- Supports compositionality of meaning
- Supports inference
- Supports generalization through variables

- → FOL terms:
  - Constants: specific objects in world;
    - $\dashv$  A, B, John
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    - ── LocationOf(SFO)
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#### Variables:

— x, e

### **FOL Representation**

#### Predicates:

- Relations among objects
  - ─ United serves Chicago. → →
  - → Serves(United, Chicago)
  - ─ United is an airline. → →
  - Airline(United)

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#### Logical connectives:

- Allow compositionality of meaning
  - Maharani serves vegetarian food and is cheap.

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  - ─ United serves Chicago. → →
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#### Logical connectives:

- Allow compositionality of meaning
  - Frontier serves Seattle and is cheap.
  - → Serves(Frontier, Seattle) / Cheap(Frontier)

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    - ── Indefinite NP, one such object for truth
    - A non-stop flight that serves Pittsburgh

 $\exists xFlight(x) \land Serves(x, Pittsburgh) \land Non-stop(x)$ 

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    - $\exists xFlight(x) \land Serves(x, Pittsburgh) \land Non-stop(x)$
  - → : universal quantifier: "for all"
    - All flights include beverages.

 $\forall xFlight(x) \Rightarrow Includes(x,beverages)$ 

### **FOL Syntax Summary**

```
Fornzula ---- AtomicFornu!a
                       Formula Connective Formula
                       Quantifier Variable . . . Forrnula
                       -. For.nula
                        (Formula)
AtonzicForrnula ----+ Predicate(Terrn ...)
            Ternz ----+ Function(Ter, n ...)
                       C'onstant
                       Variable
    Connective ---+ I\ | \ \ | \ | ==>
      Quantifier ---+ \setminus I \mid 3
       onstant ---- A | VegetarianFood | lvlaharani · · ·
        Vririable \longrightarrow x \mid y \mid \cdots
      Predicate ---- 5erves | Near | ...
       Function ---- LocationOJ | c-uisine( Jj |
```

### Compositionality

- Compositionality: The meaning of a complex expression is a function of the meaning of its parts and the rules for their combination.
  - Formal languages are compositional.
  - → Natural language meaning is largely, though not fully, compositional, but much more complex.
    - How can we derive things like loves(John, Mary) from John, loves(x,y), and Mary?

### Lambda Expressions

- $\dashv$  Lambda ( $\lambda$ ) notation: (Church, 1940)
  - → Just like lambda in Python, Scheme, etc.
  - Allows abstraction over FOL formulas
    - Supports compositionality

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    - $\dashv$  E.g.  $\lambda$  x.P(x) "Function taking x to P(x)"

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 $\dashv \lambda x.P(x) (A) \rightarrow P(A)$ 

### λ-Reduction

- $\dashv$   $\lambda$  -reduction: Apply  $\lambda$  -expression to logical term
  - → Binds formal parameter to term

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 $\lambda x.P(x)(A)$ 
 $P(A)$ 

Equivalent to function application

Lambda expression as body of another

 $\lambda x.\lambda y.Near(x, y)$ 

Lambda expression as body of another

 $\lambda x.\lambda y.Near(x, y)$ 

 $\lambda x.\lambda y.Near(x, y)(Midway)$ 

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 $\lambda y.Near(Midway, y)$ 

 $\lambda y.Near(Midway, y)(Chicago)$ 

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 $\lambda y.Near(Midway, y)$ 

 $\lambda y.Near(Midway, y)(Chicago)$ 

*Near(Midway, Chicago)* 

# Lambda Expressions

- Currying;
  - Converting multi-argument predicates to sequence of single argument predicates
  - ─ Why?

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- Currying;
  - Converting multi-argument predicates to sequence of single argument predicates
  - ─ Why?
    - Incrementally accumulates multiple arguments spread over different parts of parsetree

# Semantics of Meaning Rep.

- Model-theoretic approach:
  - → FOL terms (objects): denote elements in a domain
  - Atomic formulas are:
    - → If properties, sets of domain elements
    - → If relations, sets of tuples of elements

Formulas based on logical operators:

P	Q	$\neg P$	$P \wedge Q$	$P \lor Q$	$P \Rightarrow Q$
False	False	True	False	False	True
False	True	True	False	True	True
True	False	False	False	True	False
True	True	False	True	True	True

Compositionality provided by lambda expressions

## Inference

- Standard AI-type logical inference procedures
  - Modus Ponens
  - Forward-chaining, Backward Chaining
  - Abduction
  - Resolution
  - → Etc,...
- We'll assume we have a prover

# Representing Events

- Initially, single predicate with some arguments
  - → Serves(United, Houston)
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#### Example:

- → The flight arrived.
- → The flight arrived in Seattle
- → The flight arrived in Seattle on Saturday.
- → The flight arrived on Saturday.
- → The flight arrived in Seattle from SFO.
- The flight arrived in Seattle from SFO on Saturday.

## **Events**

• Issues?

## **Events**

- Issues?
  - → Arity how can we deal with different #s of arguments?

- Neo-Davidsonian representation:
  - Distill event to single argument for event itself
  - Everything else is additional predication

 $\exists eArriving(e) \land Arrived(e, Flight) \land Location(e, SEA) \land ArrivalDay(e, Saturday)$ 

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- No extra roles
- Logical connections can be derived

# Meaning Representation for Computational Semantics

- Requirements:
  - Verifiability, Unambiguous representation, Canonical Form, Inference, Variables, Expressiveness
- Solution:
  - → First-Order Logic
    - Structure
    - Semantics
    - Event Representation
- Next: Semantic Analysis
  - Deriving a meaning representation for an input

## Summary

- First-order logic can be used as a meaning representation language for natural language
- Principle of compositionality: the meaning of a complex expression is a function of the meaning of its parts
- $\neg$   $\lambda$  -expressions can be used to compute meaning representations from syntactic trees based on the principle of compositionality
- In the next section, we will look at a syntax-driven approach to semantic analysis in more detail