Semantics vs. Syntax

Syntactic theories and representations focus on the question of which strings in $\mathcal{V}^+$ are in the language.

Semantics is about understanding what a string in $\mathcal{V}^+$ means.

Sidestepping a lengthy and philosophical discussion of what “meaning” is, we’ll consider two meaning representations:

- Predicate-argument structures, also known as event frames
- Truth conditions represented in first-order logic
Motivating Example: Who did What to Who(m)?

- Warren bought the stock.
- They sold the stock to Warren.
- The stock was bought by Warren.
- The purchase of the stock by Warren surprised no one.
- Warren’s stock purchase surprised no one.
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- **Warren** bought the stock.
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- The stock was **bought** by **Warren**.
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In some examples, a separate “event” involving surprise did not occur.
Semantics Roles: Breaking

- Jesse broke the window.
- The window broke.
- Jesse is always breaking things.
- The broken window testified to Jesse’s malfeasance.
Semantic Roles: Breaking

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- The window broke. ?
- Jesse is always breaking things.
- The broken window testified to Jesse’s malfeasance.

A breaking event has a \textbf{Breaker} and a \textbf{Breakee}. 
Semantic Roles: Eating

- Eat!
- We ate dinner.
- We already ate.
- The pies were eaten up quickly.
- Our gluttony was complete.
Semantic Roles: Eating

- **Eat!** (you, listener) ?
- **We ate dinner.**
- **We already ate.** ?
- **The pies were eaten up quickly.** ?
- **Our gluttony was complete.** ?

An **eating** event has an **EATER** and **FOOD**, neither of which needs to be mentioned explicitly.
Abstraction?

\[ \text{Breaker} \overset{?}{=} \text{Eater} \]
Abstraction?

Breaker $\neq$ Eater

Both are actors that have some causal responsibility for changes in the world around them.
Abstraction?

\[ \text{Breaker} \equiv \text{Eater} \]

Both are actors that have some causal responsibility for changes in the world around them.

\[ \text{Breakee} \equiv \text{Food} \]
Abstraction?

\[ \text{Breaker} = \text{Eater} \]

Both are actors that have some causal responsibility for changes in the world around them.

\[ \text{Breakee} = \text{Food} \]

Both are greatly affected by the event, which “happened to” them.
Thematic Roles

(Jurafsky and Martin, 2016, with modifications)

**Agent**  The waiter spilled the soup.

**Experiencer**  John has a headache.

**Force**  The wind blows debris from the mall into our yards.

**Theme**  Jesse broke the window.

**Result**  The city built a regulation-size baseball diamond.

**Content**  Mona asked, “You met Mary Ann at a supermarket?”

**Instrument**  He poached catfish, stunning them with a shocking device.

**Beneficiary**  Ann Callahan makes hotel reservations for her boss.

**Source**  I flew in from Boston.

**Goal**  I drove to Portland.
Verb Alternation Examples: Breaking and Giving

Breaking:

- **Agent**/subject; **Theme**/object; **Instrument**/PP with
- **Instrument**/subject; **Theme**/object
- **Theme**/subject

Giving:

- **Agent**/subject; **Goal**/object; **Theme**/second-object
- **Agent**/subject; **Theme**/object; **Goal**/PP to

Levin (1993) codified English verbs into classes that share patterns (e.g., verbs of throwing: throw/kick/pass).
Remarks

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- By now, it should be clear that the expressiveness of NL (at least English) makes semantic analysis rather distinct from syntax.
- General challenges to analyzing semantic roles:
  - What are the predicates/events/frames/situations?
  - What are the roles/participants for each one?
  - What algorithms can accurately identify and label all of them?
Semantic Role Labeling

Input: a sentence $x$

Output:
- A collection of **predicates**, each consisting of:
  - a label, sometimes called the **frame**
  - a span
  - a set of **arguments**, each consisting of:
    - a label, usually called the **role**
    - a span

In principle, spans might have gaps, though in most conventions they usually do not.
The Importance of Lexicons

Like syntax, any annotated dataset is the product of extensive development of conventions.

Many conventions are specific to particular words, and this information is codified in structured objects called lexicons.

You should think of every semantically annotated dataset as both the data and the lexicon.

We consider two examples.
PropBank
(Palmer et al., 2005)

- Frames are verb senses (later extended, though)
- Lexicon maps verb-sense-specific roles onto a small set of abstract roles (e.g., ARG0, ARG1, etc.)
- Annotated on top of the Penn Treebank, so that arguments are always constituents.
fall.01 (move downward)

- **ARG1**: logical subject, patient, thing falling
- **ARG2**: extent, amount fallen
- **ARG3**: starting point
- **ARG4**: ending point
- **ARGM-LOC**: medium

- Sales fell to $251.2 million from $278.8 million.
- The average junk bond fell by 4.2%.
- The meteor fell through the atmosphere, crashing into Palo Alto.
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- *Sales* fell to $251.2 million from $278.8 million.
- The average junk bond fell by 4.2%.
- The meteor fell through the atmosphere, crashing into Palo Alto.
World Bank president Paul Wolfowitz has fallen back on his last resort.
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fall.10 (fall for a trick; be fooled by)

- **ARG1**: the fool
- **ARG2**: the trick

- Many people keep falling for the idea that lowering taxes on the rich benefits everyone.
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- **ARG2**: the trick

- **Many people** keep falling for the idea that lowering taxes on the rich benefits everyone.
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FrameNet
(Baker et al., 1998)

- Frames can be any content word (verb, noun, adjective, adverb)
- About 1,000 frames, each with its own roles
- Both frames and roles are hierarchically organized
- Annotated without syntax, so that arguments can be anything

https://framenet.icsi.berkeley.edu
change_position_on_a_scale

- **ITEM**: entity that has a position on the scale
- **ATTRIBUTE**: scalar property that the ITEM possesses
- **DIFFERENCE**: distance by which an ITEM changes its position
- **FINAL_STATE**: ITEM’s state after the change
- **FINAL_VALUE**: position on the scale where ITEM ends up
- **INITIAL_STATE**: ITEM’s state before the change
- **INITIAL_VALUE**: position on the scale from which the ITEM moves
- **VALUE_RANGE**: portion of the scale along which values of ATTRIBUTE fluctuate
- **DURATION**: length of time over which the change occurs
- **SPEED**: rate of change of the value
- **GROUP**: the group in which an ITEM changes the value of an ATTRIBUTE
FrameNet Example

Attacks on civilians decreased over the last four months change_position_on_a_scale

ITEM

The ATTRIBUTE is left unfilled but is understood from context (i.e., “frequency”).
Verbs: advance, climb, decline, decrease, diminish, dip, double, drop, dwindle, edge, explode, fall, fluctuate, gain, grow, increase, jump, move, mushroom, plummet, reach, rise, rocket, shift, skyrocket, slide, soar, swell, swing, triple, tumble

Nouns: decline, decrease, escalation, explosion, fall, fluctuation, gain, growth, hike, increase, rise, shift, tumble

Adverb: increasingly
change_position_on_a_scale

event

birth_scenario ... change_position_on_a_scale ... waking_up

change_of_temperature proliferating_in_number

(birth_scenario also inherits from sexual_reproduction_scenario.)
Semantic Role Labeling Tasks

The paper that started it all: Gildea and Jurafsky (2002) used FrameNet lexicon (which includes prototypes, not really a corpus).

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- In 2008 and 2009, the task was cast as a kind of dependency parsing.
- In 2009, seven languages were included in the task.
Methods

Boils down to labeling spans (with frames and roles).

It’s mostly about features.
Example: Path Features

The San Francisco Examiner issued a special edition around noon yesterday.
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Path from a special edition to issued: NP↑VP↓VBD
The span-labeling decisions interact a lot!

- Presence of a frame increases the expectation of certain roles
- Roles for the same predicate shouldn’t overlap
- Some roles are mutually exclusive or require each other (e.g., “resemble”)
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Ensuring well-formed outputs:

- Using syntax as a scaffold allows efficient prediction; you’re essentially labeling the parse tree (Toutanova et al., 2008).
- Others have formulated the problem as constrained, discrete optimization (Punyakanok et al., 2008).
- Also greedy methods (Björkelund et al., 2010) and joint methods for syntactic and semantic dependencies (Henderson et al., 2013).
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Current work:

- Some recent attempts to merge FrameNet and PropBank have shown promise (FitzGerald et al., 2015; Kshirsagar et al., 2015)
Related Problems in “Relational” Semantics

- **Coreference resolution**: which mentions (within or across texts) refer to the same entity or event?
- **Entity linking**: ground such mentions in a structured knowledge base (e.g., Wikipedia)
- **Relation extraction**: characterize the relation among specific mentions

**Information extraction**: transform text into a structured knowledge representation

- Classical IE starts with a predefined schema
- “Open” IE includes the automatic construction of the schema; see http://ai.cs.washington.edu/projects/open-information-extraction
General Remarks

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We’ve now had a taste of two branches of semantics:

▶ Lexical semantics (e.g., supersense tagging)
▶ Relational semantics (e.g., semantic role labeling)
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We’ve now had a taste of two branches of semantics:
- Lexical semantics (e.g., supersense tagging)
- Relational semantics (e.g., semantic role labeling)

Next up, a third:
- Compositional semantics
To-Do List

- Jurafsky and Martin (2016)
- Assignment 4 is due Tuesday.


