Natural Language Processing (CSE 447/547M): Predicate-Argument Semantics

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Semantics vs. Syntax

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

Semantics is about understanding what a string in $\mathcal{V}^\dagger$ *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 (today)
- Truth conditions represented in first-order logic (next time)

Motivating Example: Who did What to Who(m)?

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- They sold the stock to Warren.
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In some examples, a separate "event" involving surprise did not occur.

Semantic Roles: Breaking

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- The broken window testified to Jesse's malfeasance.

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A breaking event has a BREAKER and a BREAKEE.

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- 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.

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$$\textsc{Breakee} \stackrel{?}{=} \textsc{Food}$$

Both are greatly affected by the event, which "happened to" them.

Thematic Roles

(Jurafsky and Martin, 2015, 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; BENEFICIARY/object; THEME/second-object
- AGENT/subject; THEME/object; BENEFICIARY/PP_{to}

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

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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%.
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fall.08 (fall back, rely on in emergency)

- ARG0: thing falling back
- ARG1: thing fallen back on

- World Bank president Paul Wolfowitz has fallen back on his last resort.

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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

DURATION

The ATTRIBUTE is left unfilled but is understood from context (i.e., "frequency").

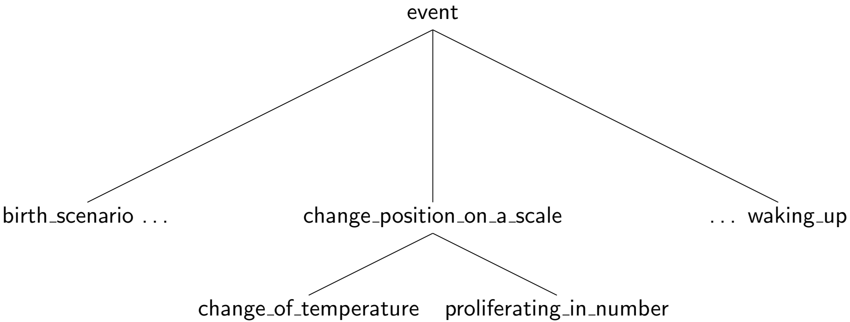
change_position_on_a_scale

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



(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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Conference on Computational Natural Language Learning (CoNLL) shared task in 2004, 2005, 2008, 2009, all PropBank-based.

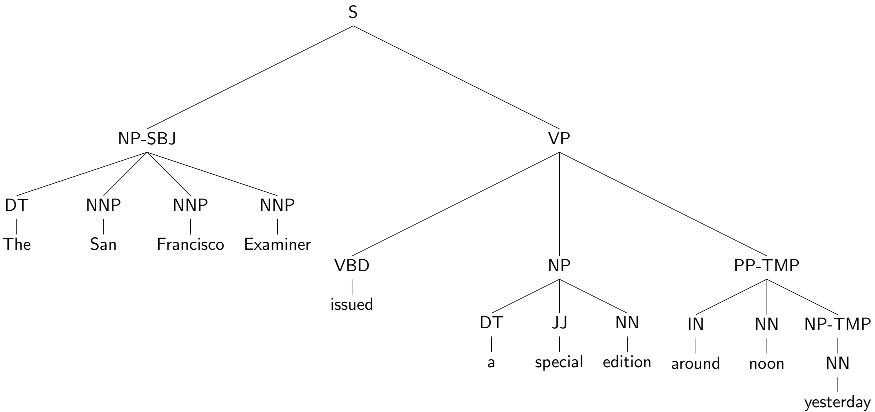
- In 2008 and 2009, the task was cast as a kind of dependency parsing.
- In 2009, seven languages were included in the task.

Methods

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

It's mostly about features.

Example: Path Features



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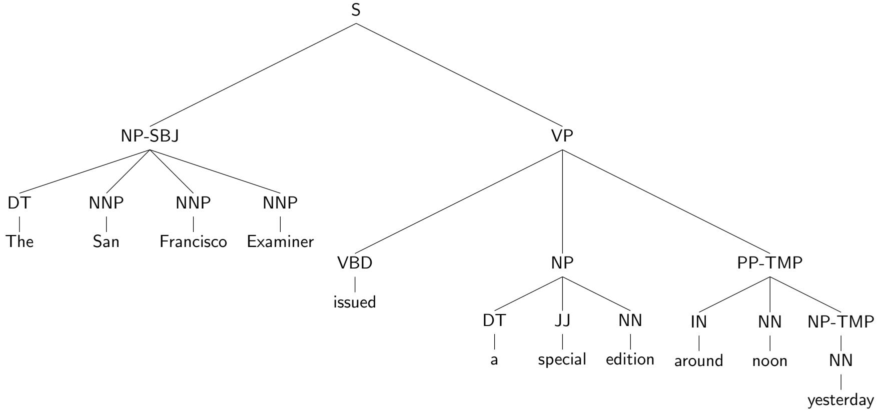

Path from NP-SBJ (The San Francisco Examiner) to issued: NP↑S↓VP↓VBD

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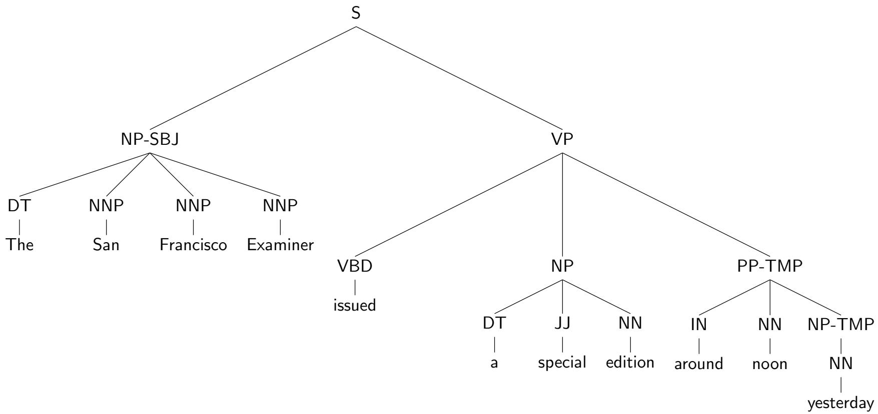

Path from NP (a special edition) to issued: NP↑VP↓VBD

Methods: Beyond Features

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
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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).
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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

Criticisms of semantic role labeling:

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Next up, a third:

- Compositional semantics

If time . . .

Acknowledgment: Nathan Schneider

dragonfly • conveyor belt • finger food • anteater • brain teaser • C++ code • leather belt • birthday • Batman • firehose • fish food • steel wool • jazz musician • staple remover • fisheye • Cookie Monster • Spanish teacher • computer science • student teacher • U.S. Constitution • Facebook status • coffee cake • iron fist • Toy Story • glue gun • baby food • Labor Day • thesis supervisor • flyswatter • dawn raid • paper clip • surge protector • project team • spaghetti monster • tomato sauce • string orchestra • rubber duck • piano key • toothbrush • heartburn • Shannon entropy • elevator button

Your job is to group these into categories and explain those categories to the class; focus on the semantic relationship between the two nouns in each compound. You may wish to think of other compounds to help make your case.

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