L98: Introduction to Computational Semantics

Lecture 3: Event Structure

Weiwei Sun and Simone Teufel

Natural Language and Information Processing Research Group
Department of Computer Science and Technology
University of Cambridge

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The explosive **eruption** of <u>Hunga-Tonga Hunga-Ha'apai</u> **sent** a shockwave **around** the world.

The **event** literally touched every corner of the globe as the pressure wave spread out in all directions to complete a full circumnavigation.

WN S: (n) event (something that happens at a given place and time)

https://www.bbc.co.uk/news/science-environment-60029815

Lecture 3: Event Structure

- 1. Events and participants
- 2. Subcategorisation, arguments and adjuncts
- 3. Sisters, aunts, great-aunts, ...
- 4. Semantic role labeling
- 5. IKEAing annotations



Events and Participants

https://www.bbc.co.uk/news/av/world-asia-60007163

WordNet vs FrameNet

WordNet send VERB.1

S: (v) send, direct (cause to go somewhere)

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FrameNet send.v SENDING

A Sender plans the Path (along with Source and Goal) of a Theme and places it in circumstances such that it travels along this Path under the power of some entity other than the Sender.

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schematic representations of the conceptual structures

Frame Semantics

- **Assumption**: To understand the meanings of the words in a language we must first have knowledge of the semantic frames
- A semantic frame is a schematic representation of an event, object, situation, or relation providing the background structure against which words are understood

from https://framenet2.icsi.berkeley.edu/docs/allslides2.pdf



C. Fillmore

Prelecture exercise

breakfast.v, consume.v, devour.v, dine.v, down.v, drink.v, eat.v, feast.v, feed.v, gobble.v, gulp.n, gulp.v, guzzle.v, have.v, imbibe.v, ingest.v, ingestion.n, lap.v, lunch.v, munch.v, nibble.v, nosh.v, nurse.v, put away.v, put back.v, quaff.v, sip.n, sip.v, slurp.n, slurp.v, snack.v, sup.v, swig.n, swig.v, swill.v, tuck.v

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Frame: INGESTION

An Ingestor consumes food or drink (Ingestibles), which entails putting the Ingestibles in the mouth for delivery to the digestive system. This may include the use of an Instrument. Sentences that describe the provision of food to others are NOT included in this frame.

The wolves DEVOURED the carcass completely .

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Lexical Units

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Frame Elements ___, ___, ...

FrameNet

A computational lexicography project based on the principles of Frame Semantics

- 1,224 frames
- 13,640 lexical units
- 10,542 frame elements
- 1,876 frame-to-frame relations
- 202,229 annotated sentences
- 14% "full-text" annotation

from https://framenet2.icsi.berkeley.edu/docs/allslides2.pdf

Useful

- Provides a shallow semantic analysis (no modality, scope);
- generalises well across some languages;
- can benefit various NLP tasks (IR, QA).

How much did Microsoft pay for Activision Blizzard?

Microsoft Corp (MSFT.O) is buying "Call of Duty" maker Activision Blizzard (ATVI.O) for \$68.7 billion in the biggest gaming industry deal in history as global technology giants stake their claims to a virtual future.

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Old course figure is reused — deep understanding is robust?



Subcategorisation, Arguments and Adjuncts

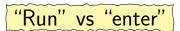
Linguistic relativity



from https://photos.com/featured/swan-and-reflection-cavemanboon.html

Lexicalisation: manner vs path





Subcategorisation

Fact 1: Verbs require a fixed configuration of required participants in the actions they denote:

- (1) a. <u>I</u> baked <u>a cake</u>.
 - b. It is raining.
 - c. <u>I</u> bet you <u>five dollars</u> I can spit further than you.
- (2) a. John ate the steak.
- (3) a. John devoured the steak.
 - b. *John devoured.
- (4) a. I dined.
 - b. *I dined pizza.

⊳expletive

Argument vs adjunct

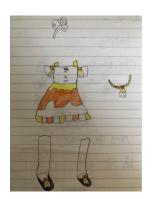
Fact 2: There are also some optional participants (that can sometimes look surprisingly similar):

- (5) a. I waited for hours.
 - b. I waited for the bus.
 - c. I waited for hours for the bus.

ARGUMENT; ADJUNCT

Uniform vs free chosen clothes





Argument vs adjunct

WN S: (n) event (something that happens at a given place and time)

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Arguments and adjuncts differ in the kind of semantic contribution they make

Arguments are selected by their head.

 A head sub-categorizes for its arguments: their presence is often (but not always!) obligatory.

Adjuncts are something additional, not selected by the head.

- An adjunct is optional.
- Time, location

After class

python decorator

Linguistic selection

A selector imposes semantic constraints on its selectees.

Head-complement construction

I have been waiting for the bus. (for-PP argument)

Selector: verb, Selectee: arguments

Head-modifier construction

graceful degradation (adjective adjunct)

I have been waiting for hours. (for-PP adjunct)

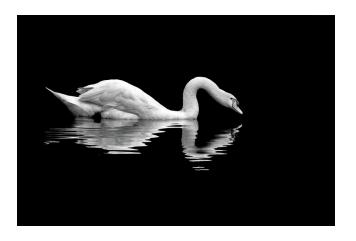
Selector: modifier, Selectee: head

Verb-subject constructions

The water froze within seconds.

Selector: verb, Selectee: subject (most linguists would agree)

Linguistic relativity



 $from \ \texttt{https://photos.com/featured/swan-and-reflection-cave manboon.html}$

Example: "gallying"

The sailors gallied the whales.

• "gally" is an archaic whaling term. What does it mean?

Example: "gallying"

The sailors gallied the whales.

- "gally" is an archaic whaling term. What does it mean?
- Whales gally easily. Has your hypothesis changed?

Hypothesis: strong correlation between syntactic behaviour and semantic class.

Diathesis alternation; Levin (1993)

Definition

Systematic variations in the expression of arguments, sometimes accompanied by changes in meaning (Levin, 1993)

Famous example:

Dative alternation

- (6) a. Doris gives flowers to the headmistress.
 - b. Doris gives the headmistress flowers.

This pattern is meaning-preserving and covers several semantic classes:

- verbs of "future having": advance, allocate, offer, owe, lend
- verbs of "sending": forward, hand, mail
- verbs of "throwing": kick, pass, throw

More diathesis alternations

- (7) a. John cuts the bread.
 - b. The bread cuts nicely. (middle)
 - c. John cut Mary's arm/Mary on the arm (bodypart possessor ascension)
 - d. John cut at the bread (conative)

Other verbs following this pattern?

An example

Diathesis Alternation	touch	hit	cut	break
conative		\otimes	\otimes	
bodypart possessor ascension	\otimes	\otimes	\otimes	
middle			\otimes	\otimes
	pat,	bash,	hack,	crack,
	stroke,	kick,	saw,	rip,
	tickle	pound,	scratch,	scatter,
		tap,	slash	snap
		whack		

Alternations and semantic dimensions

- Bodypart Possessor Ascension Alernation is sensitive to contact separating out *break* as a non-contact verb (pure change of state)
- Conative Alternation is sensitive to both motion and contact separating out touch as a verb of contact (non-change of state)
- Middle Altenation is sensitive to change of state identifying hit as non-change-of-state (contact by motion verb), whereas cut is a verb of "cause of change of state by moving sth int contact with entity that changes state"

Levin's (1993) verb classification

- Based on 79 diathesis alternations
- Covers 3200 verbs in 48 main classes (191 subdivided ones)
- break class contains: break, chip, crack, crash, crush, fracture, rip, shatter, smash, snap, splinter, split and tear.
- Diathesis alternations are difficult to detect automatically
- But: we can use the fact that similar alternations result in similar SCF (subcategorisation frames).

A particularly cool Levin Class: Class 09.7

- They are the so-called "spray/load" verbs.
- (8) a. John loaded the truck with hay.
 - b. John loaded hay on the truck.

Which is which?

There is a semantic difference...





Levin Class 09.7

Locative alternation

- (9) a. I sprayed paint on the wall \rightarrow no more paint left to spray.
 - b. I sprayed the wall with paint ightarrow no more wall left to be sprayed on.

brush cram crowd cultivate dab daub drape drizzle dust hang heap inject jam load mound pack pile plant plaster prick pump rub scatter seed settle sew shower slather smear smudge sow spatter splash splatter spray spread sprinkle spritz squirt stack stick stock strew string stuff swab vest wash wrap

VerbNet and Unified Verb Index

https://uvi.colorado.edu

VerbNet: An extension of Levin (1993)

- Actor
- Agent
- Beneficiary
- Theme
- etc.

PropBank: Annotations of semantic roles

- Arg0/A0: proto-Agent
- Arg1/A1: proto-Patient
- Arg2–6: verb-specific roles
- ArgM-Manner: adjuncts
- ArgM-...

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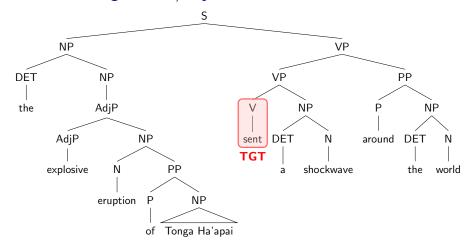
PropBank is based on the Penn TreeBank trees

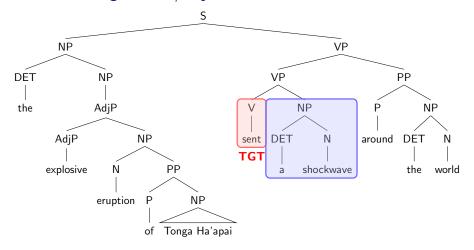
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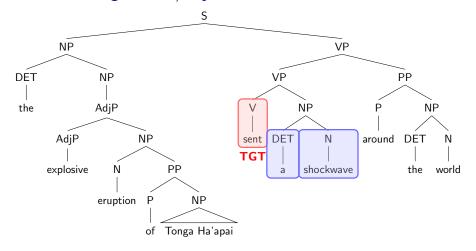


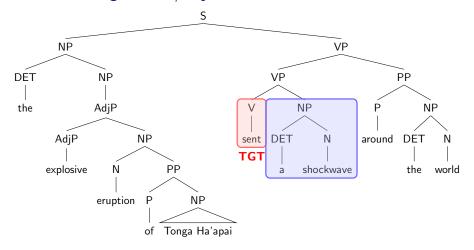
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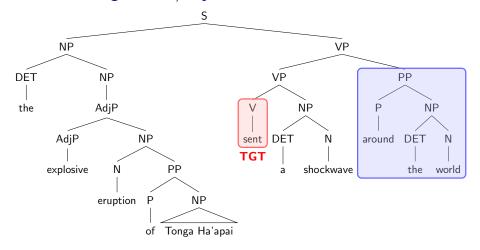
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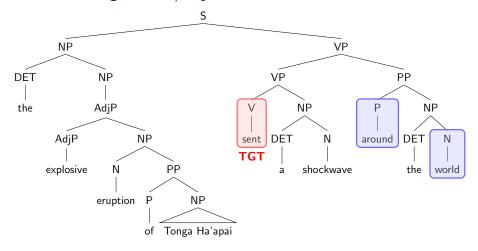


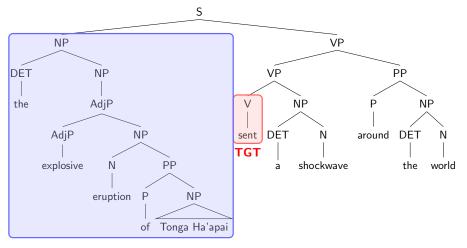


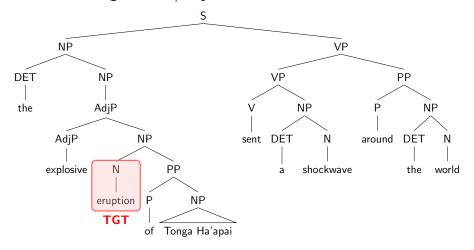






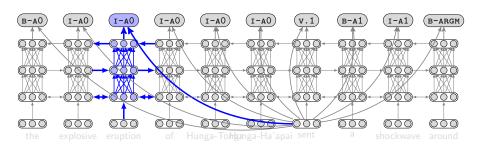


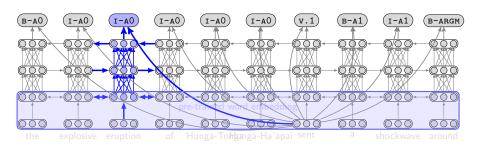


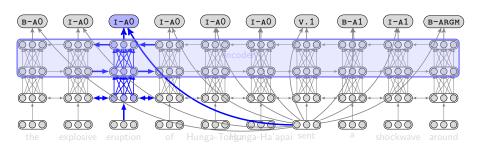


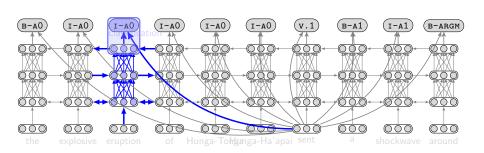


Semantic Role Labeling

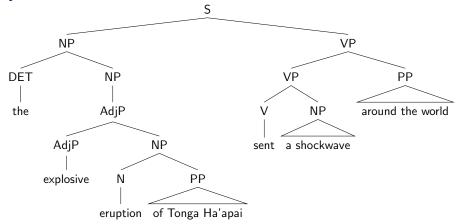


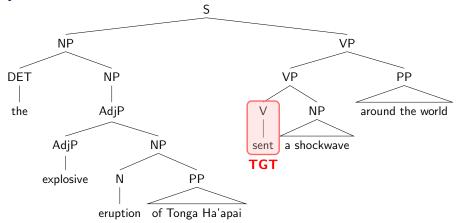


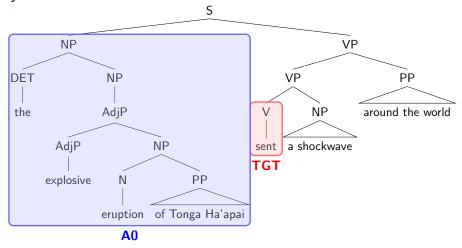


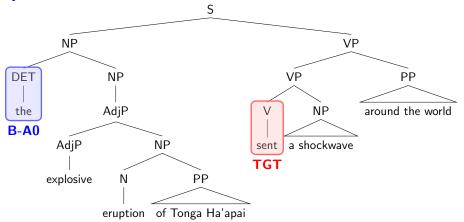


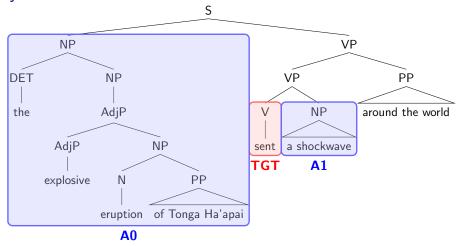
you see this everywhere

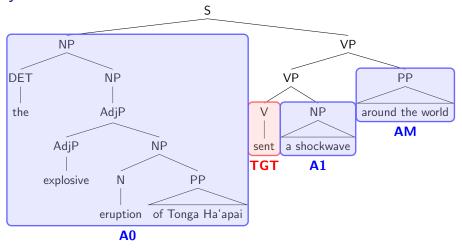


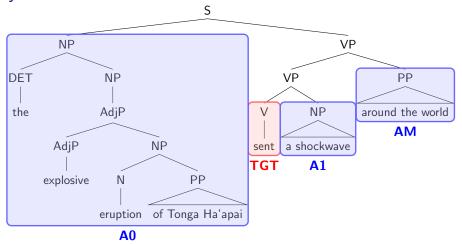




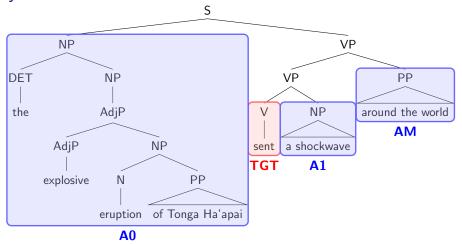








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- Syntactic parsers are not 100%-accurate.
- It is not well-studied how to encode syntactic (sub-)trees.



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IKEAing annotations

from QA-SRL

https://qasrl.org

Our goal is to advance the state of the art in broad-coverage natural language understanding. We believe the way forward is with new datasets that are:

- **Crowdsourced**: modern machine learning methods require big training sets, which means scalability is a top priority.
- Richly structured: in order to improve over powerful representations learned from unlabeled data, we need strong, structured supervision signal.
- Extensible: annotation schemas should be flexible enough to accommodate new semantic phenomena without requiring expensive rounds of reannotation or brittle postprocessing rules.

[...] The common feature between our projects is using natural language to annotate natural language. This results in interpretable structures that can be annotated by non-experts at scale, which have the further advantage of being agnostic to choices of linguistic formalism.



Crowdsoucing

Prize Money Breakdown for the Australian Open 2022

Singles

• Winner: GBP 1,602,037

Doubles

• Winner: GBP 356,026

Mixed doubles

• Winner: GBP 81,582



Extensible

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Nothing as practical as a good theory!

Discussion

Table 1 in Question-Answer Driven Semantic Role Labeling: Using Natural Language to Annotate Natural Language.

Readings

- Jurafsky and Martin. chapter 19. Semantic Role Labeling and Argument Structure.
- https://web.stanford.edu/~jurafsky/slp3/19.pdf.
- Abzianidze and Bos (2019): Thirty Musts for Meaning Banking. https://aclanthology.org/W19-3302/.