Introduction to Computational Semantics

Simon Dobnik CLASP & FloV University of Gothenburg

CS VT-2023: March 23, 2023

Outline

Welcome to the course

Semantics and computational semantics

Logic-based compositional semantics

Data-driven computational semantics



- Computational modelling of meaning of natural language and the usage of such representations in LT
 - o different ways to represent meaning of words, sentences and conversations
 - semantic similarity and compositionality
 - deal with ambiguity and underspecification in NL
 - o draw inferences with these representations
 - apply these methods to LT tasks and applications



- Computational modelling of meaning of natural language and the usage of such representations in LT
 - o different ways to represent meaning of words, sentences and conversations
 - o semantic similarity and compositionality
 - deal with ambiguity and underspecification in NL
 - o draw inferences with these representations
 - o apply these methods to LT tasks and applications
- Formal (top-down) or distributional (bottom up) representations



- Computational modelling of meaning of natural language and the usage of such representations in LT
 - o different ways to represent meaning of words, sentences and conversations
 - o semantic similarity and compositionality
 - deal with ambiguity and underspecification in NL
 - draw inferences with these representations
 - apply these methods to LT tasks and applications
- Formal (top-down) or distributional (bottom up) representations
- Relates to courses
 - Formal linguistics
 - Natural language processing
 - Machine learning for NLP



- Computational modelling of meaning of natural language and the usage of such representations in LT
 - o different ways to represent meaning of words, sentences and conversations
 - o semantic similarity and compositionality
 - deal with ambiguity and underspecification in NL
 - o draw inferences with these representations
 - apply these methods to LT tasks and applications
- Formal (top-down) or distributional (bottom up) representations
- Relates to courses
 - Formal linguistics
 - Natural language processing
 - Machine learning for NLP
- Introduces
 - logic and lambda calculus
 - vector space models and word embeddings
 - neural language models



Teachers







Simon Dobnik

Adam Ek

Nikolai Ilinykh

Practical details



- On-site (with a possibility of online participation)
- Group-work
 - One assignment per week before a seminar or a class
- 5 topics / modules:
 - a lecture (introduction and code tutorial) + a programming assignment
 - o a seminar assignment (read and discuss research papers) + seminar
 - $\circ\;$ a class (answer Qs about the programming assignment) + final submission
- To complete this course:
 - G: pass on all group assignments
 - VG (optional): G + individual course project
- Help is available:
 - Don't be afraid to ask!
 - Use different backgrounds in groups (linguistics, programming, logic, ML)

More information on the course website



- https://canvas.gu.se/courses/64394
- Requirements to pass the course
- Course materials
- Previous course evaluation
- Schedule

Outline

Welcome to the course

Semantics and computational semantics

Logic-based compositional semantics

Data-driven computational semantics





• The study of meaning



- The study of meaning
- meaning, noun (Oxford dictionary)
 - what is meant by a word, text, concept, or action: the meaning of the Hindu word is breakthrough, release' | [mass noun]: the meaning of life.
 - o (mass noun) implied or explicit significance: he gave me a look full of meaning.
 - (mass noun) important or worthwhile quality; purpose: this can lead to new meaning in the life of older people.



- The study of meaning
- meaning, noun (Oxford dictionary)
 - what is meant by a word, text, concept, or action: the meaning of the Hindu word is breakthrough, release' | [mass noun]: the meaning of life.
 - o (mass noun) implied or explicit significance: he gave me a look full of meaning.
 - (mass noun) important or worthwhile quality; purpose: this can lead to new meaning in the life of older people.
- In linguistics: signifier (symbol) \(
 \iff \text{signified (entity)}\) denotational semantics OK, but what is an entity?



- The study of meaning
- meaning, noun (Oxford dictionary)
 - what is meant by a word, text, concept, or action: the meaning of the Hindu word is breakthrough, release' | [mass noun]: the meaning of life.
 - (mass noun) implied or explicit significance: he gave me a look full of meaning.
 - (mass noun) important or worthwhile quality; purpose: this can lead to new meaning in the life of older people.
- In linguistics: signifier (symbol) ←⇒ signified (entity) denotational semantics OK, but what is an entity?
- Some knowledge about the world we have



- But language is sequences of symbols...
- The conditions under which (declarative) sentences are true



- But language is sequences of symbols...
- The conditions under which (declarative) sentences are true
- Lexical semantics
 - "Picasso": pp
 - "is alive": {x: x is alive}



- But language is sequences of symbols...
- The conditions under which (declarative) sentences are true
- Lexical semantics
 - "Picasso": pp
 - "is alive": {x: x is alive}
- Compositional semantics: the interpretations of phrases have to give us correct truth-conditions of declarative sentences
 - "Picasso is alive"pp ∈ {x: x is alive}



- But language is sequences of symbols...
- The conditions under which (declarative) sentences are true
- Lexical semantics
 - "Picasso": pp
 - "is alive": {x: x is alive}
- Compositional semantics: the interpretations of phrases have to give us correct truth-conditions of declarative sentences
 - "Picasso is alive"pp ∈ {x: x is alive}
- Truth conditions underlie the meanings of non-declarative sentences



- But language is sequences of symbols...
- The conditions under which (declarative) sentences are true
- Lexical semantics
 - "Picasso": pp
 - "is alive": {x: x is alive}
- Compositional semantics: the interpretations of phrases have to give us correct truth-conditions of declarative sentences
 - "Picasso is alive"pp ∈ {x: x is alive}
- Truth conditions underlie the meanings of non-declarative sentences
 - Questions: is the corresponding declarative sentence true? What objects provide true and complete answers?



- But language is sequences of symbols...
- The conditions under which (declarative) sentences are true
- Lexical semantics
 - "Picasso": pp
 - "is alive": {x: x is alive}
- Compositional semantics: the interpretations of phrases have to give us correct truth-conditions of declarative sentences
 - "Picasso is alive" pp ∈ {x: x is alive}
- Truth conditions underlie the meanings of non-declarative sentences
 - Questions: is the corresponding declarative sentence true? What objects provide true and complete answers?
 - Imperatives: make the corresponding declarative sentence true

Problem



- Sentences may have the same truth conditions but distinct meanings.
- Sets {x: x is alive} and {x: x is alive and x is not a rock} are identical
- Identical meaning?
 - o Picasso is alive.
 - o Picasso is alive and is not a rock.

Problem



- Sentences may have the same truth conditions but distinct meanings.
- Sets {x: x is alive} and {x: x is alive and x is not a rock} are identical
- Identical meaning?
 - o Picasso is alive.
 - o Picasso is alive and is not a rock.
- (At least) two kinds of meaning: Gottlob Frege

Problem



- Sentences may have the same truth conditions but distinct meanings.
- Sets {x: x is alive} and {x: x is alive and x is not a rock} are identical
- Identical meaning?
 - o Picasso is alive.
 - o Picasso is alive and is not a rock.
- (At least) two kinds of meaning: Gottlob Frege
 - Reference: what sentences refer to
 - Sense: what sentences are about

What is computational semantics?



- Associate situations in the world with semantic representations?
- Associate semantic representations with expressions of natural language?
- Generate linguistic descriptions from semantic representations?
- Use semantics representations of natural language expressions to automate the process of drawing inferences?

Why is CS important for language technology?



We need a fine-grained representation of meaning and be able to draw fine inferences.

More inference means better language understanding, generation, text search, document classification, question answering, translation, dialogue systems, etc.

Understanding mean representations allows us to evaluate LT models and datasets, e.g. bias, BERTology.

Google question answering, I



Google	which countries does the danube flow through									
	All	Maps	News	Shopping	Videos	More	Settings	Tools		
	About 462 000 results (0,69 seconds)									
	The longest river in the European Union, the Danube River is the second-longest river in Europe after Russia's Volga. It begins in the Black Forest region of Germany and runs through 10 countries (Germany, Austria, Slovakia, Hungary, Croatia, Serbia, Romania, Bulgaria, Moldova and Ukraine) on its way to the Black Sea. About the Danube River - Viking River Cruises www.vikingrivercruises.com/cruise-destinations/europe/rivers/danube/about.html									
	About this result • Feedback									
	People also ask									
	Where is the Danube River located?									
	Where does the Danube begin and end?									
	Which way does the Danube river flow?									
	Whe	re is the	Danub	e River bor	n?			~		
								Enadhaak		



Google question answering, II



Which way does the Danube river flow?

DANUBE RIVER FACTS. The longest river within today's European Union – and second-longest on the continent – the Danube River originates in Germany's Black Forest, and flows in a southeasterly direction through central and eastern Europe to the Black Sea.

Danube River Facts | Tauck

www.tauck.com/river-cruises/danube-river-facts.aspx

Search for: Which way does the Danube river flow?

Where is the Danube River born?

Danube River, German Donau, Slovak Dunaj, Hungarian Duna, Serbo-Croatian and Bulgarian Dunay, Romanian Dunärea, Ukrainian Dunay, river, the second longest in Europe after the Volga. It rises in the Black Forest mountains of western **Germany** and flows for some 1,770 miles (2,850 km) to its mouth on the Black Sea.

Danube River | river, Europe | Encyclopedia Britannica www.britannica.com/EBchecked/topic/151250/Danube-River

Search for: Where is the Danube River born?

Feedback

 \wedge

 \wedge



Siri question answering, I



•	•••• Telenor S	ΕŶΰ	15:14	į					
		"Whic	countries is Danube flowing through" tap to edit						
Here is what I found:									
Input interpretation									
ľ	Danube countries Result								
Romania Hungary Austria Serbia Germany Slovakia Bulgaria Croatia Ukraine Moldova (1646k 16) Geographic properties									
	total area	total	1.704×10 ⁶ km² (square kilometers)						
		largest	603 550 km² (square kilometers) (world rank: 45 th) (Ukraine)						
		smallest	33 851 km² (square kilometers) (world rank: 140 th) (Moldova)						
	land area	total	1 653 million km ² (square						
	?		.						



Siri question answering, II







Outline

Welcome to the course

Semantics and computational semantics

Logic-based compositional semantics

Data-driven computational semantics

Formal semantics



- Logical (or rule-based) techniques
- (Montague, 1974) and (Blackburn and Bos, 2005; Eijck and Unger, 2010)
- Two ways of doing this:
 - o model theory
 - proof theory

Natural language and logical forms



- Logical forms are:
 - Unambiguous
 - o Canonical
 - Verifiable
 - Interpretable
 - Allow inference
- But natural language is not like this
 - Challenges of translation
 - What is a good logical form?
 Sufficiently expressive for NL but still having most of the above properties

Logic-based compositional semantics



How do we do it?

- Parse the sentence to syntactic trees
- Each word contributes some semantics
- Compose them to get the semantics of constituents
- Semantics of each constituent can be interpreted in database/model

Simple example with SQL (Structured Query Language): sql.ipynb or sql.py (Bird et al., 2009)

Outline

Welcome to the course

Semantics and computational semantics

Logic-based compositional semantics

Data-driven computational semantics

Lexical meaning and distributional semantics



Distributional hypothesis of lexical meaning

- The meaning of a word is the set of contexts in which it occurs
- Important aspects of the meaning of a word are a function of (can be approximated by) the set of contexts in which it occurs in texts

Lexical meaning and distributional semantics



Distributional hypothesis of lexical meaning

- The meaning of a word is the set of contexts in which it occurs
- Important aspects of the meaning of a word are a function of (can be approximated by) the set of contexts in which it occurs in texts
 - 1. He filled the wampimuk, passed it around and we all drank some.
 - 2. We found a little, hairy wampimuk sleeping behind the tree.

How do we do it?



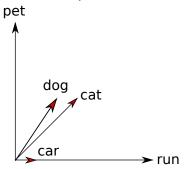
- Collect a corpus of text
- Represent the meaning of words as context-word vectors representing the distribution of a word

	leash	walk	run	owner	pet	bark
dog	3	5	2	5	3	2
cat	0	3	3	2	3	0
car	0	0	1	3	0	0

Semantic similarity



 Use geometric methods on vectors to determine distance in space defined by distributional vectors (cosine similarity)



 Connect distributional tensors of word contexts with types/categories to ensure compositionality

(Turney et al., 2010; Clark, 2015; Mitchell and Lapata, 2010; Coecke et al., 2010)



Word embeddings



• Use ML to learn contextual generalisations: neural language models

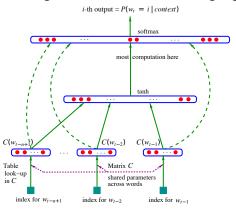


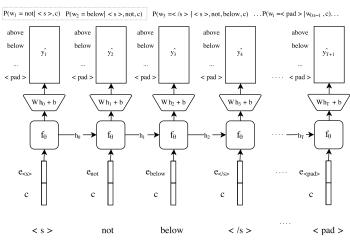
Figure 1: Neural architecture: $f(i, w_{t-1}, \dots, w_{t-n+1}) = g(i, C(w_{t-1}), \dots, C(w_{t-n+1}))$ where g is the neural network and C(i) is the i

(Bengio et al., 2003; Peters et al., 2018; Devlin et al., 2018)



Neural language models





From (Ghanimifard and Dobnik, 2017)



Perception-grounded meaning

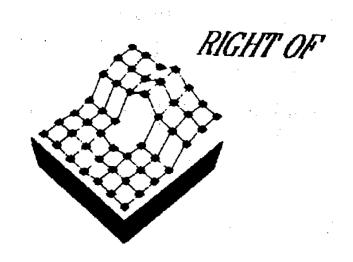


"Go to the pillar and around the table." "Where is the blue chair?"



Representing spatial descriptions



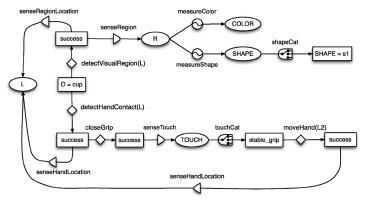


(Logan and Sadler, 1996)



Embodied meaning representations





(Roy, 2005), see also (Harnad, 1990; Barsalou, 2008)



Further reading



- On representation of meaning in NLP (Dobnik et al., 2022)
- Seminar discussion: Rule-based computational semantics

References I



- Lawrence W. Barsalou. 2008. Grounded cognition. Annual Review of Psychology, 59:617–645.
- Yoshua Bengio, Réjean Ducharme, Pascal Vincent, and Christian Janvin. 2003. A neural probabilistic language model. *Journal of Machine Learning Research*, 3(6):1137–1155.
- Steven Bird, Ewan Klein, and Edward Loper. 2009. *Natural language processing with Python*. O'Reilly.
- Patrick Blackburn and Johan Bos. 2005. *Representation and inference for natural language*. A first course in computational semantics. CSLI Publications.
- Stephen Clark. 2015. Vector space models of lexical meaning. In Shalom Lappin and Chris Fox, editors, *Handbook of Contemporary Semantics second edition*, chapter 16, pages 493–522. Wiley Blackwell.
- Bob Coecke, Mehrnoosh Sadrzadeh, and Stephen Clark. 2010. Mathematical foundations for a compositional distributional model of meaning. *arXiv*, arXiv:1003.4394 [cs.CL]:1–34.

References II

- Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2018. BERT: pre-training of deep bidirectional transformers for language understanding. arXiv, arXiv:1810.04805 [cs.CL]:1–14.
- Simon Dobnik, Robin Cooper, Adam Ek, Bill Noble, Staffan Larsson, Nikolai Ilinykh, Vladislav Maraev, and Vidya Somashekarappa. 2022. In search of meaning and its representations for computational linguistics. In *Proceedings of the 2022 CLASP Conference on (Dis)embodiment*, pages 30–44, Gothenburg, Sweden. Association for Computational Linguistics.
- J. van Eijck and Christina Unger. 2010. *Computational semantics with functional programming*. Cambridge University Press, Cambridge.
- Mehdi Ghanimifard and Simon Dobnik. 2017. Learning to compose spatial relations with grounded neural language models. In *Proceedings of IWCS 2017: 12th International Conference on Computational Semantics*, pages 1–12, Montpellier, France. Association for Computational Linguistics.

Stevan Harnad. 1990. The symbol grounding problem. Physica D, 42(1-3):335-346.

linguistic theory and studies in probability

References III

Gordon D. Logan and Daniel D. Sadler. 1996. A computational analysis of the apprehension of spatial relations. In Paul Bloom, Mary A. Peterson, Lynn Nadel, and Merrill F. Garrett, editors, *Language and Space*, pages 493–530. MIT Press, Cambridge, MA.

Jeff Mitchell and Mirella Lapata. 2010. Composition in distributional models of semantics. Cognitive Science, 34(8):1388–1429.

Richard Montague. 1974. Formal Philosophy: Selected Papers of Richard Montague. Yale University Press, New Haven. Ed. and with an introduction by Richmond H. Thomason.

Matthew Peters, Mark Neumann, Mohit Iyyer, Matt Gardner, Christopher Clark, Kenton Lee, and Luke Zettlemoyer. 2018. Deep contextualized word representations. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers), pages 2227–2237, New Orleans, Louisiana. Association for Computational Linguistics.

References IV



Deb Roy. 2005. Semiotic schemas: a framework for grounding language in action and perception. *Artificial Intelligence*, 167(1-2):170–205.

Peter D Turney, Patrick Pantel, et al. 2010. From frequency to meaning: Vector space models of semantics. *Journal of artificial intelligence research*, 37(1):141–188.