Introduction to Formal Semantics
Lecture 1: Meaning and Form

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Overview for today

- Announcements
- Recap: what is semantics and its tasks
- Meaning Representation
- Reasoning, entailments
- Models and Truth Condition
- Direct Compositionality

Reading:

- Winter, Y. (2016). Elements of formal semantics: An introduction to the mathematical theory of meaning in natural language. Edinburgh University Press. (Ch. 1)
- Coppock, E., and Champollion, L. (2021). Invitation to formal semantics. Manuscript, Boston University and New York University (Ch.1)

Important Announcements

- Tutorial Nr 1 on the **4.05.2022**
- Deadline Exercise Nr 1: **03.05.2022 at 4pm**
- Exercise sheet is on the course page and in **Teams**
- upload **PDF** on **Teams**, they will be shared/graded in **Teams**
- for questions contact **Nicolaie** in Teams or mail to `nddascalu@lsv.uni-saarland.de` tag [IDF2022]
- There is a DISCUSSION channel use this one as well!

Semantics

Semantics is the study of the meaning of natural language expressions

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Expressions include phrases and sentences

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Expressions include phrases and sentences

What is the goal of such study?

- provide a workable definition of meaning
- explain semantic relations between expressions

Tasks in Computational Semantics

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

Natural Language Semantics Tasks

- Semantic similarity: words, texts
- Semantic role labelling
- Semantic analysis
- Semantic parsing
- Recognizing textual entailment
- Sentiment Analysis.
- etc.

Complexity of Computational Semantics

- Requires:
  - Knowledge of language: words, syntax, relationships between structure and meaning, composition procedures
  - Knowledge of the world: what are the objects that we refer to, how do they relate, what are their properties?
  - Reasoning: given a representation and a world, what new conclusions – bits of meaning – can we infer?

- Effectively AI-complete
  - Need representation, reasoning, world model, etc

Different Kinds of Meaning
X means Y

- Meaning as definition

Different Kinds of Meaning
X means Y

- Meaning as definition

    A bachelor means an unmarried man

Different Kinds of Meaning
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  What did John mean by waving?

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  Eiffel Tower means

Different Kinds of Meaning
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  A bachelor means an unmarried man

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Representing Meaning

Two issues:

- How can we automate the process of associating semantic representations with expressions of natural language?
- How can we use semantic representations of NL expressions to automate the process of drawing inferences?

Goals:

- Design a semantic representation language
- Figure out how to compute the semantic representation of sentences
- Link this computation to the grammar and lexicon

Representing Meaning

I have a car

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$\boxed{First - Order\ Logic(FOL)}$

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$$\exists e \exists y\ Having(e) \land Haver(e, Speaker) \land HadThing(e, y) \land Car(y)$$

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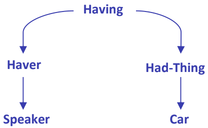

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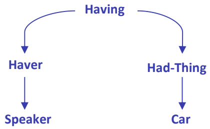

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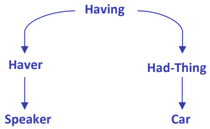

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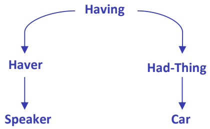

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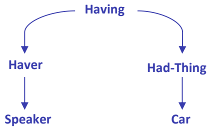

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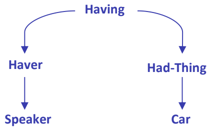

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Speaker

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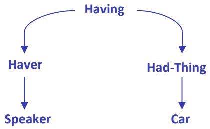

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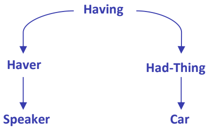

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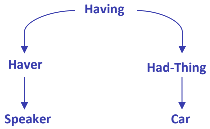

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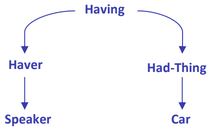

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Haver: Speaker

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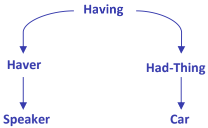

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Car	Having
$\Uparrow POSS - BY$	Haver: Speaker
Speaker	Had-Thing: Car

Meaning Representation

- Structures from set of symbols
  - representational vocabulary
- Symbol structures correspond to:
  - objects
  - 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

Representational Requirements

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

Verifiability

- Use meaning representation to determine the relationship between the meaning of a sentence and the world how we know it

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Example

Query: *Does Maharani serve vegetarian food?*

serve(maharani, vegetarian_food)

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The straightforward way:

- Make it possible for a system to compare, or match, the representation of meaning of an input against the representations (facts) in the KB

Unambiguous Representations

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Example

vague Where is David? - He is in Europe

ambiguous I saw David in my car

Unambiguous Representations

- Ambiguity
  - Lexical (word sense) ambiguity
  - Syntactic (structural) ambiguity
- Disambiguation
  - Structural information of the sentences
  - Word co-occurrence constraints
- Vagueness
  - make it difficult to determine what to do with a particular input based on its meaning representations
  - some word senses are more specific than others

Canonical Form

- Inputs talking the same thing should have the same meaning representation
- Dilemma in internal knowledge representations
  - If the knowledge based contain all possible alternative representations of the same fact
  - How to maintain consistence between various representations is a crucial problem

Overheads on KB maintenance or semantic analysis

Canonical Form

Example

The input query using various propositions:

Canonical Form

Example

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- Does Maharani have vegetarian dish?

Canonical Form

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- Does Maharani serve vegetarian food?

Canonical Form

- Assign the same meaning representation to various propositions for a query
  - simplifies the matching/reasoning tasks
  - however complicates the semantic analysis because of different words and syntax used in the propositions
    - vegetarian fare/dishes/food
    - having/serving
- We can exploit the underlying systematic meaning relationships among word senses and among grammatical constructions to make this task tractable
  - choosing the shared sense among words

Expressiveness

- The meaning representation scheme must be expressive enough to handle an extremely wide range of subject matter

That's an ideal situation!

Inference

- Simple matching of knowledge base will not always give the appropriate answer to the request

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  Can vegetarians eat at Maharani?

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- Such a process is called inference

Entailment

Example

Can we infer (2) from (1), and (4) from (3)?

Entailment

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3. All cats are animals.

Entailment

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Sentence (1) is called the **premise**, or antecedent, of the **entailment**. Sentence (2) is called the **conclusion**, or **consequent**. Any speaker who considers sentence (1) to be true, will consider sentence (2) to be true as well. We say that sentence (1) entails (2), and denote it (1) $\implies$ (2).

Entailment

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(3) does not entail (4), (3) $\not\Longrightarrow$ (4).

Entailment (cont.)

Example

Can we infer (7) from (5) and (6)

Entailment (cont.)

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We say that sentence (5) and (6) entails (7), and denote this $(5) \wedge (6) \implies (7)$.
Arguments whose premises entail conclusions called VALID.

Entailment (cont.)

Example

Can we infer (10) from (8) and (9)

Entailment (cont.)

Example

Can we infer (10) from (8) and (9)

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Entailment (cont.)

Example

Can we infer (10) from (8) and (9)

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Is argument with premises (8) and (9) and conclusion (10) VALID?

Entailment (cont.)

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Is argument with premises (8) and (9) and conclusion (10) VALID?

WHY?

Entailment (cont.)

Sentence ϕ **semantically entails** *a sentence* ψ *iff:*
every situation that makes ϕ *true, makes* ψ *true*
(or: in all worlds in which ϕ *is true,* ψ *is also true)*

Models

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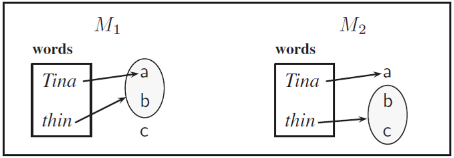
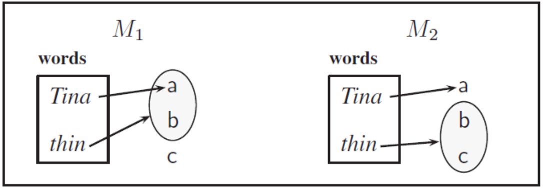


Figure: Models map words and other expressions to abstract mathematical objects. M1 and M2 are models with an entity denotation of Tina and a set denotation of thin. The arrows designate the mappings from the words to their denotations, which are part of the model definition.

Models: denotation

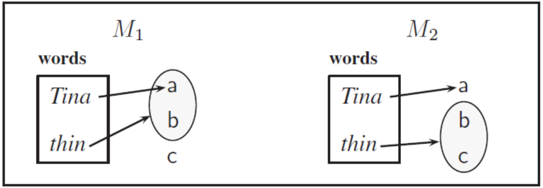
To fresh up your mind:



$$[\![Tina]\!]^{M_1} = a$$
$$[\![Tina]\!]^{M_2} = a$$

$$[\![thin]\!]^{M_1} = \{a, b\}$$
$$[\![thin]\!]^{M_2} = \{b, c\}$$

Models: truth conditions



$[\![\textit{Tina is thin}]\!]^{M_1} = 1$

$[\![\textit{Tina is thin}]\!]^{M_2} = 0$

Models: truth conditionality criterion

A semantic theory T satisfies the **truth-conditional criterion** *(TCC) for sentences S_1 and S_2 if the following two conditions are equivalent:*

1. *Sentence S_1 intuitively entails S_2.*
2. *For all models M in T: $[\![S_1]\!]^M \leq [\![S_2]\!]^M$*

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P	Q	$\neg$ P	P $\wedge$ Q	P $\vee$ Q	P $\implies$ 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

Models: truth values

(1) Tina is tall and thin.

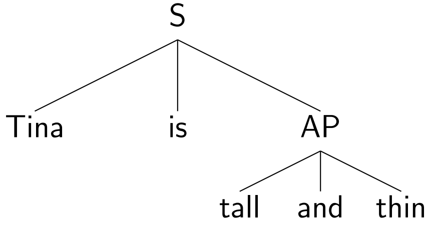
(2) Tina is tall.

(1) $\Longrightarrow$ (2)

Expression	Cat.	Type	Abstract denotation	Denotations in example models with $E = \{a, b, c, d\}$		
				M_1	M_2	M_3
Tina	PN	entity	**tina**	a	b	b
tall	A	set of entities	**tall**	{b,c}	{b,d}	{a,b,d}
thin	A	set of entities	**thin**	{a,b,c}	{b,c}	{a,c,d}
tall and thin	AP	set of entities	AND(**tall**, **thin**)	{b,c}	{b}	{a,d}
Tina is thin	S	truth-value	IS(**tina**, **thin**)	1	1	0
Tina is tall and thin	S	truth-value	IS(**tina**, AND(**tall**, **thin**))	0	1	0

Compositionality

a.



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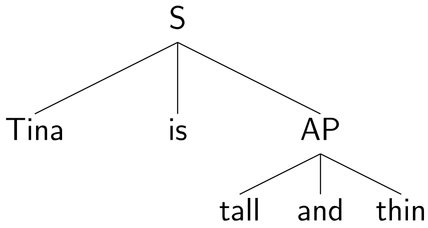
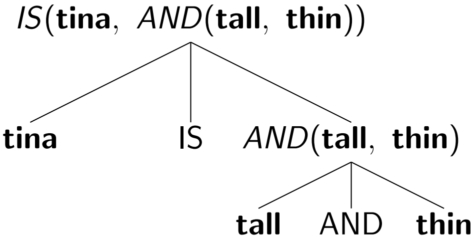


b.



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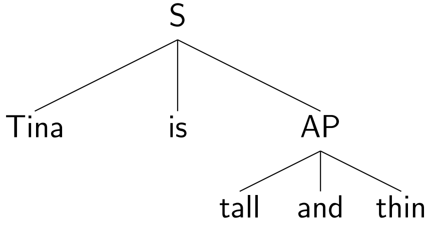

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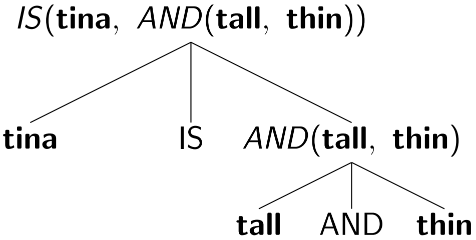


Compositionality: the denotation of a complex expressions is determined by the denotations of its immediate parts and the ways they combine with each other

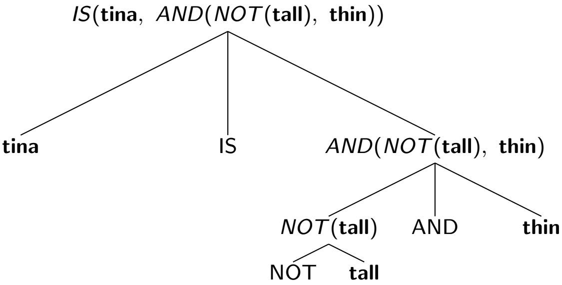
Compositionality: structural ambiguity

(3) Tina is not tall and thin.

Compositionality: structural ambiguity

(4) Tina is not tall and thin.

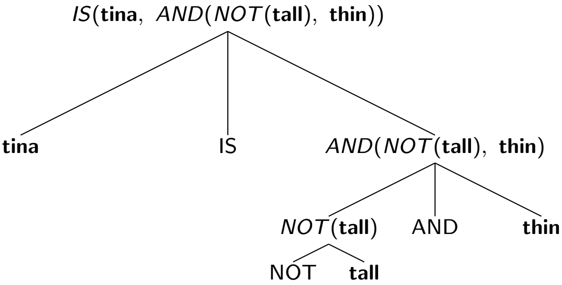
a.



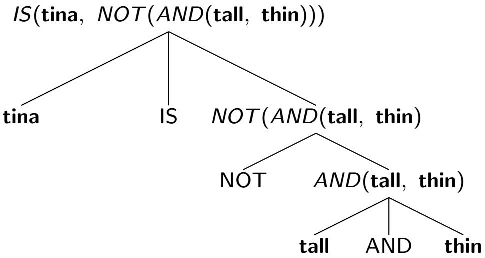
Compositionality: structural ambiguity

(5) Tina is not tall and thin.

a.



b.



Compositionality: structural ambiguity (cont.)

Other types of structural ambiguities:

Compositionality: structural ambiguity (cont.)

Other types of structural ambiguities:
Type 1 : $VP + NP + PP$ (attachment ambiguity)

Compositionality: structural ambiguity (cont.)

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Guna ate an ice cream with fruits from Chennai

Compositionality: structural ambiguity (cont.)

Other types of structural ambiguities:

Type 1 : $VP + NP + PP$ (attachment ambiguity)

Guna ate an ice cream with fruits from Chennai

Possible readings:

Compositionality: structural ambiguity (cont.)

Other types of structural ambiguities:

Type 1 : $VP + NP + PP$ (attachment ambiguity)

Guna ate an ice cream with fruits from Chennai

Possible readings:

1. Guna who is from Chennai ate an ice cream filled with fruits.

Compositionality: structural ambiguity (cont.)

Other types of structural ambiguities:

Type 1 : $VP + NP + PP$ (attachment ambiguity)

Guna ate an ice cream with fruits from Chennai

Possible readings:

1. Guna who is from Chennai ate an ice cream filled with fruits.
2. Guna ate an ice cream filled with fruits and the ice cream is brought from Chennai.

Compositionality: structural ambiguity (cont.)

Other types of structural ambiguities:

Type 1 : $VP + NP + PP$ (attachment ambiguity)

Guna ate an ice cream with fruits from Chennai

Possible readings:

1. Guna who is from Chennai ate an ice cream filled with fruits.
2. Guna ate an ice cream filled with fruits and the ice cream is brought from Chennai.
3. Guna who is from Chennai ate the ice cream with the help of fruits.

Compositionality: structural ambiguity (cont.)

Other types of structural ambiguities:

Type 1 : $VP + NP + PP$ (attachment ambiguity)

Guna ate an ice cream with fruits from Chennai

Possible readings:

1. Guna who is from Chennai ate an ice cream filled with fruits.
2. Guna ate an ice cream filled with fruits and the ice cream is brought from Chennai.
3. Guna who is from Chennai ate the ice cream with the help of fruits.
4. Guna with the help of fruits ate the ice cream which is brought from Chennai.

Compositionality: structural ambiguity (cont.)

Other types of structural ambiguities:

Type 1 : $VP + NP + PP$ (attachment ambiguity)

Guna ate an ice cream with fruits from Chennai

Possible readings:

1. Guna who is from Chennai ate an ice cream filled with fruits.
2. Guna ate an ice cream filled with fruits and the ice cream is brought from Chennai.
3. Guna who is from Chennai ate the ice cream with the help of fruits.
4. Guna with the help of fruits ate the ice cream which is brought from Chennai.

Type 2 : $Gerund + VP$ Visiting relatives can be boring.

Compositionality: structural ambiguity (cont.)

Other types of structural ambiguities:

Type 1 : $VP + NP + PP$ (attachment ambiguity)

Guna ate an ice cream with fruits from Chennai

Possible readings:

1. Guna who is from Chennai ate an ice cream filled with fruits.
2. Guna ate an ice cream filled with fruits and the ice cream is brought from Chennai.
3. Guna who is from Chennai ate the ice cream with the help of fruits.
4. Guna with the help of fruits ate the ice cream which is brought from Chennai.

Type 2 : $Gerund + VP$ Visiting relatives can be boring.

Type 3 : $VP + NP + more \ldots than + NP$ Jerry loves the fans more than Sally.

Compositionality: structural ambiguity (cont.)

Other types of structural ambiguities:

Type 1 : $VP + NP + PP$ (attachment ambiguity)

Guna ate an ice cream with fruits from Chennai

Possible readings:

1. Guna who is from Chennai ate an ice cream filled with fruits.
2. Guna ate an ice cream filled with fruits and the ice cream is brought from Chennai.
3. Guna who is from Chennai ate the ice cream with the help of fruits.
4. Guna with the help of fruits ate the ice cream which is brought from Chennai.

Type 2 : $Gerund + VP$	Visiting relatives can be boring.
Type 3 : $VP + NP + more \ldots than + NP$	Jerry loves the fans more than Sally.
Type 4 : $VP + NP + PP1 + PP2$	Put the bottle on the table in the kitchen.

Compositionality: structural ambiguity (cont.)

Other types of structural ambiguities:

Type 1 : $VP + NP + PP$ (attachment ambiguity)

Guna ate an ice cream with fruits from Chennai

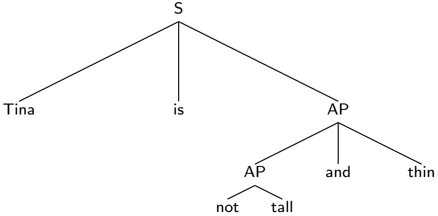
Possible readings:

1. Guna who is from Chennai ate an ice cream filled with fruits.
2. Guna ate an ice cream filled with fruits and the ice cream is brought from Chennai.
3. Guna who is from Chennai ate the ice cream with the help of fruits.
4. Guna with the help of fruits ate the ice cream which is brought from Chennai.

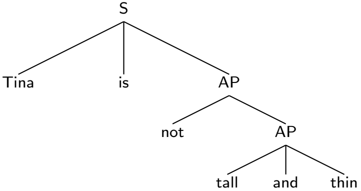
Type 2 : $Gerund + VP$	Visiting relatives can be boring.
Type 3 : $VP + NP + more \ldots than + NP$	Jerry loves the fans more than Sally.
Type 4 : $VP + NP + PP1 + PP2$	Put the bottle on the table in the kitchen.
Type 5 : $NP + Adj.\ Clause$	Tom got into the car which was parked behind the house.

Quizz for Today: Please write down and hand over to me

a.



b.



Expression	Denotations in example models with $E = \{a, b, c, d\}$		
	M_1	M_2	M_3
Tina	a	b	b
tall	{b,c}	{b,d}	{a,b,d}
thin	{a,b,c}	{b,c}	{a,c,d}
not tall			
[not tall] and thin			
Tina is [[not tall] and thin]			
tall and thin			
not [tall and thin]			
Tina is [not [tall and thin]]			
Tina is thin			