Seminar : Recent Developments in Computational Semantics

Introduction

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Summer 2012

Organizational Matters (1)

- Organization of the Seminar
  - Presentation
  - Seminar Paper
  - Oral Exam
  - Active Participation
- Deadlines
  - Registration: 01.07.
  - Seminar paper draft: 01.09.
  - Seminar paper final: 01.10.
- Grading

Organizational Matters (2)

- Schedule
- Background Reading

Basic Problems in Computational Semantics

- Lexical Semantics
  - How do we model word meaning?
- Sentence Semantics
  - How do we model sentence meaning?
- Semantic Composition/ Construction
  - How do we compute sentence meaning from word meaning?
- Disambiguation, Ambiguity Resolution
  - How do we compute the utterance meaning from linguistic content and context information?
- Inference Modeling
  - How do we obtain relevant information from meaning representations?

Logic-Based Semantics

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Computing Truth Values (1)

$[\![work(bill)]\!]^{M,g} = 1$ iff $V_M(bill) \in V_M(work)$

Let M=M1:

$V_{M1}(bill) \in V_{M1}(work)$,

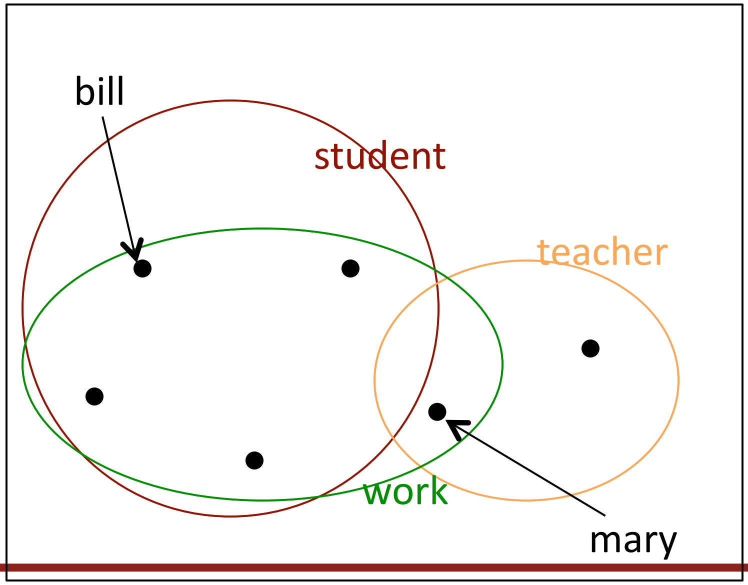
so $[\![work(bill)]\!]^{M1,g} = 1$

Let M=M2:

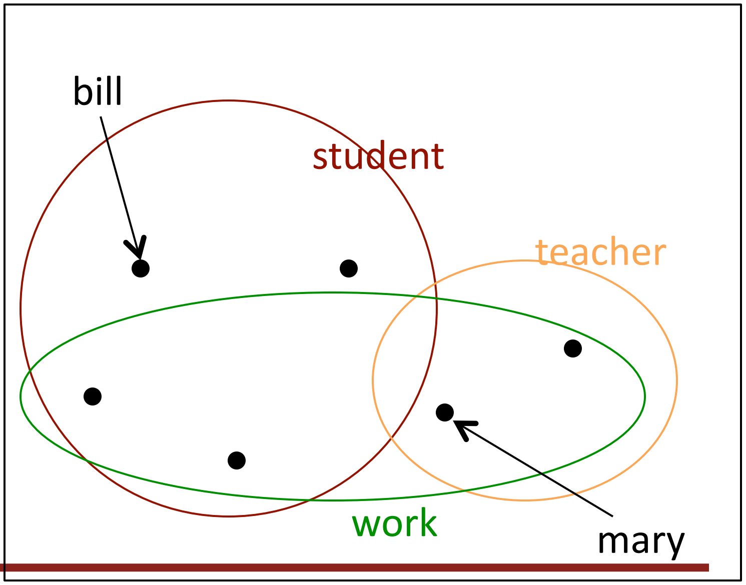
$V_{M2}(bill) \notin V_{M2}(work)$,

so $[\![work(bill)]\!]^{M2,g} = 0$

M1



M2



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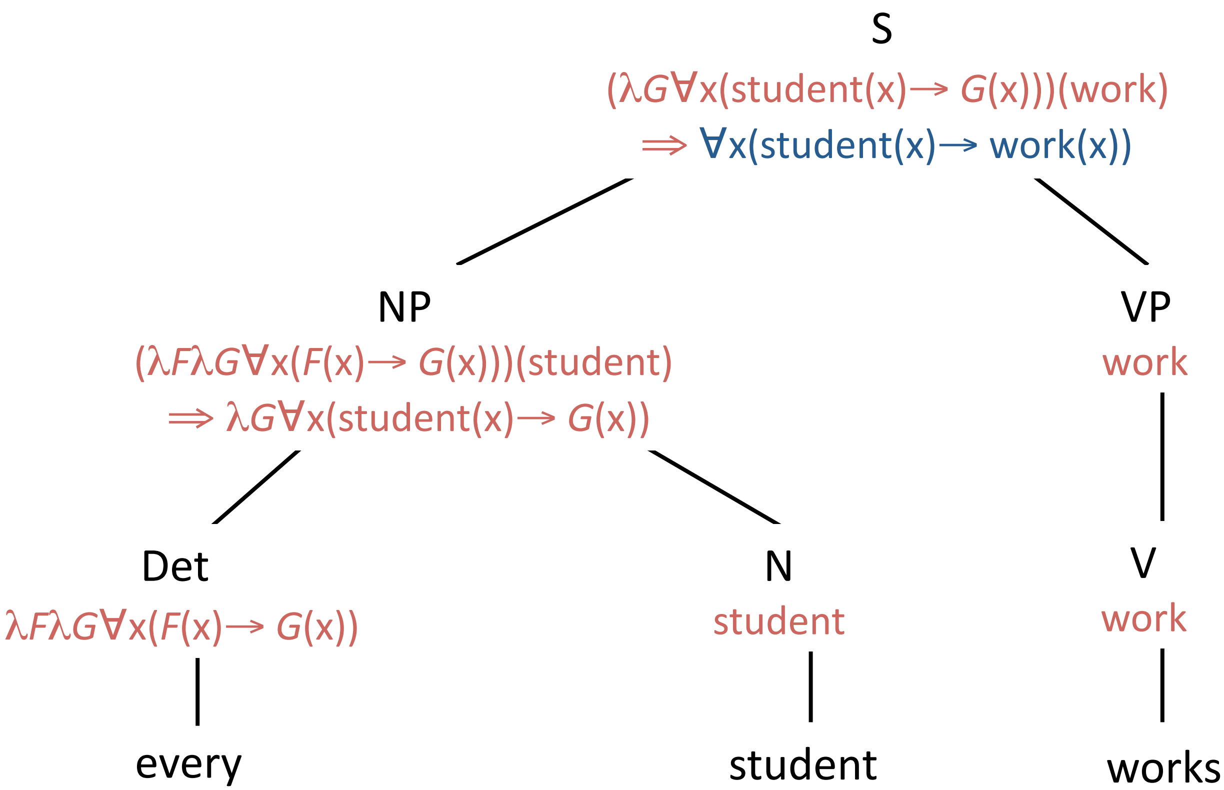
Semantic Composition



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Data-Intensive Semantics

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Ambiguity Resolution

- Yesterday night we went to a restaurant;
  I ordered an expensive dish.

Ambiguity Resolution

- Yesterday night we went to a restaurant;
  I ordered an expensive dish.

- *The box was in the pen*
  The pen was in the box

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Acquisition of Inference Patterns from Corpora

Table 3. The top-20 most similar paths to "X solves Y".

Y is solved by *X*	*Y* is resolved in *X*
X resolves *Y*	*Y* is solved through *X*
X finds a solution to *Y*	*X* rectifies *Y*
X tries to solve *Y*	*X* copes with *Y*
X deals with *Y*	*X* overcomes *Y*
Y is resolved by *X*	*X* eases *Y*
X addresses *Y*	*X* tackles *Y*
X seeks a solution to *Y*	*X* alleviates *Y*
X do something about *Y*	*X* corrects *Y*
X solution to *Y*	*X* is a solution to *Y*

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Major Seminar Topics

- Similarity Modeling in distributional semantics
- Word-sense disambiguation and discrimination
- Semantic role labeling
- Acquisition of paraphrases, inference patterns and script information
- Approaches using latent variables
- Processing of temporal information in texts
- Grounding of distributional meaning in the (visual) world

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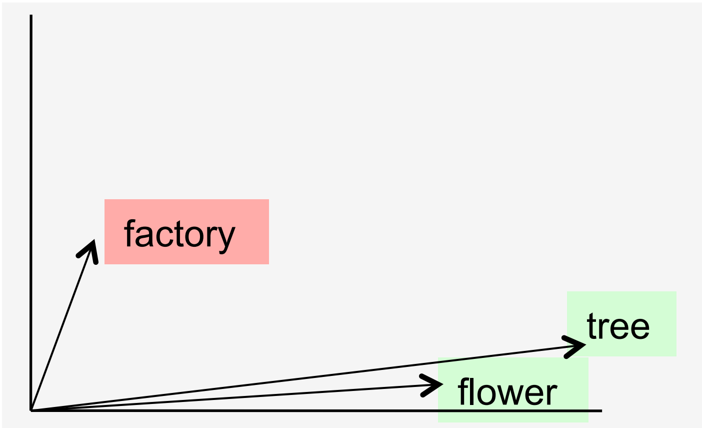
Distributional Similarity

$$sim\ (a,b) = \cos\left(\vec{a},\vec{b}\right)$$

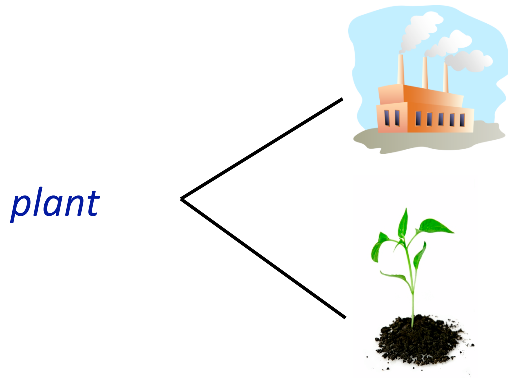
	factory	flower	tree	water	fork
...	...	...	...	...	...
grow	15	147	330	106	3
garden	5	200	198	118	17
worker	279	0	5	18	0
production	102	6	9	28	0
wild	3	216	35	30	0
...	...	...	...	...	...

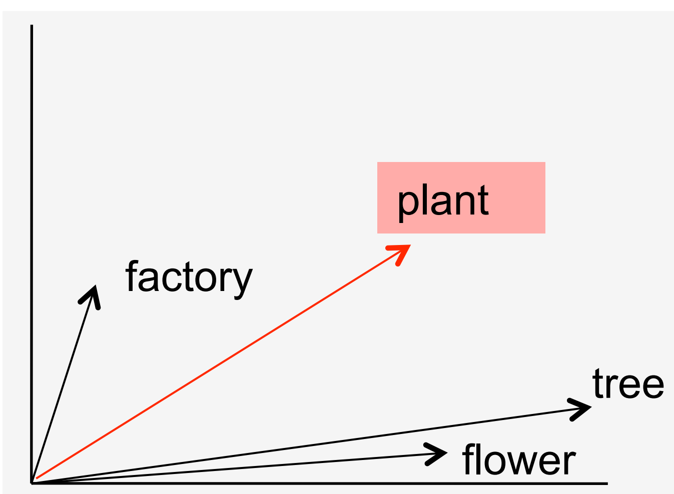


Distributional Similarity: Challenges

- Contextual variation of meaning

Kontextualisierung



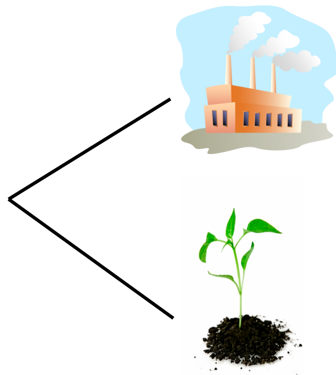


	plant	factory	flower	tree	water	fork
...	...	...	...	...	...	...
grow	517	15	147	330	106	3
garden	316	5	200	198	118	17
worker	84	279	0	5	18	0
production	130	102	6	9	28	0
wild	96	3	216	35	30	0
...	...	...	...	...	...	...

$$\vec{v}_{water}(plant) = \sum_{w} f(plant,w) * f(water,w) * \vec{e}_w$$

Kontextualisierung

plant



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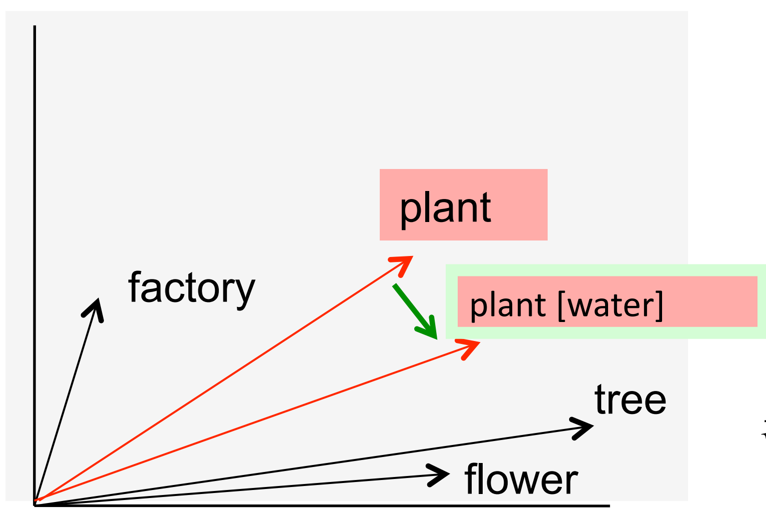
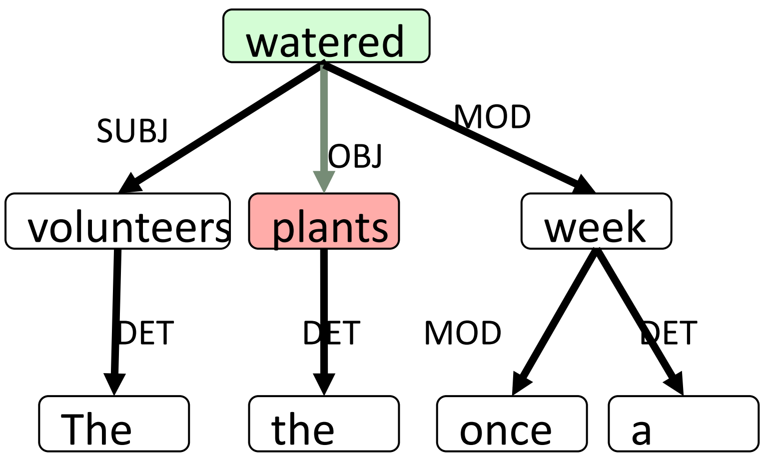


$$\vec{v}_{water}(plant) = \sum_{w} f(plant,w) * f(water,w) * \vec{e}_w$$

Distributional Similarity: Challenges

- Contextual variation of meaning
- What is similarity?
  - car – automobile
  - car – motor vehicle
  - car – drive
  - car – gas – highway

Semantic Similarity: Integrating Syntactic Information



	plant	factory	flower	water	fork
...	...	...	...	...	...
(grow, -SUBJ)	114	1	17	4	0
(close, -OBJ)	36	30	1	2	0
(car, MOD)	71	38	0	0	0
(fresh, MOD)	5	0	65	224	0
(deep, MOD)	1	0	9	166	4
(company, -MOD)	3	1	0	216	0
(worker, -MOD)	2	128	0	6	0
(wild, MOD)	45	0	167	11	0
(like, -OBJ)	42	13	107	128	8
(water, -OBJ)	23	0	5	0	0
...	...	...	...	...	...

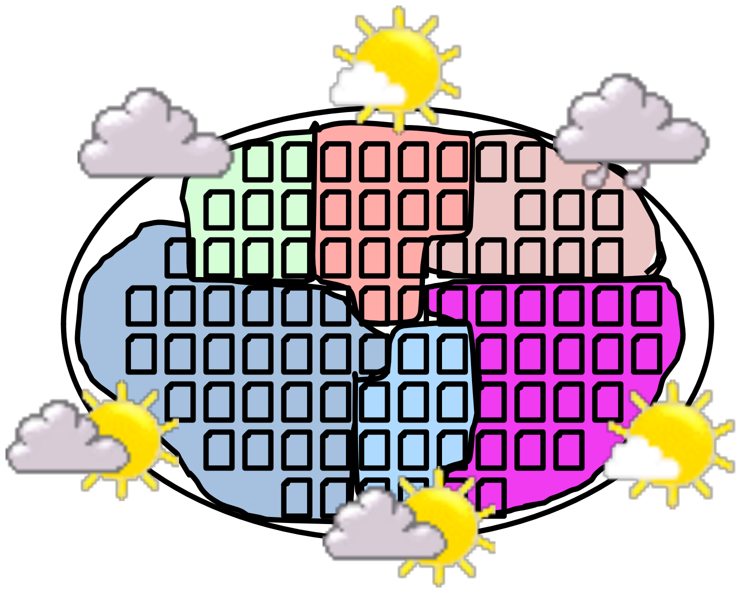
Distributional Similarity: Challenges

- Contextual variation of meaning
- What is similarity?
- Distributional Semantics and Compositionality?

Distributional Similarity: Challenges

- Contextual variation of meaning
- What is similarity?
- Distributional Semantics and Compositionality?
- Distributional Semantics and Truth?
  - Cloudy – Sunny – Overcast

Linking Documents to World States



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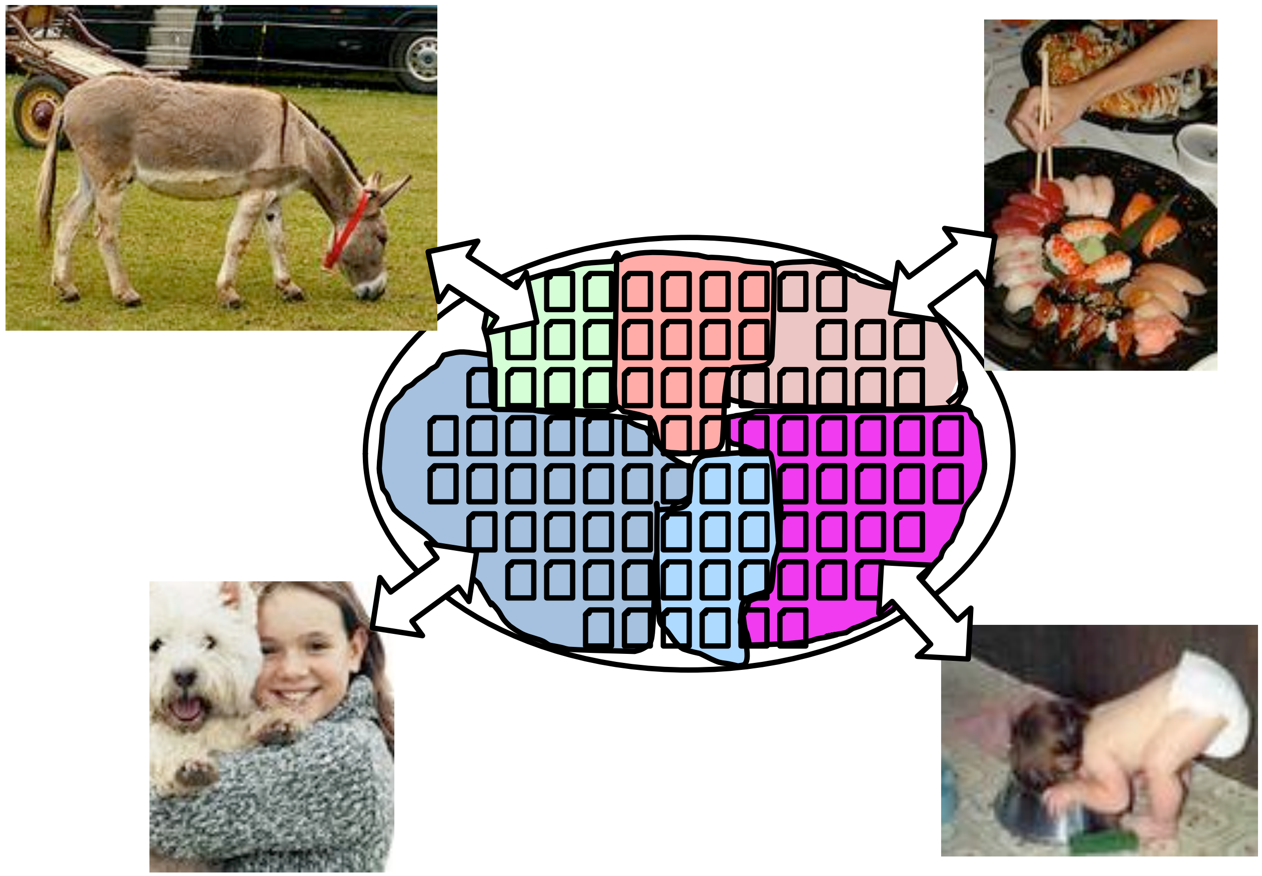

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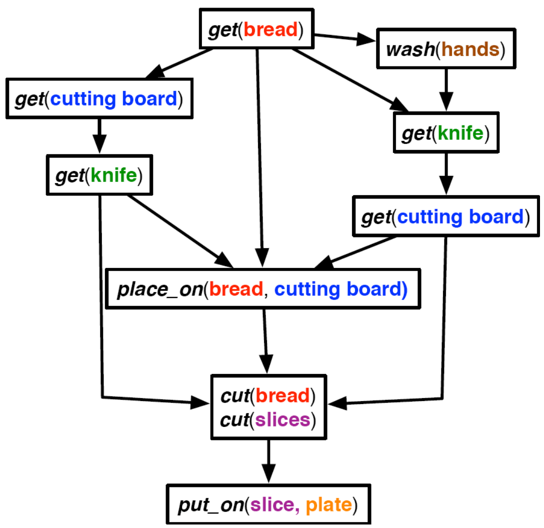
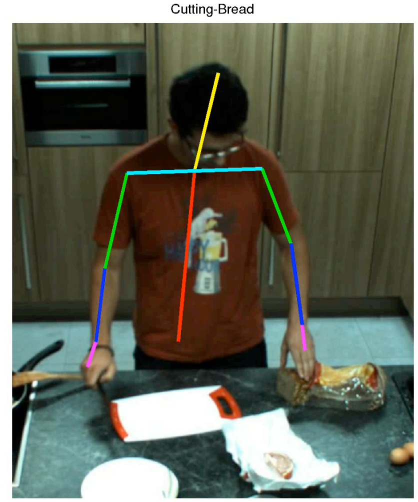


Cutting-Bread



Distributional Similarity: Challenges

- Contextual variation of meaning
- What is similarity?
- Distributional semantics and compositionality?
- Distributional semantics and truth?
- Are co-occurrence frequencies meanings?

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Background Reading Distributional Semantics:

P. D. Turney and P. Pantel (2010) "From Frequency to Meaning: Vector Space Models of Semantics", JAIR

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Topics

- Distributional Semantics and Contextualization

  Mitchell&Lapata 2008, Erk&Pado 2008 (Thater et al. 2010)

- Acquisition of Paraphrases and Inference Patterns

  Lin&Pantel 2001, (Szpektor et al. 2004),Some of: Bhagat et al. 2007, Pantel et al. 2007,Geffet&Dagan 2005