Event Knowledge in Compositional Distributional Semantics

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Contents

Aim: investigate the use of **distributional methods** in a model of **compositional meaning** that is both **linguistically motivated** and **cognitively inspired**.

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  - compositional meaning in distributional semantics
  - linguistic and cognitive models
- Model
  - description
  - evaluation
  - error analysis
- Discussion

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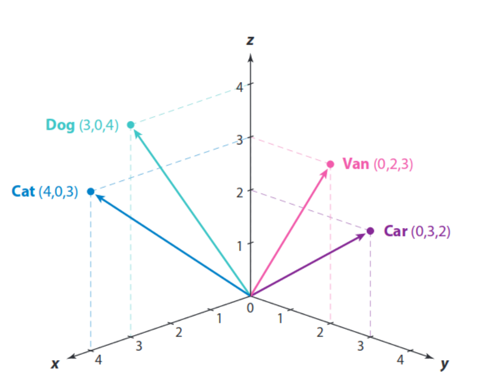
Background

Distributional hypothesis

"what people know when they know a word is not how to recite its dictionary definition – they know how to use it (when to produce it and how to understand it) in everyday discourse" (Miller e Charles 1991)



Compositional Distributional Semantics

Composing word representations into larger phrases and sentences notoriously represents a big challenge for distributional semantics[1].

Various approaches have been proposed ranging from simple arithmetic operations on word vectors, to algebraic compositional functions on higher-order objects, as well as neural networks approaches[2]

Vector addition still shows reasonable performances overall[3], its success being quite puzzling from the linguistic and cognitive point of view.

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[1] Lenci 2018

[2] Mitchell e Lapata 2008; Coecke, Clark e Sadrzadeh 2010; Socher, Manning e Ng 2010; Mikolov et al. 2013; Baroni, Bernardi e Zamparelli 2014

[3] or at least it was when we started this work

Accettability vs. Plausibility

The problem of compositionality has for long been addressed as a distinction between *possible* and *impossible* sentences:

(1) The musician plays the flute in the theater.

(2) * The nominative plays the global map in the pot.

The first class subsumes a great amount of phenomena, coalescing **typical** and **atypical** sentences:

(3) The gardener plays the castanets in the cave.

Generalized Event Knowledge

Psycholinguistic evidence shows that lexical items activate a great amount of **generalized event knowledge** (GEK)[4], and that this knowledge is crucially exploited **during** online language processing, constraining the speakers' expectations about upcoming linguistic input[5].

(4) The **man** arrested...*by the police*

(5) The **cop** arrested...*a man yesterday*

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[4] Elman 2011; Hagoort e Berkum 2007; Hare et al. 2009
[5] McRae e Matsuki 2009

The lexicon

The mental lexicon is organized as a **network of mutual expectations** which are in turn able to influence comprehension.

Sentence comprehension is phrased as the **identification of the event that best explains the linguistic cues used in the input**[6] .

[6] Kuperberg e Jaeger 2016

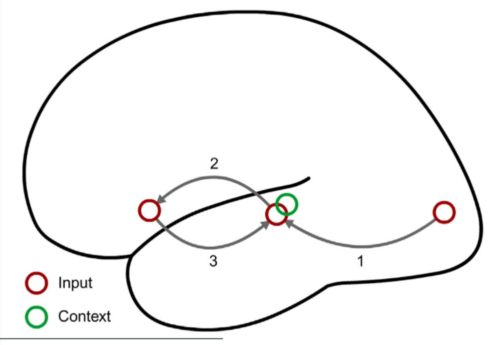
Processing - MUC

The architecture is based on the Memory, Unification and Control (MUC) model[7]:

Memory - linguistic knowledge stored in long-term memory

Unification - constraint-based assembly of linguistic items in working memory

Control - relating language to joint action and interaction



[7]Hagoort 2015

Model

The purpose is to **integrate** vector addition with **Generalized Event Knowledge** activated by lexical items.

It is directly inspired by previous models[8] and consists of two components:

Distributional Event Graph (DEG) - embeddings in a network of syntagmatic relations, modeling a fragment of semantic memory activated by lexical units;

Meaning Composition Function - dynamically builds a **structured object** using information activated from DEG through lexical items.

[8] Chersoni, Lenci e Blache 2017

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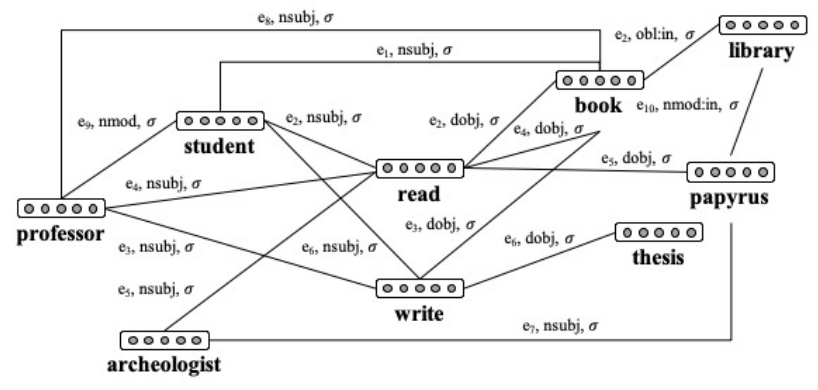
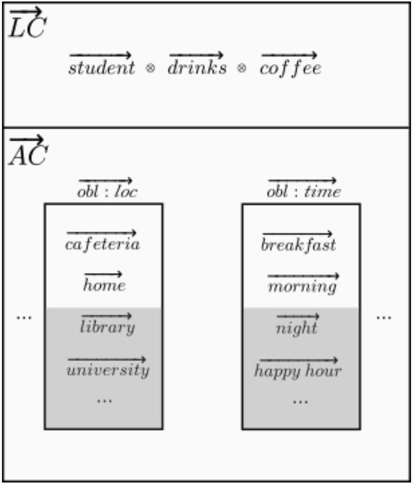
DEG

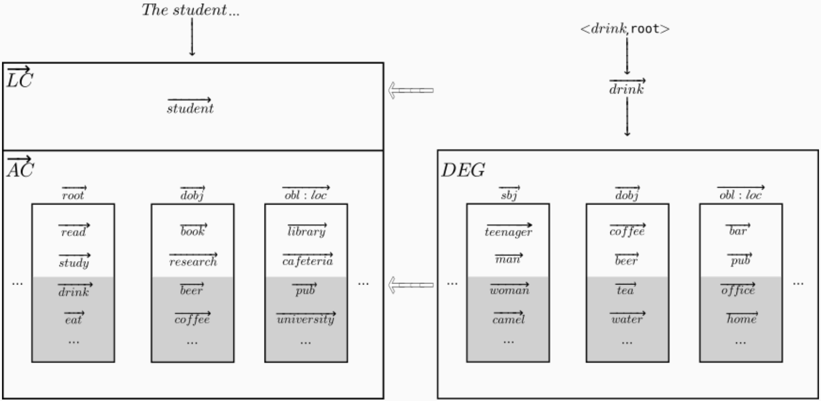


e_8, nsubj, σ
e_1, nsubj, σ
e_2, obl:in, σ
library
book
e_{10}, nmod:in, σ
e_9, nmod, σ
student
e_2, nsubj, σ
e_2, dobj, σ
e_4, dobj, σ
e_5, dobj, σ
e_4, nsubj, σ
read
papyrus
professor
e_3, dobj, σ
e_3, nsubj, σ
e_6, nsubj, σ
e_6, dobj, σ
thesis
e_5, nsubj, σ
write
e_7, nsubj, σ
archeologist

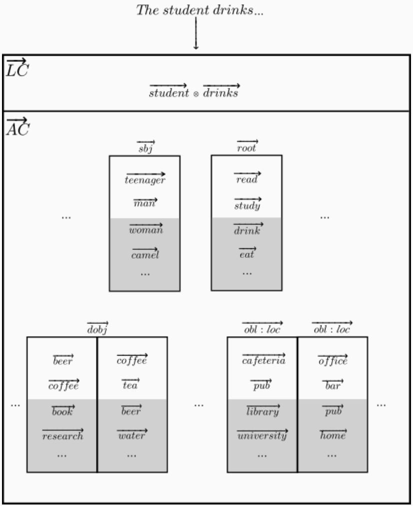
The student drinks coffee (1)



The student drinks coffee (2)



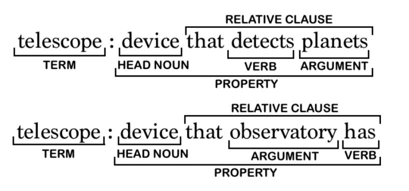
The student drinks coffee (3)



Evaluation

Sentence Comprehension Task

RELPRON:



TSS dataset:

(6) a. government use power
    b. authority exercise influence

(7) a. team win match
    b. design reduce amount

Task

RELPRON - for each target noun, we produced a ranking over all the available properties and computed Mean Average Precision

$$s = cos(\overrightarrow{target}, \overrightarrow{LC}) + cos(\overrightarrow{target}, \overrightarrow{AC}) \tag{1}$$

TSS - we evaluated the correlation of our scores with human ratings with Spearman's ρ

$$s = cos(\overrightarrow{LC_1}, \overrightarrow{LC_2}) + cos(\overrightarrow{AC_1}, \overrightarrow{AC_2}) \tag{2}$$

Results - RELPRON - MAP scores

	RELPRON		
	LC[9]	AC	LC+AC
verb	0,18	0,18	**0,20**
arg	0,34	0,34	**0,36**
hn+verb	0,27	0,28	**0,29**
hn+arg	0,47	0,45	**0,49**
verb+arg	**0,42**	0,28	0,39
hn+verb+arg	0,51	0,47	**0,55**

[9] VECTOR ADDITION ONLY

Results - Transitive sentences - ρ scores

	transitive sentences dataset		
	LC[10]	AC	LC+AC
sbj	0.432	0.475	0.**482**
root	0.525	0.547	0.**555**
obj	0.628	0.537	0.**637**
sbj+root	0.**656**	0.622	0.648
sbj+obj	0.653	0.605	0.**656**
root+obj	0.732	0.696	0.**750**
sbj+root+obj	0.732	0.686	0.**750**

[10] VECTOR ADDITION ONLY

Wrap-up

We provided a basic implementation of a meaning composition model, which aims at being **incremental** and **cognitively plausible**.

While still relying on vector addition, our results suggest that distributional vectors do not encode sufficient information about event knowledge, and that, in line with psycholinguistic results, activated GEK plays an important role in building semantic representations during online sentence processing.

Thank you! :)

- Emmanuele Chersoni, Enrico Santus, Ludovica Pannitto, Alessandro Lenci, Philippe Blache, Chu-Ren Huang (2019), “A structured distributional model of sentence meaning and processing“, Natural Language Engineering, 25: 483-502
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