Vector-based Models of Semantic Composition

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Selected Topics in Semantics and Discourse

EMLCT

UNIVERSITÄT DES SAARLANDES

Overview

- The problem of composition and previous attempts
- Composition models proposed
- Evaluation
  - Task design
  - Comparison of model's performance with human judgments

- Results
- Discussion

Composition

- Most vector-based models of word meaning are concerned with **words in isolation**

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1 vector = 1 word

Composition

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- But we want to model (compositional) **phrases or sentences** as well

Modeling composition: previous attempts

- Ignore word order (vector averaging: additive models)

a. *It was not the sales manager who hit the bottle that day, but the office worker with the serious drinking problem.*

b. *That day the office manager, who was drinking, hit the problem sales worker with a bottle, but it was not serious.*

(a = b)

Composition Models

- Formulate semantic composition as a function of two vectors **u** and **v** obtained from a Distributional model.

Expression of composition:

$$p = f(u, v, R, K)$$

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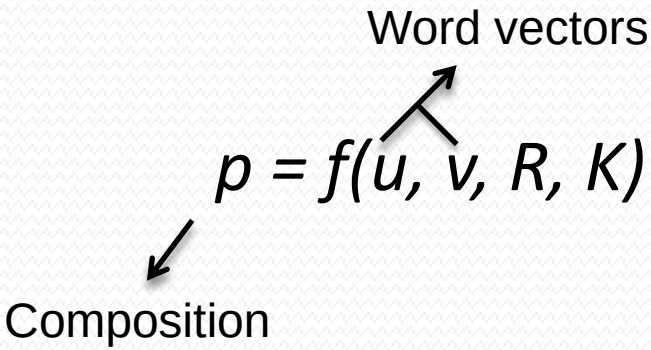

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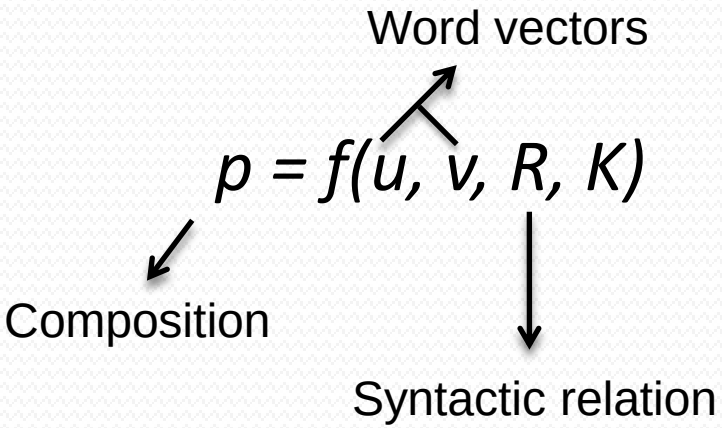

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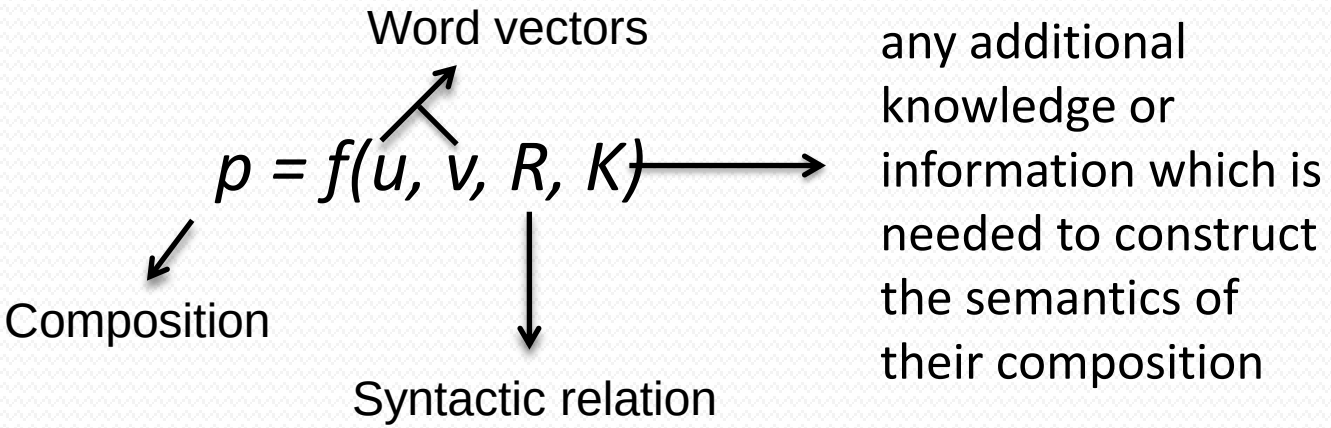

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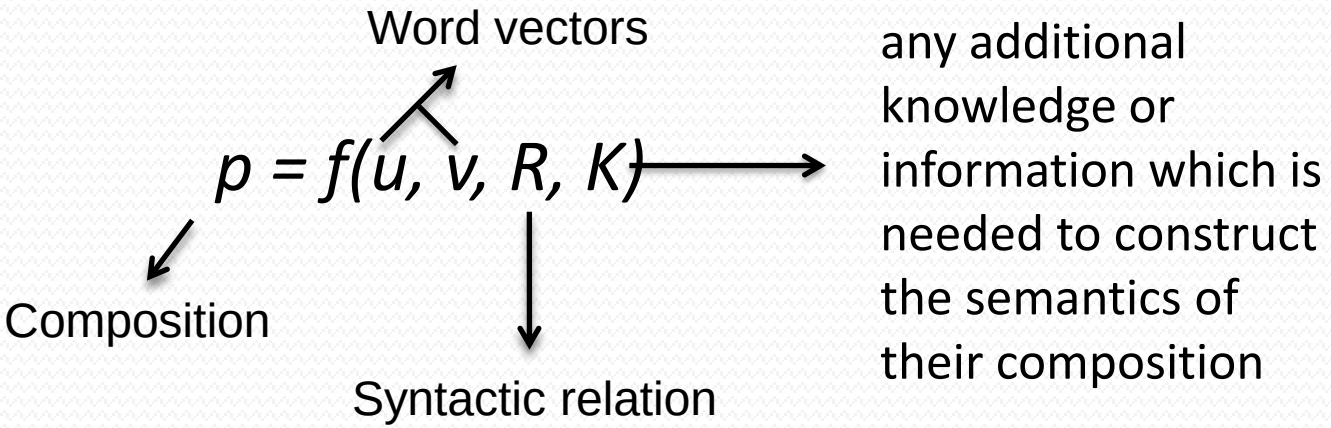

- If we fix R and ignore K: ***p = f(u, v)***

Composition Models

Additive models (p = Au + Bv)

Simple addition:

$$p_i = u_i + v_i$$

	animal	stable	village	gallop	jokey
horse	0	6	2	10	4
run	1	8	4	4	0

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(horse, run) =	(1,	14,	6,	14,	4)

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Simple addition:

$$p_i = u_i + v_i$$

Weighted addition:

$$p_i = \alpha u_i + \beta v_i \qquad (p_i = v_i)$$

Kintsch's model:

$$p = u + v + \sum n$$

Composition Models

Multiplicative models (p = Cuv)

$p_i = u_i \cdot v_i$

	animal	stable	village	gallop	jokey
horse	0	6	2	10	4
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Composition Models

Multiplicative models (p = Cuv)

$p_i = u_i \cdot v_i$

	animal	stable	village	gallop	jokey
horse	0	6	2	10	4
run	1	8	4	4	0
(horse, run) =	(0,	48,	8,	40,	0)

Composition Models

Multiplicative models (p = Cuv)

$p_i = u_i \cdot v_i$

Combined (additive and multiplicative):

$pi = \alpha u_i + \beta v_i + \gamma u_i v_i$

Evaluation

- Sentence similarity task (Kintsch, 2001)

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  *The horse **ran***

  *The color **ran***

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*The horse **ran*** (gallop)

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Different subjects select <u>different senses</u> of a verb

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- Sentence similarity task (Kintsch, 2001)

*The horse **ran*** (gallop)

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Different subjects select <u>different senses</u> of a verb

<u>Shift of position</u> in semantic space

Evaluation

- Sentence similarity task (Kintsch, 2001)

  p(horse, run) is closer to *gallop*

  p(color, run) is closer to *dissolve*

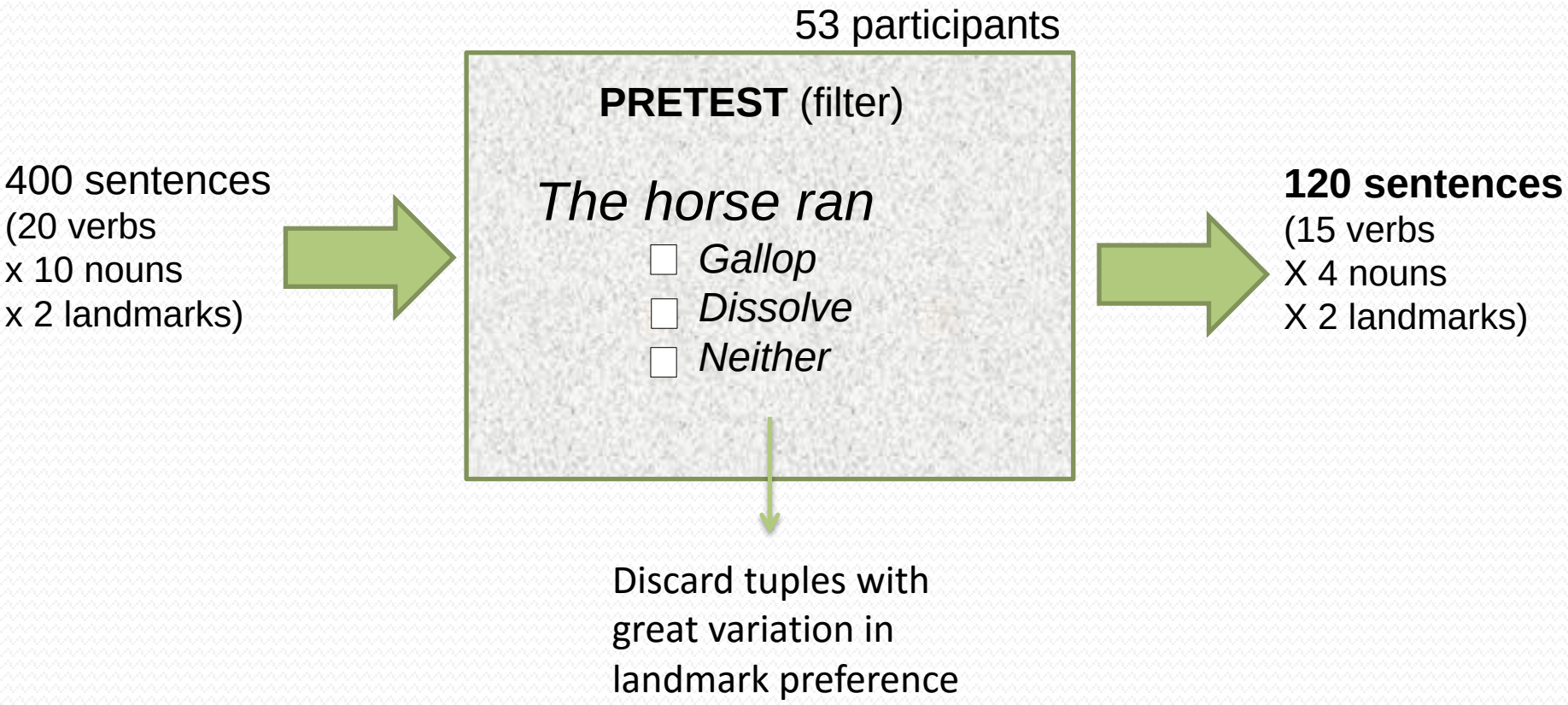
Evaluation

- Sentence similarity task: Materials and design
  - **subject + intransitive verb** structures (BNC)
  - 2 landmarks for each tuple (subject, verb), synonyms of different (incompatible) senses of the verb (WordNet)

    Landmarks of *(horse, run) = gallop, dissolve*

Evaluation

- Sentence similarity task: Materials and design



Evaluation: Procedure

The fire glowed
The fire burned

Evaluation: Procedure

The fire glowed
The fire burned

The fire glowed
The fire beamed

Evaluation: Procedure

The fire glowed
The fire burned

(HIGH) 

The fire glowed
The fire beamed

 (LOW)

Evaluation: Procedure

The fire glowed
The fire burned

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The fire glowed
The fire beamed

 (LOW)

Rate similarity from 1 to 7

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Rate similarity from 1 to 7

OBJECTIVE: See what composition model yields results closer to human judgments in this task.

Evaluation

- Sentence similarity task: Analysis of similarity ratings

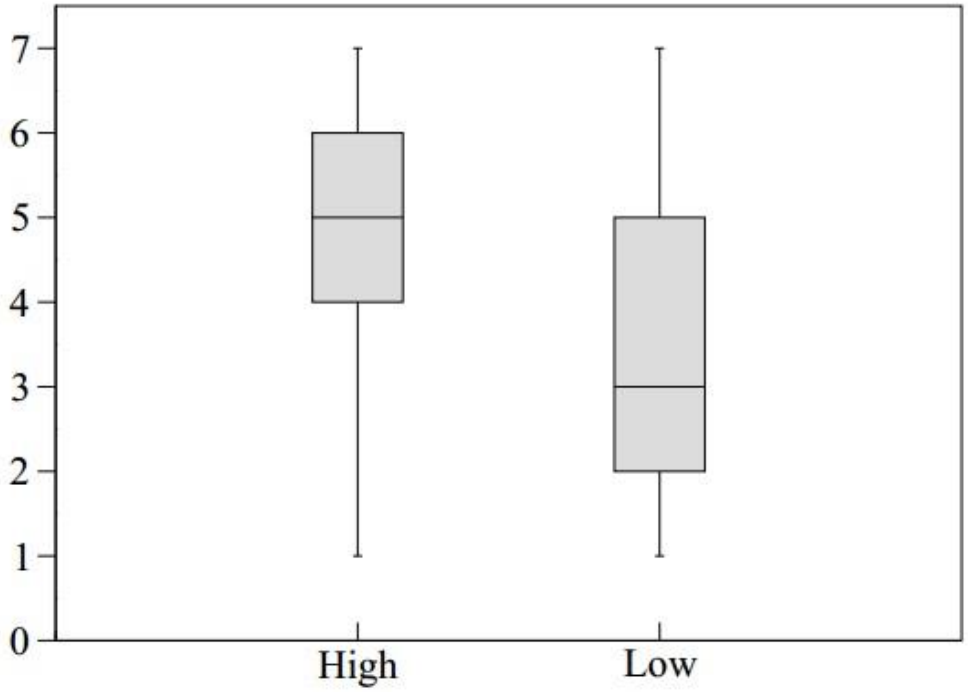

Figure 2: Distribution of elicited ratings for High and Low similarity items

Not an easy task: overlap in High and Low

But the difference is significant

Evaluation: Model Parameters

Optimize distributional parameters in a word-based semantic similarity task:

- Different contexts
- Variety of dimensions (from 50 to 500.000)
- Vector component definitions (PMI, Log likelihood ratio)
- Similarity measures (cosine, confusion probability)

Evaluation: Model Parameters

Best set of distributional parameters:

- context window of 5 words on either side of the target word
- cosine measure
- 2000 vector components (with content words)

Evaluation: Model Parameters

Adjusting concrete models' parameters

- Weights of
  - Weighted additive model: 80% verb, 20% noun
  - Combined model: 95% verb, 0% noun, 5% mult. (with held-out set)
- Neighbours in Kintsch's additive model: 1

Evaluation Methodology

- Estimate cosine similarity between sentences in each pair using the different models.

- Correlate all the individual human judgments with those of the models.

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EXPECTATION: Better models yield similarity scores like those observed in the human ratings and correlate better with them.

Results

Model	High	Low	ρ
NonComp	0.27	0.26	0.08**
Add	0.59	0.59	0.04*
WeightAdd	0.35	0.34	0.09**
Kintsch	0.47	0.45	0.09**
Multiply	0.42	0.28	0.17**
Combined	0.38	0.28	0.19**
UpperBound	4.94	3.25	0.40**

Table 2: Model means for High and Low similarity items and correlation coefficients with human judgments (*: $p < 0.05$, **: $p < 0.01$)

Results

Fail to distinguish between High and Low

Model	High	Low	ρ
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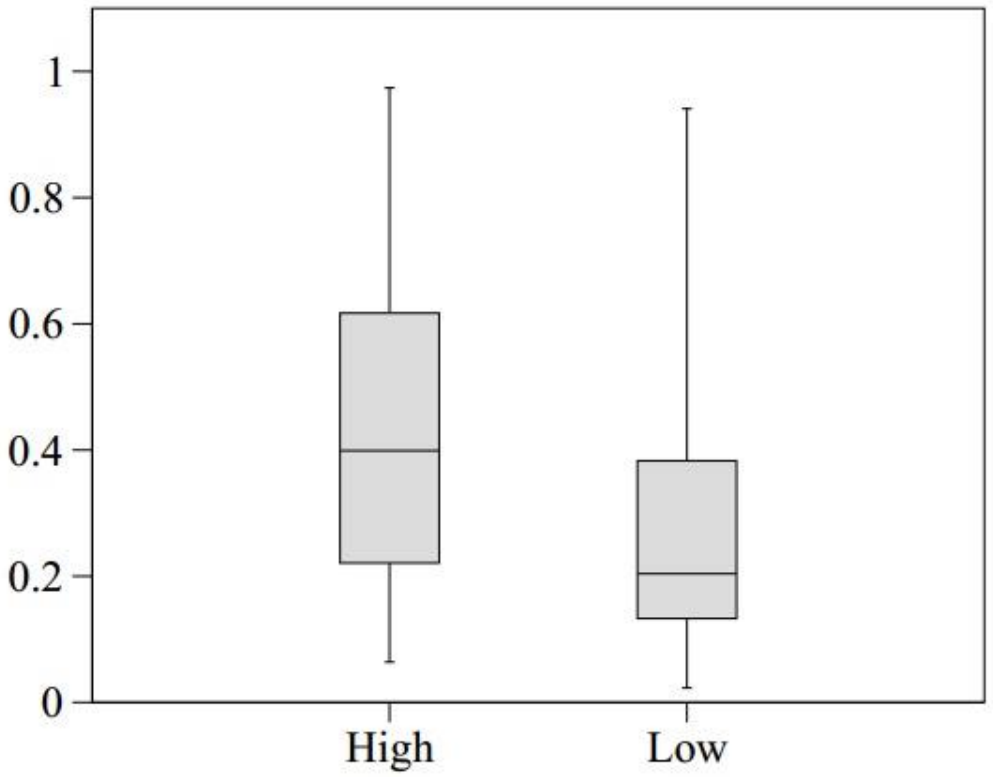

Figure 3: Distribution of predicted similarities for the vector multiplication model on High and Low similarity items

Discussion

- Models using multiplicative combinations are superior to additive models, at least for this task.
- Additive models had been used to modeling the gist of a document rather than the meaning of its sentences.

Discussion

- Additive models capture composition by considering all vector components.
- Multiplicative models consider a subset (non-zero components). The resulting vector is sparser but expresses the meaning more succinctly.

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- **Further research** is needed in
  - other structures (not only subj+verb)
  - other models

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- In particular, the general class of multiplicative models appears to be a fruitful area to explore.

Thank you for your attention!

Any questions?