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FACULTY OF HUMANITIES

Evaluating Semantic Composition of German Compounds

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Wer wurmt der Ohrwurm? An interdisciplinary, cross-lingual perspective on the role of constituents in multi-word expressions, DGfS 2017, 09.03.2017

Motivation

- vector space models of language (Mikolov et al., 2013; Pennington et al., 2014) create meaningful representations for the individual words in a language
- how to create meaningful, reusable representations for longer word sequences – in this work – for German compounds?

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Add compounds to the dictionary of the language model and directly learn representations for them.

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Solution 2

Use semantic composition to build the meaning of the compound starting from the meaning of individual words.

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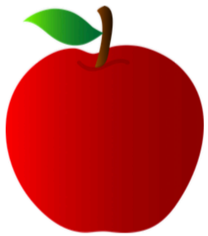
Semantic Composition



Apfel + Baum → Apfelbaum

0.3	0.1	0.7	1.3	0.2	u	0.5	0.9	0.1	0.4	1.2	v	0.2	1.0	0.6	0.7	1.1	w

$$f\left(\begin{bmatrix}0.3 & 0.1 & 0.7 & 1.3 & 0.2\end{bmatrix} u,\ \begin{bmatrix}0.5 & 0.9 & 0.1 & 0.4 & 1.2\end{bmatrix} v\right) = \begin{bmatrix}?? & ?? & ?? & ?? & ??\end{bmatrix} p$$

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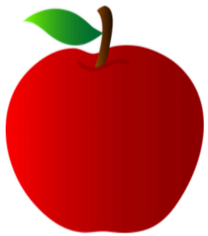

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- learn a composition function **f** that combines the representations of the constituents *Apfel* and *Baum* into the representation of the compound *Apfelbaum*

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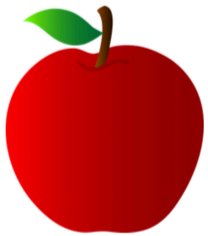

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- learn a composition function **f** that combines the representations of the constituents *Apfel* and *Baum* into the representation of the compound *Apfelbaum*
- the composed representation of *Apfelbaum* should be similar (cosine similarity) to its corpus-estimated representation

How to Choose the Composition Function?

Model	Formula
Mitchel & Lapata (2010) • vector addition, vector multiplication, etc.	$p = \lambda u + \beta v$ $p = u \odot v$
Baroni & Zamparelli (2010) • matrix for the adjective, vector for the noun	$p = \mathcal{U}v$
Zanzotto et al. (2010) • linear combination of vectors and matrices for both components	$p = M_1 u + M_2 v$
Socher et al. (2010) • global matrix to combine component vectors + nonlinearity	$p = g(W[u;v])$
Socher et al. (2012) • use a individual word matrix to modify each word before combining it though the global matrix + nonlinearity	$p = g(W[\mathcal{V}u; \mathcal{U}v])$

Empirically: Test All Models

Dataset

- 34497 compounds from the German wordnet, GermaNet, v9.0
- train-test-dev splits (70/20/10)
- with splitting information: immediate head and modifier for every compound (Henrich & Hinrichs, 2011)
- frequency filtered: modifier, head and compound with minimum frequency 500 in the support corpus

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Word representations

- Trained 50, 100, 200 and 300 dimensional word representations using GloVe (Pennington et al., 2014)
- 10 billion words corpus from DECOW14AX (Schäfer, 2015); used 1 million word vocabulary (frequency min. 100)

Train Composition Models

- estimate the parameters of the composition functions using the training split of the dataset

  - start from corpus-induced representations for

    head, **modifier**, **compound**

  - apply the composition function => composed representation

    f(head, modifier) = compound

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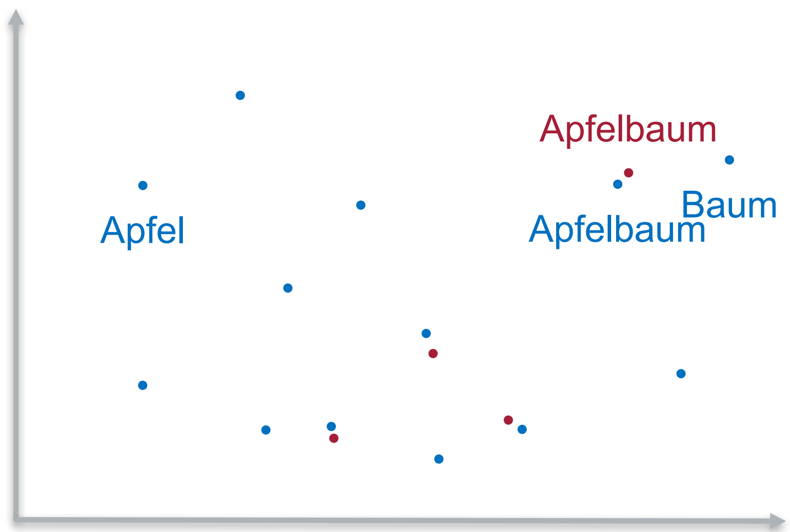
- **objective function** for training: minimize the mean squared error between the composed and the corpus-induced compound representations

  compound ⇔ compound

Evaluate Composition Models

- **intuition**: a good composition model produces composed representations such that the corpus-observed representations of the **same compounds** are their nearest neighbors in the vector space



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Evaluate Composition Models (2)

- compute the **ranks** of the composed representations in the test set

- **rank computation**
  1. compute cosine distance between the composed representation (**compound**) and *all* the **corpus-induced vectors**
  2. sort, most similar first
  3. the rank is the position of the corresponding corpus-induced vector (**compound**) in the sorted list

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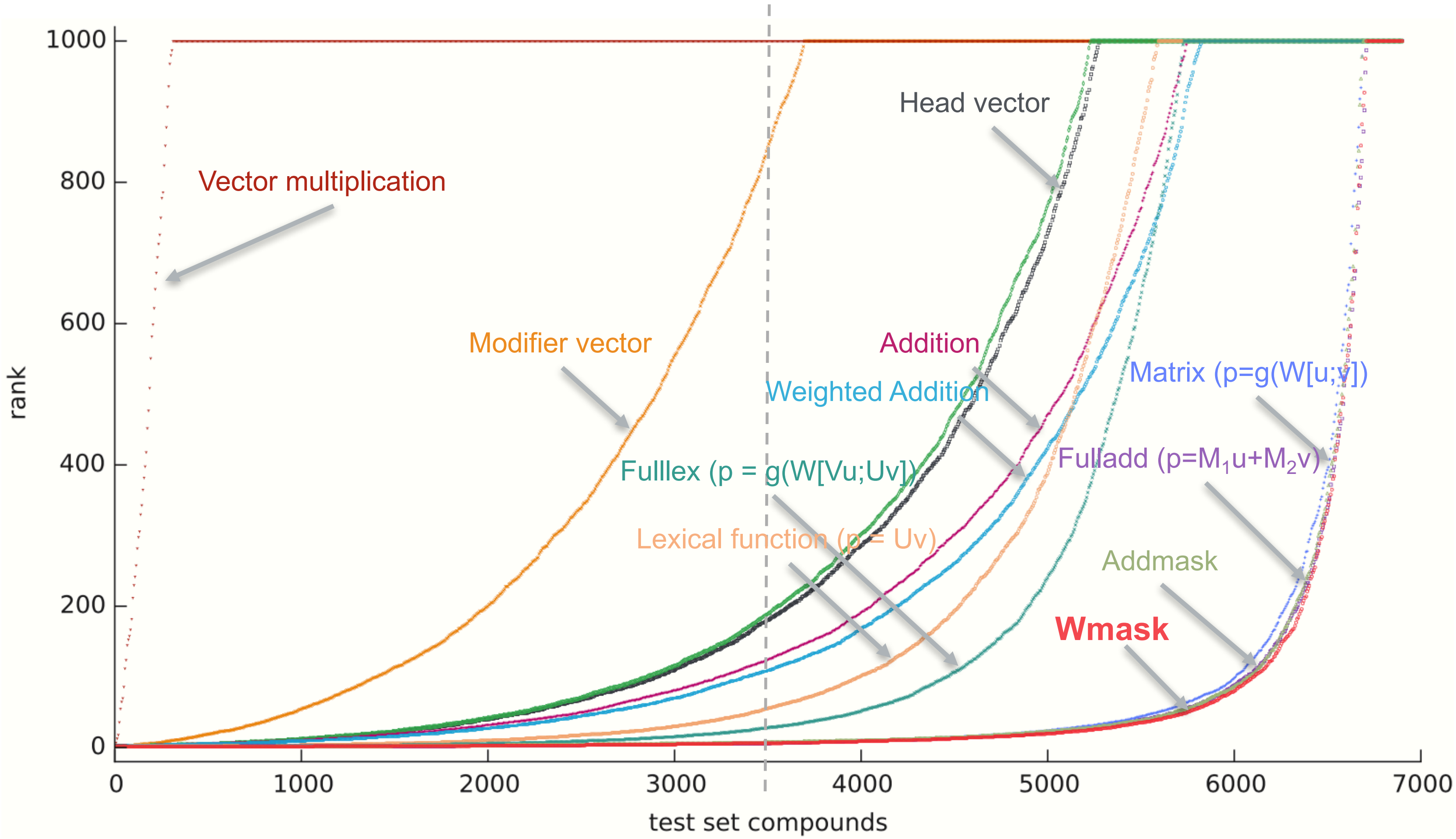
- **lower** rank is **better** ~ **composed representation** is closer neighbour to the **corpus-induced represention**

Evaluation Results



Composition with the Mask Models

- **masks**:1-dimensional vectors of the same size as the word vectors
- provide **position-dependent refinement** of the initial word vector

car factory ⇔ factory car

car => *car_as_modifier*, *car_as_head*
factory => *factory_as_modifier*, *factory_as_head*

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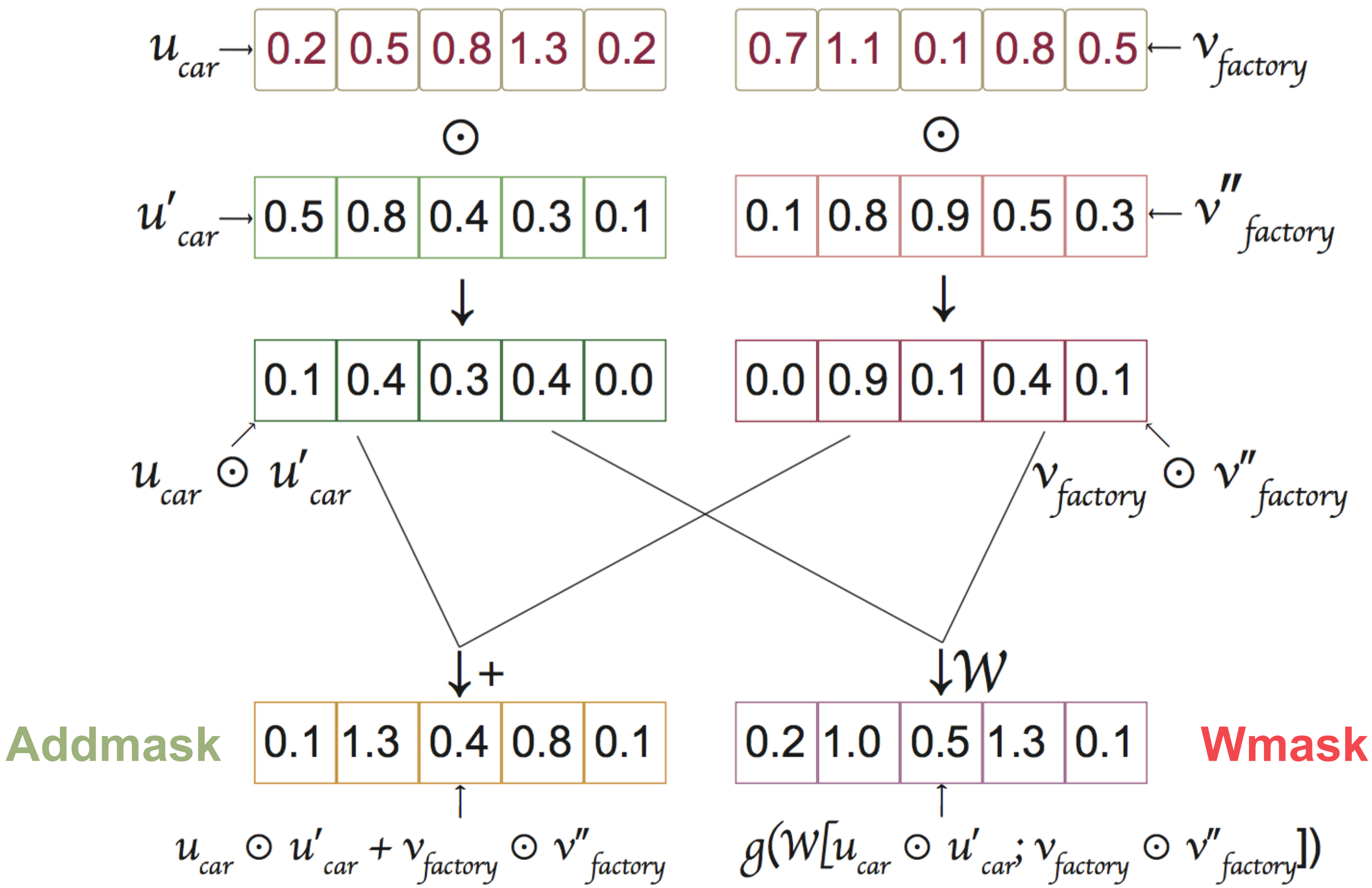
car factory ⇔ factory car

car => *car_as_modifier, car_as_head*

factory => *factory_as_modifier, factory_as_head*

- at composition time, the word vector is first multiplied with the corresponding mask vector
- train 2 vectors (one for the modifier position, one for head position) for each word

Composition with the Mask Models (2)



Wrap-up: Composition Models

- the best models create good composed representations (rank<=5) for 50% of the test data
- more details in:

  Dima, C. 2015. *Reverse-engineering Language: A Study on the Semantic Compositionality of German Compounds*. In Proceedings of EMNLP, pp. 17–21.

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- take a closer look at their results for particular compound types – e.g. compare performance on **transparency-rated compounds**

Transparency-rated compound set

- dataset from Im Walde et al. (2013)
- 244 two-part noun-noun compounds (concrete, depictable)

head / **modifier**	**transparent**	**opaque**
transparent	**Ahornblatt** ‘maple leaf’	**Feuerzeug** ‘lighter’ lit. fire+stuff
opaque	**Fliegenpilz** ‘toadstool’ lit. fly+mushroom	**Löwenzahn** ‘dandelion’ lit. lion+tooth

Transparency-rated compound set: Mturk annotation

modifier \ head	transparent (7 ← 1)	opaque
transparent (7)	**Ahornblatt** ‘maple leaf’ whole: 6.03 modifier: 5.64 head: 5.71	**Feuerzeug** ‘lighter’ lit. fire+stuff whole: 4.58 modifier: 5.87 head: 1.90
opaque (1)	**Fliegenpilz** ‘toadstool’ lit. fly+mushroom whole: 2.00 modifier: 1.93 head: 6.55	**Löwenzahn** ‘dandelion’ lit. lion+tooth whole: 1.66 modifier: 2.10 head: 2.23

Transparency-rated compound set - average ranks

- used 219 compounds (intersection of transparency & compositionality datasets)

head / modifier	transparent 7 ← 3.5	opaque 3.5 ← 1
transparent (7 – 3.5)	144 compounds Average rank **50.6**	20 compounds Average rank **68.4**
opaque (3.5 – 1)	50 compounds Average rank **81.7**	5 compounds Average rank **635.8**

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head / modifier	**transparent** 7 ← 3.5	→ **opaque** 1
transparent 7 ↑ 3.5	Ahornblatt, rank **1** Schneemann, rank **15** lit. 'snow' + 'man' Regenbogen, rank **879** lit. 'rain' + 'arch','bow', 'arc',… (5) Average rank **50.6**	Feuerzeug, rank **10** Zahnseide, rank **117** lit. 'tooth' + 'silk' Average rank **68.4**
opaque 1	Fliegenpilz, rank **40** Flohmarkt, rank **424** lit. 'flea' + 'market' Average rank **81.7**	Löwenzahn, rank **1000** Nilpferd, rank **43** 'hippo', lit. 'Nile' + 'horse' Average rank **635.8**

Transparency-rated compound set - average ranks

- used 219 compounds (intersection of transparency & compositionality datasets)

head / modifier	**transparent** (7 ← 3.5)	**opaque** (3.5 ← 1)
transparent (7 ↑ 3.5)	composition works in the majority of cases	composition possible problem: **multisense** and **metaphoric** meaning of the **head**
opaque (3.5 ↑ 1)	composition possible problem: **multisense** and **metaphoric** meaning of the **modifier**	composition **impossible**: compound representation cannot be obtained compositionally

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- **composition models** create good representations for many compounds

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- problem: **multisense** and **metaphoric** meaning of the head or modifier
  - solution ⇨ sense- & metaphor-aware word representations/ composition models

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- **composition models** create good representations for many compounds
- problem: **multisense** and **metaphoric** meaning of the head or modifier
  - solution ⇨ sense- & metaphor-aware word representations/ composition models
- problem: **opaque compounds** - compound representation cannot be obtained compositionally
  - solution ⇨ identification of opaque compounds

Thank you!

- Contact

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