



Towards a Lexicologically Informed Parameter Evaluation of Distributional Modelling in Lexical Semantics

Thomas Wielfaert, Kris Heylen, Jocelyne Daems,
Dirk Speelman & Dirk Geeraerts



KU Leuven
Quantitative Lexicology and Variational Linguistics

Purpose of the talk

THEORETICAL

- Study the **structure of lexical variation**: mapping of meaning onto lexemes in different varieties.
- Analyse how this structure is apparent in **usage data**

METHODOLOGICAL

- Semantic Vector Spaces as a method for the quantitative, large-scale, corpus-based analysis of lexical semantics
- Interactive Visualisation of distributional models as an exploratory, visual analytic tool for lexicology
- Creating a '**gold standard**' and **cluster evaluation**.



Overview

1. Linguistic Background
2. Semantic Vector Spaces
3. Visual Analytics
4. Creating a 'gold standard' and cluster evalution.
5. Discussion and future work



Overview

1. Linguistic Background
2. Semantic Vector Spaces
3. Visual Analytics
4. Creating a 'gold standard' and cluster evalution.
5. Discussion and future work



Linguistic Background

Structure of Lexical Variation (Geeraerts et al. 1994):

CONCEPT /
MEANING

CONCEPT /
MEANING

CONCEPT /
MEANING

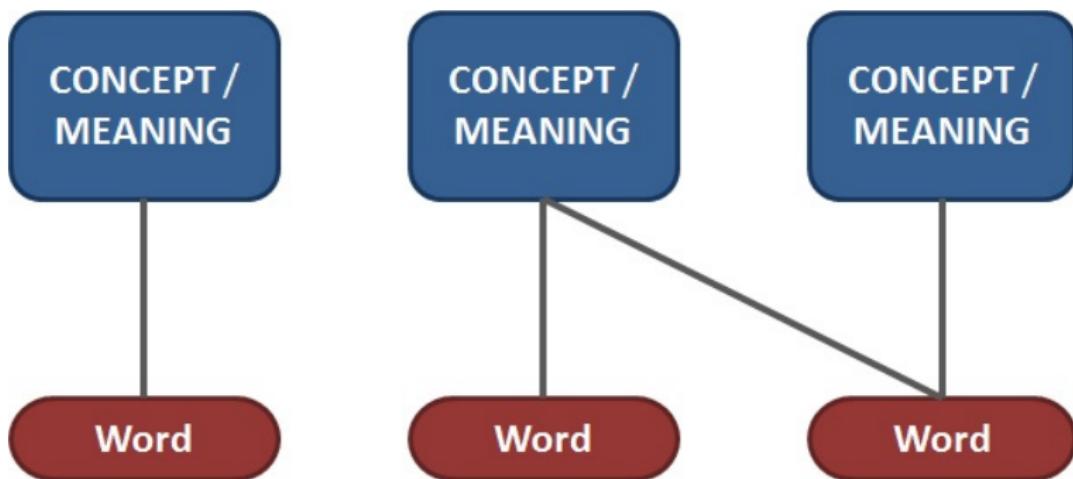
Word

Word

Word

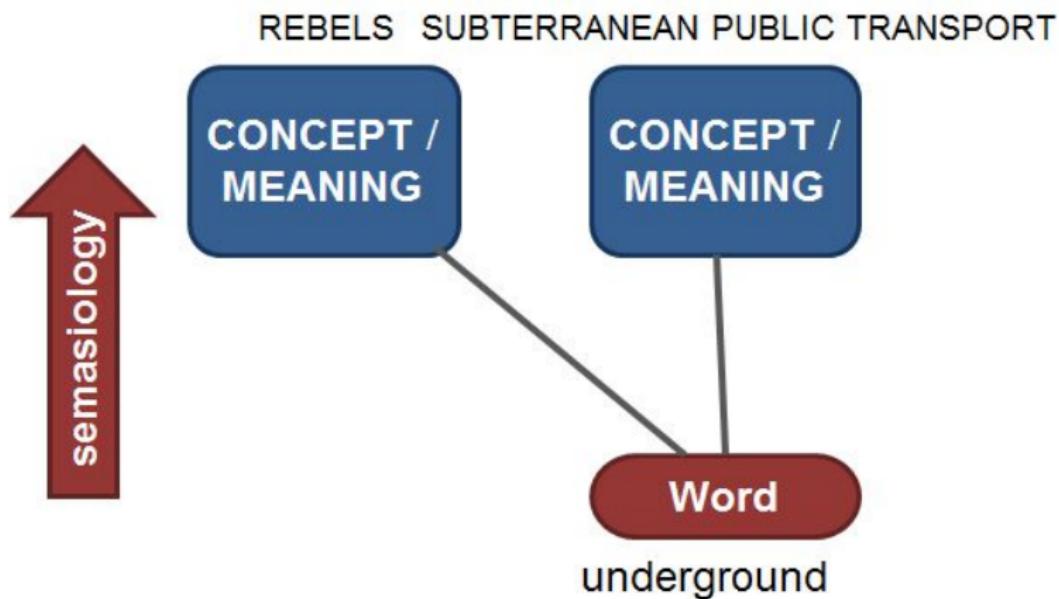
Linguistic Background

Structure of Lexical Variation (Geeraerts et al. 1994):



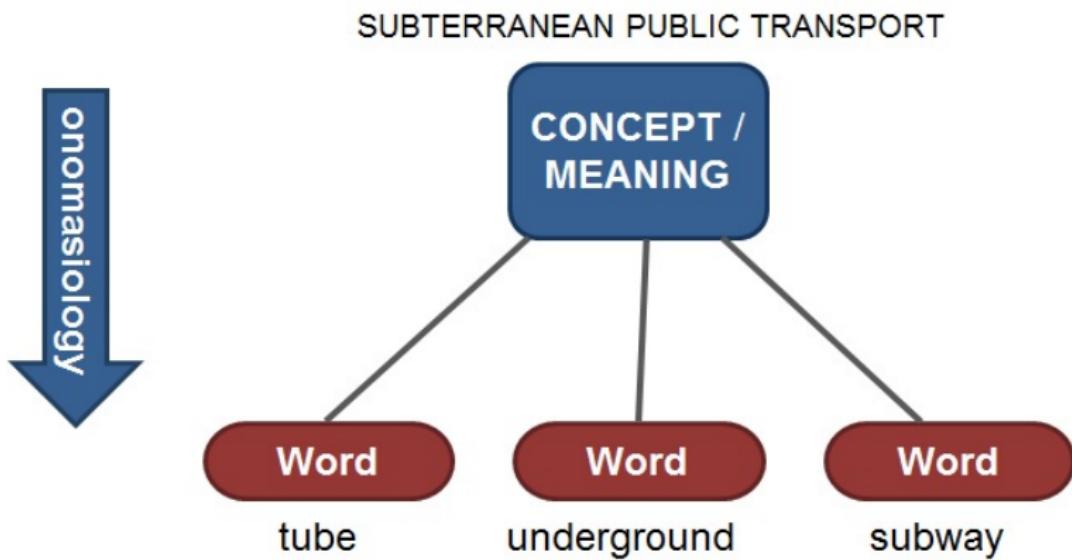
Linguistic Background

Structure of Lexical Variation (Geeraerts et al. 1994):



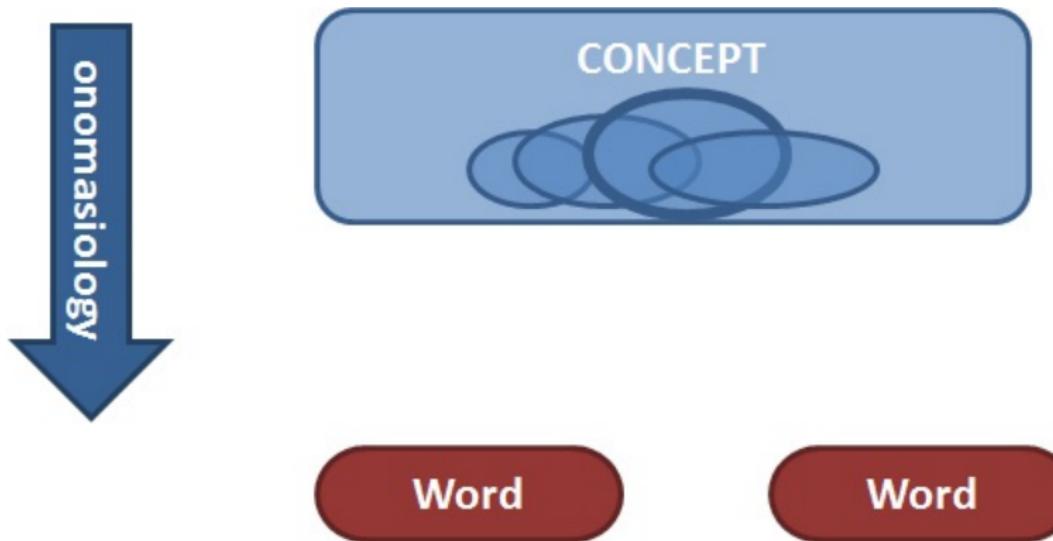
Linguistic Background

Structure of Lexical Variation (Geeraerts et al. 1994):



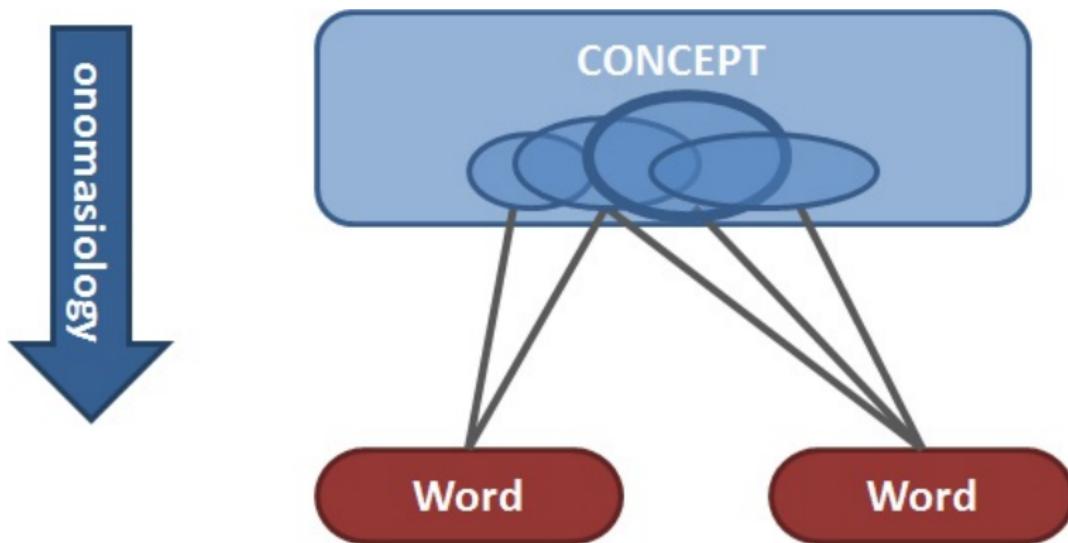
Linguistic Background

Structure of Lexical Variation (Geeraerts et al. 1994):
PROTOTYPE STRUCTURE:



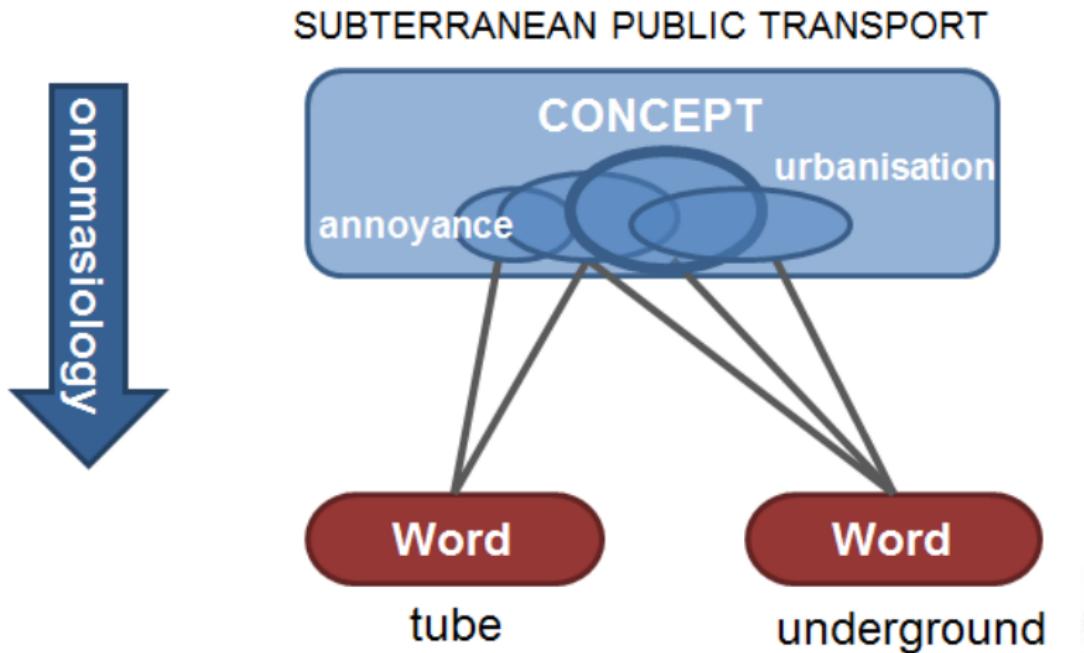
Linguistic Background

Structure of Lexical Variation (Geeraerts et al. 1994):
PROTOTYPE STRUCTURE:



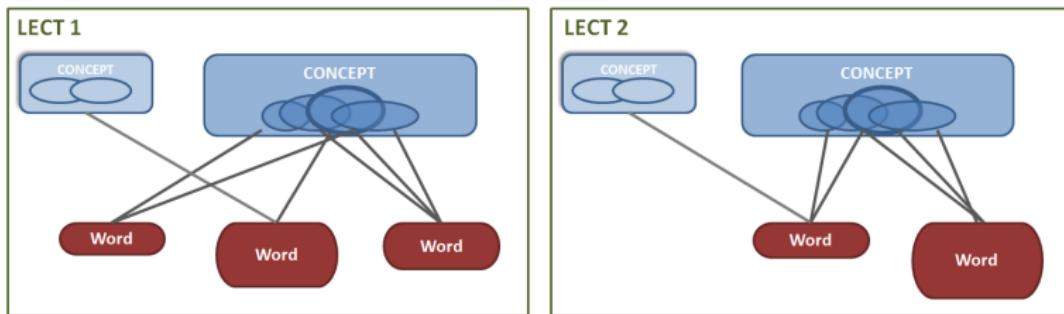
Linguistic Background

Structure of Lexical Variation (Geeraerts et al. 1994):
PROTOTYPE STRUCTURE:



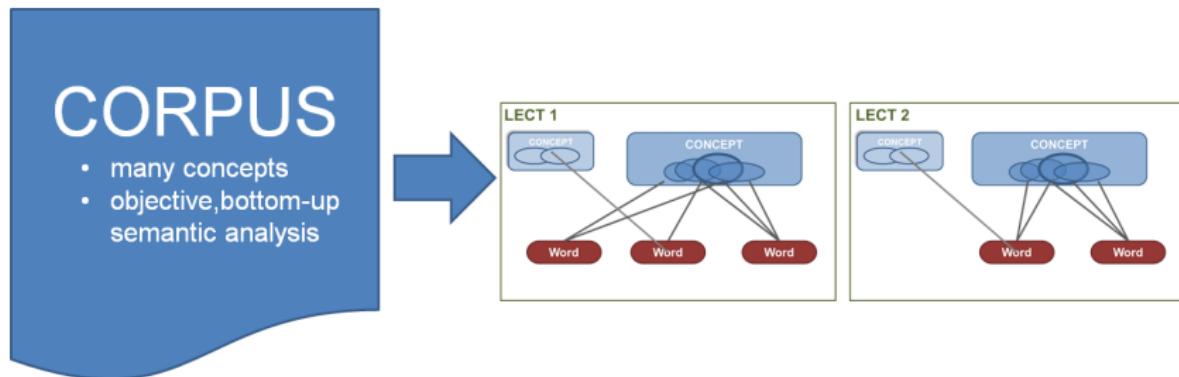
Linguistic Background

Structure of Lexical Variation (Geeraerts et al. 1994):
LECTAL VARIATION:



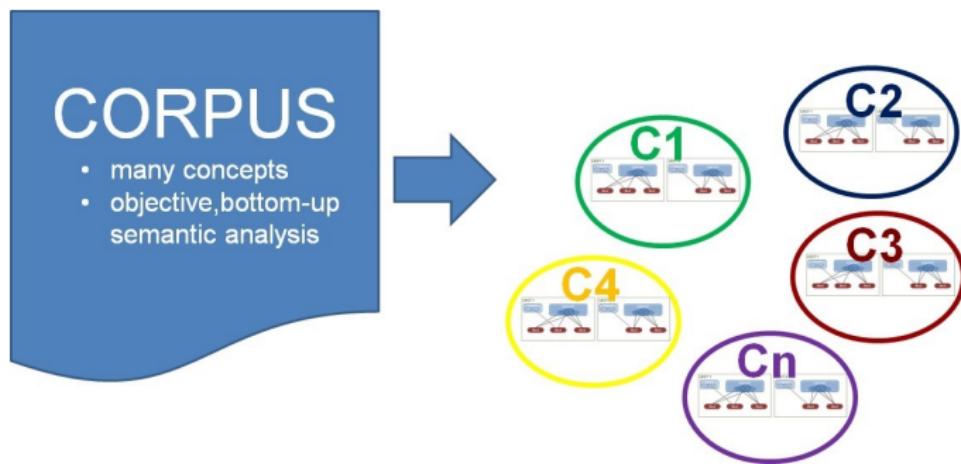
Linguistic Background

Structure of Lexical Variation (Geeraerts et al. 1994):
BASED ON BIG DATA:



Linguistic Background

Structure of Lexical Variation (Geeraerts et al. 1994):
BASED ON BIG DATA:



⇒ Automatic modelling of lexical semantics

Overview

1. Linguistic Background
2. Semantic Vector Spaces
3. Visual Analytics
4. Creating a 'gold standard' and cluster evalution.
5. Discussion and future work



2. Semantic Vector Spaces

Linguistic origin: Distributional Hypothesis

- "You shall know a word by the company it keeps" (Firth)
- a word's meaning can be induced from its **co-occurring words**
- long tradition of collocation studies in corpus linguistics

Semantic Vector Spaces in Computational Linguistics

- standard technique in **statistical NLP** for the **large-scale automatic modeling** of (lexical) semantics
- aka Vector Spaces Models, Distributional Semantic Models, Word Spaces,... (cf Turney & Pantel 2010 for overview)
- generalised, large-scale **collocation analysis**
- mainly used for automatic thesaurus extraction:
⇒ words occurring in same contexts have similar meaning

Type-level SVS

Collect co-occurrence frequencies for a large part of the vocabulary and put them in a matrix

| | <i>transport</i> | <i>train</i> | <i>commute</i> | <i>ticket</i> | <i>scene</i> | <i>sugar</i> | <i>cream</i> | <i>now</i> |
|-------------|------------------|--------------|----------------|---------------|--------------|--------------|--------------|------------|
| subway | 120 | 424 | 388 | 82 | 12 | 11 | 3 | 189 |
| underground | 154 | 401 | 376 | 99 | 305 | 20 | 1 | 123 |
| coffee | 5 | 8 | 18 | 4 | 1 | 72 | 102 | 152 |

Type-level SVS

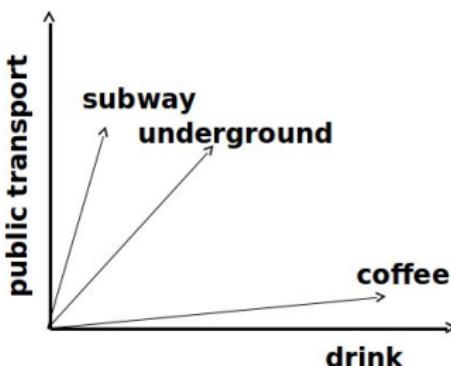
weight the raw frequencies by collocational strength (pmi)

| | <i>transport</i> | <i>train</i> | <i>commute</i> | <i>ticket</i> | <i>scene</i> | <i>sugar</i> | <i>milk</i> | <i>now</i> |
|-------------|------------------|--------------|----------------|---------------|--------------|--------------|-------------|------------|
| subway | 5.3 | 7.9 | 6.5 | 4.0 | 0.8 | 0.6 | 0.0 | 0.0 |
| underground | 4.3 | 8.1 | 5.7 | 3.2 | 6.2 | 0.5 | 0.0 | 0.1 |
| coffee | 0.1 | 0.2 | 0.4 | 0.1 | 0.0 | 6.4 | 7.2 | 0.1 |

Type-level SVS

calculate word by word similarity matrix

| | subway | underground | coffee |
|-------------|--------|-------------|--------|
| subway | 1 | .71 | .08 |
| underground | .71 | 1 | .09 |
| coffee | .08 | .09 | 1 |



Token-level SVS

Make a vector for each occurrence of the variants

the teacher saw the dog chasing the cat



Token-level SVS

Make a vector for each occurrence of the variants

| | | | |
|-----|-----|-----|-----|
| 3.2 | 4.3 | 0.8 | 7.1 |
| 5.1 | 2.2 | 3.7 | 0.1 |
| 0.2 | 3.5 | 2.3 | 0.3 |
| 3.1 | 1.9 | 2.9 | 4.1 |
| 4.7 | 0.2 | 1.3 | 3.1 |
| 2.2 | 3.1 | 4.1 | 3.8 |

the teacher saw the dog chasing the cat



Token-level SVS

Make a vector for each occurrence of the variants

| | | | | | AVERAGE |
|---------|-----|-----|---------|-----|---------|
| 3.2 | 4.3 | 0.8 | 7.1 | 3.9 | |
| 5.1 | 2.2 | 3.7 | 0.2 | 2.8 | |
| 0.2 | 3.5 | 2.3 | 0.3 | 1.6 | |
| 3.1 | 1.9 | 2.9 | 4.1 | 3.0 | |
| 4.7 | 0.2 | 1.4 | 3.1 | 2.3 | |
| 2.2 | 3.1 | 4.1 | 3.8 | 3.3 | |
| teacher | saw | dog | chasing | cat | |



Token-level SVS

Weighting

| | | | | |
|-------------|---------|-----|-----|---------|
| | 3.2 | 4.3 | 0.8 | 7.1 |
| | 5.1 | 2.2 | 3.7 | 0.1 |
| | 0.2 | 3.5 | 2.3 | 0.3 |
| | 3.1 | 1.9 | 2.9 | 4.1 |
| | 4.7 | 0.2 | 1.3 | 3.1 |
| | 2.2 | 3.1 | 4.1 | 3.8 |
| | teacher | saw | dog | chasing |
| PMI weights | 0.4 | 0.8 | 2.1 | 1.5 |
| | cat | | | |

Context words are not equally informative for the meaning of dog.



Token-level SVS

Weighted vectors

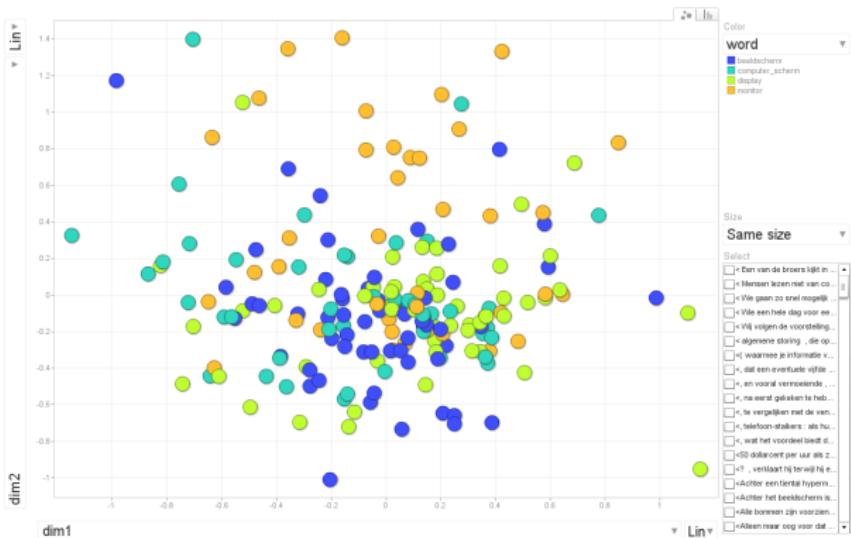
| | | | | WEIGHTED AVERAGE |
|---------|---------|---------|---------|------------------|
| 3.2x0.4 | 4.3x0.8 | 0.8x2.1 | 7.1x1.5 | 4.3 |
| 5.1x0.4 | 2.2x0.8 | 3.7x2.1 | 0.2x1.5 | 3.0 |
| 0.2x0.4 | 3.5x0.8 | 2.3x2.1 | 0.3x1.5 | 2 |
| 3.1x0.4 | 1.9x0.8 | 2.9x2.1 | 4.1x1.5 | 3.8 |
| 4.7x0.4 | 0.2x0.8 | 1.4x2.1 | 3.1x1.5 | 2.4 |
| 2.2x0.4 | 3.1x0.8 | 4.1x2.1 | 3.8x1.5 | 4.4 |
| teacher | saw | dog | chasing | cat |



Visual Analytics: Token clouds

Calculate similarity between all tokens

Version 1: use MDS and googlevis to plot interactively in 2D



Calibration problem

Semantic Vector Spaces, and especially token-level SVSs are parameter-rich.

Examples of parameters

- Bag-of-Words ↔ Dependency Models
- Size of the context window for co-occurrences
- Size of the context window for weights
- Weighting scheme:
Pointwise Mutual Information ↔ Log-Likelihood Ratio
- Include ↔ exclude highly-frequent (function words) words

Overview
o

Introduction
o

SVS
oooooooo

Visualization
ooo

ClusterEvaluation
oooooooo

Discussion
ooooo

Overview

1. Linguistic Background
2. Semantic Vector Spaces
3. Visual Analytics
4. Creating a 'gold standard' and cluster evalution.
5. Discussion and future work



3. Visual Analytics

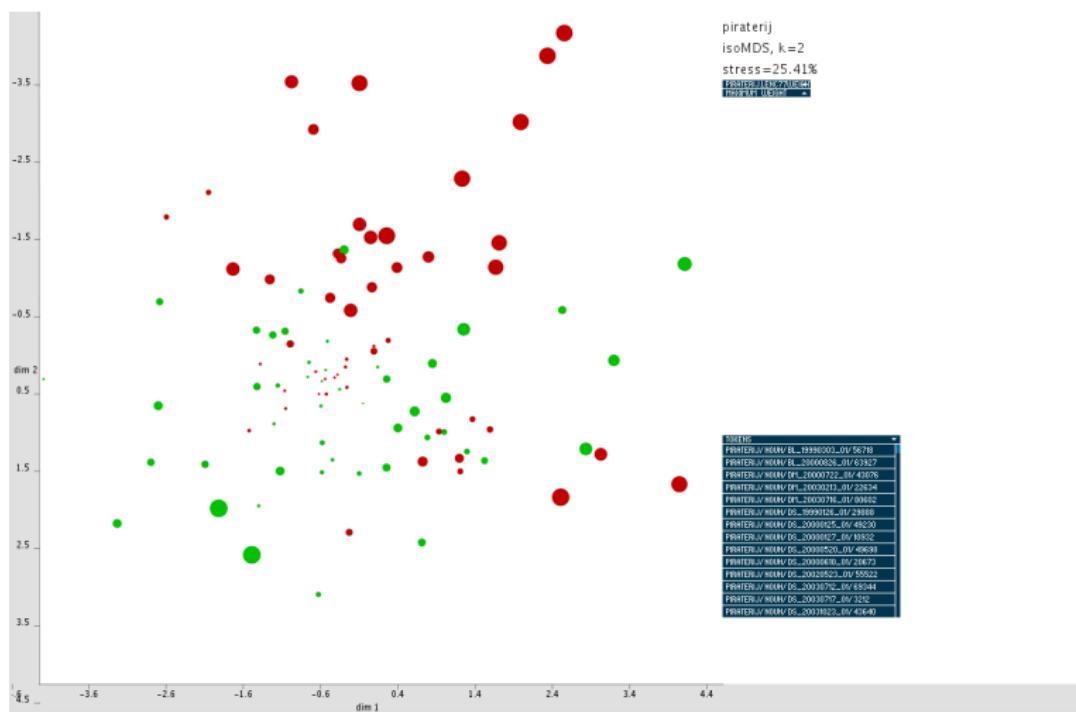
- Calibration could benefit from **visual analytics** of the different solutions.
- Using **manually disambiguated** data facilitates the visual evaluation as we can color-code the tokens for their different meanings.
- **Misclassified** tokens are quickly identified.
- We built our own, customisable tool to explore these token clouds.

3. Visual Analytics

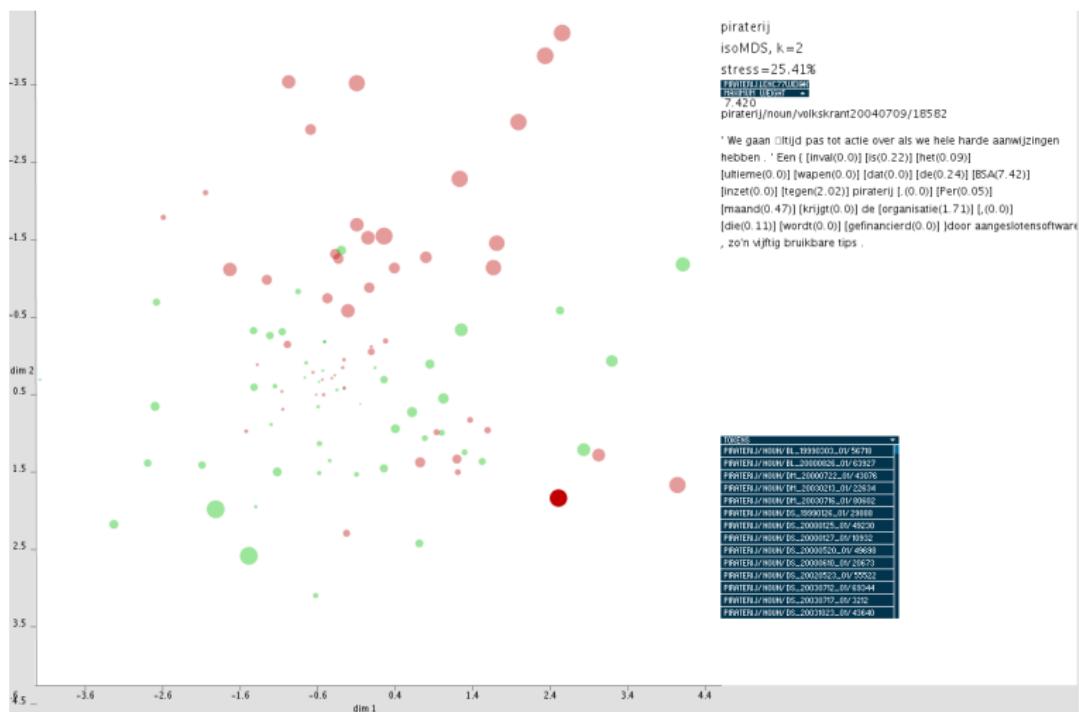
Dutch noun *piraterij*

- Data from large Dutch newspaper corpora
 - Leuven News Corpus (LeNC): 1.3 billion words
 - Twente News Corpus (TwNC): 500 million words
- Manually disambiguated data for the Dutch word type *piraterij* (piracy)
 - piraterij₁*: attack on ships
 - piraterij₂*: illegally producing and selling products

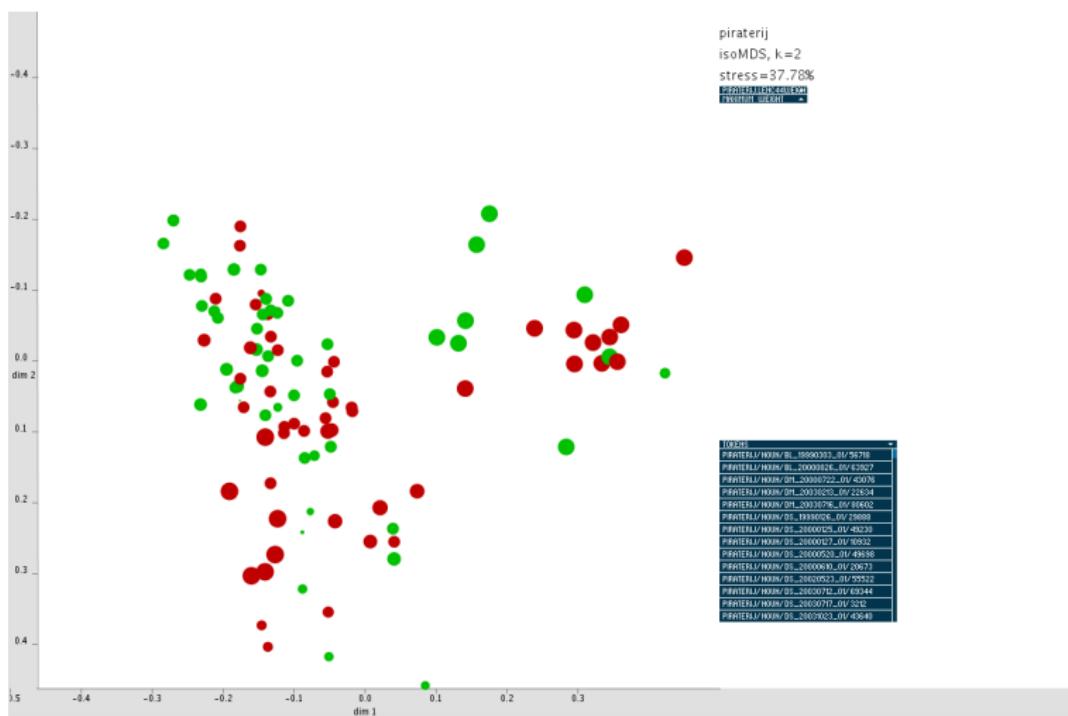
3. Visual Analytics



3. Visual Analytics



3. Visual Analytics



QM

Overview

1. Linguistic Background
2. Semantic Vector Spaces
3. Visual Analytics
4. Creating a 'gold standard' and cluster evalution.
5. Discussion and future work



'Gold standard'

Manual effort

Selection of nouns from *Algemeen Nederlands Woordenboek* (ANW)

- Highly frequent in both BE and NL newspaper corpus.
- Examples that are not purely literary use.
- At least 2 core senses with a semantic relationship (betekenisbetrekking).

Manual disambiguation of random tokens until each sense has at least 50 occurrences.

'Gold standard'

ANW selection

- aanbieder (offerer)
- koper (buyer / copper)
- match
- motor (engine / motorcycle)
- parachute
- piraterij (piracy)
- pony
- prof
- scout
- therapeut (therapist)



'Gold standard'

ANW selection

- aanbieder (offerer)
- koper (buyer / copper)
- match
- motor (engine / motorcycle)
- parachute
- **piraterij** (piracy)
- pony
- prof
- **scout**
- **therapeut** (therapist)



4. Cluster evaluation

Aggregate cluster quality

- First proposed by McClain and Rao (1975) to evaluate clustering in marketing research.
- Speelman and Geeraerts (2009) proposed a similar measure for dialectometry.

$$\text{clusterqual: } \frac{S_W/N_W}{S_B/N_B}$$

S_W : within distances

N_W : number of distances between pairs

S_B : between distances

N_B : number of distances between pairs

4. Cluster evaluation

clusterqual properties

Due to its design:

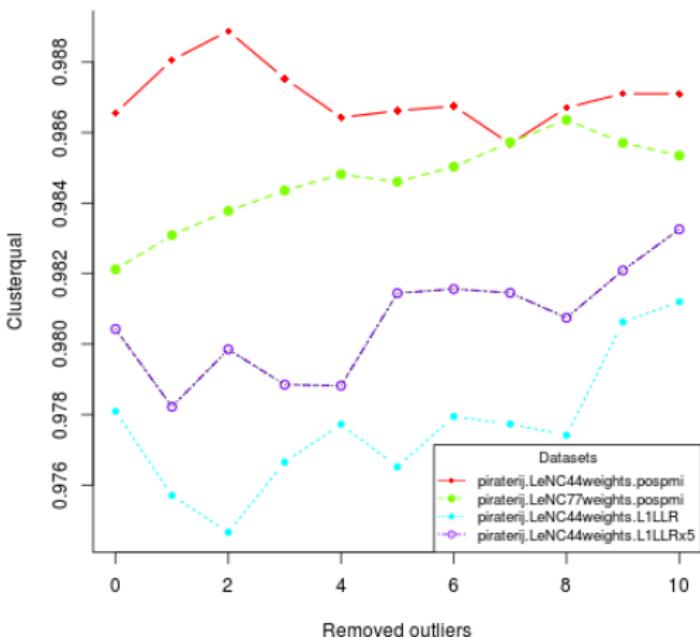
- clusterqual is sensitive to outliers.
- Unbalanced samples bias the result as our SemEval case study showed. (Wielfaert et al. 2013)

Solution:

- For each token, iteratively remove the n furthest tokens.
- Balance the sample over the different senses: 50 occurrences per sense.

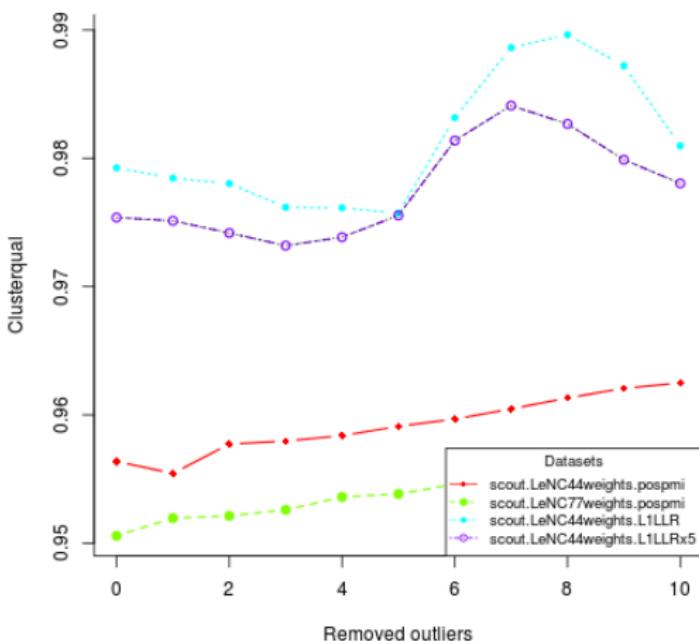
4. Cluster evaluation

piraterij



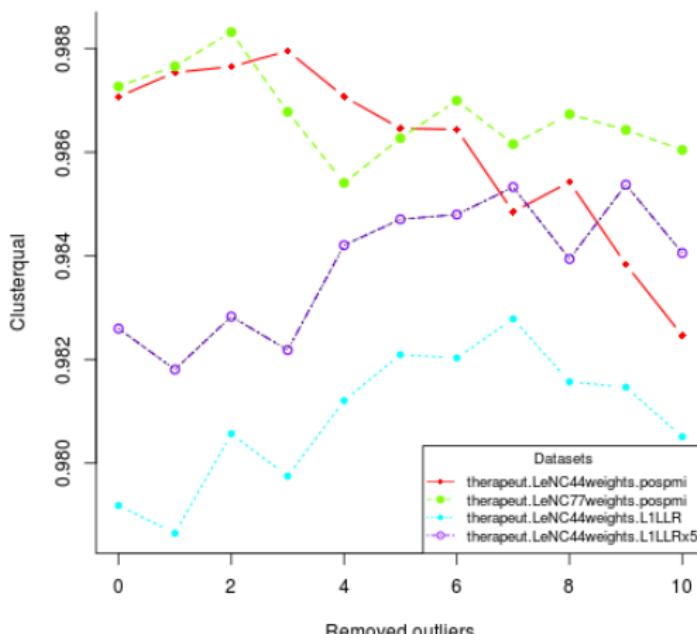
4. Cluster evaluation

scout



4. Cluster evaluation

therapeut



Overview
o

Introduction
o

SVS
oooooooo

Visualization
ooo

ClusterEvaluation
oooooooo

Discussion
ooooo

Overview

1. Linguistic Background
2. Semantic Vector Spaces
3. Visual Analytics
4. Creating a 'gold standard' and cluster evalution.
5. Discussion and future work



5. Discussion and future work

'Gold standard' as a tool for parameter choice

- Controlled sample for different target words reduces the risk of overfitting.
- Finding one fits all parameter settings is probably impossible.



5. Discussion and future work

Extending the varied parameters

- Focus on weighting scheme of first-order co-occurrences, effect rather limited.
- Previous experiments: reducing noise largest improvement so far.
- Next step: remove function words and set low weights to virtually zero.



5. Discussion and future work

Other cluster quality indices

- clusterqual has its flaws
- Whole rang of other indices implemented in R *clusterCrit* package.

5. Discussion and future work

Fitting a model

- Number solutions grow quickly explodes when varying more parameters.
- Lapesa and Evert (2013) fitted a linear model on DSM parameters for 38800 solutions.

Purpose of the talk

THEORETICAL

- Study the **structure of lexical variation**: mapping of meaning onto lexemes in different varieties.
- Analyse how this structure is apparent in **usage data**

METHODOLOGICAL

- Semantic Vector Spaces as a method for the quantitative, large-scale, corpus-based analysis of lexical semantics
- Interactive Visualisation of distributional models as an exploratory, visual analytic tool for lexicology
- Creating a '**gold standard**' and **cluster evaluation**.



For more information:

<http://wwwling.arts.kuleuven.be/qlvl>

thomas.wielfaert@arts.kuleuven.be

kris.heylen@arts.kuleuven.be

jocelyne.daems@arts.kuleuven.be

dirk.speelman@arts.kuleuven.be

dirk.geeraerts@arts.kuleuven.be