

Using Associations to identify Salient Features for Data-intensive Lexical Semantic Tasks

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Overview

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Background

- **Background:** Computational Linguistics
- **Line of Research:**
 - Data-intensive distributional lexical semantics
 - Focuses:
 - lexical acquisition
 - semantic classes and semantic relatedness
 - compositionality
 - (particle) verbs
 - evaluation
 - **Interdisciplinary research:** theory, cognition, computation

Motivation

- **Goal:** explore the potential and the limits of (text-based) distributional approaches to lexical semantics
- **Tool:** distributional models / vector space models (describe & compare by corpus-derived features)
- **Role of associations:**
 - Associations are used in gold standards for lexical semantics.
 - Associations help identifying salient semantic features.
- **Basis:**
 - *co-occurrence hypothesis*: associations \leftrightarrow corpus co-occurrence
 - *distributional hypothesis*: corpus co-occurrence \leftrightarrow meaning

Procedure

- 1 (Standard) Analyses of association norms:
 - part-of-speech analysis of associate responses
 - window co-occurrence of stimulus–associate types
 - syntax-semantic functions of associates with respect to stimuli
 - semantic relations between stimuli and associates
 - *etc.*
- 2 Apply associate information as gold standard (if appropriate).
- 3 Exploit associate knowledge with respect to semantic task.

Overview of Association Norms

- Associations to **German verbs**, collected in 2004 (Schulte im Walde et al., 2008):
 - **330 verbs** including 36 particle verbs
 - 44–54 participants per stimulus
 - 38,769/79,480 stimulus–association types/tokens
- Associations to **German particle verbs** collected in 2004 (Schulte im Walde, 2005):
 - **100 verbs** including **76 particle verbs**
 - 32–35 participants per stimulus
 - 10,009/17,442 stimulus–association types/tokens
- Associations to **German nouns**, collected in 2003/2004 (Melinger and Weber, 2006):
 - **409 nouns** referring to picturable objects
 - 50 participants per stimulus ($\times 2$ modes)
 - 30,845/116,714 stimulus–association types/tokens

Overview of Association Norms

- Associations to **German noun compounds** collected in 2010–2012:
 - web experiment with **996 compounds+constituents for 442 noun compounds** (Schulte im Walde et al., 2012):
 - 10–36 participants per stimulus
 - 28,238/47,249 stimulus–association types/tokens
 - AMT experiment with **571 compounds+constituents for 246 noun-noun compounds** (unpublished):
 - 2–120 (in general: 30) participants per stimulus
 - 26,415/59,444 stimulus–association types/tokens
- web data + AMT data contains a total of 47,523/106,693 stimulus–association types/tokens

Using the Association Norms in Distributional Semantics

Norms	Goal
Verbs Nouns	Identify salient features for distributional models
Verbs	Ditto; for semantic verb classification
Particle verbs	Gold standard to interpret distributional nearest neighbours
Compounds	Explore distributional factors of semantic relatedness between compounds and their constituents

Distributional Semantic Tasks

- 1 Semantic verb classification
- 2 Compositionality of Noun Compounds

Semantic Verb Classification: Motivation

- Resource-intensive vs. automatic methods
- Manual example classifications:
 - Levin classes based on syntax-semantics alternation behaviour (Levin, 1993)
 - *WordNet* based on synonymy (Fellbaum, 1998)
 - *FrameNet* based on situation agreement (Fillmore et al., 2003)
- Automatic example classifications:
Merlo & Stevenson (2001); Korhonen et al. (2003); Schulte im Walde (2003; 2006); Joanis et al. (2008)
- **Basis**: distributional hypothesis
- **Task**: automatic, corpus-based semantic verb classification

Semantic Verb Classification relying on Associations

- **Assumption:** semantically related verbs have common associations → they are assigned to common classes
- **Method:** agglomerative hierarchical clustering with German verbs and associations as features
- **Standard setup:**
 - similarity measure: *skew divergence*
 - merging criterion: *Ward's method* (sum-of-squares)
- **Validation as a gold standard:**

pair-wise comparison against *GermaNet* and *FrameNet*

→ F-score of 62.69% for GermaNet (upper bound: 82.35%)

→ F-score of 34.68% for FrameNet (upper bound: 60.31%)

Semantic Verb Classification relying on Associations

Example classes and verbs	Strongest association features
<p><i>bedauern</i> 'regret', <i>heulen</i> 'cry', <i>jammern</i> 'moan', <i>klagen</i> 'complain, moan, sue', <i>verzweifeln</i> 'become desperate', <i>weinen</i> 'cry'</p>	<p><i>Trauer</i> 'mourning', <i>weinen</i> 'cry', <i>traurig</i> 'sad', <i>Tränen</i> 'tears', <i>jammern</i> 'moan', <i>Angst</i> 'fear', <i>Mitleid</i> 'pity', <i>Schmerz</i> 'pain', etc.</p>
<p><i>abnehmen</i> 'lose weight', <i>abspecken</i> 'lose weight', <i>zunehmen</i> 'gain weight'</p>	<p><i>Diät</i> 'diet', <i>Gewicht</i> 'weight', <i>dick</i> 'fat', <i>abnehmen</i> 'lose weight', <i>Waage</i> 'scale', <i>Essen</i> 'food', <i>essen</i> 'eat', <i>Sport</i> 'sports', <i>dünn</i> 'thin', <i>Fett</i> 'fat', etc.</p>

Corpus-based Semantic Verb Classification

- **Goal:** compare corpus-based features in standard verb clustering with association-based and manual gold standards
- **Method:** agglomerative hierarchical clustering with German verbs and corpus-based features (details as above)
- **Features:** 20-window co-occurrence and dependency-based corpus features from 200-million word newspaper corpus
- **Gold standards:**
 - association-based clustering: 100 clusters with 330 verbs
 - GermaNet: hard random selection of 100 synsets, 233 verbs
 - FrameNet: hard version of all 77 classes with 406 verbs

Corpus-based Semantic Verb Classification

	grammar relations						
	$\langle NP_n \rangle$	$\langle NP_n, NP_a \rangle$	$\langle NP_n, NP_a \rangle$	NP	PP	NP&PP	ADV
Assoc	35.90	37.18	39.25	39.14	37.97	41.28	38.53
GN	58.01	53.37	51.90	53.10	54.21	51.77	51.82
FN	29.46	30.13	32.74	34.16	28.72	33.91	35.24

	co-occurrence: window-20				
	all	ADJ	ADV	N	V
Assoc	39.33	37.31	36.89	39.33	38.84
GN	51.53	50.88	47.79	52.86	49.12
FN	32.01	31.08	31.00	34.24	31.75

Semantic Verb Classification: Summary

- Associations provide the knowledge we need for automatic semantic classification.
→ Modelling the (syntax-)semantic relatedness between stimuli and associations can guide us towards salient features.
- Caveats:
 - There are significant differences in accuracy:
feature type ↔ gold standard type.
 - The association-based clustering is modelled worst.
- Conclusions:
 - Association-based clustering represents one gold standard semantic classification among others.
 - We need to model association knowledge beyond standard feature types.

Noun-Noun Compositionality: Motivation

- **Interest:** semantic relatedness between noun-noun compounds and their nominal constituents
- **Examples:**
 - *Blockflöte* 'flute' / *Block* 'block; fragment; pad' / *Flöte* 'flute'
 - *Fliegenpilz* 'fly agaric' / *Fliege* 'fly; bow tie' / *Pilz* 'mushroom'
 - *Schlittenhund* 'sledge dog' / *Schlitten* 'sledge' / *Hund* 'dog'
- **Basis:** distributional hypothesis
- **Task:** automatic prediction of the degree of compositionality of the compounds with respect to the constituents

Noun-Noun Compositionality: Data

- 246 depictable German noun-noun compounds (von der Heide and Borgwaldt, 2009)
- Transparent vs. opaque compounds
- **Compositionality judgements:**
 - for compounds and each constituent on a scale 1–7
 - 35 participants for each compound–constituent pair
 - gold standard: mean values of judgements
- **Associations for compounds and constituents** (85,049 tokens over 34,560 types for 571 stimuli)

Noun-Noun Compositionality: Associations

- **Assumption:** transparent compounds have more associations in common with their constituents than opaque compounds
- **Method:** standard vector space model compares vectors of compounds with vectors of constituents
- **Standard setup:**
 - features: window co-occurrence
 - similarity measure: *cosine*
- **Evaluation:** *Spearman rank-order correlation coefficient* (r_S) for cosine values against mean compositionality judgements

Noun-Noun Compositionality: Predictions

r_S varying the vector space features (using the *sdeWaC* corpus):

Features		r_S		
		both const	const1	const2
Baseline	association overlap	.5394	.5702	.5680
Vector space	associations	.5676	.5752	.6267
	window 20: <i>all</i>	.1918	.1958	.1190
	window 20: nouns	.4742	.4806	.4416
	window 20: verbs	.2773	.1883	.2432
	window 20: adjectives	.2261	.2136	.2000

Noun-Noun Compositionality: Predictions

r_S varying the corpus:

Features	Corpora				
	HGC	Wikipedia	WebKo		sdeWaC
	ext	ext	ext	int	int
	200	430	1,500	1,500	880
window 20: nouns	.2214	.3549	.4065	.3306	.4742

Noun-Noun Compositionality: Summary

- **Confirmation:** Transparent compounds have more associations in common with their constituents than opaque compounds.
- **Associations provide the knowledge we need for predicting compositionality.**
 - Modelling the overlap of associations to compounds and constituents can guide us towards salient features.
- **Association properties:** Different feature types provide complementary information for compositionality.
 - Can we distinguish between the contributions of the various parts-of-speeches?
 - Can we specify the compositionality with respect to modifier vs. head?

Conclusions

- Associations provide a lot of the knowledge we need for distributional lexical semantics.
- Questions:
 - how can we improve the automatic identification of stimulus–associate relationships?
 - what is the role of corpus domain(s)?
 - what is the role of corpus size?
 - how can we exploit world knowledge in association norms?

Colleagues

- Susanne Borgwaldt (Braunschweig/Erfurt)
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- Stefan Müller (Stuttgart)

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