Semantic Mapping for Lexical Sparseness Reduction in Parsing

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Context and motivation

- we know semantics can help syntactic parsing
  - specifically: semantic classes for mostly data-driven systems
- classes provide generalization for reducing lexical sparseness
- obtain a baseline using human-built semantic inventories for Dutch
  - issues of such an approach

Example

open a box $\boxed{\text{with knife}}$ open a box $\boxed{\text{with scissors}}$

? ?

- "open with scissors" not in training $\Longrightarrow$
- but "knife" and "scissors" share the class (cutting tools) $\Longrightarrow$
- correct analysis possible

Comparison to related work

MacKinlay et al. 2012, Henestroza and Candito 2012, Agirre et al. 2011, Koo et al. 2008 . . .

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3. usually **extremes** of granularity are taken as representation level,

$\Rightarrow$ "appropriate" level of generality

Parser

Alpino

- parser for Dutch
- manually crafted HPSG grammar, augmented to represent dependency structure
- MaxEnt disambiguation component

Lexical association component

- part of disambiguation component
- bilexical preferences measured by normalized PMI and learned from a 500M word corpus
- improvement on the base parser (Van Noord, 2010)

Example

(verb,SU) dependency type:

$$(\underbrace{\text{“drink”}}_{\text{w1}}, \underbrace{\text{verb}}_{\text{pos1}}, \underbrace{\text{su}}_{\text{relation}}, \underbrace{\text{noun}}_{\text{pos2}}, \underbrace{\text{“baby”}}_{\text{w2}}) \quad \underbrace{0.28}_{\text{pmi}}, \quad \underbrace{4.89}_{\text{feature weight}}$$

Selection of dependency types

- identify types whose bilexical sparseness hurts parser the most

⇒ correlation between coverage and parsing accuracy: Cramer's Φ, odds ratio:

Type	Odds	ϕ coef.
(adj,MOD)	2.653	0.2
(noun,CNJ)	2.042	0.12
(noun,MOD)	1.962	0.11

- correct parse of (noun,CNJ) is then **2 times** more likely with available bilexical preference

Semantic representation: 3 levels

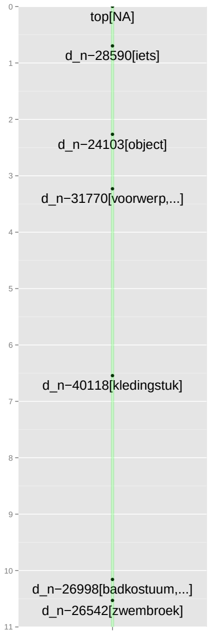
- use Cornetto, a Dutch wordnet

Fine: immediate synset (SYN)

- take the 1st most-prominent sense
- little generalization

Coarse: semantic type (ST)

- assigned to 50% of lexical units (LUs)
- $\sim$20 POS-dependent labels: “action”, “human”, “concrete” ...

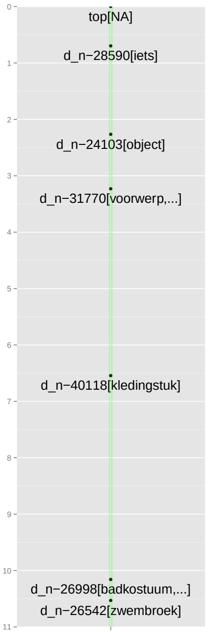


Semantic representation: 3 levels

Intermediate (INT)

- find a level that is both general and precise
- calculate generality of a synset
- if too concrete, map to a more general synset
- treat Cornetto as a tree-like directed graph
  - hypernimic relations are arcs
  - synsets are nodes
- **Information Content** is: (Sánchez et al. 2011)

$$IC(s) = -log \frac{\frac{|leaves_s|}{|subsumers_s|} + 1}{total\_leaves + 1}$$



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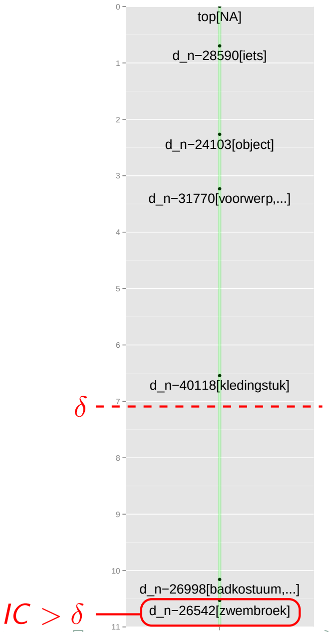

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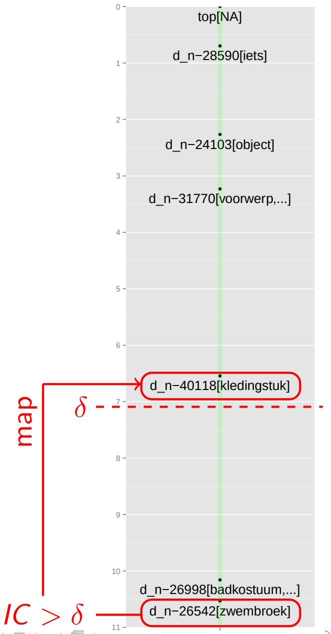

Use of classes

For training

1. obtain relevant dependencies in Lexical Association model
2. make a copy with classes replacing words
3. calculate MI scores

For testing

- use bilexical preference when possible, **back-off** to generalized classes otherwise

  Test set

  - Alpino Treebank: 7,136 sentences of newspaper texts
  - parts of Lassy Small: 3,917 sentences

Results I

Example of enhancement

"Utrechtse Camera bioscoop" (*Camera cinema in Utrecht*)

$\Rightarrow$ no bilexical preference for <Utrechtse, mod, bioscoop>

$\Rightarrow$ parser backs-off to a generalization of "Utrechtse"

$\Rightarrow$ new instance: "$place_{adj}$ Camera bioscoop"

$\Rightarrow$ preference now exists for <$place_{adj}$, mod, bioscoop>

$\Rightarrow$ parse correct

- Cornetto coverage in test: 60% (backed-off tokens only)

Results II

- **SYN**: number of improvements **levels** the number of deteriorations . . .
  - (noun/CNJ) is the best performing type
- **ST**: poor performance due to overgeneralizing
- **INT** ($\delta_{IC} = 6$): seems only slightly better than ST

All 3 dependency types

	% found	# Improved	# Deteriorated
SYN	7.8	**33**	29
ST	62.1	178	299

(noun/CNJ) only

	# Improved	# Deteriorated
SYN	**7**	2
ST	20	26
INT	16	19

Remarks

- synset level: very modest improvement on nominal conjunction
- intermediate level: no improvement
- unlike Agirre et al. 2011 and MacKinlay et al. 2012, semantic types are the worst performer
- for more impact, more generalization is needed, but it introduces noise
- parser's degree of lexicalization might affect the "working" space
  - bilexical component gets "the low-hanging fruit"

- next: distributional semantic methods
  - increased coverage
  - alternative granularity
  - sense disambiguation in context
  - composition