Modelling Word Similarity
An Evaluation of Automatic Synonymy Extraction Algorithms

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Purpose

- Use Word Space Models to find synonyms
- Compare models with different definitions of context
- Evaluate whether these models do equally well for all words: frequent and infrequent, specific and general terms, abstract and concrete

⇒ more informed model choices for specific applications
Overview

1. Introduction

2. Experimental setup

3. Evaluation scheme

4. Influence of word properties

5. Conclusions
Overview

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Introduction

Words Space or Distributional Models

- Words appearing in similar contexts have similar meanings
- Word meaning is modelled as a vector of context features
- Semantic similarity is measured as context vector similarity

Different context definitions:

Word Space Models

- document based
- word based

  - bag-of-words
  - syntactic

  - 1st order
  - 2nd order
Introduction

document based models

- context = text in which target word occurs (e.g. documents)
- 2 words are related when they often co-occur in documents
- Landauer & Dumais 1997: Latent Semantic Analysis

word based models

- context = words left and right of target word
- 2 words are related when they co-occur with the same context words, but not necessarily with each other
Introduction

Within word based models:

**bag-of-words**

- context words in window of \( n \) words left and right of target
- a bag of unstructured context features

**syntactic features**

- context words in specific syntactic relation with target
- takes clause structure into account
Introduction

Within the bag-of-words models:

1st order co-occurrences

• context = words in immediate proximity to the target
• Levy & Bullinaria 2001

2nd order co-occurrences

• context = context words of context words of target
• can generalise over semantically related context words
• Schütze 1998

NB syntactic models are also 1st order models
Introduction

Problems

- “Comparisons between the two types of models have been few and far between in the literature.” (Padó & Lapata 2007)
- What kind of semantic similarity do these models actually capture?
- Do they work equally well for all types of target words?
- Crucial in choosing the model that is best suited for a specific application (QA, WSD, IR,...)
Research goals

- Compare word-based models with different context definitions on the same data
- Analyse the type of semantic relations found
- Evaluate whether retrieval works equally well for different classes of target words

Word Space Models

- document based
- word based
  - bag-of-words
  - syntactic
    - 1st order
    - 2nd order
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Experimental setup

Three Word Space Models for Dutch

- first order bag of words
- second order bag of words
- syntactic (dependency-based)

Variation on 2 parameters

- context type: mere co-occurrence vs syntactic dependency
- order: 1st order vs 2nd order co-occurrences
Experimental setup: Context type

Bag of words
mere co-occurrence: words that appear at least 5 times in a context window of $n$ words around the target word $w$.

Syntactic contexts
dependency relations: subject, direct object, prepositional complement, adverbial prepositional phrase, adjectival modification, PP postmodification, apposition, coordination
Experimental setup: Order

1st order
words that occur in immediate proximity to the target word $w$.

2nd order
words that co-occur with the 1st order co-occurrence of the target word $w$.

⇒ Only varied for BoW models, although, in principle, 2nd order syntactic relations possible as well
Experimental setup: other parameters

- Window size (b-o-w): 3 words left and right
- Dimensionality: fixed at 4000 most frequent features,
  - cut-off of 5 (bag-of-words)
  - experiments with Random Indexing (Peirsman & Heylen 2007)
- Weighting scheme: point-wise mutual information index
- Similarity measure: cosine between vectors
- Data: Twente Nieuws Corpus, 300M words of newspaper text, parsed with Alpino (van Noord 2006)
- Test set: 10,000 most frequent nouns
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Evaluation Scheme

Evaluated Output

• for each of the 10,000 target words, the semantically most similar word was retrieved = Nearest Neighbour (NN)
• by each of the three models (1st bow, 2nd bow, dependency)

Evaluation Criteria

Gold Standard Dutch EuroWordNet (EWN) (even though...)

criterium 1 average Wu & Palmer score of NNs

criterium 2 % syno-, hypo-, hyper- en cohyponyms among NNs

NB: only pairs in EWN (syn 7479, 1st bow 6776, 2nd bow 6727)
Evaluation Scheme

Definition of semantic relationships

craft

- watercraft
- aircraft

- airplane || plane || aeroplane
- helicopter || chopper

- hydroplane || seeplane
- jetplane
  - jumbojet
Evaluation Scheme

Definition of semantic relationships

target word

craft

watercraft

aircraft

airplane \parallel \text{plane} \parallel \text{aeroplane}

hydroplane \parallel \text{seeplane}

jetplane

helicopter \parallel \text{chopper}

jumbojet
Evaluation Scheme

Definition of semantic relationships

synonyms

craft

watercraft

aircraft

airplane

plane

aeroplane

hydroplane

seeplane

jetplane

jumbojet

helicopter

chopper
Evaluation Scheme

Definition of semantic relationships

hyponyms

- craft
  - watercraft
  - aircraft
    - airplane
      - plane
        - aeroplane
    - hydroplane
      - seeplane
    - jetplane
      - jumbojet
    - helicopter
      - chopper
Evaluation Scheme

Definition of semantic relationships

hypernyms

craft

watercraft

aircraft

airplane || plane || aeroplane

helicopter || chopper

hydroplane || seeplane

jetplane

jumbojet
Evaluation Scheme

Definition of semantic relationships

cohyponyms

craft
  └── watercraft
  └── aircraft
     ├── airplane
     │   └── plane
     │       └── aeproplane
     └── helicopter
         └── chopper
     └── hydroplane
     └── seeplane
     └── jetplane
         └── jumbojet
Overall performance (Peirsman, Heylen & Speelman 2008)

The diagram shows the overall performance of different models in recognizing semantic relations. The models are:

- **dependency**: 0.62
- **1° b.o.w.**: 0.52
- **2° b.o.w.**: 0.31

The performance is measured in percentage, with higher values indicating better performance. The diagram uses different colors to represent various types of semantic relations:
- Cohyponym
- Hypernym
- Hyponym
- Synonym

The models are compared by their ability to correctly identify these relations, with the results showing a clear distinction in performance across different types of relations.
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Results: Influence of word properties

- **Up to now:** no differentiation between target words
- **But:** Can synonyms be equally well retrieved for all classes of target words?
- **Question:** Do the linguistic properties of target words influence the performance of the models?
- **Three properties:**
  1. Frequency
  2. Semantic specificity
  3. Semantic class
Influence of Frequency

natural log of target word frequency in our corpus
Influence of Frequency

- higher frequency $\Rightarrow$ more relations (synon. & hypon.)
- stronger effect for weak 2° bow model
- possible explanations:
  - technical reason: more data for frequent words
  - more frequent words are more likely to have synonyms
Influence of Semantic Specificity

Depth of target word in WordNet hierarchy

- Cohyponym
- Hypernym
- Hyponym
- Synonym

Depth in the EuroWordNet hierarchy

Percentages for:
- Dependency
- 1° bag-of-words
- 2° bag-of-words
Influence of Semantic Specificity

- No clear (linear) effect
- more synonyms for unspecific and intermediately specific terms
- intermediates mainly person nouns (teacher, thief, villain)
- possible explanations
  - Base level categories?
  - Granularity variance in EWN
Influence of Semantic Class

the but 1 highest ancestor in WordNet (5 out of 41):
object, location, event, situation, thought
Influence of Semantic Class

- number of related NNs remains constant
- significantly more synonyms for *thoughts* than for *objects*
- cline concrete-abstract: more synonyms for abstract words
- possible explanations
  - better represented in newspaper data
  - fuzzyness of abstract categories
  - more readily put in same synset in EWN
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Conclusions

Influence of target word properties on the performance of Word Space Models for Dutch

- tighter semantic relations for high frequency words
- no clear effect of semantic specificity
- more synonyms retrieved for abstract semantic classes
- similar effects for 1º, 2º bow and syntactic model
- syntactic model best performing for any subclass of words

Future work

- find out WHY these properties have an effect
- words from specific topical domains
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