Exploring Topic Models for Word Sense Discrimination

Tim Van de Cruys

University of Groningen

CLIN

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Semantic similarity

- Most work on semantic similarity relies on the DISTRIBUTIONAL HYPOTHESIS (Harris 1954)
- Take a word and its contexts:
  - tasty *smoutebol*
  - greasy *smoutebol*
  - a portion of *smoutebol*
  - *smoutebol* with loads of powdered sugar
- By looking at a word's context, one can infer its meaning

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$\Rightarrow$ **FOOD**

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Two kinds of context

1. 'Bag of words' context
   - a window around the word is used as context
   - e.g. a fixed numbers of words, the paragraph in which a word appears, ...
   - often used with some form of dimensionality reduction
2. Syntactic context
   - a corpus is parsed, dependency triples are extracted
   - e.g. <apple, obj, eat>, <apple, adj, red>
   - typically does not use any form of dimensionality reduction

Ambiguity

- **Problem**: ambiguity
  - Compare:
    a trendy bar
    $\leftrightarrow$ *an iron bar*
    $\leftrightarrow$ *today's air pressure: 1.013 bar*
  - Different meanings, but they are considered the same entity by a naive algorithm
- Main research question: can 'bag of words' context and syntactic context be combined to differentiate between various senses of a word?

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Technique

- Given a non-negative matrix V, find non-negative matrix factors W and H such that:

$$V_{nxm} \approx W_{nxr} H_{rxm} \tag{1}$$

- Choosing $r \ll n, m$ reduces data
- Constraint on factorization: all values in three matrices need to be *non-negative values* (≥ 0)
- Constraint brings about a *parts-based* representation: only additive, no subtractive relations are allowed

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Results

- Context vectors (5k nouns $\times$ 2k co-occurring nouns) extracted from CLEF corpus
- NMF is able to capture 'semantic' dimensions)
- Examples:
  - *bus* 'bus', *taxi* 'taxi', *trein* 'train', *halte* 'stop', *reiziger* 'traveler', *perron* 'platform', *tram* 'tram', *station* 'station', *chauffeur* 'driver', *passagier* 'passenger'
  - *bouillon* 'broth', *slagroom* 'cream', *ui* 'onion', *eierdooier* 'egg yolk', *laurierblad* 'bay leaf', *zout* 'salt', *deciliter* 'decilitre', *boter* 'butter', *bleekselderij* 'celery', *saus* 'sauce'

Methodology

- Goal: classification of nouns according to both 'bag of words' context and syntactic context
- $\Rightarrow$ Construct three matrices capturing co-occurrence frequencies for each mode
  - nouns cross-classified by dependency relations
  - nouns cross-classified by (bag of words) context words
  - dependency relations cross-classified by context words
- $\Rightarrow$ Apply NMF to matrices, but interleave the process
- Result of former factorization is used to initialize factorization of the next one

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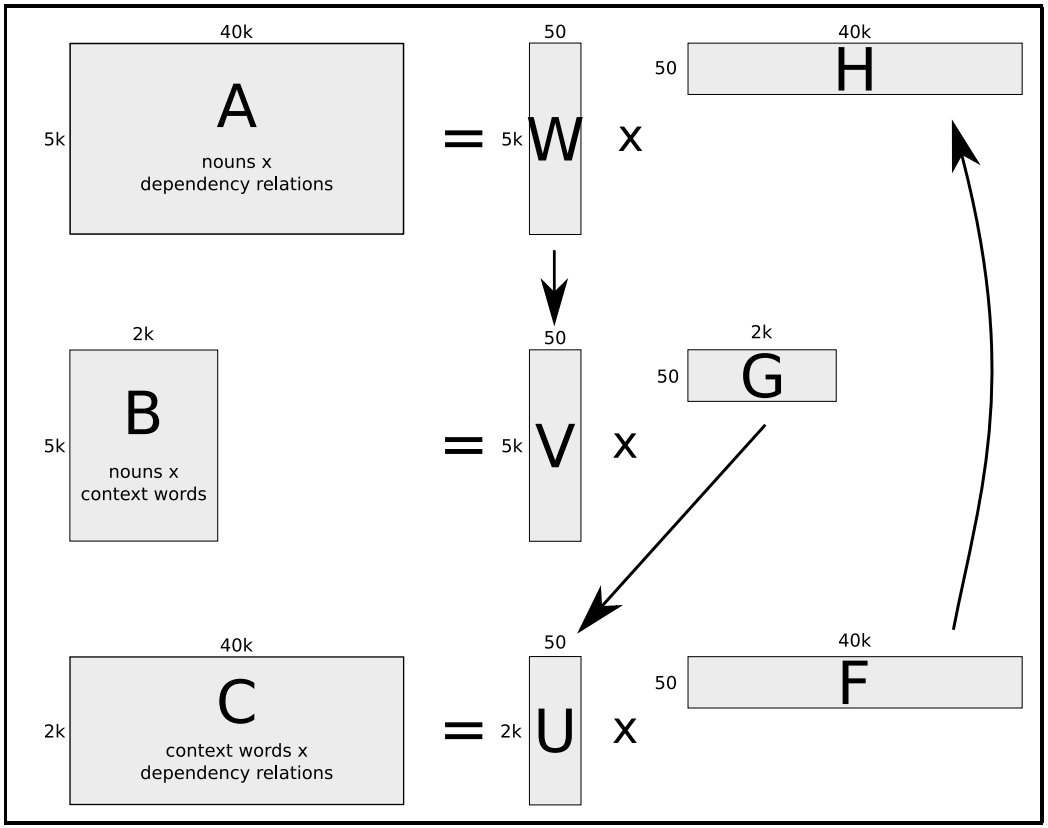
Graphical Representation



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Sense subtraction

- 'switch off' one dimension of an ambiguous word to reveal other possible senses
- From matrix W, we know which dimensions are the most important for a certain word
- Matrix H gives the importance of each dependency relation given a dimension
- 'subtract' dependency relations that are responsible for a given dimension from the original noun vector
  - $\overrightarrow{v}_{new} = \overrightarrow{v}_{orig}(\overrightarrow{1} - \overrightarrow{h}_{dim})$
  - each dependency relation is multiplied by a scaling factor, according to the load of the feature on the subtracted dimensions

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Combination with clustering

- A simple clustering algorithm (e.g. K-means) assigns ambiguous nouns to its predominant sense
- Centroid of the cluster is fold into topic model
- The dimensions that define the centroid are subtracted from the ambiguous noun vector
- Adapted noun vector is fed to the clustering algorithm again

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Experimental Design

- Approach applied to Dutch, using CLEF corpus (Dutch newspaper texts '94-'95)
- Corpus parsed with Dutch dependency parser ALPINO
- three matrices constructed with:
  - 5k nouns $\times$ 40k dependency relations
  - 5k nouns $\times$ 2k context words
  - 40k dependency relations $\times$ 2k context words
- Factorization to 100 dimensions

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Example dimension: transport

1. **nouns**: *auto* 'car', *wagen* 'car', *tram* 'tram', *motor* 'motorbike', *bus* 'bus', *metro* 'subway', *automobilist* 'driver', *trein* 'trein', *stuur* 'steering wheel', *chauffeur* 'driver'
2. **context words**: *auto* 'car', *trein* 'train', *motor* 'motorbike', *bus* 'bus', *rij* 'drive', *chauffeur* 'driver', *fiets* 'bike', *reiziger* 'reiziger', *passagier* 'passenger', *vervoer* 'transport'
3. **dependency relations**: viertraps$_{adj}$ 'four pedal', verplaats_met$_{obj}$ 'move with', toeter$_{adj}$ 'honk', tank_in_houd$_{obj}$ [parsing error], tank$_{subj}$ 'refuel', tank$_{obj}$ 'refuel', rij_voorbij$_{subj}$ 'pass by', rij_voorbij$_{adj}$ 'pass by', rij_af$_{subj}$ 'drive off', peperduur$_{adj}$ 'very expensive'

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Pop: most similar words

pop music $\leftrightarrow$ *doll*

1. *pop*, *rock*, *jazz*, *meubilair* 'furniture', *popmuziek* 'pop music', *heks* 'witch', *speelgoed* 'toy', *kast* 'cupboard', *servies* '[tea] service', *vraagteken* 'question mark'
2. *pop*, *meubilair* 'furniture', *speelgoed* 'toy', *kast* 'cupboard', *servies* '[tea] service', *heks* 'witch', *vraagteken* 'question mark' *sieraad* 'jewel', *sculptuur* 'sculpture', *schoen* 'shoe'
3. *pop*, *rock*, *jazz*, *popmuziek* 'pop music', *heks* 'witch', *danseres* 'dancer', *servies* '[tea] service', *kopje* 'cup', *house* 'house music', *aap* 'monkey'

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Pop: clusters

1. *house*, *jazz*, *pop*, *rock*
2. *elektronica* 'electronics' , *horloge* 'watch', *juweel* 'jewel', *kleding* 'clothes', *parfum* 'perfume', *pop* 'doll', *schoen* 'shoe', *sieraad* 'jewel' , *speelgoed* 'toy', *textiel* 'textile'

Barcelona: most similar words

Spanish city $\leftrightarrow$ *Spanish football club*

1. *Barcelona*, *Arsenal*, *Inter*, *Juventus*, *Vitesse*, *Milaan* 'Milan', *Madrid*, *Parijs* 'Paris', *Wenen* 'Vienna', *München* 'Munich'
2. *Barcelona*, *Milaan* 'Milan', *München* 'Munich', *Wenen* 'Vienna', *Madrid*, *Parijs* 'Paris', *Bonn*, *Praag* 'Prague', *Berlijn* 'Berlin', *Londen* 'London'
3. *Barcelona*, *Arsenal*, *Inter*, *Juventus*, *Vitesse*, *Parma*, *Anderlecht*, *PSV*, *Feyenoord*, *Ajax*

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Barcelona: clusters

1. *Anderlecht*, *Arsenal*, *Barcelona*, *Bayern*, *Inter*, *Juventus*, *Milan*, *Parma*
2. *Antwerpen* 'Antwerp', *Barcelona*, *Berlijn* 'Berlin', *Bonn*, *Bremen*, *Brussel* 'Brussels', *Frankfurt*, *Hamburg*, *Londen* 'London', *Milaan* 'Milan', *München* 'Munich', *Parijs* 'Paris', *Rome*, *Wenen* 'Vienna'

Conclusion

- Combining bag of words data and syntactic data is useful
  - bag of words data (factorized with NMF) puts its finger on topical dimensions
  - syntactic data is particularly good at finding similar words
  - a clustering approach allows one to determine which topical dimension(s) are responsible for a certain sense
  - and adapt the (syntactic) feature vector of the noun accordingly
  - subtracting the more dominant sense to discover less dominant senses

Future Work

- Proper evaluation, comparison with other WSD algorithms
- Extend the clustering part
  - Fully automatic clustering
  - Use of 'tight' clusters instead of 'broad' K-means results
- Scale the method to large data sets (20K nouns $\times$ 100K dependency relations, larger corpus)

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