Recognition of Hyponymy and Meronymy Relations in Word Embeddings for Polish

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Agenda

- Need, contradiction, goal
- Classification for hyponymy recognition
- Experiments
  - Corpora and training-testing dataset
  - Scheme
  - Tests
- Results
- Conclusions
Need, contradiction, goal

- **Need**
  - Even in a very large wordnet some relation instances can be omitted
  - Corpus-based *Measures of Semantic Relatedness* express many different lexico-semantic relations

- **Contradiction**
  - In several works, classifiers were applied to MSR to recognise hypernymy instances, e.g. (Fu et al., 2014)
  - (Levy et al., 2015) convincingly claim that this is not possible (sic!)

- **Goal**
  - to check these contradictory points of the view on large corpora and comprehensive wordnet for Polish
  - to expand this research with *meronymy* – a more difficult relation
Classification for hypernymy recognition

- Wordnet or thesaurus as source of hyponymy instances: $\langle x, y \rangle$
  - $x$ – a hyponym, and $y$ – a hypernym,
  - are lemmas belonging to two separate synsets
- $\langle x, y \rangle$ represented by $x - y$
  - $x, y$ – word embedding vectors
- Hypernymy projection (Fu et al., 2014):
  - a linear projection of the vector $x$, i.e. $\Phi x$, on a vector $y'$
- Automatically clustering $x - y$ into $n$ groups by $k$-means
- Separated classifier was trained by the linear regression method for each cluster
Experiments
Corpora and training-testing dataset (1)

- Limitations of the semantic representation based on word embeddings
  1. the whole model can be biased by the particular selection of texts
     → large corpus needed
  2. senses of polysemous words are merged together
     → separate experiments for monosemous and polysemous lemmas
  3. and the representation of less frequent words and senses can be blurred by the statistical noise
     → words with more than 1,000 occurrences
Experiments

Corpora and training-testing dataset (2)

- Gold standard: plWordNet – a very large wordnet of Polish
- Corpus: plWordNet Corpus 10
  - more than 4 billion words: several corpora supplemented with text acquired from the Web, only text in Polish, automated elimination of duplicates
- Vectors
  - word2vec (Mikolov et al., 2013), Gensim implementation (Rěhůřek and Sojka, 2010)
  - all words with the minimal frequency $\geq 8$ (min_count=8)
  - vector size: 300
- Number of clusters
  - dataset divided into: training, testing and development in the ratio 6:2:2
  - automated optimisation on a development subset
Experiments

Scheme (1)

- Two types of data sets for the experiments
  1. *random* division into subsets,
  2. *lexical train/test splits* rule proposed by (Levy et al., 2015)
     - positive cases: direct hypernyms & cannot include hypernyms from the training set
     - negative cases: excluding indirect hypernyms &

\[
T_x^+ = \{ x \mid (x,y) \in T^+ \} \\
T_y^+ = \{ y \mid (x,y) \in T^+ \} \\
S = (T_x^+ \times T_y^+) \setminus T^+ 
\]

where \( T^+ \) is a set of word pairs belonging to the given relation
Experiments
Tests

Hypo-Mono – hyponymy recognition, monosemous words: 6k positive pairs, 6k negative; two variants: random & lexical split; the vector size: 100.

Hypo-Poly – 20k hyponymy pairs including polysemous words; 20k negative, two variants; the vector size: 100

Hypo-Mono300 – as in Hypo-Mono but the vector size: 300, only lexical split

Hypo-Poly300 – as above, but 20k hyponymy pairs including polysemous words, 20k negative pairs by the lexical split, the vector size was: 300.

Mero-Poly – 7,900 meronymy pairs (only part of), 8,000 negative pairs: not connected or connected by paths longer than 3 links, the lexical split, the vector size: 100.
<table>
<thead>
<tr>
<th>Experiment</th>
<th>Acc</th>
<th>P</th>
<th>R</th>
<th>F</th>
<th>Err</th>
<th>Type</th>
<th>Vec. Size</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hypo-Mono</td>
<td>85.22%</td>
<td>78.91%</td>
<td>96.27%</td>
<td>86.72%</td>
<td>27.91%</td>
<td>Rnd</td>
<td>100</td>
</tr>
<tr>
<td>std. dev.</td>
<td>0.64%</td>
<td>1.00%</td>
<td>0.65%</td>
<td>0.65%</td>
<td>1.92%</td>
<td>Rnd</td>
<td>100</td>
</tr>
<tr>
<td>Hypo-Mono</td>
<td>84.98%</td>
<td>78.90%</td>
<td>95.18%</td>
<td>86.27%</td>
<td>28.05%</td>
<td>Split</td>
<td>100</td>
</tr>
<tr>
<td>std. dev.</td>
<td>0.61%</td>
<td>1.59%</td>
<td>0.79%</td>
<td>0.91%</td>
<td>2.22%</td>
<td>Split</td>
<td>100</td>
</tr>
<tr>
<td>Hypo-Poly</td>
<td>78.94%</td>
<td>74.35%</td>
<td>88.35%</td>
<td>80.74%</td>
<td>31.63%</td>
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<td>100</td>
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<tr>
<td>std. dev.</td>
<td>0.65%</td>
<td>0.41%</td>
<td>1.70%</td>
<td>0.79%</td>
<td>1.78%</td>
<td>Rnd</td>
<td>100</td>
</tr>
<tr>
<td>Hypo-Poly</td>
<td>77.23%</td>
<td>73.83%</td>
<td>84.66%</td>
<td>78.85%</td>
<td>30.54%</td>
<td>Split</td>
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</tr>
<tr>
<td>std. dev.</td>
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<td>1.40%</td>
<td>2.39%</td>
<td>1.04%</td>
<td>2.25%</td>
<td>Split</td>
<td>100</td>
</tr>
<tr>
<td>Hypo-Mono300</td>
<td>73.31%</td>
<td>65.16%</td>
<td>98.20%</td>
<td>78.32%</td>
<td>–</td>
<td>Split</td>
<td>300</td>
</tr>
<tr>
<td>std. dev.</td>
<td>1.11%</td>
<td>1.82%</td>
<td>0.39%</td>
<td>1.31%</td>
<td>–</td>
<td>Split</td>
<td>300</td>
</tr>
<tr>
<td>Hypo-Poly300</td>
<td>82.54%</td>
<td>84.51%</td>
<td>94.72%</td>
<td>89.32%</td>
<td>–</td>
<td>Split</td>
<td>300</td>
</tr>
<tr>
<td>std. dev.</td>
<td>1.01%</td>
<td>1.11%</td>
<td>0.69%</td>
<td>0.73%</td>
<td>–</td>
<td>Split</td>
<td>300</td>
</tr>
<tr>
<td>Mero-Poly300</td>
<td>79.95%</td>
<td>74.66%</td>
<td>90.43%</td>
<td>81.77%</td>
<td>–</td>
<td>Split</td>
<td>100</td>
</tr>
<tr>
<td>std. dev.</td>
<td>1.05%</td>
<td>1.71%</td>
<td>1.38%</td>
<td>0.99%</td>
<td>–</td>
<td>Split</td>
<td>100</td>
</tr>
</tbody>
</table>
Results

Ration: matching error vs recall for the hyponymy recognition by SVM
### Results

**Examples of clusters**

<table>
<thead>
<tr>
<th>Hyponym</th>
<th>Hyponym</th>
<th>Cluster ID</th>
</tr>
</thead>
<tbody>
<tr>
<td>wyziew ‘vapour’</td>
<td>spaliny ‘engine exhausts’</td>
<td>973</td>
</tr>
<tr>
<td>usługa ‘service’</td>
<td>przewóz ‘transport’</td>
<td>973</td>
</tr>
<tr>
<td>usługa ‘service’</td>
<td>fryzjerstwo ‘hairdressing’</td>
<td>973</td>
</tr>
<tr>
<td>usługa ‘service’</td>
<td>outsourcing ‘outsourcing’</td>
<td>973</td>
</tr>
<tr>
<td>usługa ‘service’</td>
<td>usługa powszechna ‘common service’</td>
<td>973</td>
</tr>
<tr>
<td>usługa ‘service’</td>
<td>usługa telekomunikacyjna ‘telecom. service’</td>
<td>973</td>
</tr>
<tr>
<td>usługa ‘service’</td>
<td>produkt bankowy ‘bank product’</td>
<td>973</td>
</tr>
<tr>
<td>nudziarz ‘bore’</td>
<td>sztywniak ‘staffed shirt’</td>
<td>973</td>
</tr>
<tr>
<td>dysputa ‘≈debate’</td>
<td>polemika ‘polemic’</td>
<td>1101</td>
</tr>
<tr>
<td>dostojnik ‘high official’</td>
<td>podsekretarz ‘undersecretary’</td>
<td>1101</td>
</tr>
<tr>
<td>dostojnik ‘high official’</td>
<td>wiceminister ‘vice-minister’</td>
<td>1101</td>
</tr>
<tr>
<td>dygnitarz ‘dignitary’</td>
<td>wiceminister ‘vice-minister’ 1</td>
<td>1101</td>
</tr>
<tr>
<td>oficjel ‘high-up’</td>
<td>wiceminister ‘vice-minister’</td>
<td>1101</td>
</tr>
<tr>
<td>dostojnik ‘high official’</td>
<td>wicepremier ‘deputy prime minister’</td>
<td>1101</td>
</tr>
<tr>
<td>dygnitarz ‘dignitary’</td>
<td>wicepremier ‘deputy prime minister’</td>
<td>1101</td>
</tr>
<tr>
<td>oficjel ‘high-up’</td>
<td>wicepremier ‘deputy prime minister’</td>
<td>1101</td>
</tr>
<tr>
<td>dezaprobara ‘disapproval’</td>
<td>wotum nieufności ‘vote of censure’</td>
<td>1101</td>
</tr>
</tbody>
</table>
Conclusions

- Good results in the recognition of hyponymy
  - contrary to the claim of (Levy et al., 2015) that are learning in fact that one of the words is a prototypical hypernym
  - the lexical split selection of negative samples caused the decrease of the results, but only $\approx 1 - 2\%$, not significant
  - classifiers are not deviating to prototype recognition
  - this substantial discrepancy of our findings can be also caused by the choice of different classification methods – clustering & linear regression vs SVM in (Levy et al., 2015)
  - we showed that in some settings SVM classifier can produce much worse results for this particular task

- Lower results for longer embedding vectors of 300 are surprising, but can be caused by insufficient number of training examples
Conclusions

- Manual selective analysis of clustering revealed that
  - Clusters do not represent different realisations of hyponymy, contrary to (Ruiji et al., 2014), but rather group difference vectors according to the more general lemmas
  - Pairs related to different top hypernyms, e.g. ‘animal’ and ‘furniture’ were linked together only in later stages of hierarchical clustering
  - Negative pairs first were merged together and only after this their subbranches were linked with other clusters

- Very good result for meronymy were achieved
Thank you very much for your attention!

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