Context-sensitive Sentiment Propagation in WordNet

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4.19

Main Objectives

- 1. We aimed at constructing a reliable, sense-oriented sentiment lexicon, largely based on manual emotive annotation of WordNet
- 2. To move away from handcrafted propagation rules over Wordnet
- 3. Automatic expansion of manual annotation on a large scale
- 4. Exploiting a more complex WordNet structure
- 5. More reliable evaluation using large, manually annotated part of WordNet

Classifier-based Polarity Propagation (CPP)

- **Baseline** simple, iterative, rule-based propagation on a narrow set of relations: hypernymy, hyponymy, similarity and antonymy
- **CPP-Naive** automatic rules extraction with classifier trained on manually annotated part of plWordNet using extended set of relations
- **CPP-Sorted** CPP-Naive solution extended with on-line reordering: synsets sorted by node degree (descending order)
- $< relation > _ < direction > _ < word > _ < level >: \{w_1, w_2, ..., w_k\}$

Data and Methods

Current state of emotive annotation of plWordNet:

- more than 83k annotations covering more than 54k lexical units and 41k synsets
- $\cdot 22k$ polarity annotations different than neutral (13k of lexical units and 9k synsets)
- $\cdot 1.5k$ synsets with different polarity across their units
- without *neutral* units, only 345 of synsets with varying polarity strength
- -without *neutral* and *ambiguous* annotations, only 41 synsets with conflicting polarity (it's only 3.8% of all polarized synsets!)

PoS	# Comp	# Sing	-S	-W	n	+W	+S	amb
Ν	25,919	18,574	16.62	14.64	51.59	6.05	4.23	6.87
Adj	14,817	5,392	14,87	22.59	31.39	15.03	7.50	8.62
All	40,773	24,002	15.89	17.95	43.18	9.79	5.59	7.60

Table 1: Sentiment polarity annotation of plWordNet in progress (Comp – completed, Sing – one annotator only so far); -s, -w, n, +w, +s, amb (negative strong/weak, neutral, positive weak/strong, ambiguous) are shown in percentage points.

Relation selection



Figure 2: Features generation based on synset levels: here, for selected synset at level 0 we generate features of his neighbourhood at level 1 and 2.

Clasifier-based solution:

- features: 104 bags-of-words as features
- 13 relations, 2 directions, 2 word types and 2 levels: $13 * 2^3 = 104$ features
- •classifier: Logistic Regression from scikit-learn package

We analysed the existing structure of plWordNet to select a subset of lexicosemantic relations for propagation process:

•take a subset of relations which covers more than 95% of all relation instances

• our final relation set: 13 most frequent relations

hyponymy + hypernymy					69.44	1%
fuzzynymy		9.40%	6			- / 0
similar	2	8.20%	-			
feature value	3	8.03%				
meronymy	1	.86%				
holonymy	1	.49%				
collection meronym	1	.29%				
collection holonym	1	.23%				
туре		.06%				
member		.06%		I	1	
0	%	20%	40%	60%	80%	100%

Figure 1: Frequency (as part of the whole number of relations) of the selected relations in plWordNet.

Polarity Transfer

The acquired statistics show that synsets are strongly homogeneous in terms of the units polarity, so we decided to:

- \cdot move the annotations from unit-level to synset-level
- reduce from 5-degree scale to 3-degree scale

Results

• propagation: near about 43k synsets annotated with sentiment polarity, 10-fold CV - almost 40k synsets as a seed and 3k as a test set

Measure	Baseline	CPP-Naive	CPP-Sorted
P-NEG	84.01	84.58	84.73
P-NEU	92.18	93.75	93.66
P-POS	69.20	83.11	82.95
R-NEG	68.63	75.82	75.90
R-NEU	95.80	97.02	96.97
R-POS	64.64	68.41	67.80
F-NEG	75.52	79.91	79.81
F-NEU	93.95	95.34	95.35
F-POS	66.77	74.99	74.61
	Measure P-NEG P-NEU P-POS R-NEG R-NEU R-POS F-NEG F-NEU F-NEU	MeasureBaselineP-NEG84.01P-NEU92.18P-POS69.20R-NEG68.63R-NEU95.80R-POS64.64F-NEG75.52F-NEU93.95F-POS66.77	MeasureBaselineCPP-NaiveP-NEG84.0184.58P-NEU92.1893.75P-POS69.2083.11R-NEG68.6375.82R-NEU95.8097.02R-POS64.6468.41F-NEG75.5279.91F-NEU93.9595.34F-POS66.7774.99

Table 2: Precision (P), recall (R) and F-score (F) for separate classes of polarity. BASE results are compared to CPP-N and CPP-S. Statistically significant differences are emphasised.

Conclusions

- •the proposed method performs better in almost all cases comparing to simple rule-based solution
- surprisingly the solution with sorting the synsets by node degree did not improve our results
- the classifier, as it moves away from the seed, loses information about the other parts of plWordNet solution: use another approach with re-training!

Scale-reduction procedure

- 1. Assign the following weights:
 - •weight 2 for strong variants of polarities,
 - •weight 1 for *weak* variants,
 - •weight 1 for *neutral* and *ambiguous* annotations
- 2. Reduce the polarities of annotations found in the synset using assigned weights
 - •example: synset with units like {*strong negative, negative, strong positive, neutral*}: we have value 3 for *negative* category, 2 for *positive,* 1 for *neutral* category
- 3. If some of polarity classes have equal values, use conversion rules

Future Work

- concentrate on a self-training approach, with re-training after each iteration
- evaluate once again a sorted approach using new re-training scenario
 extend manual annotation for other Parts-of-Speech (verbs, adverbs)

Acknowledgements

Work co-financed as part of the investment in the CLARIN-PL research infrastructure funded by the Polish Ministry of Science and Higher Education and in part by the National Centre for Research and Development, Poland, under grant no POIR.01.01.01-00-0472/16.