

Computational Semantics and Pragmatics

Graded Word Sense Assignment
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Article given by Raquel Fernández Rovira

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December 12, 2012

Agenda

- 1 Motivation
- 2 Corpora
- 3 Evaluation Methods
- 4 Models
- 5 Results

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- Inter-annotator agreement
 - Fine-grained word senses
 - 69 % HECTOR Dictionary (Krishnamurthy and Nicholls, 2000)
 - 73 % WordNet (Mihalcea et al., 2006)
 - Coarse-grained word senses
 - 90% OntoNotes (Hovy et al., 2006)
- Graded annotation
- Aim: Predict graded judgments of word sense applicability.

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Graded Word Sense dataset

lemma (PoS)	#	# training	
	senses	SemCor	SE-3
add (v)	6	171	238
argument (n)	7	14	195
ask (v)	7	386	236
different (a)	5	106	73
important (a)	5	125	11
interest (n)	7	111	160
paper (n)	7	46	207
win (v)	4	88	53
total training sentences		1047	1173

Table : Lemmas used in this study

- The scale used 1:= completely different, 2:= mostly different, 3:= similar, 4:= very similar, 5:= identical.
- It was obtained a single judgment for each sense with a normalized average of the three annotators, with the following normalization:

$$\text{normalized - judgment} = \frac{\text{judgment} - 1.0}{4.0}$$

- Judgments in the gold standar and assigned judgments can be represented by tuples:
 $\langle \text{lemma}, \text{sense} - \text{no.}, \text{sentence} - \text{no.}, \text{value} \rangle$

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Example

Sentence	senses							Annotator
	1	2	3	4	5	6	7	
This can be justified thermo-	2	3	3	5	5	2	3	Ann. 1
dynamically in this case, and	1	3	1	3	5	1	1	Ann. 2
this will be done in a separate	1	5	2	1	5	1	1	Ann. 3
paper which is being prepared.	1.3	3.7	2	3	5	1.3	1.7	Avg

Table : A sample annotation in the GWS experiment. The senses are:
 1 material from cellulose 2 report 3 publication 4 medium for writing
 5 scientific 6 publishing firm 7 physical object

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Correlation

- Let G be the set of golden tuples, and A the set of assigned tuples; L be the set of lemmas, and S_l the set of sense numbers for lemma l , and T , the set of sentence numbers:
- **lemma** $G_{lemma=l}$ and $A_{lemma=l} \forall l \in L$
- **lemma + sense** $G_{lemma=l,sense=i}$ and $A_{lemma=l,sense=i} \forall l \in L, i \in S_l$
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Spearman's ρ

- Uses the Pearson's coefficient:

$$\rho(X, Y) = \frac{\text{cov}(X, Y)}{\sigma_X \sigma_Y}$$

computed over rankings

- The rankings are assigned by sorting in ascending order the value of the variables. Equal values get the average of their positions
- Significance of the values is found against a probability p of the observed extreme cases

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Prototype

Cx/2	until, IN, soft, JJ, remaining, VBG, ingredient, NNS
Cx/50	for, IN, sweet-sour, NN, sauce, NN, . . . , to, TO, a, DT, boil, NN
Ch	OA, OA/ingredient/NNS

Table : Sample features for add in BNC occurrence For sweet-sour sauce, cook onion in oil until soft. **Add** remaining ingredients and bring to a boil. Cx/2 (Cx/50): context of size 2 (size 50) either side of the target. Ch: children of target.

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- **Dimensions: Features, Coordinates: Raw counts**
- Vector representation for a sense: centroid of its training occurrences
- Predicted judgment for sentence t , and sense s : similarity of its vectors.
- Like instance based-learners measures the distance between feature vectors but within a single category

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Model	by lemma			by lemma+sense			by lemma+sentence		
	ρ	*	**	ρ	*	**	ρ	*	**
WSD/single	0.267	87.5	75.0	0.053	6.3	4.2	0.28	2.8	1.8
WSD/conf	0.396	87.5	87.5	0.177	33.3	18.8	0.401	10.8	3.0
Prototype	0.245	62.5	62.5	0.053	20.8	8.3	0.396	15.3	2.5
Prototype/2	0.292	87.5	87.5	0.086	14.6	4.2	0.478	22.8	7.5
Prototype/N	0.396	100.0	100.0	0.137	22.9	14.6	0.396	15.3	2.5
Prototype/2N	0.465	100.0	100.0	0.168	29.8	23.4	0.478	22.8	7.5
baseline	0.338	87.5	87.5	0.0	0.0	0.0	0.355	10.3	3.0

Table : Evaluation: computational models, and baseline. *, **: percentage significant at $p \leq 0.05$, $p \leq 0.01$

Summary

- Graded annotation was proposed as an alternative view of sense assignment.
- Adequate measures to evaluate performance of graded sense assignment were proposed.
- Evaluation is significant, but system performance is below humans performance
- The authors have already worked a second round of annotation
- The lemma + sense and lemma + sentence correlation measures seem to be the most promising useful measures.
- The GWS should be tested with more sophisticated vector models.

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