

set of XML files (one for each word to be annotated) prior to tagging. STAMP works by displaying to the user the sentence to be annotated with the target word highlighted along with the previous and the following sentences and the senses from the sense inventory. The user can select one of the senses and move on to the next instance.

Two linguistics students annotated the words with WordNet 2.1 senses. Our annotators examined each instance upon which they disagreed and resolved their disagreements. Finally, we converted the resulting data to the Senseval format. For this dataset, we got an inter-annotator agreement (ITA) of 72% on verbs and 86% for nouns.

2.1.2 Results

A total of 14 systems were evaluated on the All Words task. These results are shown in Table 1. We used the standard Senseval scorer – `scorer2`¹ to score the systems. All the F-scores² in this table as well as other tables in this paper are accompanied by a 95% confidence interval calculated using the bootstrap resampling procedure.

2.2 OntoNotes English Lexical Sample WSD

It is quite well accepted at this point that it is difficult to achieve high inter-annotator agreement on the fine-grained WordNet style senses, and without a corpus with high annotator agreement, automatic learning methods cannot perform at a level that would be acceptable for a downstream application. OntoNotes (Hovy et al., 2006) is a project that has annotated several layers of semantic information – including word senses, at a high inter-annotator agreement of over 90%. Therefore we decided to use this data for the lexical sample task.

2.2.1 Data

All the data for this task comes from the 1M word WSJ Treebank. For the convenience of the participants who wanted to use syntactic parse information as features using an off-the-shelf syntactic parser, we decided to compose the training data of Sections 02-21. For the test sets, we use data from Sections

	Train	Test	Total
Verb	8988	2292	11280
Noun	13293	2559	15852
Total	22281	4851	

Table 2: The number of instances for Verbs and Nouns in the Train and Test sets for the Lexical Sample WSD task.

01, 22, 23 and 24. Fortunately, the distribution of words was amenable to an acceptable number of instances for each lemma in the test set. We selected a total of 100 lemmas (65 verbs and 35 nouns) considering the degree of polysemy and total instances that were annotated. The average ITA for these is over 90%.

The training and test set composition is described in Table 2. The distribution across all the verbs and nouns is displayed in Table 4

2.2.2 Results

A total of 13 systems were evaluated on the Lexical Sample task. Table 3 shows the Precision/Recall for all these systems. The same scoring software was used to score this task as well.

2.2.3 Discussion

For the all words task, the baseline performance using the most frequent WordNet sense for the lemmas is 51.4. The top-performing system was a supervised system that used a Maximum Entropy classifier, and got a Precision/Recall of 59.1% – about 8 points higher than the baseline. Since the coarse and fine-grained disambiguation tasks have been part of the two previous Senseval competitions, and we happen to have access to that data, we can take this opportunity to look at the disambiguation performance trend. Although different test sets were used for every evaluation, we can get a rough indication of the trend. For the fine-grained All Words sense tagging task, which has always used WordNet, the system performance has ranged from our 59% to 65.2 (Senseval3, (Decadt et al., 2004)) to 69% (Senseval2, (Chklovski and Mihalcea, 2002)). Because of time constraints on the data preparation, this year’s task has proportionally more verbs and fewer nouns than previous All-Words English tasks, which may account for the lower scores.

As expected, the Lexical Sample task using coarse

¹<http://www.cse.unt.edu/~rada/senseval/senseval3/scoring/>

²`scorer2` reports Precision and Recall scores for each system. For a system that attempts all the words, both Precision and Recall are the same. Since a few systems had missing answers, they got different Precision and Recall scores. Therefore, for ranking purposes, we consolidated them into an F-score.

Rank	Participant	System ID	Classifier	F
1	Stephen Tratz <stephen.tratz@pnl.gov>	PNNL	MaxEnt	59.1±4.5
2	Hwee Tou Ng <ngh@comp.nus.edu.sg>	NUS-PT	SVM	58.7±4.5
3	Rada Mihalcea <rada@cs.unt.edu>	UNT-Yahoo	Memory-based	58.3±4.5
4	Cai Junfu <caijunfu@gmail.com>	NUS-ML	naive Bayes	57.6±4.5
5	Oier Lopez de Lacalle <jibloleo@si.ehu.es>	UBC-ALM	kNN	54.4±4.5
6	David Martinez <davidm@csse.unimelb.edu.au>	UBC-UMB-2	kNN	54.0±4.5
7	Jonathan Chang <jcone@princeton.edu>	PU-BCD	Exponential Model	53.9±4.5
8	Radu ION <radu@racai.ro>	RACAI	Unsupervised	52.7±4.5
9	<i>Most Frequent WordNet Sense</i>	Baseline	N/A	51.4±4.5
10	Davide Buscaldi <dbuscaldi@dsic.upv.es>	UPV-WSD	Unsupervised	46.9±4.5
11	Sudip Kumar Naskar <sudip.naskar@gmail.com>	JU-SKNSB	Unsupervised	40.2±4.5
12	David Martinez <davidm@csse.unimelb.edu.au>	UBC-UMB-1	Unsupervised	39.9±4.5
14	Rafael Berlanga <berlanga@uji.es>	tkb-uo	Unsupervised	32.5±4.5
15	Jordan Boyd-Graber <jbg@princeton.edu>	PUTOP	Unsupervised	13.2±4.5

Table 1: System Performance for the All-Words task.

Rank	Participant	System	Classifier	F
1	Cai Junfu <caijunfu@gmail.com>	NUS-ML	SVM	88.7±1.2
2	Oier Lopez de Lacalle <jibloleo@si.ehu.es>	UBC-ALM	SVD+kNN	86.9±1.2
3	Zheng-Yu Niu <niu.zy@hotmail.com>	I2R	Supervised	86.4±1.2
4	Lucia Specia <lspecia@gmail.com>	USP-IBM-2	SVM	85.7±1.2
5	Lucia Specia <lspecia@gmail.com>	USP-IBM-1	ILP	85.1±1.2
5	Deniz Yuret <dyuret@ku.edu.tr>	KU	Semi-supervised	85.1±1.2
6	Saarikoski <harri.saarikoski@helsinki.fi>	OE	naive Bayes, SVM	83.8±1.2
7	University of Technology Brno	VUTBR	naive Bayes	80.3±1.2
8	Ana Zelaia <ana.zelaia@ehu.es>	UBC-ZAS	SVD+kNN	79.9±1.2
9	Carlo Strapparava <strappa@itc.it>	ITC-irst	SVM	79.6±1.2
10	<i>Most frequent sense in training</i>	Baseline	N/A	78.0±1.2
11	Toby Hawker <toby@it.usyd.edu.au>	USYD	SVM	74.3±1.2
12	Siddharth Patwardhan <sidd@cs.utah.edu>	UMND1	Unsupervised	53.8±1.2
13	Saif Mohammad <smm@cs.toronto.edu>	Tor	Unsupervised	52.1±1.2
-	Toby Hawker <toby@it.usyd.edu.au>	USYD*	SVM	89.1±1.2
-	Carlo Strapparava <strappa@itc.it>	ITC*	SVM	89.1±1.2

Table 3: System Performance for the OntoNotes Lexical Sample task. Systems marked with an * were post-competition bug-fix submissions.

grained senses provides consistently higher performance than previous more fine-grained Lexical Sample Tasks. The high scores here were foreshadowed in an evaluation involving a subset of the data last summer (Chen et al., 2006). Note that the best system performance is now closely approaching the ITA for this data of over 90%. Table 4 shows the performance of the top 8 systems on all the individual verbs and nouns in the test set. Owing to space constraints we have removed some lemmas that have perfect or almost perfect accuracies. At the right are mentioned the average, minimum and maximum performances of the teams per lemma, and at the bottom are the average scores per lemma (without considering the lemma frequencies) and broken down by verbs and nouns. A gap of about 10 points

between the verb and noun performance seems to indicate that in general the verbs were more difficult than the nouns. However, this might just be owing to this particular test sample having more verbs with higher perplexities, and maybe even ones that are indeed difficult to disambiguate – in spite of high human agreement. The hope is that better knowledge sources can overcome the gap still existing between the system performance and human agreement. Overall, however, this data indicates that the approach suggested by (Palmer, 2000) and that is being adopted in the ongoing OntoNotes project (Hovy et al., 2006) does result in higher system performance. Whether or not the more coarse-grained senses are effective in improving natural language processing applications remains to be seen.

Lemma	S	s	T	t	1	2	3	4	5	6	7	8	Average	Min	Max
turn.v	13	8	340	62	58	61	40	55	52	53	27	44	49	27	61
go.v	12	6	244	61	64	69	38	66	43	46	31	39	49	31	69
come.v	10	9	186	43	49	46	56	60	37	23	23	49	43	23	60
set.v	9	5	174	42	62	50	52	57	50	57	36	50	52	36	62
hold.v	8	7	129	24	58	46	50	54	54	38	50	67	52	38	67
raise.v	7	6	147	34	50	44	29	26	44	26	24	12	32	12	50
work.v	7	5	230	43	74	65	65	65	72	67	46	65	65	46	74
keep.v	7	6	260	80	56	54	52	64	56	52	48	51	54	48	64
start.v	6	4	214	38	53	50	47	55	45	42	37	45	47	37	55
lead.v	6	6	165	39	69	69	85	69	51	69	36	46	62	36	85
see.v	6	5	158	54	56	54	46	54	57	52	48	48	52	46	57
ask.v	6	3	348	58	84	72	72	78	76	52	67	66	71	52	84
fi nd.v	5	3	174	28	93	93	86	89	82	82	75	86	86	75	93
fi x.v	5	3	32	2	50	50	50	50	50	0	0	50	38	0	50
buy.v	5	3	164	46	83	80	80	83	78	76	70	76	78	70	83
begin.v	4	2	114	48	83	65	75	69	79	56	50	56	67	50	83
kill.v	4	1	111	16	88	88	88	88	88	88	88	81	87	81	88
join.v	4	4	68	18	44	50	50	39	56	57	39	44	47	39	57
end.v	4	3	135	21	90	86	86	90	62	87	86	67	82	62	90
do.v	4	2	207	61	92	90	90	93	93	90	85	84	90	84	93
examine.v	3	2	26	3	100	100	67	100	100	67	100	33	83	33	100
report.v	3	2	128	35	89	91	91	91	91	91	91	86	90	86	91
regard.v	3	3	40	14	93	93	86	86	64	86	57	93	82	57	93
recall.v	3	1	49	15	100	100	87	87	93	87	87	87	91	87	100
prove.v	3	2	49	22	90	88	82	80	90	86	70	74	82	70	90
claim.v	3	2	54	15	67	73	80	80	80	80	80	87	78	67	87
build.v	3	3	119	46	74	67	74	61	54	74	61	72	67	54	74
feel.v	3	3	347	51	71	69	69	74	76	69	61	71	70	61	76
care.v	3	3	69	7	43	43	43	43	100	29	57	57	52	29	100
contribute.v	2	2	35	18	67	72	72	67	50	61	50	67	63	50	72
maintain.v	2	2	61	10	80	80	70	100	80	90	90	80	84	70	100
complain.v	2	1	32	14	93	86	86	86	86	86	86	79	86	79	93
propose.v	2	2	34	14	100	86	100	86	100	93	79	79	90	79	100
promise.v	2	2	50	8	88	88	75	88	75	75	62	88	80	62	88
produce.v	2	2	115	44	82	82	77	73	75	75	77	80	78	73	82
prepare.v	2	2	54	18	94	83	89	89	83	86	83	83	86	83	94
explain.v	2	2	85	18	94	89	94	89	94	89	89	94	92	89	94
believe.v	2	2	202	55	87	78	78	86	84	78	74	80	81	74	87
occur.v	2	2	47	22	86	73	91	96	86	96	86	82	87	73	96
grant.v	2	2	19	5	100	80	80	80	40	80	60	80	75	40	100
enjoy.v	2	2	56	14	50	57	57	50	64	57	50	57	55	50	64
need.v	2	2	195	56	89	82	86	89	86	78	70	70	81	70	89
disclose.v	1	1	55	14	93	93	93	93	93	93	93	93	93	93	93
point.n	9	6	469	150	91	91	89	91	92	87	84	79	88	79	92
position.n	7	6	268	45	78	78	78	53	56	65	58	64	66	53	78
defense.n	7	7	120	21	57	48	52	43	48	29	48	48	46	29	57
carrier.n	7	3	111	21	71	71	71	67	71	67	71	62	70	62	71
order.n	7	4	346	57	93	95	93	91	93	92	90	91	92	90	95
exchange.n	5	3	363	61	92	90	92	85	90	88	82	79	87	79	92
system.n	5	3	450	70	79	73	66	67	59	63	63	61	66	59	79
source.n	5	5	152	35	86	80	80	63	83	68	60	29	69	29	86
space.n	5	2	67	14	93	100	93	93	93	86	86	71	89	71	100
base.n	5	4	92	20	75	80	75	50	65	40	50	75	64	40	80
authority.n	4	3	90	21	86	86	81	62	71	33	71	81	71	33	86
people.n	4	4	754	115	96	96	95	96	95	90	91	91	94	90	96
chance.n	4	3	91	15	60	67	60	60	67	73	20	73	60	20	73
part.n	4	3	481	71	90	90	92	97	90	74	66	66	83	66	97
hour.n	4	2	187	48	83	85	92	83	77	90	58	92	83	58	92
development.n	3	3	180	29	100	79	86	79	76	62	79	62	78	62	100
president.n	3	3	879	177	98	97	98	97	93	96	97	85	95	85	98
network.n	3	3	152	55	91	87	98	89	84	88	87	82	88	82	98
future.n	3	3	350	146	97	96	94	97	83	98	89	85	92	83	98
effect.n	3	2	178	30	97	93	80	93	80	90	77	83	87	77	97
state.n	3	3	617	72	85	86	86	83	82	79	83	82	83	79	86
power.n	3	3	251	47	92	87	87	81	77	77	77	74	81	74	92
bill.n	3	3	404	102	98	99	98	96	90	96	96	22	87	22	99
area.n	3	3	326	37	89	73	65	68	84	70	68	65	73	65	89
job.n	3	3	188	39	85	80	77	90	80	82	69	82	80	69	90
management.n	2	2	284	45	89	78	87	73	98	76	67	64	79	64	98
condition.n	2	2	132	34	91	82	82	56	76	78	74	76	77	56	91
policy.n	2	2	331	39	95	97	97	87	95	97	90	64	90	64	97
rate.n	2	2	1009	145	90	88	92	81	92	89	88	91	89	81	92
drug.n	2	2	205	46	94	94	96	78	94	94	87	78	89	78	96
Average				Overall Verbs	86	83	83	82	82	79	76	77			
				Nouns	78	75	73	76	73	70	65	70			
					89	87	86	81	83	80	77	76			

Table 4: All Supervised system performance per predicate. (Column legend – S=number of senses in training; s=number senses appearing more than 3 times; T=instances in training; t=instances in test.; The numbers indicate system ranks.)

3 Semantic Role Labeling

Subtask 2 evaluates Semantic Role Labeling (SRL) systems, where the goal is to locate the constituents which are arguments of a given verb, and to assign them appropriate semantic roles that describe how they relate to the verb. SRL systems are an important building block for many larger semantic systems. For example, in order to determine that question (1a) is answered by sentence (1b), but not by sentence (1c), we must determine the relationships between the relevant verbs (*eat* and *feed*) and their arguments.

- (1) a. What do lobsters like to eat?
- b. Recent studies have shown that lobsters primarily feed on live fish, dig for clams, sea urchins, and feed on algae and eel-grass.
- c. In the early 20th century, Mainers would only eat lobsters because the fish they caught was too valuable to eat themselves.

Traditionally, SRL systems have been trained on either the PropBank corpus (Palmer et al., 2005) – for two years, the CoNLL workshop (Carreras and Màrquez, 2004; Carreras and Màrquez, 2005) has made this their shared task, or the FrameNet corpus – Senseval-3 used this for their shared task (Litkowski, 2004). However, there is still little consensus in the linguistics and NLP communities about what set of role labels are most appropriate. The PropBank corpus avoids this issue by using theory-agnostic labels (ARG0, ARG1, ..., ARG5), and by defining those labels to have only verb-specific meanings. Under this scheme, PropBank can avoid making any claims about how any one verb’s arguments relate to other verbs’ arguments, or about general distinctions between verb arguments and adjuncts.

However, there are several limitations to this approach. The first is that it can be difficult to make inferences and generalizations based on role labels that are only meaningful with respect to a single verb. Since each role label is verb-specific, we can not confidently determine when two different verbs’ arguments have the same role; and since no encoded meaning is associated with each tag, we can not make generalizations across verb classes. In contrast, the use of a shared set of role labels, such

System	Type	Precision	Recall	F
UBC-UPC	Open	84.51	82.24	83.36±0.5
UBC-UPC	Closed	85.04	82.07	83.52±0.5
RTV	Closed	81.82	70.37	75.66±0.6
Without “say”				
UBC-UPC	Open	78.57	74.70	76.60±0.8
UBC-UPC	Closed	78.67	73.94	76.23±0.8
RTV	Closed	74.15	57.85	65.00±0.9

Table 5: System performance on PropBank arguments.

as VerbNet roles, would facilitate both inferencing and generalization. VerbNet has more traditional labels such as Agent, Patient, Theme, Beneficiary, etc. (Kipper et al., 2006).

Therefore, we chose to annotate the corpus using two different role label sets: the PropBank role set and the VerbNet role set. VerbNet roles were generated using the SemLink mapping (Loper et al., 2007), which provides a mapping between PropBank and VerbNet role labels. In a small number of cases, no VerbNet role was available (e.g., because VerbNet did not contain the appropriate sense of the verb). In those cases, the PropBank role label was used instead.

We proposed two levels of participation in this task: i) Closed – the systems could use only the annotated data provided and nothing else. ii) Open – where systems could use PropBank data from Sections 02-21, as well as any other resource for training their labelers.

3.1 Data

We selected 50 verbs from the 65 in the lexical sample task for the SRL task. The partitioning into train and test set was done in the same fashion as for the lexical sample task. Since PropBank does not tag any noun predicates, none of the 35 nouns from the lexical sample task were part of this data.

3.2 Results

For each system, we calculated the precision, recall, and F-measure for both role label sets. Scores were calculated using the `srl-eval.pl` script from the CoNLL-2005 scoring package (Carreras and Màrquez, 2005). Only two teams chose to perform the SRL subtask. The performance of these two teams is shown in Table 5 and Table 6.

System	Type	Precision	Recall	F
UBC-UPC	Open	85.31	82.08	83.66±0.5
UBC-UPC	Closed	85.31	82.08	83.66±0.5
RTV	Closed	81.58	70.16	75.44±0.6
Without “say”				
UBC-UPC	Open	79.23	73.88	76.46±0.8
UBC-UPC	Closed	79.23	73.88	76.46±0.8
RTV	Closed	73.63	57.44	64.53±0.9

Table 6: System performance on VerbNet roles.

3.3 Discussion

Given that only two systems participated in the task, it is difficult to form any strong conclusions. It should be noted that since there was no additional VerbNet role data to be used by the Open system, the performance of that on PropBank arguments as well as VerbNet roles is exactly identical. It can be seen that there is almost no difference between the performance of the Open and Closed systems for tagging PropBank arguments. The reason for this is the fact that all the instances of the lemma under consideration was selected from the Propbank corpus, and probably the number of training instances for each lemma as well as the fact that the predicate is such an important feature combine to make the difference negligible. We also realized that more than half of the test instances were contributed by the predicate “say” – the performance over whose arguments is in the high 90s. To remove the effect of “say” we also computed the performances after excluding examples of “say” from the test set. These numbers are shown in the bottom half of the two tables. These results are not directly comparable to the CoNLL-2005 shared task since: i) this test set comprises Sections 01, 22, 23 and 24 as opposed to just Section 23, and ii) this test set comprises data for only 50 predicates as opposed to all the verb predicates in the CoNLL-2005 shared task.

4 Conclusions

The results in the previous discussion seem to confirm the hypothesis that there is a predictable correlation between human annotator agreement and system performance. Given high enough ITA rates we can hope to build sense disambiguation systems that perform at a level that might be of use to a consuming natural language processing application. It is also encouraging that the more informative Verb-

Net roles which have better/direct applicability in downstream systems, can also be predicted with almost the same degree of accuracy as the PropBank arguments from which they are mapped.

5 Acknowledgments

We gratefully acknowledge the support of the Defense Advanced Research Projects Agency (DARPA/IPTO) under the GALE program, DARPA/CMO Contract No. HR0011-06-C-0022; National Science Foundation Grant NSF-0415923, Word Sense Disambiguation; the DTO-AQUAINT NBCHC040036 grant under the University of Illinois subcontract to University of Pennsylvania 2003-07911-01; and NSF-ITR-0325646: Domain-Independent Semantic Interpretation.

References

- Xavier Carreras and Lluís Màrquez. 2004. Introduction to the CoNLL-2004 shared task: Semantic role labeling. In *Proceedings of CoNLL-2004*.
- Xavier Carreras and Lluís Màrquez. 2005. Introduction to the CoNLL-2005 Shared Task: Semantic Role Labeling. In *Proceedings of CoNLL-2005*.
- Jinying Chen, Andrew Schein, Lyle Ungar, and Martha Palmer. 2006. An empirical study of the behavior of active learning for word sense disambiguation. In *Proceedings of HLT/NAACL*.
- Timothy Chklovski and Rada Mihalcea. 2002. Building a sense tagged corpus with open mind word expert. In *Proceedings of ACL-02 Workshop on WSD*.
- Bart Decadt, Véronique Hoste, Walter Daelemans, and Antal Van den Bosch. 2004. GAMBL, genetic algorithm optimization of memory-based wsd. In *Senseval-3*.
- Eduard Hovy, Mitchell Marcus, Martha Palmer, Lance Ramshaw, and Ralph Weischedel. 2006. Ontonotes: The 90% solution. In *Proceedings of HLT/NAACL*, June.
- Karin Kipper, Anna Korhonen, Neville Ryant, and Martha Palmer. 2006. Extending VerbNet with novel verb classes. In *LREC-06*.
- Ken Litkowski. 2004. Senseval-3 task: Automatic labeling of semantic roles. In *Proceedings of Senseval-3*.
- Edward Loper, Szu ting Yi, and Martha Palmer. 2007. Combining lexical resources: Mapping between propbank and verbnet. In *Proceedings of the IWCS-7*.
- Martha Palmer, Daniel Gildea, and Paul Kingsbury. 2005. The proposition bank: A corpus annotated with semantic roles. *Computational Linguistics*, 31(1):71–106.
- Martha Palmer. 2000. Consistent criteria for sense distinctions. *Computers and the Humanities*, 34(1-1):217–222.

SemEval-2007 Task-17: English Lexical Sample, SRL and All Words. June 2007. Edward Loper. This paper presents the coarse-grained English all-words task at SemEval-2007. We describe our experience in producing a coarse version of the WordNet sense inventory and preparing the sense-tagged corpus for the task. We present the results of participating systems and discuss future directions. Interpretable Word Sense Disambiguation with Contextualized Embeddings". 4 commits. 1 branch. Word Sense Disambiguation (WSD) is the task to identify the correct sense of the usage of a word from a (usually) fixed inventory of sense identifiers. We propose a simple approach that scans through the training data to learn the Contextualized Word Embeddings(CWE) of sense labels and classifies the ambiguous words on the basis Cosine Similarity with the learnt CWEs for that word. - semeval2007task17.xml. Before we proceed to see the steps to reproduce our results, please note a few points: In our experiments, we use Semcor and WNGT separately for training Wordnet sense identifiers and test them individually across Semeval 2007 task 7 and 17. WSD task has two variants: "lexical sample" and "all words" task. The former comprises disambiguating the occurrences of a small sample of target words which were previously selected, while in the latter all the words in a piece of running text need to be disambiguated. The latter is deemed a more realistic form of evaluation, but the corpus is more expensive to produce because human annotators have to read the definitions for each word in the sequence every time they need to make a tagging judgement, rather than once for a block of instances for the same target word. To gi... 2007. SemEval-2007 Task 17: English lexical sample, SRL and all words.