NILC_USP: ASPECT EXTRACTION USING SEMANTIC LABELS Pedro P. Balage Filho, Thiago A. S. Pardo



Interinstitutional Center for Computational Linguistics (NILC) Institute of Mathematical and Computer Sciences, University of São Paulo São Carlos - SP, Brazil {balage, taspardo}@icmc.usp.br





Abstract

This poster details the system NILC_USP that participated in the Semeval 2014: Aspect Based Sentiment Analysis task. This system uses a Conditional Random Field (CRF) algorithm for extracting the aspects mentioned in the text. Our work added semantic labels into a basic feature set for measuring the efficiency of those for aspect extraction. We used the semantic roles and the verb frame as features for the machine learning. We verified that at every new feature added to feature's set, the precision goes up, but the recall goes down. Our system achieved the second best precision value among the competing systems, but the lowest recall value.

System Description

Our system uses a sequential labeling algorithm. In our work, we use the Conditional Random Field algorithm provided by the CRF++ tool. The goal of our system was to

evaluate the performance of the semantic labels for the task. In order to model our system, we built a feature set consisting of 6 features.

1. the word

2. the part-of-speech

3. the chunk

4. the named-entity category

5. the semantic role label (SRL)

6. the most generic frame in FrameNet

These features were extracted from two important tools: the **Senna**, a semantic role labeling system, and the **ARK SEMAFOR**, a Semantic Analyzer of Frame Representations.

Example of SRL extraction

WORD	POS	CHUNK	SRL	IS_ASPECT
Great	JJ	B-NP	B-AØ	False
laptop	NN	E-NP	E-A0	False

Results for restaurants

The results are discriminated by the feature sets that were used. The reader may see that a "+ Frame" system, for example, stands for all the features discriminated above (Word, POS, Chunk, NR, SRL) plus the Frame feature. The last line shows the results scored by our system in the SemEval shared task with all the features.

System	Precision	Recall	F1-mesaure
Baseline	52.54	42.76	47.15
Word $+$ POS	83.76	68.69	75.48
+ Chunk	83.38	68.16	75.01
+ NE	83.45	68.07	74.98
+ SRL	82.79	67.46	74.34
+ Frame	87.72	34.03	49.04

Results for laptops domain

System	Precision	Recall	F1-mesaure
Baseline	44.31	29.81	35.64
Word $+$ POS	80.87	39.44	53.03
+ Chunk	78.83	39.29	52.44
+ NE	79.93	39.60	52.96
	70 00	28.00	52 04

that	WDT	S-NP	S-R-A0	False
offers	VBZ	S-VP	S-V	False
many	JJ	B-NP	B-A1	False
great	JJ	I-NP	I-A1	False
features	NNS	E-NP	E-A1	True
•	0	_		False

Example of frame extraction

WORD	FRAME	IS_ASPECT?
I	Shopping	False
shopped	Shopping	False
around	Relational_quantity	False
before	Relational_quantity	False
buying	Relational_quantity	False
•	0	False

+ SKL			02.04 95 10	
+ Frame	83.02	14.83	23.19	









Conclusion

• Semantic labels may help to achieve a more precise classifier, but it did not help to improve the overall F-measure of the system

• Our system achieved the second best precision value among the competing systems, but the lowest recall value

- If we are interested only on precision, these features may be helpful. This may be the case in scenarios where a lot of information is available, as in the web, and we want to be sure about the retrieved information
- Certainly, there is a conflict between precision and computational complexity, since the semantic features are more expensive to be achieved (in relation to the usual simpler features that may be used)
- Future work should investigate ways of also improving recall without penalty for the achieved precision