Summarization Focusing on Polarity or Opinion Fragments in Blogs

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Abstract

We present the *TUT* opinion summarization system which participated in the *TAC 2008*. The system consists of two modules: opinion/polarity automatic annotation module and fragment extraction module for summarization. Our research objective is to estimate the effectiveness of opinion/polarity annotation per sentence units for opinion summarization. The evaluation results showed that the polarity annotation is effective to improve the redundancy elimination and coherence.

1 Introduction

In this paper, we describe the *TUT* opinion summarization system developed in *TAC 2008 opinion summarization pilot track*. Our system is based on *TUT* opinion annotation system developed in the *NTCIR* workshop¹ $MOAT^2$. There are two new challenging points:

- 1. The opinionated or polar sentences should be aligned to answer the questions with considering the context information.
- 2. Opinion annotation and summarization system should be implemented for the Blog test collection. (In the *NTCIR* workshop, the target document genre is newspaper article.)

For the first point, we implemented opinion/polarity fragment extraction system. The details will be explained in this paper. On the other hand, for the second point, we only add two new modules: (A) *body* or *comment* part detection module and (B) author detection module. We did not change the opinion annotation system itself using newspaper articles as a training data this time due to time constraints.

This paper is constructed as follows. In Section 2, we explain our system overview. Section 3 introduces our opinion annotation and polarity annotation approach. Section 4 gives the result in *TAC 2008 opinion pilot* and we discuss our results and clarify our contribution. Finally, we will give our conclusion and improvement points in future in Section 5.

2 System Overview

2.1 Task definition

We summed up the task definition in *TAC 2008 opinion pilot* briefly as follows:

- Generate question-focused summaries from multiple blogs up to 7,000 characters per each question.
- Source documents are from TREC BLOG06 test collection³ relevant to 25 topics. The average size of document sets is 24.4 documents per topic.
- Answer snippets from *TAC 2008 Opinion QA track* are also provided, but organizers leave the decision to the participants whether we use it or not.

2.2 Our summarization strategy

Basically, we implemented an extractive summarization approach. However, to provide context, we regard up to three consecutive sentences as one unit (*a fragment*) and compute the importance of each unit. Three consecutive sentences are defined as follows:

- 1. All consecutive sentences should be in the same document.
- 2. All consecutive sentences should be in the same part (body or comment).

¹http://research.nii.ac.jp/ntcir

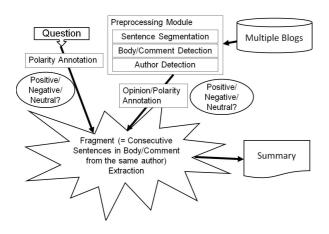
²Multilingual Opinion Analysis Task

³http://ir.dcs.gla.ac.uk/test_collections/blog06info.html

3. All consecutive sentences should be written by the same author (one blog author or one commenter).

The weighting and redundancy elimination strategies are as follows.

- Three sentence units are weighted with cosine similarity to each question, the blog heading, and the answer snippets in each article.
- Summaries are created by extracting important units up to 7,000 characters.
- Redundant units are removed using the threshold of cosine similarity with other units in the summary.
- All units extracted in the summary are ordered chronologically by each question.



TUT system architecture is described in Figure 1.

Figure 1: TUT System in TAC 2008

2.3 Details in each submission

We submitted three results, two results of which are evaluated officially. The details of two submissions are as follows.

- 1. Opinion-focused Summarization (*TUT2*: the second priority)
 - The system only extracted the units which contains at least one opinionated sentence (*opinion fragments*).
 - Opinionated sentences are automatically annotated using supervised machine learning approach. The details of opinion annotation are written in Section 3.1.
- 2. Polarity-focused Summarization (*TUT1*: the highest priority)

- The system only extracted the units which contains at least one polar (= positive/negative) sentence requested by each question (*polarity fragments*) (i.e., "What motivated positive opinions of CARMAX from car buyers?" (= *positive*) or "what motivated negative opinions regarding purchasing a car from CARMAX?" (= *negative*)).
- Polarities of questions and sentences are judged using several clue weighting learned from the analysis with *MPQA* corpus⁴ and *NTCIR-6* English Opinion corpus⁵. The details of opinion annotation is written in Section 3.2.
- Compared to the first approach, the summary construction is slightly changed to differentiate the polarity from each question when the one questions is positive and the other question is negative.

3 Opinion and Polarity Annotation

3.1 Opinion Annotation

Opinionated sentences are annotated using SVM approach. The original point of our approach is to differentiate (A) opinions written by the *author* and (B) quoted opinions expressed by the other *authority* because their writing styles were different. The selected features are as follows. They are selected based on the analysis with χ -square test using *MPQA* corpus and *NTCIR-6* English corpus, as shown in Table 4.

- 1. We utilized two type syntactic pairs: (a) subjects and verbs, (b) auxiliary verbs and verbs. Syntactic dependency was checked using Minipar (Lin, 2005).
- 2. Keyword list features were categorized by nouns, verbs, adjectives and adverbs, any part of speech (anypos) from the entries in the subjective lexicons (Wilson et al., 2005), and several other keywords.
- 3. We also used polarity term types. These features were determined using adjective entries (Hatzivassiloglou and Wiebe, 2000), which contained 1 914 word entries, and the General Inquirer (Stone, 2000), which contained 1,168 word entries.

The features are shown in Table 4. We clarified the entries in Table 4, as follows.

• The opinion verb types and the verb elements of syntactic pairs were defined based on the generalization using (A) communicative verbs entries in the lexicon

⁴http://www.cs.pitt.edu/mpqa/databaserelease/

⁵http://research.nii.ac.jp/ntcir/permission/ntcir-6/perm-en-OPINION.html

(Bloom et al., 2006) and (B) parts-of-speech with regard to the subjective lexicon (Wilson et al., 2005) and Minipar (Lin, 2005).

- The grammatical subject elements in syntactic pairs were generalized with (C) *ZeroProN* (in case they were missing), (D) named entity types, such as *GPE* or *PERCENT*, (E) case-sensitive pronouns, and (F) parts-of-speech with regard to Minipar.
- We used three count features: *cntopnoun*, *cntopadj*, and *cntopadv* that represented the numbers of the respective subjective nouns, adjectives, and adverbs in the sentence matched with the entries in the subjective lexicon (Wilson et al., 2005).

3.2 Polarity Annotation

Polarites are annotated only for the opinionated sentences using the number of positive/negative clues appeared in the sentence. The clues are selected based on the analysis with χ -square test using *MPQA* corpus and *NTCIR-6* English corpus. They are shown in Table 5. The polarity annotation strategy is as follows:

- 1. If more than three positive clues and more than three negative clues appeared in the opinionated sentence, we annotate the polarity of the sentence as "*BOTH*".
- 2. If the number of positive (negative) clues is more then the number of negative (positive) clues in the opinionated sentence, we annotate the polarity of the sentence as "*POS*" (*NEG*).
- 3. Otherwise, we annotate the polarity of the sentence as "*NEU*".

3.3 Accuracy of Opinion and Polarity Annotation

We experimented to estimate the accuracy of opinion and polarity annotation using newspaper articles in *NTCIR-7 MOAT* (Seki et al., 2008). For the polarity annotation, we implemented slightly different approach in *NTCIR-7 MOAT* using multi-label classification techniques, but we used the same clues in *TAC 2008*. The result is shown in Table 1.

 Table 1: Accuracy of Opinion and Polarity Annotation in

 NTCIR-7 MOAT

	Precision	Recall	F-value
Opinion	0.3185	0.4092	0.3582
Polarity	0.1948	0.1830	0.1885

We used these classification clues with not changing for the blogs this time due to time constraints. In future, we should improve the accuracy for the opinion and polarity annotation in Blog data.

4 Results and Discussion

4.1 Results in TAC 2008

We have shown the result from *TAC 2008* organizer in Table 2. We also show the results by topics in Table 3.

Table 2: TAC2008 Results

TeamID	F	-score	Gram	maticality	Non-Re	dundancy
	Score	Rank	Score	Rank	Score	Rank
TUT1	0.132	29	5.591	10	6.545	8
TUT2	0.133	27	5.545	12	6.045	16
	Structur	e/Coherence	Fluency	Readability	Respor	isiveness
	Score	Rank	Score	Rank	Score	Rank
TUT1	2.409	24	3.545	22	2.818	21
TUT2	2.318	29	3.591	18	3	16

The low result of F-score partially came from the misunderstanding of task definition. We created the summary based on the maximum length (7,000 characters by questions), but this seems too long. The precision seems low compared to other systems, as shown in Table 3. This defeat could be improved using threshold to include the fragments into the summary.

On the other hand, the *grammaticality* and *nonredundancy* evaluation results are above average. This proved that the sentence segmentation and redundancy elimination modules implemented well to some extent. For *non-redundancy* evaluation, *TUT1* with polarity annotation approach is quite effective and better than *TUT2* with the opinion annotation approach. This proves that polarity annotation is effective to eliminate redundant information from the summary.

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criminalizing flag burning 0.058 28 0.185 23 0.088 27 5 6 2 4 3 0.066 26 0.104 22 5 6 4 6 MAFTA NAFTA 0.034 32 0.252 22 0.059 29 2 2 3 1 0.034 32 0.053 14 4 3 4 4 3 4 4 3 4 4 3 4 4 3 4 4 3 4 4 3 4 4 3 4 4 3 4 <td< td=""><td>reminalizing Ing burning 0.058 28 0.185 23 0.088 27 5 6 2 4 3 0.066 26 0.235 19 0.104 22 5 6 4 6 NAFTA 0.034 32 0.252 22 0.059 29 4 4 3 4 System of a Down 0.205 16 0.654 14 0.312 12 6 7 2 3 111 27 0.059 29 4 4 6 7 2 3 0.111 27 0.05 31 6 5 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 3 4 6 7 2<td>324</td><td>Zillow</td><td>0.129</td><td>27</td><td>0.51</td><td>16</td><td>0.206</td><td>24</td><td>ω</td><td>×</td><td>б</td><td>ω</td><td>б</td><td>0.172</td><td>19</td><td>0.615</td><td>14</td><td>0.269</td><td>18</td><td>S</td><td>5</td><td>ω</td><td>5</td><td>9</td></td></td<>	reminalizing Ing burning 0.058 28 0.185 23 0.088 27 5 6 2 4 3 0.066 26 0.235 19 0.104 22 5 6 4 6 NAFTA 0.034 32 0.252 22 0.059 29 4 4 3 4 System of a Down 0.205 16 0.654 14 0.312 12 6 7 2 3 111 27 0.059 29 4 4 6 7 2 3 0.111 27 0.05 31 6 5 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 3 4 6 7 2 <td>324</td> <td>Zillow</td> <td>0.129</td> <td>27</td> <td>0.51</td> <td>16</td> <td>0.206</td> <td>24</td> <td>ω</td> <td>×</td> <td>б</td> <td>ω</td> <td>б</td> <td>0.172</td> <td>19</td> <td>0.615</td> <td>14</td> <td>0.269</td> <td>18</td> <td>S</td> <td>5</td> <td>ω</td> <td>5</td> <td>9</td>	324	Zillow	0.129	27	0.51	16	0.206	24	ω	×	б	ω	б	0.172	19	0.615	14	0.269	18	S	5	ω	5	9
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System of a Down 0.205 16 0.654 14 0.312 12 6 7 2 3 4 0.203 17 0.63 15 0.307 13 8 9 3 4 6 1 2 4 4 4 6 1 2 3 3 3 3 3 3 3 3 3 3 3 </td <td>System of a Down 0.205 16 0.654 14 0.312 12 6 7 2 3 4 0.203 17 0.63 15 0.307 13 8 9 3 3 World Bank 0.033 35 0.065 33 0.044 33 8 8 6 4 2 0.041 33 0.111 27 0.06 31 6 5 2 2 2 2 1 1 1 1 1 1 1 1 1 1 2 0.041 33 0.111 27 0.06 31 6 5 2</td> <td>127</td> <td>NAFTA</td> <td>0.034</td> <td>32</td> <td>0.252</td> <td>22</td> <td>0.059</td> <td>29</td> <td>5</td> <td>7</td> <td>6</td> <td>б</td> <td></td> <td>0.034</td> <td>32</td> <td>0.252</td> <td>22</td> <td>0.059</td> <td>29</td> <td>4</td> <td>4</td> <td>ŝ</td> <td>4</td> <td>-</td>	System of a Down 0.205 16 0.654 14 0.312 12 6 7 2 3 4 0.203 17 0.63 15 0.307 13 8 9 3 3 World Bank 0.033 35 0.065 33 0.044 33 8 8 6 4 2 0.041 33 0.111 27 0.06 31 6 5 2 2 2 2 1 1 1 1 1 1 1 1 1 1 2 0.041 33 0.111 27 0.06 31 6 5 2	127	NAFTA	0.034	32	0.252	22	0.059	29	5	7	6	б		0.034	32	0.252	22	0.059	29	4	4	ŝ	4	-
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A Million 0.094 17 0.247 12 0.136 13 4 6 1 2 4 0.051 29 0.161 20 0.078 24 7 1 1 1 Little Pieces 0.051 29 0.169 20 0.078 28 6 4 3 6 2 0.065 30 6 2 5 5 women on Numb3rs 0.038 17 0.556 12 0.148 17 9 10 1 4 4 0.061 19 0.458 14 0.108 18 8 10 1 4 Women on Numb3rs 0.038 31 0.077 29 0.051 30 6 2 2 2 1 4 Trader Joe's 0.0101 29 0.457 18 0.165 24 7 5 1 4 4 1 1 4 4 4 0.119 23	A Million 0.094 17 0.247 12 0.136 13 4 6 1 2 4 0.051 29 0.161 20 0.078 24 7 1 1 1 Little Pieces 0.051 29 0.169 20 0.078 28 6 4 3 0.153 22 0.065 30 6 2 2 14 0.108 18 8 10 1 4 4 0.061 19 0.458 14 0.108 18 8 10 1 4 4 4 4 0.061 19 0.458 14 0.108 18 10 1 4 4 4 0.011 25 0 1 2 <td>)33</td> <td>World Bank</td> <td>0.033</td> <td>35</td> <td>0.065</td> <td>33</td> <td>0.044</td> <td>33</td> <td>8</td> <td>8</td> <td>9</td> <td>4</td> <td>6</td> <td>0.041</td> <td>33</td> <td>0.111</td> <td>27</td> <td>0.06</td> <td>31</td> <td>9</td> <td>S</td> <td>1</td> <td>6</td> <td>4</td>)33	World Bank	0.033	35	0.065	33	0.044	33	8	8	9	4	6	0.041	33	0.111	27	0.06	31	9	S	1	6	4
	$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$)43	A Million Little Pieces	0.094	17	0.247	12	0.136	13	4	9	1	7	4	0.051	29	0.161	20	0.078	24	٢	7	1	-	З
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	women on Numb3rs 0.086 17 0.556 12 0.148 179101440.06119 0.458 14 0.108 1881014Trader Joe's 0.038 31 0.077 29 0.051 30 6 6 2 2 11 25 0.071 27 6 6 2 2 YouTube 0.101 29 0.451 18 0.165 24 7 9 1 4 4 0.111 25 0.071 27 6 6 2 2 George Clooney 0.066 28 0.178 18 0.097 25 7 5 1 2 30 0.011 25 0.071 27 6 6 2 2 Avg. 0.086 28 0.178 18 0.097 25 7 5 1 2 30 0.011 25 0.071 27 6 6 2 2 Avg. 0.086 30 0.312 18 0.097 25 2.4 3.5 2.8 0.056 29 6 6 1 4 Avg. 0.086 30 0.312 18 0.132 29 5.6 6.5 2.4 3.5 2.0 0.133 28 5.5 6.0 2.3 3.6 Avg. 0.086 30 0.319 16 0.133 28 5.5 6.0 2.3 3.6 <	44	talk show hosts	0.051	29	0.169	20	0.078	28	9	4	б	9	5	0.041	33	0.153	22	0.065	30	9	0	6	S	μ
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$)45	women on Numb3rs	0.086	17	0.556	12	0.148	17	6	10	-	4	4	0.061	19	0.458	14	0.108	18	×	10	-	4	4
YouTube 0.101 29 0.451 18 0.165 24 7 9 1 4 4 0.119 23 0.511 15 0.193 18 5 9 1 4 George Clooney 0.066 28 0.178 18 0.097 25 7 5 1 2 30 0.085 28 0.056 29 6 1 2 Avg. 0.086 30 0.312 18 0.132 29 5.6 6.5 2.4 3.5 2.8 0.035 28 5.5 6.0 2.3 3.6	YouTube 0.101 29 0.451 18 0.165 24 7 9 1 4 4 4 0.119 23 0.511 15 0.193 18 5 9 1 4 4 George Clooney 0.066 28 0.178 18 0.097 25 7 5 1 2 30 0.085 28 0.056 29 6 6 1 2 Avg. 0.086 30 0.312 18 0.132 29 5.6 6.5 2.4 3.5 2.8 0.036 29 6 6 1 2 Avg. 0.086 30 0.312 18 0.132 29 5.6 6.5 2.4 3.5 2.8 0.036 29 6 6 1 2 Avg. 0.086 30 0.312 18 0.132 29 5.6 6.5 2.4 3.5 2.8 0.036 29 6.0 2.3 3.6 Mg)47	Trader Joe's	0.038	31	0.077	29	0.051	30	9	9	0	0	-	0.052	30	0.111	25	0.071	27	9	9	6	0	-
George Clooney 0.066 28 0.178 18 0.097 25 7 5 1 2 3 0.042 30 0.056 29 6 6 1 2 Avg. 0.086 30 0.312 18 0.132 29 5.6 6.5 2.4 3.5 2.8 0.086 29 6 6 1 2 3.6	$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$	949	YouTube	0.101	29	0.451	18	0.165	24	2	6	1	4	4	0.119	23	0.511	15	0.193	18	S	6	1	4	Ś
0.086 30 0.312 18 0.132 29 5.6 6.5 2.4 3.5 2.8 0.086 29 0.319 16 0.133 28 5.5 6.0 2.3 3.6	$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$	150	George Clooney	0.066	28	0.178	18	0.097	25	2	2	1	6	m	0.042	30	0.085	28	0.056	29	9	9	-	6	
	11 11		Avg.	0.086	30	0.312	18	0.132	29	5.6	6.5	2.4	3.5	2.8	0.086	29	0.319	16	0.133	28	5.5	6.0	2.3	3.6	3.0
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S/C = Structure/Coherence R/F = Readablity/Fluency OR = Overall Responsiveness

4.2 Discussion

We found 1018 as the most improved target with polarity annotation (*TUT1* over *TUT2*) and 1021 as the most degraded one. By focusing these targets, we investigated the difference using polarity annotation in our approach.

We found the different evaluation results sometimes caused by the judgment error of nuggets from the assessors, although both *TUT1* and *TUT2* summaries contain the same fragments relevant to the same pyramid nuggets. We also found the different results came from the failure of polarity annotation for sentences written in colloquial style such as tag questions, which sometimes written in blogs, but not contained in the newspaper articles.

5 Conclusion

We described our opinion summarization system based on the opinion and polarity annotation system. We have proved that polarity annotation is effective to eliminate the redundancy.

Obviously, we have several improvement points. The first point is that summaries seem to contain slightly offtopic fragments and must be combined with QA system. The second point is to improve fluency considering discourse structure, such as question-answering pairs used in e-mail summarization (McKeown et al., 2007). We also should estimate the threshold to create the proper amount of summary from multiple blogs. Finally, we also plan to improve the accuracy of opinion and polarity annotation by creating the training dataset using Blog data.

Acknowledgments

This work was conducted when the author visited in Prof. Kathleen McKeown at Columbia University and I appreciate her precious advice for the improvements in future. Note that the author is responsible for all the results this time.

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Appendix

Features used in opinion annotation

Feature Type		Author Clues		Authority Clues	
"auxiliary verb"	will -	have	do –	declare	
- "verb"	cannot –	SbjVerb	to –	be	
	can –	say	could -	SbjVerb	
	may –	be	to –	SbjVerb	
"subject"	WDT -	SbjVerb	POS -	- NN	
- "verb"	NN –	say	they -	attitude	
	I –	VB	NNS -	SbjVerb	
	NN -	VBZ	IN -	judgment	
	ZeroProN -	conjecture	I -	declare	
	It –	VBZ	GPE -	I ID	
	it –	11	GPE -	VBG	
	ZeroProN -	declare	ZeroProN -	SbjAdj	
	NNS -	VBD	I -	admire	
	they -	VBP	We -	- VBP	
	NNP -		NN -	SbjVerb	
	WDT -	say VB	he –	SbjVerb	
	He -		I I		
		say		SbjVerb	
	NNP –	VBD	NNS -	attitude	
	it –	VBZ	NNS -	judgment	
	ZeroProN –	11	NNP -	50,1010	
	ZeroProN –	VB	PERCENT -	VBD	
	DT –	VBZ	GPE –	SbjVerb	
	ZeroProN –	SbjVerb	he –	declare	
	It –	VB	we -	SbjAdj	
	it –	SbjVerb	he –	SbjAdj	
		_	we -	VB	
		_	NNS –	say	
		_	they -	SbjVerb	
		_	he –	judgment	
		_	IN –	SbjVerb	
		_	DT –	SbjVerb	
		_	I -		
		he-VBD,he-say,NN-VB,	NN-SbjAdj		
subjective	meet.in	clude,demonstrate,SbjVerb,make,		s,denied,declare,tell,characterize	
verb type		pear,be,seem,SbjNoun,become,were		,have,apologize,voice,expand	
		add,say	,	,	
subjective					
adjective/adverb	cntopadj,	cntopadv,tragic,vicious,open,worse	unfair,angry,firmly		
subjective	antonnoun virtuo pr	opaganda, failure, diplomacy, power, influence,	baras	sment,fear,opposition	
		ght,humanity,resistance,excuse, stability	liaras	sment,reat,opposition	
noun					
subjective		tainly, should, merely, unfortunately,		condemn	
anypos	real	,perhaps,rather,seem,however		_	
polarity	huma	neness,education,defense,thing		report	
term type				•	
other keywords	",conten	t,display,perpetrate,agency,discuss	relationship,	century,spokesman,",ministry	

Table 4: Syntactic Pairs, Polarity Term Lists, and Keywords Clues Used in Author and Authority Opinion Extraction Feature Type Author Clues Author Clues Authority Clues Press of the second sec

Feature Type			Positve Clues		Negative Clues				
"auxiliary verb"	to	-	promote	do	-	SbjVerb			
- "verb"	to	-	attract	do	-	admire			
	to	-	set up	to	-	cover			
	will	-	continue	to	_	remain			
"subject"	He	-	VBD	GPE	-	VBD			
- "verb"	Ι	_	VB	NN	_	SbjVerb			
	I	_	VBN	EX	-	VBD			
	NNP	_	VBZ	GPE	_	characterize			
	PERSON	_	SbjAdj	GPE	-	say			
	he	_	VBD	IN	_	characterize			
	wood	_	say	IN	_	conjecture			
	GPE	_	admire	IN	_	judgment			
	GPE	_	judgment	JJ	_	VBD			
	I	_	SbjAdj	NN	_	VBD			
	I		VBP	NN		characterize			
	NN		admire	NN		judgment			
	NN	-	contribute to	NN	-	say			
	NN	_	judgment	NNP	_	VBD			
	NNP	-	SbjAdj	NNP	-	VBG			
	NNP	-	VB	NNS	-				
	NNP	-		NNS	-	judgment			
	NNP	-	judgment	One	-	say VBZ			
	NNS	-	say NN	PERSON	-				
	NNS	-		PERSON	-	SbjVerb NN			
	PERSON	-	judgment	POS	-	NNP			
		-	say		-				
	he	-	SbjAdj VBZ	She WDT	-	say CL:W.J.			
	he	-			-	SbjVerb			
	he	-	judgment	WP	-	SbjVerb			
	she	-	SbjAdj	ZeroProN	-	judgment			
				she	-	say			
subjective			continue,play,bring,promote,strengthen,act,			were,advise,cover,pose,deliver,whitewash,SbjVerb,have,			
verb type			emonstrate,own,generate,broaden,be,admire,			say, characterize, judgment, order, release, charge, draw,			
			ell,express,contain,reduce,attract,voice,alter			complain,plunge,gather,deem,term,notice,label,rely			
subjective			le,balanced,well,wonderful,ambitious,bright,			harmful,negative,wrong,antiAmerican,bad,cautious,central,disadvantageous,			
adjective/adverb			cooperative, credible, exemplary, glad, grateful, great,			lusive, hardline, illegitimate, impartial, intense, leftleaning, massive, odd, opportunisti			
			at,optimistic,peaceful,pleased,popular,positive			tic, unfair, unfounded, unpopular, unrealistic, unreasonable, wary, wides pread, firmly			
subjective			h,comment,dream,genius,peace,persistence,	dan		pression,lack,mistake,nature,reaction,sentiment,thought,abuse,accusation,			
noun			conciliation,remark,respect,appreciation,approval,			st,anger,blame,condemnation,constraint,critic,criticism,denunciation,			
			ration, confidence, contribution, esteem, friendship,			ction, discontent, dissatisfaction, fear, frustration, gaffe, harm, interference,			
			de,hope,knock,pledge,praise,recognition,reform,			n, irregularity, motive, objection, opposition, outcry, protest, refusal, reluctance,			
	resolve		significance,split,support,supporter,understanding	shoc	k,sorr	ow,starvation,suspicion,terrorism,threat,treason,violation,wrath,cntopnoun			
subjective			ement,good,really,wonderful,although,			claim, furthermore, seriously, wrong, against, angrily, besides,			
anypos		chan	pion,grateful,sensible,show,welcome			condemn, critical, disapprove, erroneous, odd, too, unreasonable			
polarity	IPS,quality	,inhabitant,i	mprovement, label, phenomenon, archetypal, order, Asian,	instr	ument	ality, priesthood, substance, male, politician, affirm, Sinitic, note, kill, response,			
term type	transport	,orientation	maneuver, contestant, compete, association, grow, right,		mo	otion, attitude, island, damage, INS, express, GRAP, polity, state, POLM,			
	speech,se	ction,imagi	nation,northbound,POLP,activity,capacity,clergyman,	organizat	ion,ab	straction, government, vote, document, title, associate, composer, action, statement,			
	affect, arg	umentation	,gathering,convey,unit,continent,decrease,degree,talk,	coerci	on,jud	gment, charge, choice, division, care, spokesperson, race, disapproval, objection,			
			ment, approval, conversation, measure, wish, drive, feeling,			rofessional, hominid, reformer, comment, press, crime, attach, aggression, neckwear,			
			anticipation, meet, capitalist, keep, acceptance, equivalent,			st,reject,whole,hit,resident,knock,watch,designate,complain,emotion,accusation,			
			e, affair, presentation, weekday, arouse, applaud, executive			anger, beat, denial, Russian, prejudice, penetrate, poverty, weekday, encase, larceny,			
		,				ove, formulation, discontentment, handwear, reorient, misbehavior, disappointment			

Table 5: Syntactic Pairs, Polarity Term Lists, and Keywords Clues Used in Positive and Negative Polarity Judgment