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Enhancing Automated Appraisal Recognition: A Focus on the Attitude System in Inscribed Appraisal

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Abstract

Due to the time and labor-intensive nature of human Appraisal labeling, there are not many such datasets accessible. While sentiment analysis has made great strides in determining a text's overarching meaning slant, the Attitude Appraisal component is still holding out. In order to pinpoint the source of the issues and offer suggestions for how to fix them, a simple automated recognizer was developed and tried for this research. No distinction is made between authorial and non-authorial assessment; the focus is solely on written Appraisal.

Keywords:

sentiment analysis; appraisal; NLP; recognizer; computational linguistics.

Introduction

Appraisal theory (Martin and White, 2005) was developed as part of a literacy program. It allows us to analyze the ways in which things, behaviors or people are evaluated and how writers and speakers position themselves in the text. Annotating a text in terms of Appraisal is not synonymous with finding its overall semantic orientation, since Appraisal tries to deal with the finer details. The fact that Appraisal can be inscribed (explicit) or invoked (implicit), along with its polymorphous nature, make automatic annotation a difficult task. This study deals only with inscribed Appraisal, and only with the Attitude system (Engagement and Graduation are left outside of its scope). For a clearer vision of the Appraisal system, please refer to Appendix A.

The fact that manual annotators are required limits the amount of available Appraisal-annotated corpora. Using a small amount of readyfor economic or copyright reasons, only a limited number of corpora will be available to any individual scholar. Unfortunately, this sometimes leads to research being carried out on less than optimally suitable material, material which is insufficient or skewed in a particular direction and thus not representative of the type of language which iswhich is insufficient or skewed in a particular direction and thus not representative of the type of language which is & Levin, in Mair and Hunt, 2000). It would be difficult to use most existing software, except that developed by Sano (2011) and to some extent, Garg et al (2006), for automatic Appraisal analysis.

Other software were developed with a different goal:

to extract the overall sentiment of a text, most often for commercial uses. It is not their goal to try to identify all tokens or divide them in more detailed categories that are equivalent to those used in Appraisal, even when some of them make use of Appraisal theory to some extent. The fact that Appraisal was developed as part of research carried out in the framework of a literacy program and that it deals with the way in which speakers engage their audience and position themselves, a hard terrain to navigate for most foreign language learners, means that Appraisal could be an useful tool in SLA. For this study, I set out to develop a basic automatic Appraisal recognizer, with no disambiguation strategies whatsoever, in order to identify a baseline value and reveal the most common kind of errors that such a recognizer would encounter.

Method

In order to train the recognizer, a dictionary is necessary. Although it is possible to use a web-based dictionary, I usable, dictionaries created using the Google search engine were unstable. When rerun, the results for each word were subject to change, sometimes by extreme amounts, something that Kilgarriff (2007) also notes, arguing against Thus, I decided to compile a small training

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corpus. News articles concerning financial and technological companies were downloaded in plain text format from the web version of the following English-language newspapers: The New York Times, The Washington Post, LA Times and The Chicago Tribune. No HTML code or other artifacts were left on the text. A training corpus, consisting of 32 articles was selected. 26 extra articles (13 on finance and technology, and 13 from general news) were set apart for testing purposes. The articles were loaded in a new project in UAM CorpusTool Appraisal_Max scheme that only takes into account the Attitude subsystem. For a complete version of this scheme, see Figure 2. Annotation was done following the guidelines in The Language of Evaluation: Appraisal in English (Martin and White, 2005). Invoked Appraisal was ignored. All Appraisal tokens were extracted from this small corpus and loaded into different lists according to the Appraisal system and subsystem they belong - Satisfaction:Dis- -Happiness:Misery- en there was more than one possible option, the majority sense of the word was kept. The dictionary was enriched with Appraisal terms generously provided to me by another researcher. A small program was created that performed the following functions: Load the lexicon from the files. Prompt the user to insert the text that they wanted tagged. Break the text down into tokens, filtering out punctuation marks and converting to lower case. Load the lexicon from the files. Match each token against the dictionary to see if an entry for that token exists. Save the text in an output file, inserting a tag for each recognized token. The tags cover 14 categories, according to type and polarity. The recognizer has no disambiguation strategies whatsoever and makes no use of context. It is also unable to handle multi-word expressions.

In order to eliminate any interference due to inter-annotator inconsistency, a problem that Read et al. (2007) pointed out in regards to Appraisal theory, all manually annotated texts were annotated by myself. The tagged texts were tested against manual annotation of the same texts in terms of precision and recall. 3. Results The recognizer had a precision of 52.97% and its recall was of 26.22%. The F-score was 35.08% It correctly recognized 107 of the 202 total recognized tokens, making mistakes in 95 cases. A complete detail of errors can be found in Table 7. Most of the incorrectly recognized tokens were false positives. This was expected because the program had no disambiguation modules or any other tool providing information about context. One of the most when it was used to describe the character of an individual or when it was used in a different sense. Problems were identified in dealing with negation, since the recognizer is unable to handle multi-word expressions or use POS tagging as of today, which led to polarity errors. Errors in terms of type but not in polarity were also present and are due to the lack of knowledge about the appraiser and the appraised. Other errors were due to three main reasons: the term could not be found in the dictionary, the term could be found in the dictionary but a different inflection was used, or the term could be found in the dictionary but it was used in a different sense. Possible solutions include expanding the training corpus, using lemmatization in order to solve those instances in which a different inflection was used, handling multi-word expressions, making use of a POS tagger output and using a dictionary of collocations. Table 1. Results (Attitude type).

Table 1. Results (Attitude type)

Feature	Manual annotation	Recognizer	Relative frequency
Total tokens (Attitude)	408	113	27.70%
Affect	67	14	20.90%
Judgement	69	10	14.49%
Appreciation	272	89	32.72%

Table 2. Detailed results Affect (Authorial evaluation and classification)

Feature	Manual annotation	Recognizer	Relative Frequency
Authorial evaluation	61	14	22.95%
Non-authorial evaluation	6	0	0.00%
Un/happiness	14	5	35.71%
Dis/satisfaction	16	3	18.75%
In/security	14	3	21.43%
Dis/inclination	23	3	13.04%

Table 3. Detailed results Affect (subclassification)

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Feature	Manual annotation	Recognizer	Relative Freq
Misery/cheer	12	4	33.33%
Antipathy/affection	2	1	50.00%
Ennui/interest	5	0	0.00%
Dis/pleasure	11	3	27.27%
Dis/quiet	10	1	10.00%
Dis/trust	4	2	50.00%

Table 4. Detailed results Judgement

Feature	Manual annotation	Recognizer	Relative Frequency
Normality	8	1	12.50%
Capacity	24	5	20.83%
Tenacity	7	2	28.57%
Propriety	22	2	9.09%
Veracity	6	0	0.00%
Unclear	2	0	0.00%

Table 5. Detailed results Appreciation

Feature	Manual annotation	Recognizer	Relative Freque
Reaction (impact)	13	7	53.85%
Reaction (quality)	5	4	80.00%
Composition (balance)	10	1	10.00%
Composition (complexity)	41	12	29.27%
Social valuation	203	65	32.02%

Table 6. Results Polarity

Feature	Manual annotation	Recognizer	Relative Frequency
Positive attitude	256	86	33.59%
Negative attitude	152	27	17.76%
Ambiguous	0	0	0.00%

Table 7. Recognizer Errors

Description	Percentage	Number of tokens
Total	100%	202
Correctly tagged	52.97%	107
Incorrect type	7.43%	15
Incorrect polarity	3.47%	7
Incorrect type and polarity	2.48%	5
False positives	33.66%	68

Conclusion

Although very restricted at present, it is possible to develop an automatic Appraisal recognizer with respect to written mood. In addition to the other methods suggested in this article, employing classification techniques and POS tagger output is likely to boost the recognizer's total memory. Although I concur with Wang and Manning (2012) that NBSVMs are flexible and can handle a wide variety of texts, I acknowledge that some texts will require more specialized methods of analysis. If we were to analyze in Appraisal terms a corpus of texts produced by SLA students, for example, it is very likely that some words would be misspelled, as would happen if we were to rely solely on a web corpus. However, for an appraisal recognizer, it would be interesting to include the variations of each word, even if they are misspelled.

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