Curse or Boon? Presence of Subjunctive Mood in Opinionated Text

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Abstract

In addition to the expression of positive and negative sentiments in the reviews, customers often tend to express wishes and suggestions regarding improvements in a product/service, which could be worth extracting. Subjunctive mood is often present in sentences which speak about a possibility or action that has not yet occurred. While this phenomena poses challenges to the identification of positive and negative sentiments hidden in a text, it can be helpful to identify wishes and suggestions. In this paper, we extract features from a small dataset of subjunctive mood, and use those features to identify wishes and suggestions in opinionated text. Our study validates that subjunctive features can be good features for the detection of wishes. However, with the given dataset, such features did not perform well for suggestion detection.

1 Introduction

In the context of Sentiment Analysis, presence of a variety of linguistic phenomena poses challenges for the identification of underlying sentiment in an opinionated text. Subjunctive mood is one such phenomena (Liu et al. (2013); Bloom (2011)). It is a commonly occurring language phenomenon in Indo-European languages, which is a verb mood typically used in subordinate clauses to express action that has not yet occurred, in the form of a wish, possibility, necessity etc. (Guan, 2012). Oxford dictionary defines it as, *Relating to or denoting a mood of verbs expressing what is imagined or wished or possible*. Sentiment terms present in such sentences may not necessarily contribute to the actual sentiment of the sentence, for example 'I wish it tasted as amazing as it looked' is not positive. While this is considered as a challenge for sentiment analysis, we adopt a different perspective, and discover benefits of the presence of subjunctive mood in opinionated text.

Apart from the expression of criticism and satisfaction in customer reviews, reviews might include suggestions for improvements. Suggestions can either be expressed explicitly (Brun, 2013), or by expressing wishes regarding new features and improvements(Ramanand et al., 2010) (Table 1). Extraction of suggestions goes beyond the scope of sentiment analysis, and also complements it by providing another valuable information that is worth analyzing. Table 1 presents some examples of occurrence of subjunctive mood collected from different forums on English grammar[1]. There seems to be a high probability of the occurrence of subjunctive mood in wish and suggestion expressing sentences. This observation can be exploited for the tasks of wish detection (Ramanand et al., 2010), and suggestion extraction (Brun, 2013). To the best of our knowledge, subjunctive mood has never been analysed in the context of wish and suggestion detection.

We collect a sample dataset comprising of example sentences of subjunctive mood, and identify features of subjunctive mood. We then employ a state of the art statistical classifier, and use subjunctive features in order to perform two kind of tasks on a given set of sentences: 1. Detect wish expressing sentences, and 2. Detect suggestion expressing sentences.

[1] http://grammar.about.com/od/rs/g/subjuncterm05.htm

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Description	Examples
Suggestion bearing wishes in product reviews	I wanted a dvd player that had basic features and would be able to play dvd or format discs that I had made myself. I wish canon would work out some way for that issue.
Direct suggestions in product reviews	They should improve their user interface.
Wishes in political discussions	I wish someone said that to teddy at the meeting yesterday. Perhaps I should have stopped at 8 or 9 years old. I would like to know if you re a purist or a hypocrite.
Sentences containing subjunctive mood	I wish it were summer. I suggest that Dawn drive the car. But if it weren't so big, it wouldn't be nearly so fun.

Table 1: Examples of Suggestions, Wishes, and Subjunctive Mood

2 Related work

Mood and Modality: Modality is a grammatical category that allows the expression of aspects related to the attitude of a speaker towards his statement, in terms of degree of certainty, reliability, subjectivity, sources of information, and perspective (Morante and Sporleder, 2012). Subjunctive mood originated from the typological studies of modality (Palmer, 1986; Dudman, 1988; Portner, 2009). Some works equate its presence with 'counterfactuality'(Palmer, 1986), while some do not (Anderson, 1951). Other concepts like 'event modality', 'irrealis' (Palmer, 1986), have definitions similar to that of subjunctive mood.

Benamara et al. (2012) studied modality and negation for French language, with an objective to examine its effect on sentiment polarity. Narayanan et al. (2009) performed sentiment analysis on conditional sentences. Our objective however is inclined towards wish and suggestion detection, rather than sentiment analysis.

Wish Detection: Goldberg et al. (2009) performed wish detection on datasets obtained from political discussion forums and product reviews. They automatically extracted sentence templates from a corpus of new year wishes, and used them as features with a statistical classifier.

Suggestion Detection: Ramanand et al. (2010) pointed out that wish is a broader category, which might not bear suggestions every time. They performed suggestion detection, where they focussed only on suggestion bearing wishes, and used manually formulated syntactic patterns for their detection. Brun (2013) also extracted suggestions from product reviews and used syntactico-semantic patterns for suggestion detection. None of these works on suggestion detection used a statistical classifier.

None of these works aligned the problem of wish and suggestion detection with subjunctive mood, or identified features related to it. Wish and suggestion detection remain young problems, and our work contributes towards the same.

3 Datasets

Following are the datasets which we use for our experiments.

- **Wish Detection**
  Oxford dictionary defines the noun wish as, *A desire or hope for something to happen*. Goldberg et al. (2009) follow this definition of wish and provide manually annotated datasets, where each sentence is labelled as wish or non-wish. Following two datasets are made available:
  a. Political Discussions: 6379 sentences, out of which 34% are annotated wishes.
  b. Product Reviews: 1235 sentences, out of which 12% are annotated as wishes.
  Table 1 presents some examples from these datasets.
  Ramanand et al. (2010) worked on product review dataset of the wish corpus, with an objective to extract suggestions for improvements. They considered suggestions as a subset of wishes, and

thus retained the labels of only suggestion bearing wishes. They also annotated additional product reviews, but their data is not available for open research.

- **Suggestion Detection**
  Product reviews (new): We re-annotated the product review dataset from Goldberg et al. (2009), for suggestions. This also includes wishes for improvements and new features. Out of 1235 sentences, 6% are annotated as suggestions. Table 1 presents some examples from this dataset.
  Annotation Details: We had 2 annotators annotate each sentence with a suggestion or non-suggestion tag. We support the observation of Ramanand et al. (2010) that wishes for improvements and new features are implicit expression of suggestions. Therefore, annotators were also asked to annotate suggestions which were expressed as wishes. For inter-annotator agreement, a kappa value of 0.874 was obtained. In the final dataset, we only retained the sentences where both the annotators agree.

Subjunctive Feature Extraction
Subjunctive Mood Dataset (new): Since we did not come across any corpus of subjunctive mood, we collected example sentences of subjunctive mood from various grammar websites and forums[2], which resulted in a sample dataset of 229 sentences. Table 1 shows examples from this dataset. We use this dataset for manual and automatic identification of features of subjunctive mood.

4 Approach

We use a statistical classifier to detect wishes and suggestions in corresponding datasets. We obtain the following set of features from the subjunctive mood dataset.

Lexical Features:

- **Condition indicator 'if':** This is a binary feature, whose value depends on the presence and absence of 'if' in a sentence.
- **Suggestion and Wish Verbs:** We collect some suggestion and wish indicator verbs observed in the subjunctive mood dataset. We then expand this set of verbs by using VerbNet 3.2 (Schuler, 2005). VerbNet is a wide coverage verb lexicon, which places verbs into classes whose members have common syntactic and semantic properties. We collect all members of the VerbNet verb classes *advice*, *wish*, *want*, *urge*, *require*; 28 different verbs were obtained. Ramanand et al. (2010) also used a similar but much smaller subset {*love, like, prefer and suggest*} in their rules.

Syntactic Features:

- **Frequent POS sequences:** This is a set of 3,4 length sequences of Part Of Speech (POS) tags, which are automatically extracted from the subjunctive mood dataset. Words in the sentences are replaced by their corresponding POS tag, and top 200 sequences are extracted based on their weight. The weight of each sequence is a product of Term Frequency (TF) and Inverse Document Frequency (IDF). In order to apply the concept of TF and IDF to POS tag sequences, every 3 and 4 length tag sequence occurring in the corpus is treated as a term. We separate tags within a sequence with an underscore. An example of a sequence of length 3 would be PRP_VB_PRP ie. Personal Pronoun_Base form of Verb_Personal pronoun.
- **Frequent Dependency Relations:** These are a set of dependency relations (Marneffe and Manning, 2008). Using the same method as the part of speech tags, we identify 5 most frequent dependency relations which occur in the subjunctive mood dataset. In order to apply the concept of TF/IDF, each dependency relation occurring in the corpus is treated as a term. The top 5 relations were: *advmod, aux, ccomp, mark* and *nsubj*.

[2] http://grammar.about.com/od/rs/g/subjuncterm05.htm

Data	Experiment	Features	Precision	Recall	AUC
Politics	Ours	unigrams	0.73	0.65	0.76
		subjunctive	0.70	0.34	0.63
		unigrams,subjunctive	0.75	0.67	0.78
	Goldberg et.al (2009)	templates	n/a	n/a	0.73
		unigrams,templates	n/a	n/a	**0.80**
Products	Ours	unigrams	0.78	0.21	0.60
		subjunctive	0.59	0.31	**0.64**
		unigrams,subjunctive	0.82	0.25	0.62
	Goldberg et.al (2009)	templates	n/a	n/a	0.47
		unigrams,templates	n/a	n/a	0.56

Table 2: Results of Wish Detection and Comparison with Goldberg et. al. 2009

Data	Features	Precision	Recall	AUC
products	unigrams	0.29	0.02	0.51
	subjunctive	**0.29**	**0.11**	**0.54**
	unigrams,subjunctive	0.33	0.02	0.51

Table 3: Results of Suggestion Detection

We also obtain classification results of the combination of these features with the standard unigram features (Table 2, 3).
To obtain the part of speech and dependency information, we use Stanford Parser 3.3.1 (Klein and Manning, 2003). Word stemming is not performed. We use the LibSVM implementation of SVM classifier (EL-Manzalawy and Honavar, 2005). The parameter values of SVM classifiers are: SVM type = C-SVC, Kernel Function = Radial Basis Function. Features are ranked using the Info- Gain feature selection algorithm (Mitchell, 1997). Top 1000 features are used in all the experiments ie. the size of feature vector is not more than 1000.

5 Subjunctive Feature Evaluation

Goldberg et al. (2009) evaluated their approach using a 10 fold cross validation on their datasets. In order to compare subjunctive features against their wish template features, we also perform 10 fold cross validation on their wish datasets (politics and products). The evaluation metrics include Precision, Recall, and Area Under Curve (AUC) for the positive class. AUC was also used by Goldberg et al. (2009).
To the best of our knowledge, statistical classification based approach have not yet been employed to detect suggestions in reviews. Our experiment which uses subjunctive features for suggestion detection, is the first in this regard.

Results and Discussion

Table 2 compares the AUC values obtained with unigrams, subjunctive features, a combination of both, and the results from Goldberg et al. (2009) for wish detection. Table 3 compares the AUC values obtained with unigrams, subjunctive features, and a combination of both for suggestion detection. Table 4 presents some of the top features used by the classifier.

Wish Detection:
Unigrams vs Subjunctive: One probable reason for the better performance of subjunctive features over unigrams in the case of product dataset, could be the small size of the dataset. In the case of politics dataset, similar reason (big dataset) can be attributed for the better performance of unigrams over subjunctive features.

Classification	Data	Unigrams	Subjunctive
Wish	Politics	hope, please, wish, hopefully, I, you, should, want, your, all	hope, want, nsubj, wish, MD_VB_VBN, advmod, PRP_VBP_IN, PRP_VBP_PRP, VB_DT_NN, PRP_VBP_DT
	Products	hope, wish, hoping, now, would, hopefully, sell, should, want, get	hope, wish, want, MD_VB_VBN, aux, ccomp, RB_PRP_MD, RB_PRP_MD_VB, if, nsubj
Suggestion	Products	if, you, your, now, recommend, I , better, waste, display, want	if, IN_PRP_VBP,IN_PRP_VB, recommend, suggest, DT_NN_VBZ, PRP_VBP_DT, PRP_MD_VB, IN_PRP_VB_DT, NN_PRP_MD

Table 4: Top 10 Unigram and Subjunctive features used by the Classifier

Wish templates vs Subjunctive: The wish templates of Goldberg et al. (2009) perform better than our subjunctive features for the politics data. However, subjunctive features perform much better with product data as compared to the wish templates (Table 3). This may lead to the conclusion that wish templates need larger training corpus, since they failed for the smaller dataset of product reviews (AUC less than 0.5). One additional benefit of subjunctive features could be that subjunctive mood appears in many languages, and thus such features can be easily extended to multi-lingual wish detection.

Suggestion Detection:
Subjunctive features perform better than unigrams in this case too. An overall decrease in classifier performance for the task of suggestion detection can be attributed to the fact that not all wishes are suggestions, and therefore are not tagged in this dataset. Some of these untagged wishes would contain subjunctive mood, which reduced the performance of subjunctive features, as compared to the task of wish detection.

6 Conclusion

From the results of feature evaluation, we conclude that subjunctive features are not effective for suggestion detection, but are considerably effective for the task of wish detection. This work contributes towards both, analysis and methodology for wish detection. On the analysis part, we validate that a considerable amount of wishes in opinionated text contain subjunctive mood. On the methodology part, we use subjunctive mood features as effective features for the detection of wishes. We also provide datasets for this kind of study.
Since we only deal with 2 domains here, further experiments can be performed over data from different domains. In the continuation of this work, we intend to extend the datasets and explore more syntactic and semantic features for wish and suggestion detection.

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