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Research Paper

A comprehensive survey of research based on extraction of opinion words and opinion targets from customer reviews

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Abstract

This survey paper categorizes, compares, and summarizes the algorithms, data sets and performance measurement in the published articles related to extraction of opinion targets and words from customer reviews. The systems reviewed either deploy a supervised or completely unsupervised algorithm for the process. Most of the systems rely on K-nearest neighbor algorithm or a bootstrapping approach. Most of the methods have produced a list comprising of opinion targets from the customer reviews of a product. As a result, opinion targets usually are product features or attributes. The approaches mentioned in the papers reviewed suffer either from error propagation or from lack of automation for parsing long span relations. Certain approaches have taken an initial bag of seed words and proceeded to exploit the syntactical relationship between opinion words and targets. Mainly online product reviews have been used. It is generally believed that the co- occurrence of certain target and opinion words in close proximity makes them more relevant to each other and to the product as well. Owing to the nature of online review data sets most literature have not include assessment of opinion targets and words across multiple domains.

1. Introduction

The web has witnessed a large number of product reviews added to it since its rapid accessibility to the people. Customers of a product benefit from such reviews as it helps them to gain an insight about it and make their purchasing decisions accordingly. While the manufacturers of the product can benefit from this as it helps them to improve the quality of products and services. Thus, the popularity of mining and analysis of opinions from product reviews has increased quite rapidly in the recent years which had led to a considerable amount of research in this area.

In order to mine and analyze the opinions from online reviews it is not enough to only get the general sentiment about the product. Often, customers expect to find finer details of a feature of a product from such reviews.

This paper aims to bring to attention the most suitable algorithm and programming paradigm by reviewing literature on algorithms, conclusion provide and evaluation of the various models used to achieve the desired results.

2. Literature Review

To get a fine grained approach to extracting opinion words and targets we must take into account that not all opinion words have the same meaning in every context. To tackle this issue, it is important to have aspect level sentimental analysis. The authors of [1] have adapted the double- propagation technique described in [2]. In the double propagation method a seed list of aspect terms and opinion words is moved through an unlabeled domain related collection in accordance to a set of propagation rules. The ultimate aim is to extend the list of aspect term and opinion word. Reference [2] define opinion words on the basis of their polarity. Hence, according to them, opinion words are terms that convey either a positive or negative sentiment. Initially the set of aspect terms is empty. A dependency tree is obtained by analyzing each sentence and then the rules are checked in a sequence. In case a rule is matched, then all the words corresponding to the rule are added to the set of either aspect terms or opinion words. The set to which it is to be added depends on the rule. The newly populated set of words is used to trigger the rules of propagation later. If during an iteration of the dataset, no more words are added to the set, the process stops. To assign categories to every aspect term a WordNet similarity approach has been taken. The algorithm is not robust in dealing with abstract or vague categories and aspect words. Even though the paper attempts to give a more aspect level detailed approach, it lacks in dealing with multi words like “hard disk”, “battery life” which introduces a significant amount of error in their results.

To overcome the significant challenge faced in [1] with respect to category detection, the authors of [3] have taken an algorithm, being an adapted version of [4], is inspired by the work of [5] and [6]. The work in the literature also attempts to identify the implicit aspect words i.e., aspects that are not mentioned directly, unlike the explicit aspects which are mentioned literally in [1].The above would not have been able to identify the ‘anecdotes/miscellaneous’ type of aspects because they were not directly mentioned in a sentence. A set of noun phrases is made by filtering out noun phrases that have aspect words associated with them with probability greater than 0.05. The algorithm captures the frequency of co-occurrences between words in the sentence and forms a co-occurrence matrix. This helps to map the words to aspect categories. A score is computed for each aspect category when the processing of an unlabeled sentence is done. Each sentence can have more than one aspect category associated with it based on the threshold score. However this methodology suffers from the problem of over fitting. A large number of false positive categorical fits for an aspect were generated. Two more negative factors influence the algorithm. First, if a word is not present in the training set, then its co-occurrence with any category is not noted by the algorithm. This has an effect on the recall of the algorithm. Second, even though the category thresholds, work well with training data set, they do not derive the aspect words well in the test data set.

Through all the literature reviewed so far it is evident that the relevance of the extracted words to the user is often not accurate, to overcome this, [7] used Associative Retrieval. In Associative Retrieval a network is formed to represent association among items, in which the nodes represent the information items and the links connecting the nodes represent the association among them. A technique called Spreading Activation is used in which a heuristic approach is taken to retrieve information from items which are already assessed to be relevant. If some information is already present at the time of the query, static association is made between its words. On the other hand, if some information is determined at run time, dynamic association is made within its content. The authors have used a “pure” spreading activation model, which is used in the search controlling nature of the network. The processing technique on a network data structure is simple. The network data structure here has been used to represent the semantic relationship between words in the real world. The model has “pulses”. Each pulse has a pre adjustment, spreading and post adjustment. A threshold function is used to determine is a node in the network is active or not. It is the most used function of the algorithm but it varies from node to node as it is application dependent. The output value of a node is computed and is sent to all the nodes connected to it. With each consequent pulse, the activation reaches to nodes that are farther away from the initially activated nodes, slowly it spreads throughout the entire network. However the pure SA model has a few drawbacks. The activation may spread throughout the entire network unless it is controlled carefully by means of the pre adjustment and the post adjustment phases. The semantics of the associations are not very useful as the information provided by the labels associated with the links is not completely used. This also makes inference based on the semantics of the association challenging.

S. Kiritchenko [8] proposed a system for 4 subtasks. (1) aspect categories, (2) sentiment towards aspect categories,
(3) aspect terms, and (4) sentiment towards aspect terms. Here, besides ngrams which are common surface-form features, it leverages existing and newly created word– aspect association and sentiment lexicons. A corpus of 183,935 reviews from yelp was categorized into over 500 categories, out of which 58 were food-related businesses. A subset of reviews of Amazon.com had 124,712 electronics reviews. Both of these businesses have rating based on a scale of one to five star. Four and five stars were considered as positive, three was average while one and two star reviews were considered negative. An indomain sentiment lexicon for restaurants was created and using that a sentiment score for each term in the set was calculated. Positive sentiment scores indicated greater positive sentiment and a negative score indicated greater negative sentiment. The magnitude indicated degree of association. Using Brown clustering algorithm 1000 word clusters were generated. This system scored 80.19 in the restaurant category and 68.57 in the laptop category in F1 tests for Aspect Term Extraction and this was done using entity recognition software. Aspect Category Detection scored 88.58 and the post-processing step increased by 1.46 points and elevated the total score by 0.58 points using a linear SVM classifier via LibSVM software. An accuracy of 82.93 was achieved and there was a 8.78 percentage point gain in accuracy from other proposals in terms of Aspect Category Polarity for which SVM classifiers were built. . It's downsides were that it considered out of domain information and was unable to distinguish between aspect categories and relate multiple access words.

C Brun proposed a system which involves a robust parser for lingustics based classifier. Here [10], work has been done on the restaurant domain with a corpus containing a total of 800 sentences, 1025 occurrences of aspect category, 1134 occurrences of aspect term, aspect categories of 5 different types and 555 distinct aspect terms. Lexical Enrichment and Term Detection has been done to narrow down to 1265 negative and 1082 positive polar words and 761 words of the food domain, 31 words of the price domain, 105 words related to ambiance, 42 words related to service domain. This system has been implemented in a scripting language called Knowledge in Frame designed on the rule based Xerox Incremental Parser. Terms and Category Polarity Detection achieved an accuracy of 0.77 for the polarity detection of aspect terms and 0.78 for polarity detection of aspect category. Aspect category classification, Performance was constrained as threshold was set to 0.25. The limitations of this system were that it didn't perform for neutral and conflict polarities of opinions which does not rely on a global interpretation of the content.

G Castellucci[11] proposed a system which exploits Kernel Methods using SVM. The corpus contains 20,000 words from TripAdvisor. The Aspect Term Extraction was modeled as a sequential tagging process. Representation of Lexical Information was done through Bag of Words where each text was represented with dimensions corresponding to different words in the vector, The Aspect Term Polarity scored 0.73 on F1. The Aspect Category Detection scored
0.83 in this system. Aspect Category Polarity achieved a score of 0.74. The threshold was set to 0.3 in this UNITOR system. The drawbacks of this system were that it failed to detect aspect terms composed of multiple words and the inability to capture deep semantic phenomena like irony.

3. Conclusion

Most of these works are based on systems to determine aspect and categories, and the sentiments towards them. These may be done through direct and indirect dependencies. The accuracy is verified by an F score of high precision which is also recalled by limiting threshold. Some of these measures polarities in different scales and it is compared with a reference to target entities. The might also require cleansing of undesired words i.e. features. Constraints in terms of distance, fan out, path and activation are also exercised. Some of these might contain their own factors for computation that are not applicable on a global scale. At the end, category error is measured in a percentage scale.

A lot of classifiers were deployed of which most were SVM classifiers in different forms used for different purposes. One was a linear SVM classifier for tackling multiple class classification problems. Another SVM classifier was used for maximum margins that was designed for linear discriminative models. SVM was also used to model multiple kernel classification problems. SVM classifiers were also customized with special lexicons in combination with symbolic parsers. A Conditional Random Fields classifier was also made use of for extracting features using named entity recognition, tagging, parsing, and semantic analysis.

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