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Extraction of Aspects from Customer Reviews using Life Long Learning

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Abstract: ***Aspect extraction is a challenging task of opinion mining. This paper proposes a novel statistical approach to make a major improvement in sentiment analysis of customer reviews. The approach is based on identification of customer opinions along with the framework of lifelong learning. It is implemented with LSA and Association rule mining. Experimental results show the effectiveness of the proposed approach.***

Keywords: aspect extraction, opinion mining, opinion word, Sentiment analysis, Life Long Learning

1. Introduction

The advancement of Web as well as its read-write nature has enabled more and more users to interact and share knowledge and information. Mining useful opinions and sentiments from the web became more challenging, because deep understanding of the semantic similarity as well as aspect association in the natural language is required[1]. This paper proposes to extract aspects from customer reviews under the framework of life- long machine learning

2. Related Work

There are mainly two approaches for extracting aspects: supervised and unsupervised.

Hu and Liu (2004) [3] first proposed a technique to extract product aspect based on association rule mining. Double propagation (Qiu et al., 2011) [11] further developed the idea. Jin et al. (2009a and 2009b) [13][14] utilized lexicalized HMM to extract product aspects and opinion expressions from reviews. Pang Lee et al. (2002, 2004) [2] [8] used supervised learning in sentiment analysis for determining whether it could be treated as a topic-based categorization with positive and negative topics. By using the Apriori algorithm, Hu and Liu [3][5][25] generated all strong association rules to extract implicit as well as explicit opinion features expressed in reviews.

This paper proposes to use statistical approach of LSA (Latent semantic Analysis) as the base and improve its results dramatically through aspect recommendation. The recommendation proposed are semantic similarity-based, and aspect associations-based. [1]

3. The Algorithm

3.1 Extracting Base Aspects

Stanford POS Tagger is used extract nouns/noun phrases as they mostly represent aspects. It works very well in medium size corpus. But for large corpora, this method may result in extracting many nouns/noun phrases which are not product aspects. The precision of the method plummets.

SentiWordNet is used to determine the polarity of each modifier. SentiWordNet (SWN) is a lexical resource of sentiment information for terms in the English language introduced in [15] designed to assist in opinion mining tasks. Each synonymous set in SWN has a positive sentiment score, a negative sentiment score and an objectivity score. When the sum of these scores equals one, it indicates the relative strength of the positively, negativity and objectivity of each synonymous set. The drawback in using SWN is that it requires word sense disambiguation to find the correct sense of a word and its associated scores.

Table 1: Pattern used for extracting Aspects

	First word	Second word
a.	Adjective	Noun
b.	Adverb	Adjective
c.	Adjective	Adjective
d.	Noun	Adjective
e.	Adverb	Verb

3.2 Finding Aspect Similarity

Latent Semantic Analysis is the proposed method used to find the aspect similarity.LSA is a mathematical and statistical approach, claiming that semantic information can be derived from a word-document co-occurrence matrix and words and documents can be represented as points in a (high-dimensional) Euclidean space. Dimensionality reduction is an essential part of this derivation [20].

Values close to 1 represent very similar words while values close to 0 represent very dissimilar words. The terms with similarity score above a particular threshold is returned.

3.3 Associating Aspects

The proposed work is designed specifically to identify aspects that do not occur explicitly in review sentences. Secondly, the approach discriminates between opinion words and aspect words i.e opinion words can only occur in the rule antecedents, while rule consequents must be opinion aspects

[26]. Thirdly association rules are generated directly from the LSA matrix of opinions and aspects. Association rule mining helped to mine the aspect →opinion rules from the LSA matrix. Support score threshold was taken to be 1% [3][5] so that weak rules are pruned appropriately.

3.4 Life Long Learning Using Neural Networks

Neural Network with back propagation is used as the Knowledge miner. This mining can be regarded as a meta-learning process because it learns knowledge from information resulted from learning of the past tasks. A learner has performed a sequence of supervised sentiment classification tasks, from 1 to N [1][4].

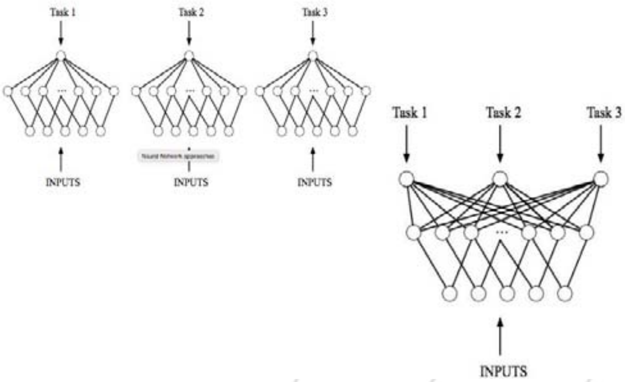

Figure 1: Implementation of Life-Long Learning using Neural Network

The experimental data set is divided into training and test sets. This step begins training process of BPN by using training data set. All optimal setting of BPN includes parameters and structure such as learning rate, training iterations, number of hidden neurons and so on are obtained by a trial-and-error experiment.

3.5 Summarization

Review summarization produces a sentiment summary, which consists of sentences from a document that capture the author's opinion. The summary may be either a single paragraph as in [27] or a structured sentence list as in [3][9][25]. The former is produced by selecting some sentences or a whole paragraph which the author expresses his or her opinion(s). The latter is generated by the auto mined aspects that the author comments on. The proposed method used is more relevant to the method used in [3][25][9] i.e. aspect based summary of opinions on an object or multiple competing objects.

4. Observations

The customer review corpus was collected from www.amazon.com which is a source of reviews, which includes user reviews for cell phones. Each of the review includes a text review.

There is a drop in precision as many nouns/noun phrases which are not product aspects were observed to be extracted. LSA has been the alleged difficulty in determining the optimal number of dimensions to use for performing the SVD was determined to be "6" as the optimal number of dimensions to use for performing the SVD as recall as 66.67% and precision as 71.42%. Too few dimensions and important patterns are left out, too many and noise caused by random word choices will creep back in.

Due to the existence of synonyms and semantically related terms, associating a opinion word to most likely feature cluster instead of a single aspect was found better. Cluster of "speaker" contains "music-system, music, phone, service, music-player". Therefore conceptual mapping of aspects with opinions helps to improve the performance.

Quite number of reasonable rules was generated due to the LSA that helps to measure semantic associations between the objects. Higher minimum support will weed out many lower frequency associations but will kill the legitimate associations as well.

In the training of neural networks, some input nodes might be considered as irrelevant and then be removed. In 70% and 90% data sets, highest accuracy 71% was achieved.

Figure 2: Example of Aspect Summarization obtained

5. Conclusion

This paper proposes a Life-long Learning-based approach to improve the syntactic rule-based method for aspect extraction. Two methods were presented which exploit two types of interesting knowledge about aspects which are aspect similarity and association. POS tagger was used to extract the aspects and SentiWordNet to find aspect orientation. Aspect similarity and reduction is Latent semantic Analysis is used. Opinion-aspect mapping is done using Apriori Algorithm. Back Propagation Neural Network is used as Life-Long Framework. Finally aspect based summary of the customer reviews a product sold online is provided. Although the methodology used here is quite reasonable in identifying implicit and explicit aspects some undesirable errors still exist in the final identification results which is due to the noises generated during segmentation and parsing.

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