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Design of a Category Independent, Aspect Based Automated Opinion Analysis Technique for Online Product Reviews

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Abstract: Customer feedback in the form of online reviews is an important source of information to manufacturers or service providers for evaluation of their products or services. Online reviews also help potential buyers in making their decisions. Manual checking of these huge amount of unstructured texts is time consuming. Several attempts have been made for opinion aggregation of online reviews but a generalized automated technique has yet to be developed. In this work, an efficient rule based technique for aspect wise summarization of online product reviews irrespective of their categories has been designed. The proposed technique develops the rules for extracting aspects and associating the opinion words to the respective aspects followed by effective grouping and summarization of aspect-opinion pairs into human interpretable form. The algorithm has been implemented on Amazon Product Reviews and evaluated against manually annotated ground truth. The result shows promising similarity with human judgement.

Keywords: Online review; aspect extraction; opinion aggregation; Word2Vec model.

1. Introduction

With the rapid and global proliferation of internet technologies, online social networks and E-commerce are increasing day by day. People now-a-days tend to express their opinions on various social platforms. Aggregation of user opinions on internet forums or social media has drawn attention due to its potential for various applications ranging from assessing social needs to customer support systems [1]. The huge information available in opinion-rich online review resources provide manufacturer or service providers to set their business strategies as well as to help the potential buyers for making an informed decision. But with thousands of reviews available for a particular product, it is difficult for the customer to read all the reviews and make a decision on buying the product. Thus the research on developing automated techniques for opinion summarization is gaining momentum [2].

Opinion mining can be studied at three levels, namely document, sentence and aspect. Document and sentence level analysis summarizes opinion based on document or sentence as one individual entity while aspect based analysis attaches opinion to various aspects or features extracted from the review. Most of the works on opinion or sentiment analysis extracts the polarities of the sentiment as negative or positive [3]. Though this analysis produces an overall idea of people's opinion, the full picture and the specific details are absent. Some researchers used a scaling system or a numerical rating to express sentiment [4].

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In this work, aspect based opinion analysis and a scale based summarization of product reviews has been focused. There are various research approaches on aspect extraction: rule based, supervised and unsupervised. Here a rule based approach has been followed in which appropriate rules for aspect extraction has been developed. The rules for associating opinion words to extracted aspects also have been designed and grouping of similar aspects has been done with the help of Word2Vec [5]. At the final stage, summarization of opinion has been expressed in a rated scale for human interpretable visualization. The proposed algorithm has been implemented on Amazon Product Reviews and the results have been evaluated by checking with manual annotation of the reviews.

The rest of the paper is as follows, section 2 describes a few related works followed by our proposed method in section 3. Section 4 represents results and discussion while section 5, the last section, contains conclusion.

2. Related Works

Opinion summarization has become one of the most challenging field of research. Plenty of researchers have put forth their knowledge to find proper method for an optimized way of text summarization. The general framework of researches on opinion aggregation of online product reviews consists of three parts, aspect extraction, related opinion finding and summarization of opinion.

Many research works focused on domain independence or domain relevance to extract aspects. In [6] a domain independent opinion extraction system has been designed by authors in which they collected the aspect opinion pair but did not put much effort on summarization. In [7] also, the main focus was on extracting aspect and opinion pair. In [8], an unsupervised domain independent aspect detection system has been designed by authors but they had to provide seed words at the beginning to make it work. In [9], a rule was developed by researchers to measure domain relevance of candidate features based on a certain domain, it assists in deciding the degree of relevance of a feature in that domain which is being considered. In [10], a method has been developed which focused mainly on domain independent sentiment word analysis, this research tried to bridge the gap between domain specific sentiment words. In [3], the researchers developed a feature based review summarization system, which works on a domain specific guideline.

For opinion analysis and summarization, researchers have also developed some supervised systems. In [11], a supervised lazy learning algorithm based on K-NN has been developed. In [12], a supervised system has been designed which used SentiWordNet (SWN) for opinion word analysis. It tries to find the dependency relationships between the words, to find the aspect - opinion pair with the help of probabilistic models. Though the approach produces good results but computational cost is high.

In [13], researchers developed an opinion mining system for specifically travel websites. They chose Naive Bayes algorithm. According to them the system is prone to errors due to typos and implicit opinion expression. In [14], authors designed a bilateral topic model which was proposed as an extension of Latent Dirichlet Allocation, a popular method for topic modeling. In [15], authors proposed to design an unsupervised system to summarize reviews based on predefined set of aspects and a rating guideline as output.

Few researchers developed systems based on seed words or user specified aspects, these kind of system extracts aspects prioritizing those seeds. In [16], authors tried to collect aspect through providing seed words and the resultant clusters of aspects are made based on those provided seed words. In this approach a domain knowledge is needed to provide the seed words. In [17], Latent Semantic Analysis based system was designed which needed seed words to train.

In [18], researchers presented an approach to select a portion of review representing the whole set. The subset is used for opinion mining. Though this approach is efficient for large data sets but some information is always lost in sampling. In [19], an application was developed for summarizing the reviews and producing an aspect based summary with the help of available online tools. In [20], researchers tried to classify the text summarization methods, according to them three major types of text summarization methods are existent, abstraction/ extraction based summary, the single document/ multi document summary, and generic/query based approach.

The present research work focuses on developing a method to extract aspect and opinion irrespective of product category and summarization of the aspect-opinion pair. The proposed approach in this paper is described in the next section.

3. Materials and Method

3.1 Data Set Used

The review corpuses used for current research purpose were collected from Amazon product data, put together by Julian McAuley, UCSD [21]. Reviews (unlabelled) of 6 products are chosen for our simulation study. They are Camera lens protector (2547 reviews), Headphone (2074 reviews), Paper shredder (2531 reviews), Television mount (1050 reviews), Phone (4397 reviews), Printer (3017 reviews).

3.2 Proposed Method

The proposed method for opinion analysis can be divided into following steps. **a)** Collecting the desired product reviews, **b**) Extracting the product aspects (they may consist of single word or a phrase), **c)** Identifying the opinion words associated with them, **d)** Grouping the similar aspects and **e)** Finally summarizing the opinions and representing in a structured manner. Figure 1 represents the flowchart of the whole process.

3.2.1 Collecting the Desired Product Reviews

The proposed algorithm is developed in a manner so that it can work for any product category. The product reviews selected are versatile in nature, they range from electronics to office products. Separate product reviews are collected from the review corpus and stored in separate text files.

3.2.2 Extracting the Product Aspects

Here, in this work Python programming language and its Natural Language Tool Kit (NLTK) are used for processing.

The text files containing the reviews are processed according to the following steps,

(1) At first, the reviews are stored in a list.
(2) The reviews are then sentence tokenized and stored in a sub list.
(3) The sentences are then word tokenized.
(4) The words were POS (Parts Of Speech) tagged.
(5) Noun words are collected, because noun words have the higher probability of being the product aspects.
(6) Only those noun words are chosen for defining the aspects whose appearance count crosses a certain threshold (based on the assumption that the most important noun words have high probability to be the aspects).

In this work two types of aspect words are considered single word and multiple word (maximum of three words).

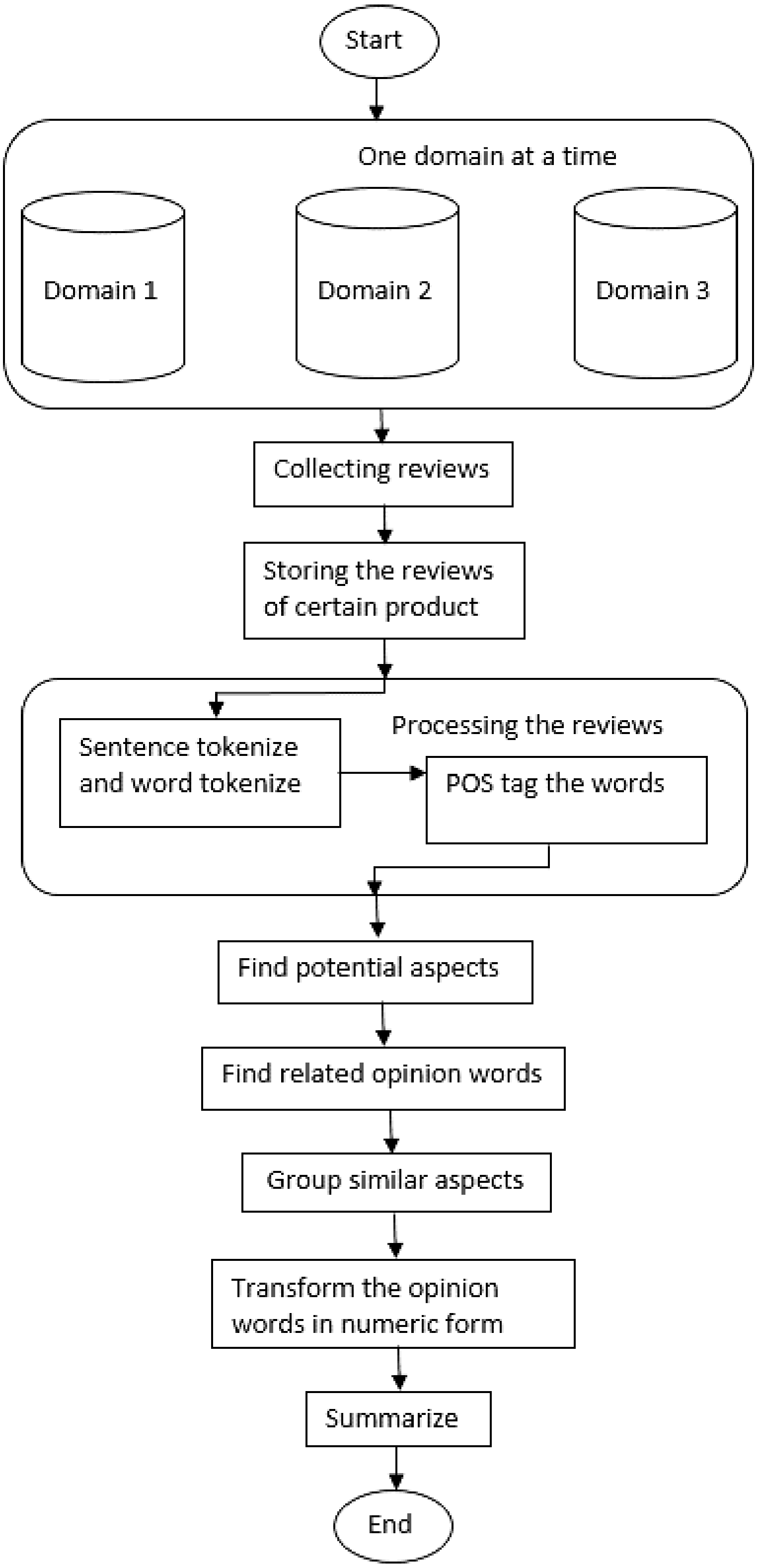

Figure 1. Flowchart of Proposed Method.

The conditions for defining the aspect words are as follows.

(1) If there is no other noun word within a certain distance of another noun word then that noun word is chosen as single word aspect. For example, *if the sentence is "The camera is good", only the word "camera" is found and it is chosen as single word aspect.*

(2) If there is a noun word within a specified distance of another noun word then those two noun words form a two word aspect. For example, *if the sentence is "The camera quality is good", the words "camera" and "quality" are found and they are chosen as two word aspect and presented as (camera, quality).*

(3) If two consecutive two word phrases have the common word with the same index (position in the sentence) as second word of the preceding aspect and as first word of the following aspect, also the distance between the first word of the preceding aspect and the second word of the following aspect are within a specified distance, then those two aspects can be merged into single aspect. *For example, if there are two consecutive two word aspects (camera, picture) and (picture, quality) where the word 'picture' is the common word with the same index in the sentence, then the aspects will merge as (camera, picture, quality).*

(4) Though there are single word and multiple word aspects, after grouping in the 4th step (explained in section 3.2.4), the most frequent word is considered as the aspect. *For example, if there are three aspects as ('camera'), ('camera', 'quality'), ('camera', 'picture', 'quality'). Among them 'camera' has the maximum frequency. So, 'camera' becomes the final aspect word.*

3.2.3 Identifying the Opinion Words (Forming Aspect-Opinion Pair)

The opinion words are the words in a sentence expressing the viewpoint of the reviewer. Our main objective is to identify the opinion words, which are associated with the product aspect. At first, the *stop words* are removed, then the words which are identified as adverb, adjective and verb and appear within 5 word distance of an aspect are chosen as opinion expressing words for that aspect.

There are some words which play very important role in determining the orientation of the opinion words, for example, *no, not, never* etc. Ex: "The camera is no good." here considering only the adjective will not serve the purpose, one has to consider "no" to have the correct meaning of the opinion.

After collecting all the opinion words of an aspect, they are stored in a dictionary, opinion words as value, along with the aspect as key.

3.2.4 Grouping Similar Aspects

In order to group aspect words having similar meaning, the semantic similarity or degree of proximity between two words need to be calculated. In order to achieve that a Word2Vec model has been trained with Wikipedia corpus. This model helps to measure the closeness in meaning of two words by providing a similarity score between any two words.

(a) Correcting the misspelled words and removing spelling differences:

Sometimes, reviews include some spelling mistakes ***(ex: pictre)*** or a little different spelling of the same word ***(ex: picture/ pictures)*** which becomes a hindrance while trying to find out the proximity between two words and putting them in the same group.

In order to overcome this problem, Fuzzy logic tool has been used. This tool is an in built tool to help assessing the similarity of spelling between two provided words. First, the first aspect is taken and if it is a single word aspect then that word alone is compared with each and every word of the rest of the aspect words list, and if the aspect contains multiple words then all of them has to be compared with the rest of the aspect words list. If the similarity between two words is over 90%, and also if both of them could be found in the Word2Vec vocabulary then the following word is replaced with the preceding word, otherwise if one of them is found in the Word2Vec vocabulary but the other is not, then the word found in the vocabulary will replace the word that was not found.

For example, if first aspect contains 'picture' and one of the following aspect contains 'pictures'. Then, 'pictures' will be replaced with 'picture', and if one of them is not found in Word2Vec model vocabulary due to spelling mistake then the word which was not found in the vocabulary will be replaced with the other which was found in the vocabulary. If one of the words is misspelled as 'pictre' and another one is 'picture'. The spelling similarity is over 90% but 'pictre' is not in Word2Vec dictionary, then, 'pictre' will be replaced with 'picture'.

(b) The rules for grouping the aspect-opinion pairs:

The next step is to group aspect opinion pairs by clustering the aspects of similar meaning. In order to accomplish that, the Word2Vec model has been used. In this step, no fixed number for the total number of aspects are predefined. The number of clusters grew as per necessity, which served to make the clusters more accurate by not forcing distant aspects to join the cluster, rather they were accommodated by making a new cluster. The algorithm for clustering the aspects is described as follows and is shown in Figure 2.

(1) First, the number of clusters is initialized to 0. The first cluster is created with the first aspect in the list. If there is any other existing cluster, the next available aspect from the list has to be compared with the first aspect of each existing cluster. The aspect which is examined is placed in the cluster with which it has the highest similarity score and the score itself crosses a predefined threshold. If the maximum similarity score does not satisfy the threshold criterion, then a new cluster is created and the aspect is placed in the new cluster.

(2) Now for similarity calculation of the aspect words in the different clusters, Word2Vec model is used. If the aspect word is not found in Word2Vec model, it is put in an exception group. Depending on the variety of aspect words, three cases arise.

Case 1: Single word aspect *vs* single word aspect.
This is the simplest case and the similarity score between the words is taken as the final similarity score between the aspect words.

Case 2: Single word aspect *vs* multi-word aspect.
Here the single word aspect is paired with all the words in multi-word aspect and the highest similarity score among all the pair wise similarity scores is taken as the final similarity score.

Case 3: Multi-word aspect *vs* multi-word aspect.
In this case, similarity scores of all possible word pairs of the multi-words aspects are calculated and the maximum among them is to be taken as the final similarity score.

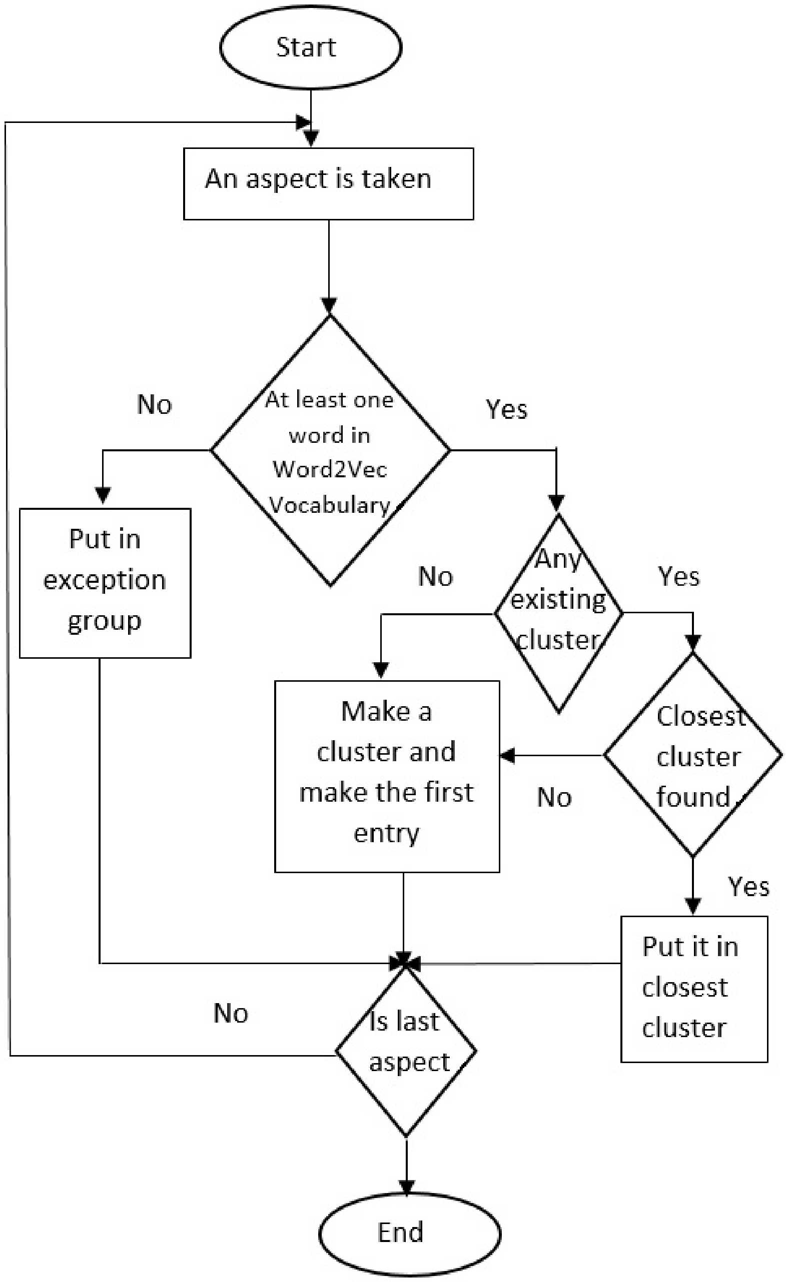

Figure 2. Aspect Grouping Process.

3.2.5 Grouping Similar Aspects

(a)Assigning scores to the opinion words:

For summarizing several opinion words associated with a particular aspect word in human interpretable form, the words need to be expressed in a numerical scale. To convert the opinion words, four numerical scales (shown below) have been proposed for adverb, positive adjective, negative adjective, and negative word respectively. For each category, the prototype words and their corresponding numerical values are set as follows:

Adverb scale: [‘nominally’, ‘moderately’, ‘very’, ‘extremely’, ‘tremendously’] (1 to 5)
Positive adjective scale: [‘good’, ‘better’, ‘best’, ‘excellent’, ‘marvellous’] (1 to 5)
Negative adjective scale: [‘bad’, ‘worse’, ‘worst’, ‘terrible’, ‘abysmal’] (-1 to -5)
Negative scale: [‘no’, ‘not’, ‘never’]

For example, for “adverb”, the words selected are “nominally”, “moderately”, “very”, “extremely” and “tremendously” with numerical scores as 1, 2, 3, 4 and 5 respectively. The numeric score for the negative scale is ’-1’ for all the three words.

The rule for assigning numeric values to the opinion words are as follows:

(1) For “adverb”, the opinion word is compared to the prototype words in the adverb scale and assigned the numeric value of the most similar prototype word according to Word2Vec model. *For example, if the word ‘exceptionally’ is obtained it is closest to the word ‘extremely’, and it will be assigned the score 4.*

(2) For “adjectives” and “verbs”, the word is compared to both the positive and negative scales with the help of Word2Vec tool, the scores of the positive scale and the negative scale is summed up separately. The score of the most similar word, from the scale with higher value is assigned as the score of the opinion word.

(3) The opinion words are stored serially as they are found in the sentence, to find out which adverb is modifying which adjective or verb. When searching through the opinion words if an adverb or negative word or both are found, its numeric score is only processed with the very next adjective or verb word. If there are multiple adverbs and adjectives or verbs for an aspect, the adverbs are processed with only the next adjective or verb.

The flowchart of this process has been shown in Figure 3.

(b) The formula for calculation of the final opinion score:

The sum total score of the opinion words is calculated according to the following equation.

$$S = \frac{1}{p} \sum_{i}^{p} \left(n_i * \frac{a_i \, * \, b_i}{5} \right) \tag{1}$$

p= number of adverb and adjective or verb pair in a sentence with respect to a single aspect.
a_i = adverb score for i th pair in a sentence. The value is one where there is no adverb present for adjective or verb.
b_i = adjective or verb score for i th pair in a sentence.
n_i = negative word score to be -1 if present otherwise +1.
This score (S) was then added with 5.

$$\text{Final score (F)} = S + 5 \tag{2}$$

The rating scale is 0 to 10, while 10 representing the best and 0 the worst.

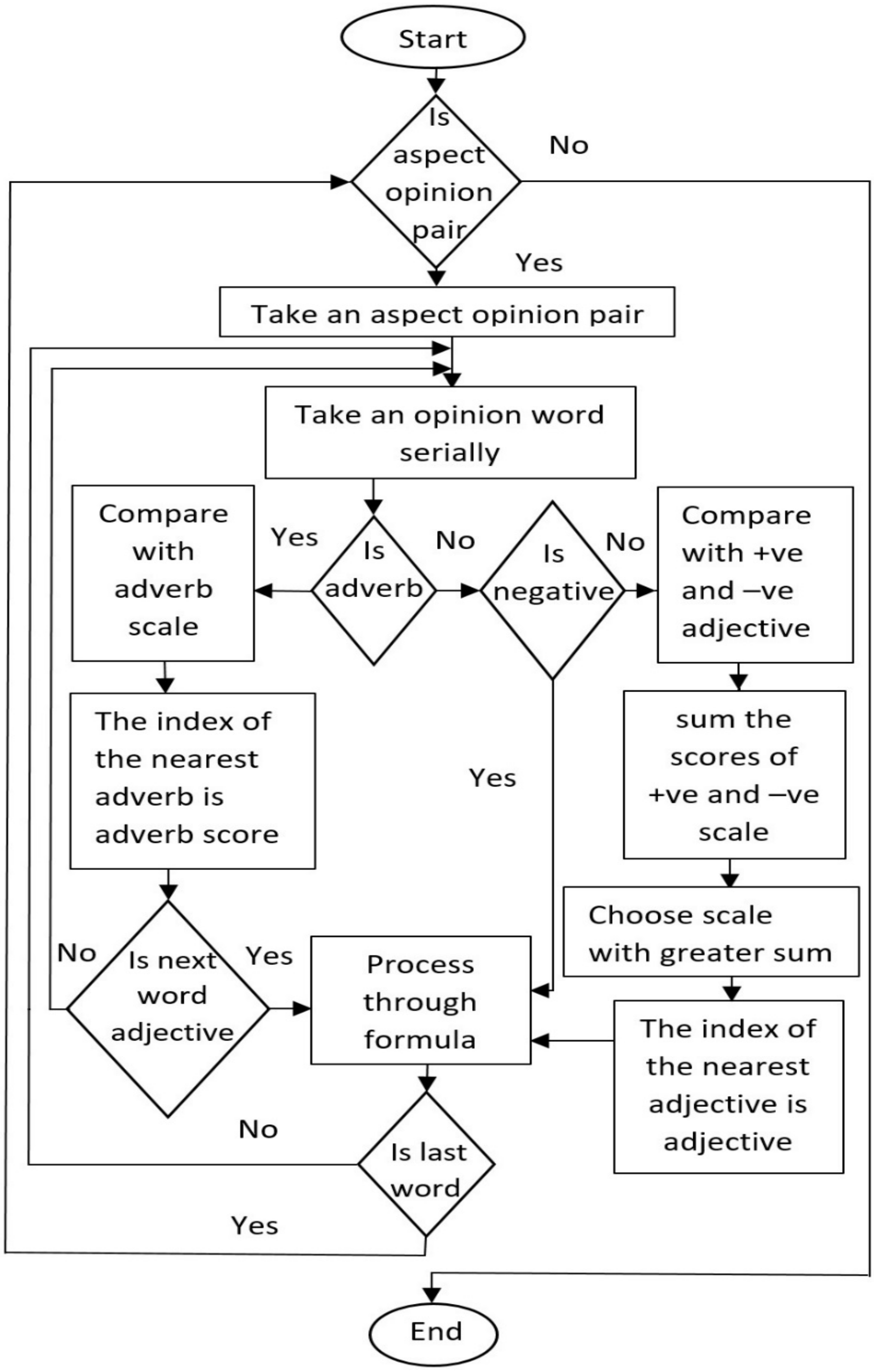

Figure 3. Evaluation of opinion words.

Now all the reviews corresponding to an aspect term are individually scored according to the scale of 0 to 10. To visualize the overall opinion regarding a particular aspect of the product by all the reviewers, an average score of all the reviews can be used. But in the process of averaging all the reviews, some information is lost. So here a distribution of opinions in the range of high, medium and low has been calculated from all the reviews. If the Final score ≥ 7, it is put in the high range, it is put in the medium range if 7 > Final score ≥ 4 and it is put in the low range if the Final score < 4. Thus the summarization of opinion is expressed in terms of the percentage of high, medium and low rating.

3.2.6 Illustration with Example:

Reviews are stored in a text file as the following.

This filter causes lens flares/internal reflections when used on my Nikon AF-S 50mm 1.4G lens. It's unusable when I have a light source in a photo because it will have a green lens flare on it. I gave it two stars instead of one because it does it protects the lens from dust/damage. Does as advertised. No problems or distortions as I can see. But I have issues with filters and flares and hot spots shooting towards the sun, but use this mostly for protection and remove in special conditions.

After processing through steps described in the section 3.2.2 to 3.2.5, aspects of the product, aspect related opinions and their final scores are obtained, a portion of processing result (regarding aspect "brand") is shown below in Table 1:

Table 1. Example of a cluster named 'Brand'.

Aspect	Opinion words	Equivalent score
'brand', 'sigma', 'cannon'	'get', 'good'	6.0
'brand'	'get', 'another'	1.0
'brand', 'filter', 'years'	'used', many', 'many'	6.0
'brand', 'name'	'ignore'	0.0
'tiffen', 'brand', 'filter'	've', 'used', 'lens', 'never'	1.0
'brand', 'lens'	'not', 'screw', 'new'	6.0
'brand', 'condition'	'arrived', 'new', 'screwed'	7.0
'brand'	'named', 'reputable'	4.0
'quality', 'brand'	'great'	6.0
'brand', 'filter', 'adorama'	'ordered', 'different'	6.0
'brand', 'i'	'better', 'many', 'used'	6.0
'brand'	'trust'	6.0

4. Results and Discussion

All the product reviews from the data set have been processed according to the proposed approach. The results from those corpuses along with the ground truth have been presented in the following tables (Table 2 - 7). The ground truth is shown in bold and italic format under the calculated values from the proposed algorithm.

Table 2. Aspect based summaries for camera lens protector.

Aspect	High	Medium	Low	Avg.
Filter	32.44% ***41.66%***	27.34% ***33.33%***	40.22% ***25.01%***	4.81 ***5.66***
Images	30.72% ***36.36%***	27.45% ***18.18%***	41.83% ***45.46%***	4.68 ***5.0***
Reflections	32% ***25%***	28% ***25%***	40% ***50%***	4.72 ***4.0***
Price	21.11% ***82.35%***	43.33% ***11.76%***	35.56% ***5.89%***	4.81 ***7.23***
Protection	38.38% ***60.0%***	26.6% ***37.5%***	35.02% ***2.5%***	5.28 ***6.88***

Table 3. Aspect based summaries for headphone.

Aspect	High	Medium	Low	Avg.
Headband	23.93% ***14.29%***	22.7% ***48.57%***	53.37% ***37.14%***	4.58 ***4.34***
Sounds	28.38% ***83.69%***	34.5% ***14.49%***	37.12% ***1.81%***	4.90 ***7.75***
Cord	24.1% ***9.52%***	26.35% ***30.96%***	49.55% ***59.52%***	4.21 ***3.45***
Price	25.44% ***92.56%***	36.1% ***6.61%***	38.46% ***0.89%***	4.57 ***7.86***
Durability	28% ***38.16%***	28% ***26.31%***	44% ***35.53%***	4.97 ***5.01***

Table 4. Aspect based summaries for paper shredder.

Aspect	High	Medium	Low	Avg.
Jam	32.0% ***20.0%***	24.0% ***46.67%***	44.0% ***33.33%***	4.92 ***4.87***
Instruction	27.27% ***11.11%***	30.30% ***77.77%***	42.43% ***11.12%***	4.42 ***5.33***
Cutters	23.08% ***30.0%***	28.21% ***40.0%***	48.71% ***30.0%***	3.97 ***5.3***
Noise	26.9% ***18.75%***	26.9% ***43.75%***	46.2% ***37.5%***	4.19 ***3.06***
Motor	36.9% ***40.0%***	17.86% ***10.0%***	45.24% ***50.0%***	4.57 ***5.10***

Table 5. Aspect based summaries for television mount.

Aspect	High	Medium	Low	Avg.
Installation	38.59% ***14.29%***	40.35% ***48.57%***	21.06% ***37.14%***	5.62 ***8.79***
Mount	34.54% ***53.33%***	35.99% ***26.66%***	29.47% ***20.01%***	5.18 ***6.0***
Screw	23.13% ***44.44%***	38.77% ***44.44%***	38.1% ***11.12%***	4.59 ***5.55***
Instructions	22.73% ***38.46%***	56.82% ***46.15%***	20.45% ***15.38%***	5.15 ***6.15***
Bolts	19.35% ***25%***	24.2% ***37.5%***	56.45% ***37.5%***	3.74 ***4.5***

Table 6. Aspect based summaries for phone.

Aspect	High	Medium	Low	Avg.
Installation	23.17% ***67.39%***	35.77% ***28.26%***	41.06% ***4.35%***	4.43 ***7.04***
Call	24.0% ***62.5%***	28.74% ***21.88%***	47.26% ***15.62%***	4.28 ***6.62***
Speaker	31.25% ***39.13%***	15.62% ***26.08%***	53.13% ***34.79%***	4.53 ***5.04***
Instruction	33.64% ***61.54%***	23.64% ***26.92%***	42.72% ***11.54%***	4.59 ***6.46***
Price	24.82% ***61.9%***	32.85% ***19.04%***	42.33% ***19.06%***	4.47 ***6.52***

Table 7. Aspect based summaries for printer.

Aspect	High	Medium	Low	Avg.
Print	27.71% ***57.9%***	32.40% ***31.58%***	39.89% ***10.52%***	4.67 ***194***
Cartridge	27.8% ***33.33%***	28.2% ***25%***	44% ***41.67%***	4.47 ***5.5***
Installation	23.46% ***52.63%***	30.09 ***36.84%***	46.45 ***10.53%***	4.19 ***6.21***
Noise	19.27% ***14.29%***	24.77% ***28.57%***	55.96% ***57.14%***	3.70 ***3.71***
Instruction	25.15% ***20.0%***	28.83% ***40.0%***	46.02% ***40.0%***	4.26 ***4.4***

From Table 2 and Table 3, it is found that for both the products “Lens Protector” and “Headphone”, the aspect “Price” did not tally much with human annotation. For the product “Phone” and “Printer”, the aspect “Installation” has quite different calculated value from the human annotated value. It seems that for the product “Paper Shredder”, the calculated value resembles the ground truth the most. As a whole, it is found that the proposed approach works moderately well while having large differences from the ground truth in a few cases. The reason behind the difference between the results of the proposed approach and the ground truth can be attributed to the following:

(1) The implicit features, which were taken into account while manually annotating the reviews, might not be considered properly by the proposed system.
(2) Multiple mention of the same topic by a single reviewer increases the aspect count in the proposed approach, but during manual annotation, the multiple instances of same aspect was considered as a single instance.
(3) People sometimes compare the products in question with other similar products, as no seed word is provided in the proposed algorithm, it is hard to recognize which product the opinion words are actually associated with.

There are several other methods which other researchers have proposed to achieve the optimum aspect and opinion words. There are some issues with these methods which were addressed in current method. A comparison of four different methods and our proposed approach is presented in Table 8 from several points of view. The numbers in the braces represent the number in References section of the corresponding research paper. The seed word based method and the supervised method need domain knowledge while in our approach no domain knowledge is needed and also it requires less human interaction compared to other methods.

Table 8. Comparison of different approaches.

Methods	Seed Word Based [16]	Supervised [12]	Unsupervised [14]	Selective [18]	Proposed Approach
Process	Providing the seed words for reference to select aspects	Senti Word Net based probabilistic system	Latent Dirichlet Allocation based Bilateral Topic Model	Selecting subset, optimally representing corpus	Aspects, opinion words are compared by the Word2Vec and analyzed.
Domain/ Context knowledge	Necessary	Necessary	Not necessary	Not necessary	Not necessary
Human interaction	Present	Present	Present	Minimal	Minimal
Restrictions	Priority on seed similar words	Online help needed	Cluster number	Information loss.	Implicit aspects
Robustness	Lesser	Lesser	Lesser	Lesser	Competitive

5. Conclusions

In this work a category independent aspect based opinion aggregation algorithm has been developed for online product reviews for helping potential buyers to make informed decisions without going through the vast amount of reviews manually. The developed algorithm is rule based and restricted to be used for the English language online reviews. The main contribution of this work is the extraction of aspects or features with the help of developed rules and Word2Vec model from the raw reviews without using domain knowledge regarding the product. The other contribution of this work is the development of rules based on English language syntax for evaluation of opinions associated to the aspect and finally summarization of opinion in a rating scale.

Though the developed algorithm works moderately well as evaluated by simulation experiments with Amazon Product reviews and compared with human annotation, there are various scopes of improvement. It is very difficult to take care of subtle difference of expression or shade of meaning in natural language. Also many reviews contain sarcasm in which the actual meaning is difficult to understand or interpret by machine based algorithms. In our work we have not considered those cases. Currently we are working for the development of effective learning based algorithms for automated aspect extraction, independent of language which we hope to report in near future.

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