Application of Associative Network Theory to Mine Relevant Aspect Terms from Customer Reviews

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Abstract—The cyberspace has matured into an abundant origin of knowledge for our trivial and relevant queries pertaining any field or domain of interest. Consumers buy variety of products online and post the pros and cons emerging from it but it is strenuous for one to view so much data and come to conclusion whether to purchase product X or product Y. Products we see online have thousands of reviews posted for them which makes it troublesome for consumer's to make a civil verdict of what to purchase. The aim of this study is to mine from so much data the most significant characteristics being discussed about the product or service making the information posted more fruitful to the larger audience by making use of associative network theory. The analysis obtained provide a good source of aspects to be worked upon to the marketing associations for present and future well being.

Index Terms—knowledge; strenuous; troublesome; character- istics; associative; aspects.

I.INTRODUCTION

The Internet has paved a revolution among individuals to avail products or services without any struggles just at a click. It has also empowered the consumer to freely declare the positivity and negativity they experience after utilizing it by providing a separate space [17]. The feedback shared by the consumer is intensely substantial not only to the population who aim to invest towards the written interest but also the brands that invent and market it [13].

Online reviews are a boon for the community of marketers as they portray a true reflection of company performance, gauge product impression and the authentic level of content- ment of the consumer. The other side of the audience reads online reviews for recommendation purposes and making an informed as well as intelligent purchasing decision [1], [10]. Word of Mouth (WoM) is surely the most awaited and requested in order to make a choice to invest in some entity or service. Social media has transformed the old style of business [8]. Sites like Facebook and Twitter give the liberty to openly announce statements with regards to products or services used. This new form of open exchange of words is termed as Electronic Word of Mouth (EWoM) [9].

EWoM has gained a significant position for interchange with respect to product and services reviews [3]. Associations like Amazon and Flipkart encourage and promote their customers to write reviews about the purchases they made and sites like Zomato provide detailed information regarding restaurants and food served [6]. A lot of research proves that reviews generated by customers are more realistic and truthful than expert written recommendations or product details listed by the seller community [11].

Though the data posted is useful to a whole lot of people it still lacks and needs to be refined in multiple ways and an enhancement in its usability is desired [11]. Today people lack time for trivial tasks because technology is automating every manual task day by day making lives more easy and comfortable. Keeping the fast pace life in mind on contrary to the amount of data posted by people all over for a single product makes it perplexive for one to make a right choice for the right entity [6], [15].

A. Motivation

Sentiment is the reflection of true feelings an individual holds towards everything. Online reviews being so beneficial need to be taken care of efficiently as the amount of informa- tion posted is not mediocre, so key aspects being discussed needs to be highlighted [7]. A significant assignment involves to determine the most relevant and frequent characteristics about the products or services being spoken about in the reviews.For example if a review reads as "Iphone has good camera quality but lacks in power backup", in this case the characteristics being spoken about are 'camera quality' and 'power backup' [2]. Research discussed in

Related Work has already worked abundantly on Sentiment Analysis (SA) finding out the positive, negative and neutral polarity. Contrary our aim involves to address research questions like beneath:

- What are the most relevant features discussed by cus- tomers in their reviews written ?
- Which words written in reviews denote implicit meaning?
- How to decide which product or service is better than its peers ?

This research augments the work already in existence (read Related Work section) by catering to the associations as well as the consumers relevant characteristics being discussed in the reviews which gives a far better picture. It also works on comparing the products based on the written content of customers who have bought it rather than the information mentioned by the seller or manufacturer [2].

B. Contribution

This work aims to fulfill the following objectives:

1. The research aims to determine most frequent and important aspects spoken about products or services.
2. It mines for aspect terms which are not directly mentioned in the reviews.
3. It has also laid out a comparison among the products based on the review highlights rather than the manufacturer updated details.
4. Finally the opinion in the reviews posted by the population is also catered.

The remaining portions of the research piece is segmented as succeeded. The section 2 Related Work provides a brief overview of the work studied and inspired to accomplish the challenges stated. It comprises of research articles highlighting the methods used along with gaps that could be addressed. The section 3 Analytical Interpretation caters a mathematical understanding of the problem area with elementary examples to give a better understanding. The section 4 Aspect Cate- gory Revelation (ACR) Framework gives the complete steps in detail carried out to achieve the objectives programmed. A system design overview is present in visual format for a quick grasp of the working. The section 5 Results and Discussions starts with introduction of the standard dataset named Customer Review Dataset (CRD) that was used for evaluation. Further results obtained are shown in which one can view how the extraction of categories is performed for explicit and implicit meaning text. By discussing the results an authentic presentation of the work is done with a conclusion to the objectives placed.

II. RELATED WORK

Most of this research inspiration is drawn from research article [9], it surely proves to be one of the most consistent research to identify the key topics that are mentioned in reviews. Both supervised as well as an unsupervised approach to perform aspect category detection is proposed here. In the unsupervised methodology using the spreading of activation graph based on association rule mining is chalked upon. Its algorithm follows a five step efficient procedure ranging from identifying the category seed words, finding out the graph, application of the spreading activation, mining the association rules and finally mapping the featured categories. Similar to this, supervised approach incorporates the probabilistic graph method adopting to co-occurrence calculation of association rule mining using dependency grammar approach. A precise four stage methodology states finding out the dependencies as well as the weight matrix, determining the optimal thresholds and finally estimating the classes. Both the approaches are faced upon by limitations like multiple parameter setting, miscellaneous categories cannot be handled efficiently, reviews must be grammatically correct and bulk of training data. The methods tend to have a convincing precision and recall scores. A lot of research under sentiment analysis revolves around flexibility and adaptability one such is described in [12] a unique process in computing online review summaries adopting a resilient and flexible fine grained sentiment analysis for online short messages. A multiple level gradation method is used to frame the sentiment classification model. To de- tangle the limitations of two topic models, an extension of LDA and BTM called eBTM is originated as an approach for determining features. The method assumes to be based on the fact that a sentence may portray a single sentiment value. Reviews that exceed that 140 character limit are filtered as soon as the data is collected. Task performed in this work is firstly aspect extraction and then sentiment classification. It evolves around movie reviews and computer product reviews originating from Naver movie data-set for Korean language, Douban data-set for Chinese language, Rotten Tomatoes for English data-set and amazon for product reviews. The model can handle multiple languages.

Much of work started to prevail to make use hybrid methods instead of following an individual approach. One such research stated in [3] indicates a classifier ensemble approach to perform feature oriented sentiment analysis. The methodology aims to be universal and exploits latent Dirichlet allocation to model a topic and to extract the core aspects that consumers write about. Later, each review is analyzed at a more depth and word dependencies that show the co-operation between words and features are distilled. An ensemble classifier devised by three machine learning's most prevalent algorithms Naive Bayes, Maximum Entropy and Support Vector Machines is constructed to map the polarity of the consumers review towards each feature. The estimated conclusions indicate effec- tive progress compared to individual classifiers and show that the ensemble classifier approach is malleable and authentic in analyzing consumers generated data and in enumerating consumers reaction and behaviour. Individual accuracy of the classifiers were not calculated and stated to get a better understanding as to which approach proves to be effective. Brief overview of methods defined over hotel reviews and data source not stated.

In [4], the research was mainly focused on the objec- tives of the SemEval-2014 involving aspect-based sentiment analysis namely detecting the sentiment and assigning the polarity. The system is also very robust for handling generic data by extracting the opinion from the reviews. Negation handling is also performed using the suffix method. Five level features are worked upon ranging from Word2vec features, overall sentiment feature, sub-sentence-level feature, aspect- opinion pairs feature, distance-based feature even the accuracy rate of each is tabulated accurately. Related labeled reviews involving bakery, cafe, restaurants are filtered from the data- sets. Arrangement of work published in the paper is perplexing to understand. Polarity Assignment and Category Detection could have been summarized as a joint approach instead of being undertaken as a secluded method. The work is based upon restaurant reviews fetched from Google API for Chinese language.

To judge the helpfulness of online reviews or how online reviews impact minds of the people in [1] has proposed to explain as to what factors makes the user give positive or negative ratings to products. A hypothesis is formulated which says : Are the ratings given by the user influenced by seeing the the reviews posted by other users or are they dependent on the past behavior of the user i.e. history of the buyer. Data- set is retrieved from TripAdvisor.com and prepared for later analysis by conducting steps like downloading all the reviews, filtering out the less frequent reviewers and calculating the bias for each user separately. After selection of a few samples econometric analysis is computed using bias formulas.

In research article [16], a depth of the flaws of the existing approaches are highlighted by indicating how having pre- defined categories already known about a specific domain can cause restrictions in working with the other ones. To overcome the challenges representation learning has been utilized to detect important aspect categories from online reviews. The problem is defined mathematically and a clear vision is stated to work upon. A two stage algorithm has been processed where first stage involves building a semi supervised word embedding model. It abducts syntactic relationships between the terms or words and aspects as well as the affinity between sentiments and aspects. In the second phase efforts are taken to build a neural network that can capture deeper and hybrid features. In the last phase logistic regression has been utilized to build a model that can finally predict the precise aspect categories.

Performing sentiment analysis for English language seems to be regular and done by many in different approaches as it a lot of guidance is available everywhere what seems difficult is to work on some regional language where minimum support is handy. In paper [14] work is done to find the aspect categories from reviews written in 'Hindi' which is the national language of India. A claim is made by the researchers that this is the first attempt to work on this language by creating a manual annotated dataset to perform the tasks of extracting out rele- vant characteristics and performing sentiment classification by building classifiers of supervised learning type. Resourcs have been collected from different sites and a database of 5,000 odd reviews which belongs to 12 different domain is build. For every domain, a list of predefined categories revolving around that domain is scripted. A multi-label classification model which helps in detecting multiple categories a single review is constructed. It is not restricted to the review containing. The implementation involves two different approaches binary relevance and label power set. Evaluations involve both with the manual datasets constructed. To determinie the sentiment value predefined four sentiment classes weere decided rather than two positive, negative, neutral and conflict and made use of point wise mutual information to assign the same.

In order to understand the base concept of sentiment anal- ysis listing all the methodologies proposed work in [18], has made an excellent effort to give an elaborate explanation of the related concepts and methods used till date by reviewing 54 articles and stating the key essence of those articles in a tabular format making it extremely easy to retrieve key information. It has also explained about the methods utilized in the 54 articles as well as their pros and cons. Scattered description given of all the techniques and mainly focused on document level sentiment analysis.

III. PROBLEM INTERPRETATION

Reviews on the Internet are outgrowing in number from product to product. In order to handle this amount of Big Data it is important to extract out topics that are spoken about and hold relevance. In order to dig deep about the topics written in reviews, aspect level attitude analysis is undertaken but in the case of voluminous data application of a more generic approach is needed to detect the aspect categories. An example of a review posted on the Internet, "The Chicken tikka , fish kebabs and brownie all tasted delicious". Here aspect level analysis would extract out 'Chicken tikka', 'fish kebabs' and 'brownie' but at the same time all these aspects belong to the category food which binds them under one roof [5] [6].

To denote it mathematically, consider a list of aspect cate- gories

$$AC = ac_1, ac_2, ac_3, ...ac_i \quad (1)$$

where AC consists of the total number of existing categories for the chosen domain and ac_i are the different aspect cate- gories. Consider a dataset DS

$$DS = rs_1, rs_2, rs_3, ..rs_i \quad (2)$$

where rs denotes the review sentences. The aim is to predict the classes in the reviews by making use of an unsupervised approach.

Characteristics of products are sometimes not mentioned directly in the reviews. For example, "It was noisy and disturbing at that coffee shop", here it is evident that reviewer is pointing out at the ambience of the coffee shop by calling it noisy and disturbing but not explicitly mentioning the topic of interest. Reviews contain both implicit and explicit characteristics written about the entity.

IV. ASPECT CATEGORY REVELATION (ACR) FRAMEWORK

The Methodology comprises of a complete framework un- dertaken in a step by step manner to accomplish the stated objectives. It makes use of Data Mining and Machine Learning concepts in the methods adopted. Much of the concepts and approaches are based on the work described in [10] with modifications and improvements to produce better results than the already available baseline methods. The framework comprises of tasks which can be again bifurcated into sub- tasks as shown in the figure below (Fig. 1) :

A. Identification of Aspect Categories

The approach for finding out relevant features from text is carried out using unsupervised form of learning which utilizes the underlying concepts of Semantic theory and Associative networks in a similar manner as [9]. It involves numerous steps before creating a bag of features as output.

- Select the domain of interest and identify from the words utilized from the sentences the categories that can branch out from it. For example if the domain of interest is restaurant then reviews would mostly consists of cate- gories like food, atmosphere and service or if the domain of interest is mobile phones then categories branching out would be weight, camera quality, battery limit etc. After a list of categories is kept ready accordingly syn- onyms are found out using WordNet dictionary for the corresponding categories and a revised list is maintained.

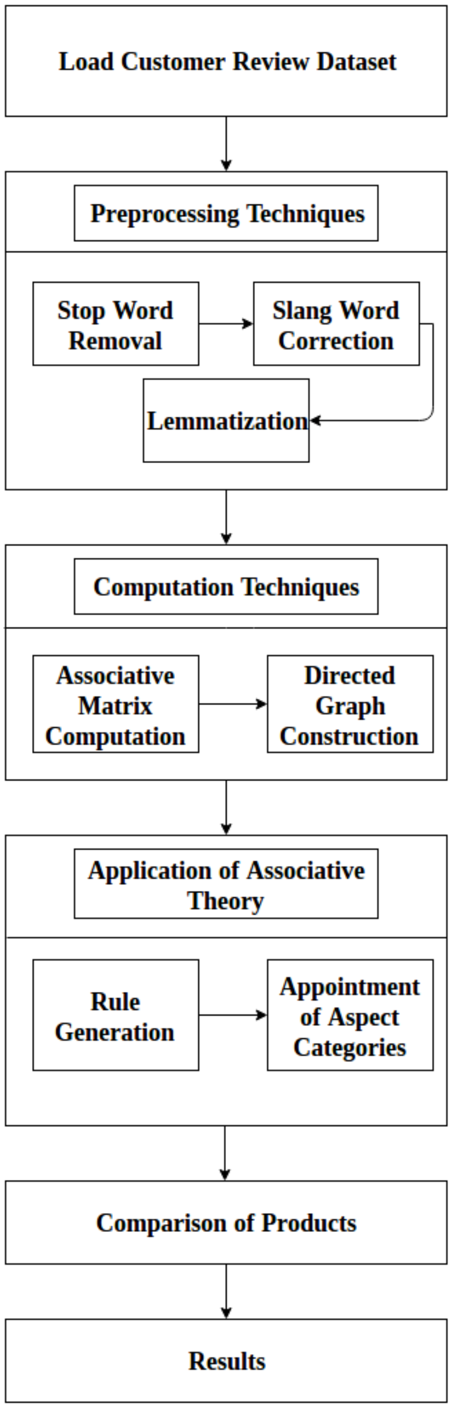

Fig. 1. Aspect Category Revelation Framework (ACR)

- After identification of categories its time to perform pre- processing tasks like removal slang language (language used in social media not grammatically appropriate), transformations of words written in short forms (exam- ples like 'brb' , 'lol' etc) to correct meaningful words, removal of stop words(words that do hold much im- portance like 'the', 'a', 'if'). To perform all the pre processing steps Stanford CoreNLP and MaxEnt tagger are used.

- Lemmatization is performed where all lemmas are kept in track and how frequently they occur is computed. A threshold is decided to discard lemmas that occur less frequently and the remaining ones along with their calculated recurrence is stored by creating a vector.
- A matrix is constructed (refer Fig. 2) which consists of the all the lemmas in a co-occurrence manner by making an entry for each word that appears before the other.

X	addition	amount	apple
addition	0	0	0
amount	0	0	0
apple	0	0	0
assortment	0	0	0
bag	0	0	0
barley	0	0	0
bathroom	0	0	0
beer	0	0	0
bit	1	0	0
book	0	0	0

Fig. 2. Matrix Generated

- Considering the matrix and the vector a co-occurrence directed graph is constructed in a similar fashion with nodes and edges as is seen in directed graphs. Every lemma in the matrix is a considered to be a node.Edges are directed among the lemmas only if the value in the matrix amongst the terms is a positive value. Since it is weighted graph every edge will have some value or weight assigned to it and this is done by making use of a formula consisting of Matrix value divided by the co-occurred word value.
- Once the graph is ready (refer Fig. 3) its the perfect time to apply semantic theory of associativity which involves activation value generation for every node in the graph. Activation value lasts between 0 and 1. The more closer it is towards 1 the more stronger hold it has which means the words co-occur frequently together. The procedure of assignment of activation value is begun by assigning every node of the graph a value. The synonyms of the categories that were computed earlier are assigned uppermost equivalent i.e. 1 while the remnant are credited undermost i.e. 0. The process is iterative in nature and starts by activating the nodes by firing one of them. The one that is fired spreads its value to others which are connected directly to each other. The connected node receives an activation value depending on the value held by the triggering node as well as the weight on the edge of the triggering and connected nodes. A lot of threshold arrangement is required.

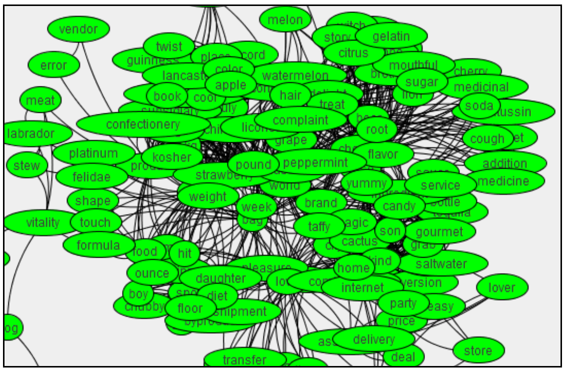

Fig. 3. Generation of Directed Graph

B. Rule Generation

After application of associative theory to the categories, corresponding matrix is obtained and from the directed graph and triggering method activation values emerged for every category. The values of activation on every category give rise to mining of rules which is totally dependent on the size of these values. The triggering nodes are the key ones that build a semantic network with their associations and from each node a rule is mined.

C. Appointment of Aspect Categories

A database of the mined rules is maintained and every review which is unrefined is worked upon to identify the category associated with it. There can be multiple categories in single review. For every review pre-processing is performed and in the database rules matching to it are searched for the assignment of category it contains.

D. Comparison of Products

Another task was to compare variety of products based on the reviews posted by consumers. This is done using SentiWordNet which is a resource build to determine three categories sentences may belong to i.e. positivity, negativity and objectivity. A sentence is made up of words and every word has different sides to it so by calculating average out of the three categories a score is given to every sentence which makes a decision how positive, negative or objective it is. So a lexical resource was used to find out how the products are assigned a value on a predetermined scale. This gives a true comparison of how good or bad or okay a product is in comparison to its peers.

V. RESULTS AND DISCUSSIONS

To evaluate the proposed steps, the training and test data from Customer Review Dataset (refer Fig. 4) are utilized. It contains 80 percent training data and 20 percent test data which involves reviews written for different categories of mobile phones. Every review has one or multiple categories that are annotated. Fig. 5 portrays that from the reviews mined, every review is speaking of at least one category. Further statistics reveal that most of them are focused on a single aspect category while a few write about multiple categories in a single sentence.For this purpose association rule mining is utilized as it can detect multiple categories from online reviews.

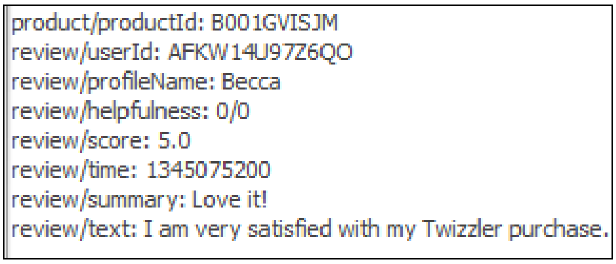
product/productId: B001GVISJM
review/userId: AFKW14U97Z6QO
review/profileName: Becca
review/helpfulness: 0/0
review/score: 5.0
review/time: 1345075200
review/summary: Love it!
review/text: I am very satisfied with my Twizzler purchase.

Fig. 4. Snapshot of Customer Review Dataset

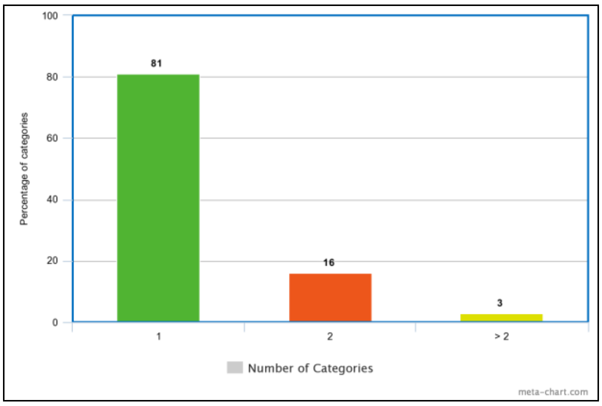

Fig. 5. Number of Categories per review

Fig. 6 reveals how frequent an aspect category is being expressing in the dataset. It caters the most significant top- ics or characteristics being discussed in the content written by consumers. Considering Electronics domain (focusing on mobile phones) it reveals that categories Camera Quality and Power backup are the most talked about in the reviews. This gives a precise direction to the marketers to enhance and stress on the features consumer is highly interested in rather than being perplexed looking at the huge amount of reviews. On the vendor side individuals can become more informed about which product to purchase depending on the feature more required and liked by them. The statistics obtained surely pave the way to accomplish the objectives defined earlier.

Fig. 7 provides the ratio of direct and indirect categories spoken in reviews. Characteristics of products are sometimes not mentioned directly in the reviews for example, “It was noisy and disturbing at that coffee shop”, here it is evident that reviewer is pointing out at the ambience of the coffee shop by calling it noisy and disturbing but not explicitly mentioning the topic of interest. Reviews contain both implicit and explicit characteristics written about the entity. An example of an explicit review would be “Samsung has an a user friendly GUI”, this gives us a direct understanding of how the user has a positive sentiment towards the ‘GUI’ of the phone. The figure provides statistics that 70 percent of people mention explicitly of what features they like or dislike about a product or service.

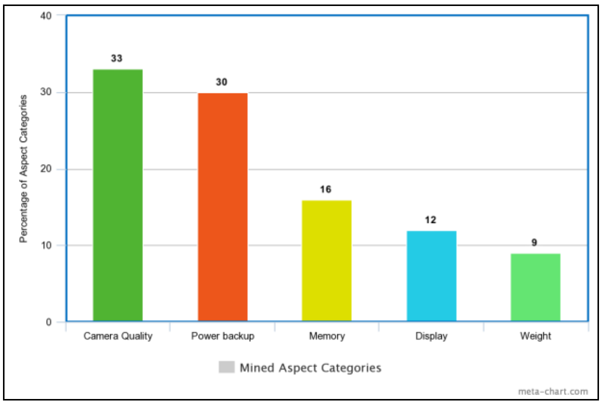

Fig. 6. Approximate prevalence of the aspect categories

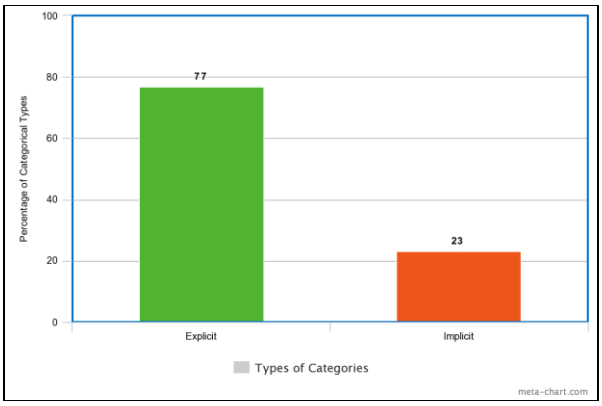

Fig. 7. Proportion between direct aspect categories and indirect mentioned ones

VI.CONCLUSION

Consumer reviews are available at various conventions in abundance. Previous studies focus more on extracting aspects merely and deciding the polarity. The Framework proposed detects the generic categories arising out from the reviews by making use of core concepts of human cognition, associative theory and data mining. Comparison of different products is also performed.The framework is robust across various do- mains and not restricted to a single domain. Customer Review Dataset was used and statistics were obtained regarding the number of categories a review may contain, the different generic categories arising from the domain and lastly whether reviews contain implicit or explicit categories.

For future work suggestion would be of detection of emotions which could give a more better analysis to seller community and vendors to gauge their satisfaction depth. A comparison of supervised and unsupervised as well other baseline methods can be performed which could pave way for more intricate research.

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