Direct-Indirect Association Rule Mining for Online Shopping Customer Data using Natural Language Processing

B.Hemalatha, T. Velmurugan

Abstract: In recent days, all kinds of service based companies and business organization needs customer feedback. Nowadays, many customers share their opinion by online about the products or services which become a process of decision making from customer and also help in making the business model more robust. These customer reviews may assist to expand their business and gain trust of the customer. In order to analyze customer feedback about their products and customer intents, most businesses perform "Market Basket Analysis". There are several existing techniques which have ignored the very essence of capturing and analyzing customer reviews for each product that has been purchased and it may switches over to other product which belongs to the same category. The existing techniques do not take into account regarding the switch over of product. Apriori algorithm alone may not predict accurately regarding which other products the person would buy along with a specified product simply based on the basket data. Sentimental analysis refers to the use of natural language processing (NLP), text analysis and computational linguistics to systematically identify, extract, quantify and study affective states and subjective information. The proposed research work considers product review analysis with Apriori algorithm based rule mining to determine the implicit association using sentiment analysis.

Keywords: Association rules, Implicit association, Natural Language Processing (NLP), Indirect rules, Sentiment analysis, Customer feedback.

I. INTRODUCTION

The key issue and significant task in knowledge discovery is data mining and rule mining [1]. These rules are relatively useful for decision making, business optimization and prediction [2]. The methods of classic rule mining basically focus on explicit co-occurrences and dependent relations, for instance Associative Rule Mining (ARM) [3] and causal rule mining [4] relationships whereas ignoring additional implicit relations. The techniques of ARM are used for finding the relationship between factors in huge databases. It helps among the attributes of a database in the task of decision making by finding the relationships [5][6].This contains Apriori, which can be accomplished using highly efficient method of pruning generation and strategies for much progress whereas the significant focus in improving the efficiency of algorithm. In many areas, Apriori approach has been applied specifically Market Basket Analysis (MBA) which is the major distinctive area of ARM. When customer wants to buy some product, what other product a customer would buy in the basket with some probability that may be identified by applying ARM [7] as a result whereas Apriori algorithm may not predict accurately.

This work describes about product customer review analysis based on rule mining with Apriori algorithm. Customer reviews are significant information source for understanding the customer provided feedback which becomes an essential for all the fields. Customers need to search for opinions by online during before and after purchasing the product. However, it assists in finding out positive or negative feedback about their product. Many numbers of users have become easier in the case of web for writing reviews based on the utilization of user's became increased. Therefore, the system receives rapidly by many numbers of reviews. Additionally the internet makes it difficult to understand by means of slang words. The present day, polarity of a sentence is determined by review analysis systems [8].

The process of analyzing about specific products by customer opinion and their characteristics is known as sentiment analysis. In order to perform the sentiment analysis, customer feedback extracted from website is given as input by user. The main component of NLP system takes customer feedback as input, then split into token by tokenizer. A part of a sequence of characters that are combined together in a text is known as token which are valuable semantic unit for processing. This tokenizer includes words, punctuation marks, symbols etc., which can converts a sentence into word level tokens. It is performed to create rules for generating word counts and even rating is done from the customers that assist an additional segregation level of best about the product. This research determines the implicit rules that connect various terms of interest in online shopping customer review data and their rating levels assist for developing a recommendation engine based on both explicit and implicit relationship from customer review analysis.

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The research paper is organized as given below: Section II presents current knowledge including substantive findings, as well as theoretical and methodological contributions from existing work to a research work. Section III outlines the proposed system overview, process pipeline, implementation details and Section IV provides experimental results using sentimental analysis. While in Section V, a summary of research work and future scope is mentioned.

II. LITERATURE REVIEW

The important research issues of rule mining have been extensively explored in this review. Here, some of the work that is closely associated to our research work of direct and indirect ARM is discussed. Wang et al., [9] described rarely co-occur or never occur by implicit relations between items whereas each of them co-occurs with the high probability and other same items. This framework gets integrated with an explicit dependency as well as hidden item dependency whereas it even captures such implicit relations by efficient algorithm of IRR Miner with implicit rule inference. Spirtes et al., [10] described for choosing the items that frequently occur from the ARM depends upon the framework of lift, support and confidence for generating rules that understand explicit and associations between them.Hence, the direct cause-effect relations between two items are discovered by causal discovery and showing the variations of causing one item from changes to the other.

Peska et al., [11] has presented analyzing rule relations though it is not insignificant to capture the implicit relations and even to make the actionable well-known rules. Chen et al., [12] provides the implicit relations which do not co-occur frequently by referring to the connections among various items but having a maximum probability occurred with identical items of third party. Jinturkar et al., [13] described for product in the framework of map-reduce by the classification of customer reviews.

Abulei et al.,[14] has utilized NLP techniques to generatesome rules to help us understand customer opinions and reviews (textual comments) written in the Arabic language for the purpose of understanding each one of them and then convert them to a structured data. Bhargav et al.,[15] consumer's sentiments are reflected in the form of 'opinion dataset' on internet using sentiment analysis for hotel reviews. Bhatt et al.,[16] propose a system by finding sentiment of the reviews that performs the classification of customer reviews. Mohan et al.,[17] proposed text mining techniques as well as sentiment analysis by analyzing the customer reviews on the restaurant domain. Moreover, priority-based algorithm is used for predicting the reviews polarity which created the rule base to the classifier. The analysis performs by K-NN create well in incremental instance counts.
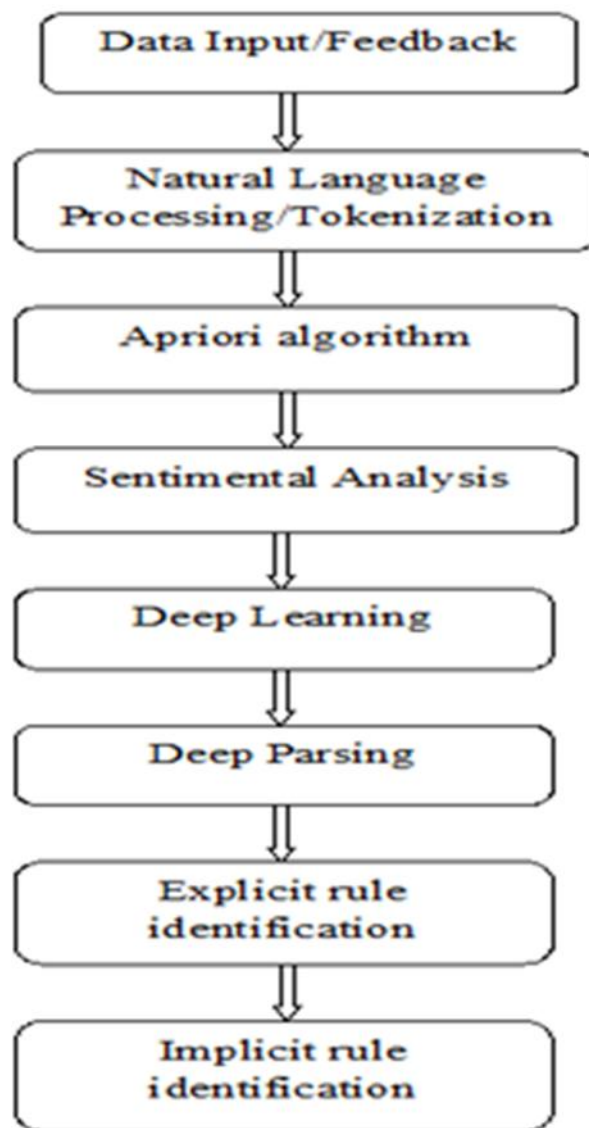
Vougeas et al.,[18] presented an analysis of high throughput molecular profiles by ARM combined with DLNN, in order to remove the cancer specific signature in the form of easily interpretable rules and to predict the pharmacological responses by use of rules as input to a large number of anti-cancer drugs. Hamano and Sato [19] proposed to analyze the targeting competitors and customers by the framework to mine the indirect ARM. Many researchers have proposed indirect association mining and realizing the implicit significance relationship among items

[20].Therefore, ARM [21] has only accomplished to the frequent items whereas the infrequent items get ignored.

The summary of the existing work cannot be effectively deriving the combination of explicit and implicit items from analyzing the considered nonconcurring and novel items. The current techniques does not take into account as a result, existing system may not be predicted accurately. In order to overcome this issue, sentiment analysis is undertaken in this paper and considers the product review analysis with Apriori algorithm based rule mining to determine the implicit association.

III. RESEARCH METHODOLOGY

This research work aims to advance an algorithm for recommendation that is derived from explicit-implicit association rule analysis. This paper considers the utilization of deep parsing using Natural Language Processing (NLP) as shown in Figure.1. Based on the starting steps, the semantic and sentiments get evaluated for the provided text are applicable with analysis of direct –indirect association rule to receive the data. Apriori algorithm and NPL/Tokenization is utilized in order to evaluate the relationship of implicit.

A. *Input Data/Feedback*

Once the model of sentimental analysis get utilized as earlier, the process of discovering and analyzing the customer feedback is essential. Nearly 500 customers feedback reviews of various product related categories namely Product ID, rating, review test, review time reviewer ID and reviewer name are used for analysis in Table 1. In this step, customer feedback has been collected from Grocery and Gourmet Food.

Table 1: Descriptive statistics of customer feedback review

Index	Product Id	Helpful	Rating	Review Text	Review Date	Reviewer ID	Reviewer Name	Summary	UnixReview Time
0	616719923X	[0, 0]	4	Just another flavor of Kit Kat but the taste i...	06 1, 2013	A1VEELTKS8NLZB	Amazon Customer	Good Taste	1370044800
1	616719923X	[0, 1]	3	I bought this on impulse and it comes from Jap…	05 19, 2014	A14R9XMZVJ6INB	amf0001	3.5 stars, sadly not as wonderful as I had hoped	1400457600
2	616719923X	[3, 4]	4	Really good. Great gift for any fan of green t…	10 8, 2013	A27IQHDZFQFNGG	Caitlin	Yum!	1381190400
3	616719923X	[0, 0]	5	I had never had it before, was curious to see…	05 20, 2013	A31QY5TASILE89	Debra Downsth	Unexpected flavor meld	1369008000
4	616719923X	[1, 2]	4	I've been looking forward to trying these afte…	05 26, 2013	A2LWK003FFMCI5	Diana X.	Not a very strong tea flavor, but still yummy…	1369526400

B. *Natural Language Processing/Tokenization*

After importing customer feedback, extracting the required term for tokenizing and generating the required relationship using NLP is done. In this process, NLP is extensively characterized as the programmed control of natural language which is concerned with connection between human language and computers by the area of computer science and artificial intelligence. NLP is used to analyze massive amount of text and handling predictive analysis. This is the branch of Machine learning whereas the technique of NLP namely chunking data, stemming and removal of stop words are used. NLP is useful in rating for dividing the words, sentences, noun and paragraphs determines whether the sentence is Positive and Negative. NLP may also be useful as translator in case translation of one language to required language. This may produce less noise and leads to a robust data. The main component of NLP system takes customer feedback as input, then split into token by tokenizer. A part of a sequence of characters that are combined together in a text is known as token whereas valuable semantic unit for processing. These tokenize includes words, punctuation marks, symbols etc., which can converts a sentence into word level tokens. In this research work Natural Language Tool Kit (NLTK) are considered and implemented in Python. It can assists and interprets to profound the sentence structure in its meaning.

Algorithm for Extracting the required terms

```
defextract_NN(sent);
grammar = r ""
NBAR: #Nouns and Adjectives,terminated with Nouns
{<NN.*>*<NN.*>}
NP:
{<NBAR>}
#Above,connected with in/of/etc..
{<NBAR><IN><NBAR>}
""
Chunker = nltk.RegexParser(grammar)
ne = set()
chunk                                    =
chunker.parse(nltk.pos_tag(nltk.word_tokenize(sent)))
for tree in chunk.subtrees(filter = lambda t:t.label() = =
'NP');
ne.add(''.join([child[0] for child in tree.leaves()]))
return ne
sub= []
for sentence in data;
#extract_NN(sentence)
```

Sub.append(extract_NN(sentence))
print(sub)

In the following, we demonstrate how our approach to convert customer feedback reviews from unstructured text to a structured data. Initially part of speech information is utilized in all NLP tasks to identify adjectives, nouns and root for each word in the text. This section finds the sentiment in a customer feedback namely adjectives, nouns and adverbs which are used as a features that depict with higher accuracy. The respective sample review shown in figure.2 is just adjectives, root and part-of-speech of each word.

['Just another flavor of Kit Kat but the taste is unique and a bit different.',

'The only thing that is bothersome is the price.',

'I thought it was a bit expensive....',

'I bought this on impulse and it comes from Japan, which amused my family, all those weird stamps and markings on the package.',

'So that was fun.',

'It said it would take about a month to arrive and it did take that long.',

'I was hoping for a more interesting taste but to our family, it just tasted a bit less flavorful or weaker than the standard milk chocolate kit kat.',

'The green tea flavor was too subtle for the sugar and it just tasted sweet.',

Figure 2: Sample review

The subsequent step of NLP is an essential and frequent noun in the text that is commonly used words which get removed in the above text. To implement this rule over a corpus of product review comments, following pre-processing will be needed.

• Extract word tokens from the corpus.
• Remove common words
• Extract all the nouns
• Find out top 5, most frequent nouns, these will be the key-words/aspects

The output of the second step is shown in Figure.3

[{'Kit Kat', 'taste', 'flavor', 'bit'}, {'thing', 'price'}, {'bit'}, {'Japan', 'package', 'impulse', 'markings', 'stamps', 'family'}, {'fun'}, {'month'}, {'bit', 'taste', 'family', 'milk chocolate kit kat'}, {'sugar', 'tea flavor'}, {'bit', 'wafers'}, set(), {'Great gift', 'fan', 'tea'}, {'candy', 'sea'}, set(), {'flavor', 'Smooth'}, {'plan'}, {'Japan', 'Kit Kat fans'}, {'warm weather'}, {'mine right', 'summer', 'room temp', 'bit'}, {'Afterwards', 'fine'}, {'tea', 'matcha flavor'}, {'outer coating'}, {'treat'}, {'tea flavor-', 'Kit-kats'}, {'tea flavor'}, {'Illinois.I', 'Mitsuwa Marketplace'}, {'mild', 'okay', 'change', 'taste', 'kit kats', 'tea candies'}, {'Matcha', 'tea', 'Creamy', 'layers', 'wafers', 'chocolate'}, {'Kitkat'}, {'guilt', 'chocolate craving', 'size'}, {'LA', 'whim', 'Little Tokyo', 'bag', 'store', 'week', 'Was'}, {'handful', 'WI'}, {'bags', 'Kitkats'}, {'Kit Kats', 'opinions'}, set(), {'matcha', 'bit', 'vanilla', 'flavor'}, set(), {'Kit Kat', 'Kit Kats', 'anyone', 'kind', 'candies', 'anyone wanting'}, {'Kit Kats', 'tea'}, {'taste'}, {'trip', 'Summer', 'course', 'freezer'}, {'year', 'cooler times', 'chocolate Kit-Kat bars', 'order', 'condition.I'}, {'US', 'store shelves', 'day'}, {'THE BEST candy bar'}, {'store'}, {'candies'}, {'goodness'}, {'KitKat folks', 'US'}, set(), set(), {'tea kitkat', 'taste', 'pack', 'chocolate', 'milk chocolate'}, {'Kit Kat', 'tea'}, {'Nothing'}, {'order'}]

Figure 3: Extraction of frequent nouns in the Customers revi

C. *Mining Association rules using Apriori algorithma*

In this phase, the major goal is about mining association rule using Apriori algorithm which has been achieved by utilizing highly effective generation of pruning methods and strategies for much progress.

Table 2: Instance of the stored data

Pid 0	Pid 1	Pid 2	Pid 3	Pid 4
1. Shrimp 2. Almonds 3. Avocado 4. Vegetables mix 5. Green grapes 6. Whole Wheat flour 7. Yams 8. Cottage cheese 9. Energy drink 10. Tomato juice 11. Low fat Yogurt 12. Green tea 13. Honey 14. Salad 15. Mineral water 16. Salmon 17. Antioxidant juice 18. Frozen smoothie	1. Burgers 2. Meatballs 3. eggs	1.Chutney	1. Turkey 2. Avocado	1. Mineral water 2. Milk 3. Energy bar 4. Whole wheat rice 5. Green tea

Therefore the framework of lift, support and confidence to generate rules and even targeted to explicit occurrence of item are identified. Each column indicates an item while the customer buy number of products with the combination of product related to product ID which represents an item has been occurred in the related transaction.

The data preprocessing with the Apriori library which is shown in Table 2 is used as dataset manipulation for the lift, support and confidence of the respective product available in the stored dataset.Thus, the whole dataset is a big list and each transaction in the dataset is an inner list within the outer big list.

Algorithm for identification of direct relationships using Apriori algorithm

// Pseudo-code for finding the direct association rule set for each item in the basket data and storing this in Big Data. dictionary_of_itemsfind_associations(basket_data) For

dictionary_of_itemsitem_dictionary; // Vectorize the basket data into a single dimensional vector. items_vector = vectorize(basket_data); / Apply Appriori algorithm (Python has direct package for this) ruleset = Appriori(items_vector); // Create a dictionary with item as a key, and a list consisting of support, confidence, and lift as value. for each (rule in rule_set) listlst; lst.add(rule[1]); lst.add(rule[2]); lst.add(rule[3]); item_dictionary.add(rule[0], lst); End returnitems_dictionary; End

In order to create a dictionary with item as a key, the list consisting of support, confidence and lift as value. For instance: RelationRecord(items = frozenset ({'shrimp', 'pasta'}0,support = 0.00506, ordered_ststistics = [ordered statistic (items_base = frozenset ({'pasta'}),items_add = frozenset ({'shrimp'}), confidence= 0.322033, lift=4.506672.

Here the lift value is higher, then the association is stronger which becomes better rule is predicting something than erratically guessing.

IV. SENTIMENT ANALYSIS

In this proposed work, sentiment analysis is used to analyze the product review feedback by customer from the website. The customer before paying the money always prefers to real reviews to the service provider but at present it is not possible to read all the feedback from the website given by the customers. Therefore, the new information is provided by every review of the product or feature of the product. Hence there is probability of missing any important feedback given by the customer. In order to overcome the above difficulty there is a need to identify the frequency of review rating. The best way for analyzing the feedback using sentiment analysis is to find out the review rating along with word count. Thus, the customer will identify the rating of the feedback reviews. Once received the results of sentiment analysis, customer will take effort as the decision faster and reduced for reading the reviews.

The following steps are used to analyze the customer feedback reviews using sentiment analysis.

Step 1: Calculation of word count

In order to calculate the word count, extract all the tokenized review words of customer feedback associated with the product ID which has been arrived through Apriori algorithm for training in deep learning. In order to train the review words by Document Frequency (DF) or Inverse Document Frequency (IDF) has utilized for determining the word count shown in Table.3.

Table 3: Calculation of word count

Product Id	Rating	Review Text	Review ID	Word Counts
616719923X	4	Just another flavor of Kit Kat but the taste i…	A1VEELTKS8NLZB	{'and': 1, 'another': 1, 'bit': 2, 'bothersome..
616719923X	3	I bought this on impulse and it comes from Jap..	A14R9XMZVJ6INB	{'about': 1, 'again': 1, 'all' 1, 'amused': 1…
616719923X	4	Really good. Great gift for any fan of green t…	A27QHDZFQFNGG	{'across': 1, 'any': 1, 'candy': 1, expensive…
616719923X	5	I had never had it before, was curious to see…	A31QY5TASILE89	{'am': 1, 'and': 1, 'before': 1, 'curious': 1,..
616719923X	4	I've been looking forward to trying these after…	A2LWK003FFMCI5	{'about': 1, 'actually': 1, 'after': 1, 'after…

Step 2: Selection of sentimental words

The reviewed word count has been vectorised in order to form a selection of sentimental words which gets associated with the product ID as shown in Figure.4.

The selected words = ['awesome', 'great', 'fantastic', 'extraordinary', 'amazing', 'super', 'magnificent', 'stunning', 'impressive', 'wonderful', 'love', 'glad', 'unhappy', 'horrible', 'regret', 'bad', 'sad', 'disappointed', 'hate', 'terrible', 'upset', 'annoyed'].

Figure 4: Plotting the frequency of sentimental words

Step 3: Frequency of Review Rating

In this step, there are many types and flavors of sentiment analysis and SA tools that focuses on rating. In this research work, the frequency of sentimental words with their corresponding rating scale from 1 to 5.The following categories of rating levels namely very positive, positive, neutral, negative and very negative. For example, mapped onto 5 star rating in a review very positive = 5 star and very negative= 1 star. The average rating with corresponding product id and rating scale is shown in Figure.5..

Figure 5: Frequency review rating

Step 4: 3D plot of the review rating frequency

In this 3D plot of review rating frequency, in order to determine both the explicit and implicit relationship from customer review analysis in Figure.6. The above Figure.5 will be Product id, Y will be rating and Z will be number of sales, based on the average rating customer buy number of products with combination of products and item infrequent are identified.
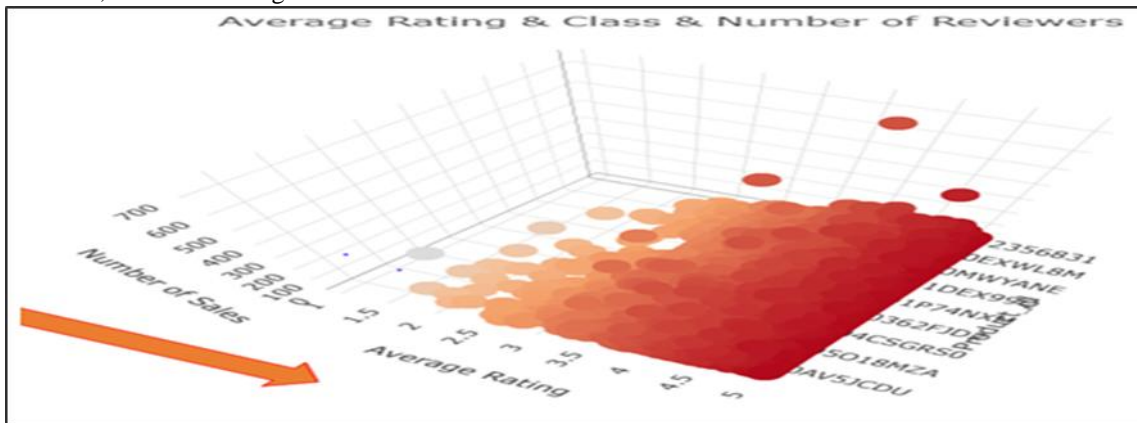

Figure 6: 3D plot of the review rating frequency

This kind of analysis assists to identify the implicit product in order to improve the sales by providing offers for respective implicit products.

V. CONCLUSION

There are several techniques exits that capture the association rules among various terms of interest. Few techniques exist to capture the implicit-indirect relationship among entities of interest. This research work enhances the accuracy of implicit association rule analysis by including NLP. As a first phase in NLP the selection of sentiment words and word count were done. After tokenizing the sentence into words as an output , the actual association rule analysis is utilized with the help of Apriori algorithm as a process to identify the implicit product.In the future work, the sentiment analysis will be evaluated by segregating the dataset as train and test dataset. Various Machine Learning (ML) algorithms namely logistic regression, Naive Bayes, Support Vector Machine (SVM) and Artificial Neural Network (ANN) can be utilized to identify the trained model accuracy of sentimental analysis and validate the test dataset of sentimental analysis using confusion matrix parameters. An algorithm for recommendation based on discovered explicit-implicit association rules can be proposed.

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