An Enhanced Web Mining Approach for Product Usability Evaluation in Feature Fatigue Analysis using LDA Model and Association Rule Mining with Fruit Fly Algorithm

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Abstract

Objectives: The rapid growth of E-commerce emphasizes the customers’ attention on product purchases through large number of websites. The customers tend to buy the products with more and best features, but those features fail to satisfy their expectations. This limitation is termed as Feature Fatigue (FF) in product usability analysis in web mining. The objective of this novel approach is to evaluate the product usability effectively and supports the designers to make decisions in future.

Methods: The consumers’ reviews are collected from various E-commerce websites using web crawler. These review sentences are preprocessed by removing the stop words and stemming. The synonym dictionary is created from the preprocessed sentences.

Findings: In order to attain usability evaluation frequent item set is identified by improved Apriori algorithm and the association rule is generated. Finally the product capability is evaluated effectively in the FF analysis using analyzed features.

Improvements: The product reviews are gathered from the E-commerce websites to analyze the feature usability of that product and obtain 95% accuracy. The feature analysis report helps the manufacture to alleviate the FF by balancing the capability and usability of the product.

Keywords: Association Rule Mining, Feature Extraction, Feature Fatigue, Usability Analysis

1. Introduction

Online shopping is now more popular, due to the rapid growth of Internet usage worldwide. With the immense development of E-commerce the amount of customers in buying online products is also increasing day by day. Once the customers decide to do online shopping, they refer the reviews about the products posted by other customers. Usually, after purchasing the products, the customer’s posts their own opinions about the products in Social websites and blogs such as Facebook, Twitter, Amazon$^1$ etc. In general, reviews are collected from two sources one is from the Sellers’ website with descriptions from review platform and the second source is from the Customers’ site or blog$^2$. The reviews collected may either positive or negative based on the features of the product and the service provided.

Based on those reviews, the reputation of the product and the organization may increase or decrease. The reviews of the customers help other customers to make decisions in buying the products, as a word-of-mouth$^3$. The goodwill of the organization is ruined by the negative reviews. Moreover, most of the negative reviews illustrate the dissatisfaction of the customers on the product features after using it. This dissatisfactory of the customers on product usability is defined as Feature Fatigue$^4$.

To study the Feature Fatigue analysis, the product usability analysis is required. The three aspects of the usability are Efficiency, Effectiveness and User satisfaction$^5$. Based on the testing methods$^6$ and the survey data$^7$
the traditional methods evaluate the usability of products. This mechanism is a time consuming process and its economics cost is high. In order to reduce cost and time, this paper proposed a novel framework which focuses on product usability analysis based on web mining.

The novel approach proposed in this article uses various customer reviews which are collected from web. The proposed approach consists of three phases. The first phase includes the data preparation process and the second phase is Usability Analysis and the third phase is Feature Fatigue Analysis. At the beginning stage the input i.e. customer review is raw review, so it is preprocessed to obtain a review sentence which is the input for Association Rule mining process. The NLP is used for POS tagging and then the synonym dictionary is developed by LDA and Synonym Lexicon method. The candidate feature set that is the synonym dictionary is created by identifying the nouns phrases from the POS tagging with LDA, which extends the Synonym Lexicon. Then filtering rules are applied to the extracted feature set to obtain the final product feature.

The Fruit Fly Association Rule Mining is used in this work to decide the semantic orientation of the review sentence to obtain and the frequent item set is obtain using the improved Apriori algorithm. The usability evaluation and the product capability is evaluated in the FF Analysis, with these evaluation FF degree is measured which is used to alleviate FF effectively.

2. Related Works

Natural language processing is research process which is related to human-computer interaction area. The proposed framework focus on usability analysis which is needed to work on Natural languages, as the customers posts their reviews in a simple speech language. This section describes some related work that uses the NLP or LDA to process the natural languages and also some related works are described for mining the opinion and Feature Fatigue analysis from the customer reviews.

In a novel grouping idea is proposed for product features. The Latent Dirichlet Allocation (LDA) is used by the author to extract large scale constraints. The topic modeling method LDA is enhanced to handle must-links constraints and the cannot-links constraint to extract the feature automatically. Then result of the constraint LDA is then applied to the extracted feature to group the product feature.

In a method to extract the opinion features from two different corpora is presented. Domain-specific domain-independent are the two corpuses used in this work. The author takes the hotel and cellphone reviews and generate a set of rule to extract the candidate opinion feature from the domain-specific corpus. Its Domain Relevance (IDR) and Extrinsic-Domain Relevance (EDR) scores are estimated. The author confirmed from the extracted feature, that it has less EDR scores and more IDR values.

In a Feature Fatigue Multi-Objective Genetic algorithm method is introduced to solve the product usability problem during the product designing stage. The fitness function represents the uncertain customer preferences and their relationship based on Bayesian network. This approach provides many solutions along the Pareto-optimal frontier but it has less focus on what kind of feature should be included to alleviating Feature Fatigue.

In an efficient algorithm based on finite state machine was developed to remove the stop words in Arabic language. A set of 242 Arabic abstracts and another dataset is extracted from the Saudi Arabian National Computer Conferences (SANCC) and another set of data chosen from the holy Quran. The novel framework verifies the combination of data to achieve minimum time utilization but it has its limitation in accessing the dictionary. This approach for stop word removal provides approximately 98% impressive result.

In a novel approach for Feature Fatigue analysis were proposed based on behavioral decision making theory. By analyzing the customer review the author describes that the customer purchase decision is varying before buying and after using the product. This leads to the customer dissatisfaction and their purchasing opinion is changed. This novel approach adopts six dimensional value models that append the features on customer perceived value before and after use. A further analysis model is applied for analyzing FF.

In a syntactic approach for opinion mining was proposed. This approach used an aggregate score, SentiWordNet, syntactic dependency and aspect table of opinion words. The author applied his work on restaurant review and made a comparison with POS tagger method. The accuracy of the annotated test set result is 78.04% which is 6% more than existing method which uses POS for feature extraction. This paper uses the POS tagger for feature extraction along with LDA and Synonym Lexicon, therefore the proposed work provides an impressive result.
In\textsuperscript{20} made an investigation to identify importance of product usability by comparing other attributes. The active information search method is applied initially to identify possible attributes. The author takes the mobile phone as the example product. Structured preference elicitation and ranking are proposed to interview and find the important attributes. A conclusion is made in terms of product choice, usability is indeed important but not as much as users believe and the other important attributes are cost, features and aesthetics.

In\textsuperscript{21} made a research based on statistical regression and correlation analysis with Multiple Linear Objective Programming (MLOP) for obtaining sensibility words. The determination can be made to analyze perceived feeling of consumer about that particular product with this analysis. The word is verified whether it is related to the product design or not. If the words had some relationship then optimal design criteria is derived to attain maximum possible perceived quality of system. This research is conducted by taking thirteen sensibility words, twelve product models with forty nine design elements. And the final result is analyzed using fuzzy set logic and MLOP.

In\textsuperscript{22} performed an investigation on dimensionality reduction using Singular Value Decomposition (SVD), stop-lists application and word stemming for improving the performance and also proposed a semantic task which is applicable to work with larger corpus. An improved SVD based method is applied for generating semantic representation.

Various authors proposed different natural language processing approaches and they are explained above. Kano’s model\textsuperscript{23}, Bass model\textsuperscript{24} and Norton-Bass model\textsuperscript{25} are the various proposed approaches existing for Feature Fatigue analysis. Moreover, the existing approaches for Feature Fatigue analysis are also discussed. Though different approaches exist they have certain limitations and to overcome that the work proposes NLP tool along with LDA to generated better accurate results. FF is analyzed by rule mining from the synonym dictionary and FF degree is evaluated for better analysis of product features and they are discussed in the following section.

3. Proposed Methodology

To evaluate the product feature effectively, a novel method has been proposed. By determining a feature, which should be included with the product to alleviate the FF. To implement, the method is proposed through 3 phases namely, 1) Data Preparation, 2) Product Usability Analysis and 3) Feature Fatigue Analysis. Figure 1 shows the framework of the proposed methodology.

During phase 1, the concept of data preparation involves collection of reviews, preprocessing procedure and creation of synonym dictionary. In the second phase, association rule mining with fruit fly algorithm and improved Apriori algorithm is applied to analyze product usability. In the final phase, FF analysis is performed. This ensures that the product feature will be evaluated effectively and supports decision making for the product designers in future. In the following subsections, the methods of three phases are discussed.

3.1 Phase 1 – Data Preparation

This phase consists of three processes: Collection of reviews, preprocessing procedure and creation of synonym dictionary.

The process of review collection is made to collect the reviews from web about the product. Those collected reviews are then processed to be converted as sentences. Hence, it is to be used by association rule mining, the reviews are converted as sentences through which the synonym dictionary is created.

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Figure 1. Framework of proposed methodology.
function words\textsuperscript{27} which contain the ambiguous meaning or little lexical meaning are also removed.

The function words express the grammatical relationship between the words or in other terms the function words might be conjunctions, prepositions, articles, pronouns. This research work focuses on extracting the relevant words that have the proper meaning about the product usability. In this case, the function words are not needed so it is removed, and the context words are generated.

The context words refer to noun, verb, etc. After the context words generated, stemming\textsuperscript{28} is applied on it. Stemming is one of the important processes in information retrieval. This is applied to extract the common words. For example, “wonder”, “wonderful”, “wondering”, “is” will be “wonder” likewise, the stem removal process removes the letter which is ending with s, ed, ing, ly.

3.1.1 Synonym Dictionary with LDA and Lexicon Algorithm

Customer posts their opinion on their own words in the review and they use different words to mention the same feature. For example, ‘photos’, ‘pictures’, ‘mention’ the same feature for the camera product. Collecting the synonyms from this kind of feature is difficult process. A Natural Language Processing (NLP) is applied for Part of Speech (POS) tagging. NLP parses each and every review sentence and produces a Part Of Speech tag, such as noun, verb, etc. The POS tagging provides the initial feature from the extracted nouns. These features are further processed by the LDA model and generate the final product feature.

The synonym dictionary is developed by Latent Dirichlet Allocation (LDA) and Lexicon Algorithm from the extracted nouns. The working procedure of the synonym dictionary creation process is explained in the Figure 2.

3.1.2 LDA Model

The LDA considers a single document as a mixture of several topics. The proposed work process with many documents such as Processor review as one document and RAM capacity review as another document and so on. The processor, Ram, Wi-Fi types, Battery is considered in LDA model and it starts to execute by sampling a word distribution from a prior Dirichlet distribution. In the synonym lexicon extension process, an extension is performed from the original feature \( F_1 \) to \( F_2 \) by appending the synonym of \( F_1 \). Finally a new feature set is created by intersecting \( F_1 \cap F_2 \). The collection of new feature is the synonym dictionary.

The Figure 3 explains LDA and Lexicon Synonym process for synonym dictionary creation. In Phase 1, the data preparation and synonym dictionary creation is performed with the help of NLP and Synonym Lexicon Algorithm. The following section describes the second phase of this paper.

3.2 Phase 2: Product Usability – Improved Association Rule Mining and Fruit Fly (ARMF)

The association rule mining\textsuperscript{29,30} is an important task in data mining and it is used to find the frequent patterns, correlations, and associations in the information repositories.

![Figure 2](image)  Procedure of synonym dictionary creation.

![Figure 3](image)  Algorithm for LDA model.
Usually the association rule mining is used to find the frequent pattern, correlations and associations in the information repositories. Similarly in the proposed work, the rule mining is applied to mining rule to check whether the generated review sentence is related to the features usability or not.

The state of the problem for mining the association rule is as follows:

\[ ls = \{ls_1, ls_2, ls_3, \ldots, ls_n \} \]

Set of items where \( ls \) is the itemset. And the set of transaction is:

\[ Trans = \{T_1, T_2, T_3, \ldots, T_n \} \]

Each \( Trans \) contains the items of the \( ls \). Association rule is in the form of \( p \rightarrow q \). \( p \) and \( q \) is the item in the \( ls \) and \( p \subset ls \), \( q \subset ls \) and \( p \cap q \). When \( p \) was in transaction then \( q \) is almost involved in the transaction too.

### 3.2.1 Frequent Itemset

An itemset is said to frequent, whenever its support is greater than or equal to minimum support threshold. In this work some of the itemsets are processor, battery, memory, display feature, Wi-Fi type, RAM, etc. and the items are “good”, “clear”, “simple”, “better”, “worst”, “nice”, etc. The set of items with high support is applied to find the association rule. The support for a rule is defined by its transaction percentage having \( p \cup q \) and it describe the show frequent, the rule is used in the transaction \( T \). The following formula represents the support of a rule:

\[ \text{Support} (p \rightarrow q) = \frac{p \cup q}{N} \]

\( p \cup q \) Represents the number of transaction of all items of the rule and \( N \) refers the total transaction. The above support formula calculates the relative support value. The confidence is defined by its transaction percentage having \( p \) that also contains \( q \).

\[ C(p \Rightarrow q) = R(q|p) = \frac{\text{support} (p \rightarrow q)}{\text{support} (p)} \]

Confidence value is an important measure that views all transaction that contains certain item defined by the rule. The precision, recall and \( f \)-measure is calculated with their respective formulas and are discussed in Section 4. And the usability evaluation operation is performed in the following section.

### 3.2.2 Apriori Algorithm

Apriori algorithm\(^{31,32}\) is utilized for frequent item set mining and association rule learning on transactional databases. This is achieved by identifying the frequent individual items in the database and then it is extended to larger item sets until it appear sufficiently often in the database. The association rules can be determined by these frequent item sets which highlight general trends in the database.

### 3.2.3 Limitation of Apriori

The main limitation of Apriori is the cost and execution time is high\(^{32,33}\). For example, to detect frequent pattern in size 100 (\( r_1, r_2 \ldots r_{100} \)) then 2100 candidate itemsets have to generate which is costly and takes more time in candidate generation. Therefore it scan database many times repeatedly for finding candidate itemsets. The Apriori for finding frequent set is very poor in efficiency when there is large number of transactions.

### 3.2.4 Improved Apriori Algorithm

The improved Apriori algorithm\(^{32,34}\) decrease the number of candidate items in the candidate item set \( C \). In the Apriori algorithm\(^1\), \( C \) is compared with support level, once it was found. If the itemsets are less than the support level then it is pruned and the itemset. \( L_k \) is produced which is connected with itself and lead to \( C \). In the improved algorithm, before the generation of candidate item sets \( C \), the prune method count the times of all items occurred in \( L_k \) and delete item sets less than \( k \), in \( L_k \). In this way, the number of connecting items sets will decrease so that the number of candidate items is reduced. In the proposed approach the Apriori is applied to obtain the frequent itemset of customer review sentences. A set of sentences \( S_i = (w_1, w_2, \ldots w_n) \), where \( w \) is the words in \( S \). The frequent set of \( S \) is obtained by the following Apriori procedure. The Figure 4 shows the Apriori algorithm.

### 3.2.5 Rule Set Reduction

The generated association rules are extremely large. Therefore it is important to prune the rules to make the classifier more effective and efficient. The Fruit fly Optimization Algorithm (FOA)\(^{34}\) has the potential to solve the difficult optimization problem. The FOA is based on the characteristic of fruit fly to find the optimal solution. Combination of Fruit Fly Optimization Algorithm (FOA) and improved Association Rule Mining is applied in the
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proposed work for mining the exact Product Feature Usability. In the data Preparation module, the NLP is used just for synonym dictionary creation. The dictionary contains so many features about the product. The required feature is mined from these features by ARMF.

The Fruit fly Optimization Technique is based on the food searching behavior of the fruit fly. They are very sharp in sensing osphresis and vision. The fruit flies have this nature because of its osphresis organs; with this it can able to find the food location from 40 Km away\(^\text{12}\). This fruit fly concept is applied in the proposed work to obtain the required product feature from the dictionary. The parameters in the dictionary are considered as the initial position of the fruit fly operation and it described as $\text{InitX\_axis}$ and $\text{InitY\_axis}$. Set of association rules are pruned by following Figure 5.

3.2.6 Usability Evaluation

Usability is important aspect especially in mobile application and web application. After the rule mining it is simple to add the rules to the new review sentence. It selects the rule which can match the sentences. Based on the confidence and support the classifier found a rule to match the sentence. The Figure 6 shows the usability evaluation summary.

The product designers should notice the usability of that product; otherwise user will leave that application/product. The usability of the product is evaluated and its result is shown in Section 4.

The association rule mining with Fruit fly Optimization Algorithm is obtained in this phase and with that rule usability evaluation is measured which is represented in the Table 1. The capability measure is calculated in the third phase by having both usability evaluation and the capability evaluation and the feature fatigue analysis is applied in third phase.

3.2.7 Phase 3 – FF Analysis

Customers need to buy the product with more feature but they dissatisfy with the product if their feature is not fulfilling their expectations. This problem is known as

| Algorithm |
| --- |
| $S_i$: set of sentences |
| $f_i$: Frequent Item set |
| $C_j$: Candidates generated from $f_i$ |
| $T$: Database |
| Min_sup: minimum support |
| Begin |
| $f_1 = \text{Frequent\_1} - \text{itemset}(d)$ |
| For ($j = 2; f_i \neq \emptyset; ++$) |
| Prune $I(f_i)$; |
| $C_j = \text{apriori\_gen}(f_i; \text{Min\_sup})$ |
| For all sentence $s \in d$ |
| Find the subset to all $C = \text{subset}(C_k, s)$ |
| For each candidate $c \in C_s$ |
| $c$\_count $++$ |
| $f_i = \{ c \in C|c$\_count $\geq \text{min\_sup}\}$ |
| Return $U_i f_i$ |

**Figure 4.** Aprori algorithm.

| FOA algorithm |
| --- |
| $X_i = X_{axis} + Rv$ |
| $Y_i = Y_{axis} + Rv$ |
| do |
| If (food position= unknown) |
| Find $D_t$ and $S$ |
| $D_t = \sqrt{X_i^2 + Y_i^2}$ |
| $S_i = \frac{1}{D_t}$ |
| End if |
| Substitute $S$ into fitness\_fn |
| $\text{Smell}_i = \text{fitness\_fn}(S_i)$ |
| While ($\text{Smell}_{i-1} > \text{Smell}_i$) |

**Figure 5.** FOA algorithm.
such as cellphones, laptops, etc users always selects the high feature products, even though they know that more features will lead to usability problem. After using that product then customer realize that usability is more important. The capability of the product is evaluated to analyze FF. The capability evaluation result is shown in Table 2.

### 3.2.9 FF Degree

The evaluation of Usability and Capability is applied to find the degree of FF. The FF degree calculated by the following formula:

\[
\text{FF Degree} = \text{UE} - \text{UC}
\]

UE and UC are normalized score of Usability and Capability:

\[
\text{UE} = \frac{\text{FUE} - \text{FUE}_{\text{min}}}{\text{FUE}_{\text{max}} - \text{FUE}_{\text{min}}}
\]

\[
\text{UC} = \frac{\text{FCE} - \text{FCE}_{\text{min}}}{\text{FCE}_{\text{max}} - \text{FCE}_{\text{min}}}
\]

FUE represents the Feature Usability Evaluation and FCE represents the Feature Capability Evaluation. FUE and FCE scores are obtained according to Tables 1 and 2.

The Capability Evaluation is obtained in this phase. The data preparation, product usability analysis and Feature Fatigue analysis is performed in the proposed methodology. Different features with various strategies

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**Figure 6.** Usability evaluation summary.

**Table 1. Usability evaluation**

| Score | Description          |
|-------|----------------------|
| 9     | Strong negative impact |
| 7     | Weak negative impact  |
| 5     | Not apparent impact   |
| 3     | Weak positive impact  |
| 1     | Strong positive impact |
| 8     | Weak negative impact  |
| 6     | Weak negative impact  |
| 4     | Weak positive impact  |
| 2     | Strong positive impact |

product usability problem/Feature Fatigue (FF). This FF dissatisfied the customers so this research work focused on alleviate FF before that an analysis of FF is made with the usability evaluation and capability evaluation.

### 3.2.8 Capability Evaluation

The two important factors are the Usability Evaluation and the Capability Evaluation. While purchasing the products

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**Table 2. Capability evaluation**

| Feature     | Synonym                                                      |
|-------------|--------------------------------------------------------------|
| Processor   | CPU, machine, company, prepares.                             |
| Speed       | move quickly, hurry, race, run, sprint, dash.                |
| Cache       | Hoard, store, stockpile, stock, supply, collection.          |
| Memory      | Recollection, remembrance, reminiscence, evocation.          |
| RAM         | Force, thrust, plunge, stab, push, sink, dig, stick, cram.   |
| Display Features | Exhibit, show, put on show, put on view, lay out, set out. |
| Screen Size | Partition, room, divider, dividing wall, separator.          |
| Resolution dpi | Exhibit, show, put on show, put on view, dispose.          |
are applied according to this analysis result to alleviate FF. The efficiency of the proposed method is shown in the experimental result.

4. Experimental Result

One of the unpopular Samsung product (Samsung laptops) review is collected from the web for proposed work and this raw review is considered as input for the proposed work. In order to evaluate the proposed approach, 2000 sentences are crawled from web. Each sentence in is manually divided into three category, 1) Positive attitude about the usability PU, 2) Negative attitude about the usability, 3) NU and not about the usability NT. There are 260 PU sentences, 228 NU sentences and 1312 NT sentences.

In the data preprocessing phase list of stop words are removed and word stemming is performed to extract the word which represent the product feature. There are totally 50,000 words are there in the reviews. After preprocessing procedure 30212 words are removed in the sentences. The LDA Model and Lexicon algorithm creates the synonym dictionary. The dictionary form is shown in Table 3.

To evaluate the performance of the product usability the parameters such as Precision, Recall, F-Measure and its Accuracy are used. The metrics are measured by applying the Association Rule Mining with Fruit Fly Algorithm.

The precision and recall is calculated to find the correctly classified review sentence. Precision is calculated to identify how many review sentences are relevant and it is the fraction of total classified sentence that are relevant. The formula for precision calculation is:

\[
\text{Precision} = \frac{n(\text{correctly classified review sentence}) \cap \text{(total classified review sentence)}}{n(\text{total classified review sentence})} * 100\\%
\]

Recall is calculated to identify how many relevant review sentences are selected and it is the fraction of correctly classified review sentence from the total classified sentence. The formula for precision calculation is:

\[
\text{Recall} = \frac{n(\text{correctly classified review sentence}) \cap \text{(total classified review sentence)}}{n(\text{correctly classified review sentence})} * 100\\%
\]

F-Measure is calculated to find the test accuracy. It is mainly used in information retrieval field. It contains both the precision and recall value and F-measure is the weighted average of precision and recall. The F-measure is calculated by the following formula:

\[
\text{fmeasure} = 2 * \frac{\text{precision} * \text{recall}}{\text{precision} + \text{recall}}
\]

The following Table 4 and Figure 7 shows the results obtained after experimentation with the collected dataset.

The results of the above experiments made on product usability and Feature Fatigue analysis provides better accuracy and is shown in this section.

Table 4. Performance metrics of usability classifier

| Score | Description          |
|-------|----------------------|
| 9     | Extremely attractive |
| 7     | Very attractive      |
| 5     | Attractive           |
| 3     | Somewhat attractive  |
| 1     | Not attractive at all|
| 8     | Very attractive      |
| 6     | Attractive           |
| 4     | Somewhat attractive  |
| 2     | Not attractive at all|

Table 3. Synonym dictionary

| Metrics of Usability Classifier | Values   |
|--------------------------------|----------|
| Precision                      | 75.1569  |
| Recall                         | 58.6116  |
| F-Measure                      | 81.478   |
| Accuracy                       | 95.0058  |

Figure 7. Performance evaluation report.
5. Conclusion

In this paper, the novel approach proposed with three phases evaluates the Product Usability and improves the Feature Fatigue. The customer review are collected through web crawler and proposed through NLP with LDA. Then Association Rule Mining with Fruit fly Algorithm is implemented to identify the review sentences. Finally Feature Fatigue degrees is measured by measuring the Product Usability and Capability to improve the Feature Fatigue. The results obtained shows better precision with 75%, Recall of 87%, F-Measure obtained 81.478% and the accuracy of the usability classifier is 95%. Further the proposed approach can be applied for various consumer products.

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