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A new fuzzy rule-based optimization approach for predicting the user behaviour classification in M-commerce

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ABSTRACT

A novel approach for classification of user behaviour prediction using proposed embracing the optimized fuzzy techniques to predicting the user data in M-commerce. Using this technique, network users can be monitored and their behavior categorized according to their activity. Unauthorized use of the website, network security breach attempts, firewalls, unauthorized access to the service and frequency of attempts. The proposed method has been adapted with the user classification to predict the predefine segregation of information to extract from user logs. Pattern recognition is a method for information discovery that results in current information patterns. Continuing items are a required task in various knowledge mining operations in pursuit of fascinating types from the data banks, including association rules, connections, sequences, episodes, classifications, bunches and much more. The functionality findings achieved in relation to precision and recall show that our technique can contribute to predicting more accurately than the different approaches. This paper focuses on to enhance the far better forecast for the mobile phone users through locating more reliable frequent patterns coming from the consumer deal data bank through looking at the body weight value of each thing collection and also examining the consumer activities on all time intervals.

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1. INTRODUCTION

Now days, monitoring the user and to predicting the user behaviour is important of each and every computer network particularly in those environments where segment the data is to be processed. Each individual customer used in this network is certain people to specify some constitutional rights and privileges and at the time of activities to be handle with him or her to restrict the online process [1]. Surveillance systems have already been put in place that does not allow users to engage in restricted activities, but the proposed system is responsible. The proposed system focuses on users trying to turn on or turn off restricted tasks. This shows the propensity of users to intentionally make mistakes [2]. The suggestion system evaluates the user's behaviour according to the user's network usage history, classifies it into one of the predefined categories, and predicts the user's future intentions [3].

Current enterprise search systems generate results based on specific keywords while not effectively victimizing search context. A previous international information corporation study of knowledge employees found that quite a twenty sixth of search sessions failed to come back with relevant search results [4]. The user behaviour model is to predict the current locating the exact resemblance in item-wise and store-wise by utilizing similarity index model (SIM) model. Better it forecasts stores and products which was recently unfamiliar to the consumer [5]. Fuzzy regulation located forecast is used to lessen the lot of itemset and also locates accurate outcome for prophecy at each mobile commerce consumer at transactions database [6]. Genetic algorithms are repetitive treatments that function on a populace of people. Each person is exemplified through a limited chain of symbolic representations, recognized as the genome [7]. It begins along with a first populace of arbitrarily or even heuristically produced people, and also breakthroughs towards far better people through administering hereditary drivers created on the hereditary procedures developing in mother nature [8]. It may be either subjected or even equally decided whether or not a policy is interesting. Finally, consumers can clearly assess whether or not a policy given is intriguing, and the view, as a person, can compete with each other [9].

2. RELATED WORK

The main factors of growth of m-commerce are information technology (IT) and new technologies of communication; and the online businesses, smart phones and mobile applications are also being constantly promoted. Song *et al*. [10] demographics of user does additionally participate in an essential function in on-line shopping. Now social media is additionally connected with on the web purchasing [11]. Customer can easily acquire different ads concerning items in various use system, yet the actual shopping experience take place in product page [12]. Mobile trade is actually a platform where user can easily acquire product along with making use of mobile device attached by means of cordless records connection [13].

The difference between on-line buying and also mobile phone purchasing is that in mobile phone shopping consumer usage portable (mobile) gadgets while in online buying they can make use of each predetermined as well as mobile devices like computer [14]. Now in the M-commerce, wireless application protocol (WAP) technology is applied for providing the internet services anywhere at any time [15].

M-commerce is more effective and efficient in this new modern smart phone era [16]. Detection and description of the phishing website is a complicated issue with several parameters [17]. Many algorithms are often used in classifying user behaviour, according to the web use of fuzzy rule-based system (FRBS), association rule mining, linear regression, reduced error pruning decision tree (REPTree), and help to preserve network protection and condensation [18]. Ramezani and Yaghmaee [19] authors summarise site logs and social networks, including Twitter, and Facebook, for automation of the opinion mining. In terms of classification precision and robustness, it is concluded that computer learns are higher [20].

In mobile phone business individual can receive tailored and area located services which assists to achieve customer total satisfaction [21]. To give location and customized solutions user's personal data bank is utilized which is a personal privacy problem [22]. In collaborative filtering methods identifies the relevant interest of purchase on the same item and that includes the item-based and user-based techniques was proposed by He *et al*. [23]. Li *et al*. [24] based on the pattern of item, user and the items' category performs the extraction process and implements the combination of interaction patterns for both of them. Wu *et al*. [25] in addition, the production of advertising and marketing services is annoying for both business and M-Commerce systems. Hou *et al*. [26] predicting web user behaviours is an emerging field of web data mining with respect to web application optimization centered on web user behaviour. Markov chain approach was applied for predicting the subsequent user's choice.

3. METHOD

The proposed pattern mining approaches to prediction of mobile device movements and shopping in mobile commercial environments have been planned. Based on our heuristics, the businesses would certainly be identical if two stores have a number of like products; if two items are sold in several different stores, it's doubtful that the stores will be similar. For the similarities of the shop, assume that two shops are more alike if their products are more similar. Zeng *et al.* [27] also recommended protocols for exploring and correctly predicting the behaviours of cell phone users and carried out a series of trials to test the feasibility of the mechanism proposed and also the methods proposed.

3.1. Similarity index model

A similarity index Dpq entry in the SIM database shows that a user bought item q in store p, while the IS Dxy entry in the ISD database reflects that a user bought item x in store y. Chen *et al*. [28] our heuristics show that, if two retailers supply very similar goods, shops are likely to be similar, and that the stores are unlikely to be similar in cases where two items are supplied by many different outlets. First find the most comparable item in sq in each item sold in sp (and respectively sq) (and, respectively, sp) as shown in (1).

$$im(sp, sq) = \frac{\sum \varphi \epsilon \Gamma sp(Maxsim(\varphi \Gamma sq)) + \sum \gamma \epsilon \Gamma sq(Maxsim(\gamma, \Gamma sp))}{|\Gamma sp| + |\Gamma sq|} \tag{1}$$

In case of two products ix and iy the similitude sim (ix, iy) is calculated by measuring the average difference of store sets which ix and iy. An SIDpq entry in the stored index data (SID) database shows a user has purchased q for item p, while an ISDxy entry in the iterm stored data (ISD) database shows that a user has buyer item x in store y.

3.2. Genetic algorithm-based method

Each person is exemplified through a limited chain of symbolic representations, recognized as the genome. It begins along with a first populace of arbitrarily or even heuristically produced people, and also breakthroughs towards far better people through administering hereditary drivers created on the hereditary procedures developing in mother of nature. Parkhimenka *et al.* [29] to develop a brand-new populace, people are actually picked depending on to their exercise. An achievable service in the health and fitness feature takes on a decoded chromosome as input, and as well as creates an unbiased worth of functionality to the input chromosome. Our aim for utilizing genetic algorithms (GAs) is actually to gather the worth's of measurable qualities right into unclear collections The base value b1 ik search space lies between the minimum and maximum value of the ik, the denoting and $max(Dik)$ attributes, respectively. All the basic values and intersection points Rik of attribute ik are listed next to Figures 1 and 2 for search intervals. Based on the assumption of having 3 fuzzy sets per attribute, as it is the case with attribute ik, a chromosome consisting of the base lengths and the intersection points is represented in:

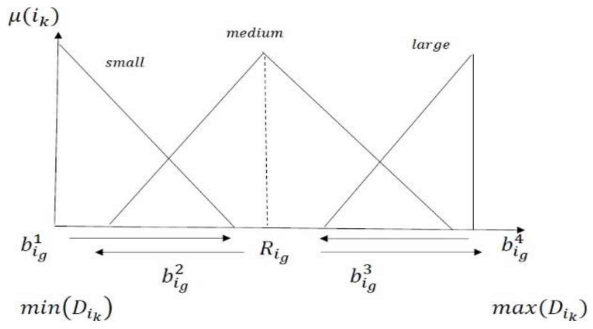

Figure 1. Membership function

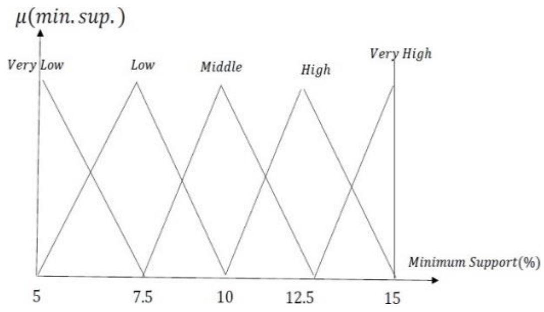

Figure 2. Fitness function

within some interval of minimum support and minimum trust, they were creating a continuous domain due to the use of minimum linguistic support and minimum trust values. The minimum support variable used to compute the fitness function will appear in Figure 1. The 5 uniform membership function of this variable is limited to [0.05, 0.15] at its definitive interval. Assume that the minimum linguistic support is indicated as "Low." First, the value will become a fluffy minimum support set (0.05, 0.075, 0.1), shown in Figure 2.

$$\mu^1_{i_k}\left(f^j_{i_k}, t_y, i_k\right) = \frac{\mu_{i_k}(f^j_{i_k}, t_y, i_k)}{\sum_{p=1}^{i_k} \mu_{i_k}(f^p_{i_k}, t_y, i_k)} \tag{2}$$

where i_k exemplifies the number of fuzzy sets associated to attribute i_k; and $\mu_{i_k}(f^p_{i_k}, t_y, i_k)$ signifies the membership degree in the j-th fuzzy set for the value of attribute ikin transaction t_y . In other words, people who are strong under parent selection are candidates for a new population. The selection of parents simulates the survival of the best people in the population. Let fitness(x,t) and avg fitness(t) indicate the fitness and average fitness of the individual x during the phase of development t respectively.

3.3. Fuzzy rule-based method

A guide of weighted fuzzy organization guidelines is actually presented in this research. Our experts introduce the level of subscription in fuzzy sets. Permit T={t1, t2, . . . , tn} be actually a database of purchases; each transaction t_y stands for the j-th tuple in T. Our experts utilize I=to express all features (items) that show up in T; each qualityi_k may possess a binary, specific or quantitative actual domain name, denoted by D_{i_k}. Each quantitative characteristic i_k; is associated with at least two blurry sets with a membership function per fuzzy set such that each worth of characteristic i_k; qualifies to be actually in one or more of the blurry sets pointed out for i_k.

Illustrate on the Figure 3 is explaining with as heavy exploration is actually concerned, things are actually delegated weights to show their relevance and heavy support and confidence values are utilized in deciding on fascinating organization policies. If C=$\{x1,x2,\ldots..xp\}is$ F=$\{f1,f2,\ldots..fp\}$ Then U=$\{y1,y2,\ldots..yp\}is$ B=$\{g1,g2,\ldots..gp\}$. where X and Y are actually disjoint collections of attributes gotten in touch with item sets, i.e., $C \cup F \subseteq I$ and $C \cap F = \varphi$; An and also B have the unclear collections related to corresponding qualities in X and also Y, respectively, i.e., fi is the collection of fuzzy collections connected to credit xi and gj is actually the collection of blurry collections related to attribute y j; 1 ≤ i ≤ p and 1 ≤ j ≤ q. Therefore, allow (t, a) represent an itemset-fuzzy set pair, where K is actually a collection of attributes and also an is actually the set of corresponding unclear collections. A mass 0 ≤ w(x, a) ≤ 1 is actually delegated to every instance (x, a) of (X, A), to reveal its own usefulness.

$F_1 = \{freqent1 - itemsets\};$

$\overline{C_1} = database$

$for(k - 2; F_{k-1} \neq \emptyset; K + +)$

$C_k = apriori - gen(F_{k-1})$

$\overline{C_1} = \emptyset$

$foreach\ entry\ t?\ \overline{C_{k-1}}$ do begin

$C_t = \{c \in C_k | (c - c[K]) \in t.set - of - itemsets^{(c-c[k-1] \in t.set-of-itemsets)}\}$

$For\ each\ c \in C_t\ do\ c.count + +;$

$if\ C_t \neq \emptyset\ then\ \overline{C_k} + = < t.TID, C_t >;$

end

$F_k = \{c \in C_k | c.count \geq minsup\};$

end

$Ans = U_k F_k;$

Figure 3. Modified fuzzy rules

3.4. Weighted membership function

Provided a data source of purchases, its set of qualities, as well as the unclear sets related to the measurable attributes, exciting fuzzy association guidelines are likely helpful consistencies. It can reveal the significance of items as linguistic terms, which are distorted as fuzzy sets of weights.

$$WFS_{(X,A,W)} = \frac{\sum_{ti} \in \mu_{x_j} \tau \in X_{aj} \in Afs(x_j,a_j).\varphi a_j(t_j,x)}{|T|} \tag{3}$$

Where an itemset-fuzzy collection pair (X, A) is referred to as large if its own weighted fuzzy support is greater than or even equal to the defined minimum required help threshold, i.e., $WFS_{(X,A,W)} \geq min\ sup$. As Fik = {f1 , f2 , … . fn } ik be a set of l fuzzy sets connected with item x. Each fuzzy set μfj (vi) has a corresponding fn association function, ik denoted vi ∈ Dik, which is a applying from the domain of ik into the interval [0,1], where . Formally, μfj ∶ Di ⟶ k. [0,1], All other values between set μfj (vi) 0 and 1, with the lower bound 0 strictly indicates "not a member", and ik the upper bound 1 indicates "total membership." All other values between 0 and 1, exclusive, specify "partial membership" degree.

4. RESULTS AND DISCUSSION

A mining version of the SIM reports a parameter-less to address this role of institution calculation, along with things like this. Two databases, respectively, SID and ISD, originate from the mobile data bank before computing the SIM. An SIDpq entry in the SID database illustrates that a consumer purchased item q the next time, while ISDxy in the ISD database shows that a customer purchased item x the next time you. Get the SIM for the similitude between shops/items. SIM delegates a similarity ranking over all products or shops. In SIM, the pair of different inference heuristic devices has been used to correlate shops and goods since certain markets, including food stores, can offer many different types of products. By adding the same heuristic similarities to shops and goods, multiple types of items may be seen to be identical as different retailers are shown to be similar. In various other terms, it is actually even more adaptable and much more reasonable for individual beings to deal with the solutions revealing the usefulness of a thing as linguistic terms.

The SIM/ISD is derived for the similitude between stores/items as in Tables 1 and 2. For the likeness of stores and products SIM employs two different inference heuristics when certain shops, including supermarkets, offer different kinds of goods. Different types of goods can be interpreted as identical by using very similar similarity inferences in both objects and stores, provided that most grocery stores are viewed as similar. In the beginning, the correlations in between the exact same shops as well as the same products both are 1, typically, they are 0. After that, all the values in the retail store or item similarity source are stabilized to the market value variation between 0 and also 1.

Table 1. SIM model

S. No	Items	Products
1	A	I_1, I_3
2	B	I_1, I_3
3	C	I_5, I_3
4	D	I_2, I_4, I_6, I_7
5	E	I_1, I_3
6	F	I_3, I_4
7	I	I_2, I_5, I_6, I_8
8	K	I_2, I_5

Table 2. ISD model

S.No	Items	Products
1	I_1	A,B,E
2	I_2	D,I,K
3	I_3	A,C,E,F
4	I_4	D,F
5	I_5	C,B,I,K
6	I_6	D,I
7	I_7	D
8	I_8	I

During an experiment, the proposed framework and its three components under various system conditions were evaluated in a series of experiments. The experimental results of the Table 3 are shows that the framework achieves very high precision in predictions of mobile trade behaviour. Furthermore, the prediction technique in our proposed context integrates the SIM mining approaches and information of similarity with regard to precision, recall and F-measurement to achieve superior performance. The data set of the WS-DREAM includes the quality of approximately 1,974,675 real world web services of 339 service users in 73 countries performing on 5,825 real-world web services.

The Figure 4 shows that the overall processing by comparing the results with Apriori, SIM, genetic based behavior prediction using weighted scoring function (GBPWS) and genetic fuzzy rule based methods (GFRM), the precision value increased by with the results of this proposed second contribution. Similarly, the reminder of recall and F-measure are increased respectively. In addition, test analysis was carried out to find accurate results and in this section the time to implement methods proposed is experimented and shown Table 3. Table 4 is obtaining the accuracy comparisons of more than four web site dataset. The results obtained after testing give the above sections greater measurement. By following the calculation, the accuracy value is calculated accordingly.

Table 3. Overall performance of the M-commerce

Data set	Performance metrices	Apriori	SIM	GBPWS	GFRM
Amazon	Precision	87.54	89.8	91.2	95.7
	Recall	85.5	82.5	90.34	95.1
	F-Measures	89.79	84.78	90.09	94.55
Flipkart	Precision	89.344	89.987	90.6574	95.3265
	Recall	88.098	89.056	91.067	95.4765
	F-Measures	87.654	88.564	92.0932	93.1532
Snapdeal	Precision	90.2345	90.6574	91.23	94.6
	Recall	89.087	91.067	93.5	95.4
	F-Measures	90.4567	92.87	94.54	94.6
Pharmeasy	Precision	92.234	93.42	94.09	95.67
	Recall	91.0345	92.4	94.3	95.93
	F-Measures	91.0965	92.45	93.42	95.765

Illustrate on the Figure 5 is shows that the overall comparisons of the parameters to be measured and accuracy parameters are calculated to determine the performance evaluation of the proposed contribution. The measurements are assessed using the approaches proposed. Table 4 to find the overall prediction of online shopping to the user to the analysis of the behavior of the user in the different algorithms to perform and produce a better outcome than the previous one.

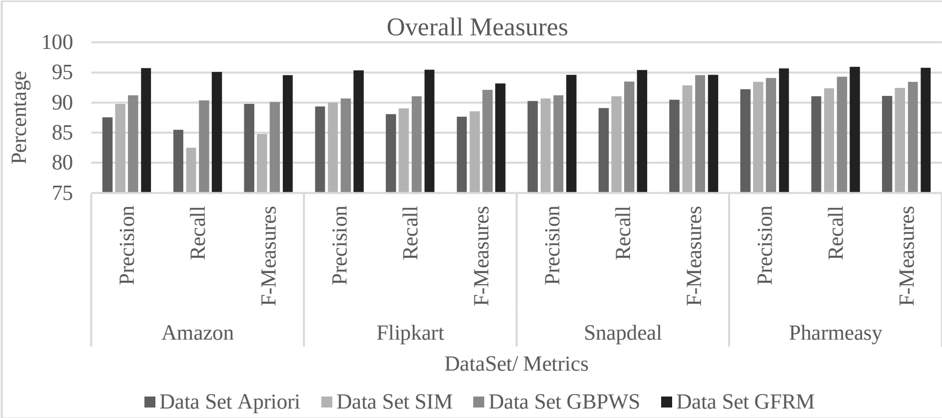

Figure 4. Overall processing to the proposed approach is assessed using different dataset to the web service

Table 4. Accuracy comparisons of M-commerce techniques

Data Set	Aprioir	SIM	GBPWS	GFRM
Amazon	90.79	89.78	92.09	97.5655
Flipkart	91.765	93.564	93.6908	96.1532
Snapdeal	93.786	94.87	95.6754	96.6575
Pharmeasy	94.9456	95.45	96.42	97.765

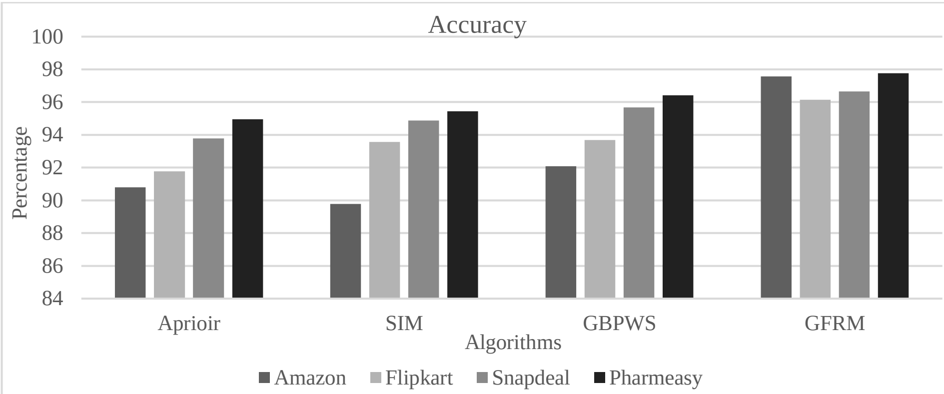

Figure 5. Overall comparisons of the accuracy

Table 5 is illustrated on overall time period calculation to the different websites such as Amazon, Flipkart, Snapdeal and Pharmeasy. Each proposed algorithm obtained with better results like Apriori algorithm is obtained with score of 2.467, SIM is 2.124, GBPWS is 1.678 and GFRM is 0.8976 for Amazon respectively. And again, another algorithm obtained with the score is 2.24, SIM is 2.0213, GBPWS is 1.908 and GFRM is 1.3024 for Flipkart respectively. And repeat another algorithm obtained with the score is 2.876, SIM is 2.312, GBPWS is 1.876 and GFRM is 0.897 for Flipkart respectively. And again, other algorithm obtained with the score is 0.8976, SIM is 1.3024, GBPWS is 0.897 and GFRM is 0.57 for Flipkart respectively. Illustrate on the above Figure 6 is shows that the overall processing time to be taken above the datasets are calculated to determine the performance evaluation of the proposed contribution. The measurements are assessed using the approaches proposed. The figure shows that Table 5.

Table 5. Overall time processing comparisons of the M-commerce datasets

Data Set	Apriori	SIM	GBPWS	GFRM
Amazon	2.467	2.124	1.678	0.8976
Flipkart	2.324	2.0213	1.908	1.3024
Snapdeal	2.876	2.312	1.876	0.897
Pharmeasy	1.9075	1.455	1.12	0.57

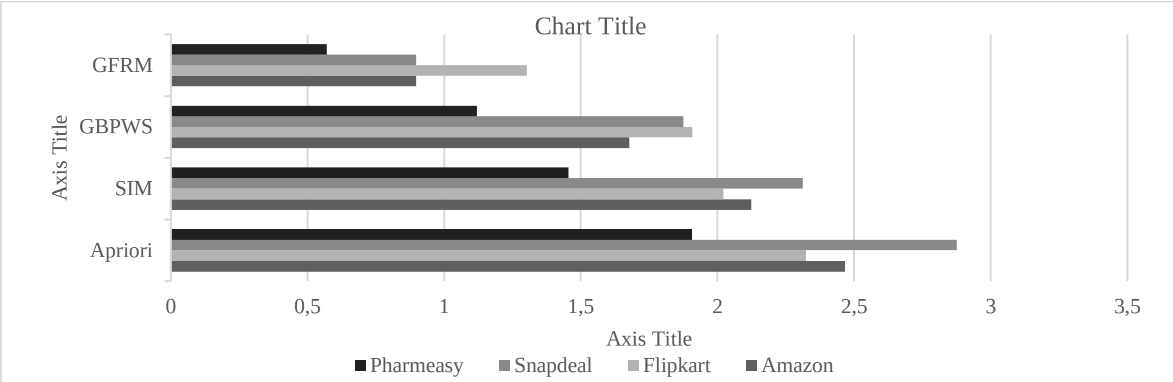

Figure 6. Overall processing time to taken above the datasets

5. CONCLUSION

In this research work is a novel approach for classification of user behaviour using proposed embracing the optimized fuzzy techniques to predicting the user data in M-commerce model has to be developed and prediction of mobile movement and transactions in mobile business environments with a three step more effective algorithm for mobile trade models and proposes prediction techniques to further optimize the proposed system. The algorithm was developed for similarity inference models using with genetic algorithm based fuzzy rule approach has done to predict the appropriate prediction of the movement of the user behaviour in M-commerce approach. For the computation of time intervals for each object collection, the proposed pattern is more exact. The weighted frequent pattern attributes of each object weight value to be calculated with every transaction as mention the output results in the table included such as improved from the current method transaction table results. The experimental findings indicate that the suggested device framework achieves a very high degree of accurate mobile commercial behaviour. The method delivers excellent results in terms of accuracy, retrieval and estimation.

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