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AN ANALYSIS AND ADAPTIVE PREDICTION OF CONSUMER ATTRITION RATE USING FUZZY COGNITIVE MAP (CARM)

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Abstract

Consumer retention is a major challenge faced in today's day to day business. Identifying approaches to predict consumer attrition or retention at an early rate is a major research work which is demandable among industry members and survey shows that business intelligence is always challenging research. This work CARM adopts consistent set of consumer data over varying time period over metrics such as accuracy of prediction and Consumer Life Time (CLV) to analyze on reasons behind attrition rate. CARM uses Fuzzy Cognitive Map as a modelling tool to determine on prediction of attrition over time period. Proposed approach is compared with traditional approaches such as Genetic algorithm, Fuzzy K-means and ANN whose performance shows that CARM shows an improved prediction accuracy of attrition rate (%) and at an early time (msecs). FCM is well adaptable to prediction compared to traditional approaches due to its early susceptibility to optimality condition.

Key Words: Consumer Attrition rate, Fuzzy Cognitive Map, Business Intelligence

1.0 Introduction

To understand the psychological behaviour of consumer and relate their analysis of buying pattern over a specific time period. Predicting consumer's intention of interest over a specific product is to be considered as major determinant of achieving prediction outcome for consumer attrition [10] based on perception of a business carried out. The primary aim of this survey and analysis is to suggest on factors of consumer satisfaction and understand the factors evolving a CRM project using an adaptive fuzzy cognitive map system (FCM) which has its relational mapping over consumer and their related consumption datasets. The phenomenon of consumer retention depends on consumer attrition. Attrition rate can be understood as number of consumers missed out based on consumer loss out or by product. Consumer Attrition discusses on considered as number of consumers missed out over number of consumer observed during start of analysis period. Prediction Accuracy Rate is expressed as percentage (%) of all products/consumers observed on specific time period.

To suggest on deterministic consumer attrition analysis and support on detailed survey exploration, Arunkumar et al [1] discussed on consumer based service level quality the demand for cognitive approach of service provisioning over product purchase and its relationship of consumer CRM outcome obtained using fuzzy multi-criteria decision making (FMCDM) along with traditional analytical approaches such as genetic computational algorithm as suggested knowledge base for primary support over ACO and ANFIS approach.

The primary objective of this work relies on (a) Early prediction of consumer attrition rate over specific market based channels. Analysis of consumer attrition over variable product demand under multiple time instant poses enormous research challenges an edge. (b) analysis or prediction of consumer attrition over a product demand under specific conditions and multi-variate situations of consumer.

Consumer attrition rate relates to benefits offered over transactional marketing. Relationship marketing offers cheaper approaches to suggest on retaining an existing consumer instead of approaching another new consumer, as well supports on providing higher value to priority based regular consumption consumers. CARM is proposed as a model for early prediction of consumer attrition approach, which adopts fuzzy cognitive mapping using demand for product in market over consumer details. This approach suggest on mechanisms for early prediction of consumer attrition over variable product utilization.

CARM considers clustering approaches over defined analytical methods which work towards improving the predictive ratio towards market demand and understanding commodity market cost. Proposed model suggests on identification of features of commodity and market analysis required for accomplishment of consistent product growth metrics over period of time. Understanding the product growth metrics[9], product behavioural aspects [4] and effective utilization rate [3] over distributed consumer data obtained from different market malls as data set is considered for analysis. Fuzzy Cognitive Mapping approach supports on variable product consumption obtained from consumers discussed by Zang et al[17]. This research work focuses on various models to create and design on product consumption rate of consumers and mechanism to predict on consumption rate. CARM detects on ratio of commodity distribution, product consumption rate, suggesting on consumers seasonal changes in utilization or consumers support on product. CARM also focuses on unexpected attrition rate which may attribute to unexpected societal conflicts, issues related to market based price fluctuation and uncertainties of socio-demographic aspects[7], which remain as need for optimality metrics to determine the consumer detection rate against a market producer[12] to sell commodities or produce at an optimal price. Research work fulfils the following objectives (a) Need for designing an optimal early prediction of consumer retention / attrition rate and understanding the commodity demand in market. (b) The need to suggest a decision support system based on commodity variable inputs, which adapts towards market based demand trend sets of selling the commodities.

The paper is arranged is follows : Section-1 introduces the need for customer attrition, challenges behind prediction of attrition, adoption of fuzzy cognitive map towards detection and data analytics. Research gaps and analysis is discussed in section-2, which suggests on aspects behind business intelligence, and need for computational approaches towards prediction. Section-3 introduces on FCM and its role in prediction of consumer retention or attrition analysis. Section-4 elaborates on CARM algorithm and its design factors towards optimization and prediction of consumer retention. The dataset and its experimental test bed is discussed in Section-5, while section-6 concludes on outcome of CARM.

2.0 Review work

Researches in the field of business intelligence had taken a major leap towards adopting technological updates in day to day business activities [2]. The success of running a business firm primarily does not just depend on various methods of executing the business, but to determine how beneficially the business trends produce profits when compared to domain centered business offices[11]. The research methodological key required to support an effective business office lies in data analytics [6] and computational methods [14], where the data transacted is being methodologically analyzed and adopted for providing intelligence of marketing approaches[15].

3.0 Role of Fuzzy Cognitive Map in Consumer retention analysis (CARM)

Computational models and its application on understanding the consumer's approaches of their purchase behavior, suggests implementation of multiple various classification algorithms being suggested for analysis and improving the accuracy of prediction over consumer attrition or defection probability rate. Attrition models are invariably selected from various performance metrics such as the area under the ROC curve[5], which considers accuracy as a variable metric for analysis. Consumers analytic metrics such as Consumer lifetime value (CLV)[13], lifecycle of a consumer, effective product utilization rate, cost involved towards acquiring a new consumer, cost of retaining a consumer, product utilization rate and related consumer metrics play a primary role in early analysis.

Though computational models do support on analytics of consumer and product utilization rate, the demand for a challengeable approach of early prediction of consumer attrition towards understanding the product is current valuable research. Computational modelling approaches in relation to consumer optimization algorithms such as ANN[9], Bee Hive optimization [16], which define on understanding the product requirement based on consumer's interest and market demand.

4.0 Approach

To support in consistent business development and growth, with focus on the need for economic stability of a firm, understanding the consumer profile and product life cycle[15] helps in business as consumer relation management. To adapt to new technological aspects as well to leverage the benefits of existing consumer and product information the support of data mining technology should be implemented. Data and analytics technology primarily helps to analyze the trends of businesses by discovering hidden patterns of business sales and consumer information. These patterns help in understanding the purchasing behaviour of their key consumers as well identifying their interest towards buying a product. Various case studies [17] had been applied in consumer volatile industries such as telecom, network, consumer market analysis, banking sectors, health insurance. Most of the examples include detection of people's usage of credit card or debit card for purchase of electronic goods or materials. Data mining primarily helps in critical data analysis such as insurance claim fraud detection, predict probable changes in financial markets, and so on.

To understand, analyse and utilize on properties [14] which are required for determining the functionality of consumer retention rate over specific duration, data analytical approaches along with an intelligent computational procedures support towards improving the business according to the change in environment of growth[10]. Multiple computational procedures [11] such as Swarm Intelligence algorithms, Genetic Modelling Algorithms, Neuro Fuzzy Logic procedures can also be adopted. The outcome is predicted towards analysis of consumer attrition, with support for consumer retention models at an early time such that the business organization manages its assets beneficially.

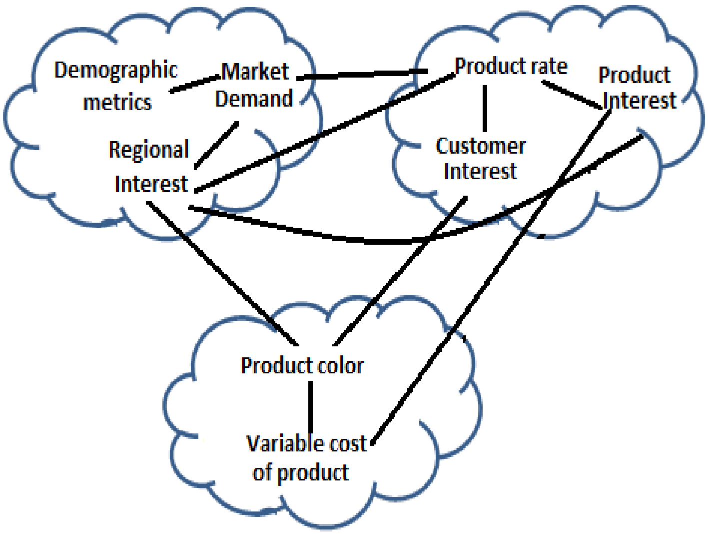

Fig-1 Clustering of Consumer and Product based features using CARM

CARM discusses on the analytical approach for early prediction of consumer attrition using Fuzzy Cognitive Map approach which is adaptive based on stochastic outliers of consumer's product consumption rate over verified time period. Design functionality of CARM adopts consistent update on stochastic consumer behavioural knowledge whose detectable consumer trained dataset follows predictable outliers to suggest on prediction of attrition rate.

5.0 CARM Algorithm

CARM algorithm adopts multiple clusters of consumer interest, product details, product utilization rate, intensity of purchase, demand for product, product recommended rate as variable consumers' criteria defined as objective function Xi.

Objective Function $Xi = (C,P, \xi,\alpha,\sigma)$ // Predicts on the fitness of consumer attrition based on search criteria

Step 1: Consumer population Cn (n=1,2…y) and product demand Pm (m=1,2,...x) to be initialized, where x, y are relative variables of Cn and Pm

Step 2: // define slack variables
Pb : consumer's product buying pattern
Ca, Cb : Observed Consumer's attrition events (Buy, Reject)
ξ : prediction of nearest consumer's attrition pattern
α : frequency of consumer attrition rate
Cw : worst vector observed - consumer attrition

Step 3:
    Create Ca; // list of products and their repeated buying behaviour
Step 4:
    for n = 0...(x^{row} -1) do
      for m = 0 …(y^{col}-1) do
        Gk[n][m] ← Pb   // variable product change in cost and product buying pattern
        Initialize (Ca, Cb)
    for each Cn do
      Create Pb, where $\forall$ Pb $\subset$ Ca OR Pb $\subset$ Cb
    end-for
Step 5:
 for n = 0 …(n^{row}-1) do
 for m = 0 ...(n^{col} -1) do
    if (Pb (Ca, Cb) < Gk[n][m]) AND (Cw != NULL) then   // verify for all customers
    begin // Check on the fitness of consumer attrition data
      Xi ' $\in$ (Xi^1, Xi^2, …. Xi^n }
     Gk[i][j] ←Xi '
    end
    Cw ← Pb // negative instances of consumer update regarded as Retention
end-for 'n'
end-for 'm'

Algorithm takes in all possible valuable inputs between consumer and their relationship with a product. Any feasible relationship can provide a positive inference towards buying the product and as well instances to move away from buying product which is to be referred as RENTENTION aspect or attrition issue. Algorithm takes consumer inputs as 'Ca' gathered at each interval of time and measures its event. 'Cb' suggests on consumer category and positive instances of product buying attitude and 'Cw' suggests on negative instances and their aspects of deferring away from product.

Fig-2 discusses on the aspect of applying consumer retention based on product demand and its establishment with quality of consumption. To establish a relation between consumers' interest and product selling pattern Fuzzy Cognitive Map helps to create a effective relationship between the metrics and behaviour. The weightage assigned over the metrics suggest on the intensity of data and its priority of assignment between consumer and product.

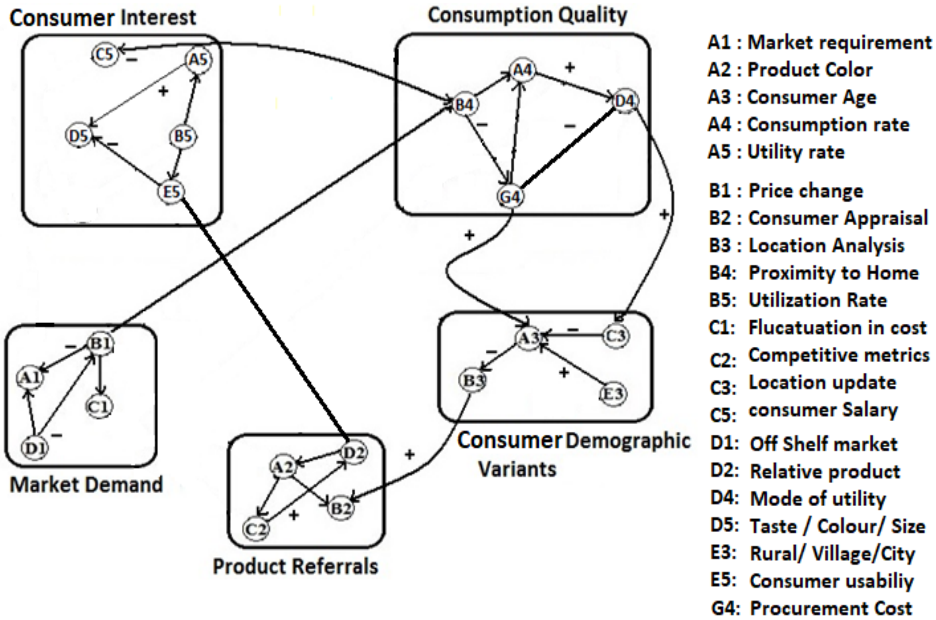

Fig-2 FCM mapping over customer, product relationship and its relation in referral

FCM works by clustering the relationship existing between consumer and product, using multiple objects as components shown as A1, A2....An, B1, B2...Bn, C1.... (Fig-2). Each component establishes its relationship with another component such that its relation supports in a positive or adverse way is analyzed. The relation B1 shows a positive relation to C1, which is related to price change and its impact on consumer. Relation B1 shows a negative impact over A1 as shown in Fig-1, such impacts being positive or negative gains momentum to finally suggest on causes for Consumer Retention and their impacts.

6.0 Experimental Analysis

Consumer data being gathered from regular consumers of different products from Jan 2016 to April 2019 is used for analysis in this research work. The dataset is pre-processed to check on data quality and adopting to research requirements. CARM adopts the following analytic experimental metrics :

a) Experiment execution period : 360 secs
b) Number of consumers active : 210
c) Number of consumer observations : 167
d) Number of consumer usage periods associated with contractual active period : 14 months

CARM algorithm takes in to consideration all beneficial set of consumers who are found to be participative or active in shopping activity from an observed dataset collected over 3 year of analysis. The algorithm adopts active list of consumer's data being maintained over period of 2016 to 2019 from different retail marts. The dataset possess around 10520 records for 356 products variable over cost as a differential parameter as shown in Table-1.

Variable Attribute density	183
No of Records used for analysis	10520
Missing Values	31%
No of Consumers	623
No of products for analysis	356
No of Categorical Attributes	43
Analytical period	Jan 2016 to April 2019

Table -1 : Dataset property

Fig-3 discusses on Consumer attrition rate observed using CARM, where consumer life time value (CLV) is considered for analysis with defined consumer buying behaviour. The average variable consumer attrition rate of 26.73% being observed is compared with Fuzzy K-Means clustering approach which is found to be 37.51%. Based on forecast analysis it can be understood that observed attrition rate (in %) on suggested analysis from CARM shows that average retaining rate of consumer is 32.29% which takes high fluctuation rate in comparison over ANN, which demonstrates average rate of 34.81%.

CARM shows an early prediction rate of 90msecs for analytical period , while Artificial Neural network suggests 138msecs and 208 msecs are suggested by Fuzzy K-Means.

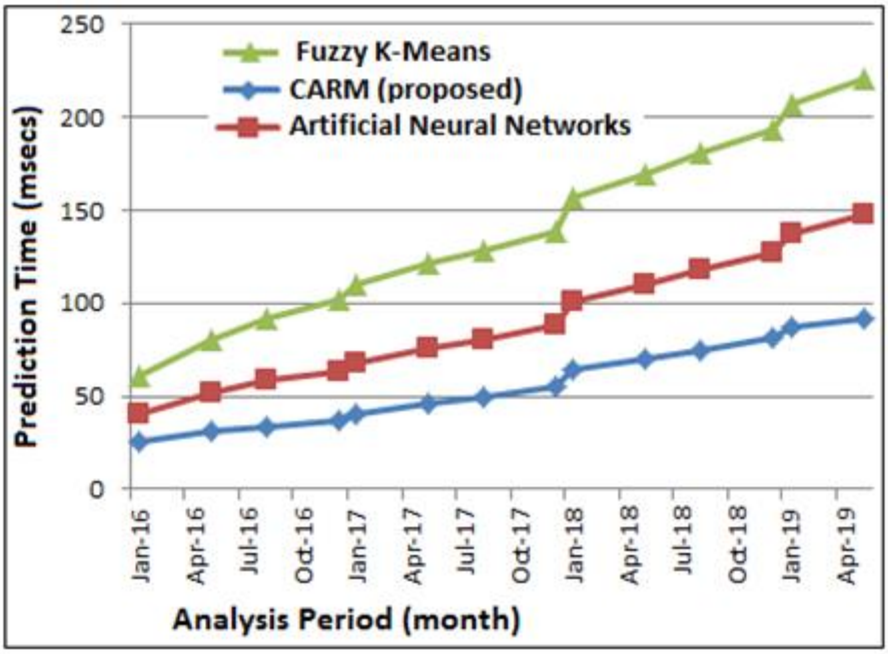

Fig-3 : Observed Prediction Time over analysed time period

Fig-4 shows the consumer attrition prediction rate or retention rate which is highly influential on consumer fluctuating price of product over varying time period. Analytical period from Jan 2016 to April 2019.

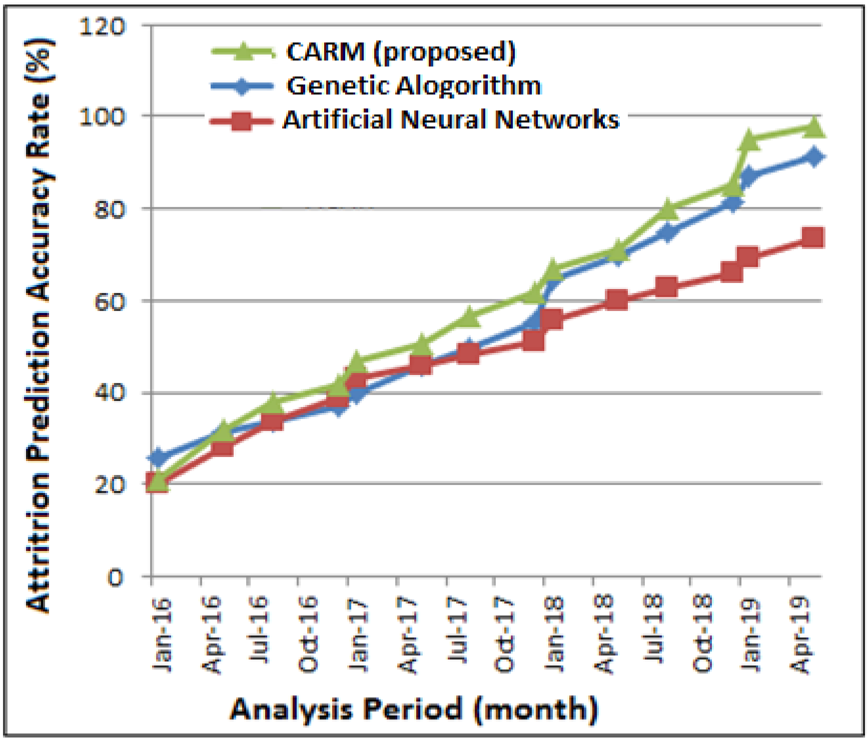

Fig-4 : Observed Attrition / Retention Prediction rate

To understand on accuracy of Attrition rate or retention rate of consumer over period of time, the dataset is compared with Genetic approach and Artificial Neural Networks. Performance of proposed CARM is optimally improved as 68.25% in comparison to ANN whose performance is 54.09% and Genetic algorithm as 62.77%. On an average performance of CARM it can be suggested that it outperforms on early prediction with well adaptation to frequent changes in prediction of consumer attrition rate.

7.0 Conclusion

Challenges in consumer attrition is always felt as a major research in field of Business Intelligence. Predicting consumer attrition at an early time support towards retaining the consumer as well minimizes cost involved in getting a new consumer. Understanding the consumer changing interests and adapting to efficiency towards carrying out regular business is discussed in this research work. The dataset is gathered from consumer over varying time period such that their change profile and variable interests are analyzed. CARM is proposed approach which uses Fuzzy Cognitive Map to analyze and suggest on consumer attrition based on their buying behaviour. CARM shows an improved early prediction rate of 92 msces compared to other approaches.

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