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From Purchase Intention to Purchase Decision - A Machine Learning Based Approach in Context of Automobile Industry of India

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Abstract

The study on consumer behavior deals with purchase intention followed by purchase decision and post purchase experience of consumption and evaluation, which can be received by manufacturer in the form of feedback. All purchase intentions do not transform into visible purchase decision because of several reasons or factors such as cognitive factors, emotional factors, situational, demographic and other factors. Certain components of these factors can be strategically dealt with by sales persons of automobile companies through fruitful communication, which is extremely useful to reduce confusion in minds of potential customers arising from perceived differences between desired and offered functionalities in the products. In this paper we propose a machine learning based method ML-ASA to assist sales persons of automobiles, in showrooms of various companies, to estimate purchase decision of potential customers and their probable choices of vehicle models. ML-ASA computes probable purchase decision based on a support vector machine or SVM which outputs 1 if the customers purchase intention from the current manufacturer is strong. Otherwise it returns 0. Also the essential set of attributes are identified which must be included in persuasion efforts from the sales person's part. Vehicle models are demonstrated in decreasing order of popularity where popularity is based on customers choice record in the showroom and prediction of sales records in the next quarter. We have used auto-regressive moving average or ARMA model for sales prediction purpose of different vehicle models belonging to automobile companies Maruti Suzuki, Honda, Kia, Porsche, Tata, Mahindra, Hyundai, Bajaj and Toyota. Experiments are conducted using R 4.0.3 and results show that our model achieves high (>90%) accuracy, precision and recall.

1. Introduction

Consumer behavior is the study of processes by which individuals, groups or organizations select, secure, use and dispose of products, services, experiences or ideas to satisfy their needs and wants. It takes into consideration possible impacts on security and its economic scenario out of the consumption of specific products (Sundareswaram et. al. (2022), Jin (2018)), Purchase intention and purchase decision are two similar but distant components of consumer behavior having different aspects and impacts on consumer as well as the manufacturer while making a purchase decision, various external factors can have an impact on consumers choice. The opinions of those you trust, socio-economic and political scenario, in-showroom discussion and many other unforeseen circumstances can shift priorities, rendering their initial purchase intentions obsolete. It is important to acknowledge that consumers' preferences may not always be in line with their actions (Kotler, Armstrong (2018)). Understanding consumer behavior is the key to success in today's market and it helps to create tailored marketing strategies, most of which transform into successful business efforts (Bashir (2019), Burton (2008)). In

this paper we have used a term visible purchase decision which denotes that actual purchase is being performed from the current manufacturer, not from a competitor. For example, if a potential customer enters into the showroom of Maruti Suzuki and after some discussions with salespersons he goes out and buys a Hyundai car, then it is not a visible purchase decision for Maruti Suzuki but for Hyundai. Similarly, if the dis-satisfied customer goes out and cancels or postpones the purchase plan, then it is not a visible purchase decision for any company; neither for Maruti Suzuki nor for Hyundai. Hence, in transforming purchase intention to visible purchase decision, sales persons have a big role to play. They have to have good knowledge about products of their employer-manufacturer along with those of competitor companies (Culiberg et. al. (2022)). Also product models should be demonstrated keeping in mind their performance issues and feedbacks of customers (Lam, Borgh (2021), march (1994)).

Judgment and decision making (JDM) of sales persons is very crucial for associated companies Also sales research that employee JDM Theories is sparse. This is surprising given that sales people constantly form judgments and engage in decision making in a complex and uncertain environment. According to Sleep ET. al. (2020), complexity of the process has elevated these days because of more knowledgeable customers, increase in number and efficiency of competitors, requirement of cross functional coordination and continuous pressure to perform better than others. Their discussions are restricted by firm's policies and productions; they have to abide by organizational norms. They have to strike balance between customers interests and manufacturer's interest which may sometimes conflict with one another; also the criterion of maintaining good relationship with the customers in long-term, is assigned great importance these days to stimulate the repurchase intention in subsequent occasions. All these make the task of decision making highly uncertain, ambiguous, self conflicting and dynamic. They have to deal with the customer's cognitive factors, emotional factors, and personal traits, situational and demographical factors which may hamper the process of taking visible purchase decision, given the fact that there exists purchase intention. Cognitive practice arises from cost-benefit analysis which goes on in minds of customers, especially during buying of expensive luxury products. It encourages him to take more time and strategically analyze ideally all of the available options. When the decision making process becomes unstructured and complex because of numerous branches of the decision tree with each one having its own advantages and disadvantages, the consumer may go for random one or withdraw himself from the Purchase process (Anderson (2003); Tversky, Shafir (1992); Xiad, Caixie (2011)). Emotional factors also contribute a huge part in converting purchase intention to purchase decision, these are mostly anticipatory in nature provided there are chances to maximize positive emotions and minimize the negative ones. According to consumer psychology theory, negative emotions generate when consumers are compelled to trade off between expected and offered functionalities of product(s). Tension, anxiety, fear etc give rise to Insecurity and disgust which encourages a person to maintain the current state and relinquish the conspicuous purchase plan (Wang et. al. (2013), Dhar et. al. (1999)).Consumer's personal traits have to be dynamically dealt with by the salesman to Convince them to buy and our scheme assists him in the process. Novelties of our proposed scheme are as below:-

1. Estimation of purchase decision based on SVM.
2. Computation of popularity of a vehicle model using ARMA model.
3. Suggesting and demonstrating features of vehicles in decreasing order of popularity within pre-specified price range, so that consumer is able to choose the desired product in shortest possible time.

4. Vehicle models priced above customer specified upper limit, are eliminated for price-constrained customers.

2. Literature review

Decision making of sales persons is aligned with theory of judgment and decision making (JDM) (March (1994)) It focuses on five key dimensions, namely, i) rationality ii) knowledge iii) individuals iv) preferences and v) decision rules. Rationality is based on number of alternatives a decision maker is able to consider. In context of sales persons of automobile industry, alternatives are the vehicle models with different features, such as price-range, color, fuel type, design, space, size etc .Based on requirements of each individual consumer, demonstration by the salesman has to be different. He is expected to match the mentioned features with those provided by the company and highlight efficiencies of the best model which encapsulates nearly all of those, abiding by constants and assertions imposed during the product selection phase. Throughout the process of illustration, there may be conversation regarding comparison of products and services with the same of competitor companies. In these cases, the salesperson has to patiently answer all the queries abiding by the companies policies and norms, optimizing interests of both the customer and the manufacturer. This requires knowledge about the employer, its position in the market, performance standards of products and services and similar information about competitors.

The third aspect of JDM theory is individual, which specifies the identification of decision maker(s) among the customers of a specific group, convincing him/her is needed utmost to persuade the entire group and engage into the desired purchase process. Preferences are all about the attributes by which the vehicles are evaluated. In context of automobiles the attributes are properties of products such as fuel efficiency, engine capacity, design, space, ground clearance etc. which may impact both purchase intuition and decision of a customer. Decision rules consist of the fifth aspect by dint of which salespersons switch from one vehicle model to another. This order is extremely important to add value to the discussion and make the indirect process of product selection easy, efficient, quiet and fruitful. There has been little research work done in the field of application of JDM theories in management. Moreover, little weightage was given in marketing research on sales people's ability To evaluate customer cues, Understand and appreciate their needs and expectations, and engage in adaptive selling (Lam, Borgh (2021), Weitz (1978)). In spite of the fact that they continuously make judgments and availability of CRM (customer relationship management data), sales and other kinds of data has prepared and ideal field for technology assisted decision Making, Still little research effort has been put to applications of these in marketing and sales research.

Among the few articles in relevant literature, Bonny ET. al. (2016) measured impact of salesperson's judgment on performance outcome and issue of ethical decision making has been discussed by Schnepker ET. al. (1997). Division of a decision making task into several subtasks and assigning one to each module facilitates the multitasking JDM as pointed out by Mayberry Et. Al. (2018); Lam Et. al. (2019) and Schepers (2018). Possibility of incorporating AI in decision making of sales persons have been focused by Shichor and Netzer (2021), Key limitations of these include explicit discussion of salespeople in Decision making process, especially in context of conspicuous products such as automobiles. Also there is no pre existing guideline on framework to contact research on salesperson JDM (Lam, Borgh (2021), Shichor and Netzer (2021)). Hence this is identified as a valid literature gap we have addressed in this paper. We particularly aim at The fifth aspect of JDM which consist of the

decision rules. In this paper we propose a machine learning based Framework for assistance in decision making and persuasion of customers by salespersons.

3. Overview of The Scheme

ML-ASA depends on various databases for decision making purpose. These databases are discussed subsection 3.1 whereas the relevant methodology appears in subsection 3.2..

3.1 The Database Backbone

In each showroom, a centralized customer database or CDT is maintained consistent of the information shown in table 1.

Table 1: attributes of the customer database CDT

Attribute name	Significance
cust(i)	Identifier of the i-th customer
oc(i)	occupation of the i-th customer
age(i)	age of the i-th customer
sex(i)	sex of the i-th customer
ed(i)	1, if i-th customer has qualification below bachelor's level
	2, if i-th customer has bachelor's degree
	3, if i-th customer has master's degree
	4, if i-th customer has qualification above master's degree
mem(i)	No. of members in family of cust(i)
dist(i)	mean distance to work as mentioned by cust(i)
loyalty(i)	1, if the customer has purchased at least one one product from the same manufacturer earlier 0, otherwise
rdc(i)	amount of royalty discount received by i-th customer, if any
sdc(i)	amount of special discount received by i-th customer, if any
Preϑ - ϑhl [i,1]	model number of immediate previous vehicle purchased by i-th customer, if any

Prc - ϑhl [i,1]	purchase price of immediate previous vehicle purchased by i-th customer
$\forall_{j=1}^{F} f$r [i,j]	1 if j-th feature has been mentioned by i-th customer
$\forall_{j=1}^{F} ft$r [i,1,j]	1 if j-th feature of immediate previous vehicle was mentioned by i-th customer during current purchase 0, otherwise please note that F is total number of features in a vehicle
Preϑ - ϑhl [i,2]	Model number of the vehicle before Preϑ - ϑhl [i,1]
Prc - ϑhl [i,2]	price of Preϑ - ϑhl [i,2]
$\forall_{j=1}^{F} ft$r [i,2,j]	1,if j-th feature of Preϑ - ϑhl [i,2] was mentioned by i-th customer during current purchase 0, otherwise
$\forall_{K=1}^{M} m$dl [i,1,k]	1, if the k-th vehicle model was chosen by i-th customer in immediate previous purchase 0, otherwise M is total number of vehicle models of the manufacturer
$\forall_{K=1}^{M} m$dl [i,2,k]	1, if the k-th vehicle model was chosen by i-th customer before immediate previous purchase 0, otherwise
ln [i,1]	Amount of vehicle loan taken by the i-th customer in immediate previous purchase
ln [i,2]	Amount of vehicle loan taken by the i-th customer before immediate previous purchase
downpay[i]	Amount of proposed down payment by i-th customer In the current purchase
P_uplim [i,1]	Upper limit of the price mentioned by i-th customer in the immediate previous purchase
P_uplim [i,2]	Upper limit of the price mentioned by i-th customer in the immediate previous purchase before the immediate previous purchase

Cur_uplim [i]	upper limit of the price mentioned by i-th customer in the current purchase
Prc_cons[i]	1, if the i-th customer doesn't want to compromise with Cur_uplim [i], even by the amount to buy the immediately next higher model of the same vehicle or lowest model of the immediately next higher priced vehicle 0, otherwise
competitor[i]	1,if the i-th customer mentioned about some competitors of the current brand 0, otherwise
ϑpd[i]	1 if the i-th customer decided to purchase 0, otherwise
$\forall_{\vartheta=1}^{M}$ model [i,ϑ]	1,if the i-th customer bought vehicle - model [ϑ] 0, otherwise
happy[i]	1,if the i-th customer seem happy after the interaction 0, otherwise

Among the above mentioned attributes, cust(i), oc(i), age(i), sex(i), ed(i) are demographical attributes while the others are related to previous two purchases. All the people who enter a given showroom have product purchase intention although conversion of it to visible purchase decision depends on expertise of the salesperson. ϑpd[i], happy[i] and $\forall_{\vartheta=1}^{M}$ model [i,ϑ] are the output variables of table 1 that are determined based on all other variable from cust(i) to competitor[i] each of which are input variables. As soon as a potential customer enters into a showroom, values of all these inputs are collected by salespersons, which are accepted as input by our proposed system ML-ASA. it computer value of $v$pd and model subsequently if clusterizes the entire set of customers using k-means clustering and finds out i) general characteristics of each cluster, and ii) cluster of the new customer from general characteristics of the estimated cluster of the new customer, The salesperson identifies features of the vehicles he/she is supposed to enthrust upon. Identification of these features and probable models enable a salesman to move forward towards conversation with the customer and demonstration of different types of vehicles. The vehicle models are demonstrated in decreasing order of popularity where popularity is measured based on i) history of sales record of the model, ii) number of times this vehicles have been explicitly mentioned as desirable by the customers, iii) Number of times those were mention and not purchased, and iv) of times those were not mentioned but purchased. These attributes are mention in table 2 which illustrate vehicle model database or MDB. Vehicle models priced above customer specified upper limit, are eliminated for price-constrained customers.. Demonstrating vehicles in decreasing order of popularity makes the entire process of purchase simple, easy, short and convenient. Table 3 contains the sales database SDB which consists of five attributes – customer-id, model-id, purchase-decision, time-to-converse and no-of-visits-per-purchase. customer-id specifies

unique identifier of a customer; model-id is unique identifier of a vehicle model (set to -1 to if the person has bought any thing); purchase-decision is 1 if the customer decides to purchase, else it is 0. The next two attributes time-to-converse and no-of-visits-per-purchase denote amount of time to persuade a customer and number of visits required for each purchase, respectively. Time-to-converse is set to 100 if the purchase didn't actually happen; in that case no-of-visits-per-purchase is set to 5.

Table 2: attributes of the vehicle model database MDB

Attribute name	Significance
ϑhl-name	name of the vehicle
ϑhl-model	unique model number of the vehicle
ϑhl-sales [ϑhl-model]	sales record history of $v\text{hl} - \text{mod}$ for last three years
mn [ϑhl-model]	number of times the vehicle $v$hl-mod has been explicitly mentioned by customers for possible purchase
mn-nc [ϑhl-model]	number of times the vehicle $v\text{hl} - \text{mod}$ have been mentioned by customers for possible purchase but not purchased actually
mnp [ϑhl-model]	number of times the vehicle $v\text{hl} - \text{mod}$ was not initially mentioned but purchased ultimately

Table 3: attributes of SDB

Attribute name	Significance
cust(u)	Unique identifier of u-th customer
modll(u)	Unique identifier of a vehicle model which u-th customer has purchased. It is set to -1 to if the person has bought any thing
Purchase – decision(u)	1 if the u-th customer has bought a vehicle from this showroom in the current purchase 0 otherwise
Time-to-converse(u)	Amount of time spent in persuasion efforts for the current or u-th customer Set to 100 if purchase-decision is 0
No-of-visits-per-purchase(u)	Number of visits required by u-th customer for purchase Set to 5 if purchase-decision is 0

From CDT, values of ϑpd and happy are computed. Subsequently set of customers are clusterized and probable models for the new customer are determined. These models consist of those which have been

chosen by other members of the same cluster and those which have been explicitly mentioned by the customer. Reliability of these models is computed and if the customer seems difficult to pursue then the salesperson should make up his/her mind to focus on patient explanation because multiple visits may be necessary before a purchase by the current customer. Otherwise demonstration of models proceeds naturally. The set of models might have to be filtered to choose the ones priced below Cur-uplim, provided the customer is price - constrained (as denoted by the condition Prc-cons = 1).

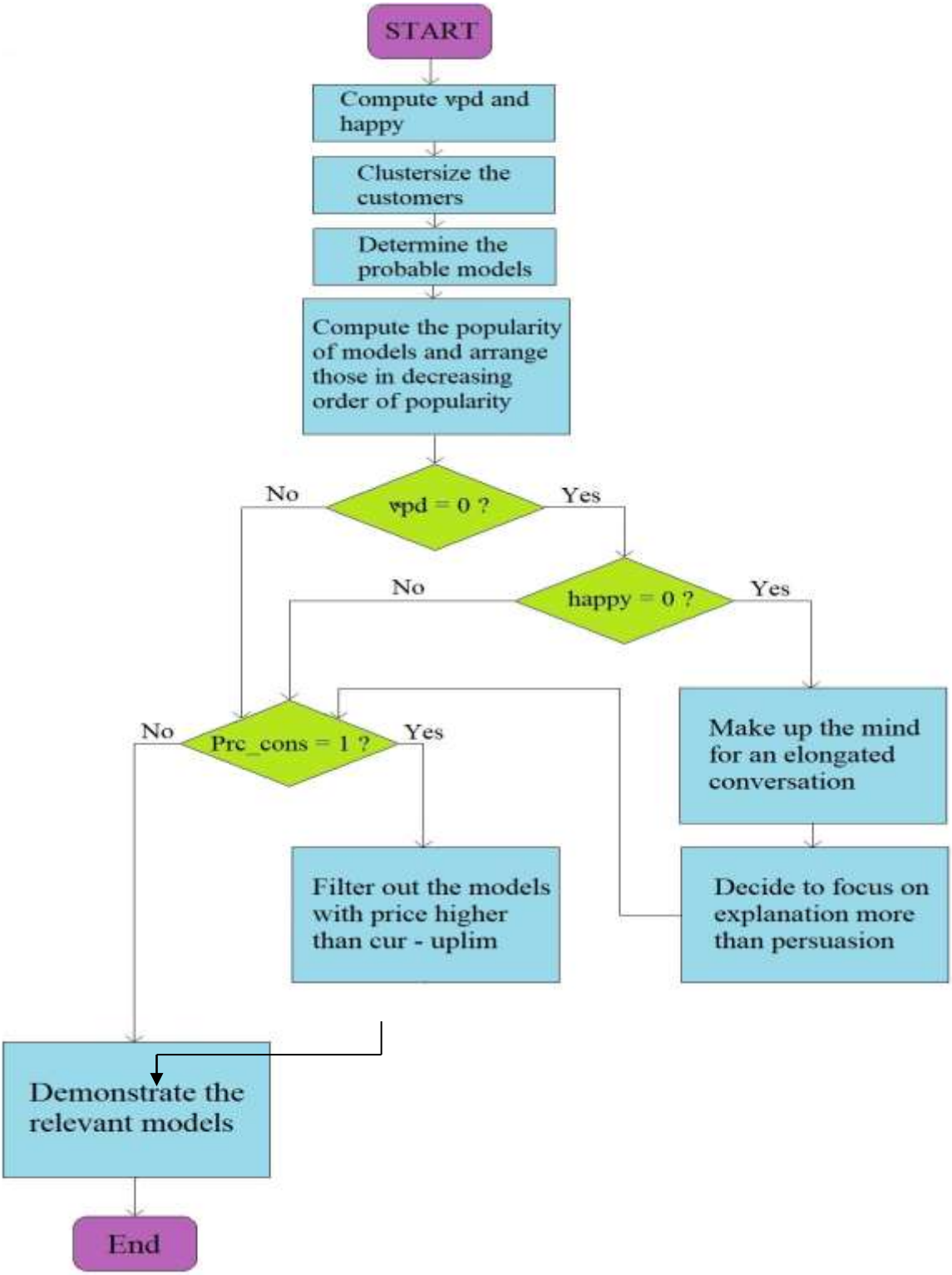

Fig 1: Block diagram of ML-ASA

4. Determination of visible Purchase Decision

4.1 Basics of SVM

Support vector Machine is heavily used supervised learning algorithm that is applicable both for classification and regression tasks. It obtains the best possible hyper plane that separates different classes of input data by maximizing the margin between decision boundary and nearest data of points of each class. It is equipped with specialized kernel functions which map input data to multi-dimensional feature space to tackle non-linear classification problems. This is effective even when number of features of the new sample is larger than those of the training samples. This is extremely useful in the current context because the new customer can always mention about more features than its predecessor entries in CDT. Another advantage of SVM is that it is comparably less sensitive to over fitting. However, it is computationally intensive for large data sets and its performance effectiveness depends upon the appropriate kernel function.

The purpose of using SVM In the current context is to obtain the best possible decision boundary between the classes 'purchaser' and 'non purchaser' where purchaser is the class for which value of ϑpd is 1 whereas it is 0 for non-purchasers. Each new customer is initially grouped into one of these two classes based on values of input variables table 1. SVM chooses utmost vectors (points) to construct the hyper plane between two classes and these vectors are called support vectors.

4.2 Practical implementation of SVM

The history tables mentioned in section 2, are all Stored in CSV files. Parameters of the SVM used here appear in table 4. Error term or penalty parameter is denoted by C. Its default value 2 remains unchanged here because it is a two class problem .Next parameter class-weight depends on possible labels. In this case the labels are 0 and 1 where 0 represents non-purchaser and 1 represents purchaser. class-weight is set to none so that both classes get equal weight. The size of each database is limited to 5000. As soon as a new record is inserted, the oldest record has to be deleted if number of records exceed 5000. coefo is an independent term that is applicable only in the case of poly and sigmoid types of functions. This is set to 0.0. 'ovr' or one-versus-rest is set to shape of the decision function. It grabs a class and creates a binary label whenever a data belongs to that class. The values of degree and gamma are 3 and auto - deprecated respectively. Degree specifies degree of the polynomial and its default value in 3. Auto - deprecated means no specific value has been passed to it. The kernel cache size is set to 5000 keeping parity with size of the database CDT and MDB. max-iter is set to -1 which indicates that no limit is there on number of iterations. A probability option is required to compute the probability estimates. It is set to False so that random state can be ignored. Default value for shrinking heuristic is true. Tolerance value or tol is the stopping criterion and its value is set to 0.001. Lesser values may increase accuracy, precision etc. although involved computational complexities are expected to be higher.

Table 4: Attributes of SVM

Name of the parameter	Value
C	100
class_weight	none
HST_tablesize	5000
cache_size	5000
coefo	0.0
decision_function_shape	ovr

degree	3
gamma	auto-deprecated
kernel	rbf
max_iter	-1
probability	False
random_state	none
shrinking	True
tol	0.001
verbose	False

4.3 Determination of vpd

let the new customer be the u-th customer in the is cust(u). Assume SI(u) be the Set of input variables to determine is purchase intention or ϑpd[u]. then SI(u) is Define in (6).

$$A(u) = \{\, \text{cust(u)}, \text{oc(u)}, \text{age(u)}, \text{sex(u)}, \text{ed(u)} \,\} \rightarrow (1)$$

$$B(u) = \{\, \text{mem(u)}, \text{dist(u)}, \text{loyalty(u)}, \text{rdc(u)}, \text{sdc(u)} \,\} \rightarrow (2)$$

$$C(u) = \left\{ \text{Pre}\vartheta - \vartheta\text{hl}\,[\text{u}, 1], \text{Prc} - \vartheta\text{hl}\,[\text{u}, 1], \underset{j=1}{\overset{F}{\forall}} ftr\,[\text{u}, 1, \text{j}], \text{Pre}\vartheta - \vartheta\text{hl}\,[\text{u}, 2], \text{Prc} - \vartheta\text{hl}\,[\text{u}, 2], \underset{j=1}{\overset{F}{\forall}} ftr\,[\text{u}, 2, \text{j}] \right\} \rightarrow (3)$$

$$D(u) = \left\{ \underset{K=1}{\overset{M}{\forall}} mdl\,[\text{u}, 1, \text{k}], \underset{K=1}{\overset{M}{\forall}} mdl\,[\text{u}, 2, \text{k}], ln\,[\text{u}, 1], ln\,[\text{u}, 2] \right\} \rightarrow (4)$$

$$E(u) = \{\text{downpay[u]}, \text{P\_uplim}\,[\text{u}, 1], \text{P\_uplim}\,[\text{u}, 2], \text{Cur\_uplim}\,[\text{u}]\} \rightarrow (5)$$

$$SI(u) = \{A(u) \cup B(u) \cup C(u) \cup D(u) \cup E(u)\} \rightarrow (6)$$

$$\vartheta\text{pd[u]} = \text{SVM} - \text{detPI}\,(SI(u), CDT) \rightarrow (7)$$

ϑpd[u] Is computer from SI(u) Using SVM - detPI Function which uses data of customers stored in CDT.

4.4 Determination of possible models

In order to determine possible models first we compute the number of clusters from PUR-CDT where PUR-CDT is the subset of CDT which consists of all those customers for whom visible purchase decision is 1, as shown in (8) .It denotes that

$$\text{PUR} - \text{CDT} \subseteq \text{CDT} \;\; \text{s.t.}$$

$$\underset{X(\beta) \in \text{PUR} - \text{CDT}}{\forall} (\text{X}(\beta) \in \text{CDT and } \vartheta\text{pd}[\beta] = 1) \rightarrow (8)$$

For each record $x(\beta) \in \text{PUR} - \text{CDT}, \text{x(u)}$ has to belong to CDT And it's visible purchase decision or ϑpd[β] should be equal to 1.

Models appropriate for the new or u-th customer is denoted by MOD[u] and defined in (9).

$$\text{MOD[u]} = \text{MOD1[u]} \cup \text{MOD2[u]} - \text{MODDEL[u]} \rightarrow (9)$$

Where MOD1[u] Is the set of models determined from PUR-CDT using SVM and MOD2[u] is the same determined using k-means clustering algorithm. MODDEL[u] is null or empty set provided Prc_cons[i] is 0, else it is the set of models priced above Cur_uplim.

$$\forall \quad \text{model}\,[u,\vartheta] \in \text{MOD1}[u] \quad \text{if} \quad \vartheta = 1 \quad \text{SVM} - \text{detmodel}[\text{SI(u)}\ \vartheta, \text{PUR} - \text{CDT}] = 1 \ \rightarrow (10)$$

There SVM - detmodel is a support vector machine based function that returns 1 if new or u-th customer has possibility of buying vehicle- model [ϑ] Intention of purchasing at least one Model is ensured by PUR-CDT.

In order to compute MOD2[u], ML-ASA clusterizes Entries of PUR-CDT in K'number of Clusters using k-mean algorithm where K' Is found out using ELB-DETNUMCLUS function that obtains optimum number of clusters using elbow method.

$$K' = ELB - DETNUMCLUS\ (PUR - CDT) \ \rightarrow (11)$$

Based on this, K' number of clusters, denoted by CLS [y] are obtained where $1 \leq y \leq K'$.the function CLUSTERIZE is used for dividing $(PUR - CDT\ \cup SI[u])$ into clusters as shown in (12).

$$\forall \quad CLS[y] = CLUSTERIZE\ (PUR - CDT\ \cup SI[u], K') \ \rightarrow (12) \quad y = 1$$

Assuming that u-th customer belongs to z-th cluster s.t. $1 \leq z \leq k'$, then

$$\forall \quad vehicle - model[q] \in MOD2[u] \text{ provided } \rightarrow \quad (13) \quad q = 1$$

$$i)\ cust(x) \in CLS[z].attrid\ and$$
$$ii)\ model\ [x,q] = 1$$

This means that a vehicle model is included in MOD2 provided it has been purchased by at least one member of CLS[z]. CLS[z].attrid specifies the customer identifier of members of CLS[z].

The q-th vehicle model or vehicle-model[q] will belong to the set MODDEL[u] provided the consumer is price constrained and price of that model is higher than mentioned upper limit of the consumer. This is shown in below mentioned conditions i, ii and iii.

$$i)\ Prc\_cons = 1$$
$$ii)\ vehicle - model[q] \in (MOD1[u] \cup MOD2[u])$$

iii) $vehicle - model[q].price > Cur\_uplim$

5. Identify The Features To Target

Product features mentioned by u-th customer is denoted by FR(u). If an attribute has been mentioned by u-th customer and also mentioned by centre by the cluster CLS[z] then that attribute is identified as essential by the Salesperson .This is mathematically illustrated in (14).

$$\forall f' \in FR(u),\ f' \ is\ extracted\ provided\ f' \in CLS[z].features \ \rightarrow \quad (14)$$

Note that CLS[z] features is the set of product features emphasized by center of cluster CLS[z].

6. Demonstration of Models

All models which may be preferred by u-th customer are specified in MOD[u]. Among these MOD[u][1] Specifies the first model, MOD[u][2] Specifies The second model, … MOD[u][n] Specifies the last model where n = cardinality of MOD[u] These models are demonstrated in decreasing order of

popularity where popularly is computed in (15). PL (MOD[u][l]) denotes popularity of l-th Model which may be preferred by u-th customer, where $1 \leq l \leq n$.

$$PI(MOD[u][l]) = \frac{ARMA - Pred - Sales\ rec\ (MOD[u][l])}{MAX\ (\ \forall_{l'=1}^{n}\ ARMA - Pred - Sales\ rec\ (MOD[u][l']))} \times \frac{MN - PR\ (MOD[u][l])}{MAX\ (\ \forall_{l'=1}^{n}\ MN - PR\ (MOD[u][l']))} \rightarrow (15)$$

Where $ARMA - Pred - Sales\ rec\ (MOD[u][l])$ specifies predicted sales record of the model $MOD[u][l]$.

$MAX\ (\ \forall_{l'=1}^{n}\ ARMA - Pred - Sales\ rec\ (MOD[u][l']))$ Denotes maximum of predicted sales records of all the models in the list of models $MOD[u]$.

$MN - PR\ (MOD[u][l])$ is defined in (16).

$$MN - PR\ (MOD[u][l]) = (\gamma(MN - PR\ (MOD[u][l])) - \delta(MN - PR\ (MOD[u][l])) + \psi(MN - PR\ (MOD[u][l]))) \rightarrow (16)$$

Where $\gamma(MN - PR\ (MOD[u][l])$ denotes the number of times $MOD[u][l]$ was explicitly mentioned by the customer; $\delta(MN - PR\ (MOD[u][l])$ is the number of times $MOD[u][l]$ Have been mentioned but not purchased and $\psi(MN - PR\ (MOD[u][l])$ denotes the number of times the vehicle model was not initially mentioned by the u-th Customer but ultimately purchased. Popularity of a model increases if i) ARMA Predicted sales record is high ii) the model has got a huge number of mentions, and iii) most of time the model was mentioned by a customer, it was purchased.

7. Experimental Results

During experimentation, we have Taken 2000 samples from fifteen different showrooms in Kolkata belonging to various reputed automobile companies such as Maruti Suzuki, Hyundai, Tata, Honda, Mahindra, Kia, Porsche, Toyota and Bajaj. Programs are written in R 4.0.3 and performance metrics are i) accuracy ii) precision iii) recall iv) MEANVPD v) MEANTTC and vi) MEANVISTPPR . Mathematical expressions for these appear in (17) t o (22).

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \times 100 \rightarrow (17)$$

$$\text{Precision} = \frac{TP}{TP+FP} \times 100 \rightarrow (18)$$

$$\text{Recall} = \frac{TP}{TP+FN} \times 100 \rightarrow (19)$$

$$\text{MEANVPD} = \frac{\sum Purchase-decision}{E} \times 100\% \rightarrow (20)$$

$$\text{MEANTTC} = \frac{\sum Time-to-convince}{E} \rightarrow (21)$$

$$\text{MEANVISTPPR} = \frac{\sum NO-of-visits-per-purchase}{E} \rightarrow (22)$$

Accuracy denotes the degree of overall correctness for a machine learning model. Precision shows how often a machine learning model is correct when predicting the target class. Recall demonstrates whether a machine learning model can find all objects of target class. MEANTTC is the mean time to convince a customer as required by a salesperson. E Is the total number of entries associated to each company's SDB or sales database. MEANTTC is mean time in hours required to convince a customer. MEANVPD is mean of the visible purchase decision where summation of purchase decision is surely less than E because each purchase decision is either 0 or 1. To simplify the process of representation and demonstrate the improvements produced by the proposed scheme ML-ASA, we express MEANVPD in percentage. MEANVISTPPR specifies mean number of visits of customers to showrooms, on per purchase basis. These metrics are measured company - wise, That is computed separately for each of the companies mentioned earlier. MEANTTC, MEANVPD and MEANVISTPP are measured with respect to their previous values and values after applying ML - ASA. The results are demonstrated below.

Table 5: accuracy, precision and recall

	Accuracy	precision	recall
Maruti Suzuki	92.01	90.83	91.67
Honda	93.45	90.22	90.59
Hyundai	91.60	89.99	91.81
Kia	93.46	91.12	93.81
Toyota	91.29	90.79	91.67
Bajaj	90.88	91.46	89.76
Tata	89.67	90.67	90.48
Mahindra	90.16	89.94	92.89
Porsche	93.48	89.78	89.83

All of these values in tables are higher than 89%. Therefore the machine learning model is very efficient. It can predict the purchase decisions of customer very well. Table 6 demonstrate MEANTTC, MEANVPD and MEANVISTPPR, Both without ML-ASA and with ML-ASA . Among these only MEANVPD is expressed with percents. Graphical representation of these appear in figures 2 to 7.

	MEANTTC		MEANVPD		MEANVISTPPR	
	without ML-ASA	with ML-ASA	without ML-ASA	with ML-ASA	without ML-ASA	with ML-ASA
Maruti	1.52	1.21	76.22%	84.09%	1.63	1.41

Suzuki						
Honda	1.27	1.16	74.82%	82.13%	2.15	1.02
Hyundai	1.40	1.14	75.21%	80.11%	2.61	1.23
kia	0.98	0.71	78.16%	84.91%	1.58	1.09
Toyota	1.18	0.90	71.89%	88.11%	1.46	1.18
Bajaj	1.47	1.10	73.73%	88.32%	1.52	1.23
Tata	1.39	1.22	69.90%	76.62%	2.34	1.17
Mahindra	1.26	1.19	68.67%	86.09%	2.78	1.51
Porsche	1.45	1.12	67.90%	73.15%	1.92	1.34

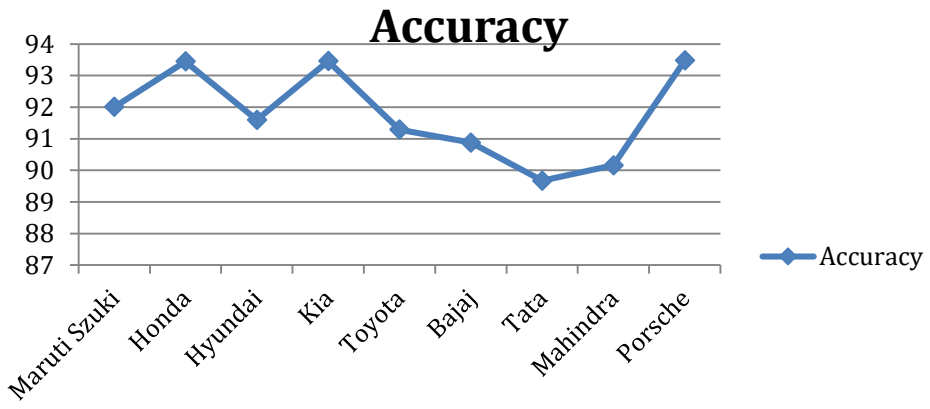

Fig 2: Accuracy w.r.t. companies

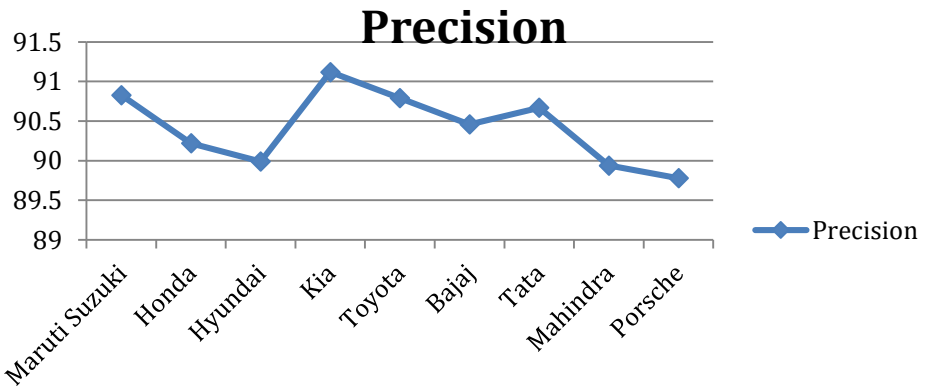

Fig 3: Precision w.r.t. companies

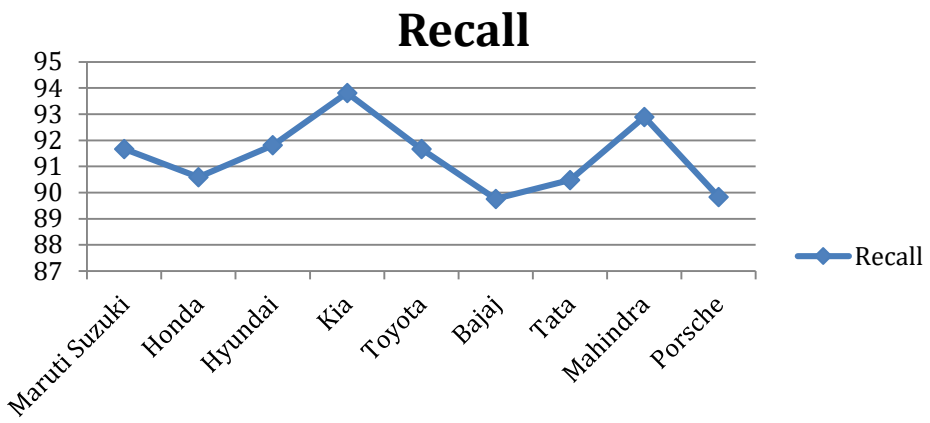

Fig 4: Recall w.r.t. companies

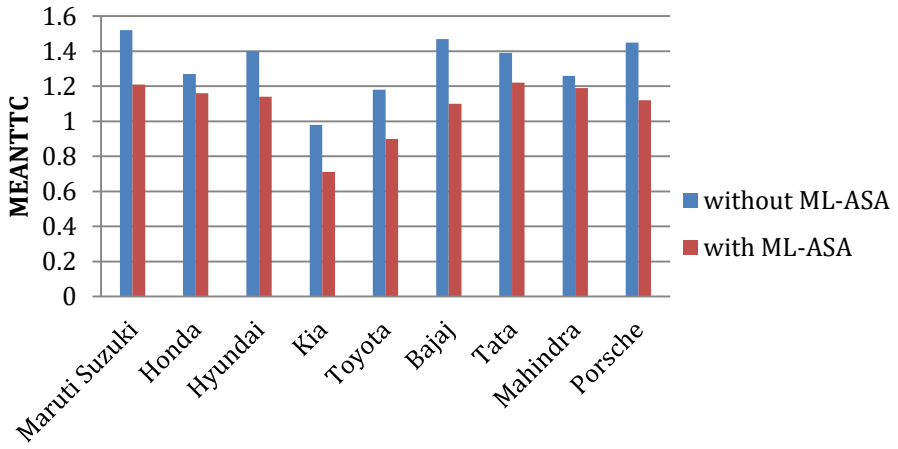

Fig 5: MEANTTC w.r.t. companies

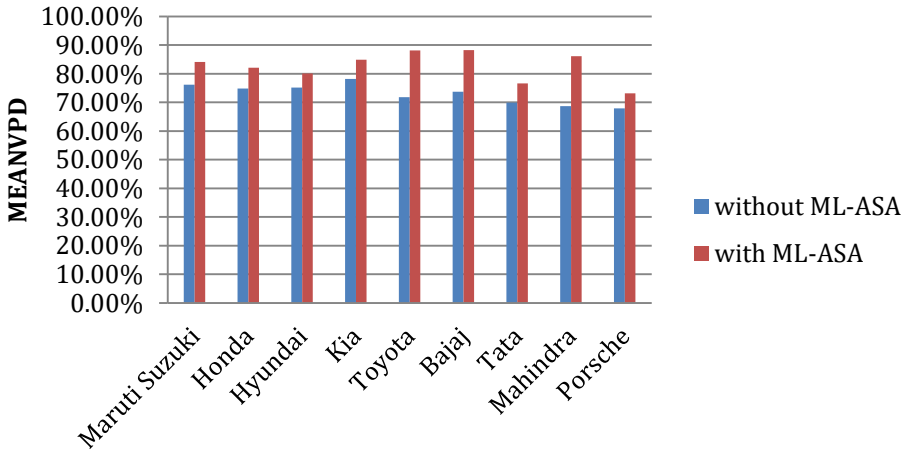

Fig 6: MEANVPD w.r.t. companies

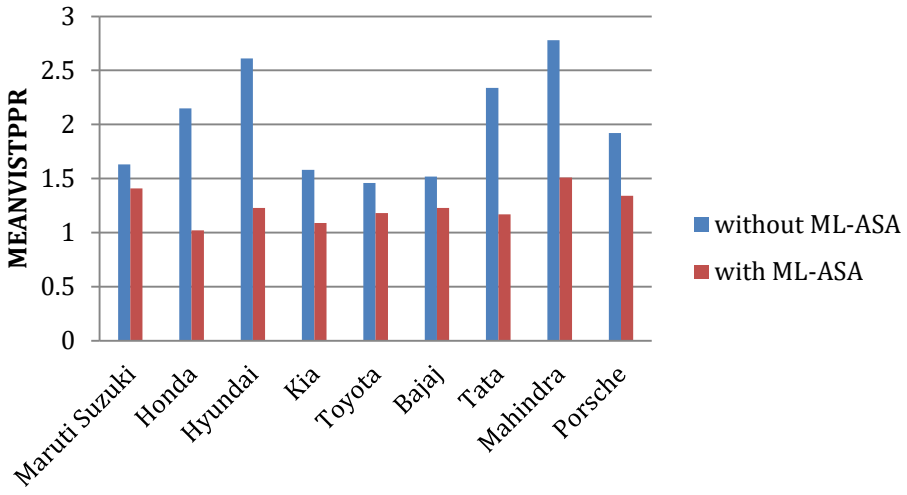

Fig 67: MEANVISTPPR w.r.t. companies

Mean time duration required to convince a customer is much less in ML-ASA applying systems because the conversation between salesperson and the customer continues in a guided manner. The talk concentrates on various features which are not just explicitly specified by the consumers but also those on which the consumer may be interested in his subconscious mind, as revealed by the center of clusters of consumers. This also reduces the number of visits of customers to showrooms per purchase, because most of the conversations become fruitful within shorter span of time. Hence, mean number of purchase decisions also improve and the benefit can be seen in each and every company, which specifies that improvement is not dependent on any one company's dataset; It is in general applicable for various automobile companies in India. This specifies that performance effectiveness brought about by ML-ASA is consistent and can be applied in different automobile companies to guide the sales person in identifying intention of the customer and conversing with them in an easy and effective way based on history of behavior of consumers revealed by records in the showroom itself.

8. Conclusion

To the best of Author's knowledge, ML-ASA is the first research work in the literature of decision making for sales persons. In each and every step it guides the sales persons regarding the optimally productive nature of conversation. It instructs if the emphasis should be on persuasion or patience and explanation. Also the method tells whether a single visit to the showroom is sufficient for the current purchase or multiple visits may be necessary. Along with that, ML-ASA provides guidance on set of models to demonstrate and in which order. If the price constraint is heavy on the customer then vehicles higher than mentioned upper limit will be eliminated from the probable set of models. Machine learning has been extensively used here to determine visible purchase decision ($v$pd) and happiness index (happy). Each of these are determined from twenty eight input features. Efficiency of the model has been tested based on showroom data from different companies such as Maruti Suzuki, Honda, Hyundai, Kia, Toyota, Bajaj, Tata, Mahindra and Porsche. For each of these companies it has been seen that accuracy, precision, recall, are higher than 89%, that is, all the values are acceptable. Moreover, it is also evident from the experimental results that mean time to convince and mean numbers of visits per purchase are significantly lesser in ML-ASA assisted conversation compared to the original unguided conversation. Also mean number of visible purchase decisions increase which means that people feel more impressed

by ML-ASA guided explanation and/or persuasion, rather than the traditional approach of vehicle demonstration. The persuasion process here takes lesser time and requires less number of visits, that is, more success is achieved in sales context which less time and effort.

In future the work may be extended to apply recursive feature elimination (RFE) to identify and eliminate the non-essential features. The research may be applied in other companies too, such as Ford, Mercedes etc. Also increase in number of observations may lead to new insights. Along with this, deep learning based techniques can be tried and resultant model can be compared with ML-ASA. Trying similar techniques in the field of sports cars may give rise to different findings because these are extremely expensive luxurious items; very much different from the vehicle products discussed in this article. In this context, particularly the impact of price constraint may be interesting. If this feature is eliminated by RFE then it will indicate that potential customers of luxury sports cars do not care about their price. Otherwise it will denote that price constraint is significant for sports car customers as well.

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