Use of Artificial Neural Network for Inquiry Follow Up System in Sales Operations for Two-Wheeler Automotive Dealership.

Vaidik Bhatt, P Sashikala

Abstract: Artificial neural network can be the good classifier based on its capabilities of supervised learning and back propagation of the error. We have used this capability of ANN for distinguishing buyers and non-buyers in the automotive industry sales to save the time of the sales consultant in order to provide the better services to the potential buyer and convert the inquiry into the sales. Based on the six parameters with the ANN consisting of one hidden layer and 4 hidden units we have checked the results which is satisfying.

Keywords: Based on the six parameters with the ANN consisting of one hidden layer and 4 hidden units we have checked the results which is satisfying.

I. INTRODUCTION

Indian automobile industry is one of the big industries in India with the sales of around 2,50,000 units of car and 16,45,791 units of two wheelers which includes bikes and scooters per month (AutoPunditz). The sales of vehicle depends upon the many factors on the product side, service delivery side and the customer side. (Kotler and Keller, 2006). On the other end the conversion ratio (the ratio of the total sales on total inquiry for the vehicle) in the industry is less compared to other industry. And all the sales responsibility comes to the authorized dealership owner with very less profit margin. There are numbers of inquiry comes every day and there are very few sales consultants there in the showroom to serve the customer and help them with their choice of car. In this case it is impossible for sales consultant to take the good and timely follow ups of the customer and sell the vehicle to them. Because of the sales consultant cannot take the timely and quality follow ups of the customer for the generated inquiry, the customer moves away and there are chances that, customer will buy a competitive vehicle, or buy the same vehicle from the competitor dealership and ultimately dealers loose their business. So, to avoid the lost sales and increase the number of unit sales and profitability and in order to achieve the monthly, quarterly and yearly target, it is very important to take the timely follow ups of the customers. But due to the less sales consultant it is not practically possible. However, sales consultant can prioritize the customer based on their interaction and differentiates the customer with the high probability to buying the vehicle from them than those who has a low probability of buying.

Sales consultant does this bifurcation based on the past experience and behaviour of the customer during the interaction over the phone call, in the show room ar during the test drive. As this method is only the perception of the sales consultant, it is not useful and chances of making the error in the predictions are very high. The strong scientific support and the statistical evidence required to take the decision, otherwise method based on the perceptions can have a dared consequence for the dealership business in automotive field.

II. ARTIFICIAL NEURAL NETWORK

It is very important to classify and distinguish the potential buyers and non-buyers. In this situation, where there are number of parameters has to be considered, Artificial Neural Network (ANN) classifier is s popular classifier with its broad application areas as it focuses on the cost sensitive binary classifications and learning (Zakaryazad and Duman, 2015). Here, in this process of automobile sales, misclassification of buyers and non-buyers can have a dared consequences for the dealership, as the sales consultant spends time and energy to the non-buyers and don’t have a time to attend and respond to the queries of potential buyers.

Moreover, there is a profit for the true classification. For example, if the system has classified buyer in the category of buyer than sales consultant can put the effort to pitch the product and take the routine and timely follow ups from which the potential buyer can turn in to the buyer of the vehicle. On the other end, if the system has classified non buyer as a non buyer than sales consultant will not put the effort rather the inquiry will be passed to the sales CRE (customer relationship executive) team for the further follow ups.

III. OBJECTIVE

This paper aims towards the using the supervised learning of the Artificial neural network using the descriptive statistics and prioritize the customer on their probability of purchasing the vehicle.

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IV. RELATED WORK

Zakaryazad and Duman (2015) has used artificial neural network for the credit card fraud detection and the direct marketing, in which they have classified the defaulters in credit card and respondents in the direct marketing event with the artificial neural network and the supervised learning.

Apart from this there are numerous studies done on the cost effective algorithm, cost sensitive boosting, meta – heuristics, heuristics etc. (Chen et al., 2011; Sahin, Bulkan and Duman, 2013; Lan, Patuwo and Zhang, 2010; Kim, Kim and Suh, 2012; Fan et al., 1999). On the other side some authors also worked on the cost effective or cost sensitive ANN (Pendharkar, 2005; Pendharkar, 2008; Pendharkar, 2002; Zheng, 2010). On the other end, Salchenbeger (1992) has distinguished healthy and failed institutions by the neural networks.

Apart from the neural network several other methods was also used for the cost sensitive learning, in which cost are associated with the right or wrong classification. (Sahin et al., 2011) has given the cost sensitive approach using the decision tree for the fraud detection for credit card usage fraud online or at the PoS (Point of Sale).

(Chen et al., 2010) also used genetic algorithm for the selection of the variables which can forecast the bankruptcy prediction. This was also a cost sensitive learning. Lan et al., 2010 also gave the classification based on the cost of misclassified items by neural networks. In which the authors have explored the issues of asymmetric misclassification cost and imbalanced group sizes by application of neural network for thyroid disease diagnostics.

Zheng (2010) developed three cost sensitive boosting algorithm and distinguished between the defect prone modules and non-defect prone modules in the context of the software with this different type of classification. The scenario of the back propagation of error and there by the correct classification if multiple cost expansion is developed by Ma et al. (2012). Saad et al.(1998) has developed an approach of minimization of root mean square error (RMS – Error) to modify the standard and original ANN.

Sun et al. (2008) has developed a novel technique for fashion retailing, which also highly complex and versatile market like the two wheeler automotive, by using novel neural network technique called as extreme lerning machines. Which investigates the relationship between the sales amount and the factors or antecedents which affects the demand, in the area of Hong Kong. By using the neural network, good amount of relationship has been established between the sales of the retail garments and the factors affecting the demand.

Problems and current practices

In the semi structured interview with the Director of Operations and ECO of different brands of a large automobile group we found the problems with their current practices.

In an interview with the director of operations the respondent told that “there are many inquiries comes in a day, but the conversion ratio is low as we have a limited number of sales force – which is a constrain” the CEO responded that “sales consultants are not able to do the proper follow-ups with the customers due to the large number of inquiries and due to that dealership is facing the issues of the lost sales”. While asking about the current practices both CEO and Director responded that “ experience consultant judge the customer on the basis of their past experience and bifurcates the potential buyers and non-purchasers, which may not be fruitful always. ”

Solution

For every decision in the business, data is important and today the data exploitation is there almost in all industry. Statistically significant data can leads towards the better decision in compare with the decision taken by the preveous experience by a sales person as there are some scientific support with the statistical evidence to explore a new relationships and find out the correlation, covariance and other statistical significant studies to predict the future behaviour of the buyer here in the automobile dealership industry.

We have decided to use the supervised learning and ANN for building an solution for the problem of prioritising the customer on the basis of the probability of buying or purchasing the vehicle. As the artificial neural networks finds out the relationship on its own by the back propagation of the error during the training, by finding out the difference between the actual outcome and the observed outcome, and recalibrating the weights at the hidden nodes.

V. RESEARCH DESIGN AND EXPERIMENTAL RESULTS

from the total of 1500 data of 2 wheelers sales and inquiries in a month with some parameters like Sales Consultants age in month with the organizations, customer’s age, customer’s last purchase, distance from the dealership and customer’s location (Home/ office), model, price and actual decision of customer to purchase or not we found 1300 correct and usable data (Table 2).

On this data we have used Bernoulli’s equation to bifurcate the supervised learning data and holdout data for the testing after the training and initial testing completed. Which resulted in the 27.5% of holdout sample. After that as per the criteria of ANN we have divided data in to 80:20 for the training and testing (Table 2).

We have used the network with one input layer with six input units, one hidden layer with four hidden units and one binary output layer (1 for purchase and 0 otherwise). The stopping criteria was not set as a number of epochs, rather we have used the one consecutive step with no decrease in error as a stopping criteria for the proposed network.

For both layers (hidden and output) activation function was set as sigmoid and the error function was set as the sum of square of the error on the one binary dependent variable (Table 3).

The Structure of the proposed ANN can be seen in figure 1.

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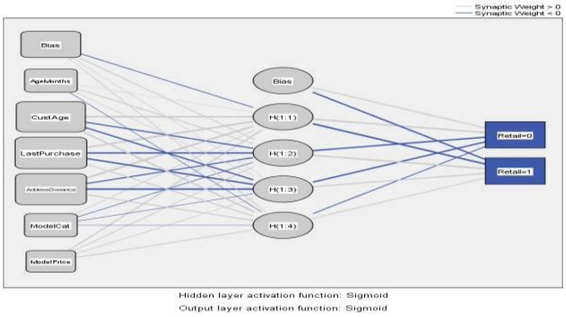

Figure 1: ANN Structure with Variables, Hidden Layers, units and output layers units

Classification

Sample	Observed	Predicted 0	Predicted 1	Percent Correct
Training	0	410	89	82.2%
	1	170	96	36.1%
	Overall Percent	75.8%	24.2%	66.1%
Testing	0	86	17	83.5%
	1	42	33	44.0%
	Overall Percent	71.9%	28.1%	66.9%
Holdout	0	184	36	83.6%
	1	97	40	29.2%
	Overall Percent	78.7%	21.3%	62.7%

Dependent Variable: Retail

Table 1: Classification results from the proposed ANN.

Case Processing Summary

		N	Percent
Sample	Training	765	58.8%
	Testing	178	13.7%
	Holdout	357	27.5%
Valid		1300	100.0%
Excluded		200	
Total		1500	

Table 2: Number and percentage of observations used and classified into various categories for running the ANN

Network Information

Input Layer	Covariates	1	AgeMonths
		2	CustAge
		3	LastPurchase
		4	AddessDistance
		5	ModelCat
		6	ModelPrice
	Number of Units[a]		6
	Rescaling Method for Covariates		Normalized
Hidden Layer(s)	Number of Hidden Layers		1
	Number of Units in Hidden Layer 1[a]		4
	Activation Function		Sigmoid
Output Layer	Dependent Variables	1	Retail
	Number of Units		2
	Activation Function		Sigmoid
	Error Function		Sum of Squares

a. Excluding the bias unit

Table 3: information about input, hidden and output layers with the activation function and error function

Model Summary

Training	Sum of Squares Error	158.240
	Percent Incorrect Predictions	33.9%
	Stopping Rule Used	1 consecutive step (s) with no decrease in error[a]
	Training Time	0:00:00.08
Testing	Sum of Squares Error	37.395
	Percent Incorrect Predictions	33.1%
Holdout	Percent Incorrect Predictions	37.3%

Dependent Variable: Retail

a. Error computations are based on the testing sample.

Table 4: Actual results for the ANN after the supervised learning on the holdout sample about total misclassified predictions

Parameter Estimates

Predictor		Predicted: Hidden Layer 1 H(1:1)	H(1:2)	H(1:3)	H(1:4)	Output Layer [Retail=0]	[Retail=1]
Input Layer	(Bias)	-.317	.458	.196	.292		
	AgeMonths	.075	.540	.237	-.174		
	CustAge	2.420	-.979	-1.192	1.591		
	LastPurchase	2.493	-1.728	-1.700	.639		
	AddessDistance	2.705	-.963	-1.973	.977		
	ModelCat	.293	-.243	-.211	-.070		
	ModelPrice	.701	.343	.308	.612		
Hidden Layer 1	(Bias)					.873	-1.194
	H(1:1)					1.908	-1.813
	H(1:2)					-1.643	1.871
	H(1:3)					-1.635	1.395
	H(1:4)					-.349	.503

Table 5: Parameter and weight estimates for the hidden layers and the output layers

on the other side, ANN gave the information about the normalized importance of the variables which are most important for a customer to purchase the vehicle which shows that time from the last purchase is most important for purchasing the new vehicle and model price are least important. Which shows that the customers are less price sensitive while purchasing the vehicle as they are buying it on the auto loan as time from the last purchase is most important as after their loan repayment period completes customers sell off the old vehicle (on the price around IDV) and purchases the new one.

Independent Variable Importance

	Importance	Normalized Importance
AgeMonths	.061	20.3%
CustAge	.267	89.2%
LastPurchase	.299	100.0%
AddessDistance	.291	97.1%
ModelCat	.062	20.9%
ModelPrice	.020	6.8%

Table 6: Normalized Importance of Variables

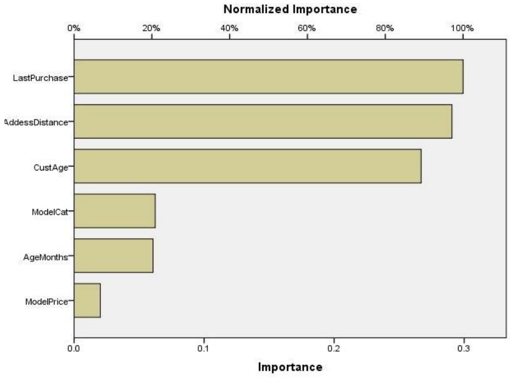

Figure 2: Normalized importance of variables

VI. DISCUSSION

After running this model on Artificial neural network in IBM Statistics 21.0 with one hidden layers and four hidden units, we have checked the same on the different artificial neural network architecture with different numbers of hidden layers and different numbers of hidden units and calculated the output, outputs are more or less similar with minor changes in to the final classification results. On the other end, we have also used logistic regression for the predicting the output for the same, as logistic regression also deals with the binary independent variable and categorical or continuous input variables. For these test also, IBM Statistics 21.0 is used. The results are shown in the table below.

Experiment No	No. of Hidden Layers	No. of unit in Layer 1	No of Unit in Layer 2	Result
1	1	4	0	66.9%
2	2	4	3	70.2%
3	2	4	5	69.1%
4	2	4	4	68.5%
5	2	3	4	68.3%
6	2	3	3	64.8%
7	Logistic Regression			69.2%

From the given table, one may infer that, Artificial neural network with the 2 hidden layers and 4 hidden units in layer one and three hidden units in layer 2 works best for this dataset. However, one may not claim that, in any situation and with any data, ANN with two hidden layers and 4 hidden units in layer one and 3 hidden units in layer two will work best. Results outputs are given below for all the experiments.

Classification

Sample	Observed	Predicted 0	Predicted 1	Percent Correct
Training	0	617	72	89.6%
	1	258	86	25.0%
	Overall Percent	84.7%	15.3%	68.1%
Testing	0	281	24	92.1%
	1	115	47	29.0%
	Overall Percent	84.8%	15.2%	70.2%

Dependent Variable: Retail

Experiment 2

Classification

Sample	Observed	Predicted 0	Predicted 1	Percent Correct
Training	0	628	85	88.1%
	1	257	96	27.2%
	Overall Percent	83.0%	17.0%	67.9%
Testing	0	254	27	90.4%
	1	107	46	30.1%
	Overall Percent	83.2%	16.8%	69.1%

Dependent Variable: Retail

Experiment 3

Classification

Sample	Observed	Predicted 0	Predicted 1	Percent Correct
Training	0	644	42	93.9%
	1	288	81	22.0%
	Overall Percent	88.3%	11.7%	68.7%
Testing	0	282	26	91.6%
	1	114	23	16.8%
	Overall Percent	89.0%	11.0%	68.5%

Dependent Variable: Retail

Experiment 4

Classification

Sample	Observed	Predicted 0	Predicted 1	Percent Correct
Training	0	602	115	84.0%
	1	216	129	37.4%
	Overall Percent	77.0%	23.0%	68.8%
Testing	0	231	46	83.4%
	1	93	68	42.2%
	Overall Percent	74.0%	26.0%	68.3%

Dependent Variable: Retail

Experiment 5

Classification

Sample	Observed	Predicted 0	Predicted 1	Percent Correct
Training	0	699	0	100.0%
	1	346	0	0.0%
	Overall Percent	100.0%	0.0%	66.9%
Testing	0	295	0	100.0%
	1	160	0	0.0%
	Overall Percent	100.0%	0.0%	64.8%

Dependent Variable: Retail

Experiment 6

Classification Table[a]

Observed			Predicted: Retail 0	Predicted: Retail 1	Percentage Correct
Step 1	Retail	0	885	109	89.0
		1	353	153	30.2
	Overall Percentage				69.2

a. The cut value is .500

Experiment 7

VII. IMPLICATIONS AND CONCLUSIONS

The results tells us that ANN can be the good classifier as it can classify more than 70% as a correct classification, which can be helpful for the industry, as the automobile industry working on the very low conversion ratio, (the conversion ratio of our dataset which we have used in 9.15% only) the correct classification above more than 70% helps a lot.

This does not mean that dealership has to occur a lost sales, as less than 30% are misclassified, which may have a potential buyers. It is a good practice that transfer that low priority calls to the CRE team, as they can also confirm the status of customer about the decision for purchasing the vehicle. If CRE calls customer and found that customer is a potential buyer than, that inquiry has to be transferred to the sales consultant.

A new finding came here is that customers who has past purchased the vehicle on the loans are going to buy the new vehicle at the end of the loan end period. Dealerships can look in to their own past data, for which customers the loan period is just ended to pitch a new product and do the cross selling.

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