An Analytical Study of Influencing Factors on Consumers' Behaviors in Facebook using ANN and RF

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Abstract. This study looks at factors that effect on consumers' intentions to buy online, especially from Facebook. We enlighten the impact and analyze how factors influence consumers to purchase products from Facebook. Specifically, we observe consumer behaviors using different viewpoints. Some viewpoints are related to psychology, and some are relevant to the experiences of consumers. We emphasize the analysis of those intentions that work behind the consumption of any product from a Facebook page or group. An analytical study in which the contributions of all assumptions are investigated and reported. We gather the perceptions of 505 people regarding buying products from Facebook pages or groups. In terms of relative contributions, we find two models and evaluation matrices that indicate the accuracy of those models to predict the consumers' purchases from Facebook pages or groups.

Keywords: Data Mining · Machine Learning (ML) · Artificial Neural Network (ANN) · Random Forest (RF) · Consumer Behavior

1 Introduction

Electronic Commerce (e-commerce) mostly focuses on web-based product buying and selling [4]. However, now a days, the main thought of e-commerce is divided into two parts. One is e-commerce another one is Facebook commerce (F-commerce) [20]. Hence, several small businesses are operating only on F-commerce though they have an e-commerce website. Our primary focus is to identify these small market aspects and how consumer behavior can have a vital role in this F-commerce. This study unfolds the direction of consumer interests in buying goods from the F-commerce groups or pages.

Consequently, the challenge being faced by all marketers today is how to influence consumers' purchasing behavior in favor of their products or services [3]. Knowledge of purchasing behavior, therefore, sheds light on the nature that how consumers think, feel, negotiate, and choose between current alternatives (e.g., brands, goods, and retailers), as well as on the consumer environment (e.g., society, friends, media). As a large number of people use FB and most of the small businesses are operating in FB, this study focuses on FB among different social media. Hawkins et al. [11] stated "All marketing decisions are based on assumptions and knowledge of consumer behavior". For acquiring the expectations of consumers towards a small market place like F-commerce, we need to know about consumers' psychology in the context of buying any product.

We illustrate the effect and apply the ANN and RF decision tree algorithm in experiments on real-world dataset from the Facebook groups, pages, and potential consumers. The visualizations of how expectations are influenced by particular acts or sequence of actions carried out by consumers have been shown in this study. Main objectives of our total study are as follows.

- To explain the reasons behind buying something from Facebook pages and groups.
- To construct ANN and RF decision tree models from the dataset for prediction.
- Lastly, to show what factors are driving consumers to purchase more.

The rest of this paper's sections are organized in the following order. In section 2, we include relevant works on the study of consumer behavior analysis, in particular, using machine learning. Section 3 illustrates the methodology. In section 4, we describe the experiment with models. We show the results and observations in section 5 and discuss future works in section 6 before we conclude.

2 Related Works

Heijden et al. [21] researched on 228 online consumers and tried to determine consumers' intentions to purchase online products. This research presented the empirical study of a conceptual model from which we can understand the types of factors effect the actions of the consumers, adapted from [8] by Fishbein et al. The foundation of this model is a relationship between online buying behavior and online buying intention. In this study, this model is a base for defining the purchase intentions of online consumers. There are some issues in the sense of competitive market and some critical factors that attract consumers to purchase where three main factors are usability, interactivity and psychological matters in online shops [6]. Kumar [16] gave a summary of the advertising actions on consumers. Besides that, the elements of consumer decision-making were identified by Khaniwale [14]. The author discussed about the internal and external factors of purchasing products.

Artificial Intelligence (AI)'s advancement helps business enterprises analyzing the consumers' behaviors to another degree. Business organizations strongly emphasize on scrutinizing consumers' feedbacks to make the best possible decisions for their businesses. As a result, in recent years, many research works have been carried out on digital signage [18], shopping atmosphere [7], and consumers' reactions [1,9,15,17]. Alhendawi et al. [1] applied ANN to develop an expert system for predicting a Management Information System (MIS)'s characteristics by reviewing end users' comments. Besides developing the AI-based tools, many sections of research are being conducted on framing consumers' emotions, such as Kumar et al. [15] analyzed the consumers' emotions on their reviews over Amazon web resources with the combination of Natural Language Processing (NLP) and Machine Learning (ML) models.

Recently, deep learning has been applied to plenty of consumers' reaction investigation tasks. Gloor et al. [9] developed a system tool named *Tirbefinder* by analyzing consumer behavior on Twitter. The research's crucial contribution is that the tool can categorize the consumers by applying word embedding and LSTM[1] RNN[2] on their tweets in three macro-categories: alternative realities, lifestyles, and recreations. Lang et al. [17] applied RNN on consumers' actions history data collected from Europe's renowned fashion platform Zalando. In this collaboration, they predicted the probability of consumers' orders without explicit feature engineering and achieved a better result than that of other machine learning algorithms.

3 Methodology

In this section, the most significant steps of this research have been described. First, the data have been collected, then have been engineered and divided into training and testing data. After that, the training dataset has been fitted with the proposed models. Finally, the testing dataset has been predicted through the RF and ANN models. From starting to prediction on testing data using the models step in Figure 1.

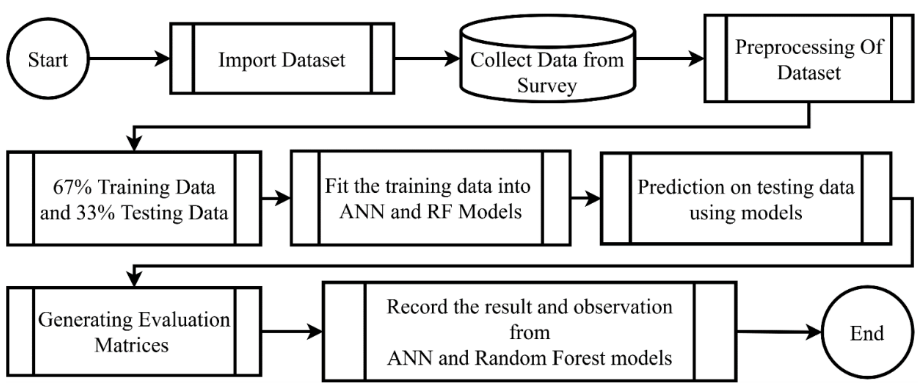


Fig. 1: Work-flow of the analysis.

[1] LSTM: Long Short-Term Memory
[2] RNN: Recurrent Neural Network

3.1 Sample Collection and Dataset

Our samples have been collected from Facebook buying and selling groups of authentic Facebook e-commerce consumers. The responses are collected through Google form. The participations of 505 people have finally been recorded from the survey. Attributes are chosen based on the parameters that require for the extraction of consumer behavior. We choose questions for survey based on Fishbein et al. [8]'s conceptual model and the attributes are chosen from those questions. Some attributes are derived from the responses of participants. The total number of dataset attributes is 22 with the number of instances being 505.

Table 1: Participants' profile sample (N=505)

Question	Count	Percentage
Age		
11-30	477	95%
31-60	25	4%
$\leq$90	03	1%
Gender		
Male	419	83%
Female	83	16%
Other	03	1%
Time spend in FB		
$\leq$ 2 Hours	69	14%
$\geq$ 2 Hours	436	86%
Years of activation in FB		
1 year	05	1%
2 years	08	2%
3 years	18	3%
4 years & more	474	94%
Buy anything from FB		
Buy from FB	294	59%
Not buy from FB	211	41%

Table 2: Influencing factors (IF) of participants from FB

Factors	Positive	Negative
Not sure	36	469
Having less time	47	458
Influenced by others	82	423
Special discount and offer	154	351
Page Ratings	139	366
Page Advertisements	92	413

The profiles of participants are described in Table 1 and the influencing factors (IF) work behind the purchase of participants from FB pages or groups are described in Table 2.

3.2 Random Forest Algorithm

A decision tree [19] is a classifier which expresses itself as a space partition of a recursive instance. From the concept of the decision tree, T.K.ho develops a tremendous ML algorithm named *Random Forest* [13]. In a decision tree, there exist low bias with high variance, whereas in RF, there exist low variance with low bias. Rather than having one decision tree, we have multiple decision trees in RF.

In Random Forest algorithm, feature and row sample $d(d_1, d_2, d_3, ...d_n)$ have been selected to construct decision trees from the training dataset D, where $d < D$. It is not obvious that each feature and row sample need to be identical. For each d there are decision tree models M $(M_1, M_2, M_3, ...M_n)$. After applying bagging on M, the final prediction has been done. In the terms of regression, RF chooses the mean or median of the individual predictions to have the final result. In comparison with other single tree classifiers, RF shows better performance than algorithm C4.5 or J48 [5]. In the context of error rate generalization and resistance to noise, RF does better though it makes computation slower.

3.3 Artificial Neural Network

Artificial Neural Network (ANN) [10] is an information processing prototype that perceives the environment's experiences inspired by the human brain. In an ANN, multiple layers are connected to create a network where each layer consists of different units. The first and last layers are the *input* and *output* layers, and the other layers are called the *hidden layer*. A unit of a particular layer is forwardly connected to its next layer's units; by following this process, the network is formed from the input layer to the output layer.

The connection between two units creates an edge, and a randomized weighted value passes from one layer to another through the units. A value is measured from an inner calculation of connected units' values and weight metrics between two layers. Then, the value passes through an activation function which is contained by an unit as it's final value is in pass. After calculation of the final layer value, a backpropagation algorithm is applied to update the weights so that the network can learn as correctly as possible [12]. The general equation for an input layer (x_{i-1}) and corresponding output layer (x_i) is given below -

$$x_i = \sigma(\sum_{k=1}^{n} W_{i-1} \cdot x_{i-1} + b); where\ k = 1, 2, 3.......n\ number\ layer$$

Here the symbol σ denotes the sigmoid activation function, W represents the weights between two units of connected layers $(k-1, k)$ and b represents the bias unit.

4 Experiment with Models

In data preprocessing, the data have been converted from text to numerical values. Then the categorical features have been deducted: age, gender, and profession for the experiment purpose. Next, the dataset is shuffled 150 times before split. The data have been divided into training and testing dataset where 67% are training dataset, and 33% are the testing dataset.

By using sklearns (scikit-learn), a python predictive data analysis library , we apply RF on our dataset. Random Forest constructs 20 identical decision trees from our given dataset. Each node split is based on the answer of a question. The question asked is based on a value of a feature. From the question's answer a data point moves down along the tree. So, no question is asked to any leaf node. From 20 trees here, we give a tree as an example (Figure 2). In the tree, each node contains an information 'gini' which is a probability of the randomly chosen sample in a node [2]. As we shift down the tree (Figure 2), the average weighted gini impurity value decreases [2]. Sample contains the number of observations in the node. The prediction of all the samples in the node is a class. In a node, a class is the majority classification for points. The leaf nodes are for the final prediction.

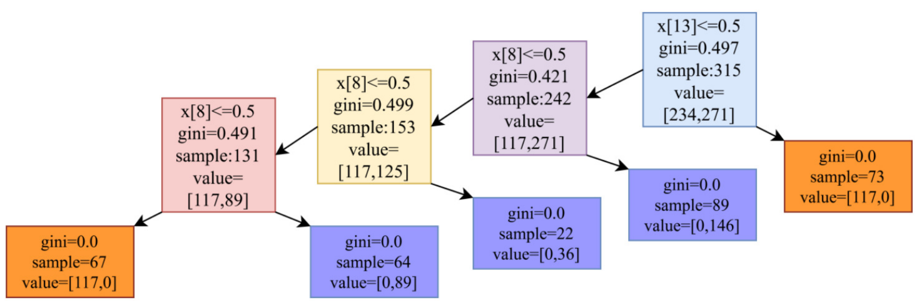


Fig. 2: A proposed random forest decision tree model.

In our proposed ANN model (Figure 3) after the data pre-processing and cross-validation, we feed the 18 featured values and a bias as the input to the ANN. The dimension of the input layer is R^{19}. The hidden layer consists of 4 units that are forwarded to the output unit with another bias unit. So, the dimension of the hidden layer and output layer are R^5 and R^1. We do experiment by using Keras, a python deep learning library where TensorFlow works in the back-end. For training, we run the model for 300 times with a learning rate of 0.01. Besides, to minimize the error, we use the binary cross-entropy loss function and stochastic gradient descent optimizer. Finally, model predicts our testing data through the trained model.

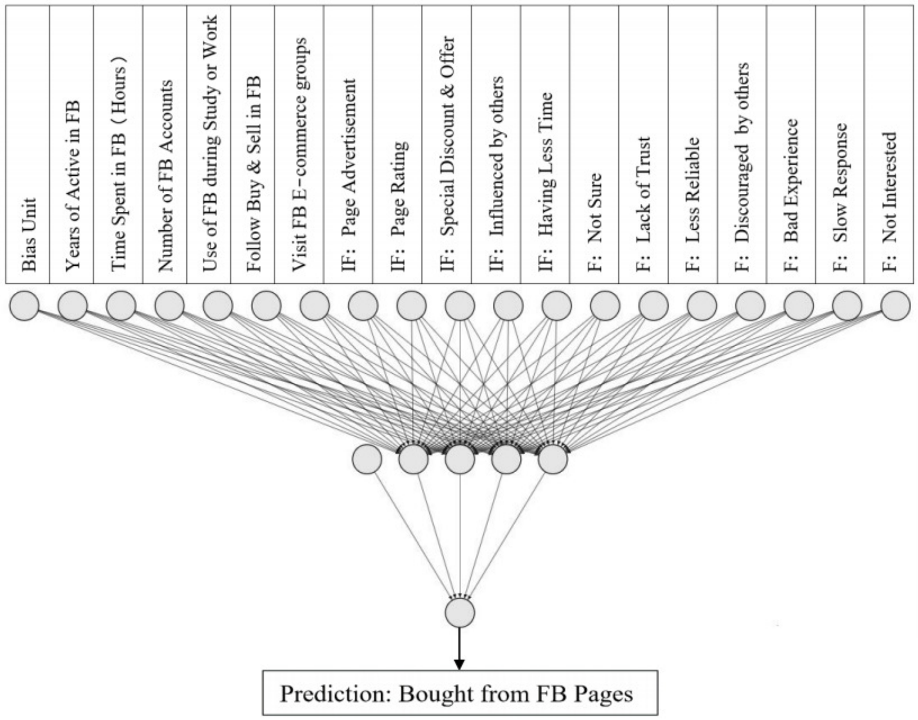


Fig. 3: Proposed Artificial Neural Network model.

5 Results and Observation

After fitting the training data into the RF and ANN model, the test data have been predicted through the models and have been represented in the confusion matrix.

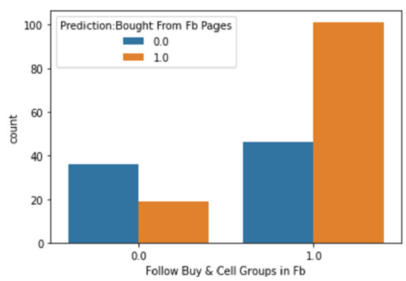
Table 3: Confusion matrix of RF and ANN
(Bought= B, Not Bought=NB)

		Actual Value		RF		ANN	
		B	**NB**	**B**	**NB**	**B**	**NB**
Predicted Value	**B**	TP	FP	118	2	119	1
	NB	FN	TN	1	81	2	80

In Table 3, a confusion matrix table is illustrated, which consists of True Positive (TP), False Positive (FP), False Negative (FN), and True Negative (TN) values from the test data.

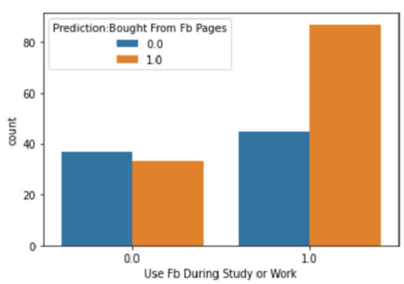
Table 4: Result Table

	Random Forest Decision Tree	Artificial Neural Network
Accuracy	**98%**	**98%**
Precision	**98%**	**99%**
Sensitivity	**99%**	**98%**
Specificity	**98%**	**99%**

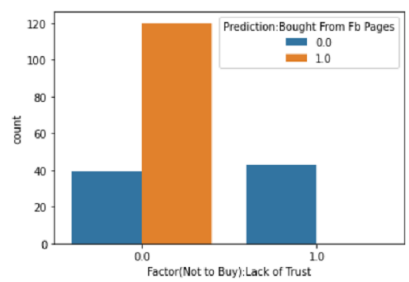


(a) Bar chart for bought from FB pages under following buy and sell FB groups: real vs. prediction

(b) Bar chart for bought from FB pages under special discount and offer: real vs. prediction



(c) Bar chart for bought from FB pages under using of FB during study or work: real vs. prediction



(d) Bar chart for bought from FB pages under the factor (not buying due to lack of trust): real vs. prediction

Fig. 4: Different bar chart analysis of predicted data.

For measuring the RF model's evaluation metrics, the scikit-learn library has been used, and the TensorFlow works in the ANN model. Both models have achieved robust results in terms of accuracy, precision, sensitivity, and specificity. According to Table 4, both models have acquired the same 98% accuracy. The ANN model has performed best in precision and in specificity metrics with 99%, whereas the RF model has attained 98% in both metrics. On the other hand, the RF model has achieved the best score in the sensitivity metrics, which is 99%, and in the case of the ANN model, it is 98% as illustrated in Figure 4.

After applying the ANN Model, The predicted values have been plotted using the matplotlib, a python plotting library. In the x-axis, attributes are taken to compare and to analyze the result. The y-axis demonstrates the count of the value of that attribute. Figure 4a shows that some participants follow FB buying and selling groups, and they have a positive intention to buy from FB pages. Another observation is that some participants do not follow the FB groups or pages, but they are buying from FB groups or pages. So, if any consumer follows any Facebook group or any Facebook page, then the probability of buying from F-commerce is high. According to Figure 4b, it can be noticed that some participants have the intention to buy from Facebook pages if there is any special discount and offer. Some consumers are still buying from Facebook pages though there is no special discount and offer. Figure 4c, reveals that how much participants involve in technology. From Figure 4d it is being seen that, if any consumer has any trust issues from any FB pages, then buying anything from Facebook is zero. Some consumers have no issues with the reliability of any Facebook pages, but have no intention to purchase. The same type of outcome has been observed in the question of reliability, bad experience, and slow response from the Facebook pages.

6 Future Research Directions and Conclusion

Although our proposed systems achieved robust results, it has some limitations which invoke future research directions. Our research has only focuses on Facebook users' activities on F-commerce, which limits the influence of other social media. In future, we would like to specify how and why some classes of the consumers are persuaded to buy products from social media frequently.

In this research work, we have proposed two machine learning models to predict consumers' buying intentions from Facebook groups or pages. We have applied RF and ANN for the prediction that has given a significant result and improve the perceptions of purchase intentions from Facebook. We aim to expand this research and analyze individual tastes more accurately. We hope this research will help to open up a more sophisticated study area for other researchers on consumers' behaviors to achieve significant outcomes.

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