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Research Article

Classifying the Customers of Telecommunication Company to Identify Profitable Customers Based on Their First Ransaction,Using Decision Tree: a Case Study of System 780

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Abstract

Effective knowledge and awareness of customers require the market segmentation, through which the customers who have the same needs and purchasing patterns as well as the same response to marketing plans are identified. The selection of a proper variable is a requirement, among other, for a successful market segmentation. In today' world, on one hand, the consumers are bombarded with new goods and new services, and on the other hand, they face the varying qualities of the goods and services. Consequently, such uncertainties will lead to more vague decisions and cumulative data. The timely and accurate analysis of these cumulative data can bring about competitive advantages to the enterprises. Furthermore, thanks to new technology and global competition, the majority of organizations have focused on Customer Relationship Management(CRM), with the goal of better serving the customers. The customer relationship planning entails the facilitation and creation of interfaces related to market segmentation, which is considered as a requirement for predicting behavior of the prospective customers in the future. Market segmentation refers to the process of dividing the customers into some segments based on their common characteristics while different groups have the least similarity to each other. This is followed by the formulation of plans for new product production, advertisement and marketing in accordance with the characteristics of each group of customers. Current study aims at identifying the profitable customers of a telecom System, based on their first transaction, using binary tree. The customers of System 780 participated in this case study. The dependent variable and independent variable of the study were identified through mining the data of customers, registered in the databases of System 780.Theresults showed the acceptable calculation error in distinguishing the profitable customers from other customers.

Keywords: Segmentation; Telecom; Decision Tree; Customer Relationship Management CRM).

1.Introduction

As the first step in Customer Relation Management, customer segmentation is of great importance in today's competitive business. Many studies have been conducted on the use of data mining technology in customer segmentation as well as its outcomes (Stone and Woodcock, 1996).However, the majority of these studies have segmented the customers from a single perspective, avoiding the use of a systematic methodology. Based on their review of literature, Chan (2008) have classified the methods of customer segmentation into two categories: method-oriented and use-oriented. Authors have proposed some modifications of data clustering techniques (e.g.self-organizing map or the combination of two or more data techniques), with the aim of achieving accurate segments or clusters(Jonker et al., 2004; Lee et al. 2004; Hwanget al., 2004; Kim et al., 2006).These authors either define and create a new variable in clustering process or make use of different variables in different stages of clustering(Stone and Woodcock, 1996;Chan, 2008;Kim and Ahn, 2008;Hsieh, 2004;Chang and Lai, 2005;Sheu et al., 2009;McCarty and Hastak, 2007).McCarty and Hastak (2007)studied CHAID, RFM and Logistic Regression as analytics methods for the segmentation of marketing in a marketing firm, using two different sets of data. The database of the firm consisted of 96551custmors, to whom the firm sent emails. The marketing segmentation was also implemented in 1991 in Digiturk, which is a satellite TV company in Turkey and has eight hundred thousand customers .It is worth noting that in the studies carried out on customer segmentation to date, the value of customers is decided from the decision maker's perspective. Khajvand et al. (2011) and Khajvand and Tarokh (2011) have made use of classic RFM to decide the value of customer. Some studies have used weighted RFM to determine the value of customers(Kaufman and Rousseeuw, 1990;Hung and Tsai, 2008;Hosseini and Ahmadinejad, 2003).

The current study focuses on the process of customers segmentation based on their behavior regarding using the System780.Today, not only are the classification techniques used for the analysis of customer behavior, but

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they are widely used for other applications as well. The classification involves the development of a model used to predict labels of the unknown object classes by making a distinction among the objects belonging to different classes. These classes have already been defined, yet they have not been made distinct and sorted(Han and Kamber, 2006). According to Zhang and Zhou (2004), classification and prediction refer to the process of the identification of a set of characteristics and common model, which are used to define and distinguish classes or the concepts of data. Neural Networks, The Naïve Bayes Networks, Decision Tree, and Support Vector Machines are some examples of classification methods. These classification methods can be used in detecting fake credit cards, fraudulent health insurance, car insurance fraud, corporate fraud and other forms of fraud. Classification is a learning model commonly used in the application of data mining, aimed at detecting financial frauds (Ngai et al, 2010). Classification is made up of two stages: in the first stage, a model is trained, using a training instance. These instances are organized in the form of some Tuples and columns(attributes). One of the attributes, i.e. the class label attribute consists of values representing the predefined class to which each Tuple is assumed to belong. This stage is also known as supervised training. In the second step, an attempt is made to classify those objects which do not belong to training instances. Here, the aim is to form a test sample (Kerkaus et al., 2014). Makhtae et al. (2017) proposeda new classification model, based on the Rough Set Theory to classify customer groups. The results of the study showed that the proposed Rough Set classification model outperforms the existing models, contributing to significant accuracy improvement.

For a long time, decision tree has been used as an important classification technique by researchers. Decision tree functions as a prediction support tool, which provides a prospect of the possible consequences. These trees classify the subjects based on the values of the attributes sorted (Han and Kamber, 2006). The leaves, nodes, and branches represent prediction, an attribute in the class, and the value each node can take(combination of features),respectively(Phua et al.,2005). These trees can be planted, using machine learning algorithms such as CAR, ID3, and C 4.5 Algorithm. These trees are used for many applications, such as the classification of customers, detection of credit cards fraud, car insurance and corporate frauds detection (Ngai et al, 2010).

This study is aimed at developing a model for identifying the profitable customers of Telecom System 780,usinga binary decision Tree. The approach proposed by this study involves identifying the profitable customers based on their first transaction after login, and making use of this information to predict the behaviors of prospective customers in the future.

This paper is organized as follows: section 2 introduces System 780, its goals, and policies. Section 3 presents the statement of the problem and examines the indices used to classify the customers as dependent and independent variables. It also discusses how decision trees are used. In section 4, the results of this study are discussed, and finally section 5 concludes the study.

2. The Introduction of System 780

In today's world, we are seeing a considerable decrease in costs, energy and time waste, thanks to electronic services and mobile payment. In the same vein, organizations and institutes have resorted to the same services, with the aim of increasing customers' satisfaction as well as facilitating their financial transactions. Accordingly, a system with USSD *780# under the control of Tehran Internet as the holding company in cooperation with Arian Pardakht Novin Company(supervised by Bank Eghtesad Novin and licensed by Shapark and Bank Markazi Iran) launched an infrastructure and diverse payment services, provided via mobile. All Iranian mobile users throughout the country can use System 780 free of charge. Using this system requires no new software application and no smart phone. All is needed is getting access to the card verification value(CVV) on the bankcard.

All holders of Shetab(Interbank Information Transfer Network)Cards can use System 780, and all three Telecommunication operators in Iran can activate this system.

2.1. Policy, Mission and Vision of System 780

Policy: being customer-oriented, increasing customers' satisfaction and their sense of belonging by providing diverse, updated services.

Mission: Taking advantage of Unstructured Supplementary Service Data (USSDs) technology for mobile-based payment, with the aim of reducing time and costs and increasing the citizens' welfare; providing the organizations with some codes so that they can serve their customers more effectively.

Vision: Turning into the biggest and most specialized mobile-based payment providers.

2.2. Activities Domains of System 780

This systems aims to achieve the best standards and quality of mobile-based payment services and to broaden its customers base.

Providing diverse, updated services via mobile including bill payment, Recharging mobile, online purchasing Internet packages, providing mobile-based value-added services in Iran such as holding contests and surveys via mobile, Facilitating the advertisement and promotional activities for marketing purposes via mobile, Providing other diverse services such as charity, citizens services, and students services.

3.Statement of the Problem

In Iran, an organization holds the monopoly of the landline phone services, continuing its operation without any concern for competition. However, it is ignorant of other telecommunication operators such as Irancell, HamraheAvval, and Rightel, which pose potential threats by capturing a considerable market share given that landline phone can be replaced by mobile phones. Moreover, an increase in the number of internet users and access to audio and video chat programs can result in a decrease in the revenues associated with providing landline phones services. Finding new customers is more costly than retaining the existing customers. Thus ,it is very important to retain the existing customers base given the increasing competition among the companies providing the same services.

Accordingly, the organizations' managers face challenging issues regarding decision-making when it comes to the identification of customers and even improving the value of them. Currently, services are provided to all customers in a similar fashion. This study seeks to identify the customers in order to achieve purposeful marketing. Identification and classification of prospective customers can bring about multiple benefits for a business as business owners can adapt the behavioral patterns of the system for purposes of finding prospective customers and turning them into loyal customers, based on their knowledge of customers. In addition, the proper identification and classification of customers are a requirement for providing special advantages to the customers such as incentive packages or discount. This study aims to propose an approach to classify the profitable, efficient customers based on their first transaction via the System. Given that this case study uses Telecom System 780, as the first step the database of the System was explored and mined to extract the dependent and independent variables, for purposes of classifying customers.

3.1. Customers classification indicators

Telecommunications companies enjoy rich customer bases. Prior to data analysis, it is necessary to identify the existing databases in the organization so as to be able to choose the right data for analysis. The organization data can be classified into five categories: demographic data, Accounting data, Service user data, statement data, and communication behavior data.

The data of this study was provided by a subsidiary of Iran's Telecommunication Company. A pilot study on 1048575 transactions were conducted.(Table 1 presents the indicators for classifying their transactions and how they were coded in classification).

Table 1
the indices for classifying the transactions recorded in Database of System 780

The Name of Indicator in Database	The Values of Indicator
ACCOUNT ID	Customer CODE
TOPUP TYPE	Package Code bought by the Customer
P-TIME	The Amount of Package Consumed by the Customer
P-DATE	The date of purchase made by the Customer
AMOUNT	The amount of Money paid by customer

Table 2 displays the various services provided by the System 780 under the title of "Topup type" for each transaction.

As data in database are stored in terms of transaction, a computer program was developed to put all the transactions of each customer in separate groups so that each group consists of all transactions done by a customer. This yielded a new database based on each customer's behavior. All transactions turned out to belong to 72622 customers. Then, based on the customers information registered in System 780, a dependent variable had to be decided to identify profitable and efficient customers.

A profitable customer is someone who pays more money to the system and consumes less volume of purchased packages. Therefore, based on the customers data in this study, the ratio of total payment made by each customer for the purchased packages to the duration of consumption (in minutes) was decided as a dependent variable, which represents the value of the customer from the moment he/she logs in the system till the time he/she exits the System. However, identifying the profitable customer entails designing a binary variable. To this end, a threshold was set for the ratio of money paid by each customer to the amount of consumption of the packages.

A customer will be profitable if this ratio threshold is surpassed. The customer will be considered a normal customer if this ratio is not surpassed. This is up to the decision-maker to set the threshold, with higher threshold representing stricter selection of profitable customers. This results in a decrease in the number of customers falling in profitable customers group and vice versa. As this study seeks to model the degree of customers' efficiency with respect to their first transaction at the time of login, the first package bought by the customer was decided as an independent variable in this study. Consequently, when the first package purchased by the prospective customer is recorded, the System will be able to have an estimate of the value and efficiency of the same customer.

3.2. Decision tree

Decision tree in learning machine serves as a predictive model, going from observations about an item to conclusions about the item's target value. The machine learning technique used to derive a tree from data is called decision tree, which is one of commonly used data mining methods. Each internal node represents a variable and each arc to descendant represents a possible value for that variable. Each node, having the values of variable drawn by a path from the root to the same leaf node represents the predicted target value.

Table 2
Diverse Services provided by the Organization to Customers along with their codes

Row	Services	Topup type
1	Irnacell Packages for Special anniversaries-Postpaid	19
2	Irnacell Packages for Special anniversaries-Prepaid	22
3	LTE-DT Internet Packages	31
4	IranCell Postpaid Packages	32
5	IranCell Postpaid Internet Packages-Daily	33
6	EW IranCell Internet Packages	34
7	IranCell Postpaid Internet Packages-Weekly	36
8	IranCell Bulletin Packages-No 1	39
9	Direct Charging	40
10	IranCell Shegeftangiz Charge	41
11	Irancell Bill	42
12	IranCellFown Payment	43
13	IranCell Internet Packages	44
14	IranCell Daily Internet Packages	46
15	IranCell Weekly Internet Packages	47
16	IranCell Monthly Internet Packages	48
17	IranCell Bulletin Packages-No 2	49
18	EW Hamrah 1000 Tomans	51
19	EW Hamrah 2000 Tomans	52
20	EW Hamrah 5000 Tomans	53
21	EW Hamrah 10000 Tomans	54
22	EW Hamrah 20000 Tomans	55
23	End of the term Hamrahs	57
24	Mid termHamrah	58
25	Direct RighTel	60
26	Hamrah 1000 Tomans	61
27	Hamrah 5000 Tomans	62
28	Hamrah 10000 Tomans	63
29	Hamrah 20000 Tomans	64
30	HamraheAvval Internet	65
31	Direct RighTel	66
32	ShoorangizRigh Tel	70
33	Hamrah 1000 Tomans(Gift)	71
34	Hamrah 2000 Tomans(Gift)	75
35	Hamrah 5000 Tomans(Gift)	76
36	Hamrah 10000 Tomans(Gift)	77
37	Hamrah 20000 Tomans(Gift)	78
38	PIN Taliya	79
39	PIN Hamrah	83
40	PIN Righ Tel	91
41	PIN IranCell	92
42	PIN HamrahEW	93
43	PIN Righ Tel EW	94
44	EW IranCell PIN	95
45	IranCellShegeftiha Package	96
46	Automatic Prepaid Recharging Registration	100
47	Automatic Postpaid Recharging Registration	101
48	Cancelling Automatic Recharging Registration	102
49	Changing Amount of Charge	103
50	Sending Notify-Prepaid	104
51	Sending Notify-Postpaid	105
52	Automatic Charging	107

A decision tree is a structure where leaves representclassification, and branches represent the combination of the attributes that make up the classes. A tree can be trained by splitting a source set into its subsets based on an attribute value test.This process is repeated repeatedly in each resulting subset and is haltedwhen splitting, no longer, adds value to the predictions,or when a new class can be applied to all instances in resulting subset. Decision trees are able to provide perceivable description of the existing relationships in an array of

data, and can be used for classification and prediction. This technique is widely used for applications such as disease diagnostics, plants classification, and customers marketing strategies. This decision structure can also function as mathematical and computing techniques to facilitate the description, classification, and generalization of an array of data. The data are given as follows: $(X,Y)=(X_1,X_2,X_3,\ldots,X_k,Y)$ variables.
Variables$X_1,X_2,\ldots,X_k$ are used to perceive, classify or generalize the dependent variable Y. The attributes indecision trees are divided in to two groups: categorical attributes and continuous attributes. Categorical attributes can take two or more discrete values while continuous attributes take their value from real numbers set. Decision trees classify instances by sorting them down the tree from the root to some leaf node. Each one of internal node tests an attribute of instance. Moreover, a class is assigned to each leaf node. An instance is classified by starting at the root node of the tree, followed by testing the attribute determined by this node, then going down the tree branch corresponding to the value of the attribute. This process is then repeated for the sub tree rooted at the new node. Generally, decision tree represents a disjunction of conjunctions of constraints on the attribute values of instances. Each path from tree root to a leaf corresponds to a conjunction of test attributes, with the tree itself corresponding with the disjunction of all these conjunctions.
ID3 can be described as a hypothesis space search to find the hypotheses which fit the training instances .The hypothesis space searched by this algorithm is a set of decision trees. The algorithm may have a hill-climbing search in this hypothesis space, starting with an empty tree. It then takes into account more hypotheses in search of a decision tree that can classify the training data correctly. The evaluation function which direct this hill-climbing search serves as a criterion for the information gain.ID3 search strategy is as follows:
1) It prefers the shorter trees over the taller ones.
2) It chooses those trees which place the attributes with highest information gain near the root.

4.Implementation and Analysis of Results

First, the customers data were randomly divided into two groups: training data and test data, with%80 and %20 of the customers falling in training group and test group, respectively.
Out of 72622 customers whose transactions had been recorded in dataset, about 58100 customers and 14522 customers were randomly placed in training phase of decision tree and training phase, respectively. The customers in the training phase were used for decision tree learning and the customers in training phase were used to estimate how big calculation error of the trained tree was. Moreover, a threshold had to be determined for the ratio of payment made by the customers to the amount of purchased packages consumed .This study sets 1 as the threshold.
As table 3 shows, first the customers data were extracted from the System 780, based on recorded transactions. Table 3 displays the information of 20 customers ,including the customer's ID number, the code of the first purchased package, and the ratio of total payments to total consumption.

Table 3
A sample of the Customers Data to be processed by Decision Tree

Profitable Customer with Respect to Threshold	The Ratio of money paid by the Customer to the total consumption of all purchased packages	The Code of the First Purchased Package	The Customer Code
-	0.44426	40	3980
-	0.34071	40	7520
-	0.16729	40	10600
-	0.25734	40	12490
-	0.55674	40	12680
✓	1.03935	40	15170
-	0.90671	40	21560
-	0.30805	40	22740
✓	1.05011	40	23530
-	0.40664	40	30790
-	0.48010	40	33430
-	0.19705	41	34270
-	0.14779	40	35350
-	0.50091	40	38540
-	0.29038	40	41680
-	0.69487	40	43060
-	0.37283	40	44020
-	0.34914	40	44200
-	0.39130	40	47370
-	0.35305	41	48260

Table 4 shows the process of binary decision tree used in 30 iterations by this study. This table indicates the following information: resulting objective function in each iteration, the estimation of objective function in each iteration, the estimated time spent on computing objective function, the least size of the leaf of decision tree in each iteration.

The value of objective function in the tree optimization process was found to be 0.13045.The total time needed for training tree was 1635808 seconds, of which, 654038 seconds were spent on computing the objective function in consequent iterations. In this study, the tree was trained, using Matlab 2017.Figure 1 shows the convergence of accurate and estimated values of objective function for the number of responses investigated in the optimization process. As the figure shows, the estimations of objective function and the accurate values actually computed are equal in the 7th iteration onward in optimization process. Figure 2 shows the changes in the estimates of objective functions or the smallest size.

Table 4
The process of Decision Tree Training

Iteration	Evaluation	Objective Function	The Duration of Computation	The Best Objective Function Obtained	The Best Estimate	The Least size of Leaf
1	Best	0.13086	48.5070	0.13086	0.13086	291
2	Accept	0.14071	1.3307	0.13086	0.1365	21692
3	Best	0.13069	1.0799	0.13069	0.1369	20
4	Best	0.13045	0.9599	0.13045	0.13045	1
5	Accept	0.13114	0.8793	0.13045	0.13045	86
6	Accept	0.13045	0.5391	0.13045	0.13045	4
7	Accept	0.13045	0.6110	0.13045	0.13045	2
8	Accept	0.13048	0.4704	0.13045	0.13045	8
9	Accept	0.13045	0.5837	0.13045	0.13045	3
10	Accept	0.13045	0.4882	0.13045	0.13045	2
11	Accept	0.13045	0.4603	0.13045	0.13045	5
12	Accept	0.13045	0.5016	0.13045	0.13045	4
13	Accept	0.13045	0.4737	0.13045	0.13045	2
14	Accept	0.13045	0.5126	0.13045	0.13045	3
15	Accept	0.13045	0.4455	0.13045	0.13045	5
16	Accept	0.13045	0.5376	0.13045	0.13045	1
17	Accept	0.13045	0.4895	0.13045	0.13045	2
18	Accept	0.14071	0.4144	0.13045	0.13045	5256
19	Accept	0.13045	0.5098	0.13045	0.13045	6
20	Accept	0.13045	0.5322	0.13045	0.13045	5
21	Accept	0.13045	0.5546	0.13045	0.13045	3
22	Accept	0.13045	0.4797	0.13045	0.13045	4
23	Accept	0.13045	0.5635	0.13045	0.13045	1
24	Accept	0.14071	0.4834	0.13045	0.13045	2223
25	Accept	0.13069	0.4636	0.13045	0.13045	12
26	Accept	0.13045	0.5813	0.13045	0.13045	6
27	Accept	0.13045	0.4811	0.13045	0.13045	6
28	Accept	0.13045	0.4991	0.13045	0.13045	6
29	Accept	0.13045	0.4881	0.13045	0.13045	3
30	Accept	0.13071	0.4831	0.13045	0.13045	50

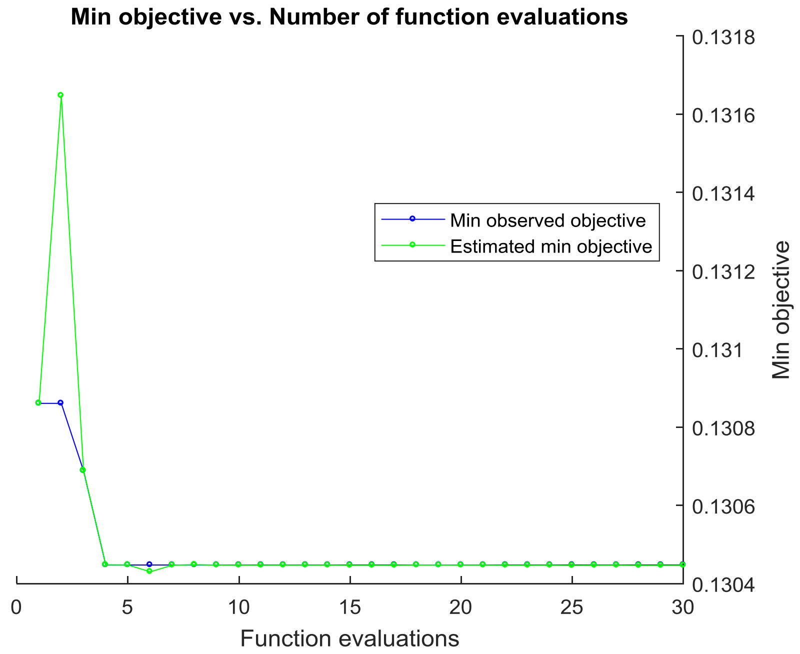

Fig. 1. Diagram of the convegence of accurate values and estimated values of objective function in the optimization process of decsion tree

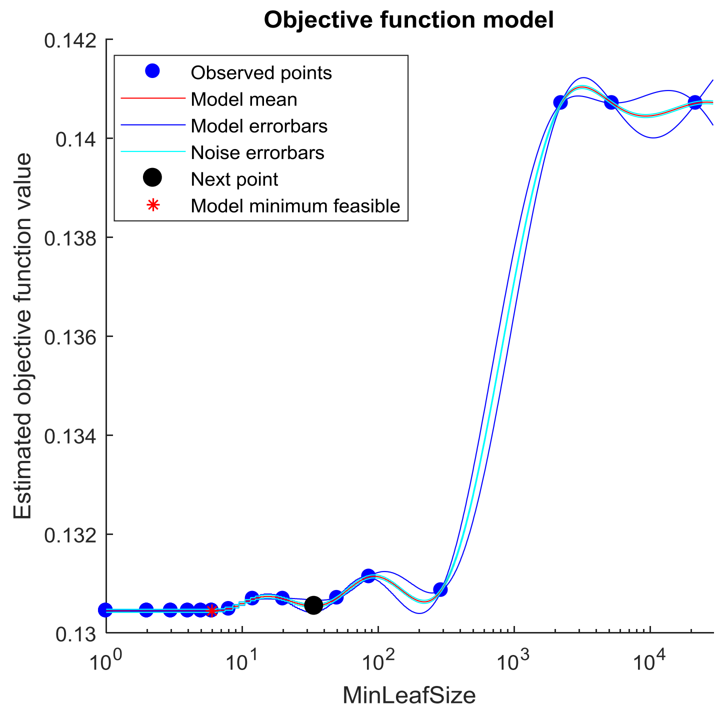

Fig. 2.The changes in estimates of objective function for the smallest sizes of the leaves of decision tress.

Figure 3 displays the final structure of decision tree. Variable X1 represents the independent variable, i.e. the first service package purchased by the customer after logging in the System. True and False denote the profitability or non-profitability of the customer, respectively. The training error of decision tree and training phase error were found to be 0.1302 and 0.1268, respectively. Consequently, if the size of test error is taken as an indicator of tree performance accuracy, it is safe to say that the accuracy of the trained tree in classifying the profitable customers is %88 in this study.

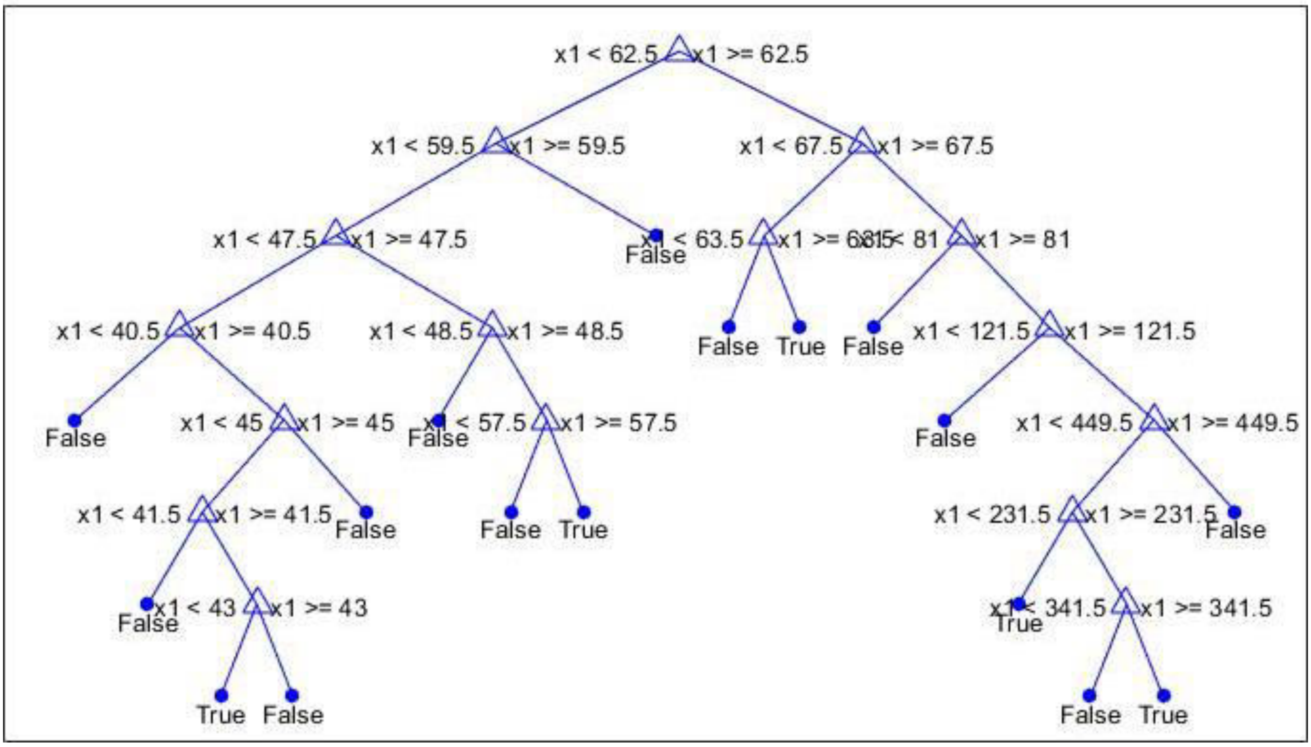

Fig. 3.Final structure of decision tree for distinguishing profitable customers from non-profitable ones customers

5. Conclusion

Effective knowledge and awareness of customers require the market segmentation, through which the customers who have the same needs and purchasing patterns, as well as the same response to marketing plans are identified. The selection of a proper variable is a requirement, among other, for a successful market segmentation. In today' context, on one hand, the consumers are bombarded with new goods and new services and, on the other hand, they face the varying qualities of the goods and services. Consequently, such uncertainties will lead to an increase in vague decisions and cumulative data. The timely and accurate analysis of these cumulative data can bring about competitive advantages to the enterprises. Furthermore, thanks to new technology and global competition, the majority of organizations have focused on customer relationship management(CRM),for purpose of better serving the customers. The customers relationship planning requires the facilitation and creation of interfaces related to market segmentation, which is considered as a requirement for predicting the future behavior of the customers. Market segmentation refers to the process of dividing the customers into segments, based on their common characteristics, with different groups having the least similarity to each other. This is followed by the formulation of plans for new product production, advertisement and marketing in accordance with the characteristics of each group of customers. Current study was aimed at identifying the profitable customers of a telecom system(System 780), based on their first transaction. The provision of incentive policies by System 780 to its customers c an be adjusted for purposes of longer retention of the customers .This study also determined the independent and dependent variables, which were used in proper classification of the customers, using a binary tree despite the complexities of the System. The threshold can be changed so as to select the profitable customer either more or less rigorously.

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