Establishing the Potential Clients Using Artificial Neural Networks

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Abstract—Today, technologies retrieving forward-looking information from the existing data are available. In this study, whether the clients would open a deposit account was estimated using the data in the marketing campaign of a bank in Portugal for its clients. The purpose of the study was to create a decision support system to determine the potential clients in future. The data set collected from 4,512 subjects consists of 16 input attributes (job, age, balance, etc.) and 1 output attribute (yes/no). In the study, the 6-fold cross validation method was used. The data obtained from 3,760 people were used for the training process and the data obtained from 752 people were used for the testing process. As classifiers; Feed Forward Neural Networks (FFNN), Probabilistic Neural Network (PNN) and k Nearest Neighbor (kNN) were used. At the end of the study, success ratios of different algorithms were compared by Receiver Operating Characteristics (ROC) analysis method. Feed forward neural network yielded the best result with an accuracy rate of 95.74%.

Index Terms—Bank data, deposit, artificial neural network, k nearest neighbor algorithm.

I. INTRODUCTION

Today, data can be digitally collected and stored due to the rapid development of computer systems. Together with the high increase of data and the need for obtaining significant extractions, the concept of data mining emerged. The main objective of data mining is to find out information such as relationships between data, patterns, changes, deviations and trends and certain structures with the combinations of mathematical theories and computer algorithms and obtain valuable information through the interpretation of this information.

Data mining is considered to consist of four main topics including classification, categorization, estimation and visualization. Marketing campaigns occupy an important place for banking institutions. In this study, the marketing campaign is based on telephone conversations.

Telephone conversations have a significant impact on the decision-making process of clients. A classification was made using the client information obtained in the telemarketing campaign the employees of the Portugal Bank carried out for its clients and whether they would be deposit account clients was tried to be determined.

In some studies carried out using bank data, whether the clients would be a deposit account subscriber or not was predicted using the information obtained from the clients and data mining techniques. For example; Moro et al. made analyses using data mining techniques in line with the information obtained as a result of telemarketing campaigns. They used support vector machine, decision tree and naive bayes classifier data mining models. In the study, the best results were obtained from the Support Vector Machine Model [1]. Moro et al. studied on the same topic in the study titled “A data mining approach for bank telemarketing using the miner package and R tool” they carried out in 2013. They performed that study using the R tool extension of rapidMiner program [2]. In the study titled “Bank direct marketing based on neural network” carried out by Elsalamony Hany A. and Elsayad Alaa. M., the data obtained as a result of the marketing campaign were analyzed with MLPNN (Multi-Layer Perceptron Neural Network) and Decision Tree-DT models [3]. In the study titled “Evaluating marketing campaigns of banking using neural networks” carried out by Qeethara Kadhim Al-Shayea, the prediction about whether the clients would be a deposit account holder or not was made in line with the information obtained from them through ANN and DT techniques [4].

II. METHOD

In the first stage, the data were preprocessed. Thus, it was aimed to obtain accurate results from the study. At this stage, data cleaning and data integration steps were applied. The missing data were deleted and the data were tried to be made consistent. In order to find out the relationships between the data and obtain information through the interpretation of them, ANN and as a different classifier apart from ANN; k nearest neighbor algorithm, which is simple and frequently used in the literature, were used. k nearest neighbor algorithm is abbreviated as kNN. In the stage of evaluation of the results, Receiver Operating Characteristic –ROC Formulas were used.
ANN has a simple structure and a directed graph format. Each node is an nth degree nonlinear circuit called “cell”. These nodes are defined as processing elements in ANN. There are links connecting the nodes to each other and each of them functions as a simplex communication path. A single output can feed several cells, in other words; each communication element can receive a desired number of input connections and a single output connection. The output of the processing element can be in a desired mathematical type. Continuously working input elements produce an output signal. The input signals carry information to ANN and the result can be obtained from the output signals. ANN is composed of three layers including Input Layer, Interlayers (Hidden Layers) and Output Layer [6].

Feed Forward Network (FFN) and Probabilistic Neural Network (PNN) were used in the application as available network types in ANN. The accuracy results of the data sets were analyzed giving different values to the variables of the number of neurons, the number of layers, goal and lr determined in FFN Network. Goal value is a value indicating how much of the error can be minimized. Generally a value near zero is given instead of giving zero. In this study, the value of 0.01 was given. It continues training till the network error value is 0.01 or the desired epoch, i.e. “cycle number” is reached. The LR value, i.e. learning rate should not be selected as a very high or very low value. If a very high value is selected, the network memorizes the data. On the contrary, if a very low value is selected, then the network either learns the data too slowly and causes loss of time or cannot learn it.

FFN includes a series of layers. The first layer has a connection from the network inputs. Each layer is connected with the previous layer. The final layer produces the network outputs. Feed Forward Networks can be used for output matching and any kind of input. A Feed Forward Network can be used in any finite input output matching problems with a hidden layer and sufficient neurons in the hidden layer [7].

PNN is a radial basis neural network. It is based on counselling learning. PNN is a neural network which uses Bayes Theorem in decision making. According to Bayes theorem, if an equality of vector x is accurate, it belongs to the 1st class, if not, it belongs to the 2nd class [8].

$k$NN method is one the learning methods which solves the classification problem. With this method, the similarities of the data to be classified to the data in the learning set is calculated, the average of the values of their k nearest neighbors is taken and they are assigned to a class according to their threshold value. In order to perform this assignment, the characteristics of each class should be clearly determined in advance.
### TABLE 1.
**INPUT DATA**

| id | Variables          | Explanation                                      | Type          | Value (digitized value) |
|----|--------------------|--------------------------------------------------|---------------|-------------------------|
| 1  | Age                | Age when contacted                               | numeric       | 18 +                    |
| 2  | Occupation         | Occupation of the contact person                 | categorical   | unknown(1), administrator(2), unemployed(3), manager(4), servant(5), contractor(6), student(7), worker(8), self-employed(9), technician(11), service personnel(12) |
| 3  | Marital status     | Marital status of the contact person             | categorical   | single(1), divorced(0), married(1) |
| 4  | Education          | Educational status of the contact person         | categorical   | unknown(1), primary school(2), secondary school(3), undergraduate(4) |
| 5  | Non-performing loan| Does the client have a non-performing loan?      | categorical   | yes(1), no(-1)          |
| 6  | Avg balance        | Average annual balance of the client’s current accounts in Euro currency | numeric       | -3313euro < ; < 71188 euro |
| 7  | Mortgage loan      | Does the client have a mortgage loan?            | symbolic      | yes(1), no(-1)          |
| 8  | Personal loan      | Does the client have a personal loan?            | symbolic      | yes(1), no(-1)          |
| 9  | Communication type | What was used as a means of communication?       | categorical   | unknown(1), telephone(0), mobile phone(-1) |
| 10 | Last contact day   | Last contact day when the clients were interviewed for the campaign | numeric       | 1<; <30 |
| 11 | Last contact month | Last contact month of the year when the clients were interviewed for the campaign | categorical   | January(1), February(2),…,December(12) |
| 12 | Length of interview sec. | Length of the interview (in seconds) | numeric       | 4 sec ≤ ; ≤3025 sec |
| 13 | Number of contacts established in the campaign | Number of contacts during the campaign | numeric       | 1 ≤ ; <50 |
| 14 | How many days after the last campaign the interview was made | How many days after the last campaign were the clients contacted? | numeric       | 1 ≤ ; ≤871 ; |
| 15 | Number of pre-campaign contacts | Number of contacts before the campaign | numeric       | 0<; ≤25 |
| 16 | Previous campaign result | Result of the previous marketing campaign | categorical   | unknown(1), imperfect(2), other(3), successful(4) |

### TABLE 2.
**OUTPUT DATA**

| id | Variables | Explanation                                      | Type     | Value                              |
|----|-----------|--------------------------------------------------|----------|------------------------------------|
| 1  | Y         | Has the client subscribed to a term deposit account? | symbolic | yes (1), no (-1)                  |
$kNN$ is an instance-based learning algorithm and used for performing classifications over the available learning data when a new instance is encountered. The algorithm determines the class of the instance looking at its k nearest neighbors when a new instance is encountered [9]. Referring to the data whose classes are known, their distance to the data whose classes are unknown is calculated and it is based on the selection of k number of observations with the minimum distance.

In the example in Figure 1, the number of nearest neighbors was taken as 5 and in which class the unknown data would be included was determined. As the number of neighbors in Class A was higher than the number of neighbors in Class B, the unknown data was included in Class A. The k value in the figure is not the value in the application, which is 511.

![Fig 1. kNN representation](image)

The steps of kNN algorithm are as follows.

1- The newcomer individual is added into the class.
2- k number of neighbors are looked at.
3- The distance is calculated using various distance function (Euclidean distance function).
4- The individual is assigned to the nearest place [10].

In equation 1, the Euclidean Distance Function formula, where $d$ is the function of distance between two points, $i$ and $j$ are the indices of the points, $x$ is the position of this point and the $p$ value is 752, which is the test value, is given.

$$d(i, j) = \sqrt{(x_{1i} - x_{1j})^2 + (x_{2i} - x_{2j})^2 + \ldots + (x_{pi} - x_{pj})^2} \quad (1)$$

The distances of a point to all the other points are calculated separately, the rows are sorted and the smallest k number is selected. In which category the selected rows are determined and the most repeated category is selected.

### G. Evaluation

Receiver Operating Characteristic (ROC) was developed for the accurate identification of the signals detected on radar in Britain during the World War II and enabling the distinction between friend and foe. Lusted suggested the use of ROC analysis in decision making in medicine in 1967 and led to the use of it in medical imaging devices in 1969. In the following years, the use of ROC analysis in the evaluation of the performance of diagnostic tests in medicine gradually became widespread. The developments emerging with ROC analysis are a natural consequence of the need for the evaluation and comparison of statistical results [11].

ROC analysis is defined as “the receiver operating characteristic” or simply “ROC curve” in signal detection theory. The ROC curve is obtained with the ratio of sensitivity to specificity in cases where the distinction threshold value varies in binary classifier systems. In simpler terms, ROC can be expressed as the fraction of true positives to false positives [11].

While performing a ROC analysis, a classification should primarily be made. Meanwhile, the threshold values are determined and divided into two classes. These classes are positive (P) and negative (N) values according to the threshold value. When subjected to this classification, the estimated and actual values are divided into four different classes.

- If the estimated value is positive (P) and the actual value is also positive (P), it is called a true positive (TP).
- If the estimated value is positive (P) and the actual value is negative (N), it is called a false positive (FP).
- If the estimated value is negative (N) and the actual value is also negative (N), it is called a true negative (TN).
- If the estimated value is negative (N) and the actual value is positive (P), it is called a false negative (FN).

| Error matrix | Classifier Outcomes |
|--------------|---------------------|
| Actual       | YES                 |
| Results      | TN                  |
|              | FP                  |
|              | NO                  |
|              | FN                  |
|              | TP                  |

Accuracy is the proximity of the measured value to the actual value. Error is the difference between the measured value and the actual value [12].

$$Accuracy = \frac{TP + TN}{(TP + TN + FP + FN)} \quad (2)$$
III. APPLICATION

All the data were divided into two groups as training and testing data to be given to the classifiers. While performing this division in the data set, the k-fold clustering algorithm was used. Firstly, a k value was selected to apply to the data set. For K=6, the data set including 4,512 data were divided into 6 equal parts (folds). The K-folds are illustrated in Table 4. During fold partition, the numbers of “yes” and “no” belonging to the outcome variable were also taken into consideration. Thus, the state of excess of “yes” or “no” in any of the folds, which is possible in a random distribution, was eliminated. In case of such a situation, the outcomes of the model will also be affected negatively.

| TABLE 4. | K-FOLDS |
|----------|---------|
| id       | Yes | No | Total |
| Fold 1   | 86  | 666 | 752   |
| Fold 2   | 86  | 666 | 752   |
| Fold 3   | 86  | 666 | 752   |
| Fold 4   | 86  | 666 | 752   |
| Fold 5   | 86  | 666 | 752   |
| Fold 6   | 86  | 666 | 752   |
| Total    | 516 | 3996 | 4512 |

As illustrated in Table 5 randomly chosen 5 folds constitute the training data (3,760 pieces) and 1 fold constitutes the testing data (752 pieces). In Table 5, how the k-folds were formed is clearly expressed (k=6). In the k-fold technique, the data were named as A-B-C-D-E-F and 6 different data sets were created.

| TABLE 3. | DATA SETS |
|----------|-----------|
| Data set | Training Folds | Testing Folds |
| A        | Fold1 - Fold 2 - Fold 3 - Fold 4 - Fold 5 | Fold 6 |
| B        | Fold 1 - Fold 2 - Fold 3 - Fold 6 - Fold 5 | Fold 4 |
| C        | Fold 2 - Fold 3 - Fold 4 - Fold 5 - Fold 6 | Fold 1 |
| D        | Fold 1 - Fold 3 - Fold 4 - Fold 5 - Fold 6 | Fold 2 |
| E        | Fold 1 - Fold 2 - Fold 4 - Fold 5 - Fold 6 | Fold 3 |
| F        | Fold 1 - Fold 2 - Fold 3 - Fold 4 - Fold 6 | Fold 5 |

The classification techniques applied in this study were realized using the data sets in Table 5. In the evaluation stage, the data set which gave the most accurate result to determine whether the client would be a deposit account subscriber in the future or not was found to be the data set B. The numbers of the training and testing data sets used by ANN are shown in Table 6.

| TABLE 6. | NUMBER OF DATA |
|----------|----------------|
|          | Yes | No | Total |
| Training | 430 | 3330 | 3760 |
| Testing  | 86  | 666 | 752  |
| Total    | 516 | 3996 | 4512 |

The training set includes a total of 3,760 data records, whereas the testing set includes 752 data records. Each row in Table 1 corresponds to a record here. The accuracy results of the data sets were examined by giving different values to the variables of the number of neurons, the number of layers, goal and lr determined in FFN network structure. The values which gave the best result were identified as follows: the number of neurons = 80, the number of layers = 1, goal = 0.01, lr = 0.005. With this identified network, the best accuracy result determined with ROC was found. The vector state of the training output was found in PNN. The reason for the conversion of the training output into a vector matrix was that it would be used in creating a network. During the creation of the neural network, the training input, the training output vector and the distribution values were taken. Upon the creation of the network, the testing data were given to the network. As the training input values had been converted into the vector state, the results were produced in index format upon obtaining the testing output in vector state. The PNN model was experimented for the selected data set B, however the algorithm did not give a good result due to the excess number of data. In the data set B, the data were classified using the kNN algorithm. The algorithm was implemented in the selected data set B. 3,760 data of the data set B were separated for training and 752 data for testing. The training input, training output and testing input data were given to the algorithm. The testing output was taken from the result of the algorithm. The classes of the data in the training input given to the algorithm were known, whereas the data whose classes were unknown belonged to the testing input data. The distance of each data in the set whose classes are known to the observation values whose classes are unknown is calculated according to the kNN algorithm. In the calculation of the distance, Manhattan distance function, Minkowski distance function and Euclidian distance function are used. K number of data with the minimum distance according to the calculation is selected. In this study, Euclidian distance function was used. K number was taken as 511. 511 data with the minimum distances calculated according to the algorithm were selected. To measure the reliability of the results, the obtained results were evaluated with ROC.

IV. CONCLUSIONS

In this study, the probability of people to open a deposit account in the bank was estimated for marketing campaigns. 3,760 of the 4,512 data were used as the training data and 752 as the testing data. The data were studied using ANN classification models; FFN and PNN networks and also kNN. As shown in Table 7. ROC Accuracy Results, the method which gave the best result was PNN. For bank marketing campaigns, the probability of people to open a deposit account was estimated with the accuracy rate of 94.22% and the probability not to open a deposit account with the accuracy rate of 94.10%.
As a result of the study, the training process was completed with the training set and processes were performed with the testing set where whether the client became a deposit account subscriber or not was not known. As a result of the testing set, the FFN classifier identified the outcome of “Yes” for “Has the client become a deposit account subscriber?” correctly with a rate of 94.22% and identified the outcome of “No” for “Has the client become a deposit account subscriber?” correctly with a rate of 94.10.

FFN achieved a better result compared to the other methods. This method is thought to be utilized by banks and all the institutions which conduct marketing activities.

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TABLE 7. ROC ACCURACY RESULTS

| Model Name | YES (%) | NO (%) |
|------------|---------|--------|
| FFN        | 94.22535 | 94.10071 |
| PNN        | 69.9468  | 69.9468 |
| KNN        | 88.56382 | 88.56382 |

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BIOGRAPHIES

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