Bank Marketing Analysis Approach Using Logistic Regression of Machine Learning

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Abstract— The banking institutions have marketing departments with more staff than most banks and credit unions have total employees. And yet institutions of all sizes tend to face marketing challenges due to improper insights. This proposed technique facilitates useful data explications for the banking sector to avoid customer attenuation. Customer relations is one of the most important factors that are to be analyzed in today's competitive business environment. This paper analyzes the machine learning techniques like Logistic Regression, Random Forest classifiers and its applications in the marketing sector.

Keywords— **Logistic Regression, Random Forest, Bank Marketing, Grid Search, Classification.**

I. Introduction

Recently, machine learning has attracted considerable attention in the real world because it can provide cutting edge analysis for marketing [1] which is very beneficial for the business to customer marketing. Machine learning works by creating models that are trained on data through various machine learning techniques such as logistic regression, etc. These trained models then used to serve the purpose of predicting the result. In many studies, the impact of marketing activities on relationship quality has played a vital role [2,4]. Data mining techniques have a tremendous amount of applications in the banking sector [5]. These could be very helpful though data mining has certain drawbacks and issues because data mining is not an easy task it has a problem of performance and requires parallel and distributed algorithms and handling of relational and complex types of data. We use machine learning for bank marketing and analysis. We trained a machine learning model on the dataset [6] to predict the result. We use logistic regression technique of machine learning to predict the bank marketing to give good marketing insights to marketers.

II. Related Work

Several studies have been delved into by many researchers in the phenomenon of Bank Direct Marketing with various marketing techniques existing nowadays. Decision Support Systems [9-10]. The Scikit-learn [8] is a Python framework comprising of various machine learning algorithms for both supervised and unsupervised learning. This Scikit-learn package is focussing to bring machine learning to beginners of various disciplines by using a general-purpose high-level language i.e python.

There have been many techniques used for statistical modeling such as Logistic regression[7] which is used to model the probability of a certain class or event existing such as pass or fail, win or lose, alive or dead. This can be further utilized to model several classes for experiments such as predicting whether an image containing a particular object. Every object which is being detected in the image would then be assigned a probability on a scale from 0 to 1. Logistic regression is used in multidimensional fields in the healthcare domain it is used for drug testing, cancer detection, etc. In stock prediction for a particular stock to buy or sell, etc. In malware detection and many more applications ahead.

III. Technologies Used

Machine learning techniques aim to automatically learn and recognize patterns from large datasets. There is a great variety of machine learning techniques available within the literature which makes the classification more and more difficult. This paper divides the literature into an artificial neural network (ANN) based and optimization-based techniques.

Table 1 shows that variations of ANNs and hybrid systems are very popular in the literature. There is a clear trend to use established ANN models and enhance them with new training algorithms and combine ANNs with emerging technologies into complex hybrid systems[3].

Technology	Number	Publications
Artificial Neural Network based	21	[10], [11], [12], [13], [14], [15], [16],[17],[18],[19], [20],[21],[22],[23], [24],[25],[26],[27], [28],[29],[30]
Optimisation & Evolutionary techniques	4	[31],[32],[33],[34]
Hybrid or Multiple	15	[35],[36],[37],[38], [39],[40],[41],[42], [43],[44],[45],[46], [47],[48],[49]

Table 1: Reviewed papers classified by machine learning technique

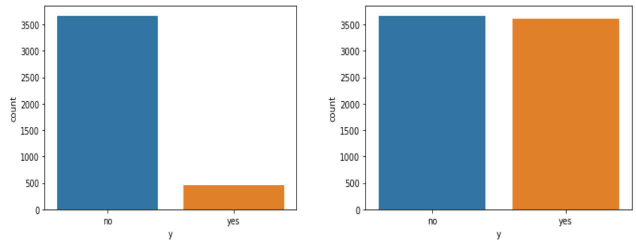
IV. Proposed Work

A. Data Preparation

The given raw data[6] is related to the direct marketing campaigns of a Portuguese banking institution. The classification goal is to predict if the client will subscribe to a term deposit.

1. First step: Making the Data Symmetric

- The final output can either be ‘yes’ or ‘no’. In the given dataset 87% of tuples belonging to the class ‘no’. Therefore the data is highly Skewed.
- To make the data symmetric, we took the tuples belonging to minority class(i.e. Class ‘yes’) and duplicated them until both the classes have an equal number of tuples in them.



Raw data Processed data

Fig 1: Graph of Balancing data

2. Second step: Splitting ‘pdays’ feature into 2 features

- The entries of ‘pdays’ feature are as follows: ○ More than 90% of the entries are 999. (i.e. Client was never contacted)
  ○ The remaining entries are in the range 0 - 20.
- Because of this, when we standardize the data, the entries corresponding to 999 will become 1 and remaining entries will be very close to zero(they all will be almost the same).
- To avoid this we split the feature into 2 features where one feature contains information about whether the client was contacted before or not(binary feature), and another feature will contain information about how long ago the client was contacted(if the client was never contacted we put 30 in this field instead of 999).

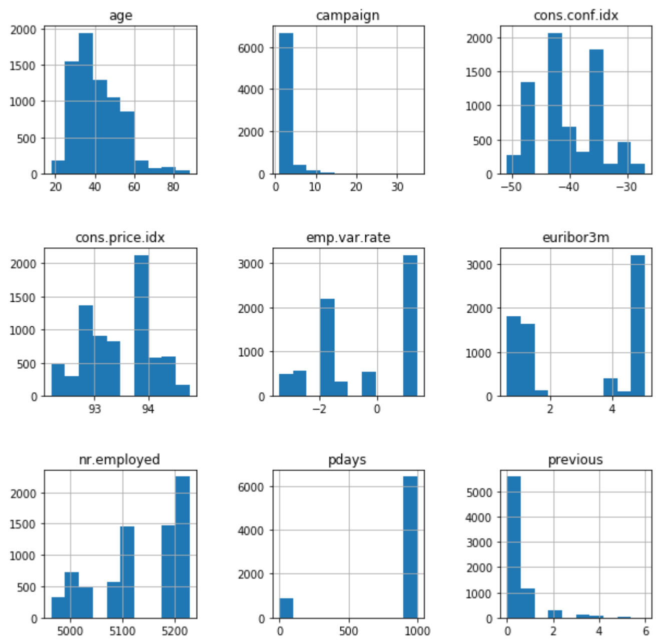


Fig 2: Plots of the finalized dataset
Count vs Input variables

3. Third step: Standardizing the data

- This step was done :
  - For faster convergence.
  - To ensure that variables measured at different scales do not contribute differently for analysis.

B. Predicting the outcome

After finalizing the data the model is trained using the Logistic Regression Model.

1. Logistic Regression Models:
   The central mathematical concept that underlies logistic regression is the logit—the natural logarithm of an odds ratio.

2. Input Variables:
   Selecting the right input variables is very important for machine learning techniques. Even the best machine learning technique can only learn from the input if there is actually some kind of correlation between input and output variables.

input variables used for prediction -

[

'age', 'job', 'marital', 'education', 'default', 'housing', 'loan', 'contact', 'month', 'day_of_week', 'campaign', 'pdays', 'previous','p outcome', 'emp.var.rate', 'cons.price.idx', 'cons.conf.idx', 'euribor3m', 'nr.employed'

]

C. Classification :

We tried out the following classifiers:

- Logistic Regression(with Linear and Polynomial Features)

- Random Forest Classifier Here is a table comparing the accuracy, precision, recall, and f1_score of all the models.

V. Result and Discussion

The performance of the proposed technique named logistic regression is evaluated in terms of accuracy, precision, F1 score and recall. The results are as shown in Tables 2 and 3.And comparison shown in fig 4.

The Random Forest classifier provides the best accuracy among all the classifiers used with an accuracy of 0.963353.

Metric	Logistic Regression with Linear Features	Logistic Regression with Features of Degree=2	Logistic Regression with Features of Degree=3	Logistic Regression with Features of Degree=3 after applying Grid Search
Accuracy	0.731104	0.81585	0.931287	0.93586
Precision	0.617375	0.829945	0.99353	1.00000
Recall	0.794293	0.804659	0.882594	0.88543
F1 Score	0.694748	0.817106	0.934783	0.93923

Table 2: Comparison between logistic regression degree 1,2 and 3

Metric	Logistic Regression with Features of Degree=3 after applying Grid Search	Random Forest
Accuracy	0.93586	0.963353
Precision	1.00000	1.00000
Recall	0.88543	0.931153
F1 Score	0.93923	0.964349

Table 3: Comparison between logistic regression degree 3 and random forest classifier

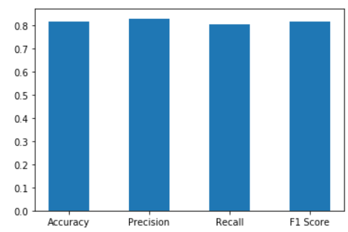


Fig 4 :(i) Logistic Regression degree=1

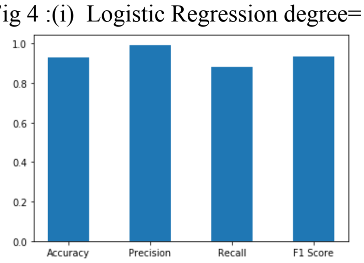


Fig 4 :(ii) Logistic Regression degree=2

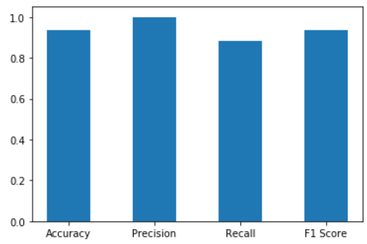


Fig 4 :(iii) Logistic Regression degree=3

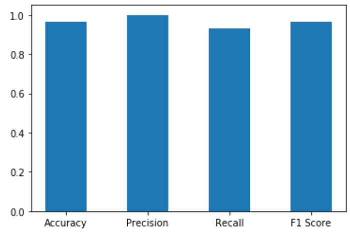


Fig 4 :(iv) Logistic Regression using grid search

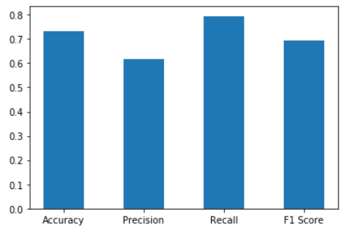


Fig 4 :(v) Random forest classifier

VI. Conclusions

Machine Learning has attracted increasing attention from the viewpoint of providing useful insights, especially for the banking sector. The use of machine learning techniques for analyzing bank marketing has limitations. To solve these limitations, we used the dataset[6] by using a content-centric concept. Random forest classifier based machine learning technique is suited for bank marketing. As the accuracy of the machine learning model is important. It has an advantage that manages computing resources because the learning function of the random forest provides faster and better results. The proposed technique meets the requirements of the machine learning model with the support of banking data. In this term, it achieves high accuracy, scalability, reliability and efficient to deal with any kind of customers.

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