Predicting The Success of Bank Marketing Using Deep Learning

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Abstract

This project aims to develop a deep learning model to predict the success of bank marketing campaigns.The data used in this project consists of various demographic, economic, and social factors of customers, as well as the outcomes of previous marketing campaigns. The model will be trained on a large dataset using various deep learning techniques such Stochastic gradient descent and neural network perceptron, to identify patterns and correlations that can help predict the success of future marketing campaigns. The effectiveness of marketing campaigns is crucial for banks to acquire and retain customers. The objective is to leverage the power of deep neural networks in analyzing large-scale customer data and identifying patterns that influence the outcome of marketing efforts.

1. Introduction

The banking industry relies heavily on effective marketing strategies to attract and retain customers. However, identifying the most effective marketing approach can be challenging, as it requires analyzing large amounts of customer data and identifying patterns and trends that can help predict the success of future campaigns. Traditional statistical models may not be effective in identifying these patterns, and mayrequire a large amount of manual input from experts in the field. Therefore, this project aims to address this challenge by developing a deep learning model that can analyze large amounts of customer data and identify patterns.

we propose the Stochastic Gradient Descent architecture that predicts whether a given customer is proper for banktelemarketing or not. it is a variant of the Gradient Descent algorithm used for optimizing machine learning models. In this variant, only one random training example is used to calculate the gradientand update the parameters at each iteration. To validate the proposed model, we use the bank marketing data of 45,211 phone calls collected during 30 months, The results of this project will provide The results of this project will provide valuable insights for banks to optimize their marketing strategies and improve their customer acquisition and retention rates. Bank marketing prediction using deep learning is a cutting-edge approach that leverages advanced machine learning techniques to analyze and forecast customer behavior in the realm of marketing campaigns within the banking industry. Deep learning models, such Stocahstic Gradient Descent, have gained significant attention and success in various domains due to their ability to extract complex patterns and relationships from vast amount of data.

The predictive model's success will be measured using appropriate evaluation metrics such as accuracy, precision, recall, and F1-score. Additionally, visualizations and statistical analyses will be employed to gain insights into the key factors influencing the success of bank marketing campaigns.

2. Related work

In this section various models by different authors are analysed for predicting the success of bank marketing. Different models have different parameters . Basically the models are divided into certain horizons. Some of the models and work done by the various researchers in this area are given below:

How does machine learning predict the success of bank telemarketing author youngkeun choi (Sangmyung university jae cho)This paper intends to understand the antecedents in the success of bank telemarketing prediction modeling better and seeks to evaluate the predictive performance of machine learning. For this, we are using a machine learning technique on the dataset of direct marketing campaigns of a Portuguese banking institution which is obtained from the UC Irvine Machine Learning Repository. Based on these results, first, among all variables, age, balance, loan, day, duration, campaign, pdays, and poutcome influence the success of bank telemarketing, while job, martial, education, default, housing, contact, month, and previous have no significance. Second, for the full model, the accuracy rate is 0.784. Predicting Bank Marketing Campaign Success using using Decision Tree and Random Forest Authors: Chaitra Hegde , Aakash Kaku, Neelang Parghi

Data from a marketing campaign run by Banco deis examined. The campaign's aim was to increase customers' subscription rates to fixed-term deposit products, such as CDs. Using knowledge from the course, a number of machine learning algorithms are implemented to answer the question: How can banks successfully market these products in the most efficient way possible and with the highest possible rate of success?

Applying AI Techniques to predict the success of bank marketing Authors: Kun-huang-chen and Hsuan wein chieu Telemarketing is one of the marketing methods valued by enterprises in marketing tools. Compared with general channel sales, it not only has lower cost, but also has better interaction with customers, and the entire sales process is faster. And where necessary processing huge owned material times, how to improve at the processing efficiency rate and the exploration of useful information is competitive advantage to the source, using AI technology to assist market segmentation and promotion is currently the commonly used. We use

python to build an AI prediction model, including Logistic Regression (LR), and a decision tree (DT) and support vector machine (SVM)

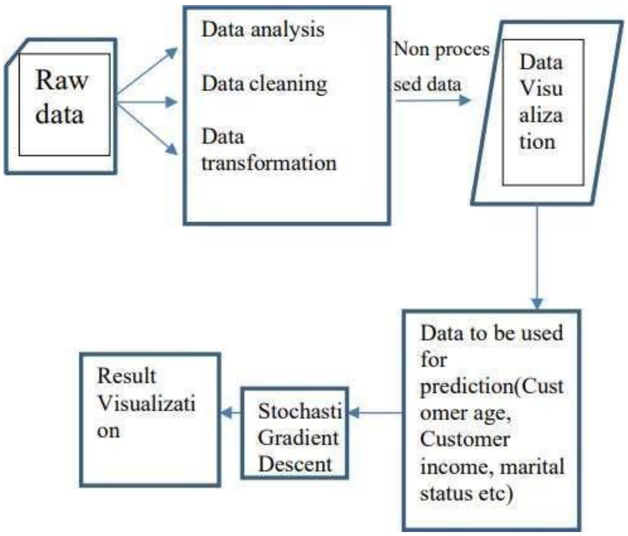
Data Driven Approach to Predict The Success of Bank Marketing Authors : Paulo Rita and Paulo Cortez

We propose a data mining (DM) approach to predict the success of telemarketing calls for selling bank long- term deposits. A Portuguese retail bank was addressed, with data collected from 2008 to 2013, thus including the effects of the recent financial crisis. We analyzed a large set of 150 features related with bank client, product and social-economic attributes. A semi-automatic feature selection was explored in the modeling phase, performed with the data prior to July 2012 and that allowed to select a reduced set of 22 features. We also compared four DM models: logistic regression, decision trees (DT), neural network (NN) and support vector machine. Using two metrics, area of the receiver operating characteristic curve (AUC) and area of the LIFT cumulative curve (ALIFT), the four models were tested on an evaluation phase, using the most recent data (after July 2012) and a rolling windows scheme. The NN presented the best results (AUC=0.8 and ALIFT=0.7).

3. Proposed Methodology

This paper highlights the methodology i.e. Stochastic Gradient. In past several years, data mining and and its implementation on various applications have earned more attention. By employing SGD, a popular optimization algorithm, we can efficiently train the predictive model on large datasets

The main phases in this proposed methodology are raw data, pre processing, and data prediction. All the steps mentioned in the proposed methodology must be followed in a right manner so as to develop a more reliable, efficient and accurate model for predicting the success of bank marketing. In the methodologies firstly the raw data is collected and is observed carefully to check whether it require pre-processing or not i.e.the available data is ready to use without any changes, if not then certain preprocessing techniques are employed over the available dataset so as to make it relevant for our use. The data which is available here has many parameters but our requirement for implementation of this methodology requires only few parameters, so to achieve this, preprocessing is required in which data dimensionality is reduced. After the preprocessing is done, the data thus obtained is refined data. Now we can employour prediction algorithms on this data so as to develop our own model to predict the success of bank marketing. The exactness of algorithm is measured in the form of different type of percentage errors



The description of each element in the systemarchitecture is described as follows:

1. Raw Data:

The raw data is basically the unprocessed or we can say the data which is not completely ready to be used for any information extraction. It is also known as the source data which has not been gone through any processing technique whether manually or through any algorithm or any automatedmachine. The below mentioned is the primary data set which has been taken from kaggle data sets. The dataset which is available has following tuples (41189) with attributes (16). The data set given in Figure 2 , so the next step is to process the data and to do this the certain algorithms and processes are used to make our data relevant to use.

	age	job	marital	education	default
0	59	admin.	married	secondary	no
1	56	admin.	married	secondary	no
2	41	technician	married	secondary	no
3	55	services	married	secondary	no
4	54	admin.	married	tertiary	no

2. Preprocessing:

In the phase of preprocessing the main objective is to select the required data which include following attributes customer age, income, marital status, education. The preprocessing here is carried out through visualization technique and training is done . It is a must step in every proposed methodologies for the development of unique and more accurate model. Data processing is basically the data filtering so as to make it more convenient to use. In these proposed methodologies after the dataset is trained with the inclusion of following attributes is depicted below. The attributes given in Figure 3 are being used for the prediction.

Data Predictions:

In this phase predictions are made out by the implementation of proper algorithms. In this paper the algorithm are used for the data prediction i.e. Stocahstic Gradient Descent.

Visualization:

Visualization is the process of analyzing of obtained result, in this phase the predicted bank marketing data is visualized and the result obtained in the form . properly analyzed to generate the predicted graphs,bar graphs and other necessary pictorial representations.

3.1Stochastic Gradient Descent basedMethodology

Stochastic Gradient Descent (SGD) is a variant of the Gradient Descent algorithm used for optimizing machine learning models. In this variant, only one random training example is used to calculate the gradient and update the parameters at each iteration

In the proposed methodology the first task is to gather the available data for implementation, collection of this type of data is based on various parameters. Here parameters are the basic environmental parameters. In pre-processing phase second task is to reduce the dimensionality of the data through data visualisation technique.

In SGD, instead of using the entire dataset for each iteration, only a single random training example (or a small batch) is selected to calculate the gradient and update the model parameters. This random selection introduces randomness into the optimization process, hence the term "stochastic" in stochastic Gradient Descent

1) Initialization:

Initialize the model parameters θ with random values.

Set the learning rate α.

Set the number of iterations or epochs

T.Shuffle the training data.

2) Repeat for t = 1 to T:

Select a mini-batch B of size m from the shuffled training data.

Compute the gradients of the loss function L(θ) with respectto the parameters θ using the mini-batch B:

$\nabla\theta L(\theta) = (1/m) \sum[i\in B]\ \nabla\theta L(\theta, xi,$
$yi)$Update the parameters θ:
$\theta = \theta - \alpha * \nabla\theta L(\theta)$

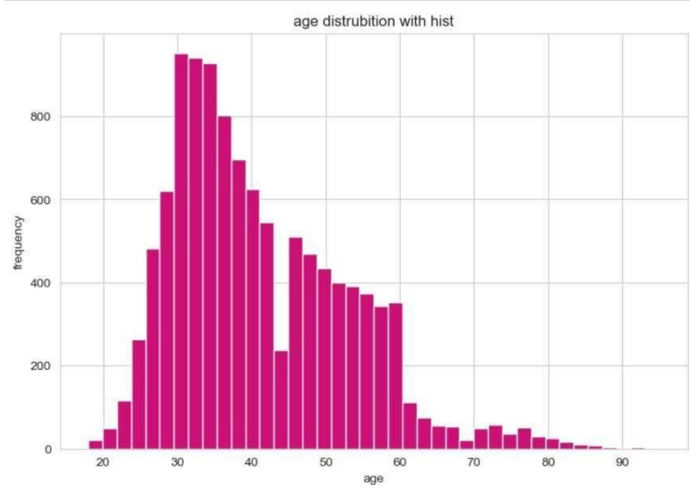
3) Output the final parameters θ.

In the above model, θ represents the model parameters (weights and biases), α is the learning rate, T is the number of iterations, and B is the mini-batch of training data. The gradient of the loss function L(θ) with respect to the parameters θ is denoted as ∇θL(θ), and it is computed by averaging the gradients of individual training examples (xi, yi) in the mini-batch B.

The update step subtracts the gradient scaled by the learning rate α from the current parameter values to move towards the minimum of the loss function. This process is repeated for a fixed number of iterations or until convergence criteria are met.

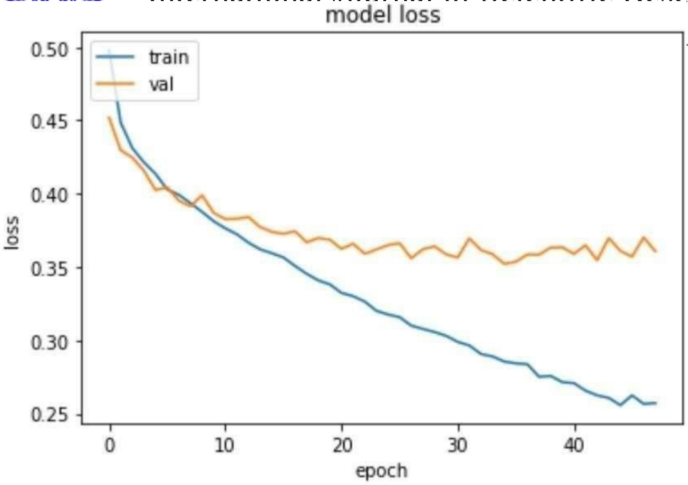
It's important to note that the this model represents the basic stochastic gradient descent algorithm. Variants of SGD, such as mini - batch SGD and adaptive learning rate methods , introduce additional complexity and modifications to this basic model.

5. Results



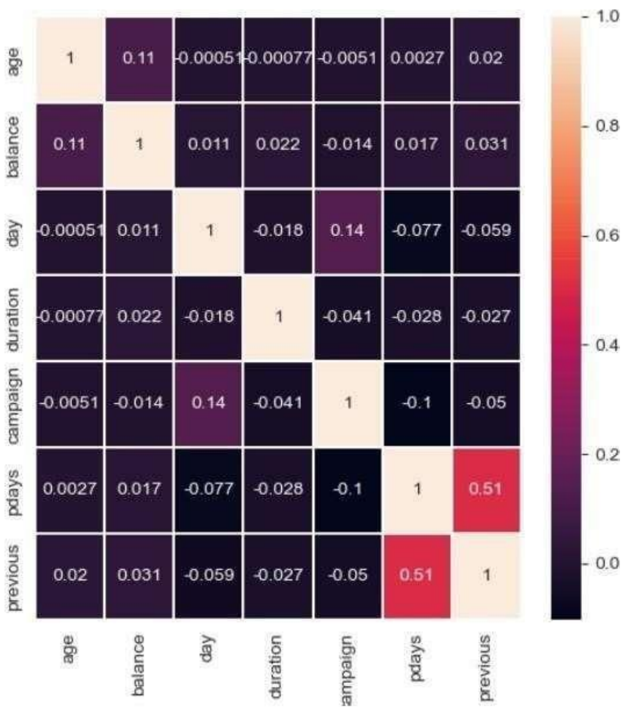
Figure(3)

From the above figure attribute age is represented in the form of histogram it is concluded that age between 30-40Are more intreseted in term subsscription



Fig(4)

Figure 4 given above shows the graph depicting the training and validation loss during the training of data done at implementation phase of these methodologies. At the time of training and validation, certain type of losses occurs, which is due to uneven occurrence of data.



Fig(5)

Above figure represents correlation matrix is a useful tool for understanding the relationships between different variables or features within a dataset. It allows us to quantify the strength and direction of linear relationships between pairs of variables

correlation matrices are a powerful tool for understanding the relationships between variables in a dataset, enabling better feature selection, data preprocessing, exploratory data analysis, and model interpretation in deep learning.

6. Conclusion

From this project, we learned how banks can improve their marketing campaigns by focusing their efforts on certain prime-grade clients and also how they can recognize market conditions which are favorable to increase client subscription for the fixed-term products they are offering. All of this was possible by implementing data science and Deep Learning methods in Python.

Through the project, we have seen that deep learning models, such as stochastic gradient descent, can effectively process various input features, such as demographic information, financial indicators, and customer behavior data, to predict the likelihood of a successful marketing outcome. The models can capture non-linear relationships, detect subtle patterns, and adaptively learn from the data, thereby enhancing the predictive power.

We have observed that stochastic gradient descent algorithm is helpful in predicting the success of bank marketing . it is a variant of the Gradient Descent algorithm used for optimizing machine learning models. In this variant, only one random training example is used to calculate the gradient and update the parameters at each iteration.

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