Marketing Campaign and Loan Status Predictor

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***Abstract* — All bank campaigns are dependent on a very large dataset which will be impossible for a human data analyst to learn patterns in the decision-making process whether to interact with a specific client for a given scheme or not. The project's base idea is to design a bank marketing campaign predictor, where we will develop a classifier that uses data of several clients to predict the outcome of the Bank marketing campaign, this will predict if the client subscribes to a term deposit after they have been contacted by phone.**

Simultaneously, this paper's intention is also to predict if any given customer is pre-approved for a loan depending on their past finances. A differential privacy mechanism is also introduced to work with the bank dataset and demonstrate how the mechanism impacts the output.

Keywords—direct marketing, bank datasets, campaign result, loan status, differential privacy

I. Introduction

Banks tend to do marketing in various ways such as direct marketing, media marketing, word of mouth, advertisements, social media promotions etcetera. It is inevitable for companies to face changes and one such change is the evolution in the way of doing advertisement. Advertisement is now done with the help of not so newfound helping hand that is Artificial Intelligence and Machine Learning.[8] Amongst all the ways, direct marketing is the only path where human labor is required, in which bank employees must directly contact every one of their customers over calls to inform and enquire about their interests in subscribing to each scheme or term deposit that a bank has to offer. This way, direct marketing is a very time taking process.

Here, one solution could be to reduce the number of customers directly from the database where a system can ignore many customers who potentially might not subscribe for a given term deposit or scheme. This is where our machine learning model comes into the picture that is to give a list of who might potentially subscribe to the term deposit and the employees could just call them instead of all their customers.

Although there are various items that banks in our financial system can market, their primary source of income comes from their credit lines. As a result, they can profit from the interest on the loans they have credited. The profitability or loss of a bank is mostly determined by the loans it makes, namely whether its customers are making their loan repayments. The bank can lower its non-performing assets by foreseeing loan defaulters. This highlights how crucial it is to examine this phenomenon. There are several ways to explore the issue of preventing loan default, according to earlier research conducted in this era. But because accurate forecasts are crucial for maximizing earnings, it is crucial to understand how the various approaches work.

The goal of this project is to build a Machine Learning model that learns the patterns from the several input features related to the details of bank customers to classify whether the client will accept a term deposit that was offered by the bank through direct marketing.

A. Motivation

In banks, huge data records information about their customers. This data can be used to create and keep clear relationship and connection with the customers to target them individually for definite products or banking offers. Usually, the selected customers are contacted directly through personal contact, telephone cellular, mail, email, or any other contacts to advertise the new product/service or give an offer, this kind of marketing is called direct marketing. In fact, direct marketing is the main strategy of many banks and insurance companies for interacting with their customers. The motivation for the project comes from an ideology to decrease the time and labor used in banks for direct marketing.

B. Problem Statement

All bank marketing campaigns are dependent on customers' huge electronic data. The size of these data sources is impossible for a human analyst to come up with interesting information that will help in the decision-making process. Data mining models are completely helping in the performance of these campaigns. The purpose is to increase the campaign effectiveness by identifying the main characteristics that affect the success based on a handful of algorithms that we will test (e.g. Decision Trees, K-Nearest Neighbor, Naïve Bayes, Random Forest, and others). With the experimental results, we will demonstrate the performance of the models by statistical metrics like accuracy, precision, recall, f1_score, etc. With the higher scoring of these metrics, we will be able to judge the success of these models in predicting the best campaign contact with the clients for subscribing deposits. The aim of the marketing campaign was to get customers to subscribe to a bank term deposit product. Whether they did this or not is variable 'y' in the data set. The bank in question is considering how to optimize this campaign in the future.

C. Contribution

This paper is a document contributing to our efforts to demonstrate how effective each prediction model is using standard machine learning metrics. Our most essential contribution to this project is addressing various issues faced in the banking sector (Marketing prediction, loan eligibility, private data integrity) and the incorporation of different models to achieve the best outcome for each section. The differential privacy algorithm that we intend to use will ensure data integrity while we work on several data processing techniques, modeling, and training.

II. Related Works

A. Campaign Result Prediction

Direct marketing is a form of communicating an offer, where organizations communicate directly to a pre-selected customer and supply a method for a direct response. Among practitioners, it is also known as direct response marketing. By contrast, advertising is of a mass-message nature.[5]

According to Rosset Saharon and Uri Eick, we must consider prediction model evaluation in the context of marketing-campaign planning. In order to evaluate and compare models with specific campaign objectives in mind, we need to concentrate our attention on the appropriate evaluation criteria. These should portray the model's ability to score accurately and to identify the relevant target population.[7]

B. Loan Status Prediction

According to Prateek Dutta,[4] the models are compared based on the performance measures such as sensitivity and specificity. The results have shown that the model produces different results. The model is marginally better because it includes variables (personal attributes of customer like age, purpose, credit history, credit amount, credit duration, etc.) other than checking account information (which shows the wealth of a customer) that should be considered to calculate the probability of default on loan correctly.[3]

C. Differential Privacy

Often, the training of models requires large, representative datasets, which may be crowdsourced and contain sensitive information. The models should not expose private information in these datasets. Addressing this goal, we develop new algorithmic techniques for learning and refined analysis of privacy costs within the framework of differential privacy.[10]

Differential Privacy is a notion that allows quantifying the degree of privacy protection provided by an algorithm on the underlying sensitive data set it operates on. Through the lens of differential privacy, we can design machine learning models and algorithms that responsibly train models on private data.

As we are working here with a banking dataset that consists of personal data, it is highly important to ensure the integrity of the datasets.

III. System Description

We will be seeing a few classifiers that predict whether a particular client will subscribe to a term deposit or not. If the classifier has very high accuracy it can help the bank to filter clients and use available resources more efficiently to achieve the campaign goal. Besides, we would also try to find influential factors for the decision so that we can establish an efficient and precise campaigning strategy. A proper strategy would reduce costs and improve long-term relations with the clients.

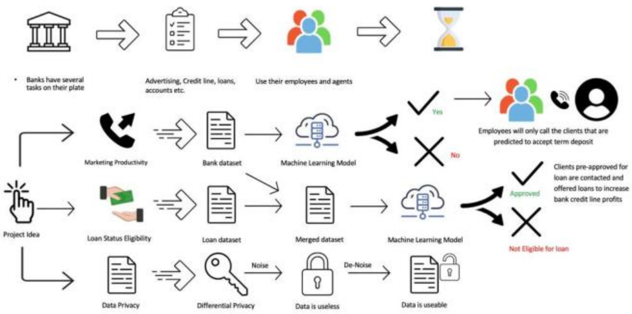

Fig. 1. **Infographic represntation of machine learning model**

A. Decision Tree Classifier

Decision tree classifiers are supervised machine learning models. This means that they use prelabelled data in order to train an algorithm that can be used to make a prediction. Decision trees can also be used for regression problems. Much of the information that you'll learn in this tutorial can also be applied to regression problems.

Decision tree classifiers work like flowcharts. Each node of a decision tree represents a decision point that splits into two leaf nodes. Each of these nodes represents the outcome of the decision and each of the decisions can also turn into decision nodes. Eventually, the different decisions will lead to a final classification.

B. K-Nearest Neighbor

The k-nearest neighbors (KNN) algorithm is a data classification method for estimating the likelihood that a data point will become a member of one group or another based on what group the data points nearest to it belong to.

The k-nearest neighbor algorithm is a type of supervised machine learning algorithm used to solve classification and regression problems. However, it's mainly used for classification problems.

KNN is a lazy learning and non-parametric algorithm. It's called a lazy learning algorithm or lazy learner because it doesn't perform any training when you supply the training data. Instead, it just stores the data during the training time and doesn't perform any calculations. It doesn't build a model until a query is performed on the dataset. This makes KNN ideal for data mining.

In short, KNN involves classifying a data point by looking at the nearest annotated data point, also known as the nearest neighbor.

C. Naïve Bayes

It is called Naïve because it assumes that the occurrence of a certain feature is independent of the occurrence of other features. Such as if the fruit is identified on the bases of color, shape, and taste, then red, spherical, and sweet fruit is recognized as an apple. Hence each feature individually contributes to identify that it is an apple without depending

on each other. It is called Bayes because it depends on the principle of Bayes' Theorem.
The formula for Bayes' theorem is given as:

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)}$$

Fig. 2. **Bayes Theorem Formula**

Where,
P(A|B) is Posterior probability: the probability of hypothesis A on the observed event B.
P(B|A) is Likelihood probability: the probability of the evidence given that the probability of a hypothesis is true.
P(A) is Prior Probability: the probability of the hypothesis before observing the evidence.
P(B) is Marginal Probability: Probability of Evidence.

Working of Naïve Bayes is firstly by converting the given dataset into frequency tables. Then, generate a Likelihood table by finding the probabilities of given features. At last, use the Bayes theorem to calculate the posterior probability.

D. Model Evaluation

The evaluation metrics proposed are appropriate given the context of the data, the problem statement, and the intended solution.[6] The performance of each classification model is evaluated using three statistical measures classification accuracy, sensitivity, and specificity. It is using true positive (TP), true negative (TN), false positive (FP) and false negative (FN). The percentage of Correct/Incorrect classification is the difference between the actual and predicted values of variables. True Positive (TP) is the number of correct predictions that an instance is true, or in other words; it is occurring when the positive prediction of the classifier coincided with a positive prediction of the target attribute. True Negative (TN) is presenting a number of correct predictions that an instance is false, (i.e.) it occurs when both the classifier, and the target attribute suggest the absence of a positive prediction. The False Positive (FP) is the number of incorrect predictions that an instance is true. Finally, False Negative (FN) is the number of incorrect predictions that an instance is false.

Classification accuracy is defined as the ratio of the number of correctly classified cases and is equal to the sum of TP and TN divided by the total number of cases (TN + FN + TP + FP).

$$Accuracy = \frac{TN + TP}{TN + FP + TP + FN}$$

Fig. 3. **Mathematical representation of Accuracy**

Precision is defined as the number of true positives (TP) over the number of true positives plus the number of false positives (FP).

$$Precision = \frac{TP}{TP + FP}$$

Fig. 4. **Mathematical representation of Precision**

Recall is defined as the number of true positives (TP) over the number of true positives plus the number of false negatives (FN).

$$Recall = \frac{TP}{TP + FN}$$

Fig. 5. **Mathematical representation of Recall**

F1 Score is needed when you want to seek a balance between Precision and Recall. F1 Score might be a better measure to use if we need to seek a balance between Precision and Recall AND there is an uneven class distribution (large number of Actual Negatives).

$$F1\ Score = 2 * \frac{Precision * Recall}{Precision + Recall}$$

Fig. 6. **Mathematical representation of F1 Score**

E. Differential Privacy

As discussed in the related works, differential privacy helps us to design algorithms that train models with private data without losing the data integrity. Differential Privacy works by adding noise to the dataset.

Firstly, we have to predict both intended outcomes (campaign prediction and loan status prediction) before adding noise. Then, drop the target column from both datasets and add noise to the resulting datasets. Later, return the output variables as they were before and start training and testing split and predict the outcome for the bank dataset and loan dataset.

IV. Data Processing

The data is related to the direct marketing campaign of a banking institution acquired from Kaggle. The marketing campaigns were based on directing marketing through phone calls. Often more than one contact with the same client was required, to access if the product (bank term deposit) would be (yes) or not (no) subscribed.

We will prepare the data by splitting feature and target/label columns and check for the quality of given data and perform data cleaning. To check if the model created is any good, we will split the data into `training` and `validation` sets to check the accuracy of the best model. We will split the given `training` data in two, 80% of which will be used to train our models and 20% we will hold back as a `validation` set. There are several non-numeric columns that need to be converted. Many of them are simply yes/no, e.g., housing. These can be reasonably converted into 1/0 (binary) values. Other columns, like profession and marital, have more than two values and are known as categorical variables. The recommended way to handle such a column is to perform Label Encoding to convert them to numerical values. Similarly, Several Data preprocessing steps like preprocessing feature columns, checking null values, deriving a summary of the dataset, identifying feature and target columns, data cleaning, and creating training and validation data splits were followed.

A. *Bank Marketing Campaign dataset*

The data is related to direct marketing campaigns of a Portuguese banking institution.[1] The marketing campaigns were based on phone calls. Often, more than one contact with the same client was required, to access if the product (bank term deposit) would be ('yes') or not ('no') subscribed. The classification goal is to predict if the client will subscribe (yes/no) to a term deposit (variable y).[2]

1. age (numeric)
2. job: type of job (categorical: "admin.", "unknown", "unemployed", "management", "housemaid", "entrepreneur", "student", "blue-collar", "self-employed", "retired", "technician", "services")
3. marital: marital status (categorical: "married", "divorced", "single"; note: "divorced" means divorced or widowed)
4. education (categorical: "unknown", "secondary", "primary", "tertiary")
5. default: has credit in default? (Binary: "yes", "no")
6. balance: average yearly balance, in euros (numeric)
7. housing: has a housing loan? (Binary: "yes", "no")
8. loan: has a personal loan? (Binary: "yes", "no")

Fig. 7. **Visualisation of Personal attributes**

Related to the last contact of the current campaign:

9. contact: contact communication type (categorical: "unknown", "telephone", "cellular")
10. day: last contact day of the month (numeric)
11. month: last contact month of the year (categorical: "Jan", "Feb", "Mar", ..., "Nov", "Dec")
12. duration: last contact duration, in seconds (numeric)

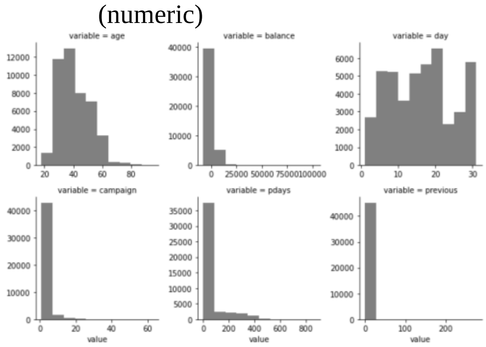

Fig. 8. **Histograms for numerical data**

Fig. 9. **Visualisation of last contacted details of current campaign**

Other attributes:

13. campaign: number of contacts performed during this campaign and for this client (numeric, includes the last contact)
14. pdays: number of days that passed by after the client was last contacted from a previous campaign (numeric, -1 means the client was not previously contacted)
15. previous: number of contacts performed before this campaign and for this client (numeric)
16. poutcome: outcome of the previous marketing campaign (categorical: "unknown", "other", "failure", "success")

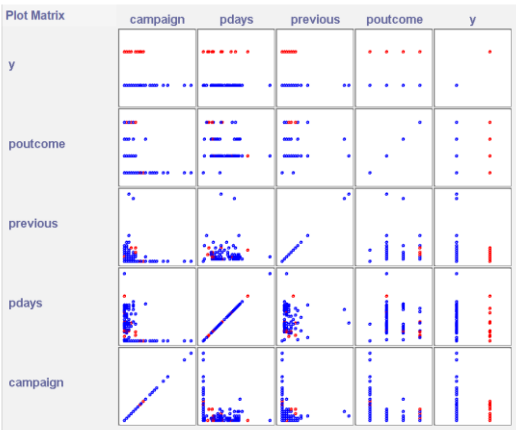

Fig. 10. **Visualisation of attributes related to previous campaigns**

Output variable (desired target):

17. y - has the client subscribed to a term deposit? (Binary: "yes", "no")

B. *Loan Status dataset*

Here, Firstly, we must drop unnecessary columns from both the bank dataset and the loan dataset[9]. Replace column values in the bank dataset to match the column values in the loan dataset. Then, Rename the columns in the loan dataset to match the column names in the bank dataset.

Merge both datasets using common columns. Thus, merged data is cleaned by removing empty rows and by using Label Encoder to convert categorical features to numerical ones.

Later, this loan dataset is trained into a decision tree classifier to predict loan eligibility.

The loan dataset has columns as follows:

1. Loan ID: Unique loan ID of the customer
2. Gender: Male/female
3. Married: Y/N
4. Dependents: number of dependents
5. Education status: Graduate/Undergraduate
6. Applicant Income
7. Co Applicant Income
8. Loan Amount: Loan amount in thousands
9. Loan Amount Term: Term of loan in months
10. Credit History: if history meets the guidelines
11. Property Area: Urban/Semi-Urban/Rural

Out of the above, we drop the Loan_ID, Gender, Dependents, Self_employed, CoapplicantIncome, Loan Amount, Loan_Amount_Term, and Property_Area which show no effect on our output variable Loan Status.

Fig. 11. **Visualisation of loan dataset after dropping unused columns**

Now, from the previous banking dataset we drop unused columns that include default, housing, contact, day, month, duration, campaign, pdays, previous, poutcome, and target. Furthermore, data points from both datasets are altered to match each other so that they can be combined and used for predicting loan status of an individual. Data preprocessing steps of the new merged dataset like preprocessing feature columns, checking null values, deriving a summary of the new merged dataset, identifying feature and target columns, data cleaning, and creating training and validation data splits were followed. Label encoding is performed to convert categorical features to numerical values. Finally, this dataset is split into a training set and a testing set to build a Decision Tree classifier and check its accuracy and plot heatmap and confusion matrix to exhibit the same.

V. Experimental Results

A. Section-I: Marketing Campaign Prediction

1) Decision Tree Classifier

```
Decision Tree Classifier accuracy on training set= 0.89
Decision Tree Classifier accuracy on testing set= 0.83
```

Fig. 12. **Decision Tree Classifier Accuracy**

```
[[1144  111]
 [ 166  231]]
```

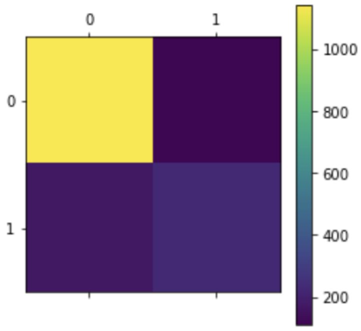

Fig. 13. **Decision Tree Confusion Matrix**

	precision	recall	f1-score	support
no	0.87	0.91	0.89	1255
yes	0.68	0.58	0.63	397
accuracy			0.83	1652
macro avg	0.77	0.75	0.76	1652
weighted avg	0.83	0.83	0.83	1652

Fig. 14. **Decision Tree Accuracy Metrics**

2) K-Nearest Neighbors Algorithm

```
K-Nearest Neighbors Algorithm accuracy on training set= 0.87
K-Nearest Neighbors Algorithm accuracy on testing set= 0.77
```

Fig. 15. **KNN Algorithm Accuracy**

```
[[1110  145]
 [ 229  168]]
```

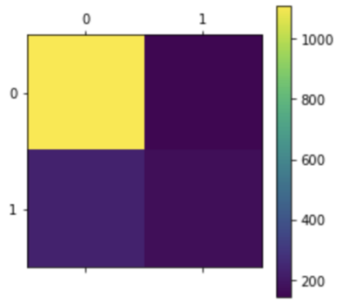

Fig. 16. **KNN Confusion Matrix**

	precision	recall	f1-score	support
no	0.83	0.88	0.86	1255
yes	0.54	0.42	0.47	397
accuracy			0.77	1652
macro avg	0.68	0.65	0.66	1652
weighted avg	0.76	0.77	0.76	1652

Fig. 17. **KNN Accuracy Matrics**

3) Naïve Bayes

```
Naive Bayes accuracy on training set= 0.81
Naive Bayes accuracy on testing set= 0.80
```

Fig. 18. **Naïve bayes Classifier Accuracy**

```
[[1067  188]
 [ 148  249]]
```

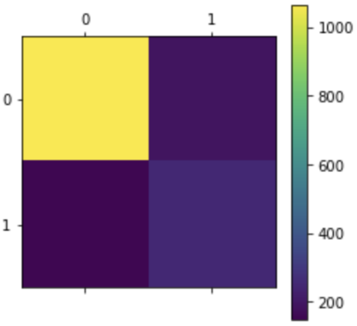

Fig. 19. **Naïve Bayes Algorithm Confusion Matrix**

```
              precision    recall  f1-score   support

          no       0.88      0.85      0.86      1255
         yes       0.57      0.63      0.60       397

    accuracy                           0.80      1652
   macro avg       0.72      0.74      0.73      1652
weighted avg       0.80      0.80      0.80      1652
```

Fig. 20. **Naïve Bayes Metrics**

As we can clearly observe that the Decision Tree has the best accuracy, we proceed with it for prediction. A Queries file is given as input to the model after label encoding its categorical values to numerical and the output column is dropped as well as the Id column is copied separately and dropped. Now, this processed queries file is given as input and marketing campaign prediction is performed. At the end of which, we acquire a text document with Ids and the predictions (either Yes or No).

	Test ID	Prediction
0	1	yes
1	2	yes
2	3	no
3	4	no
4	5	yes
...	...	...
45206	45207	yes
45207	45208	yes
45208	45209	yes
45209	45210	yes
45210	45211	no

45211 rows × 2 columns

Fig. 21. **Predictions.txt (Prediction of Bank Campaign Result)**

These predictions are again passed to the same queries file to form a csv file that consists of our campaign prediction.

B. *Section II: Loan Status Prediction*

Here, the Merged dataset acquired from both datasets is given into a decision tree classifier model.

```
Decision Tree Classifier accuracy on training set= 1.00
Decision Tree Classifier accuracy on testing set= 1.00
```

Fig. 22. **Decision Tree Classifier Accuracy on loan dataset**

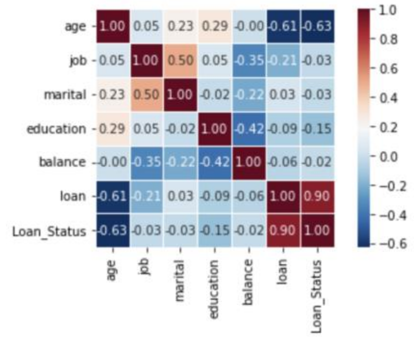

Fig. 23. **Basic linear correlation of merged dataset**

```
#get the data for the 1st row in the df_merged dataset
df_merged.iloc[0].values

array([   46,     3,     1,     0, 4301,     1,     1])

#predict the loan eligibility for the 1st row
decTreeModel.predict([[46, 3, 1, 0, 4301, 1]])
#predicted result is 1 = yes

array([1])

#get the data for the 4th row in the df_merged dataset
df_merged.iloc[3].values

array([   52,     0,     1,     1, 2281,     1,     0])

#predict the loan eligibility for the 4th row
decTreeModel.predict([[52, 0, 1, 1, 2281, 1]])

#predicted result is 0 = no

array([0])
```

Fig. 24. **Predicted results of loan eligibilty status**

C. *Section-III: Differential Privacy*

We predict both the results before and after adding noise to the datasets, which will demonstrate to us the difference that is achieved through encryption ensuring the personal data is still intact and integral.

```
Decision Tree Classifier accuracy on training set= 0.89
Decision Tree Classifier accuracy on testing set= 0.83

#get the values of the 1st row (before adding noise)
bank_data.iloc[0].values

array([33, 0, 1, 3, 0, 882, 0, 0, 1, 21, 10, 39, 1, 151, 3,
0, 'no'],
      dtype=object)

#predict the outsome using the 1st row data
decTreeModel.predict([[33, 0, 1, 3, 0, 882, 0, 0, 1, 21, 10,

array(['no'], dtype=object)
```

Fig. 25. **Bank Campaign dataset Predicted Outcome**

```
Decision Tree Classifier accuracy on training set= 1.00
Decision Tree Classifier accuracy on testing set= 1.00

#get the values of the 1st row (before adding noise)
loan_data.iloc[0].values

array([   46,     3,     1,     0, 4301,     1,     1])

#predict the outsome using the 1st row data
decTreeModel.predict([[46, 3, 1, 0, 4301, 1]])

array([1])
```

Fig. 26. **Loan dataset Predicted Outcome**

Adding Noise to the datasets using Laplacian Noise has given us the following data for a particular row.

```
array ([34.95042595489817, -0.4008837624
7430024, 1.7685514222676586, 4.331442161
447155, 1.740813256913797, 882.758783040
5311, 1.5184925590292582, 2.538284098528
475, 0.502464951174354, 22.3083252435241
,10.173801881223161, 40.285272464583834,
 2.1498417057146204, 154.44801571321702,
 3.8624327642076066, 1.001343186993205,
'no'], dtype=object)
```

Fig. 27. **One Row of dataset after adding Noise showing unusabilty**

The above data points clearly show us how the noise has affected the data belonging to a client. Such data is not usable even if the data is leaked. This is how differential privacy algorithms help to keep up data integrity. All the categorical values were turned to numerical using label encoding technique. In Fig 21. we get to observe how adding Laplacian noise has changed the dataset points into float values which when converted or processed have no chance of recognition or threat to private dataset.

```
[[1116  139]
 [ 216  181]]
```

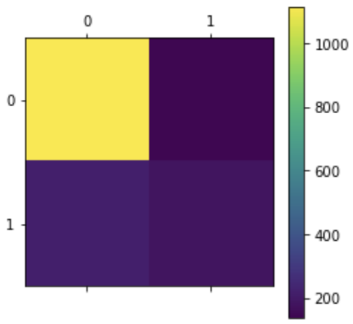

Fig. 28. **Confusion Matrix of Noisy bank dataset**

```
[[2 0]
 [1 1]]
```

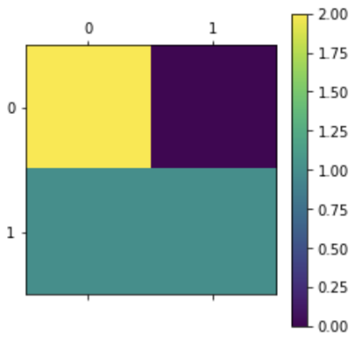

Fig. 29. **Confusion Matrix of Noisy loan dataset**

VI. Conclusion

We have implemented Data Visualization, Statistical Analysis, Data Correlation, Predictive Analytics, Cross Validation, and Machine Learning to verify that it is possible to predict Term Deposit successes and loan status with Bank Marketing client data.

Correlation Analysis demonstrated that the dataset variables that have the most correlation with Term Deposit subscriptions. The Predictive Analytics trials demonstrated that the Decision Tree classifier model produces the most accurate predictions of Term Deposits. So, we followed the same model as our most effective model to predict the campaign outcome and loan status which states if a client is pre-approved or eligible for a loan.

Duration has a positive effect on people saying "yes". This is because the longer the conversations on the phone the higher interest the customer will show to the term deposit

Banks should decrease the outbound call rate and use inbound calls for cross-selling intelligently to increase the duration of the call. Agents may pitch about profits of term deposit for a particular client during inbound calls

Employees may target clients of the job category of a housemaid, services, technician, etc. as these set of people are averse to taking risks and looking for safe deposits of their savings with fixed returns.

We have also seen how differential privacy works by adding noise to the datasets and again predicting the campaign result and loan status to demonstrate how the results differ using the same standard metrics. The result from this assures us of the integrity provided to the banking dataset.

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