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Predicting the Success of Bank Telemarketing for Selling Long-term Deposits

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GitHub link:

https://github.com/Anna-Ikeda/Predicting-the-Success-of-Bank-Telemarketing-for-Selling-Long-term-Deposits.git

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Agenda Overview

01 Introduction of our research paper

02 Introduction of the problem and the dataset

03 The methodology

04 Reproduced code

05 Suggest improvements to the model

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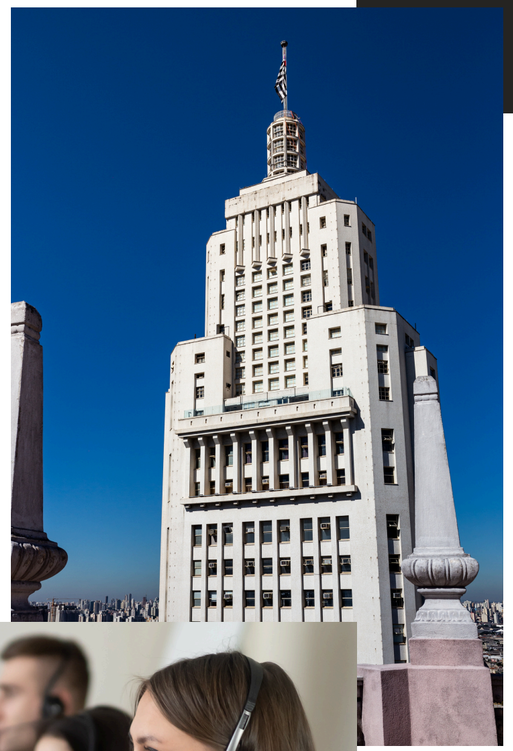
Introduction of our research paper



Predicting the Success of Bank Telemarketing for Selling Long-term Deposits: An Application of Machine Learning Algorithms(2021)

Written by
Premkumar Borugadda
Dr. Prabhakar Nandru
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https://www.researchgate.net/publication/352755139_Predicting_the_Success_of_Bank_Telem[…]erm_Deposits_An_Application_of_Machine_Learning_Algorithms

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Background of our research paper

Globalization
Expanded connections with customers across borders

Technological development
Improved customer reach and service quality

Telemarketing:
A salesperson checks customers' willingness to buy by phone

More and more banks are using telemarketing as a new marketing method to compete with other banks

For prospective customers	Telemarketing helps acquire new customers
For existing customers	Telemarketing enables better, more personalized service

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Introduction of the problem being solved

Whether telemarketing is effective for encouraging customers to subscribe to long-term bank deposits

- Few studies have predicted telemarketing success for long-term deposits using ML
- This research provided **insightful information to banks** for improving their telemarketing strategies for bank deposits

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Introduction of the dataset

Overview

- Our dataset is related with **direct marketing campaigns (phone calls) of a Portuguese banking institution**
- It collected from the UC Irvine Machine Learning Repository

https://archive.ics.uci.edu/dataset/222/bank+marketing

Number of Variables

- 21 features

Number of Rows

- 4,119 instances

Target and descriptive features

- Target feature:"**y** (Label)"
- Descriptive features: The rest of the features

Table 1. Features of the dataset

S. No	Features	Description of Features
1	Age	Age of the client
2	Job	Type of client's job
3	Marital	Client's marital status
4	Education	Highest education of the client
5	Default	Client credit
6	Housing	Housing loan
7	Loan	Personal loan
8	Contact	Type of contact communication with the client
9	Month	Last month of the year contracting to the client
10	Day of week	Last day of the week contracting to the client
11	Duration	Duration of client contact
12	Campaign	Number of contacts performed during the campaign and for this client
13	Plays	Number of days elapsed after the client's last visit
14	Previous	Number of contacts performed before this campaign and for this client
15	Poutcome	Outcome of the previous marketing campaign
16	Emp.var.rate	Employment variation rate
17	Cos.price.IDX	Consumer price index
18	Cons.conf.IDX	Consumer confidence index
19	Euribor3m	Euribor 3-month rate
20	Nr. employed	Number of employees
21	Label	Client subscription

Source: https://archive.ics.uci.edu/ml/datasets/Bank+Marketing

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Methodology

01

Data Acquisition

UCI Machin Learning Repository.
21 attributes
4119 records

02

Exploratory data analysis

Check data’s shape
Unique labels of the target variable.
Features data types
Data's descriptive statistics

03

Feature engineering

Convert categorical variable into numeric
Apply the standard scaler technique

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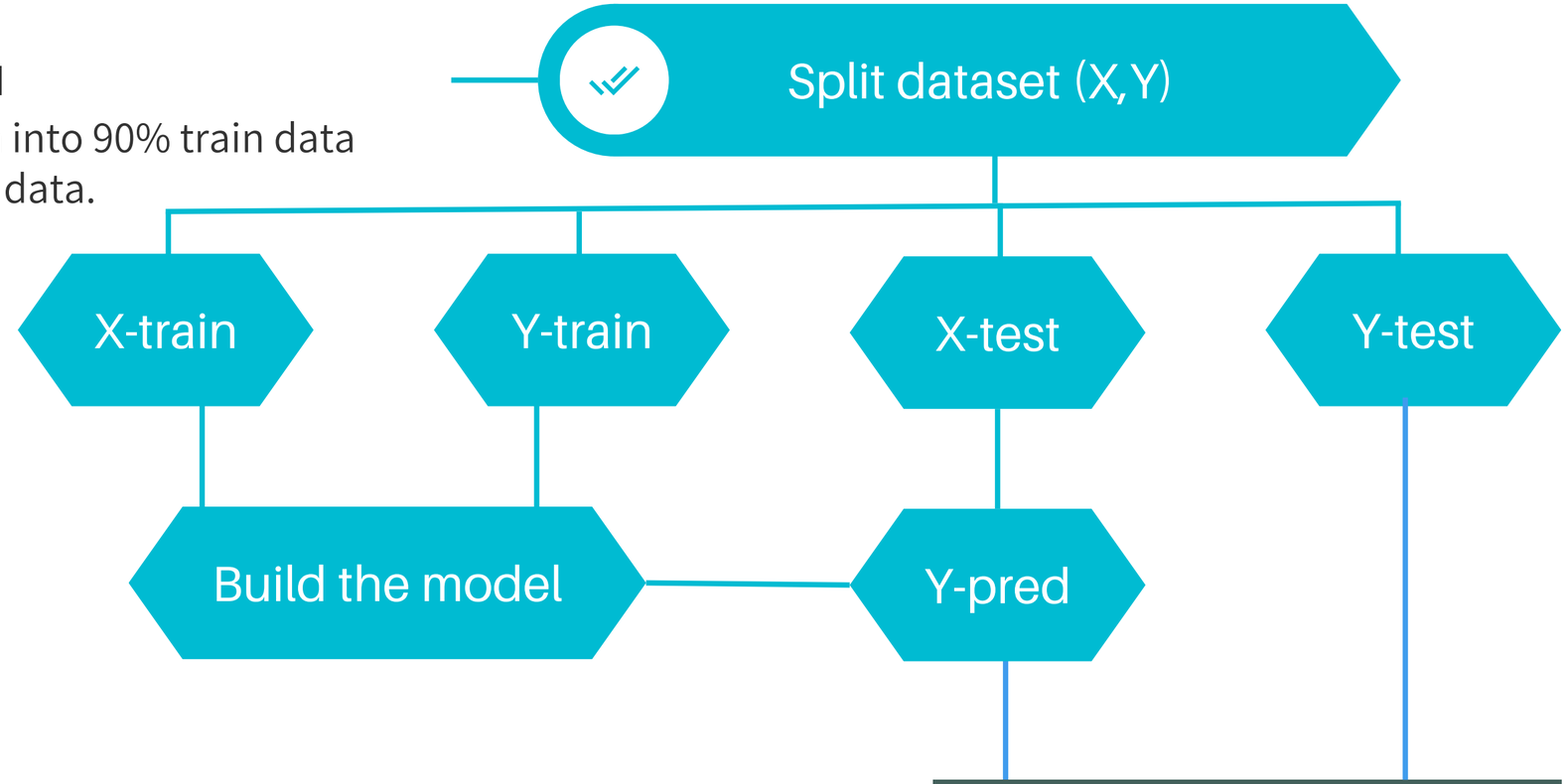
Methodology

04

Build model

Split the data into 90% train data and 10% test data.

- Logistic Regression
- Decision Tree
- Random Forest
- Gaussian Naive Bayes
- Support Vector Machine



05

Evaluation metrics

Evaluate the performance of the models through confusion matrix

- Accuracy
- Precision
- Recall
- F1 Score
- AUROC Score

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Reproduced code

Decision Tree - (Model evaluation and confusion matrix)

```
evaluate_results("Decision Tree", y_test, y_pred_dt, y_prob_dt, cm_dt)
✓ [33] 112ms

 Accuracy      : 90.29%
 Precision     : 58.62%
 Recall        : 37.78%
 F1 Score      : 45.95%
 AUC Score     : 87.90%
 Confusion Matrix:
 [[355  12]
  [ 28  17]]
```

The Decision Tree model achieved a solid accuracy of 90.29%, showing it predicts the overall outcome well. However, its precision (58.62%) and recall (37.78%) suggest it struggles to correctly identify actual positive cases, often missing them. The F1 score (45.95%) confirms this trade-off between precision and recall. Still, the AUC score of 87.90% shows it does a good job separating the two classes. The confusion matrix highlights that while the model correctly predicted 355 "no" cases, it only identified 17 true "yes" cases and missed 28, indicating a need for improvement if we want better detection of subscribers.

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Reproduced code

Decision Tree - Classification report

```
Classification Report:
              precision    recall  f1-score   support

          No       0.93      0.97      0.95       367
         Yes       0.59      0.38      0.46        45

    accuracy                           0.90       412
   macro avg       0.76      0.67      0.70       412
weighted avg       0.89      0.90      0.89       412
```

The model shows strong performance for predicting the "No" class (not subscribing), with high precision (93%) and recall (97%). However, for the "Yes" class (subscribing), both precision (59%) and recall (38%) are significantly lower, meaning many actual positive cases are missed. Overall accuracy is solid at 90%, but the model is biased toward the majority class and struggles to detect the minority class effectively. This suggests a class imbalance issue that could be addressed in future model improvements.

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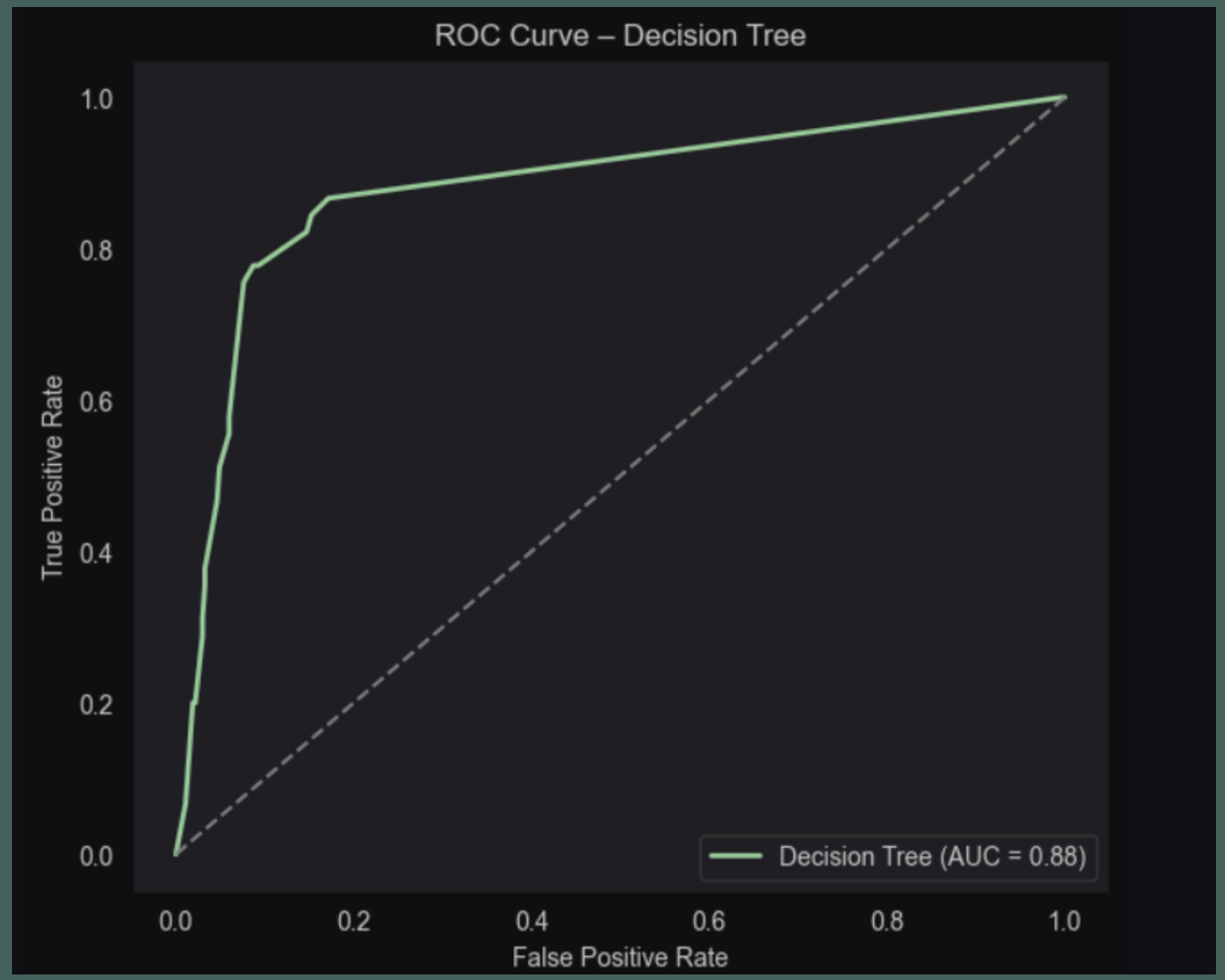
Reproduced code

Decision Tree ROC Curve



The ROC curve for the Decision Tree model shows a strong ability to distinguish between the two classes, with an AUC score of 0.88. This indicates high overall performance, as the curve stays well above the diagonal baseline, meaning the model correctly separates positive and negative classes much better than random guessing. However, while AUC is high, other metrics like recall for the "Yes" class suggest the model may still miss some true positives.

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Reproduced code

Logistic Regression - (Model evaluation and confusion matrix)

```
evaluate_results("Logistic Regression", y_test, y_pred_lr, y_prob_lr, cm_lr)
✓ [32] 88ms

 Accuracy     : 91.99%
 Precision    : 75.00%
 Recall       : 40.00%
 F1 Score     : 52.17%
 AUC Score    : 93.06%
 Confusion Matrix:
 [[361   6]
  [ 27  18]]
```

The Logistic Regression model achieved a high accuracy of 91.99% and an impressive AUC score of 93.06%, showing strong overall classification performance. It correctly identified the "Yes" class with 75% precision, though the recall is only 40%, meaning it missed some actual positives. The F1 score of 52.17% reflects this trade-off. The confusion matrix shows 18 true positives, 27 false negatives, and only 6 false positives, indicating that while the model is precise, it could improve in capturing more of the positive cases.

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Reproduced code

Classification Report of Logistic Regression

```
Classification Report:
              precision    recall  f1-score   support

          No       0.93      0.98      0.96       367
         Yes       0.75      0.40      0.52        45

    accuracy                           0.92       412
   macro avg       0.84      0.69      0.74       412
weighted avg       0.91      0.92      0.91       412
```

The classification report shows that the model performs very well in predicting the "No" class (customers who won’t subscribe), with high precision (93%) and recall (98%). However, for the "Yes" class (customers who will subscribe), precision drops to 75% and recall to 40%, meaning it misses many true positives. The overall accuracy is strong at 92%, but the imbalance in class performance indicates the model is better at detecting non-subscribers than actual subscribers.

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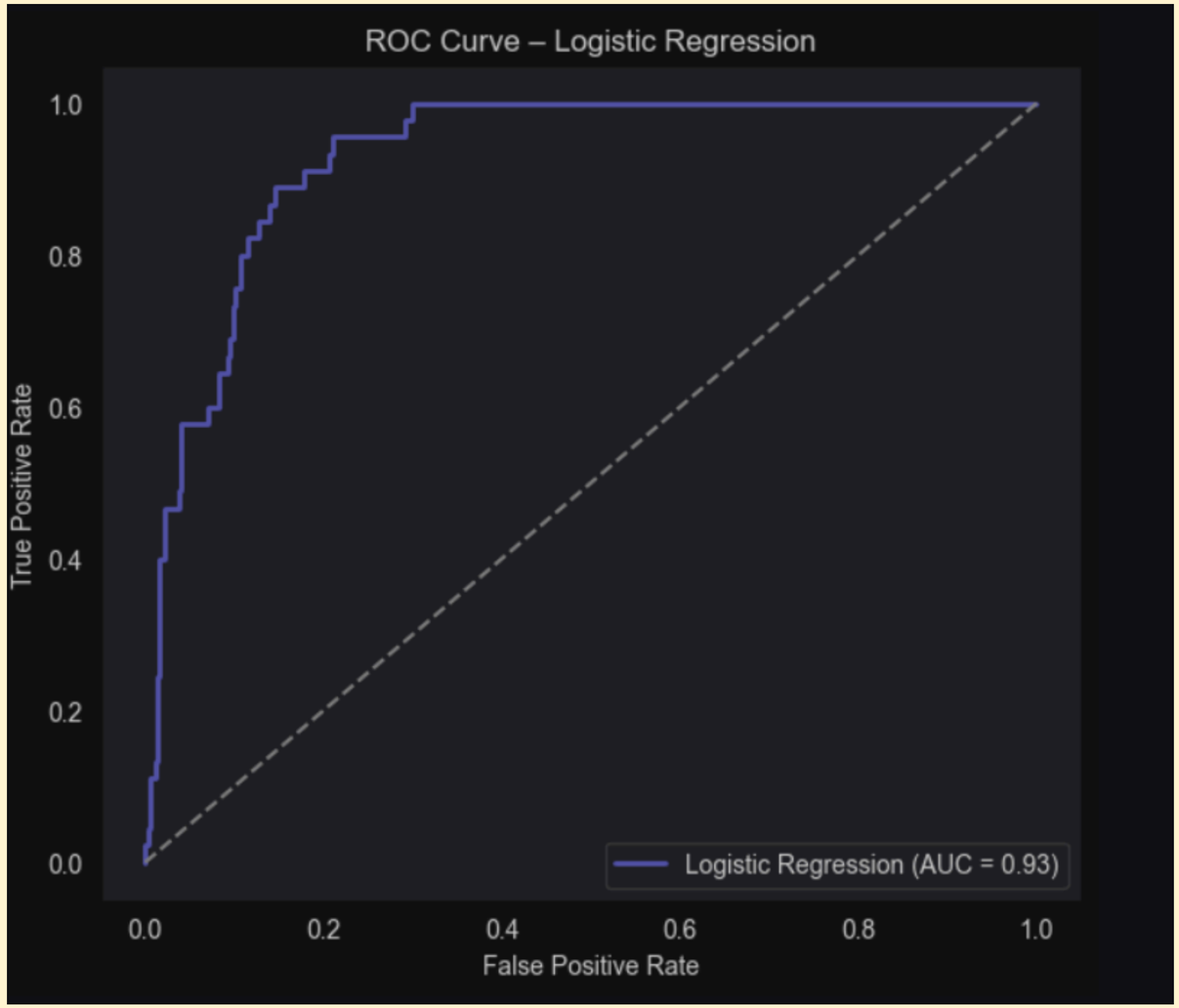
Reproduced code

ROC Curve of Logistic Regression



The ROC Curve for the Logistic Regression model shows strong performance, with an AUC score of 0.93, meaning the model has a high ability to distinguish between the two classes. The curve hugs the top-left corner, which indicates a good balance of high true positive rate and low false positive rate—ideal for a binary classifier.

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Suggest improvements to the model

01

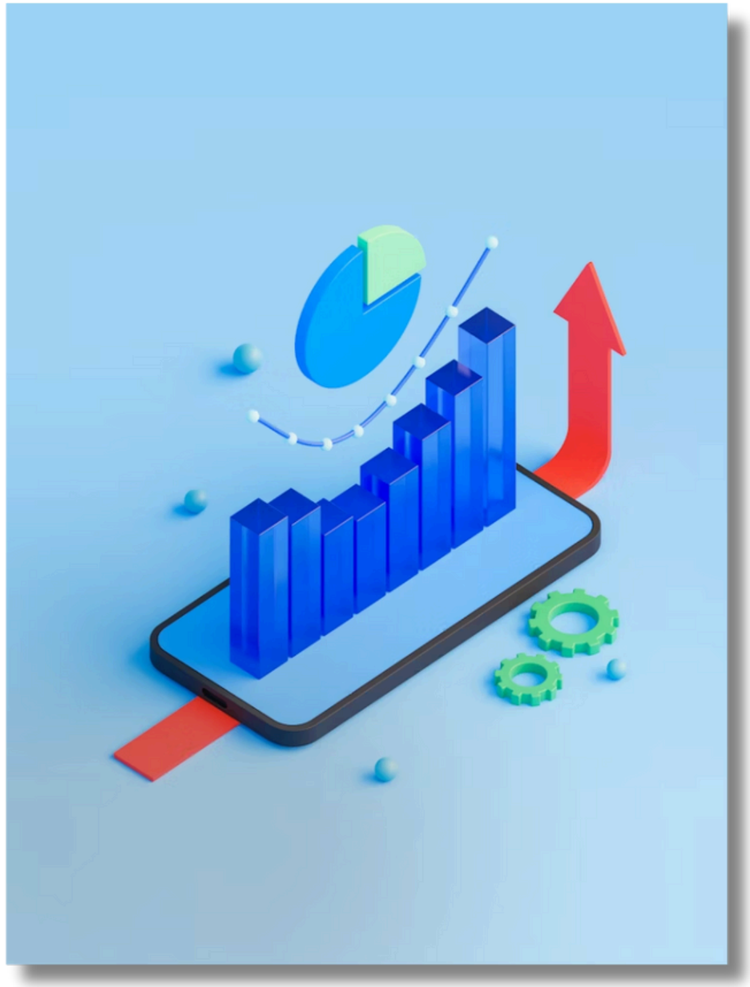
Preprocessing

- Use One Hot Encoder instead of get_dummies
- Scale only numeric features, and don't scale before tree training.

02

Models

- Use pipelines to avoid leakage
- Add class_weight = ‘balanced’



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Thank You