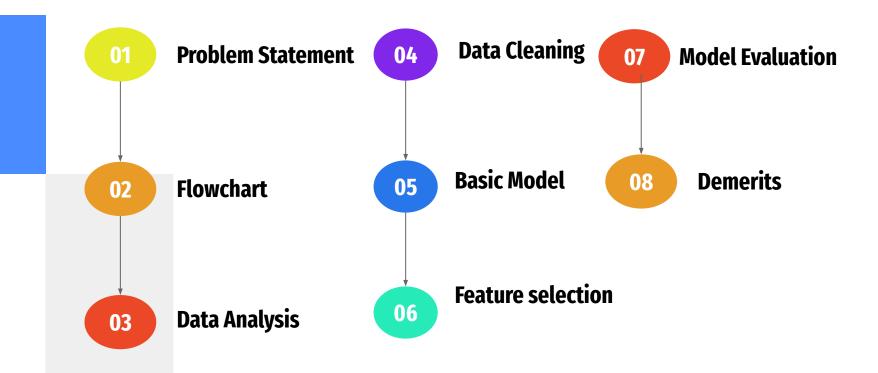
Predictive Analysis for Bank Telemarketing Success

Contents

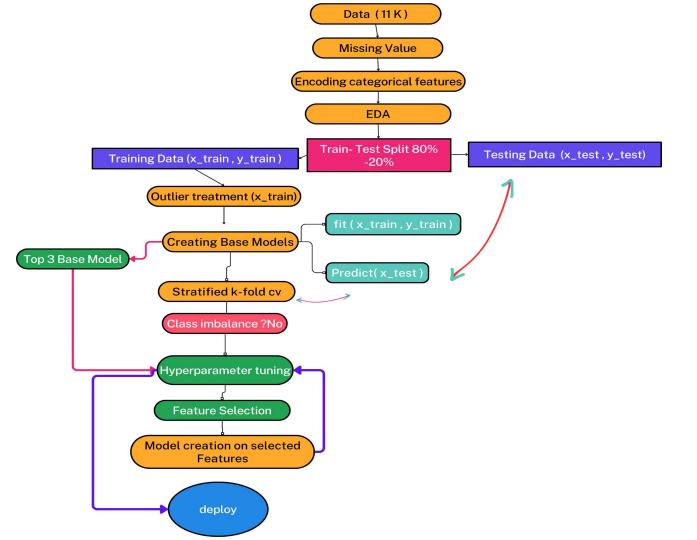


Problem Statement

Campaign Success Prediction:

Building a Predictive Model to Determine CustomerSubscription to Term Deposit Policy

Project Flowchart



Dataset Information

Dataset Shape - (11162, 17)

Dataset format - CSV File

Target Feature - Deposit (yes, no)

Independent Features -

Age,job,marital,education,default,balance,housing,loan,contact,day,month,duration,campaign,pdays,previous,poutcome

Data Analysis (EDA)

1. No Class Imbalance

2. Positive correlation between call duration and subscription likelihood.

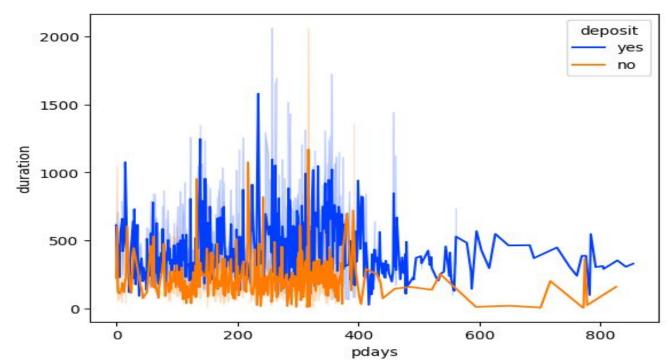
3.Impact of Categorical Columns on the Target Variable:

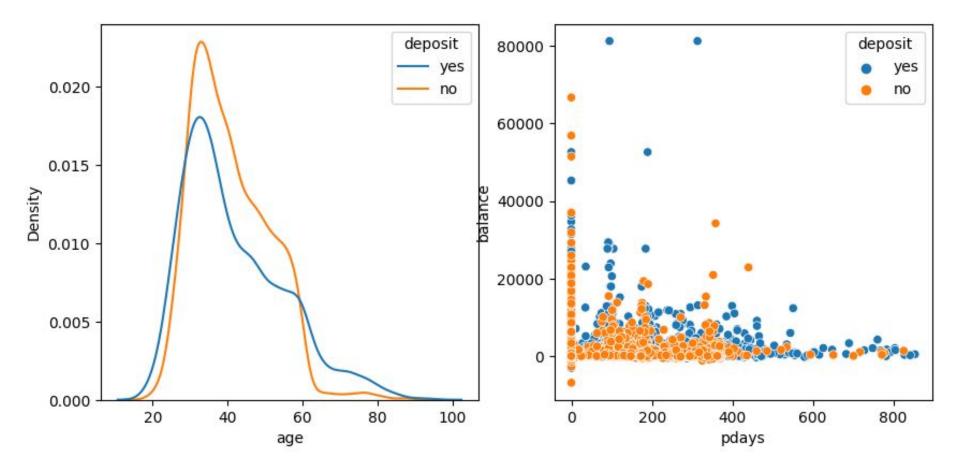
Single Marital Status, tertiary education, and do not have an existing housing loan. These demographic factors appear to influence the subscription rate positively.

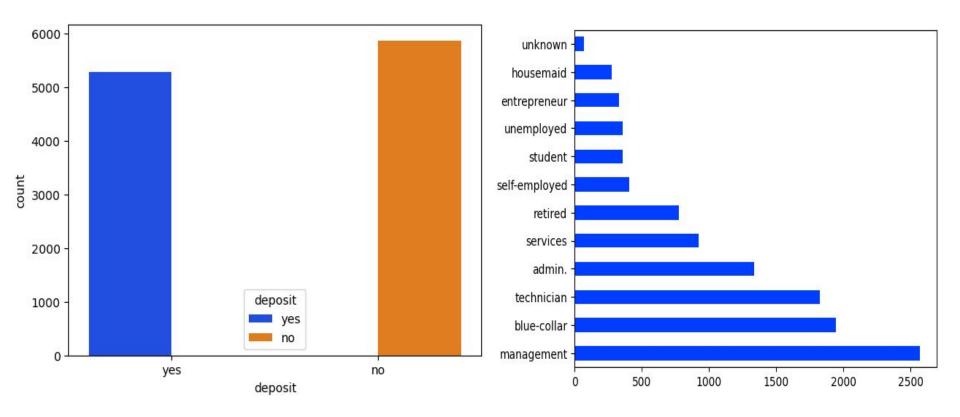
5.Effect of Last Contact Month on Subscription:

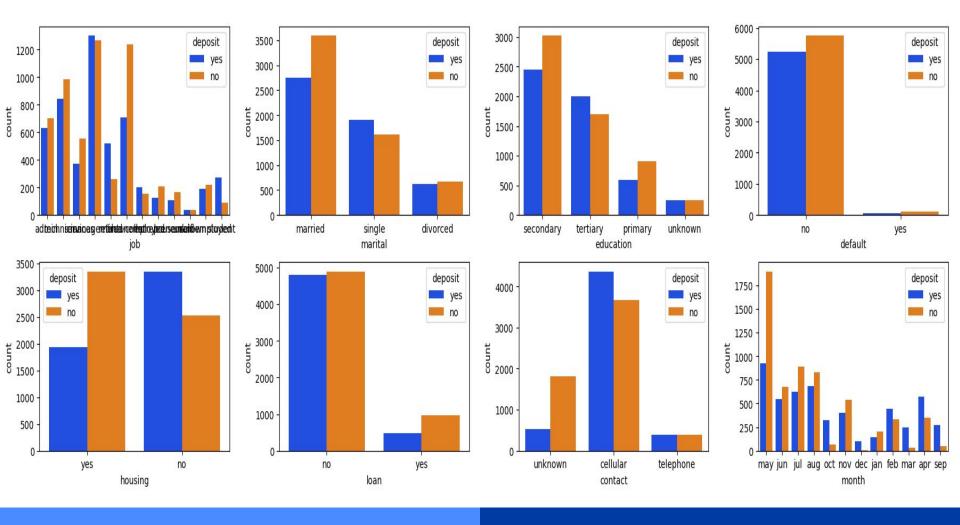
The count of customers subscribing to a term deposit is notably higher when they were last contacted in the months of February, March, April, and September.

	age	job	marital	education	default	balance	housing	loan	contact	day	month	duration	campaign	pdays	previous	poutcome	deposit
7567	37	admin.	married	secondary	no	641	yes	no	unknown	5	jun	42	1	-1	0	unknown	no
6780	30	services	single	secondary	no	-100	yes	yes	cellular	15	may	292	1	-1	0	unknown	no
5220	61	retired	married	tertiary	no	3140	yes	yes	cellular	6	aug	975	4	98	1	unknown	yes









Data Cleaning and Preprocessing

1. Special Codes Handling:

Pdays Adjustment: Replaced -1 with 0 for uniform representation of non-contacted clients.

2. Managing Missing Values:

Filled 'job', 'education', 'contact' having NaNs present as 'unknown' in data Dropped 'poutcome' Column: More than 50% missing records

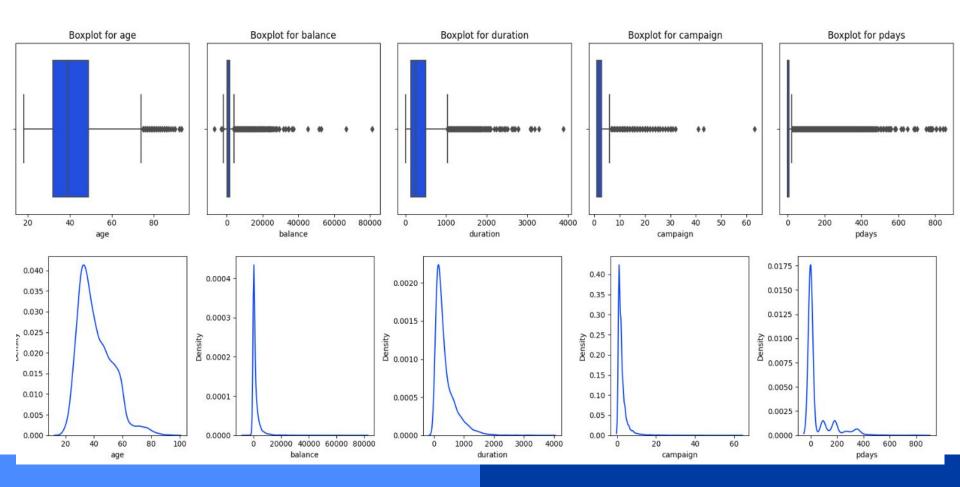
3. Missing Value Imputation:

Strategy: Used SimpleImputer replaced missing values with most frequent values.

4. Categorical to Numeric Conversion:

Label Encoding(LabelEncoder): Transformed categorical features into numeric values for analysis.

Outlier Detection



Base Models Performance Evaluation

	Model	Accuracy	Precision	Recall	F1 Score	AUC	Specificity	PRC score
0	log	75.279893	0.724138	0.793548	0.757256	0.753917	0.714286	0.674952
1	SVC	69.726825	0.702676	0.653456	0.677173	0.696066	0.738676	0.627551
2	KNN	72.637707	0.714286	0.728111	0.721132	0.726425	0.724739	0.652188
3	Random Forest	82.489924	0.807080	0.840553	0.823476	0.825329	0.810105	0.755867
4	adaboost	79.892521	0.798311	0.784332	0.791260	0.798525	0.812718	0.730933
5	Gradient Boosting	82.400358	0.808929	0.835023	0.821769	0.824306	0.813589	0.755635
6	catBoost	84.773847	0.826468	0.869124	0.847260	0.848325	0.827526	0.781895
7	XGBoost	83.161666	0.814552	0.846083	0.830018	0.832014	0.817944	0.763966
8	Decision Tree	76.175549	0.760603	0.743779	0.752097	0.761262	0.778746	0.690217

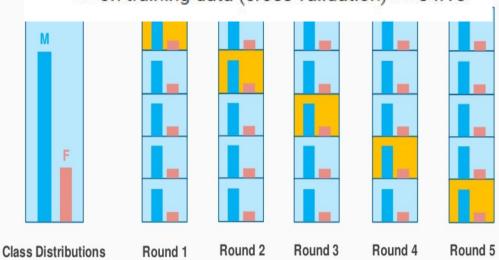
Stratified K-fold Cross Validation Results

CatBoostClassifier (cross validation results)

- on testing data => 84.77
- on training data (cross validation) => 85.32

XGBClassifier (cross validation results)

- on testing data => 83.16
- on training data (cross validation) => 84.18





Hyperparameter tuning on Top 3 base models

RandomSearchCv

Finding Best Hyperparametrs

Feature selection

Selecting Best Model

- Done Hyperparameter tuning for =>
- CatBoostClassifier
- XGBClassifier
- RandomForestClassifi er
- Selected features using feature_impotances_ attribute of models
- Generated models on their selected features
- "Evaluated model performance;
 CatBoostClassifier emerged as the top performer based on selected features."

Feature selection - Recursive Feature Elimination

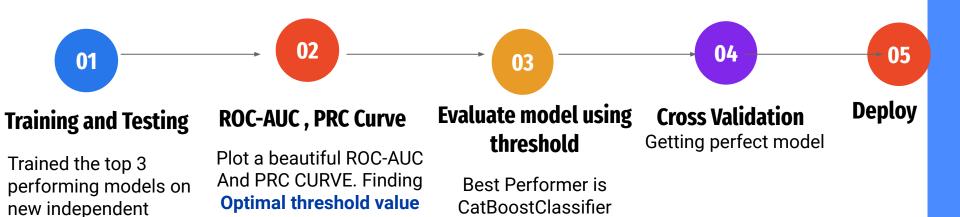
```
from sklearn.feature_selection import RFE
selector = RFE(CatBoostClassifier(verbose=False), n_features_to_select=7, step=1)
selector.fit(x_train,y_train)
```

Selected Features: ['age', 'balance', 'housing', 'day', 'month', 'duration', 'pdays']

columns rf	Feature_Score_rf2	columns_xgb	Feature_Score_xgb2	columns_cat	Feature_Score_cat
duration	0.447330	pdays	0.277740	duration	33.414440
month	0.090855	duration	0.171153	month	19.184392
age	0.081055	housing	0.147272	day	10.767175
balance	0.074622	month	0.092132	age	5.716065
day	0.064487	loan	0.057053	housing	5.343753
housing	0.045662	previous	0.038255	pdays	5.073916
previous	0.043628	dav	0.034531	balance	4.224723
pdays	0.038503	age	0.030671	job	4.158954
job	0.032323	education	0.027352	education	2.787719
campaign	0.030191	contact	0.026517	previous	2.670489
education	0.017447	campaign	0.026381	campaign	2.292366
marital	0.016666	balance	0.026284	marital	2.069355
loar	0.011808	marital	0.023796	loan	1.540071
contact	0.004521	job	0.020865	contact	0.648264
default	0.000901	default	0.000000	default	0.108317

```
x_train1=x_train[['duration','housing', 'age', 'day', 'month','balance', 'pdays']]
x_test1=x_test[['duration','housing', 'age', 'day', 'month','balance', 'pdays']]
```

Procedure on New Train -Test set



=> got 0.46

features

Evaluation on New Train & test

CatBoostClassifier

Accuracy: 85.53515450067174 f1 score: 0.8553515450067174 roc score: 0.85603293244914 Precision: 0.8318815331010453 Recall: 0.880184331797235

Confusion Matrix:

[[955 193] [130 955]]

XGBClassifier

f1 score: 0.8354430379746834 prc_score : 0.790426735771544 prc_score : 0.7703171037020241 Precision: 0.8198757763975155 Recall: 0.8516129032258064 specificity: 0.8318815331010 specificity: 0.82317073170731

Accuracy: 83.69905956112854

Confusion Matrix:

[[945 203] [161 924]]

RandomForestClassifier

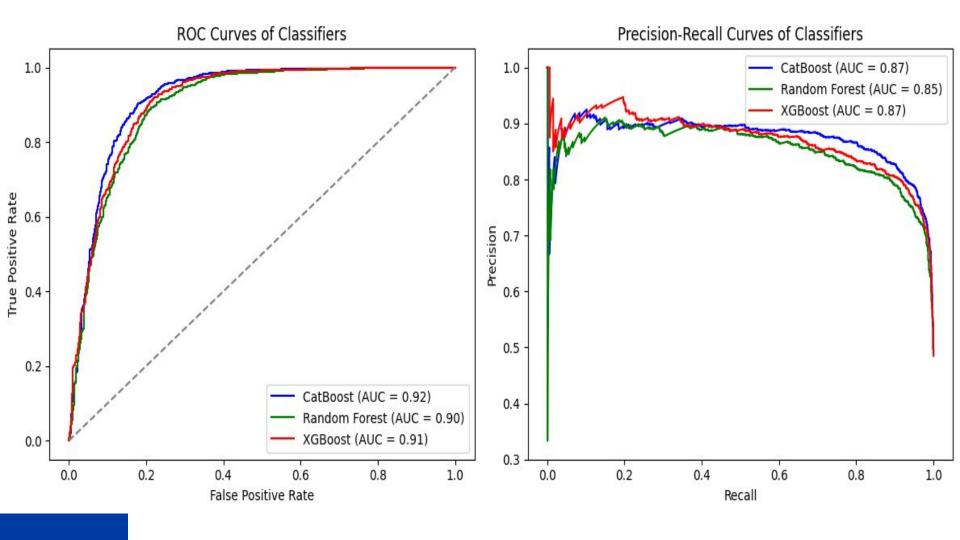
Accuracy: 82.75862068965517 f1 score: 0.8263419034731619 roc_score : 0.8373918174665618 roc_score : 0.828043160615938 prc_score : 0.7588309079852491 Precision: 0.8091872791519434 Recall: 0.8442396313364056

specificity: 0.8118466898954704

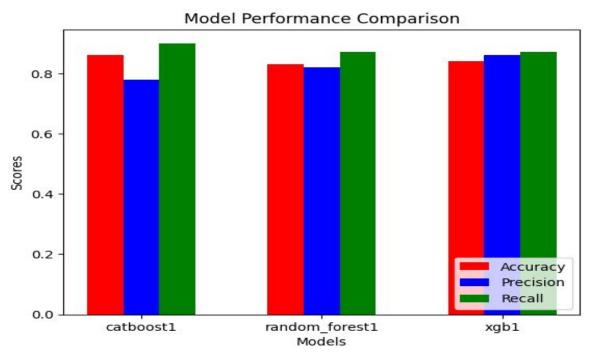
Confusion Matrix:

[[932 216] [169 916]]

	Model	Accuracy	Precision	Recall	F1 Score	AUC	Specificity
0	Random Forest	83.79	0.81	0.87	0.84	0.84	0.80
1	catBoost	86.07	0.83	0.90	0.86	0.86	0.82
2	XGBoost	84.19	0.82	0.87	0.84	0.84	0.82

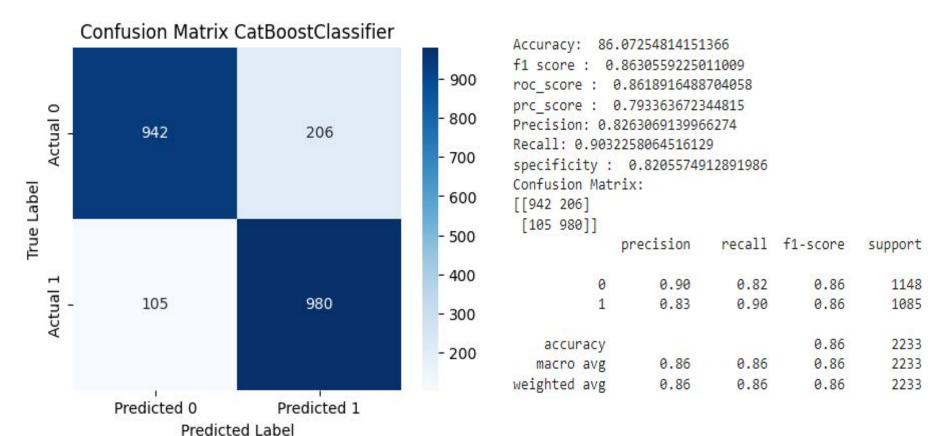


Evaluation on New Train & test



	Model	Accuracy	Precision	Recall	F1 Score	AUC	Specificity
0	Random Forest	83.79	0.81	0.87	0.84	0.84	0.80
1	catBoost	86.07	0.83	0.90	0.86	0.86	0.82
2	XGBoost	84.19	0.82	0.87	0.84	0.84	0.82

Final Result



Conclusion and Future Enhancement

- 1. The following variables seem to be the most relevant inputs in predicting the Success rate of bank direct marketing campaign
 - Duration call duration
 - Pdays Number of days since last contact
 - Month month of contact
 - Age customer age
 - housing weather customer having housing loan.
- 2. A client is more likely to subscribe term deposit if customer talks for more duration. Campaign is more likely to be successful during March, September, December (end of every trimester).
- An essential future enhancement for our project involves deploying the trained machine learning model into real-world applications
- 4. "Incorporating **advanced ensemble techniques, such as stacking and voting,** will enhance our model's accuracy and robustness, serving as a key future enhancement."

Demerits

 The absence of 'advanced ensemble techniques' such as stacking and voting in the current implementation suggests a possibility for increased accuracy.

Thanks