AN ANALYSIS OF PORTUGUESE BANK MARKETING DATA

The George Washington University (DATS 6103: An Introduction to Data Mining)

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November 21, 2022

INTRODUCTION

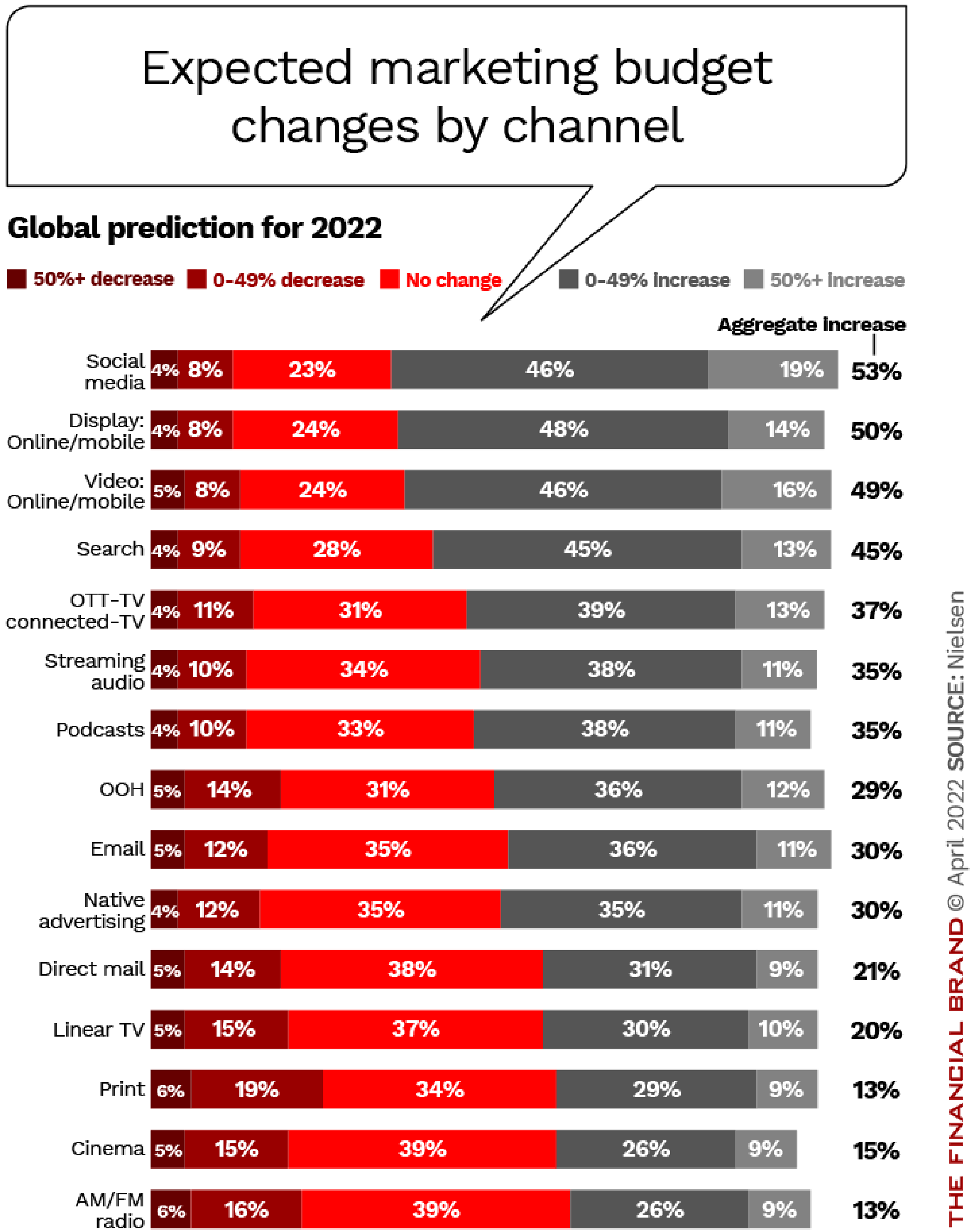
Bank marketing is the practice of attracting and acquiring new customers through traditional media and digital media strategies. The use of these media strategies helps determine what kind of customer is attracted to a certain institutions. This also includes different banking institutions purposefully using different strategies to attract the type of customer they want to do business with.

Marketing has evolved from a communication role to a revenue generating role. The consumer has evolved from being a passive recipient of marketing messages to an active participant in the marketing process. Technology has evolved from being a means of communication to a means of data collection and analysis. Data analytics has evolved from being a means of understanding the consumer to a means of understanding the consumer and the institution.

Bank marketing strategy is increasingly focused on digital channels, including social media, video, search and connected TV. As bank and credit union marketers strive to promote brand awareness, they need a new way to assess channel ROI and more accurate data to enable personalized offers. Add to that the growing importance of purpose-driven marketing.

The relentless pace of digitization is disrupting not only the established order in banking, but bank marketing strategies. Marketers at both traditional institutions and digital disruptors are feeling the pressure.

Just as bank marketers begin to master one channel, consumers move to another. Many now toggle between devices on a seemingly infinite number of platforms, making it harder than ever for marketers to pin down the right consumers at the right time in the right place.



The data may not sum to 100% because the charts do not display data for 'not applicable,' 'prefer not to say' and 'don't know.'

The Data Set

The data set used in this analysis is from a Portuguese bank. The data set contains 41,188 observations and 21 variables. The variables include the following:

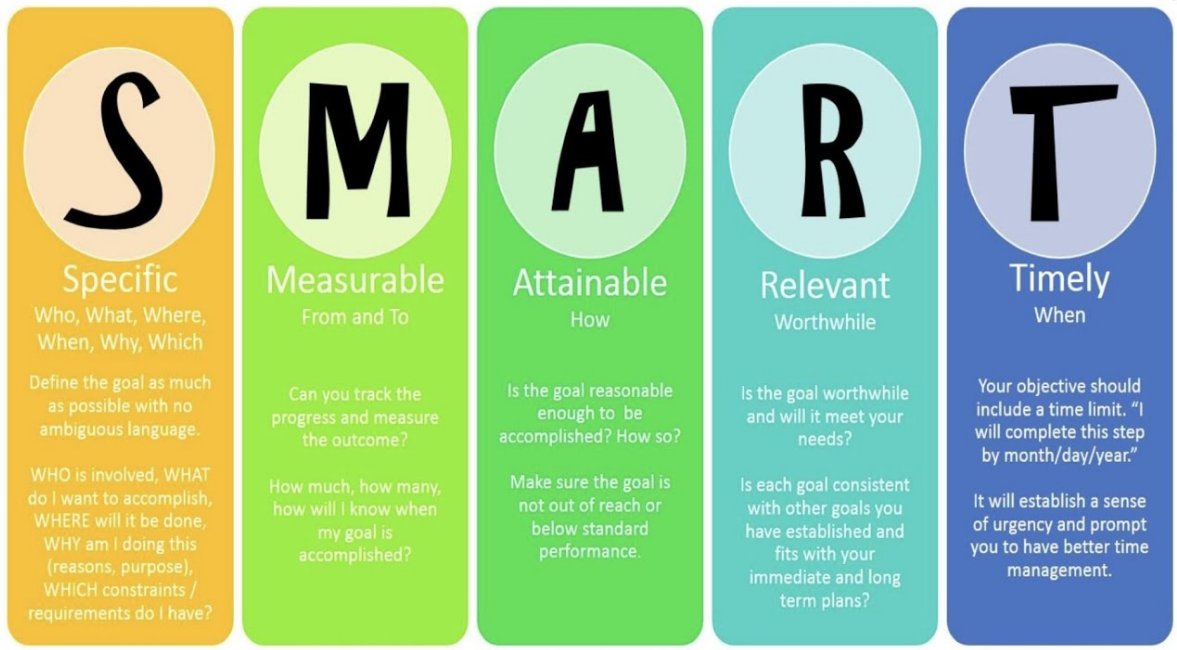
1. age (numeric)
2. job : type of job (categorical: ‘admin.’,‘blue-collar’,‘entrepreneur’,‘housemaid’,‘management’,‘retired’, employed’,‘services’,‘student’,‘technician’,‘unemployed’,‘unknown’)
3. marital : marital status (categorical: ‘divorced’,‘married’,‘single’,‘unknown’; note: ‘divorced’ means divorced or widowed)
4. education (categorical: ‘basic.4y’,‘basic.6y’,‘basic.9y’,‘high.school’,‘illiterate’,‘professional.course’,‘uni
5. default: has credit in default? (categorical: ‘no’,‘yes’,‘unknown’)
6. housing: has housing loan? (categorical: ‘no’,‘yes’,‘unknown’)
7. loan: has personal loan? (categorical: ‘no’,‘yes’,‘unknown’)
8. contact: contact communication type (categorical: ‘cellular’,‘telephone’)
9. month: last contact month of year (categorical: ‘jan’, ‘feb’, ‘mar’, …, ‘nov’, ‘dec’)
10. day_of_week: last contact day of the week (categorical: ‘mon’,‘tue’,‘wed’,‘thu’,‘fri’)
11. duration: last contact duration, in seconds (numeric). Important note: this attribute highly affects the output target (e.g., if duration=0 then y=‘no’). Yet, the duration is not known before a call is performed. Also, after the end of the call y is obviously known. Thus, this input should only be included for benchmark purposes and should be discarded if the intention is to have a realistic predictive model.
12. campaign: number of contacts performed during this campaign and for this client (numeric, includes last contact)
13. pdays: number of days that passed by after the client was last contacted from a previous campaign (numeric; 999 means client was not previously contacted)
14. previous: number of contacts performed before this campaign and for this client (numeric)
15. poutcome: outcome of the previous marketing campaign (categorical: ‘failure’,‘nonexistent’,‘success’)
16. emp.var.rate: employment variation rate - quarterly indicator (numeric)
17. cons.price.idx: consumer price index - monthly indicator (numeric)
18. cons.conf.idx: consumer confidence index - monthly indicator (numeric)
19. euribor3m: euribor 3 month rate - daily indicator (numeric)

20. • nr.employed: number of employees - quarterly indicator (numeric)

21. • balance - average yearly balance, in euros (numeric)

22. • y - has the client subscribed a term deposit? (binary: 'yes','no')

The SMART Questions



The SMART questions are as follows:

1.Relationship between subscribing the term deposit and how much the customer is contacted (last contact, Campaign, Pdays, Previous Number of contacts)

2. Find out the financially stable population? Will that affect the outcome?

3.Effect of dimensionality reduction on accuracy of the model.

4. How are the likelihood of subscriptions affected by social and economic factors?

Throughout the paper we would try to answer the questions

Importing the required libraries

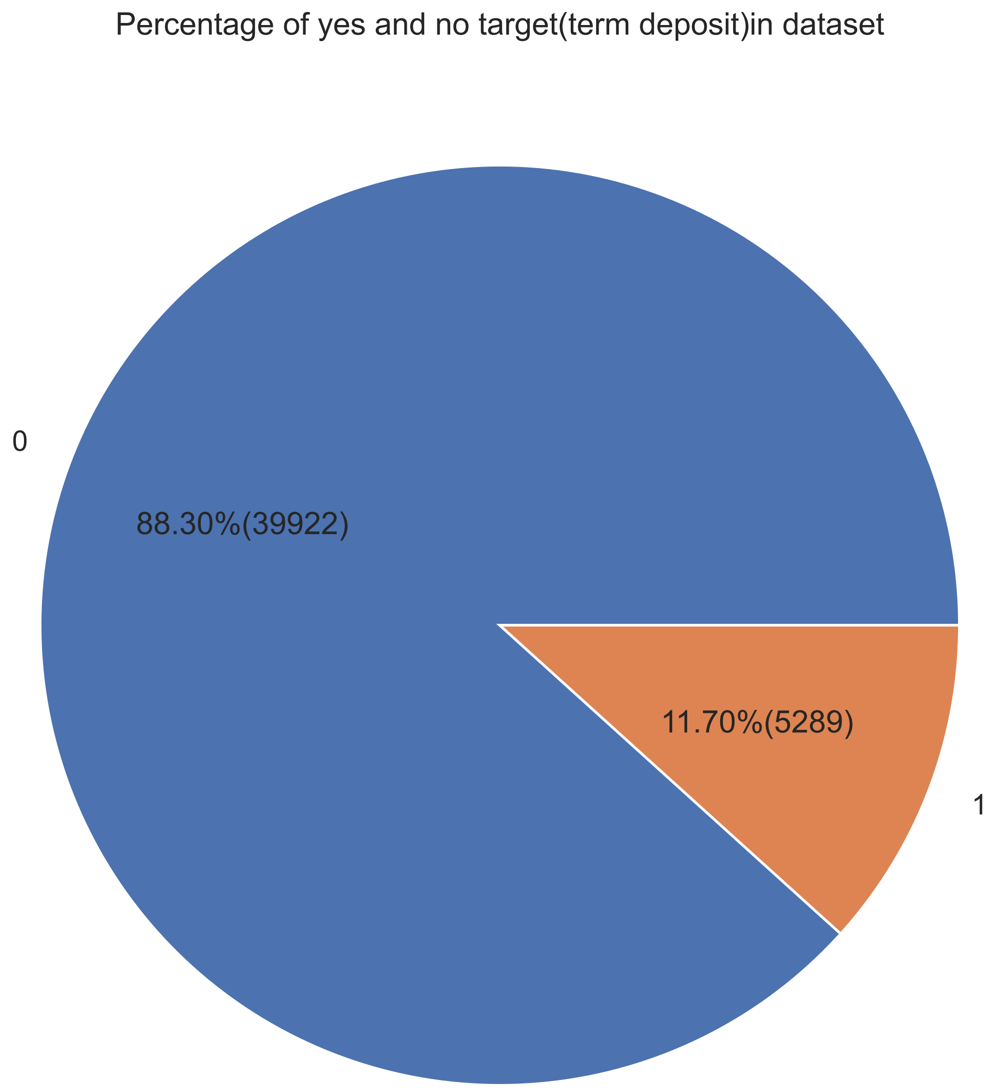
Importing the dataset

Basic Information about the data

```
Shape of dataset is : (45211, 23)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 45211 entries, 0 to 45210
Data columns (total 23 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   age             45211 non-null  int64
 1   job             45211 non-null  object
 2   marital         45211 non-null  object
 3   education       45211 non-null  object
 4   default         45211 non-null  object
 5   balance         45211 non-null  int64
 6   housing         45211 non-null  object
 7   loan            45211 non-null  object
 8   contact         45211 non-null  object
 9   day             45211 non-null  int64
 10  month           45211 non-null  object
 11  duration        45211 non-null  int64
 12  campaign        45211 non-null  int64
 13  pdays           45211 non-null  int64
 14  previous        45211 non-null  int64
 15  poutcome        45211 non-null  object
 16  y               45211 non-null  int64
 17  month_int       45211 non-null  int64
 18  cons.conf.idx   45211 non-null  float64
 19  emp.var.rate    45211 non-null  float64
 20  euribor3m       45211 non-null  float64
 21  nr.employed     45211 non-null  float64
 22  cons.price.idx  45211 non-null  float64
dtypes: float64(5), int64(9), object(9)
memory usage: 7.9+ MB
Columns in dataset
 None
```

Exploratory Data Analysis (EDA)

Distribution of y(target) variable



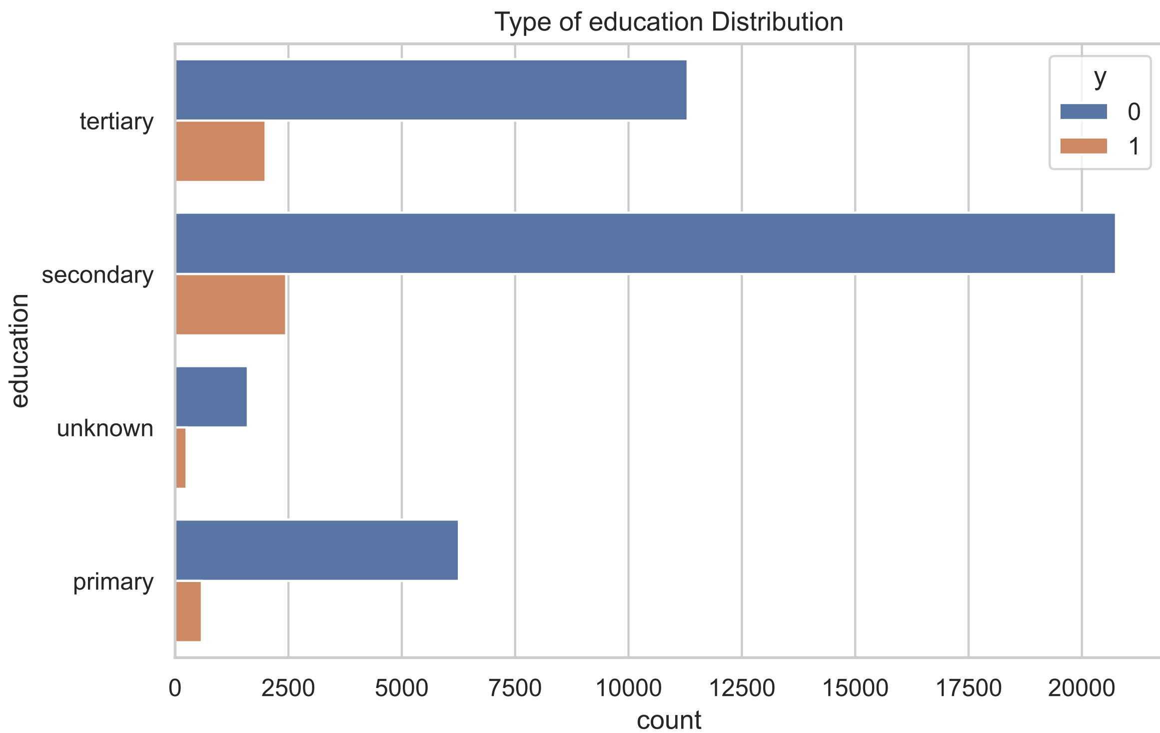
We have 45,211 datapoints, if our model predicts only 0 as output, we would still get 88% accuracy, so our dataset is unbalanced which may gives misleading results. Along with the accuracy, we will also consider precision and recall for evaluation.

Missing values and Outliers

Education

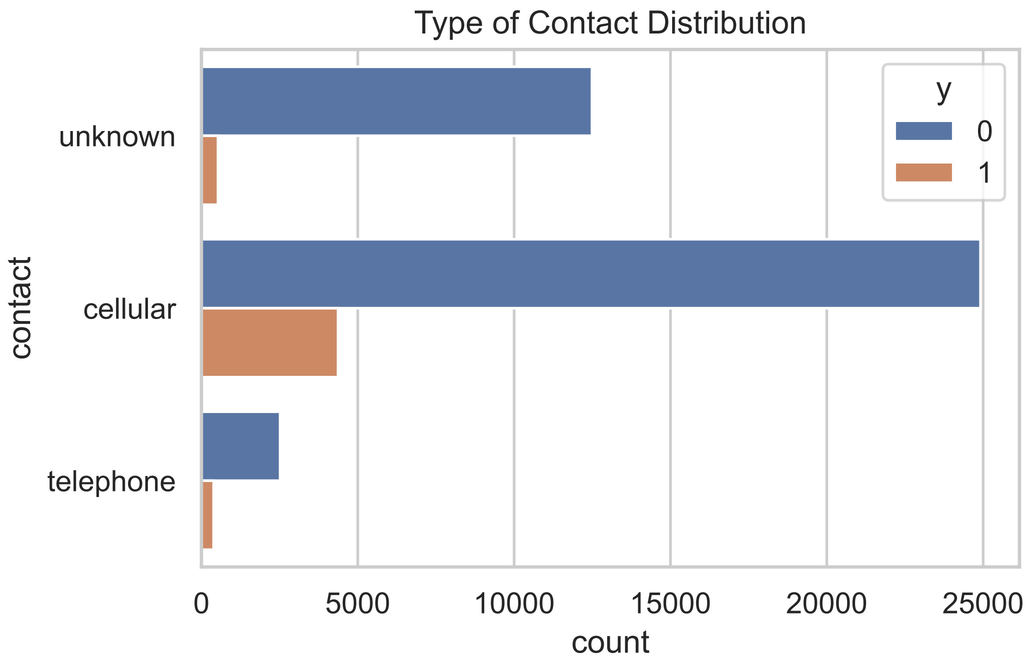
Here, even though we do not have any missing values but we have 'unknown' and 'other' as categories, so we will first get rid of them. The variables with 'unknown' rows are Education and Contact showned below.

```
Text(0.5, 1.0, 'Type of education Distribution')
```



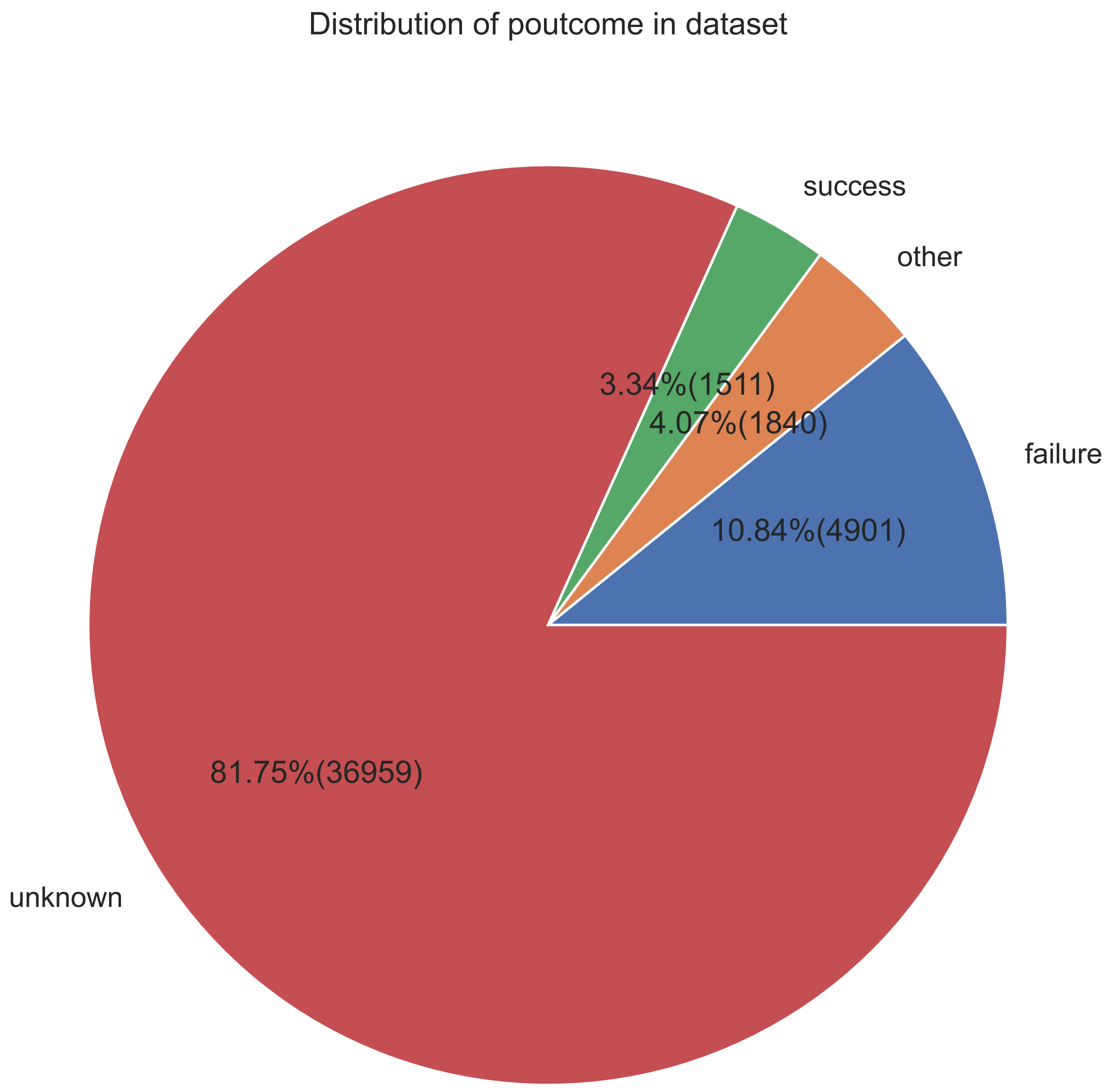
Contact

```
Text(0.5, 1.0, 'Type of Contact Distribution')
```



- since the type of communication(cellular and telephone) is not really a good indicator of subcription, we drop this variable.

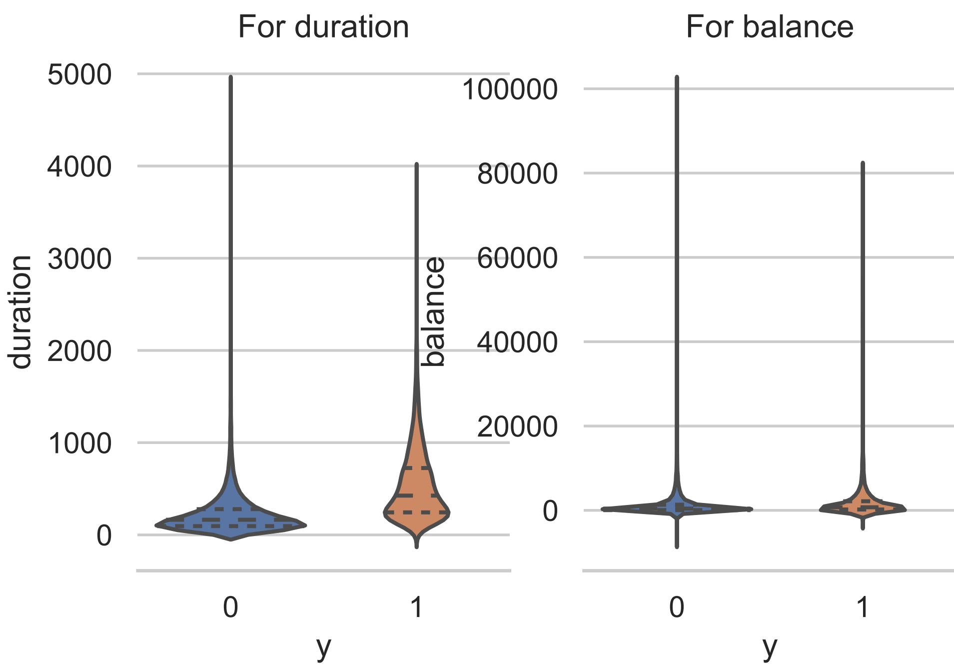
Poutcome


Distribution of poutcome in dataset
success
other
3.34%(1511)
4.07%(1840)
failure
10.84%(4901)
81.75%(36959)
unknown

	0
poutcome	
failure	4901
other	1840
success	1511
unknown	36959

There are *36959 unknown* values(82%) and 1840 values with other(4.07%) category, we will directly drop these columns.

Outliers



- There are outliers in duration and balance so we need to get rid of them.

Data Cleaning

- Contact is not useful so we drop it.
- In poutcome, we have a lot of 'unknown' and 'other' values so we drop it.

- Day is not giving any relevant infomation so we drop it.

- Removing the unknowns from ‘job’ and ‘education’ columns.
- Remove the outliers from balance and duration.

Dropping the irrelavant columns and missing values

```
for job
unknown : 288
dropping rows with value as unknown in job
for education
unknown : 1730
dropping rows with value as unknown in education
```

Outlier removal

We have outliers in balance and duration, so to get rid of them we would try to remove the enteries few standard deviation away, since from the histograms most of the enteries are around mean only, we are removing the enteries more than 3SD away.

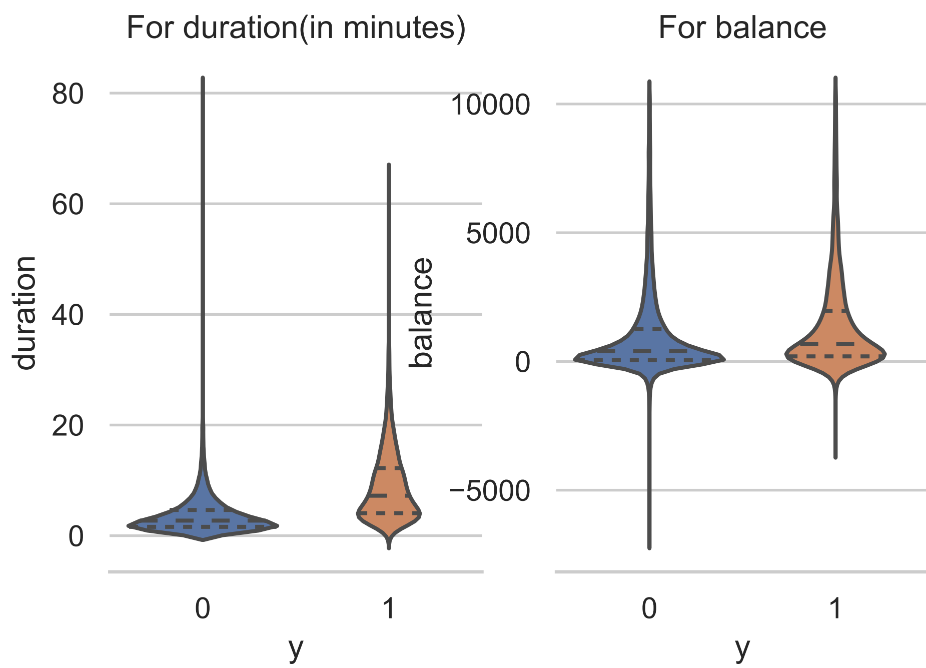
Balance - Outliers

```
removing entries before balance   -7772.283533
dtype: float64 and after balance    10480.338218
dtype: float64
```

Duration - Outliers

Dropping rows where the duration of calls is less than 5sec since that is irrelevant. And also since converting the call duration in minutes rather than seconds makes more sense we would convert it into minutes.

plotting violen plot for duration and balance after cleaning data



Data Visualization

Let' visualize important relationships between variables now.

SMART Question 1 :

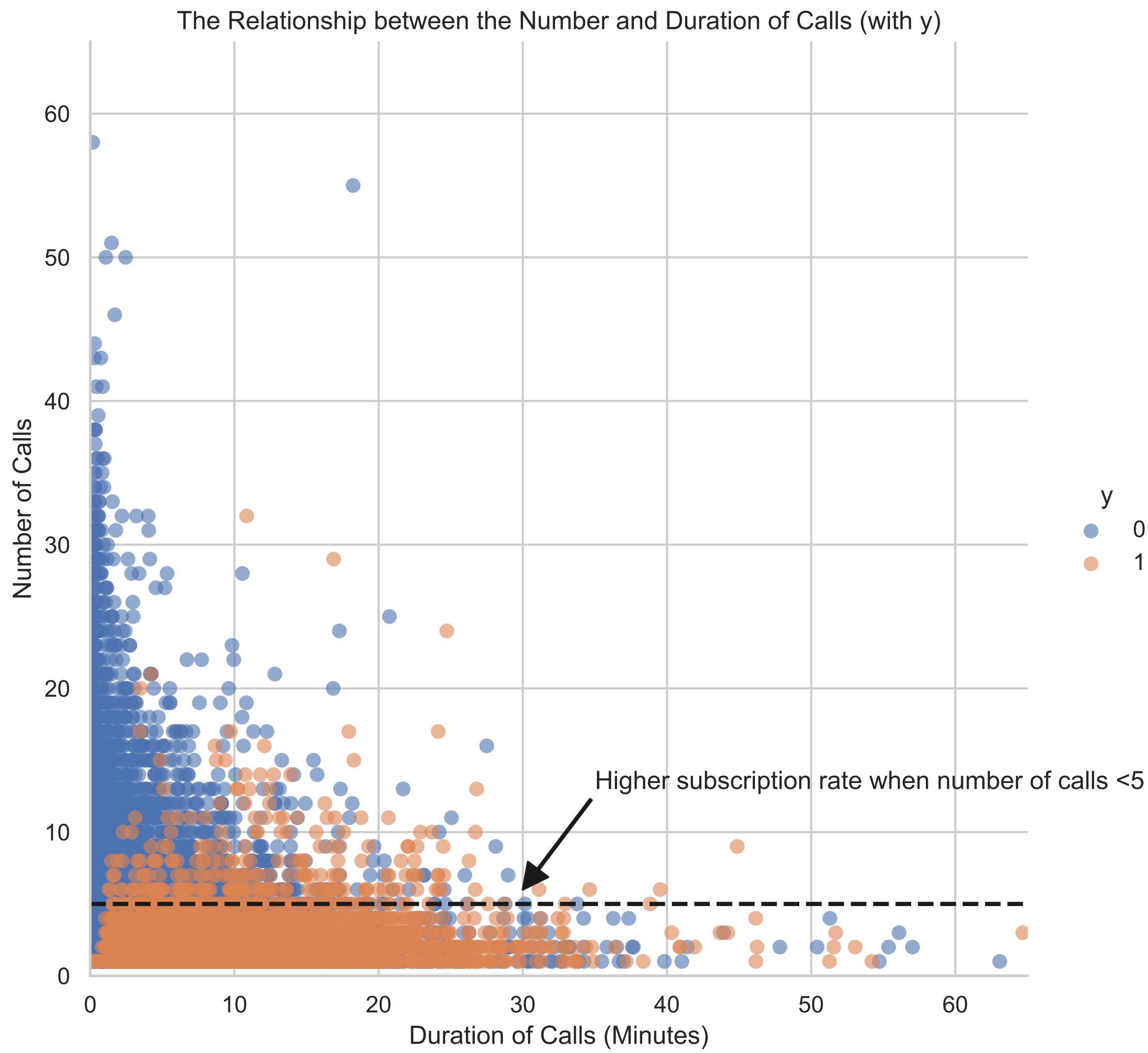
Relationship between subscribing the term deposit and how much the customer is contacted (last contact, Campaign, Pdays, Previous Number of contacts)

Answer : Based on last contact info only number of contacts performed during this campaign is contributing a lot towards subscription rates.

Suggestion: People who are contacted less than 5 times should be targeted more. Also, they could contact in less frequency in order to attract more target customers. The plot below shows the relationship between the number of calls and duration vs subscription

Number of calls versus Duration and affect on subscription

Here if we notice, people are more likely to subscribe if the number of calls are less than 5.

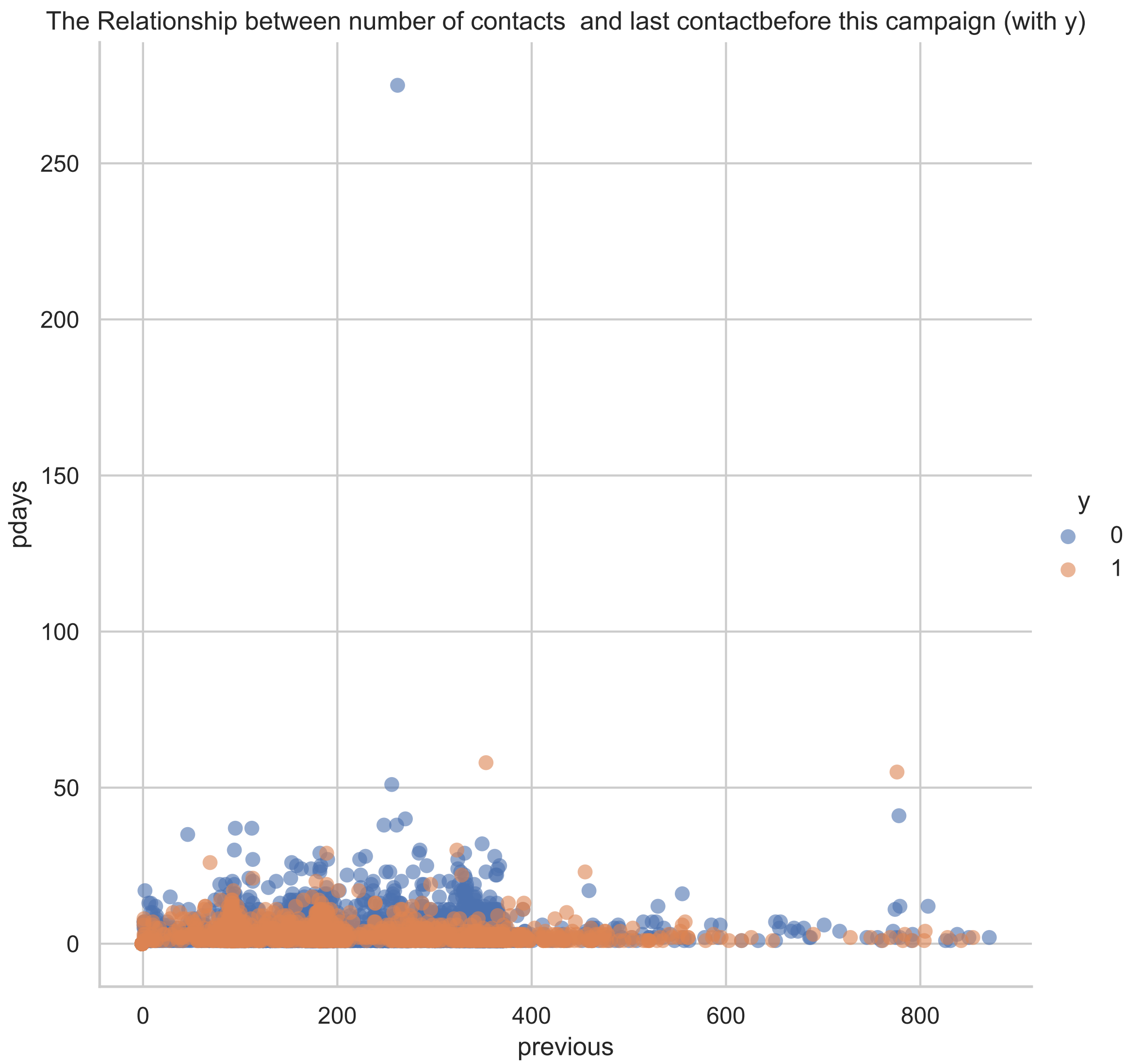


Checking between pdays and previous as well

Here as we can see from the t- test, t

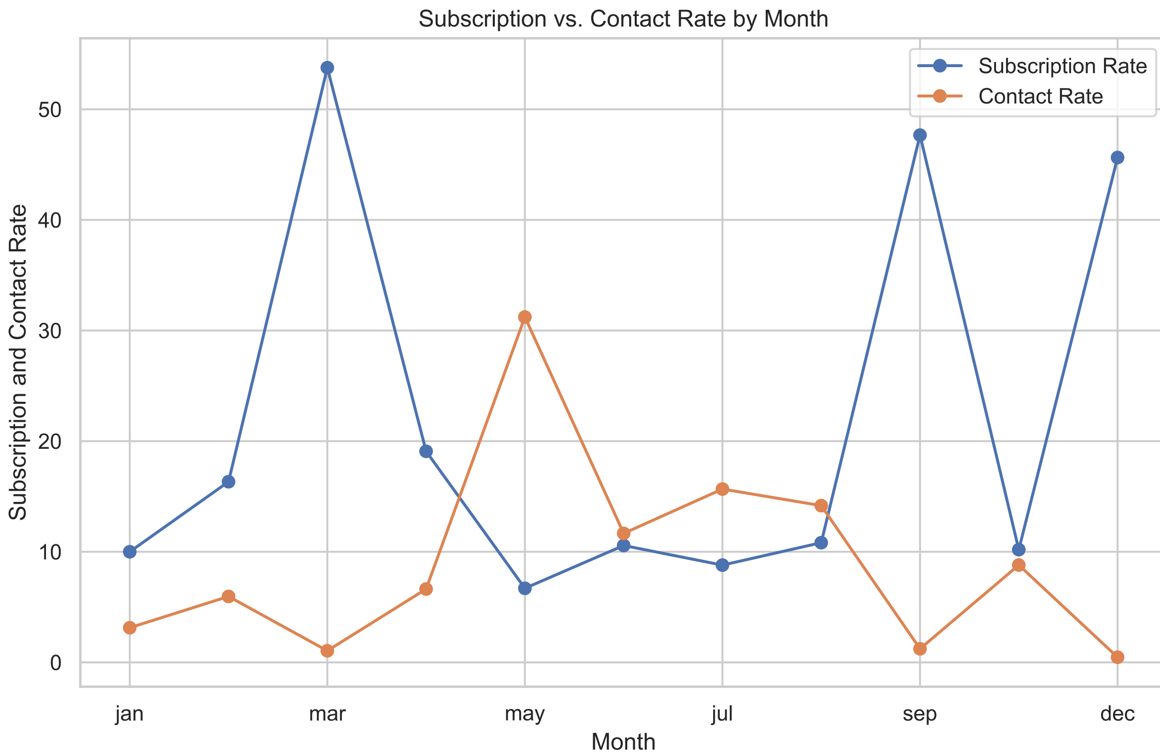
13. • pdays: number of days that passed by after the client was last contacted from a previous campaign (numeric; 999 means client was not previously contacted)
14. • previous: number of contacts performed before this campaign and for this client (numeric)

We can notice from the plot that there is no relationship between subscription with pdays or previous. The datapoints are distrubuted randomly along the axies.



Month wise subscription

```
Text(0.5, 0, 'Month')
```



Maximum percentage of people have subscribed in the month of March but bank is contacting people more in the month of May.

Suggestion:So it's better to contact customer's based on the subcription rate plot.

SMART Question 7: How are the likelihood of subscriptions affected by social and economic factors?

	month	cons.conf.idx	emp.var.rate	euribor3m	nr.employed
0	jan	1310	1310	1310	1310
1	feb	2492	2492	2492	2492
2	mar	439	439	439	439
3	apr	2772	2772	2772	2772
4	may	13050	13050	13050	13050
5	jun	4874	4874	4874	4874
6	jul	6550	6550	6550	6550
7	aug	5924	5924	5924	5924
8	sep	514	514	514	514
9	oct	661	661	661	661
10	nov	3679	3679	3679	3679

```
11   dec              195            195          195            195
```

Answer : Based on the above table we can see that there is no distinguishable difference in the month of march or may from rest of all the month, so social and economic factor **do not have major influence** on the outcome.

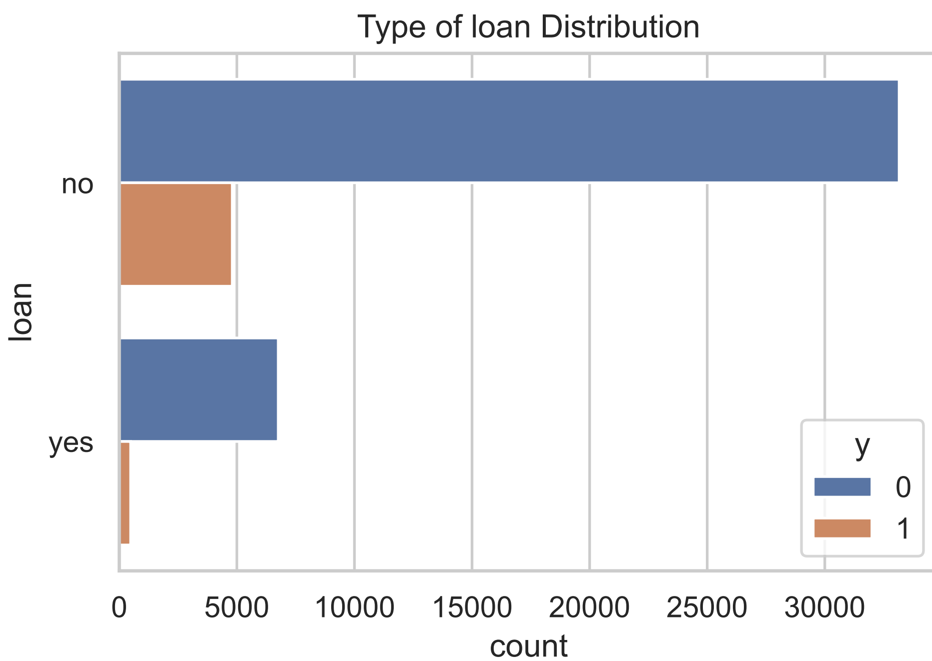
SMART Question 2

Find out the **financially stable** population? Will that affect the outcome?

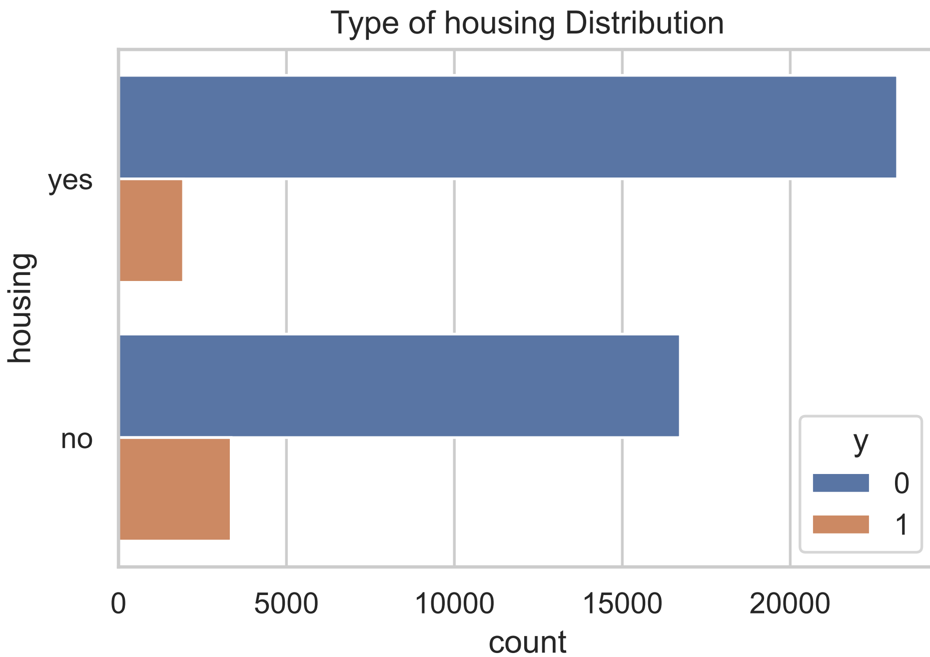
We will try to find the financially stable population based on age, jobs, loan and balance.

Loan

```
Text(0.5, 1.0, 'Type of loan Distribution')
```

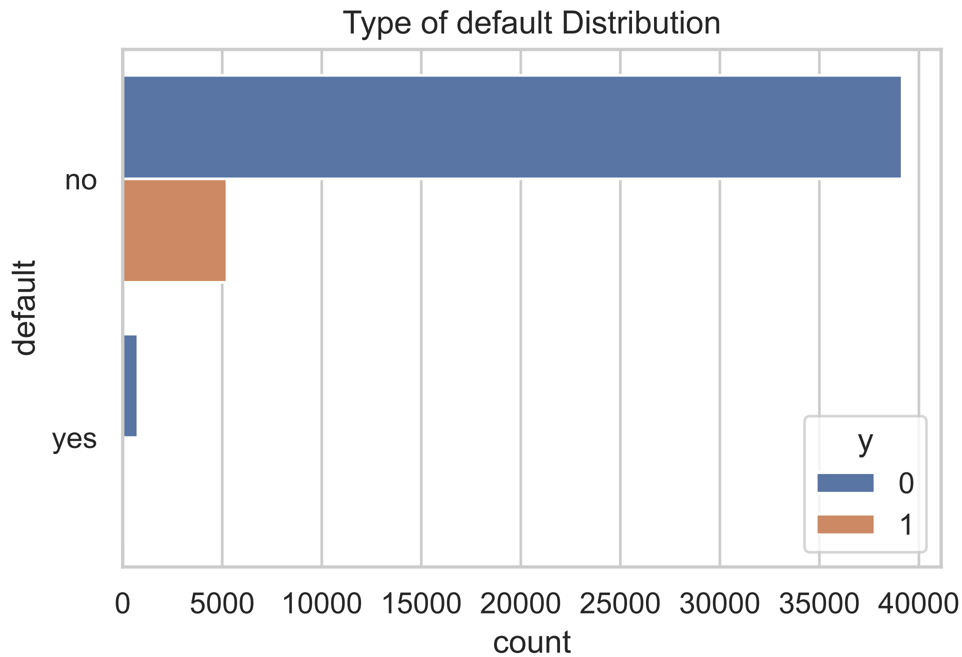



```
Text(0.5, 1.0, 'Type of housing Distribution')
```



People with housing loans are less likely to subscribe to term deposit but the difference here is not huge.

```
Text(0.5, 1.0, 'Type of default Distribution')
```

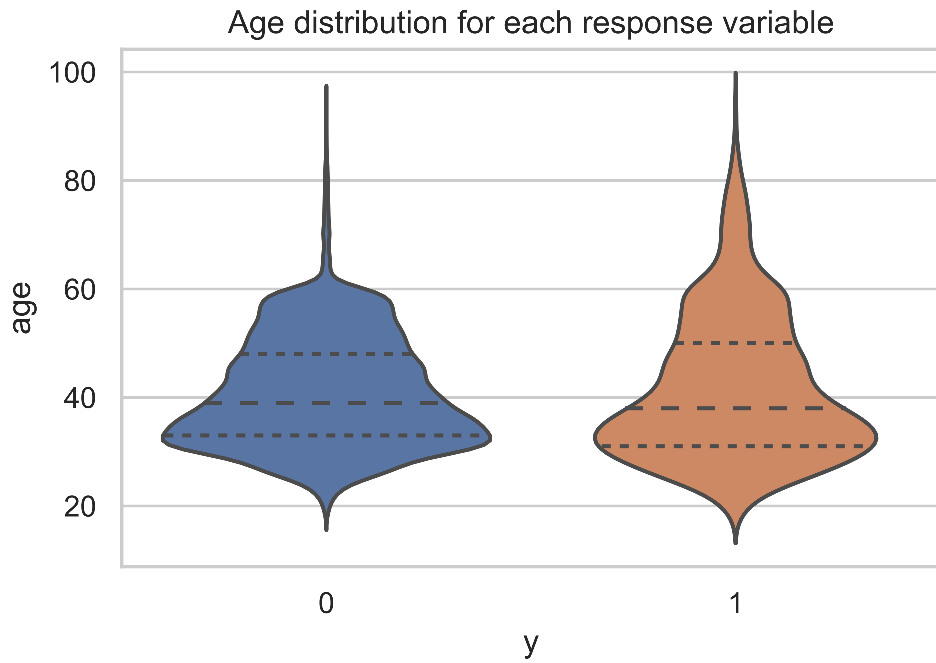


So people who have not paid back there loans and have credits, have not subcribed to the term deposit.

- people who have loans are subscribing to term deposit less.

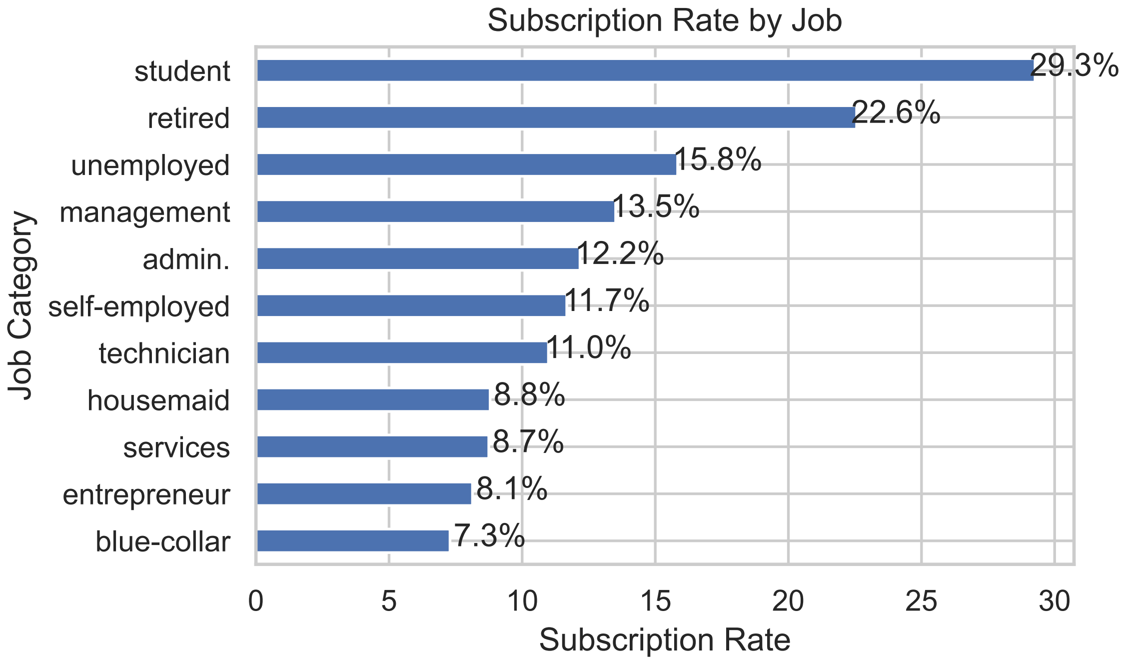
Age

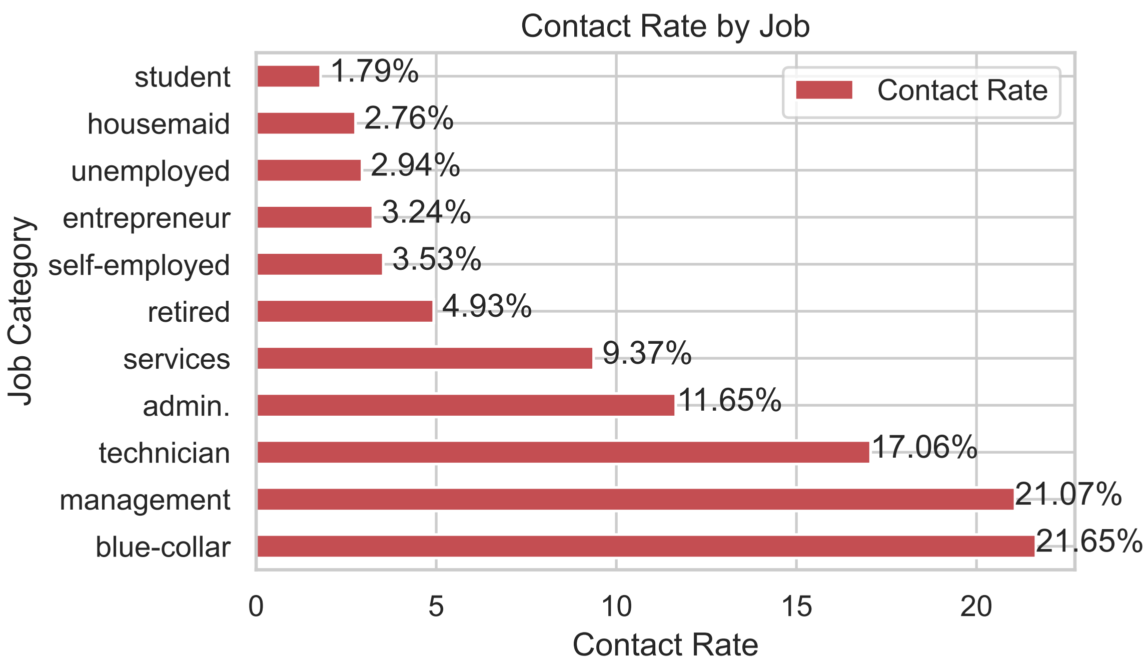
Elder people might be more financially stable since they are subscriped to the term deposit more.



- People who are old are more likely to subscribe to term deposit.

Job





People in blue collar and management jobs are contacted more, which should not be the case.

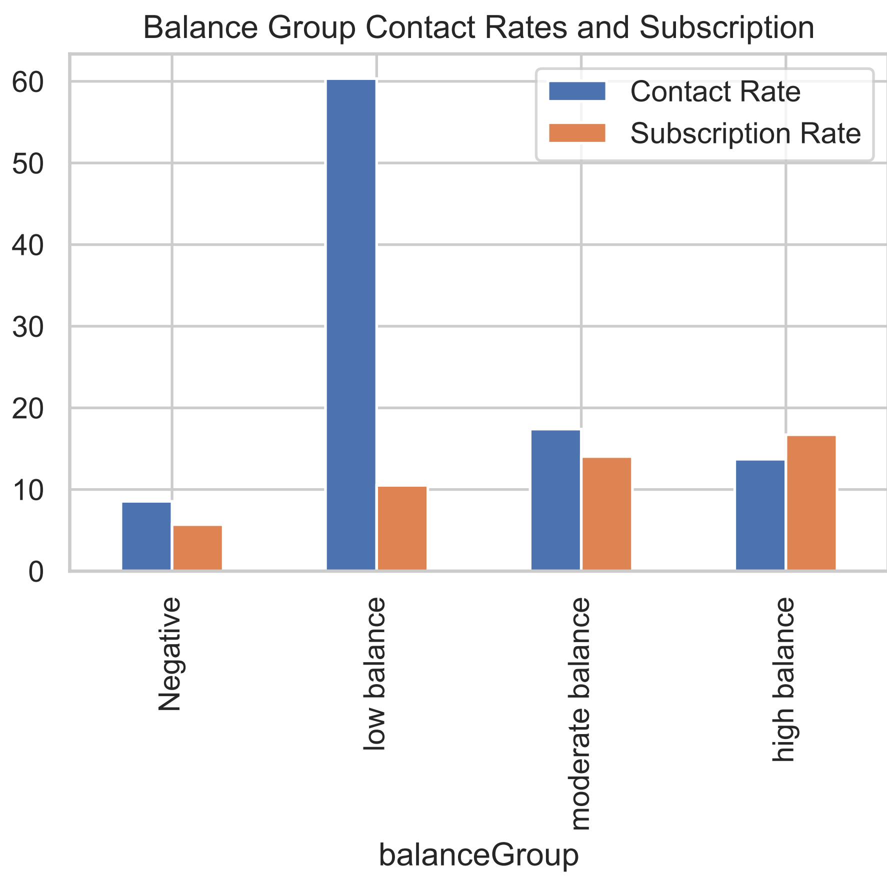
Since they have less subscription rates. Unlike popular assumption, students, retired and unemployment seem to have a high subscription rates. Even though they are contacted very less.

suggestion: The high subscripted rate group(students, retired and unemployment) should be contacted more.

Balance

Checking the subscriptions in each balance groups

```
           balGroup  % Contacted  % Subscription
0       low balance    60.339143       10.503513
1  moderate balance    17.399906       14.036275
2      high balance    13.709374       16.715341
3          Negative     8.551578        5.700909
       balanceGroup Contact Rate Subscription Rate
0          Negative     8.551578          5.700909
1       low balance    60.339143         10.503513
2  moderate balance    17.399906         14.036275
3      high balance    13.709374         16.715341
```

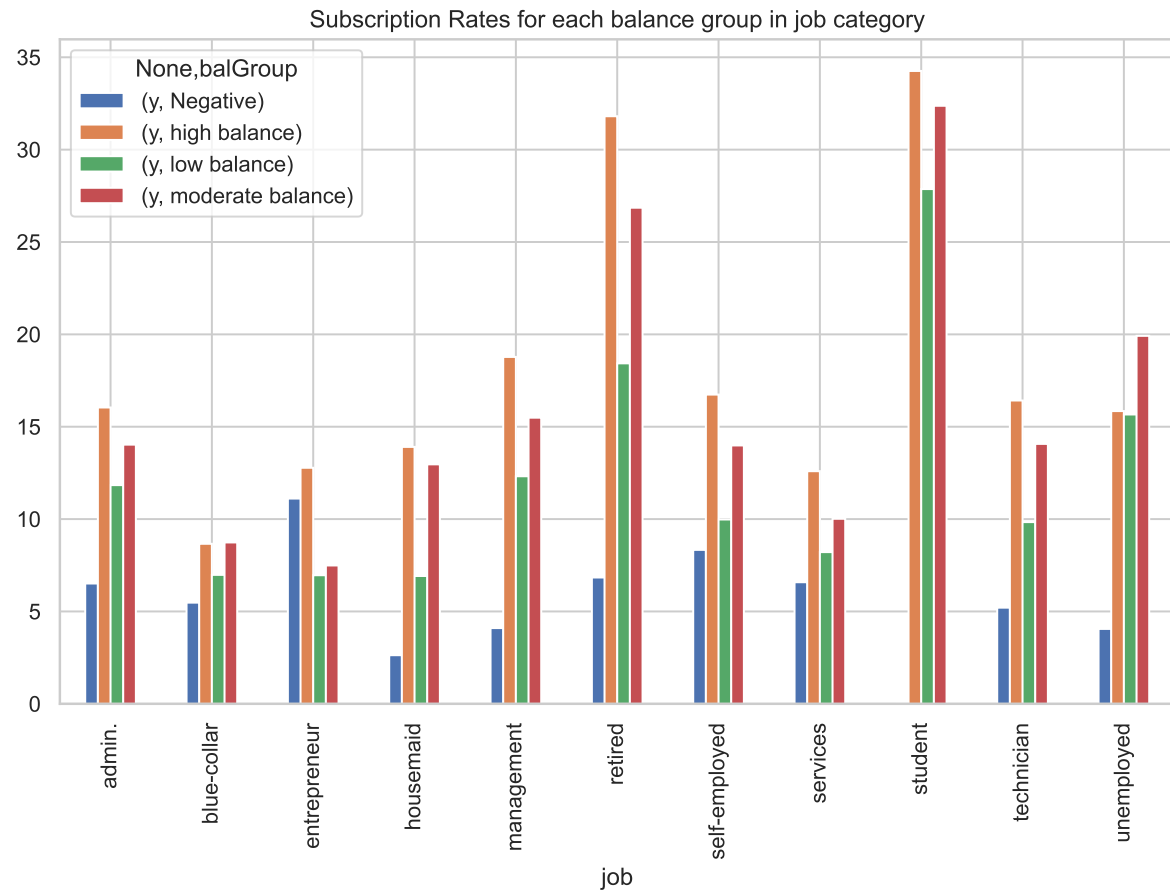


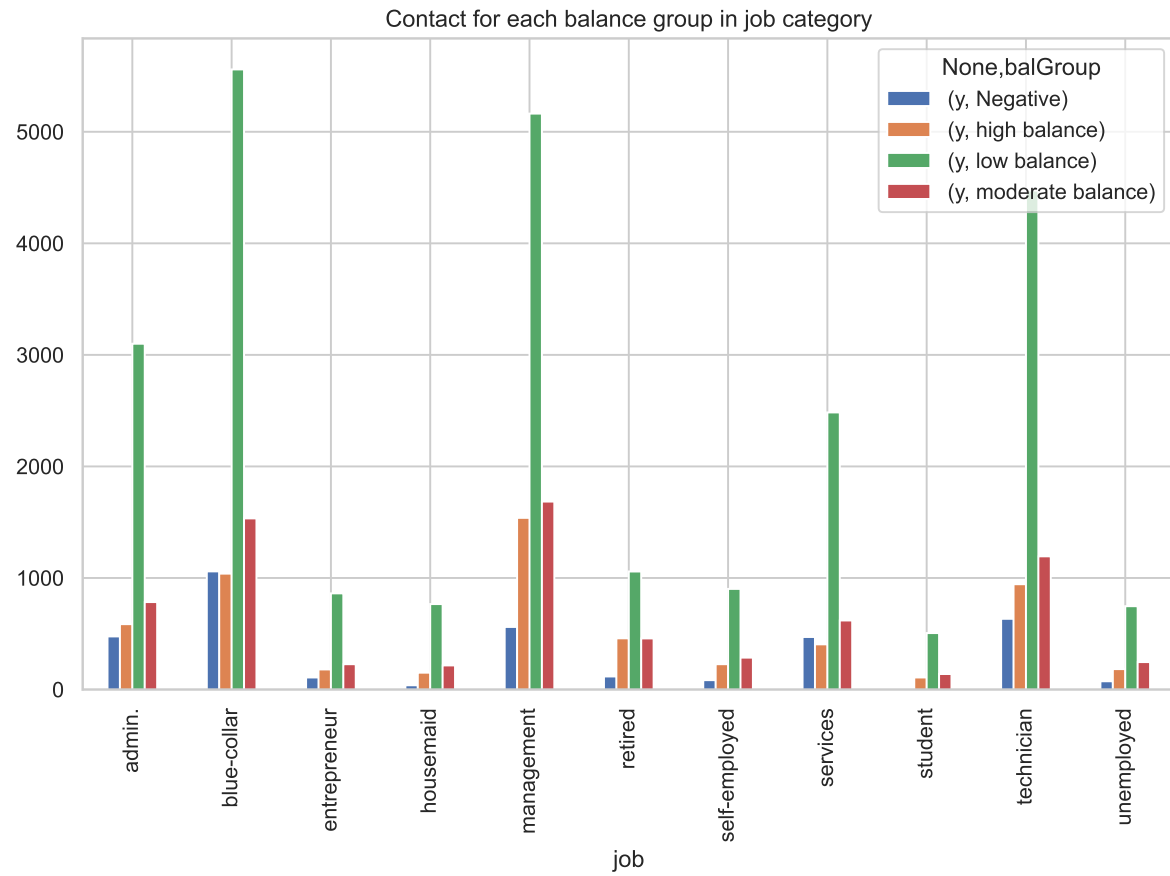
suggestion:People with moderate to high balance, are contacted less but they have high subscription rates so bank should target them more.

It might be possible that balance group and jobs are telling the same information since some jobs might have high salary and thus balance groups might be depicting jobs only, so we will try to look at them together.

Balance Group versus Job

```
Text(0.5, 1.0, 'Contact for each balance group in job category')
```


Subscription Rates for each balance group in job category
None,balGroup
(y, Negative)
(y, high balance)
(y, low balance)
(y, moderate balance)
0
5
10
15
20
25
30
35
admin.
blue-collar
entrepreneur
housemaid
management
retired
self-employed
services
student
technician
unemployed
job



Student and Retired are more likely to subscribe and usually have moderate to high balance.

We found from the second bar chart that only the low balance groups are targeted in each category even though moderate to high balance category are more likely to subscribe.

Data Encoding

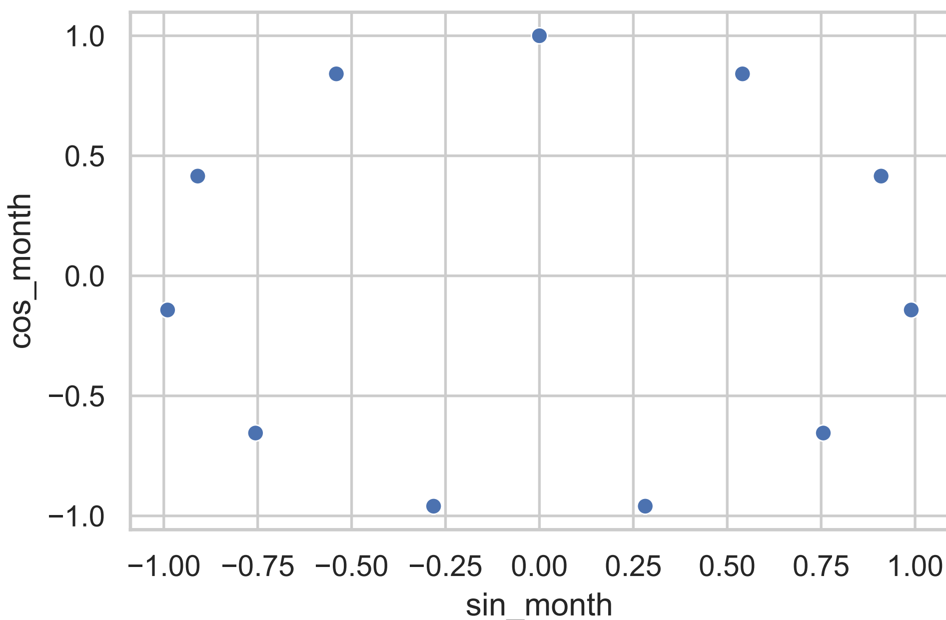
One Hot Encoding

We would encode 'housing','loan','default','job','education' and 'marital' as they are all categorical variables.

Sin - Cos encoding

Transforming month into sin and cos so that there cyclic nature (jan-dec are as close as jan-feb) is retained which is usually lost in label encoding. Unlike one hot encoding, the dimension will reduce from 12(month_jan, month_feb … month_dec) to 2(sin_month , cos_month)

```
<AxesSubplot: xlabel='sin_month', ylabel='cos_month'>
```



Dropping unnecessary columns irrelevant for modelling

Here we dropped the 'month' column as they are encoded. Also, we dropped irrelevant variables 'pdays' and enconomic factors('cons.conf.idx', 'emp.var.rate', 'euribor3m', 'nr.employed','cons.price.idx') for modelling.

Data Modeling

Splitting our Dataset

We are splitting our dataset in 1:4 ratio for training and testing set.

Balancing Our Dataset

We tried to balance our dataset using following methods: * Upsampling using SMOTE * Sin and cos transformation from month_int.

Scaling numeric variables

Scaling age, balance, duration so that our algorithms perform better and all variables are treated equally. Since all three variables are in different scales, so we transform them into same standard.

Logistic Regression

Performing Logistic Regression on both balanced and unbalanced dataset. RFE is used in selecting the most important features ## Unbalanced Dataset

```
Columns selected by RE ['duration', 'euribor3m', 'cons.price.idx', 'job_blue-collar', 'job_re
```

As we can see from RFE, the most relevant features are :

- Duration
- Housing
- Loan
- Job
- Education
- cos_month

From other features selection techniques and EDA, we can see that 'age' and 'balance' also contrubuted to the subscrption, so we added up these variables as well.

Applying model with selected features

```
Accuracy for training set 0.8714696652719666
Accuracy for testing set 0.8704672245467224
Confusion matrix
[[4750  157]
 [ 586  243]]
              precision    recall  f1-score   support

           0       0.89      0.97      0.93      4907
           1       0.61      0.29      0.40       829

    accuracy                           0.87      5736
   macro avg       0.75      0.63      0.66      5736
weighted avg       0.85      0.87      0.85      5736
```

Here, the accuracy is 89% but the precision(0.59) and recall rate value(0.20) is low. And we also check on the balanced dataset since the low recall rate might be caused because of the less number of y = 1 value.

Balanced Dataset

```
Columns selected by RE ['duration', 'cons.price.idx', 'job_admin.', 'job_blue-collar', 'job_r
```

```
Accuracy for training set 0.9059650552697265
Accuracy for testing set 0.8519874476987448
Confusion matrix
[[4451  456]
 [ 393  436]]
              precision    recall  f1-score   support

           0       0.92      0.91      0.91      4907
           1       0.49      0.53      0.51       829

    accuracy                           0.85      5736
   macro avg       0.70      0.72      0.71      5736
weighted avg       0.86      0.85      0.85      5736
```

Here, important features are * Housing * Loan * Job * Education * Marital Status We also added the important features from unbalaced dataset * Duration * Age * Month * Balance

Here even though the precision and recall have improved, and accuracy has dropped down, but the important relationships are lost since the training data now is artificially generated datapoints. We will try to find the optimal cut-off value for original dataset and compare it with the model for balanced data.

Deciding cut off value for logistic regression - Unbalance

But to have good values for cut-off we would try to find a cutoff where the precision and recall values are decent

```
Based on plot we would choose 0.25 as cut off
Accuracy for testing set 0.8594839609483961
Confusion matrix
[[4447  460]
```

```
[ 346  483]]
              precision    recall  f1-score   support

           0       0.93      0.91      0.92      4907
           1       0.51      0.58      0.55       829

    accuracy                           0.86      5736
   macro avg       0.72      0.74      0.73      5736
weighted avg       0.87      0.86      0.86      5736
```

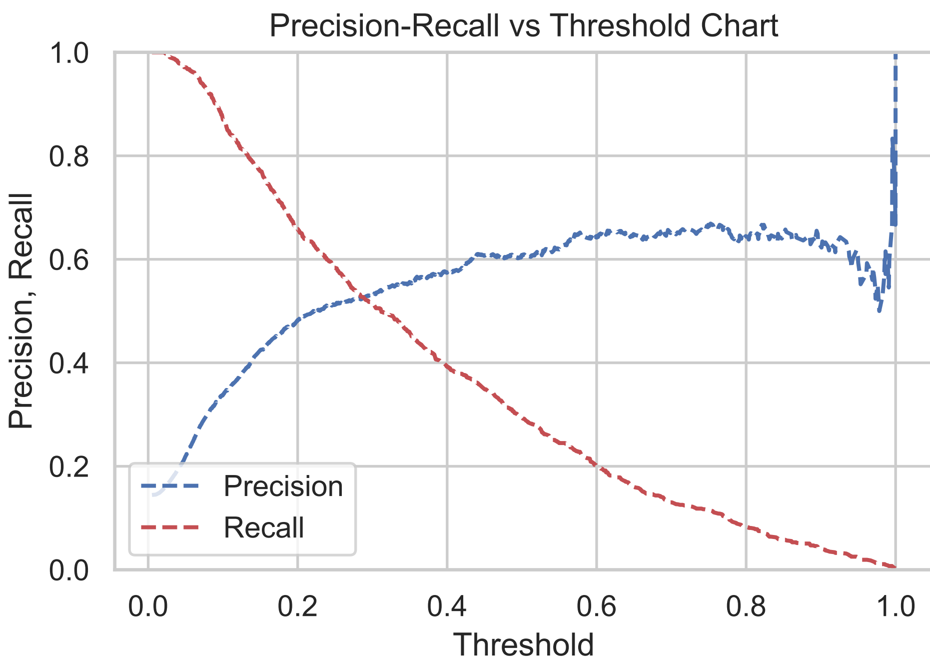


Figure 1: Optimal Cutoff at 0.25

Here as after applying feature selection, finding optimized cut-off, we are able to achieve higher accuracy with optimal precision and recall. Resulting from the comparison, we would continue our modellings with unbalance dataset.

Smart Question 5: The optimal cut off value for classification of our imbalance dataset.

Answer: The optimal cut off value for our imbalance dataset is 0.25 as the precision- recall chart indicated.

SMART Question 2.Since the dataset is imbalanced, will down sampling/up sampling or other techniques improve upon the accuracy of models.

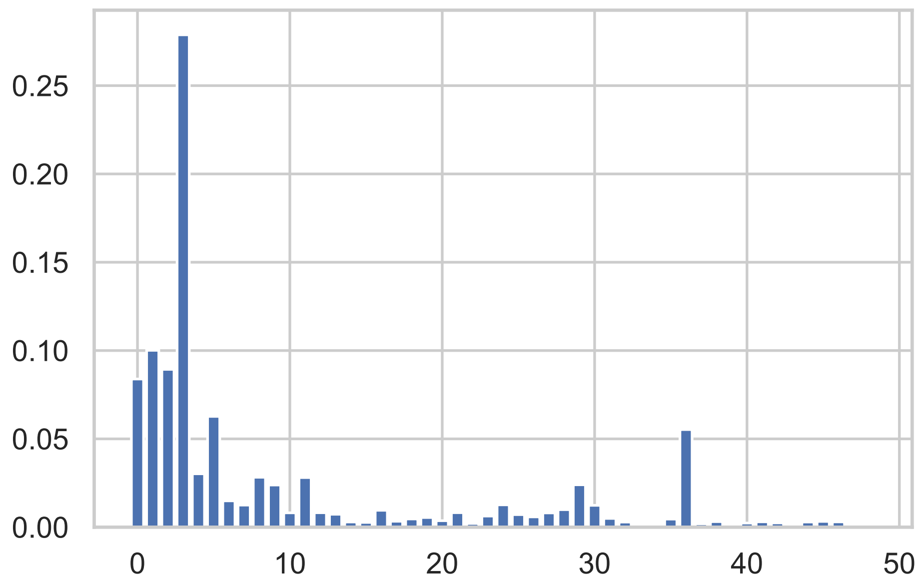
Answer: As observed from above there is a slight improvement in accuracy, precision and recall after we apply SMOTE, but that improvement can also be acheived by adjusting the cut off value as well. So, we should always try adjusting cut-off first, before upsampling.

For ROC - AUC curve refer (Figure 2). For precision recall curve refer(Figure 3).

Decision Tree

Feature Selection

```
Feature 0 variable age score 0.08
Feature 1 variable balance score 0.10
Feature 2 variable day score 0.09
Feature 3 variable duration score 0.28
Feature 4 variable campaign score 0.03
Feature 5 variable pdays score 0.06
Feature 6 variable previous score 0.01
Feature 7 variable cons.conf.idx score 0.01
Feature 8 variable emp.var.rate score 0.03
Feature 9 variable euribor3m score 0.02
Feature 11 variable cons.price.idx score 0.03
Feature 24 variable education_secondary score 0.01
Feature 29 variable housing_no score 0.02
Feature 30 variable housing_yes score 0.01
Feature 36 variable poutcome_success score 0.06
Important features from decision treee are :
['age', 'balance', 'day', 'duration', 'campaign', 'pdays', 'previous', 'cons.conf.idx', 'emp
```



Features selected from this algorithm are

- Age
- Balance
- Duration
- Campaign
- Previous
- Housing
- Job
- Education
- Marital
- Month - Sin,cos

We have all the important features from EDA here

Hyperparameter tuning

For tuning the hyperparameter's we will use GridSearch CV.

```
[CV] END bootstrap=True, max_depth=90, max_features=2, n_estimators=1000; total time=  12.7s
[CV] END bootstrap=True, max_depth=100, max_features=2, n_estimators=100; total time=   1.2s
[CV] END bootstrap=True, max_depth=100, max_features=2, n_estimators=300; total time=   3.8s
[CV] END bootstrap=True, max_depth=100, max_features=3, n_estimators=100; total time=   1.5s
[CV] END bootstrap=True, max_depth=100, max_features=3, n_estimators=100; total time=   1.6s
[CV] END bootstrap=True, max_depth=100, max_features=3, n_estimators=200; total time=   3.3s
```

```
[CV] END bootstrap=True, max_depth=100, max_features=3, n_estimators=300; total time=   5.0s
[CV] END bootstrap=True, max_depth=110, max_features=2, n_estimators=100; total time=   1.3s
[CV] END bootstrap=True, max_depth=110, max_features=2, n_estimators=200; total time=   2.7s
[CV] END bootstrap=True, max_depth=110, max_features=2, n_estimators=300; total time=   4.0s
[CV] END bootstrap=True, max_depth=110, max_features=2, n_estimators=1000; total time=  12.2

[CV] END bootstrap=True, max_depth=90, max_features=3, n_estimators=300; total time=   4.6s
[CV] END bootstrap=True, max_depth=100, max_features=2, n_estimators=200; total time=   2.5s
[CV] END bootstrap=True, max_depth=100, max_features=2, n_estimators=300; total time=   3.9s
[CV] END bootstrap=True, max_depth=100, max_features=3, n_estimators=100; total time=   1.5s
[CV] END bootstrap=True, max_depth=100, max_features=3, n_estimators=200; total time=   3.3s
[CV] END bootstrap=True, max_depth=100, max_features=3, n_estimators=200; total time=   3.3s
[CV] END bootstrap=True, max_depth=100, max_features=3, n_estimators=1000; total time=  15.6
[CV] END bootstrap=True, max_depth=110, max_features=3, n_estimators=300; total time=   4.6s

Fitting 5 folds for each of 168 candidates, totalling 840 fits
[CV] END bootstrap=True, max_depth=80, max_features=2, n_estimators=1000; total time=  13.1s
[CV] END bootstrap=True, max_depth=90, max_features=2, n_estimators=200; total time=   2.6s
[CV] END bootstrap=True, max_depth=90, max_features=2, n_estimators=1000; total time=  12.3s
[CV] END bootstrap=True, max_depth=90, max_features=3, n_estimators=1000; total time=  15.9s
[CV] END bootstrap=True, max_depth=100, max_features=3, n_estimators=1000; total time=  15.5
[CV] END bootstrap=True, max_depth=110, max_features=3, n_estimators=300; total time=   4.6s

Best parameters from Grid Search CV :
{'criterion': 'entropy', 'max_depth': 6, 'max_features': 0.8, 'splitter': 'best'}
```

Training model based on the parameters we got from Grid SearchCV.

```
0.8817991631799164
[[4630  277]
 [ 401  428]]
              precision    recall  f1-score   support

           0       0.92      0.94      0.93      4907
           1       0.61      0.52      0.56       829

    accuracy                           0.88      5736
   macro avg       0.76      0.73      0.74      5736
weighted avg       0.88      0.88      0.88      5736
```

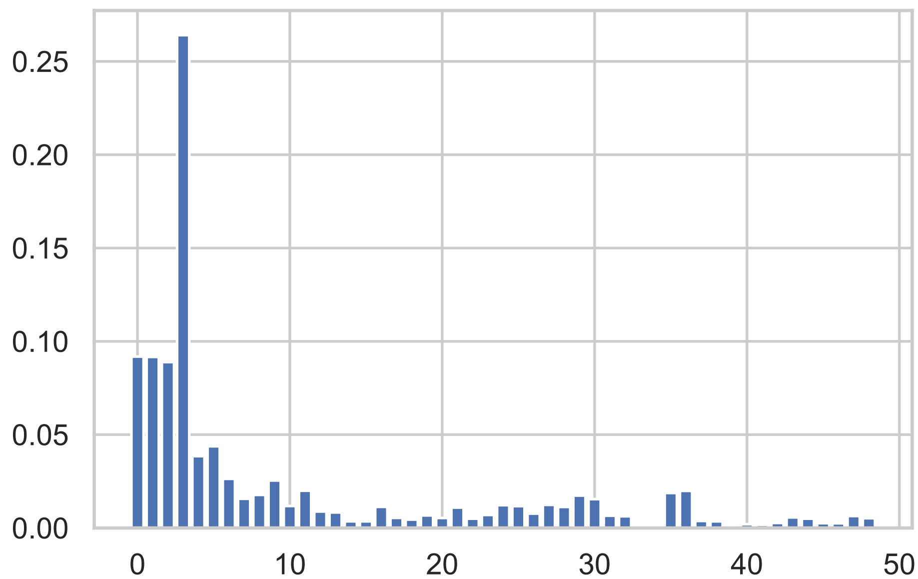
From the decision tree we have better precision, recall, accuracy and thus better f1 score. Hence, decision tree is performing better than logistic regression.

AUC Curve : Figure 2 Precision Recall Curve : Figure 3

Random Forest

Feature Selection

```
Important features from random forest :
['age', 'balance', 'day', 'duration', 'campaign', 'pdays', 'previous', 'cons.conf.idx', 'emp
```



Hyperparameter Tuning

```
Fitting 3 folds for each of 32 candidates, totalling 96 fits

[CV] END bootstrap=True, max_depth=110, max_features=2, n_estimators=300; total time=   3.9s
[CV] END bootstrap=True, max_depth=110, max_features=3, n_estimators=100; total time=   1.5s
[CV] END bootstrap=True, max_depth=110, max_features=3, n_estimators=200; total time=   3.2s
[CV] END bootstrap=True, max_depth=110, max_features=3, n_estimators=200; total time=   3.0s
[CV] END bootstrap=True, max_depth=110, max_features=3, n_estimators=1000; total time=  13.1s
[CV] END bootstrap=True, max_depth=80, max_features=2, n_estimators=200; total time=   2.5s
```

```
[CV] END bootstrap=True, max_depth=80, max_features=3, n_estimators=100; total time=   1.4s
[CV] END bootstrap=True, max_depth=80, max_features=3, n_estimators=100; total time=   1.5s
[CV] END bootstrap=True, max_depth=80, max_features=3, n_estimators=300; total time=   4.7s
[CV] END bootstrap=True, max_depth=80, max_features=3, n_estimators=1000; total time=  15.0s
[CV] END bootstrap=True, max_depth=90, max_features=3, n_estimators=300; total time=   4.4s
[CV] END bootstrap=True, max_depth=100, max_features=2, n_estimators=100; total time=   1.2s
[CV] END bootstrap=True, max_depth=100, max_features=2, n_estimators=200; total time=   2.5s
[CV] END bootstrap=True, max_depth=100, max_features=2, n_estimators=1000; total time=  12.6s

[CV] END bootstrap=True, max_depth=80, max_features=2, n_estimators=300; total time=   3.8s
[CV] END bootstrap=True, max_depth=80, max_features=3, n_estimators=300; total time=   4.5s
[CV] END bootstrap=True, max_depth=90, max_features=2, n_estimators=100; total time=   1.3s
[CV] END bootstrap=True, max_depth=90, max_features=2, n_estimators=100; total time=   1.3s
[CV] END bootstrap=True, max_depth=90, max_features=2, n_estimators=200; total time=   2.6s
[CV] END bootstrap=True, max_depth=90, max_features=2, n_estimators=1000; total time=  12.7s
[CV] END bootstrap=True, max_depth=100, max_features=2, n_estimators=100; total time=   1.4s
[CV] END bootstrap=True, max_depth=100, max_features=2, n_estimators=200; total time=   2.6s
[CV] END bootstrap=True, max_depth=100, max_features=2, n_estimators=1000; total time=  12.6s

[CV] END bootstrap=True, max_depth=110, max_features=2, n_estimators=200; total time=   2.5s
[CV] END bootstrap=True, max_depth=110, max_features=2, n_estimators=1000; total time=  12.6s

{'bootstrap': True, 'max_depth': 90, 'max_features': 3, 'n_estimators': 300}

Training accuracy 1.0
Testing set accuracy 0.8866806136680614
[[4706  201]
 [ 449  380]]
              precision    recall  f1-score   support

           0       0.91      0.96      0.94      4907
           1       0.65      0.46      0.54       829

    accuracy                           0.89      5736
   macro avg       0.78      0.71      0.74      5736
weighted avg       0.88      0.89      0.88      5736
```

We are getting best performance from Random Forest but we are not sure why we are getting such idealistic results so we would also apply cross validation to test our results

```
{'Training Accuracy scores': array([1., 1., 1., 1., 1.]),
 'Mean Training Accuracy': 100.0,
 'Training Precision scores': array([1., 1., 1., 1., 1.]),
 'Mean Training Precision': 1.0,
 'Training Recall scores': array([1., 1., 1., 1., 1.]),
 'Mean Training Recall': 1.0,
 'Training F1 scores': array([1., 1., 1., 1., 1.]),
 'Mean Training F1 Score': 1.0,
 'Validation Accuracy scores': array([0.88690346, 0.87993027, 0.89017215, 0.88428852, 0.8908
 'Mean Validation Accuracy': 88.64192984132671,
 'Validation Precision scores': array([0.65052632, 0.63333333, 0.67549669, 0.64932127, 0.676
 'Mean Validation Precision': 0.6569652802663521,
 'Validation Recall scores': array([0.46676737, 0.40120664, 0.46153846, 0.43288084, 0.466767
 'Mean Validation Recall': 0.44583213717743664,
 'Validation F1 scores': array([0.54353562, 0.49122807, 0.5483871 , 0.51945701, 0.55227882])
 'Mean Validation F1 Score': 0.5309773241904796}
```

After applying cross validation, we are getting some what real estimates.

AUC Curve : Figure 2 Precision Recall Curve : Figure 3

Linear SVC

Finding a linear hyperplane that tries to separate two classes.

```
0.8559972105997211
[[4898    9]
 [ 817   12]]
              precision    recall  f1-score   support

           0       0.86      1.00      0.92      4907
           1       0.57      0.01      0.03       829

    accuracy                           0.86      5736
   macro avg       0.71      0.51      0.48      5736
weighted avg       0.82      0.86      0.79      5736
```

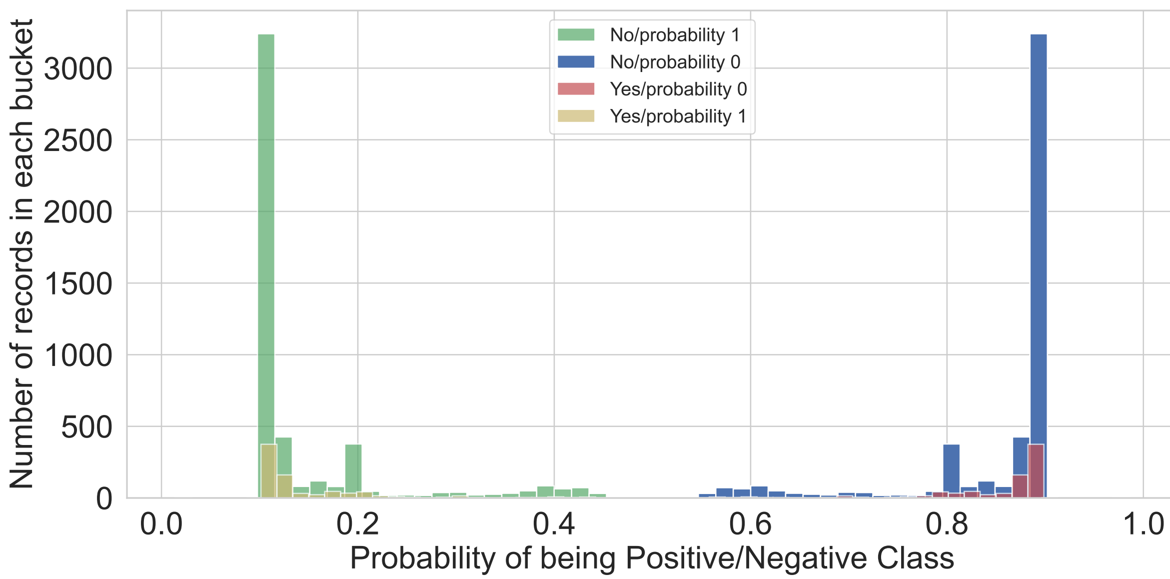
SVC

Finding a complex hyperplane that tries to separate the classes.

```
0.8554741980474198
[[4907    0]
 [ 829    0]]
              precision    recall  f1-score   support

           0       0.86      1.00      0.92      4907
           1       0.00      0.00      0.00       829

    accuracy                           0.86      5736
   macro avg       0.43      0.50      0.46      5736
weighted avg       0.73      0.86      0.79      5736
```

Naive Bayes

```
Fitting 10 folds for each of 100 candidates, totalling 1000 fits

GaussianNB(var_smoothing=0.0657933224657568)
Model score is 0.8561715481171548
```




```
test set evaluation:
0.8561715481171548
[[4892   15]
 [ 810   19]]
```

	precision	recall	f1-score	support
0	0.86	1.00	0.92	4907
1	0.56	0.02	0.04	829
accuracy			0.86	5736
macro avg	0.71	0.51	0.48	5736
weighted avg	0.81	0.86	0.80	5736

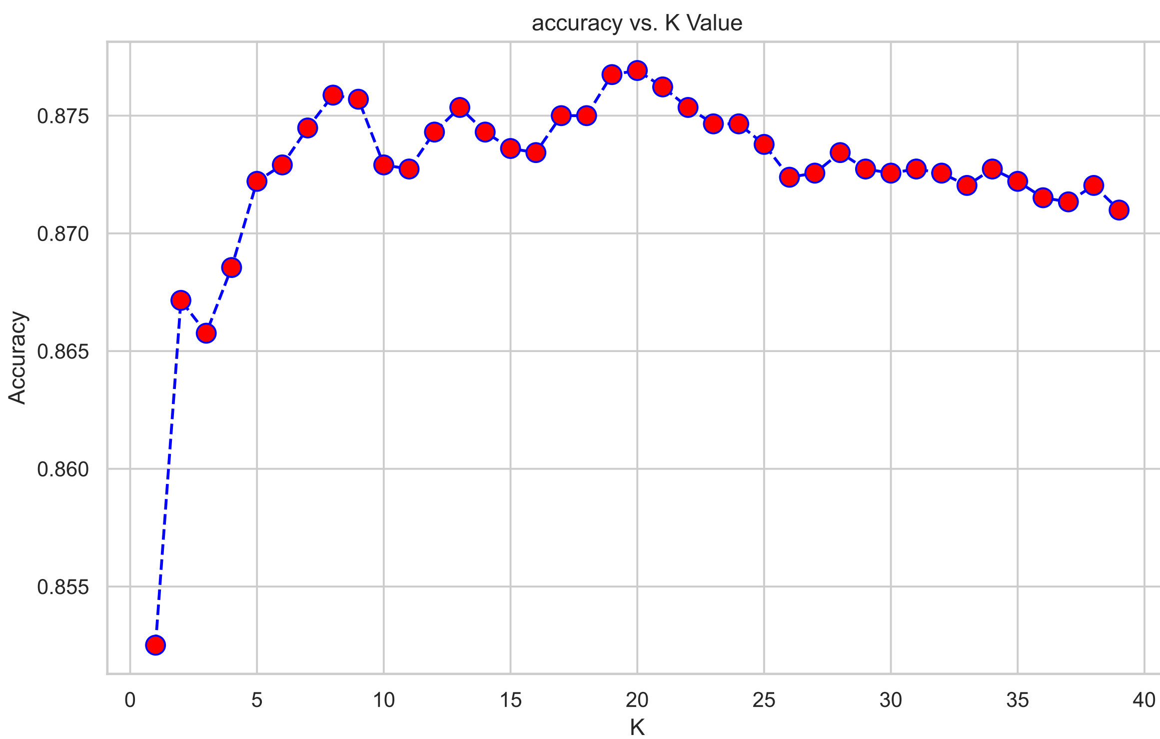
As we can see from the graph for Yes(1/have subscribed) the probabilities are coming both sides(for 0 as well as for 1) which is not correct.

AUC Curve : Figure 2 Precision Recall Curve : Figure 3

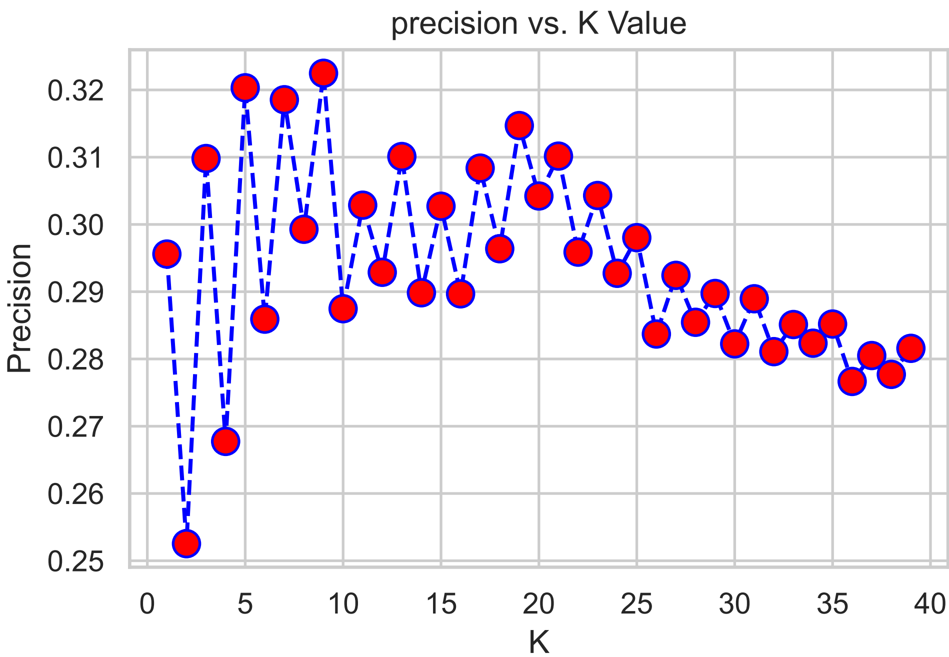
KNN

We will look into precision and accuracy curve for the optimal value of k.

```
Maximum accuracy:- 0.8769177126917713 at K = 19
```



```
Maximum Precision:- 0.32247407633937064 at K = 8
```



Based on the above plot, optimal k value is 3, with maximum f1 score of 0.64.

```
Train set accuracy 0.9197611576011158
Test set accuracy 0.8657601115760112
[[4626  281]
 [ 489  340]]
              precision    recall  f1-score   support

           0       0.90      0.94      0.92      4907
           1       0.55      0.41      0.47       829

    accuracy                           0.87      5736
   macro avg       0.73      0.68      0.70      5736
weighted avg       0.85      0.87      0.86      5736
```

AUC Curve : Figure 2 Precision Recall Curve : Figure 3

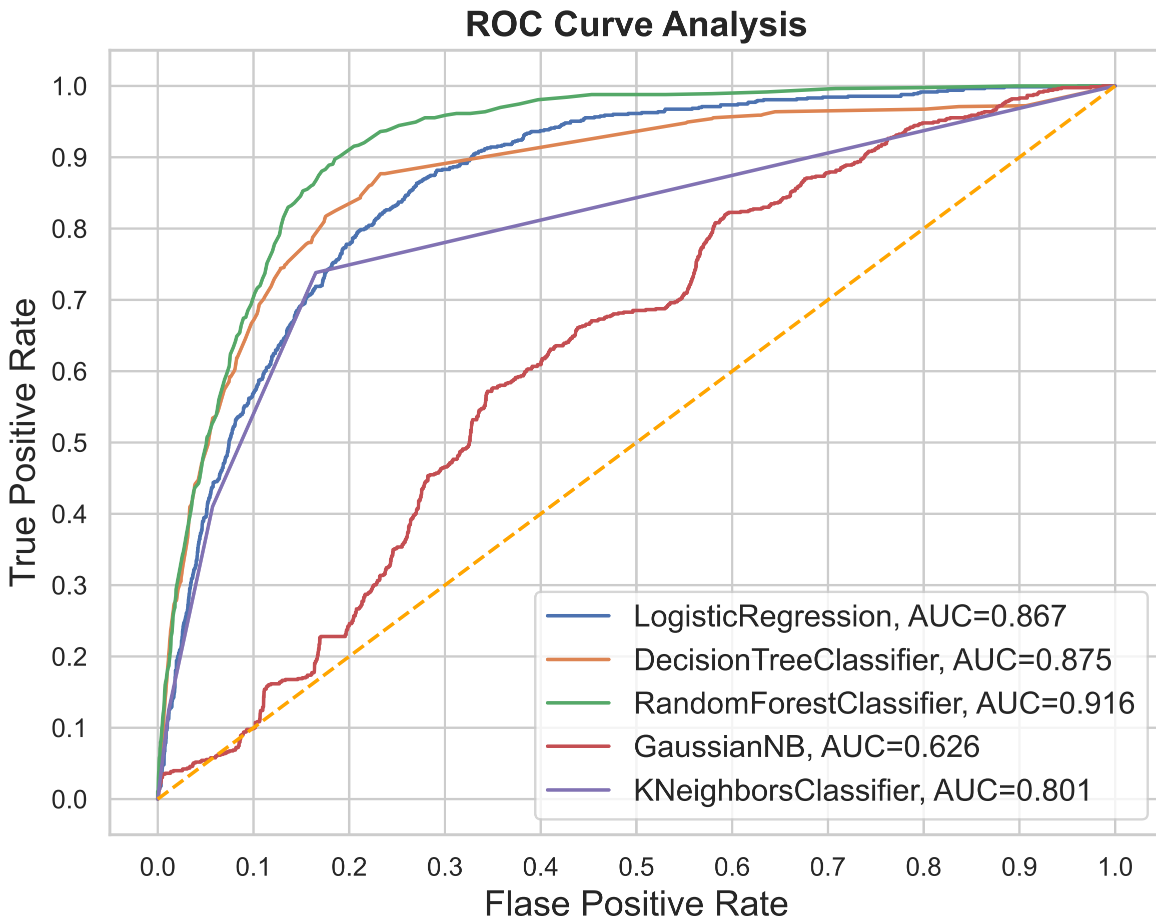


Figure 2: AUC ROC Curve for all Modeld

ROC -AUC Curve

Precision Recall Curve

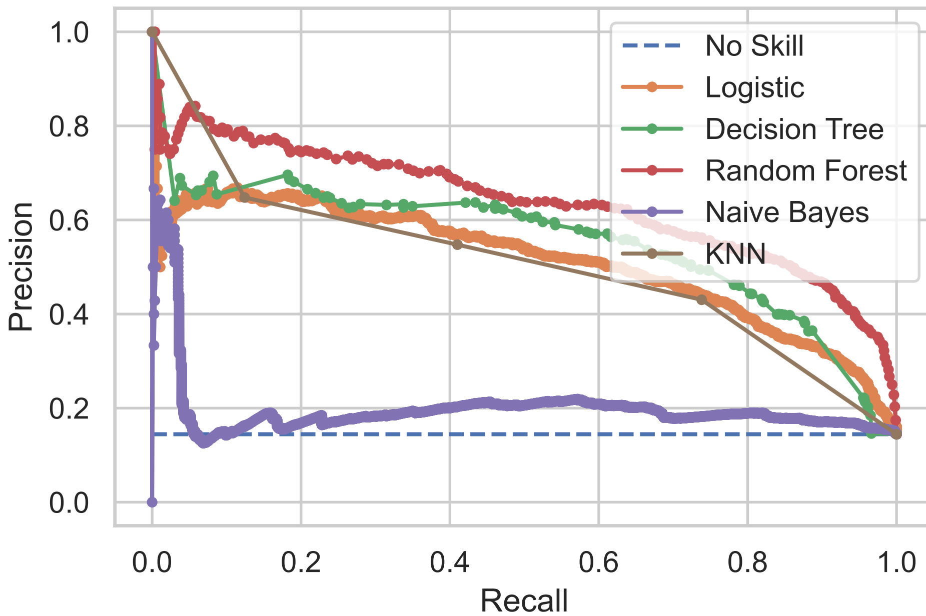


Figure 3: Precision Recall Curve for all Modeld

As per the ROC Curve and Precision Recall curve, Random Forest Classifier is performing best. Second best is KNN. Since we have unrealistic results from Random Forest, we would suggest using KNN for our model.

Summary

Table 1: Summary of Models

Model	Accuracy	Precision	Recall	AUC
Logistic	0.88	0.46	0.48	0.872
Decision Tree	0.91	0.66	0.47	0.923
Random Forest	1	1	1	1
SVC	0.89	0.75	0.15	
Linear SVC	0.89	0.62	0.16	
Gaussian Bayes	0.88	0.50	0.25	0.841

Model	Accuracy	Precision	Recall	AUC
KNN	0.92	0.78	0.54	0.965

See Table 1.

Conclusion

Our model would be beneficial in the following ways :

- For target marketing for bank campaigns, or in other events. For example based on the customer's job, age and loan history the model would can easily predict whether the customer is going to subscribe to the term deposit or not. So out of the million people, we can easily shortlist people based on our model and spend the time on them so as to improve efficiency.
- Improving buissness effficiency of banks. Since using the eda or model we can easily check the subscription insights, it would be very helpful for banks to improve their stratergies. For example, based on the monthly subscription rates, if banks are deciding the campaign promotion time, it can improve there efficiency.
- Since, we have month as a input factor in our model, and all other values are static, we can even find the best month to contact customer based on the predicted probability of the customer. As there can be a relation between the job type and the month they are subscribing or their fluctuating balance and age. This can be very useful in finding the best time to contact.
- Based on the model, since the number of contact is playing a major role, if we have the optimal time to contact them, we can restrict our calls to less than 5 and find a better turnover.
- We didn't see any relation with the social and economic factors here, but if we had the data for multiple years, there was a possibility of finding a relation. Our model can accomodate these factors as well, and if trained by accomodating these factors as well, this can be helpful for banks in finding the proper time for there campaign.

Hence, analyzing this kind of marketing dataset has given us valuable insight into how we can tweak our model to give buisness insights as well as customer insights to improve subscription of term deposits.

Reference

- https://www.kaggle.com/janiobachmann/bank-marketing-dataset *(PDF) Data Analysis of a Portuguese marketing campaign using bank ... (no date). Available at: https://www.researchgate.net/publication/339988208_Data_Analysis_of_a_Portuguese_Marketing_Can (Accessed: December 20, 2022).* Bank marketing data set. (n.d.). 1010data.com. Retrieved December 20, 2022, from https://docs.1010data.com/Tutorials/MachineLearningExamples/BankM *Manda, H., Srinivasan, S., & Rangarao, D. (2021). IBM Cloud Pak for Data: An enterprise platform to operationalize data, analytics, and AI. Packt Publishing.* Solving Bank Marketing Calssification Problem - Databricks. (n.d.). Databricks.com. Retrieved December 20, 2022, from https://databricks-prod-cloudfront.cloud.databricks.com/public/4027ec902e239c93eaaa8714f173bcfc/8143187682226564/22976133 *Solving Bank Marketing Calssification Problem - Databricks. (n.d.). Databricks.com. Retrieved December 20, 2022, from https://databricks-prod-cloudfront.cloud.databricks.com/public/4027e