Bank Marketing

Which Customer to target?

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Yes

Marketing Campaign

Investment

Statistics

Safety

Term Deposit

Finance

Banking

Rate of Interest

Client

No

Safe

The data is related to the direct marketing campaigns (phone calls) of a portuguese banking institution

The Problem

- Improve the marketing campaign by analyzing customer data & past marketing campaign and recommend which customer to target.
- Challenge : Skewed data.
  Classification problem with an imbalance Ratio of 10%.
- Built a predictive model that gives insights into which customer to target with low false positives and false negatives.

The Data

16 feature attributes divided into three groups

- Client Information
- Related to last contact of the previous campaign
- Related to current campaign

1 target attribute (y) - (yes/no)

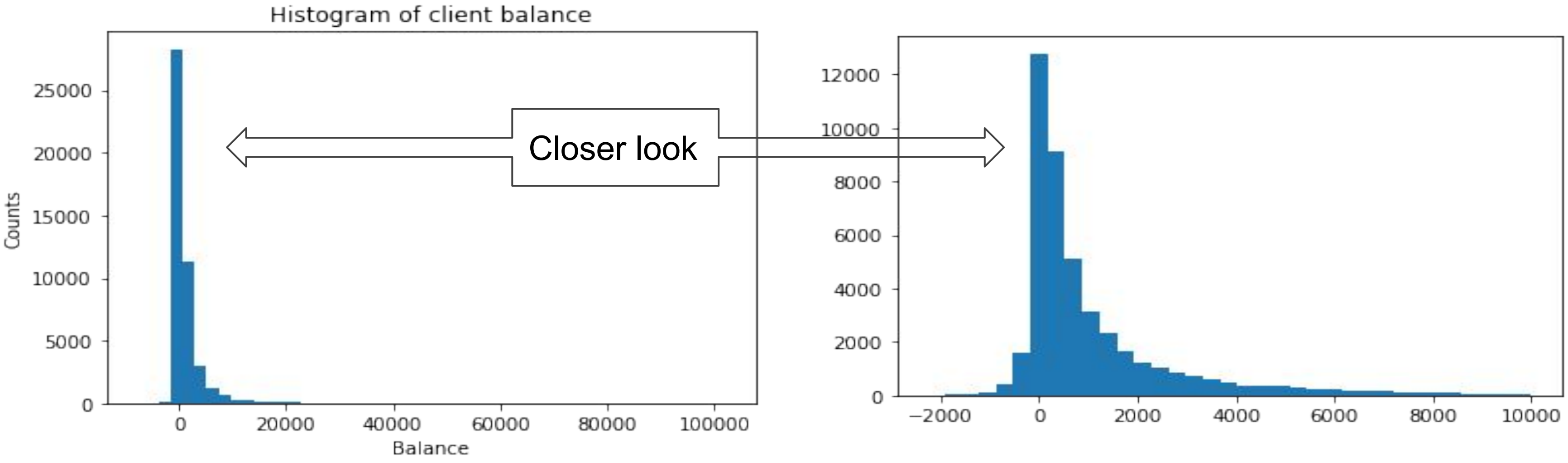
Data Wrangling

- No missing values
- Outliers were kept for further analysis
- Clean data that requires no pivoting or melting.
- Various statistics were computed on all the columns using .describe() method.

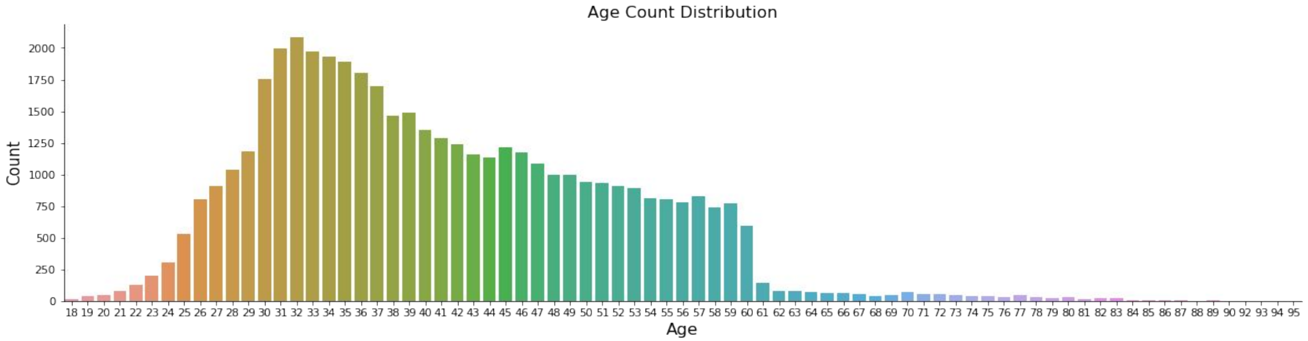
45,211 instances for training.
4521 instances of new unseen data for testing.

Data Storytelling

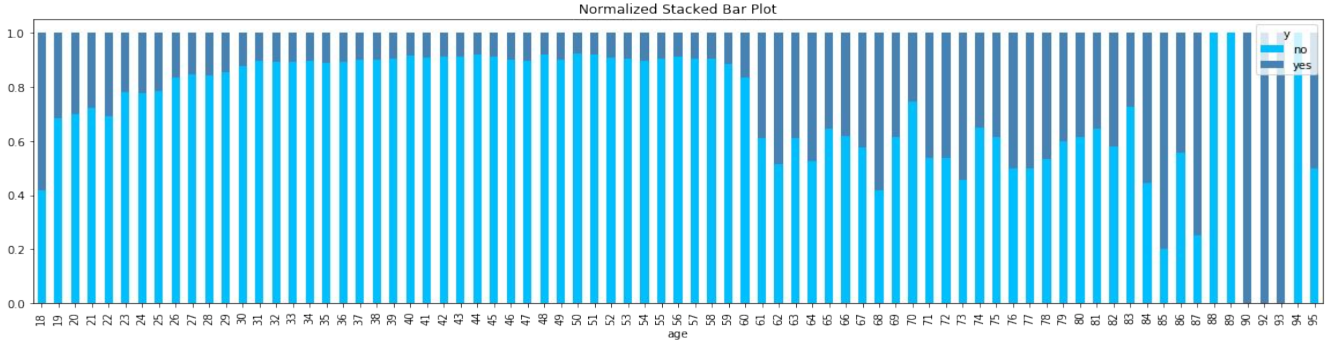
- Balance in a client's account ranges from a minimum of -8019 to a maximum of 102127. But 25th and 75th percentiles range between 72 to 1428 euros.
- Out of 7280 clients who had negative balance, 502 clients subscribed for a term deposit. Hence, even clients who had negative balances are statistically important. This attribute has a lot of outliers.



AGE



- Distributed between the ages of 18 and 95
- Mostly middle aged
- Mean age 40yrs
- STD - 10

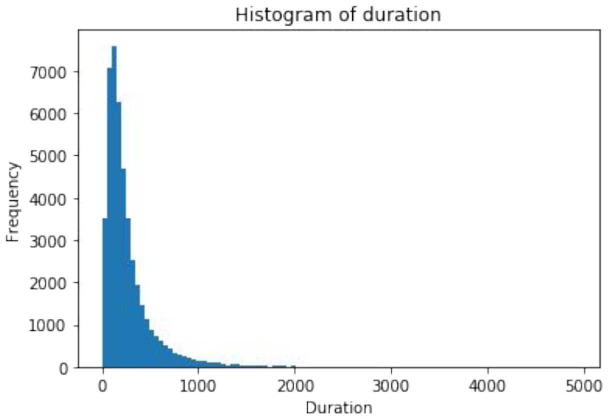


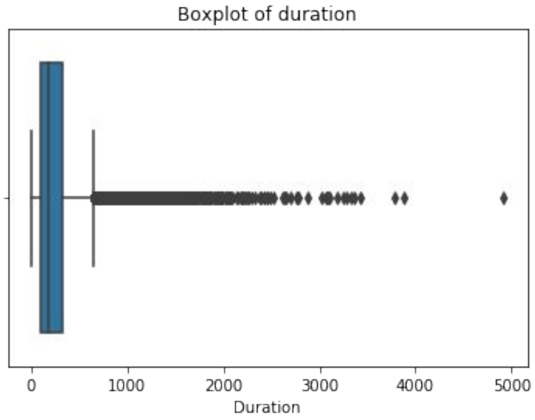
<u>Ages</u>

- Below 22
- Above 60

Have higher tendency to opt for a term deposit

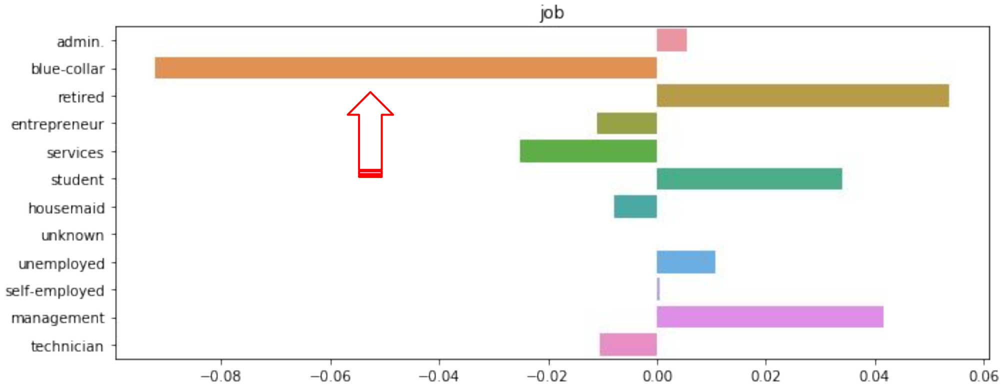
Duration of the call





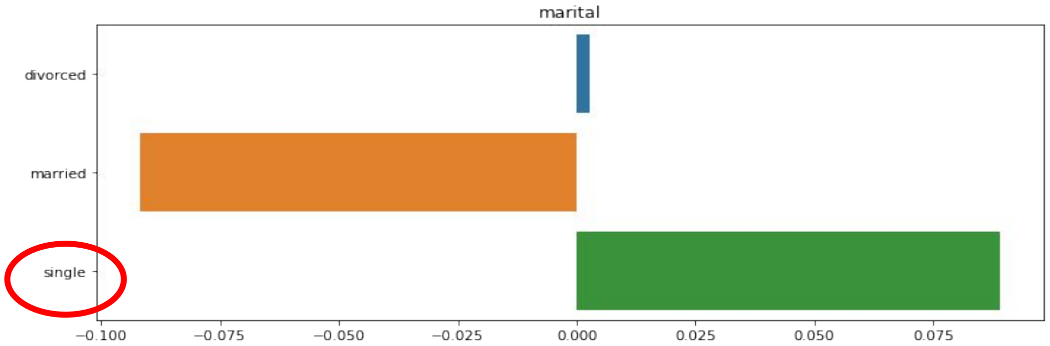
- Most of the data is skewed towards the left.
- Ranges between 0 and 4918 seconds.
- The data below the 75th percentile (319 seconds) gives a clearer picture.
- The call duration is usually about 5 minutes. But occasionally it got a little higher. And the maximum value of 4918 s could be an outlier.

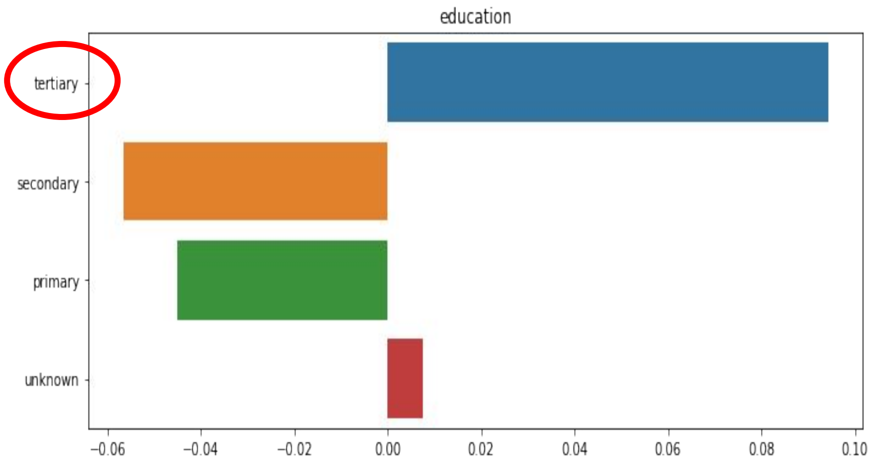
Recommendations based on EDA

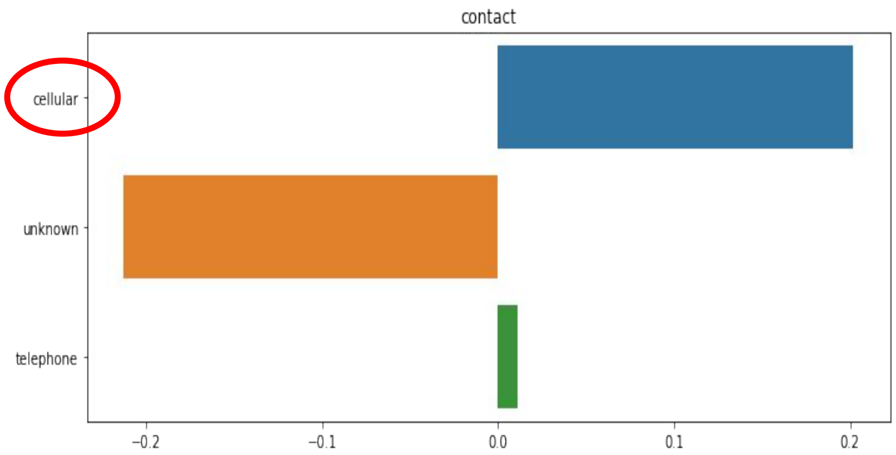


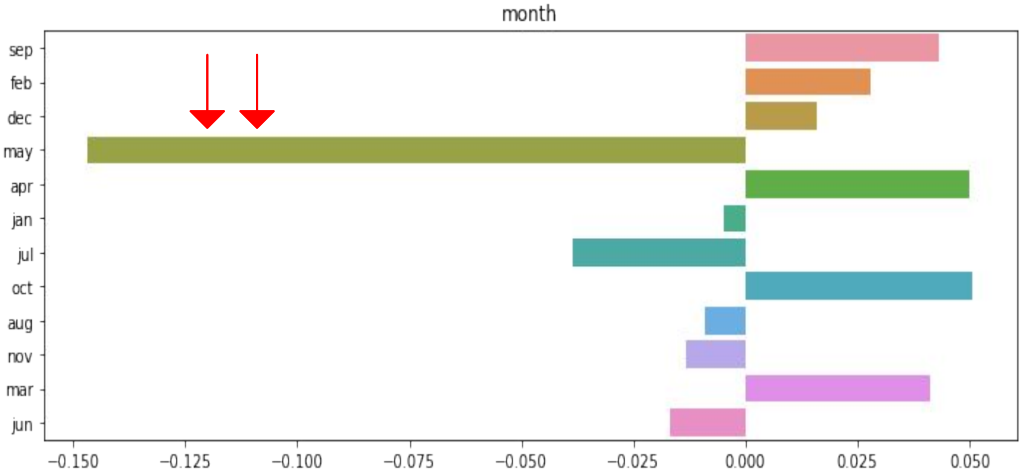
Target
- Retired
- Management
- students

Target single clients

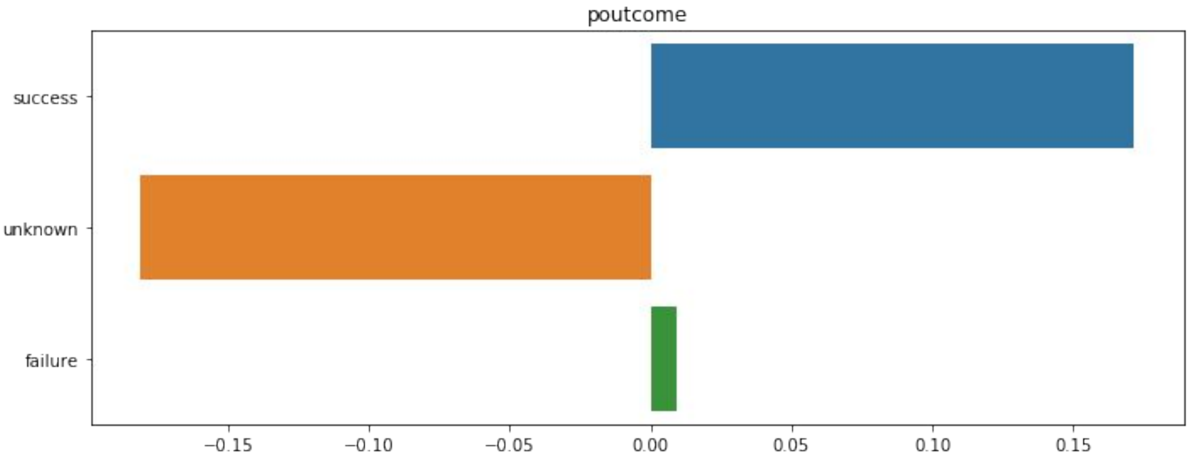






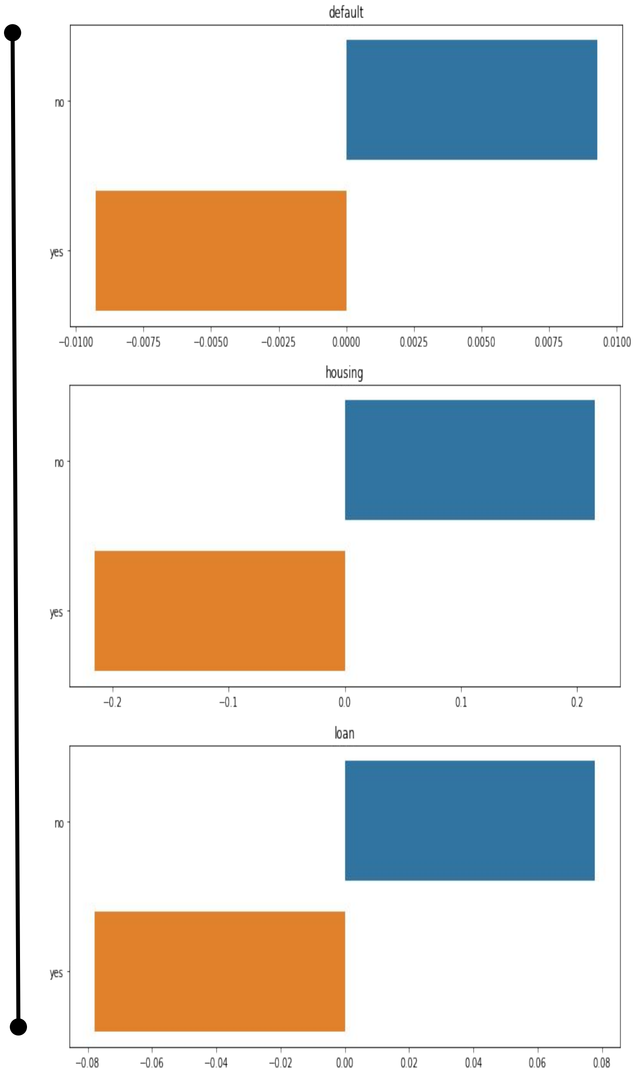


- Target more educated clients.
- Cellular contact is the best
- Try not to contact in the holiday season



Clients with success from previous campaign are more likely to subscribe to a term-deposit again.

The clients with no loans are more likely to subscribe to a term-deposit.



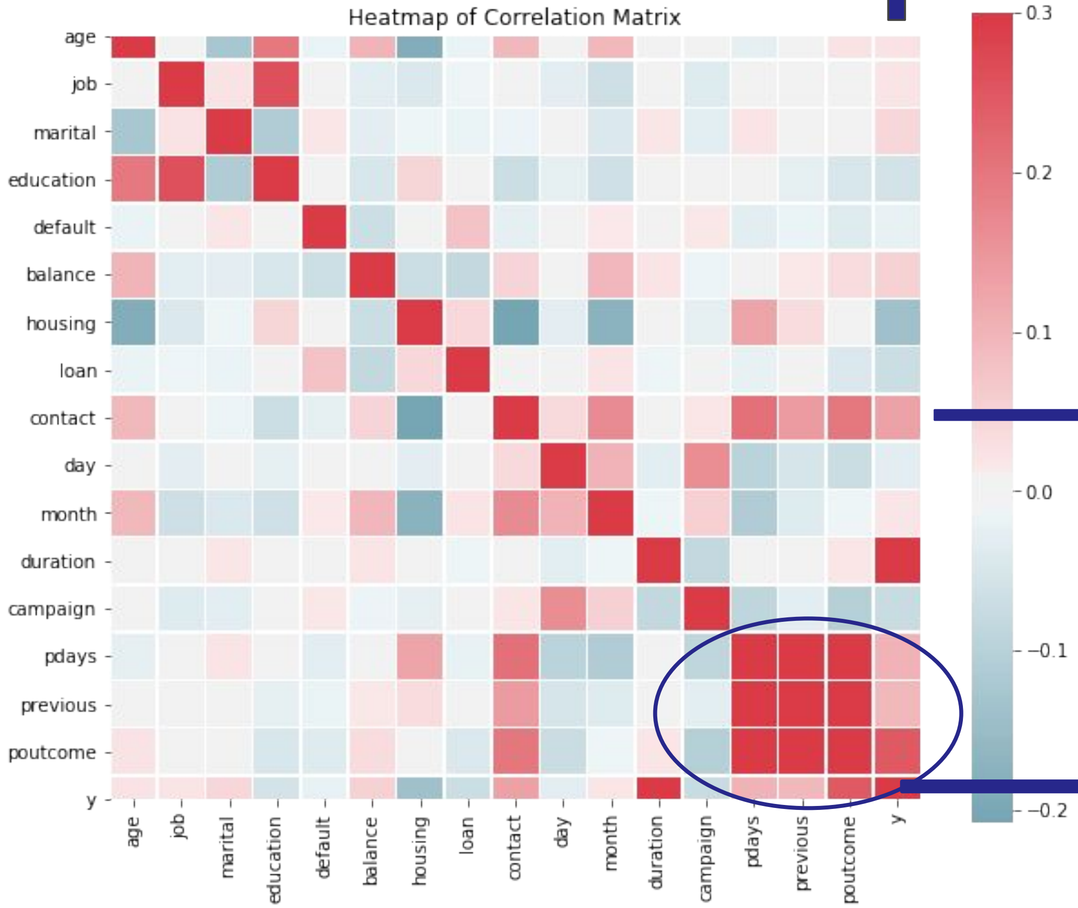
Inferential Statistics

T-test on three attributes helped us reject the Null Hypothesis with a p-value less than 10^-5.

The following attributes were tested with the group that caused ‘yes’ and the group that caused ‘no’ in the target variable:

- Age
- Balance
- Duration

One more Hypothesis test on ‘Balance’ to test the statistical significance between the group with positive balance and the group with negative balance. Null Hypothesis rejected with P-value less than 10^-300.



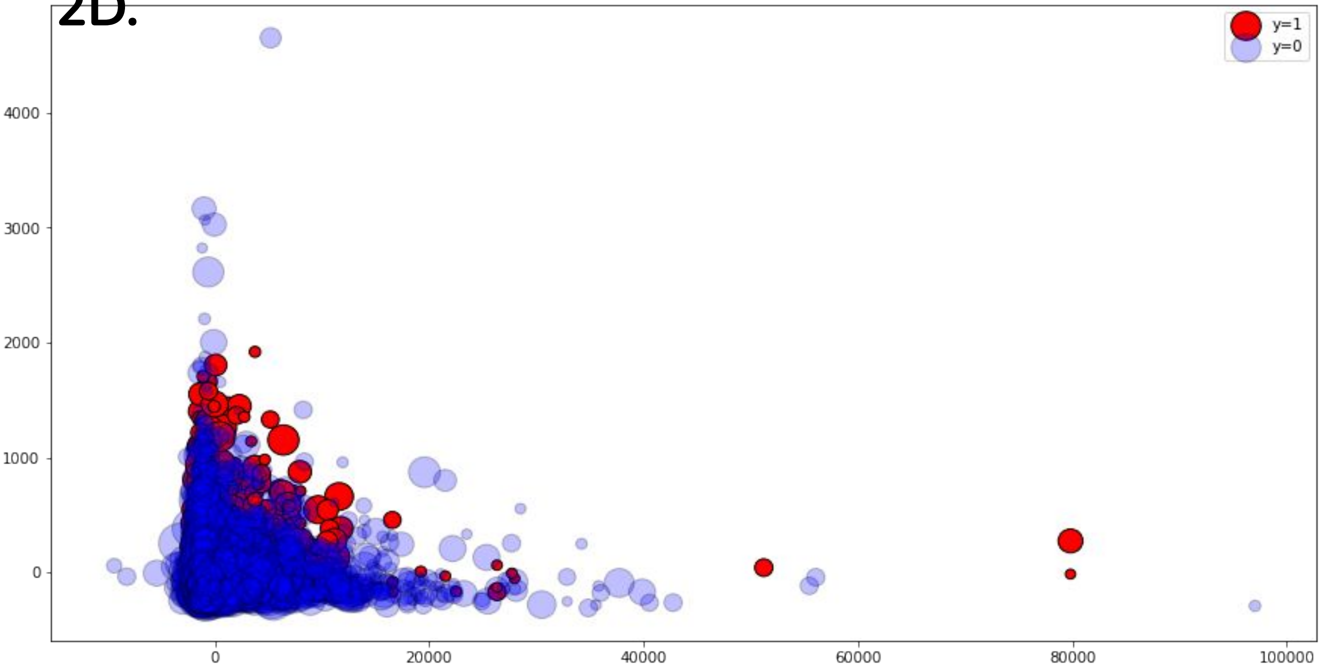
Target variable 'y' has strong positive correlation with

- Duration
- Poutcome
- Contact

The feature contact has correlations with a large number of other features

The features related to the previous campaign are highly correlated.

Principal Component Analysis (PCA) for Visualization of the data in 2D.



- Clients who did **not** subscribe for a term deposit.
- Clients who subscribed for a term deposit.

Visualization through PCA gives us a view about how skewed our data is. On a plot, we can understand our data much better.

Data Preprocessing

- Manually treating the categories in the categorical columns.
- PCA to explain variance-covariance structure of a set of variables.
- Upsampling the minority class
- StandardScalar() from sklearn
- Test-train split (1:4)
- K fold split for cross validation.

Models built:

- Linear regression
- Knn
- Support Vector Machine (SVM)
- Decision Tree
- Random Forest
- Extreme Gradient Boosting
- Gradient Boosting Classifier

Models	MCC
Random Forest Classifier	0.941
Decision Tree Classifier	0.927
K-Near Neighbors	0.863
Support Vector Machine	0.732
Gradient Boosting	0.722
XGBoost	0.718
Logistic Model	0.607

Best Model

Random Forest Classifier

Training Accuracy score : 100.0

Confusion matrix : [31995 0]
[0 31880]

Recall - train : 1.0

MCC : 1.0

Testing Accuracy score : 97.0

Confusion matrix : [7450 477]
[6 8036]

Recall - test : 0.999

MCC : 0.941

- Test Metric : Matthew's correlation coefficient (MCC)
- MCC returns a value between -1 (poorly fitted model) and 1 (best model)
- Highest MCC and lowest false negatives, false positives for Random Forest classifier

Hyper-Parameter tuning

Best Estimators for Parameters Tuned:

'n_estimators': 600,

'min_samples_split': 5,

'min_samples_leaf': 1,

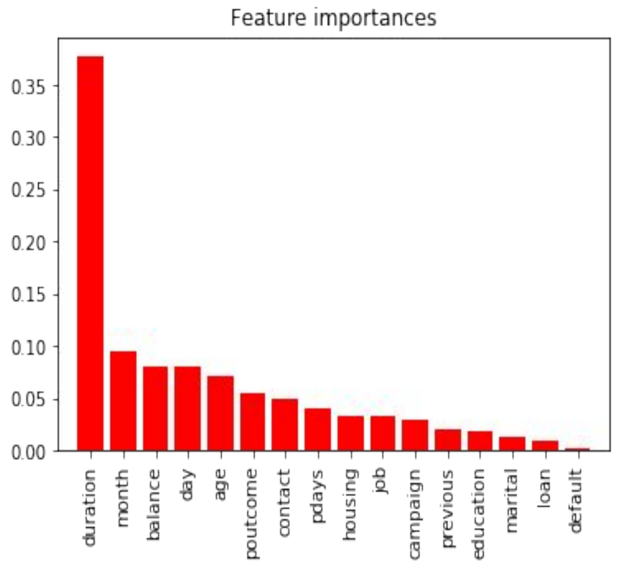
'max_features': 6,

'max_depth': 110,

'bootstrap': False

Training Accuracy score : 100.0
Confusion matrix : [31995 0]
[0 31880]
Recall - train : 1.0
MCC : 1.0

Testing Accuracy score : 97.0
Confusion matrix : [7534 393]
[11 8031]
Recall - test : 0.998
MCC : 0.957



From the best estimators from the hyper-parameter tuning, the max_features used for the model is 6. Hence the 6 most important features as interpreted from the feature importance plot are duration, month, balance, day, age, poutcome.

Evaluating The Model’s Performance with Unseen Data

Accuracy score : 0.989
Confusion matrix : [3952 48]
[1 520]
MCC : 0.95

- The new data that is imported is treated into categorical columns.
- StandardScaler is also applied to the new data to make the new data similar to the training data.
- The Random forest classifier performs very well in predicting new data.
- Matthew’s correlation coefficient is 0.95, which is as good as it works on test data.

Conclusion

- Duration of the call played a very important role.

  Engage the customer in the call long enough to understand the merits of the term deposit, the customer has a higher chance of subscribing to a term deposit.

- Most customers were contacted in May did not subscribe to a term deposit. This can be avoided in future. Avoid the holidays!
- Customers who subscribed to a term deposit in the previous campaign are more likely to go for it again.
- Targeting clients aged below 22 and above 60 yields better results.

The model has very low false negatives. It is a good sign since not many people will be missed by the marketing campaign.

Thank You