# Analysis of Bank Telemarketing Data

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### Understanding the Data



Client

Age

Job

Marital Status

Education

Credit in Default?

Housing Loan?

Personal Loan?



**Last Contact** 

Mode of Communication

Call duration

Day, Month



Socio-Economic Factors

Quarterly Employment Variation Rate

Monthly Consumer

Price Index

Monthly Consumer Confidence Index

Number of Employees

Euribor 3-month rate



Other

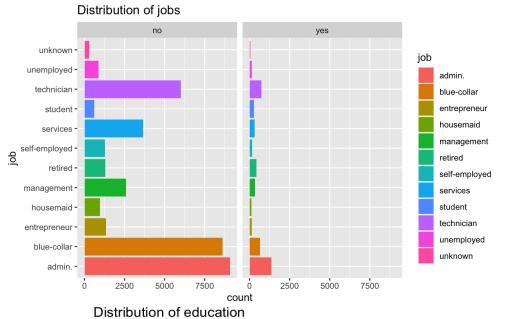
Outcome of previous campaign

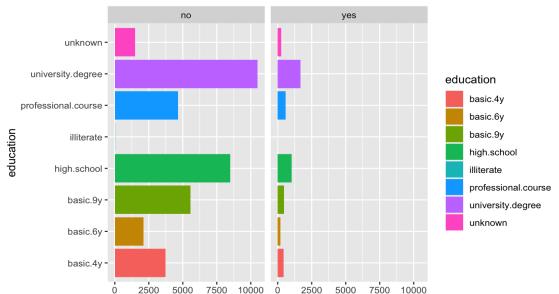
No of previous contacts in the current campaign

**GOAL**: The goal of the project is to build a classification model to predict if a client is going to subscribe to a term deposit

**INDUSTRY RELEVANCE**: The analysis is helpful in designing strategies to target prospective clients

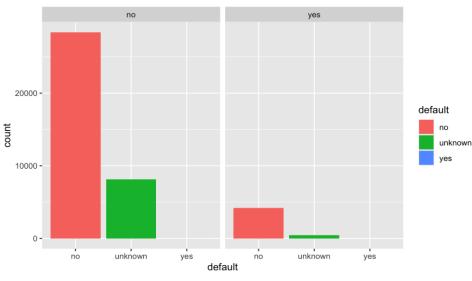
### Exploratory Data Analysis: Client Data



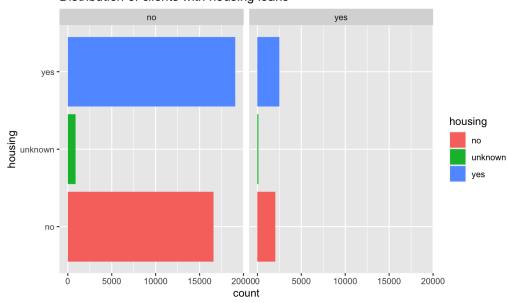


count

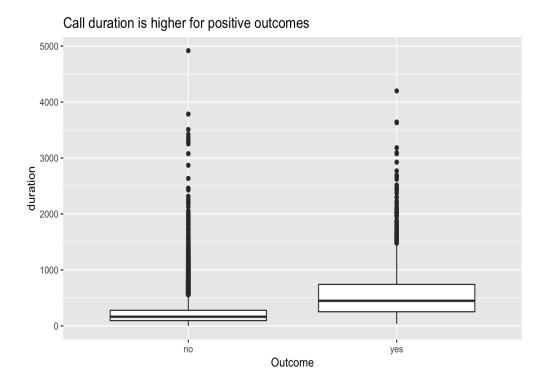
#### Distribution of defaulters

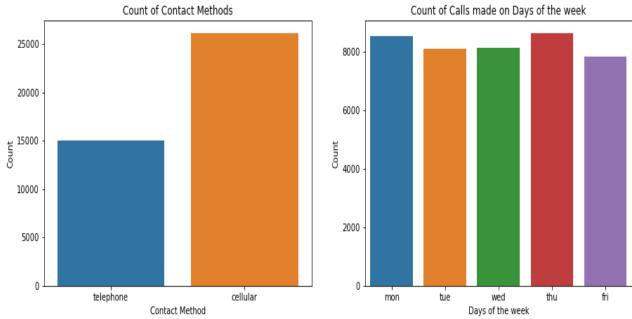


#### Distribution of clients with housing loans

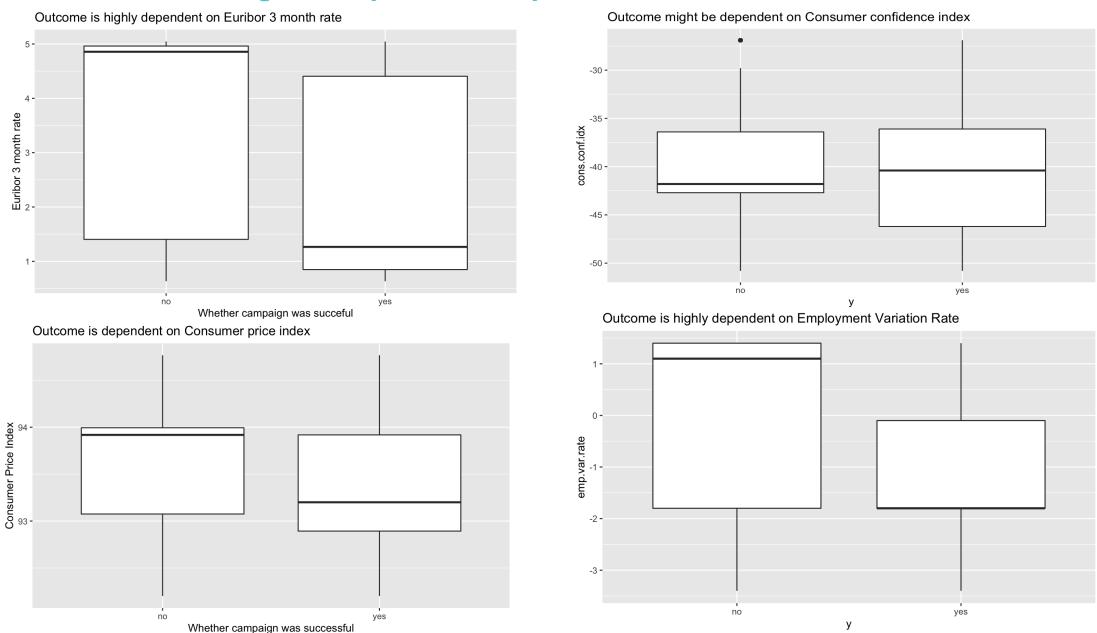


### Exploratory Data Analysis: Last Contact Data





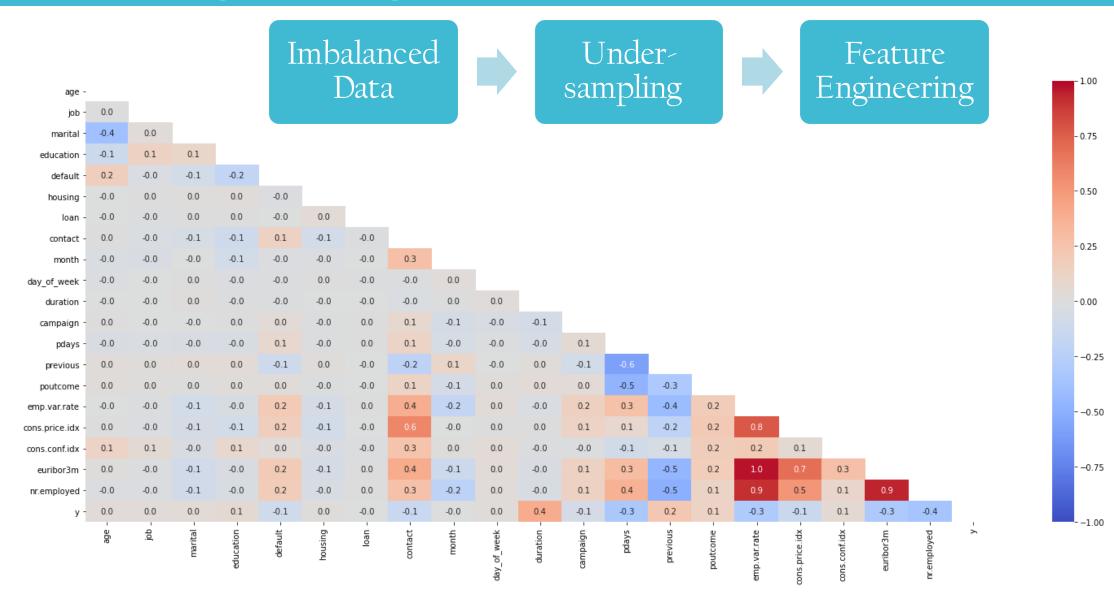
### Exploratory Data Analysis: Socio-Economic Factors

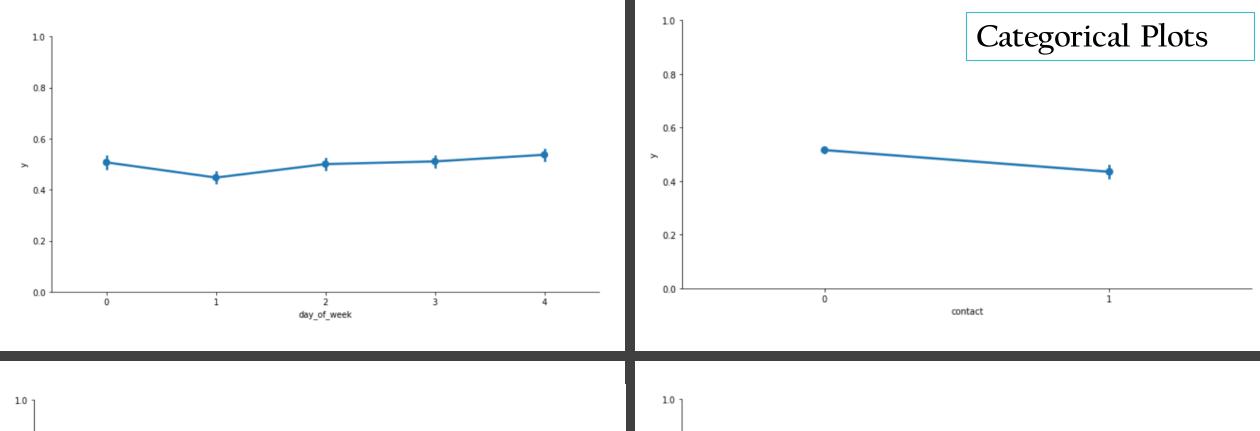


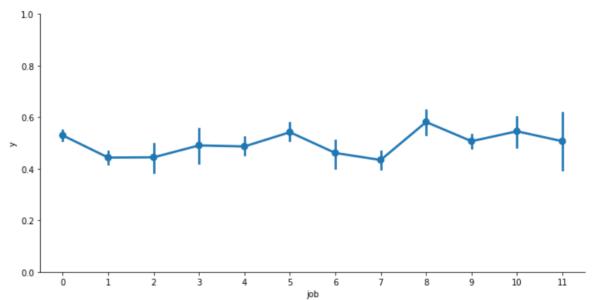
# Conclusions drawn from EDA

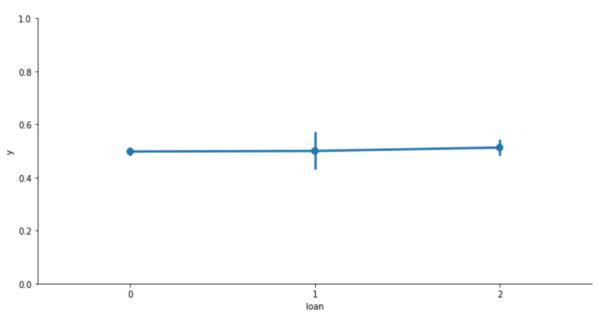
- Socio-economic factors highly influence the outcome. There might be possible correlation between these variables that needs to be checked.
- Client Data like education, job, marital status etc. does not influence the outcome.
- Call duration influences the outcome. The duration is higher for people who subscribed to the term deposit.

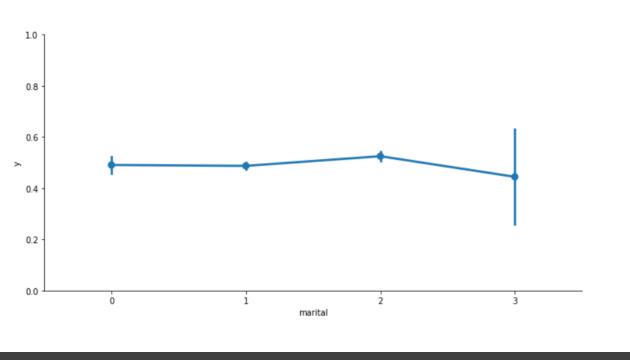
# Feature Engineering

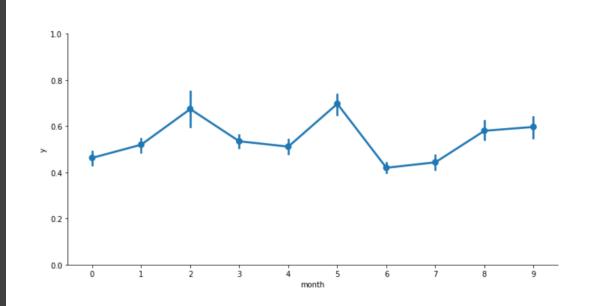


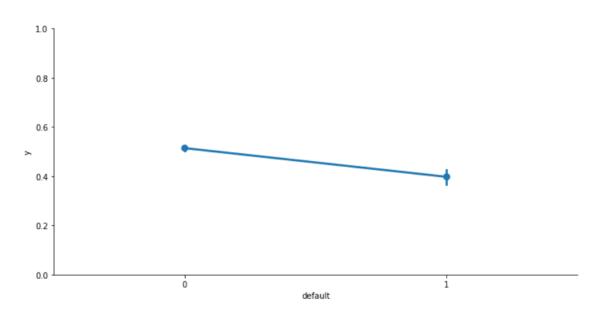


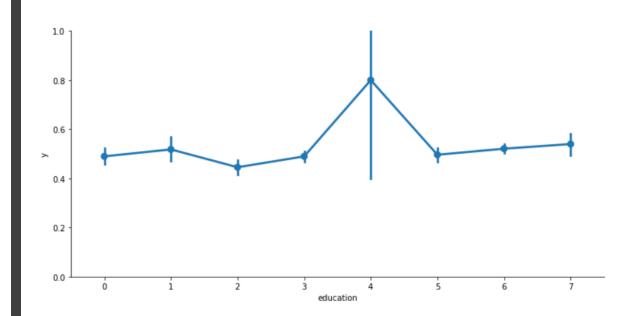












# Statistical Significance Test:

We performed Statistical significance test for every feature with the output to see if a feature is statistically significant with output.

Feature	P-Value
Age	0.551
Job	0.495
Marital	0.00604
Education	0.000896
Default	2.47e-13
Housing	0.719
Loan	0.319
Contact	6.08e-10
Month	0.839
Day of Week	0.000613
Duration	4.38e-19
Campaign	0.466
pdays	2.25e-66
previous	2.04e-19
poutcome	1.37e-56
Emp.var.rate	1.09e-10
Cons.price.idx	8.le-05
Cons.conf.idx	1.83e-05
Euribor3m	1.24e-19
Nr.employed	3.27e-38

## Conclusion After Feature Engineering

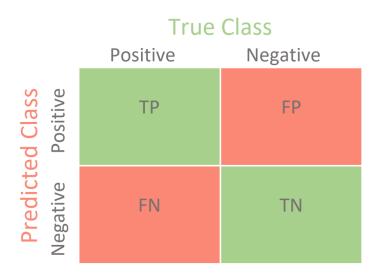
- Duration, pdays, emp.var.rate, euribor3m and nr.employed have good correlation with output therefore they might form a very good features compared to others.
- There is high correlation between the socio-economic variables.
- From categorical plot we can see that when value of **poutcome(Previous campaign outcome)** is success, there is 72.5% positive outcome.
- Age, housing, month and campaign have p-value greater than 0.05 therefore we can eliminate them as they fail to reject null hypothesis.



### Models Implemented:

Logistic Regression
Support Vector Classifier
K Nearest Neighbours
Random Forest Classifier

# Models and Evaluation Metrics



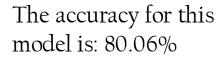
Since the problem we are trying to solve is a classification problem, we generated a confusion matrix to calculate Fl score to compare models

# Logistic Regression

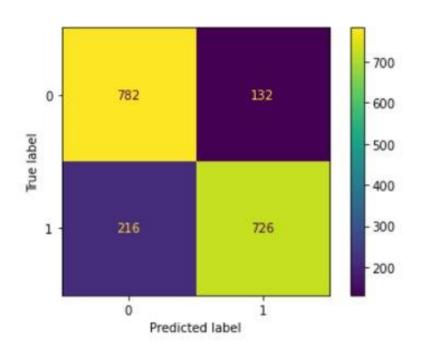
### Support Vector Classifier

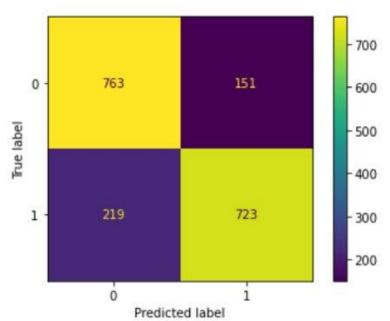
The accuracy for this model is: 81.25%

	precision	recall	f1-score	support
0	0.78	0.86	0.82	914
1	0.85	0.77	0.81	942



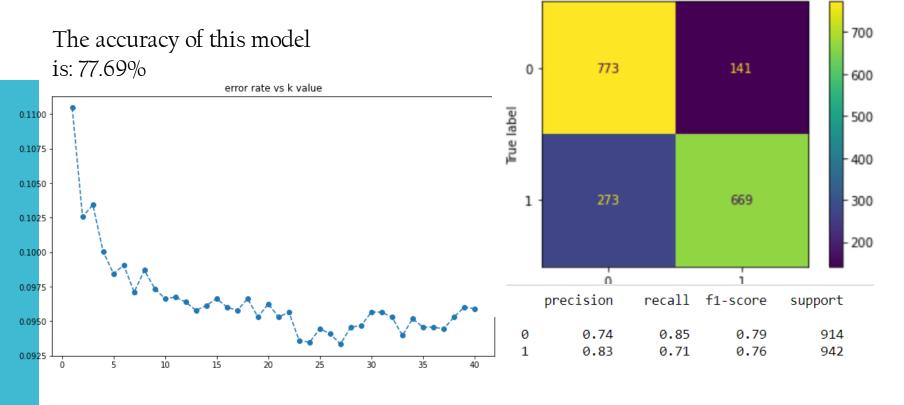
	precision	recall	f1-score	support
0	0.78	0.83	0.80	914
1	0.83	0.77	0.80	942

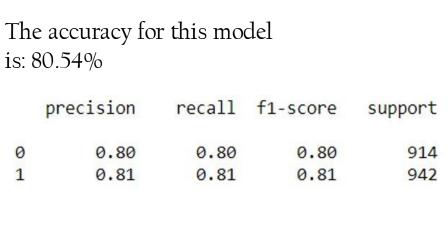


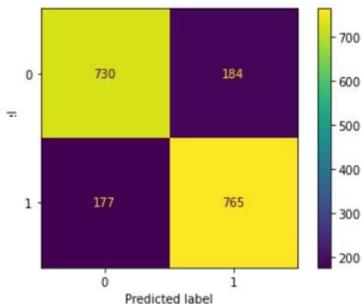


K- Nearest Neighbors (k=27)

### Random Forest Classifier







## Conclusion after Machine Learning

• Using our evaluation metrics, we can conclude that the logistic regression model was the best fit model on our data set giving an overall F1 score of 0.82

• Questions?