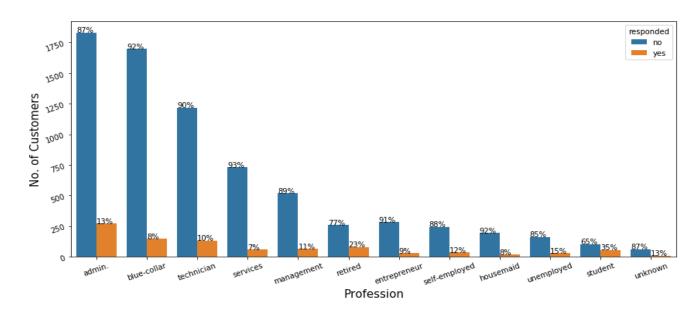
Customer Quality Prediction

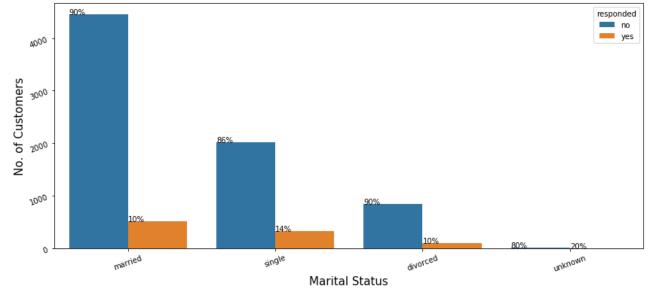
Client	Insurance Company running Marketing campaigns to sell Insurance policies to customers	
Objective	Maximize the profits by running a Targeted Marketing Campaigning	
Project Objective	Analyze the available data to develop insights into the customer quality Build a Machine Learning model to predict whether or not a customer should be targeted in order to maximize the profits	
Historical Dataset: Features used for training the predictive model	 Customers profile: Age, Marital status, Professional & Educational background, Credit history, Preferred contact type Economy indicators: Employment Variation Rate, CPI (Inflation indicator), Consumer Confidence Index, Euribor rate (Bank Interest rates), etc. Previous Campaign details: Days since previous campaign, Outcome, etc. 	
Predictive Model Output	 Whether or not a customer responded to the present campaign ('Yes' / 'No') Profit made by company if customer responded and purchased a policy 	
Approach	Data Analysis: Studying the trends to check if any strong correlations exist between the features highlighted above Build a model to predict whether or not a customer should be contacted for pitching the policy	

Insights from the Data Analysis



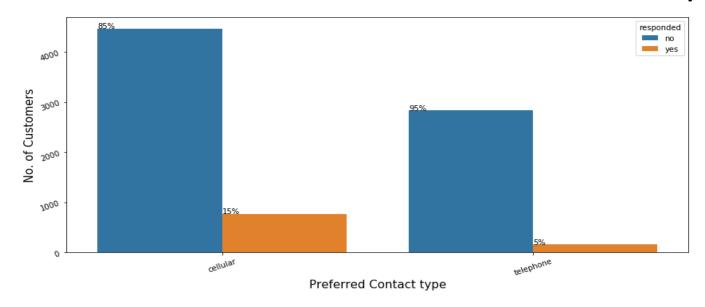
Profession:

- Customers in Admin. jobs most marketed, but positive response rate not highest
- Retired customers Highest positive response rate



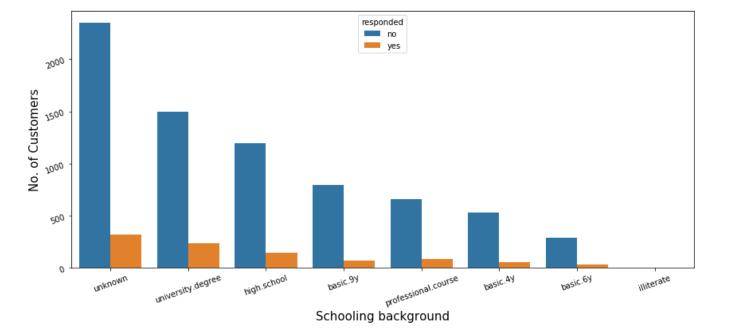
Marital Status:

- Married customers are most marketed
- Positive response rates are close
- Single customers have highest response rate



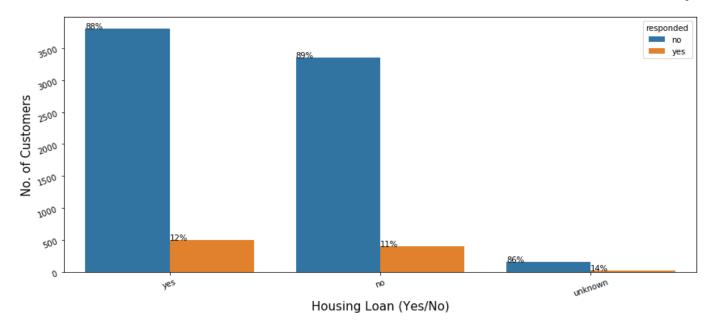
Preferred communication mode:

- Customers preferring communication over mobiles more marketed
- They are also more likely to respond



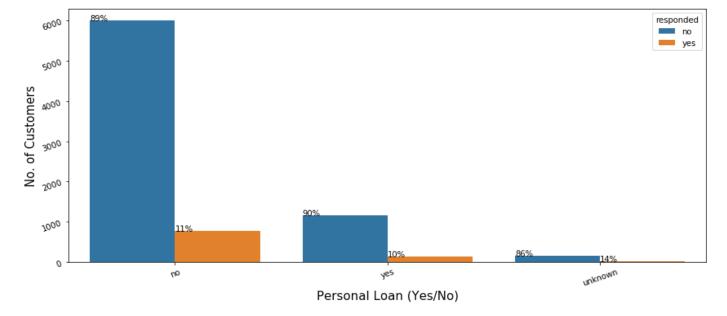
Schooling background:

- Schooling background of a large number is unknown
- Customers with University degree and High school education are most marketed



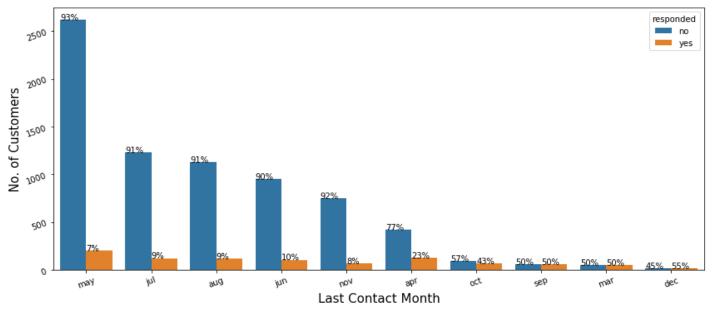
Housing Loan:

- Customers with or without Housing Loan
 almost equally marketed
- Same response rates



Personal Loan:

- Customers without Personal Loan are most marketed – Higher spending capacity
- However, Positive response rates are almost equal

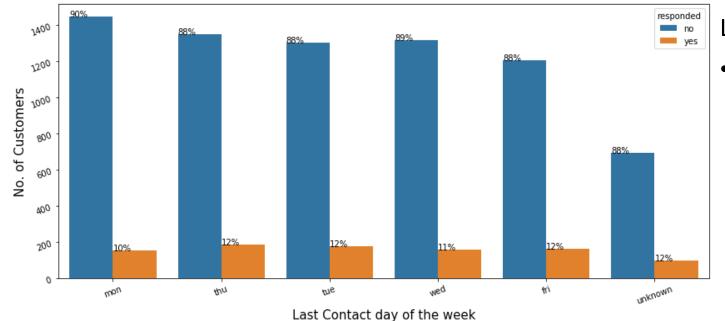


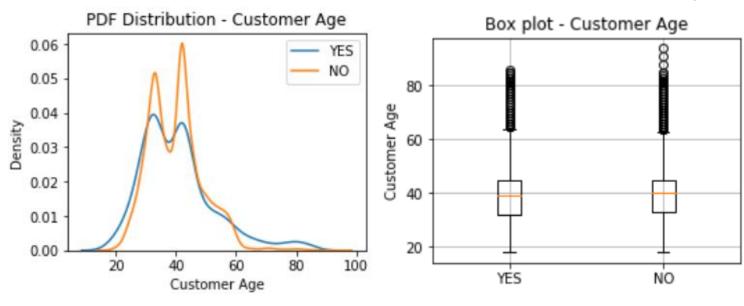
Last Contact Month:

- Marketing Campaign is aggressive in the months of May-Aug
- Highest campaigning activity in May
- However, these months do not have high Positive response rates
- Months with lower campaigning activity have higher Positive response rates

Last Contact Day of week:

 Positive response rate is also almost equal across working days of the week





Customer Age:

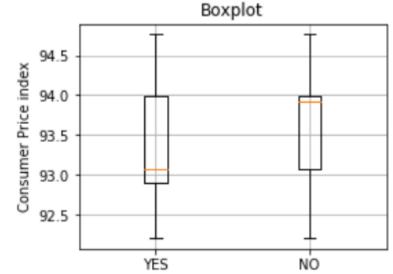
- Age distributions of customers of both classes are almost similar
- Mean = 40, Median = 38

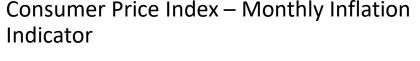


Number of times customer was contacted in campaign:

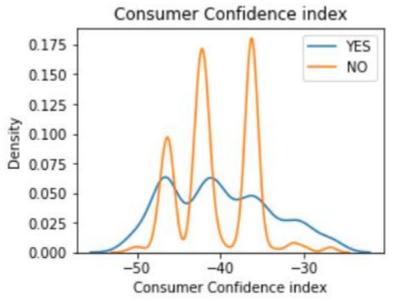
 The number of calls does not seem to be having a large impact on the customer response

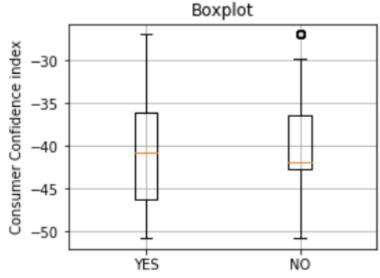






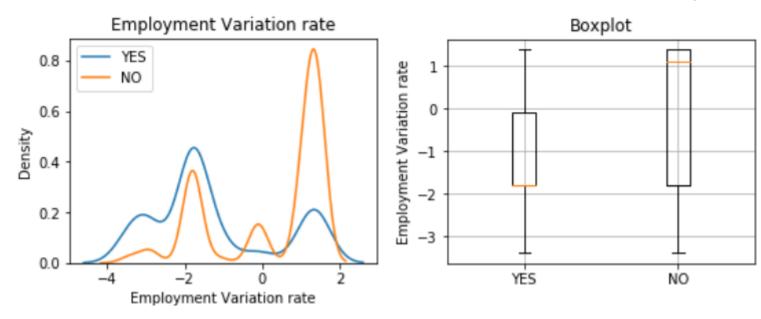
- Higher CPI = Higher Inflation rate and hence lower spending capacity
- Majority of customers who have responded have done so in lower CPI periods
- Customers are more likely to not respond during High Inflation periods
- CPI can be an important feature for our classification model





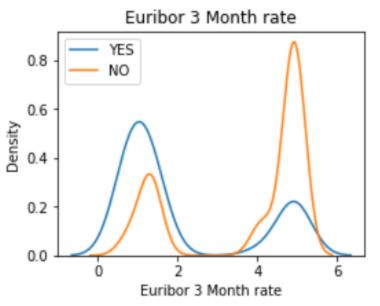
Consumer Confidence Index (CCI) – Monthly Indicator

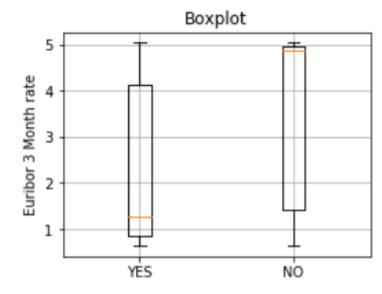
- Indicator of optimism about financial situation
- Higher CCI = Higher spending



Employment Variation Rate (EVR) – Quarterly Indicator

- Majority of customers who have responded have done so in lower EVR periods
- Customers are more likely to not respond during High EVR periods
- EVR can be an important feature for our predictive model





Euribor 3 Month Rate

- Inter-bank Rate: Rate at which European banks lend to one another
- Majority of customers who have responded have done so in lower Euribor rate periods
- Customers are more likely to not respond during High Euribor rate periods
- Euribor can be an important feature for our predictive model

Metrics used for Maximizing Total Profit

$$Total\ Profit = P * n - C * N$$

P: Avg. profit per responding Customer

n: Number of customers responding

C: Marketing cost per customer (\$30)

N: Number of customers marketed

Terminology used for assessing the predictive model's performance:

Number of customers our model correctly predicts as 'Will Respond' = True Positives (TP)

Number of customers our model incorrectly predicts as 'Will Not Respond' = False Negatives (FN)

Number of customers our model incorrectly predicts as 'Will Respond' = False Positives(FP)

To maximize Total profit:

High $\frac{TP}{TP+FP}$, i.e. **Precision** (Confidence of model when it predicts as 'Will Respond') of our model should be high

High $\frac{TP}{TP+FN}$, i.e. **Recall** (Ability to predict all potential customers who 'Will Respond') should be high

Relative importance of Precision & Recall depends on Avg. Profit (P) and Marketing Cost (C)

Objective of the predictive model: Strike a balance

Performance of this model is assessed based on the Total Profit generated from the Customers who were predicted as 'Will Respond'

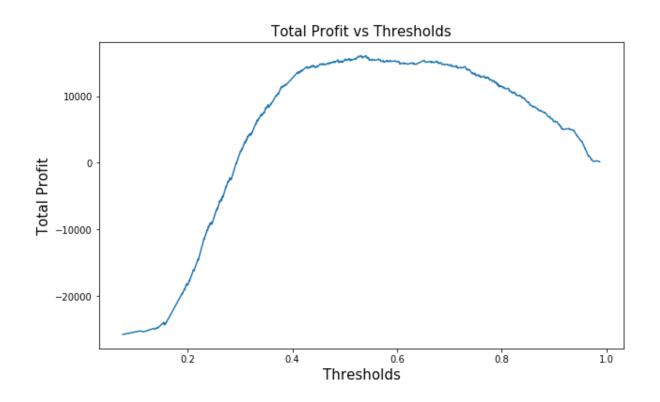
Predictive Modelling Strategy

 Training: Model learns the function f based on the relationship between Input features (X) and the desired Output Variables (Y) from the given historical dataset

$$Y = f(X_1, X_2, \dots)$$

- Model is trained on a subset of the historical dataset and its performance is assessed on a held-out Test set
- The model parameters are fine-tuned to maximize the performance using Kfold cross validation
- Different types of Machine Learning (ML) models are trained to pick the best model based on performance on the Test set
- Output of chosen ML Model: Probabilities of a customer belonging to Positive ('Will Respond') class
- A heuristic was used to choose the Threshold value beyond which the Model would classify a customer as 'Will Respond'

Predictive Model Performance



Metric	Value
Threshold	0.65
Precision	0.42
Recall	0.62
Total Profit	\$19,684