Telemarketing Campaign Predictive Analysis for Portuguese Banking Institution

The problem

Company

Portuguese Banking Institution

Context

- Firms spend massive amounts of money on marketing campaigns hoping to maximize the return on investment (ROI).
- Understanding the customers along is crucial for achieving an effective marketing strategy.
- Data analysis insights leads to an intelligent targeted marketing.

Problem statement

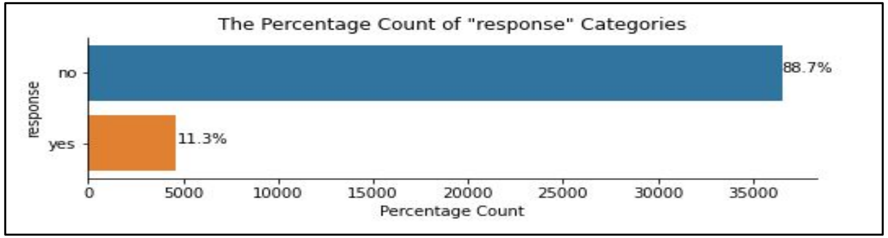
- Not satisfying ROI

Through a telemarketing campaign, there is a need for a model that predicts whether a given customer will subscribe to a term deposit service offered by the bank.

Exploratory Data Analysis (EDA)

- Contains 20 features and a binary target variable. Available in the UCI Machine Learning Repository. http://archive.ics.uci.edu/ml/datasets/Bank+Marketing#.

  - 11 categorical variables including the response variable.
  - 10 Numeric Features
  - Imbalanced dataset
  - 41188 Data points




```
Data columns (total 21 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   age             41188 non-null  int64
 1   job             41188 non-null  object
 2   marital         41188 non-null  object
 3   education       41188 non-null  object
 4   default         41188 non-null  object
 5   housing         41188 non-null  object
 6   loan            41188 non-null  object
 7   contact         41188 non-null  object
 8   month           41188 non-null  object
 9   day_of_week     41188 non-null  object
 10  duration        41188 non-null  int64
 11  campaign        41188 non-null  int64
 12  pdays           41188 non-null  int64
 13  previous        41188 non-null  int64
 14  poutcome        41188 non-null  object
 15  emp.var.rate    41188 non-null  float64
 16  cons.price.idx  41188 non-null  float64
 17  cons.conf.idx   41188 non-null  float64
 18  euribor3m       41188 non-null  float64
 19  nr.employed     41188 non-null  float64
 20  y               41188 non-null  object
dtypes: float64(5), int64(5), object(11)
```

1. Categorical Features

- Correlation with the response variable using Cramer's V
- Highest Correlation
  - poutcome: outcome of the previous marketing campaign
  - Month
  - Job

	Feature	Cramers_V
0	poutcome	0.320448
1	month	0.274123
2	job	0.151955
3	contact	0.144612
4	default	0.099123
5	education	0.067183
6	marital	0.053976
7	day_of_week	0.023143
8	housing	0.009533
9	loan	0.000000

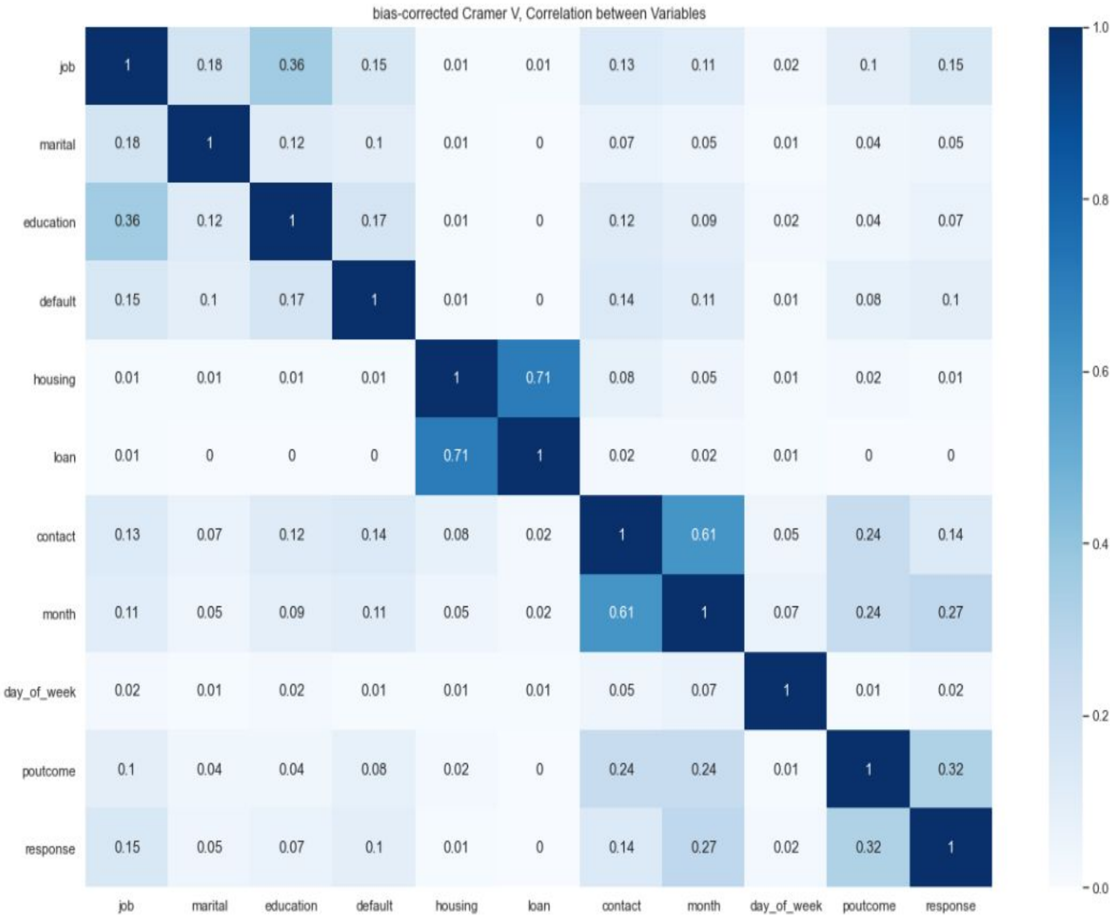
1. Categorical Features

❑ Correlation Analysis using Cramer’s V

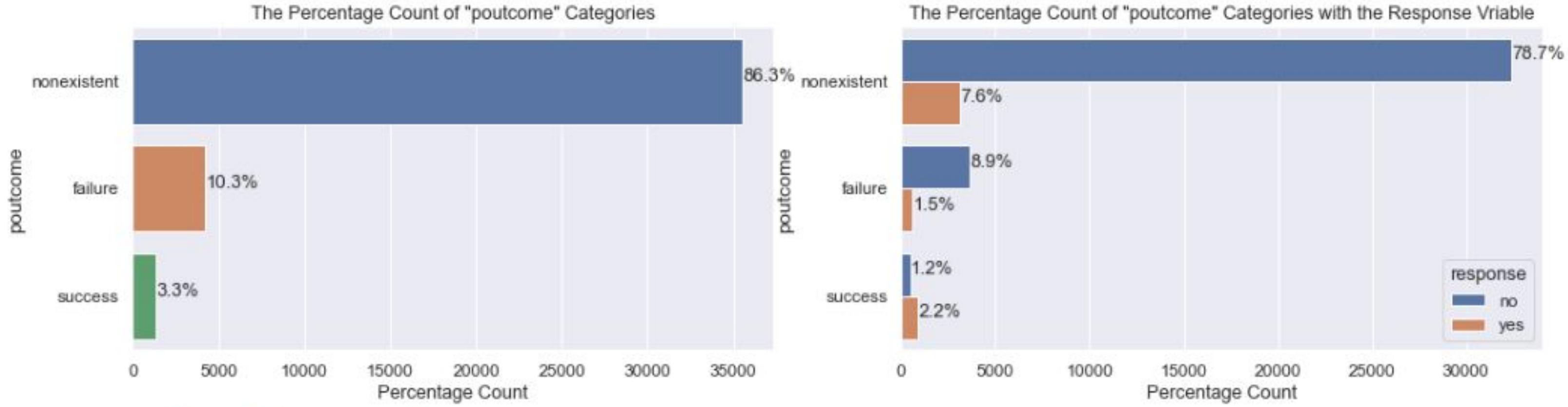
- The heatmap below shows a strong association between loan and house variables with Cramer’s V = 0.71, and a moderate association between education and job V = 0.36.

- Also, a strong association between month and contact with V = 0.61.

- poutcome, Month, and Job have weak correlation with the response variable.



❑ poutcome




```
Cramér's V =  0.32044835703020846
```

```
Notice: The "All" row and column from the calculated matrix is the sum of values in that row and column respectively.
It possible to be not located at the very end because of sorting by subscription rate.
```

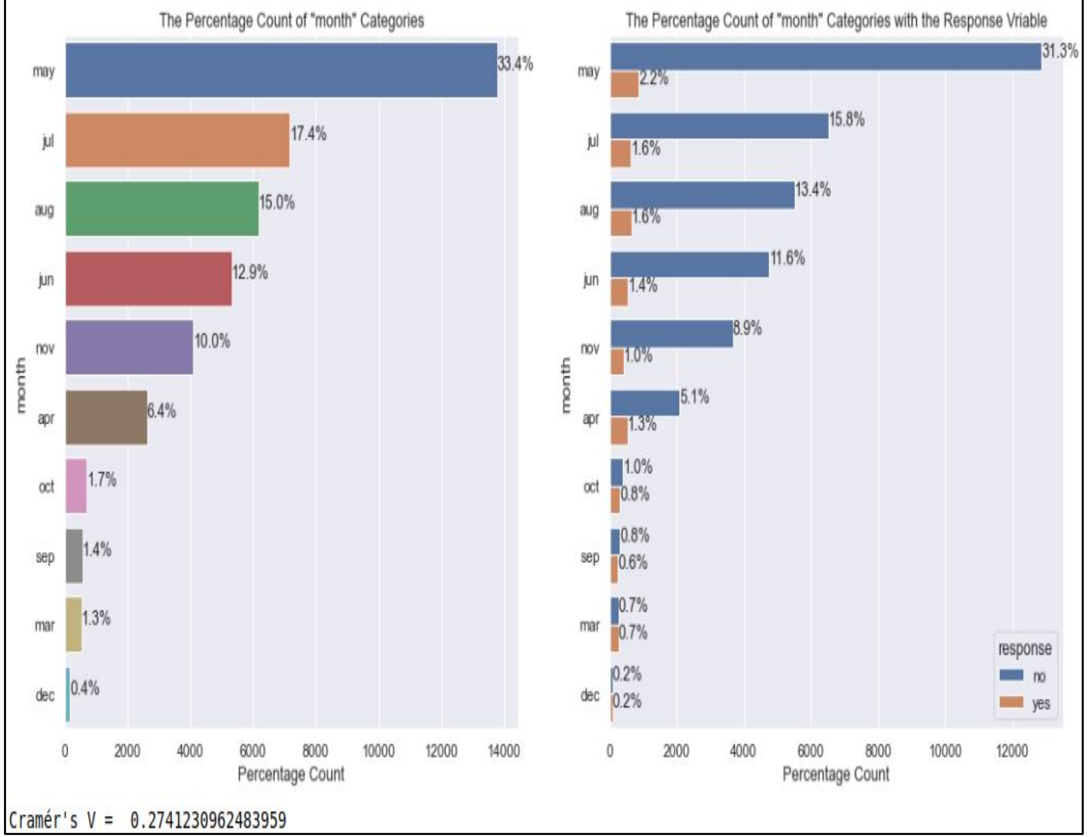
response	no	yes	All	within class subscription per poutcome %
poutcome				
success	479	894	1373	65.112891
failure	3647	605	4252	14.228598
All	36537	4639	41176	11.266272
nonexistent	32411	3140	35551	8.832382

65% of cantaccted previously subscribed subscribed again

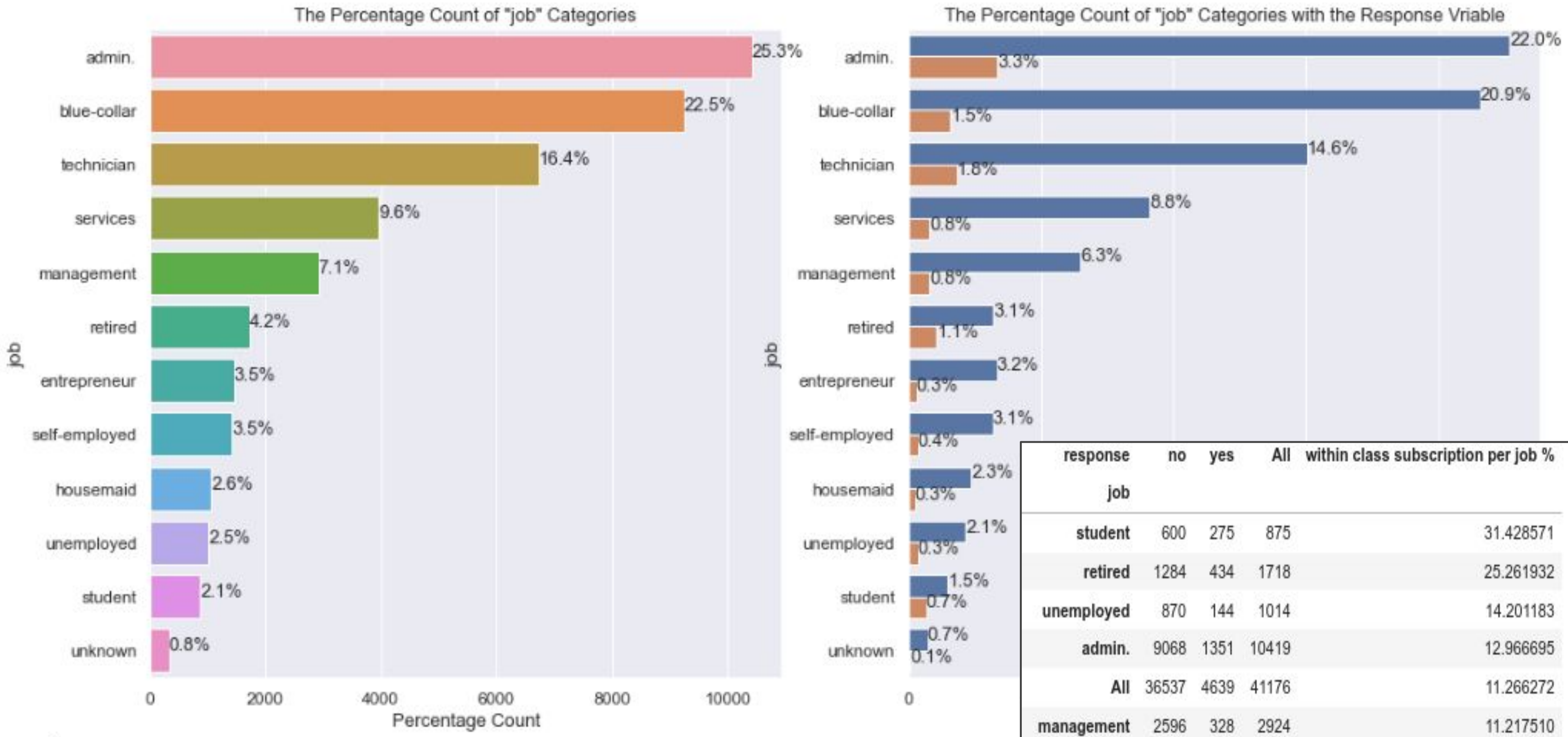
❑ Month

- May received most calls
- Mars has highest success rate

response	no	yes	All	within class subscription per month %
month				
mar	270	276	546	50.549451
dec	93	89	182	48.901099
sep	314	256	570	44.912281
oct	402	315	717	43.933054
apr	2092	539	2631	20.486507
All	36537	4639	41176	11.266272
aug	5521	655	6176	10.605570
jun	4759	559	5318	10.511470
nov	3684	416	4100	10.146341
jul	6521	648	7169	9.038918
may	12881	886	13767	6.435680



❑ Job



Cramér's V = 0.15195496226188143

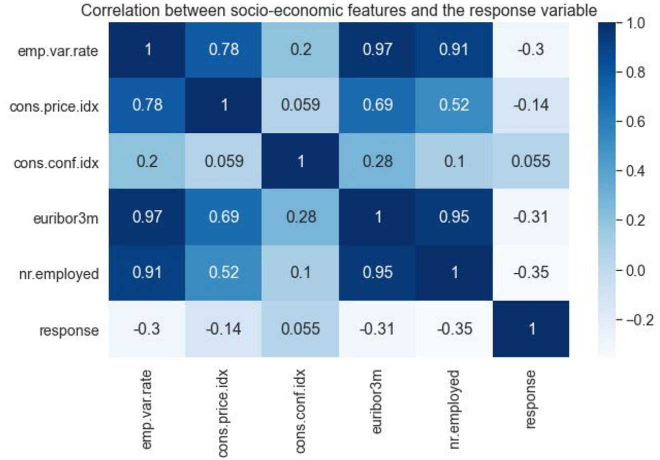
response job	no	yes	All	within class subscription per job %
student	600	275	875	31.428571
retired	1284	434	1718	25.261932
unemployed	870	144	1014	14.201183
admin.	9068	1351	10419	12.966695
All	36537	4639	41176	11.266272
management	2596	328	2924	11.217510
unknown	293	37	330	11.212121
technician	6009	730	6739	10.832468
self-employed	1272	149	1421	10.485574
housemaid	954	106	1060	10.000000
entrepreneur	1332	124	1456	8.516484
services	3644	323	3967	8.142173
blue-collar	8615	638	9253	6.895061

- admins received most calls
- Students and retired has highest success rate

1. Numerical Features

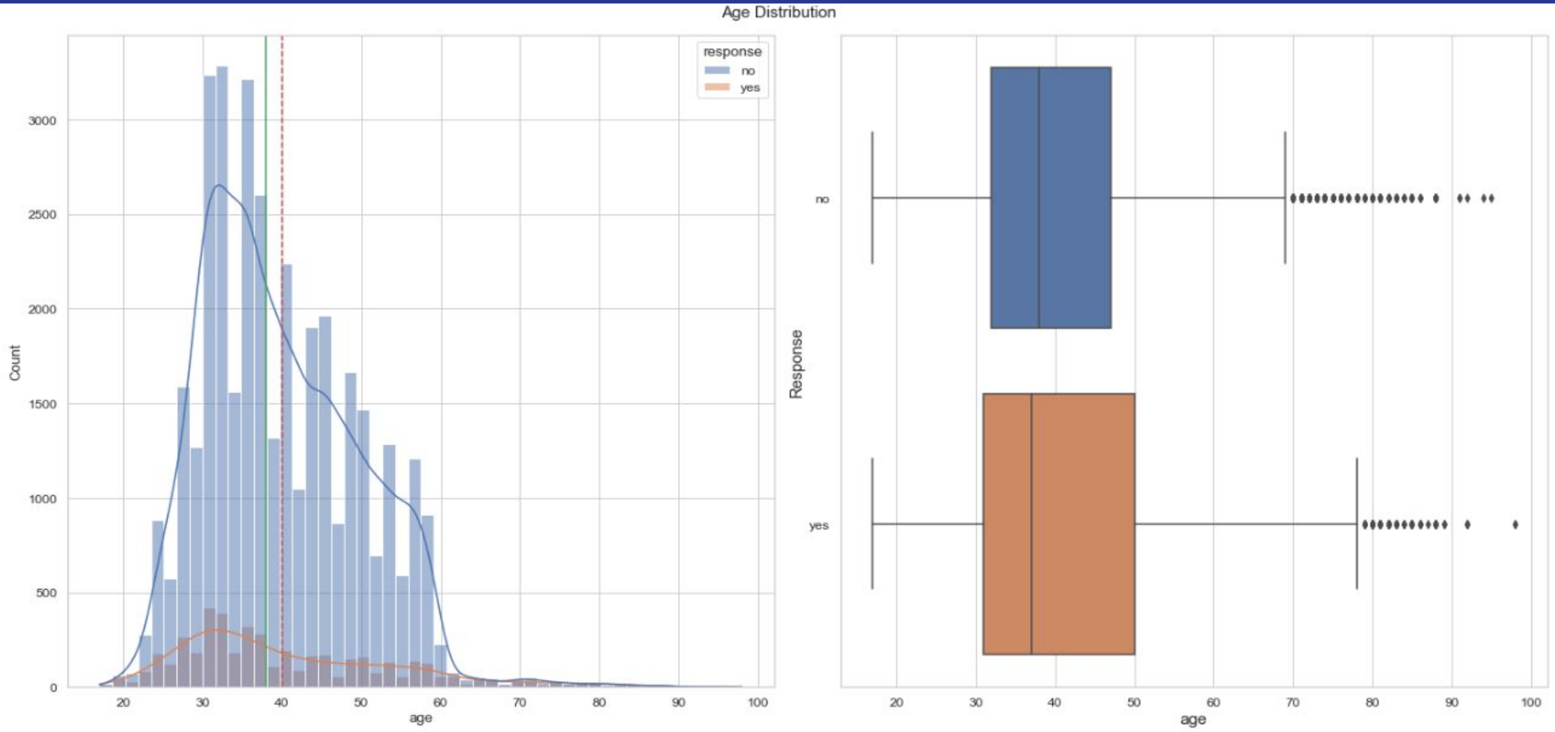
❑ Correlation Analysis using Pearson

Positive correlation between most of the social and economic context attributes.
None of these attributes correlate with the response variable



1. Numerical Features

❑ age




```
The age description for for both respnse classes =
              age
            count       mean        std   min   25%   50%   75%   max
response
no        36537.0  39.910994   9.897176  17.0  32.0  38.0  47.0  95.0
yes        4639.0  40.912266  13.838838  17.0  31.0  37.0  50.0  98.0
```

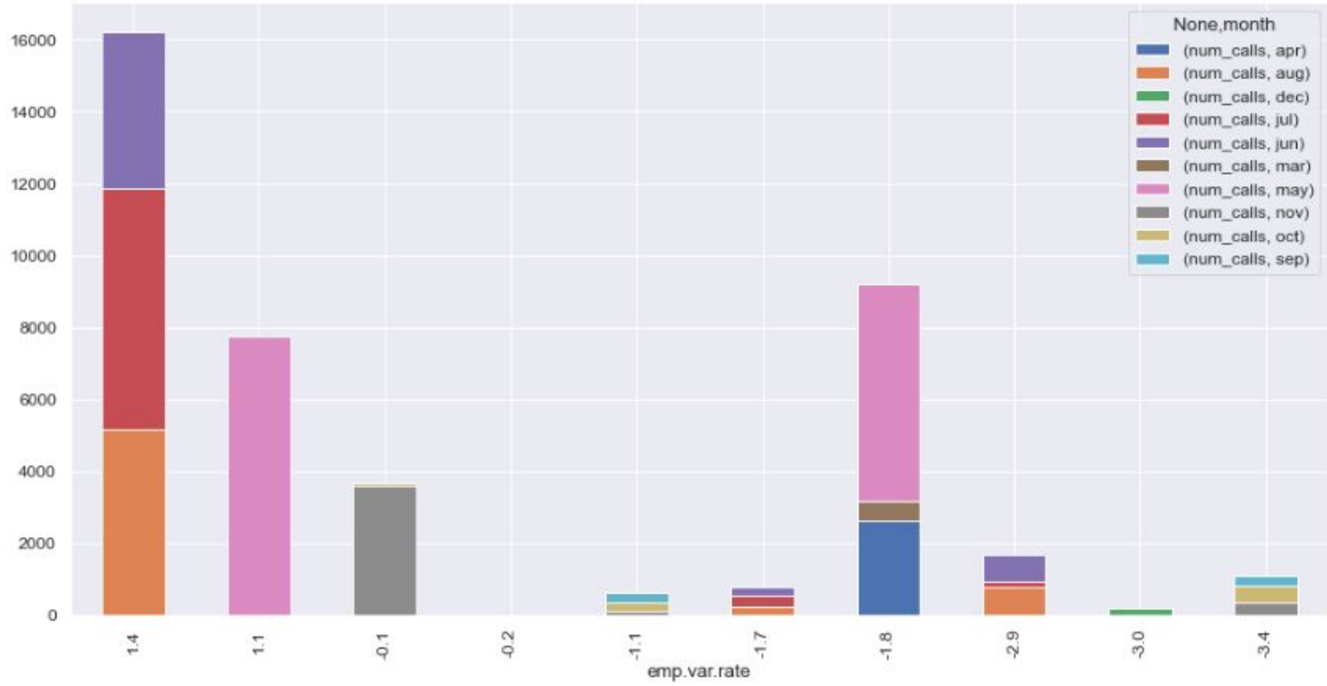
```
bank_data.groupby('response')[['age']].describe()
```

- Age overlaps across both classes
- Outliers in both classes

❑ emp.var.rate

- **emp.var.rate** feature refers to employment variation rate — quarterly indicator

- 10 distinct values
- Most calls in positive var rate
- Subscription rate highest when emp.var.rate = -1.7



emp.var.rate	-3.4	-3.0	-2.9	-1.8	-1.7	-1.1	-0.2	-0.1	1.1	1.4	All
response											
no	616.0	84.0	1069.0	7721.0	370.0	334.0	9.0	3450.0	7522.0	15362.0	36537.0
yes	454.0	88.0	593.0	1461.0	403.0	301.0	1.0	232.0	240.0	866.0	4639.0
All	1070.0	172.0	1662.0	9182.0	773.0	635.0	10.0	3682.0	7762.0	16228.0	41176.0
success_rate %	42.0	51.0	36.0	16.0	52.0	47.0	10.0	6.0	3.0	5.0	11.0

Correlation Analysis

Cramer’s V

- Pairwise Correlation between categorical variables
- Assumes symmetrical relation

Pearson Correlation (r)

- Pairwise Correlation between numerical variables
- Assumes symmetrical relation

Predictive power Score (PPS)

- Pairwise Correlation between numerical and Categorical variables
- Asymmetrical relation

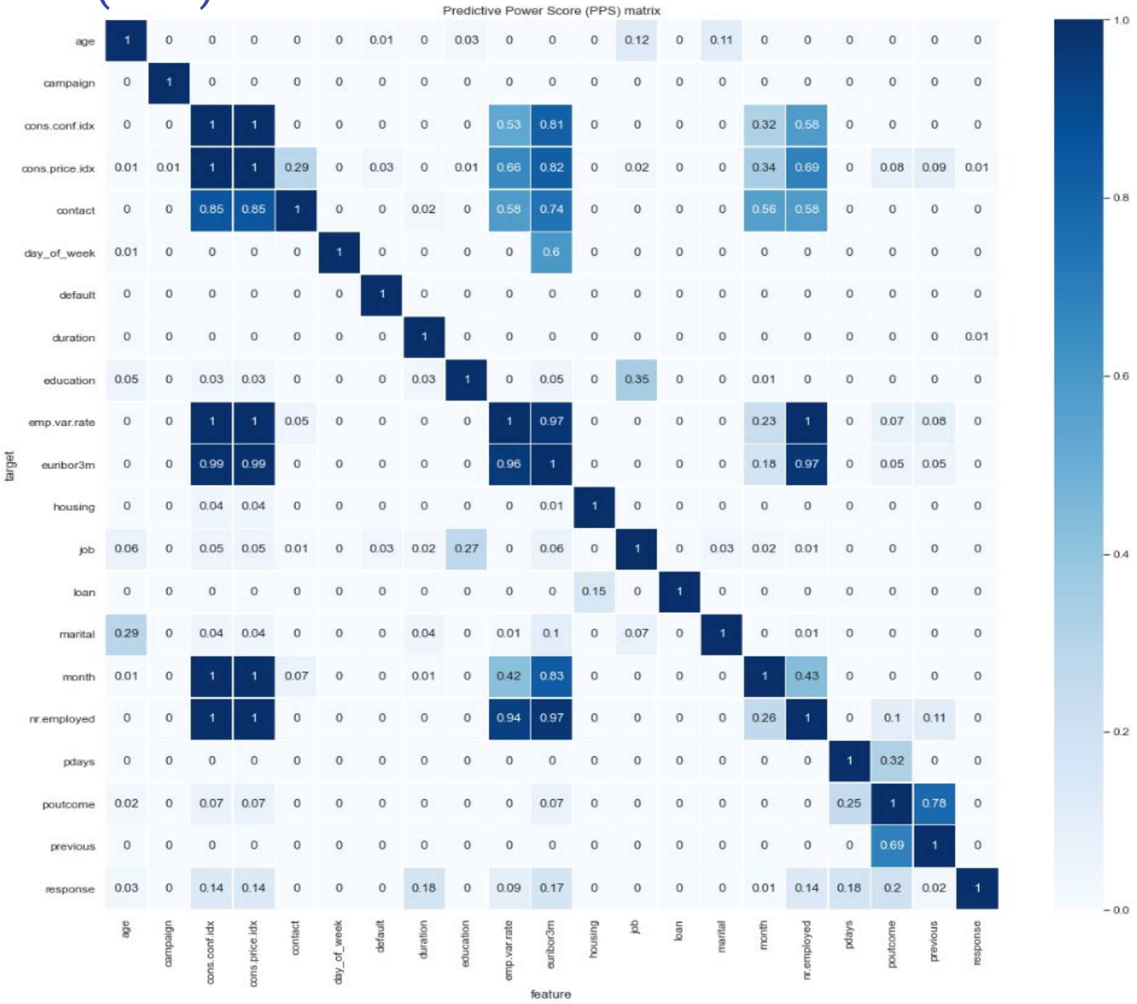
Predictive power Score (PPS)

PPS confirmed the correlation between most of the social and economic context attributes. Correlated features:

- 'euribor3m',
- ‘cons.price.idx',
- ‘cons.price.idx'
- 'emp.var.rate',
- 'nr.employed'

- Job is predictive of education

- From the table, only few features are weak predictor to the response



PPS of the response

	Feature	ppscore
1	poutcome	0.20
2	pdays	0.18
3	duration	0.18
4	euribor3m	0.17
5	nr.employed	0.14
6	cons.conf.idx	0.14
7	cons.price.idx	0.14
8	emp.var.rate	0.09
9	age	0.03
10	previous	0.02
11	month	0.01
12	marital	0.00
13	default	0.00
14	housing	0.00
15	campaign	0.00
16	job	0.00
17	day_of_week	0.00
18	contact	0.00
19	loan	0.00
20	education	0.00

Preprocessing

Preprocessing

- Label Encoder
- One Hot Encoder
- Train Test Split

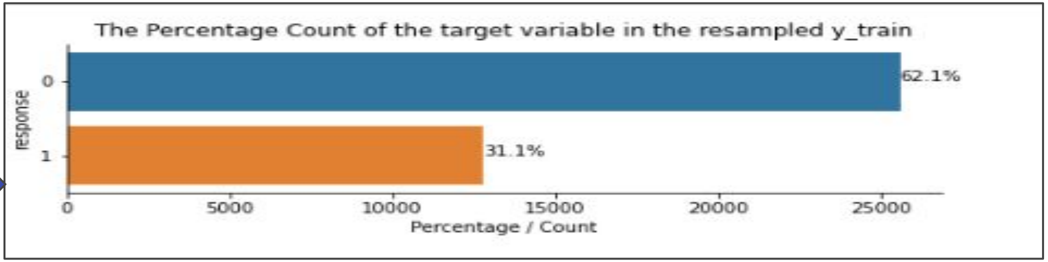
Results

```
The new features are 61:

 ['age', 'job_housemaid', 'job_services', 'job_admin.', 'job_blue-collar', 'job_technician', 'job_retired', 'job_management', 'job_unemployed', 'job_self-employed', 'job_other', 'job_entrepreneur', 'job_student', 'marital_married', 'marital_single', 'marital_divorced', 'marital_other', 'education_basic.4y', 'education_high.school', 'education_basic.6y', 'education_basic.9y', 'education_professional.course', 'education_other', 'education_university.degree', 'education_illiterate', 'default_no', 'default_yes', 'housing_no', 'housing_yes', 'loan_no', 'loan_yes', 'contact_telephone', 'contact_cellular', 'month_may', 'month_jun', 'month_jul', 'month_aug', 'month_oct', 'month_nov', 'month_dec', 'month_mar', 'month_apr', 'month_sep', 'day_of_week_mon', 'day_of_week_tue', 'day_of_week_wed', 'day_of_week_thu', 'day_of_week_fri', 'duration', 'campaign', 'pdays', 'previous', 'poutcome_nonexistent', 'poutcome_failure', 'poutcome_success', 'emp_var_rate', 'cons_price_idx', 'cons_conf_idx', 'euribor3m', 'nr_employed', 'response']
```

60 variables including the target after dropping duration.

- Oversampling using SMOTE, Synthetic Minority Oversampling Technique,



Modeling results and analysis

Modeling Method

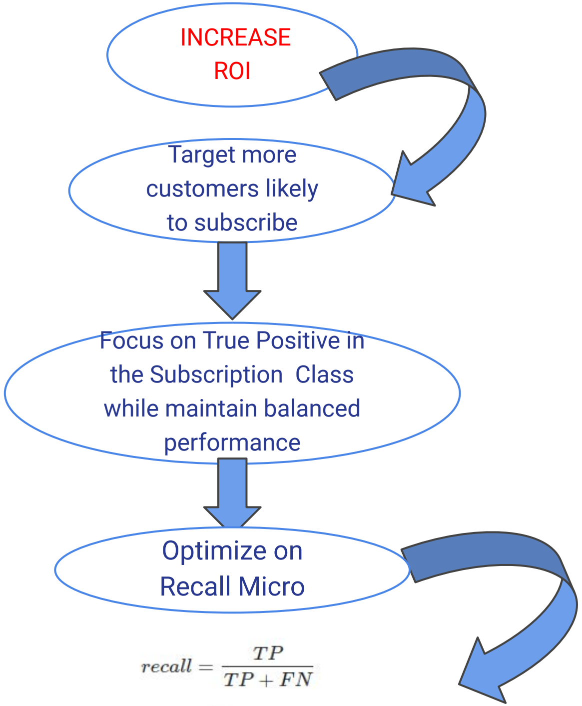
Models

- Tested classification algorithms:
  - Logistic Regression
  - Decision Tree
  - Random Forest
  - Light Gradient Boosting
  - XGboost

Hyperparameter Tuning

- Bayesian hyperparameter optimization, using Tree-structured Parzen Estimator Approach (TPE).
- Various objective functions applied.
- Recall_micro gave more balanced.

Business Objective Reflected



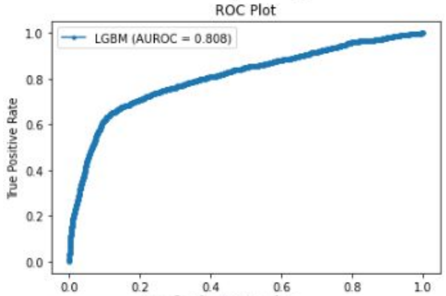
$$recall = \frac{TP}{TP + FN}$$

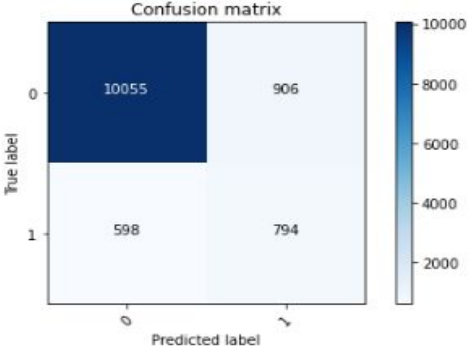
$$recall_{micro} = \frac{\sum_{classes} TP\ of\ class}{\sum_{classes} TP\ of\ class + FN\ of\ class}$$

Models Comparison

Winning Model

- Light Gradient Boosting Model
  - ROC AUC = 0.81
  - Recall Weighted avg = 0.88



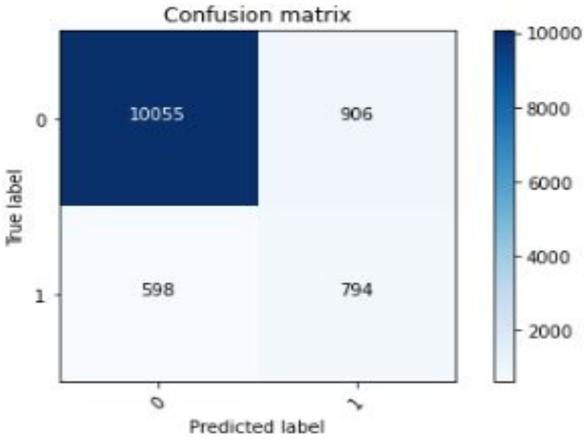


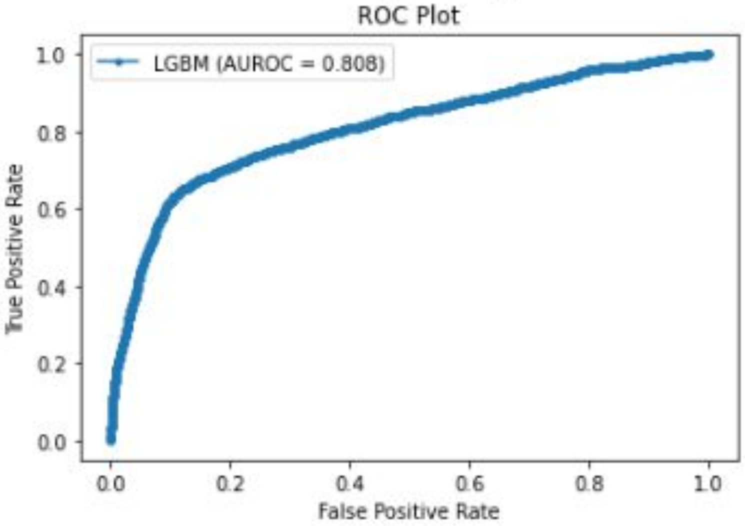
		precision	recall	f1-score	support
model / objective function					
Logistic Regression/ F1	Not Subscribed 0	0.95	0.85	0.9	10961
	Subscribed 1	0.35	0.64	0.46	1392
	accuracy				0.83
	macro avg	0.65	0.75	0.68	12353
	weighted avg	0.88	0.83	0.85	12353
	ROC AUC	0.8	0.8	0.8	0.8
lgbm / recall_micro	Not Subscribed 0	0.94	0.92	0.93	10961
	Subscribed 1	0.47	0.57	0.51	1392
	accuracy				0.88
	macro avg	0.71	0.74	0.72	12353
	weighted avg	0.89	0.88	0.88	12353
	ROC AUC	0.81	0.81	0.81	0.81
xgb / recall_micro	Not Subscribed 0	0.93	0.95	0.94	10961
	Subscribed 1	0.5	0.4	0.45	1392
	accuracy				0.89
	macro avg	0.72	0.68	0.69	12353
	weighted avg	0.88	0.89	0.88	12353
	ROC AUC	0.79	0.79	0.79	0.79
Decision Tree / recall_micro	Not Subscribed 0	0.93	0.93	0.93	10961
	Subscribed 1	0.46	0.48	0.47	1392
	accuracy				0.88
	macro avg	0.7	0.7	0.7	12353
	weighted avg	0.88	0.88	0.88	12353
	ROC AUC	0.78	0.78	0.78	0.78
Random Forest / Recall_Mic...	Not Subscribed 0	0.93	0.95	0.94	10961
	Subscribed 1	0.5	0.4	0.45	1392
	accuracy				0.89
	macro avg	0.72	0.68	0.69	12353
	weighted avg	0.88	0.89	0.88	12353
	ROC AUC	0.8	0.8	0.8	0.8

Winning Model Details

```
LGBMClassifier(class_weight='balanced', colsample_bytree='0.401',
               learning_rate=0.01, n_estimators=20, num_leaves=128,
               objective='binary')
```

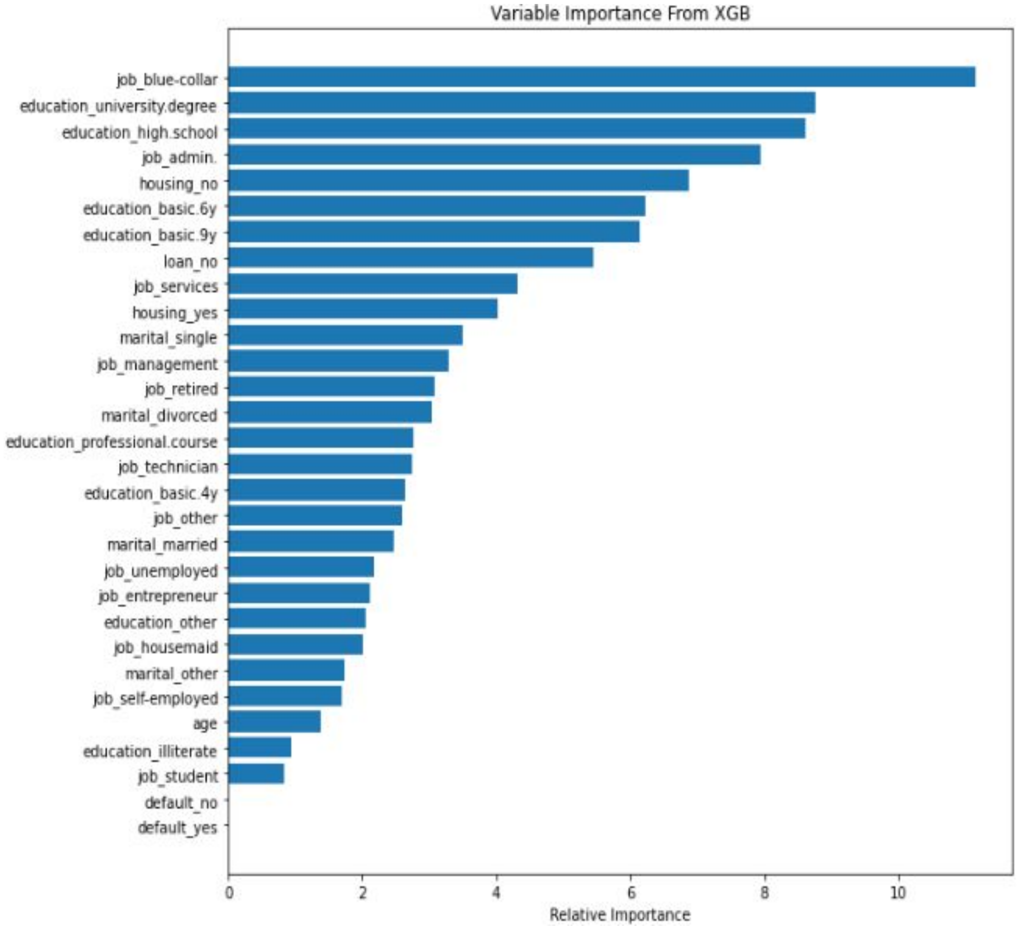
	precision	recall	f1-score	support
0	0.94	0.92	0.93	10961
1	0.47	0.57	0.51	1392
accuracy			0.88	12353
macro avg	0.71	0.74	0.72	12353
weighted avg	0.89	0.88	0.88	12353





Look as Interesting Business Features

Model Feature Importance



Permutation Importance

Weight	Feature
0.0027 ± 0.0007	contact_telephone
0.0023 ± 0.0009	contact_cellular
0.0021 ± 0.0005	month_apr
0.0011 ± 0.0005	poutcome_failure
0.0009 ± 0.0005	cons_price_idx
0.0006 ± 0.0003	poutcome_nonexistent
0.0004 ± 0.0004	pdays
0.0004 ± 0.0002	month_oct
0.0004 ± 0.0005	poutcome_success
0.0003 ± 0.0007	campaign
0.0003 ± 0.0001	month_mar
0.0003 ± 0.0005	day_of_week_mon
0.0002 ± 0.0007	day_of_week_fri
0.0002 ± 0.0004	job_technician
0.0001 ± 0.0001	marital_divorced
0.0001 ± 0.0001	job_management
0.0000 ± 0.0001	previous
0.0000 ± 0.0001	job_housemaid
0.0000 ± 0.0001	education_basic.6y
0.0000 ± 0.0002	education_other
… 39 more …	

Summary and conclusion

Business Perspective

- Without the model, the bank has 11.3% chance of randomly targeting those who are likely subscribe
- With Recall 0.57 on the subscribers class, Bank has 57% chance of targeting subscribers. ROI can be increased by 45.7% using the model
- The bank needs to invest more on collecting customers predictive features for more profitable predictive modeling

Technical Perspective

- The Light Gradient Boosting algorithm optimized for Recall Micro gave the best performance. ROC AUC = 0.81 and F1= 0.51 one minority class, (waited avg F1= 0.88).
- Optimizing the hyperparameters on the Recall Micro gave a better performance of most of the models applied on this imbalanced dataset.
- The SMOTE oversampling seemed to be helpful with this imbalanced dataset. Scores on the 30% split test set indicates that the model can be generalizable.