Predictive Analytics for Retail Banking

RETAIL BANKING ??!

- Typical mass-market banking in which individual customers use local branches of larger commercial banks. Services offered include savings and checking accounts, mortgages, personal loans, debit/credit cards. The focus is on the customer.
- The main challenges this sector are :
  - What is the suitable product to recommend to a customer ?
  - What is the best time to market the product ?
  - Which is the most effective channel to contact a customer ?

PROBLEM STATEMENT

- In this problem, the data is related with direct marketing campaigns of a banking institution. The marketing campaigns were based on phone calls. Often, more than one contact to the same client was required, in order to access if the product (bank term deposit) would be ('yes') or not ('no’) subscribed. The goal is to **predict if the client will subscribe a term deposit.**

ABOUT DATASET

- This is the classic marketing bank dataset uploaded originally in the UCI Machine Learning Repository. The dataset gives you information about a marketing campaign of a financial institution in which you will have to analyse in order to find ways to look for future strategies in order to improve future marketing campaigns for the bank.

age	job	marital	education	default	balance	housing	loan	contact	day	month	duration	campaign	pdays	previous	poutcome	deposit
59	admin.	married	secondary	no	2343	yes	no	unknown	5	may	1042	1	-1	0	unknown	yes
56	admin.	married	secondary	no	45	no	no	unknown	5	may	1467	1	-1	0	unknown	yes
41	technician	married	secondary	no	1270	yes	no	unknown	5	may	1389	1	-1	0	unknown	yes
55	services	married	secondary	no	2476	yes	no	unknown	5	may	579	1	-1	0	unknown	yes
54	admin.	married	tertiary	no	184	no	no	unknown	5	may	673	2	-1	0	unknown	yes
42	manageme	single	tertiary	no	0	yes	yes	unknown	5	may	562	2	-1	0	unknown	yes
56	manageme	married	tertiary	no	830	yes	yes	unknown	6	may	1201	1	-1	0	unknown	yes
60	retired	divorced	secondary	no	545	yes	no	unknown	6	may	1030	1	-1	0	unknown	yes
37	technician	married	secondary	no	1	yes	no	unknown	6	may	608	1	-1	0	unknown	yes
28	services	single	secondary	no	5090	yes	no	unknown	6	may	1297	3	-1	0	unknown	yes
38	admin.	single	secondary	no	100	yes	no	unknown	7	may	786	1	-1	0	unknown	yes
30	blue-collar	married	secondary	no	309	yes	no	unknown	7	may	1574	2	-1	0	unknown	yes
29	manageme	married	tertiary	no	199	yes	yes	unknown	7	may	1689	4	-1	0	unknown	yes
46	blue-collar	single	tertiary	no	460	yes	no	unknown	7	may	1102	2	-1	0	unknown	yes
31	technician	single	tertiary	no	703	yes	no	unknown	8	may	943	2	-1	0	unknown	yes
35	manageme	divorced	tertiary	no	3837	yes	no	unknown	8	may	1084	1	-1	0	unknown	yes
32	blue-collar	single	primary	no	611	yes	no	unknown	8	may	541	3	-1	0	unknown	yes
49	services	married	secondary	no	-8	yes	no	unknown	8	may	1119	1	-1	0	unknown	yes
41	admin.	married	secondary	no	55	yes	no	unknown	8	may	1120	2	-1	0	unknown	yes
49	admin.	divorced	secondary	no	168	yes	yes	unknown	8	may	513	1	-1	0	unknown	yes
28	admin.	divorced	secondary	no	785	yes	no	unknown	8	may	442	2	-1	0	unknown	yes
43	manageme	single	tertiary	no	2067	yes	no	unknown	8	may	756	1	-1	0	unknown	yes
43	manageme	divorced	tertiary	no	388	yes	no	unknown	8	may	2087	2	-1	0	unknown	yes

Here are what the columns in the data set represent:

- **Age :** Age of the client- (numeric)
- **Job :** Client’s occupation - (categorical) (admin, blue-collar, entrepreneur, housemaid, management, retired, self employed, services, student, technician, unemployed, unknown)
- **Marital :** Client’s marital status - (categorical) (divorced, married, single, unknown, note: divorced means divorced or widowed)
- **Education :** Client’s education level - (categorical)
- **Default :** Indicates if the client has credit in default - (categorical) (no, yes)
- **Balance :**average yearly balance, in euros (numeric).
- **Housing :** Does the client as a housing loan? - (categorical) (no, yes)
- **Loan :** Does the client as a personal loan? - (categorical) (no, yes)
- **Contact :** Type of communication contact - (categorical) (unknown, cellular, telephone)
- **Day :** Day of last contact with client.
- **Month :** Month of last contact with client - (categorical) (Jan - Dec)

- **Duration :** Duration of last contact with client, in seconds - (numeric)
  For benchmark purposes only, and not reliable for predictive modelling.

- **Campaign :** number of contacts performed during this campaign and for this client
  (numeric, includes last contact) - (numeric)
  (includes last contact)

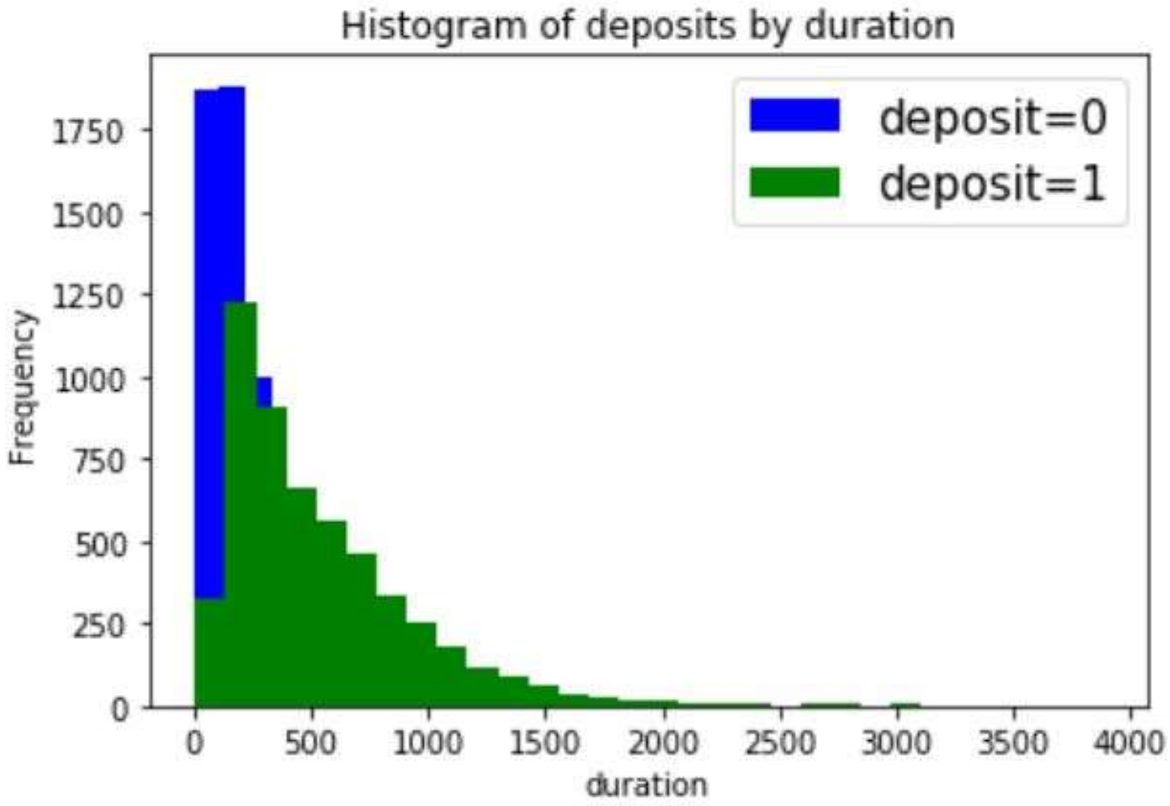
- **Pdays :** Number of days passed client was last contacted - (numeric)
  (-1 means client was not previously contacted)

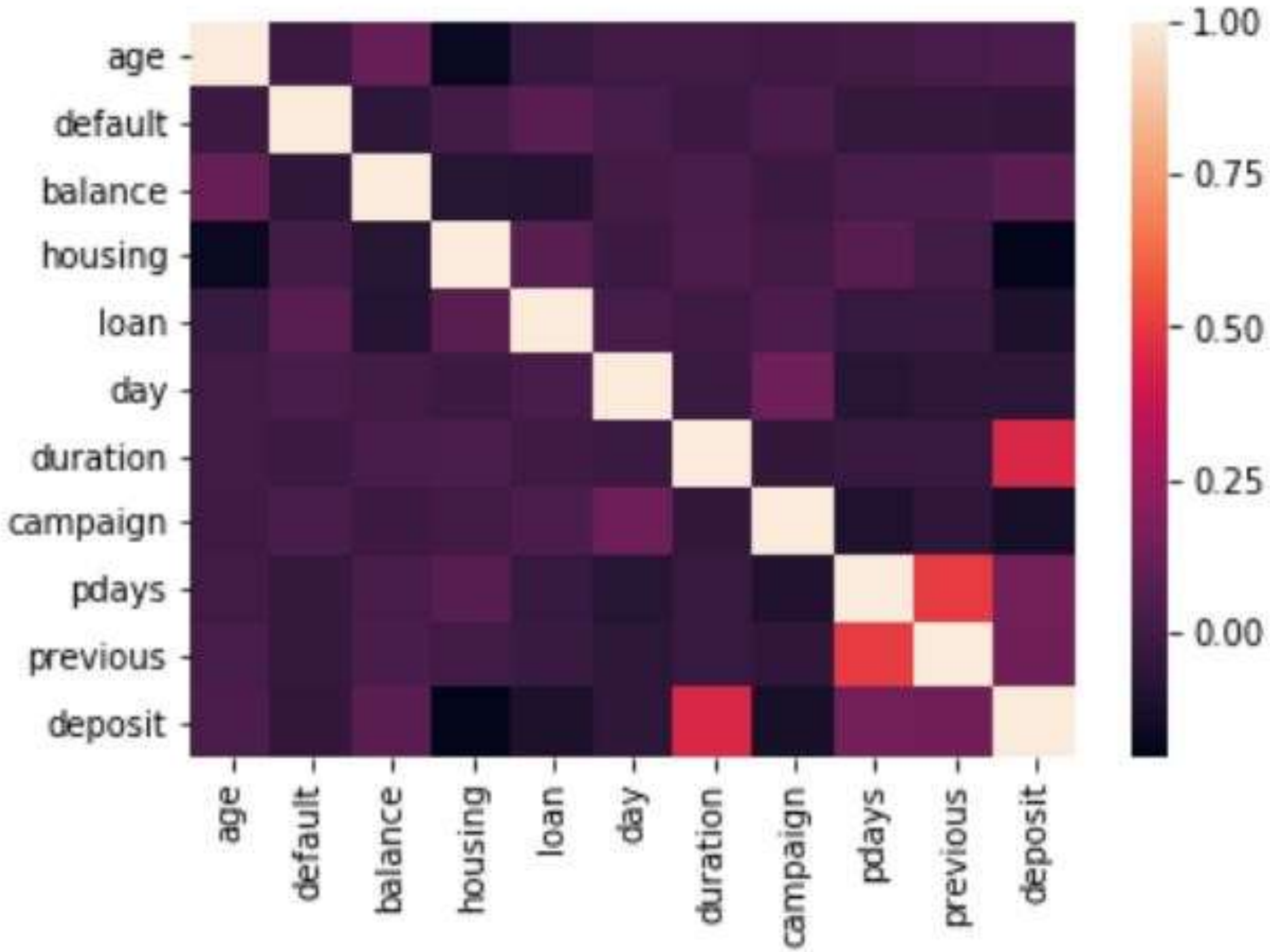
- **Previous :** Number of client contacts performed before this campaign - (numeric)

- **Poutcome :** Previous marketing campaign outcome - (categorical)

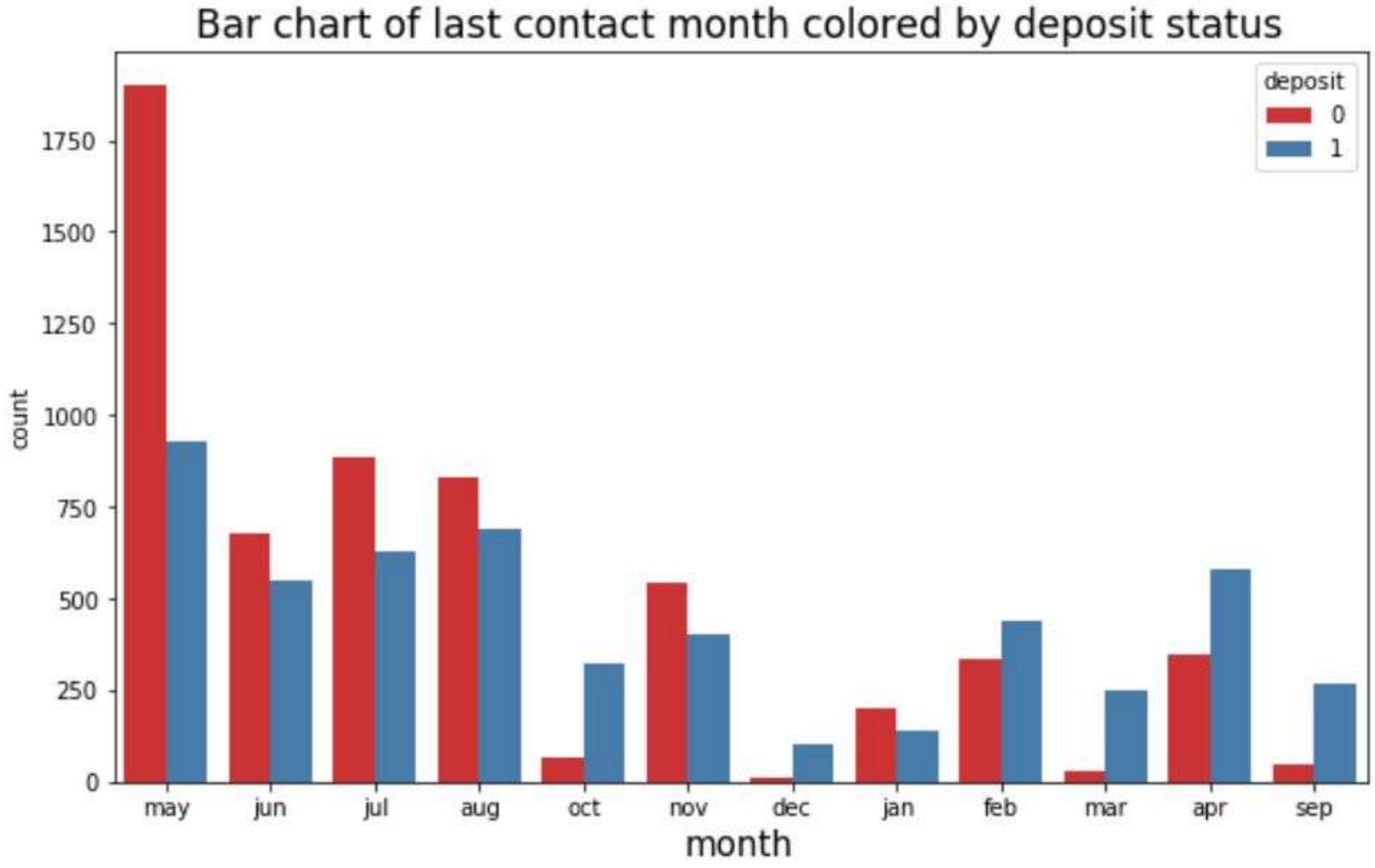
- **Deposit :** subscription verified. (output)

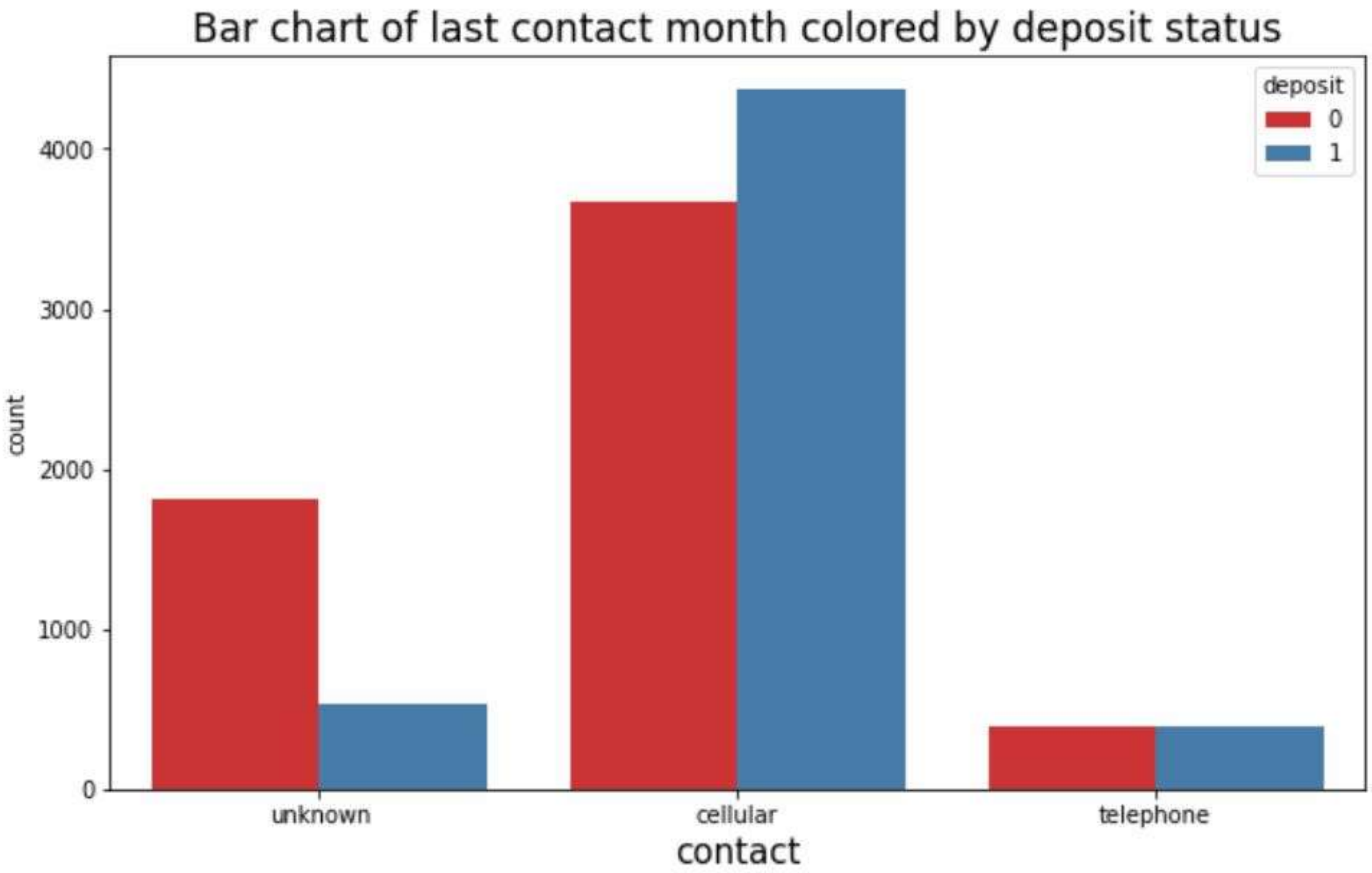
EXPLORATORY DATA ANALYSIS(EDA)

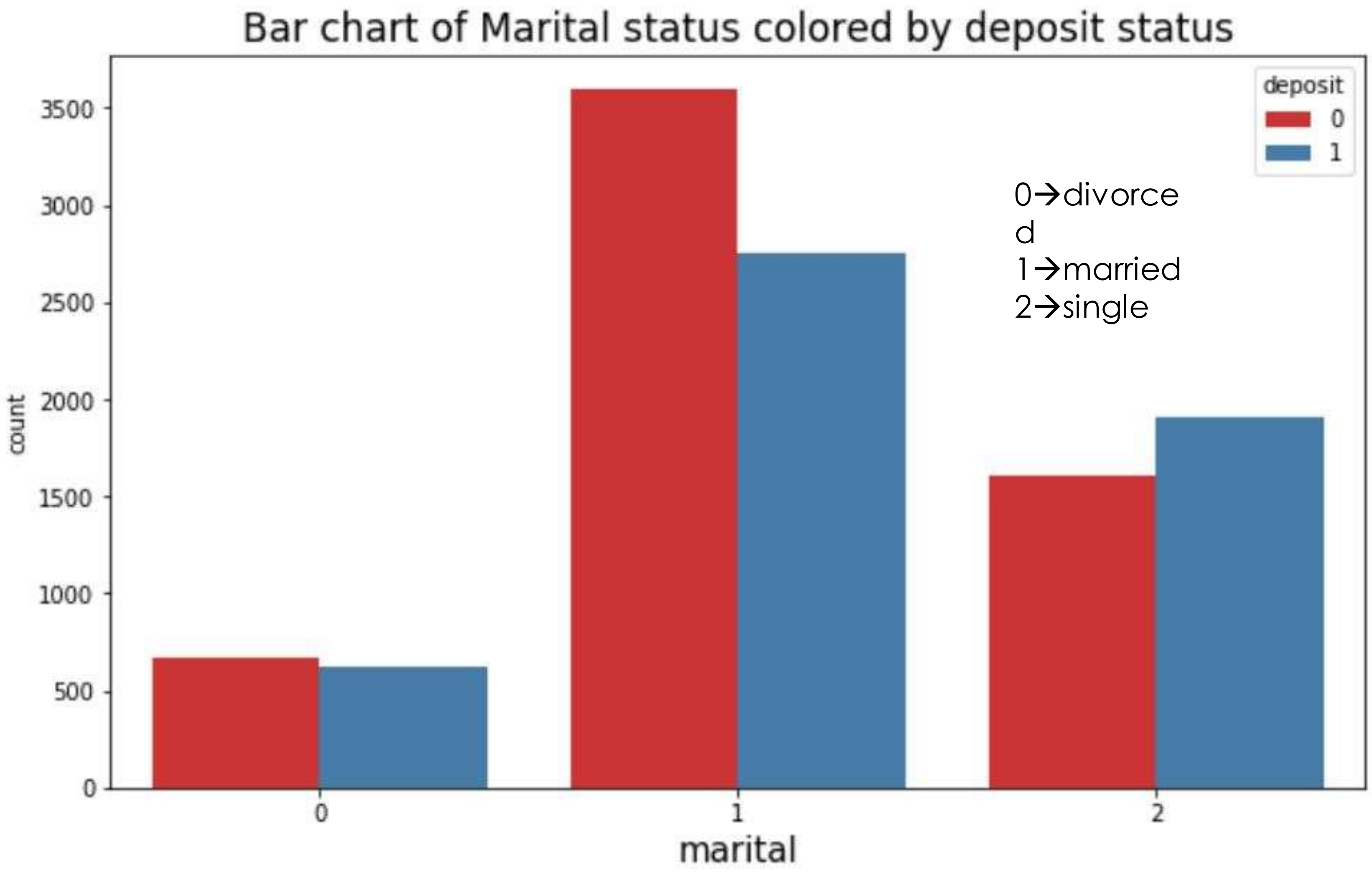




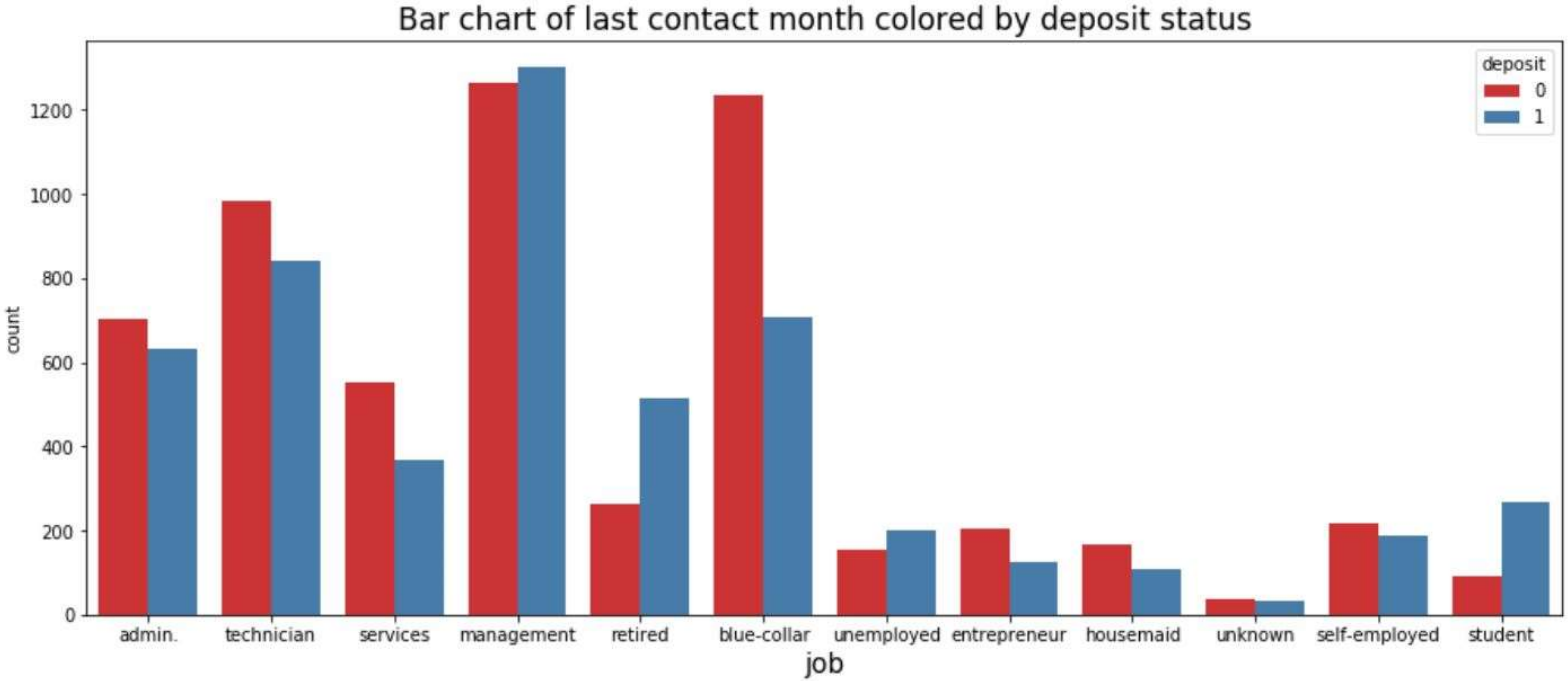
CORRELATION USING HEATMAP

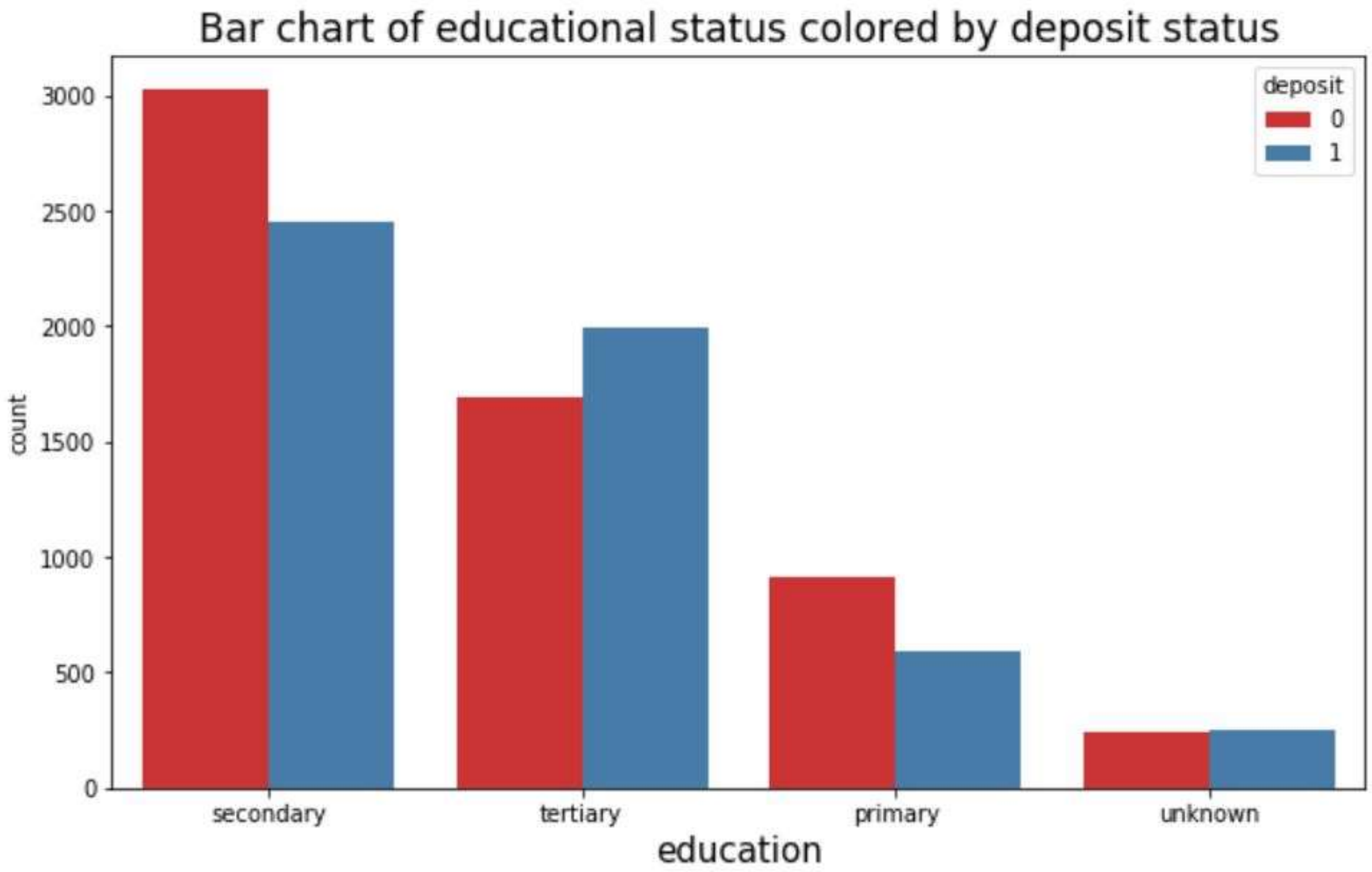

Bar chart of last contact month colored by deposit status
deposit
0
1
count
0
250
500
750
1000
1250
1500
1750
may
jun
jul
aug
oct
nov
dec
jan
feb
mar
apr
sep
month

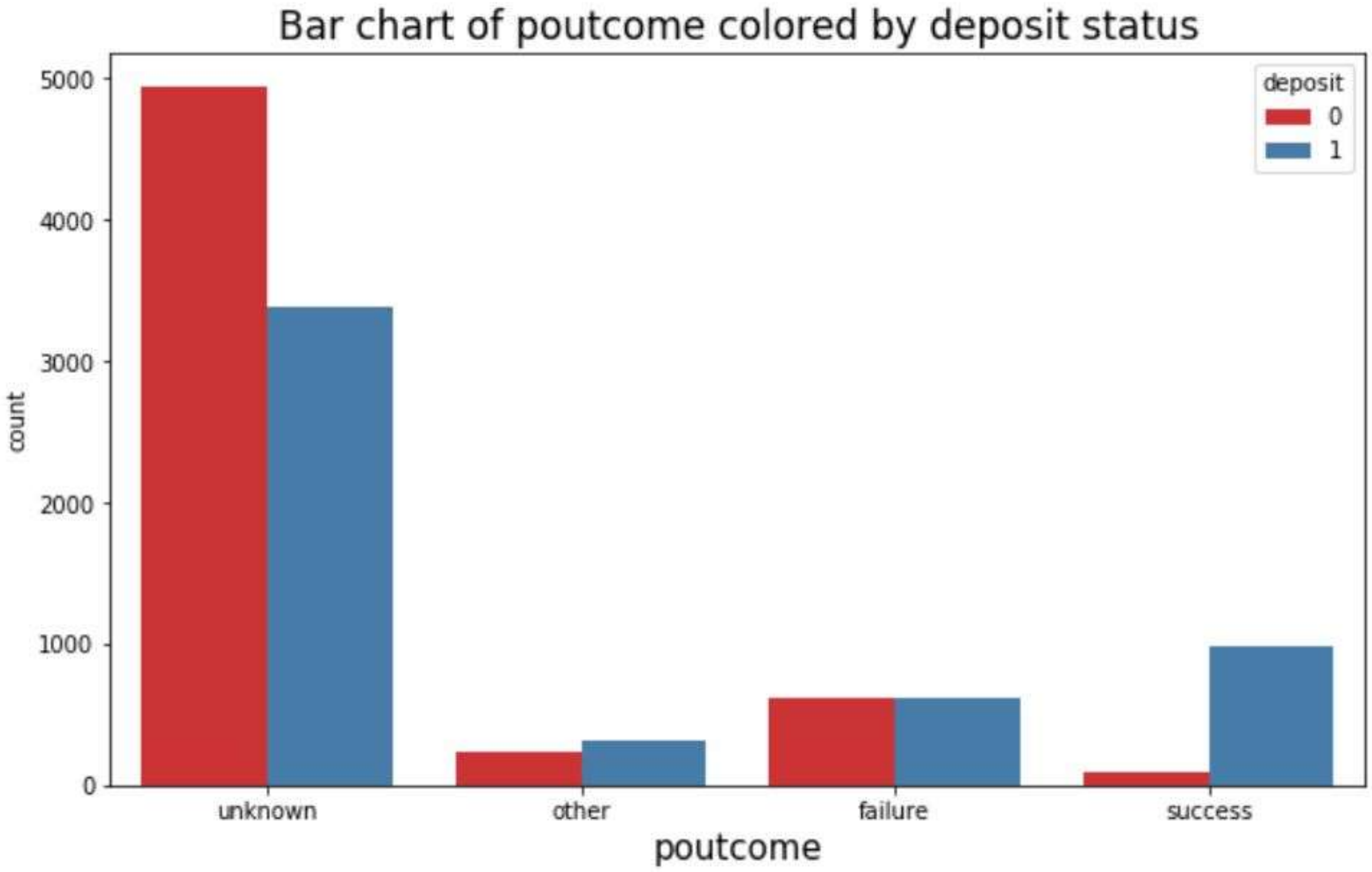

Bar chart of last contact month colored by deposit status
deposit
0
1
4000
3000
2000
1000
0
count
unknown
cellular
telephone
contact



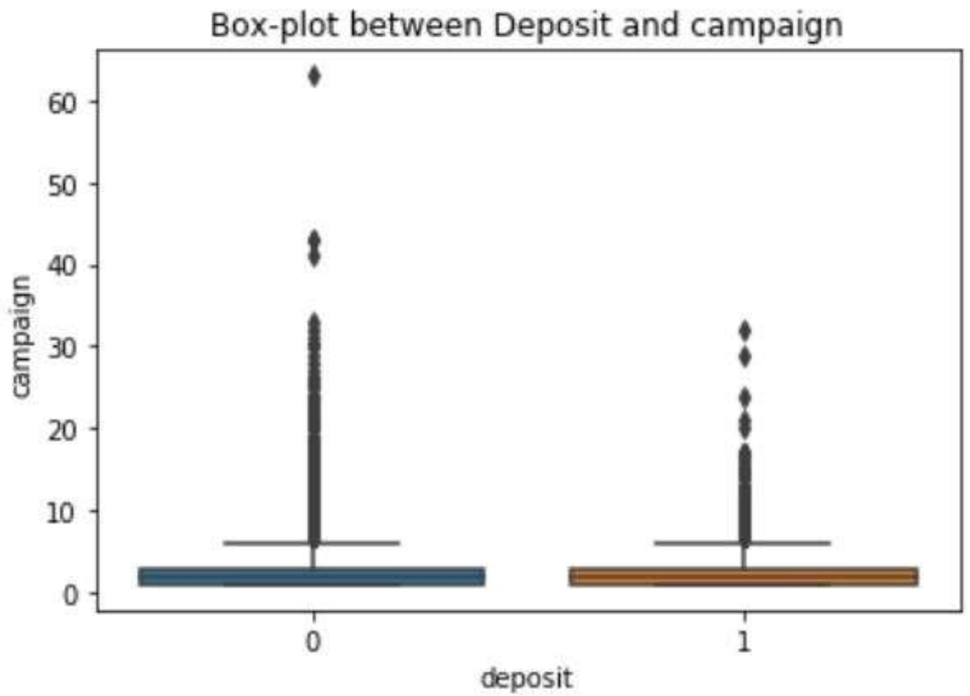
0→divorced
1→married
2→single

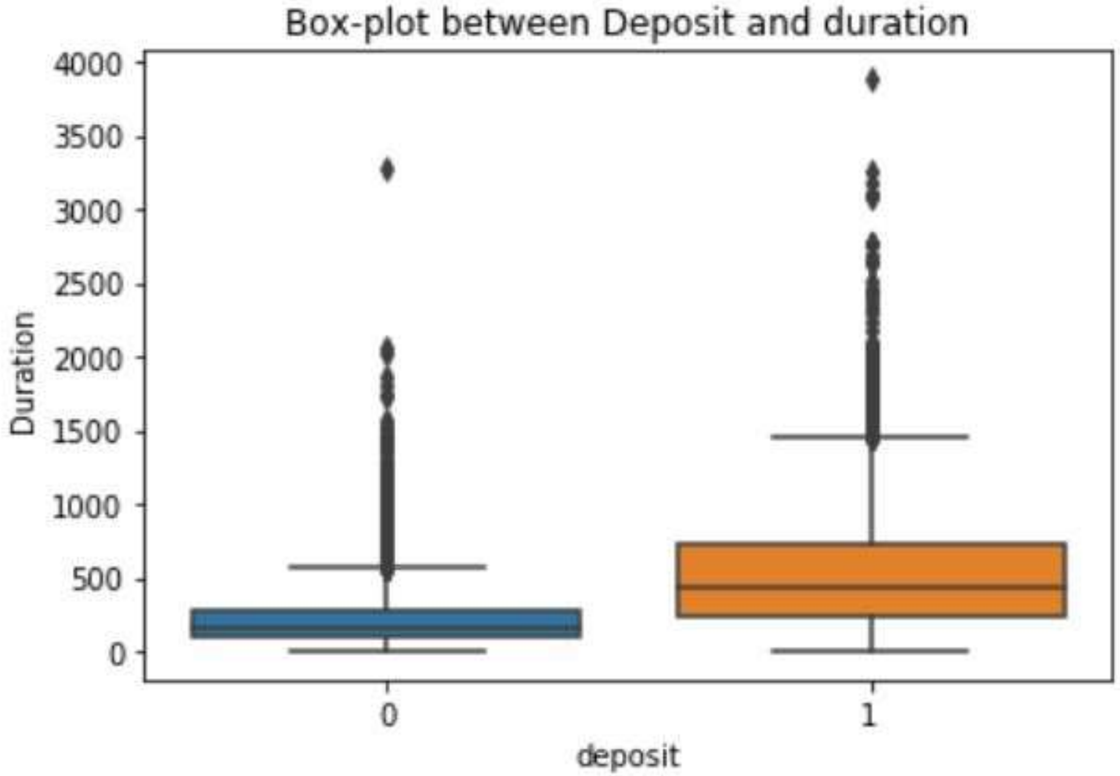

Bar chart of last contact month colored by deposit status
deposit
0
1
count
0
200
400
600
800
1000
1200
admin.
technician
services
management
retired
blue-collar
unemployed
entrepreneur
housemaid
unknown
self-employed
student
job


Bar chart of educational status colored by deposit status
deposit
0
1
3000
2500
2000
1500
1000
500
0
count
secondary
tertiary
primary
unknown
education



Bar chart of poutcome colored by deposit status
deposit
0
1
5000
4000
3000
2000
1000
0
count
unknown
other
failure
success
poutcome


Box-plot between Deposit and campaign
campaign
deposit
0
1
0
10
20
30
40
50
60


Box-plot between Deposit and duration
Duration
deposit
0
1
0
500
1000
1500
2000
2500
3000
3500
4000

Model Selection

Why Min Max Scaler?

- Since the output variable is in 0’s and 1’s form, We need to scale down our feature variables to the range of 0 and 1

TEST SIZE

80-20

*Recommended for banking sector

Accuracies compared …

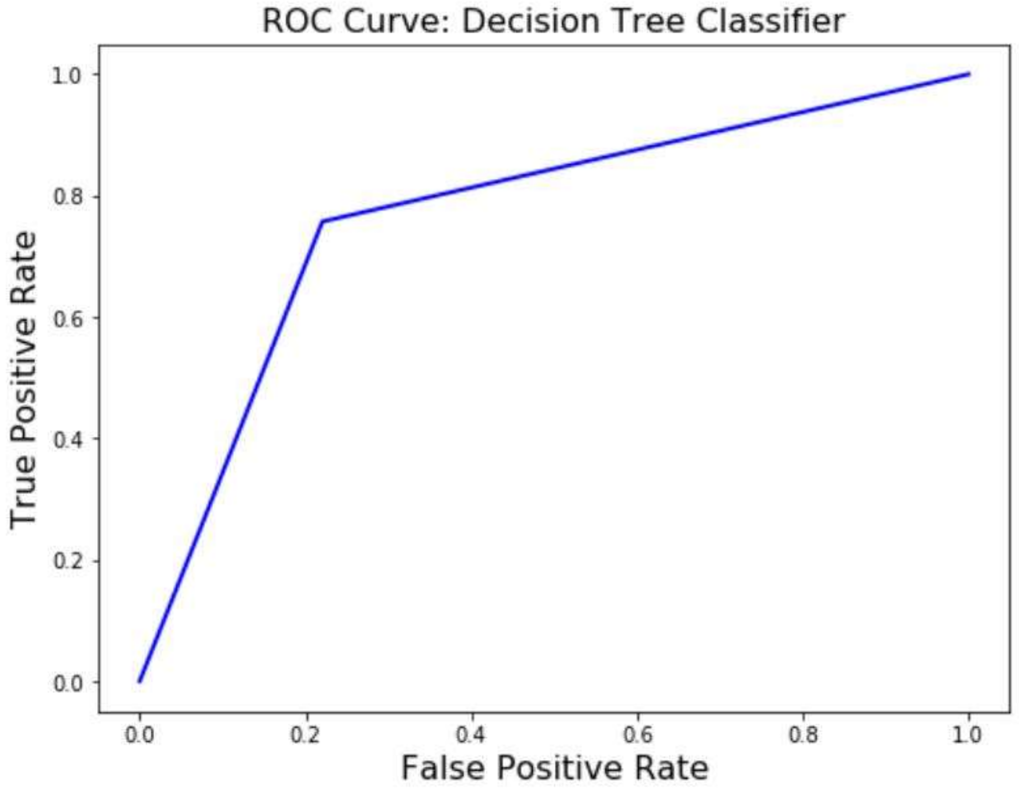
- K-nearest Neighbour: 75.3%
- Logistic Regression: 80.9%
- Decision Tree: 78.2%
- Random Forest Classifier: 78%
- Support vector Machine: 53%

Confusion Matrices..

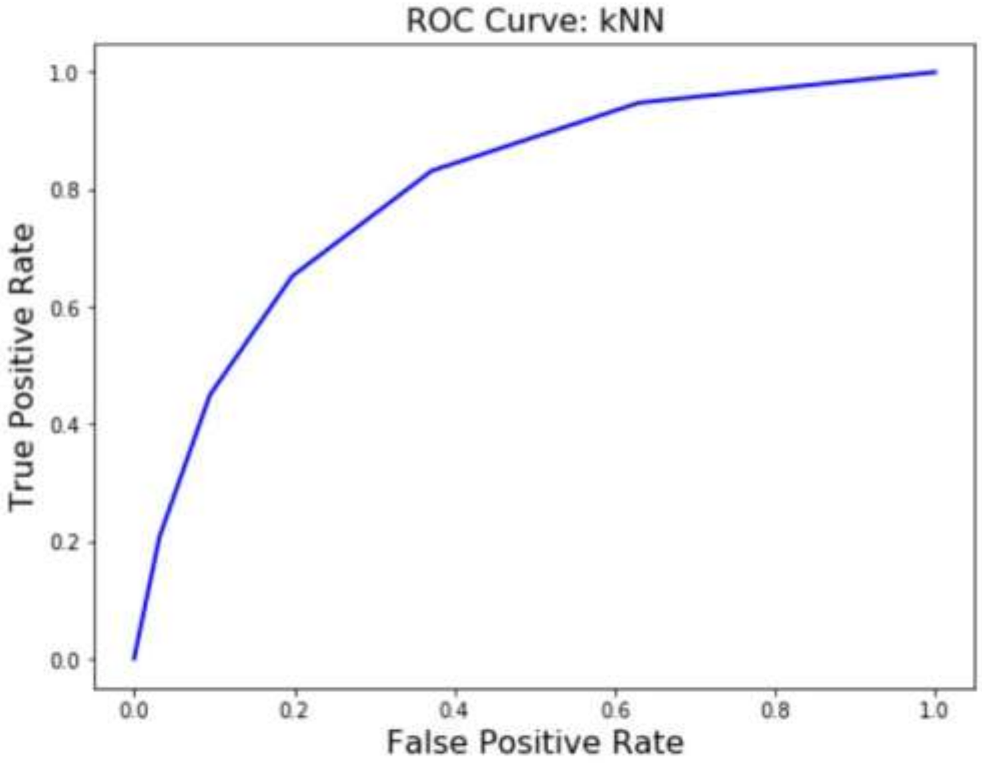
KNN	Logistic Regression	Decision Tree	Random Forest	SVM
[[903 284] [297 749]]	[[972 215] [255 791]]	[[928 259] [248 798]]	[[904 283] [253 793]]	[[1183 4] [1042 4]]

GRAPHS

AUC Score (Decision Tree Classifier): 0.77

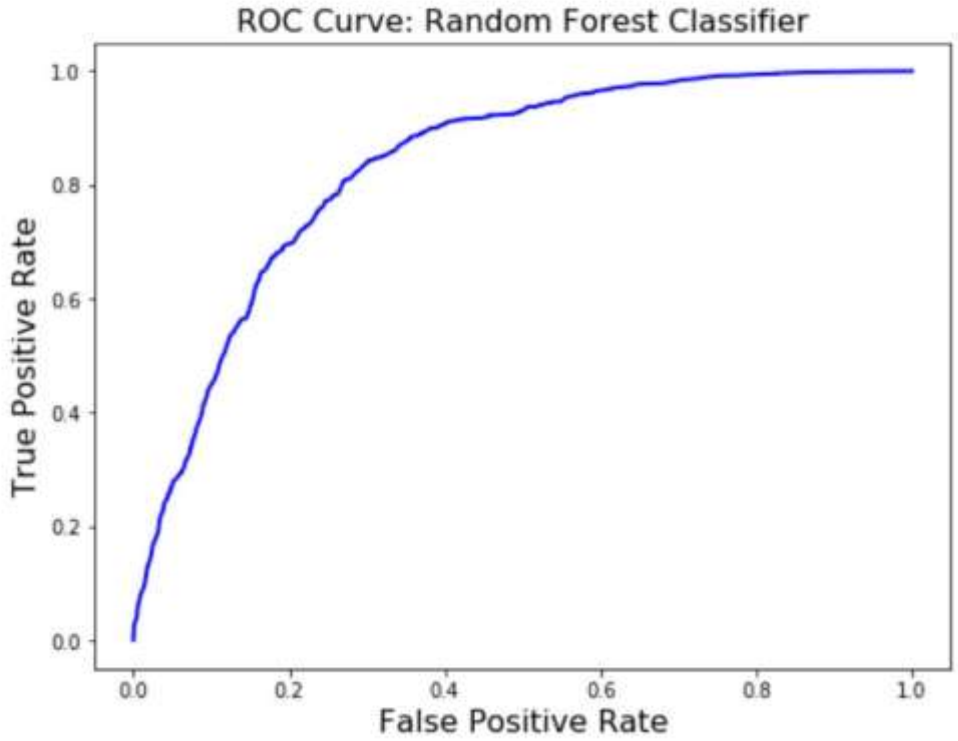


AUC Score (kNN): 0.80

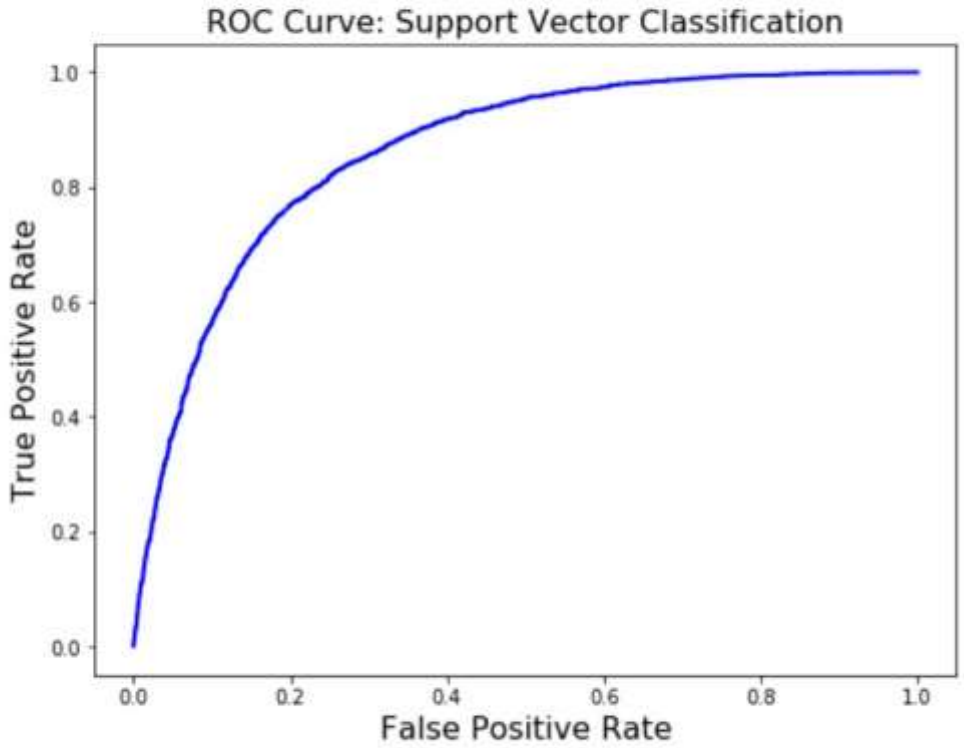


GRAPHS (CONT.)

AUC Score (Random Forest Classifier): 0.83

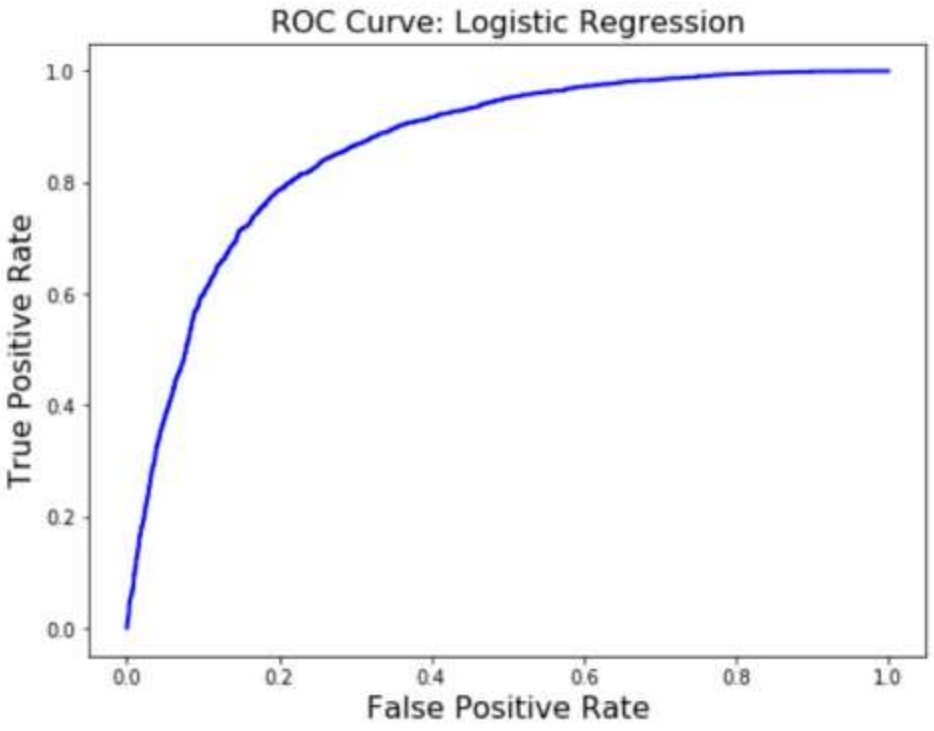


AUC Score (Support Vector Classification): 0.86



GRAPHS (CONT.)

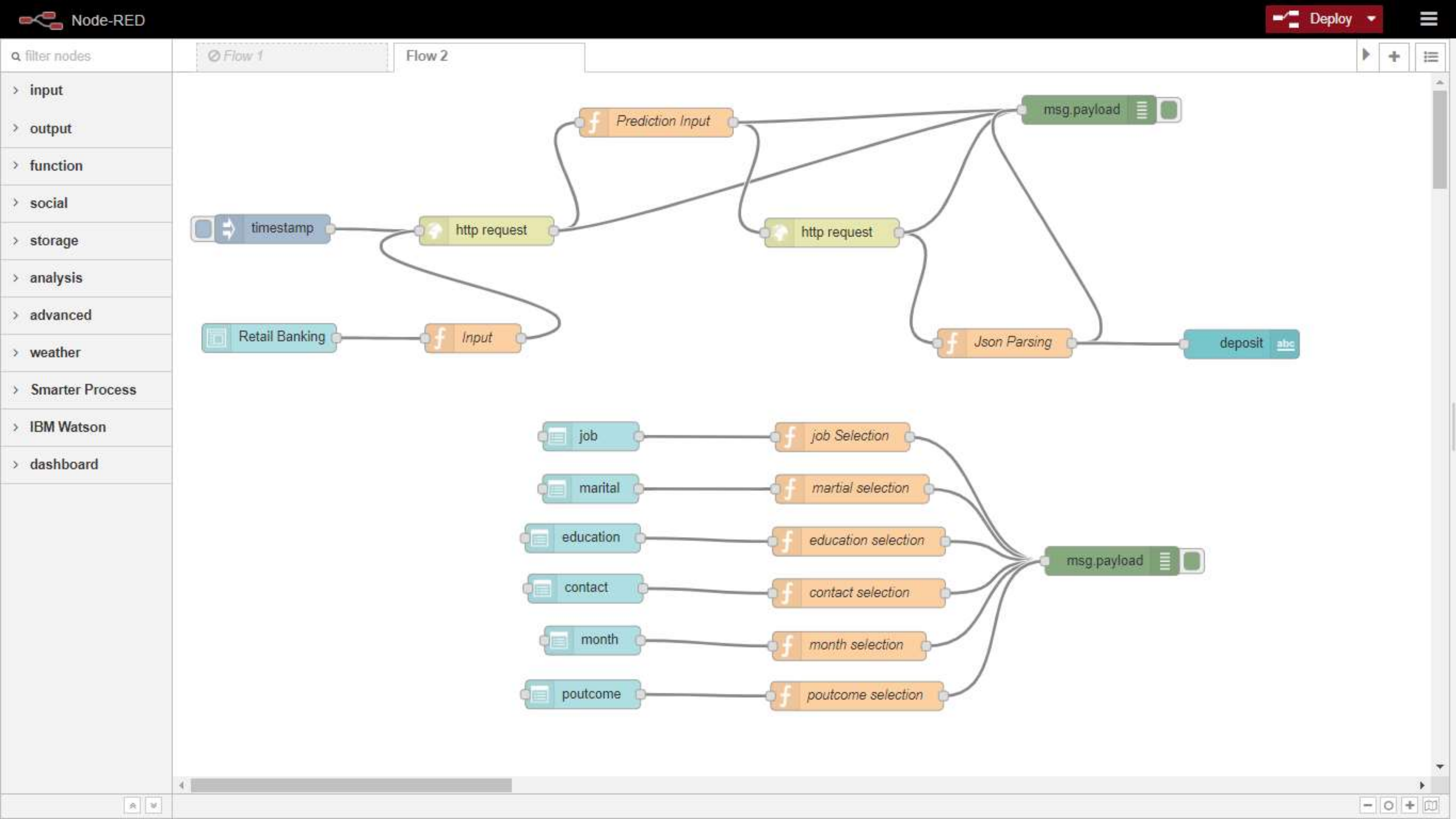
AUC Score (Logistic Regression): 0.86



WE CHOOSE

LOGISTIC REGRESSION

Accuracy = 80.9%


Node-RED
Deploy
filter nodes
Flow 1
Flow 2
input
output
function
social
storage
analysis
advanced
weather
Smarter Process
IBM Watson
dashboard
Prediction Input
msg.payload
timestamp
http request
http request
Retail Banking
Input
Json Parsing
deposit
abc
job
job Selection
marital
martial selection
education
education selection
contact
contact selection
month
month selection
poutcome
poutcome selection
msg.payload

Predictive Analytics For Retail Banking

ML Model

job retired

contact celluar

month apr

poutcome unknown

marital married

education secondary

63

defaulter *
0

balance *
2030

housing *
0

loan *
0

duration *
61

campaign *
6

pdays *
0

previous *
0

SUBMIT CANCEL

deposit

CONCLUSION

- Most classification problems in the real world are imbalanced. Also, almost always data sets have missing values. In this post, we covered strategies to deal with both missing values and imbalanced data sets. We also explored different ways of building ensembles in sklearn. Below are some takeaway points:
- Sometimes we may be willing to give up some improvement to the model if that would increase the complexity much more than the percentage change in the improvement to the evaluation metrics.
- When building ensemble models, try to use good models that are as different as possible to reduce correlation between the base learners. We could've enhanced our stacked ensemble model by adding *Dense Neural Network* and some other kind of base learners as well as adding more layers to the stacked model.
- Easy Ensemble usually performs better than any other resampling methods.