Data Glacier

Your Deep Learning Partner

Final Presentation

<ABC Bank>

<30/10/2022>

Agenda

- Group Information
- Problem Statement
  - Insights
  - Data Preparation
  - Data Visualization
  - Recommendation
  - Model Recommendation
  - Preparing the to fit on the Model
  - Model Selecting
  - Comparing Results
  - Final Result

Group information

Group name : OPG (The One Person-Group)
Specialization : Data science
Members :

Name	Email	Country	College
Mohamad Eyad Abras	2nasuri56@gmail.com	Turkey	Turkish-German University

Problem Statement

Problem : ABC Bank wants to sell it's term deposit product to customers and before launching the product they want to develop a model which help them in understanding whether a particular customer will buy their product or not (based on customer's past interaction with bank or other Financial Institution).

Task : We are analyzing the Data related to banks to help ABC make the right decision before launching their product

After understanding the problem, The work was made through 8 steps :

1. Gaining insights from the Data
2. Data preparation
3. Data Visualization
4. Conclusion and ML model Recommendations
5. Preparing the data to fit on the model
6. Model selecting
7. Comparing results
8. Final result

Insights

We have a total of 21 columns (5 of them float64 , 5 Int64 and the rest are objects) without any Null values.

#	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

Data preparation

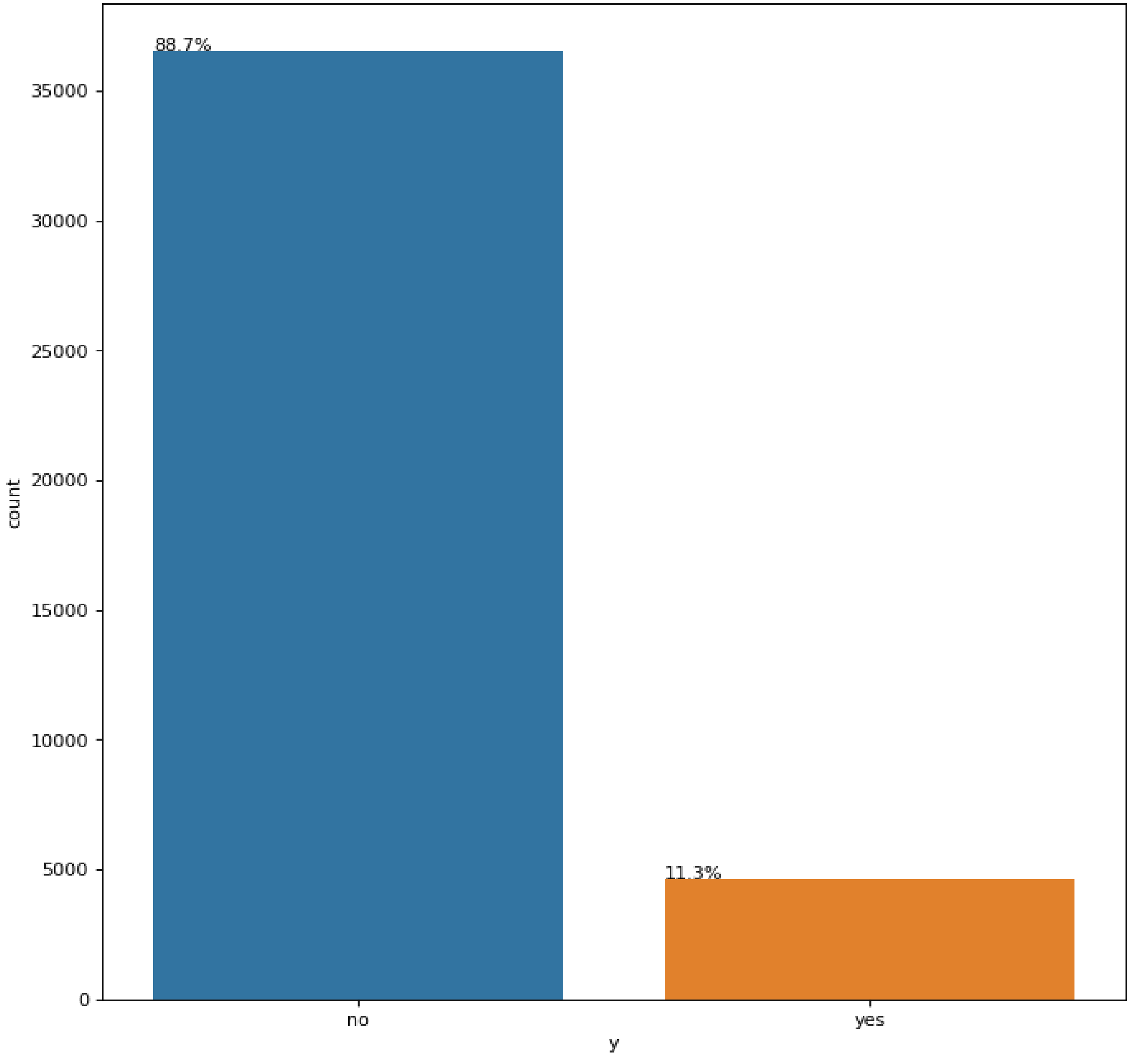
1- Data preparation phase:

- Checking for NAN values in Data and dealing with it (already checked)
- Checking whether we have imbalanced data or not
- Dealing with imbalanced data (if found)

Data Glacier

Data preparation

The Data we have contains 41188 Row and 21 Columns but the target data (y column) is unfortunately unequally distributed as shown :

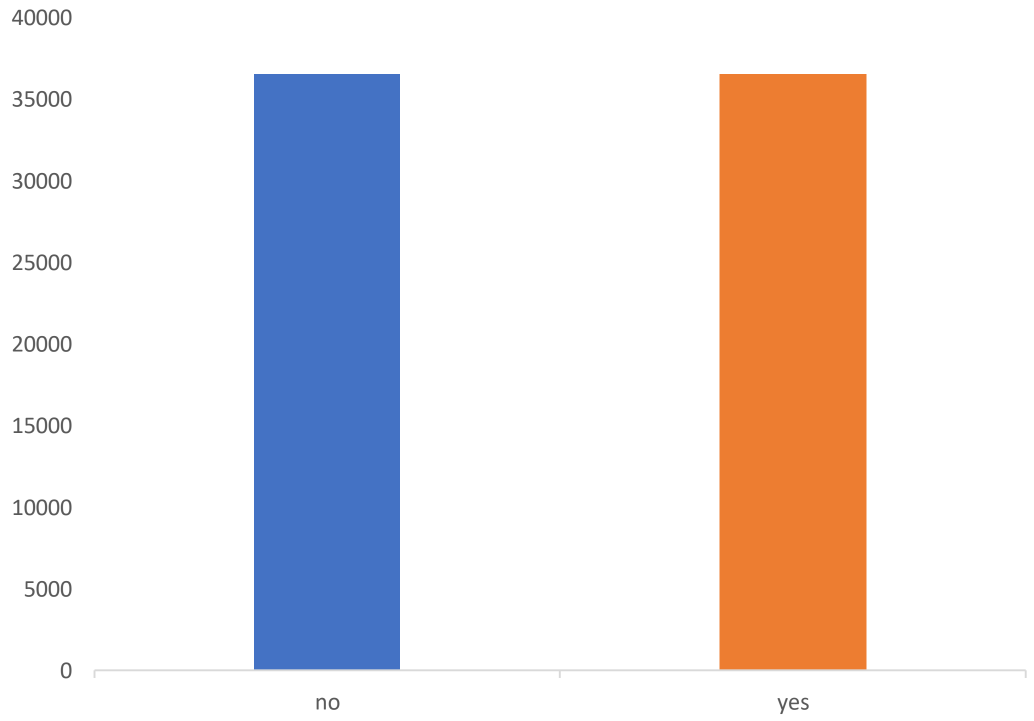


We can clearly see that more than 88% of the data is a No and only a small portion (10%) is yes

Data preparation

To overcome this problem we tried many methods including SMOTE and the results are phenomenal!

We managed to make the data 100% balanced by creating synthetic instances and now we have a total of 73096 rows (more data = better training)



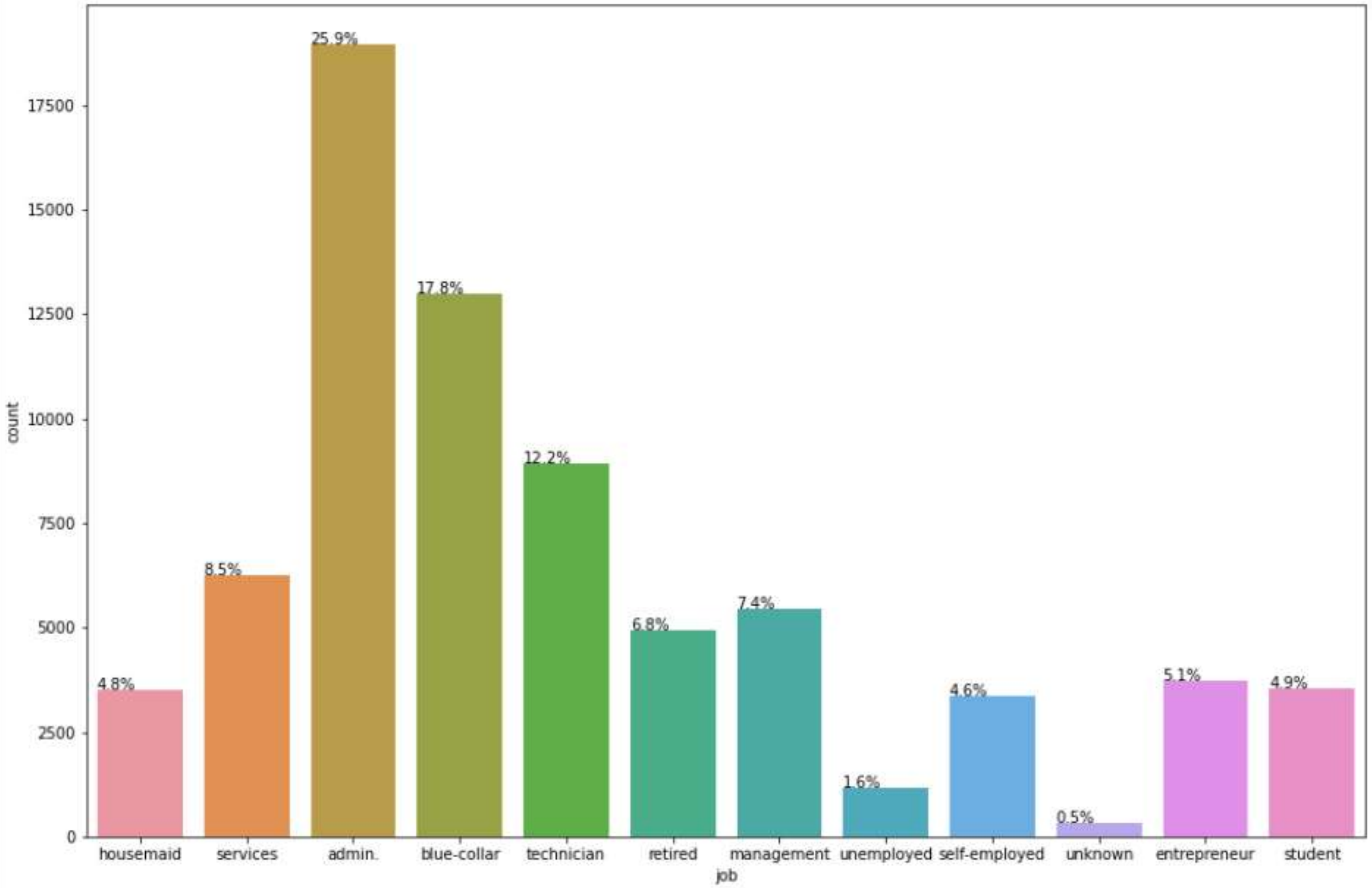
Data Glacier

Data preparation

The data before applying SMOTE method :

The data after :

Data Visualization

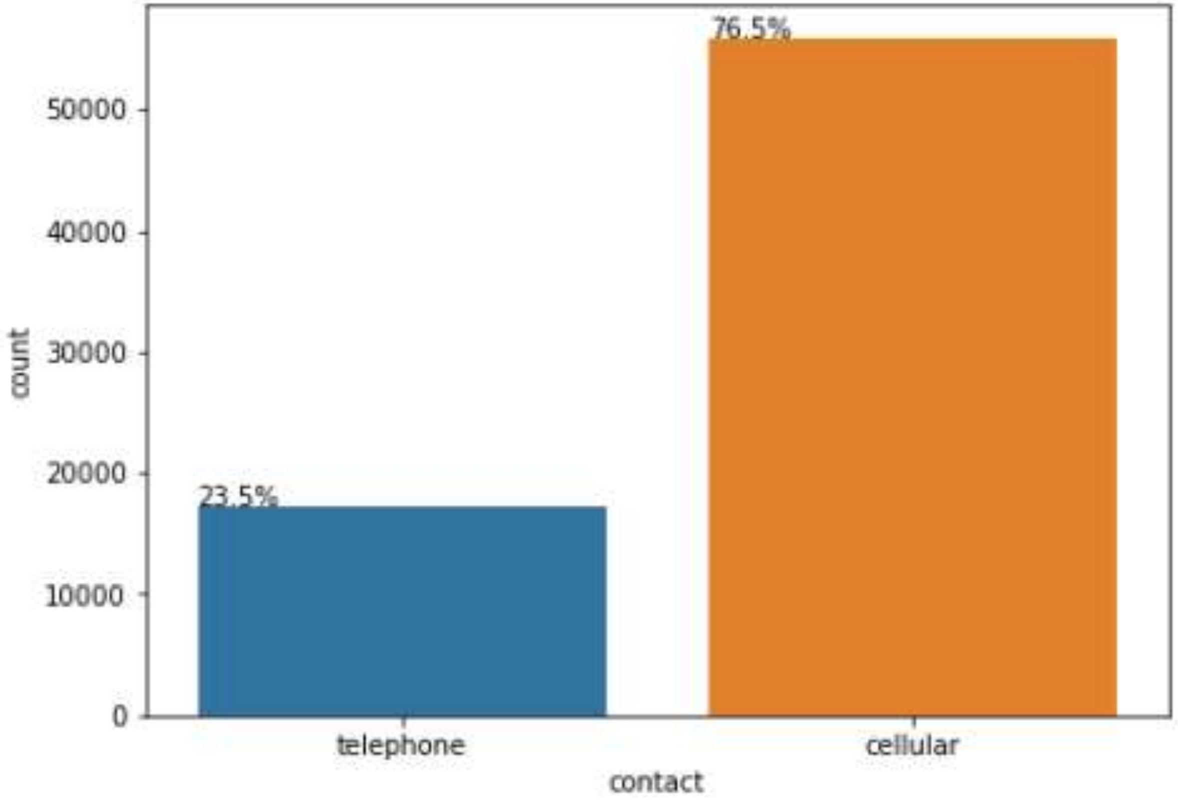


The graph shows the jobs of the bank customers, we can clearly see that admin blue-collar and technician are the top 3 jobs with more than 50% of the whole bank costumers

Data Glacier

Data Visualization

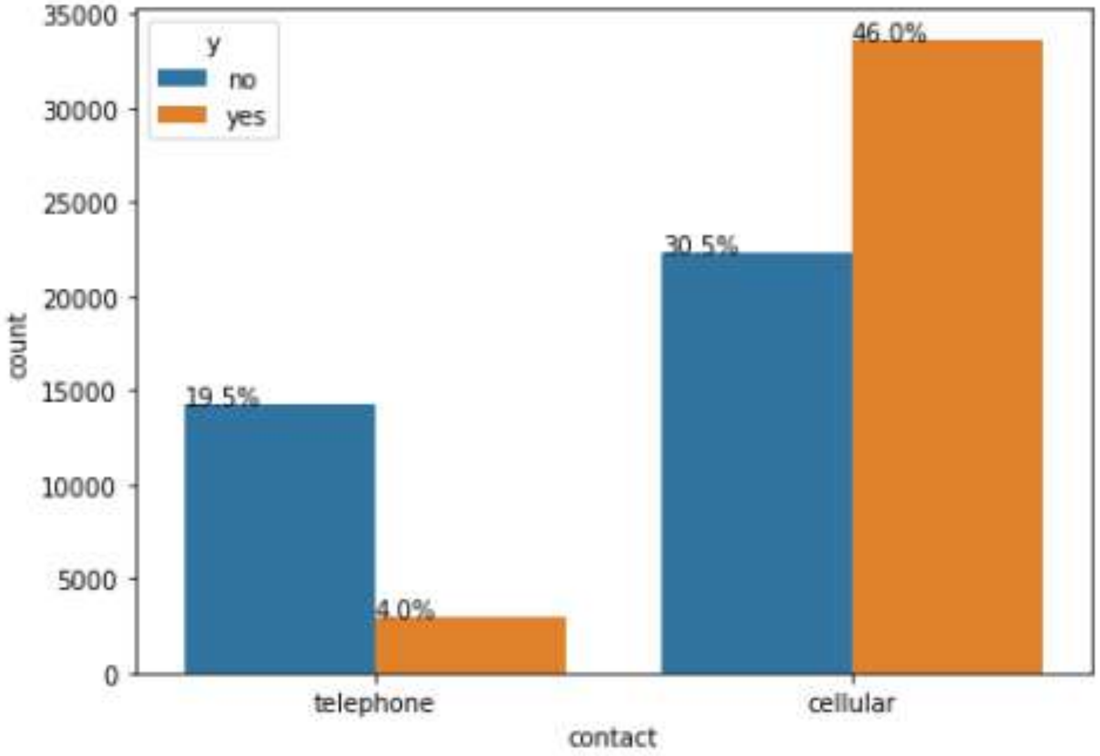
the costumer that contact the bank by cellular are greater than telephone



Data Glacier

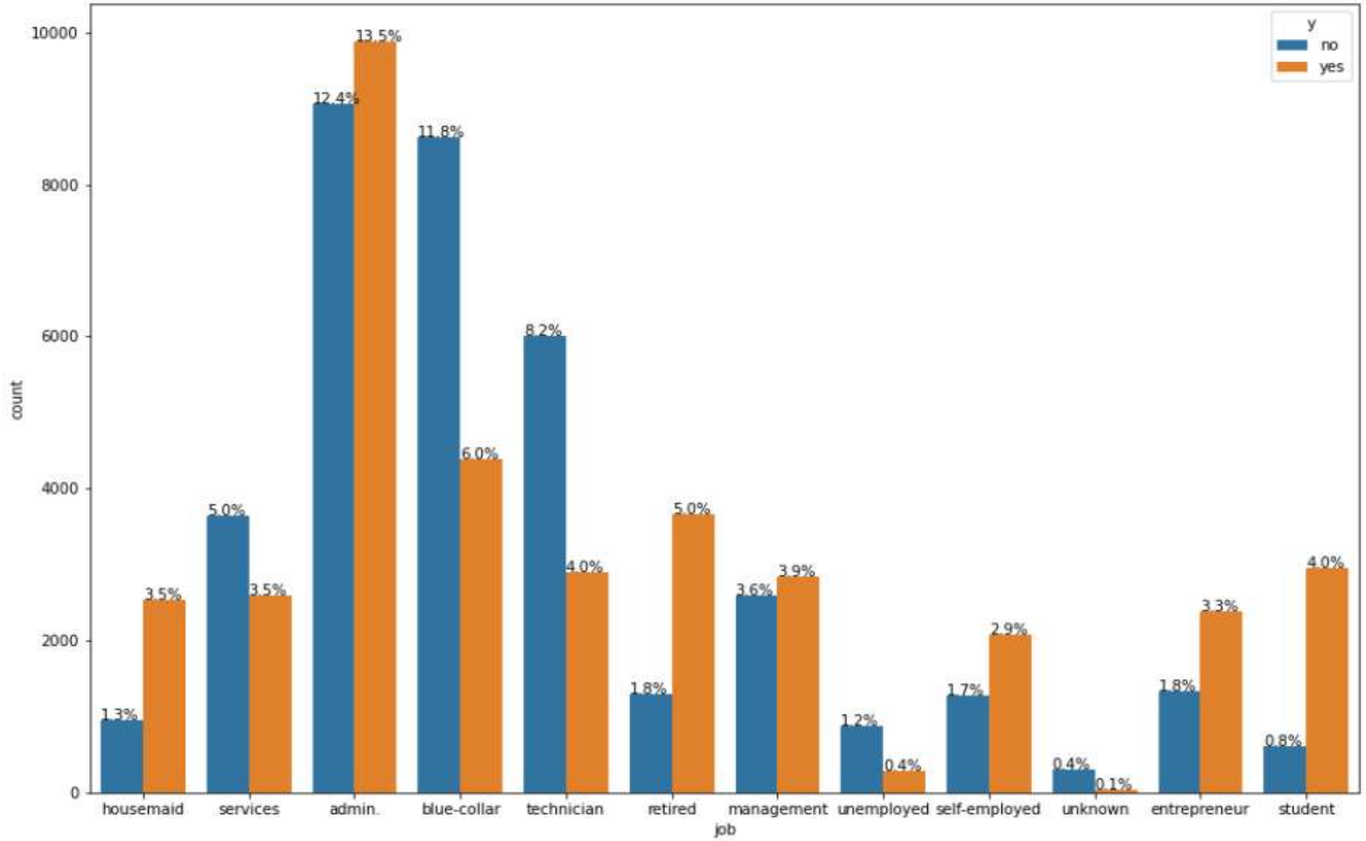
Data Visualization

And the contact's effect is clear! People who use cellular are almost 10 times more likely to subscribe to the product that people with telephone.
(46% vs 4%)



Data Glacier

Data Visualization

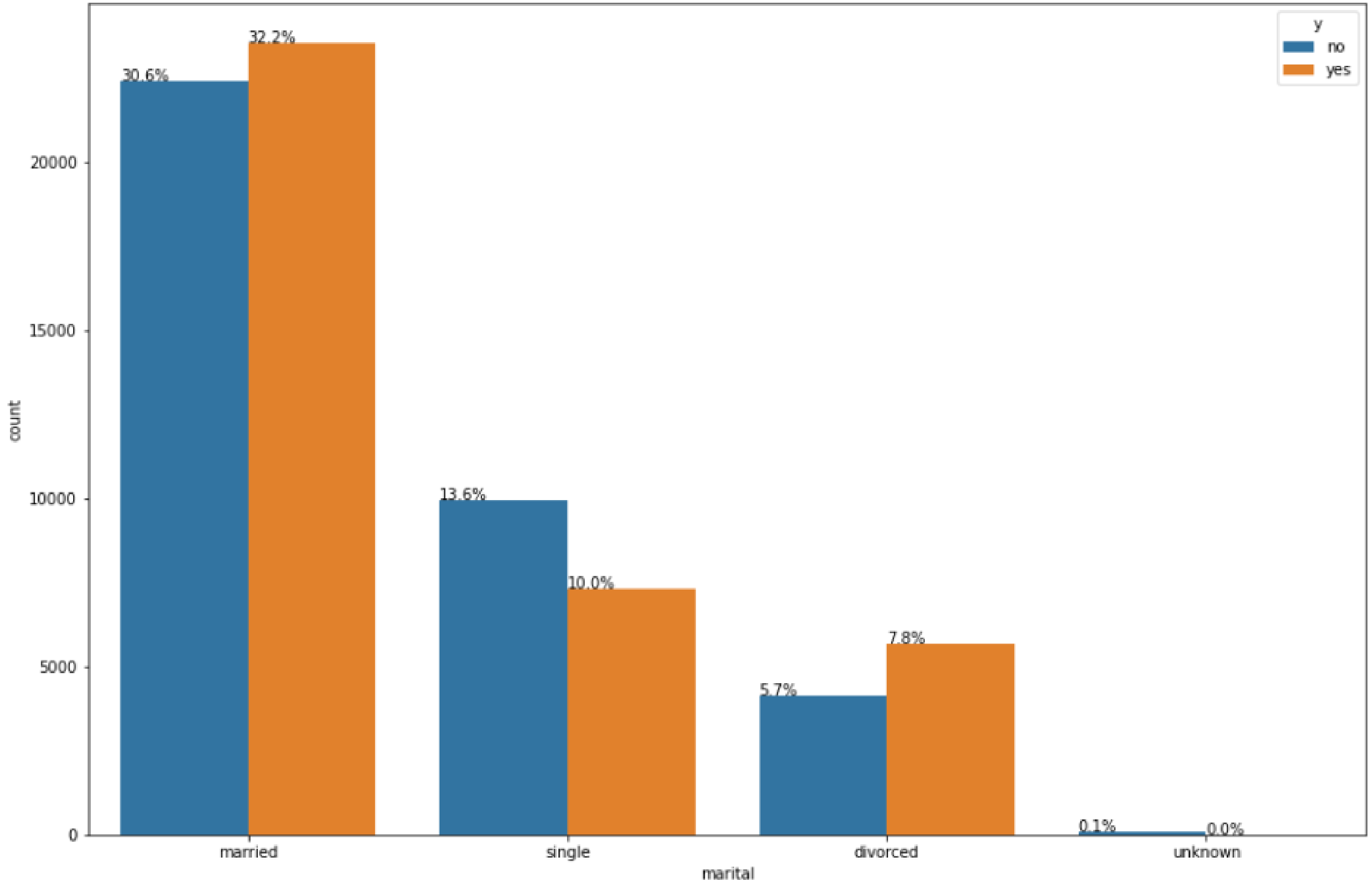


Even though the admin, blue collar and technician are the top 3 jobs in the banks customers, the people who subscribe the most are students (for every 5 subscribers 1 does not subscribe)

Data Glacier

Data Visualization

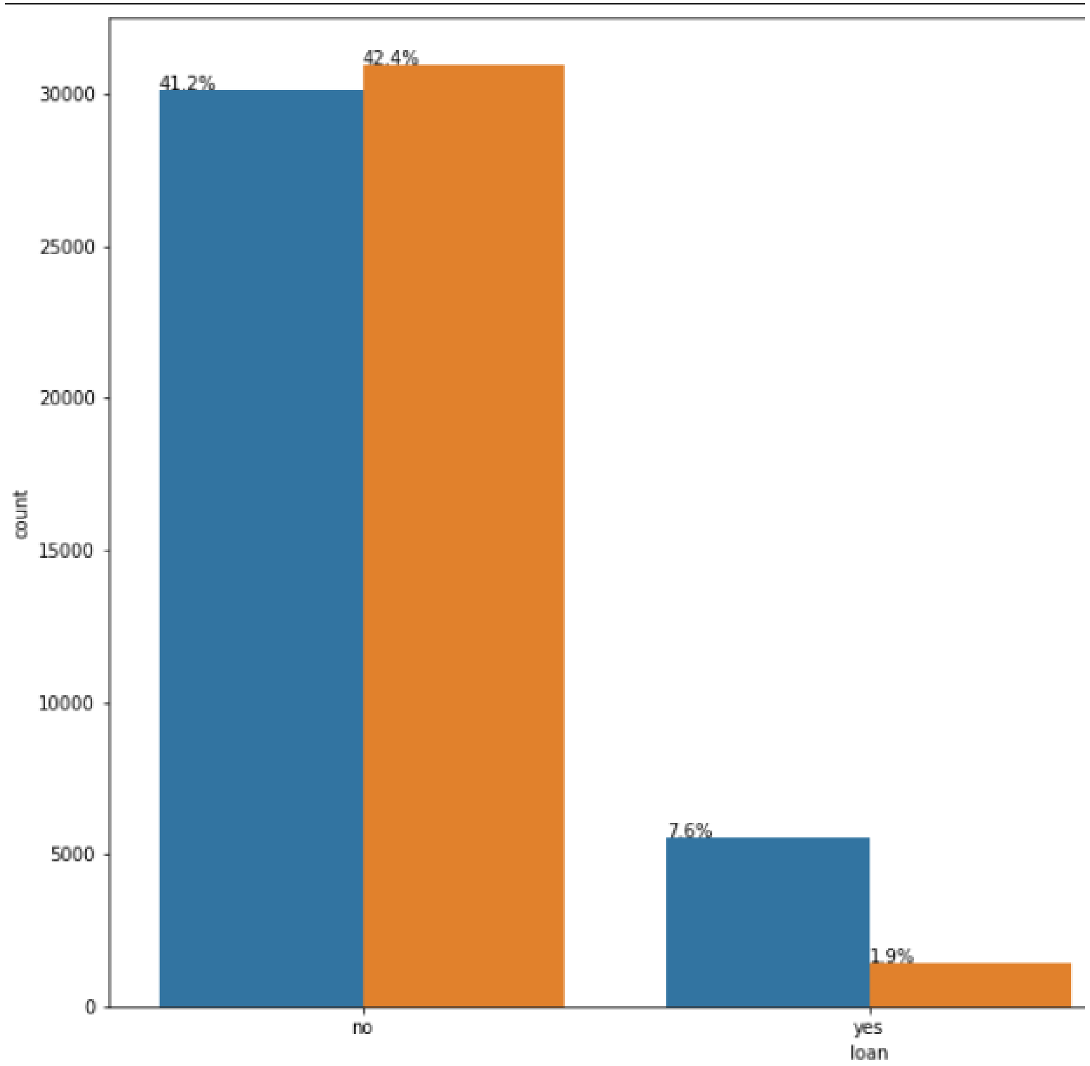
Social status seems to be somewhat important. Married and divorced people seem to be more likely to subscribe



Data Glacier

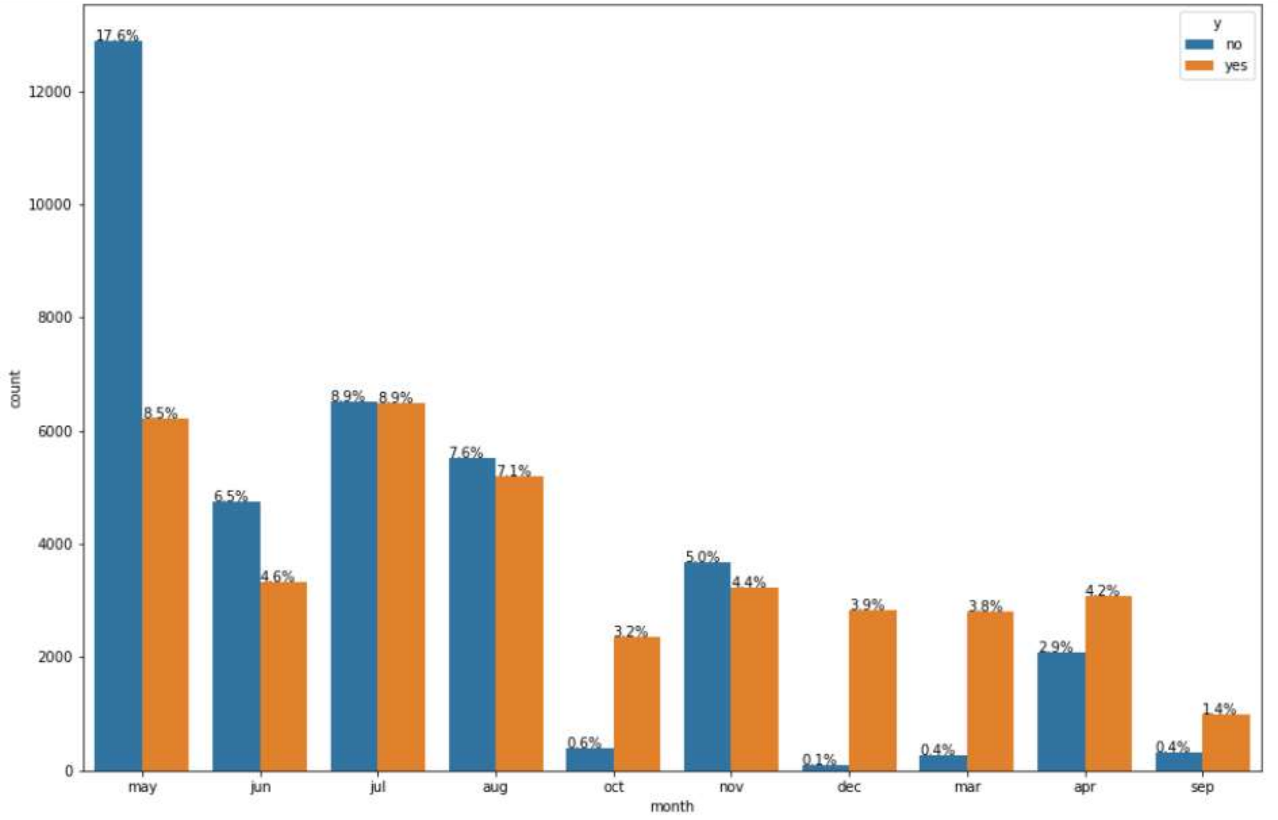
Data Visualization

People with loans are less likely to subscribe



Data Glacier

Data Visualization

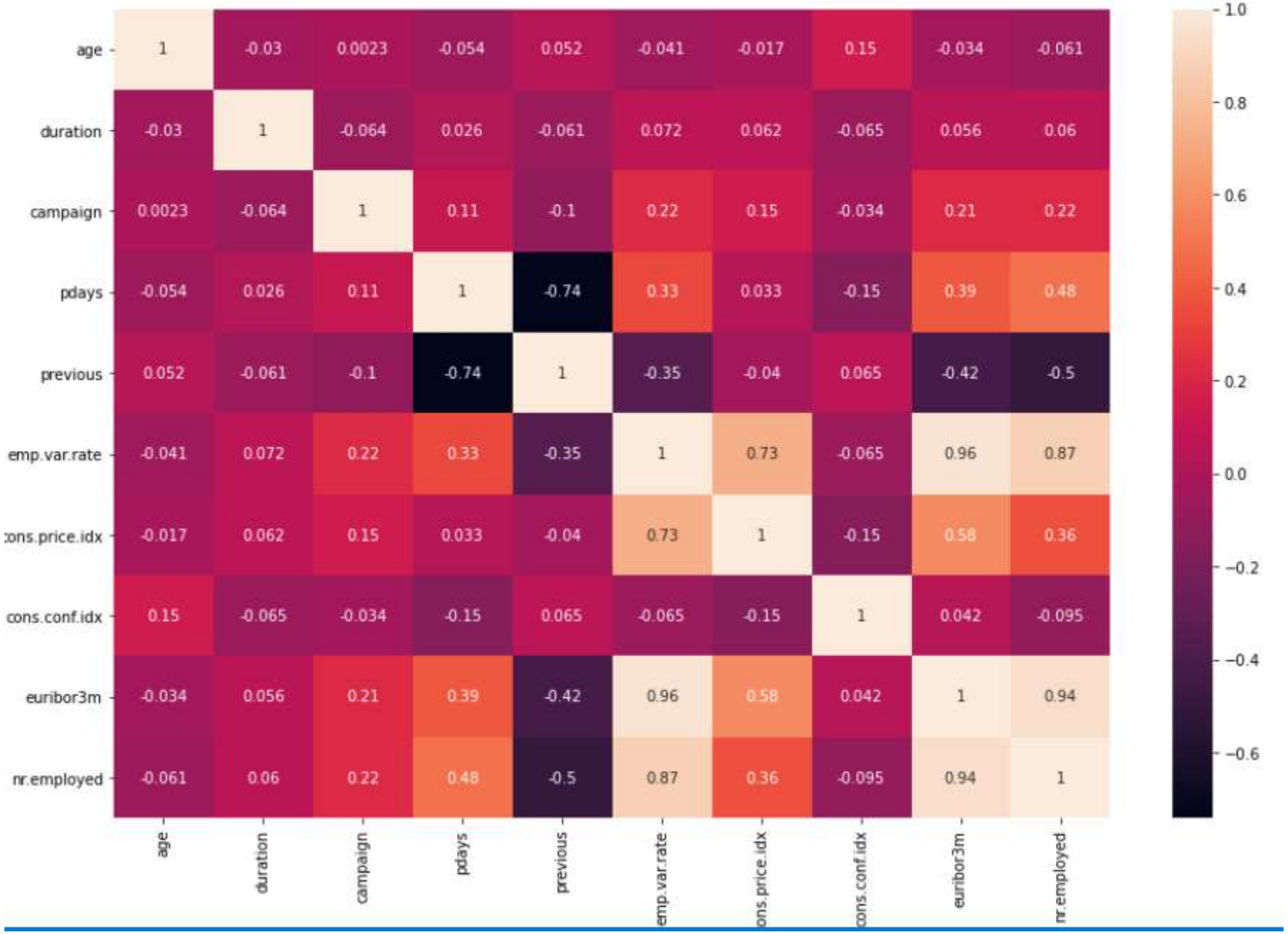


Subscriptions in Mart , April, October in December are the peak of the year, and may is the worst

Data Glacier

Data Visualization

The heat map: To show the correlation between columns



Recommendations

1.Students and home maids are most likely to subscribe to the product.

2.People who are married has been contacted more for the deposits by the bank.

3.The contact type (cellular vs telephone) plays a role.

4.People has been contacted more in the month of May than any other month. They have not been contacted in January and Februray at all.

5.Single people are less likely to subscribe.

6.People with no personal loan has been contacted more by the bank.

7.People who are in university has been contacted more by the bank.

8.Age,Duration,Campaign have outliers and are rightly skewed.

9.Pdays have more than 70% of data imputed so it is better either to impute or remove the column.

10.Euribor3m with nr.employed and emp.var.rate with nr.employed with the highest correlation

Model Recommendations

(technical user)

1.Since the data contains many columns with categorical data which are going to increase the dimensionality (e.g. after applying one-hot encoding) we recommend using PCA for dimensionality reduction.

2.We recommend starting with tree-based models like Decision Tree, Extra Tree and the Random forest classifier because they are simple yet effective models.

3.Lasso and Ridge classifiers can also be used in case PCA didn't give any improvements in the results

4.Accuracy score can be used as an accuracy metric since the problem is classification problem.

5.Only choosing the model is not sufficient, Tuning the hyper parameters plays a huge rule.

6.Finally, we recommend using more than one model, tuning the hyperparameters and settling for the best model (accuracy-wise)

Preparing the data to fit on the model

As we know, the Machine learning models work with numerical data only, so we had to convert all the non- numerical data columns into numerical and that was done with help of Ordinal Encoder for columns that contains yes or no instances and OneHotEncoding for the rest of the columns.

Another problem that appeared after applying the Onehotencodeing algorithm is the increase of the dimensions, we used PCA (Principal component analysis) to help with the dimensionality reduction After scaling the data on a Min-Max scalar

Preparing the data to fit on the model

And the final data set is now all-numeric, feature-scaled and with reasonable number of dimensions and ready to be used for training

	age	duration	campaign	pdays	previous	emp.var.rate	cons.price.idx	cons.conf.idx	euribor3m	nr.employed	contact_telephone	education_basic.9y	education_high.school	education_illiterate	education_professional.course	education_university.degree	default	housing	loan	y
0	56.000000	261.000000	1.000000	999.0	0.000000	1.100000	93.994000	-36.400000	4.857000	5191.000000	1	0	0	0	0	0	0.0	0.0	0.0	0.0
1	57.000000	149.000000	1.000000	999.0	0.000000	1.100000	93.994000	-36.400000	4.857000	5191.000000	1	0	1	0	0	0	0.0	0.0	0.0	0.0
2	37.000000	226.000000	1.000000	999.0	0.000000	1.100000	93.994000	-36.400000	4.857000	5191.000000	1	0	1	0	0	0	0.0	1.0	0.0	0.0
3	40.000000	151.000000	1.000000	999.0	0.000000	1.100000	93.994000	-36.400000	4.857000	5191.000000	1	0	0	0	0	0	0.0	0.0	0.0	0.0
4	56.000000	307.000000	1.000000	999.0	0.000000	1.100000	93.994000	-36.400000	4.857000	5191.000000	1	0	1	0	0	0	0.0	0.0	1.0	0.0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
73091	29.000000	192.173366	2.000000	3.0	3.942211	-1.700000	94.064246	-39.828894	0.721935	4991.600000	0	0	0	0	1	0	0.0	0.0	0.0	1.0
73092	35.581952	156.238885	1.059721	999.0	0.940279	-2.900000	92.963000	-40.800000	1.261553	5076.200000	0	0	0	0	0	1	0.0	0.0	0.0	1.0
73093	45.987202	844.764308	1.000000	999.0	0.000000	0.916566	93.872628	-37.256025	4.730902	5191.733736	0	0	0	0	1	0	0.0	1.0	0.0	1.0
73094	53.284890	920.569780	1.857555	999.0	0.000000	1.100000	93.994000	-36.400000	4.859573	5191.000000	1	0	0	1	0	0	0.0	0.0	0.0	1.0
73095	32.217097	723.953875	3.868389	999.0	0.000000	1.400000	93.815096	-41.267158	4.961085	5228.100000	0	0	1	0	0	0	0.0	0.0	0.0	1.0

Model selecting

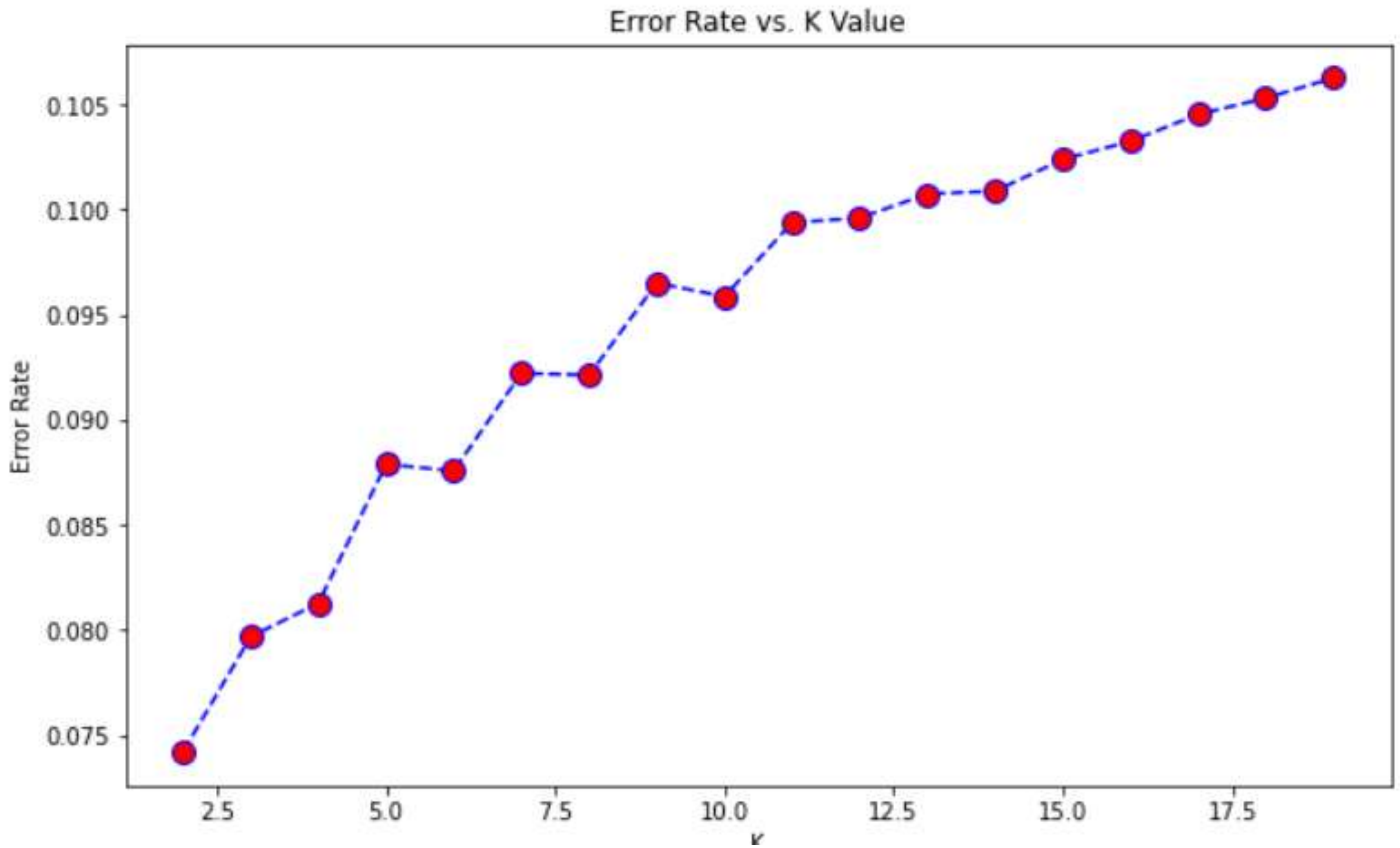
From Scikit-learn library:

- Logistic Regression
- Random Forest Classifier
- Ada Boost Classifier
- SVC (Support Vector Classifier)
- K Neighbors Classifier

Model selecting

Chossing the right parameters for the model:

- K Neighbors Classifier => K value vs. Error Rate



Comparing results

ML Algorithm	Result
Logistic Regression	0.90
Random Forest Classifier	0.93
Ada Boost Classifier	0.94
SVC (Support Vector Classifier)	0.85
K Neighbors Classifier	0.93

Final Result

We can not say for sure that one of them is the best because the results seems very close.
So the first three ML algorithm are:

- Random Forest Classifier
- Ada Boost Classifier
- K Neighbors Classifier

Thank You

Data Glacier

Your Deep Learning Partner