MACHINE LEARNING DEPLOYMENT USING IBM WATSON STUDIO

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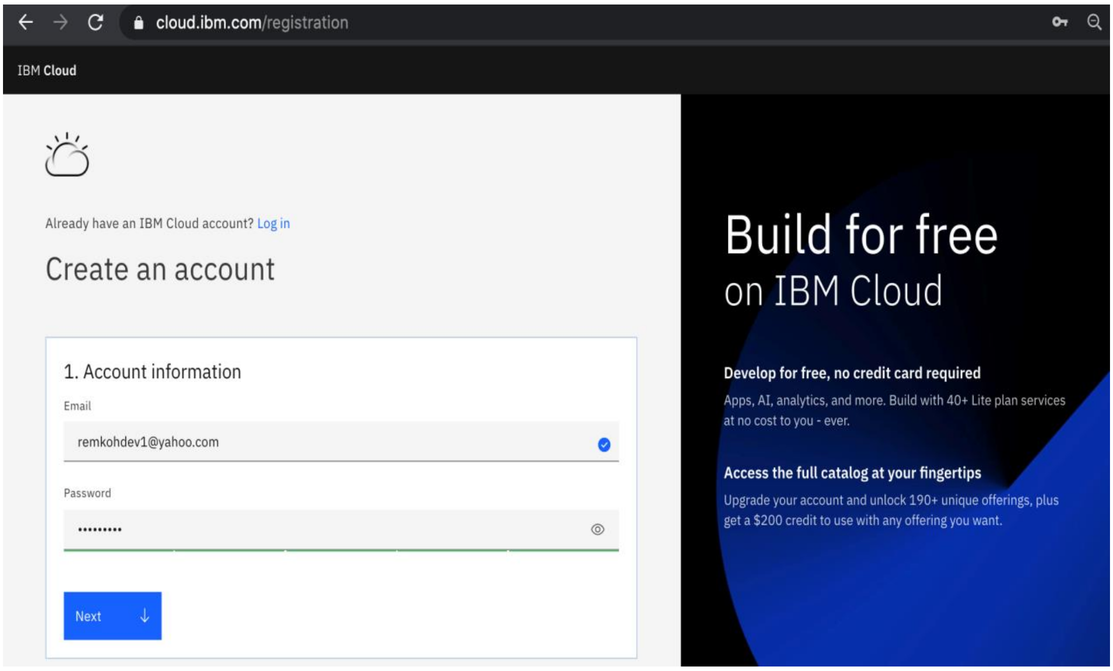
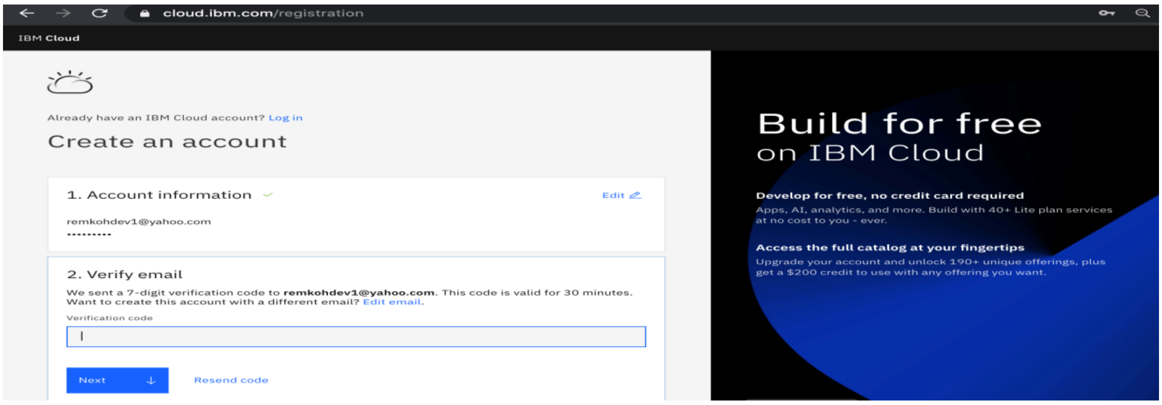
MACHINE LEARNING MODEL DEPLOYMENT USING IBM WATSON STUDIO

To create a new account, follow the steps below,

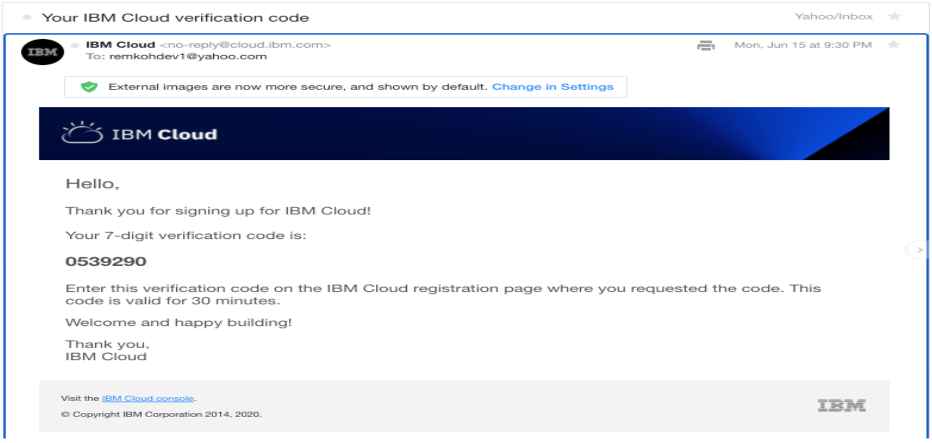
1. You need an IBM Cloud account to access your cluster,
2. If you do not have an IBM Cloud account yet, go to https://cloud.ibm.com/registration to register,
3. In the Create an account window, enter your email and password,



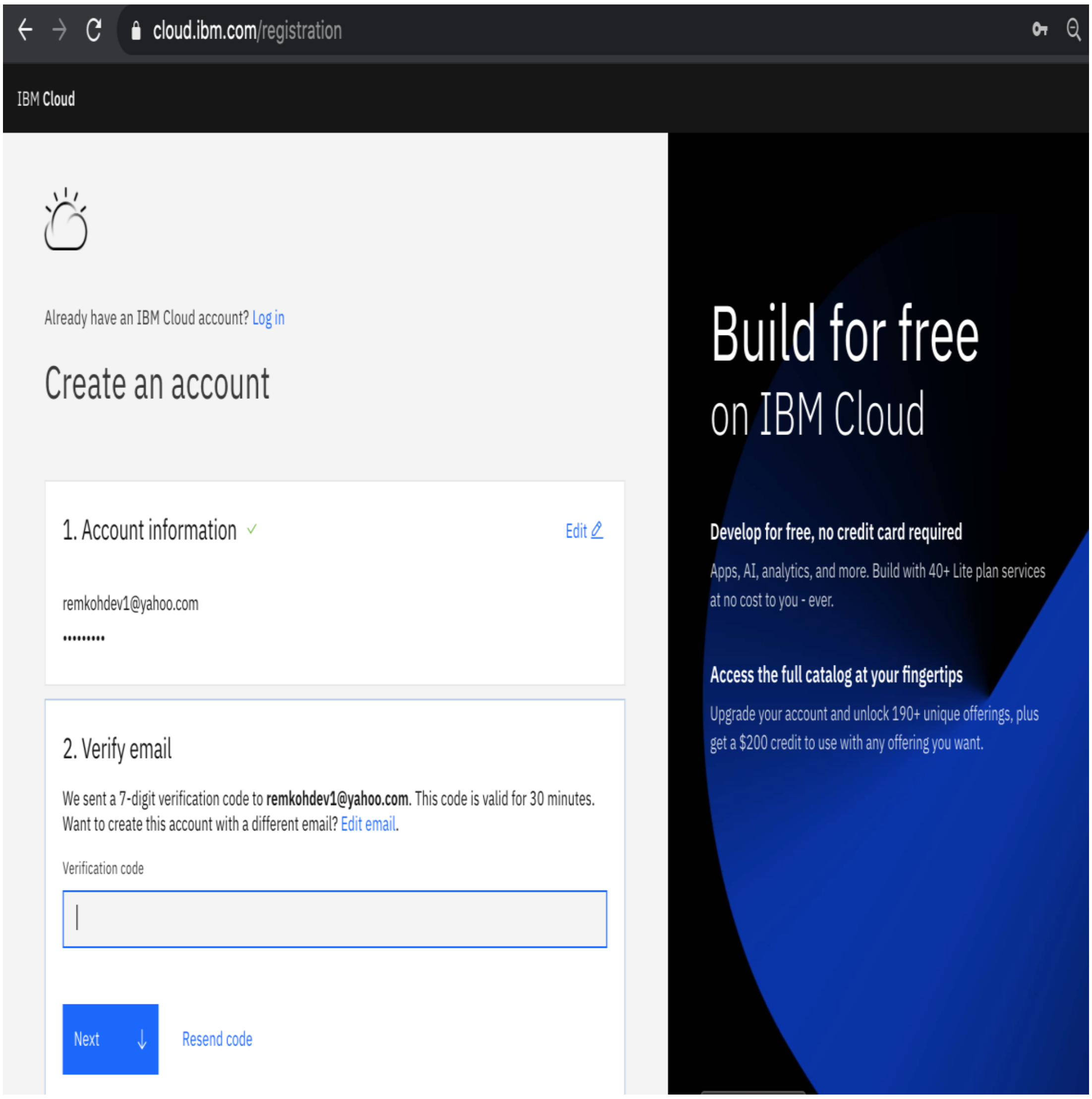
4. The Verify email section will inform you that a verification code was sent to your email,



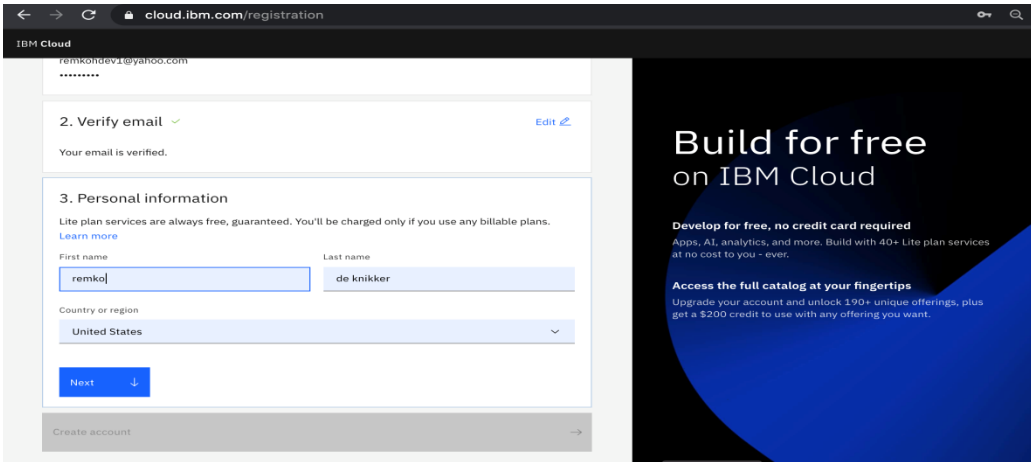
5. Switch to your email provider to retrieve the verification code,



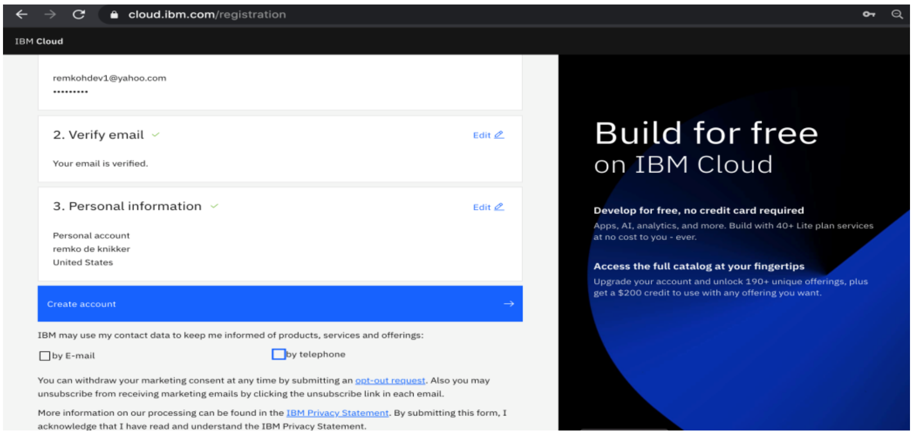
6. Enter the verification code in the `Verify email` section, and click `Next`,



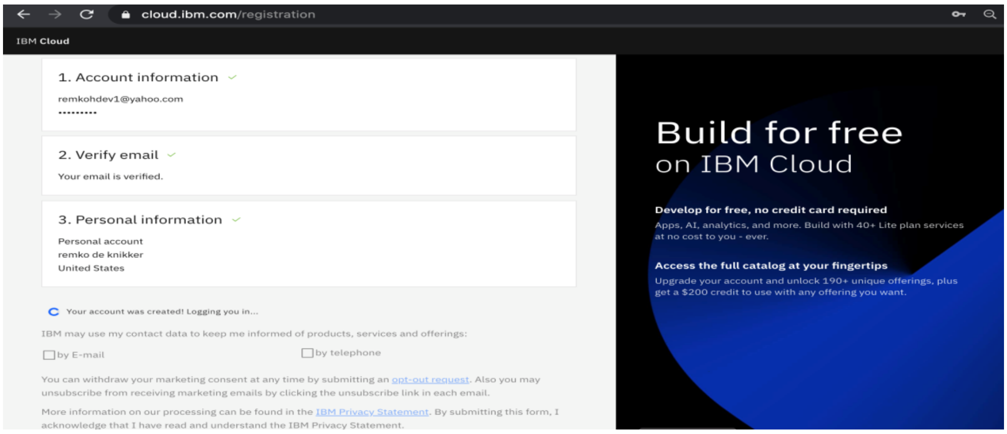
7. Enter your first name, last name and country in the Personal information section and click Next,



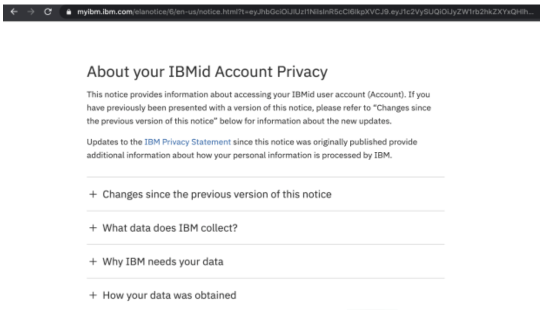
8. Click Create account,



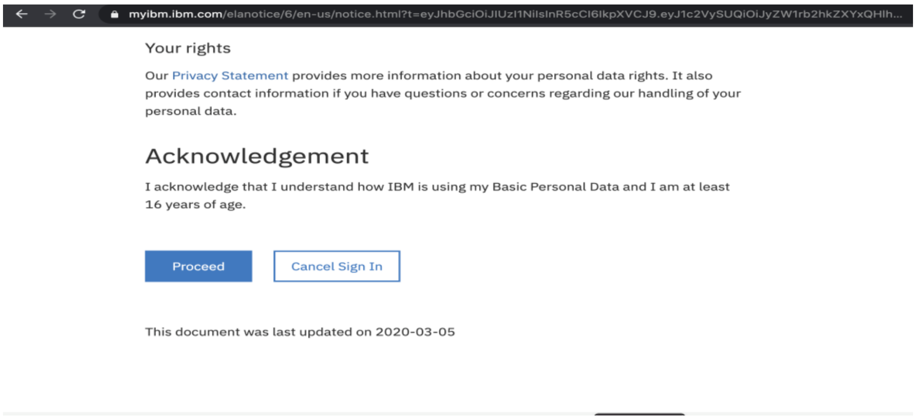
9. Your account is being created,



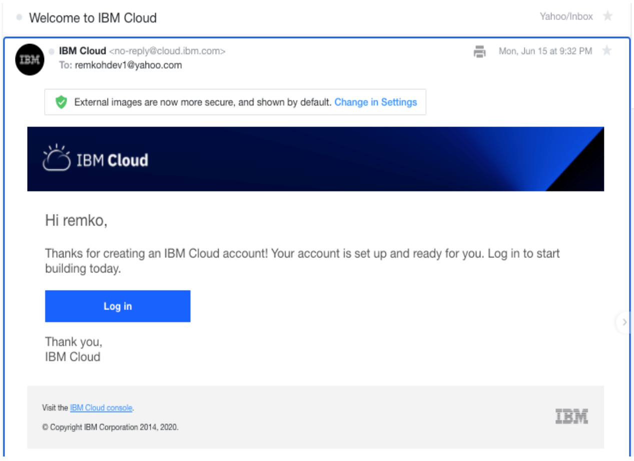
10.Review the IBM Privacy Statement,



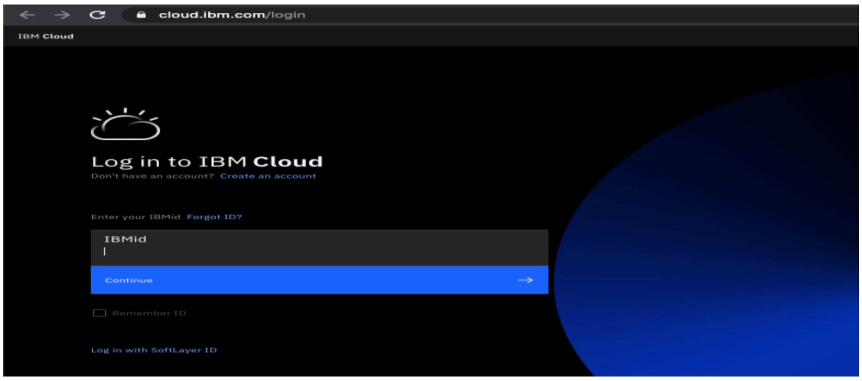
11. Click `Proceed` to acknowledge the privacy statement,



12. Switch to your email provider to review the Welcome to IBM Cloud email, and click the Login link,

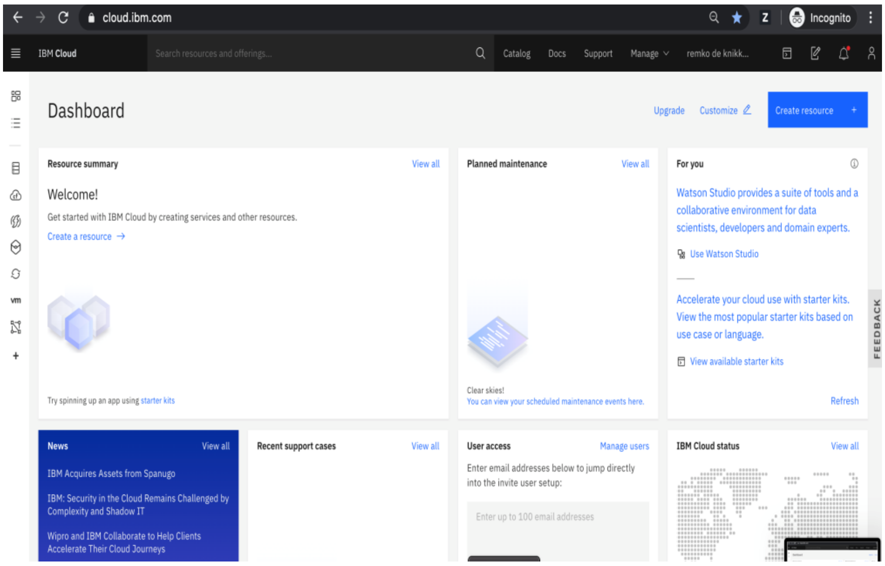


13. Enter your IBM Id to login,



14. Enter your password to login,

15. The IBM Cloud dashboard page should load,



16. You have successfully registered a new IBM Cloud account.

Churn Prediction

A Machine Learning Model That Can Predict Customers Who Will Leave The CompanyThe aim is to predict whether a bank's customers leave the bank or not. If the Client has closed his/her bank account, he/she has left.

Dataset:

- **RowNumber:** corresponds to the record (row) number and has no effect on the output.
- **CustomerId:** contains random values and has no effect on customer leaving the bank.
- **Surname:** the surname of a customer has no impact on their decision to leave the bank.
- **CreditScore:** can have an effect on customer churn, since a customer with a higher credit score is less likely to leave the bank.
- **Geography:** a customer’s location can affect their decision to leave the bank.
- **Gender:** it’s interesting to explore whether gender plays a role in a customer leaving the bank.
- **Age:** this is certainly relevant, since older customers are less likely to leave their bank than younger ones.

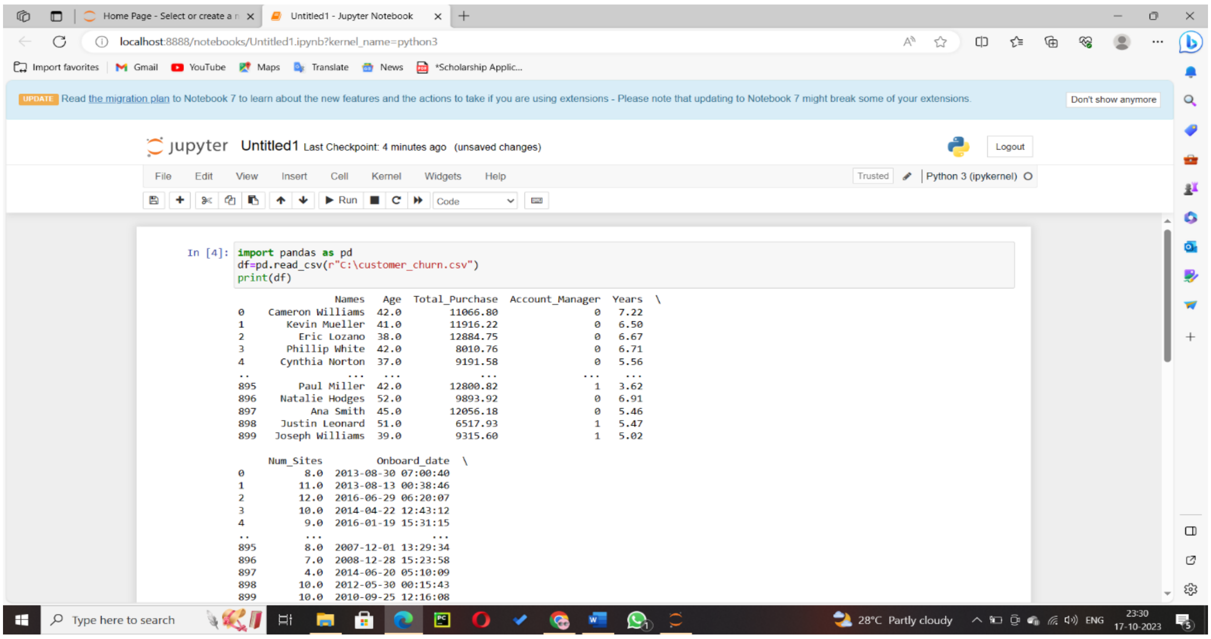
- **Tenure:** refers to the number of years that the customer has been a client of the bank. Normally, older clients are more loyal and less likely to leave a bank.
- **Balance:** also a very good indicator of customer churn, as people with a higher balance in their accounts are less likely to leave the bank compared to those with lower balances.
- **NumOfProducts:** refers to the number of products that a customer has purchased through the bank.
- **HasCrCard:** denotes whether or not a customer has a credit card. This column is also relevant, since people with a credit card are less likely to leave the bank.
- **IsActiveMember:** active customers are less likely to leave the bank.
- **EstimatedSalary:** as with balance, people with lower salaries are more likely to leave the bank compared to those with higher salaries.
- **Exited:** whether or not the customer left the bank. (0=No,1=Yes)

Code:

```
import  pandas  as pd

df=pd.read_csv(r"c:\customer_churn.csv")

print(df)
```



Exploratory Data Analysis:

The first thing we have to do in Exploratory Data Analysis is checked if there are null values in the dataset.

df.isnull().head()

	customer_id	credit_score	country	gender	age	tenure	balance	products_number	credit_card	active_member	estimated_salary	churn
0	False	False	False	False	False	False	False	False	False	False	False	False
1	False	False	False	False	False	False	False	False	False	False	False	False
2	False	False	False	False	False	False	False	False	False	False	False	False
3	False	False	False	False	False	False	False	False	False	False	False	False
4	False	False	False	False	False	False	False	False	False	False	False	False

#This is used to check any null value.

df.isnull().sum()

```
customer_id         0
credit_score        0
country             0
gender              0
age                 0
tenure              0
balance             0
products_number     0
credit_card         0
active_member       0
estimated_salary    0
churn               0
dtype: int64
```

#Checking Data types

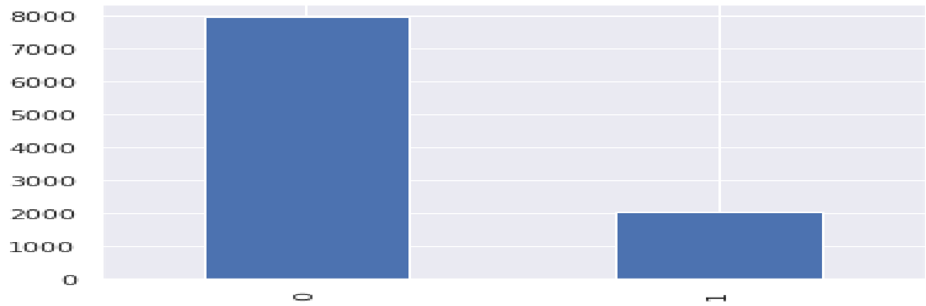
df.dtypes

```
customer_id            int64
credit_score           int64
country               object
gender                object
age                    int64
tenure                 int64
balance              float64
products_number        int64
credit_card            int64
active_member          int64
estimated_salary     float64
churn                  int64
dtype: object
```

#Counting 1 and 0 Value in Churn column

```
color_wheel = {1: "#0392cf", 2: "#7bc043"}
colors = df["churn"].map(lambda x: color_wheel.get(x + 1))
print(df.churn.value_counts())
p=df.churn.value_counts().plot(kind="bar")
```

```
0    7963
1    2037
Name: churn, dtype: int64
```



#Change value in country column

```
df['country'] = df['country'].replace(['Germany'],'0')
df['country'] = df['country'].replace(['France'],'1')
df['country'] = df['country'].replace(['Spain'],'2')
#Change value in gender column
df['gender'] = df['gender'].replace(['Female'],'0')
df['gender'] = df['gender'].replace(['Male'],'1')
```

df.head()

	customer_id	credit_score	country	gender	age	tenure	balance	products_number	credit_card	active_member	estimated_salary	churn
0	15634602	619	1	0	42	2	0.00	1	1	1	101348.88	1
1	15647311	608	2	0	41	1	83807.86	1	0	1	112542.58	0
2	15619304	502	1	0	42	8	159660.80	3	1	0	113931.57	1
3	15701354	699	1	0	39	1	0.00	2	0	0	93826.63	0
4	15737888	850	2	0	43	2	125510.82	1	1	1	79084.10	0

#convert object data types column to integer

df['country'] = pd.to_numeric(df['country'])

df['gender'] = pd.to_numeric(df['gender'])

df.dtypes

```
customer_id           int64
credit_score          int64
country               int64
gender                int64
age                   int64
tenure                int64
balance             float64
products_number       int64
credit_card           int64
active_member         int64
estimated_salary    float64
churn                 int64
dtype: object
```

#Remove customer_id column

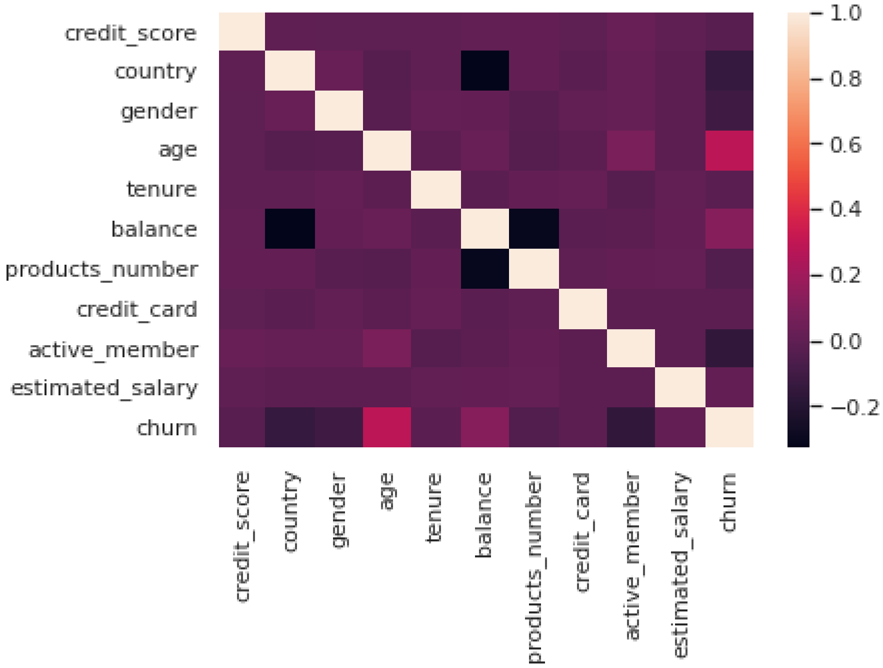
df2 = df.drop('customer_id', axis=1)

df2.head()

	credit_score	country	gender	age	tenure	balance	products_number	credit_card	active_member	estimated_salary	churn
0	619	1	0	42	2	0.00	1	1	1	101348.88	1
1	608	2	0	41	1	83807.86	1	0	1	112542.58	0
2	502	1	0	42	8	159660.80	3	1	0	113931.57	1
3	699	1	0	39	1	0.00	2	0	0	93826.63	0
4	850	2	0	43	2	125510.82	1	1	1	79084.10	0

sns.heatmap(df2.corr(), fmt='.2g')

<matplotlib.axes._subplots.AxesSubplot at 0x7f8bfc3bfa10>



Build Machine Learning Model:

X = df2.drop('churn', axis=1)

y = df2['churn']

#test size 20% and train size 80%

from sklearn.model_selection import train_test_split, cross_val_score, cross_val_predict

from sklearn.metrics import accuracy_score

X_train, X_test, y_train, y_test = train_test_split(X,y, test_size=0.2,random_state=7)

Decision Tree:

from sklearn.tree import DecisionTreeClassifier

dtree = DecisionTreeClassifier()

dtree.fit(X_train, y_train)

y_pred = dtree.predict(X_test)

```
print("Accuracy Score :", accuracy_score(y_test, y_pred)*100, "%")
```

```
Accuracy Score : 79.0 %
```

Random Forest:

```
from sklearn.ensemble import RandomForestClassifier
rfc = RandomForestClassifier()
rfc.fit(X_train, y_train)
y_pred = rfc.predict(X_test)
print("Accuracy Score :", accuracy_score(y_test, y_pred)*100, "%")
```

```
Accuracy Score : 86.85000000000001 %
```

Support Vector Machine:

```
from sklearn import svm
svm = svm.SVC()
svm.fit(X_train, y_train)
y_pred = svm.predict(X_test)
print("Accuracy Score :", accuracy_score(y_test, y_pred)*100, "%")
```

```
Accuracy Score : 79.45 %
```

XGBoost:

```
from xgboost import XGBClassifier
xgb_model = XGBClassifier()
xgb_model.fit(X_train, y_train)
y_pred = xgb_model.predict(X_test)
print("Accuracy Score :", accuracy_score(y_test, y_pred)*100, "%")
```

```
Accuracy Score : 86.45 %
```

Visualize Random Forest and XGBoost Algorithm because Random Forest and XGBoost Algorithm have the Best Accuracy:

```
#importing classification report and confusion matrix from sklearn
```

from sklearn.metrics import classification_report, confusion_matrix

Random Forest:

y_pred = rfc.predict(X_test)

print("Classification report - n", classification_report(y_test,y_pred))

```
Classification report -
              precision    recall  f1-score   support

           0       0.88      0.97      0.92      1589
           1       0.80      0.48      0.60       411

    accuracy                           0.87      2000
   macro avg       0.84      0.72      0.76      2000
weighted avg       0.86      0.87      0.86      2000
```

cm = confusion_matrix(y_test, y_pred)

plt.figure(figsize=(5,5))

sns.heatmap(data=cm,linewidths=.5, annot=True,square = True, cmap = 'Blues')

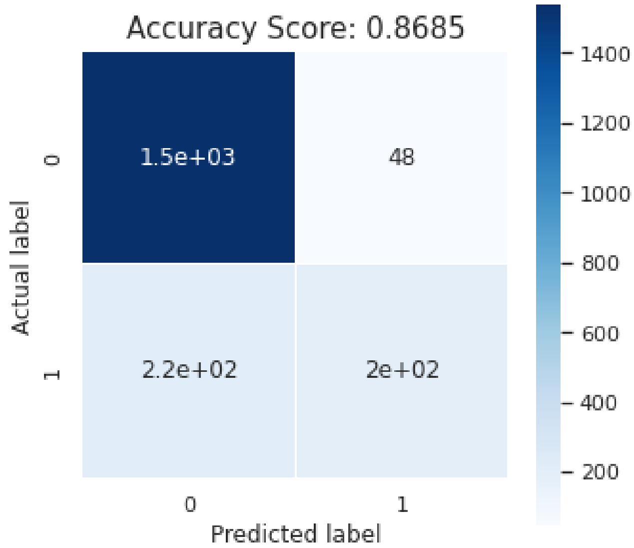
plt.ylabel('Actual label')

plt.xlabel('Predicted label')

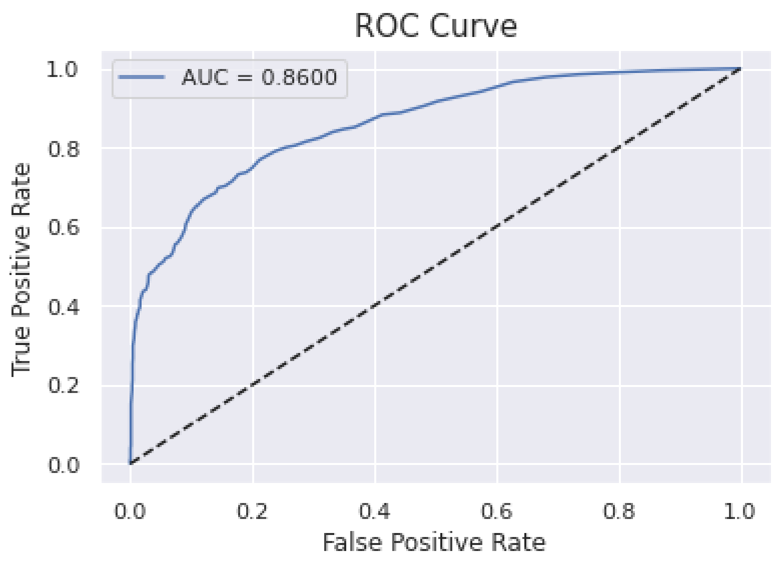
all_sample_title = 'Accuracy Score: {0}'.format(rfc.score(X_test, y_test))

plt.title(all_sample_title, size = 15)

```
Text(0.5, 1.0, 'Accuracy Score: 0.8685')
```




```
from sklearn.metrics import roc_curve, roc_auc_score
y_pred_proba = rfc.predict_proba(X_test)[:][:,1]
df_actual_predicted = pd.concat([pd.DataFrame(np.array(y_test),
columns=['y_actual']), pd.DataFrame(y_pred_proba,
columns=['y_pred_proba'])], axis=1)
df_actual_predicted.index = y_test.index
fpr, tpr, tr = roc_curve(df_actual_predicted['y_actual'],
df_actual_predicted['y_pred_proba'])
auc = roc_auc_score(df_actual_predicted['y_actual'],
df_actual_predicted['y_pred_proba'])
plt.plot(fpr, tpr, label='AUC = %0.4f' %auc)
plt.plot(fpr, fpr, linestyle = '--', color='k')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve', size = 15)
plt.legend()
```



XGBoost:

y_pred = xgb_model.predict(X_test)

print("Classification report - n", classification_report(y_test,y_pred))

```
Classification report -
               precision    recall  f1-score   support

           0       0.87      0.97      0.92      1589
           1       0.80      0.46      0.58       411

    accuracy                           0.86      2000
   macro avg       0.84      0.71      0.75      2000
weighted avg       0.86      0.86      0.85      2000
```

cm = confusion_matrix(y_test, y_pred)

plt.figure(figsize=(5,5))

sns.heatmap(data=cm,linewidths=.5, annot=True,square = True, cmap = 'Blues')

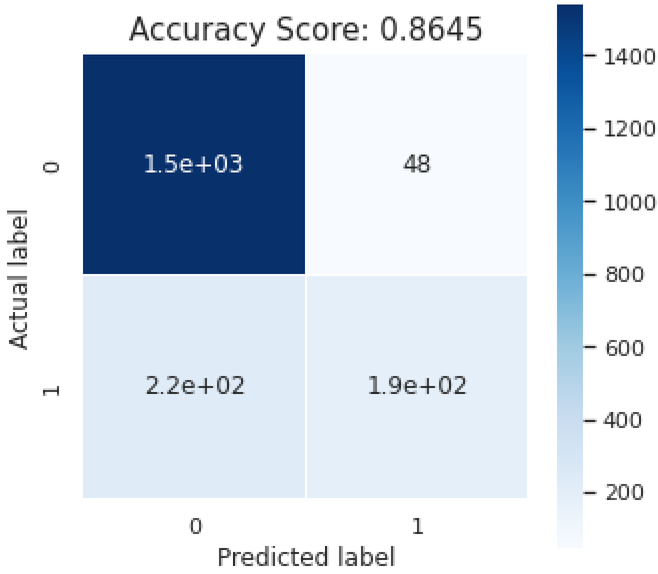
plt.ylabel('Actual label')

plt.xlabel('Predicted label')

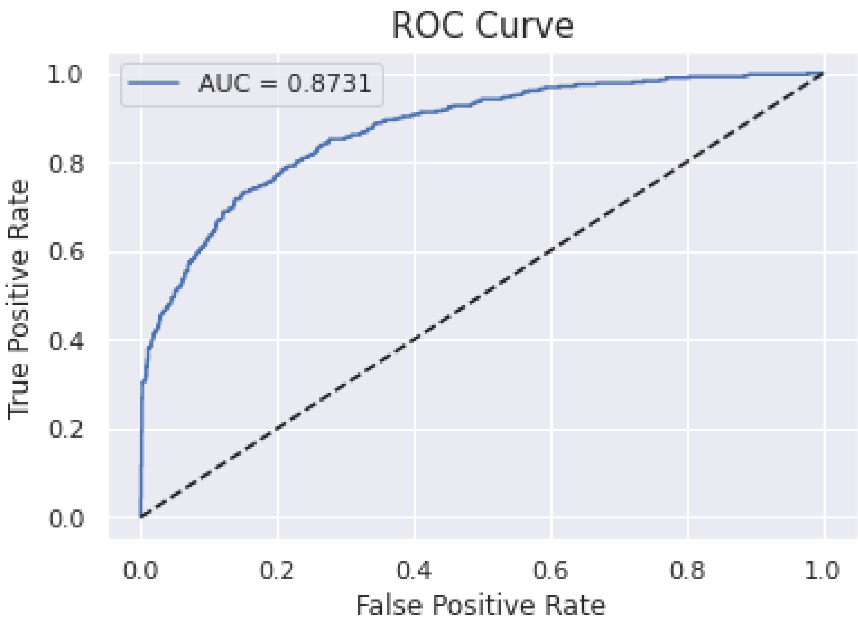
all_sample_title = 'Accuracy Score: {0}'.format(xgb_model.score(X_test, y_test))

plt.title(all_sample_title, size = 15)

```
Text(0.5, 1.0, 'Accuracy Score: 0.8645')
```




```
from sklearn.metrics import roc_curve, roc_auc_score
y_pred_proba = xgb_model.predict_proba(X_test)[:][:,1]
df_actual_predicted = pd.concat([pd.DataFrame(np.array(y_test),
columns=['y_actual']), pd.DataFrame(y_pred_proba,
columns=['y_pred_proba'])], axis=1)
df_actual_predicted.index = y_test.index
fpr, tpr, tr = roc_curve(df_actual_predicted['y_actual'],
df_actual_predicted['y_pred_proba'])
auc = roc_auc_score(df_actual_predicted['y_actual'],
df_actual_predicted['y_pred_proba'])
plt.plot(fpr, tpr, label='AUC = %0.4f' %auc)
plt.plot(fpr, fpr, linestyle = '--', color='k')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve', size = 15)
plt.legend()
```




```
# Descriptive statistics of the data set
df.describe([0.05,0.25,0.50,0.75,0.90,0.95,0.99])
```

Out[6]:

	CustomerId	CreditScore	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
count	1.000000e+04	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000	10000.00000	10000.000000	10000.000000	10000.000000
mean	1.569094e+07	650.528800	38.921800	5.012800	76485.889288	1.530200	0.70550	0.515100	100090.239881	0.203700
std	7.193619e+04	96.653299	10.487806	2.892174	62397.405202	0.581654	0.45584	0.499797	57510.492818	0.402769
min	1.556570e+07	350.000000	18.000000	0.000000	0.000000	1.000000	0.00000	0.000000	11.580000	0.000000
5%	1.557882e+07	489.000000	25.000000	1.000000	0.000000	1.000000	0.00000	0.000000	9851.818500	0.000000
25%	1.562853e+07	584.000000	32.000000	3.000000	0.000000	1.000000	0.00000	0.000000	51002.110000	0.000000

	CustomerId	CreditScore	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
50%	1.569074e+07	652.000000	37.000000	5.000000	97198.540000	1.000000	1.00000	1.000000	100193.915000	0.000000
75%	1.575323e+07	718.000000	44.000000	7.000000	127644.240000	2.000000	1.00000	1.000000	149388.247500	0.000000
90%	1.579083e+07	778.000000	53.000000	9.000000	149244.792000	2.000000	1.00000	1.000000	179674.704000	1.000000
95%	1.580303e+07	812.000000	60.000000	9.000000	162711.669000	2.000000	1.00000	1.000000	190155.375500	1.000000
99%	1.581311e+07	850.000000	72.000000	10.000000	185967.985400	3.000000	1.00000	1.000000	198069.734500	1.000000
max	1.581569e+07	850.000000	92.000000	10.000000	250898.090000	4.000000				

```
# categorical Variables
categorical_variables = [col for col in df.columns if col in "O"
                        or df[col].nunique() <=11
                        and col not in "Exited"]

categorical_variables
```

Out[7]:

```
['Geography',
 'Gender',
 'Tenure',
 'NumOfProducts',
 'HasCrCard',
 'IsActiveMember']
```

In [8]:

```
# Numeric Variables
numeric_variables = [col for col in df.columns if df[col].dtype != "object"
                        and df[col].nunique() >11
                        and col not in "CustomerId"]
numeric_variables
```

Out[8]:

```
['CreditScore', 'Age', 'Balance', 'EstimatedSalary']
```

Exited (Dependent Variable)

In [9]:

```
# Frequency of classes of dependent variable
df["Exited"].value_counts()
```

Out[9]:

```
0    7963
1    2037
Name: Exited, dtype: int64
```

In [10]:

```
# Customers leaving the bank
churn = df.loc[df["Exited"]==1]
```

In [11]:

```
# Customers who did not leave the bank
not_churn = df.loc[df["Exited"]==0]
```

Categorical Variables

Tenure

In [12]:

```
# Frequency of not_churn group according to Tenure
not_churn["Tenure"].value_counts().sort_values()
```

Out[12]:

```
0     318
10    389
6     771
9     771
4     786
3     796
5     803
1     803
8     828
2     847
7     851
Name: Tenure, dtype: int64
```

In [13]:

```
# Frequency of churn group according to Tenure
churn["Tenure"].value_counts().sort_values()
```

Out[13]:

```
0      95
10    101
7     177
6     196
8     197
2     201
4     203
5     209
9     213
```

```
3     213
1     232
Name: Tenure, dtype: int64
```

NumOfProducts

In [14]:

```
# Frequency of not_churn group according to NumOfProducts
not_churn["NumOfProducts"].value_counts().sort_values()
```

Out[14]:

```
3      46
1    3675
2    4242
Name: NumOfProducts, dtype: int64
```

In [15]:

```
# Frequency of churn group according to NumOfProducts
churn["NumOfProducts"].value_counts().sort_values()
```

Out[15]:

```
4      60
3     220
2     348
1    1409
Name: NumOfProducts, dtype: int64
```

HasCrCard

In [16]:

```
# examining the HasCrCard of the not_churn group
not_churn["HasCrCard"].value_counts()
```

Out[16]:

```
1    5631
0    2332
Name: HasCrCard, dtype: int64
```

In [17]:

```
# examining the HasCrCard of the churn group
churn["HasCrCard"].value_counts()
```

Out[17]:

```
1    1424
0     613
Name: HasCrCard, dtype: int64
```

IsActiveMember

In [18]:

```
# examining the IsActiveMember of the not_churn group
not_churn["IsActiveMember"].value_counts()
```

Out[18]:

```
1    4416
0    3547
Name: IsActiveMember, dtype: int64
```

In [19]:

```
# examining the IsActiveMember of the churn group
churn["IsActiveMember"].value_counts()
```

Out[19]:

```
0    1302
1     735
Name: IsActiveMember, dtype: int64
```

Geography

In [20]:

```
# Frequency of not_churn group according to Geography
not_churn.Geography.value_counts().sort_values()
```

Out[20]:

```
Germany    1695
Spain      2064
France     4204
Name: Geography, dtype: int64
```

In [21]:

```
# Frequency of churn group according to Geography
churn.Geography.value_counts().sort_values()
```

#Reference dataset: https://www.kaggle.com/datasets/gauravtopre/bank-customer-churn-dataset

Conclusion:

Developing a Machine Learning Model is a complex process, but it is essential for building and deploying successful machine-learning applications. By following the steps outlined in this blog, you can increase your chances of success.