

## ▼ 1- Reading the Data

```
# Primary libraries

from google.colab import drive
drive.mount('/content/drive/')

↳ Drive already mounted at /content/drive/; to attempt to forcibly remount, call drive.mou

# regular EDA and ML libraries

import numpy as np
import pandas as pd

import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline

from sklearn.model_selection import train_test_split
from sklearn import preprocessing
from sklearn.metrics import accuracy_score, confusion_matrix, precision_score, recall_score,
                           f1_score, classification_report, roc_auc_score, roc_curve, auc

# loading the dataframe

file_path = '/content/drive/My Drive/NN/project/bank.csv'
df = pd.read_csv(file_path)

# Shape,size,datatype,null values

df.shape

↳ (10000, 14)

df.info()

# Problematic columns of type 'object' :      Surname, Geography, Gender    --> to change into t

# Noise columns : RowNumber , CustomerID
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 14 columns):
 #   Column           Non-Null Count  Dtype  
--- 
 0   RowNumber        10000 non-null   int64  
 1   CustomerId       10000 non-null   int64  
 2   Surname          10000 non-null   object  
 3   CreditScore      10000 non-null   int64  
 4   Geography         10000 non-null   object  
 5   Gender            10000 non-null   object  
 6   Age               10000 non-null   int64  
 7   Tenure            10000 non-null   int64  
 8   Balance           10000 non-null   float64 
 9   NumOfProducts     10000 non-null   int64  
 10  HasCrCard        10000 non-null   int64  
 11  IsActiveMember    10000 non-null   int64  
 12  EstimatedSalary   10000 non-null   float64 
 13  Exited            10000 non-null   int64  
dtypes: float64(2), int64(9), object(3)
memory usage: 1.1+ MB
```

```
df.isna().sum()
# no missing values
```

```
↳ RowNumber      0
CustomerId      0
Surname        0
CreditScore     0
Geography       0
Gender          0
Age             0
Tenure          0
Balance         0
NumOfProducts   0
HasCrCard       0
IsActiveMember  0
EstimatedSalary 0
Exited          0
dtype: int64
```

```
#checking the numerical columns' Descriptive statistics
```

```
df.describe().transpose()
```

```
# skewness can be seen ( mean > median ) for some attributes and normalisation should be imp
```

```
↳
```

	<b>count</b>	<b>mean</b>	<b>std</b>	<b>min</b>	<b>25%</b>	<b>50%</b>
<b>RowNumber</b>	10000.0	5.000500e+03	2886.895680	1.00	2500.75	5.000500e+03
<b>CustomerId</b>	10000.0	1.569094e+07	71936.186123	15565701.00	15628528.25	1.569074e+07
<b>CreditScore</b>	10000.0	6.505288e+02	96.653299	350.00	584.00	6.520000e+02
<b>Age</b>	10000.0	3.892180e+01	10.487806	18.00	32.00	3.700000e+01
<b>Tenure</b>	10000.0	5.012800e+00	2.892174	0.00	3.00	5.000000e+00
<b>Balance</b>	10000.0	7.648589e+04	62397.405202	0.00	0.00	9.719854e+04
<b>NumOfProducts</b>	10000.0	1.530200e+00	0.581654	1.00	1.00	1.000000e+00
<b>HasCrCard</b>	10000.0	7.055000e-01	0.455840	0.00	0.00	1.000000e+00
<b>IsActiveMember</b>	10000.0	5.151000e-01	0.499797	0.00	0.00	1.000000e+00
<b>EstimatedSalary</b>	10000.0	1.000902e+05	57510.492818	11.58	51002.11	1.001939e+05
<b>Exited</b>	10000.0	2.037000e-01	0.402769	0.00	0.00	0.000000e+00

```
df.head()
```

↪	<b>RowNumber</b>	<b>CustomerId</b>	<b>Surname</b>	<b>CreditScore</b>	<b>Geography</b>	<b>Gender</b>	<b>Age</b>	<b>Tenure</b>	<b>Balance</b>
0	1	15634602	Hargrave	619	France	Female	42	2	0.00
1	2	15647311	Hill	608	Spain	Female	41	1	83807.86
2	3	15619304	Onio	502	France	Female	42	8	159660.80
3	4	15701354	Boni	699	France	Female	39	1	0.00
4	5	15737888	Mitchell	850	Spain	Female	43	2	125510.82

## ▼ 2- Dropping and casting columns

```
df = df.drop(["RowNumber", "CustomerId", "Surname"] , axis=1)
```

```
df.head()
```

↪	<b>CreditScore</b>	<b>Geography</b>	<b>Gender</b>	<b>Age</b>	<b>Tenure</b>	<b>Balance</b>	<b>NumOfProducts</b>	<b>HasCrCard</b>	<b>IsActi</b>
0	619	France	Female	42	2	0.00		1	1
1	608	Spain	Female	41	1	83807.86		1	0
2	502	France	Female	42	8	159660.80		3	1
3	699	France	Female	39	1	0.00		2	0
4	850	Spain	Female	43	2	125510.82		1	1

```
df.Geography.value_counts()
```

```
↪
```

```
df.info()

[> <class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 11 columns):
 #   Column            Non-Null Count  Dtype  
--- 
 0   CreditScore       10000 non-null   int64  
 1   Geography         10000 non-null   object  
 2   Gender             10000 non-null   object  
 3   Age                10000 non-null   int64  
 4   Tenure             10000 non-null   int64  
 5   Balance            10000 non-null   float64 
 6   NumOfProducts      10000 non-null   int64  
 7   HasCrCard          10000 non-null   int64  
 8   IsActiveMember     10000 non-null   int64  
 9   EstimatedSalary    10000 non-null   float64 
 10  Exited             10000 non-null   int64  
dtypes: float64(2), int64(7), object(2)
memory usage: 859.5+ KB
```

```
df['Geography'] = df['Geography'].astype('string')
```

```
df['Gender'] = df['Gender'].astype('string')
```

```
df.info()
```

```
[> <class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 11 columns):
 #   Column            Non-Null Count  Dtype  
--- 
 0   CreditScore       10000 non-null   int64  
 1   Geography         10000 non-null   string  
 2   Gender             10000 non-null   string  
 3   Age                10000 non-null   int64  
 4   Tenure             10000 non-null   int64  
 5   Balance            10000 non-null   float64 
 6   NumOfProducts      10000 non-null   int64  
 7   HasCrCard          10000 non-null   int64  
 8   IsActiveMember     10000 non-null   int64  
 9   EstimatedSalary    10000 non-null   float64 
 10  Exited             10000 non-null   int64  
dtypes: float64(2), int64(7), string(2)
memory usage: 859.5 KB
```

```
# Creating Dummy variables for 'Geography' and 'Gender'
```

```
df= pd.get_dummies(df,columns=['Geography','Gender'])
```

```
df.head()
```

```
[>
```

	CreditScore	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	Estimate
0	619	42	2	0.00		1	1	1
1	608	41	1	83807.86		1	0	1
2	502	42	8	159660.80		3	1	0
3	699	39	1	0.00		2	0	0
4	850	43	2	125510.82		1	1	1

## ▼ 3- Features X and Target y

```
x = df.drop(columns='Exited')
```

```
x.shape
```

```
↪ (10000, 13)
```

```
y=df['Exited']
```

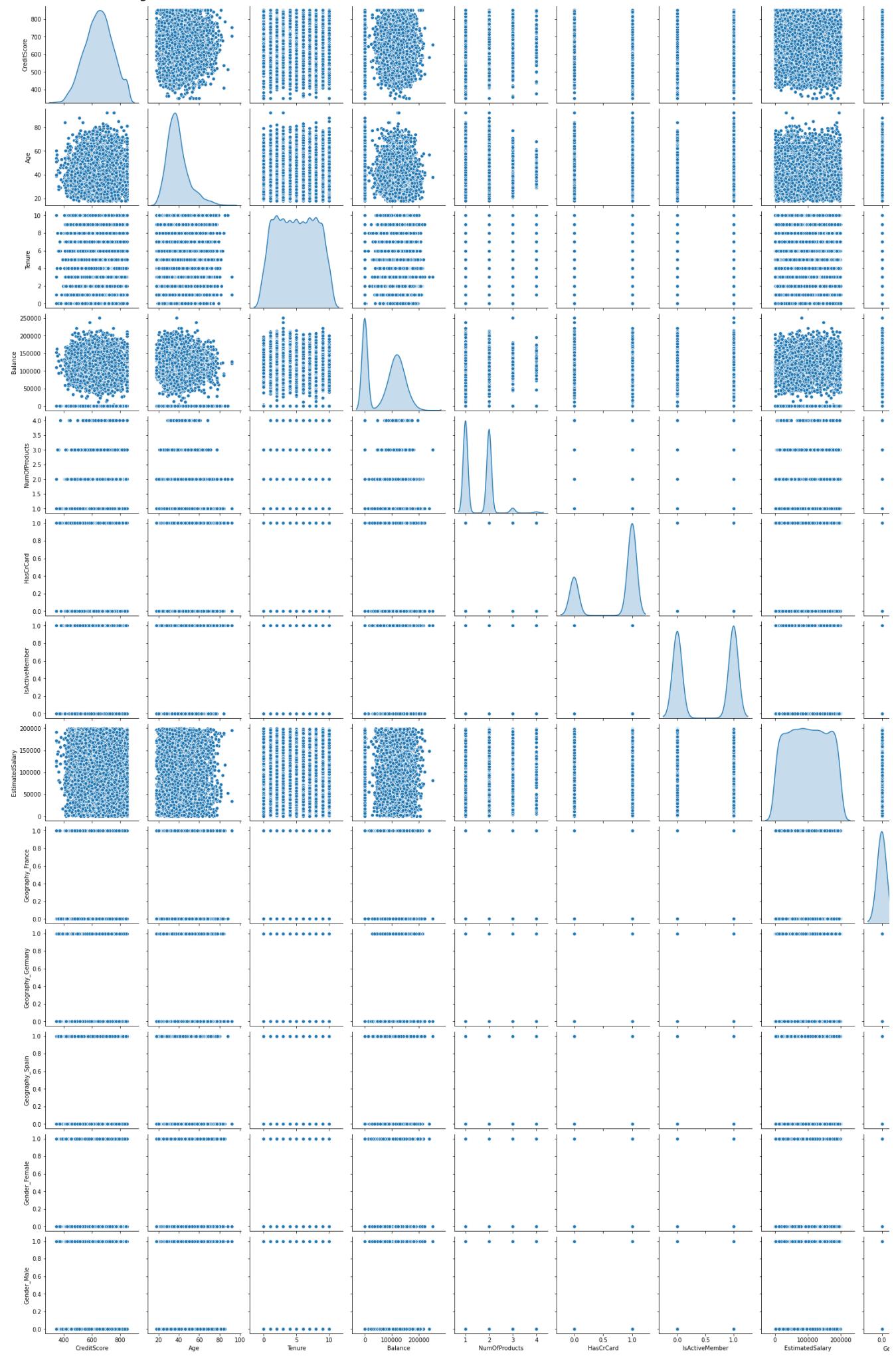
```
y.shape
```

```
↪ (10000,)
```

```
sns.pairplot(x ,diag_kind='kde')
```

```
↪
```

<seaborn.axisgrid.PairGrid at 0x7fedab2a2a90>



## ▼ 4- Train and test split

```
(X_train, X_test, y_train, y_test)= train_test_split(X, y, test_size=0.30, random_state=1)

X_train.shape
⇒ (7000, 13)

X_test.shape
⇒ (3000, 13)
```

## ▼ 5-Normalisation of X\_train and X\_test

```
from sklearn.preprocessing import StandardScaler

X_train = preprocessing.normalize(X_train)
X_test = preprocessing.normalize(X_test)
```

## ▼ 6.1- NN Model\_A

```
# Tf libraries

import tensorflow as tf

from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense

from tensorflow.keras import optimizers

# empty shell
model_A = Sequential()

# adding the layers
model_A.add(Dense(13, input_shape = (13,), activation = 'relu'))
model_A.add(Dense(16, activation = 'tanh'))
model_A.add(Dense(1, activation = 'sigmoid'))

# Optimiser and loss function
sgd = optimizers.Adam(lr = 0.001)
model_A.compile(optimizer = sgd, loss = 'binary_crossentropy', metrics=['accuracy'])

model_A.summary()
```

```
↳ Model: "sequential"
```

Layer (type)	Output Shape	Param #
<hr/>		
dense (Dense)	(None, 13)	182
dense_1 (Dense)	(None, 16)	224
dense_2 (Dense)	(None, 1)	17
<hr/>		
Total params:	423	
Trainable params:	423	
Non-trainable params:	0	

```
model_A.fit(X_train, y_train.values, batch_size = 500, epochs = 10, verbose = 1)  
# Accuracy for Model_1--> 0.7986
```

```
↳ Epoch 1/10
```

```
14/14 [=====] - 0s 2ms/step - loss: 0.7416 - accuracy: 0.2064  
Epoch 2/10  
14/14 [=====] - 0s 2ms/step - loss: 0.6843 - accuracy: 0.6159  
Epoch 3/10  
14/14 [=====] - 0s 2ms/step - loss: 0.6363 - accuracy: 0.7986  
Epoch 4/10  
14/14 [=====] - 0s 2ms/step - loss: 0.5952 - accuracy: 0.7986  
Epoch 5/10  
14/14 [=====] - 0s 2ms/step - loss: 0.5593 - accuracy: 0.7986  
Epoch 6/10  
14/14 [=====] - 0s 2ms/step - loss: 0.5323 - accuracy: 0.7986  
Epoch 7/10  
14/14 [=====] - 0s 2ms/step - loss: 0.5148 - accuracy: 0.7986  
Epoch 8/10  
14/14 [=====] - 0s 2ms/step - loss: 0.5073 - accuracy: 0.7986  
Epoch 9/10  
14/14 [=====] - 0s 2ms/step - loss: 0.5042 - accuracy: 0.7986  
Epoch 10/10  
14/14 [=====] - 0s 2ms/step - loss: 0.5022 - accuracy: 0.7986  
<tensorflow.python.keras.callbacks.History at 0x7fed08073e48>
```

## ▼ 6.2- NN Model\_B

```
# An extra dense layer with more nodes and smaller lr ---> same end accuracy as before but w:  
model_B = Sequential()  
  
model_B.add(Dense(32, input_shape = (13,), activation = 'relu'))  
model_B.add(Dense(64, activation = 'relu'))  
model_B.add(Dense(16, activation = 'relu'))  
model_B.add(Dense(1, activation = 'sigmoid'))  
  
sgd = optimizers.Adam(lr = 0.001)  
model_B.compile(optimizer = sgd, loss = 'binary_crossentropy', metrics=['accuracy'])  
model_B.summary()  
  
model_B.fit(X_train, y_train.values, batch_size = 500, epochs = 10, verbose = 1)
```

↳ Model: "sequential\_1"

Layer (type)	Output Shape	Param #
dense_3 (Dense)	(None, 32)	448
dense_4 (Dense)	(None, 64)	2112
dense_5 (Dense)	(None, 16)	1040
dense_6 (Dense)	(None, 1)	17
=====		
Total params: 3,617		
Trainable params: 3,617		
Non-trainable params: 0		

```
Epoch 1/10
14/14 [=====] - 0s 3ms/step - loss: 0.6406 - accuracy: 0.7714
Epoch 2/10
14/14 [=====] - 0s 2ms/step - loss: 0.5650 - accuracy: 0.7986
Epoch 3/10
14/14 [=====] - 0s 2ms/step - loss: 0.5170 - accuracy: 0.7986
Epoch 4/10
14/14 [=====] - 0s 2ms/step - loss: 0.5039 - accuracy: 0.7986
Epoch 5/10
14/14 [=====] - 0s 2ms/step - loss: 0.5005 - accuracy: 0.7986
Epoch 6/10
14/14 [=====] - 0s 2ms/step - loss: 0.4979 - accuracy: 0.7986
Epoch 7/10
14/14 [=====] - 0s 2ms/step - loss: 0.4965 - accuracy: 0.7986
Epoch 8/10
14/14 [=====] - 0s 2ms/step - loss: 0.4957 - accuracy: 0.7986
Epoch 9/10
14/14 [=====] - 0s 2ms/step - loss: 0.4952 - accuracy: 0.7986
Epoch 10/10
14/14 [=====] - 0s 2ms/step - loss: 0.4950 - accuracy: 0.7986
<tensorflow.python.keras.callbacks.History at 0x7fecf1653128>
```

## ▼ 6.3- NN Model\_C

```
model_C = Sequential()

model_C.add(Dense(13, input_shape = (13,), activation = 'relu'))
model_C.add(Dense(32, activation = 'relu'))
model_C.add(Dense(16, activation = 'tanh'))
model_C.add(Dense(1, activation = 'sigmoid'))

sgd = optimizers.Adam(lr = 0.01)
model_C.compile(optimizer = sgd, loss = 'binary_crossentropy', metrics=['accuracy'])
model_C.summary()

model_C.fit(X_train, y_train.values, batch_size = 500, epochs = 10, verbose = 1)
```

↳

```
Model: "sequential_2"
```

Layer (type)	Output Shape	Param #
<hr/>		
dense_7 (Dense)	(None, 13)	182
dense_8 (Dense)	(None, 32)	448
dense_9 (Dense)	(None, 16)	528
dense_10 (Dense)	(None, 1)	17
<hr/>		
Total params: 1,175		
Trainable params: 1,175		
Non-trainable params: 0		

```
Epoch 1/10  
14/14 [=====] - 0s 2ms/step - loss: 0.5321 - accuracy: 0.7884  
Epoch 2/10  
14/14 [=====] - 0s 2ms/step - loss: 0.5002 - accuracy: 0.7986  
Epoch 3/10  
14/14 [=====] - 0s 2ms/step - loss: 0.4963 - accuracy: 0.7986  
Epoch 4/10  
14/14 [=====] - 0s 2ms/step - loss: 0.4946 - accuracy: 0.7986  
Epoch 5/10  
14/14 [=====] - 0s 2ms/step - loss: 0.4942 - accuracy: 0.7986  
Epoch 6/10  
14/14 [=====] - 0s 2ms/step - loss: 0.4947 - accuracy: 0.7986  
Epoch 7/10  
14/14 [=====] - 0s 2ms/step - loss: 0.4942 - accuracy: 0.7986  
Epoch 8/10  
14/14 [=====] - 0s 2ms/step - loss: 0.4950 - accuracy: 0.7986  
Epoch 9/10  
14/14 [=====] - 0s 2ms/step - loss: 0.4945 - accuracy: 0.7986  
Epoch 10/10  
14/14 [=====] - 0s 2ms/step - loss: 0.4940 - accuracy: 0.7986  
<tensorflow.python.keras.callbacks.History at 0x7fecf15557b8>
```

the Accuracy seems stalled at at 80% --- let's try all three Model s for evaluation.

## ▼ 7- Prediction using X\_test and y\_test

```
results = model_A.evaluate(X_test, y_test.values)
```

```
↳ 94/94 [=====] - 0s 2ms/step - loss: 0.5115 - accuracy: 0.7910
```

```
results = model_B.evaluate(X_test, y_test.values)
```

```
↳ 94/94 [=====] - 0s 2ms/step - loss: 0.5079 - accuracy: 0.7910
```

```
results = model_C.evaluate(X_test, y_test.values)
```

```
↳ 94/94 [=====] - 0s 1ms/step - loss: 0.5074 - accuracy: 0.7910
```

```
# All same results : but Model_A is simpler on resources.
```

## ▼ 8- Confusion matrix

```
from sklearn.metrics import accuracy_score, confusion_matrix, precision_score, recall_score,  
  
y_pred = model_A.predict_classes(X_test, batch_size=200, verbose=0)  
  
print('Accuracy Model (Dropout):'+ str(model_A.evaluate(X_test,y_test.values)[1]))  
print('Recall_score: ' + str(recall_score(y_test.values,y_pred)))  
print('Precision_score: ' + str(precision_score(y_test.values, y_pred)))  
print('F-score: ' + str(f1_score(y_test.values,y_pred)))  
confusion_matrix(y_test.values, y_pred)  
  
[→ 94/94 [=====] - 0s 2ms/step - loss: 0.5115 - accuracy: 0.7910  
Accuracy Model (Dropout):0.7910000085830688  
Recall_score: 0.0  
Precision_score: 0.0  
F-score: 0.0  
/usr/local/lib/python3.6/dist-packages/sklearn/metrics/_classification.py:1272: Undefined  
_warn_prf(average, modifier, msg_start, len(result))  
array([[2373,      0],  
       [ 627,      0]])
```

Conclusion : Not my best project . Still lost on how to decide the number of layers and neurones and activation

It seems we are just correctly predicting around 80% of the clients that decide to leave the bank or not . Better it can improve with further elaboaration and engineering of the layering ... something that needs further study

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