Thomas Nowakowski

In [1]:

```
# !pip install tensorflow==2.0.0
import tensorflow as tf
```

In [2]:

```
print(tf.__version__) # 2 underlines are required on each side for this to work
```

```
2.2.0
```

In [3]:

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

%matplotlib inline
sns.set(color_codes=True)

from sklearn.model_selection import train_test_split
from sklearn import preprocessing
from sklearn.metrics import accuracy_score, confusion_matrix,precision_score, recall_sc
ore
from sklearn.metrics import f1_score,precision_recall_curve,auc

from tensorflow import keras
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout, BatchNormalization
from tensorflow.keras import optimizers
```

In [5]:

```
df=pd.read_csv('bank.csv')
```

EDA

General look at head of data, type of content per column, data type per column

1. Check for missing values
2. Remove columns that do not add value to prediction
3. Outlayer treatment

In [6]:

```
display (df.head())
print ( 'The number of rows is', df.shape[0])
print ( 'The number of columns is', df.shape[1])
display(df.count())
print (' Are there missing values ?',df.isnull().values.any())
```

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Bal
0	1	15634602	Hargrave	619	France	Female	42	2	
1	2	15647311	Hill	608	Spain	Female	41	1	8380
2	3	15619304	Onio	502	France	Female	42	8	15966
3	4	15701354	Boni	699	France	Female	39	1	
4	5	15737888	Mitchell	850	Spain	Female	43	2	12551

```
The number of rows is 10000
The number of columns is 14

RowNumber          10000
CustomerId         10000
Surname            10000
CreditScore        10000
Geography          10000
Gender             10000
Age                10000
Tenure             10000
Balance            10000
NumOfProducts      10000
HasCrCard          10000
IsActiveMember     10000
EstimatedSalary    10000
Exited             10000
dtype: int64

 Are there missing values ? False
```

In [7]:

```
# Another test showing there are no missing values - per column  or apply  df.isna().su
m().sum()
df.count().isnull()
```

Out[7]:

```
RowNumber          False
CustomerId         False
Surname            False
CreditScore        False
Geography          False
Gender             False
Age                False
Tenure             False
Balance            False
NumOfProducts      False
HasCrCard          False
IsActiveMember     False
EstimatedSalary    False
Exited             False
dtype: bool
```

In [8]:

```
# further exploratory data analysis by checking for unique values  in each column
df.nunique()
```

Out[8]:

```
RowNumber          10000
CustomerId         10000
Surname             2932
CreditScore          460
Geography              3
Gender                 2
Age                   70
Tenure                11
Balance             6382
NumOfProducts          4
HasCrCard              2
IsActiveMember         2
EstimatedSalary     9999
Exited                 2
dtype: int64
```

In [9]:

```
#  any duplicates to clean data set ? If so apply #df.drop_duplicates(inplace=True)
df.duplicated().any()
```

Out[9]:

```
False
```

In [10]:

```
# check each column to understand its data type before we perform operations
# for example insuring that numbers are not stored as character strings
df.info()
```

```
<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
```

In [11]:

```
df.head(0)
```

Out[11]:

RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balanc

In [12]:

```
# DROP COLUMNS WHICH ARE UNIQUE FOR ALL CUSTOMERS AND ADD NO PREDICTIVE VALUE
df.drop('RowNumber', axis=1, inplace=True)
df.drop('CustomerId',axis=1, inplace=True)
df.drop('Surname', axis=1, inplace=True)
```

In [13]:

```
# check if columns have been dropped as expeted
df.head(5)
```

Out[13]:

	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	Is
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	

In [14]:

```
# Examine the data for skewness, outlayers, etc
display(df.describe().T)
```

	count	mean	std	min	25%	50%	
CreditScore	10000.0	650.528800	96.653299	350.00	584.00	652.000	718
Age	10000.0	38.921800	10.487806	18.00	32.00	37.000	44
Tenure	10000.0	5.012800	2.892174	0.00	3.00	5.000	7
Balance	10000.0	76485.889288	62397.405202	0.00	0.00	97198.540	127644
NumOfProducts	10000.0	1.530200	0.581654	1.00	1.00	1.000	2
HasCrCard	10000.0	0.705500	0.455840	0.00	0.00	1.000	1
IsActiveMember	10000.0	0.515100	0.499797	0.00	0.00	1.000	1
EstimatedSalary	10000.0	100090.239881	57510.492818	11.58	51002.11	100193.915	149388
Exited	10000.0	0.203700	0.402769	0.00	0.00	0.000	0

In [15]:

```
# data columns look well distributed.  Only EstimatedSalary has a minimum very  far fro
m mean and 25% 1st Quartile- an outlayer,
# but we will  check for outlayers by visual inspection = boxplots
```

In [16]:

```
# IDENTIFY THE FEATURES AND TARGET VARIABLE
# THE TARGET VARIABLE IS THE ONE THAT IDENTIFIES IF THE CLIENT WILL BE LEAVING THE BANK
IN THE NEXT 6 MONTHS !
# HENCE THE TARGET VARIABLE IS  THE  EXITED COLUMN
# THE REMAINING 8 COLUMNS ARE THE FEATURE COLUMNS
```

In [17]:

```
display(df.columns)
```

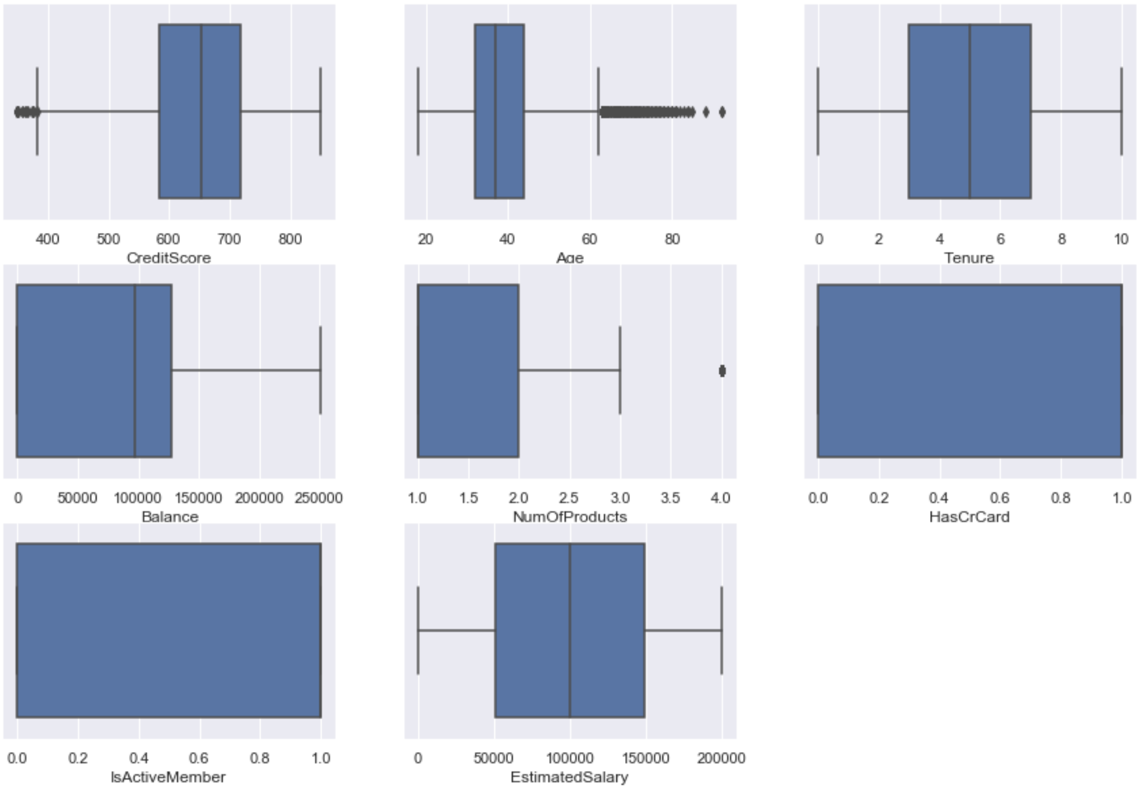
```
Index(['CreditScore', 'Geography', 'Gender', 'Age', 'Tenure', 'Balance',
       'NumOfProducts', 'HasCrCard', 'IsActiveMember', 'EstimatedSalary',
       'Exited'],
      dtype='object')
```

Outlayer Treatment Visualization Check

plt.figure(figsize=(15,10)) pos=1 for i in df.columns: plt.subplot(3,3,pos) sns.boxplot(df[i]) pos+=1

In [18]:

```
cols=['CreditScore','Age', 'Tenure', 'Balance', 'NumOfProducts', 'HasCrCard', 'IsActive
Member', 'EstimatedSalary']
# list of independent variables to be checked for outlayers

plt.figure(figsize=(15,10))
pos=1
for i in cols:
    plt.subplot(3,3,pos) #---TN: Needs to be updated based on the number of columns. If
we have more than 9 columns
    # we need to go to 4x3 grids in the plot aread. Can't have box plot for categorical
data
    sns.boxplot(df[i])
    pos+=1
```



In [19]:

```
# treatment of outlayers- use the 1.5 IQR
```

In [20]:

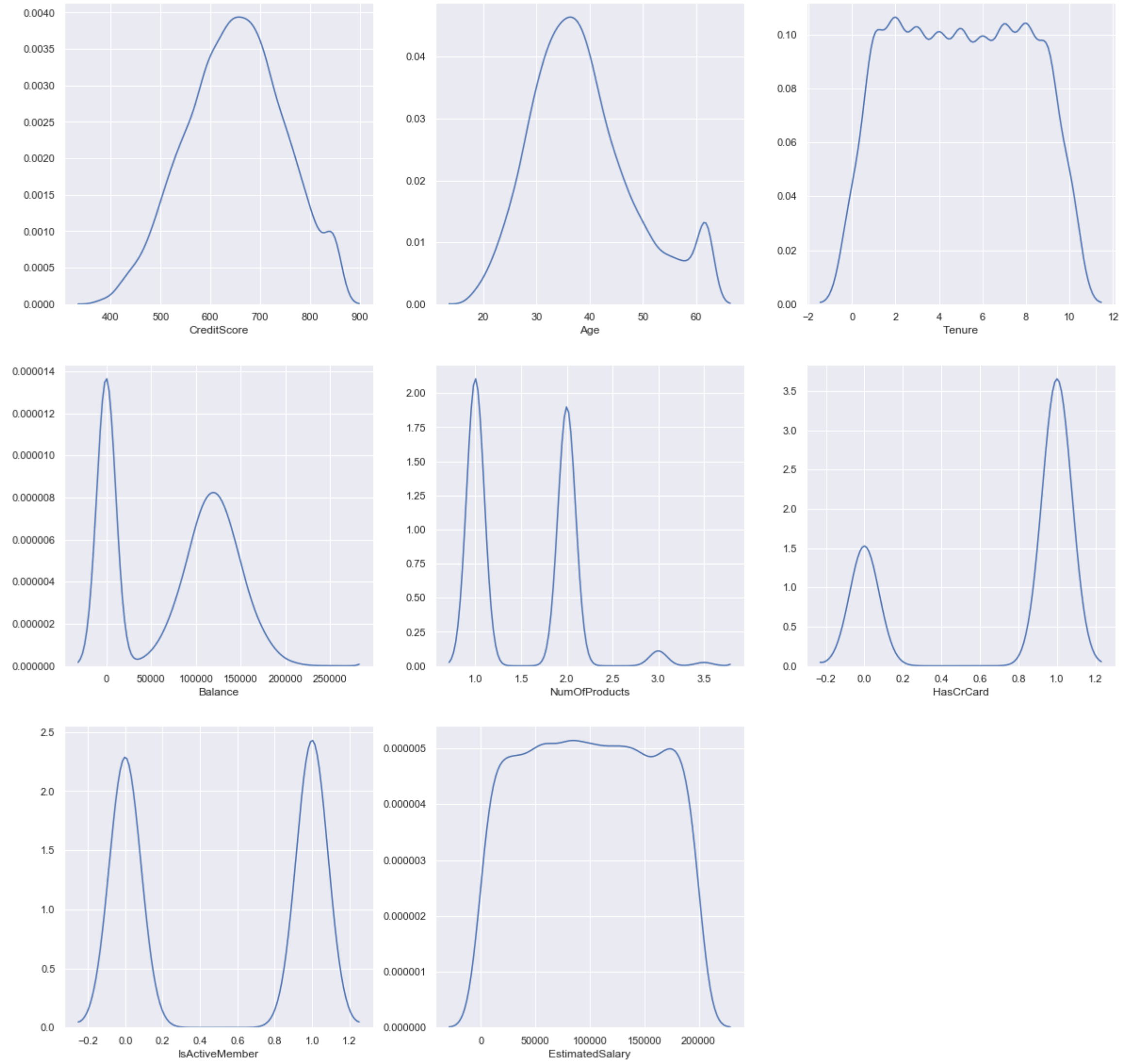
```
cols1=['CreditScore','Age', 'Tenure', 'Balance', 'EstimatedSalary']


for i in cols:
    q1,q2,q3=df[i].quantile([0.25,0.5,0.75])
    IQR=q3-q1
    upper_cap=q3+1.5*IQR
    lower_cap=q1-1.5*IQR
    df[i]=df[i].apply(lambda x: upper_cap if x>(upper_cap) else (lower_cap if x<(lower_
cap) else x))
```

In [21]:

```
# now that data has been corrected for outlayers perform  Univariate Analysis to see if
its still skewed
```

In [22]:

```
plt.figure(figsize=(20,20))
pos=1
for i in cols:
    plt.subplot(3,3,pos)
    sns.distplot(df[i], hist=False)
    pos+=1
```



In [23]:

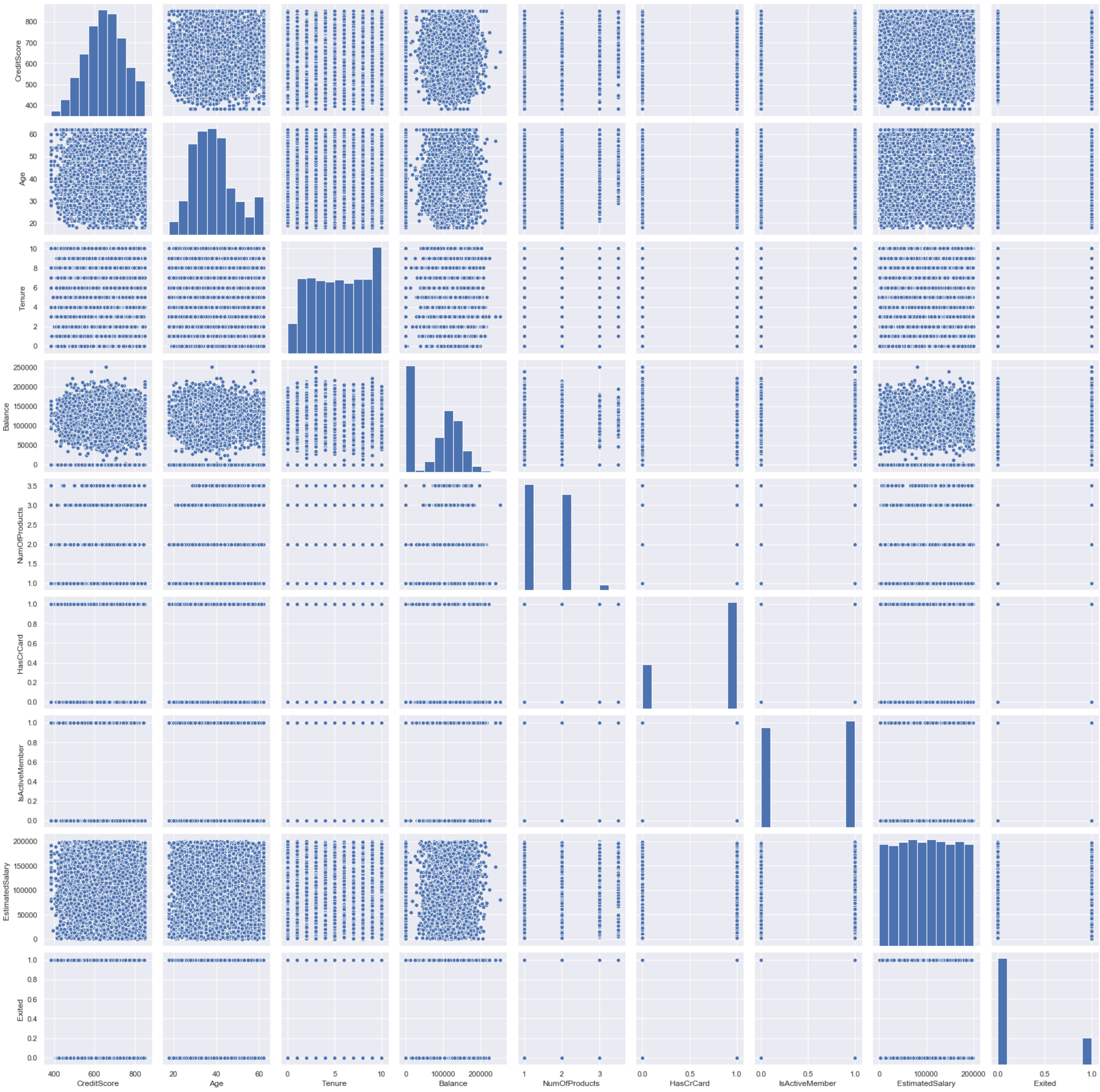
```
# UNIVARIATE ANALYSIS
# Credit score is a bit skewed, so is age- seems baby boomers,  probably due to demogra
phis are over 60 and quite a few of them
#  Balances, NumOfProducts and HasCrCard are - ideal canidates  for clustering, :) but
 we are doing supervised learning here so
# Balances - shows 2 peaks with most people having around zero money (students, unemplo
yed, retired) and quite a few have some
# money a second peak - the working class mid-aged people, which is refleted in Age and
may be correlated with Balances
```

In [24]:

```
# Bivariate Analysis
sns.pairplot(df)
```

Out[24]:

<seaborn.axisgrid.PairGrid at 0x24b9eae8d88>



In [25]:

```
# Bivariate Analysis
# the plots do not show linear correlation, seems like data displayed is independent fr
om one another
```

In [26]:

```
df.head(1)
```

Out[26]:

	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsA
0	619.0	France	Female	42.0	2	0.0	1.0	1	

In [27]:

```
# drop the dependent variable, we are checking for correlation for independent vars
df_ind=df.iloc[:,0:10]
df_ind.head(1)
```

Out[27]:

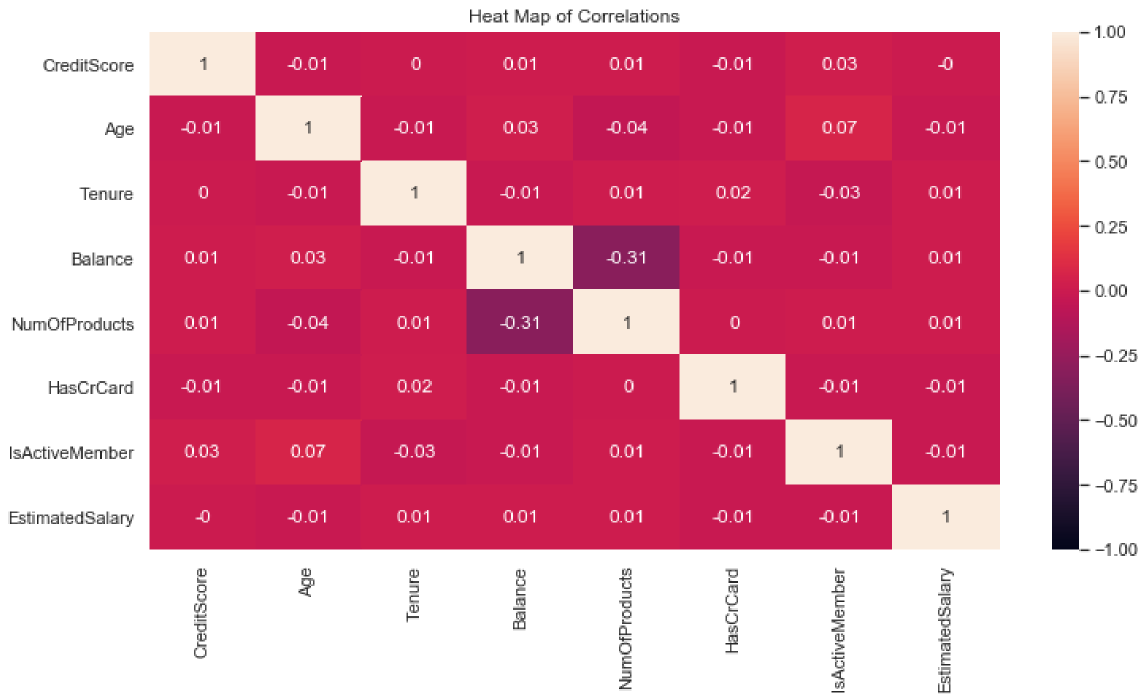
	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsA
0	619.0	France	Female	42.0	2	0.0	1.0	1	

In [28]:

```
# Check for Correlation in Independent Variables,  drop higly correlatied ones

corr_data=df_ind.corr().round(2);
fig, ax=plt.subplots()
fig.set_size_inches(12,6)

plt.title ("Heat Map of Correlations")
sns.heatmap(corr_data,annot=True,vmin=-1,vmax=1) # SOMEWHOW cmap='Y1GnBu' is not workin
g when  i add it here
```

Out[28]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x24ba3074048>
```



	CreditScore	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary
CreditScore	1	-0.01	0	0.01	0.01	-0.01	0.03	-0
Age	-0.01	1	-0.01	0.03	-0.04	-0.01	0.07	-0.01
Tenure	0	-0.01	1	-0.01	0.01	0.02	-0.03	0.01
Balance	0.01	0.03	-0.01	1	-0.31	-0.01	-0.01	0.01
NumOfProducts	0.01	-0.04	0.01	-0.31	1	0	0.01	0.01
HasCrCard	-0.01	-0.01	0.02	-0.01	0	1	-0.01	-0.01
IsActiveMember	0.03	0.07	-0.03	-0.01	0.01	-0.01	1	-0.01
EstimatedSalary	-0	-0.01	0.01	0.01	0.01	-0.01	-0.01	1

In [29]:

```
# the varaiables are not correlated, values are far below the 0.5 general threshold - n
o need to drop any columns
```

In [30]:

```
df.nunique()
```

Out[30]:

```
CreditScore         450
Geography             3
Gender                2
Age                  45
Tenure               11
Balance            6382
NumOfProducts         4
HasCrCard             2
IsActiveMember        2
EstimatedSalary    9999
Exited                2
dtype: int64
```

Hot Encode Categorical Features

In [31]:

```
#Hot Encode Categorical columns
df=pd.get_dummies(df, drop_first=True)
```

JUST NOTES FOR MYSELF - PLEASE IGNORE df=pd.get_dummies(df['Geography'], columns=['Geography']) df=pd.get_dummies(df, columns=['Gender'])

data_dummies=pd.get_dummies(df['Geography'],prefix=['Country'], columns=['Geography']) data_dummies1=pd.get_dummies(df['Gender'],prefix=['Gender'], columns=['Gender']) print(data_dummies.head(2)) data_dummies1.head(2)

df=pd.get_dummies(df) # why was the gender column also not hot encoded since it was an object column ? does this not need to go back to main dataframe with the original column being replaced (dropped) by dummies ? do i need to specidically hot encode for gender like so - df=pd.get_dummies(df, columns=['Gender']) (which is not working)

In [32]:

```
# visual view of the DF with dummies
df.tail()
```

Out[32]:

	CreditScore	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	Es
9995	771.0	39.0	5	0.00	2.0	1	0	
9996	516.0	35.0	10	57369.61	1.0	1	1	
9997	709.0	36.0	7	0.00	1.0	0	1	
9998	772.0	42.0	3	75075.31	2.0	1	0	
9999	792.0	28.0	4	130142.79	1.0	1	0	

Divide the Data Set into Training and Test Set

In [33]:

```
# dont we need to have a validation set of data ? should we not split data into 3 rathe
r than 2. Why only 20% not 30% below ?
# do all input variables mustbe float32 or same data type ? How do we change all  numer
ical columns to one datatype ?
X=df.drop(['Exited'], axis=1) # set of independent variables
Y=df['Exited']

X_train,X_test, y_train,y_test=train_test_split(X,Y, test_size=0.20, random_state=1)
```

In [34]:

```
# I HAVE SET MY DEPENDENT VARIABLE AS EXITED. I SEE IN MENTOR SESSION FRAUD DETECTION Y
HAS BEEN DEFINED AS
# y_data = credit_data.iloc[:, -1]  - IS THIS JUST AN EMPTY SET WITH NO ROWS ? MUST I D
O THAT ?
```

In [35]:

```
# we can see splitting of data has worked well- 8000 are in training set
X_train.shape
```

Out[35]:

```
(8000, 11)
```

In [36]:

```
# Scale (Normalize) the data    # why dont we scale the y ? it is a supervised learning
technique so we have to compare
# the results of actual y with predicted and must be on same scale ...
## WE DO NOT SCALE THE y_train or y_test since we are looking to compare predicted 0/1
 with actual (unscaled) 0/1.
# Besides how woudld one scale 0 and 1-ones ?

scaler=preprocessing.MinMaxScaler()

X_train=scaler.fit_transform(X_train)
X_test=scaler.fit_transform(X_test)
```

In [37]:

```
X_train.shape
```

Out[37]:

```
(8000, 11)
```

In [38]:

```
# Initiate construction of ANN
```

In [39]:

```
#model= Sequential()
```

In [41]:

```
# add layers
model = Sequential(layers=None, name=None) #--TM: Step 1: Empty Model

model.add(Dense(8,input_shape = (11,), activation = 'relu')) #--TM: Step 2: Hidden Laye
r 1; First input is number of neuron
#--TM: Step 2, Second input is number of input variables, i.e. 11; Refer to X_train.sha
pe
model.add(Dense(4,activation='relu'))
model.add(Dense(1,activation='sigmoid')) #  Output layer

sgd=optimizers.Adam(lr=0.001)

model.compile (loss='binary_crossentropy', optimizer=sgd, metrics=['accuracy'])
```

In [ ]:

```
# do we need this ?
# tf.keras.initializers.random_normal
# sgd=optimizers.Adam(lr=0.001)
```

In [ ]:

```
# Training the Model
```

In [42]:

```
model.fit(X_train,y_train.values, epochs=30, batch_size=2000, verbose=1)
 # verbose shows outpu t, epochs is number of  # runs to reduce erro

r
```

```
Epoch 1/30
4/4 [==============================] - 0s 3ms/step - loss: 0.5964 - accura
cy: 0.7794
Epoch 2/30
4/4 [==============================] - 0s 2ms/step - loss: 0.5881 - accura
cy: 0.7864
Epoch 3/30
4/4 [==============================] - 0s 0s/step - loss: 0.5802 - accurac
y: 0.7891
Epoch 4/30
4/4 [==============================] - 0s 1ms/step - loss: 0.5725 - accura
cy: 0.7918
Epoch 5/30
4/4 [==============================] - 0s 1ms/step - loss: 0.5653 - accura
cy: 0.7945
Epoch 6/30
4/4 [==============================] - 0s 1ms/step - loss: 0.5583 - accura
cy: 0.7954
Epoch 7/30
4/4 [==============================] - 0s 2ms/step - loss: 0.5517 - accura
cy: 0.7956
Epoch 8/30
4/4 [==============================] - 0s 2ms/step - loss: 0.5453 - accura
cy: 0.7961
Epoch 9/30
4/4 [==============================] - 0s 1ms/step - loss: 0.5392 - accura
cy: 0.7966
Epoch 10/30
4/4 [==============================] - 0s 3ms/step - loss: 0.5335 - accura
cy: 0.7971
Epoch 11/30
4/4 [==============================] - 0s 1ms/step - loss: 0.5281 - accura
cy: 0.7971
Epoch 12/30
4/4 [==============================] - 0s 2ms/step - loss: 0.5230 - accura
cy: 0.7972
Epoch 13/30
4/4 [==============================] - 0s 1ms/step - loss: 0.5184 - accura
cy: 0.7975
Epoch 14/30
4/4 [==============================] - 0s 2ms/step - loss: 0.5141 - accura
cy: 0.7974
Epoch 15/30
4/4 [==============================] - 0s 2ms/step - loss: 0.5103 - accura
cy: 0.7974
Epoch 16/30
4/4 [==============================] - 0s 2ms/step - loss: 0.5069 - accura
cy: 0.7974
Epoch 17/30
4/4 [==============================] - 0s 1ms/step - loss: 0.5038 - accura
cy: 0.7974
Epoch 18/30
4/4 [==============================] - 0s 2ms/step - loss: 0.5011 - accura
cy: 0.7974
Epoch 19/30
4/4 [==============================] - 0s 2ms/step - loss: 0.4987 - accura
cy: 0.7974
Epoch 20/30
4/4 [==============================] - 0s 2ms/step - loss: 0.4966 - accura
cy: 0.7974
Epoch 21/30
```

```
4/4 [==============================] - 0s 2ms/step - loss: 0.4947 - accura
cy: 0.7974
Epoch 22/30
4/4 [==============================] - 0s 1ms/step - loss: 0.4929 - accura
cy: 0.7975
Epoch 23/30
4/4 [==============================] - 0s 1ms/step - loss: 0.4913 - accura
cy: 0.7975
Epoch 24/30
4/4 [==============================] - 0s 1ms/step - loss: 0.4898 - accura
cy: 0.7975
Epoch 25/30
4/4 [==============================] - 0s 3ms/step - loss: 0.4884 - accura
cy: 0.7977
Epoch 26/30
4/4 [==============================] - 0s 1ms/step - loss: 0.4869 - accura
cy: 0.7980
Epoch 27/30
4/4 [==============================] - 0s 985us/step - loss: 0.4855 - accu
racy: 0.7984
Epoch 28/30
4/4 [==============================] - 0s 2ms/step - loss: 0.4842 - accura
cy: 0.7993
Epoch 29/30
4/4 [==============================] - 0s 3ms/step - loss: 0.4829 - accura
cy: 0.7999
Epoch 30/30
4/4 [==============================] - 0s 3ms/step - loss: 0.4817 - accura
cy: 0.8006
```

Out[42]:

```
<tensorflow.python.keras.callbacks.History at 0x24ba3004e08>
```

In [ ]:

```
# Evaluation of the model
```

In [45]:

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

```
63/63 [==============================] - 0s 1ms/step - loss: 0.4879 - accu
racy: 0.7925
```

In [49]:

```
print(model.metrics_names)
print(results)
```

```
['loss', 'accuracy']
[0.4879456162452698, 0.7925000190734863]
```

In [51]:

```
#--Creating a data frame to store model results
resultsDf = pd.DataFrame({'Iteration': None, 'Method':['Adam - Check '], 'Log Loss': re
sults[0], 'Accuracy': results[1]})
resultsDf = resultsDf[['Iteration', 'Method', 'Log Loss', 'Accuracy']]
resultsDf
```

Out[51]:

	Iteration	Method	Log Loss	Accuracy
0	None	Adam - Check	0.487946	0.7925

In [52]:

```
Y_pred_cls = model.predict_classes(X_test, batch_size=2000, verbose=0)

print('Accuracy Model1 (Dropout): '+ str(model.evaluate(X_test,y_test.values)[1]))

print('Recall_score: ' + str(recall_score(y_test.values,Y_pred_cls)))

print('Precision_score: ' + str(precision_score(y_test.values, Y_pred_cls)))

print('F-score: ' + str(f1_score(y_test.values,Y_pred_cls)))
confusion_matrix(y_test.values, Y_pred_cls)
```

```
WARNING:tensorflow:From <ipython-input-52-b98c2c46a761>:1: Sequential.pred
ict_classes (from tensorflow.python.keras.engine.sequential) is deprecated
and will be removed after 2021-01-01.
Instructions for updating:
Please use instead:* `np.argmax(model.predict(x), axis=-1)`,   if your mod
el does multi-class classification   (e.g. if it uses a `softmax` last-lay
er activation).* `(model.predict(x) > 0.5).astype("int32")`,   if your mod
el does binary classification   (e.g. if it uses a `sigmoid` last-layer ac
tivation).
63/63 [==============================] - 0s 1ms/step - loss: 0.4879 - accu
racy: 0.7925
Accuracy Model1 (Dropout): 0.7925000190734863
Recall_score: 0.007228915662650603
Precision_score: 0.5
F-score: 0.014251781472684086
```

Out[52]:

```
array([[1582,    3],
       [ 412,    3]], dtype=int64)
```

In [ ]:

```
# HYPERTUNING
# Experiment with number of neurons, & number of layers, optimizers and activation func
tion to see if you can improve results
```

In [56]:

```
# sigmoid is placed here as the output node function.
def create_model(opt):

    # create model
    model = Sequential(layers=None, name=None)
    model.add(Dense(8, input_shape = (11,), activation = 'relu'))#we are using a differ
ent activation function here than above
    model.add(Dense(4, activation = 'relu')) # create second hidden layer
    model.add(Dense(1, activation = 'sigmoid')) # single binary output node

    # Compile model
    model.compile(optimizer = opt, loss = 'binary_crossentropy', metrics=['accuracy'])

    return model
```

In [59]:

```
# try it with differenct optimizers to Hypertune completely
optimizer=['Adam','SGD','RMSProp','Adadelta','Adagrad','Adamax']
```

In [60]:

```
#  11 PICKED AS THE OPTIMAL NUMBER OF ITERATIONS IS THE INPUT VARIABLE
for j in range(1,11):

    print("Iteration:",j)

    for i in optimizer:

        mod=create_model(i)
        #print("Model:",i,end=' ')
        mod.fit(X_train, y_train.values, batch_size = 700, epochs = j, verbose = 0)
        results = mod.evaluate(X_test, y_test.values, verbose=0)
        #print(mod.metrics_names)
        #print(results)

        tempResultsDf = pd.DataFrame({'Iteration': j, 'Method':[i], 'Accuracy': results
[1], 'Log Loss': results[0]})
        resultsDf = pd.concat([resultsDf, tempResultsDf])
        resultsDf = resultsDf[['Iteration', 'Method', 'Accuracy', 'Log Loss']]
        #resultsDf
```

```
Iteration: 1
Iteration: 2
Iteration: 3
Iteration: 4
Iteration: 5
Iteration: 6
Iteration: 7
Iteration: 8
Iteration: 9
Iteration: 10
```

In [61]:

```
resultsDf=resultsDf[resultsDf['Iteration']>0]
resultsDf
```

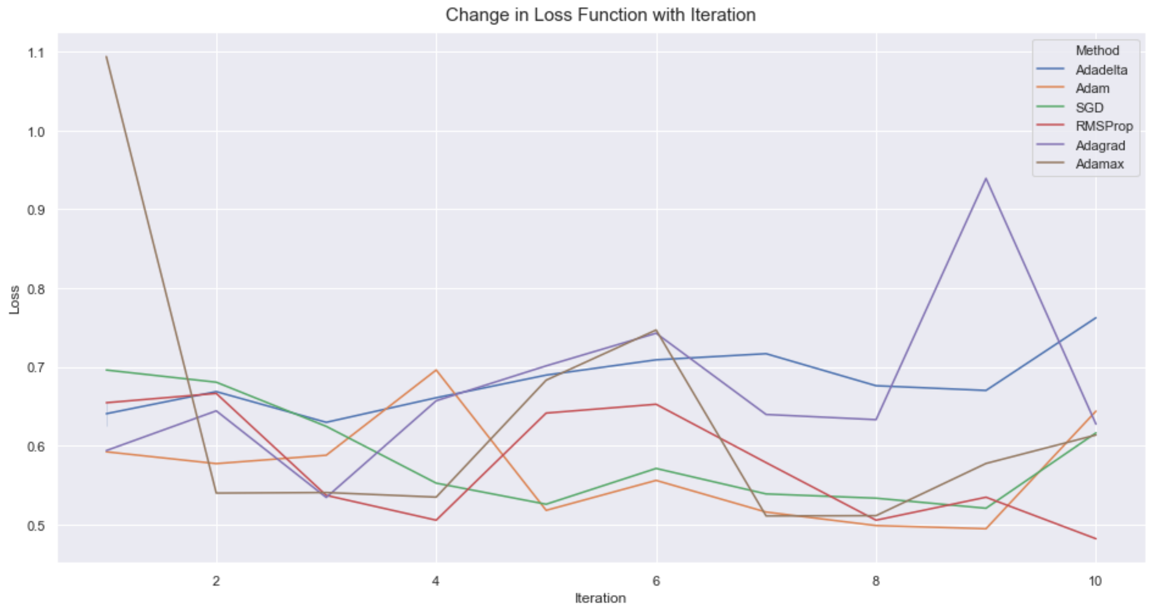
Out[61]:

	Iteration	Method	Accuracy	Log Loss
0	1	Adadelta	0.7925	0.625028
0	1	Adam	0.7715	0.592211
0	1	SGD	0.6260	0.695954
0	1	RMSProp	0.7910	0.654466
0	1	Adadelta	0.7360	0.656038
...	...	...	...	...
0	10	SGD	0.7880	0.616201
0	10	RMSProp	0.7925	0.481865
0	10	Adadelta	0.3900	0.762319
0	10	Adagrad	0.7925	0.627326
0	10	Adamax	0.7920	0.613519

61 rows × 4 columns

In [62]:

```
# A visual of the results of error reduction and approaching a minima

fig, ax = plt.subplots(figsize=(16,8)); #-----------------Setting size of the canvas

plt.title('Change in Loss Function with Iteration', fontsize=15, pad=10)
#---------------------Title of the chart


sns.lineplot(x=resultsDf['Iteration'],y=resultsDf['Log Loss'],hue=resultsDf['Method']);


ax.set(xlabel='Iteration', ylabel='Loss');
```



In [64]:

```
resultsDf_temp=resultsDf[resultsDf['Method']!='Adadelta']
resultsDf_temp=resultsDf_temp[resultsDf_temp['Method']!='Adagrad']
resultsDf_temp
```

Out[64]:

	Iteration	Method	Accuracy	Log Loss
0	1	Adam	0.7715	0.592211
0	1	SGD	0.6260	0.695954
0	1	RMSProp	0.7910	0.654466
0	1	Adamax	0.2075	1.093744
0	2	Adam	0.7925	0.577205
0	2	SGD	0.5935	0.680502
0	2	RMSProp	0.7625	0.666256
0	2	Adamax	0.7925	0.539828
0	3	Adam	0.7925	0.587831
0	3	SGD	0.7650	0.624506
0	3	RMSProp	0.7925	0.536941
0	3	Adamax	0.7925	0.540527
0	4	Adam	0.6480	0.696008
0	4	SGD	0.7925	0.552441
0	4	RMSProp	0.7925	0.505408
0	4	Adamax	0.7925	0.534682
0	5	Adam	0.7925	0.517907
0	5	SGD	0.7925	0.525671
0	5	RMSProp	0.7900	0.641346
0	5	Adamax	0.6825	0.683102
0	6	Adam	0.7925	0.555918
0	6	SGD	0.7925	0.571076
0	6	RMSProp	0.7925	0.652504
0	6	Adamax	0.3755	0.746795
0	7	Adam	0.7925	0.515731
0	7	SGD	0.7925	0.538752
0	7	RMSProp	0.7925	0.578463
0	7	Adamax	0.7925	0.510828
0	8	Adam	0.7925	0.498588
0	8	SGD	0.7925	0.533340
0	8	RMSProp	0.7925	0.505403
0	8	Adamax	0.7925	0.511161
0	9	Adam	0.7925	0.494567
0	9	SGD	0.7920	0.520574
0	9	RMSProp	0.7925	0.534559
0	9	Adamax	0.7925	0.577384
0	10	Adam	0.7585	0.643810

	Iteration	Method	Accuracy	Log Loss
0	10	SGD	0.7880	0.616201
0	10	RMSProp	0.7925	0.481865
0	10	Adamax	0.7920	0.613519

In [65]:

```
resultsDf_temp[resultsDf_temp['Log Loss']==resultsDf_temp['Log Loss'].min()]
```

Out[65]:

	Iteration	Method	Accuracy	Log Loss
0	10	RMSProp	0.7925	0.481865

In [ ]:

```
# Predict the Results  using 0.5 as a threshold
```

In [ ]:

```
Y_pred = mod.predict_classes(X_test, batch_size=2000, verbose=0)
```

In [ ]:

```
# apply threshold of 0.5
Y_pred = (Y_pred > 0.5)
print(Y_pred)
```

In [ ]:

```
cm1 = confusion_matrix(y_test, Y_pred)
print(cm1)
```

In [ ]:

```
accuracy_model1 = ((cm1[0][0]+cm1[1][1])*100)/(cm1[0][0]+cm1[1][1]+cm1[0][1]+cm1[1][0])
print (accuracy_model1, '% of testing data was classified correctly')
```