

```
In [1]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

In [2]: f = pd.read_csv("C:\\Users\\de11\\Downloads\\Compressed\\Churn_Modelling.csv")
df = pd.DataFrame(f)

In [3]: df

Out[3]:
   RowNumber  CustomerId  Surname  CreditScore  Geography  Gender  Age  Tenure  Balance  NumOfProducts  HasCrCard  IsActiveMember  EstimatedSalary  Exited
0           0           1  15634602   Hargrave         619      France  Female  42      2      0.00              1              1              1      101348.88      1
1           1           2  15647311      Hill         608      Spain  Female  41      1     83807.86              1              0              1     112542.58      0
2           2           3  15619304      Onio         502      France  Female  42      8    159660.80              3              1              0     113931.57      1
3           3           4  15701354      Boni         699      France  Female  39      1      0.00              2              0              0      93826.63      0
4           4           5  15737888   Mitchell         850      Spain  Female  43      2    125510.82              1              1              1      79084.10      0
...         ...         ...         ...         ...         ...         ...         ...         ...         ...         ...         ...         ...         ...
9995          9996  15606229   Obijaku         771      France   Male  39      5      0.00              2              1              0      96270.64      0
9996          9997  15569892   Johnstone         516      France   Male  35     10     57369.61              1              1              1     101699.77      0
9997          9998  15584532      Liu         709      France  Female  36      7      0.00              1              0              1      42085.58      1
9998          9999  15682355   Sabbatini         772      Germany  Male  42      3     75075.31              2              1              0      92888.52      1
9999         10000  15628319      Walker         792      France  Female  28      4    130142.79              1              1              0      38190.78      0

10000 rows x 14 columns

In [19]: dummies = pd.get_dummies(df.Geography)

In [20]: df_1 = pd.concat([df,dummies],axis='columns')

In [21]: df_1

Out[21]:
   RowNumber  CustomerId  Surname  CreditScore  Geography  Gender  Age  Tenure  Balance  NumOfProducts  HasCrCard  IsActiveMember  EstimatedSalary  Exited  France  Germany  Spain
0           0           1  15634602   Hargrave         619      France  Female  42      2      0.00              1              1              1      101348.88      1      1          0      0
1           1           2  15647311      Hill         608      Spain  Female  41      1     83807.86              1              0              1     112542.58      0      0          0      1
2           2           3  15619304      Onio         502      France  Female  42      8    159660.80              3              1              0     113931.57      1      1          0      0
3           3           4  15701354      Boni         699      France  Female  39      1      0.00              2              0              0      93826.63      0      1          0      0
4           4           5  15737888   Mitchell         850      Spain  Female  43      2    125510.82              1              1              1      79084.10      0      0          0      1
...         ...         ...         ...         ...         ...         ...         ...         ...         ...         ...         ...         ...         ...
9995          9996  15606229   Obijaku         771      France   Male  39      5      0.00              2              1              0      96270.64      0      1          0      0
9996          9997  15569892   Johnstone         516      France   Male  35     10     57369.61              1              1              1     101699.77      0      1          0      0
9997          9998  15584532      Liu         709      France  Female  36      7      0.00              1              0              1      42085.58      1      1          0      0
9998          9999  15682355   Sabbatini         772      Germany  Male  42      3     75075.31              2              1              0      92888.52      1      0          1      0
9999         10000  15628319      Walker         792      France  Female  28      4    130142.79              1              1              0      38190.78      0      1          0      0

10000 rows x 17 columns

In [23]: df = df_1.drop(['Geography'],axis = 'columns')

In [25]: from sklearn.preprocessing import LabelEncoder

In [27]: labelencoder = LabelEncoder()

In [29]: df.Gender = labelencoder.fit_transform(df.Gender)

In [30]: df

Out[30]:
   RowNumber  CustomerId  Surname  CreditScore  Gender  Age  Tenure  Balance  NumOfProducts  HasCrCard  IsActiveMember  EstimatedSalary  Exited  France  Germany  Spain
0           0           1  15634602   Hargrave         619      0  42      2      0.00              1              1              1      101348.88      1      1          0      0
1           1           2  15647311      Hill         608      0  41      1     83807.86              1              0              1     112542.58      0      0          0      1
2           2           3  15619304      Onio         502      0  42      8    159660.80              3              1              0     113931.57      1      1          0      0
3           3           4  15701354      Boni         699      0  39      1      0.00              2              0              0      93826.63      0      1          0      0
4           4           5  15737888   Mitchell         850      0  43      2    125510.82              1              1              1      79084.10      0      0          0      1
...         ...         ...         ...         ...         ...         ...         ...         ...         ...         ...         ...         ...         ...
9995          9996  15606229   Obijaku         771      1  39      5      0.00              2              1              1     101699.77      0      1          0      0
9996          9997  15569892   Johnstone         516      1  35     10     57369.61              1              1              1     101699.77      0      1          0      0
9997          9998  15584532      Liu         709      0  36      7      0.00              1              0              1      42085.58      1      1          0      0
9998          9999  15682355   Sabbatini         772      1  42      3     75075.31              2              1              0      92888.52      1      0          1      0
9999         10000  15628319      Walker         792      0  28      4    130142.79              1              1              0      38190.78      0      1          0      0

10000 rows x 16 columns

In [32]: y = df.Exited

In [35]: X = df.drop(['RowNumber', 'CustomerId', 'Surname', 'Exited'],axis = 'columns')

In [36]: X

Out[36]:
   CreditScore  Gender  Age  Tenure  Balance  NumOfProducts  HasCrCard  IsActiveMember  EstimatedSalary  France  Germany  Spain
0           619      0  42      2      0.00              1              1              1      101348.88      1      0      0
1           608      0  41      1     83807.86              1              0              1     112542.58      0      0      1
2           502      0  42      8    159660.80              3              1              0     113931.57      1      0      0
3           699      0  39      1      0.00              2              0              0      93826.63      1      0      0
4           850      0  43      2    125510.82              1              1              1      79084.10      0      0      1
...         ...         ...         ...         ...         ...         ...         ...         ...         ...         ...         ...
9995          771      1  39      5      0.00              2              1              1     101699.77      1      0      0
9996          516      1  35     10     57369.61              1              1              1     101699.77      1      0      0
9997          709      0  36      7      0.00              1              0              1      42085.58      1      0      0
9998          772      1  42      3     75075.31              2              1              0      92888.52      0      1      0
9999          792      0  28      4    130142.79              1              1              0      38190.78      1      0      0

10000 rows x 12 columns

In [37]: from sklearn.model_selection import train_test_split

In [38]: X_train,X_test,y_train,y_test = train_test_split(X,y,test_size = 0.2,random_state = 0)

In [39]: from sklearn.preprocessing import StandardScaler

In [40]: sc = StandardScaler()

In [41]: X_train = sc.fit_transform(X_train)

In [42]: X_test = sc.fit_transform(X_test)

In [60]: import tensorflow as tf

In [61]: classifier = tf.keras.models.Sequential()

In [64]: classifier.add(tf.keras.layers.Dense(units=6,activation='relu'))

In [66]: classifier.add(tf.keras.layers.Dense(units=6,activation='relu'))

In [67]: classifier.add(tf.keras.layers.Dense(units=1,activation='sigmoid'))

In [68]: classifier.compile(optimizer='adam',loss='binary_crossentropy',metrics = ['accuracy'])

In [69]: classifier.fit(X_train,y_train,batch_size=30,epochs = 100)

Epoch 1/100
267/267 [=====] - 1s 749us/step - loss: 0.5798 - accuracy: 0.7576
Epoch 2/100
267/267 [=====] - 0s 803us/step - loss: 0.4910 - accuracy: 0.7954
Epoch 3/100
267/267 [=====] - 0s 792us/step - loss: 0.4468 - accuracy: 0.7983
Epoch 4/100
267/267 [=====] - 0s 811us/step - loss: 0.4237 - accuracy: 0.8046
Epoch 5/100
267/267 [=====] - 0s 800us/step - loss: 0.4067 - accuracy: 0.8238
Epoch 6/100
267/267 [=====] - 0s 780us/step - loss: 0.3912 - accuracy: 0.8331
Epoch 7/100
267/267 [=====] - 0s 777us/step - loss: 0.3799 - accuracy: 0.8378
Epoch 8/100
267/267 [=====] - 0s 763us/step - loss: 0.3721 - accuracy: 0.8438
Epoch 9/100
267/267 [=====] - 0s 756us/step - loss: 0.3661 - accuracy: 0.8471
Epoch 10/100
267/267 [=====] - 0s 752us/step - loss: 0.3612 - accuracy: 0.8505
Epoch 11/100
267/267 [=====] - 0s 762us/step - loss: 0.3578 - accuracy: 0.8525
Epoch 12/100
267/267 [=====] - 0s 766us/step - loss: 0.3546 - accuracy: 0.8546
Epoch 13/100
267/267 [=====] - 0s 759us/step - loss: 0.3527 - accuracy: 0.8550
Epoch 14/100
267/267 [=====] - 0s 759us/step - loss: 0.3515 - accuracy: 0.8571
Epoch 15/100
267/267 [=====] - 0s 763us/step - loss: 0.3496 - accuracy: 0.8594
Epoch 16/100
267/267 [=====] - 0s 747us/step - loss: 0.3484 - accuracy: 0.8590
Epoch 17/100
267/267 [=====] - 0s 770us/step - loss: 0.3473 - accuracy: 0.8597
Epoch 18/100
267/267 [=====] - 0s 782us/step - loss: 0.3463 - accuracy: 0.8586
Epoch 19/100
267/267 [=====] - 0s 764us/step - loss: 0.3457 - accuracy: 0.8620
Epoch 20/100
267/267 [=====] - 0s 766us/step - loss: 0.3451 - accuracy: 0.8605
Epoch 21/100
267/267 [=====] - 0s 738us/step - loss: 0.3442 - accuracy: 0.8608
Epoch 22/100
267/267 [=====] - 0s 791us/step - loss: 0.3438 - accuracy: 0.8610
Epoch 23/100
267/267 [=====] - 0s 780us/step - loss: 0.3435 - accuracy: 0.8610
Epoch 24/100
267/267 [=====] - 0s 772us/step - loss: 0.3428 - accuracy: 0.8605
Epoch 25/100
267/267 [=====] - 0s 781us/step - loss: 0.3421 - accuracy: 0.8635
Epoch 26/100
267/267 [=====] - 0s 772us/step - loss: 0.3418 - accuracy: 0.8614
Epoch 27/100
267/267 [=====] - 0s 749us/step - loss: 0.3415 - accuracy: 0.8614
Epoch 28/100
267/267 [=====] - 0s 778us/step - loss: 0.3411 - accuracy: 0.8619
Epoch 29/100
267/267 [=====] - 0s 748us/step - loss: 0.3409 - accuracy: 0.8621
Epoch 30/100
267/267 [=====] - 0s 791us/step - loss: 0.3407 - accuracy: 0.8619
Epoch 31/100
267/267 [=====] - 0s 761us/step - loss: 0.3404 - accuracy: 0.8619
Epoch 32/100
267/267 [=====] - 0s 776us/step - loss: 0.3400 - accuracy: 0.8616
Epoch 33/100
267/267 [=====] - 0s 778us/step - loss: 0.3398 - accuracy: 0.8616
Epoch 34/100
267/267 [=====] - 0s 785us/step - loss: 0.3395 - accuracy: 0.8621
Epoch 35/100
267/267 [=====] - 0s 771us/step - loss: 0.3392 - accuracy: 0.8648
Epoch 36/100
267/267 [=====] - 0s 766us/step - loss: 0.3387 - accuracy: 0.8618
Epoch 37/100
267/267 [=====] - 0s 773us/step - loss: 0.3389 - accuracy: 0.8634
Epoch 38/100
267/267 [=====] - 0s 760us/step - loss: 0.3384 - accuracy: 0.8624
Epoch 39/100
267/267 [=====] - 0s 751us/step - loss: 0.3381 - accuracy: 0.8621
Epoch 40/100
267/267 [=====] - 0s 769us/step - loss: 0.3376 - accuracy: 0.8629
Epoch 41/100
267/267 [=====] - 0s 772us/step - loss: 0.3373 - accuracy: 0.8624
Epoch 42/100
267/267 [=====] - 0s 760us/step - loss: 0.3373 - accuracy: 0.8621
Epoch 43/100
267/267 [=====] - 0s 747us/step - loss: 0.3367 - accuracy: 0.8634
Epoch 44/100
267/267 [=====] - 0s 747us/step - loss: 0.3364 - accuracy: 0.8637
Epoch 45/100
267/267 [=====] - 0s 755us/step - loss: 0.3360 - accuracy: 0.8629
Epoch 46/100
267/267 [=====] - 0s 752us/step - loss: 0.3359 - accuracy: 0.8629
Epoch 47/100
267/267 [=====] - 0s 770us/step - loss: 0.3349 - accuracy: 0.8636
Epoch 48/100
267/267 [=====] - 0s 753us/step - loss: 0.3351 - accuracy: 0.8626
Epoch 49/100
267/267 [=====] - 0s 752us/step - loss: 0.3348 - accuracy: 0.8634
Epoch 50/100
267/267 [=====] - 0s 781us/step - loss: 0.3343 - accuracy: 0.8646
Epoch 51/100
267/267 [=====] - 0s 777us/step - loss: 0.3338 - accuracy: 0.8633
Epoch 52/100
267/267 [=====] - 0s 745us/step - loss: 0.3339 - accuracy: 0.8644
Epoch 53/100
267/267 [=====] - 0s 770us/step - loss: 0.3341 - accuracy: 0.8639
Epoch 54/100
267/267 [=====] - 0s 757us/step - loss: 0.3338 - accuracy: 0.8648
Epoch 55/100
267/267 [=====] - 0s 767us/step - loss: 0.3334 - accuracy: 0.8641
Epoch 56/100
267/267 [=====] - 0s 767us/step - loss: 0.3332 - accuracy: 0.8651
Epoch 57/100
267/267 [=====] - 0s 771us/step - loss: 0.3329 - accuracy: 0.8639
Epoch 58/100
267/267 [=====] - 0s 762us/step - loss: 0.3327 - accuracy: 0.8639
Epoch 59/100
267/267 [=====] - 0s 787us/step - loss: 0.3328 - accuracy: 0.8636
Epoch 60/100
267/267 [=====] - 0s 777us/step - loss: 0.3323 - accuracy: 0.8646
Epoch 61/100
267/267 [=====] - 0s 765us/step - loss: 0.3326 - accuracy: 0.8652
Epoch 62/100
267/267 [=====] - 0s 775us/step - loss: 0.3320 - accuracy: 0.8660
Epoch 63/100
267/267 [=====] - 0s 767us/step - loss: 0.3320 - accuracy: 0.8649
Epoch 64/100
267/267 [=====] - 0s 762us/step - loss: 0.3318 - accuracy: 0.8655
Epoch 65/100
267/267 [=====] - 0s 770us/step - loss: 0.3316 - accuracy: 0.8656
Epoch 66/100
267/267 [=====] - 0s 777us/step - loss: 0.3317 - accuracy: 0.8635
Epoch 67/100
267/267 [=====] - 0s 777us/step - loss: 0.3312 - accuracy: 0.8648
Epoch 68/100
267/267 [=====] - 0s 765us/step - loss: 0.3312 - accuracy: 0.8651
Epoch 69/100
267/267 [=====] - 0s 779us/step - loss: 0.3313 - accuracy: 0.8659
Epoch 70/100
267/267 [=====] - 0s 773us/step - loss: 0.3311 - accuracy: 0.8651
Epoch 71/100
267/267 [=====] - 0s 765us/step - loss: 0.3309 - accuracy: 0.8687
Epoch 72/100
267/267 [=====] - 0s 768us/step - loss: 0.3307 - accuracy: 0.8660
Epoch 73/100
267/267 [=====] - 0s 758us/step - loss: 0.3306 - accuracy: 0.8645
Epoch 74/100
267/267 [=====] - 0s 780us/step - loss: 0.3303 - accuracy: 0.8664
Epoch 75/100
267/267 [=====] - 0s 724us/step - loss: 0.3303 - accuracy: 0.8665
Epoch 76/100
267/267 [=====] - 0s 659us/step - loss: 0.3303 - accuracy: 0.8652
Epoch 77/100
267/267 [=====] - 0s 657us/step - loss: 0.3301 - accuracy: 0.8677
Epoch 78/100
267/267 [=====] - 0s 703us/step - loss: 0.3302 - accuracy: 0.8674
Epoch 79/100
267/267 [=====] - 0s 761us/step - loss: 0.3299 - accuracy: 0.8677
Epoch 80/100
267/267 [=====] - 0s 774us/step - loss: 0.3296 - accuracy: 0.8671
Epoch 81/100
267/267 [=====] - 0s 754us/step - loss: 0.3295 - accuracy: 0.8669
Epoch 82/100
267/267 [=====] - 0s 754us/step - loss: 0.3294 - accuracy: 0.8662
Epoch 83/100
267/267 [=====] - 0s 719us/step - loss: 0.3294 - accuracy: 0.8666
Epoch 84/100
267/267 [=====] - 0s 738us/step - loss: 0.3295 - accuracy: 0.8679
Epoch 85/100
267/267 [=====] - 0s 749us/step - loss: 0.3292 - accuracy: 0.8677
Epoch 86/100
267/267 [=====] - 0s 771us/step - loss: 0.3291 - accuracy: 0.8670
Epoch 87/100
267/267 [=====] - 0s 746us/step - loss: 0.3289 - accuracy: 0.8669
Epoch 88/100
267/267 [=====] - 0s 770us/step - loss: 0.3287 - accuracy: 0.8683
Epoch 89/100
267/267 [=====] - 0s 765us/step - loss: 0.3287 - accuracy: 0.8683
Epoch 90/100
267/267 [=====] - 0s 767us/step - loss: 0.3285 - accuracy: 0.8676
Epoch 91/100
267/267 [=====] - 0s 768us/step - loss: 0.3286 - accuracy: 0.8679
Epoch 92/100
267/267 [=====] - 0s 780us/step - loss: 0.3285 - accuracy: 0.8670
Epoch 93/100
267/267 [=====] - 0s 749us/step - loss: 0.3284 - accuracy: 0.8675
Epoch 94/100
267/267 [=====] - 0s 783us/step - loss: 0.3284 - accuracy: 0.8680
Epoch 95/100
267/267 [=====] - 0s 773us/step - loss: 0.3285 - accuracy: 0.8670
Epoch 96/100
267/267 [=====] - 0s 762us/step - loss: 0.3280 - accuracy: 0.8674
Epoch 97/100
267/267 [=====] - 0s 762us/step - loss: 0.3280 - accuracy: 0.8673
Epoch 98/100
267/267 [=====] - 0s 767us/step - loss: 0.3278 - accuracy: 0.8669
Epoch 99/100
267/267 [=====] - 0s 775us/step - loss: 0.3280 - accuracy: 0.8666
Epoch 100/100
267/267 [=====] - 0s 766us/step - loss: 0.3277 - accuracy: 0.8681
Out[69]: <keras.callbacks.History at 0x2881bd22280>

In [72]: y_pred = classifier.predict(X_test)

In [73]: y_pred = (y_pred > 0.5)

In [74]: y_pred

Out[74]:
array([[False],
       [False],
       [False],
       [False],
       [False],
       [False]])

In [75]: from sklearn.metrics import confusion_matrix

In [76]: cm = confusion_matrix(y_test,y_pred)

In [77]: cm

Out[77]:
array([[1533,      62],
       [ 205,    200]], dtype=int64)

In [79]: (1533 + 200) / 2000

Out[79]: 0.8665

In [ ]:
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