Importing Libraries & Dataset

```
In [1]:
           import numpy as np
           import pandas as pd
           import matplotlib.pyplot as plt
           import keras
           import os
           Using TensorFlow backend.
In [2]:
        In [3]:
           df = pd.read csv('Churn Modelling.csv')
In [4]:
           df.info()
           <class 'pandas.core.frame.DataFrame'>
           RangeIndex: 10000 entries, 0 to 9999
           Data columns (total 14 columns):
           RowNumber
                            10000 non-null int64
                            10000 non-null int64
           CustomerId
           Surname
                            10000 non-null object
                            10000 non-null int64
           CreditScore
                            10000 non-null object
           Geography
           Gender
                            10000 non-null object
                            10000 non-null int64
           Age
           Tenure
                            10000 non-null int64
           Balance
                            10000 non-null float64
           NumOfProducts
                            10000 non-null int64
           HasCrCard
                            10000 non-null int64
           IsActiveMember
                            10000 non-null int64
                            10000 non-null float64
           EstimatedSalary
                            10000 non-null int64
           dtypes: float64(2), int64(9), object(3)
           memory usage: 1.1+ MB
```

In [5]: ▶ df.describe()

Out[5]:

	RowNumber	CustomerId	CreditScore	Age	Tenure	Balance	١
count	10000.00000	1.000000e+04	10000.000000	10000.000000	10000.000000	10000.000000	_
mean	5000.50000	1.569094e+07	650.528800	38.921800	5.012800	76485.889288	
std	2886.89568	7.193619e+04	96.653299	10.487806	2.892174	62397.405202	
min	1.00000	1.556570e+07	350.000000	18.000000	0.000000	0.000000	
25%	2500.75000	1.562853e+07	584.000000	32.000000	3.000000	0.000000	
50%	5000.50000	1.569074e+07	652.000000	37.000000	5.000000	97198.540000	
75%	7500.25000	1.575323e+07	718.000000	44.000000	7.000000	127644.240000	
max	10000.00000	1.581569e+07	850.000000	92.000000	10.000000	250898.090000	

In [6]: ► df.head()

Out[6]:

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balar
0	1	15634602	Hargrave	619	France	Female	42	2	0
1	2	15647311	Hill	608	Spain	Female	41	1	83807
2	3	15619304	Onio	502	France	Female	42	8	159660
3	4	15701354	Boni	699	France	Female	39	1	0
4	5	15737888	Mitchell	850	Spain	Female	43	2	125510

Data Preprocessing

```
ANN - Model building, Regularization & Performance tuning - Jupyter Notebook
               df.head()
 In [9]:
     Out[9]:
                   CreditScore Geography
                                          Gender Age Tenure
                                                                  Balance
                                                                           NumOfProducts HasCrCard
                0
                          619
                                           Female
                                                    42
                                                             2
                                                                     0.00
                                                                                        1
                                                                                                   1
                                   France
                1
                          608
                                    Spain
                                           Female
                                                    41
                                                                 83807.86
                                                                                        1
                                                                                                   0
                                                             1
                2
                          502
                                   France
                                                    42
                                                                159660.80
                                                                                        3
                                           Female
                                                                                                   1
                3
                          699
                                   France
                                           Female
                                                                     0.00
                                                                                                   0
                                           Female
                                                                125510.82
                          850
                                    Spain
                                                    43
                                                             2
                                                                                                   1
In [10]:
               X_geography = pd.DataFrame(pd.get_dummies(df['Geography'], drop_first=True))
               X_gender = pd.DataFrame(pd.get_dummies(df['Gender'], drop_first=True))
In [11]:
               y = pd.DataFrame(df['Exited'])
In [12]:
In [13]:
               y.head()
    Out[13]:
                   Exited
                0
                       1
                1
                       0
                2
                3
                       0
                       0
```

In [14]:

y.shape

Out[14]: (10000, 1)

X = df.drop(['Geography', 'Gender', 'Exited'], axis=1)

```
In [16]: ► X.head()
```

Out[16]:

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

```
In [17]: ► X.shape
   Out[17]: (10000, 8)

X = pd.concat([X,X_geography,X_gender], axis=1, ignore_index=True, sort=Fals€

In [18]:
        X.head()
In [19]:
   Out[19]:
                 1 2
                           3 4 5 6
                                        7 8 9 10
           0 619 42 2
                         0.00 1 1 1 101348.88 0 0
           1 608 41 1
                      83807.86 1 0 1 112542.58 0 1
           2 502 42 8 159660.80 3 1 0 113931.57 0 0
             699
                39 1
                                   93826.63 0 0
            850 43 2 125510.82 1 1 1
                                   79084.10 0 1
In [20]:
        Out[20]: (10000, 11)
In [21]:
        X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.1, rand)
In [22]:
        In [23]:
          scale = StandardScaler()
In [24]:
```

Building an ANN

In [31]: M model.fit(X_train, y_train, batch_size=10, epochs=50)

```
Epoch 1/50
9000/9000 [======================] - 5s 584us/step - loss: 0.4733 -
accuracy: 0.7962
Epoch 2/50
accuracy: 0.7963
Epoch 3/50
accuracy: 0.7963
Epoch 4/50
accuracy: 0.8109
Epoch 5/50
9000/9000 [=======================] - 5s 537us/step - loss: 0.4166 -
accuracy: 0.8231
Epoch 6/50
accuracy: 0.8276
Epoch 7/50
accuracy: 0.8302
Epoch 8/50
9000/9000 [=========================] - 5s 534us/step - loss: 0.4106 -
accuracy: 0.8327
Epoch 9/50
accuracy: 0.8327
Epoch 10/50
accuracy: 0.8343
Epoch 11/50
accuracy: 0.8334
Epoch 12/50
accuracy: 0.8354
Epoch 13/50
accuracy: 0.8352
Epoch 14/50
accuracy: 0.8366
Epoch 15/50
accuracy: 0.8358
Epoch 16/50
accuracy: 0.8369
Epoch 17/50
accuracy: 0.8358
Epoch 18/50
accuracy: 0.8366
```

```
Epoch 19/50
accuracy: 0.8358
Epoch 20/50
9000/9000 [========================== ] - 4s 477us/step - loss: 0.4022 -
accuracy: 0.8361
Epoch 21/50
accuracy: 0.8368
Epoch 22/50
9000/9000 [=========================== ] - 4s 478us/step - loss: 0.4016 -
accuracy: 0.8384
Epoch 23/50
9000/9000 [========================== ] - 4s 467us/step - loss: 0.4017 -
accuracy: 0.8367
Epoch 24/50
accuracy: 0.8367
Epoch 25/50
accuracy: 0.8377
Epoch 26/50
accuracy: 0.8353
Epoch 27/50
accuracy: 0.8377
Epoch 28/50
accuracy: 0.8371
Epoch 29/50
accuracy: 0.8364
Epoch 30/50
accuracy: 0.8373
Epoch 31/50
accuracy: 0.8366
Epoch 32/50
accuracy: 0.8371
Epoch 33/50
accuracy: 0.8370
Epoch 34/50
accuracy: 0.8356
Epoch 35/50
accuracy: 0.8372
Epoch 36/50
accuracy: 0.8371
Epoch 37/50
9000/9000 [=======================] - 5s 506us/step - loss: 0.3985 -
accuracy: 0.8377
```

```
Epoch 38/50
accuracy: 0.8367
Epoch 39/50
accuracy: 0.8356
Epoch 40/50
accuracy: 0.8358
Epoch 41/50
9000/9000 [=========================] - 5s 509us/step - loss: 0.3985 -
accuracy: 0.8370
Epoch 42/50
accuracy: 0.8368
Epoch 43/50
accuracy: 0.8368
Epoch 44/50
accuracy: 0.8371
Epoch 45/50
accuracy: 0.8373
Epoch 46/50
accuracy: 0.8358
Epoch 47/50
9000/9000 [========================== ] - 5s 501us/step - loss: 0.3980 -
accuracy: 0.8381
Epoch 48/50
9000/9000 [=======================] - 5s 507us/step - loss: 0.3981 -
accuracy: 0.8371
Epoch 49/50
accuracy: 0.8383
Epoch 50/50
accuracy: 0.8369
```

Out[31]: <keras.callbacks.callbacks.History at 0x27e6226a388>

Evaluating the model

Cross Validation

```
In [38]:
             from keras.wrappers.scikit learn import KerasClassifier
In [39]:
             from sklearn.model selection import cross val score
In [40]:

    def classifier():

                 model = Sequential()
                 model.add(Dense(input dim=11, kernel initializer='uniform', units=6, acti
                 model.add(Dense(kernel_initializer='uniform', units=6, activation='relu')
                 model.add(Dense(kernel initializer='uniform', units=1, activation='sigmoi
                 model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['ac
                 return model
In [41]:
          ► V_model = KerasClassifier(build_fn=classifier, batch_size=10, epochs=50)
             cv score = cross val score(estimator=CV model, X=X train, y=y train, cv=10, r
In [42]:
             cv score.mean()
In [43]:
   Out[43]: 0.8406666696071625
In [44]:
            cv score.std()
   Out[44]: 0.012193903836001005
```

Dropout

^{* 83%} accuracy! Not bad eh? (false positive is too high though)Now let's implement regularization through CV & Droput; then improve the accuracy using Parameter tuning*

```
In [46]:  M def classifier():
    model = Sequential()
    model.add(Dense(input_dim=11, kernel_initializer='uniform', units=6, acti
    model.add(Dropout(p=0.1))
    model.add(Dense(kernel_initializer='uniform', units=6, activation='relu')
    model.add(Dropout(p=0.1))
    model.add(Dense(kernel_initializer='uniform', units=1, activation='sigmoi
    model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['acc
    return model
```

C:\Users\breje\AppData\Local\Continuum\anaconda3\lib\site-packages\joblib\e xternals\loky\process_executor.py:706: UserWarning: A worker stopped while some jobs were given to the executor. This can be caused by a too short wor ker timeout or by a memory leak.

"timeout or by a memory leak.", UserWarning

Parameter Tuning

```
In [55]: M def classifier(optimizer):
    model = Sequential()
    model.add(Dense(input_dim=11, kernel_initializer='uniform', units=6, acti
    model.add(Dense(kernel_initializer='uniform', units=6, activation='relu')
    model.add(Dense(kernel_initializer='uniform', units=1, activation='sigmoi
    model.compile(optimizer=optimizer, loss='binary_crossentropy', metrics=['
    return model
```

```
In [56]:
         model = KerasClassifier(build fn=classifier)
         parameters = {'batch_size':[5, 20],
                  'nb epoch':[75, 100],
                  'optimizer':['adam', 'rmsprop']}
         gs_model = GridSearchCV(estimator=model, param_grid=parameters, scoring='accu
In [57]:
      0100/0100 [----- 1033. 0.4/20
         - accuracy: 0.7948
         Epoch 1/1
         - accuracy: 0.7962
         Epoch 1/1
         curacy: 0.79 - 13s 2ms/step - loss: 0.4631 - accuracy: 0.7970
         Epoch 1/1
         8100/8100 [============== ] - 13s 2ms/step - loss: 0.4739
         - accuracy: 0.7983
         Epoch 1/1
         8100/8100 [============= ] - 13s 2ms/step - loss: 0.4735
         - accuracy: 0.7956
         Epoch 1/1
         8100/8100 [============== ] - 13s 2ms/step - loss: 0.4786
         - accuracy: 0.7975
         Epoch 1/1
         - accuracy: 0.7964
In [58]:
         gs.best params
         gs.best score
  Out[58]: 0.8001111111111111
In [ ]:
```