ANN_classifier

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The following is an ANN classifier for determining the probability that a specific customer leaves a financial institution

Geographic and financial customer attributes are included altogether, as these are believed to have an impacting factor on the decison of leaving.

```
[12]: #ANN implementation for classification problem
     # Importing libraries
     import keras
     import pandas as pd
     import numpy as np
     import matplotlib.pyplot as plt
     # Importing useful classes
     from sklearn.model_selection import train_test_split
     from keras.models import Sequential
     from keras.layers import Dense, Dropout
     from keras.wrappers.scikit_learn import KerasClassifier
     from sklearn.model_selection import GridSearchCV, cross_val_score
     from sklearn.preprocessing import LabelEncoder, OneHotEncoder, StandardScaler # J
      \rightarrowFor cat. data encoding
     from sklearn.metrics import confusion_matrix
     # Importing dataset
     ds = pd.read_csv('Churn_Modelling.csv') # Importing dataset from parent dir
     X = ds.iloc[:, 3:13].values # Selecting input array from dataset (independent
      →variables: Customer indicators)
     y = ds.iloc[:, 13].values # Selecting output vector from dataset (dependent_
      →variable: Categorical (binary) variable)
```

```
# Data pre-processing
labelencoder X 1 = LabelEncoder() # Encoder object for encoding non-numerical
\rightarrowdata into numerical data (Non-numerical data values are encoded in columns 1_{\sqcup}
\rightarrow and 2)
X[:, 1] = labelencoder X 1.fit transform(X[:, 1])
labelencoder_X_2 = LabelEncoder()
X[:, 2] = labelencoder_X_2.fit_transform(X[:, 2])
onehotencoder = OneHotEncoder(categorical_features = [1]) # There are more than_
\rightarrow 2 countries in ds, so one-hot enc. needed in column 1
X = onehotencoder.fit_transform(X).toarray()
X = X[:, 1:] # One variable removed after one-hot encoding because of data_1
\rightarrow multi-collinearity
# Splitting dataset into training and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, __
→random_state = 0) # Test size is 0.2 (20%) of total ds
# Feature scaling for easing numerical computatations
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
# Initialising ANN
# There are 11 nodes in input layer and 1 in output layer, hence (1+11)/2 nodes
→ in hidden layers
def build_classifier():
    classifier = Sequential() # Classifier object for ANN structure
    classifier.add(Dense(units = 6, kernel_initializer = 'uniform', activation_
 →= 'relu', input_dim = 11)) # Input layer has 11 neurons, rect. lin. unit_
 \rightarrow function
    classifier.add(Dropout(p = 0.1)) # Avoid overfitting
    classifier.add(Dense(units = 6, kernel_initializer = 'uniform', activation⊔
 →= 'relu')) # Second layer added
    classifier.add(Dropout(p = 0.1))
    classifier.add(Dense(units = 1, kernel_initializer = 'uniform', activation_
 →= 'sigmoid')) # Output layer has 1 node, sigmoid funct. for 0-1 range values
 \hookrightarrow (probabilities)
```

```
→metrics = ['accuracy']) # Using adam alg. for weight update
                   # Binary value (YES OR NO) classification problem:
 →binary_crossentropy loss func.
                   # Accuracy metric for monitoring model performance
    return classifier
#Fitting training set to model
classifier = KerasClassifier(build_fn = build_classifier, batch_size = 10,__
 →epochs = 100) #Weights are updated every 10 data samples
classifier.fit(X_train, y_train)
# Predicting the test set results
y_predicted = classifier.predict(X_test) # Extracting classifier predicitions
y_predicted = (y_predicted > 0.5) # Below 0.5 data value is transformed to 0, u
 \rightarrowabove 0.5 to 1
/home/alexbocc/anaconda3/lib/python3.7/site-
packages/sklearn/preprocessing/_encoders.py:414: FutureWarning: The handling of
integer data will change in version 0.22. Currently, the categories are
determined based on the range [0, max(values)], while in the future they will be
determined based on the unique values.
If you want the future behaviour and silence this warning, you can specify
"categories='auto'".
In case you used a LabelEncoder before this OneHotEncoder to convert the
categories to integers, then you can now use the OneHotEncoder directly.
  warnings.warn(msg, FutureWarning)
/home/alexbocc/anaconda3/lib/python3.7/site-
packages/sklearn/preprocessing/_encoders.py:450: DeprecationWarning: The
'categorical_features' keyword is deprecated in version 0.20 and will be removed
in 0.22. You can use the ColumnTransformer instead.
  "use the ColumnTransformer instead.", DeprecationWarning)
/home/alexbocc/anaconda3/lib/python3.7/site-packages/ipykernel launcher.py:59:
UserWarning: Update your `Dropout` call to the Keras 2 API: `Dropout(rate=0.1)`
/home/alexbocc/anaconda3/lib/python3.7/site-packages/ipykernel launcher.py:61:
UserWarning: Update your `Dropout` call to the Keras 2 API: `Dropout(rate=0.1)`
Epoch 1/100
0.7951
Epoch 2/100
```

classifier.compile(optimizer = 'adam', loss = 'binary_crossentropy',__

```
0.8015
Epoch 3/100
0.8112
Epoch 4/100
8000/8000 [============= ] - 4s 518us/step - loss: 0.4266 - acc:
0.8155
Epoch 5/100
8000/8000 [============= ] - 4s 482us/step - loss: 0.4235 - acc:
0.8202
Epoch 6/100
0.8237
Epoch 7/100
0.8205
Epoch 8/100
0.8216
Epoch 9/100
0.8249
Epoch 10/100
8000/8000 [============ ] - 4s 507us/step - loss: 0.4156 - acc:
0.8246
Epoch 11/100
8000/8000 [============ ] - 4s 509us/step - loss: 0.4199 - acc:
0.8231
Epoch 12/100
0.8261
Epoch 13/100
0.8244
Epoch 14/100
0.8251
Epoch 15/100
8000/8000 [============ ] - 4s 507us/step - loss: 0.4138 - acc:
0.8256
Epoch 16/100
0.8265
Epoch 17/100
0.8261
Epoch 18/100
```

```
0.8290
Epoch 19/100
0.8245
Epoch 20/100
8000/8000 [============= ] - 4s 498us/step - loss: 0.4120 - acc:
0.8262
Epoch 21/100
8000/8000 [============= ] - 4s 521us/step - loss: 0.4123 - acc:
0.8280
Epoch 22/100
0.8291
Epoch 23/100
0.8251
Epoch 24/100
0.8282
Epoch 25/100
0.8254
Epoch 26/100
8000/8000 [============= ] - 4s 499us/step - loss: 0.4088 - acc:
0.8286
Epoch 27/100
8000/8000 [============ ] - 4s 499us/step - loss: 0.4106 - acc:
0.8262
Epoch 28/100
0.8246
Epoch 29/100
0.8271
Epoch 30/100
0.8285
Epoch 31/100
8000/8000 [============= ] - 4s 493us/step - loss: 0.4099 - acc:
0.8300
Epoch 32/100
0.8284
Epoch 33/100
0.8264
Epoch 34/100
```

```
0.8274
Epoch 35/100
0.8251
Epoch 36/100
0.8236
Epoch 37/100
0.8309
Epoch 38/100
0.8322
Epoch 39/100
0.8321
Epoch 40/100
0.8317
Epoch 41/100
0.8282
Epoch 42/100
0.8312
Epoch 43/100
8000/8000 [============ ] - 4s 545us/step - loss: 0.4059 - acc:
0.8295
Epoch 44/100
0.8295
Epoch 45/100
8000/8000 [============= ] - 6s 739us/step - loss: 0.4027 - acc:
0.8324
Epoch 46/100
0.8316
Epoch 47/100
0.8341
Epoch 48/100
0.8295
Epoch 49/100
0.8307
Epoch 50/100
```

```
0.8326
Epoch 51/100
0.8335
Epoch 52/100
0.8284
Epoch 53/100
8000/8000 [============= ] - 4s 496us/step - loss: 0.4030 - acc:
0.8290
Epoch 54/100
0.8299
Epoch 55/100
0.8332
Epoch 56/100
0.8281
Epoch 57/100
0.8311
Epoch 58/100
8000/8000 [============= ] - 4s 526us/step - loss: 0.4043 - acc:
0.8307
Epoch 59/100
8000/8000 [============ ] - 4s 518us/step - loss: 0.4016 - acc:
0.8311
Epoch 60/100
0.8272
Epoch 61/100
0.8291
Epoch 62/100
0.8310
Epoch 63/100
8000/8000 [============= ] - 4s 546us/step - loss: 0.4028 - acc:
0.8317
Epoch 64/100
0.8294
Epoch 65/100
0.8301
Epoch 66/100
```

```
0.8307
Epoch 67/100
0.8302
Epoch 68/100
8000/8000 [============= ] - 4s 537us/step - loss: 0.4047 - acc:
0.8300
Epoch 69/100
0.8319
Epoch 70/100
0.8325
Epoch 71/100
0.8320
Epoch 72/100
0.8324
Epoch 73/100
0.8317
Epoch 74/100
8000/8000 [============ ] - 4s 500us/step - loss: 0.3989 - acc:
0.8342
Epoch 75/100
8000/8000 [============ ] - 4s 503us/step - loss: 0.3973 - acc:
0.8375
Epoch 76/100
0.8291
Epoch 77/100
0.8302
Epoch 78/100
0.8300
Epoch 79/100
8000/8000 [============= ] - 4s 498us/step - loss: 0.4001 - acc:
0.8324
Epoch 80/100
8000/8000 [============ ] - 4s 508us/step - loss: 0.4016 - acc:
0.8332
Epoch 81/100
0.8311
Epoch 82/100
```

```
0.8334
Epoch 83/100
0.8356
Epoch 84/100
8000/8000 [============= ] - 4s 482us/step - loss: 0.4018 - acc:
0.8306
Epoch 85/100
0.8336
Epoch 86/100
0.8295
Epoch 87/100
0.8344
Epoch 88/100
0.8339
Epoch 89/100
8000/8000 [============ ] - 4s 510us/step - loss: 0.3951 - acc:
0.8334
Epoch 90/100
0.8341
Epoch 91/100
8000/8000 [============ ] - 4s 510us/step - loss: 0.3927 - acc:
0.8345
Epoch 92/100
0.8347
Epoch 93/100
0.8342
Epoch 94/100
0.8349
Epoch 95/100
8000/8000 [============ ] - 4s 493us/step - loss: 0.3872 - acc:
0.8376
Epoch 96/100
0.8365
Epoch 97/100
0.8331
Epoch 98/100
```

0.0.1 After learning the correlations patterns in training dataset, the model predicts a set of customers likely to leave the institution.

0.0.2 According to the convolutional matrix, the model made 1711 correct predictions out of 2000

```
[]: # Further analysis and improvements (Computationally heavy section)
   accuracy = cross_val_score(estimator = classifier, X = X_train, y = y_train, cv⊔
    \rightarrow= 10, n_jobs = -1) # 10 fold cross validation
   mean = accuracy.mean()
   variance = accuracy.std() # Mean and variance of accuracies
   # Improving ANN classifier by tuning of parameters
   parameters = {'batch_size': [25, 32],
                  'epochs': [100, 500],
                  'optimizer': ['adam', 'rmsprop']}
   grid_search = GridSearchCV(estimator = classifier,
                               param_grid = parameters,
                               scoring = 'accuracy',
                               cv = 10) # Test ANN over grid of parameters (batch⊔
    ⇔sizes, training alq.) defined above
   grid_search = grid_search.fit(X_train, y_train)
   best_parameters = grid_search.best_params_ # Best parameters placed in array
```

 $\label{eq:best_accuracy} \begin{array}{l} \texttt{best_accuracy = grid_search.best_score} \ \, \textit{\# Best accuracy score obtained with} \\ \quad \textit{\rightarrow} parameters \ \, \textit{from best_parameters} \end{array}$