Churn_Regression

September 5, 2020

In [1]:
```
# Task 1
# Load churn_dataset.csv

import pandas as pd

df = pd.read_csv('churn_dataset.csv')

df.head(5)
```

Out[1]:
```
   customerID  gender  SeniorCitizen Partner Dependents  tenure PhoneService  \
0  7590-VHVEG  Female              0     Yes         No       1           No
1  5575-GNVDE    Male              0      No         No      34          Yes
2  3668-QPYBK    Male              0      No         No       2          Yes
3  7795-CFOCW    Male              0      No         No      45           No
4  9237-HQITU  Female              0      No         No       2          Yes

      MultipleLines InternetService OnlineSecurity  ... DeviceProtection  \
0  No phone service             DSL             No  ...               No
1                No             DSL            Yes  ...              Yes
2                No             DSL            Yes  ...               No
3  No phone service             DSL            Yes  ...              Yes
4                No     Fiber optic             No  ...               No

  TechSupport StreamingTV StreamingMovies        Contract PaperlessBilling  \
0          No          No              No  Month-to-month              Yes
1          No          No              No        One year               No
2          No          No              No  Month-to-month              Yes
3         Yes          No              No        One year               No
4          No          No              No  Month-to-month              Yes

               PaymentMethod MonthlyCharges  TotalCharges Churn
0           Electronic check          29.85         29.85    No
1               Mailed check          56.95        1889.5    No
2               Mailed check          53.85        108.15   Yes
3  Bank transfer (automatic)          42.30       1840.75    No
4           Electronic check          70.70        151.65   Yes

[5 rows x 21 columns]
```

In [2]:
```python
# Task 1
# What is the structure of dataset

print('# of columns: ', df.shape[1])
print('# of rows: ', df.shape[0], '\n')

print('Columns in Dataset: ')
list(df)
```

```
# of columns:  21
# of rows:  7043

Columns in Dataset:
```

Out[2]:
```
['customerID',
 'gender',
 'SeniorCitizen',
 'Partner',
 'Dependents',
 'tenure',
 'PhoneService',
 'MultipleLines',
 'InternetService',
 'OnlineSecurity',
 'OnlineBackup',
 'DeviceProtection',
 'TechSupport',
 'StreamingTV',
 'StreamingMovies',
 'Contract',
 'PaperlessBilling',
 'PaymentMethod',
 'MonthlyCharges',
 'TotalCharges',
 'Churn']
```

In [3]:
```python
# Task 1
# Which column(s) have null values?

import numpy as np

# the dataset contains whitespaces instead of empty cells <-- replacing whiespaces wit
df.replace(' ', np.nan, inplace=True)

lst_count_null_values = df.count() - len(df) # list with a count of null values for ea
lst_column_names = list(df) # list with column names in the df <-- if a column has nul
lst_col_null_values = np.empty(shape=[0, 2], dtype=object) # list to put the columns w
```

```
for i in range(len(lst_count_null_values)): # loop thru each column in the df and chec
  if lst_count_null_values[i] < 0:
    lst_col_null_values = np.vstack((lst_col_null_values, np.array((lst_column_names[i

print('column(s) with null values:', '\n')
for col in range(len(lst_col_null_values)):
  print(lst_col_null_values[col][0], 'with', lst_col_null_values[col][1], 'null values
```

```
column(s) with null values:

TotalCharges with 11 null values
```

In [4]:
```
# Task 1
# Which percentage of null values dataset has?

int_count_total_null_values = 0
for i in range(len(lst_col_null_values)):
  int_count_total_null_values += int(lst_col_null_values[i][1])

int_count_total_values = df.shape[1] * df.shape[0]

print('total null values in dataset:', int_count_total_null_values)
print('total size of dataset:', df.shape[1], 'columns', '*', df.shape[0], 'rows', '=',
print('percentage of null values in dataset:', '%.4f' % ((int_count_total_null_values /

# print('Train Score: %.2f RMSE' % (trainScore))
```

```
total null values in dataset: 11
total size of dataset: 21 columns * 7043 rows = 147903 values
percentage of null values in dataset: 0.0074 %
```

In [5]:
```
# Task 1
# Replace null values with best candidates

# I previously replaced the whitespace values from the csv file with this command. Wit
#   df.replace(' ', np.nan, inplace=True)

print('Looking at the dataset the missing values are supposed to be 0 instead of a whi
print('I was considering replacing filling the MonthlyCharges into the TotalCharges.')
print('However, since the tenur is 0 for these records with null values, 0 for TotalCh

df.replace(np.nan, 0, inplace=True) # replacing the np.nan values with 0
```

```
Looking at the dataset the missing values are supposed to be 0 instead of a whitespace.
I was considering replacing filling the MonthlyCharges into the TotalCharges.
However, since the tenur is 0 for these records with null values, 0 for TotalCharges is a bett
```

In [6]:
```
# Task 2
# What are the correlations between input variables and target output Churn?

from sklearn import preprocessing

# To calculate the correlation for non numerical values the data needs to be factorize

columns_original_order = list(df) # initial order of the columns
columns_2_factorize = ['customerID', 'gender', 'Partner', 'Dependents', 'PhoneService'
                       'StreamingTV', 'StreamingMovies', 'Contract', 'PaperlessBilling
columns_not_2_factorize = ['SeniorCitizen', 'tenure', 'MonthlyCharges', 'TotalCharges'

df_factorized_temp = (df[columns_2_factorize].apply(lambda x: pd.factorize(x)[0])) # f

df_factorized = pd.merge(df[columns_not_2_factorize], df_factorized_temp, left_index=T

df_factorized.Churn = df_factorized.Churn.map(dict(yes=1, Yes=1, no=0, No=0)) # manual

df_factorized = df_factorized[columns_original_order] # restoring the initial order of

# Correlation calculation

df_factorized = df_factorized.drop(columns='customerID') # drop customerID as is logic
columns_df_factorized = list(df_factorized)

# Normalizing the data (even though not required for correlation it will be required f

x = df_factorized.values #returns a numpy array
min_max_scaler = preprocessing.MinMaxScaler()
x_scaled = min_max_scaler.fit_transform(x)
df_factorized_normalized = pd.DataFrame(x_scaled, columns=columns_df_factorized)

target_output = 'Churn'

print('Pearson correlation with', target_output, ':', '\n')
for i in range(len(columns_df_factorized)-1): # go through each input variable and cal
  feature = columns_df_factorized[i]
  corr = df_factorized_normalized[feature].corr(df_factorized_normalized[target_output]
  print(feature, corr)
```

```
Pearson correlation with Churn :

gender -0.008612095078997885
SeniorCitizen 0.15088932817647324
Partner 0.15044754495917667
Dependents -0.16422140157972476
tenure -0.35222867011307796
```

```
PhoneService 0.011941980029002942
MultipleLines 0.0363104366547957
InternetService -0.04729138768314237
OnlineSecurity -0.332819191689427
OnlineBackup -0.07420530149434537
DeviceProtection -0.2814648246574705
TechSupport -0.32985226446993626
StreamingTV -0.20574215693991318
StreamingMovies -0.20725609227308128
Contract -0.396712629209844
PaperlessBilling -0.19182533166646865
PaymentMethod -0.2628182020893573
MonthlyCharges 0.19335642223784713
TotalCharges -0.1983242626039956
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/utils/validation.py:595: DataConversionWarning:
  warnings.warn(msg, DataConversionWarning)
```

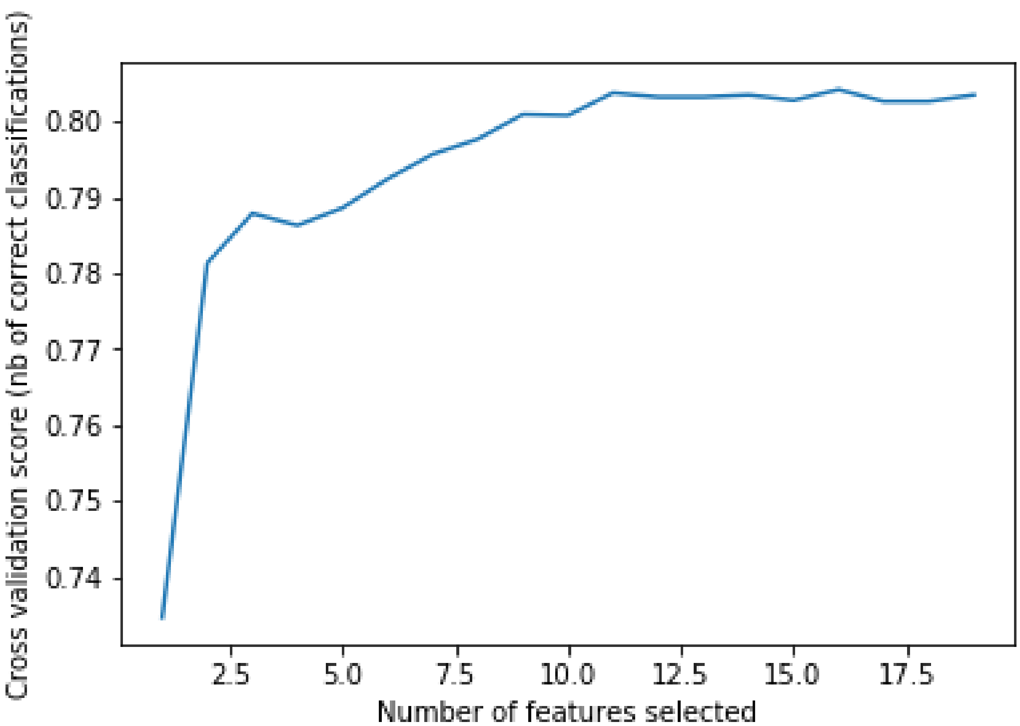
In [7]:
```
# Task 2
# What is your strategy for feature selection? (backward, forward, mixed?)

# Recursive feature elimination with cross-validation

from sklearn.svm import LinearSVC
from sklearn.feature_selection import RFECV
from sklearn.exceptions import DataConversionWarning, ConvergenceWarning
import warnings
warnings.filterwarnings(action='ignore', category=ConvergenceWarning)

array = df_factorized_normalized.values

# convert pandas df to an array for the model
X = array[:,0:19]
Y = array[:,19]

# X = array_norm[:,0:19]
# Y = array_norm[:,19]

# Feature extraction
estimator=LinearSVC(max_iter=1000)
selector=RFECV(estimator=estimator,cv=3)
selector.fit(X,Y)

print("N_features %s"%selector.n_features_)
print("Support is %s"%selector.support_) # shows whether feature is selected
print("Ranking %s"%selector.ranking_) # ranking of features <-- only rank 1 is selecte
print("Grid Scores %s"%selector.grid_scores_) # <-- correlation scores for each featur
```

```
N_features 16
Support is [False  True False  True  True  True  True  True  True  True  True  True
  True  True  True  True  True  True False]
Ranking [3 1 4 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 2]
Grid Scores [0.73463012 0.78134416 0.7878743  0.78631208 0.78858472 0.79241814
 0.79568363 0.79767144 0.80093717 0.80079491 0.80377713 0.80320897
 0.80320897 0.80349308 0.80278326 0.80420291 0.80264093 0.80264093
 0.80349272]
```

In [8]:
```python
# Task 2
# Which features you selected and why?

  # Recursive feature elimination with cross-validation

import matplotlib.pyplot as plt

lst_feature_parameters = np.empty(shape=[0, 4], dtype=object) # list to put the column
lst_column_names = list(df_factorized_normalized)
lst_features_2_use = []

for i in range(len(lst_column_names)-1): # loop thru each column in the df and check wh
    # add to the numpy array: feature, whether it's included, rank, grid score
    lst_feature_parameters = np.vstack((lst_feature_parameters, np.array((lst_column_na

print('per the Recursive feature elimination with cross-validation these are the optima
print('# of features to select:', selector.n_features_, '\n')

print('the selected features and their grid score:', '\n')
for i in range(len(lst_feature_parameters)): # print all the features that are selecte
  if lst_feature_parameters[i][1] == 'True':
    print(lst_feature_parameters[i][0], lst_feature_parameters[i][3])
    lst_features_2_use.append(lst_feature_parameters[i][0])


# Plot showing the the # of features compared grid scores
plt.figure()
plt.xlabel("Number of features selected")
plt.ylabel("Cross validation score (nb of correct classifications)")
plt.plot(range(1, len(selector.grid_scores_) + 1), selector.grid_scores_)
plt.show()
```

```
per the Recursive feature elimination with cross-validation these are the optimal features to b

# of features to select: 16

the selected features and their grid score:
```

```
SeniorCitizen 0.7813441567726823
Dependents 0.786312077689522
tenure 0.788584724128595
PhoneService 0.792418136458954
MultipleLines 0.795683629130619
InternetService 0.7976714386677012
OnlineSecurity 0.8009371732904403
OnlineBackup 0.8007949060588663
DeviceProtection 0.803777134510522
TechSupport 0.8032089729007538
StreamingTV 0.8032089729007538
StreamingMovies 0.8034930839495221
Contract 0.8027832599858652
PaperlessBilling 0.8042029079131793
PaymentMethod 0.8026409322665226
MonthlyCharges 0.8026409322665226
```



In [ ]:
```
# Task 2
# Which features you selected and why?

# Another way to select the best features. For this method the optimal number of featu
# However, I used this method to compare my optimal features from the previous techniq
```

```
## Recursive Feature Elimination

# from sklearn.feature_selection import RFE
# from sklearn.linear_model import LogisticRegression

# array = df_factorized_normalized.values

# X = array[:,0:19]
# Y = array[:,19]

# # Feature extraction
# model = LogisticRegression(solver='lbfgs', multi_class='auto', max_iter=1000) #chang
# rfe = RFE(model, 12)
# fit = rfe.fit(X, Y)

# print("Num Features: %s" % (fit.n_features_))
# print("Selected Features: %s" % (fit.support_))
# print("Feature Ranking: %s" % (fit.ranking_))
# print(fit)
```

In [10]:
```
# Task 3
# Build, train and evaluate a classifier model
# Model 1
  # Logistic Regression

from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import recall_score, precision_score, f1_score, accuracy_score

# Create Train & Test Data
array = df_factorized_normalized[lst_features_2_use + [target_output]].values
X = array[:,0:16]
Y = array[:,16]

X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.2, random_state=

# train the model
model = LogisticRegression(solver='lbfgs')
result = model.fit(X_train, Y_train)
prediction_test = model.predict(X_test)

# Calculate the metric scores

accuracy_log_regr = accuracy_score(Y_test, prediction_test) # <-- tp / (tp + fn)
recall_log_regr = recall_score(Y_test, prediction_test) # <-- tp / (tp + fn)
precision_log_regr = precision_score(Y_test, prediction_test) # <-- tp / (tp + fp)
f1_log_regr = f1_score(Y_test, prediction_test) # <-- F1 = 2 * (precision * recall) /
```

```
print('Metric scores of logistic regression model:', '\n')
print('Accuracy:', accuracy_log_regr)
print('Recall:', recall_log_regr)
print('Precision:', precision_log_regr)
print('F1 Score:', f1_log_regr)
```

```
Metric scores of logistic regression model:

Accuracy: 0.7963094393186657
Recall: 0.5135869565217391
Precision: 0.6363636363636364
F1 Score: 0.5684210526315789
```

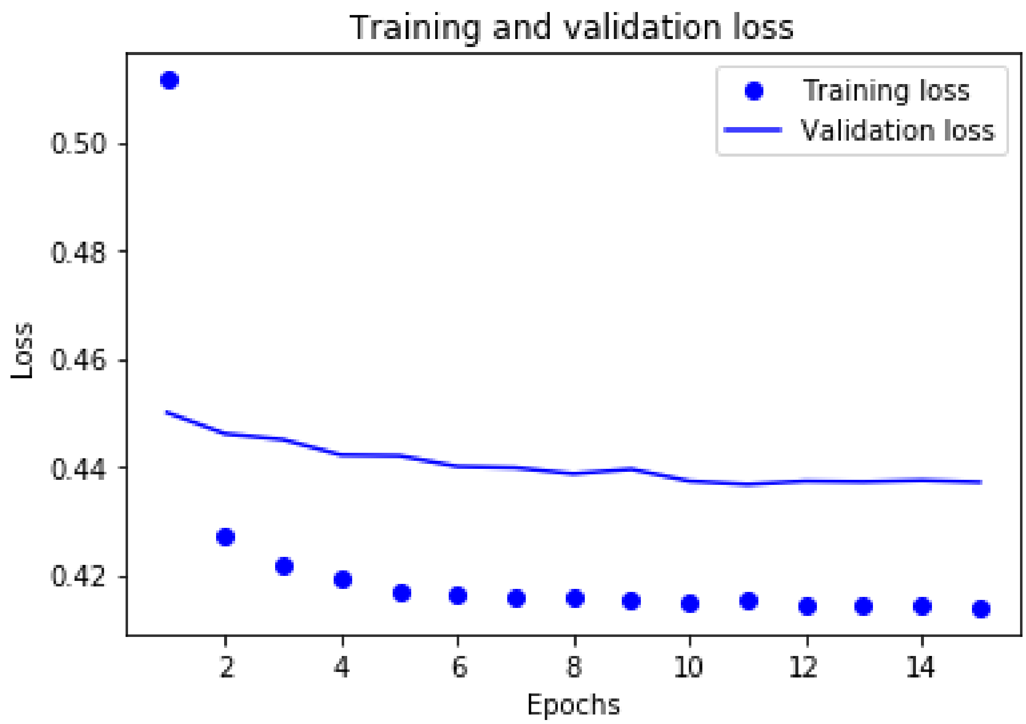
In [11]:
```
# Task 3
# Build, train and evaluate a classifier model
# Model 2

  # Artificial Neural Network

from sklearn.model_selection import train_test_split
import keras
from keras.models import Sequential
from keras.layers import Dense
from keras import optimizers
import matplotlib.pyplot as plt

# Create Train & Test Data
array = df_factorized_normalized[lst_features_2_use + [target_output]].values
X = array[:,0:16]
Y = array[:,16]

X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.2, random_state=

# Build the neural network model

classifier = Sequential()

# Input Layer
classifier.add(Dense(activation="relu", input_dim=selector.n_features_, units=8, kerne

# second hidden layer
classifier.add(Dense(activation="relu", units=8, kernel_initializer="uniform"))

# output layer
classifier.add(Dense(activation="sigmoid", units=1, kernel_initializer="uniform")) #
```

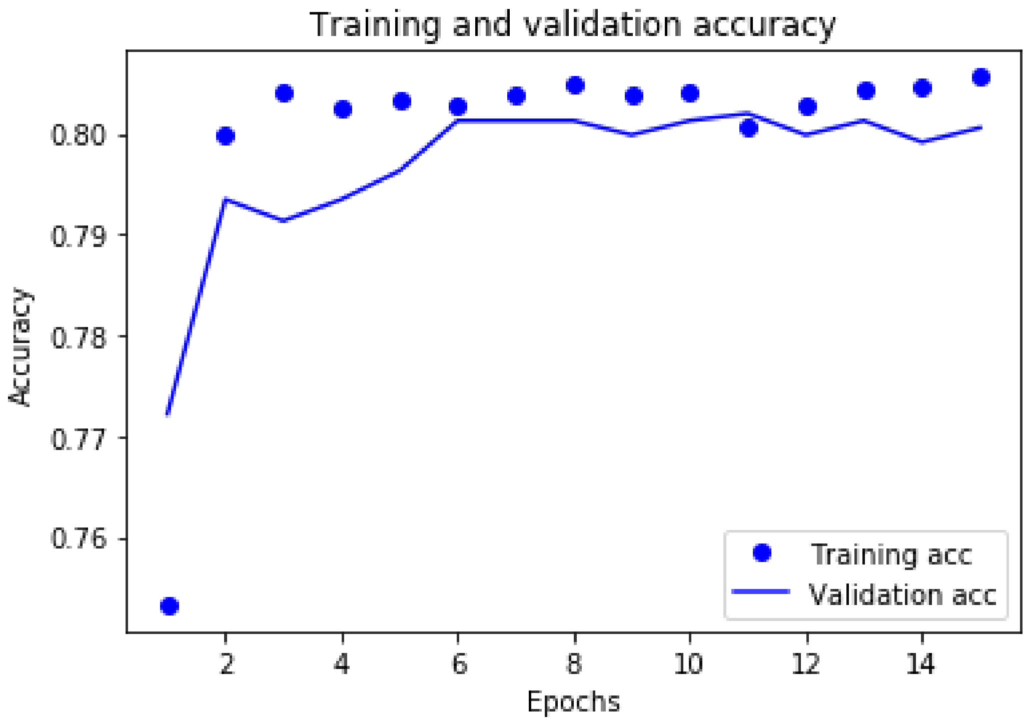
```
# Optimizer
# sgd = optimizers.SGD(lr=0.01, decay=1e-6, momentum=0.9, nesterov=True) # did not re

# compiling
classifier.compile(optimizer = 'adam', loss = 'binary_crossentropy', metrics = ['accu
# classifier.compile(loss='mean_squared_error', optimizer=sgd) # did not result in be

# Run the model
# classifier.fit(X_train, Y_train, batch_size = 10, nb_epoch = 10)
history = classifier.fit(X_train, Y_train, batch_size=10, epochs=15, validation_data=

# Evaluate
loss, accuracy = classifier.evaluate(X_test, Y_test, verbose=0)

# Calculate the metric scores
testPredict = classifier.predict(X_test)
int_testPredict = np.around(testPredict)

accuracy_ann = accuracy_score(Y_test, int_testPredict) # <-- tp / (tp + fn)
recall_ann = recall_score(Y_test, int_testPredict) # <-- tp / (tp + fn)
precision_ann = precision_score(Y_test, int_testPredict) # <-- tp / (tp + fp)
f1_ann = f1_score(Y_test, int_testPredict) # <-- F1 = 2 * (precision * recall) / (pre

print('Metric scores of artificial neural network model:', '\n')
print('Loss:', loss)
print('Accuracy:', accuracy_ann)
print('Recall:', recall_ann)
print('Precision:', precision_ann)
print('F1 Score:', f1_ann)

# Progression of the loss and accuracy with each epoch

history_dict = history.history
loss_values = history_dict['loss']
val_loss_values = history_dict['val_loss']
epochs = range(1, len(loss_values) + 1)
plt.plot(epochs, loss_values, 'bo', label='Training loss')
plt.plot(epochs, val_loss_values, 'b', label='Validation loss')
plt.title('Training and validation loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()

plt.clf()
acc = history_dict['acc']
val_acc = history_dict['val_acc']
plt.plot(epochs, acc, 'bo', label='Training acc')
```

```
plt.plot(epochs, val_acc, 'b', label='Validation acc')
plt.title('Training and validation accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.show()
```

```
Using TensorFlow backend.


WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/tensorflow/python/framework/op_
Instructions for updating:
Colocations handled automatically by placer.
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/tensorflow/python/ops/math_ops.
Instructions for updating:
Use tf.cast instead.
Train on 5634 samples, validate on 1409 samples
Epoch 1/15
5634/5634 [==============================] - 3s 535us/step - loss: 0.5115 - acc: 0.7533 - val_
Epoch 2/15
5634/5634 [==============================] - 2s 338us/step - loss: 0.4271 - acc: 0.8000 - val_
Epoch 3/15
5634/5634 [==============================] - 2s 339us/step - loss: 0.4215 - acc: 0.8042 - val_
Epoch 4/15
5634/5634 [==============================] - 2s 335us/step - loss: 0.4192 - acc: 0.8026 - val_
Epoch 5/15
5634/5634 [==============================] - 2s 335us/step - loss: 0.4170 - acc: 0.8033 - val_
Epoch 6/15
5634/5634 [==============================] - 2s 333us/step - loss: 0.4164 - acc: 0.8028 - val_
Epoch 7/15
5634/5634 [==============================] - 2s 333us/step - loss: 0.4160 - acc: 0.8039 - val_
Epoch 8/15
5634/5634 [==============================] - 2s 334us/step - loss: 0.4158 - acc: 0.8049 - val_
Epoch 9/15
5634/5634 [==============================] - 2s 333us/step - loss: 0.4155 - acc: 0.8039 - val_
Epoch 10/15
5634/5634 [==============================] - 2s 336us/step - loss: 0.4148 - acc: 0.8040 - val_
Epoch 11/15
5634/5634 [==============================] - 2s 335us/step - loss: 0.4153 - acc: 0.8007 - val_
Epoch 12/15
5634/5634 [==============================] - 2s 338us/step - loss: 0.4145 - acc: 0.8028 - val_
Epoch 13/15
5634/5634 [==============================] - 2s 331us/step - loss: 0.4142 - acc: 0.8044 - val_
Epoch 14/15
5634/5634 [==============================] - 2s 333us/step - loss: 0.4146 - acc: 0.8048 - val_
Epoch 15/15
5634/5634 [==============================] - 2s 332us/step - loss: 0.4139 - acc: 0.8056 - val_
Metric scores of artificial neural network model:
```

```
Loss: 0.43710820115653226
Accuracy: 0.8005677785663591
Recall: 0.5163043478260869
Precision: 0.6484641638225256
F1 Score: 0.5748865355521937
```






```
In [12]: # Task 3
         # Explain why you have selected that specific model

         print('I wanted to compare the the performance of two recommended models for Churn ana
         print('logistic regression and an artificial neural network.', '\n')

         print('Looking at the metric scores of each model, the logistic regression model perfo
         print('However, to make a recommandation as to which to use, more tweaking and fine tu

         print('Metric scores of artificial neural network model:', '\n')
         print('Accuracy:', accuracy_ann)
         print('Recall:', recall_ann)
         print('Precision:', precision_ann)
         print('F1 Score:', f1_ann, '\n')

         print('Metric scores of logistic regression model:', '\n')
         print('Accuracy:', accuracy_log_regr)
         print('Recall:', recall_log_regr)
         print('Precision:', precision_log_regr)
         print('F1 Score:', f1_log_regr)
```

```
I wanted to compare the the performance of two recommended models for Churn analysis (based on
logistic regression and an artificial neural network.
```

```
Looking at the metric scores of each model, the logistic regression model performs just slightl
However, to make a recommandation as to which to use, more tweaking and fine tuning of each moc

Metric scores of artificial neural network model:

Accuracy: 0.8005677785663591
Recall: 0.5163043478260869
Precision: 0.6484641638225256
F1 Score: 0.5748865355521937

Metric scores of logistic regression model:

Accuracy: 0.7963094393186657
Recall: 0.5135869565217391
Precision: 0.6363636363636364
F1 Score: 0.5684210526315789
```