# **Python Script**

# **Data Modeling Part**

```
In [1]: #pip install tensorflow
        #pip install pandas
        #pip install openpyxl
        #pip install scikit-learn
        #pip install matplotlib
        #pip install torch
        #pip install scalecast
        #pip install greykite
In [2]: import sys
        print(sys.version)
        3.10.9 | packaged by Anaconda, Inc. | (main, Mar 1 2023, 18:18:15) [MSC v.1916 64 bi
        t (AMD64)]
In [3]: ### Importing general libraries ###
        import numpy as np
        import pandas as pd
        import os
```

## Load Transformed Data from R Script

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0 -0.010782 0.009302
                                                                        0.004671
                                     -0.040822
                                                  -0.011461
          1 0.045041 0.009217
                                      0.040822
                                                   0.002110
                                                                        -0.003888
          2 -0.058684 0.009132
                                     -0.013423
                                                  -0.020147
                                                                        -0.003097
          3 -0.008276 0.006795
                                      0.000000
                                                   0.043883
                                                                        0.002816
          4 0.016484 0.005627
                                     -0.027399
                                                   0.055072
                                                                        -0.002796
          ## Feature selection based on granger causality test
          columns_to_keep = ['corn_diff', 'CPI_diff', 'USA_Avg_Temp', 'interaction_ps_di_diff',
          df = df[columns_to_keep]
          Perform Data Modelling
 In [7]:
          import pandas as pd
          import numpy as np
          import pickle
          import seaborn as sns
          import matplotlib.pyplot as plt
          from scalecast.Forecaster import Forecaster
          from dateutil.relativedelta import relativedelta
          #Create y and Yvars
 In [8]:
          y = df['corn diff']
          Xvars = df.drop(columns=['corn_diff'])
          # create list-like items
 In [9]:
          CPI diff = Xvars['CPI diff'].tolist()
          USA_Avg_Temp = Xvars['USA_Avg_Temp'].tolist()
          interaction_ps_di_diff = Xvars['interaction_ps_di_diff'].tolist()
In [10]:
          Xvars.head()
Out[10]:
             CPI_diff USA_Avg_Temp interaction_ps_di_diff
                                                             date
          0 0.009302
                          37.000000
                                              -0.000081 1980-12-01
          1 0.009217
                          30.502083
                                               0.000174 1981-01-01
          2 0.009132
                          31.941667
                                               0.000029 1981-02-01
          3 0.006795
                                               0.000000 1981-03-01
                          38.379167
          4 0.005627
                          47.885417
                                               -0.000026 1981-04-01
```

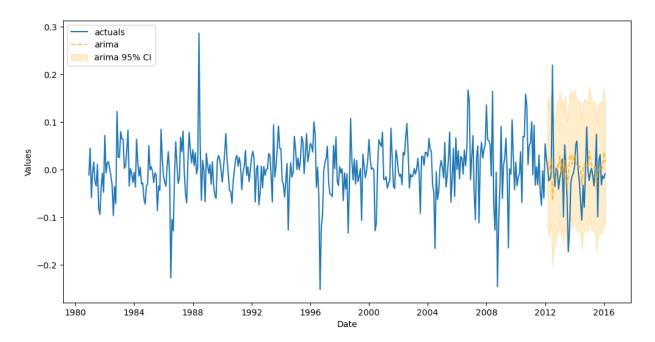
corn\_diff CPI\_diff Unemp\_rate\_diff NASDAQ\_diff disposable\_income\_diff Personal\_consumption\_

Out[5]:

In [11]:

# Create forecaster
f = Forecaster(

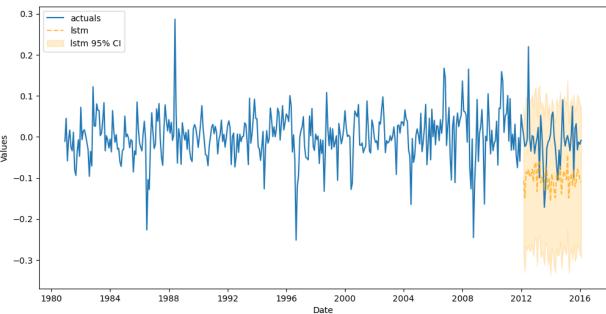
```
y=y,
             current dates=Xvars['date'],
         f
         Forecaster(
Out[11]:
             DateStartActuals=1980-12-01T00:00:00.000000000
             DateEndActuals=2016-02-01T00:00:00.000000000
             Freq=MS
             N_actuals=423
             ForecastLength=0
             Xvars=[]
             TestLength=0
             ValidationMetric=rmse
             ForecastsEvaluated=[]
             CILevel=None
             CurrentEstimator=mlr
             GridsFile=Grids
         )
In [12]: # prepare the forecast function
         f.ingest_Xvars_df(Xvars, date_col='date', use_future_dates=True) # Ingest external red
                                # 1. 48 observations to test the results
         f.set_test_length(48)
         f.generate future dates(48) # 2. 48 future points to forecast
         f.eval_cis(cilevel=0.95) # show confidence interval
In [13]: f
         Forecaster(
Out[13]:
             DateStartActuals=1980-12-01T00:00:00.000000000
             DateEndActuals=2016-02-01T00:00:00.000000000
             Freq=MS
             N actuals=423
             ForecastLength=48
             Xvars=['CPI_diff', 'USA_Avg_Temp', 'interaction_ps_di_diff']
             TestLength=48
             ValidationMetric=rmse
             ForecastsEvaluated=[]
             CILevel=0.95
             CurrentEstimator=mlr
             GridsFile=Grids
         )
In [14]: f.set_estimator('arima')
         f.manual_forecast(call_me='arima', seasonal_order=(2,1,1,12) )
         f.plot_test_set(ci=True, models='arima')
         <Axes: xlabel='Date', ylabel='Values'>
Out[14]:
```



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Epoch 1/15
9/9 [==========] - 3s 111ms/step - loss: 0.4625 - val loss: 0.477
Epoch 2/15
9/9 [==========] - 0s 13ms/step - loss: 0.4523 - val_loss: 0.4669
Epoch 3/15
9/9 [==========] - 0s 12ms/step - loss: 0.4419 - val loss: 0.4564
Epoch 4/15
9/9 [==========] - 0s 12ms/step - loss: 0.4311 - val_loss: 0.4453
Epoch 5/15
9/9 [=========] - 0s 12ms/step - loss: 0.4194 - val loss: 0.4332
Epoch 6/15
9/9 [=========] - 0s 12ms/step - loss: 0.4068 - val loss: 0.4199
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Epoch 9/15
9/9 [==========] - 0s 10ms/step - loss: 0.3606 - val loss: 0.3708
Epoch 10/15
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9/9 [==========] - 0s 10ms/step - loss: 0.3209 - val loss: 0.3290
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1/1 [======] - 1s 504ms/step
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Epoch 15/15
1/1 [=======] - 0s 343ms/step
12/12 [======== ] - 0s 1ms/step
<Axes: xlabel='Date', ylabel='Values'>
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#### Out[15]:



```
In [16]: f.set_estimator('lstm')
          f.manual_forecast(
              call_me='lstm_test',
              lags=36,
              batch_size=16,
              epochs=300,
              validation split=.2,
              shuffle=True,
              activation='tanh',
              optimizer='Adam',
              learning_rate=0.001,
              lstm layer sizes=(100,)*15,
              dropout=(0,)*15,
              plot_loss=True,
          f.plot_test_set(ci=True, models='lstm')
```

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15/15 [============= ] - 4s 256ms/step - loss: 0.0709 - val_loss: 0.1
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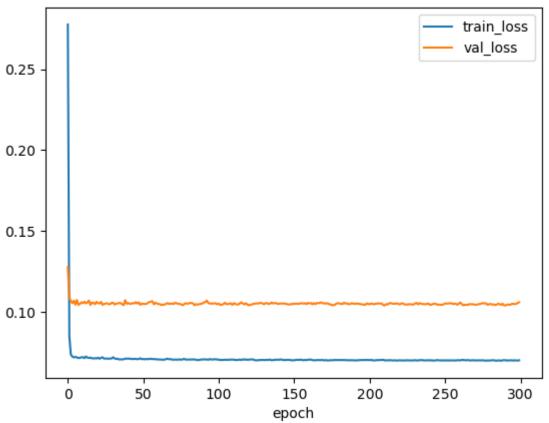
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17/17 [============== - 6s 337ms/step - loss: 0.0760 - val loss: 0.0
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17/17 [============== - 7s 384ms/step - loss: 0.0746 - val loss: 0.0
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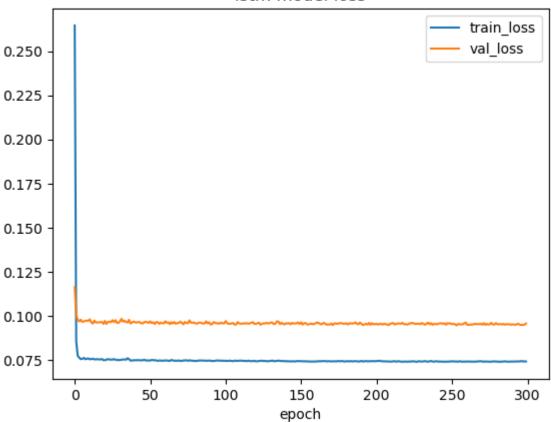
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17/17 [============== - 6s 334ms/step - loss: 0.0741 - val loss: 0.0
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```

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Epoch 261/300
950
Epoch 262/300
Epoch 263/300
950
Epoch 264/300
952
Epoch 265/300
Epoch 266/300
955
Epoch 267/300
954
Epoch 268/300
954
Epoch 269/300
954
Epoch 270/300
956
Epoch 271/300
950
Epoch 272/300
960
Epoch 273/300
Epoch 274/300
955
Epoch 275/300
951
Epoch 276/300
953
Epoch 277/300
Epoch 278/300
952
Epoch 279/300
951
Epoch 280/300
959
```

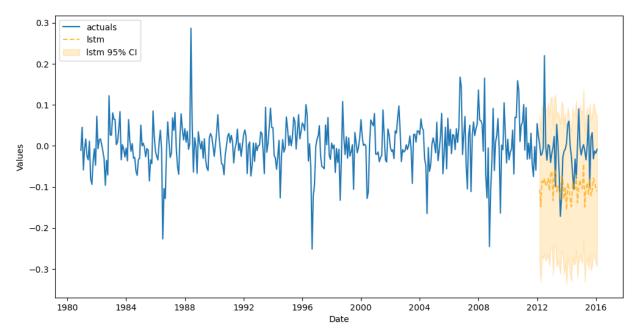
```
Epoch 281/300
954
Epoch 282/300
17/17 [============= - 7s 403ms/step - loss: 0.0740 - val loss: 0.0
Epoch 283/300
954
Epoch 284/300
952
Epoch 285/300
955
Epoch 286/300
Epoch 287/300
954
Epoch 288/300
952
Epoch 289/300
954
Epoch 290/300
950
Epoch 291/300
953
Epoch 292/300
951
Epoch 293/300
Epoch 294/300
954
Epoch 295/300
956
Epoch 296/300
950
Epoch 297/300
Epoch 298/300
950
Epoch 299/300
951
Epoch 300/300
957
```

```
1/1 [======] - 6s 6s/step
11/11 [======] - 1s 128ms/step
```

### Istm model loss



Out[16]: <Axes: xlabel='Date', ylabel='Values'>



```
11/11 [==========] - 1s 2ms/step - loss: 0.4486
                                         - 0s 149ms/step
        12/12 [============ ] - 1s 2ms/step - loss: 0.4470
        1/1 [=======] - 0s 127ms/step
        12/12 [======= ] - 0s 1ms/step
        <Axes: xlabel='Date', ylabel='Values'>
Out[17]:
                 actuals
                 mn
                 rnn 95% CI
           0.2
           0.0
          -0.2
          -0.4
          -0.6
          -0.8
                     1984
                            1988
                                   1992
                                           1996
                                                  2000
                                                         2004
                                                                2008
                                                                        2012
                                                                               2016
                                               Date
In [18]:
        import matplotlib
```

#check the current forecasting model

In [19]:

```
Forecaster(
Out[19]:
               DateStartActuals=1980-12-01T00:00:00.0000000000
               DateEndActuals=2016-02-01T00:00:00.000000000
               Freq=MS
               N actuals=423
               ForecastLength=48
               Xvars=['CPI_diff', 'USA_Avg_Temp', 'interaction_ps_di_diff', 'AR1', 'AR2', 'AR3',
          'AR4', 'AR5', 'AR6', 'AR7', 'AR8', 'AR9', 'AR10', 'AR11', 'AR12', 'AR13', 'AR14', 'AR 15', 'AR16', 'AR17', 'AR18', 'AR19', 'AR20', 'AR21', 'AR22', 'AR23', 'AR24', 'AR25',
           'AR26', 'AR27', 'AR28', 'AR29', 'AR30', 'AR31', 'AR32', 'AR33', 'AR34', 'AR35', 'AR3
          6']
               TestLength=48
               ValidationMetric=rmse
               ForecastsEvaluated=['arima', 'lstm', 'lstm test', 'rnn', 'silverkite']
               CILevel=0.95
               CurrentEstimator=silverkite
               GridsFile=Grids
           )
           Evaluation
In [20]:
          f.export('model summaries',determine best by='TestSetMAPE')[
               ['ModelNickname',
                 'TestSetMAPE',
                 'TestSetRMSE',
                 'TestSetR2',
                 'best model']
           ]
Out[20]:
              ModelNickname TestSetMAPE TestSetRMSE TestSetR2 best model
           0
                     lstm_test
                                   9.500492
                                                0.059380
                                                           -0.010701
                                                                            True
           1
                        arima
                                  10.526358
                                                0.067358
                                                           -0.300556
                                                                           False
           2
                     silverkite
                                 46.328376
                                                0.066486
                                                           -0.267082
                                                                           False
           3
                         lstm
                                 151.536190
                                                0.110654
                                                           -2.509805
                                                                           False
           4
                          rnn
                                428.203656
                                                0.245166 -16.229365
                                                                           False
          ts preds = f.export('lvl test set predictions')
In [21]:
           ts preds.head()
                   DATE
Out[21]:
                            actual
                                       arima
                                                   lstm
                                                        lstm_test
                                                                        rnn silverkite
           0 2012-03-01
                          0.004287
                                    0.018425 -0.106893
                                                        -0.006243 -0.178248
                                                                              0.025546
           1 2012-04-01 -0.023255 -0.004498
                                             -0.148176 -0.007602 -0.295018
                                                                              0.021793
           2 2012-05-01 -0.019975
                                    0.006551
                                             -0.085352 -0.008330 -0.128039
                                                                              0.019367
           3 2012-06-01 -0.005823
                                    0.023598
                                             -0.093062 -0.001215
                                                                  -0.305437
                                                                              0.017667
           4 2012-07-01
                          0.219890 -0.065216 -0.078934
                                                         0.000299 -0.043556 -0.008388
          ts_preds['actual_move'] = ts_preds['actual'].diff()
```

In [22]:

ts preds['rnn move'] = ts preds['rnn'].diff()

ts\_preds['silverkite\_move'] = ts\_preds['silverkite'].diff()

```
ts_preds['lstm_move'] = ts_preds['lstm'].diff()
ts_preds['arima_move'] = ts_preds['arima'].diff()
ts_preds = ts_preds.drop(0).reset_index(drop=True)
ts_preds.head()
```

```
Out[22]:
                DATE
                         actual
                                    arima
                                               Istm
                                                     lstm_test
                                                                     rnn
                                                                          silverkite actual_move rnn_move sil-
               2012-
            0
                      -0.023255
                                -0.004498 -0.148176
                                                     -0.007602 -0.295018
                                                                          0.021793
                                                                                       -0.027542
                                                                                                  -0.116770
               04-01
               2012-
            1
                      -0.019975
                                 0.006551
                                           -0.085352
                                                     -0.008330
                                                               -0.128039
                                                                          0.019367
                                                                                        0.003280
                                                                                                  0.166979
               05-01
               2012-
            2
                      -0.005823
                                 0.023598
                                          -0.093062
                                                     -0.001215
                                                               -0.305437
                                                                          0.017667
                                                                                        0.014152
                                                                                                  -0.177398
               06-01
               2012-
            3
                       0.219890
                                -0.065216 -0.078934
                                                      0.000299
                                                               -0.043556
                                                                          -0.008388
                                                                                        0.225713
                                                                                                  0.261881
               07-01
               2012-
            4
                      -0.002339 -0.029598 -0.097974 -0.004258 -0.221059 -0.000455
                                                                                       -0.222230
                                                                                                 -0.177503
               08-01
4
            ts_preds['actual_classification'] = ts_preds['actual_move'].apply(lambda x: 1 if x >=
 In [23]:
            ts_preds['rnn_classification'] = ts_preds['rnn_move'].apply(lambda x: 1 if x >= 0 else
             ts preds['silverkite classification'] = ts preds['silverkite move'].apply(lambda x: 1
             ts_preds['lstm_classification'] = ts_preds['lstm_move'].apply(lambda x: 1 if x >= 0 el
             ts_preds['arima_classification'] = ts_preds['arima_move'].apply(lambda x: 1 if x >= 0
            ts_preds.head()
 Out[23]:
                DATE
                         actual
                                    arima
                                                                                                rnn_move sil
                                               lstm
                                                     lstm_test
                                                                     rnn
                                                                          silverkite actual_move
               2012-
            0
                      -0.023255
                                -0.004498 -0.148176 -0.007602 -0.295018
                                                                          0.021793
                                                                                       -0.027542
                                                                                                 -0.116770
               04-01
               2012-
            1
                      -0.019975
                                 0.006551
                                           -0.085352
                                                    -0.008330 -0.128039
                                                                          0.019367
                                                                                        0.003280
                                                                                                  0.166979
               05-01
               2012-
                      -0.005823
            2
                                 0.023598
                                          -0.093062
                                                     -0.001215
                                                               -0.305437
                                                                          0.017667
                                                                                        0.014152
                                                                                                 -0.177398
               06-01
               2012-
            3
                       0.219890 -0.065216 -0.078934
                                                      0.000299
                                                               -0.043556
                                                                          -0.008388
                                                                                        0.225713
                                                                                                  0.261881
               07-01
               2012-
                      -0.002339 -0.029598 -0.097974
            4
                                                    -0.004258
                                                              -0.221059
                                                                         -0.000455
                                                                                       -0.222230
                                                                                                 -0.177503
               08-01
            from sklearn.metrics import confusion matrix
 In [24]:
             # Confusion matrix: actual vs rnn
```

```
In [24]: from sklearn.metrics import confusion_matrix
# Confusion matrix: actual vs rnn
    confusion_rnn = confusion_matrix(ts_preds['actual_classification'], ts_preds['rnn_class
    print("Confusion matrix (actual vs rnn):")
    print(confusion_rnn)

# Confusion matrix: actual vs silverkite
    confusion_silverkite = confusion_matrix(ts_preds['actual_classification'], ts_preds['s
    print("Confusion matrix (actual vs silverkite):")
    print(confusion_silverkite)

# Confusion matrix: actual vs lstm
```

```
confusion lstm = confusion matrix(ts preds['actual classification'], ts preds['lstm c]
         print("Confusion matrix (actual vs lstm):")
         print(confusion_lstm)
         # Confusion matrix: actual vs arima
         confusion_arima = confusion_matrix(ts_preds['actual_classification'], ts_preds['arima]
         print("Confusion matrix (actual vs arima):")
         print(confusion_arima)
         Confusion matrix (actual vs rnn):
         [[11 10]
          [14 12]]
         Confusion matrix (actual vs silverkite):
         [[12 9]
          [ 9 17]]
         Confusion matrix (actual vs lstm):
         [[11 10]
          [13 13]]
         Confusion matrix (actual vs arima):
         [[10 11]
          [12 14]]
In [25]: # Calculate evaluation metrics: actual vs mlr default
         tn_mlr, fp_mlr, fn_mlr, tp_mlr = confusion_rnn.ravel()
         accuracy_rnn = (tp_mlr + tn_mlr) / (tp_mlr + tn_mlr + fp_mlr + fn_mlr)
         precision rnn = tp mlr / (tp mlr + fp mlr)
         recall rnn = tp mlr / (tp mlr + fn mlr)
         f1_score_rnn = 2 * (precision_rnn * recall_rnn) / (precision_rnn + recall_rnn)
         print("Evaluation metrics (actual vs rnn):")
         print("Accuracy:", accuracy_rnn)
         print("Precision:", precision_rnn)
         print("Recall:", recall_rnn)
         print("F1 Score:", f1_score_rnn)
         print("")
         Evaluation metrics (actual vs rnn):
         Accuracy: 0.48936170212765956
         Precision: 0.5454545454545454
         Recall: 0.46153846153846156
         In [26]: # Calculate evaluation metrics: actual vs silverkit
         tn_mlr, fp_mlr, fn_mlr, tp_mlr = confusion_silverkite.ravel()
         accuracy silverkite = (tp mlr + tn mlr) / (tp mlr + tn mlr + fp mlr + fn mlr)
         precision_silverkite = tp_mlr / (tp_mlr + fp_mlr)
         recall_silverkite = tp_mlr / (tp_mlr + fn_mlr)
         f1_score_silverkite = 2 * (precision_silverkite * recall_silverkite) / (precision_silverkite)
         print("Evaluation metrics (actual vs silverkit):")
         print("Accuracy:", accuracy_silverkite)
         print("Precision:", precision_silverkite)
         print("Recall:", recall_silverkite)
         print("F1 Score:", f1_score_silverkite)
         print("")
```

```
Precision: 0.6538461538461539
         Recall: 0.6538461538461539
         F1 Score: 0.6538461538461539
In [27]: # Calculate evaluation metrics: actual vs lstm
         tn_mlr, fp_mlr, fn_mlr, tp_mlr = confusion_lstm.ravel()
         accuracy_lstm = (tp_mlr + tn_mlr) / (tp_mlr + tn_mlr + fp_mlr + fn_mlr)
          precision_lstm = tp_mlr / (tp_mlr + fp_mlr)
          recall_lstm = tp_mlr / (tp_mlr + fn_mlr)
          f1_score_lstm = 2 * (precision_lstm * recall_lstm) / (precision_lstm + recall_lstm)
          print("Evaluation metrics (actual vs lstm):")
          print("Accuracy:", accuracy_lstm)
         print("Precision:", precision_lstm)
          print("Recall:", recall_lstm)
          print("F1 Score:", f1 score lstm)
         print("")
         Evaluation metrics (actual vs lstm):
         Accuracy: 0.5106382978723404
         Precision: 0.5652173913043478
         Recall: 0.5
         F1 Score: 0.5306122448979592
In [28]: # Calculate evaluation metrics: actual vs arima
         tn_mlr, fp_mlr, fn_mlr, tp_mlr = confusion_arima.ravel()
          accuracy_arima = (tp_mlr + tn_mlr) / (tp_mlr + tn_mlr + fp_mlr + fn_mlr)
          precision_arima = tp_mlr / (tp_mlr + fp_mlr)
          recall_arima = tp_mlr / (tp_mlr + fn_mlr)
          f1 score arima = 2 * (precision arima * recall arima) / (precision arima + recall arim
          print("Evaluation metrics (actual vs arima):")
          print("Accuracy:", accuracy_arima)
         print("Precision:", precision_arima)
          print("Recall:", recall_arima)
          print("F1 Score:", f1 score arima)
          print("")
         Evaluation metrics (actual vs arima):
         Accuracy: 0.5106382978723404
         Precision: 0.56
         Recall: 0.5384615384615384
         F1 Score: 0.5490196078431373
```

Evaluation metrics (actual vs silverkit):

Accuracy: 0.6170212765957447