Sec 1 Homework #1 - Adrian

January 10, 2024

[1]:
```
import pandas as pd
import statsmodels.api as sm
```

1 1.) Import Data from FRED

[2]:
```
data = pd.read_csv("TaylorRuleData.csv", index_col = 0)
```

[3]:
```
data.index = pd.to_datetime(data.index)
```

[20]:
```
data.dropna()
```

[20]:
```
            FedFunds  Unemployment  HousingStarts  Inflation
1959-01-01      2.48           6.0         1657.0     29.010
1959-02-01      2.43           5.9         1667.0     29.000
1959-03-01      2.80           5.6         1620.0     28.970
1959-04-01      2.96           5.2         1590.0     28.980
1959-05-01      2.90           5.1         1498.0     29.040
…              …              …             …          …
2023-07-01      5.12           3.5         1451.0    304.348
2023-08-01      5.33           3.8         1305.0    306.269
2023-09-01      5.33           3.8         1356.0    307.481
2023-10-01      5.33           3.8         1359.0    307.619
2023-11-01      5.33           3.7         1560.0    307.917

[779 rows x 4 columns]
```

[23]:
```
data = data.dropna()
data
```

[23]:
```
            FedFunds  Unemployment  HousingStarts  Inflation
1959-01-01      2.48           6.0         1657.0     29.010
1959-02-01      2.43           5.9         1667.0     29.000
1959-03-01      2.80           5.6         1620.0     28.970
1959-04-01      2.96           5.2         1590.0     28.980
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…              …              …             …          …
2023-07-01      5.12           3.5         1451.0    304.348
```

```
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2023-11-01       5.33           3.7          1560.0    307.917

[779 rows x 4 columns]
```

2 2.) Do Not Randomize, split your data into Train, Test Holdout

[24]:
```python
split1 = int(len(data) * .6)
split2 = int(len(data) * .9)
data_in = data[:split1]
data_out = data[split1:split2]
data_hold = data[split2:]
```

[25]:
```python
X_in = data_in.iloc[:,1:]
y_in = data_in.iloc[:,0]
X_out = data_out.iloc[:,1:]
y_out = data_out.iloc[:,0]
X_hold = data_hold.iloc[:,1:]
y_hold = data_hold.iloc[:,0]
```

[50]:
```python
X_in = sm.add_constant(X_in)
X_out = sm.add_constant(X_out)
X_hold = sm.add_constant(X_hold)
```

3 3.) Build a model that regresses FF~Unemp, HousingStarts, Inflation

[51]:
```python
import statsmodels.api as sm
```

[52]:
```python
model = sm.OLS(y_in, X_in)

results = model.fit()

print(results.summary())
```

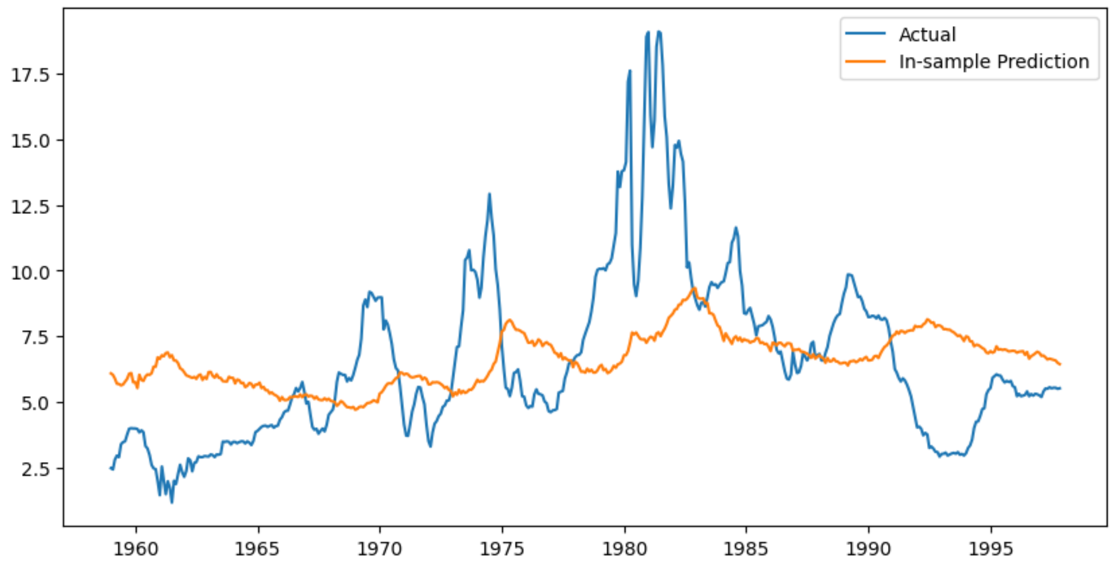
```
                            OLS Regression Results
==============================================================================
Dep. Variable:               FedFunds   R-squared:                       0.088
Model:                            OLS   Adj. R-squared:                  0.082
Method:                 Least Squares   F-statistic:                     14.83
Date:                Wed, 10 Jan 2024   Prob (F-statistic):           3.09e-09
Time:                        15:21:00   Log-Likelihood:                -1202.0
No. Observations:                 467   AIC:                             2412.
Df Residuals:                     463   BIC:                             2429.
```

```
Df Model:                           3
Covariance Type:            nonrobust
================================================================================
=
                   coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------------
-
const            3.4750      0.985      3.529      0.000       1.540
5.410
Unemployment     0.5307      0.106      5.009      0.000       0.323
0.739
HousingStarts   -0.0005      0.000     -1.046      0.296      -0.001
0.000
Inflation        0.0077      0.004      2.173      0.030       0.001
0.015
==============================================================================
Omnibus:                       77.750   Durbin-Watson:                   0.043
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              122.849
Skew:                           1.039   Prob(JB):                     2.11e-27
Kurtosis:                       4.413   Cond. No.                     1.03e+04
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 1.03e+04. This might indicate that there are
strong multicollinearity or other numerical problems.
```

4 4.) Recreate the graph fro your model

[32]:
```python
import matplotlib.pyplot as plt
```

[33]:
```python
plt.figure(figsize=(10,5))
plt.plot(y_in.index, y_in, label='Actual')
plt.plot(y_in.index, y_pred_in, label='In-sample Prediction')
plt.legend()
plt.show()
```



4.1 "All Models are wrong but some are useful" - 1976 George Box

5 5.) What are the in/out of sample MSEs

[36]:
```
from sklearn.metrics import mean_squared_error
```

[37]:
```
mse_in = mean_squared_error(y_in, y_pred_in)
mse_out = mean_squared_error(y_out, y_pred_out)
```

[38]:
```
print("Insample MSE : ", mse_in)
print("Outsample MSE : ", mse_out)
```

```
Insample MSE :  10.071422013168643
Outsample MSE :  40.36082783566727
```

6 6.) Using a for loop. Repeat 3,4,5 for polynomial degrees 1,2,3

[42]:
```
from sklearn.preprocessing import PolynomialFeatures
```

[47]:
```
max_degrees = 3
```

[48]:
```
poly = PolynomialFeatures(degree = degrees)
X_in_poly = poly.fit_transform(X_in)
X_out_poly = poly.fit_transform(X_out)
```

[41]:
```
dir(poly)
```

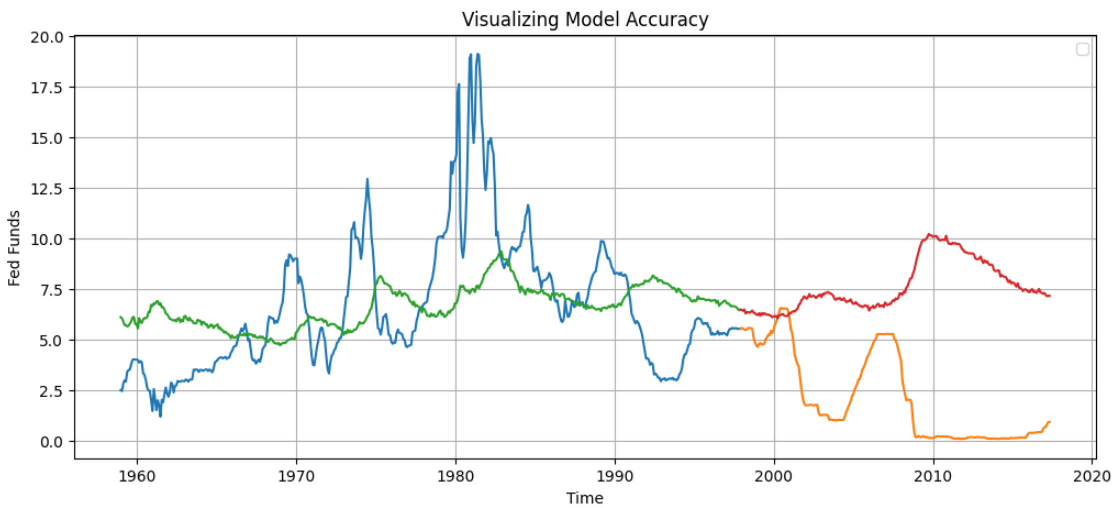
[41]:
```
['__annotations__',
 '__class__',
 '__delattr__',
 '__dict__',
 '__dir__',
 '__doc__',
 '__eq__',
 '__format__',
 '__ge__',
 '__getattribute__',
 '__getstate__',
 '__gt__',
 '__hash__',
 '__init__',
 '__init_subclass__',
 '__le__',
 '__lt__',
 '__module__',
 '__ne__',
 '__new__',
 '__reduce__',
 '__reduce_ex__',
 '__repr__',
 '__setattr__',
 '__setstate__',
 '__sizeof__',
 '__sklearn_clone__',
 '__str__',
 '__subclasshook__',
 '__weakref__',
 '_build_request_for_signature',
 '_check_feature_names',
 '_check_n_features',
 '_combinations',
 '_get_default_requests',
 '_get_metadata_request',
 '_get_param_names',
 '_get_tags',
 '_more_tags',
 '_num_combinations',
 '_parameter_constraints',
 '_repr_html_',
 '_repr_html_inner',
 '_repr_mimebundle_',
 '_sklearn_auto_wrap_output_keys',
 '_validate_data',
 '_validate_params',
```

```
'degree',
'fit',
'fit_transform',
'get_feature_names_out',
'get_metadata_routing',
'get_params',
'include_bias',
'interaction_only',
'order',
'powers_',
'set_output',
'set_params',
'transform']
```

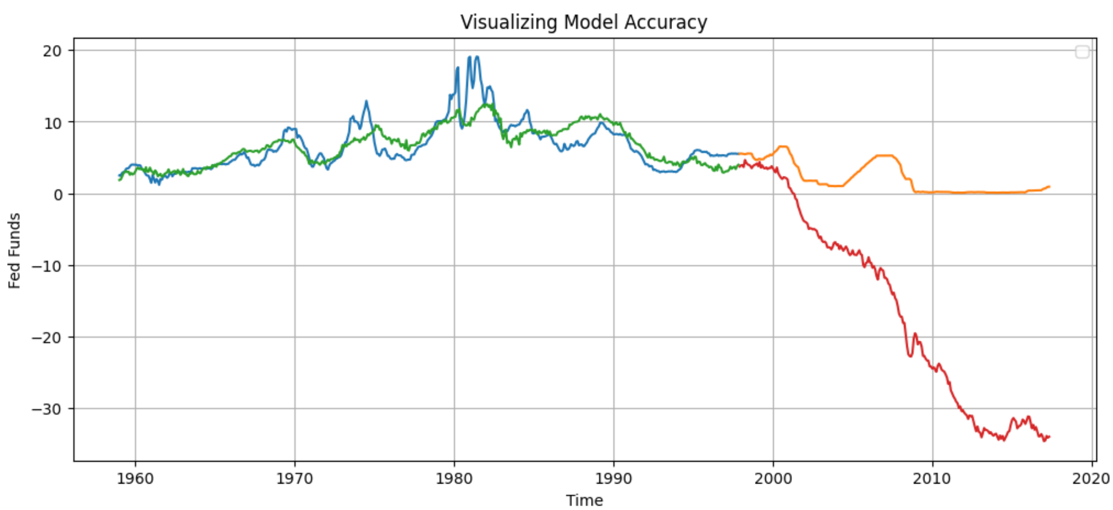
[63]:

```
for degrees in range (1, max_degrees + 1):
    print ("DEGREE : ", degrees)
    poly = PolynomialFeatures(degree =degrees)
    X_in_poly = poly.fit_transform(X_in)
    X_out_poly = poly.fit_transform(X_out)

    model1 = sm.OLS(y_in, X_in_poly).fit()
    plt.figure(figsize = (12,5))

    pred_in = model1.predict(X_in_poly)
    pred_in = pd.DataFrame(pred_in, index = y_in.index)

    ###
    plt.plot(y_in)
    plt.plot(y_out)
    plt.plot(data_in.index,model1.predict(X_in_poly))
    plt.plot(data_out.index,model1.predict(X_out_poly))
    ###

    plt.ylabel("Fed Funds")
    plt.xlabel("Time")
    plt.title("Visualizing Model Accuracy")
    plt.legend([])
    plt.grid()
    plt.show()

    in_mse_1 = mean_squared_error(model1.predict(X_in_poly), y_in)
    out_mse_1 = mean_squared_error(model1.predict(X_out_poly), y_out)

    print("Insample MSE : ", in_mse_1)
    print("Outsample MSE : ", out_mse_1)
```

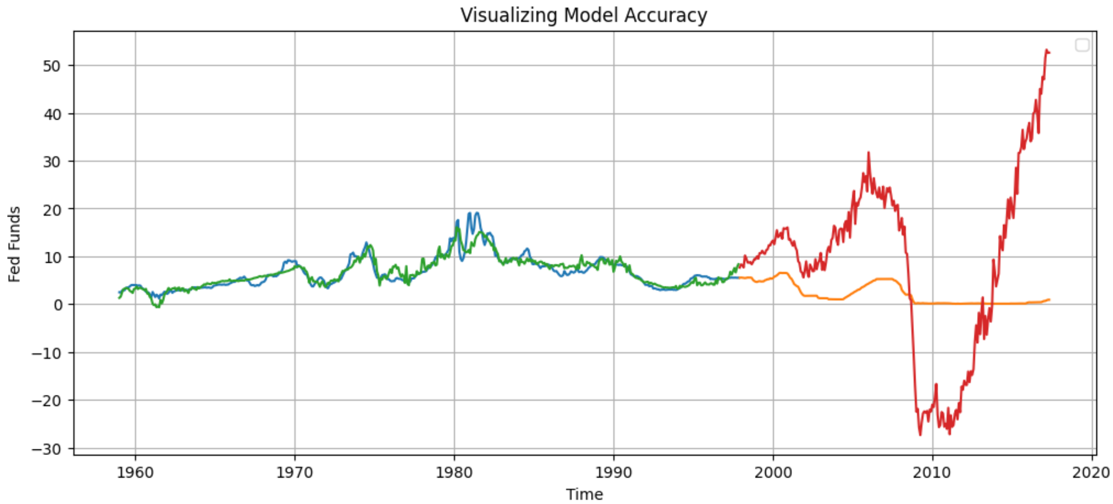
```
DEGREE :  1
```




```
Insample MSE :  10.071422013168641
Outsample MSE :  40.360827835667884
DEGREE :  2
```




```
Insample MSE :  3.863477139276068
Outsample MSE :  481.4465099288752
DEGREE :  3
```




```
Insample MSE :  1.8723636271435131
Outsample MSE :  371.7675896854977
```

7 7.) State your observations :

The consistent out-sample MSE across polynomial degrees 1, 2, and 3 suggests that increasing the complexity of the model (making the model more flexible) with higher-degree polynomials decreases in sample MSE, however, does not improve the model's predictive performance because the out sample MSE keeps on increasing which is sensitive to the training data noise.