Sec 1 Homework #1

January 10, 2024

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

1 1.) Import Data from FRED

[4]:
```python
data = pd.read_csv("TaylorRuleData.csv", index_col = 0)
data
```

[4]:
```
            FedFunds  Unemployment  HousingStarts  Inflation
1947-01-01       NaN           NaN            NaN     21.480
1947-02-01       NaN           NaN            NaN     21.620
1947-03-01       NaN           NaN            NaN     22.000
1947-04-01       NaN           NaN            NaN     22.000
1947-05-01       NaN           NaN            NaN     21.950
…                 …             …              …         …
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
2023-12-01      5.33           3.7            NaN        NaN

[924 rows x 4 columns]
```

[5]:
```python
data.dropna(inplace = True)
data
```

[5]:
```
            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]
```

[6]:
```python
data.index = pd.to_datetime(data.index)
```

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

[11]:
```python
split1 = int(len(data) * 0.6)
split2 = int(len(data) * 0.9)
data_in = data[:split1]
data_out = data[split1:split2]
data_hold = data[split2:]
```

[13]:
```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]
```

[14]:
```python
# Add Constants
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

[22]:
```python
model1 = sm.OLS(y_in, X_in).fit()
print(model1.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:                        14:57:50   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
```

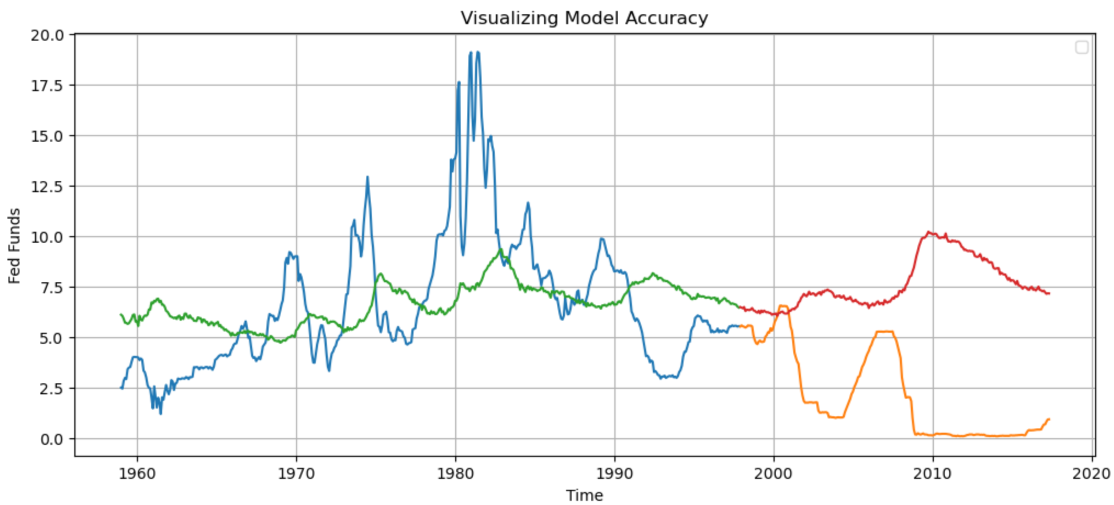
```
0.975]
------------------------------------------------------------------------------------
-
const             3.4750      0.985      3.529      0.000      1.540
5.410
Unemployment      0.5307      0.106      5.009      0.000      0.323
0.739
HousingStarts    -0.0005      0.000     -1.046      0.296     -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.
```

[24]:
```
y_pred = model1.predict(X_in)
```

4 4.) Recreate the graph fro your model

[19]:
```
import matplotlib.pyplot as plt
```

[30]:
```
plt.figure(figsize = (12,5))

###
plt.plot(y_in) #in sample actual
plt.plot(y_out) #out sample actual
plt.plot(model1.predict(X_in)) #in sample prediction
plt.plot(model1.predict(X_out)) #out sample prediction
###

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

[32]:
```
from sklearn.metrics import mean_squared_error
```

[33]:
```
in_mse_1 = mean_squared_error(model1.predict(X_in), y_in)
out_mse_1 = mean_squared_error(model1.predict(X_out), y_out)
```

[34]:
```
print("Insample MSE : ", in_mse_1)
print("Outsample MSE : ", out_mse_1)
```

```
Insample MSE :  10.071422013168643
Outsample MSE :  40.3608278356685
```

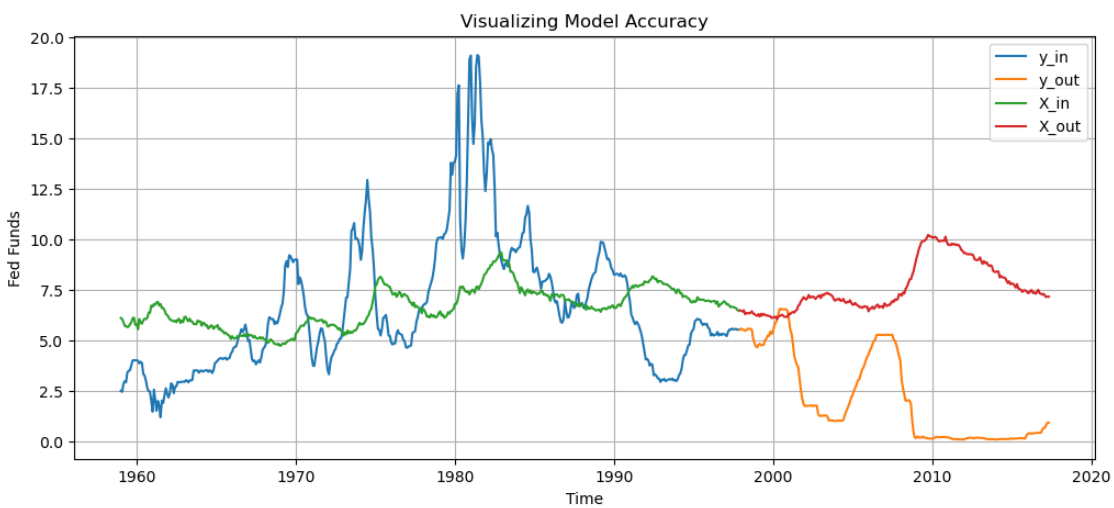
6 6.) Using a for loop. Repeat 3,4,5 for polynomial degrees 1,2,3

[48]:
```
import pandas as pd
from sklearn.preprocessing import PolynomialFeatures
```

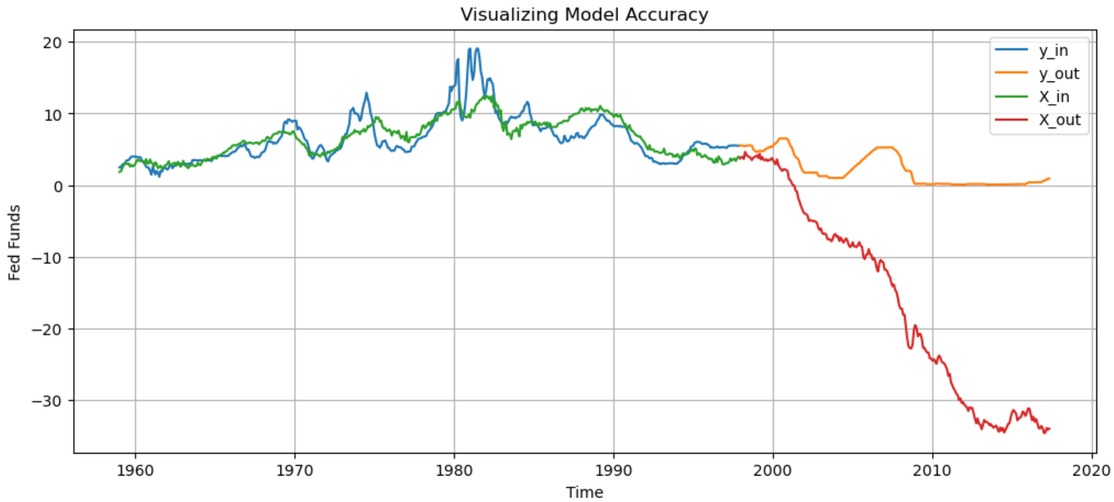
[43]:
```
max_degrees = 3
```

[55]:
```
for degrees in range(1, max_degrees+1):
    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()
```

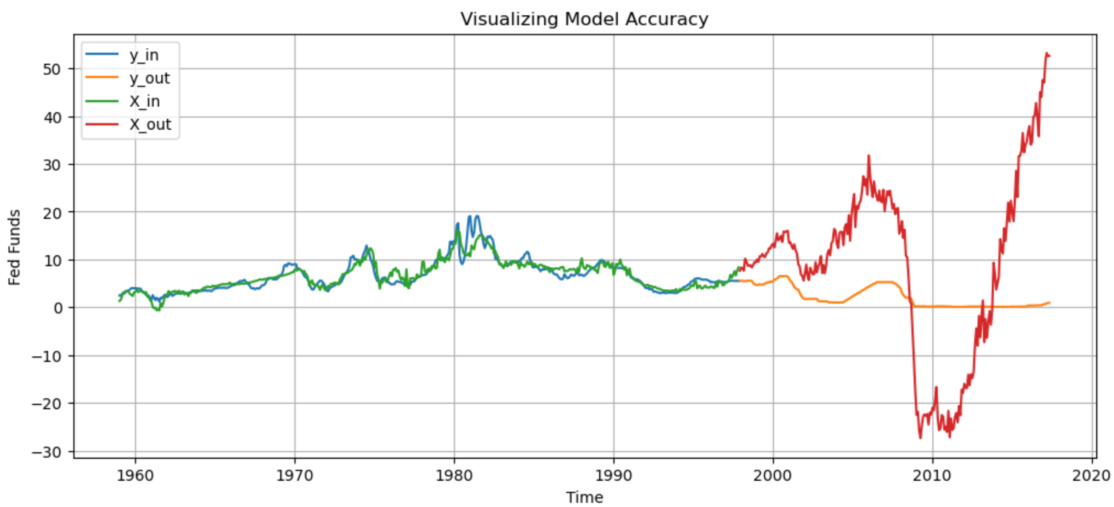
```python
plt.figure(figsize = (12,5))
##
in_preds = model1.predict(X_in_poly)
in_preds = pd.DataFrame(in_preds, index = y_in.index)
out_preds = model1.predict(X_out_poly)
out_preds = pd.DataFrame(out_preds, index = y_out.index)
###
plt.plot(y_in) #in sample actual
plt.plot(y_out) #out sample actual
plt.plot(in_preds) #in sample prediction
plt.plot(out_preds) #out sample prediction
###

plt.ylabel("Fed Funds")
plt.xlabel("Time")
plt.title("Visualizing Model Accuracy")
plt.legend(['y_in', 'y_out', 'X_in', 'X_out'])
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)

#X is the preductions, Y is the real data
```



```
Insample MSE :  10.071422013168641
Outsample MSE :  40.36082783565204
```




```
Insample MSE :  3.863477139276068
Outsample MSE :  481.4465099024405
```




```
Insample MSE :  1.8723636288250916
Outsample MSE :  371.7672642959744
```

[ ]:

7 7.) State your observations :

This look shows clearly the tradeoff between bias and variance. It is amazing how closly the third degree polynomial tracks the training data, but the foreward prediction is completely unuseable as it attempts too closly follows the noise in the training data. Of these three models, it seems like the simplest model is the best to be carried foreward.

```
[ ]:
```