Homework #1

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

1 Import Data from FRED

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

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

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

[4]:
```
split_1 = int(len(data)*.6)
split_2 = int(len(data)*.9)
data_in = data[:split_1]
data_out = data[split_1:split_2]
data_hold = data[split_2:]
```

[5]:
```
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]
```

[6]:
```
# Add Constants
X_in = sm.add_constant(X_in)
X_out = sm.add_constant(X_out)
X_hold = sm.add_constant(X_hold)
```

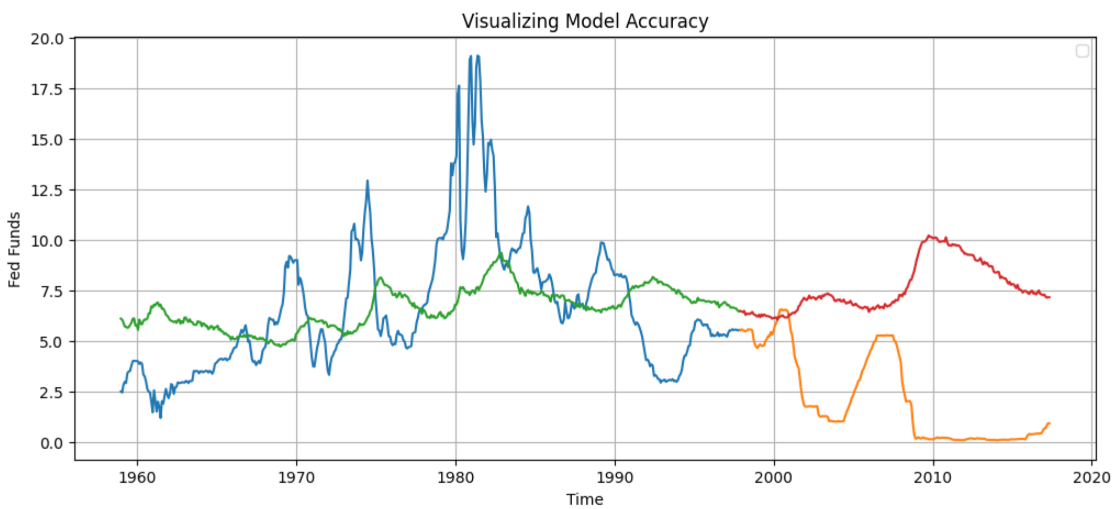
3 Build a model that regresses FF~Unemp, HousingStarts, Inflation

[7]:
```
model1 = sm.OLS(y_in,X_in).fit()
```

4 Recreate the graph fro your model

[8]:
```
import matplotlib.pyplot as plt
```

[9]:
```
plt.figure(figsize = (12,5))

###
plt.plot(y_in)
plt.plot(y_out)
plt.plot(model1.predict(X_in))
plt.plot(model1.predict(X_out))
###

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 What are the in/out of sample MSEs

[10]:
```
from sklearn.metrics import mean_squared_error
```

[11]:
```
in_mse_1 = mean_squared_error(y_in,model1.predict(X_in))
out_mse_1 = mean_squared_error(y_out,model1.predict(X_out))
```

[12]:
```
print("Insample MSE : ", in_mse_1)
print("Outsample MSE : ", out_mse_1)
```

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

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

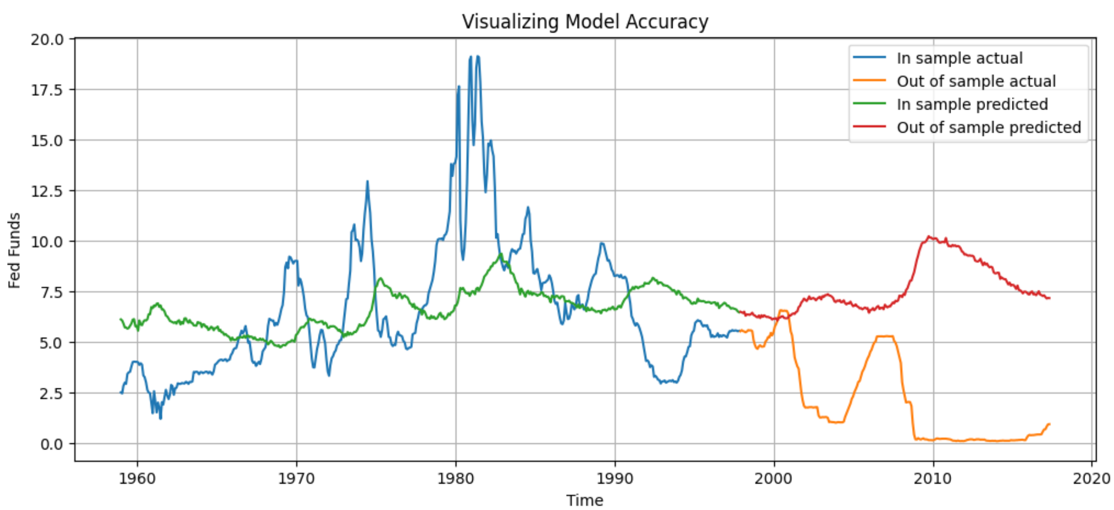
[13]:
```
from sklearn.preprocessing import PolynomialFeatures
```

[14]:
```
max_degrees = 3
```

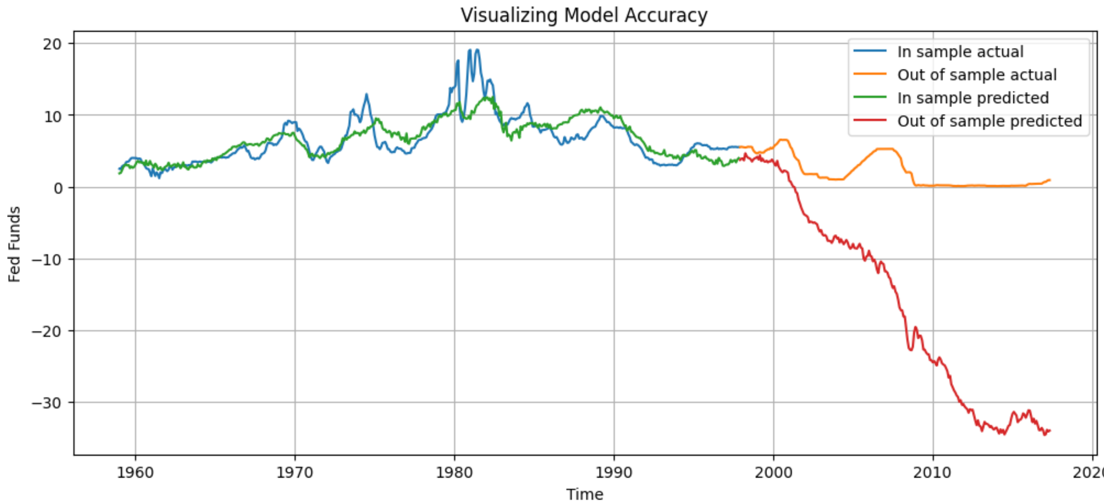
[15]:
```
for degrees in range (1,1+max_degrees):
    print("DEGREES: ", degrees)
    poly = PolynomialFeatures(degree = degrees)
    X_in_poly = poly.fit_transform(X_in)
    X_out_poly = poly.transform(X_out)

    model1 = sm.OLS(y_in, X_in_poly).fit()

    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)
    plt.plot(y_out)
    plt.plot(in_preds)
    plt.plot(out_preds)

    plt.ylabel("Fed Funds")
    plt.xlabel("Time")
    plt.title("Visualizing Model Accuracy")
    plt.legend(["In sample actual","Out of sample actual","In sample␣
↪predicted","Out of sample predicted"])
    plt.grid()
```

```
    plt.show()

    in_mse_1 = mean_squared_error(y_in, model1.predict(X_in_poly))
    out_mse_1 = mean_squared_error(y_out, model1.predict(X_out_poly))
    print("Insample MSE : ", in_mse_1 )
    print("Outsample MSE : ", out_mse_1 )
   ␣
 ↪print("_________________________________________________________________________________
 ↪ ")
    print("")
```

DEGREES: 1

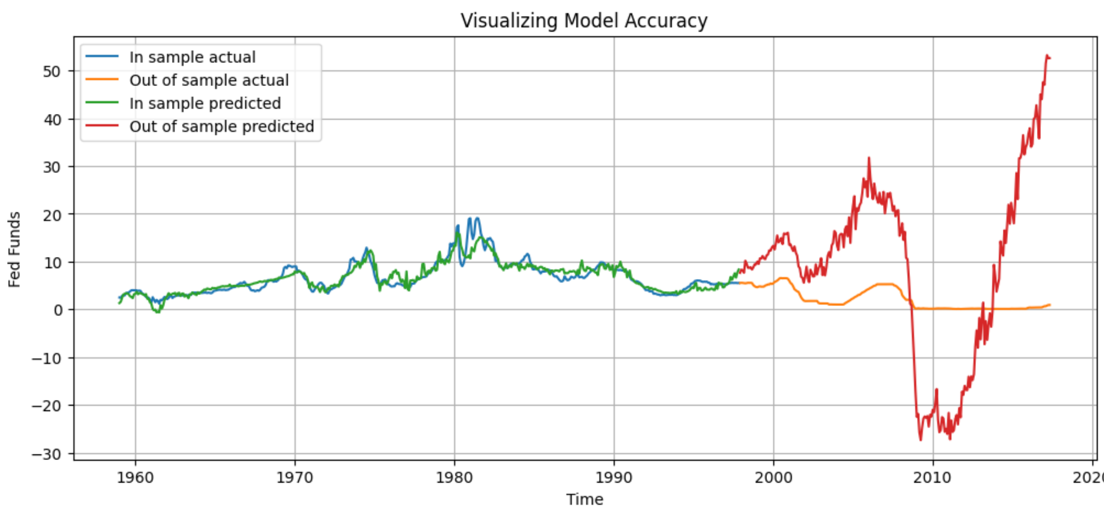



```
Insample MSE :  10.071422013168641
Outsample MSE :  40.36082783565204
________________________________________________________________________________
_________________________________

DEGREES:  2
```




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

```
DEGREES:  3
```




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

7 State your observations :

As we go on increasing the degree of the linear regression, there is tradeoff between Bias and Variance.

In the case of a first-degree model, we observe high bias as the in-data predictions do not closely follow the actual values, supported by the relatively high in-sample RMSE. This indicates an oversimplified model that fails to capture the complexity of the underlying patterns in the data. We also observe a low variance in the out-value predicted values. This is a case of under-fitting where the model is too simplistic to represent the underlying relationships in the data adequately.

In second degree model, we notice a significant improvement in the in-sample predictions. The model now captures the general trends and movements of the actual data more effectively, resulting in a closer alignment between predictions and actual values within the training dataset. Looking at the predictions for the out-data, we see a consistent trend line, althought it doesnt match with the actual out-data values.Model 2 shows a lower in-sample RMSE compared to Model 1, indicating a reduction in bias. However, the substantial increase in out-of-sample RMSE suggests a significant rise in variance, signifying potential overfitting to the training data. This indicates a slightly increased variance, signifying that while the model has improved in capturing complexity, it may not generalize well to new, unseen data

In the third degree model, we observe in-sample predictions that almost perfectly overlay the actual in-sample values. The model exhibits a high degree of flexibility, accommodating the intricacies of the training data with great precision. However, out-of-sample predictions become highly volatile and sensitive to even minor fluctuations in the data. Model 3 displays further reductions in both in-sample and out-of-sample RMSE compared to Model 2. The low in-sample RMSE suggests a model that fits the training data well, potentially capturing underlying patterns. However, the relatively high out-of-sample RMSE indicates a moderate level of variance. This is a case of the over-fitting, it fails to generalize well to new data, leading to a decline in predictive accuracy.