# WeatherAnalysys

December 22, 2024

[227]:
```
######################
# Dependency import #
######################

import seaborn as sb
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import sklearn.linear_model as linear_model
import sklearn.preprocessing as preprocessing
import sklearn.model_selection as model_selection
import sklearn.metrics as metrics
import json
```

[228]:
```
####################
# Dataset loading #
####################

dt = pd.read_csv('city_temperature.csv')
dt.head(100)
```

```
C:\Users\teodo\AppData\Local\Temp\ipykernel_5476\3705457785.py:5: DtypeWarning:
Columns (2) have mixed types. Specify dtype option on import or set
low_memory=False.
  dt = pd.read_csv('city_temperature.csv')
```

[228]:

| | Region | Country | State | City | Month | Day | Year | AvgTemperature |
|---|---|---|---|---|---|---|---|---|
| 0 | Africa | Algeria | NaN | Algiers | 1 | 1 | 1995 | 64.2 |
| 1 | Africa | Algeria | NaN | Algiers | 1 | 2 | 1995 | 49.4 |
| 2 | Africa | Algeria | NaN | Algiers | 1 | 3 | 1995 | 48.8 |
| 3 | Africa | Algeria | NaN | Algiers | 1 | 4 | 1995 | 46.4 |
| 4 | Africa | Algeria | NaN | Algiers | 1 | 5 | 1995 | 47.9 |
| .. | … | … | … | … | … | … | … | … |
| 95 | Africa | Algeria | NaN | Algiers | 4 | 6 | 1995 | 59.0 |
| 96 | Africa | Algeria | NaN | Algiers | 4 | 7 | 1995 | 54.9 |
| 97 | Africa | Algeria | NaN | Algiers | 4 | 8 | 1995 | 54.2 |
| 98 | Africa | Algeria | NaN | Algiers | 4 | 9 | 1995 | 57.8 |
| 99 | Africa | Algeria | NaN | Algiers | 4 | 10 | 1995 | 60.0 |

[100 rows x 8 columns]

[229]:
```
##################
# Data cleaning #
##################

dt.drop(columns=["State", "Region"], axis=1, inplace=True)
dt.drop(index=dt.loc[dt["Day"] <= 0].index, inplace=True)
dt.drop(index=dt.loc[dt["AvgTemperature"] <= -20].index, inplace=True)
dt.dropna()

dt
```

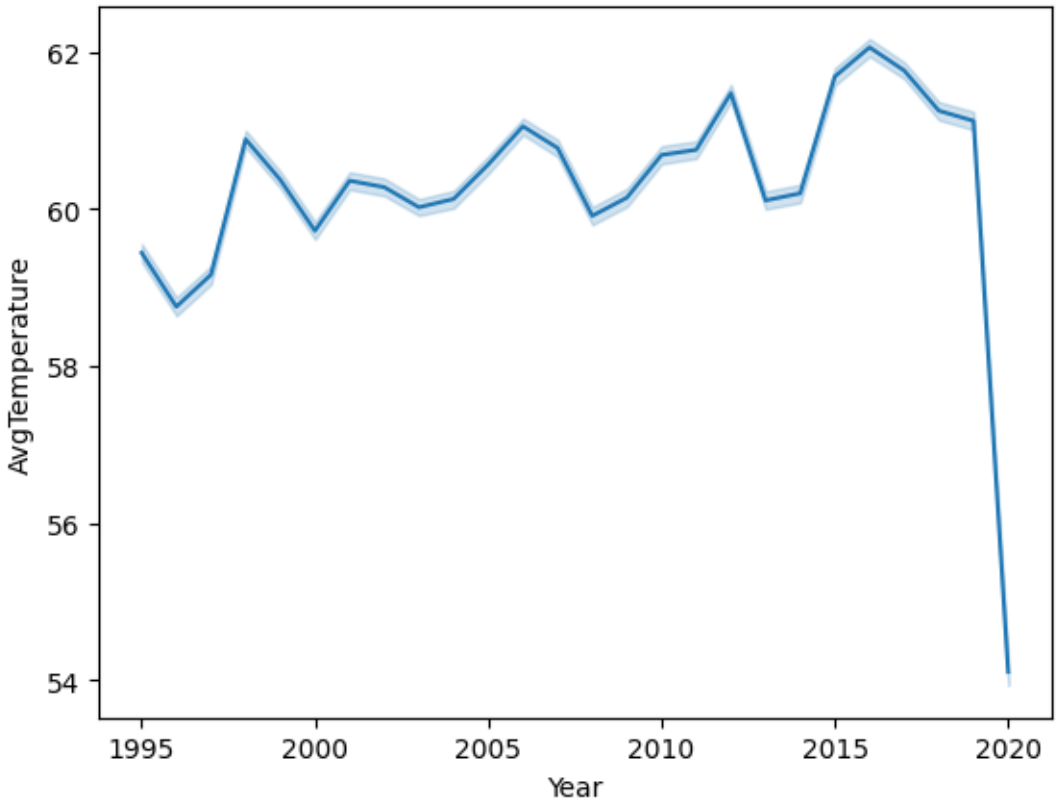
[229]:

| | Country | City | Month | Day | Year | AvgTemperature |
|---|---|---|---|---|---|---|
| 0 | Algeria | Algiers | 1 | 1 | 1995 | 64.2 |
| 1 | Algeria | Algiers | 1 | 2 | 1995 | 49.4 |
| 2 | Algeria | Algiers | 1 | 3 | 1995 | 48.8 |
| 3 | Algeria | Algiers | 1 | 4 | 1995 | 46.4 |
| 4 | Algeria | Algiers | 1 | 5 | 1995 | 47.9 |
| … | … | … | … | … | … | … |
| 2906322 | US | San Juan Puerto Rico | 7 | 27 | 2013 | 82.4 |
| 2906323 | US | San Juan Puerto Rico | 7 | 28 | 2013 | 81.6 |
| 2906324 | US | San Juan Puerto Rico | 7 | 29 | 2013 | 84.2 |
| 2906325 | US | San Juan Puerto Rico | 7 | 30 | 2013 | 83.8 |
| 2906326 | US | San Juan Puerto Rico | 7 | 31 | 2013 | 83.6 |

[2825666 rows x 6 columns]

[230]:
```
#######################################
# Visualisation of global temperature #
#######################################
sb.lineplot(data=dt, x="Year", y="AvgTemperature")
```

[230]: <Axes: xlabel='Year', ylabel='AvgTemperature'>




[231]:
```
g_mse_comp = {"Training MSE" : [], "Test MSE": []}
g_mse_comp_indexes = []
g_mse_comp_c_i = 1

g_r2_progression = {"Polynomial degree" : [], "R2": []}
g_mse_progression = {"Polynomial degree" : [], "MSE": []}

tmp = dt.groupby(by=["Day", "Month", "Year"])["AvgTemperature"].mean().
 ↪reset_index()

mse = None
r2 = None

degree = 1
global_model = None

def addMetrics(t_mse, c_mse, c_r2, d_i):
    global g_mse_comp_c_i
    g_mse_comp["Training MSE"].append(t_mse)
    g_mse_comp["Test MSE"].append(c_mse)
    g_mse_comp_indexes.append(g_mse_comp_c_i)
```

```
    g_mse_comp_c_i += 1

    g_r2_progression["Polynomial degree"].append(d_i)
    g_r2_progression["R2"].append(c_r2)

    g_mse_progression["Polynomial degree"].append(d_i)
    g_mse_progression["MSE"].append(c_mse)

for i in range(1, 100):
    poly_features = preprocessing.PolynomialFeatures(degree=i,␣
 ↪include_bias=False).fit_transform(X=tmp[["Day", "Month", "Year"]])
    x_train, x_test, y_train, y_test = model_selection.
 ↪train_test_split(poly_features, tmp["AvgTemperature"], train_size=0.7,␣
 ↪test_size=0.3)

    _model = linear_model.LinearRegression()
    poly_regression = _model.fit(x_train, y_train)

    predictions = poly_regression.predict(x_test)

    t_predictions = poly_regression.predict(x_train)

    t_mse = metrics.mean_squared_error(y_pred=t_predictions, y_true=y_train)
    c_mse = metrics.mean_squared_error(y_pred=predictions, y_true=y_test)
    c_r2 = metrics.r2_score(y_pred=predictions, y_true=y_test)

    print("\n\n")
    print("Training MSE:", t_mse)
    print("MSE:", c_mse)
    print("R2:", c_r2)

    if mse is None and r2 is None:
        addMetrics(t_mse, c_mse, c_r2, i)
        mse = c_mse
        r2 = c_r2
    else:
        if c_mse < mse:
            print("Degree: ", i)
            global_model = _model
            degree = i
            addMetrics(t_mse, c_mse, c_r2, i)
        elif c_r2 > r2:
            print("Degree: ", i)
            global_model = _model
            degree = i
            addMetrics(t_mse, c_mse, c_r2)
        else:
```

```
            break
    mse = c_mse
    r2 = c_r2


global_temp_model = {"x_intercept": global_model.intercept_,␣
 ↪"Beta_Coefficients":  global_model.coef_.tolist(), "polynomial_degree":␣
 ↪degree}
model_file = open(file="global_temp_model.json", mode="w")
jf = json.dump(obj=global_temp_model,fp= model_file, indent=4)
model_file.flush()
model_file.close()
del(model_file)


g_comp = pd.DataFrame(data=g_mse_comp, index=g_mse_comp_indexes)
g_r2_prog = pd.DataFrame(data=g_r2_progression, index=g_mse_comp_indexes)
g_mse_prog = pd.DataFrame(data=g_mse_progression, index=g_mse_comp_indexes)

g_comp
```

```
Training MSE: 121.5621496705282
MSE: 122.46552178556284
R2: 0.053904206881073335
```

```
Training MSE: 16.80185178786976
MSE: 16.898767899710265
R2: 0.8697716961793784
Degree:  2
```

```
Training MSE: 11.76102949428515
MSE: 11.167328953318023
R2: 0.9115523555030107
Degree:  3
```

```
Training MSE: 5.895723674559122
MSE: 6.23533765707124
R2: 0.9522949591240922
```

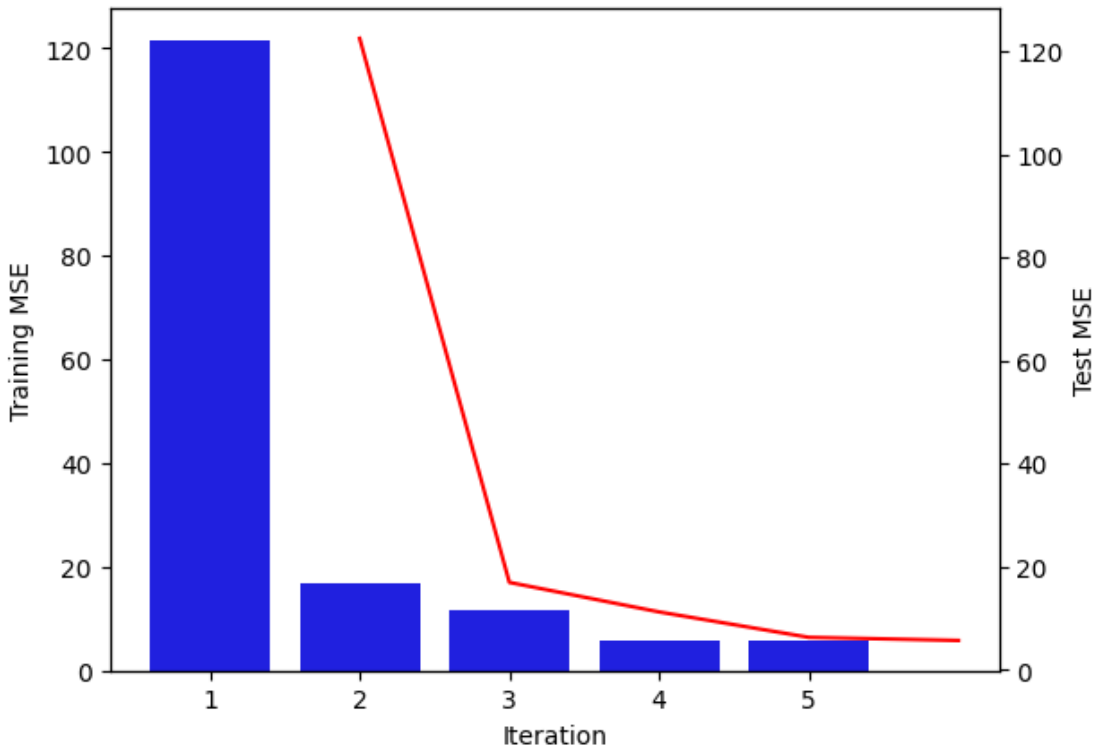
```
Degree:  4



Training MSE: 5.743684810946743
MSE: 5.633117481456719
R2: 0.9565975708981808
Degree:  5



Training MSE: 11.497984121314577
MSE: 12.09618959547283
R2: 0.9049046610404671
```

[231]:

| | Training MSE | Test MSE |
|---|---|---|
| 1 | 121.562150 | 122.465522 |
| 2 | 16.801852 | 16.898768 |
| 3 | 11.761029 | 11.167329 |
| 4 | 5.895724 | 6.235338 |
| 5 | 5.743685 | 5.633117 |

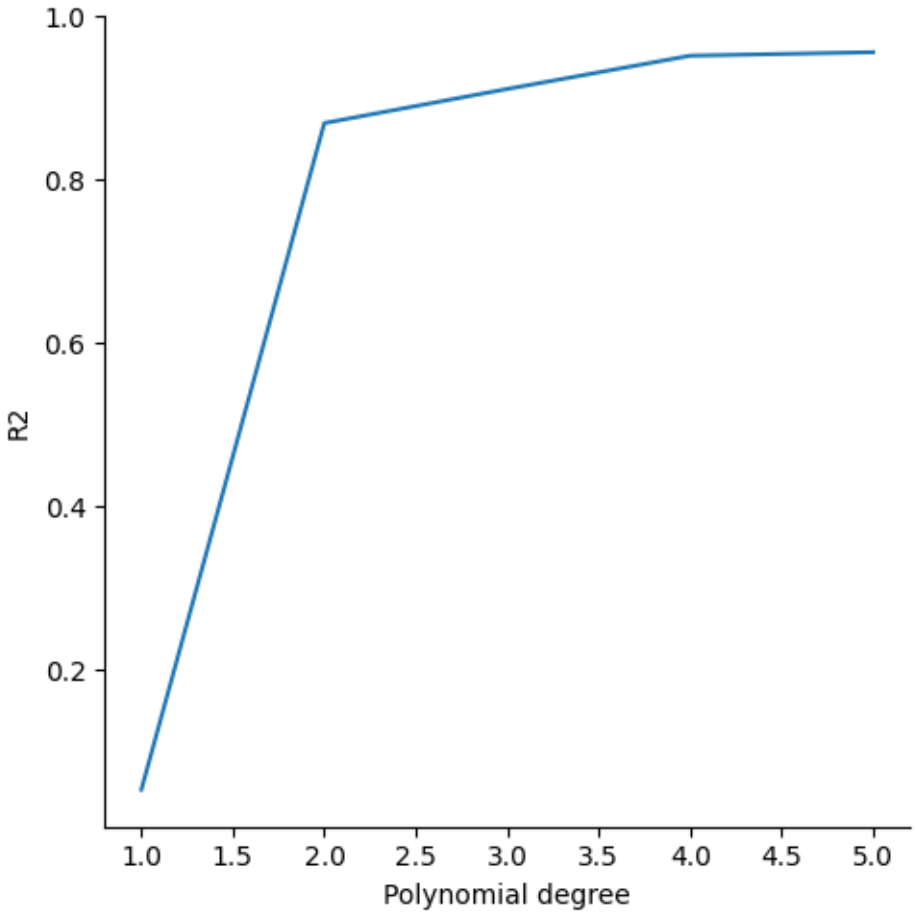
[232]:
```
##############################################################################################
# Comparison of the MSE in predicting training data VS testing data for the␣
 ↪Global model #
##############################################################################################
p1 = sb.barplot(data=g_comp, x=g_comp.index, y="Training MSE", color="b")
p1.set_xlabel("Iteration")
plt.twinx()
p2 = sb.lineplot(data=g_comp, x=g_comp.index, y="Test MSE",color="r")
p2.set_xlabel("Iteration")
```

[232]:
```
Text(0.5, 0, 'Iteration')
```



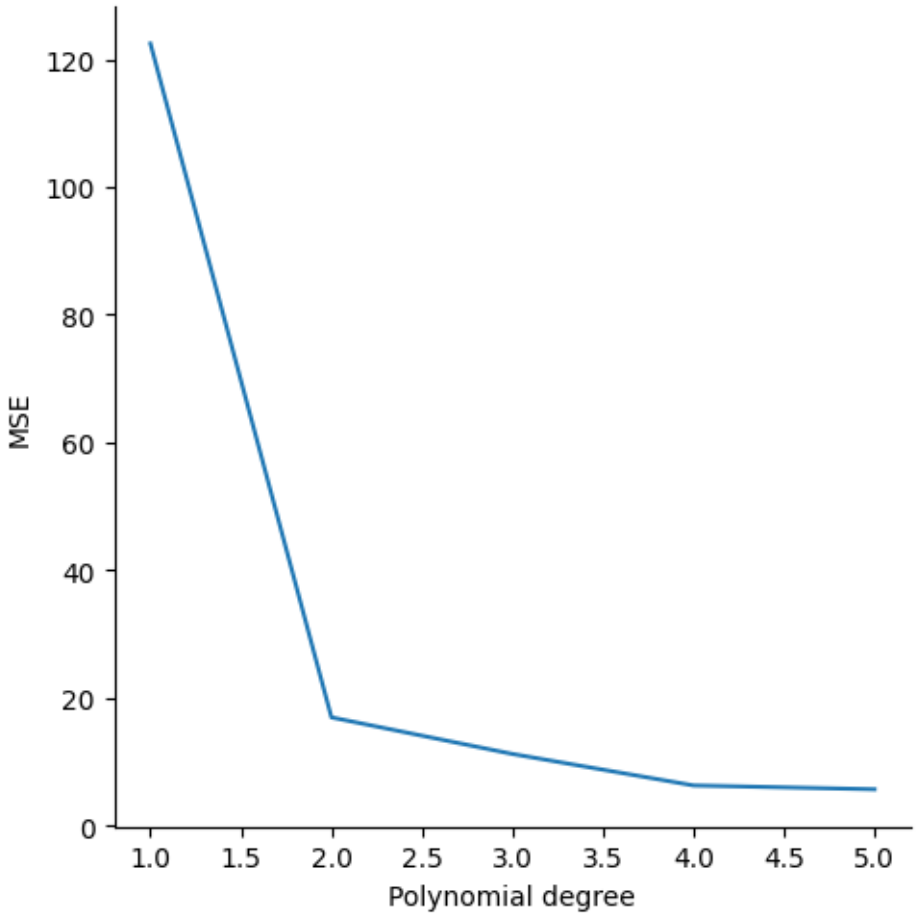

[233]:
```
##########################################################################################
# Visualisation of the R2 score progression in relation with the polynomial␣
 ↪degree for the Global model #
##########################################################################################

sb.relplot(data= g_r2_prog, x="Polynomial degree", y="R2", kind="line")
```

[233]: <seaborn.axisgrid.FacetGrid at 0x1f0e7c973b0>



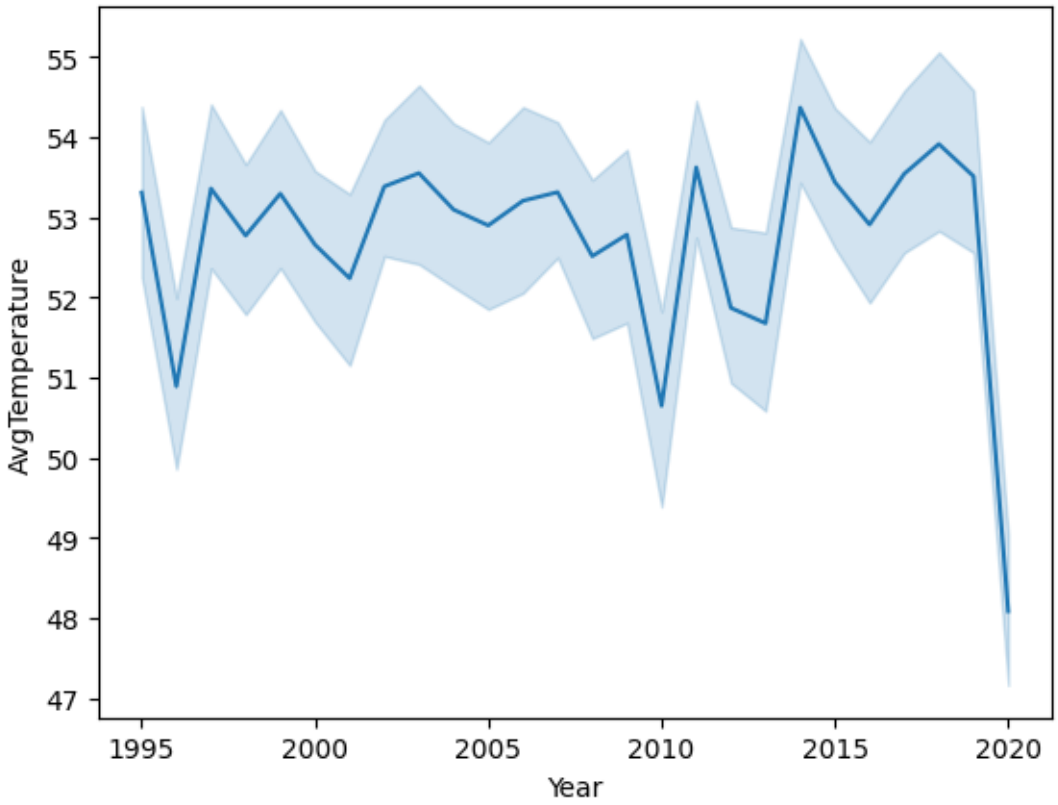

[234]:
```
##########################################################################################
# Visualisation of the MSE score progression in relation with the polynomial␣
 ↪degree for the Global model #
##########################################################################################

sb.relplot(data= g_mse_prog, x="Polynomial degree", y="MSE", kind="line")
```

[234]: <seaborn.axisgrid.FacetGrid at 0x1f0e7c983b0>




[235]:
```
##########################################
# Visualisation of London's temperature #
##########################################

dtl =  dt[(dt['Country'] == 'United Kingdom') & (dt['City'] == 'London')]
sb.lineplot(data=dtl, x="Year", y="AvgTemperature")
```

[235]: <Axes: xlabel='Year', ylabel='AvgTemperature'>




[236]:
```
l_mse_comp = {"Training MSE" : [], "Test MSE": []}
l_mse_comp_indexes = []
l_mse_comp_c_i = 1

l_r2_progression = {"Polynomial degree" : [], "R2": []}
l_mse_progression = {"Polynomial degree" : [], "MSE": []}


mse = None
r2 = None

l_degree = 1
l_model = None

def addMetrics(t_mse, c_mse, c_r2, d_i):
    global l_mse_comp_c_i
    l_mse_comp["Training MSE"].append(t_mse)
    l_mse_comp["Test MSE"].append(c_mse)
    l_mse_comp_indexes.append(l_mse_comp_c_i)
    l_mse_comp_c_i += 1
```

```
    l_r2_progression["Polynomial degree"].append(d_i)
    l_r2_progression["R2"].append(c_r2)

    l_mse_progression["Polynomial degree"].append(d_i)
    l_mse_progression["MSE"].append(c_mse)

for i in range(1, 100):
    poly_features = preprocessing.PolynomialFeatures(degree=i,␣
 ↪include_bias=False).fit_transform(X=dtl[["Day", "Month", "Year"]])
    x_train, x_test, y_train, y_test = model_selection.
 ↪train_test_split(poly_features, dtl["AvgTemperature"], train_size=0.7,␣
 ↪test_size=0.3)

    _model = linear_model.LinearRegression()
    poly_regression = _model.fit(x_train, y_train)

    predictions = poly_regression.predict(x_test)

    t_predictions = poly_regression.predict(x_train)

    t_mse = metrics.mean_squared_error(y_pred=t_predictions, y_true=y_train)
    c_mse = metrics.mean_squared_error(y_pred=predictions, y_true=y_test)
    c_r2 = metrics.r2_score(y_pred=predictions, y_true=y_test)

    print("\n\n")
    print("Training MSE:", t_mse)
    print("MSE:", c_mse)
    print("R2:", c_r2)

    if mse is None and r2 is None:
        addMetrics(t_mse, c_mse, c_r2, i)
        mse = c_mse
        r2 = c_r2
    else:
        if c_mse < mse:
            print("Degree: ", i)
            l_model = _model
            l_degree = i
            addMetrics(t_mse, c_mse, c_r2, i)
        elif c_r2 > r2:
            print("Degree: ", i)
            l_model = _model
            l_degree = i
            addMetrics(t_mse, c_mse, c_r2)
        else:
            break
    mse = c_mse
```

```
    r2 = c_r2


london_temp_model = {"x_intercept": l_model.intercept_, "Beta_Coefficients": ␣
 ↪l_model.coef_.tolist(), "polynomial_degree": l_degree}
model_file = open(file="london_temp_model.json", mode="w")
jf = json.dump(obj=london_temp_model,fp= model_file, indent=4)
model_file.flush()
model_file.close()
del(model_file)


l_comp = pd.DataFrame(data=l_mse_comp, index=l_mse_comp_indexes)
l_r2_prog = pd.DataFrame(data=l_r2_progression, index=l_mse_comp_indexes)
l_mse_prog = pd.DataFrame(data=l_mse_progression, index=l_mse_comp_indexes)

l_comp
```

```
Training MSE: 94.91235038607161
MSE: 93.70390167568904
R2: 0.05092755546273886



Training MSE: 38.363593137085445
MSE: 39.27901147011825
R2: 0.615029031431791
Degree:  2



Training MSE: 31.927607764771146
MSE: 33.056649131828074
R2: 0.66810722515969
Degree:  3



Training MSE: 26.429788542131824
MSE: 27.972825425161286
R2: 0.7207526402560392
Degree:  4
```

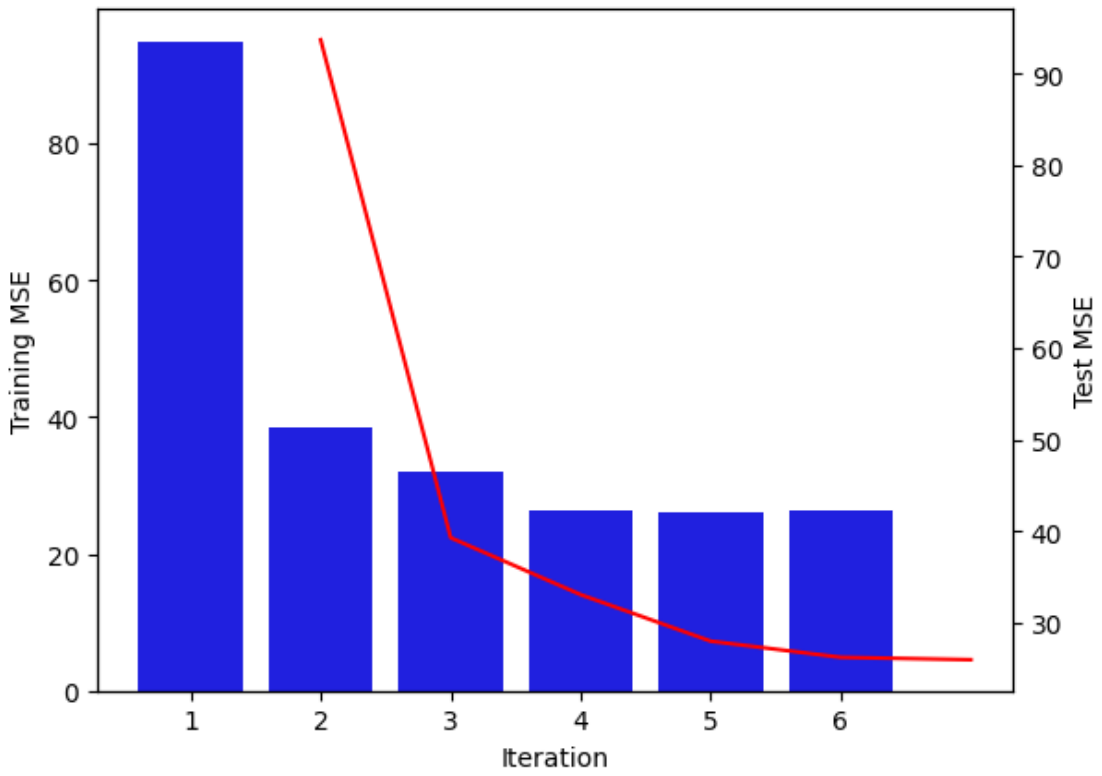
```
Training MSE: 25.95900338586485
MSE: 26.20844845253653
R2: 0.7365108315337379
Degree:  5



Training MSE: 26.296190525322505
MSE: 25.94681181626108
R2: 0.7397709094699552
Degree:  6



Training MSE: 26.3358032852251
MSE: 26.725736046344824
R2: 0.7279249226456328
```

[236]:

| | Training MSE | Test MSE |
|---|---|---|
| 1 | 94.912350 | 93.703902 |
| 2 | 38.363593 | 39.279011 |
| 3 | 31.927608 | 33.056649 |
| 4 | 26.429789 | 27.972825 |
| 5 | 25.959003 | 26.208448 |
| 6 | 26.296191 | 25.946812 |

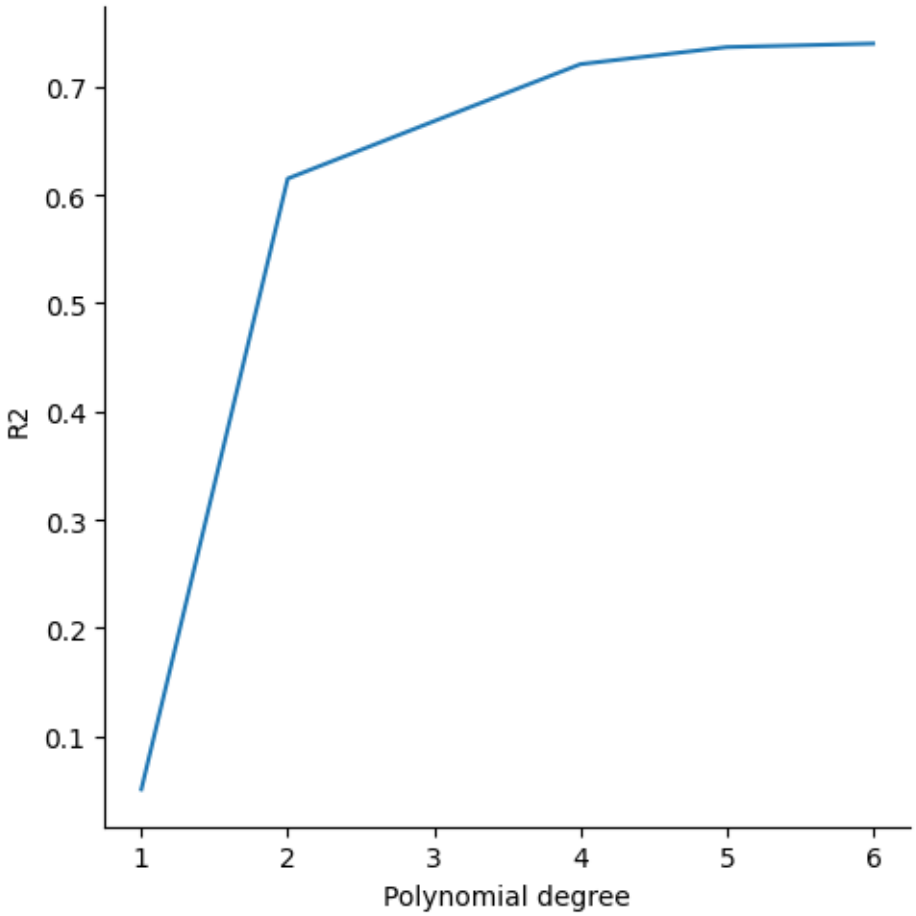
[237]:
```
##############################################################################################
# Comparison of the MSE in predicting training data VS testing data for the␣
 ↪Global model #
##############################################################################################
p1 = sb.barplot(data=l_comp, x=l_comp.index, y="Training MSE", color="b")
p1.set_xlabel("Iteration")
plt.twinx()
p2 = sb.lineplot(data=l_comp, x=l_comp.index, y="Test MSE",color="r")
p2.set_xlabel("Iteration")
```

[237]:
```
Text(0.5, 0, 'Iteration')
```



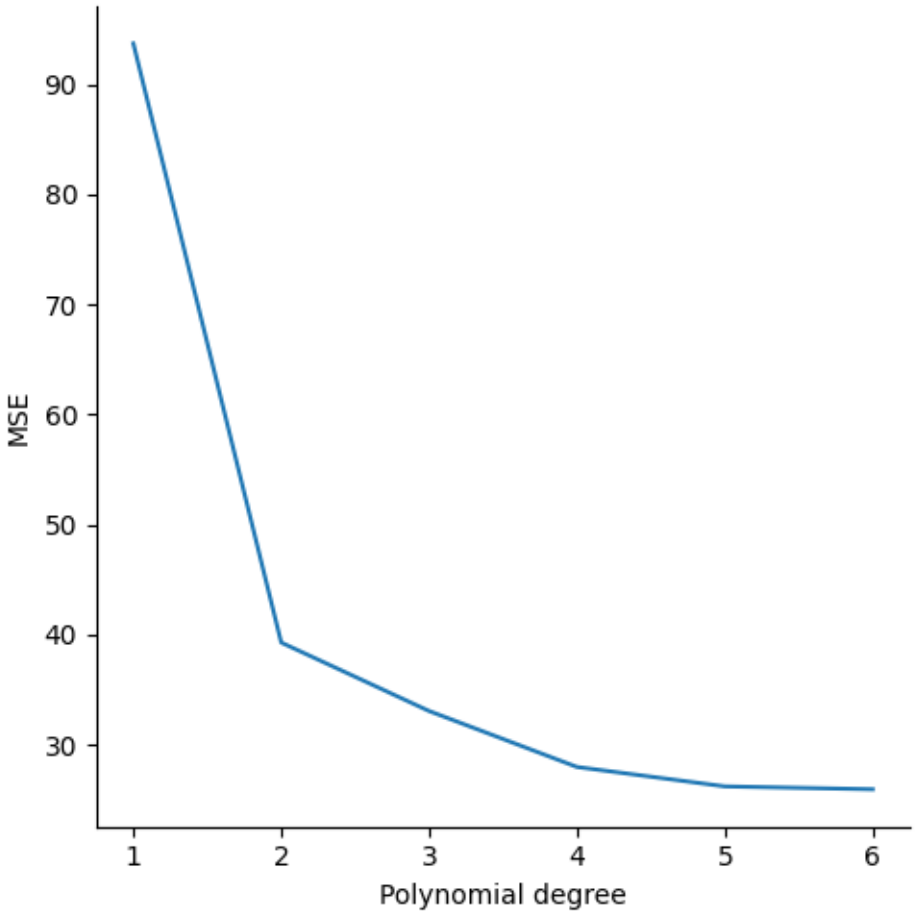

[238]:
```
##########################################################################################
# Visualisation of the R2 score progression in relation with the polynomial␣
 ↪degree for the Global model #
##########################################################################################

sb.relplot(data= l_r2_prog, x="Polynomial degree", y="R2", kind="line")
```

[238]: <seaborn.axisgrid.FacetGrid at 0x1f0b3828440>




[239]:
```
##########################################################################################
# Visualisation of the MSE score progression in relation with the polynomial␣
 ↪degree for the Global model #
##########################################################################################

sb.relplot(data= l_mse_prog, x="Polynomial degree", y="MSE", kind="line")
```

[239]: <seaborn.axisgrid.FacetGrid at 0x1f0b3768440>


90
80
70
60
50
40
30
MSE
1
2
3
4
5
6
Polynomial degree