CO2_prediction

October 3, 2023

[1]:
```
import numpy as np
import pandas as pd
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error
import matplotlib.pyplot as plt
import seaborn as sn
```

Pre-processing and creation of the datapoints

[2]:
```
lowC = pd.read_csv("/notebooks/MLProject/data/Clean/ShareElectricityLowCarbon.
 ↪csv", sep=";")
accessElec = pd.read_csv("/notebooks/MLProject/data/Clean/elecAccess.csv",␣
 ↪sep=";")
popGrowth = pd.read_csv("/notebooks/MLProject/data/Clean/popGrowth.csv", sep=";
 ↪")
energyUse = pd.read_csv("/notebooks/MLProject/data/Clean/energyUse.csv", sep=";
 ↪")
GDP = pd.read_csv("/notebooks/MLProject/data/Clean/GDP.csv", sep=";")
population = pd.read_csv("/notebooks/MLProject/data/Clean/population.csv",␣
 ↪sep=";")

totEmissions = pd.read_csv("/notebooks/MLProject/data/Clean/totEmissions.csv",␣
 ↪sep=";")

lowC.at[0,"Year"] = 2000
lowC.at[1,"1990"] = 0

y = np.array([])

X = np.array([[0,0,0,0,0,0]])

names = np.array([])
for year in range(1990,2017):
    for code in lowC["Code"]:
        X_1 = lowC.loc[lowC['Code'] == code][str(year)].values
        X_2 = accessElec.loc[accessElec['Country Code'] == code][str(year)].
 ↪values
```

```
        X_3 = popGrowth.loc[popGrowth['Country Code'] == code][str(year)].values
        X_4 = energyUse.loc[energyUse['Code'] == code][str(year)].values
        X_5 = GDP.loc[GDP['Country Code'] == code][str(year)].values
        X_6 = population.loc[population['Country Code'] == code][str(year)].
 ↪values

        if(len(X_1) == 1 and len(X_2) == 1 and len(X_3) == 1 and len(X_4) == 1␣
 ↪and len(X_5) == 1 and len(X_6) == 1 and len(totEmissions.
 ↪loc[totEmissions['Country Code'] == code][str(year)].values)==1 ):
            X = np.vstack( (X, [ X_1[0],X_2[0],X_3[0],X_4[0],X_5[0],X_6[0] ]) )
            y = np.append(y, totEmissions.loc[totEmissions['Country Code'] ==␣
 ↪code][str(year)] / X_6 * 1000)
            names = np.append(names, code + str(year))

X_train = pd.DataFrame(X[1:])
X_train.insert(6, "labels", names, True)
X_train.insert(7, "y", y, True)
X_train.head(5)
```

[2]:

```
           0         1         2            3             4           5  \
0        NaN       NaN  0.202434    2968.3160           NaN  10694796.0
1   0.000000       NaN  3.345144    1972.4146   3283.170843  11828638.0
2  86.363640  100.0000  1.799086   10214.5980   2549.746801   3286542.0
3   0.000000  100.0000  5.869033  181538.7700  83843.224680   1900151.0
4  49.264286   92.1548  1.456403   15718.7030   7183.583826  32637657.0

    labels          y
0  AFG1990   1.087519
1  AGO1990   3.650937
2  ALB1990   3.402079
3  ARE1990  41.366101
4  ARG1990   7.635008
```

[3]:

```
y = np.array([])
X = np.array([[0,0,0,0,0,0]])
names = np.array([])

for year in range(2017,2021):
    for code in lowC["Code"]:
        X_1 = lowC.loc[lowC['Code'] == code][str(year)].values
        X_2 = accessElec.loc[accessElec['Country Code'] == code][str(year)].
 ↪values
        X_3 = popGrowth.loc[popGrowth['Country Code'] == code][str(year)].values
        X_4 = energyUse.loc[energyUse['Code'] == code][str(year)].values
        X_5 = GDP.loc[GDP['Country Code'] == code][str(year)].values
        X_6 = population.loc[population['Country Code'] == code][str(year)].
 ↪values
```

```
        if(len(X_1) == 1 and len(X_2) == 1 and len(X_3) == 1 and len(X_4) == 1␣
↪and len(X_5) == 1 and len(X_6) == 1 and len(totEmissions.
↪loc[totEmissions['Country Code'] == code][str(year)].values)==1 ):
            X = np.vstack( (X, [ X_1[0],X_2[0],X_3[0],X_4[0],X_5[0],X_6[0] ]) )
            y = np.append(y, totEmissions.loc[totEmissions['Country Code'] ==␣
↪code][str(year)] / X_6 * 1000)
            names = np.append(names, code + str(year))

X_test = pd.DataFrame(X[1:])
X_test.insert(6, "labels", names, True)
X_test.insert(7, "y", y, True)
X_test.head(5)
```

[3]:

```
            0           1          2            3             4           5  \
0   85.826775   97.700000   2.866492    829.31195   2096.093111  35643418.0
1   72.003746   42.906242   3.550987   3370.89620   7216.061373  30208628.0
2  100.000000   99.890000  -0.091972  12802.36000  12770.991860   2873457.0
3    0.592698  100.000000   0.819744 135601.27000  71182.370720   9068296.0
4   28.267298  100.000000   1.037134  22503.81800  23597.117750  44044811.0

    labels          y
0  AFG2017   0.890783
1  AGO2017   2.715241
2  ALB2017   3.453775
3  ARE2017  27.705142
4  ARG2017   8.614415
```

Final cleanup of NaN

[4]:

```
X_train = X_train.dropna()
X_test = X_test.dropna()

X_train.columns=["lowC","accessElec","popGrowth","energyUse","GDP",␣
↪"population", "labels", "y"]
X_test.columns=["lowC","accessElec","popGrowth","energyUse","GDP",␣
↪"population", "labels", "y"]

X_train.reset_index()
X_test.reset_index()

y_train = pd.DataFrame(X_train["y"])
labels_train = pd.DataFrame(X_train["labels"])
X_train = X_train[["lowC","accessElec","popGrowth","energyUse","GDP"]]

y_test = X_test["y"]
labels_test = X_test["labels"]
```

```
X_test = X_test[["lowC","accessElec","popGrowth","energyUse","GDP"]]
```

[5]:
```
print(y_train.head(5))
```

```
           y
2   3.402079
3  41.366101
4   7.635008
7  28.744657
8   9.980695
```

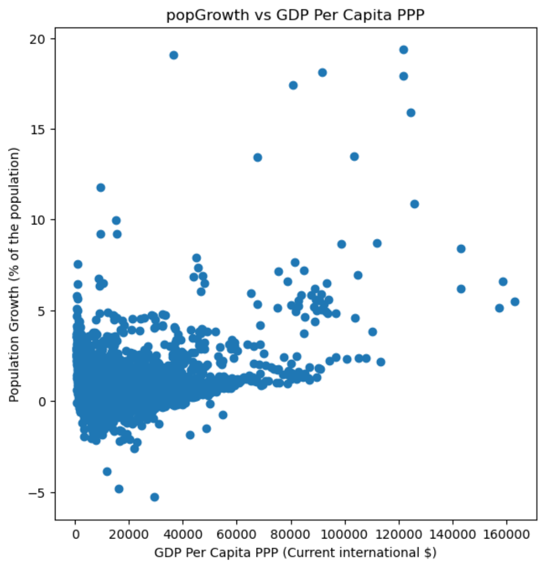
Some basic information about the dataset

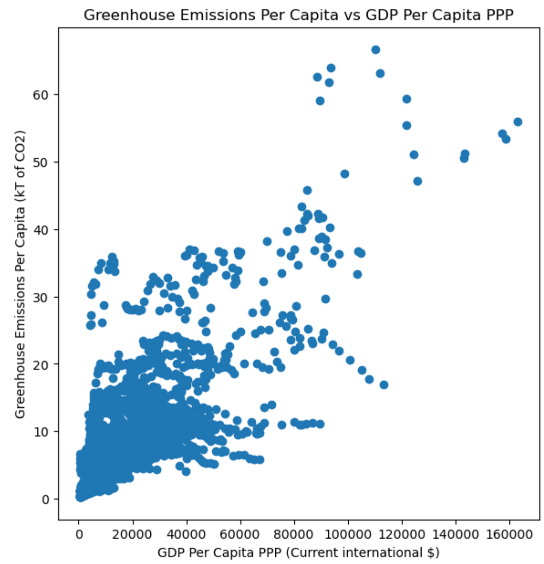
[6]:
```
X_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 3371 entries, 2 to 4967
Data columns (total 5 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   lowC        3371 non-null   float64
 1   accessElec  3371 non-null   float64
 2   popGrowth   3371 non-null   float64
 3   energyUse   3371 non-null   float64
 4   GDP         3371 non-null   float64
dtypes: float64(5)
memory usage: 158.0 KB
```

Some plot to test the data

[7]:
```
# Visualize data
fig, axes = plt.subplots(1, 2, figsize=(15,7))
axes[0].scatter(X_train['GDP'], X_train['popGrowth'])
axes[0].set_xlabel("GDP Per Capita PPP (Current international $)")
axes[0].set_ylabel("Population Growth (% of the population)")
axes[0].set_title("popGrowth vs GDP Per Capita PPP")

axes[1].scatter(X_train['GDP'], y_train) #use Emissions Per Capita to tackle
 ↪the impact of the population size in the plot
axes[1].set_title('Greenhouse Emissions Per Capita vs GDP Per Capita PPP')
axes[1].set_xlabel("GDP Per Capita PPP (Current international $)")
axes[1].set_ylabel('Greenhouse Emissions Per Capita (kT of CO2)')
plt.show()
```

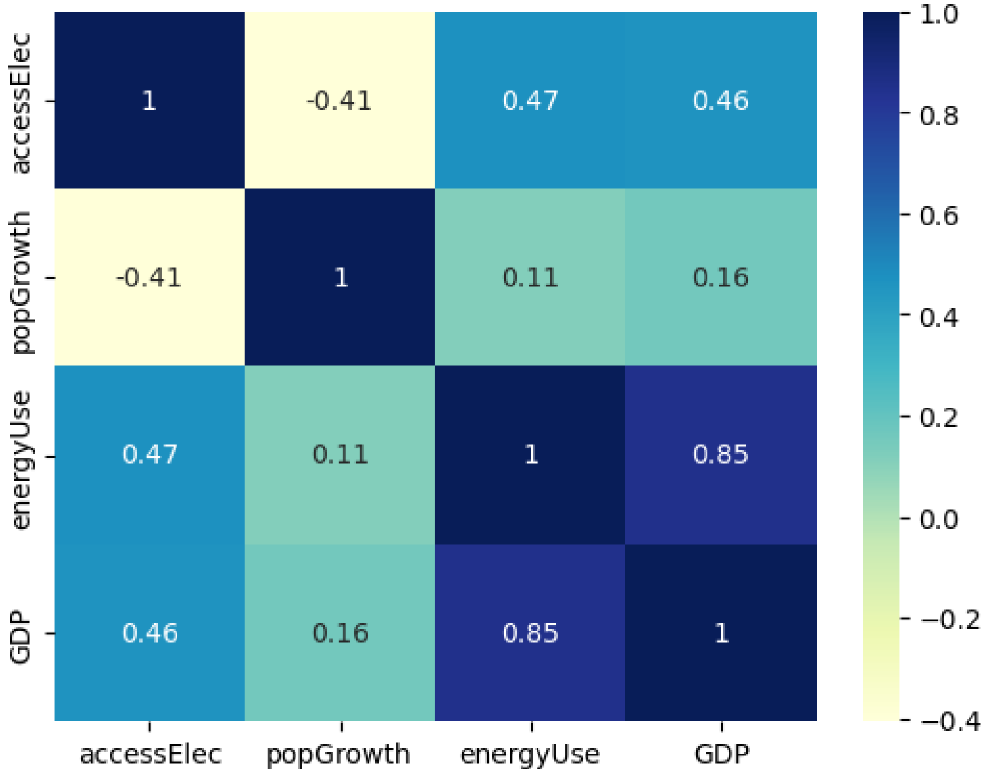




Correlation matrix

[8]:
```
print(X_train.iloc[:, 1:6].corr())
dataplot = sn.heatmap(X_train.iloc[:, 1:6].corr(), cmap="YlGnBu", annot=True)
```

```
            accessElec  popGrowth  energyUse       GDP
accessElec    1.000000  -0.405964   0.467397  0.464918
popGrowth    -0.405964   1.000000   0.110968  0.157050
energyUse     0.467397   0.110968   1.000000  0.849229
GDP           0.464918   0.157050   0.849229  1.000000
```



1 Fitting a linear regression model onto the X (lowC, accessElec, popGrowth, energyUse, GDP)

[9]:
```
from sklearn.metrics import accuracy_score, mean_squared_error, r2_score
from sklearn.preprocessing import PolynomialFeatures
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import KFold, train_test_split
```

[10]:
```
lin = LinearRegression()

v = lin.fit(X_train, y_train)
print(v.coef_)
print(v.intercept_)
```

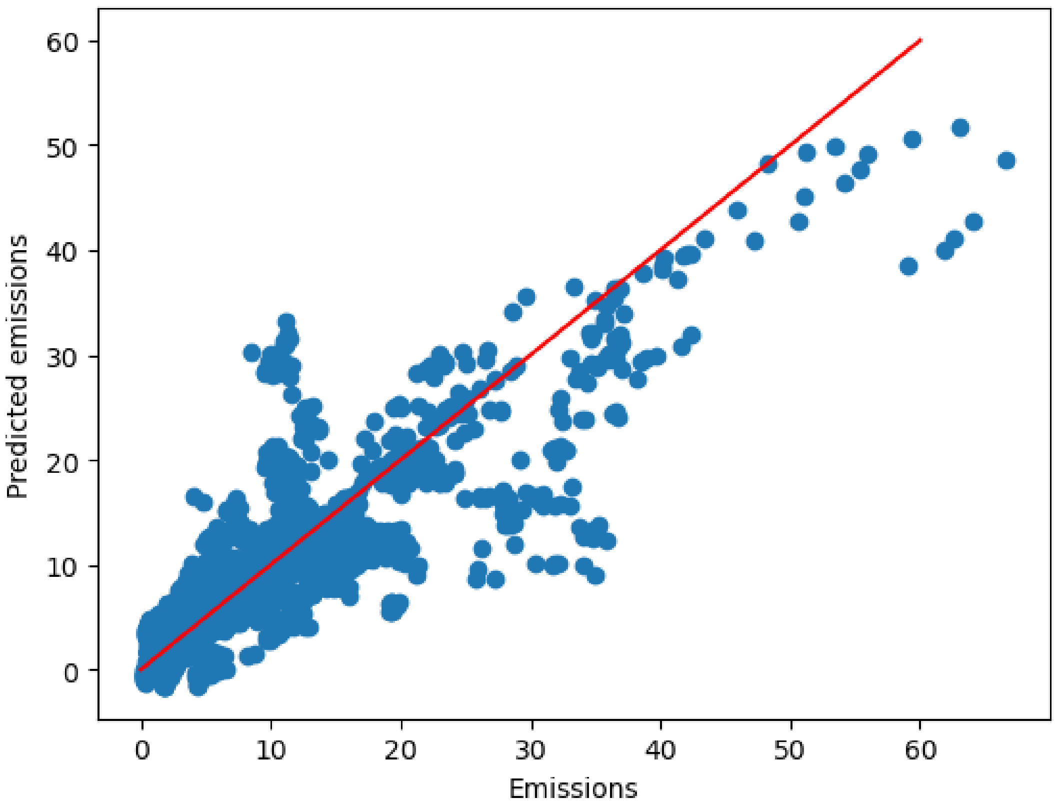
```
[[-3.96216531e-02  1.95970494e-02  3.28584421e-01  1.45163223e-04
   5.92413854e-05]]
[2.08260383]
```

Testing on training data

[11]:

```
y_pred = lin.predict(X_train)
plt.scatter(y_train, y_pred)
plt.xlabel("Emissions")
plt.ylabel("Predicted emissions")
plt.plot(np.linspace(0,60), np.linspace(0,60), color="r")

mse = mean_squared_error(y_train, y_pred)
print(mse)
```

16.112496074096796



[12]:

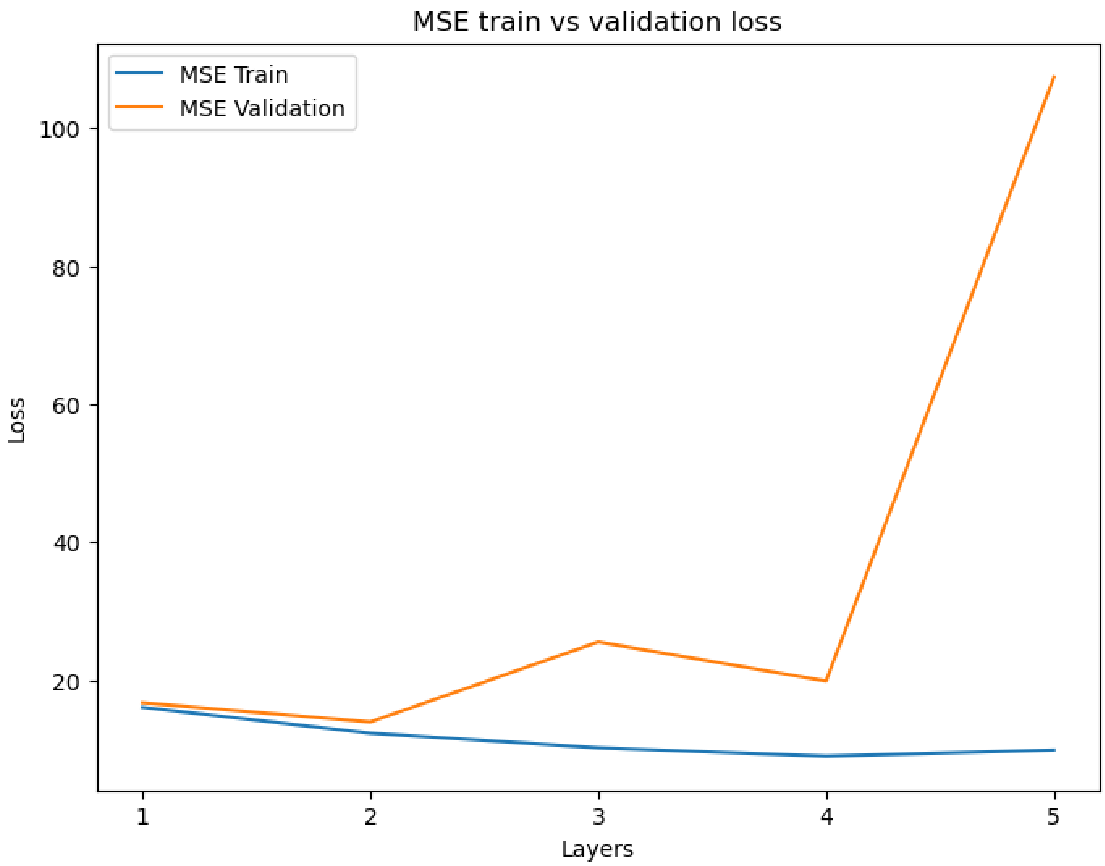
```
tr_error_val = []
tr_error_train = []
v = []
y_poly_pred = []
mean_square_error_val = []
mean_square_error_train = []

k = 5
kf = KFold(n_splits=k)
```

```
for i in range(0,5):

    tr_error_fold_val = []
    mean_square_error_fold_val = []
    tr_error_fold_train = []
    mean_square_error_fold_train = []

    poly = PolynomialFeatures(i+1)
    lin = LinearRegression()

    print(kf.split(X_train, y_train))

    for train_index, val_index in kf.split(X_train):


        X_train_fold, X_val_fold = X_train.iloc[train_index], X_train.
 ↪iloc[val_index]
        y_train_fold, y_val_fold = y_train.iloc[train_index], y_train.
 ↪iloc[val_index]

        # Transform the data using polynomial features
        X_poly_train = poly.fit_transform(X_train_fold)
        X_poly_val = poly.transform(X_val_fold)

        # Fit the linear regression model on the training data
        lin.fit(X_poly_train, y_train_fold)

        X_poly_test = poly.transform(X_test)
        y_test_pred = lin.predict(X_poly_test)

        # Predict on the validation data
        y_poly_pred_val = lin.predict(X_poly_val)
        y_poly_pred_train = lin.predict(X_poly_train)

        # Calculate R-squared score for the fold
        fold_r2_score_val = r2_score(y_val_fold, y_poly_pred_val)
        fold_mean_square_score_val = mean_squared_error(y_val_fold,␣
 ↪y_poly_pred_val)

        fold_r2_score_train = r2_score(y_train_fold, y_poly_pred_train)
        fold_mean_square_score_train = mean_squared_error(y_train_fold,␣
 ↪y_poly_pred_train)


        tr_error_fold_val.append(fold_r2_score_val)
        mean_square_error_fold_val.append(fold_mean_square_score_val)
```

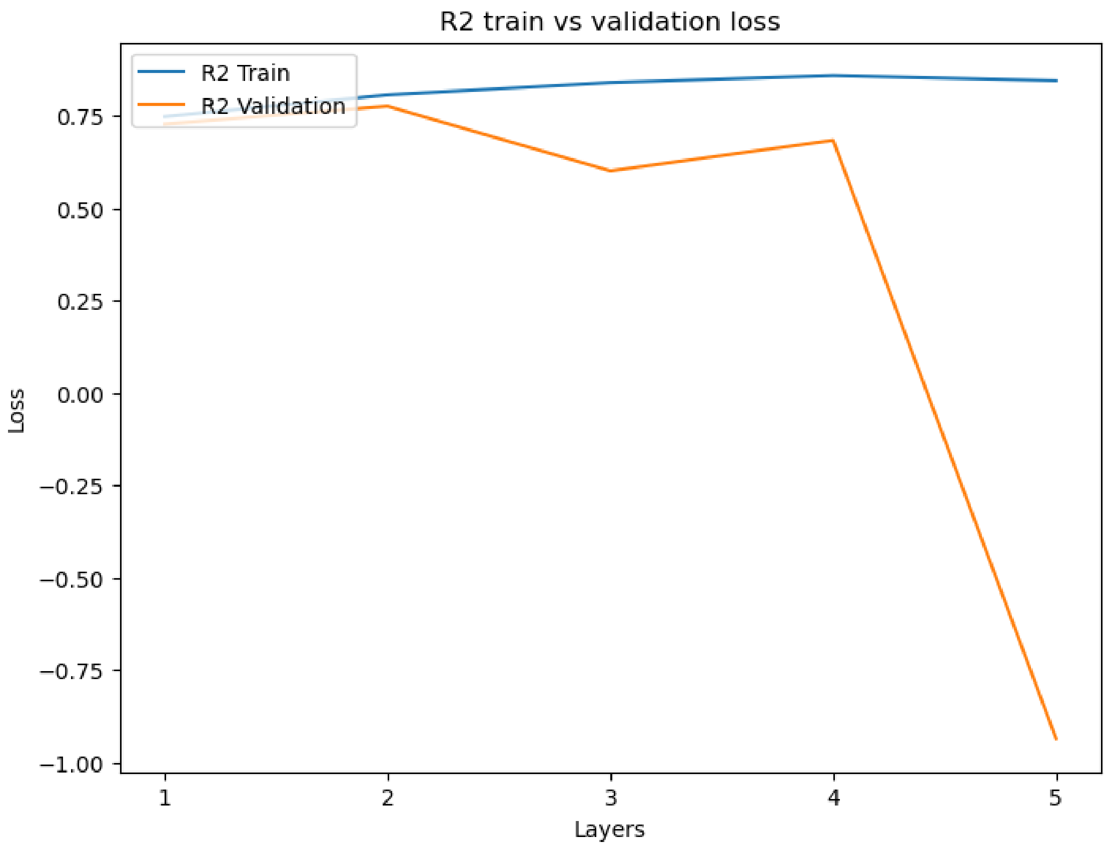
```
        tr_error_fold_train.append(fold_r2_score_train)
        mean_square_error_fold_train.append(fold_mean_square_score_train)

    tr_error_val.append(np.mean(tr_error_fold_val))
    mean_square_error_val.append(np.mean(mean_square_error_fold_val))

    tr_error_train.append(np.mean(tr_error_fold_train))
    mean_square_error_train.append(np.mean(mean_square_error_fold_train))


tr_error_df = pd.DataFrame({'R-squared_val': tr_error_val, 'R-squared_train':␣
 ↪tr_error_train})
mean_square_error_df = pd.DataFrame({'MSE_val': mean_square_error_val,␣
 ↪'MSE_train': mean_square_error_train})

print(pd.DataFrame(tr_error_df))
print(pd.DataFrame(mean_square_error_df))
```

```
<generator object _BaseKFold.split at 0x7f24c0637680>
<generator object _BaseKFold.split at 0x7f24c0637680>
<generator object _BaseKFold.split at 0x7f24c0637680>
<generator object _BaseKFold.split at 0x7f24c0637680>
<generator object _BaseKFold.split at 0x7f24c0637680>
   R-squared_val  R-squared_train
0       0.728004         0.748308
1       0.776357         0.807177
2       0.601437         0.840429
3       0.684045         0.859379
4      -0.936523         0.845612
      MSE_val  MSE_train
0   16.714726  16.049808
1   13.920726  12.303570
2   25.516501  10.179707
3   19.859919   8.968254
4  107.370373   9.858971
```

[13]:
```
plt.figure(figsize=(8,6))

plt.plot([1,2,3,4,5], mean_square_error_train, label='MSE Train')
plt.plot([1,2,3,4,5], mean_square_error_val, label='MSE Validation')
plt.xticks([1,2,3,4,5])
plt.legend(loc = 'upper left')

plt.xlabel('Layers')
plt.ylabel('Loss')
plt.title("MSE train vs validation loss")
plt.show()
```

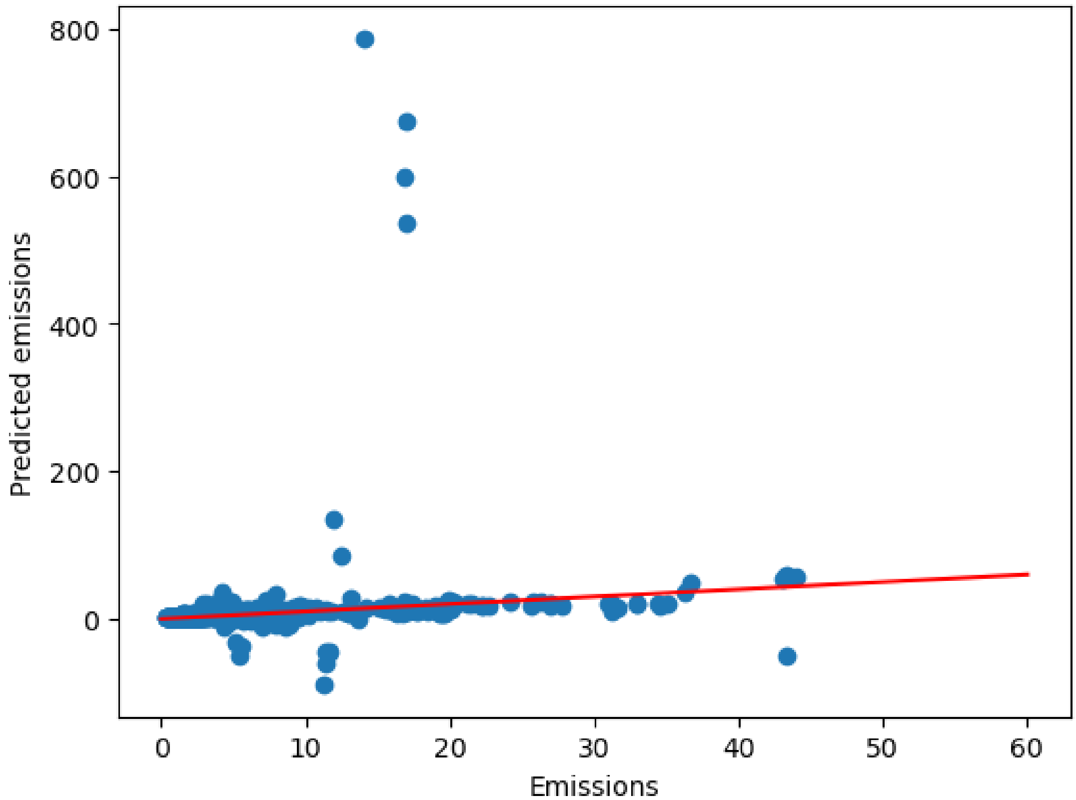


[14]:
```
plt.figure(figsize=(8,6))

plt.plot([1,2,3,4,5], tr_error_train, label='R2 Train')
plt.plot([1,2,3,4,5], tr_error_val, label='R2 Validation')
plt.xticks([1,2,3,4,5])
plt.legend(loc = 'upper left')

plt.xlabel('Layers')
plt.ylabel('Loss')
plt.title("R2 train vs validation loss")
plt.show()
```



1.1 Plot for the fifth degreen polynomial

[15]:
```
plt.scatter(y_test, y_test_pred)
plt.xlabel("Emissions")
plt.ylabel("Predicted emissions")
plt.plot(np.linspace(0,60), np.linspace(0,60), color="r")
plt.show()
```



2 Random forest

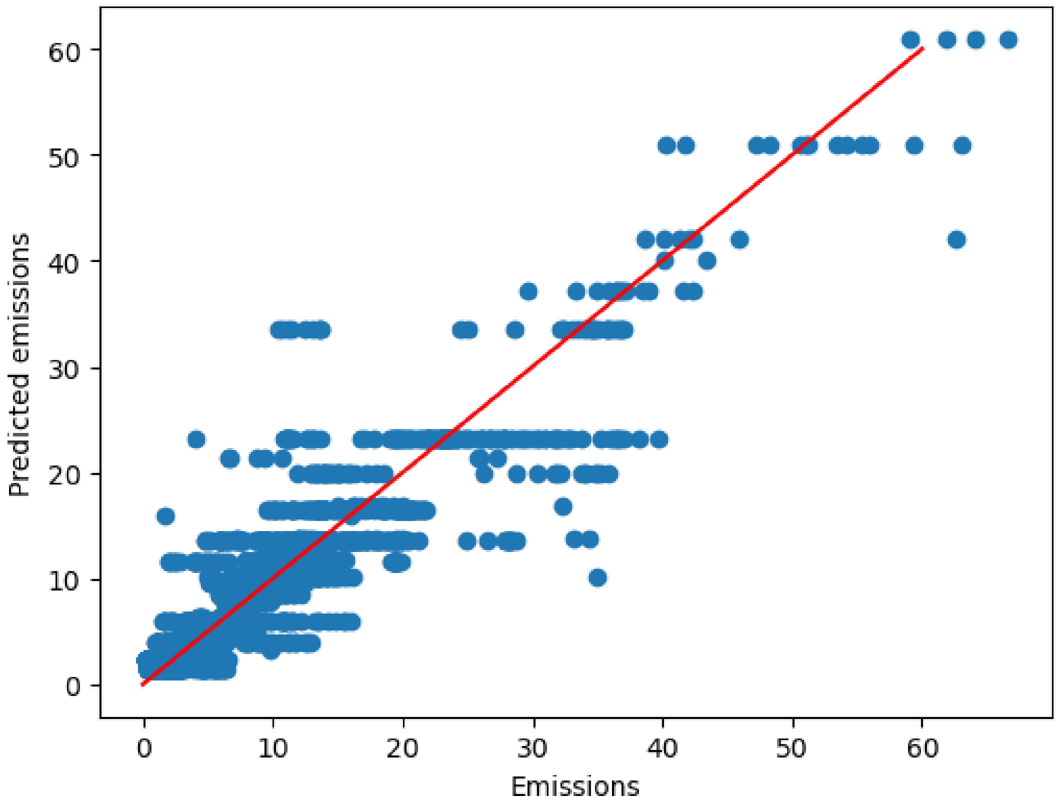
[16]:
```
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, r2_score
```

[17]:
```
rf = RandomForestRegressor(n_estimators=1, random_state=42, max_depth=5)
accuracy_scoreout = rf.fit(X_train, y_train)

y_pred_rf = rf.predict(X_train)

mse = mean_squared_error(y_train, y_pred_rf)
r2 = r2_score(y_train, y_pred_rf)
print(f"Mean Squared Error: {mse}")
print(f"R-squared: {r2}")

plt.scatter(y_train, y_pred_rf)
plt.xlabel("Emissions")
plt.ylabel("Predicted emissions")
plt.plot(np.linspace(0,60), np.linspace(0,60), color="r")
```

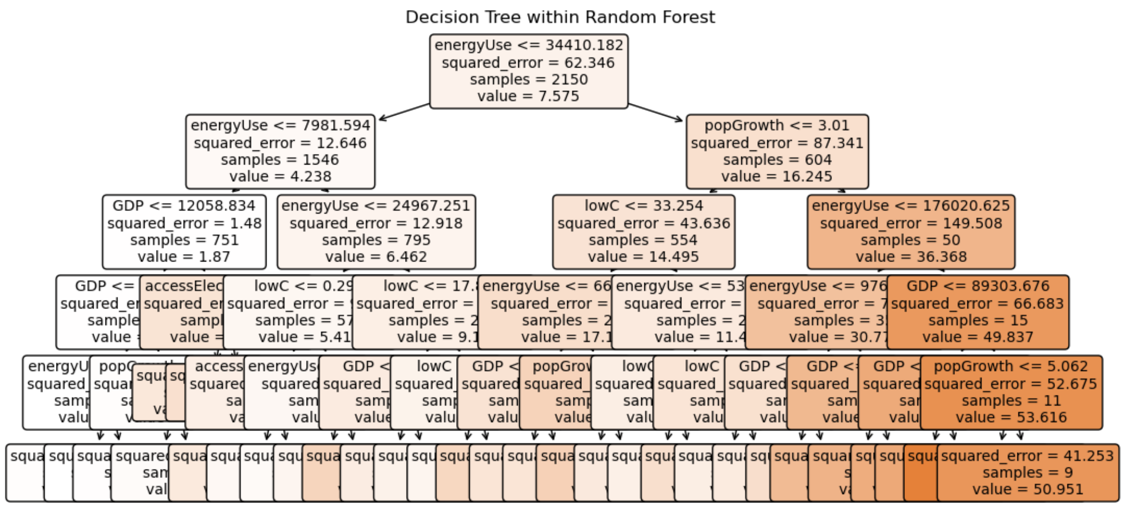
```
plt.show()
```

```
/tmp/ipykernel_19685/368208162.py:2: DataConversionWarning: A column-vector y
was passed when a 1d array was expected. Please change the shape of y to
(n_samples,), for example using ravel().
  accuracy_scoreout = rf.fit(X_train, y_train)
```

```
Mean Squared Error: 10.040126341870115
R-squared: 0.8429618663513027
```




```
[18]: from sklearn.tree import export_text, plot_tree, DecisionTreeClassifier,␣
       ↪export_graphviz

      tree_to_plot = rf.estimators_[0]  # Replace with the index of the tree you want␣
       ↪to plot
      plt.figure(figsize=(12, 6))
      plot_tree(tree_to_plot, filled=True, feature_names = ["lowC", "accessElec",␣
       ↪"popGrowth", "energyUse", "GDP"], rounded=True, fontsize=10)
      plt.title("Decision Tree within Random Forest")
      plt.show()
```



[19]:
```python
import pydotplus
d_tree = export_graphviz(tree_to_plot, feature_names = ["lowC", "accessElec",␣
 ↪"popGrowth", "energyUse", "GDP"], filled = True)
pydot_graph = pydotplus.graph_from_dot_data(d_tree)
pydot_graph.write_pdf('emissionsgraph.pdf')
```

[19]: True

3 Misc

[20]:
```python
big_ones = X_[X_["y"] >= 0.001]
plt.scatter(big_ones["GDP"], big_ones["y"])
big_ones
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
Cell In[20], line 1
----> 1 big_ones = X_[X_["y"] >= 0.001]
      2 plt.scatter(big_ones["GDP"], big_ones["y"])
      3 big_ones

NameError: name 'X_' is not defined
```

[ ]: