```
In [2]: #Importing the relevant python Libraries and the ols_pwp program
                      import numpy as np import pandas as pd import pandas as pd import matplotlib.pyplot as plt import ols_pwp from bokeh.io import output_notebook, show from bokeh.io import output_notebook, show from bokeh.io import follumnDataSource, Whisker from bokeh.plotting import figure import seaborn as ans
                       output_notebook()
                      BokehJS 2.4.3 successfully loaded.
                      Importing the datasets: train, ideal and test.
                       The next cell shows how the datasets (train, ideal and test) are imported into this notebook to begin the regression analysis using the ordinary least squares method.
In [3]: df_load = ols_pwp.pwpTasks()
                      filepath_train = n°C:\Users\tosin\GIT_clones\tosinaa_dlmdspwp@l\implement\train.csv°filepath_ideal = n°C:\Users\tosin\GIT_clones\tosinaa_dlmdspwp@l\implement\ideal.csv°filepath_ideal = n°C:\Users\tosin\GIT_clones\tosinaa_dlmdspwp@l\implement\test.csv°
                      train = df_load.df_loader(filepath_train)
ideal = df_load.df_loader(filepath_ideal)
test = df_load.df_loader(filepath_test)
In [4]: #Printing the top 5 rows of the train dataset
                      print(train.head())
                     In [5]: #Printing the top 5 rows of the ideal dataset
                      print(ideal.head())
                     x y1 y2 y3 y4 y5 y6 y7 y7 e -2.0.0 -0.912945 e .4.08802 9.087695 5.4.08802 9.08765 5.4.08802 9.08765 6.9.012945 e .0.012945 e 

        y8
        y9
        ...
        y41
        y42
        y43
        y44

        0
        -0.858919
        0.816164
        ...
        40.456474
        40.204640
        2.995732
        -0.088333

        1
        0.168518
        0.994372
        ...
        40.233820
        40.08559
        2.99972-
        0.089372

        2
        0.612391
        1.162644
        ...
        40.06836
        39.89660
        2.985692
        0.088347

        3
        0.994669
        1.3132299
        ...
        39.775787
        30.72982
        2.396619
        0.088361

        4
        0.774356
        1.462772
        ...
        -39.546980
        39.565693
        2.975530
        -0.08361

                     y45 y46 y47 y48 y49 y50 12.995732 5.298317 -5.298317 -6.186278 6.912945 8.39636 5.29336 5.29336 5.29336 5.29336 8.20546 9.86764 0.476954 21.298562 5.288267 -5.288267 -6.236563 6.813674 8.54926 12.985619 5.283264 8.2382364 -6.248387 8.751573 6.612848 12.975530 5.278115 -5.278115 -8.249389 8.681964 8.667902
                      [5 rows x 51 columns]
In [6]: #Printing the top 5 rows of the test dataset
                     print(test.head())
                      x y
0 -17.5 14492.095000
1 19.0 0.480704
2 6.5 274.085500
3 15.9 8039.792500
                      Computing the four best ideal functions using the train - ideal datasets pair
                      In doing this, we shall create an instance of the ols_pwp.pwpOLS() object from the ols_pwp program module. This will grant us access to the following methods:
                            1. squared dev(): This method is used for computing the four best functions and returns the output as a list of dictionaries containing the (y-train; y-ideal, min ssd).
                            2. idealfour_builder(): This method is used for building the dataset of the four best ideal functions.
In [7]: # Computing the ideal functions
                       # Creating the instance of the ols_pwp.pwpOLS object below
SSD = ols_pwp.pwpOLS(train, ideal)
                       # Computing the ideal4_Lst of four functions
ideal4_lst = SSD.squared_dev()
                      ruegatq_ist = Sbu.squared_dev()
print('Below are the yi-train and the corresponding yi-ideal functions columns (four best) and their minimum SSD values...:")
for idf in ideala_lst:
    print(idf)
                      Below are the yi-train and the corresponding yi-ideal functions columns (four best) and their minimum SSD values...: {'yi': ['y2i', 34.56588914719286]} {'y2': ['y2', 32.36025490316085]} {'y3': ['y2', 33.14353429428959]} {'y4': ['y2', 35.14353429428959]}
                      Validating The Results
                      To validate the results of the four best ideal functions, other model evaluation metrics shall be used. The metrics are listed below
                            1. Mean square error (MSE)
                            2. Root mean square error (RMSE)
                            3. Mean absolute error (MAD)
                            4. LogCosh Loss
In [8]: # Building a function to compute the root mean square error
                     def build_rmse(df1, df2):
    pe = ols_pwp.pwpEvaluate()
    mse_train = lstv()
    for col in df2.columns[1:]:
        mse_train.append(pe.rmse(df1, df2[col]))
    result = (['y' + str(mse_train.index(np.min(mse_train))+1), np.min(mse_train)])
    return result
                        # Implementing the rmse calculations
                       print(build_rmse(train.y1, ideal))
print(build_rmse(train.y2, ideal))
                       print(build_rmse(train.y3, ideal))
print(build_rmse(train.y4, ideal))
                      ['y21', 0.29]
['y27', 0.28]
['y2', 0.3]
['y24', 0.29]
In [9]: # Building a function to compute the mean square error
                      def build_mse(df1, df2):
    pe = ols_pwp.pwpEvaluate()
    mse_train = list()
    for col in df2.columns[1:]:
        mse_train.append(pe.mse(df1, df2[col]))
    result = (['y' + str(mse_train.index(np.min(mse_train))+1), np.min(mse_train)])
    return result
```

# Implementing the mse calculations

```
print(build_mse(train.y1, ideal))
print(build_mse(train.y2, ideal))
print(build_mse(train.y3, ideal))
print(build_mse(train.y4, ideal))
               ['y21', 0.09]
['y27', 0.08]
['y2', 0.09]
['y24', 0.08]
In [10]: # Building a function to compute the mean absolute error
                    roulid_mae(df1, df2):
pe = ols_mop.poptvaluate()
mse_train = list()
for col in df2.columns[1:]:
mse_train.append(pe.mae(df1, df2[col]))
result = (['y' + str(mse_train.index(np.min(mse_train))+1), np.min(mse_train)])
return result
               def build mae(df1, df2):
               # Implementing the mae calculations
               print(build_mae(train.y1, ideal))
print(build_mae(train.y2, ideal))
print(build_mae(train.y3, ideal))
print(build_mae(train.y4, ideal))
               ['y21', 0.26]
['y27', 0.24]
['y2', 0.26]
['y24', 0.25]
In [33]: # Building a function to compute the Logcosh loss
               def build_lgcosh(df1, df2):
    pe = ols_pwp.pwpEvaluate()
    mse_train = list()
    for col in df2.columns[1:]:
        mse_train.append(pe.logcosh(df1, df2[col]))
    result = (['y' + str(mse_train.index(np.min(mse_train))+1), round(np.min(mse_train), 2)])
    return result
               # Implementing the Logcosh calculations
               print(build_lgcosh(train.y1, ideal))
print(build_lgcosh(train.y2, ideal))
print(build_lgcosh(train.y3, ideal))
print(build_lgcosh(train.y4, ideal))
               ['y21', 16.86]
['y27', 15.79]
['y2', 17.15]
['y24', 15.89]
              C:\Users\tosin\anaconda3\lib\site-packages\pandas\core\arraylike.py:397: RuntimeWarning: overflow encountered in cosh result = getattr(ufunc, method)(*inputs, **kwargs)
               Interpreting the Result
               The results from the other model evaluation metrics show that the four ideal functions obtained from the sum of square errors is proven to be correct.
               In summary, the ideal function pairs are provided below
                  1. y1-train, y21-idealfour
                  2. y2-train, y27-idealfour
                  3. y3-train, y2-idealfour
                  4. y4-train, y24-idealfour
In [12]: ### Building the idealfour dataset
               idealfour = SSD.idealfour_builder()
print(idealfour.head())
              x y21 y27 y2 y24

0 -20.0 -8000.000 16648.000 0.480802 -16000.000

1 -19.9 -7868.099 16693.090 0.497186 15761.198

2 -19.8 -7762.392 10800.222 0.581322 -15524.784

3 -19.7 -7643.373 12018.133 0.655949 125209.746

4 -19.6 -7529.536 10077.696 0.731386 -15059.072
               Visualizing The Results
               Visualizing the results involves plotting the scatter plots of the dataset pairs to analyze and making inferences based on the findings.
               The matches or pairs are summerized below:
                  1. y1-train, y21-idealfour
                  2. y2-train, y27-idealfour
                  3. y3-train, y2-idealfour
                 4. y4-train, y24-idealfour
               The Bokeh visualization library will be used to make the plots to understand the curve fitting patterns of the paired datasets.
In [13]: # Plot of y1-train, y21-idealfour
               a = figure(plot_width=650, plot_height=300, title= "Fitting y21-idealfour on y1-train")
               a.circle(train.x, train.y1, size=12, color='black', legend_label="y1 - train")
a.square(idealfour.x, idealfour.y21, size=5,color='red', legend_label="y21 - idealfour")
In [14]: ### Computing the r-squared for this result
               pe = ols_pwp.pwpEvaluate()
rs_1 = pe.r_sqr(train['y1'], idealfour['y21'])
               print(rs_1)
               1.0
In [15]: # Plot of y2-train, y27-idealfour
               b = figure(plot_width=650, plot_height=350, title= "Fitting y27-idealfour on y2-train")
               b.circle(train.x, train.y2, size=12, color='black', legend_label="y2 - train")
b.square(idealfour.x, idealfour.y27, size=5,color='blue', legend_label="y27 - idealfour")
```

```
In [16]: ### Computing the r-squared for this result

pe = ols_pwp.pwpEvaluate()
rs_2 = pe.r_sqr(train['y2'], idealfour['y27'])

print(rs_2)

1.0

In [17]: # Plot of y3-train, y2-idealfour

c = figure(title= "Fitting y2-idealfour on y3-train")

c.circle(train.x, train.y3, size=12, color='black', legend_label="y3 - train")

c.square(idealfour.x, idealfour.y2, size=5, color='yellow', legend_label="y2 - idealfour")

c.legend.title = "Legend."

c.legend.title = "Legend."

c.legend.location = 'bottom_left"
```

b.legend.title = "Legend." b.legend.location = "top\_right"

show(b)

```
show(c)
In [18]: ### Computing the r-squared for this result
            pe = ols_pwp.pwpEvaluate()
rs_3 = pe.r_sqr(train['y3'], idealfour['y2'])
            print(rs_3)
            a 91
In [19]: # Plot of y4-train, y24-idealfour
            d = figure(plot_width=650, plot_height=350, title= "Fitting y24-idealfour on y4-train")
            d.circle(train.x, train.y4, size=12, color='black', legend_label="y4-train")
d.square(idealfour.x, idealfour.y24, size=5,color='green', legend_label="y24-idealfour")
            show(d)
In [20]: ### Computing the r-squared for this result
            pe = ols_pwp.pwpEvaluate()
rs_4 = pe.r_sqr(train['y4'], idealfour['y24'])
           print(rs_4)
            1.0
            Finding the Best Fit From the Test and IdealFour Datasets
            The second task required to find the final fitting function on the test dataset is as follows.
In [21]: # Subsetting the idealfour dataset using the test['x'] to obtain the final idf_in_test dataset.
            idf_in_test = idealfour[idealfour['x'].isin(test['x'])]
print(idf_in_test.shape)
            (92, 5)
In [22]: # Computing the test and idf_in_test datasets pair maximum deviation and determining which column has the maximum deviation
            dev = ols_pwp.pwpDeviation(test,idf_in_test)
            test_and_idf = dev.max_dev()
print(test_and_idf)
            [['y24', 20451.356]]
In [23]: # Computing the train and ideal datasets pair maximum deviation
            dev = ols_pwp.pwpDeviation(train, ideal)
train_ideal = dev.max_dev()
print(train_ideal)
            [['y27', 18648.405], ['y25', 34643.215], ['y25', 23994.92563518], ['y27', 26648.222]]
In [24]: # Performing the check for the conditions
# maximum deviation of the test-idealfour datasets pair is less than
# the product of the maximum deviation of the train-ideal datasets pair and the square root of 2.
            print(test_and_idf[0][1] < (train_ideal[1][1] * np.sqrt(2)))</pre>
            True
In [25]: # Building the fit dataset derived from the max deviation calculation # using the test and idealfour datasets pair
            fit = idf_in_test[["x", "y24"]]
print(fit.head())
           x y24
7 -19.3 -14378.114
8 -19.2 -14155.776
13 -18.7 -13078.406
14 -18.6 -12869.712
25 -17.5 -10718.750
In [26]: # Conclusively, we can plot the fit dataset (idf_in_test[[x, y24]]) on the test dataset to study the curve fit.
            e = figure(plot_width=650, plot_height=350, title= "Fitting y24-fit on y-test")
            e.circle(test.x, test.y, size=12, color='black', legend_label="y - test")
e.square(fit.x, fit.y24, size=7,color='green', legend_label="y24 - fit")
           e.legend.title = "Legend."
e.legend.location = "bottom_right"
            show(e)
In [27]: ### Computing the r-squared for this result
            pe = ols_pwp.pwpEvaluate()
rs_5 = pe.r_sqr(test['y'], idf_in_test['y24'])
            print(rs_5)
            Conclusion
            Therefore, the fitting function is that contained in the fit dataset.
            Creating the Database and Writing the Datasets into Database Tables
            At this stage, it is necessary to write all the DataFrame datasets into an sql database. So this will involve the 3 datasets provided for the project and the additional two datasets created while working on the project.
            To begin this next step, importing the important libraries is very important.
In [40]: # Importing the Libraries and creating the connection object
            import sqlite3
from sqlalchemy import create_engine, text
engine = create_engine('sqlite:///pwpDatasets', echo=True, future=True)
conn = engine.connect()
 In [ ]: # Creating the pwpDatasets Database
            query1 = "CREATE DATABASE IF NOT EXISTS pwpDatasets;"
conn.execute(text(query1))
            Creating the Tables inside the pwpDatasets Database:
              1. train
              2. ideal
              3. test
4. idealfour
In [44]: # Creating the train table inside the pwpDatasets Database
            query2 = "CREATE TABLE IF NOT EXISTS train(x DECIMAL, y1 DECIMAL, y2 DECIMAL, y3 DECIMAL, y4 DECIMAL);" result2 = conn.execute(text(query2)) conn.commit()
```

```
2023-04-20 12:15:39,435 INFO sqlalchemy.engine.Engine BEGIN (implicit)
2023-04-20 12:15:39,435 INFO sqlalchemy.engine.Engine CREATE TABLE IF NOT EXISTS train(x DECIMAL, y1 DECIMAL, y2 DECIMAL, y3 DECIMAL, y4 DECIMAL);
2023-04-20 12:15:39,437 BINFO sqlalchemy.engine.Engine (cached since 6.18s ago] ()
2023-04-20 12:15:39,438 INFO sqlalchemy.engine.Engine COMMIT
In [45]: # Creating the ideal table inside the pwpDatasets Database
                                 query3 = "CREATE TABLE IF NOT EXISTS ideal(x DECIMAL, y1 DECIMAL, y2 DECIMAL, y3 DECIMAL, y4 DECIMAL, y5 DECIMAL, y6 DECIMAL, y7 DECIMAL, y8 DECIMAL, y9 DECIMAL, y10 DECIMAL, y11 DECIMAL, y12 DECIMAL, y13 DECIMAL, y14 DEC
                                 2023-04-20 12:15:40,242 INFO sqlalchemy.engine.Engine BEGIN (implicit)
2023-04-20 12:15:40,242 INFO sqlalchemy.engine.Engine GERIFE TABLE IF NOT EXISTS ideal(x DECIMAL, y1 DECIMAL, y2 DECIMAL, y3 DECIMAL, y5 DECIMAL, y6 DECIMAL, y7 DECIMAL, y9 DECIMAL, y10 DECIMAL, y10 DECIMAL, y10 DECIMAL, y20 DECIMAL, y20 DECIMAL, y23 DECIMAL, y24 DECIMAL, y25 DECIMAL, y25 DECIMAL, y26 DECIMAL, y27 DECIMAL, y28 DECIMAL, y20 DECIMAL,
In [46]: # Creating the test table inside the pwpDatasets Datab
                                 query5 = "CREATE TABLE IF NOT EXISTS test(x DECIMAL, y DECIMAL);"
result5 = conn.execute(text(query5))
conn.commit()
                                 2023-04-20 12:15:41,329 INFO sqlalchemy.engine.Engine BEGIN (implicit)
2023-04-20 12:15:41,330 INFO sqlalchemy.engine.Engine CREATE TABLE IF NOT EXISTS test(x DECIMAL, y DECIMAL);
2023-04-20 12:15:41,313 INFO sqlalchemy.engine.Engine (generated in 0.00230s] ()
2023-04-20 12:15:41,426 INFO sqlalchemy.engine.Engine COPMIT
                                 query4 = "CREATE TABLE IF NOT EXISTS idealfour(x DECIMAL, y1 DECIMAL, y2 DECIMAL, y3 DECIMAL, y4 DECIMAL);"
result4 = conn.execute(text(query4))
conn.commit()
In [47]: # Creating the idealfour table inside the pwpDatasets Database
                                 2023-04-20 12:15:41,761 INFO sqlalchemy.engine.Engine BEGIN (implicit)
2023-04-20 12:15:41,762 INFO sqlalchemy.engine.Engine CREATE TABLE IF NOT EXISTS idealfour(x DECIMAL, y1 DECIMAL, y2 DECIMAL, y3 DECIMAL, y4 DECIMAL);
2023-04-20 12:15:41,762 INFO sqlalchemy.engine.Engine (generated in 0.00160s) ()
2023-04-20 12:15:41,764 INFO sqlalchemy.engine.Engine COMMIT
In [48]: # Creating the fit table inside the pwpDatasets Database
                                    query6 = "CREATE TABLE IF NOT EXISTS fit(x DECIMAL, y24 DECIMAL);"
                                  result6 = conn.execute(text(query6))
conn.commit()
                                 2023-04-20 12:15:42,092 INFO sqlalchemy.engine.Engine BEGIN (implicit)
2023-04-20 12:15:42,093 INFO sqlalchemy.engine.Engine CREATE TABLE IF NOT EXISTS fit(x DECIMAL, y24 DECIMAL);
2023-04-20 12:15:42,094 INFO sqlalchemy.engine.Engine (generated in 0.00150s] ()
2023-04-20 12:15:42,221 INFO sqlalchemy.engine.Engine COMMIT
                                 Ingesting the datasets into the respective tables:
                                        1 train --> train dataset
                                        2. ideal --> ideal dataset
                                        3. test --> test dataset
                                        4. idealfour --> idealfour dataset
                                        5 fit --> fit dataset
In [50]: # Ingesting the train Dataframe into the train sql table.
                                 train.to_sql("train", engine, if_exists="replace", index=False)
                                 2023-04-20 12:15:42,834 INFO sqlalchemy.engine.Engine BEGIN (implicit) 2023-04-20 12:15:42,835 INFO sqlalchemy.engine.Engine PRAGMA main.table_info("train") 2023-04-20 12:15:42,835 INFO sqlalchemy.engine.Engine [raw sql] () 2023-04-20 12:15:42,837 INFO sqlalchemy.engine.Engine ROLLBACK 2023-04-20 12:15:42,837 INFO sqlalchemy.engine.Engine BEGIN Cimplicit)
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2023-04-20 12115-42,893 NWO sqlatchesy, engine. Engine FROMW main. table_info('train')
2023-04-20 12115-42,893 NWO sqlatchesy, engine. Engine FROMW main. table_info('train')
2023-04-20 12115-42,893 NWO sqlatchesy
                                 2023-04-20 12:15:43,049 INFO sqlalchemy.engine.Engine [no key 0.00143s] ()
2023-04-20 12:15:43,136 INFO sqlalchemy.engine.Engine COMMIT
2023-04-20 12:15:43,137 INFO sqlalchemy.engine.Engine BGEIN (implicit)
2023-04-20 12:15:43,137 INFO sqlalchemy.engine.Engine INSERT INTO Train (x, y1, y2, y3, y4) VALUES (?, ?, ?, ?)
2023-04-20 12:15:43,143 INFO sqlalchemy.engine.Engine [Remerated in 0.00422s] [(-20.0, -8000.405, 106048.215, -0.07436482, -16000.222), (-19.0, -7880.5566, 10503.581, 0.047023416, -15761.586), (-19.8, -7762.513, 10360.039, 0.150917.5554.712), (-19.17, -7665.5667, 10217.865, 0.55903126), (-19.5, -7529.456), (-19.5, -7529.456), (-19.5, -7529.456), (-19.5, -7529.456), (-19.5, -7529.456), (-19.5, -7529.456), (-19.5, -7529.456), (-19.5, -7529.456), (-19.5, -7529.456), (-19.5, -7529.456), (-19.5, -7529.456), (-19.5, -7529.456), (-19.5, -7529.456), (-19.5, -7529.456), (-19.5, -7529.456), (-19.5, -7529.456), (-19.5, -7529.456), (-19.5, -7529.456), (-19.5, -7529.456), (-19.5, -7529.456), (-19.5, -7529.456), (-19.5, -7529.456), (-19.5, -7529.456), (-19.5, -7529.456), (-19.5, -7529.456), (-19.5, -7529.456), (-19.5, -7529.456), (-19.5, -7529.456), (-19.5, -7529.456), (-19.5, -7529.456), (-19.5, -7529.456), (-19.5, -7529.456), (-19.5, -7529.456), (-19.5, -7529.456), (-19.5, -7529.456), (-19.5, -7529.456), (-19.5, -7529.456), (-19.5, -7529.456), (-19.5, -7529.456), (-19.5, -7529.456), (-19.5, -7529.456), (-19.5, -7529.456), (-19.5, -7529.456), (-19.5, -7529.456), (-19.5, -7529.456), (-19.5, -7529.456), (-19.5, -7529.456), (-19.5, -7529.456), (-19.5, -7529.456), (-19.5, -7529.456), (-19.5, -7529.456), (-19.5, -7529.456), (-19.5, -7529.456), (-19.5, -7529.456), (-19.5, -7529.456), (-19.5, -7529.456), (-19.5, -7529.456), (-19.5, -7529.456), (-19.5, -7529.456), (-19.5, -7529.456), (-19.5, -7529.456), (-19.5, -7529.456), (-19.5, -7529.456), (-19.5, -7529.456), (-19.5, -7529.456), (-19.5, -7529.456), (-19.5, -7529.456), (-19.5, -7529.456), (-19.5, -7529.456), (-19.5, -7529.456), (-19.5, -7529.456), (-19.5, -7529.456),
                                    In [51]: # Querying the train table from the pwpDatasets database
                                    query7 = "SELECT * FROM train LIMIT 5
result7 = conn.execute(text(query7))
                                  for res7 in result7:
    print(res7)
                                 2023-04-20 12:15:43,256 INFO sqlalchemy.engine.Engine BEGIN (implicit) 2023-04-20 12:15:43,258 INFO sqlalchemy.engine.Engine SELECT * FROM train LIMIT * 2023-04-20 12:15:43,259 INFO sqlalchemy.engine.Engine [generated in 0.00274s] () (-20.0, -8000.405, 10648.215, -0.07436482, -15000.222) (-19.9, -7886.5566, 19693.581, 0.040723416, -15761.586) (-19.9, -7886.5566, 19693.581, 0.040723416, -15761.586) (-19.8, -7762.513, 10360.039, 0.15607175, -15524.712) (-19.7 -7864.6567.10217.876. 0.59000126. 152509.346)
                                    (-19.7, -7645.6567, 10217.856, 0.59090126, -15290.346)
(-19.6, -7529.4863, 10077.48, 0.52523214, -15058.604)
In [52]: # Ingesting the ideal Dataframe into the train sal table
                                 ideal.to_sql("ideal", engine, if_exists="replace", index=False)
```

```
2023-04-20 12:15:43,348 INFO sqlalchemy.engine.Engine BEGIN (implicit)
2023-04-20 12:15:43,358 INFO sqlalchemy.engine.Engine PRADAM main.table_info("ideal")
2023-04-20 12:15:43,358 INFO sqlalchemy.engine.Engine [Fax sql] ()
2023-04-20 12:15:43,358 INFO sqlalchemy.engine.Engine [Fax sql] ()
2023-04-20 12:15:43,358 INFO sqlalchemy.engine.Engine PRADAM main.table_info("ideal")
2023-04-20 12:15:43,358 INFO sqlalchemy.engine.Engine PRADAM main.table_info("ideal")
2023-04-20 12:15:43,358 INFO sqlalchemy.engine.Engine PRADAM main.table_info("ideal")
2023-04-20 12:15:43,358 INFO sqlalchemy.engine.Engine BEGIN (implicit)
2023-04-20 12:15:43,358 INFO sqlalchemy.engine.Engine BEGIN (implicit)
2023-04-20 12:15:43,358 INFO sqlalchemy.engine.Engine BEGIN (implicit)
2023-04-20 12:15:43,358 INFO sqlalchemy.engine.Engine FRADAM main.table_info("ideal")
2023-04-20 12:15:43,358 INFO sqlalchemy.engine.Engine [raw sql] ()
2023-04-20 12:15:43,358 INFO sqlalchemy.engine.Engine FRADAM main.index_list("ideal")
2023-04-20 12:15:43,358 INFO sqlalchemy.engine.Engine FRADAM main.index_list("ideal")
2023-04-20 12:15:43,358 INFO sqlalchemy.e
       2023-04-20 12:15:43,389 INFO sqlalchemy.engine.Engine ROLLBACK
2023-04-20 12:15:43,390 INFO sqlalchemy.engine.Engine BEGIN (implicit)
2023-04-20 12:15:43,391 INFO sqlalchemy.engine.Engine
DROF TABLE ideal
2023-04-20 12:15:43,392 INFO sqlalchemy.engine.Engine [no key 0.001165] ()
2023-04-20 12:15:43,504 INFO sqlalchemy.engine.Engine COMMIT
2023-04-20 12:15:43,506 INFO sqlalchemy.engine.Engine BEGIN (implicit)
2023-04-20 12:15:43,506 INFO sqlalchemy.engine.Engine
CREATE TABLE ideal (

X FLOAT,

Y FLOAT,
                                                 y4 FLOAT,
y5 FLOAT,
y6 FLOAT,
y7 FLOAT,
y8 FLOAT,
y10 FLOAT,
y11 FLOAT,
y12 FLOAT,
y13 FLOAT,
y14 FLOAT,
y15 FLOAT,
y16 FLOAT,
y17 FLOAT,
y18 FLOAT,
y18 FLOAT,
y19 FLOAT,
                                                   y19 FLOAT,
y20 FLOAT,
y21 FLOAT,
y22 FLOAT,
y23 FLOAT,
y24 FLOAT,
                                                   y25 FLOAT,
y26 FLOAT,
y27 FLOAT,
y28 FLOAT,
y29 FLOAT,
y30 FLOAT,
                                                   y31 FLOAT,
y32 FLOAT,
y33 FLOAT,
y34 FLOAT,
y35 FLOAT,
y36 FLOAT,
y37 FLOAT,
y38 FLOAT,
y40 FLOAT,
y41 FLOAT,
y42 FLOAT,
y43 FLOAT,
                                                       y44 FLOAT,
                                                       y48 FLOAT,
```

In [53]: # Querying the ideal table from the database query8 = "SELECT \* FROM ideal LIMIT 5" result8 = comn.execute(text(query8)) for res8 in result8: print(res8)

```
2023-04-20 12:15:43,736 INFO sqlalchemy.engine.Engine ELECT * FROM ideal LIMIT 5
2023-04-20 12:15:43,737 INFO sqlalchemy.engine.Engine [generated in 0.00121s] ()
(-20.0, -0.9:129453, 0.48080267, 9.087055, 5.408082, -9.087055, 5.408082, -9.087055, 5.408082, -9.087055, 5.408082, -9.087055, 5.408082, -9.087055, 5.408082, -9.087055, 5.408082, -9.087055, 5.408082, -9.087055, 5.408082, -9.087055, 5.408082, -9.087055, 5.408082, -9.087055, 5.408082, -9.087055, 5.408082, -9.087055, 5.408082, -9.087055, 5.408082, -9.087055, 5.408082, -9.087055, 5.408082, -9.087055, 5.408082, -9.08705, 5.408082, -9.087055, 5.408082, -9.087055, 5.408082, -9.087055, 5.408082, -9.08705, 5.408082, -9.08705, 5.408082, -9.08705, 5.408082, -9.08705, 5.408082, -9.08705, 5.408082, -9.08705, 5.408082, -9.08082, -9.08082, -9.08705, -9.122356, 0.807041, -9.122356, 0.807041, -9.122126, 0.10851768, 0.9943716, 17.266117, -19.9, -57.7, -44.8, 19.9, 12.95, 396.01, -396.01, 792.02, 406.01, 285.01, -7880.599, 7880.599, 7.5701.198, -23636.797, -5735.339, 10583.439, -7900.499, -7484.589, -8667.619, 19.9, 4.469042, 20.023244, -0.0240549, 9.9, 9.5, -19.9, -1.3640299, 395.14236, 893.5128, -40.23382, 40.04899, 2.9907198, -0.0833404283, 12.9907198, -0.0833404283, 12.9907198, -0.0833404, -0.084082, -0.0833404, -0.084082, -0.0833404, -0.084082, -0.0834082, -0.0834082, -0.0834082, -0.0834082, -0.0834082, -0.0834082, -0.0834082, -0.0834082, -0.0834082, -0.0834082, -0.0834082, -0.0834082, -0.0834082, -0.0834082, -0.0834082, -0.0834082, -0.0834082, -0.0834082, -0.0834082, -0.0834082, -0.0834082, -0.0834082, -0.0834082, -0.0834082, -0.0834082, -0.0834082, -0.0834082, -0.0834082, -0.0834082, -0.0834082, -0.0834082, -0.0834082, -0.0834082, -0.0834082, -0.0834082, -0.0834082, -0.0834082, -0.0834082, -0.0834082, -0.0834082, -0.0834082, -0.0834082, -0.0834082, -0.0834082, -0.0834082, -0.0834082, -0.0834082, -0.0834082, -0.0834082, -0.0834082, -0.0834082, -0.0834082, -0.0834082, -0.0834082, -0.0834082, -0.0834082, -0.0834082, -0.0834082, -0.0834082, -0.0834082, -0.0834082, -0.
 In [54]: # Ingesting the test Dataframe into the train sql table
                                     ### State of Comparison of the test Datyrame into the troin soit cooke.

### State of Comparison of the State of Comparison of C
                                           test.to sql("test", engine, if exists="replace", index=False)
                                           DROP TABLE test
2023-04-20 12:15:43,864 INFO sqlalchemy.engine.Engine [no key 0.000695] ()
2023-04-20 12:15:43,951 INFO sqlalchemy.engine.Engine COMMIT
2023-04-20 12:15:43,954 INFO sqlalchemy.engine.Engine BEGIN (implicit)
2023-04-20 12:15:43,955 INFO sqlalchemy.engine.Engine
ERARTE TABLE test (
                                                                             x FLOAT,
y FLOAT
                                            2023-04-20 12:15:43,955 INFO sqlalchemy.engine.Engine [no key 0.00052s] () 2023-04-20 12:15:44,036 INFO sqlalchemy.engine.Engine COMMIT
                                           2023-094-20 12:15:44,093 INFO sqlalchemy.engine.Engine COMMIT
2023-08-20 12:15:44,093 TMFO sqlalchemy.engine.Engine BGEIN (implicit)
2023-08-20 12:15:44,093 TMFO sqlalchemy.engine.Engine INSERT INTO test (x, y) VALUES (?, ?)
2023-08-20 12:15:44,0940 INFO sqlalchemy.engine.Engine [generated in 0.00131s] [(-17.5, 14492.095), (19.0, 0.4807038), (6.5, 274.0855), (15.9, 8039.7925), (-14.3, -5848.08), (0.3, 4.4066796), (0.1, -1.2131777), (4.8, 109.8
1799) ... displaying 10 of 100 total bound parameter sets ... (6.7, 601.3089), (3.9, 60.296154)]
2023-08-20 12:15:44,081 INFO sqlalchemy.engine.Engine COMMIT
In [55]: # Querying the test table from the database
                                            query9 = "SELECT * FROM test LIMIT 5
result9 = conn.execute(text(query9))
for res9 in result9:
    print(res9)
                                              2023-04-20 12:15:44,144 INFO sqlalchemy.engine.Engine SELECT * FROM test LIMIT 5
2023-04-20 12:15:44,145 INFO sqlalchemy.engine.Engine [generated in 0.00113s] ()
                                            (-17.5, 14492.095)
(19.0, 0.4807038)
(6.5, 274.0855)
(15.9, 8039.7925)
(-14.3, -5848.08)
In [56]: # Ingesting the idealfour Dataframe into the train sql table.
                                           idealfour.to_sql("idealfour", engine, if_exists="replace", index=False)
```

```
2023-04-20 12:15:44,256 INFO sqlalchemy.engine.Engine BEGIN (implicit)
2023-04-20 12:15:44,256 INFO sqlalchemy.engine.Engine PRADAM main.table_info("idealfour")
2023-04-20 12:15:44,258 INFO sqlalchemy.engine.Engine [raw sql] ()
2023-04-20 12:15:44,258 INFO sqlalchemy.engine.Engine [raw sql] ()
2023-04-20 12:15:44,252 INFO sqlalchemy.engine.Engine PRADAM main.table_info("idealfour")
2023-04-20 12:15:44,252 INFO sqlalchemy.engine.Engine PRADAM main.table_info("idealfour")
2023-04-20 12:15:44,252 INFO sqlalchemy.engine.Engine PRADAM main.table_info("idealfour")
2023-04-20 12:15:44,252 INFO sqlalchemy.engine.Engine BEGIN (implicit)
2023-04-20 12:15:44,252 INFO sqlalchemy.engine.Engine BEGIN (implicit)
2023-04-20 12:15:44,252 INFO sqlalchemy.engine.Engine BEGIN (implicit)
2023-04-20 12:15:44,252 INFO sqlalchemy.engine.Engine EFRADAM main.table_info("idealfour")
2023-04-20 12:15:44,252 INFO sqlalchemy.engine.Engine FRADAM main.table_info("idealfour")
2023-04-20 12:15:44,252 INFO sqlalchemy.engine.Engine [raw sql] ()
2023-04-20 12:15:44,272 INFO sqlalchemy.engine.Engine [ra
                                          y24 FLOAT
                                          2023-04-20 12:15:44,389 INFO sqlalchemy.engine.Engine [no key 0.00062s] ()
2023-04-20 12:15:44,780 INFO sqlalchemy.engine.Engine (COMMIT
2023-04-20 12:15:44,780 INFO sqlalchemy.engine.Engine BEGIN (implicit)
2023-04-20 12:15:44,73 INFO sqlalchemy.engine.Engine BEGIN (implicit)
2023-04-20 12:15:44,73 INFO sqlalchemy.engine.Engine INSERT INTO idealfour (x, y21, y27, y2, y24) VALUES (?, ?, ?, ?)
2023-04-20 12:15:44,473 INFO sqlalchemy.engine.Engine [Generated in 0.00176s] [(-20.0, -8000.0, 10648.0, 0.40800207, -16000.0), (-19.9, -7880.599, 10503.459, 0.4971858, -15761.198), (-19.8, -7762.392, 10360.232, 0.5813218
4, -15524.784), (-19.7, -7645.373, 10218.313, 0.65964943, -15290.746), (-19.6, -7529.536, 10077.696, 0.7313861, -15959.072), (-19.5, -7414.875, 9938.375, 0.795815, -14829.75), (-19.4, -7301.394, 9800.344, 0.8522923, -1460
2.788), (-19.3, -7189.057, 966.5597, 0.90025333, -143578.114) ... displaying 10 of 400 total bound parameter sets ... (19.8, 7762.392, -5639.752, 0.58132184, 15524.784), (19.9, 7880.599, -5735.339, 0.4971858, 15761.198)]
2023-04-20 12:15:44,477 INFO sqlalchemy.engine.Engine COMMIT
In [57]: # Querying the idealfour table from the database
                                          query10 = "SELECT * FROM test LIMIT 5"
result10 = conn.execute(text(query10))
for res10 in result10:
    print(res10)
                                          2023-04-20 12:15:44,567 INFO sqlalchemy.engine.Engine SELECT * FROM test LIMIT 5 2023-04-20 12:15:44,568 INFO sqlalchemy.engine.Engine [cached since 0.4245s ago] () (-17.5, 14492.095) (19.0, 0.4807038) (6.5, 274.0855) (15.9, 8039.7925) (-14.3, -5848.08)
 In [58]: # Ingesting the fit Dataframe into the train sql table.
                                     # Interesting the fit borsymme into the trum of Cooke.

# Int. to_Sql("fit", engine, if_exists"replace", index:False)

2023-08-20 12:15:44,770 INFO sqlalchewy, engine. Engine BEGIN (implicit)

2023-08-20 12:15:44,770 INFO sqlalchewy, engine. Engine PRAGNM main.table_info("fit")

2023-08-20 12:15:44,770 INFO sqlalchewy, engine. Engine PRAGNM main.table_info("fit")

2023-08-20 12:15:44,750 INFO sqlalchewy, engine. Engine FRAGN sqlite_exem_master WHERE type="table" AND name NOT LIKE 'sqlite_X' ESCAPE '-' ORDER BY name

2023-08-20 12:15:44,750 INFO sqlalchewy, engine. Engine FRAGN sqlite_exem_master WHERE type="table" AND name NOT LIKE 'sqlite_X' ESCAPE '-' ORDER BY name

2023-08-20 12:15:44,750 INFO sqlalchewy, engine. Engine FRAGN sqlite_exem_master UNION ALL SELECT * FROM sqlite_temp_master) WHERE name * ? AND type in ('table', 'view')

2023-08-20 12:15:44,750 INFO sqlalchewy, engine. Engine [risw sql] ('or sqlite_master UNION ALL SELECT * FROM sqlite_temp_master) WHERE name * ? AND type in ('table', 'view')

2023-08-20 12:15:44,770 INFO sqlalchewy, engine. Engine [risw sql] ('or sqlite_master UNION ALL SELECT * FROM sqlite_temp_master) WHERE name * ? AND type in ('table', 'view')

2023-08-20 12:15:44,770 INFO sqlalchewy, engine. Engine [risw sql']

2023-08-20 12:15:44,770 INFO sqlalchewy, engine. Engine [risw sql']

2023-08-20 12:15:44,770 INFO sqlalchewy, engine. Engine [risw sql']

2023-08-20 12:15:44,770 INFO s
                                          fit.to_sql("fit", engine, if_exists="replace", index=False)
                                             2023-04-20 12:15:44,796 INFO sqlalchemy.engine.Engine [no key 0.00170s] ()
                                          y24 FLOAT
                                          2023-04-20 12:15:44,881 INFO sqlalchemy.engine.Engine [no key 0.00094s] ()
2023-04-20 12:15:44,961 INFO sqlalchemy.engine.Engine COMMIT
2023-04-20 12:15:44,962 INFO sqlalchemy.engine.Engine Engine Engine Engine Engine Engine Engine Engine Engine Engine INSERT INTO fit (x, y24) VALUES (?, ?)
2023-04-20 12:15:44,963 INFO sqlalchemy.engine.Engine [generated in 0.00114s] [(-19.3, -14378.114), (-19.2, -14155.776), (-18.7, -13078.406), (-18.6, -12869.712), (-17.5, -10718.75), (-17.4, -10536.048), (-17.0, -9826.0), (-16.6, -9148.592) ... displaying 10 of 292 total bound parameter sets ... (19.4, 14602.768), (19.6, 15059.072)]
2023-04-20 12:15:44,967 INFO sqlalchemy.engine.Engine COMMIT
In [59]: # Querying the idealfour table from the database
                                          query11 = "SELECT * FROM test LIMIT 5"
result11 = conn.execute(text(query11))
for res11 in result11:
    print(res11)
```

2023-04-20 12:15:45,067 INFO sqlalchemy.engine.Engine SELECT \* FROM test LIMIT 5 2023-04-20 12:15:45,067 INFO sqlalchemy.engine.Engine [cached since 0.9237s ago] () (-17.5, 14492.095) (19.0, 0.4807038) (6.5, 274.0855) (15.9, 8039.7925) (-14.3, -5848.08)