This jupyter notebook and the associated gradient descent class do linear regression using the gradient descent method.

```
In [9]: import sys
         import os
         import matplotlib.pyplot as plt
         from matplotlib import cm
         import numpy as np
         import pandas as pd
         from sklearn.preprocessing import StandardScaler
         import statsmodels.api as sm
In [10]: # Get the absolute path of the current file
         try:
             # Works in .py scripts
             current_dir = os.path.dirname(os.path.abspath(__file__))
         except NameError:
             # Fallback for Jupyter
             current_dir = os.getcwd()
         # Go up N levels (here N=2, but you can adjust)
         # project root = os.path.abspath(os.path.join(current dir, "..", ".."))
         project_root = os.path.abspath(os.path.join(current_dir, ".."))
         # Add the project root to sys.path if not already there
         if project_root not in sys.path:
             sys.path.insert(0, project_root)
In [11]: from ML_toolbox import d_lm_analytical_solution_class
         from ML_toolbox import d_mlr_gradient_descent_class
In [12]: # specify parameters for gradient descent
         delta J threshold = 0.000001
         learning_rate = 0.001
In [13]: in_file_name = "../../data/linear_regression_test_data.csv"
         data_in_df = pd.read_csv(in_file_name)
         data_in_df.head()
```

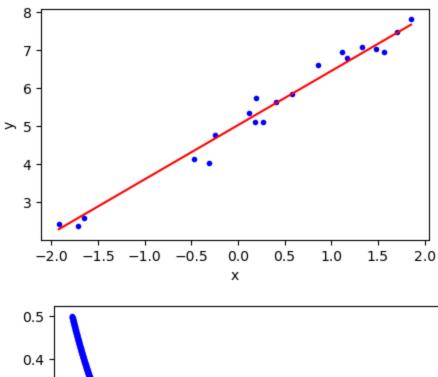
```
Out[13]:
                    Х
                              y y_theoretical
             -1.919126 2.420126
                                     2.121310
         0
             -1.715856 2.385185
                                    2.426216
             -1.651483 2.585389
                                    2.522776
            -0.466234 4.129830
                                    4.300649
            -0.305381 4.031331
                                    4.541929
In [14]: # x_name = ['size', 'number of bedrooms']
         x_n = ['x']
         y_name = ['y']
         variable_to_plot = ['x']
In [15]: fig, ax = plt.subplots(figsize=(5,3))
         ax.scatter(data_in_df[variable_to_plot], data_in_df[y_name], marker='.', col
         ax.set_xlabel(variable_to_plot[0])
         ax.set_ylabel(y_name[0])
Out[15]: Text(0, 0.5, 'y')
           8
           7
           6
        > 5
           4
           3
                   -1.5
                         -1.0 -0.5
                                      0.0
                                            0.5
                                                   1.0
                                                         1.5
                                                               2.0
                                      х
In [16]: # normalize variables to make them have similar scale
         standard_scaler_obj = StandardScaler()
         standard_scaler_obj.fit(data_in_df[x_name + y_name])
         mean_needed_df = pd.Series(standard_scaler_obj.mean_, index=x_name + y_name)
         scale_needed_df = pd.Series(standard_scaler_obj.scale_, index=x_name + y_name)
         data_normalized_df = pd.DataFrame(standard_scaler_obj.transform(data_in_df[x
                                             index=data_in_df.index, \
                                             columns=x_name + y_name)
```

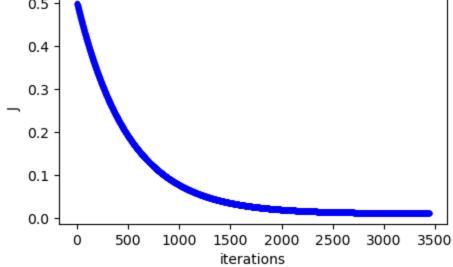
```
file:///Users/xdu4/Downloads/do_linear_regression_numerical_solution.html
```

In [17]: # get information on x (single variable) and y

X = data normalized df[x name]

```
y = data normalized df[y name]
         # augment X0
         X = sm.add\_constant(X)
         number of variables = X.shape[1]
          # including X0
         initial_theta = np.zeros((number_of_variables, 1))
In [18]: delta J threshold
         initial_theta
         learning rate
Out[18]: 0.001
In [19]: # gradient descent
         obj_MLR = d_mlr_gradient_descent_class.MLR(delta_J_threshold=delta_J_threshold
                                                         initial_theta=initial_theta,
                                                         learning_rate=learning_rate)
         obj_MLR.fit(X=X, y=y)
         optimal_theta = obj_MLR.optimal_theta
         J = obj MLR.J
In [20]: |y_hat = X @ optimal_theta
         # restore y hat to the original data space
         y_hat_restored = y_hat * scale_needed_df[y_name][y_name].values + mean_needed
         fig, ax = plt.subplots(figsize=(5,3))
         ax.scatter(data_in_df[variable_to_plot], data_in_df[y_name], marker='.', col
         ax.plot(data in df[variable to plot], y hat restored, color='red')
         ax.set_xlabel(variable_to_plot[0])
         ax.set_ylabel(y_name[0])
         fig, ax = plt.subplots(figsize=(5,3))
         ax.scatter(range(len(J)), J, marker='.', color='blue')
         ax.set xlabel('iterations')
         ax.set_ylabel('J')
Out[20]: Text(0, 0.5, 'J')
```





In []: