body-fat-prediction

October 27, 2024

0.1 Body Fat Prediction

[11]:
```
# Import necessary libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression, Ridge, Lasso, ElasticNet
from sklearn.preprocessing import PolynomialFeatures, StandardScaler,␣
↪OneHotEncoder
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.pipeline import Pipeline, make_pipeline
from sklearn.utils import shuffle
from sklearn.model_selection import cross_val_score, cross_val_predict,␣
↪cross_validate
from sklearn.linear_model import SGDRegressor
from sklearn.impute import SimpleImputer
from sklearn.compose import ColumnTransformer
```

A.Summarize the data. How much data is present? What attributes/features are continuous valued? Which attributes are categorical?

import warnings

[12]:
```
import warnings
warnings.filterwarnings("ignore")
```

[13]:
```
# Load the dataset
data = pd.read_csv("/content/bodyfat.csv")

# 1. Summarize the Data
# Display basic information about the dataset
print(data.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 252 entries, 0 to 251
Data columns (total 15 columns):
 #   Column   Non-Null Count  Dtype
```

```
---  ------   --------------  -----
 0   Density  252 non-null    float64
 1   BodyFat  252 non-null    float64
 2   Age      252 non-null    int64
 3   Weight   252 non-null    float64
 4   Height   252 non-null    float64
 5   Neck     252 non-null    float64
 6   Chest    252 non-null    float64
 7   Abdomen  252 non-null    float64
 8   Hip      252 non-null    float64
 9   Thigh    252 non-null    float64
 10  Knee     252 non-null    float64
 11  Ankle    252 non-null    float64
 12  Biceps   252 non-null    float64
 13  Forearm  252 non-null    float64
 14  Wrist    252 non-null    float64
dtypes: float64(14), int64(1)
memory usage: 29.7 KB
None
```

[14]:
```python
categorical_attributes_func = data.select_dtypes(include='object')
continuous_attributes_func = data.select_dtypes(include=np.number)
```

[15]:
```python
categorical_attributes_func
```

[15]:
```
Empty DataFrame
Columns: []
Index: [0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19,
20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39,
40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59,
60, 61, 62, 63, 64, 65, 66, 67, 68, 69, 70, 71, 72, 73, 74, 75, 76, 77, 78, 79,
80, 81, 82, 83, 84, 85, 86, 87, 88, 89, 90, 91, 92, 93, 94, 95, 96, 97, 98, 99,
…]

[252 rows x 0 columns]
```

[16]:
```python
continuous_attributes_func
```

[16]:
```
     Density  BodyFat  Age  Weight  Height  Neck  Chest  Abdomen    Hip  \
0     1.0708     12.3   23  154.25   67.75  36.2   93.1     85.2   94.5
1     1.0853      6.1   22  173.25   72.25  38.5   93.6     83.0   98.7
2     1.0414     25.3   22  154.00   66.25  34.0   95.8     87.9   99.2
3     1.0751     10.4   26  184.75   72.25  37.4  101.8     86.4  101.2
4     1.0340     28.7   24  184.25   71.25  34.4   97.3    100.0  101.9
..       …       …  …    …       …   …     …     …
247   1.0736     11.0   70  134.25   67.00  34.9   89.2     83.6   88.8
248   1.0236     33.6   72  201.00   69.75  40.9  108.5    105.0  104.5
```

```
249   1.0328     29.3   72  186.75   66.00  38.9  111.1    111.5  101.7
250   1.0399     26.0   72  190.75   70.50  38.9  108.3    101.3   97.8
251   1.0271     31.9   74  207.50   70.00  40.8  112.4    108.5  107.1

     Thigh  Knee  Ankle  Biceps  Forearm  Wrist
0     59.0  37.3   21.9    32.0     27.4   17.1
1     58.7  37.3   23.4    30.5     28.9   18.2
2     59.6  38.9   24.0    28.8     25.2   16.6
3     60.1  37.3   22.8    32.4     29.4   18.2
4     63.2  42.2   24.0    32.2     27.7   17.7
..     …     …     …      …       …       …
247   49.6  34.8   21.5    25.6     25.7   18.5
248   59.6  40.8   23.2    35.2     28.6   20.1
249   60.3  37.3   21.5    31.3     27.2   18.0
250   56.0  41.6   22.7    30.5     29.4   19.8
251   59.3  42.2   24.6    33.7     30.0   20.9

[252 rows x 15 columns]
```

[17]:
```python
continuous_attributes =␣
 ↪['Density',          'BodyFat',          'Age',          'Weight',          'Height',          'Neck'
```

OBSERVATIONS:

Total entries = 252

Total features = 15

There are no categorial attrbutes in the dataset

All attributes has continuous values.

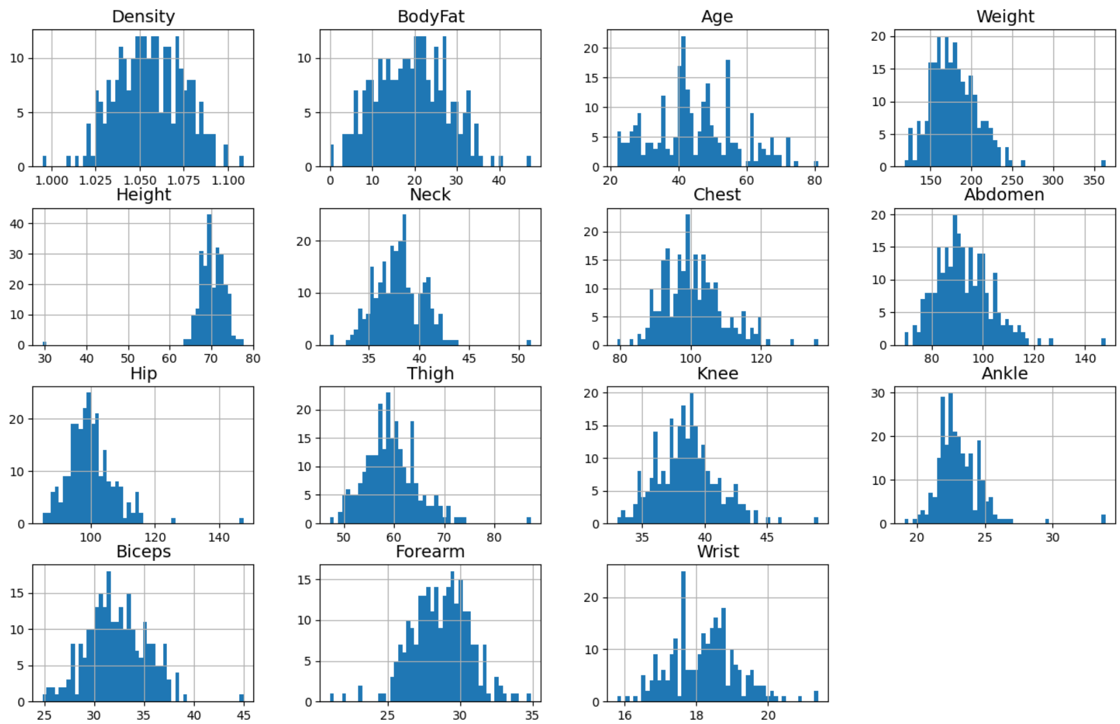
B.Display the statistical values for each of the attributes, along with visualizations (e.g., histogram) of the distributions for each attribute. Explain noticeable traits for key attributes. Are there any attributes that might require special treatment? If so, what special treatment might they require?

[9]:
```python
continuous_attributes_func.describe()
```

[9]:
```
          Density     BodyFat         Age      Weight      Height        Neck  \
count  252.000000  252.000000  252.000000  252.000000  252.000000  252.000000
mean     1.055574   19.150794   44.884921  178.924405   70.148810   37.992063
std      0.019031    8.368740   12.602040   29.389160    3.662856    2.430913
min      0.995000    0.000000   22.000000  118.500000   29.500000   31.100000
25%      1.041400   12.475000   35.750000  159.000000   68.250000   36.400000
50%      1.054900   19.200000   43.000000  176.500000   70.000000   38.000000
75%      1.070400   25.300000   54.000000  197.000000   72.250000   39.425000
max      1.108900   47.500000   81.000000  363.150000   77.750000   51.200000

            Chest     Abdomen         Hip       Thigh        Knee       Ankle  \
count  252.000000  252.000000  252.000000  252.000000  252.000000  252.000000
```

```
mean    100.824206   92.555952   99.904762   59.405952   38.590476   23.102381
std       8.430476   10.783077    7.164058    5.249952    2.411805    1.694893
min      79.300000   69.400000   85.000000   47.200000   33.000000   19.100000
25%      94.350000   84.575000   95.500000   56.000000   36.975000   22.000000
50%      99.650000   90.950000   99.300000   59.000000   38.500000   22.800000
75%     105.375000   99.325000  103.525000   62.350000   39.925000   24.000000
max     136.200000  148.100000  147.700000   87.300000   49.100000   33.900000

            Biceps     Forearm       Wrist
count   252.000000  252.000000  252.000000
mean     32.273413   28.663889   18.229762
std       3.021274    2.020691    0.933585
min      24.800000   21.000000   15.800000
25%      30.200000   27.300000   17.600000
50%      32.050000   28.700000   18.300000
75%      34.325000   30.000000   18.800000
max      45.000000   34.900000   21.400000
```

[9]:
```python
import matplotlib.pyplot as plt

# extra code – the next 5 lines define the default font sizes
plt.rc('font', size=14)
plt.rc('axes', labelsize=14, titlesize=14)
plt.rc('legend', fontsize=14)
plt.rc('xtick', labelsize=10)
plt.rc('ytick', labelsize=10)

data.hist(bins=50, figsize=(16, 10))

plt.show()
```



we observed that attribute Height is left skewed.

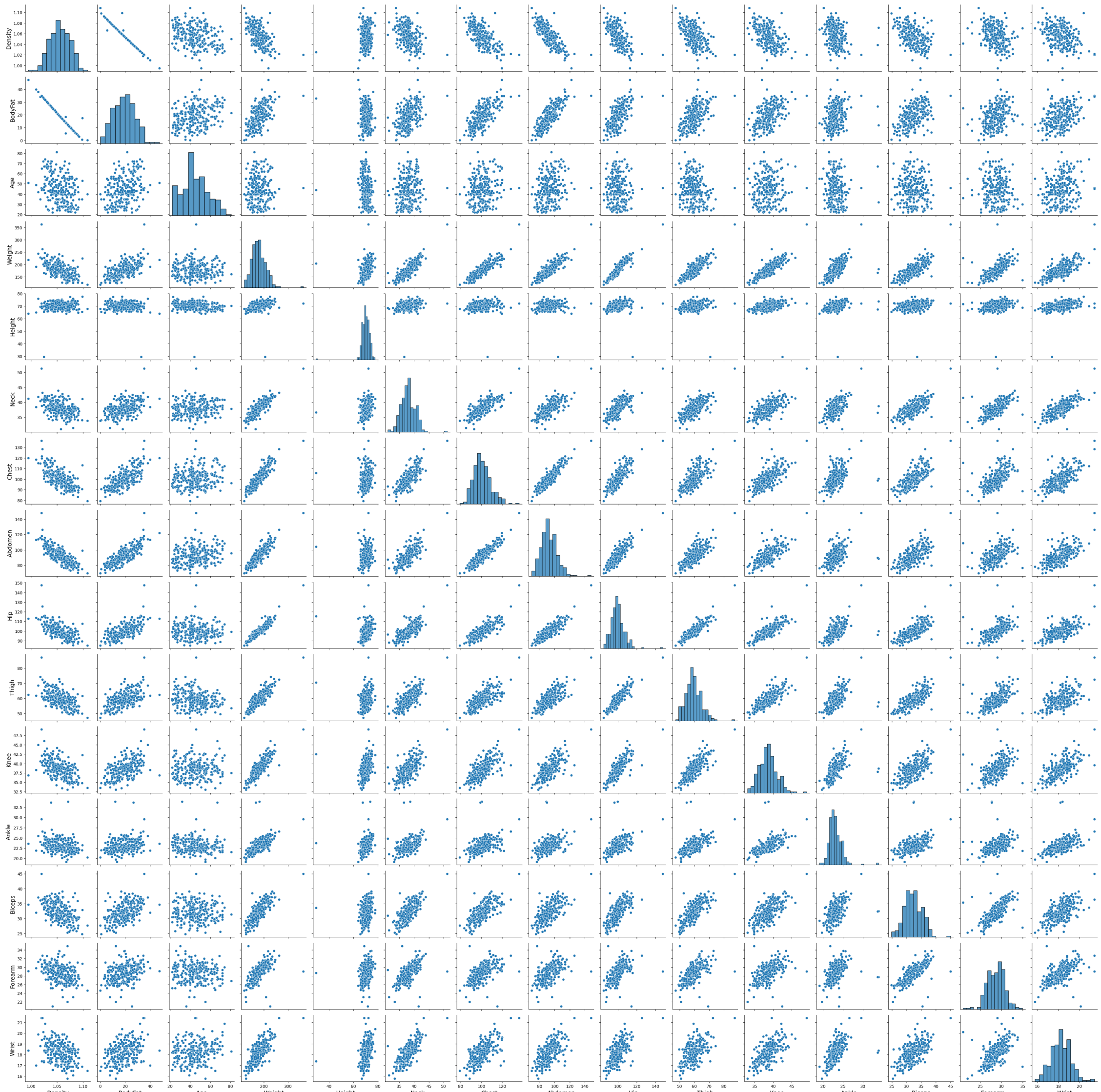
we will see any null values and replace them with median of the each feature we will consider BodyFat as Label and remove it from the data.

C. Analyze and discuss the relationships between the data attributes, and between the data attributes and label. This involves computing the Pearson Correlation Coefficient (PCC) and generating scatter plots.

[18]:
```
# 3. Analyze Relationships
# Calculate Pearson Correlation Coefficient (PCC)
correlation_matrix = data[continuous_attributes].corr()
print(correlation_matrix)

# Generate scatter plots for key attribute pairs
sns.pairplot(data[continuous_attributes])
plt.show()
```

```
          Density   BodyFat       Age    Weight    Height      Neck     Chest  \
Density  1.000000 -0.987782 -0.277637 -0.594062  0.097881 -0.472966 -0.682599
BodyFat -0.987782  1.000000  0.291458  0.612414 -0.089495  0.490592  0.702620
Age     -0.277637  0.291458  1.000000 -0.012746 -0.171645  0.113505  0.176450
Weight  -0.594062  0.612414 -0.012746  1.000000  0.308279  0.830716  0.894191
Height   0.097881 -0.089495 -0.171645  0.308279  1.000000  0.253710  0.134892
Neck    -0.472966  0.490592  0.113505  0.830716  0.253710  1.000000  0.784835
```

```
Chest   -0.682599  0.702620  0.176450  0.894191  0.134892  0.784835  1.000000
Abdomen -0.798955  0.813432  0.230409  0.887995  0.087813  0.754077  0.915828
Hip     -0.609331  0.625201 -0.050332  0.940884  0.170394  0.734958  0.829420
Thigh   -0.553091  0.559608 -0.200096  0.868694  0.148436  0.695697  0.729859
Knee    -0.495040  0.508665  0.017516  0.853167  0.286053  0.672405  0.719496
Ankle   -0.264890  0.265970 -0.105058  0.613685  0.264744  0.477892  0.482988
Biceps  -0.487109  0.493271 -0.041162  0.800416  0.207816  0.731146  0.727907
Forearm -0.351648  0.361387 -0.085056  0.630301  0.228649  0.623660  0.580173
Wrist   -0.325716  0.346575  0.213531  0.729775  0.322065  0.744826  0.660162

          Abdomen       Hip     Thigh      Knee     Ankle    Biceps   Forearm  \
Density -0.798955 -0.609331 -0.553091 -0.495040 -0.264890 -0.487109 -0.351648
BodyFat  0.813432  0.625201  0.559608  0.508665  0.265970  0.493271  0.361387
Age      0.230409 -0.050332 -0.200096  0.017516 -0.105058 -0.041162 -0.085056
Weight   0.887995  0.940884  0.868694  0.853167  0.613685  0.800416  0.630301
Height   0.087813  0.170394  0.148436  0.286053  0.264744  0.207816  0.228649
Neck     0.754077  0.734958  0.695697  0.672405  0.477892  0.731146  0.623660
Chest    0.915828  0.829420  0.729859  0.719496  0.482988  0.727907  0.580173
Abdomen  1.000000  0.874066  0.766624  0.737179  0.453223  0.684983  0.503316
Hip      0.874066  1.000000  0.896410  0.823473  0.558387  0.739273  0.545014
Thigh    0.766624  0.896410  1.000000  0.799170  0.539797  0.761477  0.566842
Knee     0.737179  0.823473  0.799170  1.000000  0.611608  0.678709  0.555898
Ankle    0.453223  0.558387  0.539797  0.611608  1.000000  0.484855  0.419050
Biceps   0.684983  0.739273  0.761477  0.678709  0.484855  1.000000  0.678255
Forearm  0.503316  0.545014  0.566842  0.555898  0.419050  0.678255  1.000000
Wrist    0.619832  0.630090  0.558685  0.664507  0.566195  0.632126  0.585588

            Wrist
Density -0.325716
BodyFat  0.346575
Age      0.213531
Weight   0.729775
Height   0.322065
Neck     0.744826
Chest    0.660162
Abdomen  0.619832
Hip      0.630090
Thigh    0.558685
Knee     0.664507
Ankle    0.566195
Biceps   0.632126
Forearm  0.585588
Wrist    1.000000
```

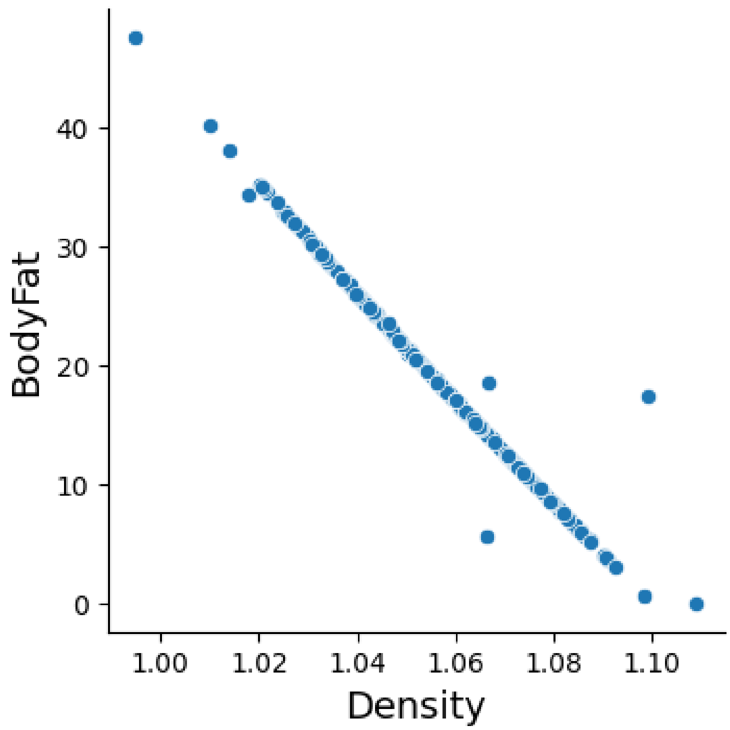


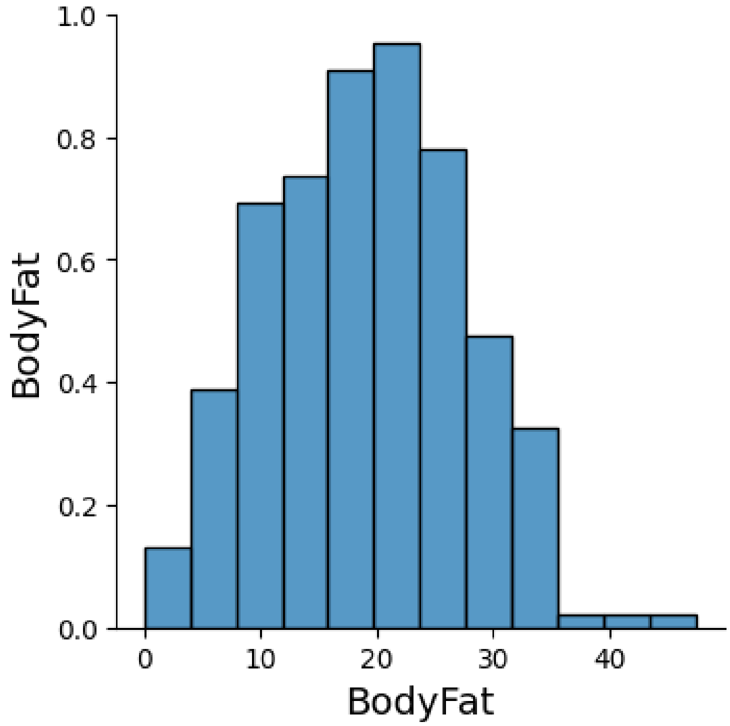
[19]:

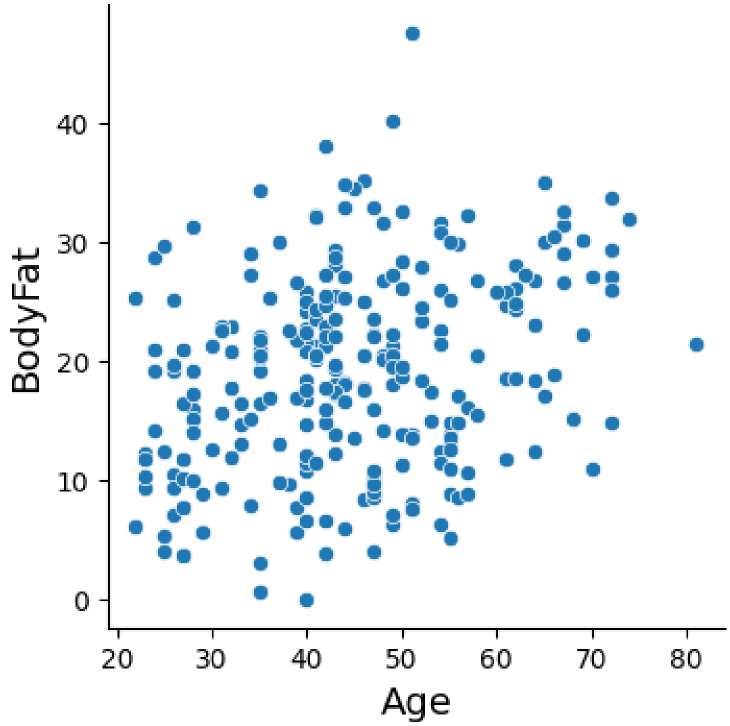
```python
# between the Label and the each attribute
correlations_matrix_2 = (data).corr()
print(correlations_matrix_2["BodyFat"].sort_values(ascending=False))



for attr in data[continuous_attributes]:
  sns.pairplot(data=data, x_vars=[attr], y_vars=["BodyFat"], kind="scatter", height=4)
  plt.show()
```

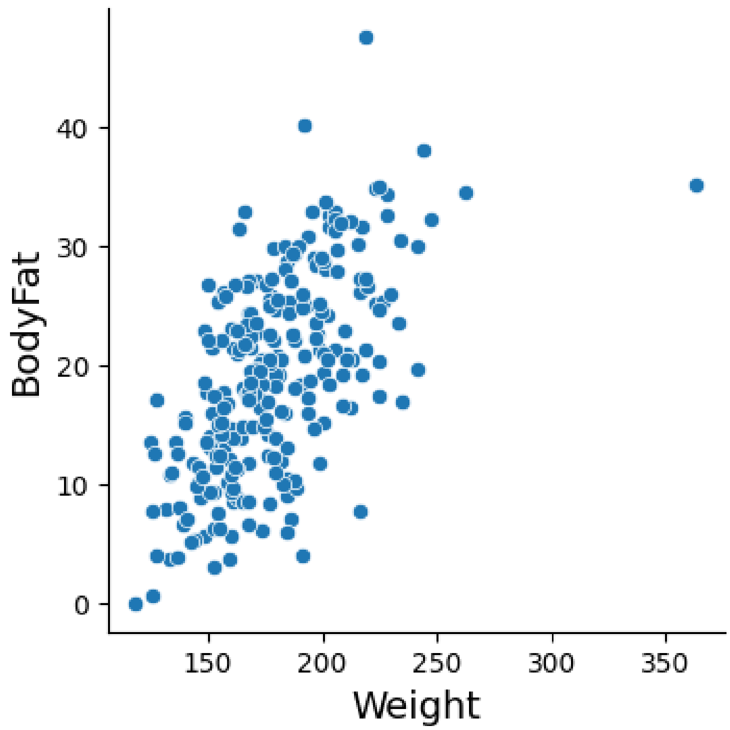
```
BodyFat     1.000000
Abdomen     0.813432
Chest       0.702620
```

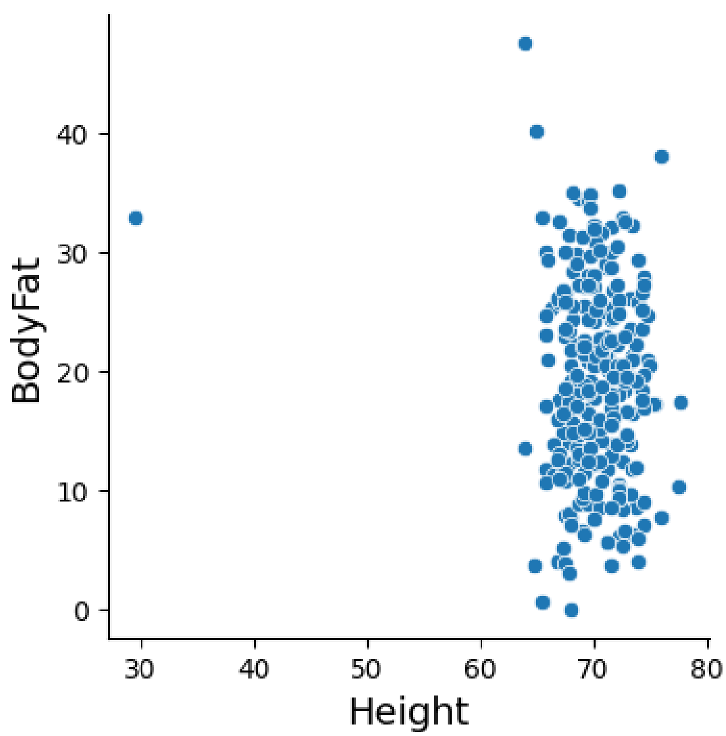
```
Hip         0.625201
Weight      0.612414
Thigh       0.559608
Knee        0.508665
Biceps      0.493271
Neck        0.490592
Forearm     0.361387
Wrist       0.346575
Age         0.291458
Ankle       0.265970
Height     -0.089495
Density    -0.987782
Name: BodyFat, dtype: float64
```

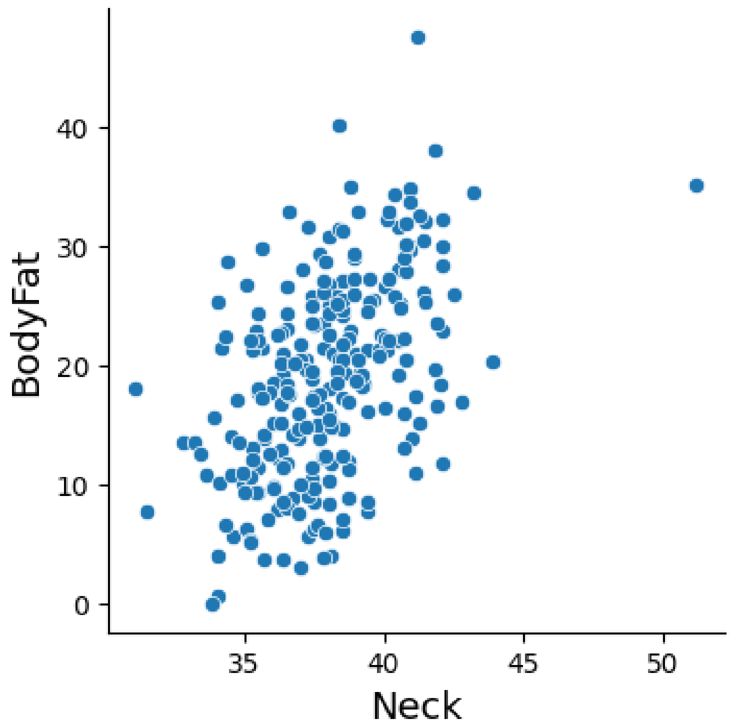


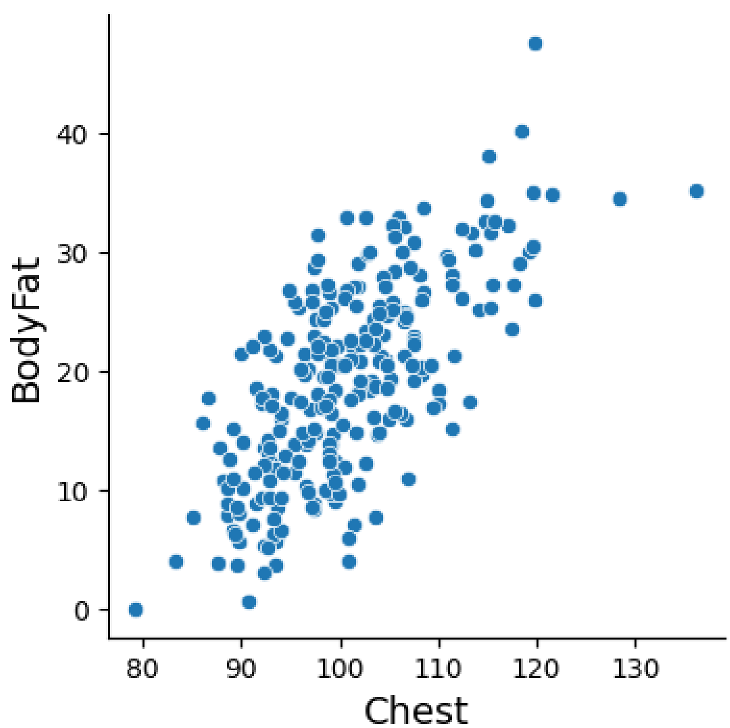

1.0
0.8
0.6
0.4
0.2
0.0
BodyFat
0
10
20
30
40
BodyFat

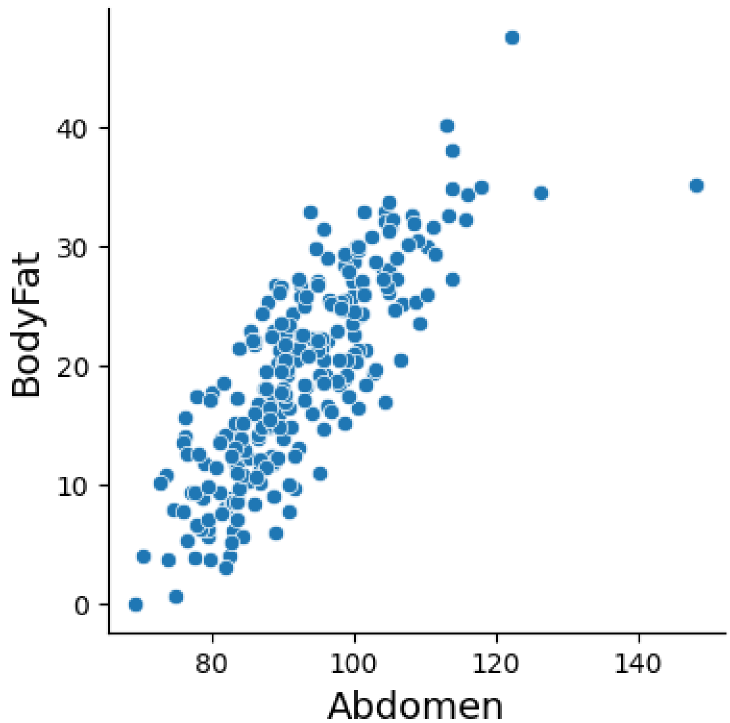

40
30
20
10
0
BodyFat
20
30
40
50
60
70
80
Age

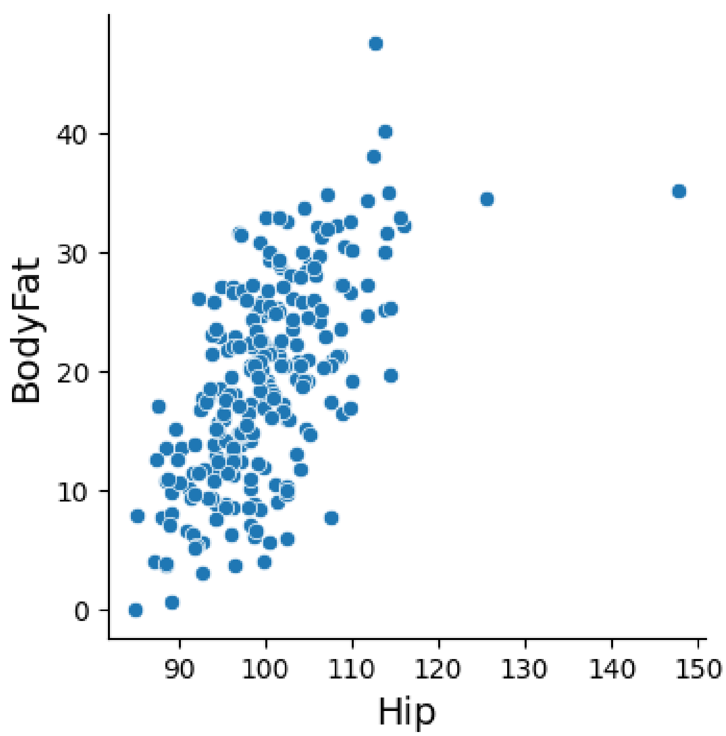

BodyFat
Weight
0
10
20
30
40
150
200
250
300
350

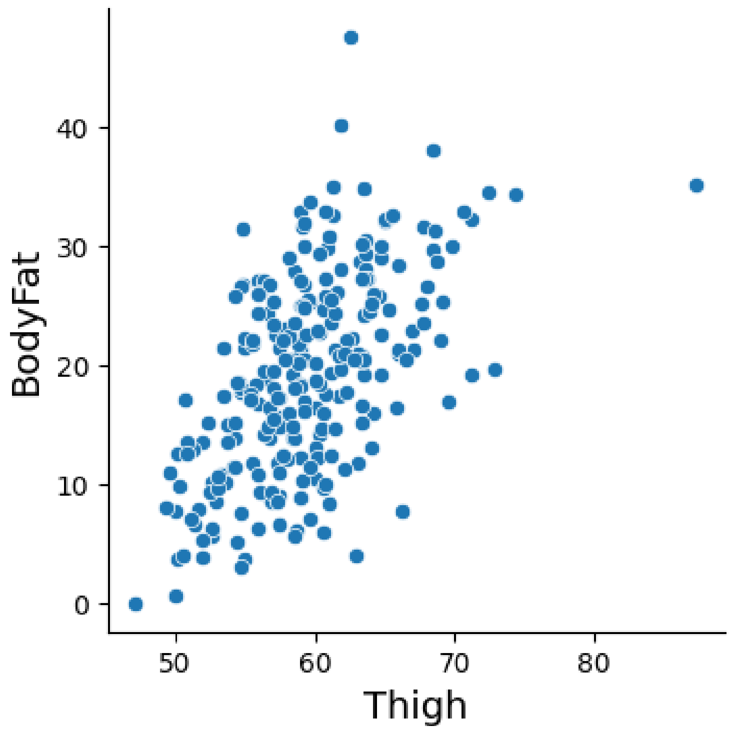

BodyFat
Height
0
10
20
30
40
30
40
50
60
70
80

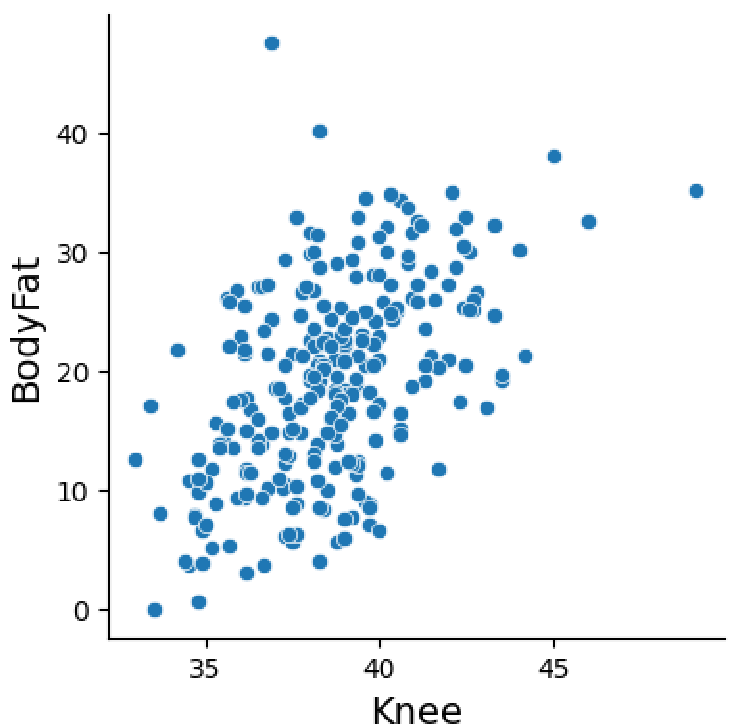

BodyFat
Neck
0
10
20
30
40
35
40
45
50

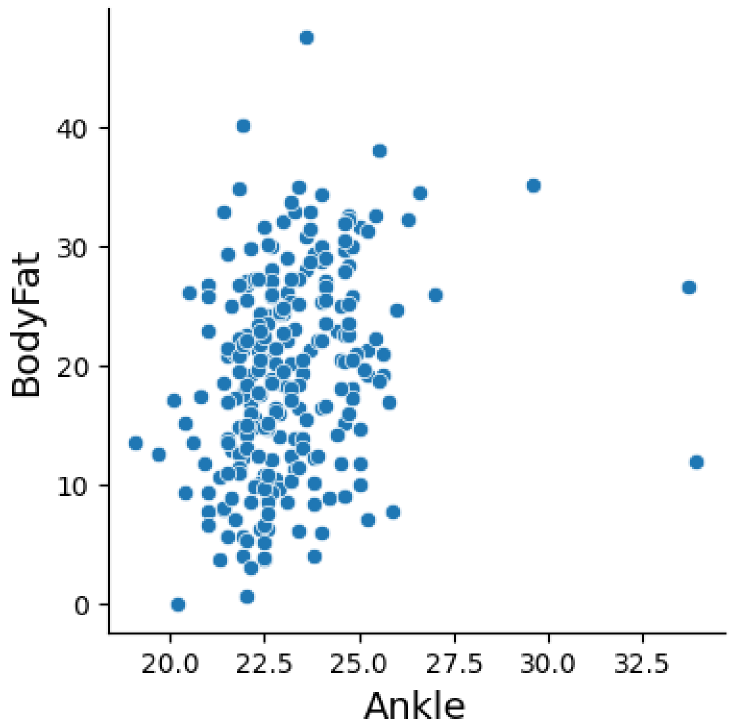

BodyFat
Chest
0
10
20
30
40
80
90
100
110
120
130

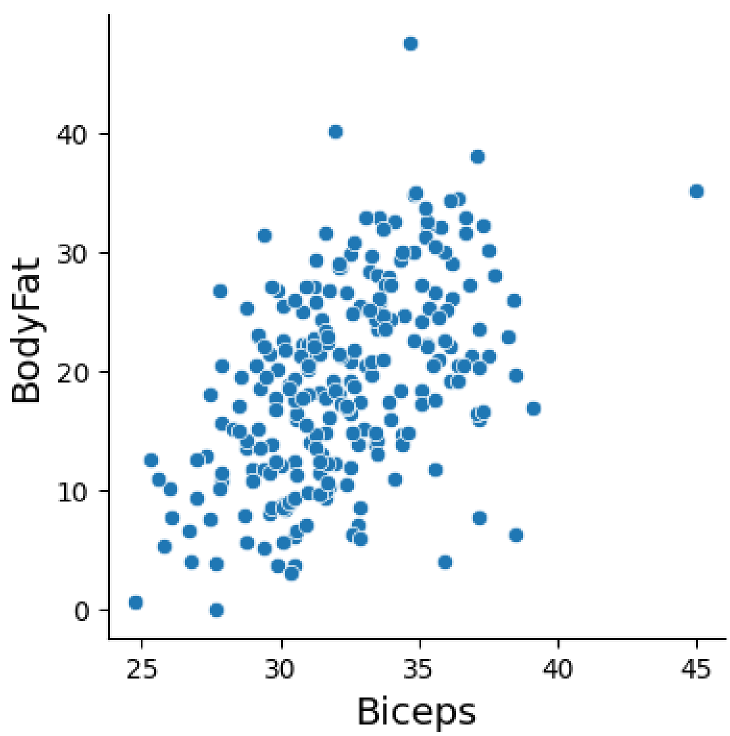

BodyFat
0
10
20
30
40
80
100
120
140
Abdomen

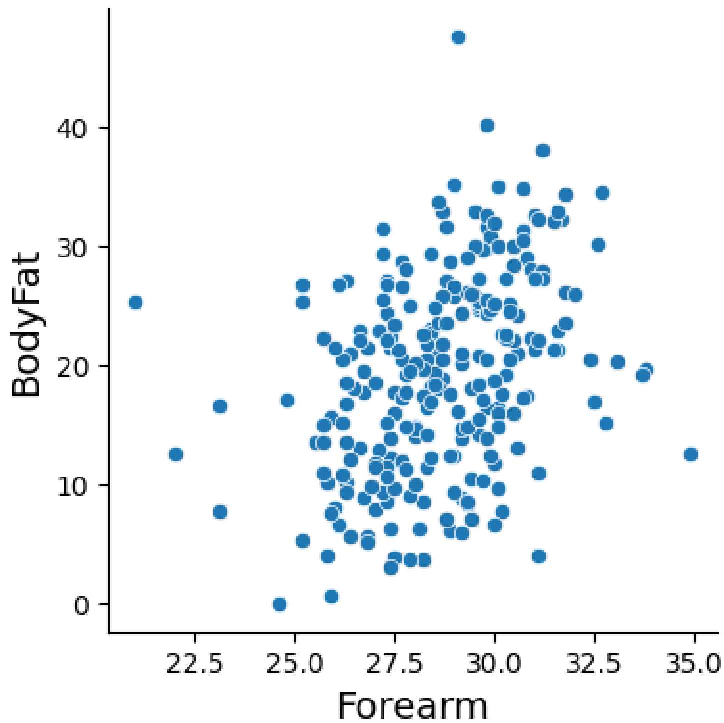

BodyFat
0
10
20
30
40
90
100
110
120
130
140
150
Hip

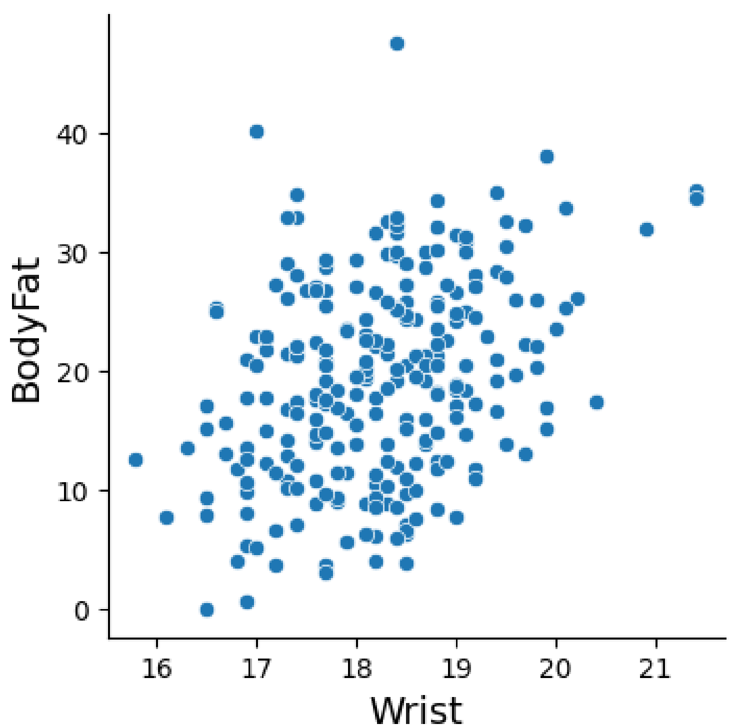

BodyFat
Thigh
0
10
20
30
40
50
60
70
80


BodyFat
Knee
0
10
20
30
40
35
40
45


BodyFat
Ankle
0
10
20
30
40
20.0
22.5
25.0
27.5
30.0
32.5


BodyFat
Biceps
0
10
20
30
40
25
30
35
40
45


BodyFat
Forearm
0
10
20
30
40
22.5
25.0
27.5
30.0
32.5
35.0


BodyFat
Wrist
0
10
20
30
40
16
17
18
19
20
21

- From the correlation table between the label and the attributes , we have observed that Abdomen,Chest,Hip,Weight and density are strongly correlated with each other.
- We can remove Height attribute as the correlation coefficient is very weak with label.

[20]:
```
# drop weak correlated colums and label
data_num_updated=data[continuous_attributes]
data_num_updated.drop(columns=["BodyFat","Height"],axis=1, inplace =True)
```

[21]:
```
data_num_updated.head()
```

[21]:
```
   Density  Age  Weight  Neck  Chest  Abdomen    Hip  Thigh  Knee  Ankle  \
0   1.0708   23  154.25  36.2   93.1     85.2   94.5   59.0  37.3   21.9
1   1.0853   22  173.25  38.5   93.6     83.0   98.7   58.7  37.3   23.4
2   1.0414   22  154.00  34.0   95.8     87.9   99.2   59.6  38.9   24.0
3   1.0751   26  184.75  37.4  101.8     86.4  101.2   60.1  37.3   22.8
4   1.0340   24  184.25  34.4   97.3    100.0  101.9   63.2  42.2   24.0

   Biceps  Forearm  Wrist
0    32.0     27.4   17.1
1    30.5     28.9   18.2
2    28.8     25.2   16.6
3    32.4     29.4   18.2
4    32.2     27.7   17.7
```

Dropping BodyFat as we consider it as label

[22]:
```
#dropping rows which have null value in the label
data =data.dropna(subset=['BodyFat'])
```

Preprocessing the dataset

Replacing null values with median values

[23]:
```
# Identify continuous and categorical attributes
continuous_attributes =␣
 ↪['Density',        'Age',        'Weight',        'Neck',        'Chest',        'Abdomen',

num_con_pipeline=␣
 ↪make_pipeline(StandardScaler(),SimpleImputer(strategy='median'))
```

[26]:
```
prep= ColumnTransformer([("cont",num_con_pipeline,continuous_attributes)])
```

[27]:
```
attri_prep= prep.fit_transform(data)
```

[28]:
```
attributes= pd.DataFrame(attri_prep,columns=prep.
 ↪get_feature_names_out(),index=data.index)
```

[29]:
```
y= pd.DataFrame(data['BodyFat'])
```

[30]:
```
attributes.describe()
```

[30]:
```
       cont__Density     cont__Age  cont__Weight    cont__Neck   cont__Chest  \
count   2.520000e+02  2.520000e+02  2.520000e+02  2.520000e+02  2.520000e+02
mean    5.688571e-15  2.220446e-16  2.819614e-16 -8.247371e-16 -5.639228e-17
std     1.001990e+00  1.001990e+00  1.001990e+00  1.001990e+00  1.001990e+00
min    -3.189163e+00 -1.819583e+00 -2.060102e+00 -2.840817e+00 -2.558224e+00
25%    -7.462399e-01 -7.263189e-01 -6.793000e-01 -6.562274e-01 -7.694810e-01
50%    -3.547554e-02 -1.498703e-01 -8.265733e-02  3.271323e-03 -1.395583e-01
75%     7.805873e-01  7.247413e-01  6.162669e-01  5.906373e-01  5.408770e-01
max     2.807582e+00  2.871515e+00  6.280963e+00  5.444135e+00  4.204531e+00

       cont__Abdomen     cont__Hip   cont__Thigh    cont__Knee   cont__Ankle  \
count   2.520000e+02  2.520000e+02  2.520000e+02  2.520000e+02  2.520000e+02
mean    3.313046e-16  8.379540e-16 -8.582200e-16  8.758426e-16  7.542468e-16
std     1.001990e+00  1.001990e+00  1.001990e+00  1.001990e+00  1.001990e+00
min    -2.151708e+00 -2.084632e+00 -2.329591e+00 -2.322577e+00 -2.366135e+00
25%    -7.416097e-01 -6.160653e-01 -6.500498e-01 -6.711535e-01 -6.517075e-01
50%    -1.492291e-01 -8.458411e-02 -7.747885e-02 -3.758855e-02 -1.787621e-01
75%     6.289966e-01  5.063391e-01  5.618921e-01  5.544311e-01  5.306560e-01
max     5.161290e+00  6.684808e+00  5.323774e+00  4.366207e+00  6.383355e+00

       cont__Biceps  cont__Forearm   cont__Wrist
count  2.520000e+02   2.520000e+02  2.520000e+02
mean  -5.991680e-17  -3.002889e-15  3.348292e-16
std    1.001990e+00   1.001990e+00  1.001990e+00
min   -2.478519e+00  -3.800254e+00 -2.607794e+00
25%   -6.876368e-01  -6.763048e-01 -6.759055e-01
50%   -7.409368e-02   1.790624e-02  7.538454e-02
75%    6.803985e-01   6.625308e-01  6.120203e-01
max    4.220708e+00   3.092269e+00  3.402526e+00
```

[31]:
```
y.describe()
```

[31]:
```
          BodyFat
count  252.000000
mean    19.150794
std      8.368740
min      0.000000
25%     12.475000
50%     19.200000
75%     25.300000
max     47.500000
```

D.Select 20% of the data for testing. Describe how you did that and verify that your test portion of the data is representative of the entire dataset.

[32]:
```python
# 4. Data Splitting
# Split data into training and testing sets


X_train, X_test, y_train, y_test = train_test_split(attributes, y, test_size=0.
 ↪2, random_state=42,shuffle=True)
```

[33]:
```python
# verification of  that our test portion of the data is representative of the␣
 ↪entire dataset.

attributes.describe()
```

[33]:
```
       cont__Density     cont__Age  cont__Weight    cont__Neck   cont__Chest  \
count   2.520000e+02  2.520000e+02  2.520000e+02  2.520000e+02  2.520000e+02
mean    5.688571e-15  2.220446e-16  2.819614e-16 -8.247371e-16 -5.639228e-17
std     1.001990e+00  1.001990e+00  1.001990e+00  1.001990e+00  1.001990e+00
min    -3.189163e+00 -1.819583e+00 -2.060102e+00 -2.840817e+00 -2.558224e+00
25%    -7.462399e-01 -7.263189e-01 -6.793000e-01 -6.562274e-01 -7.694810e-01
50%    -3.547554e-02 -1.498703e-01 -8.265733e-02  3.271323e-03 -1.395583e-01
75%     7.805873e-01  7.247413e-01  6.162669e-01  5.906373e-01  5.408770e-01
max     2.807582e+00  2.871515e+00  6.280963e+00  5.444135e+00  4.204531e+00

       cont__Abdomen     cont__Hip  cont__Thigh    cont__Knee   cont__Ankle  \
count   2.520000e+02  2.520000e+02  2.520000e+02  2.520000e+02  2.520000e+02
mean    3.313046e-16  8.379540e-16 -8.582200e-16  8.758426e-16  7.542468e-16
std     1.001990e+00  1.001990e+00  1.001990e+00  1.001990e+00  1.001990e+00
min    -2.151708e+00 -2.084632e+00 -2.329591e+00 -2.322577e+00 -2.366135e+00
25%    -7.416097e-01 -6.160653e-01 -6.500498e-01 -6.711535e-01 -6.517075e-01
50%    -1.492291e-01 -8.458411e-02 -7.747885e-02 -3.758855e-02 -1.787621e-01
75%     6.289966e-01  5.063391e-01  5.618921e-01  5.544311e-01  5.306560e-01
max     5.161290e+00  6.684808e+00  5.323774e+00  4.366207e+00  6.383355e+00

       cont__Biceps  cont__Forearm   cont__Wrist
count  2.520000e+02   2.520000e+02  2.520000e+02
mean  -5.991680e-17  -3.002889e-15  3.348292e-16
std    1.001990e+00   1.001990e+00  1.001990e+00
min   -2.478519e+00  -3.800254e+00 -2.607794e+00
25%   -6.876368e-01  -6.763048e-01 -6.759055e-01
50%   -7.409368e-02   1.790624e-02  7.538454e-02
75%    6.803985e-01   6.625308e-01  6.120203e-01
max    4.220708e+00   3.092269e+00  3.402526e+00
```

[34]:
```python
X_test.describe()
```

[34]:
```
       cont__Density  cont__Age  cont__Weight  cont__Neck  cont__Chest  \
count      51.000000  51.000000     51.000000   51.000000    51.000000
mean        0.121440  -0.215349      0.113817    0.050147     0.083816
```

```
std          0.817939   0.942349      1.173599    1.136381      0.972026
min         -1.862403  -1.740073     -1.199231   -1.563038     -1.369690
25%         -0.414550  -0.905217     -0.662253   -0.676837     -0.424806
50%          0.064558  -0.308891     -0.057087   -0.161603     -0.038533
75%          0.620007   0.446456      0.556603    0.477286      0.484422
max          1.870426   2.155924      6.280963    5.444135      4.204531

       cont__Abdomen  cont__Hip  cont__Thigh  cont__Knee  cont__Ankle  \
count      51.000000  51.000000    51.000000   51.000000    51.000000
mean       -0.025606   0.062958     0.133587    0.045502     0.245498
std         1.052099   1.170096     1.085461    1.036768     1.223944
min        -1.510543  -1.497205    -1.737935   -1.574763    -0.947298
25%        -0.553442  -0.532147    -0.468736   -0.764630    -0.415235
50%        -0.144583  -0.084584    -0.096565    0.045502    -0.119644
75%         0.352552   0.453890     0.781378    0.481727     0.589774
max         5.161290   6.684808     5.323774    4.366207     6.383355

       cont__Biceps  cont__Forearm  cont__Wrist
count     51.000000      51.000000    51.000000
mean       0.255926      -0.034597     0.045922
std        1.060918       0.982885     1.070064
min       -2.146874      -2.758938    -1.749177
25%       -0.422321      -0.626718    -0.890560
50%        0.141476      -0.180440    -0.031943
75%        1.036917       0.712117     0.719347
max        4.220708       2.497231     3.402526
```

[35]:
```python
y_train.describe()
```

[35]:
```
          BodyFat
count  201.000000
mean    19.435821
std      8.696517
min      0.000000
25%     12.400000
50%     19.600000
75%     25.800000
max     47.500000
```

If we look at the data given by test describe, min,standard deviation and the quartile range looks similiar. This means test portion of the data is the representative of the entire dataset.

E.Train a Linear Regression model using the training data with four-fold cross-validation using appropriate evaluation metric. Do this with a closed-form solution (using the Normal Equation or SVD) and with SGD. Perform Ridge, Lasso and Elastic Net regularization – try a few values of penalty term and describe its impact. Explore the impact of other hyperparameters, like batch size and learning rate (no need for grid search). Describe your findings. For SGD, display the training and validation loss as a function of training iteration.

[36]:
```
linear=LinearRegression().fit(X_train,y_train)
linear_cv=cross_validate(linear,X_train,y_train,scoring=['neg_root_mean_squared_error'],cv=4,r
```

[37]:
```
print("training loss : {:,.3f}".format(-np.
↪mean(linear_cv['train_neg_root_mean_squared_error'])))
print("validation loss : {:,.3f}".format(-np.
↪mean(linear_cv['test_neg_root_mean_squared_error'])))
```

```
training loss : 1.298
validation loss : 1.408
```

SGD

[38]:
```
sgd=SGDRegressor(max_iter=1000, tol=1e-5,eta0=0.
↪01,n_iter_no_change=100,random_state=42)
sgd.fit(X_train,y_train)
sgd_cv=cross_validate(sgd,X_train,y_train,scoring=['neg_root_mean_squared_error'],cv=4,return_
```

[39]:
```
print("training loss : {:,.3f}".format(-np.
↪mean(sgd_cv['train_neg_root_mean_squared_error'])))
print("Validation loss : {:,.3f}".format(-np.
↪mean(sgd_cv['test_neg_root_mean_squared_error'])))
```

```
training loss : 1.299
Validation loss : 1.411
```

SGD, display the training and validation loss as a function of training iteration.

[40]:
```
t_loss=[]
v_loss=[]
for i in range(1,1001,100):
  sgd1=SGDRegressor(max_iter=i, tol=1e-5,eta0=0.
↪01,n_iter_no_change=100,random_state=42)
  sgd1.fit(X_train,y_train)
 ␣
↪sgd1_cv=cross_validate(sgd1,X_train,y_train,scoring=['neg_root_mean_squared_error'],cv=4,ret
  t_loss.append(-np.mean(sgd1_cv['train_neg_root_mean_squared_error']))
  v_loss.append(-np.mean(sgd1_cv['test_neg_root_mean_squared_error']))
plt.figure(figsize=(10, 6))
plt.plot(range(1, 1000 + 1,100), t_loss, label='Training Loss')
plt.plot(range(1, 1000 + 1,100), v_loss, label='Validation Loss')
plt.xlabel('Training Iteration')
plt.ylabel('Loss')
plt.legend()
plt.title('Training and Validation Loss vs. Training Iteration')
plt.grid(True)
plt.show()
```

Perform Ridge, Lasso and Elastic Net regularization – try a few values of penalty term and describe its impact.

[41]:
```
# Define a range of alpha (penalty term) values to explore
alphas = [0.01, 0.1, 1.0, 10.0]

# Initialize lists to store results
ridge_results = []
lasso_results = []
elastic_net_results = []

# Ridge Regression
for alpha in alphas:
    ridge = Ridge(alpha=alpha)
    scores = cross_val_score(ridge, X_train, y_train, cv=4,␣
↪scoring='neg_mean_squared_error')
    rmse_scores = np.sqrt(-scores)
    rmse_mean = rmse_scores.mean()
    ridge_results.append({'Alpha': alpha, 'RMSE Mean': rmse_mean})

# Lasso Regression
for alpha in alphas:
    lasso = Lasso(alpha=alpha)
```

```
    scores = cross_val_score(lasso, X_train, y_train, cv=4,␣
↪scoring='neg_mean_squared_error')
    rmse_scores = np.sqrt(-scores)
    rmse_mean = rmse_scores.mean()
    lasso_results.append({'Alpha': alpha, 'RMSE Mean': rmse_mean})

# Elastic Net
for alpha in alphas:
    elastic_net = ElasticNet(alpha=alpha, l1_ratio=0.5)
    scores = cross_val_score(elastic_net, X_train, y_train, cv=4,␣
↪scoring='neg_mean_squared_error')
    rmse_scores = np.sqrt(-scores)
    rmse_mean = rmse_scores.mean()
    elastic_net_results.append({'Alpha': alpha, 'RMSE Mean': rmse_mean})

# Print the results for Ridge, Lasso, and Elastic Net
print("Ridge Regression Results:")
print(ridge_results)
print("Lasso Regression Results:")
print(lasso_results)
print("Elastic Net Results:")
print(elastic_net_results)
```

```
Ridge Regression Results:
[{'Alpha': 0.01, 'RMSE Mean': 1.4079079930954448}, {'Alpha': 0.1, 'RMSE Mean':
1.4090341648564462}, {'Alpha': 1.0, 'RMSE Mean': 1.4230817339735018}, {'Alpha':
10.0, 'RMSE Mean': 1.6383829473388694}]
Lasso Regression Results:
[{'Alpha': 0.01, 'RMSE Mean': 1.3837321400656646}, {'Alpha': 0.1, 'RMSE Mean':
1.376813643779178}, {'Alpha': 1.0, 'RMSE Mean': 1.7788714699232568}, {'Alpha':
10.0, 'RMSE Mean': 8.674780565174668}]
Elastic Net Results:
[{'Alpha': 0.01, 'RMSE Mean': 1.4048448530393032}, {'Alpha': 0.1, 'RMSE Mean':
1.542827475759133}, {'Alpha': 1.0, 'RMSE Mean': 3.092634206490011}, {'Alpha':
10.0, 'RMSE Mean': 7.802572198597138}]
```

Ridge Regression Results:

Ridge regression was tested with different values of alpha, which controls the regularization strength. The RMSE (Root Mean Square Error) Mean values indicate the model's predictive performance. For Ridge regression: The lowest RMSE Mean is achieved with an alpha of 0.01, indicating that this regularization strength provides the best predictive performance. As alpha increases, the RMSE Mean also increases, suggesting that stronger regularization (higher alpha values) leads to worse predictive performance. Lasso Regression Results:

Lasso regression, like Ridge, was tested with different alpha values for regularization. The RMSE Mean values are used to assess the model's predictive performance. For Lasso regression: The lowest RMSE Mean is obtained with an alpha of 0.1, indicating that this regularization strength results in the best predictive performance. When alpha is 1.0, the RMSE Mean increases significantly, suggesting that stronger regularization (higher alpha) is detrimental to predictive accuracy. An alpha of 10.0 results in an exceptionally high RMSE Mean, indicating poor model performance. Elastic Net Results:

Elastic Net combines L1 (Lasso) and L2 (Ridge) regularization and was tested with different alpha values. RMSE Mean values are used to evaluate predictive performance. For Elastic Net regression: The lowest RMSE Mean is found with an alpha of 0.01, indicating that this combination of L1 and L2 regularization provides the best predictive accuracy. As alpha increases, the RMSE Mean also increases, suggesting that stronger regularization results in poorer predictive performance.

Summary:

Regularization techniques (Ridge, Lasso, Elastic Net) are applied to regression models to prevent overfitting by adding penalty terms to the model's loss function. The choice of the regularization strength (alpha) significantly impacts the model's predictive performance. In Ridge and Elastic Net, lower alpha values tend to yield better predictive accuracy, while higher alpha values result in increased RMSE Mean, indicating over-regularization. In Lasso, an alpha of 0.1 provided the best predictive performance, but stronger regularization (alpha=1.0) led to significantly worse results. It's essential to select an appropriate alpha value based on the specific dataset and problem at hand to strike a balance between bias and variance in the model.

Hypertunning with learning rate

[42]:
```
learning_rates = [0.01, 0.1, 0.5]
#batch_sizes = [32, 64, 128]

# Initialize lists to store results
sgd_results = []

for lr_rate in learning_rates:
    #for batch_size_choosen in batch_sizes:
        sgd = SGDRegressor(learning_rate='constant', eta0=lr_rate,␣
 ↪max_iter=100, tol=1e-3, random_state=42)
        scores = cross_val_score(sgd, X_train, y_train, cv=4,␣
 ↪scoring='neg_mean_squared_error')
        rmse_scores = np.sqrt(-scores)
        rmse_mean = rmse_scores.mean()
        sgd_results.append({'Learning Rate': lr_rate,'RMSE Mean': rmse_mean})

# Print the results for SGDRegressor
print("SGDRegressor Results:")
print(sgd_results)
```

```
SGDRegressor Results:
[{'Learning Rate': 0.01, 'RMSE Mean': 1.4512721260780466}, {'Learning Rate':
0.1, 'RMSE Mean': 545.4705784391148}, {'Learning Rate': 0.5, 'RMSE Mean':
3026320421910.9756}]
```

Hypertuning with batch size and learning rate simultaneously

[43]:

```
import warnings
warnings.filterwarnings("ignore")



from sklearn.linear_model import SGDRegressor
from sklearn.metrics import mean_squared_error

# Define hyperparameters
learning_rate = [0.01,0.1,1]
max_epochs = 15
batch_sizes = [32, 64, 100]  # Explore different batch sizes
for j in learning_rate:
  # Initialize the SGDRegressor
  regressor = SGDRegressor(learning_rate='constant', eta0=j, random_state=42)

  # Training loop
  for batch_size in batch_sizes:
      for epoch in range(max_epochs):
          for i in range(0, len(X_train), batch_size):
              # Get the current mini-batch
              X_batch = X_train[i:i + batch_size]
              y_batch = y_train[i:i + batch_size]

              # Update the model parameters using the mini-batch
              regressor.partial_fit(X_batch, y_batch)

          # Make predictions on the test set
          y_pred = regressor.predict(X_test)

          # Calculate Mean Squared Error on the test set
          mse = mean_squared_error(y_test, y_pred)

          # Print the batch size and test MSE for this epoch
          print(f'Learning_rate:{j},Batch Size: {batch_size}, Epoch: {epoch +␣
↪1}, Test MSE: {mse}')
```

```
Learning_rate:0.01,Batch Size: 32, Epoch: 1, Test MSE: 11.492494254299809
Learning_rate:0.01,Batch Size: 32, Epoch: 2, Test MSE: 2.1318717540560344
Learning_rate:0.01,Batch Size: 32, Epoch: 3, Test MSE: 1.1096866914335215
Learning_rate:0.01,Batch Size: 32, Epoch: 4, Test MSE: 0.7510434907539233
Learning_rate:0.01,Batch Size: 32, Epoch: 5, Test MSE: 0.5703049603389541
Learning_rate:0.01,Batch Size: 32, Epoch: 6, Test MSE: 0.4662029852413913
Learning_rate:0.01,Batch Size: 32, Epoch: 7, Test MSE: 0.4015038908597087
Learning_rate:0.01,Batch Size: 32, Epoch: 8, Test MSE: 0.35903283041305023
Learning_rate:0.01,Batch Size: 32, Epoch: 9, Test MSE: 0.3299528008289561
Learning_rate:0.01,Batch Size: 32, Epoch: 10, Test MSE: 0.30937819633258706
```

```
Learning_rate:0.01,Batch Size: 32, Epoch: 11, Test MSE: 0.29444636015661735
Learning_rate:0.01,Batch Size: 32, Epoch: 12, Test MSE: 0.28339427374263576
Learning_rate:0.01,Batch Size: 32, Epoch: 13, Test MSE: 0.2750889499232979
Learning_rate:0.01,Batch Size: 32, Epoch: 14, Test MSE: 0.26877568636091054
Learning_rate:0.01,Batch Size: 32, Epoch: 15, Test MSE: 0.263936395897213
Learning_rate:0.01,Batch Size: 64, Epoch: 1, Test MSE: 0.2508526088782814
Learning_rate:0.01,Batch Size: 64, Epoch: 2, Test MSE: 0.24566263587107834
Learning_rate:0.01,Batch Size: 64, Epoch: 3, Test MSE: 0.2413127534752423
Learning_rate:0.01,Batch Size: 64, Epoch: 4, Test MSE: 0.2374824320881994
Learning_rate:0.01,Batch Size: 64, Epoch: 5, Test MSE: 0.23438961179839984
Learning_rate:0.01,Batch Size: 64, Epoch: 6, Test MSE: 0.2320156753564508
Learning_rate:0.01,Batch Size: 64, Epoch: 7, Test MSE: 0.23024489568072684
Learning_rate:0.01,Batch Size: 64, Epoch: 8, Test MSE: 0.22894939064723877
Learning_rate:0.01,Batch Size: 64, Epoch: 9, Test MSE: 0.2280185348228143
Learning_rate:0.01,Batch Size: 64, Epoch: 10, Test MSE: 0.22736462126233167
Learning_rate:0.01,Batch Size: 64, Epoch: 11, Test MSE: 0.2269205100202935
Learning_rate:0.01,Batch Size: 64, Epoch: 12, Test MSE: 0.22663544431167498
Learning_rate:0.01,Batch Size: 64, Epoch: 13, Test MSE: 0.22647111852839422
Learning_rate:0.01,Batch Size: 64, Epoch: 14, Test MSE: 0.22639852233596766
Learning_rate:0.01,Batch Size: 64, Epoch: 15, Test MSE: 0.22639555656162233
Learning_rate:0.01,Batch Size: 100, Epoch: 1, Test MSE: 0.20444921799221624
Learning_rate:0.01,Batch Size: 100, Epoch: 2, Test MSE: 0.19590912421298032
Learning_rate:0.01,Batch Size: 100, Epoch: 3, Test MSE: 0.19343349718004577
Learning_rate:0.01,Batch Size: 100, Epoch: 4, Test MSE: 0.1932787702404848
Learning_rate:0.01,Batch Size: 100, Epoch: 5, Test MSE: 0.1938504054853766
Learning_rate:0.01,Batch Size: 100, Epoch: 6, Test MSE: 0.1945764450056782
Learning_rate:0.01,Batch Size: 100, Epoch: 7, Test MSE: 0.19526895552638104
Learning_rate:0.01,Batch Size: 100, Epoch: 8, Test MSE: 0.1958791266548206
Learning_rate:0.01,Batch Size: 100, Epoch: 9, Test MSE: 0.19640532715469616
Learning_rate:0.01,Batch Size: 100, Epoch: 10, Test MSE: 0.19685926696214984
Learning_rate:0.01,Batch Size: 100, Epoch: 11, Test MSE: 0.19725427317292535
Learning_rate:0.01,Batch Size: 100, Epoch: 12, Test MSE: 0.19760180680915762
Learning_rate:0.01,Batch Size: 100, Epoch: 13, Test MSE: 0.19791087960617304
Learning_rate:0.01,Batch Size: 100, Epoch: 14, Test MSE: 0.19818836212203697
Learning_rate:0.01,Batch Size: 100, Epoch: 15, Test MSE: 0.19843946771415064
Learning_rate:0.1,Batch Size: 32, Epoch: 1, Test MSE: 1384.165531795583
Learning_rate:0.1,Batch Size: 32, Epoch: 2, Test MSE: 5.364551365783306
Learning_rate:0.1,Batch Size: 32, Epoch: 3, Test MSE: 2126.4786601714563
Learning_rate:0.1,Batch Size: 32, Epoch: 4, Test MSE: 373.266092938054
Learning_rate:0.1,Batch Size: 32, Epoch: 5, Test MSE: 4484.353627440377
Learning_rate:0.1,Batch Size: 32, Epoch: 6, Test MSE: 2284.793269401266
Learning_rate:0.1,Batch Size: 32, Epoch: 7, Test MSE: 10932.568806268822
Learning_rate:0.1,Batch Size: 32, Epoch: 8, Test MSE: 9578.233529306683
Learning_rate:0.1,Batch Size: 32, Epoch: 9, Test MSE: 29256.107078158733
Learning_rate:0.1,Batch Size: 32, Epoch: 10, Test MSE: 34682.55040466134
Learning_rate:0.1,Batch Size: 32, Epoch: 11, Test MSE: 83199.13080013673
Learning_rate:0.1,Batch Size: 32, Epoch: 12, Test MSE: 117115.47201001644
Learning_rate:0.1,Batch Size: 32, Epoch: 13, Test MSE: 245714.76222567004
```

```
Learning_rate:0.1,Batch Size: 32, Epoch: 14, Test MSE: 381417.5330364295
Learning_rate:0.1,Batch Size: 32, Epoch: 15, Test MSE: 742291.7538412783
Learning_rate:0.1,Batch Size: 64, Epoch: 1, Test MSE: 129994.26907929836
Learning_rate:0.1,Batch Size: 64, Epoch: 2, Test MSE: 21400.89098958631
Learning_rate:0.1,Batch Size: 64, Epoch: 3, Test MSE: 791.0624540451935
Learning_rate:0.1,Batch Size: 64, Epoch: 4, Test MSE: 342.7203450375101
Learning_rate:0.1,Batch Size: 64, Epoch: 5, Test MSE: 36.35719113450947
Learning_rate:0.1,Batch Size: 64, Epoch: 6, Test MSE: 4.333759389524058
Learning_rate:0.1,Batch Size: 64, Epoch: 7, Test MSE: 9.117008024914881
Learning_rate:0.1,Batch Size: 64, Epoch: 8, Test MSE: 9.336011585160682
Learning_rate:0.1,Batch Size: 64, Epoch: 9, Test MSE: 8.76514981135719
Learning_rate:0.1,Batch Size: 64, Epoch: 10, Test MSE: 8.936288373117097
Learning_rate:0.1,Batch Size: 64, Epoch: 11, Test MSE: 8.933177639377984
Learning_rate:0.1,Batch Size: 64, Epoch: 12, Test MSE: 8.911812481597803
Learning_rate:0.1,Batch Size: 64, Epoch: 13, Test MSE: 8.916020071232204
Learning_rate:0.1,Batch Size: 64, Epoch: 14, Test MSE: 8.915229596891566
Learning_rate:0.1,Batch Size: 64, Epoch: 15, Test MSE: 8.914514245329814
Learning_rate:0.1,Batch Size: 100, Epoch: 1, Test MSE: 282.2745450021099
Learning_rate:0.1,Batch Size: 100, Epoch: 2, Test MSE: 2463.8489693389306
Learning_rate:0.1,Batch Size: 100, Epoch: 3, Test MSE: 10536.14844850455
Learning_rate:0.1,Batch Size: 100, Epoch: 4, Test MSE: 34347.559756663126
Learning_rate:0.1,Batch Size: 100, Epoch: 5, Test MSE: 98245.15446401508
Learning_rate:0.1,Batch Size: 100, Epoch: 6, Test MSE: 262514.69474248105
Learning_rate:0.1,Batch Size: 100, Epoch: 7, Test MSE: 675644.4942846491
Learning_rate:0.1,Batch Size: 100, Epoch: 8, Test MSE: 1701709.6817101825
Learning_rate:0.1,Batch Size: 100, Epoch: 9, Test MSE: 4230639.587770734
Learning_rate:0.1,Batch Size: 100, Epoch: 10, Test MSE: 10433557.954703445
Learning_rate:0.1,Batch Size: 100, Epoch: 11, Test MSE: 25600966.525062155
Learning_rate:0.1,Batch Size: 100, Epoch: 12, Test MSE: 62614976.003330044
Learning_rate:0.1,Batch Size: 100, Epoch: 13, Test MSE: 152828223.4554554
Learning_rate:0.1,Batch Size: 100, Epoch: 14, Test MSE: 372524429.6940977
Learning_rate:0.1,Batch Size: 100, Epoch: 15, Test MSE: 907273249.668211
Learning_rate:1,Batch Size: 32, Epoch: 1, Test MSE: 5.87844127782307e+25
Learning_rate:1,Batch Size: 32, Epoch: 2, Test MSE: 3.3335406791838624e+25
Learning_rate:1,Batch Size: 32, Epoch: 3, Test MSE: 2.0139283811175606e+25
Learning_rate:1,Batch Size: 32, Epoch: 4, Test MSE: 2.9031215805786267e+25
Learning_rate:1,Batch Size: 32, Epoch: 5, Test MSE: 2.428919041070997e+25
Learning_rate:1,Batch Size: 32, Epoch: 6, Test MSE: 3.094091366731066e+25
Learning_rate:1,Batch Size: 32, Epoch: 7, Test MSE: 4.3908738520505505e+25
Learning_rate:1,Batch Size: 32, Epoch: 8, Test MSE: 5.163918183474564e+25
Learning_rate:1,Batch Size: 32, Epoch: 9, Test MSE: 6.68314911939531e+25
Learning_rate:1,Batch Size: 32, Epoch: 10, Test MSE: 1.002052188826149e+26
Learning_rate:1,Batch Size: 32, Epoch: 11, Test MSE: 6.263496299595794e+25
Learning_rate:1,Batch Size: 32, Epoch: 12, Test MSE: 5.5632470281948976e+25
Learning_rate:1,Batch Size: 32, Epoch: 13, Test MSE: 3.093560586023661e+25
Learning_rate:1,Batch Size: 32, Epoch: 14, Test MSE: 4.1492833377086565e+25
Learning_rate:1,Batch Size: 32, Epoch: 15, Test MSE: 8.59019667470553e+25
Learning_rate:1,Batch Size: 64, Epoch: 1, Test MSE: 1.0094404234572188e+26
```

```
Learning_rate:1,Batch Size: 64, Epoch: 2, Test MSE: 2.518413688320896e+25
Learning_rate:1,Batch Size: 64, Epoch: 3, Test MSE: 5.970905063527565e+25
Learning_rate:1,Batch Size: 64, Epoch: 4, Test MSE: 5.447280338002272e+25
Learning_rate:1,Batch Size: 64, Epoch: 5, Test MSE: 1.7452539211082648e+25
Learning_rate:1,Batch Size: 64, Epoch: 6, Test MSE: 2.4558951487153366e+25
Learning_rate:1,Batch Size: 64, Epoch: 7, Test MSE: 1.9852753242963524e+26
Learning_rate:1,Batch Size: 64, Epoch: 8, Test MSE: 1.324468716305645e+26
Learning_rate:1,Batch Size: 64, Epoch: 9, Test MSE: 1.6380594797444441e+25
Learning_rate:1,Batch Size: 64, Epoch: 10, Test MSE: 3.8416221660243916e+25
Learning_rate:1,Batch Size: 64, Epoch: 11, Test MSE: 2.333242561590345e+25
Learning_rate:1,Batch Size: 64, Epoch: 12, Test MSE: 5.912431219866736e+25
Learning_rate:1,Batch Size: 64, Epoch: 13, Test MSE: 2.8524608609834625e+25
Learning_rate:1,Batch Size: 64, Epoch: 14, Test MSE: 3.950114830645054e+25
Learning_rate:1,Batch Size: 64, Epoch: 15, Test MSE: 9.160531083767609e+24
Learning_rate:1,Batch Size: 100, Epoch: 1, Test MSE: 4.891343157585817e+25
Learning_rate:1,Batch Size: 100, Epoch: 2, Test MSE: 6.9878731122957686e+25
Learning_rate:1,Batch Size: 100, Epoch: 3, Test MSE: 2.380825339161894e+25
Learning_rate:1,Batch Size: 100, Epoch: 4, Test MSE: 4.024722634814477e+25
Learning_rate:1,Batch Size: 100, Epoch: 5, Test MSE: 9.915991018215322e+25
Learning_rate:1,Batch Size: 100, Epoch: 6, Test MSE: 3.790531404304652e+25
Learning_rate:1,Batch Size: 100, Epoch: 7, Test MSE: 3.0174482603765567e+25
Learning_rate:1,Batch Size: 100, Epoch: 8, Test MSE: 3.889880076440174e+25
Learning_rate:1,Batch Size: 100, Epoch: 9, Test MSE: 4.798164137154054e+25
Learning_rate:1,Batch Size: 100, Epoch: 10, Test MSE: 4.940160393390546e+25
Learning_rate:1,Batch Size: 100, Epoch: 11, Test MSE: 3.6570317133646817e+25
Learning_rate:1,Batch Size: 100, Epoch: 12, Test MSE: 2.427340449299423e+25
Learning_rate:1,Batch Size: 100, Epoch: 13, Test MSE: 2.500840315796877e+25
Learning_rate:1,Batch Size: 100, Epoch: 14, Test MSE: 7.895128220500204e+24
Learning_rate:1,Batch Size: 100, Epoch: 15, Test MSE: 3.944134024056735e+25
```

Learning Rate: 0.01

Lower learning rates, such as 0.01, tend to converge more gradually. As the number of epochs increases, the test MSE decreases, indicating improved model performance. For batch size 32, the test MSE reduces significantly from 11.49 in the first epoch to 0.26 in the 15th epoch, demonstrating steady convergence. Batch size 64 also shows a similar decreasing trend in test MSE, from 0.25 to 0.23, indicating convergence. Batch size 100 with a learning rate of 0.01 achieves test MSE reduction from 0.20 to 0.20, showing convergence but with a lower final MSE compared to smaller batch sizes. Learning Rate: 0.1

A learning rate of 0.1 is relatively high. The initial test MSE is extremely high (e.g., 1384.17 for batch size 32), indicating poor model performance. However, for batch size 64, the test MSE decreases dramatically from 129994.27 to 8.91 in the later epochs, suggesting some improvement. Batch size 100 also shows a reduction in test MSE but remains relatively high, indicating slower convergence. Learning Rate: 1

A learning rate of 1 is very high and may lead to divergence. In most cases, the test MSE starts at an extremely high value and increases substantially with each epoch, indicating that the model diverges. This is especially evident in batch size 32, where the test MSE reaches extremely large values (e.g., 5.87e+25). Summary:

Lower learning rates (e.g., 0.01) generally lead to better convergence and lower test MSE. Smaller batch sizes (e.g., 32 or 64) tend to converge faster, but batch size 100 also converges with a slightly larger final MSE. A learning rate of 0.1 can work with careful tuning and patience, but a learning rate of 1 is too high and leads to divergence. The choice of learning rate and batch size can significantly impact the training process and model convergence. It's essential to strike a balance between a learning rate that is too slow (resulting in slow convergence) and one that is too high (leading to divergence).

F. Repeat the previous step with polynomial regression. Using validation loss, explore if your model overfits/underfits the data

Polynomial Regression with Normal form

[44]:
```
from sklearn.preprocessing import PolynomialFeatures

poly_features = PolynomialFeatures(degree=2, include_bias=False)
X_train_poly = poly_features.fit_transform(X_train)
X_test_poly = poly_features.fit_transform(X_test)
```

[45]:
```
poly=LinearRegression().fit(X_train_poly,y_train)
poly_cv=cross_validate(poly,X_train_poly,y_train,scoring=['neg_root_mean_squared_error'],
 ↪cv=4 ,return_train_score=True)
```

[46]:
```
print("training loss : {:,.3f}".format(-np.
 ↪mean(poly_cv['train_neg_root_mean_squared_error'])))
print("validation loss : {:,.3f}".format(-np.
 ↪mean(poly_cv['test_neg_root_mean_squared_error'])))
```

```
training loss : 0.474
validation loss : 2.894
```

[47]:
```
for fold, val_loss in enumerate(poly_cv['test_neg_root_mean_squared_error']):
    print(f"Validation loss for Fold {fold + 1}: {-val_loss:.3f}")
```

```
Validation loss for Fold 1: 3.315
Validation loss for Fold 2: 4.352
Validation loss for Fold 3: 2.170
Validation loss for Fold 4: 1.737
```

Training Loss: The training loss of 0.474 indicates how well the model fits the training data. A low training loss suggests that the model fits the training data relatively well.

Validation Losses for Folds: The validation losses for each fold provide insights into how well the model generalizes to unseen data.

Fold 1: Validation loss of 3.315 is significantly higher than the training loss (0.474). This suggests that the model is struggling to generalize to Fold 1, indicating potential underfitting to the training data. The model is not performing well on Fold 1, which is a sign of underfitting.

Fold 2: Validation loss of 4.352 is considerably higher than the training loss (0.474). Similar to Fold 1, this indicates that the model is underfitting the training data and is unable to generalize to Fold 2.

Fold 3: Validation loss of 2.170 is lower than the training loss but still higher. This suggests that the model is showing some capacity to generalize to Fold 3, but there is room for improvement.

Fold 4: Validation loss of 1.737 is lower than both the training loss and the validation losses for Folds 1 and 2. This indicates that the model is performing relatively better on Fold 4, showing the potential for better generalization.

Overall Assessment:

The model appears to be underfitting the training data in Folds 1 and 2, as indicated by significantly higher validation losses compared to the training loss.

Folds 3 and 4, with relatively lower validation losses, suggest that the model has the potential to generalize better in certain cases.

Polynomial Regression with SGD

[48]:
```
sgd_poly=SGDRegressor(max_iter=1000, tol=1e-5,eta0=0.
↪01,n_iter_no_change=100,random_state=42)
sgd_poly.fit(X_train_poly,y_train)
sgd_cv_poly=cross_validate(sgd_poly,X_train_poly,y_train,scoring=['neg_root_mean_squared_error
```

[49]:
```
print("training loss : {:,.3f}".format(-np.
↪mean(sgd_cv_poly['train_neg_root_mean_squared_error'])))
print("Validation loss : {:,.3f}".format(-np.
↪mean(sgd_cv_poly['test_neg_root_mean_squared_error'])))
```

```
training loss : 26,639.625
Validation loss : 59,595.259
```

[50]:
```
for fold, val_loss in␣
↪enumerate(sgd_cv_poly['test_neg_root_mean_squared_error']):
    print(f"Validation loss for Fold {fold + 1}: {-val_loss:.3f}")
```

```
Validation loss for Fold 1: 43049.709
Validation loss for Fold 2: 4.407
Validation loss for Fold 3: 57851.757
Validation loss for Fold 4: 137475.163
```

Training Loss: The training loss of 26,639.625 is a measure of how well the model fits the training data. This value represents the error between the model's predictions and the actual target values on the training dataset.

Validation Losses for Folds: The validation losses for each fold provide insights into how well the model generalizes to unseen data. Here's the analysis based on the validation losses:

Fold 1: Validation loss of 43,049.709 is higher than the training loss (26,639.625). This suggests that the model is struggling to generalize to Fold 1, indicating potential underfitting to the training data. The model is not performing well on Fold 1, which is a sign of underfitting.

Fold 2: Validation loss of 4.407 is lower than the training loss (26,639.625). it is overfitting.

Fold 3: Validation loss of 57,851.757 is higher than the training loss, indicating underfitting similar to Fold 1.

Fold 4: Validation loss of 137,475.163 is significantly higher than the training loss, indicating underfitting similar to Folds 1 and 3.

Overall Assessment:

The model appears to be underfitting the training data in all folds (Folds 1, 3, and 4) as indicated by higher validation losses compared to the training loss.

Fold 2, with a lower validation loss, suggests that the model is overfitting.

SGD, display the training and validation loss as a function of training iteration.

[51]:
```
t_loss_poly=[]
v_loss_poly=[]
for i in range(1,1001,100):
  sgd_poly_1=SGDRegressor(max_iter=i, tol=1e-5,eta0=0.
↪01,n_iter_no_change=100,random_state=42)
  sgd_poly_1.fit(X_train,y_train)
␣
↪sgd1_cv_poly=cross_validate(sgd_poly_1,X_train,y_train,scoring=['neg_root_mean_squared_erro
  t_loss_poly.append(-np.
↪mean(sgd1_cv_poly['train_neg_root_mean_squared_error']))
  v_loss_poly.append(-np.mean(sgd1_cv_poly['test_neg_root_mean_squared_error']))
plt.figure(figsize=(10, 6))
plt.plot(range(1, 1000 + 1,100), t_loss_poly, label='Training Loss')
plt.plot(range(1, 1000 + 1,100), v_loss_poly, label='Validation Loss')
plt.xlabel('Training Iteration')
plt.ylabel('Loss')
plt.legend()
plt.title('Training and Validation Loss vs. Training Iteration')
plt.grid(True)
plt.show()
```

[52]:

```
# Define a range of alpha (penalty term) values to explore
alphas = [0.01, 0.1, 1.0, 10.0]

# Initialize lists to store results
ridge_results_poly = []
lasso_results_poly = []
elastic_net_results_poly = []
# Ridge Regression
for alpha in alphas:
    ridge_poly = Ridge(alpha=alpha)
    ridge_poly.fit(X_train_poly,y_train)
    scores = cross_val_score(ridge_poly, X_train_poly, y_train, cv=4,␣
 ↪scoring='neg_mean_squared_error')
    rmse_scores_poly = np.sqrt(-scores)
    rmse_mean_poly = rmse_scores_poly.mean()
    ridge_results_poly.append({'Alpha': alpha, 'RMSE Mean': rmse_mean_poly})

# Lasso Regression
for alpha in alphas:
    lasso_poly = Lasso(alpha=alpha)
    lasso_poly.fit(X_train_poly,y_train)
    scores = cross_val_score(lasso_poly, X_train_poly, y_train, cv=4,␣
 ↪scoring='neg_mean_squared_error')
```

```python
    rmse_scores_poly = np.sqrt(-scores)
    rmse_mean_poly = rmse_scores_poly.mean()
    lasso_results_poly.append({'Alpha': alpha, 'RMSE Mean': rmse_mean_poly})

# Elastic Net
for alpha in alphas:
    elastic_net_poly = ElasticNet(alpha=alpha, l1_ratio=0.5)
    elastic_net_poly.fit(X_train_poly,y_train)
    scores = cross_val_score(elastic_net_poly, X_train_poly, y_train, cv=4,␣
 ↪scoring='neg_mean_squared_error')
    rmse_scores_poly = np.sqrt(-scores)
    rmse_mean_poly = rmse_scores_poly.mean()
    elastic_net_results_poly.append({'Alpha': alpha, 'RMSE Mean':␣
 ↪rmse_mean_poly})

# Print the results for Ridge, Lasso, and Elastic Net
print("Ridge Regression Results:")
print(ridge_results_poly)
print("Lasso Regression Results:")
print(lasso_results_poly)
print("Elastic Net Results:")
print(elastic_net_results_poly)
```

```
Ridge Regression Results:
[{'Alpha': 0.01, 'RMSE Mean': 2.795796646920579}, {'Alpha': 0.1, 'RMSE Mean':
2.435908695054488}, {'Alpha': 1.0, 'RMSE Mean': 1.7311831627258445}, {'Alpha':
10.0, 'RMSE Mean': 1.713729427685311}]
Lasso Regression Results:
[{'Alpha': 0.01, 'RMSE Mean': 1.4739593134083686}, {'Alpha': 0.1, 'RMSE Mean':
1.3859431872934624}, {'Alpha': 1.0, 'RMSE Mean': 1.7788703831260322}, {'Alpha':
10.0, 'RMSE Mean': 8.674780565174668}]
Elastic Net Results:
[{'Alpha': 0.01, 'RMSE Mean': 1.490034875718038}, {'Alpha': 0.1, 'RMSE Mean':
1.453785397475395}, {'Alpha': 1.0, 'RMSE Mean': 3.1288974801266156}, {'Alpha':
10.0, 'RMSE Mean': 7.802572198597138}]
```

Ridge Regression Results:

For Ridge regression, the RMSE (Root Mean Squared Error) decreases as the alpha (regularization strength) increases. This indicates that higher regularization leads to better performance in terms of RMSE. The best RMSE mean of approximately 1.713 is achieved with an alpha of 10.0, which suggests that strong regularization is effective for this dataset when using Ridge regression. Lasso Regression Results:

In Lasso regression, the RMSE also decreases as the alpha increases, similar to Ridge regression. The lowest RMSE mean of around 1.386 is obtained with an alpha of 0.1, indicating that moderate regularization performs well in this case. Elastic Net Results:

Elastic Net combines L1 (Lasso) and L2 (Ridge) regularization. The RMSE decreases as alpha increases, similar to Ridge and Lasso. The best RMSE mean, approximately 1.454, is achieved with an alpha of 0.1, suggesting that a combination of L1 and L2 regularization is effective for this dataset. Summary:

Regularization is essential in improving the performance of regression models, and the choice of alpha determines the strength of regularization. Ridge regression with strong regularization (alpha = 10.0) performs well, achieving an RMSE mean of approximately 1.713. Lasso regression with moderate regularization (alpha = 0.1) achieves the lowest RMSE mean of around 1.386, indicating its effectiveness for this dataset. Elastic Net, which combines L1 and L2 regularization, performs well with an alpha of 0.1, yielding an RMSE mean of approximately 1.454. In summary, the choice of regularization type and strength (alpha) can significantly impact the performance of regression models. Lasso regression with moderate regularization appears to be the best-performing model in this specific case, based on the provided RMSE means. However, the choice of the best model should also consider other factors such as interpretability and the specific goals of the analysis.

Hypertuning with batch size and learning rate simultaneously

[53]:
```
warnings.filterwarnings("ignore")



from sklearn.preprocessing import PolynomialFeatures
from sklearn.linear_model import SGDRegressor
from sklearn.metrics import mean_squared_error

# Define hyperparameters
learning_rate_poly = [0.01,0.1,1]
max_epochs_poly = 15
batch_sizes_poly = [32, 64, 100]  # Explore different batch sizes
for j in learning_rate_poly:
  # Initialize the SGDRegressor
  regressor = SGDRegressor(learning_rate='constant', eta0=j, random_state=42)

  # Training loop
  for batch_size in batch_sizes_poly:
      for epoch in range(max_epochs_poly):
          for i in range(0, len(X_train_poly), batch_size):
              # Get the current mini-batch
              X_batch_poly = X_train_poly[i:i + batch_size]
              y_batch_poly = y_train[i:i + batch_size]

              # Update the model parameters using the mini-batch
              regressor.partial_fit(X_batch_poly, y_batch_poly)

          # Make predictions on the test set
          y_pred_poly = regressor.predict(X_test_poly)

          # Calculate Mean Squared Error on the test set
          mse = mean_squared_error(y_test, y_pred_poly)
```

```
        # Print the batch size and test MSE for this epoch
        print(f'Learning_rate:{j},Batch Size: {batch_size}, Epoch: {epoch +␣
↪1}, Test MSE: {mse}')
```

```
Learning_rate:0.01,Batch Size: 32, Epoch: 1, Test MSE: 2.3873187846472748e+16
Learning_rate:0.01,Batch Size: 32, Epoch: 2, Test MSE: 1.8149718149026949e+24
Learning_rate:0.01,Batch Size: 32, Epoch: 3, Test MSE: 1.282365168868426e+25
Learning_rate:0.01,Batch Size: 32, Epoch: 4, Test MSE: 1.910802588168833e+25
Learning_rate:0.01,Batch Size: 32, Epoch: 5, Test MSE: 1.2298398037246966e+25
Learning_rate:0.01,Batch Size: 32, Epoch: 6, Test MSE: 4.061544925922407e+24
Learning_rate:0.01,Batch Size: 32, Epoch: 7, Test MSE: 3.341219894165812e+24
Learning_rate:0.01,Batch Size: 32, Epoch: 8, Test MSE: 4.319929462858561e+24
Learning_rate:0.01,Batch Size: 32, Epoch: 9, Test MSE: 7.311095809621889e+24
Learning_rate:0.01,Batch Size: 32, Epoch: 10, Test MSE: 5.434951799526112e+24
Learning_rate:0.01,Batch Size: 32, Epoch: 11, Test MSE: 3.48598326981519e+24
Learning_rate:0.01,Batch Size: 32, Epoch: 12, Test MSE: 5.774897553584689e+24
Learning_rate:0.01,Batch Size: 32, Epoch: 13, Test MSE: 5.370831175814193e+24
Learning_rate:0.01,Batch Size: 32, Epoch: 14, Test MSE: 1.1845636927896328e+25
Learning_rate:0.01,Batch Size: 32, Epoch: 15, Test MSE: 1.1658900438826871e+25
Learning_rate:0.01,Batch Size: 64, Epoch: 1, Test MSE: 5.596101323424631e+24
Learning_rate:0.01,Batch Size: 64, Epoch: 2, Test MSE: 8.075574568072931e+24
Learning_rate:0.01,Batch Size: 64, Epoch: 3, Test MSE: 7.340856530561837e+24
Learning_rate:0.01,Batch Size: 64, Epoch: 4, Test MSE: 1.2711657622953406e+25
Learning_rate:0.01,Batch Size: 64, Epoch: 5, Test MSE: 1.296283104488258e+25
Learning_rate:0.01,Batch Size: 64, Epoch: 6, Test MSE: 8.660794844081536e+24
Learning_rate:0.01,Batch Size: 64, Epoch: 7, Test MSE: 8.710437360192821e+24
Learning_rate:0.01,Batch Size: 64, Epoch: 8, Test MSE: 1.6912829877423577e+25
Learning_rate:0.01,Batch Size: 64, Epoch: 9, Test MSE: 1.495736710148872e+25
Learning_rate:0.01,Batch Size: 64, Epoch: 10, Test MSE: 1.7403131572891833e+25
Learning_rate:0.01,Batch Size: 64, Epoch: 11, Test MSE: 6.37484298018132e+24
Learning_rate:0.01,Batch Size: 64, Epoch: 12, Test MSE: 1.1305945346643235e+25
Learning_rate:0.01,Batch Size: 64, Epoch: 13, Test MSE: 6.406938571960227e+24
Learning_rate:0.01,Batch Size: 64, Epoch: 14, Test MSE: 8.059517883258937e+24
Learning_rate:0.01,Batch Size: 64, Epoch: 15, Test MSE: 8.19930776536399e+24
Learning_rate:0.01,Batch Size: 100, Epoch: 1, Test MSE: 1.3087472572655838e+24
Learning_rate:0.01,Batch Size: 100, Epoch: 2, Test MSE: 3.9827626277375895e+24
Learning_rate:0.01,Batch Size: 100, Epoch: 3, Test MSE: 1.4065234695990044e+24
Learning_rate:0.01,Batch Size: 100, Epoch: 4, Test MSE: 1.9446670562954777e+24
Learning_rate:0.01,Batch Size: 100, Epoch: 5, Test MSE: 1.5725082767449326e+24
Learning_rate:0.01,Batch Size: 100, Epoch: 6, Test MSE: 6.81366129804157le+24
Learning_rate:0.01,Batch Size: 100, Epoch: 7, Test MSE: 2.0309642305379749e+24
Learning_rate:0.01,Batch Size: 100, Epoch: 8, Test MSE: 2.1925426611939864e+24
Learning_rate:0.01,Batch Size: 100, Epoch: 9, Test MSE: 1.1438623275107867e+25
Learning_rate:0.01,Batch Size: 100, Epoch: 10, Test MSE: 1.4031874147557563e+24
Learning_rate:0.01,Batch Size: 100, Epoch: 11, Test MSE: 5.054442806880453e+24
Learning_rate:0.01,Batch Size: 100, Epoch: 12, Test MSE: 3.5669771810404143e+24
```

```
Learning_rate:0.01,Batch Size: 100, Epoch: 13, Test MSE: 9.933671576030368e+24
Learning_rate:0.01,Batch Size: 100, Epoch: 14, Test MSE: 1.9119960453831864e+24
Learning_rate:0.01,Batch Size: 100, Epoch: 15, Test MSE: 4.310138634120541e+24
Learning_rate:0.1,Batch Size: 32, Epoch: 1, Test MSE: 4.11962498042025e+27
Learning_rate:0.1,Batch Size: 32, Epoch: 2, Test MSE: 1.3365831421145956e+26
Learning_rate:0.1,Batch Size: 32, Epoch: 3, Test MSE: 1.477615441896797e+27
Learning_rate:0.1,Batch Size: 32, Epoch: 4, Test MSE: 1.47184145012243e+27
Learning_rate:0.1,Batch Size: 32, Epoch: 5, Test MSE: 3.274136121224268e+27
Learning_rate:0.1,Batch Size: 32, Epoch: 6, Test MSE: 2.178346479806453e+26
Learning_rate:0.1,Batch Size: 32, Epoch: 7, Test MSE: 1.126007527135203e+27
Learning_rate:0.1,Batch Size: 32, Epoch: 8, Test MSE: 4.115263905005097e+27
Learning_rate:0.1,Batch Size: 32, Epoch: 9, Test MSE: 2.8618786169432432e+26
Learning_rate:0.1,Batch Size: 32, Epoch: 10, Test MSE: 3.3254142765771055e+26
Learning_rate:0.1,Batch Size: 32, Epoch: 11, Test MSE: 1.0010468125060558e+27
Learning_rate:0.1,Batch Size: 32, Epoch: 12, Test MSE: 2.046983837883869e+27
Learning_rate:0.1,Batch Size: 32, Epoch: 13, Test MSE: 2.235426341057193e+26
Learning_rate:0.1,Batch Size: 32, Epoch: 14, Test MSE: 2.8776957507641174e+26
Learning_rate:0.1,Batch Size: 32, Epoch: 15, Test MSE: 5.180383801005346e+26
Learning_rate:0.1,Batch Size: 64, Epoch: 1, Test MSE: 6.08767965540779e+27
Learning_rate:0.1,Batch Size: 64, Epoch: 2, Test MSE: 2.541239144625236e+27
Learning_rate:0.1,Batch Size: 64, Epoch: 3, Test MSE: 5.848270381162455e+26
Learning_rate:0.1,Batch Size: 64, Epoch: 4, Test MSE: 1.200588885815351e+27
Learning_rate:0.1,Batch Size: 64, Epoch: 5, Test MSE: 2.9729510261670257e+27
Learning_rate:0.1,Batch Size: 64, Epoch: 6, Test MSE: 9.473257271803835e+26
Learning_rate:0.1,Batch Size: 64, Epoch: 7, Test MSE: 1.4781503689706397e+27
Learning_rate:0.1,Batch Size: 64, Epoch: 8, Test MSE: 3.889814273427142e+26
Learning_rate:0.1,Batch Size: 64, Epoch: 9, Test MSE: 5.663374198219247e+26
Learning_rate:0.1,Batch Size: 64, Epoch: 10, Test MSE: 3.0898453420958143e+26
Learning_rate:0.1,Batch Size: 64, Epoch: 11, Test MSE: 4.4017556410040236e+27
Learning_rate:0.1,Batch Size: 64, Epoch: 12, Test MSE: 6.41213038196297e+26
Learning_rate:0.1,Batch Size: 64, Epoch: 13, Test MSE: 5.328989169971217e+26
Learning_rate:0.1,Batch Size: 64, Epoch: 14, Test MSE: 1.0784180416845213e+27
Learning_rate:0.1,Batch Size: 64, Epoch: 15, Test MSE: 2.2696943496825488e+27
Learning_rate:0.1,Batch Size: 100, Epoch: 1, Test MSE: 3.301288340746848e+26
Learning_rate:0.1,Batch Size: 100, Epoch: 2, Test MSE: 1.5276347736650203e+26
Learning_rate:0.1,Batch Size: 100, Epoch: 3, Test MSE: 2.4086712657271463e+26
Learning_rate:0.1,Batch Size: 100, Epoch: 4, Test MSE: 8.889845863765714e+26
Learning_rate:0.1,Batch Size: 100, Epoch: 5, Test MSE: 5.098225239726114e+26
Learning_rate:0.1,Batch Size: 100, Epoch: 6, Test MSE: 5.227821805479901e+26
Learning_rate:0.1,Batch Size: 100, Epoch: 7, Test MSE: 1.9324656490244444e+26
Learning_rate:0.1,Batch Size: 100, Epoch: 8, Test MSE: 2.1328119204458802e+26
Learning_rate:0.1,Batch Size: 100, Epoch: 9, Test MSE: 8.026360320546408e+26
Learning_rate:0.1,Batch Size: 100, Epoch: 10, Test MSE: 1.406261342610816e+27
Learning_rate:0.1,Batch Size: 100, Epoch: 11, Test MSE: 1.0057300595040098e+27
Learning_rate:0.1,Batch Size: 100, Epoch: 12, Test MSE: 5.546234110592643e+26
Learning_rate:0.1,Batch Size: 100, Epoch: 13, Test MSE: 8.096047071707685e+26
Learning_rate:0.1,Batch Size: 100, Epoch: 14, Test MSE: 2.0482152208387478e+27
Learning_rate:0.1,Batch Size: 100, Epoch: 15, Test MSE: 1.248228004440362e+27
```

```
Learning_rate:1,Batch Size: 32, Epoch: 1, Test MSE: 6.498467049904571e+28
Learning_rate:1,Batch Size: 32, Epoch: 2, Test MSE: 1.3690358192358743e+29
Learning_rate:1,Batch Size: 32, Epoch: 3, Test MSE: 2.588526832177344e+29
Learning_rate:1,Batch Size: 32, Epoch: 4, Test MSE: 1.0524253113562505e+28
Learning_rate:1,Batch Size: 32, Epoch: 5, Test MSE: 2.1753193969169688e+29
Learning_rate:1,Batch Size: 32, Epoch: 6, Test MSE: 1.309962522456235e+28
Learning_rate:1,Batch Size: 32, Epoch: 7, Test MSE: 3.164662648335035e+29
Learning_rate:1,Batch Size: 32, Epoch: 8, Test MSE: 2.5177287958334735e+29
Learning_rate:1,Batch Size: 32, Epoch: 9, Test MSE: 3.8985632336407664e+28
Learning_rate:1,Batch Size: 32, Epoch: 10, Test MSE: 1.4723334291265725e+29
Learning_rate:1,Batch Size: 32, Epoch: 11, Test MSE: 4.399454587064336e+28
Learning_rate:1,Batch Size: 32, Epoch: 12, Test MSE: 3.7823598254684566e+28
Learning_rate:1,Batch Size: 32, Epoch: 13, Test MSE: 4.889518452729919e+29
Learning_rate:1,Batch Size: 32, Epoch: 14, Test MSE: 3.910572441990028e+27
Learning_rate:1,Batch Size: 32, Epoch: 15, Test MSE: 2.9594268557032455e+28
Learning_rate:1,Batch Size: 64, Epoch: 1, Test MSE: 3.386511312292613e+28
Learning_rate:1,Batch Size: 64, Epoch: 2, Test MSE: 3.7413685091842705e+28
Learning_rate:1,Batch Size: 64, Epoch: 3, Test MSE: 5.4959810057036595e+28
Learning_rate:1,Batch Size: 64, Epoch: 4, Test MSE: 9.90950718101021e+28
Learning_rate:1,Batch Size: 64, Epoch: 5, Test MSE: 1.8648221716155314e+29
Learning_rate:1,Batch Size: 64, Epoch: 6, Test MSE: 1.5260243649228468e+29
Learning_rate:1,Batch Size: 64, Epoch: 7, Test MSE: 4.971493851370335e+28
Learning_rate:1,Batch Size: 64, Epoch: 8, Test MSE: 1.767466260098073e+29
Learning_rate:1,Batch Size: 64, Epoch: 9, Test MSE: 4.045199919320397e+29
Learning_rate:1,Batch Size: 64, Epoch: 10, Test MSE: 1.496040436759113e+29
Learning_rate:1,Batch Size: 64, Epoch: 11, Test MSE: 4.5266462765015996e+29
Learning_rate:1,Batch Size: 64, Epoch: 12, Test MSE: 2.9137980294303643e+28
Learning_rate:1,Batch Size: 64, Epoch: 13, Test MSE: 8.755243035065467e+28
Learning_rate:1,Batch Size: 64, Epoch: 14, Test MSE: 1.2157767926693985e+29
Learning_rate:1,Batch Size: 64, Epoch: 15, Test MSE: 2.697444610873926e+29
Learning_rate:1,Batch Size: 100, Epoch: 1, Test MSE: 1.440143061606741e+29
Learning_rate:1,Batch Size: 100, Epoch: 2, Test MSE: 1.2589586811471684e+28
Learning_rate:1,Batch Size: 100, Epoch: 3, Test MSE: 1.7048608574919283e+29
Learning_rate:1,Batch Size: 100, Epoch: 4, Test MSE: 8.758210623517811e+27
Learning_rate:1,Batch Size: 100, Epoch: 5, Test MSE: 4.044643181672311e+28
Learning_rate:1,Batch Size: 100, Epoch: 6, Test MSE: 1.2963902146151343e+28
Learning_rate:1,Batch Size: 100, Epoch: 7, Test MSE: 2.0284109917296416e+28
Learning_rate:1,Batch Size: 100, Epoch: 8, Test MSE: 7.0394625722816615e+28
Learning_rate:1,Batch Size: 100, Epoch: 9, Test MSE: 1.511501527885025e+28
Learning_rate:1,Batch Size: 100, Epoch: 10, Test MSE: 2.1110326566049115e+28
Learning_rate:1,Batch Size: 100, Epoch: 11, Test MSE: 4.067960528960142e+28
Learning_rate:1,Batch Size: 100, Epoch: 12, Test MSE: 1.5722658029993225e+28
Learning_rate:1,Batch Size: 100, Epoch: 13, Test MSE: 9.444478755934427e+28
Learning_rate:1,Batch Size: 100, Epoch: 14, Test MSE: 1.053706361705827e+29
Learning_rate:1,Batch Size: 100, Epoch: 15, Test MSE: 1.005577397245826e+28
```

Learning Rate: 0.01

Test MSE increases drastically with the number of epochs, indicating a potential issue with learning rate selection. Starting from an already high MSE, it reaches extremely large values, suggesting that the model may diverge or fail to converge with this learning rate. Varying the batch size doesn't seem to significantly affect the performance when the learning rate is 0.01. The high MSE remains consistent across different batch sizes. Learning Rate: 0.1

Similar to the learning rate of 0.01, the test MSE exhibits a tendency to increase with the number of epochs, especially when the learning rate is too high. This suggests that a learning rate of 0.1 might also be too large for this problem, causing unstable training. The batch size does not appear to have a substantial impact on the test MSE for this learning rate. Learning Rate: 1.0

The test MSE values are extremely high across all combinations of batch size and epochs when the learning rate is set to 1.0. This indicates a severe issue with the learning rate choice, and the model is unable to effectively learn from the data. Summary:

The choice of learning rate is critical in training neural networks. A learning rate that is too high can lead to instability and large MSE values, as observed in the results with learning rates of 0.01, 0.1, and 1.0. The problem might require a much smaller learning rate to ensure stable training and convergence. Batch size variations do not seem to have a significant impact on the model's performance, as the high MSE values persist across different batch sizes. In summary, these results suggest that careful tuning of the learning rate is necessary to achieve better model performance. Lowering the learning rate and monitoring the loss curve during training may help identify a suitable learning rate for this specific problem.

G. Make predictions of the labels on the test data, using the trained model with chosen hyperparameters. Summarize performance using the appropriate evaluation metric. Discuss the results. Include thoughts about what further can be explored to increase performance.

Model1 : Simple Linear Regression

[54]:
```
linear = LinearRegression().fit(X_train,y_train)
y_pred=linear.predict(X_test)
```

Prediction on the Test Labels

[55]:
```
k=np.array(y_test)
results_df = pd.DataFrame({'y_test': k.flatten(), 'y_pred': y_pred.flatten()})
print(results_df)
```

```
    y_test     y_pred
0     19.2  19.566294
1     19.2  19.240043
2     28.0  27.592278
3     20.5  20.496109
4     16.7  16.614561
5     12.1  12.175919
6     23.6  22.416911
7     18.6  19.222539
8     11.7  11.786891
9     11.9  11.145272
10    26.1  26.830679
11    24.5  24.789448
```

```
12    14.8  15.354283
13    22.5  21.983993
14     6.3   6.712900
15     5.3   5.294412
16    22.0  21.170134
17    20.9  20.589080
18    20.4  20.646525
19    14.0  13.416408
20    14.9  15.540109
21    16.5  17.330788
22    13.9  14.371662
23    13.8  13.728150
24    21.3  21.750961
25    30.4  31.094811
26    23.6  24.390246
27    15.0  15.382736
28     7.1   7.285164
29    13.0  13.488210
30    24.9  24.740075
31     9.6  10.596352
32    17.5  17.755348
33    18.4  19.287240
34    18.7  19.233168
35     3.7   3.906829
36    21.4  21.286169
37    16.0  16.057998
38    16.6  17.084652
39    11.5  11.537941
40    13.8  14.092585
41    23.6  24.027126
42    31.2  30.150626
43     9.4   9.169822
44    13.9  13.990001
45    22.5  22.058976
46    29.0  28.222953
47    21.5  21.121052
48    23.3  23.207996
49     9.9   9.856648
50    35.2  37.490354
```

Reporting the Evaluation Metric

[56]:
```
print("Simple Linear Regression")
print("\n Root mean Squared error(RMSE):{:.3f}".format(np.
 ↪sqrt(mean_squared_error(y_test,y_pred))))
```

```
Simple Linear Regression
```

```
Root mean Squared error(RMSE):0.600
```

Model 2: Linear Regression ith SGD

[57]:
```
sgd=SGDRegressor(max_iter=1000, tol=1e-5,eta0=0.
↪01,n_iter_no_change=100,random_state=42)
sgd.fit(X_train,y_train)
y_pred0=sgd.predict(X_test)
```

Prediction on the Test Labels

[58]:
```
k=np.array(y_test)
results_df = pd.DataFrame({'y_test': k.flatten(), 'y_pred0': y_pred0.flatten()})
print(results_df)
```

```
    y_test    y_pred0
0     19.2  19.537741
1     19.2  19.239950
2     28.0  27.597653
3     20.5  20.494440
4     16.7  16.627339
5     12.1  12.195959
6     23.6  22.413772
7     18.6  19.234228
8     11.7  11.778045
9     11.9  11.154749
10    26.1  26.804517
11    24.5  24.772724
12    14.8  15.362355
13    22.5  21.983401
14     6.3   6.727506
15     5.3   5.322147
16    22.0  21.179584
17    20.9  20.601690
18    20.4  20.651606
19    14.0  13.421906
20    14.9  15.550586
21    16.5  17.321164
22    13.9  14.371248
23    13.8  13.734314
24    21.3  21.731057
25    30.4  31.060481
26    23.6  24.360562
27    15.0  15.404462
28     7.1   7.284160
29    13.0  13.482363
30    24.9  24.742821
31     9.6  10.597787
32    17.5  17.759448
```

```
33     18.4  19.283291
34     18.7  19.229236
35      3.7   3.925929
36     21.4  21.295686
37     16.0  16.051292
38     16.6  17.072358
39     11.5  11.561578
40     13.8  14.105358
41     23.6  24.018316
42     31.2  30.129175
43      9.4   9.176268
44     13.9  13.992580
45     22.5  22.048191
46     29.0  28.208066
47     21.5  21.128654
48     23.3  23.210209
49      9.9   9.880345
50     35.2  37.407923
```

Reporting the Evaluation Metric

[59]:
```
print("Linear Regression ith SGD")
print("\n Root mean Squared error(RMSE):{:.3f}".format(np.
 ↪sqrt(mean_squared_error(y_test,y_pred0))))
```

```
Linear Regression ith SGD

 Root mean Squared error(RMSE):0.592
```

Model 3: Linear Regression with Ridge Regularization

[60]:
```
ridge = Ridge(alpha=1.0)
ridge.fit(X_train,y_train)
y_pred1=ridge.predict(X_test)
```

Prediction on the Test Labels

[61]:
```
k=np.array(y_test)
results_df = pd.DataFrame({'y_test': k.flatten(), 'y_pred1': y_pred1.flatten()})
print(results_df)
```

```
    y_test    y_pred1
0     19.2  19.530789
1     19.2  19.193384
2     28.0  27.688552
3     20.5  20.427975
4     16.7  16.603785
5     12.1  12.255433
6     23.6  22.343167
7     18.6  19.274191
```

```
8      11.7  11.792841
9      11.9  11.261321
10     26.1  26.795276
11     24.5  24.778210
12     14.8  15.417788
13     22.5  21.927097
14      6.3   6.763176
15      5.3   5.306001
16     22.0  21.115213
17     20.9  20.637803
18     20.4  20.627792
19     14.0  13.325238
20     14.9  15.589045
21     16.5  17.447483
22     13.9  14.382209
23     13.8  13.766935
24     21.3  21.796596
25     30.4  31.038084
26     23.6  24.442690
27     15.0  15.431766
28      7.1   7.320689
29     13.0  13.536560
30     24.9  24.681904
31      9.6  10.689976
32     17.5  17.816307
33     18.4  19.348413
34     18.7  19.279906
35      3.7   3.978304
36     21.4  21.283849
37     16.0  16.083150
38     16.6  17.087672
39     11.5  11.614068
40     13.8  14.120093
41     23.6  24.031362
42     31.2  30.121621
43      9.4   9.098047
44     13.9  13.924680
45     22.5  22.042902
46     29.0  28.153490
47     21.5  21.018121
48     23.3  23.145064
49      9.9   9.879291
50     35.2  37.657004
```

Reporting the Evaluation Metric

[62]:
```
print("Linear Regression ith SGD")
```

```
print("\n Root mean Squared error(RMSE):{:.3f}".format(np.
 ↪sqrt(mean_squared_error(y_test,y_pred1))))
```

```
Linear Regression ith SGD

 Root mean Squared error(RMSE):0.637
```

Model4: Linear Regression with Lasso Regularization

[63]:
```
lasso = Lasso(alpha=0.01)
lasso.fit(X_train,y_train)
y_pred2=lasso.predict(X_test)
```

Prediction on the Test Labels

[64]:
```
k=np.array(y_test)
results_df = pd.DataFrame({'y_test': k.flatten(), 'y_pred2': y_pred2.flatten()})
print(results_df)
```

```
    y_test    y_pred2
0     19.2  19.545219
1     19.2  19.226134
2     28.0  27.720157
3     20.5  20.434769
4     16.7  16.640328
5     12.1  12.256702
6     23.6  22.568367
7     18.6  19.256346
8     11.7  11.903057
9     11.9  11.316351
10    26.1  26.795666
11    24.5  24.778360
12    14.8  15.400419
13    22.5  22.011300
14     6.3   6.722744
15     5.3   5.267258
16    22.0  21.269241
17    20.9  20.719823
18    20.4  20.597475
19    14.0  13.410235
20    14.9  15.589751
21    16.5  17.335923
22    13.9  14.422504
23    13.8  13.823946
24    21.3  21.837291
25    30.4  30.993953
26    23.6  24.406975
27    15.0  15.353449
28     7.1   7.347885
```

```
29     13.0  13.528606
30     24.9  24.678819
31      9.6  10.530342
32     17.5  17.761527
33     18.4  19.267899
34     18.7  19.231250
35      3.7   3.849592
36     21.4  21.244867
37     16.0  16.173119
38     16.6  17.237427
39     11.5  11.599376
40     13.8  14.131790
41     23.6  23.924959
42     31.2  30.227298
43      9.4   9.164173
44     13.9  13.997768
45     22.5  22.131564
46     29.0  28.232062
47     21.5  21.049156
48     23.3  23.184928
49      9.9   9.873129
50     35.2  37.299918
```

Reporting the Evaluation Metric

[65]:
```
print("Linear Regression with Lasso Regularization")
print("\n Root mean Squared error(RMSE):{:.3f}".format(np.
 ↪sqrt(mean_squared_error(y_test,y_pred2))))
```

```
Linear Regression with Lasso Regularization

 Root mean Squared error(RMSE):0.572
```

Model 5: Linear Regression with Elastic Net Regularization

[66]:
```
elastic_net = ElasticNet(alpha=0.01)
elastic_net.fit(X_train,y_train)
y_pred3=elastic_net.predict(X_test)
```

Prediction on the Test Labels

[67]:
```
k=np.array(y_test)
results_df = pd.DataFrame({'y_test': k.flatten(), 'y_pred3': y_pred3.flatten()})
print(results_df)
```

```
    y_test    y_pred3
0     19.2  19.510656
1     19.2  19.180546
2     28.0  27.739630
3     20.5  20.400300
```

4	16.7	16.615962
5	12.1	12.291844
6	23.6	22.417727
7	18.6	19.296484
8	11.7	11.877711
9	11.9	11.355635
10	26.1	26.779411
11	24.5	24.771800
12	14.8	15.436225
13	22.5	21.936377
14	6.3	6.775312
15	5.3	5.298029
16	22.0	21.157752
17	20.9	20.698909
18	20.4	20.598358
19	14.0	13.317273
20	14.9	15.617933
21	16.5	17.448199
22	13.9	14.427671
23	13.8	13.809285
24	21.3	21.825909
25	30.4	30.980286
26	23.6	24.450964
27	15.0	15.426164
28	7.1	7.352554
29	13.0	13.577678
30	24.9	24.645273
31	9.6	10.649458
32	17.5	17.803068
33	18.4	19.337900
34	18.7	19.279120
35	3.7	3.949995
36	21.4	21.254334
37	16.0	16.133997
38	16.6	17.205723
39	11.5	11.634533
40	13.8	14.146773
41	23.6	23.971915
42	31.2	30.156489
43	9.4	9.100895
44	13.9	13.926009
45	22.5	22.068482
46	29.0	28.148460
47	21.5	20.979171
48	23.3	23.135332
49	9.9	9.884539
50	35.2	37.603375

Reporting the Evaluation Metric

[68]:
```
print("Linear Regression with Elastic Net Regularization")
print("\n Root mean Squared error(RMSE):{:.3f}".format(np.
 ↪sqrt(mean_squared_error(y_test,y_pred3))))
```

```
Linear Regression with Elastic Net Regularization

 Root mean Squared error(RMSE):0.629
```

Model 6: Simple Polynomial Regression

[69]:
```
poly=LinearRegression().fit(X_train_poly,y_train)
y_pred4=poly.predict(X_test_poly)
```

Prediction on the Test Labels

[70]:
```
k=np.array(y_test)
results_df = pd.DataFrame({'y_test': k.flatten(), 'y_pred4': y_pred4.flatten()})
print(results_df)
```

```
    y_test    y_pred4
0     19.2  18.573918
1     19.2  18.294056
2     28.0  29.102470
3     20.5  19.897573
4     16.7  16.376436
5     12.1  11.781529
6     23.6  23.495601
7     18.6  18.235449
8     11.7  10.822314
9     11.9  10.591846
10    26.1  27.180872
11    24.5  25.136669
12    14.8  14.790452
13    22.5  22.399053
14     6.3   7.652767
15     5.3   4.525507
16    22.0  21.824178
17    20.9  20.625431
18    20.4  19.812798
19    14.0  15.373816
20    14.9  16.876979
21    16.5  16.419937
22    13.9  13.322479
23    13.8  13.097865
24    21.3  21.344462
25    30.4  32.424656
26    23.6  24.374724
```

```
27     15.0  14.624828
28      7.1   7.806385
29     13.0  12.792902
30     24.9  23.992454
31      9.6  11.354776
32     17.5  17.131774
33     18.4  18.806690
34     18.7  18.272206
35      3.7   4.603005
36     21.4  20.901412
37     16.0  16.902059
38     16.6  16.480485
39     11.5  11.725314
40     13.8  14.223619
41     23.6  22.996480
42     31.2  33.205502
43      9.4   8.995300
44     13.9  14.383224
45     22.5  22.367026
46     29.0  28.844759
47     21.5  21.690572
48     23.3  23.435517
49      9.9   9.370174
50     35.2  28.891725
```

Reporting the Evaluation Metric

[71]:
```
print("Simple Polynomial Regression")
print("\n Root mean Squared error(RMSE):{:.3f}".format(np.
 ↪sqrt(mean_squared_error(y_test,y_pred4))))
```

```
Simple Polynomial Regression

 Root mean Squared error(RMSE):1.201
```

Model 7: Polynmial Regression ith SGD

[72]:
```
sgd_poly=SGDRegressor(max_iter=1000, tol=1e-5,eta0=0.
 ↪01,n_iter_no_change=100,random_state=42)
sgd_poly.fit(X_train_poly,y_train)
y_pred5=sgd_poly.predict(X_test_poly)
```

Prediction on the Test Labels

[75]:
```
k=np.array(y_test)
results_df = pd.DataFrame({'y_test': k.flatten(), 'y_pred5': y_pred5.flatten()})
print(results_df)
```

```
    y_test      y_pred5
0     19.2 -3645.072544
```

1	19.2	-1331.852415
2	28.0	-554.925497
3	20.5	-1516.431554
4	16.7	-1746.045523
5	12.1	-2436.517817
6	23.6	-1444.813756
7	18.6	-891.287518
8	11.7	-725.941103
9	11.9	2192.376849
10	26.1	1302.200092
11	24.5	-1339.449132
12	14.8	549.849933
13	22.5	-2036.807005
14	6.3	-823.802894
15	5.3	-1740.091112
16	22.0	-2484.459968
17	20.9	-158.515607
18	20.4	1073.719733
19	14.0	2178.326620
20	14.9	-1482.513590
21	16.5	-3348.080362
22	13.9	956.604669
23	13.8	-1240.880728
24	21.3	-1472.809347
25	30.4	-3263.096496
26	23.6	-1683.371090
27	15.0	-731.437215
28	7.1	-995.704599
29	13.0	748.718920
30	24.9	-171.105855
31	9.6	1266.237355
32	17.5	-2451.689447
33	18.4	-1191.733881
34	18.7	-1434.392575
35	3.7	132.495687
36	21.4	-3604.600452
37	16.0	3228.608119
38	16.6	-1182.777659
39	11.5	106.656900
40	13.8	-2298.628940
41	23.6	-2931.482171
42	31.2	1350.486918
43	9.4	32.817991
44	13.9	560.259501
45	22.5	-1079.655696
46	29.0	-1494.773737
47	21.5	454.183443
48	23.3	-1716.133989

```
49     9.9 -3171.045686
50    35.2 -8139.171107
```

Reporting the Evaluation Metric

[76]:
```
print("Polynmial Regression ith SGD")
print("\n Root mean Squared error(RMSE):{:.3f}".format(np.
↪sqrt(mean_squared_error(y_test,y_pred5))))
```

```
Polynmial Regression ith SGD

 Root mean Squared error(RMSE):2120.642
```

Model 8: Polynomial Regression with Ridge Regularization

[77]:
```
ridge_poly = Ridge(alpha=0.1)
ridge_poly.fit(X_train_poly,y_train)
y_pred6=ridge_poly.predict(X_test_poly)
```

Prediction on the Test Labels

[78]:
```
k=np.array(y_test)
results_df = pd.DataFrame({'y_test': k.flatten(), 'y_pred6': y_pred6.flatten()})
print(results_df)
```

```
    y_test    y_pred6
0     19.2  18.747096
1     19.2  18.401017
2     28.0  28.807356
3     20.5  19.978461
4     16.7  16.418801
5     12.1  11.819257
6     23.6  23.368954
7     18.6  18.355424
8     11.7  11.066111
9     11.9  10.029359
10    26.1  27.121409
11    24.5  25.063973
12    14.8  14.882654
13    22.5  22.348459
14     6.3   7.482515
15     5.3   4.527224
16    22.0  21.943331
17    20.9  20.680615
18    20.4  19.764517
19    14.0  15.030295
20    14.9  16.856126
21    16.5  16.391642
22    13.9  13.605235
23    13.8  13.042015
```

```
24     21.3  21.406166
25     30.4  32.145886
26     23.6  24.525020
27     15.0  14.660318
28      7.1   7.794023
29     13.0  12.713706
30     24.9  24.056361
31      9.6  11.358513
32     17.5  17.184645
33     18.4  18.778575
34     18.7  18.359860
35      3.7   4.534822
36     21.4  21.142630
37     16.0  16.676079
38     16.6  17.388057
39     11.5  11.671034
40     13.8  14.343873
41     23.6  23.187329
42     31.2  33.009174
43      9.4   8.866541
44     13.9  14.017057
45     22.5  22.297907
46     29.0  28.948908
47     21.5  21.667486
48     23.3  23.323293
49      9.9   9.511311
50     35.2  29.824014
```

Reporting the Evaluation Metric

[79]:
```
print("Polynomial Regression with Ridge Regularization")
print("\n Root mean Squared error(RMSE):{:.3f}".format(np.
 ↪sqrt(mean_squared_error(y_test,y_pred6))))
```

```
Polynomial Regression with Ridge Regularization

 Root mean Squared error(RMSE):1.077
```

Model 9: Polynomial Regression with Lasso Regularization

[80]:
```
lasso_poly = Lasso(alpha=0.1)
lasso_poly.fit(X_train_poly,y_train)
y_pred7=lasso_poly.predict(X_test_poly)
```

Prediction on the Test Labels

[81]:
```
k=np.array(y_test)
results_df = pd.DataFrame({'y_test': k.flatten(), 'y_pred7': y_pred7.flatten()})
print(results_df)
```

	y_test	y_pred7
0	19.2	19.339395
1	19.2	18.749456
2	28.0	28.114887
3	20.5	20.079392
4	16.7	16.460793
5	12.1	11.924854
6	23.6	22.480097
7	18.6	18.599721
8	11.7	12.262827
9	11.9	12.264765
10	26.1	26.488344
11	24.5	24.117775
12	14.8	15.199662
13	22.5	21.852522
14	6.3	6.898816
15	5.3	5.250302
16	22.0	21.647816
17	20.9	20.955910
18	20.4	20.268405
19	14.0	13.587310
20	14.9	15.263234
21	16.5	16.639631
22	13.9	14.664388
23	13.8	13.659926
24	21.3	21.434742
25	30.4	30.395160
26	23.6	24.173430
27	15.0	15.018641
28	7.1	8.293085
29	13.0	13.919976
30	24.9	25.513716
31	9.6	10.524224
32	17.5	17.259759
33	18.4	18.754862
34	18.7	18.934435
35	3.7	4.347437
36	21.4	21.408945
37	16.0	15.742558
38	16.6	17.058194
39	11.5	11.542832
40	13.8	14.032778
41	23.6	23.387747
42	31.2	30.412978
43	9.4	9.320992
44	13.9	13.648967
45	22.5	21.923675
46	29.0	29.091229

```
47     21.5  21.570925
48     23.3  22.867316
49      9.9   9.923960
50     35.2  37.426852
```

Reporting the Evaluation Metric

[82]:
```python
print("Polynomial Regression with Lasso Regularization")
print("\n Root mean Squared error(RMSE):{:.3f}".format(np.
 ↪sqrt(mean_squared_error(y_test,y_pred7))))
```

```
Polynomial Regression with Lasso Regularization

 Root mean Squared error(RMSE):0.553
```

Model 10: Polynomial Regression with Elastic Net Regularization

[83]:
```python
elastic_net_poly = ElasticNet(alpha=0.1, l1_ratio=0.5)
elastic_net_poly.fit(X_train_poly,y_train)
y_pred8=elastic_net_poly.predict(X_test_poly)
```

Prediction on the Test Labels

[84]:
```python
k=np.array(y_test)
results_df = pd.DataFrame({'y_test': k.flatten(), 'y_pred8': y_pred8.flatten()})
print(results_df)
```

```
    y_test    y_pred8
0     19.2  19.210941
1     19.2  18.774625
2     28.0  28.188556
3     20.5  19.884047
4     16.7  16.421291
5     12.1  12.370053
6     23.6  21.873212
7     18.6  19.018803
8     11.7  12.348487
9     11.9  12.246658
10    26.1  26.866589
11    24.5  24.149114
12    14.8  15.758872
13    22.5  21.498840
14     6.3   7.555829
15     5.3   5.146304
16    22.0  20.978028
17    20.9  21.025904
18    20.4  19.915442
19    14.0  13.141321
20    14.9  16.032982
21    16.5  17.407998
```

```
22    13.9  15.188260
23    13.8  13.689295
24    21.3  21.936735
25    30.4  30.656139
26    23.6  24.524829
27    15.0  15.110805
28     7.1   8.508209
29    13.0  14.050097
30    24.9  24.686788
31     9.6  11.582760
32    17.5  17.460268
33    18.4  19.594692
34    18.7  19.551101
35     3.7   4.824080
36    21.4  21.347260
37    16.0  15.537976
38    16.6  17.390439
39    11.5  11.865141
40    13.8  14.455941
41    23.6  23.495547
42    31.2  29.838064
43     9.4   8.921071
44    13.9  13.442946
45    22.5  21.613700
46    29.0  28.002716
47    21.5  20.705911
48    23.3  22.500671
49     9.9  10.056943
50    35.2  38.915617
```

Reporting the Evaluation Metric

[85]:
```
print("Polynomial Regression with Elastic Net Regularization")
print("\n Root mean Squared error(RMSE):{:.3f}".format(np.
 ↪sqrt(mean_squared_error(y_test,y_pred7))))
```

```
Polynomial Regression with Elastic Net Regularization

 Root mean Squared error(RMSE):0.553
```

Conclusion

We have observed that Polynomial Regression with Elastic Net Regularization and Lasso Regularization has least RMSE values i.e ~ 0.553(degree=2) with best obtained aplha value from hypertuning.

Improvements

we used only degree=2 here, we can try with different degrees and find the best fitting model. we can use grid search for hypertuning learning rate and batch size for finding best fitting model we have taken only one evaluation metric (RMSE). To understand the model better,we can consider taking other evaluation metrics like R^2 and mean absolute error. To address underfitting, consider increasing the model's complexity, adding more features, or adjusting hyperparameters to improve its ability to capture patterns in the training data. Additional data may also help improve the model's ability to fit the training data effectively. References:

https://github.com/ageron/handson-ml2
https://scikit-learn.org/stable/modules/classes.html
https://pandas.pydata.org/docs/user_guide/index.html#user-guide
https://numpy.org/doc/stable/user/index.html#user