RegressionMiniProject

June 12, 2024

[64]:
```python
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
df = pd.read_csv('boxdata.csv')
```

1 Understanding the data

[65]:
```python
df.head()
```

[65]:

	Cost	Weight	Weight1	Length	Height	Width
0	242.0	23.2	25.4	30.0	11.5200	4.0200
1	290.0	24.0	26.3	31.2	12.4800	4.3056
2	340.0	23.9	26.5	31.1	12.3778	4.6961
3	363.0	26.3	29.0	33.5	12.7300	4.4555
4	430.0	26.5	29.0	34.0	12.4440	5.1340

[66]:
```python
df.tail()
```

[66]:

	Cost	Weight	Weight1	Length	Height	Width
154	12.2	11.5	12.2	13.4	2.0904	1.3936
155	13.4	11.7	12.4	13.5	2.4300	1.2690
156	12.2	12.1	13.0	13.8	2.2770	1.2558
157	19.7	13.2	14.3	15.2	2.8728	2.0672
158	19.9	13.8	15.0	16.2	2.9322	1.8792

[67]:
```python
df.shape
```

[67]: (159, 6)

[68]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 159 entries, 0 to 158
Data columns (total 6 columns):
 #   Column   Non-Null Count  Dtype
---  ------   --------------  -----
 0   Cost     159 non-null    float64
```

```
 1   Weight   159 non-null    float64
 2   Weight1  159 non-null    float64
 3   Length   159 non-null    float64
 4   Height   159 non-null    float64
 5   Width    159 non-null    float64
dtypes: float64(6)
memory usage: 7.6 KB
```

[69]:
```
df.describe()
```

[69]:

	Cost	Weight	Weight1	Length	Height	Width
count	159.000000	159.000000	159.000000	159.000000	159.000000	159.000000
mean	398.326415	26.247170	28.415723	31.227044	8.970994	4.417486
std	357.978317	9.996441	10.716328	11.610246	4.286208	1.685804
min	0.000000	7.500000	8.400000	8.800000	1.728400	1.047600
25%	120.000000	19.050000	21.000000	23.150000	5.944800	3.385650
50%	273.000000	25.200000	27.300000	29.400000	7.786000	4.248500
75%	650.000000	32.700000	35.500000	39.650000	12.365900	5.584500
max	1650.000000	59.000000	63.400000	68.000000	18.957000	8.142000

[70]:
```
df.nunique()
```

[70]:
```
Cost       101
Weight     116
Weight1     93
Length     124
Height     154
Width      152
dtype: int64
```

---

2 Handling missing values

[71]:
```
df.isnull().sum()
```

[71]:
```
Cost       0
Weight     0
Weight1    0
Length     0
Height     0
Width      0
dtype: int64
```

Since there are no missing values, moving to next step

---

3 Handling outliers

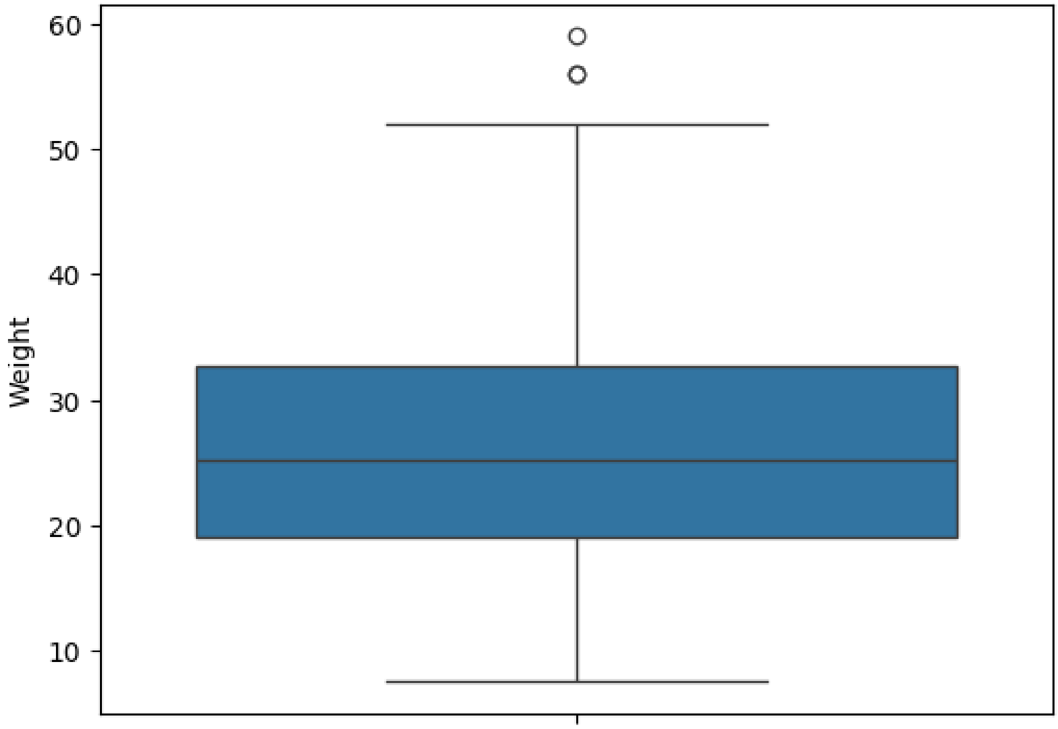
Define a function to remove outliers

[72]:
```
def removeOutliers(df, featureVariable) :
    print("Old Shape: ", df.shape)
    # IQR
    # Calculate the upper and lower limits
    Q1 = df[featureVariable].quantile(0.25)
    Q3 = df[featureVariable].quantile(0.75)
    IQR = Q3 - Q1
    lower = Q1 - 1.5*IQR
    upper = Q3 + 1.5*IQR

    upper_array = np.array(df[featureVariable] >= upper)
    lower_array = np.array(df[featureVariable] <= lower)

    print("Upper limit: ", upper)
    print("No. of datapoints greater than upper limit: ", upper_array.sum())

    print("Lower limit: ", lower)
    print("No. of datapoints less than lower limit: ", lower_array.sum())

    upper_array = np.where(df[featureVariable] >= upper)[0]
    lower_array = np.where(df[featureVariable] <= lower)[0]

    df.drop(index=upper_array, inplace=True)
    df.drop(index=lower_array, inplace=True)

    # Print the new shape of the DataFrame
    print("New Shape: ", df.shape)
    return df
```

Take column 'Weight' and analyse the outliers

[73]:
```
sns.boxplot(df['Weight'])
```

[73]:
```
<Axes: ylabel='Weight'>
```



From the above plot we can see that values greater than 53 and values below 0 are outliers. Lets remove the same using the IQR method

[74]:
```
df = removeOutliers(df,'Weight')
```

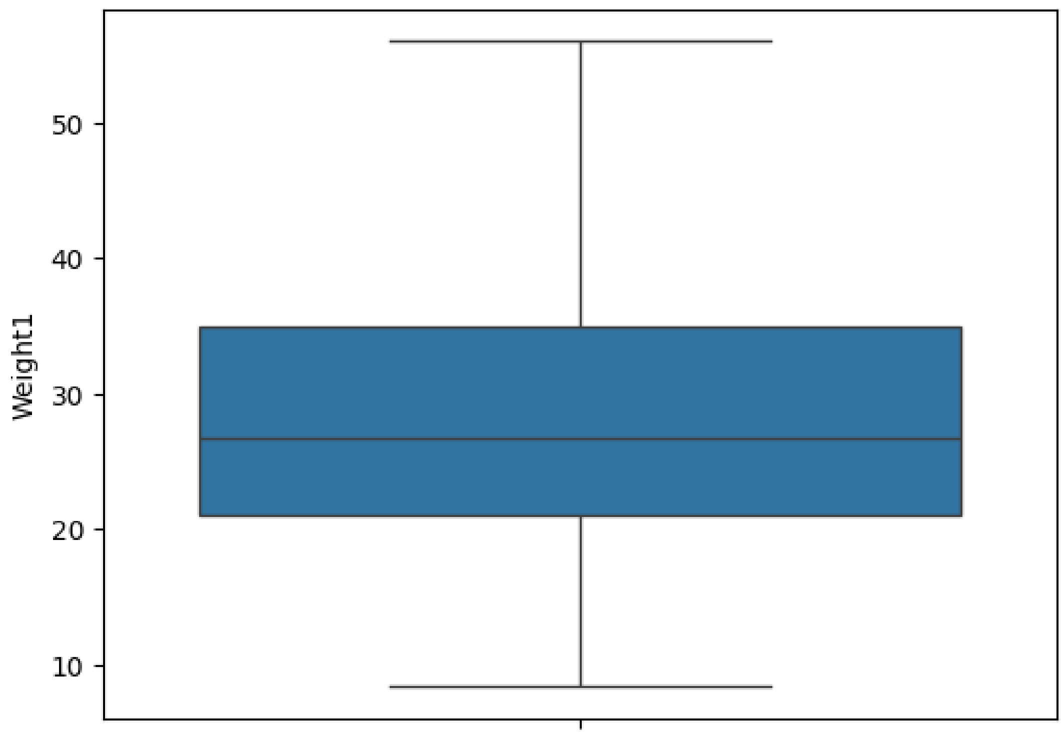
```
Old Shape:  (159, 6)
Upper limit:  53.175000000000004
No. of datapoints greater than upper limit:  3
Lower limit:  -1.4250000000000007
No. of datapoints less than lower limit:  0
New Shape:  (156, 6)
```

Lets analyse and remove outliers from other feature variables too

Take column 'Weight1' and analyse the outliers

[75]:
```
sns.boxplot(df['Weight1'])
```

[75]: <Axes: ylabel='Weight1'>



From the above plot we can see that values greater than around 55 and values below 1 are outliers. Lets remove the same using the IQR method.

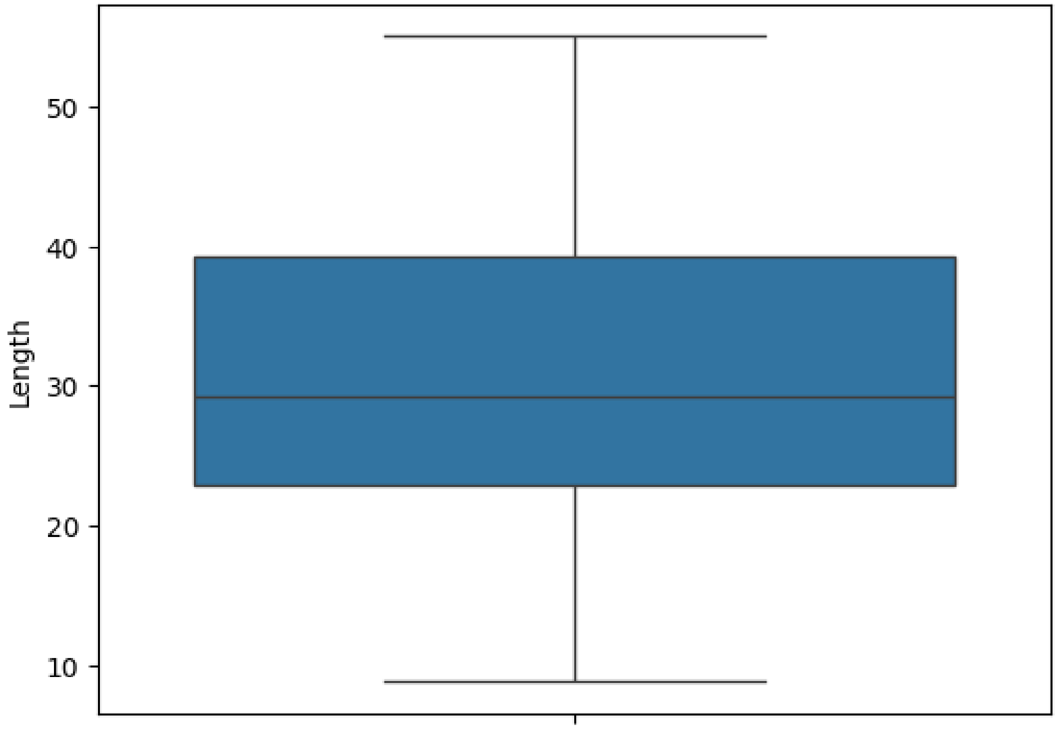
[76]:
```
df = removeOutliers(df,'Weight1')
```

```
Old Shape:  (156, 6)
Upper limit:  56.0
No. of datapoints greater than upper limit:  1
Lower limit:  0.0
No. of datapoints less than lower limit:  0
New Shape:  (155, 6)
```

Take column ‘Length’ and analyse the outliers

[77]:
```
sns.boxplot(df['Length'])
```

[77]:
```
<Axes: ylabel='Length'>
```



From the above plot we can see that values greater than around 60 and values below 1 are outliers. Lets remove the same using the IQR method.

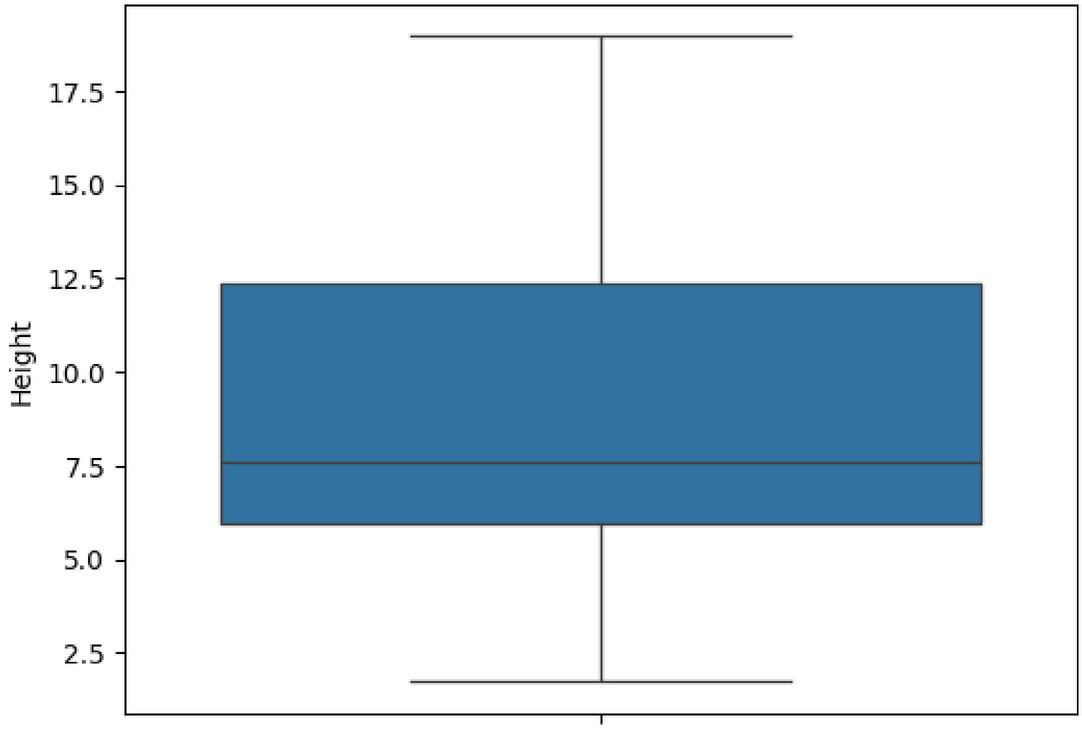
[78]:
```
df = removeOutliers(df,'Length')
```

```
Old Shape:  (155, 6)
Upper limit:  63.94999999999998
No. of datapoints greater than upper limit:  0
Lower limit:  -1.6499999999999844
No. of datapoints less than lower limit:  0
New Shape:  (155, 6)
```

Take column 'Height' and analyse the outliers

[79]:
```
sns.boxplot(df['Height'])
```

[79]: `<Axes: ylabel='Height'>`



From the above plot we can see that values greater than around 21 and values below 2 are outliers.Lets remove the same using the IQR method.

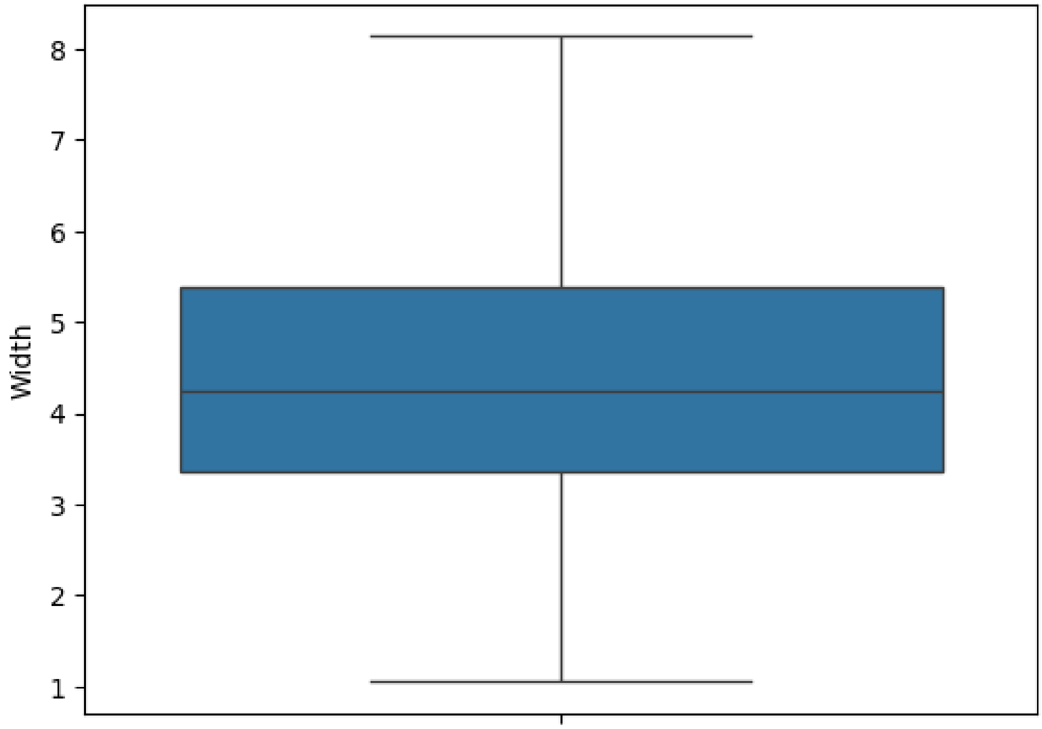
[80]:
```
df = removeOutliers(df,'Height')
```

```
Old Shape:  (155, 6)
Upper limit:  22.057825
No. of datapoints greater than upper limit:  0
Lower limit:  -3.7515750000000008
No. of datapoints less than lower limit:  0
New Shape:  (155, 6)
```

Take column 'Width' and analyse the outliers

[81]:
```
sns.boxplot(df['Width'])
```

[81]:
```
<Axes: ylabel='Width'>
```



From the above plot we can see that values greater than around 10 and values below 0 are outliers.Lets remove the same using the IQR method.

[82]:
```
df = removeOutliers(df,'Width')
```

```
Old Shape:  (155, 6)
Upper limit:  8.387600000000003
No. of datapoints greater than upper limit:  0
Lower limit:  0.34919999999999884
No. of datapoints less than lower limit:  0
New Shape:  (155, 6)
```

The final shape of our data after removing outliers is (155,6)

---

4 Relationship analysis

[83]:
```
df.corr()
```

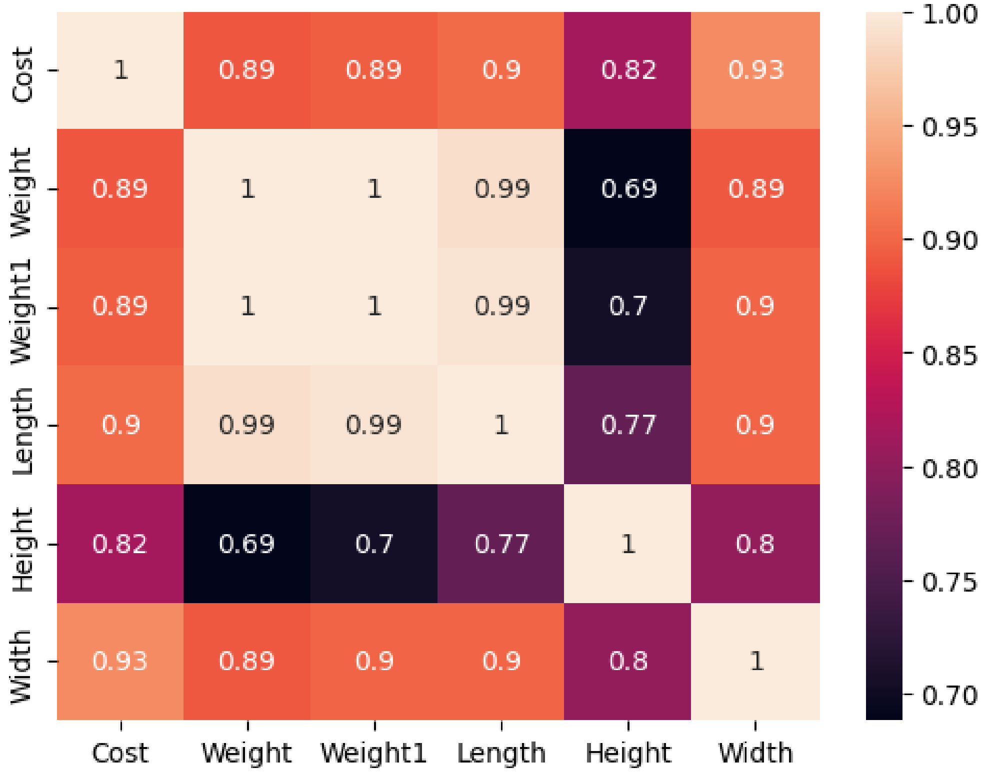
[83]:

	Cost	Weight	Weight1	Length	Height	Width
Cost	1.000000	0.890173	0.894415	0.902576	0.815237	0.925664
Weight	0.890173	1.000000	0.999385	0.990205	0.688050	0.891260
Weight1	0.894415	0.999385	1.000000	0.992765	0.704041	0.897855

Length	0.902576	0.990205	0.992765	1.000000	0.768038	0.898315
Height	0.815237	0.688050	0.704041	0.768038	1.000000	0.803268
Width	0.925664	0.891260	0.897855	0.898315	0.803268	1.000000

[84]:
```
corelation = df.corr()
sns.heatmap(corelation, xticklabels=corelation.columns, yticklabels=corelation.
↪columns, annot=True)
```

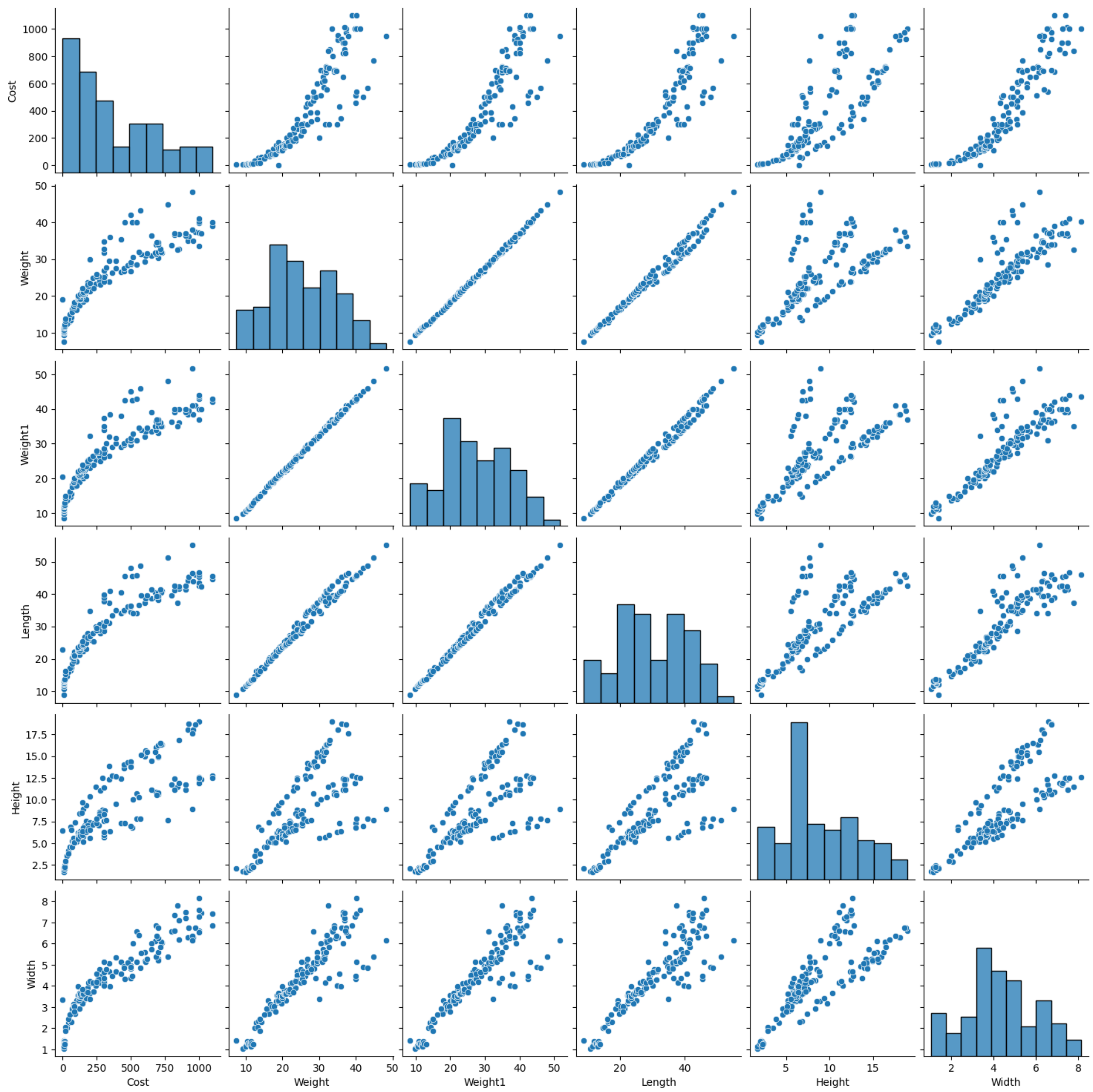
[84]: <Axes: >



From the above plot we could see weight and weight1 are highly correlated.Next highest correlation is between weight vs length and weight1 vs length.

[85]:
```
sns.pairplot(df)
```

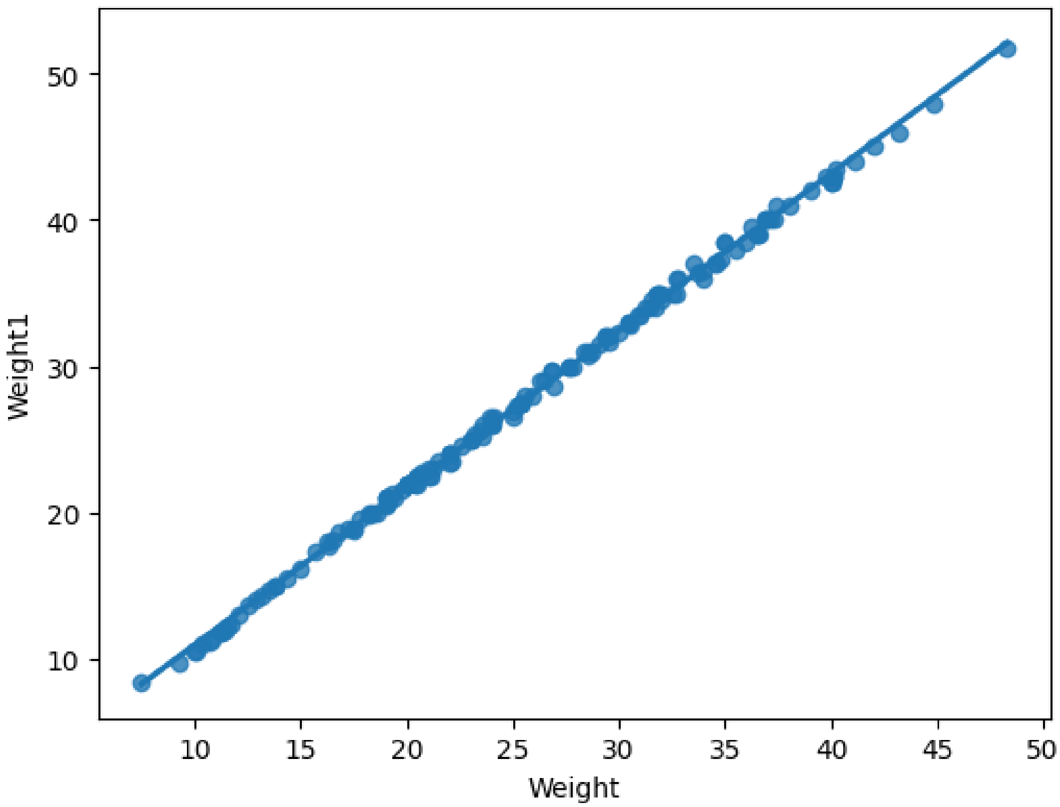
[85]: <seaborn.axisgrid.PairGrid at 0x1711f76e0>



Lets plot reg plot between all the columns to visualize better

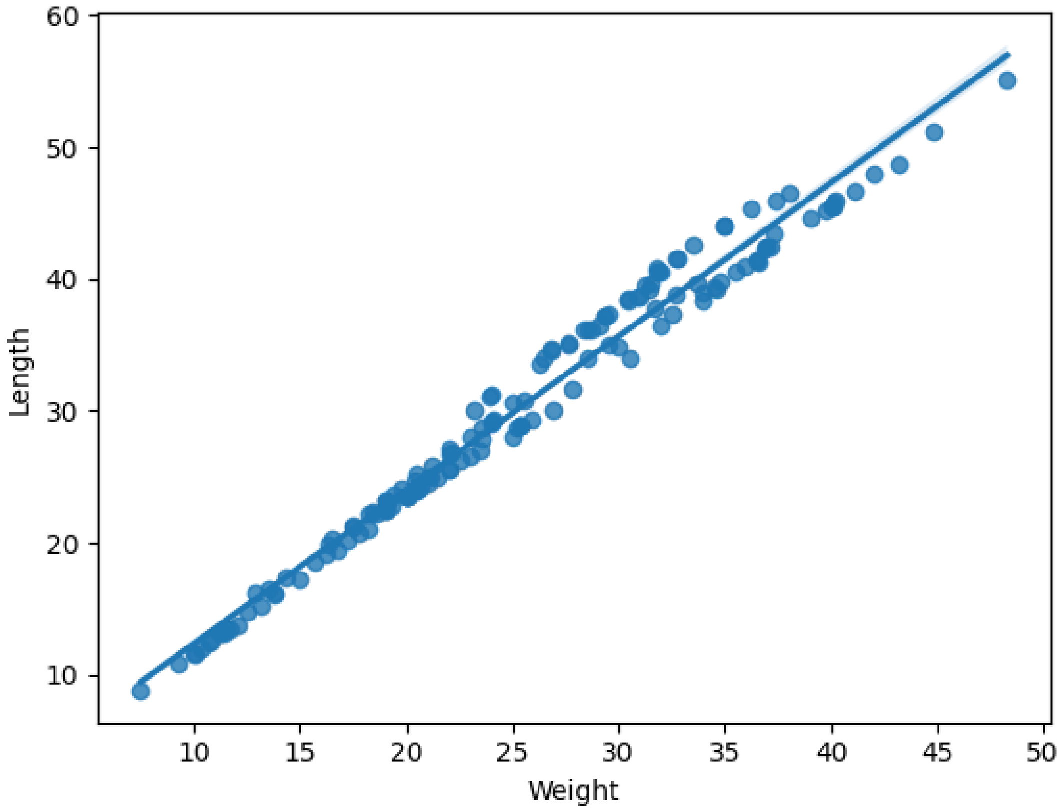
[86]:
```
sns.regplot(x="Weight", y="Weight1", data=df)
```

[86]: <Axes: xlabel='Weight', ylabel='Weight1'>



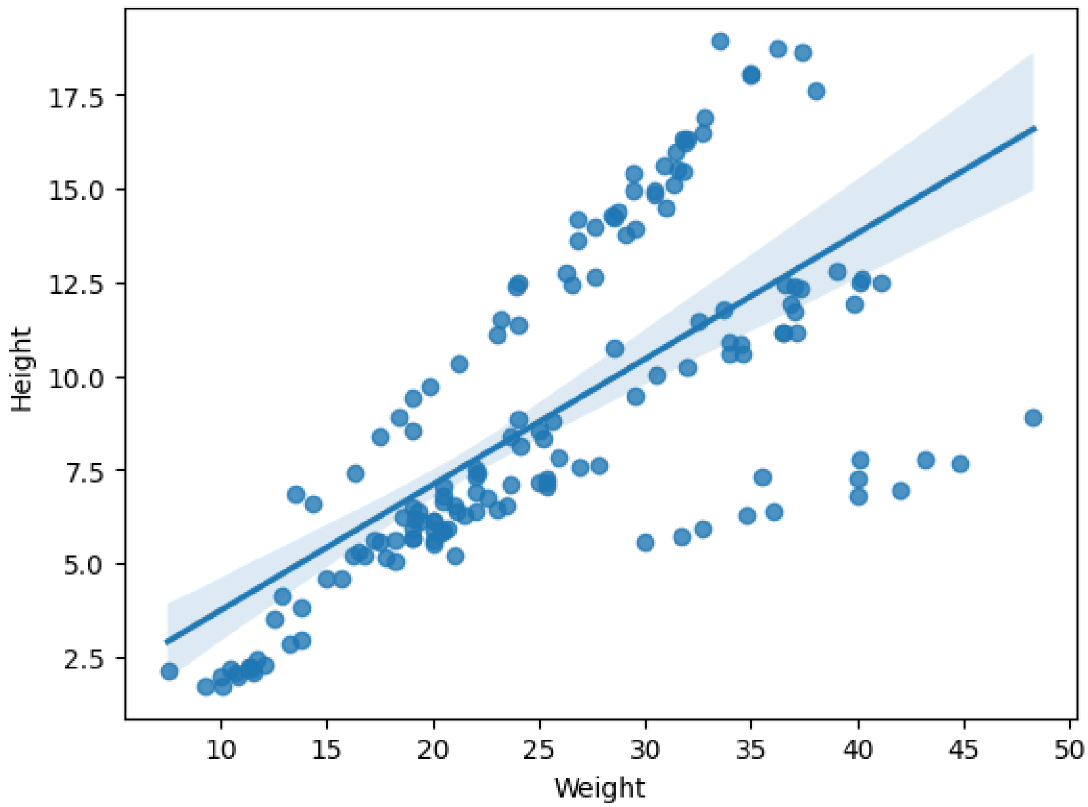
[87]:
```
sns.regplot(x="Weight", y="Length", data=df)
```

[87]: `<Axes: xlabel='Weight', ylabel='Length'>`



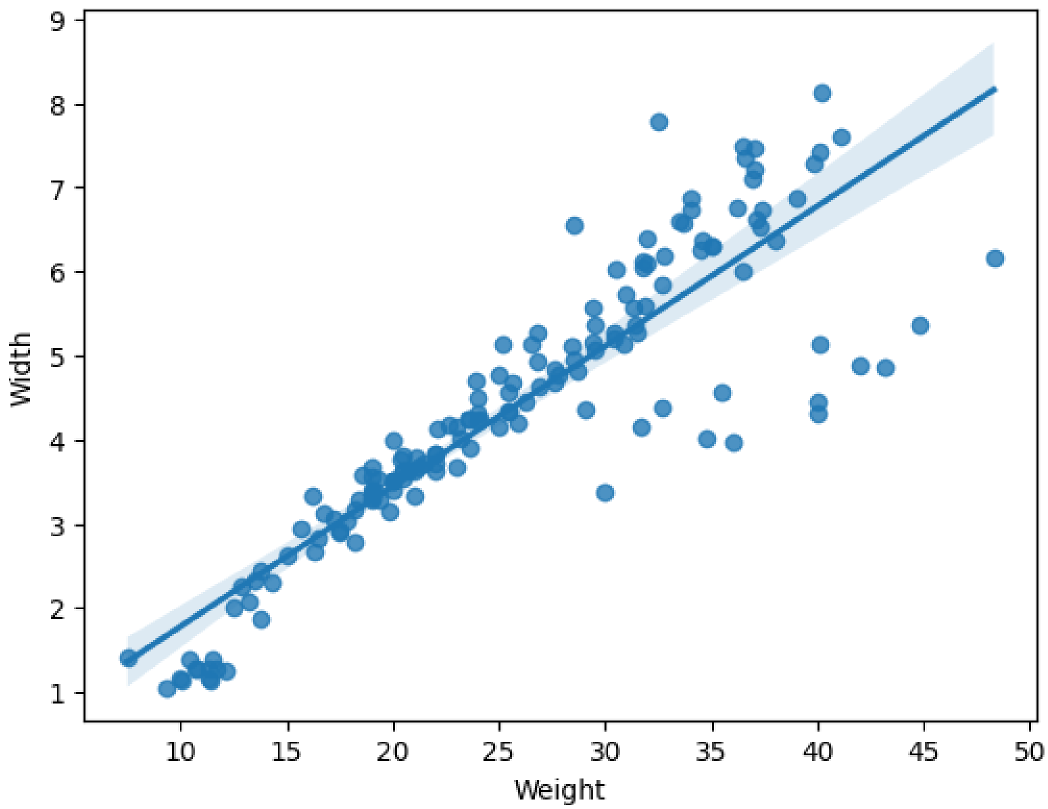
[88]:
```
sns.regplot(x="Weight", y="Height", data=df)
```

[88]: <Axes: xlabel='Weight', ylabel='Height'>



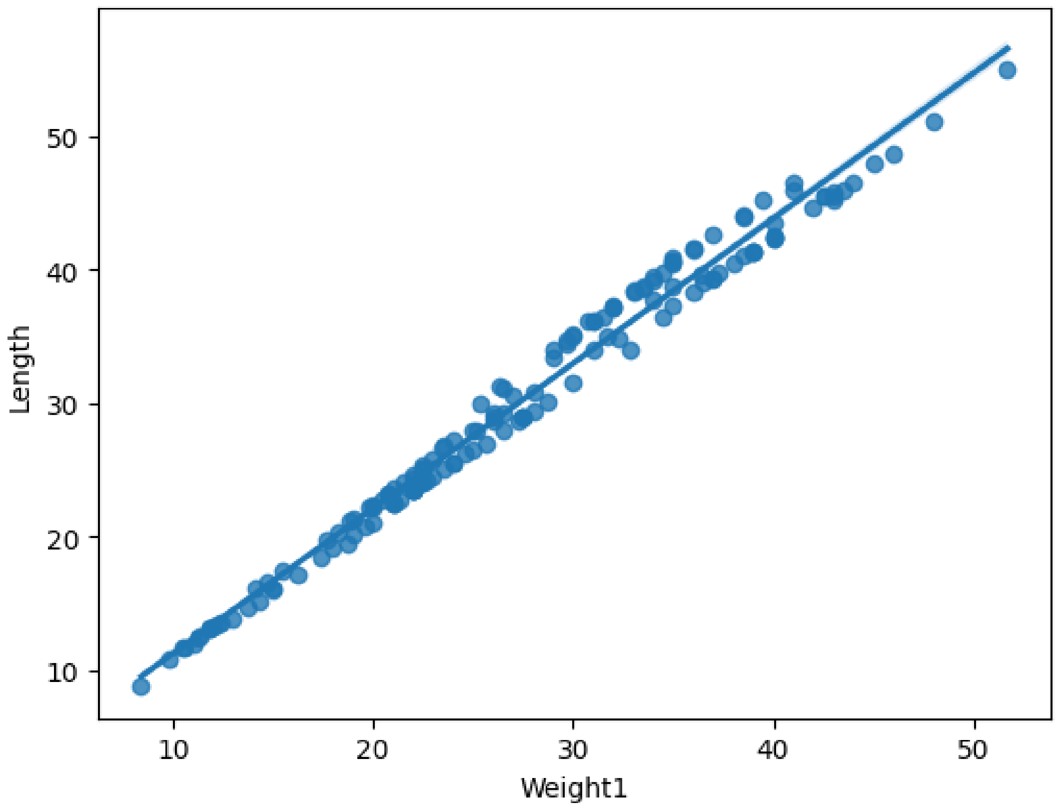
[89]:
```
sns.regplot(x="Weight", y="Width", data=df)
```

[89]: <Axes: xlabel='Weight', ylabel='Width'>



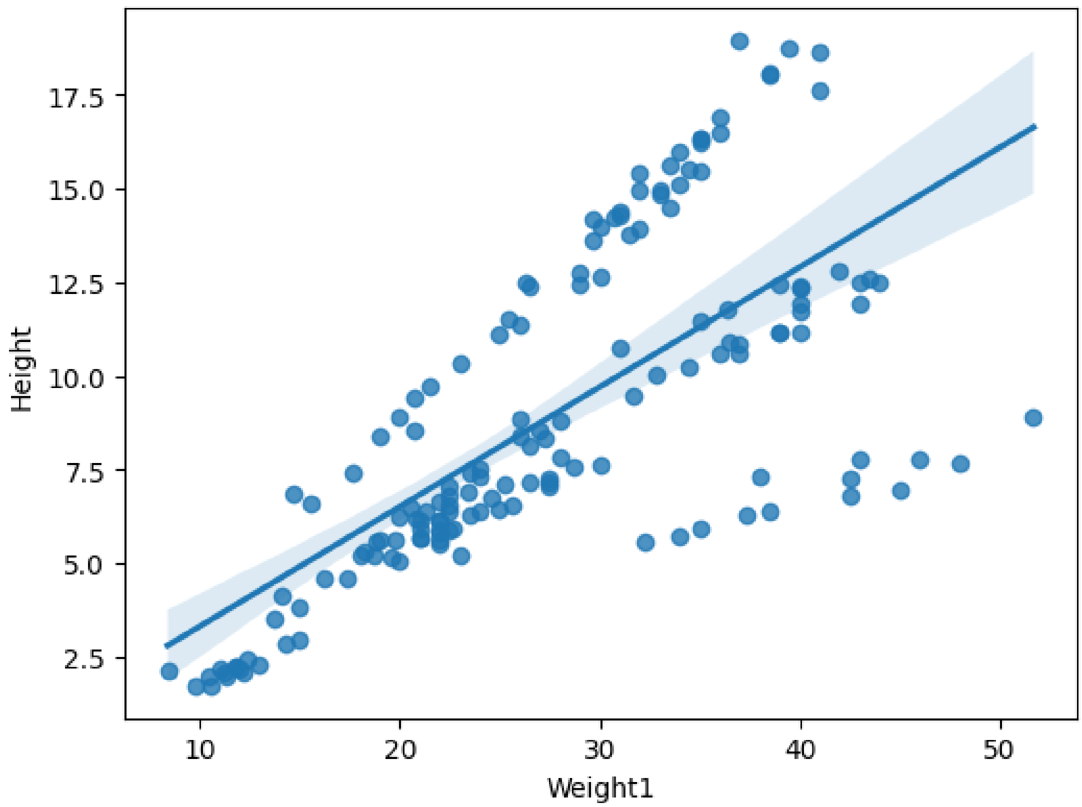
[90]:
```
sns.regplot(x="Weight1", y="Length", data=df)
```

[90]: <Axes: xlabel='Weight1', ylabel='Length'>



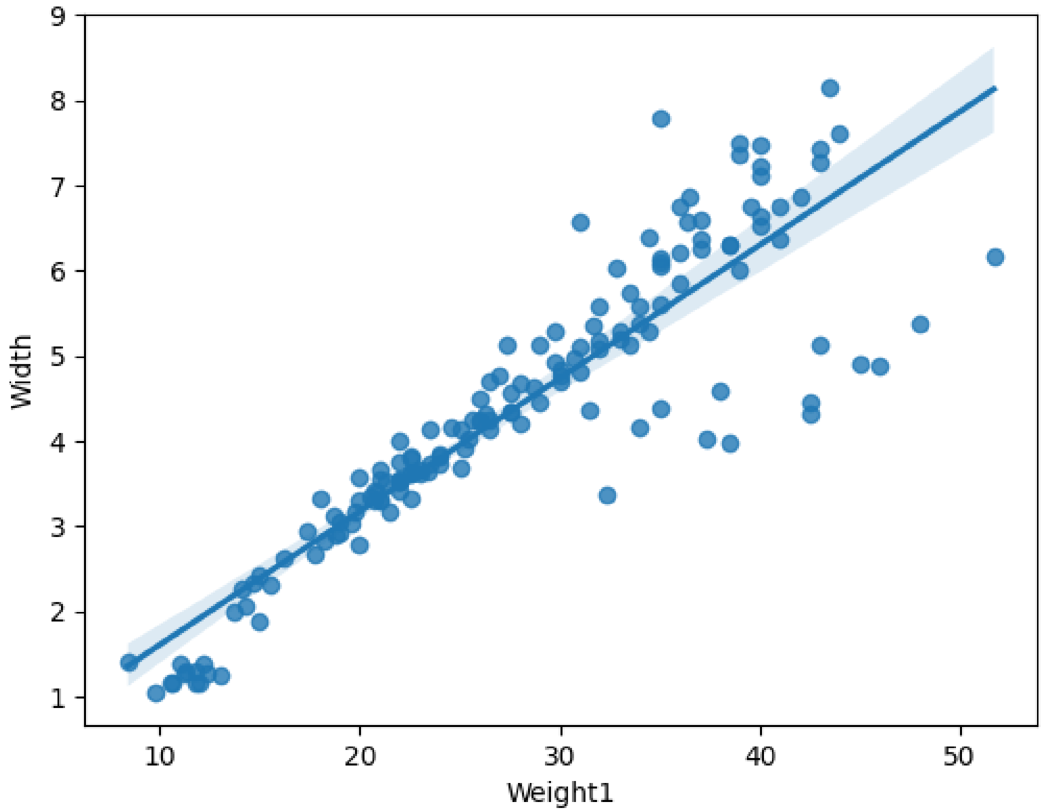
[91]:
```
sns.regplot(x="Weight1", y="Height", data=df)
```

[91]: <Axes: xlabel='Weight1', ylabel='Height'>



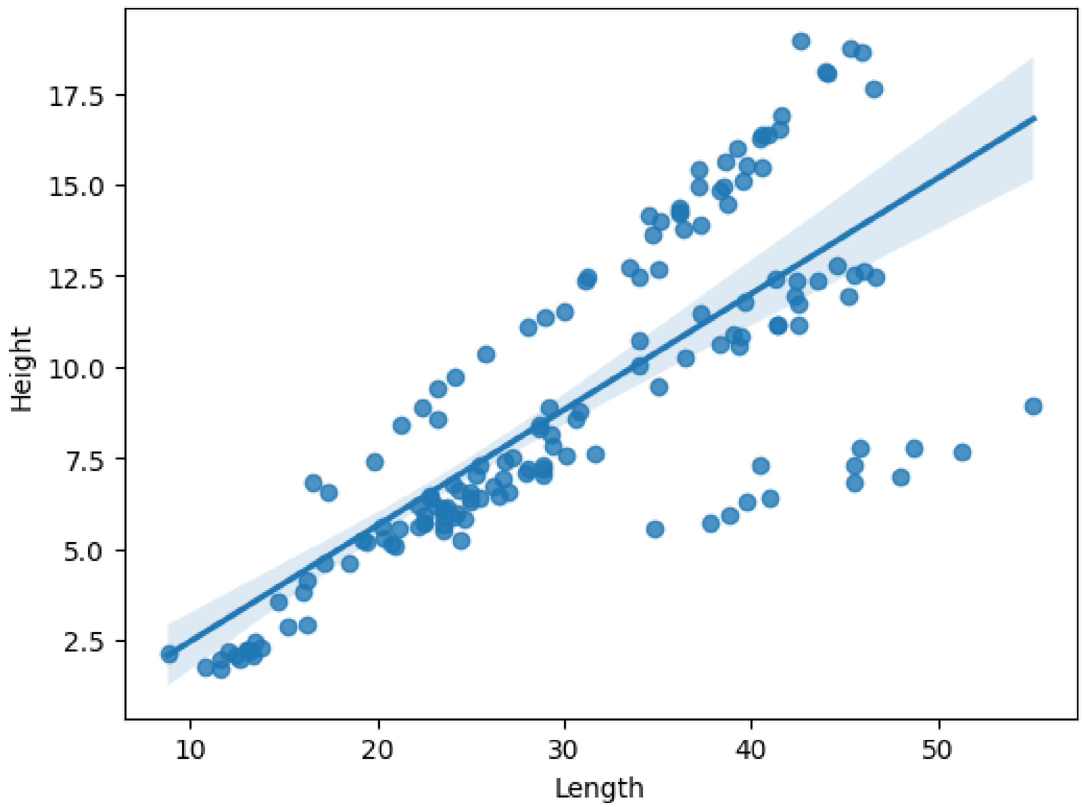
[92]:
```
sns.regplot(x="Weight1", y="Width", data=df)
```

[92]: <Axes: xlabel='Weight1', ylabel='Width'>



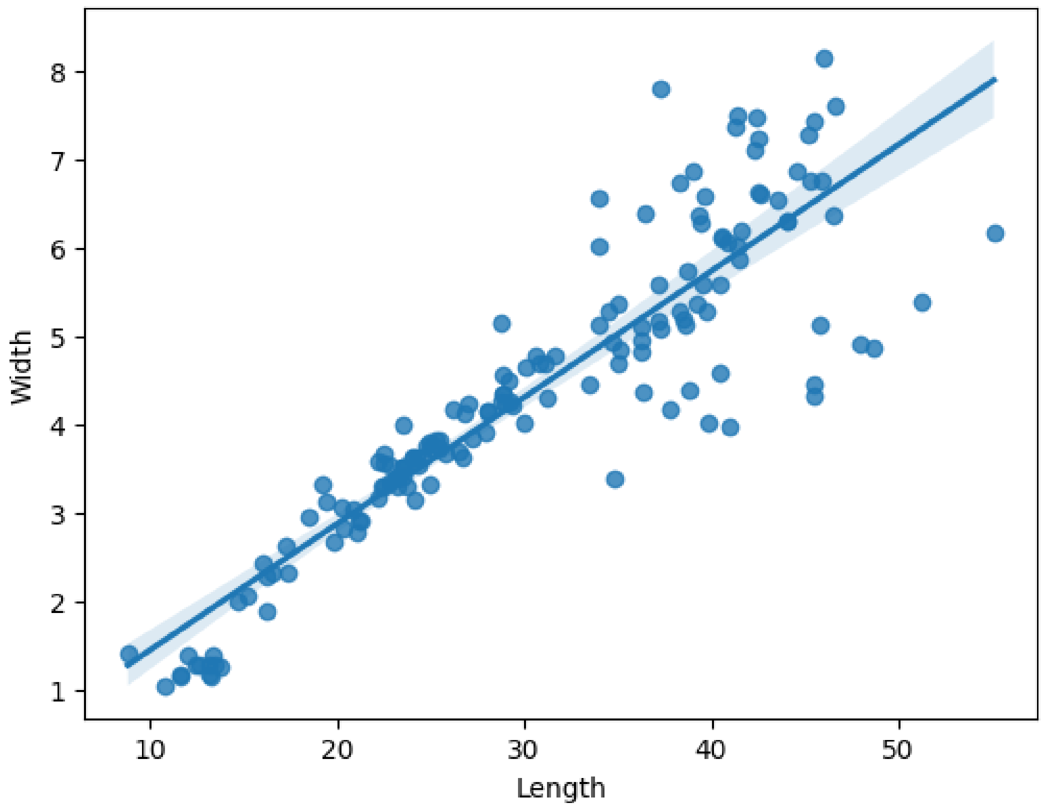
[93]:
```
sns.regplot(x="Length", y="Height", data=df)
```

[93]: <Axes: xlabel='Length', ylabel='Height'>



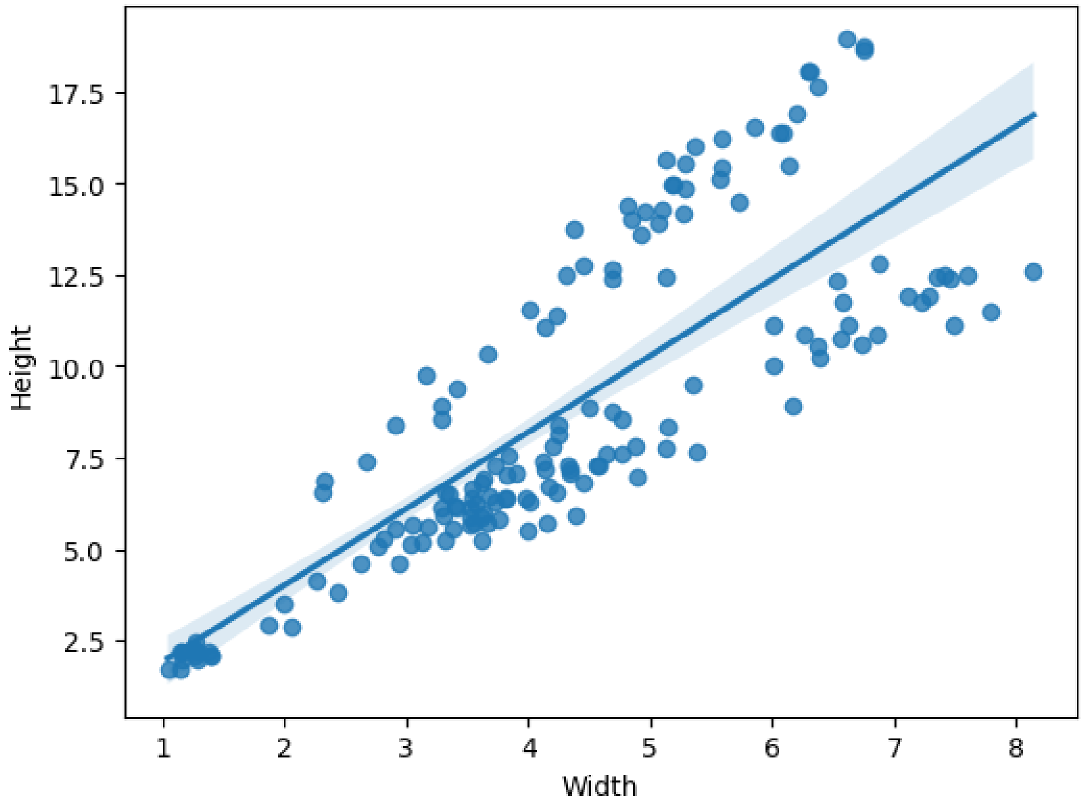
[94]:
```
sns.regplot(x="Length", y="Width", data=df)
```

[94]: <Axes: xlabel='Length', ylabel='Width'>



[95]:
```
sns.regplot(x="Width", y="Height", data=df)
```

[95]: <Axes: xlabel='Width', ylabel='Height'>



From the above plots we can finalize that Weight and Weight1 are highly correlated.

Highly correlated predictors can lead to collinearity issues and this can greatly affect the model performance.So it is better to remove one of them.

According to the given definition Weight is the weight of the bag and Weight1 is the weight, the bag can carry after expansion.Logically a cost of the bag is highly dependant on the number of items the bag can carry. If a bag can carry many items then the cost should be high and vice versa.

So we can drop weight and include only weight1.

[96]:
```
df.drop('Weight', axis=1, inplace=True)
```

[97]:
```
df.head()
```

[97]:

	Cost	Weight1	Length	Height	Width
0	242.0	25.4	30.0	11.5200	4.0200
1	290.0	26.3	31.2	12.4800	4.3056
2	340.0	26.5	31.1	12.3778	4.6961
3	363.0	29.0	33.5	12.7300	4.4555

```
4  430.0      29.0     34.0  12.4440  5.1340
```

[98]:
```
print(df.shape)
```

```
(155, 5)
```

---

[99]:
```
# Split dependant and independant variables
X = df.iloc[:, 1:].values
Y = df.iloc[:, 0].values
```

5 Normalizing the feature variables

[100]:
```
from sklearn.preprocessing import StandardScaler
sc=StandardScaler()
X=sc.fit_transform(X)
```

Now that the data is ready we can use it to train the model

6 Model Building

6.1 Multi linear regression model from sklearn (least square errors)

[101]:
```
from sklearn.model_selection import train_test_split

X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=1/5,␣
↪random_state=0)
```

[102]:
```
from sklearn.linear_model import LinearRegression

model = LinearRegression()

model.fit(X_train, Y_train)
```

[102]:
```
LinearRegression()
```

[103]:
```
Y_predicted = model.predict(X_test)
```

[104]:
```
# Compare predicted result with actual value
np.set_printoptions(precision = 2)
result = np.concatenate((Y_predicted.reshape(len(Y_predicted), 1), Y_test.
↪reshape(len(Y_test), 1)), 1)
result
```

```
[104]: array([[ 698.87,  720.  ],
       [ 216.64,  110.  ],
       [-143.97,   12.2 ],
       [ 778.08,  840.  ],
       [ 670.57,  700.  ],
       [ 454.1 ,  390.  ],
       [ 193.28,  145.  ],
       [ 392.56,  250.  ],
       [ 325.63,  270.  ],
       [ 840.52,  820.  ],
       [ 201.04,  135.  ],
       [ 201.82,  120.  ],
       [ 583.7 ,  500.  ],
       [ 485.78,  390.  ],
       [ 663.71,  556.  ],
       [ 155.37,    0.  ],
       [ 924.52,  975.  ],
       [ -64.06,   19.7 ],
       [ 411.91,  300.  ],
       [ 947.82, 1000.  ],
       [ 298.34,  188.  ],
       [ 501.24,  450.  ],
       [ 635.62,  567.  ],
       [-197.12,    8.7 ],
       [  72.49,   78.  ],
       [ 451.72,  300.  ],
       [-227.51,    6.7 ],
       [  45.72,   55.  ],
       [ 246.85,  170.  ],
       [ 419.79,  300.  ],
       [ 588.71,  700.  ]])
```

```
[105]: print('Coefficient = ', model.coef_)
       print('Intercept = ', model.intercept_)
```

```
Coefficient =  [ 533.16 -433.38  137.65   94.68]
Intercept =  374.0732059160682
```

Define a function to calculate the metrics

```
[106]: from sklearn.metrics import mean_squared_error, r2_score
       import math
       def calculateModelMetrics(Y_actual,Y_predicted) :
           mse = mean_squared_error(Y_actual, Y_predicted)
           rmse = math.sqrt(mse)
           print("Mean squared error = ", mse)
           print("Root Mean squared error = ", rmse)
           print('Variance score = ', r2_score(Y_actual, Y_predicted))
```

6.1.1 Model performance metrics

[107]:
```
calculateModelMetrics(Y_test, Y_predicted)
```

```
Mean squared error =  10692.861023880809
Root Mean squared error =  103.40629102661408
Variance score =  0.8816970799519525
```

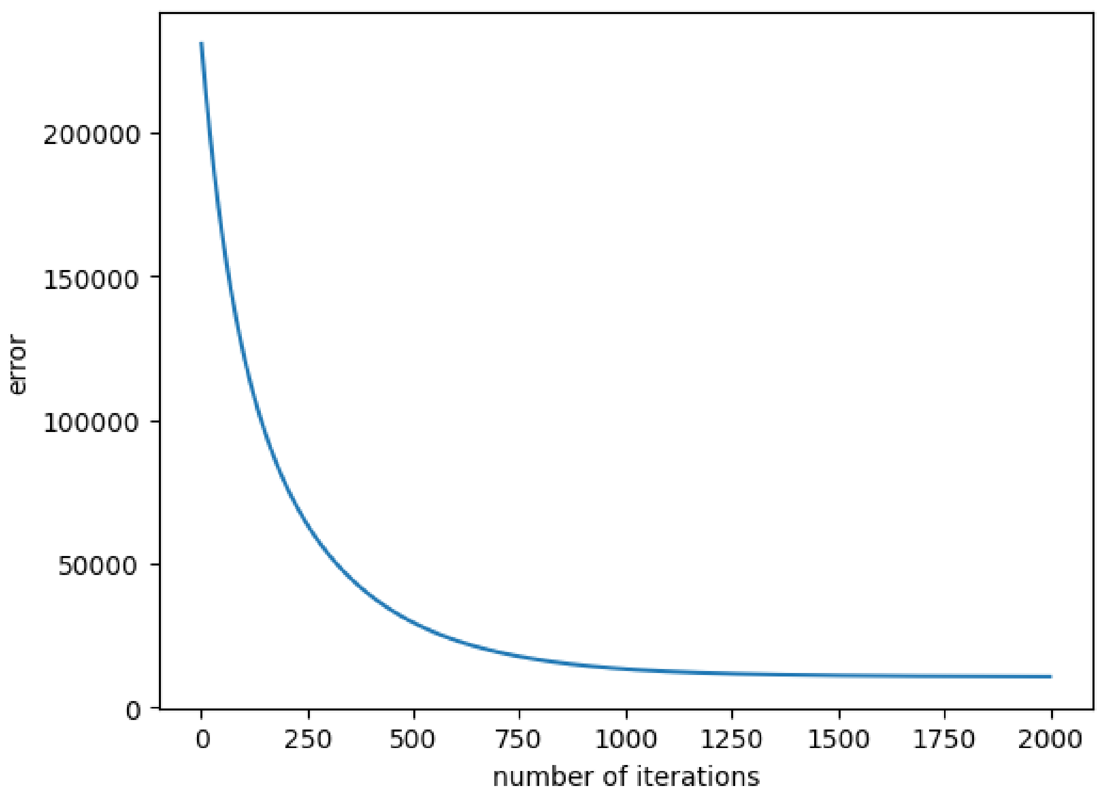
6.2 Gradient descent algorithm

Lets define the needed functions

[108]:
```
# Function to predict y
def predicted_y(coefficients,x,intercept):
    y_predicted=[]
    for i in range(len(x)):
        y_predicted.append(coefficients@x[i]+intercept)
    return np.array(y_predicted)


# error function
def error(y,y_predicted):
    n=len(y)
    s=0.0
    for i in range(n):
        s+=(y[i]-y_predicted[i])**2
    return (1/n)*s

#derivative of error w.r.t coefficients
def dldw(x,y,y_predicted):
    s=0.0
    n=len(y)
    for i in range(n):
        s+=-x[i]*(y[i]-y_predicted[i])
    return (2/n)*s


# derivative of error w.r.t interceptor
def dldb(y,y_predicted):
    n=len(y)
    s=0.0
    for i in range(len(y)):
        s+=-(y[i]-y_predicted[i])
    return (2/n) * s

# gradient function
def gradient_descent(x,y):
```

```
    coefficient_vector=np.random.randn(x.shape[1])
    intercept=0
    epoch = 2000
    n = len(x)
    linear_loss=[]
    learning_rate = 0.001

    for i in range(epoch):
        y_predicted = predicted_y(coefficient_vector,x,intercept)
        coefficient_vector = coefficient_vector - learning_rate␣
↪*dldw(x,y,y_predicted)
        intercept = intercept - learning_rate * dldb(y,y_predicted)
        linear_loss.append(error(y,y_predicted))

    plt.plot(np.arange(1,epoch),linear_loss[1:])
    plt.xlabel("number of iterations")
    plt.ylabel("error")

    return coefficient_vector,intercept
```

[109]:
```
coefficients,interceptor=gradient_descent(X,Y)
```



[110]:
```
print("Coefficients:",coefficients)
print("Interceptor:",interceptor)
```

```
Coefficients: [ 72.1   65.45  70.75 103.43]
Interceptor: 362.83163056596885
```

[111]:
```
# Predict function
def predict(inp):
    Y_predicted=[]
    for i in range(len(inp)):
        Y_predicted.append(coefficients@inp[i]+interceptor)
    return np.array(Y_predicted)
```

[112]:
```
Y_predicted=predict(X)
```

[113]:
```
# Compare predicted result with actual value
df_pred=pd.DataFrame()
df_pred["y_actual"]=Y
df_pred["y_predicted"]=np.round(Y_predicted,1)
df_pred
```

[113]:

	y_actual	y_predicted
0	242.0	364.8
1	290.0	412.7
2	340.0	436.3
3	363.0	461.0
4	430.0	501.8
..	…	…
150	12.2	-157.3
151	13.4	-157.4
152	12.2	-154.3
153	19.7	-75.3
154	19.9	-74.5

[155 rows x 2 columns]

6.2.1 GD performance metrics

[114]:
```
calculateModelMetrics(Y, Y_predicted)
```

```
Mean squared error =  10691.285852747367
Root Mean squared error =  103.39867432780446
Variance score =  0.889940945201078
```

6.3 Stochastic gradient design

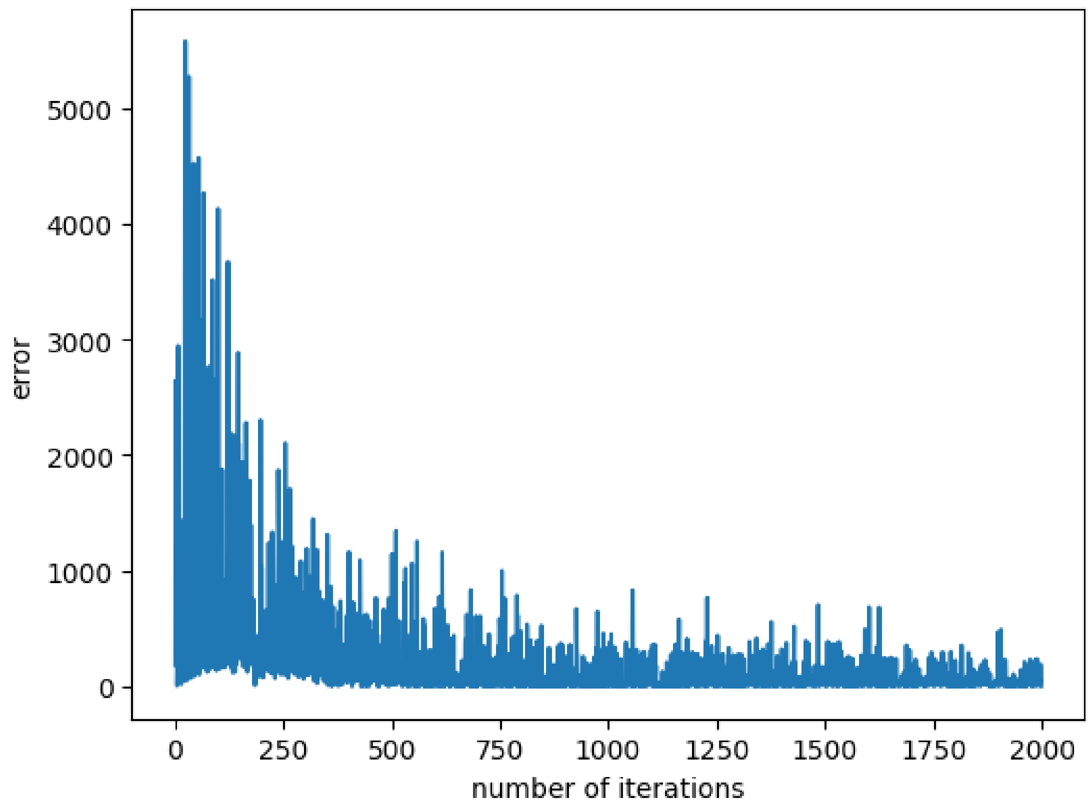
Lets define the needed functions

[115]:

```
# Function to predict the value of y at that sample point
def predicted_y(coefficient,x,intercept):
    return coefficient@x+intercept


# Error function to find the error at one sample point
def loss(y,y_predicted):
    n=X.shape[0]
    s=(y-y_predicted)**2
    return (1/n)*s

# Derivative of error w.r.t coefficient
def dldw(x,y,y_predicted):
    n=X.shape[0]
    s=-x*(y-y_predicted)
    return (2/n)*s


# Derivative of error w.r.t intercept
def dldb(y,y_predicted):
    n=X.shape[0]
    s=-(y-y_predicted)
    return (2/n) * s


# stochastic gradient function
def stochastic_gradient_descent(x,y):
    coefficient_vector=np.random.randn(x.shape[1])
    intercept=0
    epoch = 2000
    n = len(x)
    linear_loss=[]
    learning_rate = 0.001

    for i in range(epoch):

        for j in range(n):
            random_index = np.random.randint(0,n-1)

            # Find random x and y
            x_sample = x[random_index]
            y_sample = y[random_index]
            y_predicted = predicted_y(coefficient_vector,x_sample,intercept)

            coefficient_vector = coefficient_vector - learning_rate␣
↪*dldw(x_sample,y_sample,y_predicted)
            intercept = intercept - learning_rate * dldb(y_sample,y_predicted)
```

```
        linear_loss.append(loss(y_sample,y_predicted))


    plt.plot(np.arange(1,epoch),linear_loss[1:])
    plt.xlabel("number of iterations")
    plt.ylabel("error")

    return coefficient_vector,intercept
```

[116]:
```
coefficients,interceptor=stochastic_gradient_descent(X,Y)
```



[117]:
```
print("Coefficients:",coefficients)
print("Interceptor:", interceptor)
```

```
Coefficients: [ 72.59  64.78  70.79 105.13]
Interceptor: 362.08414790181786
```

[118]:
```
Y_predicted=predict(X)
```

[119]:
```
# Compare predicted result with actual value
df_pred=pd.DataFrame()
df_pred["y_actual"]=Y
df_pred["y_predicted"]=np.round(Y_predicted,1)
df_pred
```

[119]:
```
     y_actual  y_predicted
0       242.0        363.7
1       290.0        411.8
2       340.0        435.8
3       363.0        460.3
4       430.0        501.7
..        …            …
150      12.2       -160.9
151      13.4       -161.0
152      12.2       -158.0
153      19.7        -78.2
154      19.9        -77.6

[155 rows x 2 columns]
```

6.3.1 SGD performance metrics

[120]:
```
calculateModelMetrics(Y, Y_predicted)
```

```
Mean squared error =  10685.437282207555
Root Mean squared error =  103.37038880747018
Variance score =  0.890001152004488
```

6.4 Mini batch gradient design

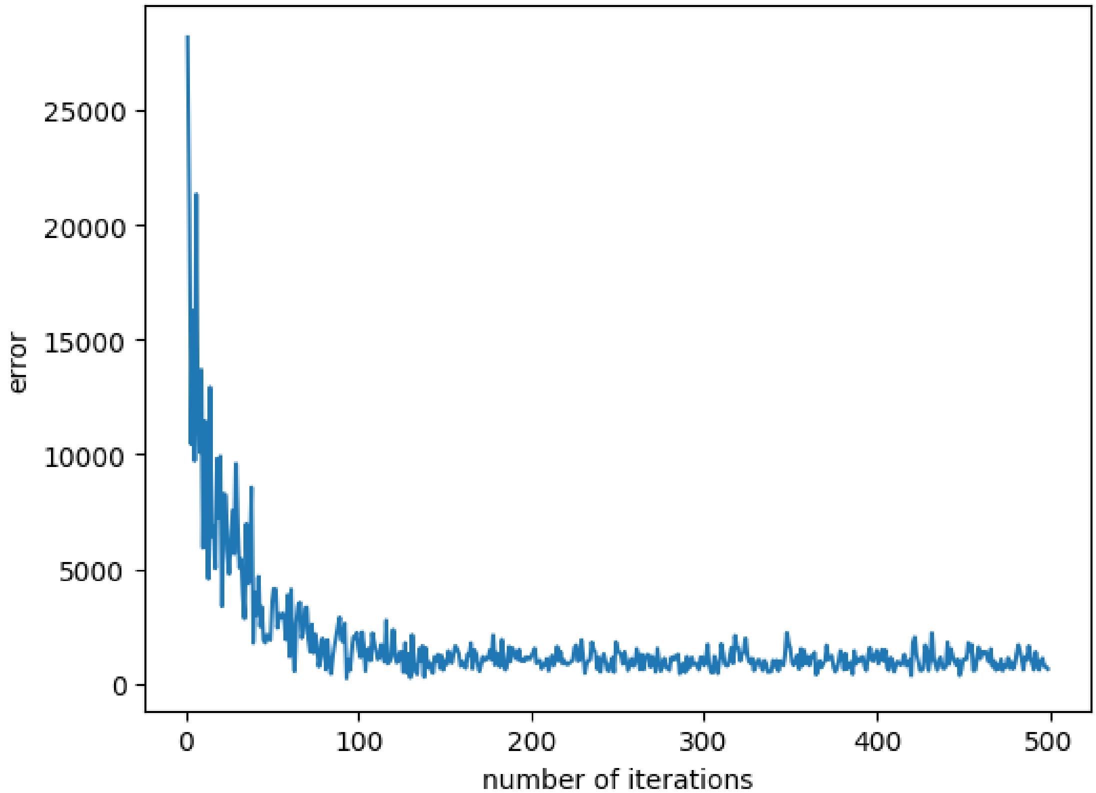
Lets define the needed functions

[121]:
```
# Function to predict the target variable
def predicted_y(coefficients,x,intercept):
    y_predicted=[]
    for i in range(len(x)):
        y_predicted.append(coefficients@x[i]+intercept)
    return np.array(y_predicted)


# Error function
def error(y,y_predicted):
    n=len(y)
    s=0
    for i in range(n):
        s+=(y[i]-y_predicted[i])**2
```

```
    return (1/X.shape[0])*s

#derivative of error w.r.t coefficient
def dldw(x,y,y_predicted):
    s=0
    n=len(y)
    for i in range(n):
        s+=-x[i]*(y[i]-y_predicted[i])
    return (2/X.shape[0])*s


# derivative of error w.r.t intercept
def dldb(y,y_predicted):
    n=len(y)
    s=0
    for i in range(len(y)):
        s+=-(y[i]-y_predicted[i])
    return (2/X.shape[0]) * s

# Mini batch gradient function
def mini_batch_gradient_descent(x,y):
    coefficient_vector=np.random.randn(x.shape[1])
    intercept=0
    epoch = 500
    n = len(x)
    linear_loss=[]
    learning_rate = 0.01
    n_iter=[]
    count=1
    batch_size=15
    for i in range(epoch):

        for j in range(int(n/batch_size)):
            random_index=np.random.choice(x.shape[0],batch_size,replace=False)
            x_sample = x[random_index]
            y_sample = y[random_index]
            y_predicted = predicted_y(coefficient_vector,x_sample,intercept)

            coefficient_vector = coefficient_vector - learning_rate
↪*dldw(x_sample,y_sample,y_predicted)
            intercept = intercept - learning_rate * dldb(y_sample,y_predicted)

        linear_loss.append(error(y_sample,y_predicted))


    plt.plot(np.arange(1,epoch),linear_loss[1:])
    plt.xlabel("number of iterations")
```

```
    plt.ylabel("error")

    return coefficient_vector,intercept
```

[122]:
```
coefficients,interceptor=mini_batch_gradient_descent(X,Y)
```



[123]:
```
print("Coefficients:",coefficients)
print("Interceptor:", interceptor)
```

```
Coefficients: [ 70.21  51.4   66.43 121.24]
Interceptor: 370.80052230694764
```

[124]:
```
Y_predicted=predict(X)
```

[125]:
```
# Compare predicted result with actual value
df_pred=pd.DataFrame()
df_pred["y_actual"]=Y
df_pred["y_predicted"]=np.round(Y_predicted,1)
df_pred
```

[125]:
```
      y_actual  y_predicted
0        242.0        367.6
1        290.0        415.7
2        340.0        443.7
3        363.0        461.8
4        430.0        509.4
..         …            …
150       12.2       -148.4
151       13.4       -150.3
152       12.2       -147.7
153       19.7        -62.8
154       19.9        -65.5

[155 rows x 2 columns]
```

6.4.1 Mini batch gradient descent model performance metrics

[126]:
```
calculateModelMetrics(Y, Y_predicted)
```

```
Mean squared error =  10446.21894279772
Root Mean squared error =  102.20674607283865
Variance score =  0.8924637317810122
```