#### lab8

#### September 10, 2020

```
[67]: import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.metrics import mean_squared_error, r2_score
import seaborn as sns
from sklearn.linear_model import LinearRegression
```

#### 1 data description

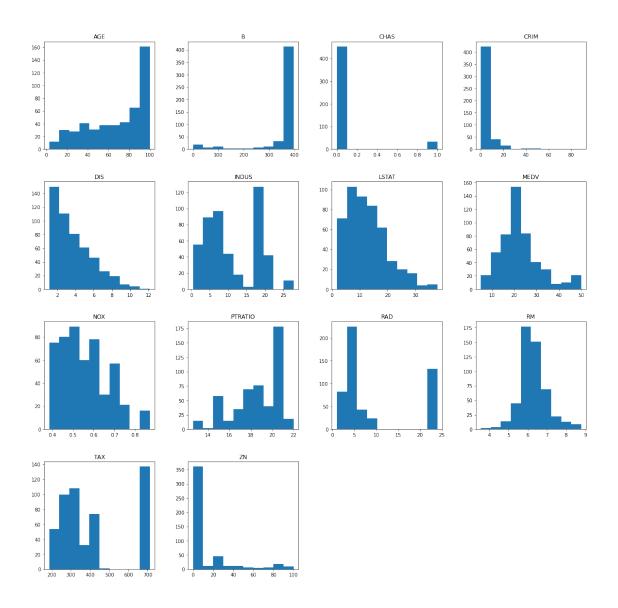
```
[68]: | housing = pd.read_csv(r'D:\msc3\machine learning\lab8\housing.csv')
      print(housing.head())
            CRIM
                        INDUS
                                CHAS
                                        NOX
                                                      AGE
                                                                    RAD
                                                                         TAX
                                                                              PTRATIO \
                    ZN
                                                 RM
                                                              DIS
       0.00632
                  18.0
                         2.31
                                 0.0
                                     0.538
                                             6.575
                                                     65.2
                                                           4.0900
                                                                         296
                                                                                  15.3
                                                                      1
        0.02731
                         7.07
                   0.0
                                 0.0
                                     0.469
                                             6.421
                                                     78.9
                                                           4.9671
                                                                         242
                                                                                 17.8
     2 0.02729
                         7.07
                                 0.0
                                     0.469
                                             7.185
                                                     61.1
                                                           4.9671
                                                                         242
                                                                                 17.8
                   0.0
     3 0.03237
                   0.0
                         2.18
                                 0.0 0.458
                                             6.998
                                                     45.8
                                                           6.0622
                                                                      3
                                                                         222
                                                                                 18.7
     4 0.06905
                   0.0
                         2.18
                                 0.0 0.458
                                             7.147
                                                     54.2 6.0622
                                                                         222
                                                                                 18.7
               LSTAT
                        MEDV
              В
        396.90
                  4.98
                        24.0
        396.90
                  9.14
                        21.6
                        34.7
        392.83
                  4.03
                  2.94
                        33.4
        394.63
        396.90
                   NaN
                        36.2
[69]: housing.head()
[69]:
            CRIM
                     ZN
                         INDUS
                                CHAS
                                         NOX
                                                 RM
                                                       AGE
                                                               DIS
                                                                    RAD
                                                                          TAX
                                                                               PTRATIO
         0.00632
                          2.31
                                      0.538
                                              6.575
                                                     65.2
                                                                          296
                                                                                  15.3
                   18.0
                                 0.0
                                                            4.0900
                                                                       1
         0.02731
                   0.0
                          7.07
                                 0.0
                                      0.469
                                              6.421
                                                     78.9
                                                            4.9671
                                                                       2
                                                                         242
                                                                                  17.8
      1
      2
         0.02729
                   0.0
                          7.07
                                 0.0
                                      0.469
                                              7.185
                                                     61.1
                                                            4.9671
                                                                       2
                                                                          242
                                                                                  17.8
      3 0.03237
                   0.0
                          2.18
                                      0.458
                                              6.998
                                                     45.8
                                                            6.0622
                                                                          222
                                                                                  18.7
                                 0.0
                                                                       3
      4 0.06905
                   0.0
                          2.18
                                 0.0
                                      0.458
                                              7.147
                                                     54.2 6.0622
                                                                       3
                                                                         222
                                                                                  18.7
```

```
B LSTAT
                         MEDV
         396.90
                  4.98
                         24.0
         396.90
                  9.14
                         21.6
      2 392.83
                  4.03
                         34.7
      3 394.63
                  2.94
                         33.4
      4 396.90
                   {\tt NaN}
                         36.2
[70]: print("Number of data:"+str(len(housing.index)))
     Number of data:506
[71]: housing.info()
     <class 'pandas.core.frame.DataFrame'>
     RangeIndex: 506 entries, 0 to 505
     Data columns (total 14 columns):
          Column
                    Non-Null Count Dtype
      0
          CRIM
                    486 non-null
                                     float64
      1
                    486 non-null
                                     float64
          ZN
      2
          INDUS
                    486 non-null
                                     float64
                    486 non-null
      3
          CHAS
                                     float64
      4
          NOX
                    506 non-null
                                     float64
      5
          RM
                    506 non-null
                                     float64
                    486 non-null
      6
          AGE
                                     float64
      7
          DIS
                    506 non-null
                                     float64
      8
          RAD
                    506 non-null
                                     int64
      9
                    506 non-null
          TAX
                                     int64
      10
          PTRATIO
                    506 non-null
                                     float64
      11
                    506 non-null
                                     float64
                    486 non-null
      12
          LSTAT
                                     float64
      13 MEDV
                    506 non-null
                                     float64
     dtypes: float64(12), int64(2)
     memory usage: 55.5 KB
[72]: housing.isnull().any()
[72]: CRIM
                  True
      ZN
                  True
      INDUS
                  True
      CHAS
                  True
      NOX
                 False
      RM
                 False
      AGE
                  True
      DIS
                 False
      RAD
                 False
```

TAX False
PTRATIO False
B False
LSTAT True
MEDV False
dtype: bool

[73]: housing.hist(bins=10,figsize=(20,20),grid=False)

```
[73]: array([[<matplotlib.axes. subplots.AxesSubplot object at 0x0000019A71DC6C08>,
              <matplotlib.axes. subplots.AxesSubplot object at 0x0000019A6FE23608>,
              <matplotlib.axes._subplots.AxesSubplot object at 0x0000019A6FE39408>,
              <matplotlib.axes._subplots.AxesSubplot object at 0x0000019A704FC548>],
             [<matplotlib.axes._subplots.AxesSubplot object at 0x0000019A7052E4C8>,
              <matplotlib.axes. subplots.AxesSubplot object at 0x0000019A6FD09E48>,
              <matplotlib.axes._subplots.AxesSubplot object at 0x0000019A6FFEECC8>,
              <matplotlib.axes._subplots.AxesSubplot object at 0x0000019A6FE64788>],
             [<matplotlib.axes. subplots.AxesSubplot object at 0x0000019A6FE64D88>,
              <matplotlib.axes._subplots.AxesSubplot object at 0x0000019A6D543808>,
              <matplotlib.axes. subplots.AxesSubplot object at 0x0000019A6D550588>,
              <matplotlib.axes._subplots.AxesSubplot object at 0x0000019A7177AE08>],
             [<matplotlib.axes._subplots.AxesSubplot object at 0x0000019A72324C88>,
              <matplotlib.axes._subplots.AxesSubplot object at 0x0000019A71A83B48>,
              <matplotlib.axes._subplots.AxesSubplot object at 0x0000019A6FCA0B48>,
              <matplotlib.axes._subplots.AxesSubplot object at 0x0000019A6FE54948>]],
            dtype=object)
```



## 2 data preprocessing

## [74]: housing.isnull().sum()

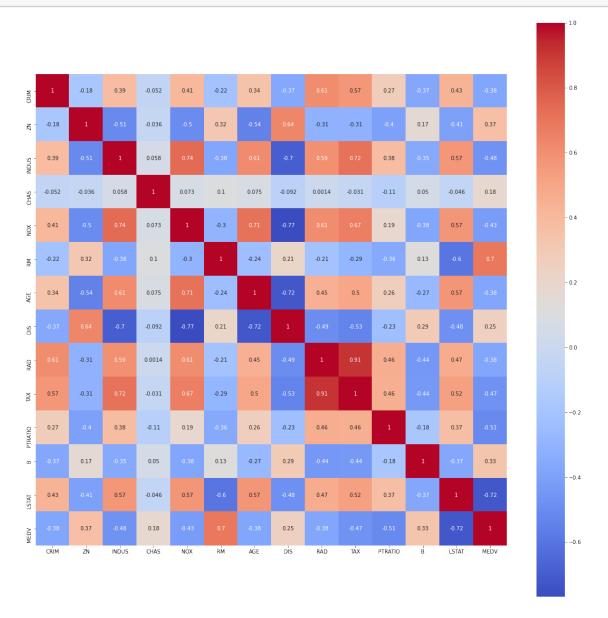
[74]:	CRIM	20
	ZN	20
	INDUS	20
	CHAS	20
	NOX	0
	RM	0
	AGE	20
	DIS	0

```
TAX
                 0
     PTRATIO
                 0
                 0
     LSTAT
                20
     MEDV
                 0
     dtype: int64
[75]: housing.fillna(housing.mean(), inplace=True)
[76]: housing.head()
                       INDUS CHAS
                                              RM
                                                   AGE
                                                                          PTRATIO \
[76]:
           CRIM
                   ZN
                                      NOX
                                                           DIS
                                                               RAD
                                                                     TAX
     0 0.00632 18.0
                        2.31
                               0.0 0.538
                                           6.575
                                                  65.2 4.0900
                                                                     296
                                                                             15.3
                                                                  1
     1 0.02731
                  0.0
                        7.07
                               0.0
                                    0.469
                                           6.421
                                                  78.9
                                                       4.9671
                                                                  2
                                                                     242
                                                                             17.8
     2 0.02729
                  0.0
                        7.07
                               0.0 0.469
                                           7.185
                                                  61.1 4.9671
                                                                  2
                                                                     242
                                                                             17.8
                                                  45.8 6.0622
     3 0.03237
                  0.0
                        2.18
                               0.0 0.458
                                           6.998
                                                                  3
                                                                     222
                                                                             18.7
     4 0.06905
                  0.0
                        2.18
                               0.0 0.458
                                           7.147
                                                  54.2 6.0622
                                                                  3
                                                                     222
                                                                             18.7
                    LSTAT
                           MEDV
             В
     0 396.90
                 4.980000 24.0
     1 396.90
                 9.140000 21.6
     2 392.83
                 4.030000
                          34.7
     3 394.63
                 2.940000
                          33.4
     4 396.90 12.715432 36.2
[77]: housing.isnull().sum()
[77]: CRIM
                0
     ZN
                0
     INDUS
                0
     CHAS
                0
     NOX
                0
     RM
                0
     AGE
                0
     DIS
     RAD
                0
     TAX
                0
     PTRATIO
                0
     В
                0
     LSTAT
                0
     MEDV
                0
     dtype: int64
[78]: plt.figure(figsize=(20,20))
     sns.heatmap(housing[housing.columns].corr(), annot=True, square=True,
```

RAD

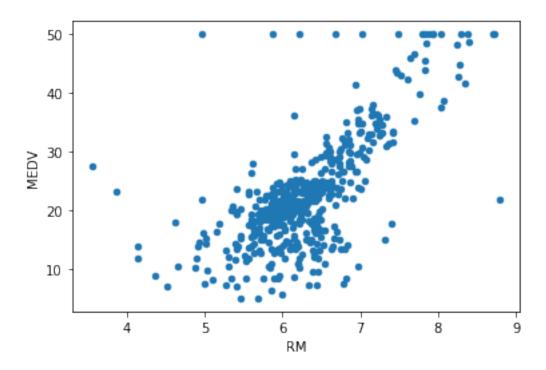
0

plt.show()



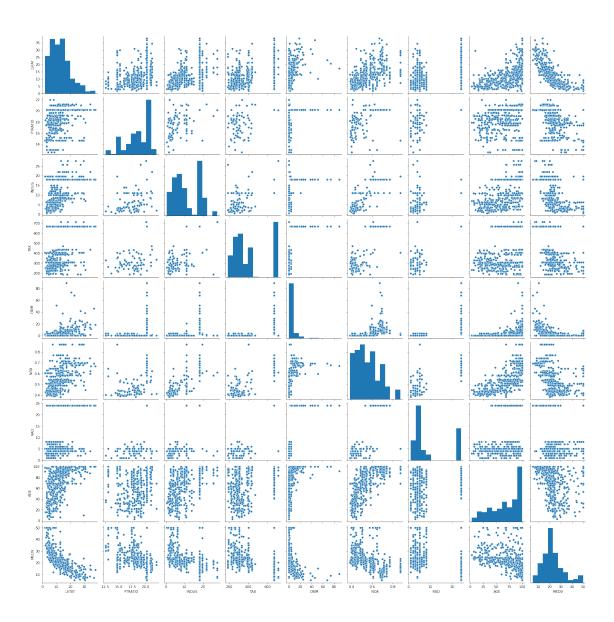
[79]: housing.plot.scatter('RM', 'MEDV')

[79]: <matplotlib.axes.\_subplots.AxesSubplot at 0x19a6fb285c8>



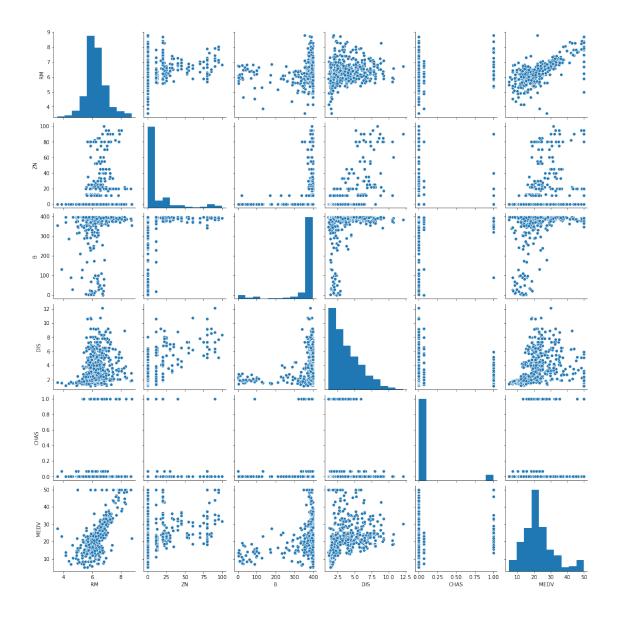
```
[80]: sns.pairplot(housing, vars = ['LSTAT', 'PTRATIO', 'INDUS', 'TAX', 'CRIM', □ → 'NOX', 'RAD', 'AGE', 'MEDV'])
```

[80]: <seaborn.axisgrid.PairGrid at 0x19a701f22c8>



```
[81]: sns.pairplot(housing, vars = ['RM', 'ZN', 'B', 'DIS', 'CHAS', 'MEDV'])
```

[81]: <seaborn.axisgrid.PairGrid at 0x19a754fd108>



```
[82]: X=housing.drop("MEDV",axis=1)
y=housing["MEDV"]
```

[84]: from sklearn.linear\_model import LinearRegression

## 3 linear regression

```
[85]: lm = LinearRegression()
lm.fit(X_train,y_train)

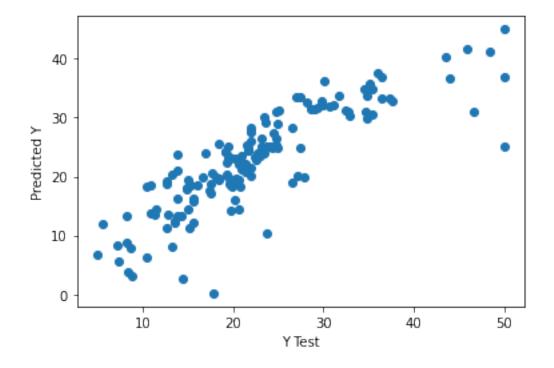
[85]: LinearRegression()

[86]: predictions = lm.predict(X_test)
```

## 4 linear regression results

```
[87]: plt.scatter(y_test,predictions)
   plt.xlabel('Y Test')
   plt.ylabel('Predicted Y')
```

[87]: Text(0, 0.5, 'Predicted Y')



```
[88]: from sklearn import metrics

print('MAE:', metrics.mean_absolute_error(y_test, predictions))

print('MSE:', metrics.mean_squared_error(y_test, predictions))

print('RMSE:', np.sqrt(metrics.mean_squared_error(y_test, predictions)))
```

MAE: 3.519967422579463

MSE: 24.648522189830697 RMSE: 4.964727806217648

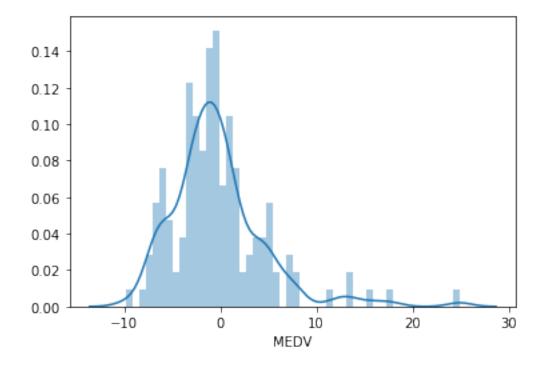
```
[89]: print('\nIntercept : ',lm.intercept_)
```

Intercept : 35.66136284369268

```
[90]: print('Variance score: ',lm.score(X_test, y_test))
```

Variance score: 0.7143713037591916

```
[91]: sns.distplot((y_test-predictions),bins=50);
```



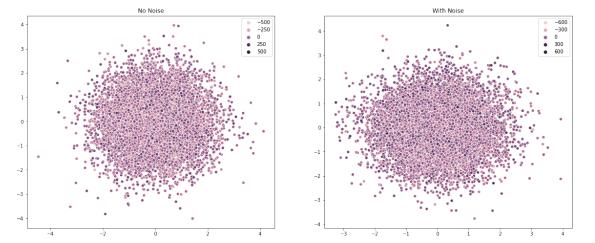
```
[92]: accuracy = lm.score(X_train, y_train)
    print("accuracy = ", accuracy * 100, "%")
    accuracy = lm.score(X_test, y_test)
    print("accuracy = ", accuracy * 100, "%")
```

accuracy = 73.16334858739746 % accuracy = 71.43713037591915 %

```
[93]: coefficients = pd.DataFrame(lm.coef_,X.columns)
coefficients.columns = ['coefficients']
coefficients
```

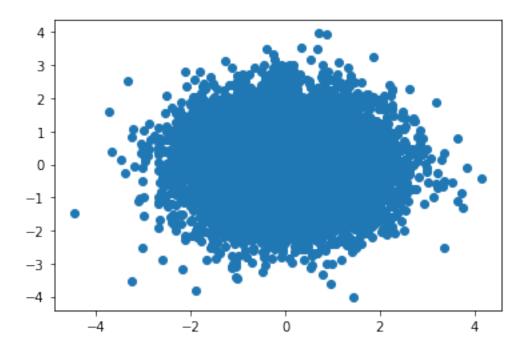
```
[93]:
               coefficients
      CRIM
                  -0.098965
      7.N
                   0.028741
      INDUS
                  -0.077475
      CHAS
                   3.580316
      NOX
                 -13.928879
      RM
                   3.709667
      AGE
                   0.001627
      DIS
                  -1.362978
      RAD
                   0.291508
      TAX
                  -0.009511
      PTRATIO
                  -1.041404
                   0.012463
      LSTAT
                  -0.555141
```

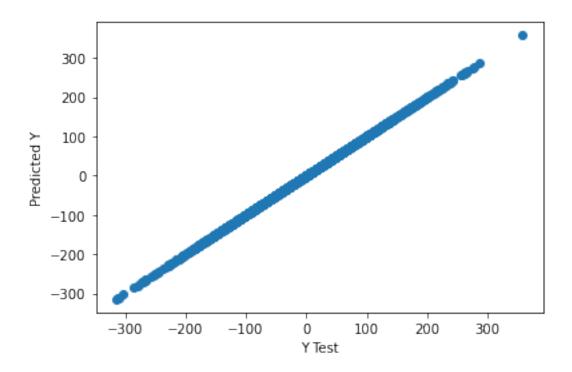
## 5 Synthetic dataset



#### 6 Noiseless data

```
[148]: A,Z = mr(n_samples=10000, n_features=10, n_informative=2, random_state=17)
[96]: df=pd.DataFrame(A)
[96]:
                                    2
      0
          -0.528957 -0.214593 0.074201 0.317663 -0.177406 0.683807 -1.067066
          1
                                                                 0.206286
      2
          -0.569527 0.409039 -1.164657 0.138132 -0.526564 -1.460420 0.275581
      3
          -0.248366 \ -1.762342 \ -0.140821 \ -1.734415 \ 1.964524 \ -0.080384 \ -0.112557
      4
           0.200572 - 1.053115 \ 0.591931 \ 0.708054 - 0.765569 \ 0.424510 \ 0.689100
      9995 0.550839 0.574948 -1.091812 -0.966188 1.443319 1.543396 1.030029
      9996 -0.258148 -0.288071 0.973084 -0.015755 -0.534004 -0.239317 1.546321
      1.177534
      9998 -0.559787 0.182400 -0.019461 0.392112 0.111563 -0.185284 -0.944699
      9999 -0.243293 0.386050 0.079252 0.963318 -0.096055 1.870573 0.215779
                 7
                           8
      0
           0.293464 -0.615365 -0.436058
      1
           0.196781 1.988881 -2.212377
      2
          -2.278527 1.429828 -0.177089
      3
           2.368334 -1.733349 0.354090
          -0.436887 0.289387 0.225677
      9995 0.899440 -1.500649 0.572351
      9996 -1.411464 -0.898505 -3.129165
      9997 0.152798 0.871737 -0.311219
      9998 -0.867091 -0.697704 0.214617
      9999 0.017291 0.347659 -0.732740
      [10000 rows x 10 columns]
[97]: df=pd.DataFrame(A)
      plt.scatter(df[0],df[1])
      plt.show()
```





```
[105]: from sklearn import metrics
    print('MAE:', metrics.mean_absolute_error(z_test, prediction))
    print('MSE:', metrics.mean_squared_error(z_test, prediction))
    print('RMSE:', np.sqrt(metrics.mean_squared_error(z_test, prediction)))

MAE: 3.466236325744276e-14
    MSE: 1.9194207552613397e-27
    RMSE: 4.381119440578332e-14

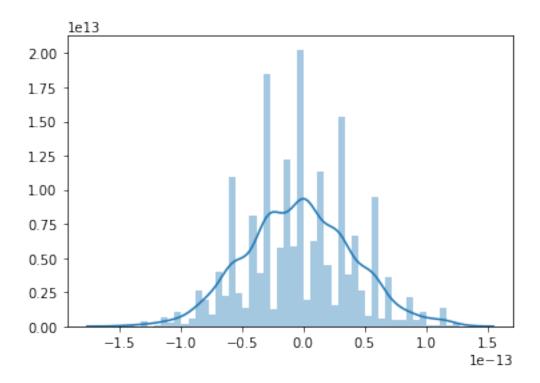
[106]: print('\nIntercept : ',lm.intercept_)

Intercept : 4.218847493575595e-15

[107]: print('Variance score: ',lm.score(A_test, z_test))

Variance score: 1.0

[108]: sns.distplot((z_test-prediction),bins=50);
```



```
[109]: accuracy = lm.score(A_train, z_train)
    print("accuracy = ", accuracy * 100, "%")
    accuracy = lm.score(A_test, z_test)
    print("accuracy = ", accuracy * 100, "%")

accuracy = 100.0 %
    accuracy = 100.0 %
```

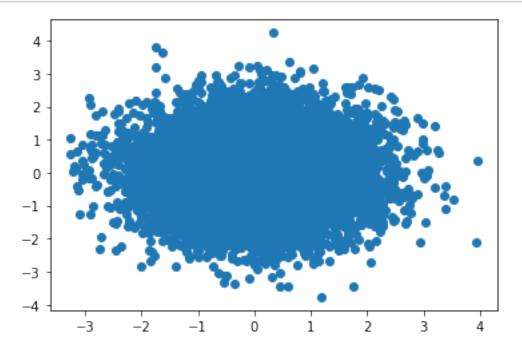
## 7 Noisy data

```
[136]: B,w = mr(n_samples=10000, n_features=10, n_informative=2, noise=20,__
       →random state=17)
[137]: df=pd.DataFrame(B)
      df
[137]:
                   0
                                       2
                                                 3
                             1
           -1.027619 -1.286558 -1.101747 -0.262808 0.304828 0.149726 -1.739105
      0
            1.090157 1.386052 1.475800 0.214197 -0.625391 2.218678 0.641034
      1
           -0.501386 -1.071103  0.710173 -1.273405  1.375302 -0.177287  1.094835
      2
           -0.903947 0.877845 -0.319021 -0.823712 -0.517133 -0.814930 -0.025050
           -1.693394 -1.037866 0.622906 2.972829 0.395215 0.367769 -0.488113
```

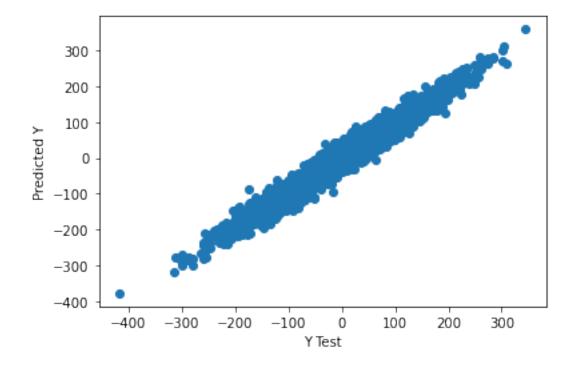
```
9995 -0.787534 -1.125008 -0.153964 -0.236301 -0.384459 -0.375466 -0.323895
9996 1.430434 1.231598 0.878692 -0.228201 0.337200 0.864389 -0.722447
9997 -1.002945 -0.645842 -0.966706 -0.944122 0.531353 1.759356 -1.944453
9998 -1.315852 -0.013712 -1.973863 -0.265874 -0.873708 -0.330170 -0.329684
9999 0.643972 0.848857 -1.105132 -0.155327 0.305212 1.017475 -0.658836
            7
                      8
0
     0.835792 -0.638274 2.068825
1
    -0.339901 0.718192 -0.762642
2
     0.150014 0.005352 0.320013
3
    -3.061606 0.465944 -0.741907
     1.632435 -0.903692 -0.289823
9995 -0.399361 -1.571562 0.783742
9996 0.583020 -0.336605 -1.204862
9997 1.770926 0.048891 -0.836193
9998 0.334905 -0.454224 0.809742
9999 0.337280 2.766441 0.613684
```

#### [10000 rows x 10 columns]

# [138]: df=pd.DataFrame(B) plt.scatter(df[0],df[1]) plt.show()



#### [142]: Text(0, 0.5, 'Predicted Y')



```
[143]: from sklearn import metrics

print('MAE:', metrics.mean_absolute_error(w_test, pred))
print('MSE:', metrics.mean_squared_error(w_test, pred))
print('RMSE:', np.sqrt(metrics.mean_squared_error(w_test, pred)))
```

MAE: 16.232067668336278 MSE: 410.0234403997351

```
RMSE: 20.24903554245819
```

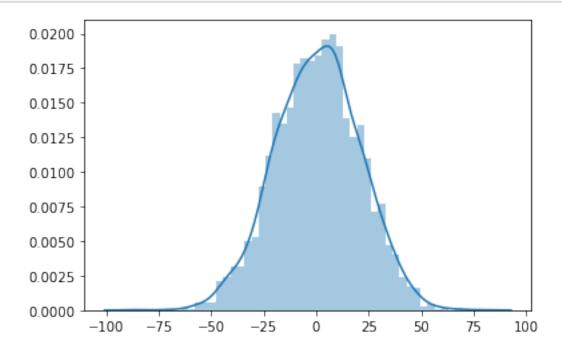
```
[144]: print('\nIntercept : ',lm.intercept_)
```

Intercept : -0.2811263071730249

```
[145]: print('Variance score: ',lm.score(B_test, w_test))
```

Variance score: 0.9583422182425166

```
[146]: sns.distplot((w_test-pred),bins=50);
```



```
[147]: accuracy = lm.score(B_train, w_train)
    print("accuracy = ", accuracy * 100, "%")
    accuracy = lm.score(B_test, w_test)
    print("accuracy = ", accuracy * 100, "%")

accuracy = 95.91527548194786 %
    accuracy = 95.83422182425167 %

[ ]:
```