Importing the required libararies

Lets import the required libraries as the first step.

```
import math
import matplotlib.pyplot as plt
import pandas as pd
import numpy as np
from sklearn.linear_model import Lasso
from sklearn.linear_model import Ridge
from sklearn.linear_model import LinearRegression

from sklearn.datasets import load_breast_cancer
from sklearn.model_selection import train_test_split
```

Loading the data:

Lets load the data and look at the features available in the data. We also print the first few records to understand about the data

```
cancer = load_breast_cancer()
print ("The list of columns are:", cancer.feature_names)

cancer_df = pd.DataFrame(cancer.data, columns=cancer.feature_names)
cancer_df.head(3)

The list of columns are: ['mean radius' 'mean texture' 'mean
perimeter' 'mean area'
 'mean smoothness' 'mean compactness' 'mean concavity'
 'mean concave points' 'mean symmetry' 'mean fractal dimension'
 'radius error' 'texture error' 'perimeter error' 'area error'
 'smoothness error' 'compactness error' 'concavity error'
 'concave points error' 'symmetry error' 'fractal dimension error'
 'worst radius' 'worst texture' 'worst perimeter' 'worst area'
 'worst smoothness' 'worst compactness' 'worst concavity'
 'worst concave points' 'worst symmetry' 'worst fractal dimension']

   mean radius  mean texture  mean perimeter  mean area  mean
smoothness  \
0        17.99         10.38           122.8     1001.0
0.11840
1        20.57         17.77           132.9     1326.0
0.08474
```

```
2        19.69         21.25           130.0     1203.0
0.10960

   mean compactness  mean concavity  mean concave points  mean
symmetry  \
0           0.27760          0.3001              0.14710
0.2419
1           0.07864          0.0869              0.07017
0.1812
2           0.15990          0.1974              0.12790
0.2069

   mean fractal dimension  ...  worst radius  worst texture  worst
perimeter  \
0                 0.07871  ...         25.38          17.33
184.6
1                 0.05667  ...         24.99          23.41
158.8
2                 0.05999  ...         23.57          25.53
152.5

   worst area  worst smoothness  worst compactness  worst concavity  \
0      2019.0            0.1622             0.6656           0.7119
1      1956.0            0.1238             0.1866           0.2416
2      1709.0            0.1444             0.4245           0.4504

   worst concave points  worst symmetry  worst fractal dimension
0                0.2654          0.4601                  0.11890
1                0.1860          0.2750                  0.08902
2                0.2430          0.3613                  0.08758

[3 rows x 30 columns]

X = cancer.data
Y = cancer.target
```

Lets split the data into train and test data using the train_test_split function available in sklearn library

```
X_train,X_test,y_train,y_test=train_test_split(X,Y, test_size=0.3,
random_state=31)
```

Building the Linear Regression model

```
lr = LinearRegression()
lr.fit(X_train,y_train)
lr_train_score=lr.score(X_train,y_train)
lr_test_score=lr.score(X_test,y_test)
```

```
print ("Linear Regression Training score:", lr_train_score)
print ("Linear Regression Test score: ", lr_test_score)

Linear Regression Training score: 0.784220619405507
Linear Regression Test score:  0.7329325010888691
```

Building a Lasso regressor

```
lasso = Lasso()
lasso.fit(X_train,y_train)
train_score=lasso.score(X_train,y_train)
test_score=lasso.score(X_test,y_test)
coeff_used = np.sum(lasso.coef_!=0)
print ("Linear Regression Training score:", train_score)
print ("Linear Regression Test score: ", test_score)
print ("Number of features used: ", coeff_used)

Linear Regression Training score: 0.5600974529893081
Linear Regression Test score:  0.5832244618818156
Number of features used:  4
```

Building a Lasso regressor with alpha = 0.01

```
lasso_alpha_01 = Lasso(alpha=0.01, max_iter=10e5)
lasso_alpha_01.fit(X_train,y_train)
train_score_01=lasso_alpha_01.score(X_train,y_train)
test_score_01=lasso_alpha_01.score(X_test,y_test)
coeff_used_01 = np.sum(lasso_alpha_01.coef_!=0)
print ("Training score when alpha is 0.01:", train_score_01)
print ("Test score when alpha is 0.01: ", test_score_01)
print ("Number of features used when alpha is 0.01:", coeff_used_01)

Training score when alpha is 0.01: 0.7037865778498829
Test score when alpha is 0.01:  0.664183157726228
Number of features used when alpha is 0.01: 10
```

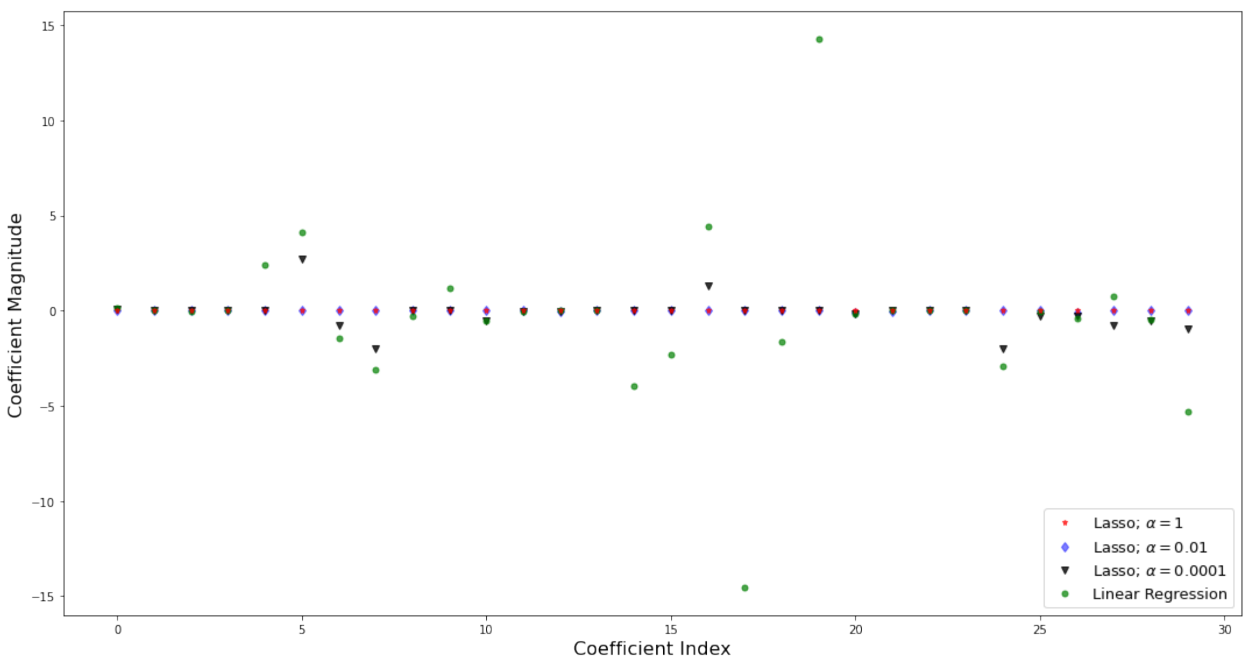
Building a Lasso regressor with alpha = 0.0001

```
lasso_alpha_0001 = Lasso(alpha=0.0001, max_iter=10e5)
lasso_alpha_0001.fit(X_train,y_train)
train_score_0001=lasso_alpha_0001.score(X_train,y_train)
test_score_0001=lasso_alpha_0001.score(X_test,y_test)
coeff_used_0001 = np.sum(lasso_alpha_0001.coef_!=0)
print ("Training score when alpha is 0.0001:", train_score_0001)
print ("Test score when alpha is 0.0001: ", test_score_0001)
```

```
print ("Number of features used when alpha is 0.0001:",
coeff_used_0001)
```

```
Training score when alpha is 0.0001: 0.7754092006936698
Test score when alpha is 0.0001:  0.7318608210757911
Number of features used when alpha is 0.0001: 22
```

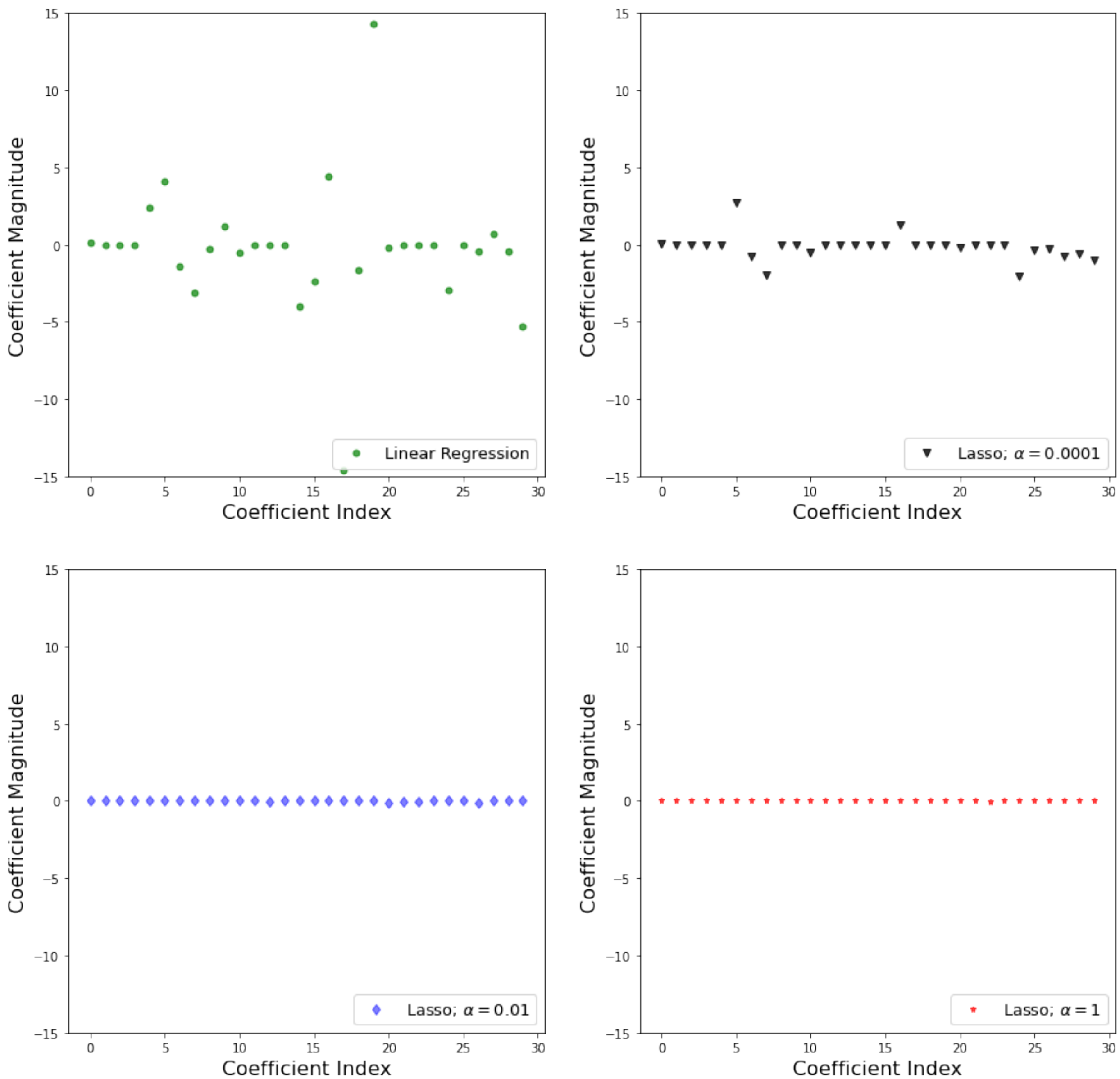
```
plt.rcParams['figure.figsize'] = [15, 8]
plt.plot(lasso.coef_,alpha=0.7,linestyle='none',marker='*',markersize=
5,color='red',label=r'Lasso; $\alpha = 1$',zorder=7) # alpha here is
for transparency
plt.plot(lasso_alpha_01.coef_,alpha=0.5,linestyle='none',marker='d',ma
rkersize=6,color='blue',label=r'Lasso; $\alpha = 0.01$') # alpha here
is for transparency
plt.plot(lasso_alpha_0001.coef_,alpha=0.8,linestyle='none',marker='v',
markersize=6,color='black',label=r'Lasso; $\alpha = 0.0001$') # alpha
here is for transparency
plt.plot(lr.coef_,alpha=0.7,linestyle='none',marker='o',markersize=5,c
olor='green',label='Linear Regression',zorder=2)
plt.xlabel('Coefficient Index',fontsize=16)
plt.ylabel('Coefficient Magnitude',fontsize=16)
plt.legend(fontsize=13,loc=4)
plt.tight_layout()
plt.show()
```




```
plt.rcParams['figure.figsize'] = [15, 15]

plt.subplot(2,2,4)
plt.plot(lasso.coef_,alpha=0.7,linestyle='none',marker='*',markersize=
```

```
5,color='red',label=r'Lasso; $\alpha = 1$',zorder=7) # alpha here is
for transparency
plt.xlabel('Coefficient Index',fontsize=16)
plt.ylabel('Coefficient Magnitude',fontsize=16)
plt.ylim([-15,15])
plt.legend(fontsize=13,loc=4)


plt.subplot(2,2,3)
plt.plot(lasso_alpha_01.coef_,alpha=0.5,linestyle='none',marker='d',ma
rkersize=6,color='blue',label=r'Lasso; $\alpha = 0.01$') # alpha here
is for transparency
plt.xlabel('Coefficient Index',fontsize=16)
plt.ylabel('Coefficient Magnitude',fontsize=16)
plt.ylim([-15,15])
plt.legend(fontsize=13,loc=4)


plt.subplot(2,2,2)
plt.plot(lasso_alpha_0001.coef_,alpha=0.8,linestyle='none',marker='v',
markersize=6,color='black',label=r'Lasso; $\alpha = 0.0001$') # alpha
here is for transparency
plt.xlabel('Coefficient Index',fontsize=16)
plt.ylabel('Coefficient Magnitude',fontsize=16)
plt.ylim([-15,15])
plt.legend(fontsize=13,loc=4)


plt.subplot(2,2,1)
plt.plot(lr.coef_,alpha=0.7,linestyle='none',marker='o',markersize=5,c
olor='green',label='Linear Regression',zorder=2)
plt.xlabel('Coefficient Index',fontsize=16)
plt.ylabel('Coefficient Magnitude',fontsize=16)
plt.ylim([-15,15])
plt.legend(fontsize=13,loc=4)
```

```
<matplotlib.legend.Legend at 0x2078d68a5e0>
```



Building a Ridge regressor with alpha = 0.01

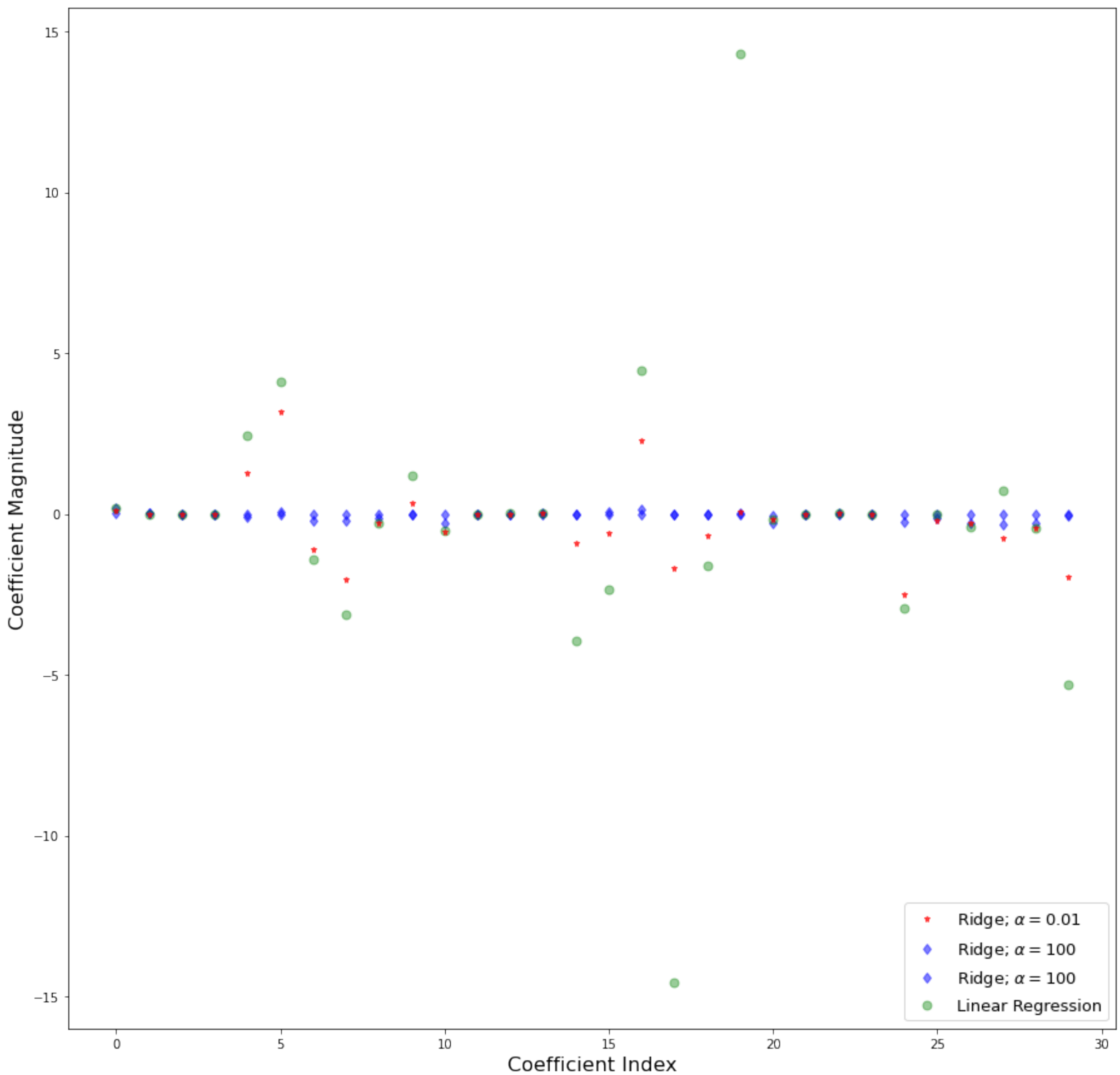
```
rr = Ridge(alpha=0.01)
rr.fit(X_train, y_train)
Ridge_train_score = rr.score(X_train,y_train)
Ridge_test_score = rr.score(X_test, y_test)
```

Building a Ridge regressor with alpha = 1

```
rr1 = Ridge(alpha=1)
rr1.fit(X_train, y_train)
Ridge_train_score = rr.score(X_train,y_train)
Ridge_test_score = rr.score(X_test, y_test)
```

Building a Ridge regressor with alpha = 100

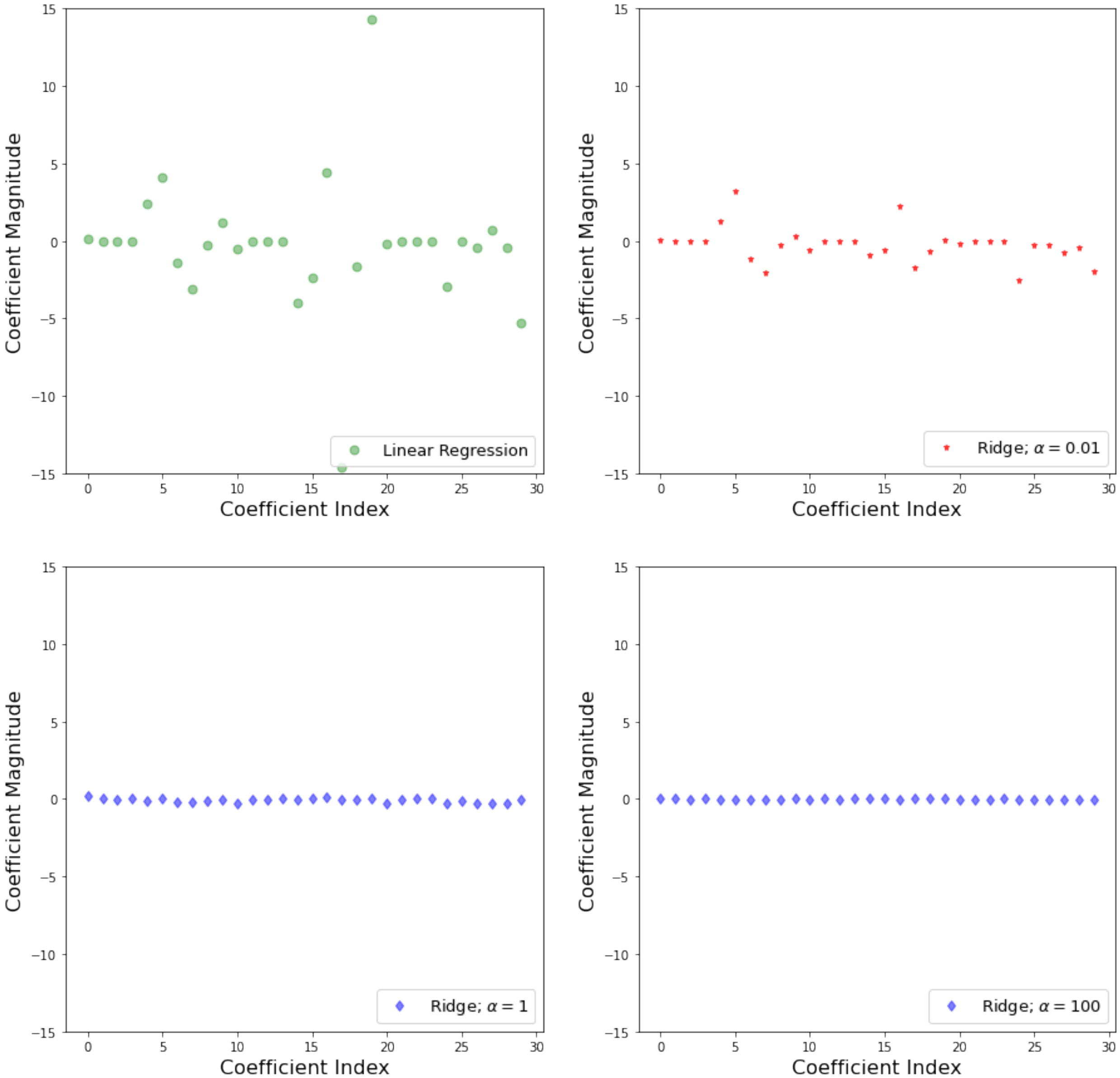
```
rr100 = Ridge(alpha=100) #  comparison with alpha value
rr100.fit(X_train, y_train)
Ridge_train_score100 = rr100.score(X_train,y_train)
Ridge_test_score100 = rr100.score(X_test, y_test)

plt.plot(rr.coef_,alpha=0.7,linestyle='none',marker='*',markersize=5,color='red',label=r'Ridge; $\alpha = 0.01$',zorder=7)
plt.plot(rr1.coef_,alpha=0.5,linestyle='none',marker='d',markersize=6,color='blue',label=r'Ridge; $\alpha = 100$')
plt.plot(rr100.coef_,alpha=0.5,linestyle='none',marker='d',markersize=6,color='blue',label=r'Ridge; $\alpha = 100$')
plt.plot(lr.coef_,alpha=0.4,linestyle='none',marker='o',markersize=7,color='green',label='Linear Regression')
plt.xlabel('Coefficient Index',fontsize=16)
plt.ylabel('Coefficient Magnitude',fontsize=16)
plt.legend(fontsize=13,loc=4)
plt.show()
```




```
plt.rcParams['figure.figsize'] = [15, 15]


plt.subplot(2,2,1)
plt.plot(lr.coef_,alpha=0.4,linestyle='none',marker='o',markersize=7,c
olor='green',label='Linear Regression')
plt.xlabel('Coefficient Index',fontsize=16)
plt.ylabel('Coefficient Magnitude',fontsize=16)
plt.ylim([-15,15])
plt.legend(fontsize=13,loc=4)


plt.subplot(2,2,2)
plt.plot(rr.coef_,alpha=0.7,linestyle='none',marker='*',markersize=5,c
```

```
olor='red',label=r'Ridge; $\alpha = 0.01$',zorder=7)
plt.xlabel('Coefficient Index',fontsize=16)
plt.ylabel('Coefficient Magnitude',fontsize=16)
plt.ylim([-15,15])
plt.legend(fontsize=13,loc=4)


plt.subplot(2,2,3)
plt.plot(rr1.coef_,alpha=0.5,linestyle='none',marker='d',markersize=6,
color='blue',label=r'Ridge; $\alpha = 1$')
plt.xlabel('Coefficient Index',fontsize=16)
plt.ylabel('Coefficient Magnitude',fontsize=16)
plt.ylim([-15,15])
plt.legend(fontsize=13,loc=4)


plt.subplot(2,2,4)
plt.plot(rr100.coef_,alpha=0.5,linestyle='none',marker='d',markersize=
6,color='blue',label=r'Ridge; $\alpha = 100$')
plt.xlabel('Coefficient Index',fontsize=16)
plt.ylabel('Coefficient Magnitude',fontsize=16)
plt.ylim([-15,15])
plt.legend(fontsize=13,loc=4)
```

```
<matplotlib.legend.Legend at 0x2078d7e8220>
```


Linear Regression
Ridge; $\alpha = 0.01$
Ridge; $\alpha = 1$
Ridge; $\alpha = 100$
Coefficient Magnitude
Coefficient Index