Task1

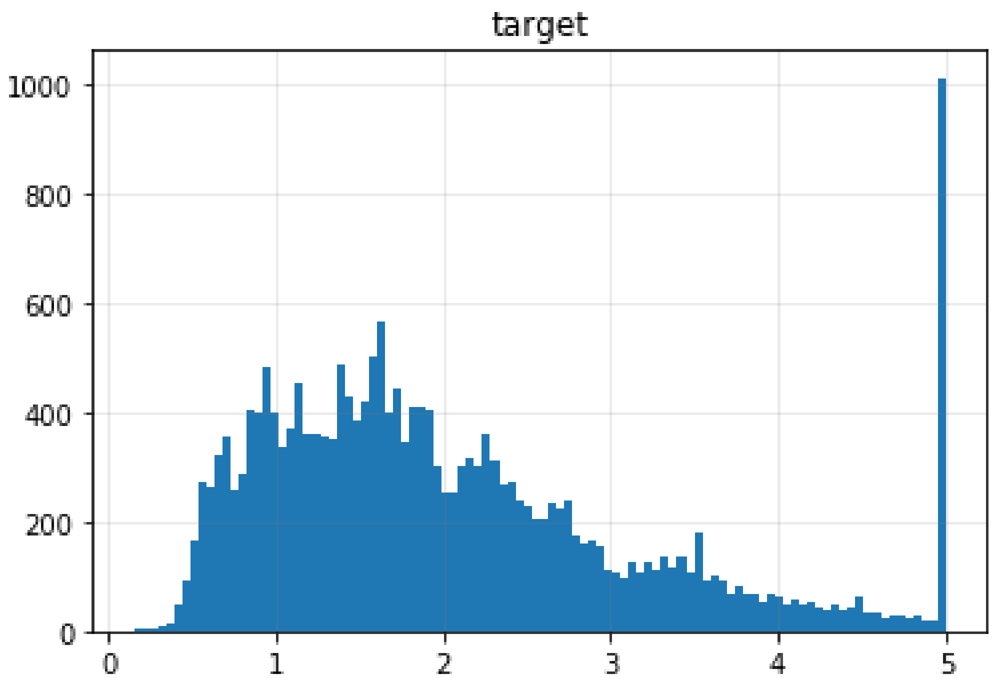
February 7, 2018

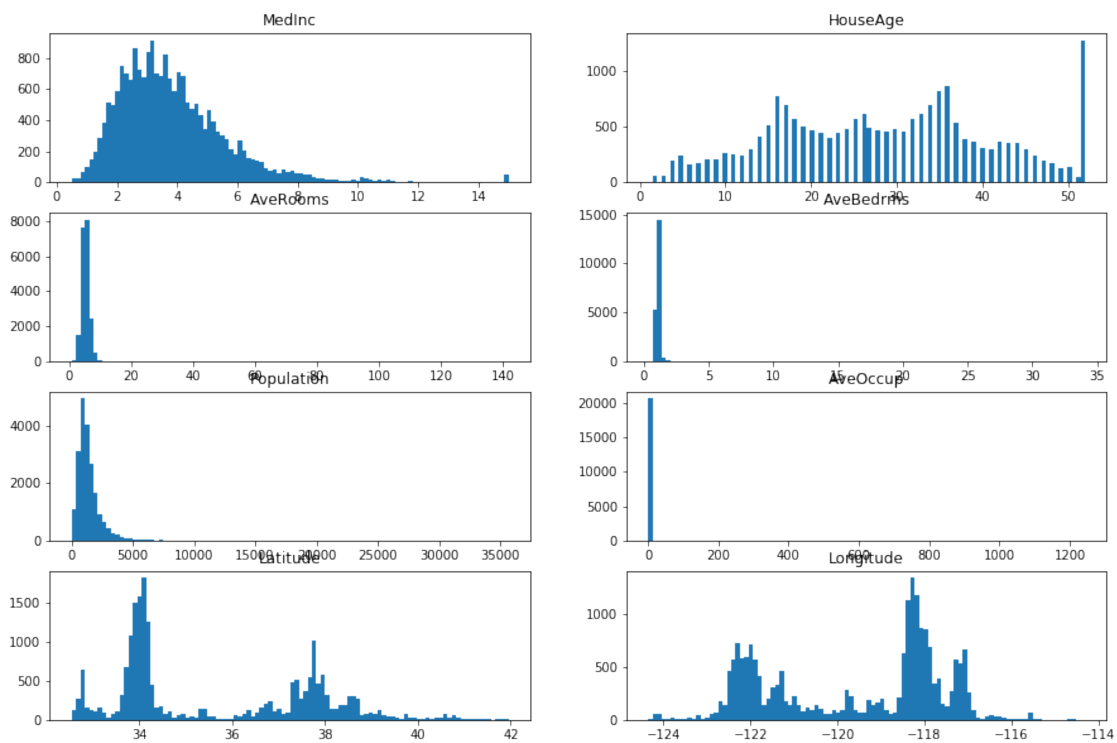
1 Task1

```
In [1]: import matplotlib.pyplot as plt
        import numpy as np
        import pandas as pd
        import sklearn.datasets
        from sklearn.linear_model import LinearRegression, Ridge, Lasso, ElasticNet
        from sklearn.model_selection import train_test_split, cross_val_score
        from sklearn.preprocessing import StandardScaler
        from sklearn.model_selection import GridSearchCV
```

1.1

```
In [18]: california_dataset = sklearn.datasets.fetch_california_housing()

         plt.hist(california_dataset['target'],bins=100)
         plt.grid(color='gray', linestyle='-', linewidth=0.5, alpha=0.3)
         plt.title('target')
         plt.show()

         fig, axes = plt.subplots(4,2,figsize=(15,10))
         for i in range(0,4):
             for j in range(0,2):
                 axes[i,j].hist(california_dataset['data'][:,i*2+j],bins=100)
                 axes[i,j].set_title(california_dataset['feature_names'][i*2+j])
         plt.show()
```

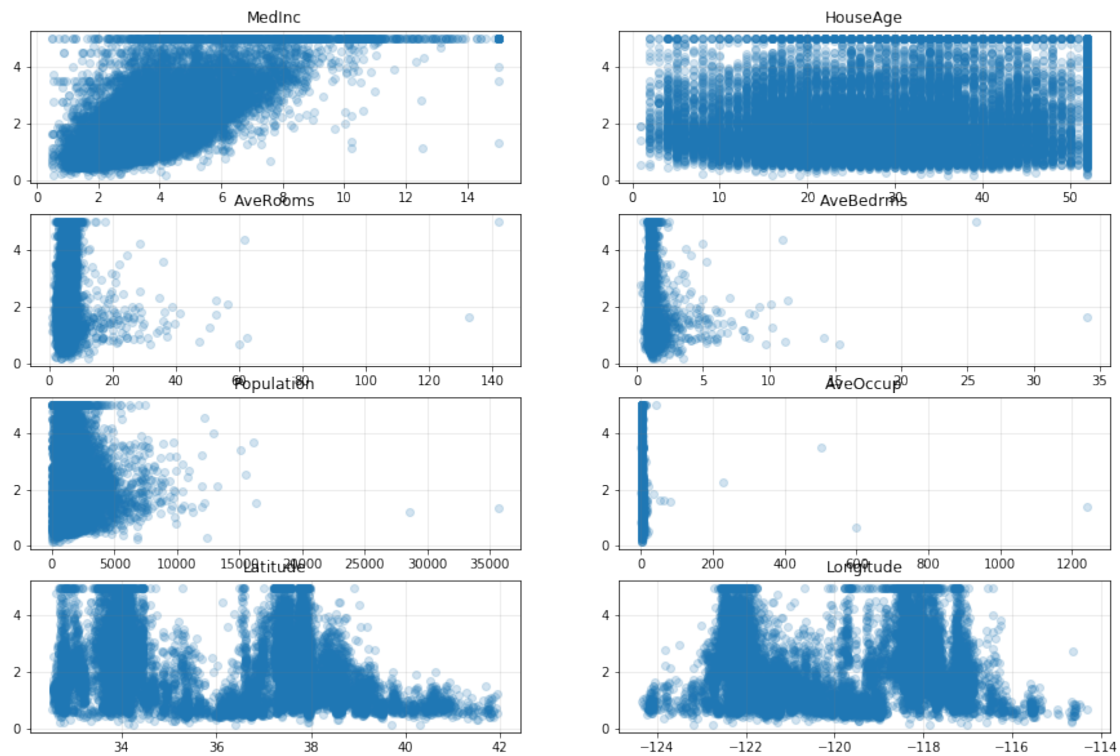

target
1000
800
600
400
200
0
0
1
2
3
4
5


MedInc
HouseAge
AveRooms
AveBedrms
Population
AveOccup
Latitude
Longitude

From the above eight feature plots, 'AveRooms', 'AveBedrms','Population' and 'AveOccup' have inappropriate x scale, which means there are some outliers on these four features. We may need to remove these outliers, than re-scale the x axis.

1.2

```
In [4]: fig, axes = plt.subplots(4,2,figsize=(15,10))
        for i in range(0,4):
            for j in range(0,2):
                axes[i,j].scatter(california_dataset['data'][:,i*2+j],california_dataset['targe
                axes[i,j].set_title(california_dataset['feature_names'][i*2+j])
        plt.show()
```



1.3

```
In [12]: X_train, X_test, y_train, y_test = train_test_split(california_dataset['data'],califor
         LRScore=np.mean(cross_val_score(LinearRegression(), X_train, y_train))
         RidgeScore=np.mean(cross_val_score(Ridge(), X_train, y_train))
         LassoScore=np.mean(cross_val_score(Lasso(), X_train, y_train))
         ElasticNetScore=np.mean(cross_val_score(ElasticNet(), X_train, y_train))
         print('LRScore:{}\nRidgeScore:{}\nLassoScore:{}\nElasticNetScore:{}'.format(LRScore,Ri
```

```
LRScore:0.6102422922538064
RidgeScore:0.6102437749800811
```

```
LassoScore:0.2819718569982819
ElasticNetScore:0.4229514321435757
```

Scaling the features

```
In [13]: scaler = StandardScaler()
         scaler.fit(X_train)
         X_train_scaled = scaler.transform(X_train)
         LRScore_S=np.mean(cross_val_score(LinearRegression(), X_train_scaled, y_train))
         RidgeScore_S=np.mean(cross_val_score(Ridge(), X_train_scaled, y_train))
         LassoScore_S=np.mean(cross_val_score(Lasso(), X_train_scaled, y_train))
         ElasticNetScore_S=np.mean(cross_val_score(ElasticNet(), X_train_scaled, y_train))
         print('LRScore:{}\nRidgeScore:{}\nLassoScore:{}\nElasticNetScore:{}'.format(LRScore_S
```

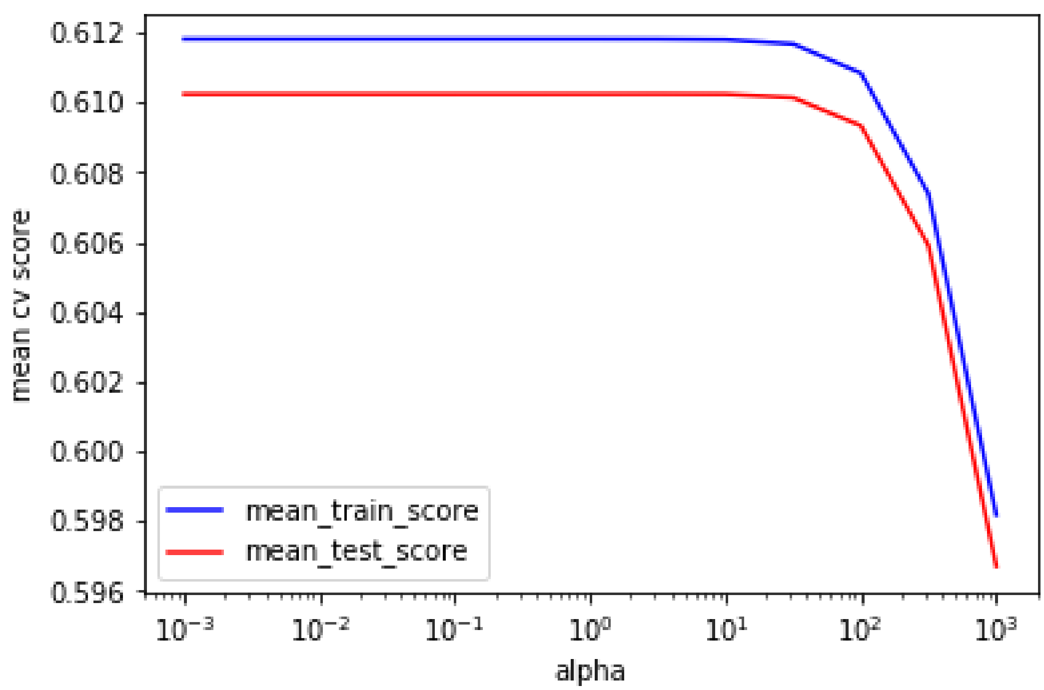
```
LRScore:0.6102422922538069
RidgeScore:0.6102441875598729
LassoScore:-0.00015307833209199373
ElasticNetScore:0.20448945641200397
```

According to the results, Scaling doesn't help the OLR and Ridge. Besides, it even has a negative influence on the Lasso and ElasticNet.

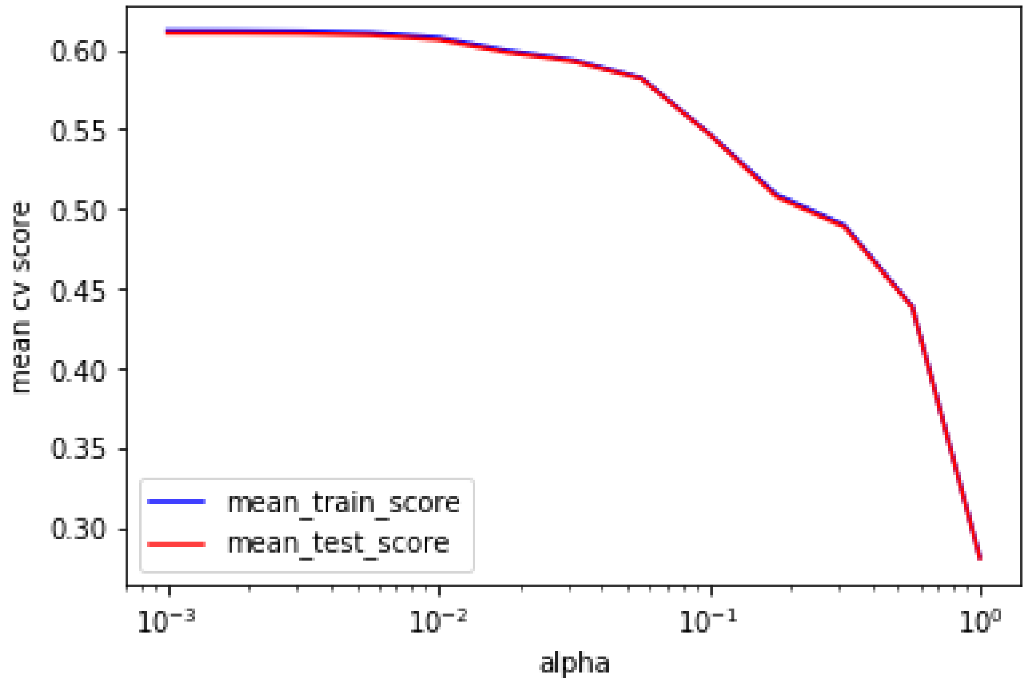
1.4

```
In [20]: # Ridge
         param_grid = {'alpha': np.logspace(-3, 3, 13)}
         grid = GridSearchCV(Ridge(), param_grid,return_train_score=True)
         grid.fit(X_train, y_train)
         plt.plot(param_grid['alpha'], grid.cv_results_['mean_train_score'],c='blue',label='mea
         plt.plot(param_grid['alpha'], grid.cv_results_['mean_test_score'],c='red',label='mean_
         plt.xlabel('alpha')
         plt.ylabel('mean cv score')
         plt.xscale('log')
         plt.legend()
         plt.show()
         ridge = grid.best_estimator_
         print('best score:{}\nbest parameters:{}'.format(grid.best_score_,grid.best_params_))

         #Lasso
         param_grid = {'alpha': np.logspace(-3, 0, 13)}
         grid = GridSearchCV(Lasso(), param_grid,return_train_score=True)
         grid.fit(X_train, y_train)
         plt.plot(param_grid['alpha'], grid.cv_results_['mean_train_score'],c='blue',label='mea
         plt.plot(param_grid['alpha'], grid.cv_results_['mean_test_score'],c='red',label='mean_
         plt.xlabel('alpha')
         plt.ylabel('mean cv score')
```

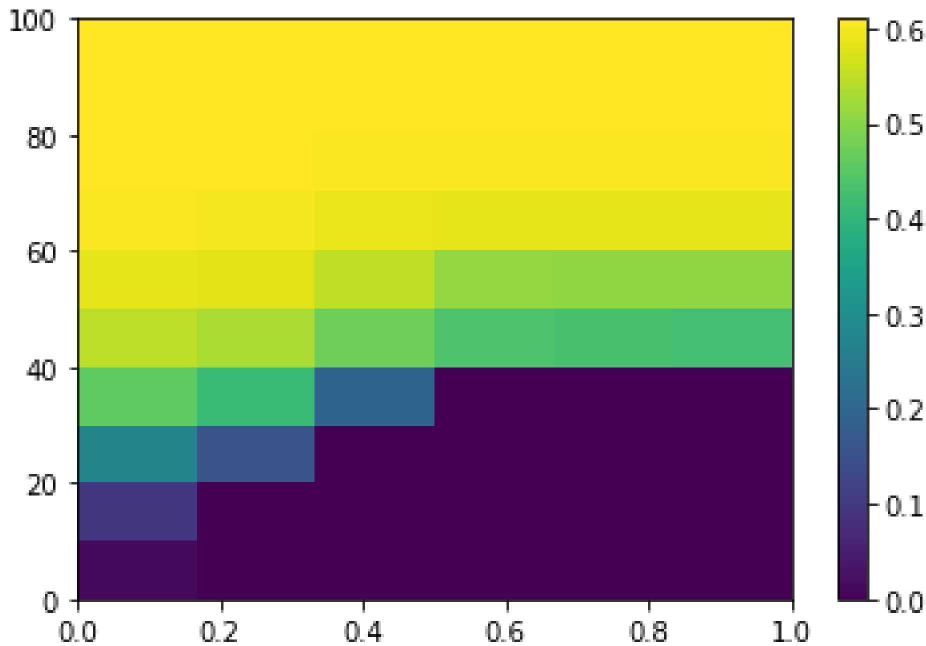
```python
plt.xscale('log')
plt.legend()
plt.show()
lasso = grid.best_estimator_
print('best score:{}\nbest parameters:{}'.format(grid.best_score_,grid.best_params_))

# ElasticNet
param_grid = {'alpha': np.logspace(-3, 2, 10),'l1_ratio': [0.01, .1, .5, .9, .98, 1]}
grid = GridSearchCV(ElasticNet(), param_grid,return_train_score=True)
grid.fit(X_train, y_train)
res = pd.pivot_table(pd.DataFrame(grid.cv_results_),values='mean_test_score', index='p
plt.imshow(res,extent=[0,1,0,100], aspect="auto")
plt.colorbar()
plt.show()
en = grid.best_estimator_
print('best score:{}\nbest parameters:{}'.format(grid.best_score_,grid.best_params_))
```




```
best score:0.6102457318944084
best parameters:{'alpha': 3.1622776601683795}
```




```
best score:0.6102299335181556
best parameters:{'alpha': 0.001}
```

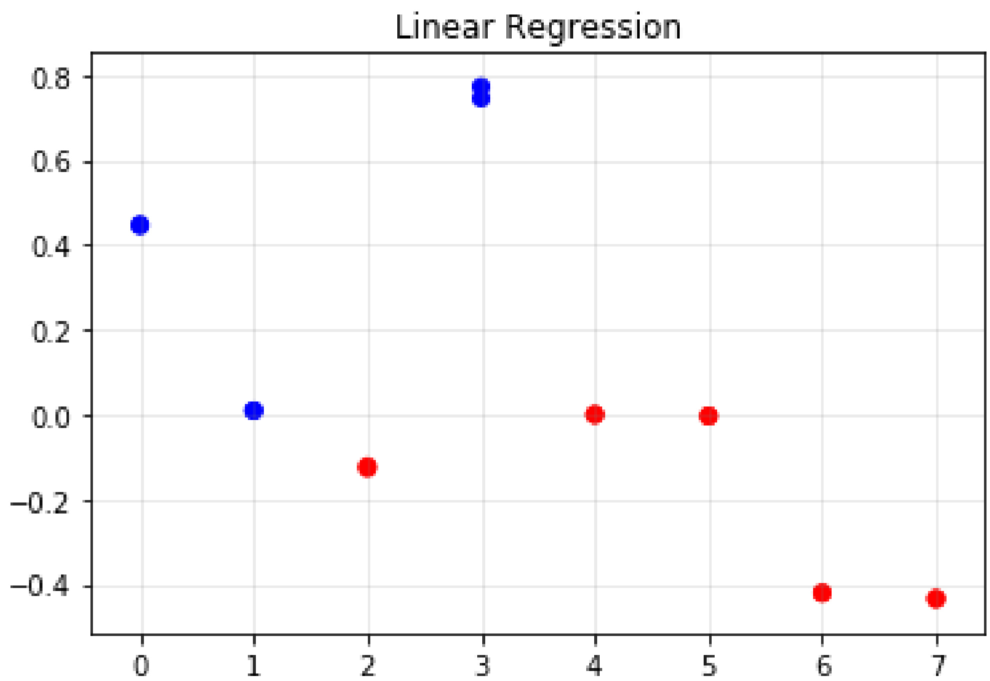


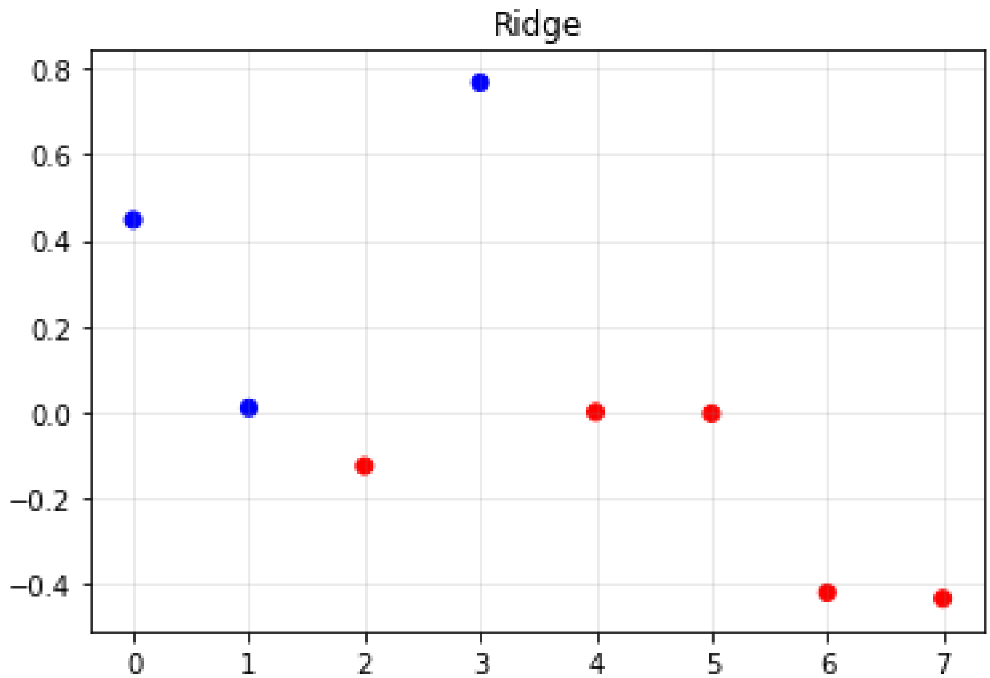
```
best score:0.6102407928395485
best parameters:{'alpha': 0.001, 'l1_ratio': 0.01}
```

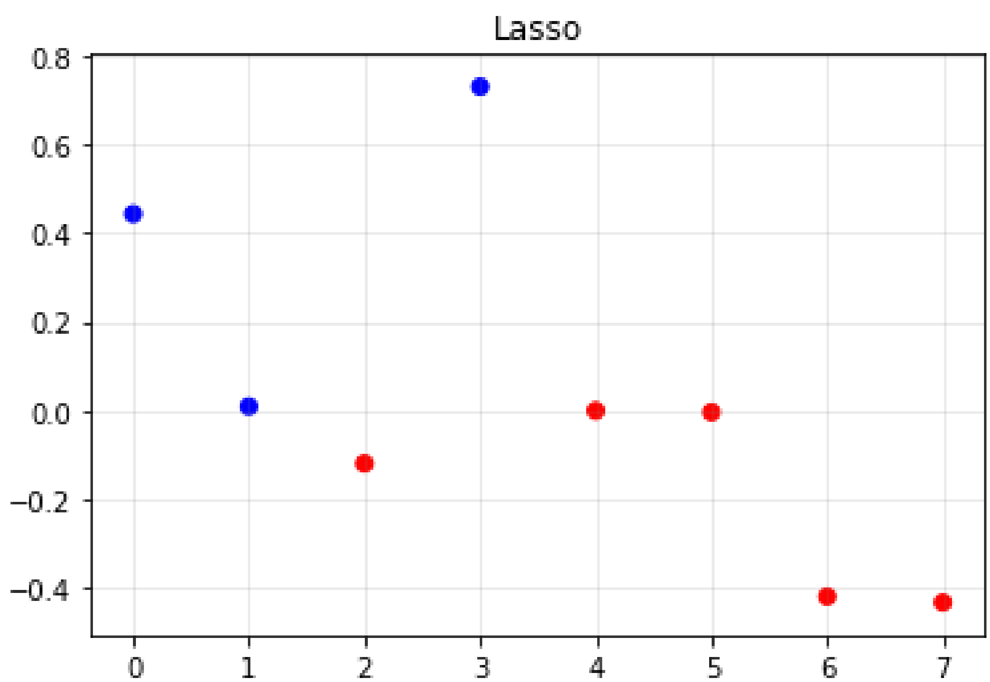
According to the results, GridSearch only can improve Lasso and ElasticNet.

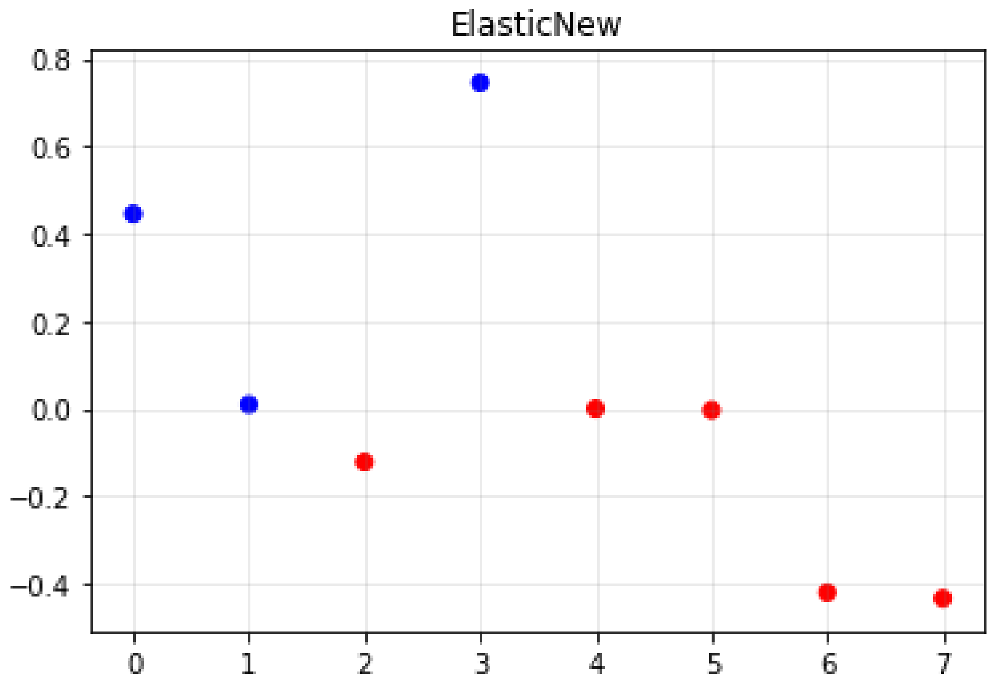
1.5

```
In [17]: lr = LinearRegression().fit(X_train, y_train)
         plt.scatter(range(X_train.shape[1]), lr.coef_,c=np.sign(lr.coef_), cmap="bwr_r")
         plt.title('Linear Regression')
         plt.show()

         plt.scatter(range(X_train.shape[1]), ridge.coef_,c=np.sign(ridge.coef_), cmap="bwr_r")
         plt.title('Ridge')
         plt.show()

         plt.scatter(range(X_train.shape[1]),lasso.coef_, c=np.sign(lasso.coef_), cmap="bwr_r")
         plt.title('Lasso')
         plt.show()

         plt.scatter(range(X_train.shape[1]),en.coef_, c=np.sign(en.coef_), cmap="bwr_r")
         plt.title('ElasticNew')
         plt.show()
```




Ridge
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4
0
1
2
3
4
5
6
7


Lasso
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4
0
1
2
3
4
5
6
7



Yes, it agrees on the features which are important.