회귀 (regression) 예측

수치형 값을 예측 (Y의 값이 연속된 수치로 표현)

예시

- 주택 가격 예측
- 매출액 예측

도큐먼트

In [4]:
```
import pandas as pd
import numpy as np

np.set_printoptions(suppress=True)
```

scikit-learn version 1.2. 이후부터는 load_boston이 삭제되어서 다음과 같이 데이터셋을 불러옴

from sklearn.datasets import fetch_openml

boston = fetch_openml(name="boston", version=1, as_frame=True)

In [6]:
```
from sklearn.datasets import fetch_openml

data = fetch_openml(name="boston", version=1, as_frame=True)
# boston은 sklearn.utils.Bunch 객체
# Python의 딕셔너리와 유사한 구조, 속성에 점(.)으로 접근 가능
print(data.keys())
```

```
dict_keys(['data', 'target', 'frame', 'categories', 'feature_names', 'target_names', 'DESCR', 'details', 'url'])
```

데이터 로드

In [8]:
```
print(data['DESCR'])
```

```
**Author**:
**Source**: Unknown - Date unknown
**Please cite**:

The Boston house-price data of Harrison, D. and Rubinfeld, D.L. 'Hedonic
prices and the demand for clean air', J. Environ. Economics & Management,
vol.5, 81-102, 1978.   Used in Belsley, Kuh & Welsch, 'Regression diagnostics
...', Wiley, 1980.   N.B. Various transformations are used in the table on
pages 244-261 of the latter.
Variables in order:
CRIM     per capita crime rate by town
ZN       proportion of residential land zoned for lots over 25,000 sq.ft.
INDUS    proportion of non-retail business acres per town
CHAS     Charles River dummy variable (= 1 if tract bounds river; 0 otherwise)
NOX      nitric oxides concentration (parts per 10 million)
RM       average number of rooms per dwelling
AGE      proportion of owner-occupied units built prior to 1940
DIS      weighted distances to five Boston employment centres
RAD      index of accessibility to radial highways
TAX      full-value property-tax rate per $10,000
PTRATIO  pupil-teacher ratio by town
B        1000(Bk - 0.63)^2 where Bk is the proportion of blacks by town
LSTAT    % lower status of the population
MEDV     Median value of owner-occupied homes in $1000's


Information about the dataset
CLASSTYPE: numeric
CLASSINDEX: last

Downloaded from openml.org.
```

data['data']에는 X 데이터, data['feature_names']에는 컬럼 명입니다.

In [10]:
```
df = pd.DataFrame(data['data'], columns=data['feature_names'])
```

Y 데이터인 price도 데이터프레임에 추가 합니다.

In [12]:
```
df['MEDV'] = data['target']
```

In [13]:
```
df.head()
```

Out[13]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT	MEDV
0	0.00632	18.0	2.31	0	0.538	6.575	65.2	4.0900	1	296.0	15.3	396.90	4.98	24.0
1	0.02731	0.0	7.07	0	0.469	6.421	78.9	4.9671	2	242.0	17.8	396.90	9.14	21.6
2	0.02729	0.0	7.07	0	0.469	7.185	61.1	4.9671	2	242.0	17.8	392.83	4.03	34.7
3	0.03237	0.0	2.18	0	0.458	6.998	45.8	6.0622	3	222.0	18.7	394.63	2.94	33.4
4	0.06905	0.0	2.18	0	0.458	7.147	54.2	6.0622	3	222.0	18.7	396.90	5.33	36.2

컬럼 소개

속성 수 : 13

- **CRIM**: 범죄율
- **ZN**: 25,000 평방 피트 당 주거용 토지의 비율
- **INDUS**: 비소매(non-retail) 비즈니스 면적 비율
- **CHAS**: 찰스 강 더미 변수 (통로가 하천을 향하면 1; 그렇지 않으면 0)
- **NOX**: 산화 질소 농도 (천만 분의 1)
- **RM**:주거 당 평균 객실 수
- **AGE**: 1940 년 이전에 건축된 자가 소유 점유 비율
- **DIS**: 5 개의 보스턴 고용 센터까지의 가중 거리
- **RAD**: 고속도로 접근성 지수
- **TAX**: 10,000 달러 당 전체 가치 재산 세율
- **PTRATIO** 도시 별 학생-교사 비율
- **B**: 1000 (Bk-0.63) ^ 2 여기서 Bk는 도시 별 검정 비율입니다.
- **LSTAT**: 인구의 낮은 지위
- **MEDV**: 자가 주택의 중앙값 (1,000 달러 단위)

In [15]:
```
# 참고
# 위와 같이 직접 데이터프레임 생성 가능
```

```python
# 또한 data.frame에 입력 데이터(data)와 타겟(target)이 합쳐진 데이터프레임이 이미 존재하므로 해당 데이터프레임을 바로 선언 가능
df2 = data.frame
df2.head()
```

Out[15]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT	MEDV
0	0.00632	18.0	2.31	0	0.538	6.575	65.2	4.0900	1	296.0	15.3	396.90	4.98	24.0
1	0.02731	0.0	7.07	0	0.469	6.421	78.9	4.9671	2	242.0	17.8	396.90	9.14	21.6
2	0.02729	0.0	7.07	0	0.469	7.185	61.1	4.9671	2	242.0	17.8	392.83	4.03	34.7
3	0.03237	0.0	2.18	0	0.458	6.998	45.8	6.0622	3	222.0	18.7	394.63	2.94	33.4
4	0.06905	0.0	2.18	0	0.458	7.147	54.2	6.0622	3	222.0	18.7	396.90	5.33	36.2

train / test 데이터를 분할 합니다.

In [17]:

```python
from sklearn.model_selection import train_test_split
```

In [18]:

```python
x_train, x_test, y_train, y_test = train_test_split(df.drop('MEDV', axis=1), df['MEDV'])
```

In [19]:

```python
x_train.shape, x_test.shape
```

Out[19]:

```
((379, 13), (127, 13))
```

In [20]:

```python
x_train.head()
```

Out[20]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT
225	0.52693	0.0	6.20	0	0.504	8.725	83.0	2.8944	8	307.0	17.4	382.00	4.63
176	0.07022	0.0	4.05	0	0.510	6.020	47.2	3.5549	5	296.0	16.6	393.23	10.11
108	0.12802	0.0	8.56	0	0.520	6.474	97.1	2.4329	5	384.0	20.9	395.24	12.27
316	0.31827	0.0	9.90	0	0.544	5.914	83.2	3.9986	4	304.0	18.4	390.70	18.33
371	9.23230	0.0	18.10	0	0.631	6.216	100.0	1.1691	24	666.0	20.2	366.15	9.53

In [21]:
```
y_train.head()
```

Out[21]:
```
225    50.0
176    23.2
108    19.8
316    17.8
371    50.0
Name: MEDV, dtype: float64
```

평가 지표 만들기

MSE(Mean Squared Error)

$(\frac{1}{n})\sum_{i=1}^{n}(y_i - x_i)^2$

예측값과 실제값의 차이에 대한 **제곱**에 대하여 평균을 낸 값

MAE (Mean Absolute Error)

$(\frac{1}{n})\sum_{i=1}^{n}|y_i - x_i|$

예측값과 실제값의 차이에 대한 **절대값**에 대하여 평균을 낸 값

RMSE (Root Mean Squared Error)

$\sqrt{(\frac{1}{n})\sum_{i=1}^{n}(y_i - x_i)^2}$

예측값과 실제값의 차이에 대한 **제곱**에 대하여 평균을 낸 뒤 **루트**를 씌운 값

평가 지표 만들어 보기

In [33]:
```python
import numpy as np
```

In [34]:
```python
pred = np.array([3, 4, 5])
actual = np.array([1, 2, 3])
```

In [35]:
```python
def my_mse(pred, actual):
    return ((pred - actual)**2).mean()
```

In [36]:
```python
my_mse(pred, actual)
```

Out[36]:
```
4.0
```

In [37]:
```python
def my_mae(pred, actual):
    return np.abs(pred - actual).mean()
```

In [38]:
```python
my_mae(pred, actual)
```

Out[38]:
```
2.0
```

In [39]:
```python
def my_rmse(pred, actual):
    return np.sqrt(my_mse(pred, actual))
```

In [40]:
```python
my_rmse(pred, actual)
```

Out[40]:
```
2.0
```

sklearn의 평가지표 활용하기

In [42]:
```python
from sklearn.metrics import mean_absolute_error, mean_squared_error
```

In [43]:
```python
my_mae(pred, actual), mean_absolute_error(pred, actual)
```

Out[43]:
```
(2.0, 2.0)
```

In [44]:
```python
my_mse(pred, actual), mean_squared_error(pred, actual)
```

Out[44]: (4.0, 4.0)

모델별 성능 확인을 위한 함수

In [46]:
```
import matplotlib.pyplot as plt
import seaborn as sns

my_predictions = {}

colors = ['r', 'c', 'm', 'y', 'k', 'khaki', 'teal', 'orchid', 'sandybrown',
          'greenyellow', 'dodgerblue', 'deepskyblue', 'rosybrown', 'firebrick',
          'deeppink', 'crimson', 'salmon', 'darkred', 'olivedrab', 'olive',
          'forestgreen', 'royalblue', 'indigo', 'navy', 'mediumpurple', 'chocolate',
          'gold', 'darkorange', 'seagreen', 'turquoise', 'steelblue', 'slategray',
          'peru', 'midnightblue', 'slateblue', 'dimgray', 'cadetblue', 'tomato'
         ]

def plot_predictions(name_, pred, actual):
    df = pd.DataFrame({'prediction': pred, 'actual': y_test})
    df = df.sort_values(by='actual').reset_index(drop=True)

    plt.figure(figsize=(12, 9))
    plt.scatter(df.index, df['prediction'], marker='x', color='r')
    plt.scatter(df.index, df['actual'], alpha=0.7, marker='o', color='black')
    plt.title(name_, fontsize=15)
    plt.legend(['prediction', 'actual'], fontsize=12)
    plt.show()

def mse_eval(name_, pred, actual):
    global predictions
    global colors

    plot_predictions(name_, pred, actual)

    mse = mean_squared_error(pred, actual)
    my_predictions[name_] = mse

    y_value = sorted(my_predictions.items(), key=lambda x: x[1], reverse=True)
```

```python
    df = pd.DataFrame(y_value, columns=['model', 'mse'])
    print(df)
    min_ = df['mse'].min() - 10
    max_ = df['mse'].max() + 10

    length = len(df)

    plt.figure(figsize=(10, length))
    ax = plt.subplot()
    ax.set_yticks(np.arange(len(df)))
    ax.set_yticklabels(df['model'], fontsize=15)
    bars = ax.barh(np.arange(len(df)), df['mse'])

    for i, v in enumerate(df['mse']):
        idx = np.random.choice(len(colors))
        bars[i].set_color(colors[idx])
        ax.text(v + 2, i, str(round(v, 3)), color='k', fontsize=15, fontweight='bold')

    plt.title('MSE Error', fontsize=18)
    plt.xlim(min_, max_)

    plt.show()

def remove_model(name_):
    global my_predictions
    try:
        del my_predictions[name_]
    except KeyError:
        return False
    return True
```

LinearRegression

도큐먼트

In [49]:
```python
from sklearn.linear_model import LinearRegression
```

In [50]:
```python
model = LinearRegression(n_jobs=-1)
```

In [51]:
```python
# 데이터의 CHAS와 RAD가 category 타입이라서 그대로 predict를 하면 TypeError가 발생
# 마찬가지로 train 데이터도 타입을 변경해서 fit을 해주는게 일관성 유지에 도움
x_test.dtypes
```

Out[51]:
```
CRIM        float64
ZN          float64
INDUS       float64
CHAS       category
NOX         float64
RM          float64
AGE         float64
DIS         float64
RAD        category
TAX         float64
PTRATIO     float64
B           float64
LSTAT       float64
dtype: object
```

- n_jobs: CPU코어의 사용

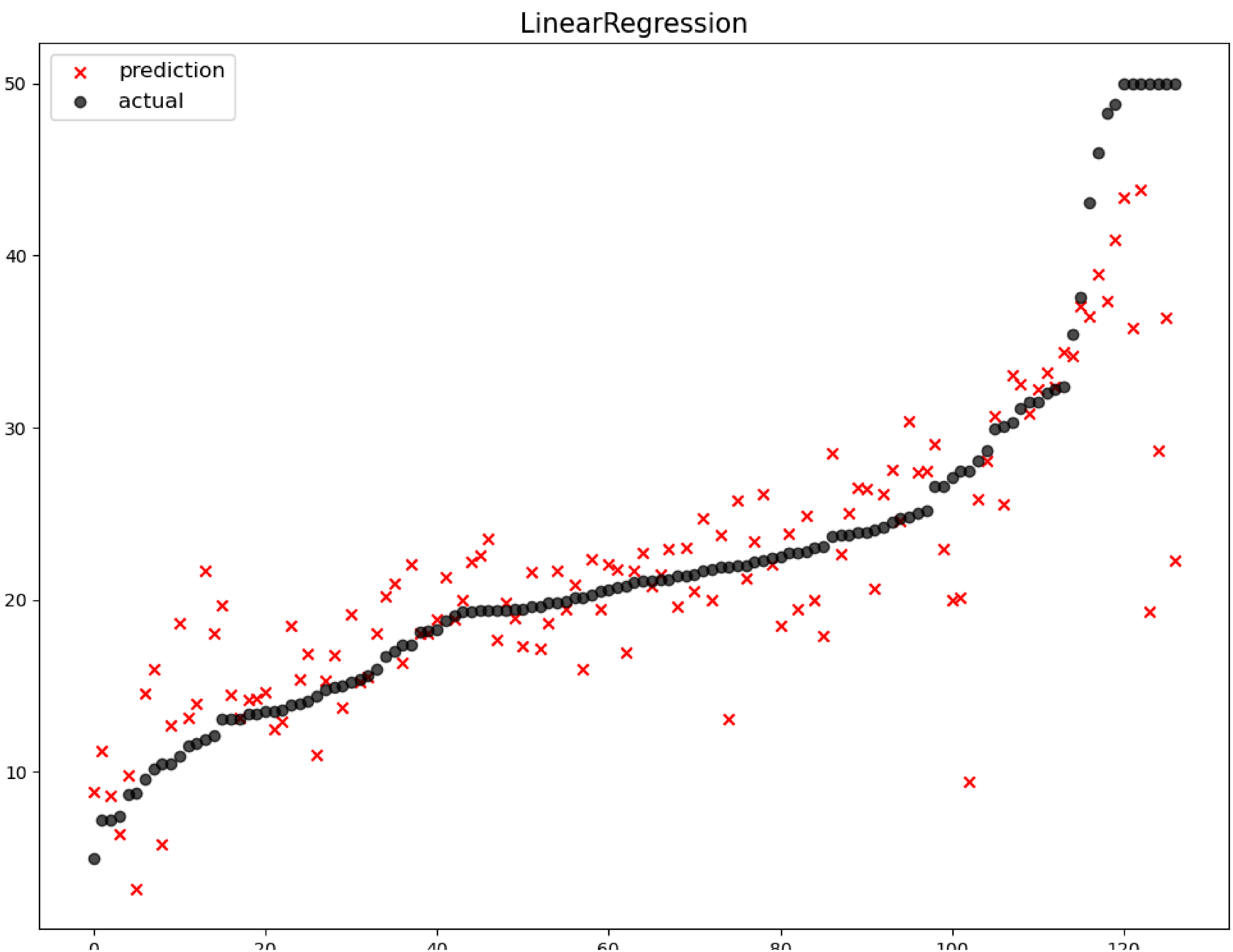
In [53]:
```python
# astype으로 타입 변경
x_train = x_train.astype(float)
x_test = x_test.astype(float)
```

In [54]:
```python
model.fit(x_train, y_train)
```

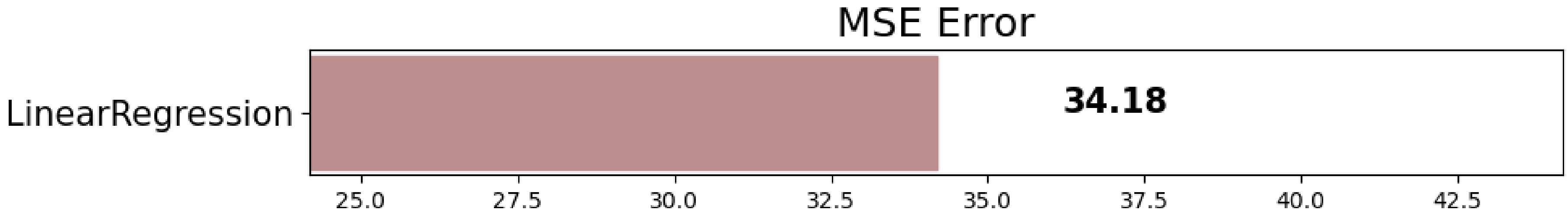
Out[54]:
```
▾ LinearRegression
LinearRegression(n_jobs=-1)
```

In [55]:
```python
pred = model.predict(x_test)
```

In [56]:
```python
mse_eval('LinearRegression', pred, y_test)
```


LinearRegression
prediction
actual
50
40
30
20
10
0
20
40
60
80
100
120

```
              model        mse
0  LinearRegression  34.179865
```



규제 (Regularization)

학습이 과대적합 되는 것을 방지하고자 일종의 **penalty**를 부여하는 것

L2 규제 (L2 Regularization)

- 각 가중치 제곱의 합에 규제 강도(Regularization Strength) λ를 곱한다.
- λ를 크게 하면 가중치가 더 많이 감소되고(규제를 중요시함), λ를 작게 하면 가중치가 증가한다(규제를 중요시하지 않음).

L1 규제 (L1 Regularization)

- 가중치의 제곱의 합이 아닌 **가중치의 합**을 더한 값에 규제 강도(Regularization Strength) λ를 곱하여 오차에 더한다.
- 어떤 가중치(w)는 실제로 0이 된다. 즉, 모델에서 완전히 제외되는 특성이 생기는 것이다.

L2 규제가 L1 규제에 비해 더 안정적이라 일반적으로는 L2규제가 더 많이 사용된다

릿지(Ridge) - L2 규제

$Error = MSE + \alpha w^2$

라쏘(Lasso) - L1 규제

$Error = MSE + \alpha |w|$

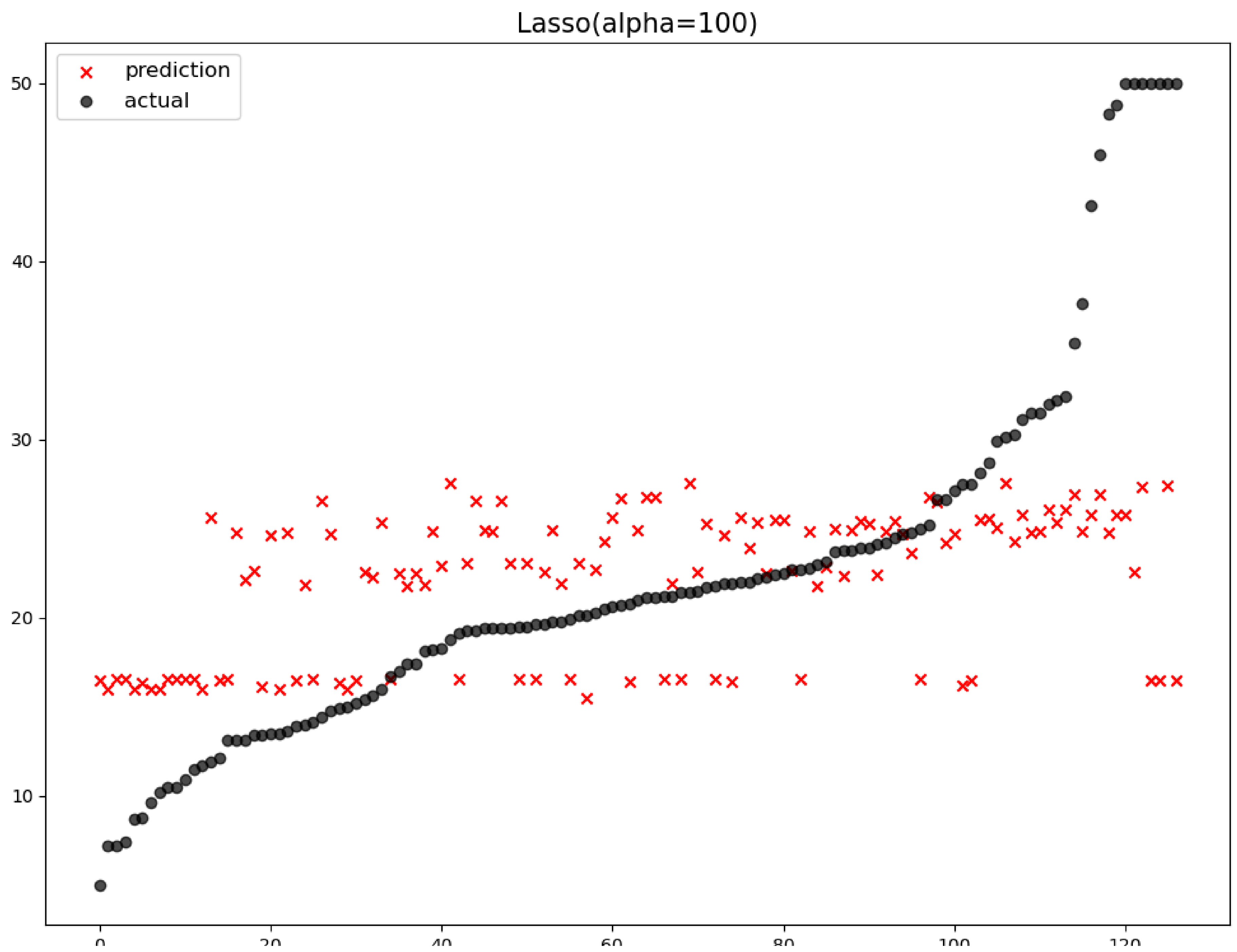
In [61]:
```python
from sklearn.linear_model import Ridge
from sklearn.model_selection import cross_val_score
```

In [62]:
```python
def plot_coef(columns, coef):
    coef_df = pd.DataFrame(list(zip(columns, coef)))
    coef_df.columns=['feature', 'coef']
    coef_df = coef_df.sort_values('coef', ascending=False).reset_index(drop=True)

    fig, ax = plt.subplots(figsize=(9, 7))
    ax.barh(np.arange(len(coef_df)), coef_df['coef'])
    idx = np.arange(len(coef_df))
    ax.set_yticks(idx)
    ax.set_yticklabels(coef_df['feature'])
    fig.tight_layout()
    plt.show()
```

In [63]:
```python
from sklearn.linear_model import Lasso
```

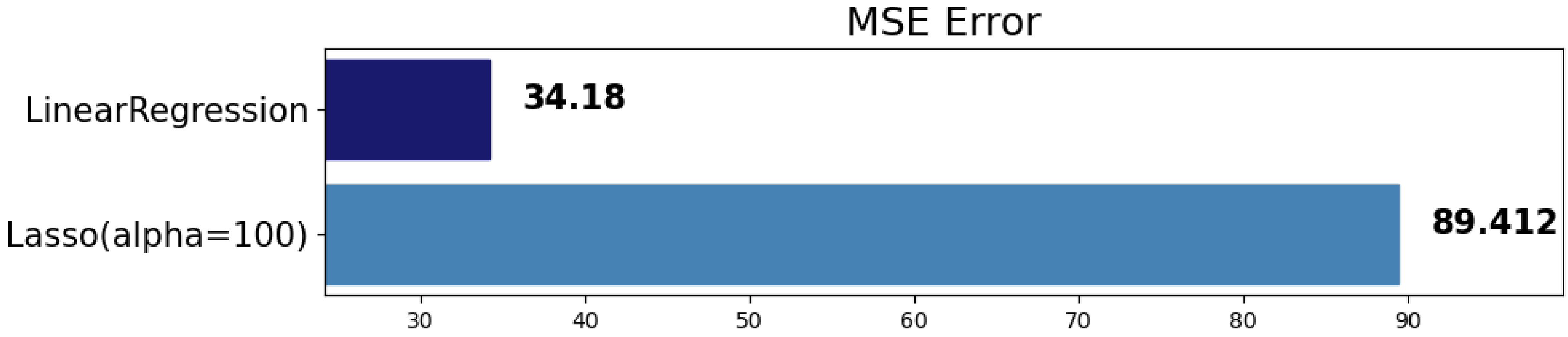
In [64]:
```python
# 값이 커질 수록 큰 규제입니다.
alphas = [100, 10, 1, 0.1, 0.01, 0.001, 0.0001]
```

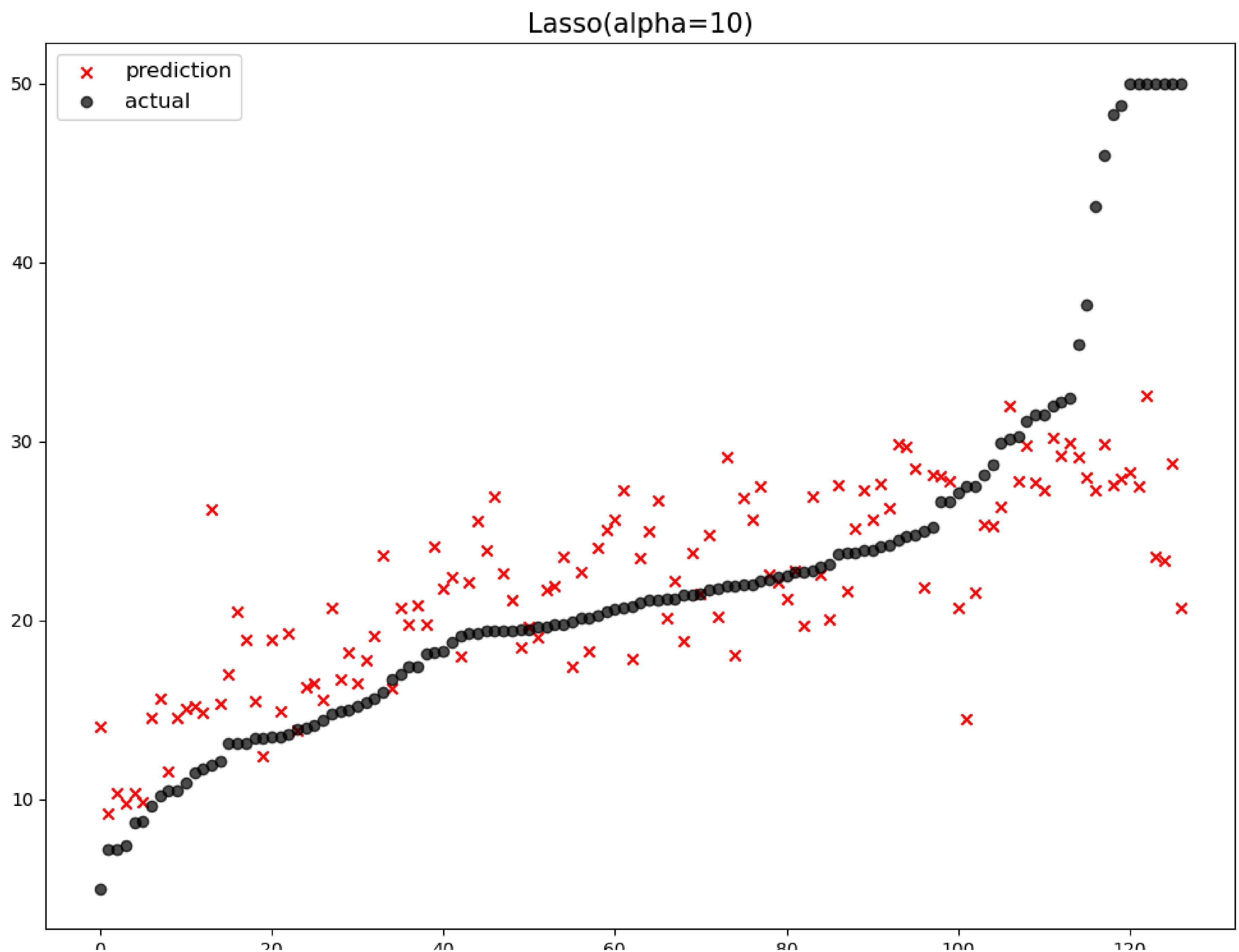
In [65]:
```python
for alpha in alphas:
    lasso = Lasso(alpha=alpha)
    lasso.fit(x_train, y_train)
    pred = lasso.predict(x_test)
    mse_eval('Lasso(alpha={})'.format(alpha), pred, y_test)
```



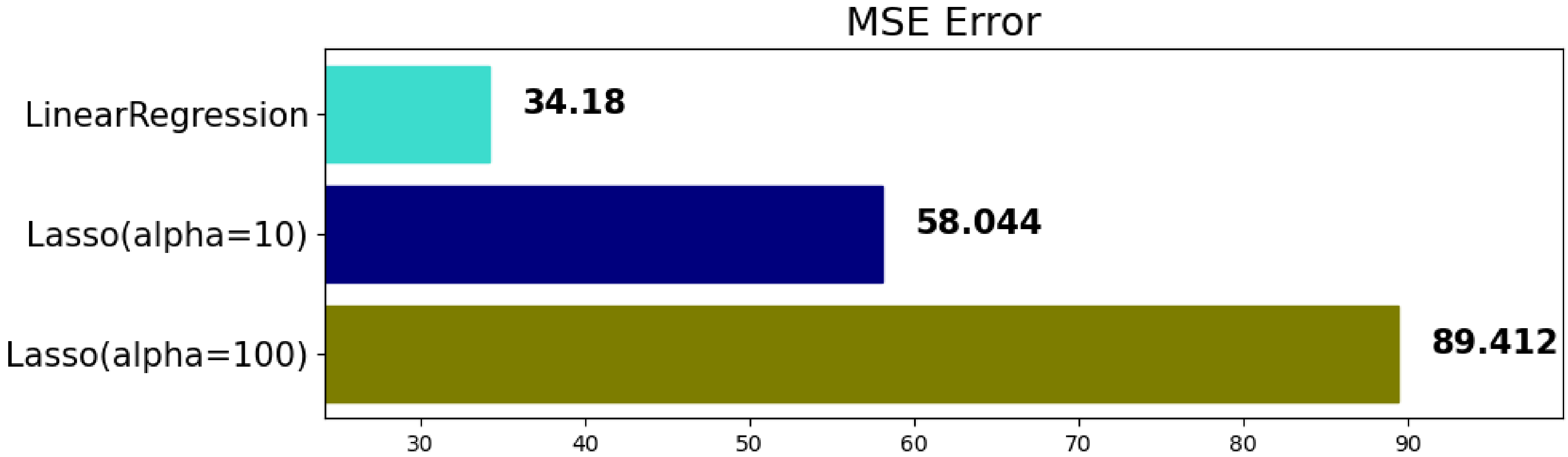
Lasso(alpha=100)
prediction
actual
50
40
30
20
10
0
20
40
60
80
100
120

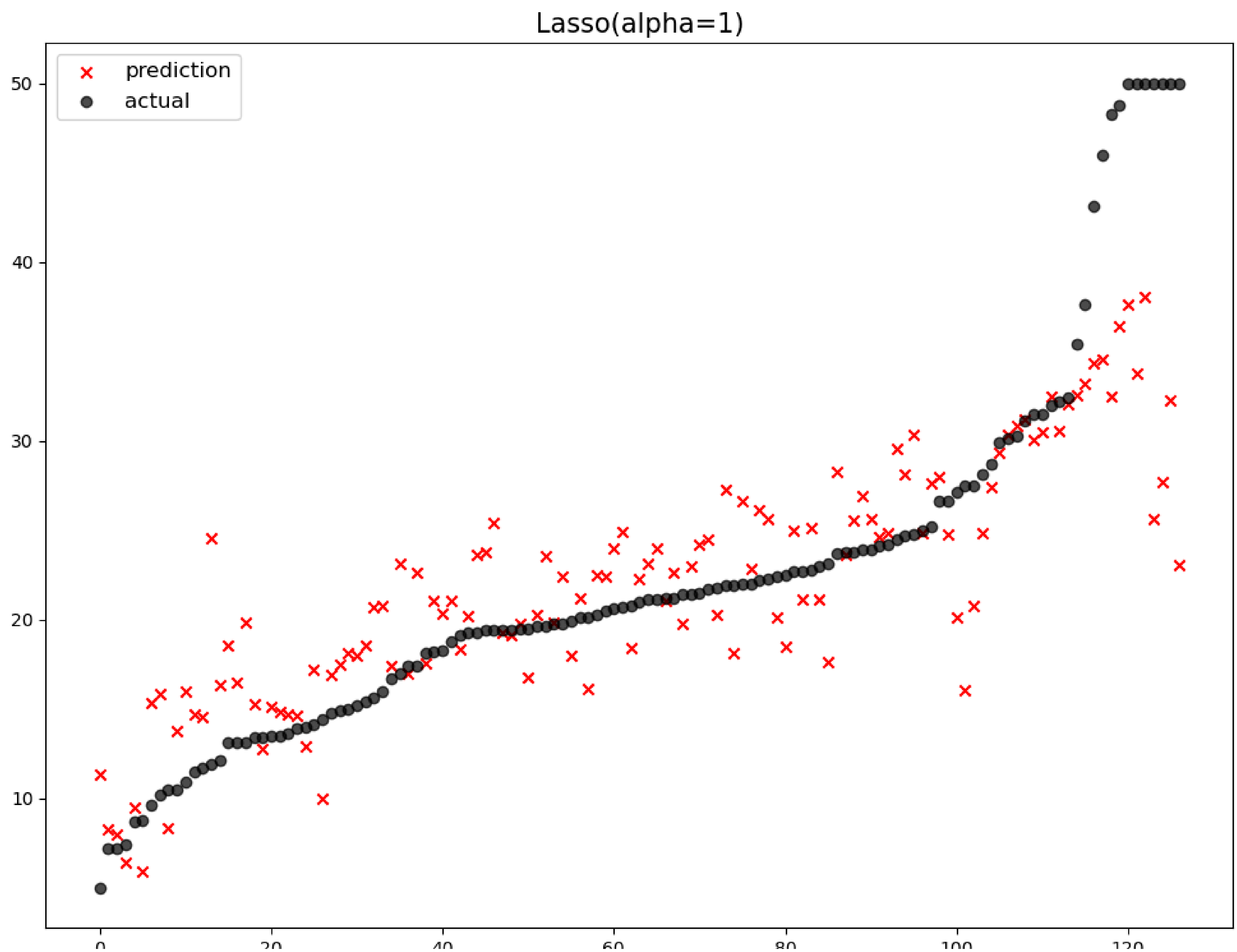
	model	mse
0	Lasso(alpha=100)	89.411990
1	LinearRegression	34.179865



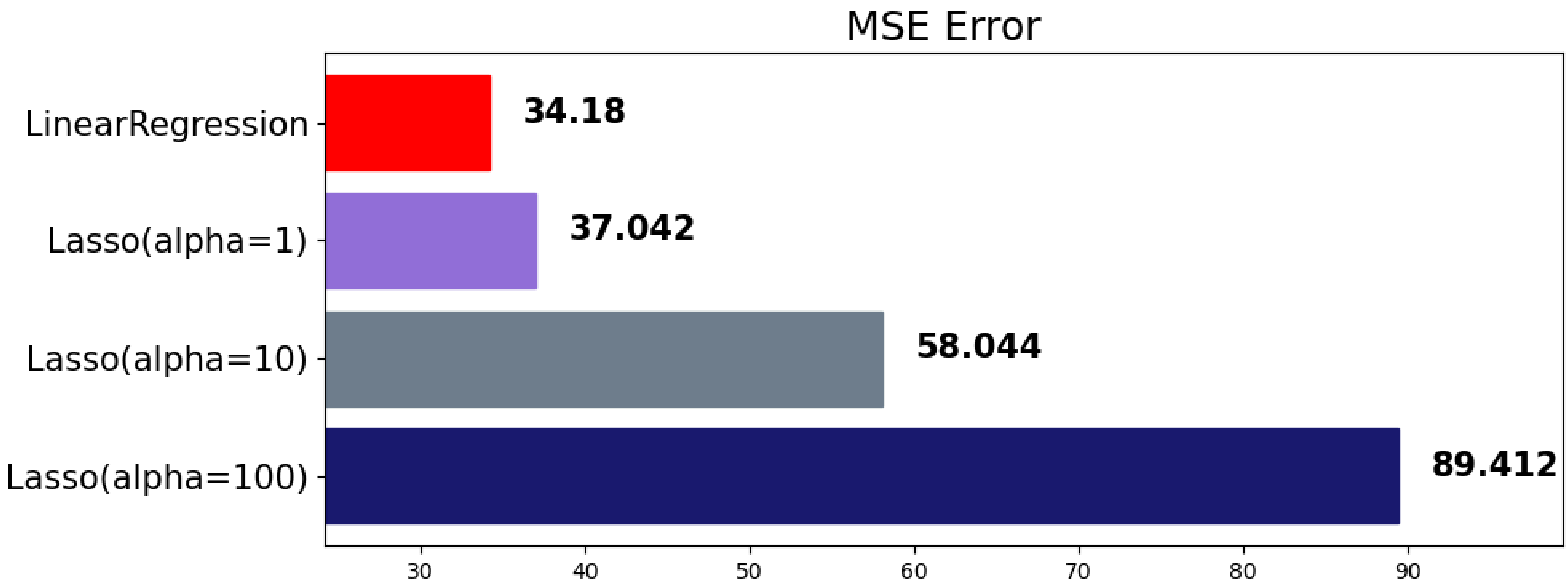

Lasso(alpha=10)
prediction
actual
50
40
30
20
10
0
20
40
60
80
100
120

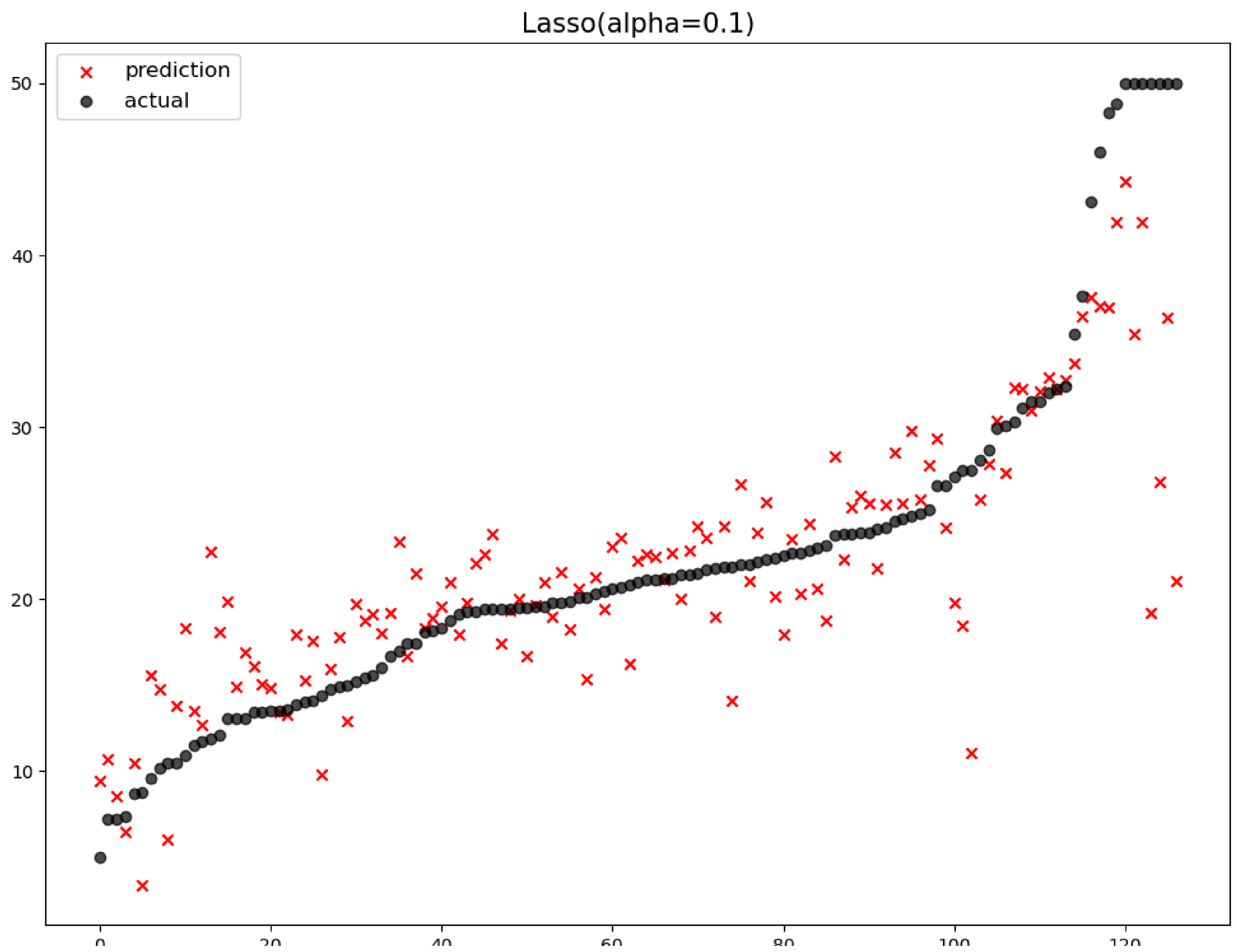
	model	mse
0	Lasso(alpha=100)	89.411990
1	Lasso(alpha=10)	58.044117
2	LinearRegression	34.179865



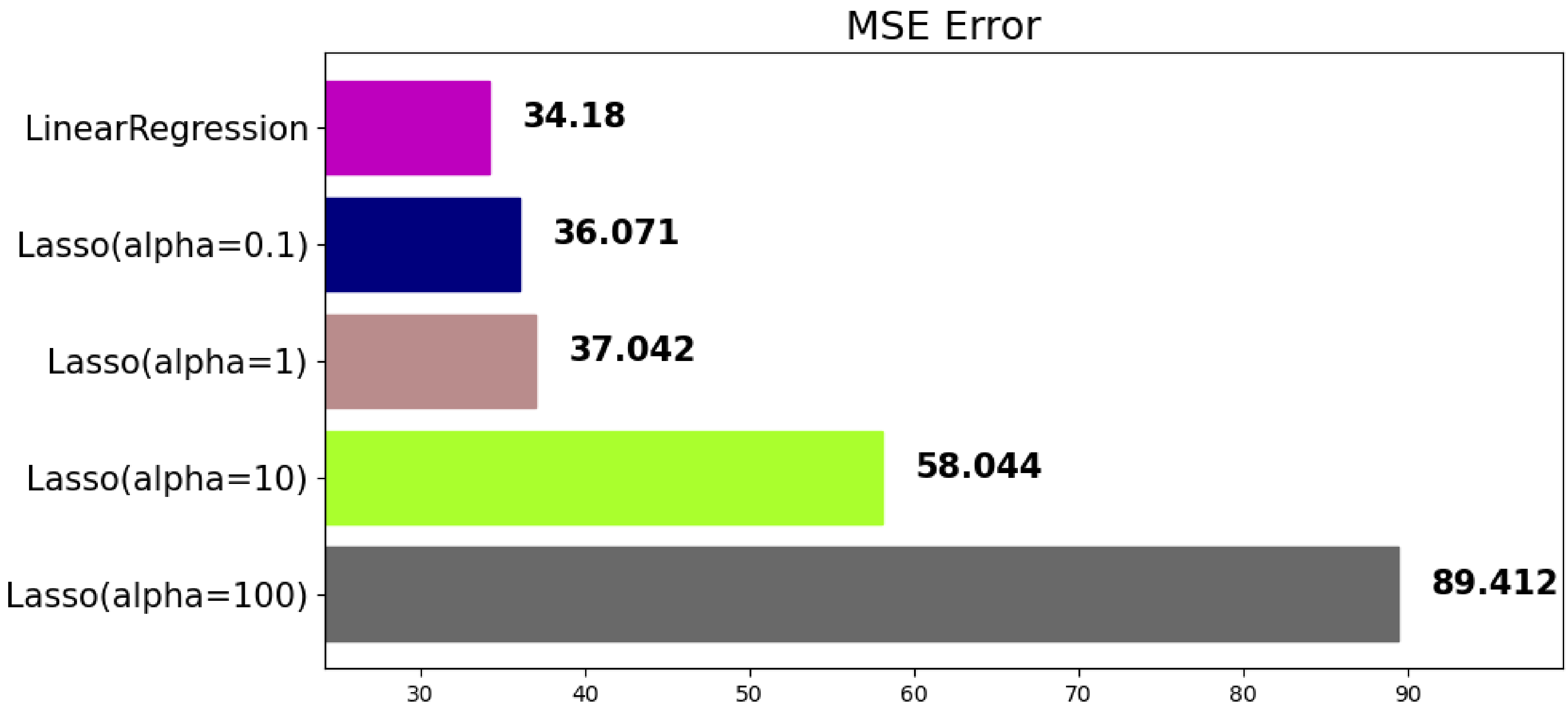

Lasso(alpha=1)
prediction
actual
10
20
30
40
50
0
20
40
60
80
100
120

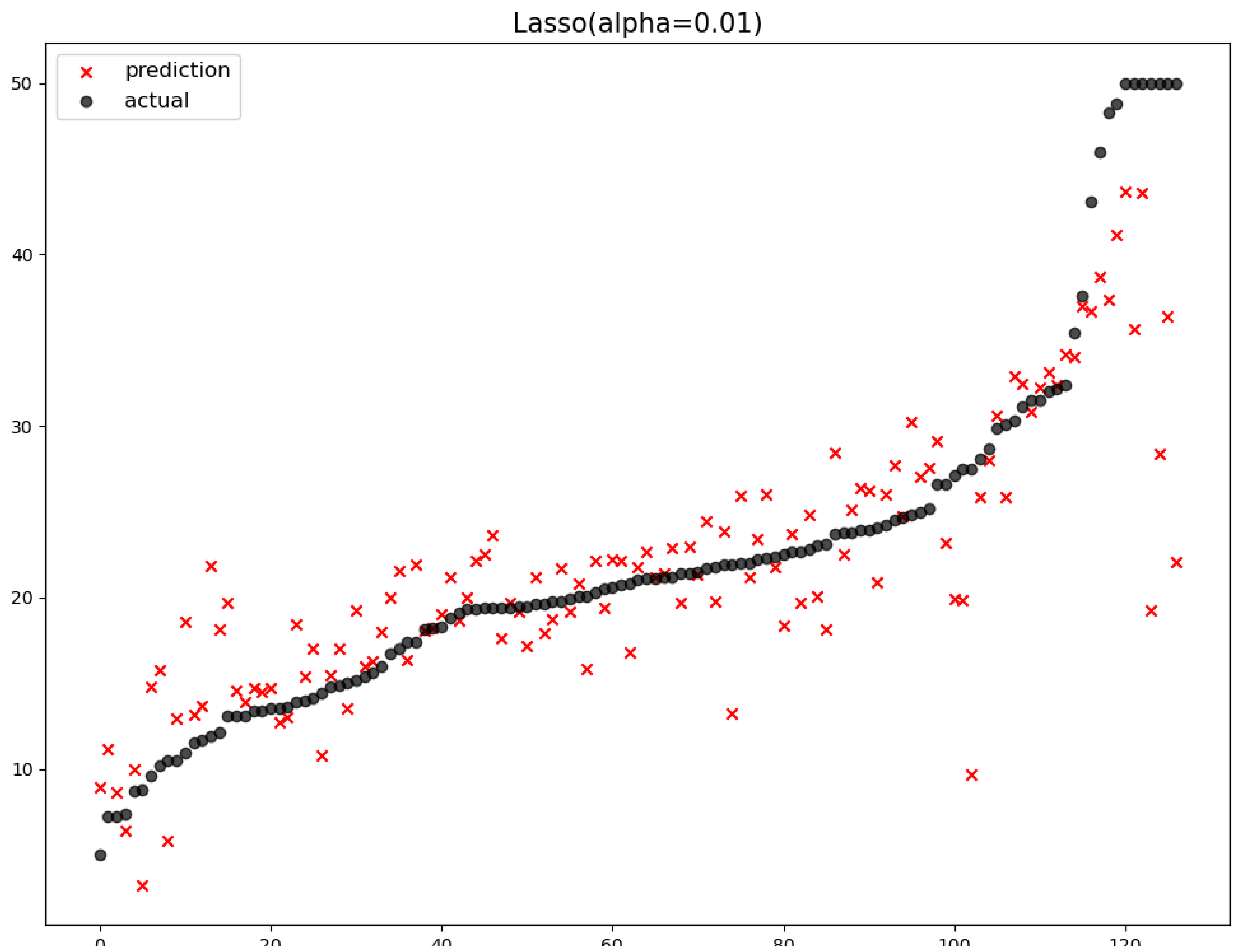
```
              model        mse
0  Lasso(alpha=100)  89.411990
1   Lasso(alpha=10)  58.044117
2    Lasso(alpha=1)  37.042408
3  LinearRegression  34.179865
```




Lasso(alpha=0.1)
prediction
actual
50
40
30
20
10
0
20
40
60
80
100
120

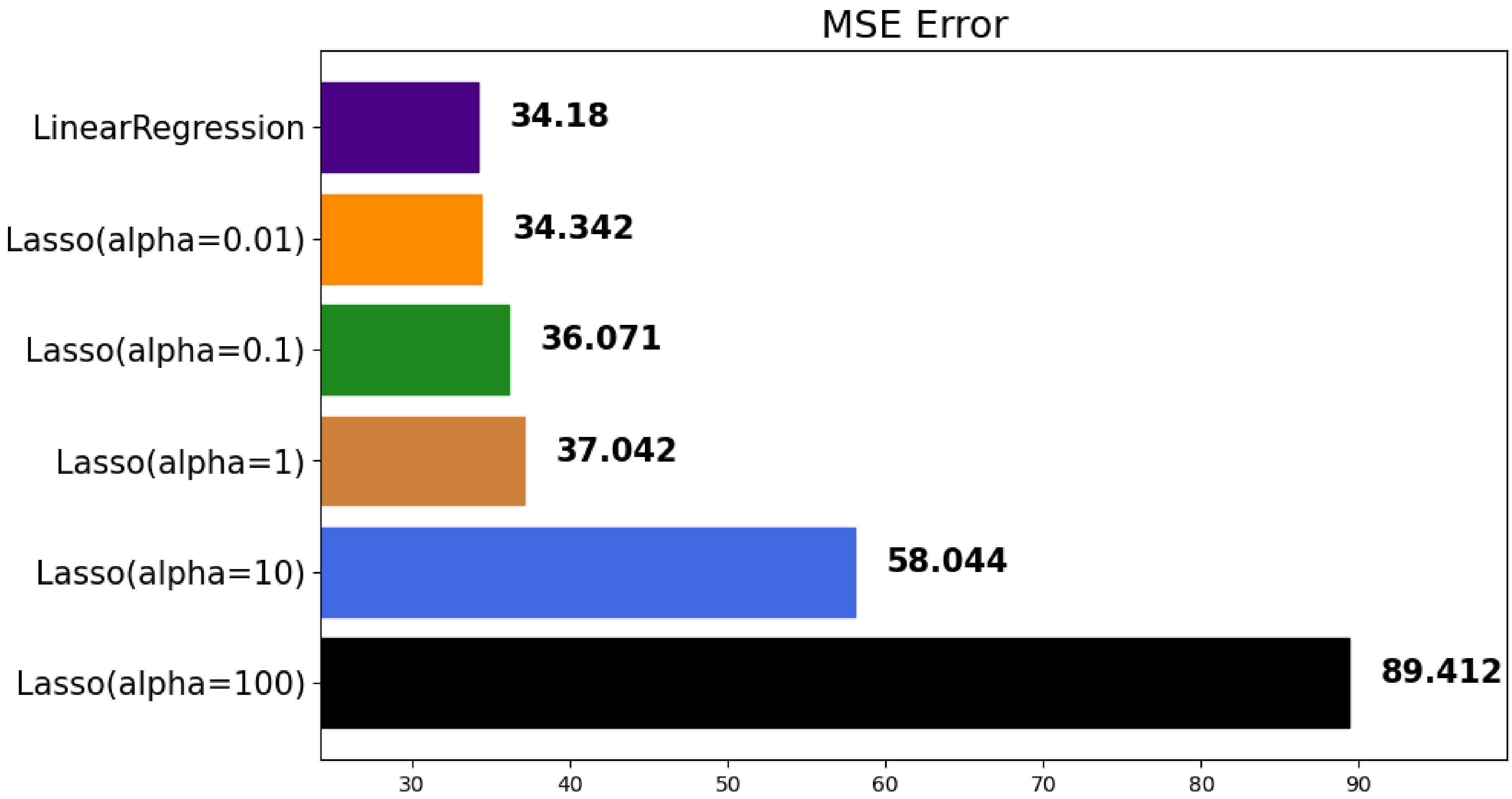
	model	mse
0	Lasso(alpha=100)	89.411990
1	Lasso(alpha=10)	58.044117
2	Lasso(alpha=1)	37.042408
3	Lasso(alpha=0.1)	36.070849
4	LinearRegression	34.179865

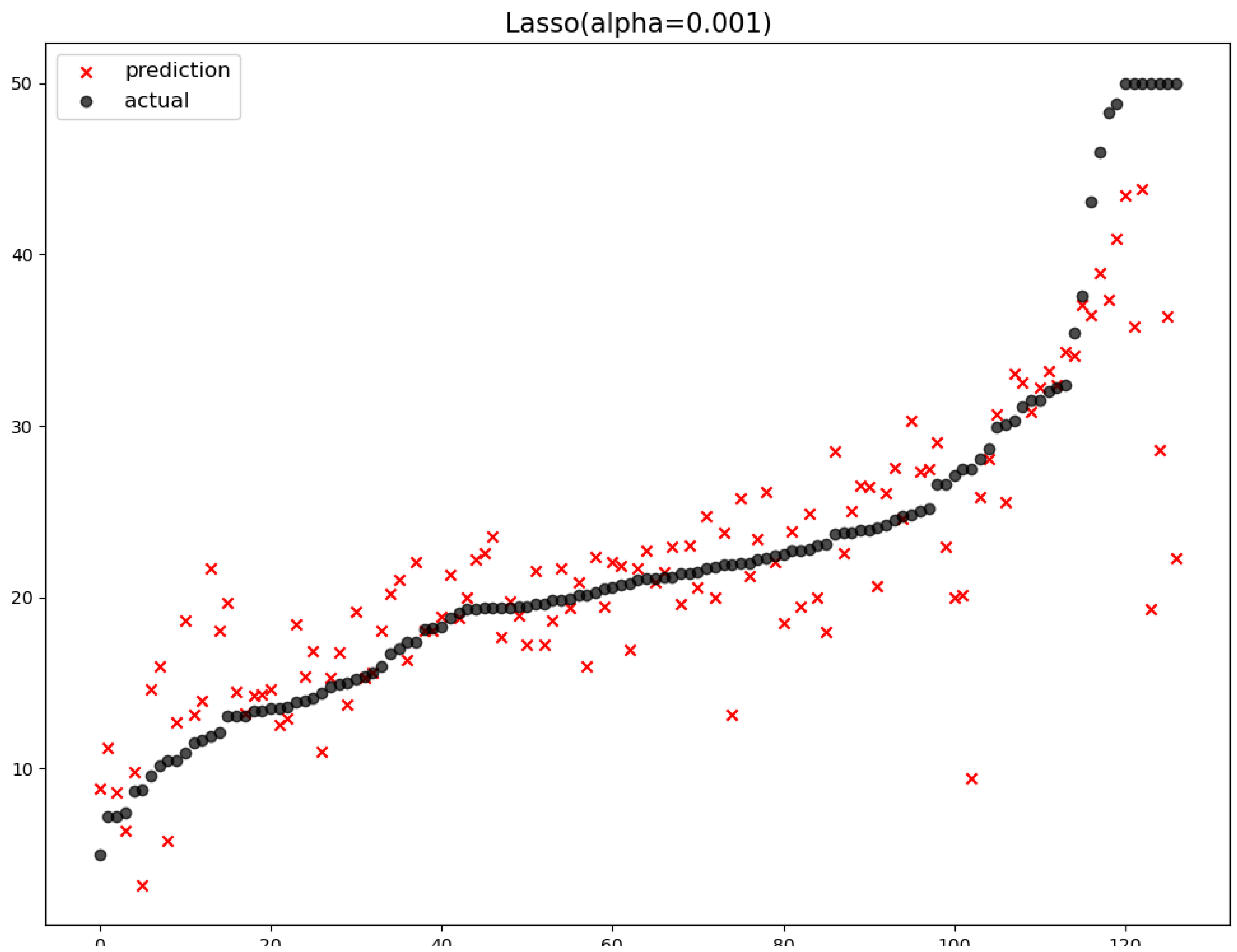




Lasso(alpha=0.01)
prediction
actual
50
40
30
20
10
0
20
40
60
80
100
120

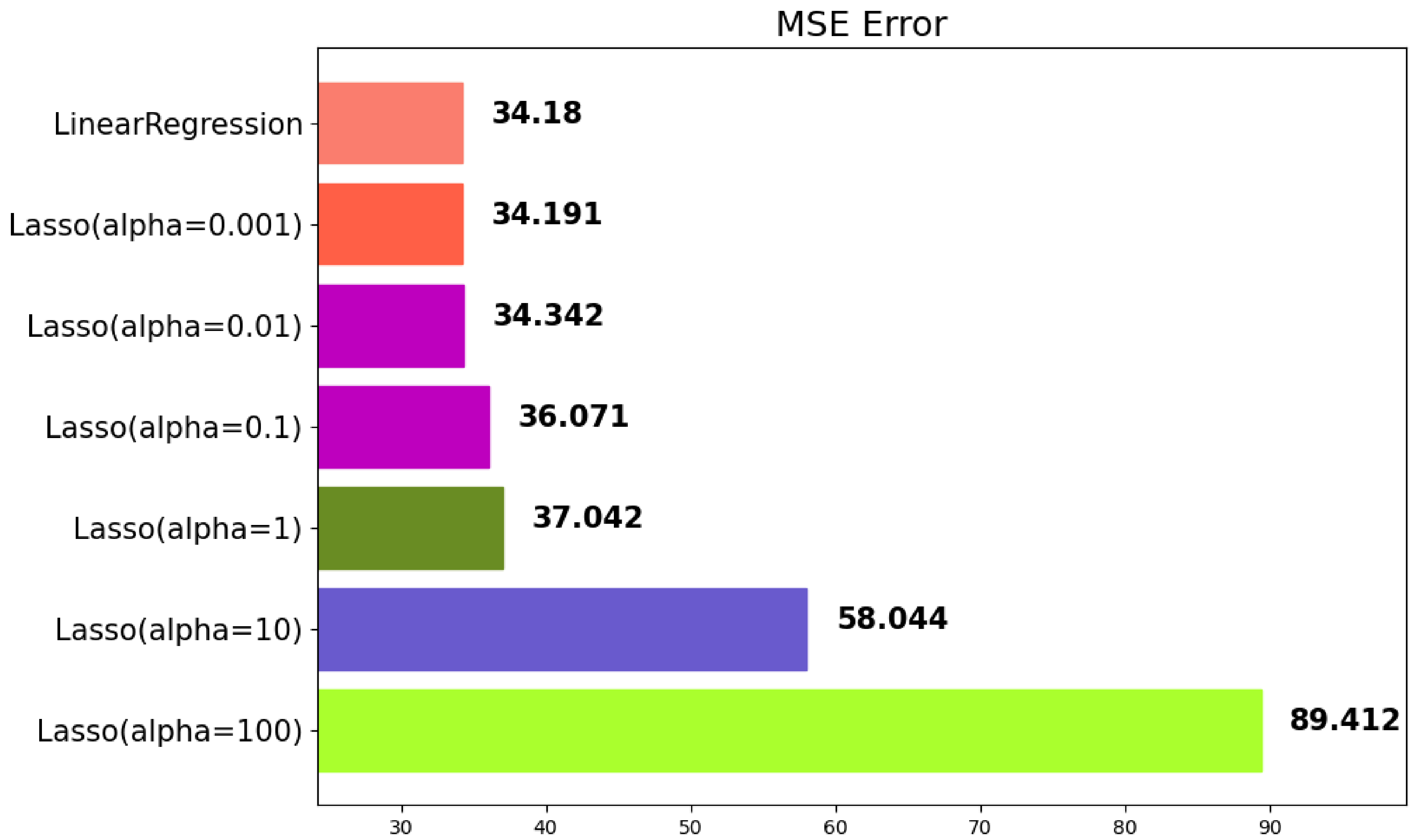
	model	mse
0	Lasso(alpha=100)	89.411990
1	Lasso(alpha=10)	58.044117
2	Lasso(alpha=1)	37.042408
3	Lasso(alpha=0.1)	36.070849
4	Lasso(alpha=0.01)	34.341542
5	LinearRegression	34.179865

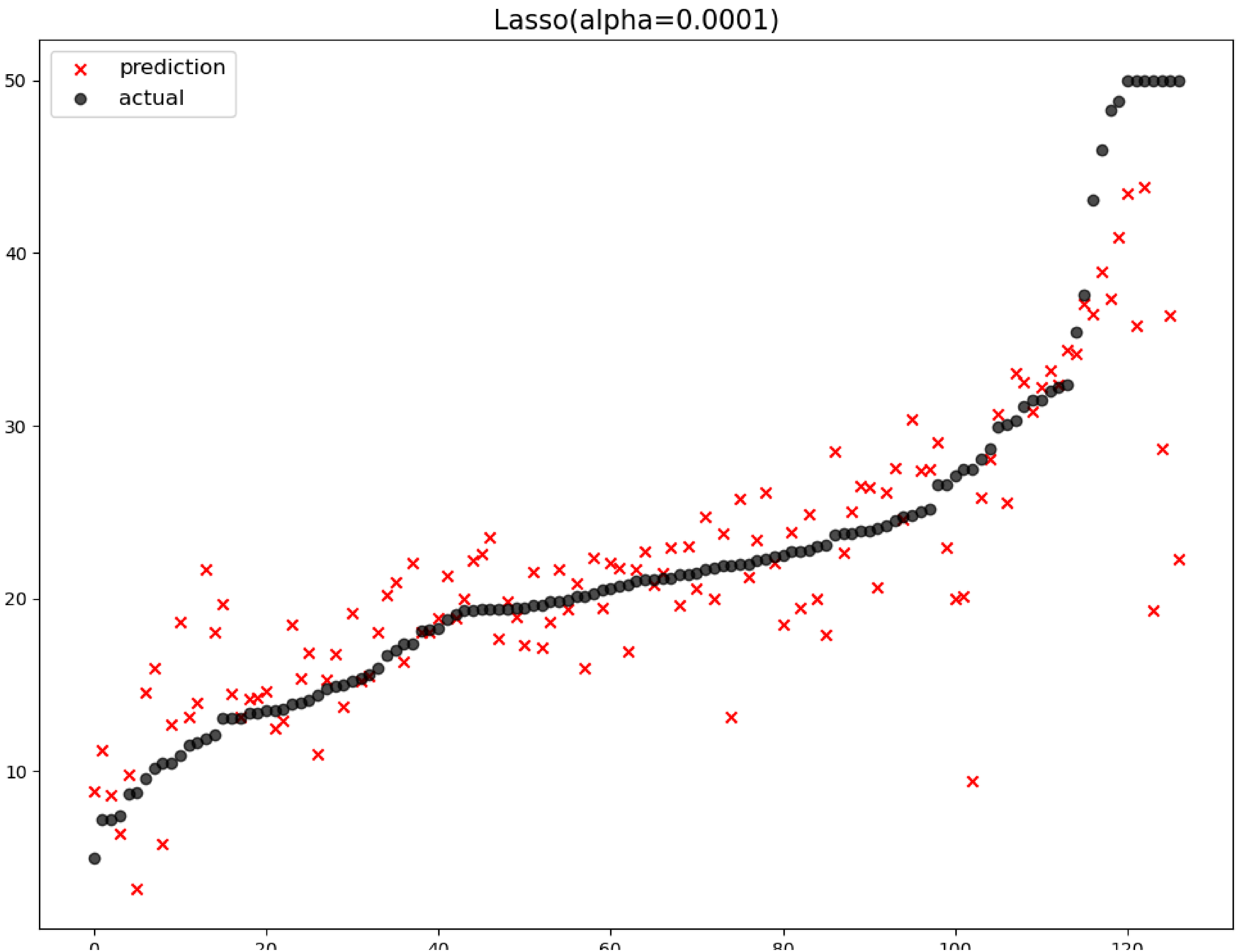




Lasso(alpha=0.001)
prediction
actual
50
40
30
20
10
0
20
40
60
80
100
120

	model	mse
0	Lasso(alpha=100)	89.411990
1	Lasso(alpha=10)	58.044117
2	Lasso(alpha=1)	37.042408
3	Lasso(alpha=0.1)	36.070849
4	Lasso(alpha=0.01)	34.341542
5	Lasso(alpha=0.001)	34.191145
6	LinearRegression	34.179865

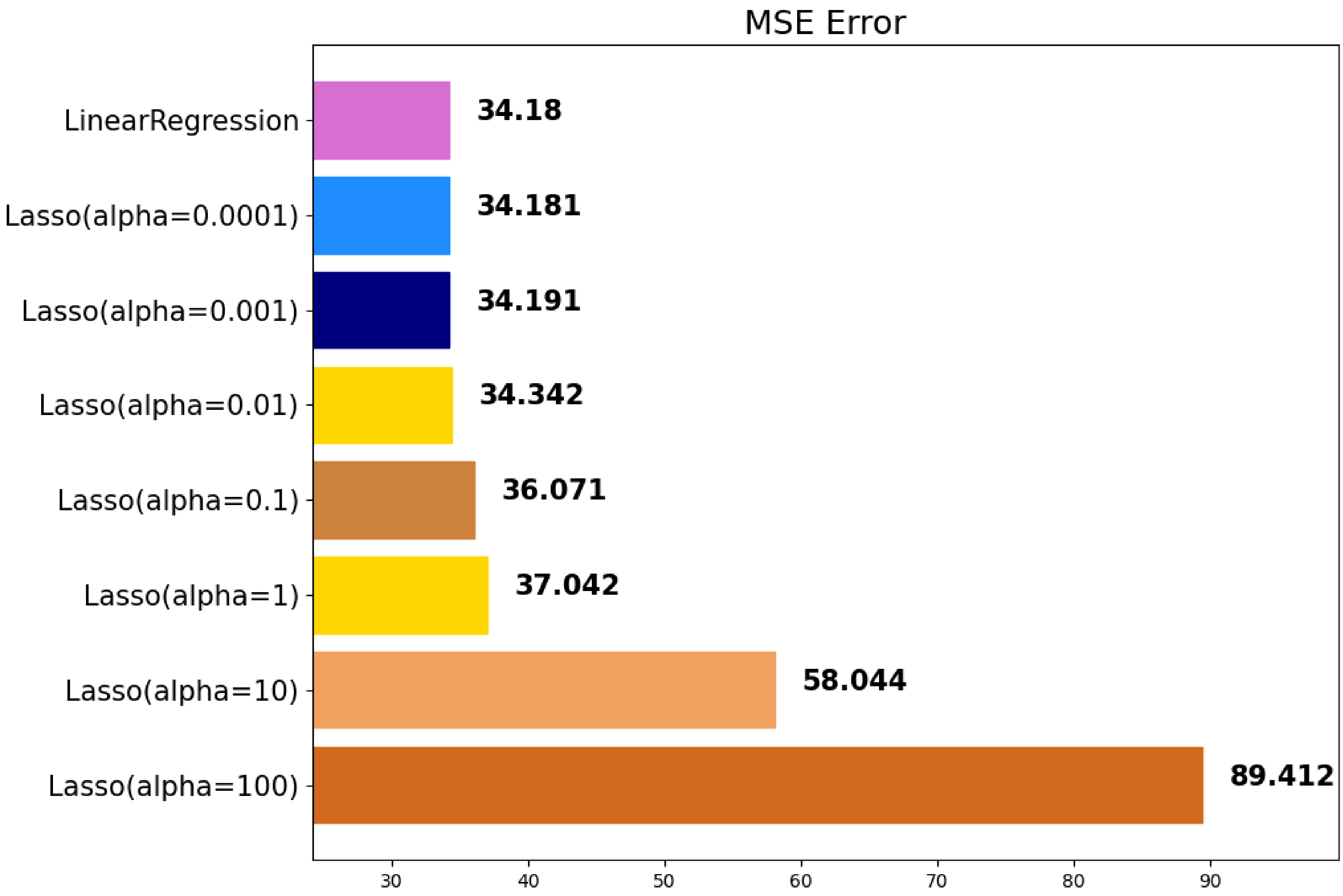

MSE Error
LinearRegression
Lasso(alpha=0.001)
Lasso(alpha=0.01)
Lasso(alpha=0.1)
Lasso(alpha=1)
Lasso(alpha=10)
Lasso(alpha=100)
34.18
34.191
34.342
36.071
37.042
58.044
89.412
30
40
50
60
70
80
90



Lasso(alpha=0.0001)
prediction
actual
50
40
30
20
10
0
20
40
60
80
100
120

0 20 40 60 80 100 120

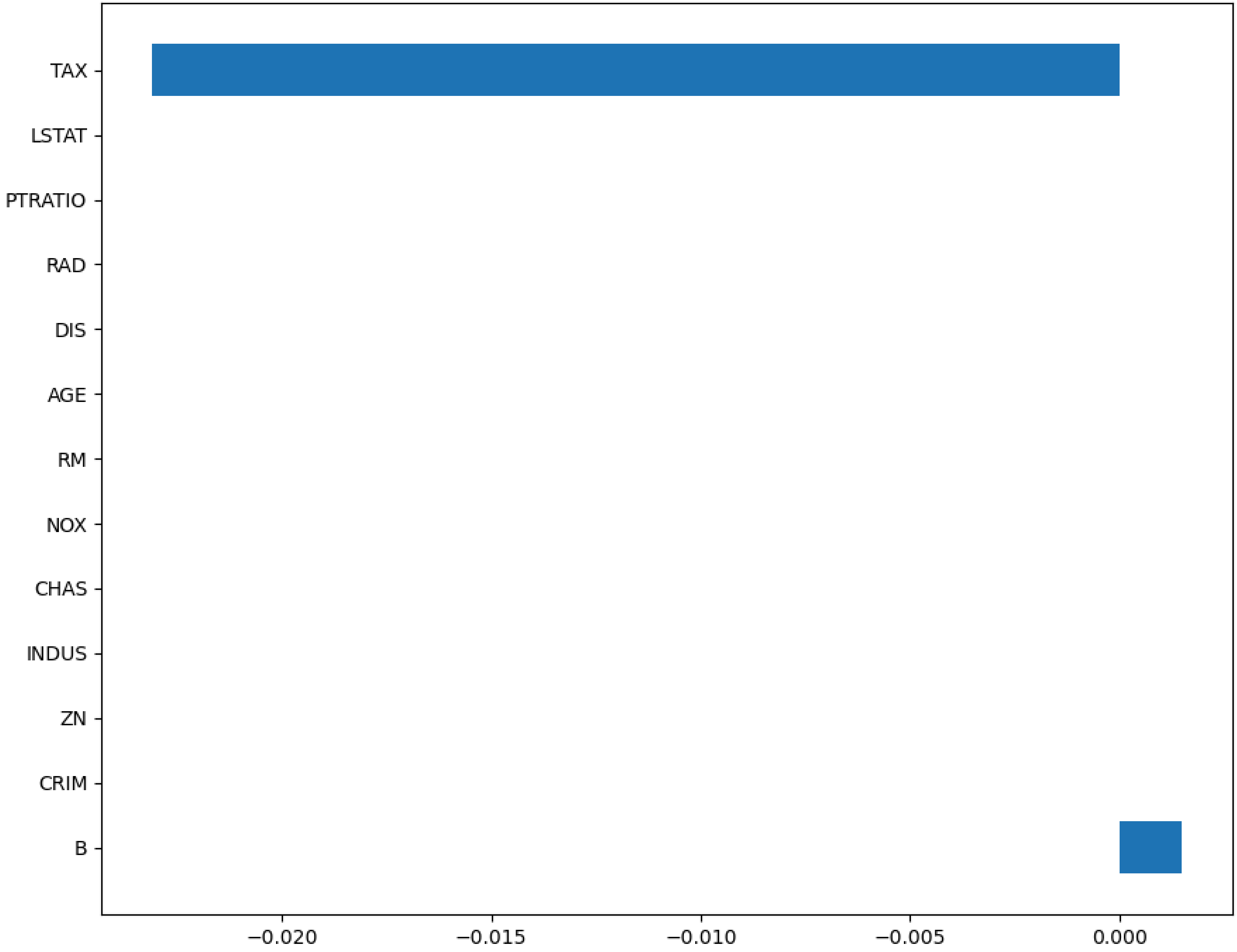
	model	mse
0	Lasso(alpha=100)	89.411990
1	Lasso(alpha=10)	58.044117
2	Lasso(alpha=1)	37.042408
3	Lasso(alpha=0.1)	36.070849
4	Lasso(alpha=0.01)	34.341542
5	Lasso(alpha=0.001)	34.191145
6	Lasso(alpha=0.0001)	34.180940
7	LinearRegression	34.179865


MSE Error
LinearRegression
Lasso(alpha=0.0001)
Lasso(alpha=0.001)
Lasso(alpha=0.01)
Lasso(alpha=0.1)
Lasso(alpha=1)
Lasso(alpha=10)
Lasso(alpha=100)
34.18
34.181
34.191
34.342
36.071
37.042
58.044
89.412
30
40
50
60
70
80
90

```
In [ ]:
```

In [66]:
```
lasso_100 = Lasso(alpha=100)
lasso_100.fit(x_train, y_train)
lasso_pred_100 = lasso_100.predict(x_test)

lasso_001 = Lasso(alpha=0.001)
lasso_001.fit(x_train, y_train)
lasso_pred_001 = lasso_001.predict(x_test)
```

In [67]:
```
plot_coef(x_train.columns, lasso_100.coef_)
```

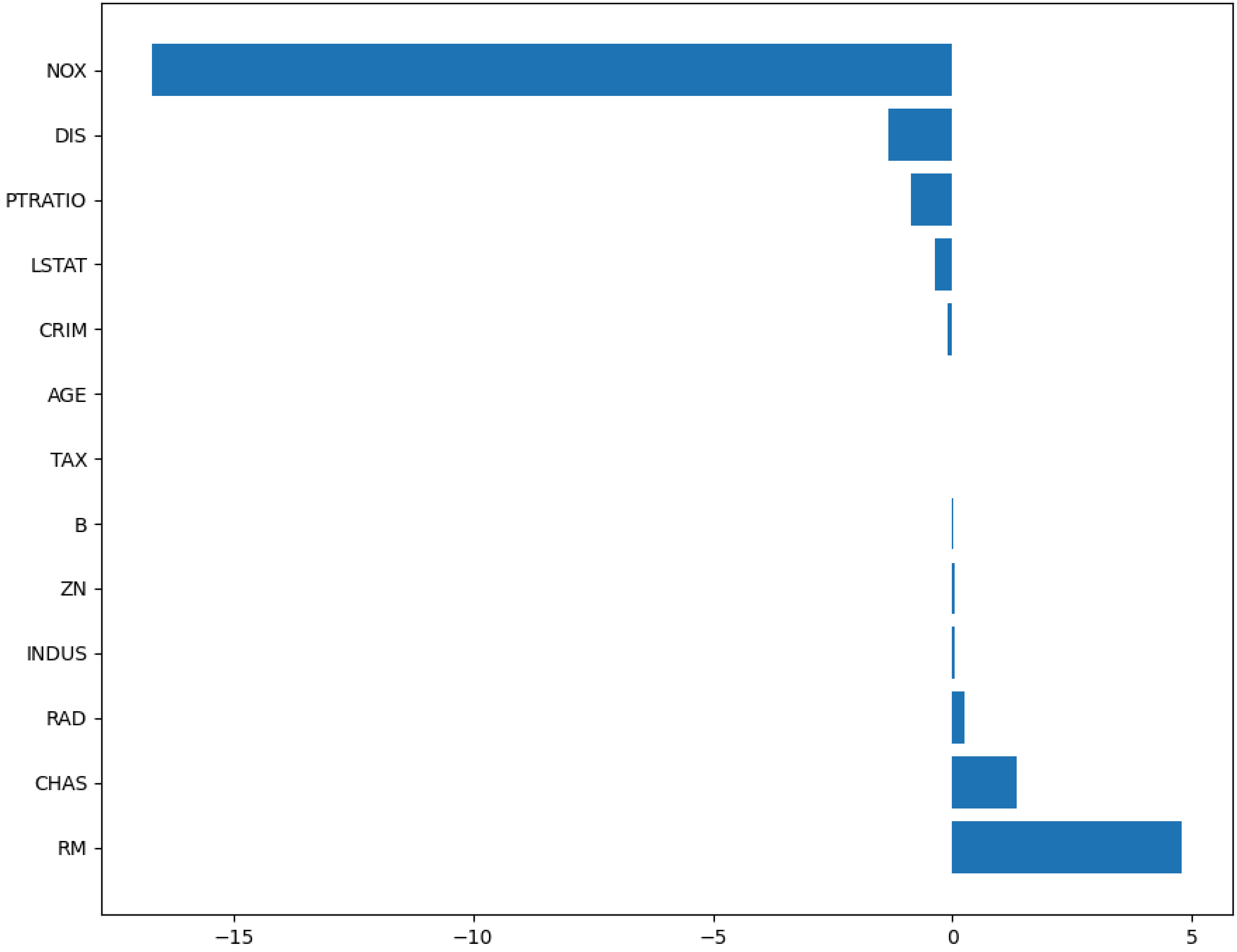


TAX
LSTAT
PTRATIO
RAD
DIS
AGE
RM
NOX
CHAS
INDUS
ZN
CRIM
B
−0.020
−0.015
−0.010
−0.005
0.000

In [68]:
```python
lasso_100.coef_
```

Out[68]:
```
array([-0.        ,  0.        , -0.        ,  0.        , -0.        ,
        0.        , -0.        ,  0.        , -0.        , -0.02308612,
       -0.        ,  0.00147183, -0.        ])
```

In [69]:
```python
plot_coef(x_train.columns, lasso_001.coef_)
```



NOX
DIS
PTRATIO
LSTAT
CRIM
AGE
TAX
B
ZN
INDUS
RAD
CHAS
RM
−15
−10
−5
0
5

In [70]:
```python
lasso_001.coef_
```

Out[70]:
```
array([ -0.08885369,   0.04077299,   0.05501038,   1.32930809,
       -16.68692403,   4.77025401,  -0.02046479,  -1.34802031,
         0.24070115,  -0.01316838,  -0.8800191 ,   0.00860612,
        -0.36576961])
```

ElasticNet

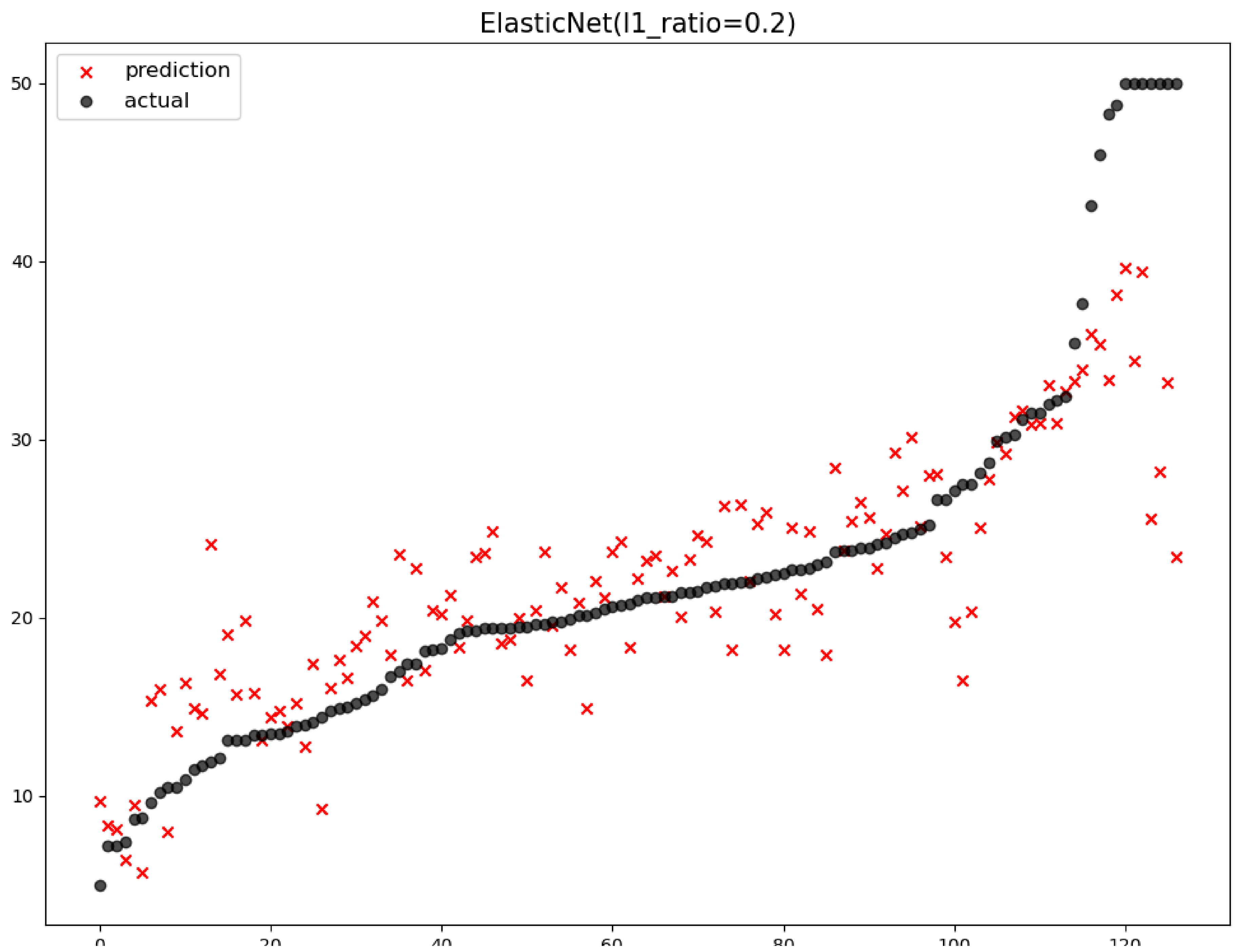
l1_ratio (default=0.5)

- l1_ratio = 0 (L2 규제만 사용).
- l1_ratio = 1 (L1 규제만 사용).
- 0 < l1_ratio < 1 (L1 and L2 규제의 혼합사용)

In [73]:
```python
from sklearn.linear_model import ElasticNet
```

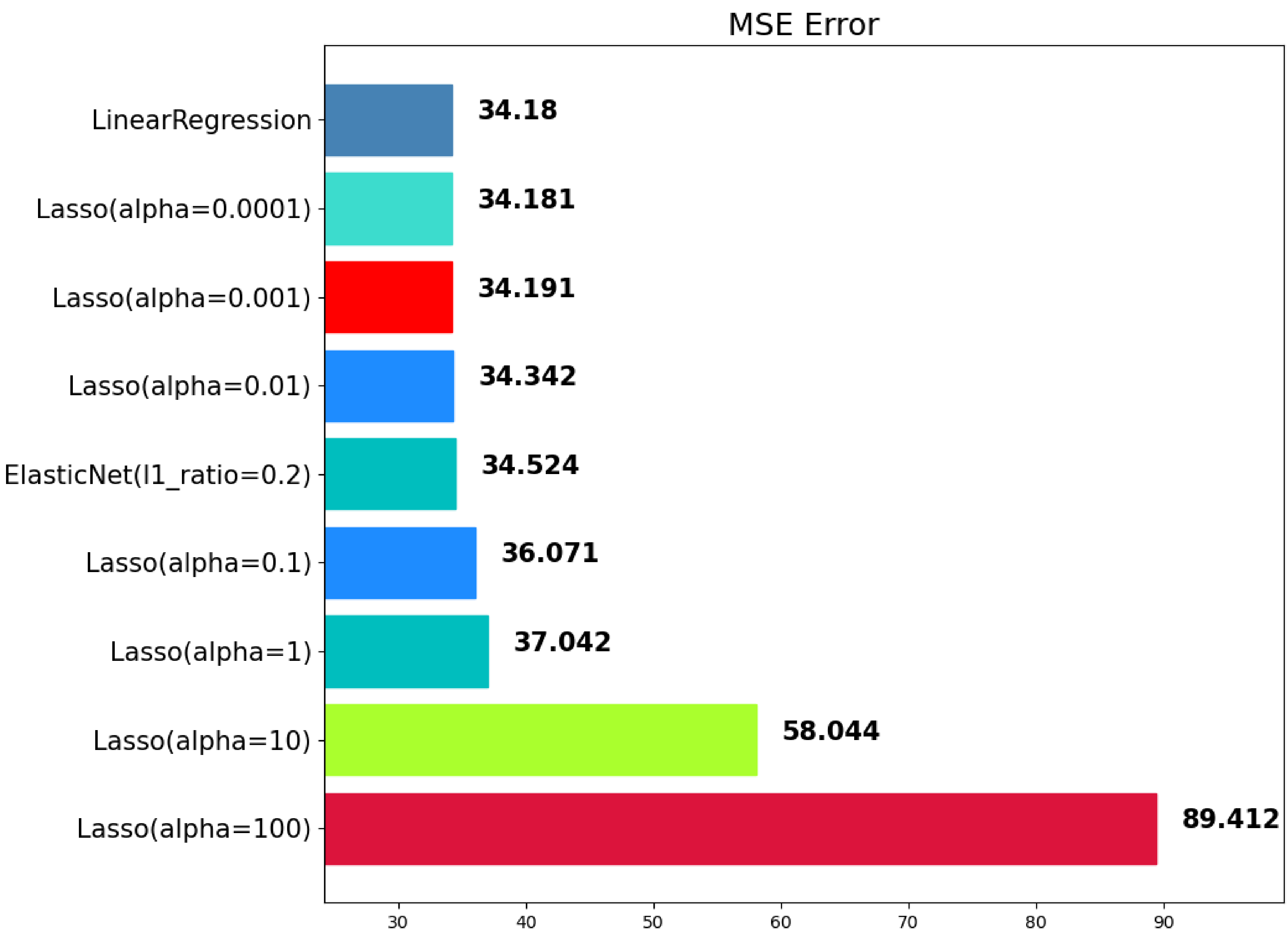
In [74]:
```python
ratios = [0.2, 0.5, 0.8]
```

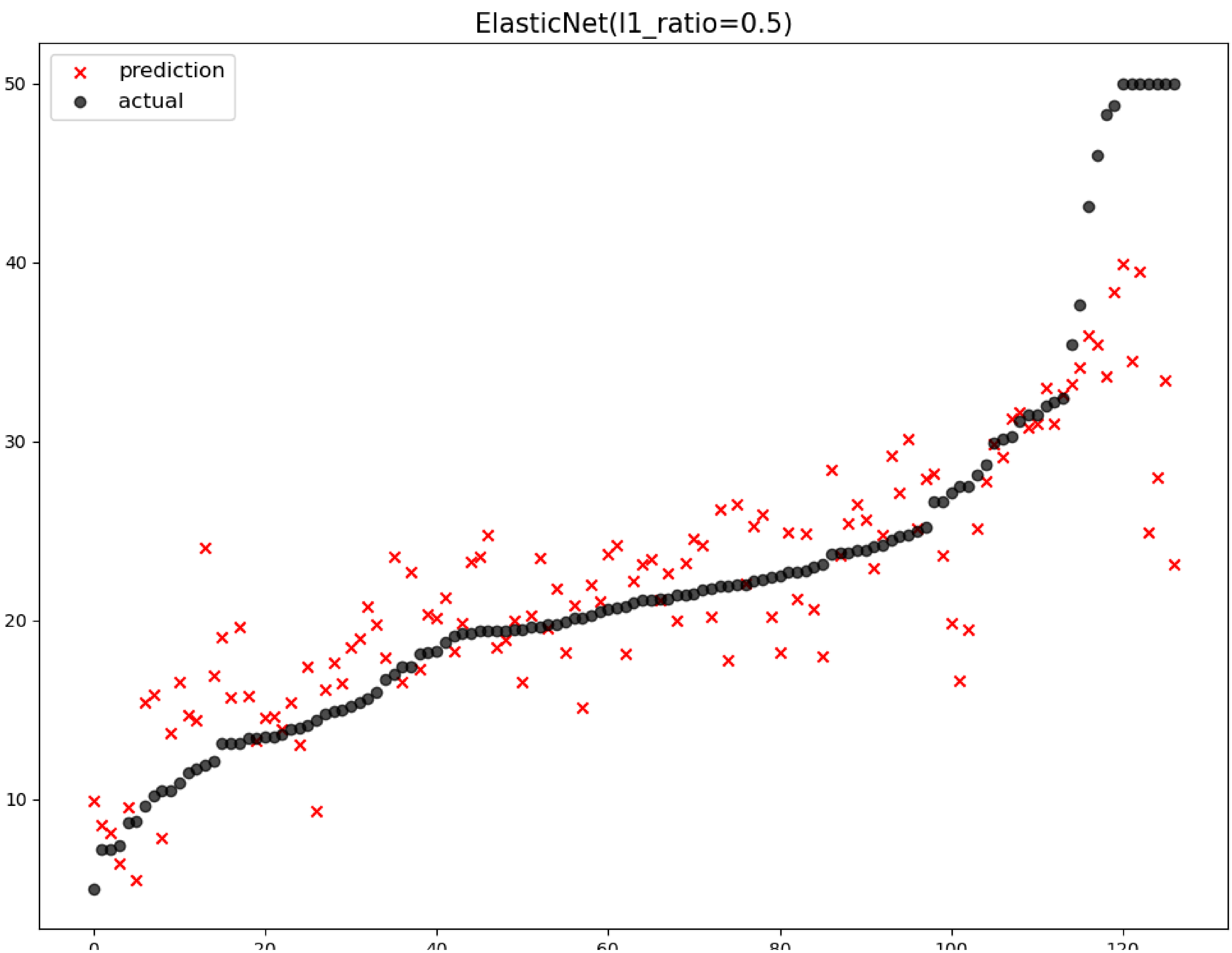
In [75]:
```python
for ratio in ratios:
    elasticnet = ElasticNet(alpha=0.5, l1_ratio=ratio)
    elasticnet.fit(x_train, y_train)
    pred = elasticnet.predict(x_test)
    mse_eval('ElasticNet(l1_ratio={})'.format(ratio), pred, y_test)
```



ElasticNet(l1_ratio=0.2)
prediction
actual
50
40
30
20
10
0
20
40
60
80
100
120

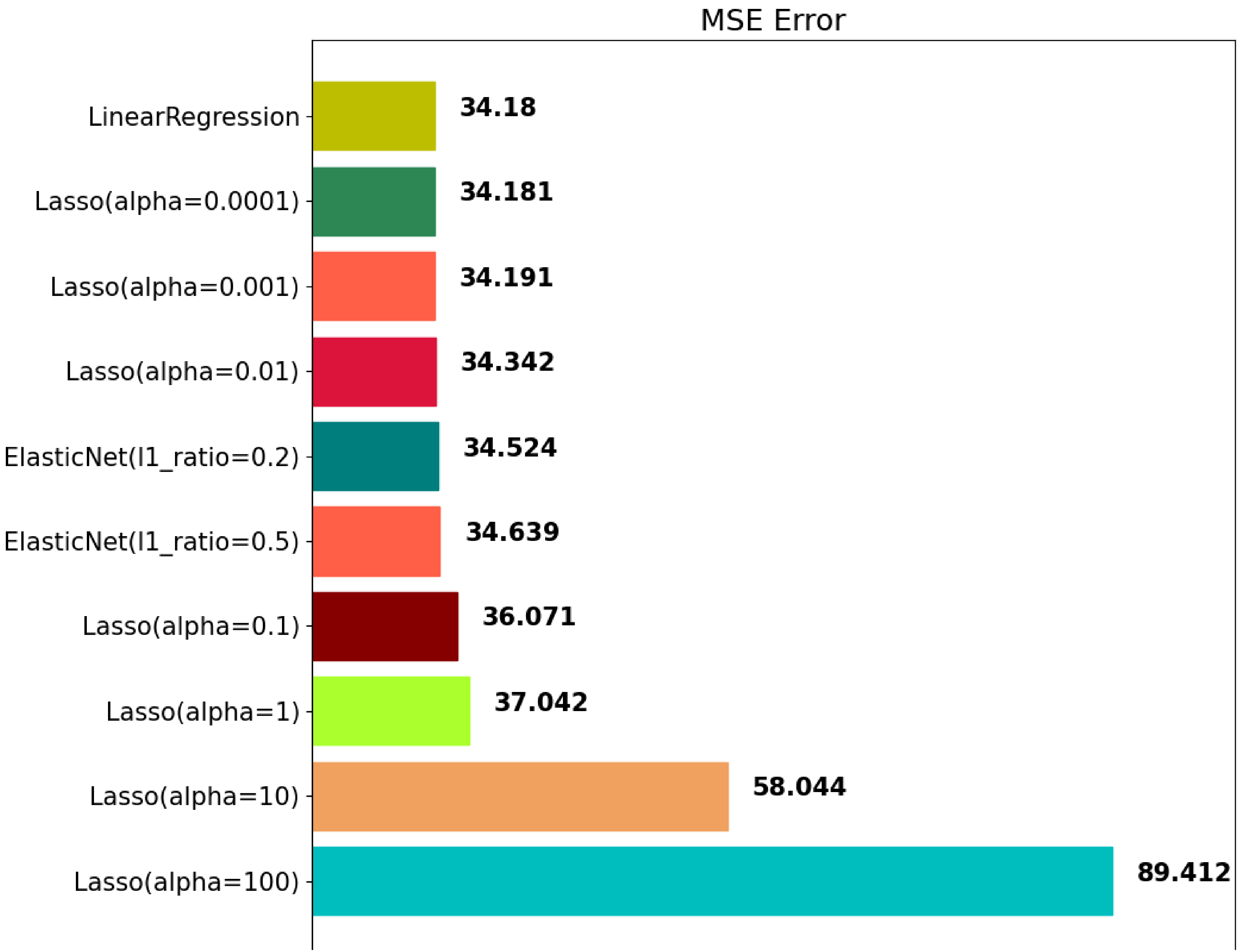
	model	mse
0	Lasso(alpha=100)	89.411990
1	Lasso(alpha=10)	58.044117
2	Lasso(alpha=1)	37.042408
3	Lasso(alpha=0.1)	36.070849
4	ElasticNet(l1_ratio=0.2)	34.523999
5	Lasso(alpha=0.01)	34.341542
6	Lasso(alpha=0.001)	34.191145
7	Lasso(alpha=0.0001)	34.180940
8	LinearRegression	34.179865


MSE Error
LinearRegression
Lasso(alpha=0.0001)
Lasso(alpha=0.001)
Lasso(alpha=0.01)
ElasticNet(l1_ratio=0.2)
Lasso(alpha=0.1)
Lasso(alpha=1)
Lasso(alpha=10)
Lasso(alpha=100)
34.18
34.181
34.191
34.342
34.524
36.071
37.042
58.044
89.412
30
40
50
60
70
80
90

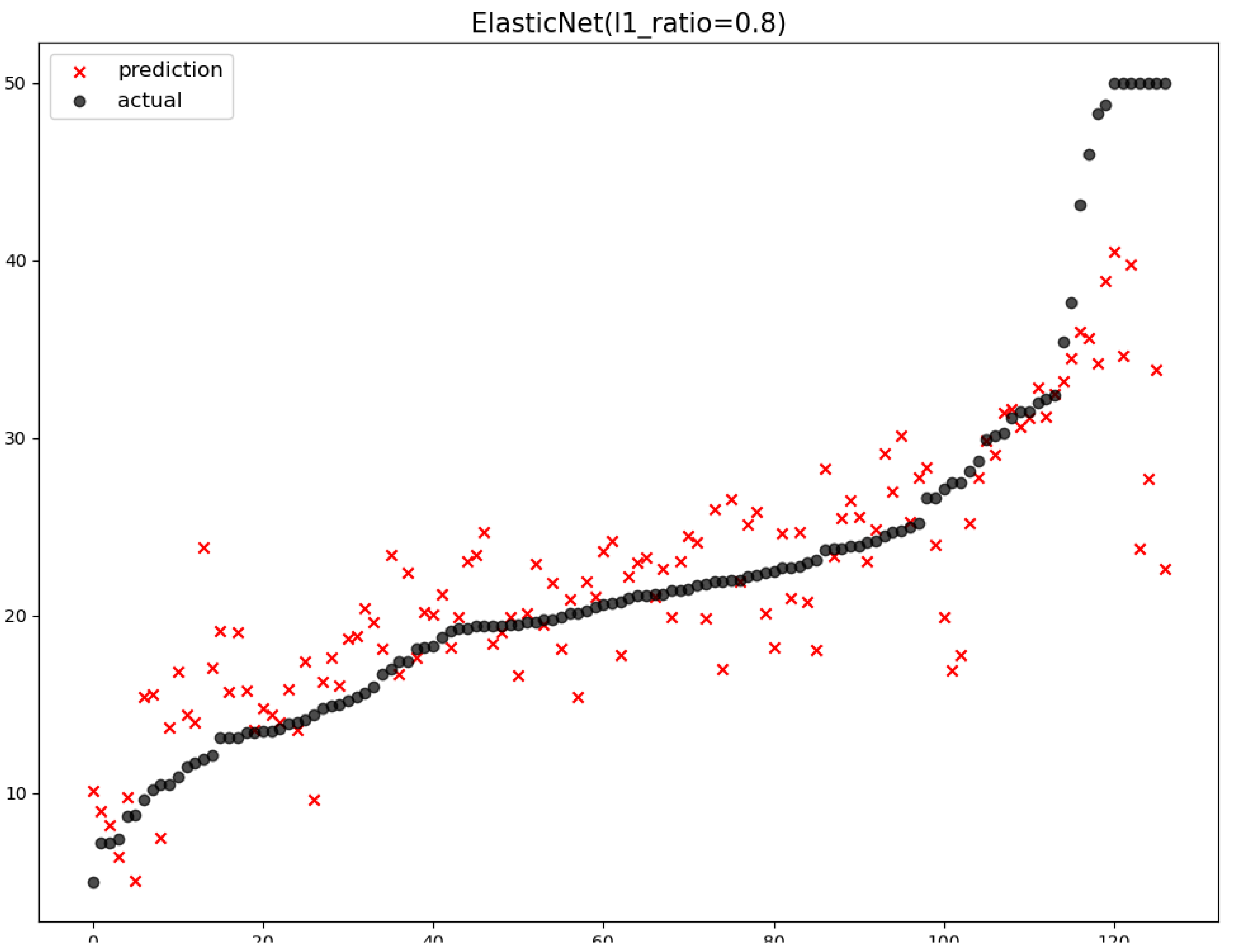


ElasticNet(l1_ratio=0.5)
prediction
actual
50
40
30
20
10
0
20
40
60
80
100
120

```
                     model        mse
0         Lasso(alpha=100)  89.411990
1          Lasso(alpha=10)  58.044117
2           Lasso(alpha=1)  37.042408
3         Lasso(alpha=0.1)  36.070849
4  ElasticNet(l1_ratio=0.5)  34.639468
5  ElasticNet(l1_ratio=0.2)  34.523999
6        Lasso(alpha=0.01)  34.341542
7       Lasso(alpha=0.001)  34.191145
8      Lasso(alpha=0.0001)  34.180940
9         LinearRegression  34.179865
```

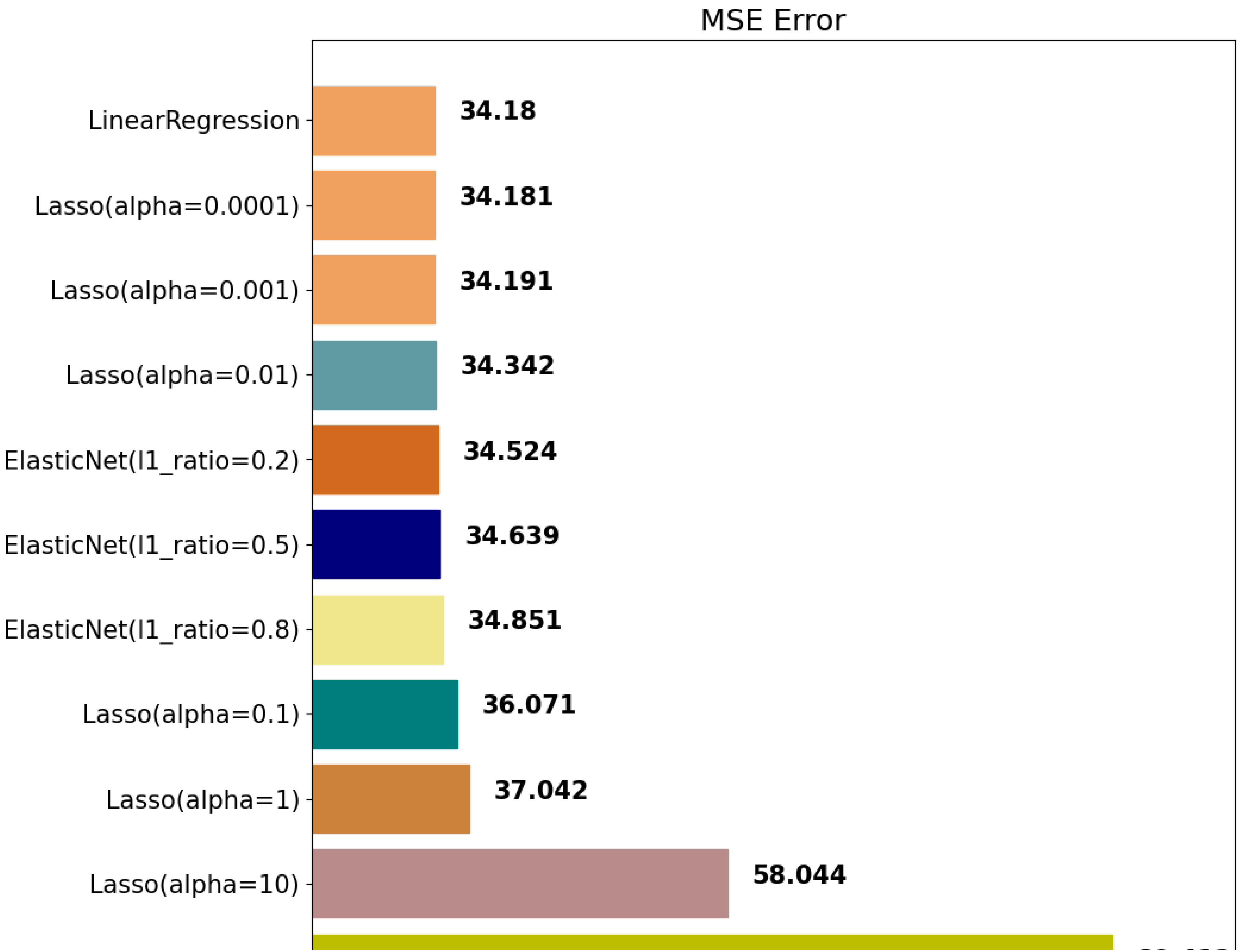

MSE Error
LinearRegression
Lasso(alpha=0.0001)
Lasso(alpha=0.001)
Lasso(alpha=0.01)
ElasticNet(l1_ratio=0.2)
ElasticNet(l1_ratio=0.5)
Lasso(alpha=0.1)
Lasso(alpha=1)
Lasso(alpha=10)
Lasso(alpha=100)
34.18
34.181
34.191
34.342
34.524
34.639
36.071
37.042
58.044
89.412

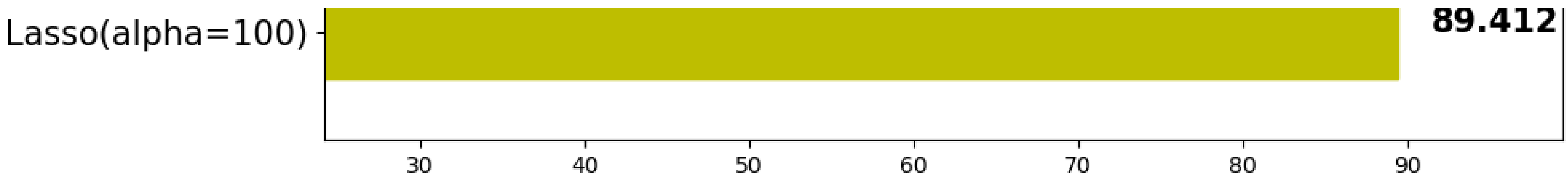

30
40
50
60
70
80
90


ElasticNet(l1_ratio=0.8)
prediction
actual
50
40
30
20
10
0
20
40
60
80
100
120

0 20 40 60 80 100 120

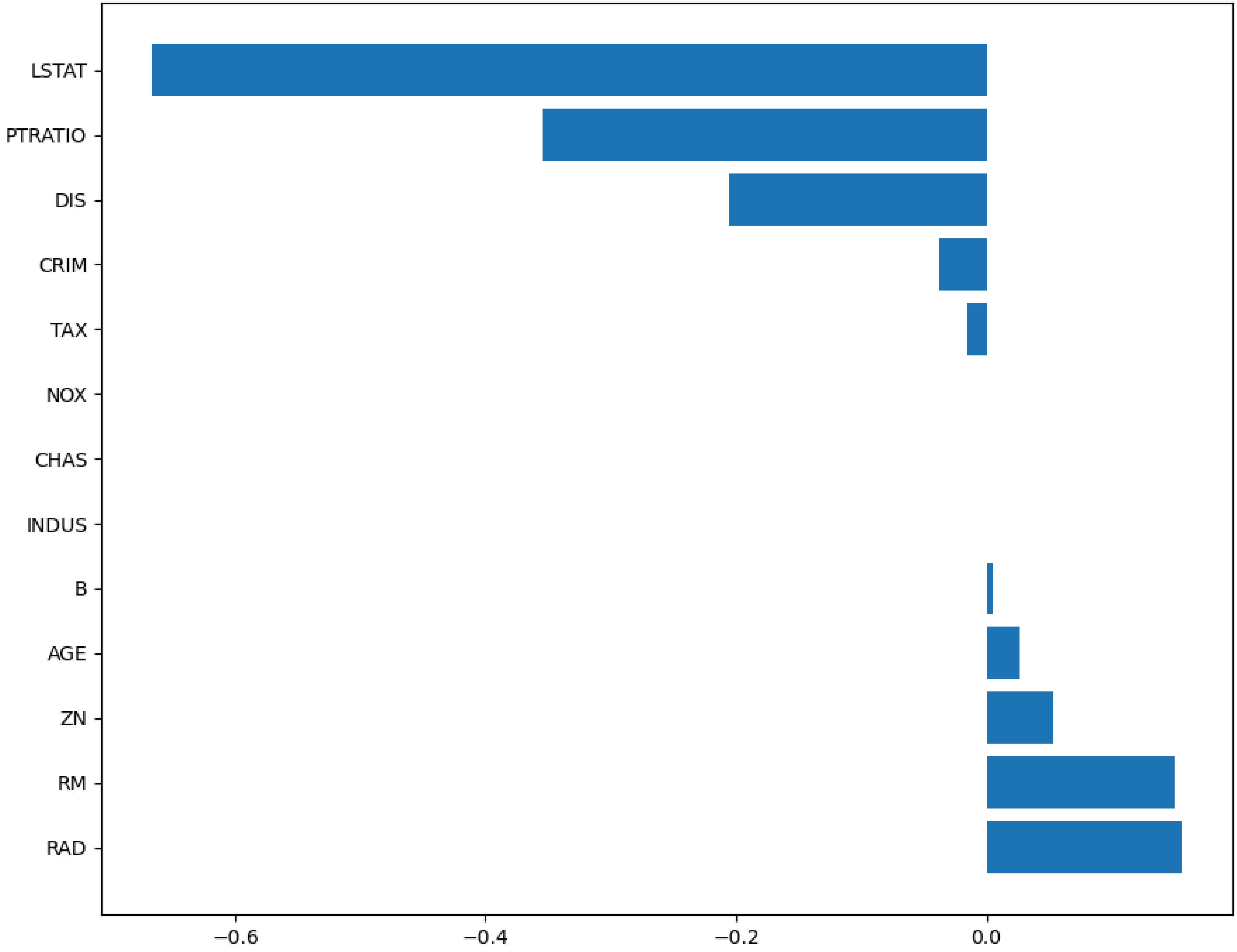
	model	mse
0	Lasso(alpha=100)	89.411990
1	Lasso(alpha=10)	58.044117
2	Lasso(alpha=1)	37.042408
3	Lasso(alpha=0.1)	36.070849
4	ElasticNet(l1_ratio=0.8)	34.851407
5	ElasticNet(l1_ratio=0.5)	34.639468
6	ElasticNet(l1_ratio=0.2)	34.523999
7	Lasso(alpha=0.01)	34.341542
8	Lasso(alpha=0.001)	34.191145
9	Lasso(alpha=0.0001)	34.180940
10	LinearRegression	34.179865


MSE Error
LinearRegression
Lasso(alpha=0.0001)
Lasso(alpha=0.001)
Lasso(alpha=0.01)
ElasticNet(l1_ratio=0.2)
ElasticNet(l1_ratio=0.5)
ElasticNet(l1_ratio=0.8)
Lasso(alpha=0.1)
Lasso(alpha=1)
Lasso(alpha=10)
34.18
34.181
34.191
34.342
34.524
34.639
34.851
36.071
37.042
58.044



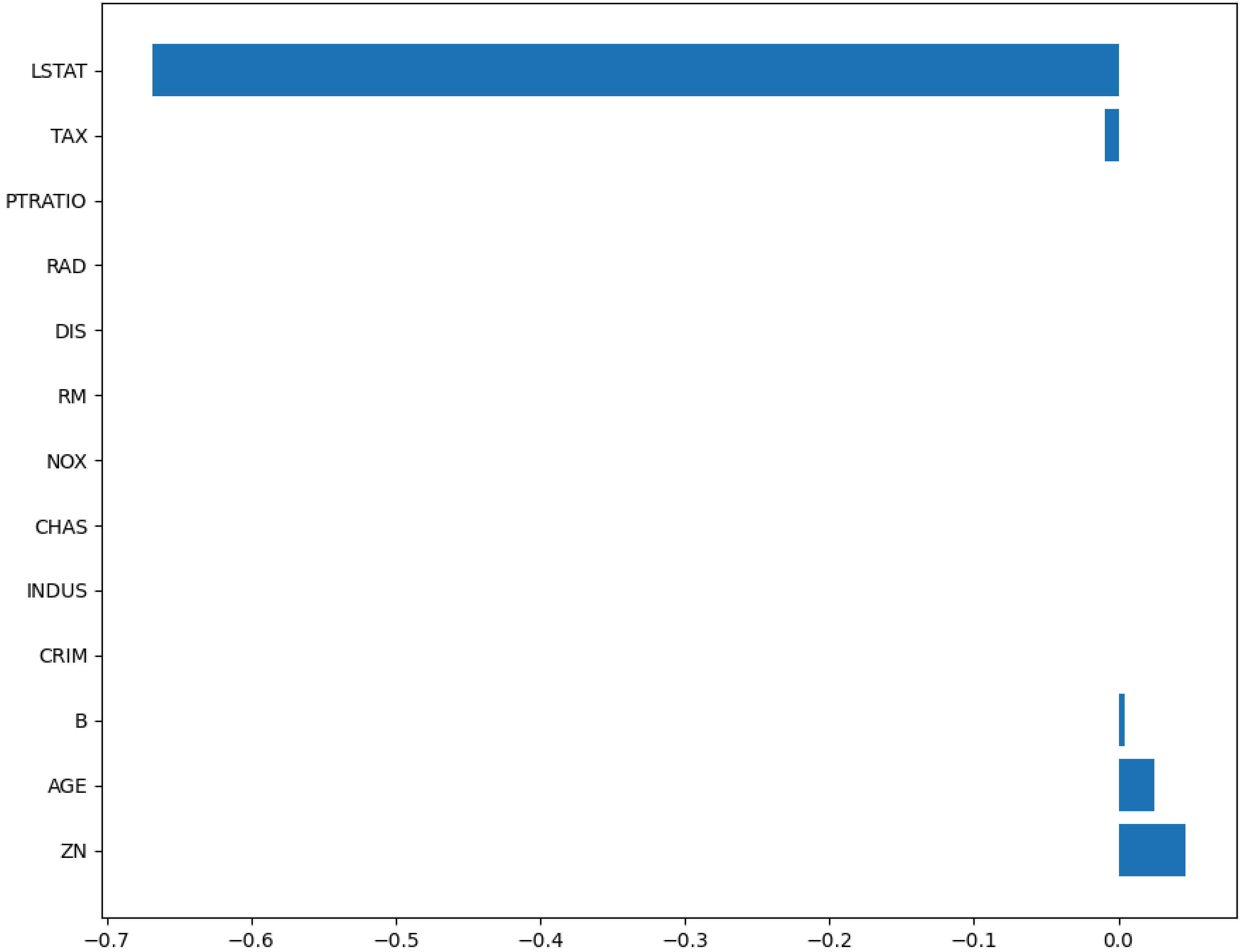
In [76]:
```
elsticnet_20 = ElasticNet(alpha=5, l1_ratio=0.2)
elsticnet_20.fit(x_train, y_train)
elasticnet_pred_20 = elsticnet_20.predict(x_test)

elsticnet_80 = ElasticNet(alpha=5, l1_ratio=0.8)
elsticnet_80.fit(x_train, y_train)
elasticnet_pred_80 = elsticnet_80.predict(x_test)
```

In [77]:
```
plot_coef(x_train.columns, elsticnet_20.coef_)
```


LSTAT
PTRATIO
DIS
CRIM
TAX
NOX
CHAS
INDUS
B
AGE
ZN
RM
RAD
−0.6
−0.4
−0.2
0.0

In [78]:

```
plot_coef(x_train.columns, elsticnet_80.coef_)
```


LSTAT
TAX
PTRATIO
RAD
DIS
RM
NOX
CHAS
INDUS
CRIM
B
AGE
ZN
−0.7
−0.6
−0.5
−0.4
−0.3
−0.2
−0.1
0.0

In [79]:
```
elsticnet_80.coef_
```

Out[79]:
```
array([-0.        ,  0.04594815, -0.        ,  0.        ,  0.        ,
        0.        ,  0.02500528, -0.        ,  0.        , -0.00981168,
       -0.        ,  0.00402508, -0.66785485])
```

Scaler

In [81]:
```
from sklearn.preprocessing import StandardScaler, MinMaxScaler, RobustScaler
```

In [82]:
```
x_train.describe()
```

Out[82]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRA
count	379.000000	379.000000	379.000000	379.000000	379.000000	379.000000	379.000000	379.000000	379.000000	379.000000	379.000
mean	3.399125	11.920844	10.696755	0.068602	0.548541	6.301731	67.548021	3.847623	9.292876	402.348285	18.447
std	8.474678	23.623431	6.848942	0.253110	0.112711	0.691178	28.064872	2.072292	8.513682	166.392966	2.117
min	0.006320	0.000000	0.460000	0.000000	0.385000	3.863000	6.000000	1.137000	1.000000	188.000000	12.600
25%	0.076890	0.000000	4.930000	0.000000	0.448000	5.901500	45.050000	2.120350	4.000000	277.000000	17.400
50%	0.222120	0.000000	8.140000	0.000000	0.524000	6.223000	74.800000	3.317500	5.000000	330.000000	18.900
75%	2.851870	20.000000	18.100000	0.000000	0.624000	6.630000	94.000000	5.214600	8.000000	666.000000	20.200
max	88.976200	100.000000	27.740000	1.000000	0.871000	8.780000	100.000000	10.710300	24.000000	711.000000	22.000

StandardScaler

평균(mean)을 0, 표준편차(std)를 1로 만들어 주는 스케일러

In [85]:
```
std_scaler = StandardScaler()
```

In [86]:
```
std_scaled = std_scaler.fit_transform(x_train)
```

In [87]:
```
round(pd.DataFrame(std_scaled).describe(), 2)
```

Out[87]:

	0	1	2	3	4	5	6	7	8	9	10	11	12
count	379.00	379.00	379.00	379.00	379.00	379.00	379.00	379.00	379.00	379.00	379.00	379.00	379.00
mean	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.00	-0.00	-0.00	0.00	0.00	0.00
std	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
min	-0.40	-0.51	-1.50	-0.27	-1.45	-3.53	-2.20	-1.31	-0.98	-1.29	-2.77	-4.02	-1.48
25%	-0.39	-0.51	-0.84	-0.27	-0.89	-0.58	-0.80	-0.83	-0.62	-0.75	-0.50	0.20	-0.77
50%	-0.38	-0.51	-0.37	-0.27	-0.22	-0.11	0.26	-0.26	-0.50	-0.44	0.21	0.38	-0.22
75%	-0.06	0.34	1.08	-0.27	0.67	0.48	0.94	0.66	-0.15	1.59	0.83	0.42	0.55
max	10.11	3.73	2.49	3.68	2.86	3.59	1.16	3.32	1.73	1.86	1.68	0.43	3.53

MinMaxScaler

min값과 max값을 0~1사이로 정규화

In [90]:
```
minmax_scaler = MinMaxScaler()
minmax_scaled = minmax_scaler.fit_transform(x_train)
```

In [91]:
```
round(pd.DataFrame(minmax_scaled).describe(), 2)
```

Out[91]:

	0	1	2	3	4	5	6	7	8	9	10	11	12
count	379.00	379.00	379.00	379.00	379.00	379.00	379.00	379.00	379.00	379.00	379.00	379.00	379.00
mean	0.04	0.12	0.38	0.07	0.34	0.50	0.65	0.28	0.36	0.41	0.62	0.90	0.30
std	0.10	0.24	0.25	0.25	0.23	0.14	0.30	0.22	0.37	0.32	0.23	0.23	0.20
min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
25%	0.00	0.00	0.16	0.00	0.13	0.41	0.42	0.10	0.13	0.17	0.51	0.95	0.14
50%	0.00	0.00	0.28	0.00	0.29	0.48	0.73	0.23	0.17	0.27	0.67	0.99	0.25
75%	0.03	0.20	0.65	0.00	0.49	0.56	0.94	0.43	0.30	0.91	0.81	1.00	0.41
max	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

RobustScaler

중앙값(median)이 0, IQR(interquartile range)이 1이 되도록 변환.

outlier 값 처리에 유용

In [94]:

```
robust_scaler = RobustScaler()
robust_scaled = robust_scaler.fit_transform(x_train)
```

In [95]:

```
round(pd.DataFrame(robust_scaled).median(), 2)
```

Out[95]:
```
0     0.0
1     0.0
2     0.0
3     0.0
4     0.0
5     0.0
6     0.0
7     0.0
8     0.0
9     0.0
10    0.0
11    0.0
12    0.0
dtype: float64
```

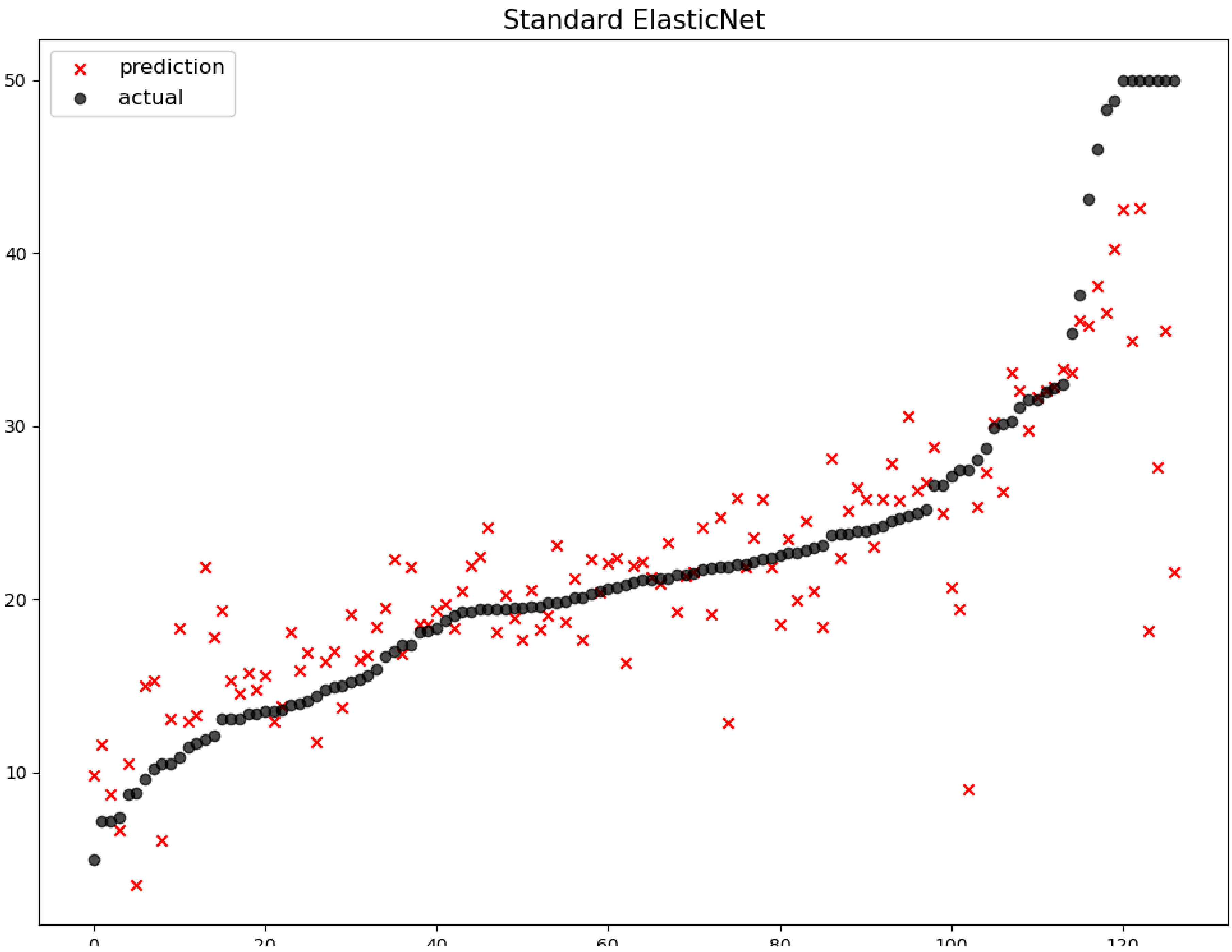
파이프라인

In [97]:
```
from sklearn.pipeline import make_pipeline
```

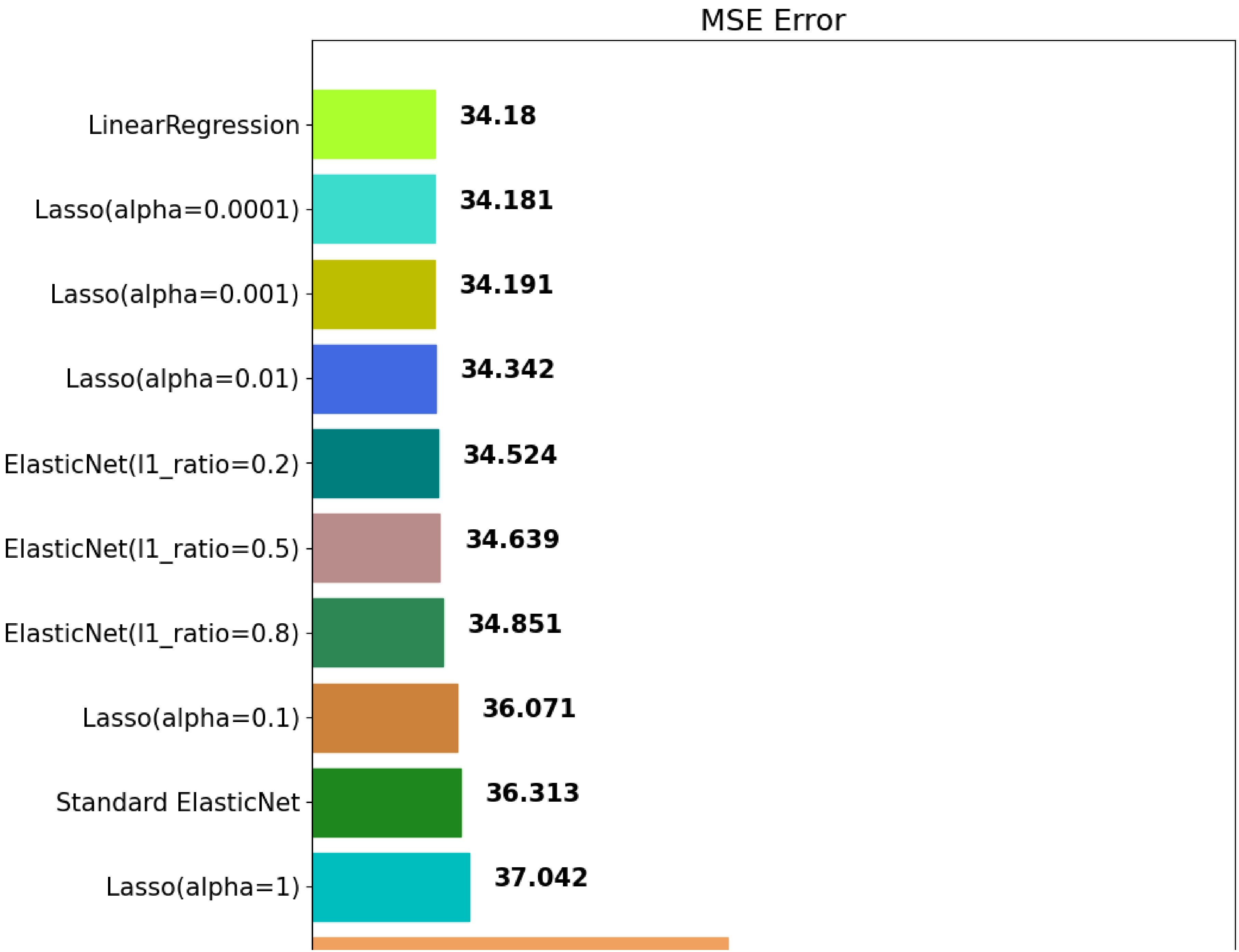
In [98]:
```
elasticnet_pipeline = make_pipeline(
    StandardScaler(),
    ElasticNet(alpha=0.1, l1_ratio=0.2)
)
```

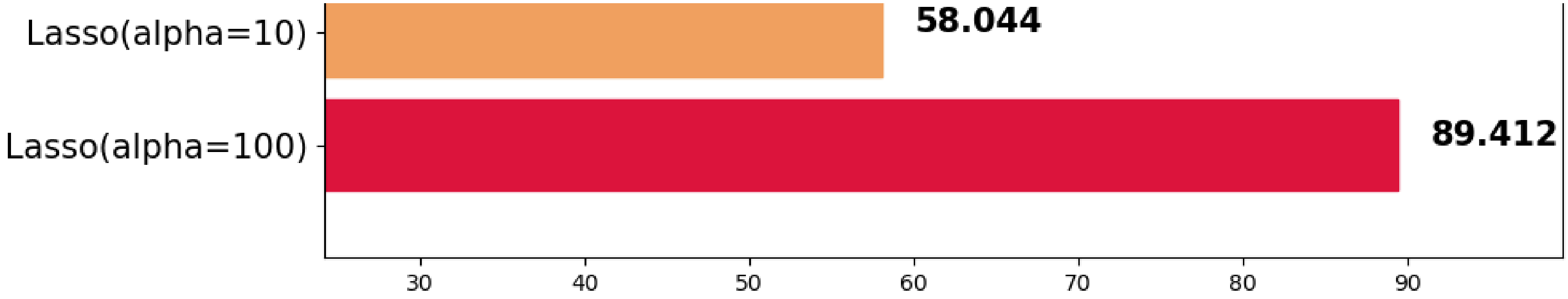
In [99]:
```
elasticnet_pred = elasticnet_pipeline.fit(x_train, y_train).predict(x_test)
```

In [100…
```
mse_eval('Standard ElasticNet', elasticnet_pred, y_test)
```


Standard ElasticNet
prediction
actual
50
40
30
20
10
0
20
40
60
80
100
120

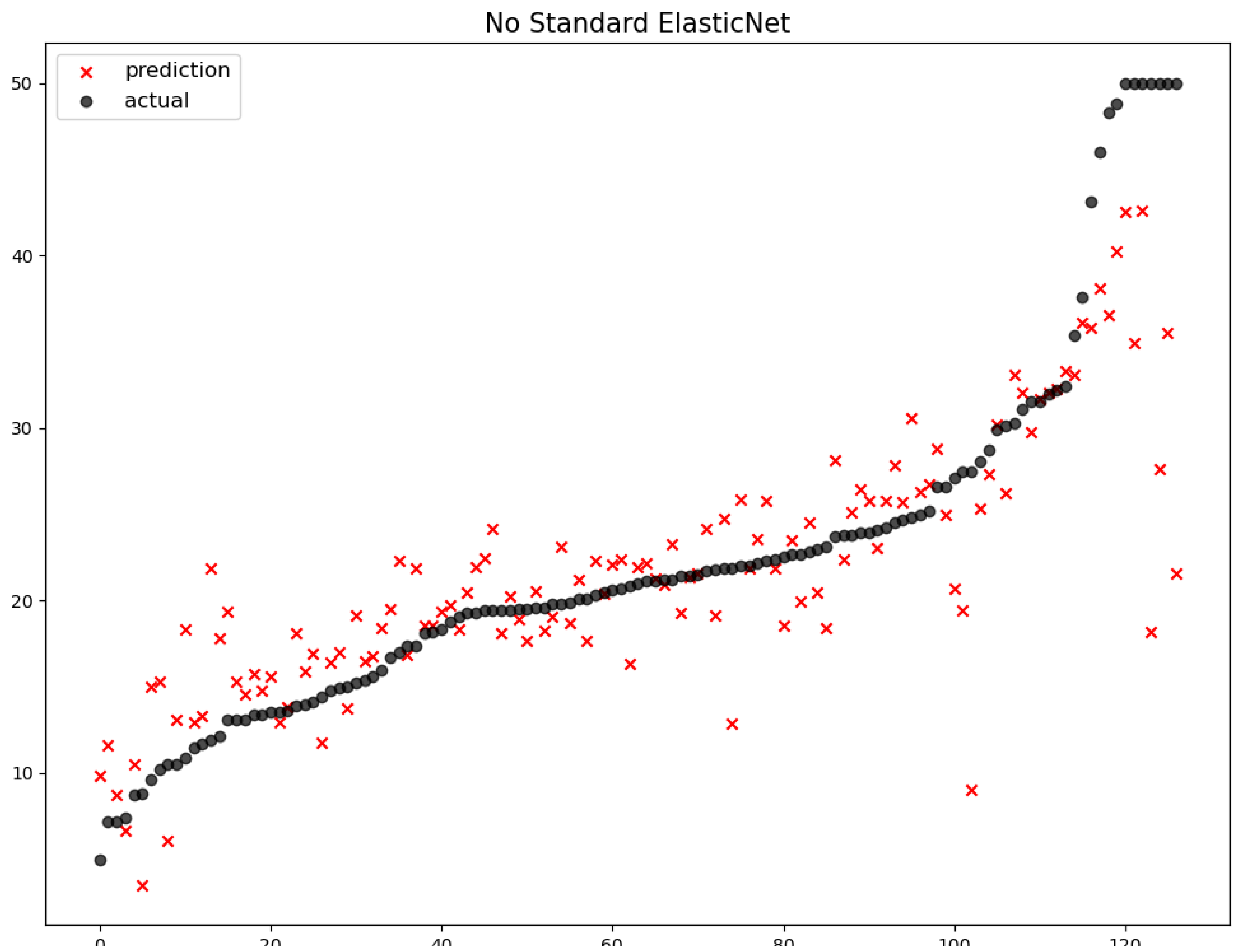
	model	mse
0	Lasso(alpha=100)	89.411990
1	Lasso(alpha=10)	58.044117
2	Lasso(alpha=1)	37.042408
3	Standard ElasticNet	36.313071
4	Lasso(alpha=0.1)	36.070849
5	ElasticNet(l1_ratio=0.8)	34.851407
6	ElasticNet(l1_ratio=0.5)	34.639468
7	ElasticNet(l1_ratio=0.2)	34.523999
8	Lasso(alpha=0.01)	34.341542
9	Lasso(alpha=0.001)	34.191145
10	Lasso(alpha=0.0001)	34.180940
11	LinearRegression	34.179865


MSE Error
LinearRegression
Lasso(alpha=0.0001)
Lasso(alpha=0.001)
Lasso(alpha=0.01)
ElasticNet(l1_ratio=0.2)
ElasticNet(l1_ratio=0.5)
ElasticNet(l1_ratio=0.8)
Lasso(alpha=0.1)
Standard ElasticNet
Lasso(alpha=1)
34.18
34.181
34.191
34.342
34.524
34.639
34.851
36.071
36.313
37.042

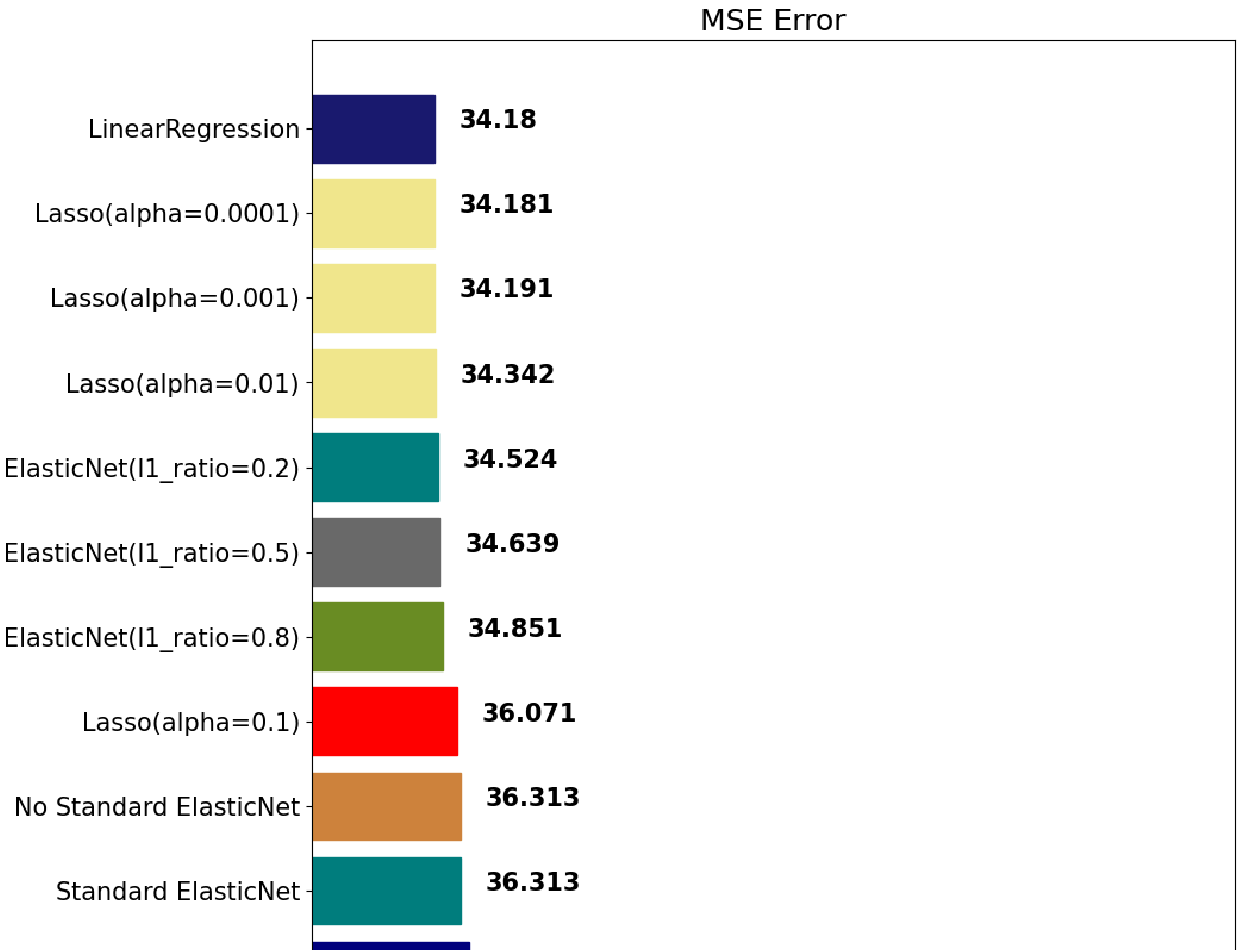


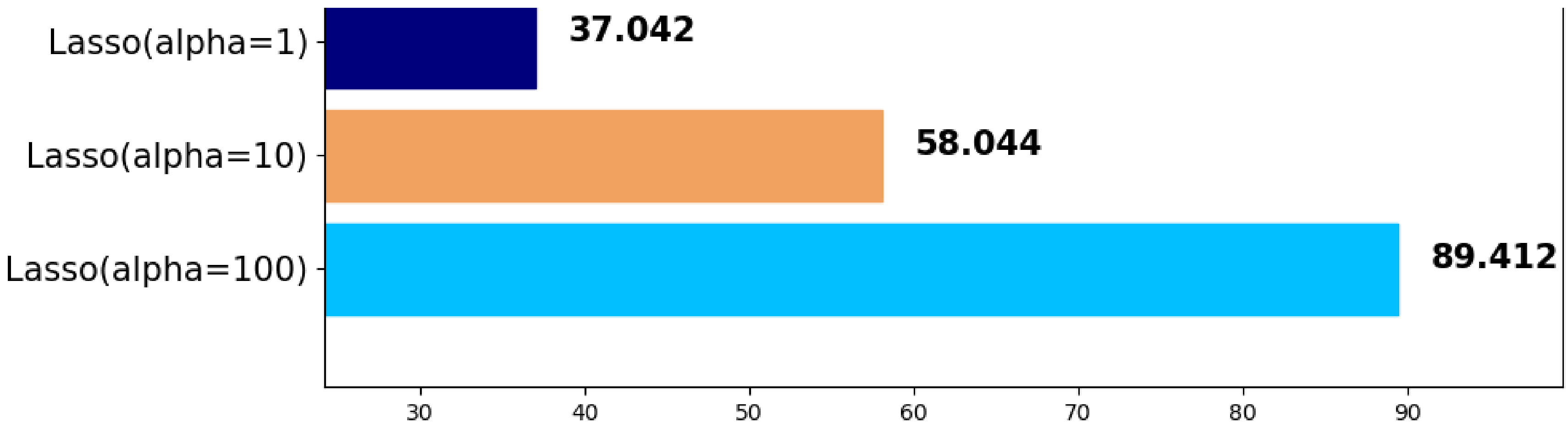
In [101…

```
elasticnet_no_pipeline = ElasticNet(alpha=0.1, l1_ratio=0.2)
no_pipeline_pred = elasticnet_no_pipeline.fit(x_train, y_train).predict(x_test)
mse_eval('No Standard ElasticNet', elasticnet_pred, y_test)
```


No Standard ElasticNet
prediction
actual
50
40
30
20
10
0
20
40
60
80
100
120

	model	mse
0	Lasso(alpha=100)	89.411990
1	Lasso(alpha=10)	58.044117
2	Lasso(alpha=1)	37.042408
3	Standard ElasticNet	36.313071
4	No Standard ElasticNet	36.313071
5	Lasso(alpha=0.1)	36.070849
6	ElasticNet(l1_ratio=0.8)	34.851407
7	ElasticNet(l1_ratio=0.5)	34.639468
8	ElasticNet(l1_ratio=0.2)	34.523999
9	Lasso(alpha=0.01)	34.341542
10	Lasso(alpha=0.001)	34.191145
11	Lasso(alpha=0.0001)	34.180940
12	LinearRegression	34.179865


MSE Error
LinearRegression
34.18
Lasso(alpha=0.0001)
34.181
Lasso(alpha=0.001)
34.191
Lasso(alpha=0.01)
34.342
ElasticNet(l1_ratio=0.2)
34.524
ElasticNet(l1_ratio=0.5)
34.639
ElasticNet(l1_ratio=0.8)
34.851
Lasso(alpha=0.1)
36.071
No Standard ElasticNet
36.313
Standard ElasticNet
36.313



Polynomial Features

도큐먼트

다항식의 계수간 상호작용을 통해 **새로운 feature를 생성**합니다.

예를들면, [a, b] 2개의 feature가 존재한다고 가정하고,

degree=2로 설정한다면, polynomial features 는 [1, a, b, a^2, ab, b^2] 가 됩니다.

In [105…
```
from sklearn.preprocessing import PolynomialFeatures
```

In [106…
```
poly = PolynomialFeatures(degree=2, include_bias=False)
```

In [107…
```
poly_features = poly.fit_transform(x_train)[0]
```

In [108…
```
poly_features
```

Out[108…

```
array([     0.52693   ,      0.        ,      6.2       ,      0.        ,
            0.504     ,      8.725     ,     83.        ,      2.8944    ,
            8.        ,    307.        ,     17.4       ,    382.        ,
            4.63      ,      0.27765522,      0.        ,      3.266966  ,
            0.        ,      0.26557272,      4.59746425,     43.73519   ,
            1.52514619,      4.21544   ,    161.76751   ,      9.168582  ,
          201.28726   ,      2.4396859 ,      0.        ,      0.        ,
            0.        ,      0.        ,      0.        ,      0.        ,
            0.        ,      0.        ,      0.        ,      0.        ,
            0.        ,      0.        ,     38.44      ,      0.        ,
            3.1248    ,     54.095     ,    514.6       ,     17.94528   ,
           49.6       ,   1903.4       ,    107.88      ,   2368.4       ,
           28.706     ,      0.        ,      0.        ,      0.        ,
            0.        ,      0.        ,      0.        ,      0.        ,
            0.        ,      0.        ,      0.        ,      0.254016  ,
            4.3974    ,     41.832     ,      1.4587776 ,      4.032     ,
          154.728     ,      8.7696    ,    192.528     ,      2.33352   ,
           76.125625  ,    724.175     ,     25.25364   ,     69.8       ,
         2678.575     ,    151.815     ,   3332.95      ,     40.39675   ,
         6889.        ,    240.2352    ,    664.        ,  25481.        ,
         1444.2       ,  31706.        ,    384.29      ,      8.37755136,
           23.1552    ,    888.5808    ,     50.36256   ,   1105.6608    ,
           13.401072  ,     64.        ,   2456.        ,    139.2       ,
         3056.        ,     37.04      ,  94249.        ,   5341.8       ,
       117274.        ,   1421.41      ,    302.76      ,   6646.8       ,
           80.562     , 145924.        ,   1768.66      ,     21.4369    ])
```

In [109…

```
x_train.iloc[0]
```

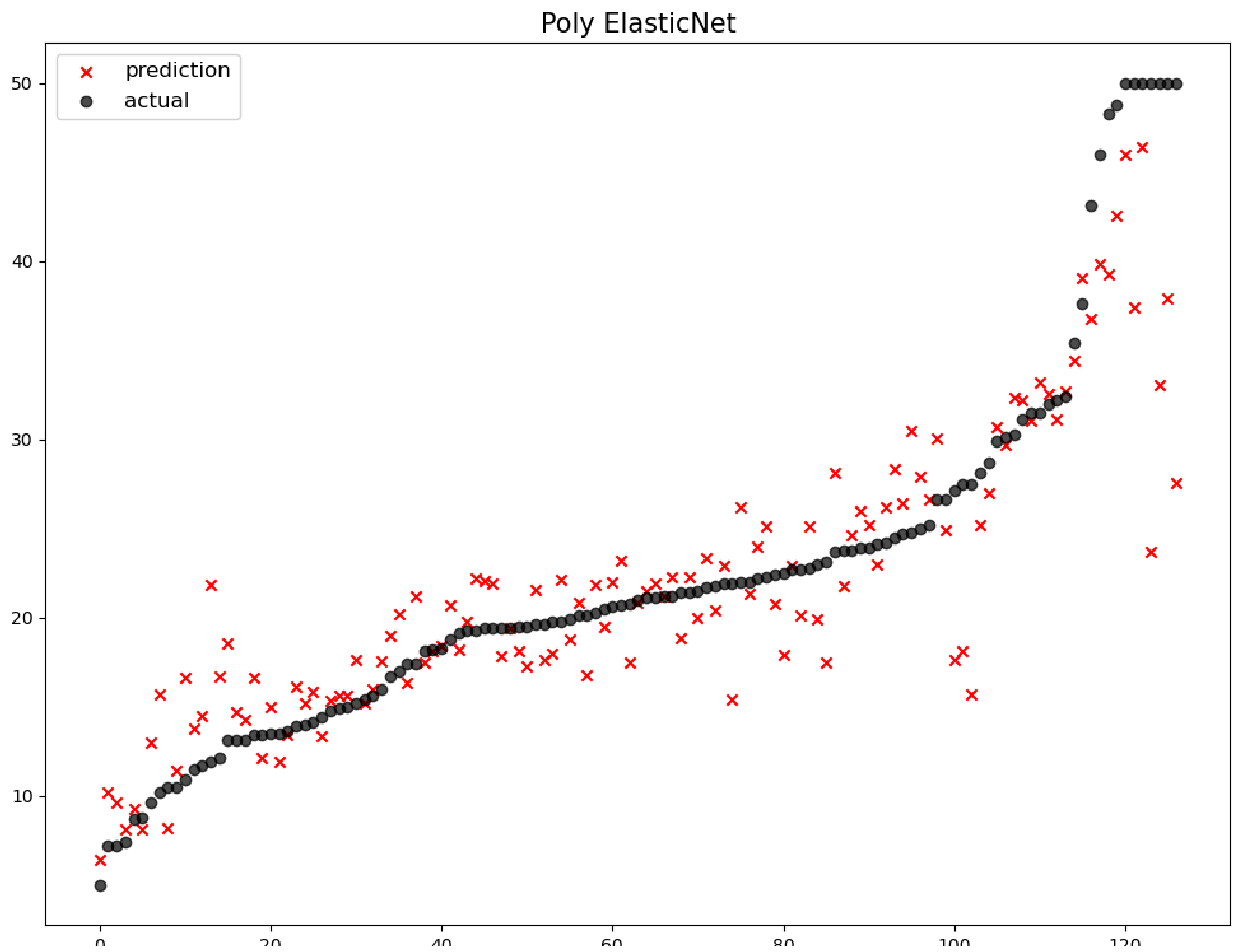
Out[109…
```
CRIM         0.52693
ZN           0.00000
INDUS        6.20000
CHAS         0.00000
NOX          0.50400
RM           8.72500
AGE         83.00000
DIS          2.89440
RAD          8.00000
TAX        307.00000
PTRATIO     17.40000
B          382.00000
LSTAT        4.63000
Name: 225, dtype: float64
```

In [110…
```
poly_pipeline = make_pipeline(
    PolynomialFeatures(degree=2, include_bias=False),
    StandardScaler(),
    ElasticNet(alpha=0.1, l1_ratio=0.2)
)
```

In [111…
```
poly_pred = poly_pipeline.fit(x_train, y_train).predict(x_test)
```

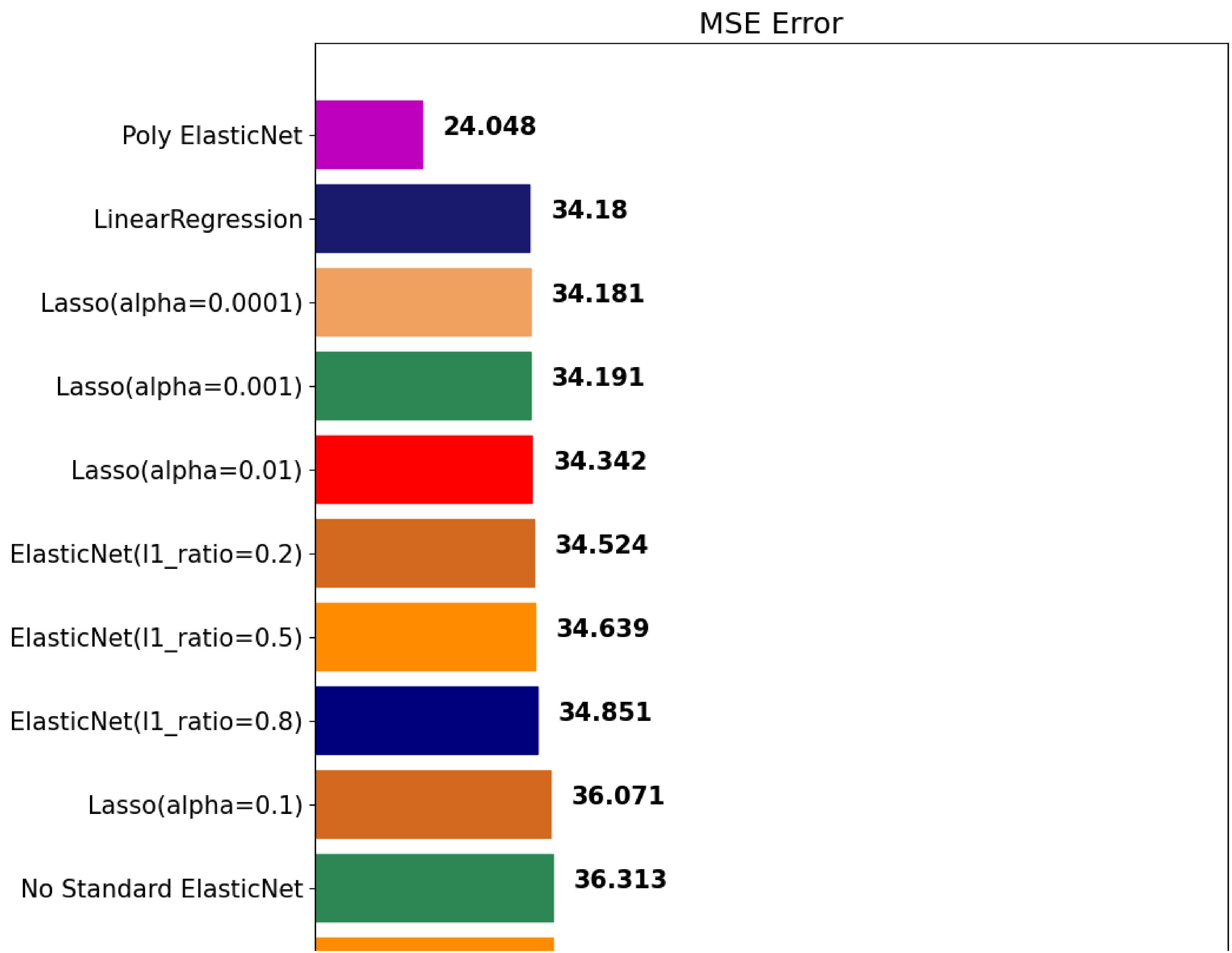
```
C:\ProgramData\anaconda3\Lib\site-packages\sklearn\linear_model\_coordinate_descent.py:697: ConvergenceWarning: Objective did n
ot converge. You might want to increase the number of iterations, check the scale of the features or consider increasing regula
risation. Duality gap: 2.638e+01, tolerance: 2.953e+00
  model = cd_fast.enet_coordinate_descent(
```

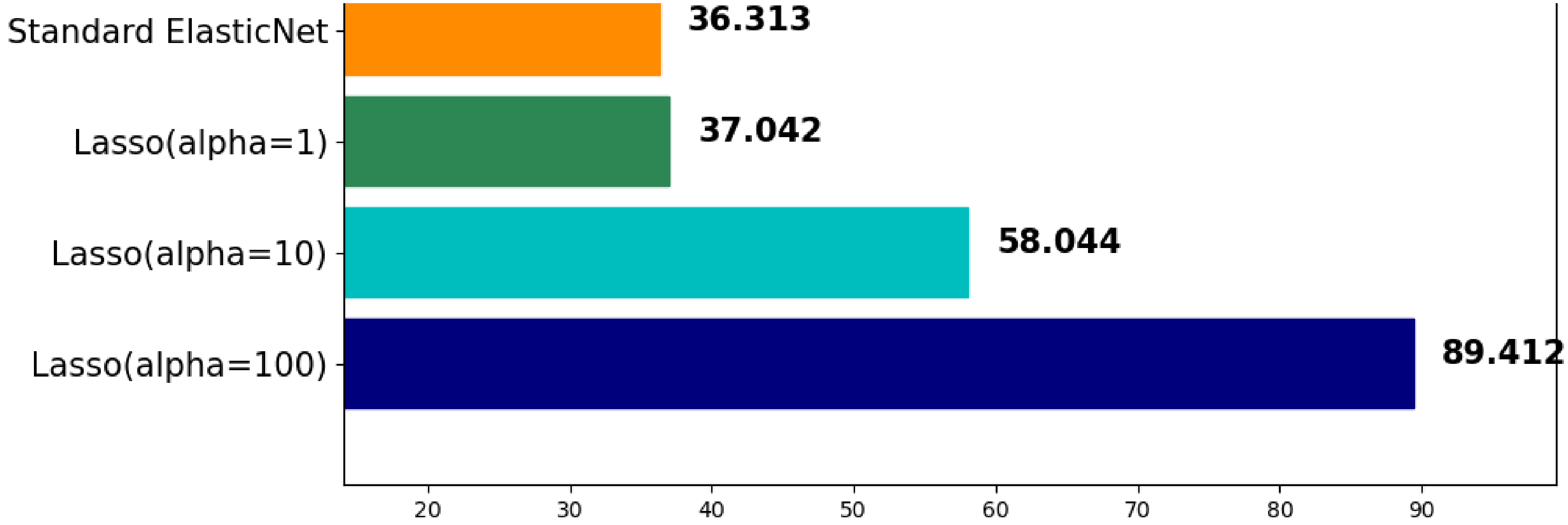
In [112…
```
mse_eval('Poly ElasticNet', poly_pred, y_test)
```



Poly ElasticNet
prediction
actual
50
40
30
20
10
0
20
40
60
80
100
120

	model	mse
0	Lasso(alpha=100)	89.411990
1	Lasso(alpha=10)	58.044117
2	Lasso(alpha=1)	37.042408
3	Standard ElasticNet	36.313071
4	No Standard ElasticNet	36.313071
5	Lasso(alpha=0.1)	36.070849
6	ElasticNet(l1_ratio=0.8)	34.851407
7	ElasticNet(l1_ratio=0.5)	34.639468
8	ElasticNet(l1_ratio=0.2)	34.523999
9	Lasso(alpha=0.01)	34.341542
10	Lasso(alpha=0.001)	34.191145
11	Lasso(alpha=0.0001)	34.180940
12	LinearRegression	34.179865
13	Poly ElasticNet	24.048146


MSE Error
Poly ElasticNet
24.048
LinearRegression
34.18
Lasso(alpha=0.0001)
34.181
Lasso(alpha=0.001)
34.191
Lasso(alpha=0.01)
34.342
ElasticNet(l1_ratio=0.2)
34.524
ElasticNet(l1_ratio=0.5)
34.639
ElasticNet(l1_ratio=0.8)
34.851
Lasso(alpha=0.1)
36.071
No Standard ElasticNet
36.313



Standard ElasticNet
Lasso(alpha=1)
Lasso(alpha=10)
Lasso(alpha=100)
36.313
37.042
58.044
89.412
20
30
40
50
60
70
80
90

In [ ]:

In [ ]:

In [ ]: