ML_Week04_HW

February 13, 2023

1 HW: Machine Learning in Finance Lab_Week 04

1.1 due 2023-02-19

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2 Basic import

[1]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import pylab
import scipy.stats as stats
import warnings
import sklearn as sk
import numpy as np
warnings.filterwarnings("ignore")
```

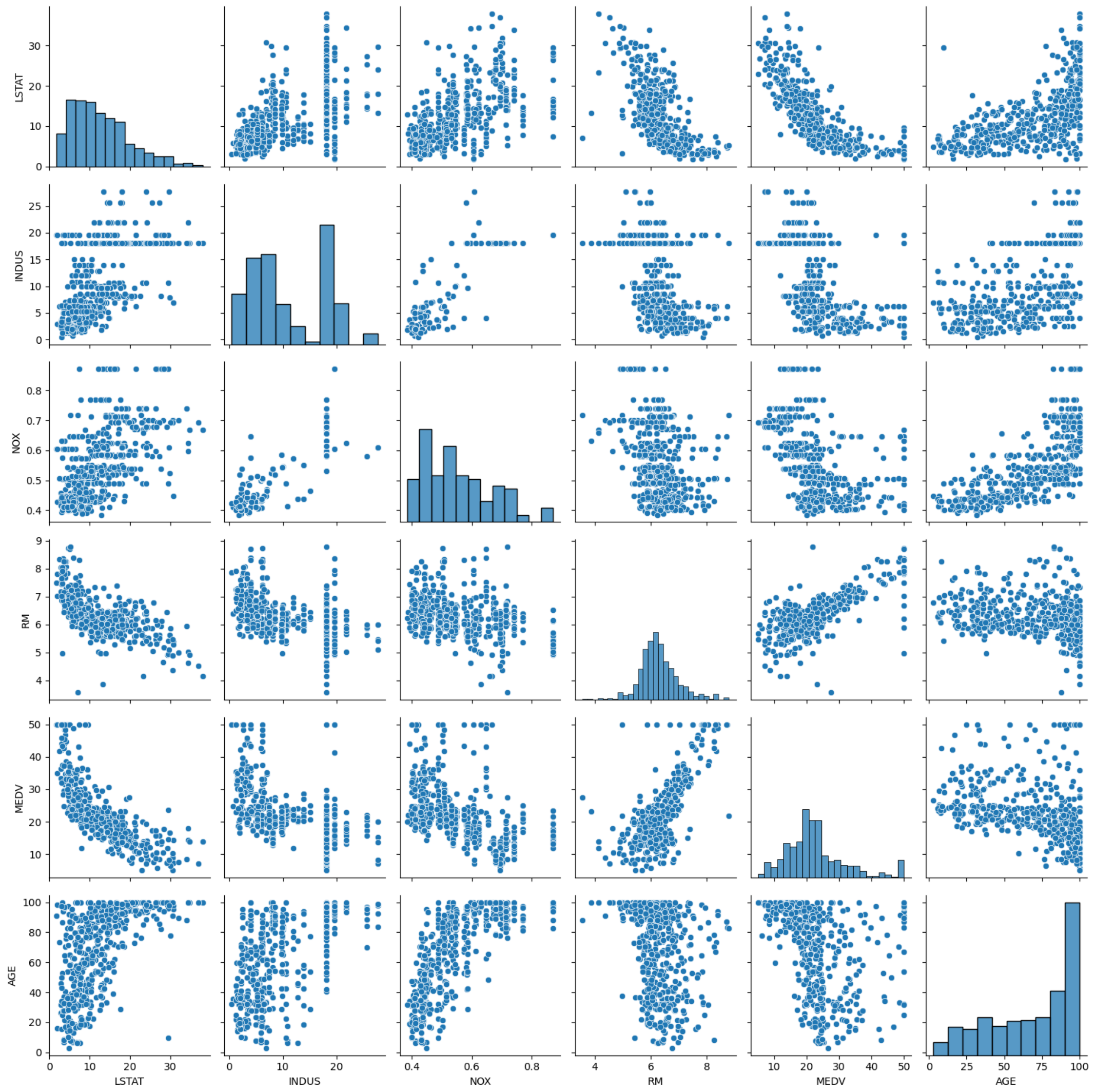
[2]:
```
from sklearn.model_selection import train_test_split
from sklearn import datasets
from sklearn import preprocessing
from sklearn import metrics
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error as MSE
from sklearn.metrics import r2_score as R2
from sklearn.linear_model import Ridge
from sklearn.linear_model import Lasso
```

[3]:
```
housing = pd.read_csv(
    "/Users/yu-chingliao/Library/CloudStorage/GoogleDrive-josephliao0127@gmail.
  ↪com/My Drive/Note/UIUC/Spring_2023/IE517A_Machine Learning in Finance Lab/
  ↪Lecture Notes/Week 04/housing.csv"
)
```

3 Part 1: EDA

3.1 Scatter Plot Martix

[4]:
```
cols = ['LSTAT', "INDUS", "NOX", "RM", "MEDV", "AGE"]
sns.pairplot(housing[cols], size = 2.5)
plt.tight_layout()
plt.show()
```



3.2 Print the shape out

[5]:
```
labels = list(housing.columns)
n_column = len(labels)
n_row = len(housing)

print("The number of Columns is", n_column, ".")
print("The number of Rows is", n_row, ".")
```

```
The number of Columns is 14 .
The number of Rows is 506 .
```

3.3 Print the nature out

[6]:
```
nl = []
sl = []
ol = []

for label in labels:
    Number = 0
    String = 0
    Other = 0

    for i in housing[label]:
        if type(i) == str:
            String += 1
        elif (type(i) == int) or (type(i) == float):
            Number += 1
        else:
            Other += 1
    nl.append(Number)
    sl.append(String)
    ol.append(Other)

Output = {
    "Label": labels,
    "Number": nl,
    "String": sl,
    "Other": ol
}
Output = pd.DataFrame(Output)
Output
```

[6]:
```
      Label  Number  String  Other
0      CRIM     506       0      0
1        ZN     506       0      0
2     INDUS     506       0      0
3      CHAS     506       0      0
```

```
4       NOX     506       0      0
5        RM     506       0      0
6       AGE     506       0      0
7       DIS     506       0      0
8       RAD     506       0      0
9       TAX     506       0      0
10  PTRATIO     506       0      0
11        B     506       0      0
12    LSTAT     506       0      0
13     MEDV     506       0      0
```

3.4 Summary of Statistics

[7]:
```
numer = np.array(housing['RM'])

#Mean, Var and Std
print('  =', numer.mean(), 'Var =', numer.var(), "  =", numer.std(),'\n')

#quantiles
def q(ds, n_q):
    result = []
    for i in range(n_q+1):
        result.append(np.percentile(ds, i*(100)/n_q))
    return result
print("Boundaries for 4 Equal Percentiles\n",q(numer, 4), "\n")

#10 equal percenetiles
print("Boundaries for 10 Equal Percentiles\n",q(numer, 10), "\n")

#catagorical analysis
cat = list(housing.columns)
neat_cat = list(set(cat))
print("Unique Label Values \n", neat_cat)

#count catagorics
counts = []
for i in neat_cat:
    counts.append(sum(housing.columns == i))
Output = {
    "Types" : neat_cat,
    "Counts" : counts
}
Output = pd.DataFrame(Output)
Output = Output.set_index("Types")
Output
```

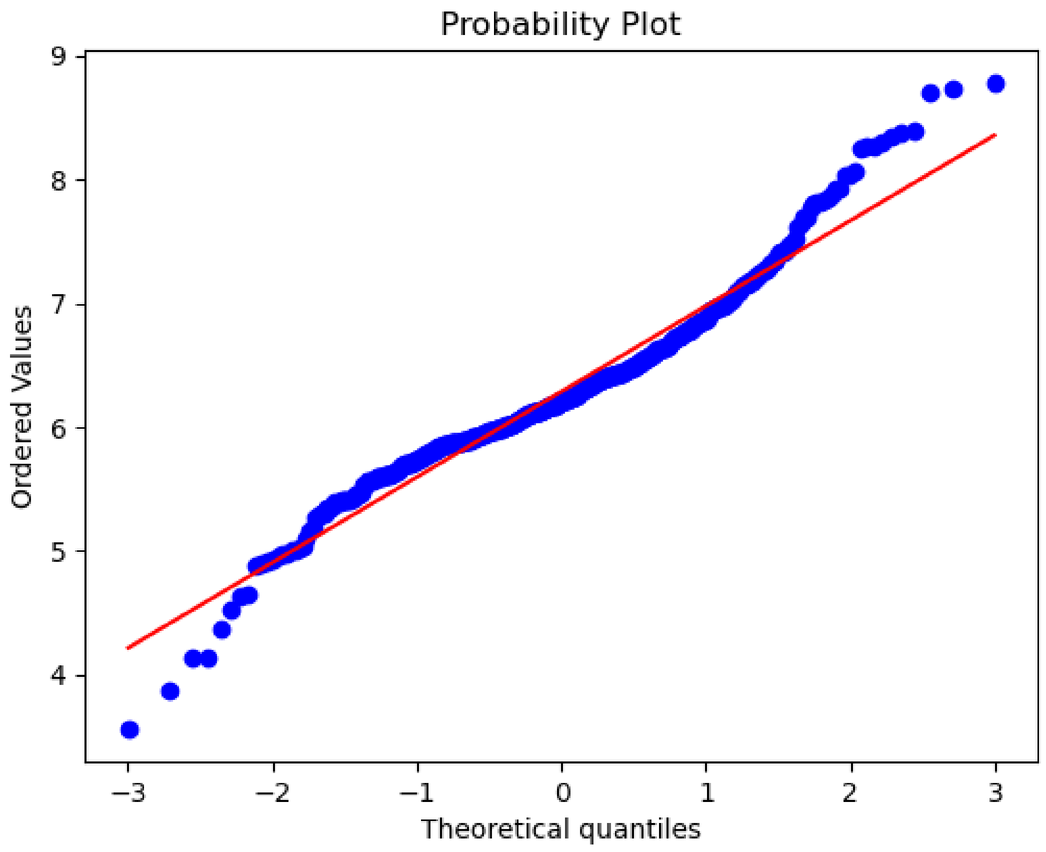
```
 = 6.284634387351779 Var = 0.49269521612976297   = 0.7019225143345689
```

```
Boundaries for 4 Equal Percentiles
 [3.561, 5.8854999999999995, 6.2085, 6.6235, 8.78]

Boundaries for 10 Equal Percentiles
 [3.561, 5.593500000000001, 5.837, 5.9505, 6.086, 6.2085, 6.376,
6.5024999999999995, 6.75, 7.1515, 8.78]

Unique Label Values
 ['TAX', 'ZN', 'INDUS', 'CRIM', 'RM', 'B', 'LSTAT', 'DIS', 'MEDV', 'NOX',
'PTRATIO', 'AGE', 'RAD', 'CHAS']
```

[7]:
```
         Counts
Types
TAX           1
ZN            1
INDUS         1
CRIM          1
RM            1
B             1
LSTAT         1
DIS           1
MEDV          1
NOX           1
PTRATIO       1
AGE           1
RAD           1
CHAS          1
```

3.5 QQ Plot

[8]:
```python
stats.probplot(housing['RM'], dist="norm", plot=pylab)
pylab.show()
print("P-Value:", stats.normaltest(housing['RM'])[1])
print("Reject H0: Client_Trade_Percentage is Normally distributed.")
```



```
P-Value: 5.902608143477 77e-09
Reject H0: Client_Trade_Percentage is Normally distributed.
```

3.6 Print Summary of data

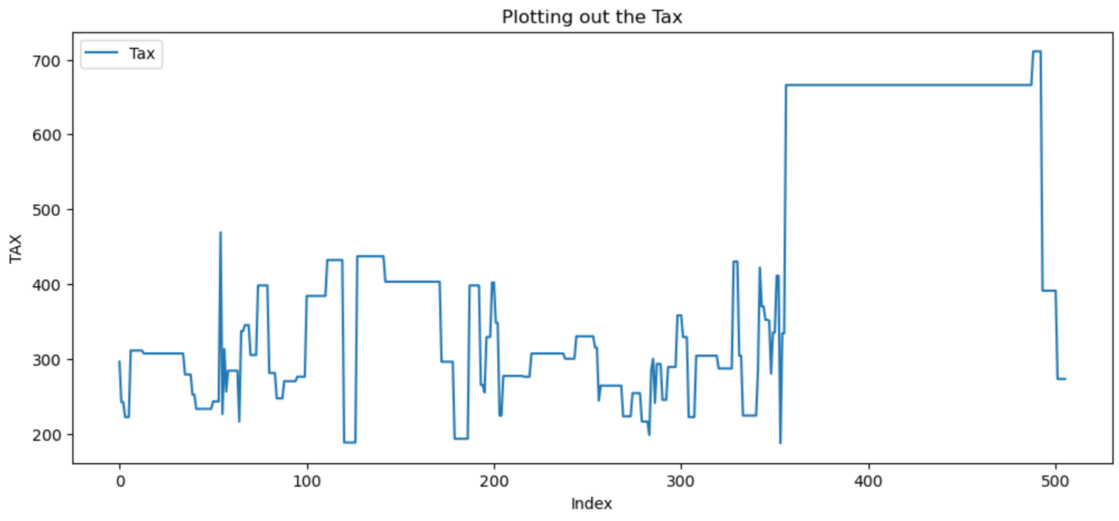
[9]:
```
summary = housing.describe()
print(summary)
```

```
             CRIM          ZN       INDUS        CHAS         NOX          RM  \
count  506.000000  506.000000  506.000000  506.000000  506.000000  506.000000
mean     3.613524   11.363636   11.136779    0.069170    0.554695    6.284634
std      8.601545   23.322453    6.860353    0.253994    0.115878    0.702617
min      0.006320    0.000000    0.460000    0.000000    0.385000    3.561000
25%      0.082045    0.000000    5.190000    0.000000    0.449000    5.885500
50%      0.256510    0.000000    9.690000    0.000000    0.538000    6.208500
75%      3.677083   12.500000   18.100000    0.000000    0.624000    6.623500
max     88.976200  100.000000   27.740000    1.000000    0.871000    8.780000

              AGE         DIS         RAD         TAX     PTRATIO           B  \
count  506.000000  506.000000  506.000000  506.000000  506.000000  506.000000
```

```
mean     68.574901    3.795043    9.549407  408.237154   18.455534  356.674032
std      28.148861    2.105710    8.707259  168.537116    2.164946   91.294864
min       2.900000    1.129600    1.000000  187.000000   12.600000    0.320000
25%      45.025000    2.100175    4.000000  279.000000   17.400000  375.377500
50%      77.500000    3.207450    5.000000  330.000000   19.050000  391.440000
75%      94.075000    5.188425   24.000000  666.000000   20.200000  396.225000
max     100.000000   12.126500   24.000000  711.000000   22.000000  396.900000

            LSTAT        MEDV
count  506.000000  506.000000
mean    12.653063   22.532806
std      7.141062    9.197104
min      1.730000    5.000000
25%      6.950000   17.025000
50%     11.360000   21.200000
75%     16.955000   25.000000
max     37.970000   50.000000
```

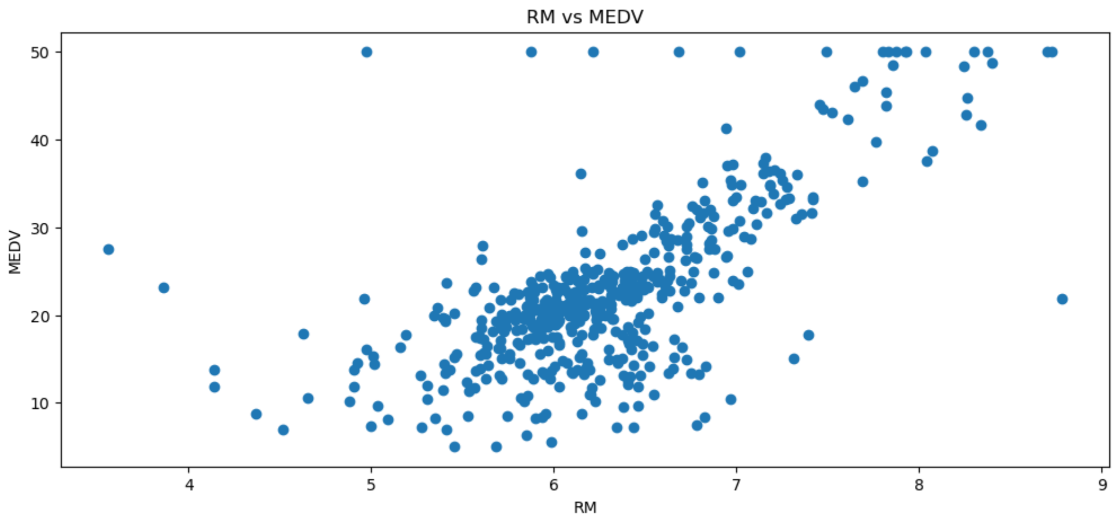
3.7 Plot out data

[10]:
```python
plt.figure(figsize=[12,5])
plt.plot(housing['TAX'], label = 'Tax')
plt.xlabel('Index')
plt.ylabel('TAX')
plt.title('Plotting out the Tax')
plt.legend()
plt.show()
```



3.8 Cross Plotting Pairs of Attributes (Scatter Plot)

[11]:
```
plt.figure(figsize=[12,5])
plt.scatter(housing['RM'], housing['MEDV'])
plt.title("RM vs MEDV")
plt.xlabel('RM')
plt.ylabel('MEDV')
plt.show()
```



3.9 Correlation

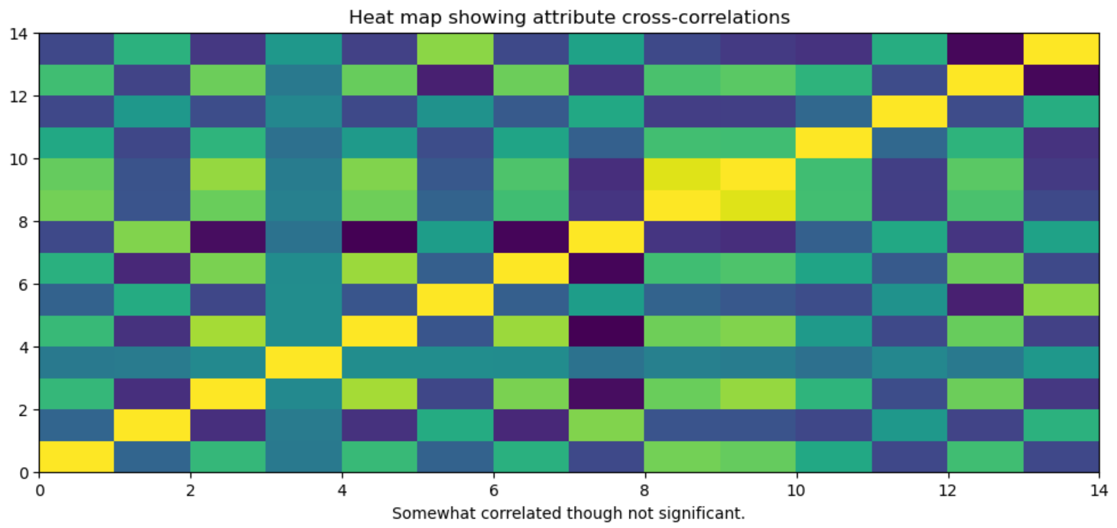
[12]:
```
housing.corr()
```

[12]:
```
             CRIM        ZN     INDUS      CHAS       NOX        RM       AGE  \
CRIM     1.000000 -0.200469  0.406583 -0.055892  0.420972 -0.219247  0.352734
ZN      -0.200469  1.000000 -0.533828 -0.042697 -0.516604  0.311991 -0.569537
INDUS    0.406583 -0.533828  1.000000  0.062938  0.763651 -0.391676  0.644779
CHAS    -0.055892 -0.042697  0.062938  1.000000  0.091203  0.091251  0.086518
NOX      0.420972 -0.516604  0.763651  0.091203  1.000000 -0.302188  0.731470
RM      -0.219247  0.311991 -0.391676  0.091251 -0.302188  1.000000 -0.240265
AGE      0.352734 -0.569537  0.644779  0.086518  0.731470 -0.240265  1.000000
DIS     -0.379670  0.664408 -0.708027 -0.099176 -0.769230  0.205246 -0.747881
RAD      0.625505 -0.311948  0.595129 -0.007368  0.611441 -0.209847  0.456022
TAX      0.582764 -0.314563  0.720760 -0.035587  0.668023 -0.292048  0.506456
PTRATIO  0.289946 -0.391679  0.383248 -0.121515  0.188933 -0.355501  0.261515
B       -0.385064  0.175520 -0.356977  0.048788 -0.380051  0.128069 -0.273534
LSTAT    0.455621 -0.412995  0.603800 -0.053929  0.590879 -0.613808  0.602339
MEDV    -0.388305  0.360445 -0.483725  0.175260 -0.427321  0.695360 -0.376955
```

```
              DIS       RAD       TAX   PTRATIO         B     LSTAT      MEDV
CRIM    -0.379670  0.625505  0.582764  0.289946 -0.385064  0.455621 -0.388305
ZN       0.664408 -0.311948 -0.314563 -0.391679  0.175520 -0.412995  0.360445
INDUS   -0.708027  0.595129  0.720760  0.383248 -0.356977  0.603800 -0.483725
CHAS    -0.099176 -0.007368 -0.035587 -0.121515  0.048788 -0.053929  0.175260
NOX     -0.769230  0.611441  0.668023  0.188933 -0.380051  0.590879 -0.427321
RM       0.205246 -0.209847 -0.292048 -0.355501  0.128069 -0.613808  0.695360
AGE     -0.747881  0.456022  0.506456  0.261515 -0.273534  0.602339 -0.376955
DIS      1.000000 -0.494588 -0.534432 -0.232471  0.291512 -0.496996  0.249929
RAD     -0.494588  1.000000  0.910228  0.464741 -0.444413  0.488676 -0.381626
TAX     -0.534432  0.910228  1.000000  0.460853 -0.441808  0.543993 -0.468536
PTRATIO -0.232471  0.464741  0.460853  1.000000 -0.177383  0.374044 -0.507787
B        0.291512 -0.444413 -0.441808 -0.177383  1.000000 -0.366087  0.333461
LSTAT   -0.496996  0.488676  0.543993  0.374044 -0.366087  1.000000 -0.737663
MEDV     0.249929 -0.381626 -0.468536 -0.507787  0.333461 -0.737663  1.000000
```

3.10 Correlation Visualization

[13]:
```
#calculate correlations between real-valued attributes
corMat = pd.DataFrame(housing.corr())
#visualize correlations using heatmap
plt.figure(figsize=[12,5])
plt.title("Heat map showing attribute cross-correlations")
plt.pcolor(corMat)
plt.xlabel('Somewhat correlated though not significant.')
plt.show()
```



4 Part 2: Linear Regression

4.1 Data Spliting

[14]:
```
X = housing.drop('MEDV', axis = 1).values
y = housing['MEDV'].values

X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42)
print(X_train.shape, y_train.shape)
```

```
(404, 13) (404,)
```

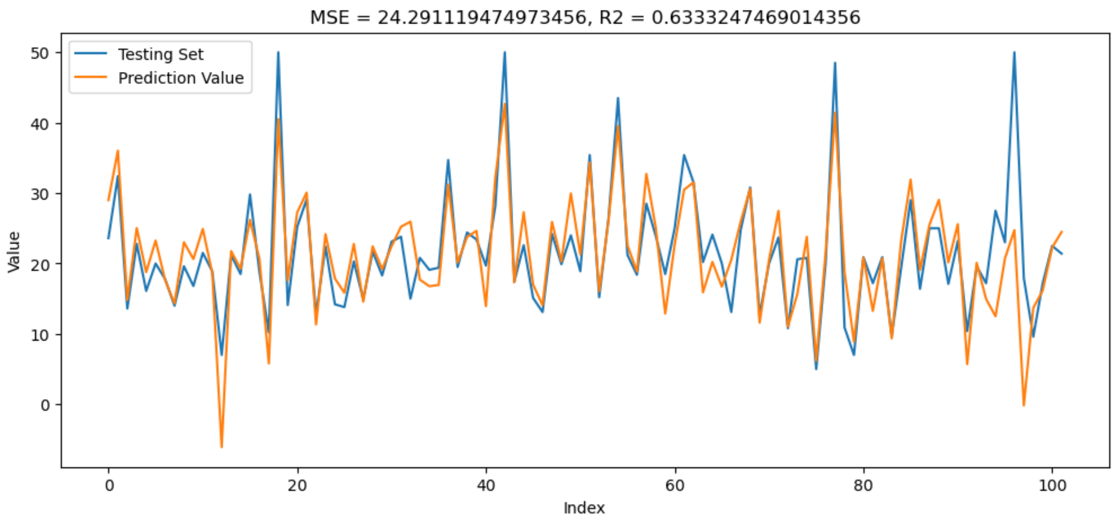
4.2 Fitting Simple Linear

[15]:
```
reg = LinearRegression()
reg.fit(X_train, y_train)

y_pred = reg.predict(X_test)

print("Coefficients: ", reg.coef_)
print("Intercept: ", reg.intercept_)
```

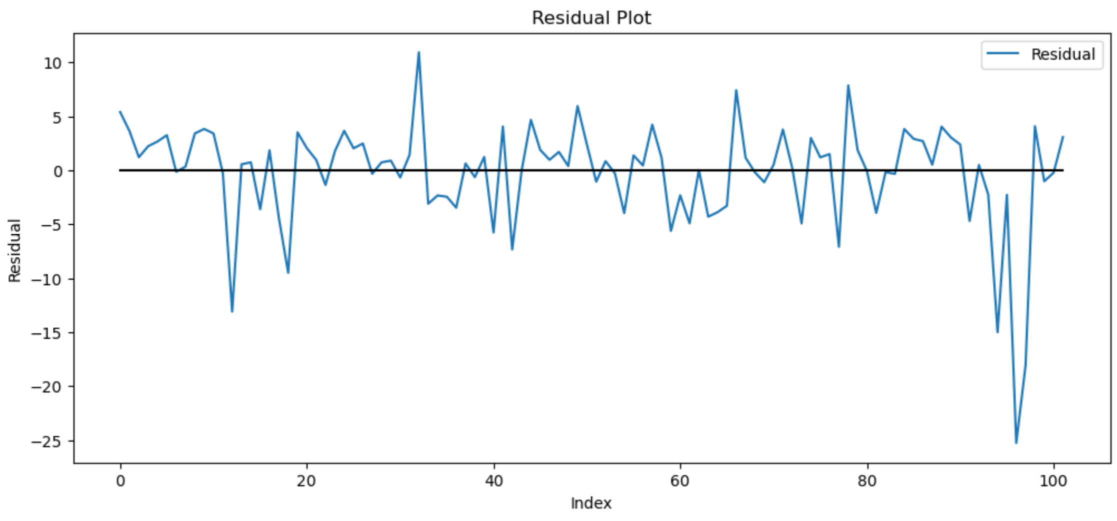
```
Coefficients:  [-1.13055924e-01  3.01104641e-02  4.03807204e-02  2.78443820e+00
 -1.72026334e+01  4.43883520e+00 -6.29636221e-03 -1.44786537e+00
  2.62429736e-01 -1.06467863e-02 -9.15456240e-01  1.23513347e-02
 -5.08571424e-01]
Intercept:  30.246750993923946
```

4.3 Plotting Out

[16]:
```
mse = MSE(y_pred, y_test)
r2 = R2(y_pred, y_test)
plt.figure(figsize=[12,5])
plt.plot(y_test, label = "Testing Set")
plt.plot(y_pred, label = "Prediction Value")
plt.legend()
plt.title("MSE = "+str(mse)+", R2 = "+str(r2))
plt.xlabel("Index")
plt.ylabel("Value")
plt.show()
```



[17]:
```
plt.figure(figsize=[12,5])
plt.plot(y_pred - y_test, label = "Residual")
plt.plot(np.zeros_like(y_pred ), c = 'black')
plt.xlabel("Index")
plt.ylabel("Residual")
plt.title("Residual Plot")
plt.legend()
plt.show()
```



5 Part 3: Ridge Regression

5.1 Fitting Ridge

Here I regress Ridge on several different alpha's, and choose the best alpha by each R2 and MSE.

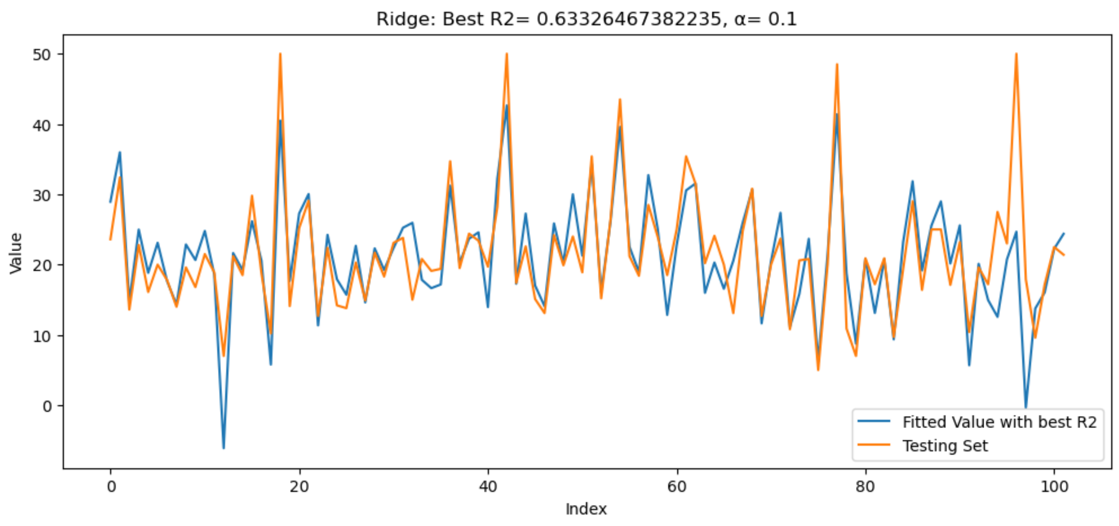
[18]:
```
alphas = [0.1, 1.0, 10.0, 100.0, 1000.0, 10000.0]

best_r2_ridge = 0
 _r2_ridge = 0
best_mse_ridge = 99999999
 _mse_ridge = 0

for alpha in alphas:
    ridge = Ridge(alpha=alpha)
    ridge.fit(X_train, y_train)

    # Obtain R-squared
    y_pred = ridge.predict(X_test)

    r2 = R2(y_pred, y_test)
    mse = MSE(y_pred, y_test)

    if best_r2_ridge < r2:
        best_r2_ridge = r2
         _r2_ridge = alpha

    if best_mse_ridge > mse:
        best_mse_ridge = mse
         _mse_ridge = alpha

    print(" = ", alpha, ", R2= ", r2, ", MSE = ", mse)
    print("Coefficients= ", ridge.coef_, ", Intercept= ", ridge.intercept_)
```

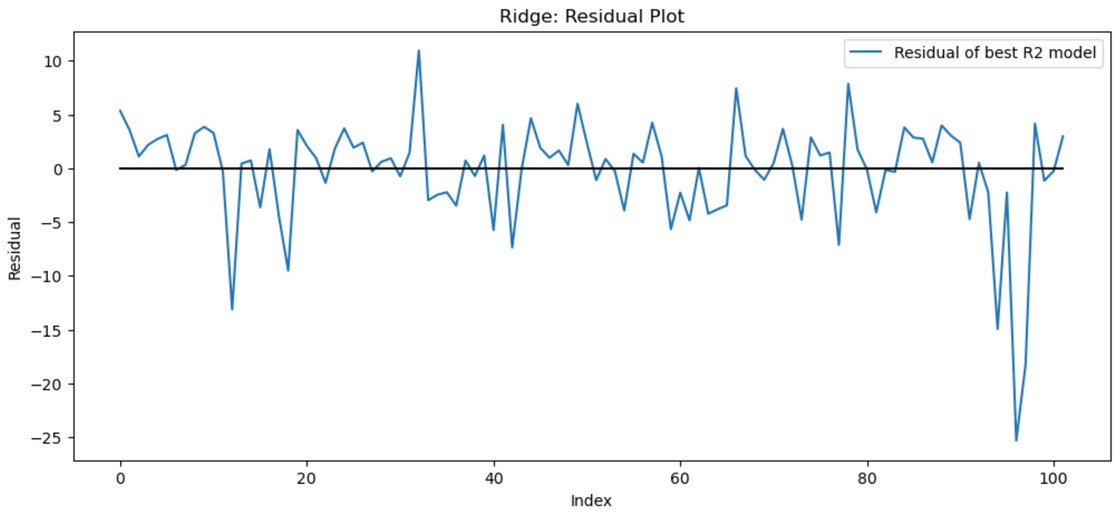
```
 =  0.1 , R2=  0.633264673822 35 , MSE =  24.301025500192765
Coefficients=  [-1.12399694e-01  3.04593914e-02  3.48958400e-02  2.75033318e+00
 -1.59244585e+01  4.44577949e+00 -7.30474388e-03 -1.42960751e+00
  2.60042840e-01 -1.07802286e-02 -9.00771040e-01  1.24004789e-02
 -5.10902332e-01] , Intercept=  29.366271272576622
 =  1.0 , R2=  0.6316692350060937 , MSE =  24.477191227708687
Coefficients=  [-1.09234061e-01  3.22706863e-02  7.49805942e-03  2.54546998e+00
 -9.53795159e+00  4.46450537e+00 -1.21910176e-02 -1.33870040e+00
  2.48881816e-01 -1.14746211e-02 -8.28604284e-01  1.26421124e-02
 -5.23833016e-01] , Intercept=  25.104099233774445
 =  10.0 , R2=  0.6289205768176517 , MSE =  24.648347618693638
Coefficients=  [-0.10713363  0.03555248 -0.02627747  1.81329133 -1.88924475
4.19532572
 -0.01534126 -1.23262135  0.24803063 -0.01274419 -0.76176896  0.01283334
 -0.561835  ] , Intercept=  22.439732052473854
 =  100.0 , R2=  0.6264261086866869 , MSE =  23.465902589086465
Coefficients=  [-1.10764853e-01  3.98919010e-02 -4.86253730e-02  5.50701733e-01
 -1.97858825e-01  2.43881473e+00  5.45476646e-04 -1.12939994e+00
  2.99013586e-01 -1.46298901e-02 -8.17852407e-01  1.19512041e-02
 -6.89539142e-01] , Intercept=  34.62659588633332
 =  1000.0 , R2=  0.5304124542345325 , MSE =  24.695930202149537
Coefficients=  [-0.10138965  0.03646488 -0.04661804  0.09060788 -0.01016072
0.5466653
  0.03242508 -0.53745604  0.27716163 -0.01427284 -0.62929043  0.01046953
 -0.78683266] , Intercept=  40.3957219751093
 =  10000.0 , R2=  0.11314483998534808 , MSE =  30.95102788046865
Coefficients=  [-7.71819520e-02  4.05566385e-02 -5.64286629e-02  1.44484713e-02
 -3.05472942e-04  9.69493388e-02  2.32547680e-02 -9.20197242e-02
  9.80524402e-02 -1.20813119e-02 -1.57963771e-01  1.15321048e-02
 -4.96254721e-01] , Intercept=  30.299557964105162
```

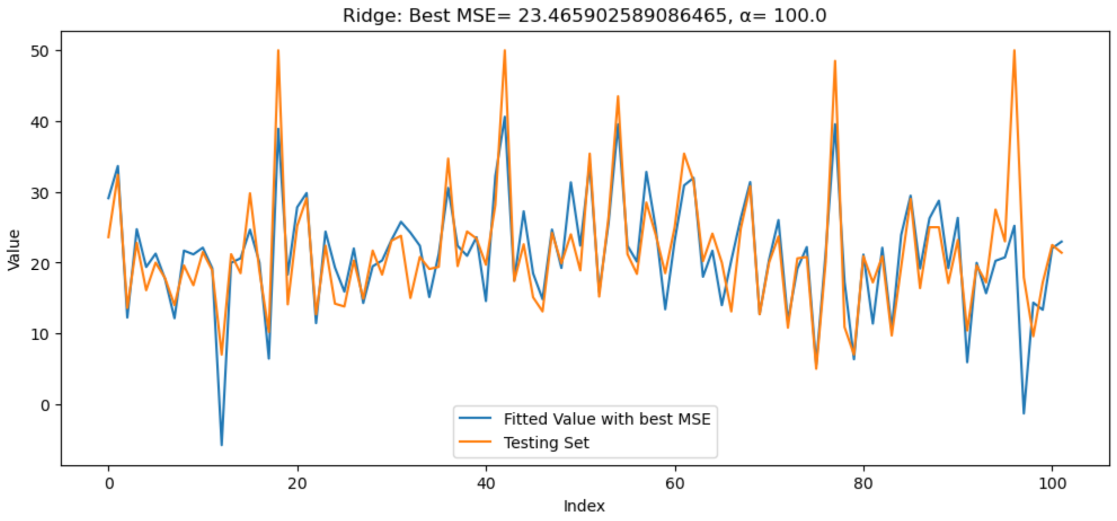
5.2 Plotting Out

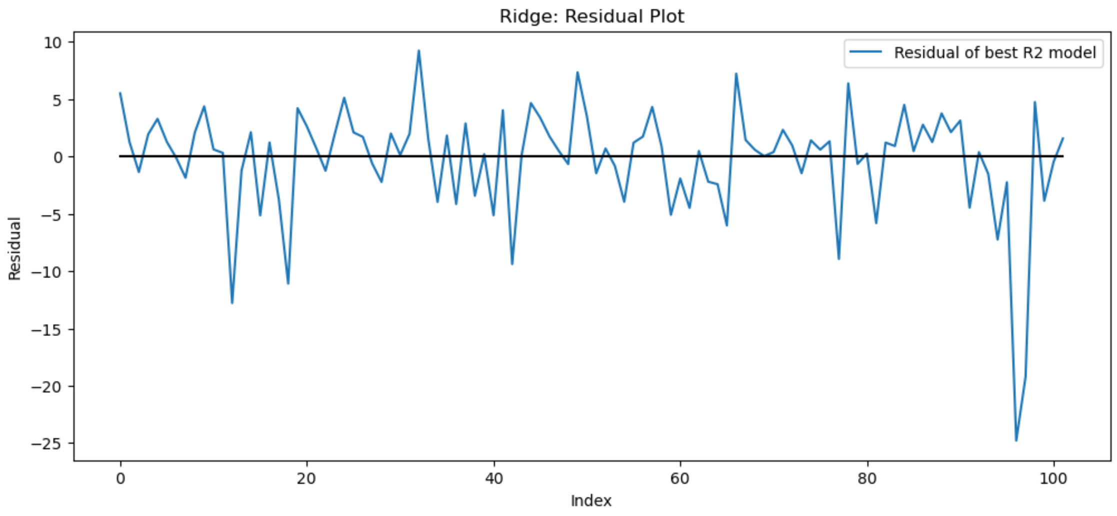
Plot the fitted value and residual for the best fit that picked by each R2 and MSE.

[19]:
```python
ridge_r2 = Ridge(alpha= _r2_ridge)
ridge_r2.fit(X_train, y_train)
y_pred_r2_ridge = ridge_r2.predict(X_test)

plt.figure(figsize=[12,5])
plt.plot(y_pred_r2_ridge, label = 'Fitted Value with best R2')
plt.plot(y_test, label = 'Testing Set')
plt.title("Ridge: Best R2= "+str(best_r2_ridge)+",  = "+str( _r2_ridge))
plt.legend()
plt.xlabel("Index")
plt.ylabel("Value")
plt.show()

plt.figure(figsize=[12,5])
plt.plot(y_pred_r2_ridge - y_test, label = "Residual of best R2 model")
plt.plot(np.zeros_like(y_pred_r2_ridge), c = 'black')
plt.xlabel("Index")
plt.ylabel("Residual")
plt.title("Ridge: Residual Plot")
plt.legend()
plt.show()

ridge_mse = Ridge(alpha= _mse_ridge)
ridge_mse.fit(X_train, y_train)
y_pred_mse_ridge = ridge_mse.predict(X_test)

plt.figure(figsize=[12,5])
plt.plot(y_pred_mse_ridge, label = 'Fitted Value with best MSE')
plt.plot(y_test, label = 'Testing Set')
plt.title("Ridge: Best MSE= "+str(best_mse_ridge)+",  = "+str( _mse_ridge))
plt.xlabel("Index")
plt.ylabel("Value")
plt.legend()
plt.show()

plt.figure(figsize=[12,5])
plt.plot(y_pred_mse_ridge - y_test, label = "Residual of best R2 model")
plt.plot(np.zeros_like(y_pred_mse_ridge), c = 'black')
plt.xlabel("Index")
plt.ylabel("Residual")
plt.title("Ridge: Residual Plot")
plt.legend()
plt.show()
```




Ridge: Residual Plot
Residual of best R2 model
Residual
Index
10
5
0
−5
−10
−15
−20
−25
0
20
40
60
80
100


Ridge: Best MSE= 23.465902589086465, α= 100.0
Fitted Value with best MSE
Testing Set
Value
Index
50
40
30
20
10
0
0
20
40
60
80
100



From the R2, alpha = 0.1 provides the best fit.

Howeverm from the MSE, alpha= 100 provides the best fit (means the simple linear regression).

6 Part 4: Lasso Regression

Here I regress Lasso on several different alpha's, and choose the best alpha by each R2 and MSE.

6.1 Fitting Lasso

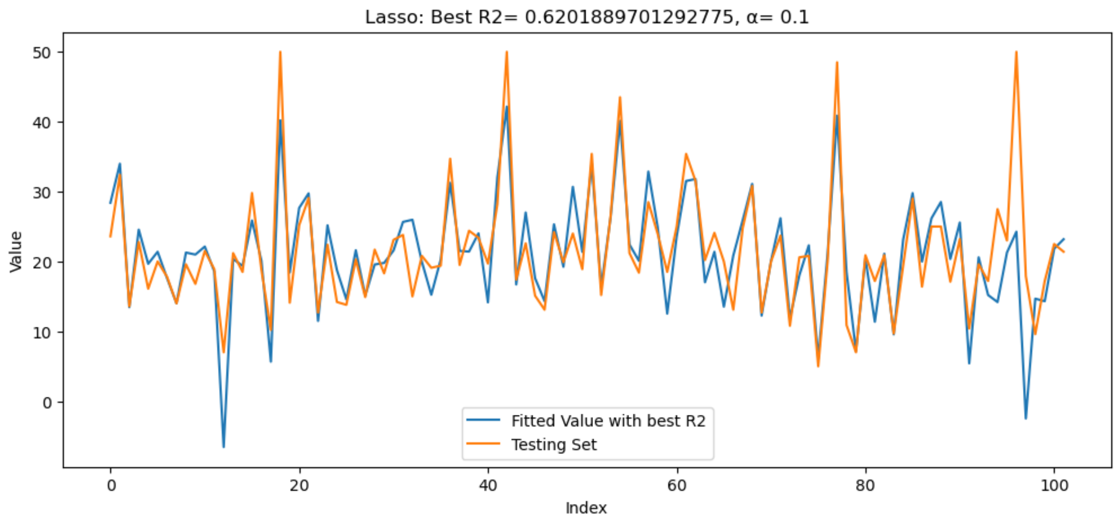
[20]:
```
alphas = [0.1, 1.0, 10.0, 100.0, 1000.0, 10000.0]
best_r2_lasso = 0
 _r2_lasso = 0
best_mse_lasso = 99999999
 _mse_lasso = 0

for alpha in alphas:
    lasso = Lasso(alpha=alpha)
    lasso.fit(X_train, y_train)

    y_pred = lasso.predict(X_test)

    r2 = R2(y_pred, y_test)
    mse = MSE(y_pred, y_test)

    if best_r2_lasso < r2:
        best_r2_lasso = r2
         _r2_lasso = alpha

    if best_mse_lasso > mse:
        best_mse_lasso = mse
         _mse_lasso = alpha

    print(" = ", alpha, ", R2= ", r2, ", MSE = ", mse)
    print("Coefficients= ", lasso.coef_, ", Intercept= ", lasso.intercept_)
```

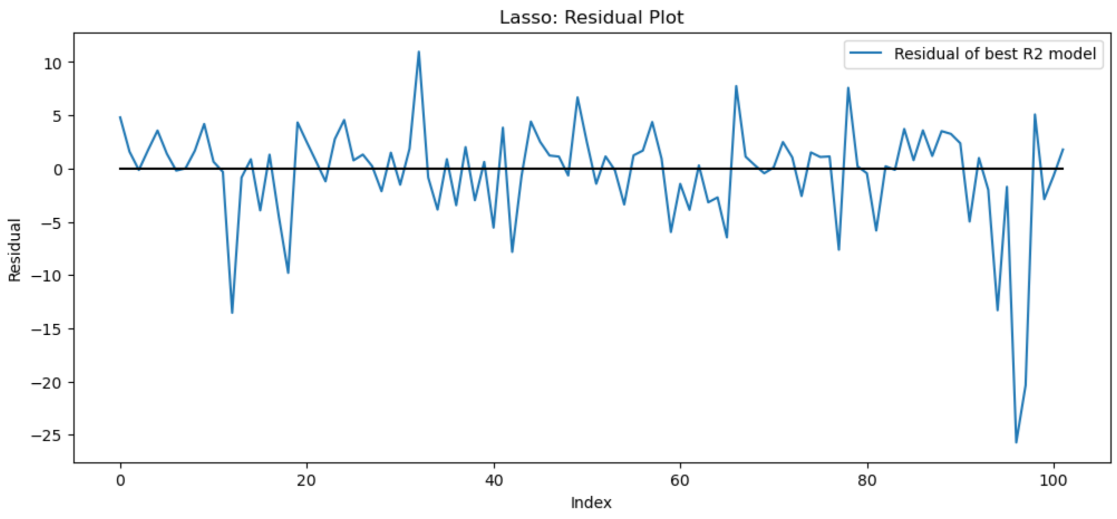
```
=  0.1 , R2=  0.6201889701292775 , MSE =  25.15559375393417
Coefficients=  [-0.10415691  0.03489335 -0.01678527  0.91995182 -0.
4.31168655
 -0.01512583 -1.15148729  0.23923695 -0.01296223 -0.73224678  0.01309057
 -0.56467442] , Intercept=  19.859769480417448
=  1.0 , R2=  0.557902070885584 , MSE =  24.409489761299707
Coefficients=  [-0.07660927  0.02850064 -0.          0.         -0.
1.63048892
  0.01639478 -0.63085765  0.21965363 -0.01228558 -0.70858233  0.0111811
 -0.74710661] , Intercept=  34.9357803779119
=  10.0 , R2=  0.04581718014897673 , MSE =  34.68576620696991
Coefficients=  [-0.          0.00632092 -0.          0.          0.          0.
  0.         -0.          0.         -0.0090727  -0.          0.00989229
 -0.60414765] , Intercept=  30.390737497013138
=  100.0 , R2=  -2.576371486602292 , MSE =  55.32016002797253
Coefficients=  [-0.          0.         -0.          0.         -0.          0.
 -0.          0.         -0.         -0.02071289 -0.          0.00607134
 -0.        ] , Intercept=  29.0021218527933
=  1000.0 , R2=  -5.94571155362359e+30 , MSE =  75.04543037399255
Coefficients=  [-0.  0. -0.  0. -0.  0. -0.  0. -0. -0. -0.  0. -0.] ,
Intercept=  22.796534653465343
=  10000.0 , R2=  -5.94571155362359e+30 , MSE =  75.04543037399255
Coefficients=  [-0.  0. -0.  0. -0.  0. -0.  0. -0. -0. -0.  0. -0.] ,
Intercept=  22.796534653465343
```

6.2 Plotting Out

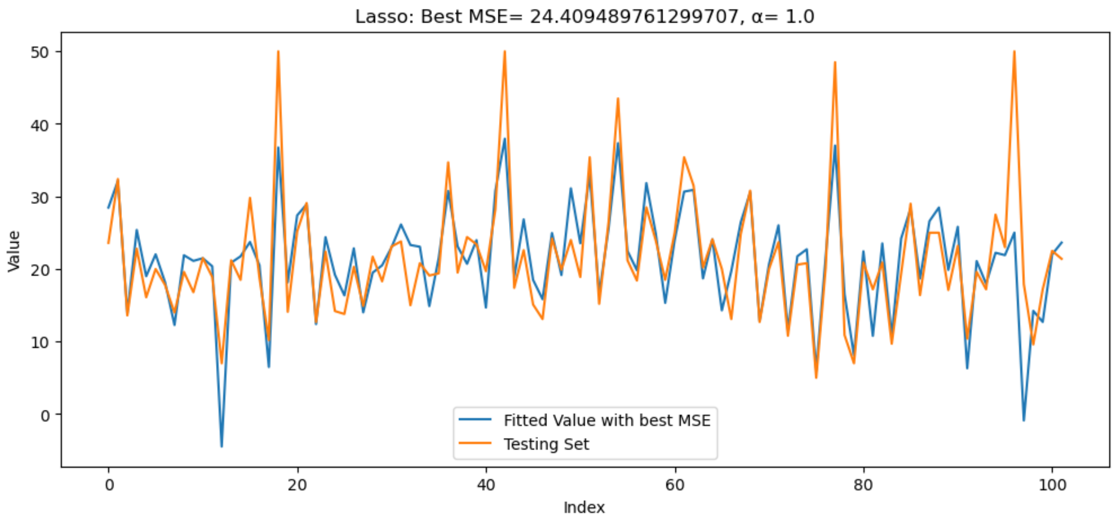
Plot the fitted value and residual for the best fit that picked by each R2 and MSE.

[21]:
```
lasso_r2 = Lasso(alpha= _r2_lasso)
lasso_r2.fit(X_train, y_train)
y_pred_r2_lasso = lasso_r2.predict(X_test)

plt.figure(figsize=[12,5])
plt.plot(y_pred_r2_lasso, label = 'Fitted Value with best R2')
plt.plot(y_test, label = 'Testing Set')
plt.title("Lasso: Best R2= "+str(best_r2_lasso)+",  = "+str( _r2_lasso))
plt.legend()
plt.xlabel("Index")
plt.ylabel("Value")
plt.show()
plt.figure(figsize=[12,5])
plt.plot(y_pred_r2_lasso - y_test, label = "Residual of best R2 model")
plt.plot(np.zeros_like(y_pred_r2_lasso), c = 'black')
plt.xlabel("Index")
plt.ylabel("Residual")
plt.title("Lasso: Residual Plot")
plt.legend()
plt.show()

lasso_mse = Lasso(alpha= _mse_lasso)
lasso_mse.fit(X_train, y_train)
y_pred_mse_lasso = lasso_mse.predict(X_test)

plt.figure(figsize=[12,5])
plt.plot(y_pred_mse_lasso, label = 'Fitted Value with best MSE')
plt.plot(y_test, label = 'Testing Set')
plt.title("Lasso: Best MSE= "+str(best_mse_lasso)+",  = "+str( _mse_lasso))
plt.xlabel("Index")
plt.ylabel("Value")
plt.legend()
plt.show()

plt.figure(figsize=[12,5])
plt.plot(y_pred_mse_lasso - y_test, label = "Residual of best R2 model")
plt.plot(np.zeros_like(y_pred_mse_lasso), c = 'black')
plt.xlabel("Index")
plt.ylabel("Residual")
plt.title("Lasso: Residual Plot")
plt.legend()
plt.show()
```

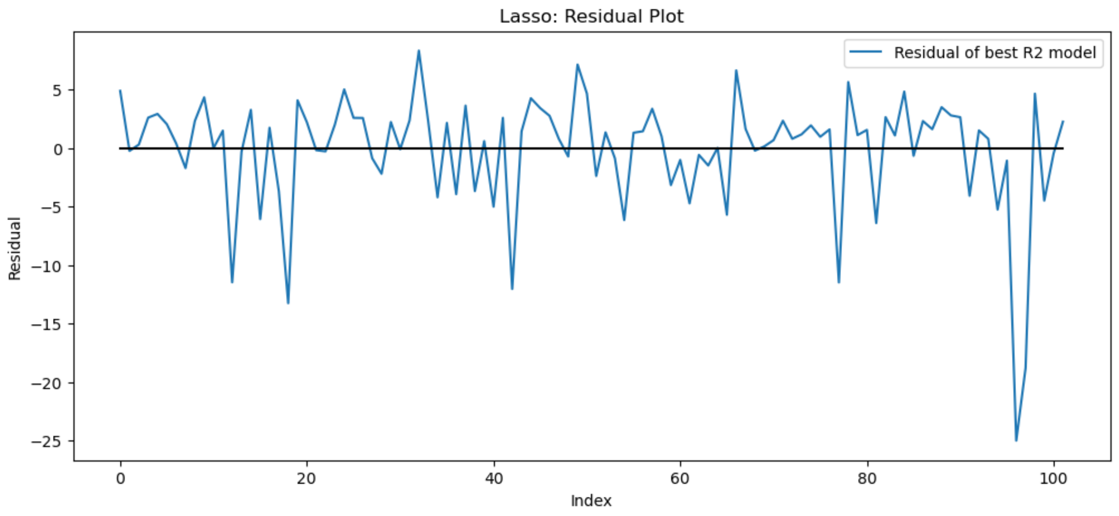




Lasso: Residual Plot
Residual of best R2 model
Residual
Index



Lasso: Best MSE= 24.409489761299707, α= 1.0
Fitted Value with best MSE
Testing Set
Value
Index



For R2, = 0.1 provides the best fit.

However, for MSE, = 1 provides the best fit.

7 Part 5: Conclusion

From the EDA, we can see that NOT ALL features have strong relationship with target. As a result, I think it will be better if we apply best subsets selection to see which features could be signifcant, rather than put all features into regression.

From simple linear regression(SLR), outsample R2 is about 63%, which is not quite decent. I would say this is because we include too much features in it, which cause "Overfitting". If I were to ameliorate this model, I will divide the dataset into 60% of training set, 20% as validation set and rest 20% as testing set. We then apply best model selection, use 60% to train the model, 20 to get the outsample R2 (or MSE) and thus get the best subset, and rest to see the performance. Putting all features in the model is not always a good idea.

From Lasso and Ridge Regression, I would say there is no big difference in their performance compared to SLR. Still overfitting. We can see that if our input is not "neat", using any kind of regression will not provide even better outcome. We still need to work on the input itself first.

8 Part 6: Signing

[22]:
```
print("My name is Yu-Ching Liao")
print("My NetID is: 656724372")
print("I hereby certify that I have read the University policy on Academic␣
 ↪Integrity and that I am not in violation.")
```

```
My name is Yu-Ching Liao
My NetID is: 656724372
```

I hereby certify that I have read the University policy on Academic Integrity and that I am not in violation.