DS Real Estates

Importing Libraries

In [1]:
```
import numpy as np
import pandas as pd
%matplotlib inline
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn import metrics
```

Loading the dataset

In [2]:
```
from sklearn.datasets import load_boston
boston = load_boston()
```

In [3]:
```
data = pd.DataFrame(boston.data)
```

In [4]:
```
data.columns = boston.feature_names
```

In [5]:
```
data.head()
```

Out[5]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT
0	0.00632	18.0	2.31	0.0	0.538	6.575	65.2	4.0900	1.0	296.0	15.3	396.90	4.98
1	0.02731	0.0	7.07	0.0	0.469	6.421	78.9	4.9671	2.0	242.0	17.8	396.90	9.14
2	0.02729	0.0	7.07	0.0	0.469	7.185	61.1	4.9671	2.0	242.0	17.8	392.83	4.03
3	0.03237	0.0	2.18	0.0	0.458	6.998	45.8	6.0622	3.0	222.0	18.7	394.63	2.94
4	0.06905	0.0	2.18	0.0	0.458	7.147	54.2	6.0622	3.0	222.0	18.7	396.90	5.33

In [6]:
```
data['MEDV']=boston.target
```

In [7]:
```
data.columns
```

Out[7]:
```
Index(['CRIM', 'ZN', 'INDUS', 'CHAS', 'NOX', 'RM', 'AGE', 'DIS', 'RAD', 'TAX',
       'PTRATIO', 'B', 'LSTAT', 'MEDV'],
      dtype='object')
```

In [8]:
```
data.dtypes
```

Out[8]:
```
CRIM       float64
ZN         float64
INDUS      float64
CHAS       float64
NOX        float64
RM         float64
AGE        float64
DIS        float64
RAD        float64
TAX        float64
PTRATIO    float64
B          float64
LSTAT      float64
MEDV       float64
dtype: object
```

In [9]:
```
# Identifying the unique number of values in the dataset
data.nunique()
```

Out[9]:
```
CRIM       504
ZN          26
INDUS       76
CHAS         2
NOX         81
RM         446
AGE        356
DIS        412
RAD          9
TAX         66
PTRATIO     46
B          357
LSTAT      455
MEDV       229
dtype: int64
```

In [10]:
```
# Check for missing values
data.isnull().sum()
```

Out[10]:
```
CRIM       0
ZN         0
INDUS      0
CHAS       0
NOX        0
RM         0
AGE        0
DIS        0
RAD        0
TAX        0
PTRATIO    0
B          0
LSTAT      0
MEDV       0
dtype: int64
```

In [11]:
```
# See rows with missing values
data[data.isnull().any(axis=1)]
```

Out[11]:

CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT	MEDV

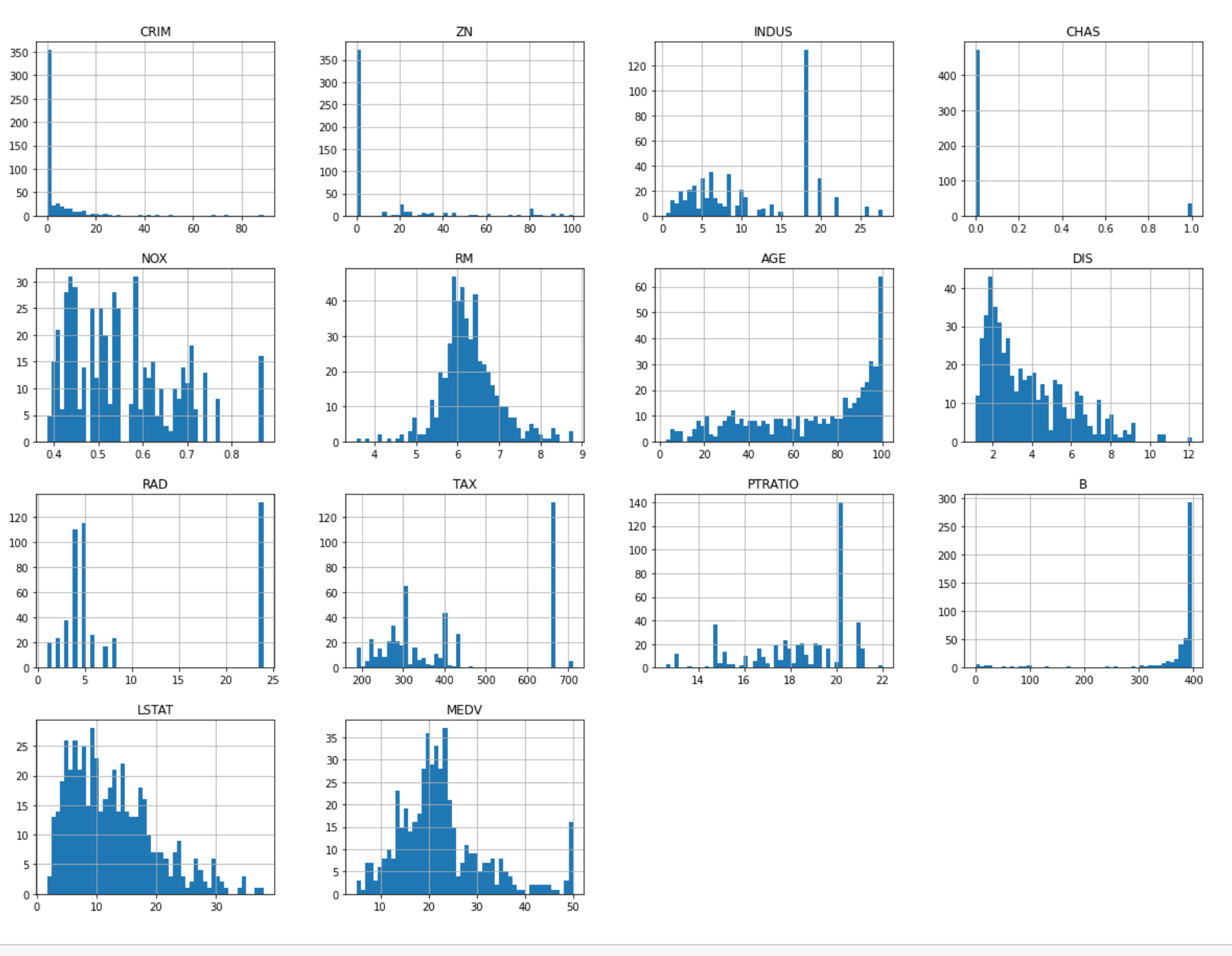
In [12]:
```
# Viewing the data statistics
data.describe()
```

Out[12]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRAT
count	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.0000
mean	3.613524	11.363636	11.136779	0.069170	0.554695	6.284634	68.574901	3.795043	9.549407	408.237154	18.4555
std	8.601545	23.322453	6.860353	0.253994	0.115878	0.702617	28.148861	2.105710	8.707259	168.537116	2.1649
min	0.006320	0.000000	0.460000	0.000000	0.385000	3.561000	2.900000	1.129600	1.000000	187.000000	12.6000
25%	0.082045	0.000000	5.190000	0.000000	0.449000	5.885500	45.025000	2.100175	4.000000	279.000000	17.4000
50%	0.256510	0.000000	9.690000	0.000000	0.538000	6.208500	77.500000	3.207450	5.000000	330.000000	19.0500
75%	3.677083	12.500000	18.100000	0.000000	0.624000	6.623500	94.075000	5.188425	24.000000	666.000000	20.2000
max	88.976200	100.000000	27.740000	1.000000	0.871000	8.780000	100.000000	12.126500	24.000000	711.000000	22.0000

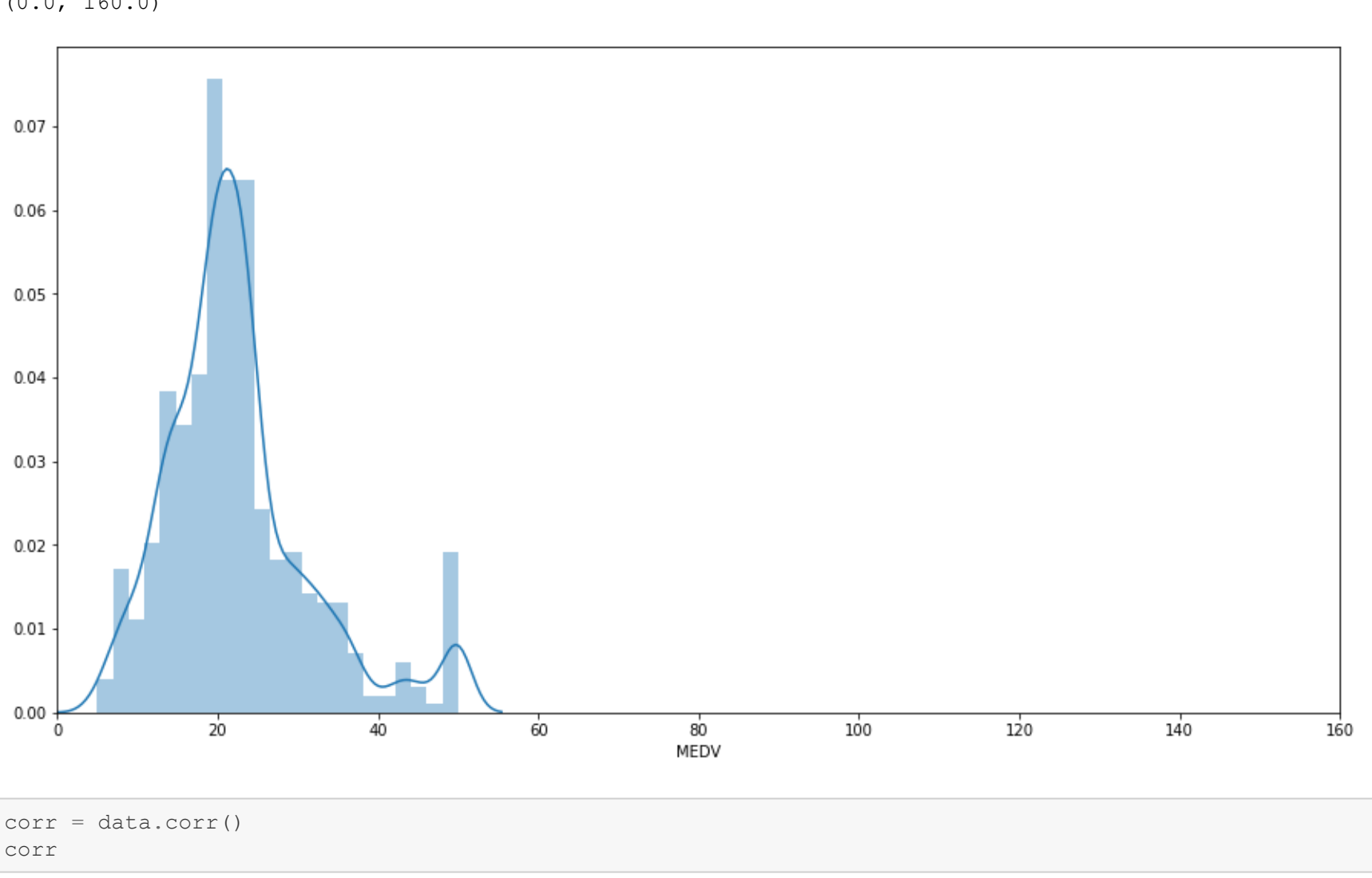
In [13]:
```
data.hist(bins=50, figsize=(20, 15))
```

Out[13]:
```
array([[<AxesSubplot:title={'center':'CRIM'}>,
        <AxesSubplot:title={'center':'ZN'}>,
        <AxesSubplot:title={'center':'INDUS'}>,
        <AxesSubplot:title={'center':'CHAS'}>],
       [<AxesSubplot:title={'center':'NOX'}>,
        <AxesSubplot:title={'center':'RM'}>,
        <AxesSubplot:title={'center':'AGE'}>,
        <AxesSubplot:title={'center':'DIS'}>],
       [<AxesSubplot:title={'center':'RAD'}>,
        <AxesSubplot:title={'center':'TAX'}>,
        <AxesSubplot:title={'center':'PTRATIO'}>,
        <AxesSubplot:title={'center':'B'}>],
       [<AxesSubplot:title={'center':'LSTAT'}>,
        <AxesSubplot:title={'center':'MEDV'}>, <AxesSubplot:>,
        <AxesSubplot:>]], dtype=object)
```



In [14]:
```
f,ax=plt.subplots(figsize=(15,8))
sns.distplot(data['MEDV'])
plt.xlim([0,160])
```

Out[14]: (0.0, 160.0)



In [15]:
```
corr = data.corr()
corr
```

Out[15]:

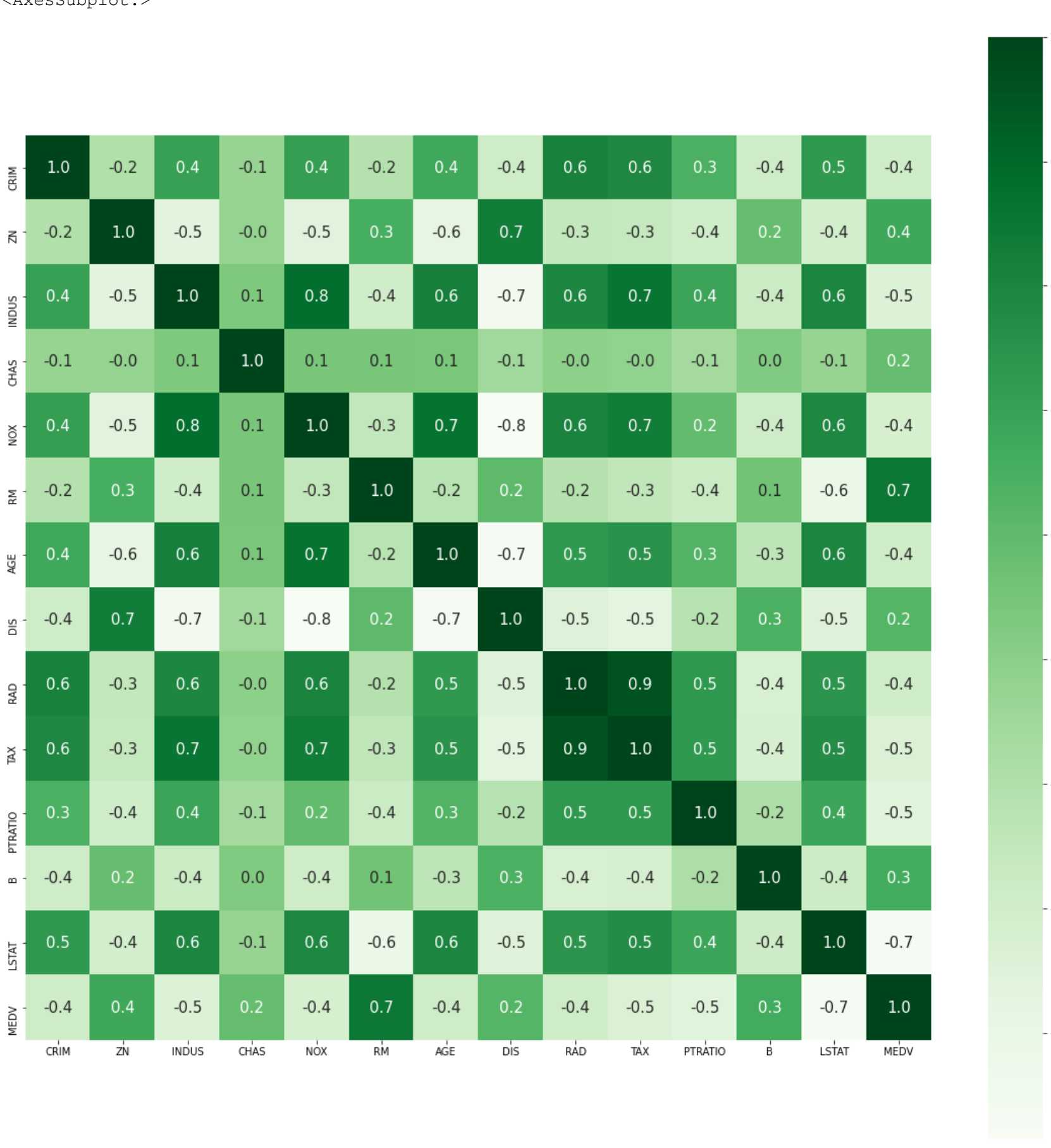
	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B
CRIM	1.000000	-0.200469	0.406583	-0.055892	0.420972	-0.219247	0.352734	-0.379670	0.625505	0.582764	0.289946	-0.38506
ZN	-0.200469	1.000000	-0.533828	-0.042697	-0.516604	0.311991	-0.569537	0.664408	-0.311948	-0.314563	-0.391679	0.17552
INDUS	0.406583	-0.533828	1.000000	0.062938	0.763651	-0.391676	0.644779	-0.708027	0.595129	0.720760	0.383248	-0.35697
CHAS	-0.055892	-0.042697	0.062938	1.000000	0.091203	0.091251	0.086518	-0.099176	-0.007368	-0.035587	-0.121515	0.04878
NOX	0.420972	-0.516604	0.763651	0.091203	1.000000	-0.302188	0.731470	-0.769230	0.611441	0.668023	0.188933	-0.38005
RM	-0.219247	0.311991	-0.391676	0.091251	-0.302188	1.000000	-0.240265	0.205246	-0.209847	-0.292048	-0.355501	0.12806
AGE	0.352734	-0.569537	0.644779	0.086518	0.731470	-0.240265	1.000000	-0.747881	0.456022	0.506456	0.261515	-0.27353
DIS	-0.379670	0.664408	-0.708027	-0.099176	-0.769230	0.205246	-0.747881	1.000000	-0.494588	-0.534432	-0.232471	0.29151
RAD	0.625505	-0.311948	0.595129	-0.007368	0.611441	-0.209847	0.456022	-0.494588	1.000000	0.910228	0.464741	-0.44441
TAX	0.582764	-0.314563	0.720760	-0.035587	0.668023	-0.292048	0.506456	-0.534432	0.910228	1.000000	0.460853	-0.44180
PTRATIO	0.289946	-0.391679	0.383248	-0.121515	0.188933	-0.355501	0.261515	-0.232471	0.464741	0.460853	1.000000	-0.17738
B	-0.385064	0.175520	-0.356977	0.048788	-0.380051	0.128069	-0.273534	0.291512	-0.444413	-0.441808	-0.177383	1.00000
LSTAT	0.455621	-0.412995	0.603800	-0.053929	0.590879	-0.613808	0.602339	-0.496996	0.488676	0.543993	0.374044	-0.36608
MEDV	-0.388305	0.360445	-0.483725	0.175260	-0.427321	0.695360	-0.376955	0.249929	-0.381626	-0.468536	-0.507787	0.33346

In [16]:
```
corr.shape
```

Out[16]: (14, 14)

In [17]:
```
# Plotting the heatmap of correlation between features
plt.figure(figsize=(20,20))
sns.heatmap(corr, cbar=True, square= True, fmt='.1f', annot=True, annot_kws={'size':15}, cmap='Greens')
```

Out[17]: <AxesSubplot:>

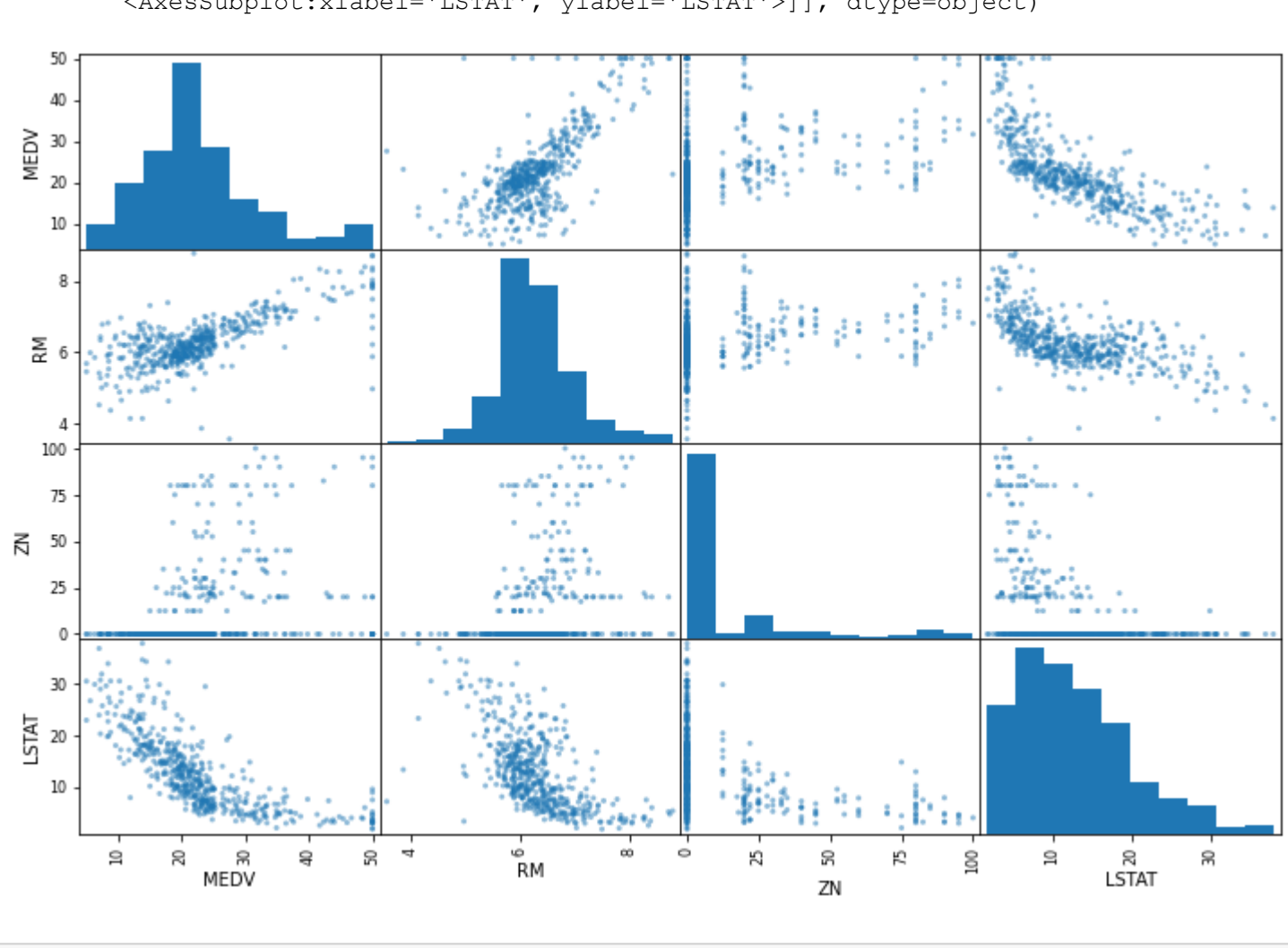


In [18]:
```
corr['MEDV'].sort_values(ascending=False)
```

Out[18]:
```
MEDV       1.000000
RM         0.695360
ZN         0.360445
B          0.333461
DIS        0.249929
CHAS       0.175260
AGE       -0.376955
RAD       -0.381626
CRIM      -0.388305
NOX       -0.427321
TAX       -0.468536
INDUS     -0.483725
PTRATIO   -0.507787
LSTAT     -0.737663
Name: MEDV, dtype: float64
```

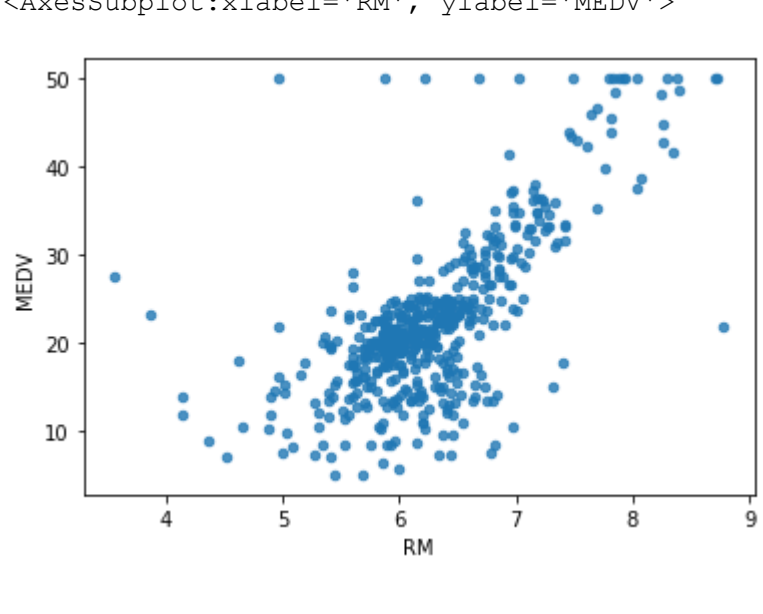
In [19]:
```
from pandas.plotting import scatter_matrix
attributes = ["MEDV", "RM", "ZN", "LSTAT"]
scatter_matrix(data[attributes], figsize = (12,8))
```

Out[19]:
```
array([[<AxesSubplot:xlabel='MEDV', ylabel='MEDV'>,
        <AxesSubplot:xlabel='RM', ylabel='MEDV'>,
        <AxesSubplot:xlabel='ZN', ylabel='MEDV'>,
        <AxesSubplot:xlabel='LSTAT', ylabel='MEDV'>],
       [<AxesSubplot:xlabel='MEDV', ylabel='RM'>,
        <AxesSubplot:xlabel='RM', ylabel='RM'>,
        <AxesSubplot:xlabel='ZN', ylabel='RM'>,
        <AxesSubplot:xlabel='LSTAT', ylabel='RM'>],
       [<AxesSubplot:xlabel='MEDV', ylabel='ZN'>,
        <AxesSubplot:xlabel='RM', ylabel='ZN'>,
        <AxesSubplot:xlabel='ZN', ylabel='ZN'>,
        <AxesSubplot:xlabel='LSTAT', ylabel='ZN'>],
       [<AxesSubplot:xlabel='MEDV', ylabel='LSTAT'>,
        <AxesSubplot:xlabel='RM', ylabel='LSTAT'>,
        <AxesSubplot:xlabel='ZN', ylabel='LSTAT'>,
        <AxesSubplot:xlabel='LSTAT', ylabel='LSTAT'>]], dtype=object)
```



In [20]:
```
data.plot(kind="scatter", x="RM", y="MEDV", alpha=0.8)
```

Out[20]: <AxesSubplot:xlabel='RM', ylabel='MEDV'>



Spliting the dataset

In [21]:
```
# Spliting target variable and independent variables
X = data.drop(['MEDV'], axis = 1)
y = data['MEDV']
```

In [22]:
```
# Splitting to training and testing data

from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X,y, test_size = 0.3, random_state = 4)
```

In [23]:
```
print(X_train.shape)
print(y_train.shape)
print(X_test.shape)
print(y_test.shape)
```

```
(354, 13)
(354,)
(152, 13)
(152,)
```

Linear regression

Training the model

In [24]:
```
# Import library for Linear Regression
from sklearn.linear_model import LinearRegression

# Create a Linear regressor
lm = LinearRegression()

# Train the model using the training sets
lm.fit(X_train, y_train)
print("Accuracy on Traing set: ",lm.score(X_train,y_train))
print("Accuracy on Testing set: ",lm.score(X_test,y_test))
```

```
Accuracy on Traing set:  0.7465991966746854
Accuracy on Testing set:  0.7121818377409181
```

In [25]:
```
# Model prediction on train data
y_pred = lm.predict(X_train)
```

In [26]:
```
# Predicting Test data with the model
y_test_pred = lm.predict(X_test)
```

In [27]:
```
# Model Evaluation
print('R^2:',metrics.r2_score(y_train, y_pred))
print('MAE:',metrics.mean_absolute_error(y_train, y_pred))
print('MSE:',metrics.mean_squared_error(y_train, y_pred))
print('RMSE:',np.sqrt(metrics.mean_squared_error(y_train, y_pred)))
```

```
R^2: 0.7465991966746854
MAE: 3.08986109497113
MSE: 19.07368870346903
RMSE: 4.367343437774162
```

In [28]:
```
# Model Evaluation
print('R^2:',metrics.r2_score(y_test, y_test_pred))
print('MAE:',metrics.mean_absolute_error(y_test, y_test_pred))
print('MSE:',metrics.mean_squared_error(y_test, y_test_pred))
print('RMSE:',np.sqrt(metrics.mean_squared_error(y_test, y_test_pred)))
```

```
R^2: 0.7121818377409181
MAE: 3.859005592370746
MSE: 30.053993307124284
RMSE: 5.482152251362988
```

In [29]:
```
y_train
train_index=pd.DataFrame(y_train.reset_index(),columns=['MEDV'])
train_index
```

Out[29]:

	MEDV
0	23.9
1	18.2
2	21.7
3	13.5
4	50.0
...	...
349	7.2
350	30.3
351	12.8
352	22.6
353	20.5

354 rows × 1 columns

In [30]:
```
df=pd.DataFrame(y_pred,columns=['predicted_price'])
df
```

Out[30]:

	predicted_price
0	24.522480
1	15.197510
2	25.577206
3	13.939400
4	39.466513
...	...
349	8.608369
350	31.511078
351	13.647191
352	26.501062
353	20.540965

354 rows × 1 columns

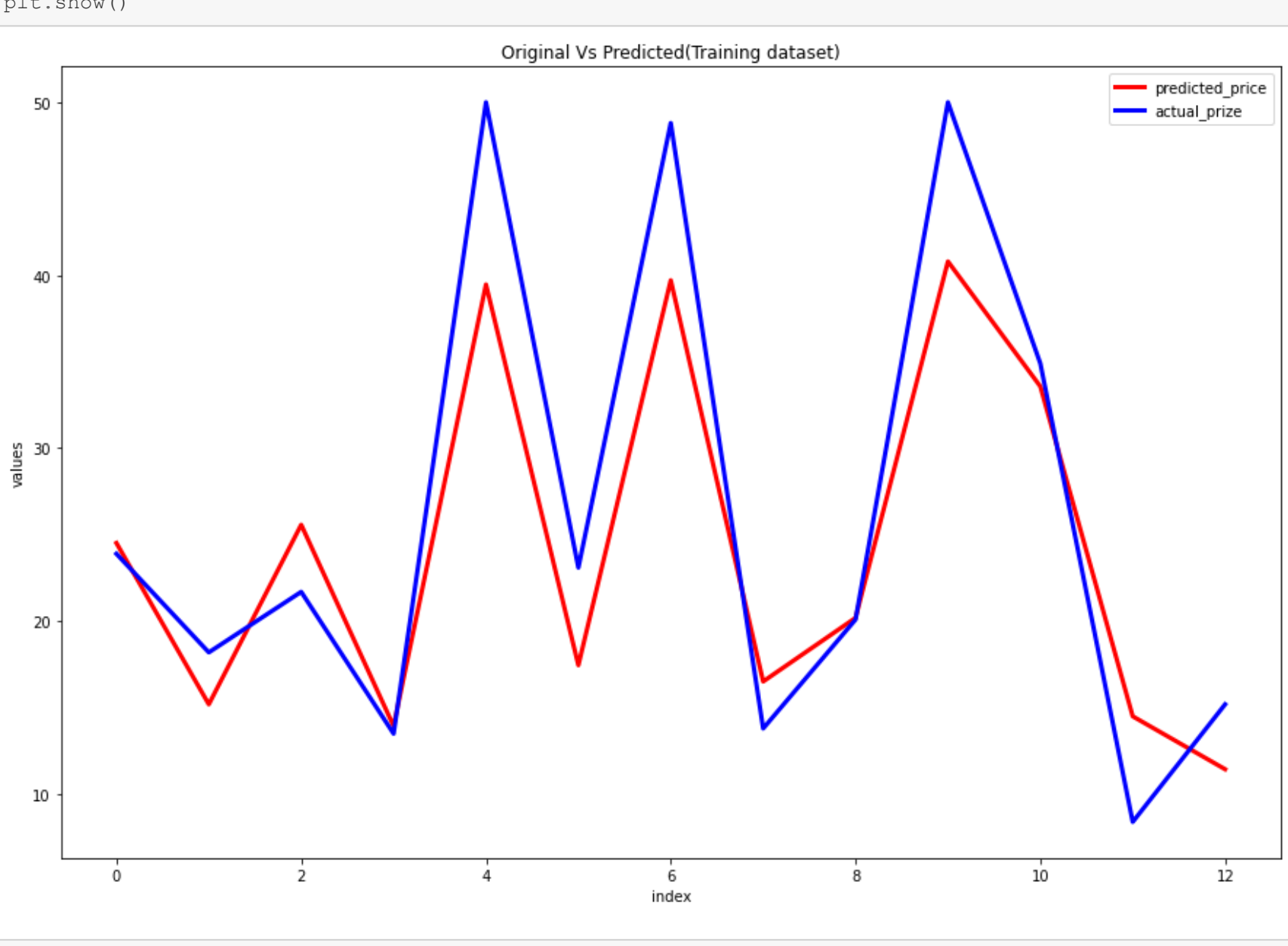
In [31]:
```
df['actual_prize']=train_index['MEDV']
df
```

Out[31]:

	predicted_price	actual_prize
0	24.522480	23.9
1	15.197510	18.2
2	25.577206	21.7
3	13.939400	13.5
4	39.466513	50.0
...	...	...
349	8.608369	7.2
350	31.511078	30.3
351	13.647191	12.8
352	26.501062	22.6
353	20.540965	20.5

354 rows × 2 columns

In [32]:
```
ax=df.iloc[0:13].plot(label="predicted",figsize=(15,10),linewidth=3,color="rb")
plt.legend(loc='upper right')
plt.title("Original Vs Predicted(Training dataset)")
plt.xlabel("index")
plt.ylabel("values")
plt.show()
```



In [33]:
```
y_test
test_index=pd.DataFrame(y_test.reset_index(),columns=['MEDV'])
test_index
```

Out[33]:

	MEDV
0	16.5
1	24.8
2	17.4
3	19.3
4	37.6
...	...
147	14.9
148	21.9
149	18.5
150	30.8
151	14.6

152 rows × 1 columns

In [34]:
```
dft=pd.DataFrame(y_test_pred,columns=['predicted_price'])
dft
```

Out[34]:

	predicted_price
0	11.073809
1	26.479103
2	17.344899
3	19.194861
4	36.361707
...	...
147	17.891931
148	38.439440
149	19.707526
150	31.671812
151	19.013091

152 rows × 1 columns

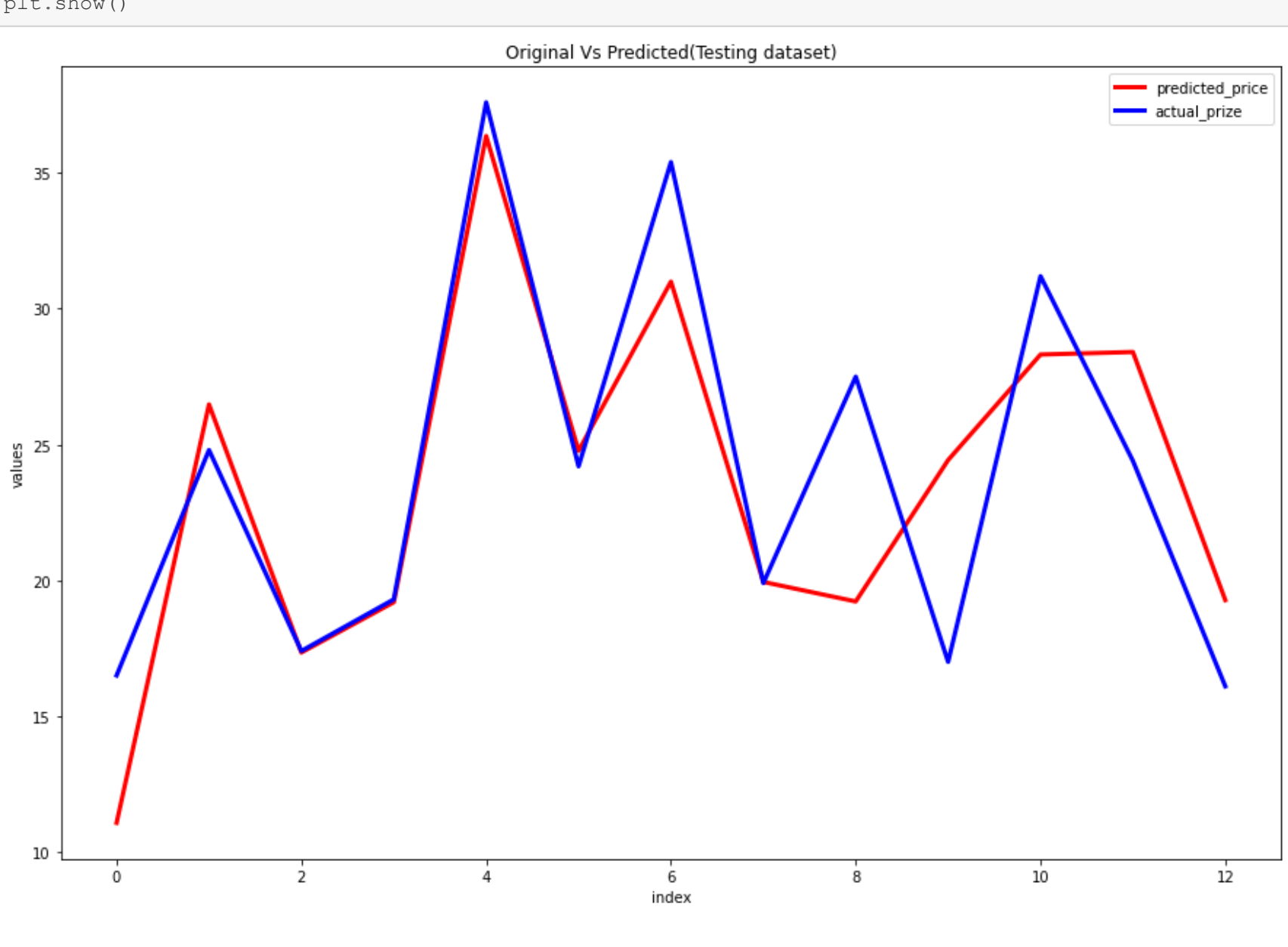
In [35]:
```
dft['actual_prize']=test_index['MEDV']
dft
```

Out[35]:

	predicted_price	actual_prize
0	11.073809	16.5
1	26.479103	24.8
2	17.344899	17.4
3	19.194861	19.3
4	36.361707	37.6
...	...	...
147	17.891931	14.9
148	38.439440	21.9
149	19.707526	18.5
150	31.671812	30.8
151	19.013091	14.6

152 rows × 2 columns

In [36]:
```
ax=dft.iloc[0:13].plot(label="predicted",figsize=(15,10),linewidth=3,color="rb")
plt.legend(loc='upper right')
plt.title("Original Vs Predicted(Testing dataset)")
plt.xlabel("index")
plt.ylabel("values")
plt.show()
```



Decision Tree Regressor

In [37]:
```
from sklearn.tree import DecisionTreeRegressor
dtr = DecisionTreeRegressor()
dtr.fit(X_train,y_train)
```

Out[37]: DecisionTreeRegressor()

In [38]:
```
print("Accuracy on Traing set: ",dtr.score(X_train,y_train))
print("Accuracy on Testing set: ",dtr.score(X_test,y_test))
```

```
Accuracy on Traing set:  1.0
Accuracy on Testing set:  0.683811925643684
```

In [39]:
```
# Model prediction on train data
y_pred = dtr.predict(X_train)
```

In [40]:
```
# Model Evaluation
print('R^2:',metrics.r2_score(y_train, y_pred))
print('MAE:',metrics.mean_absolute_error(y_train, y_pred))
print('MSE:',metrics.mean_squared_error(y_train, y_pred))
print('RMSE:',np.sqrt(metrics.mean_squared_error(y_train, y_pred)))
```

```
R^2: 1.0
MAE: 0.0
MSE: 0.0
RMSE: 0.0
```

In [41]:
```
# Predicting Test data with the model
y_test_pred = dtr.predict(X_test)
```

In [42]:
```
# Model Evaluation
print('R^2:',metrics.r2_score(y_test, y_test_pred))
print('MAE:',metrics.mean_absolute_error(y_test, y_test_pred))
print('MSE:',metrics.mean_squared_error(y_test, y_test_pred))
print('RMSE:',np.sqrt(metrics.mean_squared_error(y_test, y_test_pred)))
```

```
R^2: 0.683811925643684
MAE: 3.4743421052631582
MSE: 33.01638157894737
RMSE: 5.7459883030639185
```

In [43]:
```
y_train
train_index=pd.DataFrame(y_train.reset_index(),columns=['MEDV'])
train_index
```

Out[43]:

	MEDV
0	23.9
1	18.2
2	21.7
3	13.5
4	50.0
...	...
349	7.2
350	30.3
351	12.8
352	22.6
353	20.5

354 rows × 1 columns

In [44]:
```
df=pd.DataFrame(y_pred,columns=['predicted_price'])
df
```

Out[44]:

	predicted_price
0	23.9
1	18.2
2	21.7
3	13.5
4	50.0
...	...
349	7.2
350	30.3
351	12.8
352	22.6
353	20.5

354 rows × 1 columns

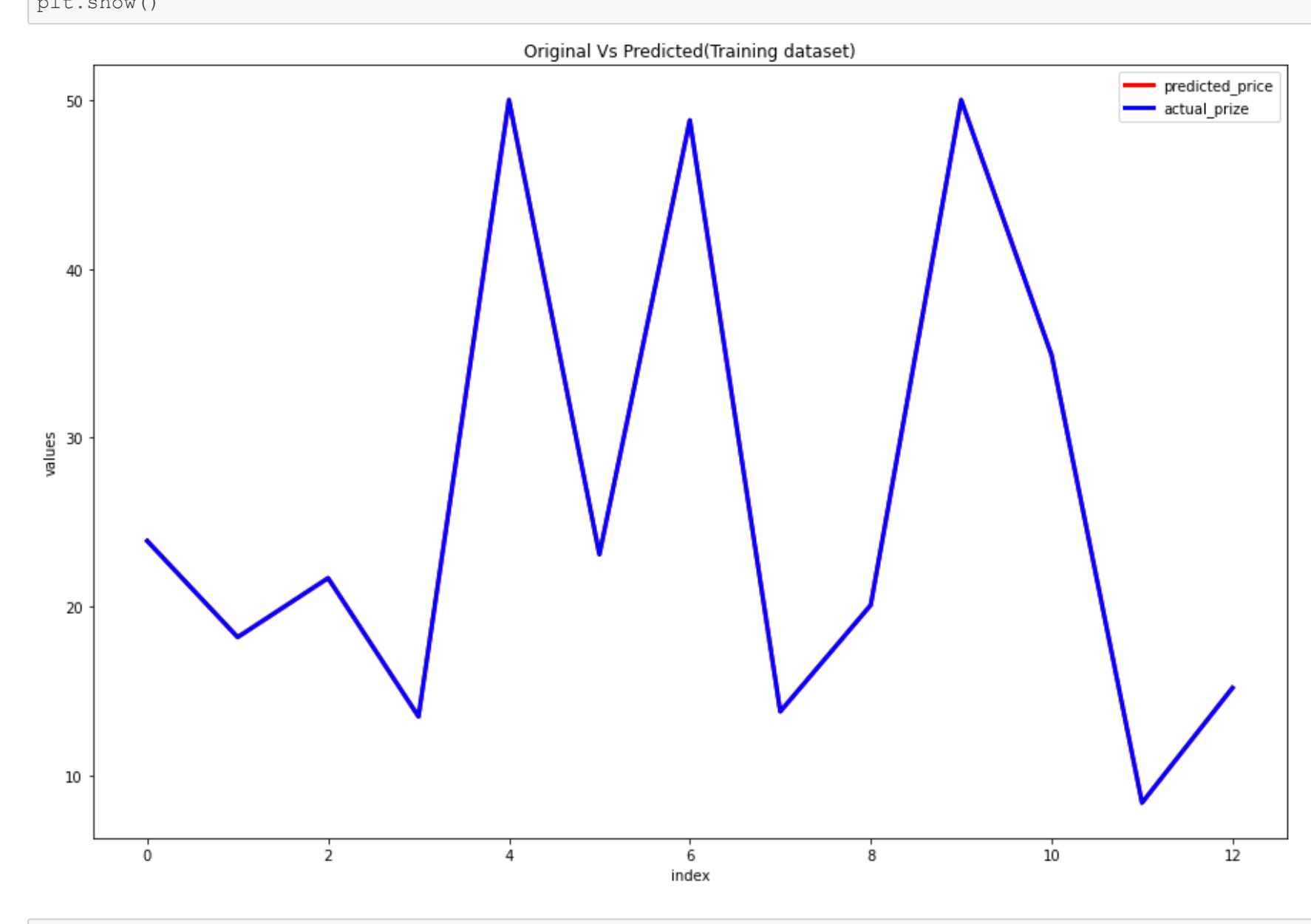
In [45]:
```
df['actual_prize']=train_index['MEDV']
df
```

Out[45]:

	predicted_price	actual_prize
0	23.9	23.9
1	18.2	18.2
2	21.7	21.7
3	13.5	13.5
4	50.0	50.0
...	...	...
349	7.2	7.2
350	30.3	30.3
351	12.8	12.8
352	22.6	22.6
353	20.5	20.5

354 rows × 2 columns

In [46]:
```
ax=df.iloc[0:13].plot(label="predicted",figsize=(15,10),linewidth=3,color="rb")
plt.legend(loc='upper right')
plt.title("Original Vs Predicted(Training dataset)")
plt.xlabel("index")
plt.ylabel("values")
plt.show()
```



In [47]:
```
y_test
test_index=pd.DataFrame(y_test.reset_index(),columns=['MEDV'])
test_index
```

Out[47]:

	MEDV
0	16.5
1	24.8
2	17.4
3	19.3
4	37.6
...	...
147	14.9
148	21.9
149	18.5
150	30.8
151	14.6

152 rows × 1 columns

In [48]:
```
dft=pd.DataFrame(y_test_pred,columns=['predicted_price'])
dft
```

Out[48]:

	predicted_price
0	14.4
1	25.1
2	20.9
3	22.5
4	48.3
...	...
147	15.2
148	35.2
149	18.7
150	28.4
151	12.6

152 rows × 1 columns

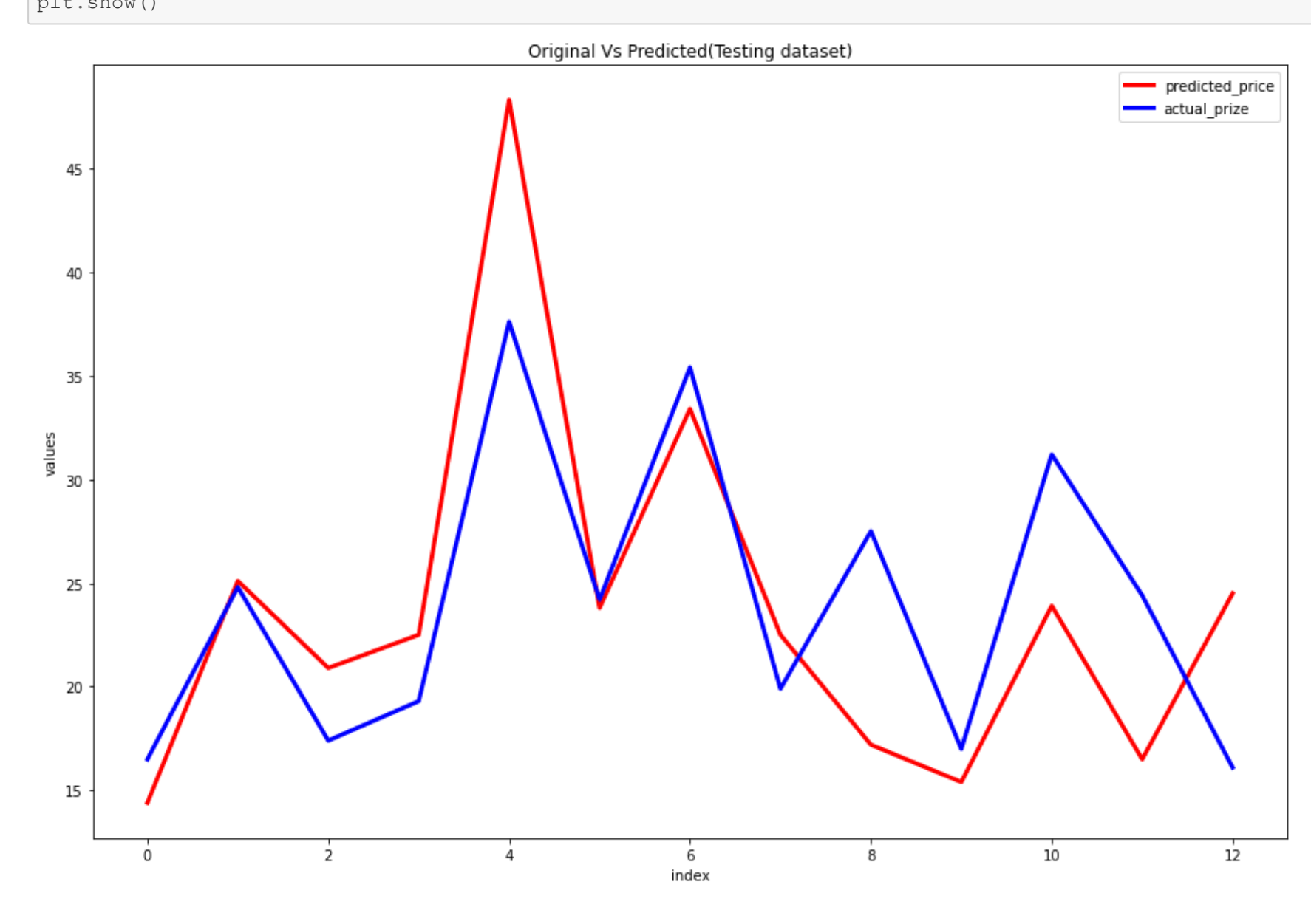
In [49]:
```
dft['actual_prize']=test_index['MEDV']
dft
```

Out[49]:

	predicted_price	actual_prize
0	14.4	16.5
1	25.1	24.8
2	20.9	17.4
3	22.5	19.3
4	48.3	37.6
...	...	...
147	15.2	14.9
148	35.2	21.9
149	18.7	18.5
150	28.4	30.8
151	12.6	14.6

152 rows × 2 columns

In [50]:
```
ax=dft.iloc[0:13].plot(label="predicted",figsize=(15,10),linewidth=3,color="rb")
plt.legend(loc='upper right')
plt.title("Original Vs Predicted(Testing dataset)")
plt.xlabel("index")
plt.ylabel("values")
plt.show()
```



Random Forest Regressor

In [51]:
```
# Import Random Forest Regressor
from sklearn.ensemble import RandomForestRegressor

# Create a Random Forest Regressor
reg = RandomForestRegressor()

# Train the model using the training sets
reg.fit(X_train, y_train)
```

Out[51]: RandomForestRegressor()

In [52]:
```
print("Accuracy on Traing set: ",reg.score(X_train,y_train))
print("Accuracy on Testing set: ",reg.score(X_test,y_test))
```

```
Accuracy on Traing set:  0.9816758194725794
Accuracy on Testing set:  0.8351878286175581
```

In [53]:
```
# Model prediction on train data
y_pred = reg.predict(X_train)
```

In [54]:
```
# Model Evaluation
print('R^2:',metrics.r2_score(y_train, y_pred))
print('MAE:',metrics.mean_absolute_error(y_train, y_pred))
print('MSE:',metrics.mean_squared_error(y_train, y_pred))
print('RMSE:',np.sqrt(metrics.mean_squared_error(y_train, y_pred)))
```

```
R^2: 0.9816758194725794
MAE: 0.8005988700564974
MSE: 1.379276271186442
RMSE: 1.1744259326098185
```

In [55]:
```
# Predicting Test data with the model
y_test_pred = reg.predict(X_test)
```

In [56]:
```
# Model Evaluation
print('R^2:',metrics.r2_score(y_test, y_test_pred))
print('MAE:',metrics.mean_absolute_error(y_test, y_test_pred))
print('MSE:',metrics.mean_squared_error(y_test, y_test_pred))
print('RMSE:',np.sqrt(metrics.mean_squared_error(y_test, y_test_pred)))
```

```
R^2: 0.8351878286175581
MAE: 2.4811776315789467
MSE: 17.209698848684212
RMSE: 4.14845740591418
```

In [57]:
```
y_train
train_index=pd.DataFrame(y_train.reset_index(),columns=['MEDV'])
train_index
```

Out[57]:

	MEDV
0	23.9
1	18.2
2	21.7
3	13.5
4	50.0
...	...
349	7.2
350	30.3
351	12.8
352	22.6
353	20.5

354 rows × 1 columns

In [58]:
```
df=pd.DataFrame(y_pred,columns=['predicted_price'])
df
```

Out[58]:

	predicted_price
0	23.092
1	18.831
2	19.957
3	13.852
4	48.002
...	...
349	8.062
350	31.247
351	12.667
352	21.895
353	20.025

354 rows × 1 columns

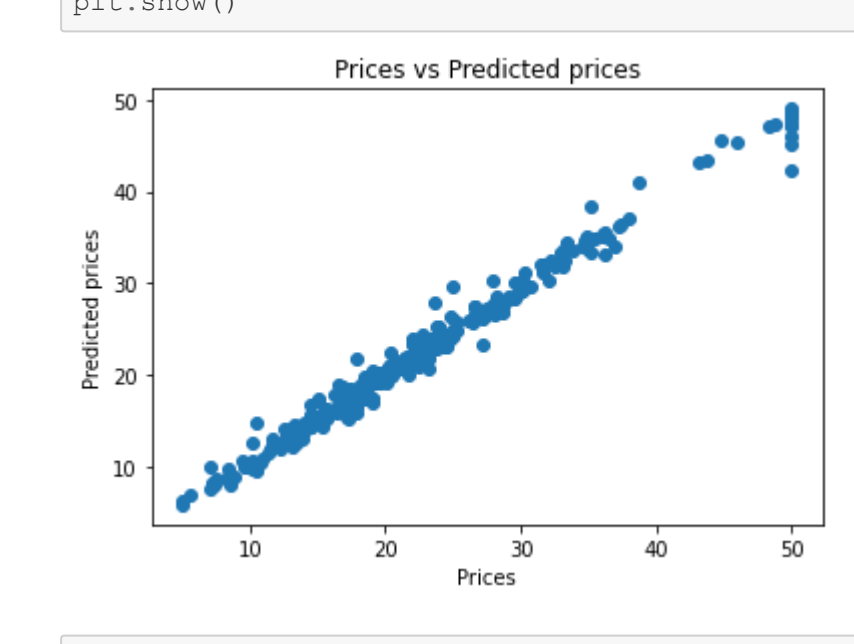
In [59]:
```
df['actual_prize']=train_index['MEDV']
df
```

Out[59]:

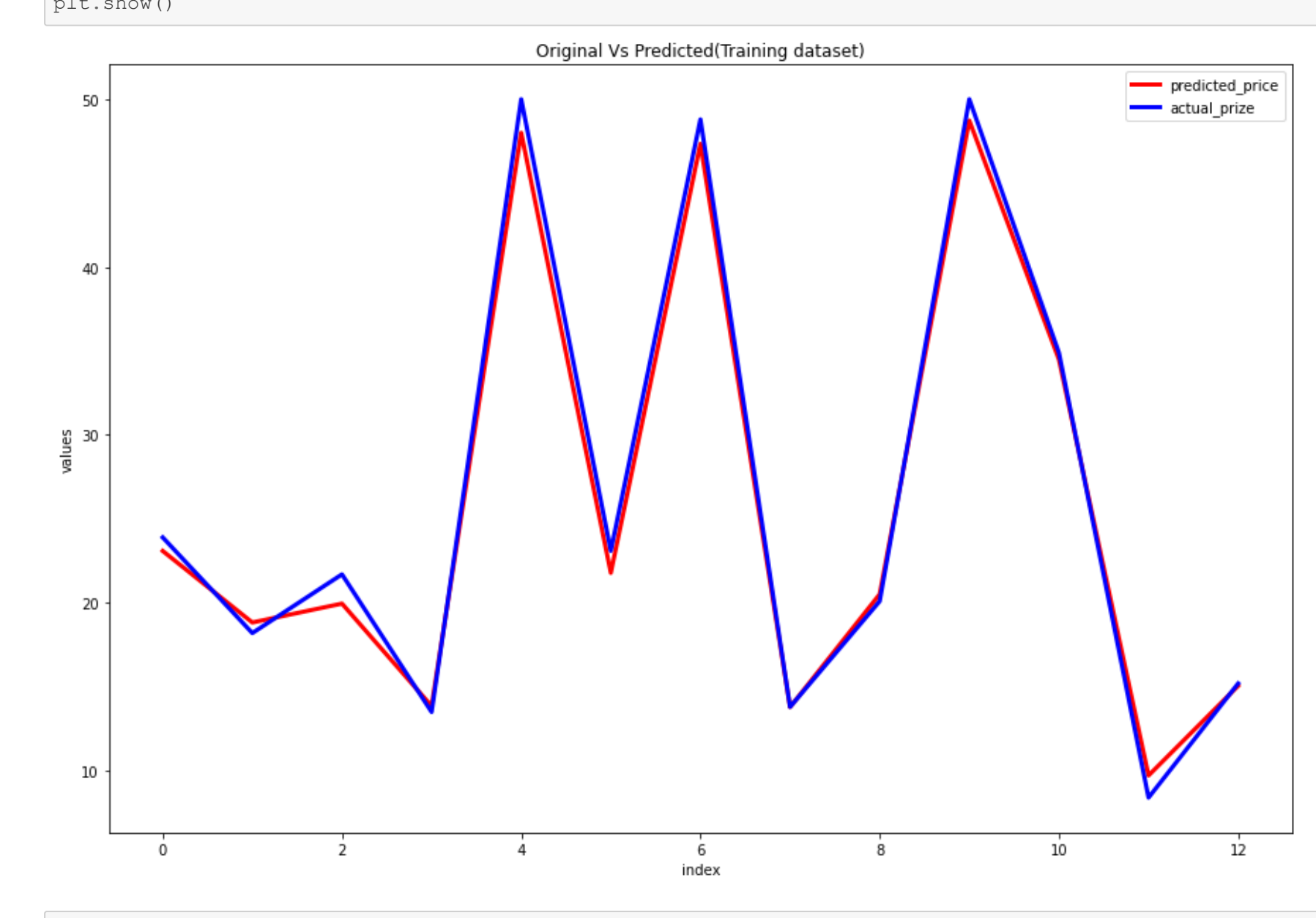
	predicted_price	actual_prize
0	23.092	23.9
1	18.831	18.2
2	19.957	21.7
3	13.852	13.5
4	48.002	50.0
...	...	...
349	8.062	7.2
350	31.247	30.3
351	12.667	12.8
352	21.895	22.6
353	20.025	20.5

354 rows × 2 columns

In [60]:
```
# Visualizing the differences between actual prices and predicted values
plt.scatter(y_train, y_pred)
plt.xlabel("Prices")
plt.ylabel("Predicted prices")
plt.title("Prices vs Predicted prices")
plt.show()
```



In [61]:
```
ax=df.iloc[0:13].plot(label="predicted",figsize=(15,10),linewidth=3,color="rb")
plt.legend(loc='upper right')
plt.title("Original Vs Predicted(Training dataset)")
plt.xlabel("index")
plt.ylabel("values")
plt.show()
```



In [62]:
```
y_test
test_index=pd.DataFrame(y_test.reset_index(),columns=['MEDV'])
test_index
```

Out[62]:

	MEDV
0	16.5
1	24.8
2	17.4
3	19.3
4	37.6
...	...
147	14.9
148	21.9
149	18.5
150	30.8
151	14.6

152 rows × 1 columns

In [63]:
```
dft=pd.DataFrame(y_test_pred,columns=['predicted_price'])
dft
```

Out[63]:

	predicted_price
0	17.667
1	23.427
2	19.332
3	17.260
4	46.642
...	...
147	15.462
148	41.664
149	19.759
150	26.616
151	15.068

152 rows × 1 columns

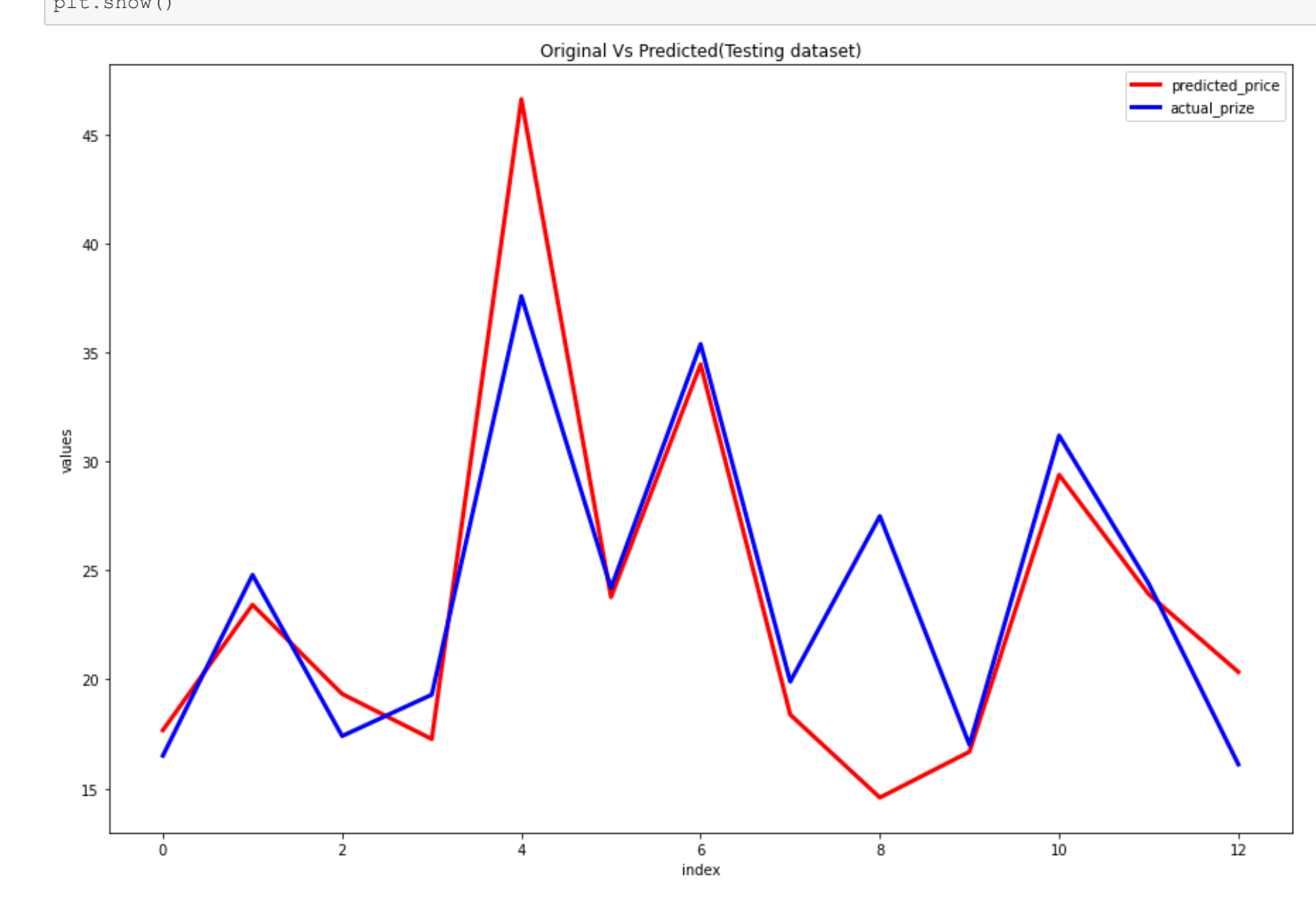
In [64]:
```
dft['actual_prize']=test_index['MEDV']
dft
```

Out[64]:

	predicted_price	actual_prize
0	17.667	16.5
1	23.427	24.8
2	19.332	17.4
3	17.260	19.3
4	46.642	37.6
...	...	...
147	15.462	14.9
148	41.664	21.9
149	19.759	18.5
150	26.616	30.8
151	15.068	14.6

152 rows × 2 columns

In [65]:
```
ax=dft.iloc[0:13].plot(label="predicted",figsize=(15,10),linewidth=3,color="rb")
plt.legend(loc='upper right')
plt.title("Original Vs Predicted(Testing dataset)")
plt.xlabel("index")
plt.ylabel("values")
plt.show()
```



We analyzed performence all the models and then selected Random Forest Regression model as it is most accuracte of all three.

Using the model to predict prices

In [66]:
```
features = np.array([[5.43942006, 4.12628155, 1.6165014, 0.67288841, 1.42262747, 11.44443979304, 49.312
38772, 7.61111401, 26.0016879 , 0.5778192 , 0.97491834, 0.41164221, 66.86091034]])
```

In [67]:
```
reg.predict(features)
```

Out[67]: array([37.687])