Build the linear regression model using scikit learn in boston data to predict 'Price' based on other dependent variable.

In [1]:
```python
import numpy as np
import pandas as pd
import scipy.stats as stats
import matplotlib.pyplot as plt
import sklearn
from sklearn.datasets import load_boston
boston = load_boston()

#Converting dataset  into dataframe

bos = pd.DataFrame(boston.data)
```

In [2]:
```python
print(boston.DESCR)
```

```
Boston House Prices dataset
===========================

Notes
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Data Set Characteristics:

    :Number of Instances: 506

    :Number of Attributes: 13 numeric/categorical predictive

    :Median Value (attribute 14) is usually the target

    :Attribute Information (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

    :Missing Attribute Values: None

    :Creator: Harrison, D. and Rubinfeld, D.L.

This is a copy of UCI ML housing dataset.
http://archive.ics.uci.edu/ml/datasets/Housing


This dataset was taken from the StatLib library which is maintained at Carnegie Mellon Univer
sity.

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.

The Boston house-price data has been used in many machine learning papers that address regres
sion
problems.

**References**

   - Belsley, Kuh & Welsch, 'Regression diagnostics: Identifying Influential Data and Sources
of Collinearity', Wiley, 1980. 244-261.
   - Quinlan,R. (1993). Combining Instance-Based and Model-Based Learning. In Proceedings on
the Tenth International Conference of Machine Learning, 236-243, University of Massachusetts,
Amherst. Morgan Kaufmann.
   - many more! (see http://archive.ics.uci.edu/ml/datasets/Housing)
```

In [3]:
```python
bos.columns = boston.feature_names
bos.head()
```

Out[3]:

	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

Data Pre-Processing

In [4]:
```python
bos.shape
```

Out[4]: (506, 13)

In [5]:
```python
bos.columns
```

Out[5]:
```
Index(['CRIM', 'ZN', 'INDUS', 'CHAS', 'NOX', 'RM', 'AGE', 'DIS', 'RAD', 'TAX',
       'PTRATIO', 'B', 'LSTAT'],
      dtype='object')
```

In [6]:
```python
bos.describe()
```

Out[6]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD
count	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000
mean	3.593761	11.363636	11.136779	0.069170	0.554695	6.284634	68.574901	3.795043	9.549407
std	8.596783	23.322453	6.860353	0.253994	0.115878	0.702617	28.148861	2.105710	8.707259
min	0.006320	0.000000	0.460000	0.000000	0.385000	3.561000	2.900000	1.129600	1.000000
25%	0.082045	0.000000	5.190000	0.000000	0.449000	5.885500	45.025000	2.100175	4.000000
50%	0.256510	0.000000	9.690000	0.000000	0.538000	6.208500	77.500000	3.207450	5.000000
75%	3.647423	12.500000	18.100000	0.000000	0.624000	6.623500	94.075000	5.188425	24.000000
max	88.976200	100.000000	27.740000	1.000000	0.871000	8.780000	100.000000	12.126500	24.000000

In [7]:
```python
#Checking for null values if any
bos.isnull().values.any()
```

Out[7]: False

Data Visualization

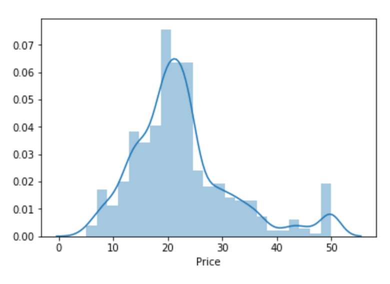
In [8]:
```python
#changing target variable name as #price

bos['Price']=boston.target
```

In [10]:
```python
# We will try to understand distribution of target variable bos.Price
# Whether target variable has been normally distributed or not.
import seaborn as sns

sns.distplot(bos['Price'])
```

Out[10]: <matplotlib.axes._subplots.AxesSubplot at 0x214fef93a58>

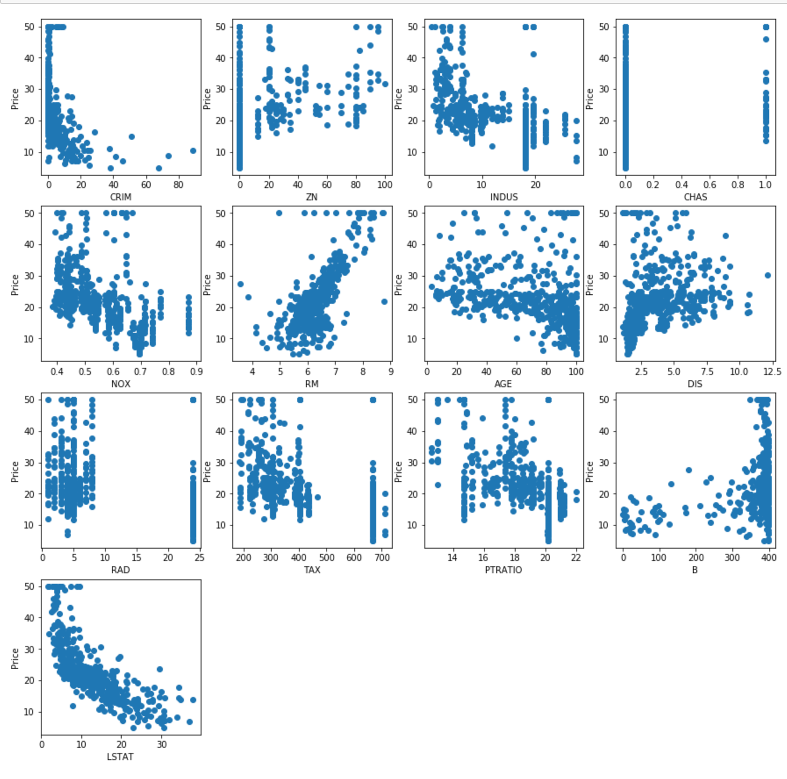


Upper figure shows the bos.Price has been normally distributed with some outliers.We can also conclude that maximum number of houses sold within price range of 20000 - 24000

In [11]:
```python
# plot each features with respect to target variable to see whether features has linear rela
tionship with target variable or not.
plt.figure(figsize=(15, 15))

features = ['CRIM', 'ZN', 'INDUS', 'CHAS', 'NOX', 'RM', 'AGE', 'DIS', 'RAD', 'TAX','PTRATIO'
, 'B', 'LSTAT']
target = boston.target

for i, col in enumerate(features):
    plt.subplot(4, len(features)-9 , i+1)
    x = bos[col]
    y = target
    plt.scatter(x, y, marker='o')
    plt.xlabel(col)
    plt.ylabel('Price')
```



If we will analyse above figures we can conclude that NOX , RM , DIS,LSTAT , AGE are showing near about linear character.Hence we can say that these features are too important for prediction of housing price.

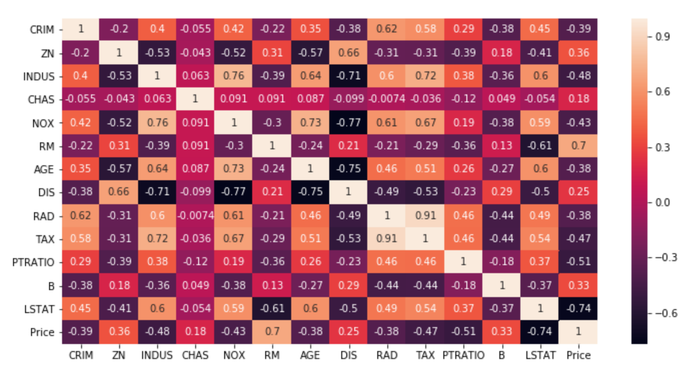
Checking multicolinearity using heat map

a. As we know while solving linear regression problem each features should be independent with one another if there will be some correlation between two independent variables(Features) then it leads to overfitting the model so with the help of heat map we will eliminate all those features which shows strong correlation with one another.

b. We also try to extract all those features which will have extensive correlation with target variable. Because , if feature will be strongly correlated with target variables then we would expect better prediction.

In [12]:
```python
plt.figure(figsize=(12,6))
corr_val=bos.corr()
sns.heatmap(data=corr_val,annot=True)
```

Out[12]: <matplotlib.axes._subplots.AxesSubplot at 0x214ff02c710>



In [13]:
```python
#Extracting all those features which is highly correlated (threshold value=0.5) with target
 variable

def HighlyCorrelated(data,threshold):
    feature=[]
    values=[]
    for ele,index in enumerate(data.index):
        if abs(data[index])> threshold:
            feature.append(index)
            values.append(data[index])
    df=pd.DataFrame(data=values,index=feature,columns= ["Correlation"])
    return df

threshold=0.5
corr_df=HighlyCorrelated(corr_val.Price,threshold)
corr_df
```

Out[13]:

	Correlation
RM	0.695360
PTRATIO	-0.507787
LSTAT	-0.737663
Price	1.000000

Here RM , PTRATIO , LSTAT are highly correlated with target variable Price.Hence these variables will give better prediction.

In [27]:
```python
# Creating Predictor variable 'X' and Target Variable 'y'
X = pd.DataFrame(bos.loc[:,["RM","LSTAT","PTRATIO"]])
Y = bos['Price']
```

In [28]:
```python
#Splitting the dataset into training and testing set

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=100)
```

In [29]:
```python
print(X_train.shape)
print(X_test.shape)
```

```
(354, 3)
(152, 3)
```

In [30]:
```python
from sklearn.linear_model import LinearRegression
```

In [31]:
```python
lin_reg = LinearRegression()
```

In [32]:
```python
lin_reg.fit(X_train,Y_train)
```

Out[32]: LinearRegression(copy_X=True, fit_intercept=True, n_jobs=1, normalize=False)

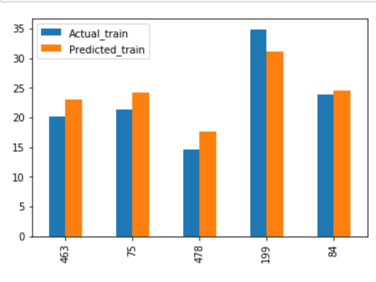
In [52]:
```python
y_train_pred = lin_reg.predict(X_train)

df1=pd.DataFrame({"Actual_train":Y_train,"Predicted_train":y_train_pred})
df2=df1.head()
df2
```

Out[52]:

	Actual_train	Predicted_train
463	20.2	23.095520
75	21.4	24.263565
478	14.6	17.634043
199	34.9	31.193055
84	23.9	24.551500

In [53]:
```python
df2.plot(kind="bar")
plt.show()
```



In [54]:
```python
coeff_df = pd.DataFrame(lin_reg.coef_,X.columns,columns=['Coefficient'])
coeff_df
```

Out[54]:

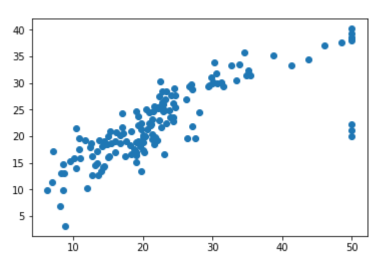
	Coefficient
RM	4.354615
LSTAT	-0.521081
PTRATIO	-0.968722

In [55]:
```python
#Prediction
pred = lin_reg.predict(X_test)
print(pred)
```

```
[35.68403644 29.38042889 21.23968667 18.96718589 20.69018408 27.40341699
 26.36782622 23.47682808 21.21584528 20.18663835 26.90052127 16.0580588
 22.14100938 17.15196267 37.63527836 27.72468407 30.36719371 16.90857423
 33.91986535 40.16371672 33.43976048 21.47099215 19.982056   18.06868458
 13.90989022 16.21326927 28.96734098 18.59737013 17.28259827 21.66301694
 16.64783735 22.78261779 38.38966642 24.90804135 29.90711906 30.49053434
 19.89722623 19.53706419 15.12714762 21.96917558 24.6423567  22.99198184
 17.07796848 23.65032286 29.7742048  28.8320534  18.91416102 18.61940545
 16.45408949 17.11772158 24.5446989  19.13867581 25.10416843 26.99744151
 10.21259253 13.5202855  29.61706871 31.49148059 13.06148634 22.25674163
 18.54706638 19.62667964 22.05643863 33.31986101 22.21078765 24.5187224
 16.19597034 30.14873027 19.51094842 22.40178213 17.61240812 18.46771133
  3.15609202 16.31227096 29.28260674 13.1028416  25.49356751 35.17065976
  9.9622534  25.77360989 34.41985231 39.32403227 14.27514921 19.22448948
 17.89380994 12.62294594 24.73552074 24.76034089 15.33065483 20.53347151
 31.11217159 21.63467877 25.61907175 25.18671547 21.83743324 24.23450081
 19.23508859 38.02354795 17.12879724 20.03954677 13.4231956  15.85030829
 15.84546576 25.38242344 33.26613613 19.0032811  27.69399917 14.74187915
  6.90508647 19.53932134 24.95874994 32.36645621 31.38409958 12.67692673
 23.64108441 16.9882021  29.31118235 19.03542266 21.05199993  9.91402091
 18.43842199 19.15917026 19.75746431 24.86226722 19.84771374 14.97640724
 20.9336381  18.91636131 20.14640528 22.34752289 28.36669687 18.38194573
 28.50945475 20.93424724 26.05759161 38.45940426 16.58420302 22.37715081
 20.38936247 23.15545935 14.58468573 11.27828814 14.11745676 30.14595185
 31.8413256  18.08958843 22.19822112 26.08830762 17.60161132 29.85001316
 18.74996551 36.95263858]
```

In [56]:
```python
#Plotting Predictions
plt.scatter(Y_test,pred)
```

Out[56]: <matplotlib.collections.PathCollection at 0x214fff6e4e0>

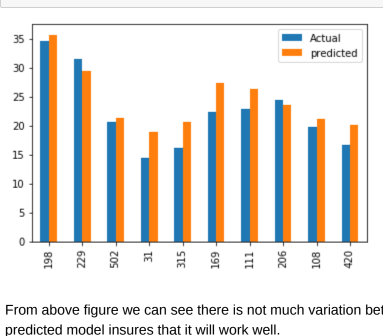


In [58]:
```python
df3=pd.DataFrame({'Actual':Y_test, 'predicted':pred})
df4=df3.head(10)
df4
```

Out[58]:

	Actual	predicted
198	34.6	35.684036
229	31.5	29.380429
502	20.6	21.239687
31	14.5	18.967186
315	16.2	20.690184
169	22.3	27.403417
111	22.8	26.367826
206	24.4	23.476828
108	19.8	21.215845
420	16.7	20.186638

In [59]:
```python
df4.plot(kind="bar")
plt.show()
```



From above figure we can see there is not much variation between predicted value and actual value hence we can say our predicted model insures that it will work well.

In [60]:
```python
from sklearn import metrics
from sklearn.metrics import r2_score
```

In [61]:
```python
# Train Set Evaluation Metrics
print("MSE:",metrics.mean_squared_error(Y_train,y_train_pred))
print("MAE:",metrics.mean_absolute_error(Y_train,y_train_pred))
print("RMSE:",np.sqrt(metrics.mean_squared_error(Y_train,y_train_pred)))
print("R_squared:",r2_score(Y_train,y_train_pred))
```

```
MSE: 23.8946850390451
MAE: 3.528005597233019
RMSE: 4.888219004816079
R_squared: 0.6903303619701531
```

In [62]:
```python
# Test Set Evaluation Metrics
print("MSE:",metrics.mean_squared_error(Y_test,pred))
print("MAE:",metrics.mean_absolute_error(Y_test,pred))
print("RMSE:",np.sqrt(metrics.mean_squared_error(Y_test,pred)))
print("R_squared:",r2_score(Y_test,pred))
```

```
MSE: 35.24035612196173
MAE: 3.871321540552555
RMSE: 5.936358826920904
R_squared: 0.6520672065112317
```

R Squared is nearer to 1 and there is not much difference between R squared value of Train set and Test set hence we can say model is not overfitted.