In [1]:
```
# Nmae : Himanshu Agarwal , Net id: HXA180027
#q1.2 Boston housing dataset
#mporting libraries
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns
```

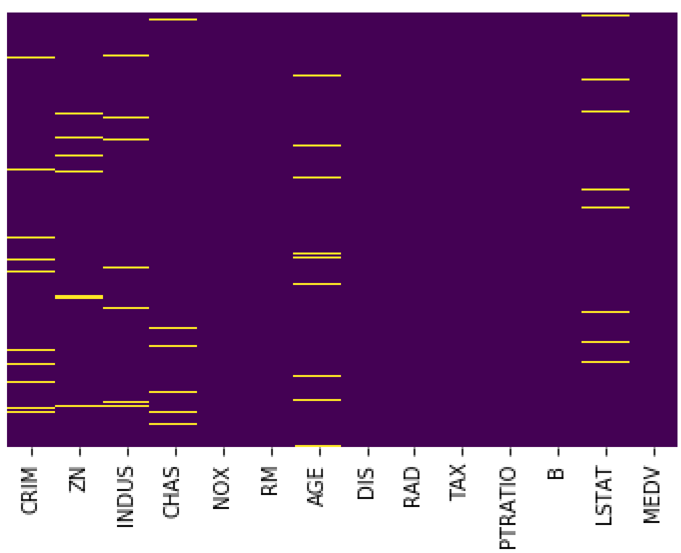
In [2]:
```
#import data using the pandas libraries.
boston_data = pd.read_csv("HousingData.csv")
boston_data.head()
```

Out[2]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTA
0	0.00632	18.0	2.31	0.0	0.538	6.575	65.2	4.0900	1	296	15.3	396.90	4.9
1	0.02731	0.0	7.07	0.0	0.469	6.421	78.9	4.9671	2	242	17.8	396.90	9.1
2	0.02729	0.0	7.07	0.0	0.469	7.185	61.1	4.9671	2	242	17.8	392.83	4.0
3	0.03237	0.0	2.18	0.0	0.458	6.998	45.8	6.0622	3	222	18.7	394.63	2.9
4	0.06905	0.0	2.18	0.0	0.458	7.147	54.2	6.0622	3	222	18.7	396.90	Na

In [3]:
```
#Heatmap to check the missig values
sns.heatmap(boston_data.isnull(),yticklabels=False,cbar=False,cmap='viridis')
```

Out[3]: <matplotlib.axes._subplots.AxesSubplot at 0x21c1f56f108>

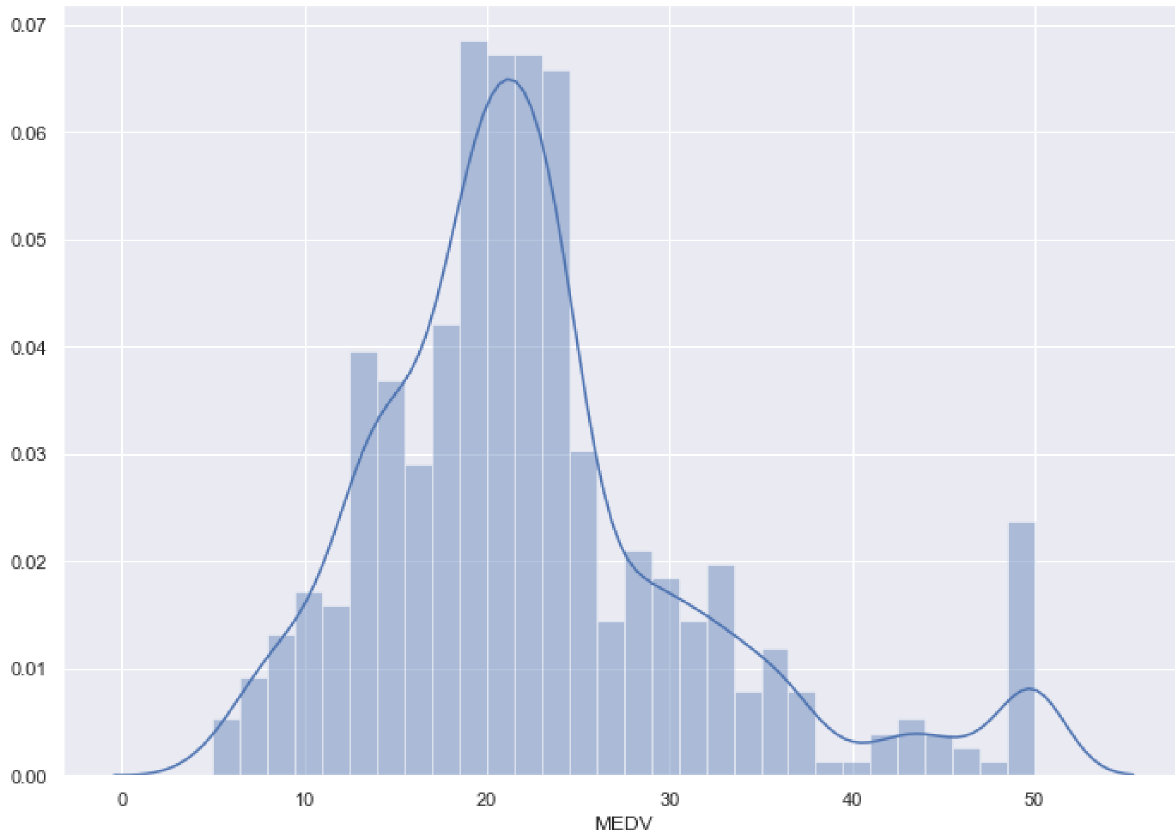


In [4]:
```
#Yellow color shows that values are missing.
# Handling missing values by replacing them by their mean values
boston_data=boston_data.fillna(boston_data.mean())
# Now checking again the count of missing/null values
boston_data.isnull().sum()
```

Out[4]:
```
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
```

All count 0, shows no any missing value present. Now, we need to perform Exploratory Data Analysis. It is a very important step before training the model. In this section, we will use some visualizations to understand the relationship of the target variable with other features.

In [5]:
```
#distribution of the target variable MEDV, using the distplot function from th
e seaborn library
sns.set(rc={'figure.figsize':(11.7,8.27)})
sns.distplot(boston_data['MEDV'], bins=30)
plt.show()
```

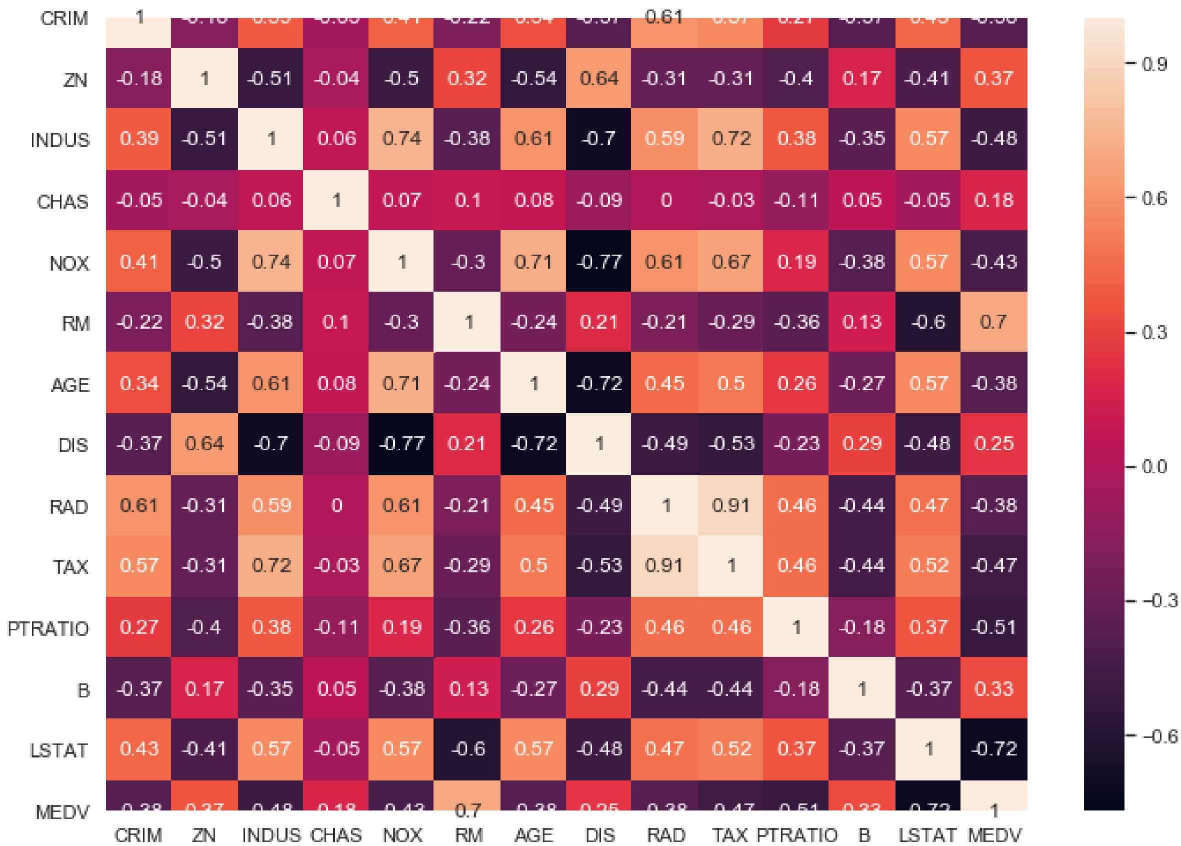


In [6]:
```
#This shows that values of MEDV are distributed normally with few outlier.
```

In [7]:
```
# create a correlation matrix that measures the linear relationships between t
he variables.
#The correlation matrix can be formed by using the corr function from the pand
as dataframe library.
#We will use the heatmap function from the seaborn library to plot the correla
tion matrix
```

In [8]:
```python
correlation_matrix = boston_data.corr().round(2)
# annot = True to print the values inside the square
sns.heatmap(data=correlation_matrix, annot=True)
```

Out[8]: <matplotlib.axes._subplots.AxesSubplot at 0x21c1f8f8108>



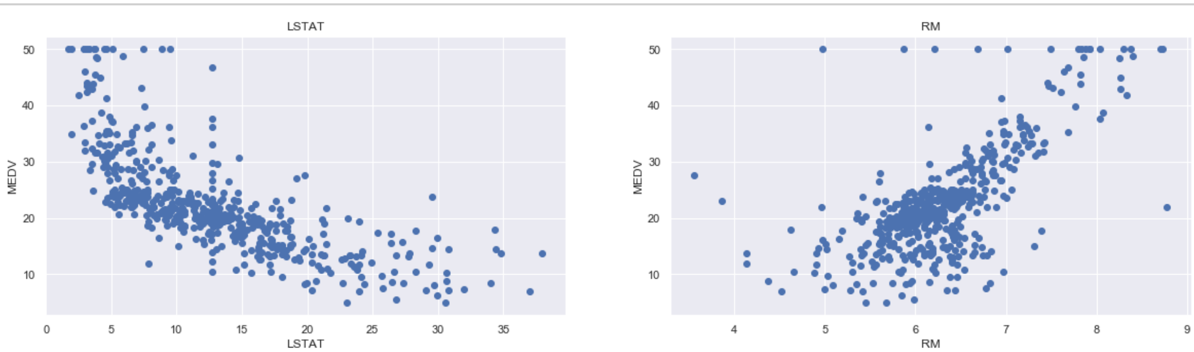
In [9]:
```
'''
Feature selection using correlation matrix:

To fit a linear regression model, we select those features which have a high c
orrelation with our target variable MEDV.
By looking at the correlation matrix we can see that RM has a strong positive
 correlation with MEDV (0.7)
where as LSTAT has a high negative correlation with MEDV(-0.72).
An important point in selecting features for a linear regression model is to c
heck for multi-co-linearity.
The features RAD, TAX have a correlation of 0.91. These feature pairs are stro
ngly correlated to each other.
We should not select both these features together for training the model. Chec
k this for an explanation.
Same goes for the features DIS and AGE which have a correlation of -0.75
'''
```

Out[9]:
```
'\nFeature selection using correlation matrix:\n\nTo fit a linear regression
model, we select those features which have a high correlation with our target
variable MEDV. \nBy looking at the correlation matrix we can see that RM has
a strong positive correlation with MEDV (0.7) \nwhere as LSTAT has a high neg
ative correlation with MEDV(-0.72).\nAn important point in selecting features
for a linear regression model is to check for multi-co-linearity. \nThe featu
res RAD, TAX have a correlation of 0.91. These feature pairs are strongly cor
related to each other.\nWe should not select both these features together for
training the model. Check this for an explanation. \nSame goes for the featur
es DIS and AGE which have a correlation of -0.75\n'
```

In [10]:
```
#Using a scatter plot let’s see how these features vary with MEDV.
plt.figure(figsize=(20, 5))
features = ['LSTAT', 'RM']
target = boston_data['MEDV']

for i, col in enumerate(features):
    plt.subplot(1, len(features) , i+1)
    x = boston_data[col]
    y = target
    plt.scatter(x, y, marker='o')
    plt.title(col)
    plt.xlabel(col)
    plt.ylabel('MEDV')
```



In [11]:
```
#The prices increase as the value of RM increases linearly. There are few outl
iers and the data seems to be capped at 50.
#The prices tend to decrease with an increase in LSTAT. Though it doesn’t look
to be following exactly a linear line.
```

In [12]:
```
#Preprocessing data to implement Linear Regression using SGD
```

In [13]:
```
#We concatenate on the LSTAT and RM columns using np.c_ provided by the numpy
 library.
boston_data = pd.DataFrame(np.c_[boston_data['LSTAT'], boston_data['RM'],bosto
n_data['MEDV']], columns = ['LSTAT','RM','MEDV'])
```

In [14]:
```
#spliting data in training and test set
#train the model with 70% of the samples and test with the remaining 30%.
n = int(len(boston_data)*0.70)
df_train, df_test = boston_data.iloc[:n, :], boston_data.iloc[n:, :]
```

In [ ]:
```

```

In [15]:
```
# Initial Coefficients
B = np.array([0, 0, 0])  #Weights array
alpha = 0.0001  # Learning rate

#Spliting the training and testing data in X,Y train and test sets.
m = len(df_train.iloc[:,:-1])
x0 = np.ones(m)
Xtrain = np.array([x0, df_train['LSTAT'],df_train['RM']]).T
ytrain = np.array(df_train['MEDV'])

m = len(df_test.iloc[:,:-1])
x0 = np.ones(m)
Xtest= np.array([x0, df_test['LSTAT'], df_test['RM']]).T
ytest= np.array(df_test['MEDV'])
```

In [16]:
```
#Cost function
def cost_function(X, Y, B):
    m = len(Y)
    J = np.sum((X.dot(B) - Y) ** 2)/(2 * m)
    return J
```

In [17]:
```python
#mplementation of linear regression for the given numbers of iterations.
def gradient_descent(boston_data, B, alpha, iterations):
    cost_history = [0] * iterations
    #B=np.zeros(shape=(1,boston_data.shape[1]-1))
    k=30
    for iteration in range(iterations):
        # Hypothesis Values
        temp= boston_data.sample(k)
        lstat = temp['LSTAT']
        rm =   temp['RM']
        m = len(lstat)
        x0 = np.ones(m)
        X1 = np.array([x0, lstat, rm]).T
        Y1 = np.array(temp['MEDV'])
        h = X1.dot(B)
        # Difference b/w Hypothesis and Actual Y
        loss = h - Y1
        # Gradient Calculation
        gradient = X1.T.dot(loss) /k
        # Changing Values of B using Gradient
        B = B - alpha * (gradient)
        # New Cost Value
        cost = cost_function(X1, Y1, B)
        cost_history[iteration] = cost

    return B, cost_history
```

In [18]:
```python
#evaluating our model using RMSE and R2-score.
def rmse(Y, Y_pred):
    rmse = np.sqrt(sum((Y - Y_pred) ** 2) / len(Y))
    return rmse

# Model Evaluation - R2 Score
def r2_score(Y, Y_pred):
    mean_y = np.mean(Y)
    ss_tot = sum((Y - mean_y) ** 2)
    ss_res = sum((Y - Y_pred) ** 2)
    r2 = 1 - (ss_res / ss_tot)
    return r2
```

In [19]:
```python
newB, cost_history = gradient_descent(df_train, B, alpha, 10000)
# New Values of B
Y_pred = Xtrain.dot(newB)
print("The model performance for training set")
print("--------------------------------------")
print('RMSE is {}'.format(rmse(ytrain, Y_pred)))
print('R2 score is {}'.format(r2_score(ytrain, Y_pred)))
print("\n")
```

```
The model performance for training set
--------------------------------------
RMSE is 4.597298269296926
R2 score is 0.7022681803288964
```

In [20]:
```
#newB, cost_history = gradient_descent(df_test, B, alpha, 10000)
Y_pred = Xtest.dot(newB)
print("The model performance for test set")
print("--------------------------------------")
print('RMSE is {}'.format(rmse(ytest, Y_pred)))
print('R2 score is {}'.format(r2_score(ytest, Y_pred)))
print("\n")
```

```
The model performance for test set
--------------------------------------
RMSE is 7.639363315209167
R2 score is 0.12037451907080365
```

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