In [ ]:
```
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Lab Assignment 4 : Data Analytics I

Problem Statement : Create a Linear Regression Model using Python/R to predict home prices using Boston Housing Dataset
(https://www.kaggle.com/c/boston-housing). The Boston Housing dataset contains information about various
houses in Boston through different parameters. There are 506 samples and 14 feature variables in this dataset.
```

In [1]:
```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
import numpy as np
from sklearn.metrics import mean_squared_error
```

In [2]:
```
df=pd.read_csv("boston.csv")
```

In [3]:
```
df
```

Out[3]:

	Unnamed: 0	crim	zn	indus	chas	nox	rm	age	dis	rad	tax	ptratio	black	lstat	medv
0	1	0.00632	18.0	2.31	0	0.538	6.575	65.2	4.0900	1	296	15.3	396.90	4.98	24.0
1	2	0.02731	0.0	7.07	0	0.469	6.421	78.9	4.9671	2	242	17.8	396.90	9.14	21.6
2	3	0.02729	0.0	7.07	0	0.469	7.185	61.1	4.9671	2	242	17.8	392.83	4.03	34.7
3	4	0.03237	0.0	2.18	0	0.458	6.998	45.8	6.0622	3	222	18.7	394.63	2.94	33.4
4	5	0.06905	0.0	2.18	0	0.458	7.147	54.2	6.0622	3	222	18.7	396.90	5.33	36.2
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
501	502	0.06263	0.0	11.93	0	0.573	6.593	69.1	2.4786	1	273	21.0	391.99	9.67	22.4
502	503	0.04527	0.0	11.93	0	0.573	6.120	76.7	2.2875	1	273	21.0	396.90	9.08	20.6
503	504	0.06076	0.0	11.93	0	0.573	6.976	91.0	2.1675	1	273	21.0	396.90	5.64	23.9
504	505	0.10959	0.0	11.93	0	0.573	6.794	89.3	2.3889	1	273	21.0	393.45	6.48	22.0
505	506	0.04741	0.0	11.93	0	0.573	6.030	80.8	2.5050	1	273	21.0	396.90	7.88	11.9

506 rows × 15 columns

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 oxide 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 centers RAD: Index of accessibility to radial highways TAX: Full-value property tax rate per
$10,000 PTRATIO : Pupil - teacherratiobytownB : 1000(Bk—0.63)^2, whereBkistheproportionof[peopleofAfricanAmericandescent]bytownLSTAT : Pe$
$: Medianvalueofowner - occupiedhomesin$
1000s

The prices of the house indicated by the variable MEDV is our target variable and the remaining are the feature variables based on which we will predict the value of a house.

In [4]:
```
df.rename({"Unnamed: 0":"a"}, axis="columns", inplace=True)

df.drop(['a'],axis=1, inplace=True)
```

In [5]:
```
df.isnull().sum()
```

Out[5]:
```
crim       0
zn         0
indus      0
chas       0
nox        0
rm         0
age        0
dis        0
rad        0
tax        0
ptratio    0
black      0
lstat      0
medv       0
dtype: int64
```

In [6]:
```
df.describe()
```

Out[6]:

	crim	zn	indus	chas	nox	rm	age	dis	rad	tax	ptratio	black	
count	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.0
mean	3.613524	11.363636	11.136779	0.069170	0.554695	6.284634	68.574901	3.795043	9.549407	408.237154	18.455534	356.674032	12.6
std	8.601545	23.322453	6.860353	0.253994	0.115878	0.702617	28.148861	2.105710	8.707259	168.537116	2.164946	91.294864	7.1
min	0.006320	0.000000	0.460000	0.000000	0.385000	3.561000	2.900000	1.129600	1.000000	187.000000	12.600000	0.320000	1.7
25%	0.082045	0.000000	5.190000	0.000000	0.449000	5.885500	45.025000	2.100175	4.000000	279.000000	17.400000	375.377500	6.9
50%	0.256510	0.000000	9.690000	0.000000	0.538000	6.208500	77.500000	3.207450	5.000000	330.000000	19.050000	391.440000	11.3
75%	3.677083	12.500000	18.100000	0.000000	0.624000	6.623500	94.075000	5.188425	24.000000	666.000000	20.200000	396.225000	16.9
max	88.976200	100.000000	27.740000	1.000000	0.871000	8.780000	100.000000	12.126500	24.000000	711.000000	22.000000	396.900000	37.9

In [7]:

```
df.shape
```

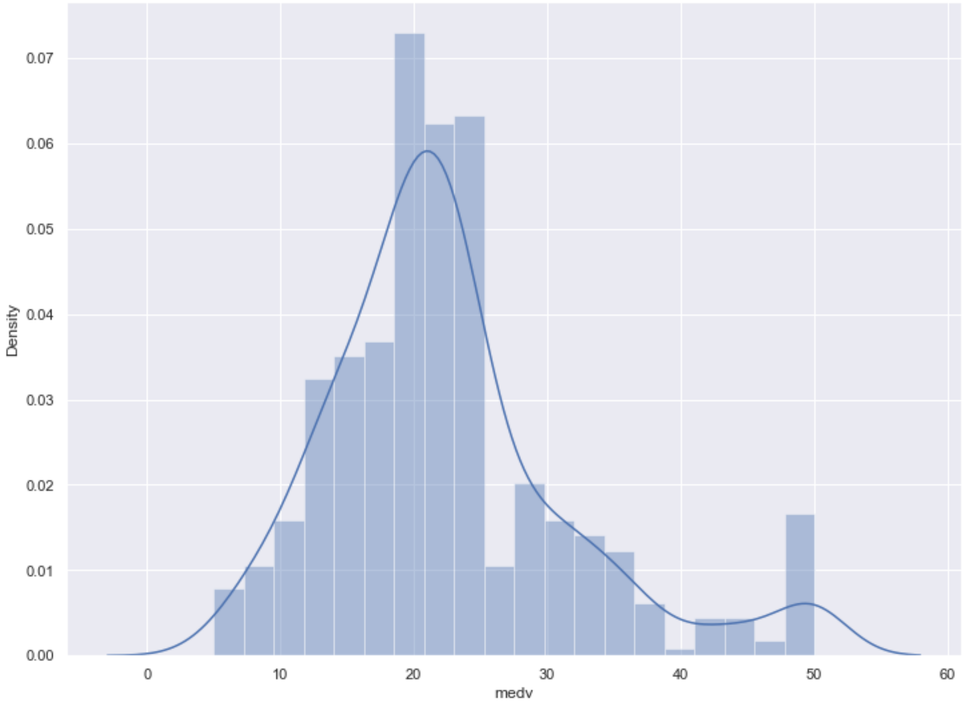
Out[7]:

```
(506, 14)
```

In [8]:

```
sns.set(rc={'figure.figsize':(12,9)})
sns.distplot(df['medv'], bins=20)
plt.show()
```

```
/Users/apple/opt/anaconda3/lib/python3.9/site-packages/seaborn/distributions.py:2619: FutureWarning: `distplot` is a deprecated func
tion and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar f
lexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```



In [9]:

```
df.corr().round(2)
```

Out[9]:

	crim	zn	indus	chas	nox	rm	age	dis	rad	tax	ptratio	black	lstat	medv
crim	1.00	-0.20	0.41	-0.06	0.42	-0.22	0.35	-0.38	0.63	0.58	0.29	-0.39	0.46	-0.39
zn	-0.20	1.00	-0.53	-0.04	-0.52	0.31	-0.57	0.66	-0.31	-0.31	-0.39	0.18	-0.41	0.36
indus	0.41	-0.53	1.00	0.06	0.76	-0.39	0.64	-0.71	0.60	0.72	0.38	-0.36	0.60	-0.48
chas	-0.06	-0.04	0.06	1.00	0.09	0.09	0.09	-0.10	-0.01	-0.04	-0.12	0.05	-0.05	0.18
nox	0.42	-0.52	0.76	0.09	1.00	-0.30	0.73	-0.77	0.61	0.67	0.19	-0.38	0.59	-0.43
rm	-0.22	0.31	-0.39	0.09	-0.30	1.00	-0.24	0.21	-0.21	-0.29	-0.36	0.13	-0.61	0.70
age	0.35	-0.57	0.64	0.09	0.73	-0.24	1.00	-0.75	0.46	0.51	0.26	-0.27	0.60	-0.38
dis	-0.38	0.66	-0.71	-0.10	-0.77	0.21	-0.75	1.00	-0.49	-0.53	-0.23	0.29	-0.50	0.25
rad	0.63	-0.31	0.60	-0.01	0.61	-0.21	0.46	-0.49	1.00	0.91	0.46	-0.44	0.49	-0.38
tax	0.58	-0.31	0.72	-0.04	0.67	-0.29	0.51	-0.53	0.91	1.00	0.46	-0.44	0.54	-0.47
ptratio	0.29	-0.39	0.38	-0.12	0.19	-0.36	0.26	-0.23	0.46	0.46	1.00	-0.18	0.37	-0.51
black	-0.39	0.18	-0.36	0.05	-0.38	0.13	-0.27	0.29	-0.44	-0.44	-0.18	1.00	-0.37	0.33
lstat	0.46	-0.41	0.60	-0.05	0.59	-0.61	0.60	-0.50	0.49	0.54	0.37	-0.37	1.00	-0.74
medv	-0.39	0.36	-0.48	0.18	-0.43	0.70	-0.38	0.25	-0.38	-0.47	-0.51	0.33	-0.74	1.00

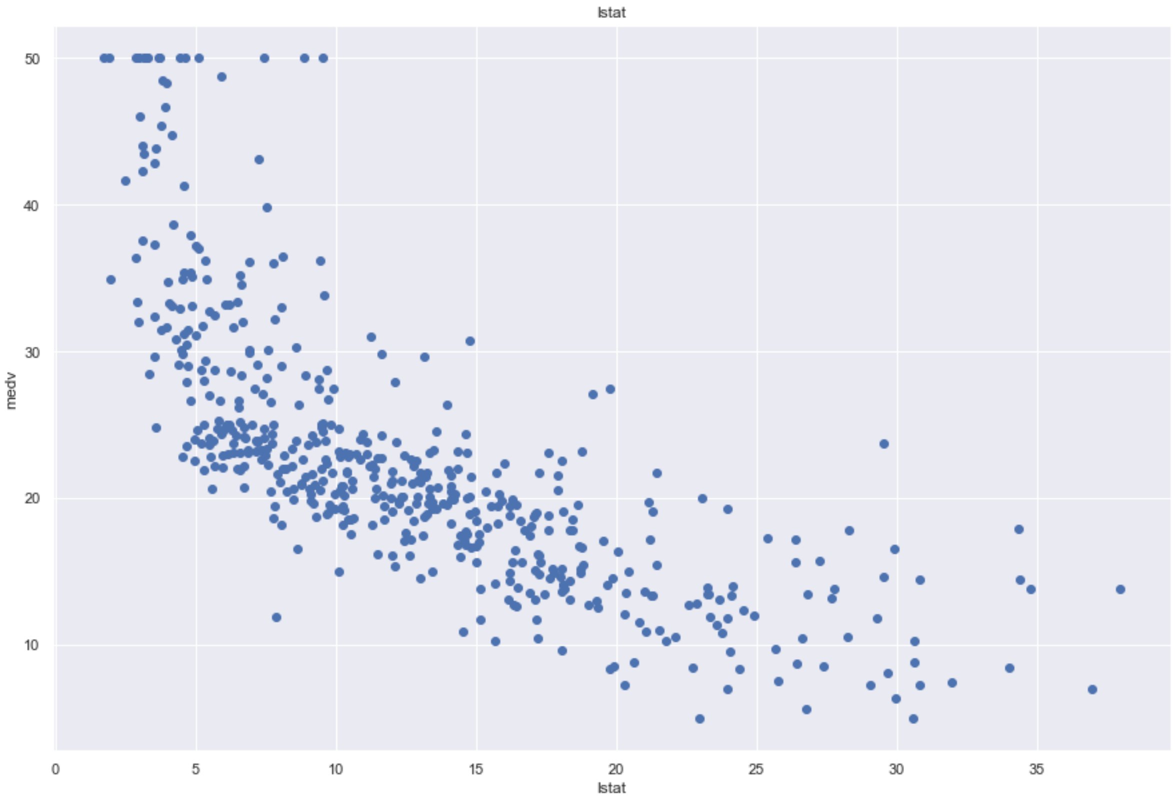
To fit a linear regression model, we select those features which have a high correlation with our target variable MEDV. By looking at the correlation matrix we can see that RM has a strong positive correlation with MEDV (0.7) where as LSTAT has a high negative correlation with MEDV(-0.74).

In [10]:
```
plt.figure(figsize=(15, 10))
plt.title("rm")
plt.xlabel("rm")
plt.ylabel('medv')
plt.scatter(df['rm'],df['medv'])
```

Out[10]: <matplotlib.collections.PathCollection at 0x7fc292664760>

In [11]:
```
plt.figure(figsize=(15, 10))
plt.title("lstat")
plt.xlabel("lstat")
plt.ylabel('medv')
plt.scatter(df['lstat'],df['medv'])
```

Out[11]: <matplotlib.collections.PathCollection at 0x7fc292be6b50>



In [12]:
```
rm= df['rm']
medv= df['medv']
```

In [13]:
```
x_train, x_test, y_train, y_test = train_test_split(rm, medv, test_size = 0.2)
```

In [14]:
```
x_train.shape
```

Out[14]: (404,)

In [15]:
```
y_train.shape
```

Out[15]: (404,)

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

Out[16]: (102,)

In [17]:
```
y_test.shape
```

Out[17]: (102,)

Converting to 2D array

In [18]:
```
x_train = np.array(x_train).reshape(-1, 1)
y_train = np.array(y_train).reshape(-1, 1)
x_test =  np.array(x_test).reshape(-1, 1)
y_test =  np.array(y_test).reshape(-1, 1)
```

In [19]:
```
model = LinearRegression()
model.fit(x_train, y_train)
```

Out[19]: LinearRegression()

In [20]:
```
y_predict = model.predict(x_test)
```

Using rm as independent variable for medv

In [21]:
```
plt.title("predicted results")
plt.xlabel("rm")
plt.ylabel('medv')
plt.scatter(x_train, y_train, color='blue')

plt.scatter(x_test, y_predict, color='red',label="aa")
plt.scatter(x_test, y_test, color="yellow")
```

Out[21]: <matplotlib.collections.PathCollection at 0x7fc292c4bf70>

Using lstat as independent variable for medv

In [22]:
```
lstat= df['lstat']
x_train, x_test, y_train, y_test = train_test_split(lstat, medv, test_size = 0.2)
x_train = np.array(x_train).reshape(-1, 1)
y_train = np.array(y_train).reshape(-1, 1)
x_test =  np.array(x_test).reshape(-1, 1)
y_test =  np.array(y_test).reshape(-1, 1)
model = LinearRegression()
model.fit(x_train, y_train)
```

```
y_predict = model.predict(x_test)
plt.title("predicted results")
plt.xlabel("lstat")
plt.ylabel('medv')
plt.scatter(x_train, y_train, color='blue')
plt.scatter(x_test, y_predict, color='red')
plt.scatter(x_test, y_test, color="yellow")
```

Out[22]: `<matplotlib.collections.PathCollection at 0x7fc29308f250>`

The model performance for testing set

In [23]:
```
X = pd.DataFrame(np.c_[df['lstat'], df['rm']], columns = ['lstat','rm'])
x_train, x_test, y_train, y_test = train_test_split(X, medv, test_size = 0.2)

model = LinearRegression()
model.fit(x_train, y_train)
y_predict = model.predict(x_test)
```

In [24]:
```
rmse = (np.sqrt(mean_squared_error(y_test, y_predict)))

print('Root Mean Squared Error is {}'.format(rmse))
```

```
Root Mean Squared Error is 4.622907645726345
```