Out[3]:

| | CRIM | ZN | INDUS | CHAS | NOX | RM | AGE | DIS | RAD | TAX | PTRATIO | В |
|-----|---------|------|-------|------|-------|-------|------|--------|-----|-----|---------|--------|
| 0 | 0.00632 | 18.0 | 2.31 | 0.0 | 0.538 | 6.575 | 65.2 | 4.0900 | 1 | 296 | 15.3 | 396.90 |
| 1 | 0.02731 | 0.0 | 7.07 | 0.0 | 0.469 | 6.421 | 78.9 | 4.9671 | 2 | 242 | 17.8 | 396.90 |
| 2 | 0.02729 | 0.0 | 7.07 | 0.0 | 0.469 | 7.185 | 61.1 | 4.9671 | 2 | 242 | 17.8 | 392.83 |
| 3 | 0.03237 | 0.0 | 2.18 | 0.0 | 0.458 | 6.998 | 45.8 | 6.0622 | 3 | 222 | 18.7 | 394.63 |
| 4 | 0.06905 | 0.0 | 2.18 | 0.0 | 0.458 | 7.147 | 54.2 | 6.0622 | 3 | 222 | 18.7 | 396.90 |
| | | | | | | | | | | | | |
| 501 | 0.06263 | 0.0 | 11.93 | 0.0 | 0.573 | 6.593 | 69.1 | 2.4786 | 1 | 273 | 21.0 | 391.99 |
| 502 | 0.04527 | 0.0 | 11.93 | 0.0 | 0.573 | 6.120 | 76.7 | 2.2875 | 1 | 273 | 21.0 | 396.90 |
| 503 | 0.06076 | 0.0 | 11.93 | 0.0 | 0.573 | 6.976 | 91.0 | 2.1675 | 1 | 273 | 21.0 | 396.90 |
| 504 | 0.10959 | 0.0 | 11.93 | 0.0 | 0.573 | 6.794 | 89.3 | 2.3889 | 1 | 273 | 21.0 | 393.45 |
| 505 | 0.04741 | 0.0 | 11.93 | 0.0 | 0.573 | 6.030 | NaN | 2.5050 | 1 | 273 | 21.0 | 396.90 |

506 rows × 14 columns

◆

In [4]: ▶

df.head()

Out[4]:

| | CRIM | ZN | INDUS | CHAS | NOX | RM | AGE | DIS | RAD | TAX | PTRATIO | В | L |
|---|---------|------|-------|------|-------|-------|------|--------|-----|-----|---------|--------|-------------|
| 0 | 0.00632 | 18.0 | 2.31 | 0.0 | 0.538 | 6.575 | 65.2 | 4.0900 | 1 | 296 | 15.3 | 396.90 | |
| 1 | 0.02731 | 0.0 | 7.07 | 0.0 | 0.469 | 6.421 | 78.9 | 4.9671 | 2 | 242 | 17.8 | 396.90 | |
| 2 | 0.02729 | 0.0 | 7.07 | 0.0 | 0.469 | 7.185 | 61.1 | 4.9671 | 2 | 242 | 17.8 | 392.83 | |
| 3 | 0.03237 | 0.0 | 2.18 | 0.0 | 0.458 | 6.998 | 45.8 | 6.0622 | 3 | 222 | 18.7 | 394.63 | |
| 4 | 0.06905 | 0.0 | 2.18 | 0.0 | 0.458 | 7.147 | 54.2 | 6.0622 | 3 | 222 | 18.7 | 396.90 | |
| 4 | | | | | | | | | | | |) | > |

In [5]: ▶

df.tail()

Out[5]:

| | CRIM | ZN | INDUS | CHAS | NOX | RM | AGE | DIS | RAD | TAX | PTRATIO | В |
|-----|---------|-----|-------|------|-------|-------|------|--------|-----|-----|---------|--------|
| 501 | 0.06263 | 0.0 | 11.93 | 0.0 | 0.573 | 6.593 | 69.1 | 2.4786 | 1 | 273 | 21.0 | 391.99 |
| 502 | 0.04527 | 0.0 | 11.93 | 0.0 | 0.573 | 6.120 | 76.7 | 2.2875 | 1 | 273 | 21.0 | 396.90 |
| 503 | 0.06076 | 0.0 | 11.93 | 0.0 | 0.573 | 6.976 | 91.0 | 2.1675 | 1 | 273 | 21.0 | 396.90 |
| 504 | 0.10959 | 0.0 | 11.93 | 0.0 | 0.573 | 6.794 | 89.3 | 2.3889 | 1 | 273 | 21.0 | 393.45 |
| 505 | 0.04741 | 0.0 | 11.93 | 0.0 | 0.573 | 6.030 | NaN | 2.5050 | 1 | 273 | 21.0 | 396.90 |
| 4 | | | | | | | | | | | | • |

In [6]: ▶

df.shape

Out[6]:

(506, 14)

In [7]: ▶

df.describe()

Out[7]:

| | CRIM | ZN | INDUS | CHAS | NOX | RM | AGE |
|-------|------------|------------|------------|------------|------------|------------|------------|
| count | 486.000000 | 486.000000 | 486.000000 | 486.000000 | 506.000000 | 506.000000 | 486.000000 |
| mean | 3.611874 | 11.211934 | 11.083992 | 0.069959 | 0.554695 | 6.284634 | 68.518519 |
| std | 8.720192 | 23.388876 | 6.835896 | 0.255340 | 0.115878 | 0.702617 | 27.999513 |
| min | 0.006320 | 0.000000 | 0.460000 | 0.000000 | 0.385000 | 3.561000 | 2.900000 |
| 25% | 0.081900 | 0.000000 | 5.190000 | 0.000000 | 0.449000 | 5.885500 | 45.175000 |
| 50% | 0.253715 | 0.000000 | 9.690000 | 0.000000 | 0.538000 | 6.208500 | 76.800000 |
| 75% | 3.560263 | 12.500000 | 18.100000 | 0.000000 | 0.624000 | 6.623500 | 93.975000 |
| max | 88.976200 | 100.000000 | 27.740000 | 1.000000 | 0.871000 | 8.780000 | 100.000000 |
| 4 | | | | | | | |

In [8]: ▶

df.dtypes

Out[8]:

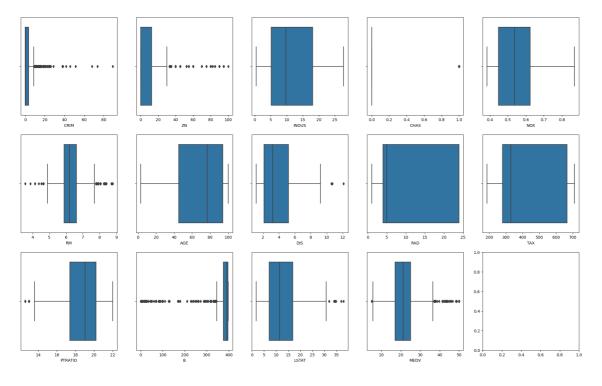
float64 CRIM ZN float64 float64 **INDUS** float64 CHAS NOX float64 float64 RMfloat64 AGE float64 DIS int64 RAD TAX int64 float64 **PTRATIO** float64 float64 **LSTAT** MEDV float64 dtype: object

In [9]: ▶

import matplotlib.pyplot as plt

In [10]:

```
fig , axs = plt.subplots(ncols = 5,nrows = 3,figsize =(25,15))
index = 0
axs = axs.flatten()
for k,v in df.items():
    sns.boxplot(v,ax=axs[index])
    index = index + 1
```



```
In [11]: ▶
```

```
for k,v in df.items():
    q1 = v.quantile(0.25)
    q3 = v.quantile(0.75)
    IQR = q3-q1
    v_col = v[(v<=q1-1.5*IQR)| (v>=q3 +1.5*IQR)]
    perc = np.shape(v_col)[0] * 100.0 / np.shape(df)[0]
    print("Column %s has outliers :- %.2f%%" %(k,perc))
```

```
Column CRIM has outliers :- 12.85%
Column ZN has outliers :- 12.45%
Column INDUS has outliers :- 0.00%
Column CHAS has outliers :- 96.05%
Column NOX has outliers :- 0.00%
Column RM has outliers :- 5.93%
Column AGE has outliers :- 0.00%
Column DIS has outliers :- 0.00%
Column RAD has outliers :- 0.00%
Column TAX has outliers :- 0.00%
Column PTRATIO has outliers :- 2.96%
Column B has outliers :- 15.22%
Column LSTAT has outliers :- 7.91%
```

```
In [12]:
                                                                                                  M
df = df[\sim(df['MEDV'] >= 50.0)]
In [13]:
df.shape
Out[13]:
(490, 14)
In [14]:
                                                                                                  M
fig,axs = plt.subplots(nrows = 3,ncols = 5,figsize=(25,15))
index = 0
axs = axs.flatten()
for k,v in df.items():
    sns.distplot(v,ax = axs[index])
    index = index+1
                                                                    Density
 0.15
 0.10
 0.7
                                  0.15
 0.35
```

The histogram also shows that columns CRIM, ZN, B has highly skewed distributions.

Also MEDV looks to have a normal distribution (the predictions) and other colums seem to have normal or bimodel ditribution of data except CHAS (which is a discrete variable).

Now let's plot the pairwise correlation on data

In [15]: ▶

```
plt.figure(figsize = (20,10))
sns.heatmap(df.corr().abs(),annot = True)
```

Out[15]:

<Axes: >



In [16]: ▶

#From correlation matrix, we see TAX and RAD are highly correlated features.
#The columns LSTAT, INDUS, RM, TAX, NOX, PTRAIO has a correlation score above 0.5 with M #indication of using as predictors. Let's plot these columns against MEDV.

| In []: | М |
|---------|---|
| | |
| | |

```
M
In [17]:
df.isna().sum()
Out[17]:
CRIM
           19
ΖN
           19
INDUS
            20
CHAS
            20
            0
NOX
            0
RM
           18
AGE
            0
DIS
             0
RAD
TAX
             0
PTRATIO
В
             0
LSTAT
           20
MEDV
dtype: int64
                                                                                            M
In [19]:
df = df.fillna(df.mean())
In [20]:
                                                                                            M
df.isna().sum()
Out[20]:
CRIM
           0
           0
ZN
INDUS
           0
           0
CHAS
NOX
           0
           0
RM
           0
AGE
DIS
           0
RAD
TAX
PTRATIO
           0
           0
LSTAT
           0
MEDV
dtype: int64
                                                                                            H
In [ ]:
#Traing the dataset and testing it
```

```
H
In [21]:
X = df[['LSTAT','RM']]
Y = df['MEDV']
In [22]:
                                                                                          M
from sklearn.model_selection import train_test_split
X_train,X_test,Y_train,Y_test = train_test_split(X,Y,test_size = 0.2,random_state = 45)
print(X_train.shape)
print(X_test.shape)
print(Y_train.shape)
print(Y_test.shape)
(392, 2)
(98, 2)
(392,)
(98,)
In [23]:
                                                                                          M
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error
model = LinearRegression()
model.fit(X_train,Y_train)
Out[23]:
LinearRegression()
In a Jupyter environment, please rerun this cell to show the HTML representation or
trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page
with nbviewer.org.
                                                                                          M
In [24]:
# model evaluation for training set
In [25]:
                                                                                          H
from sklearn.metrics import r2 score
Y train predict = model.predict(X train)
rmse = np.sqrt(mean_squared_error(Y_train,Y_train_predict))
r2 = r2_score(Y_train,Y_train_predict)
print("Model performance for Training set")
print(f"rmse score is = {rmse}")
print(f"r2 score is = {r2}")
```

Model performance for Training set rmse score is = 4.8078921735147 r2 score is = 0.6201774308171788

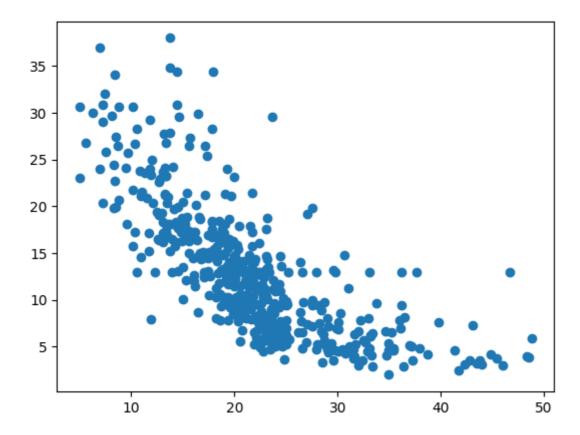
```
M
In [26]:
Y_test_predict = model.predict(X_test)
rmse = np.sqrt(mean_squared_error(Y_test,Y_test_predict))
r2 = r2_score(Y_test,Y_test_predict)
print("Model performance for testing set is ")
print(f"rmse score is = {rmse}")
print(f"r2 score is = {r2}")
Model performance for testing set is
rmse score is = 4.386171868330308
r2 \ score \ is = 0.704574214564875
In [ ]:
                                                                                        M
In [42]:
                                                                                        M
x = model.predict([[4.98,6.575]])
print(x)
print(Y_test_predict[0])
[27.63583413]
31.40957350799178
                                                                                        M
In [ ]:
```

In [44]: ▶

plt.scatter(x = df['MEDV'],y=df['LSTAT'])

Out[44]:

<matplotlib.collections.PathCollection at 0x20f390bb460>

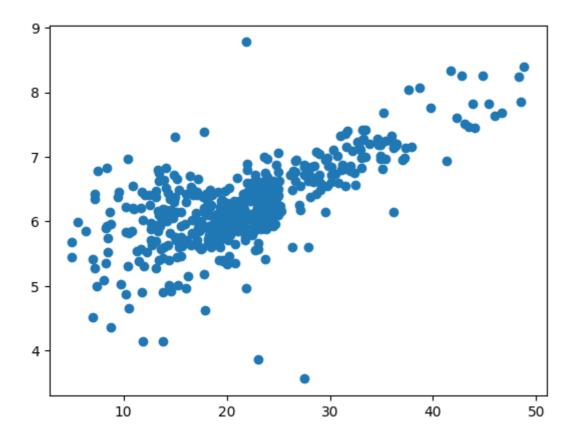


In [45]: ▶

plt.scatter(x = df['MEDV'],y=df['RM'])

Out[45]:

<matplotlib.collections.PathCollection at 0x20f38f4fdf0>



In []: