assignment-15-08-02-24

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[1]:
```
import numpy as np # linear algebra
import pandas as pd
import os
import pandas as pd
import matplotlib.pyplot as plt
plt.style.use("fivethirtyeight")
plt.style.use('dark_background')
import numpy as np
import xgboost as xgb
import seaborn as sns
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error,r2_score
from sklearn.metrics import precision_recall_fscore_support as score
from sklearn.model_selection import GridSearchCV

import warnings
warnings.filterwarnings("ignore")
```

Read Housing Data

[2]:
```
data=pd.read_csv("D:\Chools\DAY_14\HousingData.csv")
display(data.head())
display(data.columns)
```

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

        B  LSTAT  MEDV
```

```
0  396.90   4.98  24.0
1  396.90   9.14  21.6
2  392.83   4.03  34.7
3  394.63   2.94  33.4
4  396.90    NaN  36.2
```

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

3 Data Preprocessing:

[3]:
```
display(data.describe())
display(data.info())
```

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

              AGE         DIS         RAD         TAX     PTRATIO           B  \
count  486.000000  506.000000  506.000000  506.000000  506.000000  506.000000
mean    68.518519    3.795043    9.549407  408.237154   18.455534  356.674032
std     27.999513    2.105710    8.707259  168.537116    2.164946   91.294864
min      2.900000    1.129600    1.000000  187.000000   12.600000    0.320000
25%     45.175000    2.100175    4.000000  279.000000   17.400000  375.377500
50%     76.800000    3.207450    5.000000  330.000000   19.050000  391.440000
75%     93.975000    5.188425   24.000000  666.000000   20.200000  396.225000
max    100.000000   12.126500   24.000000  711.000000   22.000000  396.900000

            LSTAT        MEDV
count  486.000000  506.000000
mean    12.715432   22.532806
std      7.155871    9.197104
min      1.730000    5.000000
25%      7.125000   17.025000
50%     11.430000   21.200000
75%     16.955000   25.000000
max     37.970000   50.000000
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 506 entries, 0 to 505
Data columns (total 14 columns):
```

```
 #   Column   Non-Null Count  Dtype
---  ------   --------------  -----
 0   CRIM     486 non-null    float64
 1   ZN       486 non-null    float64
 2   INDUS    486 non-null    float64
 3   CHAS     486 non-null    float64
 4   NOX      506 non-null    float64
 5   RM       506 non-null    float64
 6   AGE      486 non-null    float64
 7   DIS      506 non-null    float64
 8   RAD      506 non-null    int64
 9   TAX      506 non-null    int64
 10  PTRATIO  506 non-null    float64
 11  B        506 non-null    float64
 12  LSTAT    486 non-null    float64
 13  MEDV     506 non-null    float64
dtypes: float64(12), int64(2)
memory usage: 55.5 KB
```

```
None
```

[4]:

```python
#Fill null values with average of each column
data["CRIM"].fillna(data["CRIM"].mean(),inplace=True)
data["ZN"].fillna(data["ZN"].mean(),inplace=True)
data["INDUS"].fillna(data["INDUS"].mean(),inplace=True)
data["CHAS"].fillna(data["CHAS"].mean(),inplace=True)
data["AGE"].fillna(data["AGE"].mean(),inplace=True)
data["LSTAT"].fillna(data["LSTAT"].mean(),inplace=True)

data.info()
```

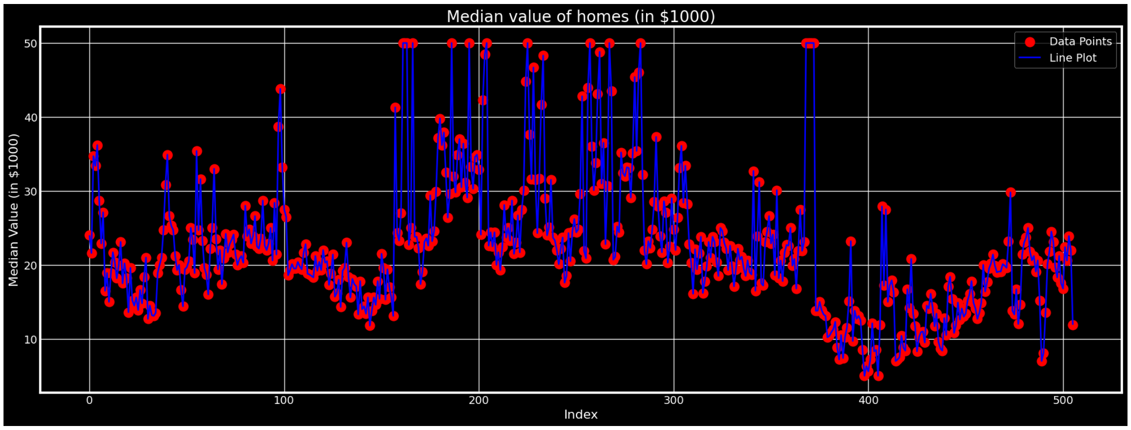
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 506 entries, 0 to 505
Data columns (total 14 columns):
 #   Column   Non-Null Count  Dtype
---  ------   --------------  -----
 0   CRIM     506 non-null    float64
 1   ZN       506 non-null    float64
 2   INDUS    506 non-null    float64
 3   CHAS     506 non-null    float64
 4   NOX      506 non-null    float64
 5   RM       506 non-null    float64
 6   AGE      506 non-null    float64
 7   DIS      506 non-null    float64
 8   RAD      506 non-null    int64
 9   TAX      506 non-null    int64
 10  PTRATIO  506 non-null    float64
 11  B        506 non-null    float64
```

```
 12  LSTAT    506 non-null    float64
 13  MEDV     506 non-null    float64
dtypes: float64(12), int64(2)
memory usage: 55.5 KB
```

4 EDA

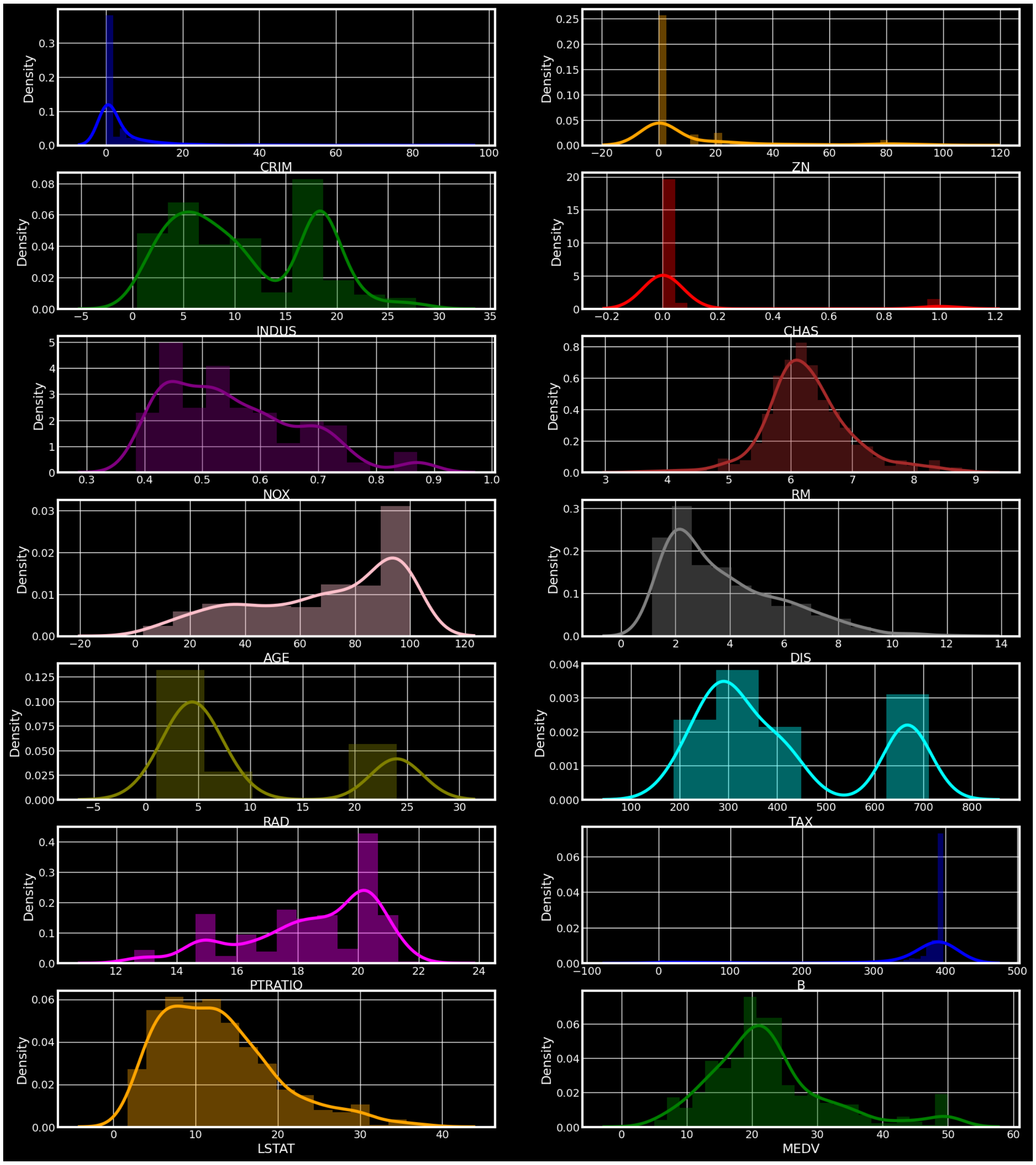
[5]:
```python
# Set a colorful palette
sns.set_palette("viridis")
```

[6]:
```python
import matplotlib.pyplot as plt

plt.figure(figsize=(22,8))

# Scatter plot with red color and larger markers
plt.scatter(data.index, data["MEDV"], color="red", lw=3, label='Data Points',␣
  ↪s=100)

# Line plot with blue color and thicker line
plt.plot(data.index, data["MEDV"], color="blue", lw=2, label='Line Plot')

plt.title("Median value of homes (in $1000)", fontsize=20)  # Increase title␣
  ↪font size
plt.xlabel("Index", fontsize=16)  # Label for x-axis
plt.ylabel("Median Value (in $1000)", fontsize=16)  # Label for y-axis
plt.grid(True)

# Add legend
plt.legend(fontsize=14)

plt.show()
```



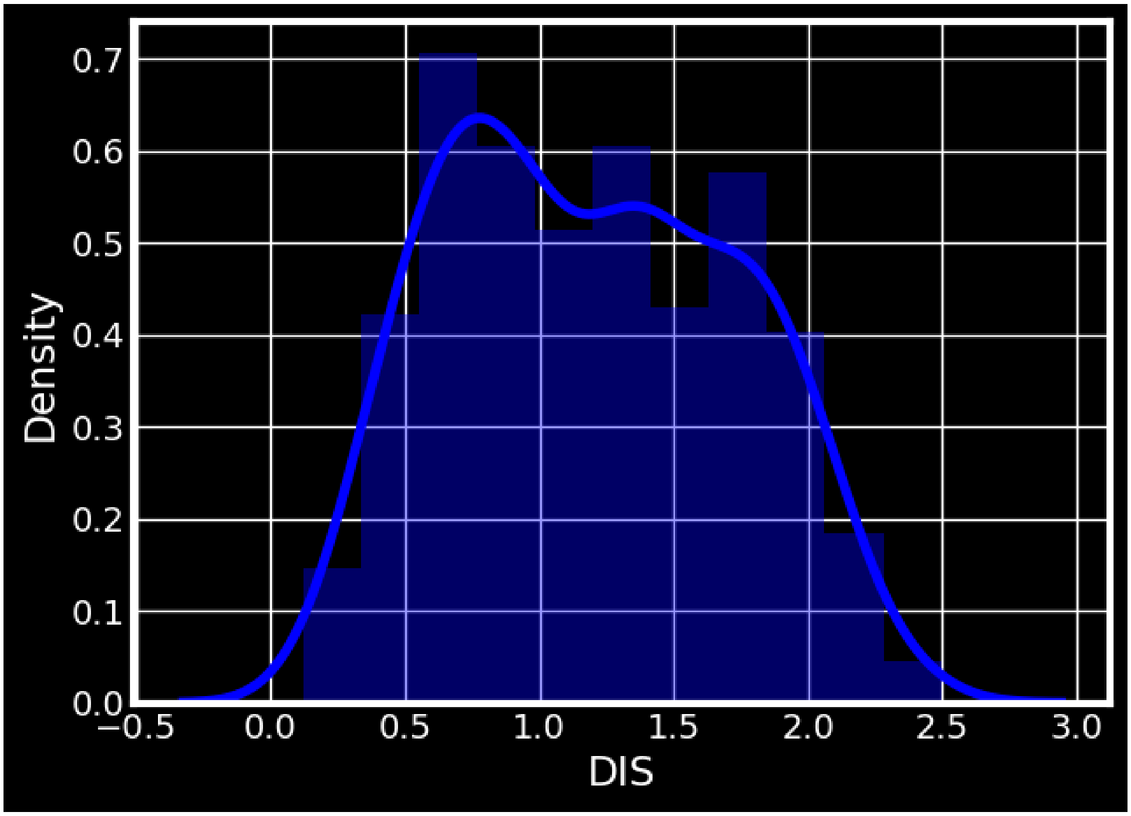
[7]:

```
import matplotlib.pyplot as plt
import seaborn as sns

fig, ax1 = plt.subplots(7, 2, figsize=(20, 25))
k = 0
columns = list(data.columns)
colors = ['blue', 'orange', 'green', 'red', 'purple', 'brown', 'pink', 'gray',␣
↪'olive', 'cyan', 'magenta']

for i in range(7):
    for j in range(2):
        sns.distplot(data[columns[k]], ax=ax1[i][j], color=colors[k %␣
↪len(colors)])  # Use modulo to repeat colors
        ax1[i][j].grid(True)
        k += 1

plt.show()
```



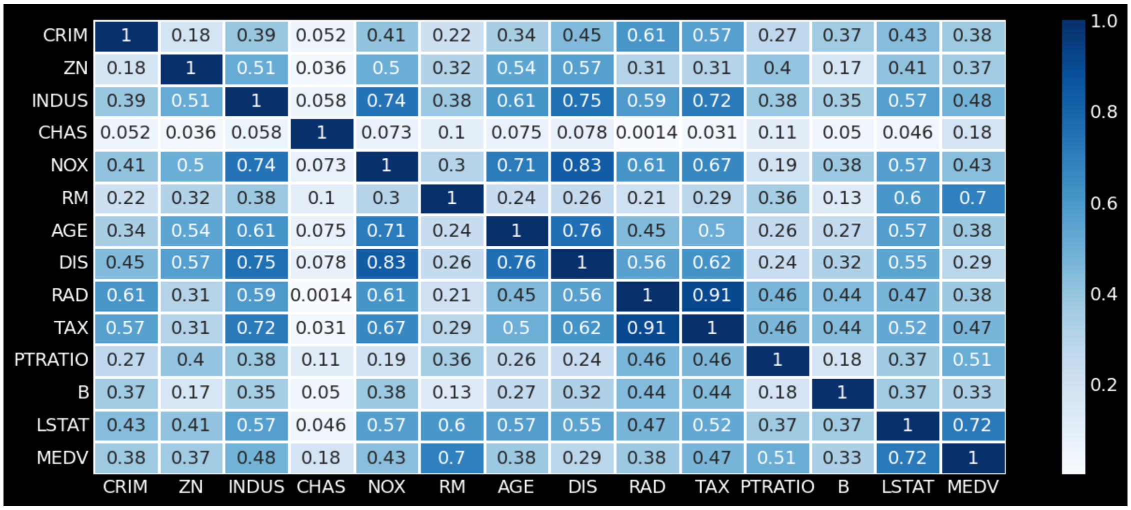
[8]:

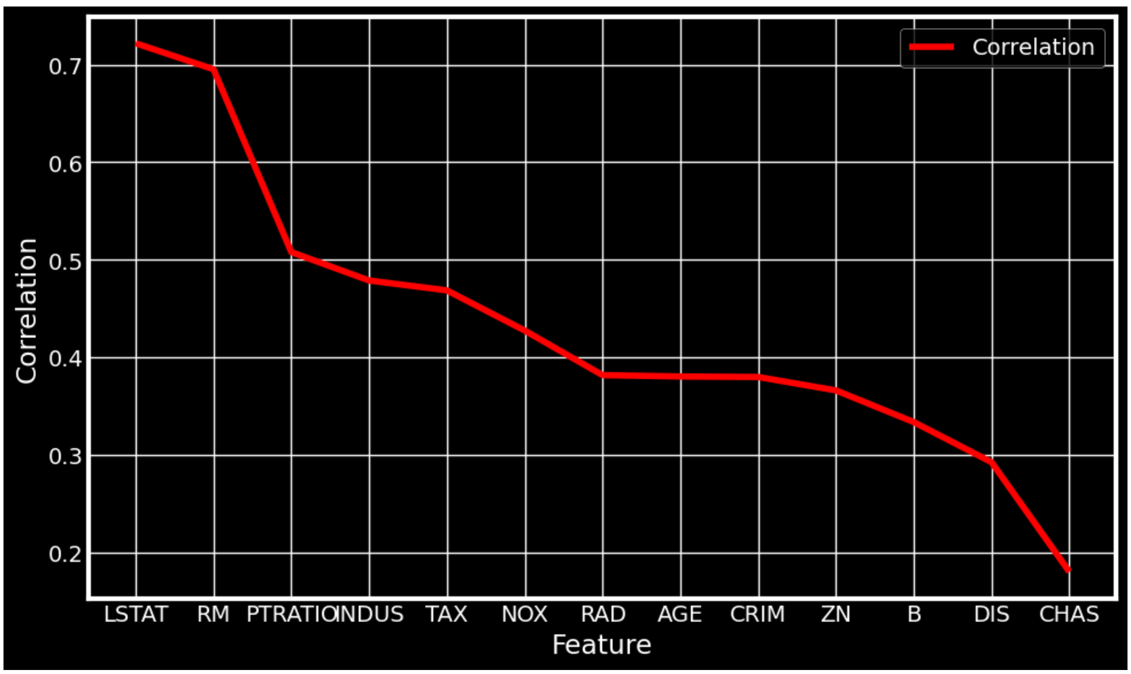
```
def log_transform(col):
    return np.log(col[0])

data["DIS"]=data[["DIS"]].apply(log_transform, axis=1)
#Plot
sns.distplot(data["DIS"], color = 'blue')
plt.grid(True)
plt.show()
```



[9]:

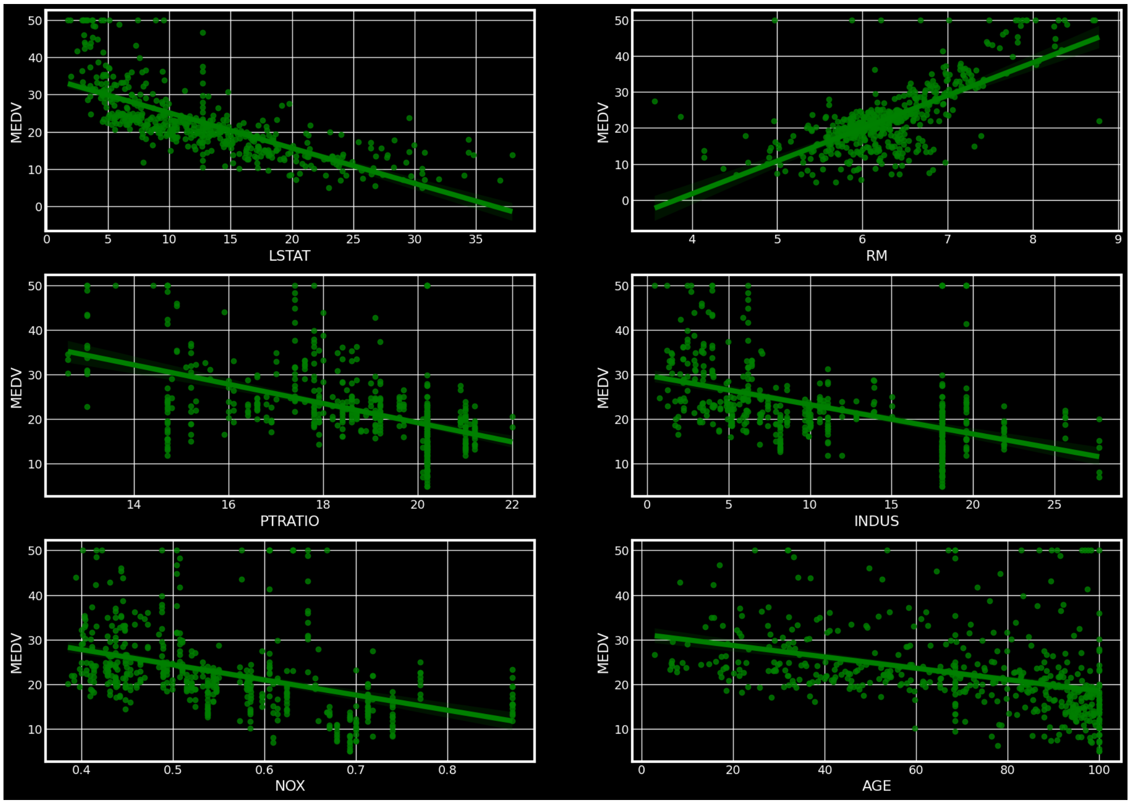
```
plt.figure(figsize=(14,6))
corr=abs(data.corr())
sns.heatmap(corr,annot=True,linewidth=1,cmap="Blues")
plt.show()

plt.figure(figsize=(10,6))
plt.plot(corr["MEDV"].sort_values(ascending=False)[1:
 ↪],label="Correlation",color="red")
plt.ylabel("Correlation")
plt.xlabel("Feature")
plt.legend()
plt.tight_layout()
plt.grid(True)
plt.show()
```





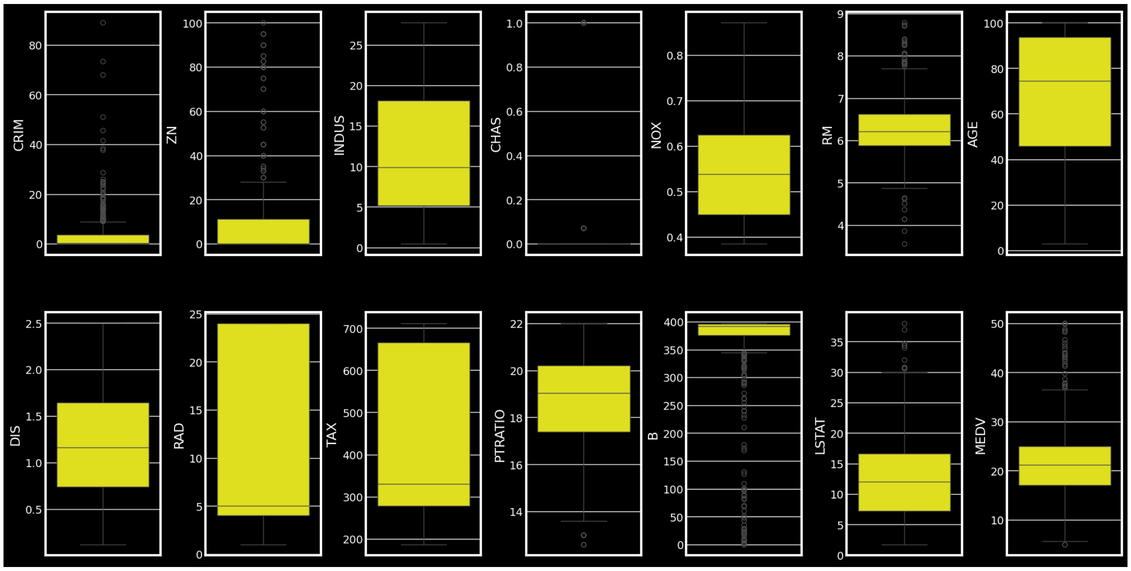
[10]:
```python
import matplotlib.pyplot as plt
import seaborn as sns

fig, ax1 = plt.subplots(3, 2, figsize=(20, 15))
columns = ["LSTAT", "RM", "PTRATIO", "INDUS", "NOX", "AGE"]
k = 0
for i in range(3):
    for j in range(2):
```

```
        sns.regplot(x=data[columns[k]], y=data["MEDV"], ax=ax1[i][j],␣
↪color="green")
        ax1[i][j].grid(True)
        k += 1
plt.show()
```



[11]:

```
fig, axs = plt.subplots(ncols=7, nrows=2, figsize=(20, 10))
index = 0
axs = axs.flatten()
for k,v in data.items():
    sns.boxplot(y=k, data=data, ax=axs[index],color="yellow")
    index += 1
plt.tight_layout(pad=0.4, w_pad=0.5, h_pad=5.0)
plt.show()

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




```
Column CRIM outliers = 12.65%
Column ZN outliers = 13.44%
Column INDUS outliers = 0.00%
Column CHAS outliers = 100.00%
Column NOX outliers = 0.00%
Column RM outliers = 5.93%
Column AGE outliers = 0.00%
Column DIS outliers = 0.00%
Column RAD outliers = 0.00%
Column TAX outliers = 0.00%
Column PTRATIO outliers = 2.96%
Column B outliers = 15.22%
Column LSTAT outliers = 2.37%
Column MEDV outliers = 7.91%
```

[12]:
```python
X=data.iloc[:,0:13]
Y=data.iloc[:,13]

print("Unscaled Data: \n")
display(X)  #Unscaled data
scaler = StandardScaler()
X = scaler.fit_transform(X)
print("Scaled Data: \n")
display(X)  #Scaled input data
```

```
Unscaled Data:


        CRIM    ZN  INDUS  CHAS    NOX     RM     AGE     DIS  RAD  TAX  \
```

```
0     0.00632  18.0   2.31   0.0  0.538  6.575  65.200000  1.408545    1  296
1     0.02731   0.0   7.07   0.0  0.469  6.421  78.900000  1.602836    2  242
2     0.02729   0.0   7.07   0.0  0.469  7.185  61.100000  1.602836    2  242
3     0.03237   0.0   2.18   0.0  0.458  6.998  45.800000  1.802073    3  222
4     0.06905   0.0   2.18   0.0  0.458  7.147  54.200000  1.802073    3  222
..        …    …     …     …    …     …         …         …   …   …
501   0.06263   0.0  11.93   0.0  0.573  6.593  69.100000  0.907694    1  273
502   0.04527   0.0  11.93   0.0  0.573  6.120  76.700000  0.827460    1  273
503   0.06076   0.0  11.93   0.0  0.573  6.976  91.000000  0.773574    1  273
504   0.10959   0.0  11.93   0.0  0.573  6.794  89.300000  0.870833    1  273
505   0.04741   0.0  11.93   0.0  0.573  6.030  68.518519  0.918289    1  273

     PTRATIO       B      LSTAT
0       15.3  396.90   4.980000
1       17.8  396.90   9.140000
2       17.8  392.83   4.030000
3       18.7  394.63   2.940000
4       18.7  396.90  12.715432
..       …      …       …
501     21.0  391.99  12.715432
502     21.0  396.90   9.080000
503     21.0  396.90   5.640000
504     21.0  393.45   6.480000
505     21.0  396.90   7.880000

[506 rows x 13 columns]
Scaled Data:


array([[-0.42232846,  0.29644292, -1.31101039, …, -1.45900038,
         0.44105193, -1.10414593],
       [-0.41986984, -0.48963852, -0.5997709 , …, -0.30309415,
         0.44105193, -0.51035272],
       [-0.41987219, -0.48963852, -0.5997709 , …, -0.30309415,
         0.39642699, -1.23974774],
       …,
       [-0.41595175, -0.48963852,  0.1264106 , …,  1.17646583,
         0.44105193, -1.00993835],
       [-0.41023216, -0.48963852,  0.1264106 , …,  1.17646583,
         0.4032249 , -0.8900378 ],
       [-0.41751548, -0.48963852,  0.1264106 , …,  1.17646583,
         0.44105193, -0.69020355]])
```

[13]:
```
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.
↪2,random_state=94)
```

[14]:
```python
xgbr = xgb.XGBRegressor(objective='reg:squarederror')  #Our XGBoost model
xgbr.fit(X_train,Y_train)

#Generate predicted values
Y_pred = xgbr.predict(X_test)

#Calculate and print the RMSE and the accuracy of our model.
mse=mean_squared_error(Y_test, Y_pred)
score=r2_score(Y_test,Y_pred)
print("Root Mean Square Error: %.2f" % (mse**(0.5)))
print("Accuracy: {} %".format(round((score*100),2)))
```

```
Root Mean Square Error: 2.85
Accuracy: 90.87 %
```

4.0.1 hyperparameter tuning

[15]:
```python
xgbr = xgb.XGBRegressor(objective='reg:squarederror',
                        random_state=50,
                        max_depth=6,
                        learning_rate = 0.08,
                        n_estimators = 500,
                        colsample_bylevel = 0.4,
                        reg_alpha = 1,
                        subsample = 1,
                       )

xgbr.fit(X_train,Y_train)
Y_pred = xgbr.predict(X_test)
mse=mean_squared_error(Y_test, Y_pred)
score=r2_score(Y_test,Y_pred)
print("Root Mean Square Error: %.2f" % (mse**(0.5)))
print("Accuracy: {} %".format(round((score*100),2)))
```

```
Root Mean Square Error: 2.56
Accuracy: 92.66 %
```

[16]:
```python
params = { 'max_depth': [6,10],
           'learning_rate': [0.01, 0.08],
           'colsample_bylevel': [0.3, 0.4],
         }

xgbr = xgb.XGBRegressor(seed=50)
clf = GridSearchCV(estimator=xgbr,
                   param_grid=params,
                   scoring='neg_mean_squared_error',
                   verbose=1)
```

```python
clf.fit(X_train, Y_train)

print("Best parameters:", clf.best_params_)
print("Lowest RMSE: ", (-clf.best_score_)**(0.5))
```

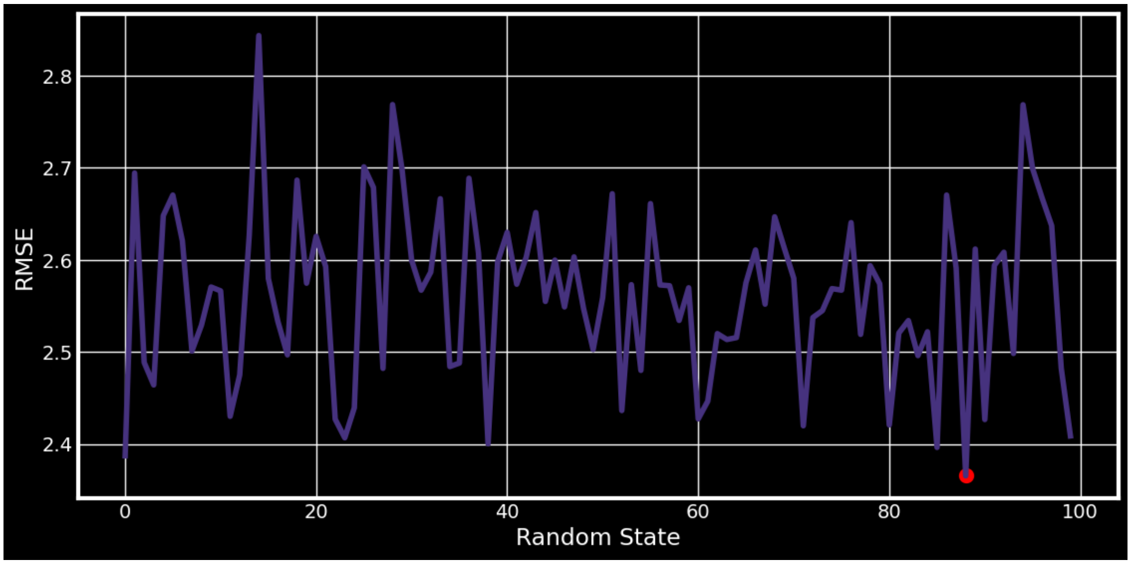
```
Fitting 5 folds for each of 8 candidates, totalling 40 fits
Best parameters: {'colsample_bylevel': 0.3, 'learning_rate': 0.08, 'max_depth':
6}
Lowest RMSE:  3.749371577673614
```

[17]:
```python
mse_dict={}  #Root mean square dictionary
acc_dict={}  #Accuracy dictionary
for n in range(100):
    xgbr = xgb.XGBRegressor(objective='reg:squarederror',
                            random_state=n,
                            max_depth=6,
                            learning_rate = 0.08,
                            n_estimators = 500,
                            colsample_bylevel = 0.4,
                            reg_alpha = 1
                           )
    xgbr.fit(X_train, Y_train)
    Y_pred = xgbr.predict(X_test)
    mse=mean_squared_error(Y_test, Y_pred)
    score=r2_score(Y_test, Y_pred)
    mse_dict.update({n:mse**(1/2.0)})
    acc_dict.update({n:round((score*100),2)})
```

[18]:
```python
#Mean Square Error
lowest=min(mse_dict.values())
res = [key for key in mse_dict if mse_dict[key] == lowest]
mse_list=mse_dict.items()
k,v = zip(*mse_list)
print("RMSE is lowest at {} for random state {} ".format(round((lowest),3),res))
```

```
RMSE is lowest at 2.365 for random state [88]
```

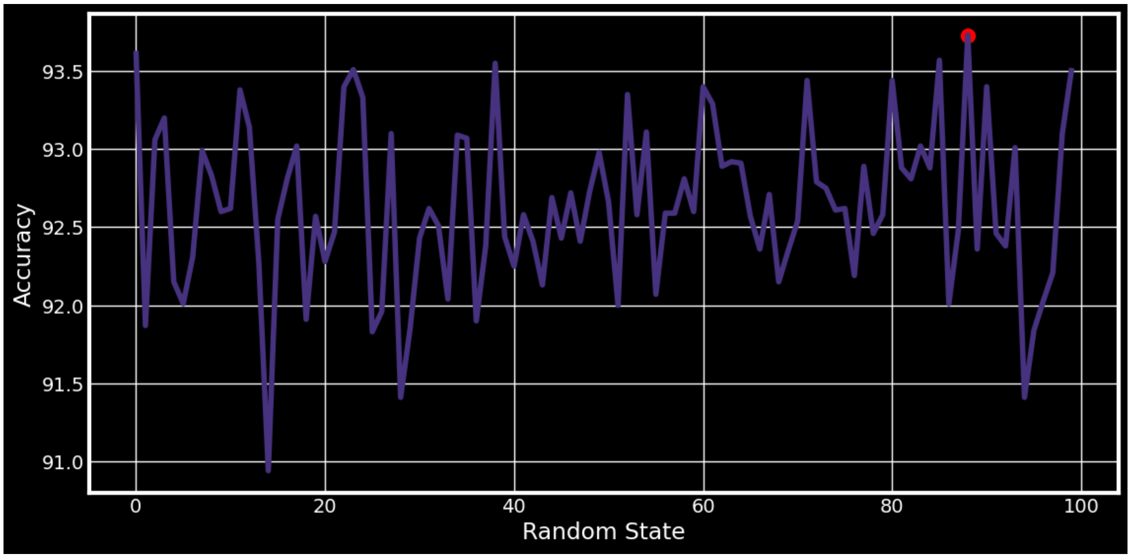
[19]:
```python
#Plot RMSE values
plt.figure(figsize=(12,6))
plt.plot(k,v)
plt.scatter(res,lowest,color="red",lw=5)
plt.xlabel("Random State")
plt.ylabel("RMSE")
plt.grid(True)
plt.show()
```



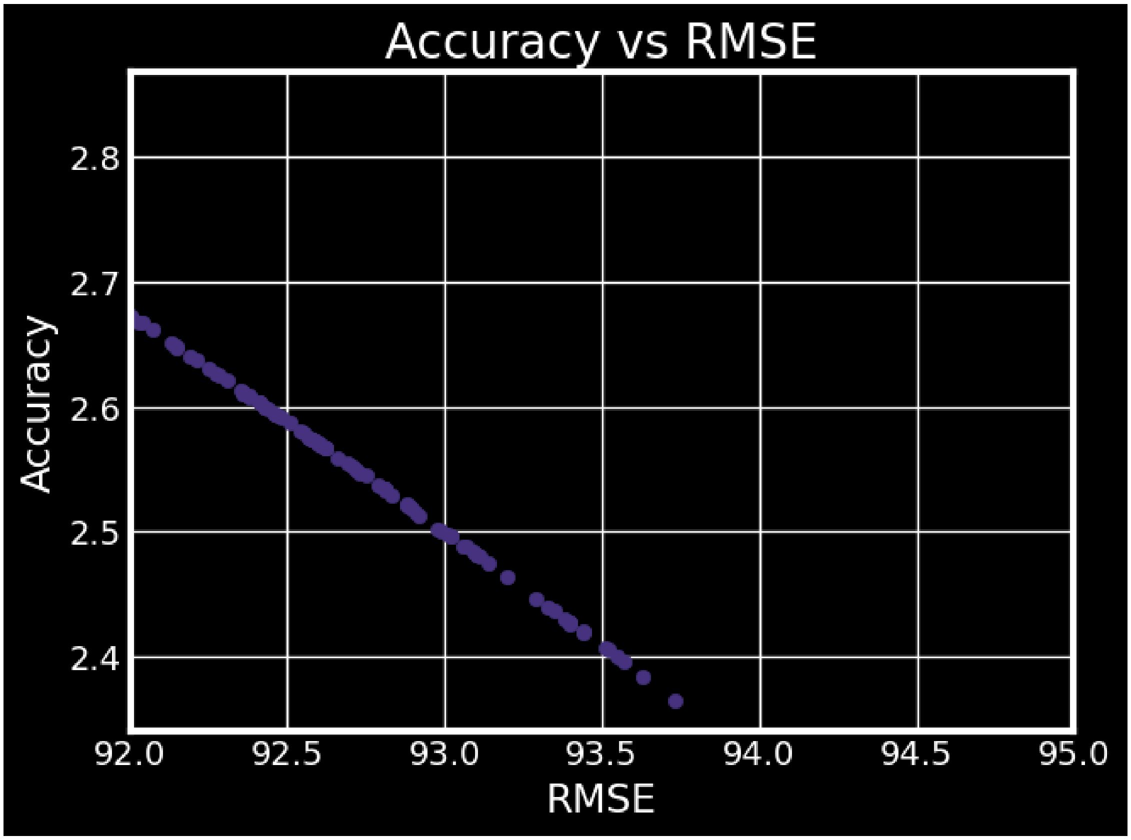
[20]:
```
#Accuracy
highest=max(acc_dict.values())
res1= [key for key in acc_dict if acc_dict[key] == highest]
acc_list=acc_dict.items()
k1,v1=zip(*acc_list)
print("Accuracy is highest at {} % for random state {} ".format(highest,res1))
```

```
Accuracy is highest at 93.73 % for random state [88]
```

[21]:
```
#Plot Accuracy values
plt.figure(figsize=(12,6))
plt.plot(k1,v1)
plt.scatter(res1,highest,color="red",lw=5)
plt.xlabel("Random State")
plt.ylabel("Accuracy")
plt.grid(True)
plt.show()
```



[22]:
```
#Plot accuracy vs RMSE
plt.scatter(v1,v)
plt.xlabel("RMSE")
plt.ylabel("Accuracy")
plt.title("Accuracy vs RMSE")
plt.xlim(92,95)
plt.grid(True)
plt.show()
```


Accuracy vs RMSE
2.8
2.7
2.6
2.5
2.4
Accuracy
92.0
92.5
93.0
93.5
94.0
94.5
95.0
RMSE