```
import os
import pandas as pd
import numpy as np
```

```
boston_df = pd.read_csv("C:\\Users\\DELL\\Downloads\\BOSTON\\boston.csv")
```

```
boston_df.head()
```

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT	MEDV
0	0.00632	18.0	2.31	0	0.538	6.575	65.2	4.0900	1	296.0	15.3	396.90	4.98	24.0
1	0.02731	0.0	7.07	0	0.469	6.421	78.9	4.9671	2	242.0	17.8	396.90	9.14	21.6
2	0.02729	0.0	7.07	0	0.469	7.185	61.1	4.9671	2	242.0	17.8	392.83	4.03	34.7
3	0.03237	0.0	2.18	0	0.458	6.998	45.8	6.0622	3	222.0	18.7	394.63	2.94	33.4
4	0.06905	0.0	2.18	0	0.458	7.147	54.2	6.0622	3	222.0	18.7	396.90	5.33	36.2

```
boston_df.columns
```

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

```
boston_df.shape
```

```
(506, 14)
```

```
boston_df.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   int64
 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   float64
 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
```

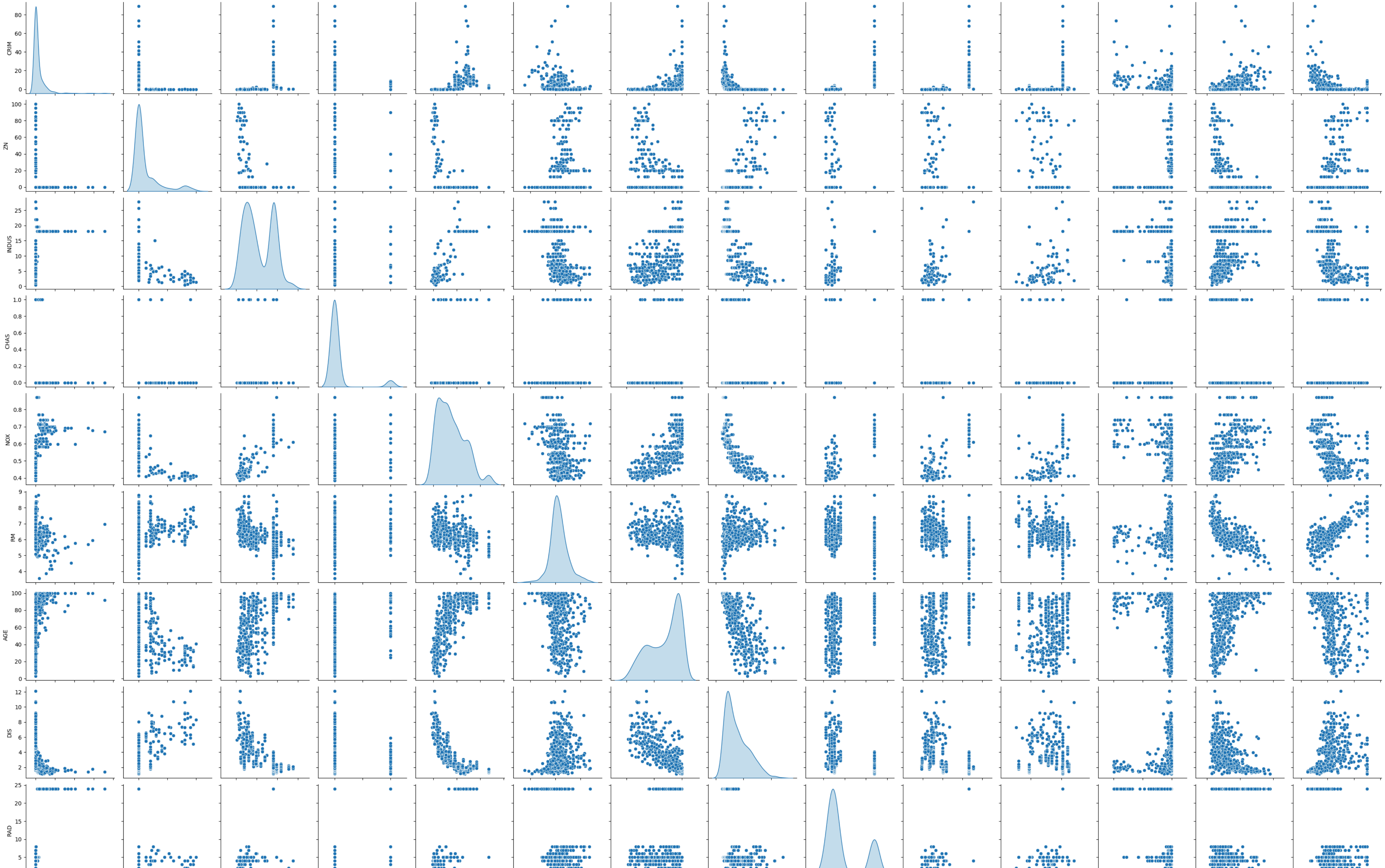
```
boston_df.describe()
```

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT	MEDV
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	506.000000	506.000000
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	12.653063	22.532806
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	7.141062	9.197104
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	1.730000	5.000000
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	6.950000	17.025000
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	11.360000	21.200000
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	16.955000	25.000000
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	37.970000	50.000000

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

sns.pairplot(boston_df, diag_kind = 'kde')
```

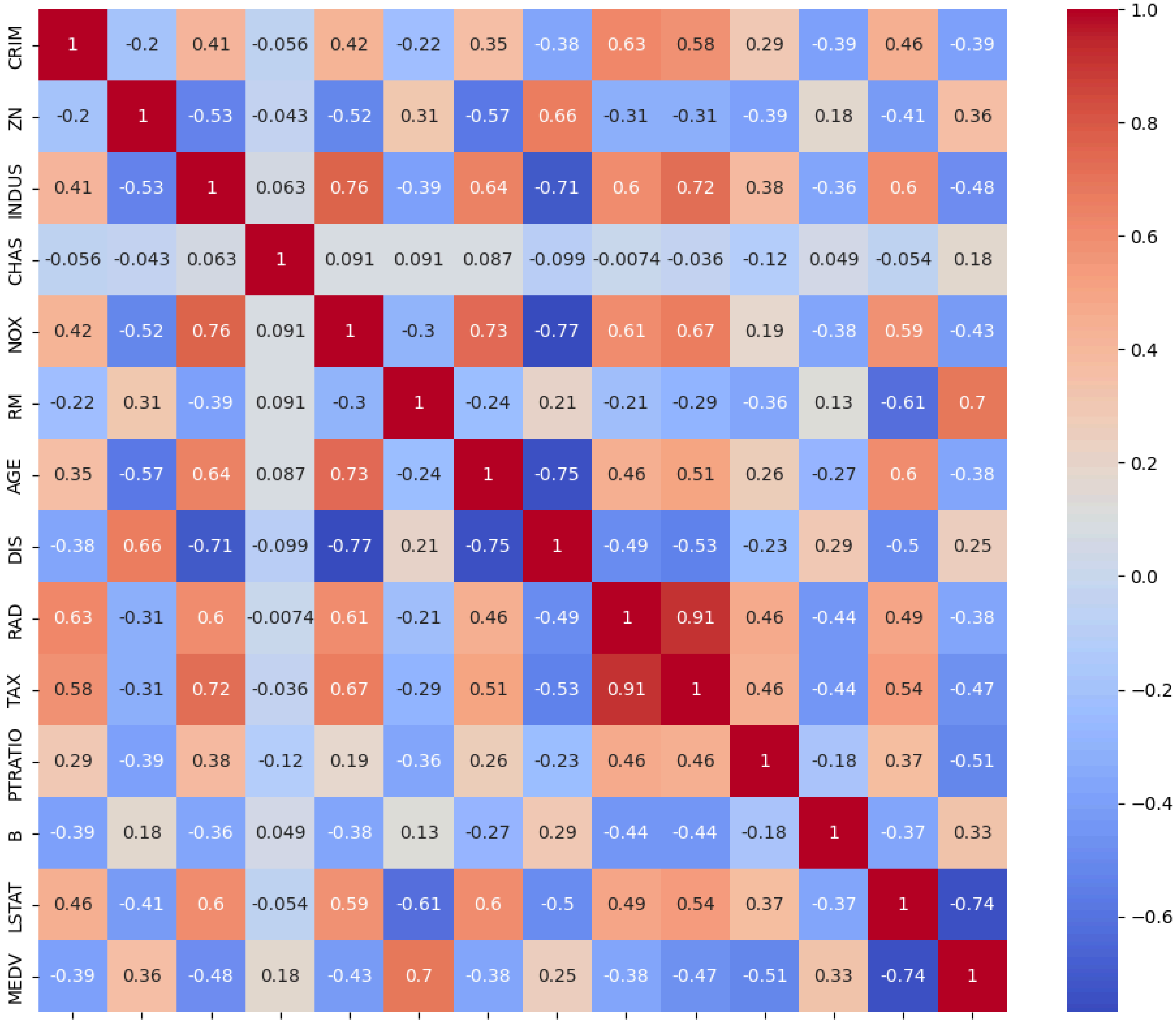
```
<seaborn.axisgrid.PairGrid at 0x1e0d69f3770>
```



TAX
PTRATIO
B
LSTAT
MEDV

```
plt.figure(figsize=(12,10))
sns.heatmap(boston_df.corr(), annot = True, cmap = 'coolwarm')
```

<Axes: >


CRIM 1 -0.2 0.41 -0.056 0.42 -0.22 0.35 -0.38 0.63 0.58 0.29 -0.39 0.46 -0.39
ZN -0.2 1 -0.53 -0.043 -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 0.063 0.76 -0.39 0.64 -0.71 0.6 0.72 0.38 -0.36 0.6 -0.48
CHAS -0.056 -0.043 0.063 1 0.091 0.091 0.087 -0.099 -0.0074 -0.036 -0.12 0.049 -0.054 0.18
NOX 0.42 -0.52 0.76 0.091 1 -0.3 0.73 -0.77 0.61 0.67 0.19 -0.38 0.59 -0.43
RM -0.22 0.31 -0.39 0.091 -0.3 1 -0.24 0.21 -0.21 -0.29 -0.36 0.13 -0.61 0.7
AGE 0.35 -0.57 0.64 0.087 0.73 -0.24 1 -0.75 0.46 0.51 0.26 -0.27 0.6 -0.38
DIS -0.38 0.66 -0.71 -0.099 -0.77 0.21 -0.75 1 -0.49 -0.53 -0.23 0.29 -0.5 0.25
RAD 0.63 -0.31 0.6 -0.0074 0.61 -0.21 0.46 -0.49 1 0.91 0.46 -0.44 0.49 -0.38
TAX 0.58 -0.31 0.72 -0.036 0.67 -0.29 0.51 -0.53 0.91 1 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 -0.18 0.37 -0.51
B -0.39 0.18 -0.36 0.049 -0.38 0.13 -0.27 0.29 -0.44 -0.44 -0.18 1 -0.37 0.33
LSTAT 0.46 -0.41 0.6 -0.054 0.59 -0.61 0.6 -0.5 0.49 0.54 0.37 -0.37 1 -0.74
MEDV -0.39 0.36 -0.48 0.18 -0.43 0.7 -0.38 0.25 -0.38 -0.47 -0.51 0.33 -0.74 1
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4
−0.6

CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT	MEDV

```
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
```

```
x = boston_df.drop(columns=('MEDV'))
y = boston_df['MEDV']
```

```
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.30, random_state=42)
```

```
x_train.shape, x_test.shape, y_train.shape, y_test.shape
```

```
((354, 13), (152, 13), (354,), (152,))
```

```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
x_train_scaled = scaler.fit_transform(x_train)
x_test_scaled = scaler.fit_transform(x_test)
```

```
Regression = LinearRegression()
Regression.fit(x_train_scaled, y_train)
```

```
▾ LinearRegression
LinearRegression()
```

```
y_pred = Regression.predict(x_test_scaled)
```

```
intercept = Regression.score(x_train_scaled, y_train)
```

```
print("The intercept for model is {}".format(intercept))
```

```
The intercept for model is 0.7434997532004697
```

```
Regression.score(x_test_scaled, y_test)
```

```
0.6761000049033605
```

```
import math
mse = np.mean(Regression.predict(x_test_scaled)-y_test)**2
math.sqrt(mse)
```

```
1.6079244721974455
```

```
from sklearn.linear_model import Ridge, Lasso
from sklearn.metrics import mean_squared_error
print("Linear Regression RMSE:", mean_squared_error(y_test, y_pred))
```

```
Linear Regression RMSE: 24.13479128906756
```

```
from sklearn.linear_model import RidgeCV, LassoCV
```

```
lasso_cv = LassoCV(alphas=[0.01, 0.1, 1.0], cv=5)
lasso_cv.fit(x_train_scaled, y_train)
print("Best Aplha for Lasso:", lasso_cv.alpha_)
```

```
Best Aplha for Lasso: 0.01
```

```
lasso = Lasso(alpha=0.01)
lasso.fit(x_train_scaled, y_train)
y_pred_lasso = lasso.predict(x_test_scaled)
print("Lasso RMSE:", mean_squared_error(y_test, y_pred_lasso))
```

```
Lasso RMSE: 24.174962542563506
```

```
ridge_cv = RidgeCV(alphas=[0.1, 1.0, 10.0], cv=5)
ridge_cv.fit(x_train_scaled, y_train)
print("Best alpha for Ridge:", ridge_cv.alpha_)
```

```
Best alpha for Ridge: 10.0
```

```
ridge = Ridge(alpha=10.0)
ridge.fit(x_train_scaled, y_train)
y_pred_ridge = ridge.predict(x_test_scaled)
print("Ridge RMSE:", mean_squared_error(y_test, y_pred_ridge))
```

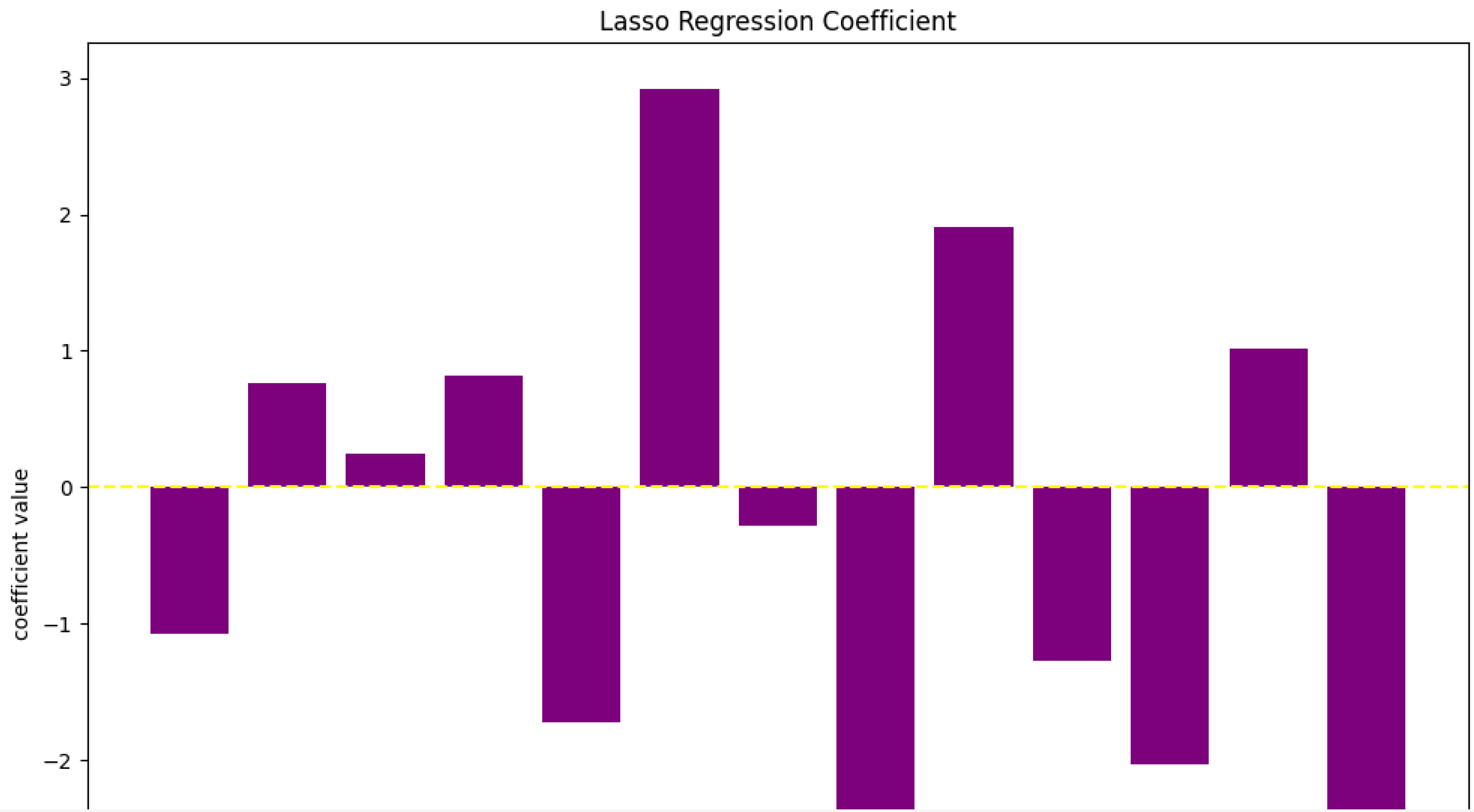
```
Ridge RMSE: 24.364185433874894
```

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

feature_names = x.columns
lasso_coef = lasso.coef_

coef_df = pd.DataFrame({
    'Feature': feature_names,
    'coefficient': lasso_coef
})
```

```
#Bars close to zero --means Lasso shrunk them down,Taller bars means those are important features and Bars at zero means those features are eliminated by lasso
plt.figure(figsize=(10,8))
bars = plt.bar(coef_df['Feature'], coef_df['coefficient'], color='Purple')
plt.axhline(0, color='yellow', linestyle='--')
plt.xticks(rotation=90)
plt.ylabel("coefficient value")
plt.title("Lasso Regression Coefficient")
plt.tight_layout()
plt.show()
```




```
#Lets see those features which are eliminated by Lasso
colors = ['red' if coef == 0 else 'Green' for coef in coef_df['coefficient']]

plt.figure(figsize=(10,8))
plt.bar(coef_df['Feature'], coef_df['coefficient'], color = colors)
plt.axhline(0, color='blue', linestyle='--')
plt.xticks(rotation=90)
plt.ylabel=("coefficient value")
plt.title("red is REMOVED FEATURES")
plt.tight_layout()
plt.show()
```