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. The objective is to predict the value of prices of the house using the given features.

import pandas as pd # for data representation and manipulation
import numpy as np # for performing numerical operations on the data
from sklearn.model_selection import train_test_split # to split data into traini
from sklearn.metrics import mean_squared_error, r2_score # to check the performa
from sklearn.linear_model import LinearRegression # the training model
import matplotlib.pyplot as plt # plotting the graph
import seaborn as sns # advanced visualization

 $url = r"C:\Users\Rutuja \ Habib\Downloads\boston_housing.csv" \quad \# \ Replace \ with \ the \ actual \ path \ or \ URL \ of \ your \ dataset \ df = pd.read_csv(url)$

df.head()

→		crim	zn	indus	chas	nox	rm	age	dis	rad	tax	ptratio	black	lstat	price
	0	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
	4	0.02731	0.0	7.07					4.9671			17.0	396.90	9.14	21.6
	1	0.02731	0.0	7.07	U	0.469	0.421	70.9	4.9071	2	242	17.0	390.90	9.14	21.0
	2	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	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	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

print(df.isnull().sum())

→ crim zn 0 indus 0 chas 0 nox 0 rm 0 age dis 0 rad 0 tax 0 ptratio 0 black 0 1stat a price 0 dtype: int64

print("Summary Statistics:")
df.describe()

→ Summary Statistics:

	crim	zn	indus	chas	nox	rm	age	dis	rad	tax	ptratio
count	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
std	8.601545	23.322453	6.860353	0.253994	0.115878	0.702617	28.148861	2.105710	8.707259	168.537116	2.164946
min	0.006320	0.000000	0.460000	0.000000	0.385000	3.561000	2.900000	1.129600	1.000000	187.000000	12.600000
25%	0.082045	0.000000	5.190000	0.000000	0.449000	5.885500	45.025000	2.100175	4.000000	279.000000	17.400000
50%	0.256510	0.000000	9.690000	0.000000	0.538000	6.208500	77.500000	3.207450	5.000000	330.000000	19.050000
75%	3.677083	12.500000	18.100000	0.000000	0.624000	6.623500	94.075000	5.188425	24.000000	666.000000	20.200000
max	88.976200	100.000000	27.740000	1.000000	0.871000	8.780000	100.000000	12.126500	24.000000	711.000000	22.000000

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X = df.drop(columns='price')
y = df['price']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=0)

model = LinearRegression()
model.fit(X_train, y_train)
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▼ LinearRegression ① ?
LinearRegression()
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```
y_pred = model.predict(X_test)

mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
print(f"Mean Squared Error: {mse}")
print(f"R-Squared: {r2}")

Mean Squared Error: 33.44897999767657
    R-Squared: 0.5892223849182503

plt.figure(figsize=(8, 6))
plt.scatter(y_test, y_pred, alpha=0.7, color='purple')
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], color='red', linestyle='--')
plt.xlabel("Actual Prices")
plt.ylabel("Predicted Prices")
plt.title("Actual vs Predicted Prices")
plt.show()
```



