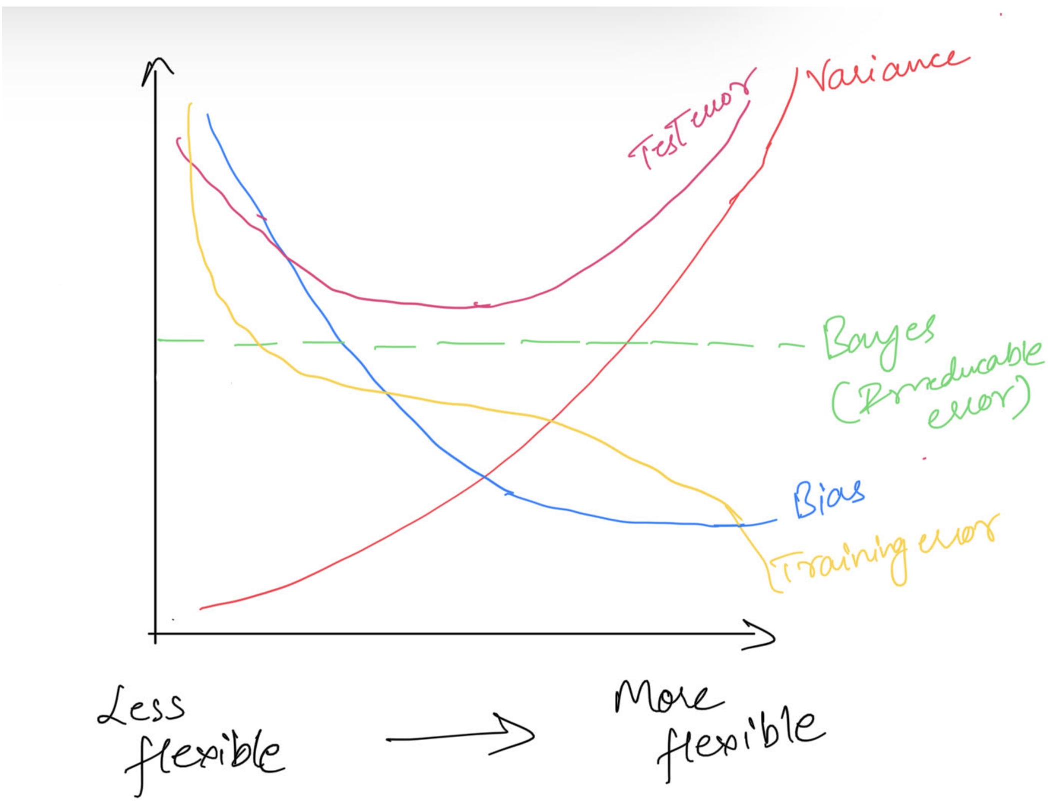
Problem Set 1

Question 1:

a) **Question 3 Part a)** Provide a sketch of typical (squared) bias, variance, training error, test error, and Bayes (or irreducible) error curves, on a single plot, as we go from less flexible statistical learning methods towards more flexible approaches. The x-axis should represent the amount of flexibility in the method, and the y-axis should represent the values for each curve. There should be five curves. Make sure to label each one.



Question 3 Part b)

Explain why each of the five curves has the shape displayed in part

The relationship between flexibility and bias, variance, training error, test error, and irreducible error can be summarized as follows:

- Bias starts high for methods with low flexibility and decreases to zero as flexibility increases, yields a closer fit

- Variance starts at zero for the least flexible approach and increases as flexibility increases, yields overfit
- Training error starts at a non-zero value. As flexibility increases, it decreases to zero, yields a closer fit.
- Test error also starts at a non-zero value. As flexibility increases, it decreases to a minimum, but never below the irreducible error, yields a closer fit before it over fits
- The irreducible error is a constant non-zero value, which defines the lower limit and is bounding the test error. Over fitting can take place depending on the training error.

b) What are the advantages and disadvantages of a very flexible(versus less flexible) approach for regression or classification? Under what circumstances might a more flexible approach be preferred to a less flexible approach? When might a less flexible approach be preferred?

Answer:

- Advantages of a very flexible approach for regression or classification can be its abilit to capture complex relationships between variables which maynot be possible with a less flexible approach.
- Also the results from a more flexible approach can be accurate as more data points are taken into account.
- Disadvantages for a very flexible approach can be that overfitting might occur, primarily due to the large number of parameters used. It can also lead unreliable results, taking more time and effort to build the model and tune the model.
- When the data is complex or the relationship is complex such as non linear or more data points are available, a more flexible approach is preferred whereas less flexible approach is preferred when there are fewer data points or relatively simple data or when there is simple relationship in data such as linear. The reason being, such an approach for such a data will be less time consuming to tune, and less prone to overfitting.

Question 1

c) **Chapter 2, Question 10**

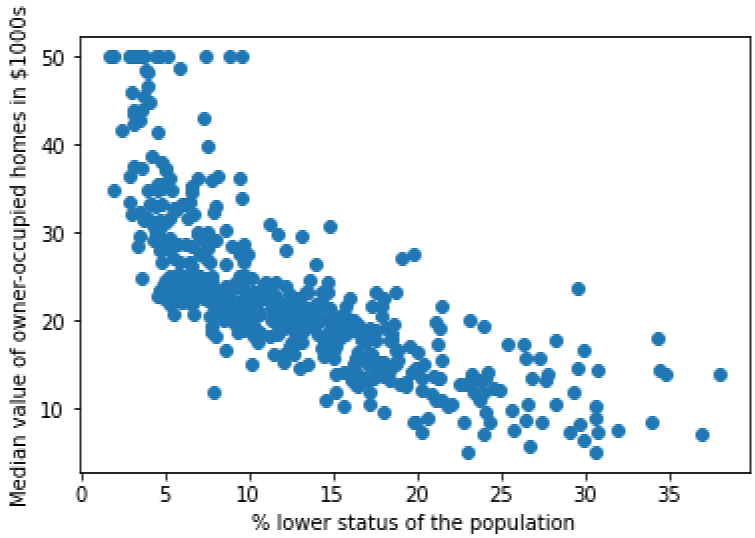
Part a)

How many rows are in this data set? How many columns? What do the rows and columns represent?

Number of Rows= **506**
Number of Columnns = **14**
Rows and columns description:
Each row represents a census tract along with its values such as per_capita_income, rooms_per_dwelling, pupil_to_teacher_ratio etc.
Each column is an independent variable in our analysis to predict the per capita crime rate in boston

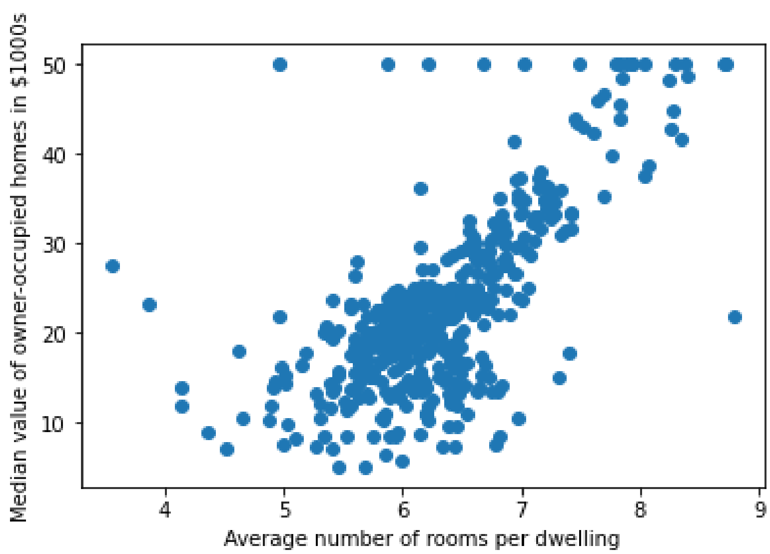
Part b) Make some pairwise scatterplots of the predictors (columns) in this data set. Describe findings.
Plot 1 LSTAT vs MDEV

From the below plot, It looks like there is a negative correlation between LSTAT and MDEV since LSTAT is the percentage of lower-status people, who usually have lower incomes and thus own cheaper houses.

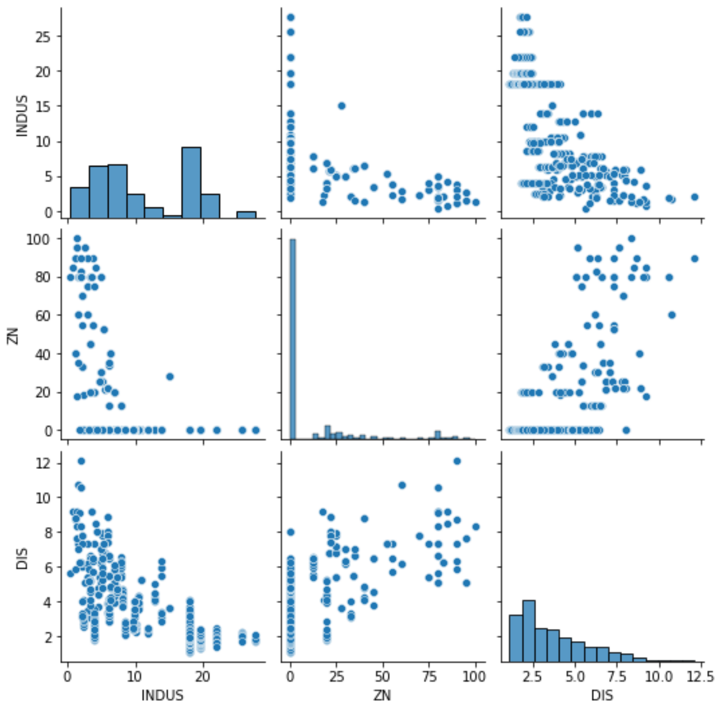


Plot 2 RM vs MDEV

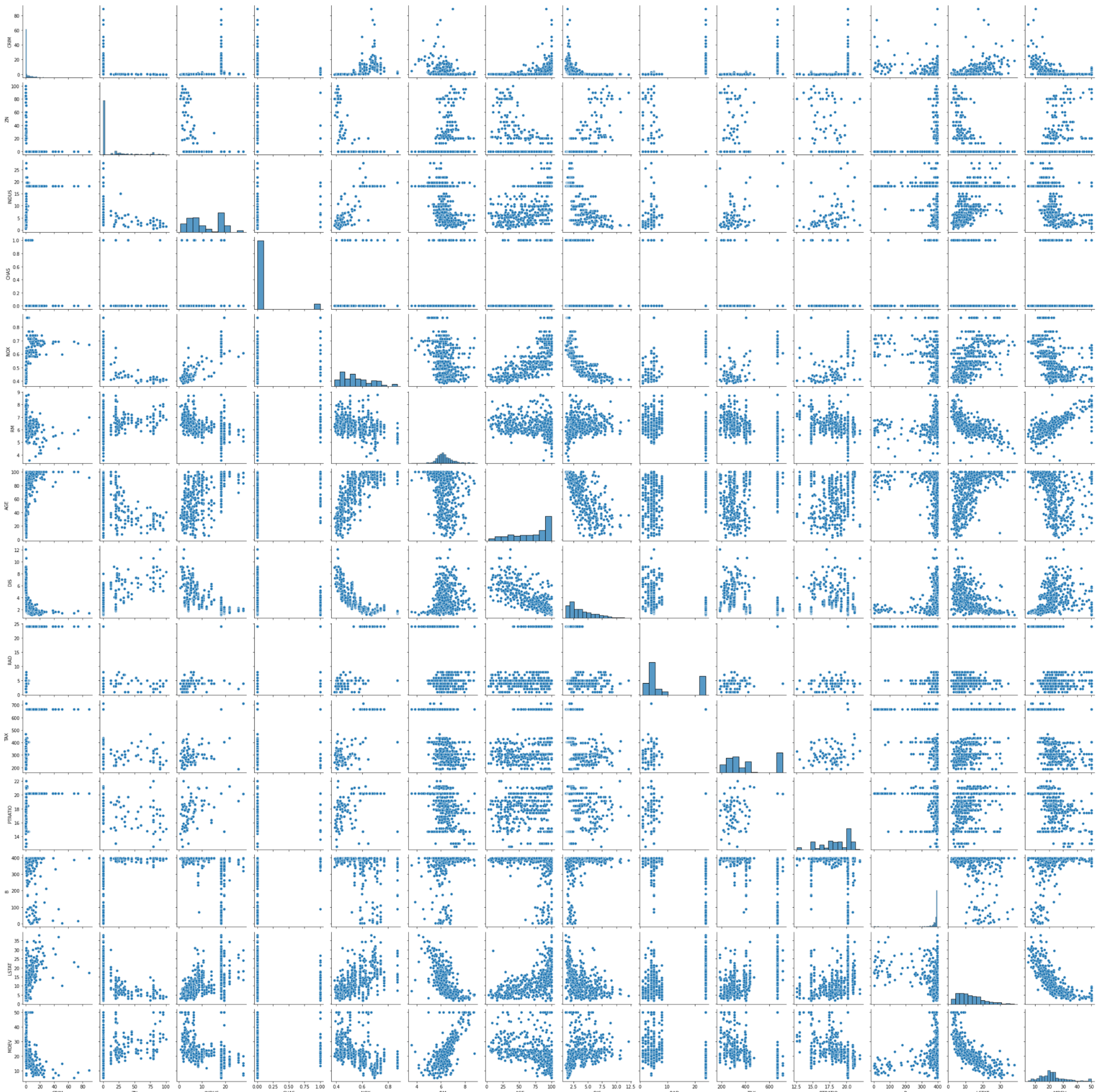
It appears that there is a positive correlation between RM(Av. number of rooms) and the MDEV(Median value of a home), which is as expected. Since more space typically leads to a higher price.



Plot 3 INDUS, ZN, DIS columns



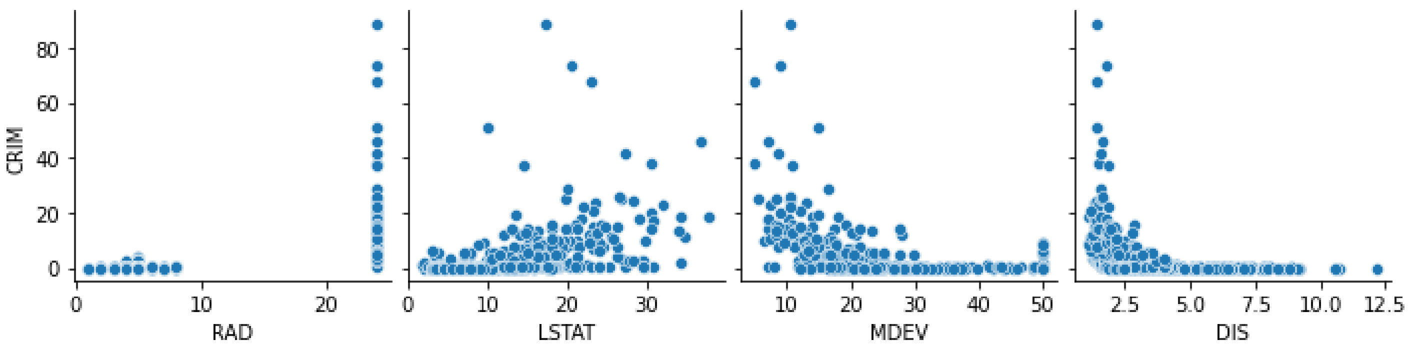
Plot 4 All columns



Part c) Are any of the predictors associated with per capita crime rate? If so, explain the relationship

Method 1: Correlation of all predictors with “per capita crime rate”. Correlation data has been included in Appendix at the end of the assignment. The predictor with the highest correlation with CRIM is RAD(accessibility to radial highways).

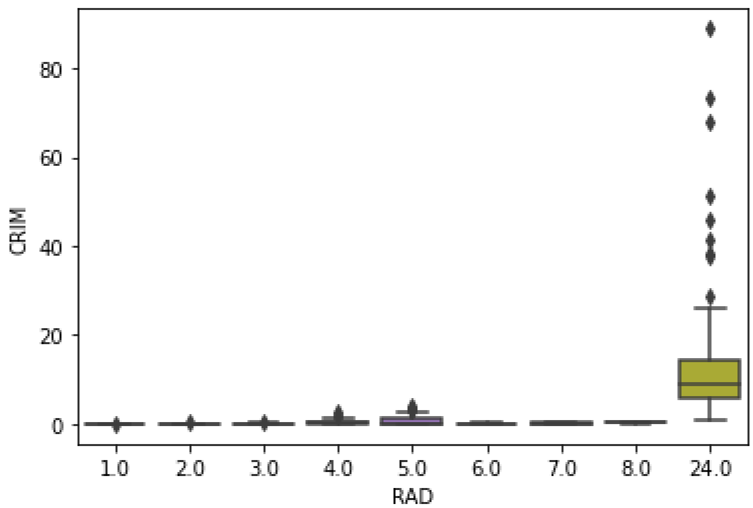
Method 2: We can also analyze the relation by plotting pair plots



From the plots, we can observe that there is clear relationship between the variables and per capita crime rate. From the plots we can say that tracts with lower home values have higher crime rate. Similarly tracts near to the Employment centers also have higher per capita crime rate. The predictor with highest correlation with CRIM is RAD(index of accessibility to radial highways)

Further analysis of the relationship between RAD-CRIM

The boxplot shows that when the value of RAD is 24, the average per capita crime rate by the town is higher and the range is also large compared to when the RAD is lower.



Part d) Do any of the census tracts of Boston appear to have particularly high crime rates? Tax rates? Pupil-teacher ratios? Comment on the range of each predictor

Top 5 crime rates:

Id	CRIM
380	88.9762
418	73.5341
405	67.9208
410	51.1358
414	45.7461

We observe that a particular **tract id 380** has the **highest crime rate at 88.9762**. The next ones are 418 73.5341, 405 67.9208, 410 1.1358, 414 45.7461.

- The minimum crime rate is 0.006320,
- the maximum is 88.97620,
- the mean and median are 3.593761, 0.256510.
- Range is 88.97.
- All units to be perceived are as per the description in dataset.

Tax rates:

If	TAX
488	711.0
489	711.0
490	711.0
491	711.0
492	711.0
356	666.0
357	666.0
358	666.0
359	666.0
360	666.0

- The largest group contains 5 tracts(488, 489, 490, 491, 492) of tax rates is at $711.0 and,
    - the next largest is at $666.
    - The minimum tax rate is $187 per $10000,
    - the maximum is $711.0,
    - the mean and median are $408.24, $330.
    - Range is $524.
    - All units to be perceived are as per the description in dataset.

Pupil-Teacher ratio

Id	PTRATIO
354	22.0
355	22.0
127	21.2
128	21.2
129	21.2
130	21.2
131	21.2
132	21.2
133	21.2
134	21.2

The largest group contains two tracts(354, 355) with 22.0 ratio and,

- the next group contain 15 trackts with a ratio of 21.2
- The minimum pupil teacher ratio is 12.60 pupils per teacher,
- the maximum is 22 pupils per teacher,
- the mean and median are 18.45, 19.05.
- Range is 9.4
- All units to be perceived are as per the description in dataset.

Part e) How many of the census tracts in this data set bound the Charles river?

35 Census tracts

CHAS Charles River dummy variable (= 1 if tract bounds river; 0 otherwise).

35 census tracts in this data set bound the Charles River.

Part f) What is the median pupil-teacher ratio among the towns in this data set?

Median 19.05

The median pupil-teacher ratio in this data set is 19.05. All units to be perceived are as per the description in dataset.

Part g) Which census tract of Boston has the lowest median value of owner-occupied homes? What are the values of the other predictors for that census tract, and how do those values compare to the overall ranges for those predictors? Comment on your findings.

The census tract with id 398 and 405 have the lowest median value of owner-occupied homes value at 5.0 (in 1000s).

The tract with id 398 has a large CRIM compared to mean, ZN below quantile 75%, greater than the mean INDUS 11.13, do not bound the Charles river, greater than the mean NOX 0.55, RM below the 25% quantile, AGE 100, DIS just greater than the minimum value 1.126, maximum RAD, TAX in 75% quantile, B is at maximum and
LSTAT above 75% quantile, and MDEV at the minimum at 5. All units are as per the description in dataset.

The tract with id 405 has a higher CRIM compared to the mean CRIM, ZN of 0, greater than the mean INDUS, does not bound the Charles river, greater than the mean NOX 0.55, RM below the 25% quantile, AGE 100, DIS just greater than the minimum value 1.126, RAD maximum of 24, TAX in 75% quantile, B is at maximum and LSTAT above 75% quantile and MDEV at the minimum at 5. All units to be perceived are as per the description in dataset.

Part h) In this data set, how many of the census tracts average more than seven rooms per dwelling? More than eight rooms per dwelling? Comment on the census tracts that average more than eight rooms per dwelling.

64 census tracts average more than 7 rooms per dwelling.
13 census tracts average more than 8 rooms per dwelling.

- For the census tracts that average more than eight rooms per dwelling, it has
    - a lower mean CRIM of 1.0 compared to the mean CRIM of 3.53,
    - a lower mean INDUS proportion at 7 compared to the overall mean INDUS of 11.14,
    - a higher proportion of the Black population at 385.0 compared to the overall mean of 356.61,
    - very high median value of 44 compared to the overall mean of 23.

Question 2:

a) **Chapter 3, Question 3**

Part a) Option (iii) is true.

For a fixed value of IQ and GPA, high school graduates earn more, on average, than college graduates, provided that the GPA is high enough.

The equation becomes

y^ = 50 + 20GPA + 0.07IQ + 0.01GPA*IQ + (35 - 10GPA)X^3

The equation becomes

GPA Range: 0-4, Low GPA: <3.5, High GPA: >3.5

Ycollege = 50 + 20GPA + 0.07IQ + 0.01GPA*IQ + (35 - 10GPA)

Yhigh = 50 + 20GPA + 0.07IQ + 0.01GPA*IQ

Thus the difference in salary comes down to the component (35 - 10GPA)X^3.

So given a high GPA, i.e >3.5 the output i.e the salary is lower for College Graduates than for the highschool graduates.

Part b) Predict the salary of a college graduate with IQ of 110 and a GPA of 4.0.

Salary = 50 + 20*4.0 + 0.07*110 + 0.01*4.0*110 + (35 - 10*4) = 137.1

I.e Salary will be **137.1 thousand dollars**.

Part c) False

The reason is, the coefficient cannot substantially determine the interaction effect. The range of the variables in the interaction along with the p-value of the coefficient can be used as evidence to determine the interaction effect between GPA and IQ. This can be done through a t-test by establishing the significance of the coefficient as hypotheses.

Question 2:

b) Chapter 3, Question 15

Part a) For each predictor, fit a simple linear regression model to predict the response. Describe your results. In which of the models is there a statistically significant association between the predictor and the response? Create some plots to back up your assertions

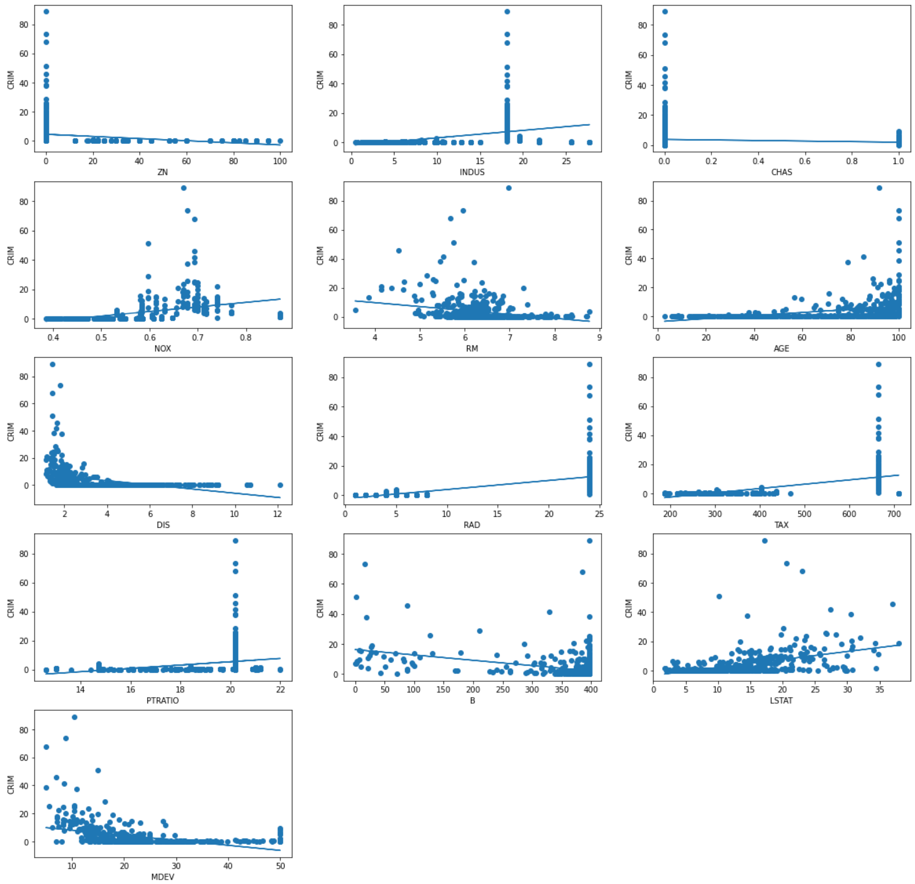
We designed the following regression model for each predictor and ran regressions.

Y = 'CRIM ~ ' + predictor

The coefficient and p-values of the regression results for each predictor are added to the appendix at the end of the assignment.

From the results(can be seen in the appendix), we can observe that there is enough statistical evidence that all predictors, except for one predictor CHAS(p-value - 0.21) are associated with CRIM i.e., the response.

Plots for the above regressions:



Part b) Fit a multiple regression model to predict the response using all of the predictors. Describe your results. For which predictors can we reject the null hypothesis H0: βj = 0?

We built the following multiple regression model to predict the response using all of the predictors.

reg_2 = 'CRIM ~ ' + all_predictors

The results show an R-squared error of 0.448, an Adjusted R-squared error of 0.434, an F-statistic of 30.73 and coefficients as shown below. One significant observation is the coefficient of NOX has reduced significantly to -10, where as others had a small change in both increase or decrease. Observing p-values and t-statistics from the results, we can reject the null hypothesis for every predictor except for DIS(0.000) and RAD(0.000) at 1% level.

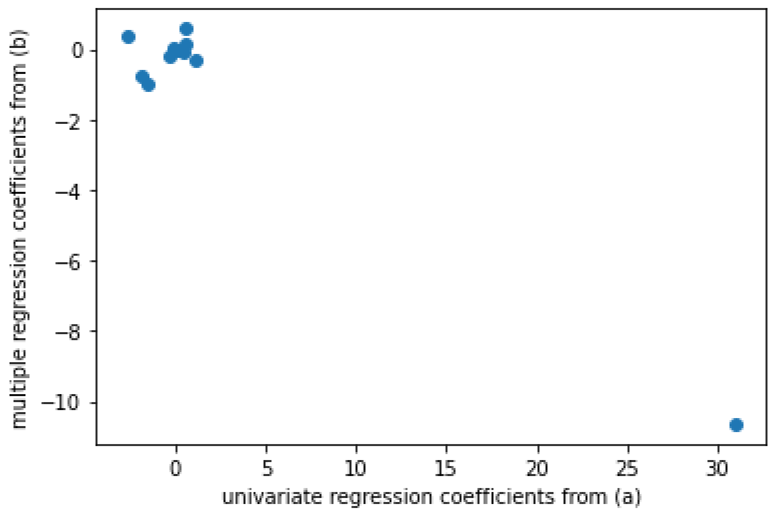
```
                            OLS Regression Results
==============================================================================
Dep. Variable:                   CRIM   R-squared:                       0.448
Model:                            OLS   Adj. R-squared:                  0.434
Method:                 Least Squares   F-statistic:                     30.73
Date:                Wed, 18 Jan 2023   Prob (F-statistic):           2.04e-55
Time:                        19:08:34   Log-Likelihood:                -1655.7
No. Observations:                 506   AIC:                             3339.
Df Residuals:                     492   BIC:                             3399.
Df Model:                          13
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept     17.4184      7.270      2.396      0.017       3.135      31.702
ZN             0.0449      0.019      2.386      0.017       0.008       0.082
INDUS         -0.0616      0.084     -0.735      0.463      -0.226       0.103
CHAS          -0.7414      1.186     -0.625      0.532      -3.071       1.588
NOX          -10.6455      5.301     -2.008      0.045     -21.061      -0.230
RM             0.3811      0.616      0.619      0.536      -0.829       1.591
AGE            0.0020      0.018      0.112      0.911      -0.033       0.037
DIS           -0.9950      0.283     -3.514      0.000      -1.551      -0.439
RAD            0.5888      0.088      6.656      0.000       0.415       0.763
TAX           -0.0037      0.005     -0.723      0.470      -0.014       0.006
PTRATIO       -0.2787      0.187     -1.488      0.137      -0.647       0.089
B             -0.0069      0.004     -1.857      0.064      -0.014       0.000
LSTAT          0.1213      0.076      1.594      0.112      -0.028       0.271
MDEV          -0.1992      0.061     -3.276      0.001      -0.319      -0.080
==============================================================================
Omnibus:                      662.271   Durbin-Watson:                   1.515
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            82701.666
Skew:                           6.544   Prob(JB):                         0.00
Kurtosis:                      64.248   Cond. No.                     1.58e+04
```

Part c)

Compared to part a, we observed that more predictors are deemed to be insignificant in our analysis in predicting in part b. Some of the coefficient estimates(Example: ZN, CHAS, RM, DIS) have also increased from part b to part c i.e univariate to multivariate. The same is shown in below the plot.

NOX has reduced significantly, also visualized in the plot below from ~30 to -10. Comparison of the coefficients between univariate and multivariate are shown in Appendix at the end of the assignment.

Plot:
X: univariate regression coefficients from part (a)
Y: multiple regression coefficients from part (b)



The outlier in the above is caused by the coefficients of NOX. Further analysis can be done by removing NOX point and showing only other coefficients.

Part d) Evidence of non-linear relationship between predictors and the response.

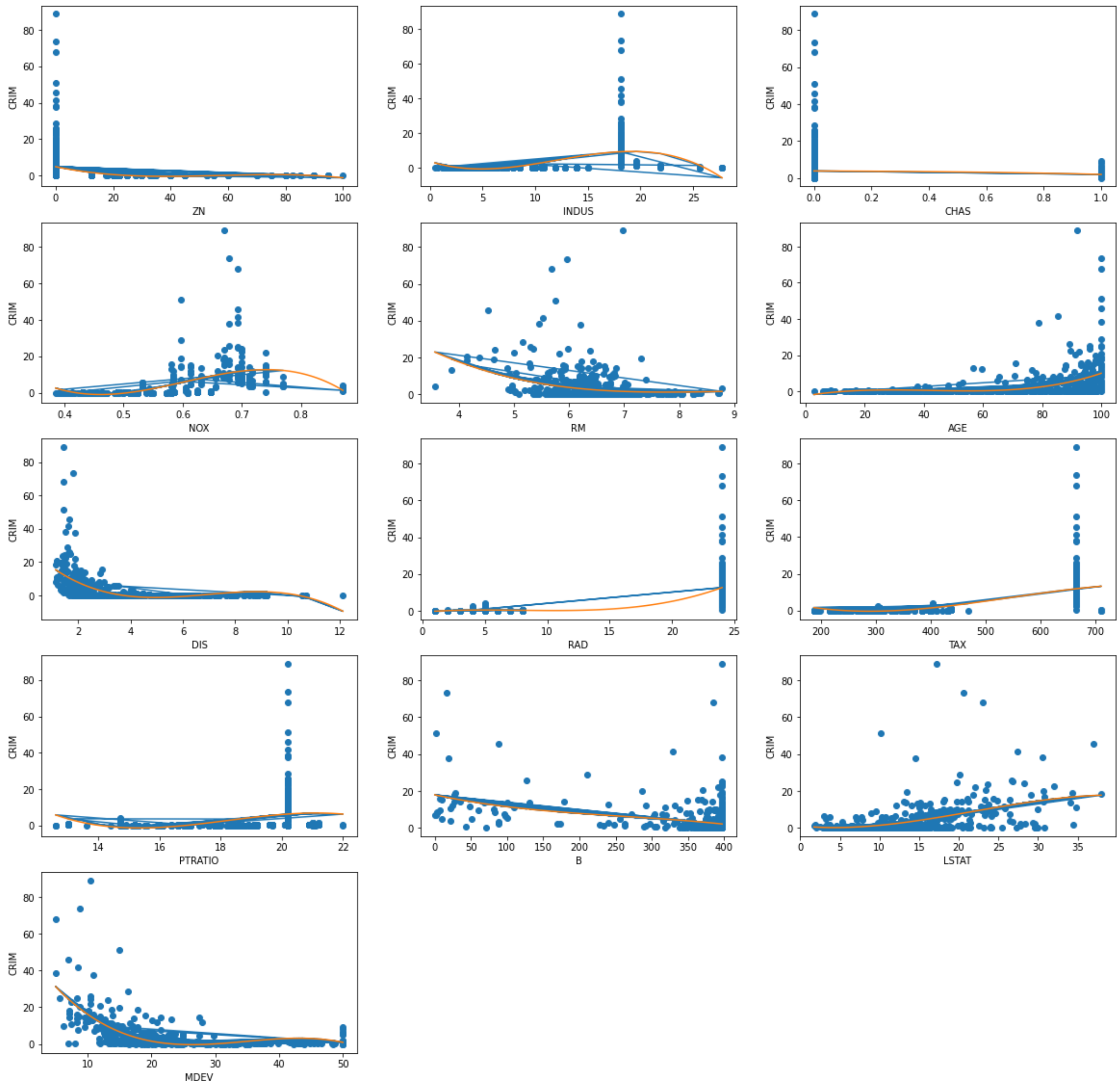
To determine the non linear relationship between the predictors and the response, we build the following model, for each predictor as suggested.

reg_3 = 'CRIM ~ ' + predictor + predictor^2 + predictor^3

The p-value for B2 i.e squared relationship is 0.141. Therefore we cannot reject the null hypothesis that B2 = 0. The p-value for B3 i.e cubic relationship is 0.247. Therefore again we cannot reject the null hypothesis that B3 = 0. This concludes that we cannot for certain say that there is a non-linear relationship between TAX and CRIM.

From the summaries of all the regressions, we can observe enough strong evidence for a non-linear association, between the predictors INDUS, AGE, NOX, DIS, PTRATIO, and MDEV with the response. The other predictors can be categorized into no evidence(ZN, RAD, CHAS, RM, TAX, B, LSTAT) of a linear relationship with response. This is also evident in the plots shown below.

Non-linear relationship plots:



Code:

```
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import seaborn as sns
import statsmodels.formula.api as smf
import statsmodels.api as sm

# Loading dataset
boston_data = pd.read_csv("E:\Winter'23\ML\PS1\Boston\Boston.csv")
```

**** Question 1 , (c)****

```
#Shape of dataset
np.shape(boston_data)

#Pairplot between a few columns
sns.pairplot(boston_data[['INDUS','ZN', 'DIS']])

#  Examining relation between LSTAT and MDEV
plt.scatter(boston_data['LSTAT'], boston_data['MDEV'])
plt.xlabel('% lower status of the population')
plt.ylabel('Median value of owner-occupied homes in $1000s')

#   Examining relation between RM and MDEV
plt.scatter(boston_data['RM'], boston_data['MDEV'])
plt.xlabel('Average number of rooms per dwelling')
plt.ylabel('Median value of owner-occupied homes in $1000s')

#Correlation between columns with per capita crime rate
boston_data.corrwith(boston_data['CRIM'])

# We can also analyze the relation by plotting pairplots
sns.pairplot(boston_data, x_vars = ["RAD", "LSTAT", "MDEV", "DIS"], y_vars = ["CRIM"])
```

```
# Futher analysis the relationship between RAD-CRIM and TAX-CRIM
sns.boxplot(boston_data['RAD'], boston_data['CRIM'])

#High crime rates
boston_data['CRIM'].nlargest(5)
boston_data['CRIM'].describe()

#High Tax rates
boston_data['TAX'].nlargest(10)
boston_data['TAX'].describe()

#High Pupil-Teacher Ratio
boston_data['PTRATIO'].nlargest(10)
boston_data['PTRATIO'].describe()

#Tracts bound by charles river
boston_data["CHAS"].sum()

#Median of PTRATIO
boston_data["PTRATIO"].median()

#Identifying tracts with lowest median value home, comparison with overall
boston_data[boston_data['MDEV'] == boston_data['MDEV'].min()]
Boston_data.iloc[398]
boston_data.iloc[405]
boston_data.describe()

#census tracts average more than seven rooms per dwelling, more than 8
len(boston_data[boston_data['RM']>7])
len(boston_data[boston_data['RM']>8])
boston_data[boston_data['RM']>8].describe().round()
```

***** Question 2 (b) ****

```
#Linear regression between predictors and CRIM, for each predictor
coefficients1 = {}
predictors = [k for k in list(boston_data) if k not in ["CRIM"]]

plt.figure(figsize=(20, 20))
for k, predictor in enumerate(predictors):
    reg = 'CRIM ~ ' + predictor
    y = smf.ols(formula = reg, data=boston_data).fit()
    coefficients1[predictor] = [y.params[predictor]]
    print(predictor + ':' +
          ' COEFF : ' + str(y.params[predictor]) +
          ' p-value : ' + str(y.pvalues[predictor]))
    plt.subplot(5,3,k + 1)
    plt.xlabel(predictor)
    plt.ylabel("CRIM")
    plt.scatter(boston_data[predictor], boston_data['CRIM'])
    plt.plot(boston_data[predictor], y.fittedvalues)
```

```
#Multiple regression with all predictors
predictors2  = "+".join([c for c in predictors if c not in ["CRIM"]])
reg_2 = 'CRIM ~ ' + predictors2
y2 =  smf.ols(reg_2, boston_data).fit()
y2.summary()

# Plotting univariate coefficients vs multivariate coefficients
for predictor in coefficients1:
    coefficients1[predictor].append(y2.params[predictor])
x = [coefficients1[predictor][0] for predictor in coefficients1]
y = [coefficients1[predictor][1] for predictor in coefficients1]
plt.scatter(x,y)
plt.xlabel('univariate regression coefficients from (a)')
plt.ylabel('multiple regression coefficients from (b)')
```

```
#Identifying non-linear relationships between predictors and CRIM

for k, predictor in enumerate(predictors):
    reg_3 = 'CRIM ~ ' + predictor + "+ np.power(" + predictor + ", 2) + np.power(" + predictor + ", 3)"
    y3 = smf.ols(formula = reg_3, data=boston_data).fit
    plt.subplot(4,4,k + 1)
    plt.xlabel(predictor)
    plt.ylabel("CRIM")
    plt.scatter(boston_data[predictor], boston_data['CRIM'])
    plt.plot(boston_data[predictor], y3.fittedvalues)
    x = np.linspace(min(boston_data[predictor]),max(boston_data[predictor]))
    y = y3.params[0] + x*y3.params[1]+ (x**2)*y3.params[2] + (x**3)*y3.params[3]
    plt.plot(x,y)
    print('Predictor : ' + predictor)
    print(y3.summary())
```

Appendix:

Correlation values between CRIM and all other predictors, for Question 1, (c), Part c

#CRIM	1.000000
#ZN	-0.199458
#INDUS	0.404471
#CHAS	-0.055295
#NOX	0.417521
#RM	-0.219940
#AGE	0.350784
#DIS	-0.377904
#RAD	0.622029
#TAX	0.579564
#PTRATIO	0.288250
#B	-0.377365
#LSTAT	0.452220
#MDEV	-0.385832

Comparable values of all parameters for Question 1, (c) , Part g

Tract id 398

#CRIM	38.3518
#ZN	0.0000
#INDUS	18.1000
#CHAS	0.0000
#NOX	0.6930
#RM	5.4530
#AGE	100.0000
#DIS	1.4896
#RAD	24.0000
#TAX	666.0000
#PTRATIO	20.2000
#B	396.9000
#LSTAT	30.5900
#MDEV	5.0000

tract id 405
#CRIM 67.9208
#ZN 0.0000
#INDUS 18.1000
#CHAS 0.0000
#NOX 0.6930
#RM 5.6830
#AGE 100.0000
#DIS 1.4254
#RAD 24.0000
#TAX 666.0000
#PTRATIO 20.2000
#B 384.9700
#LSTAT 22.9800
#MDEV 5.0000

Regression results Question 2, (b), Part a

Variable	**Coefficient**	**p-value**
ZN	-0.073521	6.151722e-06
INDUS	0.506847	2.444137e-21
CHAS	-1.871545	0.214343
NOX	30.975259	9.159490e-23
RM	-2.691045	5.838094e-07
AGE	0.107130	4.259064e-16
DIS	-1.542831	1.268832e-18
RAD	0.614137	1.620605e-55
TAX	0.029563	9.759521e-47
PTRATIO	1.144613	3.875122e-11
B	-0.035535	1.432088e-18
LSTAT	0.544406	7.124778e-27
MDEV	-0.360647	2.083550e-19

Comparision of univariate coefficients vs multivariate coefficients

Feature	Univariate	Multivariate
ZN	-0.07352128504760222	0.04491938833833401
INDUS	0.5068466125328764	-0.06157595914315692
CHAS	-1.871545128298489	-0.7414350725371751
NOX	30.975258612888144	-10.645499846398716
RM	-2.691045326373236	0.38107022871846485
AGE	0.10713083068208351	0.0020113635247454185
DIS	-1.5428311182354155	-0.9949917539066323
RAD	0.6141366715916442	0.5888381693758181
TAX	0.029562557065389287	-0.003745723476256594
PTRATIO	1.1446126207906278	-0.2787310489008296
B	-0.03553454597446593	-0.006855148529714105

LSTAT	0.5444063736854577	0.12126930458422533
MDEV	-0.3606473433413293	-0.19921780261317662

Summaries of the regression results Question 2, (b), Part d.

Predictor	Coefficient	Standard Error	t-value	P-value	Confidence Interval (0.025)	Confidence Interval (0.975)
ZN	-0.3303	0.110	-3.008	0.003	-0.546	-0.115
	0.0064	0.004	1.670	0.096	-0.001	0.014
	-3.753e-05	3.14e-05	-1.196	0.232	-9.92e-05	2.41e-05
INDUS	-1.9533	0.483	-4.047	0.000	-2.901	-1.005
	0.2504	0.039	6.361	0.000	0.173	0.328
	-0.0069	0.001	-7.239	0.000	-0.009	-0.005
CHAS	-0.6238	0.502	-1.242	0.215	-1.611	0.363
	-0.6238	0.502	-1.242	0.215	-1.611	0.363
	-0.6238	0.502	-1.242	0.215	-1.611	0.363
NOX	-1264.1021	170.860	-7.398	0.000	-1599.791	-928.414

	2223.2265	280.659	7.921	0.000	1671.816	2774.637
	-1232.3894	149.687	-8.233	0.000	-1526.479	-938.300
RM	-38.7040	31.284	-1.237	0.217	-100.167	22.759
	4.4655	5.005	0.892	0.373	-5.369	14.300
	-0.1694	0.264	-0.643	0.521	-0.687	0.348

Predictor	Coefficient	Standard Error	t-value	P-value	Confidence Interval (0.025)	Confidence Interval (0.975)
AGE	-2.5592	2.771	-0.924	0.356	-8.003	2.884
	0.2743	0.186	1.471	0.142	-0.092	0.641
	-0.0072	0.004	-1.987	0.047	-0.014	-8.25e-05
	5.737e-05	2.11e-05	2.719	0.007	1.59e-05	9.88e-05
DIS	29.9496	2.448	12.235	0.000	25.140	34.759
	-15.5172	1.737	-8.931	0.000	-18.931	-12.104
	2.4479	0.347	7.061	0.000	1.767	3.129
	-0.1185	0.020	-5.802	0.000	-0.159	-0.078
RAD	-0.6050	2.057	-0.294	0.769	-4.645	3.435
	0.5122	1.047	0.489	0.625	-1.545	2.569
	-0.0750	0.149	-0.504	0.615	-0.368	0.218
	0.0032	0.005	0.699	0.485	-0.006	0.012

TAX	19.0705	11.827	1.612	0.107	-4.166	42.307
	-0.1524	0.096	-1.589	0.113	-0.341	0.036
	0.0004	0.000	1.476	0.141	-0.000	0.001
	-2.193e-07	1.89e-07	-1.158	0.247	-5.91e-07	1.53e-07

Predictor	Coefficient	Standard Error	t-value	P-value	Confidence Interval (0.025)	Confidence Interval (0.975)
PTRATIO	474.0255	156.823	3.023	0.003	165.915	782.135
	-81.8089	27.649	-2.959	0.003	-136.131	-27.487
	4.6039	1.609	2.862	0.004	1.444	7.764
	-0.0842	0.031	-2.724	0.007	-0.145	-0.023
B	17.9898	2.312	7.782	0.000	13.448	22.531
	-0.0845	0.056	-1.497	0.135	-0.196	0.026
	0.0002	0.000	0.760	0.447	-0.000	0.001
	-2.895e-07	4.38e-07	-0.661	0.509	-1.15e-06	5.7e-07
LSTAT	1.0836	2.032	0.533	0.594	-2.909	5.076

	-0.4133	0.466	-0.887	0.375	-1.328	0.502
	0.0530	0.030	1.758	0.079	-0.006	0.112
	-0.0008	0.001	-1.423	0.155	-0.002	0.000
MDEV	52.9386	3.366	15.725	0.000	46.325	59.553
	-5.0774	0.435	-11.668	0.000	-5.932	-4.222
	0.1551	0.017	8.995	0.000	0.121	0.189
	-0.0015	0.000	-7.277	0.000	-0.002	-0.001