Question 2

Exercise 9, p. 57: prediction using automobile data. Book

Exercise 9

This exercise involves the Auto data set studied in the lab. Make sure that the missing values have been removed from the data.

1. Which of the predictors are quantitative, and which are qualitative?
2. What is the range of each quantitative predictor? You can answer this using the range() function.
3. What is the mean and standard deviation of each quantitative predictor?
4. Now remove the 10th through 85th observations. What is the range, mean, and standard deviation of each predictor in the subset of the data that remains?
5. Using the full data set, investigate the predictors graphically, using scatterplots or other tools of your choice. Create some plots highlighting the relationships among the predictors. Comment on your findings.
6. Suppose that we wish to predict gas mileage (mpg) on the basis of the other variables. Do your plots suggest that any of the other variables might be useful in predicting mpg? Justify your answer.

Load the Dataset

In [1]:

```
df <- read.csv('Auto.csv')
```

Top 5 Values in the Dataset

In [2]:

```
head(df,5)
```

mpg	cylinders	displacement	horsepower	weight	acceleration	year	origin	name
18	8	307	130	3504	12.0	70	1	chevrolet chevelle malibu
15	8	350	165	3693	11.5	70	1	buick skylark 320
18	8	318	150	3436	11.0	70	1	plymouth satellite
16	8	304	150	3433	12.0	70	1	amc rebel sst
17	8	302	140	3449	10.5	70	1	ford torino

Understand the Structure of the data.

It will help us observe the different predictors available to us

In [3]:

```
str(df)
```

```
'data.frame':	397 obs. of  9 variables:
```

```
 $ mpg         : num  18 15 18 16 17 15 14 14 14 15 ...
 $ cylinders   : int  8 8 8 8 8 8 8 8 8 8 ...
 $ displacement: num  307 350 318 304 302 429 454 440 455 390 ...
 $ horsepower  : int  130 165 150 150 140 198 220 215 225 190 ...
 $ weight      : int  3504 3693 3436 3433 3449 4341 4354 4312 4425 3850 ...
 $ acceleration: num  12 11.5 11 12 10.5 10 9 8.5 10 8.5 ...
 $ year        : int  70 70 70 70 70 70 70 70 70 70 ...
 $ origin      : int  1 1 1 1 1 1 1 1 1 1 ...
 $ name        : Factor w/ 304 levels "amc ambassador brougham",..: 49 36 231 14 161 141 54 223
241 2 ...
```

If we observe the above output then we can notice that we have in Horsepower we have some values as '?' , 4 INTEGER values **(cylinders, weight, year, origin)** and 3 NUMERICAL values **(mpg, displacement , acceleration)** and name contains the Name of Cars.

Check for missing values and Count all the missing values in entire dataframe.

In [4]:

```
lapply(lapply(df, is.na), table)
```

```
$mpg

FALSE 
  397 

$cylinders

FALSE 
  397 

$displacement

FALSE 
  397 

$horsepower

FALSE  TRUE 
  392     5 

$weight

FALSE 
  397 

$acceleration

FALSE 
  397 

$year

FALSE 
  397 

$origin

FALSE 
  397 

$name
```

```
FALSE 
  397 
```

We can observe from the above output that *HorsePower* has 5 missing values.

As we are dealing with Car data therefore we can replace missing values with mean value.

Replacing missing values in the Horsepower column

In [5]:

```r
df$horsepower[is.na(df$horsepower)] = mean(df$horsepower, na.rm=TRUE)
```

In [6]:

```r
lapply(lapply(df, is.na), table)
```

```
$mpg

FALSE 
  397 

$cylinders

FALSE 
  397 

$displacement

FALSE 
  397 

$horsepower

FALSE 
  397 

$weight

FALSE 
  397 

$acceleration

FALSE 
  397 

$year

FALSE 
  397 

$origin

FALSE 
  397 

$name
```

```
FALSE
  397
```

In [7]:

```
head(df)
```

mpg	cylinders	displacement	horsepower	weight	acceleration	year	origin	name
18	8	307	130	3504	12.0	70	1	chevrolet chevelle malibu
15	8	350	165	3693	11.5	70	1	buick skylark 320
18	8	318	150	3436	11.0	70	1	plymouth satellite
16	8	304	150	3433	12.0	70	1	amc rebel sst
17	8	302	140	3449	10.5	70	1	ford torino
15	8	429	198	4341	10.0	70	1	ford galaxie 500

Shifting `name` column to the at the first

In [8]:

```
df<-df[,c(9, 1:8)]
```

In [9]:

```
head(df)
```

name	mpg	cylinders	displacement	horsepower	weight	acceleration	year	origin
chevrolet chevelle malibu	18	8	307	130	3504	12.0	70	1
buick skylark 320	15	8	350	165	3693	11.5	70	1
plymouth satellite	18	8	318	150	3436	11.0	70	1
amc rebel sst	16	8	304	150	3433	12.0	70	1
ford torino	17	8	302	140	3449	10.5	70	1
ford galaxie 500	15	8	429	198	4341	10.0	70	1

Summary of the data

In [10]:

```
summary(df)
```

```
               name          mpg          cylinders      displacement
 ford pinto     :  6   Min.   : 9.00   Min.   :3.000   Min.   : 68.0
 amc matador    :  5   1st Qu.:17.50   1st Qu.:4.000   1st Qu.:104.0
 ford maverick  :  5   Median :23.00   Median :4.000   Median :146.0
 toyota corolla:  5   Mean   :23.52   Mean   :5.458   Mean   :193.5
 amc gremlin    :  4   3rd Qu.:29.00   3rd Qu.:8.000   3rd Qu.:262.0
 amc hornet     :  4   Max.   :46.60   Max.   :8.000   Max.   :455.0
 (Other)        :368
   horsepower        weight      acceleration        year          origin
 Min.   : 46.0   Min.   :1613   Min.   : 8.00   Min.   :70.00   Min.   :1.000
 1st Qu.: 76.0   1st Qu.:2223   1st Qu.:13.80   1st Qu.:73.00   1st Qu.:1.000
 Median : 95.0   Median :2800   Median :15.50   Median :76.00   Median :1.000
 Mean   :104.5   Mean   :2970   Mean   :15.56   Mean   :75.99   Mean   :1.574
 3rd Qu.:125.0   3rd Qu.:3609   3rd Qu.:17.10   3rd Qu.:79.00   3rd Qu.:2.000
 Max.   :230.0   Max.   :5140   Max.   :24.80   Max.   :82.00   Max.   :3.000
```

Question 1. Which of the predictors are quantitative, and which are qualitative?

Answers - The Quantitative and Qualitative predictors are :

In [11]:

```
str(df)
```

```
'data.frame':	397 obs. of  9 variables:
 $ name        : Factor w/ 304 levels "amc ambassador brougham",..: 49 36 231 14 161 141 54 223 
241 2 ...
 $ mpg         : num  18 15 18 16 17 15 14 14 14 15 ...
 $ cylinders   : int  8 8 8 8 8 8 8 8 8 8 ...
 $ displacement: num  307 350 318 304 302 429 454 440 455 390 ...
 $ horsepower  : num  130 165 150 150 140 198 220 215 225 190 ...
 $ weight      : int  3504 3693 3436 3433 3449 4341 4354 4312 4425 3850 ...
 $ acceleration: num  12 11.5 11 12 10.5 10 9 8.5 10 8.5 ...
 $ year        : int  70 70 70 70 70 70 70 70 70 70 ...
 $ origin      : int  1 1 1 1 1 1 1 1 1 1 ...
```

Quantitative : $mpg\, , cyl \in ders\, , displacement\, , h\ \text{or}\ sepower\, , weight\, , ae \leq ration\, , year\, ,$ $\text{or}\ ig \in$

Qualitative : $name$

Question 2. What is the range of each quantitative predictor? You can answer this using the range() function.

Answer - Range canbe defined as the difference between Highest Value and Lowest Value.

We can answer this question using two methods :

- 1. Subtracting *minimum value* from *maximum value*.
- 1. Calculating range using *range()* function.

Quantitative : mpg , cylinders , displacement , horsepower , weight , acceleration , year , origin

mpg - range

In [12]:

```
print("using range function")
print(range(df$mpg))

range_mpg <- (max(df$mpg) - min(df$mpg))
print('Difference between Maximum and minimum value')
print(range_mpg)
```

```
[1] "using range function"
[1]  9.0 46.6
[1] "Difference between Maximum and minimum value"
[1] 37.6
```

cylinders - range

In [13]:
```
print("using range function")
print(range(df$cylinders))

range_cylinders <- (max(df$cylinders) - min(df$cylinders))
print('Difference between Maximum and minimum value')
print(range_cylinders)
```

```
[1] "using range function"
[1] 3 8
[1] "Difference between Maximum and minimum value"
[1] 5
```

displacement - range

In [14]:
```
print("using range function")
print(range(df$displacement))

range_displacement <- (max(df$displacement) - min(df$displacement))
print('Difference between Maximum and minimum value')
print(range_displacement)
```

```
[1] "using range function"
[1]  68 455
[1] "Difference between Maximum and minimum value"
[1] 387
```

horsepower - range

In [15]:
```
print("using range function")
print(range(df$horsepower))

range_horsepower <- (max(df$horsepower) - min(df$horsepower))
print('Difference between Maximum and minimum value')
print(range_horsepower)
```

```
[1] "using range function"
[1]  46 230
[1] "Difference between Maximum and minimum value"
[1] 184
```

weight - range

In [16]:
```
print("using range function")
print(range(df$weight))

range_weight <- (max(df$weight) - min(df$weight))
print('Difference between Maximum and minimum value')
print(range_weight)
```

```
[1] "using range function"
[1] 1613 5140
[1] "Difference between Maximum and minimum value"
[1] 3527
```

acceleration - range

In [17]:
```
print("using range function")
```

```
print(range(df$acceleration))

range_acceleration <- (max(df$acceleration) - min(df$acceleration))
print('Difference between Maximum and minimum value')
print(range_acceleration)
```

```
[1] "using range function"
[1]  8.0 24.8
[1] "Difference between Maximum and minimum value"
[1] 16.8
```

year - range

In [18]:

```
print("using range function")
print(range(df$year))

range_year <- (max(df$year) - min(df$year))
print('Difference between Maximum and minimum value')
print(range_year)
```

```
[1] "using range function"
[1] 70 82
[1] "Difference between Maximum and minimum value"
[1] 12
```

origin - range

In [19]:

```
print("using range function")
print(range(df$origin))

range_origin <- (max(df$origin) - min(df$origin))
print('Difference between Maximum and minimum value')
print(range_origin)
```

```
[1] "using range function"
[1] 1 3
[1] "Difference between Maximum and minimum value"
[1] 2
```

Question 3. What is the mean and standard deviation of each quantitative predictor?

mpg

In [20]:

```
print("mean")
print(mean(df$mpg))

print("Standard Deviation")
print(sd(df$mpg))
```

```
[1] "mean"
[1] 23.51587
[1] "Standard Deviation"
[1] 7.825804
```

cylinders

In [21]:

```
print("mean")
print(mean(df$cylinders))

print("Standard Deviation")
print(sd(df$cylinders))
```

```
[1] "mean"
[1] 5.458438
[1] "Standard Deviation"
[1] 1.701577
```

displacement

In [22]:

```
print("mean")
print(mean(df$displacement))

print("Standard Deviation")
print(sd(df$displacement))
```

```
[1] "mean"
[1] 193.5327
[1] "Standard Deviation"
[1] 104.3796
```

horsepower

In [23]:

```
print("mean")
print(mean(df$horsepower))

print("Standard Deviation")
print(sd(df$horsepower))
```

```
[1] "mean"
[1] 104.4694
[1] "Standard Deviation"
[1] 38.24739
```

weight

In [24]:

```
print("mean")
print(mean(df$weight))

print("Standard Deviation")
print(sd(df$weight))
```

```
[1] "mean"
[1] 2970.262
[1] "Standard Deviation"
[1] 847.9041
```

acceleration

In [25]:

```
print("mean")
print(mean(df$acceleration))
```

```
print("Standard Deviation")
print(sd(df$acceleration))
```

```
[1] "mean"
[1] 15.55567
[1] "Standard Deviation"
[1] 2.749995
```

year

In [26]:

```
print("mean")
print(mean(df$year))

print("Standard Deviation")
print(sd(df$year))
```

```
[1] "mean"
[1] 75.99496
[1] "Standard Deviation"
[1] 3.690005
```

Origin

In [27]:

```
print("mean")
print(mean(df$origin))

print("Standard Deviation")
print(sd(df$origin))
```

```
[1] "mean"
[1] 1.574307
[1] "Standard Deviation"
[1] 0.8025495
```

Question 4. Now remove the 10th through 85th observations. What is the range, mean, and standard deviation of each predictor in the subset of the data that remains?

In [28]:

```
new_df <- df[-c(10:85),]
```

In [29]:

```
head(new_df,15)
```

	name	mpg	cylinders	displacement	horsepower	weight	acceleration	year	origin
1	chevrolet chevelle malibu	18	8	307	130	3504	12.0	70	1
2	buick skylark 320	15	8	350	165	3693	11.5	70	1
3	plymouth satellite	18	8	318	150	3436	11.0	70	1
4	amc rebel sst	16	8	304	150	3433	12.0	70	1
5	ford torino	17	8	302	140	3449	10.5	70	1
6	ford galaxie 500	15	8	429	198	4341	10.0	70	1

	name	mpg	cylinders	displacement	horsepower	weight	acceleration	year	origin
7	chevrolet impala	14	8	454	220	4354	9.0	70	1
8	plymouth fury iii	14	8	440	215	4312	8.5	70	1
9	pontiac catalina	14	8	455	225	4425	10.0	70	1
86	buick century 350	13	8	350	175	4100	13.0	73	1
87	amc matador	14	8	304	150	3672	11.5	73	1
88	chevrolet malibu	13	8	350	145	3988	13.0	73	1
89	ford gran torino	14	8	302	137	4042	14.5	73	1
90	dodge coronet custom	15	8	318	150	3777	12.5	73	1
91	mercury marquis brougham	12	8	429	198	4952	11.5	73	1

mpg

In [30]:

```
print("using range function")
print(range(new_df$mpg))

range_mpg <- (max(new_df$mpg) - min(new_df$mpg))
print('Difference between Maximum and minimum value')
print(range_mpg)

print("mean")
print(mean(new_df$mpg))

print("Standard Deviation")
print(sd(new_df$mpg))
```

```
[1] "using range function"
[1] 11.0 46.6
[1] "Difference between Maximum and minimum value"
[1] 35.6
[1] "mean"
[1] 24.43863
[1] "Standard Deviation"
[1] 7.908184
```

cylinders

In [31]:

```
print("using range function")
print(range(new_df$cylinders))

range_cylinders <- (max(new_df$cylinders) - min(new_df$cylinders))
print('Difference between Maximum and minimum value')
print(range_cylinders)

print("mean")
print(mean(new_df$cylinders))

print("Standard Deviation")
print(sd(new_df$cylinders))
```

```
[1] "using range function"
[1] 3 8
[1] "Difference between Maximum and minimum value"
```

```
[1] 5
[1] "mean"
[1] 5.370717
[1] "Standard Deviation"
[1] 1.653486
```

Displacement

In [32]:

```
print("using range function")
print(range(new_df$displacement))

range_displacement <- (max(new_df$displacement) - min(new_df$displacement))
print('Difference between Maximum and minimum value')
print(range_displacement)

print("mean")
print(mean(new_df$displacement))

print("Standard Deviation")
print(sd(new_df$displacement))
```

```
[1] "using range function"
[1]  68 455
[1] "Difference between Maximum and minimum value"
[1] 387
[1] "mean"
[1] 187.0498
[1] "Standard Deviation"
[1] 99.63539
```

Horsepower

In [33]:

```
print("using range function")
print(range(new_df$horsepower))

range_horsepower <- (max(new_df$horsepower) - min(new_df$horsepower))
print('Difference between Maximum and minimum value')
print(range_horsepower)

print("mean")
print(mean(new_df$horsepower))

print("Standard Deviation")
print(sd(new_df$horsepower))
```

```
[1] "using range function"
[1]  46 230
[1] "Difference between Maximum and minimum value"
[1] 184
[1] "mean"
[1] 100.9996
[1] "Standard Deviation"
[1] 35.67265
```

Weight

In [34]:

```
print("using range function")
print(range(new_df$weight))

range_weight <- (max(new_df$weight) - min(new_df$weight))
```

```
print('Difference between Maximum and minimum value')
print(range_weight)

print("mean")
print(mean(new_df$weight))

print("Standard Deviation")
print(sd(new_df$weight))
```

```
[1] "using range function"
[1] 1649 4997
[1] "Difference between Maximum and minimum value"
[1] 3348
[1] "mean"
[1] 2933.963
[1] "Standard Deviation"
[1] 810.6429
```

Acceleration

In [35]:

```
print("using range function")
print(range(new_df$year))

range_acceleration <- (max(new_df$acceleration) - min(new_df$acceleration))
print('Difference between Maximum and minimum value')
print(range_acceleration)

print("mean")
print(mean(new_df$acceleration))

print("Standard Deviation")
print(sd(new_df$acceleration))
```

```
[1] "using range function"
[1] 70 82
[1] "Difference between Maximum and minimum value"
[1] 16.3
[1] "mean"
[1] 15.72305
[1] "Standard Deviation"
[1] 2.680514
```

Year

In [36]:

```
print("using range function")
print(range(new_df$year))

range_year <- (max(new_df$year) - min(new_df$year))
print('Difference between Maximum and minimum value')
print(range_year)

print("mean")
print(mean(new_df$year))

print("Standard Deviation")
print(sd(new_df$year))
```

```
[1] "using range function"
[1] 70 82
[1] "Difference between Maximum and minimum value"
[1] 12
[1] "mean"
```

```
[1] 77.15265
[1] "Standard Deviation"
[1] 3.11123
```

Origin

In [37]:

```
print("using range function")
print(range(new_df$origin))

range_origin <- (max(new_df$origin) - min(new_df$origin))
print('Difference between Maximum and minimum value')
print(range_origin)

print("mean")
print(mean(new_df$origin))

print("Standard Deviation")
print(sd(new_df$origin))
```

```
[1] "using range function"
[1] 1 3
[1] "Difference between Maximum and minimum value"
[1] 2
[1] "mean"
[1] 1.598131
[1] "Standard Deviation"
[1] 0.8161627
```

Question 5. Using the full data set, investigate the predictors graphically, using scatterplots or other tools of your choice. Create some plots highlighting the relationships among the predictors. Comment on your findings.

Answer

To Observe all our variables together, Let's add a **id** column to our dataset.

We will try to visualize all our variables together and then we can visualize them separately based on the trends we observe.

In [38]:

```
df$id <- seq.int(nrow(df))
```

In [39]:

```
head(df)
```

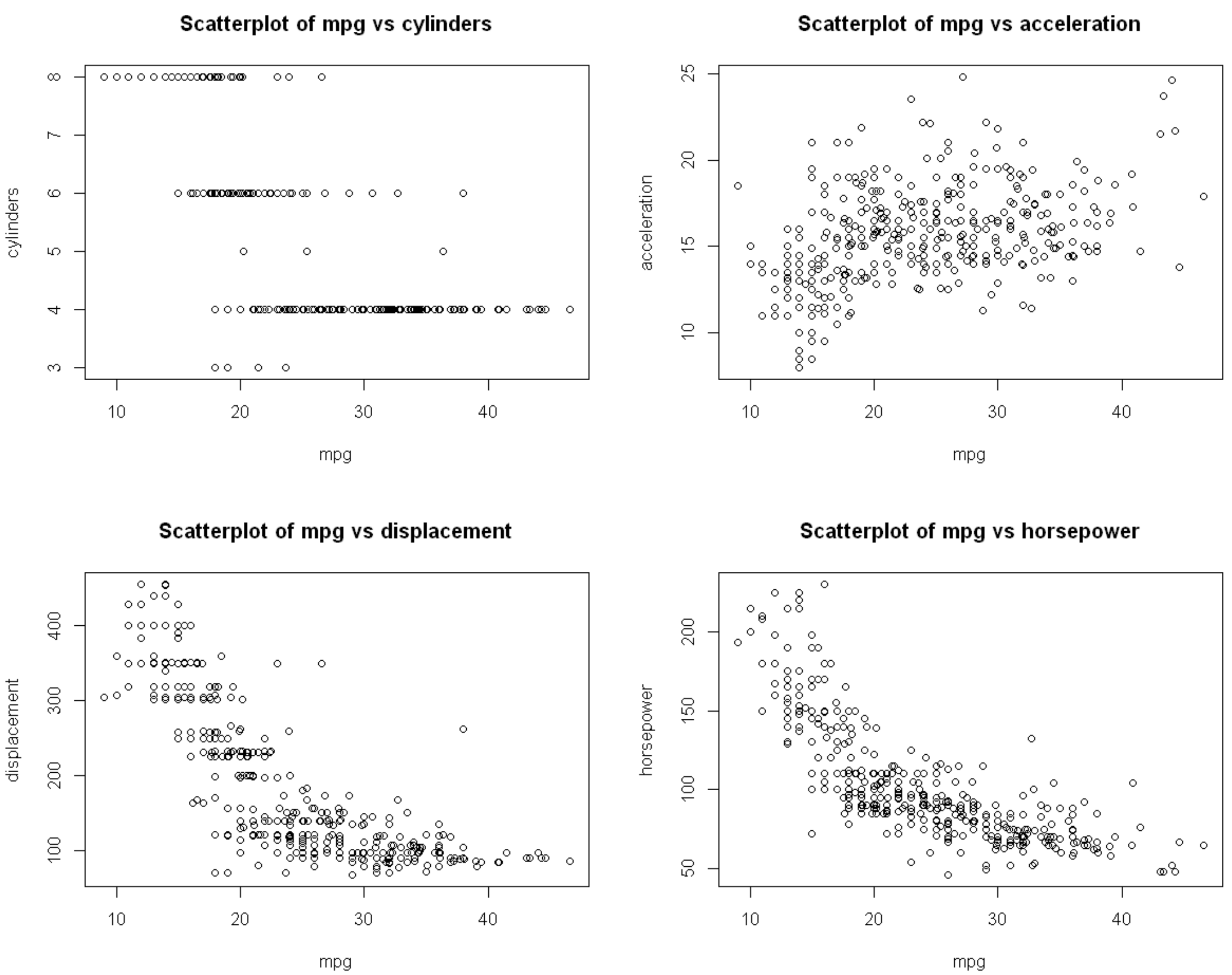
name	mpg	cylinders	displacement	horsepower	weight	acceleration	year	origin	id
chevrolet chevelle malibu	18	8	307	130	3504	12.0	70	1	1
buick skylark 320	15	8	350	165	3693	11.5	70	1	2
plymouth satellite	18	8	318	150	3436	11.0	70	1	3

name	mpg	cylinders	displacement	horsepower	weight	acceleration	year	origin	id
amc rebel sst	16	8	304	150	3433	12.0	70	1	4
ford torino	17	8	302	140	3449	10.5	70	1	5
ford galaxie 500	15	8	429	198	4341	10.0	70	1	6

Let's observe the relationship of mpg with other variables.

In [40]:

```
options(repr.plot.width = 10, repr.plot.height = 8)
df1 <- df #to avoid warnings
attach(df1) #To use variables of this dataset
par(mfrow=c(2,2)) #Creating 2 rows and 2 columns
plot(x=mpg , y=cylinders, main="Scatterplot of mpg vs cylinders")
plot(x=mpg , y=acceleration, main="Scatterplot of mpg vs acceleration")
plot(x=mpg , y=displacement, main="Scatterplot of mpg vs displacement")
plot(x=mpg , y=horsepower, main="Scatterplot of mpg vs horsepower")
```



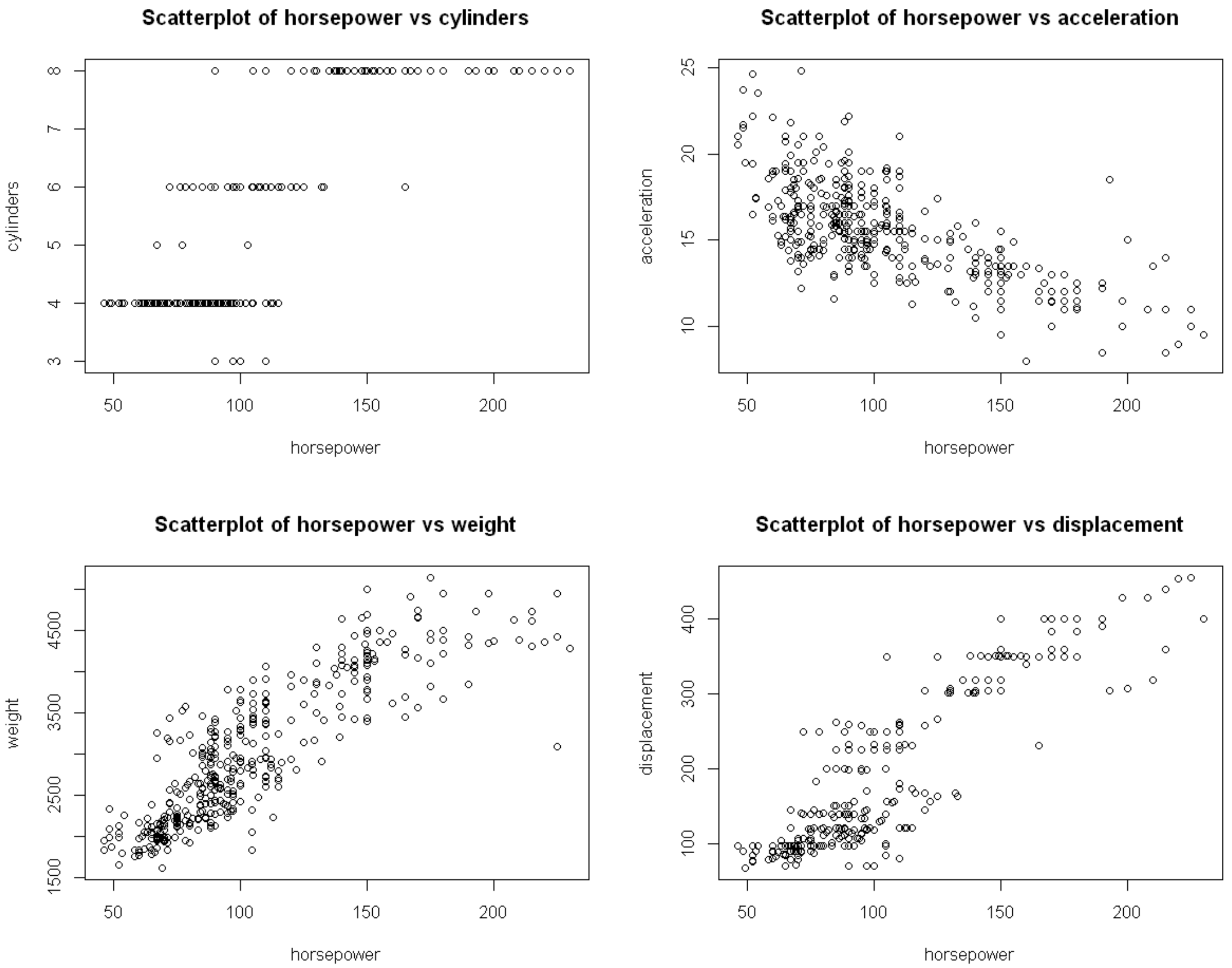
Now if we observe the above graph we can see that:

- **mpg vs cylinders** has **no correlation** with each other.
- **mpg vs acceleration** has a **weak positive correlation**.
- **mpg vs displacement** and **mpg vs horsepower** has a **Strong Negative Correlation**.

Let's observe the Relationship of horsepower against other variables

In [41]:

```
options(repr.plot.width = 10, repr.plot.height = 8)
detach(df1)  #To avoid the warnings occurring because of the masked objects
df2 <- df #to avoid warnings
attach(df2) #To use variables of this dataset
par(mfrow=c(2,2)) #Creating 2 rows and 2 columns
plot(x=horsepower , y=cylinders, main="Scatterplot of horsepower vs cylinders")
plot(x=horsepower , y=acceleration, main="Scatterplot of horsepower vs acceleration")
plot(x=horsepower , y=weight, main="Scatterplot of horsepower vs weight")
plot(x=horsepower , y=displacement, main="Scatterplot of horsepower vs displacement")
```



Now if we observe the above graph we can see that:

- **Horsepower vs cylinders** has **no correlation** with each other.
- **Horsepower vs acceleration** has a **Low Negative correlation**.
- **Horsepower vs weight** has a **Strong Positive Correlation**.
- **Horsepower vs displacement** has a **Positive Corelation**

Let's plot cylinders to find out number of cylinders present in cars

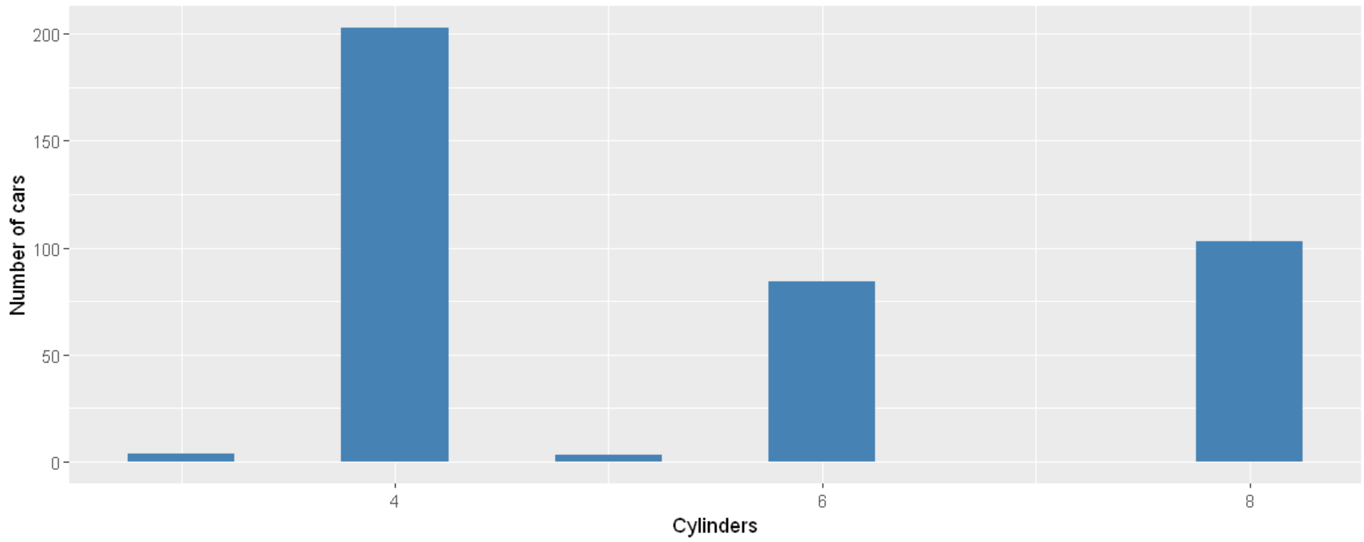
This will tell Number of cylinders present in most of the cars

In [47]:

```
# Calling tidyverse library and suppressing warings coz we are using jupyter notebook

suppressWarnings({library(tidyverse)})
```

In [43]:

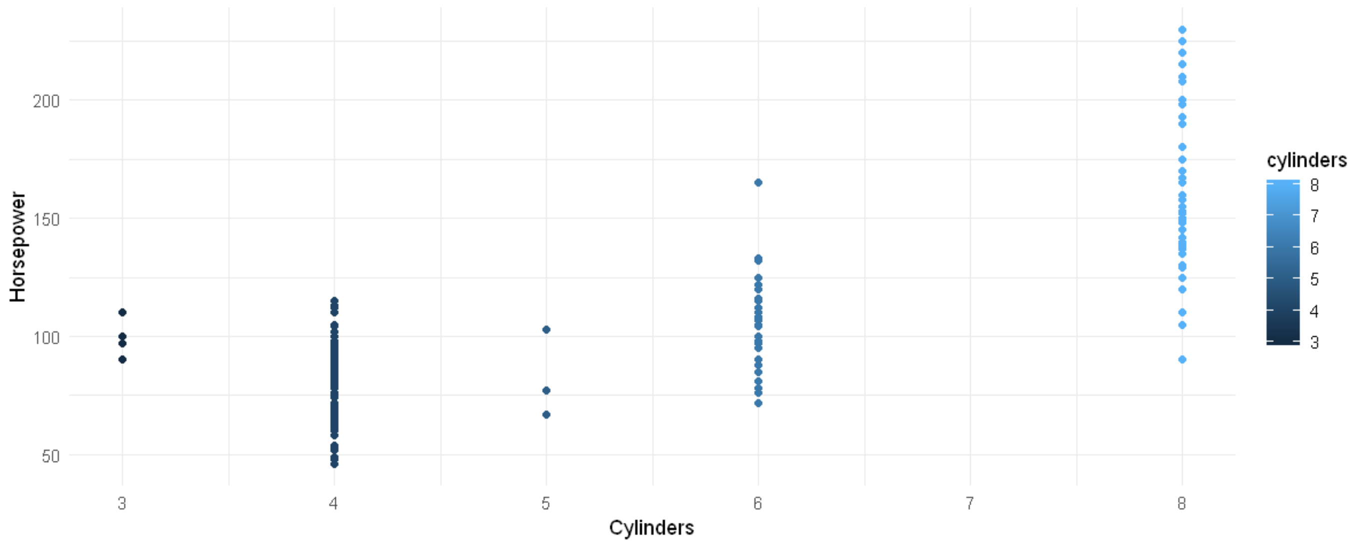
```
options(repr.plot.width = 10, repr.plot.height = 4) # Setting R environment for Plot height, wi
p1 <- ggplot(df, aes(x = cylinders)) +
      geom_bar(fill="steelblue", width = 0.50) +
      labs(x="Cylinders",y="Number of cars")

p1
```



Let's plot cylinders and Horsepower to see if there's any intresting relationship

In [44]:

```
options(repr.plot.width = 10, repr.plot.height = 4)
ggplot(df1,aes(x=cylinders,y=horsepower, group=cylinders))+
labs(x="Cylinders",y="Horsepower") +
geom_point(aes(color=cylinders)) +
theme_minimal()
```



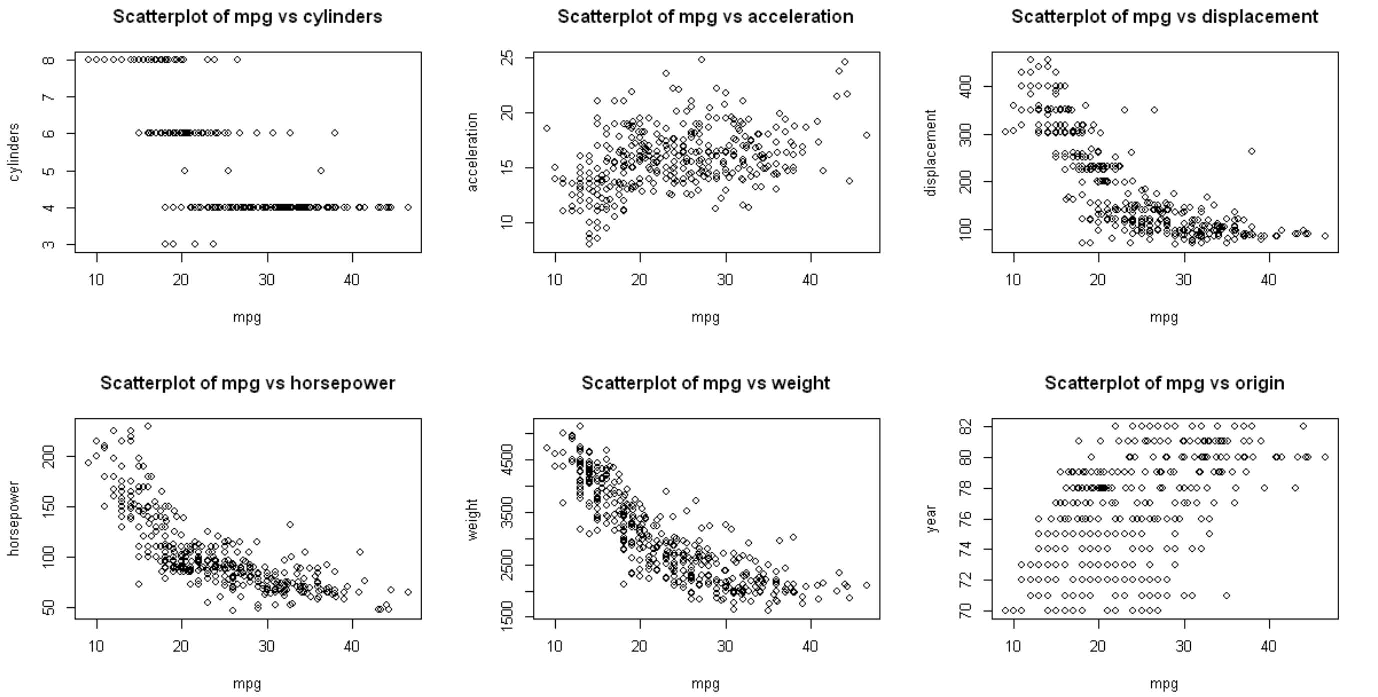
Now if we closely observe the above graph, we can notice that the more the number of cylinders present in the car, the more horsepower the car can generate. We can say horsepower is somewhat dependent on the number of cylinders present in the car.

Question 6. Suppose that we wish to predict gas mileage (mpg) on the basis of the other variables. Do your plots suggest that any of the other variables might be useful in predicting mpg? Justify your answer.

In [45]:

```
options(repr.plot.width = 10, repr.plot.height = 8)
df3 <- df #to avoid warnings
#detach(df1)
detach(df2)
attach(df3) #To use variables of this dataset
par(mfrow=c(3,3)) #Creating 2 rows and 2 columns
plot(x=mpg , y=cylinders, main="Scatterplot of mpg vs cylinders")
plot(x=mpg , y=acceleration, main="Scatterplot of mpg vs acceleration")
plot(x=mpg , y=displacement, main="Scatterplot of mpg vs displacement")
plot(x=mpg , y=horsepower, main="Scatterplot of mpg vs horsepower")
plot(x=mpg , y=weight, main="Scatterplot of mpg vs weight")
plot(x=mpg , y=year, main="Scatterplot of mpg vs origin")
```

```
The following object is masked from package:ggplot2:

    mpg
```



So on the basis of above Scatter Plots, we can

make few observations

mpg(Gas mileage) has *Strong Negative Correlation* with *Displacement, Horsepower and Weight* which basically means *mpg* tends to move in opposite direction based on the values of *Displacement, Horsepower and Weight*.

Hence, we can use these variables *Displacement, Horsepower and Weight* to predict the values of *mpg*.

mpg also has low positive correlation with acceleration which might not be so useful in predicting the values of *mpg*.

We can also test our above assumptions using a correlation function and directly calculating a value for it.

In [46]:

```
cor(df[2:9])
```

	mpg	cylinders	displacement	horsepower	weight	acceleration	year	origir
mpg	1.0000000	-0.7762599	-0.8044430	-0.7714414	-0.8317389	0.4222974	0.5814695	0.563697
cylinders	-0.7762599	1.0000000	0.9509199	0.8397152	0.8970169	-0.5040606	-0.3467172	-0.564971
displacement	-0.8044430	0.9509199	1.0000000	0.8938331	0.9331044	-0.5441618	-0.3698041	-0.610664
horsepower	-0.7714414	0.8397152	0.8938331	1.0000000	0.8605806	-0.6870393	-0.4130218	-0.453961
weight	-0.8317389	0.8970169	0.9331044	0.8605806	1.0000000	-0.4195023	-0.3079004	-0.581265
acceleration	0.4222974	-0.5040606	-0.5441618	-0.6870393	-0.4195023	1.0000000	0.2829009	0.210083
year	0.5814695	-0.3467172	-0.3698041	-0.4130218	-0.3079004	0.2829009	1.0000000	0.184314
origin	0.5636979	-0.5649716	-0.6106643	-0.4539618	-0.5812652	0.2100836	0.1843141	1.000000

After observing the values closely, we can make few assumptions.

1. mpg is slightly correlated with acceleration. We choose to ignore relation with year and origin as we are more focussed on the features which will actually play a role in Car/Auto performance. *mpg* has Strong Negative Correlation with *displacement, horsepower, weight*.

The values of mpg against displacement, mpg against horsepower and mpg against weight are -0.804430, -0.7714414 and -0.8317389 which itself explains the Strong Negative Correlation which we are observing in the plots. Hence, we can use these variables to predict MPG.

In [ ]: