

DS311 - R Lab Assignment

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2024-11-09

R Assignment 1

- In this assignment, we are going to apply some of the build in data set in R for descriptive statistics analysis.
- To earn full grade in this assignment, students need to complete the coding tasks for each question to get the result.
- After finished all the questions, knit the document into HTML format for submission.

Question 1

Using the **mtcars** data set in R, please answer the following questions.

```
# Loading the data
data(mtcars)
```

```
# Head of the data set
print(mtcars)
```

```
##           mpg  cyl  disp  hp drat   wt  qsec vs  am  gear  carb
## Mazda RX4      21.0   6 160.0 110 3.90 2.620 16.46  0   1    4    4
## Mazda RX4 Wag  21.0   6 160.0 110 3.90 2.875 17.02  0   1    4    4
## Datsun 710      22.8   4 108.0  93 3.85 2.320 18.61  1   1    4    1
## Hornet 4 Drive  21.4   6 258.0 110 3.08 3.215 19.44  1   0    3    1
## Hornet Sportabout 18.7   8 360.0 175 3.15 3.440 17.02  0   0    3    2
## Valiant         18.1   6 225.0 105 2.76 3.460 20.22  1   0    3    1
## Duster 360      14.3   8 360.0 245 3.21 3.570 15.84  0   0    3    4
## Merc 240D        24.4   4 146.7  62 3.69 3.190 20.00  1   0    4    2
## Merc 230         22.8   4 140.8  95 3.92 3.150 22.90  1   0    4    2
## Merc 280         19.2   6 167.6 123 3.92 3.440 18.30  1   0    4    4
## Merc 280C        17.8   6 167.6 123 3.92 3.440 18.90  1   0    4    4
## Merc 450SE       16.4   8 275.8 180 3.07 4.070 17.40  0   0    3    3
## Merc 450SL       17.3   8 275.8 180 3.07 3.730 17.60  0   0    3    3
## Merc 450SLC      15.2   8 275.8 180 3.07 3.780 18.00  0   0    3    3
## Cadillac Fleetwood 10.4   8 472.0 205 2.93 5.250 17.98  0   0    3    4
## Lincoln Continental 10.4   8 460.0 215 3.00 5.424 17.82  0   0    3    4
## Chrysler Imperial 14.7   8 440.0 230 3.23 5.345 17.42  0   0    3    4
## Fiat 128         32.4   4  78.7  66 4.08 2.200 19.47  1   1    4    1
## Honda Civic      30.4   4  75.7  52 4.93 1.615 18.52  1   1    4    2
## Toyota Corolla   33.9   4  71.1  65 4.22 1.835 19.90  1   1    4    1
## Toyota Corona    21.5   4 120.1  97 3.70 2.465 20.01  1   0    3    1
## Dodge Challenger 15.5   8 318.0 150 2.76 3.520 16.87  0   0    3    2
## AMC Javelin      15.2   8 304.0 150 3.15 3.435 17.30  0   0    3    2
```

## Camaro Z28	13.3	8	350.0	245	3.73	3.840	15.41	0	0	3	4
## Pontiac Firebird	19.2	8	400.0	175	3.08	3.845	17.05	0	0	3	2
## Fiat X1-9	27.3	4	79.0	66	4.08	1.935	18.90	1	1	4	1
## Porsche 914-2	26.0	4	120.3	91	4.43	2.140	16.70	0	1	5	2
## Lotus Europa	30.4	4	95.1	113	3.77	1.513	16.90	1	1	5	2
## Ford Pantera L	15.8	8	351.0	264	4.22	3.170	14.50	0	1	5	4
## Ferrari Dino	19.7	6	145.0	175	3.62	2.770	15.50	0	1	5	6
## Maserati Bora	15.0	8	301.0	335	3.54	3.570	14.60	0	1	5	8
## Volvo 142E	21.4	4	121.0	109	4.11	2.780	18.60	1	1	4	2

- a. Report the number of variables and observations in the data set.

Enter your code here!

```
ncol(mtcars)
```

```
## [1] 11
```

```
nrow(mtcars)
```

```
## [1] 32
```

Answer:

```
print("There are total of __11__ variables and __32__ observations in this data set.")
```

```
## [1] "There are total of __11__ variables and __32__ observations in this data set."
```

- b. Print the summary statistics of the data set and report how many discrete and continuous variables are in the data set.

Enter your code here!

```
discrete=mtcars[c(2,4,8,9,10,11)]
```

```
ncol(discrete)*nrow(discrete)
```

```
## [1] 192
```

```
contin=mtcars[c(1,3,5,6,7)]
```

```
ncol(contin)*nrow(contin)
```

```
## [1] 160
```

Answer:

```
print("There are __192__ discrete variables and __160__ continuous variables in this data set.")
```

```
## [1] "There are __192__ discrete variables and __160__ continuous variables in this data set."
```

- c. Calculate the mean, variance, and standard deviation for the variable **mpg** and assign them into variable names m, v, and s. Report the results in the print statement.

Enter your code here!

```
m=mean(mtcars$mpg)
```

```

v=var(mtcars$mpg)

s=sd(mtcars$mpg)

print(paste("The average of Mile Per Gallon from this data set is ",m, " with
variance ", v , " and standard deviation", s, "."))

## [1] "The average of Mile Per Gallon from this data set is  20.090625  with
variance  36.3241028225806  and standard deviation 6.0269480520891  ."

```

- d. Create two tables to summarize 1) average mpg for each cylinder class and 2) the standard deviation of mpg for each gear class.

```

# Enter your code here!
#1
library(dplyr)

##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
##
##   filter, lag

## The following objects are masked from 'package:base':
##
##   intersect, setdiff, setequal, union

mtcars %>%
  group_by(cyl) %>%
  summarize(Avgmpg = mean(mpg))

## # A tibble: 3 × 2
##   cyl Avgmpg
##   <dbl> <dbl>
## 1     4  26.7
## 2     6  19.7
## 3     8  15.1

#2
mtcars %>%
  group_by(gear) %>%
  summarize(Sdmpg = sd(mpg))

## # A tibble: 3 × 2
##   gear Sdmpg
##   <dbl> <dbl>
## 1     3  3.37
## 2     4  5.28
## 3     5  6.66

```

- e. Create a crosstab that shows the number of observations belong to each cylinder and gear class combinations. The table should show how many observations given the car has 4 cylinders with 3 gears, 4 cylinders with 4 gears, etc. Report which combination is recorded in this data set and how many observations for this type of car.

Enter your code here!

```
crosstab<-table(mtcars$cyl, mtcars$gear)
print(crosstab)
```

```
##
##      3  4  5
##  4  1  8  2
##  6  2  4  1
##  8 12  0  2
```

```
print("The most common car type in this data set is car with __8__ cylinders
and __3__ gears. There are total of __32__ cars belong to this specification
in the data set.")
```

```
## [1] "The most common car type in this data set is car with __8__ cylinders
and __3__ gears. There are total of __32__ cars belong to this specification
in the data set."
```

Question 2

Use different visualization tools to summarize the data sets in this question.

- a. Using the **PlantGrowth** data set, visualize and compare the weight of the plant in the three separated group. Give labels to the title, x-axis, and y-axis on the graph. Write a paragraph to summarize your findings.

Load the data set

```
data(PlantGrowth)
print(PlantGrowth)
```

```
##      weight group
## 1      4.17  ctrl
## 2      5.58  ctrl
## 3      5.18  ctrl
## 4      6.11  ctrl
## 5      4.50  ctrl
## 6      4.61  ctrl
## 7      5.17  ctrl
## 8      4.53  ctrl
## 9      5.33  ctrl
## 10     5.14  ctrl
## 11     4.81 trt1
## 12     4.17 trt1
## 13     4.41 trt1
```

```
## 14    3.59  trt1
## 15    5.87  trt1
## 16    3.83  trt1
## 17    6.03  trt1
## 18    4.89  trt1
## 19    4.32  trt1
## 20    4.69  trt1
## 21    6.31  trt2
## 22    5.12  trt2
## 23    5.54  trt2
## 24    5.50  trt2
## 25    5.37  trt2
## 26    5.29  trt2
## 27    4.92  trt2
## 28    6.15  trt2
## 29    5.80  trt2
## 30    5.26  trt2
```

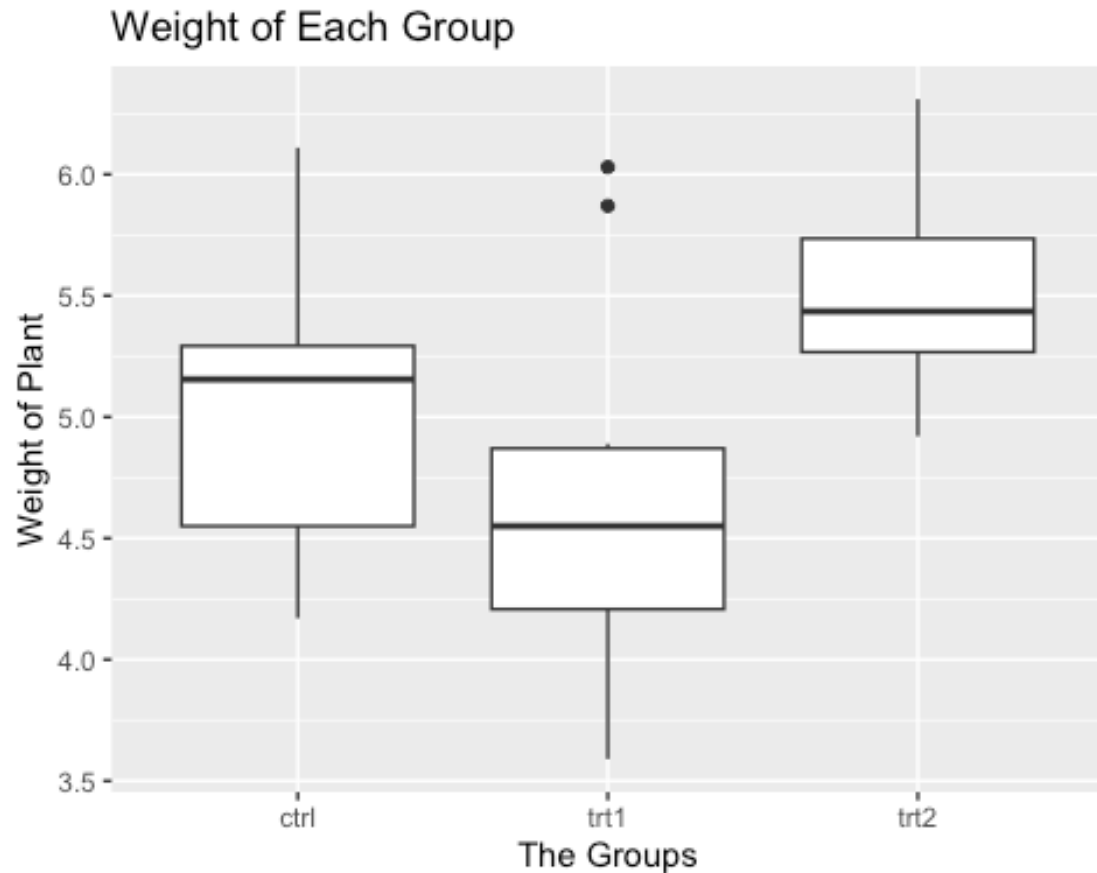
```
library(ggplot2)
```

```
# Head of the data set
head(PlantGrowth)
```

```
##   weight group
## 1   4.17  ctrl
## 2   5.58  ctrl
## 3   5.18  ctrl
## 4   6.11  ctrl
## 5   4.50  ctrl
## 6   4.61  ctrl
```

```
# Enter your code here!
```

```
ggplot(PlantGrowth, aes(y=weight, x=group)) + geom_boxplot() +
  ggtitle("Weight of Each Group") + labs(y="Weight of Plant", x="The Groups")
```



Result:

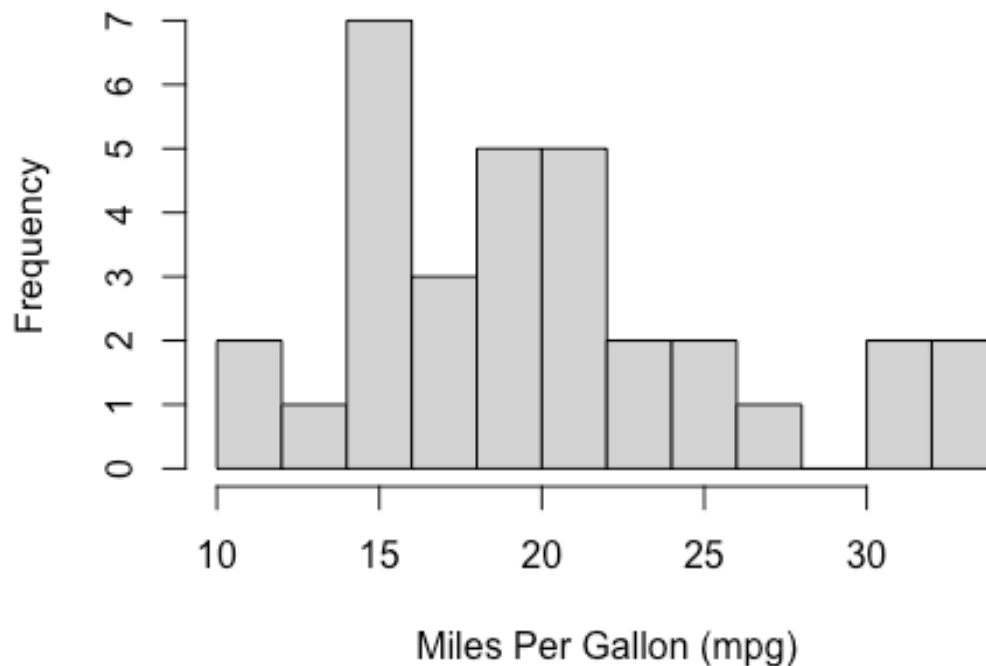
=> Report a paragraph to summarize your findings from the plot!

The line in the boxes indicates the median. We can see from the boxplot graph that trt2 group has the highest median compared to the other groups. The ctrl group is the biggest box, meaning that the weight values for that group are more dispersed than the other groups. The ctrl group is left-skewed (negatively skewed), the trt1 group is symmetric, and trt2 is right-skewed. For trt1, there are outliers, meaning that there are some weight values that fall outside of the normal majority range.

- b. Using the **mtcars** data set, plot the histogram for the column **mpg** with 10 breaks. Give labels to the title, x-axis, and y-axis on the graph. Report the most observed mpg class from the data set.

```
hist(mtcars$mpg,
     breaks = 10,
     main = "Histogram of Miles Per Gallon (mpg) in mtcars",
     xlab = "Miles Per Gallon (mpg),")
```

Histogram of Miles Per Gallon (mpg) in mtcars



```
print("Most of the cars in this data set are in the class of __15__ mile  
per gallon.")
```

```
## [1] "Most of the cars in this data set are in the class of __15__ mile  
per gallon."
```

- c. Using the **USArrests** data set, create a pairs plot to display the correlations between the variables in the data set. Plot the scatter plot with **Murder** and **Assault**. Give labels to the title, x-axis, and y-axis on the graph. Write a paragraph to summarize your results from both plots.

```
# Load the data set
```

```
data(USArrests)
```

```
# Head of the data set
```

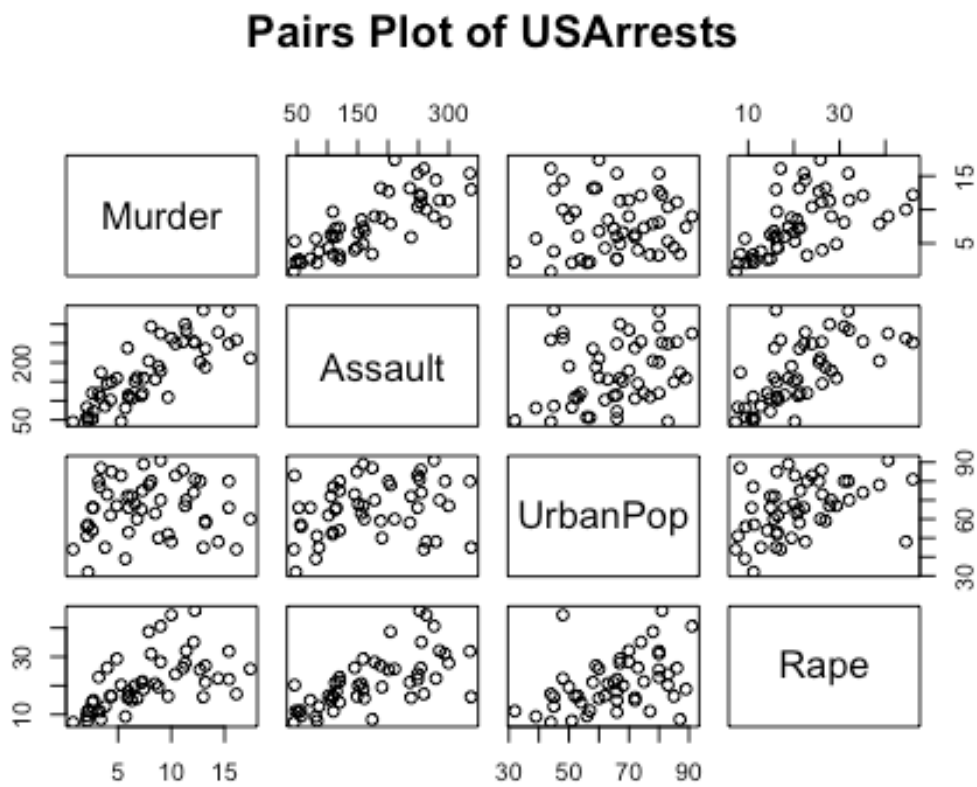
```
head(USArrests)
```

```
##           Murder  Assault  UrbanPop  Rape  
## Alabama      13.2     236         58  21.2  
## Alaska       10.0     263         48  44.5  
## Arizona       8.1     294         80  31.0  
## Arkansas      8.8     190         50  19.5  
## California    9.0     276         91  40.6  
## Colorado      7.9     204         78  38.7
```

```
# Enter your code here!
```

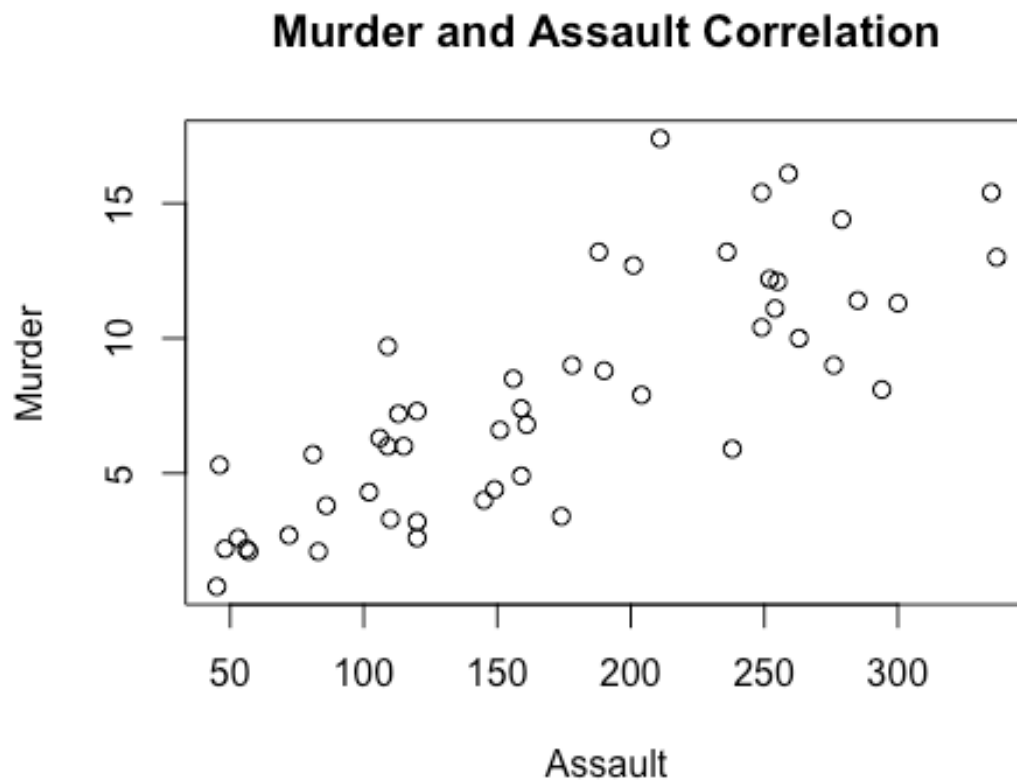
```
# pairs plot
```

```
pairs(USArrests, main = "Pairs Plot of USArrests")
```



```
#scatterplot
```

```
plot(Murder ~ Assault, data=USArrests, main="Murder and Assault Correlation")
```

Result:

=> Report a paragraph to summarize your findings from the plot! PAIRS PLOT: The scatter plots of Murder and Assault values show a positive linear pattern, meaning that the correlation between Murder and Assault is strong. The scatter plots of Murder and UrbanPop show a random pattern, meaning there is little to no correlation between them. The correlation between Murder and Rape values is quite strong due to the scatter plots showing a positive linear pattern. The scatter plots showing the relationship between Assault and Urban Pop show a weak correlation as the patterns are really scattered and random. The relationship between Assault and Rape values show a positive linear pattern, meaning the correlation is strong. The relationship between Urban Pop and Rape values show somewhat a positive linear pattern, meaning the correlation is quite strong as well.

Question 3

Download the housing data set from www.jaredlander.com and find out what explains the housing prices in New York City.

Note: Check your working directory to make sure that you can download the data into the data folder.

- a. Create your own descriptive statistics and aggregation tables to summarize the data set and find any meaningful results between different variables in the data set.

Head of the cleaned data set

```
head(housingData)
```

```
##   Neighborhood Market.Value.per.SqFt      Boro Year.Built
## 1   FINANCIAL          200.00 Manhattan    1920
## 2   FINANCIAL          242.76 Manhattan    1985
## 4   FINANCIAL          271.23 Manhattan    1930
## 5    TRIBECA          247.48 Manhattan    1985
## 6    TRIBECA          191.37 Manhattan    1986
## 7    TRIBECA          211.53 Manhattan    1985
```

Enter your code here!

```
agg_withlabels<-
```

```
aggregate(list(AvgMarketValuePerSqft=housingData$Market.Value.per.SqFt),list(
YearBuilt=housingData$Year.Built),mean)
```

```
print(agg_withlabels)
```

```
##      YearBuilt AvgMarketValuePerSqft
## 1         1825          76.36000
## 2         1836          273.77000
## 3         1853          152.79000
## 4         1860          159.64500
## 5         1874          111.17000
## 6         1875          166.05000
## 7         1879          194.52000
## 8         1881          109.70500
## 9         1883          172.10000
## 10        1890          113.28750
## 11        1891           72.83000
## 12        1892           95.21000
## 13        1893          168.85000
## 14        1894          110.62000
## 15        1895          151.77500
## 16        1896          117.26500
## 17        1897           40.83000
## 18        1898           83.25000
## 19        1899          108.16000
## 20        1900          137.55908
## 21        1901          172.36778
## 22        1902          167.62167
## 23        1903          147.97000
## 24        1904          123.09333
## 25        1905          187.76583
## 26        1906          169.03364
## 27        1907          173.80000
## 28        1908          150.35000
## 29        1909          135.23667
```

## 30	1910	147.36257
## 31	1911	179.76067
## 32	1912	159.51636
## 33	1913	175.93500
## 34	1914	160.29286
## 35	1915	147.08673
## 36	1916	128.20714
## 37	1917	73.87000
## 38	1918	181.84000
## 39	1919	63.11000
## 40	1920	145.30862
## 41	1921	122.39125
## 42	1922	118.33250
## 43	1923	115.47625
## 44	1924	165.94091
## 45	1925	147.51316
## 46	1926	148.36423
## 47	1927	131.63357
## 48	1928	153.68375
## 49	1929	106.32121
## 50	1930	142.28936
## 51	1931	129.51731
## 52	1932	91.74333
## 53	1933	40.97000
## 54	1934	203.80000
## 55	1935	176.23000
## 56	1936	46.04333
## 57	1937	51.77250
## 58	1938	99.23857
## 59	1939	93.65083
## 60	1940	154.89857
## 61	1941	111.83733
## 62	1942	128.38600
## 63	1947	113.13500
## 64	1948	186.25000
## 65	1949	44.98000
## 66	1950	141.96182
## 67	1951	132.98833
## 68	1952	97.95143
## 69	1954	81.56500
## 70	1955	130.17538
## 71	1956	178.42786
## 72	1957	127.24091
## 73	1958	159.77000
## 74	1959	108.62692
## 75	1960	104.91200
## 76	1961	106.63000
## 77	1962	129.26294
## 78	1963	152.82937
## 79	1964	103.15000

## 80	1965	121.01313
## 81	1966	79.94375
## 82	1967	91.94000
## 83	1968	126.76000
## 84	1969	157.28000
## 85	1970	214.59000
## 86	1971	57.60000
## 87	1972	185.72000
## 88	1973	196.75500
## 89	1974	124.42500
## 90	1975	201.26667
## 91	1977	161.32250
## 92	1978	254.69000
## 93	1979	155.71333
## 94	1980	161.74500
## 95	1981	175.96800
## 96	1982	151.30364
## 97	1983	114.79917
## 98	1984	179.48333
## 99	1985	182.66868
## 100	1986	157.62328
## 101	1987	142.14055
## 102	1988	126.43686
## 103	1989	109.25390
## 104	1990	99.31500
## 105	1991	145.76105
## 106	1992	83.92333
## 107	1993	55.45000
## 108	1994	73.13500
## 109	1995	75.77375
## 110	1996	152.36750
## 111	1997	137.41364
## 112	1998	138.25125
## 113	1999	145.93217
## 114	2000	165.47296
## 115	2001	124.74295
## 116	2002	117.92442
## 117	2003	121.56193
## 118	2004	113.79702
## 119	2005	122.70817
## 120	2006	119.73598
## 121	2007	134.12665
## 122	2008	144.34935
## 123	2009	96.52619
## 124	2010	90.36667

```

avg_perNeighborhood<-
aggregate(list(AvgMarketValuePerSqft=housingData$Market.Value.per.SqFt),list(
Neighborhood=housingData$Neighborhood),mean)
print(avg_perNeighborhood)

```

##	Neighborhood	AvgMarketValuePerSqft
## 1	ALPHABET CITY	148.35500
## 2	ARROCHAR-SHORE ACRES	57.75000
## 3	ASTORIA	91.48167
## 4	BATH BEACH	70.34000
## 5	BAY RIDGE	68.03500
## 6	BAYSIDE	71.42111
## 7	BEDFORD PARK/NORWOOD	38.24500
## 8	BEDFORD STUYVESANT	83.24172
## 9	BELMONT	56.45000
## 10	BENSONHURST	71.70429
## 11	BERGEN BEACH	73.27000
## 12	BOERUM HILL	96.57600
## 13	BOROUGH PARK	64.10857
## 14	BRIARWOOD	75.36250
## 15	BRIGHTON BEACH	81.91429
## 16	BRONX-UNKNOWN	32.06500
## 17	BRONXDALE	28.94333
## 18	BROOKLYN HEIGHTS	114.11778
## 19	BUSH TERMINAL	60.95000
## 20	BUSHWICK	76.13500
## 21	CANARSIE	46.58000
## 22	CARROLL GARDENS	93.40556
## 23	CHELSEA	215.94932
## 24	CHINATOWN	154.17952
## 25	CITY ISLAND	40.83000
## 26	CIVIC CENTER	174.06696
## 27	CLINTON	176.70032
## 28	CLINTON HILL	88.97385
## 29	COBBLE HILL	120.69800
## 30	COBBLE HILL-WEST	85.71125
## 31	COLLEGE POINT	65.05000
## 32	CONEY ISLAND	55.05750
## 33	CORONA	94.20706
## 34	CROWN HEIGHTS	64.26286
## 35	DOWNTOWN-FULTON FERRY	103.26857
## 36	DOWNTOWN-FULTON MALL	132.42500
## 37	DOWNTOWN-METROTECH	122.48000
## 38	DYKER HEIGHTS	68.36000
## 39	EAST NEW YORK	36.99167
## 40	EAST TREMONT	72.33333
## 41	EAST VILLAGE	207.46115
## 42	ELMHURST	69.80564
## 43	FAR ROCKAWAY	74.88500
## 44	FASHION	194.81067
## 45	FINANCIAL	199.30917
## 46	FLATBUSH-CENTRAL	65.71167
## 47	FLATBUSH-LEFFERTS GARDEN	46.27000
## 48	FLATBUSH-NORTH	54.00000
## 49	FLATIRON	223.30311

## 50	FLUSHING MEADOW PARK	58.59000
## 51	FLUSHING-NORTH	80.16992
## 52	FLUSHING-SOUTH	89.62750
## 53	FOREST HILLS	70.20706
## 54	FORT GREENE	81.76900
## 55	GLENDALE	57.39667
## 56	GOWANUS	82.45333
## 57	GRAMERCY	188.68471
## 58	GRANT CITY	47.60000
## 59	GRAVESEND	75.63526
## 60	GREAT KILLS	33.74000
## 61	GREENPOINT	86.18053
## 62	GREENWICH VILLAGE-CENTRAL	142.57767
## 63	GREENWICH VILLAGE-WEST	202.13667
## 64	GRYMES HILL	50.09000
## 65	HAMMELS	139.07200
## 66	HARLEM-CENTRAL	102.79106
## 67	HARLEM-EAST	139.93972
## 68	HARLEM-UPPER	79.25667
## 69	HARLEM-WEST	95.20500
## 70	HIGHBRIDGE/MORRIS HEIGHTS	61.82000
## 71	HILLCREST	53.95000
## 72	HOLLIS	109.56000
## 73	HOWARD BEACH	55.06000
## 74	INWOOD	62.05500
## 75	JACKSON HEIGHTS	47.79238
## 76	JAMAICA	104.76600
## 77	JAMAICA ESTATES	79.69500
## 78	JAVITS CENTER	125.09000
## 79	KENSINGTON	56.87500
## 80	KEW GARDENS	69.64300
## 81	KINGSBRIDGE HTS/UNIV HTS	23.86000
## 82	KINGSBRIDGE/JEROME PARK	58.37800
## 83	KIPS BAY	191.31769
## 84	LITTLE ITALY	142.52308
## 85	LITTLE NECK	65.85000
## 86	LONG ISLAND CITY	108.16667
## 87	LOWER EAST SIDE	173.56262
## 88	MADISON	71.26000
## 89	MANHATTAN VALLEY	111.30043
## 90	MASPETH	53.32750
## 91	MIDDLE VILLAGE	78.35857
## 92	MIDTOWN CBD	234.36154
## 93	MIDTOWN EAST	211.04750
## 94	MIDTOWN WEST	222.06489
## 95	MIDWOOD	79.50273
## 96	MORNINGSIDE HEIGHTS	74.63000
## 97	MORRIS PARK/VAN NEST	26.90000
## 98	MORRISANIA/LONGWOOD	44.21250
## 99	MOTT HAVEN/PORT MORRIS	30.96000

## 100	MURRAY HILL	206.26795
## 101	NEW BRIGHTON	41.47667
## 102	NEW BRIGHTON-ST. GEORGE	41.06000
## 103	NEW SPRINGVILLE	40.47000
## 104	OAKLAND GARDENS	66.94000
## 105	OCEAN HILL	37.92900
## 106	OCEAN PARKWAY-NORTH	76.51111
## 107	OCEAN PARKWAY-SOUTH	75.08000
## 108	OZONE PARK	54.10000
## 109	PARK SLOPE	88.01774
## 110	PARK SLOPE SOUTH	95.84200
## 111	PARKCHESTER	32.67500
## 112	PELHAM PARKWAY SOUTH	30.55000
## 113	PROSPECT HEIGHTS	79.16200
## 114	REGO PARK	62.13630
## 115	RIDGEWOOD	64.28667
## 116	RIVERDALE	57.10176
## 117	ROCKAWAY PARK	88.13600
## 118	SCHUYLerville/PELHAM BAY	49.68000
## 119	SHEEPSHEAD BAY	79.79704
## 120	SILVER LAKE	35.80500
## 121	SOHO	162.72473
## 122	SOUNDVIEW	43.40333
## 123	SOUTH OZONE PARK	40.78000
## 124	SOUTHBRIDGE	159.53333
## 125	SUNNYSIDE	61.61818
## 126	SUNSET PARK	80.58348
## 127	THROGS NECK	53.70667
## 128	TOMPKINSVILLE	35.81000
## 129	TRIBECA	180.18473
## 130	UPPER EAST SIDE (59-79)	216.83715
## 131	UPPER EAST SIDE (79-96)	202.45179
## 132	UPPER EAST SIDE (96-110)	167.41600
## 133	UPPER WEST SIDE (59-79)	200.24391
## 134	UPPER WEST SIDE (79-96)	171.84515
## 135	UPPER WEST SIDE (96-116)	134.09353
## 136	WASHINGTON HEIGHTS LOWER	65.29600
## 137	WASHINGTON HEIGHTS UPPER	93.50833
## 138	WEST NEW BRIGHTON	39.69000
## 139	WHITESTONE	72.90000
## 140	WILLIAMSBRIDGE	42.46000
## 141	WILLIAMSBURG-CENTRAL	79.97017
## 142	WILLIAMSBURG-EAST	84.32605
## 143	WILLIAMSBURG-NORTH	84.10577
## 144	WILLIAMSBURG-SOUTH	82.27618
## 145	WINDSOR TERRACE	70.21200
## 146	WOODHAVEN	38.61000
## 147	WOODSIDE	80.52625
## 148	WYCKOFF HEIGHTS	84.93000

```
total_sum_eachNeighborhood<-
aggregate(list(TotalSumMarketValuePerSqFt=housingData$Market.Value.per.SqFt),
list(Neighborhood=housingData$Neighborhood), sum)
print(total_sum_eachNeighborhood)
```

	Neighborhood	TotalSumMarketValuePerSqFt
## 1	ALPHABET CITY	3560.52
## 2	ARROCHAR-SHORE ACRES	57.75
## 3	ASTORIA	2744.45
## 4	BATH BEACH	422.04
## 5	BAY RIDGE	544.28
## 6	BAYSIDE	642.79
## 7	BEDFORD PARK/NORWOOD	76.49
## 8	BEDFORD STUYVESANT	4828.02
## 9	BELMONT	56.45
## 10	BENSONHURST	501.93
## 11	BERGEN BEACH	73.27
## 12	BOERUM HILL	1448.64
## 13	BOROUGH PARK	2243.80
## 14	BRIARWOOD	301.45
## 15	BRIGHTON BEACH	1720.20
## 16	BRONX-UNKNOWN	64.13
## 17	BRONXDALE	86.83
## 18	BROOKLYN HEIGHTS	1027.06
## 19	BUSH TERMINAL	60.95
## 20	BUSHWICK	152.27
## 21	CANARSIE	186.32
## 22	CARROLL GARDENS	840.65
## 23	CHELSEA	19003.54
## 24	CHINATOWN	3237.77
## 25	CITY ISLAND	40.83
## 26	CIVIC CENTER	4003.54
## 27	CLINTON	5477.71
## 28	CLINTON HILL	1156.66
## 29	COBBLE HILL	603.49
## 30	COBBLE HILL-WEST	685.69
## 31	COLLEGE POINT	195.15
## 32	CONEY ISLAND	220.23
## 33	CORONA	1601.52
## 34	CROWN HEIGHTS	899.68
## 35	DOWNTOWN-FULTON FERRY	1445.76
## 36	DOWNTOWN-FULTON MALL	264.85
## 37	DOWNTOWN-METROTECH	367.44
## 38	DYKER HEIGHTS	68.36
## 39	EAST NEW YORK	221.95
## 40	EAST TREMONT	217.00
## 41	EAST VILLAGE	5393.99
## 42	ELMHURST	3839.31
## 43	FAR ROCKAWAY	299.54
## 44	FASHION	2922.16

## 45	FINANCIAL	7175.13
## 46	FLATBUSH-CENTRAL	394.27
## 47	FLATBUSH-LEFFERTS GARDEN	46.27
## 48	FLATBUSH-NORTH	432.00
## 49	FLATIRON	10048.64
## 50	FLUSHING MEADOW PARK	58.59
## 51	FLUSHING-NORTH	10662.60
## 52	FLUSHING-SOUTH	717.02
## 53	FOREST HILLS	1193.52
## 54	FORT GREENE	817.69
## 55	GLENDALE	172.19
## 56	GOWANUS	247.36
## 57	GRAMERCY	3207.64
## 58	GRANT CITY	95.20
## 59	GRAVESEND	1437.07
## 60	GREAT KILLS	33.74
## 61	GREENPOINT	1637.43
## 62	GREENWICH VILLAGE-CENTRAL	8554.66
## 63	GREENWICH VILLAGE-WEST	11521.79
## 64	GRYMES HILL	50.09
## 65	HAMMELS	695.36
## 66	HARLEM-CENTRAL	9662.36
## 67	HARLEM-EAST	5037.83
## 68	HARLEM-UPPER	951.08
## 69	HARLEM-WEST	190.41
## 70	HIGHBRIDGE/MORRIS HEIGHTS	61.82
## 71	HILLCREST	53.95
## 72	HOLLIS	109.56
## 73	HOWARD BEACH	275.30
## 74	INWOOD	124.11
## 75	JACKSON HEIGHTS	1003.64
## 76	JAMAICA	523.83
## 77	JAMAICA ESTATES	159.39
## 78	JAVITS CENTER	125.09
## 79	KENSINGTON	113.75
## 80	KEW GARDENS	696.43
## 81	KINGSBRIDGE HTS/UNIV HTS	23.86
## 82	KINGSBRIDGE/JEROME PARK	291.89
## 83	KIPS BAY	2487.13
## 84	LITTLE ITALY	1852.80
## 85	LITTLE NECK	65.85
## 86	LONG ISLAND CITY	2596.00
## 87	LOWER EAST SIDE	7289.63
## 88	MADISON	1353.94
## 89	MANHATTAN VALLEY	2559.91
## 90	MASPETH	213.31
## 91	MIDDLE VILLAGE	548.51
## 92	MIDTOWN CBD	3046.70
## 93	MIDTOWN EAST	11818.66
## 94	MIDTOWN WEST	10437.05

## 95	MIDWOOD	874.53
## 96	MORNINGSIDE HEIGHTS	74.63
## 97	MORRIS PARK/VAN NEST	26.90
## 98	MORRISANIA/LONGWOOD	707.40
## 99	MOTT HAVEN/PORT MORRIS	30.96
## 100	MURRAY HILL	8044.45
## 101	NEW BRIGHTON	124.43
## 102	NEW BRIGHTON-ST. GEORGE	82.12
## 103	NEW SPRINGVILLE	364.23
## 104	OAKLAND GARDENS	66.94
## 105	OCEAN HILL	379.29
## 106	OCEAN PARKWAY-NORTH	688.60
## 107	OCEAN PARKWAY-SOUTH	75.08
## 108	OZONE PARK	54.10
## 109	PARK SLOPE	2728.55
## 110	PARK SLOPE SOUTH	958.42
## 111	PARKCHESTER	65.35
## 112	PELHAM PARKWAY SOUTH	30.55
## 113	PROSPECT HEIGHTS	395.81
## 114	REGO PARK	1677.68
## 115	RIDGEWOOD	192.86
## 116	RIVERDALE	970.73
## 117	ROCKAWAY PARK	440.68
## 118	SCHUYLERVILLE/PELHAM BAY	49.68
## 119	SHEEPSHEAD BAY	2154.52
## 120	SILVER LAKE	71.61
## 121	SOHO	8949.86
## 122	SOUNDVIEW	260.42
## 123	SOUTH OZONE PARK	40.78
## 124	SOUTHBRIDGE	1435.80
## 125	SUNNYSIDE	677.80
## 126	SUNSET PARK	1853.42
## 127	THROGS NECK	161.12
## 128	TOMPKINSVILLE	35.81
## 129	TRIBECA	13333.67
## 130	UPPER EAST SIDE (59-79)	26670.97
## 131	UPPER EAST SIDE (79-96)	15791.24
## 132	UPPER EAST SIDE (96-110)	837.08
## 133	UPPER WEST SIDE (59-79)	17421.22
## 134	UPPER WEST SIDE (79-96)	11341.78
## 135	UPPER WEST SIDE (96-116)	4559.18
## 136	WASHINGTON HEIGHTS LOWER	326.48
## 137	WASHINGTON HEIGHTS UPPER	561.05
## 138	WEST NEW BRIGHTON	39.69
## 139	WHITESTONE	145.80
## 140	WILLIAMSBRIDGE	84.92
## 141	WILLIAMSBURG-CENTRAL	4798.21
## 142	WILLIAMSBURG-EAST	3204.39
## 143	WILLIAMSBURG-NORTH	2186.75
## 144	WILLIAMSBURG-SOUTH	2797.39

## 145	WINDSOR TERRACE	351.06
## 146	WOODHAVEN	154.44
## 147	WOODSIDE	644.21
## 148	WYCKOFF HEIGHTS	254.79

#MeaningfulResults? The years with a really high average market value per square foot probably means that those years were when the rich neighborhoods were built. As for the average market value for each Neighborhood, the cost for living of neighborhoods like financial, Chelsea, and Downtown are really high and expensive.

- b. Create multiple plots to demonstrates the correlations between different variables. Remember to label all axes and give title to each graph.

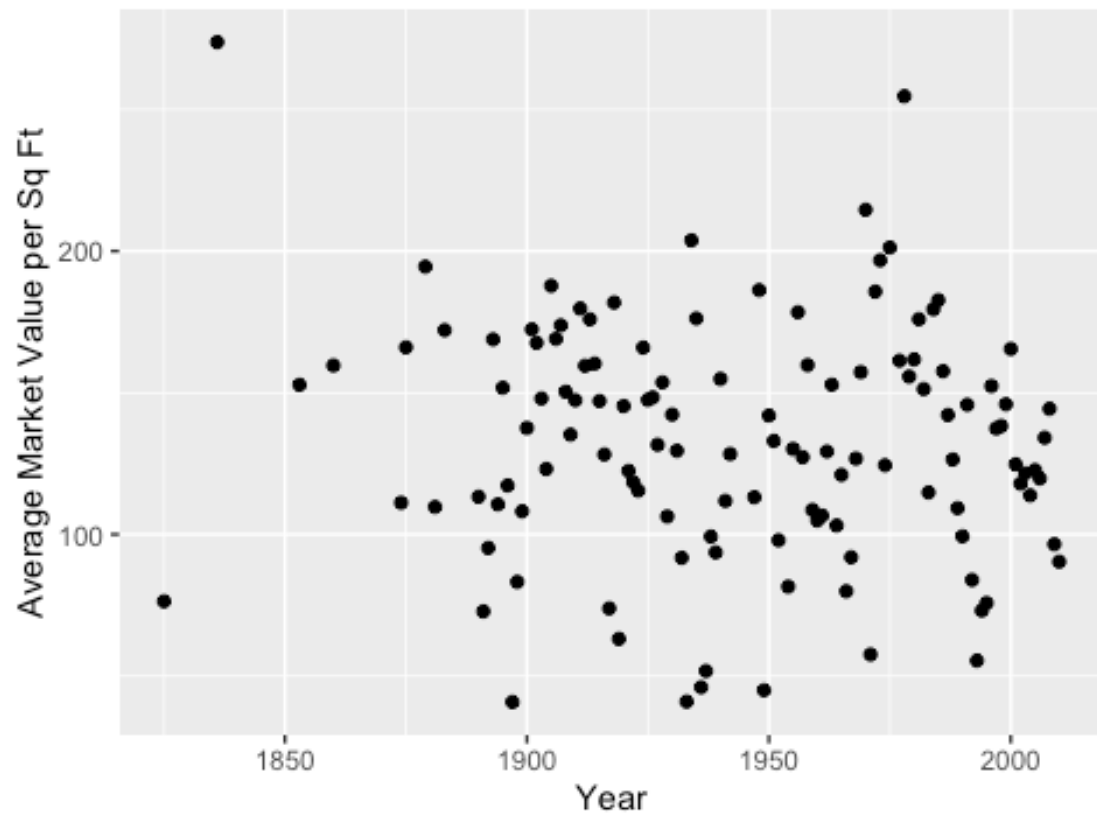
Enter your code here!

```
agg_withlabels<-
aggregate(list(AvgMarketValuePerSqft=housingData$Market.Value.per.SqFt),list(
YearBuilt=housingData$Year.Built),mean)

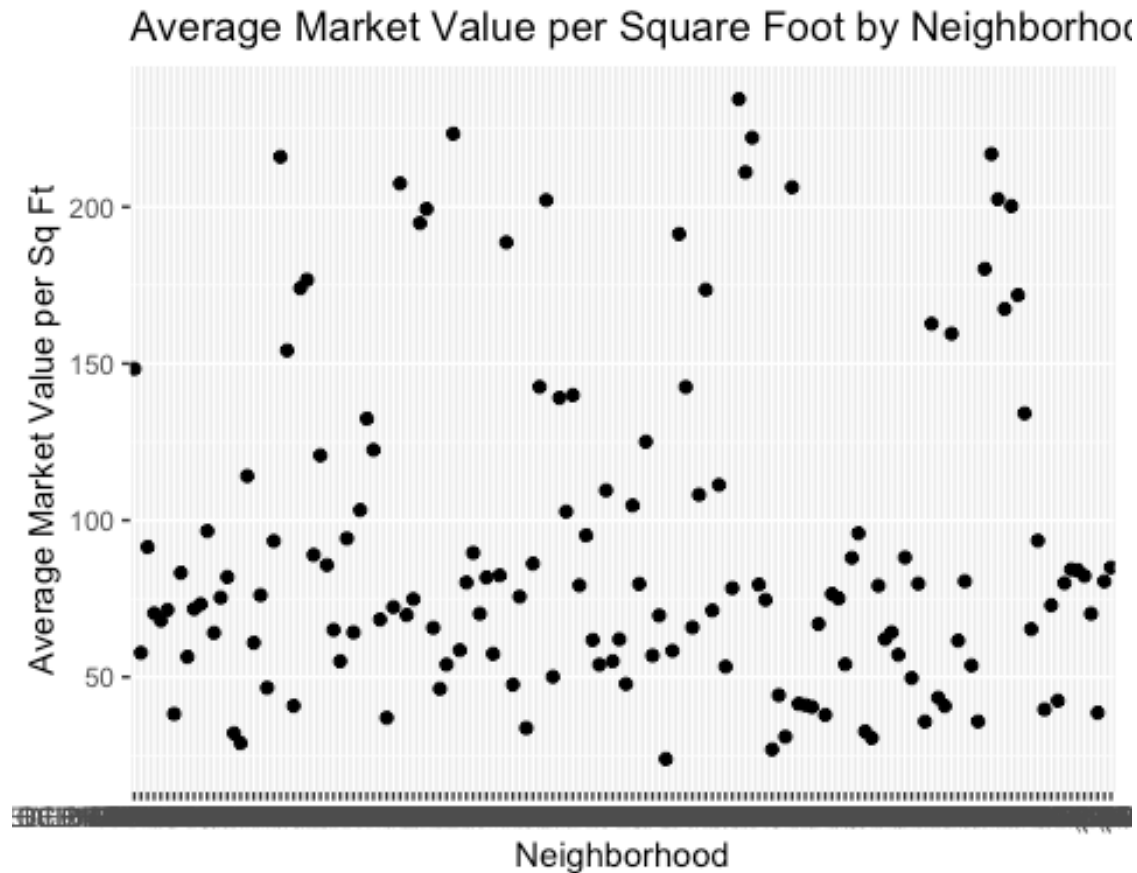
avg_perNeighborhood<-
aggregate(list(AvgMarketValuePerSqft=housingData$Market.Value.per.SqFt),list(
Neighborhood=housingData$Neighborhood),mean)

ggplot(agg_withlabels, aes(x = YearBuilt, y = AvgMarketValuePerSqft)) +
  geom_point() +
  labs(
    title = "Average Market Value per Square Foot by Year",
    x = "Year",
    y = "Average Market Value per Sq Ft"
  )
```

Average Market Value per Square Foot by Year



```
ggplot(avg_perNeighborhood, aes(x = Neighborhood, y = AvgMarketValuePerSqft))  
+  
  geom_point() +  
  labs(  
    title = "Average Market Value per Square Foot by Neighborhood",  
    x = "Neighborhood",  
    y = "Average Market Value per Sq Ft"  
  )
```



c. Write a summary about your findings from this exercise.

=> Enter your answer here! Overall, this exercise helped me learn how to make tables using summarize and aggregate functions as well making graphs/plots derived from the data of the tables. I had to come up with descriptive statistics (such as mean) of values for each group. I also had to interpret what the plot graphs show and describe the correlation between certain variables, which is an essential part to data analyzing. In addition, I learned a simple way to get rid of all missing values (NA values) on R which is using the `na.omit()` function. That function will be highly useful to simply just get rid of all missing values that are unnecessary to analyze.