

Chapter 1

```
knitr::opts_knit$set(root.dir = '~/Documents/Linear-Model-using-R')
```

Chapter 1 Introduction

1.1 Before you start

1.2 Initial Data Analysis

```
# install.packages("faraway")  
library(faraway)
```

import the dataset and have a first look at it

```
# import the dataset called `pima` from the package  
data(pima, package="faraway")  
head(pima)
```

```
##   pregnant glucose diastolic triceps insulin   bmi diabetes age test  
## 1         6     148         72      35         0 33.6    0.627  50    1  
## 2         1      85         66      29         0 26.6    0.351  31    0  
## 3         8     183         64       0         0 23.3    0.672  32    1  
## 4         1      89         66      23        94 28.1    0.167  21    0  
## 5         0     137         40      35       168 43.1    2.288  33    1  
## 6         5     116         74       0         0 25.6    0.201  30    0
```

```
# alternative way to import data  
# makes all data and functions that are included in the package available  
require(faraway)  
head(pima)
```

```
##   pregnant glucose diastolic triceps insulin   bmi diabetes age test  
## 1         6     148         72      35         0 33.6    0.627  50    1  
## 2         1      85         66      29         0 26.6    0.351  31    0  
## 3         8     183         64       0         0 23.3    0.672  32    1  
## 4         1      89         66      23        94 28.1    0.167  21    0  
## 5         0     137         40      35       168 43.1    2.288  33    1  
## 6         5     116         74       0         0 25.6    0.201  30    0
```

make numerical summaries

At this stage, we are looking for anything unusual or unexpected e.g. data-entry error

```
# obtain numerical summaries  
# summary function gives the usual univariate summary information  
summary(pima)
```

```
##   pregnant      glucose      diastolic      triceps
```

```
## Min. : 0.000 Min. : 0.0 Min. : 0.00 Min. : 0.00
## 1st Qu.: 1.000 1st Qu.: 99.0 1st Qu.: 62.00 1st Qu.: 0.00
## Median : 3.000 Median :117.0 Median : 72.00 Median :23.00
## Mean : 3.845 Mean :120.9 Mean : 69.11 Mean :20.54
## 3rd Qu.: 6.000 3rd Qu.:140.2 3rd Qu.: 80.00 3rd Qu.:32.00
## Max. :17.000 Max. :199.0 Max. :122.00 Max. :99.00
## insulin bmi diabetes age
## Min. : 0.0 Min. : 0.00 Min. :0.0780 Min. :21.00
## 1st Qu.: 0.0 1st Qu.:27.30 1st Qu.:0.2437 1st Qu.:24.00
## Median : 30.5 Median :32.00 Median :0.3725 Median :29.00
## Mean : 79.8 Mean :31.99 Mean :0.4719 Mean :33.24
## 3rd Qu.:127.2 3rd Qu.:36.60 3rd Qu.:0.6262 3rd Qu.:41.00
## Max. :846.0 Max. :67.10 Max. :2.4200 Max. :81.00
## test
## Min. :0.000
## 1st Qu.:0.000
## Median :0.000
## Mean :0.349
## 3rd Qu.:1.000
## Max. :1.000
```

We first look at the maximum value in variable **pregnant**: 17 months is not impossible although highly unlikely.

The 0 values in **diastolic** should not be correct as it means no blood pressure. (During the data analysis part, we need to have basic domain knowledge on the area or some common sense) So, we need to further investigate the variable by sorting them:

```
sort(pima$diastolic)
```

```
## [1] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
## [19] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 24
## [37] 30 30 38 40 44 44 44 46 46 48 48 48 48 48 50 50 50
## [55] 50 50 50 50 50 50 50 50 50 50 52 52 52 52 52 52 52
## [73] 52 52 52 54 54 54 54 54 54 54 54 54 54 54 55 55 56
## [91] 56 56 56 56 56 56 56 56 56 56 58 58 58 58 58 58 58
## [109] 58 58 58 58 58 58 58 58 58 58 58 58 58 58 60 60 60
## [127] 60 60 60 60 60 60 60 60 60 60 60 60 60 60 60 60 60
## [145] 60 60 60 60 60 60 60 60 60 60 60 60 60 60 61 62 62
## [163] 62 62 62 62 62 62 62 62 62 62 62 62 62 62 62 62 62
## [181] 62 62 62 62 62 62 62 62 62 62 62 62 62 62 64 64 64
## [199] 64 64 64 64 64 64 64 64 64 64 64 64 64 64 64 64 64
## [217] 64 64 64 64 64 64 64 64 64 64 64 64 64 64 64 64 64
## [235] 64 64 65 65 65 65 65 65 65 65 66 66 66 66 66 66 66
## [253] 66 66 66 66 66 66 66 66 66 66 66 66 66 66 66 66 66
## [271] 66 66 66 68 68 68 68 68 68 68 68 68 68 68 68 68 68
## [289] 68 68 68 68 68 68 68 68 68 68 68 68 68 68 68 68 68
## [307] 68 68 68 68 68 68 68 68 68 68 68 68 68 70 70 70 70
## [325] 70 70 70 70 70 70 70 70 70 70 70 70 70 70 70 70 70
## [343] 70 70 70 70 70 70 70 70 70 70 70 70 70 70 70 70 70
## [361] 70 70 70 70 70 70 70 70 70 70 70 70 70 70 72 72 72
## [379] 72 72 72 72 72 72 72 72 72 72 72 72 72 72 72 72 72
## [397] 72 72 72 72 72 72 72 72 72 72 72 72 72 72 72 72 72
## [415] 72 72 72 72 72 74 74 74 74 74 74 74 74 74 74 74 74
## [433] 74 74 74 74 74 74 74 74 74 74 74 74 74 74 74 74 74
## [451] 74 74 74 74 74 74 74 74 74 74 74 74 74 74 74 74 74
```

```
## [469] 74 74 74 75 75 75 75 75 75 75 75 76 76 76 76 76 76
## [487] 76 76 76 76 76 76 76 76 76 76 76 76 76 76 76 76 76
## [505] 76 76 76 76 76 76 76 76 76 76 76 76 76 78 78 78 78
## [523] 78 78 78 78 78 78 78 78 78 78 78 78 78 78 78 78 78
## [541] 78 78 78 78 78 78 78 78 78 78 78 78 78 78 78 78 78
## [559] 78 78 78 78 78 80 80 80 80 80 80 80 80 80 80 80 80
## [577] 80 80 80 80 80 80 80 80 80 80 80 80 80 80 80 80 80
## [595] 80 80 80 80 80 80 80 80 80 80 82 82 82 82 82 82 82
## [613] 82 82 82 82 82 82 82 82 82 82 82 82 82 82 82 82 82
## [631] 82 82 82 84 84 84 84 84 84 84 84 84 84 84 84 84 84
## [649] 84 84 84 84 84 84 84 84 84 85 85 85 85 85 85 86 86
## [667] 86 86 86 86 86 86 86 86 86 86 86 86 86 86 86 86 88
## [685] 88 88 88 88 88 88 88 88 88 88 88 88 88 88 88 88 88
## [703] 88 88 88 88 88 88 90 90 90 90 90 90 90 90 90 90 90
## [721] 90 90 90 90 90 90 90 90 90 90 90 92 92 92 92 92 92
## [739] 94 94 94 94 94 94 95 96 96 96 96 98 98 98 100 100 102
## [757] 104 104 106 106 106 108 108 110 110 110 114 122
```

From the data, it is obvious that 35 entries have value 0, which probably indicates that these 0s are used to indicate missing values. If we don't change the correct form for these missing values, these values may affect the analysis. So, we can convert these 0s to NA inferring that these values are missing.

Thus, we set all 0s in diastolic, glucose, triceps, insulin and bmi to NA.

```
# convert all the 0 values in 5 variables to NA
pima$diastolic[pima$diastolic==0] <- NA
pima$glucose[pima$glucose == 0] <- NA
pima$triceps[pima$triceps == 0] <- NA
pima$insulin[pima$insulin == 0] <- NA
pima$bmi[pima$bmi == 0] <- NA
```

Variable test is a categorical variable which means it is a factor variable.

```
# convert the `test` variable to a factor variable; otherwise, this variable will be treated as a
# quantitative variable
pima$test <- factor(pima$test)
# give a summary table for test variable
summary(pima$test)
```

```
##    0    1
## 500 268
```

We can convert the labels for factor variables to descriptive ones:

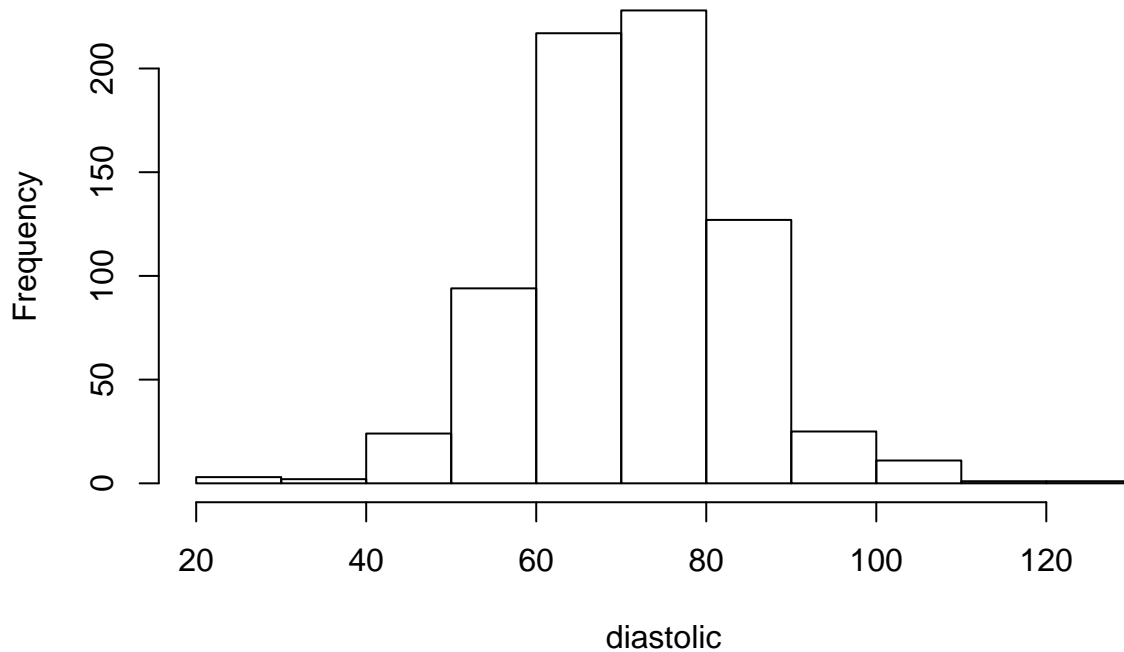
```
#convert the levels of `test` variable to descriptive labels
levels(pima$test) <- c("negative","positive")
summary(pima)
```

```
##      pregnant      glucose      diastolic      triceps
## Min.   : 0.000   Min.    : 44.0   Min.     : 24.00   Min.    : 7.00
## 1st Qu.: 1.000   1st Qu.: 99.0   1st Qu.: 64.00   1st Qu.:22.00
## Median : 3.000   Median :117.0   Median : 72.00   Median :29.00
## Mean   : 3.845   Mean    :121.7   Mean    : 72.41   Mean    :29.15
## 3rd Qu.: 6.000   3rd Qu.:141.0   3rd Qu.: 80.00   3rd Qu.:36.00
## Max.   :17.000   Max.    :199.0   Max.    :122.00   Max.    :99.00
##                NA's    :5      NA's    :35      NA's    :227
##      insulin      bmi      diabetes      age
## Min.   : 14.00   Min.    :18.20   Min.    :0.0780   Min.    :21.00
```

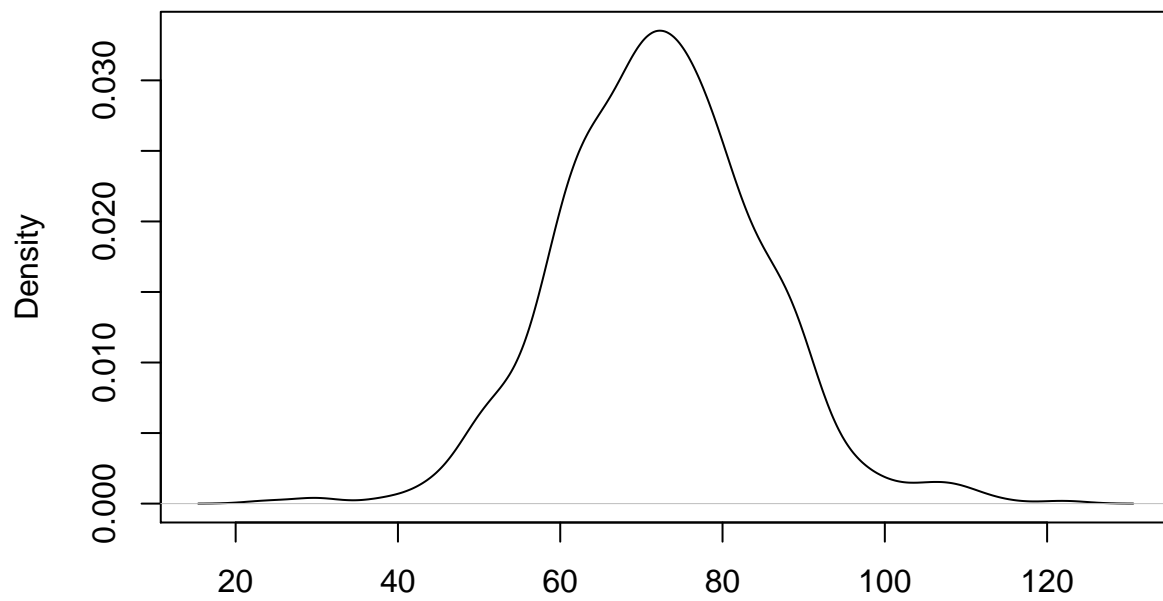
```
## 1st Qu.: 76.25    1st Qu.:27.50    1st Qu.:0.2437    1st Qu.:24.00
## Median :125.00    Median :32.30    Median :0.3725    Median :29.00
## Mean   :155.55    Mean   :32.46    Mean   :0.4719    Mean   :33.24
## 3rd Qu.:190.00    3rd Qu.:36.60    3rd Qu.:0.6262    3rd Qu.:41.00
## Max.   :846.00    Max.   :67.10    Max.   :2.4200    Max.   :81.00
## NA's   :374      NA's    :11
##      test
## negative:500
## positive:268
##
##
##
##
```

graphic descriptions

```
#histogram with bins specified by r
hist(pima$diastolic, xlab="diastolic",main="")
```

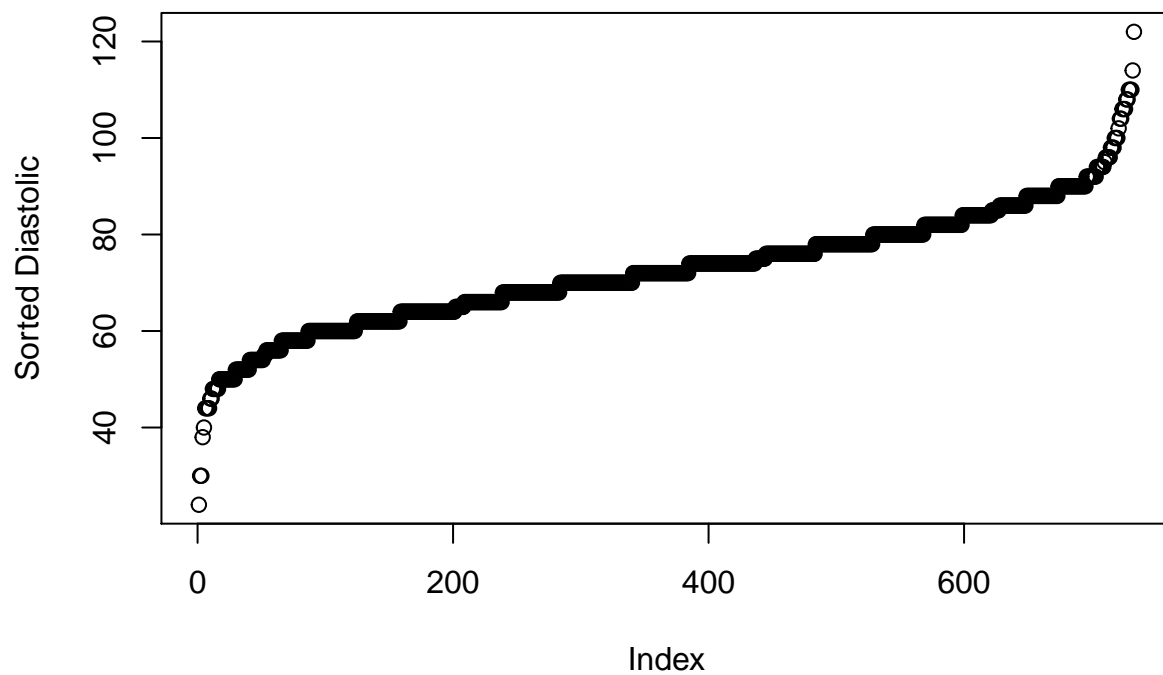


```
# kernel estimate(density plot) of histogram
plot(density(pima$diastolic, na.rm = T),main="")
```

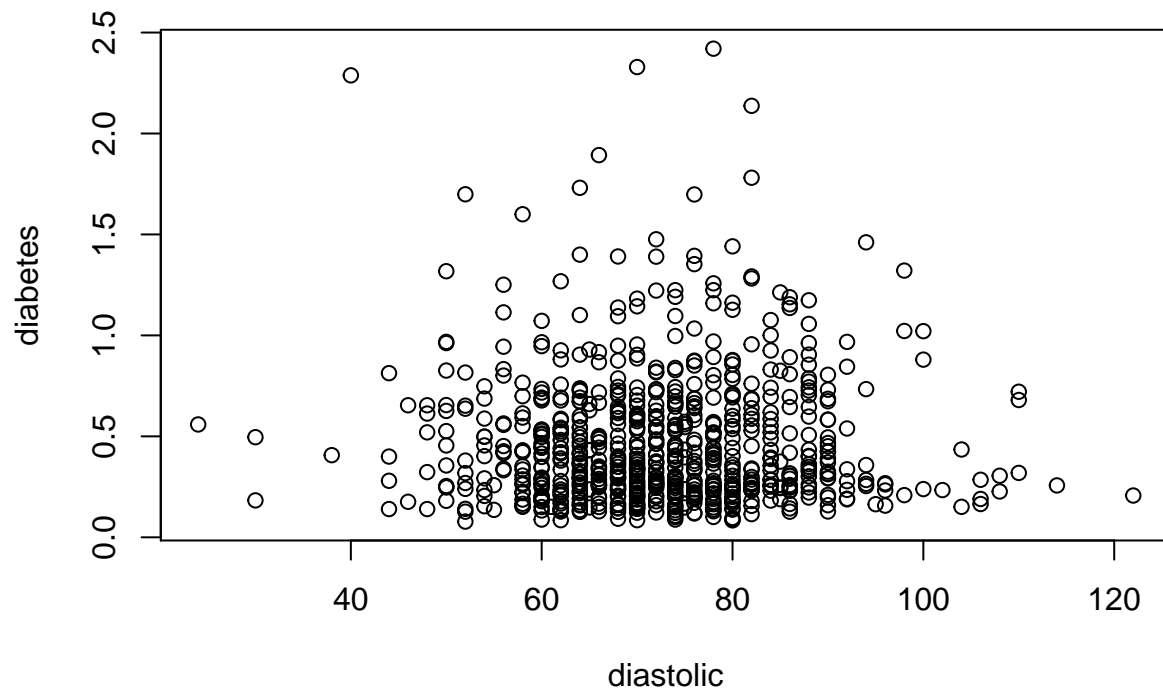


N = 733 Bandwidth = 2.872

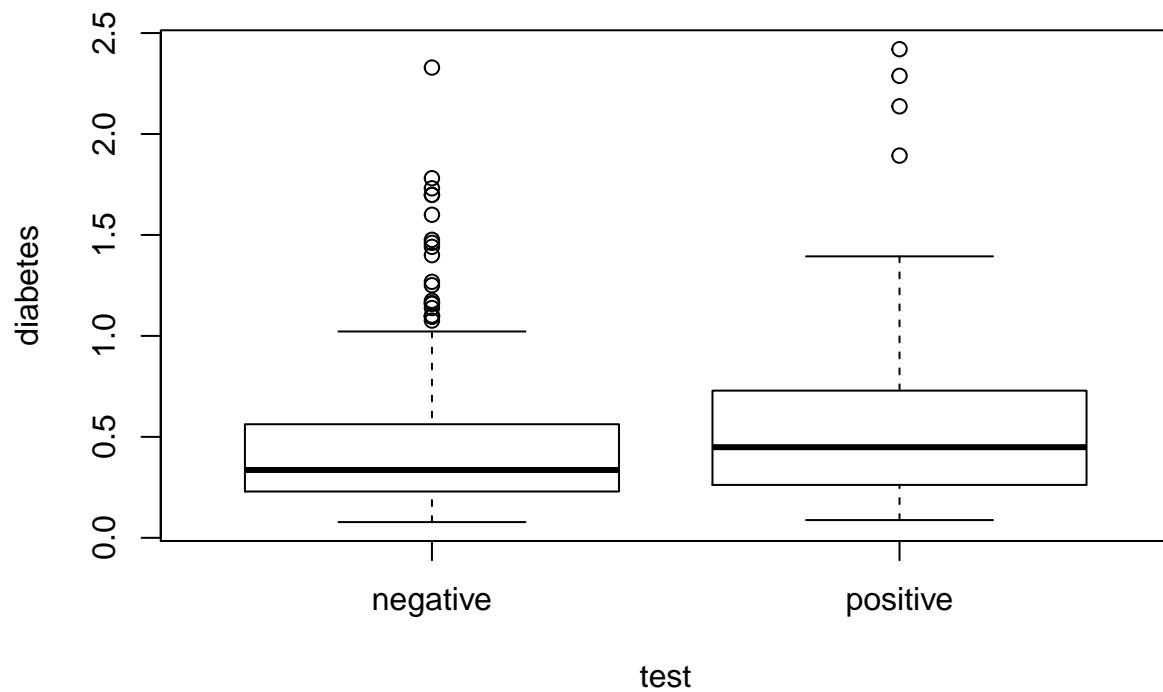
```
plot(sort(pima$diastolic),ylab="Sorted Diastolic")
```



```
# plot a scatterplot for diabetes against diastolic with the dataset pima  
plot(diabetes~diastolic,pima)
```



```
# plot two boxplots for diabetes against both positive and negative cases
plot(diabetes~test,pima)
```



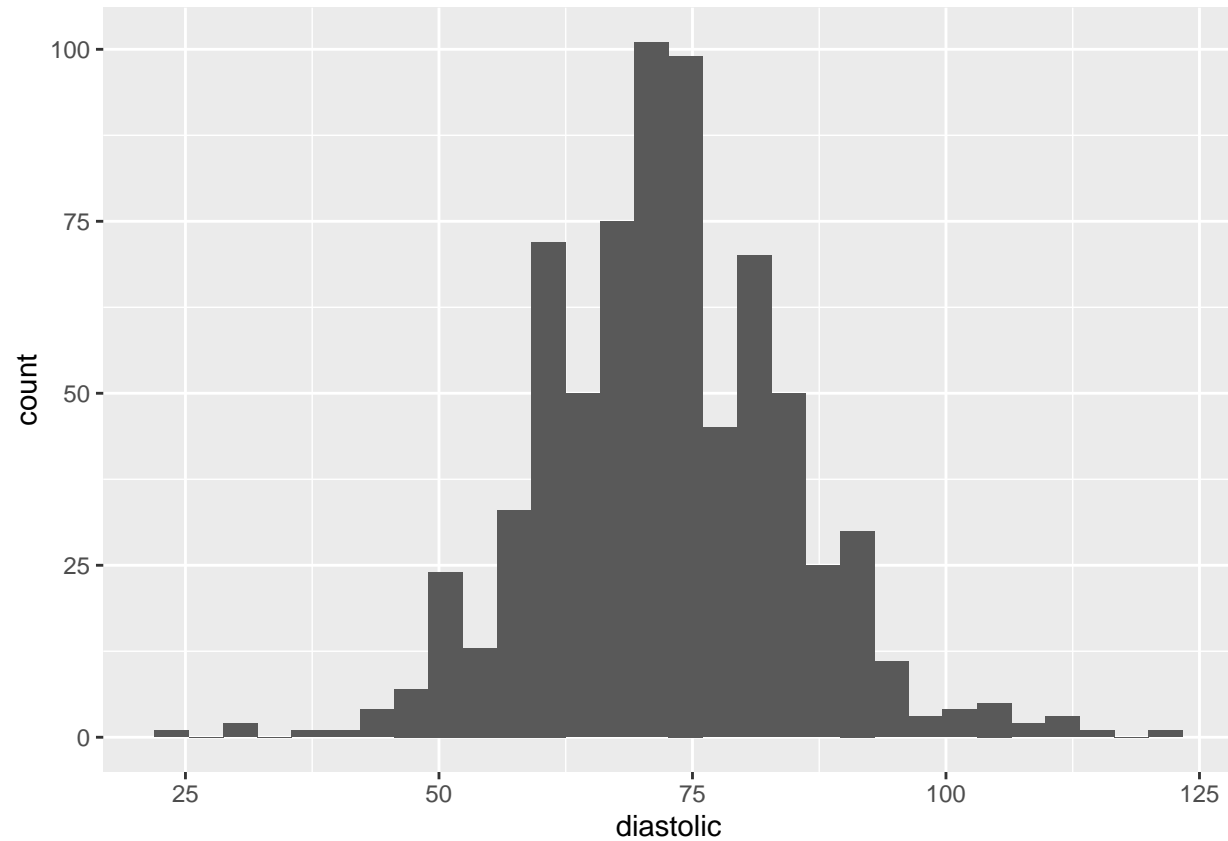
```
# install.packages("ggplot2")
require(ggplot2)
```

```
## Loading required package: ggplot2
```

```
# histogram  
ggplot(pima, aes(x=diastolic))+geom_histogram()
```

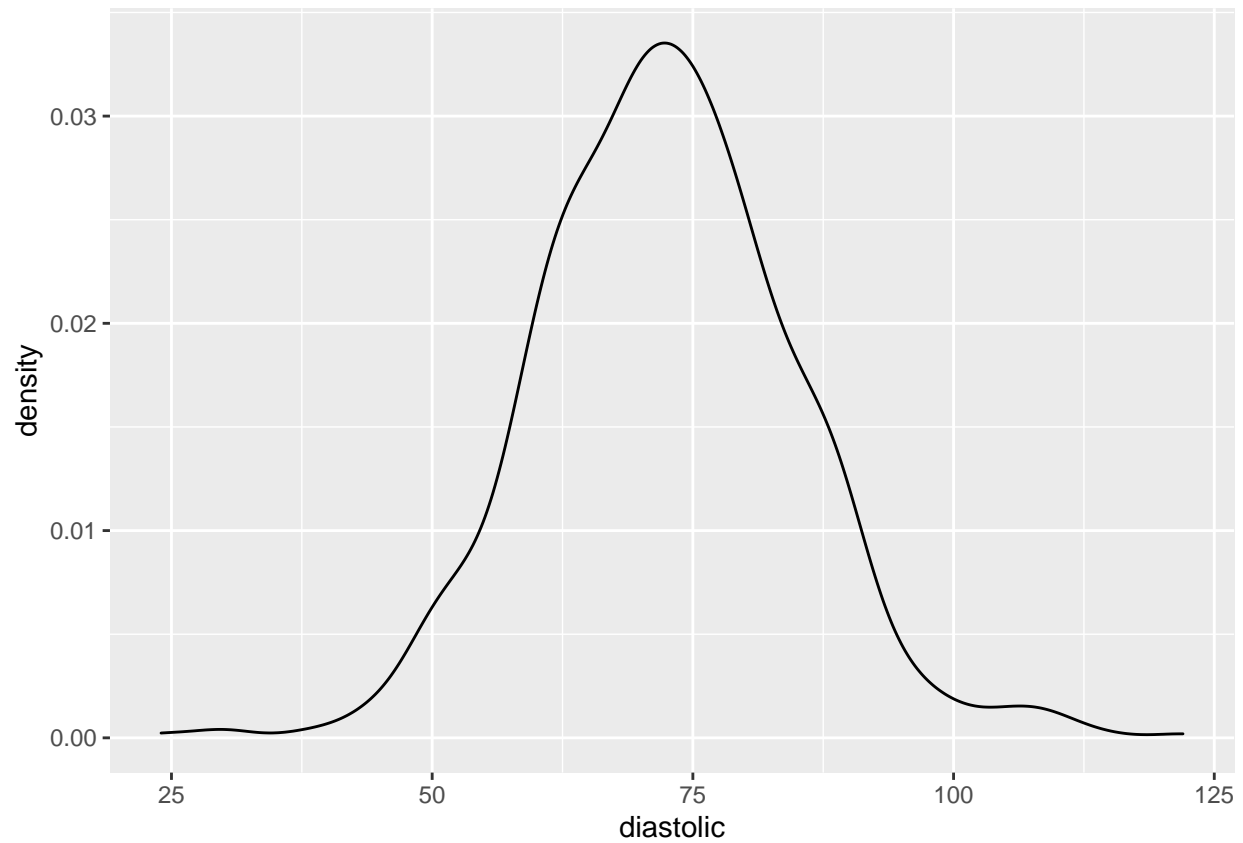
```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```

```
## Warning: Removed 35 rows containing non-finite values (stat_bin).
```



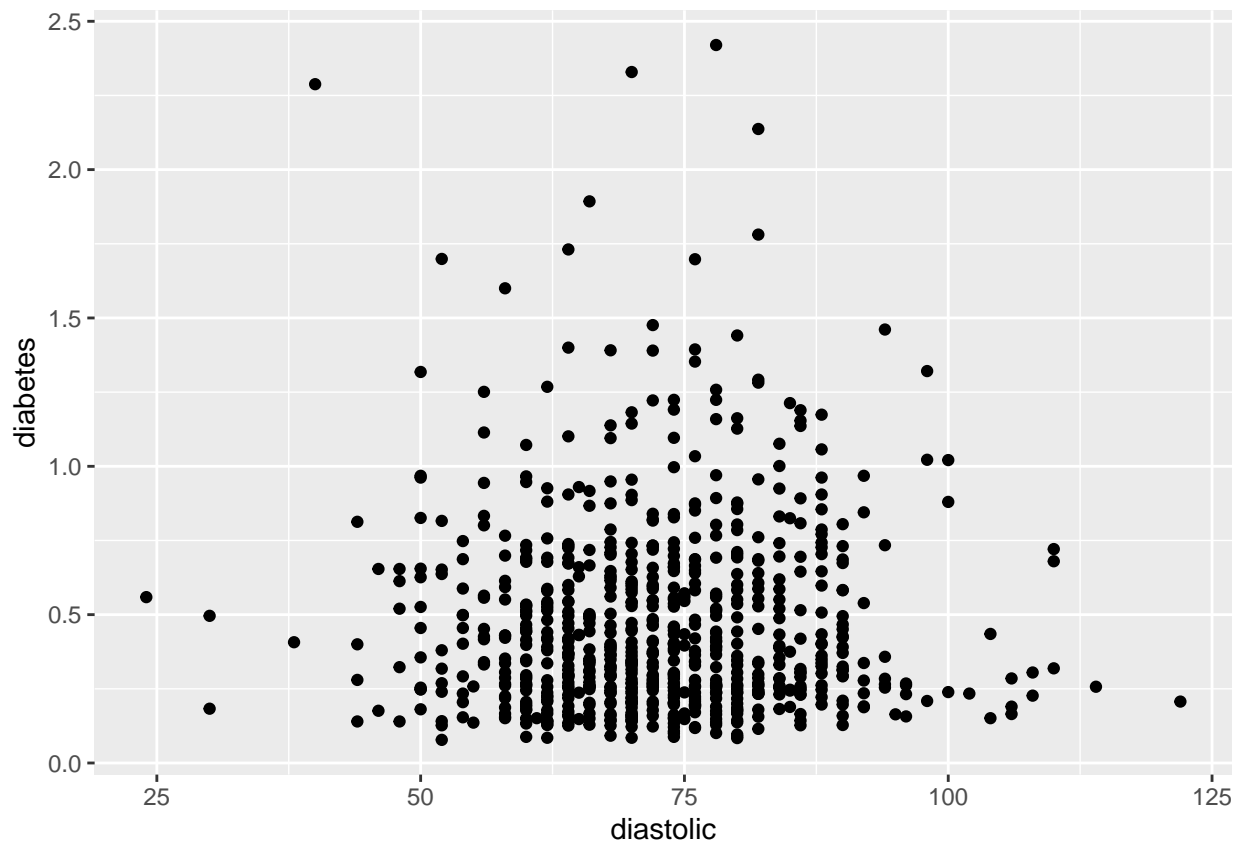
```
# kernel estimate(density plot)  
ggplot(pima, aes(x=diastolic))+geom_density()
```

```
## Warning: Removed 35 rows containing non-finite values (stat_density).
```



```
# scatterplot  
ggplot(pima, aes(x=diastolic,y=diabetes))+geom_point()
```

```
## Warning: Removed 35 rows containing missing values (geom_point).
```

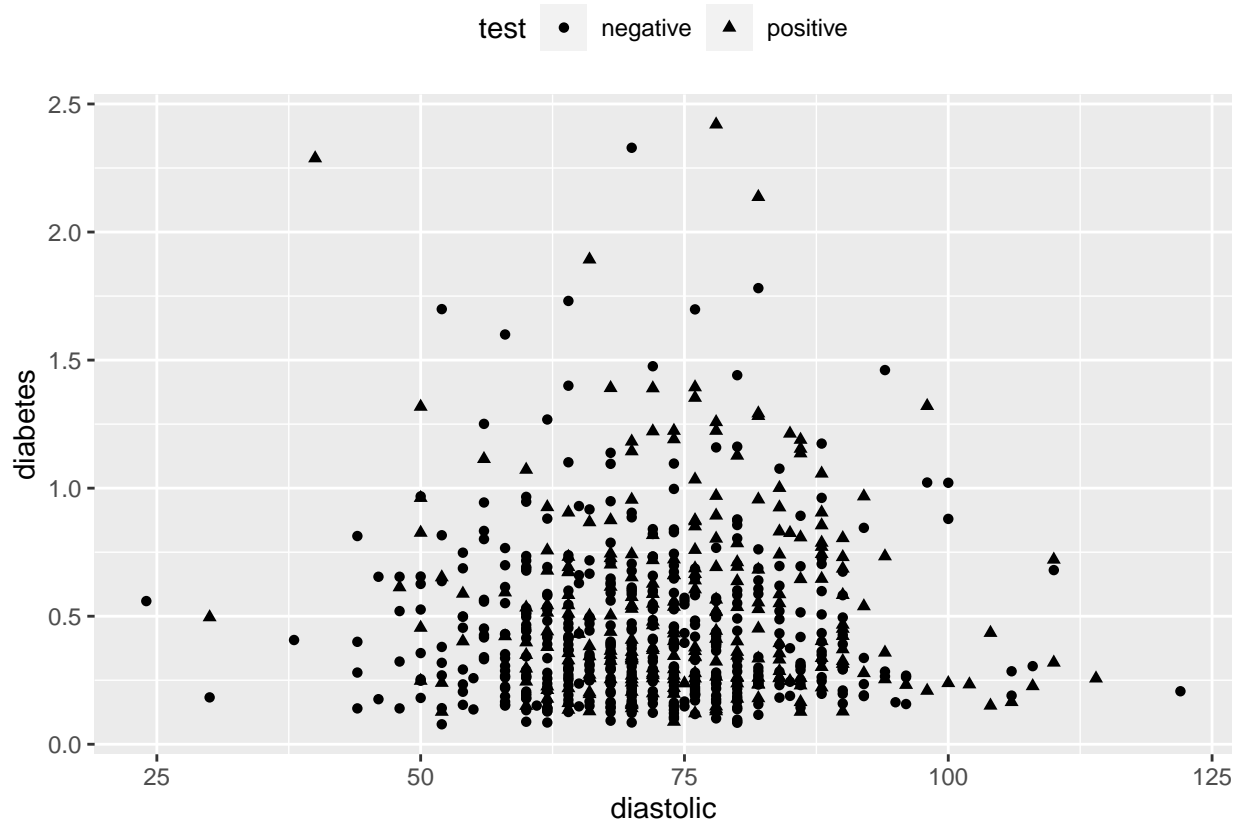



explanation of ggplot `ggplot(<dataset_name>, aes(x = <x_axis>, y = <y_axis>, colour=<colour_name>, ...))+ <geom_plots()>+theme()+facet_grid()`

ggplot arguments: - dataset - aesthetic: specify x-axis, y-axis, shape of points, colour of graph, etc - geom_plots: different sorts of plots - theme: specify options on appearance of the plot - facet_grid: form a matrix of panels defined by row and column faceting variables

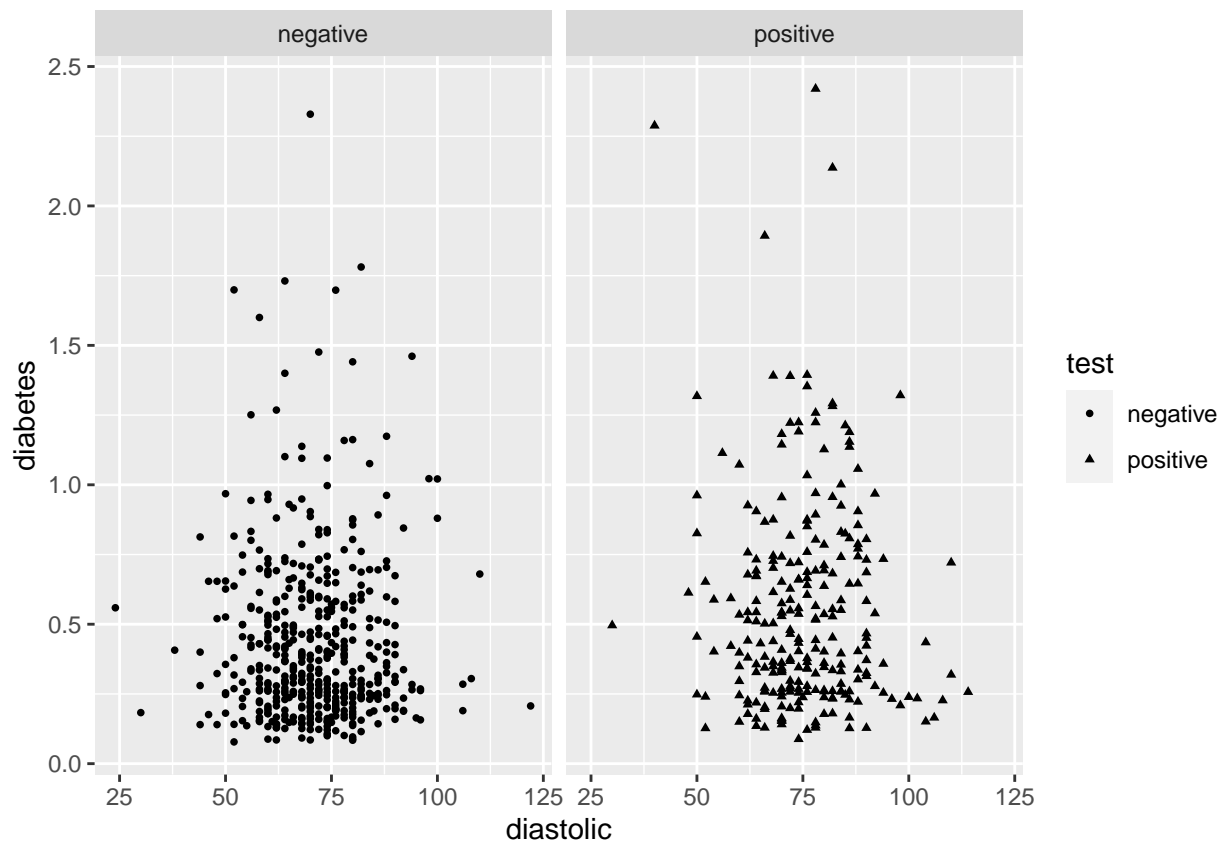
```
# scatterplot with a legend on the top
ggplot(pima, aes(x=diastolic, y=diabetes, shape=test))+geom_point()+
  theme(legend.position="top", legend.direction="horizontal")
```

Warning: Removed 35 rows containing missing values (geom_point).



```
# shape in aes function change the shape of points based on the values of test variable
ggplot(pima, aes(x=diastolic, y=diabetes, shape=test))+geom_point(size=1)+facet_grid(~test)
```

```
## Warning: Removed 35 rows containing missing values (geom_point).
```



1.3 When to use linear models

Regression analysis have two main objectives:

1. prediction of future or unseen response given specified values of predictors.
2. Assessment of the effect of, or relations between, predictors and responses. If possible, we want to infer casual relationships.

1.4 History

Use linear regression to find coefficients in physical science

```
data(manilius, package="faraway")
head(manilius)

##      arc sinang  cosang group
## 1 13.16667 0.8836 -0.4682    1
## 2 13.13333 0.9996 -0.0282    1
## 3 13.20000 0.9899  0.1421    1
## 4 14.25000 0.2221  0.9750    3
## 5 14.70000 0.0006  1.0000    3
## 6 13.01667 0.9308 -0.3654    1

lm1 <- lm(arc~sinang+cosang,data=manilius)
lm1$coef

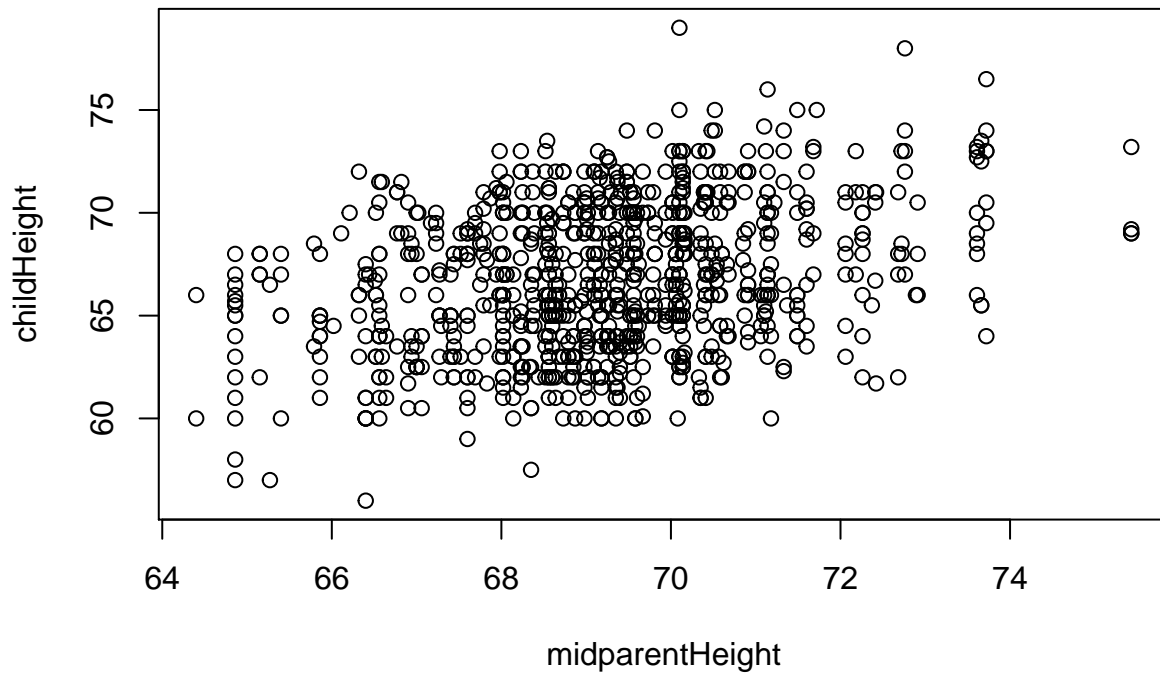
## (Intercept)      sinang      cosang
## 14.56162351 -1.50458123  0.09136504
```

Use of linear regression to find coefficients in social science

```
data(GaltonFamilies, package = "HistData")
head(GaltonFamilies)
```

```
##   family father mother midparentHeight children childNum gender childHeight
## 1    001   78.5   67.0        75.43         4        1   male       73.2
## 2    001   78.5   67.0        75.43         4        2 female       69.2
## 3    001   78.5   67.0        75.43         4        3 female       69.0
## 4    001   78.5   67.0        75.43         4        4 female       69.0
## 5    002   75.5   66.5        73.66         4        1   male       73.5
## 6    002   75.5   66.5        73.66         4        2   male       72.5
```

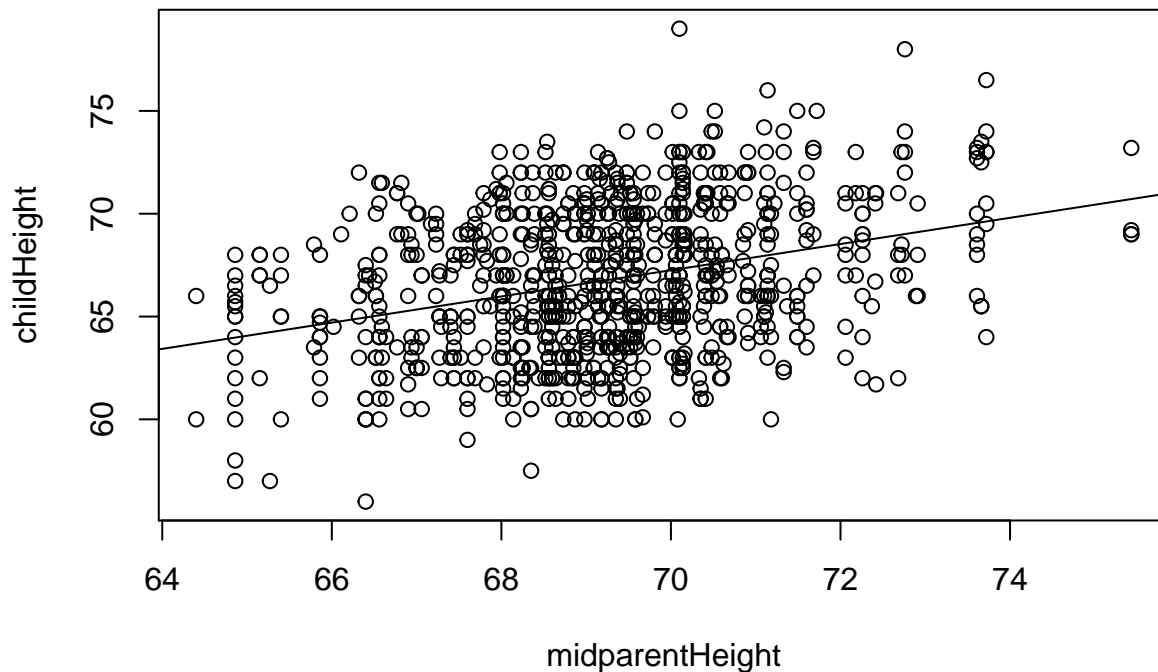
```
plot(childHeight~midparentHeight, GaltonFamilies)
```



```
lm2 <- lm(childHeight~GaltonFamilies$midparentHeight,data=GaltonFamilies)
coef(lm2)
```

```
##              (Intercept) GaltonFamilies$midparentHeight
##              22.6362405              0.6373609
```

```
plot(childHeight~midparentHeight, GaltonFamilies)
abline(lm2)
```



Exercises

```
###1
```

```
data("teengamb", package="faraway")
head(teengamb)
```

```
##   sex status income verbal gamble
## 1   1    51   2.00     8    0.0
## 2   1    28   2.50     8    0.0
## 3   1    37   2.00     6    0.0
## 4   1    28   7.00     4    7.3
## 5   1    65   2.00     8   19.6
## 6   1    61   3.47     6    0.1
```

```
summary(teengamb)
```

numerical summary

```
##      sex           status           income           verbal
##  Min.   :0.0000   Min.   :18.00   Min.   : 0.600   Min.   : 1.00
## 1st Qu.:0.0000   1st Qu.:28.00   1st Qu.: 2.000   1st Qu.: 6.00
## Median :0.0000   Median :43.00   Median : 3.250   Median : 7.00
## Mean   :0.4043   Mean   :45.23   Mean   : 4.642   Mean   : 6.66
## 3rd Qu.:1.0000   3rd Qu.:61.50   3rd Qu.: 6.210   3rd Qu.: 8.00
## Max.   :1.0000   Max.   :75.00   Max.   :15.000   Max.   :10.00
##      gamble
##  Min.   : 0.0
## 1st Qu.: 1.1
## Median : 6.0
## Mean   :19.3
## 3rd Qu.:19.4
```

```
## Max. :156.0
```

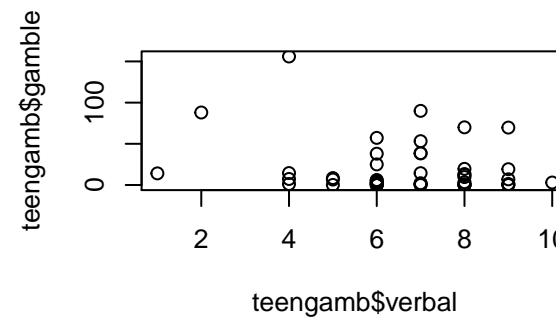
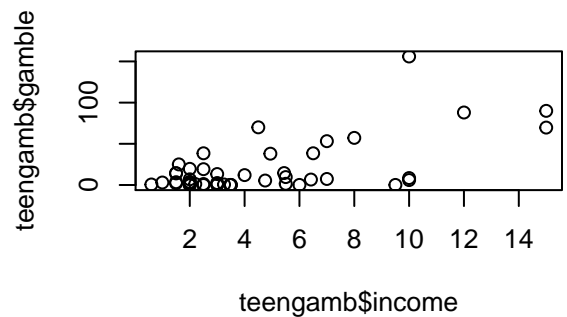
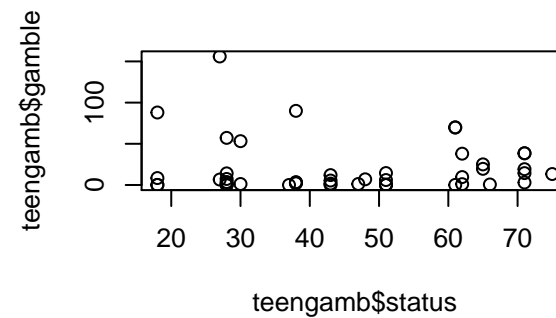
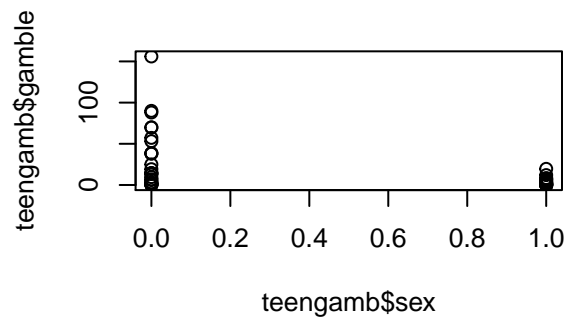
```
table(teengamb$sex)
```

```
##
```

```
## 0 1
```

```
## 28 19
```

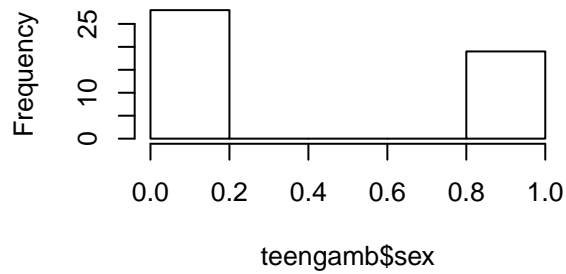
```
par(mfrow=c(2,2))
plot(teengamb$sex,teengamb$gamble)
plot(teengamb$status,teengamb$gamble)
plot(teengamb$income,teengamb$gamble)
plot(teengamb$verbal,teengamb$gamble)
```



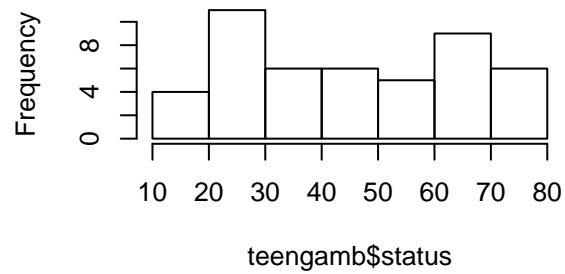
graphical summary

```
par(mfrow=c(2,2))
hist(teengamb$sex)
hist(teengamb$status)
plot(density(teengamb$income))
hist(teengamb$verbal)
```

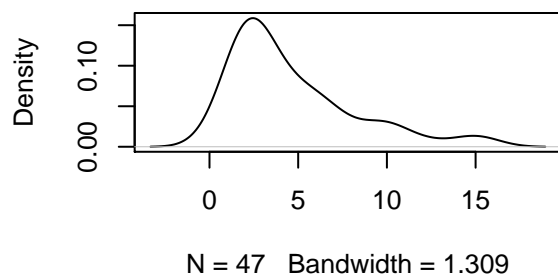
Histogram of teengamb\$sex



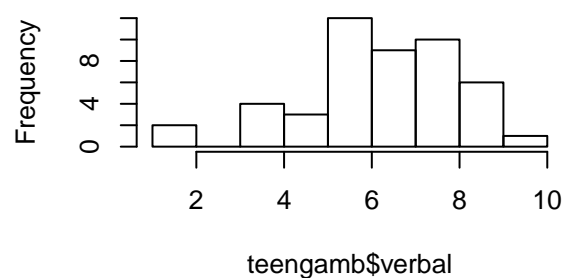
Histogram of teengamb\$status



density.default(x = teengamb\$income



Histogram of teengamb\$verbal



2

```
data("uswages",package="faraway")
head(uswages)
```

```
##      wage educ exper race smsa ne mw so we pt
## 6085  771.60  18   18   0    1  1  0  0  0  0
## 23701 617.28  15   20   0    1  0  0  0  1  0
## 16208 957.83  16    9   0    1  0  0  1  0  0
## 2720  617.28  12   24   0    1  1  0  0  0  0
## 9723  902.18  14   12   0    1  0  1  0  0  0
## 22239 299.15  12   33   0    1  0  0  0  1  0
```

```
summary(uswages)
```

numerical summary

```
##      wage      educ      exper      race
## Min.   : 50.39  Min.   : 0.00  Min.   : -2.00  Min.   : 0.000
## 1st Qu.: 308.64 1st Qu.:12.00 1st Qu.:  8.00 1st Qu.: 0.000
## Median : 522.32 Median :12.00 Median :15.00 Median : 0.000
## Mean   : 608.12 Mean   :13.11 Mean   :18.41 Mean   : 0.078
## 3rd Qu.: 783.48 3rd Qu.:16.00 3rd Qu.:27.00 3rd Qu.: 0.000
## Max.   :7716.05 Max.   :18.00 Max.   :59.00 Max.   : 1.000
##      smsa      ne      mw      so
## Min.   : 0.000  Min.   : 0.000  Min.   : 0.0000  Min.   : 0.0000
## 1st Qu.: 1.000 1st Qu.: 0.000 1st Qu.: 0.0000 1st Qu.: 0.0000
## Median : 1.000 Median : 0.000 Median : 0.0000 Median : 0.0000
```

```
## Mean :0.756 Mean :0.229 Mean :0.2485 Mean :0.3125
## 3rd Qu.:1.000 3rd Qu.:0.000 3rd Qu.:0.0000 3rd Qu.:1.0000
## Max. :1.000 Max. :1.000 Max. :1.0000 Max. :1.0000
## we pt
## Min. :0.00 Min. :0.0000
## 1st Qu.:0.00 1st Qu.:0.0000
## Median :0.00 Median :0.0000
## Mean :0.21 Mean :0.0925
## 3rd Qu.:0.00 3rd Qu.:0.0000
## Max. :1.00 Max. :1.0000
```

```
# convert quatitative variables into qualitative
```

```
uswages$race <- factor(uswages$race)
uswages$smsa <- factor(uswages$smsa)
uswages$ne <- factor(uswages$ne)
uswages$mw <- factor(uswages$mw)
uswages$we <- factor(uswages$we)
uswages$so <- factor(uswages$so)
uswages$pt <- factor(uswages$pt)
uswages$educ <- factor(uswages$educ)
levels(uswages$race) <- c("White","Black")
levels(uswages$pt) <- c("full-time","part-time")
```

```
summary(uswages)
```

```
## wage educ exper race smsa ne
## Min. : 50.39 12 :719 Min. : -2.00 White:1844 0: 488 0:1542
## 1st Qu.: 308.64 16 :280 1st Qu.: 8.00 Black: 156 1:1512 1: 458
## Median : 522.32 14 :199 Median :15.00
## Mean : 608.12 18 :197 Mean :18.41
## 3rd Qu.: 783.48 13 :154 3rd Qu.:27.00
## Max. :7716.05 15 : 86 Max. :59.00
## (Other):365
## mw so we pt
## 0:1503 0:1375 0:1580 full-time:1815
## 1: 497 1: 625 1: 420 part-time: 185
##
##
##
##
##
```

```
# summarise variable `ne`, `mw`, `we`, `so` into one variable `location`
```

```
uswages$location[uswages$ne==1] <- "North East"
uswages$location[uswages$mw==1] <- "Midwest"
uswages$location[uswages$we==1] <- "West"
uswages$location[uswages$so==1] <- "South"
uswages$location <- factor(uswages$location)
# levels(uswages$location) <- c("North East","Midwest","West","South")
# uswages$location
```

```
# sort(uswages$exper)
```

```
uswages$exper[uswages$exper<0] <- NA
sort(uswages$exper)
```

```
## [1] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
```

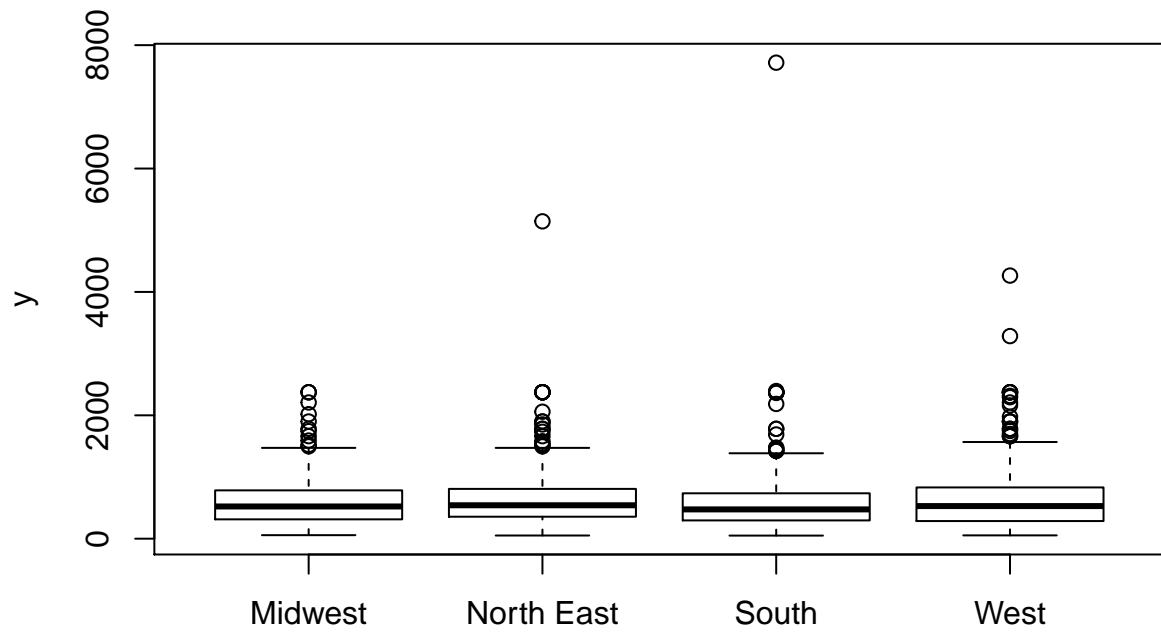

[illegible]

```
## [1321] 23 23 23 23 23 23 23 24 24 24 24 24 24 24 24 24 24 24 24 24 24
## [1345] 24 24 24 24 24 24 24 24 24 24 24 24 24 24 24 24 25 25 25 25 25
## [1369] 25 25 25 25 25 25 25 25 25 25 25 25 25 25 25 25 25 25 25 25 25
## [1393] 25 25 25 25 25 25 25 25 25 25 26 26 26 26 26 26 26 26 26 26 26
## [1417] 26 26 26 26 26 26 26 26 26 26 26 26 26 26 26 26 26 26 26 26 27
## [1441] 27 27 27 27 27 27 27 27 27 27 27 27 27 27 27 27 27 27 27 27 27
## [1465] 27 27 27 27 27 27 27 27 27 27 27 28 28 28 28 28 28 28 28 28 28
## [1489] 28 28 28 28 28 28 28 28 28 28 28 28 28 28 28 28 28 28 28 28 29
## [1513] 29 29 29 29 29 29 29 29 29 29 29 29 29 29 29 29 29 29 29 29 29
## [1537] 30 30 30 30 30 30 30 30 30 30 30 30 30 30 30 30 30 30 30 30 30
## [1561] 30 30 30 31 31 31 31 31 31 31 31 31 31 31 31 31 31 31 31 31 31
## [1585] 31 31 31 31 31 32 32 32 32 32 32 32 32 32 32 32 32 32 32 32 32
## [1609] 32 32 32 32 32 32 33 33 33 33 33 33 33 33 33 33 33 33 33 33 33
## [1633] 33 33 33 33 33 33 33 33 33 33 33 33 34 34 34 34 34 34 34 34 34
## [1657] 34 34 34 34 34 34 35 35 35 35 35 35 35 35 35 35 35 35 35 35 35
## [1681] 35 35 35 35 35 36 36 36 36 36 36 36 36 36 36 36 36 36 36 36 36
## [1705] 36 36 36 37 37 37 37 37 37 37 37 37 37 37 37 37 37 37 37 37 37
## [1729] 37 37 37 37 38 38 38 38 38 38 38 38 38 38 38 38 38 38 38 38 38
## [1753] 38 38 38 38 38 38 39 39 39 39 39 39 39 39 39 39 39 39 39 39 39
## [1777] 39 39 39 39 39 39 40 40 40 40 40 40 40 40 40 40 40 40 40 40 41
## [1801] 41 41 41 41 41 41 41 41 41 42 42 42 42 42 42 42 42 42 42 42 42
## [1825] 42 42 42 42 42 42 42 42 42 42 42 43 43 43 43 43 43 43 43 43 43
## [1849] 43 43 43 43 43 43 43 43 43 43 43 43 44 44 44 44 44 44 44 44 44
## [1873] 44 44 45 45 45 45 45 45 45 45 45 45 45 45 45 45 45 45 45 45 46
## [1897] 46 46 46 46 46 46 46 46 46 46 47 47 47 47 47 47 47 47 47 47 47
## [1921] 47 47 47 48 48 48 48 48 48 48 48 48 48 48 48 48 49 49 49 49 50
## [1945] 51 52 52 52 52 52 52 52 53 53 54 54 54 54 55 55 55 55 56 56 57
```

```
summary(uswages)
```

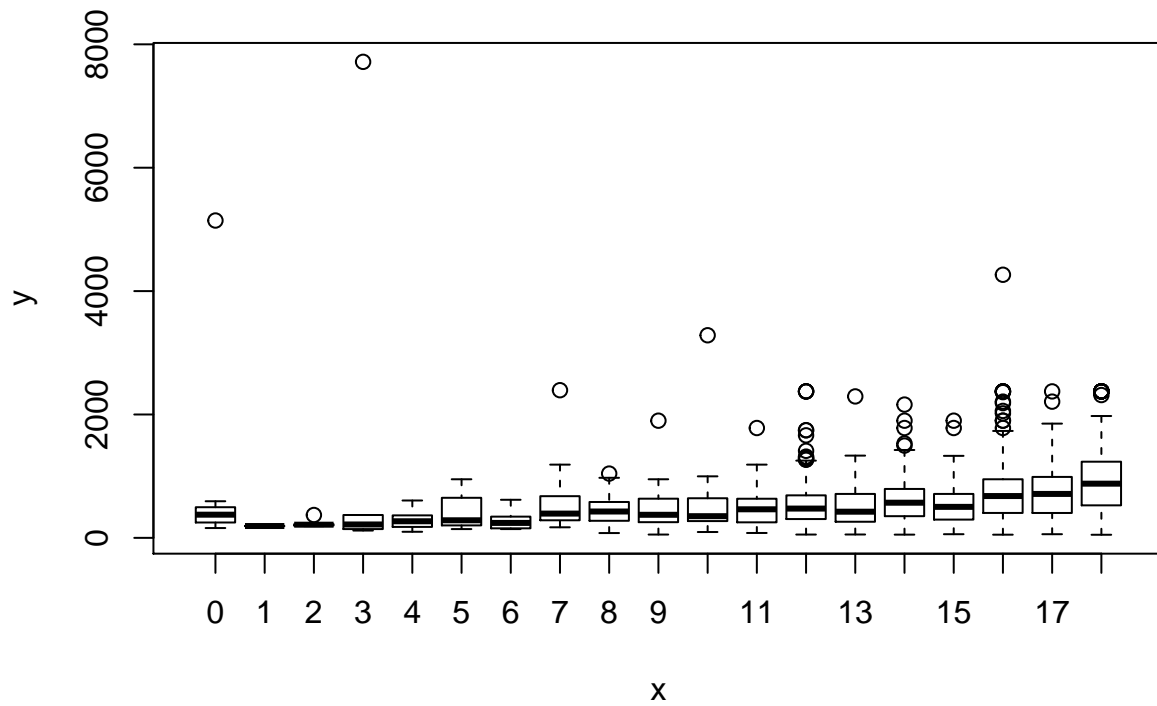
```
##      wage      educ      exper      race      smsa      ne
## Min.   : 50.39   12      :719   Min.   : 0.00   White:1844   0: 488   0:1542
## 1st Qu.: 308.64   16      :280   1st Qu.: 8.00   Black: 156   1:1512   1: 458
## Median : 522.32   14      :199   Median :16.00
## Mean   : 608.12   18      :197   Mean   :18.74
## 3rd Qu.: 783.48   13      :154   3rd Qu.:27.00
## Max.    :7716.05   15      : 86   Max.    :59.00
##      (Other):365   NA's    :33
## mw      so      we      pt      location
## 0:1503   0:1375   0:1580   full-time:1815   Midwest    :497
## 1: 497    1: 625    1: 420    part-time: 185   North East:458
##                                     South      :625
##                                     West       :420
##
##
##
```

```
# par(mfrow=c(2,2))
plot(uswages$location, uswages$wage)
```

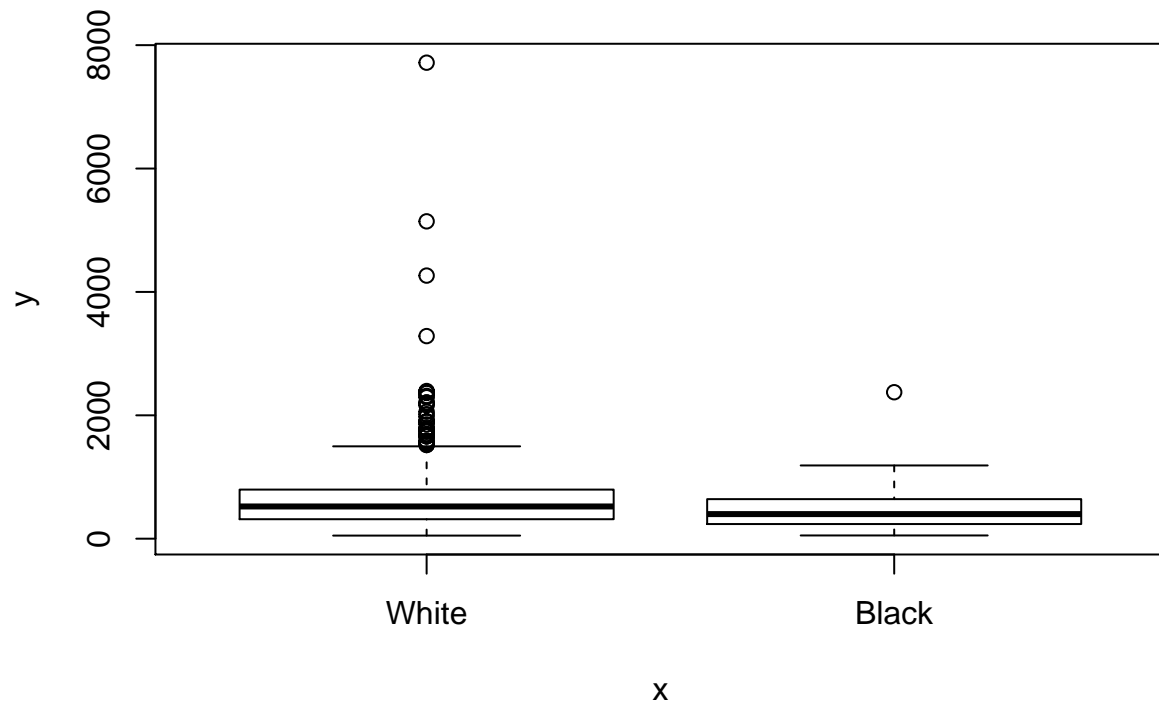


graphical summary

```
plot(uswages$educ, uswages$wage)
```



```
plot(uswages$race, uswages$wage)
```



```
plot(uswages$pt, uswages$wage)
```

