

Applied Regression With R

Bruce Campbell

July 17, 2017

Wed Jul 19 14:40:28 2017

Chapter 1 examples

```
if (!require(faraway)) {  
  install.packages("faraway")  
  library(faraway)  
}  
  
if (!require(HistData)) {  
  install.packages("HistData")  
  library(HistData)  
}
```

```
## Loading required package: HistData
```

Diabetes survey on Pima Indians

The National Institute of Diabetes and Digestive and Kidney Diseases conducted a study on 768 adult female Pima Indians living near Phoenix.

```
# Loads or lists available datasets  
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
```

```
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
```

```
# From the summary - we see that we have zero's for physical variable We set
# them to NA - this is an important part of due diligence in statistics
# Check that the values make sense. sort(pima$diastolic)
```

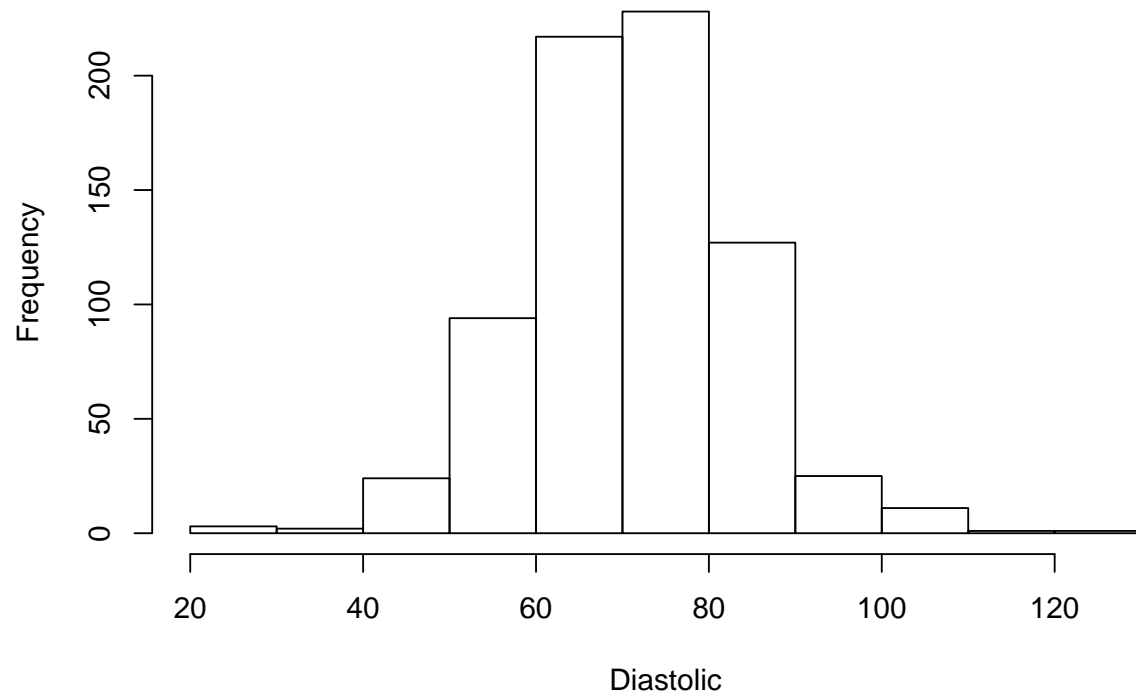
```
pima$diastolic[pima$diastolic == 0] <- NA
pima$glucose[pima$glucose == 0] <- NA
pima$triceps[pima$triceps == 0] <- NA
pima$insulin[pima$insulin == 0] <- NA
pima$bmi[pima$bmi == 0] <- NA
pima$test <- factor(pima$test)
summary(pima$test)
```

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

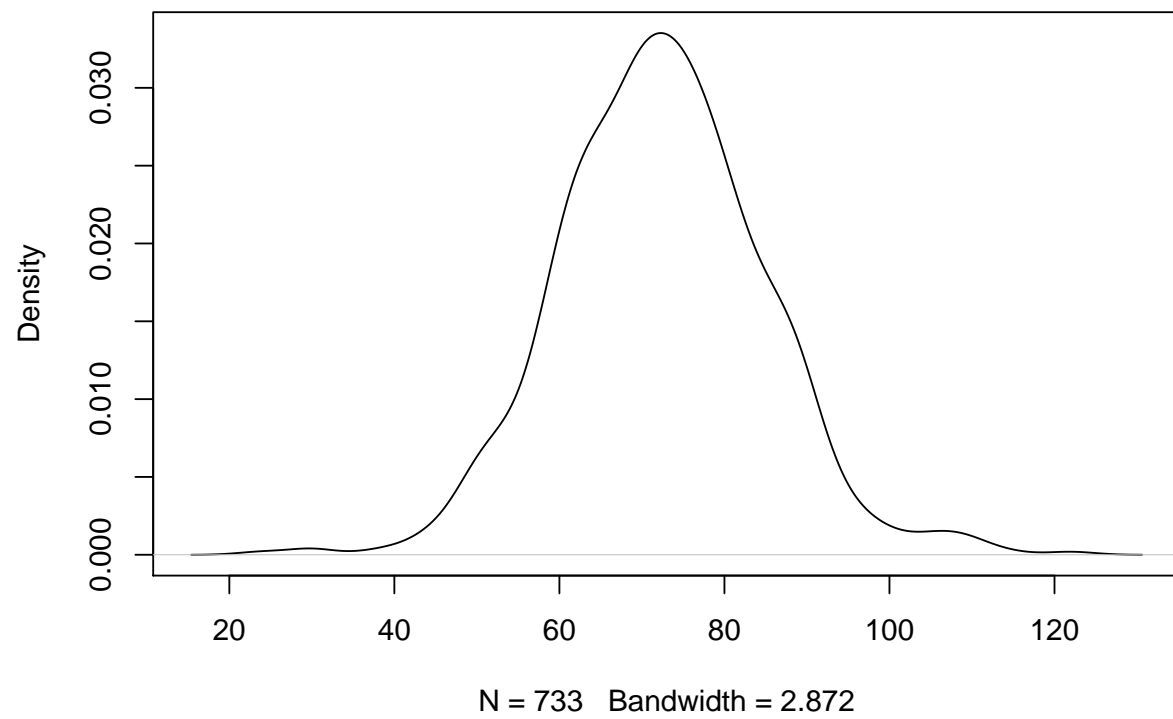
```
levels(pima$test) <- c("negative", "positive")
summary(pima)
```

```
## 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
##
##
##
##
```

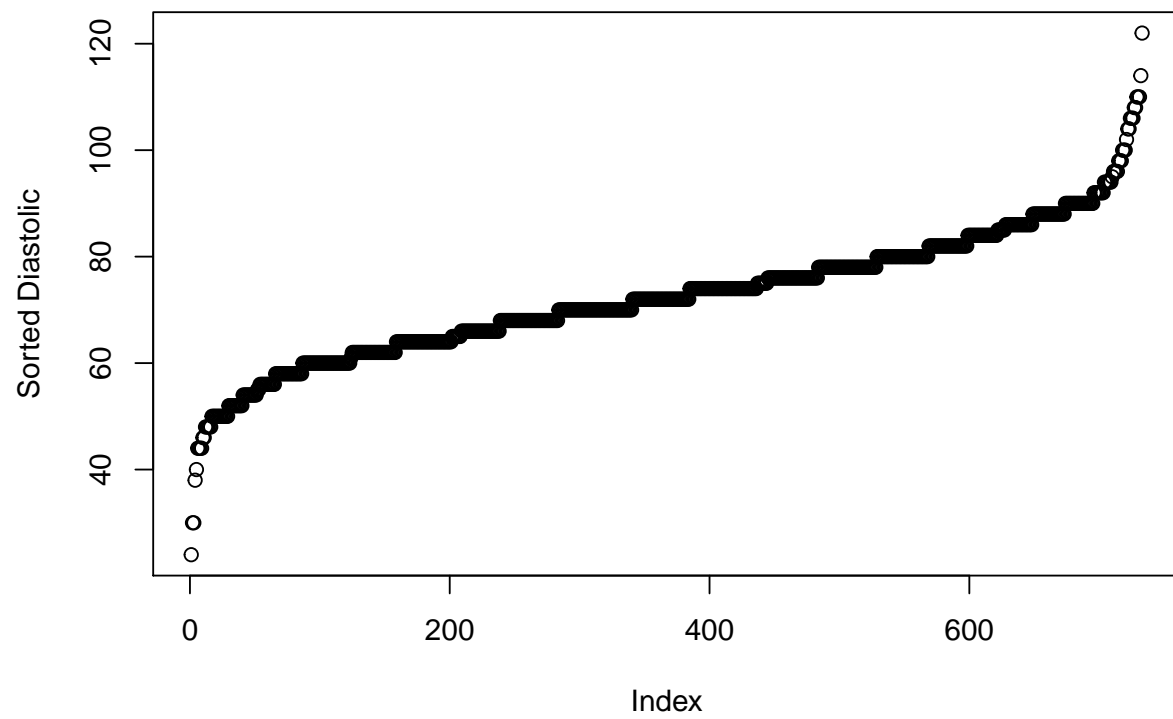
```
hist(pima$diastolic, xlab = "Diastolic", main = "")
```



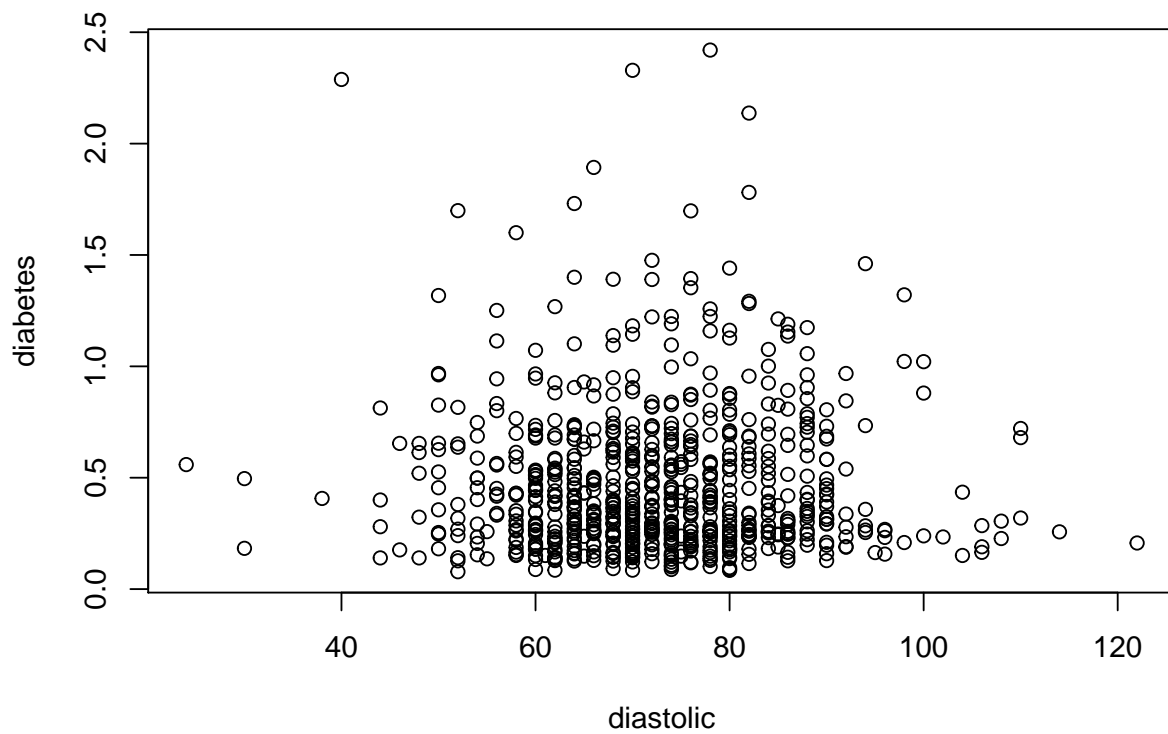
```
plot(density(pima$diastolic, na.rm = TRUE), main = "")
```



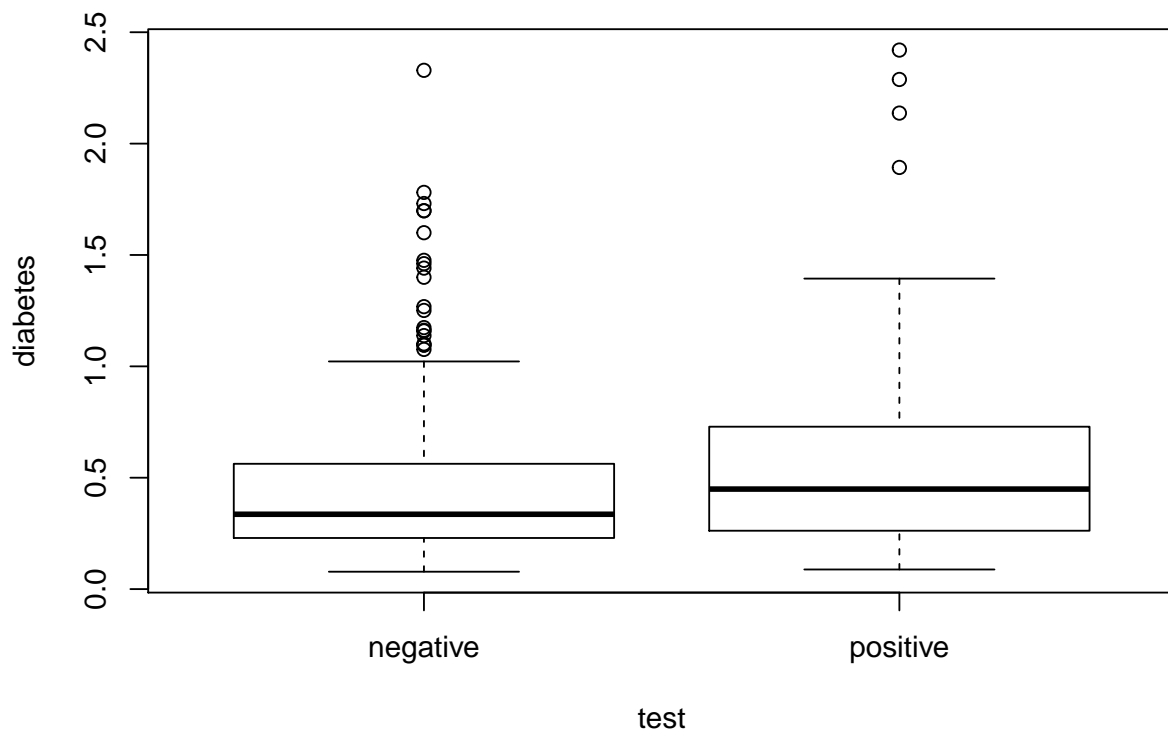
```
plot(sort(pima$diastolic), ylab = "Sorted Diastolic")
```



```
plot(diabetes ~ diastolic, pima)
```

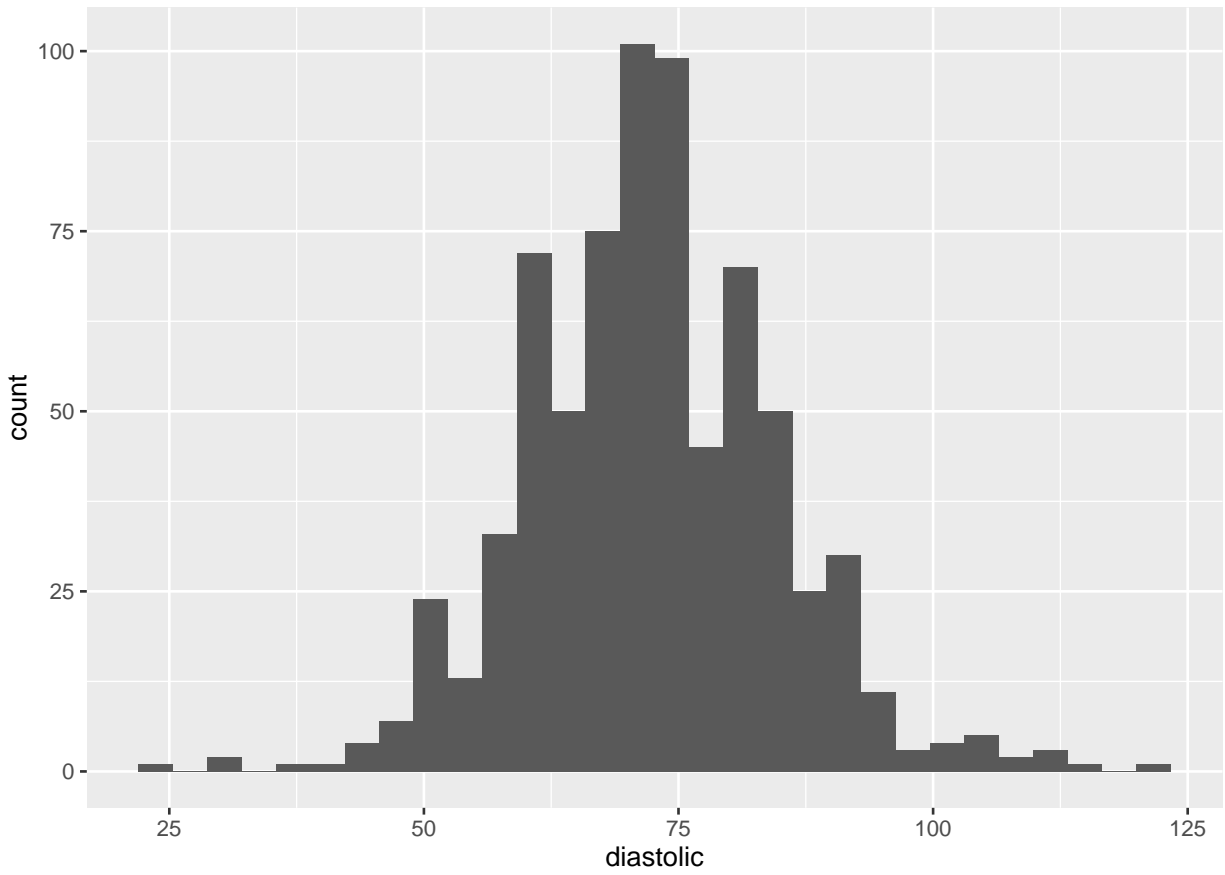


```
plot(diabetes ~ test, pima)
```

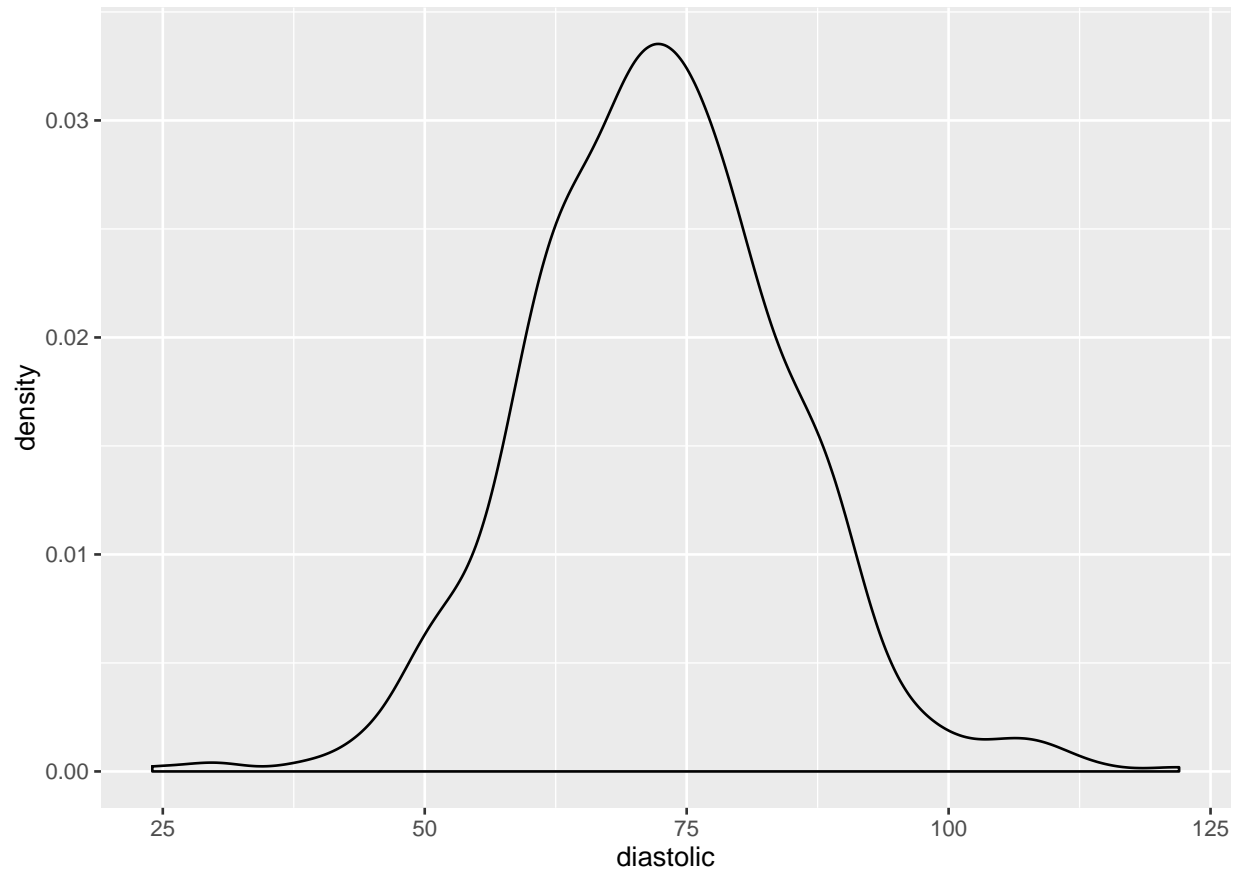


```
require(ggplot2)
ggplot(pima, aes(x = diastolic)) + geom_histogram()
```

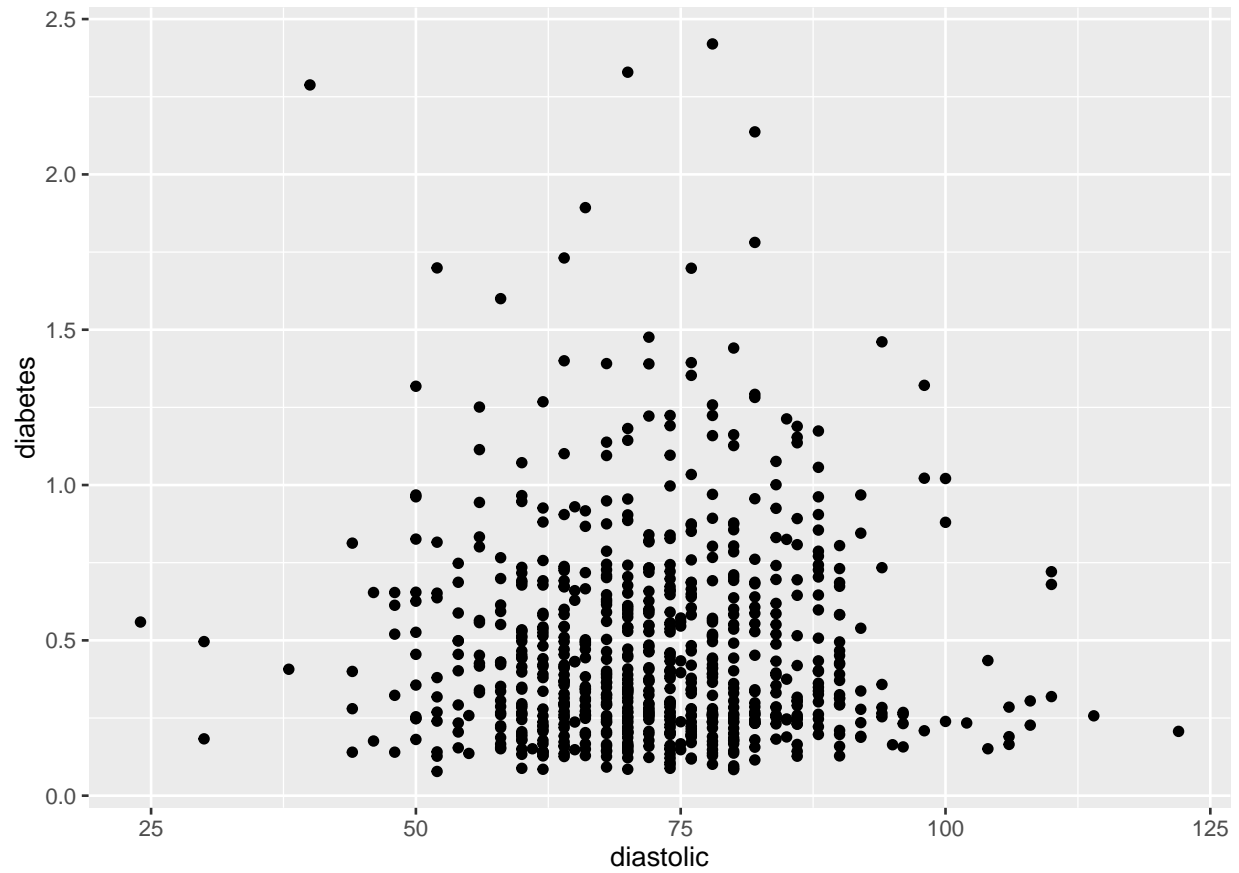
```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



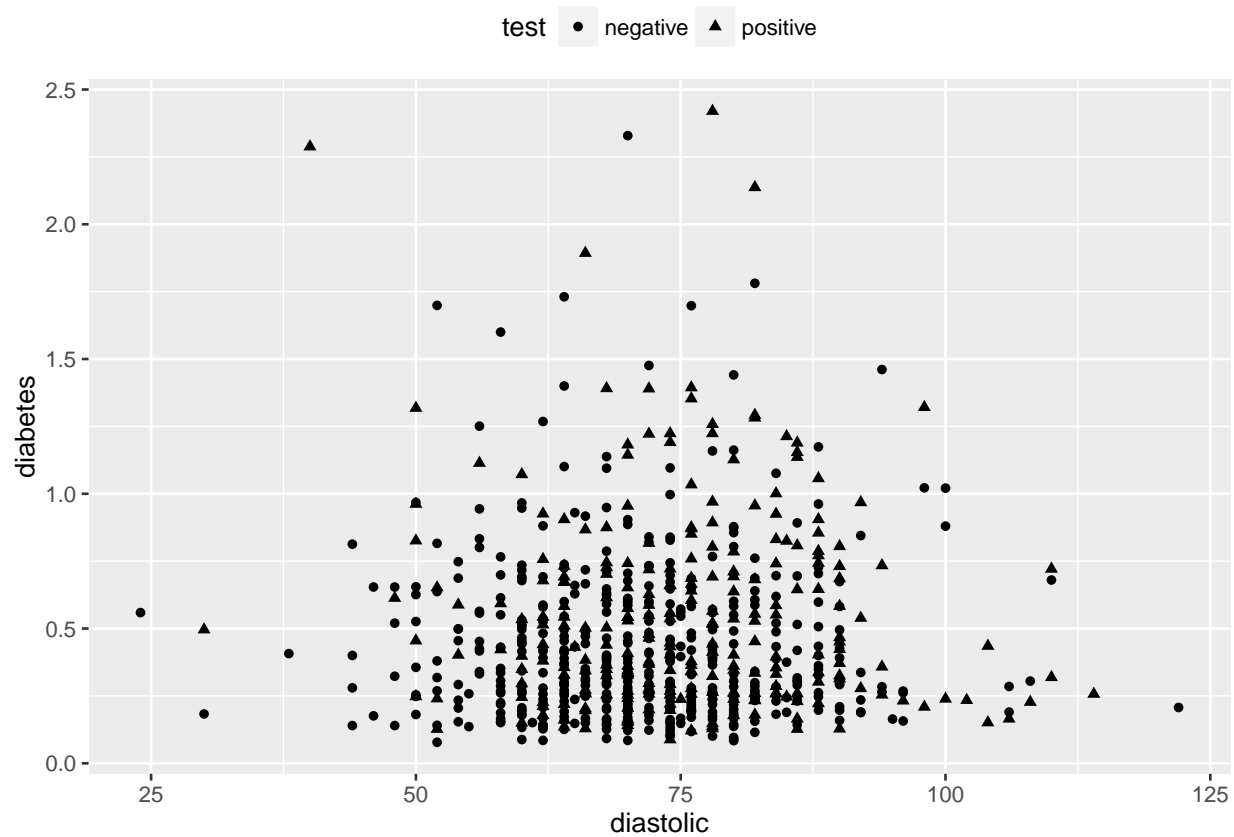
```
ggplot(pima, aes(x = diastolic)) + geom_density()
```

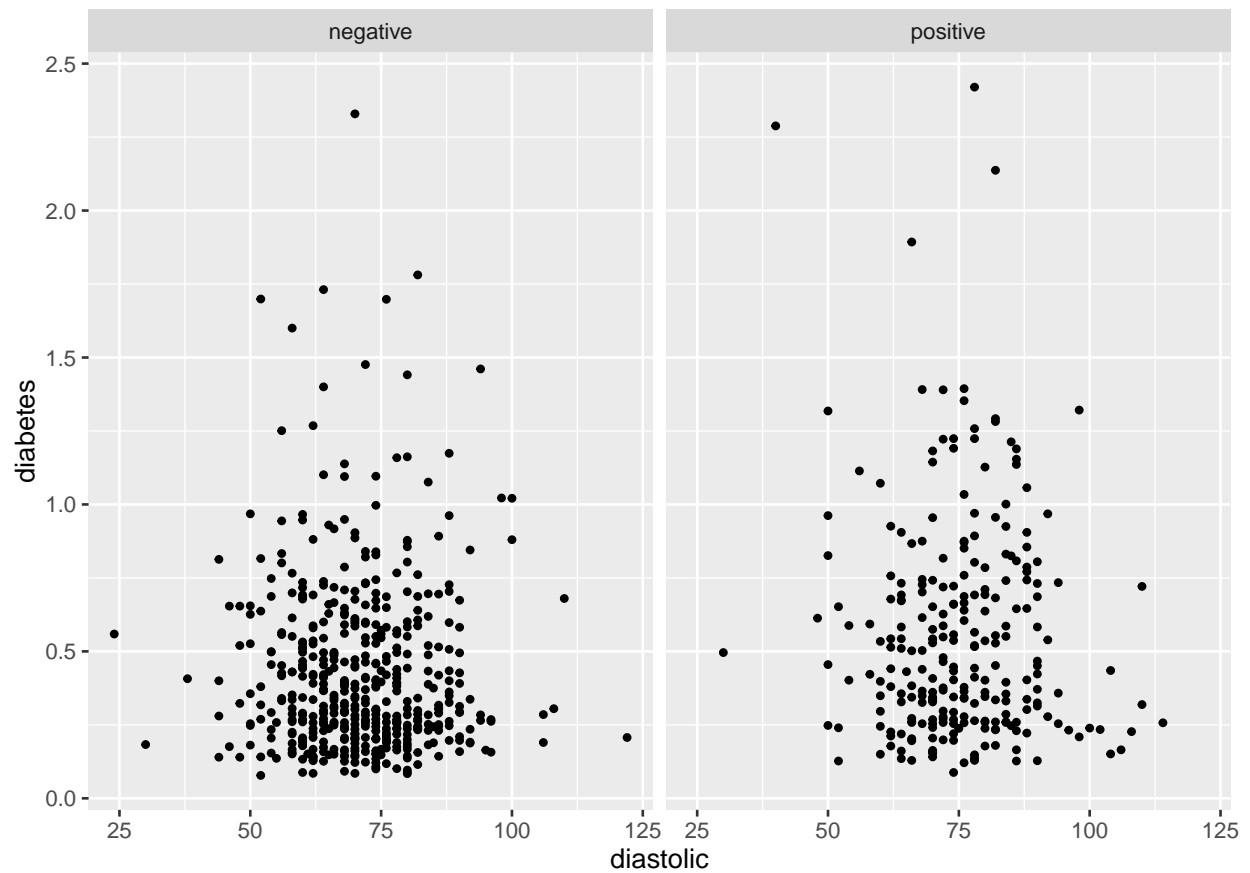
```
ggplot(pima, aes(x = diastolic, y = diabetes)) + geom_point()
```



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



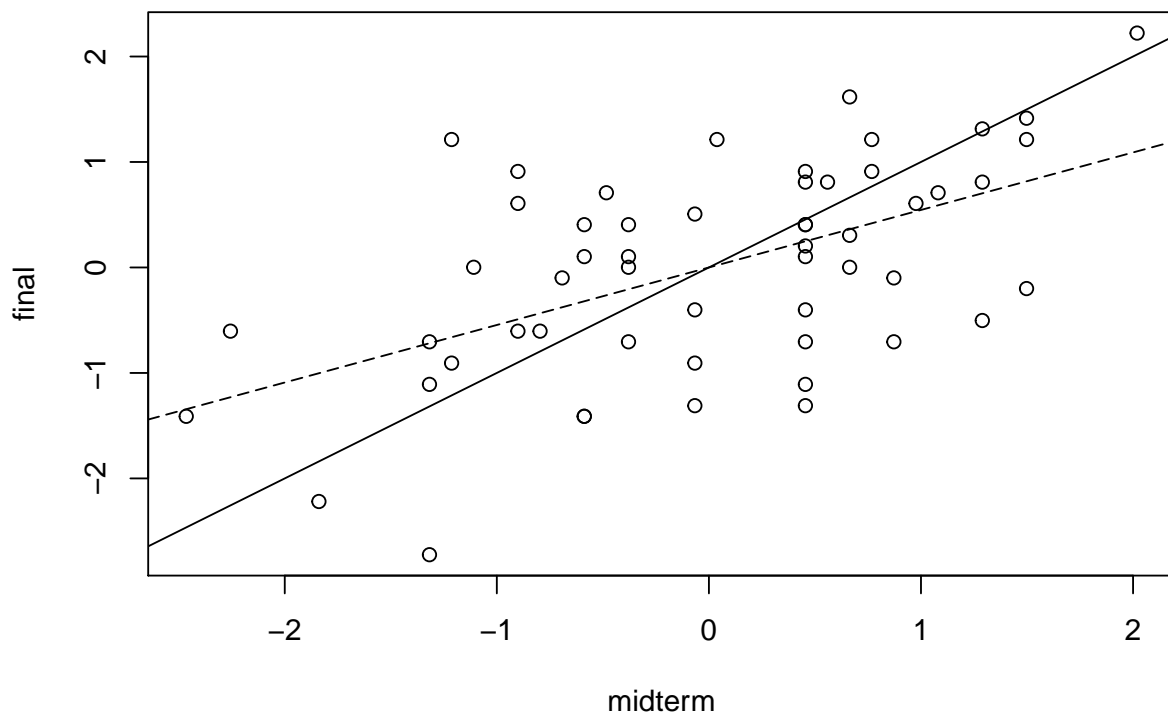
```
ggplot(pima, aes(x = diastolic, y = diabetes)) + geom_point(size = 1) + facet_grid(~test)
```



Marks in a statistics class

Marks from Statistics 500 one year at the University of Michigan

```
data(stat500)
stat500 <- data.frame(scale(stat500))
plot(final ~ midterm, stat500)
abline(0, 1)
g <- lm(final ~ midterm, stat500)
abline(coef(g), lty = 5)
```



```
cor(stat500)
```

```
##          midterm      final        hw      total
## midterm 1.0000000 0.54522775 0.27205756 0.8444568
## final   0.5452277 1.00000000 0.08733764 0.7788629
## hw      0.2720576 0.08733764 1.00000000 0.5644286
## total   0.8444568 0.77886293 0.56442864 1.0000000
```

Mayer's 1750 data on the Manilius crater on the moon

In 1750, Tobias Mayer collected data on various landmarks on the moon in order to determine its orbit. The data involving the position of the Manilius crater resulted in a least squares like problem. The example is discussed in Steven Stigler's History of Statistics

```
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
```

```

(moon3 <- aggregate(manilius[, 1:3], list(manilius$group), sum))

##   Group.1      arc  sinang  cosang
## 1      1 118.1333  8.4987 -0.7932
## 2      2 140.2833 -6.1404  1.7443
## 3      3 127.5333  2.9777  7.9649

solve(cbind(9, moon3$sinang, moon3$cosang), moon3$arc)

## [1] 14.5445859 -1.4898221  0.1341264

lmod <- lm(arc ~ sinang + cosang, manilius)
coef(lmod)

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

data(GaltonFamilies, package = "HistData")
plot(childHeight ~ midparentHeight, GaltonFamilies)
lmod <- lm(childHeight ~ midparentHeight, GaltonFamilies)
coef(lmod)

##      (Intercept) midparentHeight
##      22.6362405      0.6373609

abline(lmod)
(beta <- with(GaltonFamilies, cor(midparentHeight, childHeight) * sd(childHeight)/sd(midparentHeight)))

## [1] 0.6373609

(alpha <- with(GaltonFamilies, mean(childHeight) - beta * mean(midparentHeight)))

## [1] 22.63624

(beta1 <- with(GaltonFamilies, sd(childHeight)/sd(midparentHeight)))

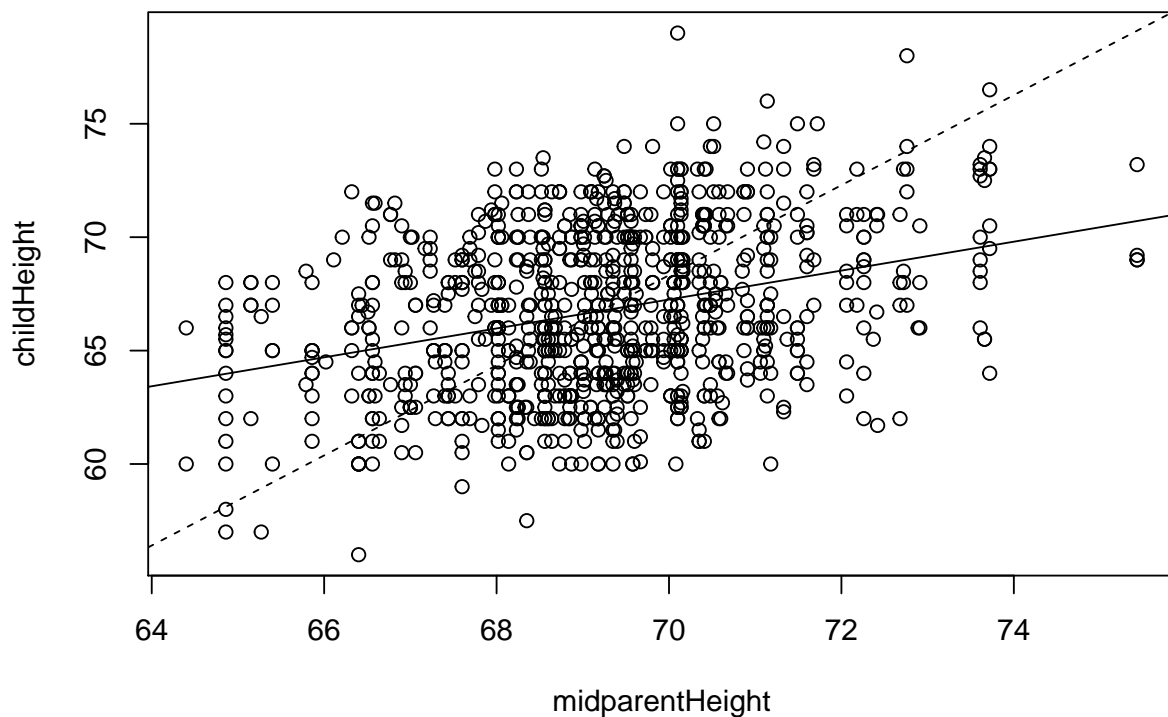
## [1] 1.985858

(alpha1 <- with(GaltonFamilies, mean(childHeight) - beta1 * mean(midparentHeight)))

## [1] -70.68889

abline(alpha1, beta1, lty = 2)

```



Homework Chapter 1

We're asked to make numerical and graphical summaries of a variety of datasets. We are instructed to limit the output to a quantity that abusus reader would find sufficient to get a basic understanding of the data.

- teengamb
- uswages
- prostate
- sat
- divusa

Study of teenage gambling in Britain

The teengamb data frame has 47 rows and 5 columns. A survey was conducted to study teenage gambling in Britain. This frame contains the following columns:

sex 0=male, 1=female

status Socioeconomic status score based on parents' occupation

income in pounds per week

verbal verbal score in words out of 12 correctly defined

gamble expenditure on gambling in pounds per year

```
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
```

```
require(GGally)
```

```
## Loading required package: GGally
```

```
##
```

```
## Attaching package: 'GGally'
```

```
## The following object is masked from 'package:faraway':
```

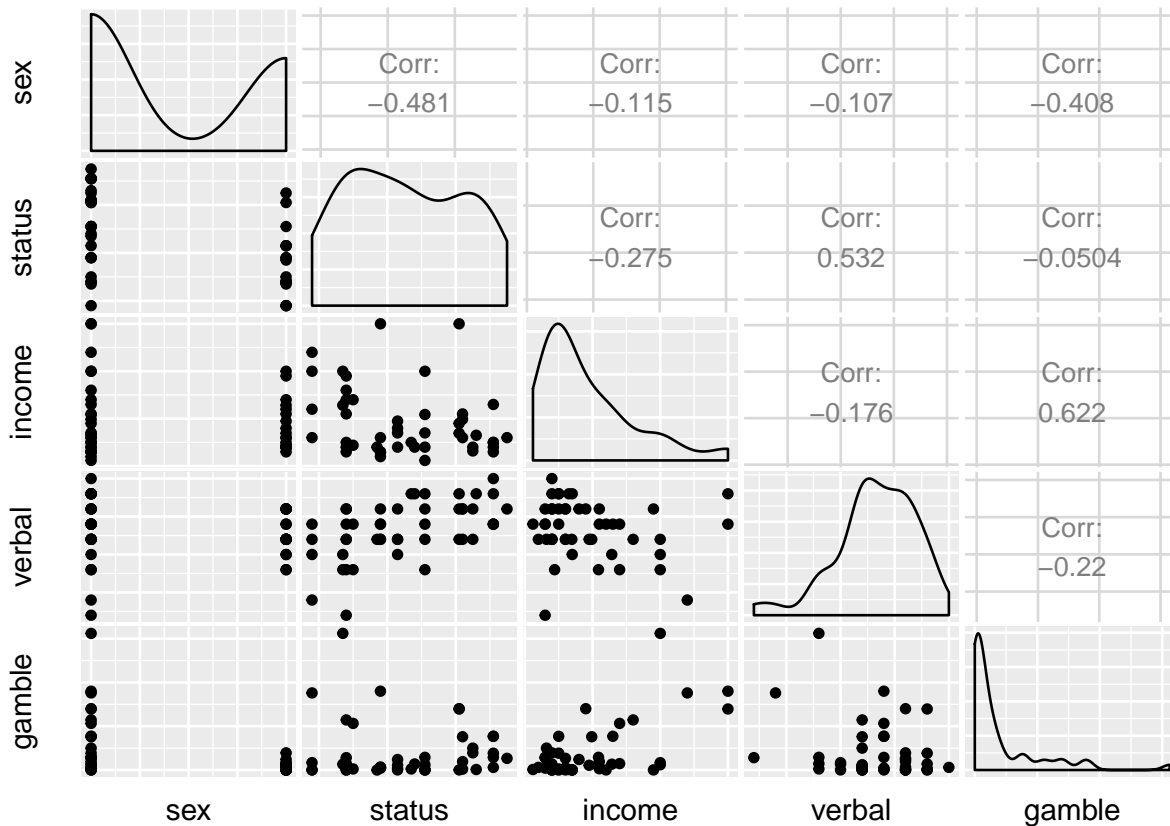
```
##
```

```
##   happy
```

```
library(ggplot2)
```

```
require(GGally)
```

```
ggpairs(teengamb) + theme(axis.line = element_blank(), axis.text = element_blank(),
  axis.ticks = element_blank())
```



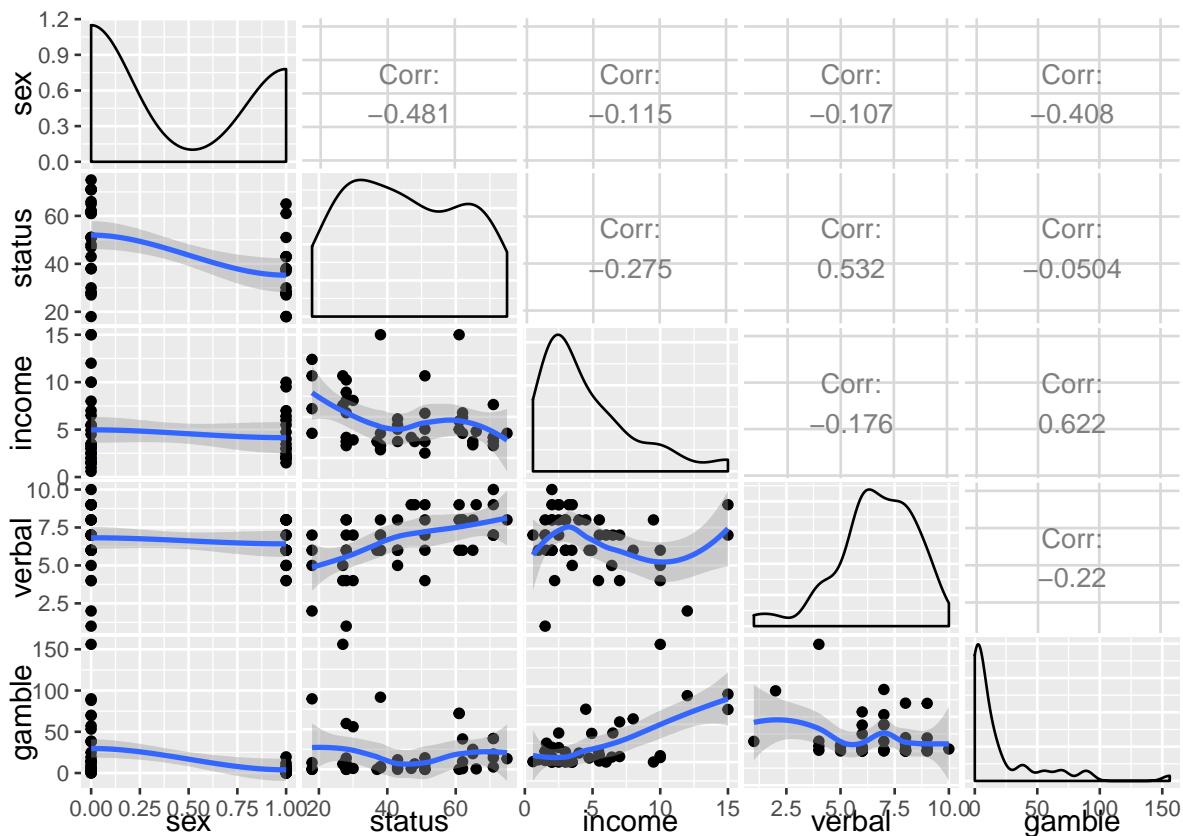
This data set is not well matched by sex so we'll be cautious in making inference on how sex influences gambling status. At first glance we may be tempted to note that gambling values are higher for males, but this may be due to variability in the population of gamblers.

We do note that there is an association between income and gamble. Gamble and Income appear to be right skewed fat tailed distributions.

Here we add LOESS and LM models to the pairs plots. LOESS is fitting by local polynomial regression.

```
my_fn <- function(data, mapping, method = "loess", ...) {
  p <- ggplot(data = data, mapping = mapping) + geom_point() + geom_smooth(method = method,
  ...)
  p
}
```

```
# Default loess curve
ggpairs(teengamb, lower = list(continuous = my_fn))
```



```
# Use wrap to add further arguments; change method to lm
ggpairs(teengamb, lower = list(continuous = wrap(my_fn, method = "lm")))
```

