Graphics in R

There are three main types of functions that deal with graphics in R

- High-level functions that produce complete plots
- Low-level functions or graphical primitives that can be added to an existing plot or assembled to build a new plot type
- A limited set of interactive features for working with graphical output

Graphics in R

When making graphics in R, you typical issue a series of calls to graphics functions, each producing a complete plot or adding to an existing plot

Sometimes, people refer to this as the “Painter’s model” meaning you add layers to a plot in steps, with later output obscuring what came before

Standard plots

A range of standard plots can be made with R and these are typically produced by a single function call (but can be added to)

These functions have embedded in them a number of “good choices” (both in terms of layout and design as well as any parameters that might need setting) to facilitate rapid iterations to support analysis

These, however, can also just be the starting point for more elaborate graphics, adding annotations, overlaying other plotting elements

The BRFSS

The Behavioral Risk Factor Surveillance System is the world's largest telephone survey and it is designed to track health risks in the United States; like many surveys, **the BRFSS works with only a *sample* of a larger *population***

With over 200 million adults in the United States, the CDC couldn't possibly contact their entire population*; instead, they selected around 400 thousand adults, calling roughly 30 thousand per month

1. Background

The Behavioral Risk Factor Surveillance System (BRFSS) is a collaborative project of the Centers for Disease Control and Prevention (CDC), and U.S. states and territories. The BRFSS, administered and supported by the Behavioral Surveillance Branch (BSB) of the CDC, is an ongoing data collection program designed to measure behavioral risk factors in the adult population 18 years of age or over living in households. The BRFSS was initiated in 1984, with 15 states collecting surveillance data on risk behaviors through monthly telephone interviews. The number of states participating in the survey increased, so that by 2000, 50 States, the District of Columbia, Puerto Rico, and the Virgin Islands were participating in the BRFSS.

The objective of the BRFSS is to collect uniform, state-specific data on preventive health practices and risk behaviors that are linked to chronic diseases, injuries, and preventable infectious diseases in the adult population. Factors assessed by the BRFSS include tobacco use, health care coverage, HIV/AIDS, physical activity, and fruit and vegetable consumption. Data are collected from a random sample of adults (one per household) through a telephone survey.

BRFSS
Turning Information Into Health

Our data

The BRFSS in 2008 consists of responses from 400 thousand people; in this discussion, we will only look at a subset (a subsample, if you will) of **40 thousand people***

Each respondent receiving the survey is asked a series of questions and **the original BRFSS data set has 292 different fields**, most of which are questions; to make things easier, we've only pulled 34 variables

Variables

`state`
Where does the respondent live?

`imonth`
Interview Month

`iday`
Interview Day

`iyear`
Interview Year

`nattempts`
Number of Attempts

`numadults`
Number of Adults in Household

`nummen`
Number of Adult Women in Household

`numwomen`
Number of Adult Women in Household

Variables

`genhlth`
Respondents were asked to evaluate their general health values are excellent, very good, good, fair, poor

`physhlth`
The number of days out of the last 30 that the respondent was in poor health

`menthlth`
The number of days out of the last 30 that the respondent was in poor mental health

`hlthplan`
1 if the respondent has some form of health coverage and 2 else

`medcost`
Was there a time in the past 12 months when you needed to see a doctor but could not because of cost?

`checkup1`
Time since the respondent’s last routine checkup

Variables

qlrest2
During the past 30 days, for about how many days have you felt you did not get enough rest or sleep?

cvdinfr4
Has the respondent ever had a heart attack? (1 yes, 2 no)

cvdcrhd4
Has the respondent ever had angina or coronary heart disease?

cvdstrk3
Has the respondent ever had a stroke?

asthma2
Does the respondent have asthma?

smoke100
1 if the respondent has smoked at least 100 cigarettes in their entire life and 2 otherwise

Variables

age in years

marital Is the respondent married?

children Number of children (< 18 years old) living at the household

educ The highest grade or year of school the respondent completed

employ Is the respondent currently employed?

income2 range

weight in pounds

height in inches

wtyrago desired weight in pounds

sex of the respondent

drnkany
Has the respondent had at least one alcoholic beverage in the last 30 days?

Variables

`lsatisfy`
How satisfied is the respondent with their life overall?

Preliminary examination

When faced with a new data set, we often have a look at a few cases; you should do this before and after the data are “loaded” into R or whatever analysis package you might end up using

What do we notice?

```
> brfss[1:20,1:13]
           state    imonth iday iyear nattempts numadults nummen numwomen   genhlth physhlth menthlth hlthplan medcost
1       Illinois   January   12  2008         1         1      1        0 Excellent        3        0        1       2
2        Florida     March   10  2008         7         2      1        1      Fair        7        0        2       1
3       Missouri  February    6  2008         5         2      1        1 Very good        2        1        1       2
4   South Dakota     March   18  2008         4         2      1        1 Very good        0        1        1       2
5    Connecticut   October   17  2008        10         3      2        1      Good        0        0        1       2
6   Pennsylvania      July   10  2008         6         4      1        3      Good        0       30        1       1
7      Tennessee      July   21  2008        12         2      1        1 Excellent        0        0        1       2
8          Texas    August    5  2008         3         2      1        1      Poor        0        0        1       2
9  New Hampshire     April    9  2008         3         2      1        1 Very good        0        0        1       2
10       Indiana      July   13  2008         5         2      1        1 Excellent        0        0        1       2
11       Florida September   14  2008        10         4      2        2      Fair       30        0        1       2
12      Illinois September   13  2008         1         3      1        2      Fair        0        0        1       2
13        Kansas    August   28  2008         8         1      0        1 Excellent        0        0        2       2
14   Puerto Rico  February    2  2008         1         4      1        3      Fair       25        0        1       2
15       Alabama    August   18  2008         5         4      2        2 Very good        0        0        1       2
16     Louisiana      June   28  2008         6         1      1        0 Very good        0        0        1       2
17         Texas     March    6  2008         5         2      1        1      Good        0        0        1       2
18      Missouri     March   28  2008         4         2      1        1 Excellent        0        0        1       2
19     Minnesota      June   10  2008         2         3      2        1 Very good        0        0        1       2
20      Illinois  December   11  2008        16         3      0        3 Very good        3        2        1       2
```

A look

The survey responses are a mix of qualitative and quantitative data; let's start slow with a look at a couple of the categorical variables

What is the gender breakdown?

What proportion of respondents have exercised in the last 30 days?

What about the respondents' general health?

Their overall satisfaction with their lives?

```
exerany

1   29726
2   10233
```

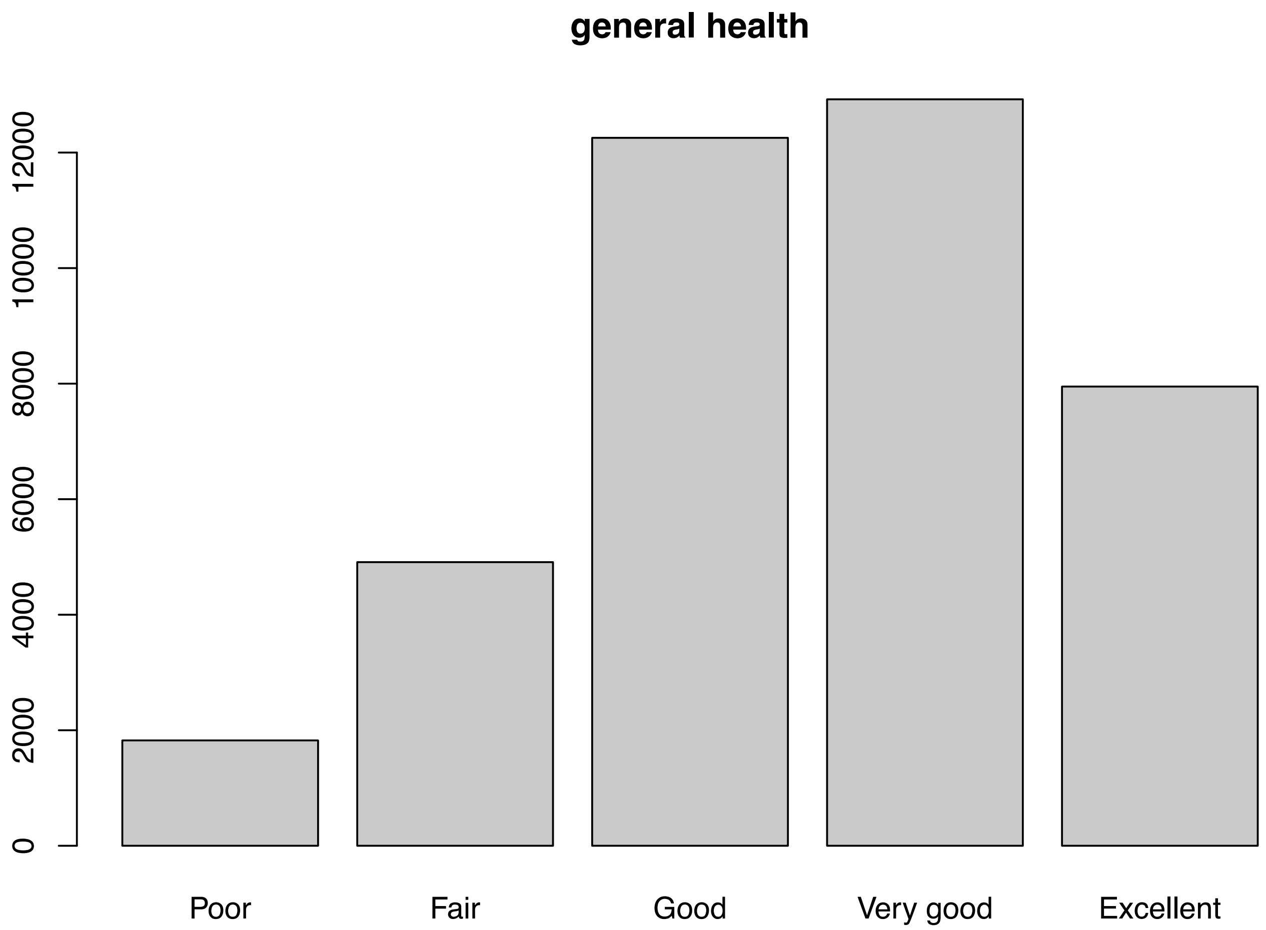
```
gender

male    19604
female  20396
```

```
genhlth

excellent   7949
very good  12922
good       12255
fair        4910
poor        1824
don't know    61
refused       79
```

```
lsatisfy

very satisfied     17590
satisfied          18806
dissatisfied       12255
very dissatisfied   4910
don't know           191
refused              364
```

Graphical displays

A **barplot** can be formed to make comparisons easier

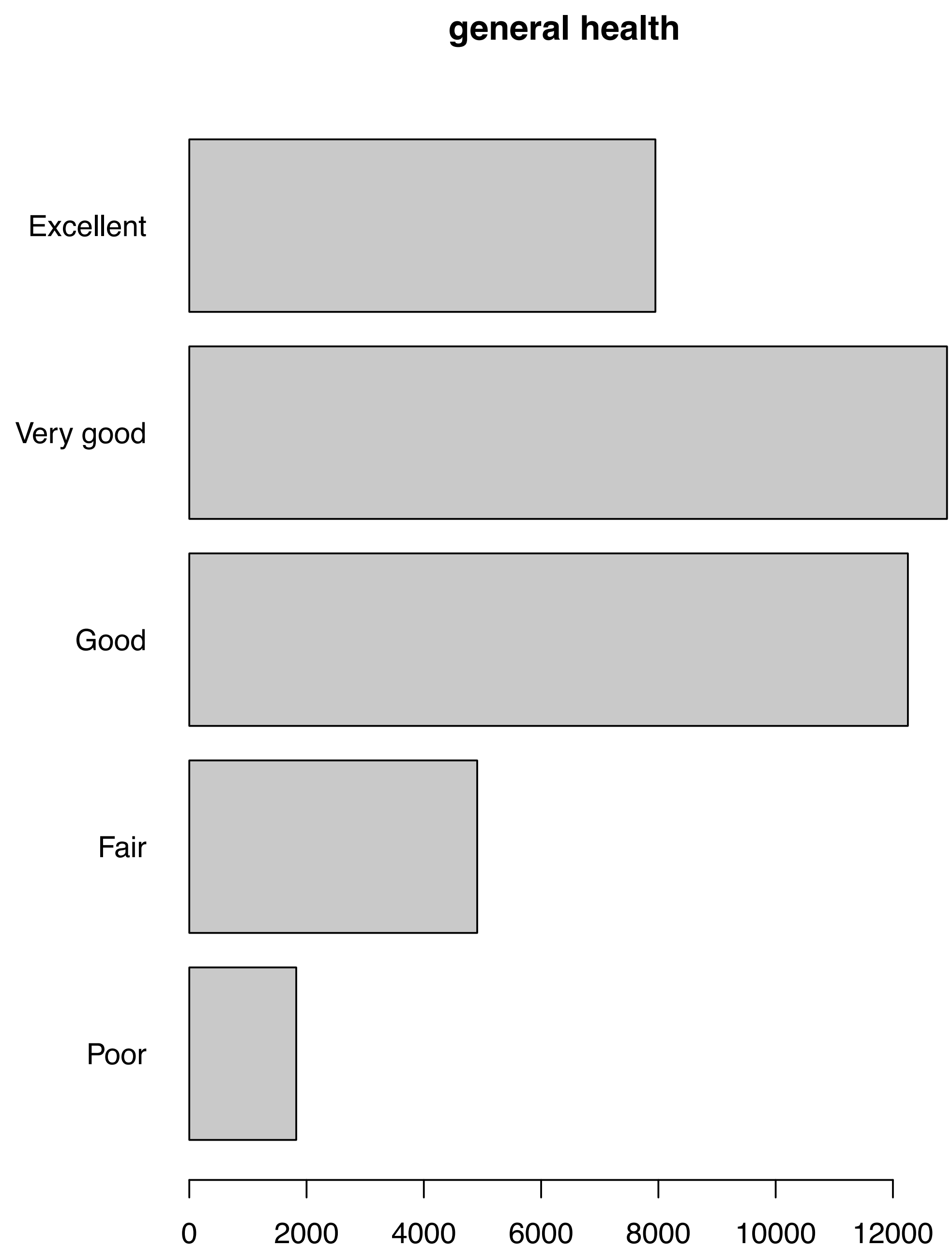


```
# let's start with tabular output

table(brfss$genhlth)

# for the moment, drop the non-responders and the unsure :)

ta = table(brfss$genhlth)
ta = ta[5:1]

# a high-level plot routine

barplot(ta,main="general health")

# ... or flipped on its side (getting fancy!)

par(oma=c(0,2,0,0))
barplot(ta,main="general health",horiz=TRUE,las=1)

?barplot
```

Graphical displays

Some have argued that comparisons are better made when the bars run horizontally*

The code on the previous slide skips ahead a fair bit, but don't worry, we'll cover all this



* Cleveland, W. S. (1993), *Visualizing Data,* Hobart Press

Questions

While these one-dimensional summaries are interesting, they can’t address certain questions we might bring to the data; for example, does exercise have any effect on what people feel about their general health?

For this, we might consider tabular displays

Tables

Here is a two-by-two table (also referred to as **a contingency table**) describing how respondents answered both the question of how good they feel and whether or not they exercise; we have added **row and column sums** to this display also

What do we see?

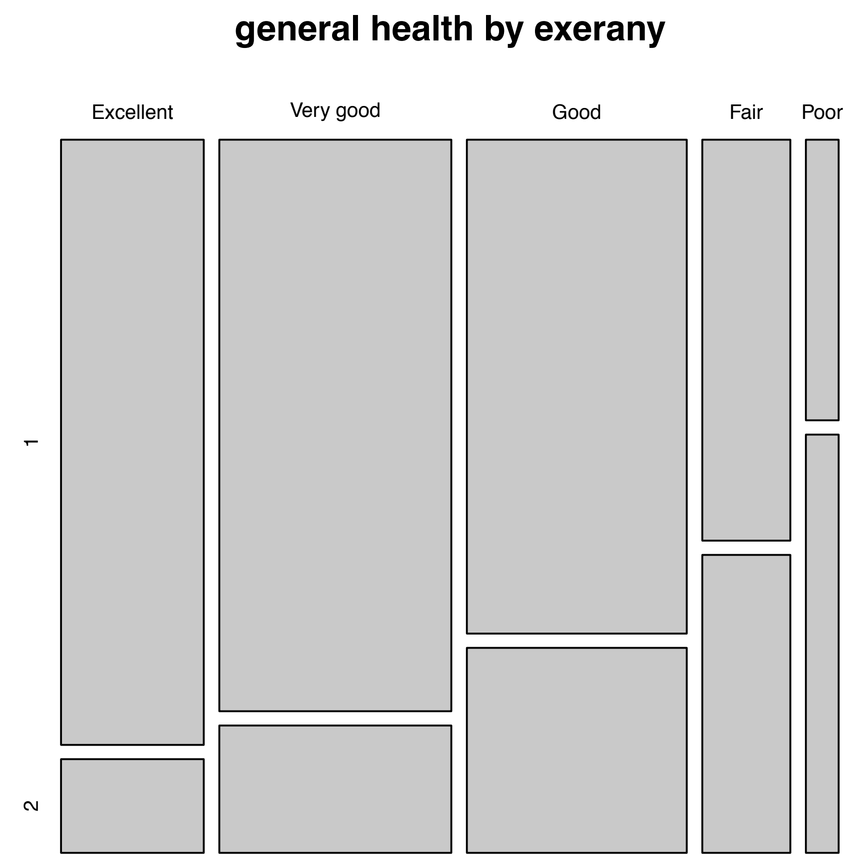
```
> table(brfss$genhlth,brfss$exerany)

                            1     2
  Excellent              6880  1065
  Very good             10561  2353
  Good                   8649  3590
  Fair                   2811  2089
  Poor                    732  1091
  Don’t know/Not Sure      36    24
  Refused                  57    21
```

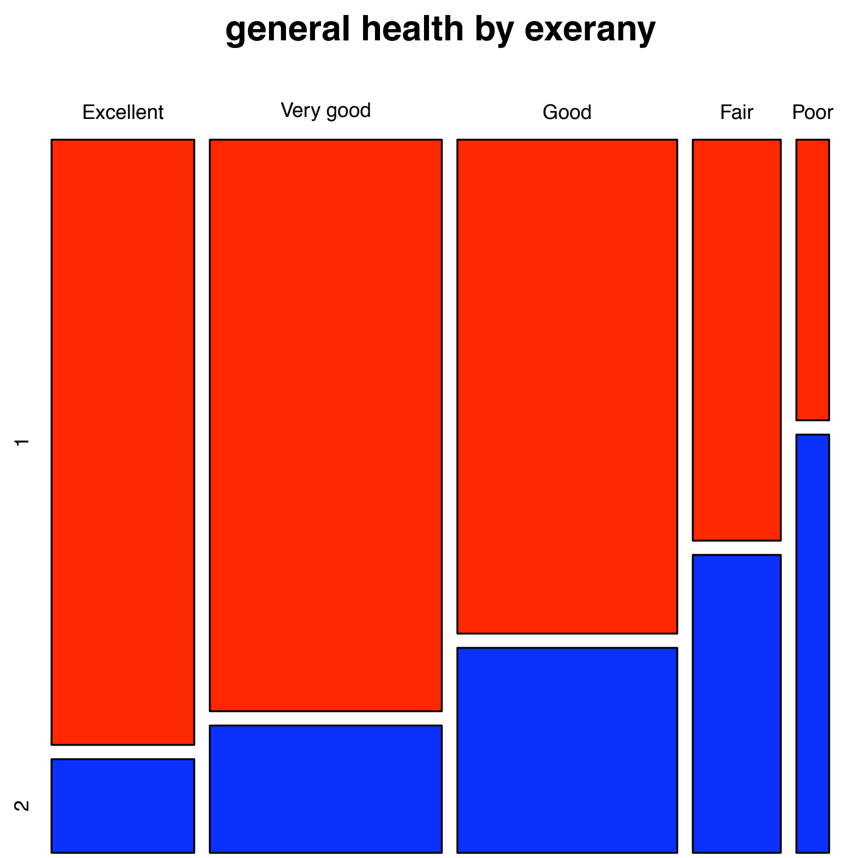
Mosaic plots

These displays represent the counts in a contingency table by tiles whose size (area) is proportional to the cell count

It is also possible to extend these displays to tabulations with more than two variables; how might this work?

Hartigan, J.A., and Kleiner, B. (1984) A mosaic of television ratings. *The American Statistician*, **38**, 32-35


general health by exerany
Excellent
Very good
Good
Fair
Poor
1
2


general health by exerany
Excellent
Very good
Good
Fair
Poor
1
2

```r
# let’s start with tabular output

table(brfss$genhlth,brfss$exerany)

# a high-level plot routine

ta = table(brfss$genhlth,brfss$exerany)
ta = ta[1:5,]

mosaicplot(ta,main="general health by exerany")

# colors!

mosaicplot(ta,color=c("red","blue"))
```

Creating new variables

BMI (Body Mass Index) is defined to be

$$\text{BMI} = 703 \times \frac{\text{weight in pounds}}{(\text{height in inches})^2}$$

We can derive this from our data set and create a new quantitative variables

The CDC interprets these limits as follows

BMI	**Weight Status**
Below 18.5	Underweight
18.5 – 24.9	Normal
25.0 – 29.9	Overweight
30.0 and Above	Obese

```
bmi = 703*brfss$weight/brfss$height^2

bmicat = (bmi > 0) + (bmi >= 18.5) + (bmi >= 25) + (bmi >= 30)

levs = c("underweight","normal","overweight","obese")
bmicat = factor(levs[bmicat],levels=levs)

ta = table(brfss$genhlth,bmicat)
ta = ta[1:5,]

mosaicplot(ta,main="general health by exerany")

mosaicplot(ta,color=heat.colors(4),
           main="general health by exerany")
```

Quantitative data

In the BMI example, we generated an ordinal variable from our computed BMI; in general, “seeing” the values of a quantitative variable (whether it be continuous or discrete with a large number of values) can be hard

But the idea of grouping comes to our rescue in the form of **grouped frequency displays or histograms**

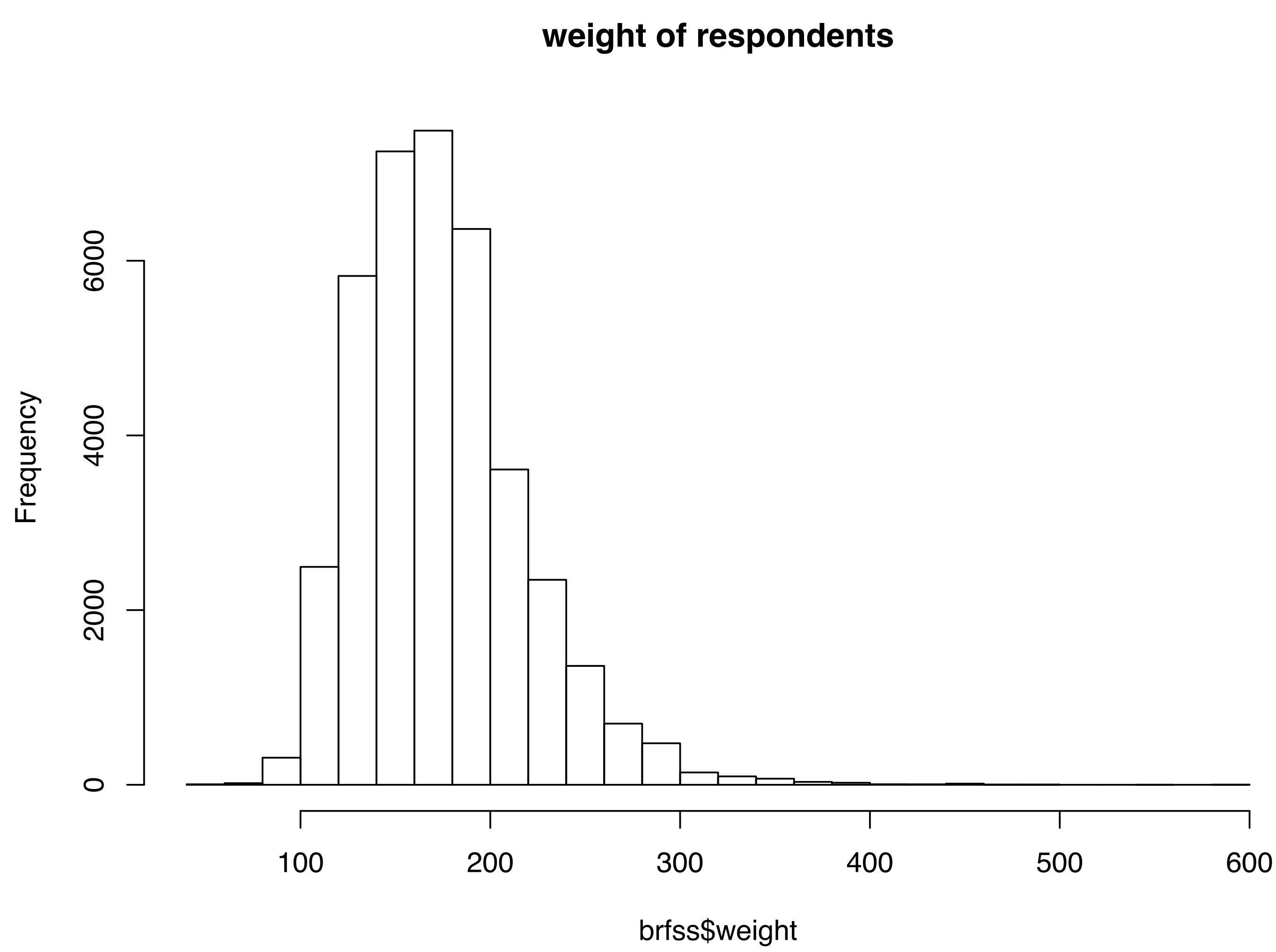
Histograms

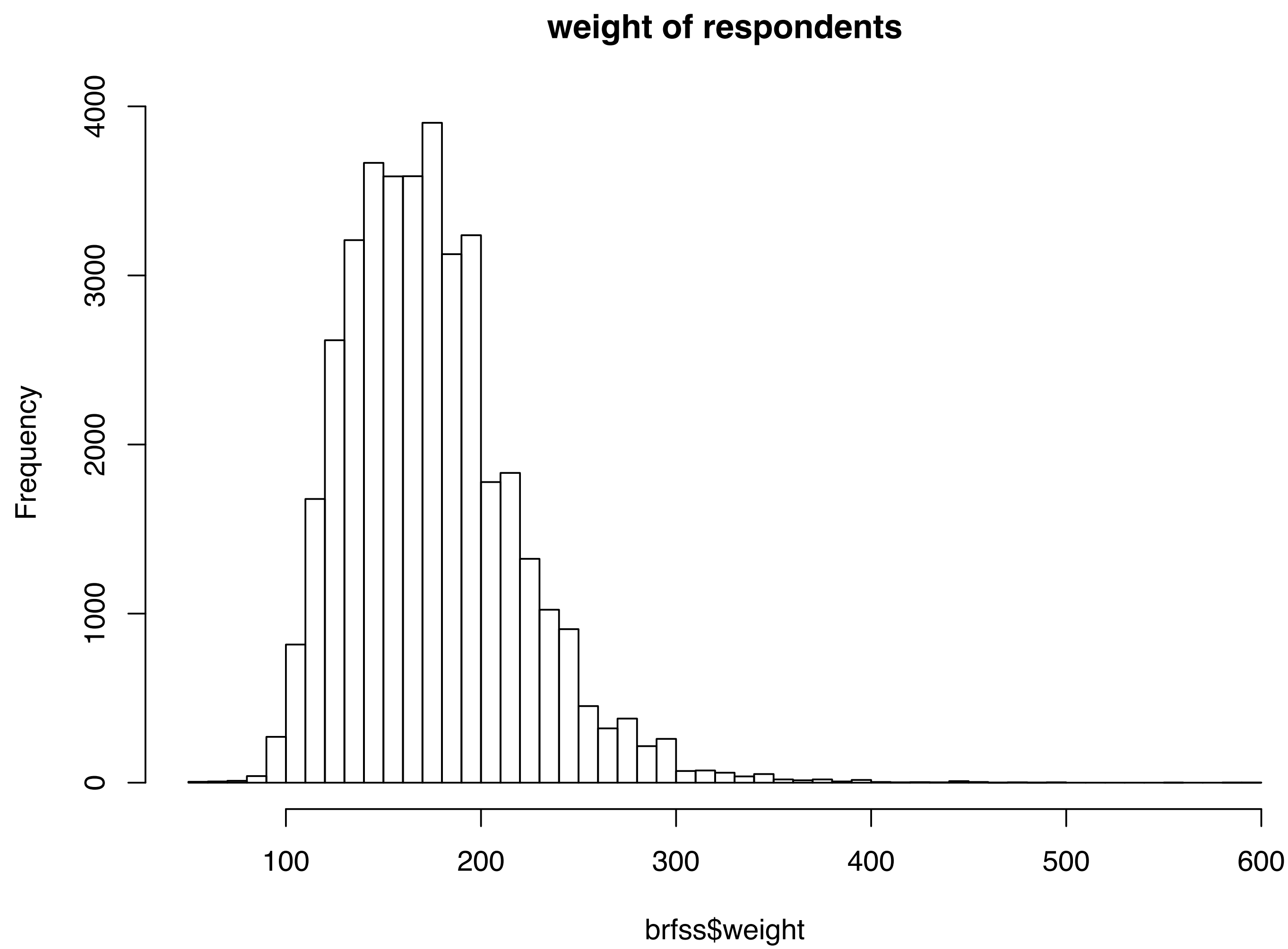
A histogram groups or bins the data and, like a barplot, presents the number of data points that fall into each group

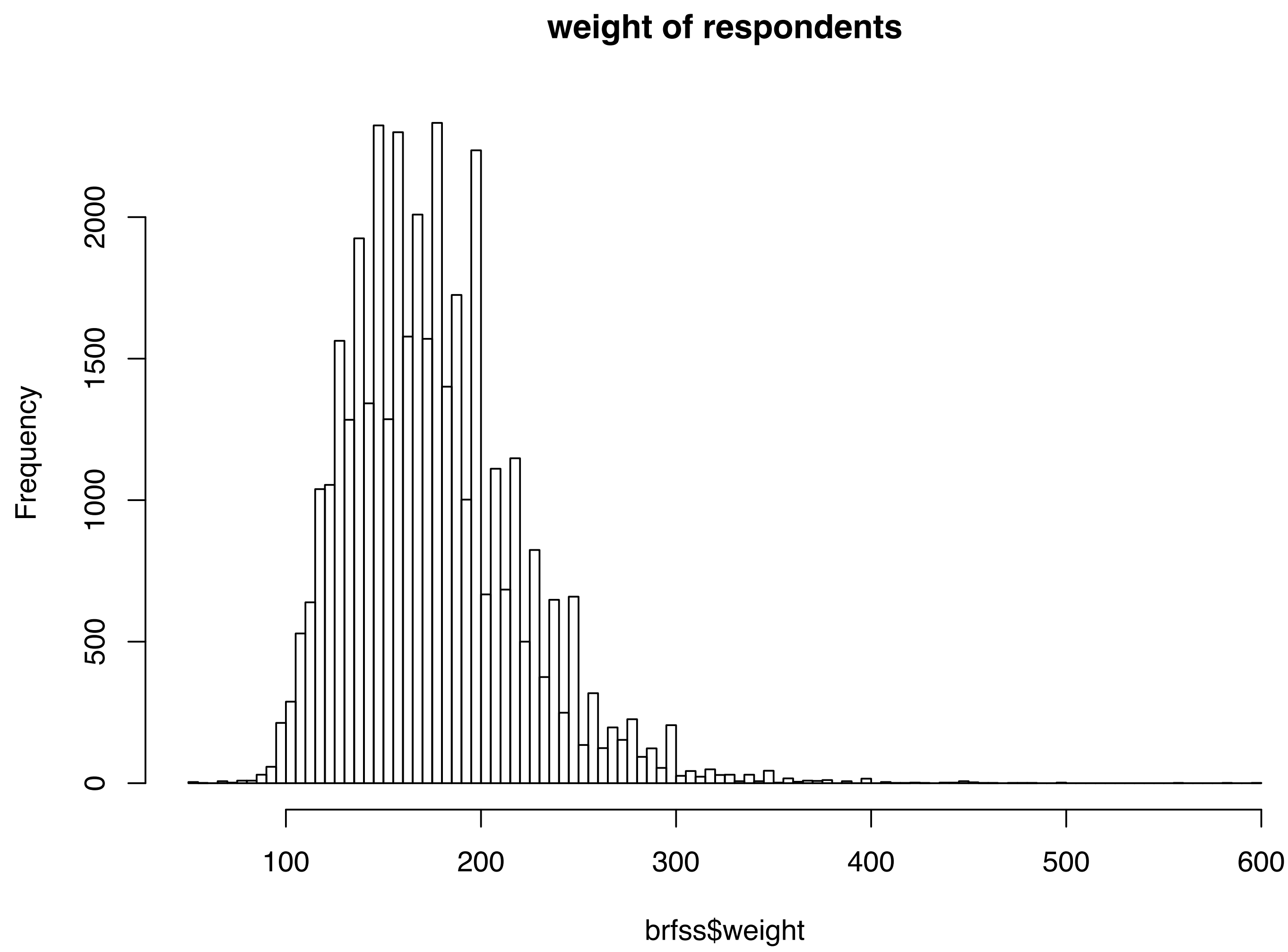
This display involves a “tuning parameter”; that is, we are free to choose how many bins we want to make the display -- this is what I meant before by there being both tuning in terms of the aesthetics (colors, fonts) as well as the underlying methodology that generates the display

In situations like this, **it is always good to vary the number of bins and examine the plot for any structure that emerge**s; in so doing, we want to get a sense of the “shape” of the data

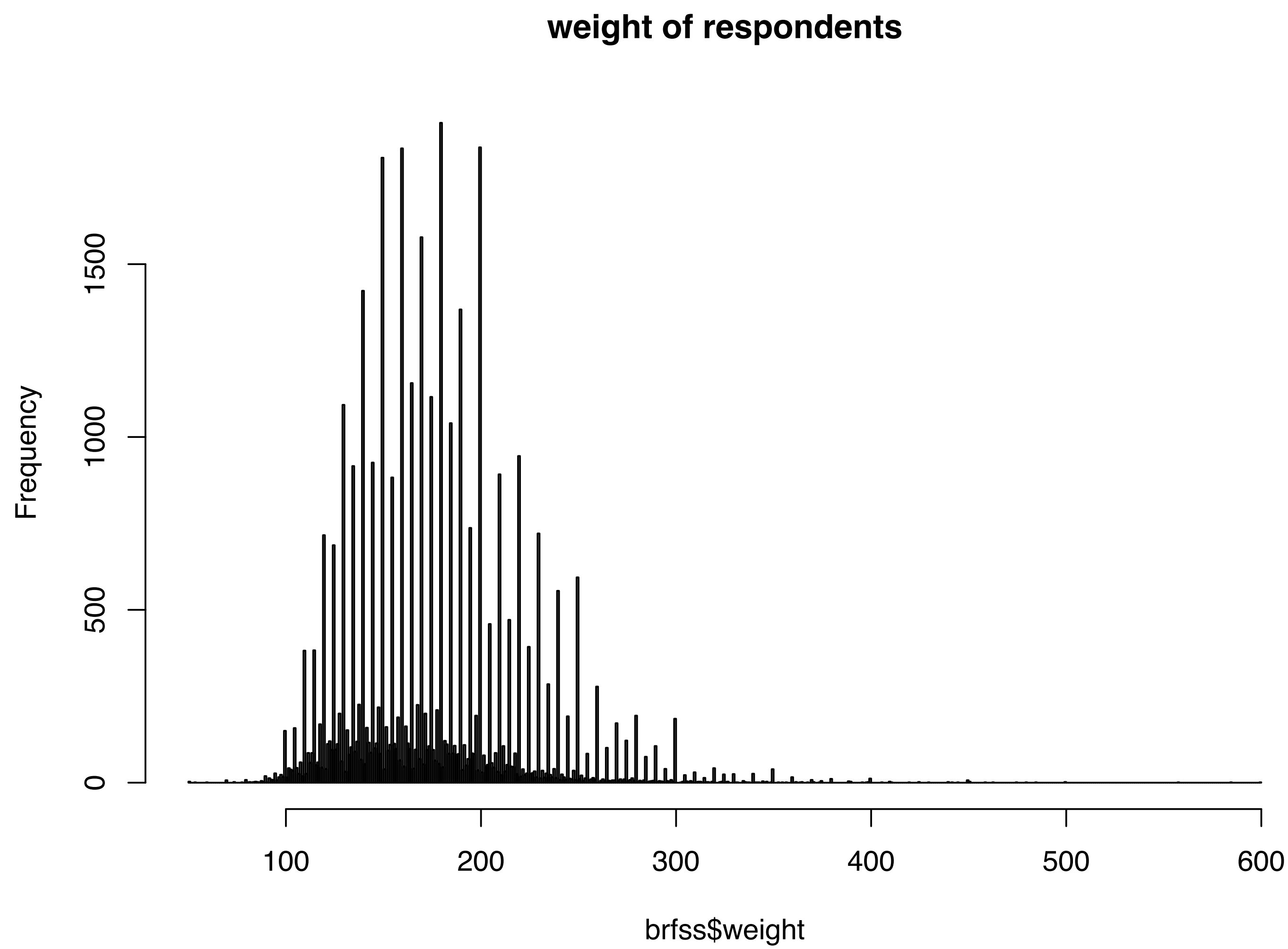
What do we see?

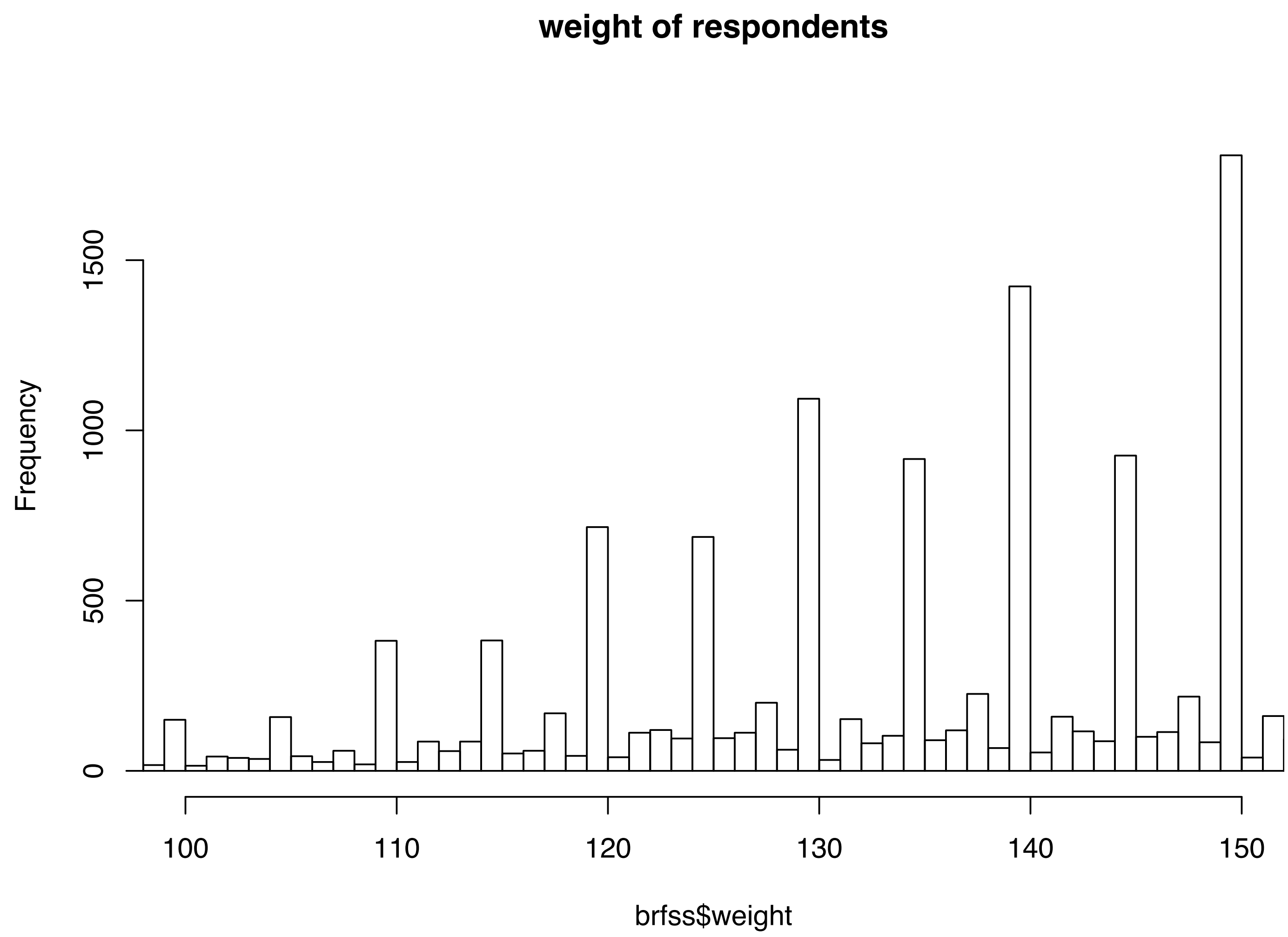

weight of respondents
Frequency
0
2000
4000
6000
100
200
300
400
500
600
brfss$weight


weight of respondents
Frequency
0
1000
2000
3000
4000
100
200
300
400
500
600
brfss$weight



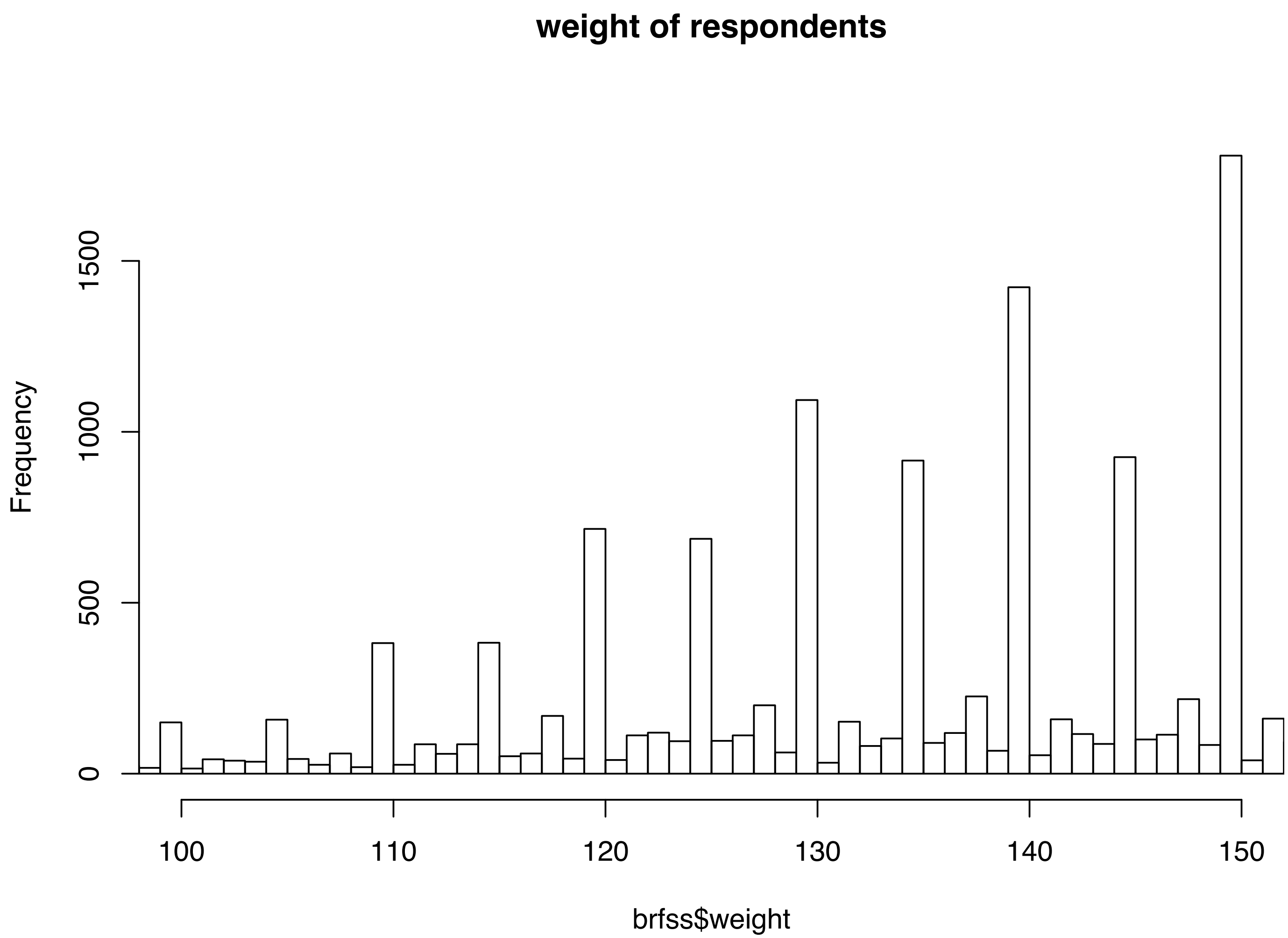
weight of respondents
Frequency
0
500
1000
1500
2000
100
200
300
400
500
600
brfss$weight


weight of respondents
Frequency
0
500
1000
1500
100
200
300
400
500
600
brfss$weight


weight of respondents
Frequency
0
500
1000
1500
100
110
120
130
140
150
brfss$weight

Varying bin sizes

By changing the bin size, we can uncover features in the data; in this case we uncover a basic fact about how people report their weights



```
hist(brfss$weight,breaks=20,main="weight of respondents")

hist(brfss$weight,breaks=50,main="weight of respondents")

hist(brfss$weight,breaks=100,main="weight of respondents")

hist(brfss$weight,breaks=500,main="weight of respondents")

hist(brfss$weight,breaks=500,main="weight of respondents",xlim=c(100,150))
```

Default bin size

It is often the case that we don't want to think very hard about how many bins or groups to use when drawing a histogram; the hist() function in R uses a rule of thumb for setting the number of bins based on our sample size

$$\text{number of bins} \approx \log_2(\mathsf{n}) + 1$$

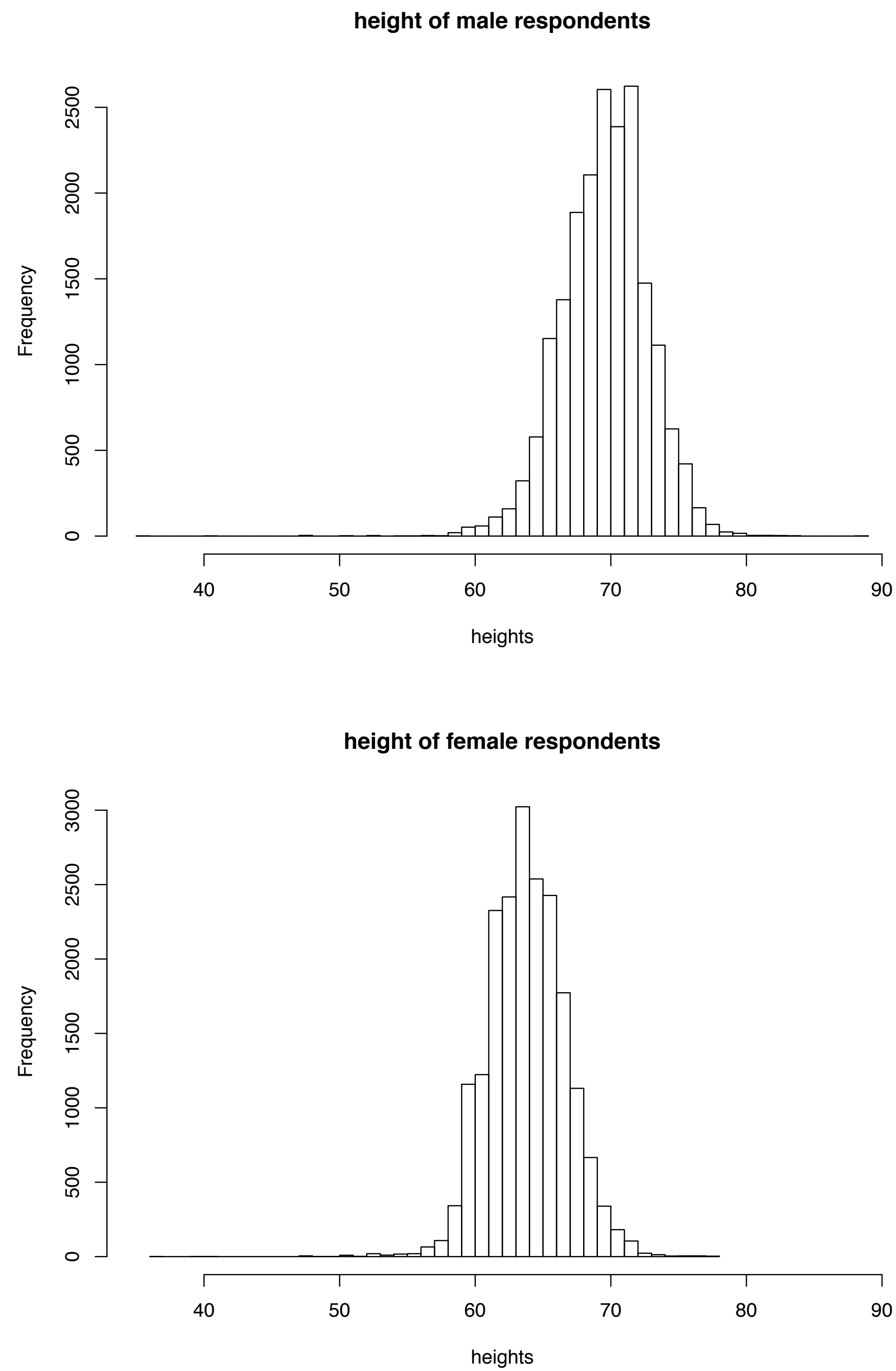
Where might a rule like this come from?

Comparing distributions (I)

We can use these displays to compare distributions

At the left we have separate histograms of the heights of males and females in the sample

What do you see?

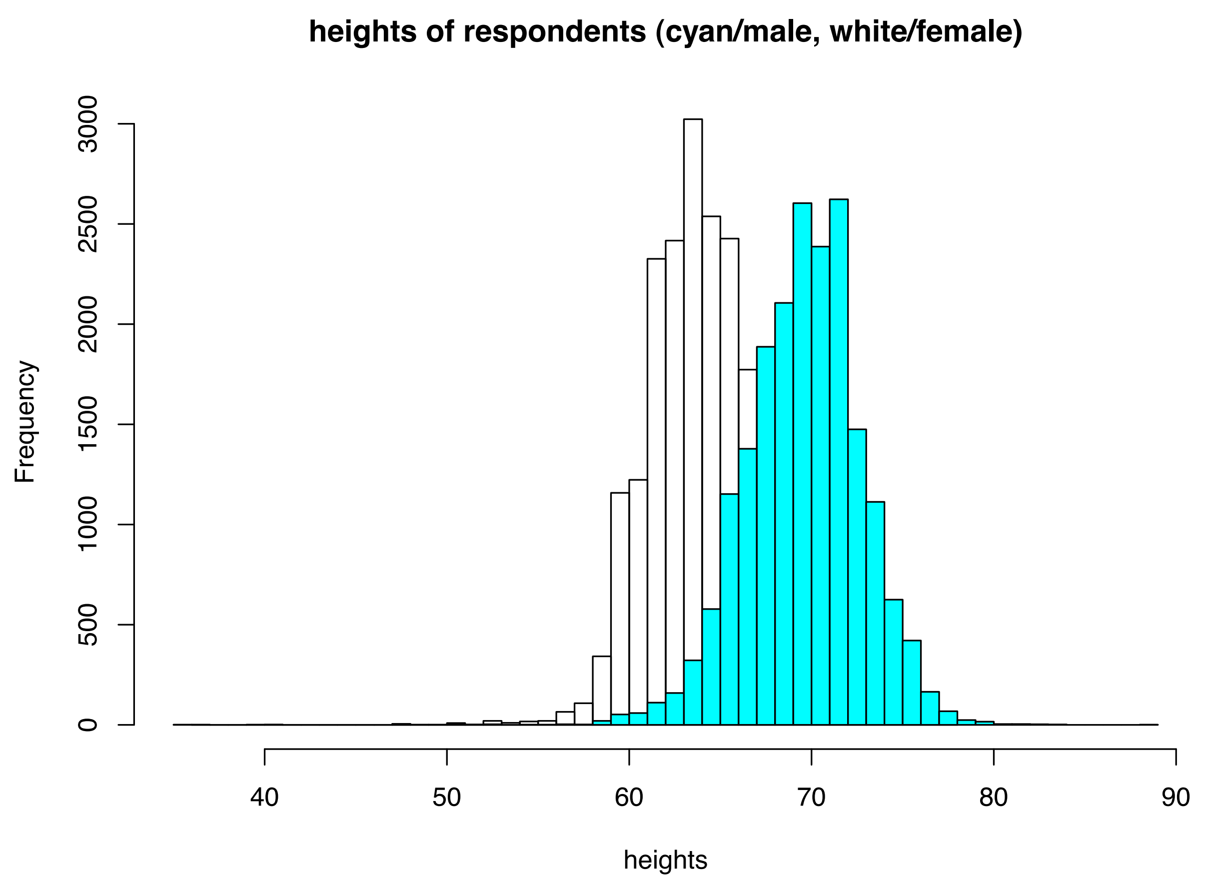


```
# compare two histograms...

# first, a common range...

ra = range(brfss$height,na.rm=T)
ra

# and now, the high-level command...

hist(brfss$height[brfss$sex=="male"],
     breaks=50,main="height of male respondents",xlim=ra,xlab="heights")

hist(brfss$height[brfss$sex=="female"],
     breaks=50,main="height of female respondents",xlim=ra,xlab="heights")
```

Comparing distributions (I)

A more effective strategy would be to simply overlay one histogram over the other, perhaps adding a snappy color

At this point it should be clear how helpful it is to have a good rule of thumb for picking the number of bins

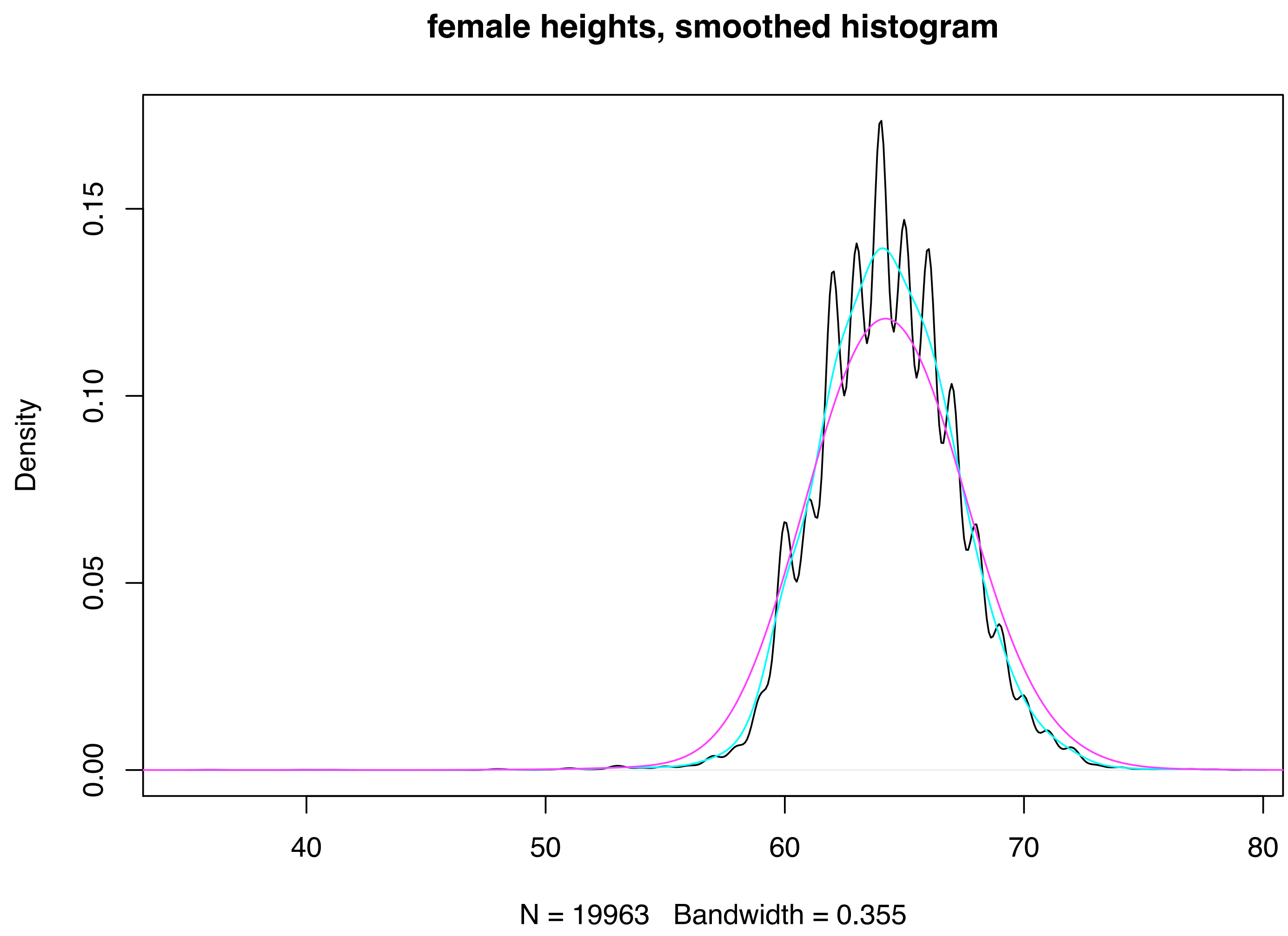


```
# compare two histograms...

# first, a common range...

ra = range(brfss$height,na.rm=T)
ra

# and now, the high-level command...

hist(brfss$height[brfss$sex=="male"],
     breaks=50,main="height of male respondents",xlim=ra,xlab="heights")

hist(brfss$height[brfss$sex=="female"],
     breaks=50,main="height of female respondents",xlim=ra,xlab="heights")

# overlay!

hist(brfss$height[brfss$sex=="female"],breaks=50,
 main="heights of respondents (cyan/male, white/female)",xlim=ra,xlab="heights")

hist(brfss$height[brfss$sex=="male"],breaks=50,add=T,col="cyan")
```

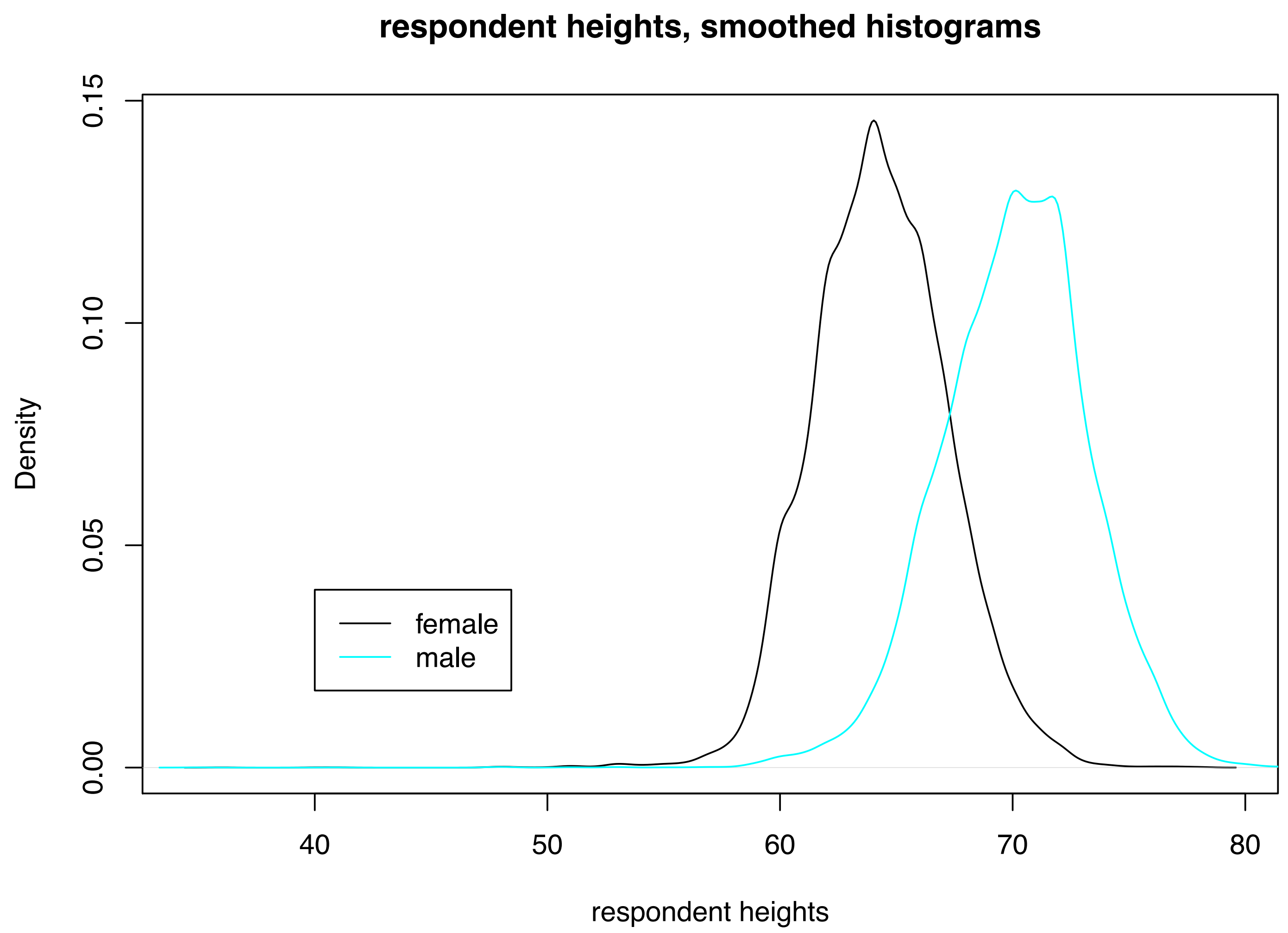
Smoothed histograms

Overlaying histograms can get tricky if we aren’t careful; one can obscure the features of the other -- here we’re lucky in that both distributions are essentially unimodal

Another approach, however, is to create a simpler view; a smoothed histogram (technically, a kernel density estimate) is one such device


female heights, smoothed histogram
Density
0.00
0.05
0.10
0.15
40
50
60
70
80
N = 19963 Bandwidth = 0.355

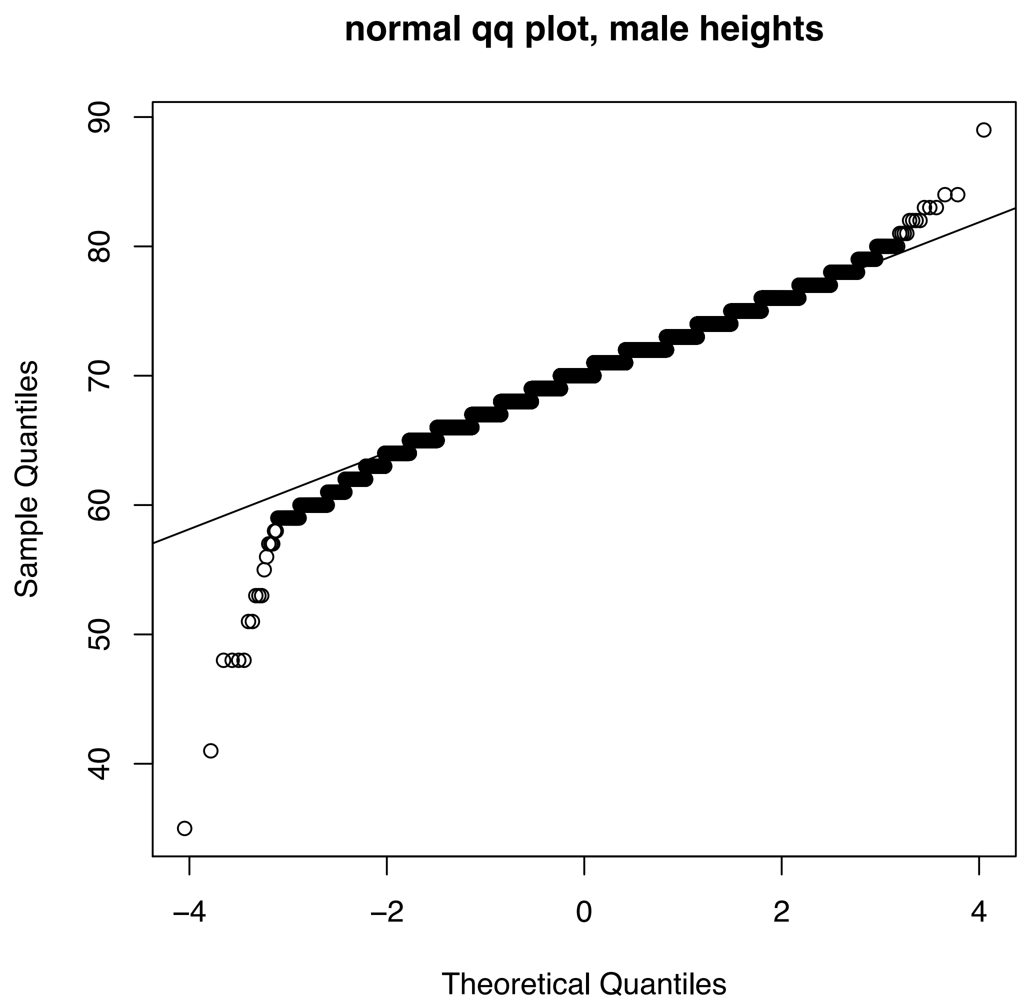
```
fsmooth = density(brfss$height[brfss$sex=="female"],na.rm=T)

plot(fsmooth,main="female heights, smoothed histogram")

fsmooth = density(brfss$height[brfss$sex=="female"],na.rm=T,adjust=2)
lines(fsmooth,col="cyan")

fsmooth = density(brfss$height[brfss$sex=="female"],na.rm=T,adjust=5)
lines(fsmooth,col="magenta")

# overlay!

fsmooth = density(brfss$height[brfss$sex=="female"],na.rm=T,adjust=1.5)
msmooth = density(brfss$height[brfss$sex=="male"],na.rm=T,adjust=1.5)

plot(fsmooth,main="respondent heights, smoothed histograms",
     xlab="respondent heights")

lines(msmooth,col="cyan")

# add a legend!

legend(40,0.04,col=c("black","cyan"),legend=c("female","male"),lty=c(1,1))
```


respondent heights, smoothed histograms
Density
0.00
0.05
0.10
0.15
40
50
60
70
80
respondent heights
female
male

A graphical measure

Often, we find ourselves asking if the distribution of data in question is normal or not; statisticians in the late 1800s were obsessed with finding normal curves in groups of body measurements

Histograms are one way to assess normality (does it look bell-shaped or not?) but a qqplot is a more refined measuring device...


normal qq plot, male heights
Sample Quantiles
Theoretical Quantiles
90
80
70
60
50
40
−4
−2
0
2
4

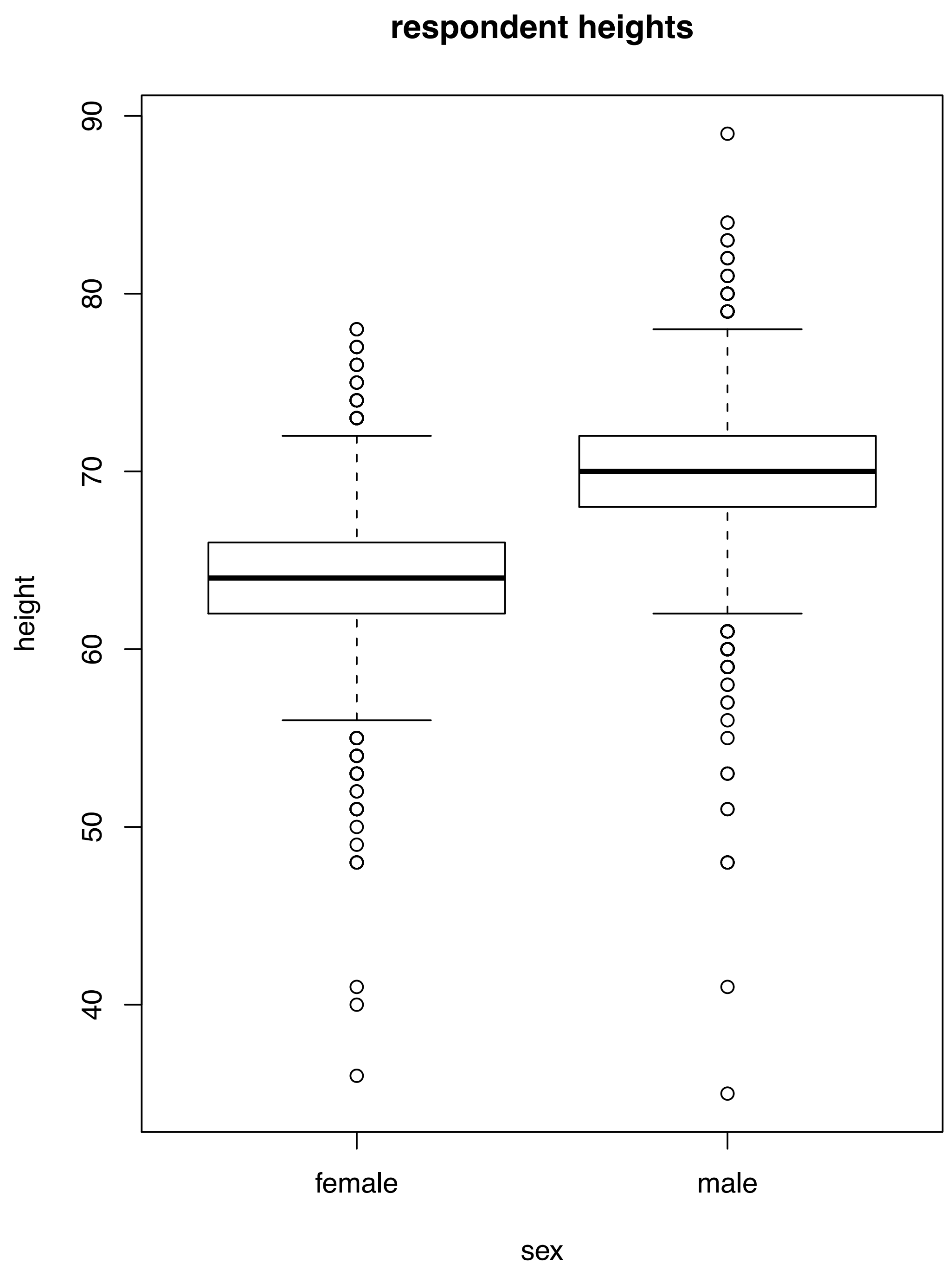
```
# normal quantile-quantile plot

qqnorm(brfss$height[brfss$sex=="male"],main="normal qq plot, male heights")

# add a guide line

qqline(brfss$height[brfss$sex=="male"])
```

Boxplots

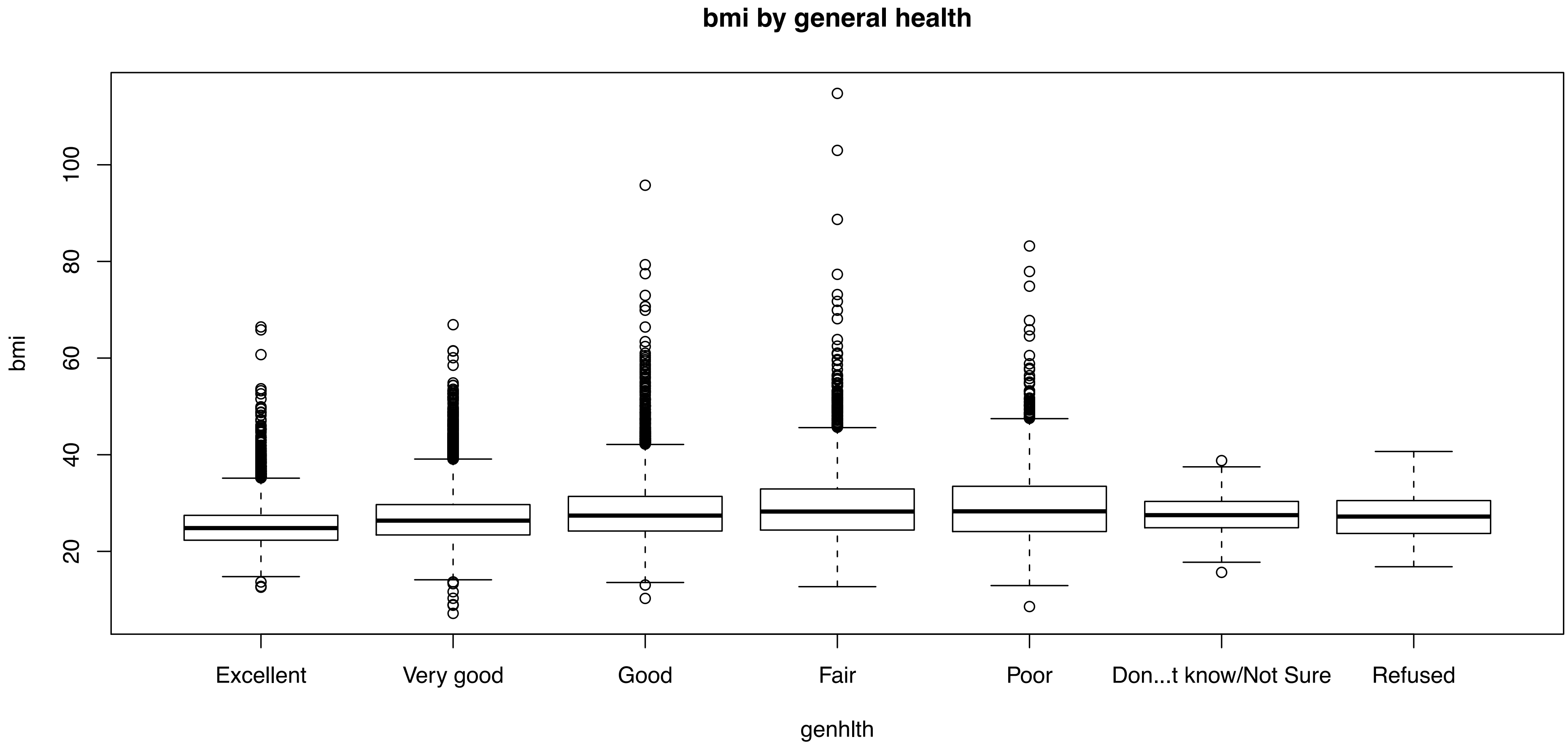
In many cases, we don't need to examine the complete distribution, but we can instead look at just a thumbnail sketch -- we're sort of creeping up on that idea as we simplify the smooth histograms

Boxplots are one form of thumbnail, focusing on the so-called five number summary; they were developed by one of the big thinkers in EDA, John Tukey

These plots let us relate a categorical and a continuous variable...


respondent heights
height
90
80
70
60
50
40
female
male
sex

```
boxplot(brfss$height[brfss$sex=="female"],brfss$height[brfss$sex=="male"])

# another way to generate the same plot...

boxplot(height~sex,data=brfss, main="respondent heights")

# ... and yet another way

plot(height~sex,data=brfss,main="respondent heights")

# and another...

plot(bmi~genhlth,data=brfss,main="bmi by general health")
```


bmi by general health
bmi
20
40
60
80
100
Excellent
Very good
Good
Fair
Poor
Don...t know/Not Sure
Refused
genhlth

Graphics in R

We have seen some high-level plots; box plots, histograms, smoothed histograms, bar plots and mosaic plots

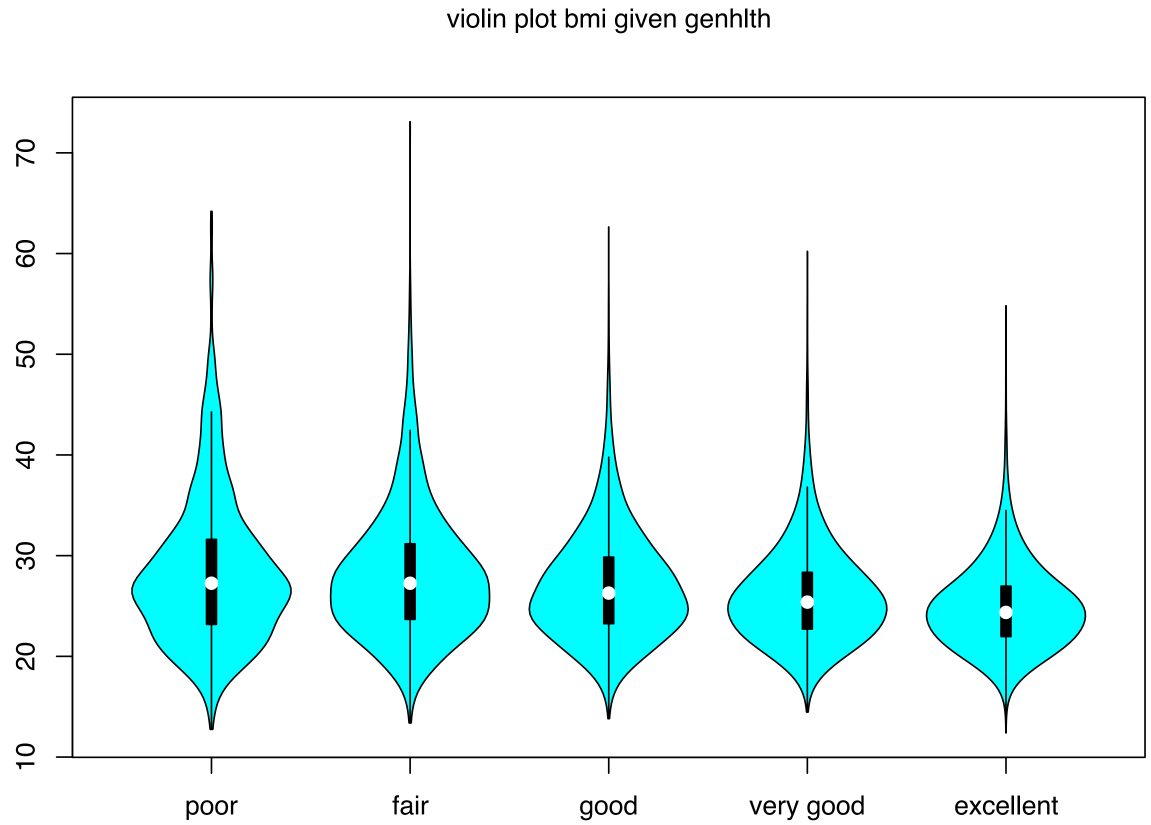
These were all called by special functions that execute one kind of graphical display; we started to see, however, that the function plot() itself, was a fairly flexible character -- we'll come back to that shortly

Now, these are by no means the only high-level functions out there; people are actively contributing all manner of interesting high-level, specialty plots

Violin plots

The so-called violin plot might be more artistry than data analysis; but it uses the smoothed histogram tipped on its side and mirrored left and right in place of a box

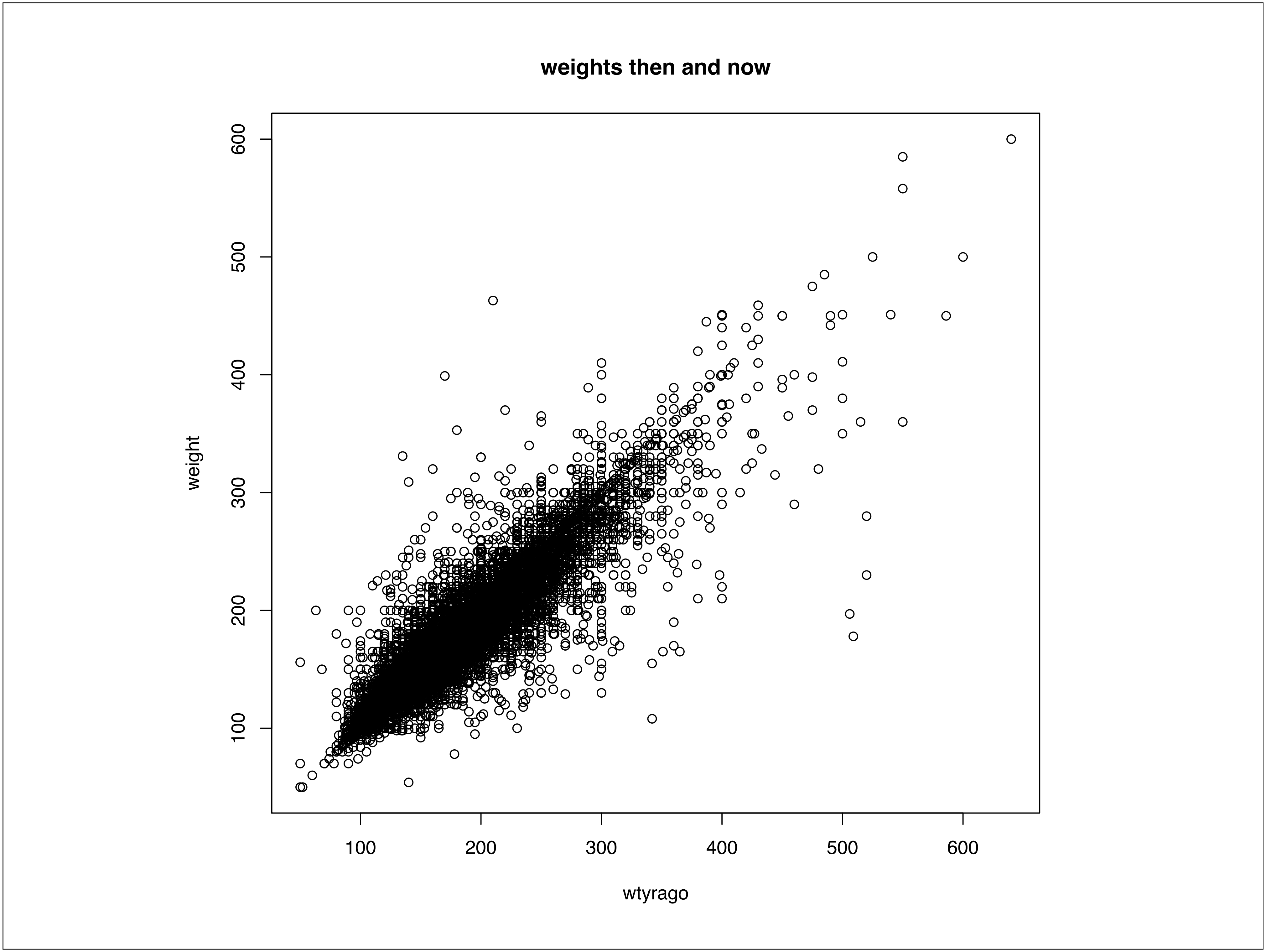
Compare this plot to the boxplot three slides back; what do you think?

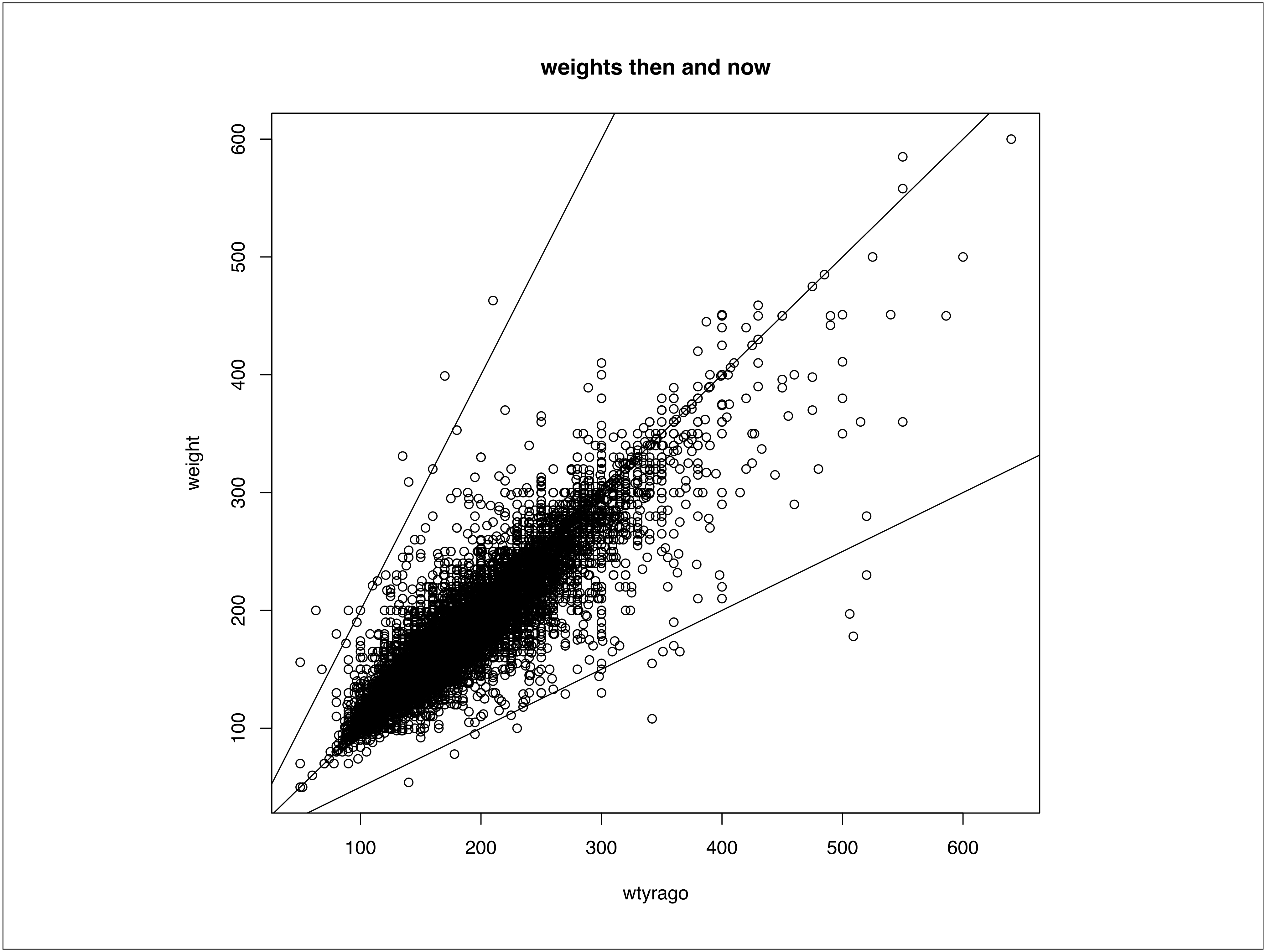


Weighty matters

To relate two continuous variables, we could consider a scatterplot (by rights, in any sane graphics introduction, this would come first)

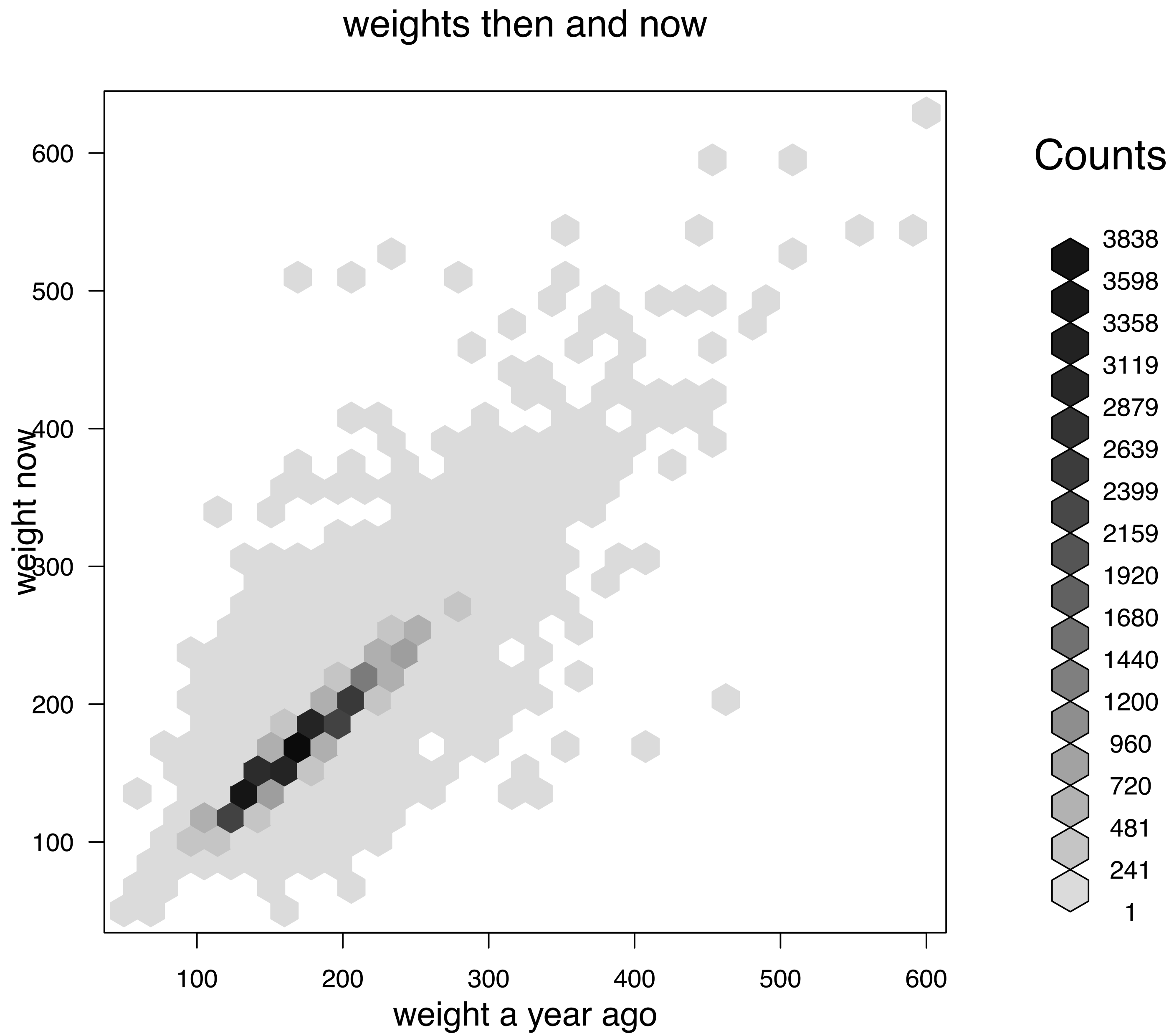
Let’s look at people’s weights this year to their weights last year...


weights then and now
weight
wtyrago
100
200
300
400
500
600
100
200
300
400
500
600


weights then and now
weight
wtyrago
100
200
300
400
500
600
100
200
300
400
500
600

```
# the many faces of plot!

plot(brfss$weight,brfss$wtyrago,main="weights then and now")

# or...

plot(weight~wtyrago,data=brfss,main="weights then and now")

# add another guide line...

abline(0,1)

abline(0,2)   # people who are twice as heavy

abline(0,0.5)   # people who are twice as heavy
```

```
library(hexbin)

# create a hexagonal grid over the data and count the points falling
# in each cell

h = hexbin(brfss$weight,brfss$wtyrago)

plot(h,main="weights then and now")

# look again what plot’s doing!!
```



weights then and now
weight now
weight a year ago
100
200
300
400
500
600
Counts
3838
3598
3358
3119
2879
2639
2399
2159
1920
1680
1440
1200
960
720
481
241
1

To sum up

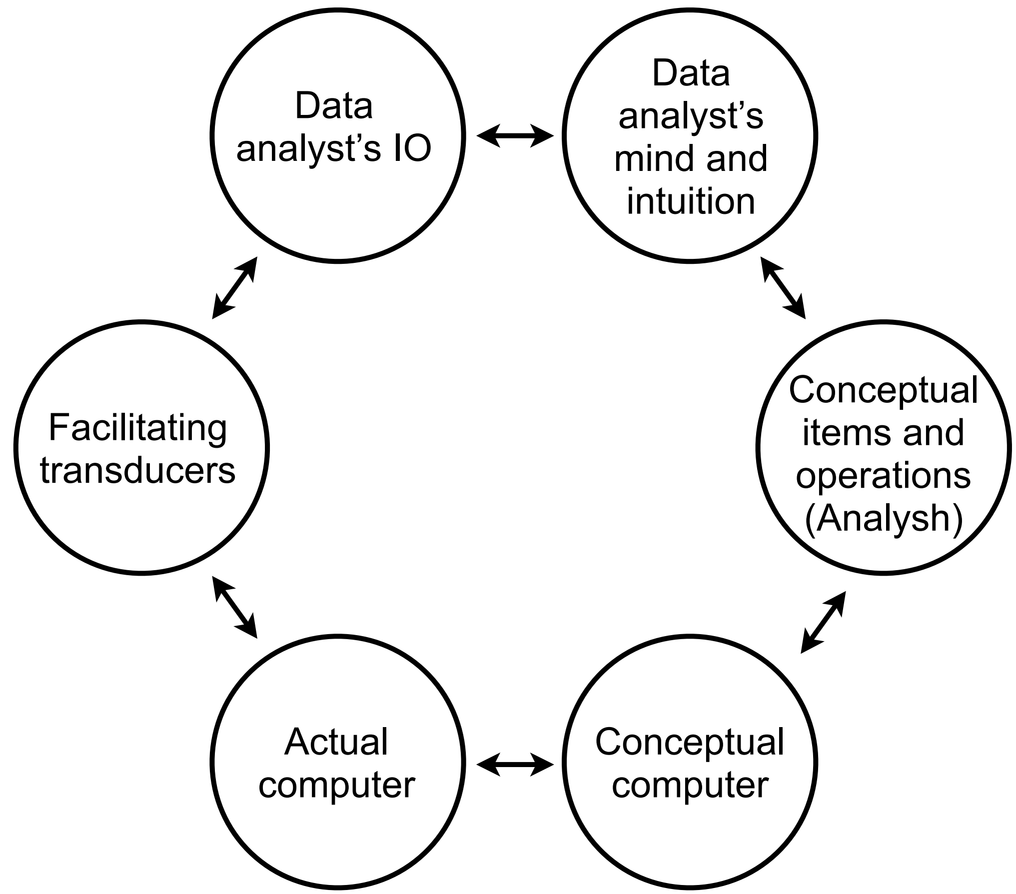
So far, we’ve executed some simple high-level commands to make basic plots in R; there are many such functions that we will encounter over the week

Notice that for the most part the basic high-level commands do the right thing; they were designed to be part of a data analysis pipeline that Tukey and others envisioned where you go back and forth with plots and computation

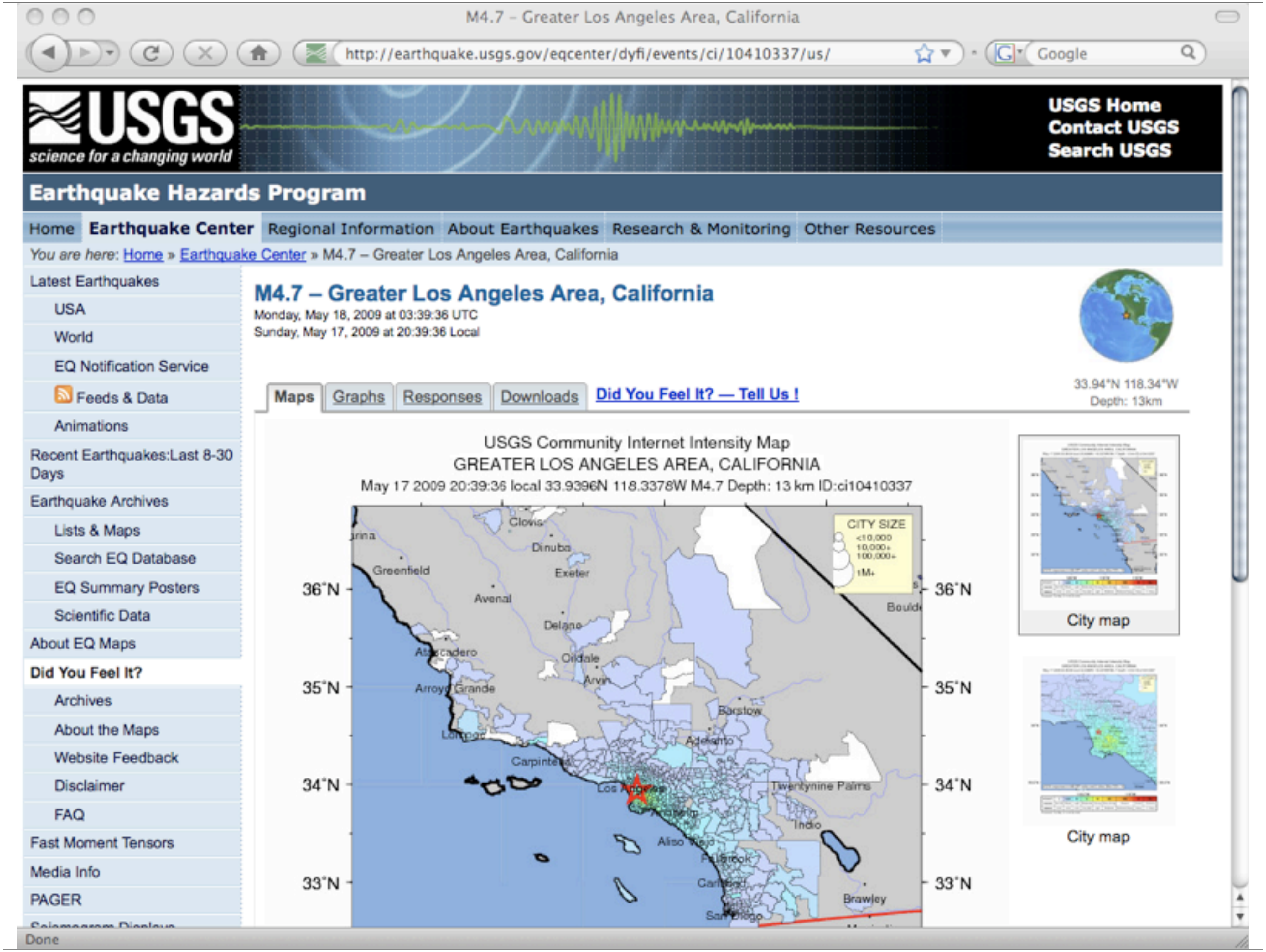
We have started customizing these plots by adding annotations and graphical elements, and we’ll talk more about that after the break -- we will also spend more time with the basic anatomy of an R plot

Follow the arrows clockwise from the Mind and Intuition block. Tukey's notion is that data analysts have an arsenal of operations applicable to data, which they describe to themselves and to each other in a combination of mathematics and (English) words, for which he coins the term Analysh. These descriptions can be made into algorithms (my term, not his) -- specific computational methods, but not yet realized for an actual computer (hence the conceptual computer). Then a further mapping implements the algorithm, and running it produces output for the data analyst. The output, of course, stimulates further ideas and the cycle continues. (The facilitating transducers I interpret to mean software that allows information to be translated back and forth between internal machine form and forms that humans can write or look at -- a transducer, in general, converts energy from one form to another. So parsers and formatting software would be examples.)

Taken from Chambers (2000)



Adapted from Chambers (2000)



M4.7 – Greater Los Angeles Area, California
http://earthquake.usgs.gov/eqcenter/dyfi/events/ci/10410337/us/
Google
USGS
science for a changing world
USGS Home
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Earthquake Hazards Program
Home
Earthquake Center
Regional Information
About Earthquakes
Research & Monitoring
Other Resources
You are here: Home » Earthquake Center » M4.7 – Greater Los Angeles Area, California
Latest Earthquakes
USA
World
EQ Notification Service
Feeds & Data
Animations
Recent Earthquakes:Last 8-30 Days
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Scientific Data
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Did You Feel It?
Archives
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Disclaimer
FAQ
Fast Moment Tensors
Media Info
PAGER
M4.7 – Greater Los Angeles Area, California
Monday, May 18, 2009 at 03:39:36 UTC
Sunday, May 17, 2009 at 20:39:36 Local
33.94°N 118.34°W
Depth: 13km
Maps
Graphs
Responses
Downloads
Did You Feel It? — Tell Us !
USGS Community Internet Intensity Map
GREATER LOS ANGELES AREA, CALIFORNIA
May 17 2009 20:39:36 local 33.9396N 118.3378W M4.7 Depth: 13 km ID:ci10410337
CITY SIZE
36°N
35°N
34°N
33°N
Clovis
Dinuba
Greenfield
Exeter
Avenal
Delano
Atascadero
Oildale
Arroyo Grande
Arvin
Barstow
Lompoc
Adelanto
Carpinteria
Twentynine Palms
Indio
Aliso Viejo
Fallbrook
Carlsbad
Brawley
San Diego
City map
City map
Done

Census 2000 5-Digit ZIP Code Tabulation Areas (ZCTAs) Cartographic Boundary Files - U.S. Census Bureau

http://www.census.gov/geo/www/cob/z52000.html

shapefile zipcodes

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Census 2000 5-Digit ZIP Code Tabulation Areas (ZCTAs)
Cartographic Boundary Files

ARC/INFO Export (.e00) | ArcView Shapefile (.shp) | ARC/INFO Ungenerate (ASCII)
Click on a file below to begin downloading...

Census 2000 5-Digit ZIP Code Tabulation Areas (ZCTAs)
in ARC/INFO Export (.e00) format

Alabama - zt01_d00_e00.zip (939,702 bytes)
Alaska - zt02_d00_e00.zip (1,634,983 bytes)
Arizona - zt04_d00_e00.zip (482,399 bytes)
Arkansas - zt05_d00_e00.zip (805,069 bytes)
California - zt06_d00_e00.zip (1,868,987 bytes)
Colorado - zt08_d00_e00.zip (525,215 bytes)
Connecticut - zt09_d00_e00.zip (178,620 bytes)
Delaware - zt10_d00_e00.zip (68,765 bytes)
District of Columbia - zt11_d00_e00.zip (12,289 bytes)
Florida - zt12_d00_e00.zip (1,182,978 bytes)
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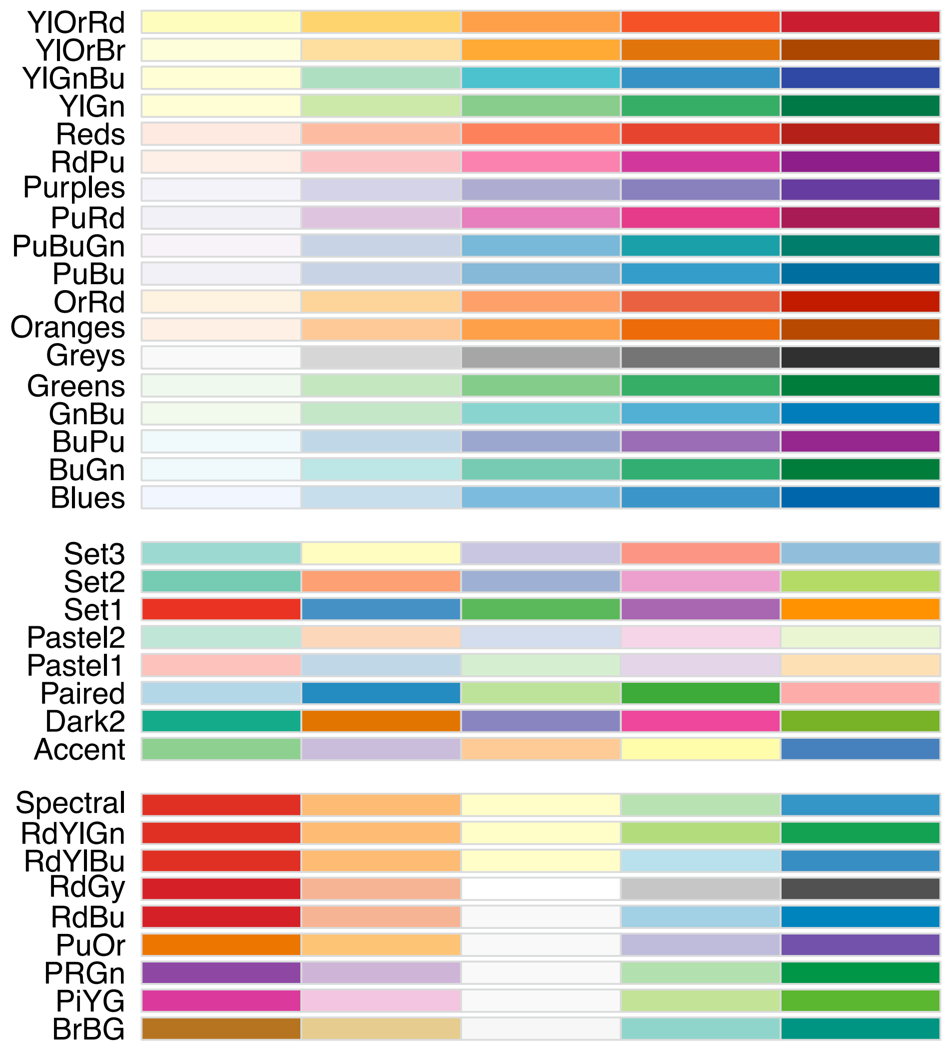
Hawaii - zt15_d00_e00.zip (101,248 bytes)
Idaho - zt16_d00_e00.zip (629,742 bytes)
Illinois - zt17_d00_e00.zip (1,036,995 bytes)
Indiana - zt18_d00_e00.zip (582,147 bytes)
Iowa - zt19_d00_e00.zip (701,864 bytes)
Kansas - zt20_d00_e00.zip (526,709 bytes)
Kentucky - zt21_d00_e00.zip (854,491 bytes)
Louisiana - zt22_d00_e00.zip (1,474,449 bytes)
Maine - zt23_d00_e00.zip (670,663 bytes)
Maryland - zt24_d00_e00.zip (420,863 bytes)
Massachusetts - zt25_d00_e00.zip (326,474 bytes)
Michigan - zt26_d00_e00.zip (948,937 bytes)
Minnesota - zt27_d00_e00.zip (1,141,294 bytes)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YlOrBr
YlGnBu
YlGn
Reds
RdPu
Purples
PuRd
PuBuGn
PuBu
OrRd
Oranges
Greys
Greens
GnBu
BuPu
BuGn
Blues
Set3
Set2
Set1
Pastel2
Pastel1
Paired
Dark2
Accent
Spectral
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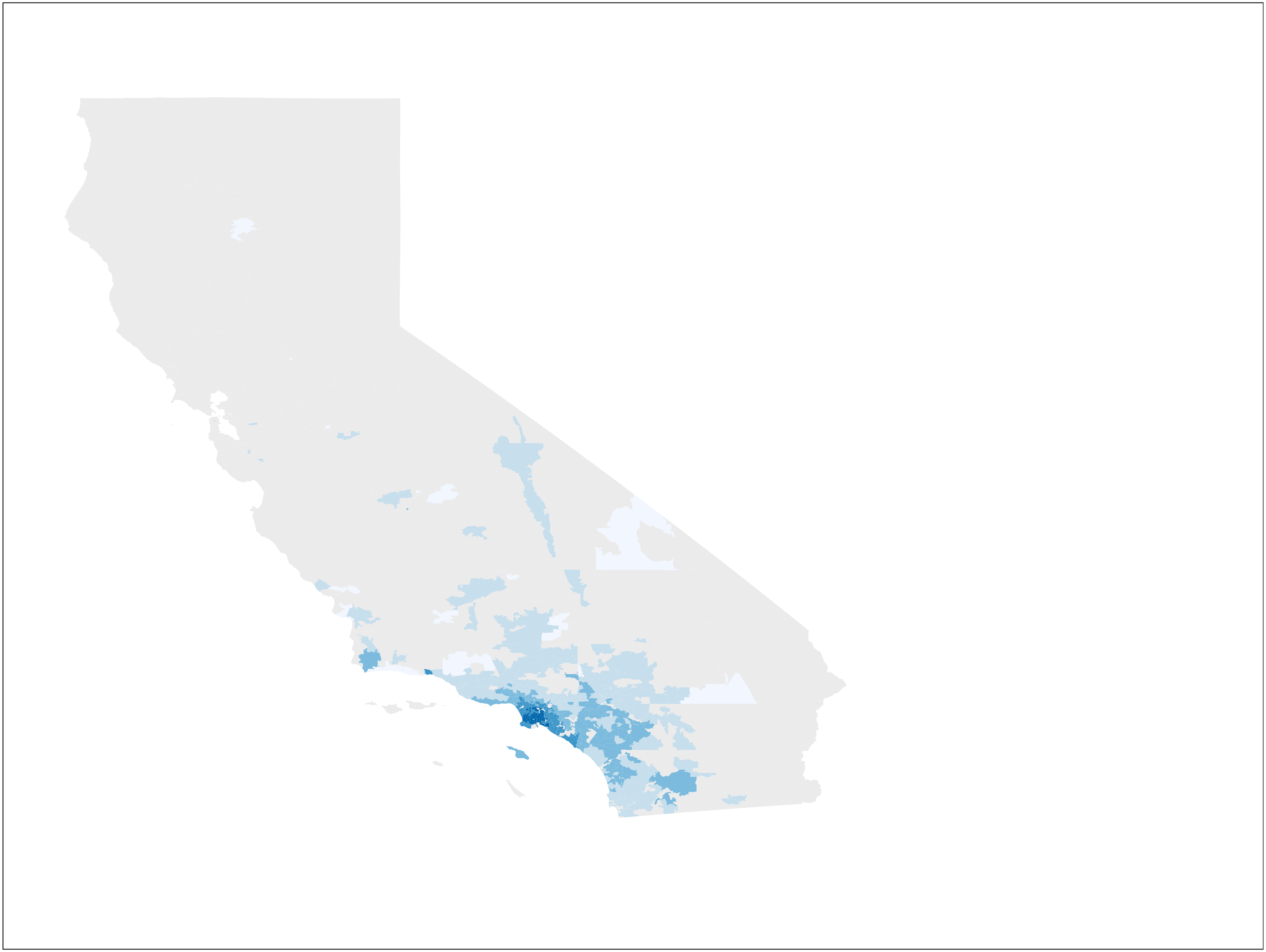
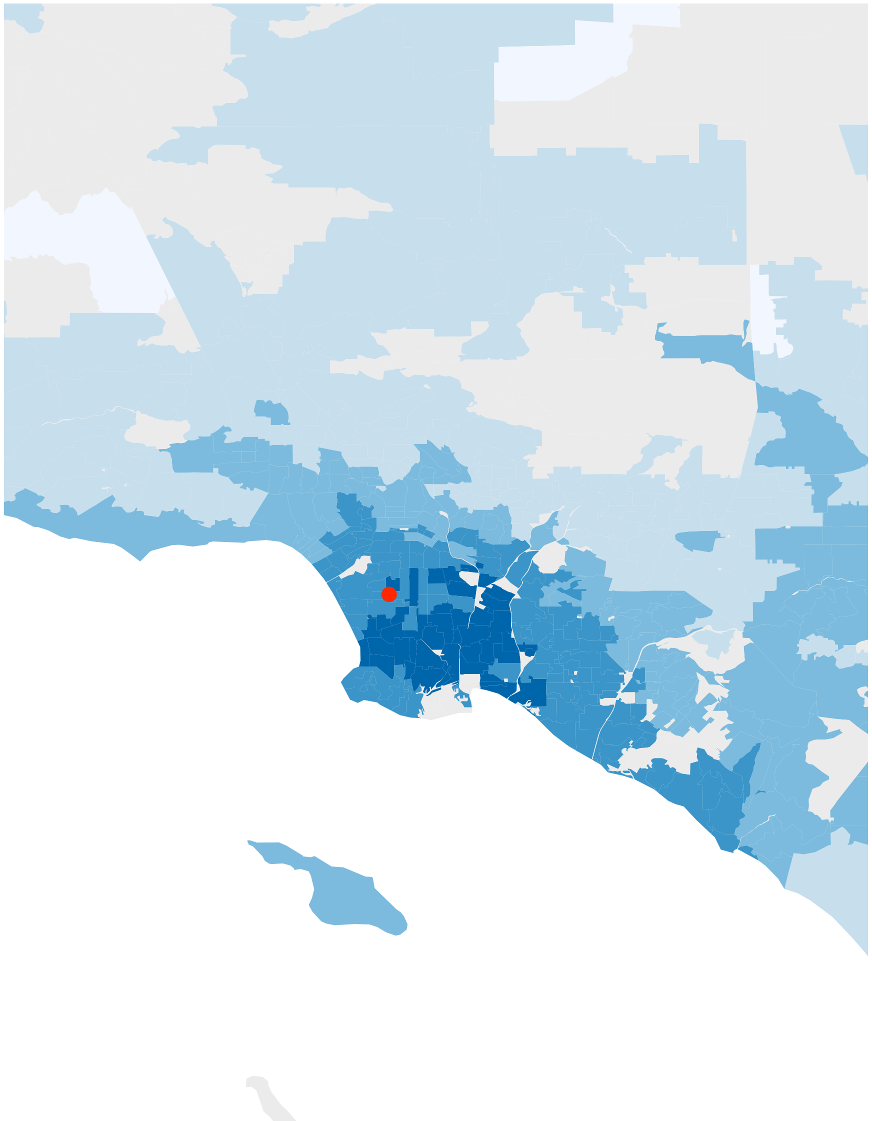
RdYlBu
RdGy
RdBu
PuOr
PRGn
PiYG
BrBG



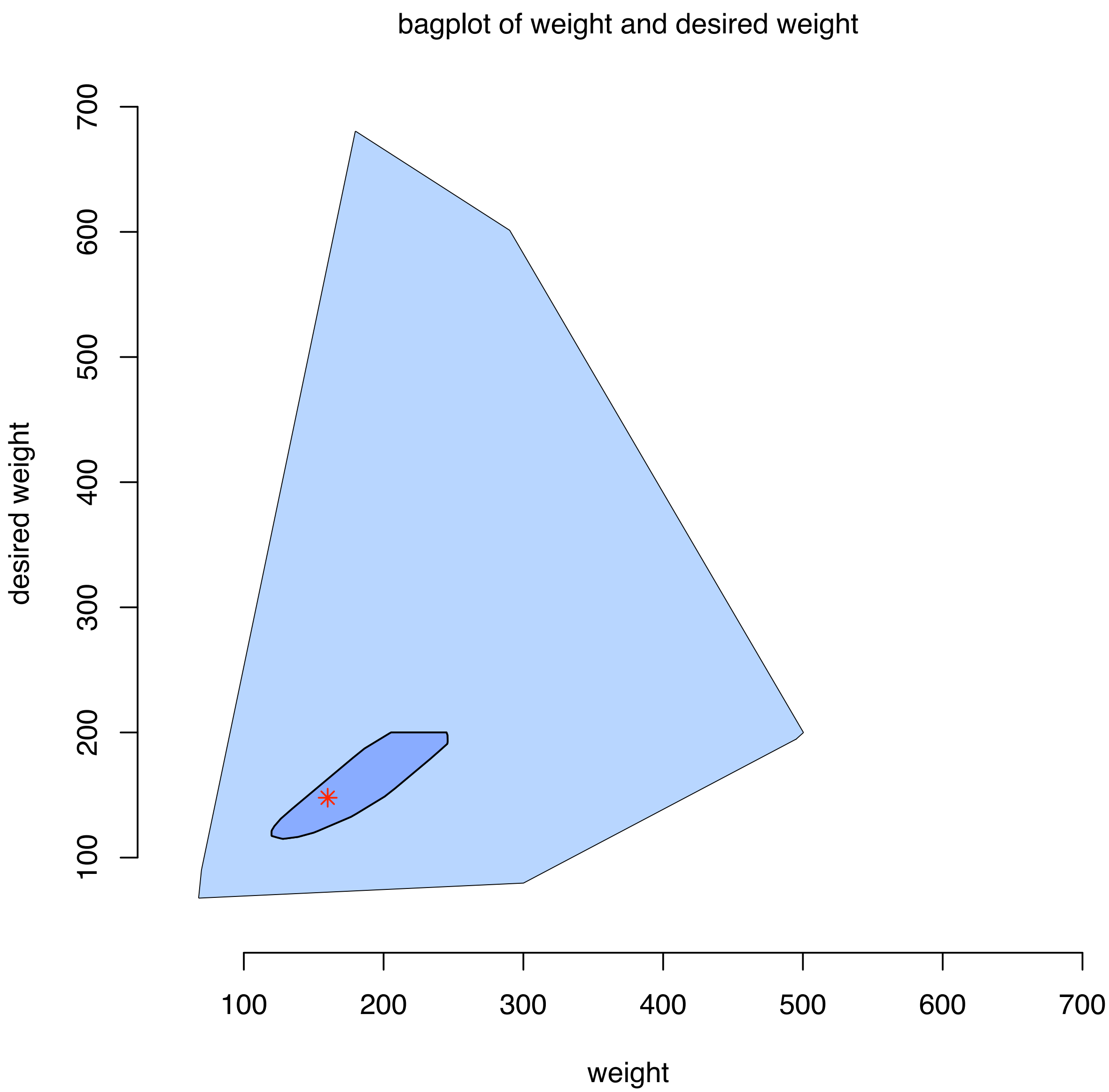
MMI Responses, Sunday's EQ in Los Angeles



Scatterplots

We've added a line with unit slope to the plot; Why? What do you notice? What strikes you as expected? Unexpected?

Now, suppose we want to create something like a boxplot for these data; what concepts do we have to extend?


bagplot of weight and desired weight
desired weight
100
200
300
400
500
600
700
weight
100
200
300
400
500
600
700

Bagplots

Bagplots are another Tukey innovation (along with the boxplot), but somehow they haven't caught on; why?

Can you see this being useful? Under what circumstances? How might they be interesting for our data?