## 2. Graphics

Ken Rice<br>Thomas Lumley

Universities of Washington and Auckland

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## Important pre-takeoff announcement:

We are assuming you know;

- ... that graphics are useful! (and may be worth $\leq 1000$ words)
- How to make some simple plots e.g. making a scatterplot with plot(), adding to existing plots using points(), lines(), text(), and legend()
- That these functions can take many three letter arguments; lwd, lty, pch and many others, which can be looked up via ?par
- That, ultimately, we want PDFs, JPEGs and other output formats - not just a window in an $R$ session


## Plotting large \& high-dimensional data

'Simple’ plots involve two-dimensional data, which we measure on the $x$ and $y$ axes.

For higher-dimensions, some traditional approaches are;

- Different colors for e.g. men, women (col)
- Different-shaped symbols (pch), or different sizes (cex)

For $\leq 100$ 's of data points, modest use of these is fine. But your eye is not good at concentrating e.g. just on the purple points, in a fully Technicolor plot;

## Plotting large \& high-dimensional data

Some of these points are not like the others...


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## Plotting large \& high-dimensional data

For large(ish) data, 'overlap' is a fundamental problem...

(California Academic Performance Index on 6194 schools)

## Plotting large \& high-dimensional data

... which remains, when we color-code.


Colors denote Elementary, Middle \& High Schools

## Plotting large \& high-dimensional data

With three dimensions + color-codes, this can happen;


Self-reported ancesty: Hispanic-American $\nabla$ European-American * Chinese-American \& Arrican-American of
( R does have persp(), for occasional use)

## Conditioning plots

A typical goal for measuring $Z$ is to see whether the $Y-X$ relationship changes at different values of $Z$. For example, we might want to see if a Blood Pressure/genotype association varies by Body Mass Index (weight/height ${ }^{2}$ )

In this case, it's useful to show plots of $Y$ against $X$ conditioned on the value of $Z$, i.e. $Y$ versus $X$ for all data with $Z$ in a small range. This is known as a conditioning plot, and can be produced with coplot().

## Conditioning plots

Ozone is a secondary pollutant, it is produced from organic compounds and atmostpheric oxygen in reactions catalyzed by nitrogen oxides and powered by sunlight.

However, looking at ozone concentrations in NY in summer ( $Y$ ) we see a non-monotone relationship with sunlight ( $X$ )

## Conditioning plots



## Conditioning plots

Here we draw a scatterplot of Ozone vs Solar.R for various subranges of Temp and Wind. For more examples like this, see the commands in the lattice package.

```
data(airquality)
coplot(Ozone ~ Solar.R | Temp * Wind, number = c(4, 4),
    data = airquality,
    pch = 21, col = "goldenrod", bg = "goldenrod")
```


## Conditioning plots

Given : Temp


## Conditioning plots

- A 4-D relationship is illustrated; the Ozone/sunlight relationship changes in strength depending on both the Temperature and Wind
- The vertical bar | is statistician-speak for 'conditioning on' ( nb this is different to use of |'s meaning as Boolean 'OR')
- The horizontal/vertical 'shingles' tell you which data appear in which plot. The overlap can be set to zero, if preferred
- coplot()'s default layout is a bit odd; try setting rows, columns to different values
- For more plotting commands that support conditioning, see library(help="lattice")


## Parallel Coordinate Plots

For even higher-dimensional data, scatterplots can not provide adequate summaries. For data where the dimensions can be ordered, the parallel co-ordinates plot is useful;

Leading Principal Components, $\mathrm{n}=279,10000$ SNPs


## Parallel Coordinate Plots

- Each multi-dimensional data point (i.e. each person) is represented by a line - not a point
- parcoord() in the MASS package is one simple implementation - writing your own version is not a big job
- Coloring the lines also helps (example later)
- Scaling of axes, and their vertical positions are arbitrary
- Doing 'Principal Components Analysis’ is just choosing axes for your data so that their variance is maximized on axis 1 , then axis $2, \ldots$


## Parallel Coordinate Plots

A pairs() plot of the same thing; (nasty!)


## Parallel Coordinate Plots

The pin cushion data++: colors indicate self-report ancestry

Whole MESA population - normalized PCs


## Transparency

The colors in the last examples were transparent. As well as specifiying e.g. col=2 or col="red", you can also specify
col="\#FF000033"

- coded as RRGGBB in hexadecimal, with transparency 33 (also hexadecimal). This is a 'pale' red $-33 / F F \approx 20 \%$.

Get from color names to RGB with col2rgb(), and from base 10 to base 16 using format(as.hexmode(11), width=2)

## Transparency

## An example; (also shows other graphics commands)

```
curve(0.8*dnorm(x), 0, 6, col="blue", ylab="density", xlab="z")
curve(0.2*dnorm(x,3,2), 0, 6, col="red", add=T)
xvals <- seq(1, 6, l=101)
polygon(
c(xvals,6,1), c(0.8*dnorm(xvals), 0,0),
density=NA, col="#0000FF80" ) # tranparent blue
polygon(
c(xvals,6,1), c(0.2*dnorm(xvals,3,2), 0,0),
density=NA, col="#FF000080" ) # tranparent red
legend("topright", bty="n", lty=1, col=c("blue","red"),
c("80% null: N(0,1)", "20% signal: N(3,2)"))
axis(3, at=qnorm(c(0.25, 0.5*10^(-1:-7)), lower=F), c(0.5, 10^(-1:-7)) )
mtext(side=3, line=2, "unadjusted p")
text(2.2, 0.07, adj=c(0,1), paste("FDR beyond 1 = ",
round(0.8*pnorm(1,lower=F)/(0.8*pnorm(1,lower=F) + 0.2*pnorm(1,3,2,lower=F)),3)))
```


## Transparency

Here's the output;


## Hexagonal binning

Using transparent plotting symbols is a quick-and-dirty way to adapt scatterplots for use with large datasets.

A better method is 'hexagonal binning'; this is a 2D analog of a histogram - where you would count the number of data in one area, and then draw a bar with height proportional to that count.

## Hexagonal binning

Binning in two dimensions;


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## Hexagonal binning

The hexbin() package does all the bin construction, and counting. It has a plot method for its hexbin objects;
install.packages(c("hexbin","survey"))
library("hexbin")
library("survey")\# for apipop data frame
with(apipop, plot(hexbin(api99,api00), style="centroids"))

## Hexagonal binning



## Hexagonal binning

Hexbin is used when you don't really care about the exact location of every single point

- Singleton points are plotted 'as usual'; you do (perhaps) care about them
- hexbin centers the 'ink' at the cell data's 'center of gravity’
- style="centroids" gives the center-of-gravity version; the default style is colorscale - usually grayscale. See ?gplot.hexagons for more options


## Hexagonal binning

For keen people: the hexbin package doesn't use the standard $R$ graphics plotting devices; instead, it operates through the Grid system (in the grid package) which defines rectangular regions on a graphics device; these viewport regions can have a number of coordinate systems. To add lines to a hexbin plot, the options are;

- Use hexVP.abline() to add these directly
- Move everything into ‘standard’ graphics - not Grid graphics (see ?Grid). The Grid system lets you alter graphics after plotting them
- Write your own plot method for hexbin objects, with standard $R$ graphics commands
- Make do with hexBinning() in the fMultivar package


## Hexagonal binning

An example; color-coded lines of best fit, by school type;


## Counts

91
$-\quad 85$
85
80
74
68
63
57
52
46

| 40 |
| :--- |
| 35 |

29

- 24
- 18
- 12
- 7

1
lm.e <- coef(lm(api00~api99, data=apipop, subset=stype=="E"))
lm.m <- coef(lm(api00~api99, data=apipop, subset=stype=="M"))
lm.h <- coef(lm(api00~api99, data=apipop, subset=stype=="H"))
hexVP.abline(vp1\$plot.vp, lm.e[1], lm.e[2], col="coral")

## File formats

Ultimately, we want to output the graph in an appropriate file format. (Cut-and-paste is possible, but not recommended)
$R$ knows more about font sizes and spacing than most users so first design the graph at the size it will end up, eg:

```
## on Windows
windows(height=4,width=6)
## on Unix
x11(height=4,width=6)
```

... and, when that's done, write a version to a file

## File formats

For example, for a $6 \times 4$ PDF file;
pdf("myprettypic.pdf", height=4, width=6) \# inches
... plotting commands here ...
dev.off() \# close the file

Some other formats: (see ?Devices for a full list)

- jpeg("mypic.jpg", w=6*288, h=4*288, res=288) - Iossy
- png("mypic.png", w=6*288, h=4*288, res=288) - Iossless
- point size of text can also be manipulated, which can be useful when making posters

PowerPoint, or Word, or AT $^{2} \mathrm{EX}$ can all rescale graphs. But when the graph gets smaller, so do the axis labels...

## File formats

## Created at full-page size ( $11 \times 8.5$ inches)



## File formats

## Created at $6 \times 5$ inches



## Color schemes

Color choice is best left to experts, or people with taste.
http://www.colorbrewer.org has color schemes designed for the National Cancer Atlas, also in package RColorBrewer
colorspace package has color schemes based on straight lines in a perceptually-based color space (rather than RGB).
dichromat package attempts to show the impact of red:green color blindness on your R color schemes.

[Code for examples is in file colorpalettes. R on course website]

## Color choice


(nb B\&W printed copies of this slide may not be helpful!)

## Color blindness


(nb B\&W printed copies of this slide may not be helpful!)

