An introduction to R Graphics

3. Grid & lattice graphics

Michael Friendly
SCS Short Course
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Statistical Consulting Service

YORK UNIVERSITÉ UNIVERSITY

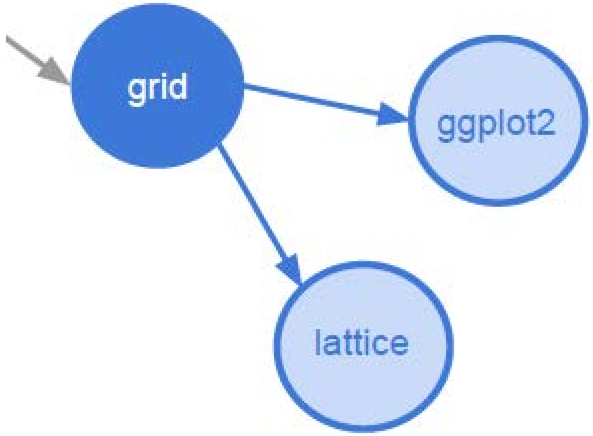
Overview

- Overview of grid-based graphics
  - grid: low-level graphics functions
  - lattice, vcd, ggplot2: high-level functions

The grid graphics system for R provides an alternative and more powerful way to develop data graphics in R

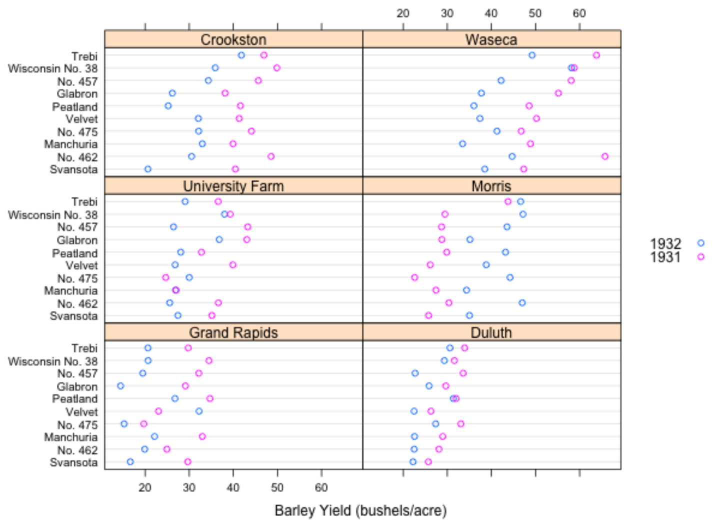
The lattice package, provides functions for drawing all standard plots, plus:

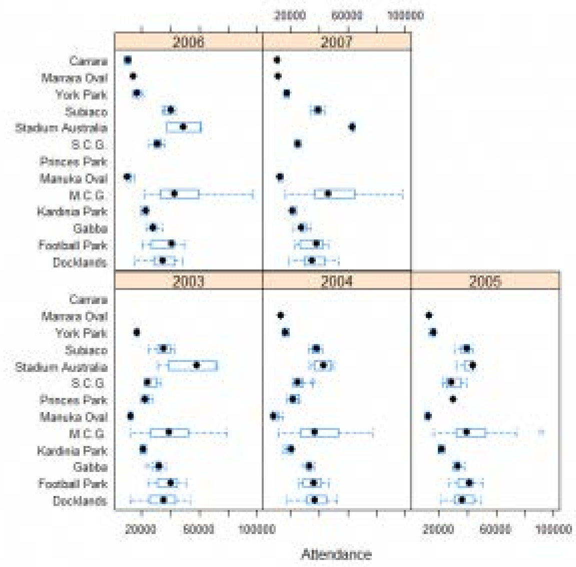
- more pleasing defaults
- create and modify graphic “themes”
- collections ("small multiples") of simpler graphs from subsets of the data.



Lattice, son of Trellis graphics

- Complex multivariate data can often be better visualized by conditioning & grouping
  - show how some relationship changes over other variables
  - Tufte: “small multiples”: separate panels, arranged for visual comparison
  - Cleveland et al.: Trellis graphs for S+, ~ 1980
  - Deepayan Sarkar: lattice package, ~ 2000





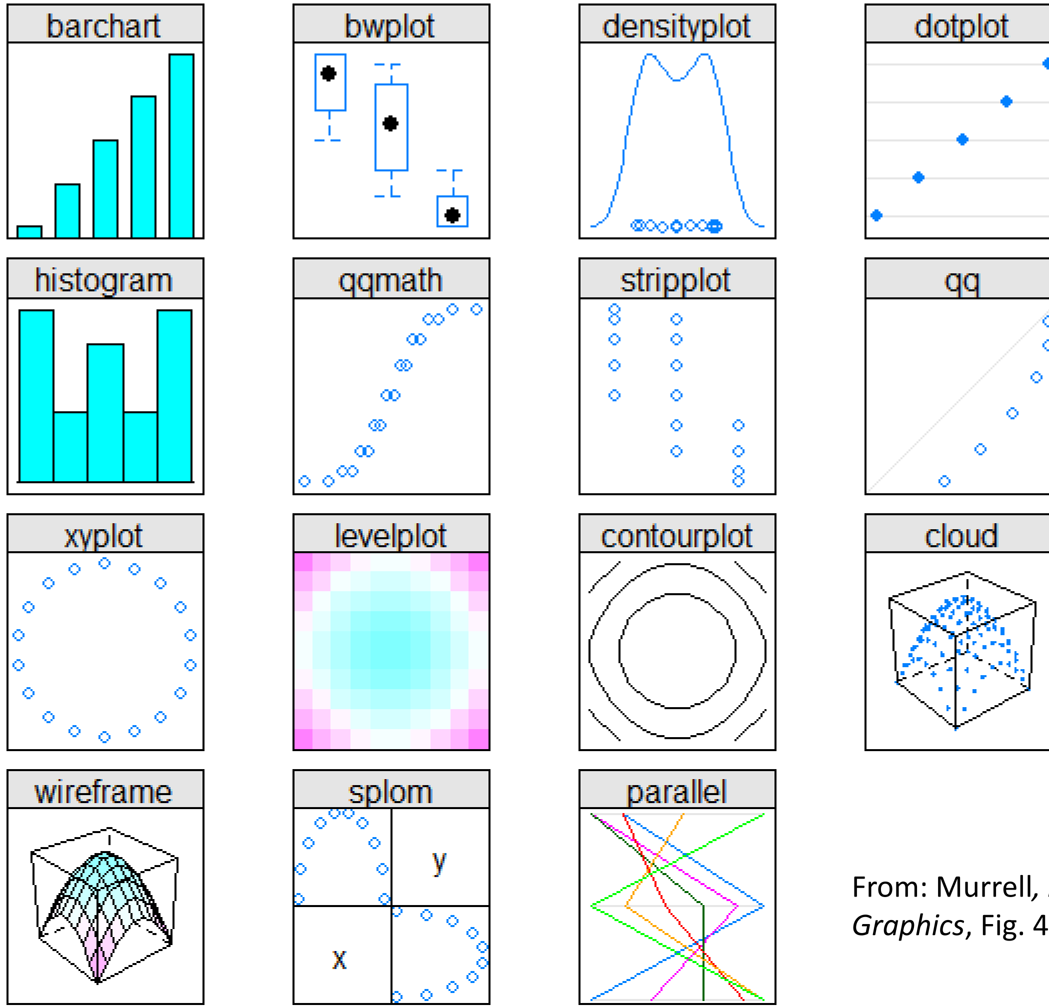
Lattice ideas in a nutshell

- All plots can be described by plot formulas
  - ~ y   Some univariate plot (boxplot, histogram, boxplot, …)
  - ~ y | A   Univariate, separate panels for levels of factor A
  - ~ y | z   Univariate, cutting z into discrete ranges
  - y ~ x   Bivariate
  - y ~ x | A Bivariate, separate panels for levels of A
  - y ~ x | A + B   multiple conditioning variables
  - y1 + y2 ~ x1 + x2   multiple Y and X variables
- Conditioning variables define “panels” in a plot
  - These can be laid out on a “page” in various ways
  - panel functions get the data for a subset and “render” (plot) it
  - High-level functions handle panel layout, and call panel functions
- Customize
  - graphic “themes” generalize par() settings
  - Combine multiple panel functions, write new ones.

Lattice plot functions

These are the high-level plot functions in lattice

These schematic examples have all been "rendered" using the default lattice theme settings



From: Murrell, *R Graphics*, Fig. 4.3

Lattice plot functions

Lattice plots have analogs in traditional graphics

All use formula-style arguments for what to plot: y ~ x, or conditioning: y ~ x|A

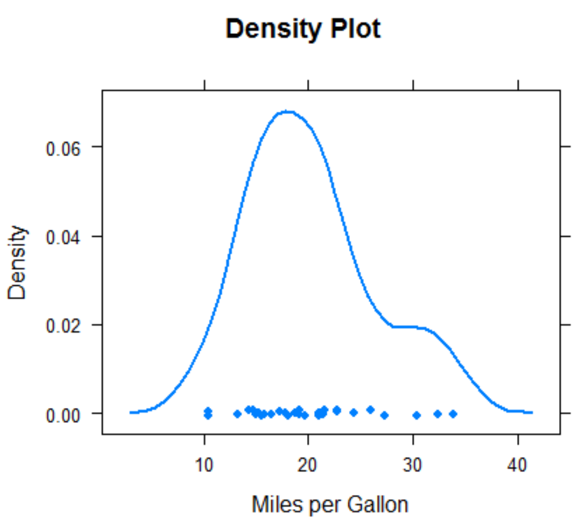
lattice function	description	formula examples	base analog
barchart()	bar chart	x~A or A~x	barplot()
bwplot()	boxplot	x~A or A~x	boxplot()
densityplot()	kernal density plot	~x|A*B	plot.density()
dotplot()	dotplot	~x|A	dotchart()
histogram()	histogram	~x	hist()
stripplot()	strip plots	A~x or x~A	stripchart()
xyplot()	scatterplot	y~x|A	plot()
contourplot()	3D contour plot	z~x*y	contour()
cloud()	3D scatterplot	z~x*y|A	NA
levelplot()	3D level plot	z~y*x	image()
parallel()	parallel coordinates plot	data frame	NA
splom()	scatterplot matrix	data frame	pairs()
wireframe()	3D surface graph	z~y*x	persp()

Lattice plots: formulas, conditioning & grouping

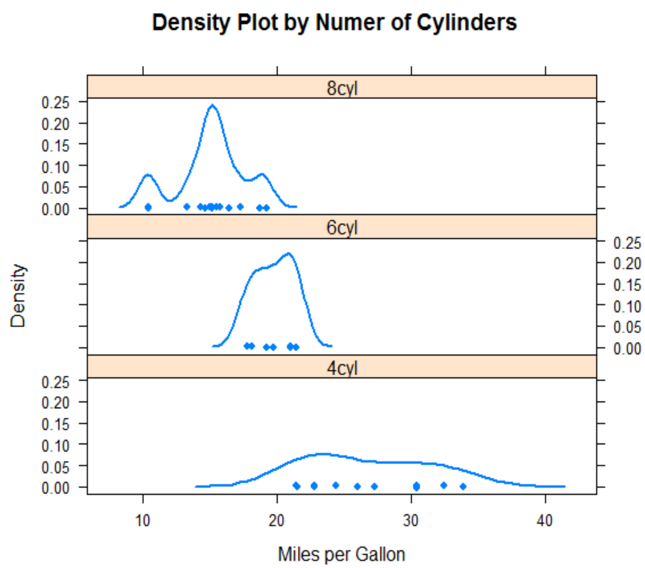
For 1D plots, the formula argument, `~y`, specifies the variable to be plotted

- Conditioning: `~y|group` gives multipanel plots for the levels of the group factor
- Grouping: `~y, group=` superposes plots for the levels of group

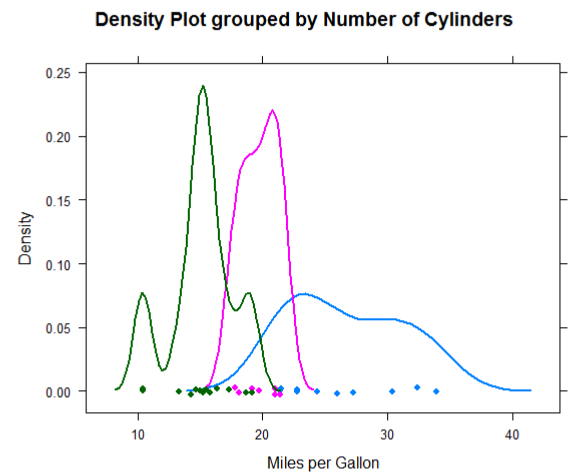
densityplot(~mpg,
  data=mtcars, ...)



densityplot(~mpg **| cyl**,
  data=mtcars, ...)

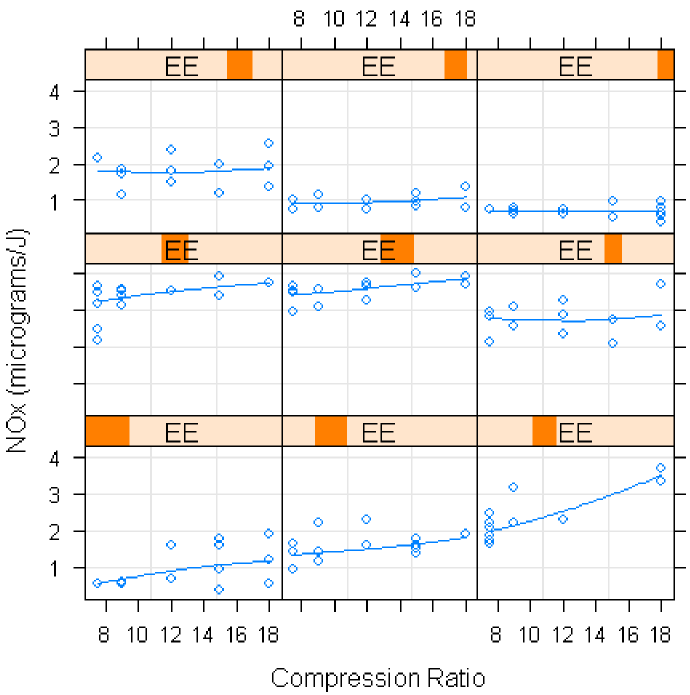


densityplot(~mpg, **groups=cyl**,
  data=mtcars, ...)



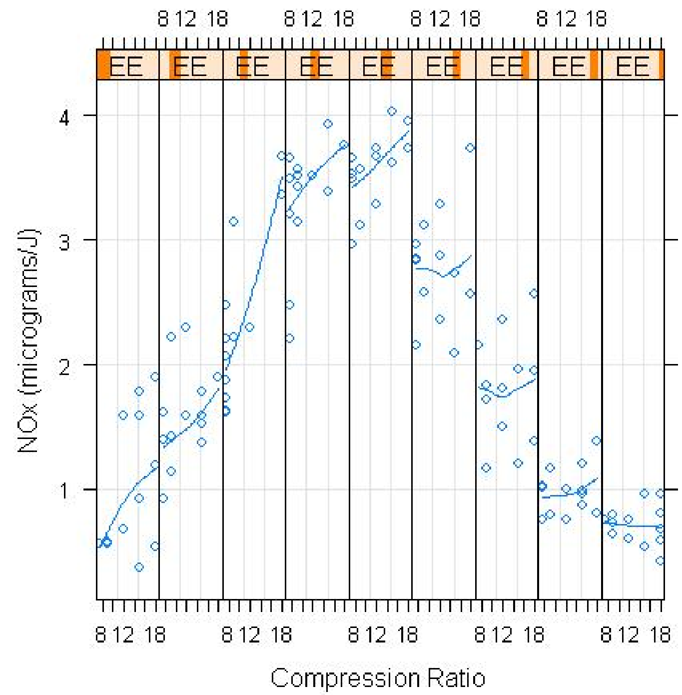
Ethanol data: Ethanol fuel was burned in a single-cylinder engine.
How do emissions of nitrous oxide (NO_x) depend on

- engine compression ratio(C) and
- equivalence ratio (EE), a measure of richness of the air and ethanol fuel mixture



xyplot() for lattice scatterplots:

xyplot(NOx ~ C | EE, data = ethanol, …)

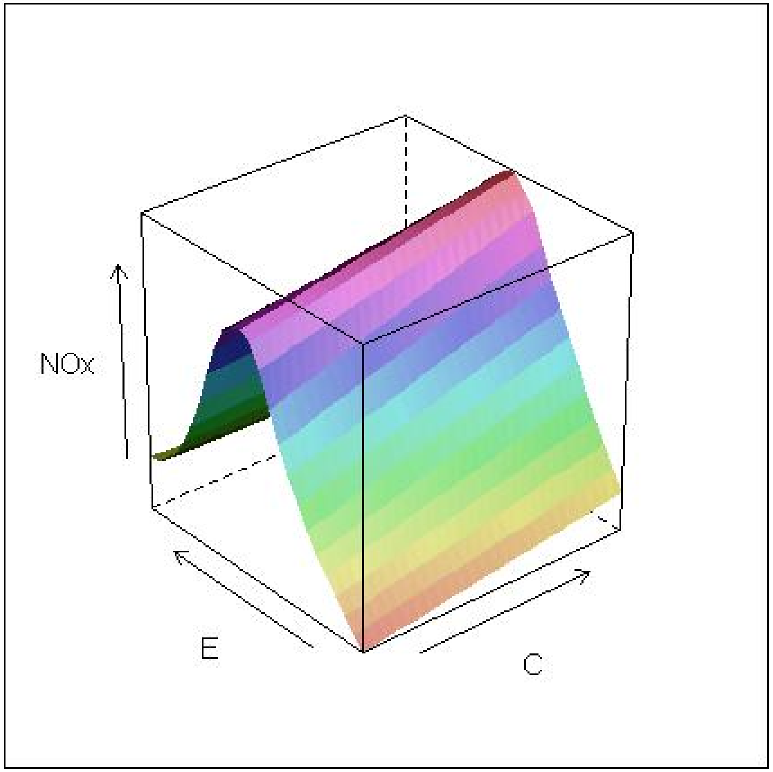


Same plot, with aspect="xy": sets aspect ratio to "bank to 45°"

As in base graphics, some computation is often required to make a simpler or better version of some plot.

- 2D plots of the ethanol data suggest something that might better be seen in 3D
- This requires calculating a fitted response surface, and drawing it
- It doesn't show the data, and uses a non-parametric smoother, not a lm() model

```
require(stats)
with(ethanol, {
  eth.lo <- loess(NOx ~ C * E, span = 1/3, parametric = "C",
                drop.square = "C", family="symmetric")
  eth.marginal <- list(C = seq(min(C), max(C), length.out = 25),
                    E = seq(min(E), max(E), length.out = 25))
  eth.grid <- expand.grid(eth.marginal)
  eth.fit <- predict(eth.lo, eth.grid)
  wireframe(eth.fit ~ eth.grid$C * eth.grid$E,
          shade=TRUE,
          screen = list(z = 40, x = -60, y=0),
          distance = .1,
          xlab = "C", ylab = "E", zlab = "NOx")
})
```



If this plot is believed, it gives a much simpler description of dependence, NOx ~ C * E

This example is complex. It uses:

- loess() to calculate smoothed values of NOx
- predict() to evaluate these over ranges of C & E
- wireframe() to plot these with nice shading

Detour: Modeling what we see

- Graphs of the ethanol data suggest a systematic, but complex relationship between NOx ~ C + E
  - Traditional parametric linear models handle this very semi-well
  - E.g., try a model with terms in C, E, E^2 and interactions

```
> eth.mod2 <- lm(NOx ~ (C + poly(E,2))^2, data=ethanol)
> Anova(eth.mod2)
Anova Table (Type II tests)

Response: NOx
             Sum Sq Df  F value    Pr(>F)
C             5.032  1  25.2282 2.925e-06 ***
poly(E, 2)   91.838  2 230.2103 < 2.2e-16 ***
C:poly(E, 2)  3.322  2   8.3271 0.0005101 ***
Residuals    16.356 82
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Detour: Modeling what we see

- The R model formula, NOx ~ (C + poly(E,2))^2 is a short-hand notation
- The expanded version is nearly

  NOx ~ C + E + E^2 + C:E + C:E^2

- Interpretation:
  - C + E : overall linear effects (slopes) of C & E on NOx
  - E^2 : quadratic effect (curvature) of equivalence ratio on NOx
  - C:E – does the slope for E change linearly with C?
  - C:E^2 – does the curvature for E change linearly with C

Detour: Modeling what we see

summary() for a given model gives significance tests of model terms

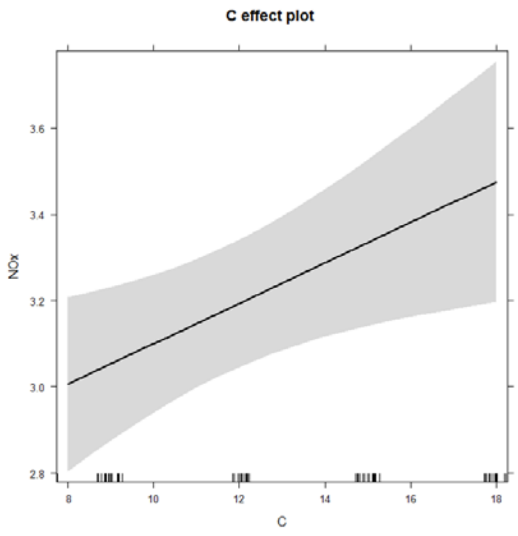
```
> summary(eth.mod2)

Call:
lm(formula = NOx ~ (C + poly(E, 2))^2, data = ethanol)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.84489 -0.37039 -0.00367  0.39327  0.76796 

Coefficients:
               Estimate Std. Error t value Pr(>|t|)    
(Intercept)     1.16206    0.16009   7.259 2.01e-10 ***
C               0.06572    0.01265   5.193 1.48e-06 ***
poly(E, 2)1     4.81844    1.56979   3.069 0.002907 ** 
poly(E, 2)2   -12.15328    1.61916  -7.506 6.60e-11 ***
C:poly(E, 2)1  -0.46307    0.11615  -3.987 0.000145 ***
C:poly(E, 2)2   0.15492    0.11720   1.322 0.189909    
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.4466 on 82 degrees of freedom
Multiple R-squared:  0.8535,    Adjusted R-squared:  0.8445 
F-statistic: 95.52 on 5 and 82 DF,  p-value: < 2.2e-16
```

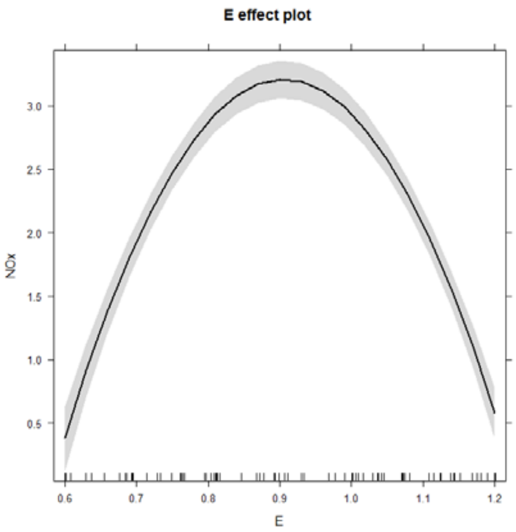
Effect plots: Seeing what we model

In many cases, effect plots help to visualize a fitted model. These all use lattice graphics to render the plot.

```
plot(Effect("C", eth.mod2))
```

```
plot(Effect("E", eth.mod2))
```

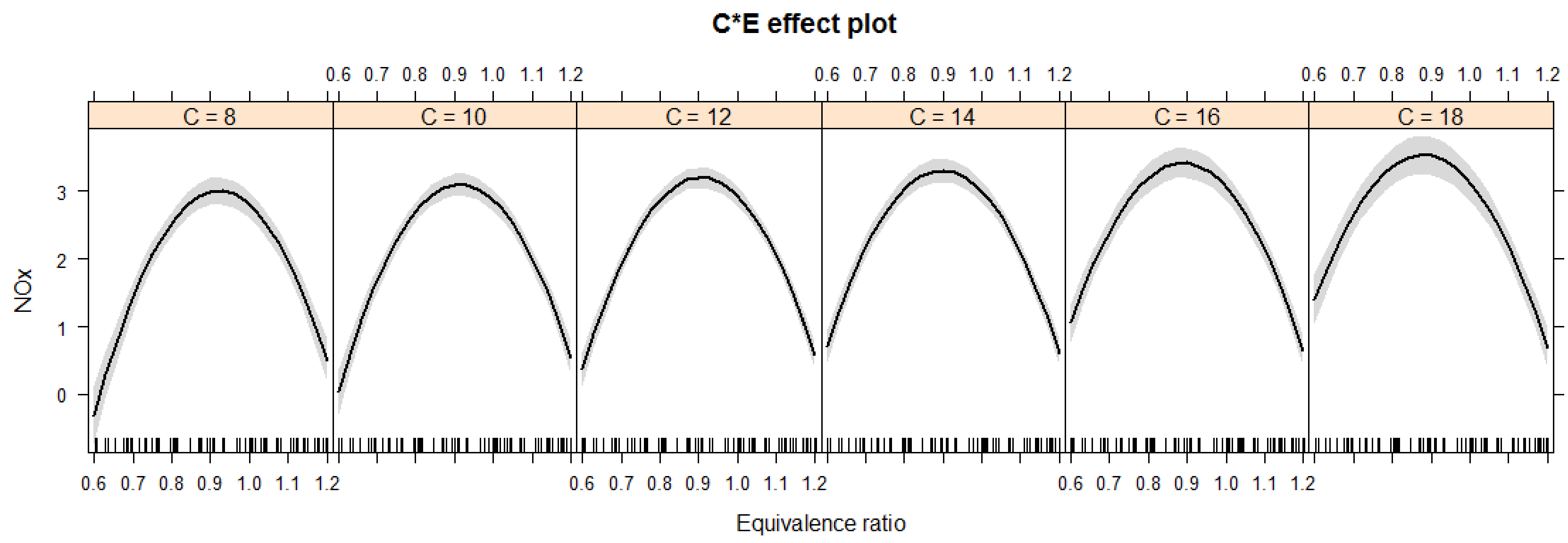




Effect plots: Seeing what we model

The strength of lattice graphics for conditioning is used in multipanel effect plots
Details of the layout and conditioning levels can all be controlled by options.

```
plot(allEffects(eth.mod2), layout=c(6,1), xlab="Equivalence ratio")
```



Detour: gam

- Generalized additive models (gam) are like generalized linear models (glm), but allow non-parametric “smoothed” s() terms
  - degree of smoothing ~ # degrees of freedom
  - models can have linear & smoothed s() terms
  - approx. significance tests are available for smooth terms

```
> library(mgcv)
> eth.gam1 <- gam(NOx ~ C + s(E), data=ethanol)
> summary(eth.gam1)

Parametric coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) 1.291342   0.088898  14.526  < 2e-16 ***
C           0.055345   0.007062   7.837 1.88e-11 ***
---

Approximate significance of smooth terms:
       edf Ref.df     F p-value
s(E) 7.553  8.469 208.8  <2e-16 ***
---
R-sq.(adj) =  0.953   Deviance explained = 95.8%
GCV = 0.067206  Scale est. = 0.05991   n = 88
```

This is sometimes called “semi-parametric regression”

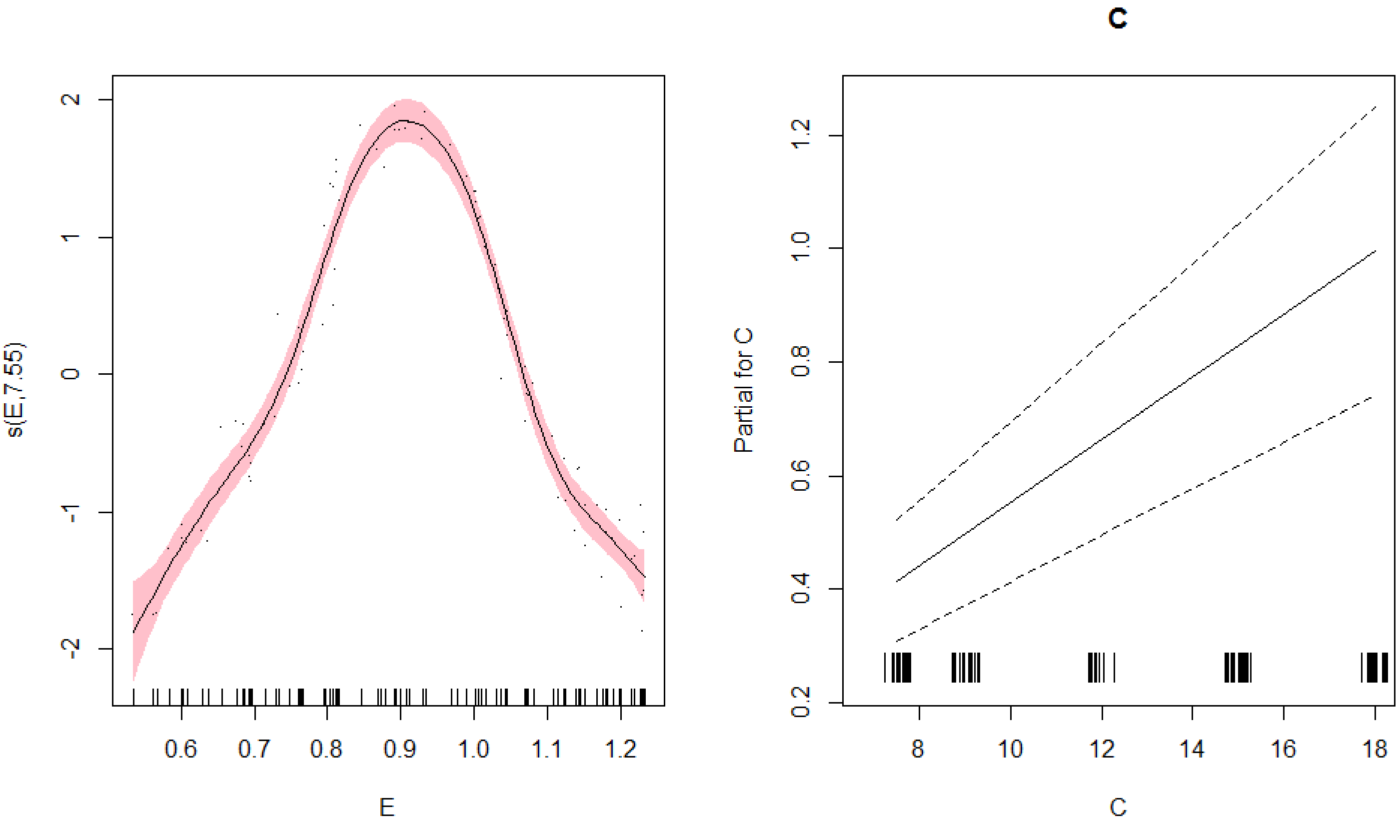
The edf for the smoothed term is found using cross-validation

There are other kinds of smoothing models

Plotting “gam” objects

The mgcv package contains a number of plot methods for “gam” objects

```
plot(eth.gam1, shade=TRUE, shade.col="pink", all.terms=TRUE, residuals=TRUE, pages=1)
```

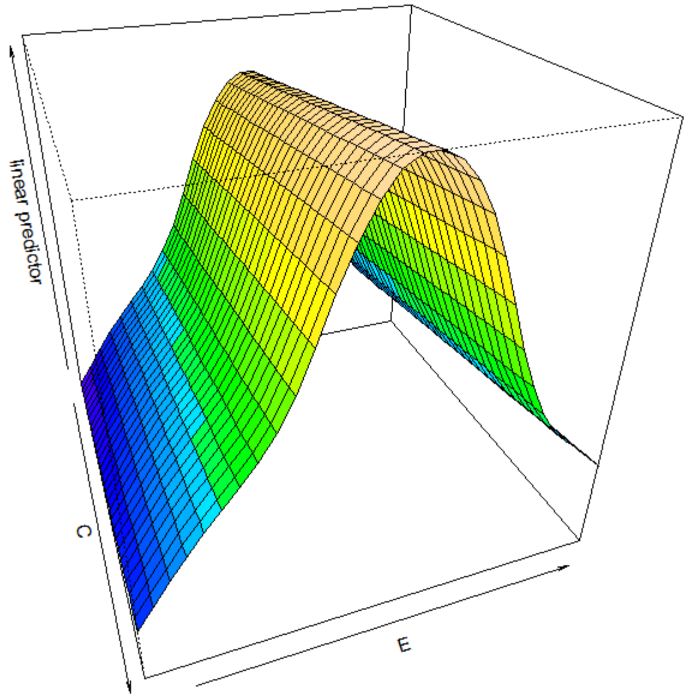


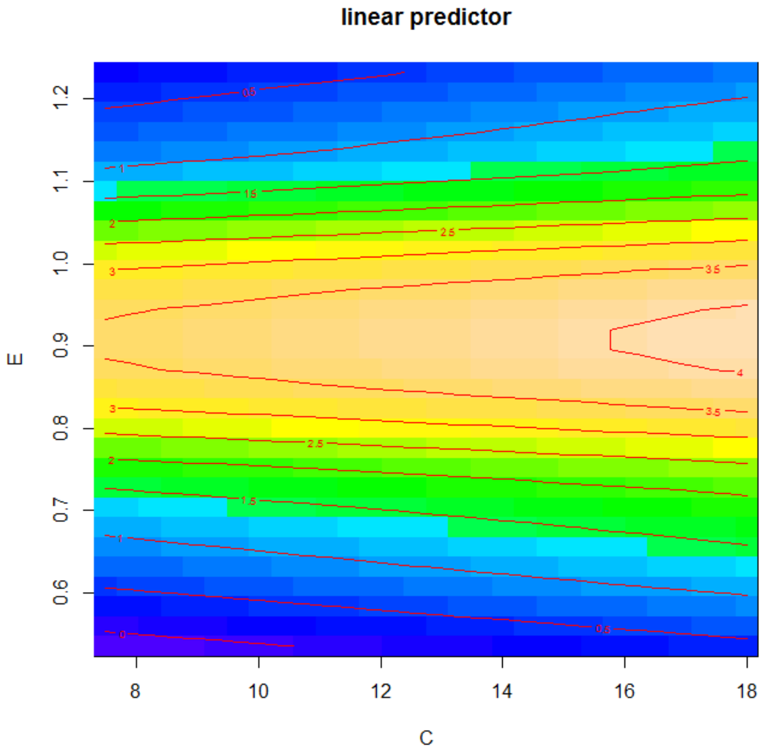
Plotting "gam" objects

vis.gam() is like a 3D version of an effect plot. It shows the fitted values for two predictors, holding constant all others.

```
vis.gam(eth.gam1, color="topo", theta=70, phi=30)
vis.gam(eth.gam1, color="topo", plot.type="contour")
```

NB: The result is similar to what we got using loess(). However, this is a full-fledged statistical model, so we can find confidence intervals, prediction intervals, etc.

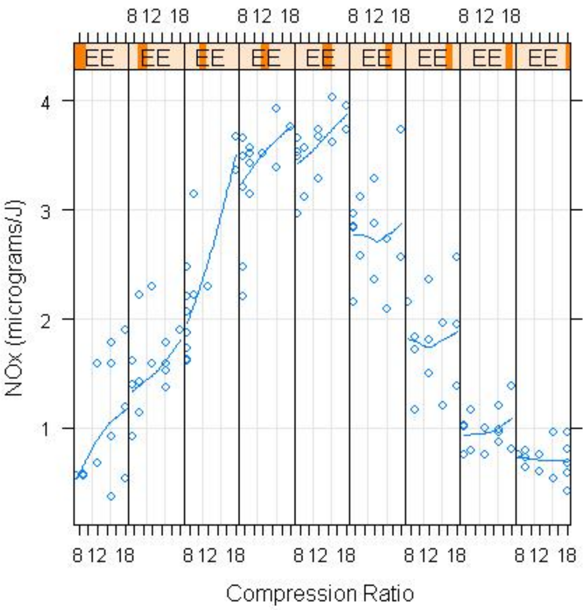




Lattice panel functions

- Lattice plots use panel functions to add info to a plot
  - panel.grid() – grid lines
  - panel.xyplot(x, y, type=, …) – various types of (x, y) plots
  - panel.lmline() – add regression line
  - panel.loess() – smoothed loess curve
  - many others …

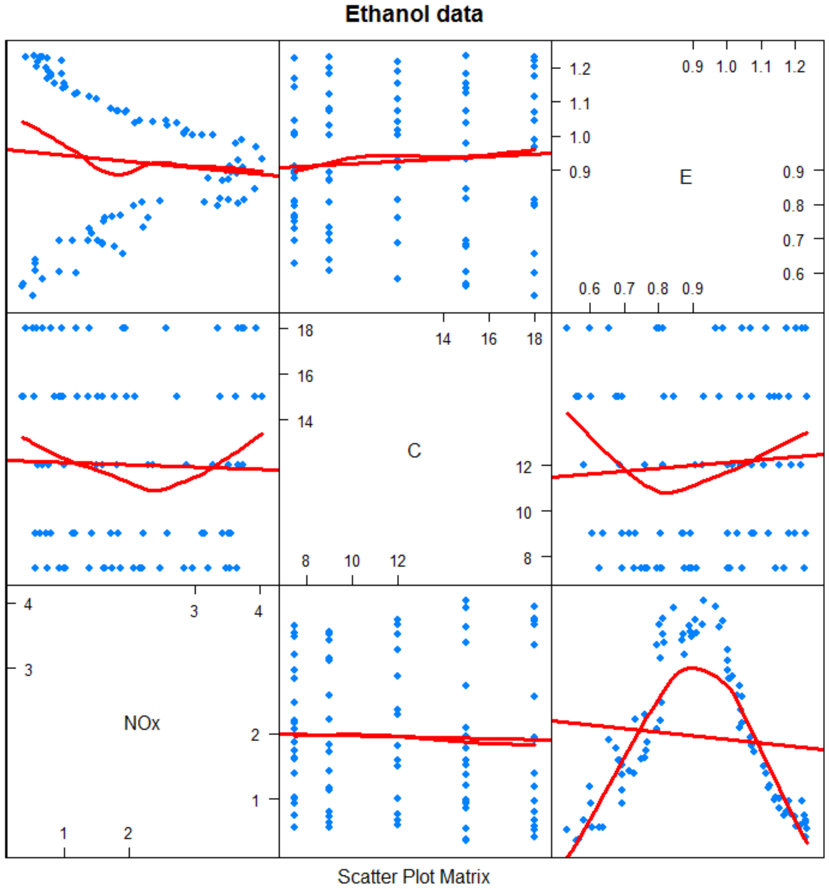
```
EE <- equal.count(ethanol$E, number=9, overlap=1/4)
xyplot(NOx ~ C | EE, data = ethanol,
      prepanel = function(x, y) prepanel.loess(x, y, span = 1),
      xlab = "Compression ratio", ylab = "NOx (micrograms/J)",
      panel = function(x, y) {
         panel.grid(h=-1, v= 2)
         panel.xyplot(x, y)
         panel.loess(x,y, span=1)
      },
      aspect = "xy")
```



splom()

splom() draws a scatterplot matrix. As with other lattice functions, a type= argument can be used to invoke several panel functions.

```
splom(ethanol,
  type=c("p", "r", "smooth"),
  col.line = "red",
  pch=16, lwd=3,
  main="Ethanol data")
```



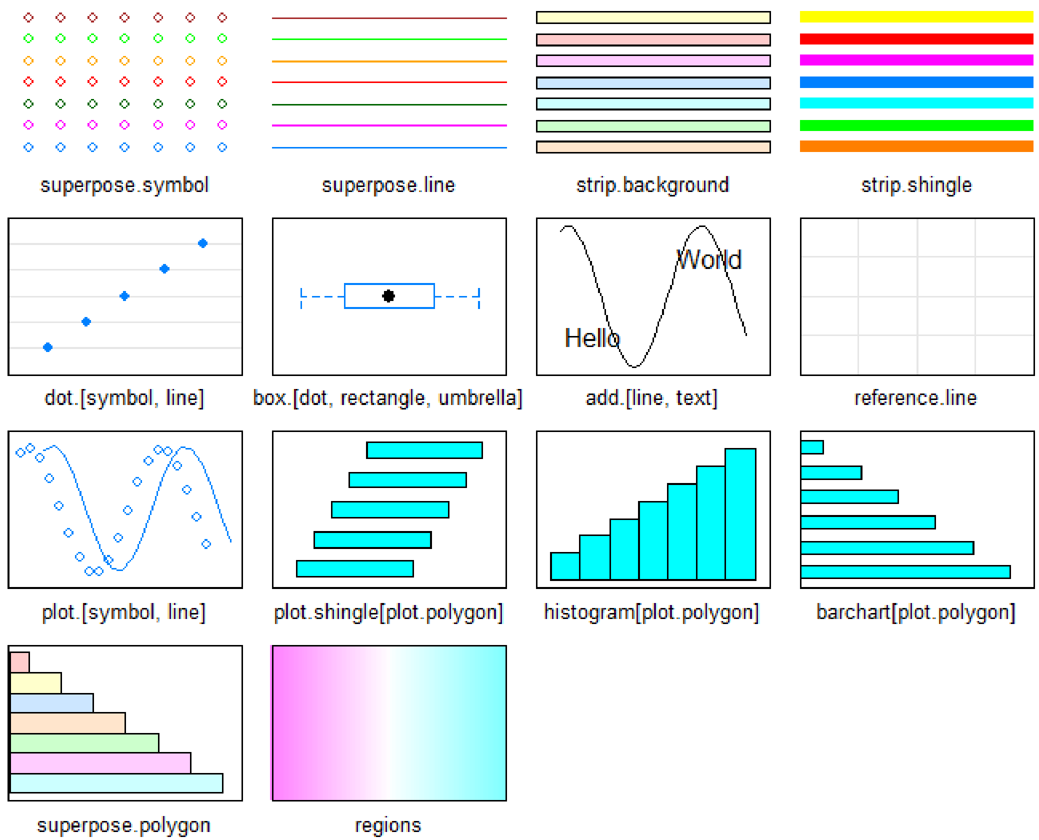
Lattice themes and settings

The Trellis approach allows creating effective graphs with a consistent look and feel. It uses “themes” to define colour, size and other features of components of a graph.

A theme consists of settings for the attributes of various graphical elements.

The current settings are displayed with show.settings()

This differs from base graphics, where par() settings are used inconsistently across different graph types



Lattice themes and settings

- Get theme settings with trellis.par.get()
- Set new ones with trellis.par.set()

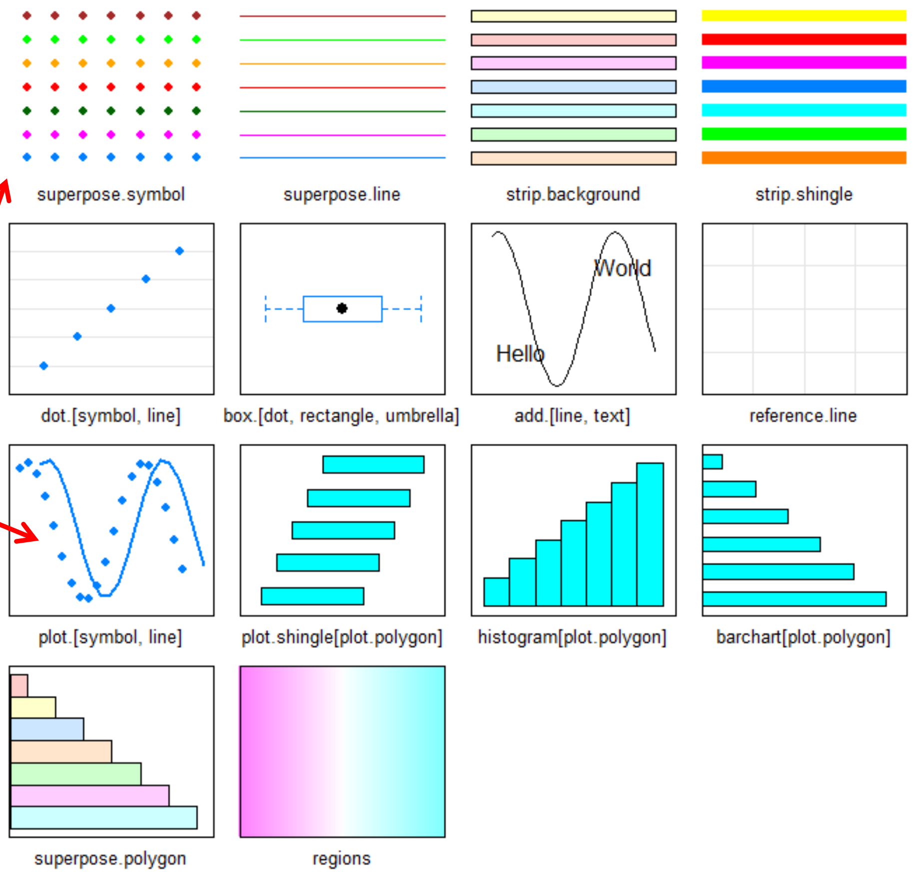
```
> my.theme <- trellis.par.get()
> names(my.theme)
 [1] "grid.pars"         "fontsize"          "background"        "panel.background"
 [5] "clip"              "add.line"          "add.text"          "plot.polygon"
 [9] "box.dot"           "box.rectangle"     "box.umbrella"      "dot.line"
[13] "dot.symbol"        "plot.line"         "plot.symbol"       "reference.line"
[17] "strip.background"  "strip.shingle"     "strip.border"      "superpose.line"
[21] "superpose.symbol"  "superpose.polygon" "regions"           "shade.colors"
[25] "axis.line"         "axis.text"         "axis.components"   "layout.heights"
[29] "layout.widths"     "box.3d"            "par.xlab.text"     "par.ylab.text"
[33] "par.zlab.text"     "par.main.text"     "par.sub.text"
```

There are 35 different attributes, each of which is a list of more basic settings

```
> names(my.theme$plot.symbol)
[1] "alpha" "cex"   "col"   "font"  "pch"   "fill"
> names(my.theme$plot.line)
[1] "alpha" "col"   "lty"   "lwd"
```

I like to use filled point symbols (pch=16) and make lines thicker

```
my.theme$plot.line$lwd <- 2
my.theme$plot.symbol$pch <- 16
my.theme$superpose.symbol$pch <- rep(16, 7)

#establish my.theme
trellis.par.set(my.theme)
show.settings()
```



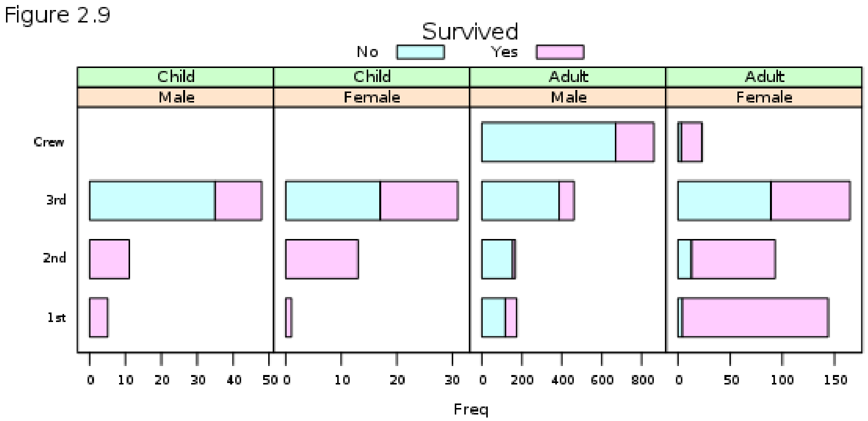
points are now filled circles & lines are thicker

NB: This is tedious, but useful if you are writing a paper or a book. Do it ONCE, for all figures!

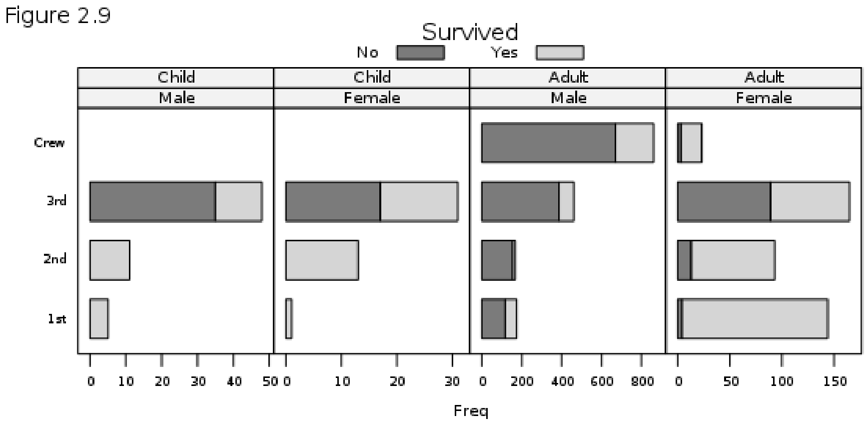
Lattice themes: color to BW

Lattice plots are “trellis” objects. They can be printed with different themes w/o changing your code

```
plt <- barchart(Class ~ Freq | Sex + Age,
    data = as.data.frame(Titanic),
    groups = Survived, stack = TRUE,
    layout = c(4, 1),
    auto.key = list(title = "Survived", columns = 2),
    scales = list(x = "free"))
print(plt)
```




```
trellis.device(color = FALSE)
print(plt)
```



As this example demonstrates, lattice themes are generally well-designed to handle color vs. B/W

Boxplots -> Violin plots

Boxplots show some aspects of the shape of distributions: median, IQR, outliers, …

Violin plots use a mirrored kernel density plot instead

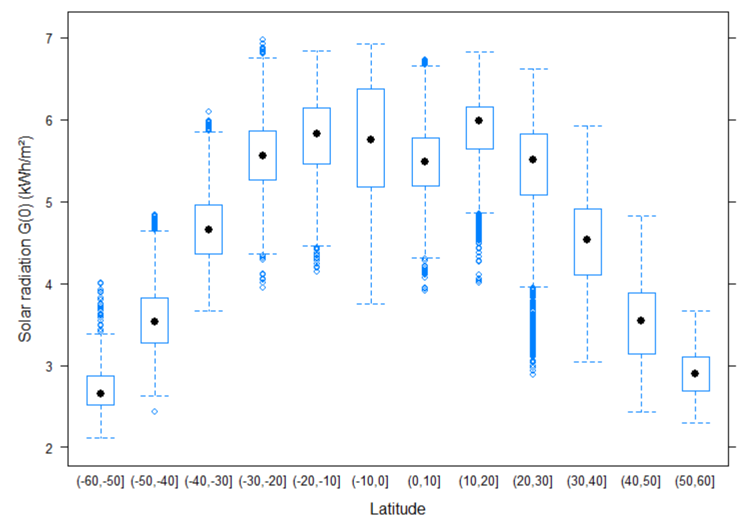
```
bwplot(Ann ~ cut(Lat, pretty(Lat, 20)),
   data=nasa,  subset=(abs(Lat)<60),
   xlab='Latitude', ylab='Solar radiation G(0) (kWh/m²)')
```

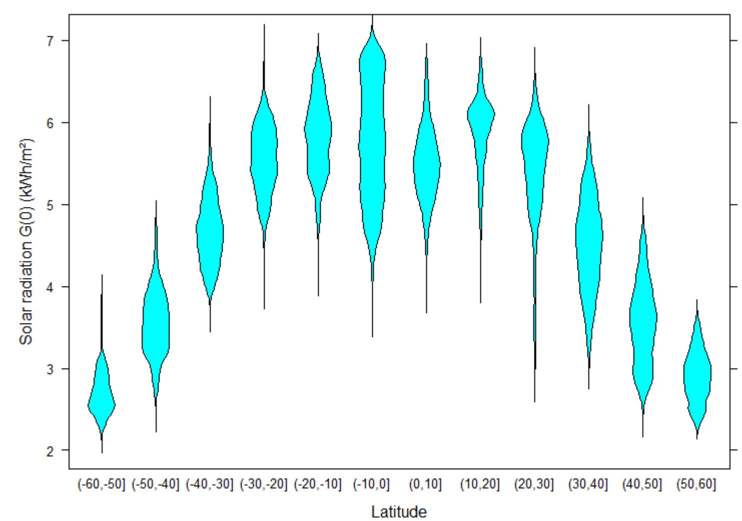
For lattice, this is just a boxplot using a different panel function: panel.violin()

```
bwplot(Ann ~ cut(Lat, pretty(Lat, 20)),
   data=nasa, subset=(abs(Lat)<60),
   xlab='Latitude', ylab='Solar radiation G(0) (kWh/m²)',
   panel = panel.violin)
```

Example from: https://www.r-bloggers.com/violin-and-boxplots-with-lattice-and-r/ by Oscar Perpiñán Lamigueiro

NASA data on average solar radiation by latitude





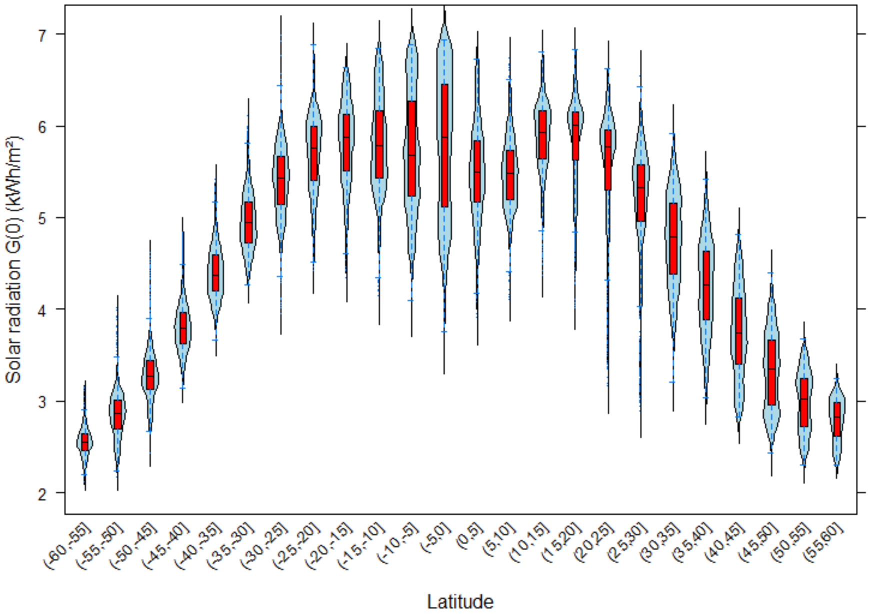
Custom panel functions

You can combine these using a custom panel function that calls both

```
my.panel <- function(..., box.ratio) {
 panel.violin(..., col = "lightblue",
    varwidth = FALSE, box.ratio = box.ratio)
 panel.bwplot(..., col='black',
    cex=0.9, pch='|', fill='red', box.ratio = .25)
 }
```

Use it:

```
bwplot(Ann ~ cut(Lat, pretty(Lat, 40)),
   data=nasa,  subset=(abs(Lat)<60),
   xlab='Latitude', ylab='Solar radiation G(0) (kWh/m²)',
   horizontal=FALSE,
   panel = my.panel,
   par.settings = list(box.rectangle=list(col='black'),
           plot.symbol = list(pch='.', cex = 0.1)),
   scales=list(x=list(rot=45, cex=0.5))
 )
```



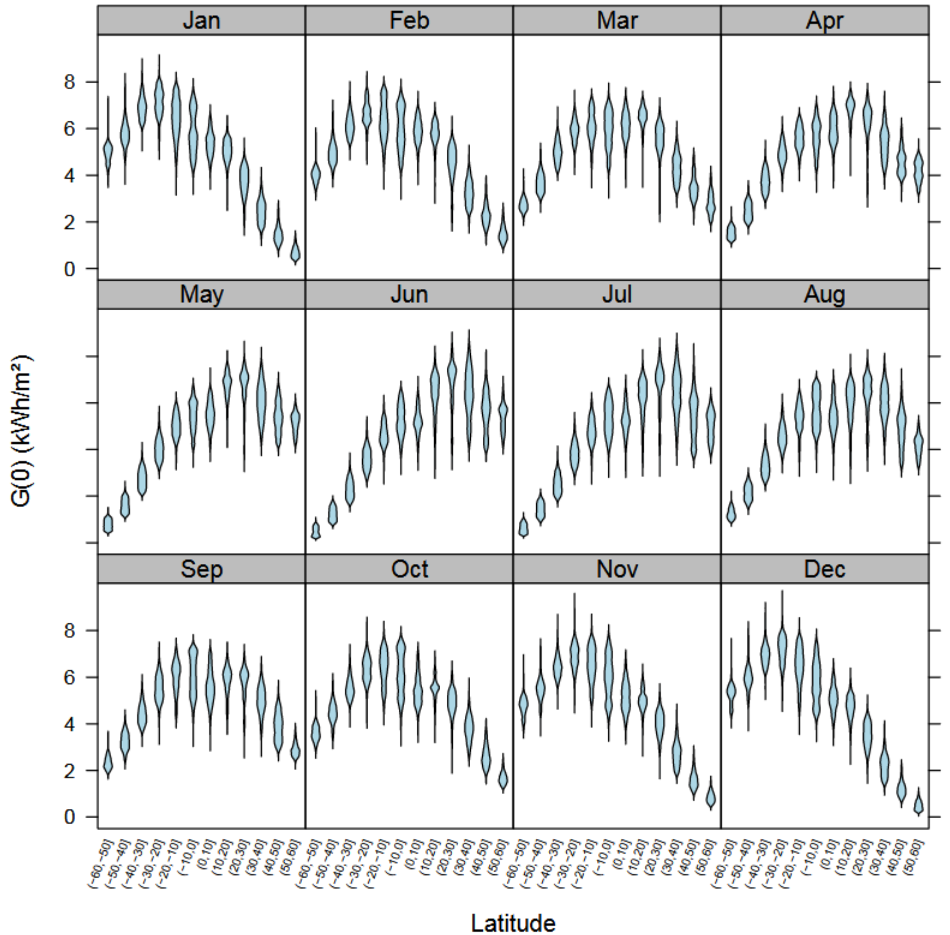
Notes:
cut(): breaks a quantitative variable to a factor
subset: use only -60 < Lat < 60
par.settings: set some plot attributes
scales: tweak labeling of x axis, rotating labels

How does solar radiation vary with latitude, over months of the year?

- The result of this plot suggests some sort of scientific explanation
- Models to confirm/reject any of these would have to take the distributions into account

How was this graph produced?

- What was the plot formula?
- What was the panel function?
- What plot attributes where modified?



Data munging for plots & models

- Very often, the difficult problems in data analysis and graphics concern:
  - How to get my data into a format required for analysis?
  - How to get my data into a format for plotting?
  - How to get my model results into a table or plot?
- The first step is to understand the structure of your data

```
> str(nasa)
'data.frame':   64800 obs. of  15 variables:
 $ Lat: int  -90 -90 -90 -90 -90 -90 -90 -90 -90 -90 ...
 $ Lon: int  -180 -179 -178 -177 -176 -175 -174 -173 -172 -171 ...
 $ Jan: num  9.63 9.63 9.63 9.63 9.63 9.63 9.63 9.63 9.63 9.63 ...
 $ Feb: num  5.28 5.28 5.28 5.28 5.28 5.28 5.28 5.28 5.28 5.28 ...
 $ Mar: num  0.75 0.75 0.75 0.75 0.75 0.75 0.75 0.75 0.75 0.75 ...
 $ Apr: num  0 0 0 0 0 0 0 0 0 0 ...
 $ May: num  0 0 0 0 0 0 0 0 0 0 ...
 $ Jun: num  0 0 0 0 0 0 0 0 0 0 ...
 $ Jul: num  0 0 0 0 0 0 0 0 0 0 ...
 $ Aug: num  0 0 0 0 0 0 0 0 0 0 ...
 $ Sep: num  0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1 ...
 $ Oct: num  3.24 3.24 3.24 3.24 3.24 3.24 3.24 3.24 3.24 3.24 ...
 $ Nov: num  8.28 8.28 8.28 8.28 8.28 8.28 8.28 8.28 8.28 8.28 ...
 $ Dec: num  11 11 11 11 11 ...
 $ Ann: num  3.19 3.19 3.19 3.19 3.19 3.19 3.19 3.19 3.19 3.19 ...
```

Previous plots used the annual average (Ann) against Latitude (Lat), with a plot formula:

Ann ~ cut(Lat, pretty(Lat, 40))

But now, we want to plot monthly values, Jan:Dec

Data munging

The solution used here works, but it is opaque, in that it tries to coerce the data into what is required for plot formulas for lattice

```
> (x <- paste(names(nasa)[3:14], collapse='+'))
[1] "Jan+Feb+Mar+Apr+May+Jun+Jul+Aug+Sep+Oct+Nov+Dec"
> (formula <- as.formula(paste(x, '~cut(Lat, pretty(Lat, 20))', sep='')))
Jan + Feb + Mar + Apr + May + Jun + Jul + Aug + Sep + Oct + Nov +
    Dec ~ cut(Lat, pretty(Lat, 20))
```

With this, the monthly plot can be produced by:

```
bwplot(formula, data=nasa, subset=(abs(Lat)<60),
    xlab='Latitude', ylab='G(0) (kWh/m²)',
    outer=TRUE, as.table=TRUE, horizontal=FALSE,
    col='lightblue',
    panel=panel.violin,
    scales=list(x=list(rot=70, cex=0.5)))
```