Visualizing Linear Models:
An R Bag of Tricks
Session 1: Getting Started

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SCS Short Course
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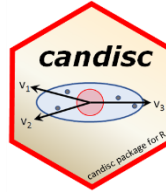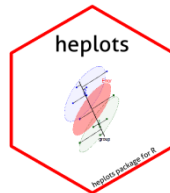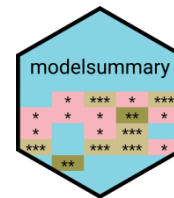https://friendly.github.io/VisMLM-course/

Today's topics

- What you need for this course

- Why plot your data?

- Data plots

- Model (effect) plots

- Diagnostic plots

What you need

- R, version >=3.6
  - Download from https://cran.r-project.org/
- RStudio IDE, highly recommended
  - https://www.rstudio.com/products/rstudio/
- R packages: see course web page
  - car
  - effects
  - heplots
  - candisc
  - visreg

Why plot your data?

Getting information from a table is like extracting sunlight from a cucumber. --- Farquhar & Farquhar, 1891

Information that is imperfectly acquired, is generally as imperfectly retained; and a man who has carefully investigated a printed table, finds, when done, that he has only a very faint and partial idea of what he has read; and that like a figure imprinted on sand, is soon totally erased and defaced.
--- William Playfair, *The Commercial and Political Atlas* (p. 3), 1786

Cucumbers

Table 7
Stevens et al. 2006, table 2: Determinants of authoritarian aggression

Variable	Coefficient (Standard Error)
Constant	.41 (.93)
Countries	
Argentina	1.31 (.33)**[B,M]
Chile	.93 (.32)**[B,M]
Colombia	1.46 (.32)**[B,M]
Mexico	.07 (.32)[A,CH,CO,V]
Venezuela	.96 (.37)**[B,M]
Threat	
Retrospective egocentric economic perceptions	.20 (.13)
Prospective egocentric economic perceptions	.22 (.12)[#]
Retrospective sociotropic economic perceptions	−.21 (.12)[#]
Prospective sociotropic economic perceptions	−.32 (.12)*
Ideological distance from president	−.27 (.07)**
Ideology	
Ideology	.23 (.07)**
Individual Differences	
Age	.00 (.01)
Female	−.03 (.21)
Education	.13 (.14)
Academic Sector	.15 (.29)
Business Sector	.31 (.25)
Government Sector	−.10 (.27)
R^2	.15
Adjusted R^2	.12
N	500

Results of a one model for authoritarian aggression

The information is overwhelmed by footnotes & significance **stars**

**p < .01, *p < .05, #p < .10 (twotailed)

[A]Coefficient is significantly different from Argentina's at p < .05;

[B]Coefficient is significantly different from Brazil's at p < .05;
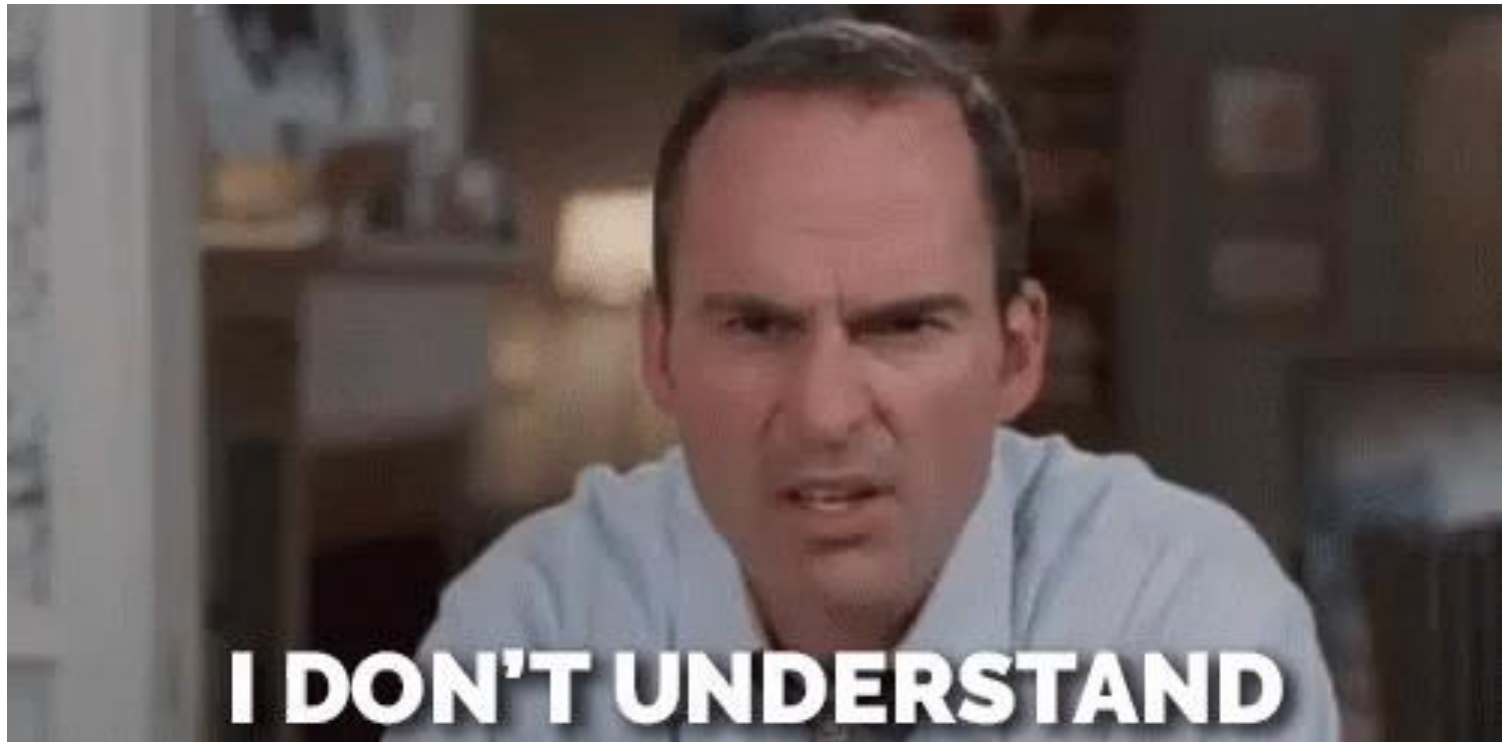
[CH]Coefficient is significantly different from Chile's at p < .05;

[CO]Coefficient is significantly different from Colombia's at p < .05;

[M]Coefficient is significantly different from Mexico's at p < .05;

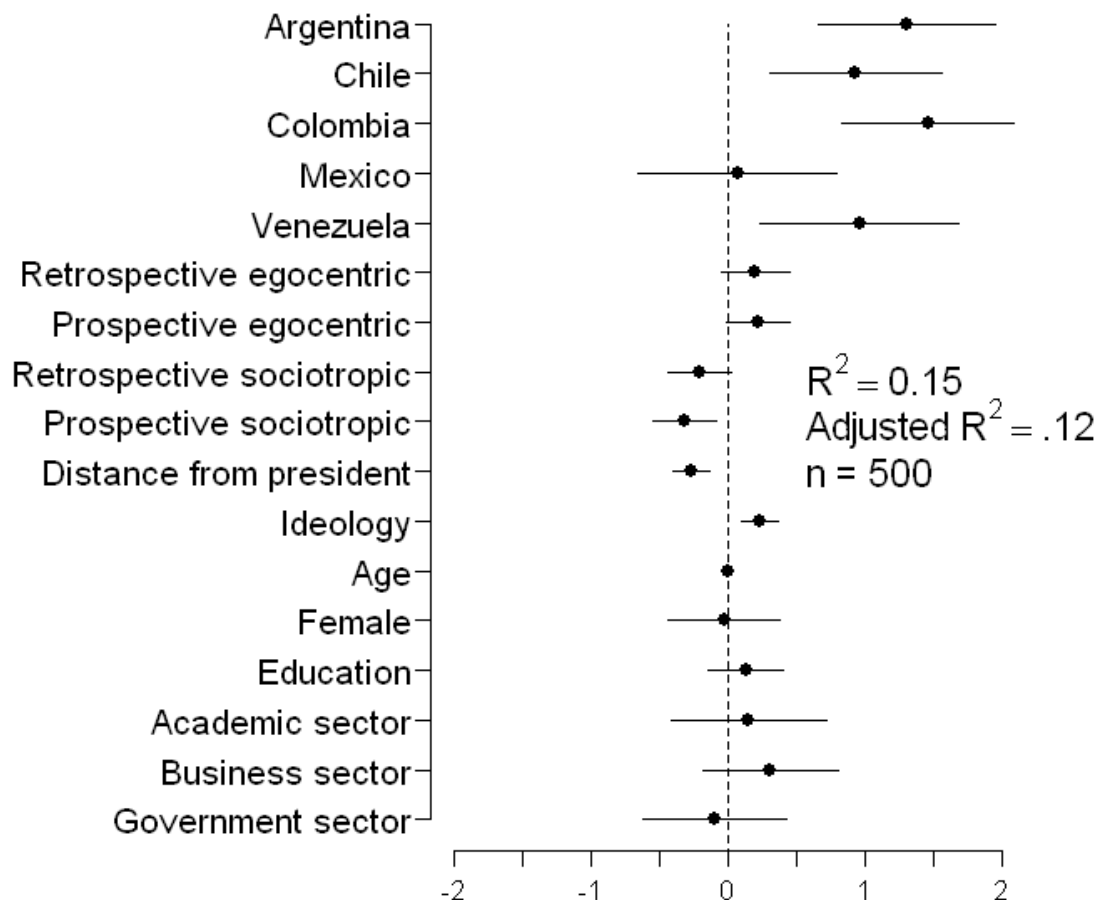[V]Coefficient is significantly different from Venezuela's at p < .05.

What's wrong with this picture?

Sunlight

coefplot(model)

Why didn't they say this in the first place?

$R^2 = 0.15$
Adjusted $R^2 = .12$
n = 500

NB: This is a presentation graph equivalent of the table

Shows coefficient with 95% CI
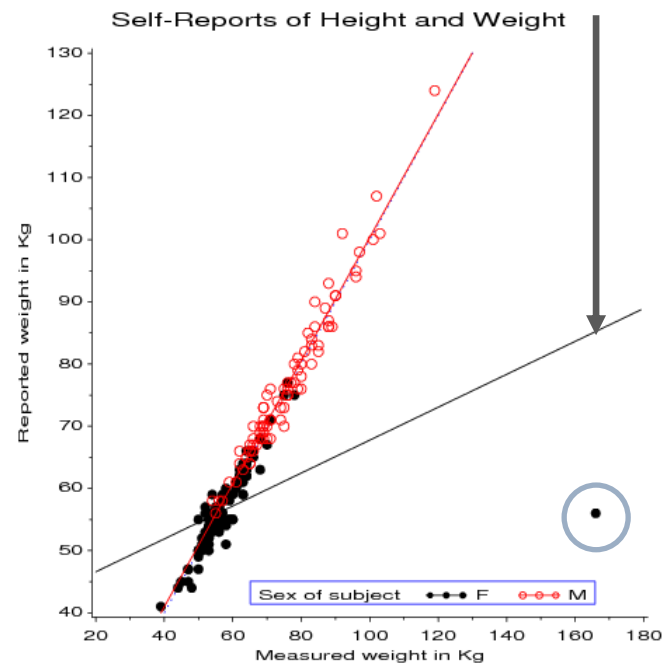
Run, don't walk toward the sunlight

Graphs can give enlightenment

The greatest value of a picture is when it forces us to notice what we never expected to see.
-- John W. Tukey

Effect of one rotten point on regression
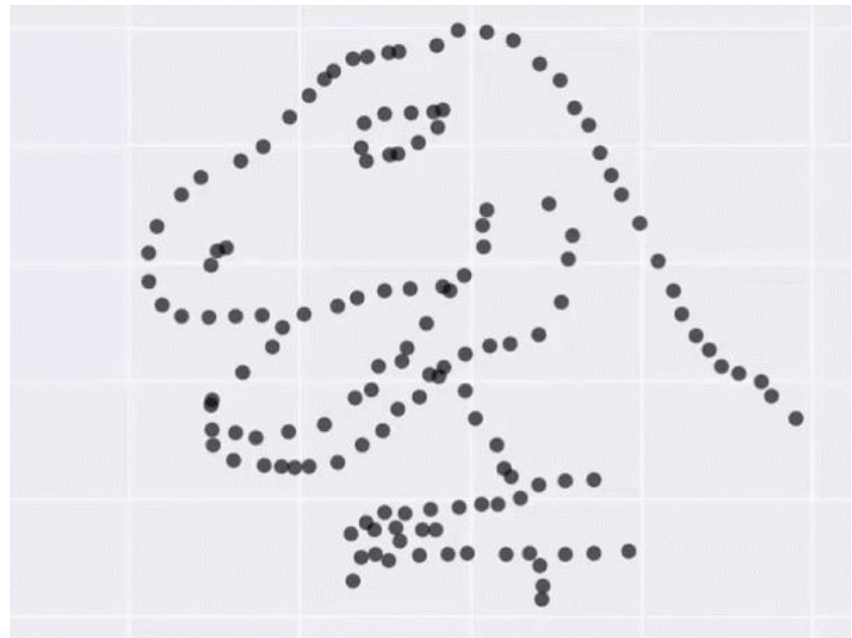
Dangers of numbers-only output

Student: You said to run descriptives and compute the correlation. What next?

Consultant: Did you plot your data?

With exactly the same stats, the data could be *any* of these plots

See how this in done in R: https://cran.r-project.org/web/packages/datasauRus/

```
X Mean:  54.26
Y Mean:  47.83
X SD  :  16.76
Y SD  :  26.93
Corr. :  -0.06
```

Sometimes, don't need numbers at all

COVID transmission risk ~ Occupancy * Ventilation * Activity * Mask? * Contact.time

A complex 5-way table, whose message is clearly shown w/o numbers

There are 1+ unusual cells here. Can you see them?

Type and level of group activity	Low occupancy			High occupancy		
	Outdoors and well ventilated	Indoors and well ventilated	Poorly ventilated	Outdoors and well ventilated	Indoors and well ventilated	Poorly ventilated
Wearing face coverings, contact for short time						
Silent	Green	Green	Green	Green	Green	Yellow
Speaking	Green	Green	Green	Green	Green	Yellow
Shouting, singing	Green	Green	Yellow	Yellow	Yellow	Red
Wearing face coverings, contact for prolonged time						
Silent	Green	Green	Yellow	Green	Yellow	Red
Speaking	Green	Green *	Yellow	Green *	Yellow	Red
Shouting, singing	Green	Yellow	Red	Yellow	Red	Red
No face coverings, contact for short time						
Silent	Green	Green	Yellow	Yellow	Yellow	Red
Speaking	Green	Yellow	Yellow	Yellow	Red	Red
Shouting, singing	Yellow	Yellow	Red	Red	Red	Red
No face coverings, contact for prolonged time						
Silent	Green	Yellow	Red	Yellow	Red	Red
Speaking	Yellow	Yellow	Red	Red	Red	Red
Shouting, singing	Yellow	Red	Red	Red	Red	Red

Risk of transmission
Low (green)   Medium (yellow)   High (red)

* Borderline case that is highly dependent on quantitative definitions of distancing, number of individuals, and time of exposure

From: N.R. Jones et-al (2020). Two metres or one: what is the evidence for physical distancing in covid-19? *BMJ* 2020;370:m3223, *doi: https://doi.org/10.1136/bmj.m3223*

If you do need tables– make them pretty

Several R packages make it easier to construct informative & pretty semi-graphic tables

Presentation graph

Perhaps too cute!

Distribution of variables shown

Flipper lengths (mm) of the famous penguins of Palmer Station, Antarctica.

Species	Distribution	Female		Male	
		Avg.	Std. Dev.	Avg.	Std. Dev.
ADÉLIE!		188	5.6	192	6.6
CHINSTRAP!		192	5.8	200	6.0
GENTOO!		213	3.9	222	5.7

Artwork by @allison_horst

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Visual table ideas: Heatmap shading

Heatmap shading: Shade the background of each cell according to some criterion

The trends in the US and Canada are made obvious

NB: Table rows are sorted by Jan. value, lending coherence

Unemployment rate in selected countries

January-August 2020, sorted by the unemployment rate in January.

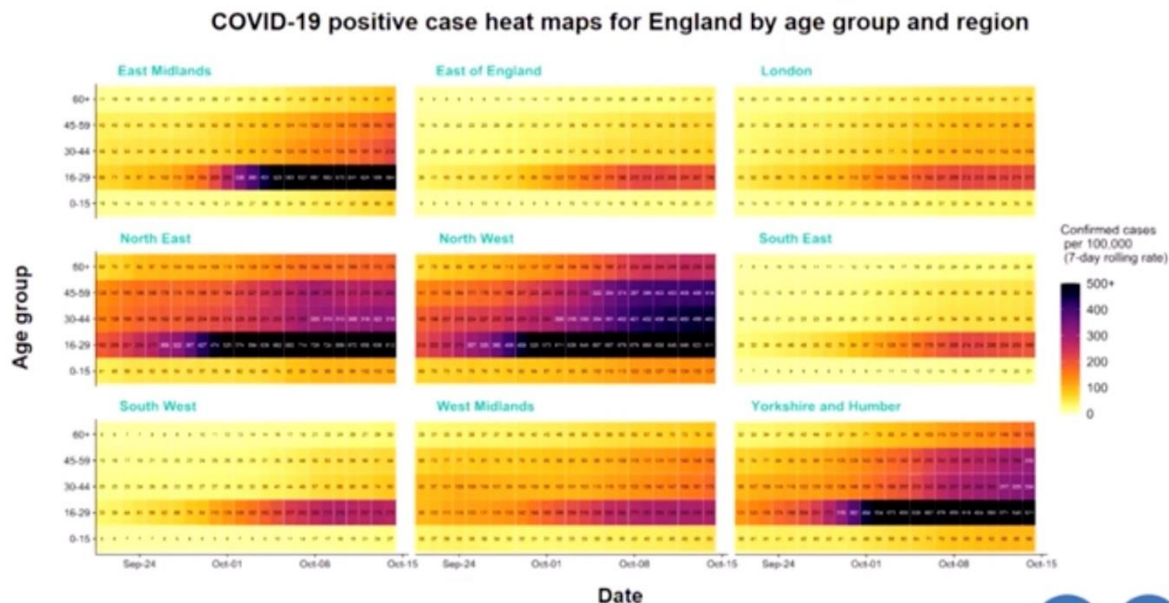| country	Jan ▲	Feb	Mar	Apr	May	Jun	Jul	Aug
Japan	2.4%	2.4%	2.5%	2.6%	2.9%	2.8%	2.9%	3.0%
Netherlands	3.0%	2.9%	2.9%	3.4%	3.6%	4.3%	4.5%	4.6%
Germany	3.4%	3.6%	3.8%	4.0%	4.2%	4.3%	4.4%	4.4%
Mexico	3.6%	3.6%	3.2%	4.8%	4.3%	5.4%	5.2%	5.0%
US	**3.6%**	**3.5%**	**4.4%**	**14.7%**	**13.3%**	**11.1%**	**10.2%**	**8.4%**
South Korea	4.0%	3.3%	3.8%	3.8%	4.5%	4.3%	4.2%	3.2%
Denmark	4.9%	4.9%	4.8%	4.9%	5.5%	6.0%	6.3%	6.1%
Belgium	5.1%	5.0%	5.0%	5.1%	5.0%	5.0%	5.0%	5.1%
Australia	5.3%	5.1%	5.2%	6.4%	7.1%	7.4%	7.5%	6.8%
Canada	**5.5%**	**5.6%**	**7.8%**	**13.0%**	**13.7%**	**12.3%**	**10.9%**	**10.2%**
Finland	6.8%	6.9%	7.0%	7.3%	7.5%	7.8%	8.0%	8.1%

Source: OECD · Get the data · Created with Datawrapper

Visual table ideas: Heatmap shading

As seen on TV …
Covid rate ~ Age x Date x UK region

Better: incorporate geography, not just arrange regions alphabetically

COVID-19 positive case heat maps for England by age group and region

Visual table ideas: Sparklines

Sparklines: Mini graphics inserted into table cells or text

Chicago's Taxi Trips Have Been on a Steady Decline
A closer look at the top 10 areas confirms taxis are suffering across the board

From: https://www.pluralsight.com/guides/tableau-playbook-sparklines

Linear models

- Model:

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_p x_{ip} + \varepsilon_i$$

- Xs: quantitative predictors, factors, interactions, …

- Assumptions:

  - **Linearity**: Predictors (possibly transformed) are linearly related to the outcome, **y**. [This just means linear in the **parameters**.]

  - **Specification**: No important predictors have been omitted; only important ones included. [This is often key & overlooked.]

  - The "holy trinity":

    - **Independence**: the errors are uncorrelated
    - **Homogeneity of variance**: Var(ε_i) = σ^2 = constant
    - **Normality**: ε_i have a normal distribution

$$\varepsilon_i \sim_{iid} N(0, \sigma^2)$$

The General Linear Model

- "linear" models can include:
  - ■ transformed predictors: $\sqrt{age}$, log(*income*)
  - ■ polynomial terms: age^2, age^3, `poly(age, `*n*`)`
  - ■ categorical "factors", coded as dummy (0/1) variables
    - treated (Yes/No), Gender (M/F/non-binary)
  - ■ interactions: effects of x_1 vary over levels of x_2
    - treated × age, treated × sex,   (2 way)
    - treated × age × sex   (3 way)
- Linear model means linear in the parameters (β_i),

$$y = \beta_0 + \beta_1 \text{age} + \beta_2 \text{age}^2 + \beta_3 \log(\text{income}) + \beta_4 (\text{sex=''F''}) + \beta_5 \text{age} \times (\text{sex=''F''}) + \grave{\text{o}}$$

- In R, all handled by `lm(y ~ …)`

Fitting linear models in R: lm()

- In R, **lm()** for everything

  - Regression models (X1, ... quantitative)

    ```
    lm(y ~ X1, data=dat)              # simple linear regression
    lm(y ~ X1+X2+X3, data=dat)        # multiple linear regression
    lm(y ~ (X1+X2+X3)^2, data=dat)    # all two-way interactions
    lm(log(y) ~ poly(X,3), data=dat)  # arbitrary transformations
    ```

  - ANOVA/ANCOVA models (A, B, ... factors)

    ```
    lm(y ~ A)           # one way ANOVA
    lm(y ~ A*B)         # two way: A + B + A:B
    lm(y ~ X + A)       # one way ANCOVA
    lm(y ~ (A+B+C)^2)   # 3-way ANOVA: A, B, C, A:B, A:C, B:C
    ```

Fitting linear models in R: lm()

- Multivariate models: **lm()** with 2+ y vars

  - Multivariate regression

    ```
    lm(cbind(y1, y2) ~ X1 + X2 + X3)              # std MMreg: all linear
    lm(cbind(y1, y2) ~ poly(X1,2) + poly(X2,2))   # response surface
    ```

  - MANOVA/MANCOVA models

    ```
    lm(cbind(y1, y2, y3) ~ A * B)        # 2-way MANOVA: A + B + A:B
    lm(cbind(y1, y2, y3) ~ X + A)        # MANCOVA (equal slopes)
    lm(cbind(y1, y2) ~ X + A + X:A)      # heterogeneous slopes
    ```

General*ized* Linear Models: glm()

Transformations of y & other error distributions

- y $\in$ (0/1): lived/died; success/fail; …

- logit (log odds) model:

  - logit(y) $= \log \dfrac{\Pr(y=1)}{\Pr(y=0)}$

  - linear logit model:
    logit(y) $= \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots$

glm(better ~ age + treat, family=binomial, data=Arthritis)

Female
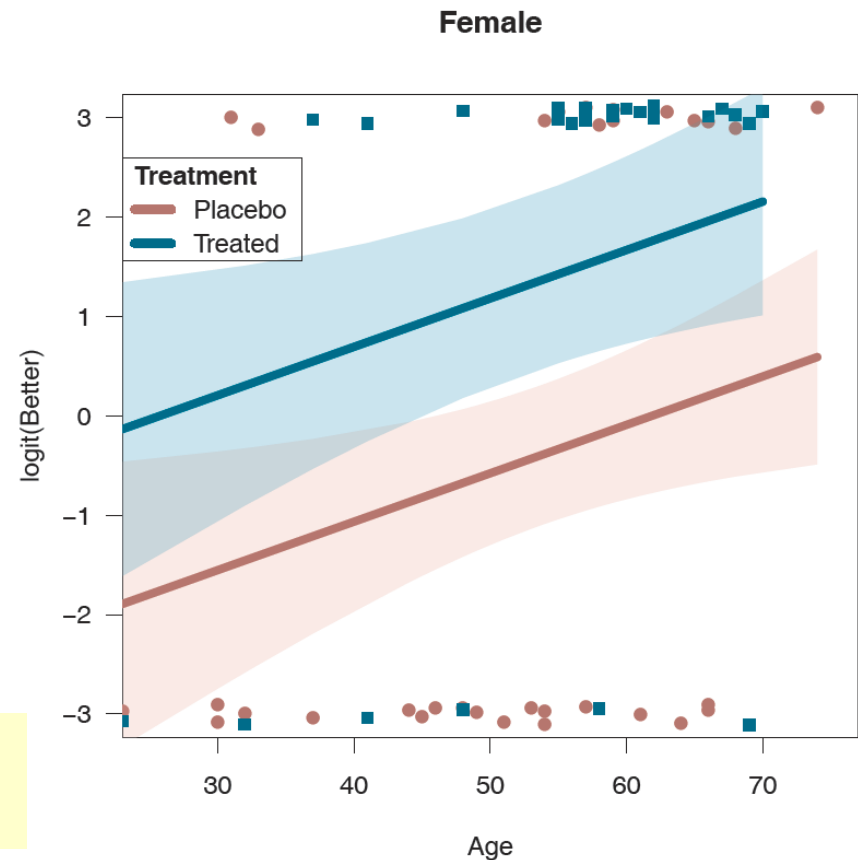
General*ized* Linear Models

Ordinal responses

- Improved $\in$ ("None" < "Some" < "Marked")

- Models: Proportional odds, generalized logits, …

```
library(MASS)
polr(Improved ~ Sex + Treat + Age,
        data=Arthritis)

library(nnet)
multinom(Improved ~ Sex + Treat + Age,
            data=Arthritis)
```
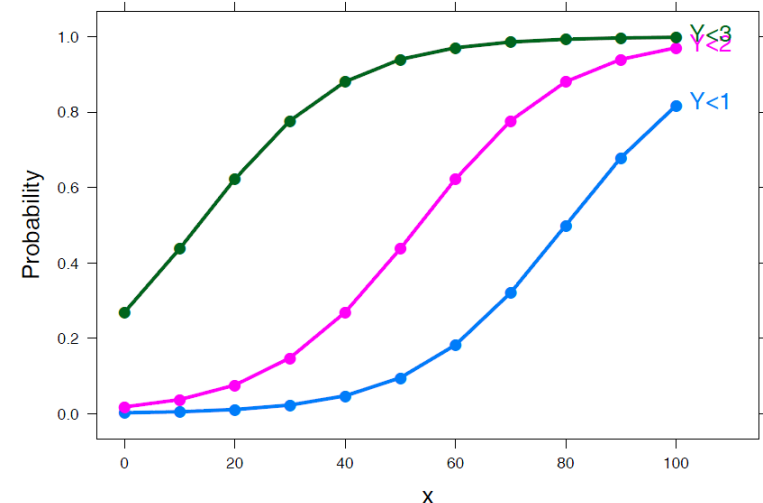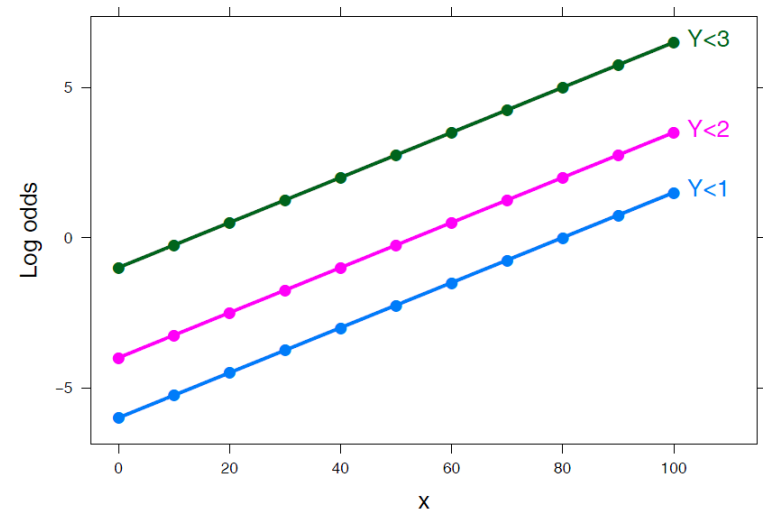
Model-based methods: Overview
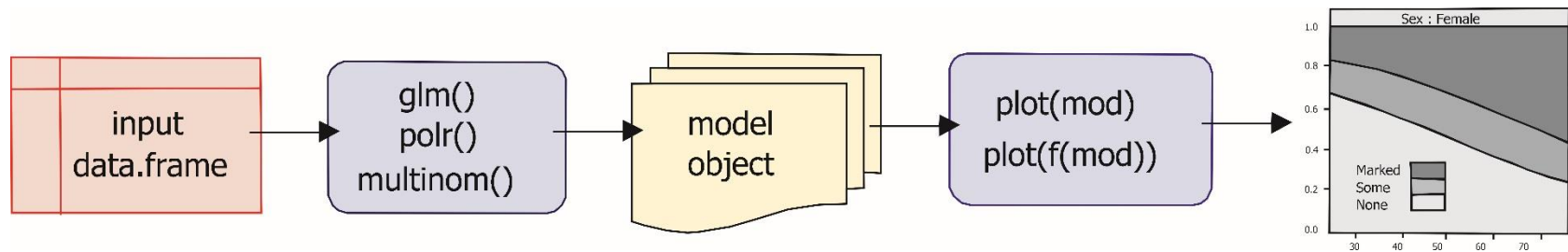
- models in R are specified by a symbolic model formula, applied to a data.frame
  - mod<-lm(prestige ~ income + educ, data=Prestige)
  - mod<-glm(better ~ age + sex + treat, data=Arthritis, family=binomial)
  - mod<-MASS:polr(improved ~ age + sex + treat, data=Arthritis)
- result (mod) is a "model object", of class "lm", "glm", …
- method functions:
  - plot(mod), plot(f(mod)), …
  - summary(mod), coef(mod), predict(mod), …

Plots for linear models

- Data plots:
  - plot response (y) vs. predictors, with smooth summaries
  - scatterplot matrix --- all pairs

- Model (effect) plots
  - plot predicted response ($\hat{y}$) vs. predictors, controlling for variables not shown.

- Diagnostic plots
  - Influence plots: leverage & outliers
  - Spread-level plots (non-constant variance?)

R packages

- `car`
  - Enhanced scatterplots
  - Diagnostic plots
- `effects`
  - Plot fitted effects of one predictor, controlling all others
- `visreg`
  - similar to effect plots, simpler syntax
- Both `effects` & `visreg` handle nearly all formula-based models
  - lm(), glm(), gam(), rlm, nlme(), …

Occupational Prestige data

- Data on prestige of 102 occupations and
  - average education (years)
  - average income ($)
  - % women
  - type (Blue Collar, Professional, White Collar)

```
> head(Prestige)
                    education income women prestige census type
gov.administrators      13.11  12351 11.16     68.8   1113 prof
general.managers        12.26  25879  4.02     69.1   1130 prof
accountants             12.77   9271 15.70     63.4   1171 prof
purchasing.officers     11.42   8865  9.11     56.8   1175 prof
chemists                14.62   8403 11.68     73.5   2111 prof
physicists              15.64  11030  5.13     77.6   2113 prof
```

Informative scatterplots

Scatterplots are most useful when enhanced with annotations & statistical summaries

Data ellipse and regression line show the linear model, prestige ~ income

Point labels show possible outliers

Smoothed (loess) curve and CI show the trend

Boxplots show marginal distributions
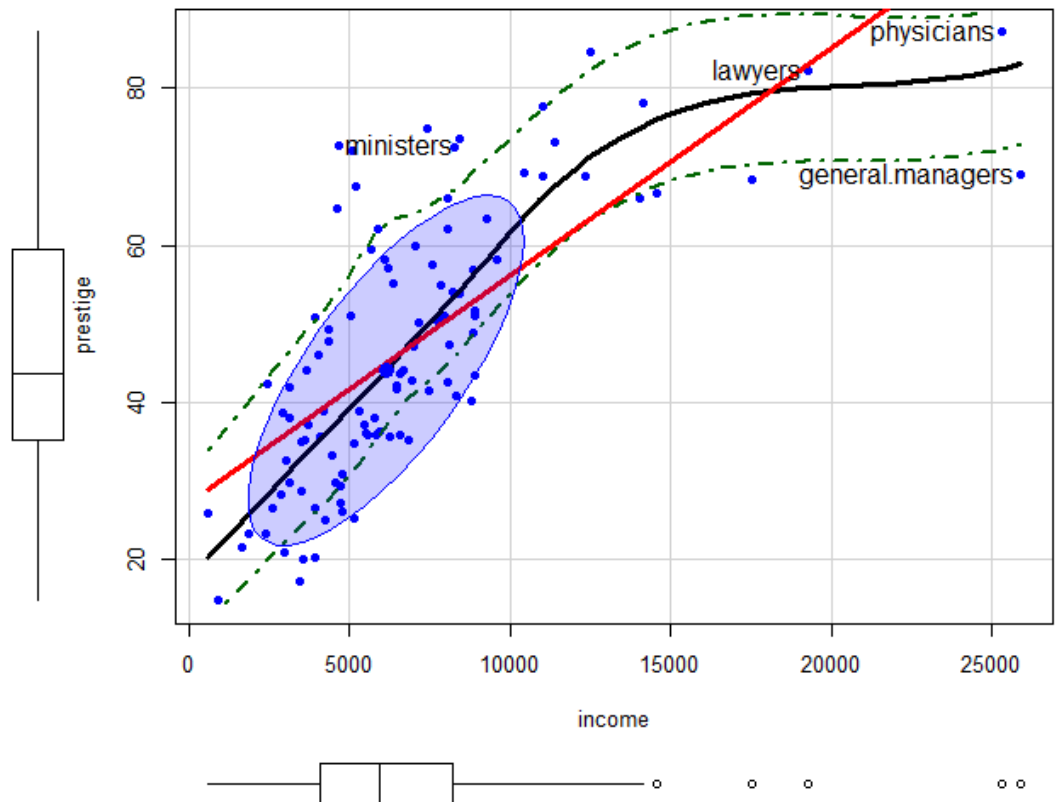
Informative scatterplots

`car::scatterplot()` provides all these enhancements

```
scatterplot(prestige ~ income, data=Prestige,
            pch = 16,
            regLine = list(col = "red", lwd=3),
            smooth = list(smoother=loessLine,
                          lty.smooth = 1, col.smooth = "black",
                          lwd.smooth=3, col.var = "darkgreen"),
            ellipse = list(levels = 0.68),
            id = list(n=4, col="black", cex=1.2))
```

Skewed distribution of income & non-linear relation suggest need for a transformation

Arrow rule: move on the scale of powers in direction of the bulge
e.g.: x → sqrt(income) or log(income)
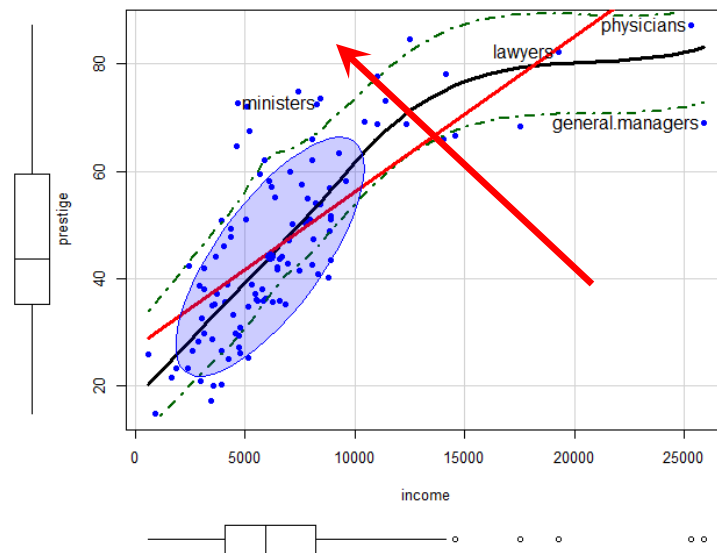
Try log(income)

```
scatterplot(prestige ~ income, data=Prestige,
            log = "x",
            pch = 16,
            regLine = list(col = "red", lwd=3),
            … )
```

Income now ~ symmetric

Relation closer to linear
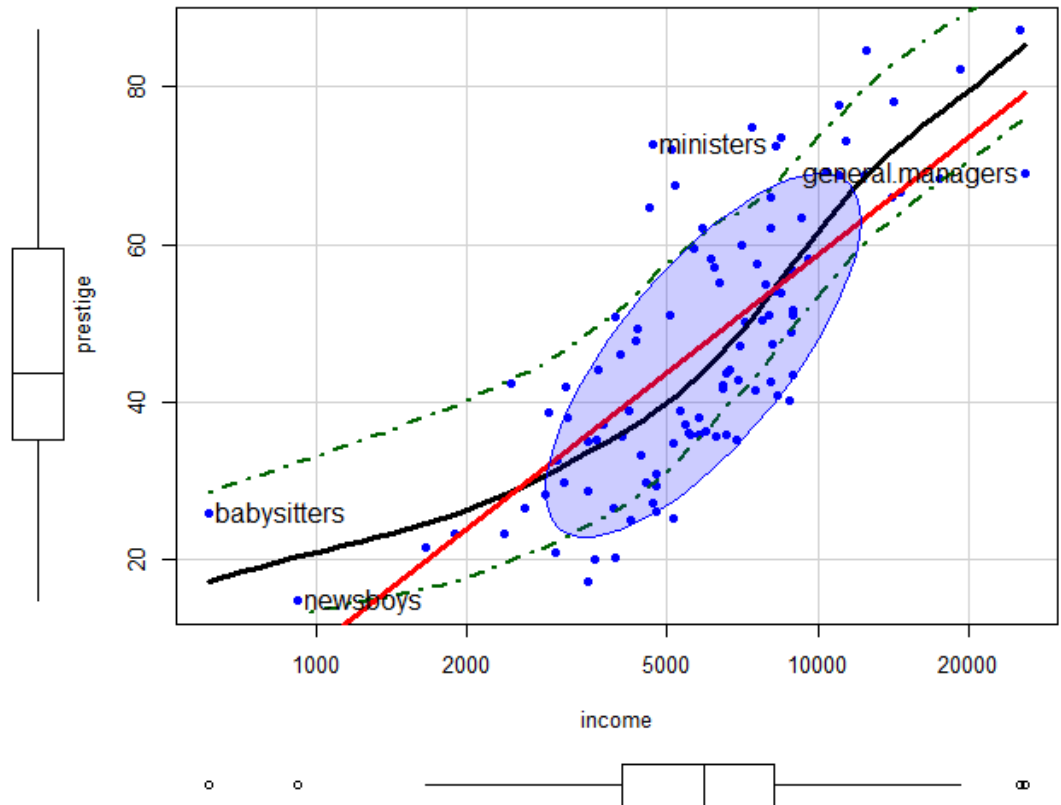
Stratify by type?

```
scatterplot(prestige ~ income | type, data=Prestige,
        col = c("blue", "red", "darkgreen"),
        pch = 15:17,
        legend = list(coords="bottomright"),
        smooth=list(smoother=loessLine, var=FALSE, span=1, lwd=4))
```

Formula: | type → "given type"

Different slopes: interaction of income * type

Provides another explanation of the non-linear relation

This is a new finding!
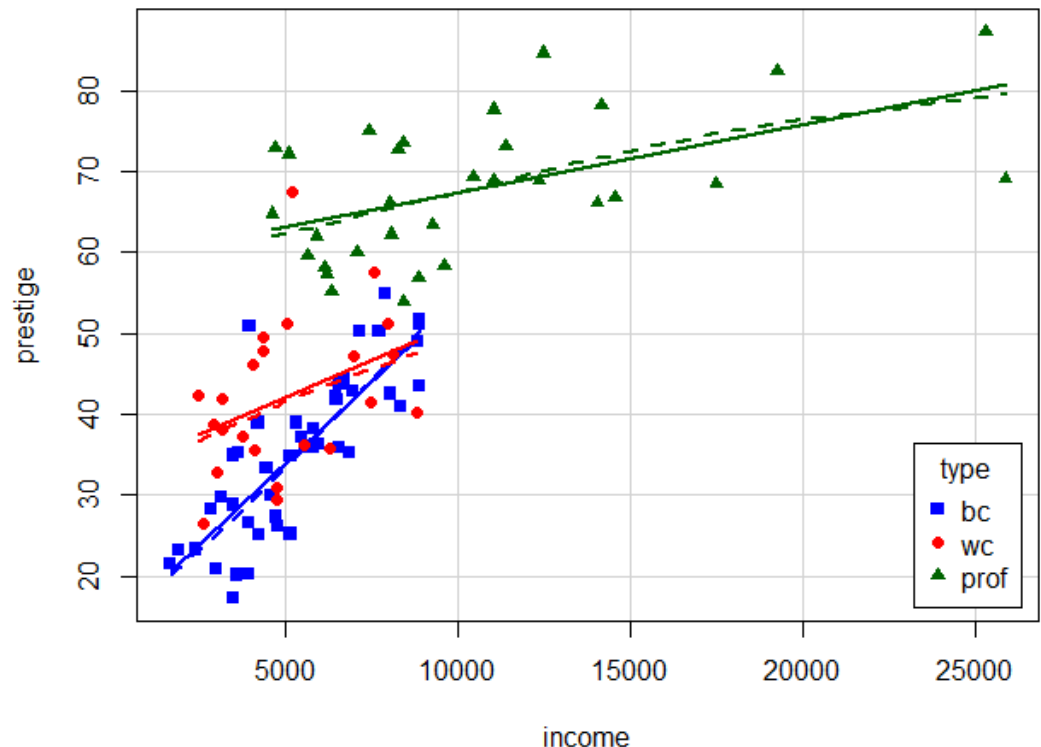
Scatterplot matrix

```
scatterplotMatrix(~ prestige + education + income + women ,
      data=Prestige,
      regLine = list(method=lm, lty=1, lwd=2, col="black"),
      smooth=list(smoother=loessLine, spread=FALSE,
              lty.smooth=1, lwd.smooth=3, col.smooth="red"),
      ellipse=list(levels=0.68, fill.alpha=0.1))
```

prestige vs. all predictors

diagonal: univariate distributions
- income: + skewed
- %women: bimodal

off-diagonal: relations among predictors
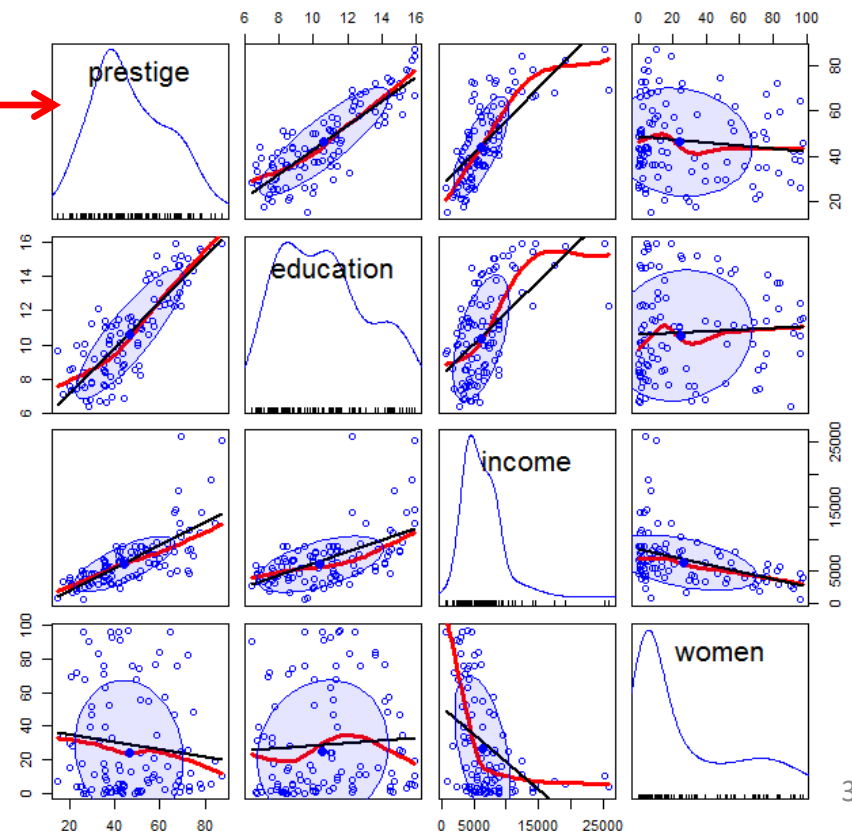
Fit a model

```
> mod1 <- lm(prestige ~ education + poly(women, 2) +
+                       log(income)*type, data=Prestige)
> summary(mod1)

Coefficients:
                    Estimate Std. Error t value Pr(>|t|)
(Intercept)         -137.500     23.522   -5.85  8.2e-08 ***
education              2.959      0.582    5.09  2.0e-06 ***
poly(women, 2)1       28.339     10.190    2.78   0.0066 **
poly(women, 2)2       12.566      7.095    1.77   0.0800 .
log(income)           17.514      2.916    6.01  4.1e-08 ***
typeprof              74.276     30.736    2.42   0.0177 *
typewc                 0.969     39.495    0.02   0.9805
log(income):typeprof  -7.698      3.451   -2.23   0.0282 *
log(income):typewc    -0.466      4.620   -0.10   0.9199
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' '
1

Multiple R-squared: 0.879,   Adjusted R-squared:  0.868
F-statistic: 81.1 on 8 and 89 DF,  p-value: <2e-16
```

- allow women^2 term
- interaction of log(income) and type

Fits very well!

Model (effect) plots

- We'd like to see plots of the predicted value ($\hat{y}$) of the response against predictors (x_j)
  - Ordinary plot of y vs. x_j doesn't allow for other correlations
  - $\rightarrow$ Must control for other predictors (x_{-j}) not shown in a given plot
  - Variables not shown (x_{-j}) are averaged over.
  - Slopes of lines reflect the partial coefficient in the model
  - Partial residuals can be shown also

For details, see `vignette("predictor-effects-gallery", package="effects)`

Model (effect) plots: education

```
library("effects")
mod1.e1 <- predictorEffect("education", mod1)
plot(mod1.e1)
```

This graph shows the partial slope for education

For each ↑ year in education, fitted prestige ↑2.96 points, (other predictors held fixed)

education predictor effect plot
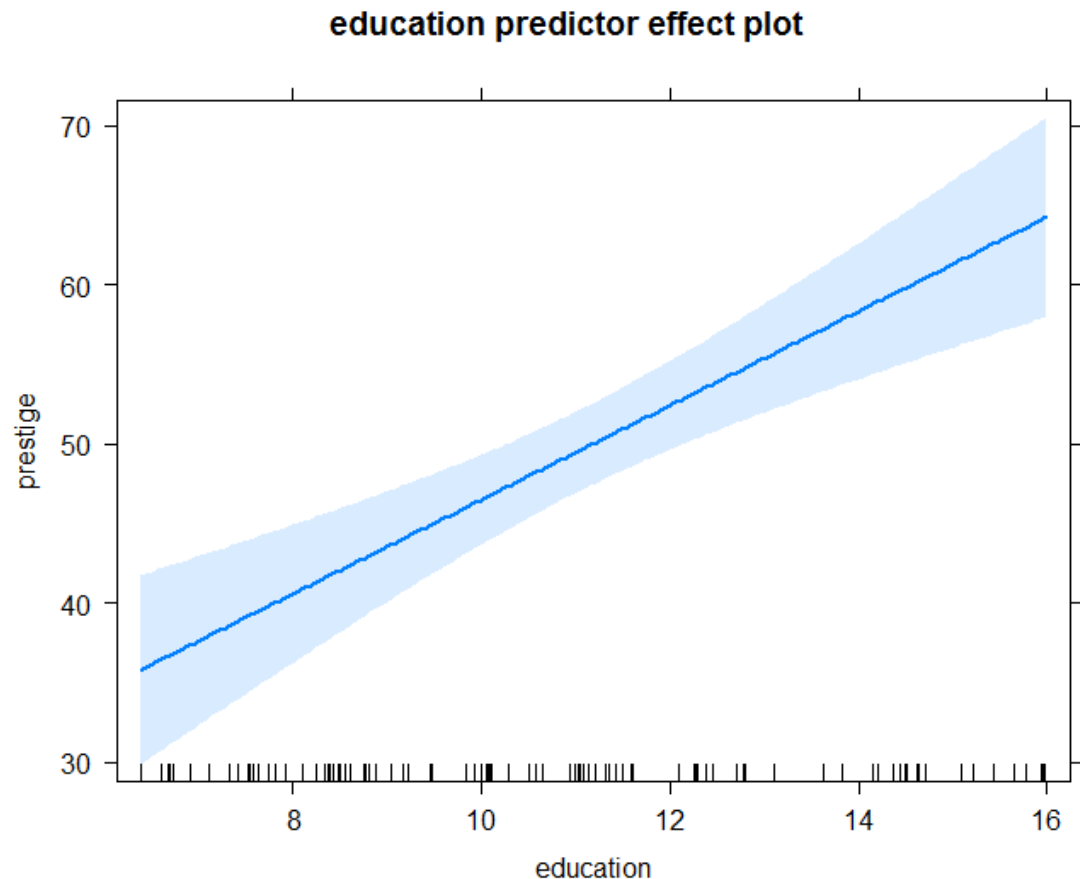
Model (effect) plots

```
mod1.e1a <- predictorEffect("education", mod1, residuals=TRUE)
plot(mod1.e1a,
     residuals.pch=16, id=list(n=4, col="black"))
```

Partial residuals show the residual of prestige controlling for other predictors

Unusual points here would signal undue influence

education predictor effect plot
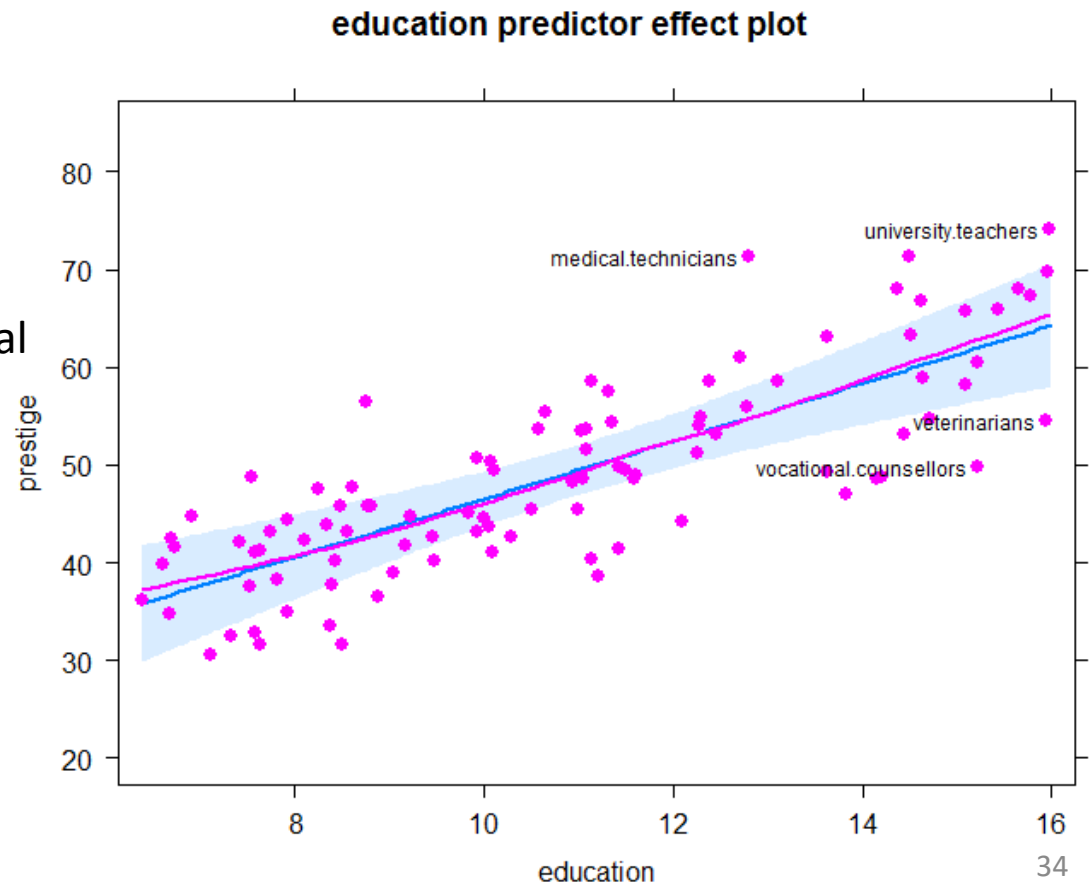
Model (effect) plots: women

```
mod1.e2 <- predictorEffect("women", mod1, residuals=TRUE)
plot(mod1.e2, ylim=c(40, 65), lwd=4,
     residuals.pch=16)
```

Surprise!
Prestige of occupations ↑
with % women (controlling
for other variables)

women predictor effect plot
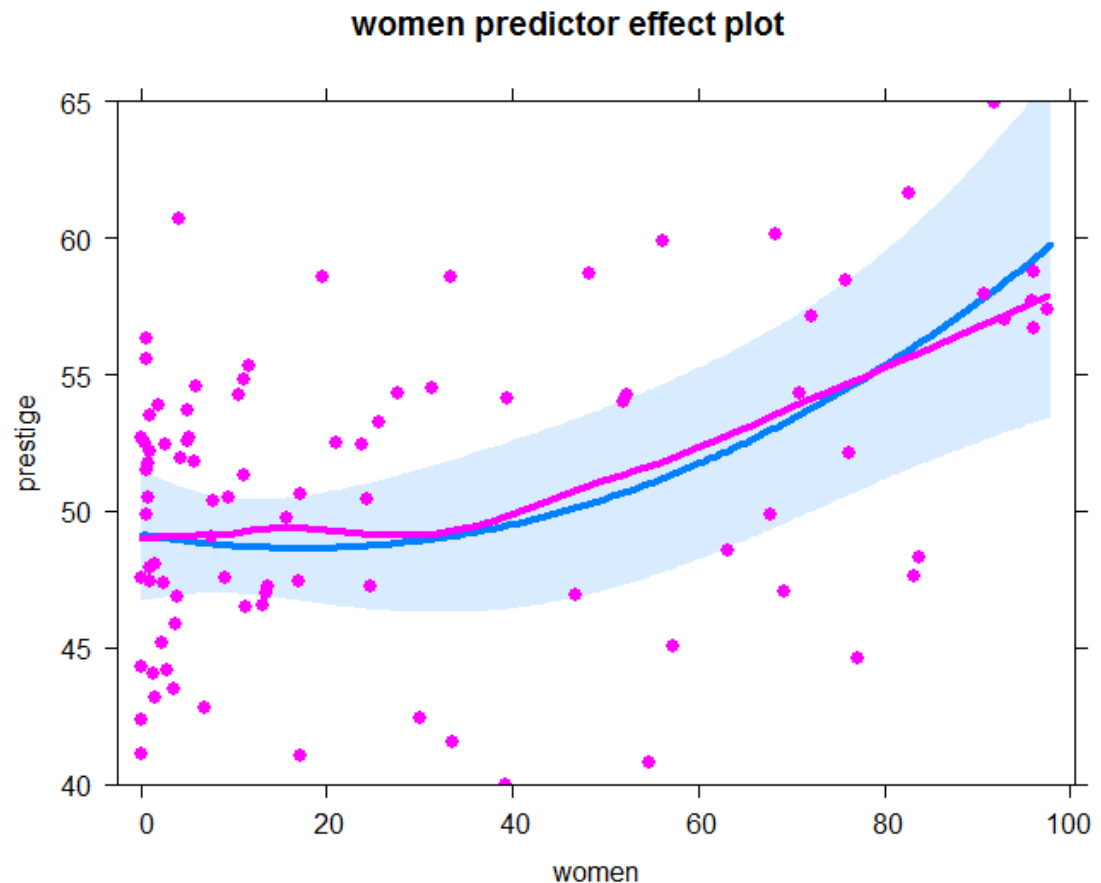
Model (effect) plots: income

```
plot(predictorEffect("income", mod1),
     lines=list(multiline=TRUE, lwd=3),
     key.args = list(x=.7, y=.35))
```

Income interacts with type in the model

The plot is curved because log(income) is in the model

income predictor effect plot
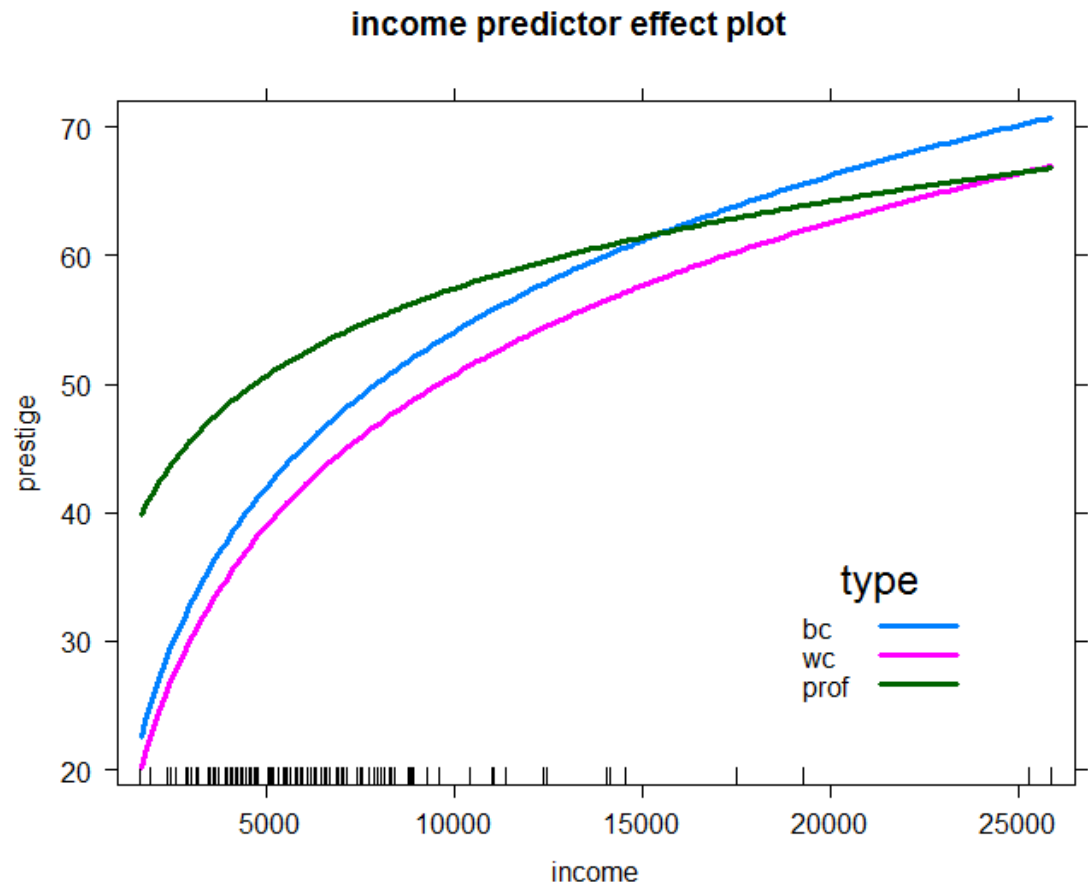
visreg plots: Air quality data

Daily air quality measurements in New York, May - Sep 1973

How does Ozone concentration vary with solar radiation, wind speed & temperature?

```
> head(airquality)
  Ozone Solar.R Wind Temp Month Day
1    41     190  7.4   67     5   1
2    36     118  8.0   72     5   2
3    12     149 12.6   74     5   3
4    18     313 11.5   62     5   4
5    NA      NA 14.3   56     5   5
6    28      NA 14.9   66     5   6
```

see: https://pbreheny.github.io/visreg/ for examples & details

Air quality: main effects model

```
> fit1 <- lm(Ozone ~ Solar.R + Wind + Temp, data=airquality)
> summary(fit1)

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) -64.3421    23.0547   -2.79   0.0062 **
Solar.R       0.0598     0.0232    2.58   0.0112 *
Wind         -3.3336     0.6544   -5.09  1.5e-06 ***
Temp          1.6521     0.2535    6.52  2.4e-09 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 21.18 on 107 degrees of freedom
  (42 observations deleted due to missingness)
Multiple R-squared:  0.6059,    Adjusted R-squared:  0.5948
F-statistic: 54.83 on 3 and 107 DF,  p-value: < 2.2e-16
```

visreg conditional plots

```
op <- par(mfrow=c(1,3), cex.lab=1.5)
visreg(fit1, "Solar.R")
visreg(fit1, "Wind")
visreg(fit1, "Temp")
par(op)
```

model summary =
  predicted values (line) +
  confidence band (uncertainty) +
  partial residuals (objections)
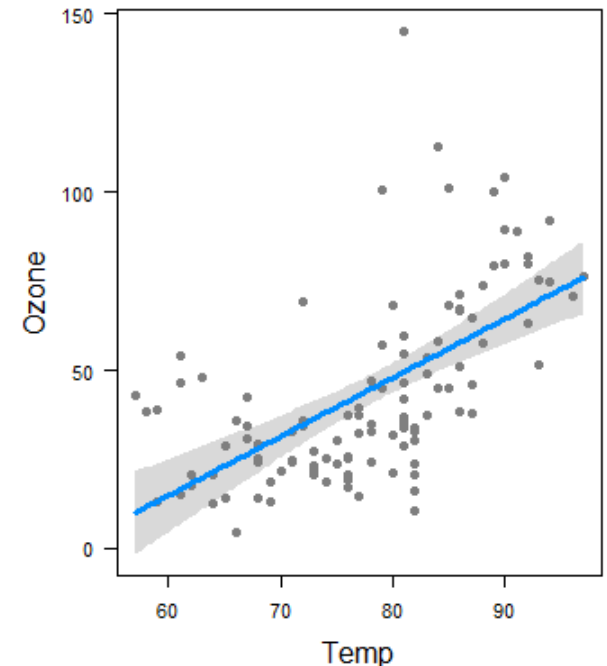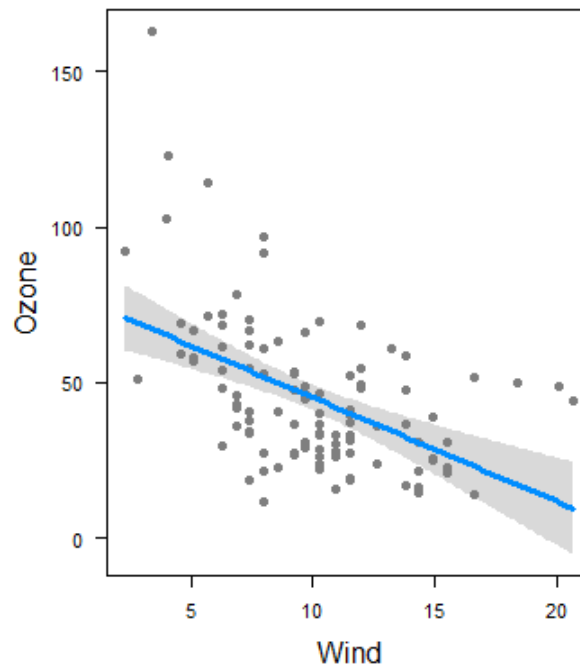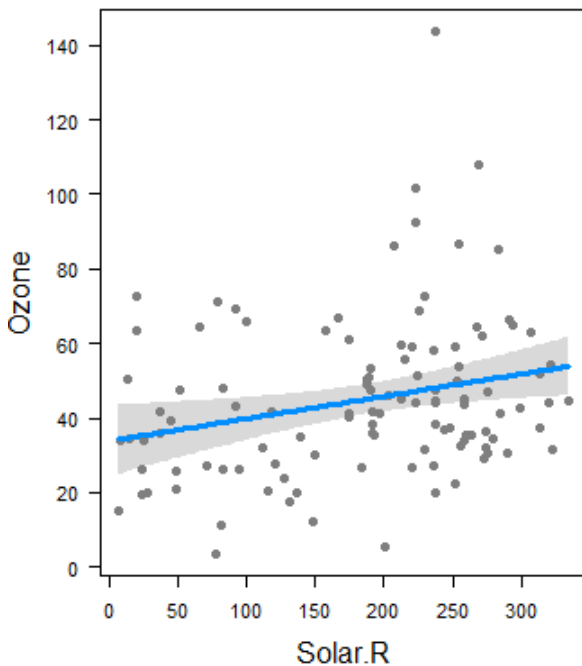
Factor variables & interactions

```
                                    # cut Temp into three ordered levels of equal range
airquality$Heat <- cut(airquality$Temp, 3,
                 labels=c("Cool","Mild","Hot"))


                                    # fit model with interaction  of Wind * Heat
fit2 <- lm(Ozone ~ Solar.R + Wind*Heat, data=airquality)
visreg(fit2, "Wind", by="Heat", layout=c(3,1), points=list(cex=1))
```
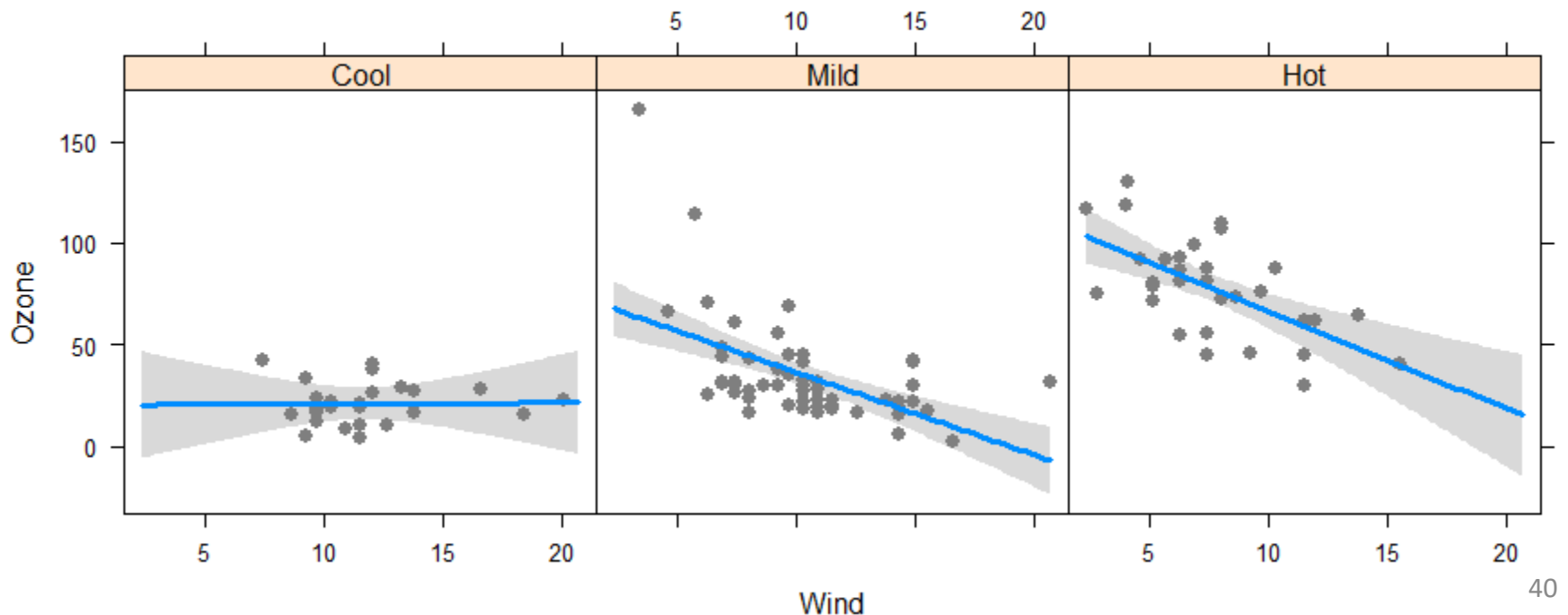
Factor variables & interactions

```
visreg(fit2, "Wind", by="Heat",
        overlay=TRUE,
            gg=TRUE,
        points=list(size=2)) +
  theme_bw()
```

overlay=TRUE → superpose panels
gg=TRUE → uses ggplot

This allow slope for Wind to vary with Heat e.g., Wind has no effect when Cool

This model still assumes linear effects of Heat & Wind
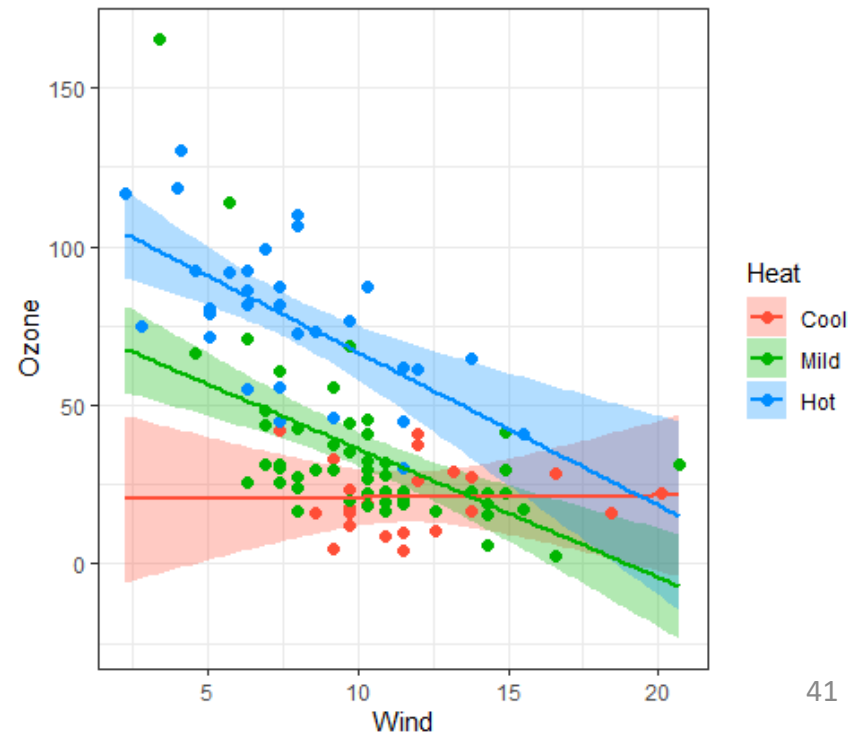
Non-linear effects

fit <- lm(Ozone ~ Solar.R + poly(Wind,2) + Temp, data=airquality)
visreg(fit, "Wind")
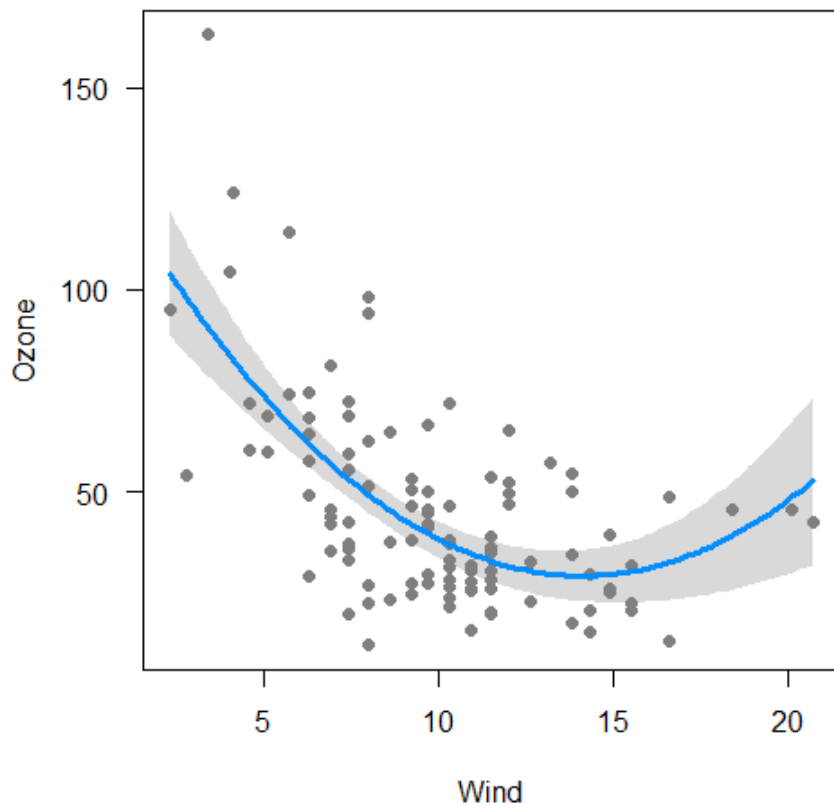
fit <- lm(Ozone ~ Solar.R + Wind + poly(Temp,2), data=airquality)
visreg(fit, "Temp")
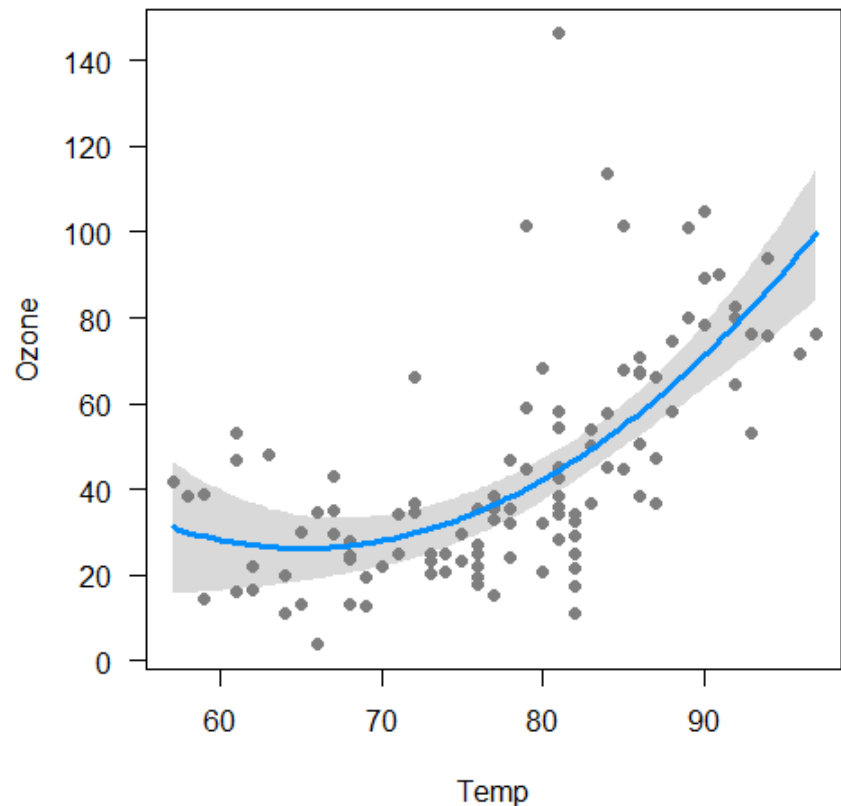
Response surface models (visreg2d)

# Fit quadratics in both Wind & Temp and interaction Wind * Temp
fitp <- lm(Ozone ~ Solar.R + poly(Wind,2) * poly(Temp,2), data=airquality)

visreg2d(fitp, "Wind", "Temp", plot.type="gg") +
    geom_contour(aes(z=z), color="black")
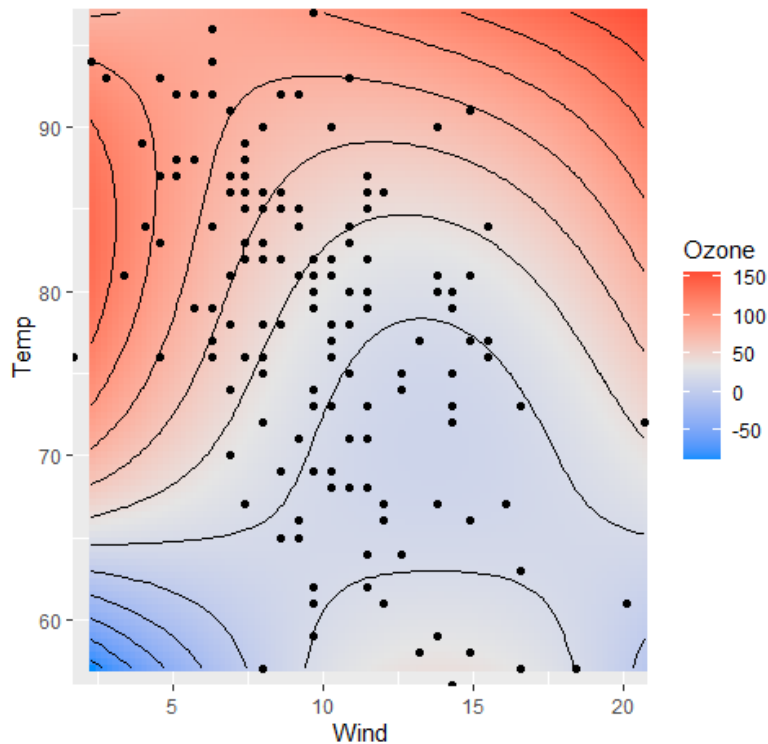
visreg2d(fitp, "Wind", "Temp", plot.type="persp")
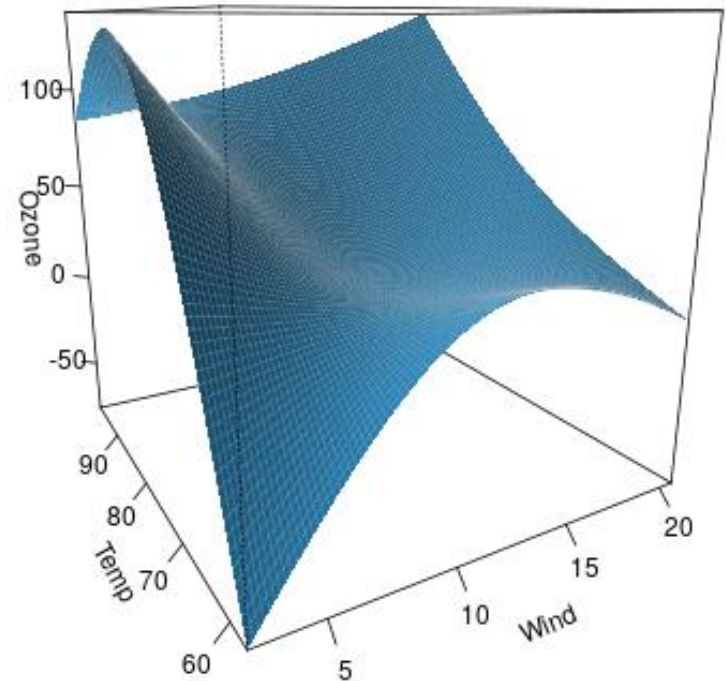
Diagnostic plots

- The linear model, $\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \grave{\mathbf{o}}$ assumes:
    - Residuals, ε_i are normally distributed, $\varepsilon_i \sim N(0,\sigma^2)$
    - (Normality not required for **X**s)
    - Constant variance, $Var(\varepsilon_i) = \sigma^2$
    - Observations y_i are statistically independent
- Violations $\rightarrow$ inferences may not be valid
- A variety of plots can diagnose all these problems
- Other methods (boxCox, boxTidwell) diagnose the need for transformations of **y** or **X**s.

The "regression quartet"

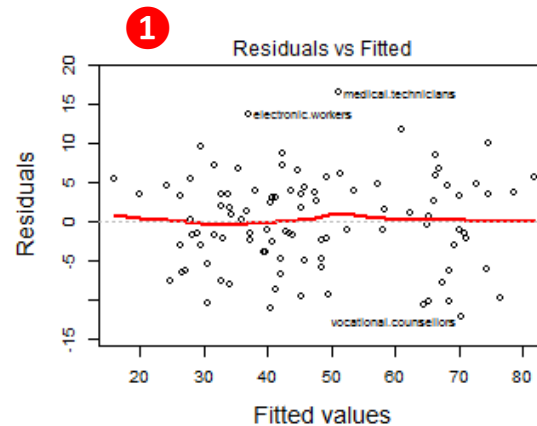In R, plotting a `lm` model object → the "regression quartet" of plots

`plot(mod1, lwd=2, cex.lab=1.4)`

❶ Residuals: should be flat vs. fitted values

❷ Q-Q plot: should follow the 45° line

**❸** Scale-location: should be flat if constant variance

❹ Resids vs. leverage: can show influential observations
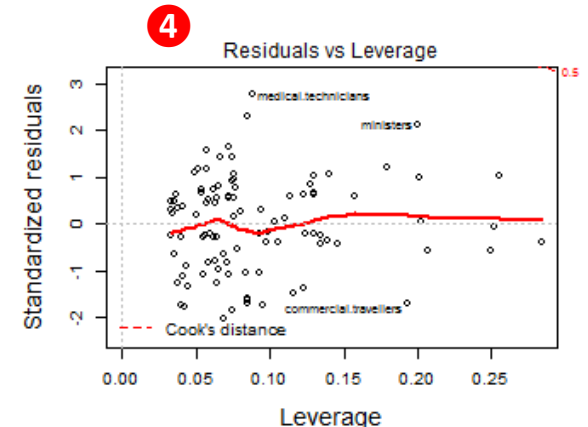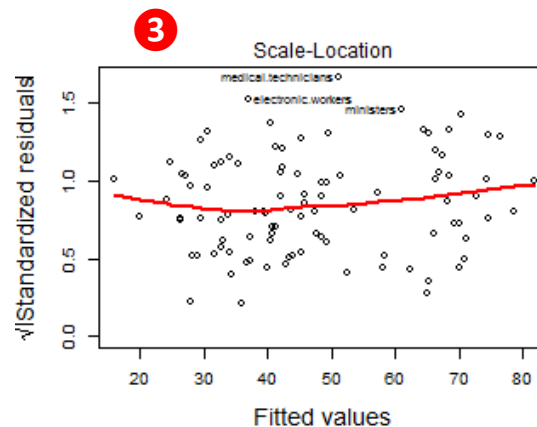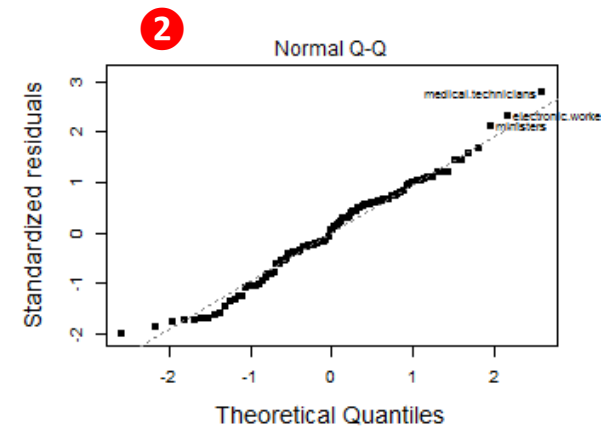
Unusual data: Leverage & Influence

- "Unusual" observations can have dramatic effects on least-squares estimates in linear models

- Three archetypal cases:
    - Typical X (low leverage), bad fit   -- Not much harm
    - Unusual X (high leverage), good fit   -- Not much harm
    - Unusual X (high leverage), bad fit   -- BAD, BAD, BAD

- Influential observations: unusual in *both* X & Y

- Heuristic formula:

$$\text{Influence} = \text{X leverage} \times \text{Y residual}$$
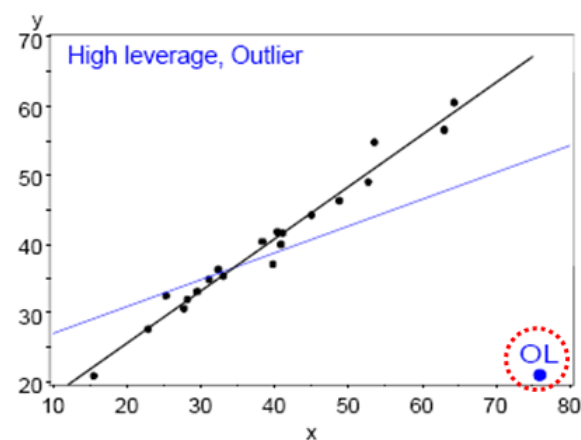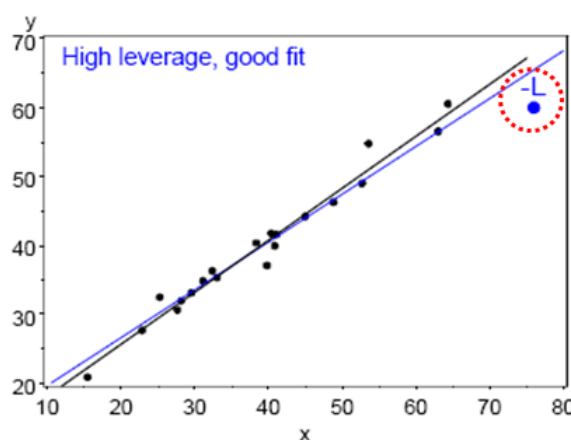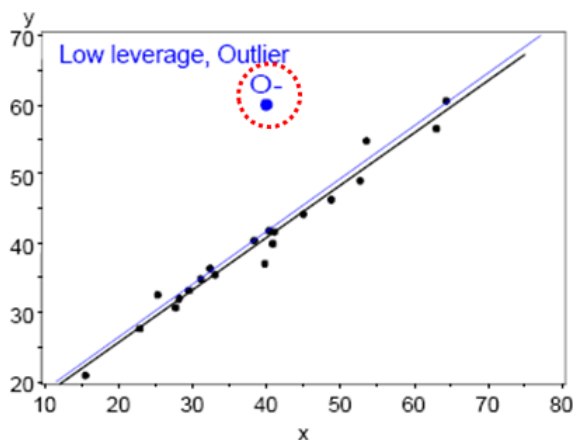
Influence plots

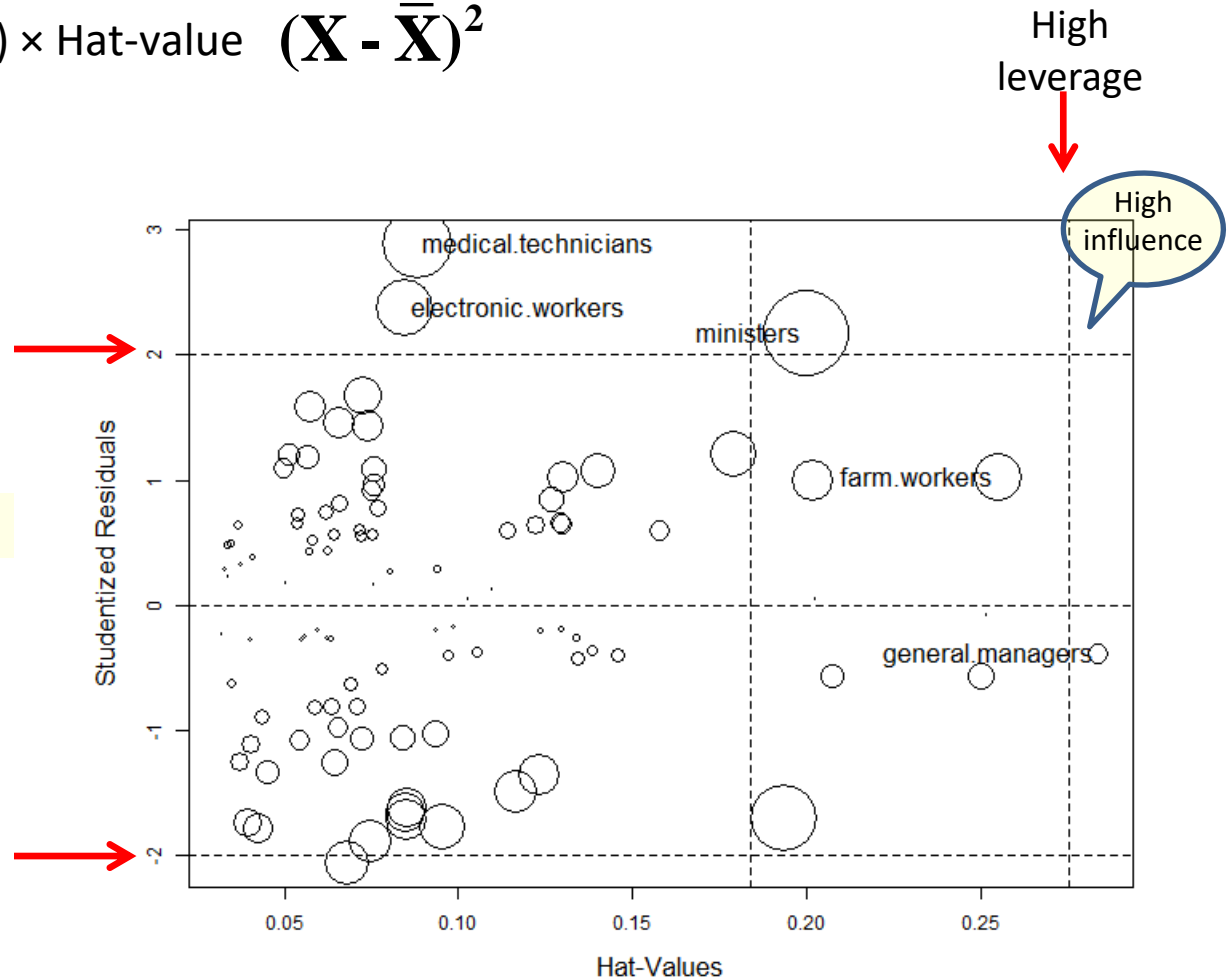Influence (Cook's D) measures impact of individual obs. on coefficients, fitted values

Influence ~ Residual (y -ŷ) × Hat-value $(\mathbf{X} - \bar{\mathbf{X}})^2$

Bubble size ~ influence

`influencePlot(mod1)`

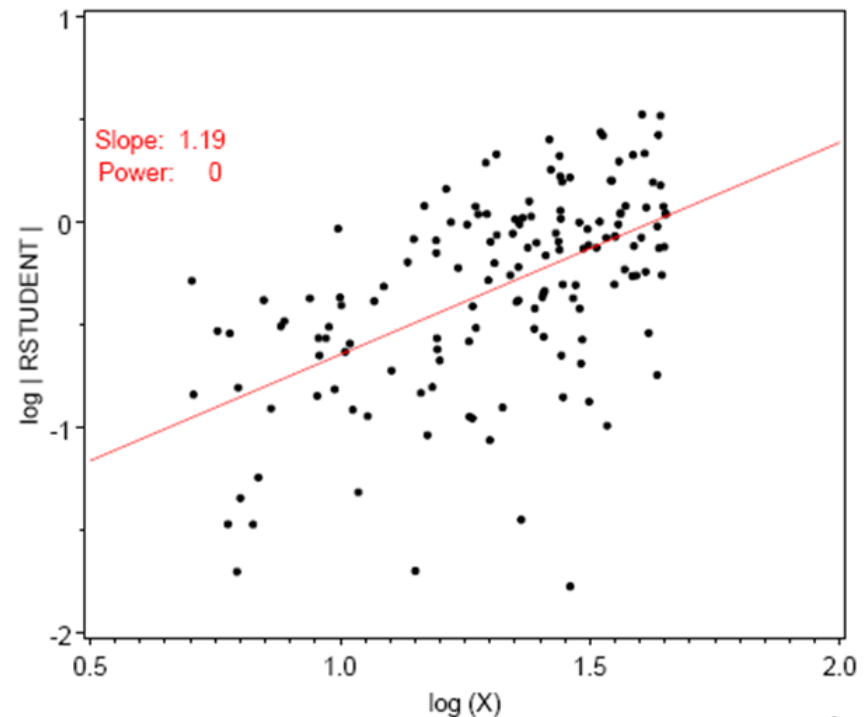# Spread-level plots

- ## To diagnose non-constant variance, plot:
  - log |Std. residual| vs. log (x)
  - log (IQR) vs log (median)   [for grouped data]
- ## If ≈ linear w/ slope b, transform y → y $^{(1-b)}$

Artificial data, generated so σ ~ x
- b ≈ 1 → power = 0
- → analyze log(y)

Spread-level plot: baseball data

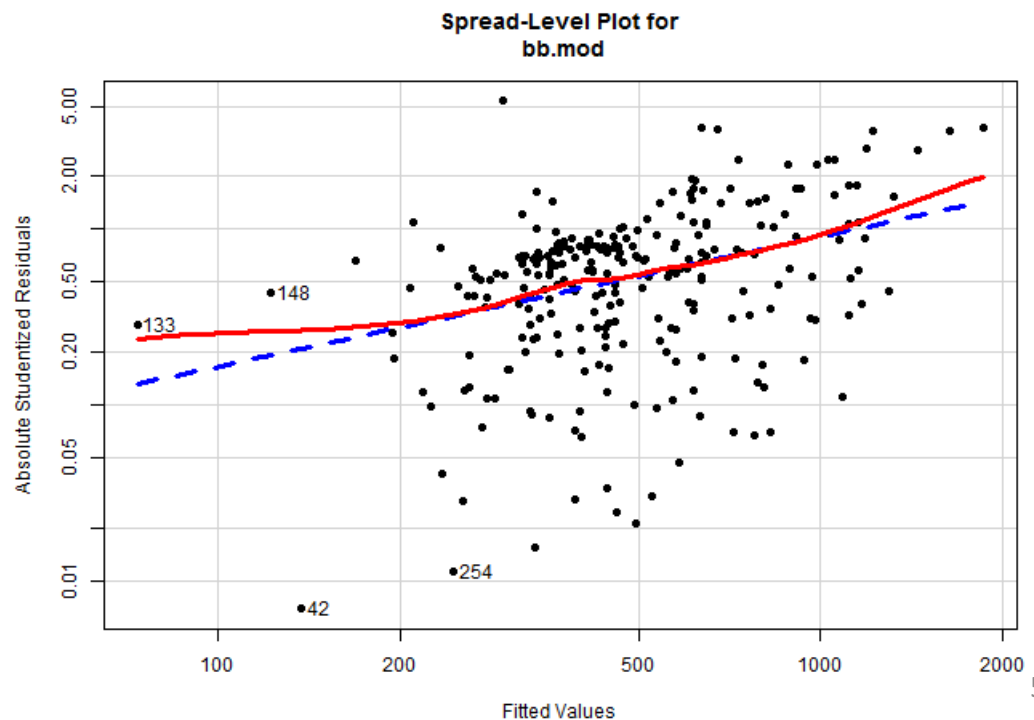Data on salary and batter performance from 1987 season

```
data("Baseball", package="vcd")
bb.mod <- lm(sal87 ~ years + hits + runs + homeruns, data=Baseball)
spreadLevelPlot(bb.mod, pch=16, lwd=3,
                id=list(n=2))

## Suggested power transformation: 0.2609
```

slope = .74 → p = .26

i.e., y → log(y) or y$^{1/4}$

NB: both axes plotted on log scale

Spread-Level Plot for bb.mod

Box Cox transformation

- Box & Cox proposed to transform y to a power, $y \rightarrow y^{(\lambda)}$ to minimize the residual SS (or maximize the likelihood)
  - Makes $y^{(\lambda)}$ more nearly normal
  - Makes $y^{(\lambda)}$ more nearly linear in with X

Formula for $y^{(\lambda)}$
- $y^{(0)}$: $\log_e(y)$
- $\lambda < 0$: flip sign to keep same order

$$y_i^{(\lambda)} = \begin{cases} \dfrac{y_i^{\lambda} - 1}{\lambda} & \text{if } \lambda \neq 0, \\ \ln(y_i) & \text{if } \lambda = 0, \end{cases}$$

Power(p)	Transformation	Name
2	Y^2	Square
1	Y (No transformation)	Original Data
½	√ Y	Square root
"0"	log Y or $\log_{10}$ (Y)	Logarithm
-½	-1 / √ Y	Reciprocal Root
-1	-1 / Y	Reciprocal
-2	-1 / Y^2	Reciprocal Square

Example: Cars93 data

How does gas mileage (MPG.city) depend on vehicle weight?
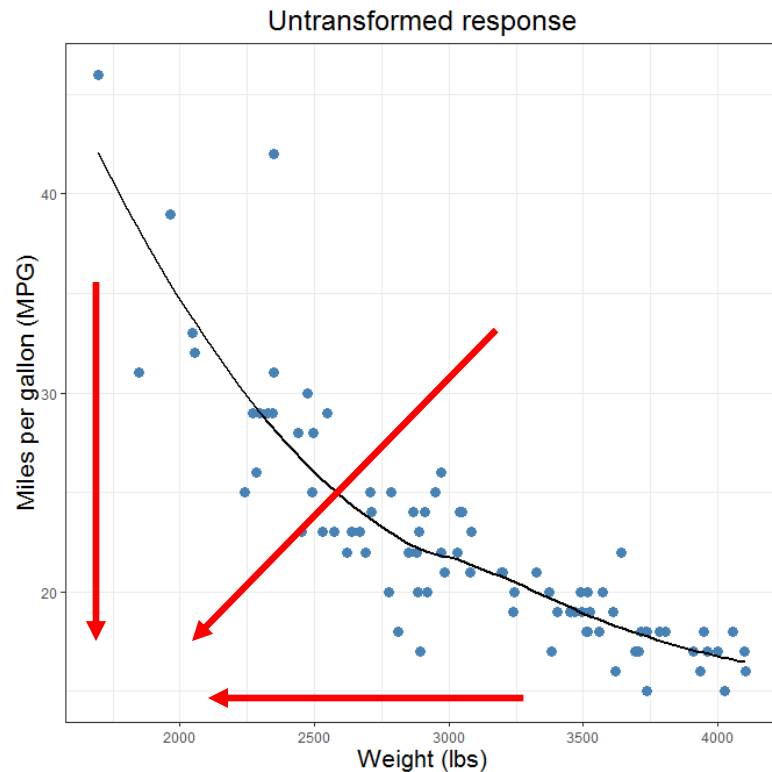
```
> cars.mod <- lm(MPG.city ~ Weight, Cars93)
> coef(cars.mod)
(Intercept)      Weight
   47.04835    -0.00803
```

Relationship clearly non-linear

Tukey arrow rule: transform Y (or X)
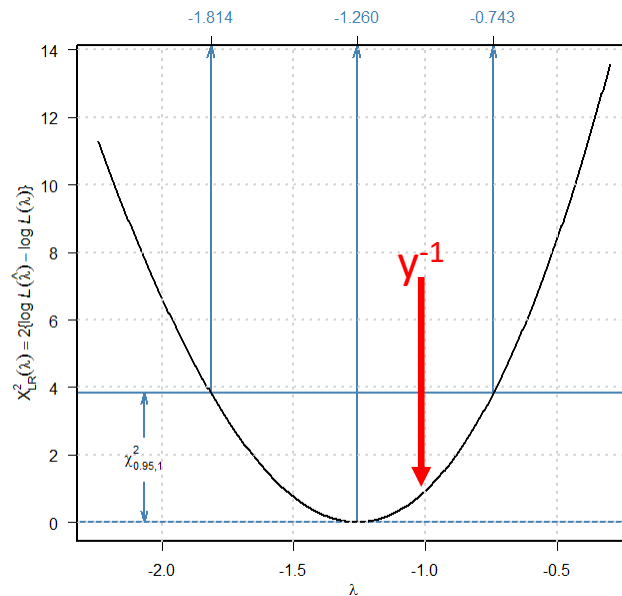as arrow thru the curve bulges
$y \rightarrow \sqrt{y}$, log(y), 1/y
$x \rightarrow \sqrt{x}$, log(x), 1/x

Untransformed response

MASSextra package

```
> library(MASSExtra)
> box_cox(cars.mod)      # plot log likelihood vs. lambda
> lamba(cars.mod)
[1] -1.26
```

The plot of – log(L) ~ RSS shows the minimum & CI

plot (bc(MPG.city, lamba(cars.mod))

Summary

- Tables are for look-up; graphs can give insight
- "Linear" models include so much more than ANOVA & regression
- Data plots are more effective when enhanced
  - data ellipses $\rightarrow$ strength & precision of correlation
  - regression lines and smoothed curves
  - point identification $\rightarrow$ noteworthy observations
- Effect plots show informative views of models
  - Visualize conditional effects, holding others constant
- Diagnostic plots can reveal influential observations and need for transformations.