

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

Michael Friendly SCS Short Course Oct-Nov, 2021

https://friendly.github.io/VisMLM-course/

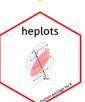
Today's topics

- What you need for this course
- Why plot your data?
- Data plots
- Model (effect) plots
- Diagnostic plots

What you need

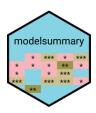
- R, version >= 3.6
 - Download from https://cran.r-project.org/
- RStudio IDE, highly recommended
 - https://www.rstudio.com/products/rstudio/
- R packages: see course web page
 - car
 - effects
 - heplots
 - candisc
 - visreg















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	.93 (.32)**B,M 1.46 (.32)**B,M			
Mexico	.07 (.32)4,04,00,0			
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)

^Coefficient is significantly different from Argentina's at

p < .05;

BCoefficient is significantly different from Brazil's at p < .05;

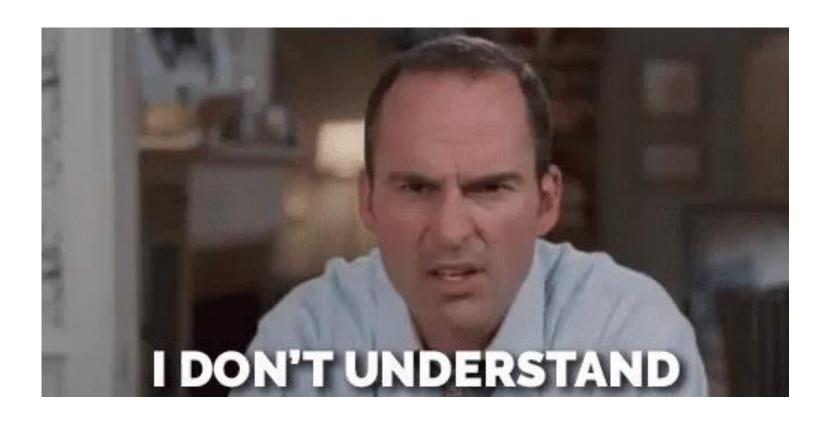
CHCoefficient is significantly different from Chile's at p < .05;

Coefficient is significantly different from Colombia's at p < .05;</p>

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

 $^{\text{V}}$ Coefficient is significantly different from Venezuela's at p < .05.

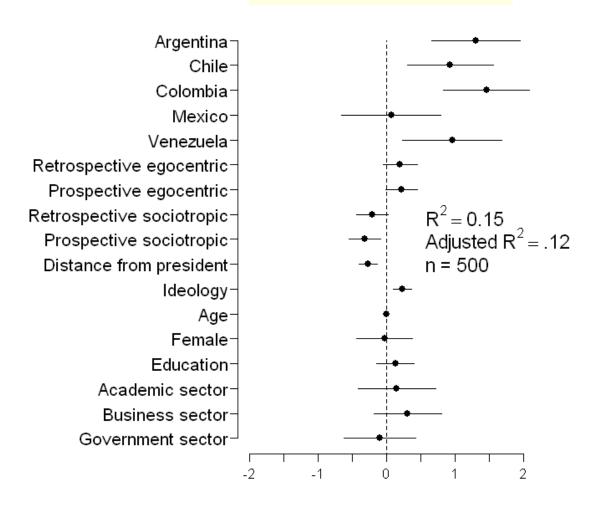
What's wrong with this picture?





Sunlight

coefplot(model)



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

NB: This is a presentation graph equivalent of the table

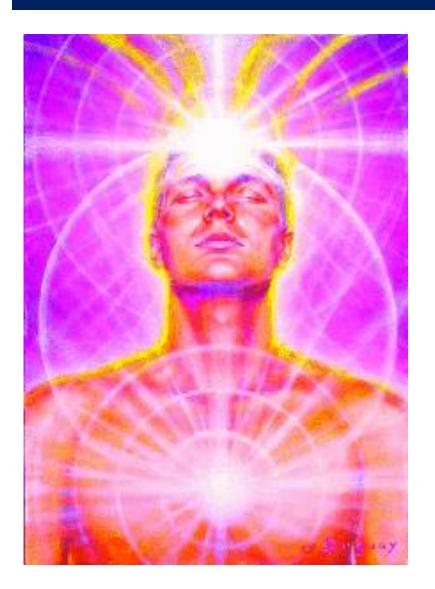
Shows standardized coefficient with 95% CI

Factors (Country) are shown relative to the baseline category

Run, don't walk toward the sunlight



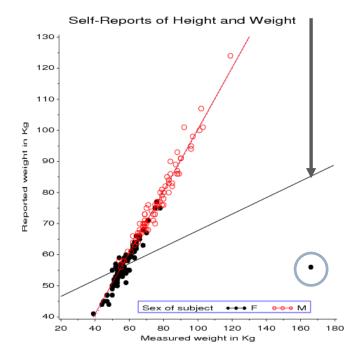
Graphs can give enlightenment



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

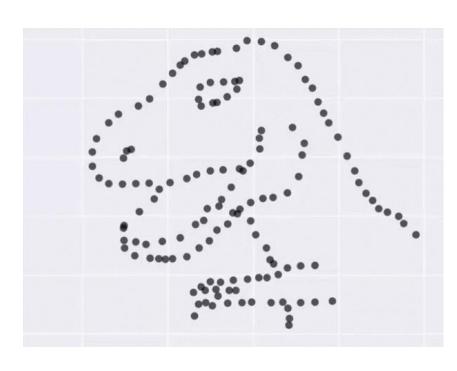
Student: You said to run descriptives and compute the correlation. What next?

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



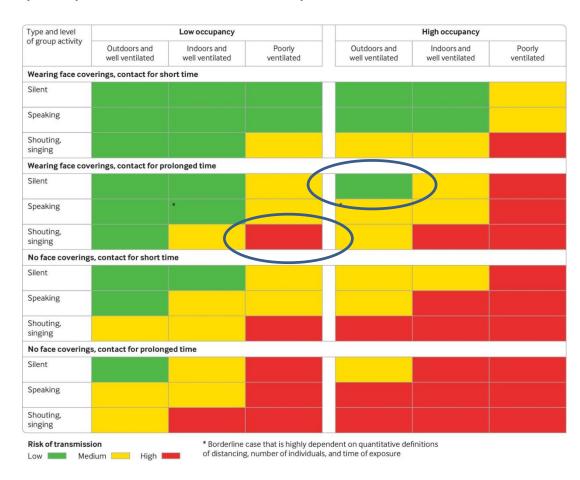
Sometimes, don't need numbers at all

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?

A semi-graphic table shows the patterns in the data



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

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

Presentation graph

Perhaps too cute!

Distribution of variables shown

		Fe	emale	Male		
Species	Distribution	Avg.	Std. Dev.	Avg.	Std. Dev.	
ADĒLIE/		188	5.6	192	6.6	
CHINSTRAD		192	5.8	200	6.0	
GENTOO!		213	3.9	222	5.7	

Artwork by @allison_horst

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

Background shading ~ value:

US & Canada are made to stand out.

Tech note: use white text on a darker background

Unemployment rate in selected countries

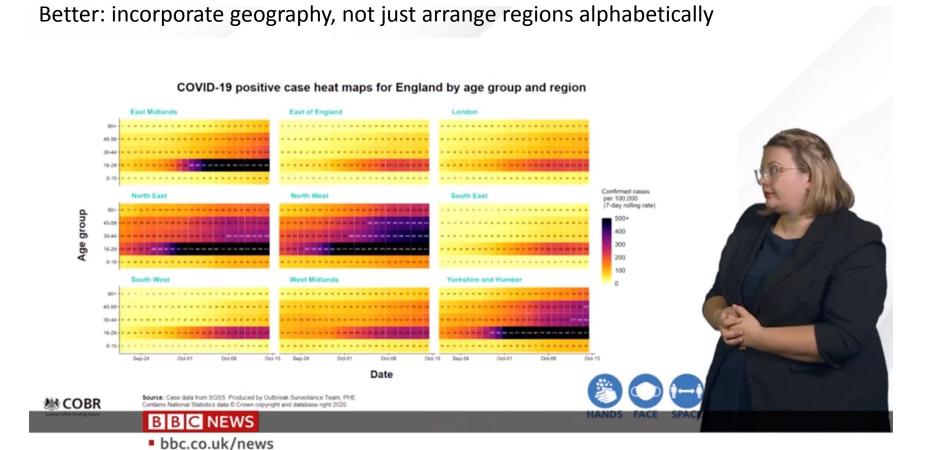
January-August 2020, sorted by the unemployment rate in January.

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%

Visual table ideas: Heatmap shading

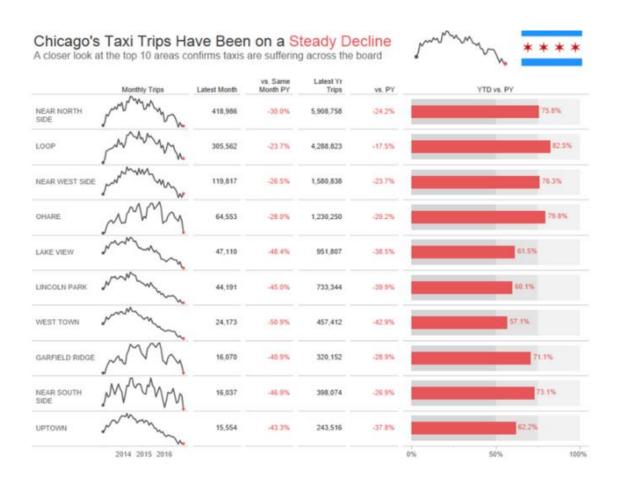
As seen on TV ...

Covid rate ~ Age x Date x UK region



Visual table ideas: Sparklines

Sparklines: Mini graphics inserted into table cells or text



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

Linear models

Model:

$$\mathbf{y}_{i} = \beta_{0} + \beta_{1} \mathbf{x}_{i1} + \beta_{2} \mathbf{x}_{i2} + \dots + \beta_{p} \mathbf{x}_{ip} + \varepsilon_{i}$$

- 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: $Var(\varepsilon_i) = \sigma^2 = constant$
 - Normality: ε_i have a normal distribution

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

The General Linear Model

- "linear" models can include:
 - transformed predictors: \sqrt{age} , $\log(income)$
 - polynomial terms: age², age³, poly(age, n)
 - categorical "factors", coded as dummy (0/1) variables
 - treated (Yes/No), Gender (M/F/non-binary)
 - interactions: effects of x₁ vary over levels of x₂
 - treated × age, treated × sex, (2 way)
 - treated × age × sex (3 way)
- Linear model means linear in the parameters (β_i) ,

$$y = \beta_0 + \beta_1 age + \beta_2 age^2 + \beta_3 \log(income) + \beta_4 (sex = "F") + \beta_5 age \times (sex = "F") + \epsilon$$

In R, all handled by lm(y ~ ...)

Fitting linear models in R: lm()

- In R, lm() for everything
 - Regression models (X1, ... quantitative)

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

Fitting linear models in R: lm()

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

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

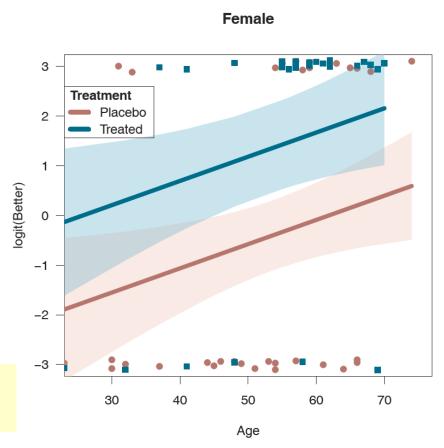
MANOVA/MANCOVA models

Generalized Linear Models: glm()

Transformations of y & other error distributions

- y ∈ (0/1): lived/died;
 success/fail; ...
- logit (log odds) model:
 - $\log it(y) = \log \frac{\Pr(y=1)}{\Pr(y=0)}$
 - Inear logit model: $logit(y) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + ...$

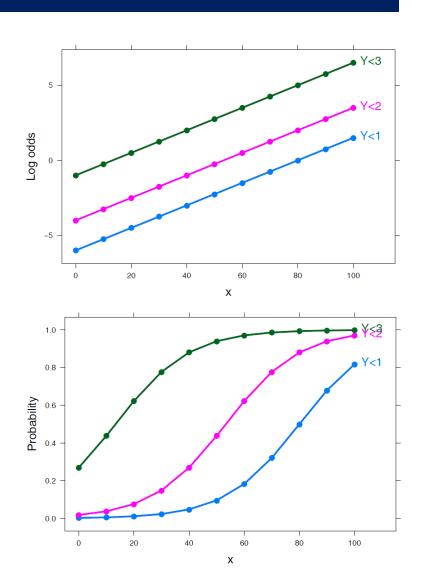
glm(better ~ age + treat, family=binomial, data=Arthritis)



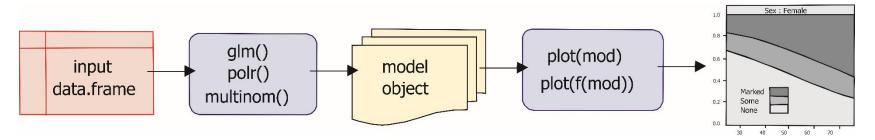
Generalized Linear Models

Ordinal responses

- Improved ∈ ("None" < "Some" < "Marked")
- Models: Proportional odds, generalized logits, ...



Model-based methods: Overview

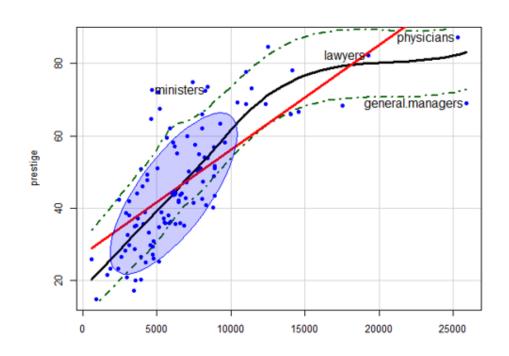


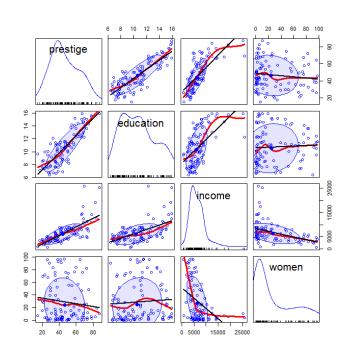
- models in R are specified by a symbolic model formula, applied to a data.frame
 - mod<-lm(prestige ~ income + educ, data=Prestige)</p>
 - mod<-glm(better ~ age + sex + treat, data=Arthritis, family=binomial)
 - mod<-MASS:polr(improved ~ age + sex + treat, data=Arthritis)
- result (mod) is a "model object", of class "lm", "glm", ...
- method functions:
 - plot(mod), plot(f(mod)), ...
 - summary(mod), coef(mod), predict(mod), ...

Plots for linear models

Data plots:

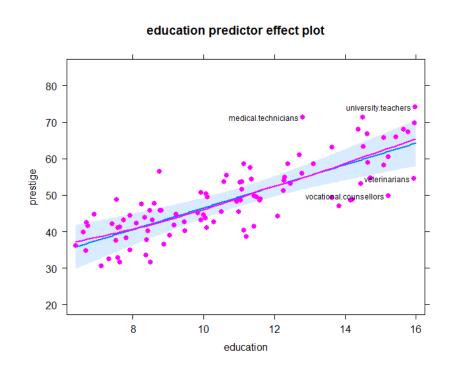
- plot response (y) vs. predictors, with smooth summaries
- scatterplot matrix --- all pairs





Plots for linear models

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

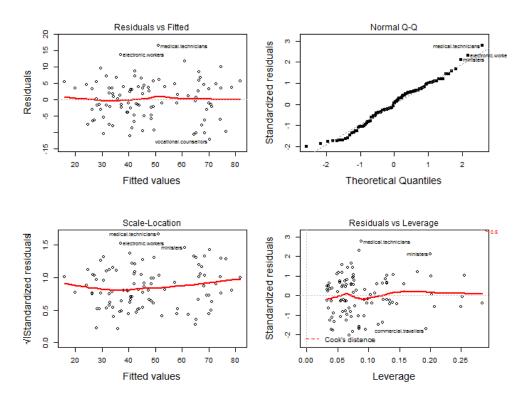


70 - 60 - type bc prof wc - 5000 10000 15000 20000 25000 income

income predictor effect plot

Plots for linear models

- Diagnostic plots
 - N QQ plot: normality of residuals? outliers?
 - 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
 - Im(), 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)

```
> car::some(Prestige, 6)
                 education income women prestige census type
architects
                     15.44
                           14163
                                 2.69
                                          78.1 2141 prof
physicians
                           25308 10.56
                                          87.2 3111 prof
                     15.96
commercial.artists
                     11.09 6197 21.03
                                          57.2
                                                3314 prof
tellers.cashiers
                                          42.3
                     10.64 2448 91.76
                                                4133
                                                        WC
                                          38.9 8213
bakers
                      7.54 4199 33.30
                                                        bc
aircraft.workers
                                          43.7
                      8.78 6573 5.78
                                                 8515
                                                        bc
```

Follow along

The R script (prestige-ex.R) for this example is linked on the course page. Download and open in R Studio to follow along.

- Examples: <a>
 - Prestige data prestige-ex.R | prestige-ex.html
 - Penguin data penguins-lm-ex.R || penguins-lm-ex.html

The script was run with 'knitr' (ctrl+shift+K) in R Studio to create the HTML output (prestige-ex.html)

The **Code** button there allows you to download the R code and comments

Linear models example: Occupational Prestine Code data



Michael Friendly

(These show a simple way to turn R scripts into finished documents)

Informative scatterplots

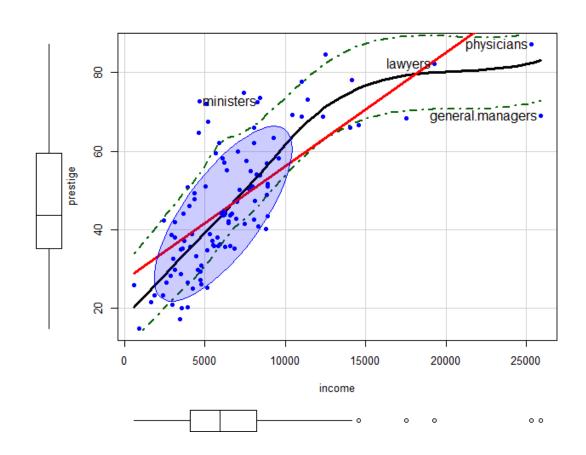
Scatterplots are most useful when enhanced with annotations & statistical summaries

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

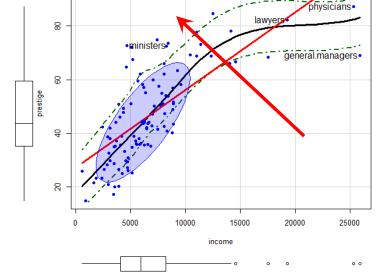


Informative scatterplots

car::scatterplot() provides all these enhancements

Skewed distribution of income & nonlinear relation suggest need for a transformation

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



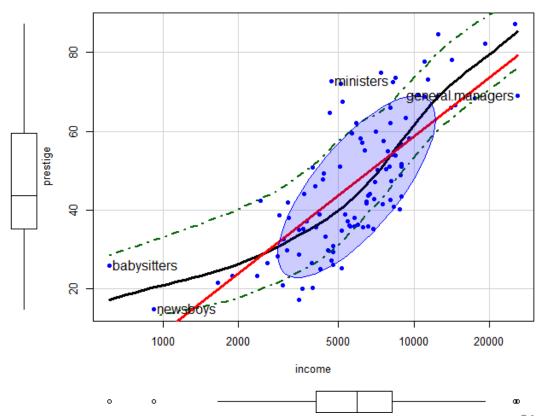
Try log(income)

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

Income now ~ symmetric

Relation closer to linear

log(income): interpret as effect of a multiple



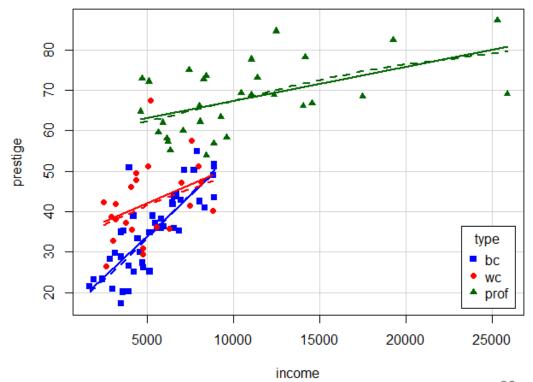
Stratify by type?

Formula: $| \text{ type} \rightarrow \text{"given type"} |$

Different slopes: interaction of income * type

Provides another explanation of the non-linear relation

This may be a new finding!



Scatterplot matrix

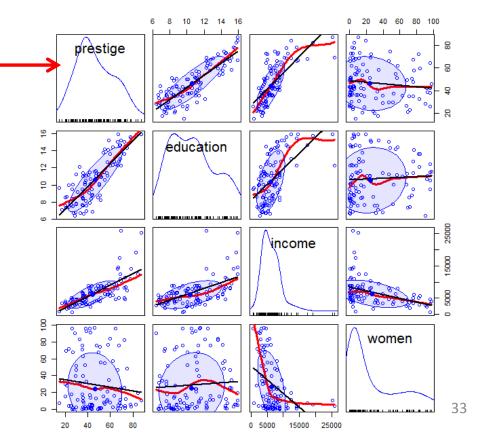
diagonal: univariate distributions

• income: + skewed

%women: bimodal

off-diagonal: relations among

predictors



Fit a simple model

Fits very well

But this ignores:

- nonlinear relation with income: should use log(income)
- occupation type
- possible interaction of income*type

Fit a more complex model

```
> mod1 <- lm(prestige ~ education + women +</pre>
                                                            add interaction of log
             log(income)*type, data=Prestige)
> summary(mod1)
                                                            income by type
Coefficients:
                     Estimate Std. Error t value Pr(>|t|)
                   -152.20589 23.24988 -6.547 3.54e-09 ***
(Intercept)
education
                      2.92817 0.58828 4.978 3.08e-06
                      women
log(income)
                     18.98191 2.82853 6.711 1.67e-09 ***
                               30.45819 2.799 0.00626 **
typeprof
                     85.26415
typewc
                     29.41334
                               36.50749 0.806 0.42255
log(income):typeprof
                     -9.01239 3.41020 -2.643 0.00970 **
log(income):typewc
                     -3.83343
                               4.26034 -0.900 0.37063
              0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Signif. codes:
                                                              Fits even better!
Multiple R-squared: (0.8751,) Adjusted R-squared: 0.8654
F-statistic: 90.07 on / and 90 DF, p-value: < 2.2e-16
                                                              But how to understand?
```

Coefs for type compare mean "wc" and "prof" to "bc"

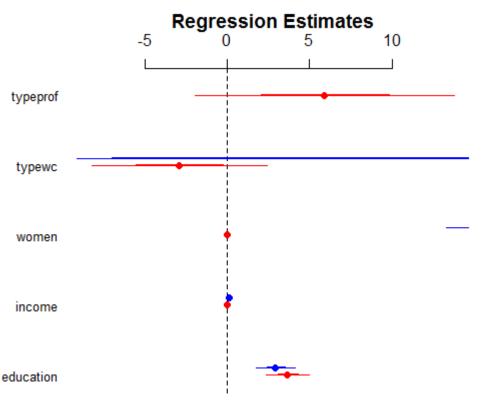
Coefs for log(income) *type compare "wc" and "prof" slopes with that of "bc"

Coefficient plots

Plots of coefficients with CI often more informative that tables

```
arm::coefplot(mod0, col.pts="red", cex.pts=1.5)
arm::coefplot(mod1, add=TRUE, col.pts="blue", cex.pts=1.5)
```

This plots raw coefficients, and the Xs are on different scales, so effect of income doesn't appear significant.



Model (effect) plots

- We'd like to see plots of the predicted value (\hat{y}) of the response against predictors (x_i)
 - Ordinary plot of y vs. x_i doesn't allow for other correlations
 - → Must control (adjust) for other predictors (x_{-j}) not shown in a given plot
- Effect plots
 - Variables not shown (x_{-i}) 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)

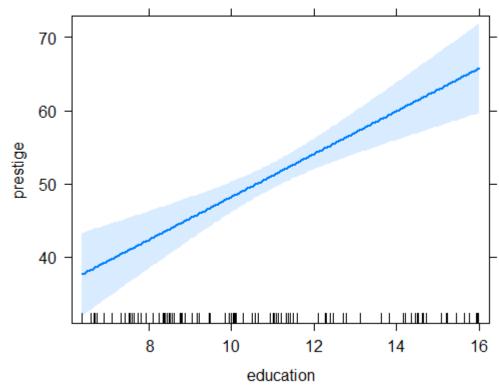
Model (effect) plots: education

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

This graph shows the partial slope for education, controlling for all others

For each ↑ year in education, fitted prestige ↑2.93 points, (other predictors held fixed)

education predictor effect plot



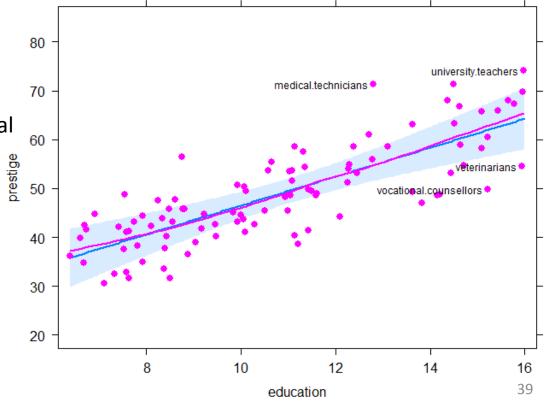
Model (effect) plots

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

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

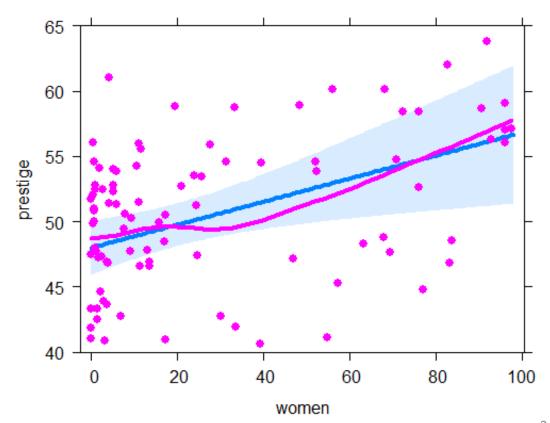
Surprise!

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

Another 10% women ↑ prestige by 0.88 points

How to interpret this?

women predictor effect plot



Model (effect) plots: income

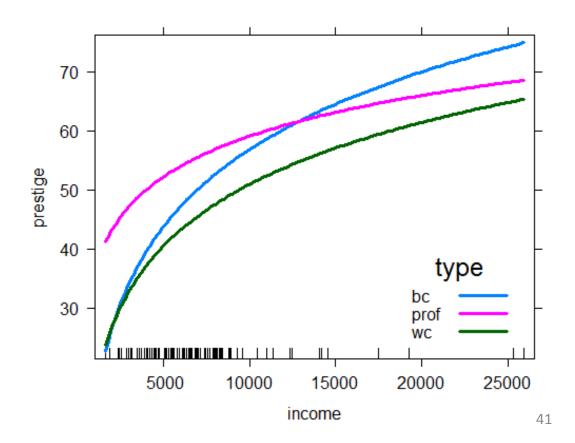
```
plot(predictorEffect("income", mod1),
    lines=list(multiline=TRUE, lwd=3),
    key.args = list(x=.7, y=.35))
```

Income interacts with type in the model

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

Curvature reflects marginal effect of income for each occupation type

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
           190 7.4
    41
                     67
                           5
2
    36
           118 8.0 72
3
                           5
    12
           149 12.6 74
                           5
4
    18
           313 11.5 62
                               4
                           5
5
                               5
        NA 14.3 56
    NA
                           5
6
    28
           NA 14.9 66
```

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

Air quality: main effects model

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

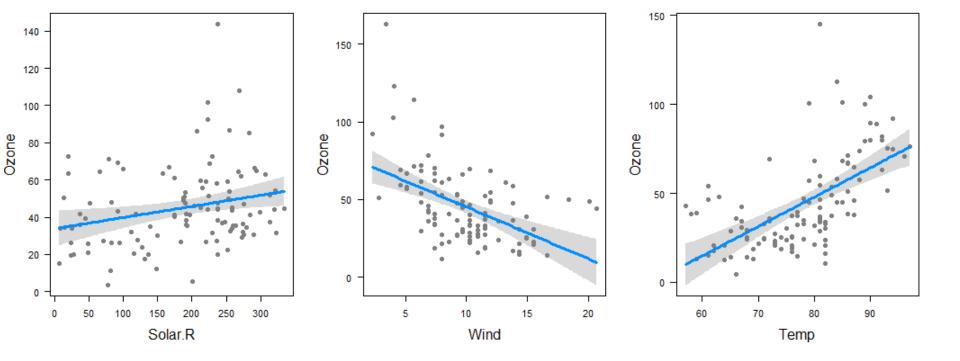
```
visreg(fit1, "Solar.R")
visreg(fit1, "Wind")
visreg(fit1, "Temp")
```

model summary =

predicted values (line) +

confidence band (uncertainty) +

partial residuals (objections)



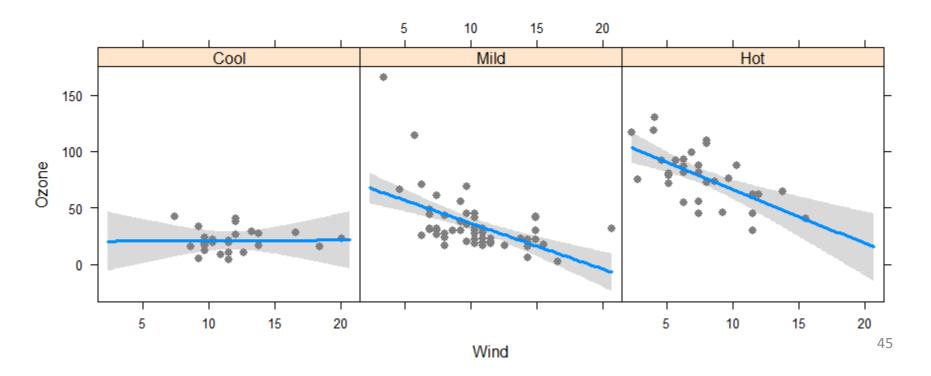
Factor variables & interactions

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 <- Im(Ozone ~ Solar.R + Wind*Heat, data=airquality) visreg(fit2, "Wind", by="Heat", layout=c(3,1), points=list(cex=1))

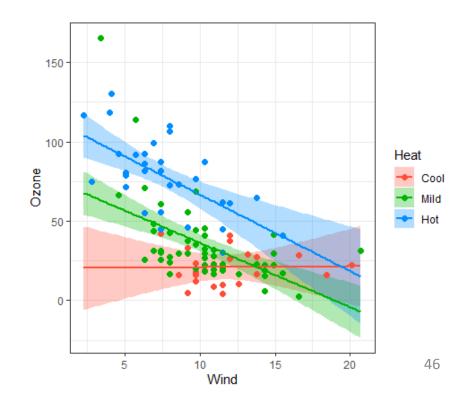


Factor variables & interactions

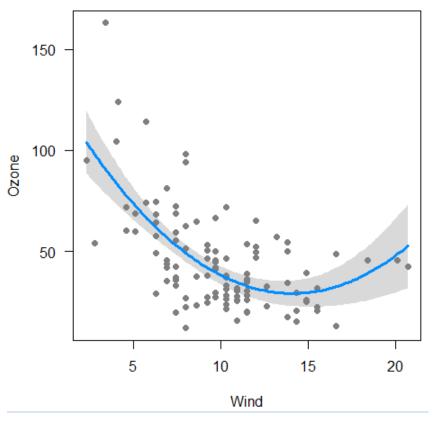
overlay=TRUE → superpose panels gg=TRUE → uses ggplot

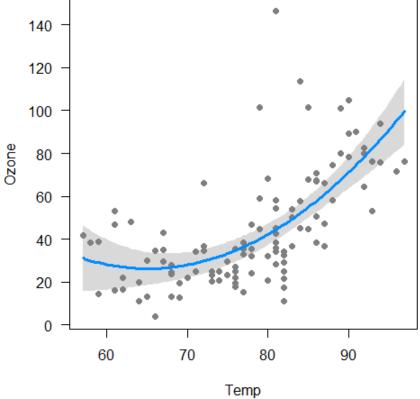
This allow slope for Wind to vary with Heat e.g., Wind has no effect when Cool

This model still assumes linear effects of Heat & Wind



Non-linear effects



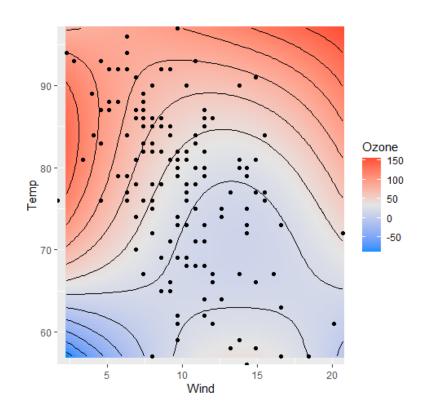


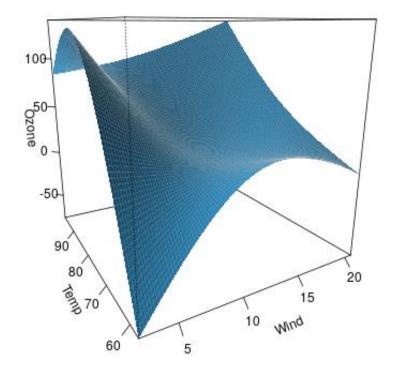
Response surface models (visreg2d)

Fit quadratics in both Wind & Temp and interaction Wind * Temp fitp <- Im(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")

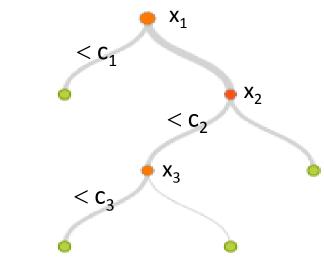




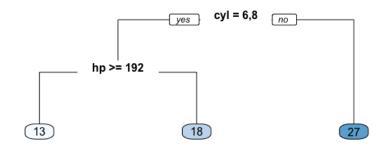
Regression trees

Regression trees are a non-parametric alternative to linear models

- Essential ideas:
 - Find predictor and split value which minimizes SSE
 - fitted value in each subgroupmean
 - repeat, recursively, splitting by next best predictor
- Large literature
 - cost, complexity tradeoff
 - pruning methods
 - boosting, cross-validation
 - tree averaging



e.g.: $mpg \sim cyl + hp$

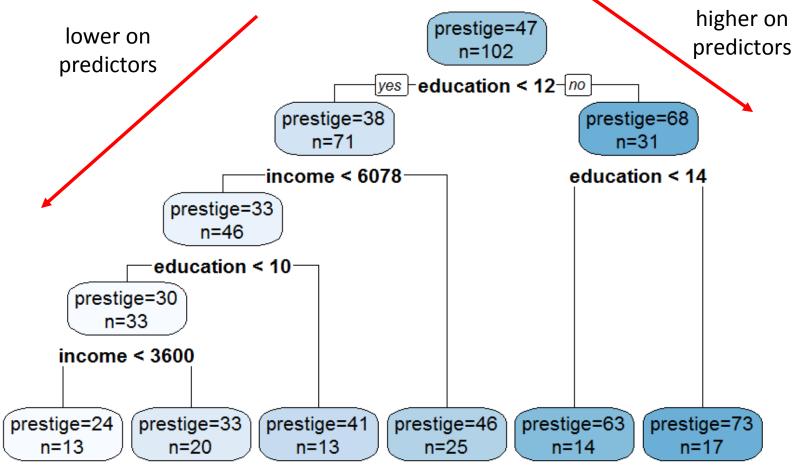


Prestige data: rpart tree

```
> library(rpart) # calculating regression trees
> library(rpart.plot) # plotting regression trees
> rmod <- rpart(prestige ~ education + income + women + type,
       data=Prestige,
       method = "anova")
> rpart.rules(rmod) # print prediction rules
prestige
   24 when education < 10 & income < 3600
   33 when education < 10 & income is 3600 to 6078
   41 when education is 10 to 12 & income < 6078
   46 when education < 12 & income >=
                                               6078
   63 when education is 12 to 14
   73 when education \geq 14
```

Prestige data: rpart tree

rpart.plot(rmod, prefix="prestige=")



Diagnostic plots

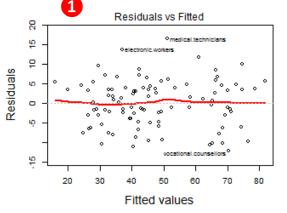
- The linear model, $y=X\beta+\epsilon$ assumes:
 - Residuals, ε_i are normally distributed, $\varepsilon_i \sim N(0,\sigma^2)$
 - (Normality not required for Xs)
 - Constant variance, $Var(\varepsilon_i) = \sigma^2$
 - Observations y_i are statistically independent
- Violations → inferences may not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

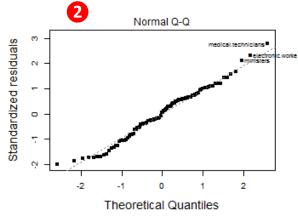
The "regression quartet"

In R, plotting a 1m model object \rightarrow the "regression quartet" of plots

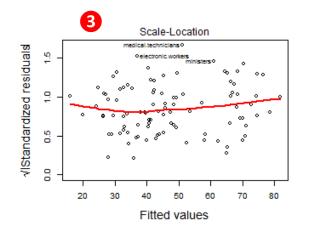
plot(mod1, lwd=2, cex.lab=1.4)

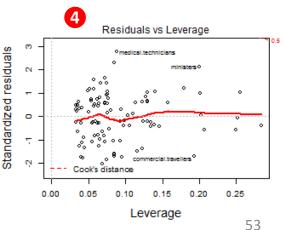
- Residuals: should be flat vs. fitted values
- **Q**-Q plot: should follow the 45° line





- 3 Scale-location: should be flat if constant variance
- 4 Resids vs. leverage: can show influential observations

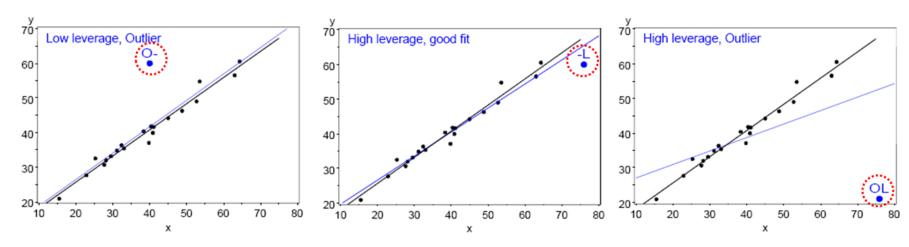




Unusual data: Leverage & Influence

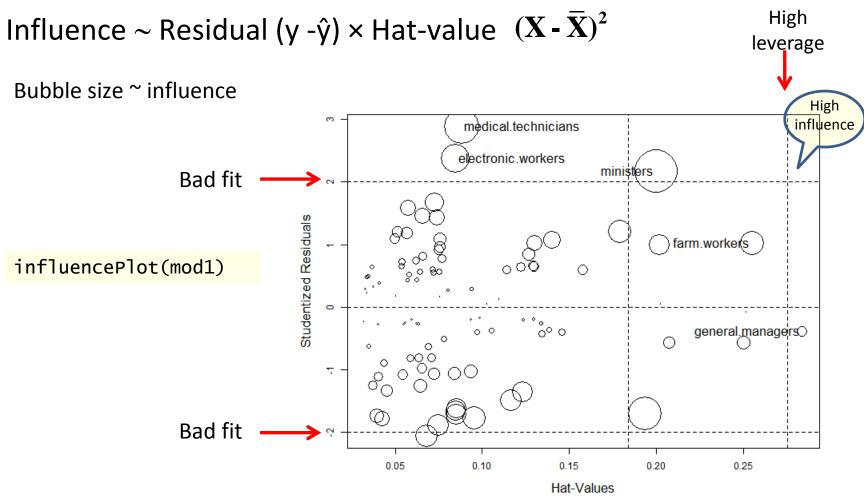
- "Unusual" observations can have dramatic effects on least-squares estimates in linear models
- Three archetypal cases:
 - Typical X (low leverage), bad fit -- Not much harm
 - Unusual X (high leverage), good fit -- Not much harm
 - Unusual X (high leverage), bad fit -- BAD, BAD, BAD
- Influential observations: unusual in both X & Y
- Heuristic formula:

Influence = X leverage x Y residual



Influence plots

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

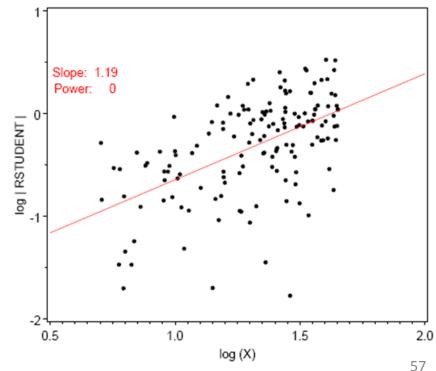


Spread-level plots

- To diagnose non-constant variance, plot:
 - log |Std. residual | vs. log (x)
 - log (IQR) vs log (median) [for grouped data]
- If \approx linear w/slope b, transform y \rightarrow y (1-b)

Artificial data, generated so $\sigma \sim x$

- $b \approx 1 \rightarrow power = 0$
- \rightarrow analyze log(y)



Spread-level plot: baseball data

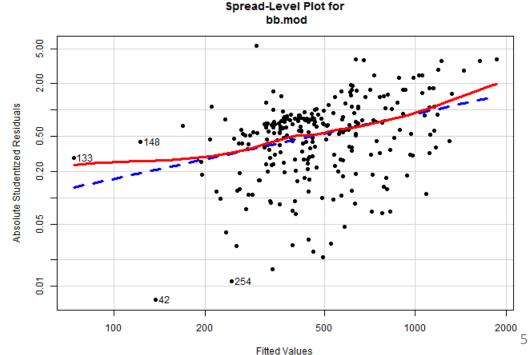
Data on salary and batter performance from 1987 season

```
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 =
$$.74 \rightarrow p = .26$$

i.e., $y \rightarrow \log(y)$ or $y^{1/4}$

NB: both axes plotted on log scale



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 $y^{(\lambda)}$

- $y^{(0)} : log_e(y)$
- λ < 0: flip sign to keep same order

$$y_i^{(\lambda)} = egin{cases} rac{y_i^{\lambda} - 1}{\lambda} & ext{if } \lambda
eq 0, \ \ln{(y_i)} & ext{if } \lambda = 0, \end{cases}$$

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

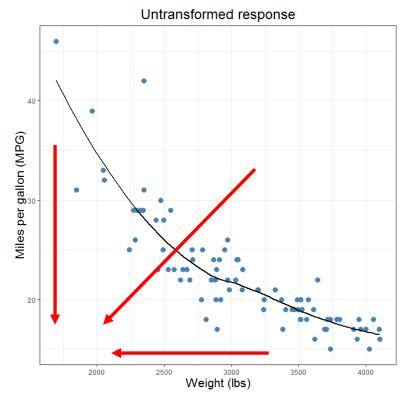
Example: Cars93 data

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

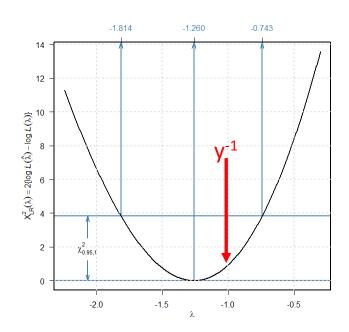
Tukey arrow rule: transform Y (or X) as arrow thru the curve bulges $y \to \sqrt{y}$, $\log(y)$, 1/y $x \to \sqrt{x}$, $\log(x)$, 1/x



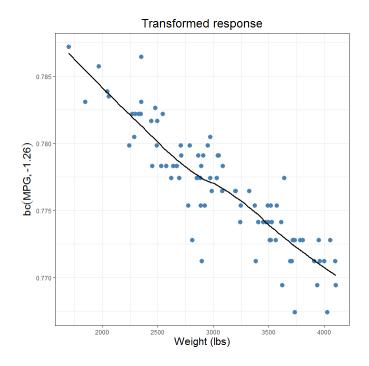
MASSextra package

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

The plot of $-\log(L) \sim RSS$ 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 → strength & precision of correlation
 - regression lines and smoothed curves
 - point identification → 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.