# FISH 604 Module 3: Exploratory data analysis

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## Review/preview

- Visualizing data
- Assessing distributions
- Outliers
- Standardization
- Transformations
- Correlations

Today



## Objectives & outcomes

### **Objectives**

Review standard methods for Exploratory Data
 Analysis to conduct prior to statistical modeling

#### **Outcomes**

- Know how to detect outliers and what to do in the presence of outliers
- Be able to identify when and how to apply appropriate data standardizations
- Be able to identify when and how to apply appropriate data transformations
- Be proficient in quickly exploring correlations among a set of variables (graphically & statistically)

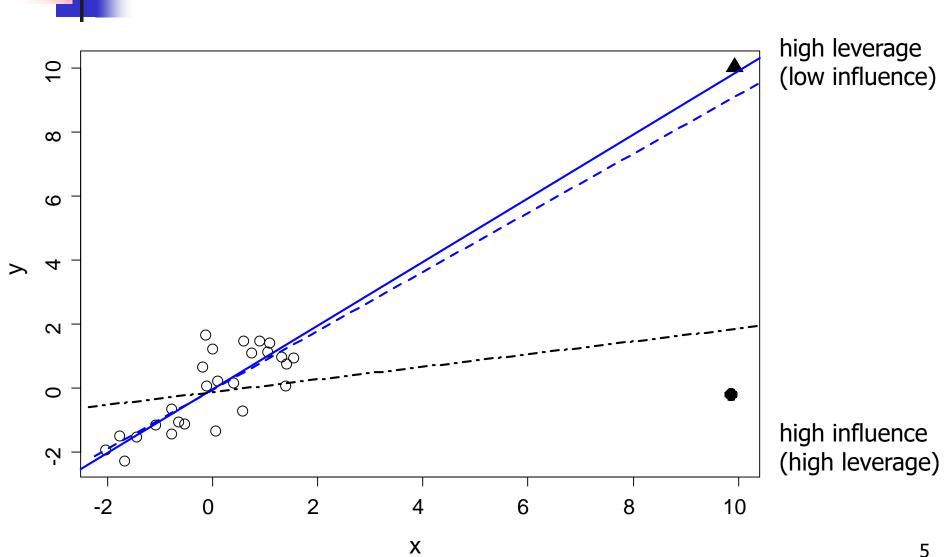


### Outlier detection

- Why?
  - Tests and model fitting algorithms (least-squares, likelihood) are often sensitive to outliers
- How?
  - Graphical, distance from mean
- What to do?
  - Ignore
  - Eliminate (Compare results)
  - Use robust measures / estimation



## Outliers: Influence & leverage





## Outliers: Leverage & Influence

### <u>Leverage</u>

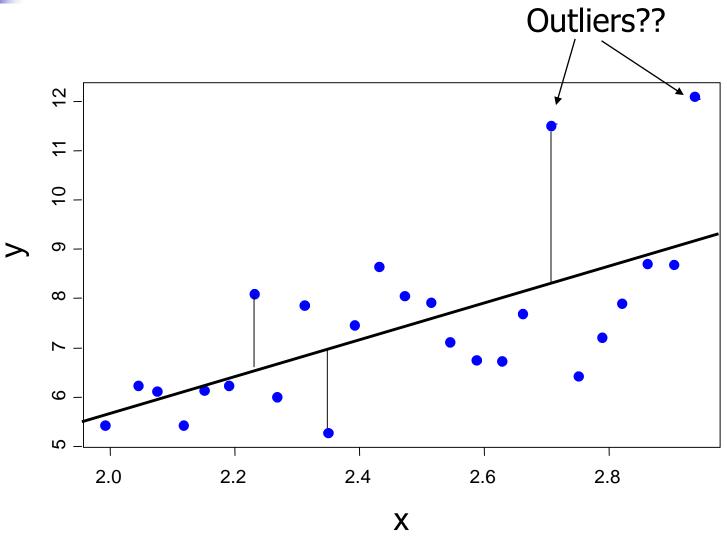
- Defined as diagonals of "hat matrix": H<sub>ii</sub>
- Large values often due to extreme values in X
- Rule of thumb: If leverage
   2p/n, look at the data
   point more closely
- Point with high leverage may or may not also be influential!

### <u>Influence</u>

- Removal of influential point results in large change in fit!
- Usually measured by change in predicted values or regression coefficient(s) when i<sup>th</sup> observation is removed,
- Cook's distance is a common measure of influence



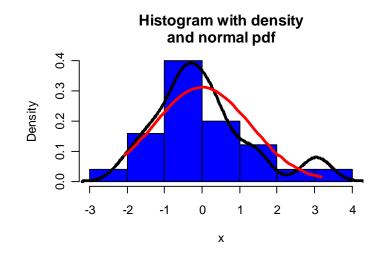
## Regression with outliers?

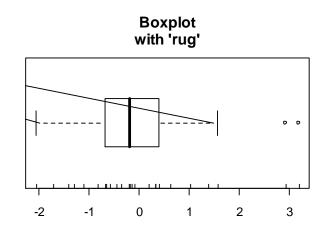


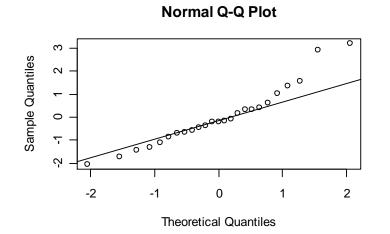


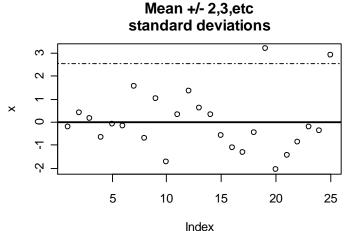
### Outlier detection (linear models or 'normalized' residuals)

### Examine distribution of <u>residuals</u> from a model fit



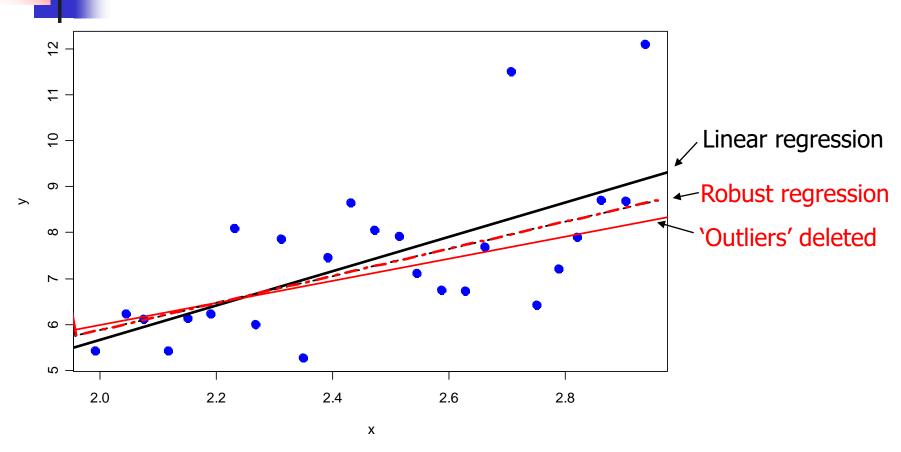








## Robust regression



 $\frac{R \ code}{fit}: plot(x,y)$  fit <- lm(y~x); abline(fit) fit.rob <- rlm(y~x); abline(fit.rob) (rlm in MASS package)



## Dealing with outliers: Re-run analysis with outliers removed

YES

Do the conclusions change when the case is deleted?

Proceed with case included.
Examine case to see if anything can be learned from it.

(acknowledge outlier)

Omit case and proceed!

NO

Is there a reason to believe that outlier comes from a different population (or is an error)?

YES NO

YES

Does the case have unusually "distant" explanatory variables?

NO

Omit the case and proceed!
Report conclusions for the reduced range of explanatory variables

Need more data or info to resolve! Report conclusions for analysis w/ and w/out the influential case!



### Standardizations

- Why?
  - Plot / compare variables on common scale
  - Variables in multivariate analyses
    - To make sure each variable has the same influence
  - Multiple regression
    - Stabilize numerical estimation methods
    - Make coefficients comparable
- How?
  - Standardize to N(0,1)
  - Standardize to common maximum
  - Standardize relative to mean



## Standardization / scaling

• Normalize to N(0,1): (any continuous variable)

$$x' = (x_i - \overline{x})/sd(x)$$
  $\xrightarrow{\text{R function}}$ 

• Relative to mean (x > 0):

$$x' = (x_i - \overline{x})/\overline{x} \implies \overline{x}' = 0$$
  
 $x' = x_i/\overline{x} \implies \overline{x}' = 1$ 

• Same maximum (x > 0):

$$x' = x_i / \max(x) \implies 0 < x' < 1$$



### Transformations

### Why?

- To meet regression assumptions:
  - Normalize residuals
  - Eliminate / reduce heteroscedasticity
  - Ensure additivity of effects
- Reduce leverage of extreme values
- Linearize relationships (e.g. log-log plots)

### How?

- Logarithmic (natural log) transformation
- Square-root transformation
- Arc-sine transformation
- Power transformations
- Box-Cox transformations



## Log-transformation

—— Add small constant if x may include 0

- $x' = \log(x + 1)$  OR  $x' = \log(x)$  (typically base 10 or **natural logarithm**)
- Log-transform dependent variable in ANOVA when
  - Multiplicative effects are present (Non-additive)
- Log-transform <u>dependent</u> variable in regression when:
  - standard deviations are proportional to mean, i.e. CV is constant (heteroscedasticity)
- Try log-transforming both dependent (y) and independent (x) variable when
  - Errors are multiplicative:  $y = f(x) * e^{\varepsilon}$

$$\rightarrow log(y) = log\{f(x)\} + \varepsilon$$



## Log-transform for additivity

### Example: two-way ANOVA

1. Additive effects	ŀ				
		Level 1	Level 2	Level 3	
<b>.</b>	Level 1	10 —	+10 -	<u>+5</u> 25	+10
Factor B	Level 2	20 —	30 —	35	110

2. Multiplicative effects			_		
		Level 1	Level 2	Level 3	<u>violates</u>
<b>.</b>	Level 1	10 —	30 -	*2 60	ANOVA
Factor B	level2	20 —	<sup>→5</sup> 60 —	→ 120	assumption

2. Log-transformed (log10)					
-> additivity restored!	Level 1	Level 2	Level 3	meets	
Factor B	Level 1	1.00 —	1.48	1.78	ANOV
	Level 2		1.78	2.08	assumpt

20



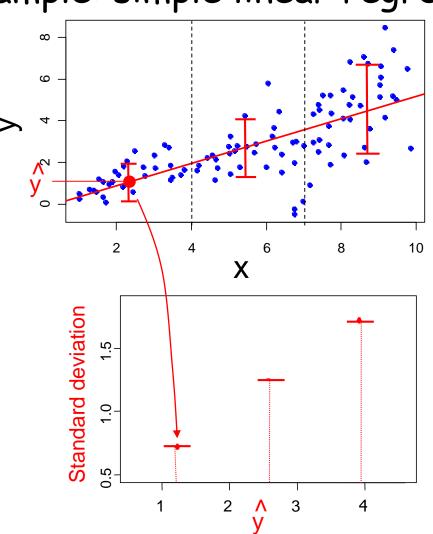
## Log-transform for homoscedasticity

### Example: simple linear regression

Standard deviation of y increases in proportion to mean of y

Plot standard deviation of residuals against predicted y

→ Linear increase



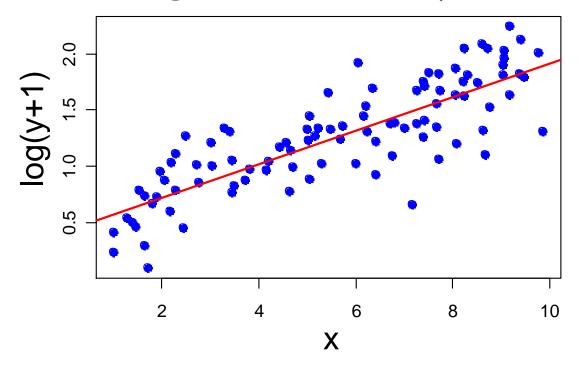
Heteroscedasticity
violates
regression
assumption!
(affects CIs
& p-values)

Visualize
distribution of
responses in
vertical 'slices'
to determine
relationship
between SD of
response and
predicted values



## Log-transform for homoscedasticity

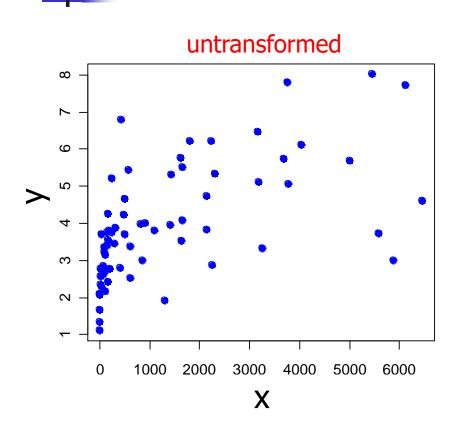
Example: simple linear regression with log-transformed y-variable



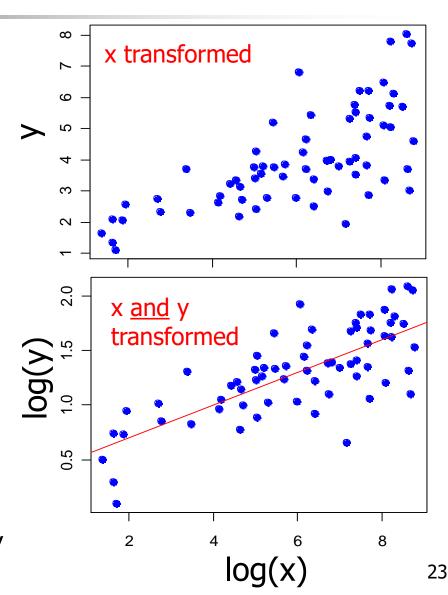
Transformed variable has <u>constant</u> standard deviation (Homoscedasticity)

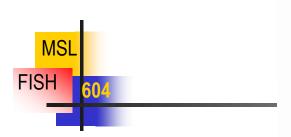
### MSL FISH 604

## Log-transform both y and x

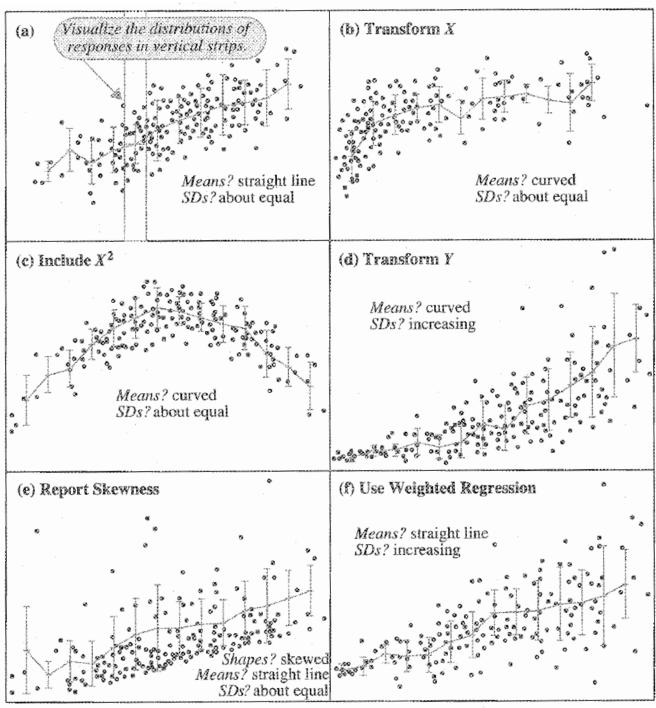


→ In some cases, this can result in both linearity & homoscedasticity (and simplify analyses)





If possible, aim for equal variances and a 'linear' relationship





### Other transformations

- Square-root transformation
  - When <u>variances</u> are proportional to the mean (e.g. in biology: samples from a Poisson distribution)

$$y' = \sqrt{y + 3/8}$$

- Arc-sine
  - To normalize proportions, as long as they are not too close to zero (~ 0.2 - 0.8)

$$p' = \arcsin \sqrt{p}$$



### Other transformations

- Power transformation
  - When standard deviations decrease with the mean and/or if distribution is left-skewed:

$$y'=y^2$$
 (rare!)

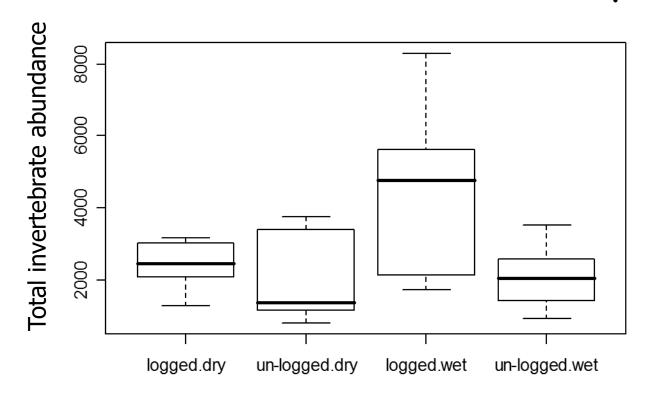
- Box-cox transformation
  - General approach to determine optimal transformation for normalizing data

$$y' = \begin{cases} y^{\lambda} - 1/\lambda & \lambda \neq 0 \\ \log(y) & \lambda = 0 \end{cases}$$



### Box-Cox transformation

Which transformation, if any?



**R-code**: boxplot(totalN ~ treatment \* ecoregion, data=logging)



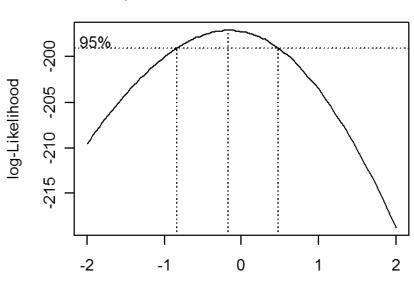
### Box-Cox transformation

### Fit desired model:

### Determine "best" transformation:

boxcox(fit)

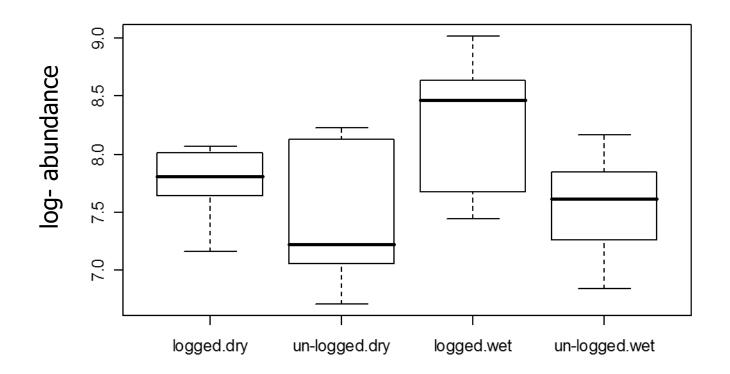
log-transform!?





### Box-Cox transformation

 Approximately normal distribution and equal variances:



**R-code**: boxplot(log(totalN) ~ treatment \* ecoregion, data=logging)



### Correlations

- Correlation matrix
- Pearson's product moment correlation
- Robust correlations (rank based)
  - Spearman's rho
  - Kendall's tau
- Testing significance of correlations

#### Some useful R functions

```
cor(); cor.test(x,y,method="pearson")
cor.test(x,y,method="spearman")
rcorr() # library(Hmisc)]
corrplot() # library(corrplot)
ggcorrplot() # library(ggcorrplot)
```



DW.sum

-0.17

-0.10

-0.20

## Correlation matrix

p < 0.05 p < 0.01	airT.Kodiak	airT.Sitka	GAK1.SST	GAK1.SSS	GAK1.BS	FW.spring	FW.annual	DW.win	DW.sum
airT.Kodiak	1	0.68	0.69	-0.58	0.08	0.50	0.27	0.04	-0.17
airT.Sitka	0.68	1	0.65	-0.83	0.19	0.69	0.60	-0.30	-0.10
GAK1.SST	0.69	0.65	1	-0.55	-0.20	0.70	0.36	0.01	-0.20
GAK1.SSS	-0.58	-0.83	-0.55	1	-0.35	-0.68	-0.38	0.44	0.16
GAK1.BS	0.08	0.19	-0.20	-0.35	1	-0.08	0.01	-0.39	0.31
FW.spring	0.50	0.69	0.70	-0.68	-0.08	1	0.40	-0.04	-0.13
FW.annual	0.27	0.60	0.36	-0.38	0.01	0.40	1	-0.26	-0.30
DW.win	0.04	-0.30	0.01	0.44	-0.39	-0.04	-0.26	1	0.04

0.16

0.31

-0.13

-0.30

0.04



## Reading assignment

 Zuur et al. (2007). Analyzing Ecological Data. Springer. Chapter 4: Exploration (see pdf posted on Canvas)



## Further reading

### Graphical analysis

- Cleveland, W.S., 1993. Visualizing Data. AT&T Bell Laboratories, Murray Hill, NJ.
- Wilkinson, L. 1999. The Grammar of Graphics. Springer, New York
- Yau, Nathan 2013. Data Points: Visualization that means something.
   Wiley.

#### Multivariate data

 Cook, D., Swayne, D.F., and Buja, A. 2007. Interactive and Dynamic Graphics for Data Analysis: With R and GGobi. Springer, New York.

### General exploratory analyses

- Zar, J.H., 1984. Biostatistical Analysis. Prentice-Hall, Englewood Cliffs, NJ.
- Barnett V, 2004. Environmental Statistics: methods and applications, John Wiley & Sons, Chichester, England.