
Design & Analysis of Experiments

Experimental Designs & AN(C)OVA & MAN(C)OVA

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Outline

- Designs
 - One-way Between-Groups ANOVA (Analysis of Variance)
 - One-way Within-Groups ANOVA
 - Two-way Factorial ANOVA
 - ANCOVA: Adjusting for Covariates
 - MANOVA: Multivariate Analysis of Variable (>1 Response Vars)
 - MANCOVA: Multivariate Analysis of Covariance
- Fitting ANOVA and ANCOVA Models in R
 - Formulas for different types of designs
 - Order matters: Type I, II, and III ordering of formula terms
 - Examples: ANOVA and ANCOVA
 - Assessing ANOVA and ANCOVA Assumptions
- Fitting MANOVA Models in R
 - Examples: One-way MANOVA
 - Assessing MANOVA Assumptions

Experimental Designs

AN(C)OVA & MAN(C)OVA

Focus: **Design of experiments** \equiv **ANalysis Of VAriance**

Design #1: One-way **Between-Groups** ANOVA

- Exemplar Study: Goal: To study two treatments of anxiety
 - **Treatment (Independent Variable):** Two treatments
 - CBT: Cognitive Behavior Therapy
 - EMDR: Eye Movement Desensitization & Reprocessing Therapy
 - **Response (Dependent Variable):** (collected after 5 weeks of treatment)
 - STAI: State-Trait Anxiety Inventory; a self-report measure of anxiety
 - **Subjects:**
 - Randomly divided between two **independent groups**: CBT & EMDR

		Subjects
Treatment	CBT	s_1
		s_2
		...
		$s_{n/2}$
	EMDR	$s_{n/2+1}$
		...
		...
		s_n

One-way Between-Groups Balanced ANOVA

- Treatment is a **between-groups** factor with two levels
- **Balanced design**: equal number of subjects in each treatment condition; otherwise, **unbalanced**
- **One-way**: because a single classification variable

F-tests to assess the effects in ANOVA designs

- If the F-test for Treatment is significant then reject the null hypothesis: H_0 : the mean STAI scores are the same
- Conclude: the mean STAI scores changed over time for two therapies differed after five weeks of treatment

Design #2: One-way **Within-Groups** ANOVA

- Exemplar Study: Goal: To study *longitudinally* one treatment of anxiety
 - **Treatment (Independent Variable):** One treatment
 - CBT: Cognitive Behavior Therapy
 - **Response (Dependent Variable):** (collected after 5 weeks of treatment)
 - STAI: State-Trait Anxiety Inventory; a self-report measure of anxiety
 - **Subjects:**
 - The same subjects over different time points (**dependent groups**)
 - **Time:** Two different time points: 5 weeks & 6 months

One-way Within-Groups Balanced ANOVA

- Time is a **within-groups** factor with two levels: each subject is measured under both levels
 - **Repeated measures** ANOVA
- **One-way:** because a single classification variable

Paired F-tests to assess effects in ANOVA designs

- If the F-test for Treatment is significant then reject the null hypothesis: H_0 : the mean STAI scores are the same
- Conclude: the mean STAI scores change over time: between 5 weeks and 6 months

CBT Treatment	Time	
	5 weeks	6 months
	s_1	s_1
	s_2	s_2

	s_n	s_n

Design #3: Factorial (Mixed-Model) ANOVA

- Exemplar Study: Goal: To study *two treatments* of anxiety *longitudinally*
 - **Treatment (Independent Variable):** Two treatments
 - CBT: Cognitive Behavior Therapy
 - EMDR: Eye Movement Desensitization & Reprocessing Therapy
 - **Response (Dependent Variable):** (collected after 5 weeks of treatment)
 - STAI: State-Trait Anxiety Inventory; a self-report measure of anxiety
 - **Subjects:** Randomly assigned to two *independent groups*: CBT & EMDR
 - **Time:** Two *dependent groups* over time: 5 weeks & 6 months

		5 wks	6 mo.
Treatment	CBT	s_1	s_1
		s_2	s_2
	
		$s_{n/2}$	$s_{n/2}$
	EMDR	$s_{n/2+1}$	$s_{n/2+1}$
	
	
		s_n	s_n

Two-way Factorial ANOVA Design

- **Main effects:** Impact of Therapy (averaged across Time) and Time (averaged across Therapy type)
- **Interaction effect:** Interaction of Therapy & Time
- **Factorial ANOVA:** cross 2 factors (*two-way*) or more

Three F-tests to assess ANOVA design effects

- F-test for Therapy: Significant → CBT & EMDR differ
- F-test for Time: Significant → change over time
- F-test for Therapy × Time interaction: Significant → two treatments had a differential impact over time: different change from 5 wks to 6 mo. for 2 therapies₆

Design #4: ANCOVA

- Goal: To study the treatments of anxiety with *confounding factors*
- **Confounding Factor (Nuisance Variable)**: Other factors (than Treatment) that could explain the post-therapy differences on the dependent variable
 - Depression level:
 - A self-reported measure such as Beck Depression Inventory (BDI)
 - Although subjects were assigned randomly to treatment conditions, it is possible that two therapy groups differed in patient depression levels at the start of the study
 - → Any post-therapy differences might be due to the preexisting depression differences and not to experimental manipulations

ANCOVA Design

- Because depression could also explain the group difference on the dependent variable, it is a **confounding factor**
- Because the study is not interested in depression, this confounding factor is called a **nuisance variable**

Design #5-6: MANOVA & MANCOVA

- Goal: To study the treatments of anxiety with *multiple dependent variables* and/or *confounding factors*
- **Multiple Dependent Variables:** To increase the validity of the study
 - STAI: One dependent variable
 - Family ratings: Another dependent variable
 - Therapy ratings: Yet another dependent variable
 - A measure assessing the impact of anxiety on the daily functioning
- **MANOVA:** Multivariate Analysis of Variance
 - There is more than one dependent variable
- **MANCOVA:** Multivariate Analysis of Covariance
 - Besides multiple dependent variables, there are covariates present

Experimental Designs

FITTING ANOVA & ANCOVA MODELS

ANOVA and ANCOVA in R: Formula

aov (*formula*, data = dataframe)

Design	Formula
One-way ANOVA	Response.STAI ~ Treatments.CBT.EMDR
One-way ANCOVA with one covariate	Response.STAI ~ Covariate.Depression + Treatments.CBT.EMDR
Two-way Factorial ANOVA	Response.STAI ~ Treatments.CBT.EMDR * Times.5wks.6mo
Two-way Factorial ANCOVA with two covariates	Response.STAI ~ Covariate.Depression + Covariate.Gender + Treatments.CBT.EMDR * Times.5wks.6mo
One-way within groups ANOVA	Response.STAI ~ Times.5wks.6mo + Error (Subject/Times.5wks.6mo)
Repeated measures ANOVA with one within groups factor (W) and one between-groups factor (B)	Response ~ B * W + Error (Subject/W)

Formula Terms: Order Counts!

- The order in which the effects appear in a formula matters when
 - More than one factor
 - Design is unbalanced: the greater the imbalance in sample sizes, the greater the impact the order of the terms will have on the results
 - Covariates are present
 - $y \sim A * B$ and $y \sim B * A$ will produce different results
- **Type I (sequential) Ordering:** $y \sim A + B + A * B$
 - The impact of A on y
 - The impact of B on y , controlling for A
 - The interaction of A and B , controlling for the A and B main effects
 - Summary: the effects are adjusted for those factors that appear earlier in the formula. A is unadjusted. B is adjusted for the A . The $A:B$ interaction is adjusted for A and B .
- **Best Practices:**
 - Strive for balanced designs
 - Place more fundamental effects earlier in the formula
 - List covariates first in the formula
 - Followed by main factors, followed by two-way interactions, followed three-way interactions, and so on

Other Formula Term Ordering Schemes

- **Type I (sequential) Ordering:** $y \sim A + B + A * B$
 - Effects are adjusted for those factors that appear earlier in the formula. A is unadjusted. B is adjusted for A . The $A:B$ interaction is adjusted for A and B .
 - R's `aov()` function deploys Type I approach by default
- **Type II (hierarchical) Ordering:** :
 - Effects are adjusted for other effects at the same or lower level. A is adjusted for B and B is adjusted for A . The $A:B$ interaction is adjusted for both A and B .
 - `help(Anova, package="car")`: allows to choose Type I, II, or III
- **Type III (hierarchical) Ordering:** :
 - Each effect is adjusted for every other effect in the model. A is adjusted for B and $A:B$. B is adjusted for A and $A:B$. The $A:B$ interaction is adjusted for both A and B .
 - SAS and SPSS employ Type III approach by default

Fitting ANOVA Models

ONE-WAY BETWEEN-GROUPS

Ex: One-way Between-Groups ANOVA

```
10 # install.packages("multcomp")
11 require (multcomp)
12 attach (cholesterol)
13 head (cholesterol)
```

```
> table(trt)
trt
 1time 2times 4times  drugD  drugE
    10    10    10    10    10

> aggregate (response, by=list(trt), FUN=mean)
  Group.1      x
1  1time  5.78197
2  2times  9.22497
3  4times 12.37478
4  drugD 15.36117
5  drugE 20.94752

> aggregate (response, by=list(trt), FUN=sd)
  Group.1      x
1  1time 2.878113
2  2times 3.483054
3  4times 2.923119
4  drugD 3.454636
5  drugE 3.345003
```

```
Treatments (trt: Dependent Var):
* Same drug but administered differently
  - 20 mg once per day (1time)
  - 10 mg twice per day (2times)
  - 5 mg four times per day (4times)
* drugD
* drugE
Response Var: cholesterol Reduction
```

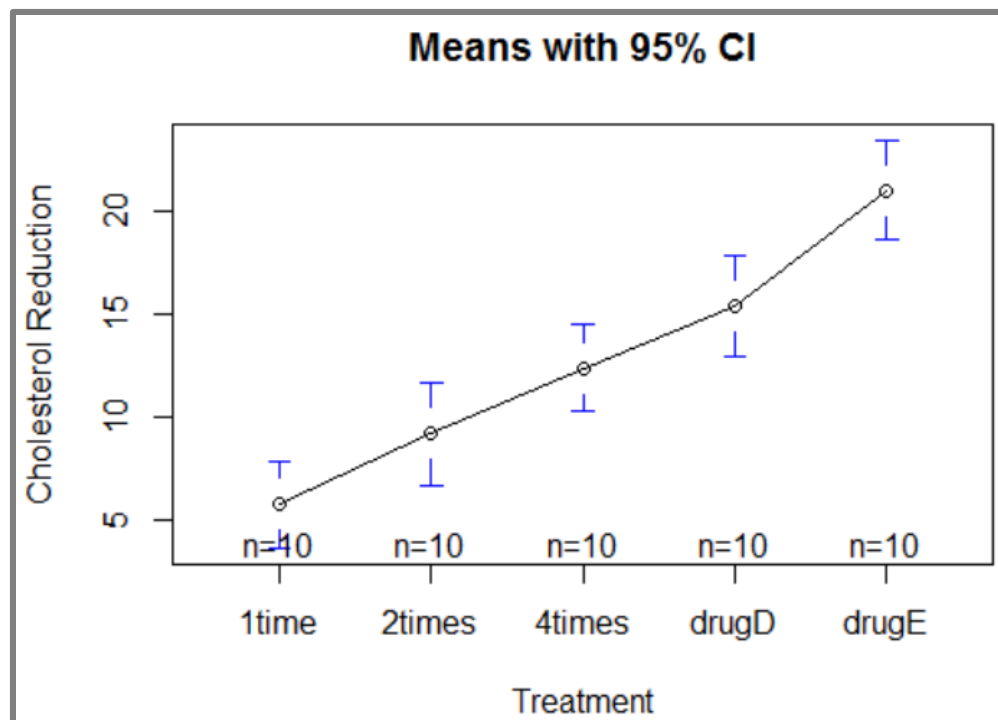
Ex: One-way Between-Groups ANOVA (cont.)

```
> fit <- aov (response ~ trt)
> summary(fit)
```

	Df	Sum Sq	Mean Sq	<u>F value</u>	<u>Pr(>F)</u>	
trt	4	1351.4	337.8	32.43	9.82e-13	***
Residuals	45	468.8	10.4			

signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

- F-test is significant:
 - five treatments are not equally effective
 - it does not tell which treatments differ from one another
- drugE appears to produce the greatest cholesterol reduction based on the plotmeans()



```
35 library (gplots)
36 plotmeans (response ~trt, xlab="Treatment",
37            ylab = "Cholesterol Reduction",
38            main="Means with 95% CI")
```

Multiple Comparisons: TukeyHSD(): pairwise

- F-test is significant:
 - Conclusion: five treatments are not equally effective
 - But: it does not tell which treatments differ from one another

TukeyHSD() provides a test of all **pairwise differences** between group means

```
> TukeyHSD(fit)
Tukey multiple comparisons of means
 95% family-wise confidence level

Fit: aov(formula = response ~ trt)

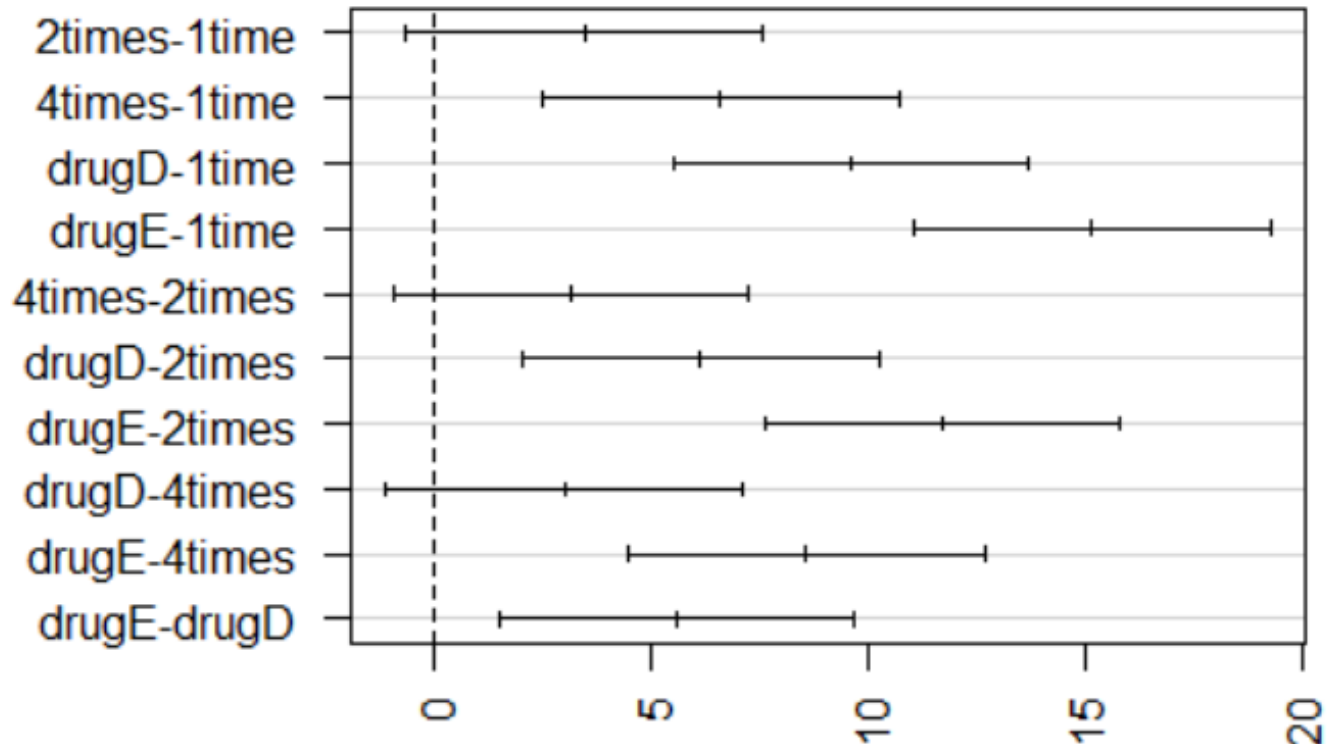
$trt
              diff            lwr            upr      p adj
2times-1time  3.44300 -0.6582817  7.544282 0.1380949
4times-1time  6.59281  2.4915283 10.694092 0.0003542
drugD-1time   9.57920  5.4779183 13.680482 0.0000003
drugE-1time  15.16555 11.0642683 19.266832 0.0000000
4times-2times  3.14981 -0.9514717  7.251092 0.2050382
drugD-2times   6.13620  2.0349183 10.237482 0.0009611
drugE-2times  11.72255  7.6212683 15.823832 0.0000000
drugD-4times   2.98639 -1.1148917  7.087672 0.2512446
drugE-4times   8.57274  4.4714583 12.674022 0.0000037
drugE-drugD    5.58635  1.4850683  9.687632 0.0030633
```



Plot: TukeyHSD(): pairwise comparisons

```
50 par(las=2)
51 par (mar=c(5,8,4,2))
52 plot (TukeyHSD(fit))
```

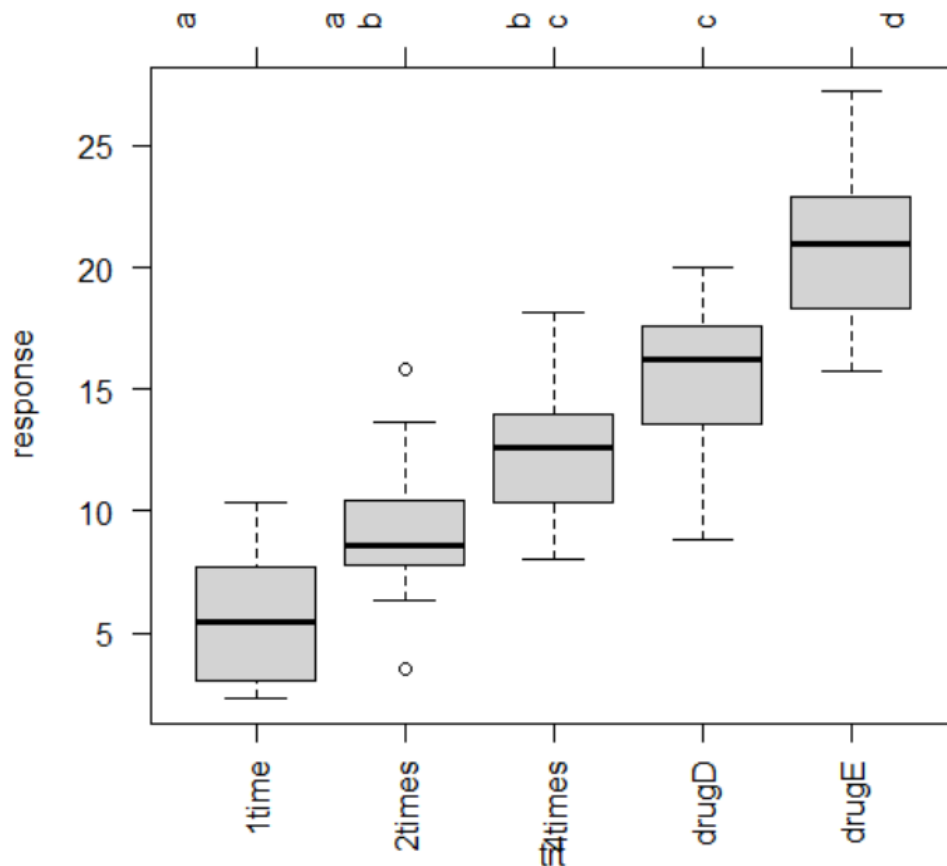
95% family-wise confidence level



Differences in mean levels of trt

Multiple Comparisons: glht()

glht() provides a test of **comparing multiple** group means



- 1time & 2times are not significantly different (share letter a)
- 2times & 4times are not significantly different (share letter b)
- 1time & 4times are different (they do not share a letter)
- drugE is superior and is different from all the competitors

```
55 library(multicomp)
56 par(mar = c(5,4,6,2))
57 comp <- glht(fit, linfct=mcp(trt="Tukey"))
58 plot(cld(comp, level=0.05), col="lightgrey")
```

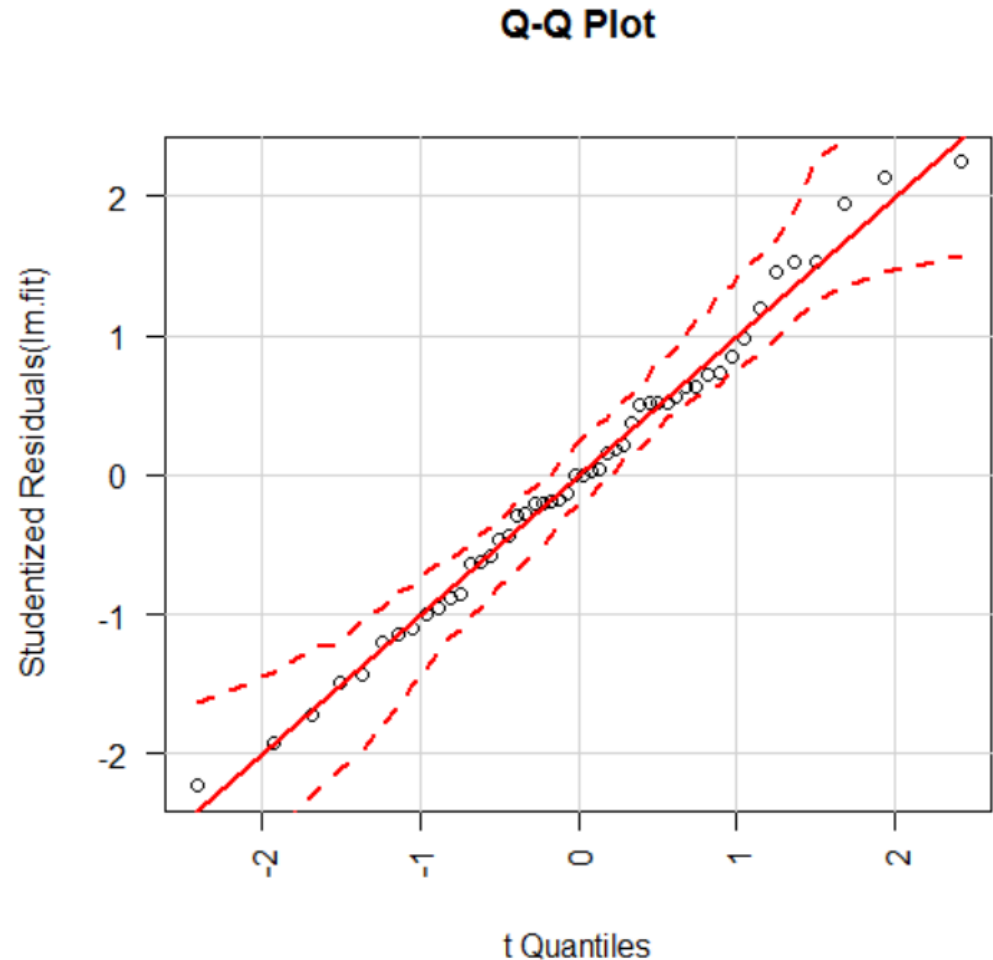
Assumptions: One-way ANOVA

- **Assumptions underlying the statistical tests:**
 - Dependent variable is normally distributed
 - Dependent variable has equal variance in each trt group
 - ANOVA results could be sensitive to outliers

Normality Assumption: One-way ANOVA

Dependent variable must
be normally distributed

*Data falls within 95% CI →
normality assumption is met*



```
63 library (car)
64 lm.fit <- lm(response ~ trt, data=cholesterol)
65 qqPlot (lm.fit, simulate=TRUE,
66         main="Q-Q Plot", labels=FALSE)
```

Equal Variance Assumption: One-way ANOVA

Dependent variable must have equal variance for each group

```
> bartlett.test (response ~ trt, data=cholesterol)
```

```
Bartlett test of homogeneity of variances
```

```
data: response by trt
```

```
Bartlett's K-squared = 0.5797, df = 4, p-value = 0.9653
```

- Fail to reject the null hypothesis (p -value=0.96)
- H_0 : Equality / homogeneity of variances

Lack of Outliers Assumption: One-way ANOVA

ANOVA can be sensitive to the presence of outliers

```
> library(car)
> outlierTest(fit)
```

```
No Studentized residuals with Bonferonni p < 0.05
```

```
Largest |rstudent|:
```

	rstudent	unadjusted p-value	Bonferonni p
19	2.251149	0.029422	NA

- Fail to reject the null hypothesis (NA: $p\text{-value} > 1$)
- H_0 : There is no outliers in the data

Fitting ANCOVA Models

ONE-WAY BETWEEN-GROUPS

Ex: One-way Between-Groups ANCOVA

- **Treatments:** four doses of drugs administered to pregnant mice
- **Response:** Post-birth weight
- **Covariate:** Gestation time

```
87 data (litter, package="multcomp")
88 attach(litter)
89 head(litter)
90 table(dose)
91 fit <- aov(weight ~ gesttime + dose)
92 summary(fit)
```

	Df	Sum Sq	Mean Sq	F value	Pr(>F)	
gesttime	1	134.3	134.30	8.049	0.00597	**
dose	3	137.1	45.71	2.739	0.04988	*
Residuals	69	1151.3	16.69			

signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.'						
0.1 ' ' 1						

- Gestation time was related to birth weight
- Drug dosage was related to birth weight after controlling for gestation time
- Mean birth weight isn't the same for each of the drug dosages, after controlling for gestation time:
 - F-test does not say which treatments do not have the same mean birth weight, i.e. which means differ from one another
 - → use `glht()` for multiple comparisons

ANCOVA: Adjusting Group Means

- Original group means before adjusting for the covariate

```
> aggregate(weight, by=list(dose), mean)
  Group.1      x
1      0 32.30850
2      5 29.30842
3     50 29.86611
4    500 29.64647
```

- Adjusted group means after partialing out the effects of the covariate

```
99 install.packages("effects")
100 library(effects)
101 effect("dose", fit)
```

```
dose effect
dose
      0      5      50      500
32.35367 28.87672 30.56614 29.33460
```

ANCOVA: Multiple Comparisons

- Mean birth weight isn't the same for each of the drug dosages, after controlling for gestation time:
 - F-test does not say which treatments do not have the same mean birth weight, i.e. which means differ from one another
 - → use `glht()` for multiple comparisons

```
104 # c(3, -1, -1, -1): comparison of the no-drug group
105 # with the average of the other three drug groups
106 library(multcomp)
107 contrast <- rbind("no drug vs drug" = c(3, -1, -1, -1))
108 summary(glht(fit, linfct=mcp(dose=contrast)))
```

Simultaneous Tests for General Linear Hypotheses

Multiple Comparisons of Means: User-defined Contrasts

Fit: `aov(formula = weight ~ gesttime + dose)`

Linear Hypotheses:

	Estimate	Std. Error	t value	Pr(> t)
no drug vs drug == 0	8.284	3.209	2.581	0.012 *

signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
(Adjusted p values reported -- single-step method)

- Significant t -statistic (p -value < 0.05) →
- Fail to reject H_0
- No-drug group has higher birth weight than drug conditions

Assumptions: One-way ANCOVA

- Assumptions underlying the statistical tests:
 - Dependent/response variable is *normally distributed*
 - Response variable has *equal variance* in each group
 - ANOVA results could be sensitive to *outliers*
 - *Homogeneity / equality of regression slopes* between response variable and covariate for each group

Homogeneity of Regression Slopes: ANCOVA

```
120 library (multcomp)
121 fit2 <- aov (weight ~ gesttime*dose, data=litter)
122 summary(fit2)
```

	Df	Sum Sq	Mean Sq	F value	Pr(>F)	
gesttime	1	134.3	134.30	8.289	0.00537	**
dose	3	137.1	45.71	2.821	0.04556	*
gesttime:dose	3	81.9	27.29	1.684	0.17889	←
Residuals	66	1069.4	16.20			

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

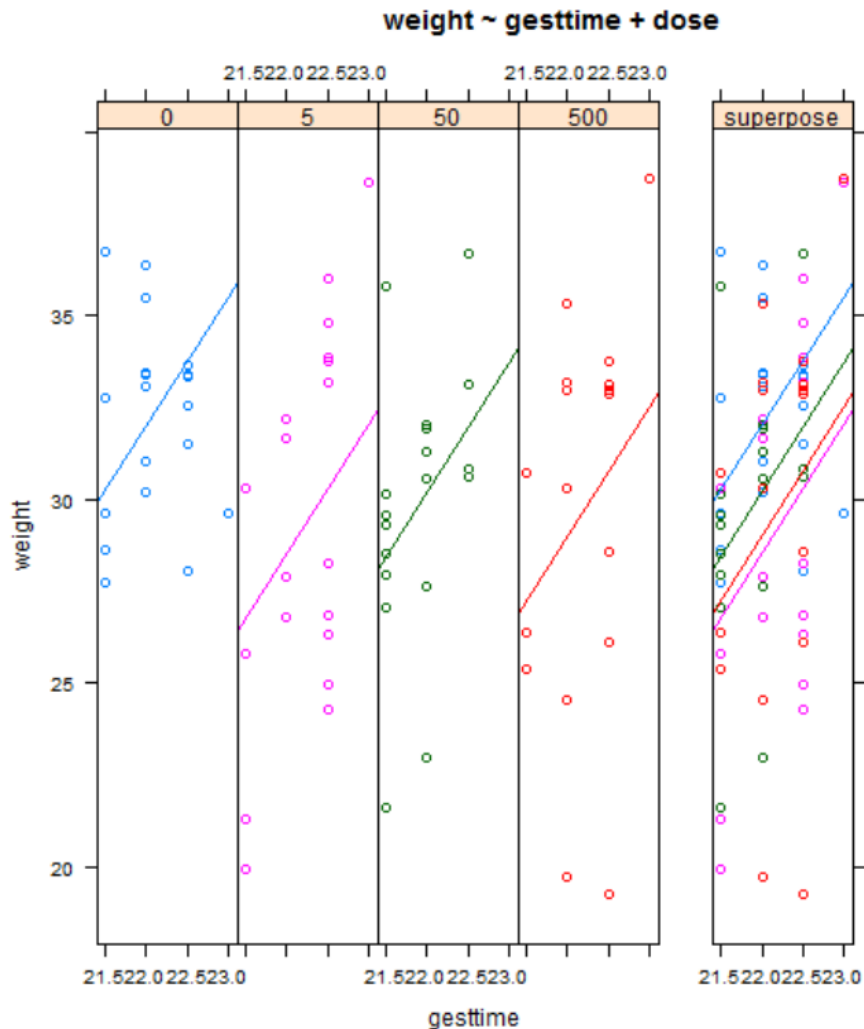
- Fail to reject H_0
- The gestation*dose interaction is nonsignificant supporting the assumption of equality of slopes

If H_0 were rejected then other tests could be tried out:

- nonparametric ANCOVA: `help(sm.ancova, package="sm")`

ANCOVA: Visualization

```
131 library (HH)
132 ancova (weight ~ gesttime + dose, data=litter)
```



Relationship between the dependent variable (birth weight), the covariate (gestation time), and the factor (dose)

- Regression lines for predicting birth weight from gestation time are parallel in each group but have different intercepts

Fitting ANOVA Models

TWO-WAY FACTORIAL

Ex: Two-Way Between-Groups Factorial ANOVA

Subjects are assigned to groups from the **cross-classification of factors**

- Cross-classification of factors (Independent variable):
 - dose: Three levels of ascorbic acid (0.5, 1, and 2)
 - supp: Two delivery methods (Orange Juice (OJ) and Vitamic C (VC))
- Dependent Variable: Response
 - Tooth length (len) for pigs

```
139 attach (ToothGrowth)
140 table (supp, dose)

      dose
supp 0.5  1  2
OJ   10 10 10
VC   10 10 10
```

**balanced
design**

```
> fit <- aov(len ~ supp*dose)
> summary(fit)
```

	Df	Sum Sq	Mean Sq	F value	Pr(>F)	
supp	1	205.4	205.4	12.317	0.000894	***
dose	1	2224.3	2224.3	133.415	< 2e-16	***
supp:dose	1	88.9	88.9	5.333	0.024631	*
Residuals	56	933.6	16.7			

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```
> aggregate (len,
+           by=list(supp,dose),
+           FUN=mean)

  Group.1 Group.2      x
1      OJ    0.5 13.23
2      VC    0.5  7.98
3      OJ    1.0 22.70
4      VC    1.0 16.77
5      OJ    2.0 26.06
6      VC    2.0 26.14
```

- Main effects: sup and dose
 - significant (p-value < 0.05)
- Interaction between factors: sup*dose
 - significant (p-value < 0.05)
- Reject the null hypothesis of equal means

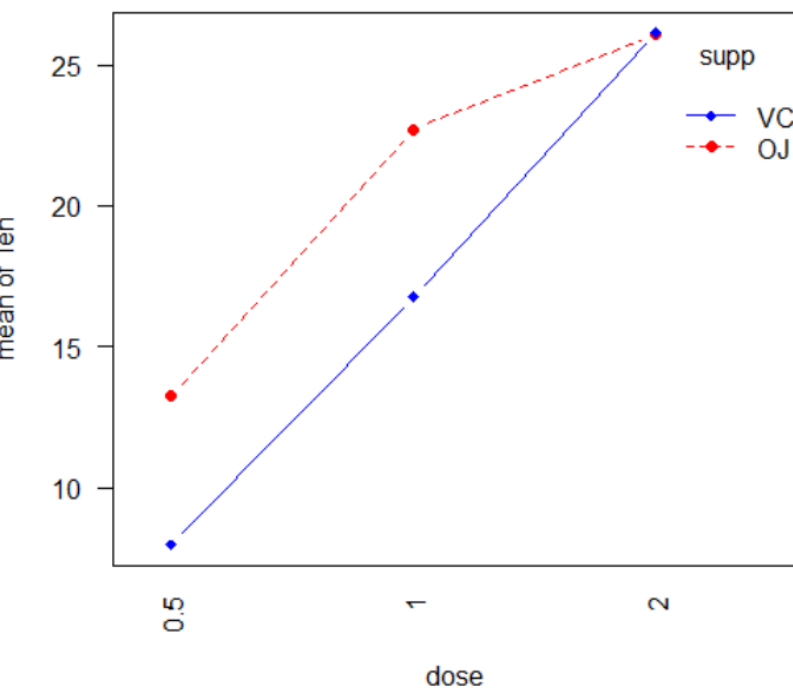
Visualization: Two-Way Factorial ANOVA

```

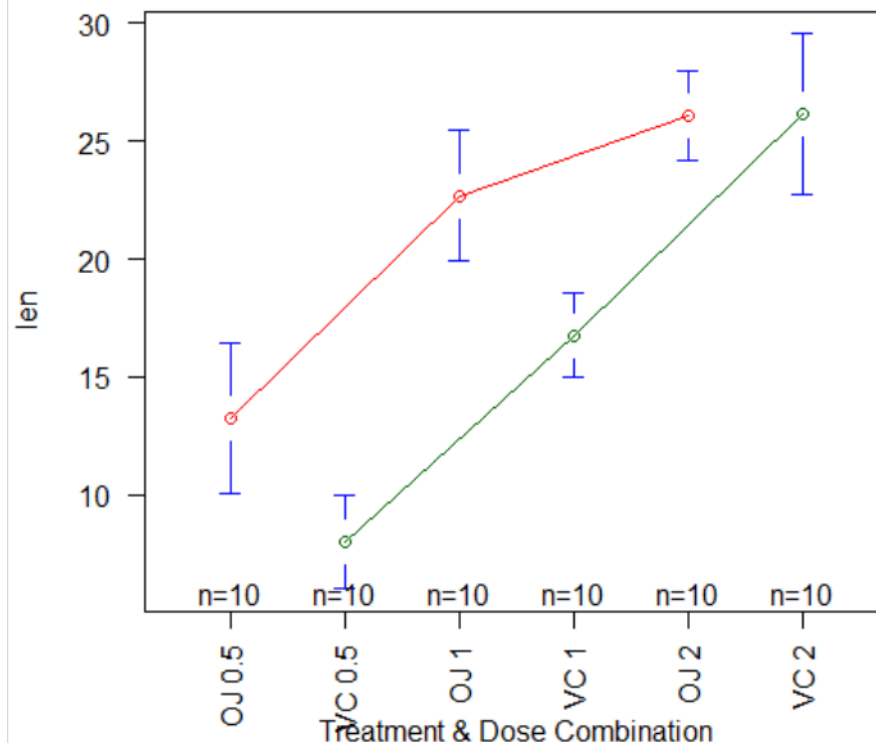
153 interaction.plot (dose, supp, len, type="b",
154                  col=c("red","blue"), pch=c(16,18),
155                  main="Interaction: Dose & Supplement Type")

```

Interaction: Dose & Supplement Type



Interaction with 95% CI

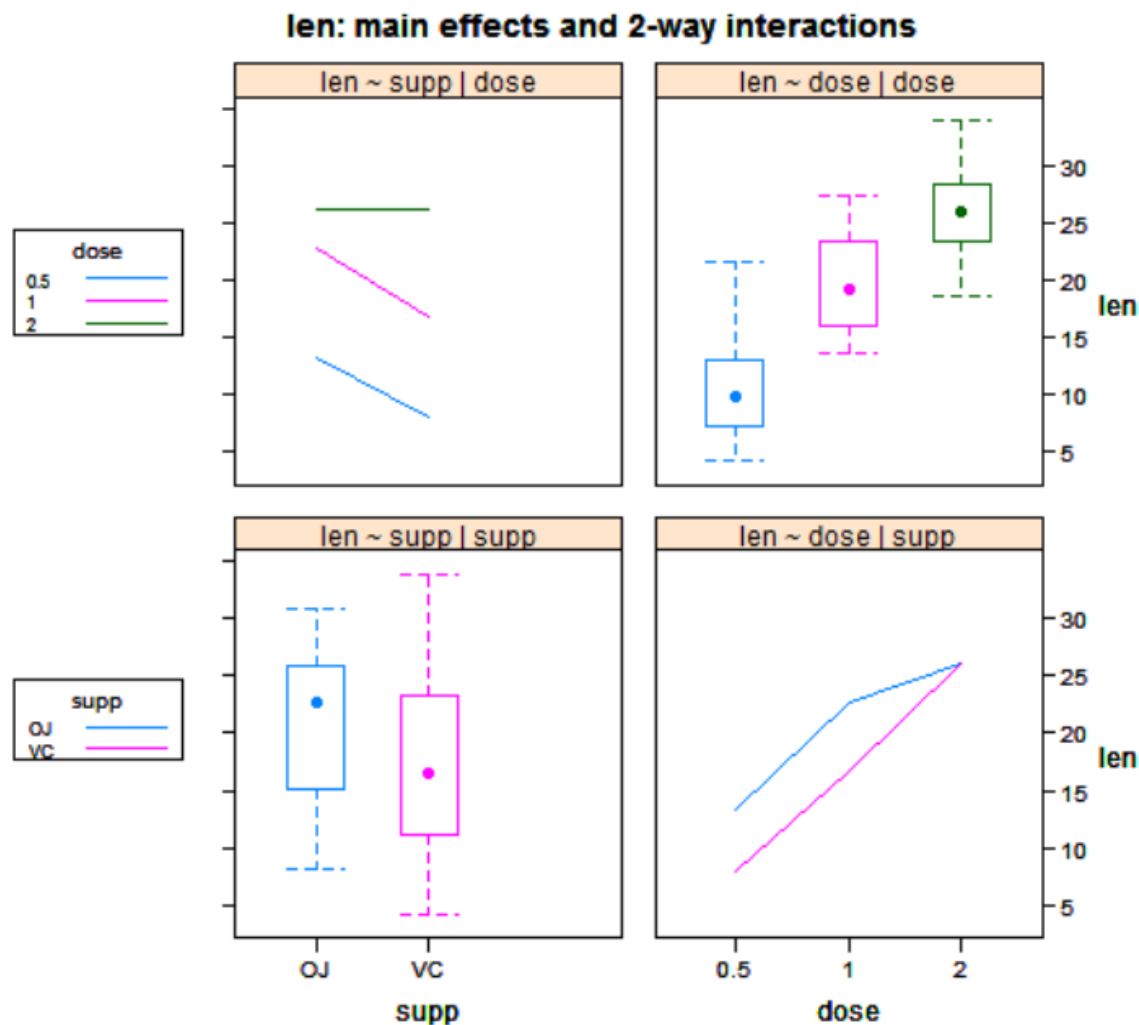


```

157 library(gplots)
158 plotmeans(len~interaction(supp,dose, sep=" "),
159           connect=list(c(1,3,5), c(2,4,6)),
160           col=c("red","darkgreen"),
161           main="Interaction with 95% CI",
162           xlab="Treatment & Dose Combination")

```


Visualization: Two-Way Factorial ANOVA



```
167 library (HH)
168 interaction2wt (len~supp*dose)
```

Fitting ANOVA Models

REPEATED MEASURES

- *The same subjects are measured more than once*

Ex: Repeated Measures ANOVA

Subjects are measured **more than once**

- Factors (Independent variables):
 - Type: Quebec vs Mississippi (Between-Group)
 - Conc: CO_2 concentration (Within-Group)
- Dependent Variable / Response:
 - Uptake: CO_2 uptake by plants
- The Type and concentration main effects are significant
- Type x conc interaction is significant

```
179 data (co2)
180 head(co2)
181 w1b1 <- subset(co2, Treatment=='chilled')
182 attach(w1b1)
183 fit <- aov(uptake ~ conc*Type +
184           Error(Plant/(conc), w1b1))
185 summary(fit)
```

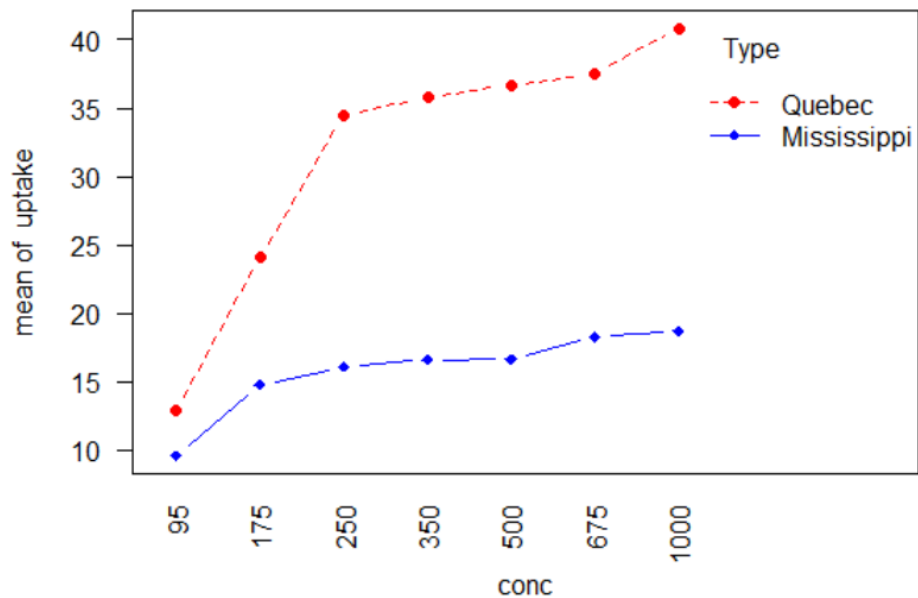
```
Error: Plant
      Df Sum Sq Mean Sq F value    Pr(>F)
Type    1 2667.2   2667.2    60.41 0.00148 **
Residuals 4  176.6     44.1
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05

Error: Plant:conc
      Df Sum Sq Mean Sq F value    Pr(>F)
conc    1  888.6   888.6   215.46 0.000125 ***
conc:Type 1  239.2   239.2    58.01 0.001595 **
Residuals 4   16.5     4.1
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05

Error: within
      Df Sum Sq Mean Sq F value    Pr(>F)
Residuals 30   869   28.97
```

Visualization: Repeated Measures ANOVA

Interaction: Plant Type & Concentration



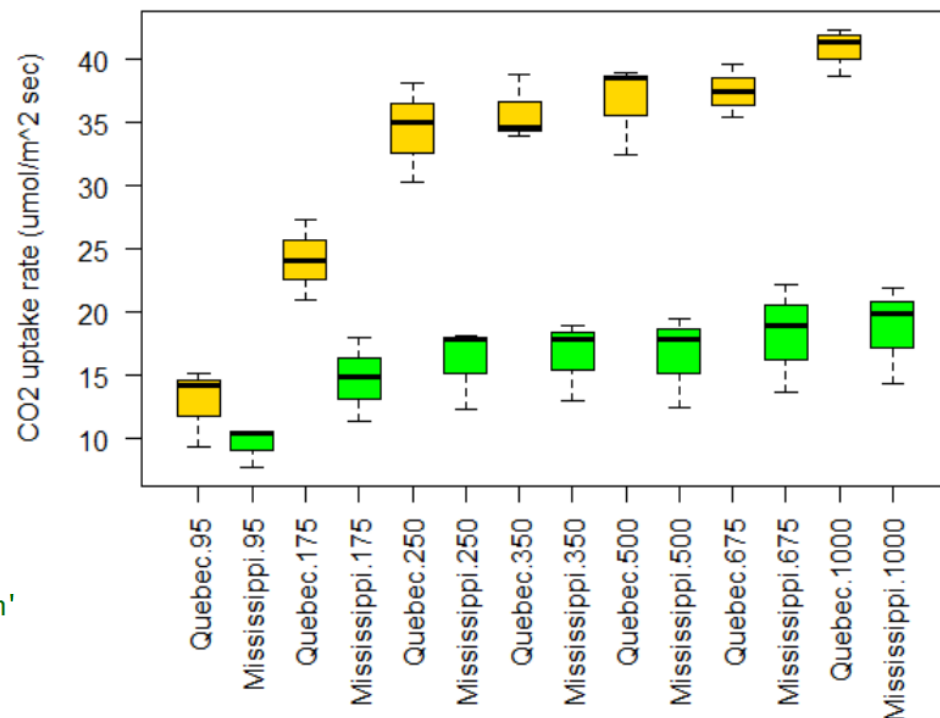
```

191 par(las=2)
192 par(mar=c(10,4,4,2))
193 with(w1b1,
194   interaction.plot (conc, Type, uptake,
195     type="b", col=c("red","blue"), pch=c(16,18),
196     main="Interaction: Plant Type & Concentration")
  
```

```

198 boxplot(uptake ~ Type*conc, data=w1b1,
199   col=c("gold","green"),
200   main="chilled Quebec & Mississippi plants",
201   ylab="CO2 uptake rate (umol/m^2 sec)")
  
```

Chilled Quebec & Mississippi Plants



Experimental Designs

FITTING MANOVA & MANCOVA

There is more than one dependent (outcome) variable

Ex: MANOVA: Multivariate Analysis of Variance

There is **more than one dependent** (outcome) variable

- Factors (Independent variables):
 - shelf: Store shelf (1 is bottom; 2 is middle, 3 is top) (Between-Group)
- Dependent Variables / Outcome:
 - calories
 - fat
 - sugars

```
208 library(MASS)
209 attach(UScereal)
210 y <- cbind(calories, fat, sugars)
211 aggregate(y, by=list(shelf), FUN=mean)
```

	Group.1	calories	fat	sugars
1	1	119.4774	0.6621338	6.295493
2	2	129.8162	1.3413488	12.507670
3	3	180.1466	1.9449071	10.856821

```
> fit <- manova (y ~ shelf)
> summary(fit)
```

	Df	Pillai	approx F	num Df	den Df	Pr(>F)
shelf	1	0.19594	4.955	3	61	0.00383 **
Residuals	63					

signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

- Significant F-value indicates that the three groups differ on the set of nutritional measures
 - Use `summary.aov(fit)` for pairwise comparison
 - Use `TukeyHSD()` to determine which shelves differ from each other

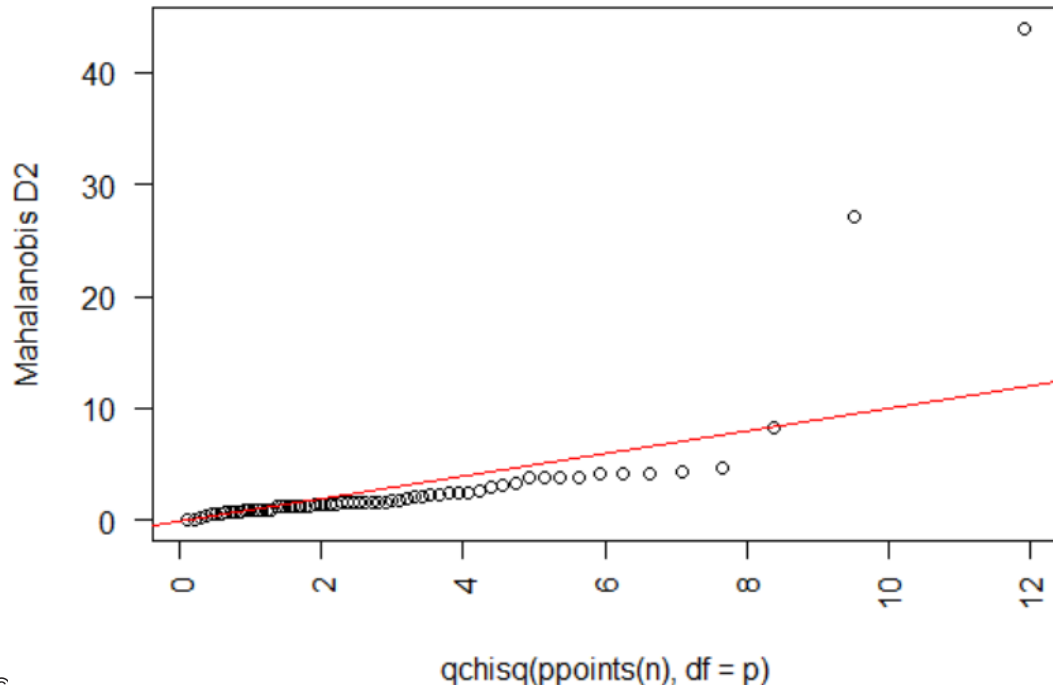
Assumptions: One-way MANOVA

- Assumptions underlying the statistical tests:
 - *Multivariate normality* of response
 - *Homogeneity / equality of variance-covariance matrices:*
 - Use Box M test: sensitive to normality assumption
 - *Multivariate outliers*
- If any of the assumptions are not met:
 - Consider robust nonparametric MANOVA provided by `Wilks.test()` in the "rrcov" package
 - Also, `Adonis()` function in the "vegan" package

Multivariate Normality Assumption: MANOVA

```
225 center <- colMeans(y)
226 n <- nrow(y)
227 p <- ncol(y)
228 cov <- cov(y)
229 d <- mahalanobis(y, center, cov)
230 coord <- qqplot(qchisq(ppoints(n), df=p),
231                d, main="Q-Q Plot: Multivariate Normality",
232                ylab="Mahalanobis D2")
233 abline(a=0, b=1, col=c("red"))
```

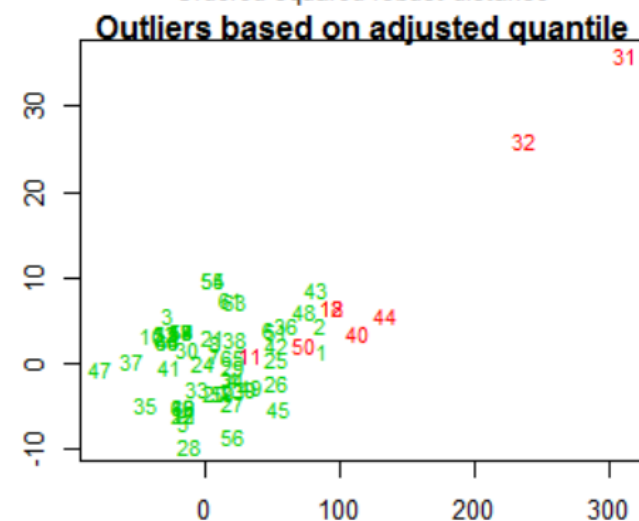
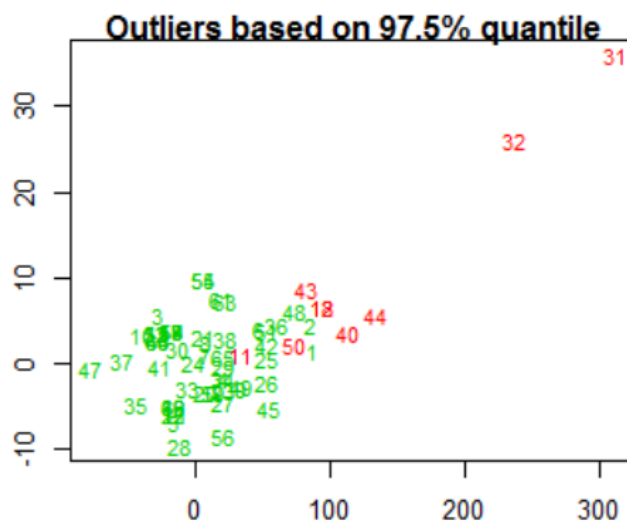
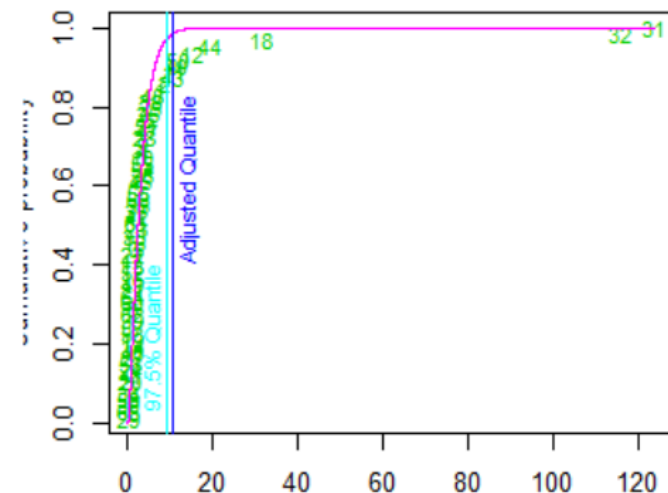
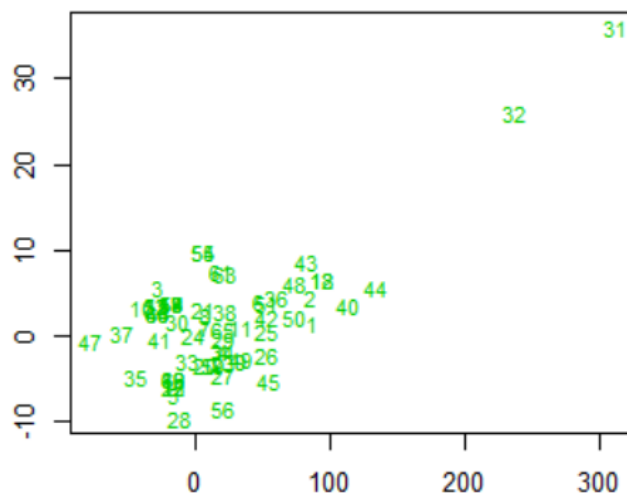
Q-Q Plot: Multivariate Normality



- The data appears to violate multivariate normality (due to a couple of outliers):
 - Wheaties Honey Gold
 - Wheaties
- Delete them and re-run

Outliers: One-way MANOVA

```
237 library(mvoutlier)
238 outliers <- aq.plot(y)
239 outliers
```



Robust MANOVA

```
248 library (rrcov)
249 wilks.test(y, shelf, method="mcd")
```

Robust One-way MANOVA (Bartlett chi2)

```
data:  x
wilks' Lambda = 0.5107, chi2-value = 23.311, DF =
4.845, p-value = 0.0002549
sample estimates:
  calories      fat      sugars
1 119.8210 0.7010828  5.663143
2 128.0407 1.1849576 12.537533
3 160.8604 1.6524559 10.352646
```

Summary

- Designs
 - One-way Between-Groups ANOVA (Analysis of Variance)
 - One-way Within-Groups ANOVA
 - Two-way Factorial ANOVA
 - ANCOVA: Adjusting for Covariates
 - MANOVA: Multivariate Analysis of Variable (>1 Response Vars)
 - MANCOVA: Multivariate Analysis of Covariance
- Fitting ANOVA and ANCOVA Models in R
 - Formulas for different types of designs
 - Order matters: Type I, II, and III ordering of formula terms
 - Examples: ANOVA and ANCOVA
 - Assessing ANOVA and ANCOVA Assumptions
- Fitting MANOVA Models in R
 - Examples: One-way MANOVA
 - Assessing MANOVA Assumptions