Analysis of Variance

Example: Data on blood pressure reductions for patients receiving 3 different drugs.

- Six patients randomized to each drug
- Sitting diastolic pressure measured before randomization (baseline) and after 4 weeks of treatment.

Drug 1: 10, 11, 15, 11, 12, 37
Drug 2: 8, 7, 8, 10, 12, 11
Drug 3: 7, 9, 11, 9, 4, 2

Question: Any difference among the 3 drugs with respect to their effects on BP reduction?

One-Way ANOVA

- Data: $Y_{ij}, i = 1, \cdots, I; j = 1, \cdots, n_i$

Y_{ij} is distributed normally with mean μ_i, and constant variance

Wish to test:

$$H_0 : \mu_1 = \cdots = \mu_I$$

against the alternative $H_1 : \mu_i \neq \mu_j$ for at least one pair $(i, j), i \neq j$.

One approach to model the data is to use the following formulation,

$$Y_{ij} = \mu_i + \epsilon_{ij}$$

Under the normality assumption, the maximum likelihood estimators of the means are given by

$$\hat{\mu}_i = \frac{\Sigma_j Y_{ij}}{n_i}$$

which also correspond to the OLS estimators obtained by minmizing

$$\sum_{ij}(Y_{ij} - \mu_i)^2$$

Decompose total sum of squares (SST) into diff sources of variation:

- Between samples (SSTrt)
- Within sample (SSE)

$$\sum_i \sum_j (Y_{ij} - \bar{Y}_{..})^2 = \sum_i n_i (Y_{i.} - \bar{Y}_{..})^2 + \sum_{ij} (Y_{ij} - \bar{Y}_{i.})^2$$

One-Way ANOVA Table

Source of Variation	df	Sum of Squares	Mean Squares
Treatment	I-1	SSTrt	SSTrt/(I-1)
Error	N-I	SSE	SSE/N-I
Total	N-1	SST	

A test statistic for H_o may be constructed based on the ratio

$$F = MSTrt/MSE$$

which, under H_o and model assumptions, has an $F_{I-1,N-I}$ distribution, where $N = \Sigma_i n_i$.

Implementation

R: aov() or glm()

SAS: PROC ANOVA, PROC GLM, and PROC MIXED.

```
> anov1 <- aov(Y~drug)
> summary(anov1)
             Df  SS    MSq   F Value  Pr(F)
drug         2   261.8 130.9 3.16     0.072
Residuals    15  621.3  41.4
```

If $\bar{Y}_{i.}$ has a normal distribution with mean μ_i and variance σ^2/n_i,

$$\frac{n_i(\bar{Y}_{i.} - \mu_i)}{\sqrt{MSE}}$$

has a t-distribution with N-I degrees of freedom. This result may be used to construct confidence interval for μ_i or the difference between two means $\mu_i - \mu_j$.

For the latter:

a $100(1-\alpha)\%$ confidence interval is given by

$$D_{12} \pm t_{\alpha/2,N-I}\sqrt{MSE(1/n_i + 1/n_j)}$$

$$D_{ij} = \bar{Y}_{i.} - \bar{Y}_{j.}$$

- Suppose Ho is rejected,

$$H_0 : \mu_1 = \cdots = \mu_I$$

Interested in determining which means are different from which other ones.

If there are g > 2 comparisons, the probability that at least one interval not including the true difference is no longer α.

Assuming independence, the probability that at least one of the *k* comparisons will reject a true null hypothesis $= 1 - (1 - \alpha)^k$

k	1	2	3	4	5	…	10
α_F	0.05	0.10	0.14	0.19	0.23	…	0.40

For *k* = 10 comparisons, there is a 40% chance that we will reject erroneously at least one true null hypothesis!

Goal: construct simultaneous confidence intervals, such that the joint or simultaneous level is at least the desired level, 1 - α

Bonferroni Method

Given g pairs of comparisons, the Bonferroni method constructs confidence intervals, each at level $\alpha' = \alpha/g$.

$$D_{ij} \pm t_{\alpha'/2,N-I}\sqrt{MSE(1/n_i + 1/n_j)}$$

Then the coverage probability of the joint or simultaneous confidence intervals is at least $1 - \alpha$.

Tukey Method

$$D_{ij} \pm Q^{\alpha}_{I,N-I}\sqrt{MSE(1/n_i + 1/n_j)}$$

where $Q^{\alpha}_{I,N-I}$ is the critical point of a Studentized range distribution with I means and N-I error degrees of freedom.

Scheffe Intervals

A procedure that results in wider intervals than the Tukey intervals, but with correct coverage, is given by

$$D_{ij} \pm \sqrt{(I-1)F_{\alpha,I,N-I}}\sqrt{MSE(1/n_i + 1/n_j)}$$

Fisher's Least Significant Difference

A procedure that is often used for pre-defined comparisons, is

$$D_{ij} \pm F_{\alpha,I,N-I}\sqrt{MSE(1/n_i + 1/n_j)}$$

This procedure does not control the experiment-wise error rate, and results in narrow confidence intervals.

Dunnett's Procedure

When interest lies in comparing I-1 groups against a reference group:

$$D_{ij} \pm d^{\alpha}_{I,N-I}\sqrt{MSE(1/n_i + 1/n_j)}$$

Reading Assignment. For p-values:

```
help(p.adjust)
 p.adjust(p, method = p.adjust.methods)
p.adjust.methods
    # c("holm", "hochberg", "hommel", "bonferroni",… "fdr", "none")
help(pairwise.t.test)
```

Departures From Assumptions

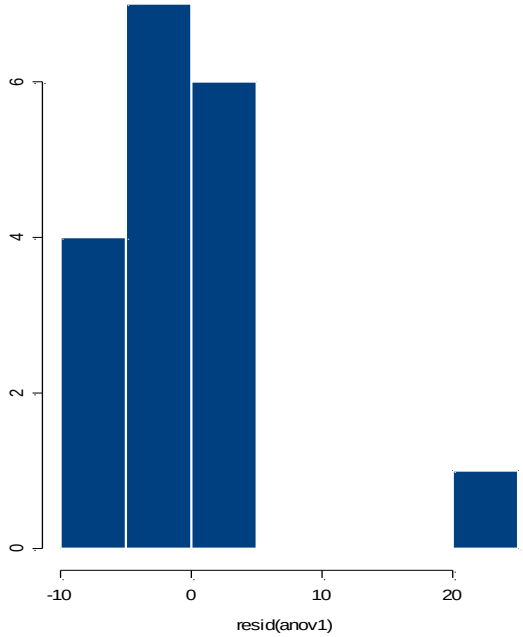
Non-normality

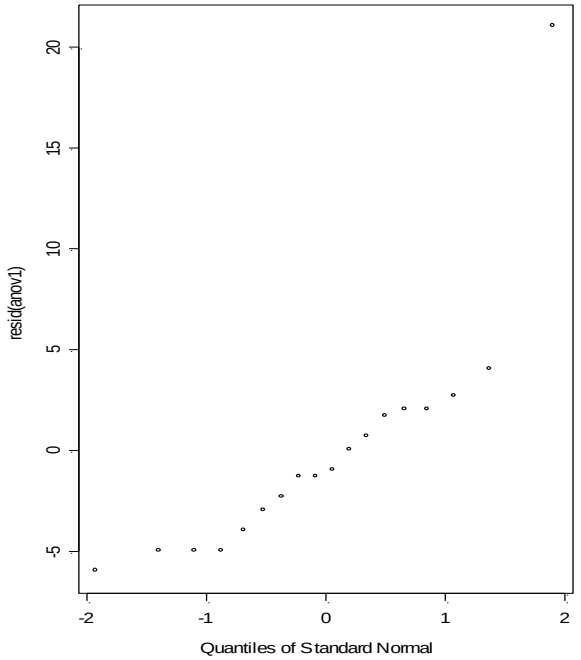
- Validity of the p-values suspect in small samples.
- For large samples, the F-test is generally Robust
- Accompanying loss in efficiency may be substantial
- Confidence intervals will not be accurate

Detection:

- Residual analysis: qqnorm, histograms, etc.

- hist(resid(anov1));
- qqnorm(resid(anov1)





Measures against *Non-normality:*

- Transformations: Box-Cox

$$y(\lambda) = \begin{cases} \frac{y^\lambda - 1}{\lambda}, & \text{if } \lambda \neq 0; \\ \log y, & \text{if } \lambda = 0. \end{cases}$$

Alternatively, one may use nonparametric or robust procedures.

The Kruskal-Wallis test

- A generalization of the Wilcoxon rank-sum test, when there are more than two groups.
- Based on the joint ranks of the observations (i.e., ranked from 1 to N= $\Sigma_{i=1}^{I} n_1$)

•Let R_i. = mean of ranks for i'th group
•R.. be the overall mean rank.
•Then assuming no ties:

$$T_{KW} = \frac{12}{N(N+1)} \sum_{i=1}^{I} n_i (\bar{R}_{i.} - R_{..})^2$$

which under $H_0 : \mu_1 = \cdots = \mu_I$ has an approximate χ^2_{I-1} distribution.

Remarks:

- Approximation is good provided $n_i > 5$
- If there are ties, appropriate correction factors must be used. (Reading Assignment)
- Kruskal-Wallis test assumes ordinal or numeric data
- Also assumes the shapes of the I distributions are the same.

One also may perform multiple comparisons using the following:

$$\bar{R}_{i.} - \bar{R}_{k.} \pm Z_{1-\alpha/2g}\left[\frac{N(N+1)}{12}(1/n_i + 1/n_k)\right]^{1/2}$$

> kruskal.test(Y,drug)

Kruskal-Wallis rank sum test

data: Y and drug

Kruskal-Wallis chi-square = 7.9476, df = 2, p-value = 0.0188

alternative hypothesis: two.sided

Departures From Assumptions

Unequal Variances

- p-values may not be reliable.

effect is mor serious if the large σ_i is associated with the samller n_i's. This typically leads to more frequent false rejections.

Test for homogeneity of variances:

- Bartlett's test
- Levene's test
- Box's test
- Hartley's max test

Bartlett's test

$$T = c^{-1}(\nu ln(\hat{\sigma}^2) - \sum_i \nu_i ln(\hat{\sigma}_i^2)$$

where $\nu_i = n_i - 1$, $\nu = \Sigma_i \nu_i$, and

$$c = 1 + \frac{1}{3(I-1)}(\sum_i \nu_i^{-1} - \nu^{-1})$$

and $\hat{\sigma}_i$ and $\hat{\sigma}$ are the i'th sample and pooled variances. The test rejects when $T > \chi^2_{I-1}$.

The test is highly dependent on normality assumption.

Two-Way ANOVA

In many applications, one-way ANOVA may not be adequate.

Examples: Data on blood pressure reductions for patients receiving 3 different drugs (cont'd)

Male	Female:
Drug 1: 11, 15, 11,	Drug 1: 10, 12, 37
Drug 2: 8, 7, 8	Drug 2: 10, 12, 11
Drug 3: 7, 9, 11	Drug 3: 9, 4, 2

Two-Way ANOVA

A second variable included in a model to:

- Improve precision
- Reduce dependence within the levels of a factor of interest
- Reduce bias arising as a result of confounding

When the stratification variable is numeric, Analysis of Covariance (ANCOVA).

•When the variable is a factor with two or more levels, two-way ANOVA.

Two-Way ANOVA

ANOVA model is given by:

$$Y_{ijk} = \mu_{ij} + \epsilon_{ijk}$$

where $i = 1, \cdots, I, j = 1, \cdots, J, k = 1, \cdots, n_{ij}$, and ϵ_{ijk} are typically assumed to be i.i.d. $N(0, \sigma^2)$.

OLS estimator:

$$\hat{\mu}_{ij} = \bar{Y}_{ij\cdot}$$

It is often more convenient to use the following alternative formulation

$$Y_{ijk} = \mu + \alpha_i + \beta_j + \gamma_{ij} + \epsilon_{ijk}$$

When the design is balanced, i.e., all $n_{ij} = n$, the least squares estimators of the unknown parameters are given as follows:

$$\hat{\mu} = \bar{Y}_{...}$$

$$\hat{\alpha}_i = \bar{Y}_{i..} - \bar{Y}_{...}$$

$$\hat{\beta}_j = \bar{Y}_{.j.} - \bar{Y}_{...}$$

$$\hat{\gamma}_{ij} = \bar{Y}_{ij.} - \bar{Y}_{i..} - \bar{Y}_{.j.} + \bar{Y}_{...}$$

Decomposition of SST for balanced 2-way designs:

$$SSA = nJ \sum_{i=1}^{I} (\bar{Y}_{i..} - \bar{Y}_{...})^2$$

$$SSB = nJ \sum_{j=1}^{J} (\bar{Y}_{.j.} - \bar{Y}_{...})^2$$

$$SSAB = n \sum_{i=1}^{I} \sum_{j=1}^{J} (\bar{Y}_{ij.} - \bar{Y}_{i..} - \bar{Y}_{.j.} + \bar{Y}_{...})^2$$

$$SSE = \sum_{ijk} (Y_{ijk} - \hat{Y}_{ij.})^2$$

Two-Way ANOVA Table: Balanced Design

Source	df	SS	MS
A	I-1	SSA	MSA=SSA/(I-1)
B	J-1	SSB	MSB=SSB/(J-1)
AB	(I-1)(J-1)	SSAB	MSAB=SSAB/(I-1)(J-1)
Error	IJ(n-1)	SSE	MSE=SSE/IJ(n-1)
Total	IJN-1	SST	

hypothesis of no treatment effect,

$$H_0 : \alpha_1 = \cdots = \alpha_I$$

the normal-model test statistic is given by

$$F = \frac{MSA}{MSE}$$

which under H_o has an $F_{I-1,IJ(n-1)}$ distribution.

When there is no significant interaction, it is often advisable to work with the reduced model,

$$Y_{ijk} = \mu + \alpha_i + \beta_j + \epsilon_{ijk}$$

Advantages of additive model formulation:

- More error degrees of freedom is obtained, giving more powerful F tests for the main effects.

- Estimation of main effect parameters straightforward even when the design is unbalanced or some cells are empty .

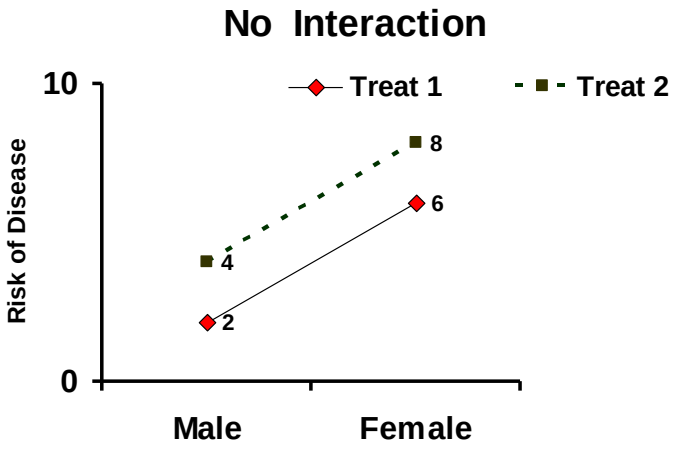
$$\hat{\mu}_{ij} = \hat{\mu} + \hat{\alpha}_i + \hat{\beta}_j$$

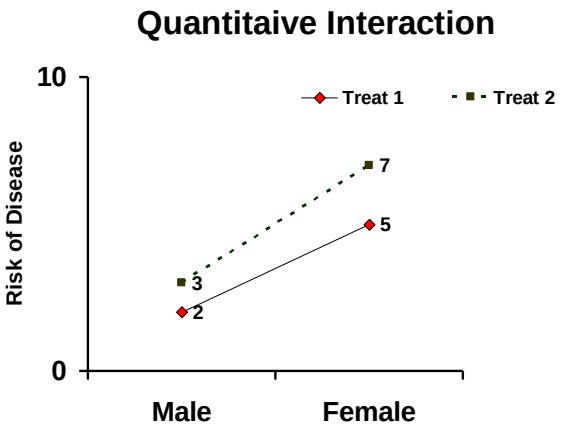
so that the i'th marginal mean is estimated by

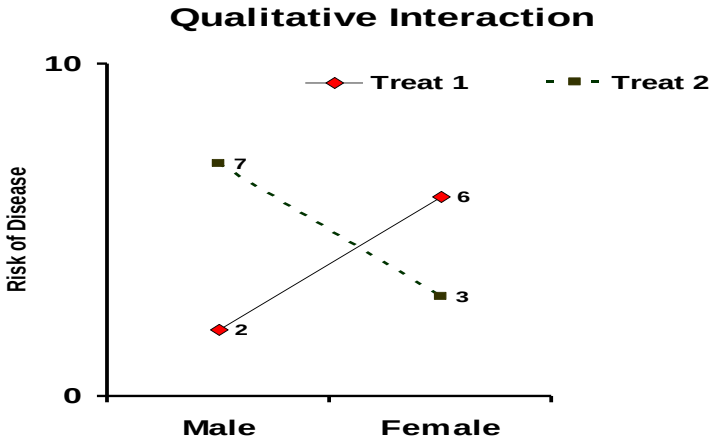
$$\hat{\mu}_{i.} = \frac{\Sigma_{j=1}^{J} \hat{\mu}_{ij}}{J}$$

When the interaction term is significant:

- Evaluate the nature and strength of the interaction.

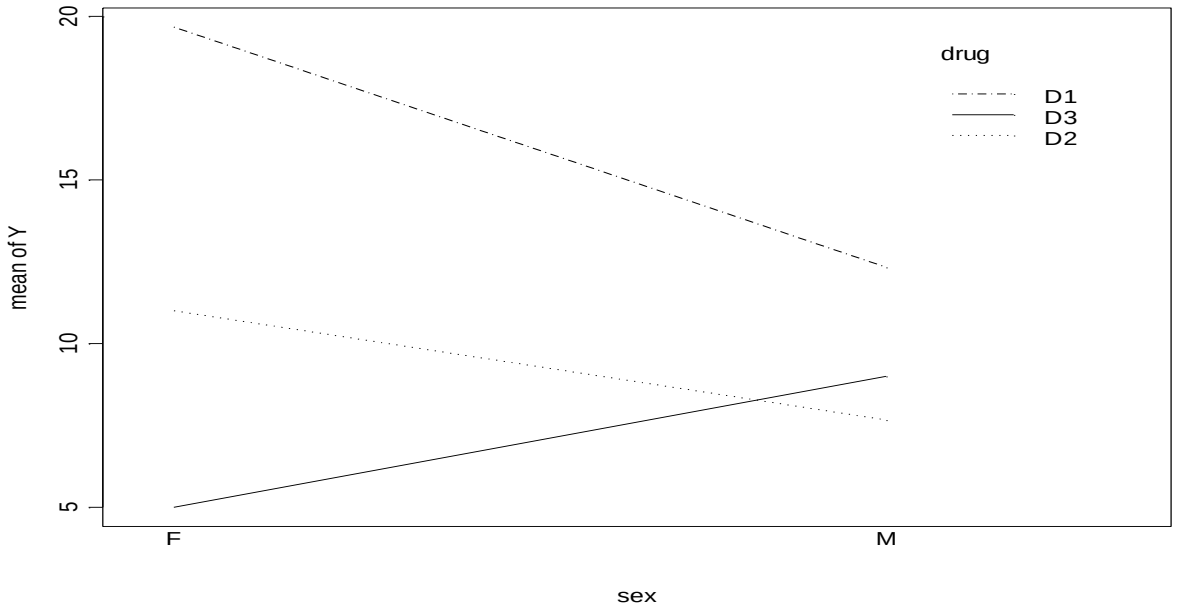






When the interaction term is significant:

- Evaluate the nature and strength of the interaction.
  - Commonly used test to determine whether the interaction qualitative or quantitative: Gail-Simon test
    [Biometrics. Vol. 41 No. 2 (June 1985): 361-372]
  - Plot using interaction.plot(block,trt,Y)



```
> fit2way <- aov(Y~drug*sex)
> summary(fit2way)
             Df   SSq      Mean Sq    F Value    Pr(F)
     drug    2   261.78    130.89     3.14         0.08
      sex    1   22.22     22.22      0.53         0.48
 drug:sex    2   99.11     49.56      1.19         0.34
Residuals   12   500.0     41.67
```

The Friedman rank-sum test

- Assumes a randomized block design without replication

$$Y_{ij} = \mu + \alpha_i + \beta_j + \epsilon_{ij}$$

and the null hypothesis of interest

$$H_o : \alpha_1 = \cdots = \alpha_I$$

Within each block (ie., $j = 1, \cdots, J$), rank the observations separately from 1 to I. Let $\bar{R}_{i.}$ be the mean rank for the observations in the i'th group. Then under H_0, $\bar{R}_{1.} \approx \cdots \approx \bar{R}_{I.}$.

$$F = \frac{12J}{I(I+1)} \sum_{i=1}^{I} (\bar{R}_{i.} - \bar{R}_{..})^2$$

which, under H_0, is approximately χ^2_{I-1}.

Implementation:
friedman.test(Y,groups,blocks)
SAS: PROC FREQ.

```
> tapply(Y,list(sex,drug),mean)
     D1   D2 D3
F  19.7 11.0  5
M  12.3  7.7  9
```

```
> Ymean <- c(19.7,12.3,11,7.7,5,9)
> Drug <-rep(c("D1","D2","D3"),c(2,2,2))
> Sex <-c("F","M","F","M","F","M")
> Drug <-factor(Drug)
> Sex <-factor(Sex)
```

```
> friedman.test(Ymean,Drug,Sex)

        Friedman rank sum test

data:  Ymean and Drug and Sex
Friedman chi-square = 3, df = 2, p-value = 0.2231
alternative hypothesis: two.sided
```

Other tests in PROC FREQ

- The Van Elteren test

Example: Subjects randomized to Drug or Placebo.

Data on **Blood Pressure** reduction (Y) after 4 weeks of treatment,

Baseline Blood Pressure (Base)

Ho: No Difference in Mean BP Reduction (Y) for Drug & Placebo

ID	Y	Base	trt
1	7.1	61	Drug
2	6.6	56	Drug
3	7.8	58	Drug
4	6.8	68	Drug
5	9.4	64	Drug
6	9.7	57	Drug
7	8.5	55	Drug
8	9.9	59	Drug
9	6.1	51	Drug
10	8.0	60	Drug
11	8.8	88	Placebo
12	8.5	85	Placebo
13	8.1	81	Placebo
14	8.9	89	Placebo
15	8.7	87	Placebo
16	8.4	84	Placebo
17	8.1	81	Placebo
18	7.8	78	Placebo
19	8.1	81	Placebo
20	8.5	85	Placebo

One-Way ANOVA:

> summary(aov(Y ~ trt))

	Df	SS	MeanSq	F	Pr(F)
trt	1	0.42	0.42	0.60	**0.450**
Resid	18	12.68	0.70		

	Base Mean	**Y Mean**
Drug	59.7	8.07
Placebo	83.6	8.34

Regression Effect

Regression to the Mean

Analysis of Covariance
ANCOVA

Suppose X_{ij} is a covariate of interest, and consider the ANOCVA model

$$Y_{ij} = \mu_i + \beta X_{ij} + \epsilon_{ij}$$

Note that

$$\bar{Y}_{i.} \approx \hat{\mu}_i + \beta \bar{X}_{i.}$$

Thus, comparing μ_i and μ_k based on $\bar{Y}_{i.} - \bar{Y}_{k.}$ would be inappropriate unless $\bar{X}_{i.} = \bar{X}_{k.}$. So , comparison is generally performed at a common value of X, say $\bar{X}_{..}$. For convenience, let

$$Y_{ij} = \mu_i + \beta(X_{ij} - \bar{X}_{..}) + \epsilon_{ij}$$

Adjusted mean (a.k.a. LS Mean)

$$\hat{\mu}_i = \hat{Y}_{i.} - \hat{\beta}(\bar{X}_{i.} - \bar{X}_{..})$$

In the above

$$\hat{\beta} = \frac{\Sigma_{i=1}^{I} \Sigma_{j=1}^{n_i} (y_{ij} - \bar{Y}_{i.})(X_{ij} - \bar{X}_{i.})}{\Sigma_{i=1}^{I} \Sigma_{j=1}^{n_i} (X_{ij} - \bar{X}_{i.})^2}$$

$$\hat{\sigma}^2 = \frac{1}{N - I - 1} \sum_{ij} (Y_{ij} - \hat{\mu}_{i.} - \hat{\beta}(\bar{X}_{i.} - \bar{X}_{..}))^2$$

$$var(\hat{\beta}) = \frac{\sigma^2}{\Sigma_{i=1}^{I} \Sigma_{j=1}^{n_i} (X_{ij} - \bar{X}_{i.})^2}$$

One-Way ANOVA:

> summary(aov(Y ~ trt))

	Df	SS	MeanSq	F	Pr(F)
trt	1	0.42	0.42	0.60	**0.450**
Resid	18	12.68	0.70		

ANCOVA

> summary(aov(Y ~ Base+trt))

	Df	SS	MeanSq	F	Pr(F)
Base	1	2.40	2.40	5.9	0.026
trt	1	3.81	3.81	9.41	**0.007**
Resid	17	6.89	0.41		

	Base	**Y**	**LSM**
Drug	59.7	8.07	9.3
Placebo	83.6	8.34	7.1

Nonparallel Regression Lines

Suppose now that

$$Y_{ij} = \mu_i + \beta_i(X_{ij} - \bar{X}_{..}) + \epsilon_{ij}$$

The above arises when the marginal mean differences are different for different values of X_{ij} .

- In the blood pressure example, patients may respond differently to different drugs depending on the values of their baseline blood pressure.

When the lines are not parallel, different lines have to be fitted for each i.

$$\hat{\beta}_i = \frac{\Sigma_{j=1}^{n_i}(y_{ij} - \bar{Y}_{i.})(X_{ij} - \bar{X}_{i.})}{\Sigma_{j=1}^{n_i}(X_{ij} - \bar{X}_{i.})^2}$$

giving

$$\hat{\mu}_i = \hat{Y}_{i.} - \hat{\beta}_i(\bar{X}_{i.} - \bar{X}_{..})$$

A test for parallelism may be performed by testing for the significance of treatment-by-covariate interaction

$$H_0 : \beta_1 = \cdots \beta_I$$

The test statistic is given by

$$\frac{\Sigma_{i=1}^{I}(\hat{\beta}_i - \hat{\beta})^2 \, \Sigma_j (X_{ij} - \bar{X}_{i.})^2}{(I-1)\hat{\sigma}^2}$$

which under H_0 has an $F_{I-1,N-2I}$ distribution.

In the above

$$\hat{\beta} = \frac{\Sigma_{i=1}^{I} \, \Sigma_{j=1}^{n_i} (Y_{ij} - \bar{Y}_{i.})(X_{ij} - \bar{X}_{i.})}{\Sigma_{i=1}^{I} \, \Sigma_{j=1}^{n_i} (X_{ij} - \bar{X}_{i.})^2}$$

Test for Parallelism

```
> summary(aov(Y ~  Base*trt))
            Df  SS   MeanSq  F      Pr(F)
Base     1  2.401  2.40     5.590    0.031
   trt      1  3.814  3.81     8.88     0.009
Base:trt  1  0.017  0.017  0.04     0.840
```

When Ho is rejected, inference about the marginal mean differences must be performed for each X = x

$)^2$

Remarks:

For non-normal data, use rank-based ANCOVA:

- Iman and Conover: Ranks are substituted for Y and X, if both random
- Stephen and Jacobson: Transform only Y, if X is fixed (e.g., X=Age).

Problem Set

Reading Assignment: Ramsey and Shafer; Chapters 5 (Comparing Among Several Samples), 6 (Multiple Comp),13 (ANOVA)

Consider the Diet Experiment data available at:
https://www.stat.wisc.edu/~yandell/pda/data/Diet/

The experiment involved cows which were randomly assigned to one of 6 diets and followed for a number of weeks. Diets were begun after the third week, allowing the animals some initial time to adjust to their new environment. Interest focuses on the effect of diet on the average dry matter intake (dmi), the amount of food eaten by each cow. The data you have are a baseline value (covar = dmi for week 3), average dmi during subsequent weeks, the number of subsequent weeks. Randomization was blocked by time, the first 6 cows were randomly assigned among the 6 diets, and so on. (Wattiaux MA, Combs DK and Shaver RD (1994) ``Lactational responses to ruminally undegradable protein by dairy cows fed diets based on alfalfa silage'', *J Dairy Science 77*, 1604-1617. Ref Brian Yandell's book *Practical Data Analysis for Designed Experiments*.)

1) Determine whether there is a significant difference in the mean weights of the six diet groups, using a one-way ANOVA(i.e., ignoring block).
    a) Without adjusting for Week 3 weight
    b) Adjusting for Week 3 weight. Give the LS Means (i.e., adjusted for Week 3 weight), and compare the results with (1a).
    c) Use a test for parallelism to evaluate the appropriateness of performing inference based the adjusted means.
    d) Check the validity of your assumptions, including parallelism. Suggest measures that you would take if the assumptions are not satisfied.

2) Comment on the use of the "*average dmi during subsequent weeks*" as a response variable.

cow	trt	block	covar	dmi	weeks
747	4	4	22.4757	24.4895	14
755	5	5	24.5157	26.7524	14
819	4	3	22.1100	25.4132	8
835	3	10	18.9529	27.6605	14
849	5	2	20.0657	17.0912	14
850	2	8	21.0600	26.4908	14
852	1	6	23.8933	27.8113	13
855	3	2	27.0329	27.0967	14
869	3	5	25.0800	25.1205	14
872	1	10	21.4414	27.7596	12
890	5	6	24.6457	23.7472	14
894	6	9	23.7971	26.0426	13
1549	4	8	21.8886	25.1794	14
3135	1	9	18.7286	21.4793	14
3164	2	2	19.5083	22.6606	12
3231	5	4	18.5886	23.0251	14
3240	2	7	19.8500	27.5362	14
3353	1	4	.	24.7224	14
3366	5	1	20.1900	24.2389	14
3372	4	9	23.5571	27.1255	14
3408	6	1	20.2600	23.9520	14
3440	1	8	19.2750	26.2302	14
3455	4	5	17.0886	24.9188	14
3460	3	9	20.4257	25.1809	14
3466	2	3	24.6114	28.0106	14
3467	4	1	14.8033	22.9552	14
3471	1	1	16.9200	24.3709	14
3478	6	3	23.4171	22.9222	14
3499	1	2	22.0329	26.2007	14

cow	trt	block	covar	dmi	weeks
3508	3	1	27.0543	32.9527	14
3520	6	6	23.3329	27.4932	14
3527	6	4	20.9614	23.8124	14
3528	2	9	18.5557	23.3623	14
3529	5	10	20.4143	25.1781	14
3531	2	1	20.8167	24.6142	14
3542	2	6	25.7871	28.0095	14
3561	2	4	25.6457	26.9496	14
3564	5	9	23.8586	27.8948	14
3580	3	4	22.4071	24.8609	14
3586	4	2	24.5700	24.9605	14
3589	6	7	15.9386	22.3435	14
3593	1	5	21.6429	24.2462	14
3594	3	3	.	24.9867	12
3595	2	5	19.0300	28.0241	14
3596	6	5	27.1671	27.2993	14
3598	6	2	21.5667	25.4685	14
3604	4	10	20.8714	26.6923	14
3605	1	3	19.7671	28.1831	14
3611	3	6	18.5186	23.6910	14
3613	3	8	24.3829	26.6503	14
3615	5	7	22.8329	25.3444	14
3622	4	7	19.0857	22.9824	14
3623	6	10	19.0486	23.3875	14
3624	4	6	21.3286	21.6679	14
3629	3	7	18.5771	18.9699	14
3630	6	8	24.1200	26.3490	7
3643	2	10	17.6314	23.7072	14

	Name: Last, First	Name: Last, First	Name: Last, First	Name: Last, First	Name: Last, First	Name: Last, First	Name: Last, First	Name: Last, First	Name: Last, First	Name: Last, First
1	Wang, Yicheng	Xue, Yichao	He, Hanming	Zhang, Tian	Yi, Ziyun	Tao, Mengyuan	Tian, Jiani	Wang, Shiyu		
2	Li, Jingwei	Liu, Ao	Wu, Xiangyu	Yang, Yutong	Aoyuan, Liao	Yi, Jian	Zhang, Wanyi	Wang, Jia	Gao, Duanhong	Shi, Hanqing
3	Bai, Silvia	Cai, Weipan	Dai, Di	Han, Siqi	Xie, Tianzhao	Yang, Mengting	Zeng, Cen	Zhuang, Shiyu	Zhang, Yifan	Huang, Rui
4	Zuo,Nianyao	Chen,Jiayang	Huang,Xiangkai	Tang,Mingzhen	He,Jin	Li,Weihan	Gao,Fei	Qin,Liwen	Zuo,Zhaoyu	
5	Yang, Chuhan	Duan, Ziying	Chen, Jinglin	Huang, Yirui	Zhu, Ming	Liu, Zhaoze	Yin, Qing	Zhang, Baizheng	Yue, Wenshu	Zeng, Neng
6	You, Guanzhong	Wang, Lu	Zhou, Xingyu	Luan, Sitao	Bao, Wenhang	Liu, Chang	Yang, Tianmeng	Zhu, Feiran	Chen, Jie	
7	Zhang, Yunyi	Qin, Yunlin	Liu, Haojiang	Fei, Yang	Kim, Hayoung	Cho, Younhyuk	Song, Hyoungmook	Fan, Yang	Wang, Weitong	
8	Jin, Chengzhe	Liu, Youzhu	Yu, Xingzao	Zhu, Ying	You, Jiwen	Li, Linna	Lyu, Yihua	Ye, Hexiu	Lin, Chi-Heng	Jiang, Bo
9	Wang, Suling	Cheng, Tianyuan	Li, Cheng	Wang, Han	Shang, Renfei	Yao, Wei	Yu, Zhao			
10	Chen, Haoyang	lin	Zhou, Longwei	Chen, Zachary	Huang, Biyue	Qian, Quan				
11	Nian,Yiqun	An,Huilong	Lin, Zida	Zhang,Xiaohan	Hu, Yifei	Qin, Yu	Dai, Peijun	Gu, Kexin		
12	Gao, Chenying	Yao, Weichi								
13	Sun, Yuhan	Zhou, Jingying	Jiang, Chencheng	Teng, Yueying	Wang, Yanran	Gu, Xinghao	Chen, Ying	Meng, Ziwei		
14	Jin, Zhaoyan	Ji, Chenlu	Wang, Jiayi	Lu, Ke	Zhang, Xuan	Zhang, Chi	Lang, Yifei	Yu, Tianying		
15	Chen, Geer	Wang, Bo	Zhao, Edward	Zhang, Keren	Bao, Yu	Ren, Ruoxi	Zhang, Yunyi	Wang, Xiaoxiao	Zhou, Xiaoyu	Sun, Sirui

	Name: Last, First	Name: Last, First	Name: Last, First	Name: Last, First	Name: Last, First	Name: Last, First	Name: Last, First	Name: Last, First	Name: Last, First	Name: Last, First
16	Wang, Yiren	Li, Yanjin	Wen, Litong	Lu, Yicheng	Sun, Xuechun	Wang, Yue	Zhao, Fei			
17	Chen, Yihe	Lao, Palmer	Li, Daitong	Shuai, Ziyue	Zhang, Eric					
18	Mu, Jing	Zhou, Wuge	Tao, Ye	Yu, Xiuying	Zhang, Yueqi	Feng, Lingkang	Shi, Yuchen	Chen, Yanxi	Zhang, Qianyun	Min, Shengjie
19	Xiao, Han	Cui, Han	Wang, Danmo	Feng, Jingjing	Sheng, Tian	Zhao, Ran	Zhang, Yimin	Zhi, Chi	Xin, Xieke	Xue, Lifu
20	Shi,Ruixiong	Meng,Bai	Shi,Yuchen	Sha,Ouwen	Tan,Xiaolu	Zhang,Shijia				
21	Qian,Chao	Wu,Lepeng	Gao,Qian	Xia, Fenglin	Sun,Yifan	Zhao,Pengcheng	Huang,Yuqing	Zhang,Daqi	Wei,Chaojie	Zhou,Wenjing
22	Li, Rong	Su, Zijian	Gao, Qianyu	Zhou, Jiajun	Zhong, Jiayi	Jin, Zexin				
23	Sun, Yating	Ru, Xiao	Dai, Minghao	Lin, Xu	Ren, Wen	Wang, Jiayu	Ye, Chen	Song, Shuli	Chen,Yeyun	
24	Wang, Zehao	Li, Chi	Liu, Yi	Wang, Siying	Jin, Yong	Wang, Yuqing	Hao, Weilin	Cai, Yanrui	Wang, Zhaoxing	
25	Sanchez Azcarate, Juan Jose	Diego Joaquin, Juan Jose	Campos Gutierrez, Juan Pablo	Setia, Ekansha	Sharma, Vrinda	Khilnani, Nisha	Zhang, Jingya			
26	Chen,Tianyi	Zhang, Shaotian	Ni, Mengjia	Zhao, Mojia	Sun, Yixin					
27	Zhao, Jingdan	Yao, Mi	Zhang, Sumi	Zhang, Jinglun	Sun, Haocheng	Che, Yilin	Wang, Yuanyuan			
28	Xu, Linyihui	Kun Fan	Shuzhe Wu	Xi Lu	An, Ji	Gao, Qihua	Fan, Zhenlan	Sheng,Ming	Zhang, Lu	
29	Dessouky, Omar									
30	William Raikes									

Presenters 10/14/2016

7:50-8:00	Group 16
8:00 -8:10	Group 7
8:10-8:20	Group 3
8:20-8:30	Group 19

16	Wang, Yiren	Li, Yanjin	Wen, Litong	Lu, Yicheng	Sun, Xuechun	Wang, Yue	Zhao, Fei	
7	Zhang, Yunyi	Qin, Yunlin	Liu, Haojiang	Fei, Yang	Kim, Hayoung	Cho, Younhyuk	Song, Hyoungmook	Fan, Yang	Wang, Weitong	
3	Bai, Silvia	Cai, Weipan	Dai, Di	Han, Siqi	Xie, Tianzhao	Yang, Mengting	Zeng, Cen	Zhuang, Shiyu	Zhang, Yifan	Huang, Rui
19	Xiao, Han	Cui, Han	Wang, Danmo	Feng, Jingjing	Sheng, Tian	Zhao, Ran	Zhang, Yimin	Zhi, Chi	Xin, Xieke	Xue, Lifu