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PRACTICAL INFORMATION

Today's lecture — another new method/analysis...

- **main topic:** one-way ANOVA (analysis of variance),¹
 - * the step from two to multiple (≥ 2) independent samples for quantitative data,
 - * some similarity with 2-sample analysis, but also many new features,
- **contrasts** are not part of the course curriculum²,
- **additional topic:** Kruskal-Wallis test (PSLS Chapter 27)
— a non-parametric one-way ANOVA.

Schedule news:

- **home assignment 2** returned today; midterm not marked yet but solution posted,
- **home assignment 3** posted: worth 10 or 15% of course mark, due Thursday 7/11,
- optional **project proposal**: due on Monday 11/11,
- now **jumping ahead** in textbooks:
 - * we will come back to regression and correlation,
 - * **skip over** (for now) textbook references to residuals and R^2 .

¹ PSLs 4e: Chapters 24 & 26; S: Section 11.3 (too briefly); IPS 7e: Chapter 12.

² Contrasts are useful!: Yossa & Verdegem (2015), *Aquaculture* 437, 344–350; see media page.

DATA EXAMPLE(S): READING SCORES

Teaching reading comprehension³:

- 66 students, randomly assigned to one of 3 teaching groups, with 22 students in each group,
 - * Basal: traditional method,
 - * DRTA and Strat: innovative methods,
- 2 pre-tests (before teaching) and 3 post-tests (after teaching),
- **questions of interest**: compare the 3 groups, in particular the new ones versus Basal, and also DRTA versus Strat,
- in the lecture, we look at pre1 and post3:

Variable	Group	observations (22 in each row)							mean	sd
pre1	Basal	4	6	9	12	16	...	9	10.5	2.97
	DRTA	7	7	12	10	16	...	10	9.7	2.69
	Strat	11	7	4	7	7	...	8	9.1	3.34
post3	Basal	41	41	43	46	46	...	32	41.0	5.64
	DRTA	31	40	48	30	42	...	49	46.7	7.39
	Strat	53	47	41	49	43	...	42	44.3	5.77

³ IPS textbook dataset, from a study conducted by Jim Baumann and Leah Jones at the Purdue University School of Education.

NOTATION FOR ONE-WAY ANOVA

Data layout
and notation:

	group	observations (j)	number	mean	std.dev.
	1	$X_{11} \quad X_{12} \quad \dots \quad X_{1n_1}$	n_1	\bar{X}_1	s_1
row	2	$X_{21} \quad X_{22} \quad \dots \quad \dots \quad X_{2n_2}$	n_2	\bar{X}_2	s_2
(i)	\vdots	$\vdots \quad \vdots \quad \dots \quad \dots \quad \vdots$	\vdots	\vdots	\vdots
	I	$X_{I1} \quad X_{I2} \quad \dots \quad X_{In_I}$	n_I	\bar{X}_I	s_I

- X_{ij} = j th observation in i th group (row), where
 - * $i = 1, \dots, I$, and I = number of groups (rows),
 - * $j = 1, \dots, n_i$, and n_i = number of observations in i th group,
- denote also by $N = n_1 + \dots + n_I$ the **total** number of observations, and by $\bar{X} = \sum_{ij} X_{ij}/N$ the **overall mean**,
- the dataset/design is **balanced**, if all groups are equally large (i.e., $n_1 = \dots = n_I$), otherwise **unbalanced** (some groups of different size) — **balanced designs** are “nice”.⁴

The **natural model** would seem to be (assuming normal distributions),

$$\begin{array}{ccc}
 X_{11}, \dots, X_{1n_1} & \text{i.i.d. } & N(\mu_1, \sigma_1), \\
 \vdots & & \vdots \\
 X_{I1}, \dots, X_{In_I} & \text{i.i.d. } & N(\mu_I, \sigma_I),
 \end{array}$$

but we make the **additional assumption**: $\sigma_1 = \dots = \sigma_I$.

⁴ Making some calculations and formulas simpler, but when using a computer unbalancedness is not a problem.

STATISTICAL MODEL

Model: $X_{ij} = \mu_i + \varepsilon_{ij}, \quad i = 1, \dots, I; \quad j = 1, \dots, n_i,$

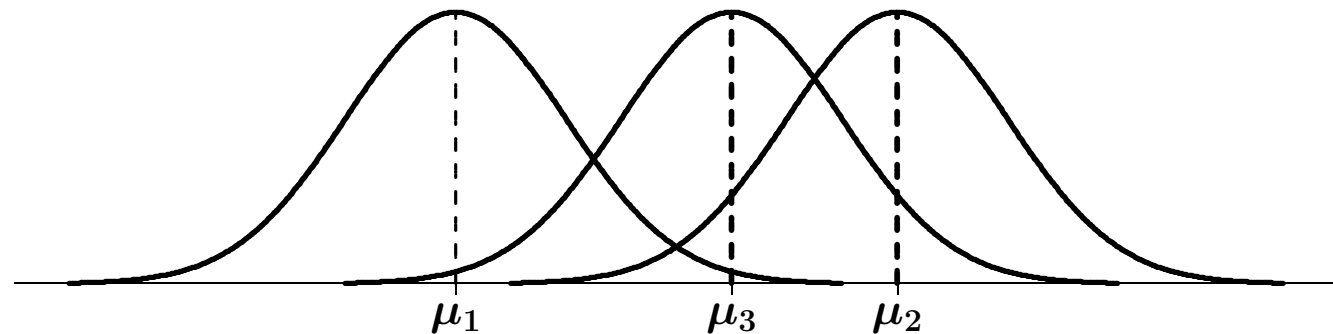
where ε_{ij} 's are i.i.d. and $\sim N(0, \sigma)$.

i	observations			
1	$X_{11} = \mu_1 + \varepsilon_{11}$	$X_{12} = \mu_1 + \varepsilon_{12}$...	$X_{1n_1} = \mu_1 + \varepsilon_{1n_1}$
2	$X_{21} = \mu_2 + \varepsilon_{21}$	$X_{22} = \mu_2 + \varepsilon_{22}$...	$X_{2n_2} = \mu_2 + \varepsilon_{2n_2}$
\vdots	\vdots	\vdots	...	\vdots
I	$X_{I1} = \mu_I + \varepsilon_{I1}$	$X_{I2} = \mu_I + \varepsilon_{I2}$...	$X_{In_I} = \mu_I + \varepsilon_{In_I}$

- **parameters:** μ_1, \dots, μ_I (group means) and σ (common standard deviation of all X 's and ε 's),
- $\varepsilon_{ij} = X_{ij} - \mu_i$, i.e. **the deviation of X_{ij} from its mean** $\Rightarrow \varepsilon$'s are interpreted as random errors / perturbations / noise,

- **same model** as on previous slide:
 $X_{ij} \sim N(\mu_i, \sigma)$.

Normal distributions for 3 groups:



ESTIMATION

Rules and formulas for estimation of model parameters:

- group sample means as estimates for μ 's:

$$\hat{\mu}_i = \bar{X}_i \sim N(\mu_i, \sigma/\sqrt{n_i}), \quad i = 1, \dots, I,$$
$$\text{SE}(\hat{\mu}_i) = s_p/\sqrt{n_i},$$

- pooled sample variance estimate for σ^2 (a weighted average of group variances s_i^2):

$$\hat{\sigma}^2 = s_p^2 = \sum_i \frac{n_i - 1}{N - I} s_i^2 = \sum_{ij} \frac{(X_{ij} - \bar{X}_i)^2}{N - I} = \text{SSE}/\text{DFE},$$
$$\hat{\sigma} = s_p = \sqrt{s_p^2},$$

where we have introduced the **new notation**:

- * $\text{SSE} = \sum_{ij} (X_{ij} - \bar{X}_i)^2$ — the within-group sum of squares,
- * $\text{DFE} = N - I = (n_1 - 1) + \dots + (n_I - 1)$ — the degrees of freedom for s_p^2 .

Confidence intervals for μ_i computed the “usual way”, e.g.

$$(1 - \alpha) \text{ CI for } \mu_i : \hat{\mu}_i \pm t^* \text{SE}(\hat{\mu}_i), \quad t^* = t_{1-\alpha/2}(\text{DFE}),$$

note: using the pooled standard deviation s_p and its DF for the confidence intervals.

MODEL CHECKING I

Summary of model assumptions:

- (1) all observations are **independent**,
- (2) all observations are **normally distributed**,
- (3) all observations have the **same standard deviation** (often called variance homogeneity or homoscedasticity),
- (4) all observations **within a group** have the **same mean**.

Useful graphical displays:

- **boxplots/stemplots/dotplots for all groups in same diagram** (overview of data, assumptions (2) and (3)),
- normal probability plots for each of the groups (2).

Useful statistics:

- standard descriptive statistics for each group (3),
- normality tests for each of the groups (2), **not overall**.

MODEL CHECKING II

Extra tool for model checking: **residuals** — to be introduced in the context of regression (next lecture), but **equally applicable** to ANOVA.

Practical considerations:

- assumption of **equal standard deviations**:
 - * textbook (PSLS/IPS) **guideline** based on group standard deviations s_i :
 - okay, if ratio of largest to smallest standard deviation less than 2,
 - may be too prescriptive for small group sizes (n_i) where the s_i are quite noisy,
 - * possible to **test** for equal standard deviations (in software):
 - **not** (necessarily) a good idea, because the test is more sensitive to unequal standard deviations and non-normality than the ANOVA itself \Rightarrow risk of stating a problem where there really is none. . . ,
 - however fine if such tests (Levene's test is preferable) are non-significant,
- dealing with **violations of assumptions**:
 - * if all groups show the **same non-normal pattern** (e.g., skewness), transformation may be a solution,
 - * in particular, if higher group means are associated with higher standard deviation, transformation with \log or $\sqrt{\cdot}$ may work well.

HYPOTHESIS AND TEST

Overall group equality hypothesis:

$H_0: \mu_1 = \dots = \mu_I$ (all groups equal, homogeneity between groups),

- alternative hypothesis H_a : some μ 's differ (“two-sided”),⁵
- test statistic calculated in several steps,
 - * define group sum of squares: $SSG = \sum_i n_i (\bar{X}_i - \bar{X})^2$ — a weighted sum of squared deviations between group means and the overall mean
 - * define group degrees of freedom: $DFG = I - 1$,
 - * introduce group mean square⁶: $MSG = SSG/DFG$,
 - * finally, the test statistic is: $F = MSG/s_p^2$,
- some “motivations”:
 - * F compares variation between groups with variation within groups,
 - * nominator and denominator have similar forms: $F = MSG/MSE$,⁷
- under H_0 : F -statistic $\sim F(DFG, DFE)$, and large values are critical for $H_0 \Rightarrow$ P -value calculated as: $P = P(F(DFG, DFE) > F_{obs})$.

⁵ It is a common misunderstanding that H_a implies all the μ 's to be different, but the opposite of H_0 is just that the means are **not all the same**.

⁶ Generally, a mean square is a sum of squares divided by the corresponding degrees of freedom.

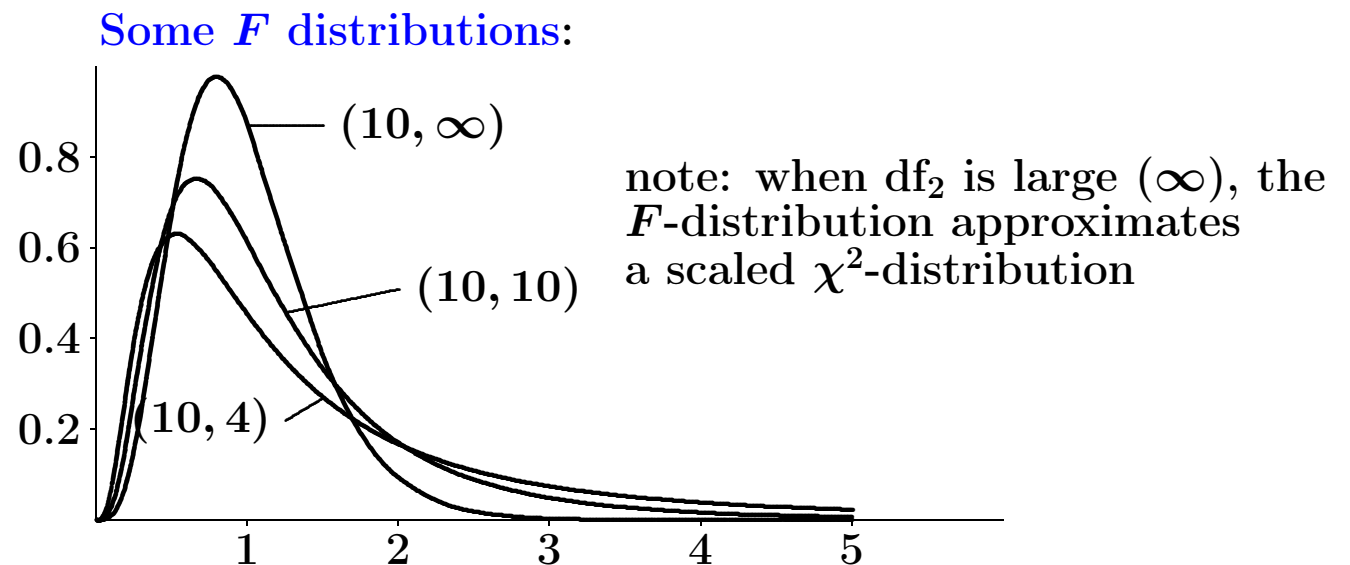
⁷ We previously (slide 9L-5) introduced notation to make $s_p^2 = SSE/DFE = MSE$.

F-DISTRIBUTIONS

Another distribution — to be used for **tests in normal models** (that are more complex than one or two samples):

- *F*-distributions have two parameters, and we write $F(df_1, df_2)$ to indicate them:
 - * df_1, df_2 are numbers in $\{1, 2, 3, \dots\}$
 - * called **numerator** (df_1) and **denominator** (df_2) **degrees of freedom**, because *F* variables are usually ratios,
 - * given from the data, and not to be estimated,
 - * the order of df_1 and df_2 is important: $F(df_1, df_2) \neq F(df_2, df_1)$,
- distributions on $(0, \infty)$
— only positive values,

- right skewed;
decreasing mean
and standard dev.
with increasing df_2 ;
Table F/E of
of PSLS/IPS
has percentiles.



ANOVA TABLE

Analysis of variance table = convenient layout for summarizing the analysis:

- idea: split variation in the data into parts:

$$\begin{aligned} \text{total variation} &= \text{variation between groups ("Groups")} \\ &+ \text{variation within groups ("Error"),} \end{aligned}$$

- collect quantities related to each source of variation on a separate line,
- provides **good overview** and eases computations (if done by hand),
- generalizes** to models with more variables than one.

Source	Degrees of freedom	Sum of squares	Mean square	F	P
Groups	$DFG = I - 1$	$SSG = \sum_i n_i (\bar{X}_i - \bar{X})^2$	$MSG = SSG / DFG$	MSG / MSE	$P(F \geq F_{\text{obs}})$
Error	$DFE = N - I$	$SSE = \sum_{ij} (X_{ij} - \bar{X}_i)^2$	$MSE = SSE / DFE$	$F \sim F(DFG, DFE)$	
Total	$DFT = N - 1$	$SST = \sum_{ij} (X_{ij} - \bar{X})^2$	$(MST = SST / DFT)$		

Notes:

- MST often omitted from table (\neq MSG + MSE),
- always remember:** $\hat{\sigma} = s_p = \sqrt{MSE}$.

EXERCISES 12.1, 12.9, 12.25

Exercise 12.1: (response, populations, I , n_i 's and N)

- (a) response = tomato yield, $I = 4$ varieties, all $n_i = 12$, and $N = 48$,
- (b) response = rate of attractiveness, $I = 5$ types of packaging, all $n_i = 40$, and $N = 200$,
- (c) response = weight loss, $I = 3$ programs, all $n_i = 20$, and $N = 60$.

Exercise 12.9: (degrees of freedom and hypotheses) For all settings, the hypotheses are:

$H_0 : \mu_1 = \mu_2 = \mu_3 = \mu_4$, $H_a : \text{some } \mu\text{'s different}$,
 where $I = 4, 5$ and 3 , respectively.

- (a) varieties (DF = 3), error (DF = 44), total (DF = 47), $F(3, 44)$,
- (b) packagings (DF = 4), error (DF = 195), total (DF = 199), $F(4, 195)$,
- (c) programs (DF = 2), error (DF = 57), total (DF = 59), $F(2, 57)$.

Exercise 12.25:

Source	Degrees of freedom	Sum of squares	Mean square	F
(a) Groups	3	104,855.87		
Error	32	70,500.59		
Total				

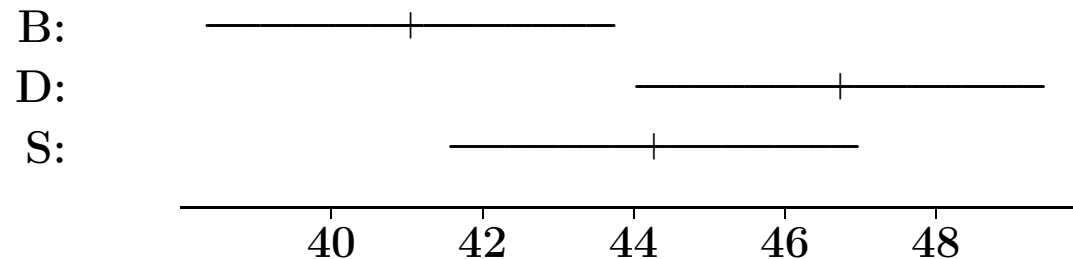
- (b) $H_0 : \mu_1 = \mu_2 = \mu_3 = \mu_4$, $H_a : \text{some } \mu\text{'s different}$,
- (c) $F \sim F(3, 32)$ under H_0 , $P = P(F(3, 32) > 15.9) \ll 0.001 \Rightarrow \text{reject } H_0$;
conclusion: there are some differences between groups,
- (d) $s_p^2 = \text{MSE} = 2203$, $s_p = \sqrt{2203} = 46.9$.

COMPARING AND PRESENTING GROUPS

Group comparisons based on confidence intervals for group means μ_i :

- principal method uses test/CI for difference between parameters (next slide),
- but conclusions available from group CIs in 2/3 cases (see figure):

example: reading data — 95% CIs for post3:



- * **B vs. D:** disjoint (non-overlapping) CIs \Rightarrow significance ($P < 0.05$),
 - * **D vs. S:** estimate inside another CI \Rightarrow no significance ($P > 0.05$),
 - * **B vs. S:** need CI for difference ($\mu_B - \mu_S$) to assess significance,
- method assumes **independent estimates**, and is unadjusted for multiple testing (following slides),
 - method is **applicable** to many other settings than one-way ANOVA.

PAIRWISE COMPARISONS

Generally, **how to proceed** after ANOVA? (and any pre-planned contrasts (appendix))

If **overall H_0** is **non-significant**: no further analysis needed (relevant), report $\hat{\mu}$ and P .

If **overall H_0** is **significant**:

- for **illustration**: plot of $\hat{\mu}_i$'s with error bars (previous page),
- for **informal comparisons** of group levels — LSD (least significant difference):

- * margin of error of CIs for pairwise difference $\mu_i - \mu_j$ based on $\bar{X}_i - \bar{X}_j$:

$$\text{LSD}_{1-\alpha} = t^* s_p \sqrt{\frac{1}{n_i} + \frac{1}{n_j}}, \quad t^* = t_{1-\alpha/2}(\text{DFE}),$$

- * **most useful for *balanced data*** (all n_i are equal), because one LSD-value applies to comparisons between any two groups,
- * **example** (reading data, post3):

$$\text{LSD}_{0.95} = t_{0.975}(63) \times 6.314 \times \sqrt{2/22} = 3.80,$$

- * **interpretation**: smallest distance between \bar{X}_i and \bar{X}_j so that CI for $\mu_i - \mu_j$ does not contain 0 ($\Rightarrow H_0 : \mu_i = \mu_j$ significant at level α , if pre-planned⁸),
- * same as pairwise 2-sample t -tests based on s_p (also called **Fisher** method),
- for **formal comparisons** of group levels we must take into account an increase in overall (simultaneous) error level for multiple unplanned⁸ comparisons.

⁸ The theory behind statistical hypothesis testing is based on pre-determined hypotheses, and **does not apply** to hypotheses suggested by the data!

BONFERRONI METHOD FOR MULTIPLE TESTS

Basis: If A and B are events, it always holds that: $P(A \text{ or } B) \leq P(A) + P(B)$.

In particular, in the context of performing several tests,

$$P(\text{error in one or more tests}) \leq \text{sum of error probabilities}$$

Therefore, **if we make k tests/comparisons**, we can achieve the **simultaneous** error probability for all tests to be $\leq \alpha$, by taking the error prob. **for each test** equal to α/k .

Adjustment of LSD method

for k preplanned tests:

$$\text{LSD}_{1-\alpha/k} = t_{1-\alpha/(2k)}(\text{DFE}) s_p \sqrt{\frac{1}{n_i} + \frac{1}{n_j}}$$

Adjustment of LSD method for unplanned comparisons (suggested by the data):

- take $k = \text{total number of comparisons} = \text{“}I \text{ choose } 2\text{”} = I(I-1)/2$,
- use above LSD-formula with that value of k .

Notes for Bonferroni method:

- is **conservative** (wider CIs and higher P -values),
- is flexible and applicable to many situations (not only one-way ANOVA).

Alternative **Tukey method** for multiple comparisons, described in Chapter 26 of PSLS:

- acceptable method, less conservative than Bonferroni,
- method difficult to explain, and less flexible than Bonferroni.

SUMMARY OF ONE-WAY ANOVAS FOR READING SCORES

Statistical models (for pre1 and post3 variables):

$$X_{ij} = \mu_i + \varepsilon_{ij},$$

where $i = 1, 2, 3$ (B, D, S), $j = 1, \dots, 22$ (students), and ε_{ij} 's i.i.d. and $\sim N(0, \sigma)$.

ANOVA tables:

		pre1				post3			
Source	DF	SS	MS	<i>F</i>	<i>P</i>	SS	MS	<i>F</i>	<i>P</i>
Groups	2	20.58	10.29	1.13	0.33	357.3	178.7	4.48	0.015
Error	63	572.45	9.09			2511.7	39.9		
Total	65	593.03				2869.0			

Hypothesis $H_0 : \mu_1 = \mu_2 = \mu_3$ (no differences), H_a : not H_0 ,

Test of $H_0 \rightarrow$ table *F*-tests: not significant for pre1, but significant for pre3.

Estimation/
Presentation:

(using t^*
= $t_{0.975}(63)$
= 2.00)

statistic	pre1	post3		
	overall	Basal	DRTA	Strat
mean	9.79	41.05	46.73	44.27
std.dev. s_p	$\sqrt{9.09} = 3.01$	$\sqrt{39.9} = 6.31$		
SE(mean)	$s_p/\sqrt{66} = 0.37$	$s_p/\sqrt{22} = 1.35$		
95% CI	± 0.74	± 2.69		
LSD _{0.95}	—	3.80		

Conclusions: (pre1): no differences before teaching,

(post3): no differences D/S or B/S; difference D/B.

METHOD FOR PRESENTING GROUP COMPARISONS

Issue: pairwise comparison results are not easy to present compactly, because the number of comparisons is larger than number of groups (I), and growing fast with I (slide 9L–14).

Idea: indicate significance between groups by codes displayed in list of groups (e.g., table of group estimates or CIs).

Most **common system**⁹ uses letter codes $a, b, c \dots$, so that:

- groups with the same letter are **not** significantly different,
- for **manual construction** of codes, proceed as follows:
 - * **order** group means from lowest to highest,
 - * **designate** a to highest group + all groups not significantly different from it,
 - * **designate** b to next group in the same way (but drop if same pattern as for a),
 - * **continue** through all groups,
- **example:** reading data with uncorrected 5% error coding:

$$B^b \quad S^{ab} \quad D^a ,$$

⇒ only significant difference is between B and D (as previously shown).

⁹ Available in both Minitab and Stata.

KRUSKAL-WALLIS TEST

- **Model:** I independent samples from different distributions:

$$\begin{array}{ccc} X_{11}, \dots, X_{1n_1} & \text{i.i.d.} & \text{with distribution } \text{Dist}_1, \\ \vdots & & \vdots \\ X_{I1}, \dots, X_{In_I} & \text{i.i.d.} & \text{with distribution } \text{Dist}_I, \end{array}$$

- **Hypotheses** — two possibilities:

(1) H_0 : $\text{Dist}_1 = \dots = \text{Dist}_I$ (same distribution), H_a : not H_0 ,¹⁰

(2) **assuming** “ $\text{Dist}_i = \text{Dist}_0 + \Delta_i$ ” (distributions differ only in positions Δ_i)¹¹,
 H_0 : Δ_i 's = 0 (corresponding to same medians) versus two-sided alternative H_a ,

- **Test procedure:**

- * **rank all observations** as if a single sample, and compute rank averages \bar{R}_i for each group i ,

- * **test statistic:** sum of squares for ranks,

$$H = \text{constant} \times \sum_i n_i (\bar{R}_i - \bar{R})^2, \quad \bar{R} = (N+1)/2,$$

corresponding to SSG in a one-way ANOVA for ranks,

- * **under H_0 :** distribution of Y has **no easy form**, and software use different approximations for the P -value (based on the $\chi^2(I-1)$ -distribution).

¹⁰ More specific wording of H_a : for some (i, i') , P_i is systematically larger than $P_{i'}$; see Chapter 27 of PSLS.

¹¹ The same assumption as for the Mann-Whitney-Wilcoxon test, implying all distributions to have the **same shape**.

NOTES ON HOME ASSIGNMENT 2

- **10% or 15%:** most of you chose the 15% version \Rightarrow less work for home assignment 3,
- **Overall impression** — quite variable in (visible) effort and marks:
repeating the same text over and over is not really helpful, focus instead on the differences from one analysis to the next, both in **methods** and **conclusions**,
- **When is a statistical analysis approximate?:**
 - * if the statistical methods involve approximate distributions (with real concern about their validity), e.g. normal approximation to z -test for a binomial distribution,
 - * if the model assumptions are violated to some degree, e.g. assumed normal distributions for visibly non-normal data, but the procedures are robust (e.g. as discussed on 6L–9),
 - * *not* automatically because of small sample size (many statistical methods account for this), but there may be a concern that a sample is not representative for the population,
- **When can we have high confidence in a conclusion?:** if methods are exact, or if conclusions are so clear that they are unlikely to be affected by any approximations,
- **Always** assess model assumptions and conditions for methods,
 - * the assumptions for analysis of paired sampled are *entirely* for the differences,
- Include in **conclusions**: statement of significance and “plain language” wording about the evidence offered by the data, and the magnitude and direction of any important (e.g., significant) effects,
- Some **presentation** comments:
 - * Minitab results do not need to be duplicated by manual calculation (unless requested),
 - * Minitab’s “P=0.000” means $P < 0.0005$, not $P = 0$,
 - * “statistical difference” is not a meaningful term.

SUMMARY NOTES

Key words and concepts for one-way ANOVA:

- comparison of multiple samples (SRS or i.i.d.), assumed normally distributed with separate means but same variance,
- **estimation**: sample means, pooled variance/standard deviation,
- **model checking**: normality in each sample, equal standard deviation rule,
- **hypothesis and test**: F -statistic and F -distribution, calculations organized in ANOVA table with:
 - * sum of squares (SS), degrees of freedom (DF), mean square (MS),
- **after ANOVA**: significant test is followed by pairwise comparisons (or contrasts, not in course syllabus),
 - * pre-planned or unplanned comparisons,
 - * Bonferroni adjustment for multiple comparisons,
- **nonparametric** rank-based one-way ANOVA: Kruskal-Wallis test.

APPENDIX: CONTRASTS

Another type of null hypothesis:

- more specific than overall homogeneity of groups (illustrated by the reading data):
 - (1) involves two particular groups, e.g. $H_0: \mu_D = \mu_S$, or
 - (2) involves a linear combination of several group means, e.g.: $\mu_B = (\mu_D + \mu_S)/2$,
- often (not necessarily) considered **after** test of overall H_0 ,
- ideally decided prior to data collection/analysis (otherwise different methods needed).

Definition: A **contrast** is a linear combination of group mean parameters of the form,

$$L = \sum_i c_i \mu_i, \quad (\text{PSLS notation})$$

where the c_i 's are **known constants** with sum 0 ($\sum_i c_i = 0$).

Examples from above: (1): $c_D = 1, c_S = -1, c_B = 0$, and (2): $c_B = 1, c_D = -0.5, c_S = -0.5$.

Statistical inference for contrasts:

- **estimate:** $\hat{L} = \sum_i c_i \bar{X}_i$ (sample contrast),
- **standard error:** $SE_{\hat{L}} = s_p \sqrt{\sum_i c_i^2 / n_i}$,
- $(1 - \alpha)$ **confidence interval** for L : $\hat{L} \pm t^* SE_{\hat{L}}$, $t^* = t_{1-\alpha/2}(\text{DFE})$,
- **test** of $H_0: L = 0$ by: $t = \hat{L} / SE_{\hat{L}} \sim t(\text{DFE})$ under H_0 .