Basic Analysis of Variance and the General Linear Model

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Why is it called analysis of variance anyway?

- If we are interested in group mean differences, why are we looking at variance?
- $\mathcal{L}_{\mathcal{A}}$ t-test only one place to look for variability
- More groups, more places to look
- $\frac{1}{2}$ Variance of group means around a central tendency (grand mean – ignoring group membership) really tells us, on average, how much each group is different from the central tendency (and each other)

Why is it called analysis of variance anyway?

- Average mean variability around GM needs to be compared to average variability of scores around each group mean
- **Nationalle Solution Canada Exercise 1.1 Variability in any distribution can be broken** down into conceptual parts:

total variability $=$ (variability of each group mean around the grand mean) $+$ (variability of each person's score around their group mean)

General Linear Model (GLM)

- The basis for most inferential statistics (e.g. 420, 520, 524, etc.)
- Simple form of the GLM

score=grand mean + independent variable + error $Y = \mu + \alpha + \varepsilon$

General Linear Model (GLM)

- The basic idea is that everyone in the population has the same score (the grand mean) that is changed by the effects of an independent variable (A) plus just random noise (error)
- Some levels of A raise scores from the GM, other levels lower scores from the GM and yet others have no effect.

General Linear Model (GLM)

- Error is the "noise" caused by other variables you aren't measuring, haven't controlled for or are unaware of.
	- \bigcap Error like A will have different effects on scores but this happens independently of A.
	- \overline{O} If error gets too large it will mask the effects of A and make it impossible to analyze the effects of A
	- \circ Most of the effort in research designs is done to try and \circ minimize error to make sure the effect of A is not "buried" in the noise.
	- \circ The error term is important because it gives us a "yard stick" with which to measure the variability cause by the A effect. We want to make sure that the variability attributable to A is greater than the naturally occurring variability (error)

 $\mathcal{L}_{\mathcal{A}}$

Example of GLM – ANOVA backwards

- \bigcirc We can generate a data set using the GLM formula
- Ω We start off with every subject at the GM (e.g. $\mu=5$)

 - Then we add in the effect of A (a1 adds 2 points and a2 subtracts 2 points)

 \bigcirc Changes produced by the treatment represent deviations around the GM

$$
n\sum (\overline{Y}_j - GM)^2 = n[(7-5)^2 + (3-5)^2] =
$$

5(2)² + 5(-2)² or 5[(2)² + (-2)²] = 40

$\frac{1}{2}$ Now if we add in some random variation (error)

- Now if we calculate the variance for each group:

 \circ The average variance in this case is also going to be $1.5(1.5 + 1.5/2)$

• We can also calculate the total variability in the data regardless of treatment group

$$
s_{N-1}^{2} = \frac{\sum Y^{2} - \frac{(\sum Y)^{2}}{N}}{N-1} = \frac{302 - \frac{50^{2}}{10}}{9} = 5.78
$$

The average variability of the two groups is $\mathcal{L}_{\mathcal{A}}$ smaller than the total variability.

The total variability can be partitioned into between group variability and error.

$$
\left(Y_{ij}-GM\right)=\left(Y_{ij}-\overline{Y}_{j}\right)+\left(\overline{Y}_{j}-GM\right)
$$

- If you ignore group membership and calculate the mean of all subjects this is the grand mean and total variability is the deviation of all subjects around this grand mean
- Remember that if you just looked at deviations it would most likely sum to zero so…

$$
\sum_{i} \sum_{j} \left(Y_{ij} - GM\right)^2 = n \sum_{j} \left(\overline{Y}_{j} - GM\right)^2 + \sum_{i} \sum_{j} \left(Y_{ij} - \overline{Y}_{j}\right)^2
$$

SS_{total} = SS_{bg} + SS_{wg}
SS_{total} = SS_A + SS_{S/A}

 $52 = 40 + 12$

- degrees of freedom
	- \circ DF_{total} = N 1 = 10 -1 = 9

$$
OF_A = a - 1 = 2 - 1 = 1
$$

 $\text{OF}_{S/A} = a(S-1) = a(n-1) = an - a = 0$ $N - a = 2(5) - 2 = 8$

- Variance or Mean square
	- \circ MS_{total} = 52/9 = 5.78

$$
\circ \quad \text{MS}_A = 40/1 = 40
$$

$$
\circ \quad \, MS_{S/A} = 12/8 = 1.5
$$

- Test statistic
	- \bigcirc \circ F = MS_A/MS_{S/A} = 40/1.5 = 26.67
	- \circ Critical value is looked up with df_A, df_{S/A} \bigcirc and alpha. The test is always nondirectional.

 $\mathcal{L}_{\mathcal{A}}$ ANOVA summary table

 Under each part of the equations, you divide by the number of scores it took to get the number in the numerator

Analysis – computational approach

Analysis of sample problem

$$
SST = 302 - \frac{50^2}{10} = 52
$$

$$
SSA = \frac{35^2 + 15^2}{5} - \frac{50^2}{10} = 40
$$

$$
SSS/A = 302 - \frac{35^2 + 15^2}{5} = 12
$$

Analysis – regression approach

Analysis - regression approach

$$
Y = a + bX + e
$$

$$
e = Y - Y'
$$

Analysis – regression approach

 Sums of squares ()2 ϵ Ω 2 $(2 \cdot 7 \cdot 7)$ 200 20 $\frac{(2)^{r}}{2} = \frac{302}{50}$ $(Y) = \sum Y^2 - \frac{(2.3)}{15} = 302 - \frac{50}{10} = 52$ 10*Y* $SS(Y) = \sum Y^2$ *N*= [−] ⁼ [−] ⁼∑ $\sum Y^2 \frac{1}{\sqrt{2}}$ ()2 \sim 2 2 $(2 \tbinom{2}{10}$ 0 $(X) = \sum X^2 - \frac{(21)}{10} = 10 - \frac{1}{10} = 10$ 10*X* $SS(X) = \sum X$ *N* $=$ $\sum A$ $\frac{ }{ }$ $\frac{ }{ }$ \equiv $\frac{ }{ }$ ∑ $\sum X^2 (\sum Y)(\sum X)$ (50)(0) $(YX) = \sum_{X} YX - \frac{2\sqrt{2\pi}}{X} = 20 - \frac{(2\sqrt{2})(3)}{10} = 20$ 10 $SP(YX) = \sum YX - \frac{(\sum Y)(\sum X)}{N} = 20 - \frac{(50)^{7}}{1}$ *N* $=$ $\sum_{i=1}^{n} I \Lambda - \frac{2 \pi i}{\Delta I} = 20 - \frac{2 \pi}{\Delta I} =$ $\sum YX - \frac{(\sum Y)(\sum X)}{N} = 20 - \frac{(50)(0)}{10}$

Analysis – regression approach

$$
SS_{(Total)} = SS(Y) = 52
$$

$$
SS_{(regression)} = \frac{[SP(YX)]^2}{SS(X)} = \frac{20^2}{10} = 40
$$

$$
SS_{(residual)} = SS_{(total)} - SS_{(regression)} = 52 - 40 = 12
$$

Intercept $\mathcal{L}_{\mathcal{A}}$

$$
a = \overline{Y} - b\overline{X} = 5 - 2(0) = 5
$$

Analysis - regression approach

$$
Y' = a + bX
$$

For a_1 :

$$
Y' = 5 + 2(1) = 7
$$

For a_2 :

$$
Y' = 5 + 2(-1) = 3
$$

Analysis – regression approach

Degrees of freedom \circ at $\alpha_{\rm max}$ = # of prediction \circ df_(reg.) = # of predictors \bigcirc \circ df_(total) = number of cases –1 \bigcirc \circ df_(resid.) = df(total) – df(reg.) = $9 - 1 = 8$

- Any type of measurement will include a certain amount of random variability.
- In the F-test this random variability is seen in two places, random variation of each person around their group mean and each group mean around the grand mean.
- \blacksquare The effect of the IV is seen as adding further variation of the group means around their grand mean so that the F-test is really:

$$
F = \frac{effect + error_{BG}}{}
$$

error

WG

If there is no effect of the IV than the equation breaks down to just:

$$
F = \frac{error_{BG}}{error_{WG}} \approx 1
$$

 \overline{O} which means that any differences between the groups is due to chance alone.

- The F-distribution is based on having a between groups variation due to the effect that causes the F-ratio to be larger than 1.
- Like the t-distribution, there is not a single F-distribution, but a family of distributions. The F distribution is determined by both the degrees of freedom due to the effect and the degrees of freedom due to the error.

 Robust – a robust test is one that is said to be fairly accurate even if the assumptions of the analysis are not met. ANOVA is said to be a fairly robust analysis. With that said…

- Normality of the sampling distribution of means
	- This assumes that the sampling distribution of each level of the IV is relatively normal.
	- o The assumption is of the sampling distribution not the scores themselves
	- This assumption is said to be met when there is relatively equal samples in each cell and the degrees of freedom for error is 20 or more.

- Normality of the sampling distribution of means
	- \circ If the degrees of freedom for error are small \bigcirc than:
		- The individual distributions should be checked for skewness and kurtosis (see chapter 2) and the presence of outliers.
		- **If the data does not meet the distributional** assumption than transformations will need to be done.

- Independence of errors the size of the error for one case is not related to the size of the error inanother case.
	- \bigcirc This is violated if a subject is used more than once (repeated measures case) and is still analyzed with between subjects ANOVA
	- o This is also violated if subjects are ran in groups. This \overline{O} is especially the case if the groups are pre-existing
	- This can also be the case if similar people exist within \overline{O} a randomized experiment (e.g. age groups) and can be controlled by using this variable as a blocking variable.

- Homogeneity of Variance since we are assuming that each sample comes from the same population and is only affected (or not) by the IV, we assume that each groups has roughly the same variance
	- \overline{O} Each sample variance should reflect the population variance, they should be equal to each other
	- \overline{O} Since we use each sample variance to estimate an average within cell variance, they need to be roughly equal

Homogeneity of Variance \circ An easy test to assess this assumption is:

max $F_{\text{max}} \leq 10$, than the variances are roughly homogenous

Absence of outliers

- Outliers a data point that doesn't really belong with the others
	- \Box Either conceptually, you wanted to study only women and you have data from a man
	- \Box Or statistically, a data point does not cluster with other data points and has undue influence on the distribution
	- \Box This relates back to normality

$\overline{\mathbb{R}^n}$ Absence of outliers

FIGURE 3.3 Assessing Outliers through Disconnectedness Where the Low Score at a_1 in (a) Is More Likely to Be a True Outlier than the Same Low Score in (b)