

Statistics

Week 11: Single Factor Experiments (Chapters 12)

ESD, SUTD

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Information

Tuesday second half: last guest lecture.

Thursday 1pm: homework 3 due. You can submit on *eDimension*, or in the homework box labeled 'Statistics' on level 7, building 1.

Outline

- 1 Analysis of single factor experiments

Introduction

Independent samples design allows us to compare two groups. Now we look at techniques for comparing *more than two* groups.

More formally, we look at an experiment which measures a response from more than two groups (or **treatments**). The treatments are levels of a single treatment **factor**.

The available experimental units are randomly assigned to each treatment (no matching).

Example: we might want to measure the compression during a crash for small, medium, and large cars.

Set up

Group (or treatment)			
1	2	...	k
y_{11}	y_{21}	\cdots	y_{k1}
y_{12}	y_{22}	\cdots	y_{k2}
\vdots	\vdots	\vdots	\vdots
y_{1n_1}	y_{2n_2}	\cdots	y_{kn_k}

The group sizes n_i do *not* necessarily equal.

Total sample size: $N = \sum_{i=1}^k n_i$.

Sample mean for group i : \bar{y}_i .

Sample standard deviation for group i : s_i .

Grand mean: $\bar{\bar{y}} = \frac{1}{N} \sum_{i,j} y_{ij}$. Note: this is a double sum.

Set up, continued

We assume that for each group, the response is *normally* distributed, and that all the groups have the same variance σ^2 but not necessarily the same mean μ_i .

Exercise

(1) Show that

$$\sum_{i=1}^k n_i (\bar{y}_i - \bar{\bar{y}}) = 0.$$

(2) If all the group sizes are the same, give an interpretation of $\bar{\bar{y}}$.

Confidence interval

Since each s_i^2 is an estimator of σ^2 , we can pool them together to get a better estimate for σ^2 :

$$s^2 := \frac{\sum_{i,j} (y_{ij} - \bar{y}_i)^2}{N - k} = \frac{\sum_i (n_i - 1) s_i^2}{\sum_i (n_i - 1)}.$$

Using s , we can write down the $(1 - \alpha)$ -level confidence interval for μ_i (the true mean of group i):

$$\bar{y}_i - t_{N-k, 1-\alpha/2} \frac{s}{\sqrt{n_i}} \leq \mu_i \leq \bar{y}_i + t_{N-k, 1-\alpha/2} \frac{s}{\sqrt{n_i}}.$$

The null hypothesis

Our primary interest is in comparing whether the μ_i 's are actually different. Set up $H_0 : \mu_1 = \mu_2 = \cdots = \mu_k$.

A preliminary test can be carried out using side-by-side box plots.

Can we use confidence intervals to test for H_0 ? It turns out that even if all the CI's contain a number in common, it is not obvious how strongly this supports H_0 .

The tabular set up of the data values y_{ij} suggests that we can use a tool encountered before: *analysis of variance*.

The idea behind ANOVA

The idea is to compare the variation *between* the groups to the variation *within* each group.

The total variance can (once again) be decomposed into the above two terms.

$$\mathbf{SST} := \sum_{i,j} (y_{ij} - \bar{y})^2, \quad \text{df} = N - 1 \quad (\text{total}),$$

$$\mathbf{SSE} := \sum_{i,j} (y_{ij} - \bar{y}_i)^2, \quad \text{df.} = N - k \quad (\text{within}),$$

$$\mathbf{SSA} := \sum_{i=1}^k n_i (\bar{y}_i - \bar{y})^2, \quad \text{df} = k - 1 \quad (\text{between}).$$

The ANOVA identity

SSA is the weighted sum of squared errors between all treatments, and can also be written as $\sum_{i,j} (\bar{y}_i - \bar{\bar{y}})^2$. Its degree of freedom is $(k - 1)$ due to the relation in the previous exercise.

A 'large enough' value of SSA would indicate that H_0 is false.

Let **MSA** = $SSA/(k - 1)$, **MSE** = $SSE/(N - k) = s^2$, and $F = MSA/MSE$.

The ANOVA identity

$$\mathbf{SST} = \mathbf{SSA} + \mathbf{SSE}.$$

The set up here is just like regression (in fact, it is because the data can be written as a regression model).

Proof of the ANOVA identity

$$\begin{aligned}
 \sum_{i=1}^k \sum_{j=1}^{n_i} (y_{ij} - \bar{y})^2 &= \sum_{i,j} (y_{ij} - \bar{y}_i + \bar{y}_i - \bar{y})^2 \\
 &= \sum_{i,j} (\bar{y}_i - \bar{y})^2 + \sum_{i,j} (y_{ij} - \bar{y}_i)^2 + 2 \sum_i (\bar{y}_i - \bar{y}) \sum_j (y_{ij} - \bar{y}_i) \\
 &= \sum_i n_i (\bar{y}_i - \bar{y})^2 + \sum_{i,j} (y_{ij} - \bar{y}_i)^2 + 0.
 \end{aligned}$$

As in regression, F satisfies a $F_{k-1, N-k}$ distribution if H_0 is true.

We can reject H_0 with $(1 - \alpha)$ confidence if $F > f_{k-1, N-k, 1-\alpha}$.

Exercises

Use $\alpha = 0.05$ throughout.

(1) Complete all the calculations using the formulas, in the spreadsheet '*cars*'.

Check your answers against *Excel*'s Anova: Single Factor function.

(2) Complete all the calculations in the spreadsheet '*sugar*'; think about how to find SSE and SST.

(3) Construct the ANOVA tables in the spreadsheet '*anorexia*', and answer the question.