

Reminders: Propagation of Error, and Standard Errors for Derived Quantities

36-402, Advanced Data Analysis

Suppose we are trying to estimate some quantity θ . We compute an estimate $\hat{\theta}$, based on our data. Since our data is more or less random, so is $\hat{\theta}$. One convenient way of measuring the purely statistical noise or uncertainty in $\hat{\theta}$ is its standard deviation. This is the **standard error** of our estimate of θ .¹ Standard errors are not the only way of summarizing this noise, nor a completely sufficient way, but they are often useful.

Suppose that our estimate $\hat{\theta}$ is a function of some intermediate quantities $\hat{\psi}_1, \hat{\psi}_2, \dots, \hat{\psi}_p$, which are also estimated:

$$\hat{\theta} = f(\hat{\psi}_1, \hat{\psi}_2, \dots, \hat{\psi}_p) \quad (1)$$

For instance, θ might be the difference in expected values between two groups, with ψ_1 and ψ_2 the expected values in the two groups, and $f(\psi_1, \psi_2) = \psi_1 - \psi_2$. If we have a standard error for each of the original quantities $\hat{\psi}_i$, it would seem like we should be able to get a standard error for the **derived quantity** $\hat{\theta}$. There is in fact a simple if approximate way of doing so, which is called **propagation of error**².

We start with (what else?) a Taylor expansion. We'll write ψ_i^* for the true (ensemble or population) value which is estimated by $\hat{\psi}_i$.

$$f(\psi_1^*, \psi_2^*, \dots, \psi_p^*) \approx f(\hat{\psi}_1, \hat{\psi}_2, \dots, \hat{\psi}_p) + \sum_{i=1}^p (\psi_i^* - \hat{\psi}_i) \left. \frac{\partial f}{\partial \psi_i} \right|_{\psi=\hat{\psi}} \quad (2)$$

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$$\hat{\theta} \approx \theta^* + \sum_{i=1}^p (\hat{\psi}_i - \psi_i^*) f'_i(\hat{\psi}) \quad (4)$$

introducing f'_i as an abbreviation for $\frac{\partial f}{\partial \psi_i}$. The left-hand side is now the quantity whose standard error we want. I have done this manipulation because now it is a lin-

¹It is not, of course, to be confused with the standard deviation of the data. It is not even to be confused with the standard error of the mean, unless θ is the expected value of the data and $\hat{\theta}$ is the sample mean.

²Or, sometimes, the **delta method**.

ear function (approximately!) of some random quantities whose variances we know, and some derivatives which we can calculate.

Remember the rules for arithmetic with variances: if X and Y are random variables, and a , b and c are constants,

$$\text{Var}[a] = 0 \quad (5)$$

$$\text{Var}[a + bX] = b^2 \text{Var}[X] \quad (6)$$

$$\text{Var}[a + bX + cY] = b^2 \text{Var}[X] + c^2 \text{Var}[Y] + 2bc \text{Cov}[X, Y] \quad (7)$$

While we don't know $f(\psi_1^*, \psi_2^*, \dots, \psi_p^*)$, it's constant, so it has variance 0. Similarly, $\text{Var}[\widehat{\psi}_i - \psi_i^*] = \text{Var}[\widehat{\psi}_i]$. Repeatedly applying these rules to Eq. 4,

$$\text{Var}[\widehat{\theta}] \approx \sum_{i=1}^p (f'_i(\widehat{\psi}))^2 \text{Var}[\widehat{\psi}_i] + 2 \sum_{i=1}^{p-1} \sum_{j=i+1}^p f'_i(\widehat{\psi}) f'_j(\widehat{\psi}) \text{Cov}[\widehat{\psi}_i, \widehat{\psi}_j] \quad (8)$$

The standard error for $\widehat{\theta}$ would then be the square root of this.

If we follow this rule for the simple case of group differences, $f(\psi_1, \psi_2) = \psi_1 - \psi_2$, we find that

$$\text{Var}[\widehat{\theta}] = \text{Var}[\widehat{\psi}_1] + \text{Var}[\widehat{\psi}_2] - \text{Cov}[\widehat{\psi}_1, \widehat{\psi}_2] \quad (9)$$

just as we would find from the basic rules for arithmetic with variances. The approximation in Eq. 8 comes from the nonlinearities in f .

If the estimates of the initial quantities are uncorrelated, Eq. 8 simplifies to

$$\text{Var}[\widehat{\theta}] \approx \sum_{i=1}^p (f'_i(\widehat{\psi}))^2 \text{Var}[\widehat{\psi}_i] \quad (10)$$

and, again, the standard error of $\widehat{\theta}$ would be the square root of this. This special case is sometimes called *the* propagation of error formula, but that seems like a bad usage.