

# Behrens-Fisher (Extra Credit)

## Problem Setup

Recall the two sample testing scenario

$$\begin{aligned}x_i &\sim N(\theta_x, \sigma_x^2), & i = 1, \dots, N_x, \\y_i &\sim N(\theta_y, \sigma_y^2), & i = 1, \dots, N_y.\end{aligned}$$

There are *three* important cases to distinguish regarding the variances  $\sigma_x^2$  and  $\sigma_y^2$ : case 1) both  $\sigma_x^2$  and  $\sigma_y^2$  known, case 2)  $\sigma_x^2 = \sigma_y^2$  but unknown, and case 3)  $\sigma_x^2 \neq \sigma_y^2$  with both unknown..

Cases 1 and 2 do not typically involve approximations (since the sampling distributions are known to be Normally distributed).

For case 1, we know:  $\bar{X} - \bar{Y} \sim N(\theta_x - \theta_y, \sigma_x^2 + \sigma_y^2)$ .

For case 2, we know:  $\bar{X} - \bar{Y} \sim T_\nu(\theta_x - \theta_y, S_p^2)$ , where  $S_p^2 = \frac{(N_x-1)S_x^2 + (N_y-1)S_y^2}{N_x + N_y - 2}$ , with  $S_x^2 = \frac{\sum_{i=1}^{N_x} (x_i - \bar{X})^2}{N_x - 1}$ ,  $S_y^2 = \frac{\sum_{i=1}^{N_y} (y_i - \bar{Y})^2}{N_y - 1}$ , and  $\nu = N_x + N_y - 2$ .

## One-sided Testing

Consider the one sided hypothesis test:

$$\begin{aligned}H_0 : \theta_x - \theta_y &= 0 \\H_A : \theta_x - \theta_y &< 0.\end{aligned}$$

For case 1, with data generated under  $H_0 : (\theta_x = \theta_y)$ , we incur a “Type 1 Error” if,  $\frac{\bar{X} - \bar{Y}}{(\sigma_x^2/N_x + \sigma_y^2/N_y)^{1/2}} > R$ . For this particular test, if  $R = 1.6449$  (very approximately the 95<sup>th</sup> quantile), the theoretical Type 1 Error is 0.05.

Similarly, for case 2, with data generated under  $H_0 : (\theta_x = \theta_y)$ , we incur a Type 1 Error if,  $\frac{\bar{X} - \bar{Y}}{(S_p^2(1/N_x + 1/N_y))^{1/2}} > R$ . For the Type 1 Error to be 0.05,  $R$  would be specified as the 95<sup>th</sup> quantile from a *standard* T-distribution (shift=0, scale=1), with

degrees of freedom  $N_x + N_y - 2$ .

For cases where  $\sigma_x^2 \neq \sigma_y^2$ , The “Welch” statistic follows as:

$$T = \frac{\bar{X} - \bar{Y}}{(s_x^2/N_x + s_y^2/N_y)^{1/2}}. \quad (1)$$

It is a fact that with  $\sigma_x^2 \neq \sigma_y^2$ ,  $T$  does not follow a T-distribution. However, in the “old -days”, people were inclined to suggest that  $T$  was very close to a T-distribution, with degrees of freedom:

$$\nu_{ws} = \frac{(S_x^2/N_x + S_y^2/N_y)^2}{S_x^4/(N_x^2(N_x - 1)) + S_y^4/(N_y^2(N_y - 1))},$$

which is often referred to as the Welch-Satterthwaite correction. In class, we showed that (note that we used normally distributed data) if we let  $T > R$  define a Type 1 Error, where  $R$  was specified as the 95<sup>th</sup> quantile from a *standard* T-distribution (shift=0, scale=1), with degrees of freedom  $\nu_{ws}$ , the Type 1 Error was *approximately 0.05*.

## 10% Midterm Credit Points

### Verification

1. Simulate data according to Cases 1, 2, and 3, and check the actual Type 1 Error rates. It is your job to decide how many variations of data simulations are necessary.

### Bayesian Testing

1. Under marginal Jefferys priors, code up a Gibbs Sampler for obtaining posterior draws:  $\delta_{x,y}^{(i)} = \theta_x^{(i)} - \theta_y^{(i)}$ . After “burning-in”, and collecting *enough* of these samples, show how to compute  $Pr(H_0|\{x_1, \dots, x_{N_x}\}, \{y_1, \dots, y_{N_y}\})$ .
2. Specify a reasonable prior for testing  $H_0$  VS.  $H_A$ , and provide some justification for why it is reasonable.
3. Let the rule:  $Pr(H_0|\{x_1, \dots, x_{N_x}\}, \{y_1, \dots, y_{N_y}\}) < 0.05$ , be the rule you use for rejecting  $H_0$ . From the data that you simulated in the preceding section, report your Type 1 Error rates. Just to be clear, you’re simulating this.
4. How would you modify your prior after observing your results?

## 5% Additional Midterm Credit Points

Repeat the exercises above, but this time consider the *sharp* test:

$$\begin{aligned}H_0 : \theta_x - \theta_y &= 0 \\H_A : \theta_x - \theta_y &\neq 0.\end{aligned}$$

## 5% Additional Midterm Credit Points

Show how the exercises above change under varied specifications of the sampling distributions. That is, let

$$\begin{aligned}x_i &\sim f, & i = 1, \dots, N_x \\y_i &\sim g, & i = 1, \dots, N_y,\end{aligned}$$

where  $f$  and  $g$  are arbitrary distributions. Of course you won't be able to consider all cases concerning arbitrary  $f$  and  $g$ , so as a step, perhaps check how the results change under '*heavily skewed*' distributions.