

Math 181B: Homework 1

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Exercise 1

We have that $H_0 = \{\mu_X = \mu_Y \in \mathbb{R}, \sigma^2 \in \mathbb{R}^+\}$ and $\Omega = \{\mu_X, \mu_Y \in \mathbb{R}, \sigma^2 \in \mathbb{R}^+\}$. The likelihood function is

$$\begin{aligned} L(\theta) &= \prod_{i=1}^n \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{1}{2} \left(\frac{X_i - \mu_X}{\sigma}\right)^2\right) \prod_{i=1}^m \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{1}{2} \left(\frac{Y_i - \mu_Y}{\sigma}\right)^2\right) \\ &= (2\pi\sigma^2)^{-\frac{n+m}{2}} \exp\left(-\frac{1}{2\sigma^2} \left(\sum_{i=1}^n (X_i - \mu_X)^2 + \sum_{i=1}^m (Y_i - \mu_Y)^2\right)\right) \end{aligned}$$

The log likelihood is

$$\log L(\theta) = -\frac{n+m}{2} \log(2\pi\sigma^2) - \frac{1}{2\sigma^2} \left(\sum_{i=1}^n (X_i - \mu_X)^2 + \sum_{i=1}^m (Y_i - \mu_Y)^2\right)$$

Under H_0 we have that

$$\begin{aligned} \frac{\partial}{\partial \mu} \log L(\theta) &= \frac{1}{\sigma^2} \left(\sum_{i=1}^n (X_i - \mu) + \sum_{i=1}^m (Y_i - \mu)\right) = 0 \\ \implies \sum_{i=1}^n X_i + \sum_{i=1}^m Y_i &= (n+m)\hat{\mu} \\ \implies \hat{\mu} &= \frac{n\bar{X} + m\bar{Y}}{n+m} \end{aligned}$$

$$\begin{aligned} \frac{\partial}{\partial \sigma^2} \log L(\theta) &= -\frac{n+m}{2\sigma^2} + \frac{1}{2\sigma^4} \left(\sum_{i=1}^n (X_i - \mu)^2 + \sum_{i=1}^m (Y_i - \mu)^2\right) = 0 \\ \implies \left(\sum_{i=1}^n (X_i - \mu)^2 + \sum_{i=1}^m (Y_i - \mu)^2\right) &= (n+m)\hat{\sigma}^2 \\ \implies \hat{\sigma}^2 &= \frac{1}{n+m} \left(\sum_{i=1}^n (X_i - \hat{\mu})^2 + \sum_{i=1}^m (Y_i - \hat{\mu})^2\right) \end{aligned}$$

$$\begin{aligned} \max_{\theta \in H_0} L(\theta) &= (2\pi\hat{\sigma}^2)^{-\frac{n+m}{2}} \exp\left(-\frac{1}{2\hat{\sigma}^2} \left(\sum_{i=1}^n (X_i - \hat{\mu})^2 + \sum_{i=1}^m (Y_i - \hat{\mu})^2\right)\right) \\ &= \left(\frac{2\pi}{n+m} \left(\sum_{i=1}^n (X_i - \hat{\mu})^2 + \sum_{i=1}^m (Y_i - \hat{\mu})^2\right)\right)^{-\frac{n+m}{2}} \exp\left(-\frac{n+m}{2}\right) \end{aligned}$$

Under Ω we have that

$$\begin{aligned}\frac{\partial}{\partial \mu_x} \log L(\theta) &= \frac{1}{\sigma^2} \sum_{i=1}^n (X_i - \mu_X) = 0 \\ \implies n\hat{\mu}_X &= \frac{1}{\sigma^2} \sum_{i=1}^n X_i \\ \implies \hat{\mu}_X &= \bar{X}\end{aligned}$$

Since its symmetric we also have $\hat{\mu}_y = \bar{Y}$.

$$\begin{aligned}\frac{\partial}{\partial \sigma^2} \log L(\theta) &= -\frac{n+m}{2\sigma^2} + \frac{1}{2\sigma^4} \left(\sum_{i=1}^n (X_i - \mu_X)^2 + \sum_{i=1}^m (Y_i - \mu_Y)^2 \right) = 0 \\ \implies \left(\sum_{i=1}^n (X_i - \bar{X})^2 + \sum_{i=1}^m (Y_i - \bar{Y})^2 \right) &= (n+m)\hat{\sigma}^2 \\ \implies \hat{\sigma}^2 &= \frac{1}{n+m} \left(\sum_{i=1}^n (X_i - \bar{X})^2 + \sum_{i=1}^m (Y_i - \bar{Y})^2 \right)\end{aligned}$$

$$\begin{aligned}\max_{\theta \in \Omega} L(\theta) &= (2\pi\hat{\sigma}^2)^{-\frac{n+m}{2}} \exp \left(-\frac{1}{2\hat{\sigma}^2} \left(\sum_{i=1}^n (X_i - \bar{X})^2 + \sum_{i=1}^m (Y_i - \bar{Y})^2 \right) \right) \\ &= \left(\frac{2\pi}{n+m} \left(\sum_{i=1}^n (X_i - \bar{X})^2 + \sum_{i=1}^m (Y_i - \bar{Y})^2 \right) \right)^{-\frac{n+m}{2}} \exp \left(-\frac{n+m}{2} \right)\end{aligned}$$

The likelihood ratio is

$$\begin{aligned}\Lambda &= \frac{(\sum_{i=1}^n (X_i - \bar{X})^2 + \sum_{i=1}^m (Y_i - \bar{Y})^2)^{-\frac{n+m}{2}}}{(\sum_{i=1}^n (X_i - \hat{\mu})^2 + \sum_{i=1}^m (Y_i - \hat{\mu})^2)^{-\frac{n+m}{2}}} \\ &= \left(\frac{\sum_{i=1}^n (X_i - \bar{X})^2 + n(\bar{X} - \hat{\mu})^2 + \sum_{i=1}^m (Y_i - \hat{\mu})^2 + m(\bar{Y} - \hat{\mu})^2}{\sum_{i=1}^n (X_i - \bar{X})^2 + \sum_{i=1}^m (Y_i - \bar{Y})^2} \right)^{\frac{n+m}{2}} \\ &= \left(1 + \frac{n \left(\frac{m}{n+m} (\bar{X} - \bar{Y}) \right)^2 + m \left(-\frac{n}{n+m} (\bar{X} - \bar{Y}) \right)^2}{\sum_{i=1}^n (X_i - \bar{X})^2 + \sum_{i=1}^m (Y_i - \bar{Y})^2} \right)^{\frac{n+m}{2}} \\ &= \left(1 + \frac{nm}{n+m} \frac{(\bar{X} - \bar{Y})^2}{\sum_{i=1}^n (X_i - \bar{X})^2 + \sum_{i=1}^m (Y_i - \bar{Y})^2} \right)^{\frac{n+m}{2}}\end{aligned}$$

For some c , the test is rejects when

$$\left(1 + \frac{nm}{n+m} \frac{(\bar{X} - \bar{Y})^2}{\sum_{i=1}^n (X_i - \bar{X})^2 + \sum_{i=1}^m (Y_i - \bar{Y})^2} \right)^{\frac{n+m}{2}} \leq c$$

We can rewrite this as

$$\frac{\bar{X} - \bar{Y}}{\sqrt{\sum_{i=1}^n (X_i - \bar{X})^2 + \sum_{i=1}^m (Y_i - \bar{Y})^2}} \leq c'$$

for some c' , which is equivalent to the two sample t-test.

Exercise 2

1.

```
# Do a HT on H0: mu_X = mu_Y and H1: mu_X > mu_Y.
# We cannot assume that sigma_x = sigma_y,
# so we use Welch's approximation for this calculation.

# Import files
setwd("C:/Users/merri/Documents/MATH-31H/MATH 181B/Homework 1")
phone = unlist(read.csv("Phone.csv"))
noPhone = unlist(read.csv("NoPhone.csv"))

# Calculate mean and std
Xbar = mean(phone)
Ybar = mean(noPhone)
Sx = sd(unlist(phone))
Sy = sd(unlist(noPhone))
n = length(phone)
m = length(noPhone)

# The test statistic is
Tv = (Xbar - Ybar)/sqrt(Sx^2/n + Sy^2/m)

# v degrees of freedom
v = round((Sx^2/n + Sy^2/m)^2/(Sx^4/n^2/(n-1) + Sy^4/m^2/(m-1)))

# Find P(t_56 > 2.44)
pt(Tv, v, lower=F)

# Since p = 0.008970693 < 0.05, we reject the null hypothesis
```
2.

```
# Calculate Confidence interval
diffMean = Xbar - Ybar
ME = qt(0.005, df = v, lower.tail=FALSE)*sqrt(Sx^2/n + Sy^2/m)
cat("(", diffMean - ME, ", ", diffMean + ME, ")")
# The confidence interval is ( -2.976387 , 66.66539 )

99% of confidence intervals have the mean in it. We reject if  $\mu_X - \mu_Y = 0$ 
is not in the confidence interval. Since 0 is in the interval, we fail to reject,
which is in contrast to a).
```
3.

```
# Verify
t.test(phone, noPhone, alternative = "greater")$p.value
t.test(phone, noPhone, conf.level = 0.99)$conf.int
# Output
# 0.008956362
# -2.965777 66.654780
```

Exercise 3

The pooled variance is

$$S_p^2 = \frac{1^2 + 1.5^2}{2} = 1.625$$

The margin of error is

$$ME = t_{0.005, 18} \sqrt{1.625} \sqrt{1/10 + 1/10} = 1.640964$$

Therefore the values that ? can take on are in the confidence interval (3.36, 6.64).