## Homework 1

#### Michael Pena

2024-02-07

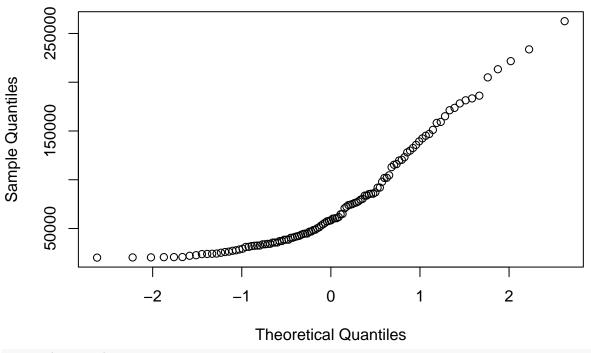
### Question 1

```
# load data
data <- read.csv("HW1P1.csv")
```

#### Part a:

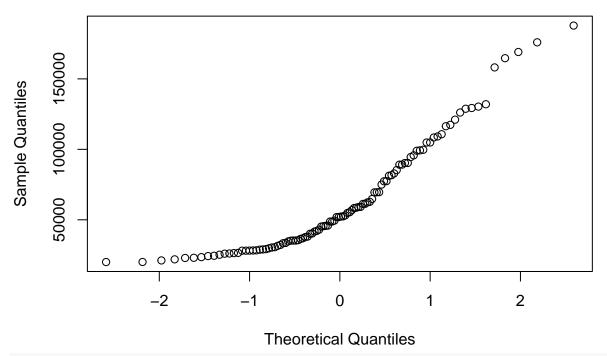
```
# make a new column that is the difference between the two
male_vec <- data$Males
fem_vec <- na.omit(data$Females)
# check normality of the difference
qqnorm(male_vec)</pre>
```

### Normal Q-Q Plot



qqnorm(fem\_vec)

# Normal Q-Q Plot



# let H\_alt be mu > 0 with 99% confidence
# run student t.test
t.test(male\_vec,fem\_vec, alternative = "greater", paired = F, conf.level = .99)

The selected  $\alpha = 0.01$  and here p-value is greater that 0.01. Thus we fail to reject the null hypothesis.

conclusion: There is not sufficient sample evidence to support the claim that "males are making more than females."

#### part b.

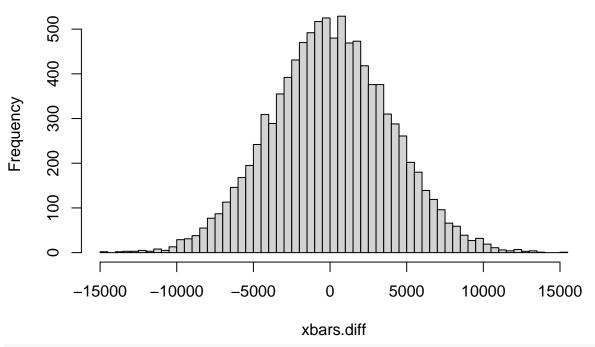
```
# find population mean
set.seed(536)
BS.male_vec <- male_vec - mean(male_vec)
BS.fem_vec <- fem_vec - mean(fem_vec)
BS.pop.mean <- mean(male_vec) - mean(fem_vec)

# bootstrapping

xbars.diff <- rep(0,10000)
for (i in 1:10000){
    sampleM <- sample(BS.male_vec,300, replace = T)
    sampleF <- sample(BS.fem_vec,300, replace = T)
    xbars.diff[i] <- mean(sampleM - sampleF)
}

# render histogram
hist(xbars.diff, breaks = 80)</pre>
```

### Histogram of xbars.diff



# finding a p-value
pval <- length(xbars.diff[xbars.diff > BS.pop.mean])/10000
pval

#### ## [1] 1e-04

The histogram suggests we can follow a normally distributed data set with our bootstrapped data. Because the original question was asking if the company paid men more than women; we ran a right tailed test with an alternative hypothesis  $\mu_d > 0$  where  $\mu_d$  represents the average male income minus the average female income. We took several samples samples of 300 with replacement from male and female incomes, recorded the average difference, and repeated this process ten thousand times. The P-value we return is very small number that is degrees smaller than our chosen  $\alpha = 0.01$  (I chose 99% significance). This bootstrap method concludes that there is significant evidence that males incomes is by average higher than that of their female counterparts. It may be necessary for the company to address this pay disparity.

#### Question 2

#generate observations
obs <- rnorm(100000)</pre>

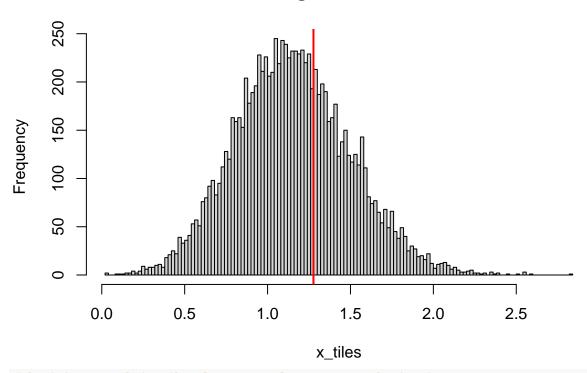
#### part a.

```
x_tiles <- rep(0,10000)
true_90th <- quantile(obs, .9)

for (i in 1:10000){
   samp <- sample(obs,20,replace = T)
   x_tiles[i] <- quantile(samp, .9)
}

hist(x_tiles, breaks = 160)
abline(v = true_90th,col = "red", lwd = 2)</pre>
```

# Histogram of x\_tiles

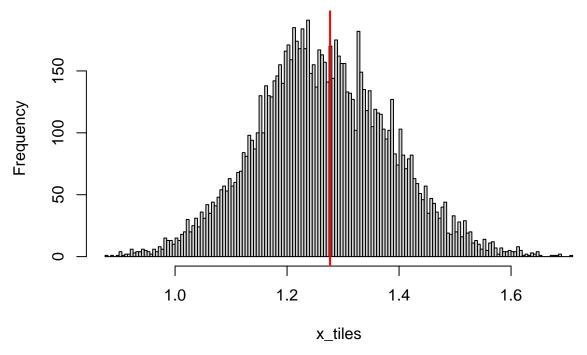


```
# bootstrap now but with a larger sample size in each iteration

for (i in 1:10000){
   samp <- sample(obs,200,replace = T)
    x_tiles[i] <- quantile(samp, .9)
}

hist(x_tiles, breaks = 160)
abline(v = true_90th,col = "red", lwd = 2)</pre>
```

### Histogram of x\_tiles



Using only a sample size of 20 is biased as when I highered the sample size in the second graphic, the true 90% tile got closer to median.

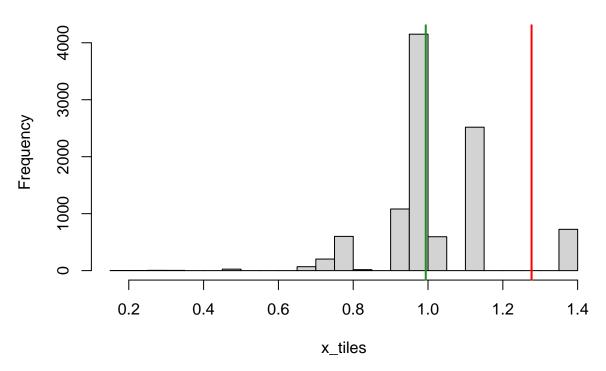
#### part b.

```
single.samp <- sample(obs,20,replace = T)
single.samp.90 <- quantile(single.samp,.9)

for (i in 1:10000){
    samp <- sample(single.samp,20,replace = T)
    x_tiles[i] <- quantile(samp, .9)
}

hist(x_tiles, breaks = 20)
abline(v = true_90th,col = "red", lwd = 2)
abline(v = single.samp.90,col = "forestgreen", lwd = 2)</pre>
```

### Histogram of x\_tiles



There seems to be heavy bias in our current method but we also notice how unnormal the data is distributed. This would be difficult to argue as the graph looks really bad (lacking data to make an solid conclusion).

```
# quantifying bias
bias <- mean(x_tiles) - single.samp.90</pre>
```

#### part c.

we will account for bias by taking the mean of our boostrapped 90th percentiles vector and and finding the difference between that and our randomly sampled 90th percentile from the sample of size 20.