

Take Home Final

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Part I

1

a)

$$\begin{aligned}\int_{-A}^A f(x)dx &= 1 \\ \int_{-A}^A c(A^2 - x^2)dx &= 1 \\ \int_{-A}^A (cA^2 - cx^2)dx &= 1 \\ cA^2x - \frac{1}{3}cx^3 \Big|_{-A}^A &= 1 \\ cA^3 - \frac{1}{3}cA^3 - (-cA^3 + \frac{1}{3}cA^3) &= 1 \\ \frac{4}{3}cA^3 &= 1 \\ c &= \frac{3}{4A^3}\end{aligned}$$

b)

Sample mean

$$\begin{aligned}\mu = E[f(x)] &= \int_{-A}^A x \frac{3}{4A^3} (A^2 - x^2) dx \\ &= \int_{-A}^A \left(\frac{3x}{4A} - \frac{3x^3}{4A^3} \right) dx\end{aligned}$$

Since $\frac{3x}{4A} - \frac{3x^3}{4A^3}$ is an odd function and domain $[-A, A]$ is symmetric,

$$\begin{aligned}\mu = E[f(x)] &= \int_{-A}^A \left(\frac{3x}{4A} - \frac{3x^3}{4A^3} \right) dx = 0 \\ \mu_{\bar{X}} &= \mu = 0\end{aligned}$$

Sample Variance

$$\begin{aligned}
 E[(f(x))^2] &= \int_{-A}^A x^2 \frac{3}{4A^3} (A^2 - x^2) dx \\
 &= \int_{-A}^A \left(\frac{3x^2}{4A} - \frac{3x^4}{4A^3} \right) dx \\
 &= \left. \frac{x^3}{4A} - \frac{3x^5}{20A^3} \right|_{-A}^A \\
 &= \frac{A^2}{4} - \frac{3A^2}{20} + \frac{A^2}{4} - \frac{3A^2}{20} \\
 &= \frac{A^2}{5}
 \end{aligned}$$

$$Var(f(x)) = E[(f(x))^2] - E^2[f(x)] = \frac{A^2}{5}$$

$$\sigma = \sqrt{Var(f(x))} = \frac{A}{\sqrt{5}}$$

$$\sigma_{\bar{X}} = \frac{\sigma}{\sqrt{n}} = \frac{A}{\sqrt{5n}}$$

By **Central Limit Theorem**, the sample mean \bar{X} for sample size n approximately follows normal distribution with mean 0 and variance $\frac{A^2}{5n}$ ($\bar{X} \sim N(0, \frac{A^2}{5n})$).

2

a)

$$\begin{aligned}
 P\{Y_i = x\} &= \begin{cases} p + (1-p)P\{X_i = 0\} & \text{when } x = 0 \\ (1-p)P\{X_i = x\} & \text{otherwise} \end{cases} \\
 P\{Y_i = x\} &= \begin{cases} p + (1-p)e^{-\lambda} & \text{when } x = 0 \\ \frac{(1-p)e^{-\lambda}\lambda^x}{x!} & \text{otherwise} \end{cases}
 \end{aligned}$$

b)

When $p = \frac{1}{3}$,

$$P\{Y_i = x\} = \begin{cases} \frac{1+2e^{-\lambda}}{3} & \text{when } x = 0 \\ \frac{2e^{-\lambda}\lambda^x}{3x!} & \text{otherwise} \end{cases}$$

Likelihood function given sample

$$\begin{aligned}
 \mathcal{L}(\lambda|\text{sample}) &= \left(\frac{1+2e^{-\lambda}}{3}\right)^2 \left(\frac{2}{3}e^{-\lambda}\lambda\right)^2 \left(\frac{1}{3}e^{-\lambda}\lambda^2\right)^3 \left(\frac{1}{36}e^{-\lambda}\lambda^4\right)^2 \frac{1}{180}e^{-\lambda}\lambda^5 \\
 \ell(\lambda) = \log \mathcal{L}(\lambda) &= \log\left[\left(\frac{1+2e^{-\lambda}}{3}\right)^2 \left(\frac{2}{3}e^{-\lambda}\lambda\right)^2 \left(\frac{1}{3}e^{-\lambda}\lambda^2\right)^3 \left(\frac{1}{36}e^{-\lambda}\lambda^4\right)^2 \frac{1}{180}e^{-\lambda}\lambda^5\right] \\
 &= 2\log(1+2e^{-\lambda}) - 2\log 3 + 2\log \frac{2}{3} - 2\lambda + 2\log \lambda - 3\lambda + 6\log \lambda - 3\log 3 - 2\lambda + 8\log \lambda - 2\log 36 - \lambda + 5\log \lambda \\
 &\quad - \log 180 \\
 \ell'(\lambda) &= -\frac{4e^{-\lambda}}{1+2e^{-\lambda}} - 8 + \frac{21}{\lambda} \stackrel{\text{set}}{=} 0 \\
 \lambda &\approx 2.54
 \end{aligned}$$

3

```

set.seed(1)
sample.median <- c()
median.mean <- c()
n <- 25
N <- 100
for (i in 1:N){
  s3 <- sample(1:100, n, replace = FALSE)
  sample.median <- c(sample.median, median(s3))
  median.list <- replicate(1000, median(sample(s3, n, replace = TRUE)))
  median.mean <- c(median.mean, mean(median.list))
}
t.test(sample.median, median.mean, paired = TRUE)

##
## Paired t-test
##
## data: sample.median and median.mean
## t = 0.46828, df = 99, p-value = 0.6406
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
## -0.3933567 0.6363767
## sample estimates:
## mean of the differences
## 0.12151

```

Sample S contains 25 random integers from 1 to 100, and then we obtain 1000 bootstrap samples from S and calculate average of 1000 medians. We save sample medians and median averages to paired vectors. By making a two-sample paired t test, we want to study whether there's difference between them. P-value is 0.6406, which is far larger than 0.0500. We fail to reject null hypothesis. There is not enough evidence to show that $E[X] = m$ is always true.

Furthermore, in this case, m is the estimate computed from sample S . Thus, bootstrap cannot give better parameter estimates.

4

```

set.seed(2)
N <- 30000
x <- rnorm(N)
y <- 1/x[x>1]
mu <- mean(y)
sigma.sq <- var(y)
cat("E[Y] =", mu)

## E[Y] = 0.7028457

cat("Var(Y) =", sigma.sq)

## Var(Y) = 0.03013073

```

We want $P\{|\bar{Y}_n - \mu_Y| \leq 0.01\} \geq 0.99$. By **Chebyshev Inequality** for sample mean,

$$P\{|\bar{Y}_n - \mu_Y| \geq 0.01\} \leq \frac{\sigma^2}{0.01^2 n}$$

From the sampling result above, σ^2 is approximately 0.03. Therefore, n must be chosen so that

$$\frac{0.03}{0.01^2 n} \leq (1 - 0.99) = 0.01$$

$$n \geq 30,000$$

It requires the number of simulations to be at least 30,000 so that we can achieve two decimal digits accuracy for 99% of the time.

Part II

5

H_0 : Age of mother and length of pregnancy are independent.

H_1 : Age of mother and length of pregnancy are dependent.

(a)

```
set.seed(3)
birth <- read.csv("D:/Courses/ANLY 511/NCBirths2004.csv")
mytest.1 <- function(mydf){
  agg <- aggregate(Gestation ~ MothersAge, data = mydf, FUN = mean)
  return(agg$Gestation[1] - agg$Gestation[2])
}
permute.sample.1 <- function(mydf){
  n <- dim(mydf)[1]
  mydf$MothersAge <- mydf$MothersAge[sample(n, n, replace = F)]
  return(mytest.1(mydf))
}
birth.permute <- birth
N <- 1000
test.1 <- replicate(N, permute.sample.1(birth.permute))
cat("P-value =", mean(test.1 > mytest.1(birth)))
```

P-value = 0.671

Since p-value is 0.671, greater than 0.05, we fail to reject H_0 . There's not enough evidence to show that the age of the mother and the length of pregnancy are dependent.

(b)

```
mytable <- table(birth$MothersAge, birth$Gestation)
mytable
```

```
##
##      37  38  39  40  41  42
## 15-19    9  30  25  33  12   1
## 20-24   25  58  85  75  31   5
## 25-29   16  58 102  68  33   1
## 30-34   25  47  74  55  19   2
## 35-39    6  20  35  27   6   1
```

```
## 40-44      3  6  4  6  2  0
## 45-49      0  0  1  1  0  0
## under 15   0  0  1  0  1  0
```

```
chisq.test(mytable)
```

```
## Warning in chisq.test(mytable): Chi-squared approximation may be incorrect
```

```
##
```

```
## Pearson's Chi-squared test
```

```
##
```

```
## data: mytable
```

```
## X-squared = 28.526, df = 35, p-value = 0.7723
```

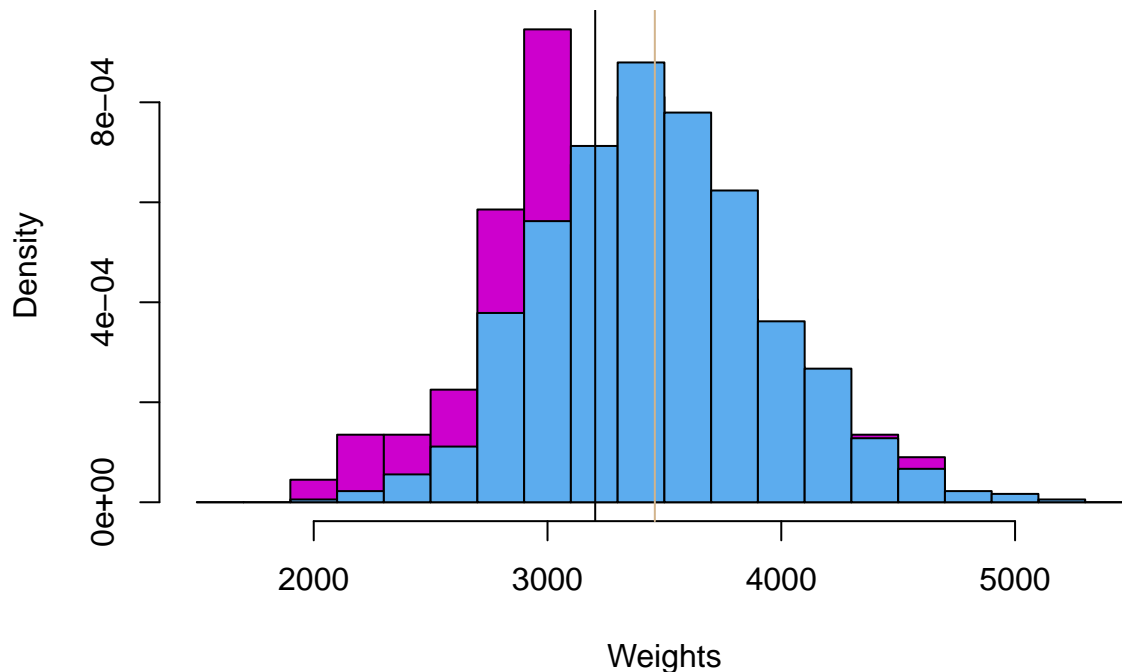
χ^2 test statistics is 28.526 with degree of freedom 35

Because the p-value is 0.7723, greater than 0.05, there's still not enough evidence that the age of the mother and the length of pregnancy are dependent.

6

```
set.seed(4)
weight.smoke <- birth$Weight[birth$Smoker == "Yes"]
weight.non <- birth$Weight[birth$Smoker == "No"]
hist(weight.smoke, freq = F, breaks = seq(1500,5500,200), col = "magenta3",
     main = "Birth Weights for Smoking and Non-smoking Mothers", xlab = "Weights")
hist(weight.non, freq = F, breaks = seq(1500,5500,200), col = "steelblue2", add = T)
abline(v = median(weight.smoke), col = "gray0")
abline(v = median(weight.non), col = "tan")
```

Birth Weights for Smoking and Non-smoking Mothers



```
ls <- length(weight.smoke)
ln <- length(weight.non)
N <- 1000
weight.smoke.boot <- replicate(N, median(sample(weight.smoke, ls, replace = TRUE)))
weight.non.boot <- replicate(N, median(sample(weight.non, ln, replace = TRUE)))
var.smoke <- var(weight.smoke.boot)/N
var.non <- var(weight.non.boot)/N
test.stat <- (mean(weight.non.boot) - mean(weight.smoke.boot))/sqrt(var.smoke + var.non)
cat("Test statistics is", test.stat)
```

```
## Test statistics is 109.1062
```

```
degree <- (var.smoke^2 + var.non^2)^2/(var.smoke^2/(N-1) + var.non^2/(N-1))
crit <- qt(0.975, df = degree)
cat("Critical value at 5% significance level is", crit)
```

```
## Critical value at 5% significance level is 1.960059
```

```
cat("Test statistics greater than critical value is", test.stat > crit)
```

```
## Test statistics greater than critical value is TRUE
```

```
quantile(weight.non.boot - weight.smoke.boot, 0.05)
```

```
## 5%
```

```
## 113
```

Figure above is an overlapping histogram of birth weights for smoking and non-smoking mothers. Purple is for smoking mothers and Blue is non-smoking. Black line is the median of weights for smoking mothers and

orange line is for non-smoking.

Based on this histogram, we assume that median birth weight for smoking mothers is less than that for non-smoking mothers. Therefore, we construct a one-sided hypothesis testing with bootstrap.

H_0 : Median birth weight is the same for both smoking and non-smoking mothers

H_1 : Median birth weight for smoking mothers is less than that for non-smoking mothers

From the R code results above, the test statistics, 109.1062, is greater than the critical value at 5% significance level and null hypothesis value 0 does not lie in the confidence interval $([113, +\infty))$. Therefore, we conclude that median birth weights for smoking mothers is less than median birth weights for non-smoking mothers.

7

```
weight37 <- birth$Weight[birth$Gestation == 37]
weight38 <- birth$Weight[birth$Gestation == 38]
weight39 <- birth$Weight[birth$Gestation == 39]
weight40 <- birth$Weight[birth$Gestation == 40]
weight41 <- birth$Weight[birth$Gestation == 41]
t.test(weight38, weight37, alternative = "greater")
```

```
##
## Welch Two Sample t-test
##
## data: weight38 and weight37
## t = 4.2934, df = 141.45, p-value = 1.624e-05
## alternative hypothesis: true difference in means is greater than 0
## 95 percent confidence interval:
## 164.3856      Inf
## sample estimates:
## mean of x mean of y
## 3298.986 3031.417
```

H_0 : $\text{Weight}_{38} = \text{Weight}_{37}$

H_1 : $\text{Weight}_{38} > \text{Weight}_{37}$

Two-sample one-sided t test

Confidence interval is $[164.3856, +\infty)$

```
t.test(weight39, weight38, alternative = "greater")
```

```
##
## Welch Two Sample t-test
##
## data: weight39 and weight38
## t = 4.1078, df = 459.78, p-value = 2.364e-05
## alternative hypothesis: true difference in means is greater than 0
## 95 percent confidence interval:
## 98.02006      Inf
## sample estimates:
## mean of x mean of y
## 3462.688 3298.986
```

H_0 : $\text{Weight}_{39} = \text{Weight}_{38}$

H_1 : $\text{Weight}_{39} > \text{Weight}_{38}$

Two-sample one-sided t test

Confidence interval is $[98.02006, +\infty)$

```
t.test(weight40, weight39, alternative = "greater")

##
## Welch Two Sample t-test
##
## data: weight40 and weight39
## t = 3.2391, df = 568.32, p-value = 0.0006345
## alternative hypothesis: true difference in means is greater than 0
## 95 percent confidence interval:
##  58.65858      Inf
## sample estimates:
## mean of x mean of y
## 3582.068 3462.688

H0: Weight40 = Weight39
H1: Weight40 > Weight39
Two-sample one-sided t test
Confidence interval is [58.65858, +∞)

t.test(weight41, weight40, alternative = "greater")
```

```
##
## Welch Two Sample t-test
##
## data: weight41 and weight40
## t = 2.0229, df = 178.6, p-value = 0.02229
## alternative hypothesis: true difference in means is greater than 0
## 95 percent confidence interval:
## 19.78943      Inf
## sample estimates:
## mean of x mean of y
## 3690.413 3582.068

H0: Weight41 = Weight40
H1: Weight41 > Weight40
Two-sample one-sided t test
Confidence interval is [19.78943, +∞)
```

Because we want to study weight gains between each gestation week k and $k + 1$, we construct 4 two-sample one-sided t tests for each group pair to find whether higher gestation week brings gains more weight. Overall from test results, confidence intervals are all positive, which means that null hypothesis value 0 lies outside confidence intervals. We reject H_0 and conclude that weight increases in consecutive 4 weeks from gestation week 37.

Bonus question

```
gestation.y <- birth$Gestation[birth$Tobacco == "Yes"]
gestation.n <- birth$Gestation[birth$Tobacco == "No"]
t.test(gestation.y, gestation.n, alternative = "less")

##
## Welch Two Sample t-test
##
## data: gestation.y and gestation.n
```



```
## t = -1.757, df = 139.19, p-value = 0.04056
## alternative hypothesis: true difference in means is less than 0
## 95 percent confidence interval:
##      -Inf -0.01151172
## sample estimates:
## mean of x mean of y
## 38.93694 39.13697
```

H_0 : Usage of tobacco by mothers does not change gestation length

H_1 : Mother using tobacco will shorten gestation length

Two-sample one-sided t test

P-value = $0.04056 < 0.05 = \alpha$

Reject H_0

We conclude that tobacco use by mother shortens the gestation length.