MAST20005/MAST90058: Week 10 Lab Solutions

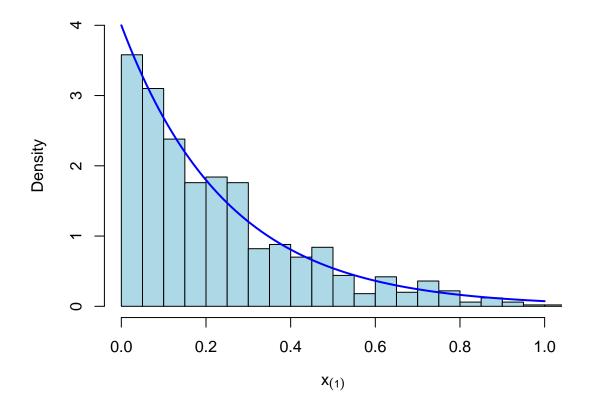
1. The theoretical pdf for $X_{(1)}$ in this case is

$$g_1(x) = 4e^{-4x}, \quad x > 0.$$

Doing the simulations:

```
x1.simulated <- numeric(1000) # initialise an empty vector
for (i in 1:1000) {
    x <- rexp(4)
    x1.simulated[i] <- min(x)
}</pre>
```

Then creating the plots:



2. Note that we can simulate from this distribution by simulating from a standard (unshifted) exponential distribution and adding θ to each realisation.

```
t.simulated <- matrix(nrow = 1000, ncol = 2)  # initialise an empty matrix
for (i in 1:1000) {
    x <- 3 + rexp(10)  # theta = 3, n = 10
    x <- sort(x)
    t1 <- mean(x) - 1
    t2 <- x[1] - 0.1
    t.simulated[i, ] <- c(t1, t2)
}</pre>
```

Now, let's compare the estimators.

```
apply(t.simulated, 2, mean)
## [1] 2.976587 2.999145
apply(t.simulated, 2, var)
## [1] 0.094744084 0.009470275
```

We see that both estimators seem to be unbiased (means are close to $\theta = 3$) and that the variance of T_2 is about 10 times smaller than that of T_1 .

3. For compactness, we present the solutions in a different order to the question parts. Firstly, note that since the population distribution is uniform on a unit interval centered on θ , $X_{(3)}$ will have a beta distribution that has been shifted accordingly. On the standard unit interval it would have an expectation of 3/4; after shifting this gets mapped to $\theta+1/4$. Therefore, we need a=-0.25 to make W_5 unbiased.

Doing all of the simulations:

```
theta <- 0.5
w.simulated <- matrix(nrow = 1000, ncol = 5)  # initialise an empty matrix
for (i in 1:1000) {
    x <- runif(3, theta - 0.5, theta + 0.5)
    x <- sort(x)
    w1 <- mean(x)
    w2 <- x[2]
    w3 <- (x[1] + x[3]) / 2
    w4 <- x[3] - 0.5
    w5 <- x[3] - 0.25
    w.simulated[i, ] <- c(w1, w2, w3, w4, w5)
}
apply(w.simulated, 2, mean) - theta  # bias
## [1] 0.006302829 0.006275741 0.006316373 -0.241077574 0.008922426
apply(w.simulated, 2, var)
## [1] 0.02739359 0.04906474 0.02472136 0.03646129 0.03646129</pre>
```

- (a) The simulations estimate the bias to be -0.241 (we know the true bias is -0.25).
- (b) a = 0.25
- (c) The estimated variance of W_5 is lower than that of W_2 but higher than the other estimators.
- 4. Set up and run the simulations:

```
f <- function() {
    X <- runif(11)
    Y <- sort(X)
    c(Y[2], Y[9])
}
nsimulations <- 100
c1 <- t(replicate(nsimulations, f()))
inside.interval <- (c1[, 1] < 0.5) & (0.5 < c1[, 2])</pre>
```

Note that we end up with a simulation of a binary (Bernoulli) variable and wish to estimate the proportion. We can use the standard method of calculating a confidence interval for a proportion:

```
prop.test(sum(inside.interval), nsimulations)$conf.int

## [1] 0.9375880 0.9994778

## attr(,"conf.level")

## [1] 0.95
```

Repeat for 1000 simulations:

```
nsimulations <- 1000
c1 <- t(replicate(nsimulations, f()))
inside.interval <- (c1[, 1] < 0.5) & (0.5 < c1[, 2])
prop.test(sum(inside.interval), nsimulations)$conf.int

## [1] 0.9557545 0.9784915
## attr(,"conf.level")
## [1] 0.95</pre>
```

This interval is much narrower.

```
5. x <- c(0.67, 2.46, 1.00, 8.89, 8.85, 28.45, 2.95,
2.36, 0.37, 5.66, 6.26, 1.80, 1.88, 4.66)
n <- length(x)
```

The 'automatic' way of doing this is to simply rely on qbinom():

```
qbinom(c(0.025, 0.975), n, 0.5)
## [1] 3 11
```

```
sort(x)[c(3, 11)]
## [1] 1.00 6.26

pbinom(10, n, 0.5) - pbinom(2, n, 0.5) # exact coverage
## [1] 0.9648438
```

Note that this gives a slightly different answer to the more considered one that is given in the solution for tutorial problem.

6. Calculate T:

Generate the bootstrapped statistics:

```
B <- 1000
t.boot <- numeric(B)
for (i in 1:B) {
    x.ast <- sample(x, size = 25, replace = TRUE)
    t.boot[i] <- 1 / mean(x.ast)
}</pre>
```

Calculate a 95% confidence interval:

```
quantile(t.boot, c(0.025, 0.975))
## 2.5% 97.5%
## 3.370262 6.269043
```