- 1. When conducting the work of Lab 11, we conducted the test that uses the Central Limit Theorem even though the sample size was "small" (i.e., n < 30). It turns out, that how "far off" the t-test is can be computed using a first-order Edgeworth approximation for the error. Below, we will do this for the the further observations.
  - (a) Boos and Hughes-Oliver (2000) note that

$$P(T \le t) \approx F_Z(t) + \underbrace{\frac{\text{skew}}{\sqrt{n}} \frac{(2t^2 + 1)}{6} f_Z(t)}_{\text{error}},$$

where  $f_Z(\cdot)$  and  $F_Z(\cdot)$  are the Gaussian PDF and CDF and skew is the skewness of the data. What is the potential error in the computation of the *p*-value when testing  $H_0: \mu_X = 0; H_a: \mu_X < 0$  using the zebra finch further data?

(b) Compute the error for t statistics from -10 to 10 and plot a line that shows the error across t. Continue to use the skewness and the sample size for the zebra finch further data.

```
t.vecs <- seq(-10,10,0.1)
results <- tibble(
    t = t.vecs,
    fz = dnorm(t.vecs),
    error = (skew / sqrt(n)) * ((2 * (t.vecs^2) + 1) / 6) * dnorm(t.vecs)
)

error.plot <- ggplot(results) +
    theme_bw()+
    geom_line(aes(x = t, y = error))+
    labs(
    x = "T values",
    title = "Edgeworth Approximation Error"
)</pre>
```

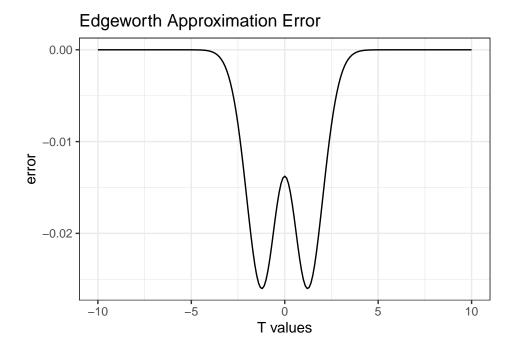


Figure 1: Edgeworth Error across span of t values

(c) Suppose we wanted to have a tail probability within 10% of the desired  $\alpha = 0.05$ . Recall we did a left-tailed test using the further data. How large of a sample size would we need? That is, we need to solve the error formula equal to 10% of the desired left-tail probability:

$$0.10\alpha \stackrel{set}{=} \underbrace{\frac{\text{skew}}{\sqrt{n}} \frac{(2t^2+1)}{6} f_Z(t)}_{\text{even}},$$

which yields

$$n = \left(\frac{\text{skew}}{6(0.10\alpha)}(2t^2 + 1)f_Z(t)\right)^2.$$

```
alpha = 0.05
t.val <- qnorm(alpha)
pdf <- dnorm(t.val)
(target.size = ((skew / (6*(0.1*alpha))) * (2 * (t.val^2) + 1) * pdf)^2)
## [1] 520.8876</pre>
```

We would need a sample size of at least 521 for a left-tailed test.

- 2. Complete the following steps to revisit the analyses from lab 11 using the bootstrap procedure.
  - (a) Now, consider the zebra finch data. We do not know the generating distributions for the closer, further, and difference data, so perform resampling to approximate the sampling distribution of the T statistic:

$$T = \frac{\bar{x}_r - 0}{s/\sqrt{n}},$$

where  $\bar{x}_r$  is the mean computed on the  $\mathbf{r}^{th}$  resample and s is the sample standard deviation from the original samples. At the end, create an object called resamples.null.closer, for example, and store the resamples shifted to ensure they are consistent with the null hypotheses at the

average (i.e., here ensure the shifted resamples are 0 on average, corresponding to t = 0, for each case).

**Answer:** All of the shifted means of the t values are so small that they are practically 0.

```
###########################
# Part 2:Boot strapping #
##############################
R <- 10000
muO = 0
fur.sd <- sd(zebra.finches.dat$further)</pre>
close.sd <- sd(zebra.finches.dat$closer)</pre>
diff.sd <- sd(zebra.finches.dat$diff)</pre>
resample <- tibble(close.t=numeric(R),</pre>
                    far.t=numeric(R),
                    diff.t=numeric(R),
                    close.mean =numeric(R),
                    far.mean =numeric(R).
                    diff.mean =numeric(R)
resamples.shifted <- tibble()</pre>
for(i in 1:R){
  close.sample <- sample(x=zebra.finches.dat$closer,</pre>
                          size=n,
                          replace=T)
  far.sample <- sample(x=zebra.finches.dat$further,</pre>
                        size=n,
                        replace=T)
  diff.sample <- sample(x=zebra.finches.dat$diff,</pre>
                         size=n,
                         replace=T)
  resample$close.t[i] = (mean(close.sample)-mu0)/(close.sd/sqrt(n))
  resample$far.t[i] = (mean(far.sample)-mu0)/(fur.sd/sqrt(n))
  resample$diff.t[i] = (mean(diff.sample)-mu0)/(diff.sd/sqrt(n))
  resample$close.mean[i] = mean(close.sample)
  resample$far.mean[i] = mean(far.sample)
  resample$diff.mean[i] = mean(diff.sample)
## shifting the means
close.change <- mean(resample$close.t)</pre>
far.change <- mean(resample$far.t)</pre>
diff.change <- mean(resample$diff.t)</pre>
resamples.shifted <- resample |>
  mutate(close.shifted = close.t - close.change) |>
  mutate(far.shifted = far.t - far.change) |>
  mutate(diff.shifted = diff.t - diff.change) |>
  select(c(close.shifted, far.shifted, diff.shifted ))
(mean(resamples.shifted$close.shifted))
```

```
## [1] -3.974598e-17
(mean(resamples.shifted$far.shifted))
## [1] -3.303358e-16
(mean(resamples.shifted$diff.shifted))
## [1] 6.024785e-16
```

(b) Compute the bootstrap p-value for each test using the shifted resamples. How do these compare to the t-test p-values?

**Answer:** Table 1 below shows that the comparison of the p-values. While t-tests did produce nonzero p-values, they were so small that they are essentially 0, which is what the bootstrap test shows for each case.

```
# Bootstrap P-Value
boot.p.closer <- mean(resamples.shifted$close.shifted >= close.change)
boot.p.far <- mean(resamples.shifted$far.shifted <= far.change)
low = -diff.change
high = diff.change
p.low <- mean(resamples.shifted$diff.shifted <= low)</pre>
p.high <- mean(resamples.shifted$diff.shifted >= high)
boot.p.diff <- p.low +p.high
# T-Test P-Value
test.close <- t.test(zebra.finches.dat$closer,</pre>
                      mu = 0,
                      alternative = "greater")
close.ttest.p <- test.close$p.value</pre>
test.far <- t.test(zebra.finches.dat$further,</pre>
                      mu = 0,
                      alternative = "less")
far.ttest.p <- test.far$p.value</pre>
test.diff <- t.test(zebra.finches.dat$diff,</pre>
                    mu = 0.
                    alternative = "two.sided")
diff.ttest.p <- test.diff$p.value</pre>
comparisons.p <- tibble(" "= c("close", "far", "diff"), Bootstrapped =</pre>
                         c(boot.p.closer, boot.p.far, boot.p.diff),
                       t.test = c(close.ttest.p, far.ttest.p, diff.ttest.p))
```

Data	Bootstrapped	T test
closer	0.00	0.00
further	0.00	0.00
difference	0.00	0.00

Table 1: Comparison of p-values between bootstrapping and T test

(c) What is the  $5^{th}$  percentile of the shifted resamples under the null hypothesis?

**Answer:** Table 2 below shows that the comparison of the  $5^{th}$  percentile of the shifted resamples: closer = -1.54, further = -1.70, and difference = -1.61. They approximate the T-test, which is

Data	Bootstrapped	T-test
Closer	-1.54	-1.71
Further	-1.70	-1.71
Difference	-1.61	-1.71

Table 2: Comparison of the 5th percentile between bootstrapping and T test

Note this value approximates  $t_{0.05,n-1}$ . Compare these values in each case.

(d) Compute the bootstrap confidence intervals using the resamples. How do these compare to the *t*-test confidence intervals?

**Answer:** Table 3 below shows that the comparison of the confidence intervals of the shifted resamples with those of the T-tests. Respectively for the closer, further, and difference cases, bootstrapping produced 95% confidence intervals of (0.12, 0.18), (-0.26, -0.17), and (0.27, 0.42) while the T-tests produced CIs of (0.12, 0.20), (-0.26, -0.15), and (0.27, 0.45). They are pretty similar to each other for each case

```
## Part d
lower.close <- quantile(resample$close.mean, 0.025)</pre>
upper.close <- quantile(resample$close.mean, 0.925)
Bootstrap.CI.close <- c(lower.close, upper.close)
  lower.far <- quantile(resample$far.mean, 0.025)</pre>
upper.far <- quantile(resample$far.mean, 0.925)
Bootstrap.CI.far <- c(lower.far, upper.far)</pre>
  lower.diff <- quantile(resample$diff.mean, 0.025)</pre>
upper.diff <- quantile(resample$diff.mean, 0.925)</pre>
Bootstrap.CI.diff <- c(lower.diff, upper.diff)</pre>
# t tests confidence intervals
test.close <- t.test(zebra.finches.dat$closer,</pre>
                     mu = 0, conf.level = 0.95,
                     alternative = "two.sided")
close.CI <- test.close$conf.int</pre>
test.far <- t.test(zebra.finches.dat$further,</pre>
                     mu = 0, conf.level = 0.95,
                     alternative = "two.sided")
far.CI <- test.far$conf.int</pre>
```

Data	Bootstrapped Lower	Bootstrapped Upper	t-test Lower	t-test Upper
close	0.12	0.18	0.12	0.20
$\operatorname{far}$	-0.26	-0.17	-0.26	-0.15
diff	0.27	0.42	0.27	0.45

Table 3: Comparison of the Confidence Interval between bootstrapping and T test, separated into lower and upper bounds

- 3. Complete the following steps to revisit the analyses from lab 11 using the randomization procedure.
  - (a) Now, consider the zebra finch data. We do not know the generating distributions for the closer, further, and difference data, so perform the randomization procedure
  - (b) Compute the randomization test *p*-value for each test.
  - (c) Compute the randomization confidence interval by iterating over values of  $\mu_0$ . **Hint:** You can "search" for the lower bound from  $Q_1$  and subtracting by 0.0001, and the upper bound using  $Q_3$  and increasing by 0.0001. You will continue until you find the first value for which the two-sided p-value is greater than or equal to 0.05.
- 4. **Optional Challenge:** In this lab, you performed resampling to approximate the sampling distribution of the T statistic using

$$T = \frac{\bar{x}_r - 0}{s/\sqrt{n}}.$$

I'm curious whether it is better/worse/similar if we computed the statistics using the sample standard deviation of the resamples  $(s_r)$ , instead of the original sample (s)

$$T = \frac{\bar{x}_r - 0}{s_r / \sqrt{n}}.$$

- (a) Perform a simulation study to evaluate the Type I error for conducting this hypothesis test both ways.
- (b) Using the same test case(s) as part (a), compute bootstrap confidence intervals and assess their coverage how often do we 'capture' the parameter of interest?

## References

Boos, D. D. and Hughes-Oliver, J. M. (2000). How large does n have to be for z and t intervals? The American Statistician, 54(2):121–128.