Kasdin et al. (2025) show that dopamine in the brains of young zebra finches acts as a learning signal, increasing when they sing closer to their adult song and decreasing when they sing further away, effectively guiding their vocal development through trial-and-error. This suggests that complex natural behaviors, like learning to sing, are shaped by dopamine-driven reinforcement learning, similar to how artificial intelligence learns. You can find the paper at this link: https://www.nature.com/articles/s41586-025-08729-1..

Note they measure dopamine using fibre photometry, changes in the fluorescence indicate dopamine changes in realtime. Their specific measurement considers changes in flourescence in 100-ms windows between 200 and 300 ms from the start of singing, averaged across development.

1. Using the `pwr` package for `R` (Champely, 2020), conduct a power analysis. How many observations would the researchers need to detect a moderate-to-large effect ($d = 0.65$) when using $\alpha = 0.05$ and default power (0.80) for a two-sided one sample t test.

```
library(pwr)
pwr.t.test(n = NULL, d = 0.65, sig.level = 0.05, power = 0.8, type = "one.sample", alternative = "t

##
##      One-sample t test power calculation
##
##               n = 20.58039
##               d = 0.65
##       sig.level = 0.05
##           power = 0.8
##     alternative = two.sided
```

Researchers would need approximately 21 observations to detect a moderate-to-large effect.

2. Click the link to go to the paper. Find the source data for Figure 2. Download the Excel file. Describe what you needed to do to collect the data for Figure 2(g). Note that you only need the `closer_vals` and `further_vals`. Ensure to `mutate()` the data to get a difference (e.g., `closer_vals - further_vals`).

```
data = read_csv("lab11data.csv")
view(data)
data = data |>
  mutate(difference = Closer.vals - Farther.vals)
view(data)
```

3. Summarize the data.

   (a) Summarize the further data. Do the data suggest that dopamine in the brains of young zebra finches decreases when they sing further away?

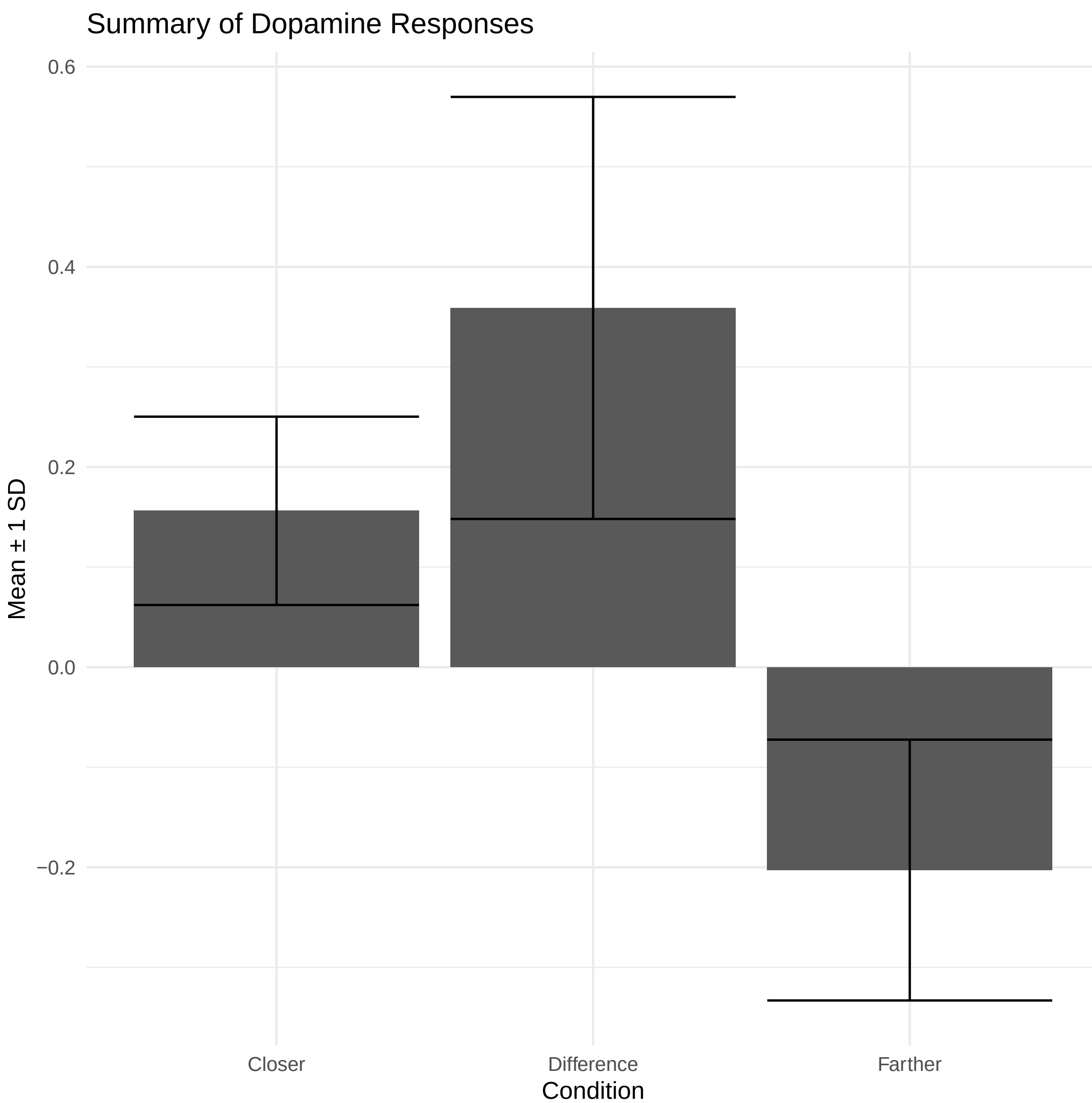
   (b) Summarize the closer data. Do the data suggest that dopamine in the brains of young zebra finches increases when they sing closer to their adult song?

   (c) Summarize the paired differences. Do the data suggest that there is a difference between dopamine in the brains of young zebra finches when they sing further away compared to closer to their adult song?

   (d) **Optional Challenge:** Can you reproduce Figure 2(g)? Note that the you can use `geom_errorbar()` to plot the range created by adding the mean ± one standard deviation.

```
data = read_csv("lab11data.csv")

data = data |>
```

```r
  mutate(difference = Closer.vals - Farther.vals)

summary = tibble(
  Condition = c("Farther", "Closer", "Difference"),
  Mean = c(mean(data$Farther.vals), mean(data$Closer.vals), mean(data$difference)),
  SD = c(sd(data$Farther.vals), sd(data$Closer.vals), sd(data$difference))
)

ggplot(summary, aes(x = Condition, y = Mean)) +
  geom_col() +
  geom_errorbar(aes(ymin = Mean - SD, ymax = Mean + SD)) +
  labs(
    title = "Summary of Dopamine Responses",
    x = "Condition",
    y = "Mean ± 1 SD"
  ) +
  theme_minimal()
```



4. Conduct the inferences they do in the paper. Make sure to report the results a little more comprehensively – that is your parenthetical should look something like: ($t = 23.99$, $p < 0.0001$; $g = 1.34$; 95% CI: 4.43, 4.60).
Note: Your numbers may vary slightly as they performed some unclear correction of their p-values. I'm waiting to hear back from them via email!

   (a) "The close responses differed significantly from 0 ($p = 1.63 \times 10^{-8}$)."
   (b) "The far responses differed significantly from 0 ($p = 5.17 \times 10^{-8}$)."
   (c) "The difference between populations was significant ($p = 1.04 \times 10^{-8}$)."

```
data = read_csv("lab11data.csv")

data = data |>
  mutate(difference = Closer.vals - Farther.vals)
```

```r
# a
ttest.closer = t.test(data$Closer.vals, mu = 0, alternative = "two.sided")
ttest.closer

##
##  One Sample t-test
##
## data:  data$Closer.vals
## t = 8.3024, df = 24, p-value = 1.626e-08
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  0.1173875 0.1950586
## sample estimates:
## mean of x
## 0.1562231

# b
ttest.farther = t.test(data$Farther.vals, mu = 0, alternative = "two.sided")
ttest.farther

##
##  One Sample t-test
##
## data:  data$Farther.vals
## t = -7.778, df = 24, p-value = 5.175e-08
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -0.2565176 -0.1489313
## sample estimates:
##  mean of x
## -0.2027244

# c
ttest.difference = t.test(data$difference, mu = 0, alternative = "two.sided")
ttest.difference

##
##  One Sample t-test
##
## data:  data$difference
## t = 8.5109, df = 24, p-value = 1.037e-08
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  0.2719028 0.4459921
## sample estimates:
## mean of x
## 0.3589475
```

5. Reverse engineer the hypothesis test plot from Lecture 20 to create accurate hypothesis testing plots for each part of the previous question.

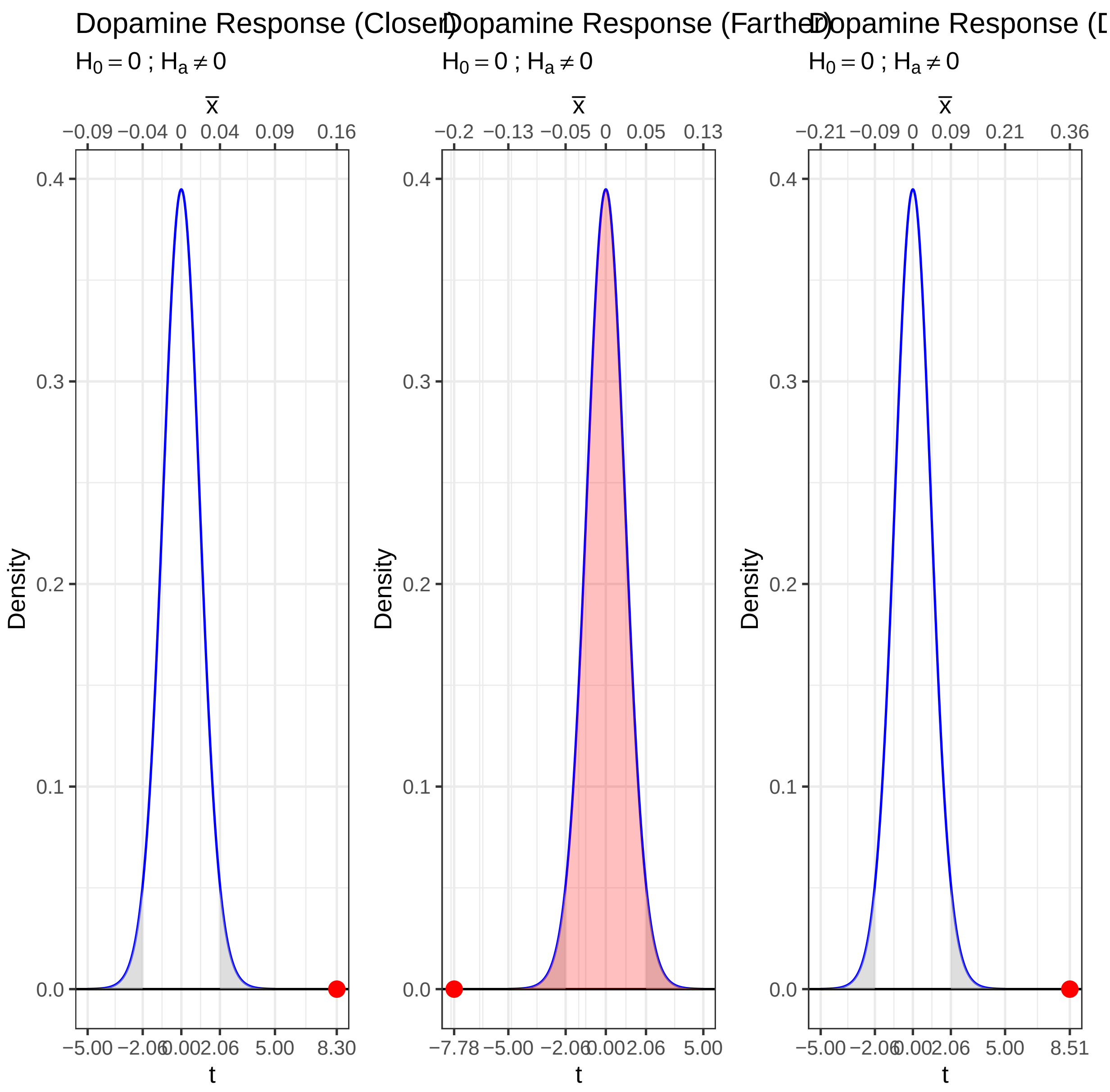
   (a) Question 4, part(a).

   (b) Question 4, part(b).

(c) Question 4, part(c).

```
library(patchwork)
data = read_csv("lab11data.csv")

data = data |>
  mutate(difference = Closer.vals - Farther.vals)

plot.t.test = function(x, mu0 = 0, test_title = "T-Test", subtitle = NULL) {
  n = length(x)
  xbar = mean(x)
  s = sd(x)
  t.stat = (xbar - mu0) / (s / sqrt(n))
  df = n - 1

  # Generate theoretical null distribution
  ggdat.t = tibble(t = seq(-5, 5, length.out = 1000)) |>
    mutate(pdf.null = dt(t, df = df))
  ggdat.obs = tibble(t = t.stat, y = 0)

  # Critical values & matching x for second axis
  t.breaks = c(-5, qt(0.025, df = df), 0, qt(0.975, df = df), 5, t.stat)
  xbar.breaks = t.breaks * (s / sqrt(n)) + mu0

  # Final plot
  ggplot() +
    geom_line(data = ggdat.t, aes(x = t, y = pdf.null), color = "blue") +
    geom_hline(yintercept = 0) +
    geom_ribbon(data = subset(ggdat.t, t <= qt(0.025, df = df)),
                aes(x = t, ymin = 0, ymax = pdf.null), fill = "grey", alpha = 0.5) +
    geom_ribbon(data = subset(ggdat.t, t >= qt(0.975, df = df)),
                aes(x = t, ymin = 0, ymax = pdf.null), fill = "grey", alpha = 0.5) +
    geom_ribbon(data = subset(ggdat.t, t >= t.stat),
                aes(x = t, ymin = 0, ymax = pdf.null), fill = "red", alpha = 0.25) +
    geom_point(data = ggdat.obs, aes(x = t, y = y), color = "red", size = 3) +
    theme_bw() +
    scale_x_continuous("t",
                       breaks = round(t.breaks, 2),
                       sec.axis = sec_axis(~.,
                                           name = expression(bar(x)),
                                           breaks = t.breaks,
                                           labels = round(xbar.breaks, 2))) +
    ylab("Density") +
    ggtitle(test_title, subtitle = subtitle)
}

closer = plot.t.test(data$Closer.vals,
            mu0 = 0,
            test_title = "Dopamine Response (Closer)",
            subtitle = bquote(H[0]==0 ~ ";" ~ H[a] != 0))

farther = plot.t.test(data$Farther.vals,
            mu0 = 0,
```

```
            test_title = "Dopamine Response (Farther)",
            subtitle = bquote(H[0]==0 ~ ";" ~ H[a] != 0))

diff = plot.t.test(data$difference,
            mu0 = 0,
            test_title = "Dopamine Response (Difference)",
            subtitle = bquote(H[0]==0 ~ ";" ~ H[a] != 0))
(closer | farther) | diff
```



References

Champely, S. (2020). *pwr: Basic Functions for Power Analysis*. R package version 1.3-0.

Kasdin, J., Duffy, A., Nadler, N., Raha, A., Fairhall, A. L., Stachenfeld, K. L., and Gadagkar, V. (2025). Natural behaviour is learned through dopamine-mediated reinforcement. *Nature*, pages 1–8.