Lecture 15: Introduction to Multilevel Models

Nov 28, 2022

> **!** Important
>
> The AE is due on GitHub by Thursday, December 01, 11:59pm.

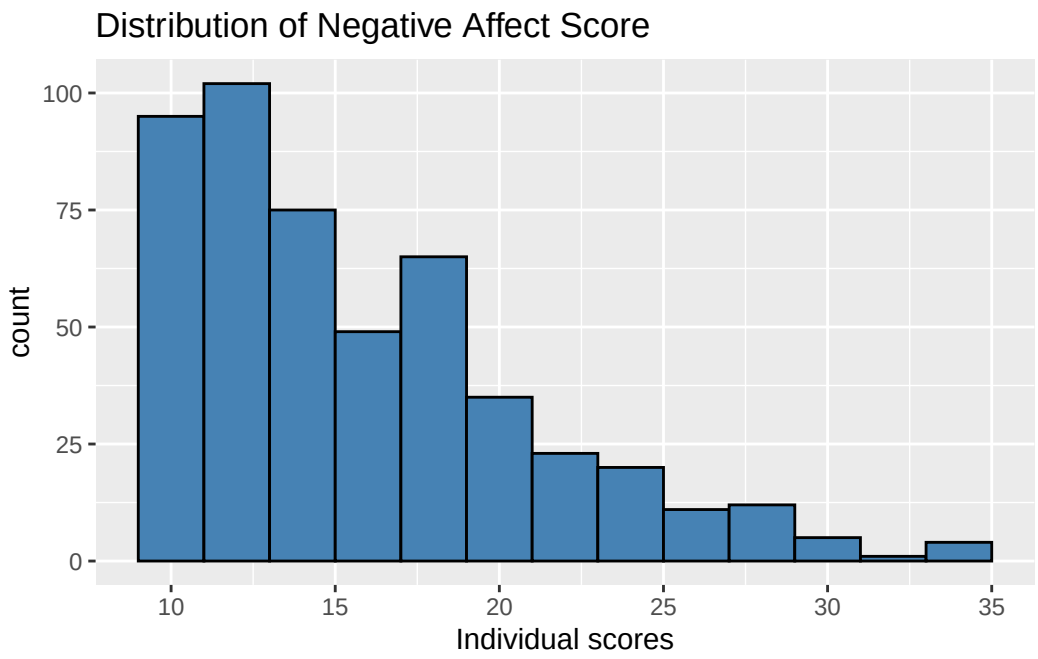
```
library(tidyverse)
library(tidymodels)
library(knitr)
library(patchwork)
```

```
music <- read_csv("data/musicdata.csv") |>
  mutate(orchestra = if_else(instrument == "orchestral instrument", 1, 0),
         large_ensemble = if_else(perform_type == "Large Ensemble", 1, 0))
```

Part 1: Univariate EDA

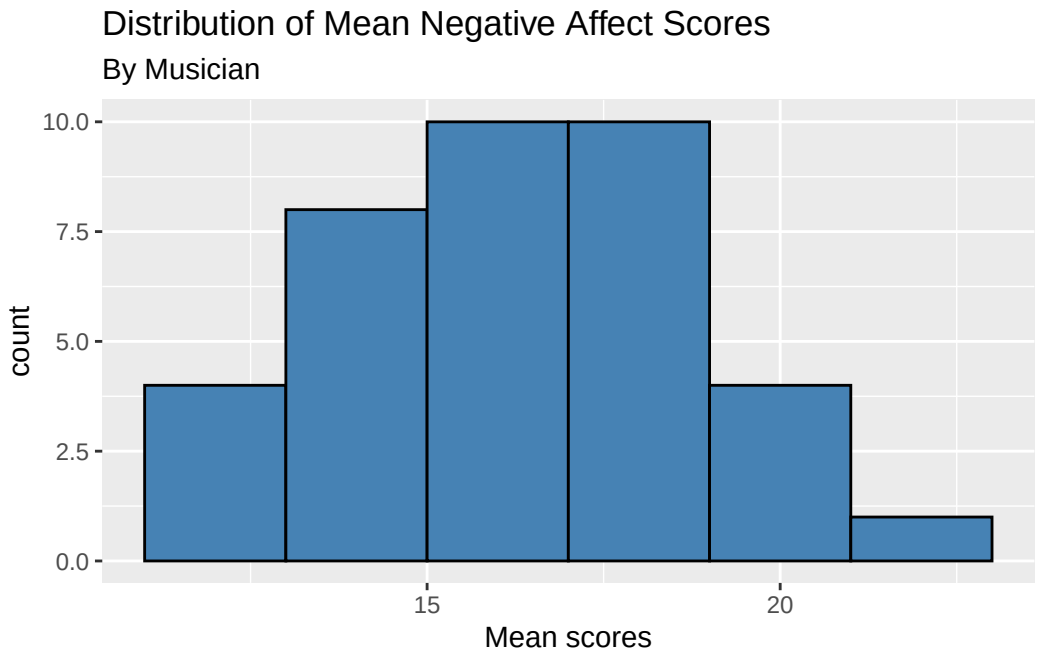
1. Plot the distribution of the response variable negative affect (`na`) using individual observations.

```
ggplot(data  = music, aes(x = na)) +
  geom_histogram(fill = "steelblue", color = "black", binwidth = 2) +
  labs(x = "Individual scores",
       title ="Distribution of Negative Affect Score")
```



2. Plot the distribution of the response variable using an aggregated value (or single observation) for each Level Two observation (musician).

```
music |>
  group_by(id) |>
  summarise(mean_na = mean(na)) |>
  ungroup() |>
  ggplot(aes(x = mean_na)) +
  geom_histogram(fill = "steelblue", color = "black", binwidth = 2) +
  labs(x = "Mean scores",
       title = "Distribution of Mean Negative Affect Scores",
       subtitle = "By Musician")
```



3. How do the plots compare? How do they differ?

The plots are similar in that they both have a center somewhere just above 15, and a somewhat similar range. However, they are not exactly the same. The first plot, at the individual level, is highly right-skewed and ranges from <10 to 35. The second plot, at the aggregated level, follows a roughly normal distribution (the CLT in action!) with a range from around 10 to 25.

4. What are some advantages of each plot? What are some disadvantages?

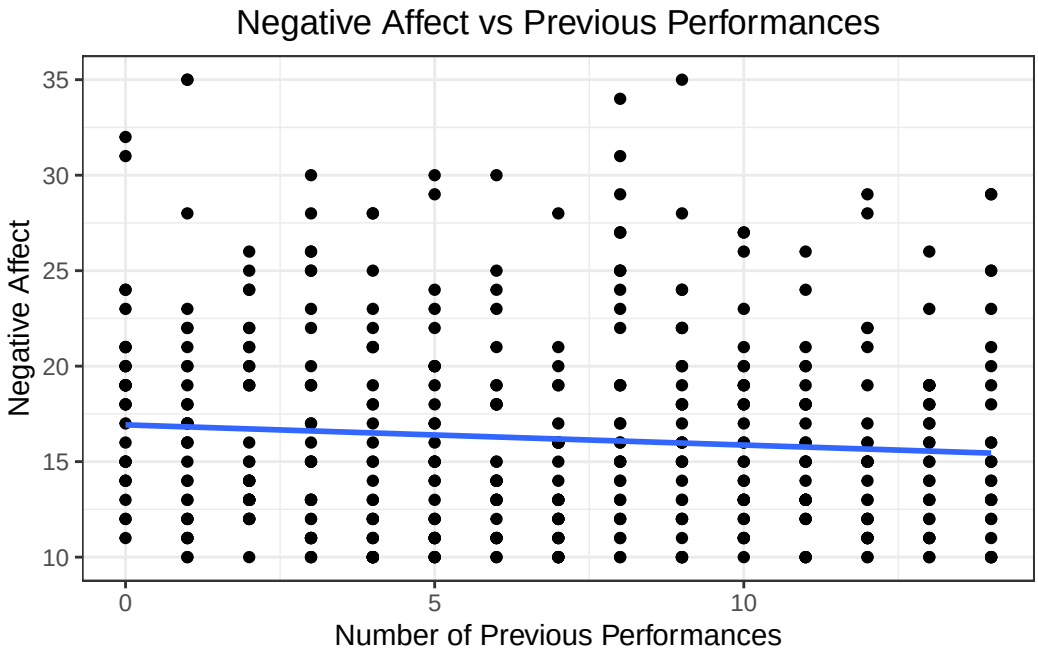
For the first plot, the main advantage is seeing all of the data. You can see that usually, performances give a NA score of somewhere between 10 and 15, although some performers will have scores up to 35. However, it does not show us anything about how much this is contained within each musician - i.e., whether musicians are likely to have similar NA scores across performances, or whether they vary more randomly.

For the second plot, the main advantage is seeing the average scores across performers. From this, we can see that the average NA score is somewhere around 17.5, which was not as apparent in the first graph. However, this hides a lot of the variability in the data, and still does not tell us anything about the variance within a given performer.

Part 2: Bivariate EDA

1. Make a single scatterplot of the negative affect versus number of previous performances (`previous`) using the individual observations. Use `geom_smooth()` to add a linear regression line to the plot.

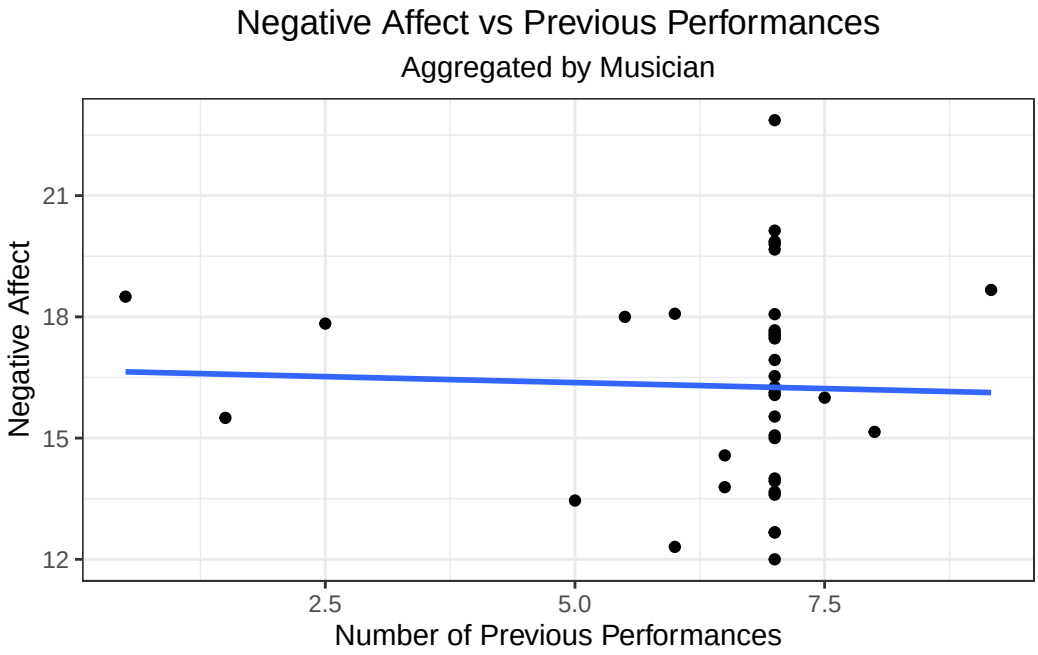
```
ggplot(music, aes(x = previous, y = na)) +
  geom_point() +
  geom_smooth(method = "lm", se = F) +
  theme_bw() +
  labs(x = "Number of Previous Performances", y = "Negative Affect",
       title = "Negative Affect vs Previous Performances") +
  theme(plot.title = element_text(hjust = 0.5))
```



2. Make a separate scatterplot of the negative affect versus number of previous performances (`previous`) faceted by musician (`id`). Use `geom_smooth()` to add a linear regression line to each plot.

```
music %>%
  group_by(id) %>%
  summarize(meanNA = mean(na), meanPrev = mean(previous)) %>%
  ggplot(aes(x = meanPrev, y = meanNA)) +
```

```
geom_point() +
geom_smooth(method = "lm", se = F) +
theme_bw() +
labs(x = "Number of Previous Performances", y = "Negative Affect",
     title = "Negative Affect vs Previous Performances", subtitle = "Aggregated by Music
theme(plot.title = element_text(hjust = 0.5), plot.subtitle = element_text(hjust = 0.5))
```



3. How do the plots compare? How do they differ?

Both plots show minimal correlation, with a demonstrated negative linear trend but not one that would be particularly visible if we did not forcibly fit a linear regression line through it. The un-aggregated plot much more clearly shows the variance in the two variables.

4. What are some advantages of each plot? What are some disadvantages?

The advantages of the unaggregated plot are that it shows the variance and true range of the observations, but it fails to show any possible relationships within any musician and thus does not tell us whether musicians tend to have similar scores across performances. The advantages of the aggregated plot are giving us a more clear understanding of which findings tended to be the most common and how individual musicians behaved, on average, but it still fails to give us an understanding of the distribution of the variables.

Part 3: Level One Models

Code to fit and display the Level One model for Observation 22 is below.

```
id_22 <- music |>
  filter(id == 22)

linear_reg() |>
  set_engine("lm") |>
  fit(na ~ large_ensemble, data = id_22) |>
  tidy() |> kable(digits = 3)
```

term	estimate	std.error	statistic	p.value
(Intercept)	24.500	1.96	12.503	0.000
large_ensemble	-7.833	2.53	-3.097	0.009

Code to fit the Level One model and get the fitted slope, intercept, and R^2 values for all musicians is below.

```
# set up tibble for fitted values

model_stats <- tibble(slopes = rep(0,37),
                intercepts = rep(0,37),
                r.squared = rep(0, 37))


ids <- music |> distinct(id) |> pull()

# counter to keep track of row number to store model_stats

count <- 1

for(i in ids){

id_data <- music |>
  filter(id == i)

level_one_model <- linear_reg() |>
  set_engine("lm") |>
  fit(na ~ large_ensemble, data = id_data)
```

```
level_one_model_tidy <- tidy(level_one_model)

model_stats$slopes[count] <- level_one_model_tidy$estimate[2]
model_stats$intercepts[count] <- level_one_model_tidy$estimate[1]
model_stats$r.squared[count] <- glance(level_one_model)$r.squared

count = count + 1
}
```

Part 4: Level Two Models

```
# Make a Level Two data set
musicians <- music |>
  distinct(id, orchestra) |>
  bind_cols(model_stats)
```

Model for intercepts

```
a <- linear_reg() |>
  set_engine("lm") |>
  fit(intercepts ~ orchestra, data = musicians)

tidy(a) |>
  kable(digits = 3)
```

term	estimate	std.error	statistic	p.value
(Intercept)	16.283	0.671	24.249	0.000
orchestra	1.411	0.991	1.424	0.163

Model for slopes

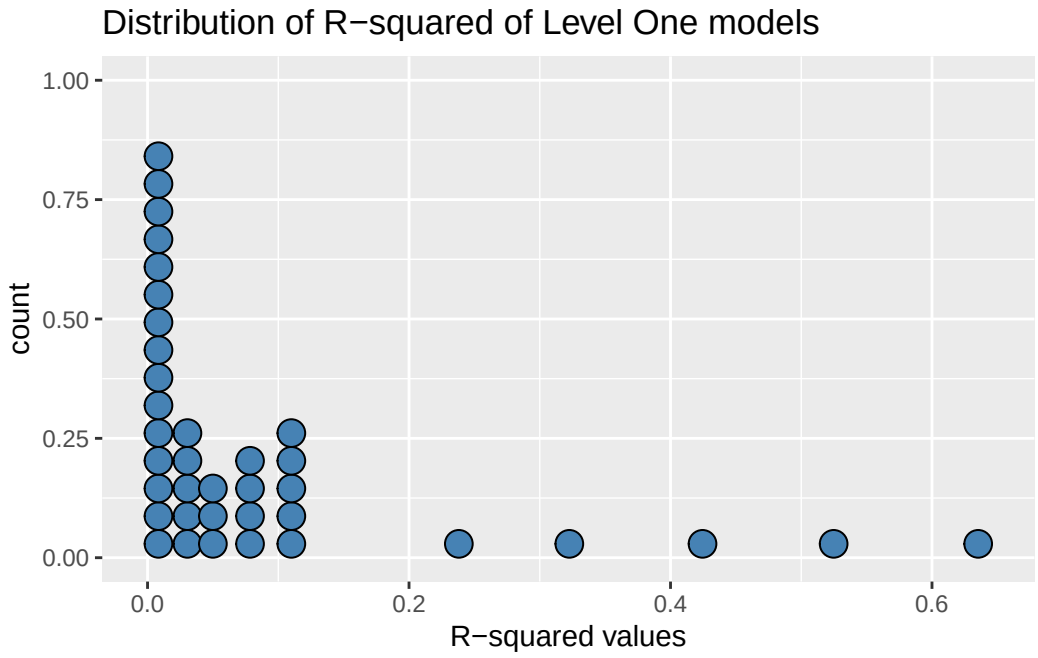
```
b <- linear_reg() |>
  set_engine("lm") |>
  fit(slopes ~ orchestra, data = musicians)

tidy(b) |>
  kable(digits = 3)
```

term	estimate	std.error	statistic	p.value
(Intercept)	-0.771	0.851	-0.906	0.373
orchestra	-1.406	1.203	-1.168	0.253

Part 5: Distribution of R^2 values

```
ggplot(data = model_stats, aes(x = r.squared)) +
  geom_dotplot(fill = "steelblue",  color = "black") +
  labs(x = "R-squared values",
       title = "Distribution of R-squared of Level One models")
```



! Important

To submit the AE:

- Render the document to produce the PDF with all of your work from today's class.
- Push all your work to your `ae-15-` repo on GitHub. (You do not submit AEs on Gradescope).