Let's convert both the cocktail `glass` and `ingredient` columns to lower case (because there are some differences in capitalization across rows), and count up totals for each combination.

```
library(tidyverse)
library(tidylo)
library(tidytuesdayR)

tuesdata <- tt_load(2020, week = 22)
cocktails <- tuesdata$cocktails

cocktail_counts <- cocktails %>%
  mutate(
    glass = str_to_lower(glass),
    ingredient = str_to_lower(ingredient)
  ) %>%
  count(glass, ingredient, sort = TRUE)

cocktail_counts
```

```
## # A tibble: 900 x 3
##    glass          ingredient       n
##
##  1 cocktail glass gin             39
##  2 collins glass  vodka           24
##  3 cocktail glass dry vermouth    19
##  4 cocktail glass lemon juice     19
##  5 cocktail glass triple sec      19
##  6 collins glass  sugar           19
##  7 highball glass vodka           18
##  8 highball glass gin             16
##  9 collins glass  orange juice    15
## 10 highball glass orange juice    15
## # … with 890 more rows
```

Now let's use the `bind_log_odds()` function from the tidylo package to find the weighted log odds for each bigram. The weighted log odds computed by this function are also z-scores for the log odds; this quantity is useful for comparing frequencies across categories or sets but its relationship to an odds ratio is not straightforward after the weighting.

What are the ingredients with the highest weighted log odds for these glasses?

```
cocktail_log_odds <- cocktail_counts %>%
  bind_log_odds(glass, ingredient, n)

cocktail_log_odds %>%
  filter(n > 5) %>%
  arrange(-log_odds_weighted)
```

```
## # A tibble: 83 x 4
##    glass              ingredient         n log_odds_weighted
##
##  1 coffee mug         coffee            10              8.52
##  2 coffee mug         chocolate          6              8.25
##  3 coffee mug         sugar              6              7.94
##  4 coffee mug         milk              11              7.63
##  5 champagne flute    champagne          6              7.26
##  6 whiskey sour glass powdered sugar     6              6.56
```

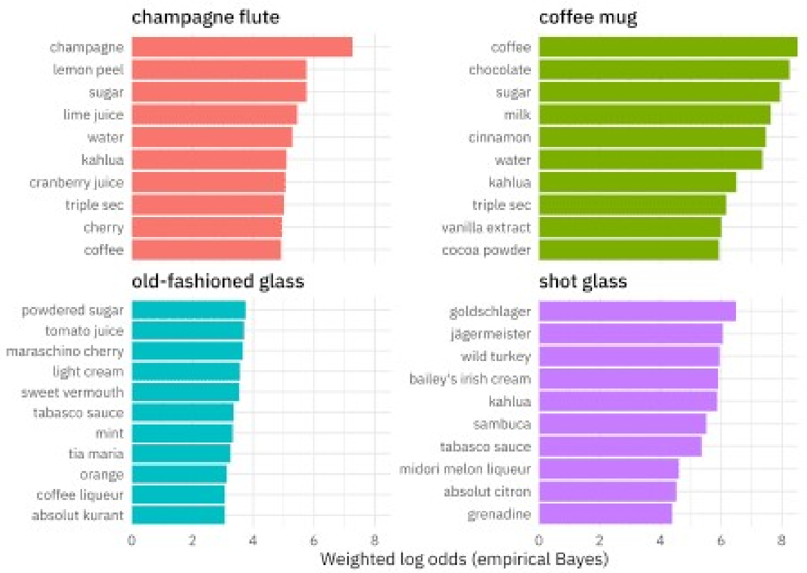
```
##   7 highball glass     yoghurt                 9             6.42
##   8 cocktail glass     orange bitters         11             6.35
##   9 cocktail glass     dry vermouth           19             6.32
## 10 shot glass         bailey's irish cream    9             5.91
## # … with 73 more rows
```

We can see right away that the highest weighted log odds ingredients in the dataset are coffee, chocolate, sugar, and milk for a coffee mug. Let's create a visualization to see the highest weighted log odds ingredients for four different types of glasses.

```
library(tidytext)

glasses <- c("coffee mug", "champagne flute", "old-fashioned glass", "shot
glass")

cocktail_log_odds %>%
  filter(glass %in% glasses) %>%
  group_by(glass) %>%
  top_n(10) %>%
  ungroup() %>%
  mutate(ingredient = reorder_within(ingredient, log_odds_weighted, glass)) %>%
  ggplot(aes(log_odds_weighted, ingredient, fill = glass)) +
  geom_col(show.legend = FALSE) +
  facet_wrap(~glass, scales = "free_y") +
  scale_y_reordered() +
  scale_x_continuous(expand = c(0, 0)) +
  labs(y = NULL, x = "Weighted log odds (empirical Bayes)")
```

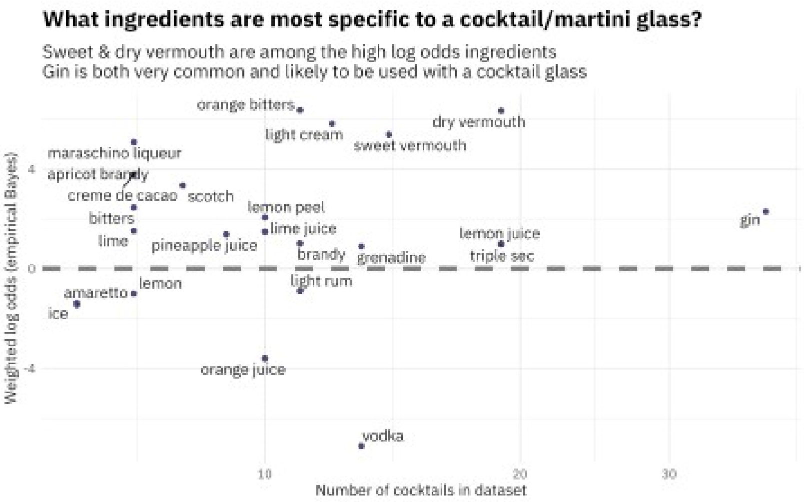


OH BOY, seeing all these ingredients mixed up like this makes me feel a little queasy. 🤢 These are the ingredients most likely to be used with each glass, assuming the prior estimated from the data itself. Notice also that the ingredients for the coffee mug are the **most** distinctive, and the ingredients for the old-fashioned glass are the **least** distinctive.

Perhaps we want to understand one type of glass in more detail, and examine the relationship between weighted log odds and how common an ingredient is. Let's look at the "cocktail glass", which you might know as a martini glass.

```
library(ggrepel)
cocktail_log_odds %>%
  filter(glass == "cocktail glass",
         n > 5) %>%
  ggplot(aes(n, log_odds_weighted, label = ingredient)) +
```

```
  geom_hline(yintercept = 0, color = "gray50", lty = 2, size = 1.5) +
  geom_point(alpha = 0.8, color = "midnightblue") +
  geom_text_repel(family = "IBMPlexSans") +
  scale_x_log10() +
  labs(x = "Number of cocktails in dataset",
       y = "Weighted log odds (empirical Bayes)",
       title = "What ingredients are most specific to a cocktail/martini
glass?",
       subtitle = "Sweet & dry vermouth are among the high log odds
ingredients\nGin is both very common and likely to be used with a cocktail
glass")
```



Vodka is common, but it is used among so many different kinds of glasses that is does not have a high weighted log odds for a cocktail/martini glass.

Weighty matters

By default, the prior in tidylo is estimated from the data itself as shown with the cocktail ingredients, an empirical Bayes approach, but an uninformative prior is also available. To demonstrate this, let's look at everybody's favorite data about cars. 🚗 What do we know about the relationship between number of gears and engine shape `vs`?

```
gear_counts <- mtcars %>%
  count(vs, gear)

gear_counts
```

```
##   vs gear  n
## 1  0    3 12
## 2  0    4  2
## 3  0    5  4
## 4  1    3  3
## 5  1    4 10
## 6  1    5  1
```

Now we can use `bind_log_odds()` to find the weighted log odds for each number of gears and engine shape. First, let's use the default empirical Bayes prior. It regularizes the values.

```
regularized <- gear_counts %>%
  bind_log_odds(vs, gear, n)

regularized
```

```
##   vs gear  n log_odds_weighted
```

```
## 1  0    3 12         1.1728347
## 2  0    4  2        -1.3767516
## 3  0    5  4         0.4033125
## 4  1    3  3        -1.1354777
## 5  1    4 10         1.5661168
## 6  1    5  1        -0.4362340
```

For engine shape `vs = 0`, having three gears has the highest weighted log odds while for engine shape `vs = 1`, having four gears has the highest weighted log odds. This dataset is small enough that you can look at the count data and see how this is working.

Now, let's use the uninformative prior, and compare to the unweighted log odds. These log odds will be farther from zero than the regularized estimates.

```
unregularized <- gear_counts %>%
  bind_log_odds(vs, gear, n, uninformative = TRUE, unweighted = TRUE)

unregularized
```

```
##   vs gear  n   log_odds log_odds_weighted
## 1  0    3 12  0.6968169         1.8912729
## 2  0    4  2 -1.2527630        -1.9691060
## 3  0    5  4  0.3249262         0.5549172
## 4  1    3  3 -0.9673459        -1.7407107
## 5  1    4 10  1.1451323         2.8421436
## 6  1    5  1 -0.5268260        -0.6570674
```

Most importantly, you can notice that this approach is useful both for text data, for our example of cocktail ingredients, but also more generally whenever you have counts in some kind of groups or sets and you want to find what feature is more likely to come from a group, compared to the other groups.