Challenges

Overview

Initial analysis of survey Q9: "How frequently have you encountered the following challenges while working on open-source projects?"

Import packages and utilities

```
project_root <- here::here() # requires that you be somewhere in the
# project directory (not above it)
# packages
suppressMessages(source(file.path(project_root, "scripts/packages.R")))
# functions and objects used across scripts
suppressMessages(source(file.path(project_root, "scripts/utils.R")))
```

Set seed

```
set.seed(42)
```

Define functions

multiple_plots

- Arguments:
  - `df`: In this script, this will always be the `to_plot` data frame. Must contain (at least) three columns: `challenge`, `challenge_level` (a character column), and `total`.

- `title_codes`: In this script, this will always be the `titles` list. Keys are shorthand codes for each challenge, and values are the full challenge from the survey.
- `challenges_of_interest`: A character vector of the challenges you want to plot.

- Details:
  - A simple function to call my `basic_bar_chart` function (from scripts/utils.R) on multiple challenges, producing multiple plots.
- Outputs:
  - Prints n plots, where n is the number of challenges of interest.

```r
multiple_plots <- function(df, title_codes, challenges_of_interest) {
  for (ch in challenges_of_interest) {
    df_ch <- filter(df, challenge == ch)
    plot_title <- title_codes[[ch]]
    p <- basic_bar_chart(
      df_ch,
      x_var = "challenge_level",
      y_var = "total",
      title = plot_title,
      show_grid = TRUE
    )
    print(p)
  }
}
```

Load data

```r
challenges <- load_qualtrics_data("clean_data/challenges_Q9.tsv")
```

Wrangle data

Remove empty rows, i.e. rows from respondents who didn't receive this question. As with many questions in this survey, we can cut some corners in the code because the question was mandatory. For example, no need to worry about incomplete answers.

```r
nrow(challenges)
```

```
[1] 332
```

```r
challenges <- exclude_empty_rows(challenges) # from scripts/utils.R
nrow(challenges)
```

```
[1] 233
```

Let's reshape the data from wide to long format for easier plotting later. We'll also recode the Likert values to integers, so we can get descriptive statistics of the responses. ("Never" = 0, "Non-applicable" = 0,"Rarely" = 1, "Occasionally" = 2, "Frequently" = 3, "Always" = 4)

```r
long_data <- challenges %>%
  pivot_longer(
    cols = everything(),
    names_to = "challenge",
    values_to = "challenge_level"
  )

long_data <- long_data %>%
  mutate(
    challenge_score = recode(
      challenge_level,
      "Never"           = 0L,
      "Non-applicable"  = 0L,
      "Rarely"          = 1L,
      "Occasionally"    = 2L,
      "Frequently"      = 3L,
      "Always"          = 4L
    )
  )
# Using interger literals 0L, 1L, etc., ensures that
# the new column will be integers, not doubles.

long_data
```

```
# A tibble: 3,262 x 3
   challenge          challenge_level challenge_score
   <chr>              <chr>                     <int>
 1 Coding time        Always                        4
 2 Documentation time Always                        4
 3 Managing issues    Always                        4
 4 Attracting users   Always                        4
 5 Recognition        Always                        4
```

```
 6 Hiring             Always                         4
 7 Security           Always                         4
 8 Finding peers      Always                         4
 9 Finding mentors    Always                         4
10 Education time     Always                         4
# i 3,252 more rows
```

Next, let's calculate some simple descriptive statistics. I will choose:
* The total "score", that is, the total number of "points" a challenge received * The mean (which might be misleading if 0s drag it down, and also, who's to say what a 2.5 really means? Are the distances between the Likert points equal? We assume so, but this is hand-wavy.) * The mode * The standard deviation

```r
# Helper to compute the (numeric) mode
get_mode <- function(x) {
  ux <- unique(x)
  ux[which.max(tabulate(match(x, ux)))]
}

summary_df <- long_data %>%
  group_by(challenge) %>%
  summarise(
    total  = sum(challenge_score),
    mean   = mean(challenge_score, na.rm = TRUE),
    mode   = get_mode(challenge_score),
    st_dev = sd(challenge_score, na.rm = TRUE)
  ) %>%
  ungroup()

# Order by highest total "score"
summary_df <- summary_df %>%
    arrange(desc(total))

summary_df
```

```
# A tibble: 14 x 5
   challenge             total  mean  mode st_dev
   <chr>                 <int> <dbl> <int>  <dbl>
 1 Documentation time      686  2.94     3   1.08
 2 Coding time             606  2.60     3   1.24
 3 Education time          539  2.31     3   1.26
 4 Managing issues         451  1.94     2   1.29
```

```
 5 Attracting users        442  1.90     0   1.45
 6 Securing funding        438  1.88     0   1.74
 7 Finding funding         432  1.85     0   1.68
 8 Educational resources   369  1.58     1   1.19
 9 Recognition             334  1.43     0   1.35
10 Legal                   333  1.43     0   1.24
11 Finding mentors         323  1.39     0   1.31
12 Security                307  1.32     0   1.31
13 Hiring                  291  1.25     0   1.53
14 Finding peers           267  1.15     0   1.13
```

Cool! It looks like finding the time for documentation, coding, and self-education are the challenges encountered most frequently. These are the only responses that had a mode of 3 ("Frequently") and a mean of **greater** than 2 ("Occasionally").

Out of curiosity, how does it look when we order by variability?

```r
sd_df <- summary_df %>%
    arrange(desc(st_dev))

sd_df
```

```
# A tibble: 14 x 5
   challenge             total  mean  mode st_dev
   <chr>                 <int> <dbl> <int>  <dbl>
 1 Securing funding        438  1.88     0   1.74
 2 Finding funding         432  1.85     0   1.68
 3 Hiring                  291  1.25     0   1.53
 4 Attracting users        442  1.90     0   1.45
 5 Recognition             334  1.43     0   1.35
 6 Security                307  1.32     0   1.31
 7 Finding mentors         323  1.39     0   1.31
 8 Managing issues         451  1.94     2   1.29
 9 Education time          539  2.31     3   1.26
10 Legal                   333  1.43     0   1.24
11 Coding time             606  2.60     3   1.24
12 Educational resources   369  1.58     1   1.19
13 Finding peers           267  1.15     0   1.13
14 Documentation time      686  2.94     3   1.08
```

Fascinating! The greatest standard deviations are from securing funding, finding funding, and hiring. This makes sense, as these are, at least in my perception, "manager tasks"–tasks that only some people face, but they're likely to be a big challenge for those who face them. I would guess that these might show a bimodal distribution. Let's plot them and find out!

Plot the distributions

Prepare data for plotting

```
ordered_levels <- c(
  "Non-applicable",
  "Never",
  "Rarely",
  "Occasionally",
  "Frequently",
  "Always"
)

to_plot <- long_data %>%
  mutate(
    challenge_level = factor(
      challenge_level,
      levels = ordered_levels
    )
  ) %>%
  count(
    challenge,
    challenge_level,
    name = "total"
  ) %>%
  ungroup()

to_plot
```

```
# A tibble: 84 x 3
   challenge        challenge_level total
   <chr>            <fct>           <int>
 1 Attracting users Non-applicable     50
 2 Attracting users Never              15
 3 Attracting users Rarely             24
 4 Attracting users Occasionally       53
 5 Attracting users Frequently         52
 6 Attracting users Always             39
```

```
 7 Coding time      Non-applicable     21
 8 Coding time      Never               4
 9 Coding time      Rarely             13
10 Coding time      Occasionally       54
# i 74 more rows
```

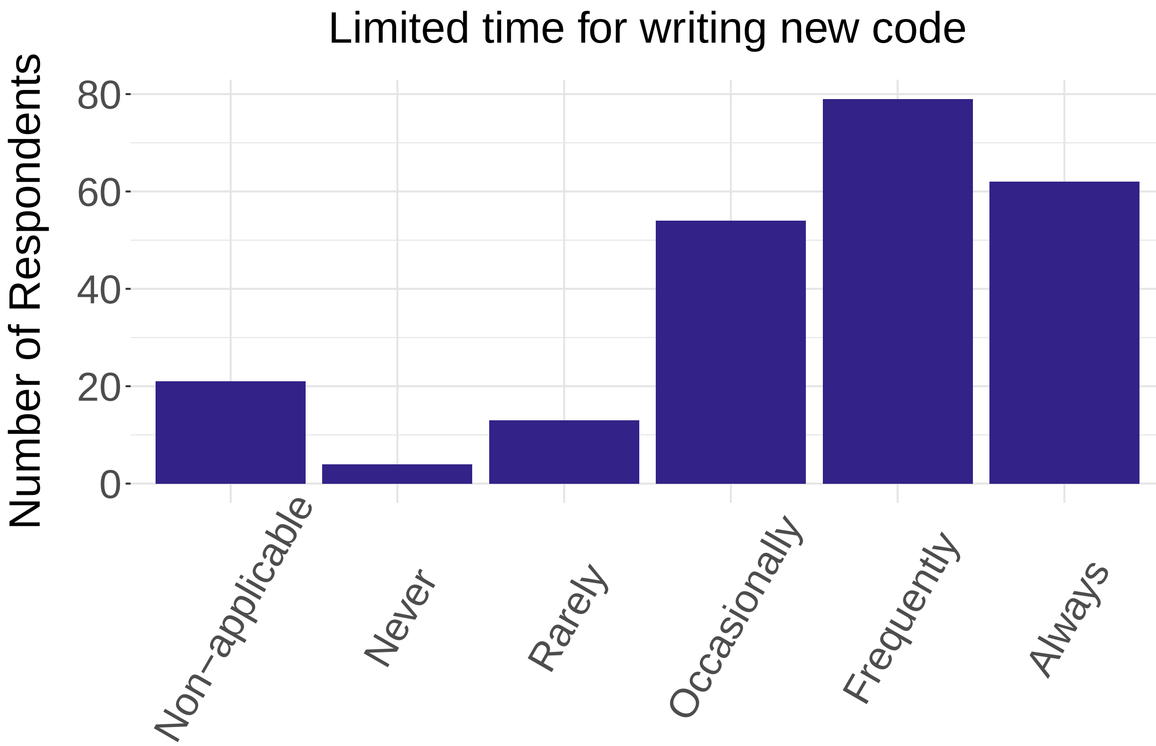
Create a plot for each "challenge". After inspecting the plots, I attempted to order them into groups based on the shape of their distribution. These are the shapes I observed (this is extremely subjective):
* Right-skewed: Documentation time, coding time, education time * Interpretation: Common tasks that are frequently challenging * Highly bimodal: Securing funding, identifying funding, hiring * Interpretation: Tasks that are not as common, but they are frequently challenging for the people tasked with them. * Normal: Educational resources, Legal * Interpretation: Moderately common tasks that are challenging with moderate frequency. * NA-skewed but otherwise normal: Attracting users, Receiving recognition, finding mentors, managing security risks, managing issues * Interpretation: Less-common tasks that are challenging with moderate frequency. * Left-skewed: Finding peers * Interpretation: Moderately common tasks that are infrequently challenging.

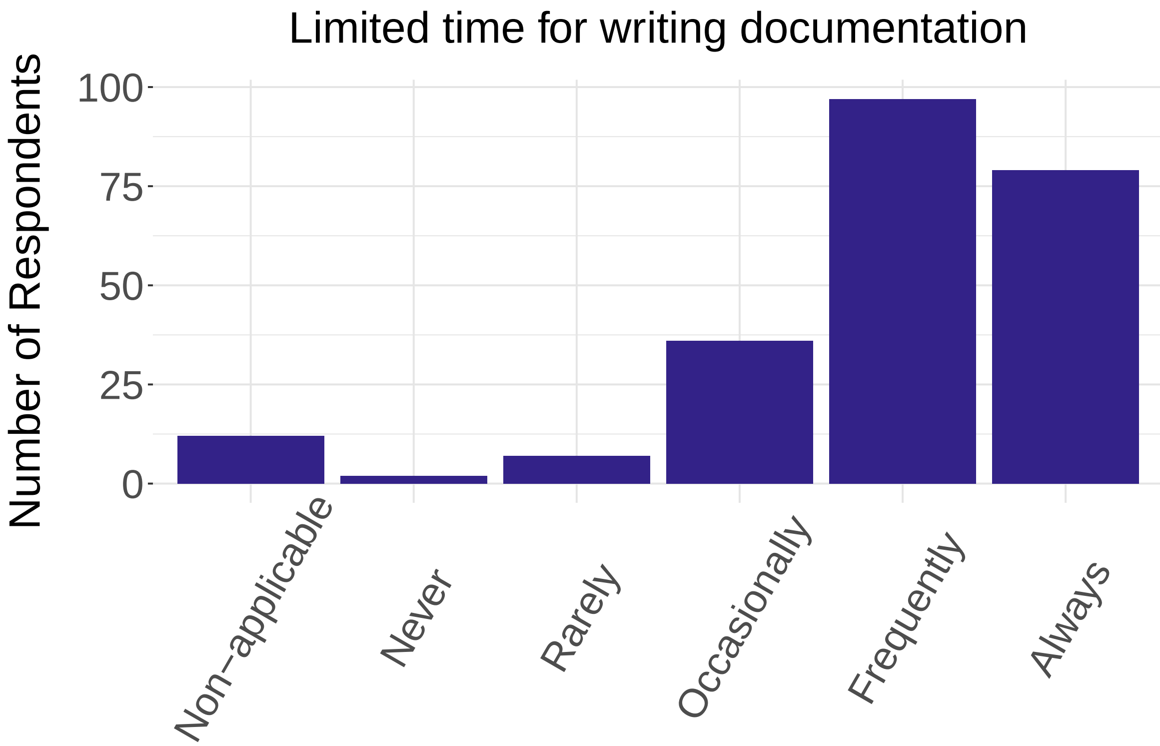
```r
titles <- list(
    "Coding time" = "Limited time for writing new code",
    "Documentation time" = "Limited time for writing documentation",
    "Managing issues" = "Managing issues and pull requests",
    "Attracting users" = "Attracting users and/or contributors",
    "Recognition" = "Receiving recognition for my contributions",
    "Hiring" = "Finding and hiring qualified personnel",
    "Security" = "Managing security risks",
    "Finding peers" = "Finding a community of peers who share my interests",
    "Finding mentors" = "Finding mentors",
    "Education time" = "Finding time to educate myself",
    "Educational resources" = "Identifying helpful educational resources",
    "Legal" = "Navigating licensing and other legal issues",
    "Finding funding" = "Identifying potential funding sources\nfor my open source projects"
    "Securing funding" = "Securing funding for my open source projects"
)

right_skewed <- c(
    "Coding time",
    "Documentation time",
    "Education time"
)
bimodal <- c(
```

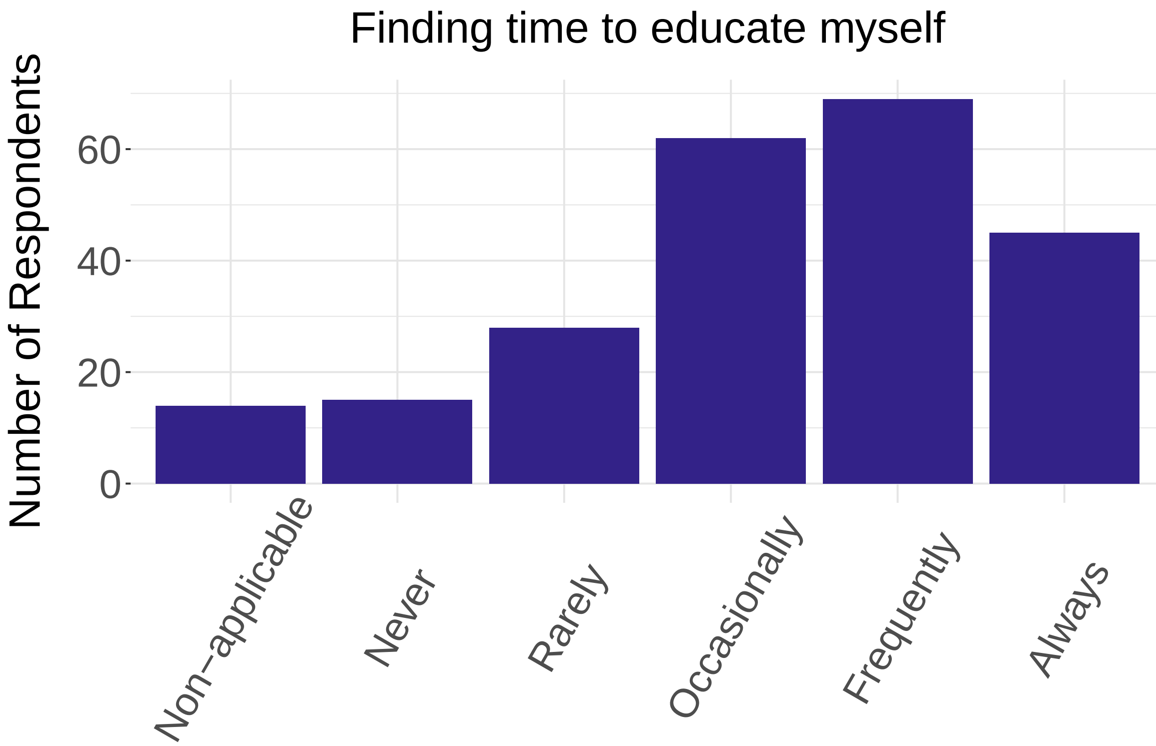
```
    "Finding funding",
    "Securing funding",
    "Hiring"
)
normal <- c(
    "Educational resources",
    "Legal"
)
na_skewed <- c(
    "Managing issues",
    "Attracting users",
    "Recognition",
    "Security",
    "Finding mentors"
)
left_skewed <- c(
    "Finding peers"
)
```

"right-skewed"

```
multiple_plots(to_plot, titles, right_skewed)
```

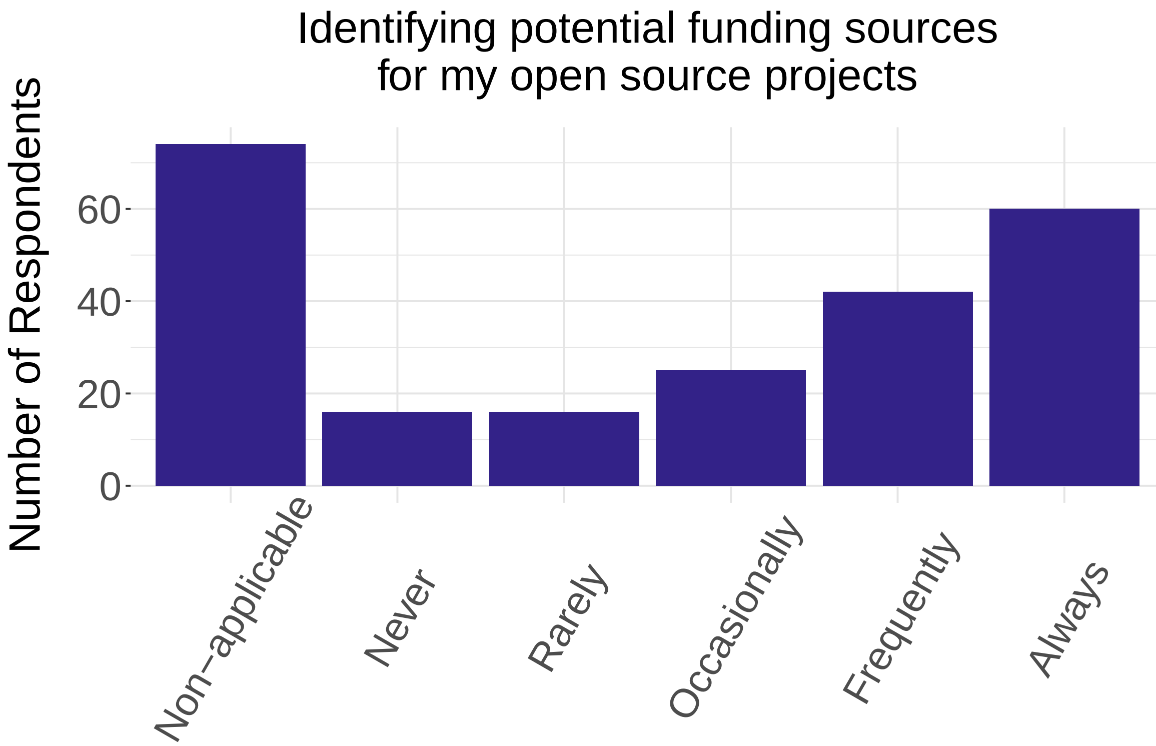

Limited time for writing new code
Number of Respondents
0
20
40
60
80
Non–applicable
Never
Rarely
Occasionally
Frequently
Always

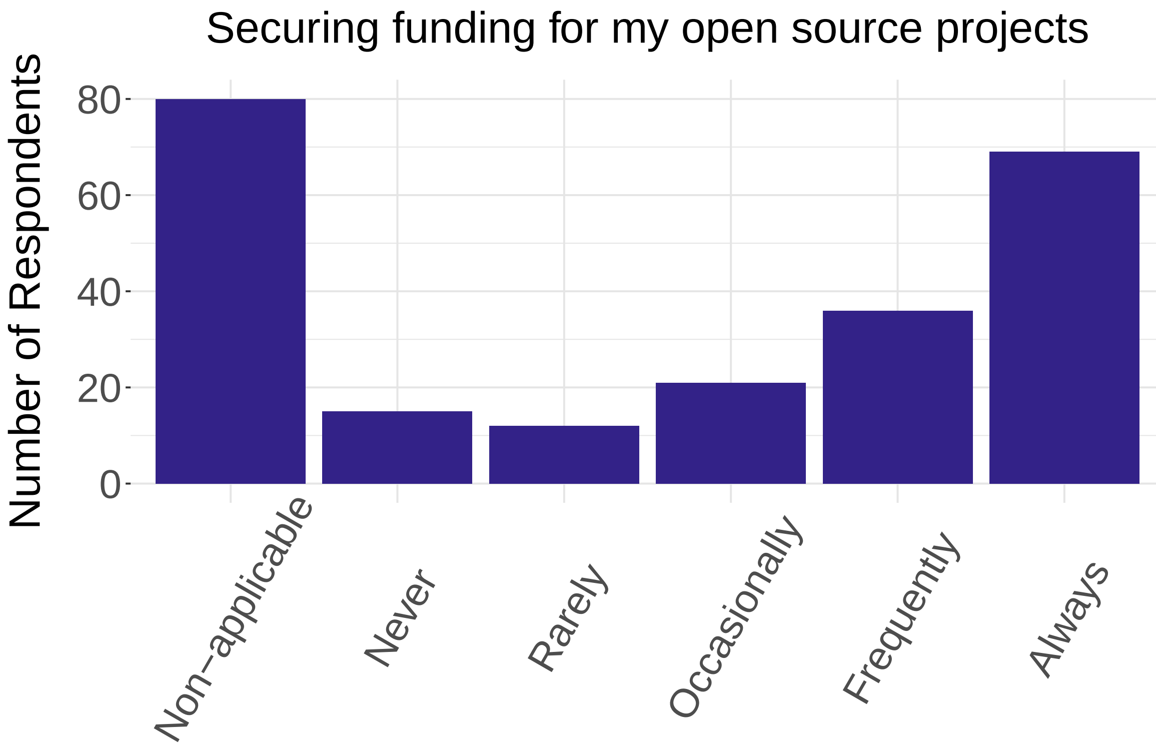

Limited time for writing documentation
Number of Respondents
100
75
50
25
0
Non–applicable
Never
Rarely
Occasionally
Frequently
Always

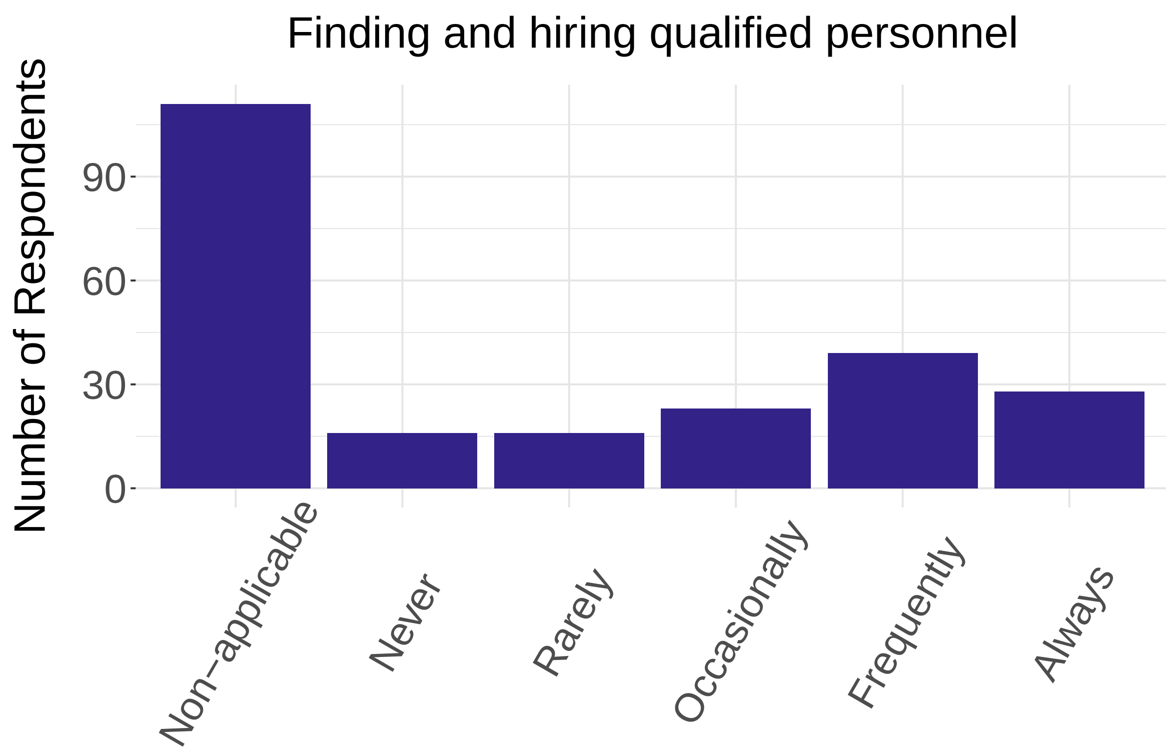


"highly bimodal"

```
multiple_plots(to_plot, titles, bimodal)
```

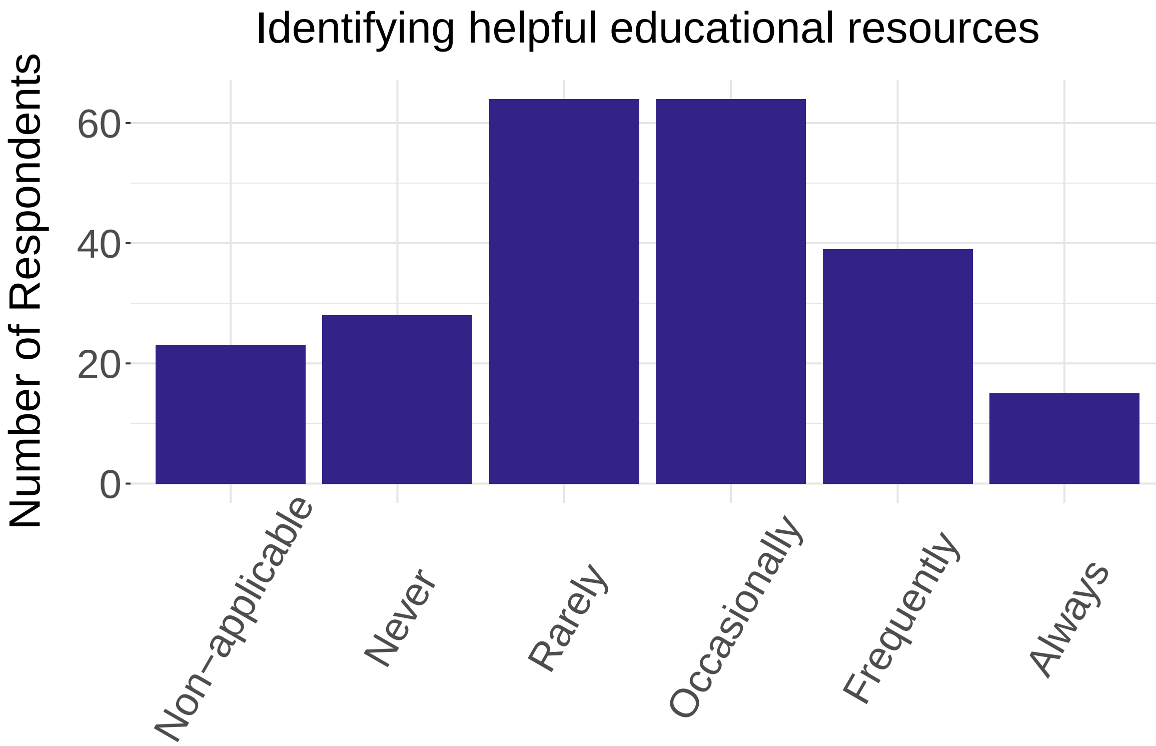

Identifying potential funding sources
for my open source projects
Number of Respondents
0
20
40
60
Non–applicable
Never
Rarely
Occasionally
Frequently
Always

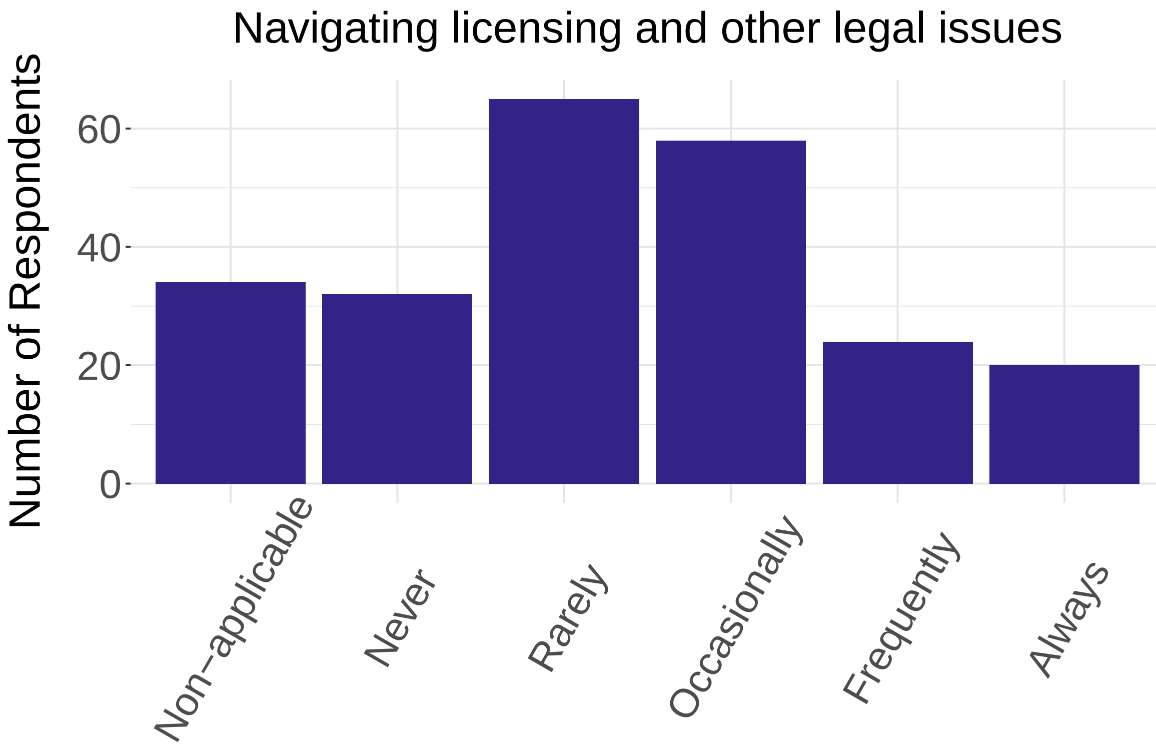

Securing funding for my open source projects
Number of Respondents
80
60
40
20
0
Non–applicable
Never
Rarely
Occasionally
Frequently
Always



"normal"

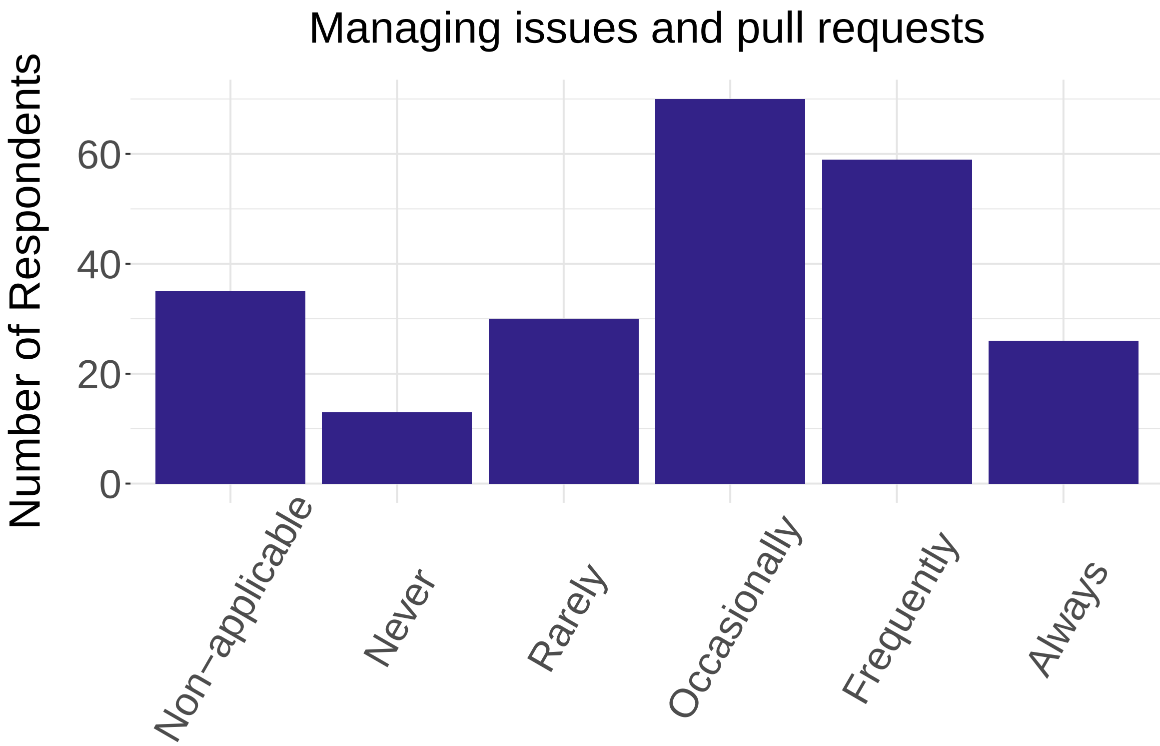
```
multiple_plots(to_plot, titles, normal)
```

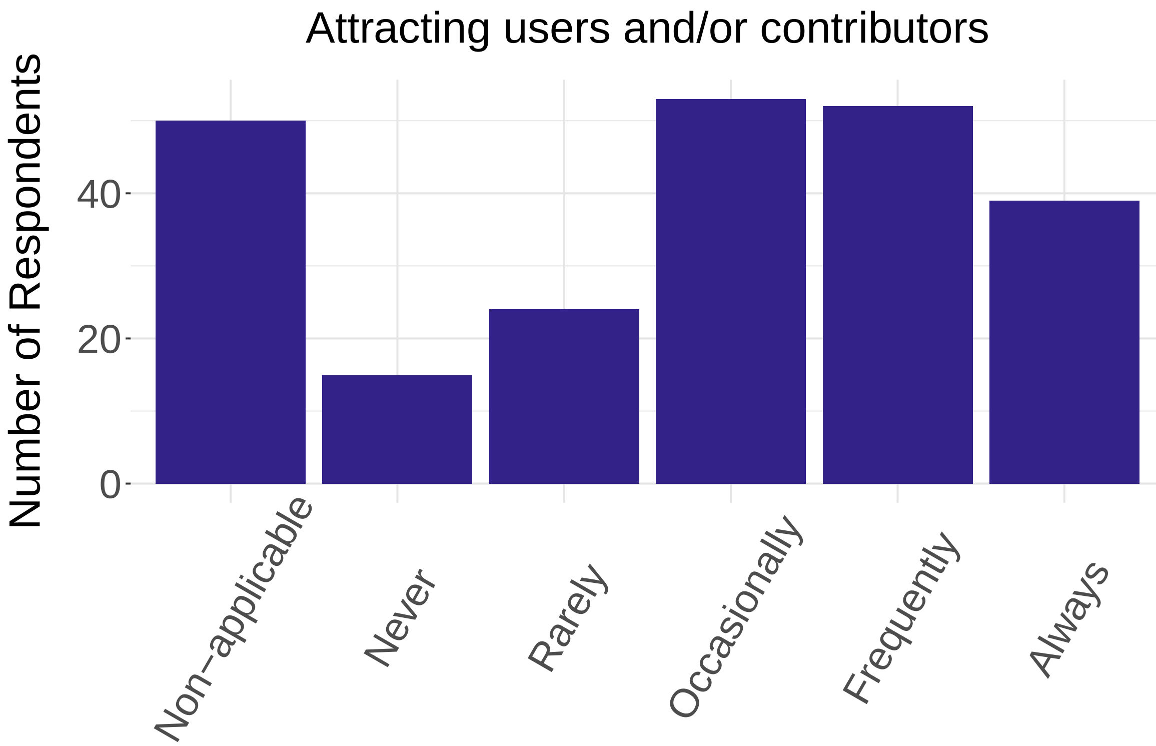

Identifying helpful educational resources
Number of Respondents
60
40
20
0
Non−applicable
Never
Rarely
Occasionally
Frequently
Always

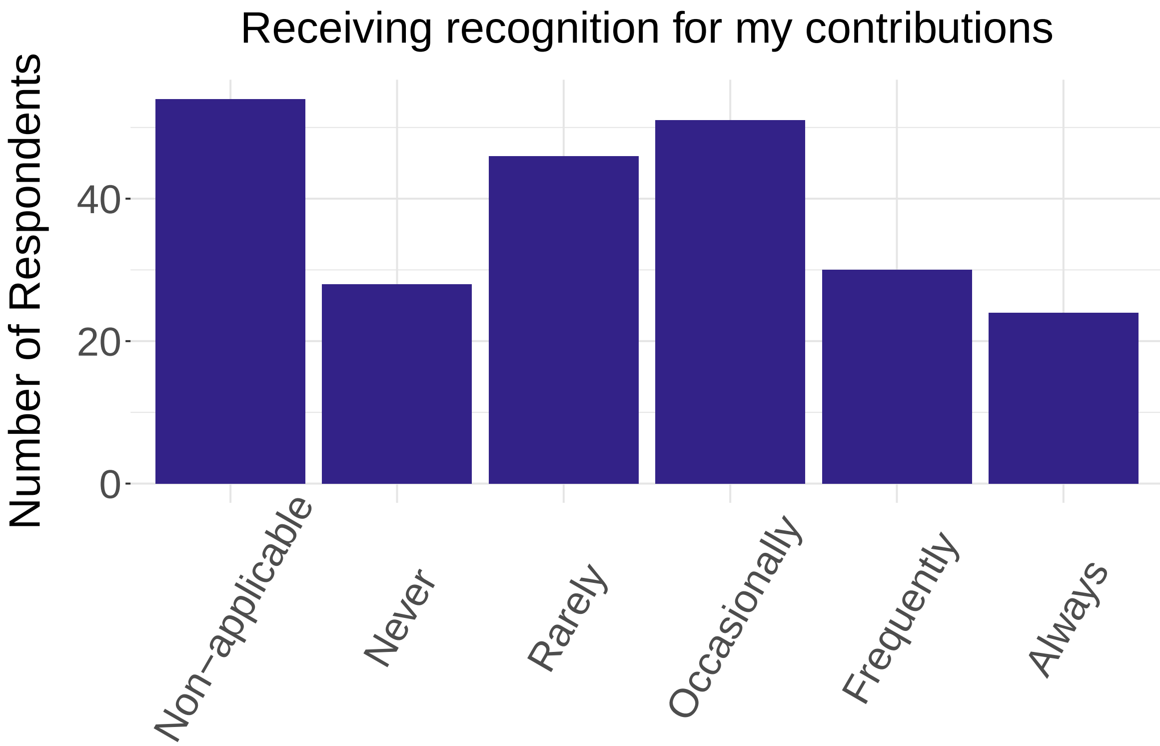


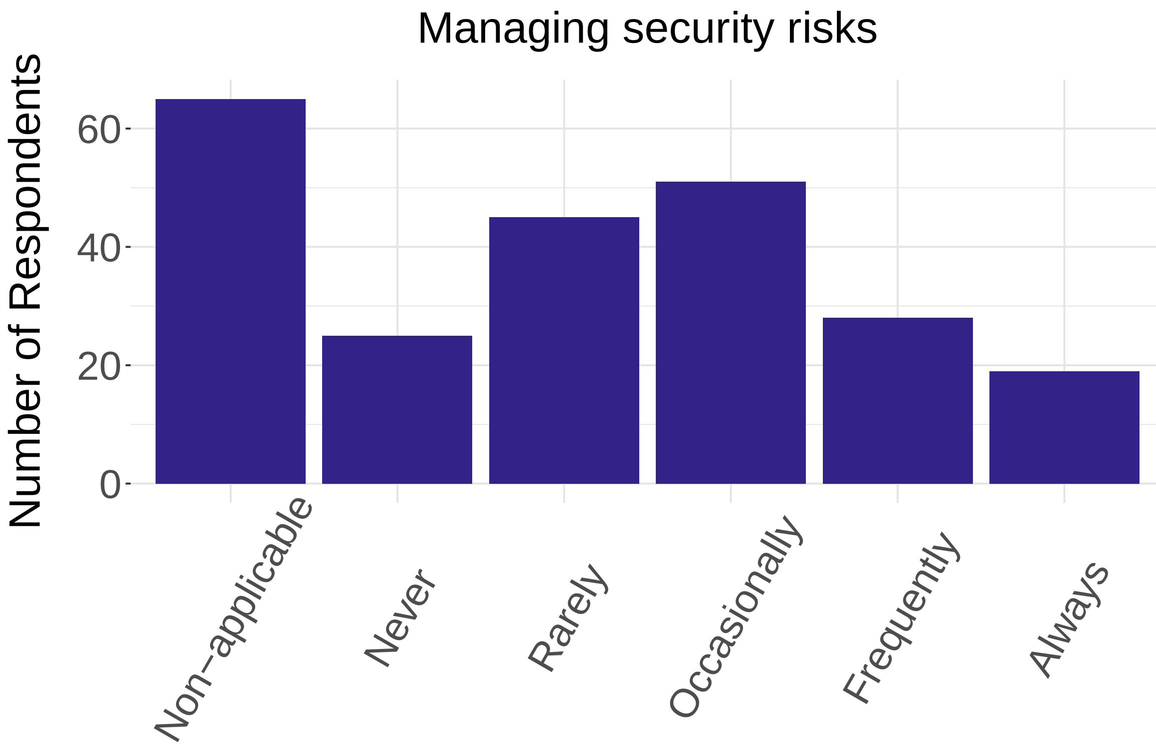
"na-skewed"

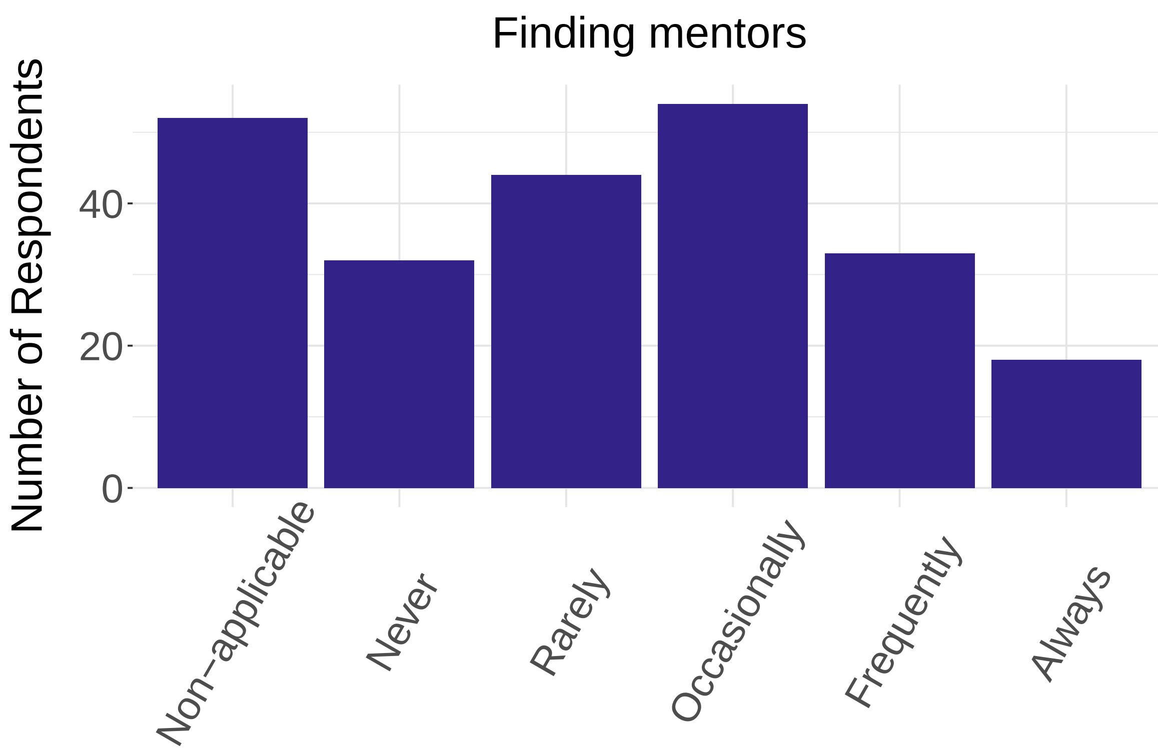
```
multiple_plots(to_plot, titles, na_skewed)
```


Managing issues and pull requests
Number of Respondents
60
40
20
0
Non−applicable
Never
Rarely
Occasionally
Frequently
Always


Attracting users and/or contributors
Number of Respondents
0
20
40
Non–applicable
Never
Rarely
Occasionally
Frequently
Always

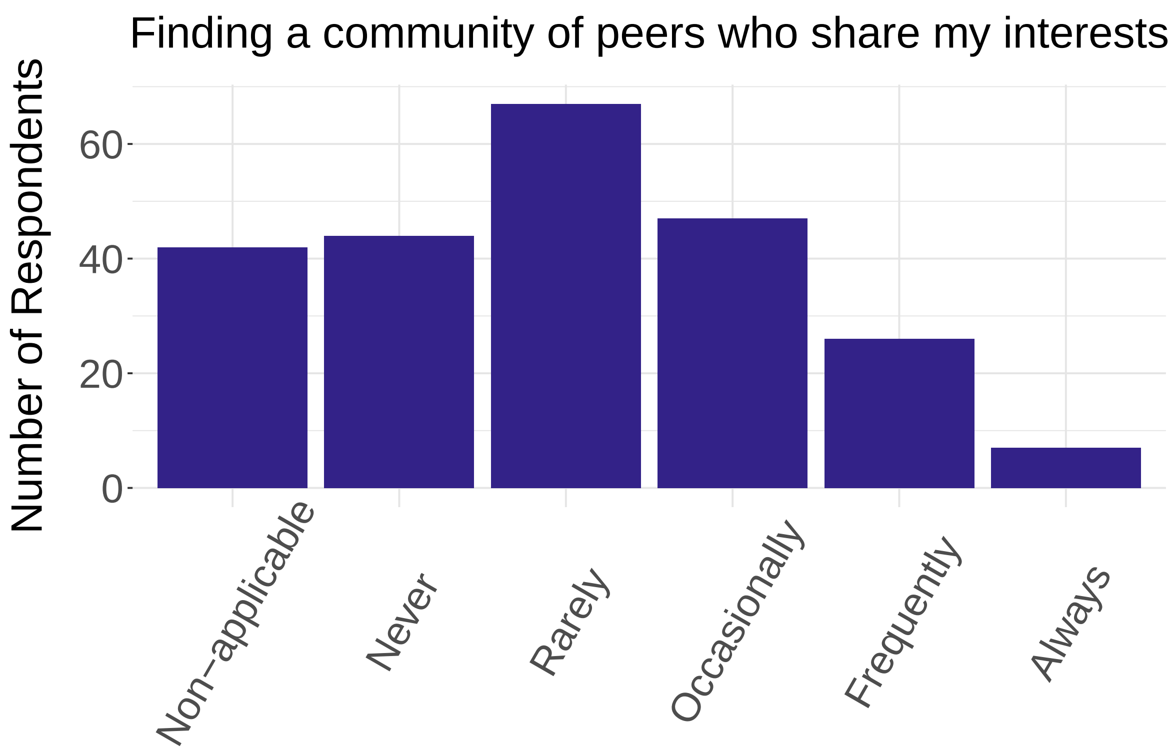

Receiving recognition for my contributions
Number of Respondents
0
20
40
Non−applicable
Never
Rarely
Occasionally
Frequently
Always


Managing security risks
Number of Respondents
0
20
40
60
Non–applicable
Never
Rarely
Occasionally
Frequently
Always



"left-skewed"

```
multiple_plots(to_plot, titles, left_skewed)
```



K-means clustering of distributions

This seems like an interesting line of inquiry. Let's make it a little more rigorous by clustering the challenges based on the response rates (actually, the absolute response numbers).

Wrangle data

```
wide_counts <- to_plot %>%
  pivot_wider(
    names_from   = challenge_level,
    values_from  = total,
    values_fill  = 0
  )

wide_counts <- data.frame(wide_counts)
# Turn this categorical column into row names
```

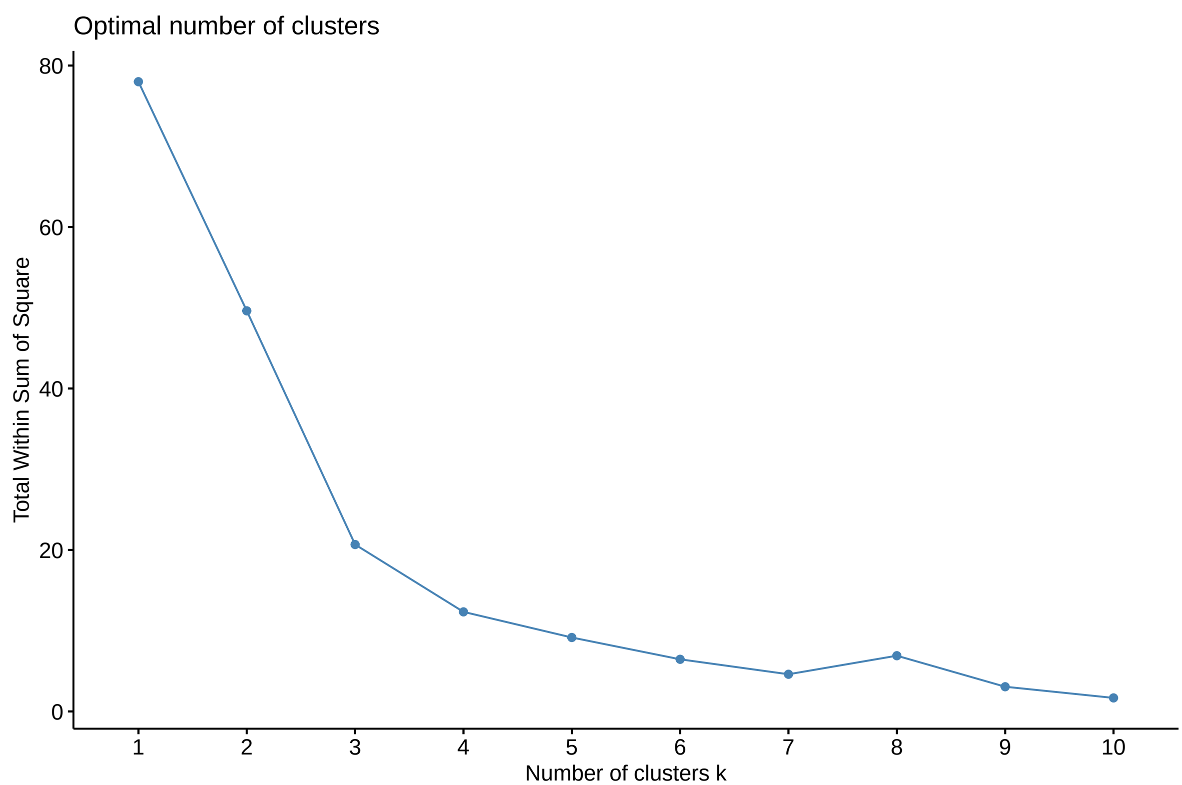
```r
rownames(wide_counts) <- wide_counts$challenge
wide_counts <- wide_counts[,2:(ncol(wide_counts))]

# Scaling probably isn't necessary?
# We have the same number of responses throughout,
# so the units for each challenge are the same
# (number of responses).
scaled <- scale(wide_counts)
scaled
```

```
                     Non.applicable      Never     Rarely Occasionally
Attracting users         0.08407151 -0.4615675 -0.4780961   0.33347644
Coding time             -0.95026278 -1.4093196 -1.0002719   0.39743082
Documentation time      -1.27126308 -1.5816381 -1.2850951  -0.75374811
Education time          -1.19992968 -0.4615675 -0.2882139   0.90906590
Educational resources   -0.87892938  0.6585030  1.4207252   1.03697467
Finding funding          0.94007229 -0.3754083 -0.8578603  -1.45724635
Finding mentors          0.15540491  1.0031401  0.4713146   0.39743082
Finding peers           -0.20126209  2.0370514  1.5631368  -0.05024987
Hiring                   2.25974018 -0.3754083 -0.8578603  -1.58515512
Legal                   -0.48659569  1.0031401  1.4681957   0.65324836
Managing issues         -0.45092899 -0.6338861 -0.1932729   1.42070098
Recognition              0.22673830  0.6585030  0.5662556   0.20556767
Securing funding         1.15407249 -0.4615675 -1.0477424  -1.71306389
Security                 0.61907200  0.4000252  0.5187851   0.20556767
                     Frequently     Always
Attracting users      0.2440265  0.1098315
Coding time           1.4739199  1.1202809
Documentation time    2.2938488  1.8671349
Education time        1.0184038  0.3734270
Educational resources -0.3481444 -0.9445506
Finding funding       -0.2114896  1.0324157
Finding mentors       -0.6214541 -0.8127528
Finding peers         -0.9403153 -1.2960113
Hiring                -0.3481444 -0.3734270
Legal                 -1.0314186 -0.7248876
Managing issues        0.5628877 -0.4612921
Recognition           -0.7581089 -0.5491573
Securing funding      -0.4847993  1.4278090
Security              -0.8492121 -0.7688202
attr(,"scaled:center")
Non.applicable          Never         Rarely   Occasionally     Frequently
```

```
      47.64286        20.35714        34.07143        47.78571        46.64286
        Always
      36.50000
attr(,"scaled:scale")
Non.applicable           Never          Rarely   Occasionally     Frequently
      28.03736        11.60641        21.06570        15.63614        21.95312
        Always
      22.76215
```

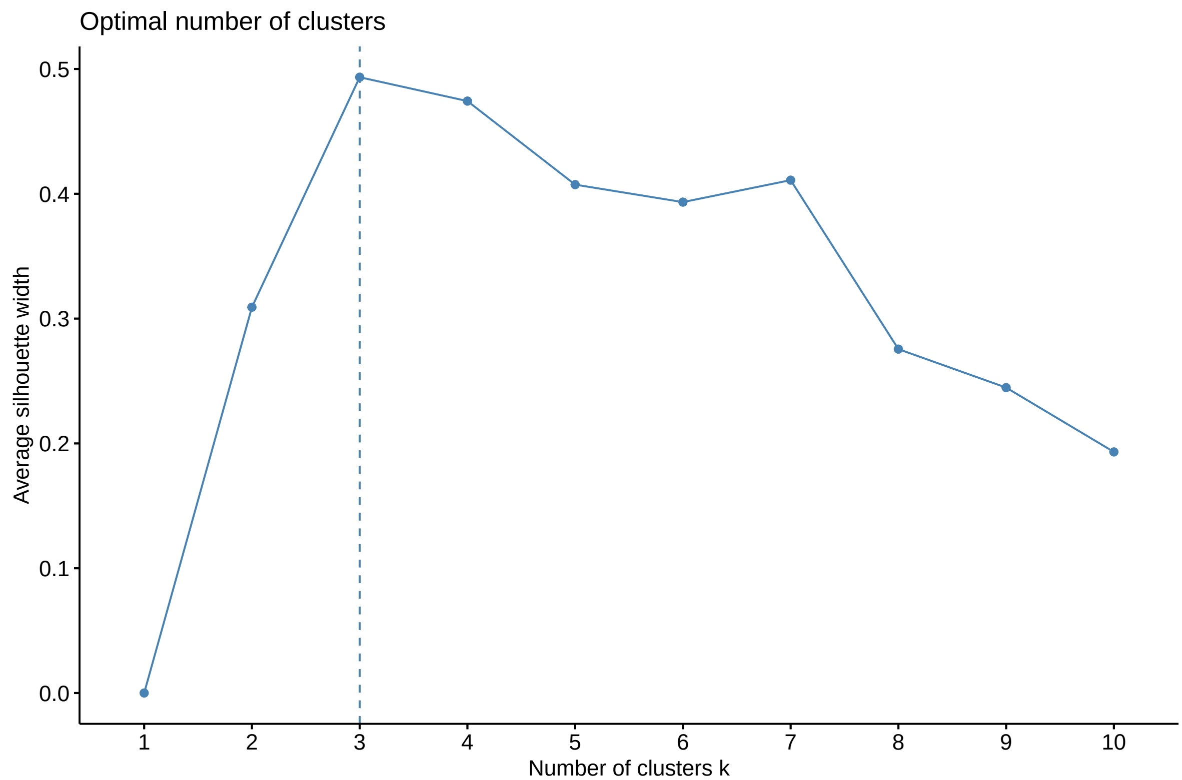
Plot an elbow plot to find the point of diminishing returns.

```r
factoextra::fviz_nbclust(scaled, kmeans, method = "wss")
```



I seem to get diminishing returns around k=4.

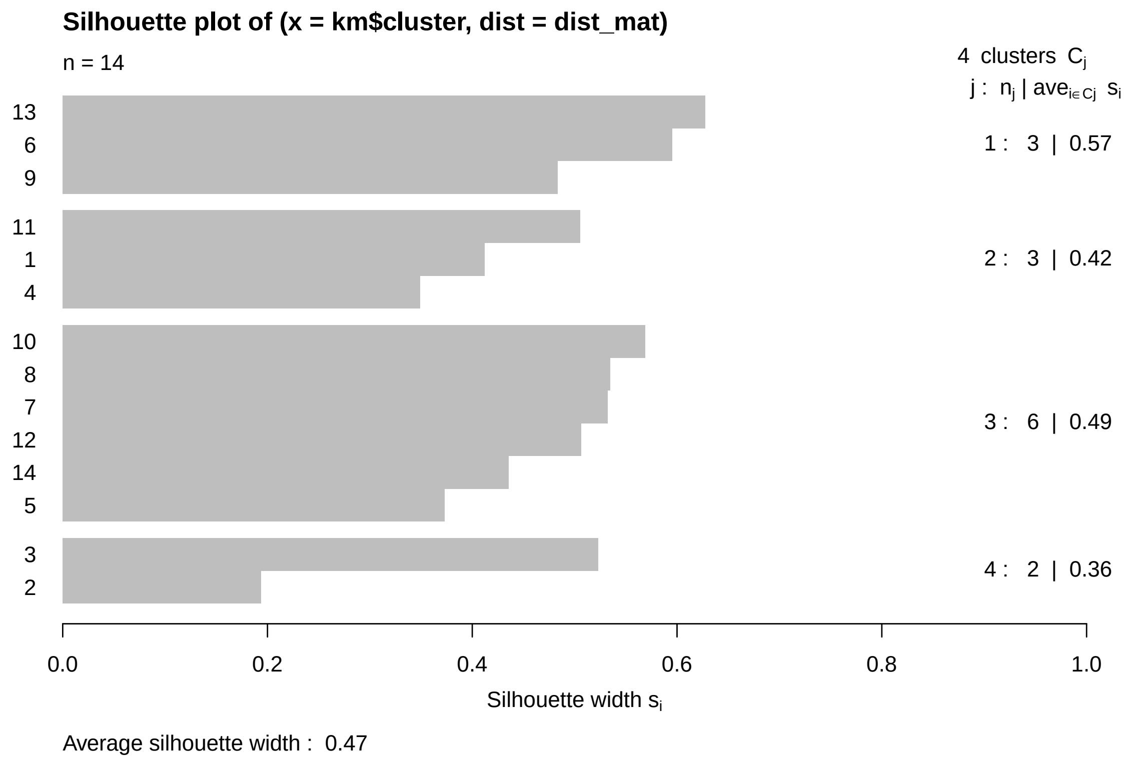
```r
factoextra::fviz_nbclust(scaled, kmeans, method = "silhouette")
```



Hm. The silhouette plot indicates I should use k=3.

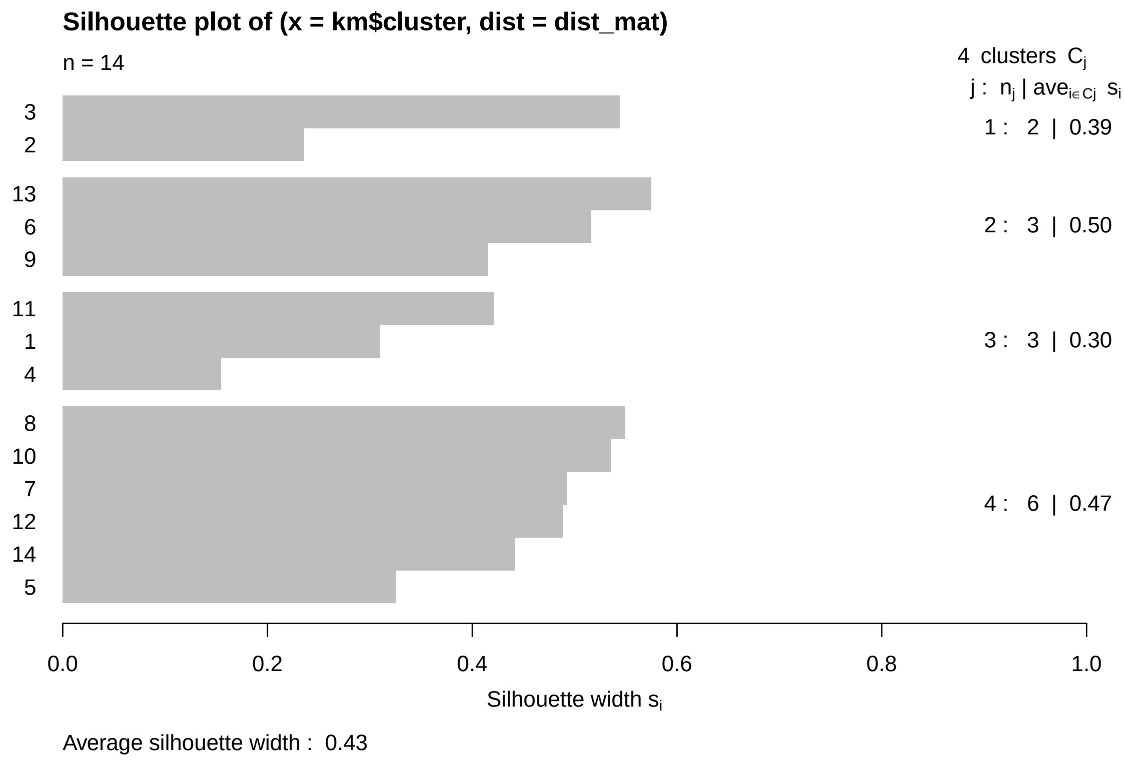
I think I'll try k=4 first, since it's closer to the number I got from eyeballing. Let's look at a different type of silhouette plot, which shows us the silhouette width of each cluster and on average across the clusters.

```
km <- kmeans(scaled, centers = 4, nstart = 25)
dist_mat <- dist(scaled)
sil <- cluster::silhouette(km$cluster, dist_mat)
plot(sil)
```



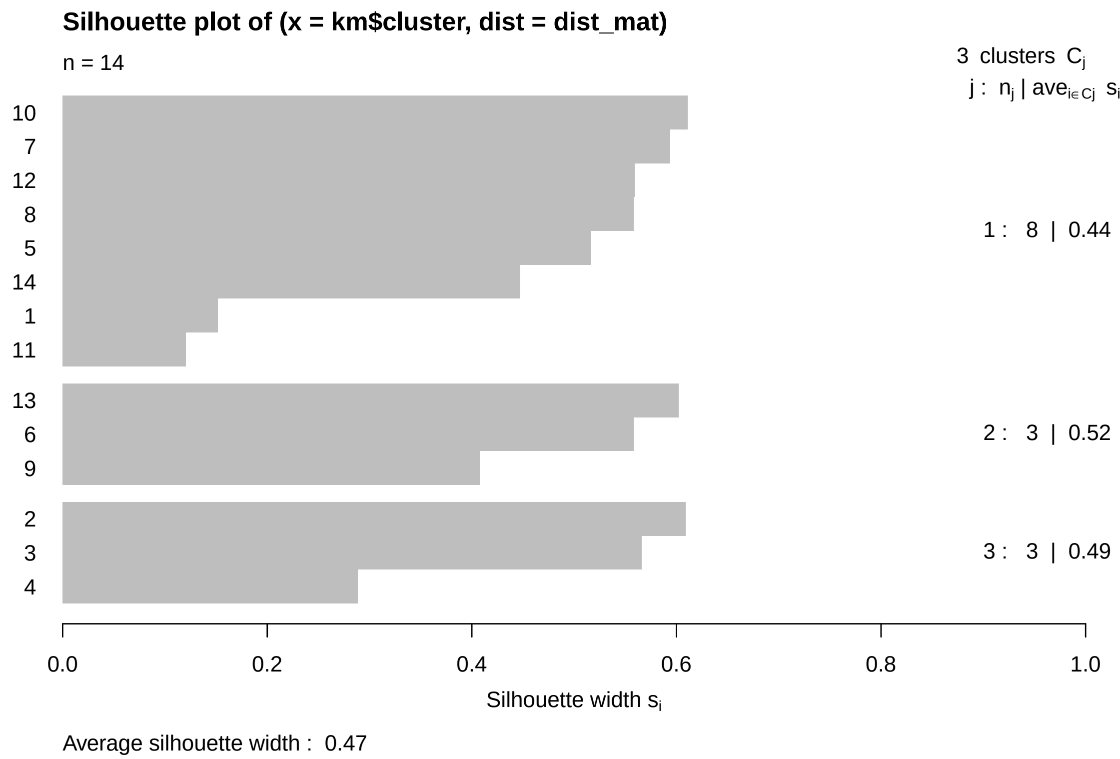
Hm. Looks… acceptable. From Wikipedia: "A clustering with an average silhouette width of over 0.7 is considered to be"strong", a value over 0.5 "reasonable" and over 0.25 "weak"." Let's try unscaled data.

```
km <- kmeans(wide_counts, centers = 4, nstart = 25)
dist_mat <- dist(wide_counts)
sil <- cluster::silhouette(km$cluster, dist_mat)
plot(sil)
```



Looks slightly worse. Still, I think we should probably stick with unscaled data because it's simpler, and I don't think we should add extra unnecessary procedures. What if we try 3 clusters?

```
km <- kmeans(wide_counts, centers = 3, nstart = 25)
dist_mat <- dist(wide_counts)
sil <- cluster::silhouette(km$cluster, dist_mat)
plot(sil)
```



With an average silhouette width of 0.43-0.47, our clusters aren't looking amazing. But they're not terrible, either. I prefer to use unscaled data with k=3, which results in an average silhouette score of 0.47. I think these results are consistent with my hunch that the data for the challenges are not all drawn from the same distribution. These are the cluster assignments:

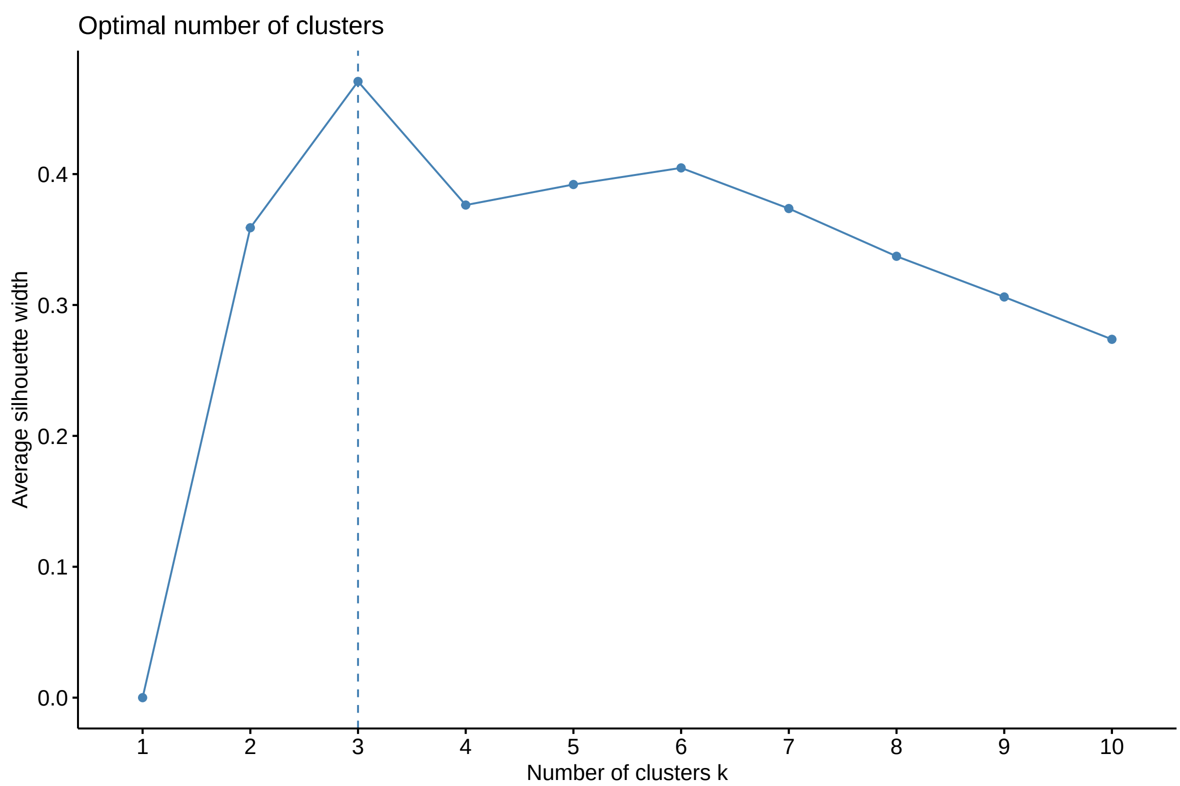
```
# A little extra code to achieve prettier printing
cluster_df <- data.frame(sort(km$cluster))
cluster_df$challenge <- rownames(cluster_df)
clusters <- unique(cluster_df[,1])
for (cl in clusters) {
  print(cluster_df[cluster_df[,1] == cl,], row.names = FALSE)
  cat("\n")
}
```

```
 sort.km.cluster.              challenge
                1       Attracting users
                1 Educational resources
                1        Finding mentors
                1          Finding peers
                1                  Legal
```

```
                1       Managing issues
                1           Recognition
                1              Security

sort.km.cluster.         challenge
                2  Finding funding
                2           Hiring
                2 Securing funding

sort.km.cluster.           challenge
                3        Coding time
                3 Documentation time
                3     Education time
```

Let's look at a silhouette plot for the PAM method, too.

```
factoextra::fviz_nbclust(wide_counts, FUNcluster = pam, method = "silhouette")
```



This also says that 3 clusters is ideal.

Let's try PAM clustering on the unscaled data with k=3.

```
pm <- cluster::pam(wide_counts, k=3)
```

Print the clusters in a more readable format.

```
cluster_df <- data.frame(sort(pm$cluster))
cluster_df$challenge <- rownames(cluster_df)
clusters <- unique(cluster_df[,1])
for (cl in clusters) {
  print(cluster_df[cluster_df[,1] == cl,], row.names = FALSE)
  cat("\n")
}
```

```
 sort.pm.cluster.              challenge
                1      Attracting users
                1 Educational resources
                1       Finding mentors
                1         Finding peers
                1                 Legal
                1       Managing issues
                1           Recognition
                1              Security

 sort.pm.cluster.           challenge
                2         Coding time
                2  Documentation time
                2      Education time

 sort.pm.cluster.         challenge
                3   Finding funding
                3            Hiring
                3  Securing funding
```

We see the same groups we saw with k-means clustering. Good!

One last check: what about a stability assessment by bootstrap resampling?

```
# Note I'm hiding the printed status update from each iteration
boot_res <- fpc::clusterboot(
  wide_counts,
  clustermethod = fpc::kmeansCBI,
```

```
  krange = 3
)
# Annoyingly, the documentation doesn't explain 'krange',
# but I'm pretty sure that this argument lets you specify
# a desired k or range of k values (e.g. 5:7)
```

```
boot_res
```

```
* Cluster stability assessment *
Cluster method:  kmeans
Full clustering results are given as parameter result
of the clusterboot object, which also provides further statistics
of the resampling results.
Number of resampling runs:  100

Number of clusters found in data:  3

 Clusterwise Jaccard bootstrap (omitting multiple points) mean:
[1] 0.7761190 0.8803333 0.8630714
dissolved:
[1] 30 16  1
recovered:
[1] 61 80 71
```

```
mean(boot_res$bootmean)
```

```
[1] 0.8398413
```

The clusterwise Jaccard bootstrap means are around 0.8-0.9, which is pretty respectable. Although this analysis was brief, I think we can conclude that these three clusters are reasonably stable and meaningful.

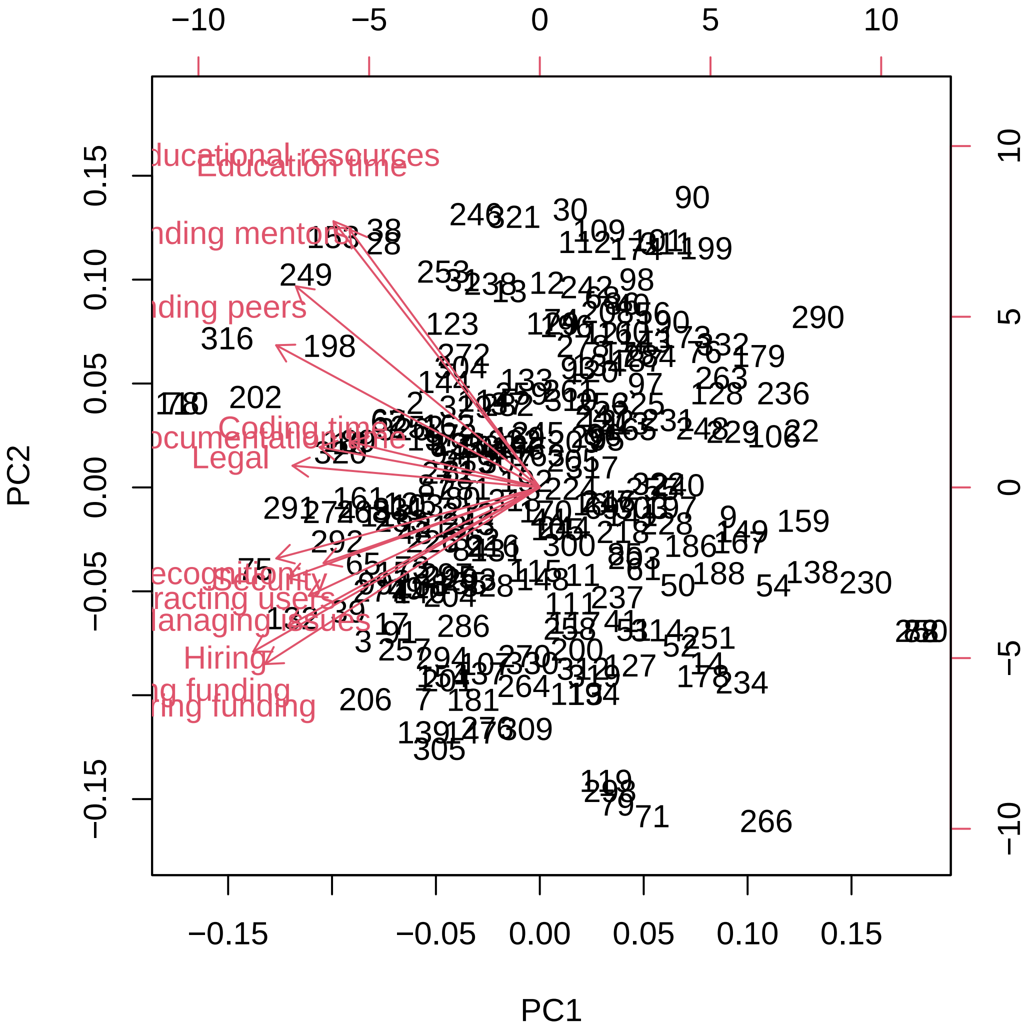
PCA (Abandoned)

In the above sections, I was clustering challenges into groups. Here, I started clustering people into groups. However, this didn't seem too promising, and I don't know if I care enough to pursue it. NOTE THE DIFFERENT CODING SCHEME

```r
challnumeric <- challenges %>%
  mutate(
    across(
      everything(),
      ~ recode(
        .x,
        "Never" = 0L,
        "Non-applicable" = -1L, # THIS IS DIFFERENT (-1, not 0)
        "Rarely" = 1L,
        "Occasionally" = 2L,
        "Frequently" = 3L,
        "Always" = 4L
      )
    )
  )


pca <- prcomp(challnumeric, scale = TRUE)
summary(pca)
```

```
Importance of components:
                          PC1    PC2    PC3     PC4    PC5    PC6     PC7
Standard deviation     2.1561 1.3366 1.1930 1.06788 0.9642 0.8606 0.79525
Proportion of Variance 0.3321 0.1276 0.1017 0.08146 0.0664 0.0529 0.04517
Cumulative Proportion  0.3321 0.4597 0.5613 0.64279 0.7092 0.7621 0.80726
                           PC8     PC9    PC10    PC11    PC12    PC13    PC14
Standard deviation     0.74086 0.70184 0.67486 0.64866 0.62517 0.56317 0.26958
Proportion of Variance 0.03921 0.03518 0.03253 0.03005 0.02792 0.02265 0.00519
Cumulative Proportion  0.84647 0.88165 0.91418 0.94424 0.97215 0.99481 1.00000
```

```r
biplot(pca)
```


Education time
Coding time
Legal
Security
Hiring
PC1
PC2