Reviewer Insights and Participation Trends in the Aave Grants DAO

Omniacs.DAO

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Introduction

The Aave Grants DAO exists to provide grants to innovative ideas and projects which have a direct benefit to the broader Aave community. The DAO funds grants from a broad array of categories including developer tooling, events, and applications.

In this analysis, we've collected data on the historical grants that have been submitted to the DAO. The information includes data on the grant proposal itself, as well as information on the reviews of that proposal. This analysis is produced in an effort to provide the utmost transparency about the Aave Grants DAO, and to derive insights into what types of projects have consistently done the best in terms of acceptance, and ultimate outcomes.

This document focuses on a reviewer-based analysis, where we analyze metrics of the reviews and interviews conducted.

```
library(tidyverse)
library(readr)
library(readxl)
library(lubridate)
library(omnitheme)
library(ngram)
library(knitr)
library(topicmodels)
library(tidytext)
```

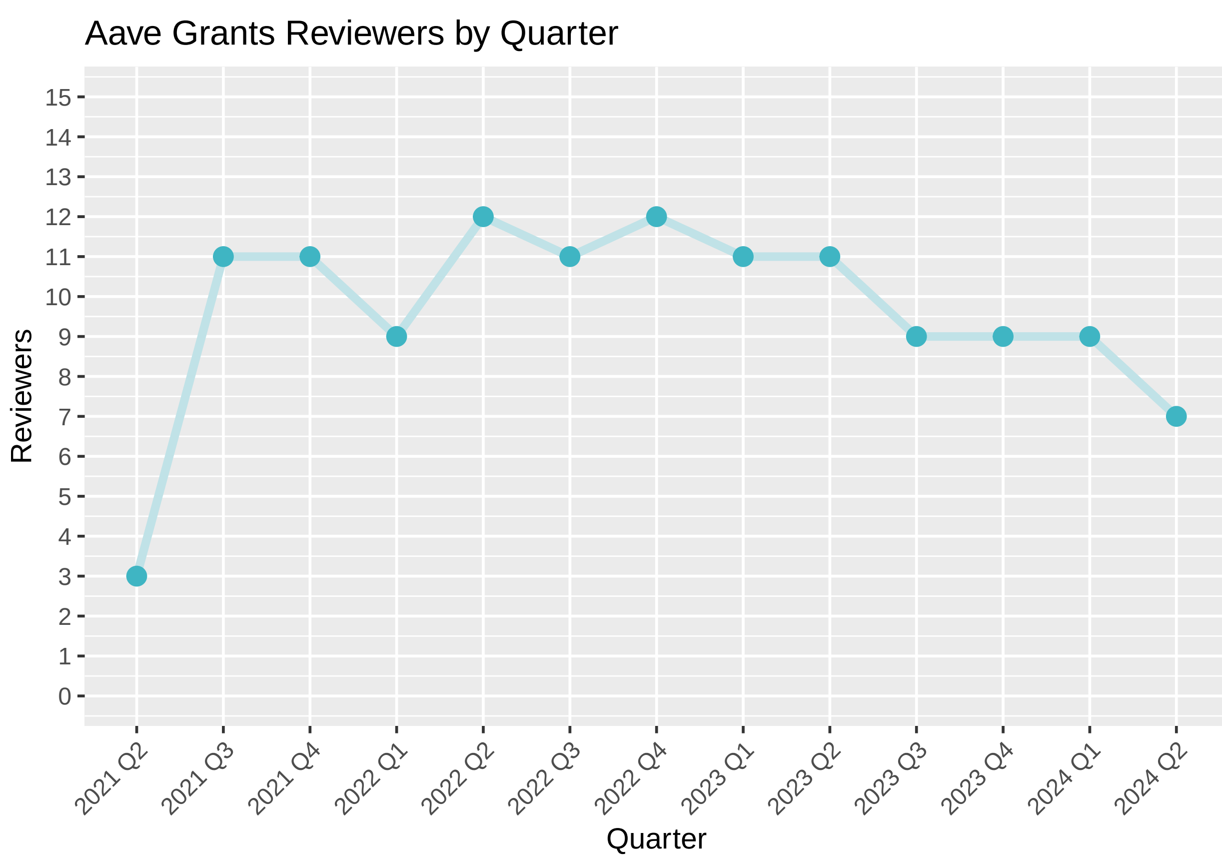
```
library(ggrepel)

grants <- read_csv("data/ApplicationsAnonymized.csv",show_col_types = FALSE) %>%
            as_tibble() %>%
            unnest() %>%
            rename(`Interview Rationale` = `Interview Rational`)

col_pal <- c("#2B2D42", "#F7E733", "#0A369D", "#294D4A", "#ED254E", "#BA2D0B",
             "#003E1F", "#4F517D", "#6A0136", "#B81365", "#8E518D", "#395B50", "#A4036F")

col_pal <- c("#7DC5EE", "#9D5C9E", "#69B4C1", "#99D17B", "#B4654A",
             "#1E3231", "#F6C0D0", "#556F44", "#283F3B", "#1B2432",
             "#121420", "#EE8434", "#FCF0CC")
```

Reviewer-based Analysis

Here, we are going to look at the reviewers of the grants themselves, their characteristics in terms of the number of reviews they've done, their acceptance rates, and the typical length of their reviews. Let's get started!

First, a simple plot of the number of reviewers by quarter shows that for about the last year, the number of unique reviewers has been around a dozen.

```
grants %>%
    select(`Project Name`, Month, starts_with("Reviewer")) %>%
    mutate(Date = ymd(paste(Month, "-", "01")),
           Quarter = paste(year(Date), paste0("Q", quarter(Date))),
           `Reviewer ID`) %>%
    mutate(`Reviewer ID` = strsplit(`Reviewer ID`, ",")) %>%
    unnest(`Reviewer ID`) %>%
    group_by(Quarter) %>%
    summarise(Reviewers = length(unique(`Reviewer ID`[!is.na(`Reviewer ID`)]))) %>%
    ggplot(aes(x = Quarter, y = Reviewers, group = 1)) +
    geom_line(colour = "#C0E2E7", size = 1.5) +
    geom_point(colour = "#3FB5C3", size = 3) +
    scale_y_continuous(breaks = seq(0, 15), limits = c(0, 15)) +
    labs(
        title = "Aave Grants Reviewers by Quarter"
    ) +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))
```

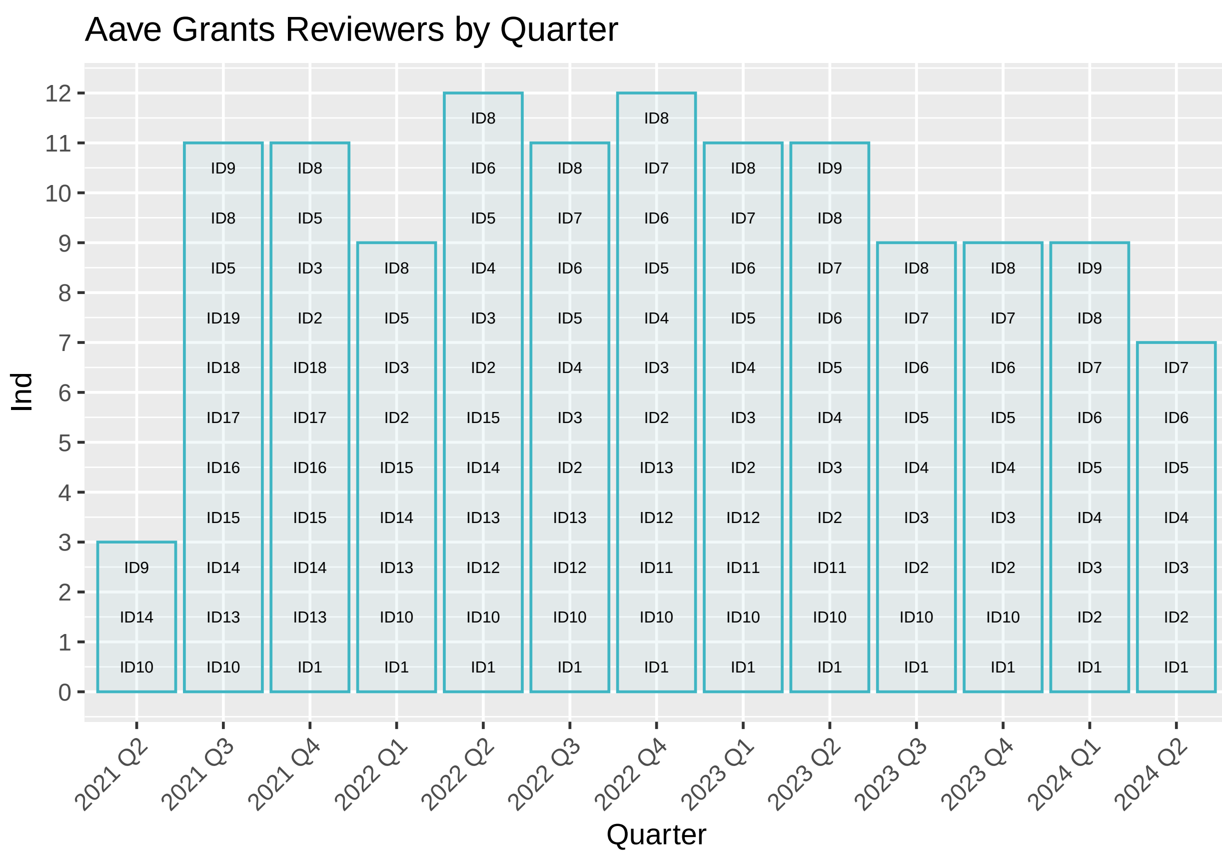


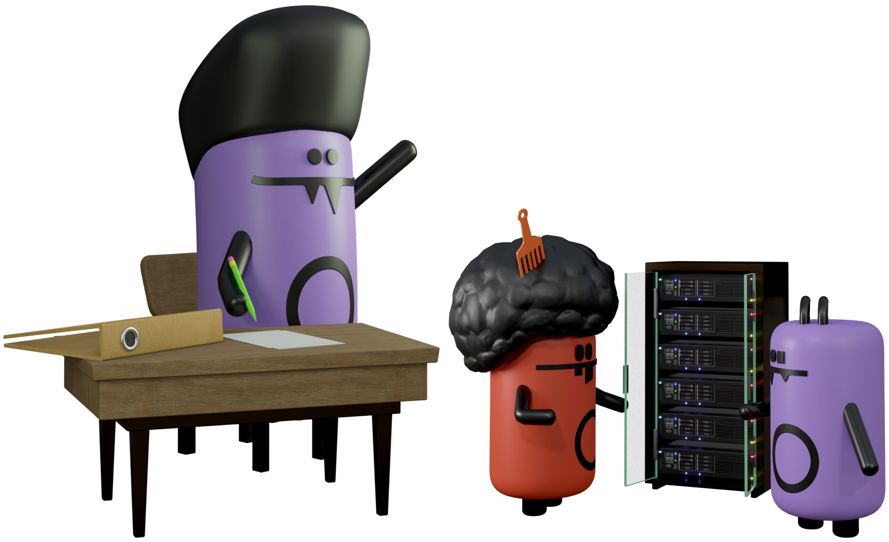
We can plot this and display the name of the reviewers inside the bar. We clearly see certain reviewers have been around since quite early on in the Grants DAO!

```
grants %>%
    select(`Project Name`, Month, starts_with("Reviewer")) %>%
    mutate(Date = ymd(paste(Month, "-", "01")),
           Quarter = paste(year(Date), paste0("Q", quarter(Date))),
           `Reviewer ID`) %>%
```

```
    mutate(`Reviewer ID` = strsplit(`Reviewer ID`, ",")) %>%
    unnest(`Reviewer ID`) %>%
    group_by(Quarter) %>%
    summarise(Reviewers = unique(`Reviewer ID`[!is.na(`Reviewer ID`)])) %>%
    unnest(Reviewers) %>%
    arrange(Quarter, Reviewers) %>%
    mutate(Ind = seq(0.5, length(Reviewers) - 0.5, by = 1),
           Reviewers = sub("ReviewerID","ID", Reviewers)) %>%
    ggplot(aes(x = Quarter)) +
    geom_bar(stat = "count", alpha = .2, fill = "#C0E2E7", colour = "#3FB5C3") + # #3FB5C3
    geom_text(aes(y = Ind, label = Reviewers), size = 2) +
    scale_y_continuous(breaks = seq(0, 15)) +
    labs(
        title = "Aave Grants Reviewers by Quarter"
    ) +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))
```

```
## `summarise()` has grouped output by 'Quarter'. You can override using the
## `.groups` argument.
```





We can also look at acceptance rates by reviewer. Though the sample size for many reviewers is low, we can see at the high end, there is a reviewer with a 40% acceptance rate, while there are several that thus far have not accepted a single proposal.

```
grants %>%
    filter(!is.na(`Reviewer ID`)) %>%
    mutate(Status2 = ifelse(`Status` %in%
                                c("1st payment made ", "Approved", "Paid in full"),
                              "Accepted", ifelse(`Status` %in%
                                                    c("Denial confirmed",
                                                      "Denial Confirmed",
                                                      "Review failed",
                                                      "Screening failed"
                                                      ) |
                                                    is.na(Status),
                                                  "Rejected",
                                                  "Pending Review"))) %>%
    select(-Status) %>%
    rename(Status = Status2) %>%
    group_by(`Reviewer ID`) %>%
    summarise(Count = n(),
          `Num Accepted` = sum(Status == "Accepted"),
          `Num Rejected` = sum(Status == "Rejected"),
          `Num Pending` = sum(Status == "Pending Review"),
          `Acceptance Rate` = scales::percent(sum(Status == "Accepted") / Count)) %>%
    kable()
```

Reviewer ID	Count	Num Accepted	Num Rejected	Num Pending	Acceptance Rate
ReviewerID1	204	20	183	1	10%
ReviewerID10	197	10	184	3	5%
ReviewerID11	94	4	89	1	4%
ReviewerID12	37	7	29	1	19%
ReviewerID13	65	16	38	11	25%
ReviewerID14	49	10	28	11	20%
ReviewerID15	47	9	36	2	19%
ReviewerID16	8	1	4	3	12%

Reviewer ID	Count	Num Accepted	Num Rejected	Num Pending	Acceptance Rate
ReviewerID17	10	4	3	3	40%
ReviewerID18	3	0	2	1	0%
ReviewerID19	3	1	1	1	33%
ReviewerID2	247	27	214	6	11%
ReviewerID3	195	28	153	14	14%
ReviewerID4	201	19	180	2	9%
ReviewerID5	362	23	326	13	6%
ReviewerID6	227	11	205	11	5%
ReviewerID7	468	29	431	8	6%
ReviewerID8	142	23	113	6	16%
ReviewerID9	119	15	45	59	13%

Average Number of Words per Review

Next, let's do a word count analysis. We'll first look at the average number of words per review, using the text reviews, as encompassed in the `Review Rationale` column. We will then perform the same analysis using `Interviewer Rationale` to compare, and finally combine the two.

```
wc <- round(mean(sapply(grants$`Review Rationale`[!is.na(grants$`Review Rationale`)],
                        wordcount)),
            digits = 1)
```

The overall average number of words per review is 32.9. Let's break this down by reviewer. We see that there is pretty significant variability, with some reviewers averaging well over 50 words, and others under 20.

```
grants %>%
    select(`Reviewer ID`, `Review Rationale`) %>%
    filter(!is.na(`Review Rationale`),
           !is.na(`Reviewer ID`)) %>%
    rowwise() %>%
    mutate(Words = wordcount(`Review Rationale`)) %>%
    group_by(`Reviewer ID`) %>%
    summarise(
        `Average Words` = round(mean(Words), digits = 1),
        `Median Words` = median(Words),
        `Min Words` = min(Words),
        `Max Words` = max(Words)
    ) %>%
    kable()
```

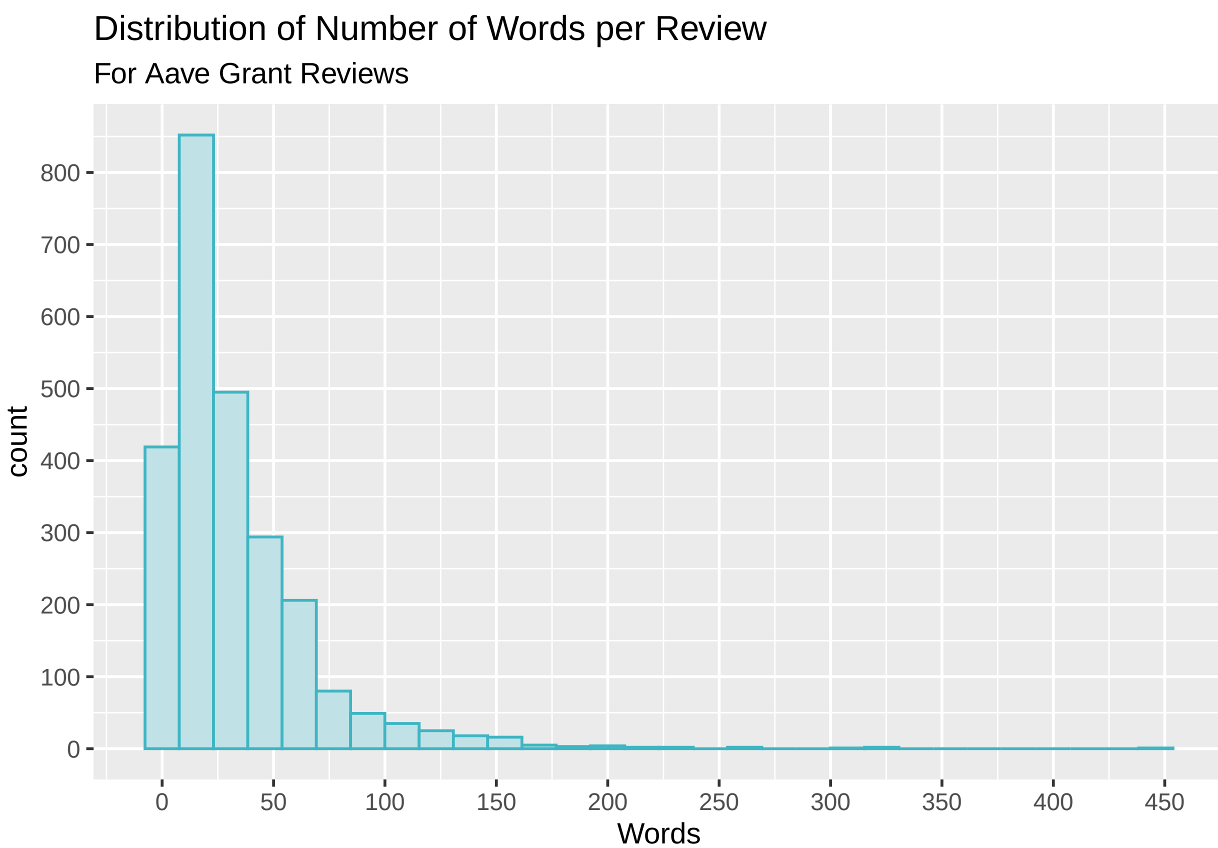
Reviewer ID	Average Words	Median Words	Min Words	Max Words
ReviewerID1	49.3	44.0	4	447
ReviewerID10	38.9	29.0	1	308
ReviewerID11	19.8	13.0	2	73
ReviewerID12	33.6	24.5	2	154
ReviewerID13	11.7	7.5	1	70

Reviewer ID	Average Words	Median Words	Min Words	Max Words
ReviewerID14	26.2	19.0	2	139
ReviewerID15	11.7	7.0	1	85
ReviewerID16	140.6	131.0	63	321
ReviewerID17	28.6	29.0	13	45
ReviewerID18	26.0	30.0	14	34
ReviewerID19	26.7	34.0	10	36
ReviewerID2	24.0	19.0	1	111
ReviewerID3	39.4	37.0	3	126
ReviewerID4	25.0	16.0	1	201
ReviewerID5	21.3	14.0	1	268
ReviewerID6	31.2	25.0	1	231
ReviewerID7	47.7	34.0	1	217
ReviewerID8	23.8	17.0	1	175
ReviewerID9	61.8	28.0	12	321

The distribution overall is very right tailed, with most reviews tending to be shorter, but then a few outlier reviews with a significant number of words.

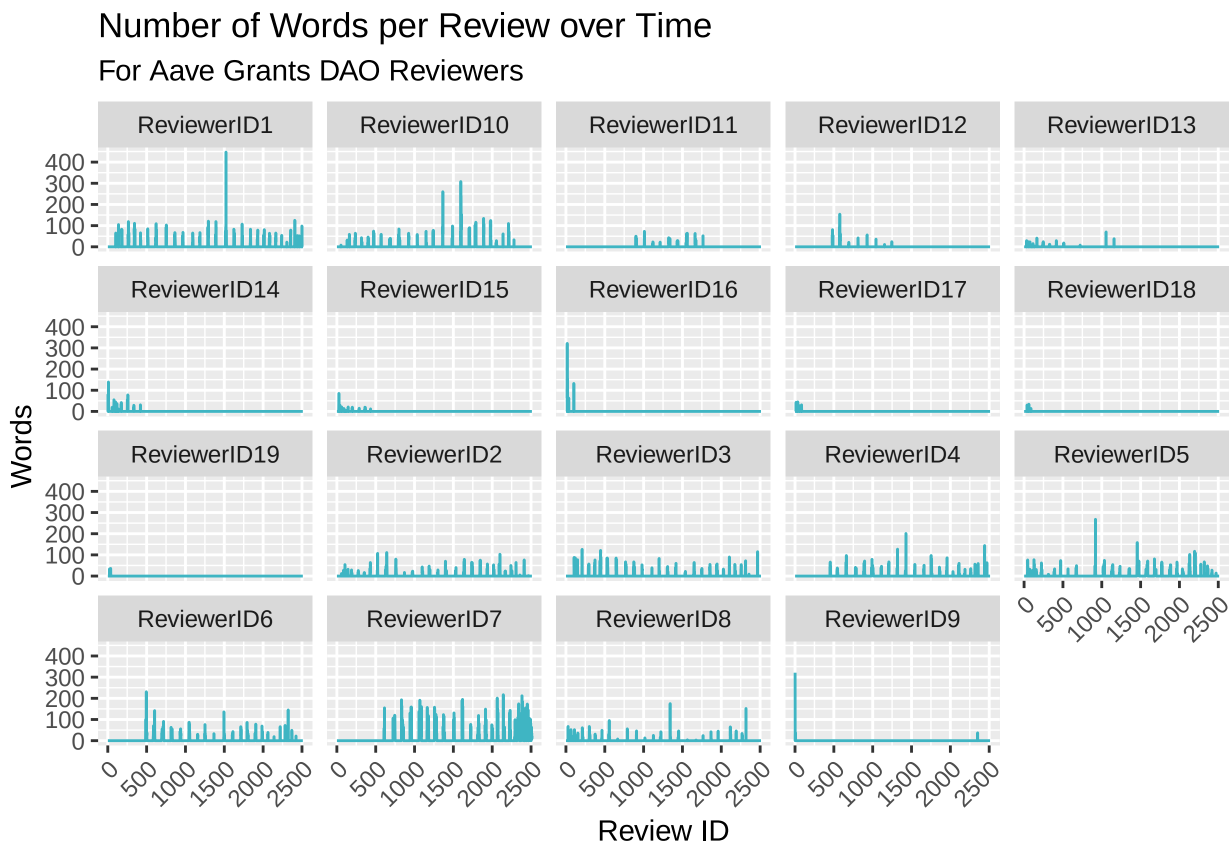
```
grants %>%
    filter(!is.na(`Review Rationale`),
           !is.na(`Reviewer ID`)) %>%
    rowwise() %>%
    mutate(Words = wordcount(`Review Rationale`)) %>%
    ggplot(aes(x = Words)) +
    geom_histogram(fill = "#C0E2E7", colour = "#3FB5C3") +
    scale_x_continuous(breaks = scales::pretty_breaks(n = 10)) +
    scale_y_continuous(breaks = scales::pretty_breaks(n = 10)) +
    labs(
        title = "Distribution of Number of Words per Review",
        subtitle = "For Aave Grant Reviews"
    )
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



Breaking down each reviewer individually, we can plot the number of words over time to see the variability at the reviewer level. We also immediately see those that have consistently conducted reviews, vs. those that are newer or haven't done so recently.

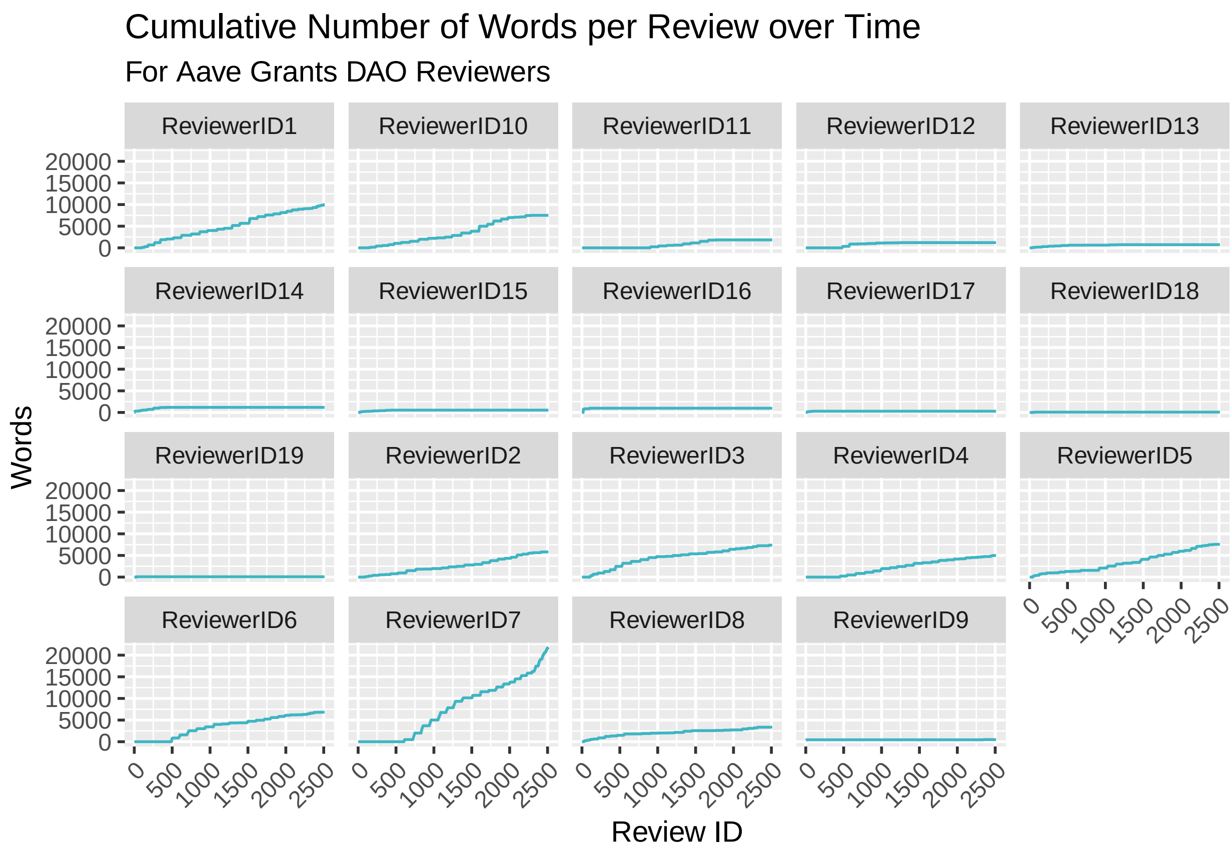
```
grants %>%
    filter(!is.na(`Review Rationale`),
           !is.na(`Reviewer ID`)) %>%
    mutate(Date = ymd(paste(Month, "-", "01"))) %>%
    arrange(Date) %>%
    select(`Reviewer ID`, `Review Rationale`, Date) %>%
    rowwise() %>%
    mutate(Words = wordcount(`Review Rationale`)) %>%
    ungroup() %>%
    mutate(`Review ID` = factor(1:nrow(.))) %>%
    mutate(`Reviewer ID` = factor(`Reviewer ID`)) %>%
    complete(`Review ID`, `Reviewer ID`) %>%
    mutate(`Words` = ifelse(is.na(Words), 0, Words)) %>%
    mutate(`Review ID` = as.numeric(`Review ID`)) %>%
    ggplot(aes(x = `Review ID`, y = Words)) +
    facet_wrap(~`Reviewer ID`) +
    geom_line(colour = "#3FB5C3") +
    scale_y_continuous(breaks = scales::pretty_breaks(n = 5)) +
    labs(
        title = "Number of Words per Review over Time",
        subtitle = "For Aave Grants DAO Reviewers"
    ) +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))
```



The same data above can be plotted cumulatively. At the upper end, some reviewers have written around 2000 words already!

```
grants %>%
    filter(!is.na(`Review Rationale`),
           !is.na(`Reviewer ID`)) %>%
    mutate(Date = ymd(paste(Month, "-", "01"))) %>%
    arrange(Date) %>%
    select(`Reviewer ID`, `Review Rationale`, Date) %>%
    rowwise() %>%
    mutate(Words = wordcount(`Review Rationale`)) %>%
    ungroup() %>%
    mutate(`Review ID` = factor(1:nrow(.))) %>%
    mutate(`Reviewer ID` = factor(`Reviewer ID`)) %>%
    complete(`Review ID`, `Reviewer ID`) %>%
    mutate(`Words` = ifelse(is.na(Words), 0, Words)) %>%
```

```
    group_by(`Reviewer ID`) %>%
    mutate(Words = cumsum(Words)) %>%
    mutate(`Review ID` = as.numeric(`Review ID`)) %>%
    ggplot(aes(x = `Review ID`, y = Words)) +
    facet_wrap(~`Reviewer ID`) +
    geom_line(colour = "#3FB5C3") +
    scale_y_continuous(breaks = scales::pretty_breaks(n = 5)) +
    labs(
        title = "Cumulative Number of Words per Review over Time",
        subtitle = "For Aave Grants DAO Reviewers"
    ) +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))
```



Average Number of Words per Interview

Now, let's perform the same analysis by interview.

```
wc <- round(mean(sapply(grants$`Review Rationale`[!is.na(grants$`Interview Rationale`)],
                        wordcount)),
            digits = 1)
```

The overall average number of words per interview is 65.1. Let's break this down by reviewer. We again see variability, but it seems as if the rationale based on the interview tends to be a bit longer on average, for most reviewers.

```
grants %>%
    select(`Reviewer ID`, `Interview Rationale`) %>%
    filter(!is.na(`Interview Rationale`),
           !is.na(`Reviewer ID`)) %>%
    rowwise() %>%
    mutate(Words = wordcount(`Interview Rationale`)) %>%
    group_by(`Reviewer ID`) %>%
    summarise(
        `Average Words` = round(mean(Words), digits = 1),
        `Median Words` = median(Words),
        `Min Words` = min(Words),
        `Max Words` = max(Words)
    ) %>%
    kable()
```

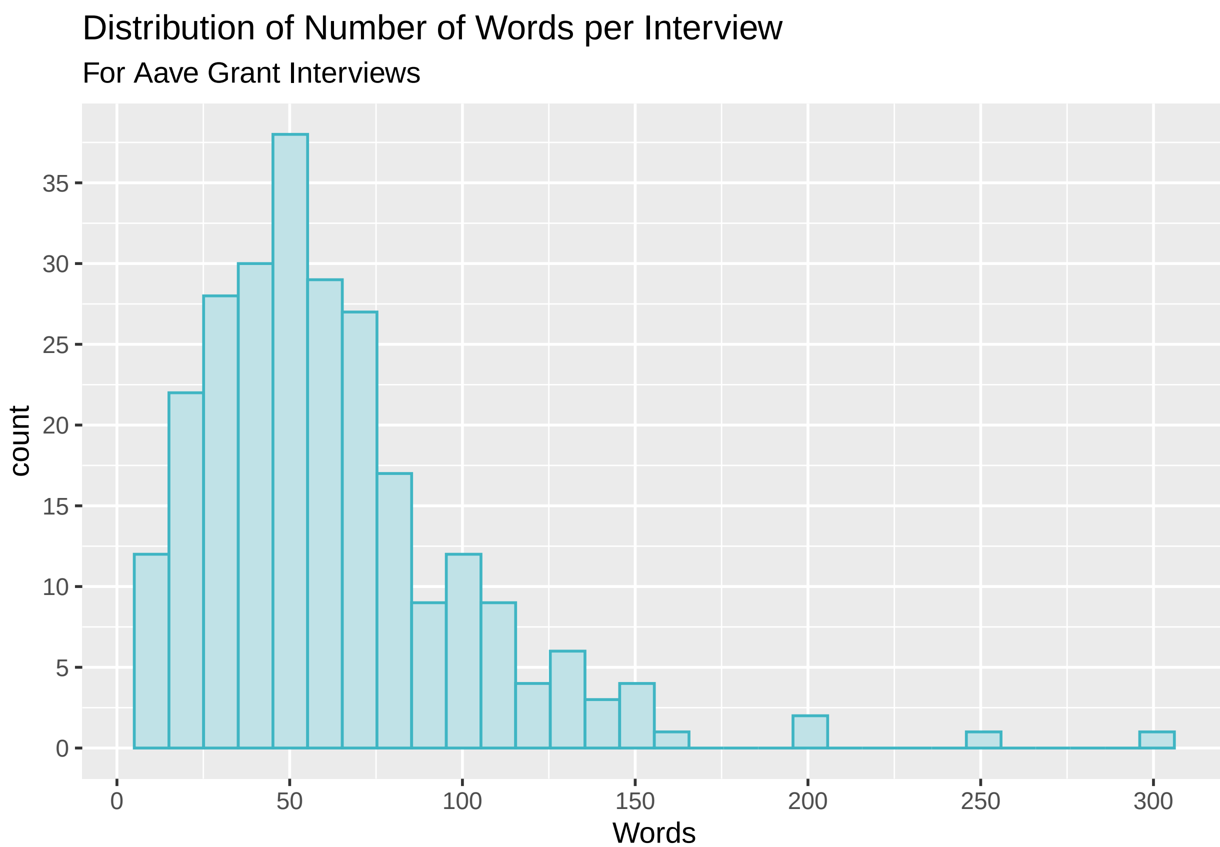
Reviewer ID	Average Words	Median Words	Min Words	Max Words
ReviewerID1	61.6	63.5	13	160
ReviewerID10	76.5	75.5	40	115
ReviewerID12	54.8	50.5	27	96
ReviewerID13	63.8	53.0	17	137
ReviewerID14	62.5	56.5	14	196
ReviewerID15	51.7	33.5	10	129
ReviewerID16	42.7	45.0	15	68
ReviewerID17	58.0	58.0	53	63
ReviewerID19	19.0	19.0	17	21
ReviewerID2	59.2	51.0	13	148
ReviewerID3	63.6	52.0	8	299
ReviewerID4	75.6	68.0	20	149
ReviewerID5	63.9	57.5	17	154
ReviewerID6	77.8	77.0	35	109
ReviewerID7	71.5	66.0	19	197
ReviewerID8	58.1	46.0	10	252
ReviewerID9	58.5	58.5	9	108

This finding is especially visible in the distribution, where it is much less right tailed and instead there is a noticeably larger mass on the higher end of the word count values.

```
grants %>%
    filter(!is.na(`Interview Rationale`),
           !is.na(`Reviewer ID`)) %>%
    rowwise() %>%
    mutate(Words = wordcount(`Interview Rationale`)) %>%
    ggplot(aes(x = Words)) +
```

```r
    geom_histogram(fill = "#C0E2E7", colour = "#3FB5C3") +
    scale_x_continuous(breaks = scales::pretty_breaks(n = 10)) +
    scale_y_continuous(breaks = scales::pretty_breaks(n = 10)) +
    labs(
        title = "Distribution of Number of Words per Interview",
        subtitle = "For Aave Grant Interviews"
    )
```

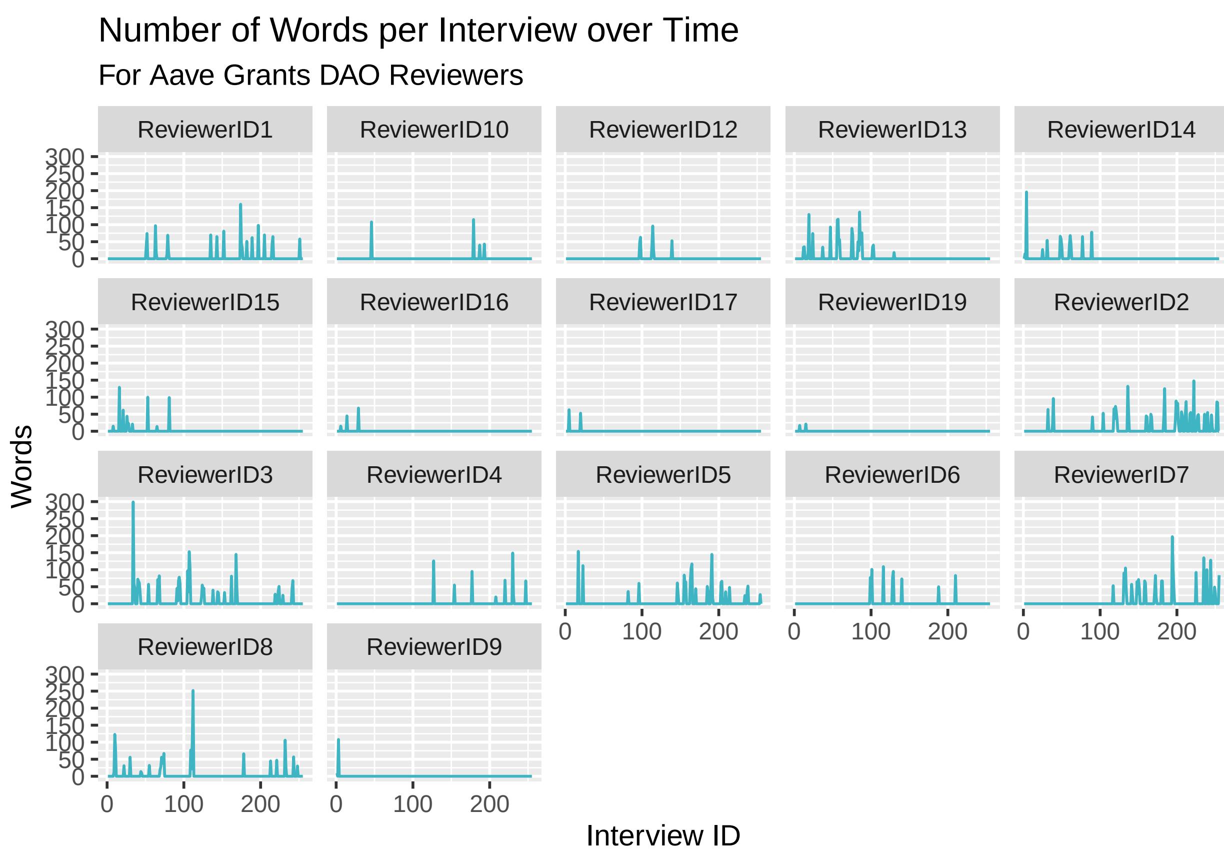
```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



Once again we can look per reviewer. Because video interviews and the associated rationales are less common, we see a lot less noise in this plot than for the application-based reviews.

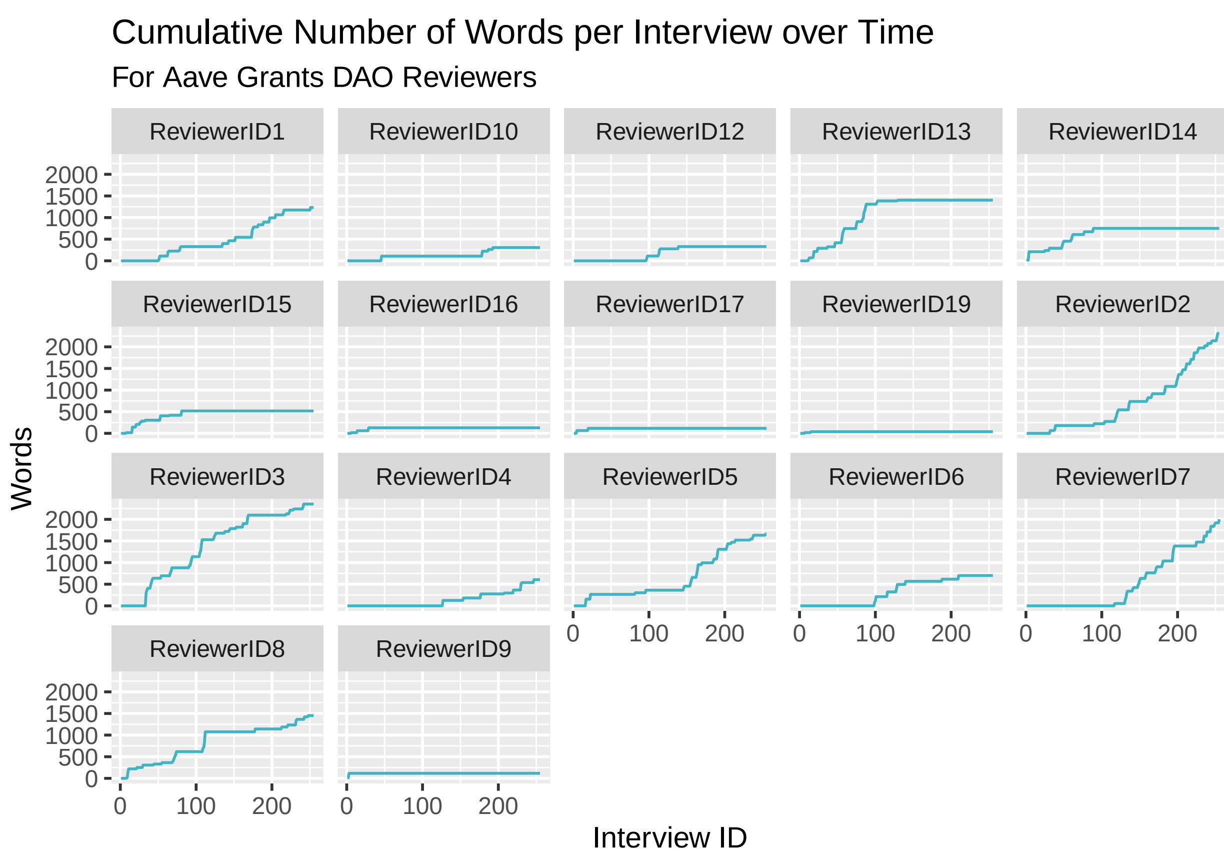
```r
grants %>%
    filter(!is.na(`Interview Rationale`),
           !is.na(`Reviewer ID`)) %>%
    mutate(Date = ymd(paste(Month, "-", "01"))) %>%
    arrange(Date) %>%
    select(`Reviewer ID`, `Interview Rationale`, Date) %>%
    rowwise() %>%
    mutate(Words = wordcount(`Interview Rationale`)) %>%
    ungroup() %>%
    mutate(`Interview ID` = factor(1:nrow(.))) %>%
    mutate(`Reviewer ID` = factor(`Reviewer ID`)) %>%
    complete(`Interview ID`, `Reviewer ID`) %>%
    mutate(`Words` = ifelse(is.na(Words), 0, Words)) %>%
    mutate(`Interview ID` = as.numeric(`Interview ID`)) %>%
```

```r
ggplot(aes(x = `Interview ID`, y = Words)) +
facet_wrap(~`Reviewer ID`) +
geom_line(colour = "#3FB5C3") +
scale_y_continuous(breaks = scales::pretty_breaks(n = 5)) +
labs(
    title = "Number of Words per Interview over Time",
    subtitle = "For Aave Grants DAO Reviewers"
)
```



The cumulative charts show that the most prolific reviewer in terms of interview rationale has written over 1000 words of justification.

```r
grants %>%
    filter(!is.na(`Interview Rationale`),
           !is.na(`Reviewer ID`)) %>%
    mutate(Date = ymd(paste(Month, "-", "01"))) %>%
    arrange(Date) %>%
    select(`Reviewer ID`, `Interview Rationale`, Date) %>%
    rowwise() %>%
    mutate(Words = wordcount(`Interview Rationale`)) %>%
    ungroup() %>%
    mutate(`Interview ID` = factor(1:nrow(.))) %>%
    mutate(`Reviewer ID` = factor(`Reviewer ID`)) %>%
    complete(`Interview ID`, `Reviewer ID`) %>%
    mutate(`Words` = ifelse(is.na(Words), 0, Words)) %>%
    group_by(`Reviewer ID`) %>%
    mutate(Words = cumsum(Words)) %>%
    mutate(`Interview ID` = as.numeric(`Interview ID`)) %>%
    ggplot(aes(x = `Interview ID`, y = Words)) +
    facet_wrap(~`Reviewer ID`) +
    geom_line(colour = "#3FB5C3") +
    scale_y_continuous(breaks = scales::pretty_breaks(n = 5)) +
    labs(
        title = "Cumulative Number of Words per Interview over Time",
        subtitle = "For Aave Grants DAO Reviewers"
    )
```



Average Number of Words per Review+Interview Combined

We will now combine the review and interview rationale into one text field, to look at an analysis of the two combined.

```
grants$`Combined Rationale` <- paste(grants$`Review Rationale`,
                                     grants$`Interview Rationale`)

wc <- round(mean(sapply(grants$`Review Rationale`[!is.na(grants$`Interview Rationale`)],
                        wordcount)),
            digits = 1)
```

The overall average number of words per combined review/interview is 65.1. Breaking down by reviewer shows a familiar amount of intra-reviewer variability.

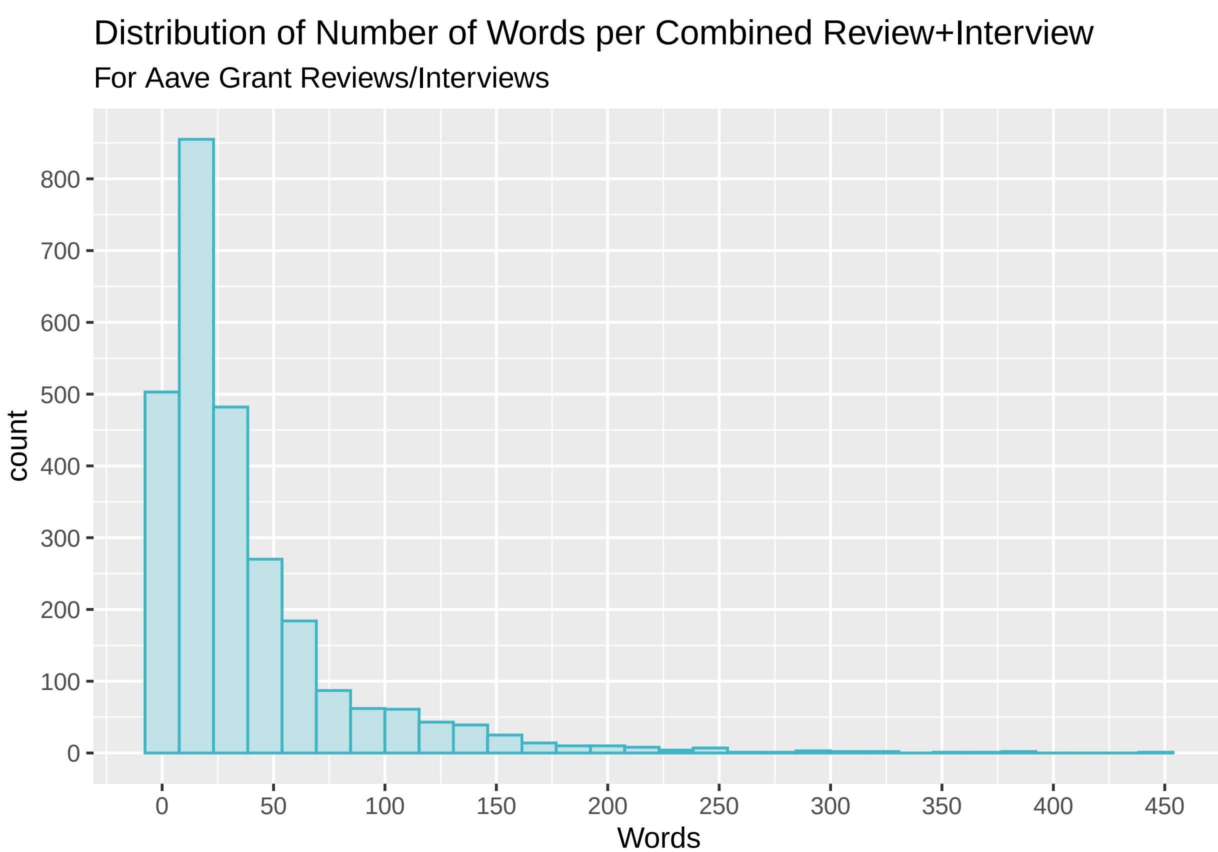
```
grants %>%
    select(`Reviewer ID`, `Combined Rationale`) %>%
    filter(!is.na(`Combined Rationale`),
           !is.na(`Reviewer ID`)) %>%
    rowwise() %>%
    mutate(Words = wordcount(`Combined Rationale`)) %>%
    group_by(`Reviewer ID`) %>%
    summarise(
        `Average Words` = round(mean(Words), digits = 1),
        `Median Words` = median(Words),
        `Min Words` = min(Words),
        `Max Words` = max(Words)
    ) %>%
    kable()
```

Reviewer ID	Average Words	Median Words	Min Words	Max Words
ReviewerID1	56.0	44.5	2	448
ReviewerID10	40.7	28.0	2	375
ReviewerID11	20.6	14.0	2	74
ReviewerID12	42.5	25.0	2	250
ReviewerID13	33.5	11.0	2	149
ReviewerID14	40.2	19.0	2	250
ReviewerID15	23.3	8.0	2	159
ReviewerID16	139.8	127.5	16	322
ReviewerID17	41.0	34.5	14	89
ReviewerID18	27.0	31.0	15	35
ReviewerID19	39.7	51.0	11	57
ReviewerID2	33.8	20.0	2	212
ReviewerID3	50.7	38.0	2	385
ReviewerID4	28.8	17.0	2	223
ReviewerID5	26.5	15.0	2	299
ReviewerID6	34.1	25.0	2	308
ReviewerID7	52.0	33.5	2	387
ReviewerID8	34.7	18.0	2	291
ReviewerID9	7.1	2.0	2	330

The resulting distribution combines characteristics of each of the previous two we've seen, yielding a right-tailed distribution that is not as dramatic as for the reviewer-based distribution.

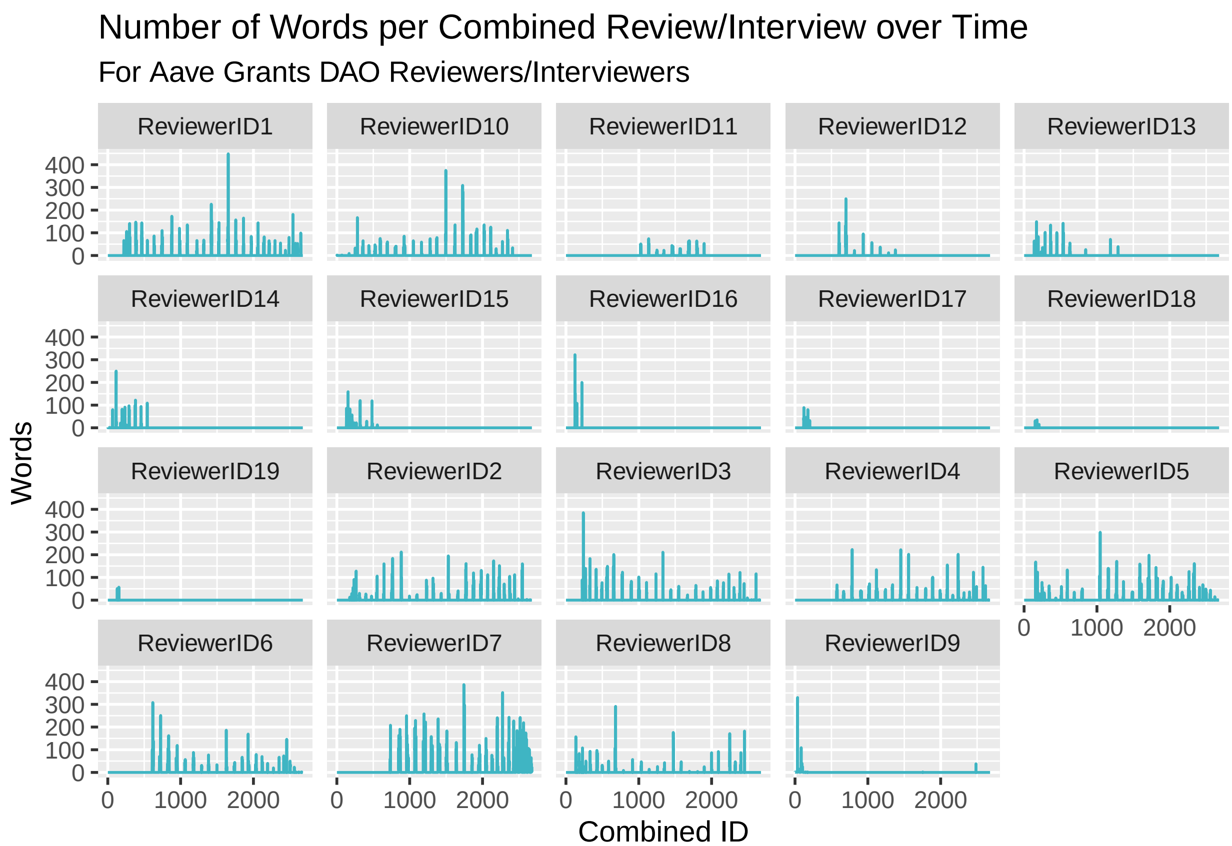
```
grants %>%
    rowwise() %>%
    mutate(Words = wordcount(`Combined Rationale`)) %>%
    ggplot(aes(x = Words)) +
    geom_histogram(fill = "#C0E2E7", colour = "#3FB5C3") +
    scale_x_continuous(breaks = scales::pretty_breaks(n = 10)) +
    scale_y_continuous(breaks = scales::pretty_breaks(n = 10)) +
    labs(
        title = "Distribution of Number of Words per Combined Review+Interview",
        subtitle = "For Aave Grant Reviews/Interviews"
    )
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



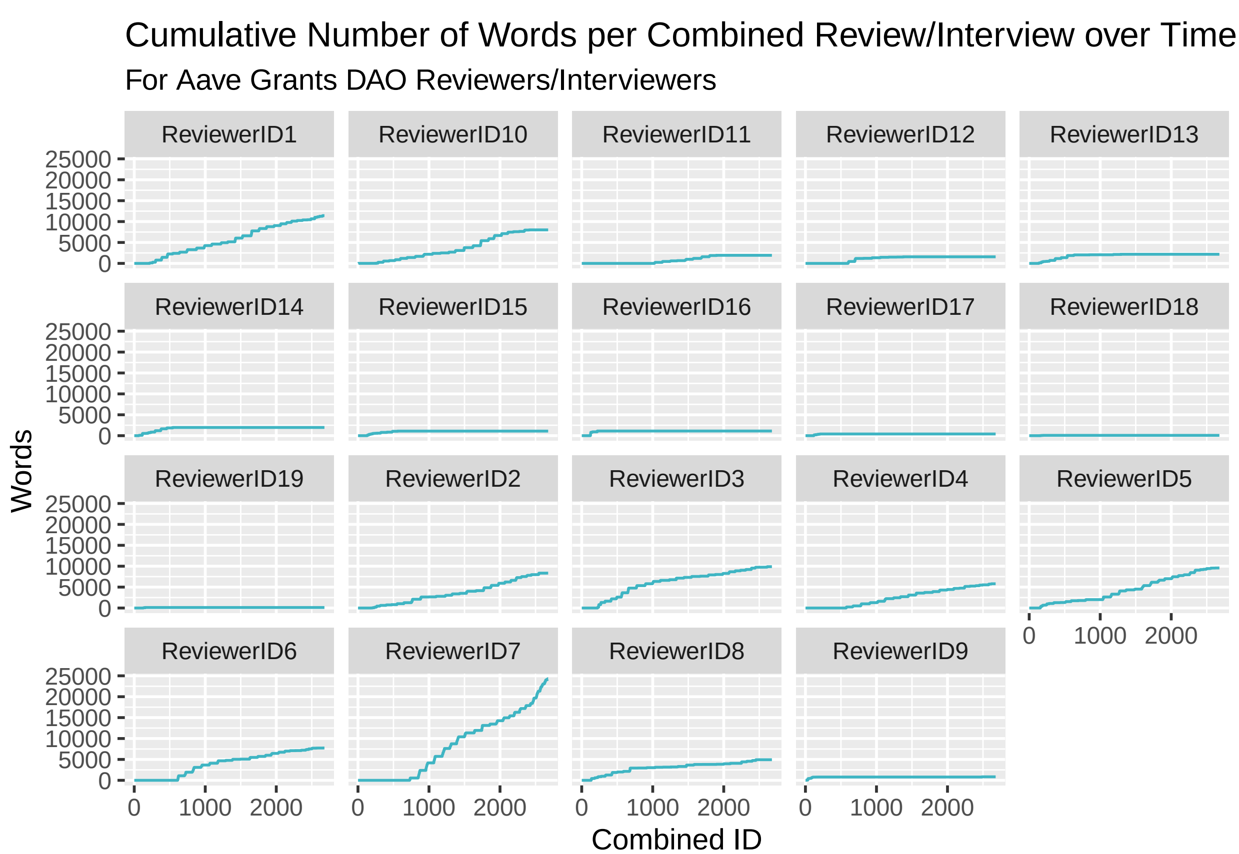
The plot of the word counts for each reviewer now combines both the review and interview-based rationales, but tells a similar story.

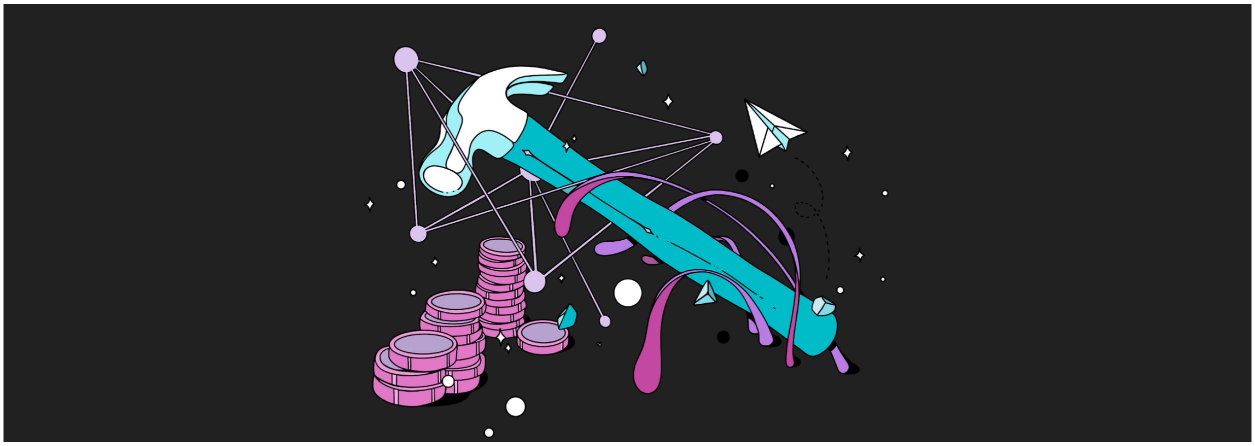
```
grants %>%
    filter(!is.na(`Combined Rationale`),
           !is.na(`Reviewer ID`)) %>%
    mutate(Date = ymd(paste(Month, "-", "01"))) %>%
    arrange(Date) %>%
    select(`Reviewer ID`, `Combined Rationale`, Date) %>%
    rowwise() %>%
    mutate(Words = wordcount(`Combined Rationale`)) %>%
    ungroup() %>%
    mutate(`Combined ID` = factor(1:nrow(.))) %>%
    mutate(`Reviewer ID` = factor(`Reviewer ID`)) %>%
    complete(`Combined ID`, `Reviewer ID`) %>%
    mutate(`Words` = ifelse(is.na(Words), 0, Words)) %>%
    mutate(`Combined ID` = as.numeric(`Combined ID`)) %>%
    ggplot(aes(x = `Combined ID`, y = Words)) +
    facet_wrap(~`Reviewer ID`) +
    geom_line(colour = "#3FB5C3") +
    scale_y_continuous(breaks = scales::pretty_breaks(n = 5)) +
    labs(
        title = "Number of Words per Combined Review/Interview over Time",
        subtitle = "For Aave Grants DAO Reviewers/Interviewers"
    )
```



When using the combined method, the most prolific combined reviewer/interviewer has written over 2500 words of rationale.

```
grants %>%
    filter(!is.na(`Combined Rationale`),
           !is.na(`Reviewer ID`)) %>%
    mutate(Date = ymd(paste(Month, "-", "01"))) %>%
    arrange(Date) %>%
    select(`Reviewer ID`, `Combined Rationale`, Date) %>%
    rowwise() %>%
    mutate(Words = wordcount(`Combined Rationale`)) %>%
    ungroup() %>%
    mutate(`Combined ID` = factor(1:nrow(.))) %>%
    mutate(`Reviewer ID` = factor(`Reviewer ID`)) %>%
    complete(`Combined ID`, `Reviewer ID`) %>%
    mutate(`Words` = ifelse(is.na(Words), 0, Words)) %>%
    group_by(`Reviewer ID`) %>%
    mutate(Words = cumsum(Words)) %>%
    mutate(`Combined ID` = as.numeric(`Combined ID`)) %>%
    ggplot(aes(x = `Combined ID`, y = Words)) +
    facet_wrap(~`Reviewer ID`) +
    geom_line(colour = "#3FB5C3") +
    scale_y_continuous(breaks = scales::pretty_breaks(n = 5)) +
    labs(
        title = "Cumulative Number of Words per Combined Review/Interview over Time",
        subtitle = "For Aave Grants DAO Reviewers/Interviewers"
    )
```





Conclusion

This analysis reveals important dynamics in the reviewer ecosystem of the Aave Grants DAO. Over the past several years, the DAO has successfully maintained a robust and stable pool of active reviewers, with approximately a dozen contributors per quarter, and a core group providing consistent participation over time.

While the average review tends to be concise—under 100 words—the presence of significant outliers indicates deeper engagement from certain reviewers, especially in interviews, where rationales are often more detailed. The data also highlight marked differences in reviewer acceptance rates and productivity, with a few reviewers standing out for both their frequency and the length of their feedback.

These findings point to the importance of reviewer diversity and sustained engagement for the health of the DAO's grant-making process. Ensuring a mix of experienced and newer reviewers can help balance consistency with fresh perspectives, and tracking both qualitative (word count, rationale depth) and quantitative (number of reviews, acceptance rates) metrics will continue to improve transparency and the overall grant evaluation process.

Continued monitoring of these trends can inform future improvements to the review process, potentially increasing fairness and efficiency in funding high-impact projects for the Aave community.