Week 2 Lab

1. Using the `delay_2022` data, plot the five stations with the highest mean delays. Facet the graph by `line`
2. Using the `opendatatoronto` package, download the data on mayoral campaign contributions for 2014. Hints:
    - find the ID code you need for the package you need by searching for 'campaign' in the `all_data` tibble above
    - you will then need to `list_package_resources` to get ID for the data file
    - note: the 2014 file you will get from `get_resource` has a bunch of different campaign contributions, so just keep the data that relates to the Mayor election
3. Clean up the data format (fixing the parsing issue and standardizing the column names using `janitor`)
4. Summarize the variables in the dataset. Are there missing values, and if so, should we be worried about them? Is every variable in the format it should be? If not, create new variable(s) that are in the right format.
5. Visually explore the distribution of values of the contributions. What contributions are notable outliers? Do they share a similar characteristic(s)? It may be useful to plot the distribution of contributions without these outliers to get a better sense of the majority of the data.
6. List the top five candidates in each of these categories:
    - total contributions
    - mean contribution
    - number of contributions
7. Repeat 5 but without contributions from the candidates themselves.
8. How many contributors gave money to more than one candidate?

```
library(opendatatoronto)
```

```
## Warning: package 'opendatatoronto' was built under R version 4.2.2
```

```
library(tidyverse)
```

```
## Warning: package 'ggplot2' was built under R version 4.2.2
```

```
## Warning: package 'tibble' was built under R version 4.2.2
```

```
## Warning: package 'dplyr' was built under R version 4.2.2
```

```
## Warning: package 'forcats' was built under R version 4.2.2
```

```
library(stringr)
library(skimr) # EDA
```

```
## Warning: package 'skimr' was built under R version 4.2.2
```

```
library(visdat) # EDA
```

```
## Warning: package 'visdat' was built under R version 4.2.2
```

```
library(janitor)
```

```
## Warning: package 'janitor' was built under R version 4.2.2
```

```
library(lubridate)
library(ggrepel)
```

```
## Warning: package 'ggrepel' was built under R version 4.2.2
```

```
all_data <- list_packages(limit = 500)
head(all_data)
```

```
## # A tibble: 6 x 11
##   title     id    topics civic~1 publi~2 excerpt datas~3 num_r~4 formats refre~5
##   <chr>     <chr> <chr>  <chr>   <chr>   <chr>   <chr>     <int> <chr>   <chr>
## 1 Traffic ~ a330~ Trans~ <NA>    Transp~ This d~ Map          12 GPKG,S~ As ava~
## 2 Polls co~ 7bce~ City ~ <NA>    City C~ Polls ~ Table         5 JSON,X~ Daily
## 3 Short Te~ 2ab2~ Permi~ Afford~ Munici~ This d~ Table         4 JSON,C~ Daily
## 4 Toronto'~ c6d6~ <NA>   <NA>    City M~ This d~ Table         4 JSON,C~ Daily
## 5 Apartmen~ 4ef8~ Locat~ Afford~ Munici~ This d~ Table         4 JSON,C~ Daily
## 6 Address ~ abed~ Locat~ <NA>    Inform~ This d~ Docume~       3 SHP,TX~ Daily
## # ... with 1 more variable: last_refreshed <date>, and abbreviated variable
## #   names 1: civic_issues, 2: publisher, 3: dataset_category, 4: num_resources,
## #   5: refresh_rate
```

```
res <- list_package_resources("996cfe8d-fb35-40ce-b569-698d51fc683b") # obtained code from searching da
res <- res |> mutate(year = str_extract(name, "202.?"))
delay_2022_ids <- res |> filter(year==2022) |> select(id) |> pull()
delay_2022 <- get_resource(delay_2022_ids)
# make the column names nicer to work with
delay_2022 <- clean_names(delay_2022)
```

Let's also download the delay code and readme, as reference.

1.

Get the five stations with the highest mean delay.

```
temp = delay_2022 |>
  group_by(line)

summarize(temp, Mean_Delay = mean(min_delay)) |>
            arrange(desc(Mean_Delay))
```

```
## # A tibble: 22 x 2
##    line            Mean_Delay
##    <chr>                <dbl>
##  1 SRT                   5.91
##  2 BD                    3.75
##  3 SHP                   3.63
##  4 YU                    3.53
##  5 <NA>                  0.25
##  6 506 CARLTON           0
##  7 57 MIDLAND            0
##  8 69 WARDEN SOUTH       0
##  9 96 WILSON             0
## 10 B/D                   0
## # ... with 12 more rows
```

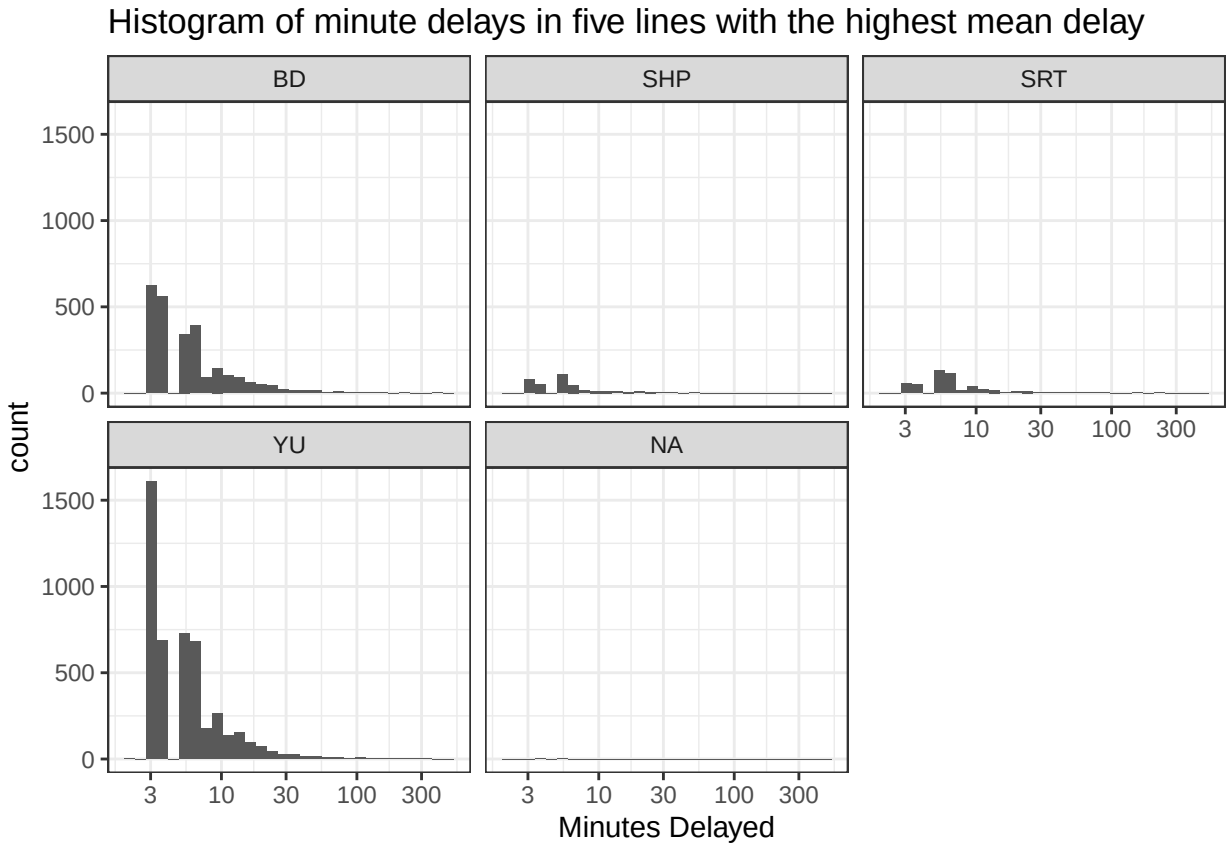
So we see that SRT, BD, SHP, YU, and NA(possible representing the case where we do not know where the delay was, even though there was a delay) have the highest mean delay.

```
top_5_mean = delay_2022 |>
  filter(line == "SRT"|line == "BD"|line == "SHP"|line == "YU"|is.na(line))
ggplot(data = top_5_mean)+
  geom_histogram(aes(x=min_delay))+
  scale_x_log10()+
  facet_wrap(~line)+
  labs(title = "Histogram of minute delays in five lines with the highest mean delay")+
  xlab("Minutes Delayed")+
  theme_bw()
```

```
## Warning: Transformation introduced infinite values in continuous x-axis
```

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

```
## Warning: Removed 9615 rows containing non-finite values (`stat_bin()`).
```



2.

```
library(opendatatoronto)
#search by title
campaign_package = search_packages("campaign contributions 2014")

#get the id
id_2014 = campaign_package$id

temp = list_package_resources(id_2014)

temp
```

```
## # A tibble: 2 x 4
##   name                                id                   format last_mod~1
##   <chr>                               <chr>                <chr>  <date>
## 1 campaign-contributions-2014-data    5b230e92-0a22-4a15-9~ ZIP    2019-07-23
## 2 campaign-contributions-2014-readme-xls aaf736f4-7468-4bda-9~ XLS    2019-07-23
## # ... with abbreviated variable name 1: last_modified
```

```
#5b230e92-0a22-4a15-9572-0b19cc222985 is the id

mayor_2014 = get_resource("5b230e92-0a22-4a15-9572-0b19cc222985")$`2_Mayor_Contributions_2014_election.
```

```
## New names:
```

```
## New names:
## New names:
## New names:
## New names:
## New names:
## New names:
## * `` -> `...2`
## * `` -> `...3`
```

```
head(mayor_2014)
```

```
## # A tibble: 6 x 13
##   2014 Munic~1 ...2  ...3  ...4  ...5  ...6  ...7  ...8  ...9  ...10 ...11 ...12
##   <chr>        <chr> <chr> <chr> <chr> <chr> <chr> <chr> <chr> <chr> <chr> <chr>
## 1 Contributor~ Cont~ Cont~ Cont~ Cont~ Good~ Cont~ Rela~ Pres~ Auth~ Cand~ Offi~
## 2 A D'Angelo,~ <NA>  M6A ~ 300   Mone~ <NA>  Indi~ <NA>  <NA>  <NA>  Ford~ Mayor
## 3 A Strazar, ~ <NA>  M2M ~ 300   Mone~ <NA>  Indi~ <NA>  <NA>  <NA>  Ford~ Mayor
## 4 A'Court, K ~ <NA>  M4M ~ 36    Mone~ <NA>  Indi~ <NA>  <NA>  <NA>  Chow~ Mayor
## 5 A'Court, K ~ <NA>  M4M ~ 100   Mone~ <NA>  Indi~ <NA>  <NA>  <NA>  Chow~ Mayor
## 6 A'Court, K ~ <NA>  M4M ~ 100   Mone~ <NA>  Indi~ <NA>  <NA>  <NA>  Chow~ Mayor
## # ... with 1 more variable: ...13 <chr>, and abbreviated variable name
## #   1: `2014 Municipal Election - List of Contributors to Mayoralty Candidates`
```

We will clean the data set in 3.

3.

```
library(janitor)
#we can fix the parsing issue
mayor_2014 = row_to_names(mayor_2014, row_number= 1)

head(mayor_2014)
```

```
## # A tibble: 6 x 13
##   Contributor'~1 Contr~2 Contr~3 Contr~4 Contr~5 Goods~6 Contr~7 Relat~8 Presi~9
##   <chr>          <chr>   <chr>   <chr>   <chr>   <chr>   <chr>   <chr>   <chr>
## 1 A D'Angelo, T~ <NA>    M6A 1P5 300     Moneta~ <NA>    Indivi~ <NA>    <NA>
## 2 A Strazar, Ma~ <NA>    M2M 3B8 300     Moneta~ <NA>    Indivi~ <NA>    <NA>
## 3 A'Court, K Su~ <NA>    M4M 2J8 36      Moneta~ <NA>    Indivi~ <NA>    <NA>
## 4 A'Court, K Su~ <NA>    M4M 2J8 100     Moneta~ <NA>    Indivi~ <NA>    <NA>
## 5 A'Court, K Su~ <NA>    M4M 2J8 100     Moneta~ <NA>    Indivi~ <NA>    <NA>
## 6 Aaron, Robert~ <NA>    M6B 1H7 250     Moneta~ <NA>    Indivi~ <NA>    <NA>
## # ... with 4 more variables: `Authorized Representative` <chr>,
## #   Candidate <chr>, Office <chr>, Ward <chr>, and abbreviated variable names
## #   1: `Contributor's Name`, 2: `Contributor's Address`,
## #   3: `Contributor's Postal Code`, 4: `Contribution Amount`,
## #   5: `Contribution Type Desc`, 6: `Goods or Service Desc`,
## #   7: `Contributor Type Desc`, 8: `Relationship to Candidate`,
## #   9: `President/ Business Manager`
```

```
#and standardize the column names
mayor_2014 = clean_names(mayor_2014)

head(mayor_2014)
```

```
## # A tibble: 6 x 13
##   contributors~1 contr~2 contr~3 contr~4 contr~5 goods~6 contr~7 relat~8 presi~9
##   <chr>          <chr>   <chr>   <chr>   <chr>   <chr>   <chr>   <chr>   <chr>
## 1 A D'Angelo, T~ <NA>    M6A 1P5 300     Moneta~ <NA>    Indivi~ <NA>    <NA>
## 2 A Strazar, Ma~ <NA>    M2M 3B8 300     Moneta~ <NA>    Indivi~ <NA>    <NA>
## 3 A'Court, K Su~ <NA>    M4M 2J8 36      Moneta~ <NA>    Indivi~ <NA>    <NA>
## 4 A'Court, K Su~ <NA>    M4M 2J8 100     Moneta~ <NA>    Indivi~ <NA>    <NA>
## 5 A'Court, K Su~ <NA>    M4M 2J8 100     Moneta~ <NA>    Indivi~ <NA>    <NA>
## 6 Aaron, Robert~ <NA>    M6B 1H7 250     Moneta~ <NA>    Indivi~ <NA>    <NA>
## # ... with 4 more variables: authorized_representative <chr>, candidate <chr>,
## #   office <chr>, ward <chr>, and abbreviated variable names
## #   1: contributors_name, 2: contributors_address, 3: contributors_postal_code,
## #   4: contribution_amount, 5: contribution_type_desc,
## #   6: goods_or_service_desc, 7: contributor_type_desc,
## #   8: relationship_to_candidate, 9: president_business_manager
```

4.

We can first check for missing values using skim package.

```
skim(mayor_2014)
```

Table 1: Data summary

Name	mayor_2014
Number of rows	10199
Number of columns	13
Column type frequency:	
character	13
Group variables	None

Variable type: character

skim_variable	n_missing	complete_rate	min	max	empty	n_unique	whitespace
contributors_name	0	1	4	31	0	7545	0
contributors_address	10197	0	24	26	0	2	0
contributors_postal_code	0	1	7	7	0	5284	0
contribution_amount	0	1	1	18	0	209	0
contribution_type_desc	0	1	8	14	0	2	0
goods_or_service_desc	10188	0	11	40	0	9	0
contributor_type_desc	0	1	10	11	0	2	0
relationship_to_candidate	10166	0	6	9	0	2	0
president_business_manager	10197	0	13	16	0	2	0

skim_variable	n_missing	complete_rate	min	max	empty	n_unique	whitespace
authorized_representative	10197	0	13	16	0	2	0
candidate	0	1	9	18	0	27	0
office	0	1	5	5	0	1	0
ward	10199	0	NA	NA	0	0	0

We first see that the ward variable is useless as all the values are missing. We also remove other variables that have that have 99% of the values missing, except the 8th column which describes the relationship of the contributor to the candidate.

```
mayor_2014 = mayor_2014 |>
  select(-c(2,6,9,10,13))
```

The relationship to candidate column is relevant.

```
mayor_2014$relationship_to_candidate[which(!is.na(mayor_2014$relationship_to_candidate))]
```

```
##  [1] "Candidate" "Candidate" "Candidate" "Candidate" "Candidate" "Candidate"
##  [7] "Candidate" "Candidate" "Candidate" "Candidate" "Candidate" "Candidate"
## [13] "Candidate" "Candidate" "Candidate" "Candidate" "Spouse"    "Spouse"
## [19] "Candidate" "Candidate" "Candidate" "Candidate" "Candidate" "Candidate"
## [25] "Candidate" "Candidate" "Candidate" "Candidate" "Candidate" "Candidate"
## [31] "Candidate" "Candidate" "Spouse"
```

We want to know whether or not candidate made any contribution for 7. Hence, we make a new column where it's 1 if the candidate contributed themselves, and 0 otherwise.

```
#replace NA with FALSE
mayor_2014$relationship_to_candidate[which(is.na(mayor_2014$relationship_to_candidate))]=
  FALSE
#make a column of 1 if the contributor is candidate
#0 otherwise
mayor_2014 = mayor_2014 |>
  mutate(relationship = ifelse(relationship_to_candidate == "Candidate",1,0)) |>
  select(-6)
```

Contribution amount should be in numeric.

```
mayor_2014$contribution_amount=as.numeric(mayor_2014$contribution_amount)
```

The "Office" variable has the same value for each data point, so we may remove it.

```
unique(mayor_2014$office)
```

```
## [1] "Mayor"
```

```
mayor_2014 = mayor_2014 |>
  select(-7)
```

We will first look at summary statistics for the contribution amount.

```
summary(mayor_2014$contribution_amount)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##       1     100     300     608     500  508225
```

The median is smaller than the mean by 308 dollars, so this may suggest some higher-end donations that skew the distribution.

The maximum of 508225 dollars is also notable.

Next, we will look at composition of the contribution type.

```
unique(mayor_2014$contribution_type_desc)
```

```
## [1] "Monetary"       "Goods/Services"
```

```
temp = mayor_2014$contribution_type_desc
#percentage of monetary donation
(length(which(temp == "Monetary"))/length(temp) )*100
```

```
## [1] 99.89215
```

And we look at the composition of the contributor type.

```
unique(mayor_2014$contributor_type_desc)
```

```
## [1] "Individual"  "Corporation"
```

```
temp = mayor_2014$contributor_type_desc
#percentage of individual donation
(length(which(temp == "Individual"))/length(temp) )*100
```

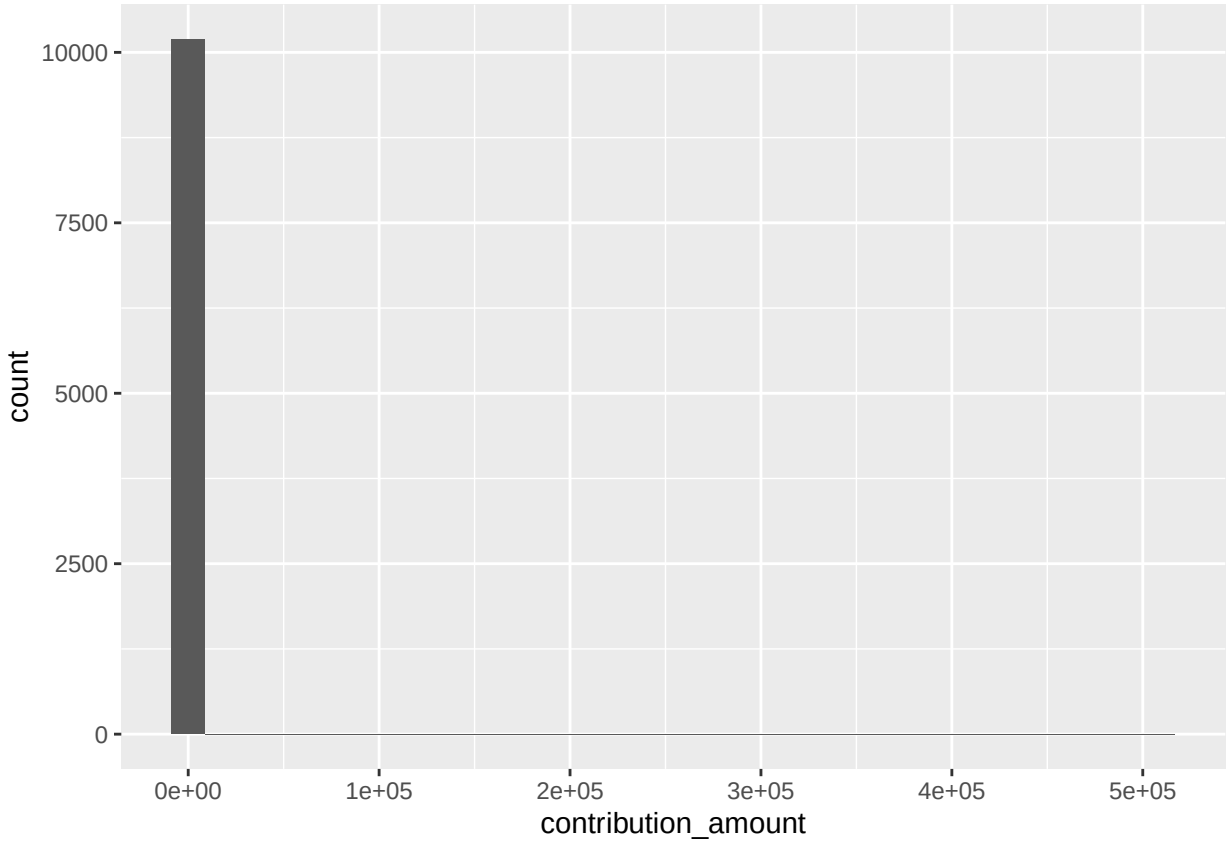
```
## [1] 99.98039
```

5.

We first graph a histogram of the contribution amounts.

```
ggplot(data = mayor_2014, aes(x=contribution_amount))+
  geom_histogram()
```

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



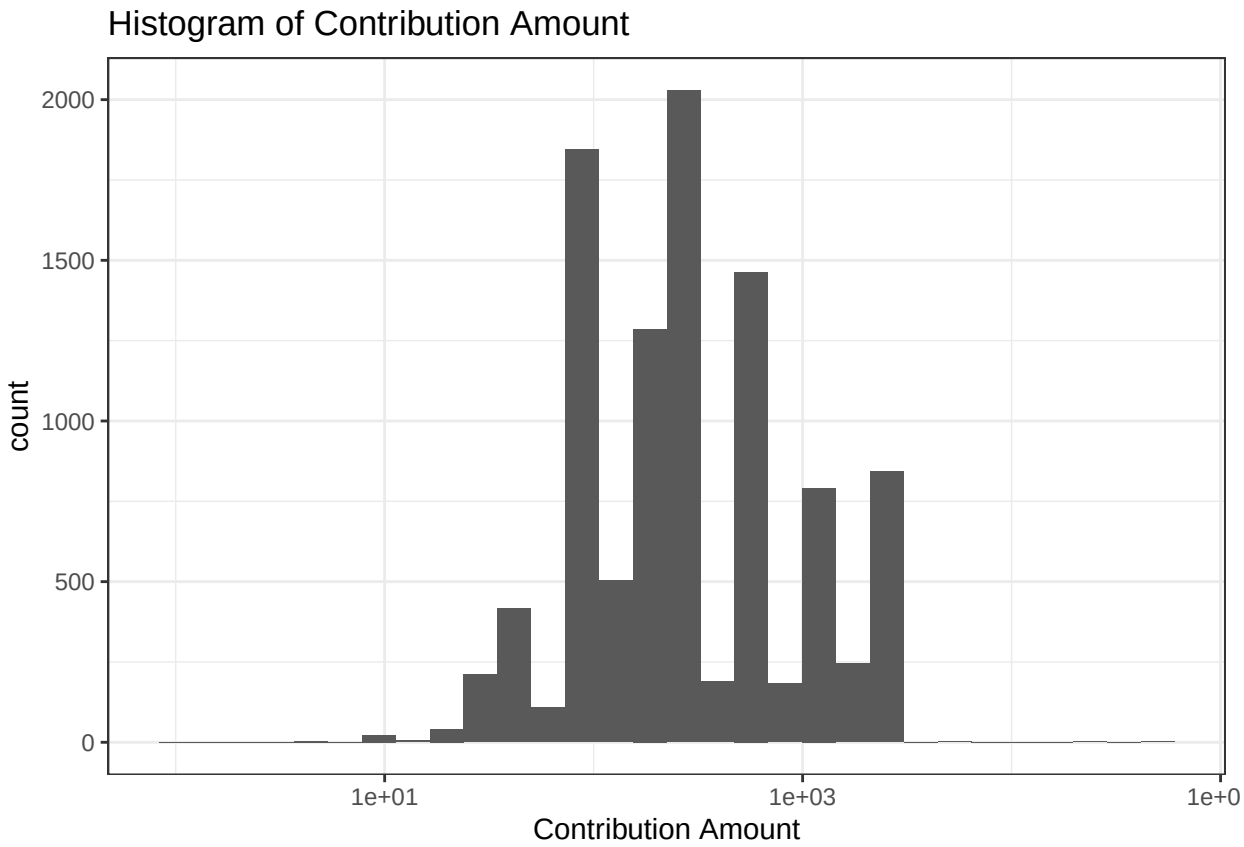
The histogram breaks because of outliers. We will remove contributions of more than 50000 dollars. There are 2 of them.

```
length(which(mayor_2014$contribution_amount > 50000))
```

```
## [1] 2
```

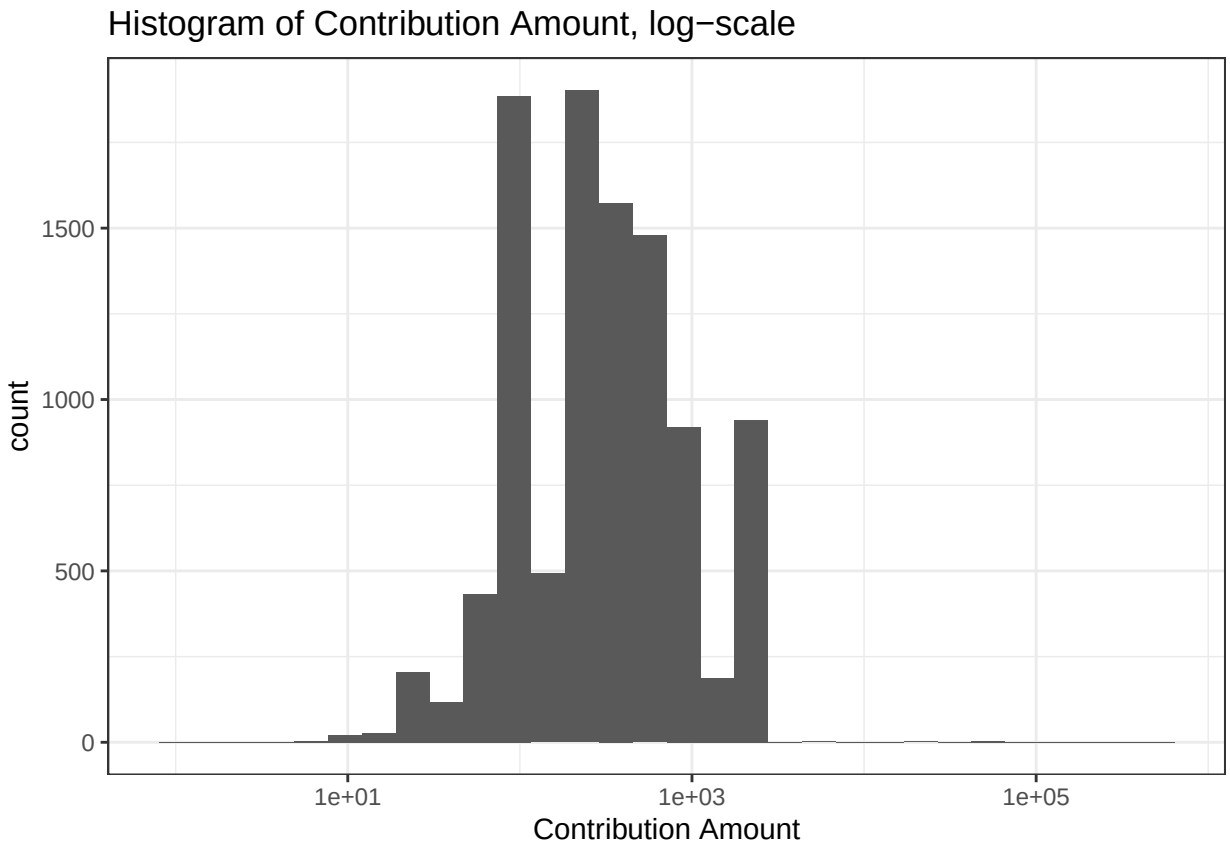
```
temp = mayor_2014 |>
  filter(contribution_amount <=50000)


ggplot(data = temp)+
  geom_histogram(aes(x=contribution_amount))+
  xlab("Contribution Amount")+
  scale_x_log10()+
  labs(title = "Histogram of Contribution Amount")+
  theme_bw()
```

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




```
#We can also plot it on the log-scale
#in which case we do not need to remove the outlier

ggplot(data = mayor_2014)+
  geom_histogram(aes(x=contribution_amount))+
  xlab("Contribution Amount")+
  scale_x_log10()+
  labs(title = "Histogram of Contribution Amount, log-scale")+
  theme_bw()
```

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



Notably, there's an outlier with the contribution of 508224.73.

```
mayor_2014 |>
  filter(contribution_amount == 508224.73)
```

```
## # A tibble: 1 x 7
##   contributors_name contributors_posta~1 contr~2 contr~3 contr~4 candi~5 relat~6
##   <chr>             <chr>                  <dbl> <chr>   <chr>   <chr>     <dbl>
## 1 Ford, Doug        M9A 2C3               508225. Moneta~ Indivi~ Ford, ~       1
## # ... with abbreviated variable names 1: contributors_postal_code,
## #   2: contribution_amount, 3: contribution_type_desc,
## #   4: contributor_type_desc, 5: candidate, 6: relationship
```

This contribution turns out to be Doug Ford self-financing his own campaign.

A frequency table can also be interesting. We print top 15 contribution amount with respect to frequency.

```
sort(table(mayor_2014$contribution_amount), decreasing = TRUE)[1:15]
```

```
##
##  100  500  300  200 2500 1000  250   50  150   25  750 1500  400 2000   60
## 1767 1392 1367 1245  825  735  605  323  243  181  133  130  118   93   92
```

Another thing of interest is the number of "small" contribution. OpenSecrets, a non-profit organization that tracks campaign financing, defines small contributions as contribution of less than 200 dollars. So we will use this definition.

```
small = length(which(mayor_2014$contribution_amount < 200))

#the percentage of small contribution

small/nrow(mayor_2014) * 100
```

```
## [1] 31.28738
```

So less than half of the donations were "small" contributions.

6.

```
temp = mayor_2014 |>
  group_by(candidate)

total_contribution = temp|>
  summarize(Total = sum(contribution_amount))|>
  arrange(desc(Total))

total_contribution
```

```
## # A tibble: 27 x 2
##    candidate             Total
##    <chr>                 <dbl>
##  1 Tory, John         2767869.
##  2 Chow, Olivia       1638266.
##  3 Ford, Doug          889897.
##  4 Ford, Rob           387648.
##  5 Stintz, Karen       242805
##  6 Soknacki, David     132431
##  7 Goldkind, Ari        41125.
##  8 Thomson, Sarah       34628.
##  9 Di Paola, Rocco      21126
## 10 Underhill, Richard   15660
## # ... with 17 more rows
```

So the top five candidates in total contribution is Tory, Chow, Ford, Doug, Ford Rob, and Stintz.

```
temp = mayor_2014 |>
  group_by(candidate)

mean_contribution = temp|>
  summarize(Mean = mean(contribution_amount))|>
  arrange(desc(Mean))

mean_contribution
```

```
## # A tibble: 27 x 2
##    candidate         Mean
##    <chr>            <dbl>
##  1 Sniedzins, Erwin 2025
```

```
##  2 Syed, Hïmy       2018
##  3 Ritch, Carlie    1887.
##  4 Ford, Doug       1456.
##  5 Clarke, Kevin    1200
##  6 Di Paola, Rocco  1174.
##  7 Tory, John       1064.
##  8 Gardner, Norman  1000
##  9 Stintz, Karen     995.
## 10 Kalevar, Chai     900
## # ... with 17 more rows
```

So the top five candidates in mean contribution is Sniedzin, Syed, Ritch, Ford, Doug and Clarke.

```
temp = mayor_2014 |>
  group_by(candidate)

num_contribution = temp|>
  summarize(num = length(contribution_amount))|>
  arrange(desc(num))

num_contribution
```

```
## # A tibble: 27 x 2
##    candidate            num
##    <chr>              <int>
##  1 Chow, Olivia        5708
##  2 Tory, John          2602
##  3 Ford, Doug           611
##  4 Ford, Rob            538
##  5 Soknacki, David      314
##  6 Stintz, Karen        244
##  7 Goldkind, Ari         47
##  8 Underhill, Richard    41
##  9 Thomson, Sarah        40
## 10 Di Paola, Rocco       18
## # ... with 17 more rows
```

So the top five candidates in number of contribution is Chow, TOry, Ford, Doug, Ford, Rob and Soknacki.

7.

We remove donation made by the candidates themselves

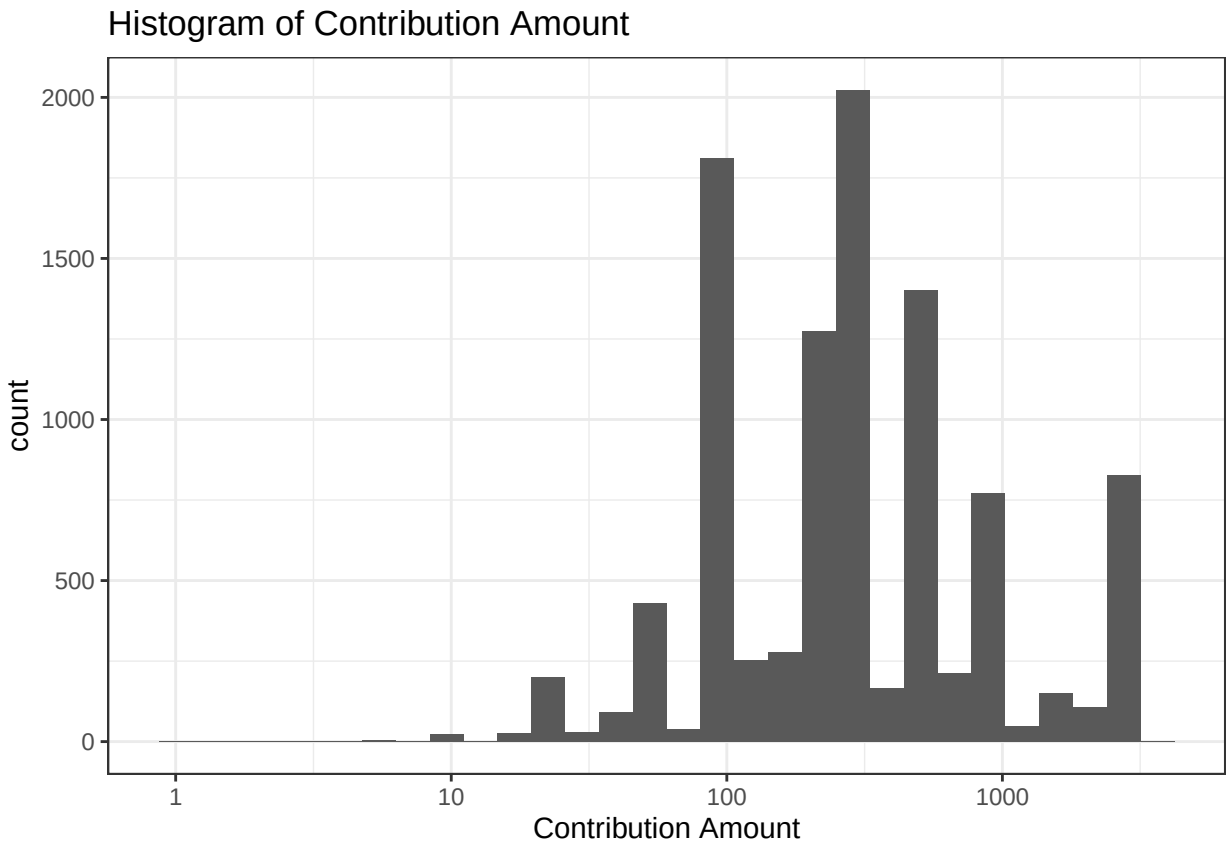
```
temp = mayor_2014 |>
  filter(relationship == 0)

#the maximum donation is now 3660.

max(temp$contribution_amount)
```

```
## [1] 3660
```

We plot the histograms again, with outliers removed. The distributions look similar, but the plot is better visually as the bins do not have to spread far apart.

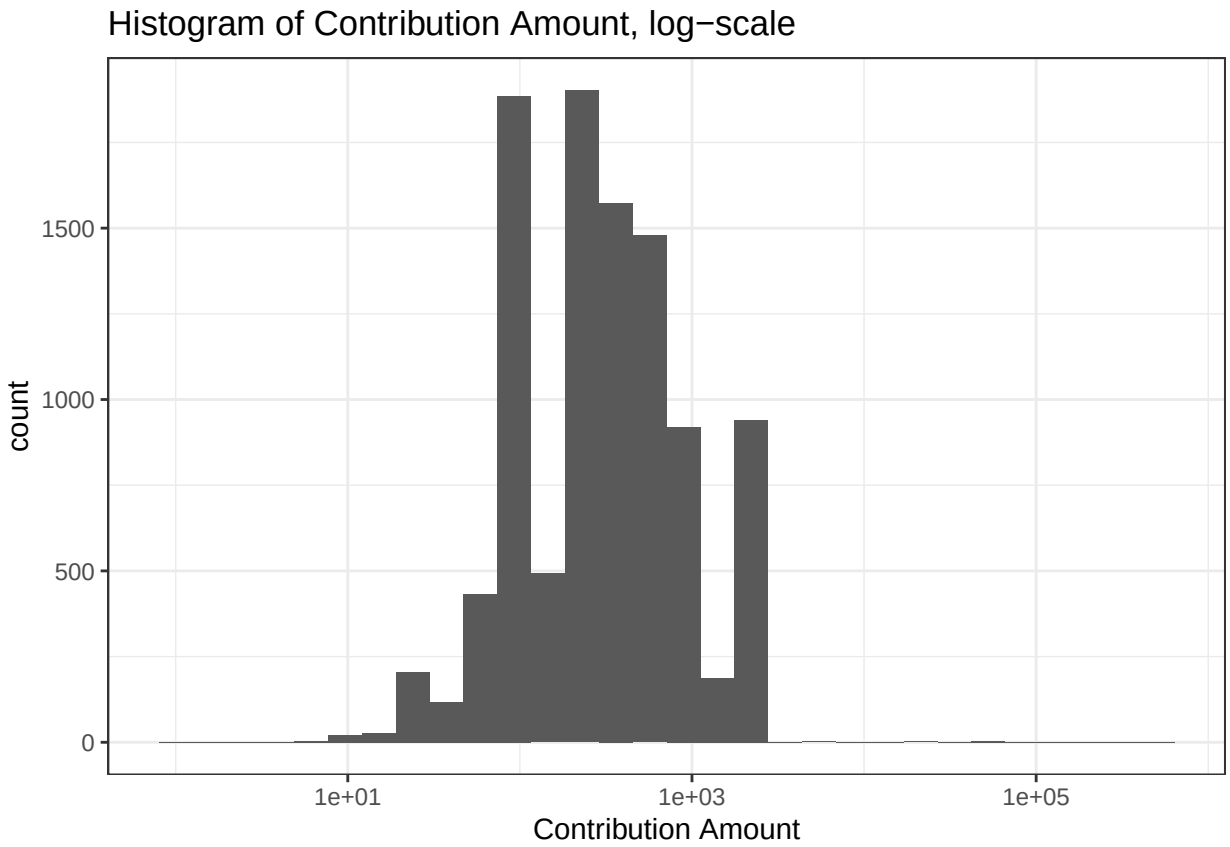
```
ggplot(data = temp)+
  geom_histogram(aes(x=contribution_amount))+
  xlab("Contribution Amount")+
  scale_x_log10()+
  labs(title = "Histogram of Contribution Amount")+
  theme_bw()
```

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




```
#We can also plot it on the log-scale

ggplot(data = mayor_2014)+
  geom_histogram(aes(x=contribution_amount))+
  xlab("Contribution Amount")+
  scale_x_log10()+
  labs(title = "Histogram of Contribution Amount, log-scale")+
  theme_bw()
```

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



8.

Since it's possible for two people to have the same name, we first filter by the address. We will assume that people with the same name and the same address is a one person, even though it's possible that two people with the same name are living in the same address.

```
#choosing contributor address that appears twice.
temp = mayor_2014|>
  group_by(contributors_postal_code)|>
  filter(length(contributors_postal_code) > 1)

#We then group by name, choosing people that appear twice.

temp = temp|>
  group_by(contributors_name)|>
  filter(length(contributors_name)>1)

#the number of people who made more than one contribution is

length(unique(temp$contributors_name))
```

```
## [1] 1849
```