Homework 1 Solutions

PSTAT 134/234

Homework 1 Solutions

For this assignment, you may use R or Python, or a combination of both, to complete both case studies. You can use the code that we include in Labs 1 and 2 to answer these questions. You also may need to use other functions. I encourage you to make use of our textbook(s) and use the Internet to help you solve these problems. You can also work together with your classmates. If you do work together, you should provide the names of those classmates below.

Names of Collaborators (if any):

Case Study: New York Times Ad Impressions (Simulated)

There are 10 data sets in the `/data` subdirectory named `nyt1.csv`, `nyt2.csv`, …, `nyt10.csv`. Each file represents one day's worth of simulated data on ad impressions and clicks on the New York Times homepage. Each row represents a single user. There are five columns:

- `Age` (user's age)
- `Gender` (user's gender, coded as `0` = female, `1` = male)
- `Impressions` (number of ads displayed during the user's visit)
- `Clicks` (number of clicks made by the user)
- `Signed_In` (whether or not the user was signed in as a member)

Load **a single data file**. Then do the following.

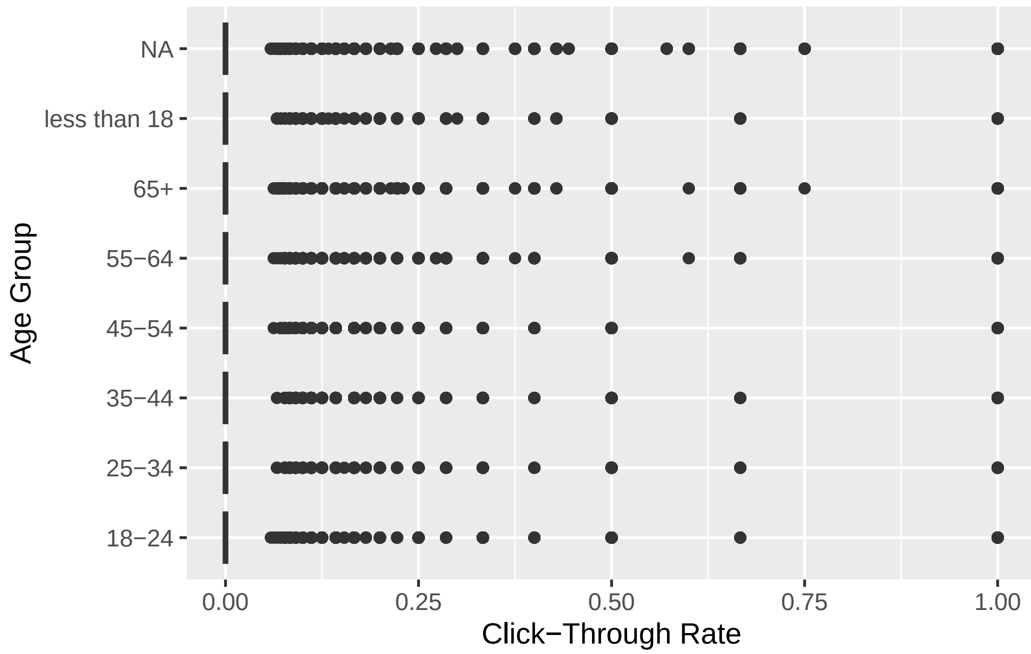
1. Create a new variable, `age_group`, that categorizes users into the following age groups: < 18, 18-24, 25-34, 35-44, 45-54, 55-64, and 65+.

Note that, ideally, students should recognize that an age of 0 is not a valid number, and replace those with `NA`. Students do **not** have to use the `clean_names()` function.

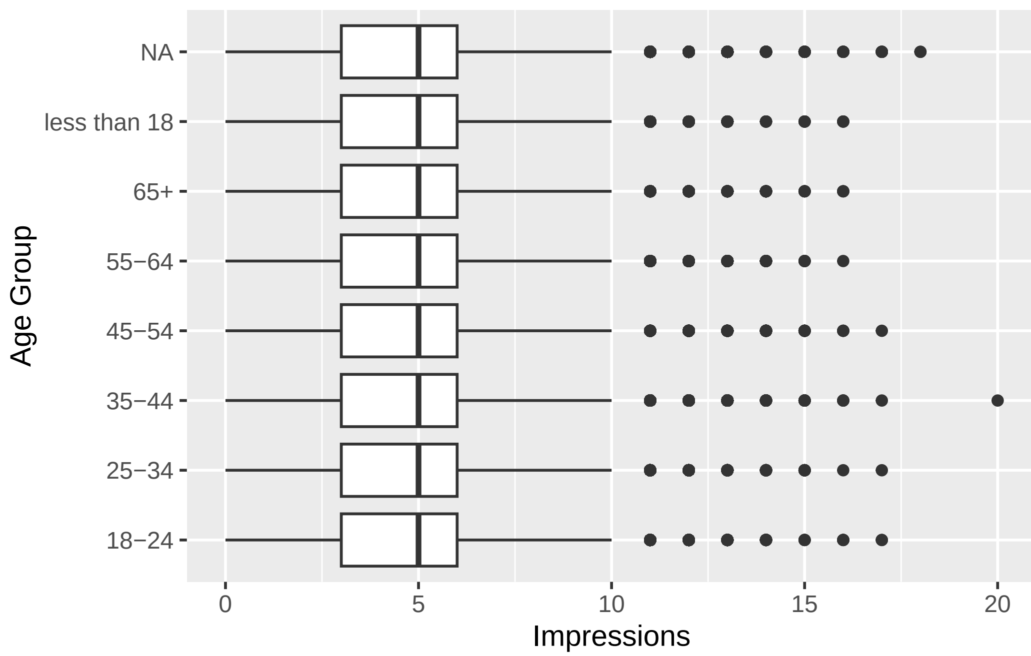
```
library(tidyverse)
library(janitor)
nyt_day1 <- read_csv("data/nyt1.csv") %>%
  clean_names()
nyt_day1 <- nyt_day1 %>%
  mutate(age_group = case_when(
    age == 0 ~ NA,
    age < 18 ~ "less than 18",
    age <= 24 ~ "18-24",
    age <= 34 ~ "25-34",
    age <= 44 ~ "35-44",
    age <= 54 ~ "45-54",
    age <= 64 ~ "55-64",
    age > 64 ~ "65+",
    .default = "age"
  ))
```

2. Plot the distributions of impressions and "click-through rate" for all 6 age categories. (*Note:* Click-through rate is defined as the number of clicks divided by the number of impressions; it represents the proportion of ads that generated clicks.)

```
nyt_day1 <- nyt_day1 %>%
  mutate(click_through_rate = clicks/impressions)
ggplot(nyt_day1, aes(x = click_through_rate)) +
  geom_boxplot(aes(y = age_group)) +
  labs(x = "Click-Through Rate", y = "Age Group")
```




```
ggplot(nyt_day1, aes(x = impressions)) +
  geom_boxplot(aes(y = age_group)) +
  labs(x = "Impressions", y = "Age Group")
```



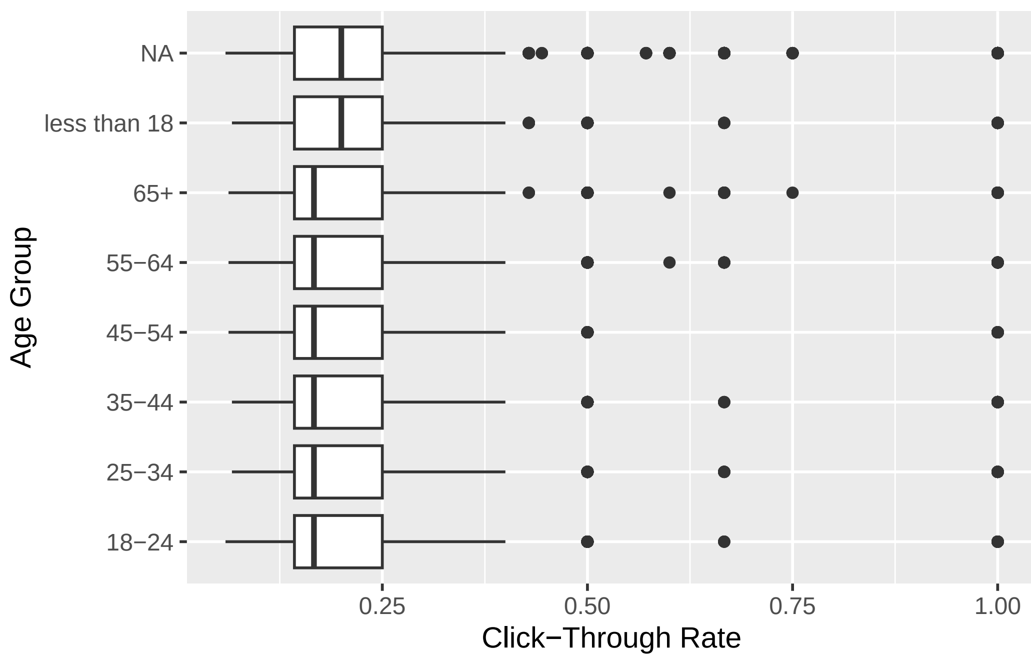
Box plots or violin plots are most likely the best option to compare distributions that are heavily skewed across multiple groups like this. The main takeaway here is that there is really not much difference in terms of the distributions of click-through rate and impressions across age groups.

3. Create a new variable to categorize users based on their click behavior. (The name and categories for this variable are up to you. Explain what decision[s] you make and why.)

```
nyt_day1 <- nyt_day1 %>%
  mutate(clicker_or_not = case_when(
    clicks == 0 ~ "Nonclicker",
    clicks <= 2 ~ "Clicker",
    clicks > 2 ~ "Frequent Clicker"
  ))
```

Note: The question doesn't ask, but it might be interesting to then use this variable to assess the distribution of click-through rate by age group for those users who click at all (essentially filtering out the zeros):

```
nyt_day1 %>%
  filter(clicker_or_not != "Nonclicker") %>%
    ggplot(aes(x = click_through_rate)) +
     geom_boxplot(aes(y = age_group)) +
     labs(x = "Click-Through Rate", y = "Age Group")
```

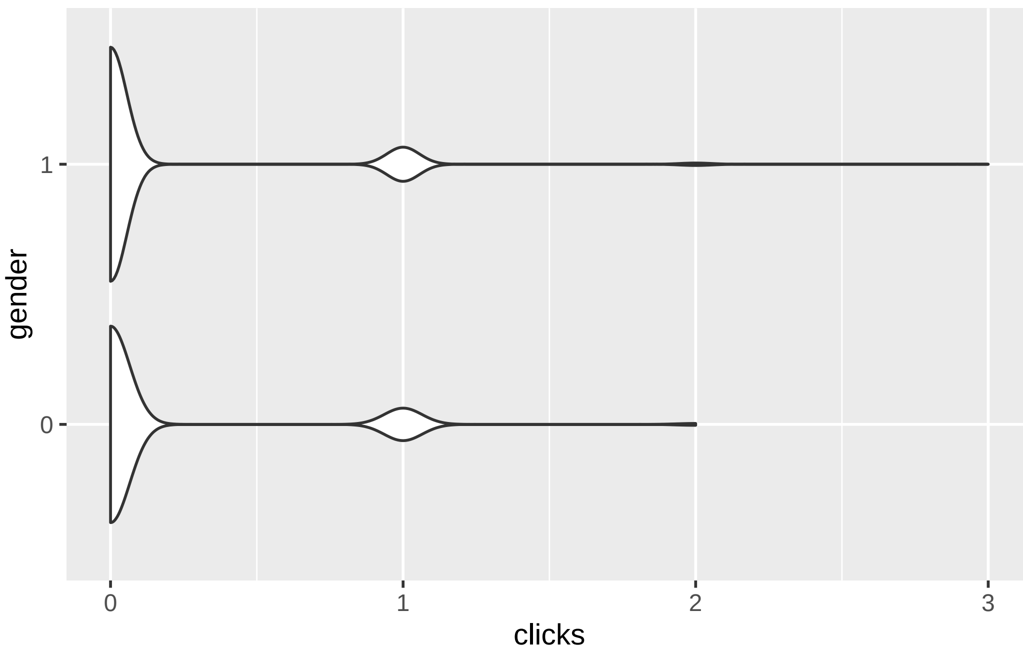


When we are looking just at those users who click at least once, the click-through rate tends to be higher for users under 18 or who are signed-out.

4. Explore the data and make visual and quantitative comparisons across user segments/demographics to answer the following:

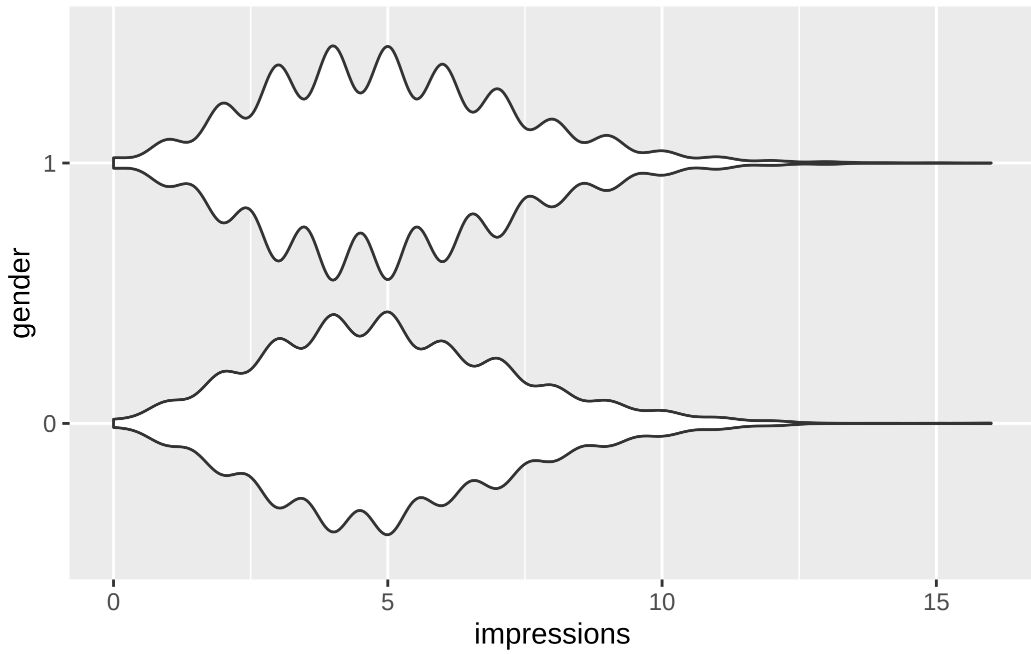
    - How do <18 year old males differ from <18 year old females in terms of clicks and impressions?

```
nyt_day1 %>%
  filter(age_group == "less than 18") %>%
  mutate(gender = factor(gender)) %>%
  ggplot(aes(x = clicks, y = gender)) +
  geom_violin()
```



A box plot or violin plot would work best for this question. There is really not much, if any, difference.

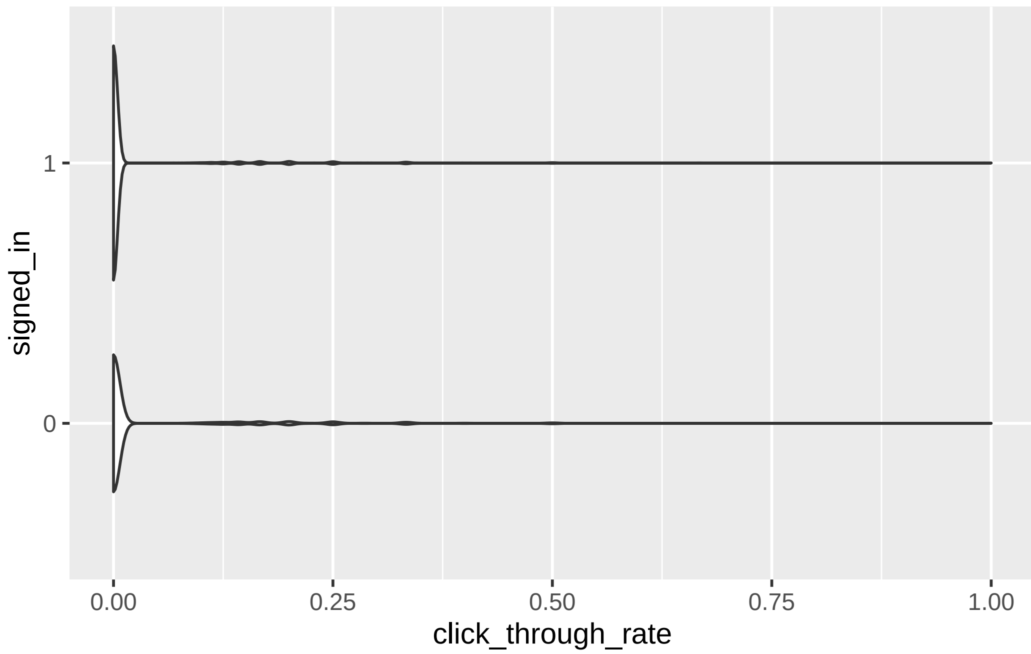
```
nyt_day1 %>%
  filter(age_group == "less than 18") %>%
  mutate(gender = factor(gender)) %>%
  ggplot(aes(x = impressions, y = gender)) +
  geom_violin()
```



Again a box plot or violin plot would work best for this question. There is really not much, if any, difference.

```
-   How does the distribution of click-through rate for users who are signed in differ from t
```

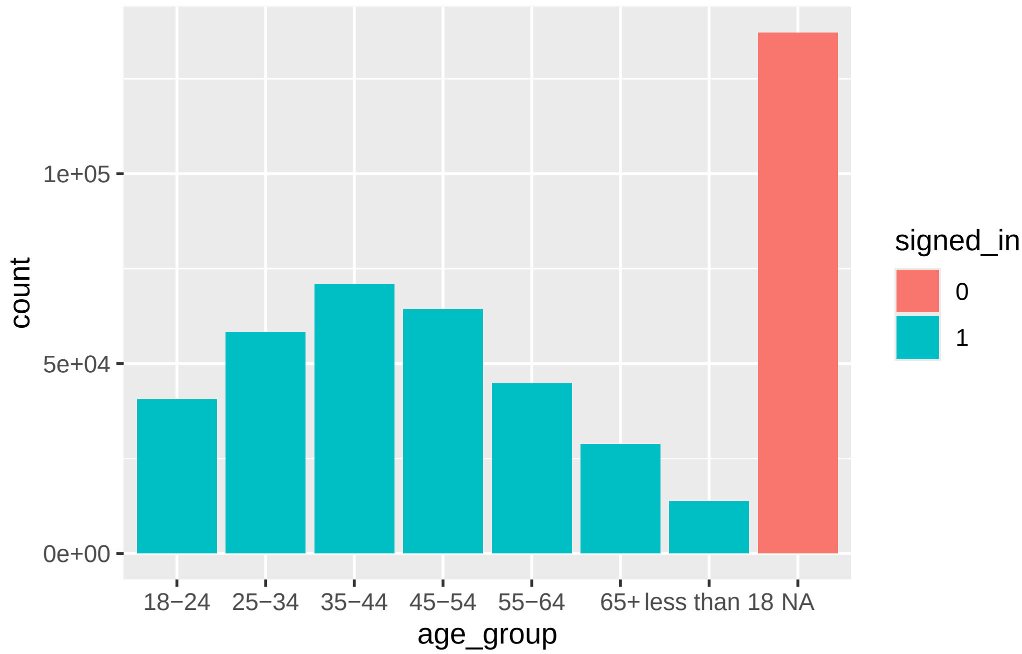
```
nyt_day1 %>%
  mutate(signed_in = factor(signed_in)) %>%
  ggplot(aes(x = click_through_rate, y = signed_in)) +
  geom_violin()
```



There is really not much, if any, difference.

- Are certain age groups more likely to be signed in than others? Which ones?

```
nyt_day1 %>%
  mutate(signed_in = factor(signed_in)) %>%
  ggplot(aes(x = age_group,
             fill = signed_in)) + geom_bar()
```



Part of the goal of this question is to hint at the fact that we do not have age data for signed-out users – all their ages are listed as 0. If students don't recognize this, they will likely (incorrectly) say that "all the signed-out users are under 18."

5. Calculate summary statistics for the click-through rate. These should include (1) quartiles, (2) mean, (3) median, (4) minimum and maximum, and (5) variance. Choose two user segments to compare these statistics across (for example, compare the mean, median, and quartiles for users 25-34 to those for users 65+).

General summary statistics for click-through rate:

```
library(kableExtra)
stats <- nyt_day1$click_through_rate %>%
  summary() %>%
  unname()
variance <- var(nyt_day1$click_through_rate,
    na.rm = T)
tibble("Statistic" = c("Minimum", "1st Quartile",
                       "Median", "Mean", "3rd Quartile",
                       "Maximum", "Variance"),
       "Value" = c(stats[1], stats[2], stats[3],
                   stats[4], stats[5], stats[6],
                   variance)) %>%
  kbl() %>%
  scroll_box(width = "275px", height = "275px")
```

Statistic	Value
Minimum	0.0000000
1st Quartile	0.0000000
Median	0.0000000
Mean	0.0184705
3rd Quartile	0.0000000
Maximum	1.0000000
Variance	0.0047658

Statistics comparing the rates for users less than 18 years of age to users 65 and up:

```
stats_a <- nyt_day1 %>%
  filter(age_group == "less than 18") %>%
  .$click_through_rate %>%
  summary() %>%
  unname()
stats_b <- nyt_day1 %>%
  filter(age_group == "65+") %>%
  .$click_through_rate %>%
  summary() %>%
  unname()
variance_a <- nyt_day1 %>%
  filter(age_group == "less than 18") %>%
  .$click_through_rate %>%
  var(na.rm = T)
variance_b <- nyt_day1 %>%
  filter(age_group == "65+") %>%
  .$click_through_rate %>%
  var(na.rm = T)
tibble("Statistic" = c("Minimum", "1st Quartile",
                       "Median", "Mean", "3rd Quartile",
                       "Maximum", "Variance"),
       "Users <18" = c(stats_a[1:6],
                       variance_a),
       "Users 65+" = c(stats_b[1:6],
                         variance_b)) %>%
  kbl() %>%
  scroll_box(width = "275px", height = "275px")
```

Statistic	Users <18	Users 65+
Minimum	0.0000000	0.0000000
1st Quartile	0.0000000	0.0000000
Median	0.0000000	0.0000000
Mean	0.0302772	0.0298027
3rd Quartile	0.0000000	0.0000000
Maximum	1.0000000	1.0000000
Variance	0.0076910	0.0070643

6. Summarize your findings in a brief (1-2 paragraph) report intended for a New York Times (NYT) advertising team.

Answers may vary. An ideal report might mention the following: It's difficult to learn much information about the users who are not signed in, because we don't have their demographic details (age or gender). About 29.91% of users are not signed in. Of those who are signed in, age follows a somewhat normal distribution, with a small number of users less than 18 and over 65, and the majority of users more middle-aged, between 35 and 54. In terms of gender, of users who are signed in, about 63% are female. Overall, the distributions of clicks, impressions, and click-through rates are heavily positively skewed, indicating that a vast majority of users, regardless of demographics, are not clicking on ads, etc, although some users click as many as 4 times. It might be worth further investigating what variables drive some users to click or engage and not others.

Additional Questions for 231 Students

*Now read in at least **three to four more** of these data files and extend your analyses.*

7. Visualize impressions and click-through rate for signed-in versus signed-out users over time.

Students do not have to read more than three or four of these files in, but they can read in all ten if they choose. The following code reads in all ten files.

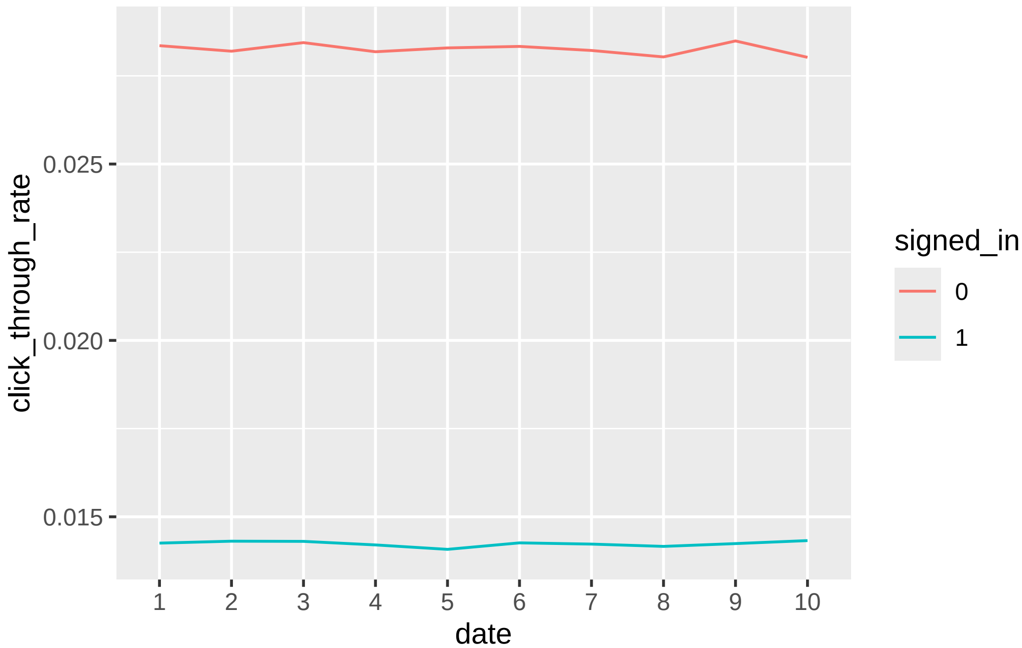
Visualizations can vary but should include (1) impressions, (2) signed-in vs. signed-out, and (3) time, measured in terms of what day it is. The following displays two line graphs of impressions and click-through rate over time, broken down by whether or not users are signed in:

```
nyt_day <- list()
for(i in 1:10){
  nyt_day[[i]] <- read_csv(paste0("data/nyt", i, ".csv")) %>%
    clean_names()
  nyt_day[[i]] <- nyt_day[[i]] %>%
```

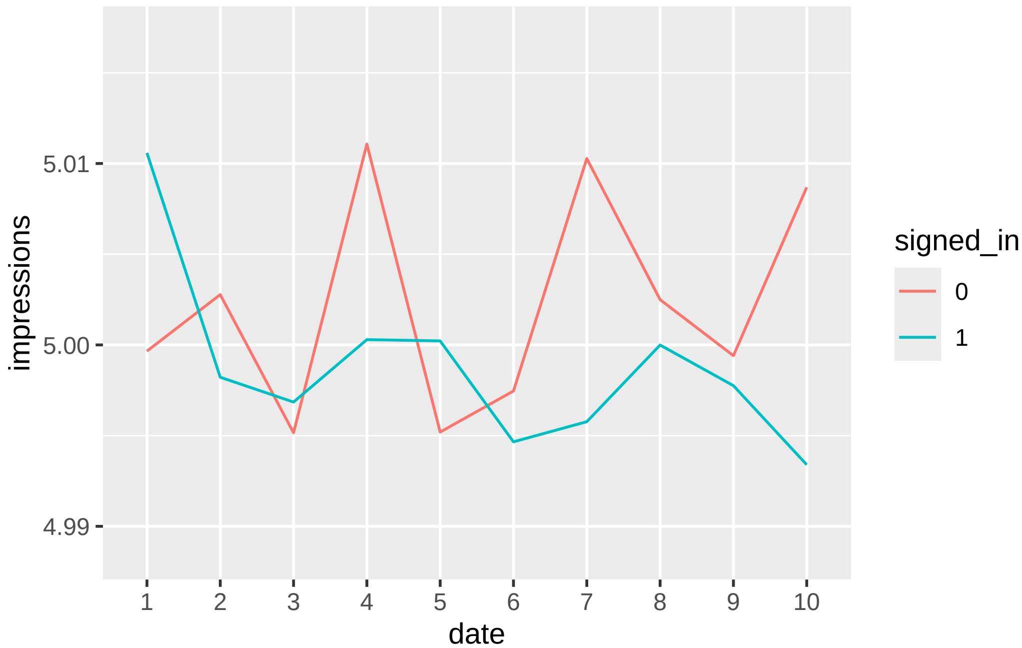
```r
    mutate(date = rep(i, dim(nyt_day[[i]])[1]))
}
nyt_all <- do.call(rbind, nyt_day) %>%
  tibble()

nyt_all <- nyt_all %>%
  mutate(click_through_rate = clicks/impressions) %>%
  mutate(age_group = case_when(
    age == 0 ~ NA,
    age < 18 ~ "less than 18",
    age <= 24 ~ "18-24",
    age <= 34 ~ "25-34",
    age <= 44 ~ "35-44",
    age <= 54 ~ "45-54",
    age <= 64 ~ "55-64",
    age > 64 ~ "65+",
    .default = "age"
  ))

head(nyt_all)
```

```
# A tibble: 6 x 8
    age gender impressions clicks signed_in  date click_through_rate age_group
  <dbl>  <dbl>       <dbl>  <dbl>     <dbl> <int>              <dbl> <chr>
1    36      0           3      0         1     1             0      35-44
2    73      1           3      0         1     1             0      65+
3    30      0           3      0         1     1             0      25-34
4    49      1           3      0         1     1             0      45-54
5    47      1          11      0         1     1             0      45-54
6    47      0          11      1         1     1             0.0909 45-54
```

```r
nyt_all %>%
  mutate(signed_in = factor(signed_in),
         date = factor(date)) %>%
  ggplot(aes(x = date, group = signed_in)) +
  geom_line(aes(y = click_through_rate,
                color = signed_in), stat="summary")
```




```
nyt_all %>%
  mutate(signed_in = factor(signed_in),
         date = factor(date)) %>%
  ggplot(aes(x = date, group = signed_in)) +
  geom_line(aes(y = impressions,
                color = signed_in), stat="summary")
```



The click-through rate and impressions rates over time are, in general, very consistent. The only noticeable difference is the fact that users who are not signed-in tend to have a higher click-through rate, regardless of time.

Users can simply make three or four different plots, one per day, although this is less effective for comparisons over time.

8. Calculate summary statistics to compare signed-in versus signed-out users over time.

Answers may vary; note that the problem doesn't specify a variable to compare on. It might make sense to use click-through rate. It probably doesn't make sense to compare age or gender, since that information isn't provided for users who are not signed in. To use click-through rate:

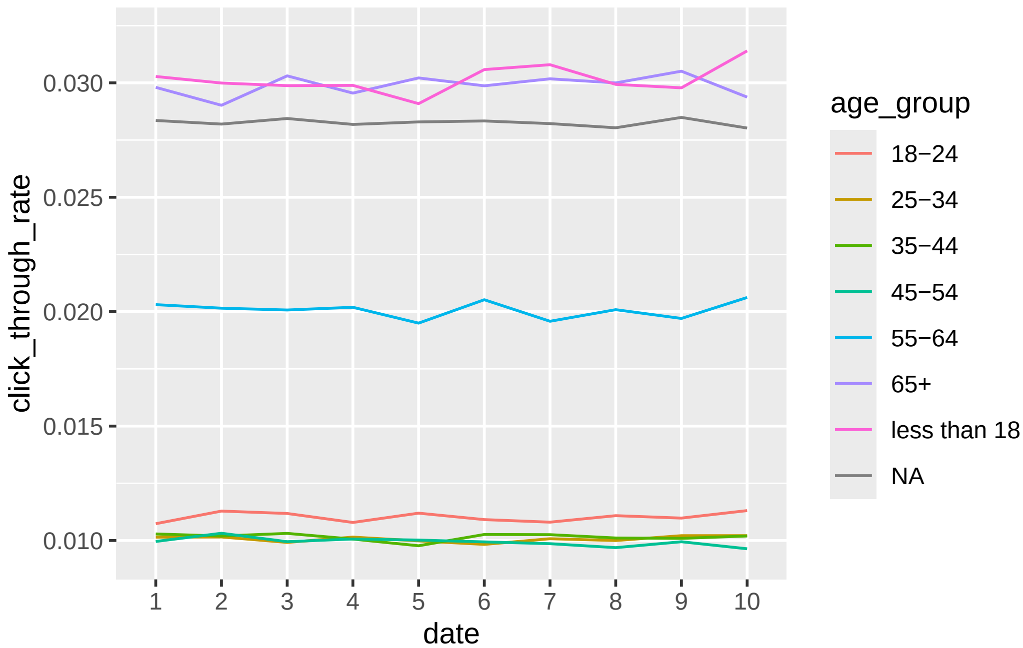
```
summarystats <- list()
variances <- list()
for(i in 1:10){
  summarystats[[i]] = nyt_all %>%
  filter(date == i) %>%
  .$click_through_rate %>%
  summary() %>%
  unname()
  variances[[i]] = nyt_all %>%
  filter(date == i) %>%
  .$click_through_rate %>%
```

```
  var(na.rm = T)
}

tibble("Statistic" = c("Minimum", "1st Quartile",
                       "Median", "Mean", "3rd Quartile",
                       "Maximum", "Variance"),
       "Day 1" = c(summarystats[[1]][1:6],
                   variances[[1]]),
       "Day 2" = c(summarystats[[2]][1:6],
                     variances[[2]]),
       "Day 3" = c(summarystats[[3]][1:6],
                     variances[[3]]),
       "Day 4" = c(summarystats[[4]][1:6],
                     variances[[4]]),
       "Day 5" = c(summarystats[[5]][1:6],
                     variances[[5]]),
       "Day 6" = c(summarystats[[6]][1:6],
                     variances[[6]]),
       "Day 7" = c(summarystats[[7]][1:6],
                     variances[[7]]),
       "Day 8" = c(summarystats[[8]][1:6],
                     variances[[8]]),
       "Day 9" = c(summarystats[[9]][1:6],
                     variances[[9]]),
       "Day 10" = c(summarystats[[10]][1:6],
                     variances[[10]])) %>%
  kbl() %>%
  scroll_box(width = "800px", height = "275px")
```

Statistic	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day
Minimum	0.0000000	0.0000000	0.0000000	0.0000000	0.0000000	0.0000000	0.0000000	0.000000
1st Quartile	0.0000000	0.0000000	0.0000000	0.0000000	0.0000000	0.0000000	0.0000000	0.000000
Median	0.0000000	0.0000000	0.0000000	0.0000000	0.0000000	0.0000000	0.0000000	0.000000
Mean	0.0184705	0.0184623	0.0185438	0.0184100	0.0183516	0.0184824	0.0184217	0.018341
3rd Quartile	0.0000000	0.0000000	0.0000000	0.0000000	0.0000000	0.0000000	0.0000000	0.000000
Maximum	1.0000000	1.0000000	1.0000000	1.0000000	1.0000000	1.0000000	1.0000000	1.000000
Variance	0.0047658	0.0047405	0.0048267	0.0047397	0.0046816	0.0048084	0.0047269	0.004761

9. Visualize click-through rate for the six different age groups over time.

```
nyt_all %>%
  mutate(date = factor(date)) %>%
  ggplot(aes(x = date, group = age_group)) +
  geom_line(aes(y = click_through_rate,
                color = age_group), stat="summary")
```



The question doesn't ask students to describe the pattern in words, but it's worth noting that the click-through rate for users who are 65 or older and less than 18 is virtually the same, approximately 3 times that of the other groups. (The click-through rate for signed-out users is also three times that of the other groups.)

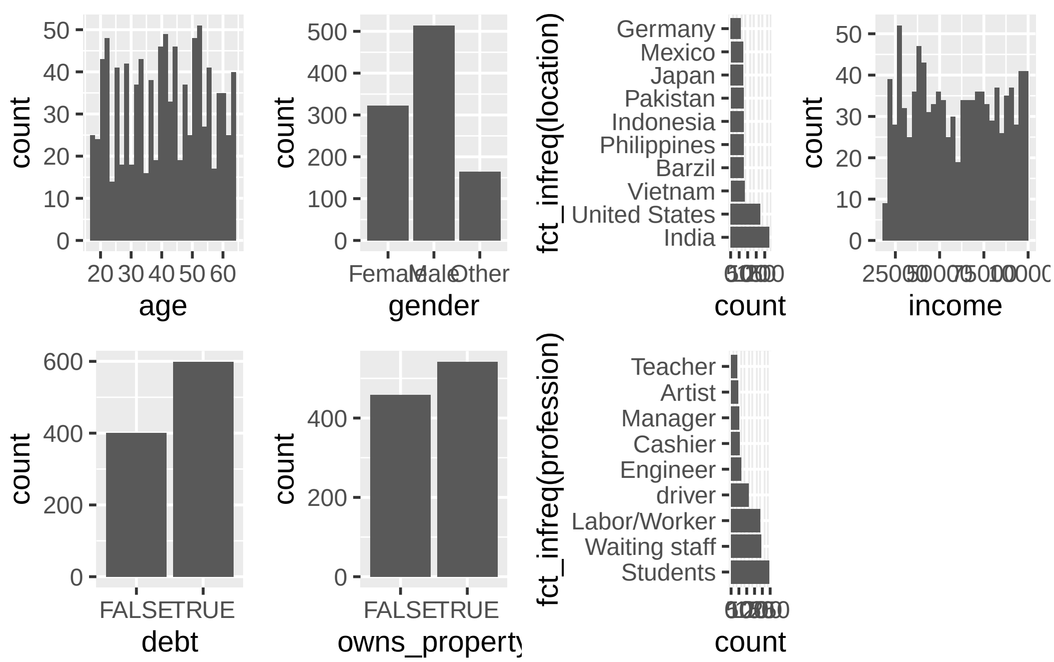
Case Study: Social Media Engagement (Simulated)

The data file `Time-Wasters on Social Media.csv` contains a considerable amount of simulated data intended to mimic real-world social media usage scenarios. It comes from this source on Kaggle: https://www.kaggle.com/datasets/zeesolver/dark-web

Read through and familiarize yourself with the variables in the dataset. Then answer the following.

10. Produce a summary of the user data (the information about users: age, gender, location, debt, whether they own property, their profession). If you were asked to describe the "average user," what would you say?

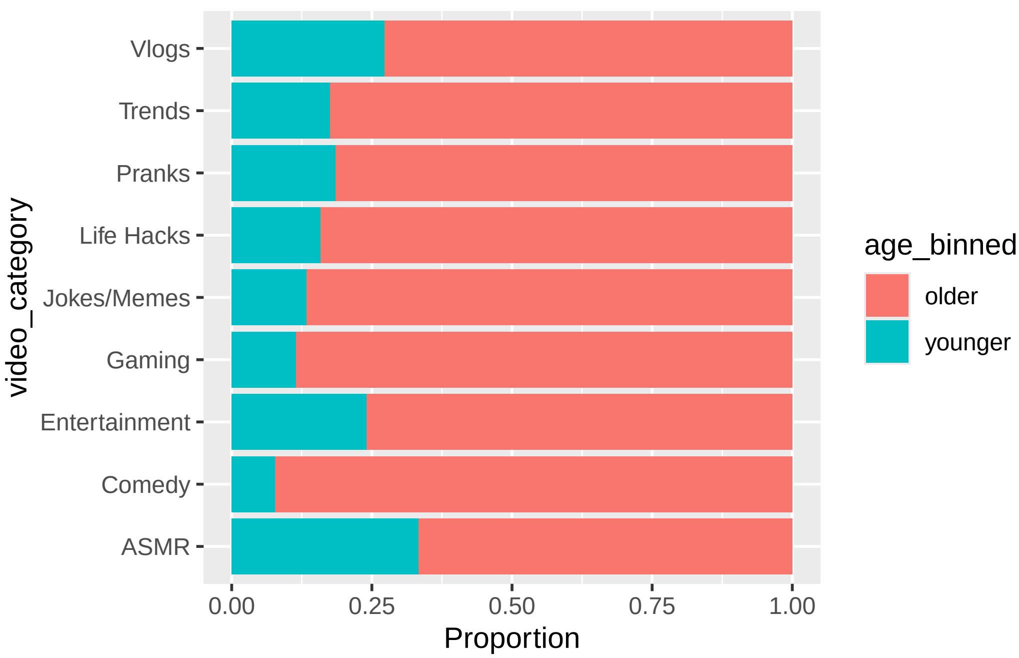
```r
library(gridExtra)
social_media <- read_csv("data/Time-Wasters on Social Media.csv") %>%
  clean_names()
p1 <- social_media %>%
  ggplot(aes(x = age)) + geom_histogram()
p2 <- social_media %>%
  ggplot(aes(x = gender)) + geom_bar()
p3 <- social_media %>%
  ggplot(aes(y = fct_infreq(location))) + geom_bar()
p4 <- social_media %>%
  ggplot(aes(x = income)) + geom_histogram()
p5 <- social_media %>%
  ggplot(aes(x = debt)) + geom_bar()
p6 <- social_media %>%
  ggplot(aes(x = owns_property)) + geom_bar()
p7 <- social_media %>%
  ggplot(aes(y = fct_infreq(profession))) + geom_bar()

grid.arrange(p1, p2, p3, p4, p5, p6, p7,
             nrow = 2)
```



Students can summarize the demographic variables using tables or visualizations, whichever they prefer. It's probably more effective to use visualizations. In terms of the average user, most users are students, waitstaff, or laborers/workers; most are in some amount of debt, and slightly more than half own property. Users' average income is about $\$59,524.21$ and their average age is about 41; the distributions of age and income are relatively uniform. More users are male and most users are from either the United States or India.

11. What video categories are more popular with younger users (up to or below age 20)? What categories are more popular with older users (age 50 or above)? Create a plot or table of the distribution of video categories preferred by younger vs. older users.

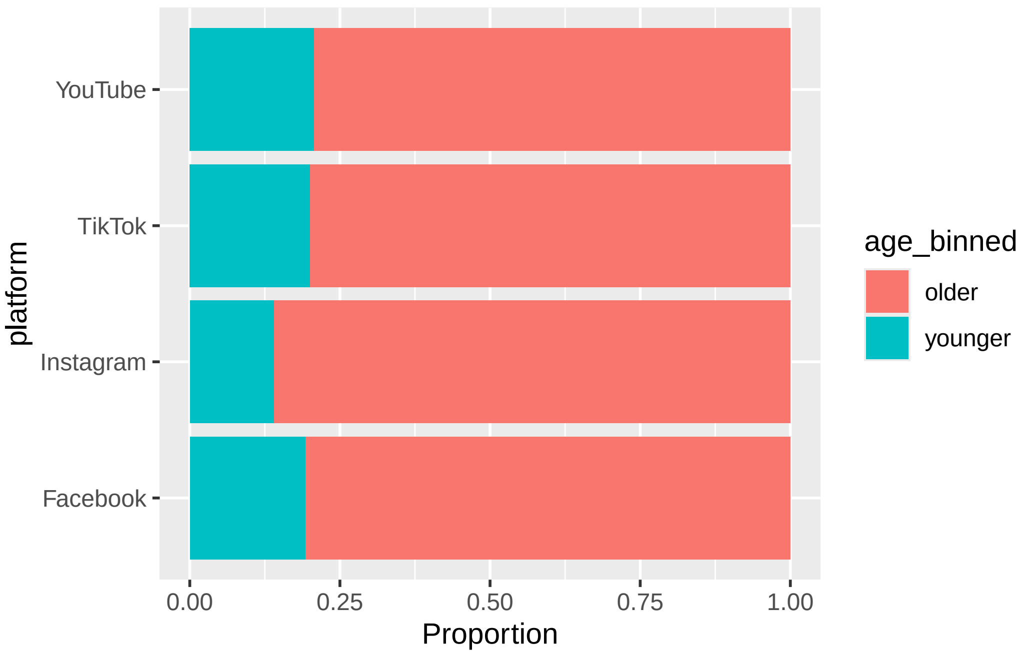
```
social_media %>%
  filter(age <= 20 | age >= 50) %>%
  mutate(age_binned = case_when(
    age <= 20 ~ "younger",
    age >= 50 ~ "older"
  )) %>%
  ggplot(aes(y = video_category, fill = age_binned)) +
  geom_bar(position="fill") +
  labs(x = "Proportion")
```



Older users tend to engage with comedy, gaming, jokes/memes; younger users tend to engage with ASMR, vlogs, or entertainment videos.

12. What platforms are more popular with younger users (up to or below age 20)? What platforms are more popular with older users (age 50 or above)? Create a plot or table of the distribution of platforms preferred by younger vs. older users.

```r
social_media %>%
  filter(age <= 20 | age >= 50) %>%
  mutate(age_binned = case_when(
    age <= 20 ~ "younger",
    age >= 50 ~ "older"
  )) %>%
  ggplot(aes(y = platform, fill = age_binned)) +
  geom_bar(position="fill") +
  labs(x = "Proportion")
```



Older users tend to use Instagram slightly more. Other than that, there aren't many differences.

Additional Questions for 231 Students

13. Explore the data. What are some patterns that you notice? Create one to two visualizations.

Answers to this may vary. Students should create at least one to two visualizations of other variables in the dataset and describe any patterns they observe.

14. Summarize your findings in a brief (1-2 paragraphs) report.

Answers may vary. Conclusions described should be accurate.