Assignment 2

Due at 11:59pm on October 3.

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You may work in pairs or individually for this assignment. Make sure you join a group in Canvas if you are working in pairs. Turn in this assignment as an HTML or PDF file to ELMS. Make sure to include the R Markdown or Quarto file that was used to generate it.

```r
library(tidyverse)
library(gtrendsR)
library(censusapi)
```

In this assignment, you will pull from APIs to get data from various data sources and use your data wrangling skills to use them all together. You should turn in a report in PDF or HTML format that addresses all of the questions in this assignment, and describes the data that you pulled and analyzed. You do not need to include full introduction and conclusion sections like a full report, but you should make sure to answer the questions in paragraph form, and include all relevant tables and graphics.

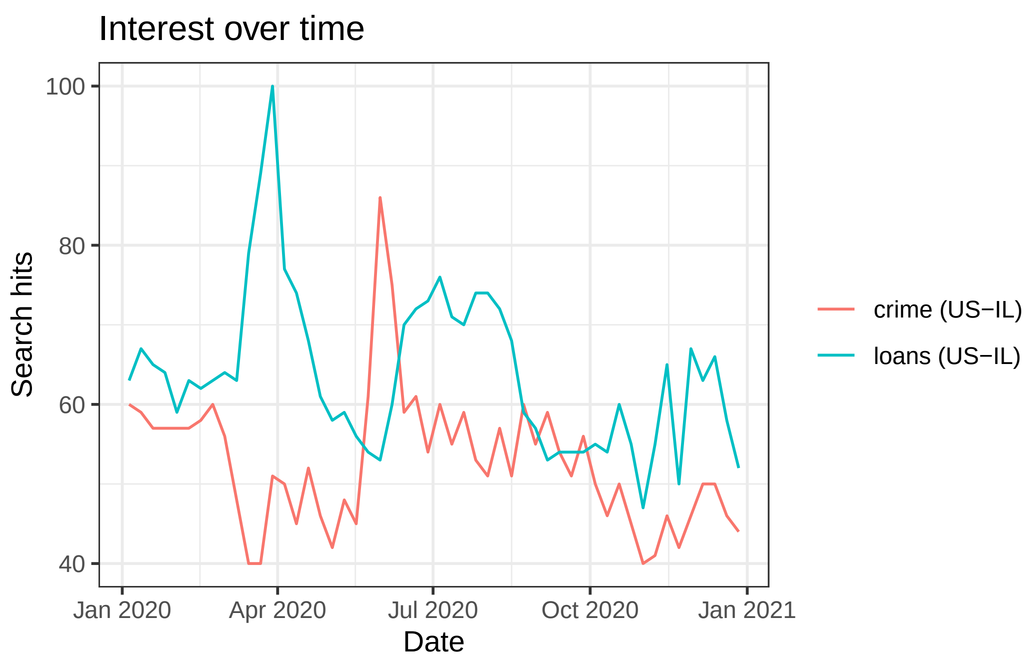
Whenever possible, use piping and `dplyr`. Avoid hard-coding any numbers within the report as much as possible.

Pulling from APIs

`crime` and `loans`

Our first data source is the Google Trends API. Suppose we are interested in the search trends for `crime` and `loans` in Illinois in the year 2020. We could find this using the following code:

```r
res = gtrends(c("crime", "loans"),
              geo = "US-IL",
              time = "2020-01-01 2020-12-31",
              low_search_volume = TRUE)
plot(res)
```



Answer the following questions for the keywords "crime" and "loans".

- Find the mean, median and variance of the search hits for the keywords.

```
# transfer the data into tibble
rest = as_tibble(res$interest_over_time)

# find the mean, median and variance of the search hits
library(dplyr)
library(tidyr)
library(knitr)

descriptive = rest %>%
  group_by(keyword) %>%
  summarise(n = n(),
            mean = mean(hits),
            median = median(hits),
            variance = var(hits))
kable(descriptive, caption = "Descriptive Statistics of Keywords")
```

Table 1: Descriptive Statistics of Keywords

keyword	n	mean	median	variance
crime	52	52.71154	51.5	72.40535
loans	52	63.82692	63.0	99.36161

According to Table 1, we can find that the keyword `crime` has a mean of 55.00000, a median of 54 and a variance of 86.43137. The keyword `loans` has a mean of 66.48077, a median of 65 and a variance of 95.39178.

- Which cities (locations) have the highest search frequency for `loans`? Note that there might be multiple rows for each city if there were hits for both "crime" and "loans" in that city. It might be easier to answer this question if we had the search hits info for both search terms in two separate variables. That is, each row would represent a unique city.

```
rescity = as_tibble(res$interest_by_city) %>%
  pivot_wider(., names_from = keyword, values_from = hits) %>%
  arrange(., desc(loans))
kable(head(rescity), caption = "Highest Search Frequency for Loans")
```

Table 2: Highest Search Frequency for Loans

location	geo	gprop	crime	loans
Granville	US-IL	web	NA	100
Alorton	US-IL	web	NA	85
Bement	US-IL	web	NA	84
Cuba	US-IL	web	NA	77
Long Lake	US-IL	web	NA	76
Rosemont	US-IL	web	NA	68

According to Table 2, Midlothia has the highest search frequency for `loans` with the value of 100.

- Is there a relationship between the search intensities between the two keywords we used?

```
crime = rest %>%
  filter(keyword == "crime") %>%
  select(date, hits) %>%
  rename(., crimehits = hits)
```

```r
loan = rest %>%
  filter(keyword == "loans") %>%
  select(date, hits) %>%
  rename(., loanshits = hits)

crimloan = left_join(crime, loan, by = "date")
cor.test(crimloan$crimehits, crimloan$loanshits)
```

```
	Pearson's product-moment correlation

data:  crimloan$crimehits and crimloan$loanshits
t = -0.32497, df = 50, p-value = 0.7466
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 -0.3148653  0.2298705
sample estimates:
        cor
-0.04590986
```

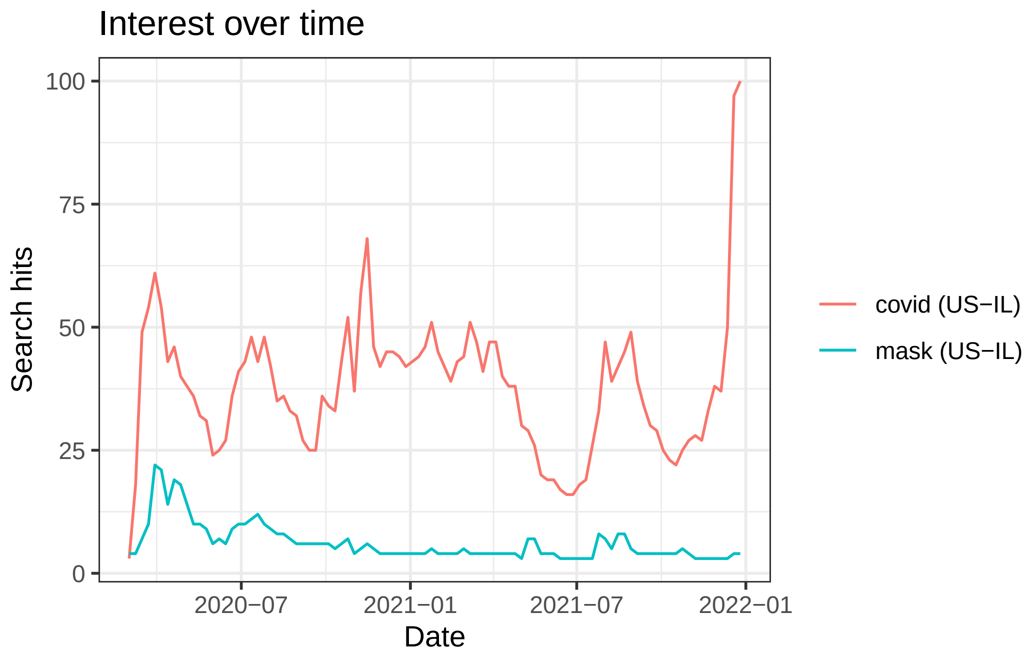
From the plot above, it seems like there is a negative correlation between crime and loans. However, if we use the quantitative method to compute the t-statistic and corresponding p-value, we can see that the p-value is bigger than 0.05, which means there is no significant negative relationship between crime and loans.

`covid` and `mask`

Repeat the above for keywords related to covid. Make sure you use multiple keywords like we did above. Try several different combinations and think carefully about words that might make sense within this context.

We choose `covid` and `mask` as our keywords for analysis.

```r
res2 = gtrends(c("covid", "mask"),
               geo = "US-IL",
               time = "2020-03-01 2021-12-31",
               low_search_volume = TRUE)
plot(res2)
```




```r
# transfer the data into tibble
rest2 = as_tibble(res2$interest_over_time)

# find the mean, median and variance of the search hits
descriptive2 = rest2 %>%
  group_by(keyword) %>%
  summarise(n = n(),
            mean = mean(hits),
            median = median(hits),
            variance = var(hits))
kable(descriptive2, caption = "Descriptive Statistics of Keywords")
```

Table 3: Descriptive Statistics of Keywords

keyword	n	mean	median	variance
covid	96	37.906250	38	206.6332
mask	96	6.145833	4	14.7364

From the table, we can find that the keyword `covid` has a mean of 37.906250, a median of 38 and a variance of 206.6332. The keyword `mask` has a mean of 6.145833, a median of 4 and a variance of 14.7364.

```r
rescity2 = as_tibble(res2$interest_by_city) %>%
  pivot_wider(., names_from = keyword, values_from = hits) %>%
  arrange(., desc(covid))
kable(head(rescity2), caption = "Highest Search Frequency for mask")
```

Table 4: Highest Search Frequency for mask

location	geo	gprop	covid	mask
Barrington	US-IL	web	100	66
Evergreen Park	US-IL	web	97	NA
Oak Lawn	US-IL	web	96	44
Evanston	US-IL	web	96	NA
Wheaton	US-IL	web	96	NA
Lake Forest	US-IL	web	96	70

From the table, we can see that Barrington has the highest search frequency for `covid` with the value of 100.

```r
mask = rest2 %>%
  filter(keyword == "mask") %>%
  select(date, hits) %>%
  rename(., maskhits = hits)

covid = rest2 %>%
  filter(keyword == "covid") %>%
  select(date, hits) %>%
  rename(., covidhits = hits)

maskcovid = left_join(mask, covid, by = "date")
cor.test(maskcovid$maskhits, maskcovid$covidhits)
```

```
	Pearson's product-moment correlation

data:  maskcovid$maskhits and maskcovid$covidhits
t = 2.3488, df = 94, p-value = 0.02093
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 0.03670029 0.41628875
sample estimates:
```

```
      cor
0.2354538
```

From the correlation test, we can see that `covid` has a significant correlation with `mask` at 0.05 level. The correlation probably means that people will search for mask when Covid-19 is severe in one place.

Google Trends + ACS

`crime` and `loans`

Now lets add another data set. The `censusapi` package provides a nice R interface for communicating with this API. However, before running queries we need an access key. This (easy) process can be completed here:

https://api.census.gov/data/key_signup.html

Once you have an access key, store this key in the `cs_key` object. We will use this object in all following API queries.

```r
cs_key <- "c0fd12402e23b7a95923e694f046015d624c91c5"
```

In the following, we request basic socio-demographic information (population, median age, median household income, income per capita) for cities and villages in the state of Illinois.

```r
acs_il <- getCensus(name = "acs/acs5",
                    vintage = 2020,
                    vars = c("NAME",
                             "B01001_001E",
                             "B06002_001E",
                             "B19013_001E",
                             "B19301_001E"),
                    region = "place:*",
                    regionin = "state:17",
                    key = cs_key)
head(acs_il)
```

```
  state place                          NAME B01001_001E B06002_001E B19013_001E
1    17 15261 Coatsburg village, Illinois         180        35.6       55714
2    17 15300    Cobden village, Illinois        1018        44.2       38750
3    17 15352      Coffeen city, Illinois         640        33.4       35781
```

```
4     17 15378   Colchester city, Illinois        1347         42.2         43942
5     17 15469    Coleta village, Illinois         230         27.7         56875
6     17 15495    Colfax village, Illinois        1088         32.5         58889
  B19301_001E
1       27821
2       19979
3       26697
4       24095
5       23749
6       24861
```

Convert values that represent missings to NAs.

```
acs_il[acs_il == -666666666] <- NA
```

Now, it might be useful to rename the socio-demographic variables (`B01001_001E` etc.) in our data set and assign more meaningful names.

```
acs_il <-
  acs_il %>%
  rename(pop = B01001_001E,
         age = B06002_001E,
         hh_income = B19013_001E,
         income = B19301_001E)
```

It seems like we could try to use this location information listed above to merge this data set with the Google Trends data. However, we first have to clean `NAME` so that it has the same structure as `location` in the search interest by city data. Add a new variable `location` to the ACS data that only includes city names.

```
library(stringr)
pattern = c("St." = "Saint")

acs_il = acs_il %>%
  mutate(location = str_remove_all(NAME, c(" town,| city,| village,| Illinois"))) %>%
  mutate(location = str_replace_all(location, coll(pattern)))
```

Answer the following questions with the "crime" and "loans" Google trends data and the ACS data.

- First, check how many cities don't appear in both data sets, i.e. cannot be matched. Then, create a new data set by joining the Google Trends and the ACS data. Keep only cities that appear in both data sets.

```r
check = left_join(acs_il, rescity, by = "location")
check %>% filter(is.na(geo)) %>% count()
```

```
     n
1 1128
```

```r
joint = inner_join(rescity, acs_il, by = "location")
```

- Compute the mean of the search popularity for both keywords for cities that have an above average median household income and for those that have an below average median household income. When building your pipe, start with creating the grouping variable and then proceed with the remaining tasks. What conclusions might you draw from this?

```r
group1 = joint %>%
  mutate(mean = mean(hh_income, na.rm = TRUE)) %>%
  mutate(group = ifelse(hh_income > mean, "high", "low")) %>%
  group_by(group) %>%
  summarise(crime = mean(crime, na.rm = TRUE),
            loans = mean(loans, na.rm = TRUE)) %>%
  filter(!is.na(group))
kable(group1, caption = "Search Popularity by Household Income")
```

Table 5: Search Popularity by Household Income

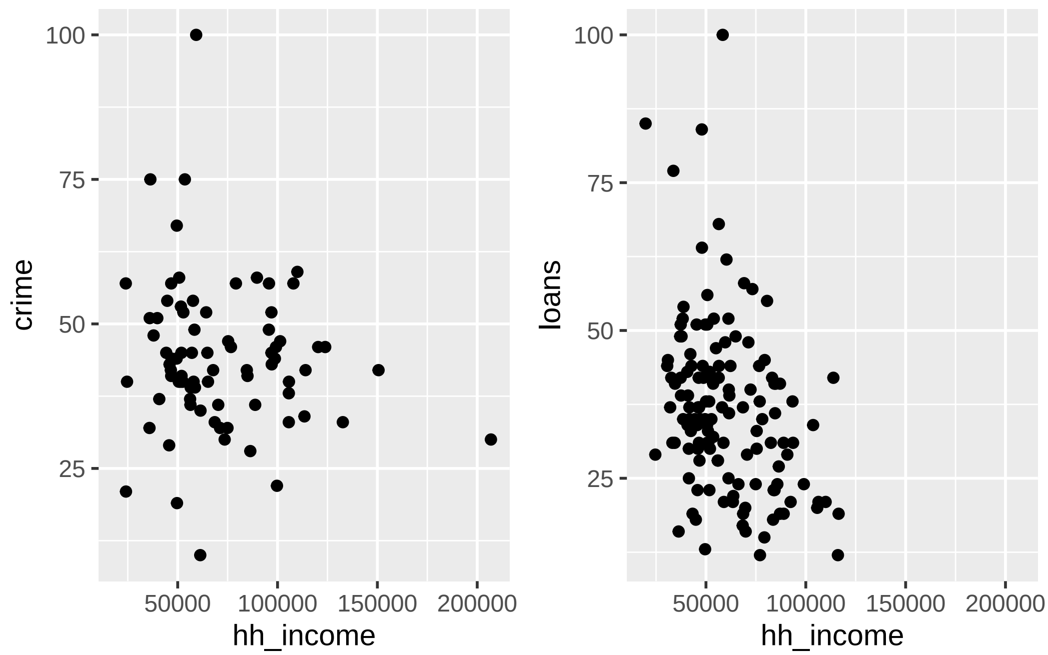
group	crime	loans
high	42.15789	30.32000
low	45.62500	40.60241

From the table, cities that have an above average median household income have lower crime hits and lower loans hits, which means crime and loans may correlate with income.

- Is there a relationship between the median household income and the search popularity of the Google trends terms? Describe the relationship and use a scatterplot with `qplot()`.

```r
library(ggpubr)

p1 = qplot(x = hh_income, y = crime, data = joint)
p2 = qplot(x = hh_income, y = loans, data = joint)
```

```r
ggarrange(p1, p2, ncol = 2, nrow = 1)
```



According to the scatterplots, we can see that the income is not significantly correlated with crime hits while income has a negative correlation with loans negatively.

`covid` and `mask`

Repeat the above steps using the covid data and the ACS data.

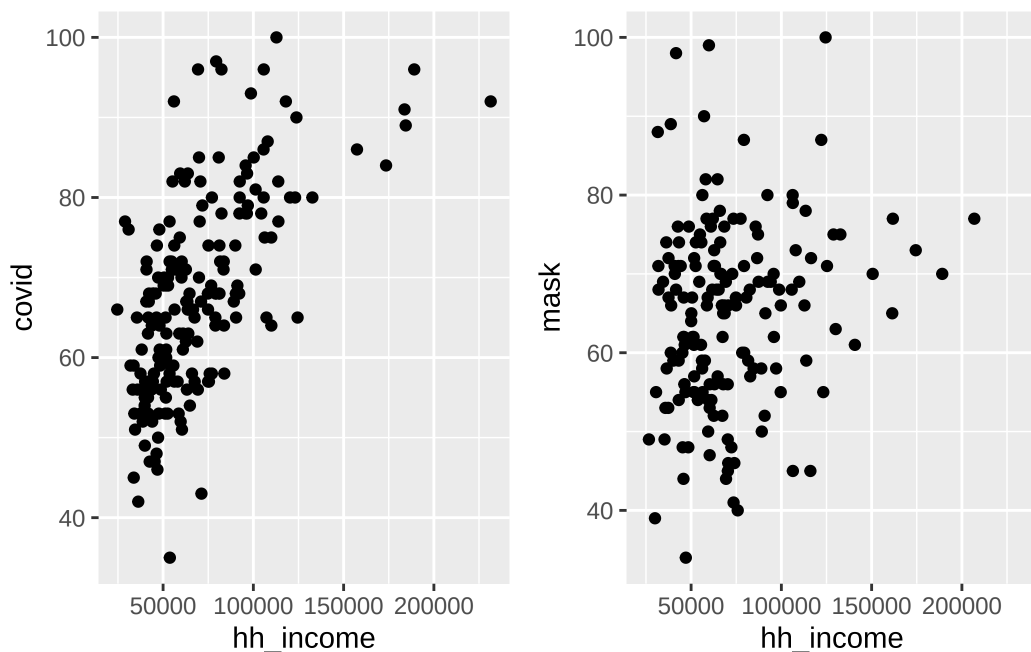
```r
joint2 = inner_join(rescity2, acs_il, by = "location")

group2 = joint2 %>%
  mutate(mean = mean(hh_income, na.rm = TRUE)) %>%
  mutate(group = ifelse(hh_income > mean, "high", "low")) %>%
  group_by(group) %>%
  summarise(covid = mean(covid, na.rm = TRUE),
            mask = mean(mask, na.rm = TRUE)) %>%
  filter(!is.na(group))
kable(group2, caption = "Search Popularity by Household Income")
```

Table 6: Search Popularity by Household Income

group	covid	mask
high	75.90909	65.25714
low	62.31579	64.62245

From the table, we can see cities that have an above average median household income have higher covid hits and higher mask hits, which means search hits of covid and mask may correlate with income positively.

```
p3 = qplot(x = hh_income, y = covid, data = joint2)
p4 = qplot(x = hh_income, y = mask, data = joint2)
ggarrange(p3, p4, ncol = 2, nrow = 1)
```



According to the scatterplots, we can see that the income is positively correalted with covid and mask. This indicates that people in rich areas may pay attention to covid and its protection more, showing one kind of social inequality.