

Tutorial 8: Line Charts, Annotations and Themes

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Today's tutorial focuses on line charts. Line charts, as you should know from today's lecture, are for showing change over time.

We also discuss how to add text and line segments onto a plot using the `annotate()` command, and we discuss `ggplot` theme options.

We review summarizing, use of factor variables, and making data long (from wide). We also do give an example of data cleaning to prepare a file to load.

A. Load packages

Let's begin by loading packages. The only addition from what we've used before is `scales`, which helps put commas into numbers so they are legible, among other things.

```
library(tidyverse)
```

```
## -- Attaching packages -----
```

```
## v ggplot2 3.2.1    v purrr  0.3.3
## v tibble  2.1.3    v dplyr  0.8.4
## v tidyr   1.0.2    v stringr 1.4.0
## v readr   1.3.1    v forcats 0.4.0
```

```
## -- Conflicts ----- tidy
```

```
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
```

```
library(scales) # for making numbers with commas
```

```
##
```

```
## Attaching package: 'scales'
```

```
## The following object is masked from 'package:purrr':
```

```
##
```

```
##   discard
```

```
## The following object is masked from 'package:readr':
```

```
##
```

```
##   col_factor
```

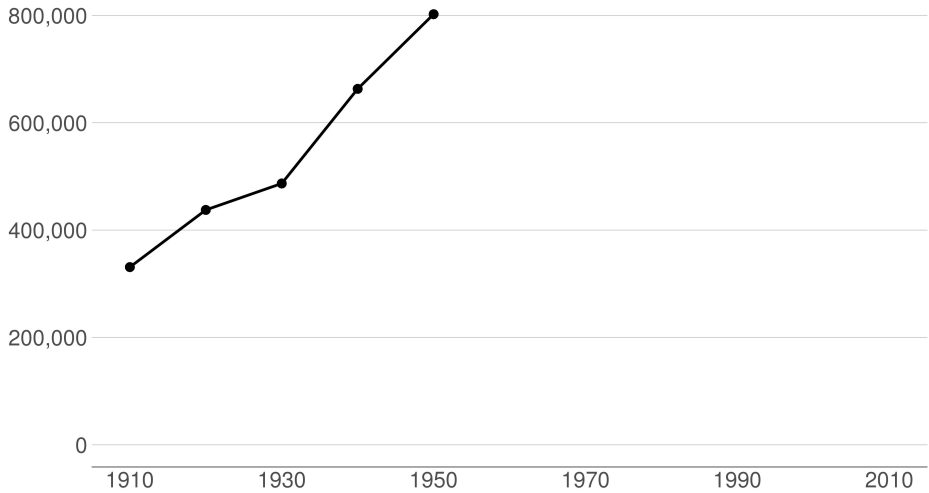
B. Basic line graph and annotations

We are going to begin with a “simple” line graph. Below I give the example of a “simple” line graph that took a quite a bit of work to look so simple.

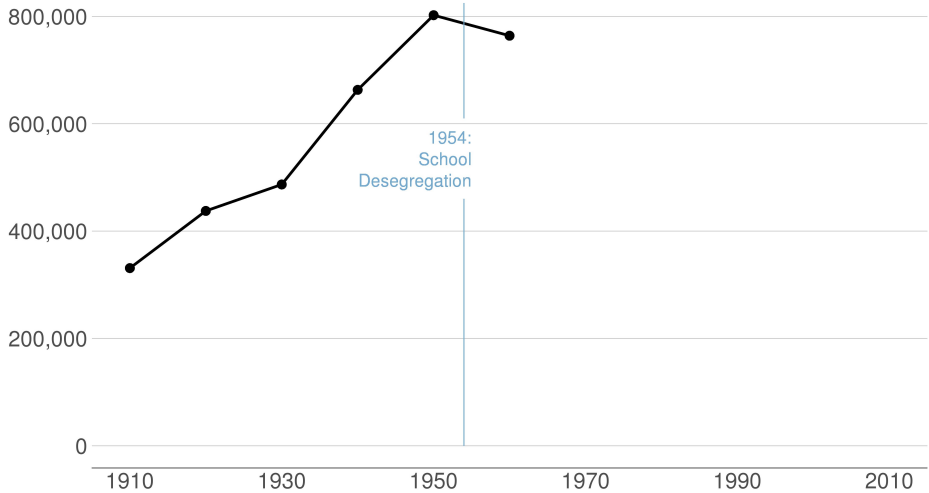
B.1. Look at the final product

Here are the sequential slides that I used in my presentation of this graph. I want the audience to know when DC's population declined, when it rebounded and to have sense of the magnitude of the decline.

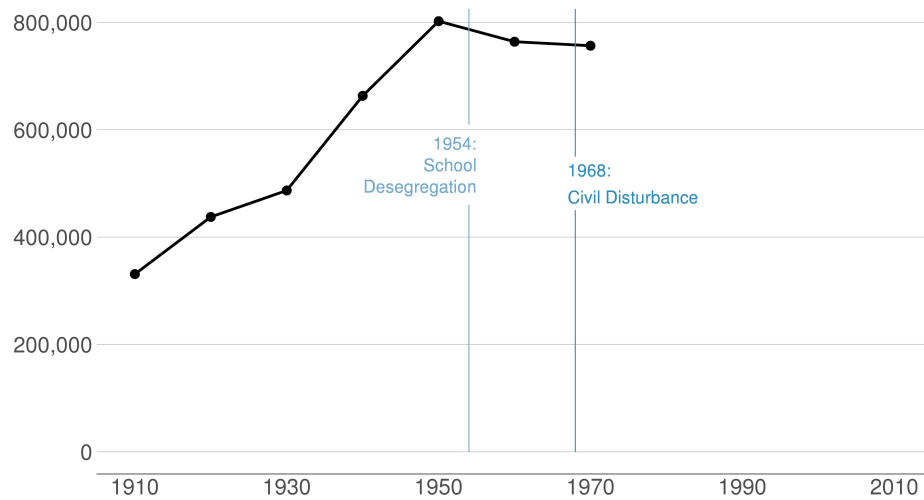
DC Gains Population Through 1950



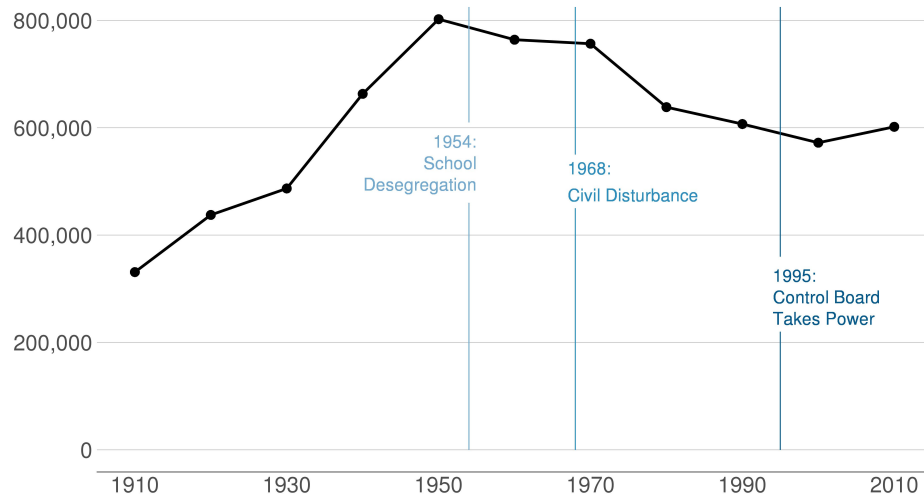
Population Loses Start with Desegregation



Continue After Civil Disturbance



Population Turns Up After 2000



B.2 Load and prepare data

Now we'll go through some code to build up to this chart.

Begin by downloading data from [here](#). These are county-level data on population 1910 to 2010 (among other variables). I created these data for a research project from Decennial Census data.

Use `read.csv` to grab these data as we've done before.

```
# load data
counties <- read.csv("h:/pppa_data_viz/2019/tutorial_data/lecture08/counties_1910to2010_20180116.csv")
```

Now just limit the data to DC. You could do this in the `ggplot` call itself. However, in this case when we are only planning to use DC, this gives us a smaller dataset to work with and that speeds processing. This will also make the coding easier, since we won't have to subset in each graph.

Take a look at the data after we subset to DC. Does it have the right number of observations?

```
# get just dc
dct <- counties[which(counties$statefips == 11),]
dim(dct)
```

```
## [1] 11 68
```

```
dct[,c("year", "statefips", "countyfips", "cv1")]
```

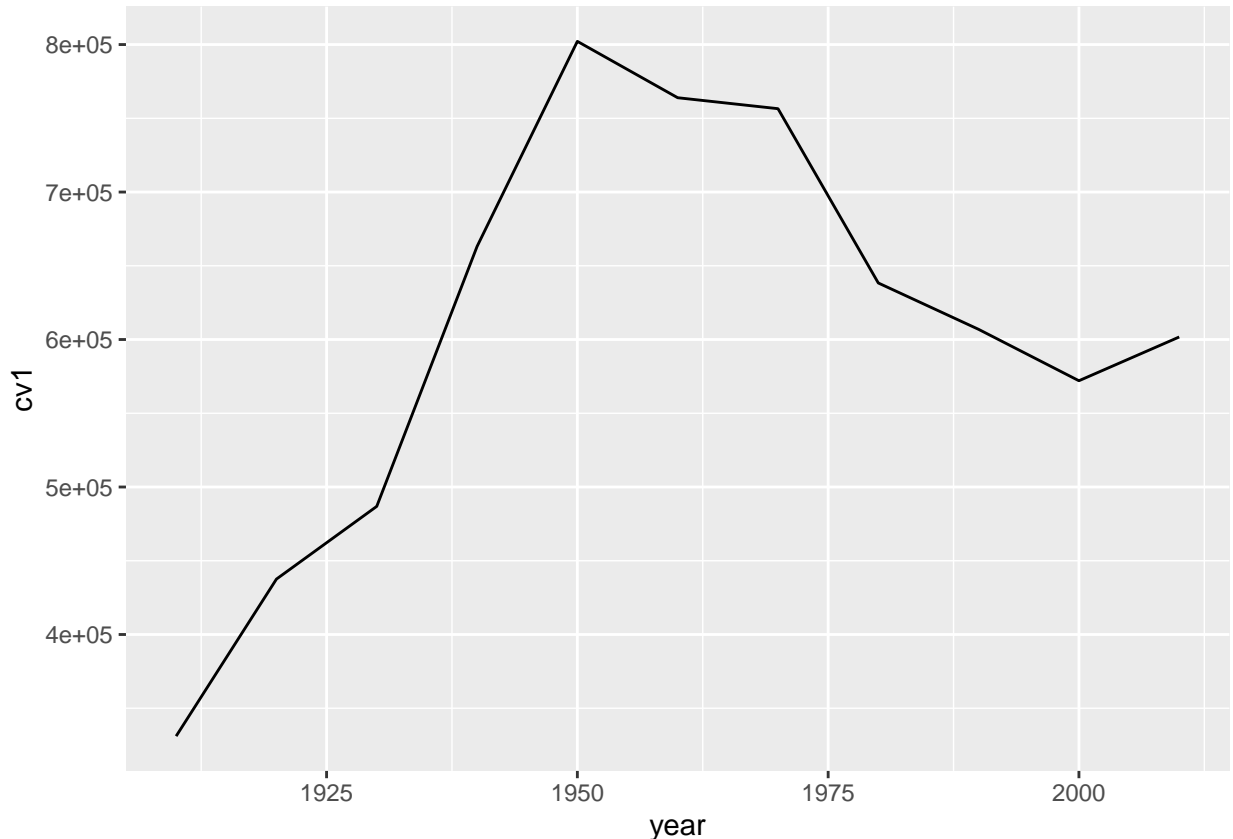
```
##      year statefips countyfips   cv1
## 285  1910         11          1 331069
## 3244 1920         11          1 437571
## 6314 1930         11          1 486869
## 9418 1940         11          1 663091
## 12520 1950         11          1 802178
## 15626 1960         11          1 763956
## 18764 1970         11          1 756510
## 21899 1980         11          1 638333
## 25039 1990         11          1 606900
## 28182 2000         11          1 572059
## 31326 2010         11          1 601723
```

We have only one state and one county in that state. We observe data from 1910 to 2010. This all looks good.

B.3. Make the simplest line graph

Now that you know many `ggplot` commands, it will not be a shock to hear that you make a line graph using `geom_line()`. As for all `ggplot` graphs, you should specify a dataframe and x and y variables. Below we make the simplest possible line graph.

```
b3 <- ggplot() +
  geom_line(data = dct,
            mapping = aes(x = year, y = cv1))
b3
```



Note that line graphs do not default to a y-axis baseline of zero.

B.4. Make some improvements

The line graph above is great for getting a sense of the data. It's not so good for communicating. The x-axis labels don't line up with the years in the data. The vertical axis labels are hard to read. And the grey background does not help tell the story.

We fix the horizontal axis to put 20-year labels with

```
scale_x_continuous(limits= c(1910, 2010), breaks = c(seq(1910,2010,20)))
```

This tells R to start in 1910, and stop in 2010 (`limits= c(1910, 2010)`). It also tells R to make breaks on the axis at 1910 and every 20 years until 2010 (`breaks = c(seq(1910,2010,20))`).

We fix the vertical axis with

```
scale_y_continuous(labels = comma, limits = c(0, 825000), breaks = c(seq(0,800000,200000)))
```

This tells R to use commas in the numbers, to start at 0 and end at 825,000, and to make value labels every 200,000.

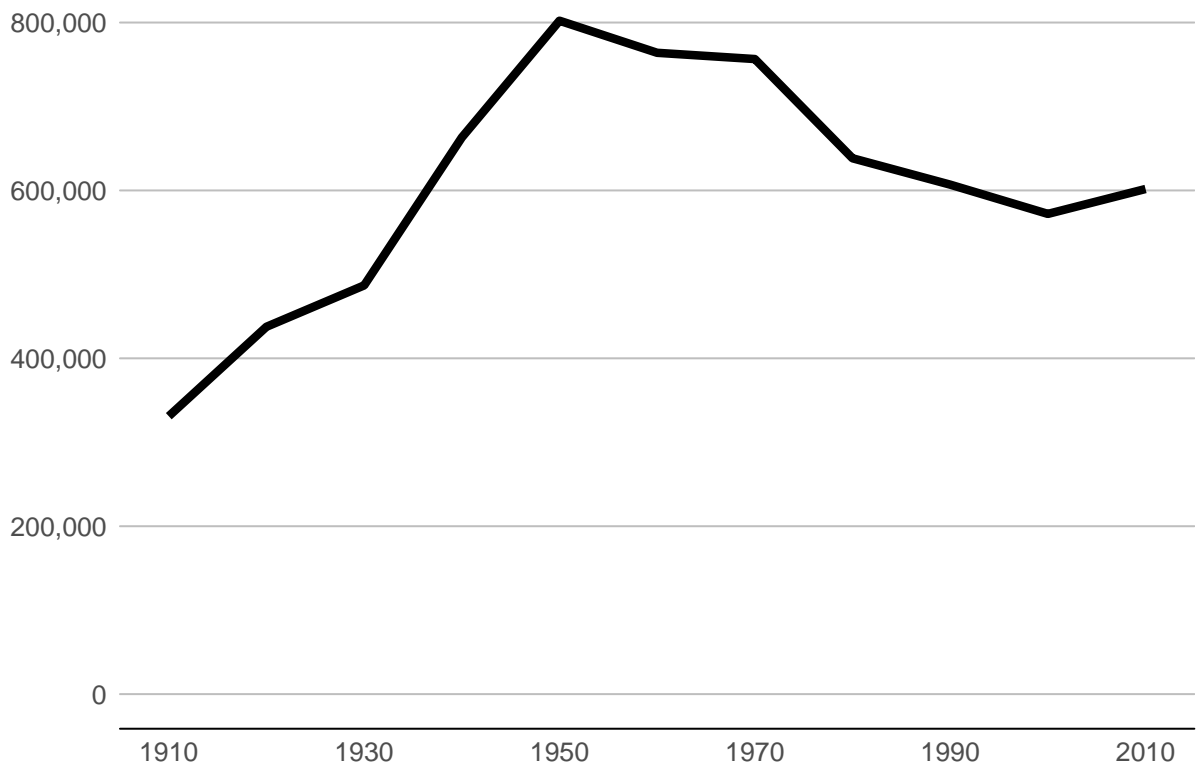
Generally, `ggplot` line graphs are easier to read when lines are thicker. We adjust the line width with the `geom_line()` option of `size = 1.5`. Note that this goes outside of the `aes()` command. Things inside the `aes()` describe how “variables in the data are mapped to visual properties (aesthetics) of geoms” (see [cite](#)). Things outside of the `aes()` command are for more general settings.

In addition, we modify the theme to do the following:

- omit major gridlines: `panel.grid.major = element_blank()`

- omit minor gridlines: `panel.grid.minor = element_blank()`
- (FYI: you can also omit both major and minor at once with `panel.grid = element_blank()`)
- omit panel background: `panel.background = element_blank()`
- add back in y-axis gridlines: `panel.grid.major.y = element_line(color="gray")`
- omit legend: `legend.position = "none"`
- make the x-axis line black: `axis.line.x = element_line(color = "black")`
- get rid of x- and y-axis ticks: `axis.ticks = element_blank()`
- change size of axis text: `axis.text = element_text(size = 10)`

```
done <-
  ggplot() +
  geom_line(data = dct,
            mapping = aes(x=year, y=cv1), size=1.5) +
  scale_y_continuous(labels = comma, limits = c(0, 825000), breaks = c(seq(0,800000,200000))) +
  scale_x_continuous(limits= c(1910, 2010), breaks = c(seq(1910,2010,20))) +
  labs(x="", y="") +
  theme(panel.grid.major = element_blank(),
        panel.grid.minor = element_blank(),
        panel.background = element_blank(),
        panel.grid.major.y = element_line(color="gray"),
        legend.position = "none",
        axis.line.x = element_line(color = "black"),
        axis.ticks = element_blank(),
        axis.text = element_text(size = 10))
done
```

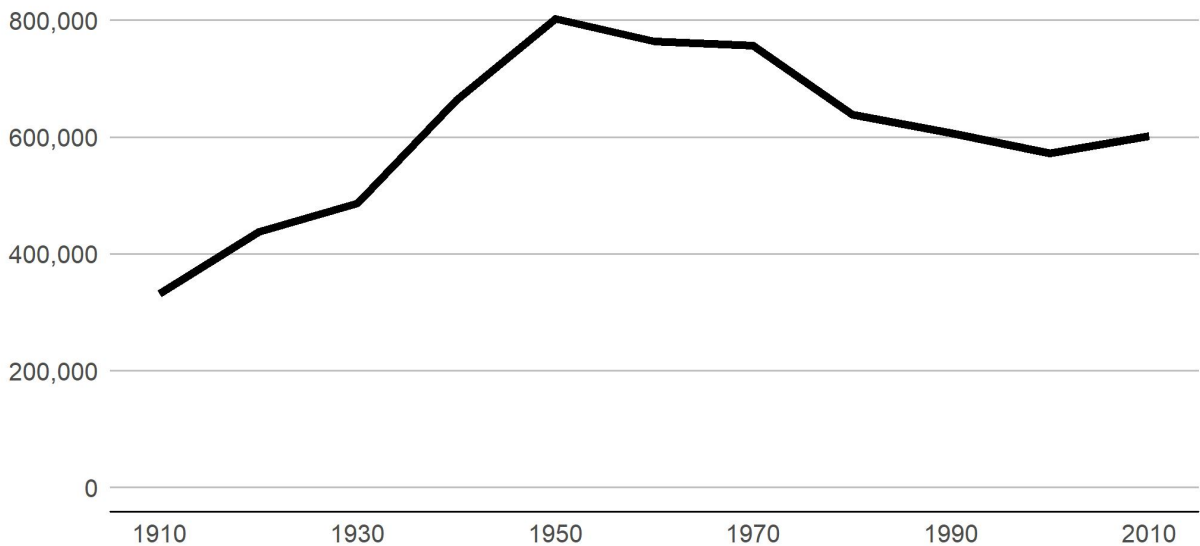


Beware that things can look different in the plot window and the final graphics output. To judge, save it in

the proportions you'd like for a final product and then look at it with an image viewer. Here's code to save this one.

```
fn <- "H:/pppa_data_viz/2020/tutorials/tutorial_08/b4_testerv1.jpg"
ggsave(plot = done,
        file = fn,
        dpi = 300,
        units = c("in"),
        width = 7,
        height = 3.5)
```

Then I pull in the final image:



Different! When doing final edits, work with the properly-sized graph.

B.5 A few more improvements via annotations

I'd call the above plot functional, but the point of this graph is to point out specific historical moments that explain the shape of the plot. To do that we add text and lines to the plot.

We add data points on the line via `geom_point()`. This hints to readers that the data are only actually at the points. The line between the points is really just made up – or extrapolated if you'd like to be fancier.

To add “stuff” to your graph that is not data, use the `annotate` command. Until recently, I was under the incorrect impression that `annotate(geom = "text")` and `geom_text()` did the same thing. I recently learned that `annotate()` is much more efficient, as it draws just once. In contrast, `geom_text()` will draw as many times as you have data points – again and again in the same place.

The `annotate()` command has some basic options. The first is `geom`, which is what you want to show. Choices include, but are not limited to, “segment”, “rect”, or “text”. You specify the location with `x` and `y` for text, or, for rectangles and the like, `xmin`, `xmax`, `ymin`, and `ymax` (alternatively, `x` and `xend`, etc).

You can also adjust other options such as size (`size=`) or justification (`hjust` and `vjust`; see [here](#)). See how to implement these in the example below. We use both `hjust = 0` (left align) and `hjust = 1` (right align).

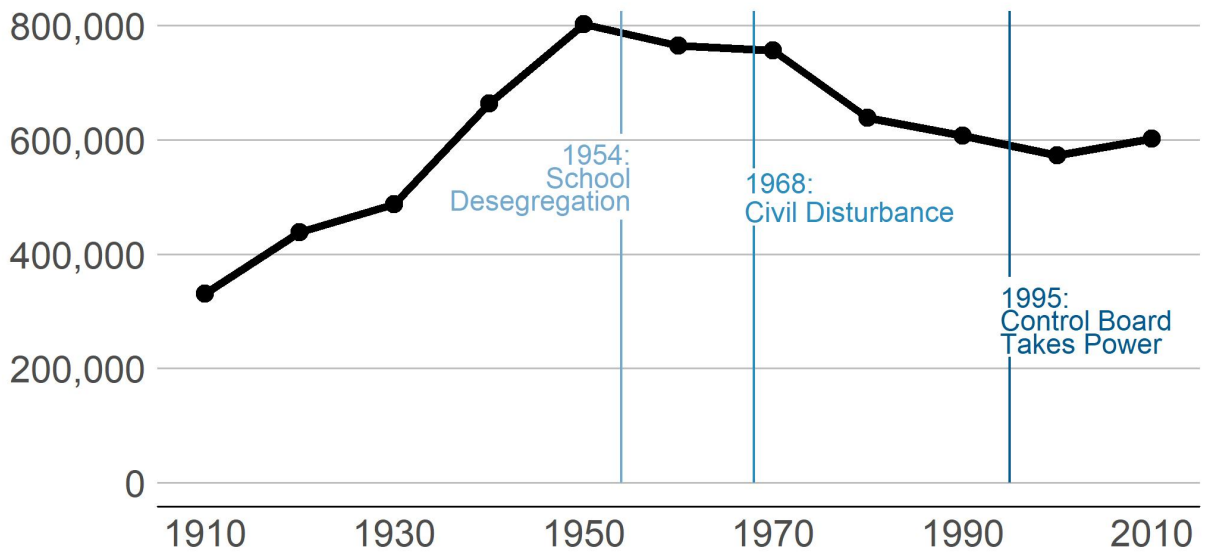
Note that I set the on-graph-text size variable at the beginning (`on.g.text.size`). I use this for the size of the text that goes on the `annotate` command. That way if I don't like it, I change it once, rather than eight

times.

```
on.g.text.size <- 4
done2 <-
  ggplot(dct) +
  geom_line(dct, mapping = aes(x=year, y=cv1), size=1.5) +
  geom_point(dct, mapping = aes(x=year, y=cv1), size=3) +
  scale_y_continuous(labels = comma, limits = c(0, 825000), breaks = c(seq(0,800000,200000))) +
  scale_x_continuous(limits= c(1910, 2010), breaks = c(seq(1910,2010,20))) +
  labs(x="", y="") +
  theme(panel.grid.major = element_blank(),
        panel.grid.minor = element_blank(),
        panel.background = element_blank(),
        panel.grid.major.y = element_line(color="gray"),
        legend.position = "none",
        axis.line.x = element_line(color = "black"),
        axis.ticks.x = element_blank(),
        axis.ticks.y = element_blank(),
        axis.text = element_text(size = 15)) +
  annotate(geom = "segment", x=1995, y=0, xend=1995, yend=220000, color="#045a8d") +
  annotate(geom = "segment", x=1995, y=360000, xend=1995, yend=825000, color="#045a8d") +
  annotate(geom = "segment", x=1968, y=0, xend=1968, yend=450000, color = "#2b8cbe") +
  annotate(geom = "segment", x=1968, y=550000, xend=1968, yend=825000, color = "#2b8cbe") +
  annotate(geom = "segment", x=1954, y=0, xend=1954, yend=460000, color = "#74a9cf") +
  annotate(geom = "segment", x=1954, y=610000, xend=1954, yend=825000, color = "#74a9cf") +
  annotate(geom = "text", x=1955, y=575000, label="1954:", color = "#74a9cf",
        size=on.g.text.size, hjust=1) +
  annotate(geom = "text", x=1955, y=535000, label="School", color = "#74a9cf",
        size=on.g.text.size, hjust=1) +
  annotate(geom = "text", x=1955, y=495000, label="Desegregation", color = "#74a9cf",
        size=on.g.text.size, hjust=1) +
  annotate(geom = "text", x=1967, y=525000, label="1968:", color = "#2b8cbe",
        size=on.g.text.size, hjust=0) +
  annotate(geom = "text", x=1967, y=475000, label="Civil Disturbance", color = "#2b8cbe",
        size=on.g.text.size, hjust=0) +
  annotate(geom = "text", x=1994, y=325000, label="1995:", color="#045a8d",
        size=on.g.text.size, hjust=0) +
  annotate(geom = "text", x=1994, y=285000, label="Control Board", color="#045a8d",
        size=on.g.text.size, hjust=0) +
  annotate(geom = "text", x=1994, y=245000, label="Takes Power", color="#045a8d",
        size=on.g.text.size, hjust=0)

## save it
fn2 <- "H:/pppa_data_viz/2020/tutorials/tutorial_08/b4_testerv2.jpg"
ggsave(plot = done2,
       file = fn2,
       dpi = 300,
       units = c("in"),
       width = 7,
       height = 3.5)
```

Pulling in the final image:



C. Themes

Now we take a detour from line graphs to discuss themes.

C.1. Modifying individual elements of themes

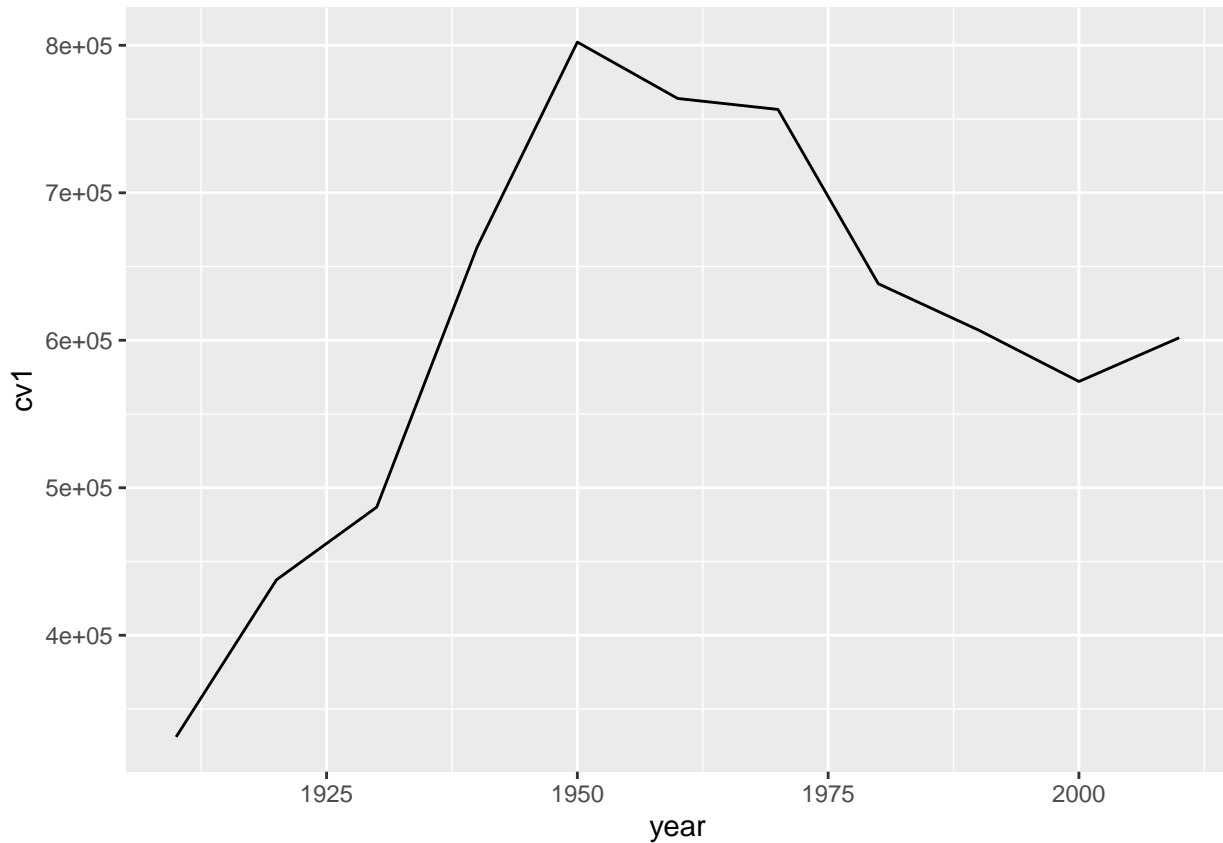
In the previous graph, we substantially changed the look of the graph by modifying elements in the `theme()` portion of the command. There are many, many different elements you can change in the `ggplot` theme, and you can find the complete list [here](#).

C.2. Using ggplot's built-in themes

In addition to modifying individual elements of a theme, you can use `ggplot`'s built-in themes to modify a graph. You can see the full list [here](#), and we'll do examples with `theme_minimal()` and `theme_bw()`.

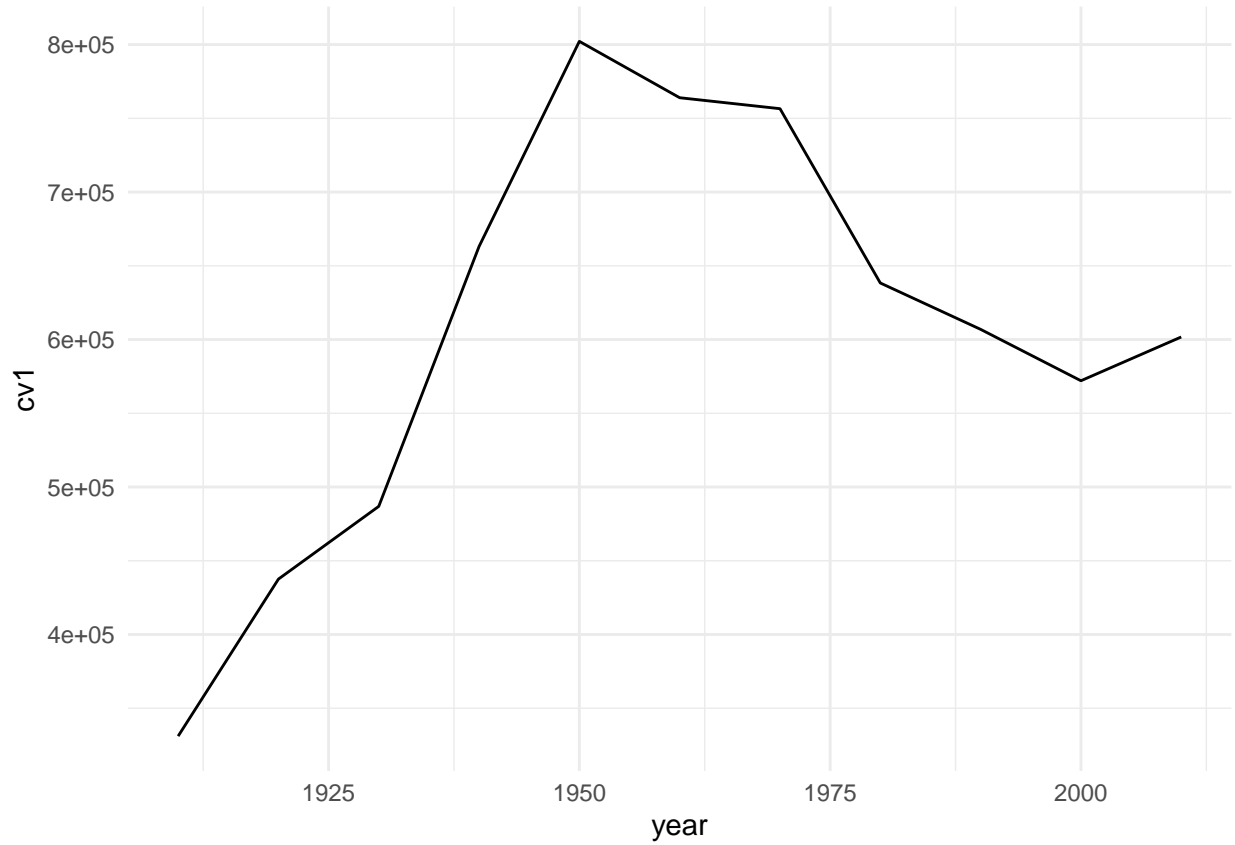
To make sure we understand what the themes are doing, let's return to our original, somewhat ugly, graph of DC population over time.

```
b3 <- ggplot() +  
  geom_line(data = dct,  
           mapping = aes(x = year, y = cv1))  
b3
```



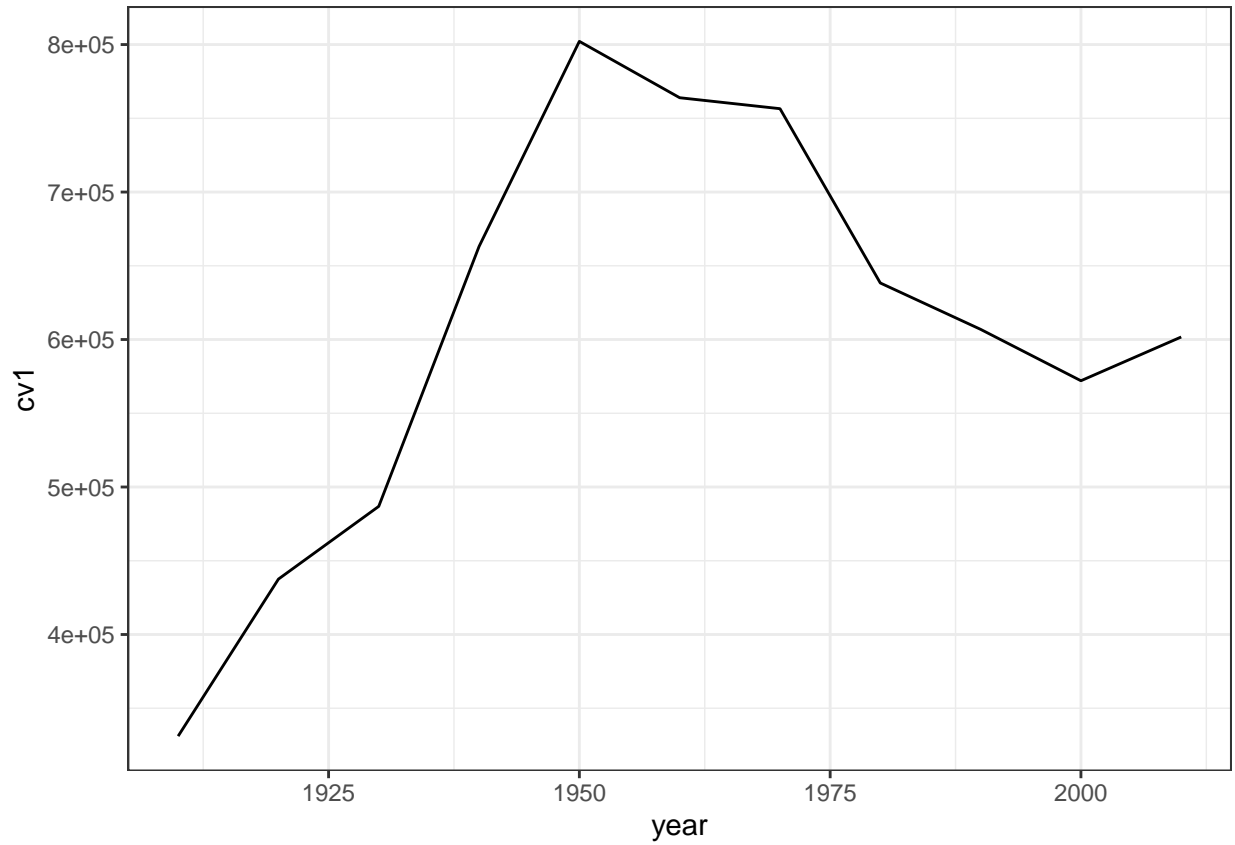
First, we'll apply the `ggplot`'s minimal theme. Notice that instead of retyping the graphing command, we just add the theme to the basic graph with a plus. You can see that many aspects of the graph's look are changed.

```
c1 <- b3 + theme_minimal()  
c1
```



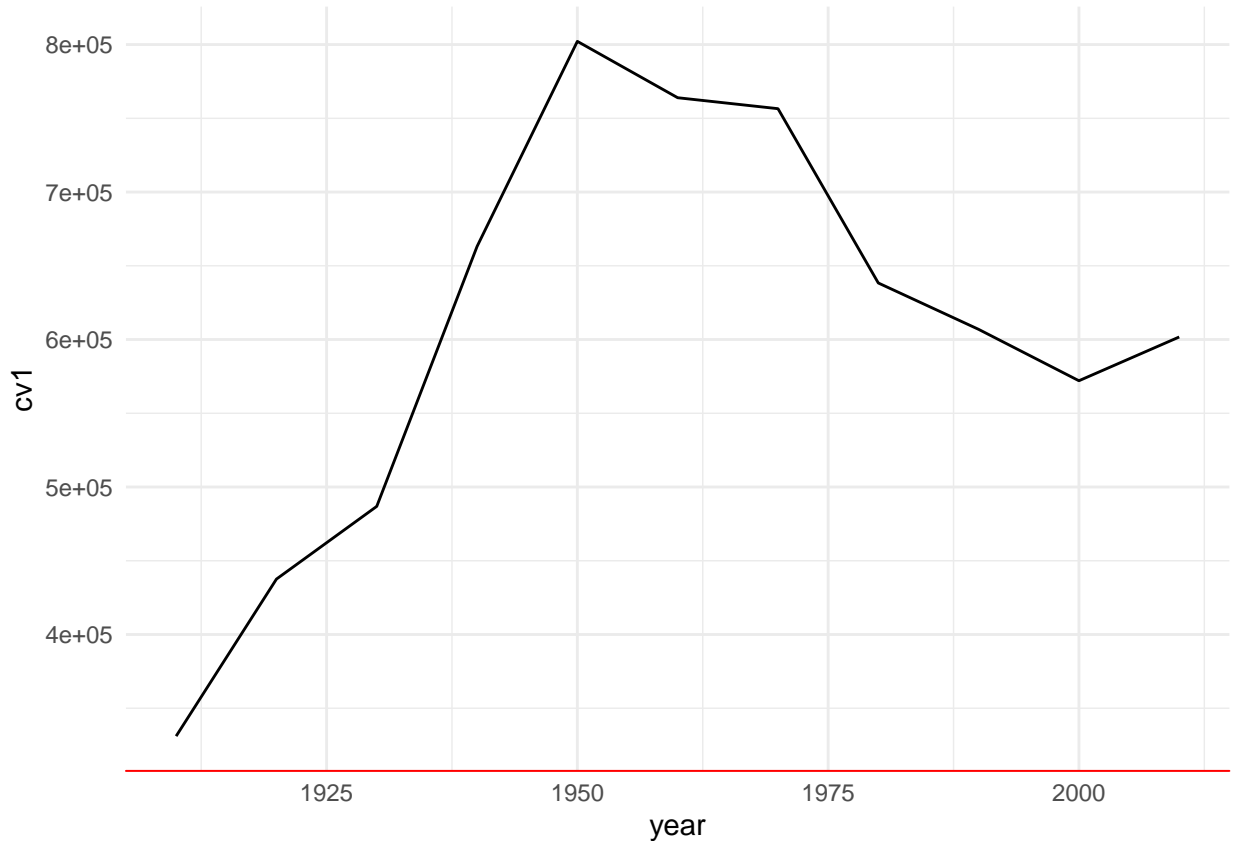
We can try a different built-in theme, `theme_gw()`, for black and white:

```
c2 <- b3 + theme_bw()  
c2
```



Finally, you can use a built-in theme and then also modify additional elements, as in

```
c3 <- b3 + theme_minimal() +  
  theme(axis.line.x = element_line(color = "red"))  
c3
```



I don't recommend this modification, but hopefully what it's changing is clear.

C.3. Other peoples' themes

Users have also created a variety of pre-packaged themes that you can use if you like. This [webpage](#) shows a variety of examples. To use these additional themes, you usually need to install a package.

C.4. Make your own theme

Finally, it can be quite helpful to create your own theme if you want to make a consistent look across many graphs.

Written as below, the theme modifies R's default theme. We declare a function that has no inputs, but which creates the theme `theme_me` – you can call it `theme_myself` or whatever you'd like.

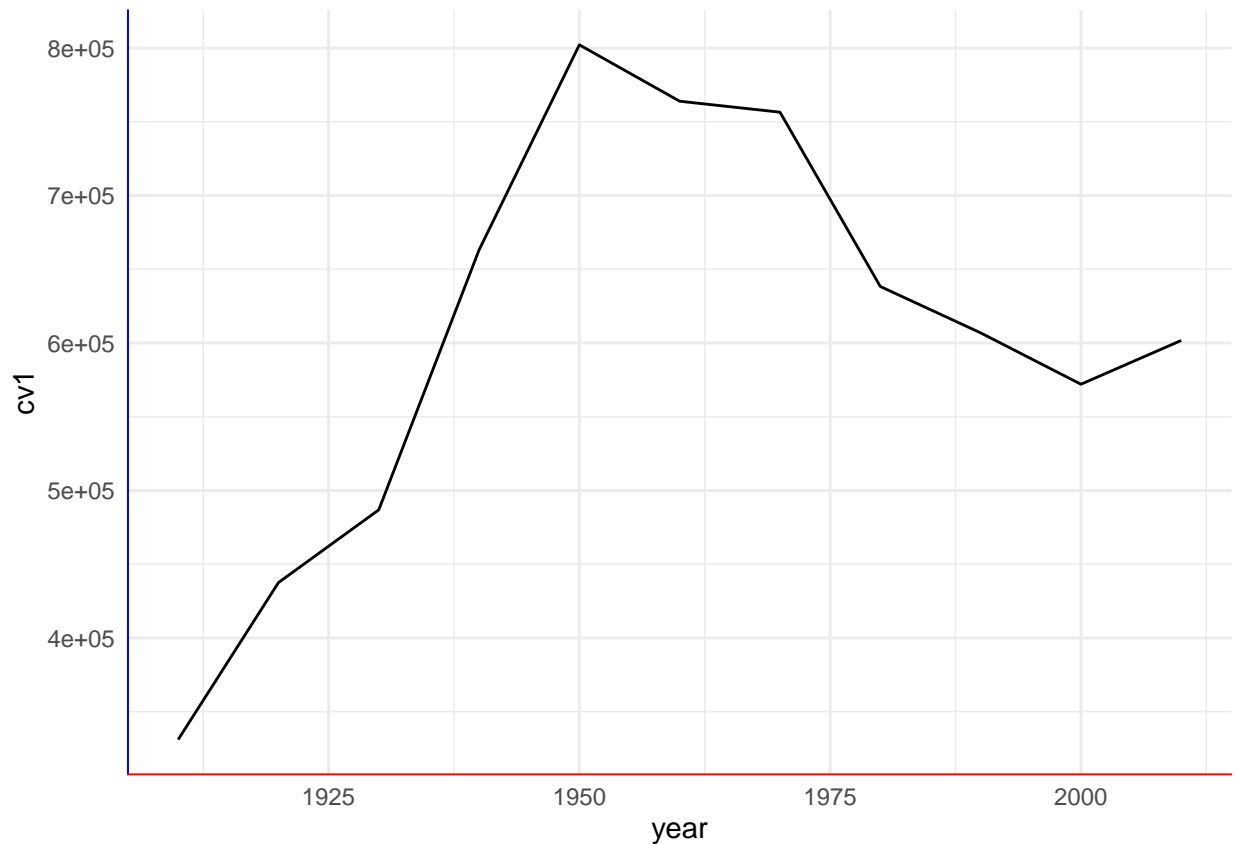
```
theme_me <- function(){
  theme(axis.line.x = element_line(color = "red"),
        axis.line.y = element_line(color = "blue"))
}
```

You could include one of R's other themes below, too, if you'd prefer, as in

```
theme_me <- function(){
  theme_minimal() +
  theme(axis.line.x = element_line(color = "red"),
        axis.line.y = element_line(color = "blue"))
}
```

Then apply your theme to the line graph:

```
c4 <- b3 + theme_me()
c4
```



Bottom line: themes modify the look and feel of a graph. You need to alter them to make decent looking graphics. Making a custom theme can help create consistency across multiple graphics.

D. Grouped Line Graph: Multiple counties

The section above graphs just DC. In this section, we graph multiple counties and make them distinguishable.

D.1 Keep just a few counties

Here we subset the `counties` data to just keep DC (state 11), Maryland's Montgomery and Prince George's counties (state 24, counties 31 and 33), and Virginia's Arlington, Alexandria and Fairfax jurisdictions (state 51, counties 13, 510 and 59).

We also make the year variable numeric for ease of plotting. And then to save space, we get rid of the counties dataframe with `rm(counties)`. You can use `rm()` for any objects that you no longer want.

```
dcm <- counties[which(counties$statefips == 11 |
                    counties$statefips == 24 & counties$countyfips %in% c(31,33) |
                    counties$statefips == 51 & counties$countyfips %in% c(13,510,59)),]
dcm$year <- as.numeric(dcm$year)
rm(counties)
```

Finally, to identify a county in `ggplot`, we need both the state and county variables together. I use `paste0` to concatenate the state and county variables. "Concatenate" means stick together. The `paste0` command

takes as many strings as you like and puts them together.

Here is a small example of what `paste0` does. The first use of `paste0` below just sticks strings `s1` and `s2` together. The next two examples, where we create `p2` and `p3`, use different separators.

```
ex.df <- data.frame(s1 = c("fred", "ted", "pj"),
                   s2 = c("dog", "cat", "pig"))
ex.df$p1 <- paste0(ex.df$s1, ex.df$s2)
ex.df$p2 <- paste0(ex.df$s1, ex.df$s2, sep = "XX")
ex.df$p3 <- paste0(ex.df$s1, ex.df$s2, sep = " is a ")
ex.df
```

```
##   s1 s2   p1      p2      p3
## 1 fred dog freddog freddogXX freddog is a
## 2 ted cat tedcat  tedcatXX  tedcat is a
## 3  pj pig  pjpig   pjpigXX   pjpig is a
```

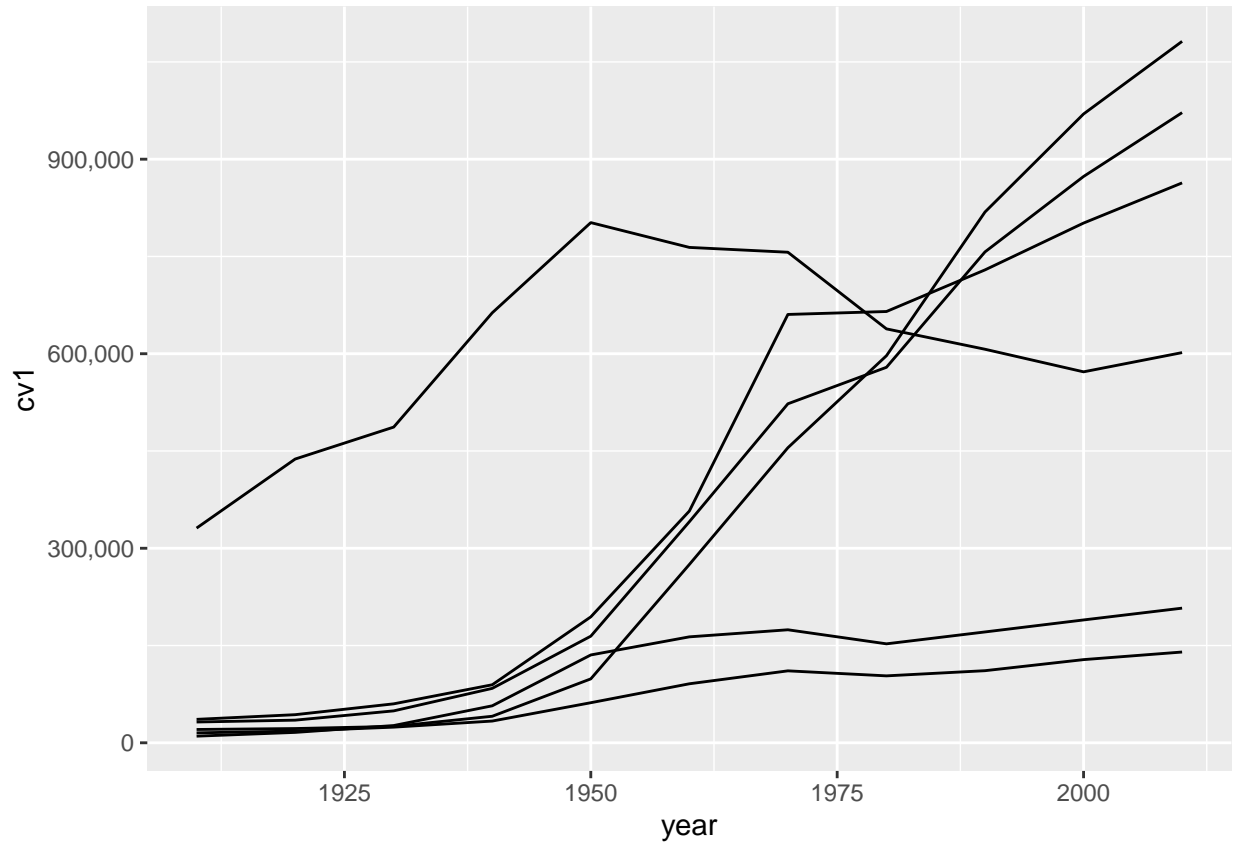
And here we use this `paste0` command to stick the state and county identifiers together:

```
# make a state+county variable
dcm$stc <- paste0(dcm$statefips, dcm$countyfips)
```

D.2. Plot all counties

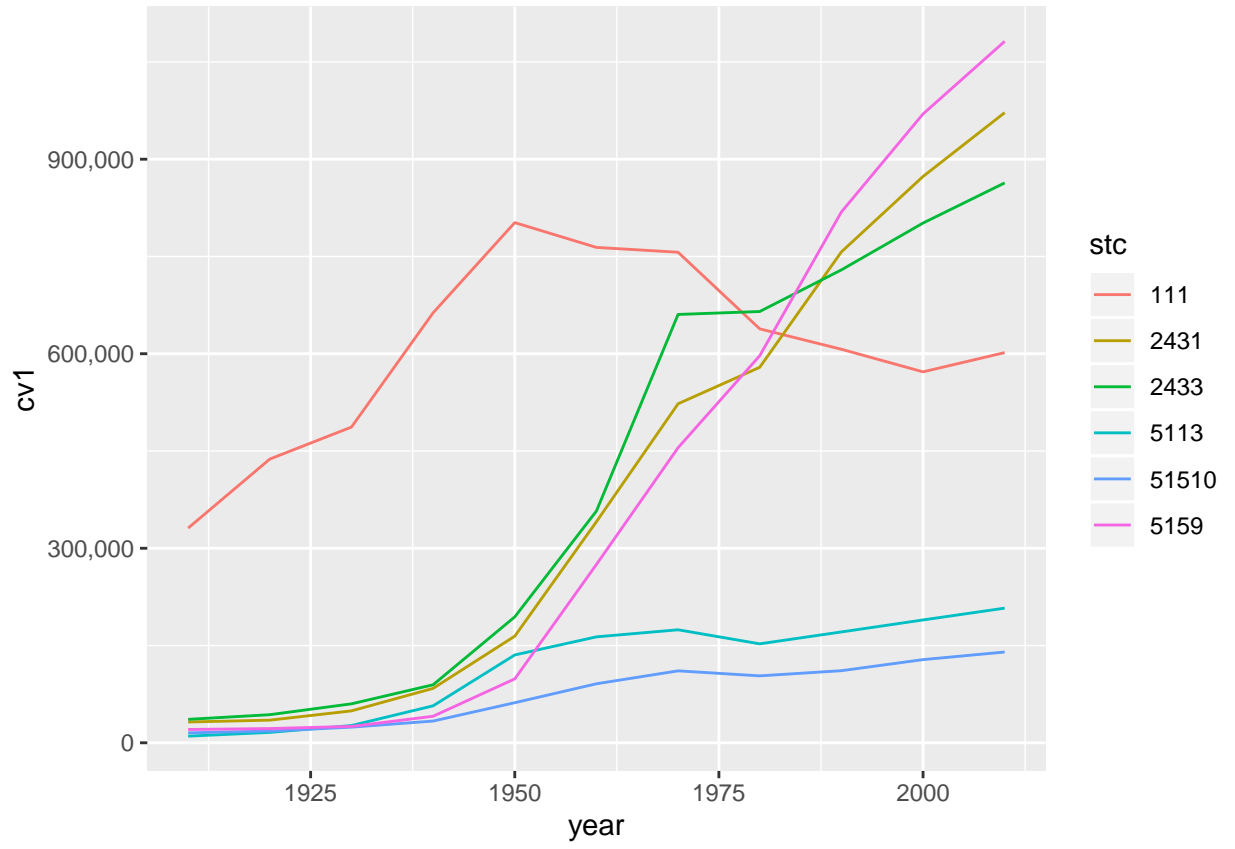
To plot multiple counties at one time, we use the `group()` command and tell R that the groups are by the `stc` variable. For legibility, I add commas in the y-axis values.

```
# all counties
ac <- ggplot() +
  geom_line(data = dcm, aes(x=year, y=cv1, group = stc)) +
  scale_y_continuous(labels = comma)
ac
```

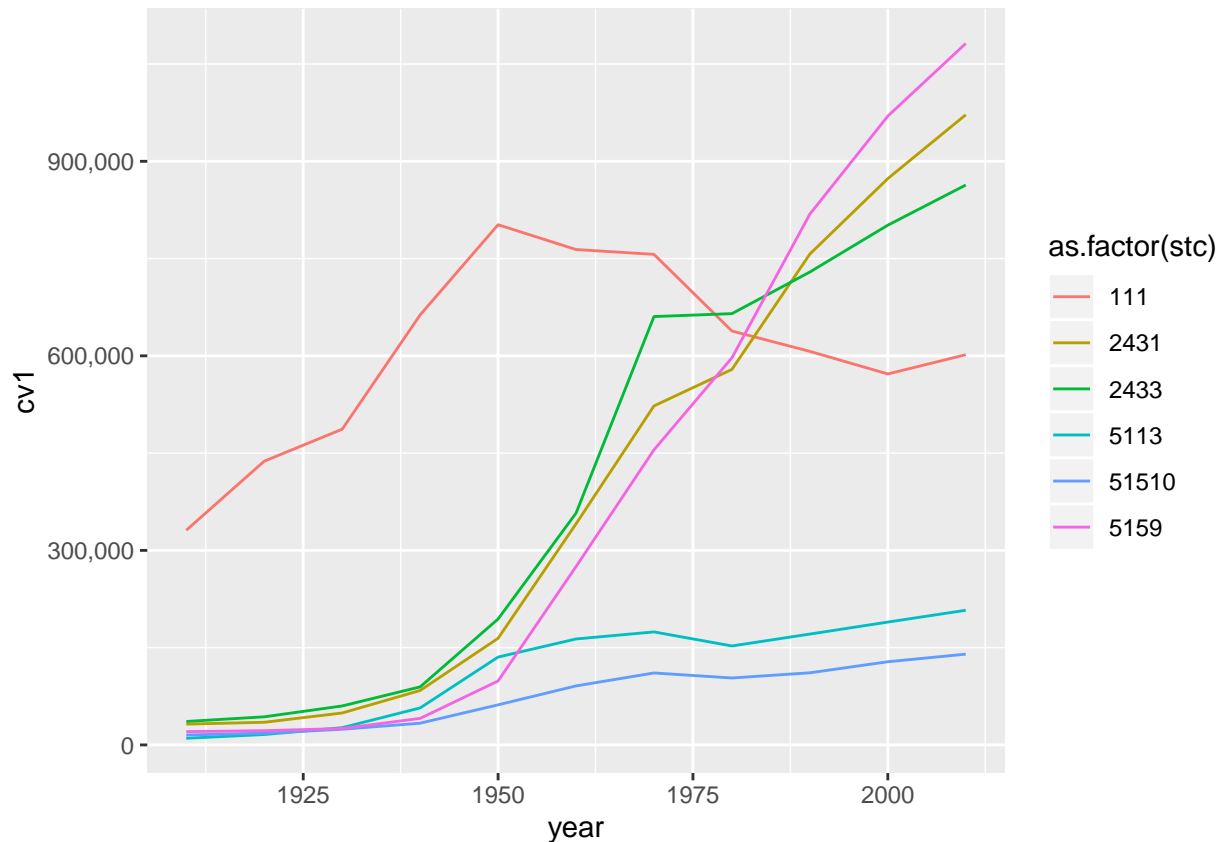
Of course, without a legend or identifying features, this graph is very hard to interpret. We add `color = stc` so that we can see which counties are which on the graph.

```
# color by state
ac <- ggplot() +
  geom_line(data = dcm, aes(x=year, y=cv1,
                           group = stc,
                           color = stc)) +
  scale_y_continuous(labels = comma)
ac
```



This graph is an improvement, but it has the very unfortunate feature that it presents the county code as if it were a continuous variable. I use `as.factor()` around the county variable to let R know it is categorical.

```
# color by state, itemized legend
ac <- ggplot() +
  geom_line(data = dcm, aes(x=year, y=cv1,
                           group = as.factor(stc),
                           color = as.factor(stc))) +
  scale_y_continuous(labels = comma)
ac
```



There are still many improvements we could make to this graph. For basic legibility, we should made the county codes names rather than numbers. We can do this by making `stc` a factor variable and assigning names to its levels. (We have done this is in a previous tutorial.) Even better, and depending on the point of the graph, omit the legend and put the jurisdiction names directly on the graph using `annotate()`.

E. Preparing Data for Line Graphs

E.1 Capital Bikeshare data

This section walks you through the kind of prep work you might need to do to get to a line graph. Specifically, we

- practice with functions
- work with date variables
- summarize data

First, download the 2019/02 Capital bikeshare data from [here](#). These data are individual bike trips on Capital

Bikeshare for 2019. These data are provided for public use by Capital Bikeshare; you can download more recent data if you would like [here](#).

Use `read.csv()` to load the data.

```
cabi.201901 <- read.csv("H:/pppa_data_viz/2019/tutorial_data/lecture08/201902-capitalbikeshare-tripdata.csv")
head(cabi.201901)
```

```
##      Duration      Start.date      End.date Start.station.number
## 1         206 2019-02-01 00:00:20 2019-02-01 00:03:47          31509
## 2         297 2019-02-01 00:04:40 2019-02-01 00:09:38          31203
## 3         165 2019-02-01 00:06:34 2019-02-01 00:09:20          31303
## 4         176 2019-02-01 00:06:49 2019-02-01 00:09:45          31400
## 5         105 2019-02-01 00:10:41 2019-02-01 00:12:27          31270
## 6         757 2019-02-01 00:12:37 2019-02-01 00:25:14          31503
##                                     Start.station End.station.number
## 1                                     New Jersey Ave & R St NW          31636
## 2                                     14th & Rhode Island Ave NW          31519
## 3 Tenleytown / Wisconsin Ave & Albemarle St NW          31308
## 4                                     Georgia & New Hampshire Ave NW          31401
## 5                                     8th & D St NW          31256
## 6                                     Florida Ave & R St NW          31126
##                                     End.station Bike.number Member.type
## 1 New Jersey Ave & N St NW/Dunbar HS          W21713          Member
## 2                                     1st & O St NW          E00013          Member
## 3                                     39th & Veazey St NW          W21703          Member
## 4                                     14th St & Spring Rd NW          W21699          Member
## 5                                     10th & E St NW          W21710          Member
## 6                                     11th & Girard St NW          W22157          Member
```

These data show us one row per CaBi trip.

To get these data ready for a line chart, we need to get the time variable into a useful format. Currently the time data are text. Text variables are categorical, not quantitative, so they will not line up properly along the x axis.

We also need to shrink the size of these data through summary statistics since 150,000 is too many to plot. We'll do each of these in turn.

E.2. Prepare bikeshare data

Let's begin with calculating date variables. Date variables are a special kind of variable. They store time and date as the number of days since January 1, 1970. To convert the string variables `Start.date` and `End.date`, we use the `as.POSIXct` [command](#), which takes character variables and makes a R date.

We also use `strptime()` which makes appropriate character variables (to get ready for `as.POSIXct`) from a date and time string. For `strptime`, you tell R what parts of the string correspond to which parts of the date.

```
cabi.201901$time.start <- as.POSIXct(strptime(x = cabi.201901$Start.date,
                                             format = "%Y-%m-%d %H:%M:%S"))
cabi.201901$time.stop  <- as.POSIXct(strptime(x = cabi.201901$End.date,
                                             format = "%Y-%m-%d %H:%M:%S"))
```

Date variables are very useful for making calculations and graphs over time.

E.3. Use date variables for duration calculation

Now that we have two date variables, we can make our own measure of duration and check the bikeshare's measure.

```
# my duration calculation
cabi.201901$my.duration <- cabi.201901$time.stop - cabi.201901$time.start

# comparing my results to built-in results
summary(cabi.201901$my.duration)
```

```
## Length Class Mode
## 158130 difftime numeric
```

Wait – this variable is not returning a normal summary output. We need to tell R that it is a numeric variable in the `summary()` command.

```
summary(as.numeric(cabi.201901$my.duration))
```

```
## Min. 1st Qu. Median Mean 3rd Qu. Max.
## 1.000 5.817 9.633 14.939 15.967 1435.000
```

```
summary(as.numeric(cabi.201901$Duration))
```

```
## Min. 1st Qu. Median Mean 3rd Qu. Max.
## 60.0 349.0 577.0 895.9 957.0 86100.0
```

This looks similar, but our calculated duration measure is in minutes and the bikeshare's measure is in seconds. I could divide `cabi$Duration` by 60 to see if they are the same. I can also look at the correlation between the two measures using `cor()`. Here is the correlation method:

```
# look at the correlation -- looks like 1
cor(x = as.numeric(cabi.201901$my.duration),
    y = as.numeric(cabi.201901$Duration),
    method = c("pearson"))
```

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

I find that the correlation between the two measures is 1. This makes us suspect that the bikeshare people calculated the duration in the exact way we did.

Now I do the other check: divide our measure by 60.

```
cabi.201901$Duration.minutes <- cabi.201901$Duration / 60
summary(cabi.201901$Duration.minutes)
```

```
## Min. 1st Qu. Median Mean 3rd Qu. Max.
## 1.000 5.817 9.617 14.931 15.950 1435.000
```

OK – it's the same.

E.4. Make hour level summary statistics

The trick to successfully plotting these data is to reduce their dimensionality. “Dimensionality” means size, or the number of observations by the number of variables. Our dataframe has about 150,000 observations – way too many to show on any plot.

One way to shrink what we show is to show data by hour, rather than by ride. Therefore, for each hour, we will find the average number of rides and the average duration of rides.

To do this, we first need a variable that tells us the hour of the trip. We extract the hour component from the date variable using the date notation. We can use the `format()` function because we already created a date

variable called `time.start`. We write `format(df$varname, "%H")` to get the hour from the time variable. (This is the benefit of the time variable!) We then check the output using both `summary()` and `table()`.

```
# get the hour out of the date variable
cabi.201901$start.hour <- as.numeric(format(cabi.201901$time.start, "%H"))
summary(cabi.201901$start.hour)
```

```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##      0.00   9.00   14.00   13.63   17.00   23.00
```

```
table(cabi.201901$start.hour)
```

```
##
##      0      1      2      3      4      5      6      7      8      9     10     11     12
##    949    539    383    162    284   1369   3931   9314  15908  9409   6123   6818   8025
##     13     14     15     16     17     18     19     20     21     22     23
##   8304   8311   9728  12994  18785  13846   8570   5713   4082   2904   1679
```

From the summary command, we see that mean start hour is about 1:30 (13.6 hours). That seems fine, as does the max start hour of 11 pm (23 hours) and the min start hour of 0 (midnight).

Looking at the table output, the hour with the single largest number of rides is 17 – or 5 pm. This also seems reasonable.

Now that we are reassured the times are ok, we use `group_by()` and `summarize()` to find hourly traveling information. We calculate both the number of rides (`no_rides`) and the average duration of those rides (`mean_dur`).

```
# summarize to hourly data
cabi.201901 <- group_by(cabi.201901, start.hour)
cabisum <- summarize(.data = cabi.201901, no_rides = n(), mean_dur = mean(Duration))
dim(cabisum)
```

```
## [1] 24 3
```

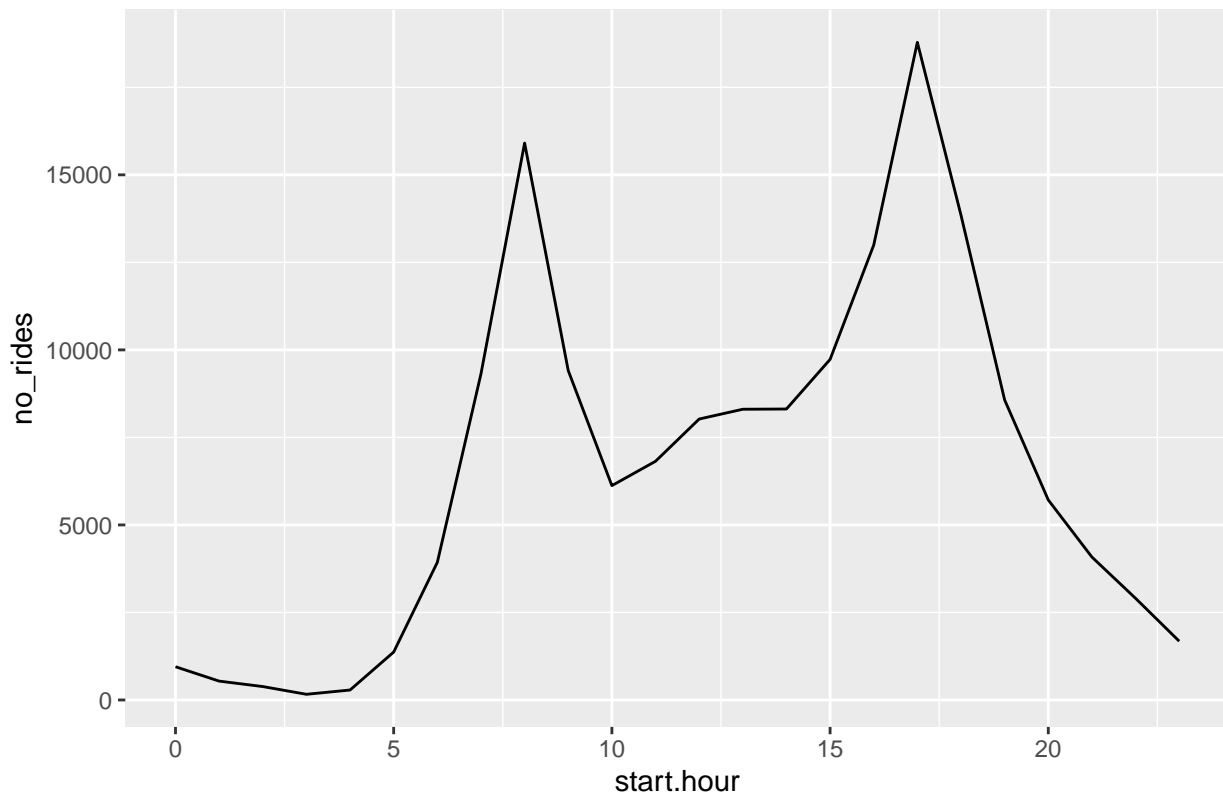
E.5. Plot of number of rides and mean duration

Now we'll plot the results, which is another reasonability check on the data. To plot both variables the same way, it is a good idea to make a function. However, the first rule of writing functions is to get the code working outside of a function first.

Following this commandment, we plot the number of rides by hour.

```
# get it to work outside of a function
c3 <- ggplot() +
  geom_line(data = cabisum, mapping = aes(x = start.hour, y = no_rides)) +
  labs(title = "Total number of rides by hour")
c3
```

Total number of rides by hour



This seems to have gone smoothly. We see morning and afternoon peaks, which seems entirely reasonable.

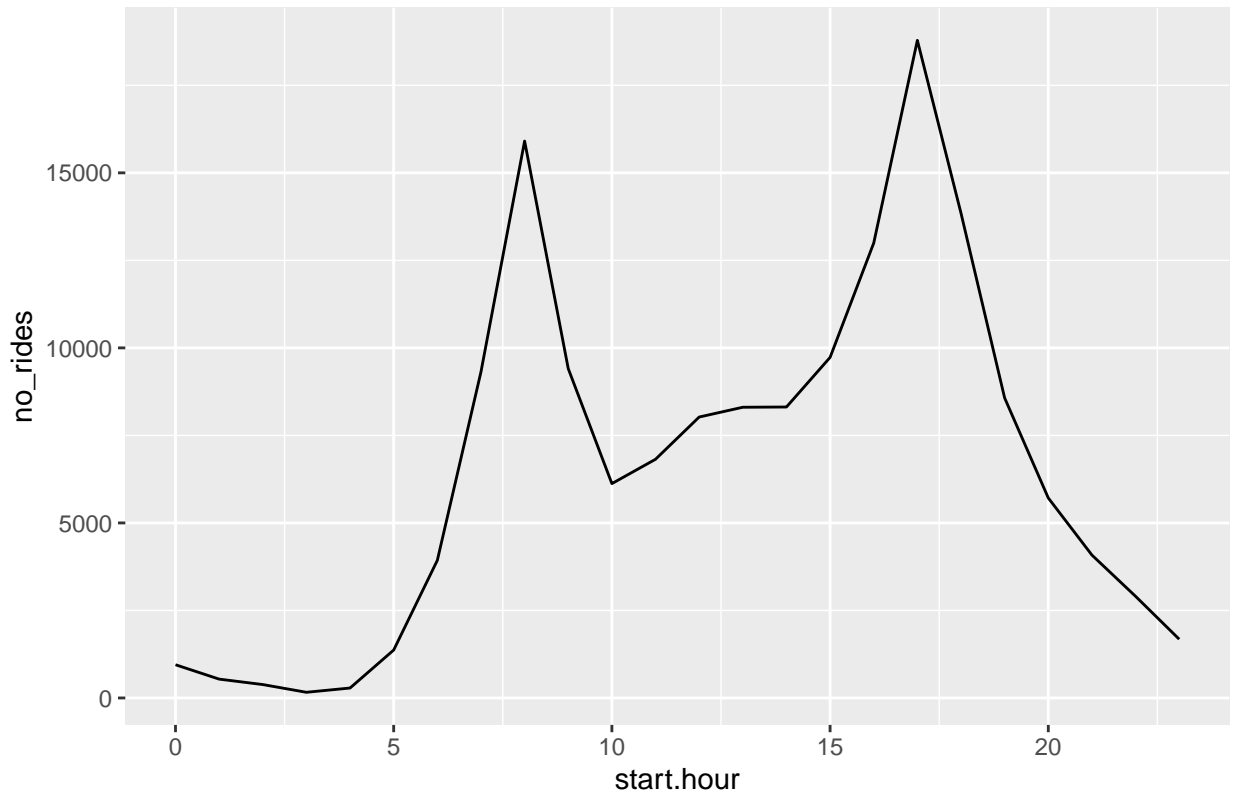
For making multiple graphs, we'd prefer not to copy and paste this code for reasons we discussed in class. Instead, make a function. The below shows you how to iterate through `ggplot` with a function. [This document](#) explains the why this is not as straightforward as you might think.

Importantly, `ggplot()` uses non-standard evaluation, so it takes in text in a different way than base R commands. Thus, to replace text in a `ggplot` command, you need to input it with `quo()` and get rid of the `quo()` with `!!` before the new text.

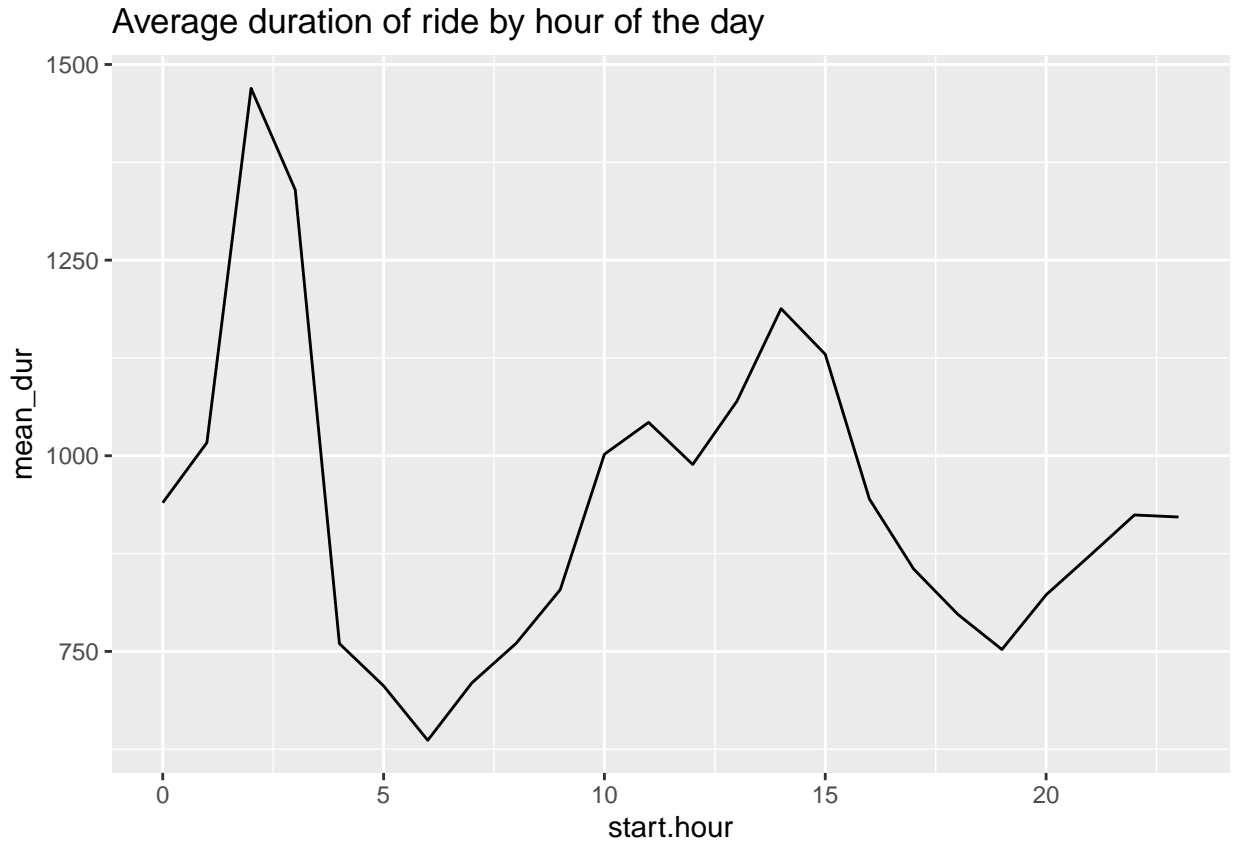
```
# write a simple function for two variables
# see examples here
# https://dplyr.tidyverse.org/articles/programming.html
c3func <- function(varin, vardescp){
  c3 <- ggplot() +
    geom_line(data = cabisum, mapping = aes(x = start.hour, y = {{varin}})) +
    labs(title = vardescp)
  print(c3)
}

c3a <- c3func(varin = no_rides,
              vardescp = "Total number of rides by hour of the day")
```

Total number of rides by hour of the day



```
c3a <- c3func(varin = mean_dur,  
             vardescp = "Average duration of ride by hour of the day")
```

F. Stacked lines, useful for money

The final type of line graph we’re trying today is a stacked line chart, which can sometimes be very helpful to convey change over time along with the relative importance of categories.

F.1. Load data

Since this is a policy class, it seems fitting to graph at least some budget data. We are introducing a new dataset: US federal budget statistics. You can find the data from the Office of Management and Budget [here](#). Download the zip file from the top of the page and unzip it.

I am not prepping these data for you, since I want to make sure you learn how to put raw data into R. You will find that there are many small issues that cause trouble. This is not atypical, so it is helpful to show how to handle them.

Unzip the file you downloaded, and you’ll see a bunch of files in this new folder. They follow the naming convention on the page from which you downloaded. Open up Tables 1.3 (hist01z3.xls; for homework) and 2.3 (hist02z3.xls; for now) in Excel.

From Table 2.3, we want the year and columns B, C, D, G, H and I. Create a new excel document with just this information, and make one row at top with names that you’ll understand. Keep just through 2017, and make sure that you don’t have any junk at the bottom of the table. Save this file as csv (file, save as, choose “csv” option for file type). If there are numeric variables that take the value *, make them “.”, which is code for missing.

Load the csv file you just created into R.

```
### makeup of receipts ###
hist02z3 <- read.csv("H:/pppa_data_viz/2018/tutorials/lecture05/omb_data/hist02z3.csv")
names(hist02z3)
```

```
## [1] "year"          "income.taxes" "corp.taxes"   "social.ins"   "excise"
## [6] "other"         "total"
```

Begin by making sure that what you’ve imported into R is what you expect. We run through the problems I encountered – your problems may differ! The goal here is to give you enough tools that you know how to look for problems and how to fix them once you find them.

We’ll start with the `year` variable, using `tables()`.

```
# make sure year is always ok
table(hist02z3$year)
```

```
##
##      1934 1935 1936 1937 1938 1939 1940 1941 1942 1943 1944 1945 1946 1947 1948
##      6    1    1    1    1    1    1    1    1    1    1    1    1    1    1
## 1949 1950 1951 1952 1953 1954 1955 1956 1957 1958 1959 1960 1961 1962 1963 1964
##      1    1    1    1    1    1    1    1    1    1    1    1    1    1    1
## 1965 1966 1967 1968 1969 1970 1971 1972 1973 1974 1975 1976 1977 1978 1979 1980
##      1    1    1    1    1    1    1    1    1    1    1    1    1    1    1
## 1981 1982 1983 1984 1985 1986 1987 1988 1989 1990 1991 1992 1993 1994 1995 1996
##      1    1    1    1    1    1    1    1    1    1    1    1    1    1    1
## 1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012
##      1    1    1    1    1    1    1    1    1    1    1    1    1    1    1
## 2013 2014 2015 2016 2017   TQ
##      1    1    1    1    1    1
```

Notice that there are some odd things here. A few observations with no year at all, and one observation where year is “TQ”. Let’s fix this.

We use subset the data to get rid of the strange years.

```
hist02z3 <- hist02z3[which(hist02z3$year != ""),]
hist02z3 <- hist02z3[which(hist02z3$year != "TQ"),]
```

Next, we check out and then create a numeric variable from a factor using an alternative method. We use `summary()` to make sure this cleaned up variable takes on reasonable values.

```
hist02z3$nyear <- as.numeric(levels(hist02z3$year))[hist02z3$year]
```

```
## Warning: NAs introduced by coercion
```

```
summary(hist02z3$nyear)
```

```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##      1934   1955   1976   1976   1996   2017
```

Good – the year variable now seems to have just numeric years.

F.2. Make data long

To make a stacked line (or really, any multiple line), the data need to be long, not wide. As a refresher, wide data look like this, with one observation per unit:

```
wide <- data.frame(state = c("6", "36", "48"),
                   female_pop = c("10", "12", "14"),
```

```
male_pop = c("11", "13", "12")
wide
```

```
## state female_pop male_pop
## 1 6 10 11
## 2 36 12 13
## 3 48 14 12
```

Long data look like this, with one observation per unit and type:

```
long <- data.frame(state = c("6", "36", "48", "6", "36", "48"),
  pop = c("10", "12", "14", "11", "13", "12"),
  sex = c("female", "female", "female", "male", "male", "male"))
long
```

```
## state pop sex
## 1 6 10 female
## 2 36 12 female
## 3 48 14 female
## 4 6 11 male
## 5 36 13 male
## 6 48 12 male
```

Note how this dataset requires a variable that tells you which type of population the row contains.

Neither data format is “right.” If you were doing a regression and wanted to control for male and female population, you’d need the wide format. However, to make a line graph with multiple lines in R, you need a long dataset.

To make the data long, first I tried the code below

```
## make this wide dataset long
head(hist02z3)
r.long <- pivot_longer(data = hist02z3,
  cols = c("income.taxes", "corp.taxes", "social.ins", "excise", "other", "total"),
  names_to = "revenue_type",
  values_to = "revenue")
r.long[1:15,]
```

This code delivers this error message: **Error: No common type for ‘income.taxes’ <double> and ‘social.ins’ <factor<1c022>.**

This error message is telling us that not all our income variables are the same type. Check this:

```
str(hist02z3)
## 'data.frame': 84 obs. of 8 variables:
## $ year : Factor w/ 86 levels "", "1934", "1935", ...: 2 3 4 5 6 7 8 9 10 11 ...
## $ income.taxes: num 0.7 0.7 0.8 1.2 1.4 1.1 0.9 1.1 2.2 3.5 ...
## $ corp.taxes : num 0.6 0.8 0.9 1.2 1.4 1.2 1.2 1.8 3.2 5.2 ...
## $ social.ins : Factor w/ 41 levels "", ".", "0.1", "0.7", ...: 2 2 3 4 8 9 9 8 8 7 ...
## $ excise : num 2.2 2 2 2.1 2.1 2.1 2 2.2 2.3 2.2 ...
## $ other : num 1.3 1.5 1.1 0.9 0.9 0.7 0.7 0.7 0.5 0.4 ...
## $ total : num 4.8 5.1 4.9 6.1 7.5 7 6.7 7.5 9.9 13 ...
## $ nyear : num 1934 1935 1936 1937 1938 ...
```

Sadly, it seems that `social.ins` is a factor variable – all other taxes are numeric. So let’s fix this.

We fix `social.ins` by doing

```
hist02z3$social.ins <- as.numeric(as.character(hist02z3$social.ins))
```

```
## Warning: NAs introduced by coercion
```

```
str(hist02z3$social.ins)
```

```
## num [1:84] NA NA 0.1 0.7 1.7 1.8 1.8 1.7 1.7 1.6 ...
```

The new structure says `social.ins` is now a numeric variable.

Now try the `pivot_longer()` command again:

```
## make this wide dataset long
```

```
r.long <- pivot_longer(data = hist02z3,  
  cols = c("income.taxes", "corp.taxes", "social.ins", "excise", "other", "total"),  
  names_to = "revenue_type",  
  values_to = "revenue")
```

```
r.long[1:15,]
```

```
## # A tibble: 15 x 4  
##   year nyear revenue_type revenue  
##   <fct> <dbl> <chr>         <dbl>  
## 1 1934  1934 income.taxes    0.7  
## 2 1934  1934 corp.taxes     0.6  
## 3 1934  1934 social.ins     NA  
## 4 1934  1934 excise        2.2  
## 5 1934  1934 other         1.3  
## 6 1934  1934 total         4.8  
## 7 1935  1935 income.taxes    0.7  
## 8 1935  1935 corp.taxes     0.8  
## 9 1935  1935 social.ins     NA  
## 10 1935  1935 excise         2  
## 11 1935  1935 other         1.5  
## 12 1935  1935 total         5.1  
## 13 1936  1936 income.taxes    0.8  
## 14 1936  1936 corp.taxes     0.9  
## 15 1936  1936 social.ins     0.1
```

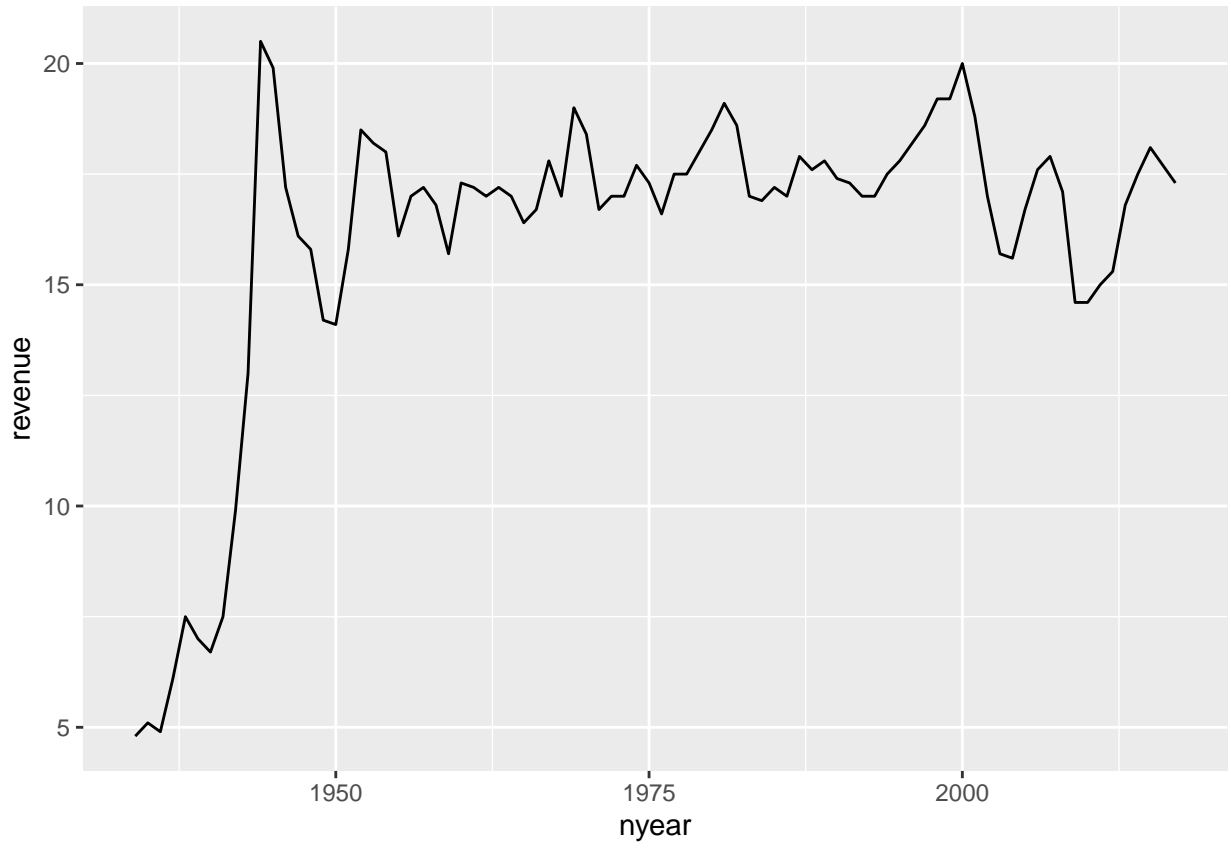
This looks like what we want. Notice that there are NA values for social insurance spending in the 1930s. If you go back to your original download, you can see that this isn't a mistake. In 1935, there was no social insurance spending.

F.3. Graphs

Let's start with total tax revenue over time. As in the previous section, we need to note `group=1`, and recall that total is `r.long$rtype == 6`.

```
#### line chart of total receipts
```

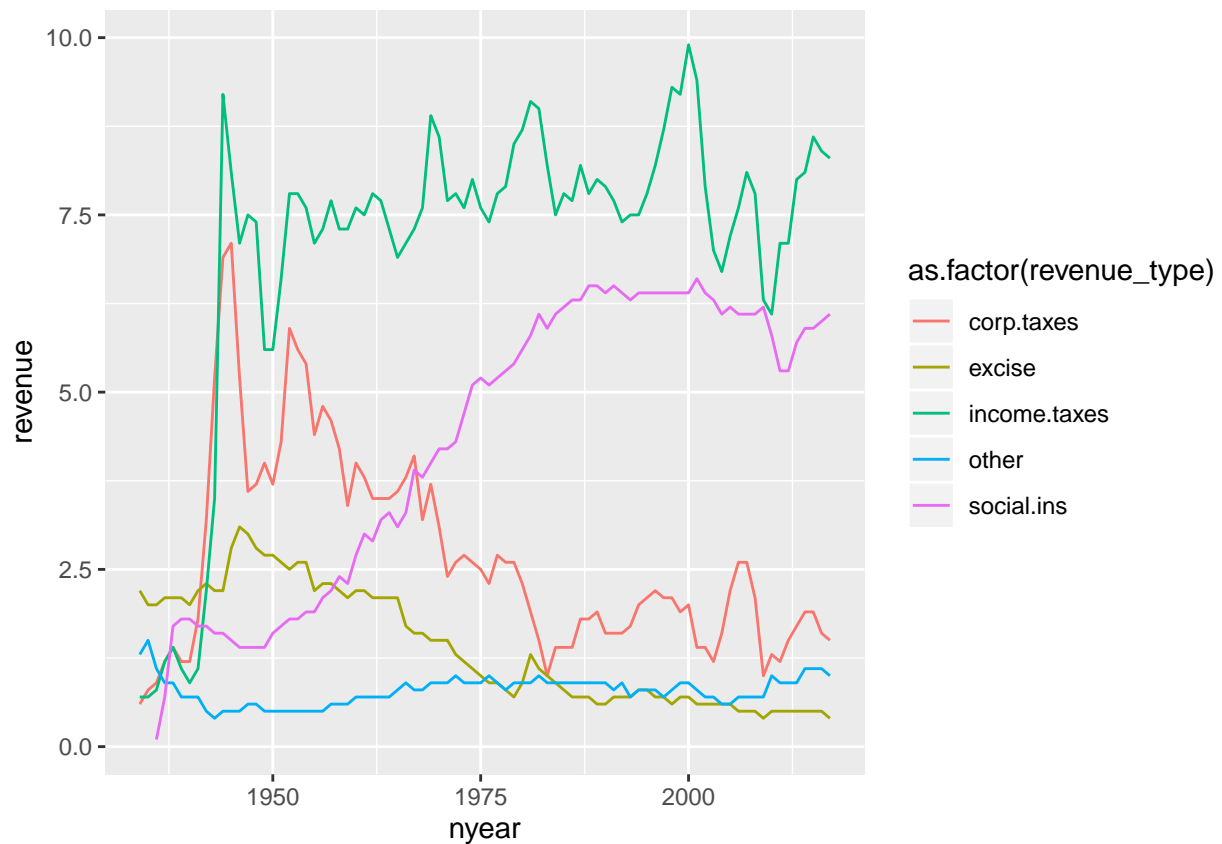
```
g4.1 <-  
  ggplot() +  
  geom_line(data = r.long[which(r.long$revenue_type=="total"),],  
    mapping = aes(x=nyear, y=revenue, group=1))  
g4.1
```



Now we'll modify the chart to have all the categories but the total. I do this by subsetting `r.long` into all record types that are not total revenue. In addition, I tell R that the group by which we want to make the graph is a variable called `revenue_type`, which R should treat as a factor. We also tell `r` to color the lines by `revenue_type`, taken as a factor.

```
#### line chart of total receipts by type ####
g4.2 <-
  ggplot() +
  geom_line(data = r.long[which(r.long$revenue_type != "total"),],
            mapping = aes(x=nyear, y=revenue,
                          group=as.factor(revenue_type),
                          color=as.factor(revenue_type)))
g4.2
```

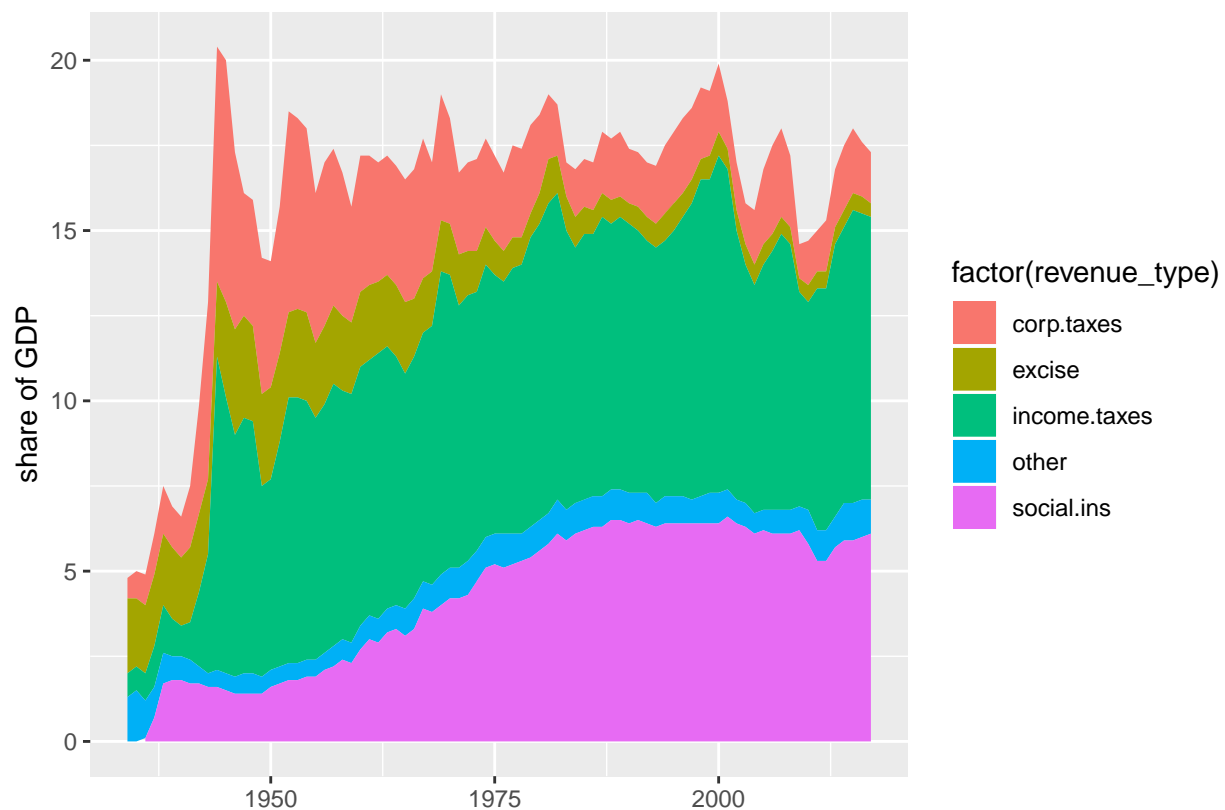
Warning: Removed 2 rows containing missing values (geom_path).



This graph is very hard to read. There are too many lines, and we don't get a sense of the total, which may be a key point. An alternative is a stacked line. Stacked lines highlight the total amount, and give readers some sense of the relative share of different categories.

```
#### stacked chart of total receipts by type ####
## without factor() this doesnt work
g4.3 <- ggplot() +
  geom_area(data = r.long[which(r.long$revenue_type != "total"),],
            mapping = aes(x=year, y=revenue,
                          group=factor(revenue_type),
                          fill=factor(revenue_type)),
            position="stack") +
  labs(x="", y="share of GDP")
g4.3
```

Warning: Removed 2 rows containing missing values (position_stack).



If you do this, it is frequently wise to put labels on the area portions of the graph and omit the legend. If the areas are too small to label, consider whether you need them individually.

These charts have the same downsides of stacked bars: the numbers for only the bottom category are directly legible from the graph.

F. Homework

1. In my example of DC population over time in section B.1., I present the graph of three steps. Modify your code to make these same three steps.

2. Using the bikeshare data,
 - (a) Re-do one of the by-hour pictures as a minute-by-minute picture showing total ridership
 - (b) Use one of the y variables we used or an alternative one. Add some annotations to your graph to point out salient features.
3. More stacked areas

Now you try to load your own budget data!

Use Table 1.3 (his01z3.xls), from which we want the year and columns E, F, G and columns I, J and K. Create a new excel document with just this information, and make one row at top with names that you'll understand. Keep just through 2017, and make sure that you don't have any junk at the bottom of the table. Save this file as csv (file, save as, choose "csv" option for file type).

Load it into R and make a stacked area graph of receipts, outlays and deficits over time.

Having done this myself, here are a few suggestions

- make long data, as we did above
- make year numeric, as we did for the social insurance revenue above
- get rid of commas in the data. My command to do this, for one variable, is

```
hist01z3$b1 <- as.numeric(gsub(",", "", hist01z3$cd.receipts, fixed = TRUE))
```