Introducing RStudio

Hands-On Learning and Career Readiness in the Social, Behavioral, and Educational Sciences

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Contents

1 Preface

Data analysis is more than a set of formulaic procedures—it is a method for understanding the world around us. This lab manual was developed to help students begin working in RStudio so that they can analyze data to answer authentic questions in the social, behavioral, and educational sciences. By working directly with real datasets and using professional analytical tools, students will gain practical skills that bridge the gap between classroom learning and workplace application.

The activities in this manual align with the key topics of data visualization and descriptive statistics that are often taught in introductory statistics courses. Each activity invites students to use their skills in meaningful contexts, strengthening both data literacy and problem-solving abilities.

A distinctive feature of this manual is its integration of **RStudio** as the primary computational platform. RStudio provides a modern, open-source environment for data analysis, widely used in research and professional settings. Through repeated hands-on practice, students will learn to write and adapt R code, interpret outputs, create publication-quality graphics, and present results in ways that meet professional standards.

1.1 Use of GSS Data

To ground activities in relevant, real-world examples, this manual draws extensively from the General Social Survey (GSS) for years 2000–2024. The GSS contains a rich array of information on U.S. society, making it particularly valuable for students in the social, behavioral, and educational sciences. A cleaned subset of the data is available at the author's GitHub page and its codebook is in the appendix. The full dataset for years 1972-2024 is available from the GSS Data Explorer, which instructors may use to create alternative subsets for classroom use.

1.2 Career Readiness and NACE Competencies

In addition to developing data analysis skills, this manual is designed to help students connect their academic work to professional competencies valued in the workplace. The National Association of Colleges and Employers (NACE) identifies eight core career readiness competencies:

1. Career and Self-Development
2. Communication
3. Critical Thinking
4. Equity and Inclusion
5. Leadership
6. Professionalism
7. Teamwork
8. Technology

Each activity in this manual intentionally builds one or more of these competencies. For example, students may develop *Critical Thinking* by interpreting `ggplot` outputs to guide evidence-based decisions, or *Technology* skills by automating data cleaning processes in R. By engaging with these competencies throughout the manual, students can see how the skills they build translate into tangible career preparation.

1.3 Use of AI in Development

The creation of this manual incorporated AI-assisted tools for formatting, content organization, and resource curation. This reflects a commitment to leveraging emerging technologies in educational publishing, while ensuring that all instructional content has been carefully reviewed and aligned with learning objectives.

1.4 How to Use This Manual

Students are encouraged to complete activities sequentially, as later exercises build on skills developed earlier. Instructors may adapt the activities to fit the structure of their courses or the specific needs of their students. Supplementary files are available on the author's GitHub page for easy access and customization.

By the end of this manual, students will not only be able to apply the methods of data visualization and summarization using RStudio, but also recognize the value of these skills in a variety of career paths across the social, behavioral, and educational sciences.

2 Navigating the RStudio IDE

In this chapter, you will learn to navigate RStudio, install and load packages, and avoid common beginner pitfalls. By the end, you will be able to open a new R script, write and run R code, install the packages you need, and troubleshoot common errors. At this point you should have RStudio downloaded and opened alongside this lab manual.

2.1 The RStudio Interface

RStudio is divided into four panes:

- **Source (Top Left)**: Where you write and save R scripts. To open a new script press Ctrl+Shift+N (Windows) or Cmd+Shift+N (Mac)
- **Console (Bottom Left)**: Where you run code for immediate execution.
- **Environment/History (Top Right)**: Lists objects and variables in memory, plus a history of commands.
- **Files/Plots/Packages/Help/Viewer/Presentation (Bottom Right)**: Used to browse files, view plots, documents, or presentations, manage packages, and access help files.

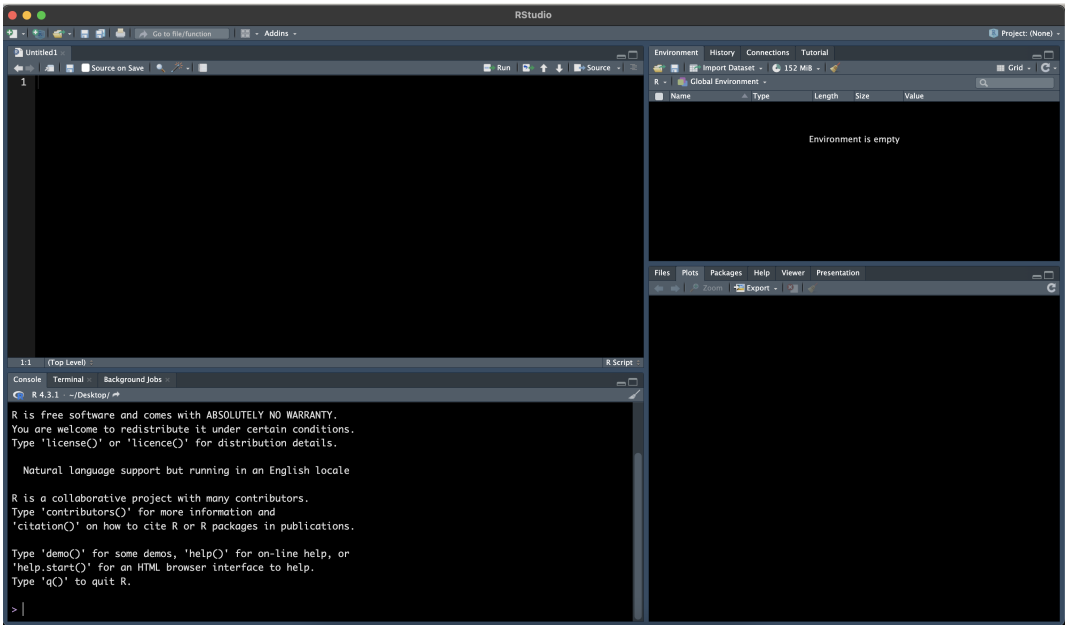


Figure 1: The four-pane layout of RStudio.

2.2 Installing and Loading Packages

R's core functions are extended by packages. We will use `tidyverse` frequently so it is a good idea to install it now. Type the following code into your R script and use Ctrl+R (Windows) or Cmd+R (Mac) to run each line.

- Install once: `install.packages("tidyverse")`

- Load in each session: `library(tidyverse)`

Installing a package is like screwing in a light bulb. Loading a package is like turning on the light switch. You only need to install the package (light bulb) once but you need to load the package (turn on the light) each time you open RStudio (enter the room).

2.3 Console vs. Source

The console is for one-time commands; the source is for writing and saving code.

- Try typing `2 + 2` in both places.
- You can save your R script with `Ctrl+S` (Windows) or `Cmd+S` (Mac).
- You can repopulate the console with the previous line of code using the up arrow
- Code typed into the Console is not saved!

2.4 Common Beginner Mistakes and How to Fix Them

Forgetting quotes around strings: `paste(apple)` causes an error; use `"apple"` for strings.

Running code in the wrong pane: If nothing happens, check if you typed into the source but forgot to press `Ctrl+Enter` (Windows) or `Cmd+Enter` (Mac).

Forgetting to load a package: Restarting R clears loaded packages and their functions will not be found; run `library(package_name)` again.

Overwriting variables: Accidentally reusing names (e.g., `mean <- 5`) will hide the original function. Restart R to reset.

Misplaced working directory: Errors like "file not found" often mean R is looking in the wrong folder. Check with `getwd()`.

Knowing these pitfalls can save hours of frustration. Learning to code in R takes time and practice so be prepared for some frustration and determine now to continue persevering despite this.

2.5 Summary

You now have the essential navigation skills to work effectively in RStudio. The more time you spend working in RStudio the more comfortable you will become using these and other skills. There is a wealth of RStudio documentation online. It is always a good idea to search for help online and bookmark any useful tips for future reference.

3 Introduction to the Tidyverse and Core Data Skills

The **tidyverse** is a collection of R packages designed to make data science easier, more consistent, and more readable. Think of it as a "toolbox" filled with tools that all work in a similar way, so once you learn one, the others feel familiar. We will use the tidyverse throughout this manual for data wrangling, visualization, and analysis.

While R has many built-in, or **base R**, functions, the tidyverse provides a consistent "grammar" for data analysis that's easier to learn for beginners and widely used by professionals in research, government, and industry.

3.1 Why Use the Tidyverse?

- **Consistency** – The same style and function names appear across different tasks.
- **Readability** – Code often reads like a sentence describing the analysis.
- **Efficiency** – Complex tasks can often be completed with fewer lines of code.
- **Career relevance** – Tidyverse skills are in demand for data roles across the social, behavioral, and educational sciences.

3.2 Core Packages

When you load the tidyverse, you get several packages at once:

Package	Purpose
ggplot2	Create high-quality visualizations
dplyr	Manipulate and summarize data (filter rows, select columns, group, arrange)
tidyr	Reshape and clean data
readr	Import data from CSV and text files
stringr	Work with text data (strings)
forcats	Manage categorical variables (factors)

We will mostly focus on **ggplot2**, **dplyr**, **tidyr**, and **readr**.

3.3 Installing and Loading the Tidyverse

You only need to install the **tidyverse** **once** on your computer. The code is included below in case if you have not already done so.

```
install.packages("tidyverse")
```

You must **load** the **tidyverse** each time you open RStudio:

```
library(tidyverse)
```

```
## -- Attaching core tidyverse packages ------------------------ tidyverse 2.0.0 --
## v dplyr     1.1.2     v readr     2.1.4
## v forcats   1.0.0     v stringr   1.5.0
## v ggplot2   3.5.1     v tibble    3.2.1
## v lubridate 1.9.2     v tidyr     1.3.0
## v purrr     1.0.2
## -- Conflicts ------------------------------------------ tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
## i Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to become errors
```

3.4 A Note on Tibbles

When you work with `tidyverse` functions, you will often see data printed in a slightly different format called a **tibble**. Tibbles are modern versions of data frames:

- They show only the first few rows and columns by default.
- They display column data types under the names.
- They never change variable names or types without your permission.

3.5 The Pipe Operator (|>)

A key feature of tidyverse workflow is the **pipe** operator, `|>`. It passes the result of one function into the next.

Without the pipe:

```
summarise(group_by(txhousing, year), avg_sales = mean(sales, na.rm = TRUE))
```

```
## # A tibble: 16 x 2
##     year avg_sales
##    <int>     <dbl>
##  1  2000      478.
##  2  2001      496.
##  3  2002      532.
##  4  2003      539.
##  5  2004      577.
##  6  2005      636.
##  7  2006      665.
##  8  2007      621.
##  9  2008      520.
## 10  2009      469.
## 11  2010      440.
## 12  2011      447.
## 13  2012      520.
## 14  2013      608.
## 15  2014      626.
## 16  2015      659.
```

With the pipe:

```r
txhousing |>
  group_by(year) |>
  summarise(avg_sales = mean(sales, na.rm = TRUE))
```

```
## # A tibble: 16 x 2
##     year avg_sales
##    <int>     <dbl>
##  1  2000      478.
##  2  2001      496.
##  3  2002      532.
##  4  2003      539.
##  5  2004      577.
##  6  2005      636.
##  7  2006      665.
##  8  2007      621.
##  9  2008      520.
## 10  2009      469.
## 11  2010      440.
## 12  2011      447.
## 13  2012      520.
## 14  2013      608.
## 15  2014      626.
## 16  2015      659.
```

Think of it as saying:

1. Start with `txhousing`.
2. Group by `year`.
3. Summarize with the average number of sales.

We'll explain what `summarise` and `group_by` do later, but notice that both chunks of code produce the same result. However, code written with the pipe is easier to read.

3.6 The Five Core `dplyr` Verbs

In the following examples, we will use the **General Social Survey** dataset. Read in the dataset from your computer and save it as `gssdat`. The dataset should be saved in the same location on your computer as the R script that you are working in.

```r
# read from a downloaded file in your working directory
gssdat <- read.csv("files/gssdat.csv")
```

3.6.1 `select()` — Choose the variables you need

Datasets can be overwhelming. If you check the dimensions of the GSS data with `dim(gssdat)` you will see that it is a large dataset. Selecting specific variables keeps your workspace and analysis focused. For example, you can select the variables `year`, `age`, `degree`, and `income` using the code below. We use `slice_sample(n = 10)` to return only a random sample of ten rows rather than the entire dataset. We will use this throughout and it should be used before knitting to avoid generating cumbersome output.

```r
gssdat |>
  select(year, age, degree, income) |>
  slice_sample(n = 10)
```

```
##    year age                degree income
## 1  1987  28           high school      9
## 2  2004  23           high school     12
## 3  2000  21 less than high school     11
## 4  1976  24           high school      8
## 5  1988  69 less than high school      4
## 6  1994  63           high school     NA
## 7  2004  27              graduate     12
## 8  2000  40           high school     12
## 9  1978  41            bachelor's     11
## 10 2024  41              graduate     12
```

3.6.2 `filter()` — Keep only the rows you want

Social science researchers often focus on specific subgroups (e.g., only people of a certain age, education level, or survey year). Filtering lets us zoom in. For example, we may want to study the `age`, `degree`, and `income` of respondents from 2022 who have a bachelor's degree or higher.

```r
gssdat |>
  select(year, age, degree, income) |>
  filter(year == 2022, degree %in% c("bachelor's", "graduate")) |>
  slice_sample(n = 10)
```

```
##    year age     degree income
## 1  2022  23 bachelor's     12
## 2  2022  48 bachelor's     NA
## 3  2022  32   graduate     10
## 4  2022  58 bachelor's     12
## 5  2022  66   graduate     12
## 6  2022  75 bachelor's     12
## 7  2022  34 bachelor's     NA
## 8  2022  47 bachelor's     12
## 9  2022  35   graduate     12
## 10 2022  31 bachelor's     12
```

The `%in%` operator determines whether elements of the vector on the left-hand side are present in the right-hand side vector. There are many different ways to use this operator. A few examples are given below along with the output that they return. The length of the resulting logical vector will be the same as that for the left-hand side vector.

```r
# length one vector
5 %in% c(1, 3, 5, 7, 9)
```

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

```r
# length three vector
c(1, 3, 5) %in% c(1, 2, 4, 6, 3)
```

```
## [1]  TRUE  TRUE FALSE
```

```r
# toy dataset
toydat <- data.frame(letter = c("A", "B", "C", "D", "E", "F", "I", "A"))

# length two vector against variable
c("A", "F") %in% toydat$letter
```

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

```r
# variable against length two vector
toydat$letter %in% c("A", "F")
```

```
## [1]  TRUE FALSE FALSE FALSE FALSE  TRUE FALSE  TRUE
```

3.6.3 `mutate()` — Create new variables

Sometimes the variable you need is not readily available in the dataset and you have to create it from other variables in the dataset. For example, we can create a new variable for whether a respondent is considered a "young adult" (18–30) or not.

```r
gssdat |>
  mutate(young_adult = if_else(age >= 18 & age <= 30, "Yes", "No")) |>
  select(year, young_adult, degree, income) |>
  slice_sample(n = 10)
```

```
##    year young_adult                degree income
## 1  2021          No less than high school     NA
## 2  1987          No               graduate     12
## 3  1980          No               graduate     12
## 4  1989          No            high school     12
## 5  2021          No               graduate     12
## 6  2006          No            high school      9
## 7  1998          No             bachelor's     12
## 8  1978         Yes            high school      5
## 9  1998         Yes            high school     12
## 10 1984          No less than high school      1
```

3.6.4 `summarise()` — Condense data into summaries

Summarizing helps researchers describe trends, central tendencies, and group differences. For example, we can find the average age of respondents by highest degree. Setting `na.rm = TRUE` removes missing values before R calculates the mean. Missing values are commonly found in all types of data, including survey data were respondents may choose not to answer a question.

```
gssdat |>
  group_by(degree) |>
  summarise(avg_age = mean(age, na.rm = TRUE))
```

```
## # A tibble: 6 x 2
##   degree                   avg_age
##   <chr>                      <dbl>
## 1 associate/junior college    44.0
## 2 bachelor's                  45.2
## 3 graduate                    49.9
## 4 high school                 44.8
## 5 less than high school       52.5
## 6 <NA>                        47.4
```

3.6.5 `arrange()` — Order the rows

Sorting results can make patterns easier to see and tables easier to interpret. For example, we can arrange degrees by average income bracket from lowest to highest.

```
gssdat |>
  group_by(degree) |>
  summarise(avg_income = mean(income, na.rm = TRUE)) |>
  arrange(avg_income)
```

```
## # A tibble: 6 x 2
##   degree                   avg_income
##   <chr>                         <dbl>
## 1 less than high school          8.08
## 2 <NA>                           8.45
## 3 high school                   10.3
## 4 associate/junior college      11.1
## 5 bachelor's                    11.3
## 6 graduate                      11.6
```

To see what income brackets 1-12 correspond to monetarily use `unique(gssdat$income_cat)`. Income bracket one is under $1,000, bracket two is $1,000 to $2,999 and so on.

```
unique(gssdat$incomecat)
```

```
##  [1] NA                   "$10,000 to $14,999" "$7,000 to $7,999"
##  [4] "$4,000 to $4,999"   "$1,000 to $2,999"   "$15,000 to $19,999"
##  [7] "$5,000 to $5,999"   "$20,000 to $24,999" "$3,000 to $3,999"
## [10] "under $1,000"       "$8,000 to $9,999"   "$25,000 or more"
## [13] "$6,000 to $6,999"
```

To sort the data from highest to lowest income bracket we can use `desc`. Notice that we use the numeric form of income here.

```r
gssdat |>
  group_by(degree) |>
  summarise(avg_income = mean(income, na.rm = TRUE)) |>
  arrange(desc(avg_income))
```

```
## # A tibble: 6 x 2
##   degree                    avg_income
##   <chr>                          <dbl>
## 1 graduate                        11.6
## 2 bachelor's                      11.3
## 3 associate/junior college        11.1
## 4 high school                     10.3
## 5 <NA>                             8.45
## 6 less than high school            8.08
```

3.7 Working with Text: `stringr` Functions

3.7.1 `str_detect()` — Find patterns in text

Many survey variables are stored as text (e.g., job titles, open-ended responses). Pattern matching helps you find specific entries. For example, we can find respondents whose job titles contain "teacher", "nurse", or "emergency".

```r
gssdat |>
  filter(str_detect(occ10, regex("teacher|nurse|emergency"))) |>
  select(age, incomecat, occ10) |>
  slice_sample(n = 10)
```

```
##    age          incomecat                                  occ10
## 1   59    $25,000 or more elementary and middle school teachers
## 2   58    $25,000 or more                     registered nurses
## 3   34    $25,000 or more   preschool and kindergarten teachers
## 4   37    $25,000 or more             secondary school teachers
## 5   41    $25,000 or more            special education teachers
## 6   23    $25,000 or more elementary and middle school teachers
## 7   36    $25,000 or more   preschool and kindergarten teachers
## 8   59    $25,000 or more                    teacher assistants
## 9   58 $20,000 to $24,999                     registered nurses
## 10  80 $15,000 to $19,999             secondary school teachers
```

In the above code the bar (|) is interpreted as `or`; asking do any of these terms appear? To filter based on the detection of a single string we do not need to use `regex` as below.

```r
gssdat |>
  filter(str_detect(occ10, "teacher")) |>
  select(age, incomecat, occ10) |>
  slice_sample(n = 10)
```

```
##    age          incomecat                                 occ10
## 1   74    $25,000 or more elementary and middle school teachers
## 2   52    $25,000 or more             secondary school teachers
## 3   59    $25,000 or more elementary and middle school teachers
## 4   56    $25,000 or more                    teacher assistants
## 5   38    $25,000 or more                    teacher assistants
## 6   33 $15,000 to $19,999                    teacher assistants
## 7   35    $25,000 or more             secondary school teachers
## 8   24    $25,000 or more                    teacher assistants
## 9   27    $25,000 or more             secondary school teachers
## 10  54    $25,000 or more             secondary school teachers
```

3.7.2 `str_replace()` — Clean up or standardize text

Standardizing text responses can make them easier to analyze. Cleaning up strings with repetition can also make analysis easier. For example, we can shorten the word miscellaneous to misc for brevity in the occupation variable.

```
gssdat |>
  filter(str_detect(occ10, "miscellaneous")) |>
  mutate(occ10 = str_replace(occ10, "miscellaneous", "misc")) |>
  select(occ10)  |>
  slice_sample(n = 10)
```

```
##                                                                    occ10
## 1  misc healthcare support occupations, including medical equipment preparers
## 2                                                  misc legal support workers
## 3                                                  misc legal support workers
## 4                                  misc health technologists and technicians
## 5                                                  misc legal support workers
## 6                           misc entertainment attendants and related workers
## 7                                             misc assemblers and fabricators
## 8                                                   misc agricultural workers
## 9                                                   misc agricultural workers
## 10                                            misc assemblers and fabricators
```

3.8 Career Readiness Connection

These skills mirror real-world research and data tasks:

- Filtering/selecting data is like narrowing a literature review to relevant studies.
- Creating variables mirrors coding qualitative data into categories.
- String matching is useful in cleaning resumes, job postings, or survey responses.

By starting with tidyverse now, you are learning tools that can directly transfer to internships, research assistant roles, and jobs involving data analysis.

4 Importing and Cleaning Data

In this section, you will learn how to import, inspect, and clean data using the **tidyverse**. These are the first steps in almost every data analysis project, and mastering them will help you prepare datasets for meaningful analysis.

4.1 Inspecting Data

We will continue using the **General Social Survey (GSS)** dataset introduced earlier. If you have not already loaded it, you can do so now. If you closed RStudio since the last section, reload the dataset before proceeding.

If you already have the `gssdat` dataset and `tidyverse` loaded from Section 1.2, you can skip this step. Otherwise, run the following code:

```
# load package
library(tidyverse)

# Load the GSS dataset from your working directory
gssdat <- read.csv("files/gssdat.csv")
```

Before cleaning data, it's important to understand what you have. Use these functions to explore the dataset:

```
# Number of rows and columns
dim(gssdat)
```

```
## [1] 75699    27
```

```
# First ten variable names
names(gssdat)
```

```
##  [1] "year"      "age"       "degree"    "income"    "occ10"     "incomecat"
##  [7] "trustfam"  "trustdoc"  "wrkstat"   "id"        "marital"   "agewed"
## [13] "conjudge"  "realrinc"  "hrs1"      "conpress"  "race"      "consci"
## [19] "fepol"     "happy"     "childs"    "health"    "realinc"   "coneduc"
## [25] "conlegis"  "sex"       "educ"
```

```
# Summary of one variable
summary(gssdat$age)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##   18.00   32.00   44.00   46.72   60.00   89.00     870
```

These simple checks help you identify issues such as missing values, inconsistent variable names, or unusual data entries.

4.2 Handling Missing Data

Missing values are common in survey data. They can appear as NA. Rows with missing data should not be removed unless if information is missing for all variables. Rather we can omit missing values as needed during the analysis. We already saw this in the previous section where we used `na.rm = TRUE` to calculate summary statistics (e.g. `mean`, `median`) on variables with missing values. Below are some examples of how we can also handle missing data:

```
# Count number of missing values in each column
gssdat |>
  is.na() |>
  colSums()
```

```
##      year       age    degree    income     occ10 incomecat  trustfam  trustdoc
##         0       870       199      9329      8447      9329     74321     74334
##   wrkstat        id   marital    agewed  conjudge  realrinc      hrs1  conpress
##        47         0        66     49156     26388     33366     32371     25474
##      race    consci     fepol     happy    childs    health   realinc   coneduc
##       172     27826     39112      4830       292     17251     10787     25135
##  conlegis       sex      educ
##     25853       131       286
```

```
# How many rows do not have a missing income bracket
gssdat |>
  filter(!is.na(income)) |>
  nrow()
```

```
## [1] 66370
```

Removing or recoding missing data helps avoid bias and ensures analyses run correctly. We can also summarize the number of missing values in one variable for each category of another variable. This may help us to discover any patterns in the missingness.

4.3 Reshaping Data

Sometimes variables are stored in a "wide" format but need to be "long" for analysis. The pivot_longer() function from `tidyr` changes wide data to long.

Suppose that we want to compare responses to trust questions across types. Below we compare types of trusts between trusting one's family versus their doctor.

```
# Example with two trust variables
gssdat |>
  select(trustfam, trustdoc) |>
  pivot_longer(cols = c(trustfam, trustdoc),
               names_to = "trust_type",
               values_to = "trust_level") |>
  group_by(trust_type, trust_level) |>
  summarize(count = n())
```

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

```
## # A tibble: 12 x 3
## # Groups:   trust_type [2]
##    trust_type trust_level   count
##    <chr>      <chr>         <int>
##  1 trustdoc   a great deal    400
##  2 trustdoc   completely      381
##  3 trustdoc   not at all       49
##  4 trustdoc   only a little    94
##  5 trustdoc   somewhat        441
##  6 trustdoc   <NA>          74334
##  7 trustfam   a great deal    242
##  8 trustfam   completely     1025
##  9 trustfam   not at all       17
## 10 trustfam   only a little    17
## 11 trustfam   somewhat         77
## 12 trustfam   <NA>          74321
```

We can also expand the data in one column based on another column using `pivot_wider()`. Suppose that we want to view the work status of respondents for surveys after 2020.

```
# widen workstatus by year
gssdat |>
  select(id, year, wrkstat) |>
  pivot_wider(names_from = year,
              values_from = wrkstat) |>
  select('2021', '2022', '2024') |>
  slice_sample(n = 10)
```

```
## # A tibble: 10 x 3
##    `2021`                                `2022`            `2024`
##    <chr>                                 <chr>             <chr>
##  1 retired                               working full time retired
##  2 <NA>                                  <NA>              <NA>
##  3 working full time                     working full time other
##  4 working part time                     keeping house     working full time
##  5 in school                             working full time working full time
##  6 working full time                     working part time retired
##  7 retired                               retired           working full time
##  8 retired                               working full time keeping house
##  9 <NA>                                  working full time working full time
## 10 unemployed, laid off, looking for work <NA>              <NA>
```

4.4 Recoding Values

Recoding helps combine categories or fix inconsistent entries.

```
# Combine 'separated' and 'divorced' into 'not married'
gssdat |>
  mutate(marital = recode(marital,
                          "separated" = "not married",
                          "divorced" = "not married")) |>
  count(marital)
```

```
##         marital     n
## 1       married 38959
## 2 never married 16963
## 3   not married 12706
## 4       widowed  7005
## 5          <NA>    66
```

```
# compare
gssdat |>
  count(marital)
```

```
##         marital     n
## 1      divorced 10158
## 2       married 38959
## 3 never married 16963
## 4     separated  2548
## 5       widowed  7005
## 6          <NA>    66
```

4.5 Career Readiness Connection

Data cleaning is a critical step in real-world research and professional work. The following career competencies were touched on in this section:

- **Technology**: Learning reproducible, code-based methods for preparing data.
- **Critical Thinking**: Deciding how to handle missing or inconsistent data involves judgment and awareness of the research context.
- **Equity and Inclusion**: Fair handling of missing responses and careful recoding can reduce bias in your analysis.

By mastering these skills, you will be able to prepare datasets for valid, trustworthy analysis. This is an essential ability in both academic research and data-driven careers.

5 Visualizing and Summarizing Data

5.1 Introduction

In this chapter, we learn to visualize and summarize data. You will learn about five types of graphs commonly used in the social sciences:

- Histograms
- Line graphs
- Scatterplots
- Bar charts
- Boxplots

These plots help us identify patterns, compare groups, and communicate findings clearly. Visualizations are especially useful for exploring relationships between variables while tables are useful for summarizing large datasets. We will again use the General Social Survey (GSS) data throughout this chapter.

If you have not already done so you can load the data and the `tidyverse` using the code below.

```
# load the package
library(tidyverse)

# load the data
gssdat <- read.csv("gssdat.csv")
```

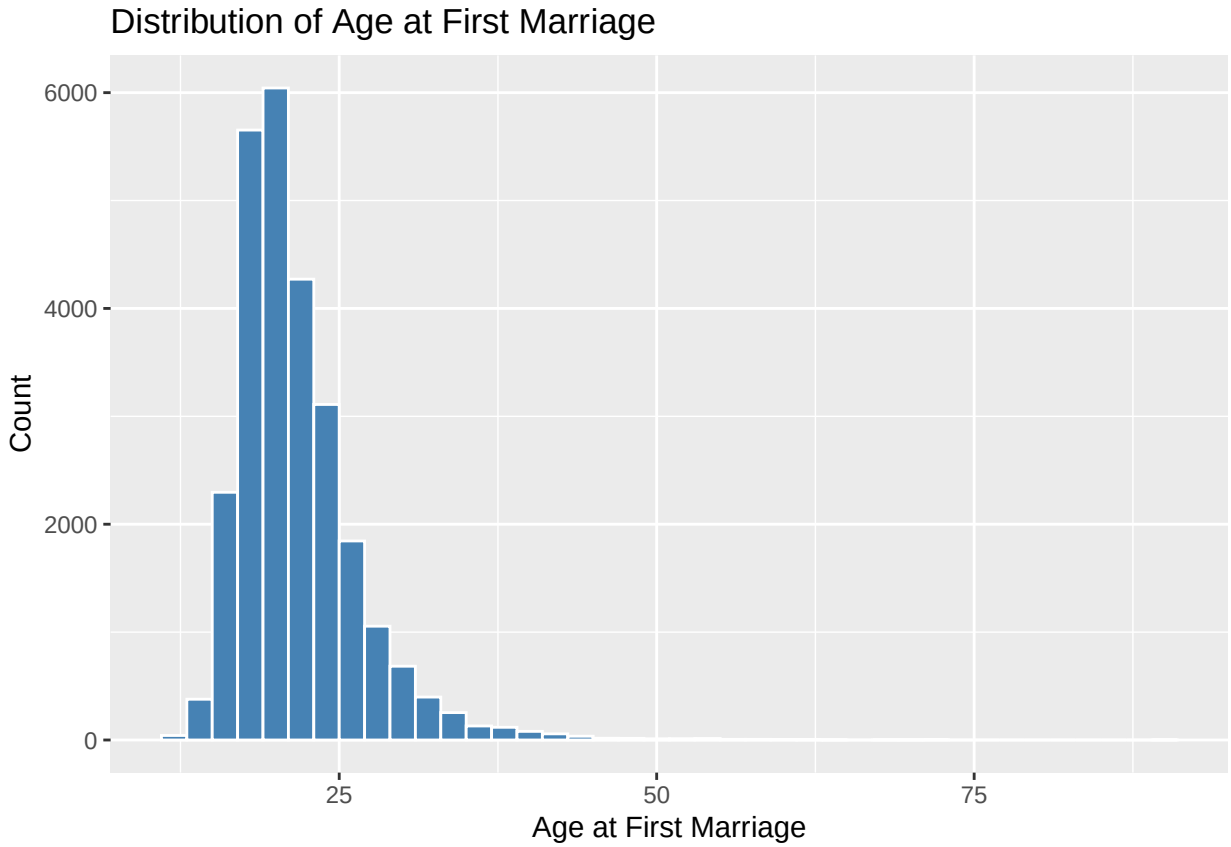
5.2 Histograms: Distributions of Numerical Variables

A **histogram** displays how often each range of values occurs for a numerical variable. They are useful for numerical variables that take a wide range of values. They tell us about the center, shape, and spread of the distribution.

Here we examine the distribution of age at first marriage (`agewed`):

```
gssdat |>
  ggplot(aes(x = agewed)) +
  geom_histogram(binwidth = 2, fill = "steelblue", color = "white") +
  labs(title = "Distribution of Age at First Marriage",
       x = "Age at First Marriage",
       y = "Count")
```

```
## Warning: Removed 49156 rows containing non-finite outside the scale range
## (`stat_bin()`).
```



We see that most respondents married in their early 20s. The histogram is slightly right-skewed since the outliers lie to the right. In this case the mean age at first marriage will be greater than the median age. We can impose the mean and median on the plots but first we must compute them using `summarize`.

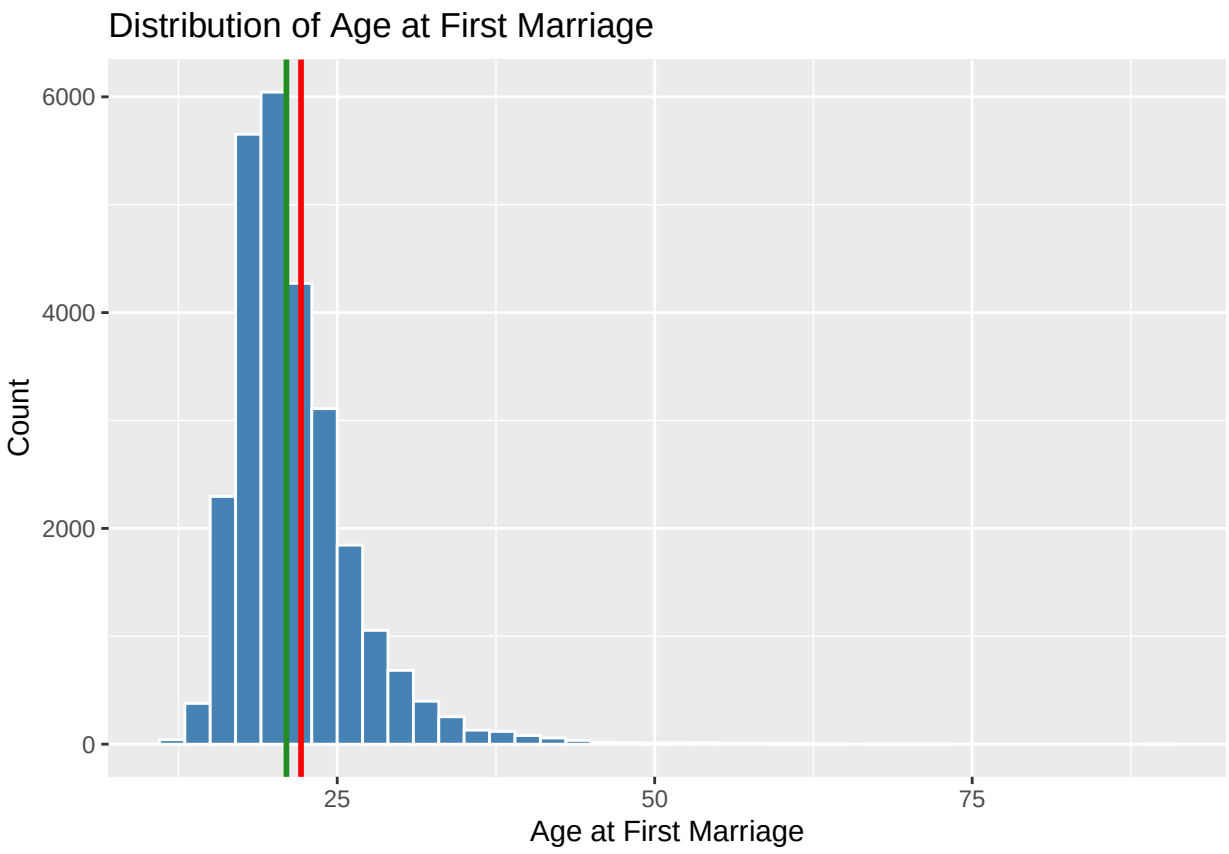
```
agewed_summary <- gssdat |>
  summarize(mean_age = mean(agewed, na.rm = TRUE),
            med_age = median(agewed, na.rm = TRUE))

agewed_summary
```

```
##   mean_age med_age
## 1 22.15006      21
```

To add the mean and median we use `geom_vline` which adds a vertical line to a plot at the specified x-intercept. For a horizontal line we would use `geom_hline`. Since we are using two different datasets in the same plot we need to specify the `agewed_summary` dataset in the `geom_vline` layer:

```
gssdat |>
  ggplot(aes(x = agewed)) +
  geom_histogram(binwidth = 2, fill = "steelblue", color = "white") +
  geom_vline(data = agewed_summary, aes(xintercept = mean_age), color = "red", linewidth = 1) +
  geom_vline(data = agewed_summary, aes(xintercept = med_age), color = "forestgreen", linewidth = 1) +
  labs(title = "Distribution of Age at First Marriage",
       x = "Age at First Marriage",
       y = "Count")
```

```
## Warning: Removed 49156 rows containing non-finite outside the scale range
## (‘stat_bin()‘).
```



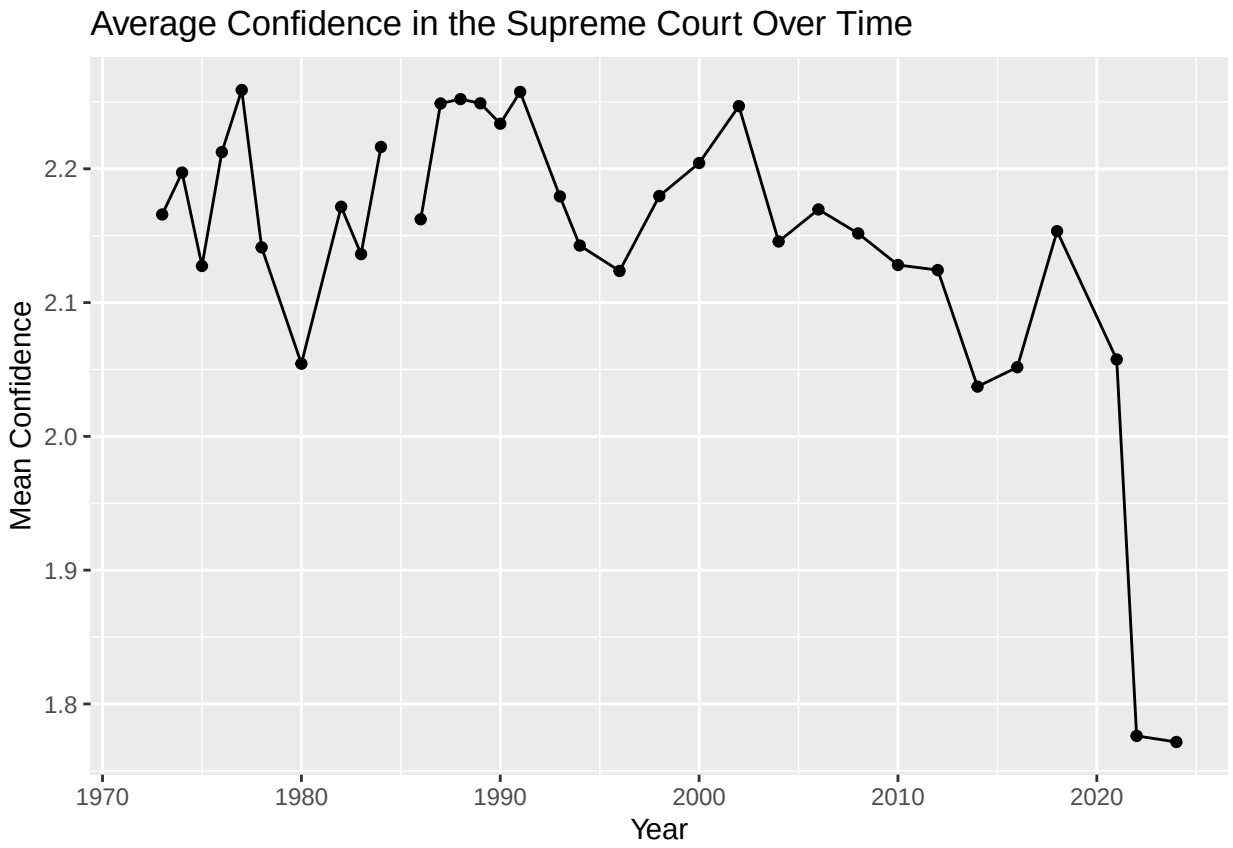
5.3 Line Graphs: Trends Over Time

Line graphs show how the value of a variable changes over time. For example, we can examine how average confidence in the U.S. Supreme Court (`conjudge`) has changed across survey years. We first mutate the data so that a one represents hardly any confidence and a three represent a great deal of confidence. Then, we calculate the summary table and pipe this into `ggplot`:

```
gssdat |>
  group_by(year) |>
  mutate(conjudge = recode(conjudge, `1` = 3L, `3` = 1L, `2` = 2L)) |>
  summarize(mean_conf = mean(conjudge, na.rm = TRUE)) |>
  ggplot(aes(x = year, y = mean_conf)) +
  geom_line() +
  geom_point() +
  labs(title = "Average Confidence in the Supreme Court Over Time",
       x = "Year",
       y = "Mean Confidence")
```

```
## Warning: Removed 1 row containing missing values or values outside the scale range
## (‘geom_line()‘).
```

```
## Warning: Removed 2 rows containing missing values or values outside the scale range
## (‘geom_point()‘).
```

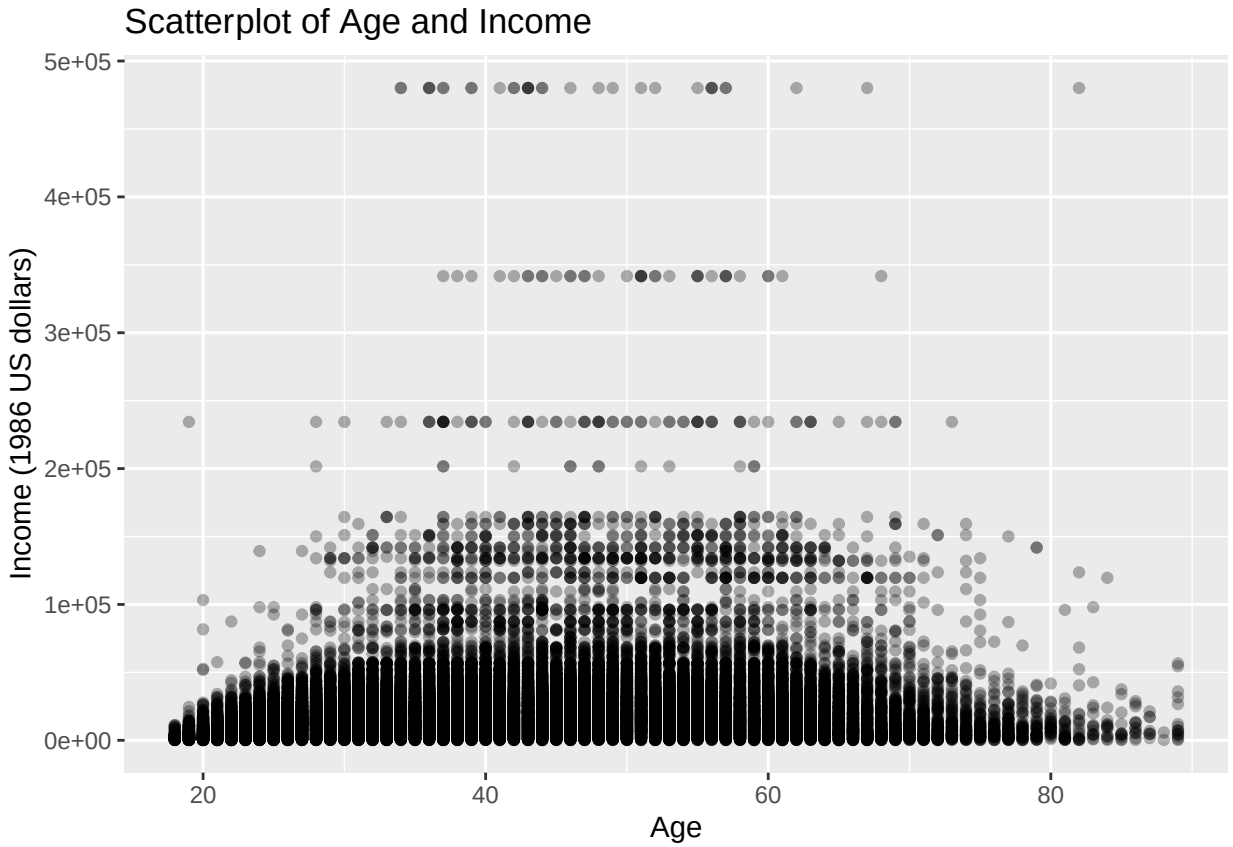


5.4 Scatterplots: Relationships Between Two Numerical Variables

Scatterplots help us examine relationships between two numerical variables. For example, we can compare age (`age`) and income in constant 1986 US dollars (‘realrinc“):

```
gssdat |>
  ggplot(aes(x = age, y = realrinc)) +
  geom_point(alpha = 0.3) +
  labs(title = "Scatterplot of Age and Income",
       x = "Age",
       y = "Income (1986 US dollars)")
```

```
## Warning: Removed 33608 rows containing missing values or values outside the scale range
## (‘geom_point()‘).
```



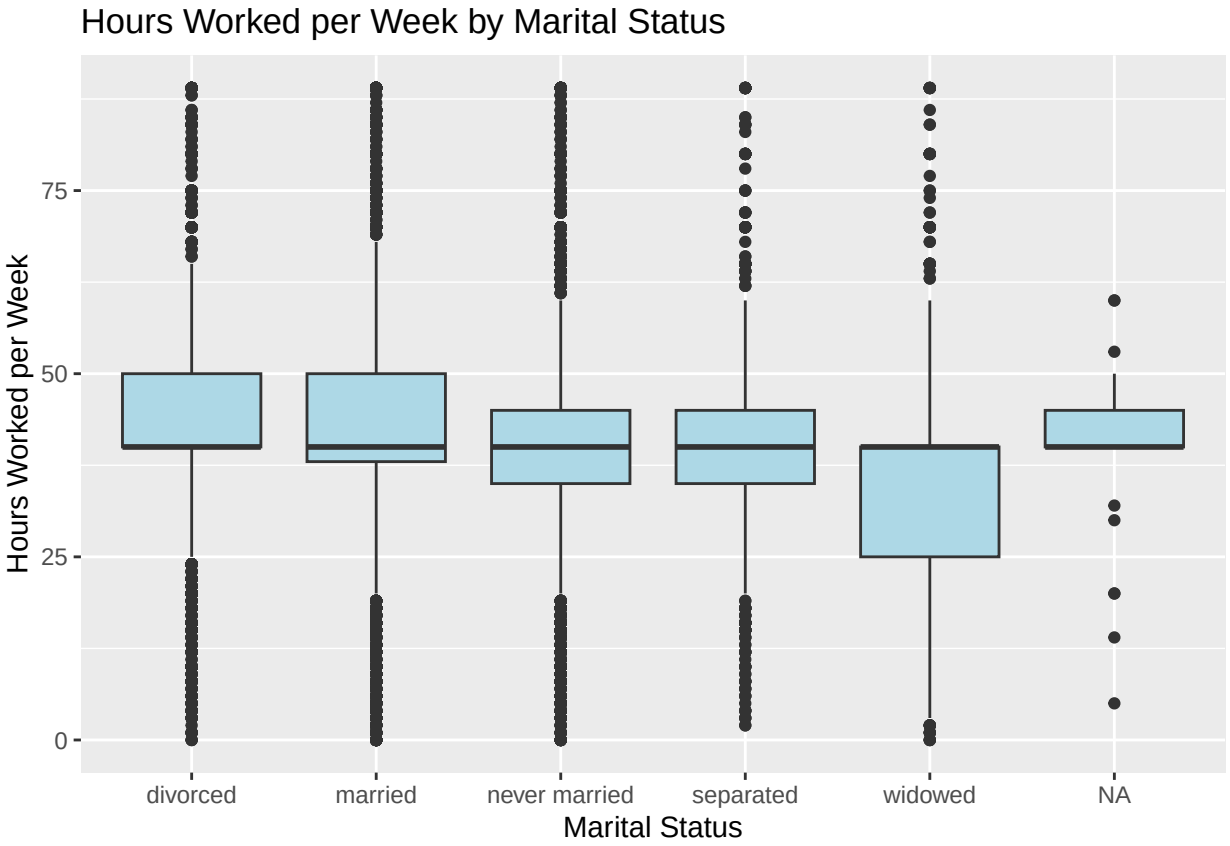
It seem that income is greater for respondents in their middle ages (30-70) while it is less for respondents whose ages are less than 30 or greater than 70.

5.5 Boxplots: Comparing Numerical Distributions Across Groups

Boxplots display the distribution of a numerical variable and are especially useful for comparing groups. We can compare medians (center bar), ranges (sides of box), and variability across categories. Outliers are plotted as actual points. Below we compare hours worked per week (`hrs1`) across marital status:

```
gssdat |>
  ggplot(aes(x = marital, y = hrs1)) +
  geom_boxplot(fill = "lightblue") +
  labs(title = "Hours Worked per Week by Marital Status",
       x = "Marital Status",
       y = "Hours Worked per Week")
```

```
## Warning: Removed 32371 rows containing non-finite outside the scale range
## (`stat_boxplot()`).
```



The distribution of hours worked is very similar for those never married and separated. It is actually a bit hard to determine which group has the highest work hours. Therefore a plot like this would be well accompanied by the summary table below:

```
gssdat |>
  group_by(marital) |>
  summarize(avg_hrs = mean(hrs1, na.rm = TRUE)) |>
  arrange(avg_hrs)
```

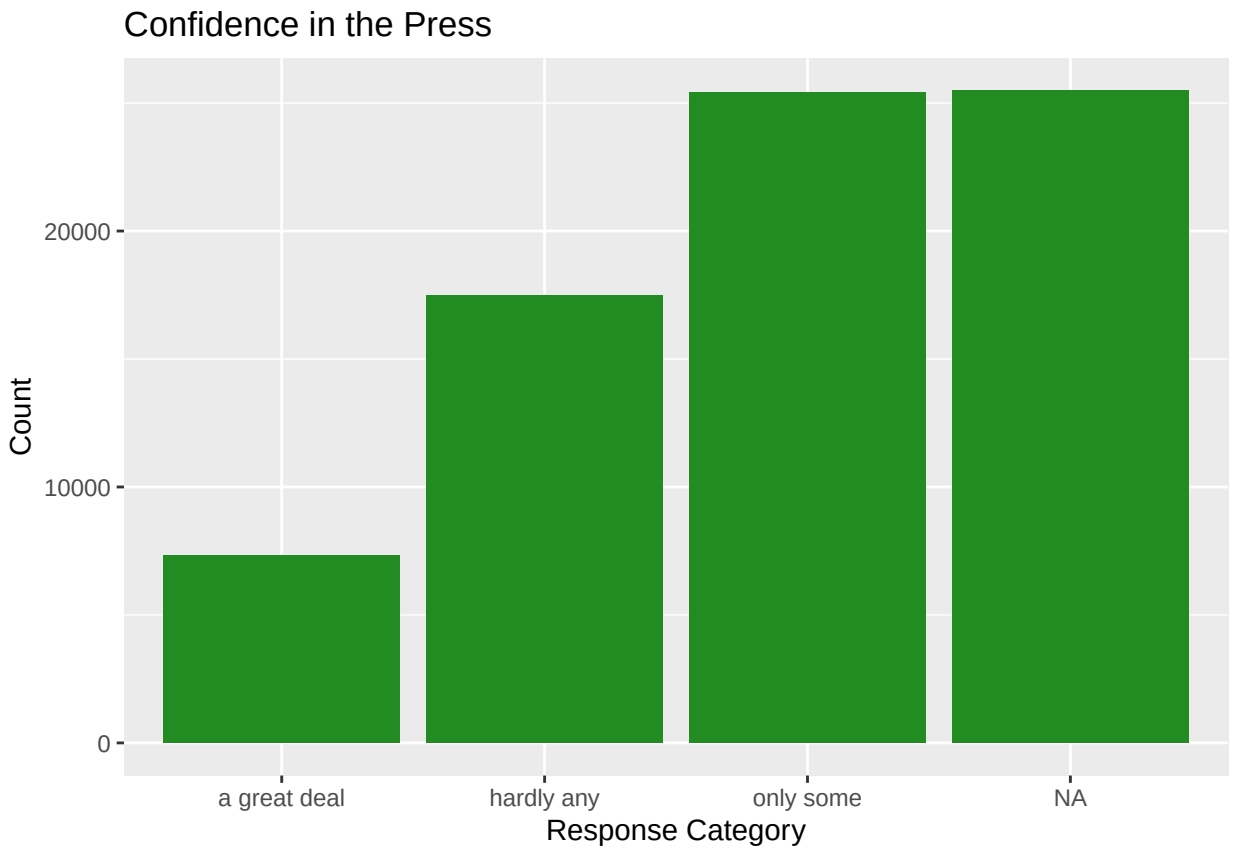
```
## # A tibble: 6 x 2
##   marital       avg_hrs
##   <chr>           <dbl>
## 1 widowed          35.3
## 2 <NA>             39.0
## 3 never married    40.0
## 4 separated        41.0
## 5 married          41.7
## 6 divorced         42.3
```

We see that divorced respondents reported the greatest working hours, on average, and those widowed reported the lowest.

5.6 Bar Charts: Summarizing Categorical Variables

Bar charts summarize counts or proportions for categorical variables. We look at confidence in the press (`conpress`) below:

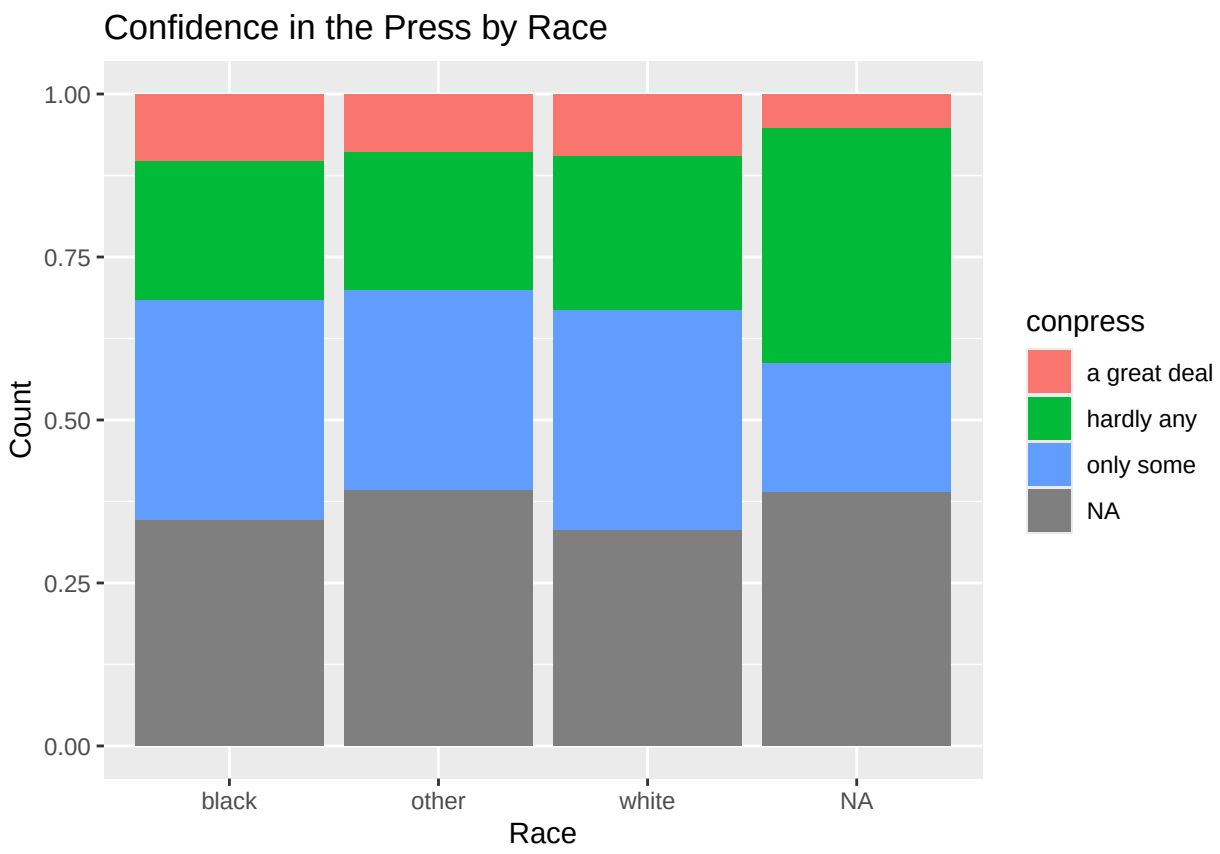
```
gssdat |>
  ggplot(aes(x = conpress)) +
  geom_bar(fill = "forestgreen") +
  labs(title = "Confidence in the Press",
       x = "Response Category",
       y = "Count")
```



5.7 Bar Charts with Group Comparisons

We can also compare responses across groups using side-by-side bar charts. For example, we examine confidence in the press by race (`race`) below:

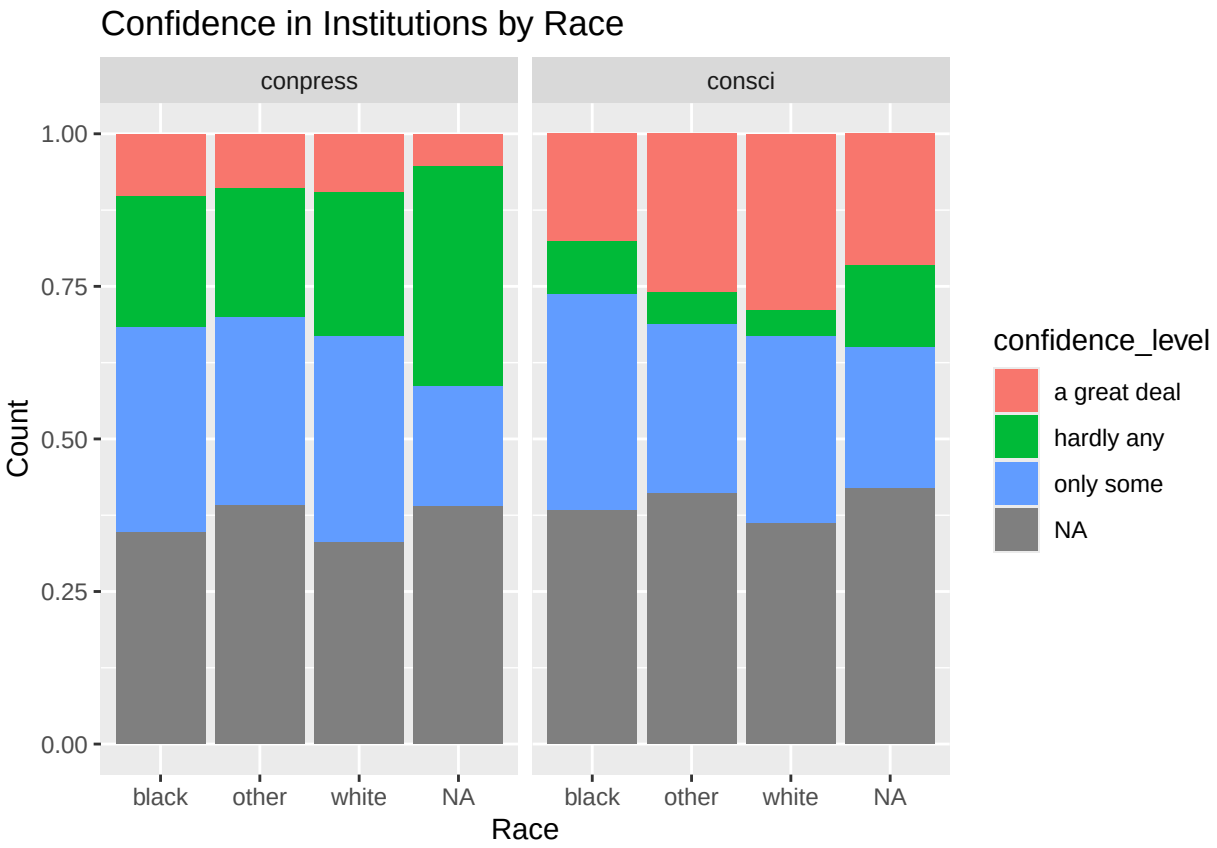
```
gssdat |>
  ggplot(aes(x = race, fill = conpress)) +
  geom_bar(position = "fill") +
  labs(title = "Confidence in the Press by Race",
       x = "Race",
       y = "Count")
```



5.8 Faceting: Small Multiples for Subgroup Comparisons

Faceting is a technique that creates multiple small plots for subgroups. Faceting is helpful when we want to examine subgroup differences without cluttering a single plot. For example, we reshape the dataset to analyze multiple confidence variables together. Below we use `pivot_longer` to gather several confidence variables into a long format before again making comparisons across races:

```
gssdat |>
  select(conpress, consci, race) |>
  pivot_longer(cols = c(conpress, consci),
               names_to = "confidence_type",
               values_to = "confidence_level") |>
  ggplot(aes(x = race, fill = confidence_level)) +
  geom_bar(position = "fill") +
  facet_wrap(~confidence_type) +
  labs(title = "Confidence in Institutions by Race",
       x = "Race",
       y = "Count")
```



There are higher rates of respondents indicating a great deal of confidence in science in comparison to the press. Individuals identifying as Black responded in this manner at a lower rate than all other groups though. There are quite a few missing values across all racial groups and confidence types (gray colored portion of the bars). The use of faceting has allowed to plot four variable (count, confidence level, confidence type, and race) simultaneously.

5.9 Summary

In this chapter, we practiced creating and interpreting five core visualization types:

- Histograms for distributions of numerical variables.
- Line graphs for trends over time.
- Scatterplots for relationships between two numerical variables.
- Boxplots for comparing numerical distributions across categories.
- Bar charts for summarizing categorical data and comparing groups.

We also learned to:

- Gather related variables into long format for grouped visualizations.
- Use stacked bar charts to compare categories.
- Apply faceting to explore subgroup patterns.

These tools are essential for exploring data in the social sciences and for communicating findings clearly and responsibly.

6 Practice Problems

6.1 RStudio

Complete each task below to familiarize yourself with RStudio:

1. Open the help file for the `mean` function with `?mean`.
2. Create a simple plot with `plot(1:5)`.
3. Change the RStudio theme using `Tools` → `Global Options` → `Appearance`

6.2 Tidyverse

Be sure to use the codebook for the GSS data subset provided at the author's GitHub page. It contains variable names and definitions which will be useful for completing practice activities involving the dataset. At times it may be best to use `slice_sample(n=10)` before knitting to avoid cumbersome output.

4. Select only the variables needed to explore whether people's views on whether women are not suited for politics (`fepol`) have changed over time (`year`). Return a random sample of 10 rows.
5. How many respondents in 2018 reported that they are "very happy"? Keep only that `year` and happiness category (`happy`). Return the resulting dataset with only the variables used for filtering.
6. Create a variable `above_med_inc` for whether a respondent's `income` bracket is above or below the median income bracket in the dataset. Return a sample of 10 rows from the resulting dataset containing only `income` and `above_med_inc`.
7. What is the average number of children (`childs`) for each `marital` status?
8. Arrange `marital` status categories by average `age` (oldest to youngest).
9. Find all respondents whose job title (`occ10`) includes "nurse" (case-insensitive). Return a random sample of 10 rows from the resulting dataset that contains only `occ10`, `income`, and `age`.
10. Replace "telephone" with "phone" in the occupation variable (`occ10`). Return a random sample of 10 rows from the resulting dataset that contains only `occ10` and `income` filtered to only those occupations whose titles incude "phone' '.
11. **Challenge** Define "young professionals" as respondents aged 25–40 whose occupation contains "manager," "teacher," or "engineer." How has the number of young professionals changed over time?

6.3 Cleaning

12. How many rows and columns does the dataset have? What type of variable is degree?
13. Create a new dataset that removes any rows with missing values for income. Return a random sample of 10 rows with the variables income and age
14. Use pivot_longer() to create a dataset with happy and health responses in a single column called response_type. Return a random sample of 10 rows of the resulting dataset with the two new variables.
15. In the happy variable, change "not too happy" to "unhappy" and return the counts for each category using this new level.
16. **Challenge:** Create a dataset with only respondents from 2010–2020, remove any rows with missing age, and then calculate the average age for each marital status.

6.4 Data Visualization and Summarization

17. Use `realinc` (respondent's inflation-adjusted income) to visualize the income distribution. Set binwidth = 10000, use a different fill and color, and add appropriate axis labels and a title. What shape does the income distribution take? Is it symmetric or skewed? Are there clusters or long tails that suggest income inequality?

18. Create a line graph to examine how confidence in the education system (`coneduc`) has changed across survey years. First mutate the data so that one represents hardly any confidence and three represents a great deal of confidence. Then group the data by year and calculate the mean value of `coneduc` for each year. Plot these averages as a line graph with points added along the line. Use a custom color to make the graph visually distinctive. Be sure to include a descriptive title as well as appropriate axis labels so that the plot is easy to interpret. Do you notice any periods where confidence in the education system increased or decreased sharply? How might these changes connect to historical or social events?

19. First create a stacked bar chart that shows the distribution of confidence in Congress (`conlegis`) responses by race, then facet this plot by sex Do changes in confidence in congress across races remain consistent across sexes?

20. Create a boxplot to compare education across different racial groups. Use years of education (educ) as the numerical variable and race (race) as the grouping variable. Add a descriptive title and axis labels to clarify the purpose of the visualization. If helpful for interpretation, you may also order the groups in a meaningful way (for example, by median education). Which racial group shows the highest median education level? Are the differences between groups large or small compared to the spread within each group?

7 Appendix: Shorter GSS Dataset Codebook

Variable	Label / Meaning	Type	Common Values / Categories
year	Survey year	Numeric	1972–2022
age	Respondent's age	Numeric	18–89+
degree	Highest degree earned	Ordinal	lt high school, high school, junior college, bachelor, graduate
income	Respondent's income	Numeric	Continuous, self-reported
occ10	Occupation code (2010 scheme)	Categorical	4-digit census occupation codes
incomecat	Income grouped into categories	Ordinal	low, middle, high (varies by coding)
trustfam	Trust in family	Ordinal	not at all, only some, a lot
trustdoc	Trust in doctors	Ordinal	not at all, only some, a lot
wrkstat	Labor force status	Categorical	working full-time, part-time, unemployed, retired
id	Respondent identifier	Numeric	Unique ID
marital	Marital status	Categorical	married, widowed, divorced, separated, never married
agewed	Age when first married	Numeric	15–80+
conjudge	Confidence in courts/judges	Ordinal	not at all, only some, a lot
realrinc	Respondent's income (1986 constant dollars)	Numeric	Continuous
hrs1	Hours worked last week	Numeric	0–80+
conpress	Confidence in press	Ordinal	not at all, only some, a lot
race	Race of respondent	Categorical	White, Black, Other
consci	Confidence in science	Ordinal	not at all, only some, a lot
fepol	Attitude: women suited for politics	Ordinal	agree, disagree
happy	General happiness	Ordinal	not too happy, pretty happy, very happy
childs	Number of children	Numeric	0–8+
health	Self-rated health	Ordinal	poor, fair, good, excellent
realinc	Family income (1986 constant dollars)	Numeric	Continuous
coneduc	Confidence in education system	Ordinal	not at all, only some, a lot
conlegis	Confidence in Congress	Ordinal	not at all, only some, a lot
sex	Respondent's sex	Categorical	male, female
educ	Years of education completed	Numeric	0–20+

8 Practice Solutions

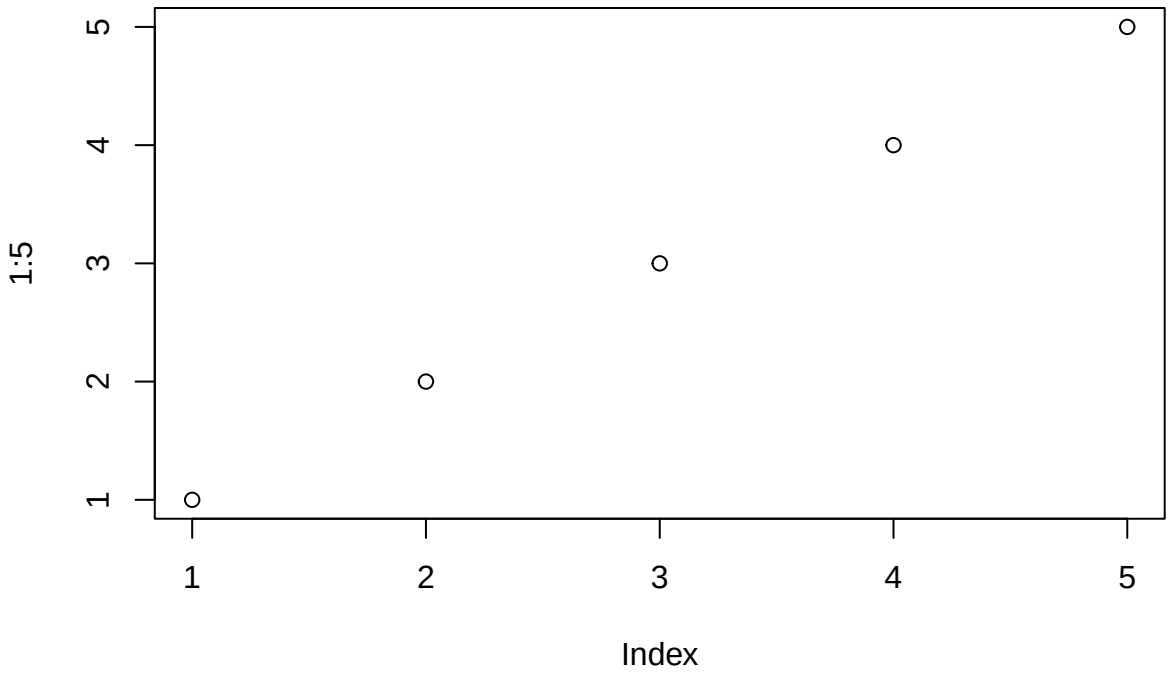
8.1 RStudio

1. Open the help file for the `mean` function with `?mean`.

```
?mean
```

2. Create a simple plot with `plot(1:5)`.

```
plot(1:5)
```



3. Change the RStudio theme using `Tools` → `Global Options` → `Appearance`

Use `Tools` → `Global Options` → `Appearance` to select an editor theme. Tomorrow Night Bright is a great option.

8.2 Tidyverse

4. Select only the variables needed to explore whether people's views on whether women are not suited for politics (`fepol`) have changed over time (`year`).

```
gssdat |>
  select(fepol, year) |>
  slice_sample(n = 10)
```

```
##       fepol year
## 1      <NA> 1991
```

```
## 2      <NA> 1984
## 3  disagree 2000
## 4      <NA> 2000
## 5     agree 1983
## 6      <NA> 2022
## 7     agree 2016
## 8      <NA> 2024
## 9      <NA> 1984
## 10 disagree 2018
```

5. How many respondents in 2018 reported that they are "very happy"? Keep only that `year` and happiness category (`happy`). Return the resulting dataset with only the variables used for filtering.

```
gssdat |>
  filter(year == 2018, happy == "very happy") |>
  select(year, happy) |>
  slice_sample(n = 10)
```

```
##    year      happy
## 1  2018 very happy
## 2  2018 very happy
## 3  2018 very happy
## 4  2018 very happy
## 5  2018 very happy
## 6  2018 very happy
## 7  2018 very happy
## 8  2018 very happy
## 9  2018 very happy
## 10 2018 very happy
```

6. Create a variable `above_med_inc` for whether a respondent's `income` bracket is above or below the median income bracket in the dataset. Return the resulting dataset containing only `income` and `above_med_inc`.

```
gssdat |>
  mutate(above_med_inc = income >= median(income, na.rm = TRUE)) |>
  select(above_med_inc, income) |>
  slice_sample(n = 10)
```

```
##    above_med_inc income
## 1          FALSE     10
## 2          FALSE      2
## 3           TRUE     12
## 4           TRUE     12
## 5          FALSE      8
## 6          FALSE     10
## 7           TRUE     12
## 8          FALSE      9
## 9           TRUE     12
## 10          TRUE     12
```

7. What is the average number of children (`childs`) for each `marital` status?

```r
gssdat |>
  group_by(marital) |>
  summarize(mean_child = mean(childs, na.rm = TRUE))
```

```
## # A tibble: 6 x 2
##   marital       mean_child
##   <chr>              <dbl>
## 1 divorced           2.09
## 2 married            2.26
## 3 never married      0.541
## 4 separated          2.60
## 5 widowed            2.73
## 6 <NA>               1.69
```

8. Arrange `marital` status categories by average `age` (oldest to youngest).

```r
gssdat |>
  group_by(marital) |>
  summarize(mean_age = mean(age, na.rm = TRUE)) |>
  arrange(desc(mean_age))
```

```
## # A tibble: 6 x 2
##   marital       mean_age
##   <chr>            <dbl>
## 1 widowed           70.3
## 2 <NA>              52.0
## 3 divorced          50.1
## 4 married           47.5
## 5 separated         44.5
## 6 never married     33.6
```

9. Find all respondents whose job title (`occ10`) includes "nurse" (case-insensitive). Return a random sample of 10 rows from the resulting dataset that contains only `occ10`, `income`, and `age`.

```r
gssdat |>
  filter(str_detect(occ10, "nurse")) |>
  select(occ10, income, age) |>
  slice_sample(n = 10)
```

```
##                                          occ10 income age
## 1  licensed practical and licensed vocational nurses     12  22
## 2                                registered nurses      9  77
## 3                                registered nurses     12  72
## 4                                registered nurses     12  77
## 5  licensed practical and licensed vocational nurses      7  54
## 6                                registered nurses     NA  80
## 7                                registered nurses      8  42
## 8  licensed practical and licensed vocational nurses      3  63
## 9                                registered nurses     NA  25
## 10 licensed practical and licensed vocational nurses      7  77
```

10. Replace "telephone" with "phone" in the occupation variable (`occ10`). Return the resulting dataset that contains only `occ10` and `income` filtered to only those occupations whose titles incude "phone' '.

```
gssdat |>
  mutate(occ10 = str_replace(occ10, "telephone", "phone")) |>
  select(occ10, income) |>
  filter(str_detect(occ10, "phone")) |>
  slice_sample(n = 10)
```

```
##              occ10 income
## 1  phone operators     NA
## 2  phone operators     NA
## 3  phone operators     10
## 4  phone operators      9
## 5  phone operators     NA
## 6  phone operators     NA
## 7  phone operators      3
## 8  phone operators     11
## 9  phone operators      7
## 10 phone operators     12
```

11. **Challenge** Define "young professionals" as respondents aged 25–40 whose occupation contains "manager," "teacher," or "engineer." How has the number of young professionals changed over time?

```
gssdat |>
  filter((age <= 40 | age >= 25) & str_detect(occ10, regex("manager|teacher|engineer"))) |>
  select(year, occ10) |>
  group_by(year) |>
  summarize(count = n())
```

```
## # A tibble: 34 x 2
##     year count
##    <int> <int>
##  1  1972   189
##  2  1973   171
##  3  1974   180
##  4  1975   147
##  5  1976   191
##  6  1977   183
##  7  1978   159
##  8  1980   191
##  9  1982   212
## 10  1983   205
## # i 24 more rows
```

8.3 Cleaning

12. How many rows and columns does the dataset have? What type of variable is degree?

```
dim(gssdat)
```

```
## [1] 75699    27
```

```
gssdat |>
  select(degree) |>
  glimpse()
```

```
## Rows: 75,699
## Columns: 1
## $ degree <chr> "bachelor's", "less than high school", "high school", "bachelor~
```

13. Create a new dataset that removes any rows with missing values for income. Return a dataset with the variables income and age.

```
gssdat |>
  filter(!is.na(income)) |>
  select(income, age) |>
  slice_sample(n = 10)
```

```
##    income age
## 1      12  NA
## 2      11  34
## 3      12  25
## 4       4  28
## 5      11  58
## 6       9  35
## 7      12  53
## 8       6  79
## 9      12  55
## 10     10  30
```

14. Use pivot_longer() to create a dataset with happy and health responses in a single column called response_type. Return the resulting dataset with the two new variables.

```
gssdat |>
  select(happy, health) |>
  pivot_longer(cols = c(happy, health),
               names_to = "response_type",
               values_to = "response") |>
  slice_sample(n = 10)
```

```
## # A tibble: 10 x 2
##    response_type response
##    <chr>         <chr>
##  1 health        excellent
##  2 happy         pretty happy
##  3 health        fair
##  4 health        <NA>
##  5 health        good
##  6 happy         very happy
##  7 happy         pretty happy
##  8 health        good
##  9 health        fair
## 10 health        excellent
```

15. In the happy variable, change "not too happy" to "unhappy" and return the counts for each category using this new level.

```
gssdat |>
  mutate(happy = recode(happy,
                        "not too happy" = "unhappy")) |>
  count(happy)
```

```
##          happy     n
## 1 pretty happy 39705
## 2      unhappy 10095
## 3   very happy 21069
## 4         <NA>  4830
```

16. **Challenge:** Create a dataset with only respondents from 2010–2020, remove any rows with missing age, and then calculate the average age for each marital status.

```
gssdat |>
  filter((year <= 2020 | year >= 2010) & !is.na(age)) |>
  group_by(marital) |>
  summarize(mean_age = mean(age))
```

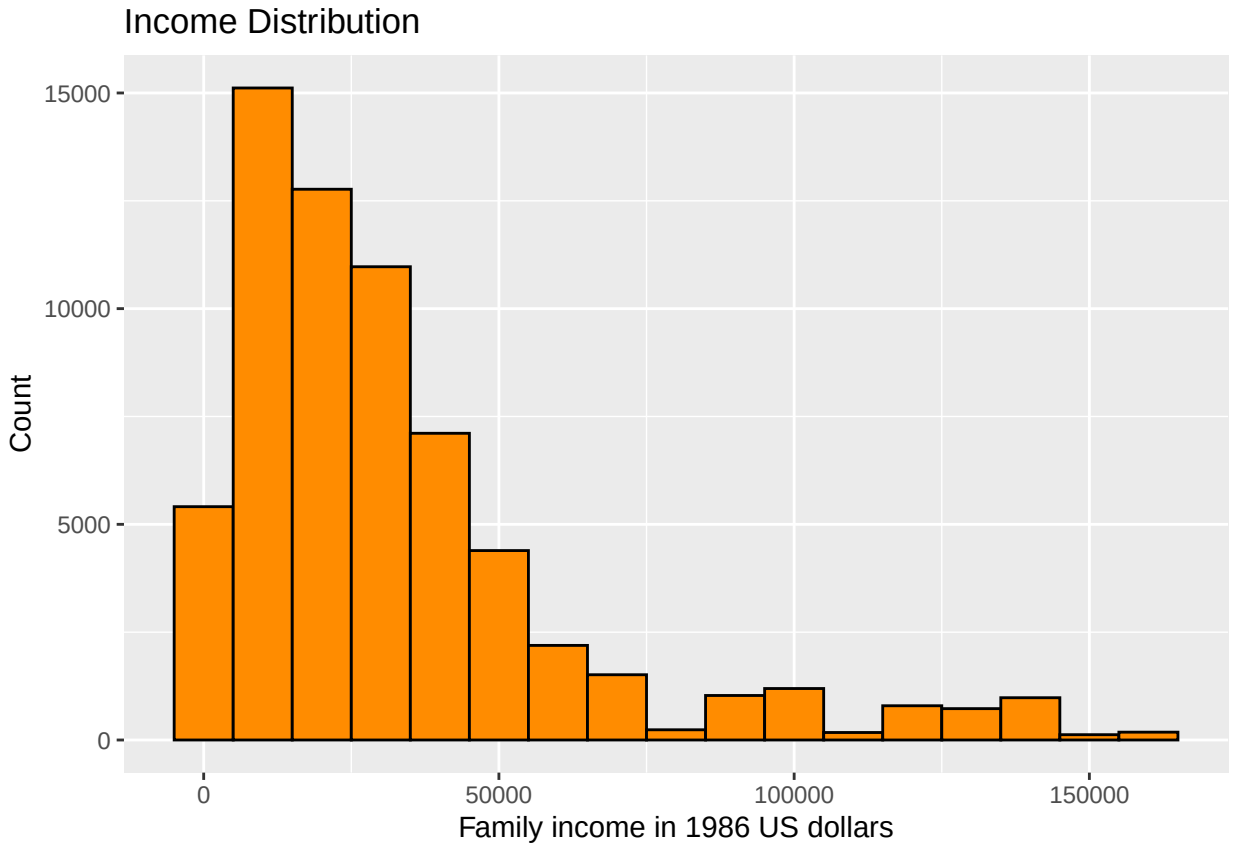
```
## # A tibble: 6 x 2
##   marital       mean_age
##   <chr>            <dbl>
## 1 divorced          50.1
## 2 married           47.5
## 3 never married     33.6
## 4 separated         44.5
## 5 widowed           70.3
## 6 <NA>              52.0
```

8.4 Data Visualization and Summarization

17. Use `realinc` (respondent's inflation-adjusted income) to visualize the income distribution. Set binwidth = 10000, use a different fill and color, and add appropriate axis labels and a title. What shape does the income distribution take? Is it symmetric or skewed? Are there clusters or long tails that suggest income inequality?

```
gssdat |>
  ggplot(aes(x = realinc)) +
  geom_histogram(fill = "darkorange", color = "black", binwidth = 10000) +
  labs(x = "Family income in 1986 US dollars", y = "Count", title = "Income Distribution")
```

```
## Warning: Removed 10787 rows containing non-finite outside the scale range
## (`stat_bin()`).
```

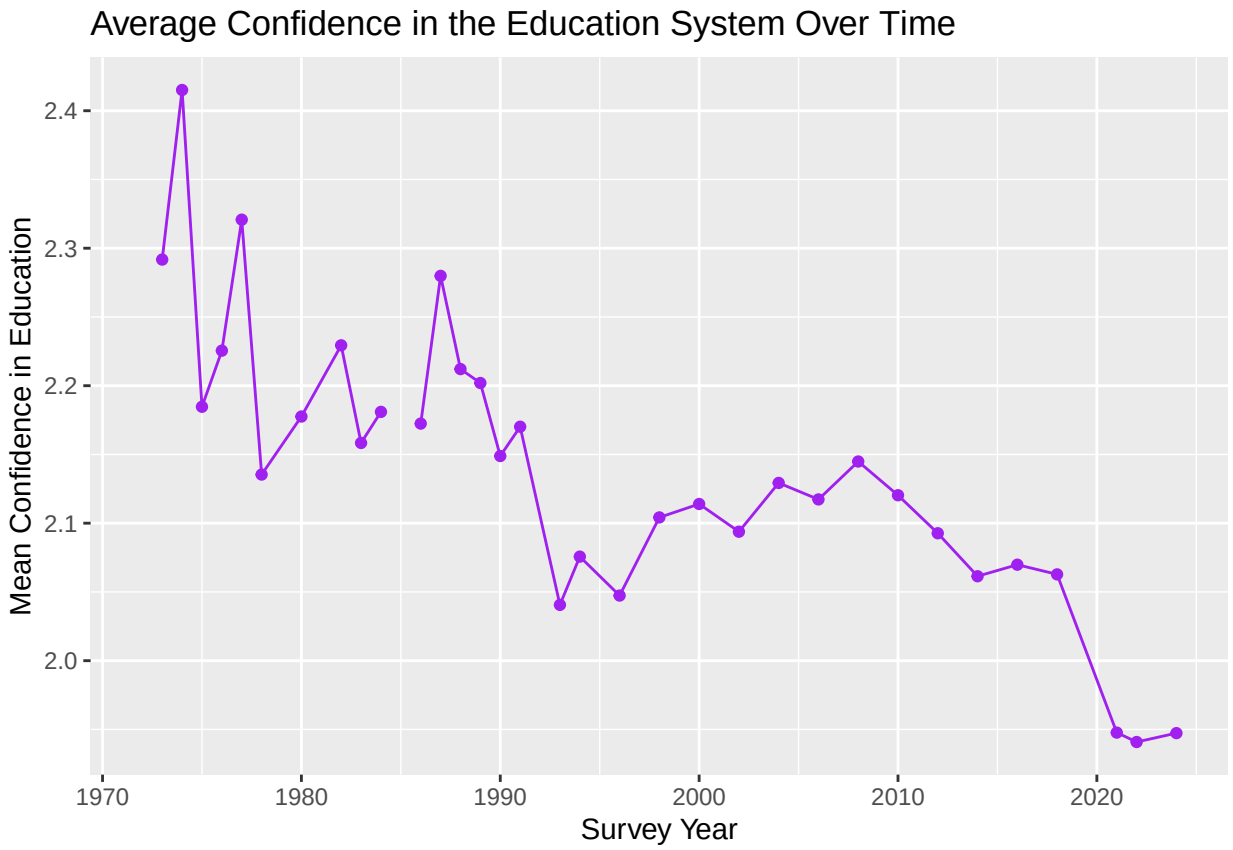


18. Create a line graph to examine how confidence in the education system (`coneduc`) has changed across survey years. First mutate the data so that one represents hardly any confidence and three represents a great deal of confidence. Then group the data by year and calculate the mean value of `coneduc` for each year. Plot these averages as a line graph with points added along the line. Use a custom color to make the graph visually distinctive. Be sure to include a descriptive title as well as appropriate axis labels so that the plot is easy to interpret. Do you notice any periods where confidence in the education system increased or decreased sharply? How might these changes connect to historical or social events?

```
gssdat %>%
  mutate(coneduc = recode(coneduc, `1` = 3L, `3` = 1L, `2` = 2L)) |>
  group_by(year) %>%
  summarise(mean_coneduc = mean(coneduc, na.rm = TRUE)) %>%
  ggplot(aes(x = year, y = mean_coneduc)) +
  geom_line(color = "purple") +
  geom_point(color = "purple") +
  labs(title = "Average Confidence in the Education System Over Time",
       x = "Survey Year",
       y = "Mean Confidence in Education")
```

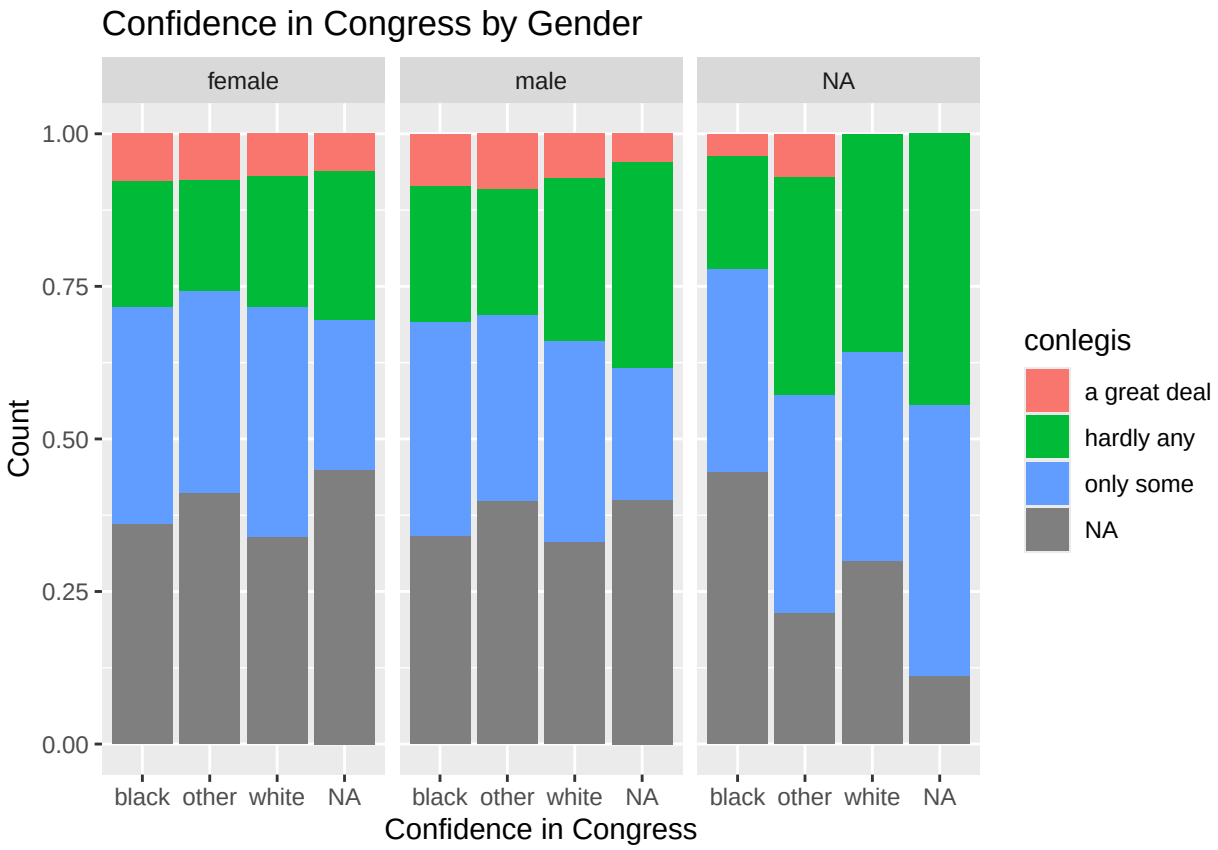
```
## Warning: Removed 1 row containing missing values or values outside the scale range
## (`geom_line()`).
```

```
## Warning: Removed 2 rows containing missing values or values outside the scale range
## (`geom_point()`).
```



19. First create a stacked bar chart that shows the distribution of confidence in Congress (`conlegis`) responses by race, then facet this plot by gender. Do changes in confidence in congress across races remain consistent across genders?

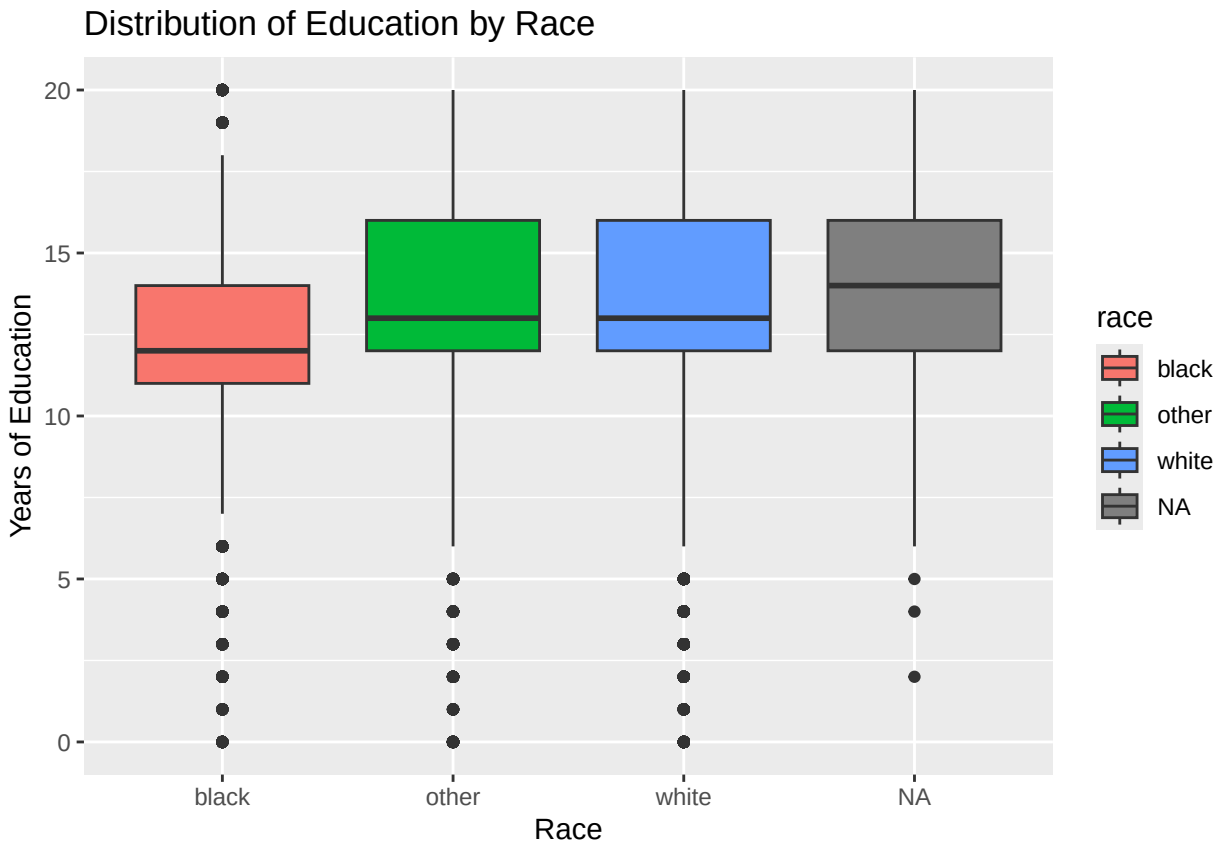
```
gssdat %>%
  ggplot(aes(x = race, fill = conlegis)) +
  geom_bar(position = "fill") +
  facet_wrap(~sex) +
  labs(title = "Confidence in Congress by Gender", x = "Confidence in Congress", y = "Count")
```



21. Create a boxplot to compare education across different racial groups. Use years of education (educ) as the numerical variable and race (race) as the grouping variable. Add a descriptive title and axis labels to clarify the purpose of the visualization. If helpful for interpretation, you may also order the groups in a meaningful way (for example, by median education). Which racial group shows the highest median education level? Are the differences between groups large or small compared to the spread within each group?

```
gssdat %>%
  ggplot(aes(x = race, y = educ, fill = race)) +
  geom_boxplot() +
  labs(
    title = "Distribution of Education by Race",
    x = "Race",
    y = "Years of Education"
  )
```

```
## Warning: Removed 286 rows containing non-finite outside the scale range
## (`stat_boxplot()`).
```


Distribution of Education by Race
Years of Education
20
15
10
5
0
black
other
white
NA
Race
race
black
other
white
NA