Part II. Continue. Case study

March 27, 2025

1 4 Case Study: ER Injuries

1.1 4.1 Introduction

To reinforce key concepts, we'll build a Shiny app exploring an ER injuries dataset. We'll start with data analysis outside Shiny, then gradually enhance the app.

First, let's install and load the required packages: **Shiny**, **vroom** (for fast file reading), and **tidyverse** (for data analysis).

[1]:
```r
library(shiny)

if (!requireNamespace("vroom", quietly = TRUE)) {
  install.packages("vroom")  # Install vroom package
}
library(vroom)

if (!requireNamespace("tidyverse", quietly = TRUE)) {
  install.packages("tidyverse")  # Install tidyverse package
}
library(tidyverse)
```

```
 Attaching core tidyverse packages                tidyverse
2.0.0
 dplyr     1.1.4      readr     2.1.5
 forcats   1.0.0      stringr   1.5.1
 ggplot2   3.5.1      tibble    3.2.1
 lubridate 1.9.4      tidyr     1.3.1
 purrr     1.0.4
 Conflicts
tidyverse_conflicts()
 readr::col_character()   masks
vroom::col_character()
 readr::col_date()        masks
vroom::col_date()
 readr::col_datetime()    masks
vroom::col_datetime()
 readr::col_double()      masks
vroom::col_double()
```

```
 readr::col_factor()      masks
vroom::col_factor()
 readr::col_guess()       masks
vroom::col_guess()
 readr::col_integer()     masks
vroom::col_integer()
 readr::col_logical()     masks
vroom::col_logical()
 readr::col_number()      masks
vroom::col_number()
 readr::col_skip()        masks
vroom::col_skip()
 readr::col_time()        masks
vroom::col_time()
 readr::cols()            masks
vroom::cols()
 readr::date_names_lang() masks
vroom::date_names_lang()
 readr::default_locale()  masks
vroom::default_locale()
 dplyr::filter()          masks
stats::filter()
 readr::fwf_cols()        masks
vroom::fwf_cols()
 readr::fwf_empty()       masks
vroom::fwf_empty()
 readr::fwf_positions()   masks
vroom::fwf_positions()
 readr::fwf_widths()      masks
vroom::fwf_widths()
 dplyr::lag()             masks
stats::lag()
 readr::locale()          masks
vroom::locale()
 readr::output_column()   masks
vroom::output_column()
 readr::problems()        masks
vroom::problems()
 Use the conflicted package
(<http://conflicted.r-lib.org/>) to force all conflicts to
become errors
```

2 4.2 The Data

We'll explore data from the **National Electronic Injury Surveillance System (NEISS)**, collected by the **Consumer Product Safety Commission**. This long-term study records accidents reported in a representative sample of U.S. hospitals.

It's an engaging dataset because it's familiar to most people, and each observation includes a **short narrative** describing the accident. More details are available at GitHub: hadley/neiss.

For this section, we'll focus on **2017 data**.
If you want to get the data on to your own computer, run this code:

[2]:
```
dir.create("neiss")
#> Warning in dir.create("neiss"): 'neiss' already exists
download <- function(name) {
  url <- "https://raw.github.com/hadley/mastering-shiny/main/neiss/"
  download.file(paste0(url, name), paste0("neiss/", name), quiet = TRUE)
}
download("injuries.tsv.gz")
download("population.tsv")
download("products.tsv")
```

```
Warning message in dir.create("neiss"):
"'neiss' already exists"
```

The main dataset we'll use is injuries, which contains around 250,000 observations:

[3]:
```
injuries <- vroom::vroom("neiss/injuries.tsv.gz")
injuries
```

```
Rows: 255064 Columns: 10
  Column specification

Delimiter: "\t"
chr  (6): sex, race, body_part, diag, location, narrative
dbl  (3): age, prod_code, weight
date (1): trmt_date

  Use `spec()` to retrieve the full column specification for this
data.
  Specify the column types or set `show_col_types = FALSE` to quiet
this message.
```

A spec_tbl_df: 255064 × 10

trmt_date	age	sex	race	body_part	diag
<date>	<dbl>	<chr>	<chr>	<chr>	<chr>
2017-01-01	71	male	white	Upper Trunk	Contusion Or Abrasion
2017-01-01	16	male	white	Lower Arm	Burns, Thermal
2017-01-01	58	male	white	Upper Trunk	Contusion Or Abrasion
2017-01-01	21	male	white	Lower Trunk	Strain, Sprain
2017-01-01	54	male	white	Head	Inter Organ Injury
2017-01-01	21	male	white	Hand	Fracture
2017-01-01	35	female	not stated	Lower Trunk	Strain, Sprain
2017-01-01	62	female	not stated	Lower Arm	Laceration
2017-01-01	22	male	not stated	Knee	Dislocation
2017-01-01	58	female	not stated	Lower Leg	Fracture
2017-01-01	69	female	not stated	Lower Trunk	Other Or Not Stated
2017-01-01	74	male	not stated	Knee	Strain, Sprain
2017-01-01	31	female	not stated	Head	Concussion
2017-01-01	83	female	not stated	Toe	Fracture
2017-01-01	38	female	not stated	Hand	Other Or Not Stated
2017-01-01	59	female	not stated	Shoulder	Other Or Not Stated
2017-01-01	34	male	not stated	Finger	Dislocation
2017-01-01	42	male	not stated	Lower Trunk	Contusion Or Abrasion
2017-01-01	96	male	not stated	Elbow	Laceration
2017-01-01	83	male	not stated	N.S./Unk	Other Or Not Stated
2017-01-01	31	male	not stated	Eyeball	Contusion Or Abrasion
2017-01-01	79	female	not stated	Wrist	Fracture
2017-01-01	2	male	not stated	Shoulder	Contusion Or Abrasion
2017-01-01	82	female	not stated	N.S./Unk	Other Or Not Stated
2017-01-01	33	female	not stated	Lower Trunk	Other Or Not Stated
2017-01-01	6	female	not stated	Upper Arm	Fracture
2017-01-01	22	female	not stated	Knee	Strain, Sprain
2017-01-01	87	female	not stated	Head	Inter Organ Injury
2017-01-01	45	female	not stated	Ankle	Other Or Not Stated
2017-01-01	58	female	not stated	Finger	Laceration
2017-11-29	4	male	not stated	Head	Inter Organ Injury
2017-11-29	12	female	not stated	Ankle	Strain, Sprain
2017-11-29	64	female	other	Knee	Dislocation
2017-11-29	79	male	hispanic	Head	Other Or Not Stated
2017-11-29	39	female	not stated	Knee	Strain, Sprain
2017-11-29	29	female	not stated	Upper Trunk	Other Or Not Stated
2017-11-29	13	female	not stated	Elbow	Strain, Sprain
2017-11-29	8	male	white	Toe	Strain, Sprain
2017-11-29	24	female	black	Foot	Other Or Not Stated
2017-11-30	15	male	not stated	Upper Trunk	Other Or Not Stated
2017-11-30	72	male	white	Toe	Fracture
2017-11-30	0	male	other	N.S./Unk	Other Or Not Stated
2017-11-30	59	male	black	Finger	Laceration
2017-11-30	24	male	white	Ankle	Other Or Not Stated
2017-11-30	1	male	not stated	Head	Other Or Not Stated
2017-11-30	3	female	not stated	Ear	Laceration
2017-11-30	0	female	not stated	Head	Contusion Or Abrasion
2017-11-30	77	male	not stated	Lower Trunk	Other Or Not Stated
2017-10-28	42	female	black	N.S./Unk	Other Or Not Stated
2017-10-28	59	male	black	Wrist	Other Or Not Stated

Each row in the dataset represents a single accident with **10 variables**:

- **trmt_date** – Date the person was seen in the hospital.
- **age, sex, race** – Demographic details of the injured person.
- **body_part** – Location of the injury (e.g., ankle, ear).
- **location** – Where the accident happened (e.g., home, school).
- **diag** – Basic diagnosis (e.g., fracture, laceration).
- **prod_code** – Product associated with the injury.
- **weight** – Estimated number of similar injuries in the U.S. population.
- **narrative** – Brief description of how the accident occurred.

We'll also use two additional datasets:
- **products** – Maps product codes to product names.
- **population** – Provides the U.S. population in 2017 by age and sex.

[4]:
```
products <- vroom::vroom("neiss/products.tsv")
products
```

```
Rows: 38 Columns: 2
  Column specification

Delimiter: "\t"
chr (1): title
dbl (1): prod_code

 Use `spec()` to retrieve the full column specification for this
data.
 Specify the column types or set `show_col_types = FALSE` to quiet
this message.
```

A spec_tbl_df: 38 × 2

prod_code	title
<dbl>	<chr>
464	knives, not elsewhere classified
474	tableware and accessories
604	desks, chests, bureaus or buffets
611	bathtubs or showers
649	toilets
676	rugs or carpets, not specified
679	sofas, couches, davenports, divans or st
1141	containers, not specified
1200	sports or recreational activity, n.e.c.
1205	basketball (activity, apparel or equip.)
1211	football (activity, apparel or equip.)
1233	trampolines
1242	slides or sliding boards
1244	monkey bars or other playground climbing
1267	soccer (activity, apparel or equip.)
1333	skateboards
1615	footwear
1616	jewelry
1807	floors or flooring materials
1817	porches, balconies, open-side floors or
1819	nails, screws, tacks or bolts
1842	stairs or steps
1871	fences or fence posts
1884	ceilings and walls (part of completed st
1893	doors, other or not specified
1894	windows & window glass, excl storm windo
3265	weight lifting (activity, apparel or equ
3274	swimming (activity, apparel or equipment
3299	exercise (activity or apparel, w/o equip
4014	furniture, not specified
4056	cabinets, racks, room dividers and shelv
4057	tables, not elsewhere classified
4074	chairs, other or not specified
4076	beds or bedframes, other or not spec
4078	ladders, other or not specified
5034	softball (activity, apparel or equipment
5040	bicycles and accessories (excl mountain
5041	baseball (activity, apparel or equipment

[5]:
```
population <- vroom::vroom("neiss/population.tsv")
population
```

```
Rows: 170 Columns: 3
  Column specification

Delimiter: "\t"
```

```
chr (1): sex
dbl (2): age, population

 Use `spec()` to retrieve the full column specification for this
data.
 Specify the column types or set `show_col_types = FALSE` to quiet
this message.
```

A spec_tbl_df: 170 × 3

age	sex	population
<dbl>	<chr>	<dbl>
0	female	1924145
0	male	2015150
1	female	1943534
1	male	2031718
2	female	1965150
2	male	2056625
3	female	1956281
3	male	2050474
4	female	1953782
4	male	2042001
5	female	1956268
5	male	2045050
6	female	1976331
6	male	2069201
7	female	1979376
7	male	2063003
8	female	1980666
8	male	2062172
9	female	2043456
9	male	2128715
10	female	2051237
10	male	2140682
11	female	2034143
11	male	2123819
12	female	2029693
12	male	2116260
13	female	2035757
13	male	2119558
14	female	2022552
14	male	2104753
70	female	1765955
70	male	1558707
71	female	1307666
71	male	1136177
72	female	1290521
72	male	1108765
73	female	1255382
73	male	1066091
74	female	1280269
74	male	1077532
75	female	1115294
75	male	923942
76	female	1019726
76	male	827432
77	female	959502
77	male	769612
78	female	894185
78	male	713055
79	female	853738
79	male	664775

3 4.3 Exploration

Before building the app, let's explore the data. We'll start with an interesting product: **649, "toilets"**.

First, we'll extract injuries related to this product.

[6]:
```
selected <- injuries %>% filter(prod_code == 649)
nrow(selected)
#> [1] 2993
```

2993

Next, we'll summarize **toilet-related injuries** by **location**, **body part**, and **diagnosis**.

We'll use the **weight** variable to estimate total injuries across the U.S.

[7]:
```
selected %>% count(location, wt = weight, sort = TRUE)
```

A spec_tbl_df: 6×2

location	n
<chr>	<dbl>
Home	99603.1282
Other Public Property	18662.8753
Unknown	16267.4425
School	658.9078
Street Or Highway	16.1828
Sports Or Recreation Place	14.7756

[8]:
```
selected %>% count(body_part, wt = weight, sort = TRUE)
```

A spec_tbl_df: 24 × 2

body_part	n
<chr>	<dbl>
Head	31369.8516
Lower Trunk	26854.9891
Face	13015.8050
Upper Trunk	12508.2622
Knee	6967.6275
N.S./Unk	6741.3277
Lower Leg	5086.5870
Shoulder	3590.4152
All Of Body	3437.8113
Ankle	3314.6366
Lower Arm	2921.3352
Upper Leg	2479.7206
Neck	2099.2340
Pubic Region	1969.4491
Finger	1897.9442
Hand	1866.8244
Upper Arm	1820.0949
Mouth	1682.5800
Wrist	1601.2997
Foot	1527.7118
Elbow	1290.1689
Toe	822.0298
Eyeball	195.7405
Ear	161.8659

[9]:
```
selected %>% count(diag, wt = weight, sort = TRUE)
```

A spec_tbl_df: 20 × 2

diag	n
<chr>	<dbl>
Other Or Not Stated	32896.9686
Contusion Or Abrasion	22493.3176
Inter Organ Injury	21525.4240
Fracture	21497.4841
Laceration	18734.4788
Strain, Sprain	7608.8992
Dislocation	2712.7536
Hematoma	2386.2644
Avulsion	1777.7466
Nerve Damage	1090.6113
Poisoning	927.9857
Concussion	822.1667
Dental Injury	198.9528
Hemorrhage	166.5358
Crushing	114.1257
Dermat Or Conj	84.2018
Burns, Not Spec	67.2099
Puncture	67.2099
Burns, Thermal	33.9838
Burns, Scald	16.9919

As expected, **toilet-related injuries** most often occur at home. The most common body parts suggest these are likely **falls** (since the head and face are rarely involved in routine toilet usage), and the diagnoses vary widely.

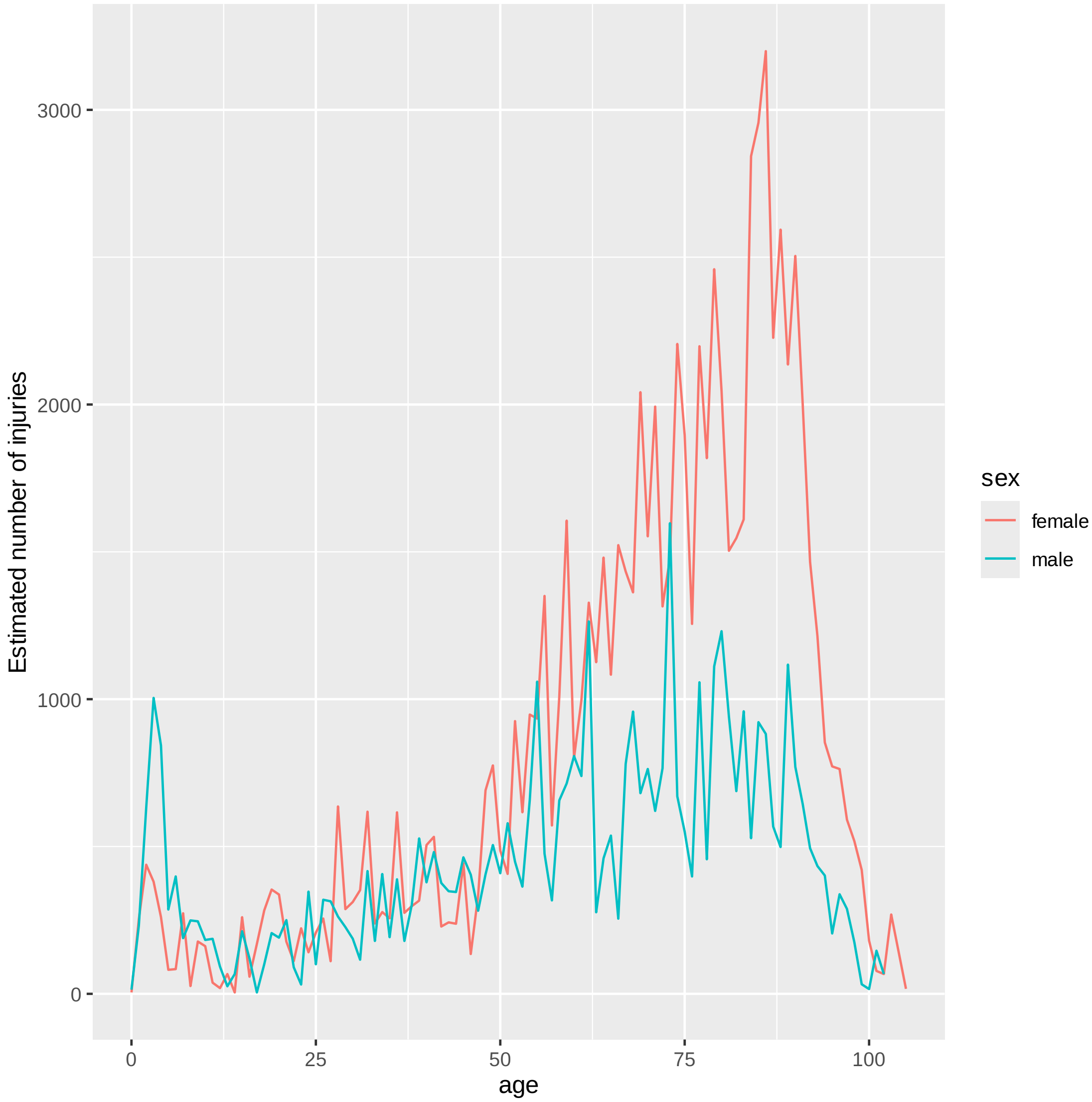
Next, we'll explore the injury patterns across **age** and **sex**. Given the amount of data, a table would be less helpful, so we'll create a plot to make the patterns more apparent.

[10]:
```
summary <- selected %>%
  count(age, sex, wt = weight)
summary
```

A spec_tbl_df: 208 × 3

age	sex	n
<dbl>	<chr>	<dbl>
0	female	4.7570
0	male	14.2710
1	female	253.3526
1	male	231.4887
2	female	438.1403
2	male	631.8107
3	female	380.6827
3	male	1004.2973
4	female	260.7669
4	male	842.9424
5	female	81.5684
5	male	286.1037
6	female	83.9301
6	male	398.3910
7	female	273.3854
7	male	189.0717
8	female	26.5059
8	male	249.1751
9	female	177.6361
9	male	246.1359
10	female	161.8302
10	male	182.8303
11	female	37.9317
11	male	186.7536
12	female	19.5326
12	male	92.5570
13	female	67.2099
13	male	25.6968
14	female	4.7570
14	male	67.2099
89	female	2135.8845
89	male	1117.2312
90	female	2504.1995
90	male	770.1125
91	female	2002.0119
91	male	644.3634
92	female	1466.2633
92	male	494.2811
93	female	1213.8332
93	male	433.6991
94	female	853.1754
94	male	401.5058
95	female	771.8488
95	male	204.9048
96	female	763.0160
96	male	337.9039
97	female	591.1458
97	male	288.2537
98	female	518.3817
98	male	175.3381

[11]:
```
summary %>%
  ggplot(aes(age, n, colour = sex)) +
  geom_line() +
  labs(y = "Estimated number of injuries")
```



The data reveals a **spike in injuries for young boys**, peaking at age 3, and an **increase for women** starting around middle age, with a gradual decline after age 80. The peak for young boys is likely due to the fact that they typically use the toilet standing up. The increase for women may be related to **osteoporosis** (women may experience injuries at the same rate as men, but more women end up in the ER due to their higher risk

One problem with interpreting this pattern is that we know there are fewer older people than younger people, so the population available to be injured is smaller. We can control for this by comparing the number of people injured with the total population and calculating an injury rate.

Here, I use a rate per 10,000.

[12]:
```
summary <- selected %>%
  count(age, sex, wt = weight) %>%
  left_join(population, by = c("age", "sex")) %>%
  mutate(rate = n / population * 1e4)

summary
```

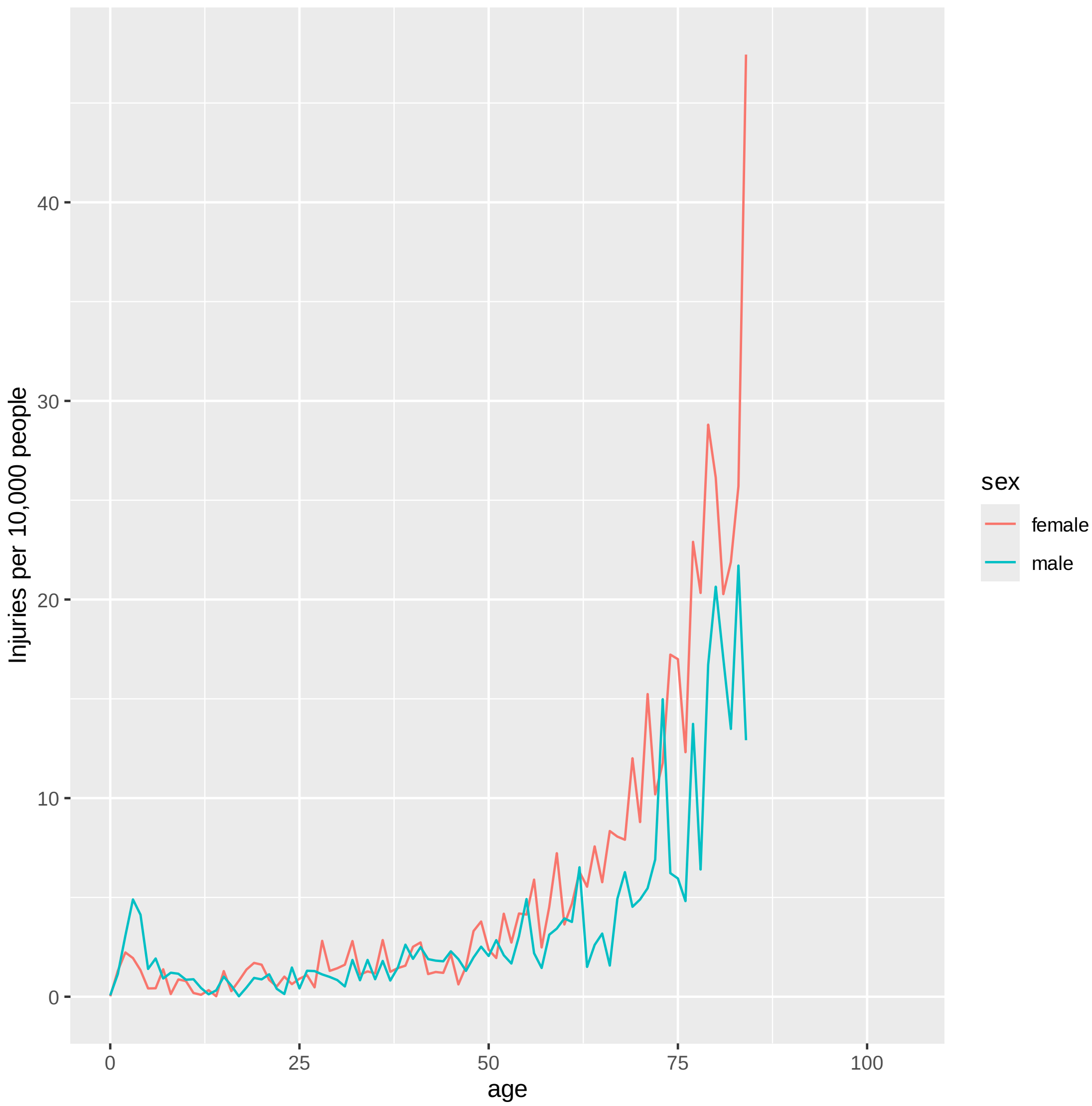
A tibble: 208 × 5

age	sex	n	population	rate
<dbl>	<chr>	<dbl>	<dbl>	<dbl>
0	female	4.7570	1924145	0.02472267
0	male	14.2710	2015150	0.07081855
1	female	253.3526	1943534	1.30356660
1	male	231.4887	2031718	1.13937417
2	female	438.1403	1965150	2.22955143
2	male	631.8107	2056625	3.07207537
3	female	380.6827	1956281	1.94595102
3	male	1004.2973	2050474	4.89787873
4	female	260.7669	1953782	1.33467756
4	male	842.9424	2042001	4.12802148
5	female	81.5684	1956268	0.41695923
5	male	286.1037	2045050	1.39900589
6	female	83.9301	1976331	0.42467633
6	male	398.3910	2069201	1.92533736
7	female	273.3854	1979376	1.38116962
7	male	189.0717	2063003	0.91648776
8	female	26.5059	1980666	0.13382317
8	male	249.1751	2062172	1.20831386
9	female	177.6361	2043456	0.86929251
9	male	246.1359	2128715	1.15626516
10	female	161.8302	2051237	0.78893955
10	male	182.8303	2140682	0.85407501
11	female	37.9317	2034143	0.18647509
11	male	186.7536	2123819	0.87932917
12	female	19.5326	2029693	0.09623426
12	male	92.5570	2116260	0.43736119
13	female	67.2099	2035757	0.33014697
13	male	25.6968	2119558	0.12123660
14	female	4.7570	2022552	0.02351979
14	male	67.2099	2104753	0.31932441
89	female	2135.8845	NA	NA
89	male	1117.2312	NA	NA
90	female	2504.1995	NA	NA
90	male	770.1125	NA	NA
91	female	2002.0119	NA	NA
91	male	644.3634	NA	NA
92	female	1466.2633	NA	NA
92	male	494.2811	NA	NA
93	female	1213.8332	NA	NA
93	male	433.6991	NA	NA
94	female	853.1754	NA	NA
94	male	401.5058	NA	NA
95	female	771.8488	NA	NA
95	male	204.9048	NA	NA
96	female	763.0160	NA	NA
96	male	337.9039	NA	NA
97	female	591.1458	NA	NA
97	male	288.2537	NA	NA
98	female	518.3817	NA	NA
98	male	175.3381	NA	NA

Plotting the **injury rate** reveals a different trend, especially after age 50. The difference between **men and women** becomes much smaller, and the decline seen in the raw data disappears.

This change is likely due to the fact that **women tend to live longer than men**, so at older ages, there are more women alive to be injured by toilets.

[13]:
```
summary %>%
  ggplot(aes(age, rate, colour = sex)) +
  geom_line(na.rm = TRUE) +
  labs(y = "Injuries per 10,000 people")
```



Finally, we can look at some of the narratives. Browsing through these is an informal way to check our hypotheses, and generate new ideas for further exploration. Here I pull out a random sample of 10:

[14]:
```
selected %>%
  sample_n(10) %>%
  pull(narrative)
```

1. '61YOF W/LUMBAR MUSCLE STRAIN. REPORTS WAS SITTING ON TOILET & WHEN SHEWENT TO STAND UP SHE HAD ACUTE ONSET OF LUMBAR PAIN.' 2. '70 YOF - SYNCOPE - PT WAS SITTING ON TOILET AND FELL @ HOME.' 3. '68YOF S/P FALL HIT HEAD ON TOILET FOUND ON FLOORDX:MECHANICAL FALL,BHT,LOW BACK STRAIN,CULT CONTS' 4. '77 YOM WITH SYNCOPE WHILE SITTING ON TOILET FELL AND STRUCK HIS HEAD ONTHE WALL DX NO INJURY' 5. '91YOF INJ/BP NS- STOOD FROM BEDSIDE TOILET, FELL ON BED' 6. '34YOF STANDING UP FROM TOILET AND PUT DIRECT WEIGHT ON R FOOT W SUDDENONSET OF R ANKLE AND LEG PAIN DX R LEG PAIN' 7. '28YOF CLSD HD INJ- SYNC & SEIZURE, FELL OFF TOILET ONTO FLOOR AT ***' 8. '42YOF HIP PAIN STANDING FROM TOILET' 9. '69YF AMB C CANE WAS ATTEMPTING TO LOWER SELF DOWN ON THE TOILET&MISSEDIT FALLING BWD»HUMRUS FX, HYPOTENSION' 10. '77YOF AT HOME TRYING TO GET UP FROM TOILET WITH WALKER LOST BALANCEFELL DX R KNEE SPRAIN MECH FALL, SEPSIS 2ND TO UTI'

Having explored the data for one product, it would be useful to repeat this process for other products without retyping the code each time.

So, let's build a **Shiny app** to easily explore different products!

4 4.4 Prototype

When building a complex app, it's best to start as simple as possible to confirm the basic mechanics work before adding complexity. For this app, we'll begin with one input (the product code), three tables, and one plot.

Designing the first prototype involves balancing simplicity with future flexibility. Too narrow a focus may require a lot of rework later, while over-planning could result in wasted effort. To strike this balance, I often sketch the **UI** and **reactive graph** on paper before committing to code.

For this prototype:
- **One row** for the input (with the understanding that more inputs may be added later)
- **One row** for the three tables, with each table taking up 4 columns (out of the 12-column width)
- **One row** for the plot

[15]:
```
prod_codes <- setNames(products$prod_code, products$title)

ui <- fluidPage(
  fluidRow(
    column(6,
      selectInput("code", "Product", choices = prod_codes)
    )
  ),
  fluidRow(
    column(4, tableOutput("diag")),
    column(4, tableOutput("body_part")),
```

```
    column(4, tableOutput("location"))
  ),
  fluidRow(
    column(12, plotOutput("age_sex"))
  )
)
```

The **server function** is straightforward. We first convert the selected and summary variables (from the previous section) into **reactive expressions**. This is a common approach: you create variables in your data analysis to break the process into steps, and avoid redundant computations, which reactive expressions help manage in Shiny apps.

It's often useful to spend some time cleaning up your analysis code before starting the Shiny app. This allows you to think through the problem in regular R code, without the added complexity of reactivity.

[16]:
```
server <- function(input, output, session) {
  selected <- reactive(injuries %>% filter(prod_code == input$code))

  output$diag <- renderTable(
    selected() %>% count(diag, wt = weight, sort = TRUE)
  )
  output$body_part <- renderTable(
    selected() %>% count(body_part, wt = weight, sort = TRUE)
  )
  output$location <- renderTable(
    selected() %>% count(location, wt = weight, sort = TRUE)
  )

  summary <- reactive({
    selected() %>%
      count(age, sex, wt = weight) %>%
      left_join(population, by = c("age", "sex")) %>%
      mutate(rate = n / population * 1e4)
  })

  output$age_sex <- renderPlot({
    summary() %>%
      ggplot(aes(age, rate, colour = sex)) +
      geom_line() +
      labs(y = "Estimated number of injuries")
  }, res = 96)
}
```

[17]:
```
shinyApp(ui, server)
```

```
Listening on http://127.0.0.1:6535
```

5 4.5 Polish Tables

Now that the basic components are working, we can progressively improve the app. One issue with the current app is that the tables display too much information. Instead, we likely just want to show the most important highlights.

To address this, we'll **truncate the tables**. We use a combination of **forcats** functions to: 1. Convert the variable to a factor 2. Order the levels by frequency 3. Lump together all levels after the top 5

This simplifies the tables, making them more focused and easier to interpret.

[18]:
```
injuries %>%
  mutate(diag = fct_lump(fct_infreq(diag), n = 5)) %>%
  group_by(diag) %>%
  summarise(n = as.integer(sum(weight)))
```

A tibble: 6 × 2

diag <fct>	n <int>
Other Or Not Stated	1806436
Fracture	1558961
Laceration	1432407
Strain, Sprain	1432556
Contusion Or Abrasion	1451987
Other	1929147

Now we automate this for any variable:

[19]:
```
count_top <- function(df, var, n = 5) {
  df %>%
    mutate({{ var }} := fct_lump(fct_infreq({{ var }}), n = n)) %>%
    group_by({{ var }}) %>%
    summarise(n = as.integer(sum(weight)))
}
```

Then we use this in the server function as follows:

[20]:
```
server <- function(input, output, session) {
  selected <- reactive(injuries %>% filter(prod_code == input$code))

  output$diag <- renderTable(count_top(selected(), diag), width = "100%")
  output$body_part <- renderTable(count_top(selected(), body_part), width =␣
↪"100%")
  output$location <- renderTable(count_top(selected(), location), width =␣
↪"100%")

  summary <- reactive({
    selected() %>%
```

```
      count(age, sex, wt = weight) %>%
      left_join(population, by = c("age", "sex")) %>%
      mutate(rate = n / population * 1e4)
  })

  output$age_sex <- renderPlot({
    summary() %>%
      ggplot(aes(age, n, colour = sex)) +
      geom_line() +
      labs(y = "Estimated number of injuries")
  }, res = 96)
}
```

[21]:
```
shinyApp(ui, server)
```

```
Listening on http://127.0.0.1:6535
```

6 4.6 Rate vs Count

So far, we've been displaying just a single plot. However, it would be useful to allow the user to choose between visualizing the **number of injuries** or the **population-standardized rate**.

To achieve this, we add a new control to the UI. We've chosen **selectInput()**, as it clearly presents both options and can easily accommodate additional options in the future.

[22]:
```
ui <- fluidPage(
  #<< first-row
  fluidRow(
    column(8,
           selectInput("code", "Product",
                       choices = setNames(products$prod_code, products$title),
                       width = "100%"
           )
    ),
    column(2, selectInput("y", "Y axis", c("rate", "count")))
  ),
  #>>
  fluidRow(
    column(4, tableOutput("diag")),
    column(4, tableOutput("body_part")),
    column(4, tableOutput("location"))
  ),
  fluidRow(
    column(12, plotOutput("age_sex"))
  )
```

```
)

count_top <- function(df, var, n = 5) {
  df %>%
    mutate({{ var }} := fct_lump(fct_infreq({{ var }}), n = n)) %>%
    group_by({{ var }}) %>%
    summarise(n = as.integer(sum(weight)))
}
```

We default to showing the **rate** because we think it's a safer choice; the user doesn't need to understand the population distribution to correctly interpret the plot.

Next, we condition the plot generation on the user's input, so that the plot updates based on whether they choose to display the **rate** or the **count**.

[23]:
```
server <- function(input, output, session) {
  selected <- reactive(injuries %>% filter(prod_code == input$code))

  #<< tables
  output$diag <- renderTable(count_top(selected(), diag), width = "100%")
  output$body_part <- renderTable(count_top(selected(), body_part), width =␣
↪"100%")
  output$location <- renderTable(count_top(selected(), location), width =␣
↪"100%")
  #>>

  summary <- reactive({
    selected() %>%
      count(age, sex, wt = weight) %>%
      left_join(population, by = c("age", "sex")) %>%
      mutate(rate = n / population * 1e4)
  })

  #<< plot
  output$age_sex <- renderPlot({
    if (input$y == "count") {
      summary() %>%
        ggplot(aes(age, n, colour = sex)) +
        geom_line() +
        labs(y = "Estimated number of injuries")
    } else {
      summary() %>%
        ggplot(aes(age, rate, colour = sex)) +
        geom_line(na.rm = TRUE) +
        labs(y = "Injuries per 10,000 people")
    }
  }, res = 96)
  #>>
```

```
}
```

[24]:
```
shinyApp(ui, server)
```

```
Listening on http://127.0.0.1:6535
```

7 4.7 Narrative

Finally, we want to provide a way to access the **narratives**, as they offer interesting insights and an informal way to cross-check hypotheses derived from the plots. While the R code samples multiple narratives at once, the app can allow for interactive exploration instead.

There are two parts to the solution:

1. **Add a new row** at the bottom of the UI.
2. Use an **action button** to trigger the display of a new narrative and show the narrative in a **textOutput()**.

[25]:
```
ui <- fluidPage(
  #<< first-row
  fluidRow(
    column(8,
           selectInput("code", "Product",
                       choices = setNames(products$prod_code, products$title),
                       width = "100%"
           )
    ),
    column(2, selectInput("y", "Y axis", c("rate", "count")))
  ),
  #>>
  fluidRow(
    column(4, tableOutput("diag")),
    column(4, tableOutput("body_part")),
    column(4, tableOutput("location"))
  ),
  fluidRow(
    column(12, plotOutput("age_sex"))
  ),
  #<< narrative-ui
  fluidRow(
    column(2, actionButton("story", "Tell me a story")),
    column(10, textOutput("narrative"))
  )
  #>>
)
```

```r
count_top <- function(df, var, n = 5) {
  df %>%
    mutate({{ var }} := fct_lump(fct_infreq({{ var }}), n = n)) %>%
    group_by({{ var }}) %>%
    summarise(n = as.integer(sum(weight)))
}
```

Then we use **eventReactive()** to create a reactive expression that only updates when:

1. The **button is clicked**.
2. The underlying **data changes**.

This ensures that the narrative is updated only when needed, optimizing performance and providing a more interactive experience for the user.

[26]:
```r
server <- function(input, output, session) {
  selected <- reactive(injuries %>% filter(prod_code == input$code))

  #<< tables
  output$diag <- renderTable(count_top(selected(), diag), width = "100%")
  output$body_part <- renderTable(count_top(selected(), body_part), width =␣
↪"100%")
  output$location <- renderTable(count_top(selected(), location), width =␣
↪"100%")
  #>>

  summary <- reactive({
    selected() %>%
      count(age, sex, wt = weight) %>%
      left_join(population, by = c("age", "sex")) %>%
      mutate(rate = n / population * 1e4)
  })

  #<< plot
  output$age_sex <- renderPlot({
    if (input$y == "count") {
      summary() %>%
        ggplot(aes(age, n, colour = sex)) +
        geom_line() +
        labs(y = "Estimated number of injuries")
    } else {
      summary() %>%
        ggplot(aes(age, rate, colour = sex)) +
        geom_line(na.rm = TRUE) +
        labs(y = "Injuries per 10,000 people")
    }
  }, res = 96)
  #>>
```

```
  #<< narrative-server
  narrative_sample <- eventReactive(
    list(input$story, selected()),
    selected() %>% pull(narrative) %>% sample(1)
  )
  output$narrative <- renderText(narrative_sample())
  #>>
}
```

[27]:
```
shinyApp(ui, server)
```

```
Listening on http://127.0.0.1:6535
```