Homework 3

Solutions

2026-01-05

Introduction

In this assignment you will practice (1) choosing appropriate plots based on variable type and analytic goal, and (2) using `dplyr` pipelines to move from raw data → transformed data → a final plot.

You will use two data sets:

- `ncbirths` (from the `openintro` package)
- `flights` (from the `nycflights13` package)

Use the following code chunk to load the necessary packages (`tidyverse`, `ggpubr` and `sjPlot`), and load the data listed above.

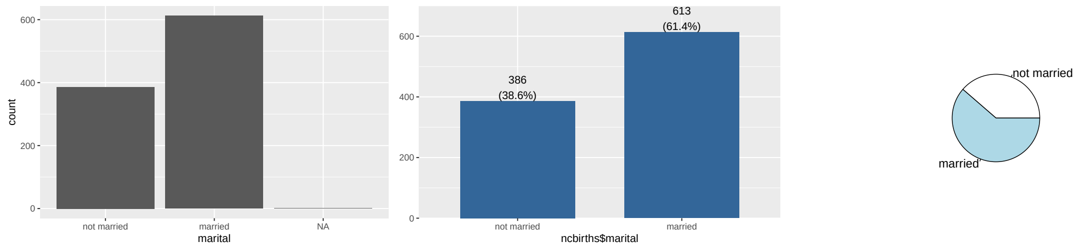
```
library(tidyverse)
library(ggpubr)
library(sjPlot)
library(gtsummary)
flights <- nycflights13::flights
ncbirths <- openintro::ncbirths
```

Part I: Creating plots (ncbirths)

1. Create appropriate visualizations for the `marital` status, and the mothers age (`mage`).

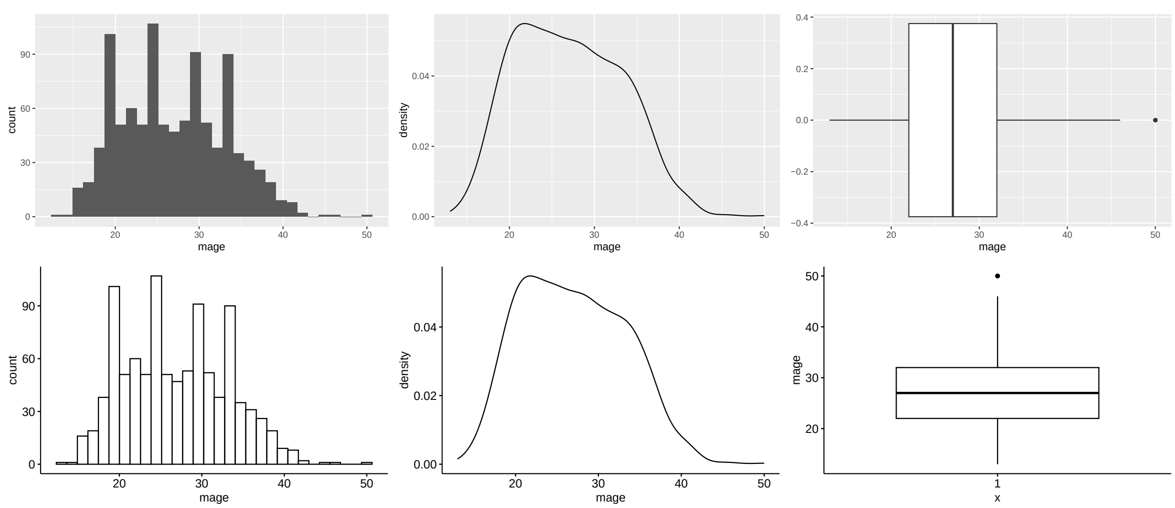
a. `marital` status

```
ggplot(ncbirths, aes(x = marital)) + geom_bar()
plot_frq(ncbirths$marital)
table(ncbirths$marital) |> pie()
```



b. Mothers age (`mage`)

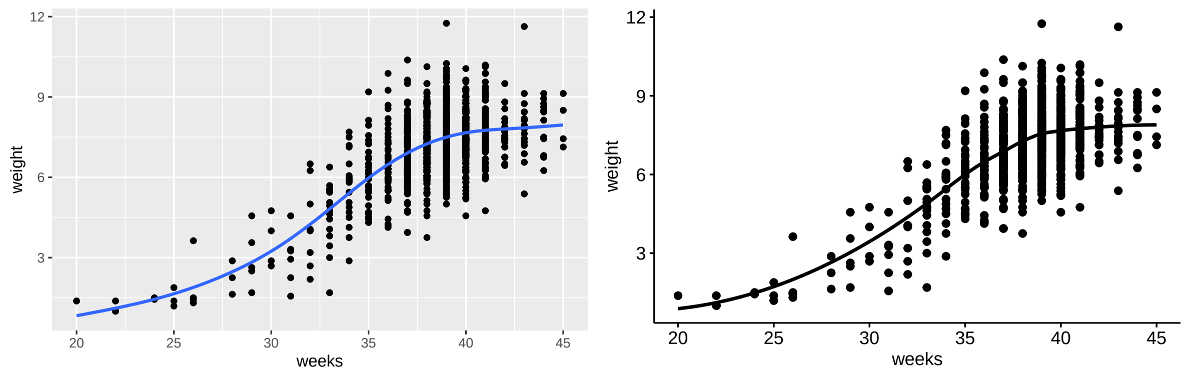
```
ggplot(ncbirths, aes(x = mage)) + geom_histogram()
ggplot(ncbirths, aes(x = mage)) + geom_density()
ggplot(ncbirths, aes(x = mage)) + geom_boxplot()
gghistogram(ncbirths, x="mage")
ggdensity(ncbirths, x="mage")
ggboxplot(ncbirths, y="mage")
```



2. Bivariate Relationships

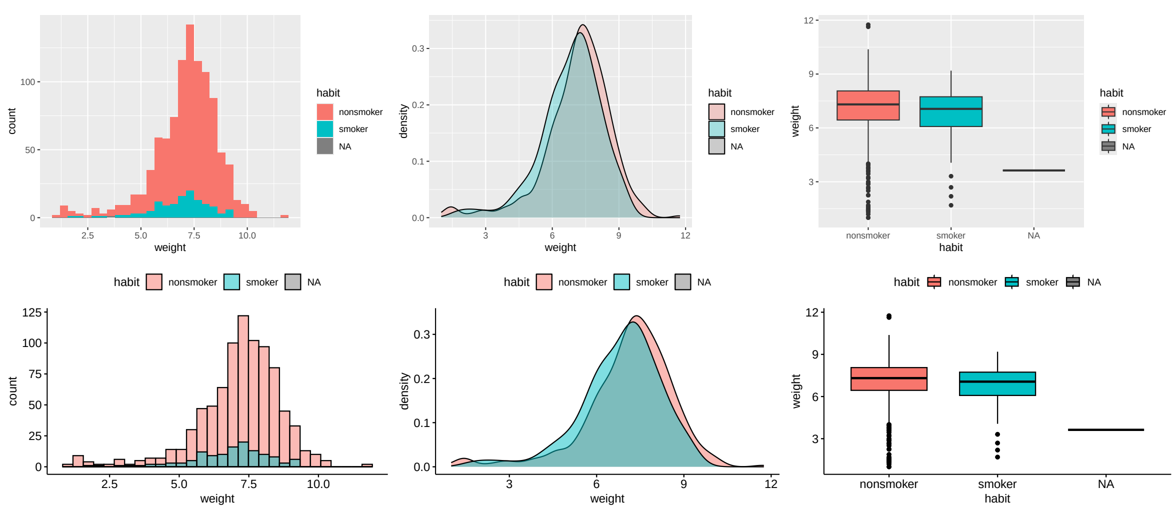
a. Is birth weight related to length of pregnancy? Create a scatterplot of `weight` versus `weeks`. Add **one** smoother to your plot (either a loess smoother *or* a linear model line).

```
ggplot(ncbirths, aes(x = weeks, y = weight)) +
  geom_point() + geom_smooth(se = FALSE)
ggscatter(ncbirths, x="weeks", y="weight", add = "loess")
```



b. Do babies of smokers tend to have different birth weights than babies of non-smokers? Create a plot that compares the distribution of `weight` across levels of `habit`.

```
ggplot(ncbirths, aes(x = weight, fill = habit)) + geom_histogram()
ggplot(ncbirths, aes(x = weight, fill = habit)) + geom_density(alpha = .3)
ggplot(ncbirths, aes(x = habit, y = weight, fill = habit)) +
  geom_boxplot()
gghistogram(ncbirths, x="weight", fill = "habit")
ggdensity(ncbirths, x="weight", fill = "habit")
ggboxplot(ncbirths, x = "habit", y = "weight", fill = "habit")
```



c. Does smoking habit differ by mothers maturity status? Create a table to display the distribution of smoking `habit` by the mothers maturity status (`mature`).

Characteristic	nonsmoker N = 873[1]	smoker N = 126[1]
mature		
mature mom	121 (92%)	11 (8.3%)
younger mom	752 (87%)	115 (13%)

[1] n (%)

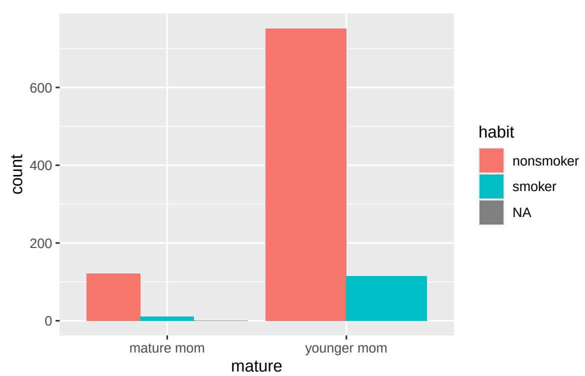
```
table(ncbirths$mature, ncbirths$habit) |> prop.table(margin=1)  |> round(3)
```

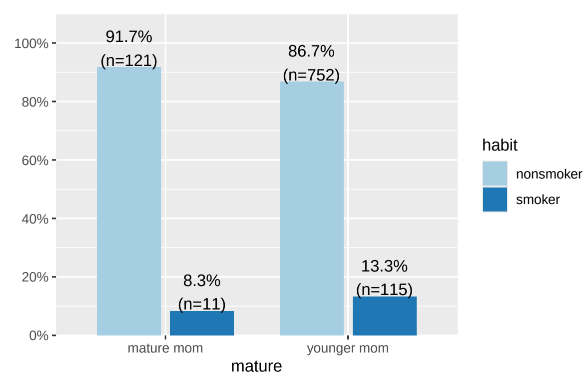
```
             nonsmoker smoker
  mature mom     0.917  0.083
  younger mom    0.867  0.133
```

```
tbl_summary(ncbirths, include = "mature", by = "habit", percent = "row")
```

d. Create a side by side bar chart that visually reflects the comparison above.

```
ggplot(ncbirths, aes(x=mature, fill=habit)) + geom_bar(position = "dodge")
plot_xtab(x = ncbirths$mature, grp = ncbirths$habit, show.total = "false",
          margin = "row")
```





Part II: Efficient Data Management → Plot (NYC Flights)

Each question starts with the full `flights` data set and will use multiple dplyr verbs so chaining is advised. Your final result should be shown as a printed tibble use `head()` for long output or a table where appropriate.

1. Create a new data set that contains only flights that:

- departed from **JFK**
- traveled at least **1000 miles**
- have non-missing `air_time`

Keep only the variables `origin`, `dest`, `distance`, and `air_time`. Then create a new variable called `speed` defined as `distance / air_time * 60`. Finally, sort from fastest to slowest `speed` and display the first 10 rows.

```
flights %>%
  filter(origin == "JFK", distance >= 1000, !is.na(air_time)) %>%
  select(origin, dest, distance, air_time) %>%
  mutate(speed = distance / air_time * 60) %>%
  arrange(desc(speed)) %>%
  head(10)
```

```
# A tibble: 10 x 5
   origin dest  distance air_time speed
   <chr>  <chr>    <dbl>    <dbl> <dbl>
 1 JFK    SJU       1598      170  564
 2 JFK    SJU       1598      172  557.
 3 JFK    STT       1623      175  556.
 4 JFK    SJU       1598      173  554.
 5 JFK    SJU       1598      173  554.
 6 JFK    SJU       1598      173  554.
 7 JFK    SJU       1598      173  554.
 8 JFK    SJU       1598      173  554.
 9 JFK    SJU       1598      173  554.
10 JFK    SJU       1598      173  554.
```

2. What are the most popular destinations?

> This question is broken down into a few smaller parts to help you ensure that you are on the right track before moving to the next step. Only add one command at a time and "trust but verify" to make sure your code works as intended. You do not need to report the results of each step, just the final result.

a. Use `filter()` to keep only flights with a non-missing distance, then `group_by(origin, dest)` to group the data by origin first, then destination within origin.
b. Use `summarise()` to calculate, for each origin–destination pair:

   - the number of flights as `n_flights`

- the average distance as `avg_distance`

c. Keep only the top 3 destination using `slice_head(n=3)` after sorting by the number of flights.
d. Use `relocate()` so the columns appear in the order: `origin`, `dest`, `avg_distance`, `n_flights`, and display the resulting table.

```
flights %>%
  filter(!is.na(distance)) %>%
  group_by(origin, dest) %>%
  summarise(
    n_flights = n(),
    avg_distance = mean(distance)) %>%
  arrange(desc(n_flights)) %>%
  slice_head(n=3) %>%
  relocate(n_flights, .after = last_col())
```

```
# A tibble: 9 x 4
# Groups:   origin [3]
  origin dest  avg_distance n_flights
  <chr>  <chr>        <dbl>     <int>
1 EWR    ORD            719      6100
2 EWR    BOS            200      5327
3 EWR    SFO           2565      5127
4 JFK    LAX           2475     11262
5 JFK    SFO           2586      8204
6 JFK    BOS            187      5898
7 LGA    ATL            762     10263
8 LGA    ORD            733      8857
9 LGA    CLT            544      6168
```

Challenge question

or plot distribution of daily average departure delays

Does one month have more delays on average than others? Starting from the `flights` data set group by day, use `case_when()` to create a new variable called `dep_delay_cat` based on `dep_delay`.

- Create **at least three categories**

- Choose and briefly describe your cutoff values
- Use category names that correspond to intuitive delay types (e.g., “short,” “medium,” “long”).
- A reasonable approach is to look at the distribution of the departure delay first (histogram), then choose cutoffs based on where the distribution naturally changes.

Verify that your categories make sense by creating a plot that compares `dep_delay_cat` across levels of `dep_delay`.