p8105_hw3_rk3445

Rosie Kwon

```r
library(tidyverse)
```

```
## -- Attaching core tidyverse packages ------------------------ tidyverse 2.0.0 --
## v dplyr     1.1.4     v readr     2.1.5
## v forcats   1.0.0     v stringr   1.5.1
## v ggplot2   3.5.2     v tibble    3.3.0
## v lubridate 1.9.4     v tidyr     1.3.1
## v purrr     1.1.0
## -- 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
```

```r
library(patchwork)
```

Problem 1

```r
library(p8105.datasets)
data("instacart")
```

The `instacart` dataset provides item-level records of customer grocery orders from the Instacart delivery service. This dataset contains 1384617 observations and 15 variables (columns), where each row represents a single product within an order.

Key variables in the dataset are following:

```r
user =
  instacart |>
  janitor::clean_names() |>
  group_by(user_id) |>
  summarize(n_order = n()) |>
  arrange(desc(n_order))
```

- `user_id` is used for identifying each customers in the dataset, there are 131209 distinct customers in the instacart, which enables to analyze behavior at the customer level. Both 149753 and 197541 ordered the most, with 80 orders each.

```r
pop_product =
  instacart |>
  janitor::clean_names() |>
```

```r
  group_by(product_name) |>
  summarize(n_product = n()) |>
  arrange(desc(n_product))
```

- `product_name` and `product_id` are for identifying the specific product purchased, having 39123 unique products in the dataset. The most popular product are Banana with 18726 orders , followed by Bag of Organic Bananas with 15480 orders.
- `aisle_id`, `aisle`, `department_id` and `department` are variables for identifying the location of products and enabling grouping products. The products are organized into 134 aisles and 21 departments.

```r
day_order =
  instacart |>
  janitor::clean_names() |>
  mutate(
    order_dow_label = wday(order_dow + 1, label = TRUE, abbr = FALSE)
  ) |>
  group_by(order_dow_label) |>
  summarize(n_order = n())
```

- `order_dow`, `order_hour_of_day` indicate the time of orders from users. `days_since_prior_order` shows the how many days passed between orders with an average of 17.1 days. Those variables are used to see shopping habits of customers over time. `order_dow` is formatted in number so I created `order_dow_label` variable to easily notice the day of week. People usually buy their groceries on Sunday the most.

For example, in the first row of the dataset:

- `user_id`: 112108
- `order_id`: 1
- `order_hour_of_day` : 10
- `product_name`: Bulgarian Yogurt
- `aisle`: yogurt

This shows that customer with id 112108 placed 1 order at 10 o'clock and purchased Bulgarian Yogurt from the yogurt aisle.

How many aisles are there, and which aisles are the most items ordered from?

```r
instacart |>
  group_by(aisle) |>
  summarise(count = n()) |>
  arrange(desc(count))
```

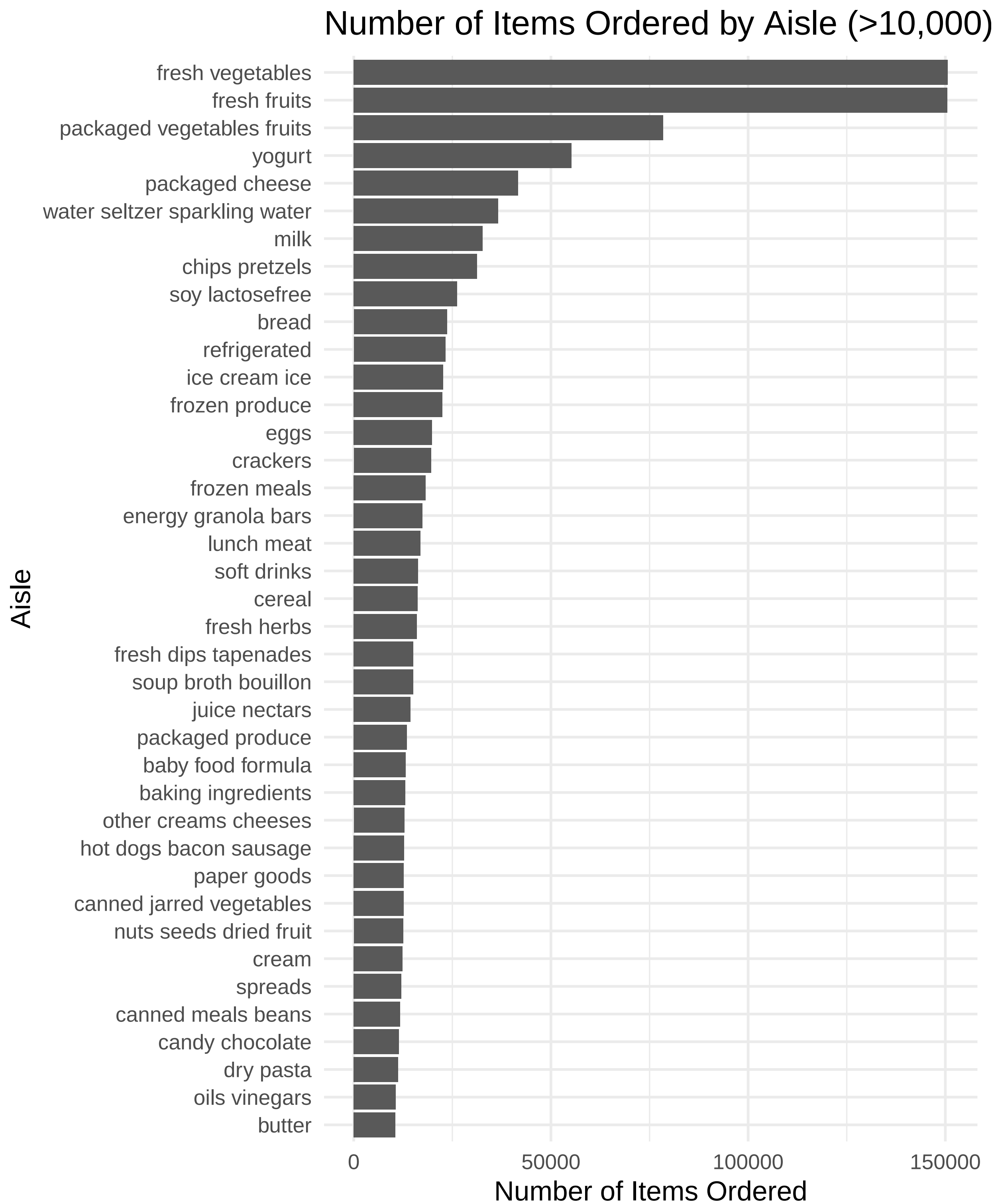
```
## # A tibble: 134 x 2
##    aisle                          count
##    <chr>                          <int>
##  1 fresh vegetables              150609
##  2 fresh fruits                  150473
```

```
##   3 packaged vegetables fruits     78493
##   4 yogurt                        55240
##   5 packaged cheese               41699
##   6 water seltzer sparkling water  36617
##   7 milk                          32644
##   8 chips pretzels                31269
##   9 soy lactosefree               26240
##  10 bread                         23635
## # i 124 more rows
```

The total number of unique aisles in the instacart dataset is 134 and the most items are ordered from fresh vegetables aisle.

Make a plot that shows the number of items ordered in each aisle, limiting this to aisles with more than 10000 items ordered. Arrange aisles sensibly, and organize your plot so others can read it.

```r
instacart |>
  group_by(aisle) |>
  summarise(count = n()) |>
  filter(count > 10000) |>
  ggplot(aes(x = reorder(aisle, count), y = count)) +
  geom_col() +
  coord_flip() +
  labs(
    title = "Number of Items Ordered by Aisle (>10,000)",
    x = "Aisle",
    y = "Number of Items Ordered"
  ) +
  theme_minimal(base_size = 13)
```



Make a table showing the three most popular items in each of the aisles “baking ingredients”, “dog food care”, and “packaged vegetables fruits”. Include the number of times each item is ordered in your table.

```r
instacart |>
  filter(
    aisle %in% c("baking ingredients", "dog food care", "packaged vegetables fruits")
    ) |>
  group_by(aisle, product_name) |>
  summarize(n_items = n(), .groups = "drop") |>
  arrange(aisle, desc(n_items)) |>
  slice_max(n = 3, order_by = n_items, by = aisle) |>
  knitr::kable()
```

aisle	product_name	n_items
baking ingredients	Light Brown Sugar	499
baking ingredients	Pure Baking Soda	387
baking ingredients	Cane Sugar	336
dog food care	Snack Sticks Chicken & Rice Recipe Dog Treats	30
dog food care	Organix Chicken & Brown Rice Recipe	28
dog food care	Small Dog Biscuits	26
packaged vegetables fruits	Organic Baby Spinach	9784
packaged vegetables fruits	Organic Raspberries	5546
packaged vegetables fruits	Organic Blueberries	4966

Make a table showing the mean hour of the day at which Pink Lady Apples and Coffee Ice Cream are ordered on each day of the week; format this table for human readers (i.e. produce a 2 x 7 table).

As `order_dow` variable has values from 0 to 6, I converted these numbers into human-readable weekday names in variable `order_dow_label`.

```r
instacart |>
  filter(product_name %in% c("Pink Lady Apples", "Coffee Ice Cream")) |>
  mutate(
    order_dow_label = wday(order_dow + 1, label = TRUE, abbr = FALSE)
  ) |>
  group_by(product_name, order_dow_label) |>
  summarize(
    mean_hour = round(mean(order_hour_of_day, na.rm = TRUE), digit = 2),
    .groups = "drop"
  ) |>
  pivot_wider(
    names_from = order_dow_label,
    values_from = mean_hour
  ) |>
  knitr::kable()
```

product_name	Sunday	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday
Coffee Ice Cream	13.77	14.32	15.38	15.32	15.22	12.26	13.83
Pink Lady Apples	13.44	11.36	11.70	14.25	11.55	12.78	11.94

From the table, Coffee Ice Cream is ordered the latest on Tuesday, with an average order time of 15.38 hours. Pink Lady Apples are ordered the latest on Wednesday, with an average order time of 14.25 hours, and the earliest on Monday.

Problem 2

Import, clean, and tidy Zillow datasets Import, clean, tidy NYC zipcode dataset

```
zipcode =
  read_csv("data/Zip Codes.csv") |>
  janitor::clean_names()
```

```
## Rows: 322 Columns: 7
## -- Column specification --------------------------------------------------------
## Delimiter: ","
## chr (4): County, County Code, File Date, Neighborhood
## dbl (3): State FIPS, County FIPS, ZipCode
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

Import, clean, tidy Zillow Observed Rent Index (ZORI) in New York City dataset

```
zillow_nyc =
  read_csv("data/Zip_zori_uc_sfrcondomfr_sm_month_NYC.csv") |>
  janitor::clean_names() |>
  rename(
    zip_code = region_name
  ) |>
  pivot_longer(
    x2015_01_31:x2024_08_31,
    names_to = "date",
    values_to = "zori",
    names_prefix = "x"
  ) |>
  mutate(
    county_name = str_remove(county_name, " County$")
  )
```

```
## Rows: 149 Columns: 125
## -- Column specification --------------------------------------------------------
## Delimiter: ","
## chr   (6): RegionType, StateName, State, City, Metro, CountyName
## dbl (119): RegionID, SizeRank, RegionName, 2015-01-31, 2015-02-28, 2015-03-3...
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

There are 116 months between January 2015 and August 2024. How many ZIP codes are observed 116 times? How many are observed fewer than 10 times? Why are some ZIP codes are observed rarely and others observed in each month?

```
zipcode_all =
  zillow_nyc |>
  drop_na(zori) |>
  group_by(zip_code) |>
```

```r
  summarize(
    n_month = n()
  ) |>
  filter(n_month == 116)
```

```r
zipcode_10counts =
  zillow_nyc |>
  drop_na(zori) |>
  group_by(zip_code) |>
  summarize(
    n_month = n()
  ) |>
  filter(n_month < 10)
```

48 zipcodes are observed 116 times and 26 zipcodes are observed fewer than 10 times from January 2015 to August 2024. These zipcodes are rarely observed likely due to limited data or missing/incomplete data. For example, some ZIP codes have more housing units tracked by Zillow, others fewer. ZIP codes with very few units or newly created ZIP codes may appear only rarely. Additionally, reporting gaps can cause a month of data for certain ZIP codes to be missing.

Create a table showing the average rental price in each borough and year (not month). Comment on trends in this table.

```r
zillow_nyc |>
  mutate(year = str_sub(date, 1, 4)) |>
  group_by(county_name, year) |>
  summarize(
    avg_rental_price = mean(zori, na.rm = TRUE)
  ) |>
  knitr::kable(
    digits = 0,
    caption = "Average Rental Price (ZORI) by NYC counties and Year",
    col.names = c("Borough (County)", "Year", "Average ZORI")
  )
```

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

Table 3: Average Rental Price (ZORI) by NYC counties and Year

Borough (County)	Year	Average ZORI
Bronx	2015	1760
Bronx	2016	1520
Bronx	2017	1544
Bronx	2018	1639
Bronx	2019	1706
Bronx	2020	1811
Bronx	2021	1858
Bronx	2022	2054
Bronx	2023	2285
Bronx	2024	2497

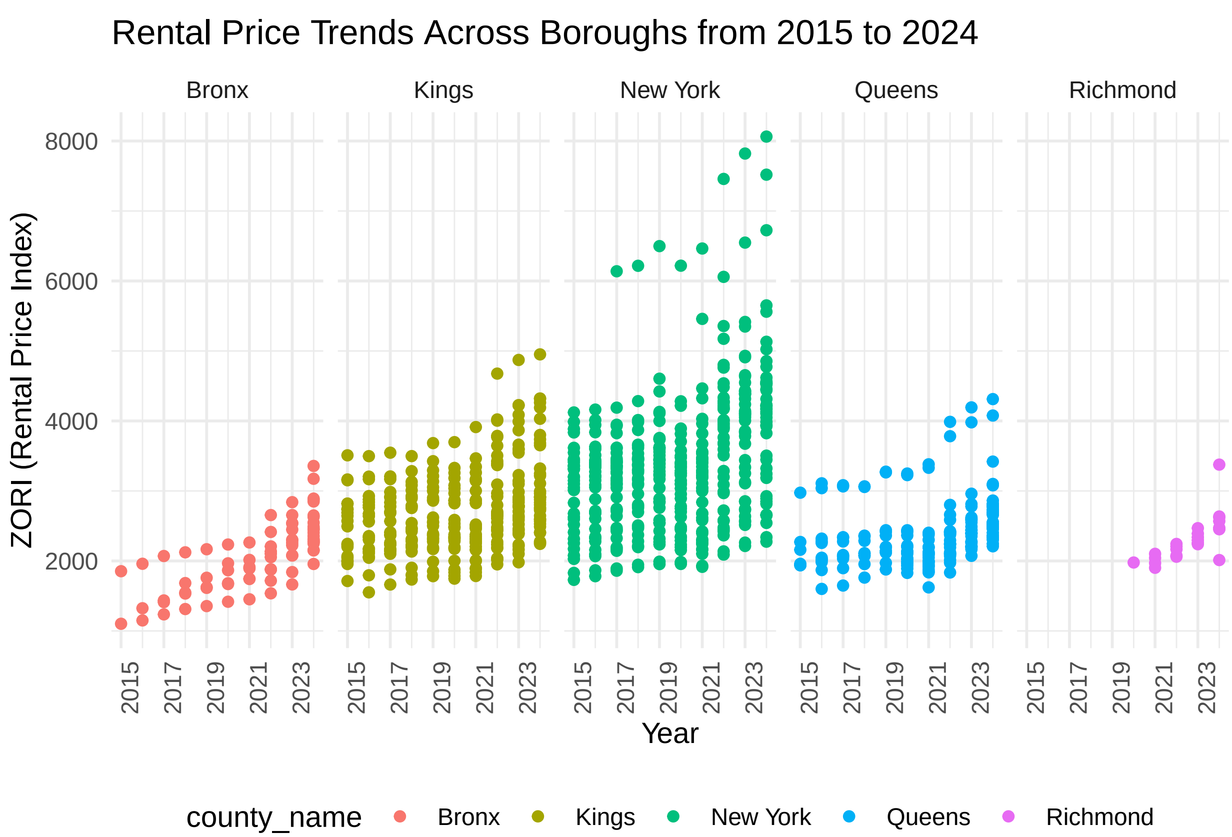
Borough (County)	Year	Average ZORI
Kings	2015	2493
Kings	2016	2520
Kings	2017	2546
Kings	2018	2547
Kings	2019	2631
Kings	2020	2555
Kings	2021	2550
Kings	2022	2868
Kings	2023	3015
Kings	2024	3127
New York	2015	3022
New York	2016	3039
New York	2017	3134
New York	2018	3184
New York	2019	3310
New York	2020	3107
New York	2021	3137
New York	2022	3778
New York	2023	3933
New York	2024	4078
Queens	2015	2215
Queens	2016	2272
Queens	2017	2263
Queens	2018	2292
Queens	2019	2388
Queens	2020	2316
Queens	2021	2211
Queens	2022	2406
Queens	2023	2562
Queens	2024	2694
Richmond	2015	NaN
Richmond	2016	NaN
Richmond	2017	NaN
Richmond	2018	NaN
Richmond	2019	NaN
Richmond	2020	1978
Richmond	2021	2045
Richmond	2022	2147
Richmond	2023	2333
Richmond	2024	2536

From the table, we can see the upward trend in rental prices over time for all boroughs in New York City. However, in 2021, both Kings and Queens has dropped compared to year of 2020. This was mainly due to the COVID-19 pandemic. By 2022 and 2023, prices in all boroughs, including Kings and Queens, rebounded sharply, surpassing pre-pandemic price.

Make a plot showing NYC Rental Prices within ZIP codes for all available years. Your plot should facilitate comparisons across boroughs. Comment on any significant elements of this plot.

```
rental_allyear =
  zillow_nyc |>
```

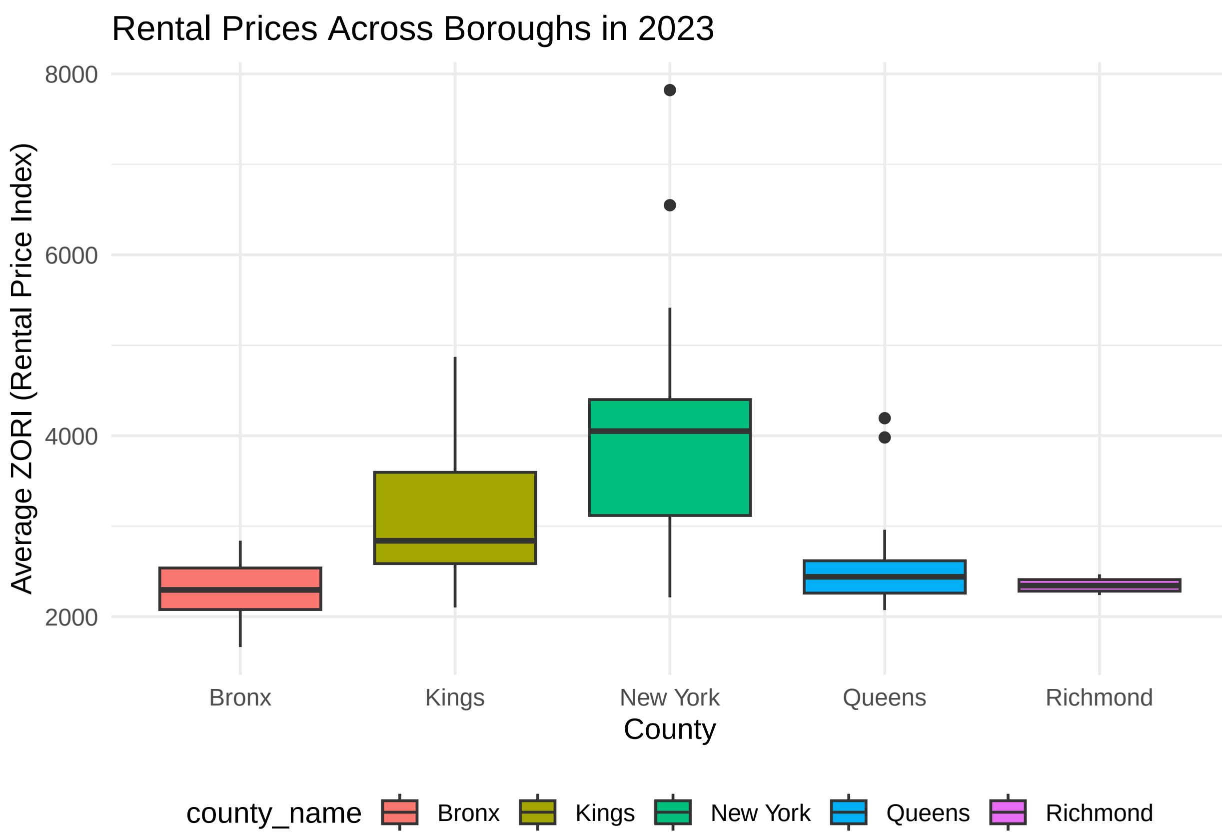
```r
  mutate(year = as.integer(str_sub(date, 1, 4)))  |>
  filter(!is.na(zori)) |>
  group_by(zip_code, county_name, year) |>
  summarize(avg_zori = mean(zori, na.rm = TRUE), .groups = "drop") |>
  ggplot(aes(x = year, y = avg_zori, group = zip_code, color = county_name)) +
  geom_point() +
  facet_grid(. ~ county_name) +
  labs(
    title = "Rental Price Trends Across Boroughs from 2015 to 2024",
    x = "Year",
    y = "ZORI (Rental Price Index)"
  ) +
  scale_x_continuous(
    breaks = c(2015, 2017, 2019, 2021, 2023),
    labels = c("2015", "2017", "2019", "2021", "2023")
  ) +
  theme_minimal() +
  theme(
    axis.text.x = element_text(angle = 90, hjust = 1),
    legend.position = "bottom"
  )

rental_allyear
```



This plot shows rental price trends in New York City across ZIP codes and counties from 2015 to 2024. Only Richmond county has a record from 2020 to 2024. The Zillow Observed Rent Index (ZORI) has a steady upward trend, with a noticeable acceleration after 2021. The thin lines indicate individual ZIP codes, showing substantial within-county variation. New York county has the widest spread up until 8000 ZORI and it stands out with the highest rent levels among five counties and the steepest increase from 2021 to 2022.

Compute the average rental price within each ZIP code over each month in 2023. Make a reader-friendly plot showing the distribution of ZIP-code-level rental prices across boroughs; put differently, your plot should facilitate the comparison of the distribution of average rental prices across boroughs. Comment on this plot.

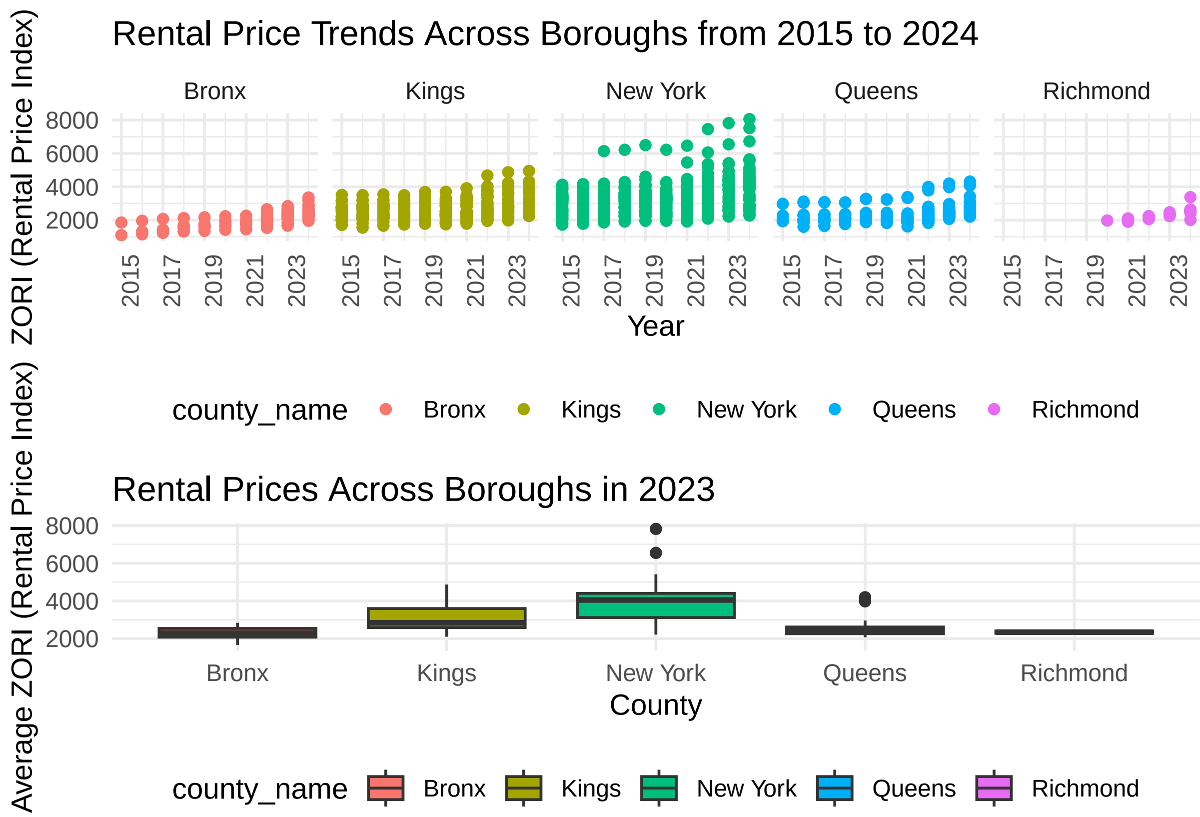
```
rental_2023 =
  zillow_nyc |>
  separate(
    date, into = c("year", "month", "day")
  )  |>
  filter(year == 2023) |>
  group_by(zip_code, county_name) |>
  summarize(avg_zori = mean(zori), .groups = "drop") |>
  ggplot(aes(x = county_name, y = avg_zori, fill = county_name)) +
  geom_boxplot(na.rm = TRUE) +
  labs(
    title = "Rental Prices Across Boroughs in 2023",
    x = "County",
    y = "Average ZORI (Rental Price Index)"
  ) +
  theme_minimal() +
  theme(legend.position = "bottom")

rental_2023
```



The plot shows the rental prices across counties in 2023. There are differences in median rental prices and the speadness of prices among zipcodes within each county. New York has the highest median rent price and the greatest variability having two outliers. On the other hands, Rickmond has the least variability and the lowest median rental prices.

Combine the two previous plots into a single graphic, and export this to a results folder in your repository.

```
rental_allyear / rental_2023
```




```
rental_plot = rental_allyear + rental_2023 + plot_layout(ncol = 2)

ggsave("results/rental_combined.png", rental_plot, width = 12, height = 5, dpi = 300)
```

Problem 3

Load, tidy, merge, and organize the data sets. - exclude participants less than 21 years of age, and those with missing demographic data - encode data with reasonable variable classes (i.e. not numeric, and using factors with the ordering of tables and plots in mind).

```
#accelerometer data
accel =
  read_csv("data/nhanes_accel.csv") |>
  janitor::clean_names()
```

```
## Rows: 250 Columns: 1441
## -- Column specification --------------------------------------------------------
## Delimiter: ","
## dbl (1441): SEQN, min1, min2, min3, min4, min5, min6, min7, min8, min9, min1...
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```r
#demographic data
covar =
  read_csv("data/nhanes_covar.csv", skip = 4) |>
  janitor::clean_names() |>
  filter(age >= 21) |>
  drop_na() |>
  mutate(
    sex = case_match(
      sex,
      1 ~ "male",
      2 ~ "female"
    ),
    education = case_match(
      education,
      1 ~ "Less than high school",
      2 ~ "High school equivalent",
      3 ~ "More than high school"
    )
  )
```

```
## Rows: 250 Columns: 5
## -- Column specification --------------------------------------------------------
## Delimiter: ","
## dbl (5): SEQN, sex, age, BMI, education
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

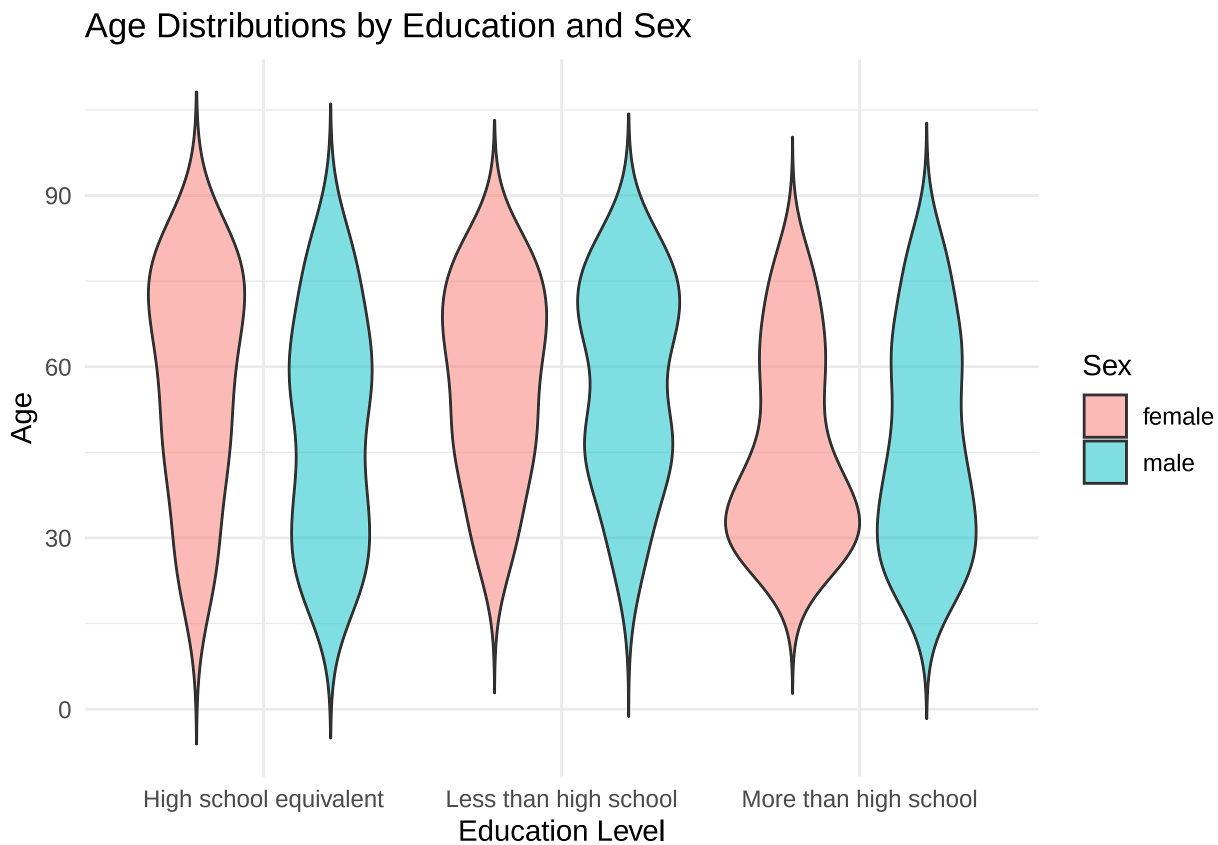
Produce a reader-friendly table for the number of men and women in each education category

```r
final_merged =
  left_join(covar, accel, by = "seqn")

final_merged |>
  group_by(education, sex) |>
  summarize(
    n_count = n(),
    .groups = "drop"
  ) |>
  pivot_wider(
    names_from = sex,
    values_from = n_count
  ) |>
  knitr::kable()
```

education	female	male
High school equivalent	23	35
Less than high school	28	27
More than high school	59	56

create a visualization of the age distributions for men and women in each education category.

```r
final_merged |>
  ggplot(aes(x = education, y = age, fill = sex)) +
  geom_violin(trim = FALSE, alpha = .5) +
  labs(
    title = "Age Distributions by Education and Sex",
    x = "Education Level",
    y = "Age",
    fill = "Sex"
  ) +
  theme_minimal()
```



From the summarized table of the number of men and women in each education category, both sex with more than high school education represent the largest proportion of participants compared to the other education levels. The violin plot shows that individuals with more than high school education are concentrated in their 30s, while those with less than high school and high school equivalent education level groups show a broader and older age distribution. This demonstrates that higher education levels are common among young adults while old people are likely to have lower education level.

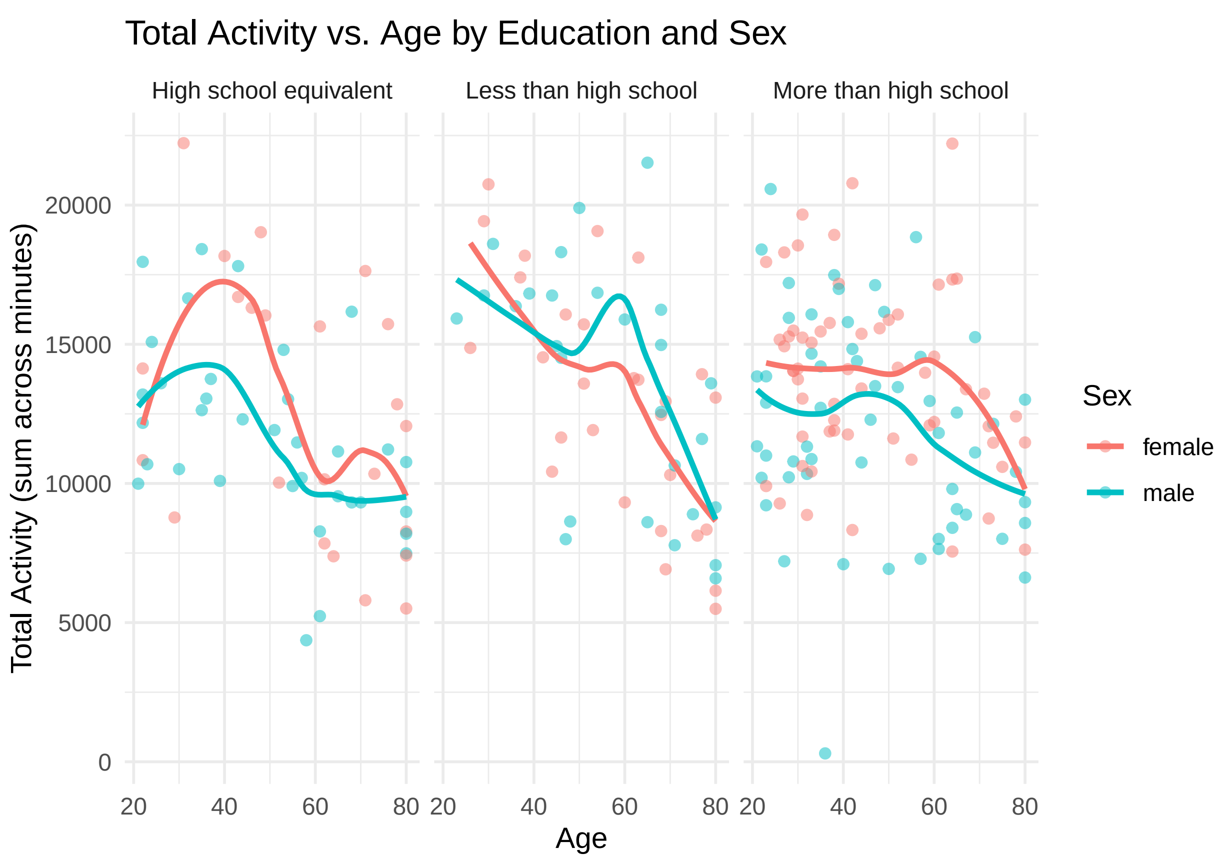
Using your tidied dataset, aggregate across minutes to create a total activity variable for each participant.

```r
total =
  final_merged |>
  mutate(
    total_activity = rowSums(select(final_merged, starts_with("min")), na.rm = TRUE))
```

Plot these total activities (y-axis) against age (x-axis); your plot should compare men to women and have separate panels for each education level. Include a trend line or a smooth to illustrate differences.

```
total |>
  ggplot(aes(x = age, y = total_activity, color = sex)) +
  geom_point(alpha = 0.5) +
  geom_smooth(method = 'loess', se = FALSE) +
  facet_grid(. ~ education) +
  labs(
    title = "Total Activity vs. Age by Education and Sex",
    x = "Age",
    y = "Total Activity (sum across minutes)",
    color = "Sex"
  ) +
  theme_minimal()
```

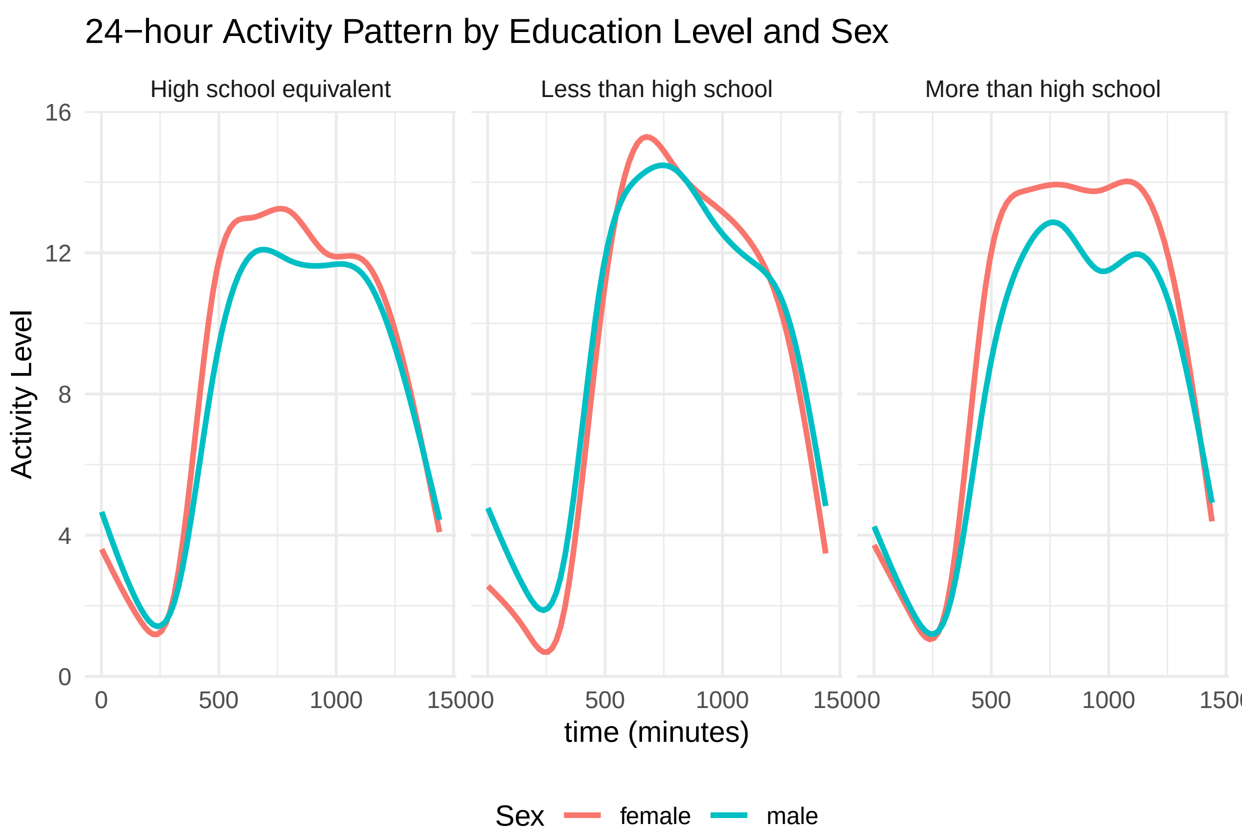
```
## `geom_smooth()` using formula = 'y ~ x'
```



The plot illustrates the relationship between total activity and age, separated by sex and education level. There is a declining trend in total activity with increasing age, showing that older people tend to be less total activity than younger ones. The trend lines show peaks in activity during ages 30-40, followed by a steady decline afterward. Especially, participants with less than high school education level exhibit the steepest decline showing the largest difference between age groups. Women tend to have higher activity levels than man in the younger to middle-aged groups. Only in less than high school group, men surpass women in activity level after their 40s. Overall, both age and education level are important factors influencing activity levels.

Accelerometer data allows the inspection activity over the course of the day. Make a three-panel plot that shows the 24-hour activity time courses for each education level and use color to indicate sex. Describe in words any patterns or conclusions you can make based on this graph; including smooth trends may help identify differences.

```
final_merged |>
  pivot_longer(
    cols = min1:min1440,
    names_to = "time",
    values_to = "activity"
  ) |>
  mutate(time = as.numeric(gsub("min", "", time))) |>
  ggplot(aes(x = time, y = activity, color = sex)) +
  geom_smooth(se = FALSE, linewidth = 1) +
  facet_wrap(education ~ .) +
  labs(
    title = "24-hour Activity Pattern by Education Level and Sex",
    x = "time (minutes)",
    y = "Activity Level",
    color = "Sex"
  ) +
  theme_minimal() +
  theme(legend.position = "bottom")
```



The plot displays the 24-hour activity level trends by education level and sex. Across all groups, activity levels are low during the early morning (around 0–300 minutes), rise sharply around mid-morning, and peak during daytime (approximately 600–1000 minutes), followed by a steady decline toward nighttime (after 1000 minutes).

Individuals with less than high school education show a sharper rise and the highest daytime peaks, possibly reflecting irregular daily routines. Across all education levels, men and women show broadly similar temporal activity trends. However, women tend to have slightly higher daytime activity levels across the day.