P8105_hw3_zj2358

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Problem 1

```r
data("instacart")
instacart %>% head
```

```
## # A tibble: 6 x 15
##   order_id product_id add_to_cart_order reordered user_id eval_set order_number
##      <int>      <int>             <int>     <int>   <int> <chr>           <int>
## 1        1      49302                 1         1  112108 train               4
## 2        1      11109                 2         1  112108 train               4
## 3        1      10246                 3         0  112108 train               4
## 4        1      49683                 4         0  112108 train               4
## 5        1      43633                 5         1  112108 train               4
## 6        1      13176                 6         0  112108 train               4
## # i 8 more variables: order_dow <int>, order_hour_of_day <int>,
## #   days_since_prior_order <int>, product_name <chr>, aisle_id <int>,
## #   department_id <int>, aisle <chr>, department <chr>
```

Description of the dataset:

The dataset `instacart` has 1384617 observations and 15 variables. Variables in the dataset include order_id, product_id, add_to_cart_order, reordered, user_id, eval_set, order_number, order_dow, order_hour_of_day, days_since_prior_order, product_name, aisle_id, department_id, aisle, department. Some key variables include unique order identifiers (`order_id`, e.g., 13749), the sequence products are added to the cart (`add_to_cart_order`, e.g., 2 for the second item), indicators for product reorders (`reordered`, e.g., 0 for previously ordered), the day an order was placed (`order_dow`, e.g., 2 for Tuesday), and specific product names (`product_name`, e.g., Clean Linen Candle). Among these, there are 4 character variables and 11 numeric variables.

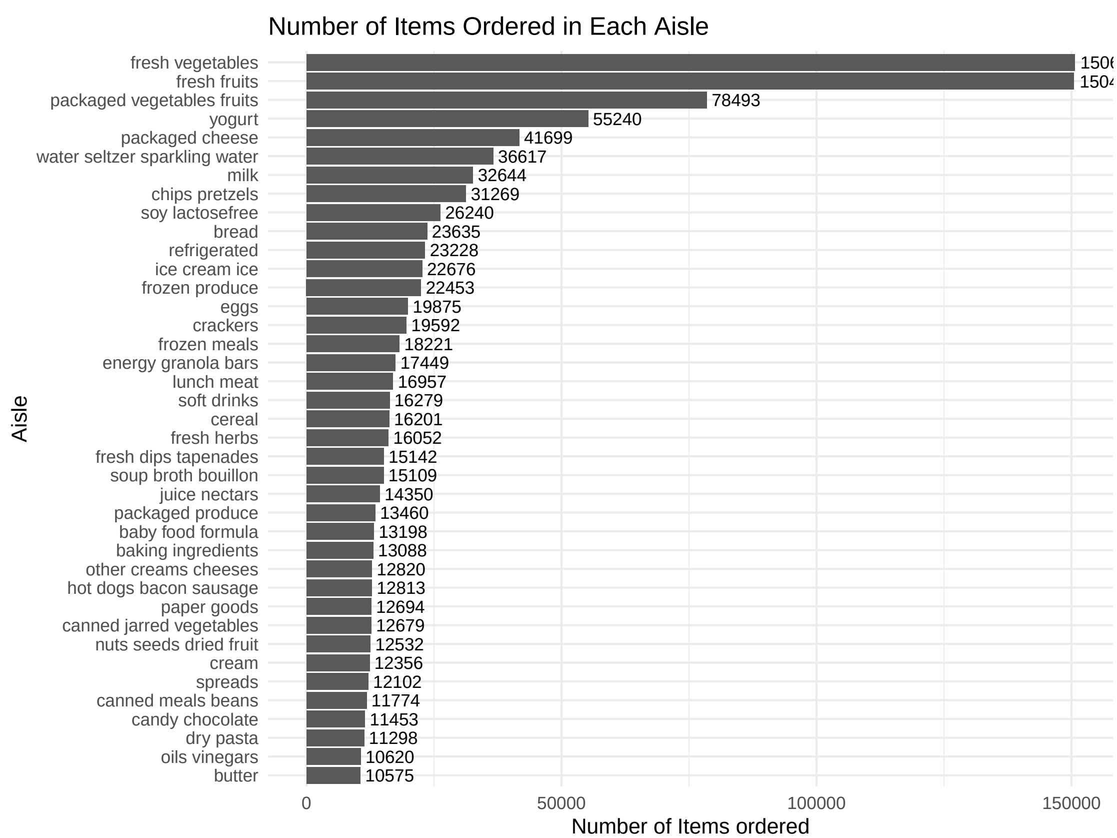
How many aisles are there, and which aisles are the most items ordered from?

```r
num_aisles <- n_distinct(instacart$aisle)

top_aisle <- instacart %>%
  group_by(aisle) %>%
  summarise(count = n()) %>%
  arrange(-count) %>%
  slice(1) %>%
  pull(aisle)
```

There are 134 unique aisles, and the most items are ordered from the fresh vegetables.

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.

```
aisle_plot <- instacart %>%
  group_by(aisle) %>%
  summarise(item_count = n()) %>%
  filter(item_count > 10000) %>%
  arrange(-item_count)

ggplot(aisle_plot, aes(x = reorder(aisle, item_count), y = item_count)) +
  geom_bar(stat="identity") +
  geom_text(aes(label=item_count), position=position_dodge(width=0.9), hjust=-0.1, size=3) +
  coord_flip() +
  labs(title = "Number of Items Ordered in Each Aisle",
       x = "Aisle",
       y = "Number of Items ordered")
```



The bar chart above visualizes the number of items ordered in each aisle, specifically for aisles that have more than 10,000 items ordered. The aisles are sorted in descending order based on the number of items ordered, making it easy to identify the most popular aisles. The `fresh vegetables` aisle is evidently the most popular, with the highest number of items ordered. This is closely followed by `fresh fruits` and `packaged vegetables fruits`.Aisles like `oils vinegars`, `dry pasta`, `canned meals beans`, and `butter` have the lowest order counts among those displayed, but they still have more than 10,000 orders.

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
popular_items <- instacart %>%
  filter(aisle %in% c("baking ingredients", "dog food care", "packaged vegetables fruits")) %>%
  group_by(aisle, product_name) %>%
  summarise(item_count = n(), .groups = "drop") %>%
  arrange(aisle, -item_count) %>%
  group_by(aisle) %>%
  slice_head(n = 3)

knitr::kable(popular_items,caption = "Top 3 Items in Selected Aisles", align = c('l', 'l', 'r'))
```

Table 1: Top 3 Items in Selected Aisles

aisle	product_name	item_count
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

From the table above, it's clear that each aisle has distinct top-selling items. Here are the details:

Baking Ingredients Aisle:

The most ordered item is Light Brown Sugar with 499 orders. This is followed by Pure Baking Soda with 387 orders and Cane Sugar with 336 orders.

Dog Food Care Aisle:

The most ordered item in this aisle is Snack Sticks Chicken & Rice Recipe with 30 orders. Next is Organix Chicken & Brown Rice Recipe with 28 orders and Small Dog Biscuits with 26 orders. It's worth noting that the item counts for this aisle are notably lower than the other two aisles in the table.

Packaged Vegetables Fruits Aisle:

Dominating this category is Organic Baby Spinach with a significant 9,784 orders. Following this are Organic Raspberries with 5,546 orders and Organic Blueberries with 4,966 orders. All three items in this category have substantial order counts, indicating their popularity among shoppers.

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.

```r
product_hour <- instacart %>%
  filter(product_name %in% c("Pink Lady Apples", "Coffee Ice Cream")) %>%
  group_by(product_name, order_dow) %>%
  summarise(mean_hour = mean(order_hour_of_day, na.rm = TRUE), .groups = "drop") %>%
  mutate(order_dow = case_when(
    order_dow == 0 ~ "Monday",
    order_dow == 1 ~ "Tuesday",
    order_dow == 2 ~ "Wednesday",
    order_dow == 3 ~ "Thursday",
    order_dow == 4 ~ "Friday",
```

```r
    order_dow == 5 ~ "Saturday",
    order_dow == 6 ~ "Sunday"
  )) %>%
  spread(key = order_dow, value = mean_hour) %>%
  select(product_name, "Monday", "Tuesday", "Wednesday", "Thursday", "Friday", "Saturday", "Sunday")

knitr::kable(product_hour, caption = "Mean Hour of Order by Product and Day of the Week", digits = 2)
```

Table 2: Mean Hour of Order by Product and Day of the Week

product_name	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
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

The table illustrates the average hour of the day when "Coffee Ice Cream" and "Pink Lady Apples" are typically ordered throughout the week. For "Coffee Ice Cream," the mean ordering time revolves around the early to mid-afternoon across all days. The average order time starts at around 1:45 PM on Monday and reaches its latest around 3:30 PM on Thursday. In comparison, "Pink Lady Apples" consistently show an average ordering time during the early afternoon across the entire week. The time starts at about 11:30 AM on Tuesday and fluctuates slightly but stays around the early to mid-afternoon range for the rest of the days.

Problem 2

```r
data("brfss_smart2010")
```

Data cleaning

```r
colnames(brfss_smart2010)
```

```
##  [1] "Year"                       "Locationabbr"
##  [3] "Locationdesc"               "Class"
##  [5] "Topic"                      "Question"
##  [7] "Response"                   "Sample_Size"
##  [9] "Data_value"                 "Confidence_limit_Low"
## [11] "Confidence_limit_High"      "Display_order"
## [13] "Data_value_unit"            "Data_value_type"
## [15] "Data_Value_Footnote_Symbol" "Data_Value_Footnote"
## [17] "DataSource"                 "ClassId"
## [19] "TopicId"                    "LocationID"
## [21] "QuestionID"                 "RESPID"
## [23] "GeoLocation"
```

```r
brfss_smart2010 <- brfss_smart2010 %>%
  rename(
    location_abbr = Locationabbr,
    location_desc = Locationdesc,
    class_id = ClassId,
```

```r
    data_source = DataSource,
    topic_id = TopicId,
    location_id = LocationID,
    question_id = QuestionID,
    resp_id = RESPID,
    geo_location = GeoLocation
  ) %>%
    janitor::clean_names() %>%
  filter(topic == "Overall Health",
         response %in% c("Excellent", "Very good", "Good", "Fair", "Poor")) %>%
  mutate(response = factor(response,
                          levels = c("Poor", "Fair", "Good", "Very good", "Excellent"),
                          ordered = TRUE))
```

In 2002, which states were observed at 7 or more locations? What about in 2010?

```r
states_with_7_or_more_locations <- brfss_smart2010 %>%
  filter(year %in% c(2002, 2010)) %>%
  group_by(year, location_abbr) %>%
  summarise(num_entries = n_distinct(location_desc)) %>%
  filter(num_entries >= 7)
```

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

```r
states_2002 <- states_with_7_or_more_locations %>%
  filter(year == 2002)  %>%
  pull(location_abbr)

states_2010 <- states_with_7_or_more_locations %>%
  filter(year == 2010) %>%
  pull(location_abbr)
```

In 2002, states observed at 7 or more locations were CT, FL, MA, NC, NJ, PA. In 2010, states observed at 7 or more locations were CA, CO, FL, MA, MD, NC, NE, NJ, NY, OH, PA, SC, TX, WA.

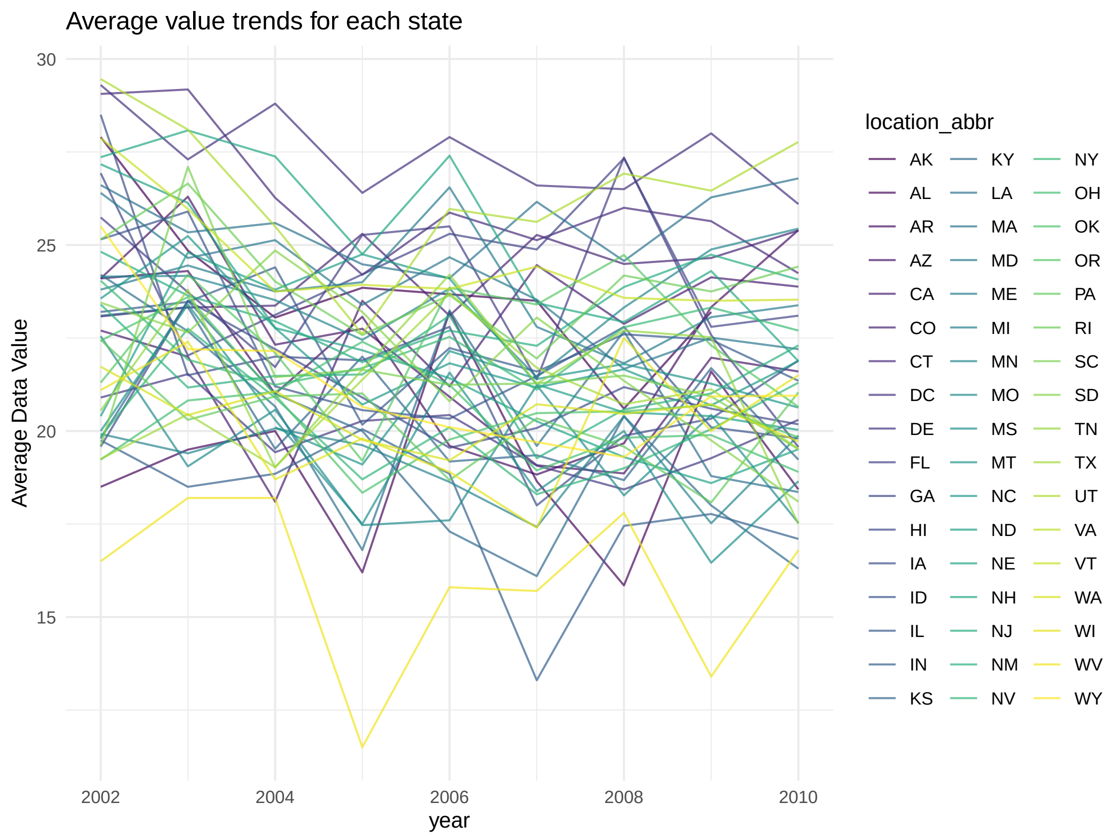
Construct a dataset that is limited to Excellent responses, and contains, year, state, and a variable that averages the data_value across locations within a state.

```r
excellent_responses <- brfss_smart2010 %>%
  filter(response == "Excellent") %>%
  group_by(year, location_abbr) %>%
  summarise(avg_data_value = round(mean(data_value, na.rm = TRUE),2))
```

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

Make a "spaghetti" plot of this average value over time within a state

```r
ggplot(excellent_responses, aes(x = year, y = avg_data_value, group = location_abbr)) +
  geom_line(aes(color = location_abbr), alpha = 0.7) +
  labs(title = "Average value trends for each state",
       y = "Average Data Value") +
  theme_minimal()
```

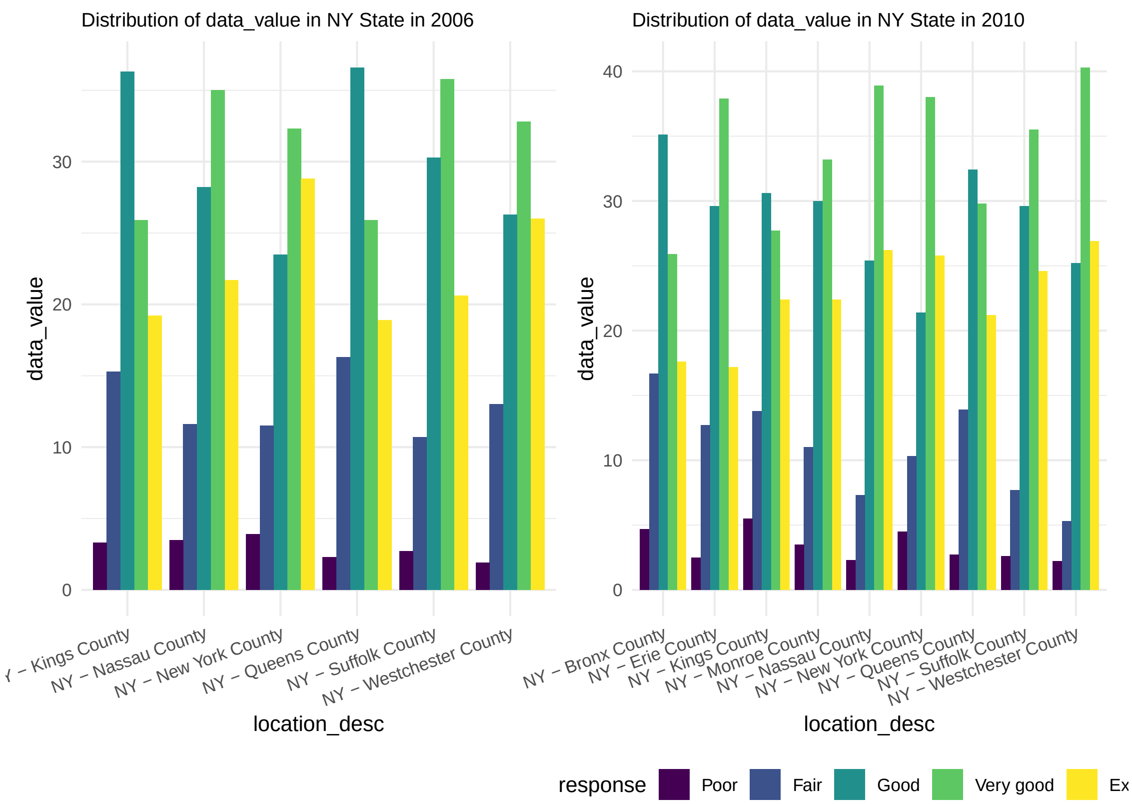


From the Visualization:

The plot depicts the trends of "Excellent" responses over time, averaged across locations within each state. There's a noticeable variance in the average values of these "Excellent" responses across states over the years. The dense overlapping of lines around the 20-25 mark suggests that a significant number of states had their "Excellent" responses average in this range during various years.

Make a two-panel plot showing, for the years 2006, and 2010, distribution of data_value for responses ("Poor" to "Excellent") among locations in NY State.

```
plot_2006=
  brfss_smart2010 |>
  filter(location_abbr=="NY",year==2006)|>
  ggplot(aes(x =location_desc , y = data_value,fill=response)) +
  geom_bar(position="dodge",stat="identity") +
  labs(title = "Distribution of data_value in NY State in 2006") +
  theme(plot.title = element_text(size = 10), axis.text.x = element_text(angle = 20, hjust = 1),legend.p

plot_2010=
  brfss_smart2010 |>
  filter(location_abbr=="NY",year==2010)|>
  ggplot(aes(x =location_desc , y = data_value,fill=response)) +
  geom_bar(position="dodge",stat="identity") +
  labs(title = "Distribution of data_value in NY State in 2010") +
  theme(plot.title = element_text(size = 10), axis.text.x = element_text(angle = 20, hjust = 1))

plot_2006 + plot_2010
```



From the Visualization:

The plot displays the health perceptions of residents across various New York counties for 2006 and 2010. While there is variation among counties, the overall distribution appears somewhat consistent between the two years. While many counties exhibit bars of similar heights between the two years (e.g., Kings County, Queens County), some show noticeable changes. For instance, the "Very good" category appears to decrease in some counties from 2006 to 2010, while others see an increase.

Problem 3

Load and clean the datasets

```
nhanes_accel <- read_csv("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.
```

```
nhanes_covar <- read_csv("nhanes_covar.csv") %>%
  janitor::clean_names()
```

```
## New names:
## Rows: 254 Columns: 5
## -- Column specification
## -------------------------------------------------------- Delimiter: "," chr
## (5): ...1, 1 = male, ...3, ...4, 1 = Less than high school
## 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.
## * ‘‘ -> ‘...1‘
## * ‘‘ -> ‘...3‘
## * ‘‘ -> ‘...4‘
```

Tidy the data

```r
nhanes_covar <- nhanes_covar[-c(1:4),]
colnames(nhanes_covar) <- c("seqn", "sex", "age", "bmi", "education")
nhanes_covar$seqn <- as.integer(nhanes_covar$seqn)
nhanes_covar$age <- as.numeric(nhanes_covar$age)
nhanes_covar$bmi <- as.numeric(nhanes_covar$bmi)

nhanes_accel$seqn <- as.integer(nhanes_accel$seqn)
```

Filter the data

```r
nhanes_covar <- nhanes_covar %>%
  filter(age >= 21, !is.na(sex), !is.na(age), !is.na(bmi), !is.na(education))
```

Merge

```r
nhanes <- inner_join(nhanes_covar, nhanes_accel, by = "seqn")
```

Encode data

```r
nhanes$sex <- factor(nhanes$sex, levels = c("1", "2"),
                          labels = c("Male", "Female"))

nhanes$education <- factor(nhanes$education,
                               levels = c("1", "2", "3"),
                               labels = c("Less than high school",
                                          "High school equivalent",
                                          "More than high school"))
```

Produce a Reader-Friendly Table

```r
education_table <- table(nhanes$sex, nhanes$education)
knitr::kable(education_table,
             caption = "Number of Men and Women in Each Education Category")
```

Table 3: Number of Men and Women in Each Education Category

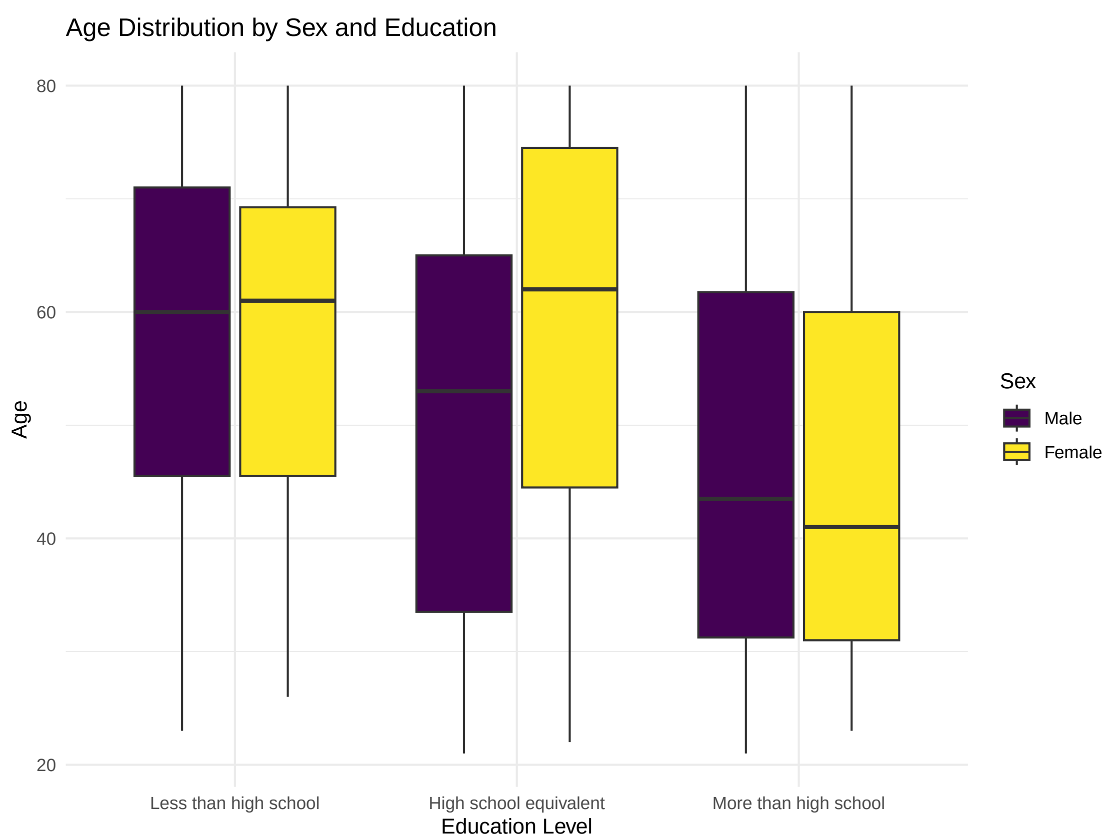
	Less than high school	High school equivalent	More than high school
Male	27	35	56
Female	28	23	59

From the Table:

The dataset contains a fairly balanced distribution of men and women across different education levels, with no extreme disparities in numbers. More males (35) have an education equivalent to high school compared to females (23). In contrast, for education levels beyond high school, females (59) outnumber males (56).

Visualization of the age distributions

```
ggplot(nhanes, aes(x = education, y = age, fill = sex)) +
  geom_boxplot() +
  labs(title = "Age Distribution by Sex and Education",
       x = "Education Level",
       y = "Age",
       fill = "Sex") +
  theme_minimal()
```



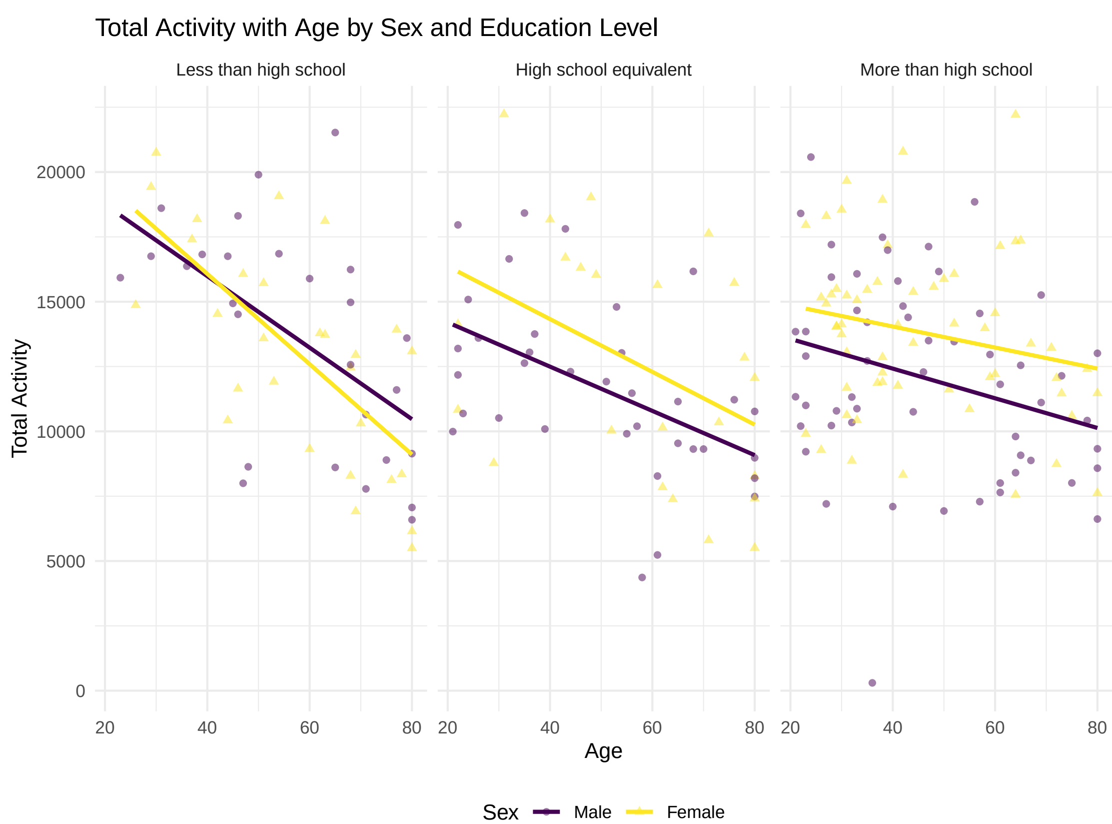
From the Visualization:

The people from group with a education level more than high school are the youngest on average, compared to the people from group with a education level less than high school, who are the oldest on average. The group with a education level high school equivalent has a wider age range. The group with the largest gap in age distribution between male and female is the group with a education level of high school equivalent.

Create a total activity variable for each participant & Plotting

```
nhanes$total_activity <- rowSums(nhanes[, grep("^min", names(nhanes))])
ggplot(nhanes, aes(x = age, y = total_activity, color = sex)) +
  geom_point(aes(shape = sex), alpha = 0.5) +
  geom_smooth(method = "lm", se = FALSE) +
  facet_wrap(~ education) +
  labs(title = "Total Activity with Age by Sex and Education Level",
       x = "Age",
       y = "Total Activity",
       color = "Sex",
       shape = "Sex")
```

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



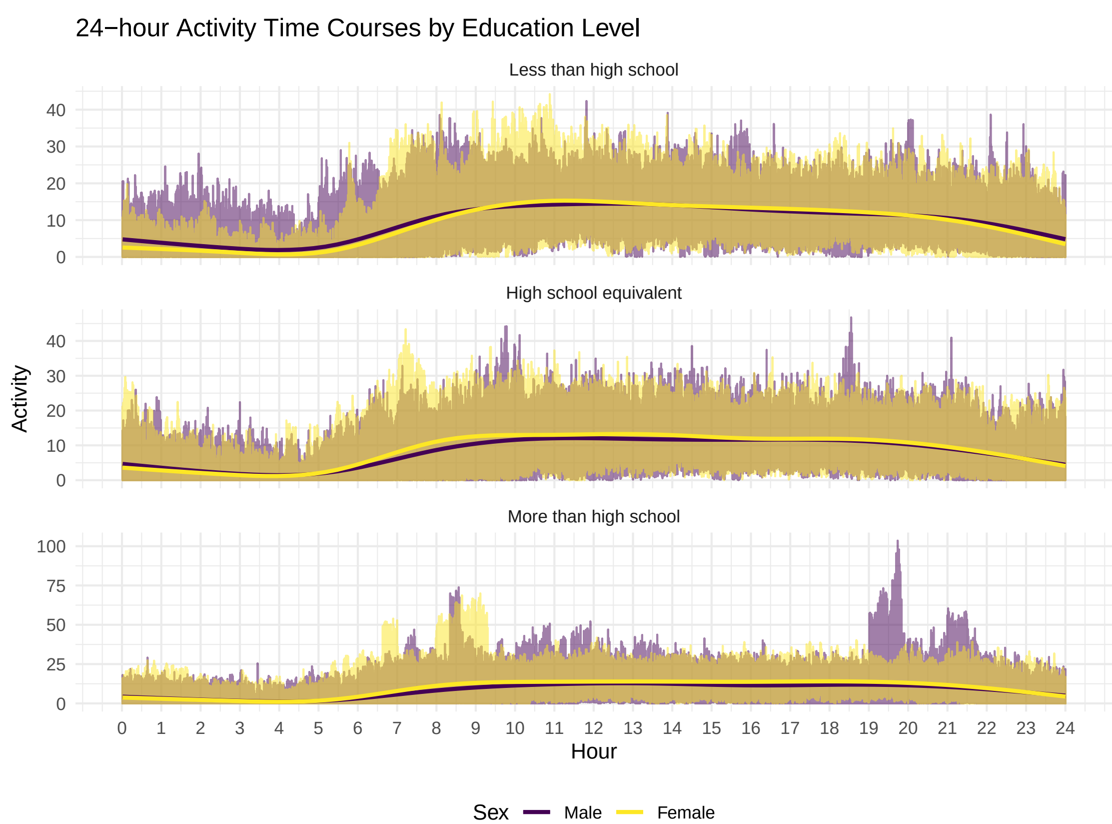
From the Visualization:

The trend consistent across education levels. For all education levels, there is a negative correlation between the total activity and age, which means the total activity decrease with age, and the trend is the same for men and women. The group with the education level less than high school shows more total activity than the other two groups for both male and female. For groups of high school equivalent and more than high school, women always have more total activity than men at the same age.

Make a three-panel plot

```
nhanes_new <-nhanes %>%
  pivot_longer(cols = starts_with("min"),
               names_to = "minute",
               values_to = "activity") %>%
  mutate(minute = as.integer(gsub("min", "", minute)))

ggplot(nhanes_new, aes(x = minute, y = activity, color = sex)) +
  geom_line(alpha = 0.5) +
  geom_smooth(se = FALSE) +
  facet_wrap(~ education, scales = "free_y", ncol = 1) +
  scale_x_continuous(name = "Hour", breaks = seq(0, 1440, 60), labels = 0:24) +
  labs(title = "24-hour Activity Time Courses by Education Level",
       y = "Activity",
       color = "Sex")
```

```
## 'geom_smooth()' using method = 'gam' and formula = 'y ~ s(x, bs = "cs")'
```



From the Visualization, we can conclude that:

1. There's nearly no gender difference in activity patterns across three education groups from the smooth trends.
2. For all three groups, they are more active from about 9 am to 8 pm.
3. The average daily activity time of the three groups is ranked as: less than high school > high school equivalent > more than high school.

4. The group with more than high school education shows more consistent activity with less peaks and troughs.