›— title: “p8105_hw3_zj2379” author: “Zheshu Jiang” date: “2023-10-12” output: github_document —

Problem1

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

```
## -- Attaching core tidyverse packages ------------------------ tidyverse 2.0.0 --
## v dplyr     1.1.3     v readr     2.1.4
## v forcats   1.0.0     v stringr   1.5.0
## v ggplot2   3.4.3     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
```

```
library(ggridges)
library(patchwork)
```

```
instacart |>
  count(aisle) |>
  arrange(desc(n))
```

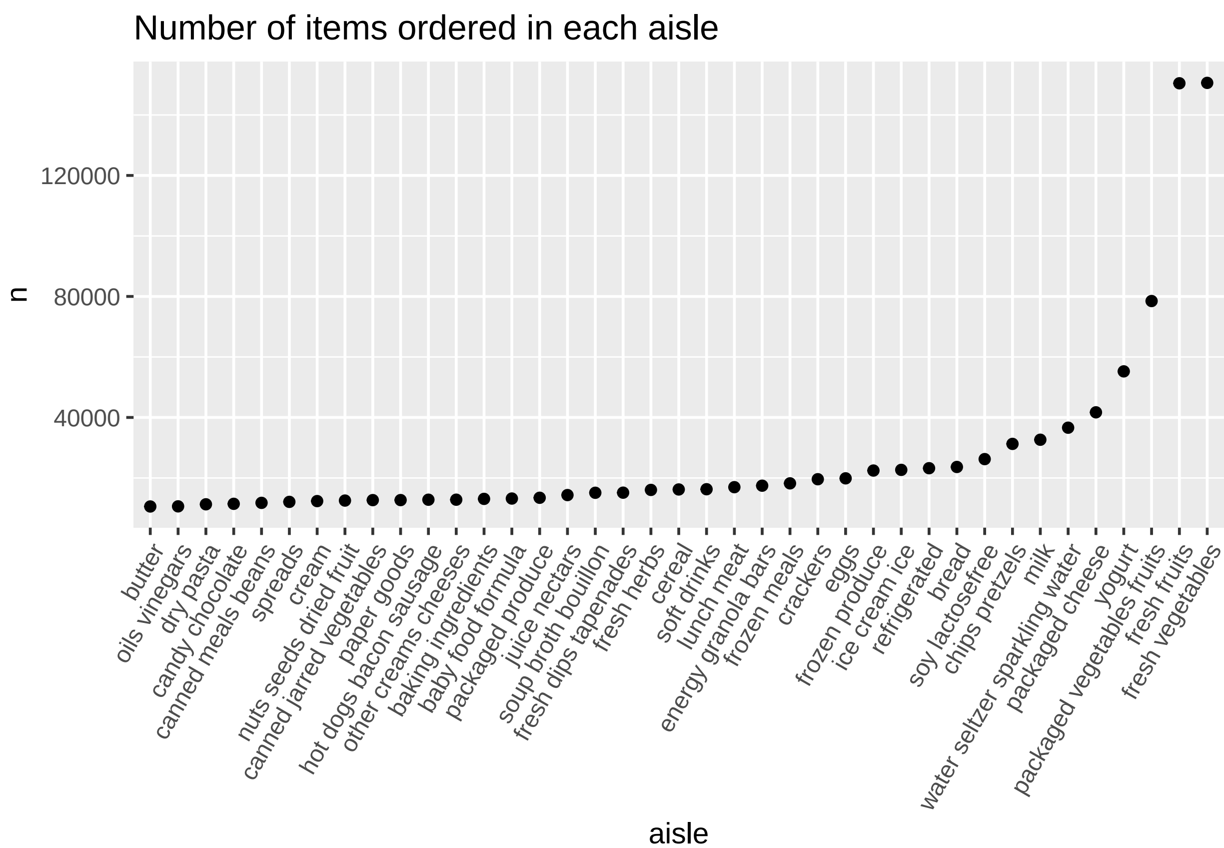
```
## # A tibble: 134 x 2
##    aisle                              n
##    <chr>                          <int>
##  1 fresh vegetables              150609
##  2 fresh fruits                  150473
##  3 packaged vegetables fruits     78493
##  4 yogurt                         55240
##  5 packaged cheese                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
```

There are 134 aisles, with fresh vegetables and fresh fruits holding the most items ordered.

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.

```
instacart |>
  count(aisle) |>
  filter(n > 10000) |>
  mutate(aisle = fct_reorder(aisle, n)) |>
```

```r
  ggplot(aes(x = aisle, y = n)) +
  geom_point() +
  labs(title = "Number of items ordered in each aisle")+
  theme(axis.text.x = element_text(angle = 60, hjust = 1))
```



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) |>
  count(product_name) |>
  mutate(rank = min_rank(desc(n))) |>
  filter(rank < 4) |>
  arrange(desc(n)) |>
  knitr::kable()
```

aisle	product_name	n	rank
packaged vegetables fruits	Organic Baby Spinach	9784	1
packaged vegetables fruits	Organic Raspberries	5546	2
packaged vegetables fruits	Organic Blueberries	4966	3
baking ingredients	Light Brown Sugar	499	1
baking ingredients	Pure Baking Soda	387	2
baking ingredients	Cane Sugar	336	3

aisle	product_name	n	rank
dog food care	Snack Sticks Chicken & Rice Recipe Dog Treats	30	1
dog food care	Organix Chicken & Brown Rice Recipe	28	2
dog food care	Small Dog Biscuits	26	3

Finally is 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. This table has been formatted in an untidy manner for human readers. Pink Lady Apples are generally purchased slightly earlier in the day than Coffee Ice Cream, with the exception of day 5.

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).

```
instacart |>
  filter(product_name %in% c("Pink Lady Apples", "Coffee Ice Cream")) |>
  group_by(product_name, order_dow) |>
  summarize(mean_hour = mean(order_hour_of_day)) |>
  pivot_wider(
    names_from = order_dow,
    values_from = mean_hour) |>
  knitr::kable(digits = 2)
```

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

product_name	0	1	2	3	4	5	6
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

Problem 2

```
#load the data
library(p8105.datasets)
data("brfss_smart2010")
brfss_smart2010
```

```
## # A tibble: 134,203 x 23
##     Year Locationabbr Locationdesc     Class Topic Question Response Sample_Size
##    <int> <chr>        <chr>            <chr> <chr> <chr>    <chr>          <int>
##  1  2010 AL           AL - Jefferson ~ Heal~ Over~ How is ~ Excelle~          94
##  2  2010 AL           AL - Jefferson ~ Heal~ Over~ How is ~ Very go~         148
##  3  2010 AL           AL - Jefferson ~ Heal~ Over~ How is ~ Good             208
##  4  2010 AL           AL - Jefferson ~ Heal~ Over~ How is ~ Fair             107
##  5  2010 AL           AL - Jefferson ~ Heal~ Over~ How is ~ Poor              45
##  6  2010 AL           AL - Jefferson ~ Heal~ Fair~ Health ~ Good or~         450
##  7  2010 AL           AL - Jefferson ~ Heal~ Fair~ Health ~ Fair or~         152
##  8  2010 AL           AL - Jefferson ~ Heal~ Heal~ Do you ~ Yes              524
##  9  2010 AL           AL - Jefferson ~ Heal~ Heal~ Do you ~ No                77
```

```
## 10  2010 AL          AL - Jefferson ~ Heal~ Unde~ Adults ~ Yes              316
## # i 134,193 more rows
## # i 15 more variables: Data_value <dbl>, Confidence_limit_Low <dbl>,
## #   Confidence_limit_High <dbl>, Display_order <int>, Data_value_unit <chr>,
## #   Data_value_type <chr>, Data_Value_Footnote_Symbol <chr>,
## #   Data_Value_Footnote <chr>, DataSource <chr>, ClassId <chr>, TopicId <chr>,
## #   LocationID <chr>, QuestionID <chr>, RESPID <chr>, GeoLocation <chr>
```

First, do some data cleaning: format the data to use appropriate variable names; focus on the "Overall Health" topic include only responses from "Excellent" to "Poor" organize responses as a factor taking levels ordered from "Poor" to "Excellent"

```r
#do some data cleaning following the above guideline
brfss_smart =
  brfss_smart2010 |>
  as_tibble()
brfss_smart =
  brfss_smart |>
  janitor::clean_names() |>
  rename(state = locationabbr, location_state = locationdesc) |>
  filter(topic %in% "Overall Health") |>
  mutate(response = fct_relevel(response, "Poor","Fair","Good","Very good","Excellent"))
```

```r
# keep only data from 2002 to see which states were observed at 7 or more locations
brfss_smart |>
  filter(year == "2002") |>
  group_by(state) |>
  summarize(n = n_distinct(location_state)) |>
  filter(n >= 7)
```

```
## # A tibble: 6 x 2
##   state     n
##   <chr> <int>
## 1 CT        7
## 2 FL        7
## 3 MA        8
## 4 NC        7
## 5 NJ        8
## 6 PA       10
```

This plot shows a line for each state across years from 2002 to 2010. In 2002, CT, FL, MA, NC, Nj, PA were observed at 7 or more locations.

```r
# keep only data from 2010 to see which states were observed at 7 or more locations
brfss_smart |>
  filter(year == "2010") |>
  group_by(state) |>
  summarize(n = n_distinct(location_state)) |>
  filter(n >= 7)
```

```
## # A tibble: 14 x 2
##    state     n
```

```
##     <chr> <int>
##   1 CA       12
##   2 CO        7
##   3 FL       41
##   4 MA        9
##   5 MD       12
##   6 NC       12
##   7 NE       10
##   8 NJ       19
##   9 NY        9
##  10 OH        8
##  11 PA        7
##  12 SC        7
##  13 TX       16
##  14 WA       10
```

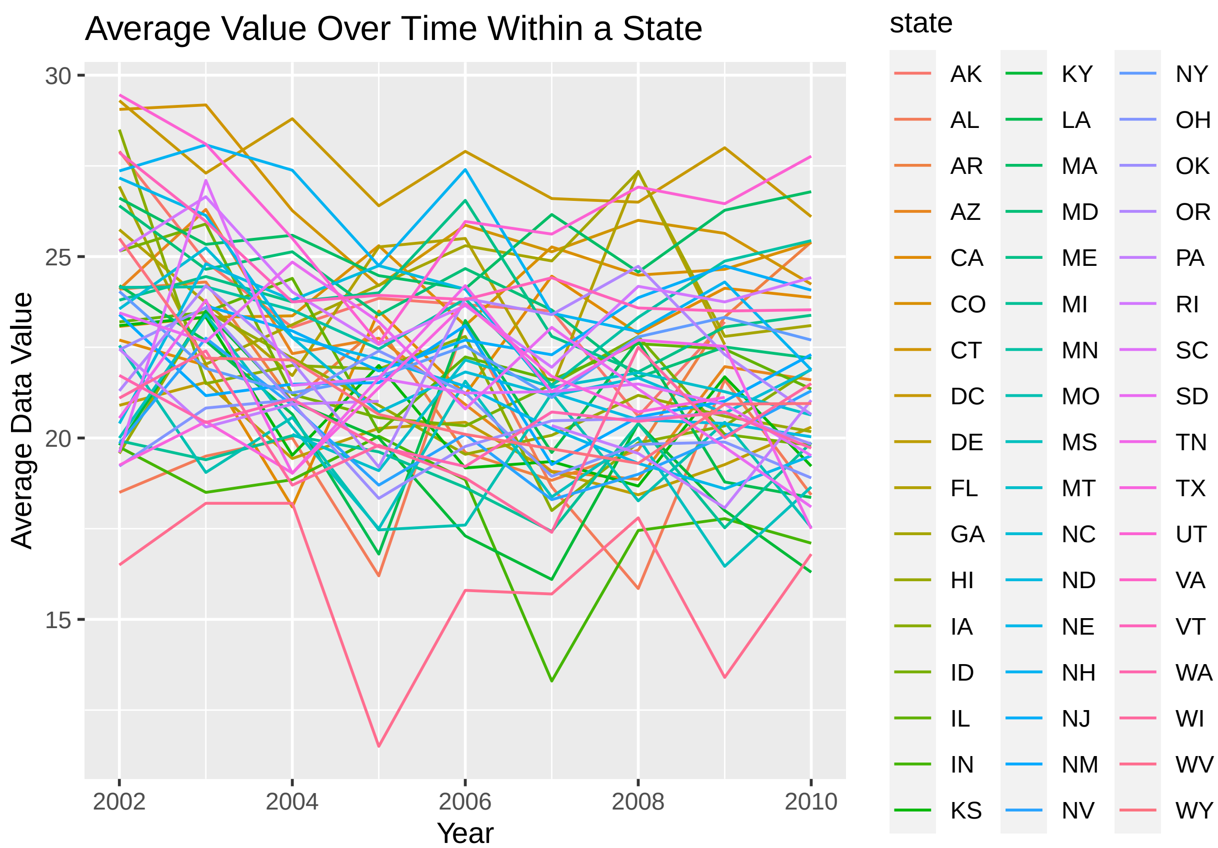
In 2010, CA, CO, FL, MA, MD, NC, NE, NJ, HY, OH, PA, SC, TX, WA were observed at 7 or more locations.

make a plot showing a line for each state across years

```
brfss_smart |>
  filter(response=="Excellent")|>
  select(year, state, data_value)|>
  group_by(year, state)|>
  summarise(average_data_value = mean(data_value))|>
  ggplot(aes(x = year, y = average_data_value, color = state, group = state)) +
  geom_line()+
  labs(
    x = "Year",
    y = "Average Data Value",
    title = "Average Value Over Time Within a State"
  )
```

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

```
## Warning: Removed 3 rows containing missing values (`geom_line()`).
```




```
ggsave("line plot for each state.pdf")
```

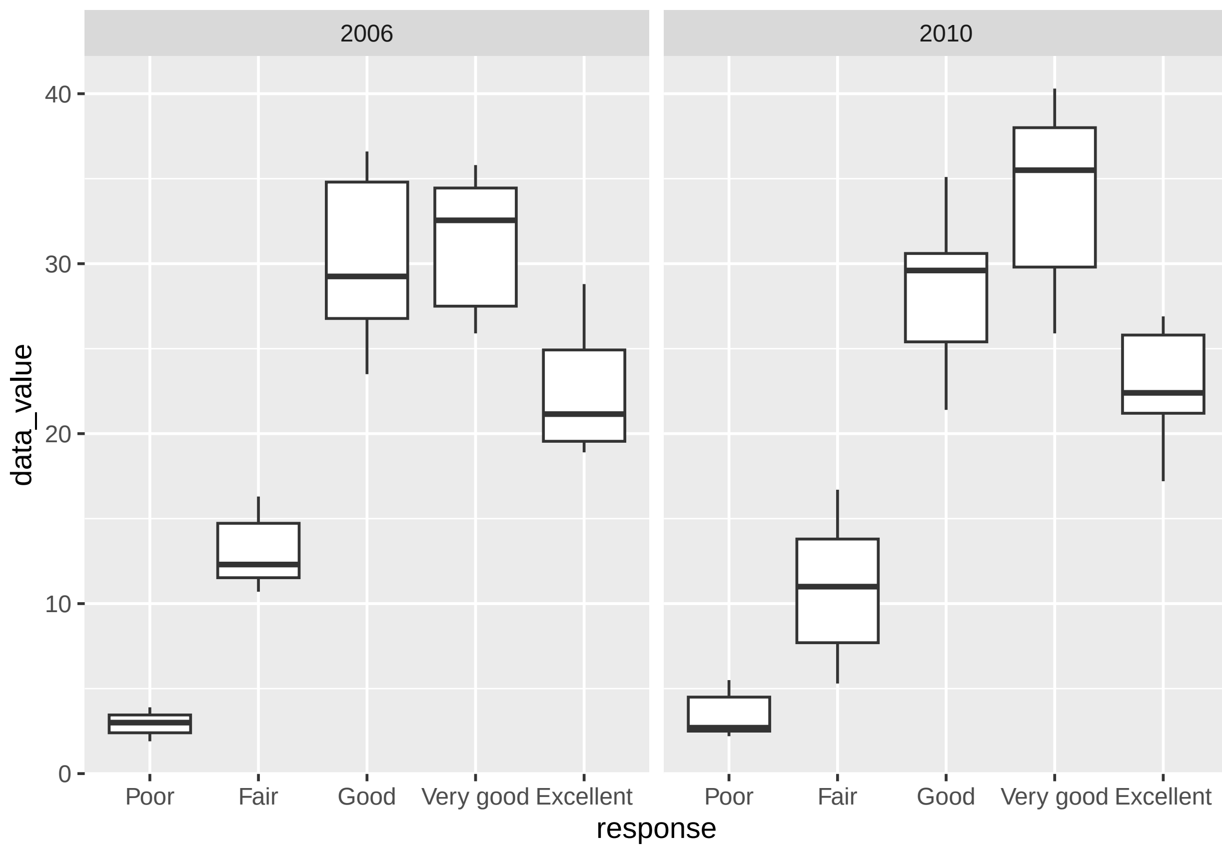
```
## Saving 6.5 x 4.5 in image

## Warning: Removed 3 rows containing missing values (‘geom_line()‘).
```

This plot shows a line for each state across years from 2002 to 2010.

Make a two-panel plot showing, for the years 2006, and 2010

```
brfss_smart |>
  group_by(year,response,state,data_value) |>
  filter(year %in% c("2006","2010")) |>
  filter(state %in% "NY")|>
  ggplot(aes(x = response, y = data_value)) +
  geom_boxplot() +
  facet_grid(. ~ year)
```




```
ggsave("two-panel plot for 2006 and 2010.pdf")
```

```
## Saving 6.5 x 4.5 in image
```

This plot shows the distribution of data_value for responses ("Poor" to "Excellent") among locations in NY State in 2006 and 2010 respectively. Based on the graphs, the group with "poor" responses has the lowest data values at both years, good and very good responses have relatively high data values.

Problem3

```
nhanes_covar =
  read_csv("nhanes_covar.csv",skip = 4) |>
  janitor::clean_names() |>
  # exclude participants less than 21 years of age
  filter(age > 21) |>
  mutate(
    sex = recode(sex, "1" = "male", "2" = "female"),
      education = recode(
      education,
      "1" = "Less than high shcool",
      "2" = "High school equivalent",
      "3" = "More than high school"),
  )|>
```

```r
 mutate(
   sex = as.factor(sex),
   education = as.factor(education)
 )|>
  #exclude those observations with missing demographic data
  na.omit()
```

```
## 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.
```

```r
nhanes_covar
```

```
## # A tibble: 225 x 5
##     seqn sex      age   bmi education
##    <dbl> <fct>  <dbl> <dbl> <fct>
##  1 62161 male      22  23.3 High school equivalent
##  2 62164 female    44  23.2 More than high school
##  3 62174 male      80  33.9 More than high school
##  4 62177 male      51  20.1 High school equivalent
##  5 62178 male      80  28.5 High school equivalent
##  6 62180 male      35  27.9 More than high school
##  7 62184 male      26  22.1 High school equivalent
##  8 62189 female    30  22.4 More than high school
##  9 62199 male      57  28   More than high school
## 10 62202 male      36  24.7 Less than high shcool
## # i 215 more rows
```

```r
nhanes_accel =
  read_csv("nhanes_accel.csv") |>
  janitor::clean_names()|>
   pivot_longer(
    min1:min1440,
    names_to = "number",
    values_to = "counts",
    names_prefix = "min"
  )
```

```
## 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
nhanes_accel
```

```
## # A tibble: 360,000 x 3
##     seqn number counts
##    <dbl> <chr>   <dbl>
##  1 62161 1       1.11
##  2 62161 2       3.12
##  3 62161 3       1.47
##  4 62161 4       0.938
##  5 62161 5       1.60
##  6 62161 6       0.145
##  7 62161 7       2.10
##  8 62161 8       0.509
##  9 62161 9       1.63
## 10 62161 10      1.20
## # i 359,990 more rows
```

```r
# combine the two datasets
nhanes_df = left_join(nhanes_covar,nhanes_accel,by = "seqn")
```

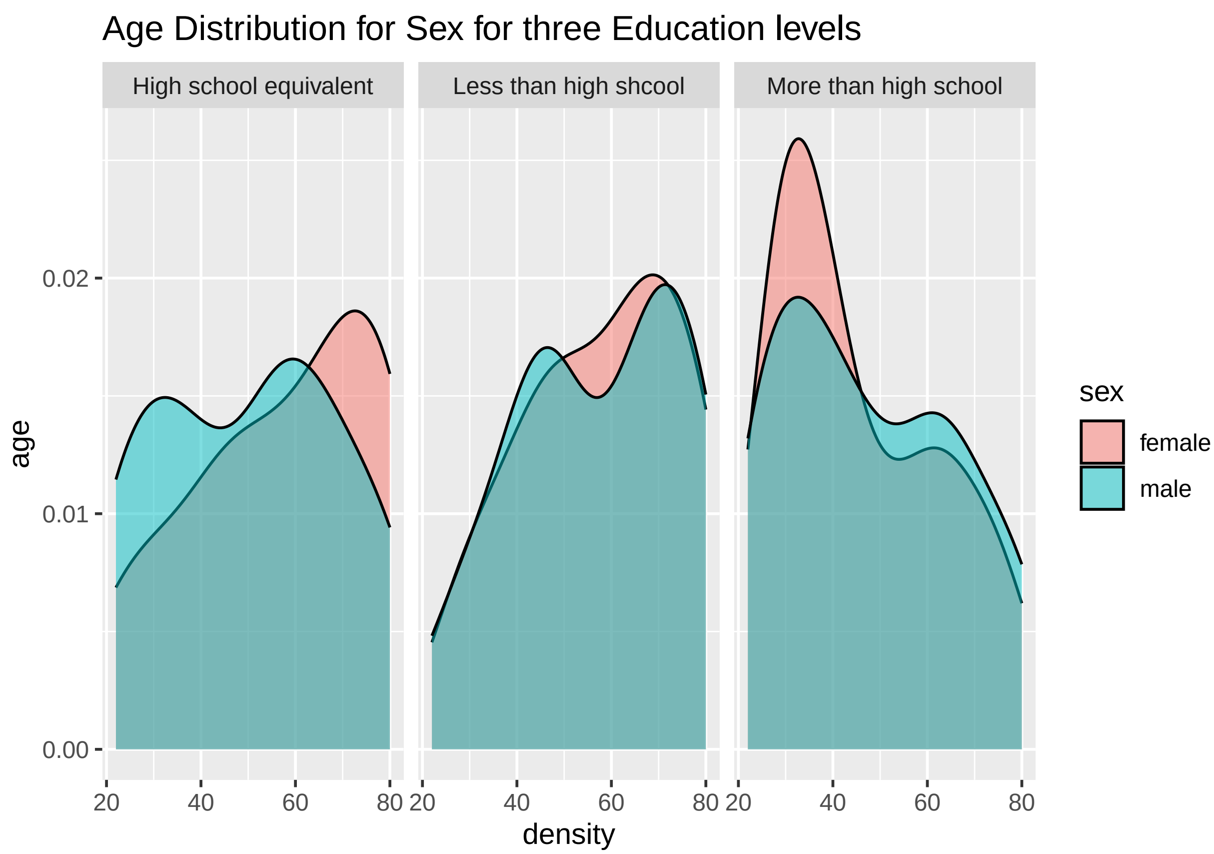
Produce a reader-friendly table for the number of men and women in each education category, and create a visualization of the age distributions for men and women in each education category.

```r
#make a table
education_table=select(nhanes_covar, sex | education)
table(education_table)
```

```
##         education
## sex      High school equivalent Less than high shcool More than high school
##   female                     23                    28                    59
##   male                       34                    27                    54
```

At the High school equivalent education level, the number of male is 34 and the number of female is 23, more male than female. At less than high school education level,the number of male is 28 and the number of female is 27, more male than female. At more than high school education level,the number of male is 59 and the number of female is 54, more male than female.

```r
nhanes_covar |>
ggplot(aes(x = age, fill = sex )) +
  geom_density(alpha = .5) +
  facet_grid(. ~ education)+
  labs( title = "Age Distribution for Sex for three Education levels",
    y = "age",
    x = "density")
```




```
ggsave("Age Distribution for Sex for three Education levels.pdf")
```

```
## Saving 6.5 x 4.5 in image
```

Based on the graphs, at the high school equivalent education level, the number of females exceeds the number of males as age increases. At the less than high school education level, the number of females first exceeds the number of males then becomes lower than that of males as age increases. At the more than high school education level, the number of females is originally higher than the number of males and then becomes lower than that of males as age increases.Overall, females and younger people have relatively higher education level than other age groups.

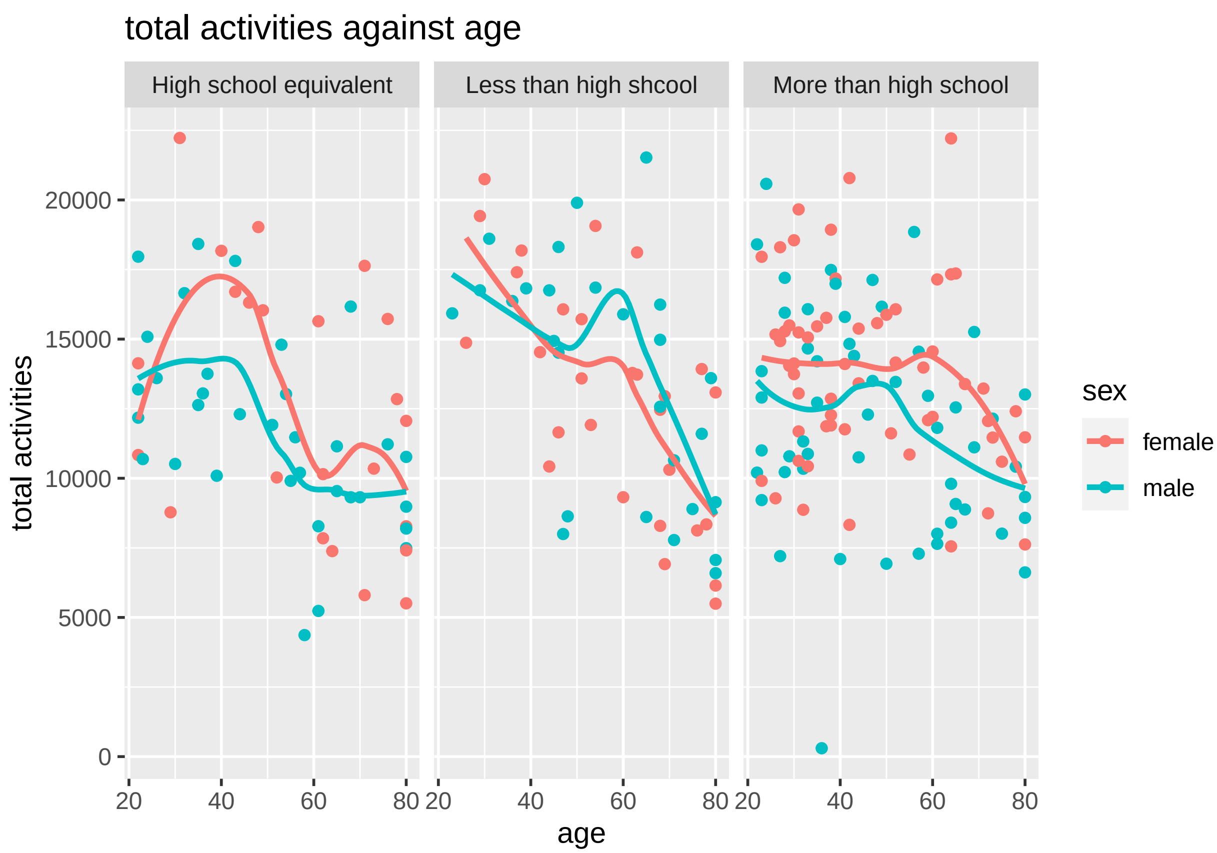
create a total activity variable for each participant

```
accel_clean =
  nhanes_df |>
  group_by(seqn, sex, age, education) |>
  summarize(
    total_activity = sum(counts)
  )
```

```
## ‘summarise()‘ has grouped output by ’seqn’, ’sex’, ’age’. You can override
## using the ‘.groups‘ argument.
```

```r
accel_clean|>
ggplot(aes(x = age, y = total_activity, color = sex)) +
  geom_point() +
  geom_smooth(se = FALSE) +
  facet_grid(. ~ education)+
  labs(
    title = "total activities against age",
    x = "age",
    y = "total activities",
  )
```

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




```r
ggsave("total activities against age.pdf")
```

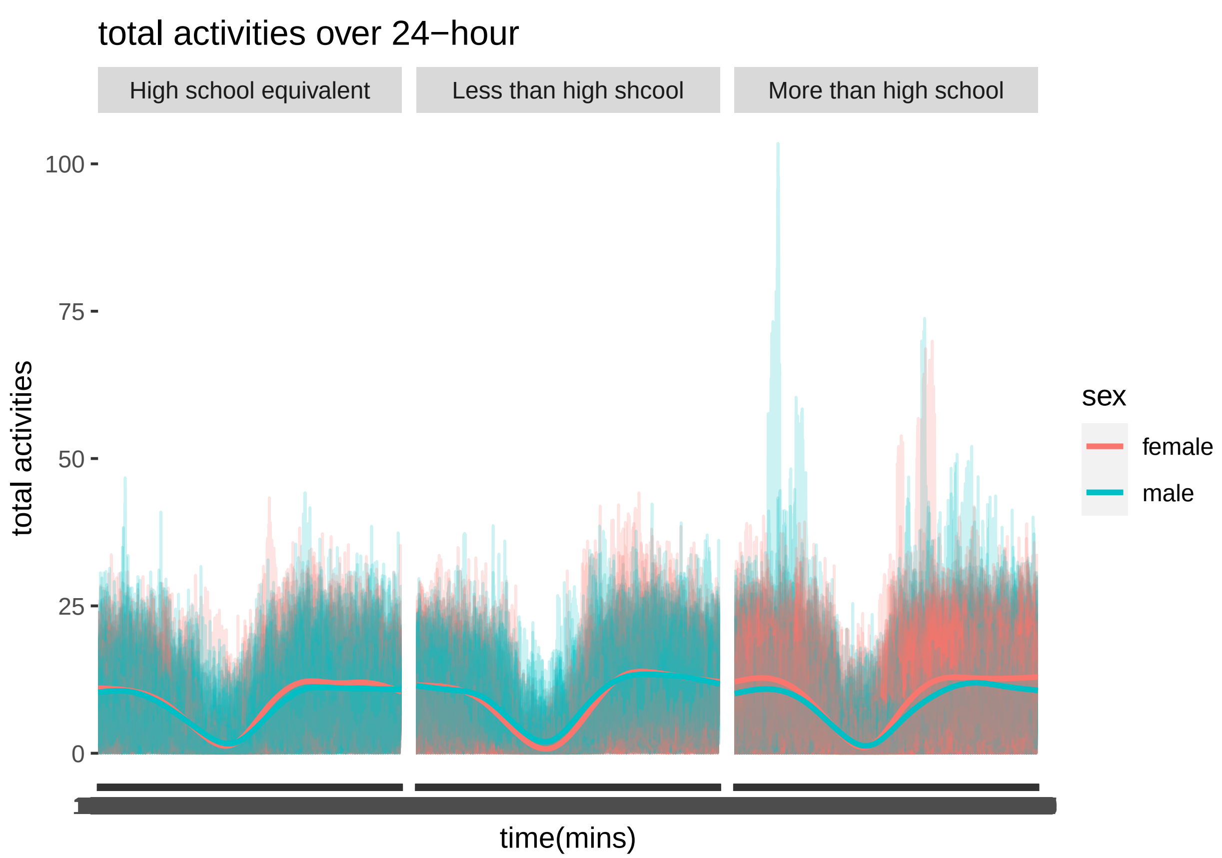
```
## Saving 6.5 x 4.5 in image
## `geom_smooth()` using method = 'loess' and formula = 'y ~ x'
```

At high school equivalent and more than high school education level, overall females activity is higher than males for people 22yr+. At less than high school education level, the overall males activity is higher than females between 40 and 80, but lower than that of females between 20 and 40. At more than high school education level,overall females activity is higher than males at all age groups. No matter education level and gender, total activity decreases as the age increases.

a three-panel plot that shows the 24-hour activity time courses for each education level and use color to indicate sex.

```r
nhanes_df |>
ggplot(aes(x = number, y = counts, group = seqn, color = sex)) +
  geom_line(alpha = .2) +
  facet_grid(. ~ education) +
  geom_smooth(aes(group = sex), se = FALSE)+
  labs(
    title = "total activities over 24-hour",
    x = "time(mins)",
    y = "total activities",
  )
```

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




```r
ggsave("total activities over 24-hour.pdf")
```

```
## Saving 6.5 x 4.5 in image
## `geom_smooth()` using method = 'gam' and formula = 'y ~ s(x, bs = "cs")'
```

Based on the plot, the 24-hour activity time courses for high school equivalent and less than high school education levels are similar. At more than high school education level, there are two peaks of activities. In addition, females have higher activities than males do.From the smooth trends, we could see a decrease for every education level.