p8105_hw3_jl6048

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```
library(tidyverse)
library(p8105.datasets)
library(ggridges)
library(patchwork)
library(readxl)

knitr::opts_chunk$set(
  echo = TRUE,
  warning = FALSE,
  fig.width = 8,
  fig.height = 6,
  out.width = "90%"
  )
```

Problem 1

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

- There are 134 aisles in this data set and the most items are ordered from the fresh vegetables and fresh fruits aisles.

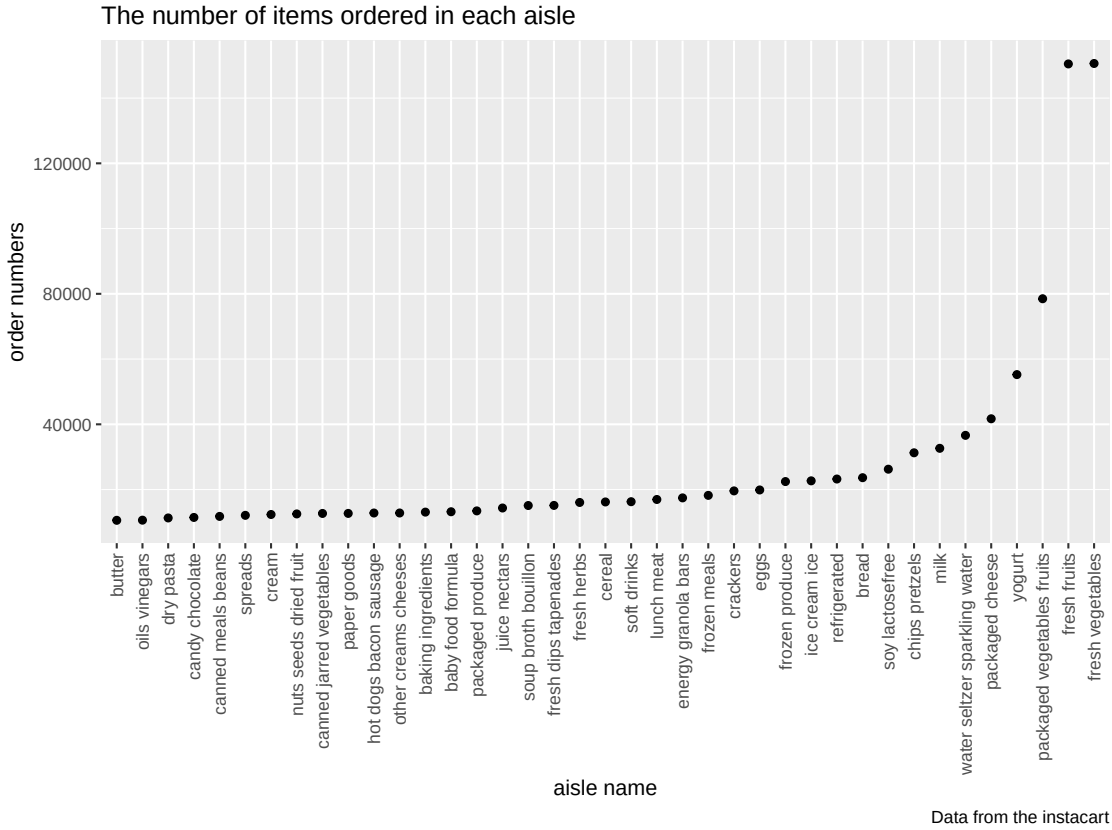
```
data("instacart")
instacart_df =
  instacart %>%
  janitor::clean_names()%>%
  count(aisle) %>%
  arrange(desc(n))
instacart_df
```

```
## # 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
## # ... with 124 more rows
```

Make a plot that shows the number of items ordered in each aisle, limiting this to aisles with more than 10000 items ordered

```
instacart_df %>%
  filter(n > 10000) %>%
  mutate(
    aisle = factor(aisle),
    aisle = fct_reorder(aisle, n)) %>%
   ggplot(aes(x = aisle, y = n)) +
  geom_point() +
  labs(
    title = "The number of items ordered in each aisle",
    x = "aisle name",
    y = "order numbers",
    caption = "Data from the instacart") +
  theme(axis.text.x = element_text(angle = 90, vjust = 0.5, hjust = 1))
```



Make a table showing the three most popular items

```
popitems_df =
  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(aisle, rank) %>%
    knitr::kable()
popitems_df
```

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

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;

```
meanhour_df =
  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) %>%
  rename(
    sun. = "0", mon. = "1", tue. = "2",
    wed. = "3", thu. = "4", fri. = "5", sat. = "6") %>%
  knitr::kable()
```

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

```
 meanhour_df
```

product_name	sun.	mon.	tue.	wed.	thu.	fri.	sat.
Coffee Ice Cream	13.77419	14.31579	15.38095	15.31818	15.21739	12.26316	13.83333
Pink Lady Apples	13.44118	11.36000	11.70213	14.25000	11.55172	12.78431	11.93750

Description: This datasets has 1384617 observations and 15 variables.

The key variables are as follows: * `product_name`: name of the product * `aisle`: name of the aisle * `order_dow`: the day of the week on which the order was placed * `order_hour_of_day`: the hour of the day on which the order was placed * `order_id`: order identifier * `product_id`: product identifier

For example, the individual with user id 66177 ordered 21 and they are most from the snacks department.

Problem 2

data cleaning

```
data("brfss_smart2010")
brfss_smart=
  brfss_smart2010 %>%
  janitor::clean_names() %>%
  filter(topic == "Overall Health") %>%
  mutate(
    response = forcats::fct_relevel(response, c("Excellent", "Very good", "Good", "Fair", "Poor"))) %>%
  arrange(desc(response))
brfss_smart
```

```
## # A tibble: 10,625 x 23
##     year locationabbr locationdesc  class  topic  question  response sample_size
##    <int> <chr>        <chr>         <chr>  <chr>  <chr>     <fct>          <int>
##  1  2010 AL           AL - Jeffers~ Healt~ Overa~ How is y~ Poor              45
##  2  2010 AL           AL - Mobile ~ Healt~ Overa~ How is y~ Poor              66
##  3  2010 AL           AL - Tuscalo~ Healt~ Overa~ How is y~ Poor              35
##  4  2010 AZ           AZ - Maricop~ Healt~ Overa~ How is y~ Poor              62
##  5  2010 AZ           AZ - Pima Co~ Healt~ Overa~ How is y~ Poor              49
##  6  2010 AZ           AZ - Pinal C~ Healt~ Overa~ How is y~ Poor              30
##  7  2010 AR           AR - Benton ~ Healt~ Overa~ How is y~ Poor              21
##  8  2010 AR           AR - Pulaski~ Healt~ Overa~ How is y~ Poor              36
##  9  2010 AR           AR - Washing~ Healt~ Overa~ How is y~ Poor              16
## 10  2010 CA           CA - Alameda~ Healt~ Overa~ How is y~ Poor              23
## # ... with 10,615 more rows, and 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>,
## #   data_source <chr>, class_id <chr>, topic_id <chr>, location_id <chr>,
## #   question_id <chr>, respid <chr>, geo_location <chr>
```

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

```
states_2002_df =
  brfss_smart2010 %>%
  janitor::clean_names() %>%
  filter(year == 2002) %>%
  group_by(locationabbr) %>%
  summarize(
    country_num = n_distinct(locationdesc)) %>%
  filter(country_num >= 7)
states_2002_df
```

```
## # A tibble: 6 x 2
##   locationabbr country_num
##   <chr>              <int>
## 1 CT                     7
## 2 FL                     7
## 3 MA                     8
## 4 NC                     7
```

```
## 5 NJ                    8
## 6 PA                   10
```

```
states_2010_df =
  brfss_smart2010 %>%
  janitor::clean_names() %>%
  filter(year == 2010) %>%
  group_by(locationabbr) %>%
  summarize(
    country_num = n_distinct(locationdesc)) %>%
  filter(country_num >= 7)
states_2010_df
```

```
## # A tibble: 14 x 2
##    locationabbr country_num
##    <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
```

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

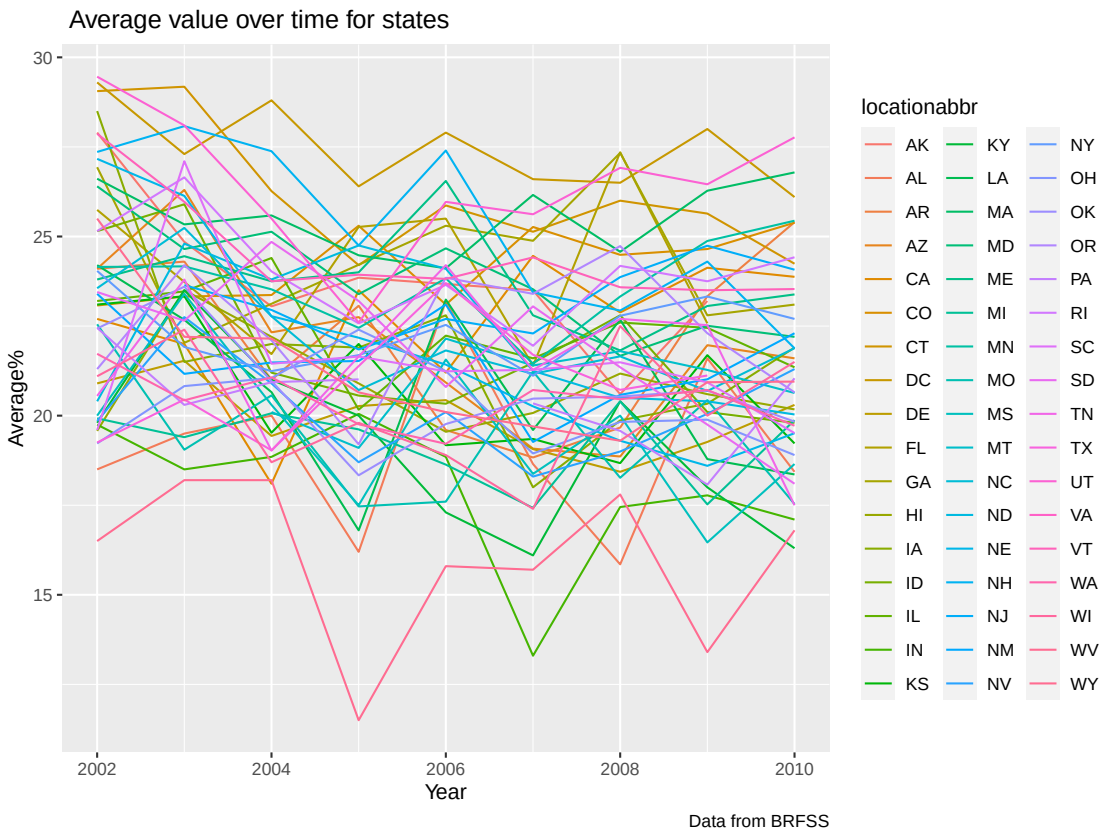
Construct a dataset that is limited to Excellent responses. Make a "spaghetti" plot of this average value over time within a state .

```
excellent_resp =
  brfss_smart2010 %>%
  janitor::clean_names() %>%
  filter(response == "Excellent") %>%
  group_by(locationabbr,year) %>%
  summarize(
    ave_value = mean(data_value)) %>%
  select(year, locationabbr, ave_value)  %>%

   ggplot(aes(x = year, y = ave_value,  color = locationabbr)) +
  geom_line(aes(group = locationabbr)) +
  labs(
    title = " Average value over time for states ",
    x = "Year",
    y = "Average%",
    caption = "Data from BRFSS")
```

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

```
excellent_resp
```



*Solution:

Above is the spaghetti plot of average value over time within the 51 states. Because there are many states, it cannot easy to distinguish each one. However, we can still observe the extreme decrease in 2005.

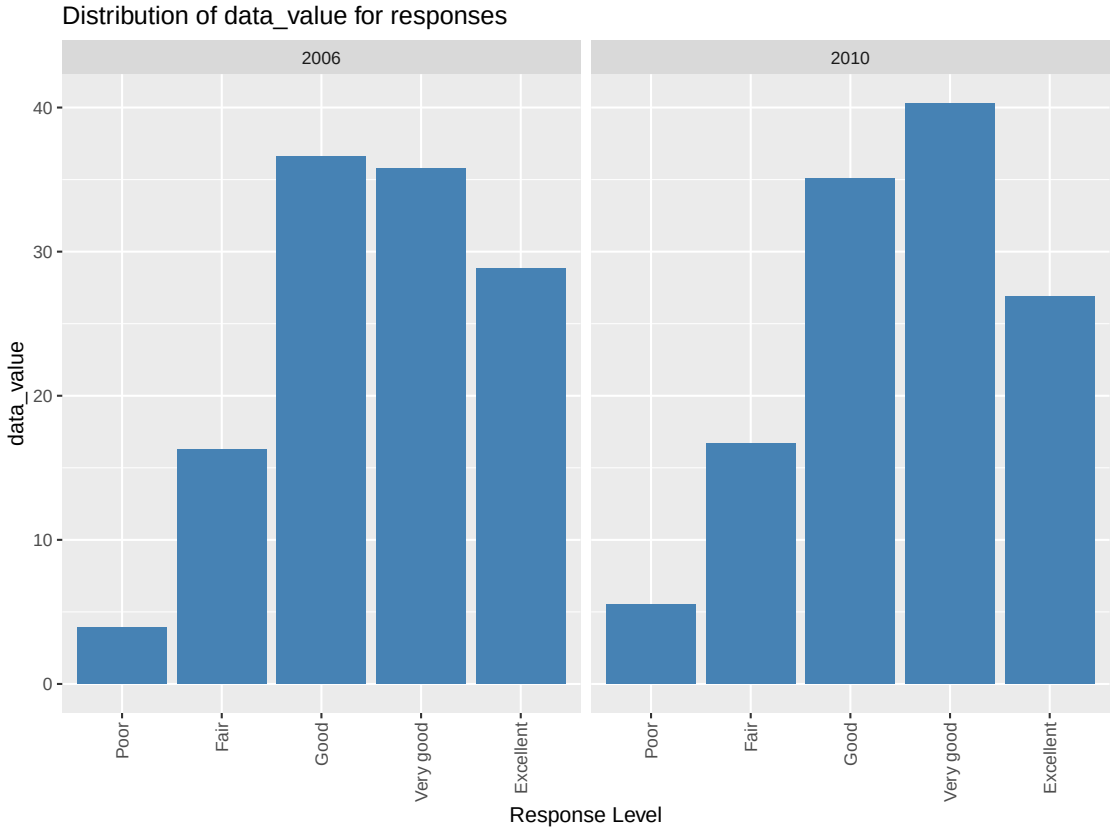
Make a two-panel plot for the years 2006, and 2010

```
two_panel =
  brfss_smart2010 %>%
  janitor::clean_names() %>%
  filter(year == "2006" | year == "2010")%>%
  filter(locationabbr == "NY") %>%
  mutate(data_value = as.numeric(data_value),
         year = as.factor(year),
         locationdesc = as.factor(locationdesc),
         response = as.factor(response)) %>%
  filter(response %in% c("Poor", "Fair", "Good", "Very good", "Excellent")) %>%
  mutate(
    response = factor(response, levels = c("Poor", "Fair", "Good", "Very good", "Excellent")))%>%
  select(year, data_value, locationdesc, response) %>%

  ggplot(aes(x = response, y = data_value)) +
  geom_bar(stat = "identity", fill="steelblue", position=position_dodge()) + facet_grid(. ~year) +
  labs(
    title = "Distribution of data_value for responses",
    x = "Response Level",
```

```
    y = "data_value") +
  theme(axis.text.x = element_text(angle = 90, vjust = 0.5, hjust = 1))

two_panel
```



*Solution The distribution of response in NY state between 2006 and 2010 are quite similar.

Problem 3

Load, tidy, and otherwise wrangle the data

```
accel_data =
  read_csv("./data/accel_data.csv") %>%
  janitor::clean_names() %>%
pivot_longer(
    cols = activity_1:activity_1440,
    names_to = "minute",
    values_to = "activity_amount",
    names_prefix = "activity_") %>%
mutate(day_type = ifelse(day == "Saturday" | day == "Sunday", "Weekend", "Weekday"))  %>%
  mutate(day = forcats::fct_relevel(day, c("Monday", "Tuesday", "Wednesday", "Thursday", "Friday", "Satu
```

```
## Rows: 35 Columns: 1443
```

```
## -- Column specification --------------------------------------------------------
```

```
## Delimiter: ","
## chr    (1): day
## dbl (1442): week, day_id, activity.1, activity.2, activity.3, activity.4, ac...


##
## 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.
```

```
accel_data
```

```
## # A tibble: 50,400 x 6
##     week day_id day    minute activity_amount day_type
##    <dbl>  <dbl> <fct>  <chr>            <dbl> <chr>
##  1     1      1 Friday 1                 88.4 Weekday
##  2     1      1 Friday 2                 82.2 Weekday
##  3     1      1 Friday 3                 64.4 Weekday
##  4     1      1 Friday 4                 70.0 Weekday
##  5     1      1 Friday 5                 75.0 Weekday
##  6     1      1 Friday 6                 66.3 Weekday
##  7     1      1 Friday 7                 53.8 Weekday
##  8     1      1 Friday 8                 47.8 Weekday
##  9     1      1 Friday 9                 55.5 Weekday
## 10     1      1 Friday 10                43.0 Weekday
## # ... with 50,390 more rows
```

*Description: The data set contain 50400 observations of 6 variables. These variables include "week", "day_id","day","minute", "activity_amount", "day_type".

aggregate accross minutes to create a total activity variable for each day

```
aggre_table =
  accel_data %>%
  group_by(week, day, day_id) %>%
  summarize(sum_day = sum(activity_amount)) %>%
select(week, day, sum_day) %>%
arrange(desc(day)) %>%
knitr::kable()
```

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

```
aggre_table
```

week	day	sum_day
1	Sunday	631105.00
2	Sunday	422018.00
3	Sunday	467052.00
4	Sunday	260617.00
5	Sunday	138421.00
1	Saturday	376254.00
2	Saturday	607175.00
3	Saturday	382928.00

week	day	sum_day
4	Saturday	1440.00
5	Saturday	1440.00
1	Friday	480542.62
2	Friday	568839.00
3	Friday	467420.00
4	Friday	154049.00
5	Friday	620860.00
1	Thursday	355923.64
2	Thursday	474048.00
3	Thursday	371230.00
4	Thursday	340291.00
5	Thursday	549658.00
1	Wednesday	340115.01
2	Wednesday	440962.00
3	Wednesday	468869.00
4	Wednesday	434460.00
5	Wednesday	445366.00
1	Tuesday	307094.24
2	Tuesday	423245.00
3	Tuesday	381507.00
4	Tuesday	319568.00
5	Tuesday	367824.00
1	Monday	78828.07
2	Monday	295431.00
3	Monday	685910.00
4	Monday	409450.00
5	Monday	389080.00

*Solution: I think the table didn't show any trends apparent.

Make a single-panel plot that shows the 24-hour activity time courses for each day

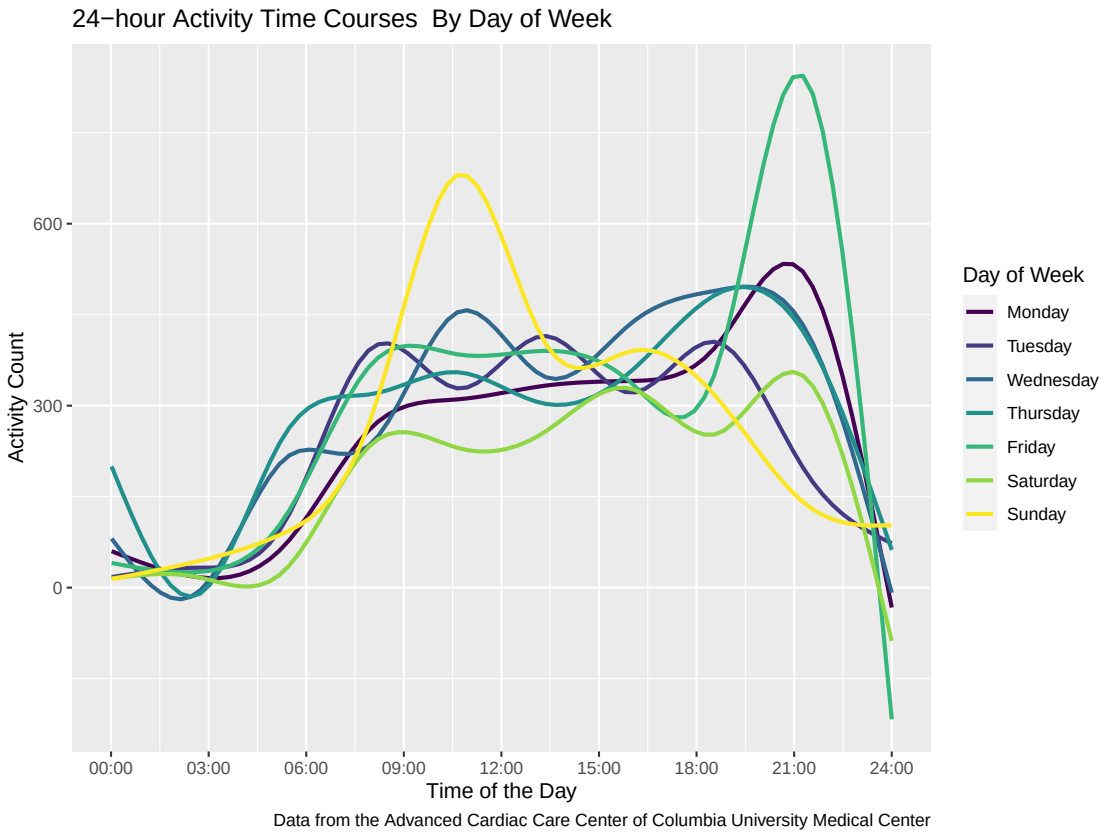
```
activity_day_plot =
  accel_data %>%
  mutate(
    minute = as.numeric(as.character(minute))
  ) %>%
  group_by(day, minute) %>%
  summarize(
    mean_activity_day = mean(activity_amount)
  ) %>%
  ggplot(aes(x = minute, y = mean_activity_day, color = day, group = day)) +
  geom_smooth(se = FALSE) +
  labs(
    title = "24-hour Activity Time Courses  By Day of Week ",
    x = "Time of the Day",
    y = "Activity Count",
    caption = "Data from the Advanced Cardiac Care Center of Columbia University Medical Center") +
  viridis::scale_color_viridis(
    name = "Day of Week",
    discrete = TRUE
  ) +
```

```
  scale_x_continuous(
   breaks = c(0, 180, 360, 540, 720, 900, 1080, 1260, 1440),
   labels = c("00:00","03:00", "06:00", "09:00","12:00", "15:00", "18:00", "21:00", "24:00"),
   limits = c(0, 1440))
```

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

```
activity_day_plot
```

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



*Conclusion: On average, this person is most active between 6 and 10 in the evening and is always less active in the morning. On Sunday, most of his activities are at noon.