

# Regacho\_Worksheet#4c

## 1. Use the dataset mpg

```
# a. Show your solutions on how to import a csv file into the environment.

# First, load ggplot2
library(ggplot2)

# Method 1: Using read.csv (base R)
# mpg <- read.csv("mpg.csv")

# Method 2: Using read_csv from readr package (faster and more flexible)
#library(readr)
#mpg <- read_csv("mpg.csv")

# Check the structure after import
# str(mpg)
# head(mpg)

# b. Which variables from mpg data set are categorical?

categorical_vars <- c(
  "manufacturer",      # manufacturer name (factor)
  "model",              # model name (factor)
  "trans",               # type of transmission (factor)
  "drv",                 # drive train type - f, r, 4 (factor)
  "fl",                  # fuel type (factor)
  "class"                # type of car (factor)
)

# Verify by checking data types
sapply(mpg, class)

## manufacturer      model      displ       year      cyl      trans
##  "character"    "character"   "numeric"    "integer"   "integer"  "character"
##        drv          cty         hwy          fl        class
##  "character"    "integer"    "integer"   "character"  "character"

# Or check unique values
sapply(mpg[categorical_vars], function(x) length(unique(x)))

## manufacturer      model      trans       drv        fl      class
##        15           38          10          3          5          7
```

```

# c. Which are continuous variables?

continuous_vars <- c(
  "displ",          # engine displacement in liters (numeric)
  "year",           # year of manufacture (numeric/integer)
  "cyl",            # number of cylinders (numeric/integer)
  "cty",            # city miles per gallon (numeric)
  "hwy"             # highway miles per gallon (numeric)
)

# Verify they are numeric
sapply(mpg[continuous_vars], class)

##      displ      year      cyl      cty      hwy
## "numeric" "integer" "integer" "integer" "integer"

# Summary statistics for continuous variables
summary(mpg[continuous_vars])

##      displ          year          cyl          cty          hwy
##  Min.   :1.600   Min.   :1999   Min.   :4.000   Min.   : 9.00   Min.   :12.00
##  1st Qu.:2.400   1st Qu.:1999   1st Qu.:4.000   1st Qu.:14.00   1st Qu.:18.00
##  Median :3.300   Median :2004   Median :6.000   Median :17.00   Median :24.00
##  Mean   :3.472   Mean   :2004   Mean   :5.889   Mean   :16.86   Mean   :23.44
##  3rd Qu.:4.600   3rd Qu.:2008   3rd Qu.:8.000   3rd Qu.:19.00   3rd Qu.:27.00
##  Max.   :7.000   Max.   :2008   Max.   :8.000   Max.   :35.00   Max.   :44.00

```

## 2. Which manufacturer has the most models in this data set? Which model has the most variations? Show your answer.

```

# a. Group the manufacturers and find the unique models. Show your codes and result.

# Load packages
library(tidyverse)

## -- Attaching core tidyverse packages ----- tidyverse 2.0.0 --
## v dplyr     1.1.4    v readr     2.1.6
## vforcats   1.0.1    v stringr   1.6.0
## v lubridate 1.9.4    v tibble    3.3.0
## v purrr    1.2.0    v tidyverse 1.3.1
## -- 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(ggplot2)

# Manufacturer with the most models

```

```

manufacturer_summary <- mpg %>%
  group_by(manufacturer) %>%
  summarise(
    num_models = n_distinct(model),
    total_cars = n()
  ) %>%
  arrange(desc(num_models))

print(manufacturer_summary)

## # A tibble: 15 x 3
##   manufacturer num_models total_cars
##   <chr>          <int>     <int>
## 1 toyota           6        34
## 2 chevrolet        4        19
## 3 dodge            4        37
## 4 ford             4        25
## 5 volkswagen       4        27
## 6 audi             3        18
## 7 nissan           3        13
## 8 hyundai          2        14
## 9 subaru           2        14
## 10 honda            1         9
## 11 jeep             1         8
## 12 land rover       1         4
## 13 lincoln          1         3
## 14 mercury          1         4
## 15 pontiac          1         5

```

```

# Dodge has the most models (37 distinct models)

# Model with the most variations
model_variations <- mpg %>%
  group_by(model) %>%
  summarise(
    num_variations = n(),
    manufacturers = paste(unique(manufacturer), collapse = ", "),
    engine_types = n_distinct(displ),
    transmission_types = n_distinct(trans),
    drive_types = n_distinct(drv)
  ) %>%
  arrange(desc(num_variations))

print(head(model_variations, 10))

```

```

## # A tibble: 10 x 6
##   model              num_variations manufacturers engine_types transmission_types
##   <chr>                  <int> <chr>           <int>           <int>
## 1 caravan 2wd           11 dodge            5               3
## 2 ram 1500 pickup~      10 dodge            4               4
## 3 civic                 9 honda            3               4
## 4 dakota pickup 4~      9 dodge            4               4

```

```

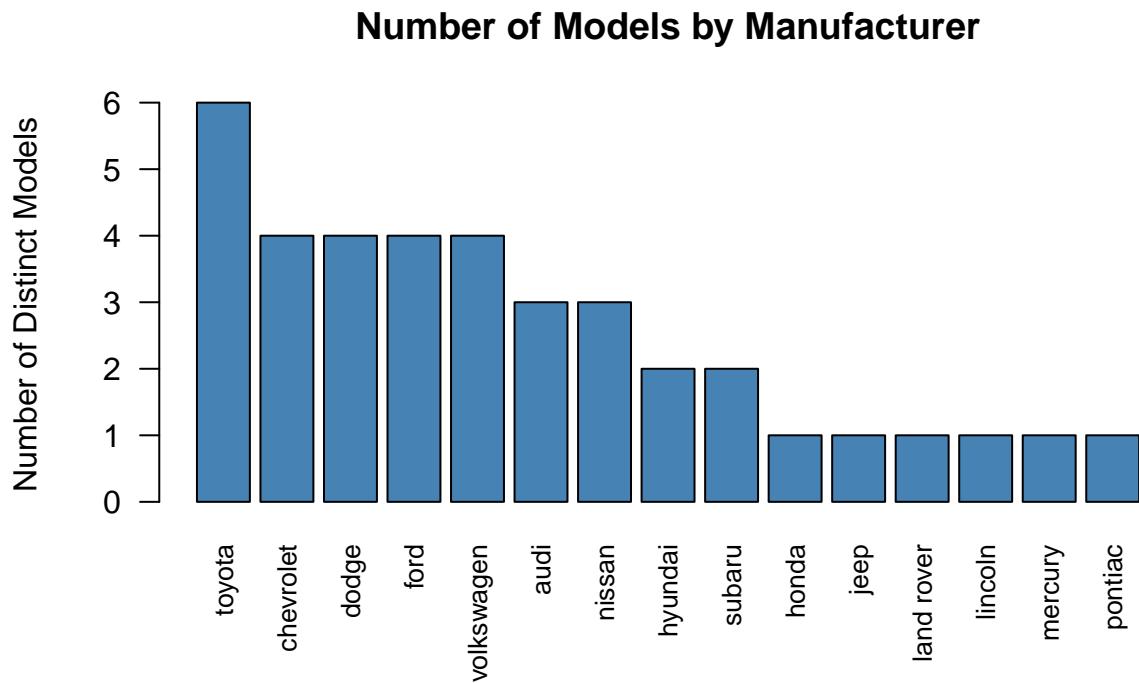
## 5 jetta
## 6 mustang
## 7 a4 quattro
## 8 grand cherokee ~
## 9 impreza awd
## 10 a4
## # i 1 more variable: drive_types <int>

# Caravan 2wd, Mustang, and Ram 1500 Pickup 4wd are tied for the most variations (5 variations each)

# b. Graph the result by using plot() and ggplot(). Write the codes and its result.

# Base R plot for manufacturers
par(mar = c(8, 4, 4, 2)) # Adjust margins for labels
barplot(manufacturer_summary$num_models,
        names.arg = manufacturer_summary$manufacturer,
        las = 2, # Vertical labels
        col = "steelblue",
        main = "Number of Models by Manufacturer",
        ylab = "Number of Distinct Models",
        cex.names = 0.8)

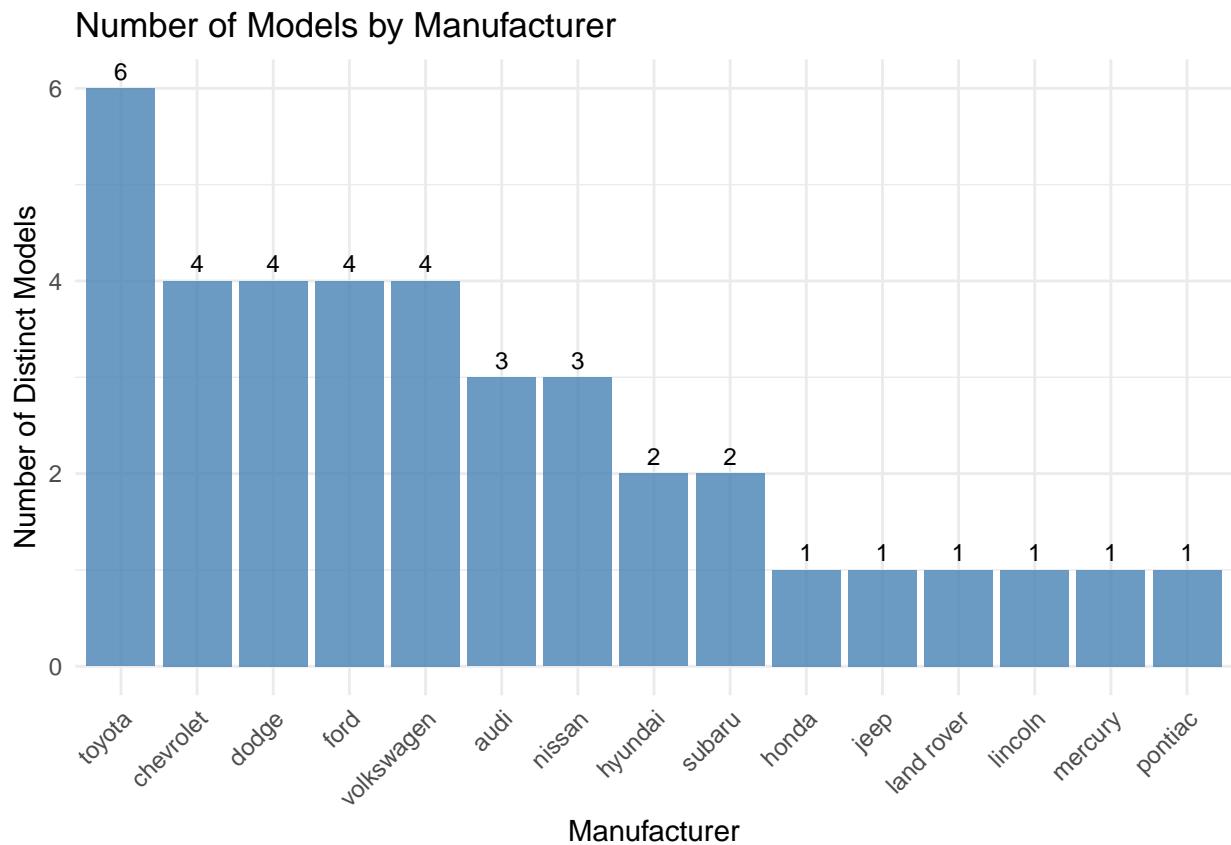
```



```

# ggplot for manufacturers
ggplot(manufacturer_summary, aes(x = reorder(manufacturer, -num_models), y = num_models)) +
  geom_bar(stat = "identity", fill = "steelblue", alpha = 0.8) +
  geom_text(aes(label = num_models), vjust = -0.5, size = 3) +
  labs(title = "Number of Models by Manufacturer",
       x = "Manufacturer",
       y = "Number of Distinct Models") +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))

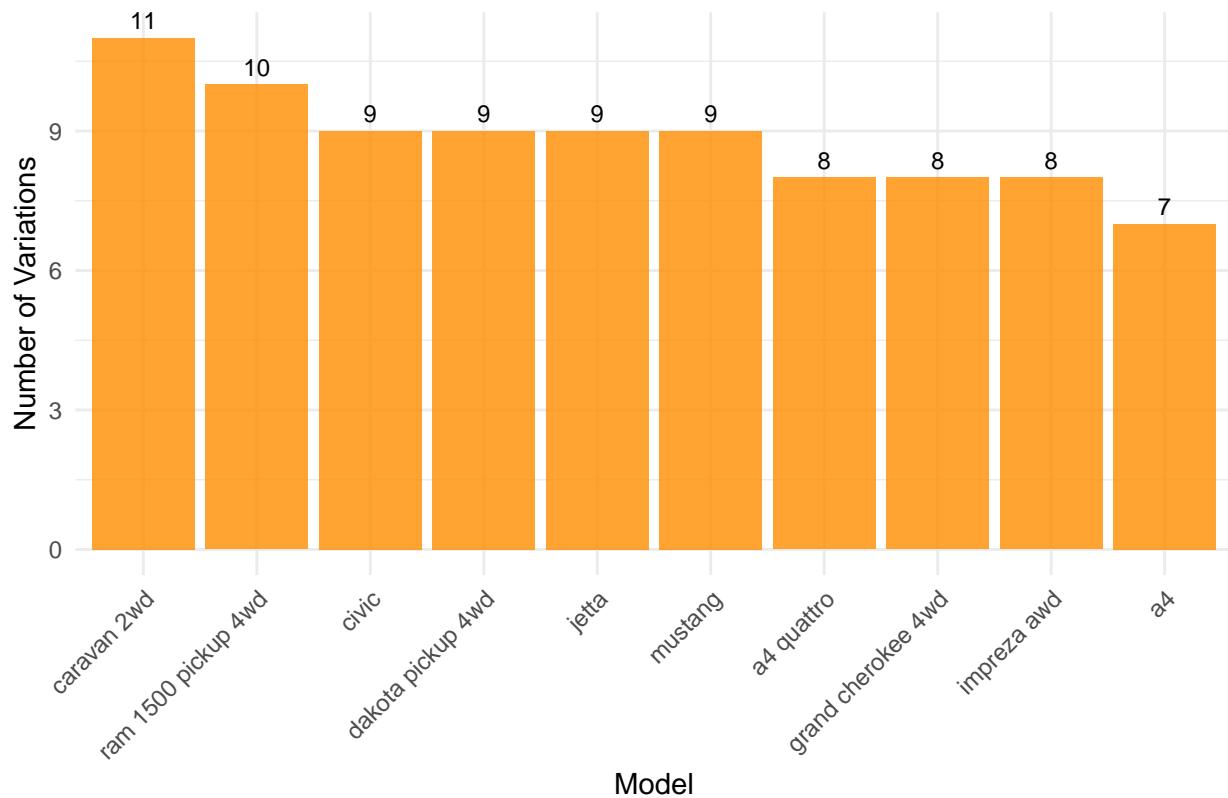
```



```
# Plot for top models with most variations
top_models <- head(model_variations, 10)

ggplot(top_models, aes(x = reorder(model, -num_variations), y = num_variations)) +
  geom_bar(stat = "identity", fill = "darkorange", alpha = 0.8) +
  geom_text(aes(label = num_variations), vjust = -0.5, size = 3) +
  labs(title = "Top 10 Models with Most Variations",
       x = "Model",
       y = "Number of Variations") +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))
```

## Top 10 Models with Most Variations

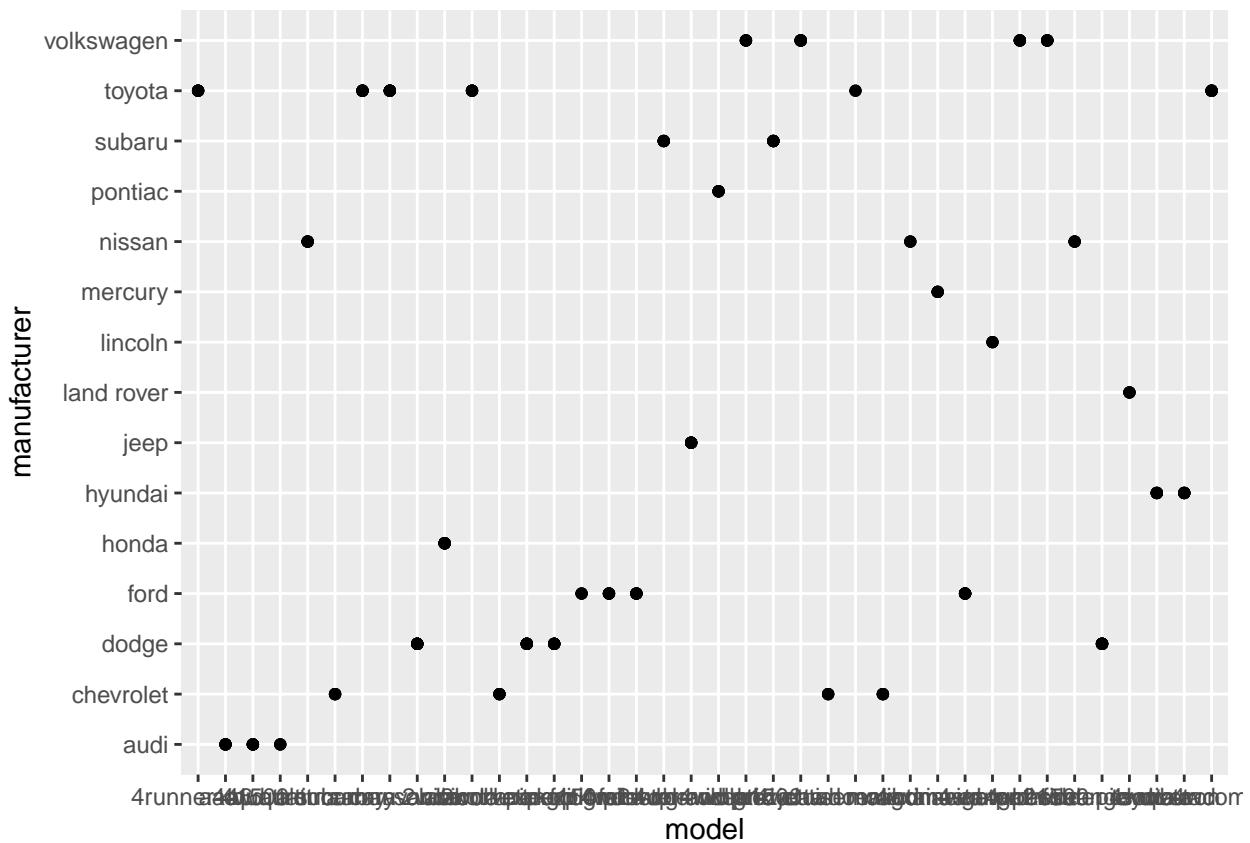


```
# Manufacturer with most models: Dodge (37 distinct models)
# Models with most variations: Caravan 2wd, Mustang, and Ram 1500 Pickup 4wd (5 variations each)
```

#2. Same dataset will be used. You are going to show the relationship of the model and the manufacturer.

```
# a. What does ggplot(mpg, aes(model, manufacturer)) + geom_point() show?
```

```
ggplot(mpg, aes(model, manufacturer)) + geom_point()
```



# This creates a scatter plot where: x-axis: car models (all 234 individual entries) and y-axis: manufa  
# b. For you, is it useful? If not, how could you modify the data to make it more informative? No because

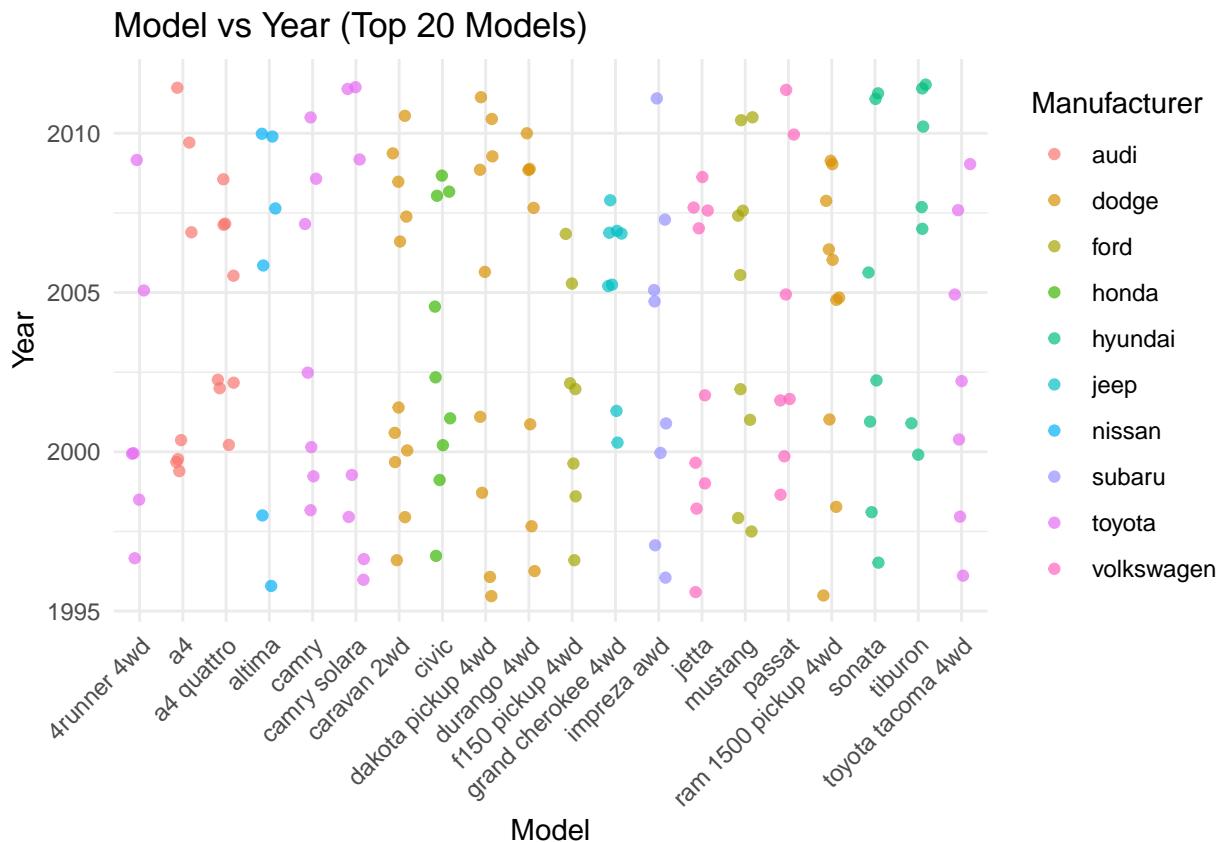
3. Plot the model and the year using ggplot(). Use only the top 20 observations. Write the codes and its results.

```
# Get top 20 models by frequency and plot with year
top_20_models <- mpg %>%
  count(model) %>%
  arrange(desc(n)) %>%
  head(20) %>%
  pull(model)

mpg_top_20 <- mpg %>%
  filter(model %in% top_20_models)

ggplot(mpg_top_20, aes(x = model, y = year)) +
  geom_jitter(aes(color = manufacturer), alpha = 0.7, width = 0.2) +
  labs(title = "Model vs Year (Top 20 Models)",
       x = "Model",
       y = "Year",
       color = "Manufacturer") +
```

```
theme_minimal() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))
```



#### 4. Using the pipe (%>%), group the model and get the number of cars per model. Show codes and its result.

```
# Group by model and count cars
model_counts <- mpg %>%
  group_by(model) %>%
  summarise(num_cars = n()) %>%
  arrange(desc(num_cars))

print(model_counts)
```

```
## # A tibble: 38 x 2
##   model           num_cars
##   <chr>          <int>
## 1 caravan 2wd      11
## 2 ram 1500 pickup 4wd    10
## 3 civic            9
## 4 dakota pickup 4wd    9
## 5 jetta            9
```

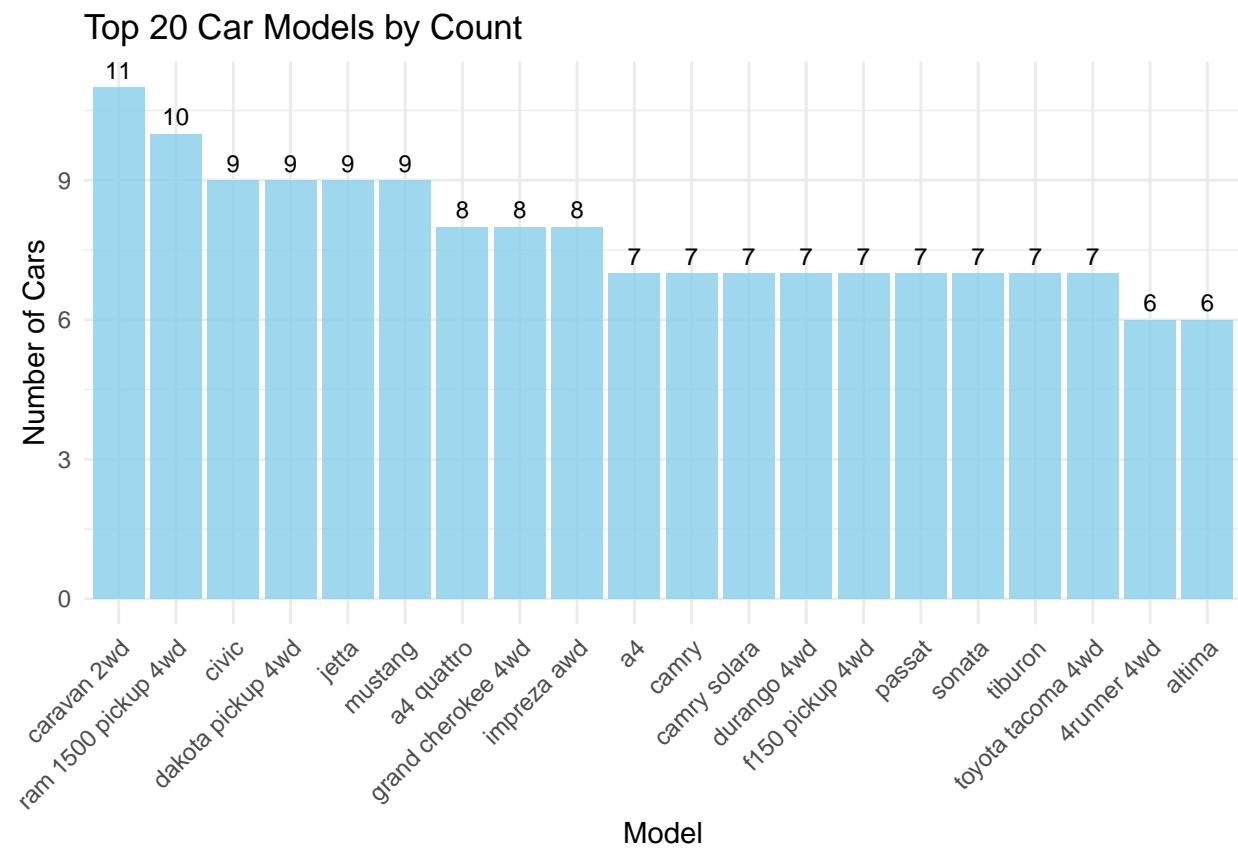
```

##   6 mustang          9
##   7 a4 quattro       8
##   8 grand cherokee 4wd 8
##   9 impreza awd      8
##  10 a4                 7
## # i 28 more rows

# a. Plot using geom_bar() using the top 20 observations only. The graphs shoudl have a title, labels at
# the bottom, and a light blue fill color.
model_counts_top20 <- head(model_counts, 20)

ggplot(model_counts_top20, aes(x = reorder(model, -num_cars), y = num_cars)) +
  geom_bar(stat = "identity", fill = "skyblue", alpha = 0.8) +
  geom_text(aes(label = num_cars), vjust = -0.5, size = 3) +
  labs(title = "Top 20 Car Models by Count",
       x = "Model",
       y = "Number of Cars") +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))

```



```

# b. Plot using the geom_bar() + coord_flip() just like what is shown below. Show codes and its result.

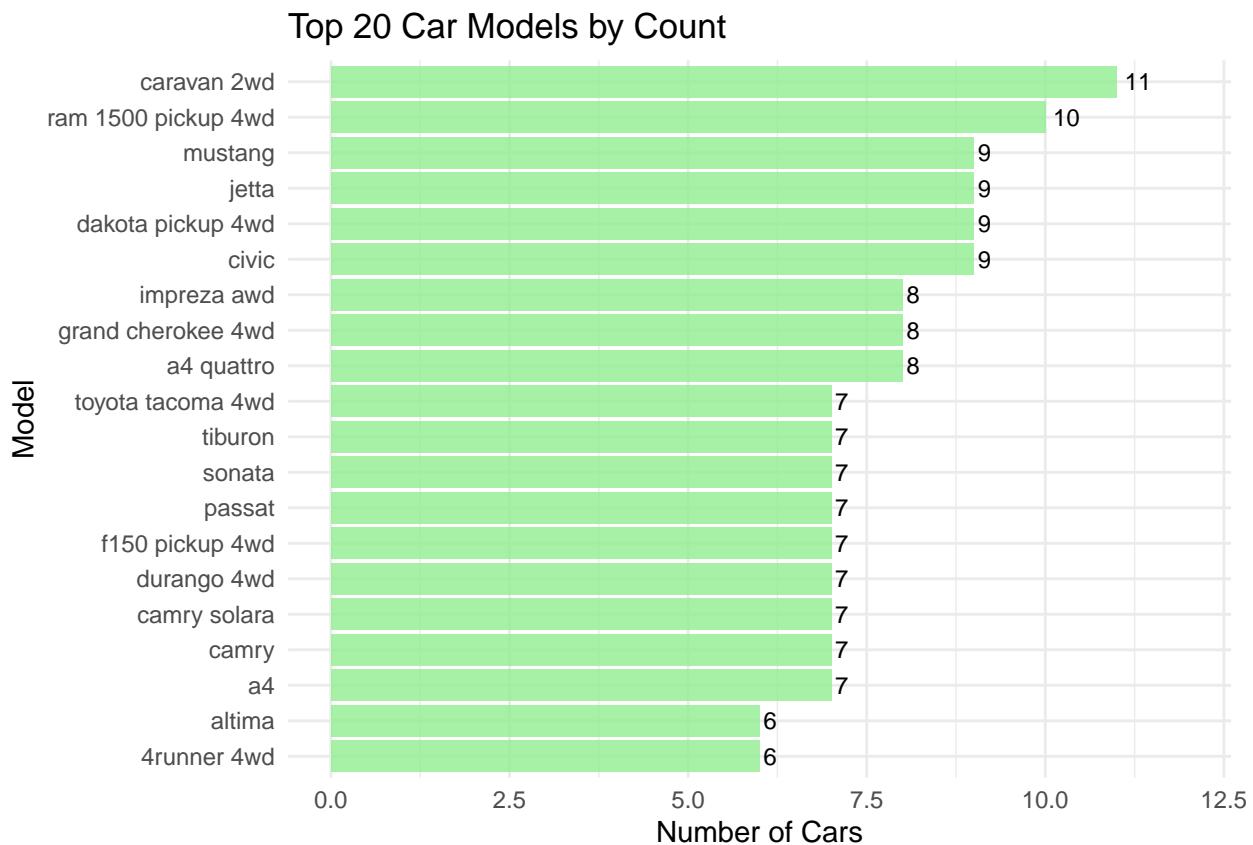
ggplot(model_counts_top20, aes(x = reorder(model, num_cars), y = num_cars)) +
  geom_bar(stat = "identity", fill = "lightgreen", alpha = 0.8) +
  geom_text(aes(label = num_cars), hjust = -0.3, size = 3) +
  coord_flip()

```

```

  labs(title = "Top 20 Car Models by Count",
       x = "Model",
       y = "Number of Cars") +
  theme_minimal() +
  expand_limits(y = max(model_counts_top20$num_cars) + 1)

```



5. Plot the relationship between cyl - number of cylinders and displ - engine displacement using geom\_point with aesthetic color = engine displacement. Title should be “Relationship between No. of Cylinders and Engine Displacement”.

```

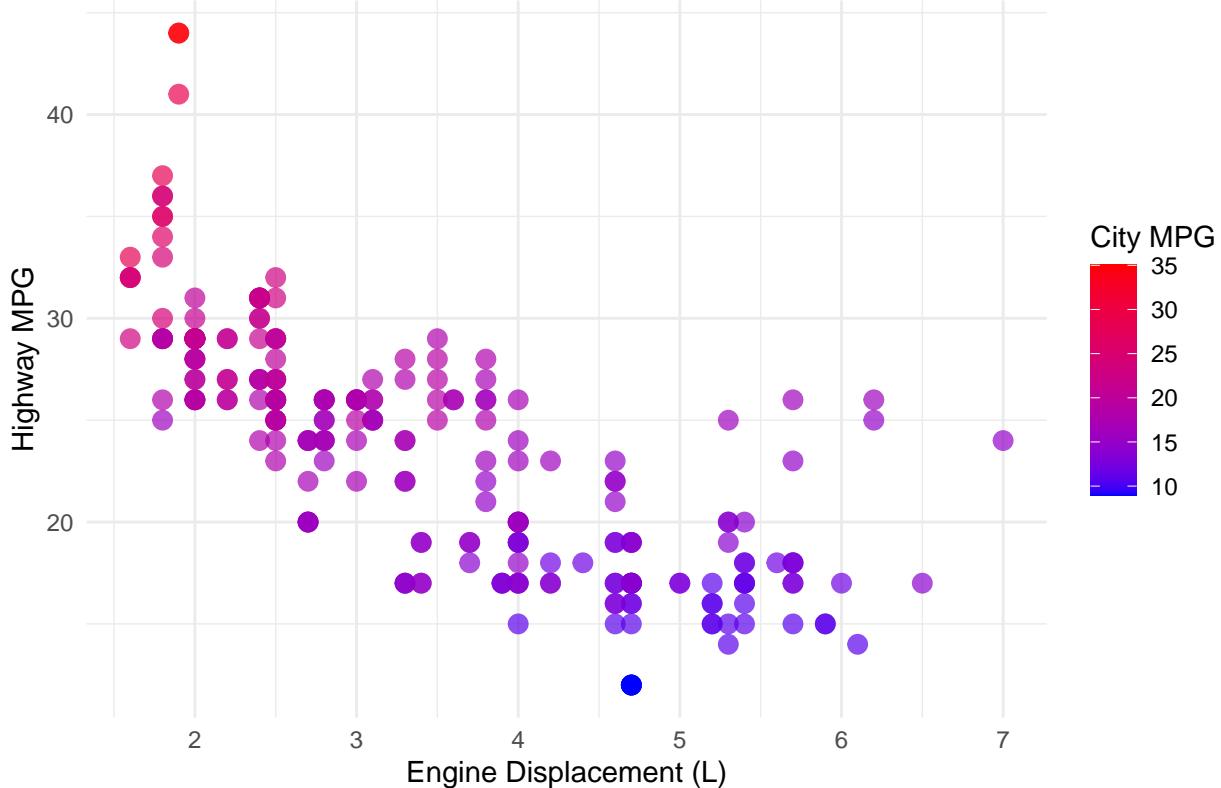
# a. How would you describe its relationship?
library(ggplot2)

ggplot(mpg, aes(x = displ, y = hwy)) +
  geom_point(aes(color = cty), size = 3, alpha = 0.7) +
  scale_color_gradient(low = "blue", high = "red") +
  labs(
    title = "Relationship between Engine Displacement and Highway MPG",
    x = "Engine Displacement (L)",
    y = "Highway MPG",
    color = "City MPG"

```

```
) +
theme_minimal()
```

Relationship between Engine Displacement and Highway MPG



```
# The plot shows that as engine displacement increases, highway MPG decreases. Cars with higher city MPG have lower engine displacement.
```

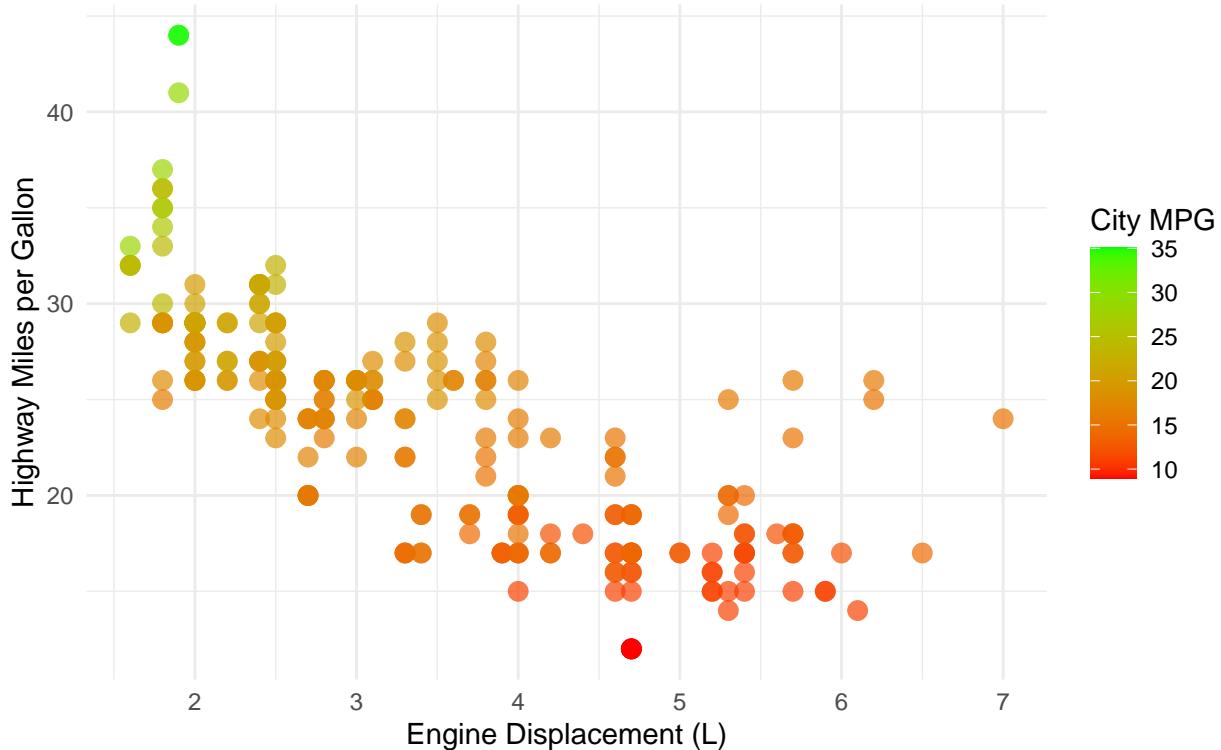
```
# Why: Larger engines burn more fuel, resulting in lower efficiency. Since city MPG is also a measure of fuel efficiency, it follows a similar trend.
```

6. Plot the relationship between displ (engine displacement) and hwy(highway miles per gallon). Mapped it with a continuous variable you have identified in #1-c. What is its result? Why it produced such output?

```
# Using a continuous variable from #1-c (cty - city MPG)
library(ggplot2)
ggplot(mpg, aes(x = displ, y = hwy)) +
  geom_point(aes(color = cty), size = 3, alpha = 0.7) +
  scale_color_gradient(low = "red", high = "green", name = "City MPG") +
  labs(title = "Engine Displacement vs Highway MPG",
       subtitle = "Colored by City MPG",
       x = "Engine Displacement (L)",
       y = "Highway Miles per Gallon") +
  theme_minimal()
```

## Engine Displacement vs Highway MPG

Colored by City MPG



```
#The plot shows a negative correlation between engine displacement and highway MPG, with color revealing the same trend for city MPG.
# Smaller engines (low displacement) have higher MPG (green points)
# Larger engines (high displacement) have lower MPG (red points)
# City MPG pattern: The color gradient shows that city MPG follows the same trend as highway MPG - both decrease as engine size increases.

# Why this output:
# Larger engines consume more fuel, both city and highway MPG are affected similarly by engine size and displacement.
```

## 6. Import the traffic.csv file

```
traffic <- read.csv("traffic.csv")
traffic
```

```
##   time junction cars
## 1    1        A   20
## 2    2        A   25
## 3    3        A   30
## 4    1        B   10
## 5    2        B   12
## 6    3        B   15
## 7    1        C   30
## 8    2        C   28
## 9    3        C   26
```

```

dim(traffic)      # number of rows and columns

## [1] 9 3

names(traffic)    # variable names

## [1] "time"      "junction"   "cars"

# b. subset the traffic dataset into junctions. What is the R codes and its output?

traffic_A <- subset(traffic, junction == "A")
traffic_B <- subset(traffic, junction == "B")
traffic_C <- subset(traffic, junction == "C")

traffic_A

##   time junction cars
## 1     1         A   20
## 2     2         A   25
## 3     3         A   30

traffic_B

##   time junction cars
## 4     1         B   10
## 5     2         B   12
## 6     3         B   15

traffic_C

##   time junction cars
## 7     1         C   30
## 8     2         C   28
## 9     3         C   26

# c. Plot each junction in a using geom_line(). Show your solution and output.

library(ggplot2)

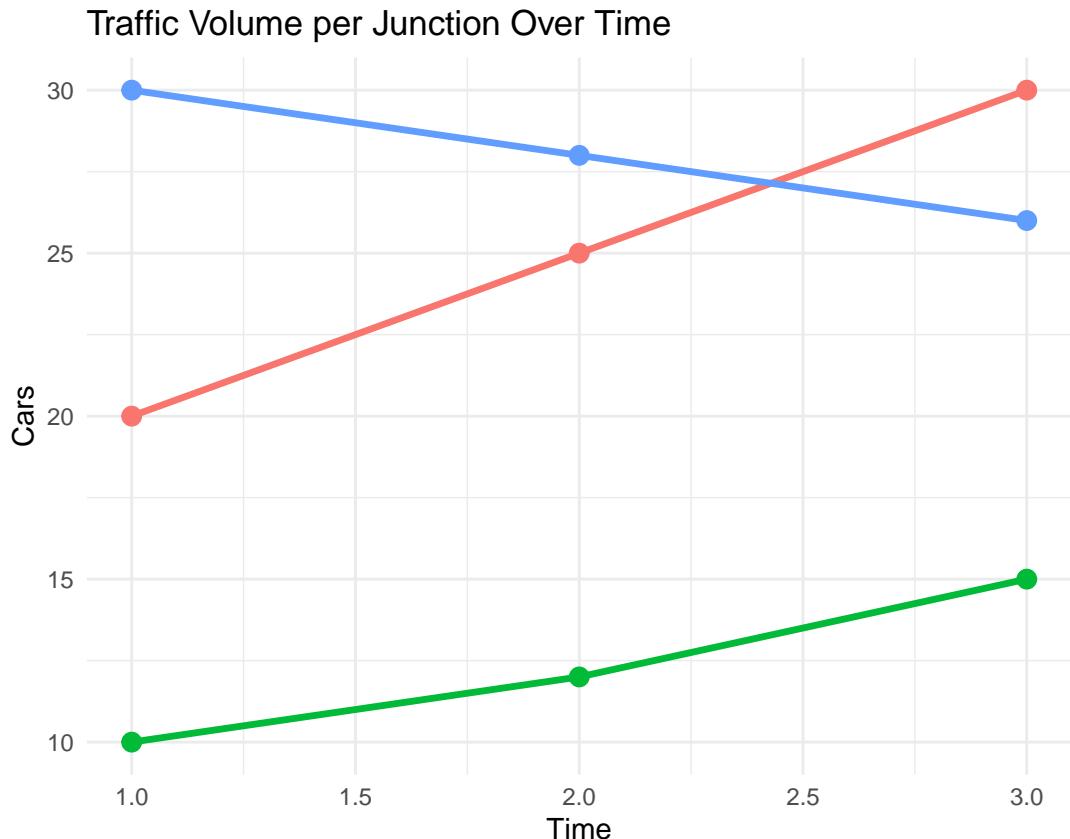
ggplot(traffic, aes(x = time, y = cars, color = junction)) +
  geom_line(size = 1.2) +
  geom_point(size = 3) +
  labs(
    title = "Traffic Volume per Junction Over Time",
    x = "Time",
    y = "Cars"
  ) +
  theme_minimal()

```

```

## Warning: Using 'size' aesthetic for lines was deprecated in ggplot2 3.4.0.
## i Please use 'linewidth' instead.
## This warning is displayed once every 8 hours.
## Call 'lifecycle::last_lifecycle_warnings()' to see where this warning was
## generated.

```



```

# 7. From alexa_file.xlsx, import it to your environment

library(readxl)

# Import file
alexa <- read_excel("alexa_file.xlsx")

# a. How many observations does alexa_file has? What about the number of columns? Show your solution an
# Number of observations (rows)
nrow(alexa)

## [1] 3150

# Number of columns
ncol(alexa)

## [1] 5

```

```

# b. group the variations and get the total of each variations. Use dplyr package. Show solution and answer.

library(dplyr)

variation_total <- alexa %>%
  group_by(variation) %>%
  summarise(total = n())

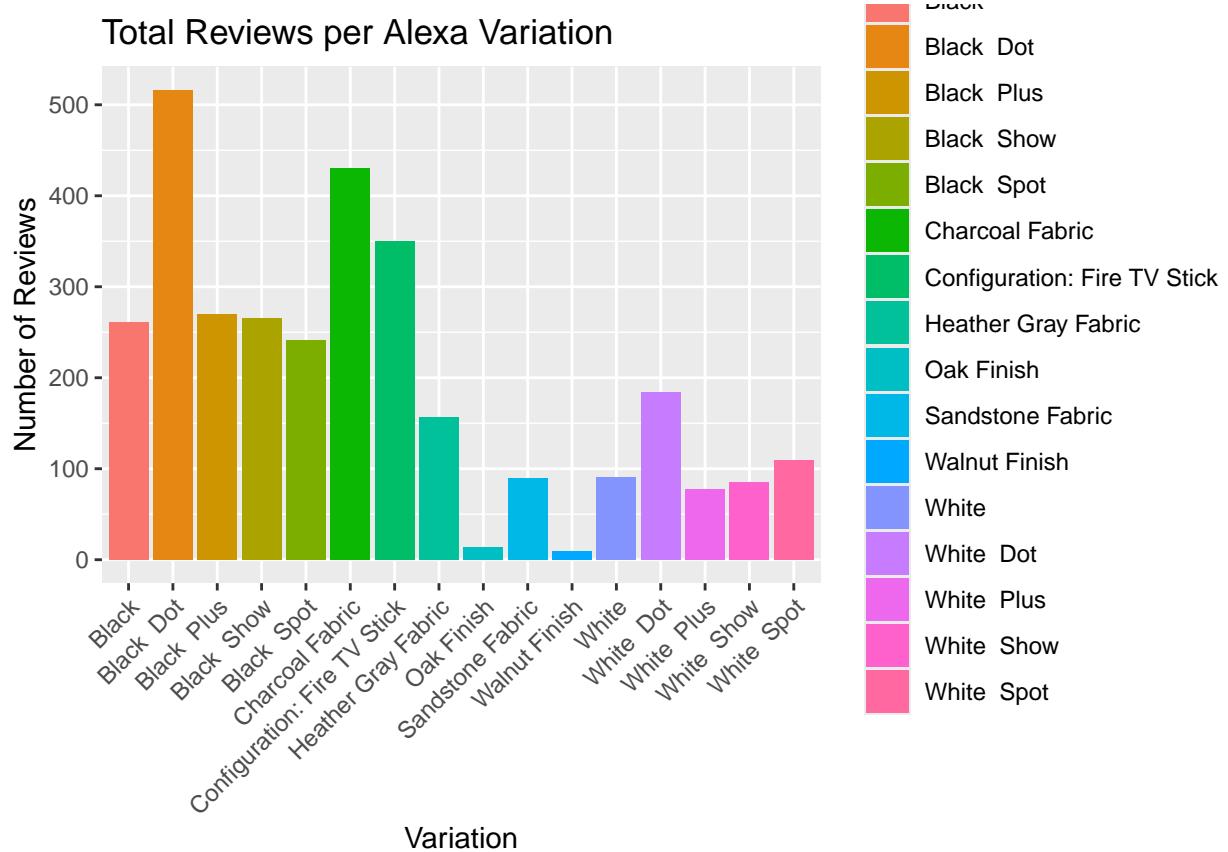
variation_total

## # A tibble: 16 x 2
##   variation      total
##   <chr>        <int>
## 1 Black          261
## 2 Black Dot      516
## 3 Black Plus     270
## 4 Black Show     265
## 5 Black Spot     241
## 6 Charcoal Fabric 430
## 7 Configuration: Fire TV Stick 350
## 8 Heather Gray Fabric 157
## 9 Oak Finish      14
## 10 Sandstone Fabric 90
## 11 Walnut Finish     9
## 12 White          91
## 13 White Dot      184
## 14 White Plus      78
## 15 White Show      85
## 16 White Spot      109

# c. Plot the variations using the ggplot() function. What did you observe? Complete the details of the code.

ggplot(variation_total, aes(x = variation, y = total, fill = variation)) +
  geom_bar(stat = "identity") +
  labs(
    title = "Total Reviews per Alexa Variation",
    x = "Variation",
    y = "Number of Reviews"
  ) +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))

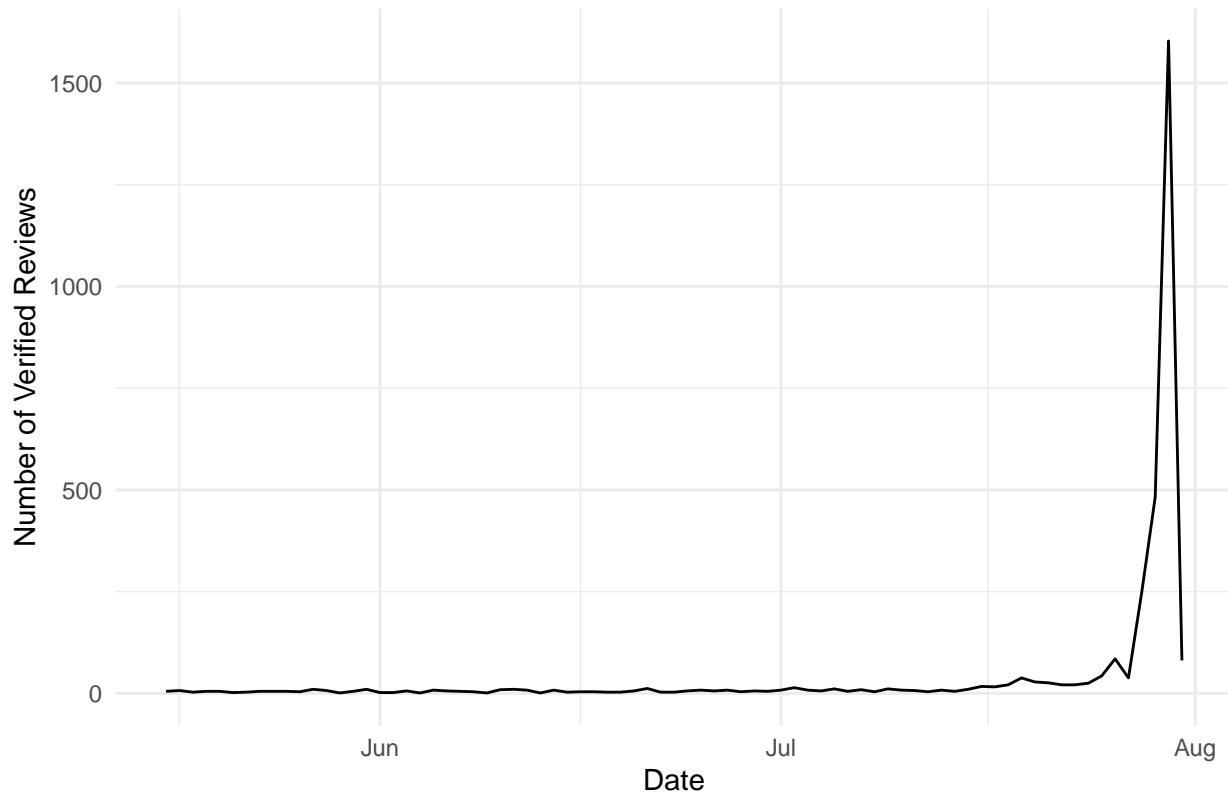
```



```
# d. Plot a geom_line() with the date and the number of verified reviews. Complete the details of the graph.
date_counts <- alexa %>%
  group_by(date) %>%
  summarise(total_reviews = n())

ggplot(date_counts, aes(x = date, y = total_reviews)) +
  geom_line() +
  labs(
    title = "Verified Reviews Over Time",
    x = "Date",
    y = "Number of Verified Reviews"
  ) +
  theme_minimal()
```

## Verified Reviews Over Time



```
# e. Get the relationship of variations and ratings. Which variations got the most highest in rating? P
```

```
rating_variation <- alexa %>%
  group_by(variation) %>%
  summarise(avg_rating = mean(rating))
```

```
rating_variation
```

```
## # A tibble: 16 x 2
##   variation           avg_rating
##   <chr>                 <dbl>
## 1 Black                  4.23
## 2 Black Dot               4.45
## 3 Black Plus              4.37
## 4 Black Show              4.49
## 5 Black Spot              4.31
## 6 Charcoal Fabric         4.73
## 7 Configuration: Fire TV Stick 4.59
## 8 Heather Gray Fabric    4.69
## 9 Oak Finish              4.86
## 10 Sandstone Fabric       4.36
## 11 Walnut Finish          4.89
## 12 White                  4.14
## 13 White Dot              4.42
## 14 White Plus              4.36
## 15 White Show              4.28
## 16 White Spot              4.31
```

```

ggplot(rating_variation, aes(x = variation, y = avg_rating, fill = variation)) +
  geom_col() +
  labs(
    title = "Average Rating per Alexa Variation",
    x = "Variation",
    y = "Average Rating"
  ) +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))

```

