Statistical Computing in R: Comprehensive Review Notebook

Introduction

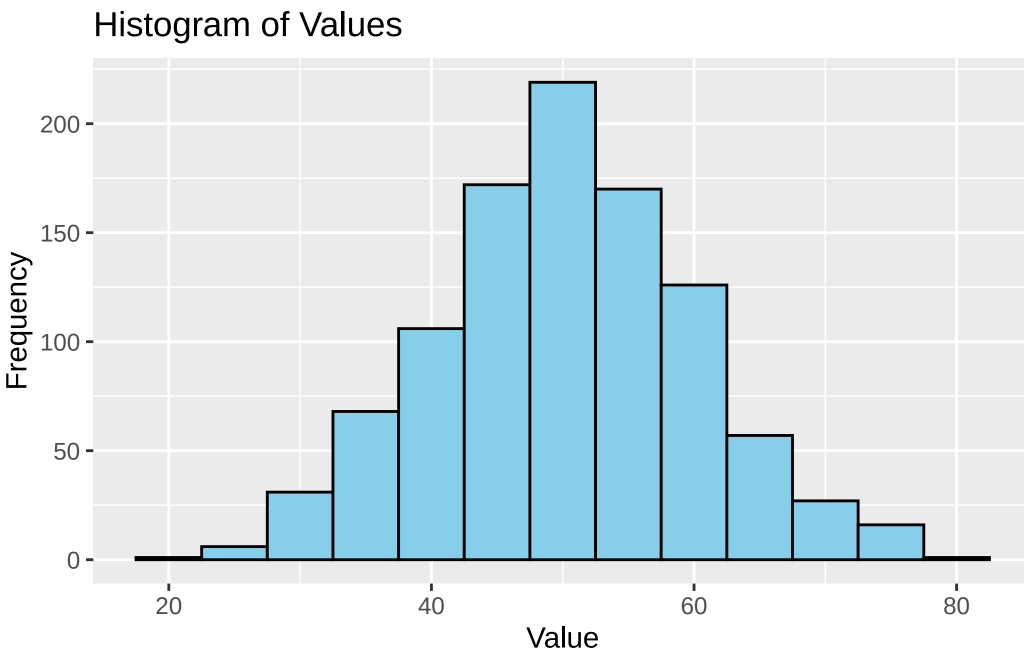
This notebook is designed to review key elements required for the Stat 250 Final for Dr. Richardson.

Univariate Data

Histogram

This example creates a basic histogram for a variable using `ggplot2`.

```r
library(ggplot2)
# Generate sample data
set.seed(123)
data_univariate <- data.frame(value = rnorm(1000, mean = 50, sd = 10))

# Plot a histogram with custom settings
ggplot(data_univariate, aes(x = value)) +
  geom_histogram(binwidth = 5, color = "black", fill = "skyblue") +
  labs(title = "Histogram of Values",
       x = "Value",
       y = "Frequency")
```



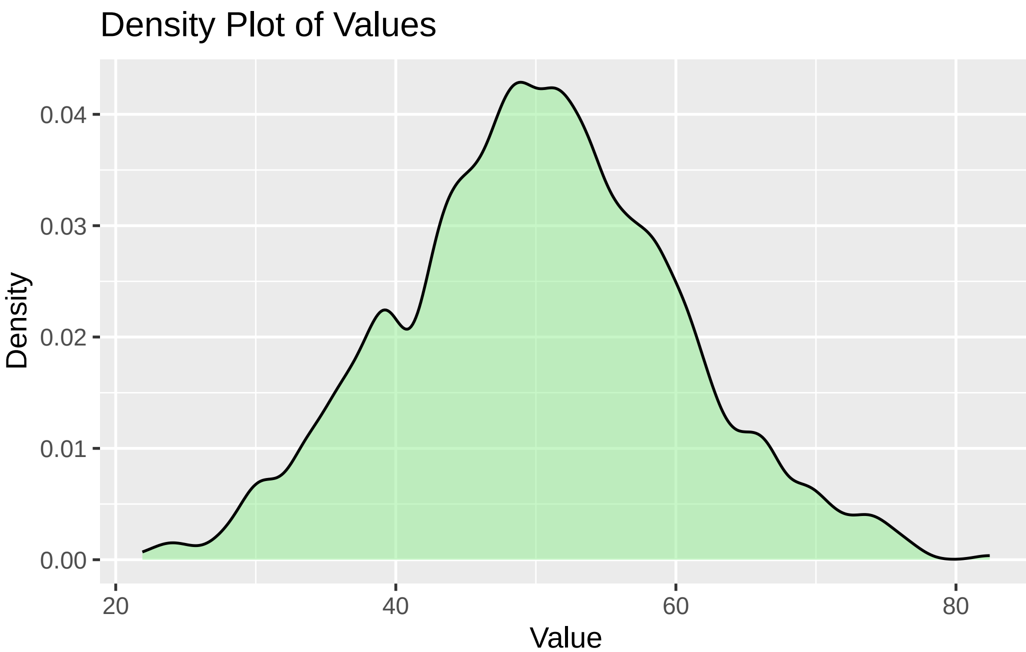
Consider the following

- What do each of the customizations of this histogram do (bin_width, color, fill)
- How do I change the title and axis labels

Density Plot

A density plot provides a smooth estimate of the distribution.

```
ggplot(data_univariate, aes(x = value)) +
  geom_density(fill = "lightgreen", alpha = 0.5,adjust = .5) +
  labs(title = "Density Plot of Values",
       x = "Value",
       y = "Density")
```



Consider the following

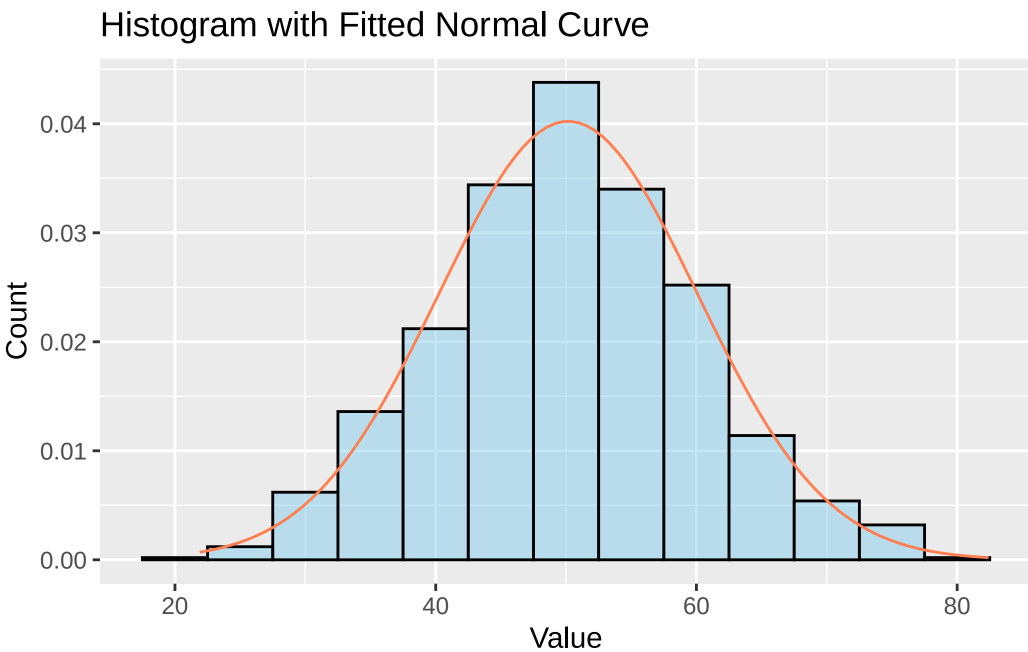
- What do each of the customizations of this plot do (fill, alpha, adjust)
- How do I change the title and axis labels

Overlaying a Theoretical (Normal) Distribution

Overlay a fitted normal curve on a histogram.

```
# Calculate mean and standard deviation
mean_val <- mean(data_univariate$value)
sd_val <- sd(data_univariate$value)


ggplot(data_univariate, aes(x = value)) +
  geom_histogram(aes(y = ..density..), binwidth = 5,
                 color = "black", fill = "skyblue", alpha = 0.5) +
  stat_function(fun = dnorm,
                args = list(mean = mean_val,
                            sd = sd_val),
                col = "coral") +
  labs(title = "Histogram with Fitted Normal Curve",
       x = "Value",
       y = "Count")
```

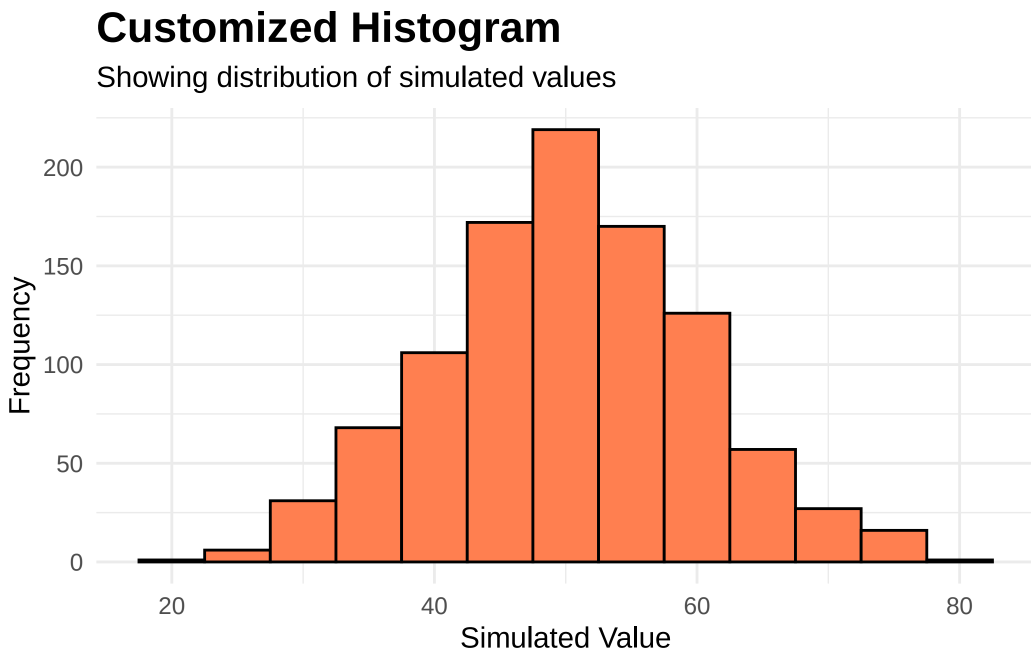
```
Warning: The dot-dot notation (`..density..`) was deprecated in ggplot2 3.4.0.
i Please use `after_stat(density)` instead.
```



Customizing Plots

Customize the look of a histogram using themes and additional labels.

```r
ggplot(data_univariate, aes(x = value)) +
  geom_histogram(binwidth = 5, color = "black", fill = "coral") +
  labs(title = "Customized Histogram",
       subtitle = "Showing distribution of simulated values",
       x = "Simulated Value",
       y = "Frequency") +
  theme_minimal() +
  theme(plot.title = element_text(size = 16, face = "bold"))
```



Consider

- You do not need to memorize every possible customization, but be aware of how to use resources to determine how to modify different elements, like font size, rotating axis labels, etc.

Bivariate Data

Choosing the Right Plot

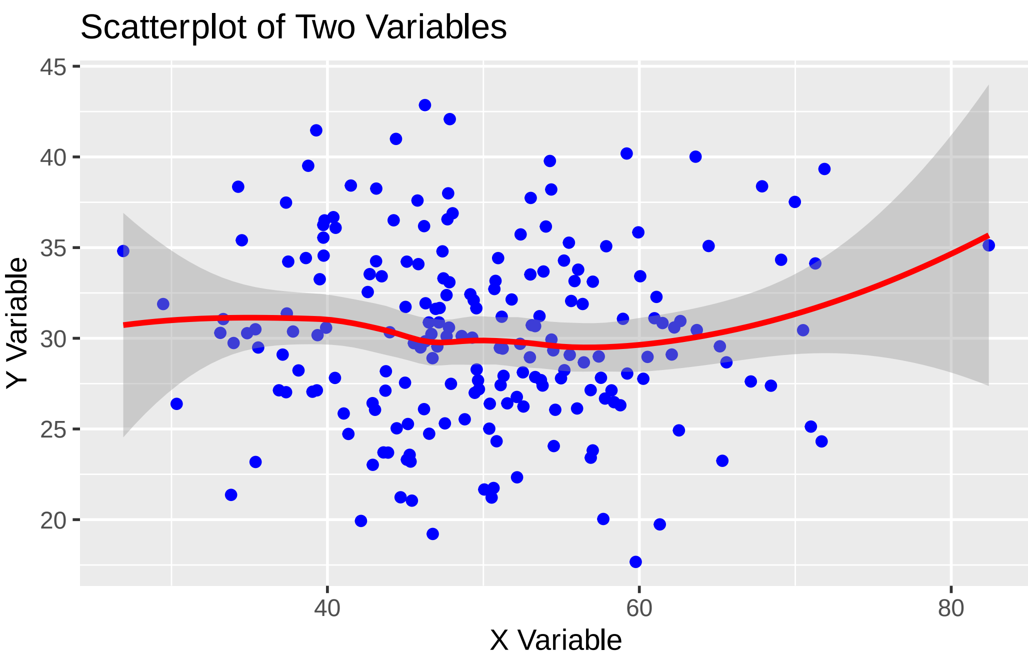
For bivariate data, the type of plot depends on the variables' types. For numerical vs. numerical, a scatterplot works best. For numerical vs. categorical, side-by-side boxplots or violin plots are very informative. You should be able to choose which plot to use based on the data types.

Scatterplots

A basic scatterplot for two numeric variables.

```r
set.seed(123)
data_bivariate <- data.frame(
  x = rnorm(200, mean = 50, sd = 10),
  y = rnorm(200, mean = 30, sd = 5)
)
ggplot(data_bivariate, aes(x = x, y = y)) +
  geom_point(color = "blue") +
  geom_smooth(span = .7,color = "red") +
  labs(title = "Scatterplot of Two Variables",
       x = "X Variable",
       y = "Y Variable")
```

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



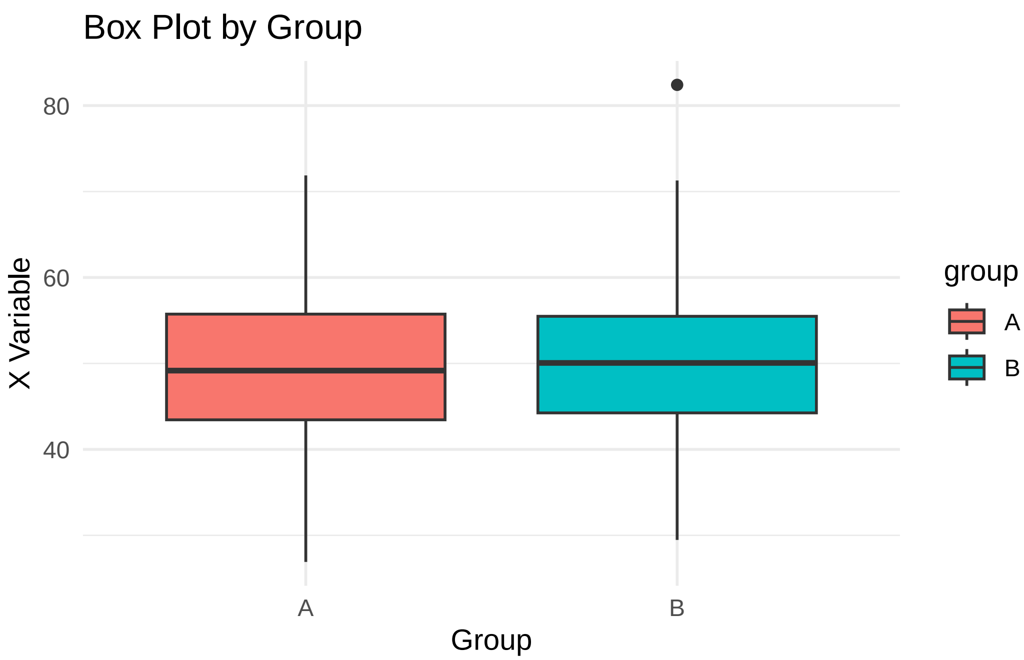
Consider

- How we get the fitted line with shaded interval, and how to adjust the wiggliness
- How to customize the color, shape, size of the scatterplot points

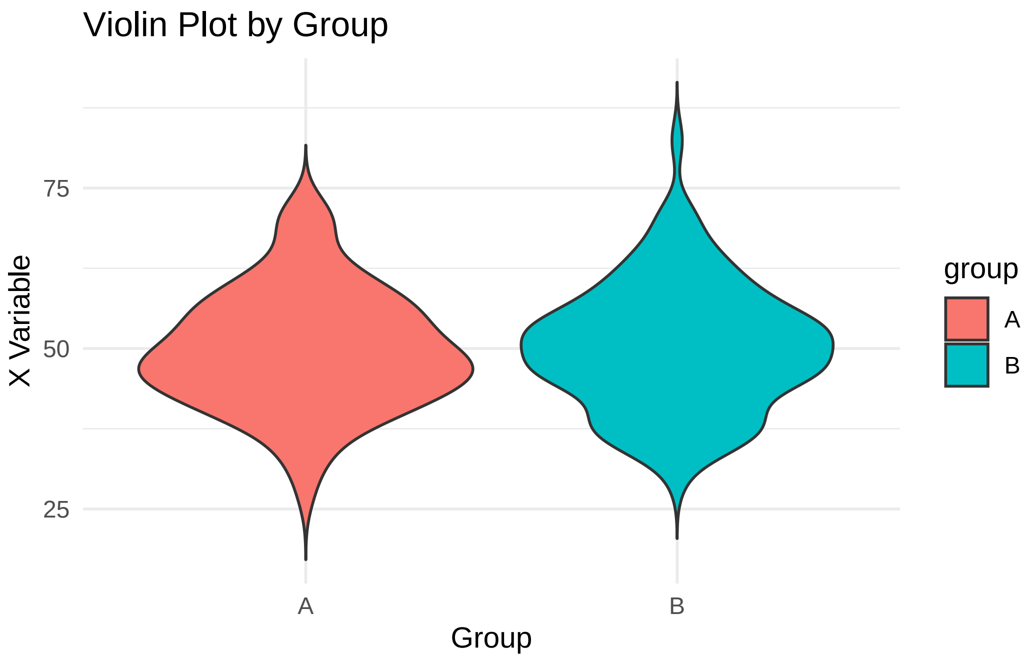
Side by Side Box Plots and Violin Plots

Comparing distributions across groups by plotting boxplots and violin plots.

```r
# Add a grouping variable
set.seed(123)
data_bivariate$group <- sample(c("A", "B"), size = 200, replace = TRUE)

# Box Plot
ggplot(data_bivariate, aes(x = group, y = x, fill = group)) +
  geom_boxplot() +
  labs(title = "Box Plot by Group",
       x = "Group",
       y = "X Variable") +
  theme_minimal()
```




```r
# Violin Plot
ggplot(data_bivariate, aes(x = group, y = x, fill = group)) +
  geom_violin(trim = FALSE) +
  labs(title = "Violin Plot by Group",
       x = "Group",
       y = "X Variable") +
  theme_minimal()
```



Consider

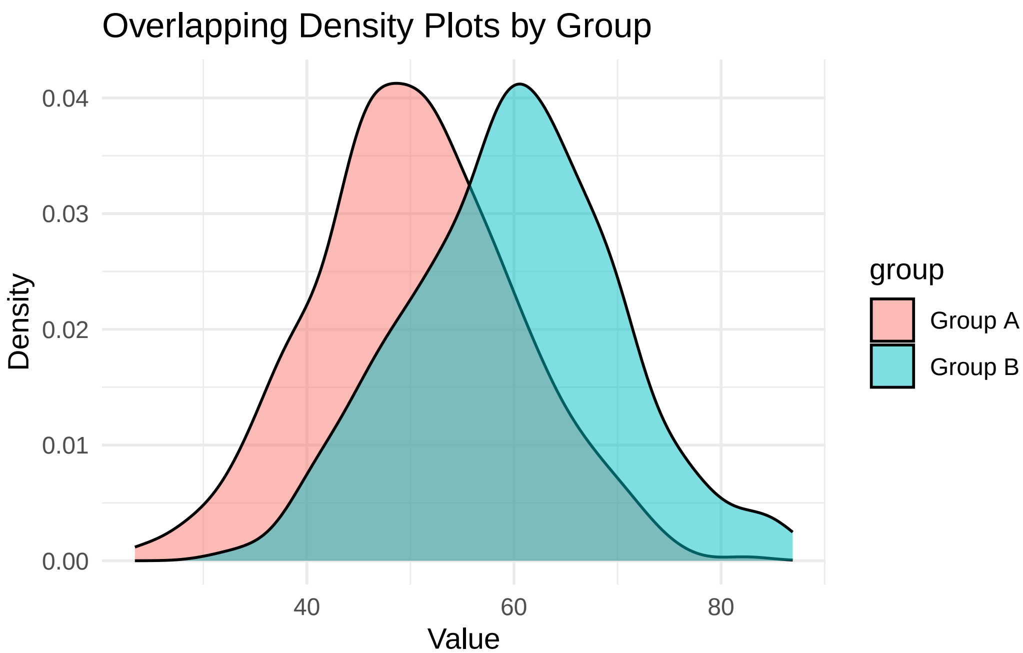
- How do I flip the orientation
- If there are too many categorical variables, how might I modify my data sat to get a better plot (we'll do this later)

Side-by-Side Density Plots

This section shows how to create side-by-side density plots where the density curve of a continuous variable is split by an additional categorical variable. This visualization is useful for comparing distributions across groups.

```
# Create sample data with a grouping variable
set.seed(123)
data_density <- data.frame(
  value = c(rnorm(500, mean = 50, sd = 10), rnorm(500, mean = 60, sd = 10)),
  group = rep(c("Group A", "Group B"), each = 500)
)

ggplot(data_density, aes(x = value, fill = group)) +
  geom_density(alpha = 0.5) +
  labs(title = "Overlapping Density Plots by Group",
       x = "Value",
```

```
      y = "Density") +
  theme_minimal()
```



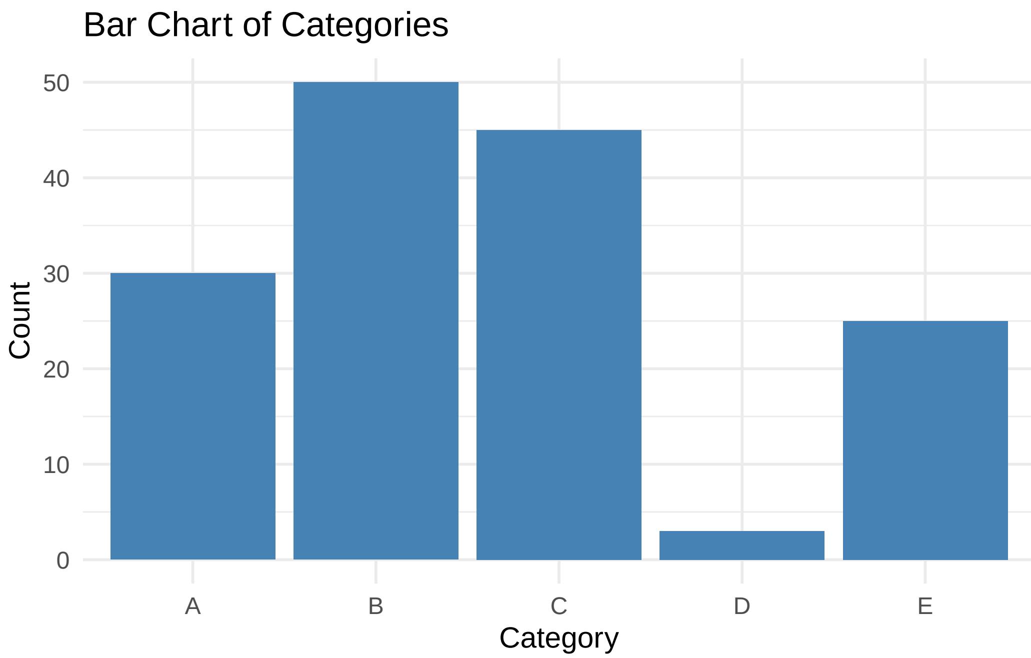
Consider

- How might I modify the transparency, color, wiggliness of each.

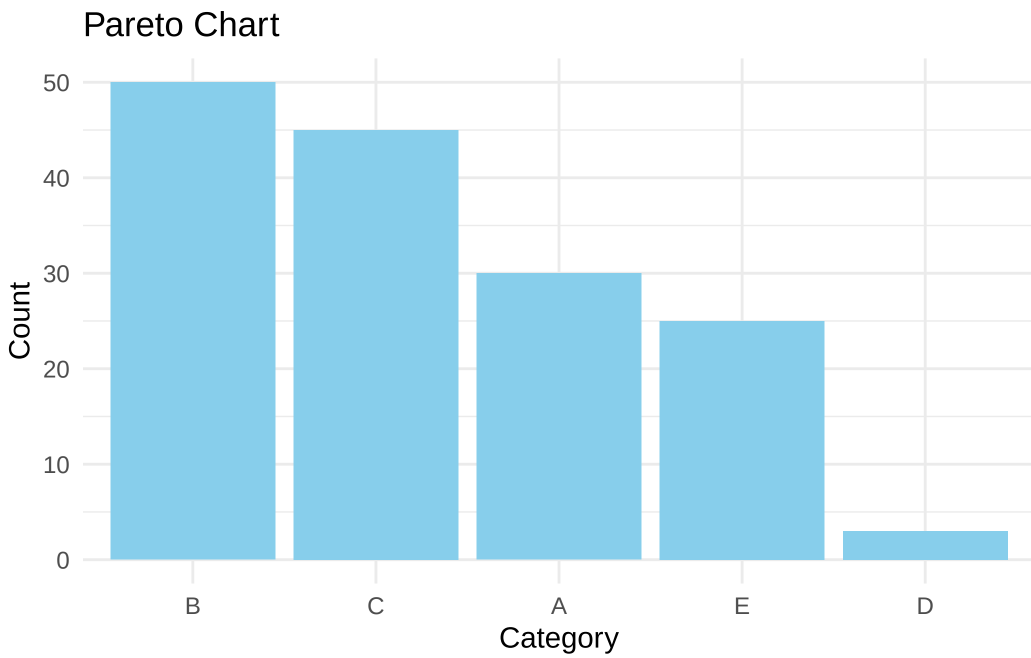
Bar and Pareto Charts

Visualize categorical data using bar charts and add a Pareto chart to show cumulative percentages.

```
# Create a categorical data sample
categories <- data.frame(category = rep(LETTERS[1:5], times = c(30, 50, 45, 3, 25)))

# Bar Chart
ggplot(categories, aes(x = category)) +
  geom_bar(fill = "steelblue") +
  labs(title = "Bar Chart of Categories",
       x = "Category",
       y = "Count") +
  theme_minimal()
```




```r
ggplot(categories, aes(x = fct_infreq(category))) +
  geom_bar(fill = "skyblue") +
  labs(title = "Pareto Chart",
       x = "Category",
       y = "Count") +
  theme_minimal()
```



Two-Way Tables

Create and display a two-way table using the **table1** package.

```
# Install table1 if necessary
if (!require(table1)) install.packages("table1", repos = "http://cran.rstudio.com/")
```

```
Loading required package: table1


Attaching package: 'table1'


The following objects are masked from 'package:base':

    units, units<-
```

```
library(table1)

# Create sample two-way categorical data
set.seed(123)
data_twoway <- data.frame(
```

```r
  group = sample(c("A", "B"), 100, replace = TRUE),
  outcome = sample(c("Success", "Failure"), 100, replace = TRUE)
)

# Generate a summary table by group
table1(~ outcome | group, data = data_twoway)
```

```
Get nicer `table1` LaTeX output by simply installing the `kableExtra` package
```

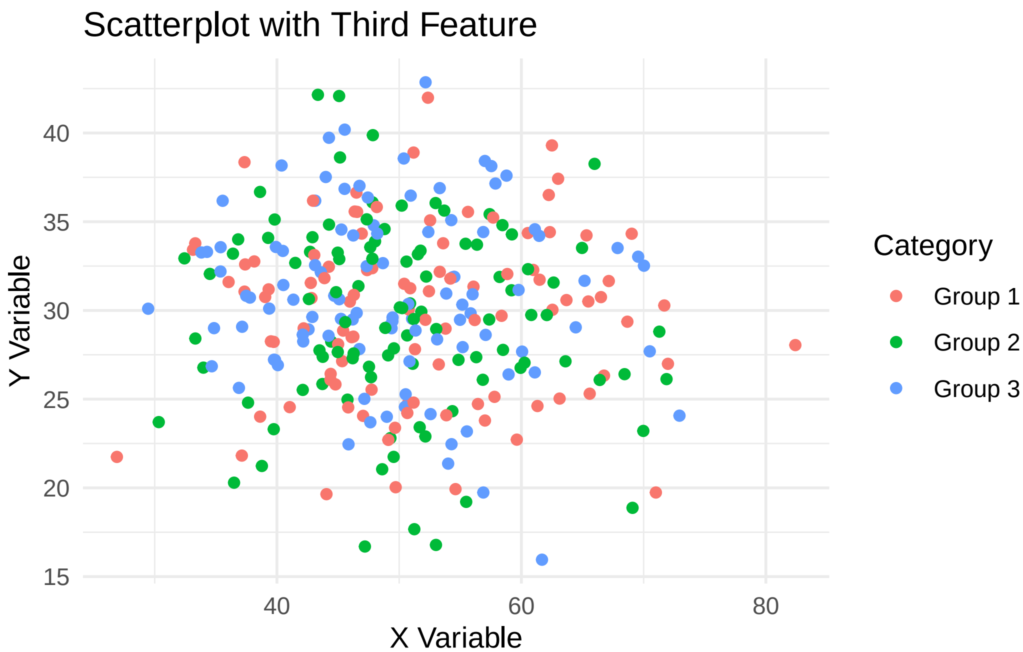
	A	B	Overall
	(N=57)	(N=43)	(N=100)
outcome			
Failure	31 (54.4%)	23 (53.5%)	54 (54.0%)
Success	26 (45.6%)	20 (46.5%)	46 (46.0%)

Multivariate Data

Scatterplots with a Third Feature

Enhance a scatterplot by mapping a third variable (such as a group factor) to color.

```r
set.seed(123)
data_multivariate <- data.frame(
  x = rnorm(300, mean = 50, sd = 10),
  y = rnorm(300, mean = 30, sd = 5),
  category = sample(c("Group 1", "Group 2", "Group 3"), 300, replace = TRUE)
)

ggplot(data_multivariate, aes(x = x, y = y, color = category)) +
  geom_point() +
  labs(title = "Scatterplot with Third Feature",
       x = "X Variable",
       y = "Y Variable",
       color = "Category") +
  theme_minimal()
```



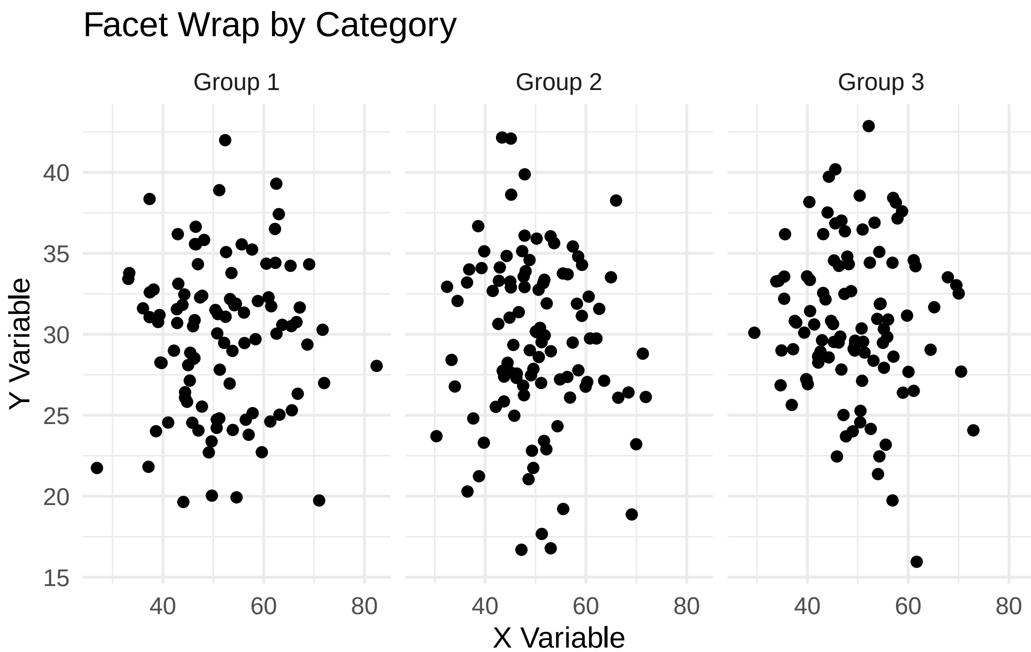
Consider

- How would I instead modify the shape/size.
- What if I wanted a fourth variable also included
- What if the color of the scatterplot points depended on a numeric variable

Facet Wraps

Use faceting to create separate panels for each category.

```
ggplot(data_multivariate, aes(x = x, y = y)) +
  geom_point() +
  facet_wrap(~ category) +
  labs(title = "Facet Wrap by Category",
       x = "X Variable",
       y = "Y Variable") +
  theme_minimal()
```



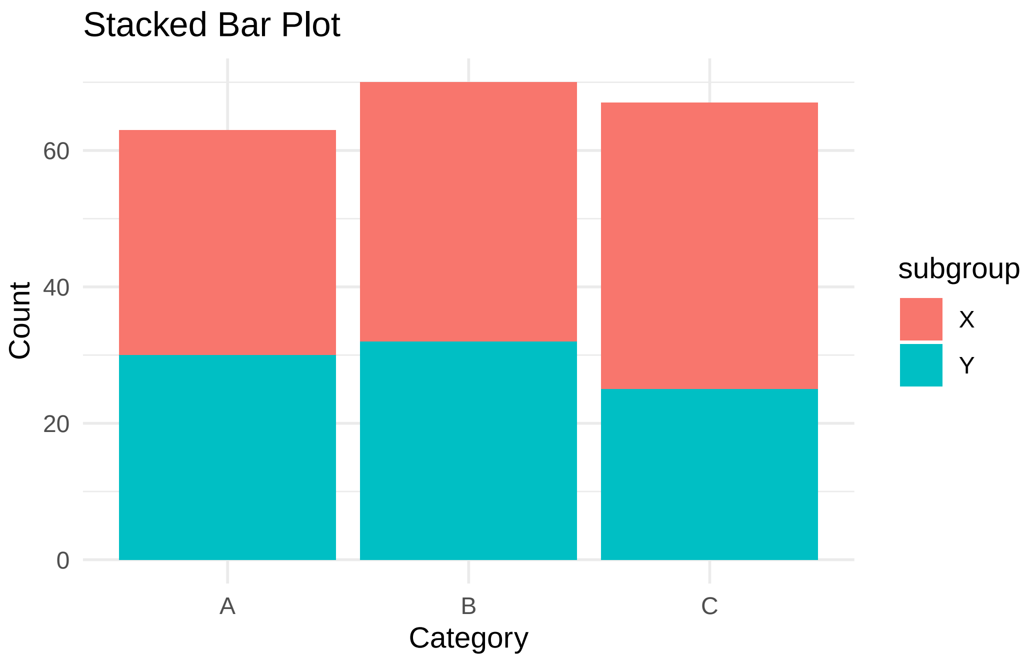
Consider

- How might I modify the layout of the facet wrap
- What if there are two variables I want to split the plot by?

Stacked Bar Plots

A stacked bar plot shows the contribution of subgroups within each category.

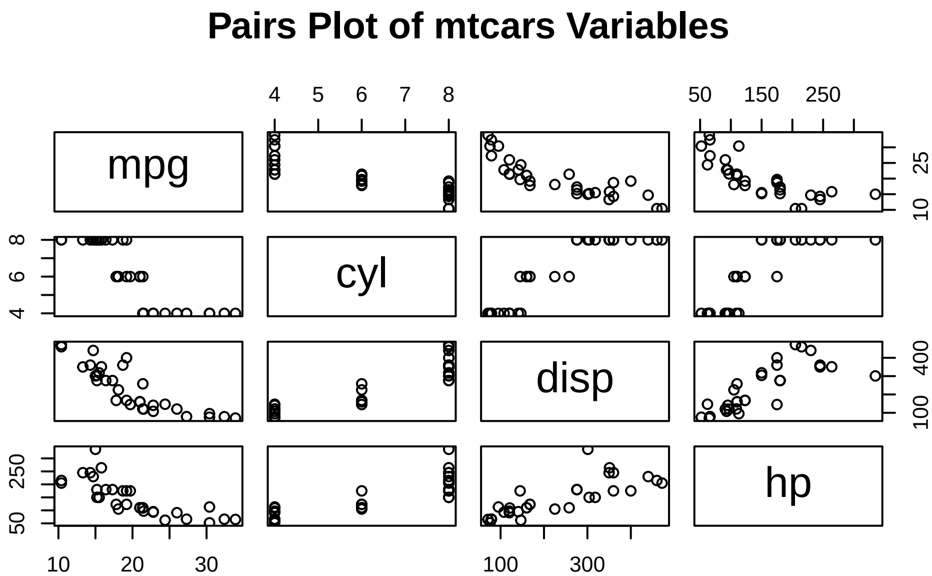
```
set.seed(123)
data_stacked <- data.frame(
  category = sample(c("A", "B", "C"), 200, replace = TRUE),
  subgroup = sample(c("X", "Y"), 200, replace = TRUE)
)

ggplot(data_stacked, aes(x = category, fill = subgroup)) +
  geom_bar(position = "stack") +
  labs(title = "Stacked Bar Plot",
       x = "Category",
       y = "Count") +
  theme_minimal()
```



Pairs Plots

Examine pairwise relationships among several variables. You can use base R's `pairs` or the advanced `GGally` package.

```
# Base R pairs plot
pairs(mtcars[, 1:4], main = "Pairs Plot of mtcars Variables")
```



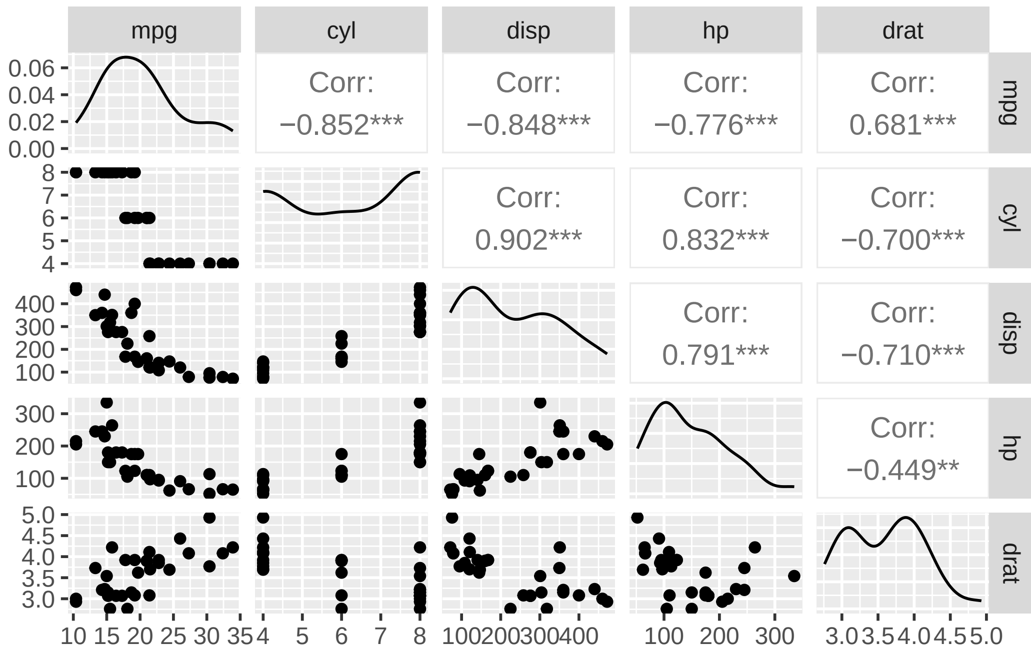
And using the **GGally** package for an enhanced pairs plot:

```
if (!require(GGally)) install.packages("GGally", repos = "http://cran.rstudio.com/")
```

```
Loading required package: GGally
```

```
Registered S3 method overwritten by 'GGally':
  method from
  +.gg   ggplot2
```

```
library(GGally)
ggpairs(mtcars[, 1:5])
```



- How can I modify the individual compenents of these plots, i.e. color, splitting on an additional category, etc.

Data Operations

This section demonstrates basic data operations using functions like `select`, `filter`, `mutate`, `transmute`, `rename`, and `slice`.

Creating a Sample Data Frame

```
library(tidyverse)
# Create sample dataset
set.seed(123)
data_ops <- tibble(
  id = 1:10,
  name = c("Alice", "Bob", "Charlie", "David", "Eva", "Frank", "Grace", "Hannah", "Ian", "Ja
  score = sample(50:100, 10, replace = TRUE),
  age = sample(20:40, 10, replace = TRUE),
```

```r
  height = rnorm(10, 170, 10)
)

data_ops
```

```
# A tibble: 10 x 5
      id name    score   age height
   <int> <chr>   <int> <int>  <dbl>
 1     1 Alice      80    24   150.
 2     2 Bob        64    38   177.
 3     3 Charlie   100    28   165.
 4     4 David      63    22   159.
 5     5 Eva        52    27   168.
 6     6 Frank      91    26   160.
 7     7 Grace      99    29   163.
 8     8 Hannah     92    28   164.
 9     9 Ian        86    38   153.
10    10 Jane       63    23   178.
```

Example 1: Selecting and Filtering

Select specific columns and filter rows where the score is above 75.

```r
data_ops %>%
  select(id, name, score) %>%
  filter(score > 75)
```

```
# A tibble: 6 x 3
     id name    score
  <int> <chr>   <int>
1     1 Alice      80
2     3 Charlie   100
3     6 Frank      91
4     7 Grace      99
5     8 Hannah     92
6     9 Ian        86
```

Example 2: Mutating, Transmuting, and Renaming

Add a new variable (score as a percentage), rename a column, and then create a new table using `transmute` to only return selected variables.

```
data_ops_mut <- data_ops %>%
  mutate(score_percent = score / 100) %>%
  rename(student_name = name)

# Using transmute to only include id and score_percent
data_ops_mut %>%
  transmute(id, score_percent)
```

```
# A tibble: 10 x 2
      id score_percent
   <int>         <dbl>
 1     1          0.8
 2     2          0.64
 3     3          1
 4     4          0.63
 5     5          0.52
 6     6          0.91
 7     7          0.99
 8     8          0.92
 9     9          0.86
10    10          0.63
```

Example 3: Slicing Rows

Select a subset of rows, such as the first five rows.

```
data_ops %>%
  slice(1:5)
```

```
# A tibble: 5 x 5
     id name    score   age height
  <int> <chr>   <int> <int>  <dbl>
1     1 Alice      80    24   150.
2     2 Bob        64    38   177.
3     3 Charlie   100    28   165.
4     4 David      63    22   159.
5     5 Eva        52    27   168.
```

Consider:

- The distinction between `mutate` (which retains all columns) and `transmute` (which only returns newly created variables).
- What if you need to filter by multiple conditions.
- What if column names aren't valid R variable names
- Advanced consideration with string operations: How you might use helpers such as `starts_with()`, `ends_with()`, or `contains()` with `select`.

Grouping and Summarizing / Mutating

Grouping data can help derive summary statistics by groups or create group-specific transformations.

Example 1: Grouping and Summarizing

Add a grouping variable and calculate the mean score and age per group.

```r
data_ops_group <- data_ops %>%
  mutate(group = sample(c("A", "B"), n(), replace = TRUE))

data_ops_group %>%
  group_by(group) %>%
  summarize(
    avg_score = mean(score),
    avg_age = mean(age),
    count = n()
  )
```

```
# A tibble: 2 x 4
  group avg_score avg_age count
  <chr>     <dbl>   <dbl> <int>
1 A          79.2    24.8     5
2 B          78.8    31.8     5
```

Example 2: Grouping and Mutating

Create a new column that centers the score within each group.

```
data_ops_group %>%
  group_by(group) %>%
  mutate(centered_score = score - mean(score))
```

```
# A tibble: 10 x 7
# Groups:   group [2]
      id name    score   age height group centered_score
   <int> <chr>   <int> <int>  <dbl> <chr>          <dbl>
 1     1 Alice      80    24   150. A              0.800
 2     2 Bob        64    38   177. B            -14.8
 3     3 Charlie   100    28   165. B             21.2
 4     4 David      63    22   159. A            -16.2
 5     5 Eva        52    27   168. B            -26.8
 6     6 Frank      91    26   160. A             11.8
 7     7 Grace      99    29   163. A             19.8
 8     8 Hannah     92    28   164. B             13.2
 9     9 Ian        86    38   153. B              7.2
10    10 Jane       63    23   178. A            -16.2
```

Consider: - How you might apply functions across multiple columns using `across()`. - Strategies for grouping by more than one variable.

Working with Dates and Times

Use the **lubridate** package to effectively manage date and time data.

Example 1: Parsing Dates

Convert character strings into proper Date objects.

```r
library(lubridate)

data_dates <- tibble(
  event = c("Event 1", "Event 2", "Event 3"),
  date_str = c("2023-01-15", "2022-12-31", "2023-02-20")
)

data_dates <- data_dates %>%
  mutate(event_date = ymd(date_str),
         Year = year(event_date))
data_dates
```

```
# A tibble: 3 x 4
  event   date_str   event_date  Year
  <chr>   <chr>      <date>     <dbl>
1 Event 1 2023-01-15 2023-01-15  2023
2 Event 2 2022-12-31 2022-12-31  2022
3 Event 3 2023-02-20 2023-02-20  2023
```

Example 2: Date Arithmetic

Compute the number of days between events and a reference date.

```r
reference_date <- ymd("2023-01-01")
data_dates %>%
  mutate(days_since = as.numeric(event_date - reference_date))
```

```
# A tibble: 3 x 5
  event   date_str   event_date  Year days_since
  <chr>   <chr>      <date>     <dbl>      <dbl>
1 Event 1 2023-01-15 2023-01-15  2023         14
2 Event 2 2022-12-31 2022-12-31  2022         -1
3 Event 3 2023-02-20 2023-02-20  2023         50
```

Consider: - Other parsing functions like `mdy()` or `dmy()` for different date formats.

Working with Factors

Factors are essential for categorical data. We cover recoding, reordering, and lumping for plotting.

Example 1: Reordering and Recoding Factors

Create a factor variable and adjust its levels.

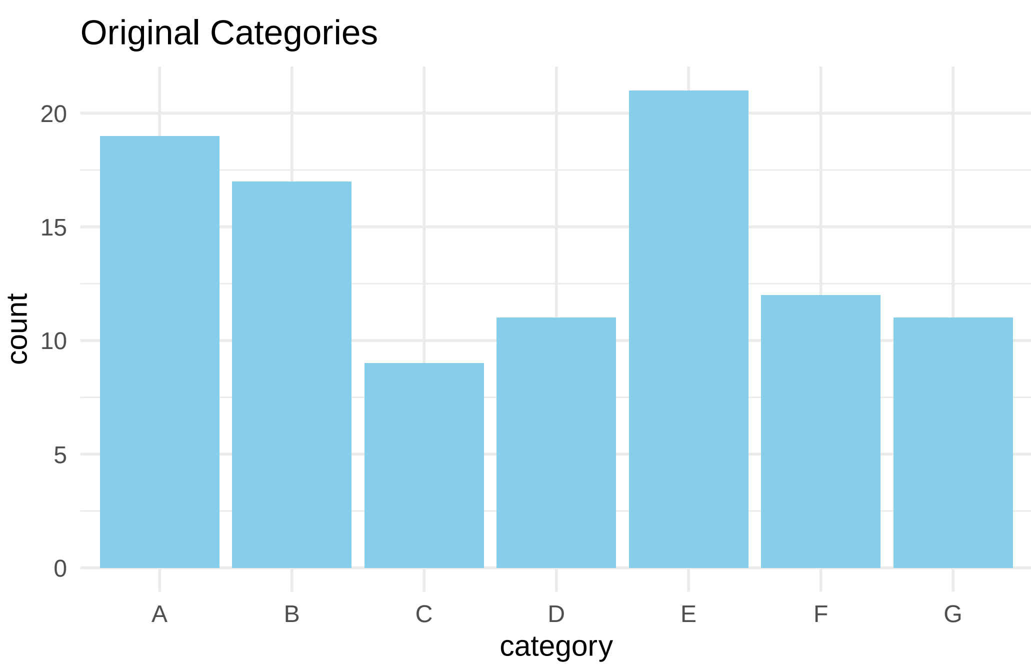
```r
data_factors <- tibble(
  category = sample(c("Low", "Medium", "High", "Very High"), 50, replace = TRUE),
  value = rnorm(50)
)

data_factors <- data_factors %>%
  mutate(category = fct_relevel(category, "Low", "Medium", "High", "Very High"),
         category = fct_recode(category,
                               "Low" = "Low",
                               "Medium" = "Medium",
                               "High" = "High",
                               "VH" = "Very High"))
data_factors
```

```
# A tibble: 50 x 2
   category  value
   <fct>     <dbl>
 1 Low       0.585
 2 Medium    0.124
 3 Low       0.216
 4 Low       0.380
 5 High     -0.502
 6 Low      -0.333
 7 Medium   -1.02
 8 Low      -1.07
 9 High      0.304
10 Low       0.448
# i 40 more rows
```

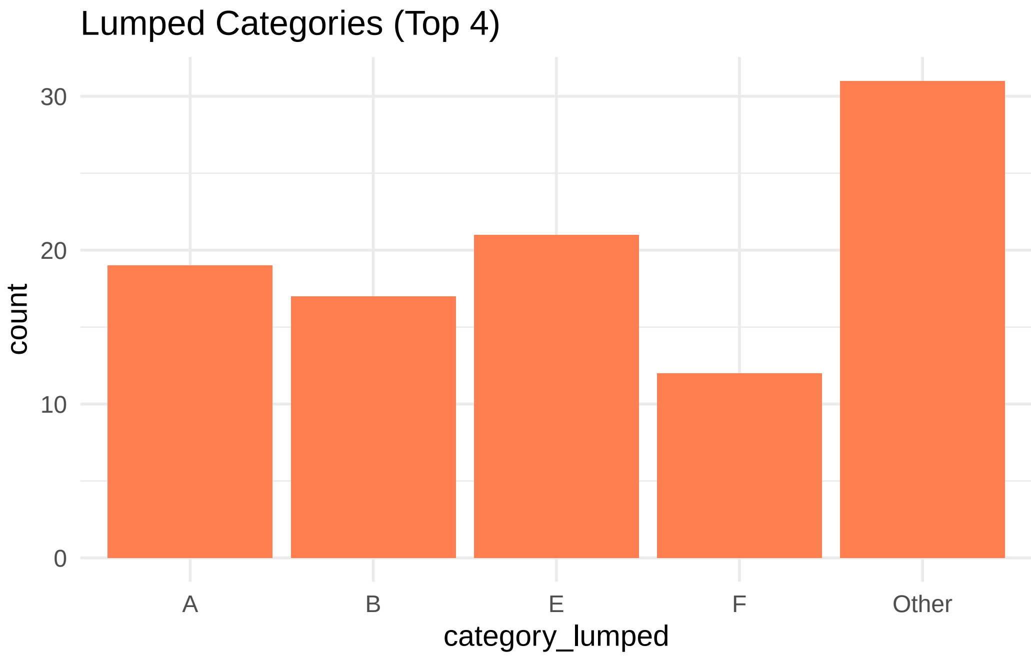
Example 2: Lumping Factors for Plotting

Reduce the number of factor levels by lumping smaller groups together.

```r
data_factors_extra <- tibble(
  category = sample(c("A", "B", "C", "D", "E", "F", "G"), 100, replace = TRUE),
  value = rnorm(100)
)

data_factors_extra <- data_factors_extra %>%
  mutate(category_lumped = fct_lump(category, n = 4))

library(ggplot2)

p1 <- ggplot(data_factors_extra, aes(x = category)) +
  geom_bar(fill = "skyblue") +
  labs(title = "Original Categories") +
  theme_minimal()

p2 <- ggplot(data_factors_extra, aes(x = category_lumped)) +
  geom_bar(fill = "coral") +
  labs(title = "Lumped Categories (Top 4)") +
  theme_minimal()

print(p1)
```



```
print(p2)
```



Consider: - How functions like `fct_infreq()`, `fct_rev()`, or `fct_drop()` can further modify factor levels. - The importance of setting factor orders when plotting for more readable graphs. - Using `fct_lump_min()` or specifying a proportion threshold to control lumping.

Working with Strings

String manipulation is key when cleaning textual data. Below are several examples using the **stringr** package.

Example 1: Basic String Manipulation

Convert text to lower case and replace specific words.

```
library(stringr)

data_strings <- tibble(
  sentence = c("The quick Brown fox", "jumps OVER the lazy DOG", "Data WRANGLING in R is FUN"
```

```
)

data_strings %>%
  mutate(
    sentence_lower = str_to_lower(sentence),
    sentence_clean = str_replace(sentence_lower, "fun", "great")
  )
```

```
# A tibble: 3 x 3
  sentence                     sentence_lower               sentence_clean
  <chr>                        <chr>                        <chr>
1 The quick Brown fox          the quick brown fox          the quick brown fox
2 jumps OVER the lazy DOG      jumps over the lazy dog      jumps over the lazy dog
3 Data WRANGLING in R is FUN data wrangling in r is fun data wrangling in r is ~
```

Example 2: Extracting and Detecting Patterns

Extract words of a certain length and detect the presence of a pattern.

```
data_strings %>%
  mutate(
    extracted = str_extract(sentence, "\\b\\w{5}\\b"),
    has_the = str_detect(sentence, regex("the", ignore_case = TRUE))
  )
```

```
# A tibble: 3 x 3
  sentence                     extracted has_the
  <chr>                        <chr>     <lgl>
1 The quick Brown fox          quick     TRUE
2 jumps OVER the lazy DOG      jumps     TRUE
3 Data WRANGLING in R is FUN <NA>      FALSE
```

Example 3: Splitting and Concatenating Strings

Split sentences into words and then concatenate a subset of the split elements.

```
data_strings %>%
  mutate(
    split_text = str_split(sentence, " "),
    first_two = map_chr(split_text, ~ paste0(.x[1:2], collapse = " "))
  )
```

```
# A tibble: 3 x 3
  sentence                    split_text first_two
  <chr>                       <list>     <chr>
1 The quick Brown fox         <chr [4]>  The quick
2 jumps OVER the lazy DOG     <chr [5]>  jumps OVER
3 Data WRANGLING in R is FUN <chr [6]>  Data WRANGLING
```

Consider: - Functions such as `str_sub()`, `str_trim()`, and `str_pad()` to further manipulate text. - How to use more complex regular expressions for pattern matching. - Combining multiple string operations to form custom cleaning pipelines.

Joining Data Sets

Combining data from different sources is done via various join functions.

Example 1: Inner Join

Join two datasets by a shared key, keeping only common rows.

```r
df1 <- tibble(
  id = 1:5,
  value1 = letters[1:5]
)

df2 <- tibble(
  id = c(3, 4, 5, 6),
  value2 = LETTERS[3:6]
)

inner_join(df1, df2, by = "id")
```

```
# A tibble: 3 x 3
     id value1 value2
  <dbl> <chr>  <chr>
1     3 c      C
2     4 d      D
3     5 e      E
```

Example 2: Left and Right Joins

Demonstrate a left join (keeping all rows from the first data set) and a right join (keeping all rows from the second).

```
# Left join: keep all rows from df1
left_join(df1, df2, by = "id")
```

```
# A tibble: 5 x 3
     id value1 value2
  <dbl> <chr>  <chr>
1     1 a      <NA>
2     2 b      <NA>
3     3 c      C
4     4 d      D
5     5 e      E
```

```
# Right join: keep all rows from df2
right_join(df1, df2, by = "id")
```

```
# A tibble: 4 x 3
     id value1 value2
  <dbl> <chr>  <chr>
1     3 c      C
2     4 d      D
3     5 e      E
4     6 <NA>   F
```

Consider: - When to use joins such as full, semi, or anti joins. - How to join on multiple keys by passing a named vector to the `by` argument. - Strategies for ensuring unique join keys before merging.

Merging / Binding Data Sets

Binding operations let you combine datasets by stacking rows or adding columns.

Example 1: Binding Rows

Stack two datasets vertically.

```r
df_row1 <- tibble(
  id = 1:3,
  value = c("A", "B", "C")
)

df_row2 <- tibble(
  id = 4:6,
  value = c("D", "E", "F")
)

bind_rows(df_row1, df_row2)
```

```
# A tibble: 6 x 2
     id value
  <int> <chr>
1     1 A
2     2 B
3     3 C
4     4 D
5     5 E
6     6 F
```

Example 2: Binding Columns

Combine two datasets side by side.

```r
df_col1 <- tibble(
  id = 1:3,
  var1 = c(10, 20, 30)
)

df_col2 <- tibble(
  var2 = c("X", "Y", "Z")
)

bind_cols(df_col1, df_col2)
```

```
# A tibble: 3 x 3
     id  var1 var2
  <int> <dbl> <chr>
1     1    10 X
2     2    20 Y
3     3    30 Z
```

Consider: - The differences between joining (merging on keys) and binding (stacking or combining dimensions). - How mismatches in row or column counts are handled. - Techniques for aligning data frames before binding.

General Cleaning Strategies

Data cleaning involves handling missing values, standardizing formats, and renaming columns.

Example 1: Handling Missing Data

Filter out rows with missing values.

```r
data_clean <- tibble(
  id = 1:10,
  value = c(5, NA, 7, 8, NA, 6, 5, 7, 8, 9)
)

data_clean %>%
  filter(!is.na(value))
```

```
# A tibble: 8 x 2
     id value
  <int> <dbl>
1     1     5
2     3     7
3     4     8
4     6     6
5     7     5
6     8     7
7     9     8
8    10     9
```

Example 2: Standardizing Column Names

Use the **janitor** package to clean and standardize column names.

```r
if (!require(janitor)) install.packages("janitor", repos = "http://cran.rstudio.com/")
```

```
Loading required package: janitor


Attaching package: 'janitor'

The following objects are masked from 'package:stats':

    chisq.test, fisher.test
```

```r
library(janitor)

data_clean_names <- tibble(
  `ID Number` = 1:5,
  `First Name` = c("Alice", "Bob", "Charlie", "David", "Eva"),
  `Score (%)` = c(88, 92, 75, 85, 90)
)

data_clean_names %>%
  clean_names()
```

```
# A tibble: 5 x 3
  id_number first_name score_percent
      <int> <chr>              <dbl>
1         1 Alice                 88
2         2 Bob                   92
3         3 Charlie               75
4         4 David                 85
5         5 Eva                   90
```
