The tidyverse

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Pipe (%>%), Tibbles, dplyr-verbs, long/wide format and more.

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1 What is the Tidyverse?

The tidyverse is a collection of R packages designed to make data science easier and more intuitive. Think of it as a toolkit where all the tools work well together and share a similar design philosophy. The packages help you:

- Import data
- Clean and organize data
- Transform and manipulate data
- Visualize data
- Model data

1.1 Installing Tidyverse

Before we can use the tidyverse, we need to install it. First, let's install a helpful package manager called `pacman`:

```r
# Install pacman if you haven't already
#install.packages("pacman")

# Load pacman
library(pacman)

# Now use pacman to install and load tidyverse
#pacman::p_load(tidyverse)
# (install &) load packages
pacman::p_load(
  broom,
  conflicted,
  here,
  janitor,
  naniar,
  readxl,
  tibble,
  tidyverse
)

# Alternative: traditional installation
# install.packages("tidyverse")
# library(tidyverse)
conflicts_prefer(dplyr::filter)
```

```r
conflicts_prefer(dplyr::select)
#dplyr::select()
```

1.2 Core Tidyverse Packages

Here are the main packages you'll use most often:

Package	Purpose
ggplot2	Creating beautiful graphs
dplyr	Data manipulation
tibble	Modern data frames
tidyr	Tidying data
readr	Reading data files

2 Understanding Data Tables: Base R vs Tidyverse

2.1 Base R: data.frame

In base R, we work with `data.frame` objects. Let's look at a built-in dataset:

```r
# Base R approach
# Load the built-in PlantGrowth dataset
data(PlantGrowth)
#data(iris)

# Create a copy to work with
df <- PlantGrowth

# View the first few rows
head(df)
```

```
  weight group
1   4.17  ctrl
2   5.58  ctrl
3   5.18  ctrl
4   6.11  ctrl
5   4.50  ctrl
6   4.61  ctrl
```

```r
# Check the structure
str(df)
```

```
'data.frame':	30 obs. of  2 variables:
 $ weight: num  4.17 5.58 5.18 6.11 4.5 4.61 5.17 4.53 5.33 5.14 ...
 $ group : Factor w/ 3 levels "ctrl","trt1",..: 1 1 1 1 1 1 1 1 1 1 ...
```

```r
# Get summary statistics
summary(df)
```

```
     weight       group   
 Min.   :3.590   ctrl:10  
 1st Qu.:4.550   trt1:10  
 Median :5.155   trt2:10  
 Mean   :5.073            
 3rd Qu.:5.530            
 Max.   :6.310            
```

2.1.1 Accessing columns in Base R:

```r
# Method 1: Using $ notation
df$weight
```

```
 [1] 4.17 5.58 5.18 6.11 4.50 4.61 5.17 4.53 5.33 5.14 4.81 4.17 4.41 3.59 5.87
[16] 3.83 6.03 4.89 4.32 4.69 6.31 5.12 5.54 5.50 5.37 5.29 4.92 6.15 5.80 5.26
```

```r
# Method 2: Using brackets with column name
df[, "weight"]
```

```
 [1] 4.17 5.58 5.18 6.11 4.50 4.61 5.17 4.53 5.33 5.14 4.81 4.17 4.41 3.59 5.87
[16] 3.83 6.03 4.89 4.32 4.69 6.31 5.12 5.54 5.50 5.37 5.29 4.92 6.15 5.80 5.26
```

```r
# Method 3: Using brackets with column number
df[, 1]
```

```
 [1] 4.17 5.58 5.18 6.11 4.50 4.61 5.17 4.53 5.33 5.14 4.81 4.17 4.41 3.59 5.87
[16] 3.83 6.03 4.89 4.32 4.69 6.31 5.12 5.54 5.50 5.37 5.29 4.92 6.15 5.80 5.26
```

2.2 Tidyverse: tibble

Now let's see how tidyverse handles the same data:

```
# Convert to tibble
tbl <- as_tibble(df)

# View the tibble
tbl
```

```
# A tibble: 30 x 2
   weight group
    <dbl> <fct>
 1   4.17 ctrl
 2   5.58 ctrl
 3   5.18 ctrl
 4   6.11 ctrl
 5   4.5  ctrl
 6   4.61 ctrl
 7   5.17 ctrl
 8   4.53 ctrl
 9   5.33 ctrl
10   5.14 ctrl
# i 20 more rows
```

2.2.1 Key differences with tibbles:

1. **Better printing**: Only shows what fits on screen
2. **Type information**: Shows data types under column names
3. **No partial matching**: More predictable behavior
4. **Preserves data types**: Doesn't automatically convert strings to factors

2.2.2 Accessing columns in tidyverse:

```
# Still can use $ notation
tbl$weight
```

```
 [1] 4.17 5.58 5.18 6.11 4.50 4.61 5.17 4.53 5.33 5.14 4.81 4.17 4.41 3.59 5.87
[16] 3.83 6.03 4.89 4.32 4.69 6.31 5.12 5.54 5.50 5.37 5.29 4.92 6.15 5.80 5.26
```

```
# Or use select() function (we'll learn more about this)
tbl %>% select(weight)
```

```
# A tibble: 30 x 1
   weight
    <dbl>
 1   4.17
 2   5.58
 3   5.18
 4   6.11
 5   4.5 
 6   4.61
 7   5.17
 8   4.53
 9   5.33
10   5.14
# i 20 more rows
```

3 Creating Plots: Base R vs ggplot2

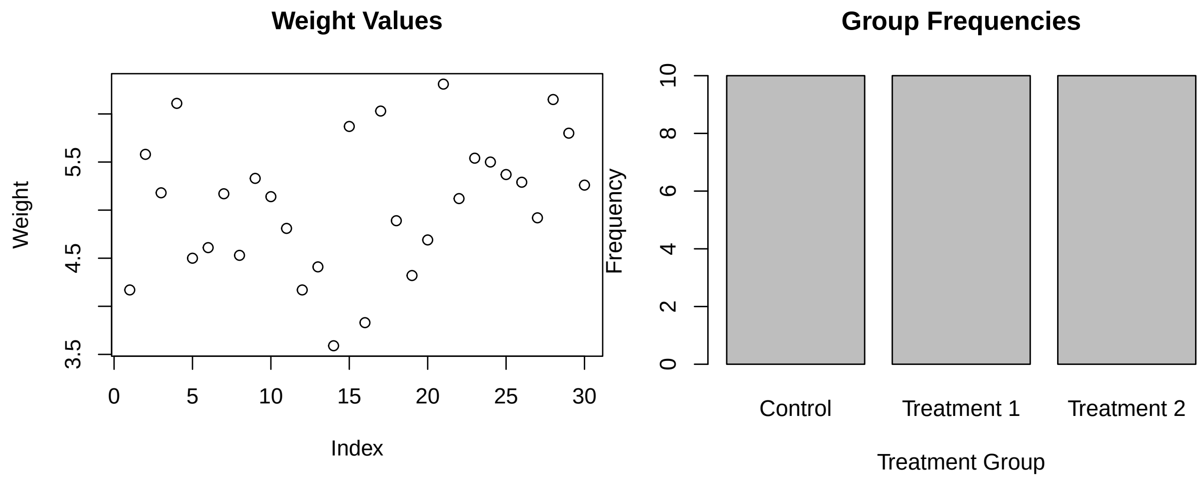
3.1 Base R Plotting

Base R has simple plotting functions that are quick but limited:

```
# Scatter plot
plot(df$weight, main = "Weight Values",
     xlab = "Index",
     ylab = "Weight")
# Bar plot with better labels
plot(df$group,
     main = "Group Frequencies",
     xlab = "Treatment Group",
     ylab = "Frequency",
     names.arg = c("Control", "Treatment 1", "Treatment 2"))
```

3.2 ggplot2 (Tidyverse)

ggplot2 builds plots in layers, like creating a painting. Let's break it down:



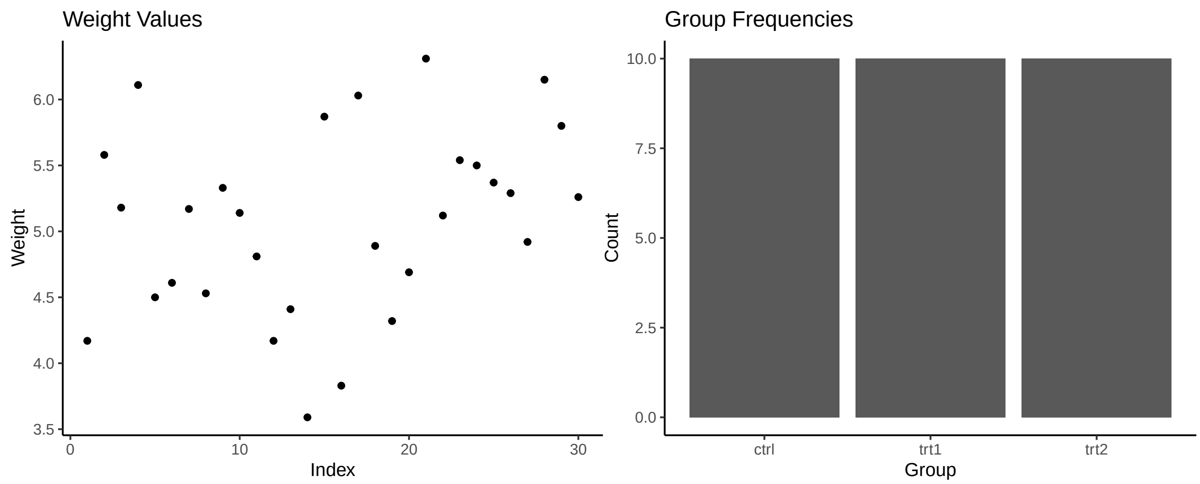
3.2.1 Understanding ggplot2 basics:

1. **ggplot()** - Creates the canvas
2. **aes()** - Stands for "aesthetics" - tells ggplot which data to use
3. **+** - Adds layers to your plot (like adding paint to canvas)
4. **geom_*()** - Geometric objects (the actual marks on the plot)

Let's build our plots step by step:

```
# Scatter plot with index
# Step 1: Create the canvas and specify the data
# aes(x = ..., y = ...) maps data to x and y axes
ggplot(data = tbl, aes(x = 1:nrow(tbl), y = weight)) +
  # Step 2: Add points to the plot
  geom_point() +
  # Step 3: Add labels
  labs(title = "Weight Values",
       x = "Index",
       y = "Weight") +
  theme_classic()
# Bar plot
# Step 1: Create canvas with data mapping
# When we only specify x, ggplot counts occurrences
ggplot(data = tbl, aes(x = group)) +
  # Step 2: Add bars (geom_bar counts automatically)
  geom_bar() +
  # Step 3: Add descriptive labels
  labs(title = "Group Frequencies",
```

```
       x = "Group",
       y = "Count") +
  theme_classic()
```



3.2.2 Breaking down the code:

For the scatter plot:
- `ggplot(data = tbl, ...)` - Use the 'tbl' dataset
- `aes(x = 1:nrow(tbl), y = weight)` - Put row numbers on x-axis, weight values on y-axis
- `geom_point()` - Draw points at each (x,y) coordinate
- The `+` sign connects these layers together

For the bar plot:
- `aes(x = group)` - Put group categories on x-axis
- `geom_bar()` - Count how many times each group appears and draw bars
- ggplot automatically counts for us!

3.2.3 Think of it like a recipe:

1. Start with your data (ggplot + data)
2. Decide what goes where (aes)
3. Choose how to show it (geom_point, geom_bar, etc.)
4. Add finishing touches (labs, themes, colors)

3.2.4 Common geom_ functions and how to explore more:

Here are the most common geometric layers you'll use:

```
# Create sample data for demonstrations
demo_data <- tibble(
  x = 1:10,
  y = c(2, 4, 3, 7, 5, 8, 6, 9, 7, 10),
  group = rep(c("A", "B"), 5)
)
```

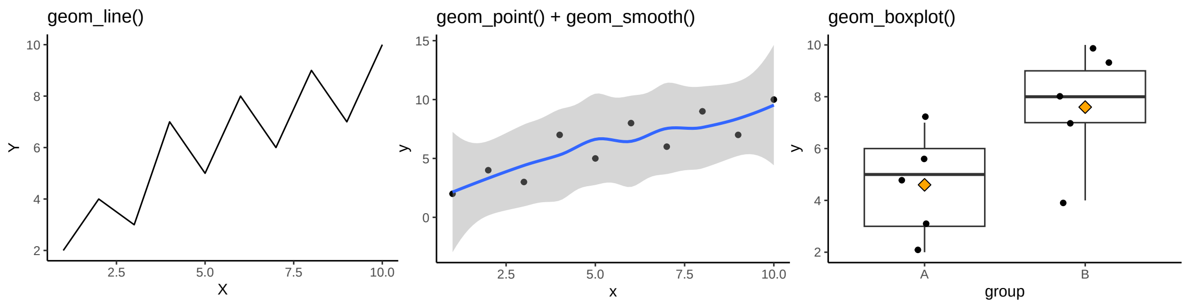
Essential geom_ functions:

geom_ function	What it draws	When to use
`geom_point()`	Points/dots	Scatter plots, showing individual values
`geom_line()`	Lines connecting points	Time series, trends
`geom_bar()`	Bars (counts data)	Frequency of categories
`geom_col()`	Bars (uses y values)	When you already have heights
`geom_histogram()`	Histogram	Distribution of continuous data
`geom_boxplot()`	Box plots	Comparing distributions between groups
`geom_smooth()`	Trend lines	Adding regression/smooth lines

3.2.5 Quick examples:

```
# Line plot
ggplot(demo_data, aes(x = x, y = y)) +
  geom_line() +
  labs(title = "geom_line()",
       x = "X",
       y = "Y") +
  theme_classic()
# Points + smooth line
ggplot(data = demo_data, aes(x = x, y = y)) +
  geom_point() +
  geom_smooth() +
```

```r
  labs(title = "geom_point() + geom_smooth()") +
  theme_classic()
# Box plot by group
ggplot(demo_data, aes(x = group, y = y)) +
  geom_boxplot() +
  stat_summary(fun = mean,
               geom = "point",
               shape = 23,
               size = 3,
               fill = "orange") +
  geom_jitter(width=0.2) +
  labs(title = "geom_boxplot()") +
  theme_classic()
```



Use `?pch` or `?shape` to know more about shapes.

3.2.6 How to discover more geom_ functions:

1. **In RStudio**: Type `geom_` and press TAB to see all available options

   ```r
   # Try this in your console:
   # ggplot(data, aes(x, y)) + geom_[TAB]
   ```

2. **Get help on any function**:

   ```r
   # Learn about a specific geom
   ?geom_violin

   # See examples
   example(geom_violin)
   ```

3. **Useful resources**:

- ggplot2 cheatsheet - Visual guide to all geoms
- R Graph Gallery - Examples of every plot type
- ggplot2 documentation - Official reference
- from Data to Viz - Has robust way to show plotting options

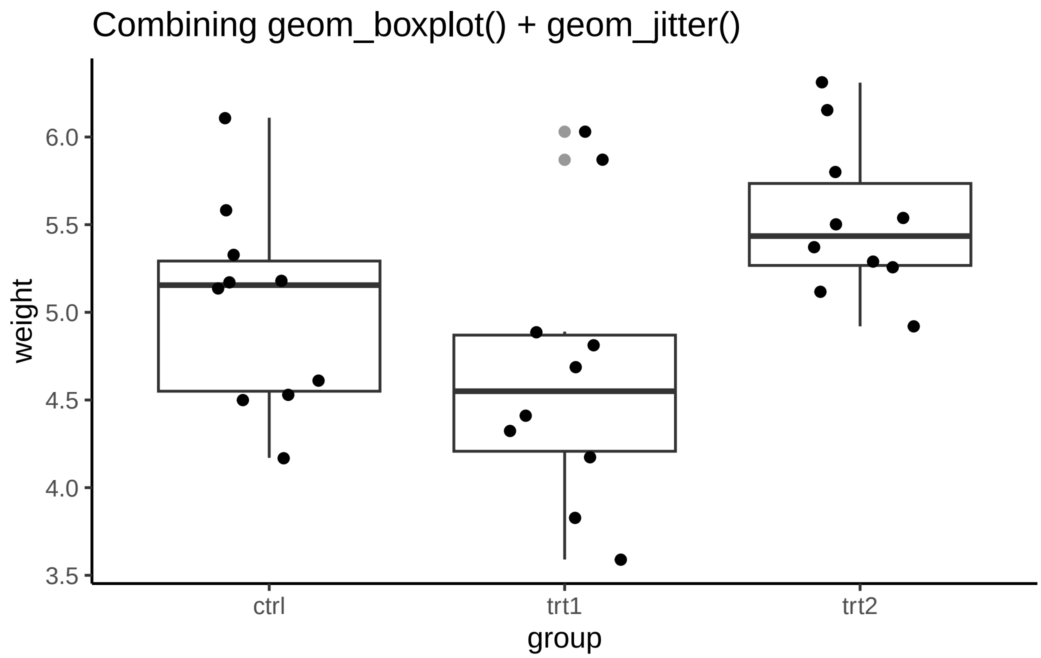
4. **Experiment!** Try different geoms with your data:

```r
# Start with basic plot
p <- ggplot(tbl, aes(x = group, y = weight))

# Try different visualizations
p + geom_boxplot()    # Box plot
p + geom_violin()     # Violin plot
p + geom_jitter()     # Scattered points
p + geom_dotplot(binaxis = "y")  # Dot plot
```

3.2.7 Pro tip: Layer multiple geoms!

```r
# You can combine multiple geoms for rich visualizations
ggplot(tbl, aes(x = group, y = weight)) +
  geom_boxplot(alpha = 0.5) +      # Semi-transparent box plot
  geom_jitter(width = 0.2) +        # Add individual points
  labs(title = "Combining geom_boxplot() + geom_jitter()") +
  theme_classic()
```



4 The Magic of the Pipe (%>%) Operator

The pipe operator is one of the most powerful features in tidyverse. It makes your code readable by allowing you to chain operations together. It takes the output of the expression on its left and passes it as the first argument to the function on its right

4.1 Without pipes (Base R approach):

```
# Step 1: Get ctrl group only
ctrl_only <- df[df$group == "ctrl", ]

# Step 2: Extract weight values
weights <- ctrl_only$weight

# Step 3: Calculate square root
sqrt_weights <- sqrt(weights)

# Step 4: Round to 1 decimal
rounded <- round(sqrt_weights, 2)
```

```r
# Step 5: Sort
sorted <- sort(rounded, decreasing = TRUE)

sorted
```

```
 [1] 2.47 2.36 2.31 2.28 2.27 2.27 2.15 2.13 2.12 2.04
```

4.2 With pipes (Tidyverse approach):

```r
df %>%
  filter(group == "ctrl") %>%   # Step 1: Get ctrl group
  pull(weight) %>%              # Step 2: Extract weights
  sqrt() %>%                    # Step 3: Square root
  round(1) %>%                  # Step 4: Round
  sort(decreasing = TRUE)                         # Step 5: Sort
```

```
 [1] 2.5 2.4 2.3 2.3 2.3 2.3 2.1 2.1 2.1 2.0
```

Tip: To type `%>%` quickly in RStudio, use `Ctrl+Shift+M` (Windows/Linux) or `Cmd+Shift+M` (Mac)

5 Essential dplyr Functions

5.1 1. `mutate()` - Add or modify columns

5.1.1 Base R approach:

```r
# Add a new column
df_copy <- df
df_copy$weight_kg <- df_copy$weight / 1000

# Modify existing column
df_copy$weight <- df_copy$weight * 2

head(df_copy)
```

```
  weight group weight_kg
1   8.34  ctrl   0.00417
2  11.16  ctrl   0.00558
3  10.36  ctrl   0.00518
4  12.22  ctrl   0.00611
5   9.00  ctrl   0.00450
6   9.22  ctrl   0.00461
```

5.1.2 Tidyverse approach:

```r
tbl %>%
  mutate(
    weight_kg = weight/1000,  # Add new column
    weight = weight*2
  ) %>%
  head()
```

```
# A tibble: 6 x 3
  weight group weight_kg
   <dbl> <fct>     <dbl>
1   8.34 ctrl    0.00417
2  11.2  ctrl    0.00558
3  10.4  ctrl    0.00518
4  12.2  ctrl    0.00611
5   9    ctrl    0.0045
6   9.22 ctrl    0.00461
```

N.B. We could make the doubling operation on the same `weight` *column as well. It would make in-place modification. You have to think when to do that operation then.*

5.2 2. `select()` - Choose columns

5.2.1 Base R approach:

```r
# Select specific columns
df_subset <- df[0:nrow(df), c("group", "weight")]
head(df_subset)
```

```
  group weight
1  ctrl   4.17
2  ctrl   5.58
3  ctrl   5.18
4  ctrl   6.11
5  ctrl   4.50
6  ctrl   4.61
```

5.2.2 Tidyverse approach:

```
tbl <- tbl %>%
  select(group, weight)
```

N.B. ***select()*** *helps to rearrange columns as well.*

5.3 3. `filter()` - Choose rows

5.3.1 Base R approach:

```
# Filter for weight > 5
df_filtered <- df[df$weight > 5, ]
df_filtered
```

```
   weight group
2    5.58  ctrl
3    5.18  ctrl
4    6.11  ctrl
7    5.17  ctrl
9    5.33  ctrl
10   5.14  ctrl
15   5.87  trt1
17   6.03  trt1
21   6.31  trt2
22   5.12  trt2
23   5.54  trt2
24   5.50  trt2
25   5.37  trt2
26   5.29  trt2
28   6.15  trt2
```

```
29   5.80  trt2
30   5.26  trt2
```

5.3.2 Tidyverse approach:

```
tbl %>%
  filter(weight > 5)
```

```
# A tibble: 17 x 2
   group weight
   <fct>  <dbl>
 1 ctrl    5.58
 2 ctrl    5.18
 3 ctrl    6.11
 4 ctrl    5.17
 5 ctrl    5.33
 6 ctrl    5.14
 7 trt1    5.87
 8 trt1    6.03
 9 trt2    6.31
10 trt2    5.12
11 trt2    5.54
12 trt2    5.5
13 trt2    5.37
14 trt2    5.29
15 trt2    6.15
16 trt2    5.8
17 trt2    5.26
```

5.4 4. `arrange()` - Sort rows

5.4.1 Base R approach:

```
# Sort by weight
df_sorted <- df[order(df$weight), ]
head(df_sorted)
```

```
   weight group
14   3.59  trt1
16   3.83  trt1
1    4.17  ctrl
12   4.17  trt1
19   4.32  trt1
13   4.41  trt1
```

```
df_sorted <- df[order(df$weight, decreasing=TRUE), ]
```

5.4.2 Tidyverse approach:

```
tbl %>%
  arrange(weight)
```

```
# A tibble: 30 x 2
   group weight
   <fct>  <dbl>
 1 trt1    3.59
 2 trt1    3.83
 3 ctrl    4.17
 4 trt1    4.17
 5 trt1    4.32
 6 trt1    4.41
 7 ctrl    4.5 
 8 ctrl    4.53
 9 ctrl    4.61
10 trt1    4.69
# i 20 more rows
```

5.5 5. `summarise()` with `group_by()` - Calculate summaries

5.5.1 Base R approach:

```
# Calculate mean by group
aggregate(weight ~ group, data = df, FUN = mean)
```

```
  group weight
1  ctrl  5.032
2  trt1  4.661
3  trt2  5.526
```

5.5.2 Tidyverse approach:

```
tbl %>%
  group_by(group) %>%
  summarise(
    mean_weight = mean(weight),
    sd_weight = sd(weight),
    n = n()
  )
```

```
# A tibble: 3 x 4
  group mean_weight sd_weight     n
  <fct>       <dbl>     <dbl> <int>
1 ctrl         5.03     0.583    10
2 trt1         4.66     0.794    10
3 trt2         5.53     0.443    10
```

6 Working with Data Formats: Long vs Wide

Sometimes you need to reshape your data. Here's how:

6.1 Creating example data:

```
# Create a small dataset
long_data <- data.frame(
  student = c("Alice", "Alice", "Alice", "Bob", "Bob", "Bob"),
  test = c("Math", "English", "Chemistry", "Math", "English", "Chemistry"),
  score = c(85, 90, 78, 82, 78, 90)
)

long_data
```

```
  student      test score
1   Alice      Math    85
2   Alice   English    90
3   Alice Chemistry    78
4     Bob      Math    82
5     Bob   English    78
6     Bob Chemistry    90
```

6.2 Convert to wide format:

6.2.1 Base R approach:

```r
# Using reshape function
wide_base <- reshape(long_data,
                     idvar = "student",
                     timevar = "test",
                     direction = "wide")
wide_base
```

```
  student score.Math score.English score.Chemistry
1   Alice         85            90              78
4     Bob         82            78              90
```

6.2.2 Tidyverse approach:

```r
wide_data <- long_data %>%
  pivot_wider(names_from = test,
              values_from = score)
wide_data
```

```
# A tibble: 2 x 4
  student  Math English Chemistry
  <chr>   <dbl>   <dbl>     <dbl>
1 Alice      85      90        78
2 Bob        82      78        90
```

6.3 Convert back to long format:

6.3.1 Tidyverse approach:

```
wide_data %>%
  pivot_longer(cols = -student,
               names_to = "test",
               values_to = "score")
```

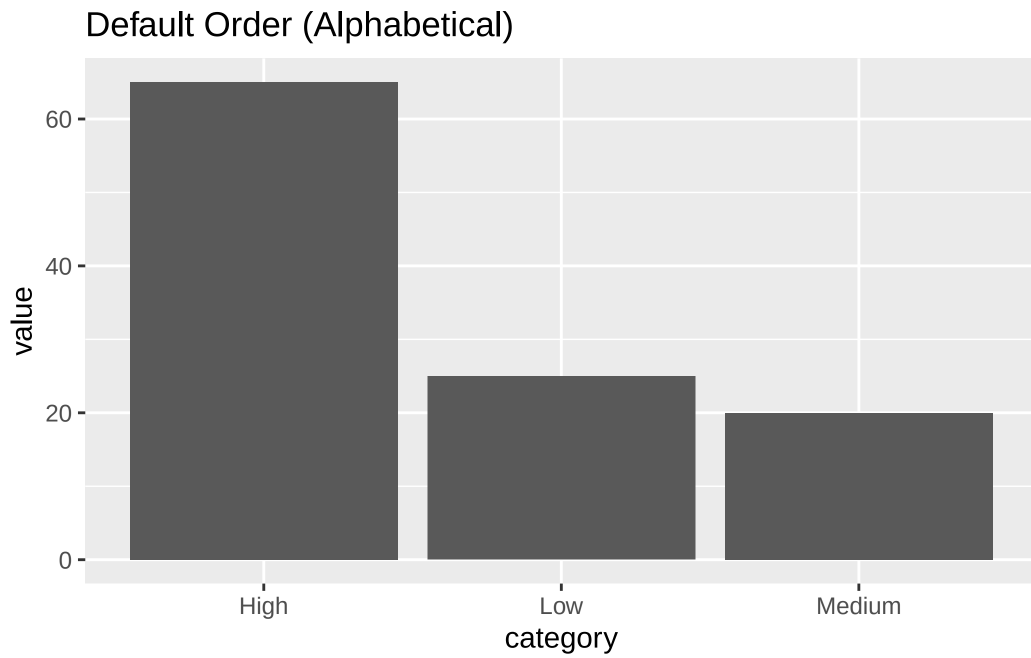
```
# A tibble: 6 x 3
  student test      score
  <chr>   <chr>     <dbl>
1 Alice   Math         85
2 Alice   English      90
3 Alice   Chemistry    78
4 Bob     Math         82
5 Bob     English      78
6 Bob     Chemistry    90
```

7 Working with Factors (forcats)

Factors are categorical variables. The order matters for plotting:

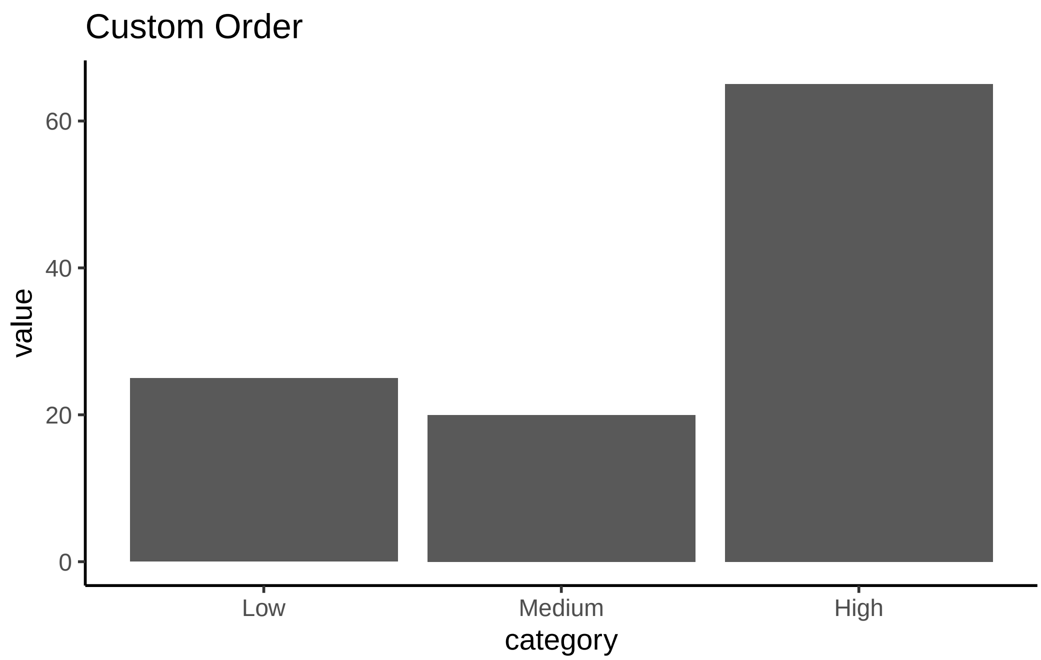
```
# Create example data
plot_data <- tibble(
  category = c("Low", "Medium", "High", "Low", "High"),
  value = c(10, 20, 30, 15, 35)
)

# Default alphabetical order
ggplot(plot_data, aes(x = category, y = value)) +
  geom_col() +
  labs(title = "Default Order (Alphabetical)")
```



7.1 Reordering factors:

```
# Specify custom order
plot_data %>%
  mutate(category = fct_relevel(category, "Low", "Medium", "High")) %>%
  ggplot(aes(x = category, y = value)) +
  geom_col() +
  labs(title = "Custom Order") +
  theme_classic()
```



8 Working with Strings (stringr)

8.1 Common string operations:

```
# Example strings
messy_string <- "  Hello   World!  "
names <- c("John Smith", "Jane Doe", "Bob Johnson")

# Remove extra spaces
str_trim(messy_string)
```

```
[1] "Hello   World!"
```

```
str_squish(messy_string)
```

```
[1] "Hello World!"
```

```
# Replace text
str_replace(names, "John", "Jonathan")
```

```
[1] "Jonathan Smith"  "Jane Doe"        "Bob Jonathanson"
```

```
# Detect pattern
str_detect(names, "John")
```

```
[1]  TRUE FALSE  TRUE
```

```
# Extract substring
str_sub(names, 1, 4)
```

```
[1] "John" "Jane" "Bob "
```

9 Practical Example: Complete Analysis

Let's combine everything we learned:

```
# Load and prepare data
mtcars %>%
  as_tibble() %>%
  # Add car names as a column
  mutate(car = rownames(mtcars)) %>%
  # Select relevant columns
  select(car, mpg, cyl, hp, wt) %>%
  # Filter for efficient cars
  filter(mpg > 20) %>%
  # Add categorical variable
  mutate(efficiency = case_when(
    mpg > 30 ~ "High",
    mpg > 25 ~ "Medium",
    TRUE ~ "Low"
  )) %>%
  # Sort by mpg
  arrange(desc(mpg)) %>%
  # Show top 5
  head(5)
```

```
# A tibble: 5 x 6
  car              mpg   cyl    hp    wt efficiency
```

```
  <chr>          <dbl> <dbl> <dbl> <dbl> <chr>
1 Toyota Corolla  33.9     4    65  1.84 High
2 Fiat 128        32.4     4    66  2.2  High
3 Honda Civic     30.4     4    52  1.62 High
4 Lotus Europa    30.4     4   113  1.51 High
5 Fiat X1-9       27.3     4    66  1.94 Medium
```

10 Summary: Base R vs Tidyverse

Task	Base R	Tidyverse
Select columns	`df[, c("col1", "col2")]`	`df %>% select(col1, col2)`
Filter rows	`df[df$col > 5, ]`	`df %>% filter(col > 5)`
Add column	`df$new <- df$old * 2`	`df %>% mutate(new = old * 2)`
Sort	`df[order(df$col), ]`	`df %>% arrange(col)`
Group summary	`aggregate()`	`df %>% group_by() %>% summarise()`

11 Homework Assignment

11.1 Part 1: Basic Operations

Using the built-in `iris` dataset:

11.2 Plotting Challenge:

Create a visualization that shows the relationship between Petal.Length and Petal.Width, colored by Species, with: - Proper labels and title - A theme of your choice - Regression lines for each species

And try more plotting as you wish!

11.3 Problem 1: Data Manipulation

Using the built-in `iris` dataset:
1. Convert it to a tibble
2. Create a new column called `Petal.Ratio` that is `Petal.Length / Petal.Width`
3. Filter for only “setosa” species with Sepal.Length > 5

4. Select only the Species, Sepal.Length, and your new Petal.Ratio columns
5. Arrange the results by Petal.Ratio in descending order

11.4 Problem 2: Grouping and Summarizing

Using the full `iris` dataset:

1. Group by Species

2. Calculate the following for each species:

   - Mean Sepal.Length
   - Standard deviation of Sepal.Width
   - Minimum and maximum Petal.Length
   - Count of observations

3. Create a bar plot showing the mean Sepal.Length by Species

11.5 Problem 3: Data Reshaping

1. Create a subset of iris with the first 3 rows of each species
2. Add a row number within each species (call it "plant_id")
3. Convert this to wide format where:

   - Each row represents one plant_id
   - Columns show the Sepal.Length for each species

11.6 Submission Instructions:

- Submit your R Markdown file
- Include comments explaining your code, discuss with your peer and improve
- Make sure your code runs without errors
- Due date: Friday 10PM BD Time

11.7 Grading Rubric:

- Code correctness: 70%
- Code style and comments: 20%
- Output interpretation: 10%

Good luck! Remember to use the pipe operator `%>%` to make your code readable!