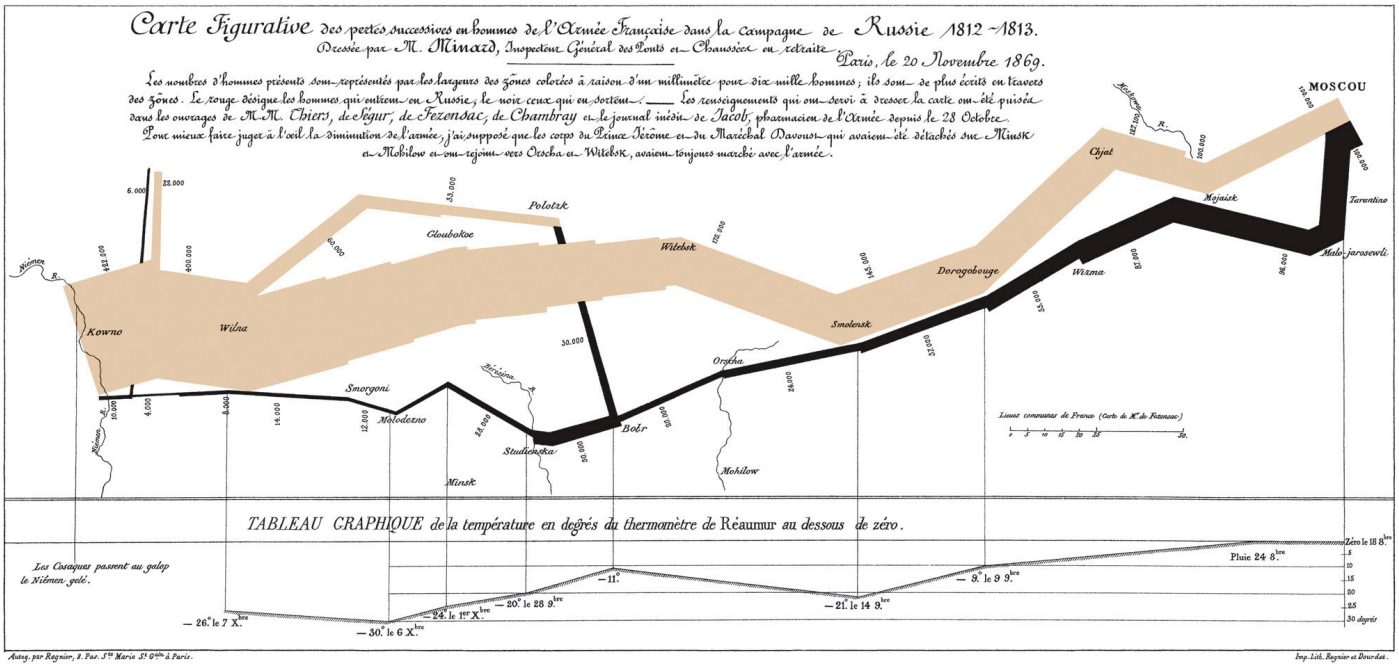
BUSINESS INTELLIGENCE AND DATA ANALYTICS | IOA Institute of Analytics Recognized Programme | University of Petra

5.1_Introduction to ggplot2

Introduction to ggplot2

Grammar of Graphics



Minard's Map or Minard's Flow Map, is a remarkable example of how data visualization can tell a powerful and complex story in a single image.

The map, created in 1869, is widely considered one of the most effective and impactful pieces of statistical graphics ever produced.

The maps tells us the following:

1. **Army Size Decrease**: The size of Napoleon's army drastically reduced from over 400,000 men at the start to fewer than 10,000 by the end of the campaign.
2. **Geographical Journey**: The army's route from the western border of Russia to Moscow and back is clearly depicted.
3. **Impact of Weather**: The map highlights the severe cold temperatures during the retreat, which significantly contributed to the army's losses.
4. **Temporal Progression**: Dates along the route show when the army reached different points, illustrating the timeline of the campaign.

5. **Catastrophic Loss**: The map visually emphasizes the catastrophic nature of the Russian campaign and its role in Napoleon's downfall.

Minard's map relates to the "Grammar of Graphics" concept by exemplifying how complex data can be effectively communicated through systematic visual components.

The "Grammar of Graphics" is a framework that describes the building blocks of data visualization, allowing for the structured and meaningful presentation of data.

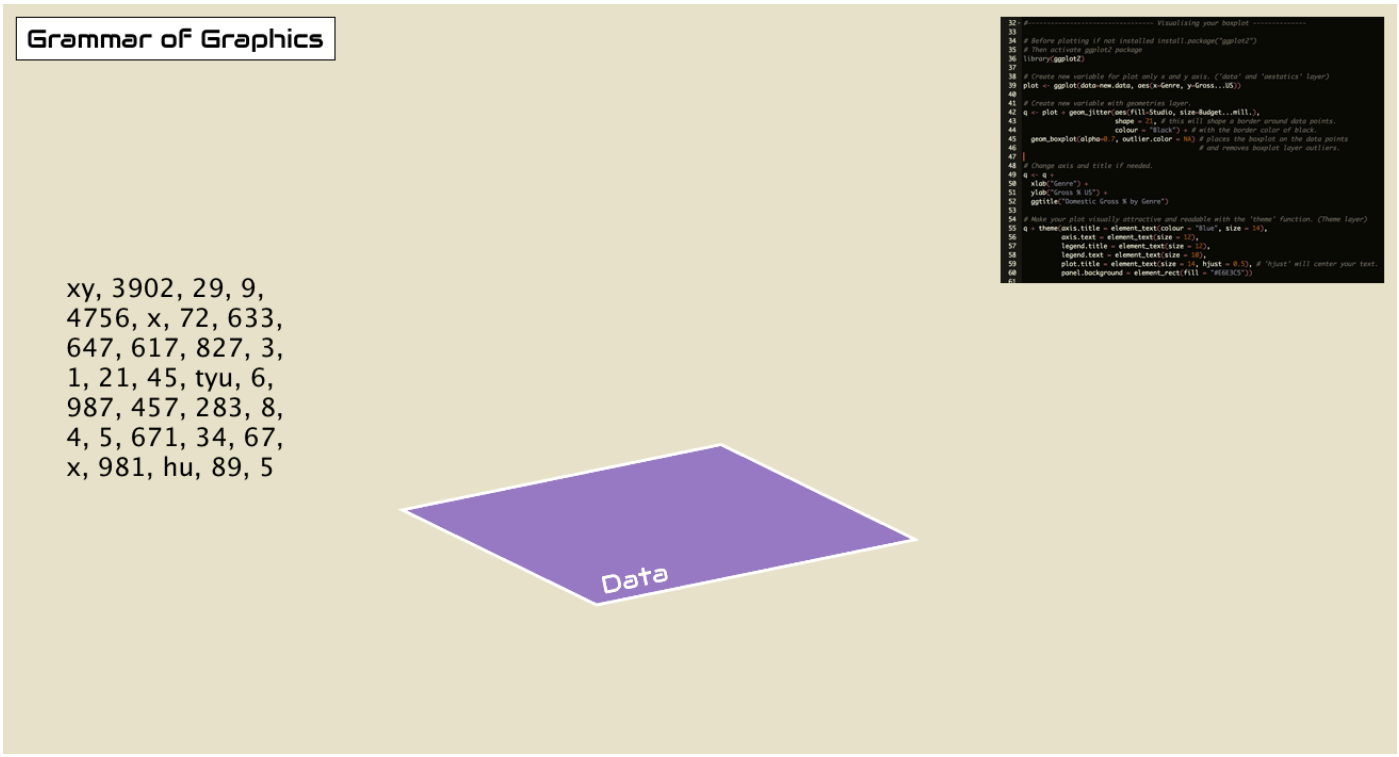
What is ggplot2?

`ggplot2` is a powerful and highly versatile plotting system for R, designed to help researchers, analysts, and data scientists create meaningful and visually appealing data visualizations. Based on the principles of the Grammar of Graphics, `ggplot2` allows users to construct plots by specifying graphical primitives that represent data in a declarative way. This approach enables a clear and logical structure for creating a wide variety of charts, from simple scatter plots to complex multi-panel graphics.

At the core of `ggplot2` is the idea that a plot can be broken down into components or layers. These layers include: -

- **Data**: The actual data that you want to visualize.
- **Aesthetics (Aes)**: Mappings between the data and visual properties of the plot such as axes, colors, sizes, or shapes.
- **Geometries (Geoms)**: The geometric shapes that represent the data, such as bars in a bar chart or lines in a line chart.
- **Scales**: Control how data values are mapped to visual properties like colors or sizes.
- **Coordinate systems**: The space in which data is plotted, for instance, Cartesian or polar coordinates.
- **Faceting**: Creates grids of plots by splitting the data on one or more variables.
- **Statistical transformations**: Summarizes data in many useful ways, e.g., binning, counting, or calculating means.
- **Themes**: Control the finer details of the display like fonts, labels, legends, and background.

Grammar of Graphics: A layered approach to elegant data stories



`ggplot2`'s layering approach makes it distinctively powerful for iterative data exploration.

You can start with a basic plot and incrementally add layers until you reach the desired level of complexity or aesthetics.

This makes it not only an effective tool for exploratory data analysis but also for creating sophisticated static and interactive graphics tailored for publications or presentations.

In the following sections, we will explore how to use `ggplot2` through step-by-step instructions, building from simple examples to more complex plots, and discussing how to adjust and customize each component of a plot.

This guide will equip you with the knowledge to harness the full potential of `ggplot2` in your data visualization tasks.

Step 1: Loading ggplot2 and Data

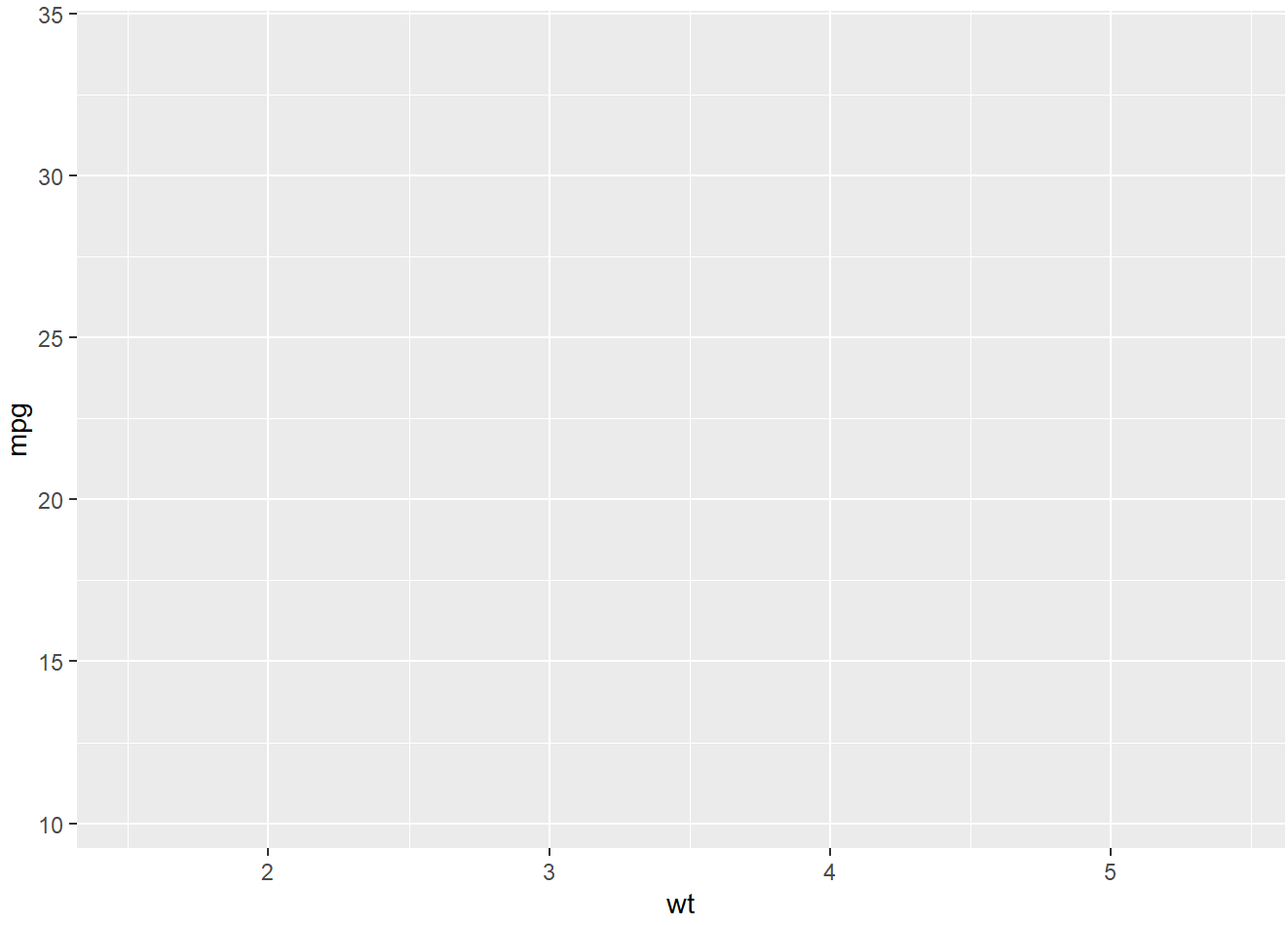
To begin working with `ggplot2`, you first need to load the package and prepare a dataset. For our examples, we will use the `mtcars` dataset which is built into R.

```
library(ggplot2)
data(mtcars)
```

Step 2: Initiating a ggplot Object

Every ggplot2 graph begins with the `ggplot` function. It sets up a plot with data and aesthetic mappings. Aesthetics describe how variables in the data are mapped to visual properties (aesthetics) of the graph.

```
ggplot(data = mtcars, aes(x = wt, y = mpg))
```

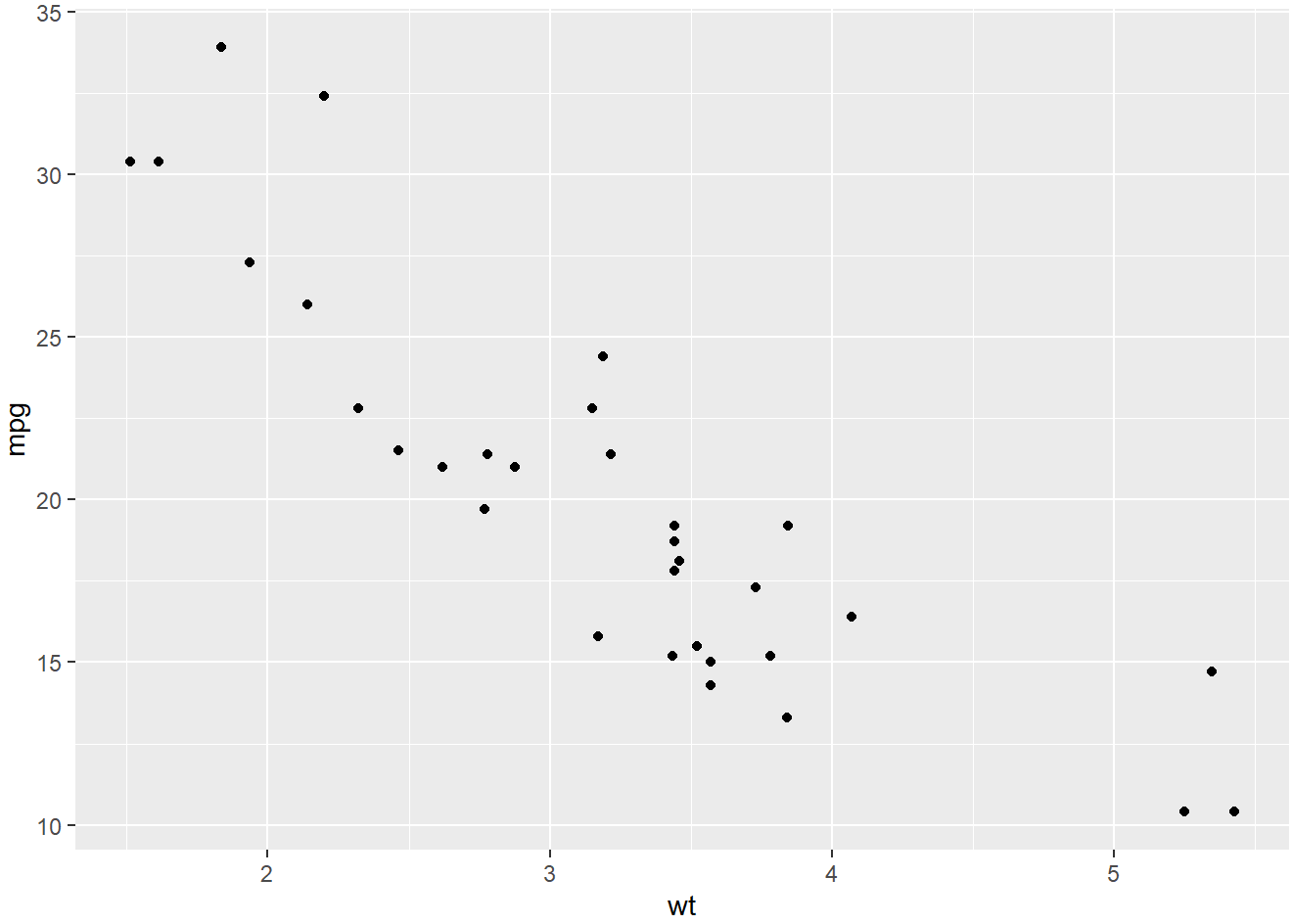


Here, `data` specifies the dataset to use, and `aes` is used to define the primary aesthetic mappings - placing car weight on the x-axis and miles per gallon on the y-axis.

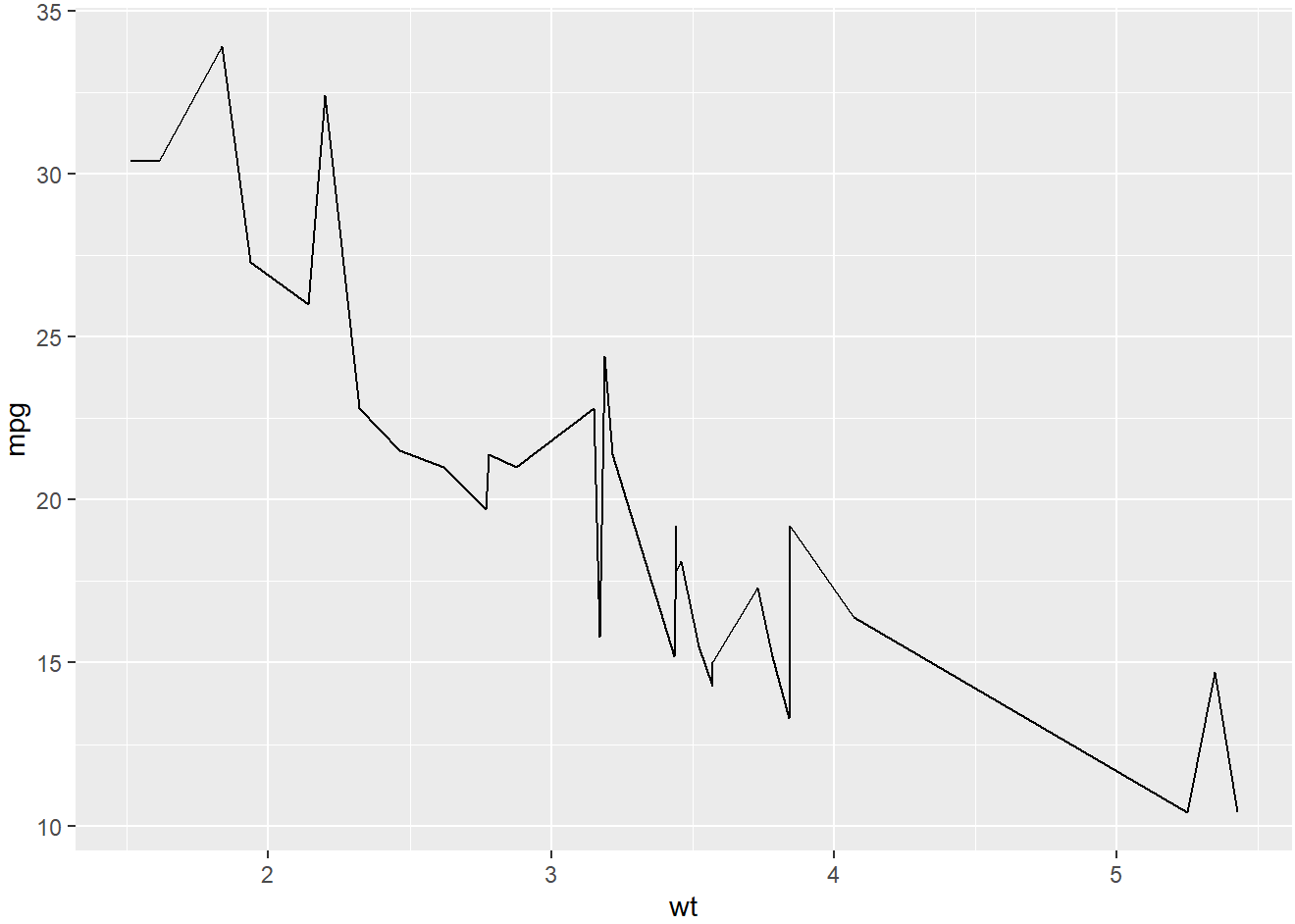
Step 3: Adding Geometric Objects

Geometric objects (geoms) visually represent data. For a scatter plot, we use `geom_point()`, which plots a point for each observation in the dataset.

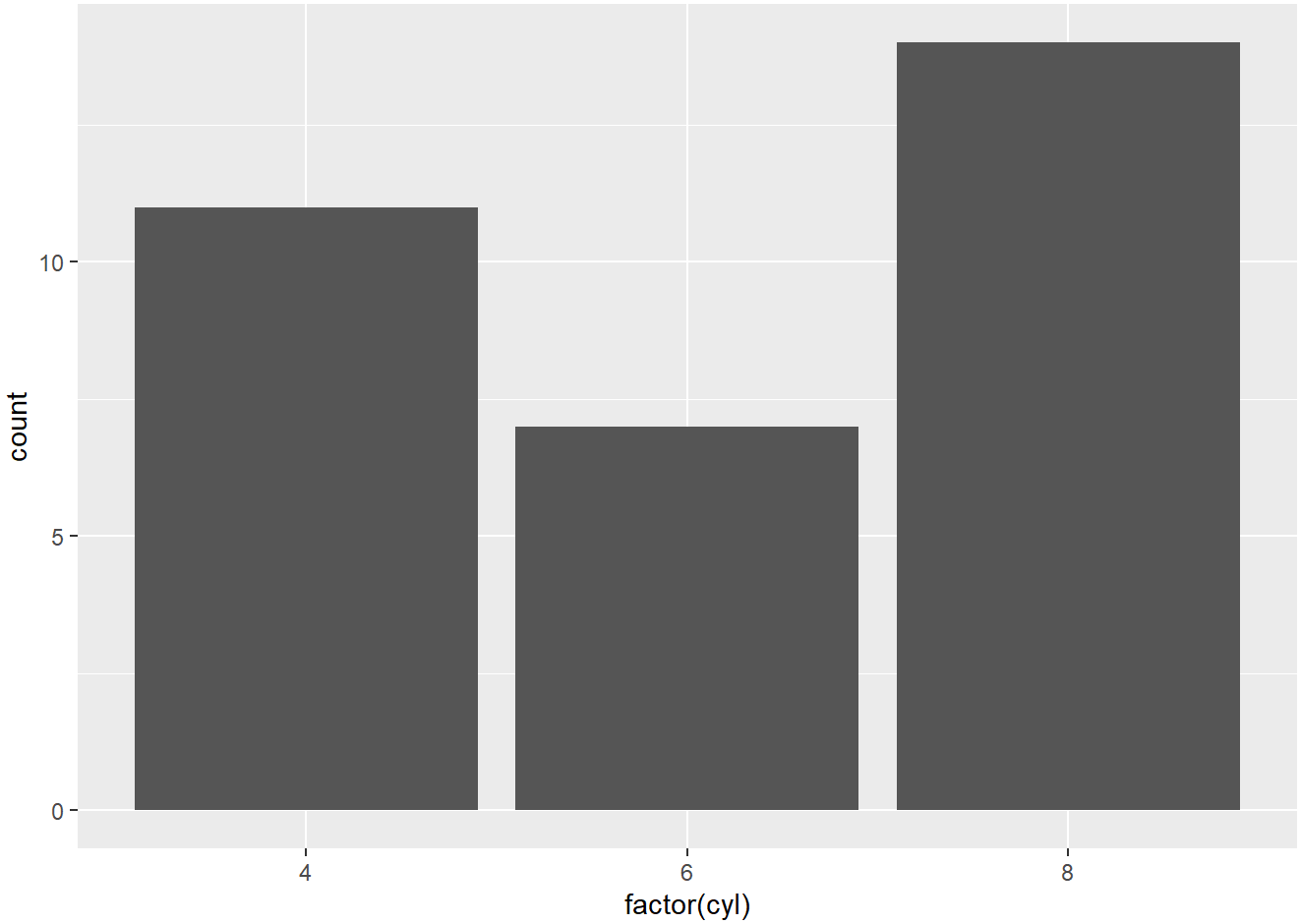
```
# Scatter plot with points
ggplot(mtcars, aes(x = wt, y = mpg)) +
  geom_point()
```




```
# Line plot
ggplot(mtcars, aes(x = wt, y = mpg)) +
  geom_line()
```




```
# Bar plot
ggplot(mtcars, aes(x = factor(cyl))) +
  geom_bar()
```

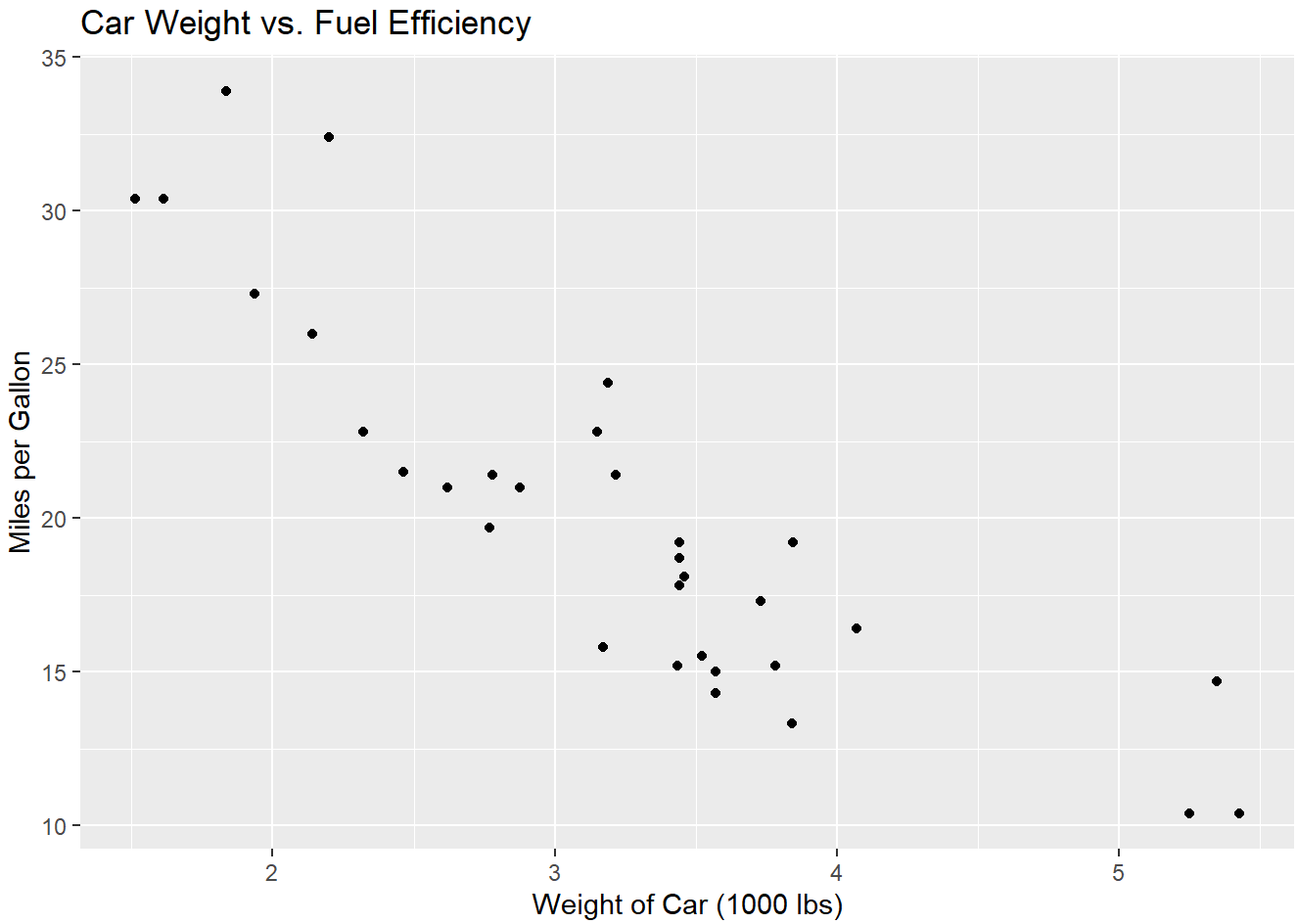


This line of code adds a layer to the ggplot object that plots points based on the aesthetic mappings we defined.

Step 4: Enhancing the Plot with Labels and Titles

Labels and titles help make your plots informative. `labs()` allows you to add a main title, as well as custom labels for the x and y axes.

```
ggplot(data = mtcars, aes(x = wt, y = mpg)) +
  geom_point() +
  labs(title = "Car Weight vs. Fuel Efficiency",
       x = "Weight of Car (1000 lbs)",
       y = "Miles per Gallon")
```

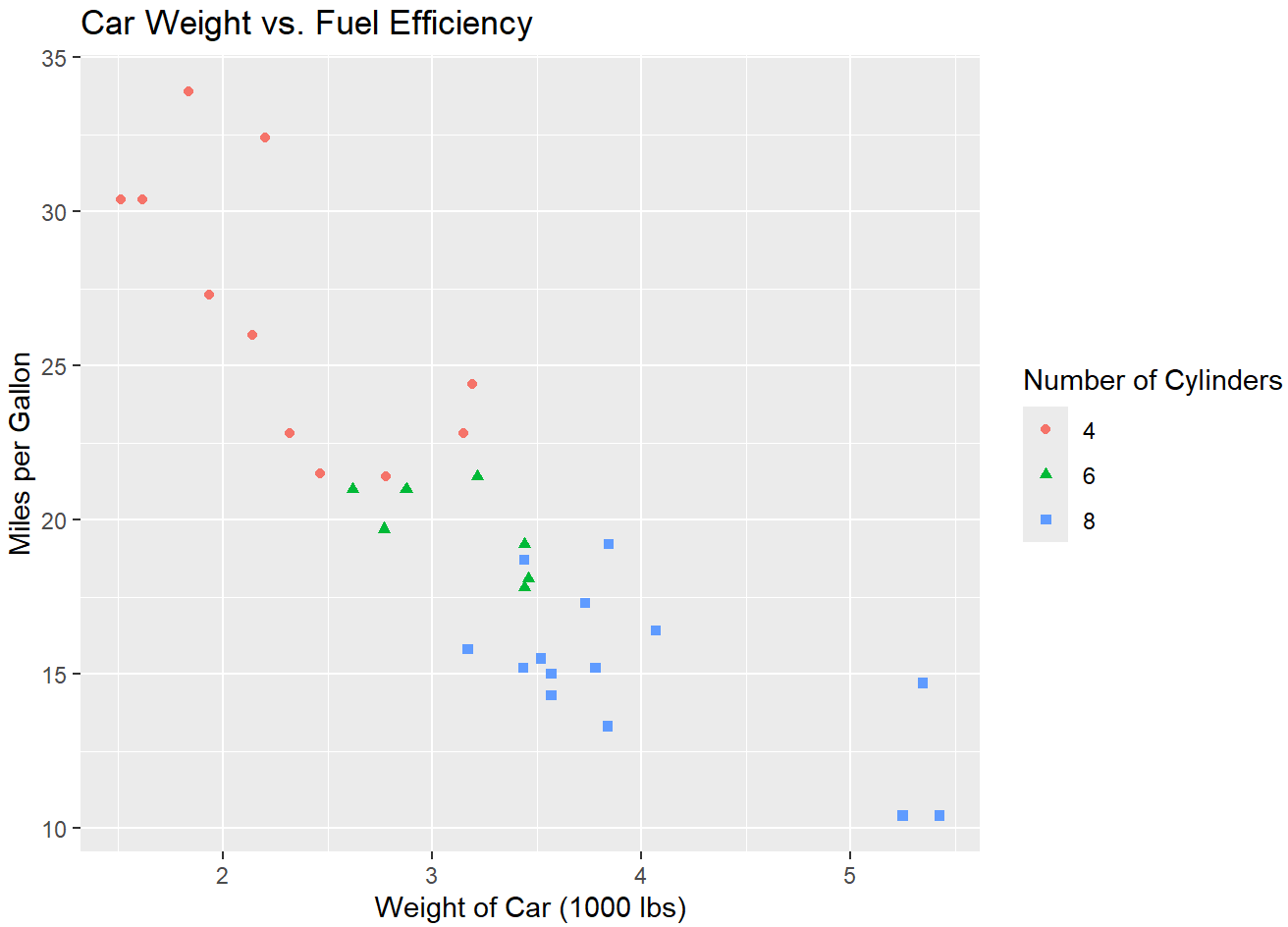


This code sets the title of the plot and labels each axis.

Step 5: Customizing Colors and Shapes

Customizing the appearance of your plot can help highlight specific data or make your plot easier to read. Use color and shape within your aesthetic mappings to differentiate groups or categories.

```
ggplot(data = mtcars, aes(x = wt, y = mpg, color = factor(cyl), shape = factor(cyl))) +
  geom_point() +
  labs(title = "Car Weight vs. Fuel Efficiency",
       x = "Weight of Car (1000 lbs)",
       y = "Miles per Gallon",
       color = "Number of Cylinders",
       shape = "Number of Cylinders")
```



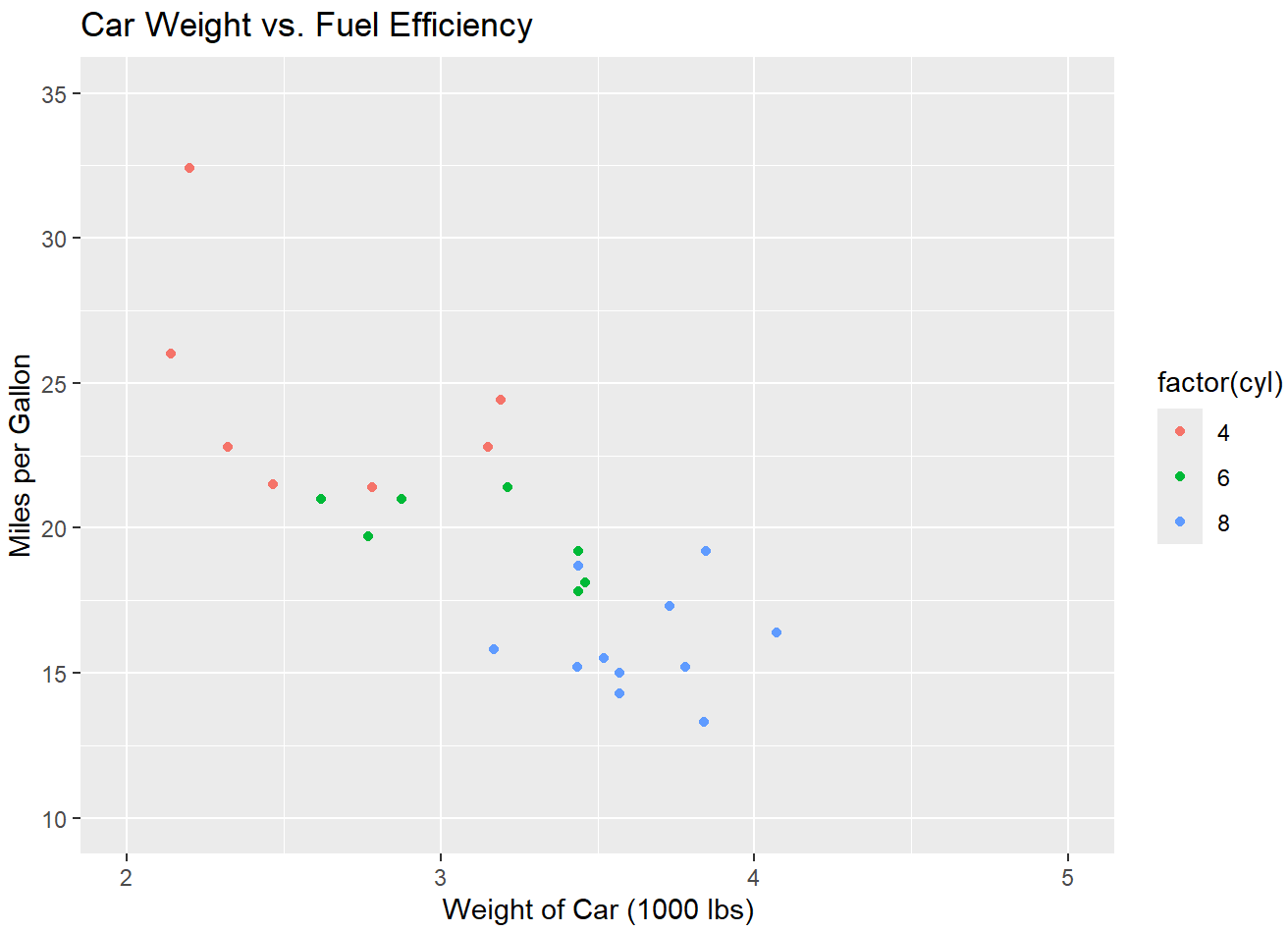
Here, cars are colored and shaped according to the number of cylinders, which helps in distinguishing between different groups visually.

Step 6: Adjusting X and Y Axis Limits

Adjusting the scales and limits of your axes can focus your analysis on specific areas of interest. `xlim()` and `ylim()` functions control the limits of the x-axis and y-axis respectively.

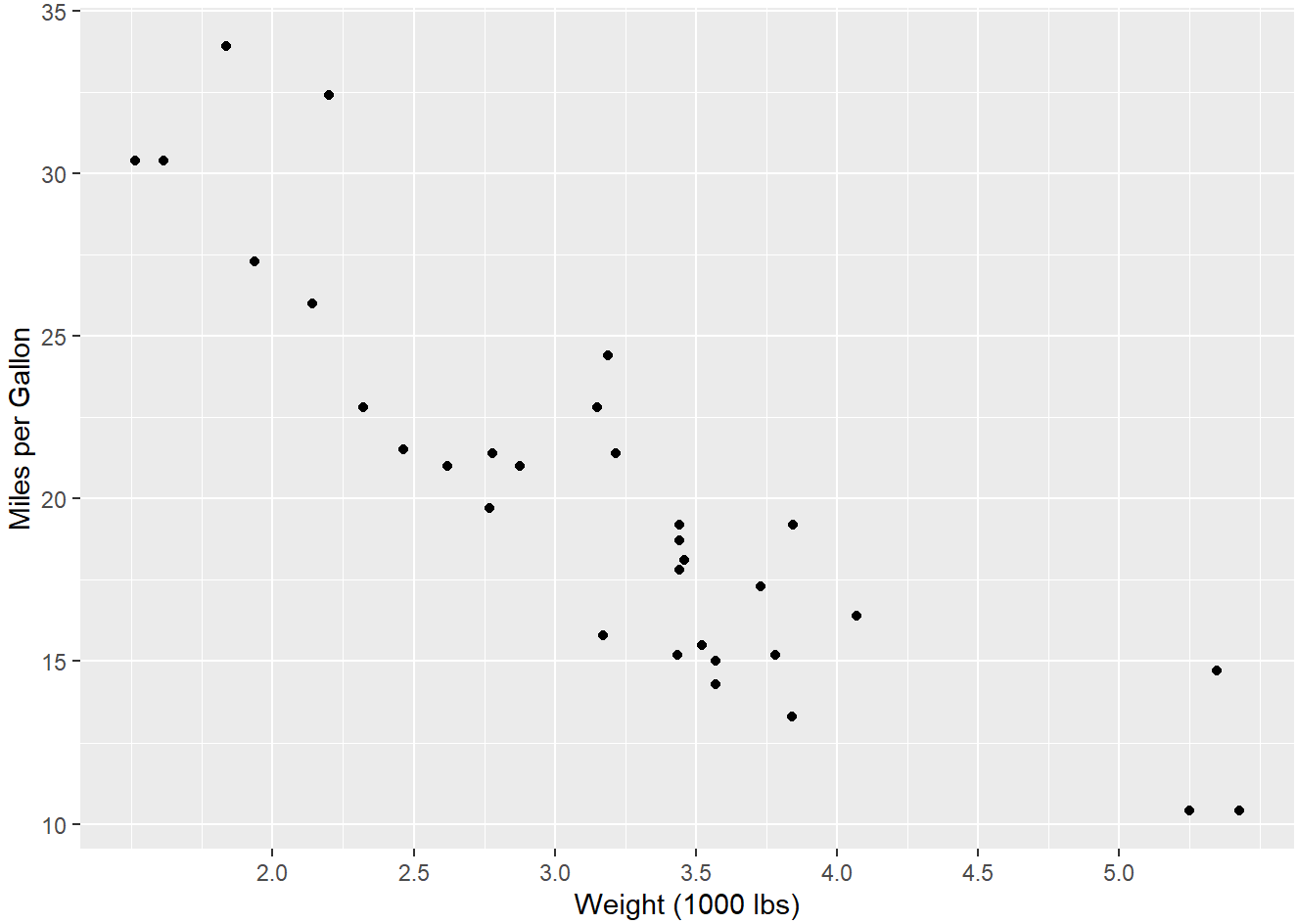
```
ggplot(data = mtcars, aes(x = wt, y = mpg, color = factor(cyl))) +
  geom_point() +
  xlim(2, 5) +
  ylim(10, 35) +
  labs(title = "Car Weight vs. Fuel Efficiency",
       x = "Weight of Car (1000 lbs)",
       y = "Miles per Gallon")
```

```
Warning: Removed 7 rows containing missing values or values outside the scale range
(`geom_point()`).
```



This adjustment restricts the display to cars weighing between 2,000 and 5,000 lbs and with MPG between 10 and 35.

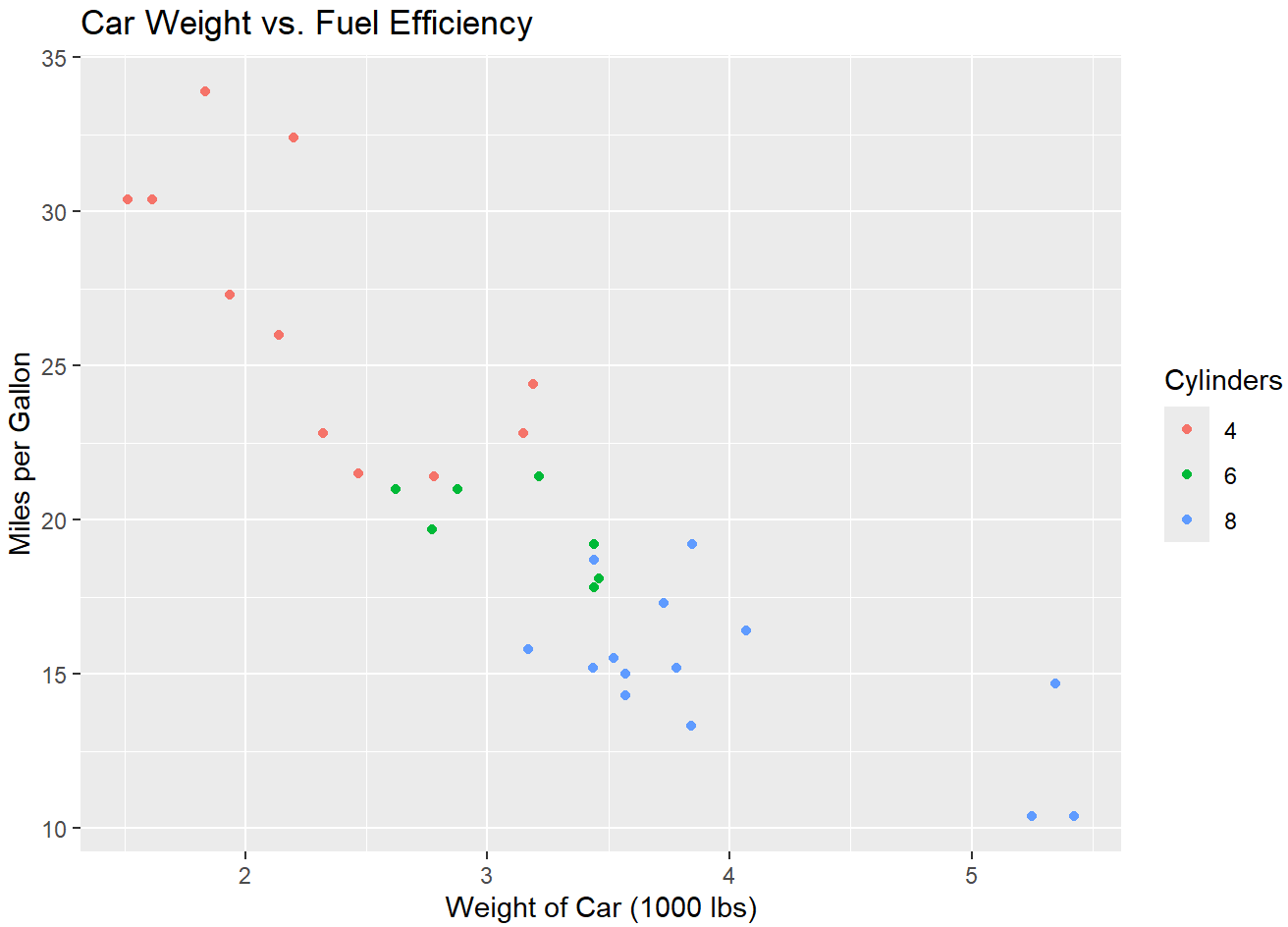
```
# Customizing scales
ggplot(mtcars, aes(x = wt, y = mpg)) +
  geom_point() +
  scale_x_continuous(name = "Weight (1000 lbs)", breaks = seq(2, 5, by = 0.5)) +
  scale_y_continuous(name = "Miles per Gallon")
```



Step 7: Modifying the Legend

Legends are key to understanding the plotted data. They can be adjusted with the `guides()` or through direct specifications in the `scale_color_*` or `scale_shape_*` functions.

```
ggplot(data = mtcars, aes(x = wt, y = mpg, color = factor(cyl))) +
  geom_point() +
  labs(title = "Car Weight vs. Fuel Efficiency",
       x = "Weight of Car (1000 lbs)",
       y = "Miles per Gallon",
       color = "Number of Cylinders") +
  guides(color = guide_legend(title = "Cylinders"))
```



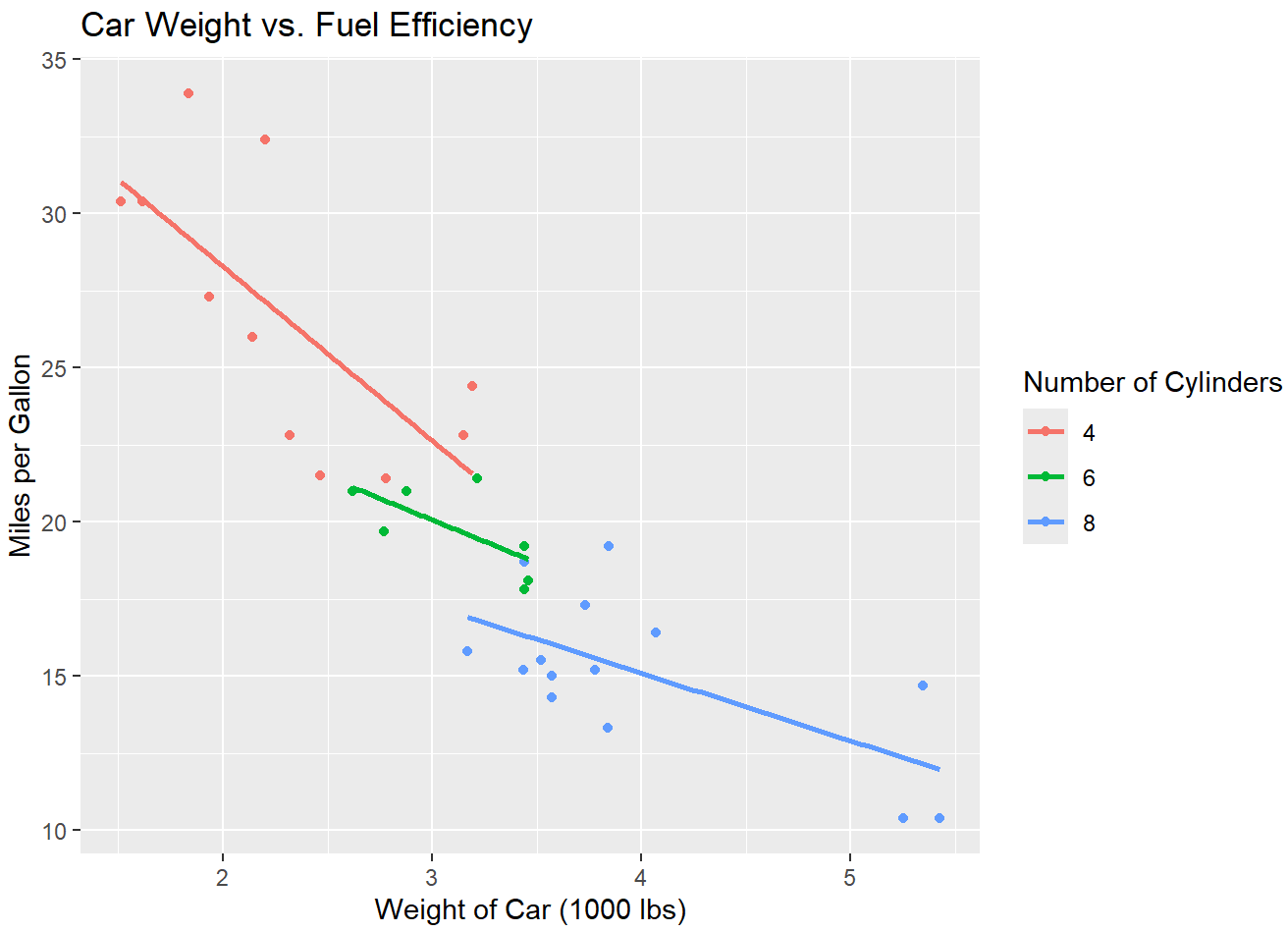
This code ensures that the legend is clearly labeled as "Cylinders".

Step 8: Adding More Geoms

Sometimes, additional layers can help further analyze the data. Adding a smooth line can help visualize trends.

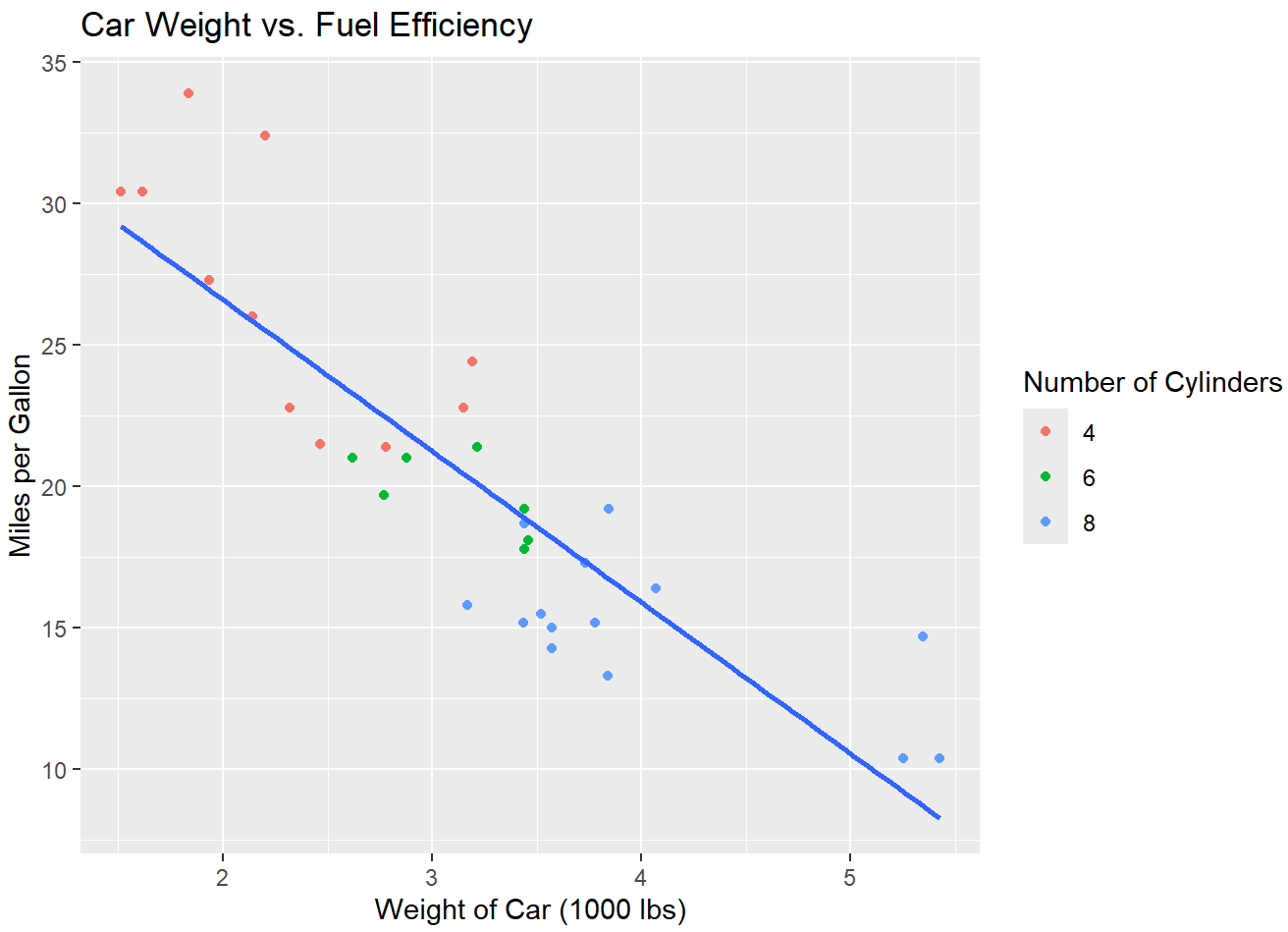
```
ggplot(data = mtcars, aes(x = wt, y = mpg, color = factor(cyl))) +
  geom_point() +
  geom_smooth(method = "lm", se = FALSE) +
  labs(title = "Car Weight vs. Fuel Efficiency",
       x = "Weight of Car (1000 lbs)",
       y = "Miles per Gallon",
       color = "Number of Cylinders")
```

```
`geom_smooth()` using formula = 'y ~ x'
```




```
# Create one line
ggplot(data = mtcars, aes(x = wt, y = mpg)) +
  geom_point(aes(color = factor(cyl))) +
  geom_smooth(method = "lm", se = FALSE) +
  labs(title = "Car Weight vs. Fuel Efficiency",
       x = "Weight of Car (1000 lbs)",
       y = "Miles per Gallon",
       color = "Number of Cylinders")
```

```
`geom_smooth()` using formula = 'y ~ x'
```



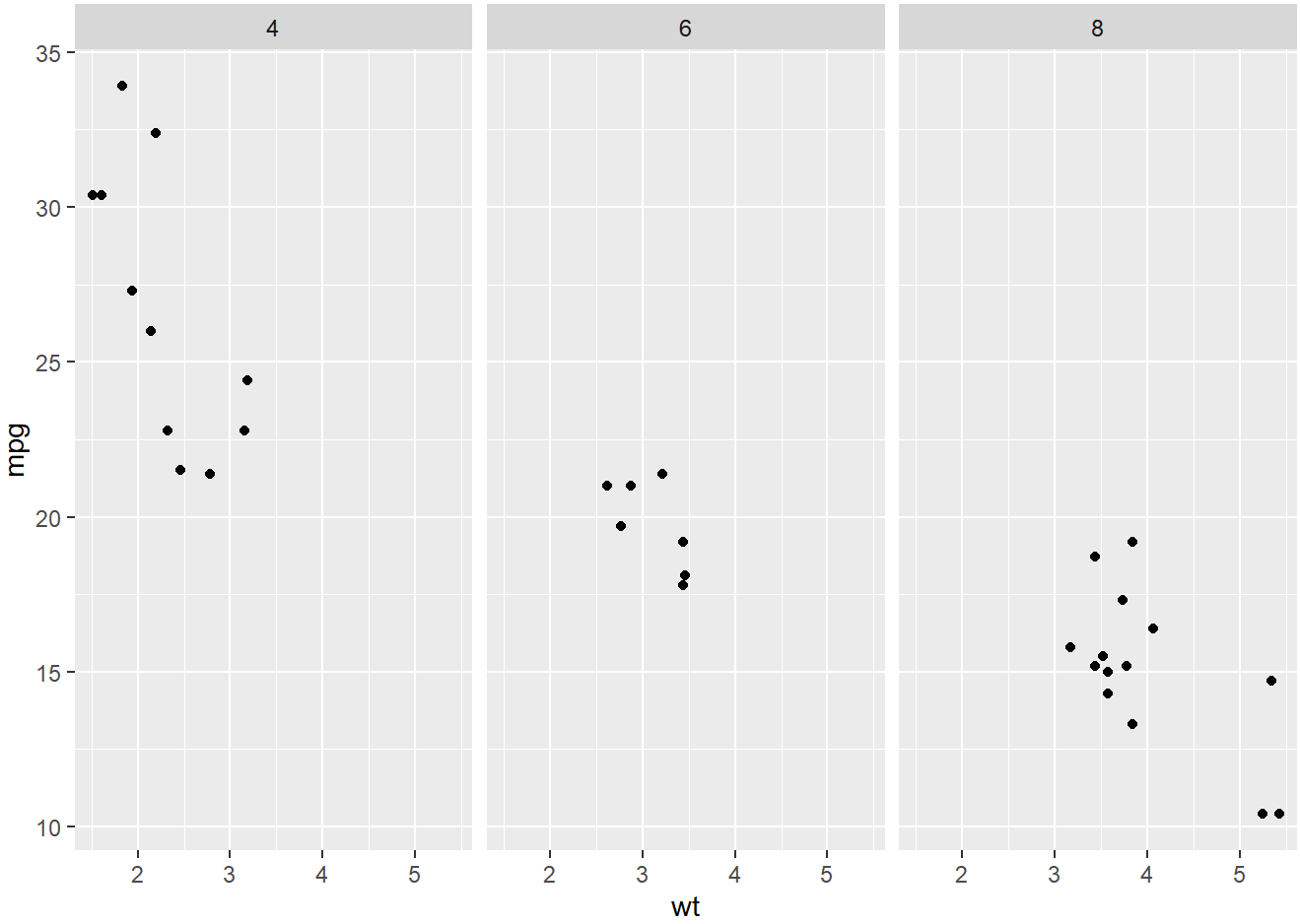
In the first code, multiple regression lines are plotted — one for each cylinder category because `color = factor(cyl)` is part of the global aesthetics and affects all layers, including `geom_smooth()`.

- In the second code, only one regression line is plotted for all the data combined, with `color = factor(cyl)` only applied to `geom_point()` and not affecting `geom_smooth()`.

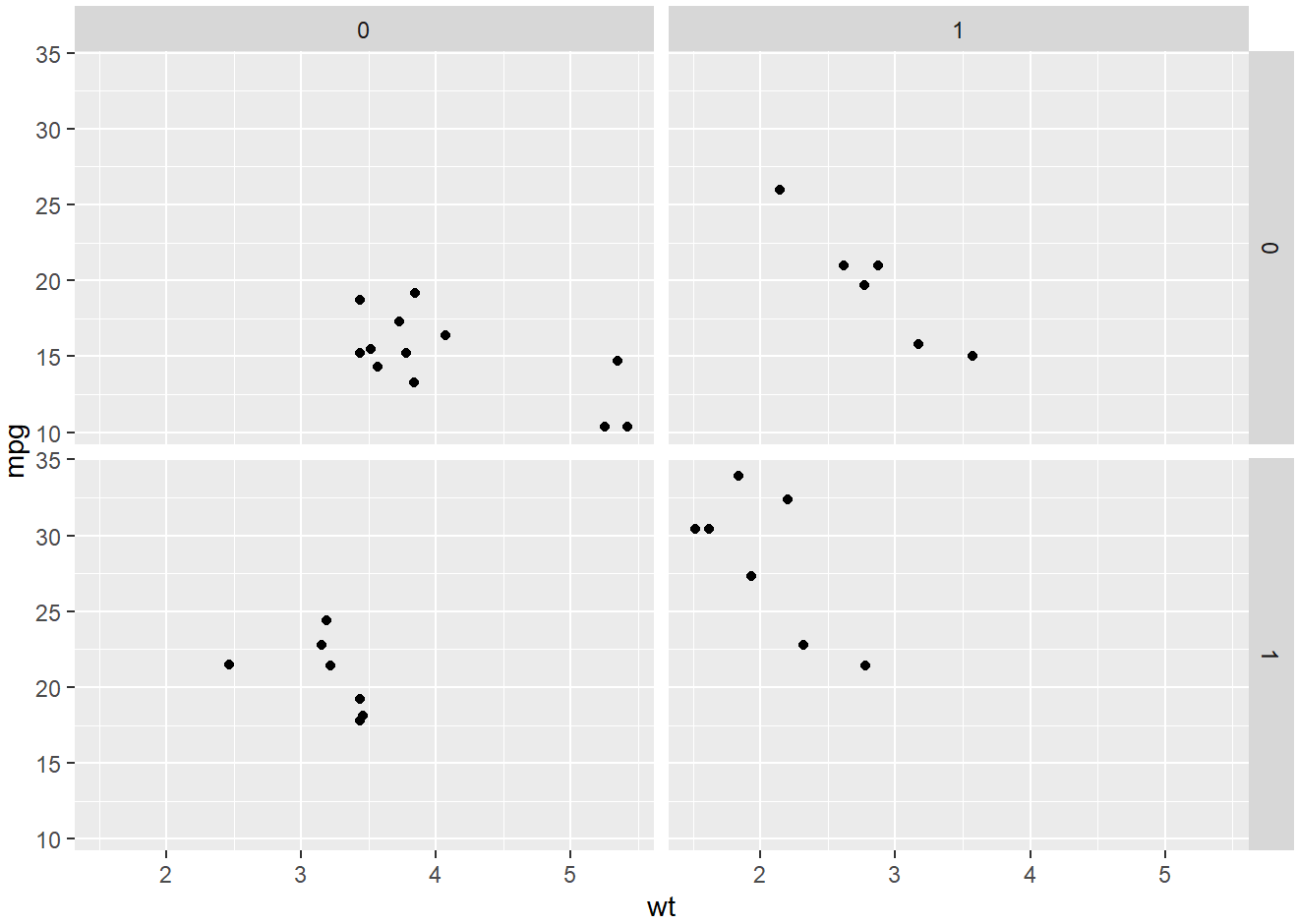
Faceting

Faceting in `ggplot2` is a feature that allows you to split one plot into multiple plots based on a factor or factors contained in the dataset. Each resulting panel (or facet) displays a subset of the data and is a standalone plot with the same axes and scales. This makes it easy to compare different subsets of the data visually.

```
library(ggplot2)
# Faceting by number of cylinders
ggplot(mtcars, aes(x = wt, y = mpg)) +
  geom_point() +
  facet_wrap(~ cyl)
```

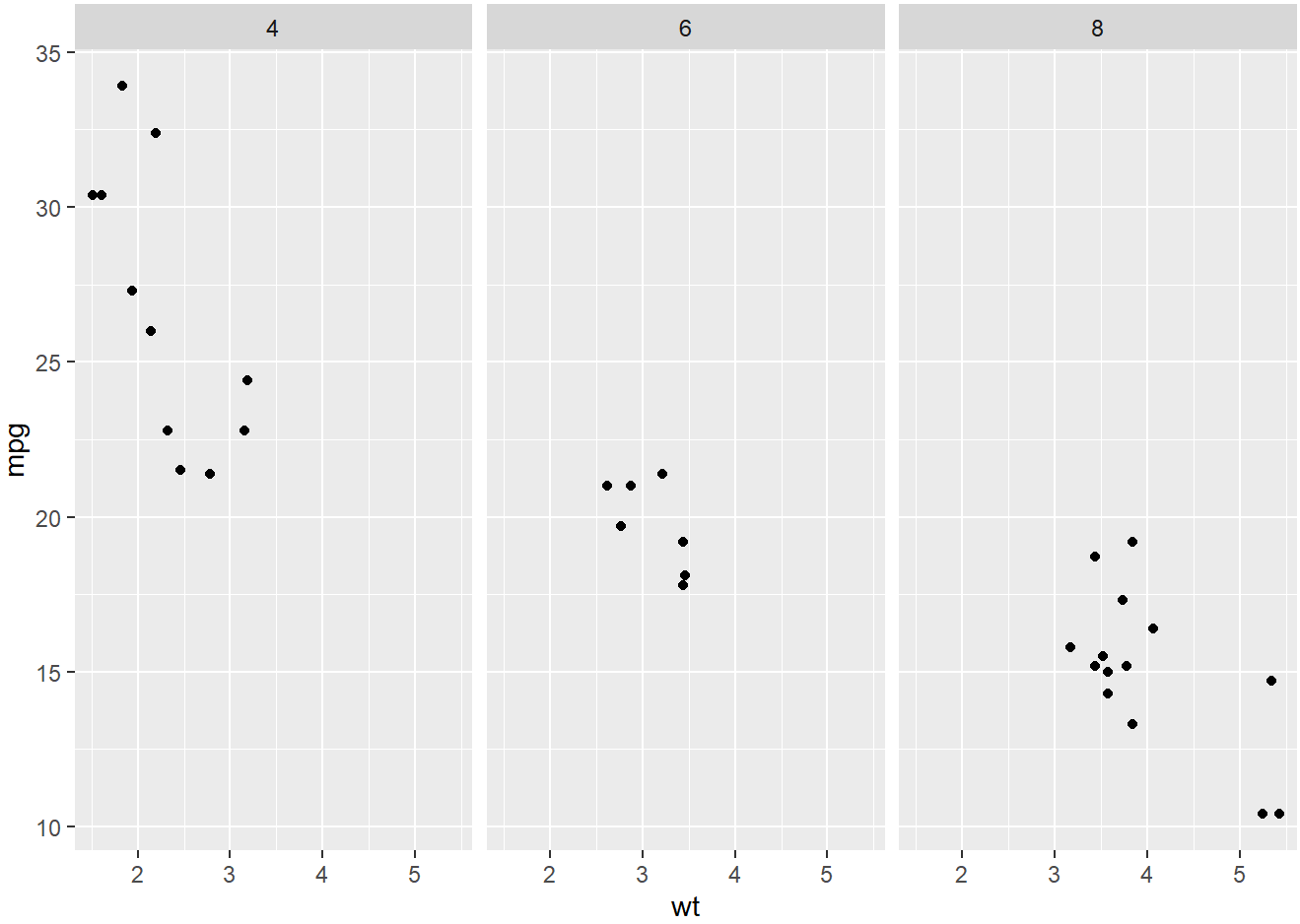



```
# Faceting with grid
ggplot(mtcars, aes(x = wt, y = mpg)) +
  geom_point() +
  facet_grid(vs ~ am)
```



Faceting by Number of Cylinders

```
ggplot(mtcars, aes(x = wt, y = mpg)) +
  geom_point() +
  facet_wrap(~ cyl)
```

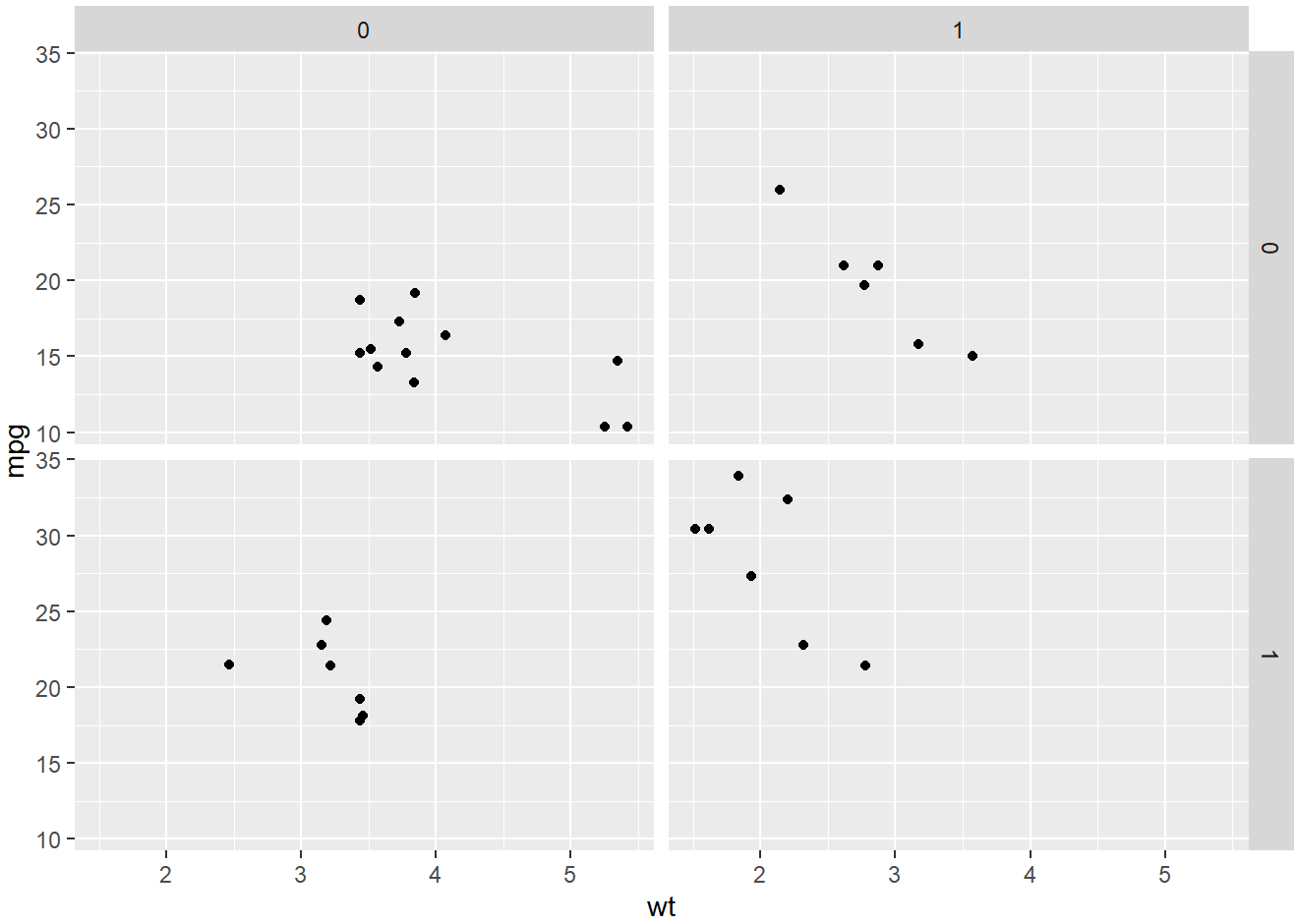


Explanation:

- `facet_wrap(~ cyl)` : This function creates a separate plot (facet) for each unique value of the `cyl` (cylinders) variable. The `~ cyl` notation indicates that faceting should be done based on the `cyl` variable. The resulting plot will have multiple panels, each showing the relationship between `wt` and `mpg` for cars with a specific number of cylinders.

Faceting with Grid

```
ggplot(mtcars, aes(x = wt, y = mpg)) +
  geom_point() +
  facet_grid(vs ~ am)
```



Explanation:

- `facet_grid(vs ~ am)`: This function creates a grid of plots based on the combinations of the `vs` and `am` variables. The `vs` variable is used to create rows, and the `am` variable is used to create columns.
- The resulting plot will have multiple panels arranged in a grid, with each panel showing the relationship between `wt` and `mpg` for a specific combination of `vs` (engine type) and `am` (transmission type).

Visual Representation:

- `facet_wrap(~ cyl)`: If `cyl` has three unique values (e.g., 4, 6, 8), this will produce three panels, each showing the scatter plot of `wt` vs. `mpg` for cars with 4, 6, and 8 cylinders, respectively.

```
|---------------------|
|      cyl = 4        |
|  (scatter plot)     |
|---------------------|
|      cyl = 6        |
|  (scatter plot)     |
|---------------------|
|      cyl = 8        |
|  (scatter plot)     |
|---------------------|
```

- `facet_grid(vs ~ am)`: If `vs` has two unique values (e.g., 0, 1) and `am` has two unique values (e.g., 0, 1), this will produce a 2x2 grid of panels, each showing the scatter plot of `wt` vs. `mpg` for the combinations of `vs` and `am`.

```
|---------------------|---------------------|
|      vs = 0, am = 0 |      vs = 0, am = 1 |
|  (scatter plot)     |  (scatter plot)     |
|---------------------|---------------------|
|      vs = 1, am = 0 |      vs = 1, am = 1 |
|  (scatter plot)     |  (scatter plot)     |
|---------------------|---------------------|
```

In summary, faceting allows you to split your data into multiple sub-plots based on the values of one or more variables, making it easier to compare subsets of your data visually.

Demonstrating Different GEOM Types

Below are code examples using different geometric objects (`geoms`) in `ggplot2`, utilizing commonly available datasets in R like `mtcars`, `mpg`, and `iris`. Each example demonstrates how to use these geoms effectively:

1. `geom_point()` - Scatter plot

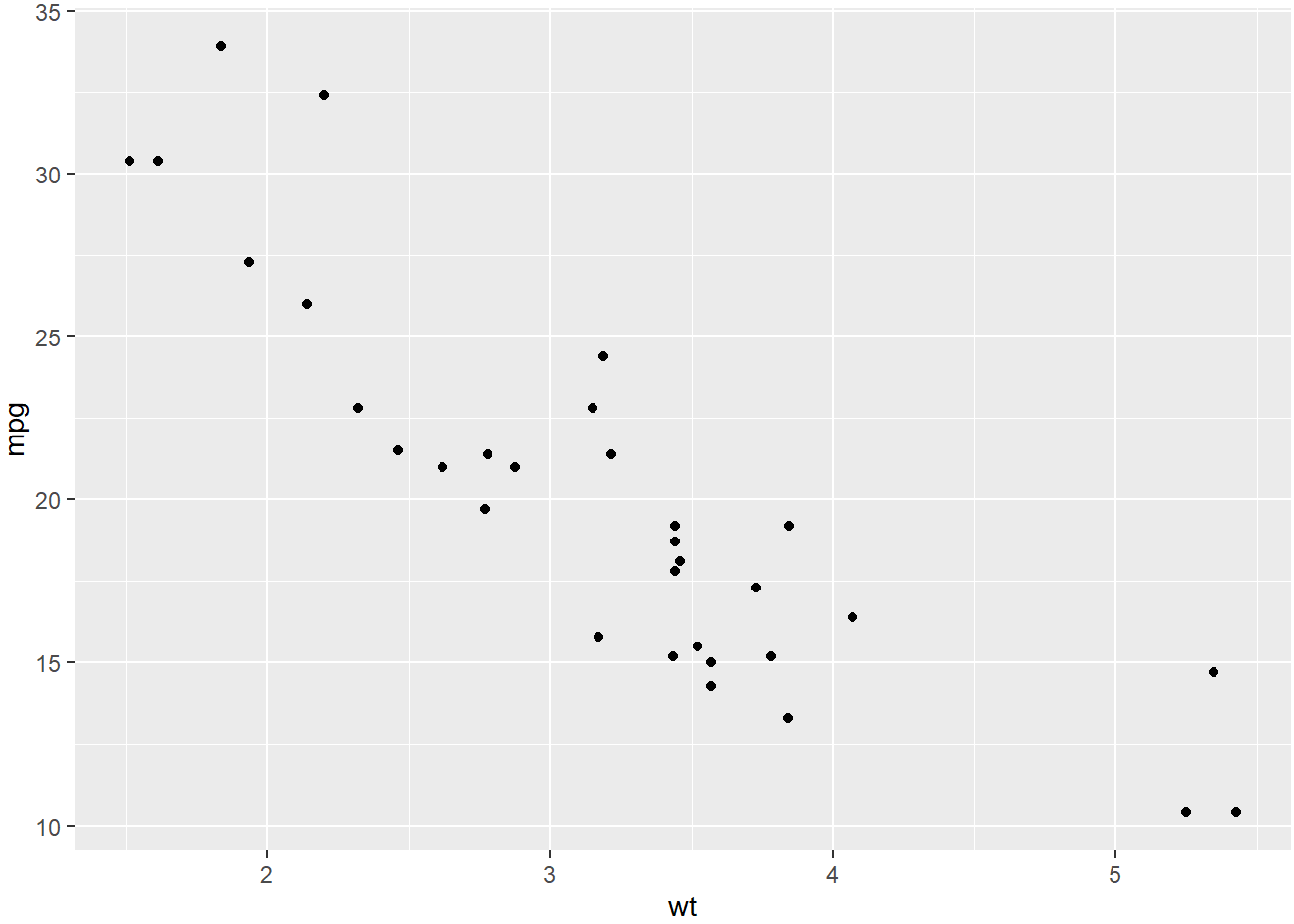
Data Types: Numerical on both axes.

Uses: Primarily used for showing relations between data items. Scatter plots are excellent for visualizing how two continuous variables relate to each other, identifying correlations, trends, clusters, or potential outliers.

Business Examples: Scatter plots are fundamental for examining the relationship or correlation between two continuous variables. They are frequently used in business to analyze trends, such as sales performance against advertising spend, or customer age versus product preference.

Code Example: The point plot shown below uses the `mtcars` dataset to create a scatter plot of car weight (`wt`) against miles per gallon (`mpg`). Each point represents a car, with its position determined by these two variables. The plot can be used to analyze the relationship between a car's weight and its fuel efficiency. Generally, one might expect to see a trend where heavier cars achieve lower fuel efficiency.

```
library(ggplot2)
ggplot(mtcars, aes(x = wt, y = mpg)) +
  geom_point()
```



2. `geom_line()` - Line plot

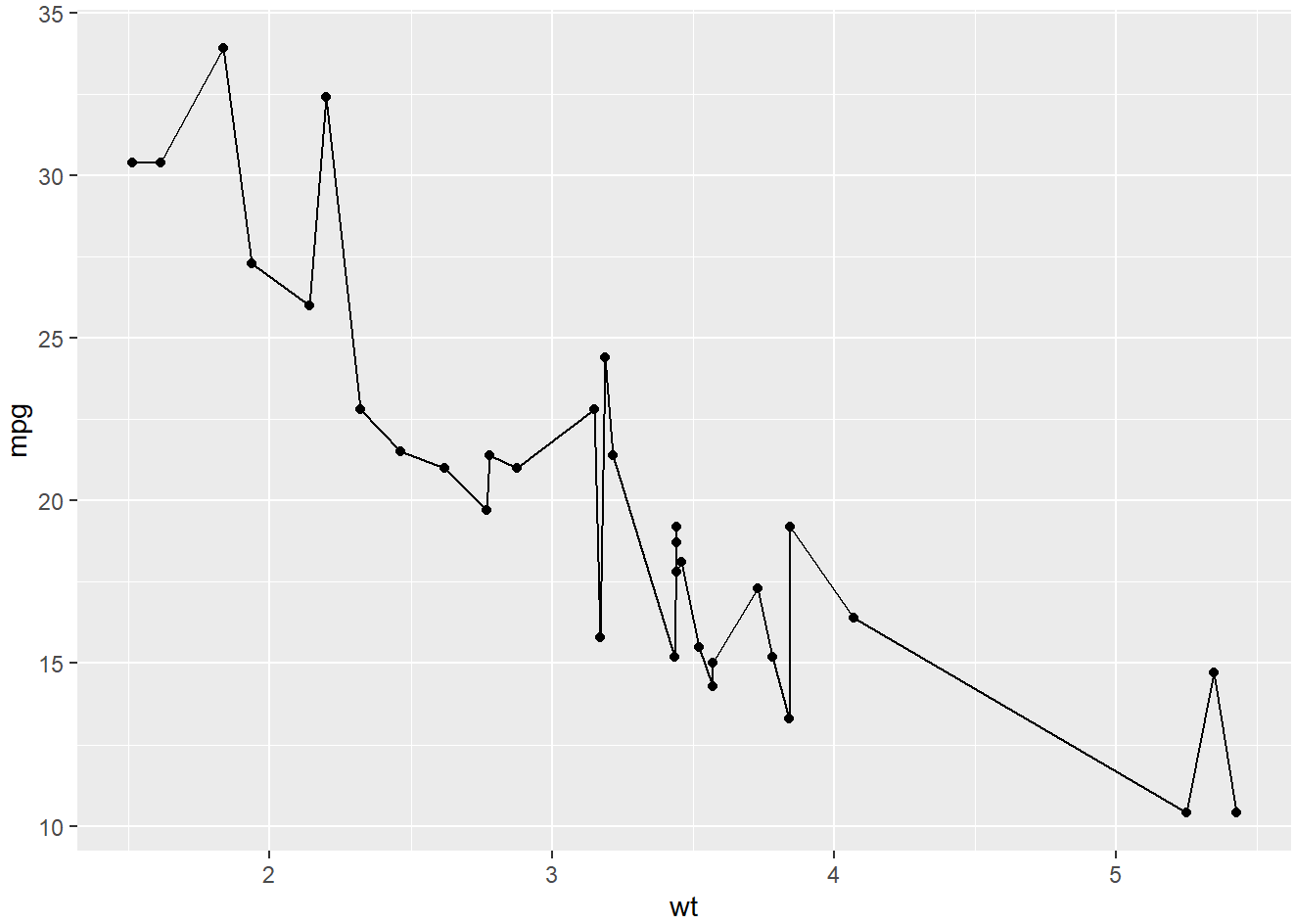
Data Types: Typically, a continuous or ordered categorical variable on the x-axis and a numerical variable on the y-axis.

Uses: Best used for showing trends and relationships over time. Line plots are ideal for tracking changes, making them suitable for time-series data analysis but less so for direct comparisons or distributions

Business Examples: Line plots are ideal for tracking changes over time, such as revenue growth, stock prices, or website traffic trends. This makes them invaluable for time series analysis in financial reporting and market analysis.

Code Example: The line plot presented below is also based on the `mtcars` dataset, displaying a continuous line connecting points plotted by car weight (`wt`) against miles per gallon (`mpg`). The addition of points helps to highlight the actual data positions. This plot is useful for observing the trend of how fuel efficiency changes as car weight increases, suggesting a potential negative correlation.

```
ggplot(mtcars, aes(x = wt, y = mpg)) +
  geom_line() + geom_point()  # Adding points for clarity
```



3. `geom_smooth()` - Smoothed line plot

Data Types: Numerical on both axes.

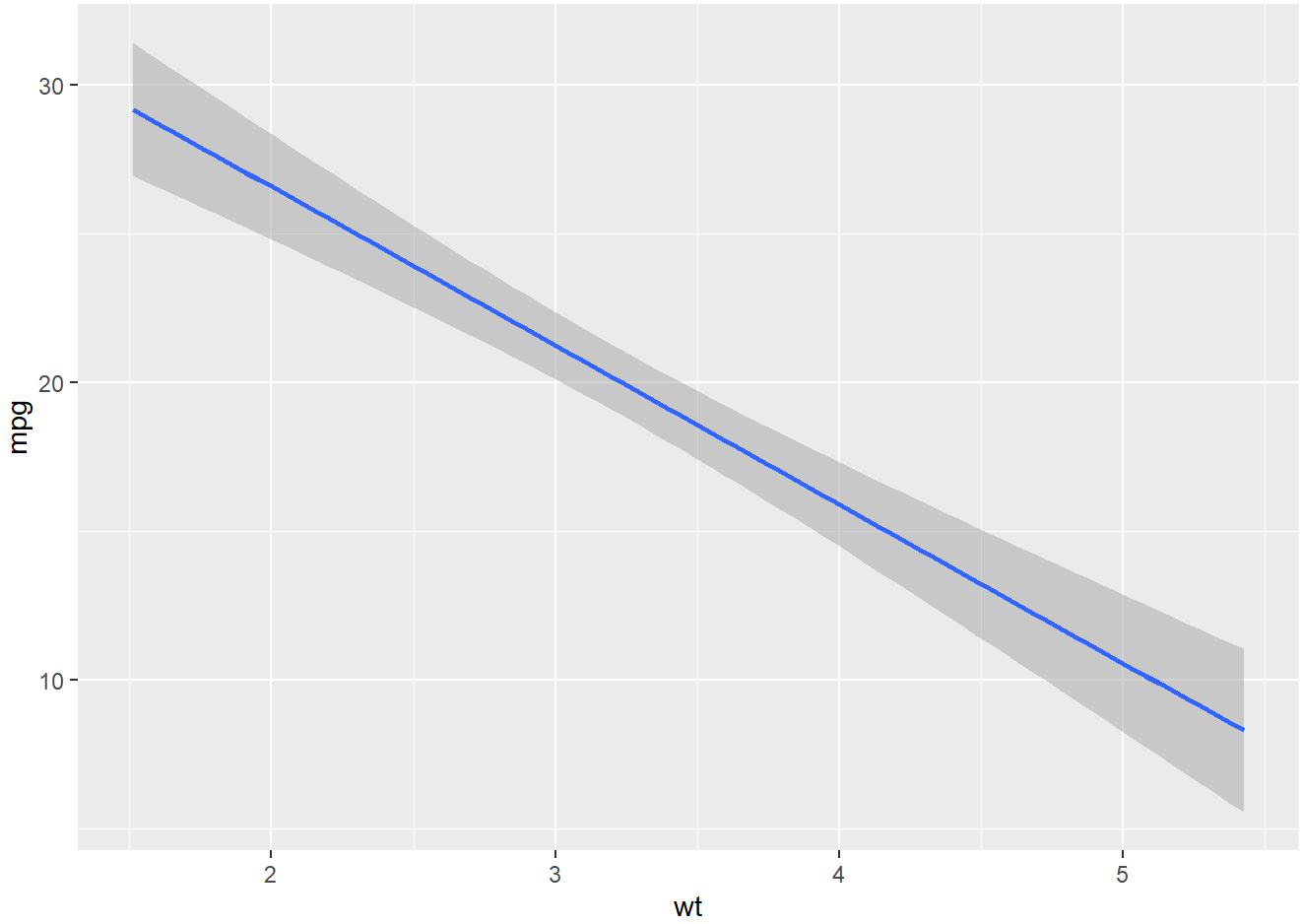
Uses: Focused on showing relationships with a smoothed perspective, often used to highlight underlying trends in data. While it helps in visualizing the general direction and strength of relationships, it's not typically used for showing distributions or detailed comparisons.

Business Examples: Used to visualize trends in data by adding a smoothed line, which can help identify underlying patterns in volatile datasets. Common uses include smoothing out random fluctuations in financial data or sales data to better understand long-term trends.

Code Example: Here, a smoothed line plot is created using a linear model (`lm`) to approximate the relationship between `wt` (weight of the cars) and `mpg` (miles per gallon). This plot helps in visualizing a clear trend or pattern, smoothing out any outliers or anomalies, which can be particularly useful for presentations or reports where a simplified visual explanation is required.

```
ggplot(mtcars, aes(x = wt, y = mpg)) +
  geom_smooth(method = "lm")  # Linear model
```

```
`geom_smooth()` using formula = 'y ~ x'
```



4. `geom_bar()` - Bar chart

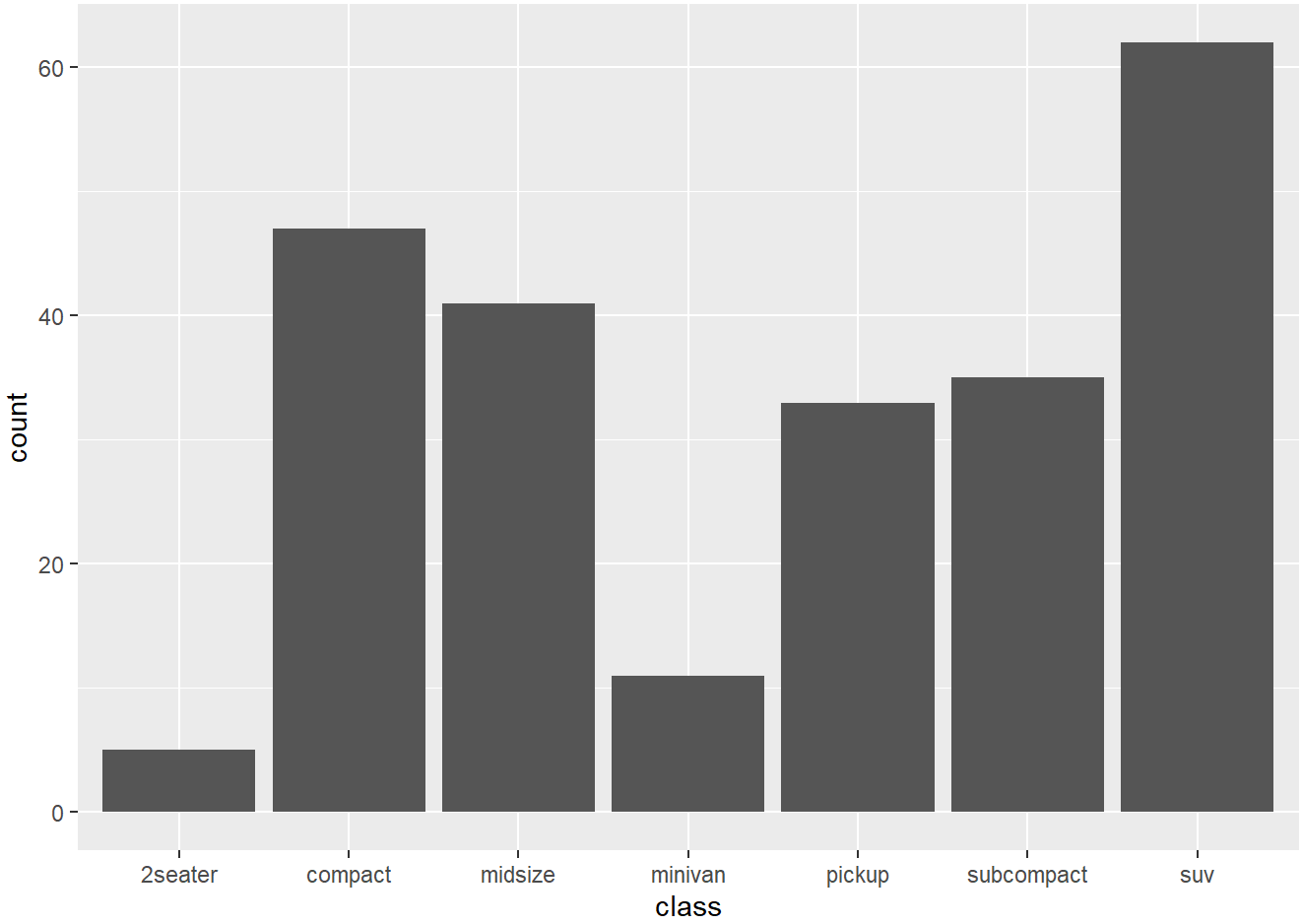
Data Types: Categorical on the x-axis and numerical on the y-axis (counts or computed summaries).

Uses: Excellent for making comparisons and showing components. Bar charts are used to compare the size of different categories using the height of bars, making it clear how individual categories stack up against each other.

Business Examples: Bar charts are one of the most common tools for business reporting, useful for comparing quantities across different categories, such as sales by product category, customer counts by region, or performance metrics across departments.

Code Example: This bar chart presented below uses the `mpg` dataset to display the count of cars in each vehicle class. Each bar represents a different class, and its height indicates the number of cars in that class. This type of visualization is excellent for comparing categorical data, showing which vehicle classes are more or less common.

```
ggplot(mpg, aes(x = class)) +
  geom_bar()
```



5. `geom_histogram()` - Histogram

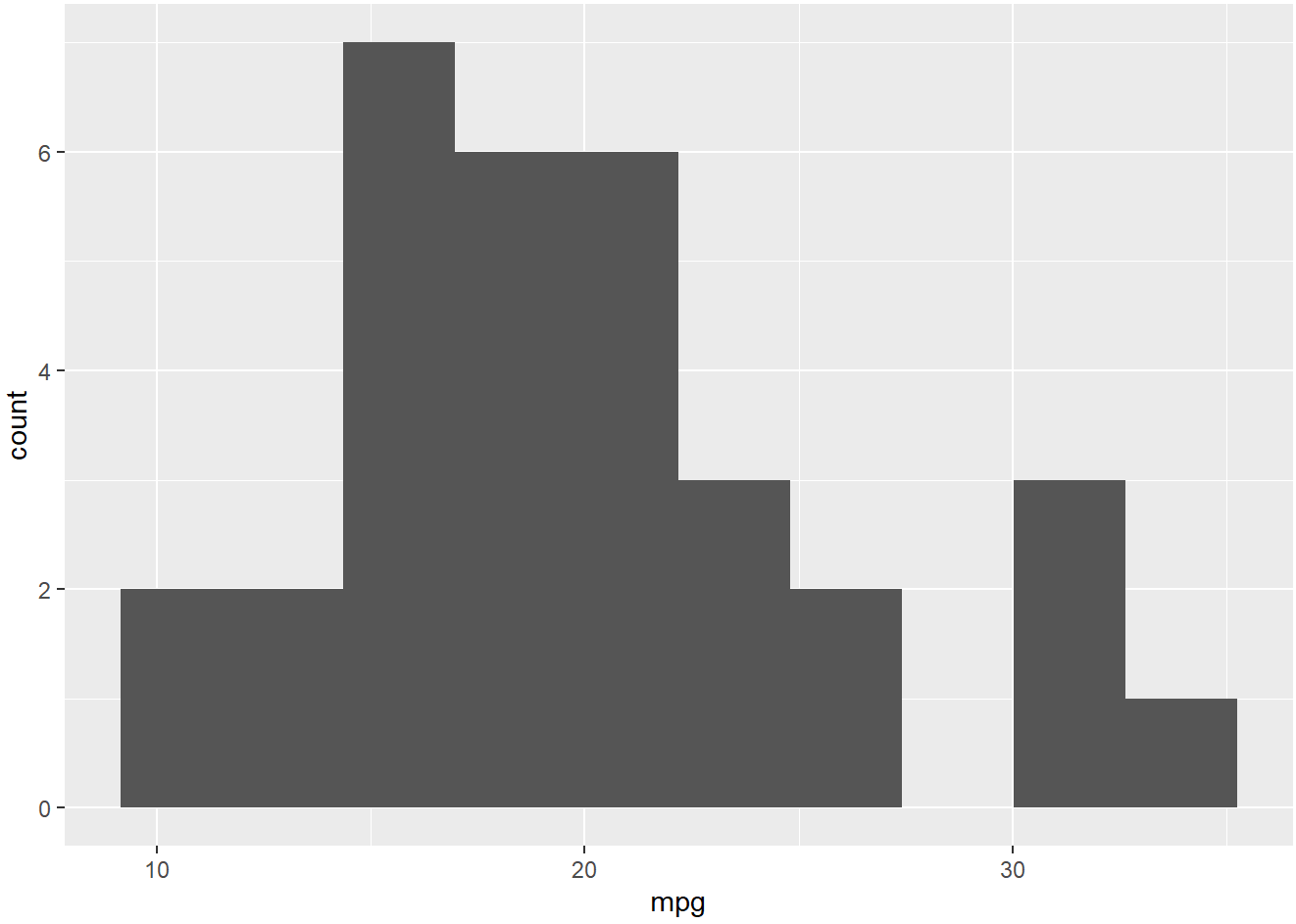
Data Types: Numerical data divided into bins on the x-axis.

Uses: Specifically designed for showing distributions of data. Histograms provide a visual interpretation of numerical data by indicating the number of data points that fall within a range of values, known as bins.

Business Examples: Histograms are used to examine the distribution of a dataset, helping to understand the central tendency, variability, and shape of data distribution. In business, this could be used for analyzing the distribution of transaction sizes, customer age groups, or service response times.

Code Example: The histogram example below plots the distribution of miles per gallon (`mpg`) across the cars in the `mtcars` dataset. By dividing the `mpg` values into bins (in this case, 10 bins), it shows how many cars fall into each range of fuel efficiency. This is useful for understanding the overall distribution of fuel efficiency across the dataset.

```
ggplot(mtcars, aes(x = mpg)) +
  geom_histogram(bins = 10)  # Specify number of bins
```



6. `geom_boxplot()` - Boxplot

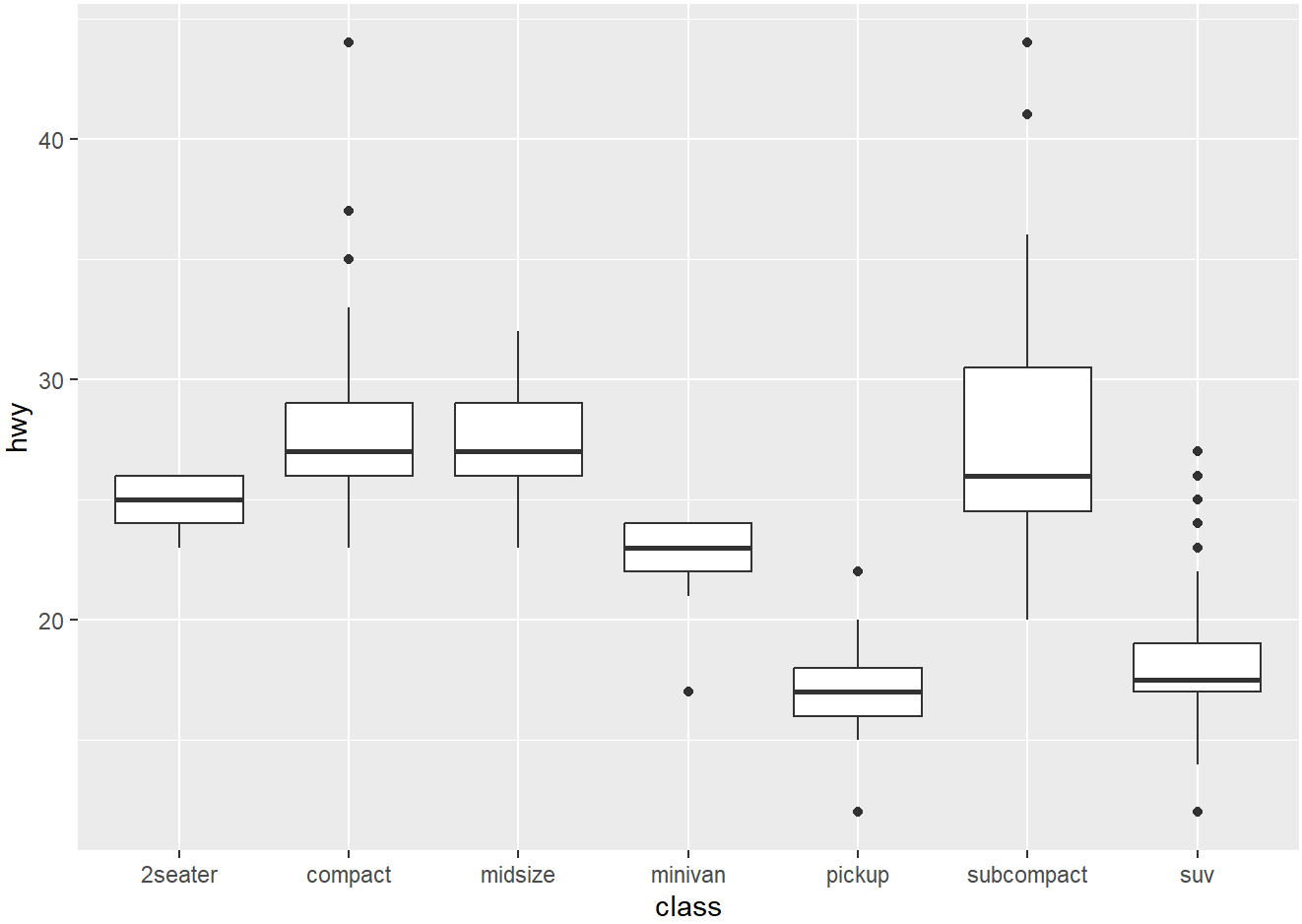
Data Types: Categorical on the x-axis and numerical on the y-axis.

Uses: Highly effective for both showing distributions and making comparisons. Boxplots summarize the distribution of data through quartiles, while also highlighting outliers. They allow comparisons across different categories or groups.

Business Examples: Boxplots provide a concise summary of the distribution of numerical data and are particularly good at highlighting outliers. Businesses use them for comparing distributions across groups, such as comparing employee satisfaction scores across branches or sales distributions across regions.

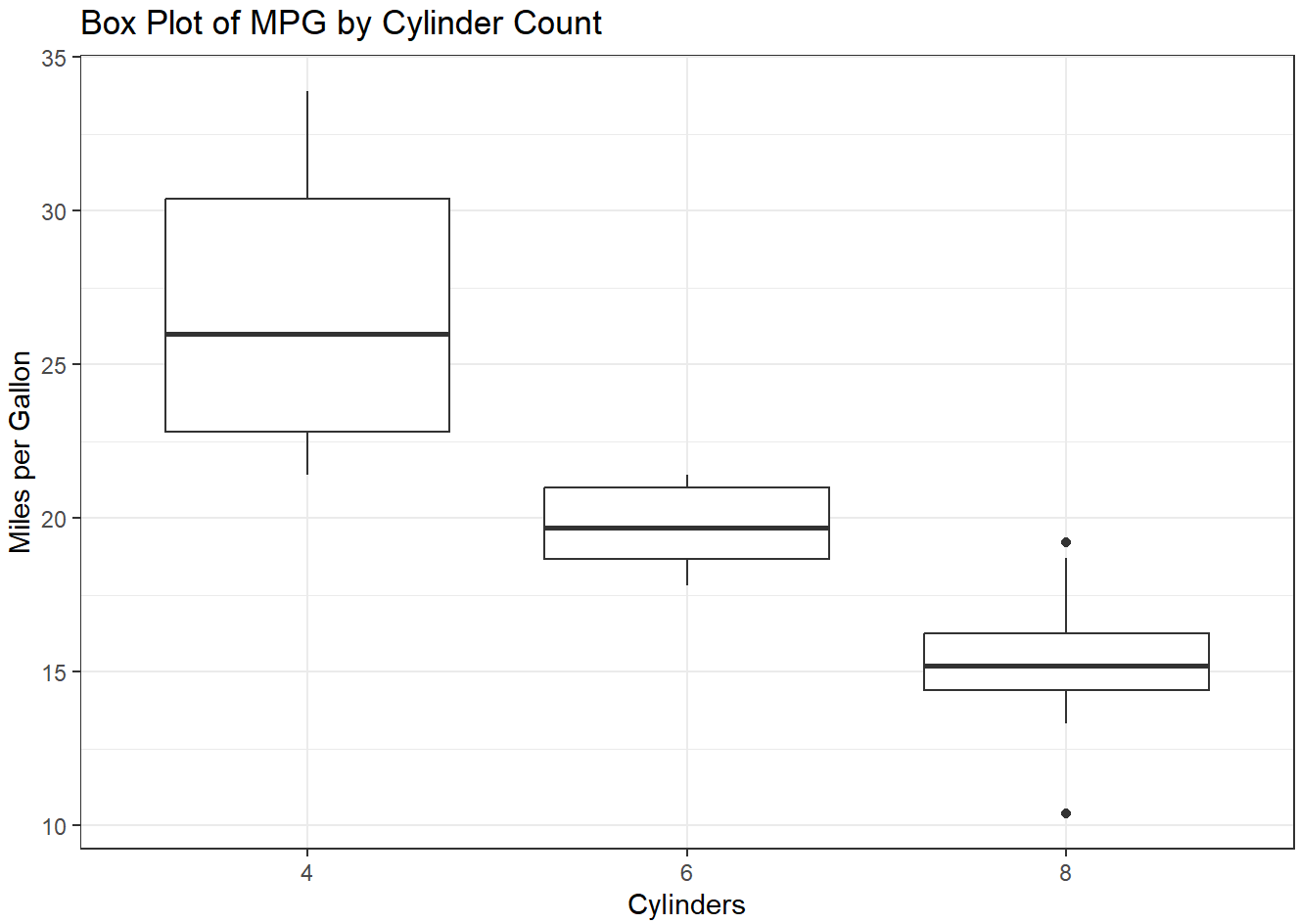
Code Example: This boxplot example provides a visual summary of highway miles per gallon (`hwy`) across different vehicle classes in the `mpg` dataset. Boxplots show the median, quartiles, and outliers, giving a clear statistical summary of the distribution within each category. This plot is particularly valuable for identifying differences and spread in highway efficiency across vehicle types.

```
ggplot(mpg, aes(x = class, y = hwy)) +
  geom_boxplot()
```

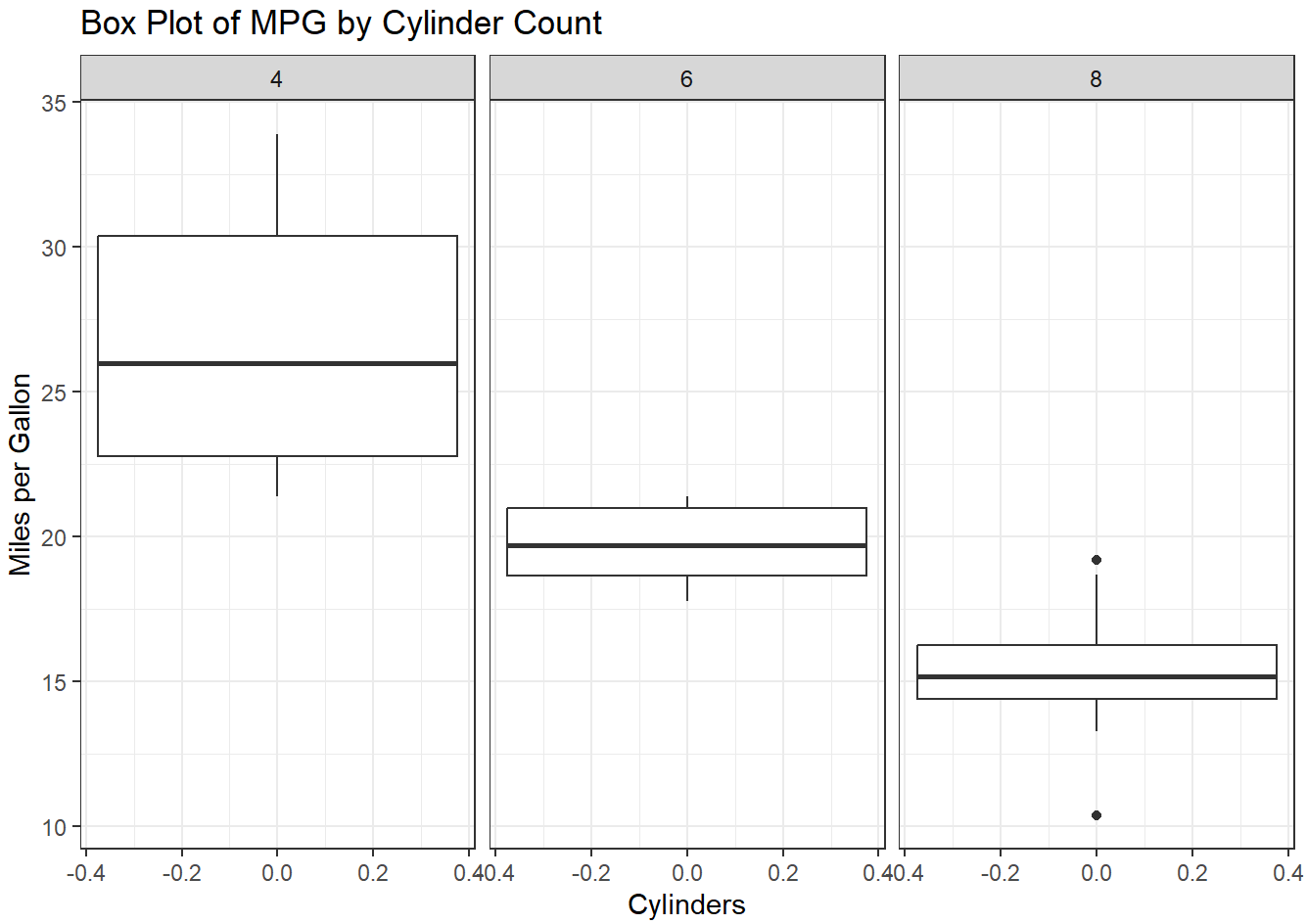


Boxplots are usually used for making comparisons between different categories.

```
library(ggplot2)
ggplot(data = mtcars, aes(x = factor(cyl), y = mpg)) +
  geom_boxplot() +
  labs(title = "Box Plot of MPG by Cylinder Count", x = "Cylinders", y = "Miles per Gallon") +
  theme_bw()
```




```
ggplot(data = mtcars, aes( y = mpg)) +
  geom_boxplot() +
  facet_wrap(~cyl) +
  labs(title = "Box Plot of MPG by Cylinder Count", x = "Cylinders", y = "Miles per Gallon") +
  theme_bw()
```



7. `geom_area()` - Area plot

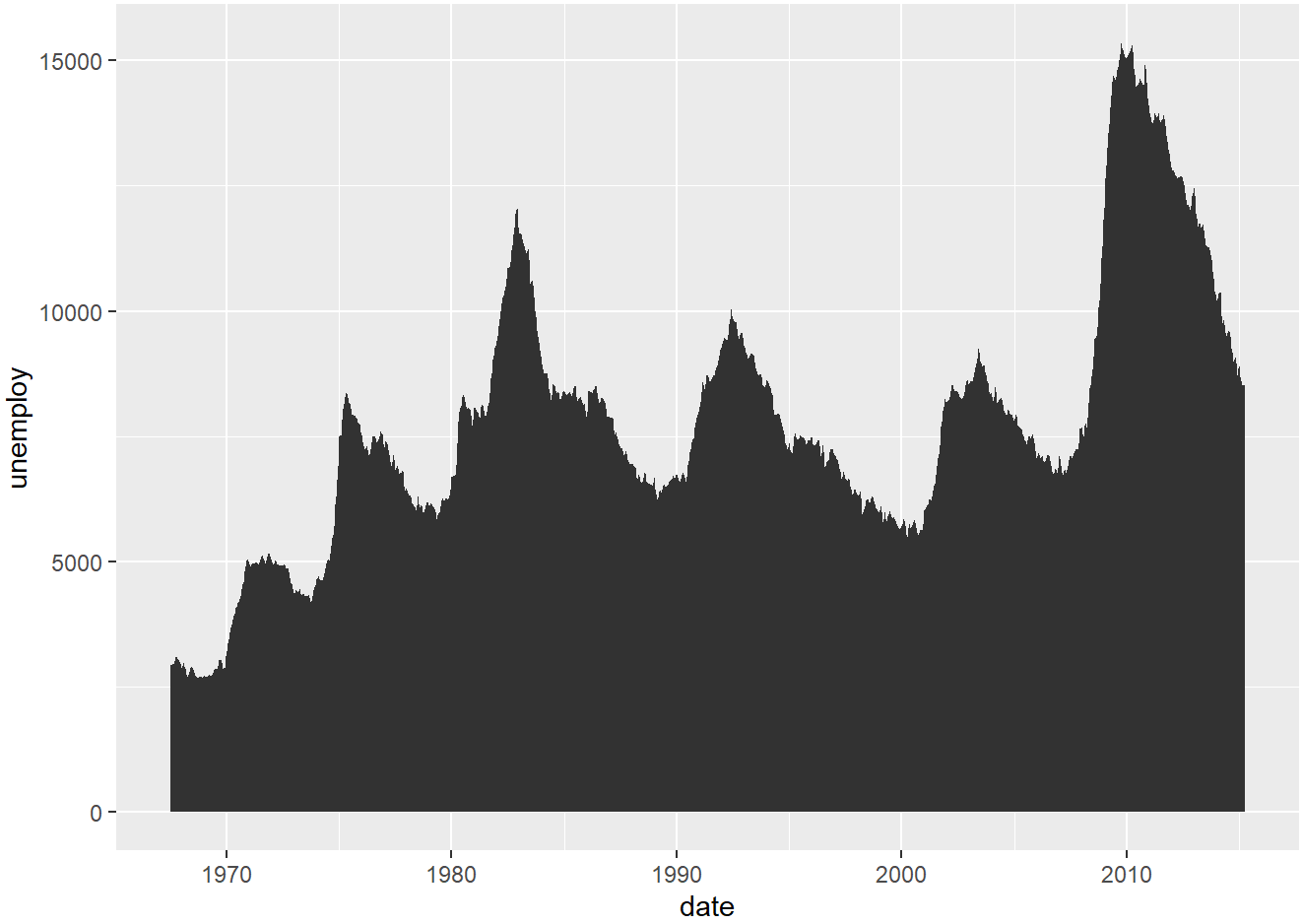
Data Types: Continuous or ordered categorical on the x-axis, numerical on the y-axis.

Uses: Mainly used for showing components of data, especially how they accumulate over time. Area plots are great for visualizing stacked or cumulative data that contribute to a whole, showing how each part contributes to total values.

Business Examples: Area plots are useful for visualizing cumulative totals over time, providing insights into growth trends, and the contribution of different components, such as cumulative sales over time segmented by product type.

Code Example: The area plot show below visualizes unemployment data (`unemploy`) from the `economics` dataset over time (`date`). The area under the line is filled, emphasizing the volume of unemployment over time. This plot is effective for showing trends in data, such as increases or decreases in unemployment rates, and can be particularly impactful for economic reporting.

```
ggplot(economics, aes(x = date, y = unemploy)) +
  geom_area()
```



8. `geom_density()` - Density plot

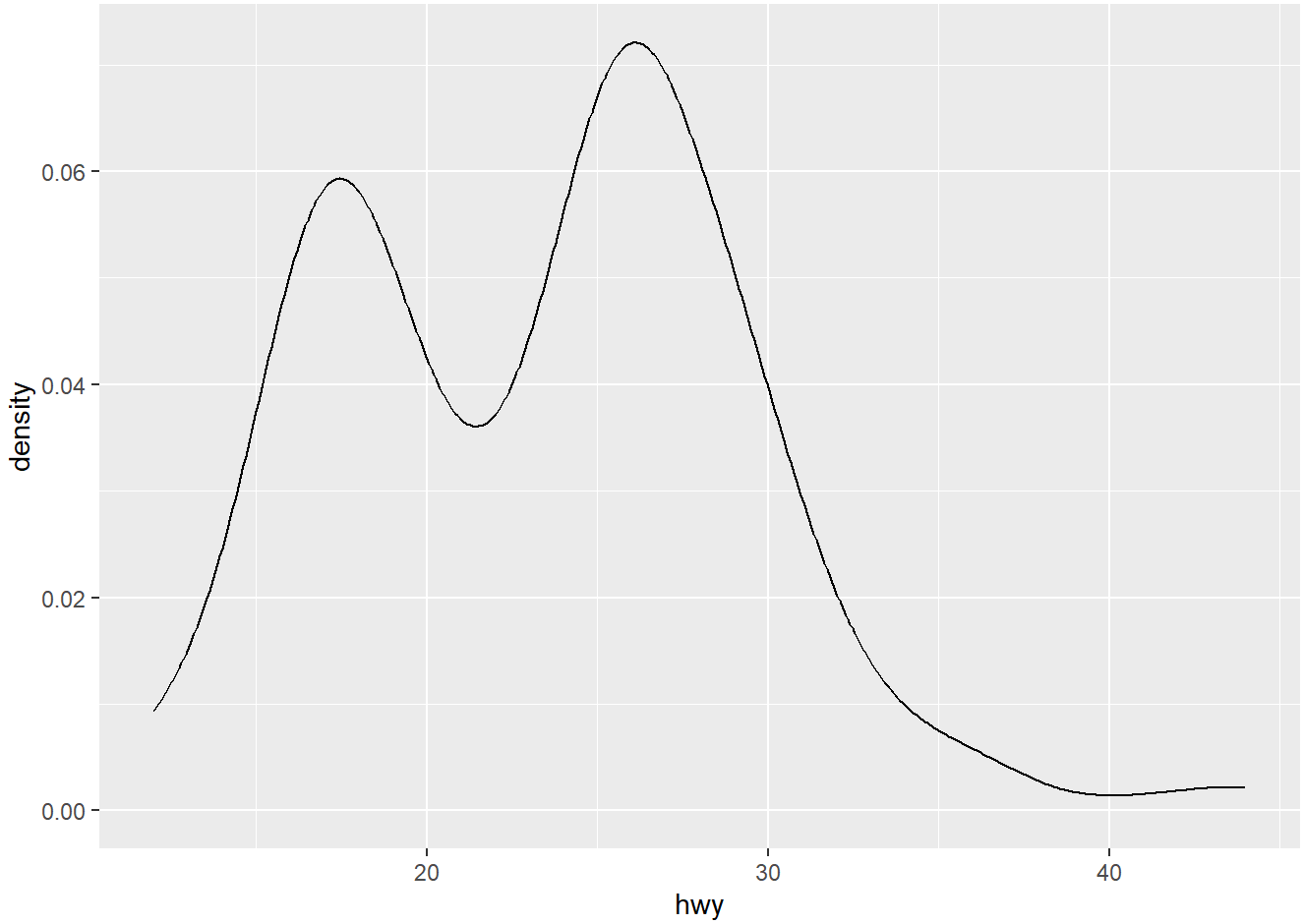
Data Types: Numerical data on the x-axis.

Uses: Ideal for showing distributions of data. Density plots smooth out the frequency of data for a continuous variable, providing a continuous curve that represents the distribution.

Business Examples: Density plots are useful for visualizing the distribution of data where the smoothness of the curve can provide insights into the data's characteristics, such as market analysis for product pricing or understanding income distribution within consumer segments.

Code Example: The density plot is used here to show the distribution of highway miles per gallon (`hwy`) in the `mpg` dataset. Unlike a histogram, the density plot provides a smooth curve that is useful for identifying where the data concentrates, indicating the most common fuel efficiency values observed on the highway.

```
ggplot(mpg, aes(x = hwy)) +
  geom_density()
```



9. `geom_violin()` - Violin plot

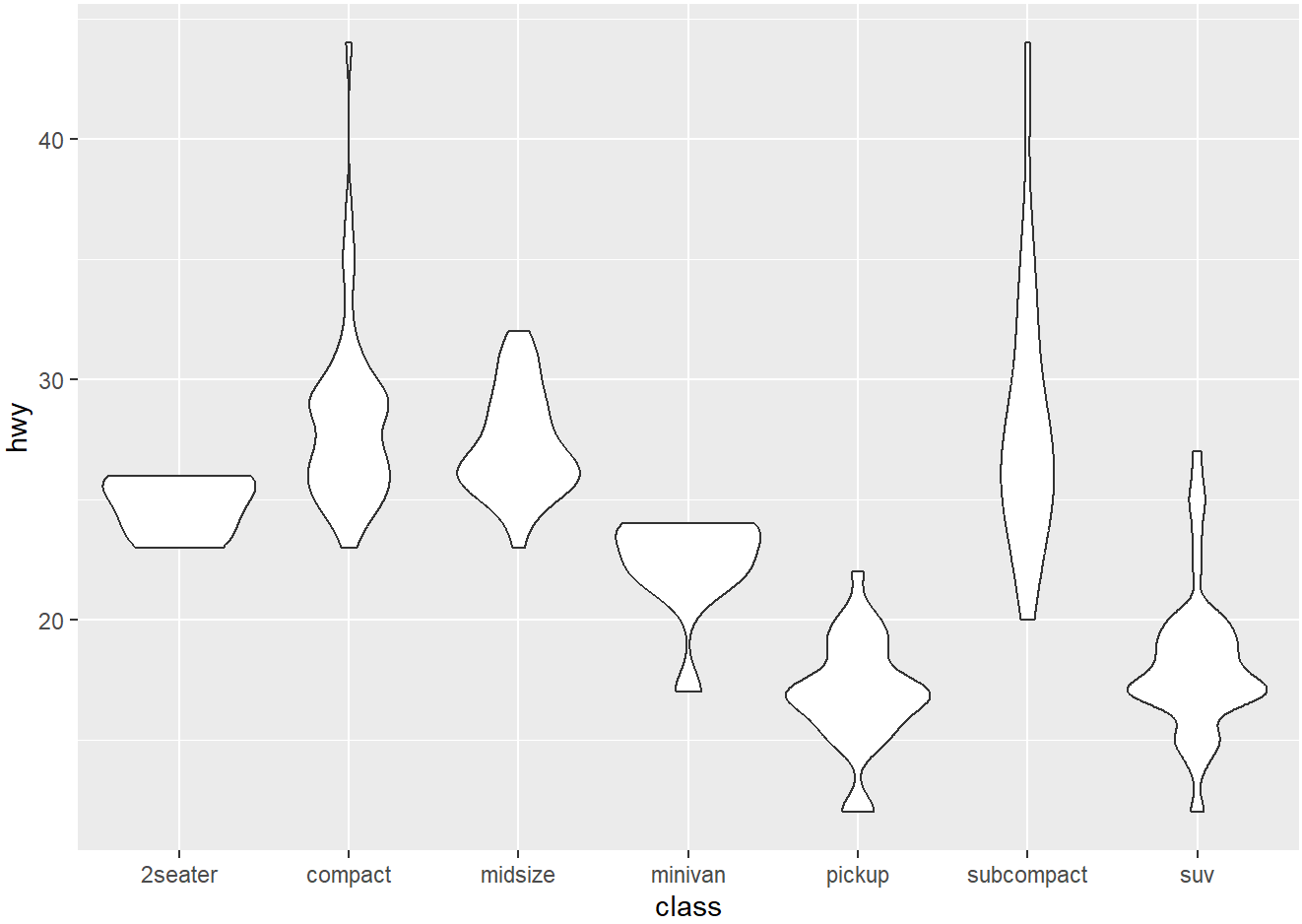
Data Types: Categorical on the x-axis and numerical on the y-axis.

Uses: Suitable for showing distributions and making comparisons. Violin plots are effective at showing the distribution of data within categories and comparing these across different categories.

Business Examples: Violin plots provide rich density estimates visualized similarly to boxplots, and are particularly useful for comparing distributions between groups. They are often used in comparing customer satisfaction scores or product ratings across different categories.

Code Example: This violin plot compares the distribution of highway miles per gallon (`hwy`) across different vehicle classes (`class`). Violin plots combine boxplot and density plot features, showing both the summary statistics and the density estimates. This helps in comparing how fuel efficiency varies among classes, highlighting differences in distribution shapes and widths.

```
ggplot(mpg, aes(x = class, y = hwy)) +
  geom_violin()
```



10. `geom_col()` - Column chart

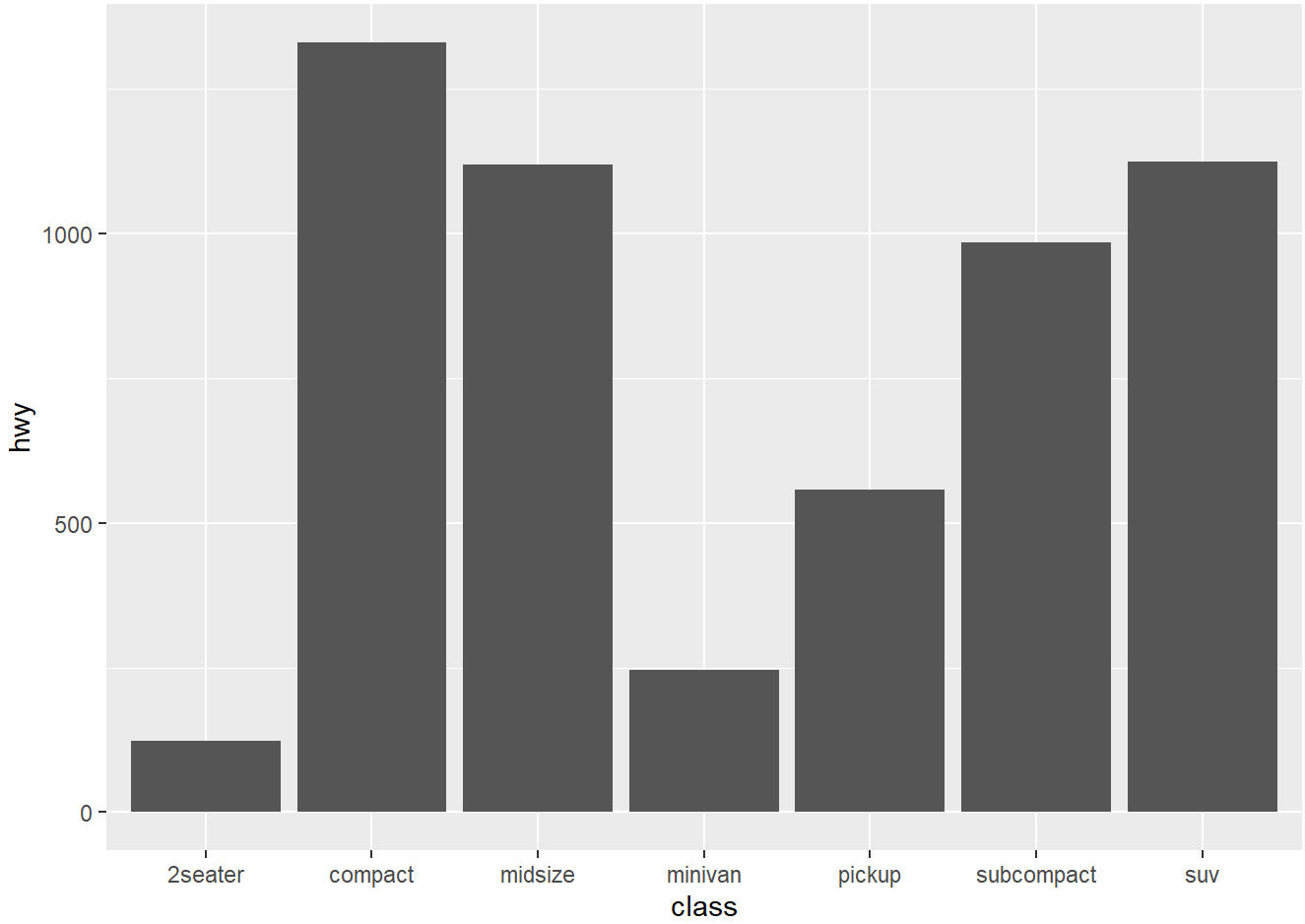
Data Types: Categorical on the x-axis, numerical on the y-axis.

Uses: Best used for making comparisons. Similar to bar charts, column charts display categorical data with the length of each column representing the value, allowing for easy comparison across different categories.

Business Examples: Column charts are used almost identically to bar charts but are particularly effective for emphasizing variation among items. They are commonly used for displaying data such as monthly revenue, sales by category, or inventory levels.

Code Example: The column chart here represents average highway miles per gallon (`hwy`) for different vehicle classes (`class`) in the `mpg` dataset. Each column's height is proportional to the average `hwy` value, allowing for direct comparison across categories. This plot is useful for straightforward visual comparisons and is often used in business contexts to compare averages across different groups or categories.

```
ggplot(mpg, aes(x = class, y = hwy)) +
  geom_col()
```



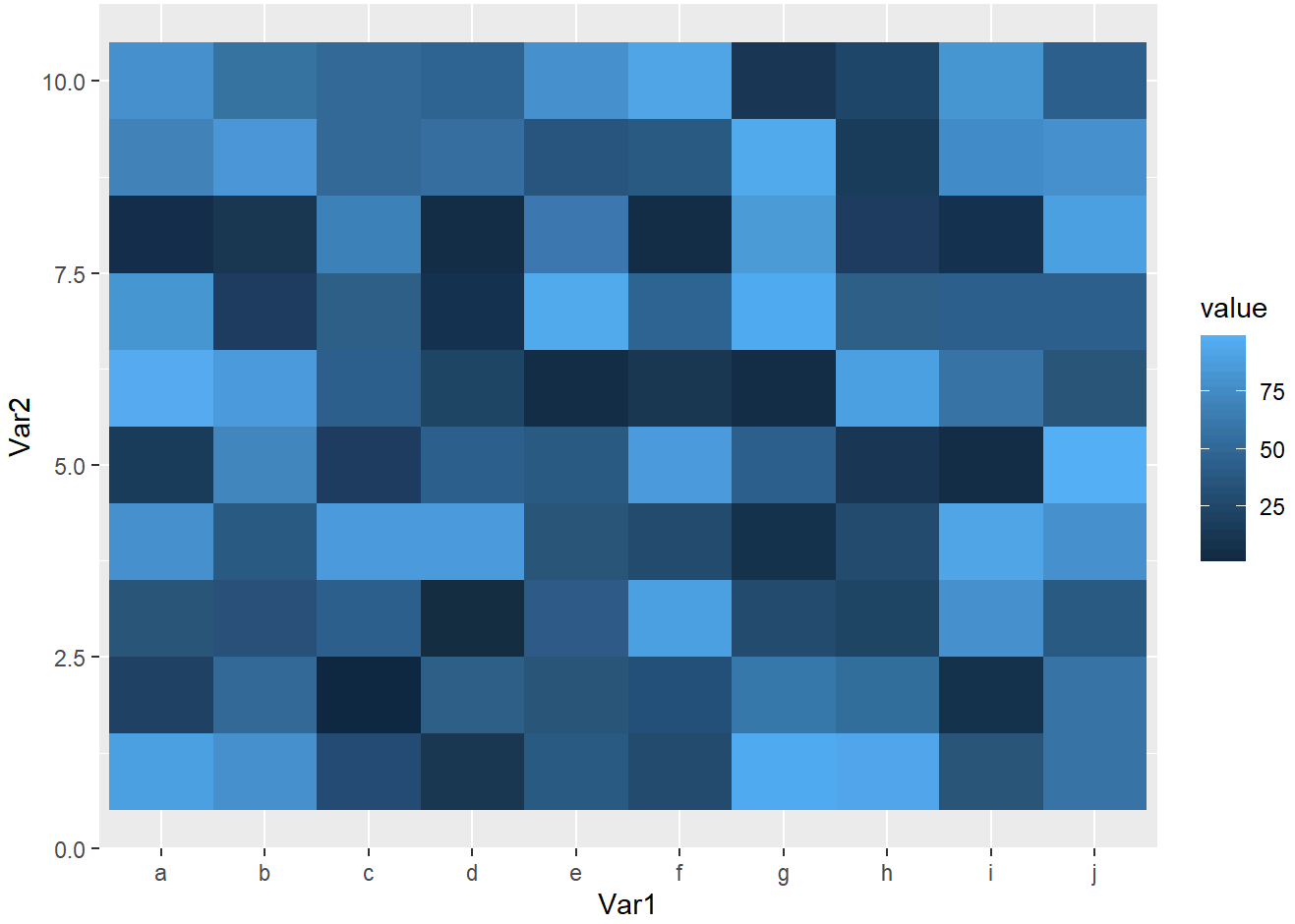
11. `geom_tile()` - Heatmap

Data Types: Categorical or discrete numerical variables on both axes, with a third variable represented by color.

Business Examples: Heatmaps are great for cross-tabulating variables and visualizing the intensity of data, like website traffic by day and hour, sales performance by region and product, or correlation matrices in finance.

Code Example: This heatmap uses an example data frame created with 10 rows and 10 columns labeled by letters and numbers, respectively. The `value` for each tile varies randomly between 0 and 100. In this visualization, each tile's color intensity represents its associated value, providing a quick visual summary of how values are distributed across two dimensions. Heatmaps like this are commonly used in business analytics to display data density across different categories or times, making it easy to spot patterns, concentrations, and outliers.

```
# Create some example data
data <- expand.grid(Var1 = letters[1:10], Var2 = 1:10)
data$value <- runif(100, min = 0, max = 100)
ggplot(data, aes(x = Var1, y = Var2, fill = value)) +
  geom_tile()
```



12. `geom_text()` and `geom_label()` - Adding text/labels

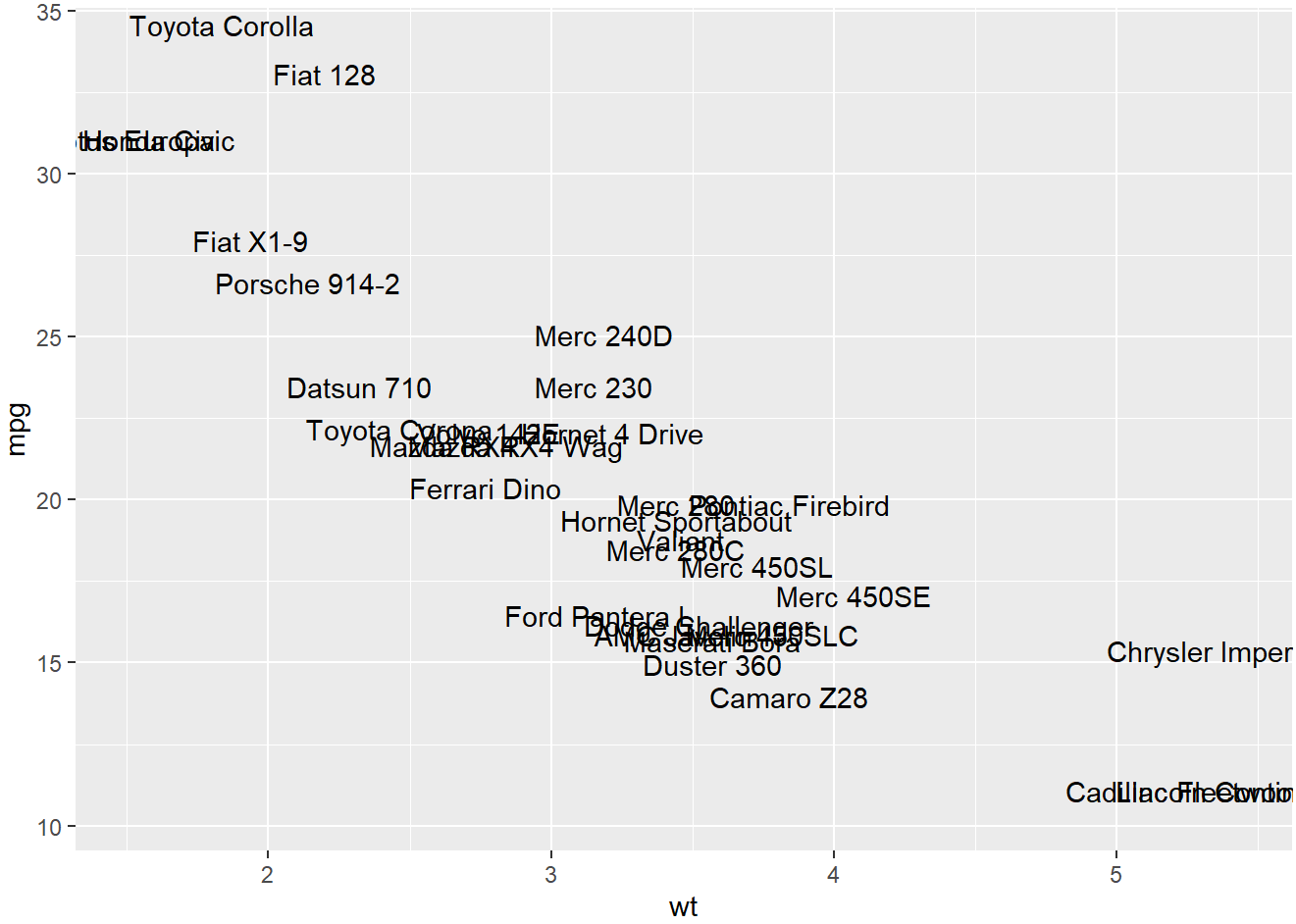
Data Types: Numerical or categorical data on both axes.

Uses: These are auxiliary geoms used to enhance clarity and provide additional information in plots, rather than for showing distributions, comparisons, or components on their own.

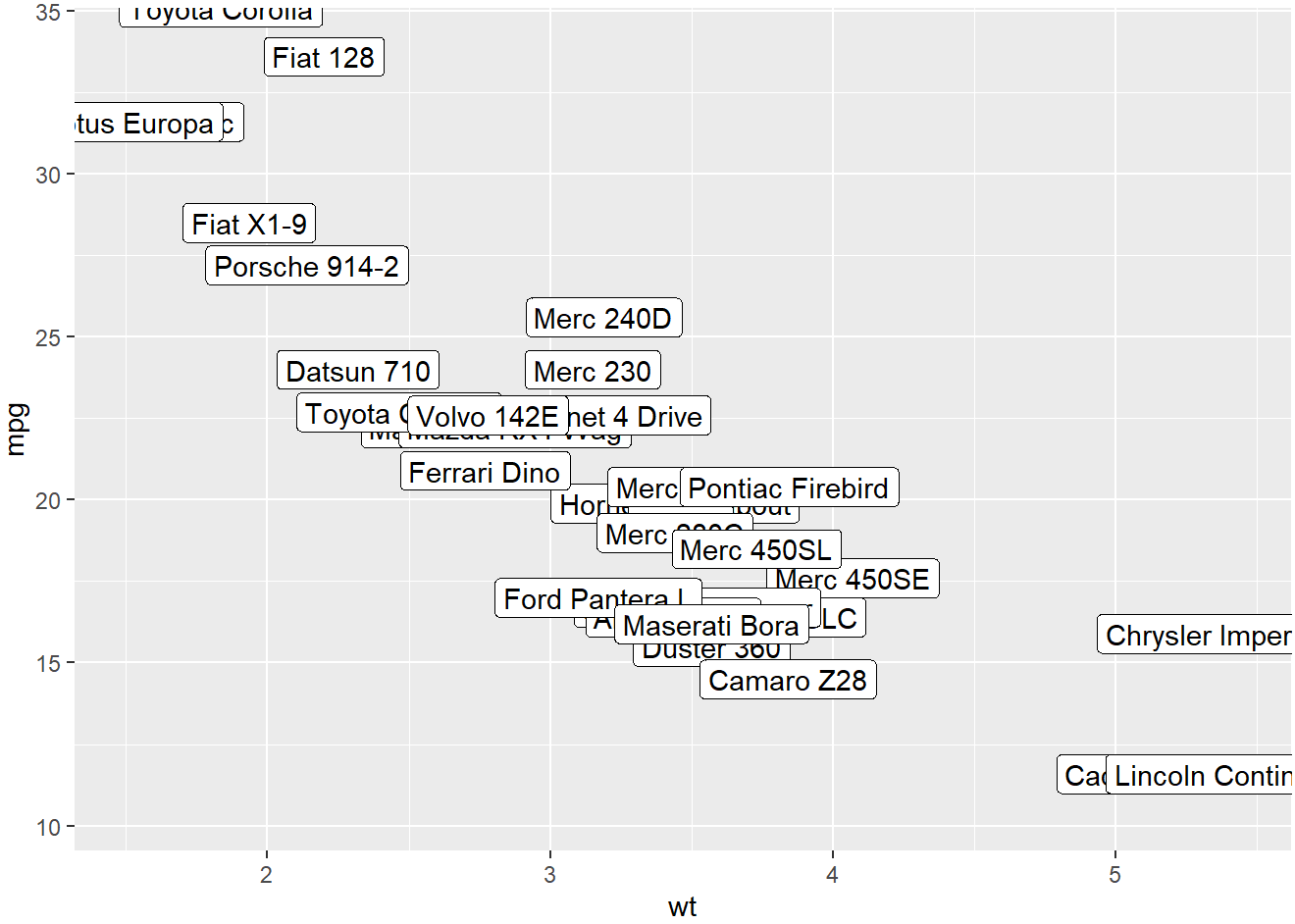
Business Examples: Adding text or labels to plots enhances clarity, particularly in dashboards and presentations where specific data points need to be highlighted or annotated, such as labeling outliers, significant points, or totals directly on charts.

Code Example: Both of these plots use the `mtcars` dataset, mapping car weight to miles per gallon, and label each point with the car model. `geom_text()` adds labels directly to the plot without any background, which can help in identifying specific points clearly. `geom_label()`, however, adds a background to each label, enhancing readability especially in crowded plots. These methods are useful in presentations or detailed reports where clarity in data point identification is crucial.

```
# Use geom_text for adding text
ggplot(mtcars, aes(x = wt, y = mpg, label = rownames(mtcars))) +
  geom_text(vjust = -0.5)
```




```
# Use geom_label for labels with background
ggplot(mtcars, aes(x = wt, y = mpg, label = rownames(mtcars))) +
  geom_label(vjust = -0.5)
```



13. `geom_ribbon()` - Ribbon plot

Data Types: Continuous or ordered categorical on the x-axis, with a range for the y-axis.

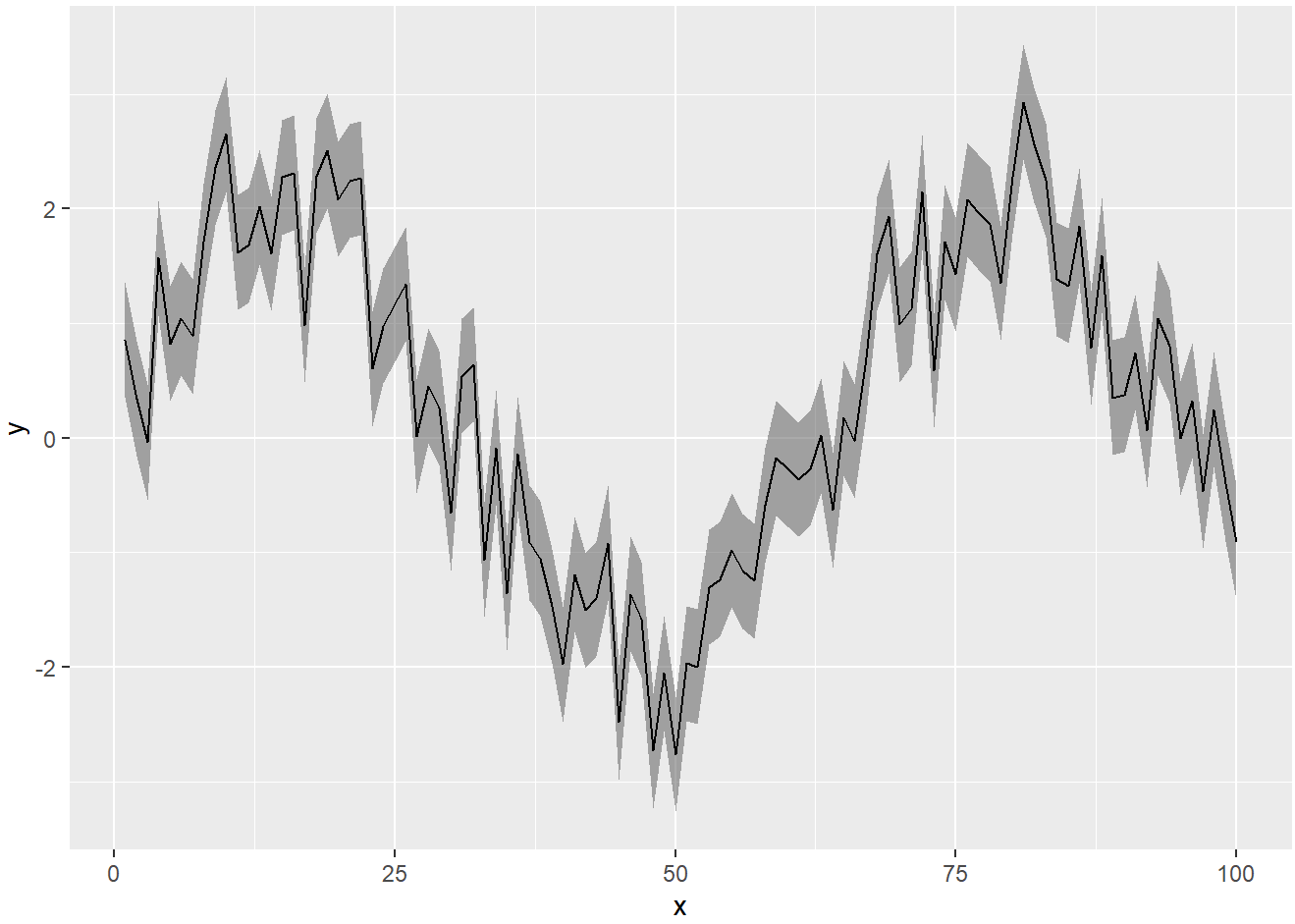
Uses: Used for showing relationships and components, particularly useful in time series to show confidence intervals or prediction ranges around a central measure, thus providing a sense of variability or uncertainty.

Business Examples: Ribbons are often used to indicate uncertainty or variability around a central measure, ideal for financial forecasts, economic data predictions, or displaying confidence intervals in scientific measurements.

Example: The ribbon plot shown below illustrates variability around a central line, created using simulated data. It shows a sinusoidal trend (the central line), with ribbons representing a confidence interval or variability range around this trend. This type of visualization is particularly useful for representing uncertainty in predictions, such as economic forecasts, stock price projections, or any other metric where expressing the confidence of predictions is valuable.

```
# Simulate some data
df <- data.frame(x = 1:100)
df$y <- sin(df$x / 10) * 2 + rnorm(100, sd = 0.5)
df$ymax <- df$y + 0.5
df$ymin <- df$y - 0.5
```

```
ggplot(df, aes(x = x, ymin = ymin, ymax = ymax, y = y)) +
  geom_ribbon(alpha = 0.4) +
  geom_line()
```



14. `geom_jitter()` - Jitter plot

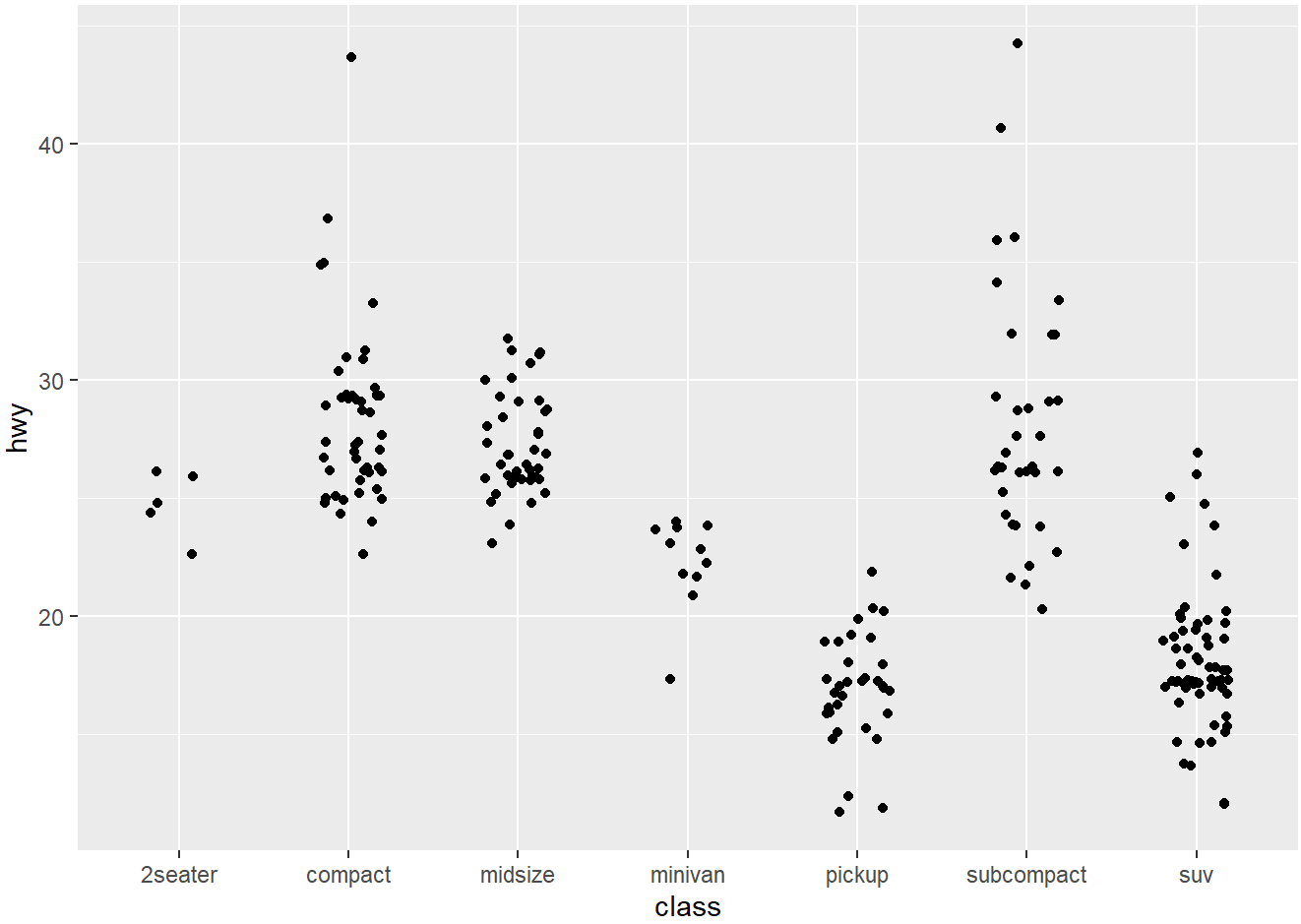
Data Types: Categorical and numerical.

Uses: Primarily enhances scatter plots to show relationships and avoid overplotting, which helps in understanding the distribution of data points across categorical axes, thus aiding in comparisons and distributions indirectly.

Business Examples: Jitter plots help to avoid overplotting when data points overlap, useful in displaying individual transaction data over time or customer ratings where data points may stack vertically.

Code Example: The jitter plot is an adaptation of a scatter plot that adds a small, random displacement to each point. This is particularly useful when dealing with categorical data on one axis (like `class` in this example) to avoid overplotting where multiple points have exactly the same position. In the example show below which uses the `mpg` dataset, the jitter helps visualize the distribution of highway miles per gallon (`hwy`) for different vehicle classes, making it easier to discern individual data points within each category.

```
ggplot(mpg, aes(x = class, y = hwy)) +
  geom_jitter(width = 0.2)
```



Each of these examples is tailored to show we how different types of visual representations can be achieved using `ggplot2` and R's built-in datasets. They illustrate how versatile and powerful `ggplot2` can be for data visualization.

15. `geom_point()` - Bubble plot

Uses: Bubble plots are an extension of scatter plots, allowing we to represent three dimensions of data. Each point on the plot has coordinates (x and y), and the size of each bubble (point) represents the third dimension. This type of plot is used for showing relationships between numerical data points and can also visually represent the magnitude of the data.

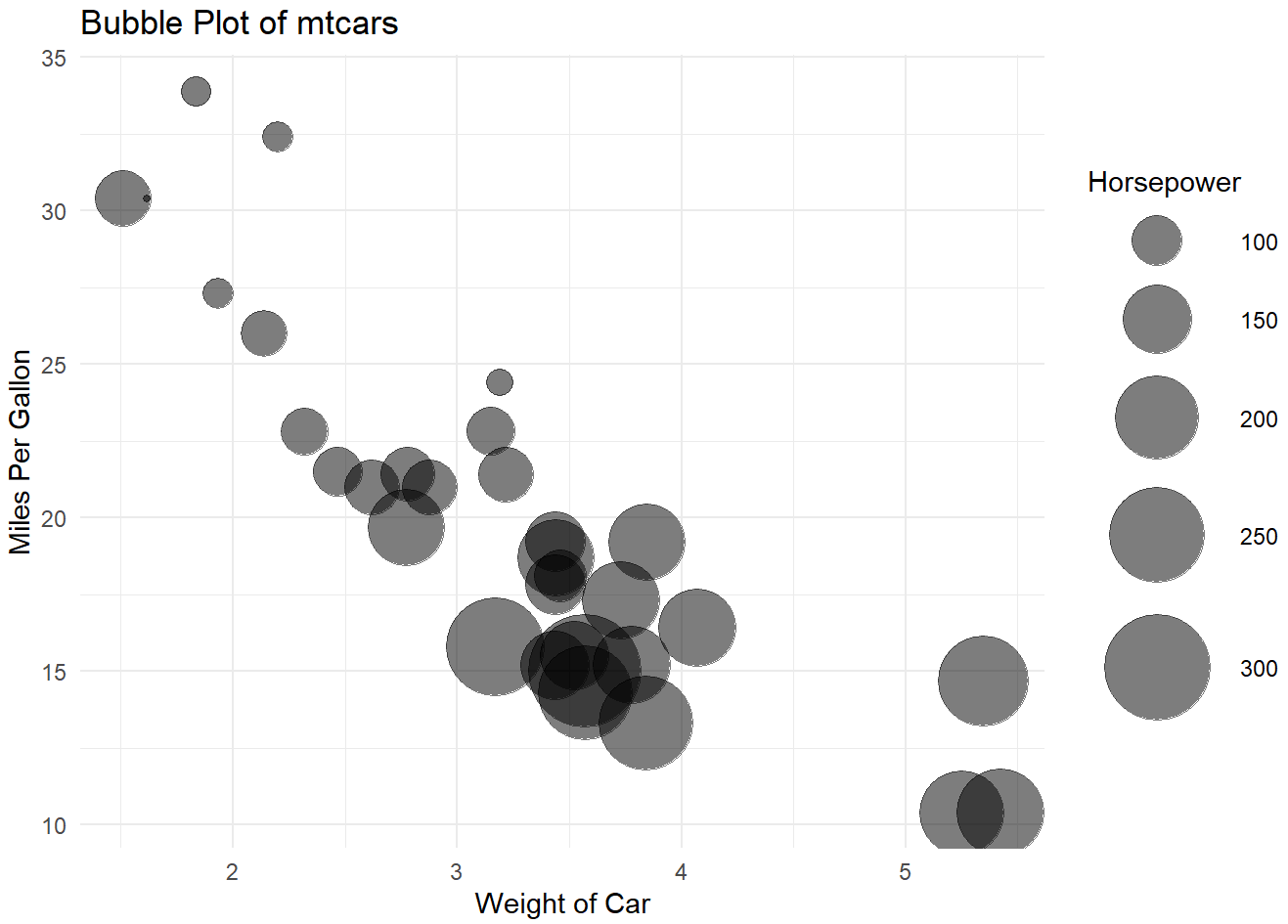
Business Examples: Bubble plots are particularly useful in business for visualizing complex relationships that include sizes or volumes, which can't be effectively captured with traditional scatter plots. For instance, a company might use a bubble plot to visualize the relationship between advertising spend and sales, with bubble size representing the number of sales transactions. This can provide insights into the efficiency of advertising spend per transaction volume. They are also used to compare and visualize financial metrics across different business units, regions, or product categories where the bubble size might represent profit margin, customer base size, or market potential.

Code Example: For this example, we'll use the `mtcars` dataset that comes built into R. We'll plot the relationship between `wt` (car weight) and `mpg` (miles per gallon) with the bubble size representing `hp` (horsepower).

```
library(ggplot2)

# Load the mtcars dataset
data(mtcars)

# Create a bubble plot
ggplot(mtcars, aes(x = wt, y = mpg, size = hp)) +
  geom_point(alpha = 0.5) +  # Set transparency to see overlapping points
  scale_size_continuous(range = c(1, 20)) +  # Adjust the range of bubble sizes
  labs(title = "Bubble Plot of mtcars",
       x = "Weight of Car",
       y = "Miles Per Gallon",
       size = "Horsepower") +
  theme_minimal()
```



Explanation of the Code:

- `aes(x = wt, y = mpg, size = hp)`: This sets the aesthetics for the plot, with car weight on the x-axis, miles per gallon on the y-axis, and bubble size proportional to horsepower.

- `geom_point(alpha = 0.5)`: This creates the bubbles, with `alpha = 0.5` providing some transparency so that overlapping points can be viewed more easily.

- `scale_size_continuous(range = c(1, 20))`: This controls the range of the bubble sizes, making it clear how they correspond to horsepower.

- `labs(...)`: Adds labels for the axes and the legend.

- `theme_minimal()`: Applies a minimalistic theme for a cleaner look.

This bubble plot will visually demonstrate how weight and fuel efficiency interact and how horsepower varies within those parameters, providing a multi-dimensional analysis in a single plot, ideal for strategic planning or operational analysis in business contexts.