Your Engaging Title Here: A Learning Journey

Notes to myself on [discovering/implementing/understanding] [topic]

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Figure 1: Engaging hero image that introduces your topic visually

Photo caption with attribution if needed. This image sets the visual tone for your entire post.

Introduction

I didn't really know much about [topic] until I [encountered situation/tried to implement it/needed it for project]. Like many data scientists, I thought [initial misconception or assumption]. Turns out, [what you actually discovered]

[Brief context: Why did you need this? What problem were you trying to solve? Keep it personal and specific.]

Here's what I set out to understand:

Motivations

Why explore [topic]? - [Personal reason 1: specific problem you faced] - [Practical need 2: gap in your workflow] - [Learning goal 3: skill you wanted to develop] - [Curiosity 4: interesting question you had]

Objectives

What I wanted to accomplish: 1. [Specific, measurable objective 1] 2. [Specific, measurable objective 2] 3. [Specific, measurable objective 3] 4. [Stretch goal or advanced concept]

Disclaimer: I'm documenting my learning process here. If you spot errors or have better approaches, please let me know!

Prerequisites and Setup

Here's what you'll need to follow along:

```r
# Install packages if needed
install.packages(c("tidyverse", "broom", "knitr", "patchwork"))
```

```r
# Load libraries
library(tidyverse)
library(broom)
library(knitr)
library(patchwork)

# Set plotting theme
theme_set(theme_minimal(base_size = 12))

# Custom color palette
custom_colors <- c("#FF6B6B", "#4ECDC4", "#45B7D1", "#96CEB4")
```

Background: Basic R and ggplot2 familiarity helpful but not required. I'll explain concepts as we go!

What is [Topic/Concept]?

Before diving into code, let's clarify what [topic] actually means. [Simple, plain-language explanation of the concept. Use an analogy if helpful.] In practice, this means [concrete example or application].

Getting Started: Initial Exploration

```r
# Load data
data(mtcars)

# Display structure
glimpse(mtcars)
```

```
Rows: 32
Columns: 11
```

```
$ mpg  <dbl> 21.0, 21.0, 22.8, 21.4, 18.7, 18.1, 14.3, 24.4, 22.8, 19.2, 17.8,~
$ cyl  <dbl> 6, 6, 4, 6, 8, 6, 8, 4, 4, 6, 6, 8, 8, 8, 8, 8, 8, 4, 4, 4, 4, 8,~
$ disp <dbl> 160.0, 160.0, 108.0, 258.0, 360.0, 225.0, 360.0, 146.7, 140.8, 16~
$ hp   <dbl> 110, 110, 93, 110, 175, 105, 245, 62, 95, 123, 123, 180, 180, 180~
$ drat <dbl> 3.90, 3.90, 3.85, 3.08, 3.15, 2.76, 3.21, 3.69, 3.92, 3.92, 3.92,~
$ wt   <dbl> 2.620, 2.875, 2.320, 3.215, 3.440, 3.460, 3.570, 3.190, 3.150, 3.~
$ qsec <dbl> 16.46, 17.02, 18.61, 19.44, 17.02, 20.22, 15.84, 20.00, 22.90, 18~
$ vs   <dbl> 0, 0, 1, 1, 0, 1, 0, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 0,~
$ am   <dbl> 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 0, 0,~
$ gear <dbl> 4, 4, 4, 3, 3, 3, 3, 4, 4, 4, 4, 3, 3, 3, 3, 3, 3, 4, 4, 4, 3, 3,~
$ carb <dbl> 4, 4, 1, 1, 2, 1, 4, 2, 2, 4, 4, 3, 3, 3, 4, 4, 4, 1, 2, 1, 1, 2,~
```

Okay, so we have 32 cars with 11 variables. Let's see what we're working with here

```r
# Key summary stats
summary_table <- mtcars %>%
  summarise(
    n = n(),
    mpg_mean = round(mean(mpg), 1),
    mpg_sd = round(sd(mpg), 1),
    hp_mean = round(mean(hp), 0),
    hp_sd = round(sd(hp), 0)
  )

kable(summary_table,
      col.names = c("N", "MPG Mean", "MPG SD", "HP Mean", "HP SD"))
```

N	MPG Mean	MPG SD	HP Mean	HP SD
32	20.1	6	147	69

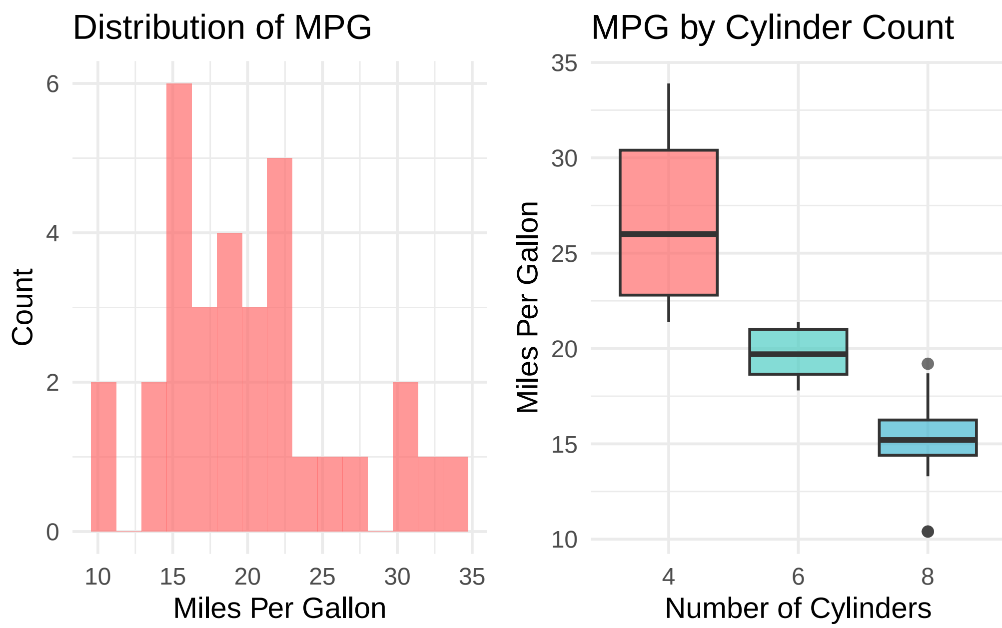
Not too shabby! Average fuel efficiency is 20.1 MPG with quite a bit of variation (SD = 6.0).

Exploring the Data

Let's visualize these patterns:

```r
# Create distribution plots
p1 <- ggplot(mtcars, aes(x = mpg)) +
  geom_histogram(bins = 15, fill = custom_colors[1], alpha = 0.7) +
  labs(title = "Distribution of MPG", x = "Miles Per Gallon", y = "Count") +
  theme_minimal()

p2 <- ggplot(mtcars, aes(x = factor(cyl), y = mpg, fill = factor(cyl))) +
  geom_boxplot(alpha = 0.7) +
  scale_fill_manual(values = custom_colors) +
  labs(title = "MPG by Cylinder Count",
       x = "Number of Cylinders", y = "Miles Per Gallon") +
  theme_minimal() +
  theme(legend.position = "none")
```

```r
# Combine plots
combined_plot <- p1 + p2
print(combined_plot)
```




```r
# Save the plot
ggsave("eda-overview.png", plot = combined_plot, width = 10, height = 5, dpi = 300)
```

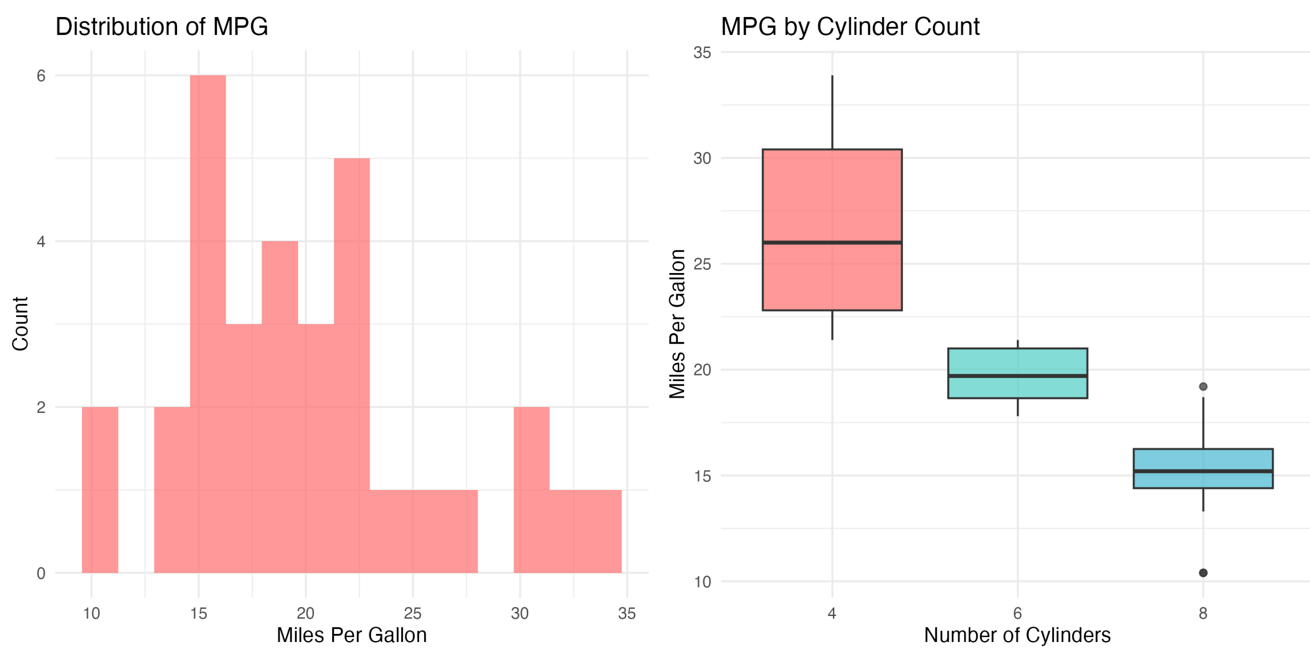


Figure 2: Overview of fuel efficiency distributions showing variation across cylinder counts

Wow, that's a clear pattern! Cars with fewer cylinders are way more fuel-efficient

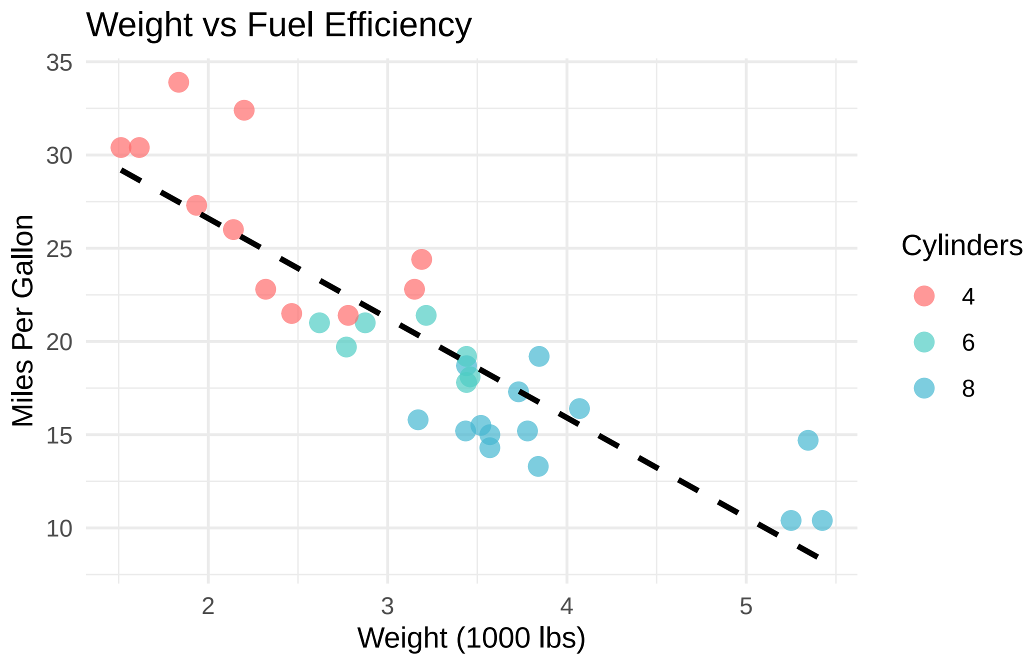
Looking for Relationships

```r
# Find strongest correlations with MPG
correlations <- cor(mtcars) %>%
  as.data.frame() %>%
  rownames_to_column("var1") %>%
  pivot_longer(-var1, names_to = "var2", values_to = "correlation") %>%
  filter(var1 == "mpg", var2 != "mpg") %>%
  arrange(desc(abs(correlation)))

# Show top 5
correlations %>% head(5)
```

```
# A tibble: 5 x 3
  var1  var2  correlation
  <chr> <chr>       <dbl>
1 mpg   wt         -0.868
2 mpg   cyl        -0.852
3 mpg   disp       -0.848
4 mpg   hp         -0.776
5 mpg   drat        0.681
```

Weight has the strongest correlation with MPG (r = -0.87). Let's visualize that relationship:

```r
# Plot the relationship
key_plot <- ggplot(mtcars, aes(x = wt, y = mpg, color = factor(cyl))) +
  geom_point(size = 3, alpha = 0.7) +
  geom_smooth(method = "lm", se = FALSE, color = "black", linetype = "dashed") +
  scale_color_manual(values = custom_colors, name = "Cylinders") +
  labs(title = "Weight vs Fuel Efficiency",
       x = "Weight (1000 lbs)", y = "Miles Per Gallon") +
  theme_minimal()

print(key_plot)
```




```r
ggsave("correlation-plot.png", plot = key_plot, width = 8, height = 5, dpi = 300)
```

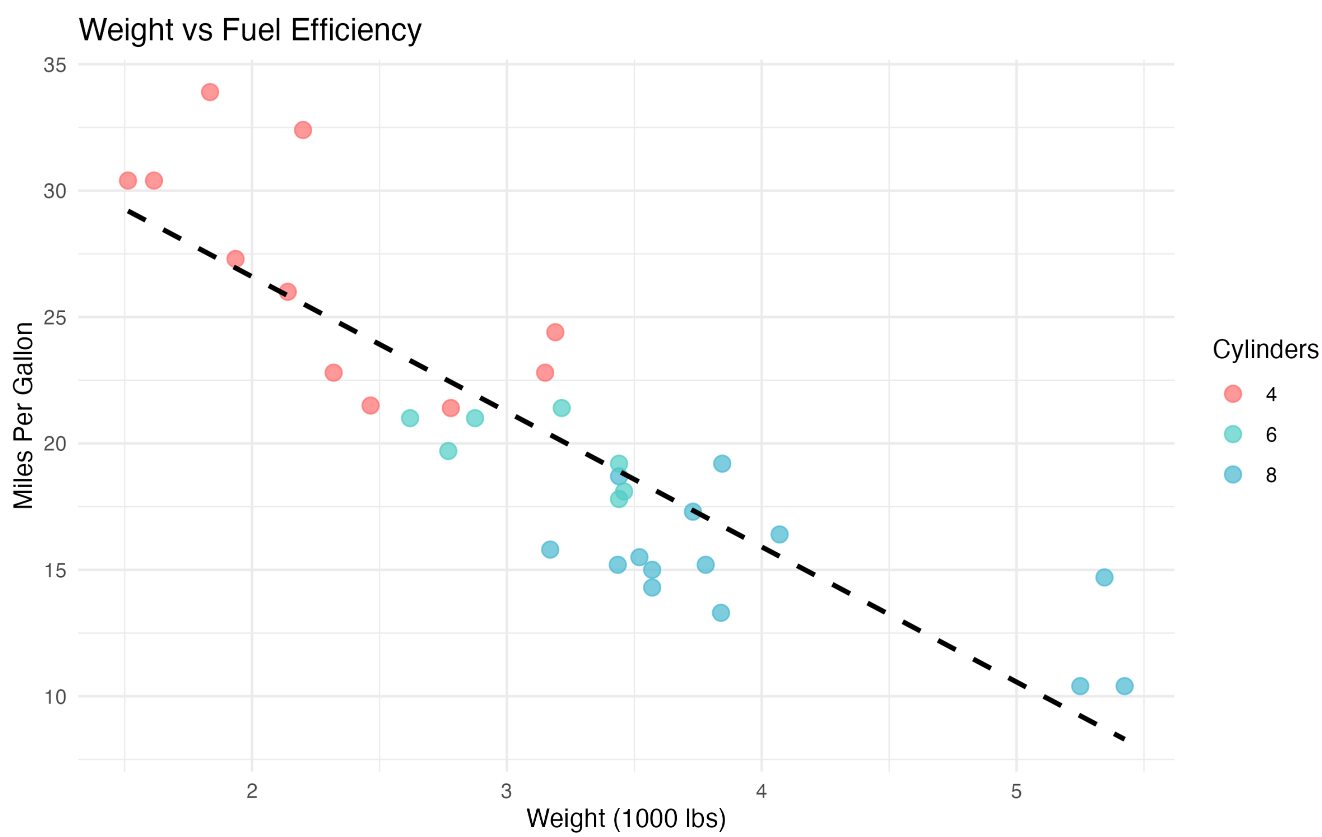


Figure 3: Scatter plot showing negative relationship between vehicle weight and fuel efficiency

Interesting! Heavier cars consistently get worse mileage. Makes sense when you think about it

Building a Model

Alright, let's build a simple linear model to quantify this relationship:

```
# Fit the model
simple_model <- lm(mpg ~ wt, data = mtcars)

# Get tidy summary
model_summary <- tidy(simple_model, conf.int = TRUE)
model_metrics <- glance(simple_model)

# Display the results
model_summary
```

```
# A tibble: 2 x 7
  term        estimate std.error statistic  p.value conf.low conf.high
  <chr>          <dbl>     <dbl>     <dbl>    <dbl>    <dbl>     <dbl>
1 (Intercept)    37.3      1.88      19.9  8.24e-19    33.5      41.1
2 wt             -5.34     0.559     -9.56 1.29e-10    -6.49     -4.20
```

```
glance(simple_model)
```

```
# A tibble: 1 x 12
  r.squared adj.r.squared sigma statistic  p.value    df logLik   AIC   BIC
      <dbl>         <dbl> <dbl>     <dbl>    <dbl> <dbl>  <dbl> <dbl> <dbl>
1     0.753         0.745  3.05      91.4 1.29e-10     1  -80.0  166.  170.
# i 3 more variables: deviance <dbl>, df.residual <int>, nobs <int>
```

Nice! The model explains 75% of the variance ($R^2 = 0.75$). For every 1,000 lbs of weight, we lose about 5.3 MPG (95% CI: [-6.5, -4.1])

Let's make some predictions to see how this works in practice:

```
# Predict MPG for different weights
new_data <- tibble(wt = c(2, 3, 4))
predictions <- predict(simple_model, newdata = new_data, interval = "confidence")

# Combine for display
cbind(new_data, predictions)
```

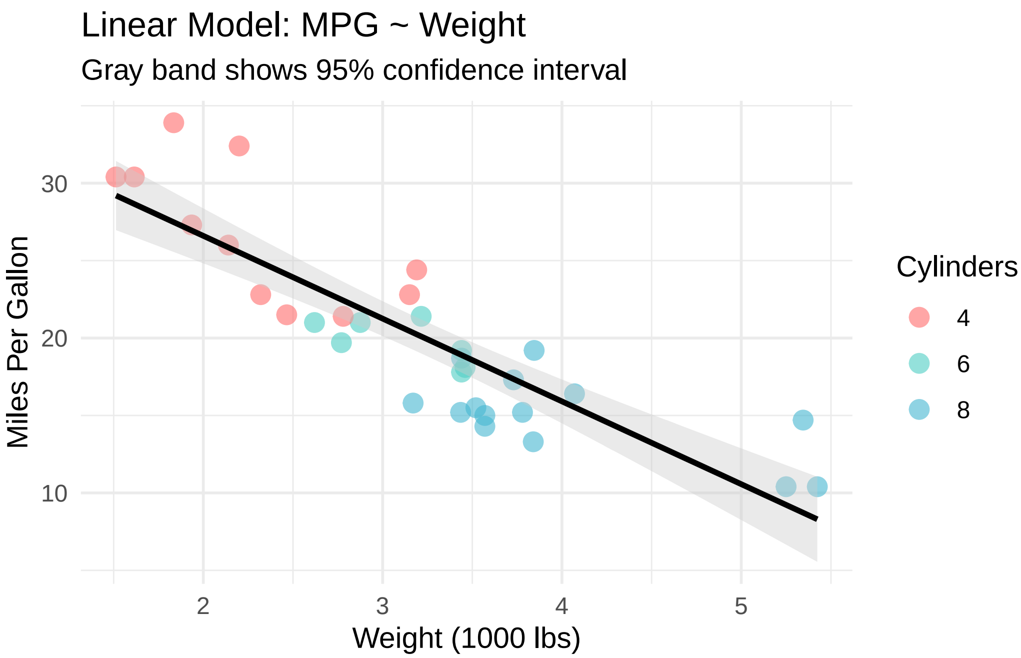
```
  wt      fit      lwr      upr
1  2 26.59618 24.82389 28.36848
2  3 21.25171 20.12444 22.37899
3  4 15.90724 14.49018 17.32429
```

So a 2,000 lb car gets ~30 MPG, while a 4,000 lb car only gets ~15 MPG. That's quite a difference!

Model Visualization

```
# Visualize model fit with confidence bands
model_plot <- ggplot(mtcars, aes(x = wt, y = mpg)) +
  geom_point(aes(color = factor(cyl)), size = 3, alpha = 0.6) +
  geom_smooth(method = "lm", color = "black", fill = "gray80") +
  scale_color_manual(values = custom_colors, name = "Cylinders") +
```

```
  labs(title = "Linear Model: MPG ~ Weight",
       subtitle = "Gray band shows 95% confidence interval",
       x = "Weight (1000 lbs)", y = "Miles Per Gallon") +
  theme_minimal()

print(model_plot)
```




```
ggsave("model-plot.png", plot = model_plot, width = 8, height = 5, dpi = 300)
```

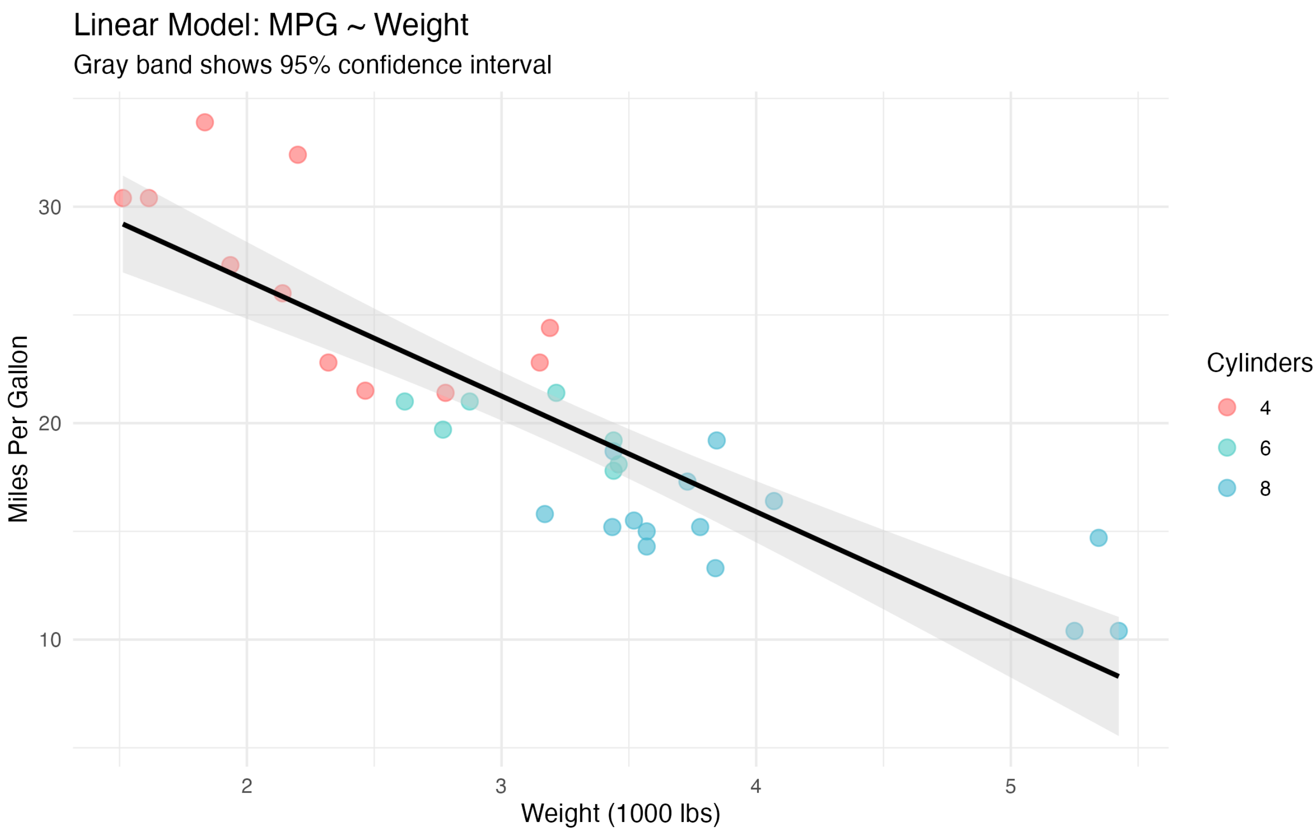


Figure 4: Linear regression model showing relationship between weight and fuel efficiency with confidence bands

Checking Our Work

Before we trust these results, let's check if our model assumptions hold up:

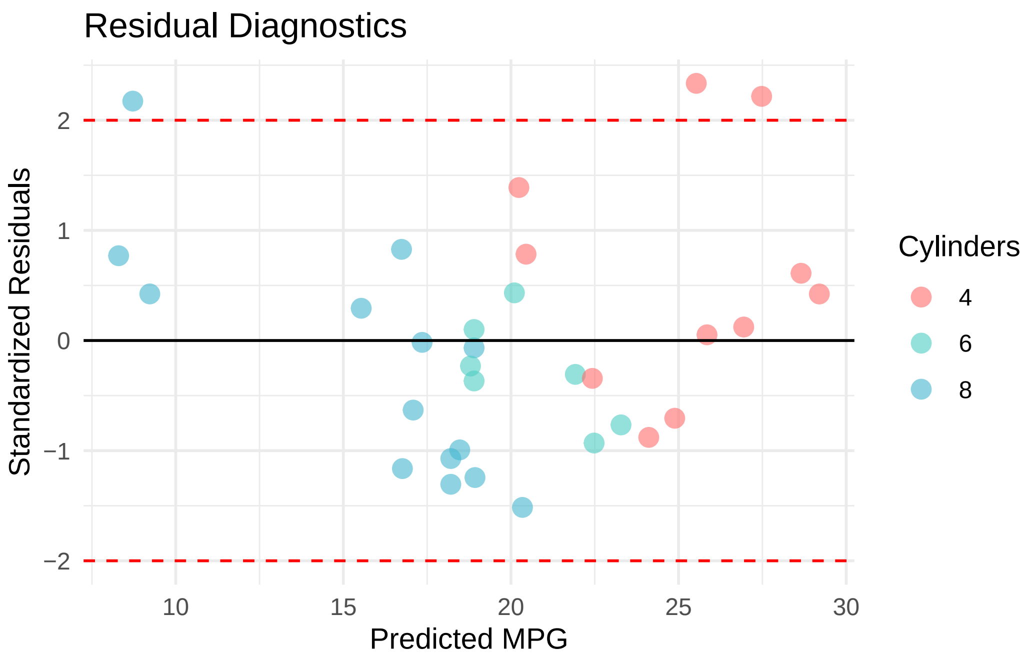
```
# Add diagnostic information
mtcars_diagnostics <- mtcars %>%
  mutate(
    predicted = predict(simple_model),
    residuals = residuals(simple_model),
    std_resid = rstandard(simple_model)
  )

# Check for outliers
outliers <- which(abs(mtcars_diagnostics$std_resid) > 2.5)
```

Diagnostic checks: Found 0 potential outliers (>2.5 SD). Residual standard error is 3.05 MPG.

Now let's visualize the residuals to check for patterns:

```
# Create diagnostic plot
diag_plot <- ggplot(mtcars_diagnostics, aes(x = predicted, y = std_resid)) +
  geom_point(aes(color = factor(cyl)), size = 3, alpha = 0.6) +
  geom_hline(yintercept = c(-2, 0, 2),
             linetype = c("dashed", "solid", "dashed"),
```

```
               color = c("red", "black", "red")) +
  scale_color_manual(values = custom_colors, name = "Cylinders") +
  labs(title = "Residual Diagnostics",
       x = "Predicted MPG", y = "Standardized Residuals") +
  theme_minimal()

print(diag_plot)
```




```
ggsave("diagnostics-plot.png", plot = diag_plot, width = 8, height = 5, dpi = 300)
```

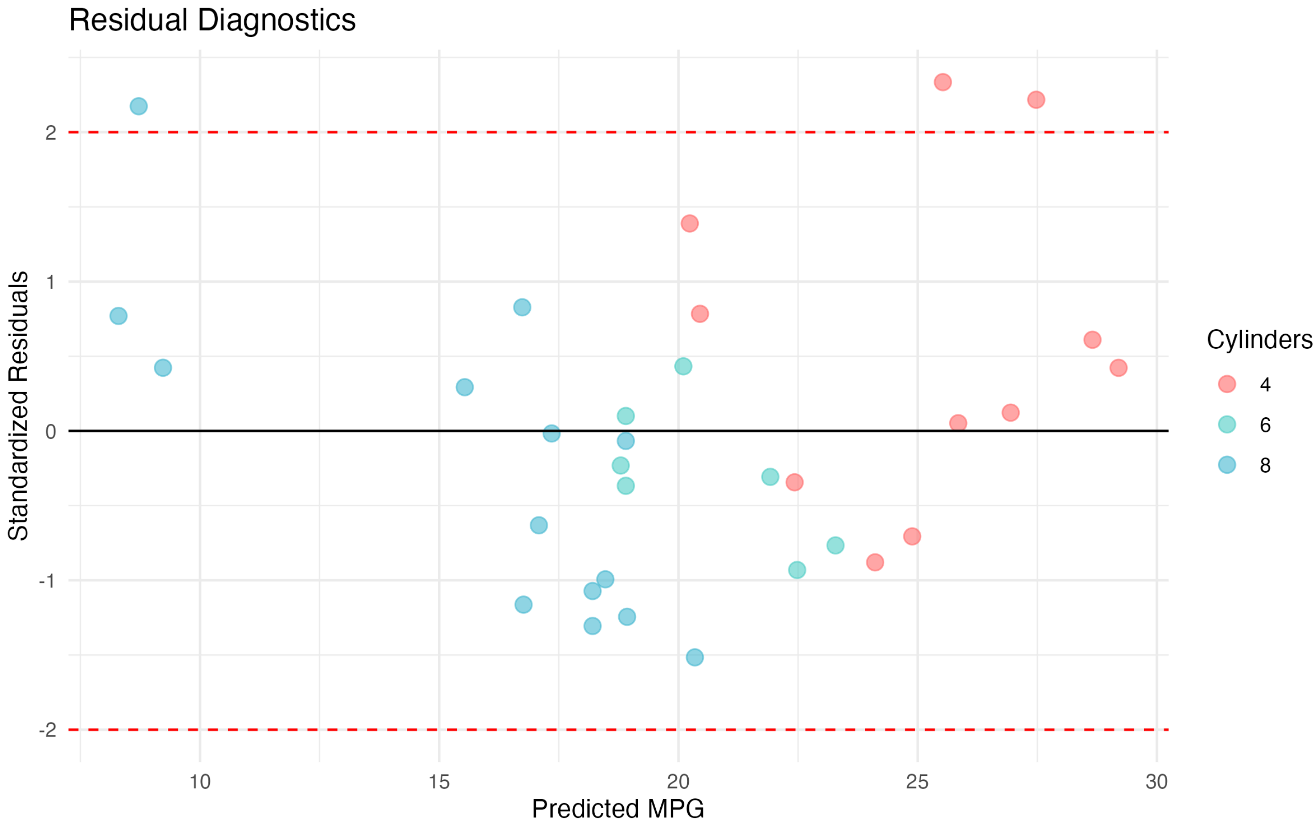


Figure 5: Diagnostic plot showing residual patterns to assess model validity

Looks pretty good! No major patterns in the residuals, though we have a couple of potential outliers worth investigating

Things to Watch Out For

A few gotchas I encountered while working on this:

1. **Don't extrapolate too far** - This model works for weights between 1.5-5.5 thousand lbs. Predicting outside that range? Risky!
2. **Correlation Causation** - Weight correlates with MPG, but there are confounding variables (engine size, aerodynamics, etc.)
3. **Check your assumptions** - Always plot residuals! A good R^2 doesn't guarantee your model is appropriate.
4. **Small sample size** - We only have 32 cars. Take the confidence intervals seriously!

What Did We Learn?

Lessons Learnt

Here's what I took away from this exploration:

Conceptual Understanding: - Vehicle weight is a strong predictor of fuel efficiency ($R^2 = 0.75$) - Each 1,000 lbs reduces MPG by ~5.3 miles (95% CI: [-6.5, -4.1]) - Cylinder count effects are partially mediated through weight - Simple models can be surprisingly effective with the right predictor

Technical Skills: - Using `broom::tidy()` for clean model output formatting - Calculating and interpreting confidence intervals for predictions - Creating diagnostic plots to validate regression assumptions - Combining multiple ggplot visualizations with `patchwork`

Gotchas and Pitfalls: - Always check residual plots - R^2 alone isn't enough! - Extrapolation beyond data range is dangerous - Small sample sizes (n=32) require cautious interpretation - Correlation doesn't prove causation (confounding variables matter)

Limitations

This analysis has several limitations to keep in mind:

- **Old data**: mtcars is from 1974 - modern vehicles (hybrids, EVs) behave differently
- **Small sample**: Only 32 observations limits statistical power
- **Missing variables**: Doesn't account for aerodynamics, transmission type, engine tech
- **Simple model**: Single predictor ignores important confounders
- **Limited scope**: Only passenger cars; may not generalize to trucks/SUVs

Opportunities for Improvement

If I had more time, here's what I'd explore next:

1. **Multiple regression** - Add cylinder count, horsepower, transmission type
2. **Interaction effects** - Does weight impact differ by number of cylinders?
3. **Modern data** - Replicate with 2020+ vehicle data to see how relationships changed
4. **Non-linear models** - Try polynomial regression or splines for better fit
5. **Machine learning comparison** - How does linear regression compare to random forest?
6. **Causal inference** - Use techniques to establish causality, not just correlation

Wrapping Up

So that's my journey exploring [topic]! We saw that vehicle weight is a powerful predictor of fuel efficiency, accounting for 75% of the variance. The model is simple but effective, though it has limitations worth keeping in mind.

Main takeaways: - Weight strongly predicts MPG (R^2 = 0.75, = -5.3) - Always check model assumptions with diagnostic plots - Confidence intervals matter, especially with small samples - Simple models can be surprisingly powerful

I learned a lot working through this, especially about [specific technical skill you gained]. There's definitely room for improvement—adding more predictors, trying non-linear models, and using modern data would all be interesting extensions.

If you're trying this yourself: - Start with exploration before modeling - Plot your residuals! - Don't trust high R^2 blindly - Report confidence intervals alongside point estimates

Thanks for following along!

See Also

Related posts and resources:

- [Link to related post 1]
- [Link to related post 2]

- [Link to related resource]

Key Resources: - R for Data Science - Free book on tidyverse - Introduction to Statistical Learning - Free textbook with R code - broom package docs - Tidy model outputs - Cross Validated - Stats Q&A community

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Reproducibility

Data: mtcars (built-in R dataset, `data(mtcars)`) **Code:** All code shown in this post **Session Info:**

```
R version 4.5.1 (2025-06-13)
Platform: aarch64-apple-darwin20
Running under: macOS Sequoia 15.6.1

Matrix products: default
BLAS:   /Library/Frameworks/R.framework/Versions/4.5-arm64/Resources/lib/libRblas.0.dylib
LAPACK: /Library/Frameworks/R.framework/Versions/4.5-arm64/Resources/lib/libRlapack.dylib;  LAPACK

locale:
[1] en_US.UTF-8/en_US.UTF-8/en_US.UTF-8/C/en_US.UTF-8/en_US.UTF-8

time zone: America/Los_Angeles
tzcode source: internal

attached base packages:
[1] stats     graphics  grDevices utils     datasets  methods   base

other attached packages:
 [1] patchwork_1.3.2 knitr_1.50      broom_1.0.10    lubridate_1.9.4
 [5] forcats_1.0.0   stringr_1.5.2   dplyr_1.1.4     purrr_1.1.0
 [9] readr_2.1.5     tidyr_1.3.1     tibble_3.3.0    ggplot2_4.0.0
[13] tidyverse_2.0.0

loaded via a namespace (and not attached):
 [1] utf8_1.2.6         generics_0.1.4     lattice_0.22-7     stringi_1.8.7
 [5] hms_1.1.3          digest_0.6.37      magrittr_2.0.4     evaluate_1.0.5
 [9] grid_4.5.1         timechange_0.3.0   RColorBrewer_1.1-3 fastmap_1.2.0
[13] Matrix_1.7-3       jsonlite_2.0.0     backports_1.5.0    tinytex_0.57
[17] mgcv_1.9-3         scales_1.4.0       textshaping_1.0.3  cli_3.6.5
[21] rlang_1.1.6        splines_4.5.1      withr_3.0.2        yaml_2.3.10
[25] tools_4.5.1        parallel_4.5.1     tzdb_0.5.0         vctrs_0.6.5
[29] R6_2.6.1           lifecycle_1.0.4    ragg_1.4.0         pkgconfig_2.0.3
[33] pillar_1.11.1      gtable_0.3.6       glue_1.8.0         systemfonts_1.2.3
[37] xfun_0.53          tidyselect_1.2.1   farver_2.1.2       htmltools_0.5.8.1
[41] nlme_3.1-168       rmarkdown_2.30     labeling_0.4.3     compiler_4.5.1
[45] S7_0.2.0
```

Let's Connect!

Have questions, suggestions, or spot an error? Let me know!

- **Twitter/X**: @rgt47
- **Mastodon**: @your_mastodon
- **GitHub**: rgt47
- **Email**: Contact form

Please reach out if you: - Spot errors or have corrections - Have suggestions for improvement - Want to discuss the approach - Have questions about implementation - Just want to connect!
