

# Predictive Modeling of Penguin Body Mass

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Figure 1: Palmer penguins in their Antarctic habitat

*Penguins at Palmer Station, Antarctica.*

## Introduction

How dramatically can a single confounding variable flip a statistical relationship? The Palmer Penguins dataset provides a striking demonstration. When predicting body mass from bill measurements, the overall correlation between bill depth and body mass appears negative. However, separating the data by species reveals that every single within-species relationship is positive. This is Simpson's Paradox in action.

The Palmer Penguins dataset, collected by Dr. Kristen Gorman at Palmer Station Antarctica, provides morphometric measurements for three penguin species: Adelie (*Pygoscelis adeliae*), Chinstrap (*Pygoscelis antarcticus*), and Gentoo (*Pygoscelis papua*). Body mass serves as a key indicator of

penguin health, reproductive success, and population dynamics, so accurate predictive models carry genuine conservation value (Gorman et al., 2014).

We walk through the full regression workflow: from exploratory analysis to tidymodels cross-validation, from simple linear regression to species-aware models with interaction terms. The journey teaches as much about confounding and model selection as it does about penguins.

## Motivations

- To provide a concrete example of Simpson’s Paradox visible in scatter plots rather than only in textbooks.
- To examine whether adding species as a covariate meaningfully improves a regression model or just adds complexity.
- To practice the tidymodels framework for systematic model comparison and cross-validation.
- To understand when interaction terms justify their added complexity and when a simpler additive model suffices.
- To create publication-quality coefficient plots and diagnostic visualizations.

## Objectives

1. Build and validate multiple regression models for predicting penguin body mass from morphometric measurements.
2. Demonstrate Simpson’s Paradox with real data and show how species identity reverses the bill depth-body mass correlation.
3. Compare linear regression and regularized regression (elastic net) using the tidymodels framework with 10-fold cross-validation.
4. Create publication-quality visualizations including coefficient plots, partial regression plots, and diagnostic panels.

Errors and better approaches are welcome; see the Feedback section at the end.



Figure 2: A clean workspace ready for data exploration.

## Prerequisites and Setup

**Background:** This post assumes familiarity with basic R syntax, the tidyverse, and an introductory understanding of linear regression (what R-squared means, what a residual is).

### Required Packages:

```
install.packages(  
  c("palmerpenguins", "tidyverse", "tidymodels",  
    "broom", "car", "corrplot", "GGally",  
    "patchwork", "lmtest")  
)
```

### Load Libraries:

```
library(palmerpenguins)  
library(tidyverse)  
library(tidymodels)  
library(broom)  
library(car)  
library(corrplot)  
library(GGally)  
library(patchwork)  
  
theme_set(theme_minimal(base_size = 12))
```

```
species_colors <- c(
  "Adelie" = "#FF6B35",
  "Chinstrap" = "#7B68EE",
  "Gentoo" = "#2E8B57"
)
```

## What is Regression Modeling?

Regression modeling is a way to express the relationship between a response variable (here, body mass) and one or more predictor variables (here, bill length, bill depth, flipper length, and species). In simple terms, a regression model draws the best straight line through a cloud of points, and the R-squared value reports what fraction of the scatter that line explains.

The key idea is that regression coefficients are conditional: they describe the relationship between a predictor and the response *after accounting for everything else in the model*. That distinction matters enormously when confounding variables like species are in play.

## Getting Started: Initial Exploration

Before fitting any models, an exploration of the data helps to understand distributions and spot potential issues.

```
data(penguins)
glimpse(penguins)

penguins |>
  summarise(
    across(everything(), ~sum(is.na(.)))
  ) |>
  pivot_longer(
    everything(),
    names_to = "variable",
    values_to = "missing"
  ) |>
  filter(missing > 0)

penguins_clean <- penguins |>
  drop_na()

cat(
  "Dataset dimensions after removing NAs:",
  nrow(penguins_clean), "rows and",
  ncol(penguins_clean), "columns\n"
)
```

## Univariate Distributions

Plotting histograms and boxplots side-by-side by species immediately reveals the structure in the data.

```
p1 <- ggplot(
  penguins_clean,
  aes(x = body_mass_g, fill = species)
) +
  geom_histogram(
    bins = 30, alpha = 0.7,
    position = "identity"
  ) +
  scale_fill_manual(values = species_colors) +
  labs(
    title = "Distribution of Body Mass by Species",
    x = "Body Mass (g)", y = "Count"
  ) +
  theme(legend.position = "none")

p2 <- ggplot(
  penguins_clean,
  aes(x = body_mass_g, y = species,
    fill = species)
) +
  geom_boxplot(alpha = 0.7) +
  scale_fill_manual(values = species_colors) +
  labs(x = "Body Mass (g)", y = NULL) +
  theme(legend.position = "none")

p3 <- ggplot(
  penguins_clean,
  aes(x = flipper_length_mm, fill = species)
) +
  geom_histogram(
    bins = 30, alpha = 0.7,
    position = "identity"
  ) +
  scale_fill_manual(values = species_colors) +
  labs(
    title = "Flipper Length by Species",
    x = "Flipper Length (mm)", y = "Count"
  ) +
  theme(legend.position = "none")

p4 <- ggplot(
  penguins_clean,
  aes(x = flipper_length_mm, y = species,
```

```

    fill = species)
) +
  geom_boxplot(alpha = 0.7) +
  scale_fill_manual(values = species_colors) +
  labs(x = "Flipper Length (mm)", y = NULL)

(p1 + p2) / (p3 + p4) +
  plot_annotation(
    title = paste(
      "Morphometric Distributions",
      "Across Penguin Species"
    )
  )
)

```

The distributions reveal clear species-level differences. Gentoo penguins exhibit the largest body mass and flipper length, followed by Chinstrap and Adelie. These patterns indicate early on that any predictive model should account for species identity.

## Correlation Analysis

Understanding the correlation structure informs model building and helps flag multicollinearity:

```

numeric_vars <- penguins_clean |>
  select(
    bill_length_mm, bill_depth_mm,
    flipper_length_mm, body_mass_g
  )

correlation_matrix <- cor(numeric_vars)

corrplot(
  correlation_matrix,
  method = "color",
  type = "upper",
  order = "hclust",
  tl.cex = 0.9,
  tl.col = "black",
  addCoef.col = "black",
  number.cex = 0.8,
  col = colorRampPalette(
    c("#2166AC", "white", "#B2182B")
  )(100)
)

```

Flipper length shows the strongest correlation with body mass ( $r = 0.87$ ), followed by bill length ( $r = 0.60$ ). Bill depth shows a weaker positive correlation ( $r = 0.43$ ). The strong flipper-body mass correlation is consistent with allometric scaling relationships in vertebrates.

## Simpson's Paradox: A Cautionary Tale

This finding is perhaps the most striking. The overall correlation between bill depth and body mass appears negative, but within each species the relationship is positive. Pearl (2014) calls this Simpson's Paradox.

```
p_overall <- ggplot(
  penguins_clean,
  aes(x = bill_depth_mm, y = body_mass_g)
) +
  geom_point(alpha = 0.5) +
  geom_smooth(
    method = "lm", se = TRUE, color = "black"
  ) +
  labs(
    title = "Overall: Negative Relationship",
    subtitle = paste(
      "r =",
      round(
        cor(penguins_clean$bill_depth_mm,
            penguins_clean$body_mass_g), 2
      )
    ),
    x = "Bill Depth (mm)",
    y = "Body Mass (g)"
  )

p_species <- ggplot(
  penguins_clean,
  aes(x = bill_depth_mm, y = body_mass_g,
      color = species)
) +
  geom_point(alpha = 0.7) +
  geom_smooth(method = "lm", se = TRUE) +
  scale_color_manual(values = species_colors) +
  labs(
    title = "Within Species: Positive",
    x = "Bill Depth (mm)",
    y = "Body Mass (g)"
  ) +
  theme(legend.position = "bottom")

p_overall + p_species
```

The reversal occurs because Gentoo penguins have larger bodies but shallower bills than Adelie penguins, and species acts as a confounding variable. This example proves more instructive than many textbook explanations of confounding.

## Species-Specific Patterns

A comprehensive view of all pairwise relationships by species:

```
ggpairs(  
  penguins_clean,  
  columns = c(  
    "bill_length_mm", "bill_depth_mm",  
    "flipper_length_mm", "body_mass_g"  
  ),  
  aes(color = species, alpha = 0.7),  
  lower = list(continuous = "smooth_loess"),  
  upper = list(continuous = "cor"),  
  diag = list(continuous = "densityDiag")  
) +  
  scale_color_manual(values = species_colors) +  
  scale_fill_manual(values = species_colors) +  
  theme_minimal()
```



Figure 3: Penguin research in progress

*Midway through the analysis: time for a closer look at the models.*

## Building a Model

### Simple Linear Regression

The analysis starts with the simplest possible model: flipper length as the sole predictor, given its strong correlation with body mass.

```
model_simple <- lm(
  body_mass_g ~ flipper_length_mm,
  data = penguins_clean
)

summary(model_simple)

simple_metrics <- glance(model_simple)
cat(
  "\nSimple Model R-squared:",
  round(simple_metrics$r.squared, 3), "\n"
)
cat(
  "Simple Model RMSE:",
  round(sqrt(mean(model_simple$residuals^2)), 1),
  "g\n"
)
```

The simple model explains approximately 76% of the variance in body mass, with each millimeter increase in flipper length associated with a 49.7g increase in body mass. Not bad for one predictor; species likely matters as well.

### Multiple Linear Regression

Adding the remaining morphometric predictors:

```
model_multiple <- lm(
  body_mass_g ~ bill_length_mm +
    bill_depth_mm + flipper_length_mm,
  data = penguins_clean
)

summary(model_multiple)

vif_values <- vif(model_multiple)
cat("\nVariance Inflation Factors:\n")
print(round(vif_values, 2))
```

The VIF values are all below 5, indicating that multicollinearity is not a serious concern. Checking this before adding more terms is reassuring.

## Species-Aware Model

Including species as a factor should improve predictions by accounting for the systematic differences observed in the exploratory analysis:

```
model_species <- lm(
  body_mass_g ~ bill_length_mm +
    bill_depth_mm + flipper_length_mm + species,
  data = penguins_clean
)

summary(model_species)
```

This is where things got interesting. All morphometric coefficients changed in magnitude and direction when species was included, consistent with the Simpson's Paradox observed earlier. Bill depth, which appeared to have a negative coefficient in the multiple regression, now shows a positive coefficient within the species-stratified framework.

## Interaction Effects

The next step explores whether the relationships between morphometric variables and body mass differ across species:

```
model_interactions <- lm(
  body_mass_g ~ (bill_length_mm +
    bill_depth_mm + flipper_length_mm) * species,
  data = penguins_clean
)

summary(model_interactions)

anova(model_species, model_interactions)
```

## Making Predictions

To see how the species-aware model performs in practice, the following code generates predictions with 95% prediction intervals:

```
predictions <- predict(
  model_species,
  interval = "prediction",
  level = 0.95
)

results_df <- penguins_clean |>
```

```

mutate(
  predicted = predictions[, "fit"],
  lower_pi = predictions[, "lwr"],
  upper_pi = predictions[, "upr"],
  residual = body_mass_g - predicted
)

ggplot(
  results_df,
  aes(x = predicted, y = body_mass_g)
) +
  geom_point(
    aes(color = species),
    alpha = 0.7, size = 2
  ) +
  geom_abline(
    slope = 1, intercept = 0,
    linetype = "dashed",
    color = "gray40", linewidth = 1
  ) +
  scale_color_manual(values = species_colors) +
  labs(
    title = "Predicted vs Actual Body Mass",
    subtitle = paste(
      "Species-aware model, R-squared =",
      round(
        summary(model_species)$r.squared, 3
      )
    ),
    x = "Predicted Body Mass (g)",
    y = "Actual Body Mass (g)",
    color = "Species"
  ) +
  theme(legend.position = "bottom") +
  coord_equal()

```

The points cluster tightly around the identity line, and the model performs well across all three species rather than fitting one species at the expense of the others.

## The tidymodels Approach

Following the workflow demonstrated by Julia Silge in her TidyTuesday screencast on Palmer Penguins, the tidymodels framework provides systematic model comparison and validation.

## Data Splitting

```
set.seed(123)

penguin_split <- initial_split(
  penguins_clean, prop = 0.75, strata = species
)
penguin_train <- training(penguin_split)
penguin_test <- testing(penguin_split)

cat(
  "Training set:",
  nrow(penguin_train), "observations\n"
)
cat(
  "Test set:",
  nrow(penguin_test), "observations\n"
)
```

## Recipe Specification

```
penguin_recipe <- recipe(
  body_mass_g ~ bill_length_mm +
    bill_depth_mm + flipper_length_mm +
    species + sex + island,
  data = penguin_train
) |>
  step_dummy(all_nominal_predictors()) |>
  step_normalize(all_numeric_predictors())

penguin_recipe
```

## Model Specifications

The analysis compares linear regression with regularized regression (elastic net) to see whether penalizing coefficient size improves out-of-sample performance:

```
lm_spec <- linear_reg() |>
  set_engine("lm")

glmnet_spec <- linear_reg(
  penalty = tune(), mixture = tune()
) |>
  set_engine("glmnet")
```

## Workflow Creation

```
lm_workflow <- workflow() |>
  add_recipe(penguin_recipe) |>
  add_model(lm_spec)

glmnet_workflow <- workflow() |>
  add_recipe(penguin_recipe) |>
  add_model(glmnet_spec)
```

## Cross-Validation Setup

```
set.seed(234)
penguin_folds <- vfold_cv(
  penguin_train, v = 10, strata = species
)
```

## Linear Regression Results

```
lm_results <- fit_resamples(
  lm_workflow,
  resamples = penguin_folds,
  control = control_resamples(save_pred = TRUE)
)

collect_metrics(lm_results)
```

## Regularized Regression with Tuning

```
glmnet_grid <- grid_regular(
  penalty(range = c(-4, 0)),
  mixture(range = c(0, 1)),
  levels = 10
)

glmnet_results <- tune_grid(
  glmnet_workflow,
  resamples = penguin_folds,
  grid = glmnet_grid,
  control = control_grid(save_pred = TRUE)
)
```

```
show_best(glmnet_results, metric = "rmse", n = 5)
```

## Final Model Selection

```
best_glmnet <- select_best(
  glmnet_results, metric = "rmse"
)

final_workflow <- finalize_workflow(
  glmnet_workflow, best_glmnet
)

final_fit <- last_fit(
  final_workflow, penguin_split
)

collect_metrics(final_fit)
```

## Checking Our Work

### Residual Analysis

The species-aware linear model is examined for assumption violations:

```
par(mfrow = c(2, 2))
plot(model_species)
par(mfrow = c(1, 1))
```

The diagnostic plots reveal:

- **Residuals vs Fitted:** No clear pattern, suggesting the linearity assumption holds.
- **Q-Q Plot:** Residuals approximately follow a normal distribution with slight deviation in tails.
- **Scale-Location:** Relatively constant spread; homoscedasticity appears reasonable.
- **Residuals vs Leverage:** No high-leverage outliers with large residuals.

### Formal Diagnostic Tests

```

shapiro_test <- shapiro.test(
  residuals(model_species)
)
cat(
  "Shapiro-Wilk test p-value:",
  round(shapiro_test$p.value, 4), "\n"
)

library(lmtest)
bp_test <- bptest(model_species)
cat(
  "Breusch-Pagan test p-value:",
  round(bp_test$p.value, 4), "\n"
)

```

## Things to Watch Out For

1. **Simpson's Paradox is easy to miss.** Pooling data across species produced misleading coefficient signs. Always check within-group relationships before interpreting aggregate patterns.
2. **VIF alone does not tell the full story.** Even with low VIF values, adding species flipped the sign of the bill depth coefficient.
3. **Interaction terms add complexity fast.** The interaction model added six parameters for marginal improvement in adjusted R-squared (0.868 to 0.872).
4. **Stratified splitting matters.** Without `strata = species` in `initial_split()`, the training set could under-represent Chinstrap penguins (the smallest group).
5. **Residual normality tests can be overly sensitive.** With 333 observations, the Shapiro-Wilk test may flag small deviations that have little practical effect on inference.

## Advanced Visualizations

### Coefficient Plot

```

coef_df <- tidy(
  model_species, conf.int = TRUE
) |>
  filter(term != "(Intercept)") |>
  mutate(term = fct_reorder(term, estimate))

ggplot(coef_df, aes(x = estimate, y = term)) +
  geom_vline(
    xintercept = 0,
    linetype = "dashed",
    color = "gray50"
  )

```

```

) +
geom_errorbarh(
  aes(xmin = conf.low, xmax = conf.high),
  height = 0.2, color = "gray40"
) +
geom_point(size = 3, color = "#2E8B57") +
labs(
  title = paste(
    "Regression Coefficients with",
    "95% Confidence Intervals"
  ),
  subtitle = paste(
    "Predicting body mass from",
    "morphometric variables and species"
  ),
  x = "Coefficient Estimate (g)",
  y = NULL
) +
theme(panel.grid.major.y = element_blank())

```

## Partial Regression Plots

```

p1 <- ggplot(
  penguins_clean,
  aes(x = flipper_length_mm, y = body_mass_g)
) +
geom_point(
  aes(color = species), alpha = 0.6
) +
geom_smooth(
  method = "lm", se = TRUE,
  color = "gray30"
) +
scale_color_manual(values = species_colors) +
labs(
  title = "Flipper Length",
  x = "Flipper Length (mm)",
  y = "Body Mass (g)"
) +
theme(legend.position = "none")

p2 <- ggplot(
  penguins_clean,
  aes(x = bill_depth_mm, y = body_mass_g,
      color = species)

```

```

) +
  geom_point(alpha = 0.6) +
  geom_smooth(method = "lm", se = TRUE) +
  scale_color_manual(values = species_colors) +
  labs(
    title = "Bill Depth (by Species)",
    x = "Bill Depth (mm)",
    y = "Body Mass (g)"
  ) +
  theme(legend.position = "none")

p3 <- ggplot(
  penguins_clean,
  aes(x = bill_length_mm, y = body_mass_g,
       color = species)
) +
  geom_point(alpha = 0.6) +
  geom_smooth(method = "lm", se = TRUE) +
  scale_color_manual(values = species_colors) +
  labs(
    title = "Bill Length (by Species)",
    x = "Bill Length (mm)",
    y = "Body Mass (g)"
  ) +
  theme(legend.position = "bottom")

p1 + p2 + p3 +
  plot_annotation(
    title = "Morphometric Predictors of Body Mass"
  )

```

## Model Comparison Summary

```

model_comparison <- tibble(
  Model = c(
    "Simple (Flipper)", "Multiple",
    "Species-Aware", "Interactions"
  ),
  R_squared = c(
    summary(model_simple)$r.squared,
    summary(model_multiple)$r.squared,
    summary(model_species)$r.squared,
    summary(model_interactions)$r.squared
  ),
  Adj_R_squared = c(

```

```

summary(model_simple)$adj.r.squared,
summary(model_multiple)$adj.r.squared,
summary(model_species)$adj.r.squared,
summary(model_interactions)$adj.r.squared
),
RMSE = c(
  sqrt(mean(model_simple$residuals^2)),
  sqrt(mean(model_multiple$residuals^2)),
  sqrt(mean(model_species$residuals^2)),
  sqrt(mean(model_interactions$residuals^2))
)
)

model_comparison |>
  mutate(
    across(where(is.numeric), ~round(.x, 3))
  ) |>
  knitr::kable(
    caption = "Model Performance Comparison"
  )

model_comparison |>
  pivot_longer(
    cols = c(R_squared, RMSE),
    names_to = "Metric",
    values_to = "Value"
  ) |>
  ggplot(
    aes(x = fct_reorder(Model, Value),
        y = Value, fill = Model)
  ) +
  geom_col() +
  facet_wrap(~Metric, scales = "free") +
  labs(
    title = "Model Performance Comparison",
    x = NULL, y = "Value"
  ) +
  theme(
    axis.text.x = element_text(
      angle = 45, hjust = 1
    ),
    legend.position = "none"
  ) +
  scale_fill_viridis_d(option = "D")

```



Figure 4: Final reflections on the analysis

*Stepping back to reflect on what the models revealed.*

## What Did We Learn?

### Lessons Learned

#### Conceptual Understanding:

- Flipper length is the strongest single predictor of body mass ( $R^2 = 0.76$ ), consistent with allometric scaling in vertebrates.
- Including species raises the  $R^2$  from 0.76 to 0.87, confirming that species identity is a first-order driver of morphometric variation.
- Simpson's Paradox reversed the sign of the bill depth coefficient: negative overall, positive within each species.
- Interaction terms yielded marginal improvement (adjusted  $R^2$  from 0.868 to 0.872), suggesting the additive species-aware model captures most of the relevant structure.

#### Technical Skills:

- The tidymodels pipeline covers recipe specification, workflow creation, cross-validation with `vfold_cv()`, and hyperparameter tuning with `tune_grid()`.
- The broom package (`tidy()`, `glance()`, `augment()`) made it straightforward to extract model summaries into tidy data frames for plotting.
- `corrplot` and `GGally::ggpairs()` provided quick multivariate overviews that guided variable selection.

- The `car::vif()` function gave a fast check on multicollinearity before building larger models.

### Gotchas and Pitfalls:

- Pooling data across species without checking within-group patterns led to misleading conclusions about bill depth.
- The Shapiro-Wilk normality test flagged minor tail deviations that had no practical effect on model predictions.
- Forgetting to set `strata = species` in data splitting could under-represent the 68 Chinstrap observations in either the training or test set.
- Using `position = "identity"` in histograms is essential when comparing overlapping distributions; the default stacking obscures the shape of each group.

### Limitations

- The dataset contains 333 complete observations, adequate for these analyses but limiting for complex interaction models with many parameters.
- Data spans 2007 to 2009 and does not account for potential year-to-year environmental variation that could affect body mass.
- All data comes from Palmer Station, limiting generalizability to other Antarctic regions or penguin populations.
- The regression coefficients describe associations, not causal effects. Morphometric variables are biologically related and may not represent independent causal pathways.
- Sex was not included in the base regression models (only in the `tidymodels` recipe), so sexual dimorphism is only partially addressed.

### Opportunities for Improvement

1. **Mixed-effects models:** Account for island as a random effect to improve population-level inference.
2. **Sex-specific models:** Develop separate models for males and females to address known sexual dimorphism (Gorman et al., 2014).
3. **Temporal analysis:** Incorporate year effects to understand environmental influences on morphometry.
4. **Tree-based comparison:** Compare regularized regression with random forests and gradient boosting to assess nonlinear relationships.
5. **External validation:** Test model performance on penguin data from other Antarctic research stations.
6. **Bayesian regression:** Use informative priors based on allometric scaling theory to improve small-sample inference.

## Wrapping Up

The main finding is that a species-aware linear model explains 87% of the variance in penguin body mass with a prediction error of approximately 289 grams. That is a strong result for a model using only four predictors.

The key lesson is that confounding variables can completely reverse apparent relationships. The Simpson's Paradox demonstration warrants careful attention whenever aggregate patterns are interpreted. The tidymodels workflow, with its recipe-workflow-resample pattern, proves systematic and reproducible.

For analysts attempting similar work, the advice is to start with thorough exploratory analysis before fitting any models. The EDA phase revealed the species structure that turned out to be the single most important predictor, and it surfaced Simpson's Paradox before it could silently distort model coefficients.

In conclusion, four points merit emphasis. First, flipper length alone predicts body mass with  $R\text{-squared} = 0.76$ , establishing a strong single-predictor baseline. Second, adding species raises  $R\text{-squared}$  to 0.87 and corrects misleading coefficient signs introduced by confounding. Third, interaction terms provide marginal improvement (adjusted  $R\text{-squared}$  0.868 to 0.872) at the cost of six additional parameters, a trade-off that the additive model renders unnecessary for most purposes. Fourth, the Palmer Penguins dataset serves as an instructive teaching resource for confounding, Simpson's Paradox, and the role of domain knowledge in statistical modeling.

## See Also

### Related posts:

- Palmer Penguins Part 1: EDA and Simple Regression
- Palmer Penguins Part 3: Cross-Validation and ML Comparison
- Palmer Penguins Part 4: Model Diagnostics

### Key resources:

- Gorman, K.B., Williams, T.D., & Fraser, W.R. (2014). Ecological sexual dimorphism and environmental variability within a community of Antarctic penguins (genus *Pygoscelis*). *PLOS ONE*, 9(3), e90081. <https://doi.org/10.1371/journal.pone.0090081>
- Horst, A.M., Hill, A.P., & Gorman, K.B. (2022). Palmer Archipelago Penguins Data in the palmerpenguins R Package. *The R Journal*, 14(1), 244-254. <https://doi.org/10.32614/RJ-2022-020>
- Silge, J. (2020). Get started with tidymodels and Palmer penguins. <https://juliasilge.com/blog/palmer-penguins/>
- Scherer, C. (2020). TidyTuesday 2020/31: Palmer Penguins visualization. <https://github.com/z3tt/TidyTuesday>
- [palmerpenguins package documentation](#)
- [tidymodels framework](#)

## Reproducibility

**Data source:** The palmerpenguins R package (version 0.1.1), which provides the penguins dataset collected at Palmer Station, Antarctica.

**Analysis pipeline:**

```
Rscript analysis/scripts/01_prepare_data.R
Rscript analysis/scripts/02_fit_models.R
Rscript analysis/scripts/03_generate_figures.R
quarto render index.qmd
```

Session information:

## Let's Connect

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

- **GitHub:** [rgt47](#)
- **Twitter/X:** [@rgt47](#)
- **LinkedIn:** [Ronald Glenn Thomas](#)
- **Email:** [Contact form](#)

I would enjoy hearing from you if:

- An error or a better approach to any of the code in this post comes to mind.
- There are suggestions for topics to see covered.
- The interest is in discussing R programming, data science, or reproducible research.
- There are questions about anything in this tutorial.
- The goal is simply to say hello and connect.

## Related posts in this cluster

This post is part of the *Palmer Penguins Analysis Arc* series. Recommended reading order:

1. Post 50: [Palmer Penguins Part 1: Exploratory Data Analysis](#)
2. Post 51: [Palmer Penguins Part 2: Multiple Regression](#)
3. Post 52: [Palmer Penguins Part 3: Cross-Validation](#)
4. Post 53: [Palmer Penguins Part 4: Model Diagnostics](#)
5. Post 54: [Palmer Penguins Part 5: Random Forest versus Linear](#)
6. **Post 55: Predictive Modeling of Penguin Body Mass** (this post)
7. Post 56: [Functional Plot Generation with purrr](#)