# Predicting Car Sticker Price Regression

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# Agenda

In this presentation, we will

- Describe our research questions
- Show our exploratory data analysis
- Fit 2 regression models to the data
    - Ridge regression model
    - Lasso regression model
- Compare & Test a New Vehicle
- Discuss Outcome & Lessons Learned


# Research Question

Our research question is “What is the sticker price of this car?”

From our experience, we know that the following factors impact the price of a car

- Brand *Is it a luxury brand?*
- Size *Is it a larger car?*
- Fuel type *Does it use gas or diesel?*
- Horsepower *Is it “stronger”?*

We built 2 models which use factors like these from a Kaggle dataset to predict the car price.

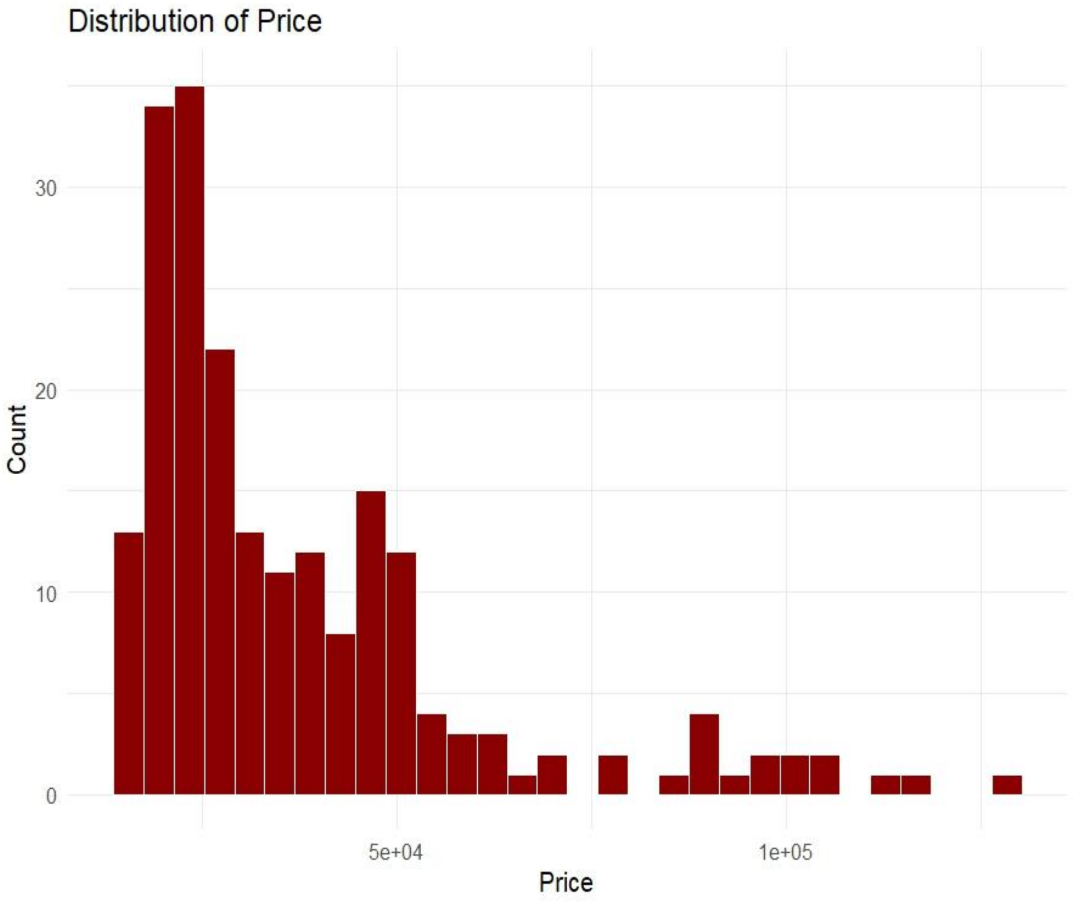
# Understanding the Dataset

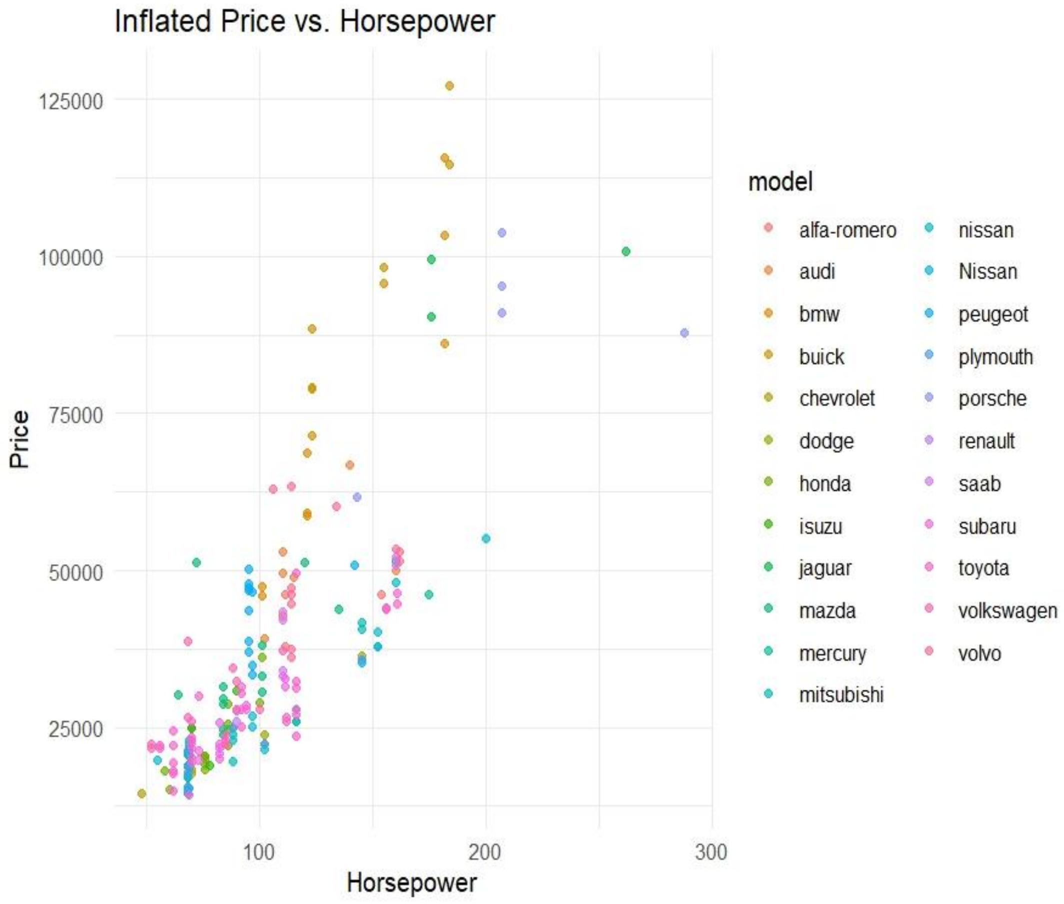
- The dataset contains 205 observations and 16 features.
- Features include a mix of continuous and categorical variables.
- No missing data.
- New price created based on the inflation factor, to make the dataset mode realistic.

| wheelbase | carlength | carwidth | carheight | curbweight | enginesize | boreratio | stroke | compressionratio | horsepower | peakrpm | highwaympg | new_price | fueltype | doornumber | carbody | drivewheel | model |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 96.5 | 175.4 | 62.5 | 54.1 | 2372 | 110 | 3.15 | 3.580 | 9.0 | 86 | 5800 | 33 | 28826.0 | gas | four | sedan | fwd | honda |
| 95.3 | 169.0 | 65.7 | 49.6 | 2385 | 70 | 3.33 | 3.255 | 9.4 | 101 | 6000 | 23 | 38206.0 | gas | two | hatchback | rwd | mazda |
| 110.0 | 190.9 | 70.3 | 58.7 | 3750 | 183 | 3.58 | 3.640 | 21.5 | 123 | 4350 | 25 | 79094.4 | diesel | four | wagon | rwd | buick |
| 99.1 | 186.6 | 66.5 | 56.1 | 2847 | 121 | 3.54 | 3.070 | 9.0 | 160 | 5500 | 26 | 52136.0 | gas | four | sedan | fwd | saab |
| 102.9 | 183.5 | 67.7 | 52.0 | 3016 | 171 | 3.27 | 3.350 | 9.3 | 161 | 5200 | 24 | 44794.4 | gas | two | hatchback | rwd | toyota |
| 97.3 | 171.7 | 65.5 | 55.7 | 2275 | 109 | 3.19 | 3.400 | 9.0 | 85 | 5250 | 34 | 23786.0 | gas | four | sedan | fwd | volkswagen |
| 86.6 | 144.6 | 63.9 | 50.8 | 1819 | 92 | 2.91 | 3.410 | 9.2 | 76 | 6000 | 38 | 19194.0 | gas | two | hatchback | fwd | honda |
| 102.7 | 178.4 | 68.0 | 54.8 | 2910 | 140 | 3.78 | 3.120 | 8.0 | 175 | 5000 | 24 | 46208.4 | gas | two | hatchback | rwd | mercury |
| 94.5 | 155.9 | 63.6 | 52.0 | 1874 | 90 | 3.03 | 3.110 | 9.6 | 70 | 5400 | 43 | 24966.2 | gas | two | sedan | fwd | isuzu |
| 98.4 | 176.2 | 65.6 | 52.0 | 2551 | 146 | 3.62 | 3.500 | 9.3 | 116 | 4800 | 30 | 27969.2 | gas | two | hatchback | rwd | toyota |

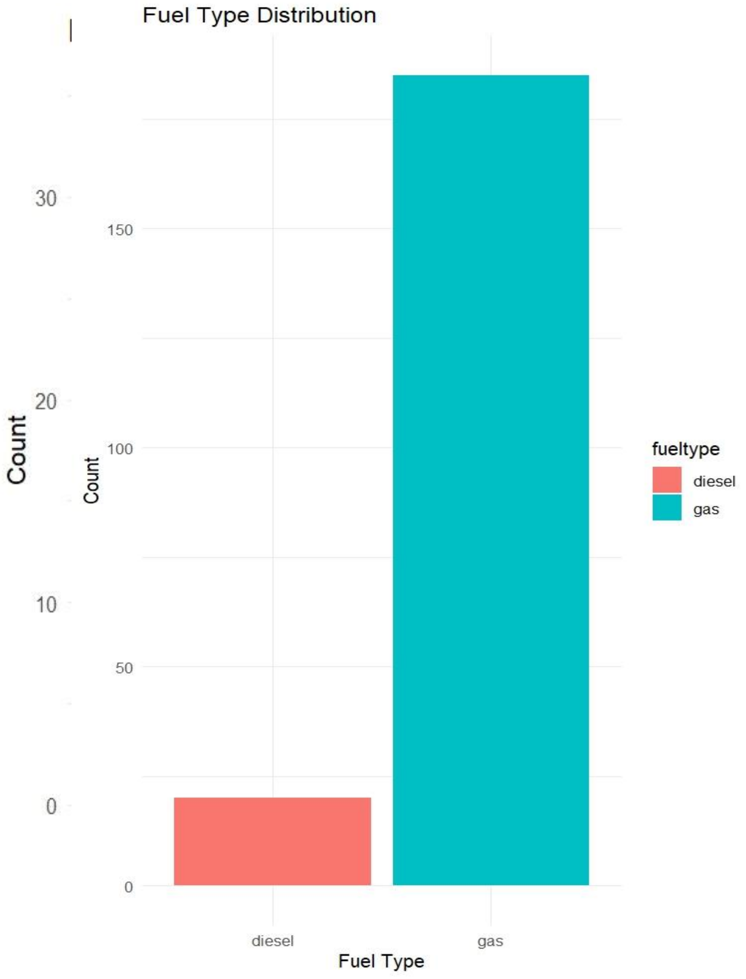
Mean Price by Car Brand
jaguar
buick
porsche
bmw
volvo
audi
mercury
alfa-romero
peugeot
saab
nissan
mazda
volkswagen
toyota
renault
mitsubishi
isuzu
subaru
honda
plymouth
dodge
chevrolet
Nissan
Car Brand (model)
25000
50000
75000
100000
Mean Price
model
alfa-romero
audi
bmw
buick
chevrolet
dodge
honda
isuzu
jaguar
mazda
mercury
mitsubishi
nissan
Nissan
peugeot
plymouth
porsche
renault
saab
subaru
toyota
volkswagen
volvo

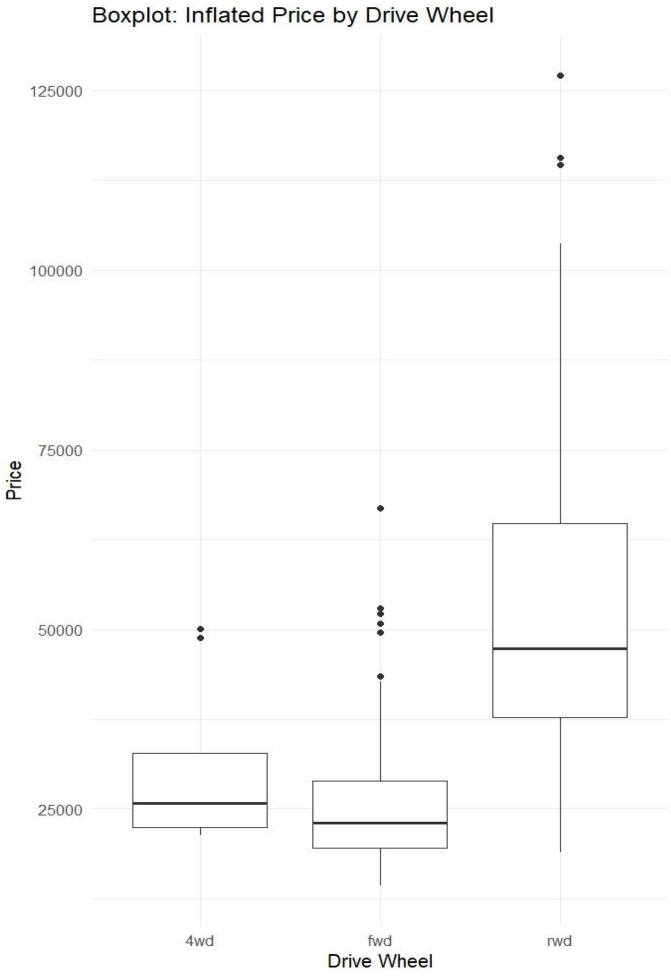
# Univariate Analysis

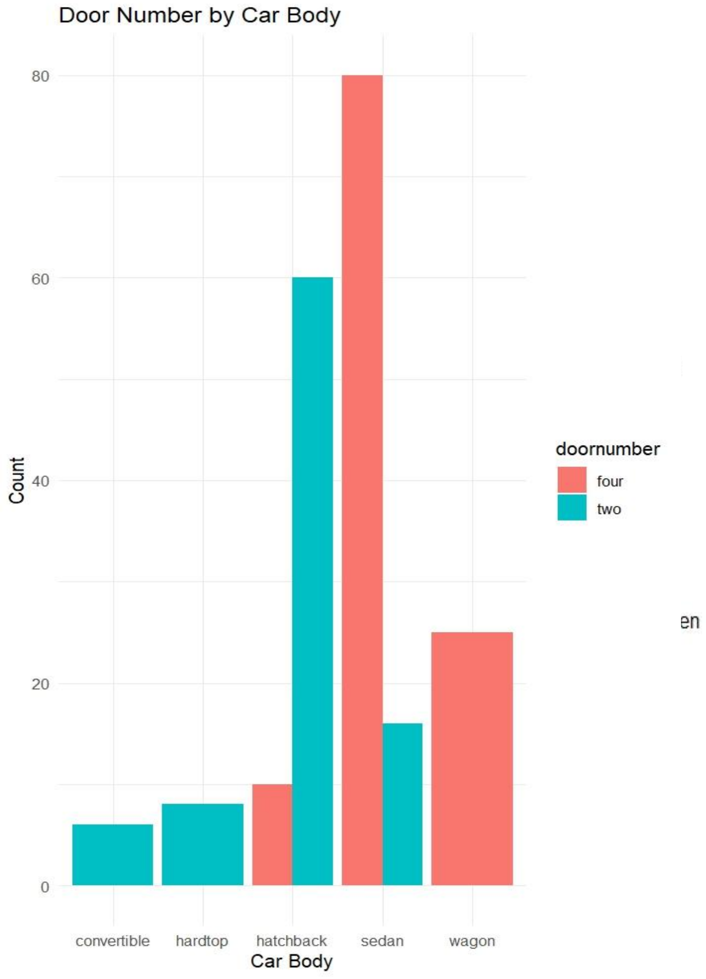


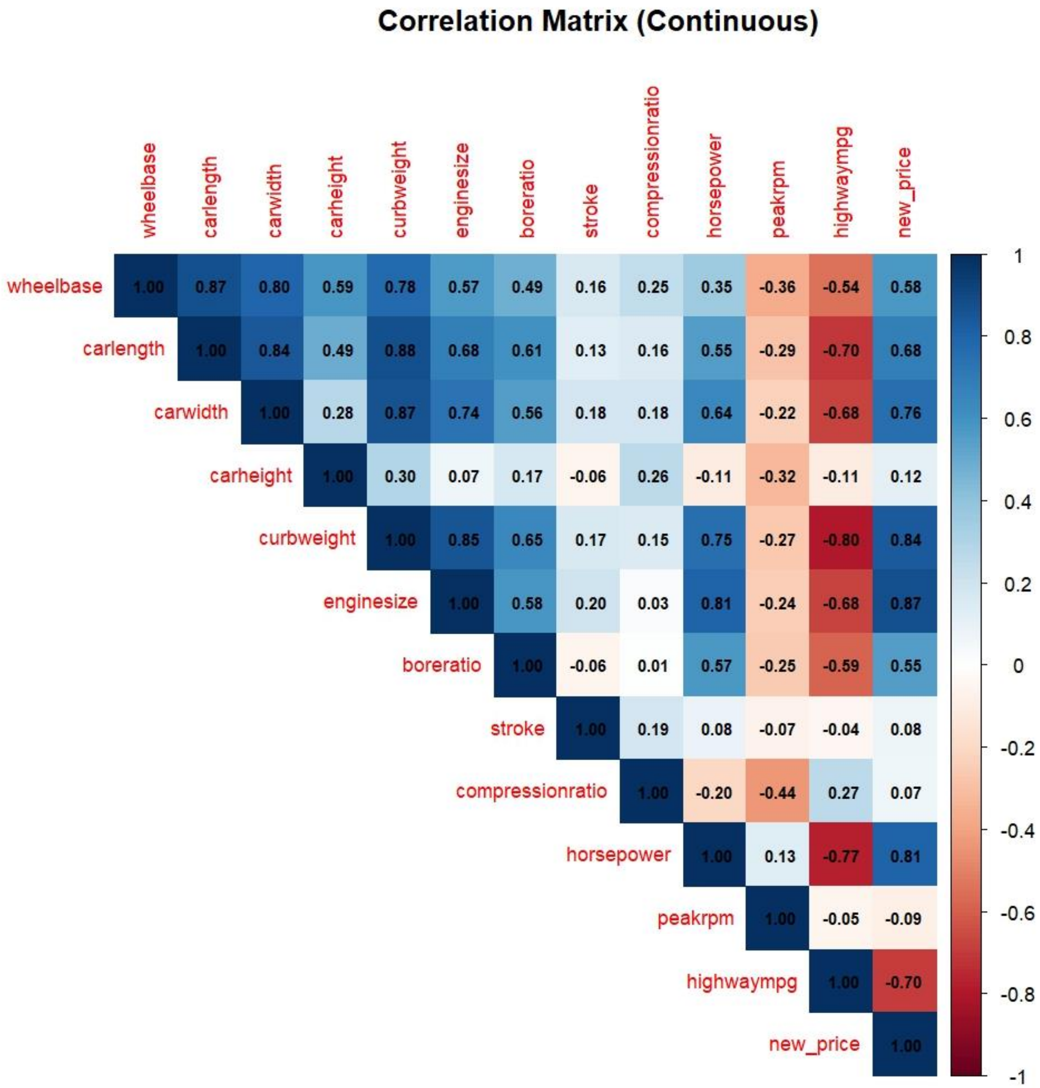
# Univariate Analysis



# Feature Relationships




- Strong positive correlation between curb weight, engine size, and new price.
- Negative correlation between highwaympg and price.

# Model 1: Ridge Regression

**Problem**:

**Collinearity** in predictors → unstable OLS coefficients (high variance).

Removing variables via **VIF** risks losing relevant predictors.

**Key Question**:
Are we certain variables removed by VIF are truly unrelated to the response?

**VIF** identifies **redundancy** (correlation between predictors), not **irrelevance**.

**The need to use RIDGE:**

**Retain all variables** but shrink coefficients via **L2 penalty**.

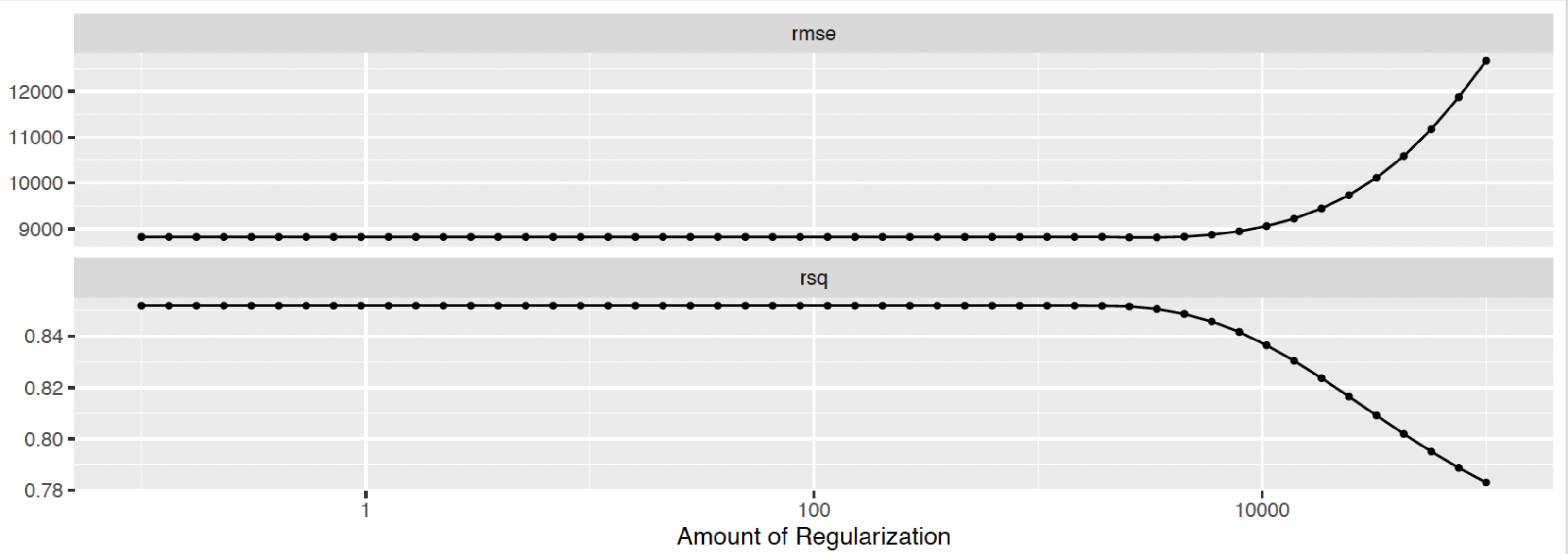
Addresses collinearity without assuming irrelevance.

Ridge preserves variables while stabilizing estimates → better for **prediction** and **collinear data**.

## Coefficients of the model

```
   term              estimate penalty
   <chr>                <dbl>   <dbl>
 1 (Intercept)         37935.     0.1
 2 wheelbase             638.     0.1
 3 carlength           -1155.     0.1
 4 carwidth             3756.     0.1
 5 carheight            1325.     0.1
 6 curbweight           2566.     0.1
 7 enginesize           9206.     0.1
 8 boreratio           -1096.     0.1
 9 stroke              -1776.     0.1
10 compressionratio      474.     0.1
# i 11 more rows
```

RMSE=8947
RSQ = 0.834
Lambda = 0.1



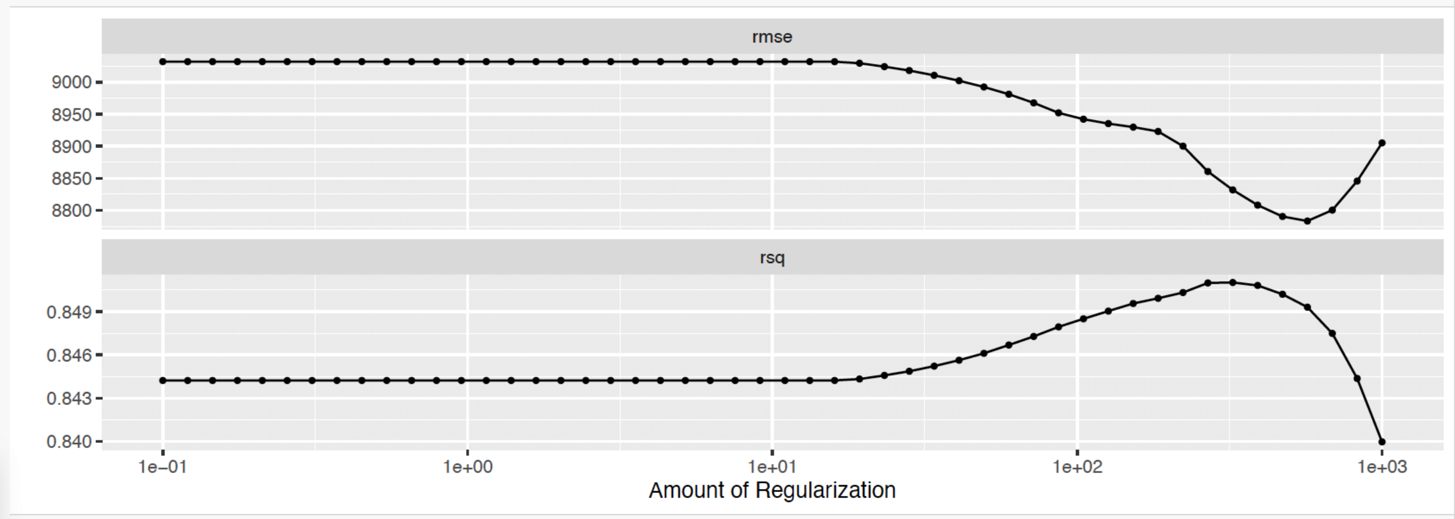
# Model 2: Lasso Regression

| **Problem** |
|---|
| VIF identifies multicollinearity but does not distinguish between relevance and irrelevance. |
| We might miss relevant variables via vif approach. |
| **Lasso Regression** |
| Applies an **L1 penalty** to shrink coefficients of irrelevant or redundant variables to **zero**, automatically excluding them from the model. |
| Outcome: |
| Focuses only on influential predictors. |
| Mitigates overfitting by eliminating noise. |

## Coefficients of the model

```
   term             estimate penalty
   <chr>               <dbl>   <dbl>
 1 (Intercept)      37935.      184.
 2 wheelbase            0       184.
 3 carlength           -0.129   184.
 4 carwidth          4039.      184.
 5 carheight         1644.      184.
 6 curbweight           0       184.
 7 enginesize       12419.      184.
 8 boreratio        -1010.      184.
 9 stroke           -1954.      184.
10 compressionratio     0       184.
# i 11 more rows
```

RMSE = 8960
RSQ = 0.835
Lambda = 184.0



# Comparison

As a baseline, we fit a MLR (OLS) model using the same training dataset to compare the test RMSE and $R^2$ to that of our ridge & lasso models.

Looking at both model metrics, of the three models, it looks like both ridge & lasso do a better job of predicting the data, with roughly half the test RMSE.

| Model | RMSE (2025 USD) | $R^2$ |
|---|---|---|
| **OLS Model** | 11,623 | 0.82 |
| **Ridge Model** | 8,947 | 0.834 |
| **Lasso Model** | 8,960 | 0.835 |

# New Vehicle Test

This dataset, however, is from 1987 (with prices adjusted for inflation). The auto industry is very different now.

How well can these models predict newer car prices? We tried with 2 vehicles

- 2005 Honda Civic LX
- 2025 Honda Civic LX

| Model | 2005 Civic* | 2025 Civic* |
|---|---|---|
| Truth | 26,065 | 24,250 |
| Ridge Model | 37,979 | 54,539 |
| Lasso Model | 37,104 | 53,931 |

*both in USD 2025, adjusted for inflation. 2005 Civic sticker price was 16,025

# Conclusions & Lessons Learned

- We used lasso & ridge models to predict car price with RMSE of roughly $9000 USD.
- We used a training dataset where $n = 205$ and $p = 16$. With more data or more insight about predictors, we could fit a better model, or even a more flexible one.
- Both models perform poorly on newer cars. Even though we did not regress over time, changes in vehicles, safety, customers, supply & demand all have different impact over time.

# Thank you!

# Q&A

# Final

Ethan, Sylvester, Navid

```r
library(tidyverse)
library(tidymodels)
library(scales)
library(corrplot)
library(olsrr)
library(caret)
library(gridExtra)
library(glmnet)
library(dials)
```

```r
data <- read_csv(choose.files())
```

```r
glimpse(data)
```

```
Rows: 205
Columns: 26
$ car_ID           <dbl> 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16~
$ symboling        <dbl> 3, 3, 1, 2, 2, 2, 1, 1, 1, 0, 2, 0, 0, 0, 1, 0, 0, 0,~
$ CarName          <chr> "alfa-romero giulia", "alfa-romero stelvio", "alfa-ro~
$ fueltype         <chr> "gas", "gas", "gas", "gas", "gas", "gas", "gas", "gas~
$ aspiration       <chr> "std", "std", "std", "std", "std", "std", "std", "std~
$ doornumber       <chr> "two", "two", "two", "four", "four", "two", "four", "~
$ carbody          <chr> "convertible", "convertible", "hatchback", "sedan", "~
$ drivewheel       <chr> "rwd", "rwd", "rwd", "fwd", "4wd", "fwd", "fwd", "fwd~
$ enginelocation   <chr> "front", "front", "front", "front", "front", "front",~
$ wheelbase        <dbl> 88.6, 88.6, 94.5, 99.8, 99.4, 99.8, 105.8, 105.8, 105~
$ carlength        <dbl> 168.8, 168.8, 171.2, 176.6, 176.6, 177.3, 192.7, 192.~
$ carwidth         <dbl> 64.1, 64.1, 65.5, 66.2, 66.4, 66.3, 71.4, 71.4, 71.4,~
$ carheight        <dbl> 48.8, 48.8, 52.4, 54.3, 54.3, 53.1, 55.7, 55.7, 55.9,~
$ curbweight       <dbl> 2548, 2548, 2823, 2337, 2824, 2507, 2844, 2954, 3086,~
```

```
$ enginetype       <chr> "dohc", "dohc", "ohcv", "ohc", "ohc", "ohc", "ohc", "~
$ cylindernumber   <chr> "four", "four", "six", "four", "five", "five", "five"~
$ enginesize       <dbl> 130, 130, 152, 109, 136, 136, 136, 136, 131, 131, 108~
$ fuelsystem       <chr> "mpfi", "mpfi", "mpfi", "mpfi", "mpfi", "mpfi", "mpfi~
$ boreratio        <dbl> 3.47, 3.47, 2.68, 3.19, 3.19, 3.19, 3.19, 3.19, 3.13,~
$ stroke           <dbl> 2.68, 2.68, 3.47, 3.40, 3.40, 3.40, 3.40, 3.40, 3.40,~
$ compressionratio <dbl> 9.00, 9.00, 9.00, 10.00, 8.00, 8.50, 8.50, 8.50, 8.30~
$ horsepower       <dbl> 111, 111, 154, 102, 115, 110, 110, 110, 140, 160, 101~
$ peakrpm          <dbl> 5000, 5000, 5000, 5500, 5500, 5500, 5500, 5500, 5500,~
$ citympg          <dbl> 21, 21, 19, 24, 18, 19, 19, 19, 17, 16, 23, 23, 21, 2~
$ highwaympg       <dbl> 27, 27, 26, 30, 22, 25, 25, 25, 20, 22, 29, 29, 28, 2~
$ price            <dbl> 13495.00, 16500.00, 16500.00, 13950.00, 17450.00, 152~
```

We'll work with these 4 categorical variables. Also, there were no Missing Values.

```r
data$fueltype       <- as.factor(data$fueltype)
data$doornumber     <- as.factor(data$doornumber)
data$carbody        <- as.factor(data$carbody)
data$drivewheel     <- as.factor(data$drivewheel)
```

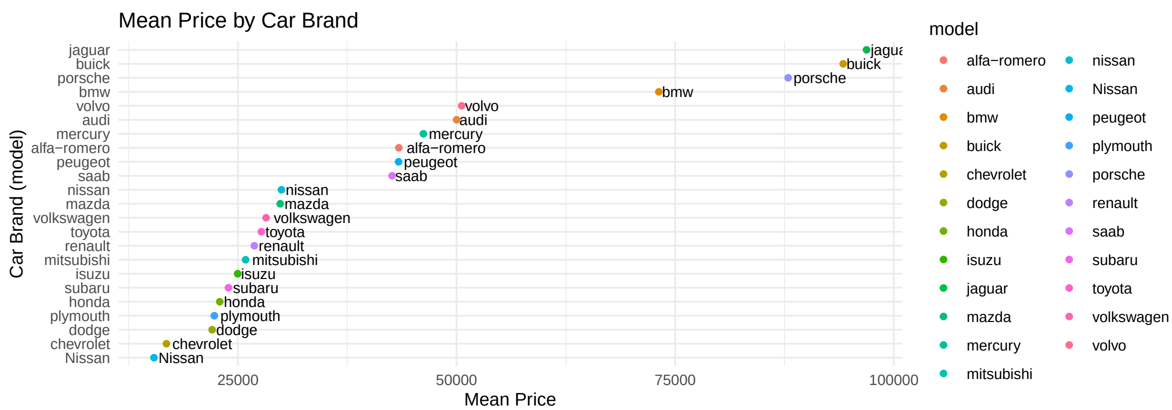
```r
data <- data |>
  mutate(model = word(CarName, 1)) |>    # extract first token
  mutate(model = case_when(
    model %in% c("maxda")                      ~ "mazda",
    model %in% c("mazda")                       ~ "mazda",
    model %in% c("nissan")                      ~ "nissan",
    model %in% c("porcshce", "porsche")          ~ "porsche",
    model %in% c("toyouta", "toyota")            ~ "toyota",
    model %in% c("vokswagen", "vw", "volkswagen") ~ "volkswagen",
    TRUE ~ model
  ))
```

The inflation price which we had talked about. I called it `new_price`

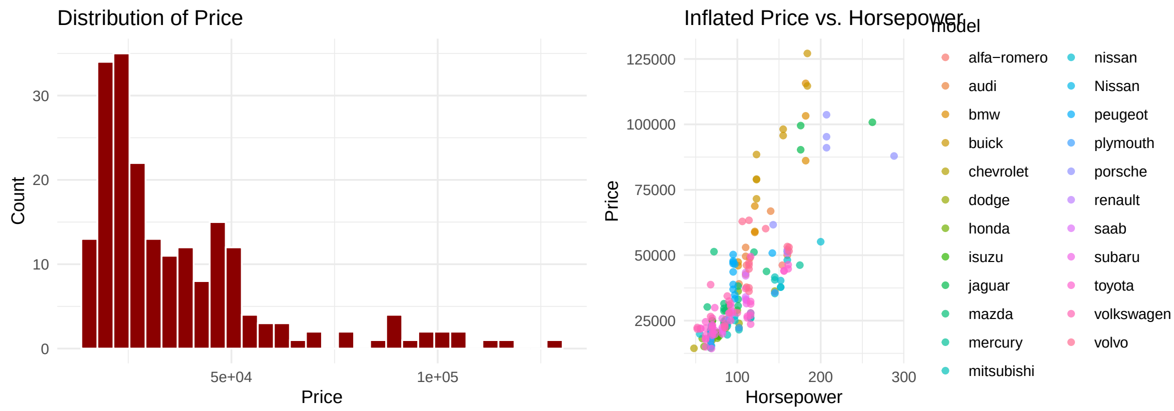
```r
data <- data |>  select(-car_ID, -CarName, -symboling)
data <- data |>
  mutate(new_price = 2.8 * price)
```

```r
brand_avg_price <- data |>
  group_by(model) |>
  summarise(mean_new_price = mean(new_price, na.rm = TRUE)) |>
```

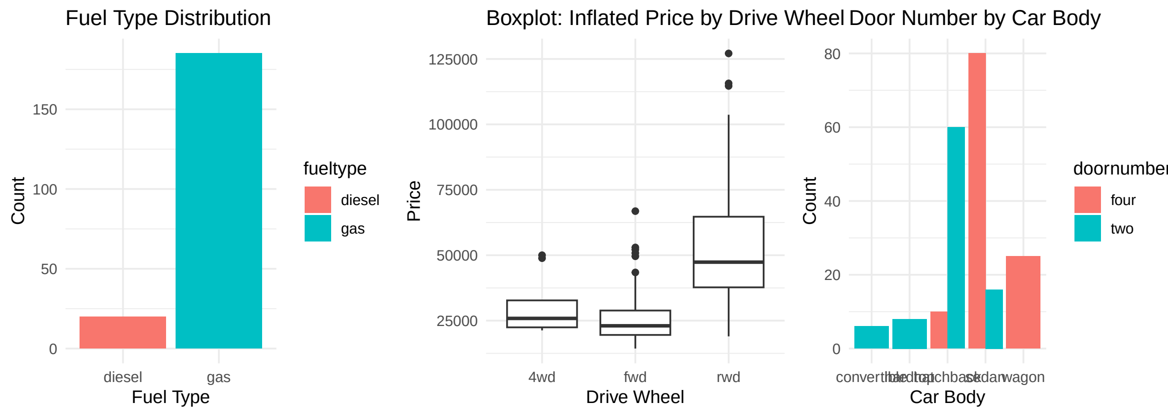
```r
  arrange(mean_new_price)

p_brand_mean <- ggplot(brand_avg_price,
                       aes(x = reorder(model, mean_new_price), y = mean_new_price)) +
  geom_point(aes(color = model)) +
  geom_text(aes(label = model), hjust = -0.1, size = 3) +
  coord_flip() +
  labs(title = "Mean Price by Car Brand",
       x = "Car Brand (model)",
       y = "Mean Price") +
  theme_minimal()

print(p_brand_mean)
```




```r
p_cont2 <- ggplot(data, aes(x = new_price)) +
  geom_histogram(bins = 30, color = "white", fill = "red4") +
  labs(title = "Distribution of Price",
       x = "Price", y = "Count") +
  theme_minimal()

# 3c. Scatter: new_price vs. horsepower
p_cont3 <- ggplot(data, aes(x = horsepower, y = new_price, color = model)) +
  geom_point(alpha = 0.7) +
  labs(title = "Inflated Price vs. Horsepower",
       x = "Horsepower", y = "Price") +
  theme_minimal()

grid.arrange(p_cont2, p_cont3, nrow = 1)
```

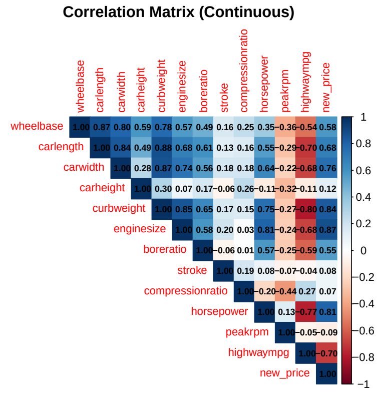



```
# 4a. Bar chart of fueltype
p_cat1 <- ggplot(data, aes(x = fueltype)) +
  geom_bar(aes(fill = fueltype)) +
  labs(title = "Fuel Type Distribution",
       x = "Fuel Type", y = "Count") +
  theme_minimal()

# 4b. Boxplot of new_price by drivewheel
p_cat2 <- ggplot(data, aes(x = drivewheel, y = new_price)) +
  geom_boxplot() +
  labs(title = "Boxplot: Inflated Price by Drive Wheel",
       x = "Drive Wheel", y = "Price") +
  theme_minimal()

# 4c. Bar chart: doornumber by carbody
p_cat3 <- ggplot(data, aes(x = carbody, fill = doornumber)) +
  geom_bar(position = "dodge") +
  labs(title = "Door Number by Car Body",
       x = "Car Body", y = "Count") +
  theme_minimal()

grid.arrange(p_cat1, p_cat2, p_cat3, nrow = 1)
```




```r
cont_vars <- c("wheelbase", "carlength", "carwidth", "carheight",
               "curbweight", "enginesize", "boreratio", "stroke",
               "compressionratio", "horsepower", "peakrpm", "highwaympg",
               "new_price")

cat_vars <- c("fueltype", "aspiration", "doornumber",
              "carbody", "drivewheel", "enginelocation", "enginetype",
              "fuelsystem", "model")
```

```r
corr_mat <- cor(data[cont_vars], use = "complete.obs")

p_cont1 <- corrplot(corr_mat,
                    method = "color",
                    type = "upper",
                    addCoef.col = "black",
                    number.cex = 0.7,
                    tl.cex = 0.8,
                    title = "Correlation Matrix (Continuous)",
                    mar = c(0,0,2,0))
```




```
cat("Average Price by Fuel Type:\n")
```

```
Average Price by Fuel Type:
```

```
print(data %>% group_by(fueltype) %>% summarise(mean_price = mean(new_price)) %>% arrange(
```

```
# A tibble: 2 x 2
  fueltype mean_price
  <fct>         <dbl>
1 gas          36399.
2 diesel       44347.
```

```
cat("Average Price by Aspiration:\n")
```

```
Average Price by Aspiration:
```

```
print(data %>% group_by(aspiration) %>% summarise(mean_price = mean(new_price)) %>% arrang
```

```
# A tibble: 2 x 2
  aspiration mean_price
  <chr>           <dbl>
1 std            35312.
2 turbo          45635.
```

```r
cat("Average Price by Carbody:\n")
```

```
Average Price by Carbody:
```

```r
print(data %>% group_by(carbody) %>% summarise(mean_price = mean(new_price)) %>% arrange(m
```

```
# A tibble: 5 x 2
  carbody     mean_price
  <fct>            <dbl>
1 hatchback       29055.
2 wagon           34641.
3 sedan           40164.
4 convertible     61293.
5 hardtop         62184.
```

```r
cat("Average Price by Drivewheel:\n")
```

```
Average Price by Drivewheel:
```

```r
print(data %>% group_by(drivewheel) %>% summarise(mean_price = mean(new_price)) %>% arrang
```

```
# A tibble: 3 x 2
  drivewheel mean_price
  <fct>           <dbl>
1 fwd            25870.
2 4wd            31045.
3 rwd            55750.
```

```r
cat("Average Price by Enginelocation:\n")
```

```
Average Price by Enginelocation:
```

```r
print(data %>% group_by(enginelocation) %>% summarise(mean_price = mean(new_price)) %>% ar
```

```
# A tibble: 2 x 2
  enginelocation mean_price
  <chr>               <dbl>
1 front              36291.
2 rear               96678.
```

```r
cat("Average Price by Enginetype:\n")
```

```
Average Price by Enginetype:
```

```r
print(data %>% group_by(enginetype) %>% summarise(mean_price = mean(new_price)) %>% arrang
```

```
# A tibble: 7 x 2
  enginetype mean_price
  <chr>           <dbl>
1 ohc            32407.
2 rotor          36456
3 ohcf           38468.
4 l              40957.
5 dohc           50726.
6 ohcv           70275.
7 dohcv          87921.
```

```r
cat("Average Price by Fuelsystem:\n")
```

```
Average Price by Fuelsystem:
```

```r
print(data %>% group_by(fuelsystem) %>% summarise(mean_price = mean(new_price)) %>% arrang
```

```
# A tibble: 8 x 2
  fuelsystem mean_price
  <chr>           <dbl>
1 2bbl           20939.
2 1bbl           21156.
3 spdi           30773.
4 spfi           30934.
5 4bbl           34006
```

```
6 mfi              36299.
7 idi              44347.
8 mpfi             49713.
```

```r
cat("Average Price by Model:\n")
```

```
Average Price by Model:
```

```r
print(data %>% group_by(model) %>% summarise(mean_price = mean(new_price)) %>% arrange(des
```

```
# A tibble: 23 x 2
   model        mean_price
   <chr>             <dbl>
 1 jaguar           96880
 2 buick            94212.
 3 porsche          87921.
 4 bmw              73132.
 5 volvo            50577.
 6 audi             50006.
 7 mercury          46208.
 8 alfa-romero      43395.
 9 peugeot          43369.
10 saab             42625.
# i 13 more rows
```

Modeling

```r
tidymodels_prefer()   # optional, to prefer tidymodels functions
set.seed(1372)
```

Just Continuous variables.

```r
# Just Continuous

data1 <- data[cont_vars]

data_split <- initial_split(data1, prop = 0.8)
train_data <- training(data_split)
test_data  <- testing(data_split)
```

```r
model_full <- lm(new_price ~ ., data = train_data)
# Use olsrr's function which can handle aliased coefficients
vif_values <- ols_vif_tol(model_full)
cat("VIF values for full model:\n")
```

```
VIF values for full model:
```

```r
print(vif_values)
```

```
          Variables  Tolerance       VIF
1         wheelbase 0.14380190  6.954011
2         carlength 0.11683808  8.558853
3          carwidth 0.16663830  6.001022
4         carheight 0.43668239  2.289994
5        curbweight 0.04331503 23.086677
6        enginesize 0.12803537  7.810342
7         boreratio 0.48008907  2.082947
8            stroke 0.86149090  1.160778
9  compressionratio 0.50941347  1.963042
10       horsepower 0.13143902  7.608091
11          peakrpm 0.52624950  1.900239
12       highwaympg 0.17579580  5.688418
```

VIFs.

```r
# VIF more than 10
vif_values |>
  filter(VIF > 10)
```

```
   Variables  Tolerance      VIF
1 curbweight 0.04331503 23.08668
```

Simple multiple regression model.

```r
## just curbweight
train_data_without_vif_10 <- train_data |>
  select(!curbweight)
```

```r
model_full <- lm(new_price ~ ., data = train_data_without_vif_10)
summary(model_full)
```

```
Call:
lm(formula = new_price ~ ., data = train_data_without_vif_10)

Residuals:
     Min       1Q   Median       3Q      Max 
-29064.6  -4468.6   -527.2   3985.8  28284.7 

Coefficients:
                   Estimate Std. Error t value Pr(>|t|)    
(Intercept)      -1.196e+05  4.389e+04  -2.725  0.00718 ** 
wheelbase         2.591e+02  2.782e+02   0.931  0.35323    
carlength        -1.935e+02  1.518e+02  -1.274  0.20446    
carwidth          1.295e+03  7.135e+02   1.815  0.07148 .  
carheight         5.974e+02  4.013e+02   1.489  0.13865    
enginesize        3.219e+02  4.105e+01   7.841 7.28e-13 ***
boreratio        -2.748e+03  3.426e+03  -0.802  0.42378    
stroke           -7.518e+03  2.046e+03  -3.675  0.00033 ***
compressionratio  9.163e+02  2.193e+02   4.178 4.94e-05 ***
horsepower        1.248e+02  4.351e+01   2.869  0.00470 ** 
peakrpm           5.802e+00  1.882e+00   3.083  0.00243 ** 
highwaympg       -3.863e+02  1.949e+02  -1.982  0.04931 *  
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 8177 on 152 degrees of freedom
Multiple R-squared:  0.8566,	Adjusted R-squared:  0.8463 
F-statistic: 82.57 on 11 and 152 DF,  p-value: < 2.2e-16
```

```r
pred_baseline <- predict(model_full, newdata = test_data)
rmse_baseline <- sqrt(mean((pred_baseline - test_data$new_price)^2))
r2_baseline   <- cor(pred_baseline, test_data$new_price)^2
cat("Baseline Linear Regression RMSE:", round(rmse_baseline, 2), "\n")
```

```
Baseline Linear Regression RMSE: 11623.55
```

```r
cat("Baseline Linear Regression R2:", round(r2_baseline, 2), "\n")
```

```
Baseline Linear Regression R2: 0.82
```

```r
# ###
# # VIF more than 5
#
# vif_values |>
#   filter(VIF > 5)
#
# ## just curbweight
#
# train_data_without_vif_5 <- train_data |>
#   select(-c(wheelbase, carlength, carwidth, curbweight, enginesize, horsepower, highwaym
#
# model_full <- lm(new_price ~ ., data = train_data_without_vif_5)
# summary(model_full)
#
#
# pred_baseline <- predict(model_full, newdata = test_data)
# rmse_baseline <- sqrt(mean((pred_baseline - test_data$new_price)^2))
# r2_baseline   <- cor(pred_baseline, test_data$new_price)^2
# cat("Baseline Linear Regression RMSE:", round(rmse_baseline, 2), "\n")
# cat("Baseline Linear Regression R2:", round(r2_baseline, 2), "\n")
#
# ## It seems that VIF more than 10 works much better than VIF more than 5
#
```

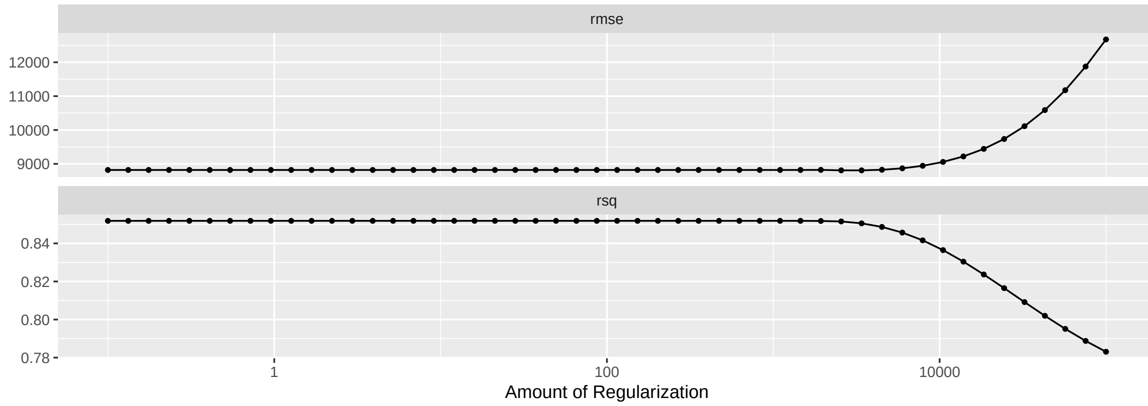
Ridge

```r
## RIDGE
car_fold <- vfold_cv(train_data, v = 10)

ridge_recipe <-
  recipe(formula = new_price ~ ., data = train_data) |>
  step_novel(all_nominal_predictors()) |>
  step_dummy(all_nominal_predictors()) |>
  step_zv(all_predictors()) |>
  step_normalize(all_predictors())

ridge_spec <-
```

```
  linear_reg(penalty = tune(), mixture = 0) |>
  set_mode("regression") |>
  set_engine("glmnet")

ridge_workflow <- workflow() |>
  add_recipe(ridge_recipe) |>
  add_model(ridge_spec)

penalty_grid <- grid_regular(dials::penalty(range = c(-1, 5)), levels = 50)
penalty_grid
```

```
# A tibble: 50 x 1
   penalty
     <dbl>
 1   0.1
 2   0.133
 3   0.176
 4   0.233
 5   0.309
 6   0.409
 7   0.543
 8   0.720
 9   0.954
10   1.26
# i 40 more rows
```

```
tune_res <- tune_grid(
  ridge_workflow,
  resamples = car_fold,
  grid = penalty_grid
)

autoplot(tune_res)
```




Ridge Metrics

```
collect_metrics(tune_res) |>
  tail()
```

```
# A tibble: 6 x 7
  penalty .metric .estimator      mean     n   std_err .config
    <dbl> <chr>   <chr>          <dbl> <int>     <dbl> <chr>
1  56899. rmse    standard   11176.       10 1507.     Preprocessor1_Model48
2  56899. rsq     standard       0.795    10    0.0340 Preprocessor1_Model48
3  75431. rmse    standard   11875.       10 1557.     Preprocessor1_Model49
4  75431. rsq     standard       0.789    10    0.0351 Preprocessor1_Model49
5 100000  rmse    standard   12675.       10 1599.     Preprocessor1_Model50
6 100000  rsq     standard       0.783    10    0.0360 Preprocessor1_Model50
```

```
best_penalty <- select_best(tune_res, metric = "rmse")
best_penalty
```

```
# A tibble: 1 x 2
  penalty .config
    <dbl> <chr>
1   3393. Preprocessor1_Model38
```

```
ridge_final <- finalize_workflow(ridge_workflow, best_penalty)
ridge_final_fit <- fit(ridge_final, data = train_data)
```

```r
augment(ridge_final_fit, new_data = test_data) |>
  rsq(truth = new_price, estimate = .pred)
```

```
# A tibble: 1 x 3
  .metric .estimator .estimate
  <chr>   <chr>          <dbl>
1 rsq     standard       0.815
```

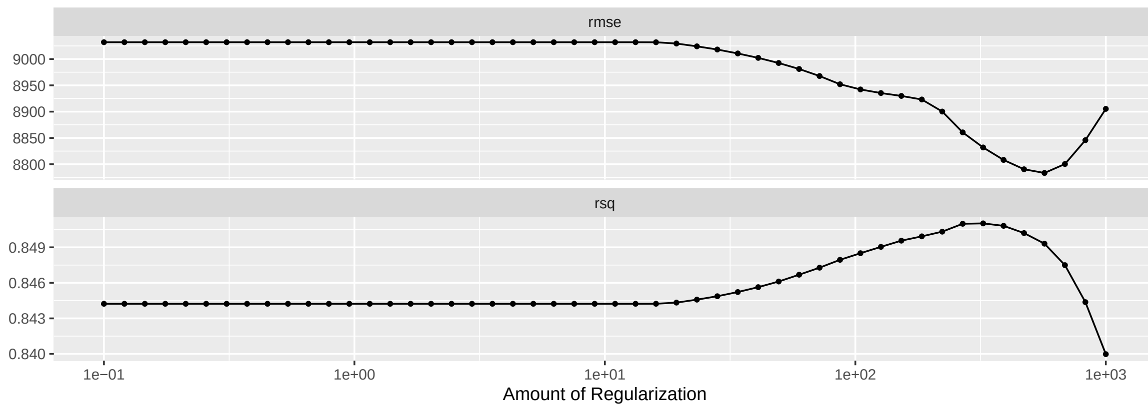
```r
augment(ridge_final_fit, new_data = test_data) |>
  rmse(truth = new_price, estimate = .pred)
```

```
# A tibble: 1 x 3
  .metric .estimator .estimate
  <chr>   <chr>          <dbl>
1 rmse    standard      12575.
```

Lasso

```r
### LASSO
lasso_recipe <-
  recipe(formula = new_price ~ ., data = train_data) |>
  step_novel(all_nominal_predictors()) |>
  step_dummy(all_nominal_predictors()) |>
  step_zv(all_predictors()) |>
  step_normalize(all_predictors())

lasso_spec <-
  linear_reg(penalty = tune(), mixture = 1) |>
  set_mode("regression") |>
  set_engine("glmnet")

lasso_workflow <- workflow() |>
  add_recipe(lasso_recipe) |>
  add_model(lasso_spec)

penalty_grid <- grid_regular(penalty(range = c(-1, 3)), levels = 50)

tune_res <- tune_grid(
  lasso_workflow,
```

```
  resamples = car_fold,
  grid = penalty_grid
)

autoplot(tune_res)
```




Lasso Metrics

```
best_penalty <- select_best(tune_res, metric = "rmse")

lasso_final <- finalize_workflow(lasso_workflow, best_penalty)

lasso_final_fit <- fit(lasso_final, data = train_data)

augment(lasso_final_fit, new_data = test_data) |>
  rsq(truth = new_price, estimate = .pred)
```

```
# A tibble: 1 x 3
  .metric .estimator .estimate
  <chr>   <chr>          <dbl>
1 rsq     standard       0.813
```

```
augment(lasso_final_fit, new_data = test_data) |>
  rmse(truth = new_price, estimate = .pred)
```

```
# A tibble: 1 x 3
```

```
  .metric .estimator .estimate
  <chr>   <chr>          <dbl>
1 rmse    standard      12359.
```

```
tidy(lasso_final_fit)
```

```
# A tibble: 13 x 3
   term             estimate penalty
   <chr>               <dbl>   <dbl>
 1 (Intercept)       36415.     569.
 2 wheelbase             0      569.
 3 carlength             0      569.
 4 carwidth           1000.     569.
 5 carheight            26.1    569.
 6 curbweight         5715.     569.
 7 enginesize         8900.     569.
 8 boreratio             0      569.
 9 stroke            -1667.     569.
10 compressionratio   1737.     569.
11 horsepower         4429.     569.
12 peakrpm            1811.     569.
13 highwaympg            0      569.
```

```
tidy(ridge_final_fit)
```

```
# A tibble: 13 x 3
   term             estimate penalty
   <chr>               <dbl>   <dbl>
 1 (Intercept)        36415.   3393.
 2 wheelbase            349.   3393.
 3 carlength           -282.   3393.
 4 carwidth            2146.   3393.
 5 carheight            323.   3393.
 6 curbweight          4238.   3393.
 7 enginesize          7289.   3393.
 8 boreratio           -190.   3393.
 9 stroke             -1780.   3393.
10 compressionratio    2401.   3393.
11 horsepower          5106.   3393.
12 peakrpm             1809.   3393.
13 highwaympg         -1435.   3393.
```

Adding 4 categorical variables. [fueltype, doornumber, carbody, drivewheel]

```
data2 <- data1 |>
  bind_cols(data[cat_vars][c(1, 3, 4, 5)])

data_split_2 <- initial_split(data2, prop = 0.8)
train_data_2 <- training(data_split_2)
test_data_2  <- testing(data_split_2)


model_full_2 <- lm(new_price ~ ., data = train_data_2)
# Use olsrr's function which can handle aliased coefficients
vif_values_2 <- ols_vif_tol(model_full_2)
cat("VIF values for full model:\n")
```

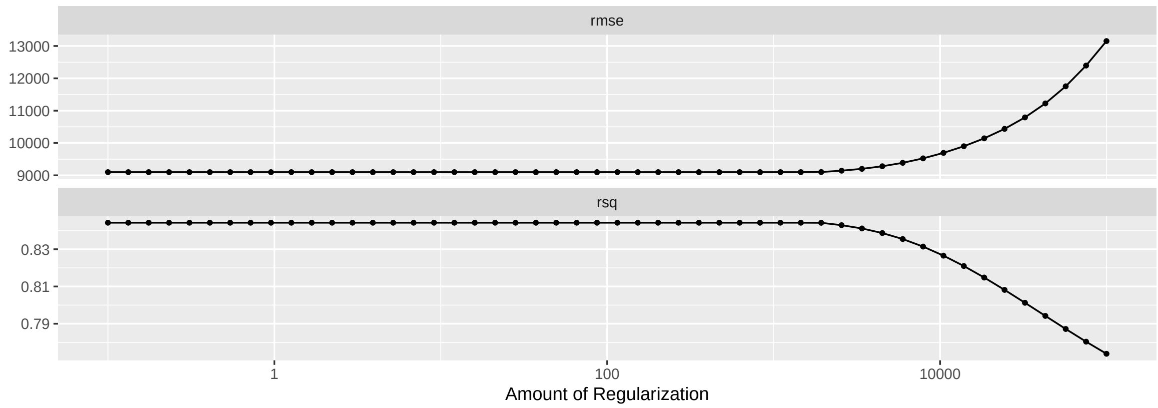
```
VIF values for full model:
```

```
print(vif_values_2)
```

```
            Variables  Tolerance       VIF
1           wheelbase 0.10584039  9.448189
2           carlength 0.08109906 12.330599
3            carwidth 0.16113389  6.206019
4           carheight 0.35739561  2.798020
5          curbweight 0.02954480 33.846900
6          enginesize 0.10281097  9.726589
7           boreratio 0.40700031  2.457001
8              stroke 0.62090518  1.610552
9    compressionratio 0.01593290 62.763225
10         horsepower 0.11778886  8.489767
11            peakrpm 0.42839379  2.334301
12         highwaympg 0.15164860  6.594192
13        fueltypegas 0.01492706 66.992431
14      doornumbertwo 0.34539557  2.895231
15     carbodyhardtop 0.32494701  3.077425
16   carbodyhatchback 0.09157985 10.919433
17        carbodysedan 0.06997934 14.289931
18        carbodywagon 0.14411081  6.939105
19      drivewheelfwd 0.08205005 12.187683
20      drivewheelrwd 0.08197961 12.198155
```

Ridge for Continuous and Categoricals

```
car_fold_2 <- vfold_cv(train_data_2, v = 10)

ridge_recipe_2 <-
  recipe(formula = new_price ~ ., data = train_data_2) |>
  step_novel(all_nominal_predictors()) |>
  step_dummy(all_nominal_predictors()) |>
  step_zv(all_predictors()) |>
  step_normalize(all_predictors())

ridge_spec_2 <-
  linear_reg(penalty = tune(), mixture = 0) |>
  set_mode("regression") |>
  set_engine("glmnet")

ridge_workflow_2 <- workflow() |>
  add_recipe(ridge_recipe_2) |>
  add_model(ridge_spec_2)

penalty_grid_2 <- grid_regular(dials::penalty(range = c(-1, 5)), levels = 50)

tune_res_2 <- tune_grid(
  ridge_workflow_2,
  resamples = car_fold_2,
  grid = penalty_grid_2
)

autoplot(tune_res_2)
```



Best Penalty

```r
best_penalty_2 <- select_best(tune_res_2, metric = "rmse")
best_penalty_2
```

```
# A tibble: 1 x 2
  penalty .config
    <dbl> <chr>
1     0.1 Preprocessor1_Model01
```

Ridge Metrics

```r
ridge_final_2 <- finalize_workflow(ridge_workflow_2, best_penalty_2)
ridge_final_fit_2 <- fit(ridge_final_2, data = train_data_2)

augment(ridge_final_fit_2, new_data = test_data_2) |>
  rsq(truth = new_price, estimate = .pred)
```

```
# A tibble: 1 x 3
  .metric .estimator .estimate
  <chr>   <chr>          <dbl>
1 rsq     standard       0.834
```

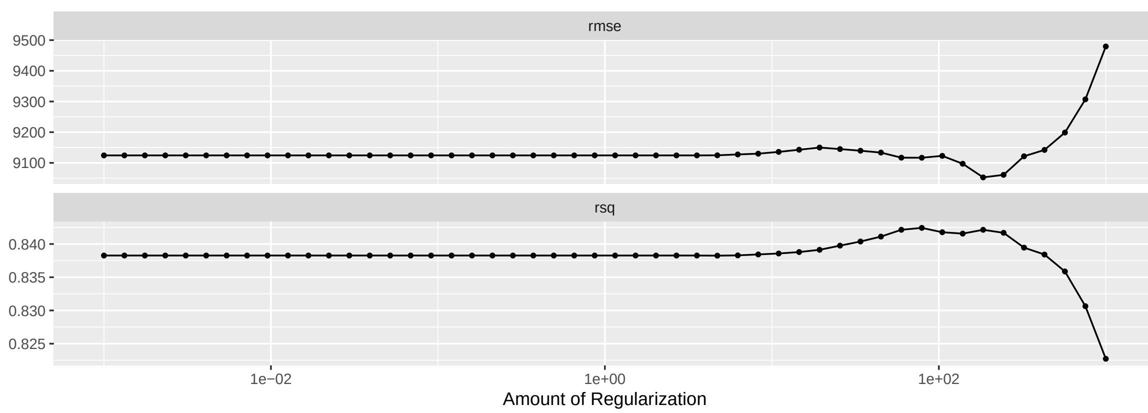
```r
augment(ridge_final_fit_2, new_data = test_data_2) |>
  rmse(truth = new_price, estimate = .pred)
```

```
# A tibble: 1 x 3
  .metric .estimator .estimate
  <chr>   <chr>          <dbl>
1 rmse    standard       8947.
```

Lasso for Continuous and Categoricals

```r
### LASSO
lasso_recipe_2 <-
  recipe(formula = new_price ~ ., data = train_data_2) |>
  step_novel(all_nominal_predictors()) |>
  step_dummy(all_nominal_predictors()) |>
  step_zv(all_predictors()) |>
```

```r
  step_normalize(all_predictors())

lasso_spec_2 <-
  linear_reg(penalty = tune(), mixture = 1) |>
  set_mode("regression") |>
  set_engine("glmnet")

lasso_workflow_2 <- workflow() |>
  add_recipe(lasso_recipe_2) |>
  add_model(lasso_spec_2)

penalty_grid_2 <- grid_regular(penalty(range = c(-3, 3)), levels = 50)

tune_res_2 <- tune_grid(
  lasso_workflow_2,
  resamples = car_fold_2,
  grid = penalty_grid_2
)

autoplot(tune_res_2)
```




Lasso Penalty

```r
best_penalty_2 <- select_best(tune_res_2, metric = "rmse")
best_penalty_2
```

```
# A tibble: 1 x 2
  penalty .config
```

```
    <dbl> <chr>
1    184. Preprocessor1_Model44
```

Lasso Metrics

```r
lasso_final_2 <- finalize_workflow(lasso_workflow_2, best_penalty_2)

lasso_final_fit_2 <- fit(lasso_final_2, data = train_data_2)

augment(lasso_final_fit_2, new_data = test_data_2) |>
  rsq(truth = new_price, estimate = .pred)
```

```
# A tibble: 1 x 3
  .metric .estimator .estimate
  <chr>   <chr>          <dbl>
1 rsq     standard       0.835
```

```r
augment(lasso_final_fit_2, new_data = test_data_2) |>
  rmse(truth = new_price, estimate = .pred)
```

```
# A tibble: 1 x 3
  .metric .estimator .estimate
  <chr>   <chr>          <dbl>
1 rmse    standard       8960.
```

```r
tidy(lasso_final_fit_2)
```

```
# A tibble: 21 x 3
   term              estimate penalty
   <chr>                <dbl>   <dbl>
 1 (Intercept)      37935.       184.
 2 wheelbase            0        184.
 3 carlength           -0.129    184.
 4 carwidth          4039.       184.
 5 carheight         1644.       184.
 6 curbweight           0        184.
 7 enginesize       12419.       184.
 8 boreratio        -1010.       184.
 9 stroke           -1954.       184.
```

```
10 compressionratio     0        184.
# i 11 more rows
```

```r
tidy(ridge_final_fit_2)
```

```
# A tibble: 21 x 3
   term             estimate penalty
   <chr>               <dbl>   <dbl>
 1 (Intercept)        37935.     0.1
 2 wheelbase            638.     0.1
 3 carlength          -1155.     0.1
 4 carwidth            3756.     0.1
 5 carheight           1325.     0.1
 6 curbweight          2566.     0.1
 7 enginesize          9206.     0.1
 8 boreratio          -1096.     0.1
 9 stroke             -1776.     0.1
10 compressionratio     474.     0.1
# i 11 more rows
```

Prediction of civic 2025

```r
civic2025 <- data.frame(           fueltype = "gas",
                                   carbody = "sedan",
                                   drivewheel = "fwd",
                                   doornumber = "four",
                                   wheelbase = 107.7,
                                   carlength = 184.8,
                                   carwidth = 70.9,
                                   carheight = 55.7,
                                   curbweight = 2875,
                                   enginesize = 122,
                                   boreratio = 3.2,
                                   stroke = 3.8,
                                   compressionratio = 13,
                                   horsepower = 150,
                                   citympg = 32,
                                   highwaympg = 41,
                                   peakrpm = 6500
)
```

```r
predict(ridge_final_fit, new_data = civic2025)
```

```
# A tibble: 1 x 1
   .pred
   <dbl>
1 52419.
```

```r
predict(lasso_final_fit, new_data = civic2025)
```

```
# A tibble: 1 x 1
   .pred
   <dbl>
1 50858.
```

```r
predict(ridge_final_fit_2, new_data = civic2025)
```

```
# A tibble: 1 x 1
   .pred
   <dbl>
1 54539.
```

```r
predict(lasso_final_fit_2, new_data = civic2025)
```

```
# A tibble: 1 x 1
   .pred
   <dbl>
1 53931.
```

Prediction of civic 2005

```r
civic2005 <- data.frame(fueltype = "gas",
                               carbody = "sedan",
                               drivewheel = "fwd",
                               doornumber = "four",
                               wheelbase = 103.1,
                               carlength = 175.4,
                               carwidth = 67.5,
```

```
                                     carheight = 55.1,
                                     curbweight = 2449,
                                     enginesize = 103.7,
                                     boreratio = 2.95,
                                     stroke = 3.74,
                                     compressionratio = 9.5,
                                     horsepower = 115,
                                     citympg = 27,
                                     highwaympg = 34,
                                     peakrpm = 6100)
```

```
predict(ridge_final_fit, new_data = civic2005)
```

```
# A tibble: 1 x 1
   .pred
   <dbl>
1 35511.
```

```
predict(lasso_final_fit, new_data = civic2005)
```

```
# A tibble: 1 x 1
   .pred
   <dbl>
1 33450.
```

```
predict(ridge_final_fit_2, new_data = civic2005)
```

```
# A tibble: 1 x 1
   .pred
   <dbl>
1 37979.
```

```
predict(lasso_final_fit_2, new_data = civic2005)
```

```
# A tibble: 1 x 1
   .pred
   <dbl>
1 37104.
```