Modeling With Data In The Tidyverse

Your Name Here

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Preface

This material is from the DataCamp course Modeling with Data in the Tidyverse by Albert Y. Kim.

Course Description: In this course, you will learn to model with data. Models attempt to capture the relationship between an outcome variable of interest and a series of explanatory/predictor variables. Such models can be used for both explanatory purposes, e.g. "Does knowing professors' ages help explain their teaching evaluation scores?", and predictive purposes, e.g., "How well can we predict a house's price based on its size and condition?" You will leverage your tidyverse skills to construct and interpret such models. This course centers around the use of linear regression, one of the most commonly-used and easy to understand approaches to modeling. Such modeling and thinking is used in a wide variety of fields, including statistics, causal inference, machine learning, and artificial intelligence.

Reminder to self: each `*.qmd` file contains one and only one chapter, and a chapter is defined by the first-level heading `#`.

1 Introduction to Modeling

This chapter will introduce you to some background theory and terminology for modeling, in particular, the general modeling framework, the difference between modeling for explanation and modeling for prediction, and the modeling problem. Furthermore, you'll start performing your first exploratory data analysis, a crucial first step before any formal modeling.

Background on modeling for explanation - (video)

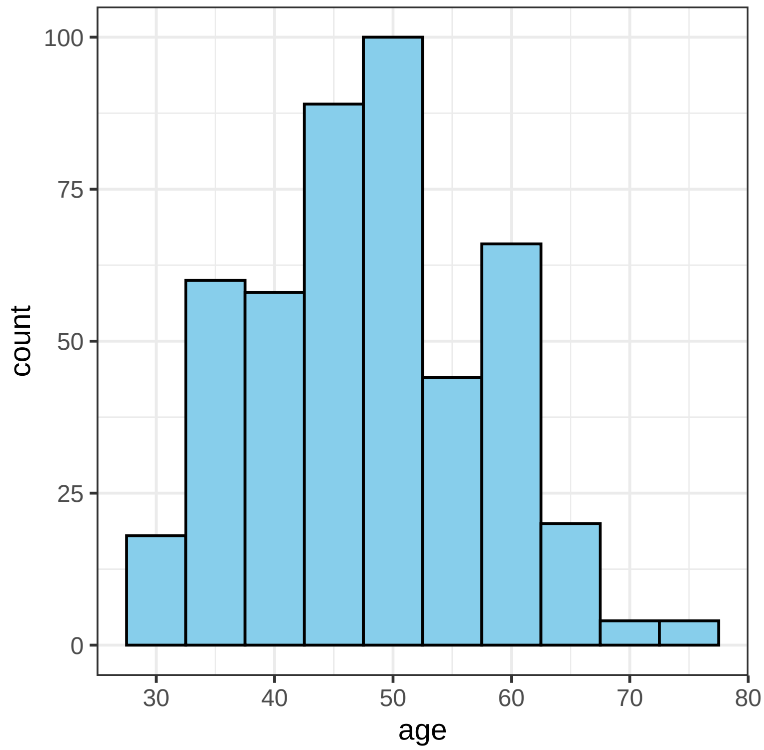
1.1 Exploratory visualization of age

Let's perform an exploratory data analysis (EDA) of the numerical explanatory variable `age`. You should always perform an exploratory analysis of your variables before any formal modeling. This will give you a sense of your variable's distributions, any outliers, and any patterns that might be useful when constructing your eventual model.

- Use the `evals` data set from the `moderndive` package along with `ggplot2` to create a histogram of `age` with bins in 5 year increments.
- Label the `x` axis with `age` and the `y` axis with count.

```
# Load packages
library(moderndive)
library(ggplot2)

# Plot the histogram
ggplot(evals, aes(x = age)) +
  geom_histogram(binwidth = 5, fill = "skyblue", color = "black") +
  labs(x = "age", y = "count") +
  theme_bw()
```



1.2 Numerical summaries of age

Let's continue our exploratory data analysis of the numerical explanatory variable `age` by computing summary statistics. Summary statistics take many values and summarize them with a single value. Let's compute three such values using `dplyr` data wrangling: mean (AKA the average), the median (the middle value), and the standard deviation (a measure of spread/variation).

- Calculate the mean, median, and standard deviation of `age`.

```
# Load packages
library(moderndive)
library(dplyr)

# Compute summary stats
evals |>
  summarize(mean_age = mean(age),
            median_age = median(age),
            sd_age = sd(age),
```

```r
            iqr = IQR(age),
            e1071::skewness(age)) |>
  kable()
```

mean_age	median_age	sd_age	iqr	e1071::skewness(age)
48.36501	48	9.802742	15	0.0483567

Background on modeling for prediction - (video)

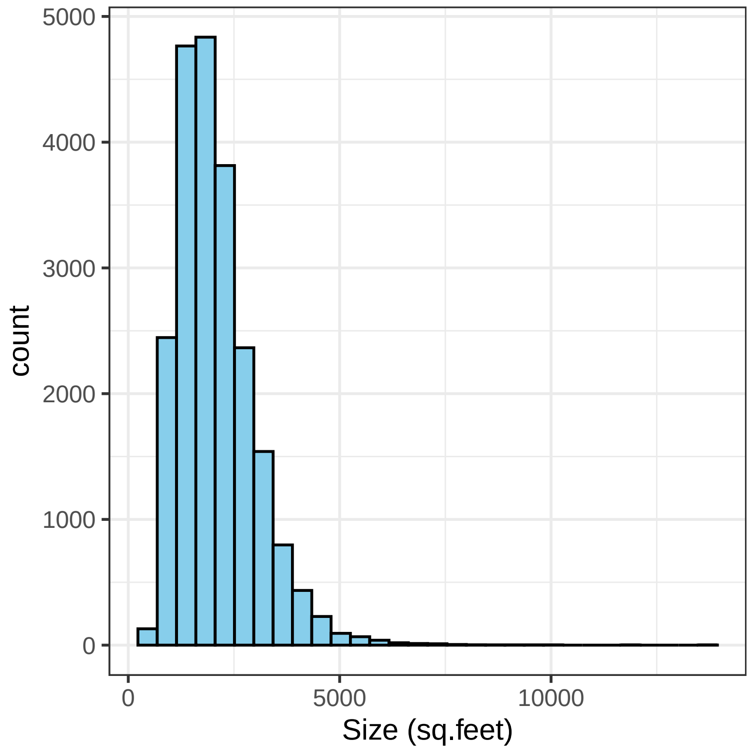
1.3 Exploratory visualization of house size

Let's create an exploratory visualization of the predictor variable reflecting the size of houses: `sqft_living` the square footage of living space where 1 sq.foot $\approx$ 0.1 sq.meter.

After plotting the histogram, what can you say about the distribution of the variable `sqft_living`?

- Create a histogram of `sqft_living` using the `house_prices` data set from the `moderndive` package.
- Label the `x` axis with `"Size (sq.feet)"` and the `y` axis with `"count"`.

```r
# Plot the histogram
ggplot(house_prices, aes(x = sqft_living)) +
  geom_histogram(fill = "skyblue", color = "black") +
  labs(x = "Size (sq.feet)", y = "count") +
  theme_bw()
```



1.4 Log10 transformation of house size

You just saw that the predictor variable `sqft_living` is right-skewed and hence a log base 10 transformation is warranted to unskew it. Just as we transformed the outcome variable price to create `log10_price` in the video, let's do the same for `sqft_living`.

- Using the `mutate()` function from `dplyr`, create a new column `log10_size` and assign it to `house_prices_2` by applying a `log10()` transformation to `sqft_living`.

```
# Add log10_size
house_prices_2 <- house_prices |>
  mutate(log10_size = log10(sqft_living))
```

- Visualize the effect of the `log10()` transformation by creating a histogram of the new variable `log10_size`.

```
# Plot the histogram
ggplot(house_prices_2, aes(x = log10_size)) +
  geom_histogram(fill = "skyblue", color = "black") +
```

```r
  labs(x = "log10 size", y = "count") +
  theme_bw()
```

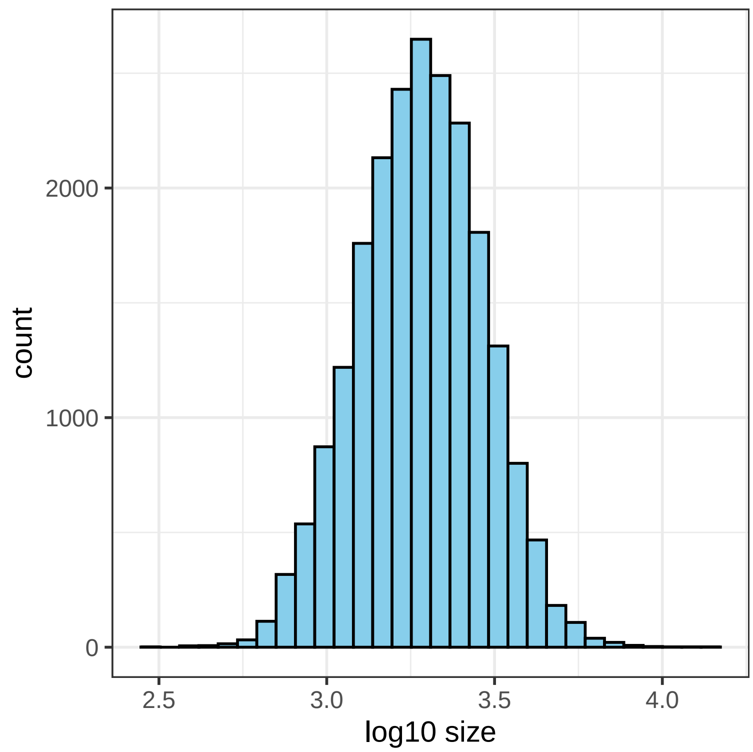


Figure 1.1: Histogram of log10 transformed data

Notice how the distribution is much less skewed in Figure 1.1. Going forward, you will use this new transformed variable to represent the size of houses.

The modeling problem for explanation - (video)

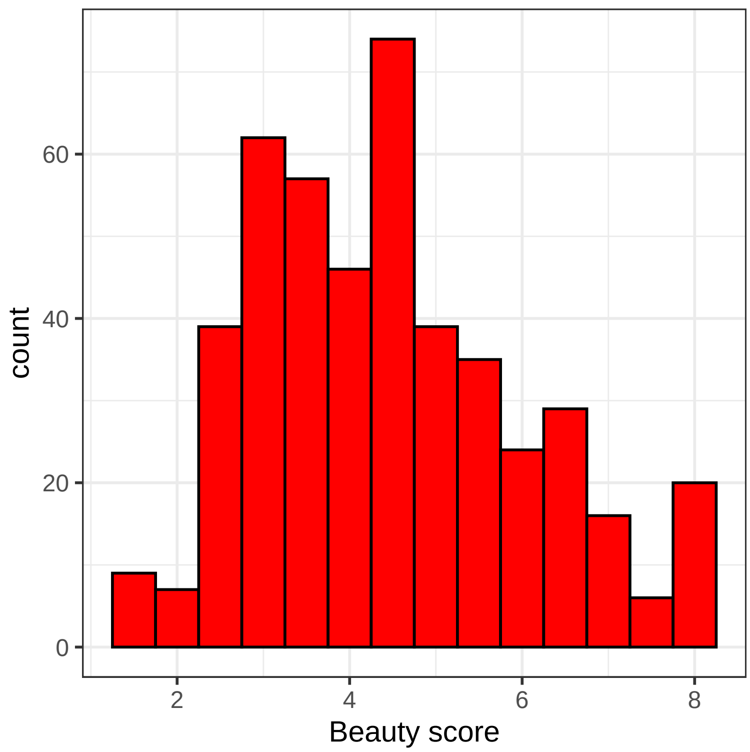
1.5 EDA of relationship of teaching & "beauty" scores

The researchers in the UT Austin created a "beauty score" by asking a panel of 6 students to rate the "beauty" of all 463 instructors. They were interested in studying any possible impact of "beauty" of teaching evaluation scores. Let's do an EDA of this variable and its relationship with teaching `score`. The data are stored in the `evals` data frame from the `moderndive` package.

From now on, assume that ggplot2, dplyr, and moderndive are all available in your workspace unless you're told otherwise.

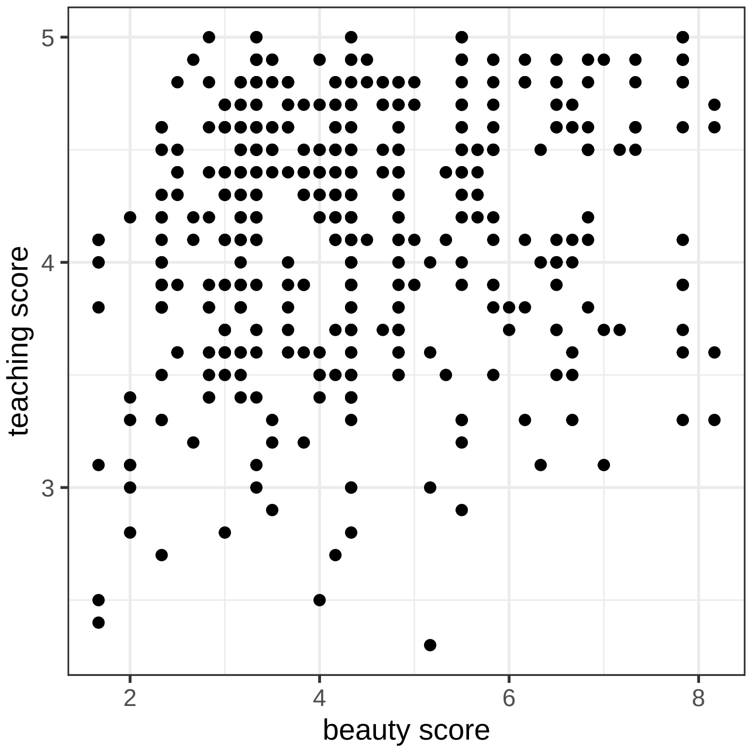
- Create a histogram of bty_avg "beauty scores" with bins of size 0.5.

```
### Plot the histogram
ggplot(evals, aes(x = bty_avg)) +
  geom_histogram(color = "black", fill = "red", binwidth = 0.5) +
  labs(x = "Beauty score", y = "count") +
  theme_bw()
```



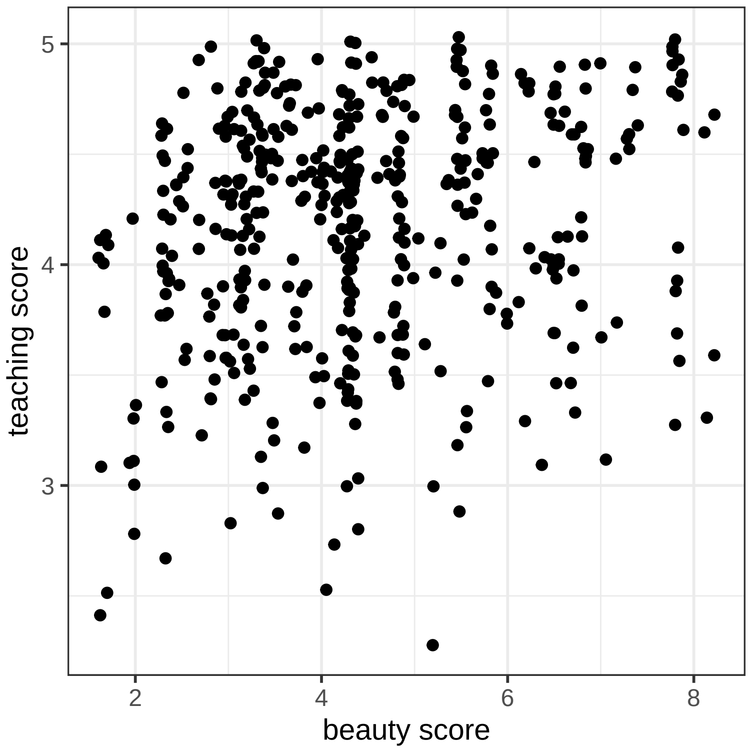
- Create a scatterplot with the outcome variable score on the y-axis and the explanatory variable bty_avg on the x-axis.

```
# Scatterplot
ggplot(evals, aes(x = bty_avg, y = score)) +
  geom_point() +
  labs(x = "beauty score", y = "teaching score") +
  theme_bw()
```



- Let's now investigate if this plot suffers from overplotting, whereby points are stacked perfectly on top of each other, obscuring the number of points involved. You can do this by jittering the points. Update the code accordingly!

```
# Jitter plot
ggplot(evals, aes(x = bty_avg, y = score)) +
  geom_jitter() +
  labs(x = "beauty score", y = "teaching score") +
  theme_bw()
```



It seems the original scatterplot did suffer from overplotting since the jittered scatterplot reveals many originally hidden points. Most `bty_avg` scores range from 2-8, with 5 being about the center.

1.6 Correlation between teaching and "beauty" scores

Let's numerically summarize the relationship between teaching score and beauty score `bty_avg` using the correlation coefficient. Based on this, what can you say about the relationship between these two variables?

- Compute the correlation coefficient of `score` and `bty_avg`.

```
# Compute correlation
evals %>%
  summarize(correlation = cor(score, bty_avg)) -> tr
tr
```

```
# A tibble: 1 x 1
  correlation
```

```
        <dbl>
1       0.187
```

- Highlight the appropriate answer:
  - `score` and `bty_avg` are strongly negatively associated.
  - `score` and `bty_avg` are weakly negatively associated.
  - **`score` and `bty_avg` are weakly positively associated.**
  - `score` and `bty_avg` are strongly positively associated.

While there seems to be a positive relationship, 0.187 is still a long ways from 1, so the correlation is only weakly positive.

The modeling problem for prediction - (video)

1.7 EDA of relationship of house price and waterfront

Let's now perform an exploratory data analysis of the relationship between `log10_price`, the log base 10 house price, and the binary variable `waterfront`. Let's look at the raw values of waterfront and then visualize their relationship.

The column `log10_price` has been added for you in the `house_prices` dataset.

```
house_prices |>
  mutate(log10_price = log10(price)) -> house_prices
```

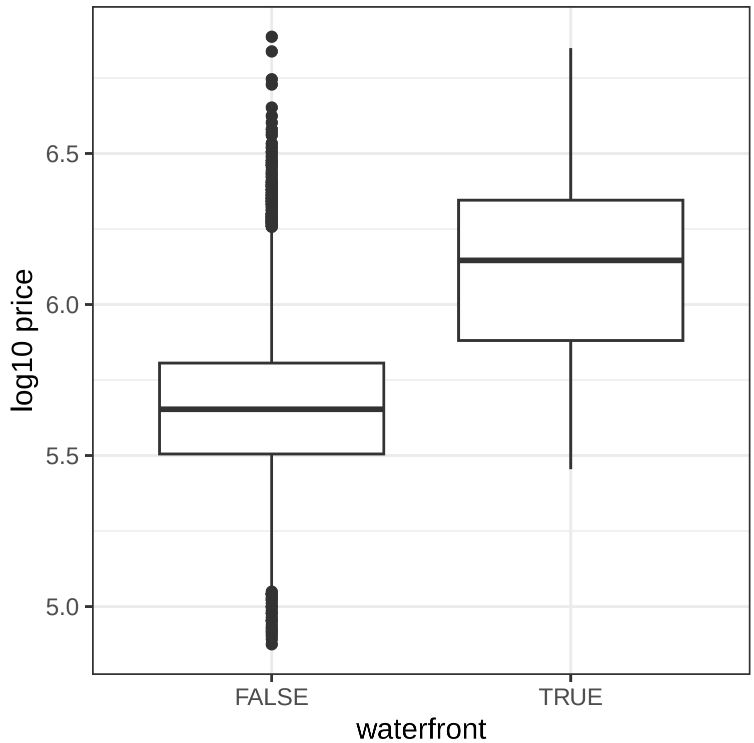
- Use `glimpse()` to view the structure of only two columns: `log10_price` and `waterfront`.

```
# View the structure of log10_price and waterfront
house_prices |>
  select(log10_price, waterfront) |>
  glimpse()
```

```
Rows: 21,613
Columns: 2
$ log10_price <dbl> 5.346157, 5.730782, 5.255273, 5.781037, 5.707570, 6.088136~
$ waterfront  <lgl> FALSE, FALSE, FALSE, FALSE, FALSE, FALSE, FALSE, FALSE, FA~
```

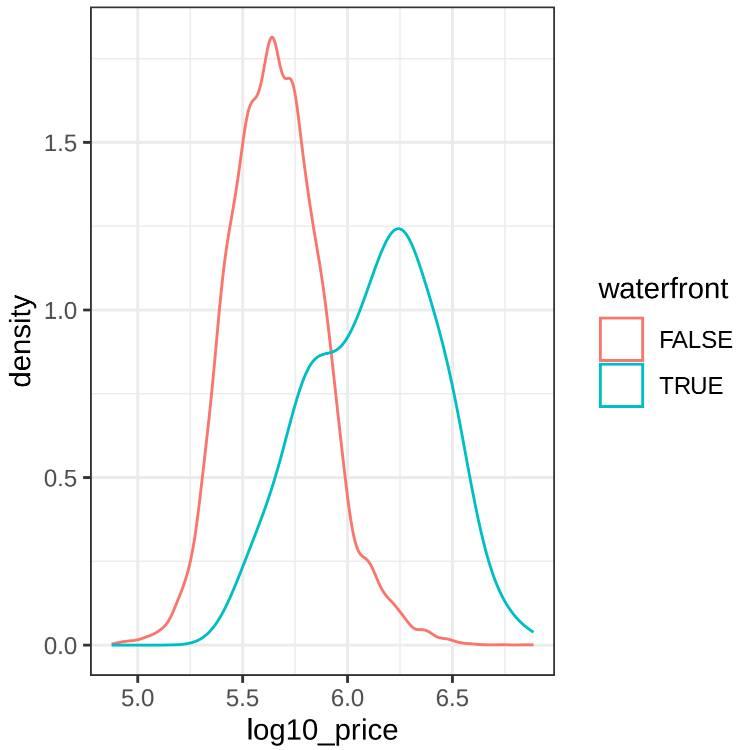
- Visualize the relationship between `waterfront` and `log10_price` using an appropriate `geom_*` function. Remember that `waterfront` is categorical.

```
# Plot
ggplot(house_prices, aes(x = waterfront, y = log10_price)) +
  geom_boxplot() +
  labs(x = "waterfront", y = "log10 price") +
  theme_bw()
```



Look at that boxplot! Houses that have a view of the waterfront tend to be MUCH more expensive as evidenced by the much higher log10 prices!

```
ggplot(data = house_prices, aes(x = log10_price, color = waterfront)) +
  geom_density() +
  theme_bw()
```



1.8 Predicting house price with waterfront

You just saw that houses with a view of the `waterfront` tend to be much more expensive. But by how much? Let's compute group means of `log10_price`, convert them back to dollar units, and compare!

- Return both the mean of `log10_price` and the count of houses in each level of `waterfront`

```
# Calculate stats
house_prices |>
  group_by(waterfront) |>
  summarize(mean_log10_price = mean(log10_price), n = n()) -> hp
hp |>
  kable()
```

waterfront	mean_log10_price	n
FALSE	5.663114	21450
TRUE	6.124689	163

- Using these group means for `log10_price`, return "good" predicted house prices in the original units of US dollars.

```
# Prediction of price for houses with view
10^(6.12)
```

```
[1] 1318257
```

```
10^hp$mean_log10_price[1]
```

```
[1] 460377.2
```

```
# Prediction of price for houses without view
10^(5.66)
```

```
[1] 457088.2
```

```
10^hp$mean_log10_price[2]
```

```
[1] 1332567
```

```
## Or
house_prices |>
  group_by(waterfront) |>
  summarize(mean_log10_price = mean(log10_price), n = n()) |>
  mutate(pred_price = 10^mean_log10_price) -> hp2
hp2 |>
  kable()
```

waterfront	mean_log10_price	n	pred_price
FALSE	5.663114	21450	460377.2
TRUE	6.124689	163	1332566.9

Most houses don't have a view of the `waterfront` ($n = 21,450$), but those that do ($n = 163$) have a MUCH higher predicted price. Look at that difference! $460,377 versus $1,332,567! In the upcoming Chapter 2 on basic regression, we'll build on such intuition and construct our first formal explanatory and predictive models using basic regression!

2 Modeling with Basic Regression

Equipped with your understanding of the general modeling framework, in this chapter, we will cover basic linear regression where you will keep things simple and model the outcome variable y as a function of a single explanatory/ predictor variable x. We will use both numerical and categorical x variables. The outcome variable of interest in this chapter will be teaching evaluation scores of instructors at the University of Texas, Austin.

References