MODELING WITH DATA IN THE TIDYVERSE

Modeling with data in the tidyverse

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Course overview

1. Introduction to modeling: theory and terminology
2. Basic regression
3. Multiple regression
4. Model assessment

Background: General modeling framework formula

$$y = f(\vec{x}) + \epsilon$$

where

- y: outcome variable of interest
- $\vec{x}$: explanatory/predictor variables
- $f()$: function of the relationship between y and $\vec{x}$ AKA *the signal*
- ϵ: unsystematic error component AKA *the noise*

Background: Two modeling scenarios

Modeling for either:

- Explanation: $\vec{x}$ are *explanatory* variables
- Prediction: $\vec{x}$ are *predictor* variables

Modeling for explanation example

A University of Texas in Austin study on teaching evaluation scores (available at openintro.org).

Question: Can we explain differences in teaching evaluation score based on various teacher attributes?

Variables:

- y: Average teaching `score` based on students evaluations
- $\vec{x}$: Attributes like `rank`, `gender`, `age`, and `bty_avg`

Modeling for explanation example

From the `moderndive` package for ModernDive.com:

```
library(dplyr)
library(moderndive)
glimpse(evals)

Observations: 463
Variables: 13
$ ID           <int> 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17,
$ score        <dbl> 4.7, 4.1, 3.9, 4.8, 4.6, 4.3, 2.8, 4.1, 3.4, 4.5, 3.8, 4.5,
$ age          <int> 36, 36, 36, 36, 59, 59, 59, 51, 51, 40, 40, 40, 40, 40, 40,
$ bty_avg      <dbl> 5.000, 5.000, 5.000, 5.000, 3.000, 3.000, 3.000, 3.333, 3.3
$ gender       <fct> female, female, female, female, male, male, male, male, mal
$ ethnicity    <fct> minority, minority, minority, minority, not minority, not m
$ language     <fct> english, english, english, english, english, english, engli
$ rank         <fct> tenure track, tenure track, tenure track, tenure track, ter
$ pic_outfit   <fct> not formal, not formal, not formal, not formal, not formal,
$ pic_color    <fct> color, color, color, color, color, color, color, color, col
$ cls_did_eval <int> 24, 86, 76, 77, 17, 35, 39, 55, 111, 40, 24, 24, 17, 14, 37
$ cls_students <int> 43, 125, 125, 123, 20, 40, 44, 55, 195, 46, 27, 25, 20, 25,
$ cls_level    <fct> upper, upper, upper, upper, upper, upper, upper, upper, upp
```

Exploratory data analysis

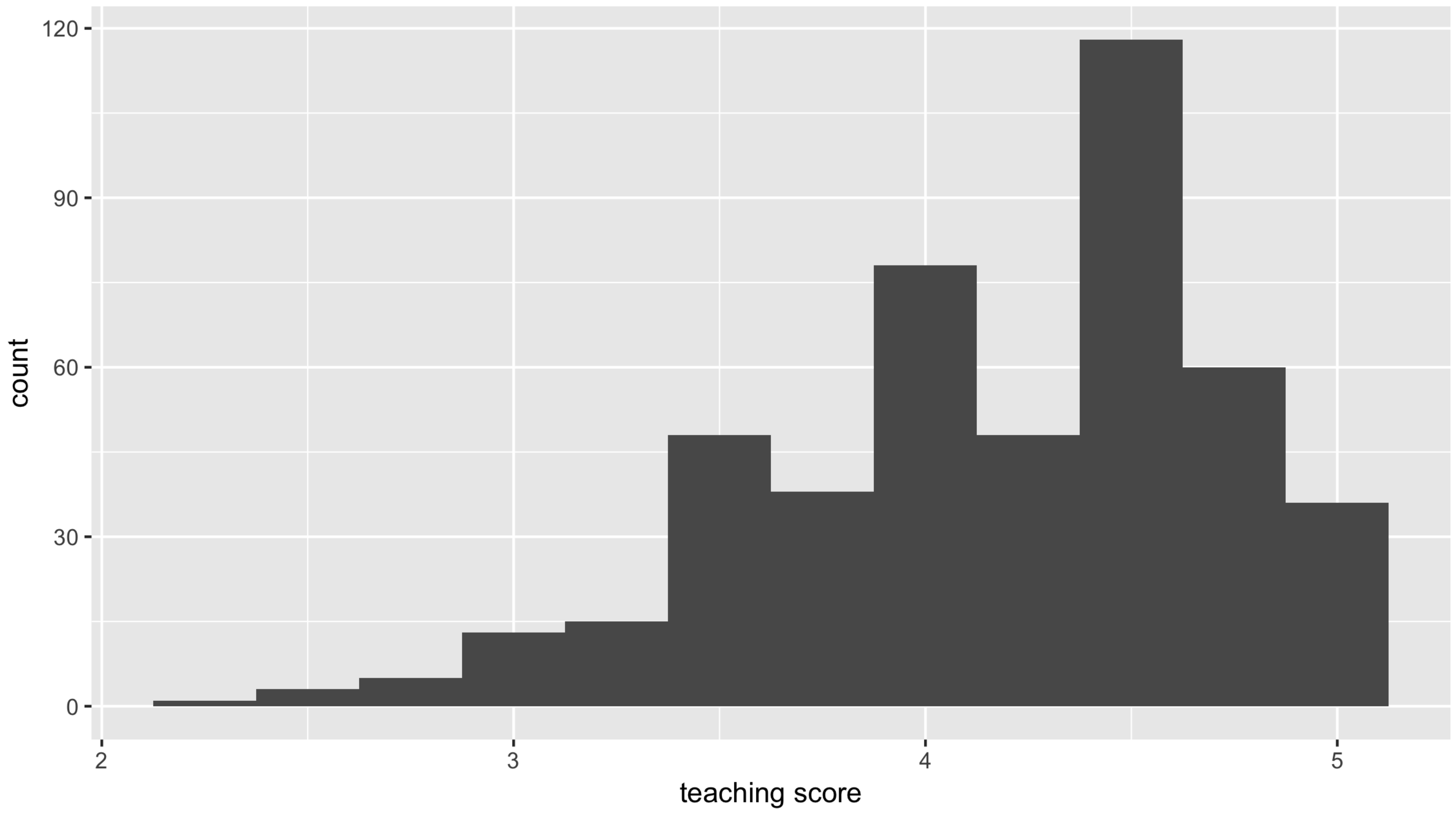
Three basic steps to exploratory data analysis (EDA):

1. Looking at your data
2. Creating visualizations
3. Computing summary statistics

Exploratory data analysis

```
library(ggplot2)
ggplot(evals, aes(x = score)) +
  geom_histogram(binwidth = 0.25) +
  labs(x = "teaching score", y = "count")
```

Exploratory data analysis



Exploratory data analysis

```
# Compute mean, median, and standard deviation
evals %>%
  summarize(mean_score = mean(score),
            median_score = median(score),
            sd_score = sd(score))

# A tibble: 1 x 3
  mean_score median_score sd_score
       <dbl>        <dbl>    <dbl>
1       4.17          4.3    0.544
```

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Let's practice!

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Background on modeling for prediction

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Modeling for prediction example

A dataset of house prices in King County, Washington State, near Seattle (available at Kaggle.com).

Question: Can we predict the sale price of houses based on their features?

Variables:

- y: House sale `price` is US dollars
- $\vec{x}$: Features like `sqft_living`, `condition`, `bedrooms`, `yr_built`, `waterfront`

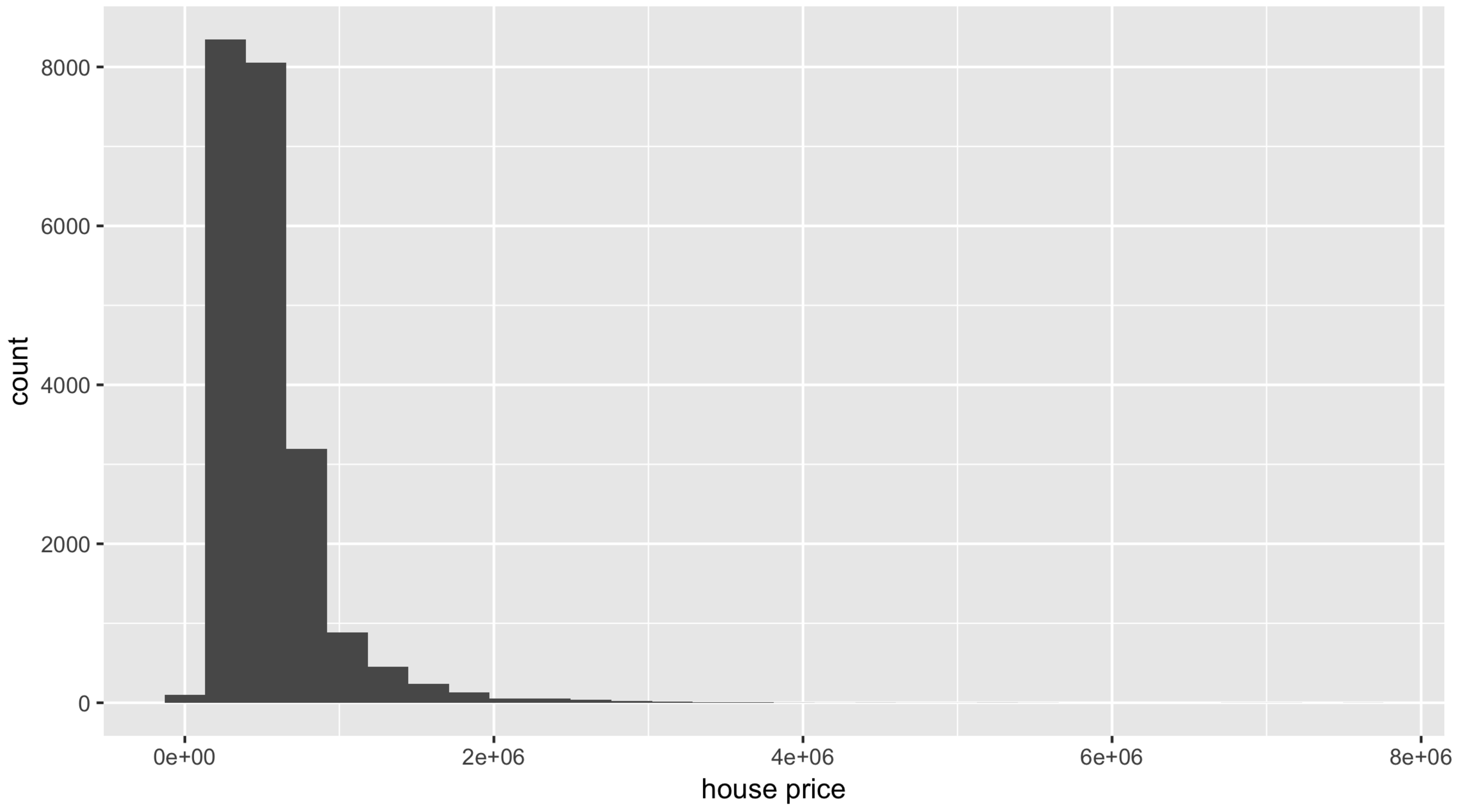
Modeling for prediction example

From the `moderndive` package for ModernDive:

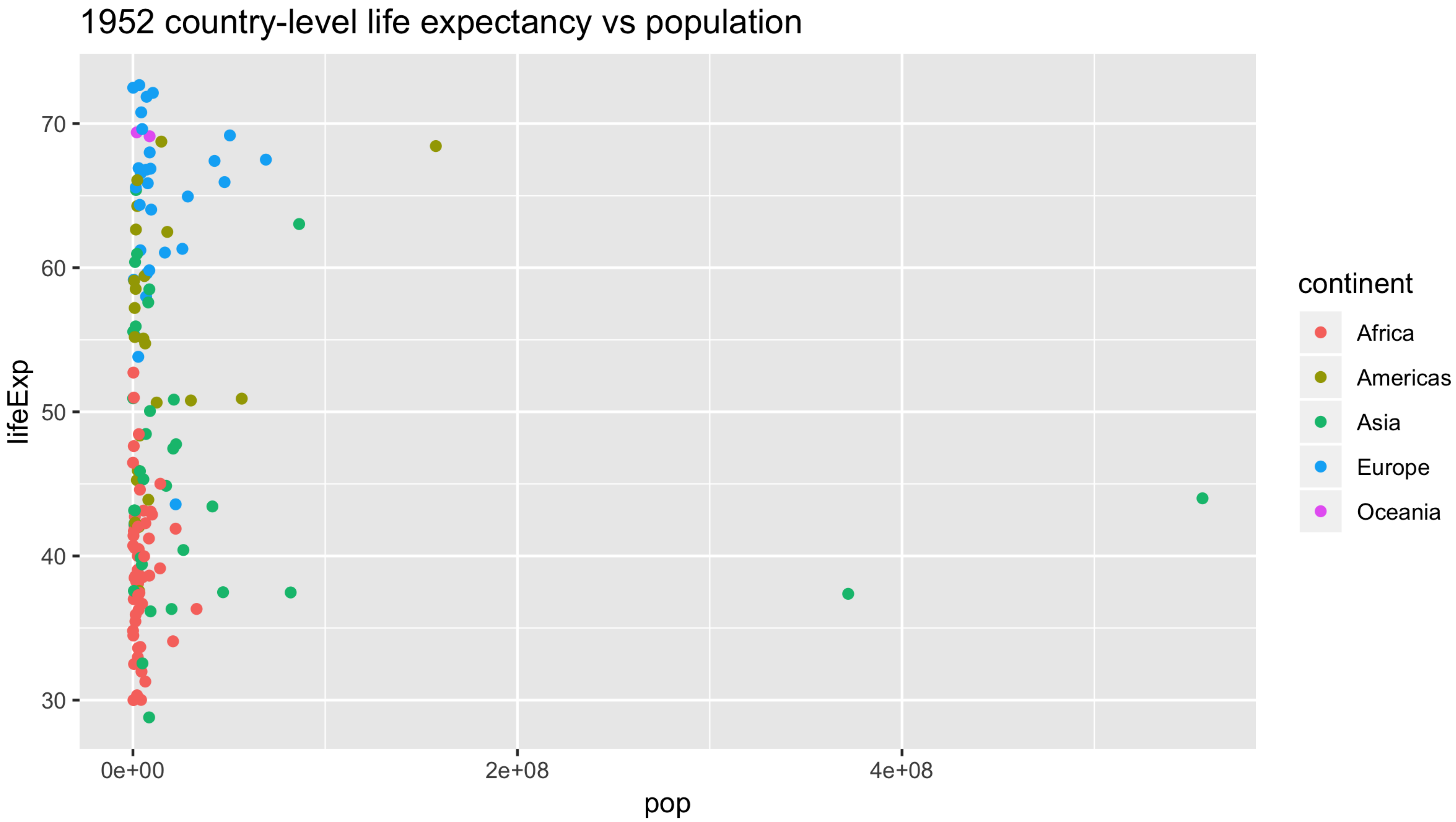
Exploratory data analysis

```
library(ggplot2)
ggplot(house_prices, aes(x = price)) +
  geom_histogram() +
  labs(x = "house price", y = "count")
```

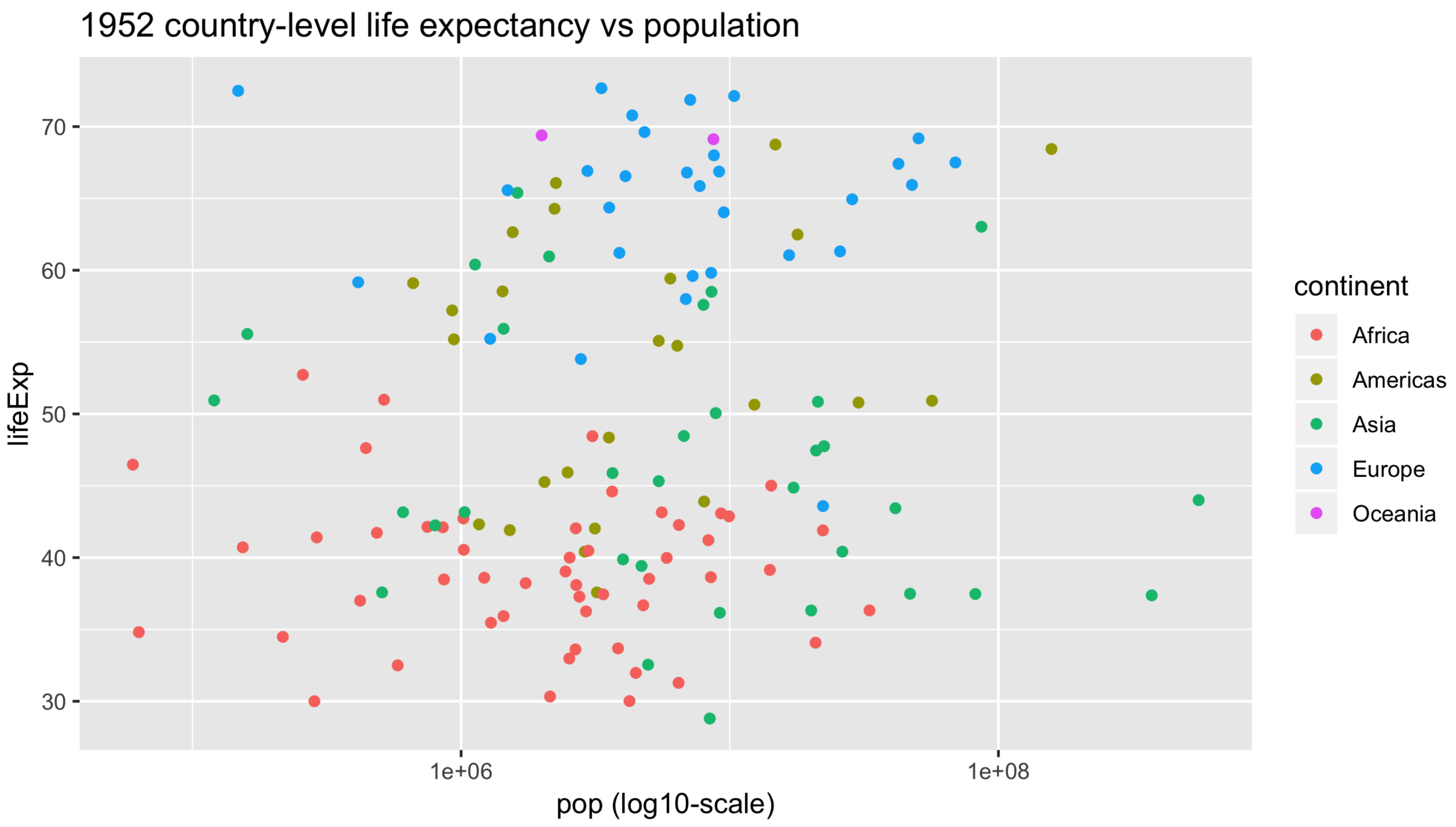
Histogram of outcome variable



Gapminder data



Log10 rescaling of x-axis



Log10 transformation

```
# log10() transform price and size
house_prices <- house_prices %>%
  mutate(log10_price = log10(price))

# View effects of transformation
house_prices %>%
  select(price, log10_price)

# A tibble: 21,613 x 2
     price log10_price
     <dbl>       <dbl>
 1  221900        5.35
 2  538000        5.73
 3  180000        5.26
 4  604000        5.78
 5  510000        5.71
 6 1225000        6.09
 7  257500        5.41
 8  291850        5.47
 9  229500        5.36
10  323000        5.51
# ... with 21,603 more rows
```

Histogram of new outcome variable

```
# Histogram of original outcome variable
ggplot(house_prices, aes(x = price)) +
  geom_histogram() +
  labs(x = "house price", y = "count")

# Histogram of new, log10-transformed outcome variable
ggplot(house_prices, aes(x = log10_price)) +
  geom_histogram() +
  labs(x = "log10 house price", y = "count")
```

Comparing before and after log10-transformation

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The modeling problem for explanation

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Recall: General modeling framework formula

$$y = f(\vec{x}) + \epsilon$$

where

- y: outcome variable of interest
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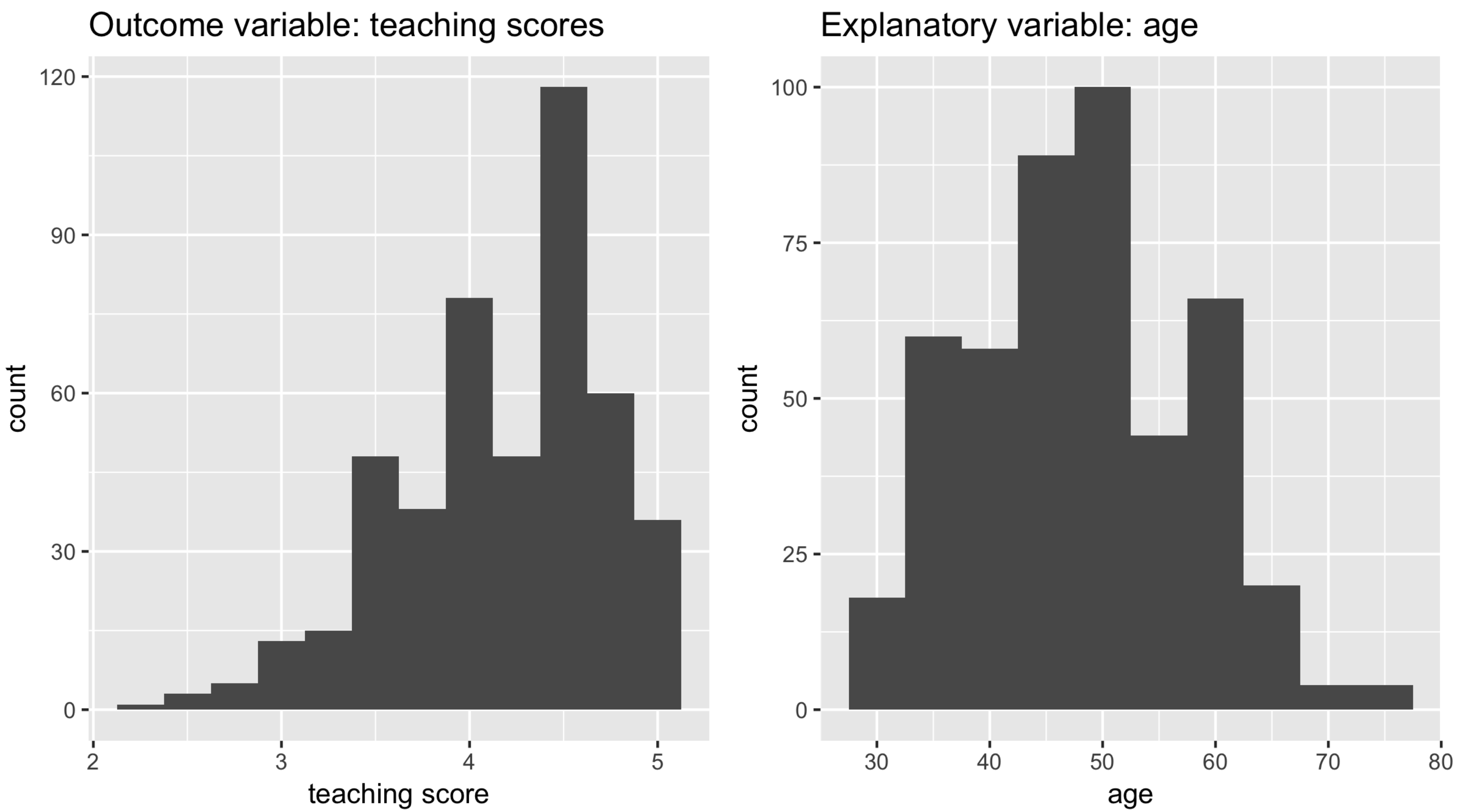
- ϵ: unsystematic error component AKA *the noise*

The modeling problem

Consider $y = f(\vec{x}) + \epsilon$.

1. $f()$ and ϵ are unknown
2. n observations of y and $\vec{x}$ are known/given in the data
3. **Goal**: Fit a model $\hat{f}()$ that *approximates* $f()$ while ignoring ϵ
4. **Goal restated**: *Separate the signal from the noise*
5. Can then generate *fitted/predicted* values $\hat{y} = \hat{f}(\vec{x})$

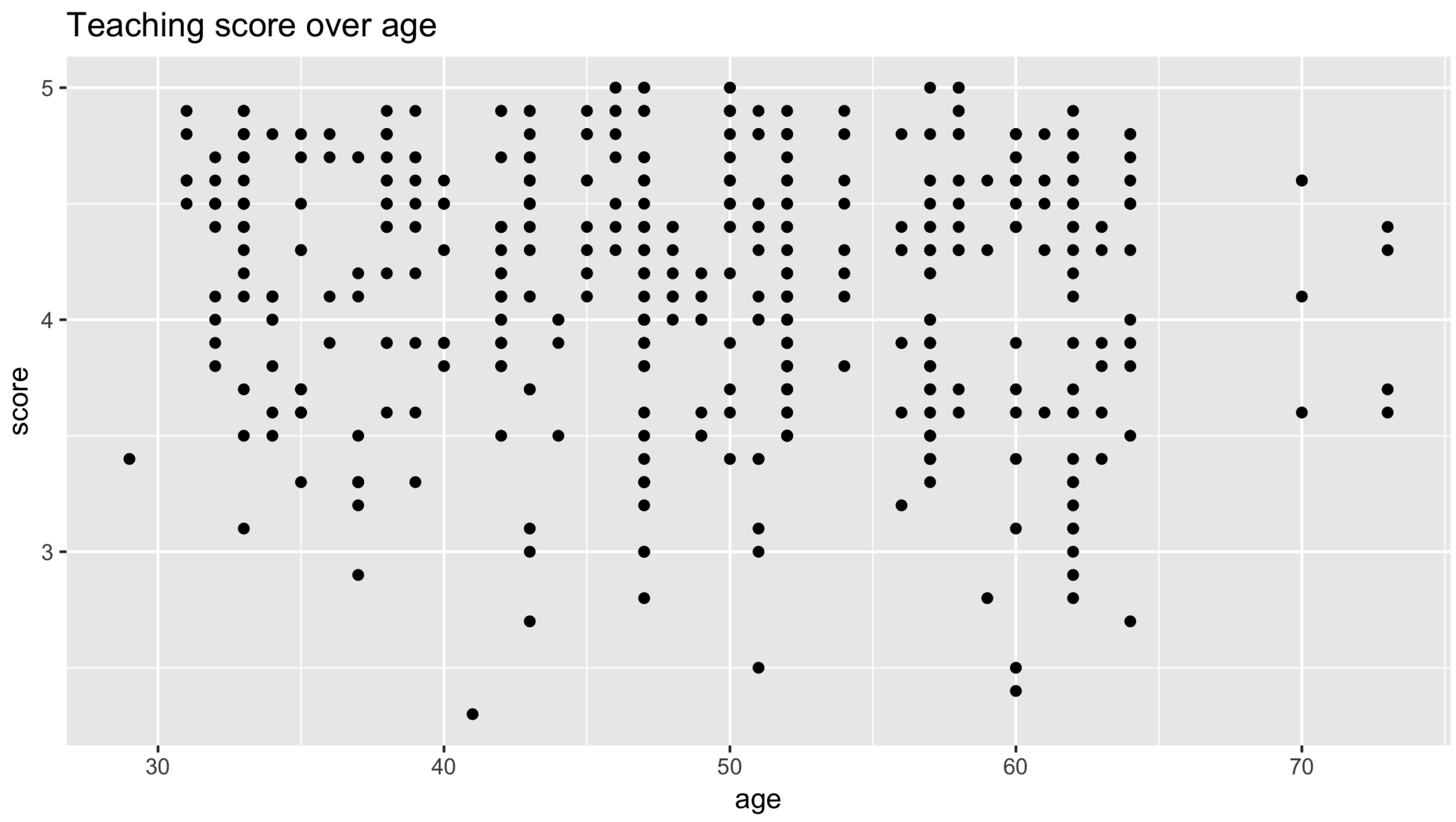
Modeling for explanation example



EDA of relationship

```
library(ggplot2)
library(dplyr)
library(moderndive)

ggplot(evals, aes(x = age, y = score)) +
  geom_point() +
  labs(x = "age", y = "score", title = "Teaching score over age")
```

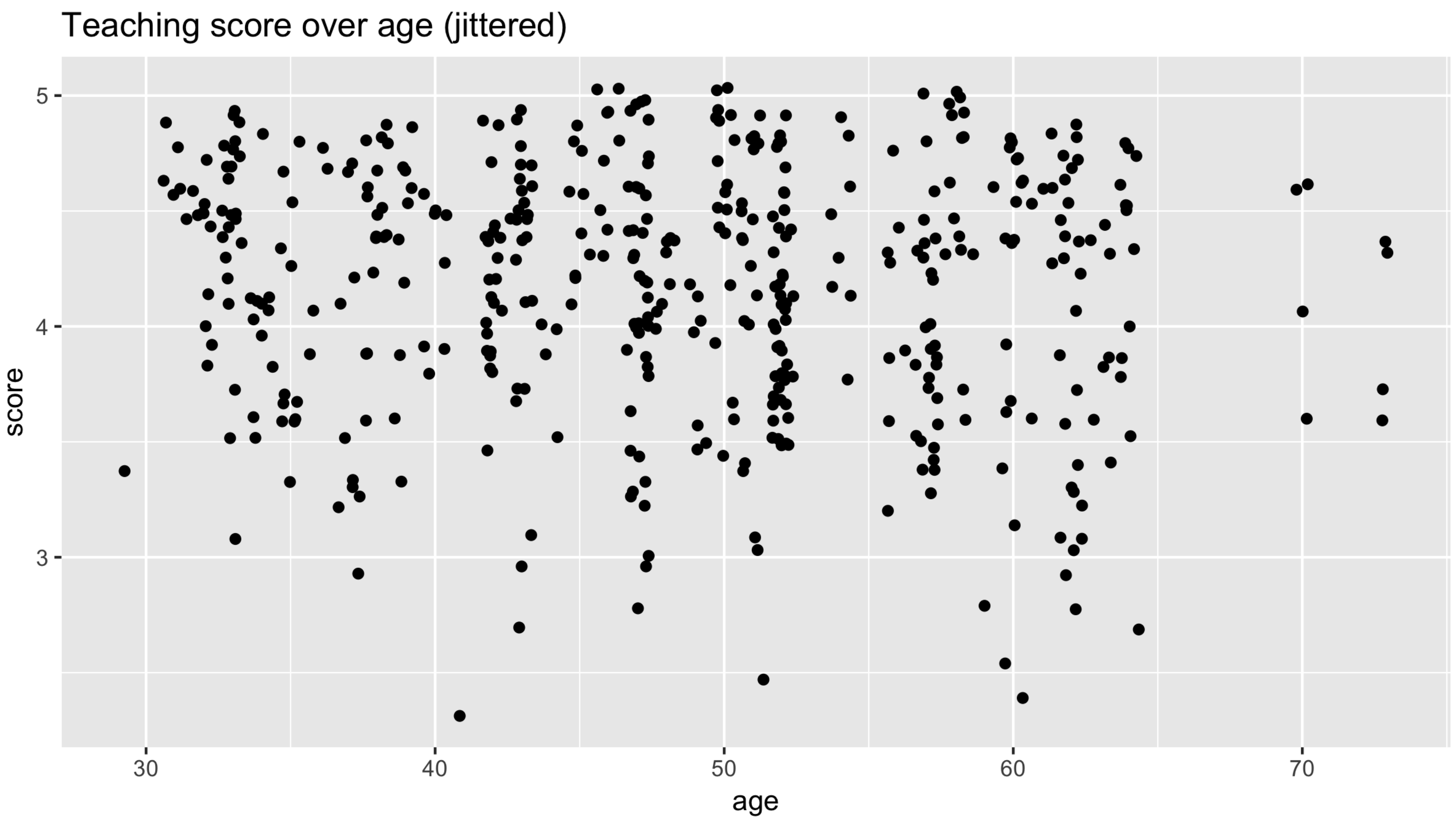
EDA of relationship



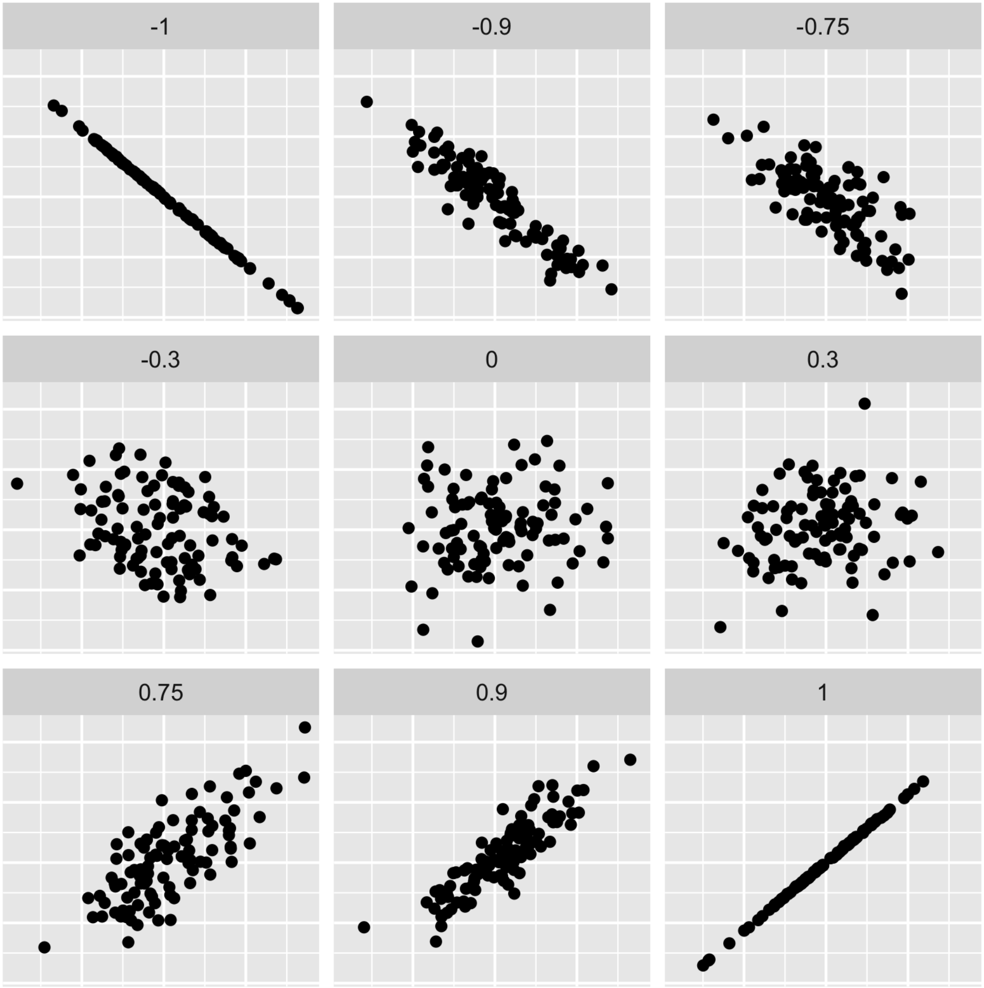
Jittered scatterplot

```
library(ggplot2)
library(dplyr)
library(moderndive)

# Instead of geom_point() ...
ggplot(evals, aes(x = age, y = score)) +
  geom_point() +
  labs(x = "age", y = "score", title = "Teaching score over age")

# Use geom_jitter()
ggplot(evals, aes(x = age, y = score)) +
  geom_jitter() +
  labs(x = "age", y = "score", title = "Teaching score over age (jittered)")
```

Jittered scatterplot



Correlation coefficient



Computing the correlation coefficient

```
evals %>%
  summarize(correlation = cor(score, age))

# A tibble: 1 x 1
  correlation
        <dbl>
1      -0.107
```

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The modeling problem for prediction

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Modeling problem

Consider $y = f(\vec{x}) + \epsilon$.

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3. **Goal**: Fit a model $\hat{f}()$ that *approximates* $f()$ while ignoring ϵ
4. **Goal restated**: Separate the *signal* from the *noise*
5. Can then generate *fitted/predicted* values $\hat{y} = \hat{f}(\vec{x})$

Difference between explanation and prediction

Key difference in modeling goals:

1. **Explanation**: We care about the form of $\hat{f}()$, in particular any values quantifying relationships between y and $\vec{x}$
2. **Prediction**: We don't care so much about the form of $\hat{f}()$, only that it yields "good" predictions $\hat{y}$ of y based on $\vec{x}$

Condition of house

```
house_prices %>%
  select(log10_price, condition) %>%
  glimpse()

Observations: 21,613
Variables: 2
$ log10_price <dbl> 5.346157, 5.730782, 5.255273, 5.781037, 5.707570, 6.088136,
$ condition   <fct> 3, 3, 3, 5, 3, 3, 3, 3, 3, 3, 3, 4, 4, 4, 3, 3, 3, 4, 4, 4,
```

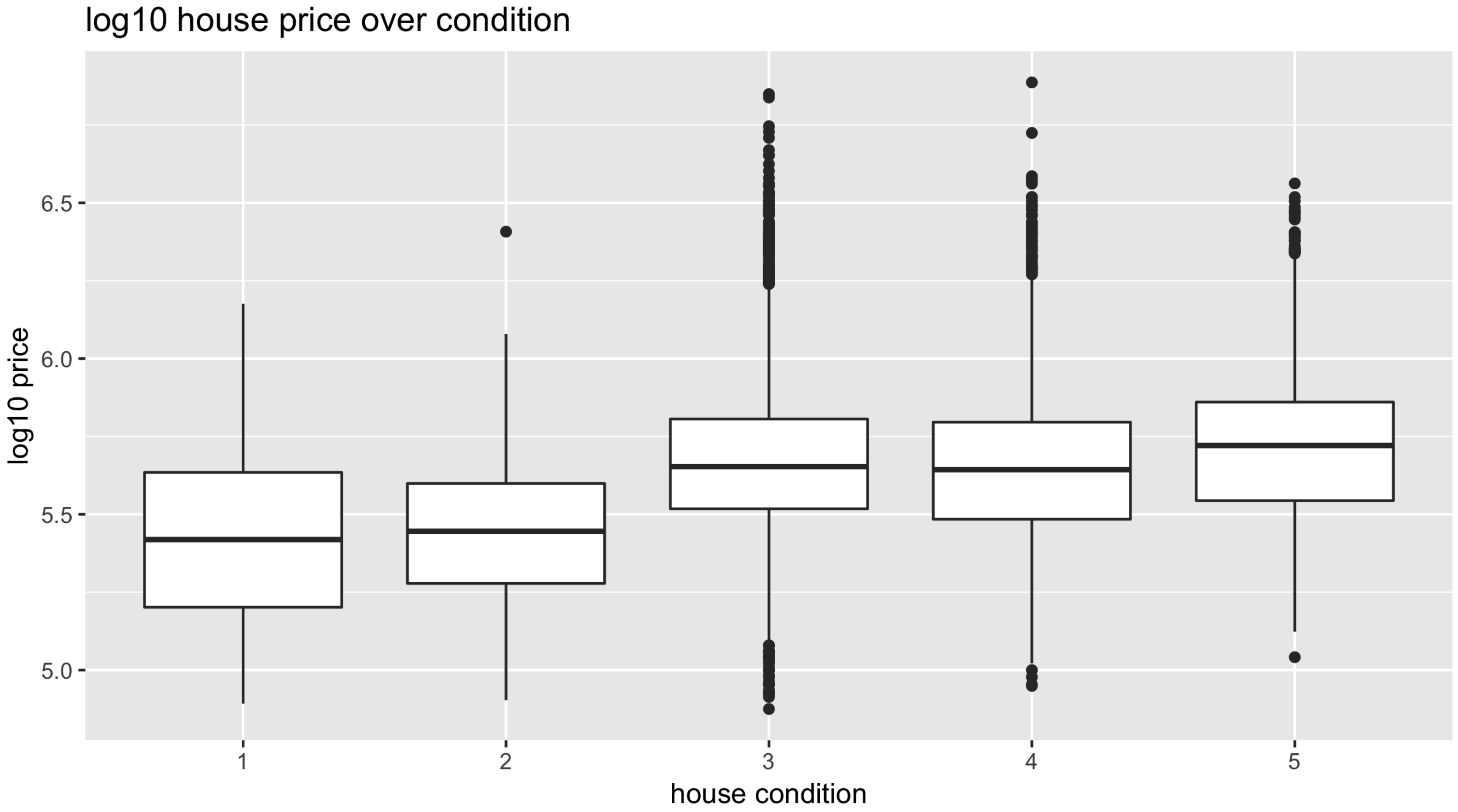
Exploratory data visualization: boxplot

```
library(ggplot2)
library(dplyr)
library(moderndive)

# Apply log10-transformation to outcome variable
house_prices <- house_prices %>%
  mutate(log10_price = log10(price))

# Boxplot
ggplot(house_prices, aes(x = condition, y = log10_price)) +
  geom_boxplot() +
  labs(x = "house condition", y = "log10 price",
       title = "log10 house price over condition")
```

Exploratory data visualization: boxplot



Exploratory data summaries

```
house_prices %>%
  group_by(condition) %>%
  summarize(mean = mean(log10_price), sd = sd(log10_price), n = n())

# A tibble: 5 x 4
  condition  mean    sd     n
  <fct>     <dbl> <dbl> <int>
1 1          5.42 0.293    30
2 2          5.45 0.233   172
3 3          5.67 0.224 14031
4 4          5.65 0.228  5679
5 5          5.71 0.244  1701

# Prediction for new house with condition 4 in dollars
10^(5.65)

446683.6
```

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