MODELING WITH DATA IN THE TIDYVERSE

Model assessment and selection

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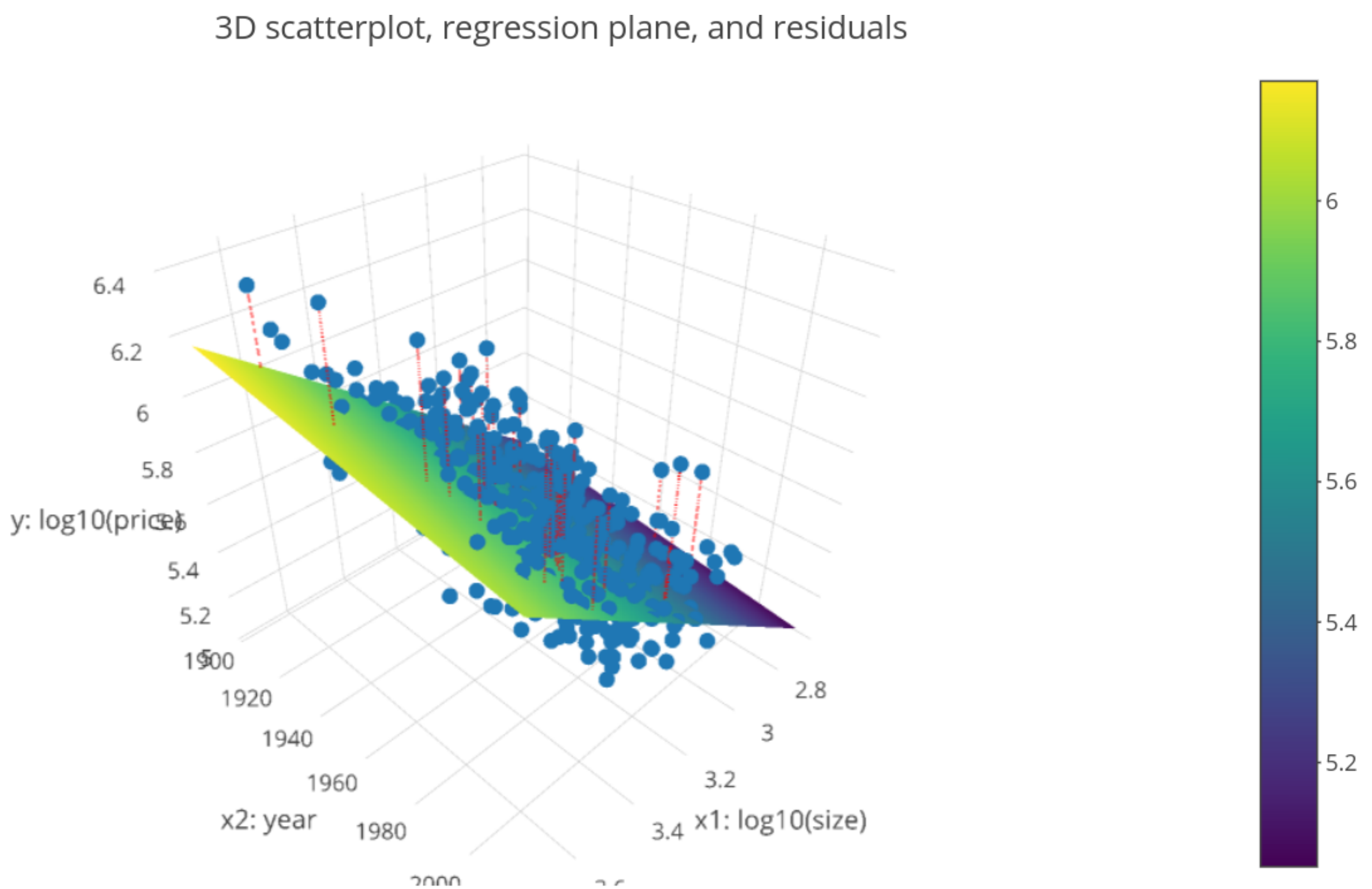
Refresher: Multiple regression

Two models with different pairs of explantory/predictor variables:

```
# Model 1 - Two numerical:
model_price_1 <- lm(log10_price ~ log10_size + yr_built,
                    data = house_prices)

# Model 3 - One numerical & one categorical:
model_price_3 <- lm(log10_price ~ log10_size + condition,
                    data = house_prices)
```

Refresher: Sum of squared residuals



Refresher: Sum of squared residuals

```
# Model 1
model_price_1 <- lm(log10_price ~ log10_size + yr_built,
                    data = house_prices)
get_regression_points(model_price_1) %>%
  mutate(sq_residuals = residual^2) %>%
  summarize(sum_sq_residuals = sum(sq_residuals))

# A tibble: 1 x 1
  sum_sq_residuals
             <dbl>
1             585.

# Model 3
model_price_3 <- lm(log10_price ~ log10_size + condition,
                    data = house_prices)
get_regression_points(model_price_3) %>%
  mutate(sq_residuals = residual^2) %>%
  summarize(sum_sq_residuals = sum(sq_residuals))

# A tibble: 1 x 1
  sum_sq_residuals
             <dbl>
1             608.
```

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Let's practice!

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Assessing model fit with R-squared

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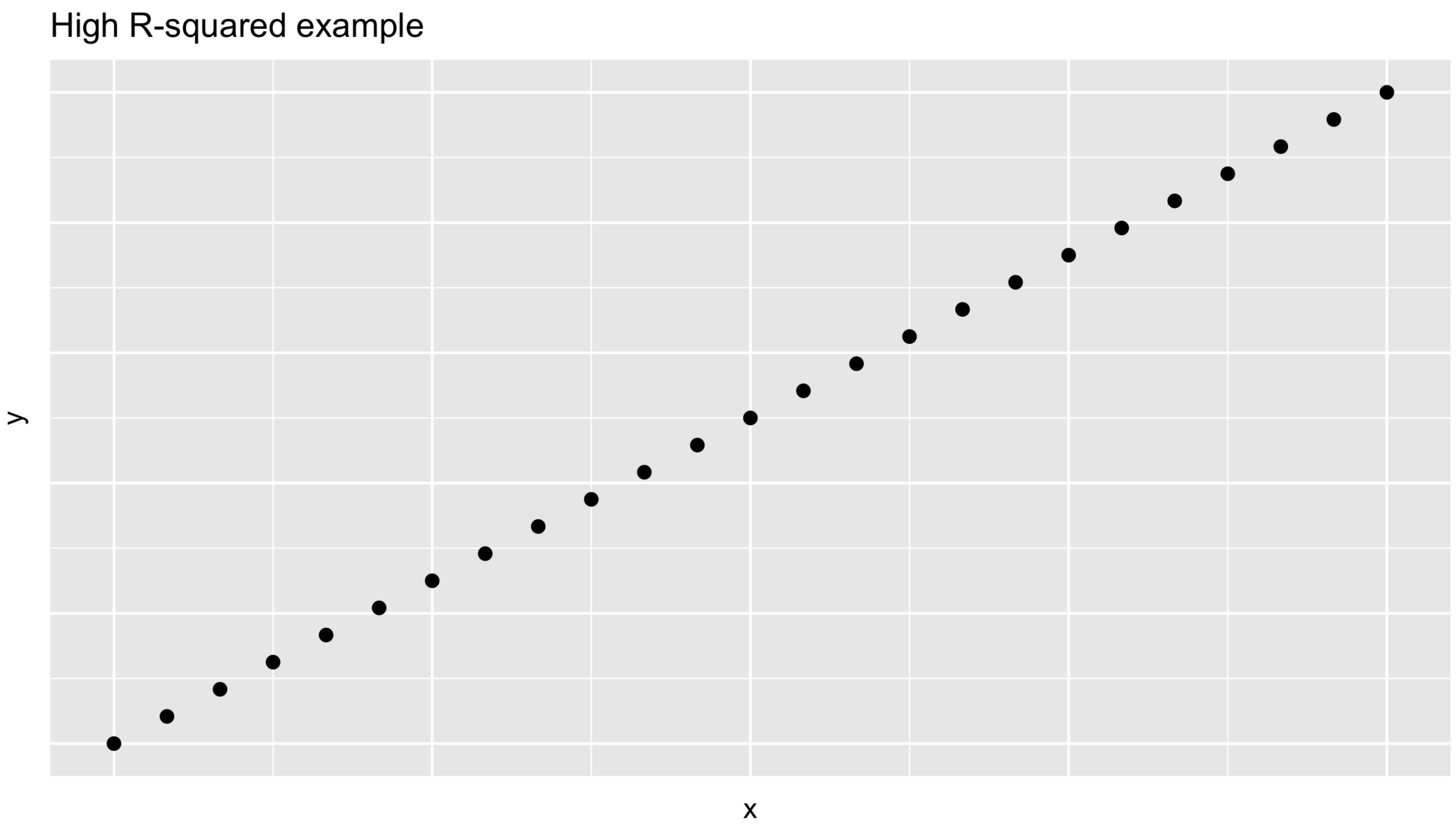
R-squared

$$R^2 = 1 - \frac{\text{Var(residuals)}}{\text{Var}(y)}$$

- R^2 is between 0 & 1
- Smaller R^2 ~ "poorer fit"
- $R^2 = 1$ ~ "perfect fit" and $R^2 = 0$ ~ "no fit"

High R-squared value example

$$R^2 = 1 - \frac{\text{Var(residuals)}}{\text{Var}(y)}$$

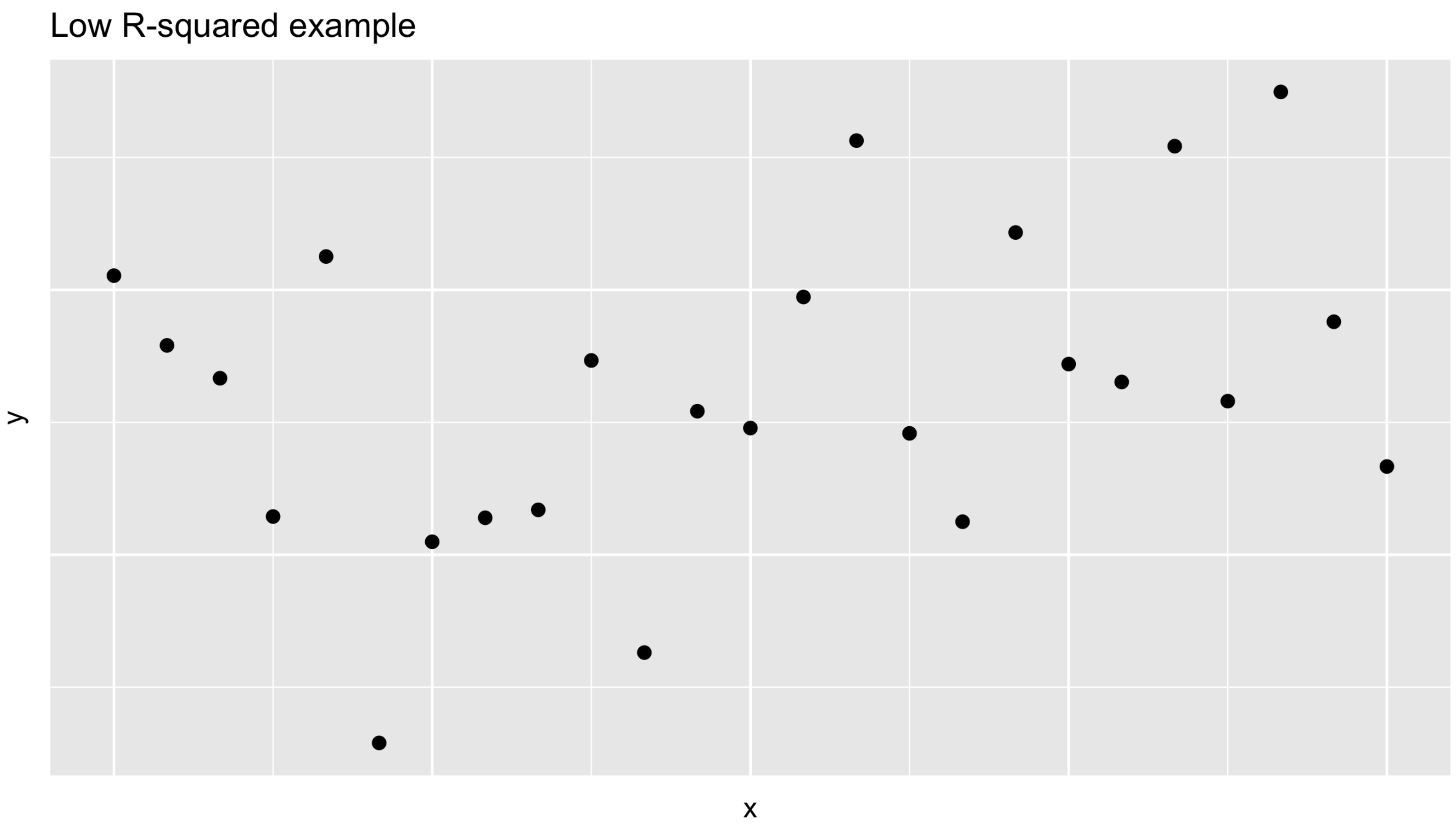


High R-squared value: "Perfect" fit

$$R^2 = 1 - \frac{\text{Var(residuals)}}{\text{Var}(y)}$$

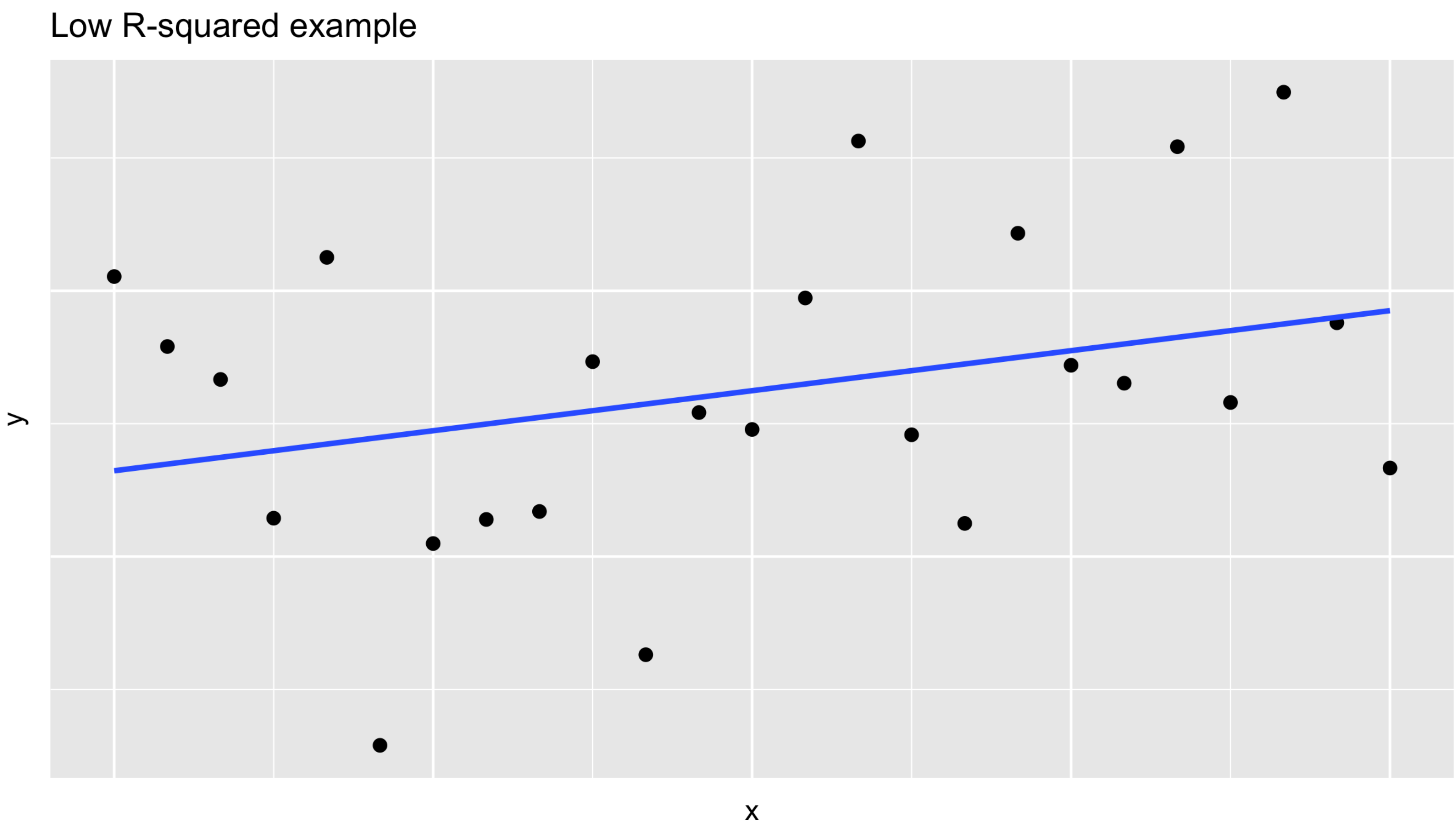
Low R-squared value example

$$R^2 = 1 - \frac{\text{Var(residuals)}}{\text{Var}(y)}$$



Low R-squared value example

$$R^2 = 1 - \frac{\text{Var(residuals)}}{\text{Var}(y)}$$



Numerical interpretation

Since $\mathrm{Var}(y) \geq \mathrm{Var}(\mathrm{residuals})$ and $R^2 = 1 - \frac{\mathrm{Var}(\mathrm{residuals})}{\mathrm{Var}(y)} = \frac{\mathrm{Var}(y) - \mathrm{Var}(\mathrm{residuals})}{\mathrm{Var}(y)}$

R^2's interpretation is: *the proportion of the total variation in the outcome variable* y *that the model explains*.

Computing R-squared

```
# Model 1: price as a function of size and year built
model_price_1 <- lm(log10_price ~ log10_size + yr_built,
                    data = house_prices)

get_regression_points(model_price_1) %>%
  summarize(r_squared = 1 - var(residual) / var(log10_price))

# A tibble: 1 x 1
  r_squared
      <dbl>
1     0.483

# Model 3: price as a function of size and condition
model_price_3 <- lm(log10_price ~ log10_size + condition,
                    data = house_prices)

get_regression_points(model_price_3) %>%
  summarize(r_squared = 1 - var(residual) / var(log10_price))

# A tibble: 1 x 1
  r_squared
      <dbl>
1     0.462
```

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Assessing predictions with RMSE

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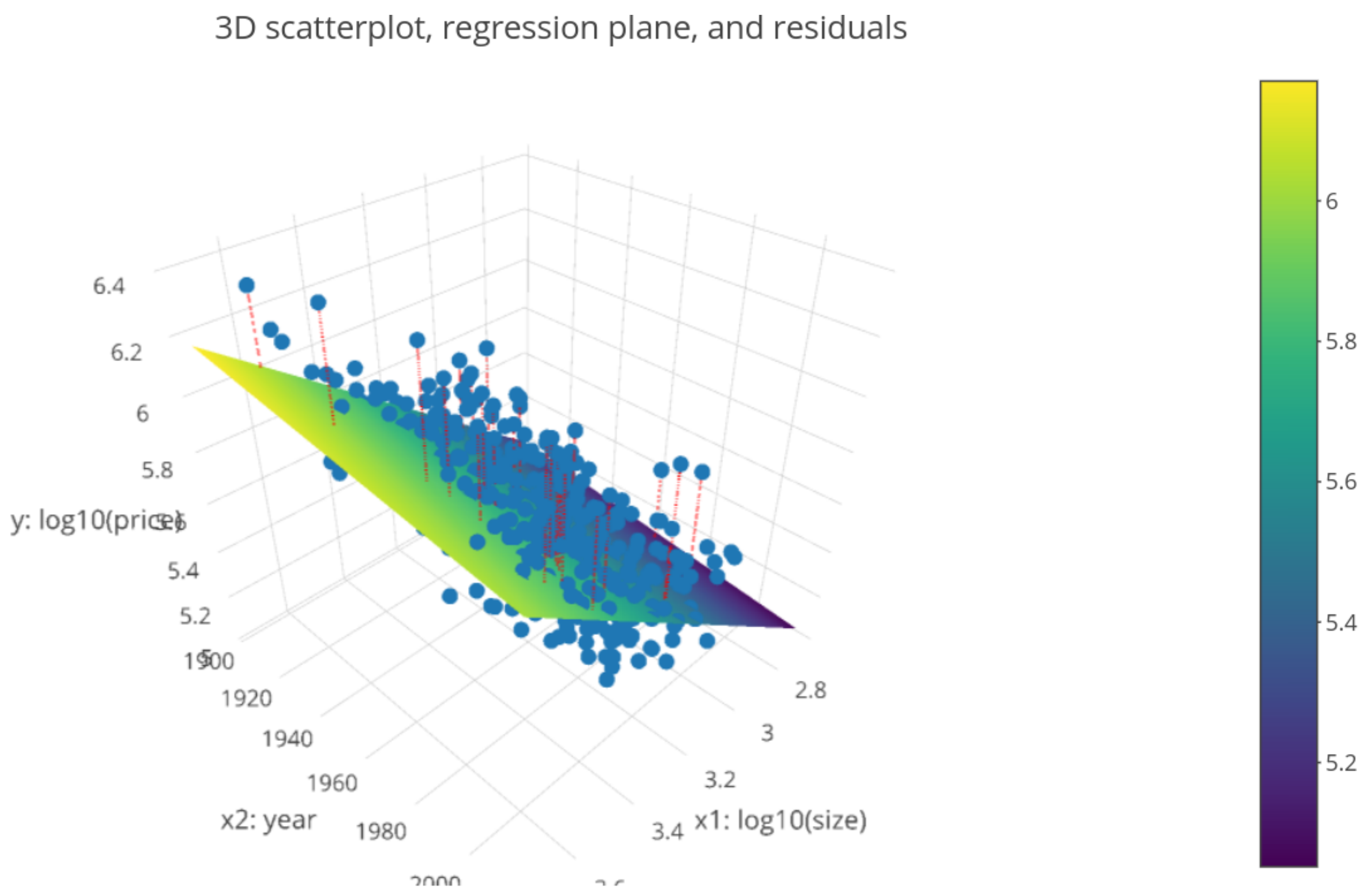
Refresher: Residuals



Mean squared error

```
# Model 1: price as a function of size and year built
model_price_1 <- lm(log10_price ~ log10_size + yr_built,
                    data = house_prices)

# Sum of squared residuals:
get_regression_points(model_price_1) %>%
  mutate(sq_residuals = residual^2) %>%
  summarize(sum_sq_residuals = sum(sq_residuals))

# A tibble: 1 x 1
  sum_sq_residuals
             <dbl>
1             585.

# Mean squared error: use mean() instead of sum():
get_regression_points(model_price_1) %>%
  mutate(sq_residuals = residual^2) %>%
  summarize(mse = mean(sq_residuals))

# A tibble: 1 x 1
     mse
   <dbl>
1 0.0271
```

Root mean squared error

```
# Root mean squared error:
get_regression_points(model_price_1) %>%
  mutate(sq_residuals = residual^2) %>%
  summarize(mse = mean(sq_residuals)) %>%
  mutate(rmse = sqrt(mse))

# A tibble: 1 x 2
     mse  rmse
   <dbl> <dbl>
1 0.0271 0.164
```

RMSE of predictions on new houses

```
# Recreate data frame of "new" houses
new_houses <- data_frame(
  log10_size = c(2.9, 3.6),
  condition = factor(c(3, 4))
)
new_houses

# A tibble: 2 x 2
  log10_size condition
       <dbl> <fct>
1        2.9 3
2        3.6 4

# Get predictions
get_regression_points(model_price_3, newdata = new_houses)

# A tibble: 2 x 4
     ID log10_size condition log10_price_hat
  <int>      <dbl> <fct>               <dbl>
1     1        2.9 3                    5.34
2     2        3.6 4                    5.94
```

RMSE of predictions on new houses

```
# Get predictions
get_regression_points(model_price_3, newdata = new_houses)

# A tibble: 2 x 4
     ID log10_size condition log10_price_hat
  <int>      <dbl> <fct>               <dbl>
1     1        2.9 3                    5.34
2     2        3.6 4                    5.94

# Compute RMSE
get_regression_points(model_price_3, newdata = new_houses) %>%
  mutate(sq_residuals = residual^2) %>%
  summarize(mse = mean(sq_residuals)) %>%
  mutate(rmse = sqrt(mse))

Error in mutate_impl(.data, dots) :
  Evaluation error: object 'residual' not found.
```

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Validation set prediction framework

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Validation set approach

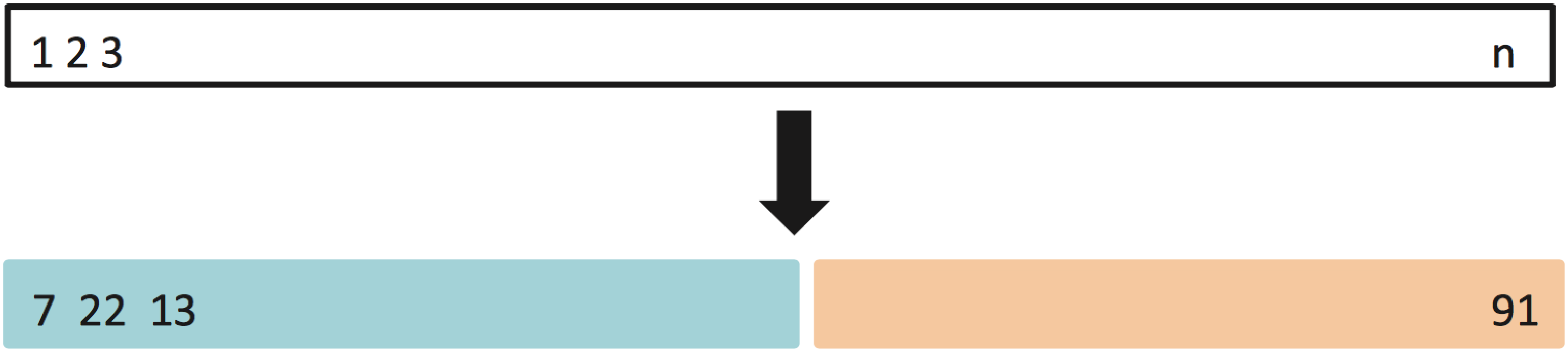
Use two independent datasets to:

1. Train/fit your model
2. Evaluate your model's predicitive power i.e. validate your model

Training/test set split

Randomly split all n observations (white) into

1. A *training set* (blue) to fit models
2. A *test set* (orange) to make predictions on



Training/test set split in R

```
library(dplyr)

# Randomly shuffle order of rows:
house_prices_shuffled <- house_prices %>%
  sample_frac(size = 1, replace = FALSE)

# Split into train and test:
train <- house_prices_shuffled %>%
  slice(1:10000)
test <- house_prices_shuffled %>%
  slice(10001:21613)
```

Training models on training data

```
train_model_price_1 <- lm(log10_price ~ log10_size + yr_built,
                          data = train)
get_regression_table(train_model_price_1)

# A tibble: 3 x 7
  term       estimate std_error statistic p_value lower_ci upper_ci
  <chr>         <dbl>     <dbl>     <dbl>   <dbl>    <dbl>    <dbl>
1 intercept     5.34      0.111      48.3       0     5.13     5.56
2 log10_size    0.923     0.009      97.5       0     0.905    0.942
3 yr_built     -0.001     0         -23.0       0    -0.001   -0.001
```

Making predictions on test data

```
# Train model on train:
train_model_price_1 <- lm(log10_price ~ log10_size + yr_built,
                          data = train)

# Get predictions on test:
get_regression_points(train_model_price_1, newdata = test)

# A tibble: 11,613 x 6
      ID log10_price log10_size yr_built log10_price_hat residual
   <int>       <dbl>      <dbl>    <dbl>           <dbl>    <dbl>
 1     1        5.83       3.29     1951            5.71    0.127
 2     2        5.88       3.40     1922            5.84    0.033
 3     3        6.15       3.67     2002            5.99    0.159
 4     4        5.62       3        1953            5.43    0.19
 5     5        5.42       2.89     1948            5.34    0.079
 6     6        5.51       3.29     2000            5.63   -0.126
 7     7        5.63       3.37     1978            5.74   -0.109
 8     8        6.24       3.58     2013            5.89    0.352
 9     9        5.74       3.62     2006            5.93   -0.191
10    10        5.81       3.52     1919            5.96   -0.147
# ... with 11,603 more rows
```

Assessing predictions with RMSE

```
# Train model:
train_model_price_1 <- lm(log10_price ~ log10_size + yr_built,
                          data = train)

# Get predictions and compute RMSE:
get_regression_points(train_model_price_1, newdata = test) %>%
  mutate(sq_residuals = residual^2) %>%
  summarize(rmse = sqrt(mean(sq_residuals)))

# A tibble: 1 x 1
   rmse
  <dbl>
1 0.165
```

Comparing RMSE

```
# Train model:
train_model_price_3 <- lm(log10_price ~ log10_size + condition,
                          data = train)

# Get predictions and compute RMSE:
get_regression_points(train_model_price_3, newdata = test) %>%
  mutate(sq_residuals = residual^2) %>%
  summarize(rmse = sqrt(mean(sq_residuals)))

# A tibble: 1 x 1
   rmse
  <dbl>
1 0.168
```

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Conclusion - Where to go from here?

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R source code for all videos

Available at http://bit.ly/modeling_tidyverse

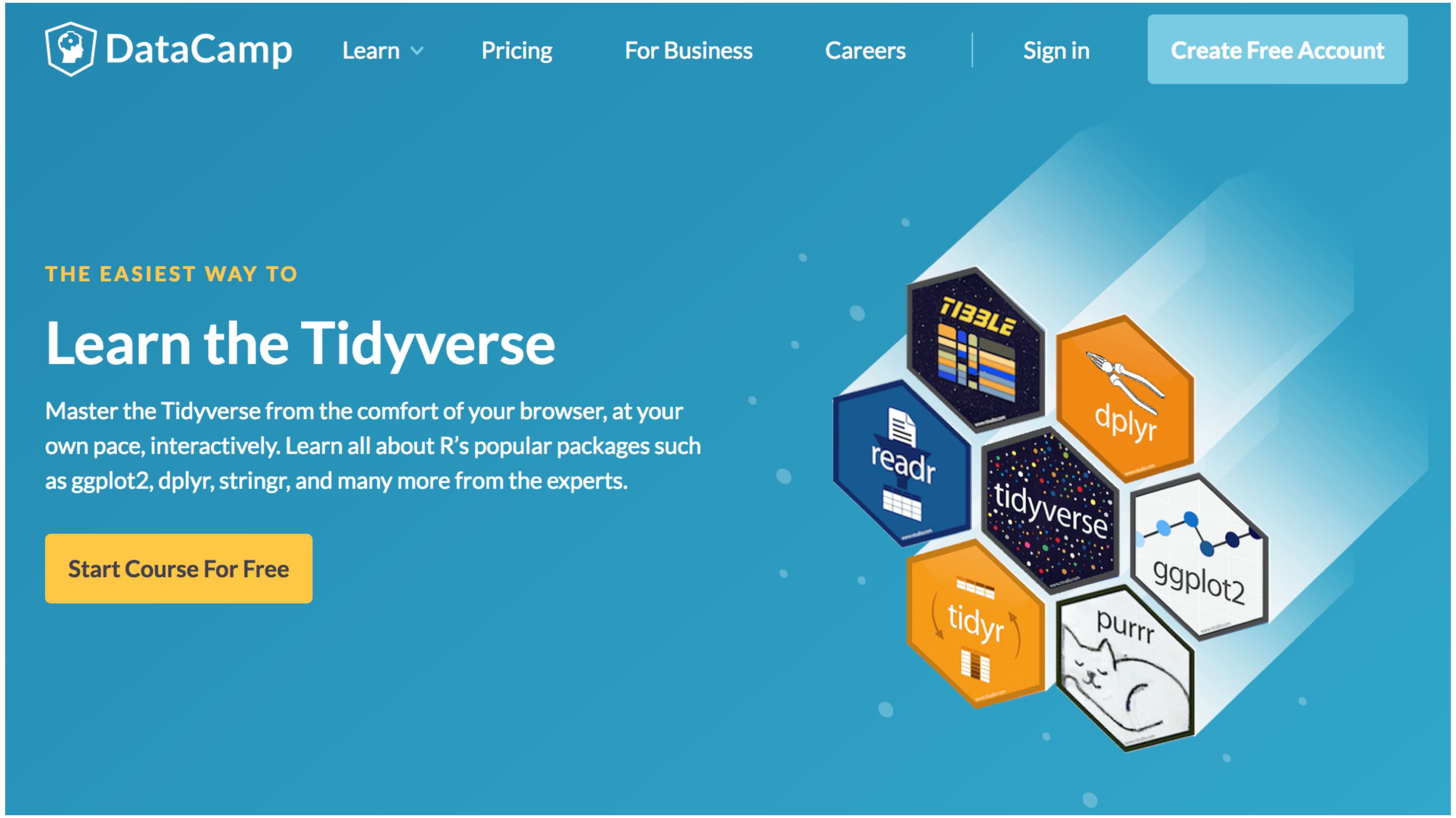
R source code for "Modeling with Data in the Tidyverse" DataCamp course

modeling_with_data_tidyverse.R

```
# R source code for all slides/videos in Albert Y. Kim's "Modeling with Data in
# the Tidyverse" DataCamp course:

# Load all necessary packages -----
library(ggplot2)
library(dplyr)
library(moderndive)

# Chapter 1 - Video 1: Background on modeling for explanation -----
## Modeling for explanation example
glimpse(evals)

## Exploratory data analysis
ggplot(evals, aes(x = score)) +
  geom_histogram(binwidth = 0.25) +
  labs(x = "teaching score", y = "count")

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

Other Tidyverse courses

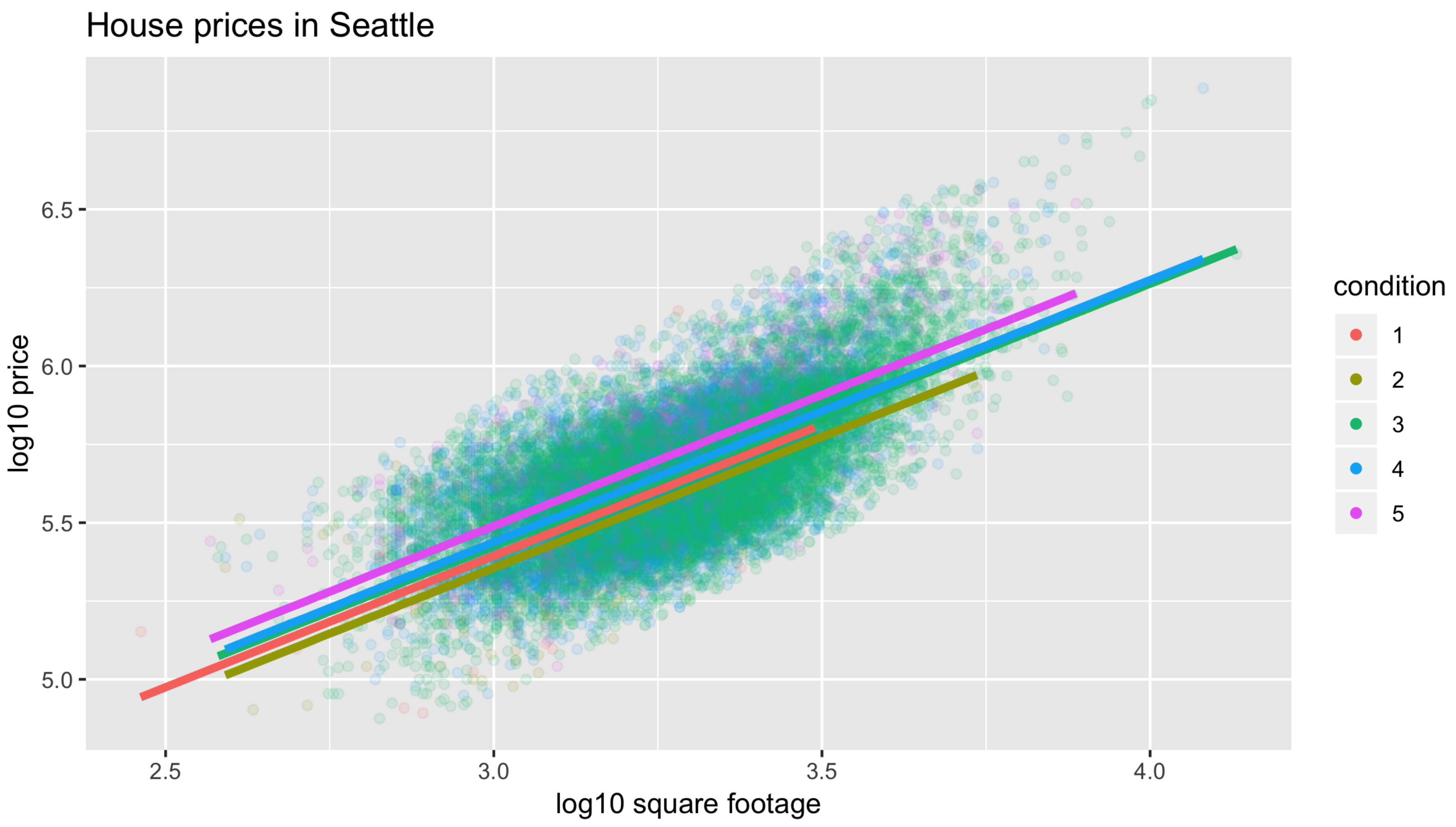
Available here



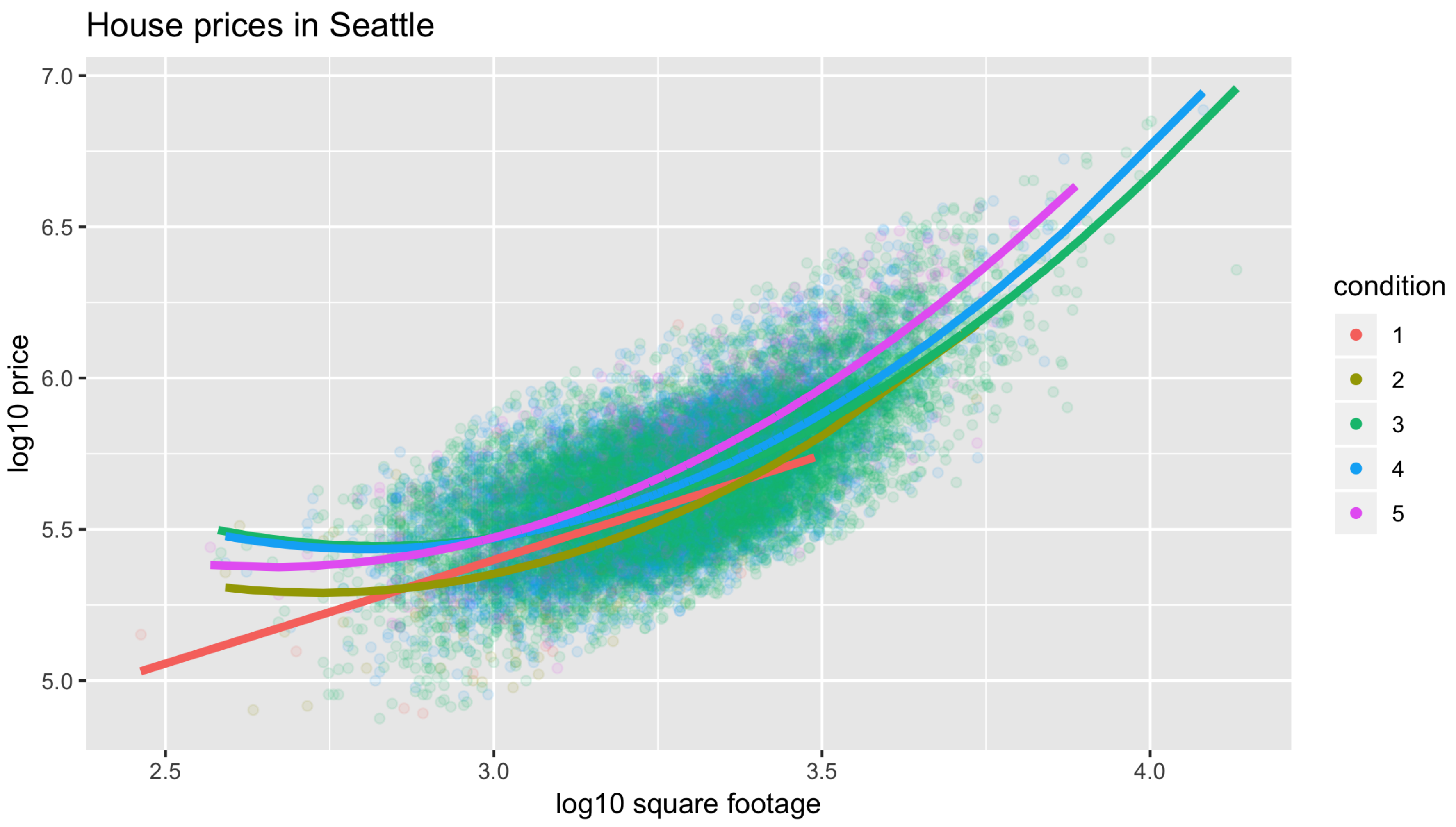
Refresher: General modeling framework

- In general: $y = f(\vec{x}) + \epsilon$
- Linear regression models: $y = \beta_0 + \beta_1 \cdot x_1 + \epsilon$

Parallel slopes model



Polynomial model



Tree models


Tree model for log10 price
log10_sqft_living< 3.387
log10_sqft_living< 3.184
5.509
n=6553
5.642
n=8875
5.87
n=6185

DataCamp courses using other models

Courses with different $f()$ in $y = f(\vec{x}) + \epsilon$:

- Machine Learning with Tree-Based Models in R
- Supervised Learning in R: Case Studies

Refresher: Regression table

```
# Fit model:
model_score_1 <- lm(score ~ age, data = evals)

# Output regression table:
get_regression_table(model_score_1)

# A tibble: 2 x 7
  term      estimate std_error statistic p_value lower_ci upper_ci
  <chr>        <dbl>     <dbl>     <dbl>   <dbl>    <dbl>    <dbl>
1 intercept    4.46      0.127     35.2    0         4.21     4.71
2 age         -0.006     0.003     -2.31   0.021    -0.011   -0.001
```

ModernDive: Online textbook

- Uses `tidyverse` tools: `ggplot2` and `dplyr`
- Expands on the regression models from this course
- Uses `evals` and `house_prices` datasets (and more)
- **Goal**: Statistical inference via data science
- Available at ModernDive.com

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Good luck!