# Model building

Cross validation

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*The following content is based on Mine Çetinkaya-Rundel's excellent book Data Science in a Box*

# Data and exploration


the office

# Data

```
office_ratings <- read_csv("data/office_ratings.csv")
office_ratings
```

```
## # A tibble: 188 x 6
##   season episode title         imdb_rating total_votes air_date
##    <dbl>   <dbl> <chr>               <dbl>       <dbl> <date>
## 1      1       1 Pilot                 7.6        3706 2005-03-24
## 2      1       2 Diversity Day         8.3        3566 2005-03-29
## 3      1       3 Health Care           7.9        2983 2005-04-05
## 4      1       4 The Alliance          8.1        2886 2005-04-12
## 5      1       5 Basketball            8.4        3179 2005-04-19
## 6      1       6 Hot Girl              7.8        2852 2005-04-26
## # … with 182 more rows
```

Source: The data come from data.world, by way of TidyTuesday.

# IMDB ratings

Code Plot

```
ggplot(office_ratings, aes(x = imdb_rating)) +
  geom_histogram(binwidth = 0.25) +
  labs(
    title = "The Office ratings",
    x = "IMDB Rating"
  )
```

# IMDB ratings vs. number of votes

Code Plot

```
ggplot(office_ratings, aes(x = total_votes, y = imdb_rating, color = season)) +
  geom_jitter(alpha = 0.7) +
  labs(
    title = "The Office ratings",
    x = "Total votes",
    y = "IMDB Rating",
    color = "Season"
  )
```

# Outliers

Code Plot

```
ggplot(office_ratings, aes(x = total_votes, y = imdb_rating)) +
  geom_jitter() +
  gghighlight(total_votes > 4000, label_key = title) +
  labs(
    title = "The Office ratings",
    x = "Total votes",
    y = "IMDB Rating"
  )
```

If you like the Dinner Party episode, I highly recommend this "oral history" of the episode published on Rolling Stone magazine.

# IMDB ratings vs. seasons

Code Plot

```
ggplot(office_ratings, aes(x = factor(season), y = imdb_rating, color = season)) +
  geom_boxplot() +
  geom_jitter() +
  guides(color = FALSE) +
  labs(
    title = "The Office ratings",
    x = "Season",
    y = "IMDB Rating"
  )
```

# Modeling

# Train / test

- Create an initial split

```
set.seed(1122)
office_split <- initial_split(office_ratings) # prop = 3/4 by default
```

- Save training data

```
office_train <- training(office_split)
dim(office_train)
```

```
## [1] 141   6
```

- Save testing data

```
office_test  <- testing(office_split)
dim(office_test)
```

```
## [1] 47  6
```

# Specify model

```
office_mod <- linear_reg() %>%
  set_engine("lm")

office_mod
```

```
## Linear Regression Model Specification (regression)
##
## Computational engine: lm
```

# Build recipe

Code Output

```
office_rec <- recipe(imdb_rating ~ ., data = office_train) %>%
  # title isn't a predictor, but keep around to ID
  update_role(title, new_role = "ID") %>%
  # extract month of air_date
  step_date(air_date, features = "month") %>%
  step_rm(air_date) %>%
  # make dummy variables of month
  step_dummy(contains("month")) %>%
  # remove zero variance predictors
  step_zv(all_predictors())
```

# Build workflow

Code Output

```
office_wflow <- workflow() %>%
  add_model(office_mod) %>%
  add_recipe(office_rec)
```

# Fit model

Code Output

```
office_fit <- office_wflow %>%
  fit(data = office_train)
```

# Evaluate model

# Make predictions for training data

```
office_train_pred <- predict(office_fit, office_train) %>%
  bind_cols(office_train %>% select(imdb_rating, title))

office_train_pred
```

```
## # A tibble: 141 x 3
##   .pred imdb_rating title
##   <dbl>       <dbl> <chr>
## 1  8.48         7.6 Pilot
## 2  8.45         8.3 Diversity Day
## 3  8.10         8.1 The Alliance
## 4  8.30         8.4 Basketball
## 5  8.18         7.8 Hot Girl
## 6  8.90         8.7 The Dundies
## # … with 135 more rows
```

# R-squared

Percentage of variability in the IMDB ratings explained by the model

```
rsq(office_train_pred, truth = imdb_rating, estimate = .pred)
```

```
## # A tibble: 1 x 3
##   .metric .estimator .estimate
##   <chr>   <chr>          <dbl>
## 1 rsq     standard       0.533
```

> Are models with high or low $R^2$ more preferable?

# RMSE

An alternative model performance statistic: **root mean square error**

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{n}}$$

```
rmse(office_train_pred, truth = imdb_rating, estimate = .pred)
```

```
## # A tibble: 1 x 3
##   .metric .estimator .estimate
##   <chr>   <chr>          <dbl>
## 1 rmse    standard       0.350
```

> Are models with high or low RMSE are more preferable?

# Interpreting RMSE

> Is this RMSE considered low or high?

```
rmse(office_train_pred, truth = imdb_rating, estimate = .pred)
```

```
## # A tibble: 1 x 3
##   .metric .estimator .estimate
##   <chr>   <chr>          <dbl>
## 1 rmse    standard       0.350
```

```
office_train %>%
  summarise(min = min(imdb_rating), max = max(imdb_rating))
```

```
## # A tibble: 1 x 2
##     min   max
##   <dbl> <dbl>
## 1   6.8   9.7
```

but, really, who cares about predictions on **training** data?

# Make predictions for testing data

```
office_test_pred <- predict(office_fit, office_test) %>%
  bind_cols(office_test %>% select(imdb_rating, title))

office_test_pred
```

```
## # A tibble: 47 x 3
##   .pred imdb_rating title
##   <dbl>       <dbl> <chr>
## 1  8.11         7.9 Health Care
## 2  8.68         8.2 Halloween
## 3  8.36         8.3 The Secret
## 4  8.56         8.1 Michael's Birthday
## 5  8.47         8   Grief Counseling
## 6  8.49         8.2 Initiation
## # … with 41 more rows
```

# Evaluate performance on testing data

- RMSE of model fit to testing data

```
rmse(office_test_pred, truth = imdb_rating, estimate = .pred)
```

```
## # A tibble: 1 x 3
##   .metric .estimator .estimate
##   <chr>   <chr>          <dbl>
## 1 rmse    standard       0.482
```

- $R^2$ of model fit to testing data

```
rsq(office_test_pred, truth = imdb_rating, estimate = .pred)
```

```
## # A tibble: 1 x 3
##   .metric .estimator .estimate
##   <chr>   <chr>          <dbl>
## 1 rsq     standard       0.496
```

# Training vs. testing

| metric | train | test | comparison |
|---|---|---|---|
| RMSE | 0.350 | 0.482 | RMSE lower for training |
| R-squared | 0.533 | 0.496 | R-squared higher for training |

# Evaluating performance on training data

- The training set does not have the capacity to be a good arbiter of performance.
- It is not an independent piece of information; predicting the training set can only reflect what the model already knows.
- Suppose you give a class a test, then give them the answers, then provide the same test. The student scores on the second test do not accurately reflect what they know about the subject; these scores would probably be higher than their results on the first test.

Source: tidymodels.org

# Cross validation

# Cross validation

More specifically, **v-fold cross validation**:

- Shuffle your data v partitions
- Use 1 partition for validation, and the remaining v-1 partitions for training
- Repeat v times

You might also heard of this referred to as k-fold cross validation.

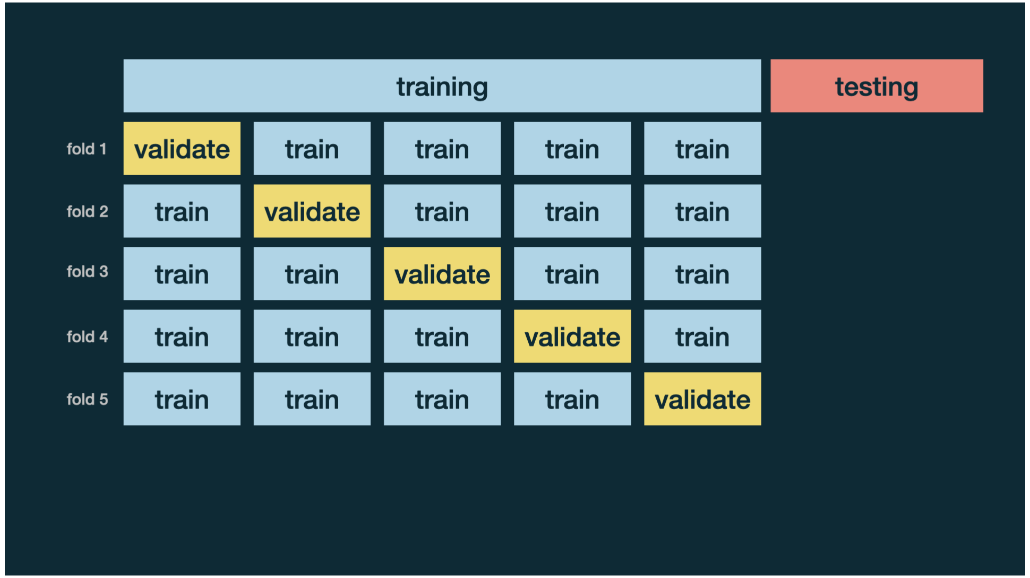
# Cross validation

# Split data into folds

```r
set.seed(345)

folds <- vfold_cv(office_train, v = 5)
folds
```

```
## #  5-fold cross-validation
## # A tibble: 5 x 2
##   splits            id
##   <list>            <chr>
## 1 <split [112/29]> Fold1
## 2 <split [113/28]> Fold2
## 3 <split [113/28]> Fold3
## 4 <split [113/28]> Fold4
## 5 <split [113/28]> Fold5
```

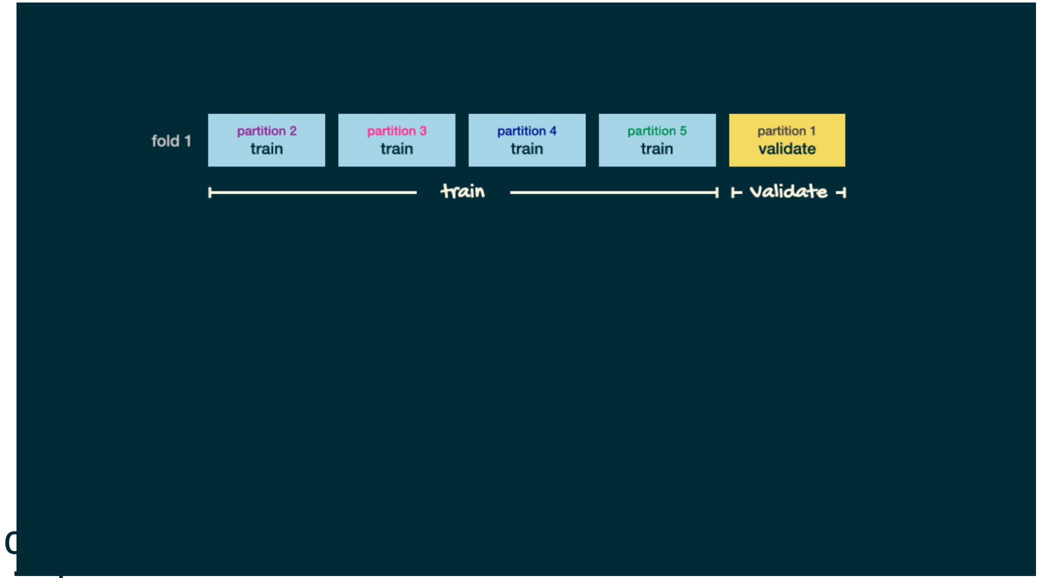


# Fit resamples

```r
set.seed(456)

office_fit_rs <- office_wflow %>%
  fit_resamples(folds)

office_fit_rs
```




```
## # Resampling results
## # 5-fold cross-validation
## # A tibble: 5 x 4
##   splits            id    .metrics         .no
##   <list>            <chr> <list>           <list>
## 1 <split [112/29]> Fold1 <tibble [2 × 4]> <tibble [0 × 1]>
## 2 <split [113/28]> Fold2 <tibble [2 × 4]> <tibble [0 × 1]>
## 3 <split [113/28]> Fold3 <tibble [2 × 4]> <tibble [0 × 1]>
## 4 <split [113/28]> Fold4 <tibble [2 × 4]> <tibble [0 × 1]>
## 5 <split [113/28]> Fold5 <tibble [2 × 4]> <tibble [0 × 1]>
```

# Collect CV metrics

```
collect_metrics(office_fit_rs)
```

```
## # A tibble: 2 x 6
##   .metric .estimator  mean     n std_err .config
##   <chr>   <chr>      <dbl> <int>   <dbl> <chr>
## 1 rmse    standard   0.378     5  0.0260 Preprocessor1_Model1
## 2 rsq     standard   0.442     5  0.0816 Preprocessor1_Model1
```

# Deeper look into CV metrics

Raw Tidy

```
collect_metrics(office_fit_rs, summarize = FALSE) %>%
  print(n = 10)
```

```
## # A tibble: 10 x 5
##    id    .metric .estimator .estimate .config
##    <chr> <chr>   <chr>          <dbl> <chr>
##  1 Fold1 rmse    standard       0.399 Preprocessor1_Model1
##  2 Fold1 rsq     standard       0.449 Preprocessor1_Model1
##  3 Fold2 rmse    standard       0.306 Preprocessor1_Model1
##  4 Fold2 rsq     standard       0.749 Preprocessor1_Model1
##  5 Fold3 rmse    standard       0.438 Preprocessor1_Model1
##  6 Fold3 rsq     standard       0.390 Preprocessor1_Model1
##  7 Fold4 rmse    standard       0.419 Preprocessor1_Model1
##  8 Fold4 rsq     standard       0.280 Preprocessor1_Model1
##  9 Fold5 rmse    standard       0.327 Preprocessor1_Model1
## 10 Fold5 rsq     standard       0.344 Preprocessor1_Model1
```

# How does RMSE compare to y?

- Cross validation RMSE stats

```
## # A tibble: 1 x 6
##     min   max  mean   med     sd    IQR
##   <dbl> <dbl> <dbl> <dbl>  <dbl>  <dbl>
## 1 0.306 0.438 0.378 0.399 0.0581 0.0918
```

- Training data IMDB score stats

```
## # A tibble: 1 x 6
##     min   max  mean   med    sd   IQR
##   <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
## 1   6.8   9.7  8.26   8.3 0.514 0.700
```

# What's next?