Modeling with `tidymodels` in R

Your Name Here

Last modified on February 18, 2025 16:54:52 Eastern Standard Time

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Preface

This material is from the DataCamp course Modeling with tidymodels in R by David Svancer.

Course Description: Tidymodels (Kuhn and Wickham 2024) is a powerful suite of R packages designed to streamline machine learning workflows. Learn to split datasets for cross-validation, preprocess data with tidymodels' recipe package, and fine-tune machine learning algorithms. You'll learn key concepts such as defining model objects and creating modeling workflows. Then, you'll apply your skills to predict home prices and classify employees by their risk of leaving a company.

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

1 Machine Learning with `tidymodels`

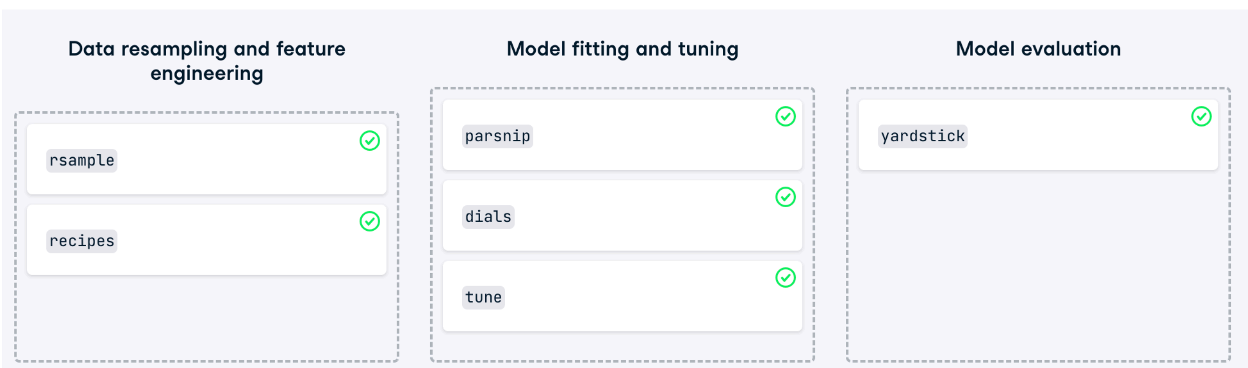
In this chapter, you'll explore the rich ecosystem of R packages that power `tidymodels` (Kuhn and Wickham 2024) and learn how they can streamline your machine learning workflows. You'll then put your `tidymodels` skills to the test by predicting house sale prices in Seattle, Washington.

The tidymodels ecosystem video

1.1 Tidymodels packages

`tidymodels` is a collection of machine learning packages designed to simplify the machine learning workflow in R.

In this exercise, you will assign each package within the `tidymodels` ecosystem to its corresponding process within the machine learning workflow.



The core packages within `tidymodels` are designed to help with every stage in a machine learning workflow.

1.2 Creating training and test datasets

The `rsample` package (Frick et al. 2024) is designed to create training and test datasets. Creating a test dataset is important for estimating how a trained model will likely perform on new data. It also guards against overfitting, where a model memorizes patterns that exist only in the training data and performs poorly on new data.

In this exercise, you will create training and test datasets from the `home_sales` data. This data contains information on homes sold in the Seattle, Washington area between 2015 and 2016.

The outcome variable in this data is `selling_price`.

The `tidymodels` package will be pre-loaded in every exercise in the course. The `home_sales` tibble has also been loaded for you.

```
library(tidymodels)
home_sales <- readRDS("./data/home_sales.rds")
head(home_sales)
```

```
# A tibble: 6 x 8
  selling_price home_age bedrooms bathrooms sqft_living sqft_lot sqft_basement
          <dbl>    <dbl>    <dbl>     <dbl>       <dbl>    <dbl>         <dbl>
1        487000       10        4      2.5         2540     5001             0
2        465000       10        3      2.25        1530     1245           480
3        411000       18        2      2           1130     1148           330
4        635000        4        3      2.5         3350     4007           800
5        380000       24        5      2.5         2130     8428             0
6        495000       21        3      3.5         1650     1577           550
# i 1 more variable: floors <dbl>
```

Instructions

- Create an `rsample` object, `home_split`, that contains the instructions for randomly splitting the `home_sales` data into a training and test dataset. Allocate 70% of the data into training and stratify the results by `selling_price`.

```
set.seed(156)
# Create a data split object
home_split <- initial_split(home_sales,
                            prop = 0.70,
                            strata = selling_price)
```

```r
home_split
```

```
<Training/Testing/Total>
<1042/450/1492>
```

- Create a training dataset from `home_split` called `home_training`.

```r
# Create the training data
home_training <- home_split |>
 training()
str(home_training)
```

```
tibble [1,042 x 8] (S3: tbl_df/tbl/data.frame)
 $ selling_price: num [1:1042] 380000 355000 356000 381000 398000 ...
 $ home_age     : num [1:1042] 24 19 24 25 14 9 37 30 26 7 ...
 $ bedrooms     : num [1:1042] 5 3 2 3 3 3 3 3 3 3 ...
 $ bathrooms    : num [1:1042] 2.5 2.25 1 2 1.5 2.5 2.25 2.25 2.5 2.25 ...
 $ sqft_living  : num [1:1042] 2130 1430 1430 1680 1310 1600 1410 1410 1600 1410 ...
 $ sqft_lot     : num [1:1042] 8428 4777 365904 8946 2996 ...
 $ sqft_basement: num [1:1042] 0 0 420 740 0 0 120 120 0 120 ...
 $ floors       : num [1:1042] 2 2 1 1 2 2 2 2 2 2 ...
```

- Create the `home_test` tibble by passing `home_split` into the appropriate function for generating test datasets.

```r
# Create the test data
home_test <- home_split |>
  testing()
str(home_test)
```

```
tibble [450 x 8] (S3: tbl_df/tbl/data.frame)
 $ selling_price: num [1:450] 411000 425000 535000 559900 552321 ...
 $ home_age     : num [1:450] 18 11 3 20 29 6 22 25 26 24 ...
 $ bedrooms     : num [1:450] 2 4 4 3 3 3 3 3 5 3 ...
 $ bathrooms    : num [1:450] 2 2.5 2.75 2.75 2.5 2.25 2.5 2.5 3.75 2.25 ...
 $ sqft_living  : num [1:450] 1130 1920 2360 2930 1960 ...
 $ sqft_lot     : num [1:450] 1148 9000 15100 5569 8469 ...
 $ sqft_basement: num [1:450] 330 0 0 1070 0 350 0 0 0 145 ...
 $ floors       : num [1:450] 2 2 1 1 2 2 2 2 2 2 ...
```

- Check the number of rows in the training and test datasets by passing them into the `nrow()` function.

```r
# Check number of rows in each dataset
nrow(home_training)
```

```
[1] 1042
```

```r
nrow(home_test)
```

```
[1] 450
```

> Note
>
> Since the `home_sales` data has 1492 rows, it is appropriate to allocate more rows into the test set. This will provide more data for the model evaluation step.

1.3 Distribution of outcome variable values

Stratifying by the outcome variable when generating training and test datasets ensures that the outcome variable values have a similar range in both datasets.

Since the original data is split at random, stratification avoids placing all the expensive homes in `home_sales` into the test dataset, for example. In this case, your model would most likely perform poorly because it was trained on less expensive homes.

In this exercise, you will calculate summary statistics for the `selling_price` variable in the training and test datasets. The `home_training` and `home_test` tibbles have been loaded from the previous exercise.

Instructions

- Calculate the minimum, maximum, mean, and standard deviation of the `selling_price` variable in `home_training`.

```r
# Distribution of selling_price in training data
home_training |>
  summarize(min_sell_price = min(selling_price),
            max_sell_price = max(selling_price),
            mean_sell_price = mean(selling_price),
            sd_sell_price = sd(selling_price)) |>
```

```
  kable()
```

min_sell_price	max_sell_price	mean_sell_price	sd_sell_price
350000	650000	478448.6	80394.43

- Calculate the minimum, maximum, mean, and standard deviation of the `selling_price` variable in `home_test`.

```
# Distribution of selling_price in test data
home_test |>
  summarize(min_sell_price = min(selling_price),
            max_sell_price = max(selling_price),
            mean_sell_price = mean(selling_price),
            sd_sell_price = sd(selling_price)) |>
  kable()
```

min_sell_price	max_sell_price	mean_sell_price	sd_sell_price
350000	650000	480556.9	82387.91

Note

The minimum and maximum selling prices in both datasets are the same. The mean and standard deviation are also similar. Stratifying by the outcome variable ensures the model fitting process is performed on a representative sample of the original data.

Linear regression with tidymodels video

1.4 Fitting a linear regression model

The `parsnip` package (Kuhn and Vaughan 2025) provides a unified syntax for the model fitting process in R.

With `parsnip`, it is easy to define models using the various packages, or engines, that exist in the R ecosystem.

In this exercise, you will define a `parsnip` linear regression object and train your model to predict `selling_price` using `home_age` and `sqft_living` as predictor variables from the `home_sales` data.

The `home_training` and `home_test` tibbles that you created in the previous lesson have been loaded into this session.

Instructions

- Initialize a linear regression object, `linear_model` (this is often called a specification and will frequently be stored as `linear_spec` versus `linear_model`), with the appropriate `parsnip` function. Use the `"lm"` engine. Set the mode to `"regression"`.

```
# Initialize a linear regression object, linear_model
linear_model <- linear_reg() |>
  # Set the model engine
  set_engine('lm') |>
  # Set the model mode
  set_mode('regression')
linear_model
```

```
Linear Regression Model Specification (regression)

Computational engine: lm
```

- Train your model to predict `selling_price` using `home_age` and `sqft_living` as predictor variables from the `home_training` dataset. Print `lm_fit` to view the model information.

```
# Train the model with the training data
lm_fit <- linear_model |>
  fit(selling_price ~ home_age + sqft_living,
      data = home_training)

# Print lm_fit to view model information
lm_fit
```

```
parsnip model object


Call:
stats::lm(formula = selling_price ~ home_age + sqft_living, data = data)

Coefficients:
(Intercept)     home_age  sqft_living
```

```
291587.2       -1550.0         103.8
```

```r
tidy(lm_fit) |>
  kable()
```

term	estimate	std.error	statistic	p.value
(Intercept)	291587.211	7445.953323	39.160494	0
home_age	-1549.992	173.052920	-8.956754	0
sqft_living	103.789	2.706057	38.354335	0

> Note
>
> You have defined your model with `linear_reg()` and trained it to predict `selling_price` using `home_age` and `sqft_living`. Printing a `parsnip` model fit object displays useful model information, such as the training time, model formula used during training, and the estimated model parameters.

1.5 Exploring estimated model parameters

In the previous exercise, you trained a linear regression model to predict `selling_price` using `home_age` and `sqft_living` as predictor variables.

Your trained model, `lm_fit`, has been loaded into this session.

Pass your trained model object, `lm_fit` into the appropriate function to explore the estimated model parameters.

Which of the following statements is correct?

- The standard error, std.error, for the `sqft_living` predictor variable is 175.
- The estimated parameter for the `home_age` predictor variable is 305.
- **The estimated parameter for the `sqft_living` predictor variable is 104.**
- The estimated intercept is 127825.

> Note
>
> The `tidy()` function automatically creates a tibble of estimated model parameters. Since `sqft_living` has a positive estimated parameter, the selling price of homes increases with the square footage. Conversely, since `home_age` has a negative estimated parameter, older homes tend to have lower selling prices.

Predicting home selling prices

After fitting a model using the training data, the next step is to use it to make predictions on the test dataset. The test dataset acts as a new source of data for the model and will allow you to evaluate how well it performs.

Before you can evaluate model performance, you must add your predictions to the test dataset.

In this exercise, you will use your trained model, `lm_fit`, to predict `selling_price` in the `home_test` dataset.

Your trained model, `lm_fit`, as well as the test dataset, `home_test` have been loaded into your session.

Instructions

- Create a tibble, `home_predictions`, that contains the predicted selling prices of homes in the test dataset.

```
# Predict selling_price
home_predictions <- predict(lm_fit,
                            new_data = home_test)

# View predicted selling prices
head(home_predictions) |>
  kable()
```

.pred
380968.9
473812.2
531879.3
564689.1
450063.9
535532.4

- Create a tibble with the `selling_price`, `home_age`, and `sqft_living` columns from the test dataset and the predicted home selling prices named `home_test_results`.

```
# Combine test data with predictions
home_test_results <- home_test |>
  select(selling_price, home_age, sqft_living) |>
```

```r
  bind_cols(home_predictions)
head(home_test_results) |>
  kable()
```

selling_price	home_age	sqft_living	.pred
411000	18	1130	380968.9
425000	11	1920	473812.2
535000	3	2360	531879.3
559900	20	2930	564689.1
552321	29	1960	450063.9
485000	6	2440	535532.4

```r
# Or
broom::augment(lm_fit, new_data = home_test) |>
  select(.pred, selling_price, home_age,
         sqft_living) -> home_test_results
head(home_test_results) |>
  kable()
```

.pred	selling_price	home_age	sqft_living
380968.9	411000	18	1130
473812.2	425000	11	1920
531879.3	535000	3	2360
564689.1	559900	20	2930
450063.9	552321	29	1960
535532.4	485000	6	2440

Note

You have trained a linear regression model and used it to predict the selling prices of homes in the test dataset! The model only used two predictor variables, but the predicted values in the `.pred` column seem reasonable!

Evaluating model performance video

1.6 Model performance metrics

Evaluating model results is an important step in the modeling process. Model evaluation should be done on the test dataset in order to see how well a model will generalize to new datasets.

In the previous exercise, you trained a linear regression model to predict `selling_price` using `home_age` and `sqft_living` as predictor variables. You then created the `home_test_results` tibble using your trained model on the `home_test` data.

In this exercise, you will calculate the RMSE and R^2 metrics using your results in `home_test_results`.

The `home_test_results` tibble has been loaded into your session.

Instructions

- Execute the first two lines of code which print the `home_test_results`. This tibble contains the actual and predicted home selling prices in the `home_test dataset`. Using `home_test_results`, calculate the RMSE and R squared metrics.

```
# Print home_test_results
head(home_test_results)
```

```
# A tibble: 6 x 4
    .pred selling_price home_age sqft_living
    <dbl>         <dbl>    <dbl>       <dbl>
1 380969.        411000       18        1130
2 473812.        425000       11        1920
3 531879.        535000        3        2360
4 564689.        559900       20        2930
5 450064.        552321       29        1960
6 535532.        485000        6        2440
```

```
# Calculate the RMSE metric
home_test_results |>
  rmse(truth = selling_price, estimate = .pred) -> ARMSE
kable(ARMSE)
```

.metric	.estimator	.estimate
rmse	standard	49988.89

```
# Same as
home_test_results |>
  summarize(RMSE = sqrt(mean((selling_price - .pred)^2)))
```

```
# A tibble: 1 x 1
    RMSE
   <dbl>
1 49989.
```

```
# Calculate the R squared metric
home_test_results |>
  rsq(truth = selling_price, estimate = .pred) -> AR2
kable(AR2)
```

.metric	.estimator	.estimate
rsq	standard	0.6315395

```
# Same as
home_test_results |>
  summarize(R2 = cor(selling_price, .pred)^2)
```

```
# A tibble: 1 x 1
     R2
  <dbl>
1 0.632
```

> Note
>
> The RMSE metric indicates that the average prediction error for home selling prices is $49,988.89. Not bad considering you only used `home_age` and `sqft_living` as predictor variables!

1.7 R squared plot

In the previous exercise, you got an R^2 value of 0.6315395. The R^2 metric ranges from 0 to 1, 0 being the worst and 1 the best.

Calculating the R^2 value is only the first step in studying your model's predictions.

Making an R^2 plot is extremely important because it will uncover potential problems with your model, such as non-linear patterns or regions where your model is either over or under-predicting the outcome variable.

In this exercise, you will create an R^2 plot of your model's performance.

The `home_test_results` tibble has been loaded into your session.

Instructions

- Create an R^2 plot of your model's performance. The x-axis should have the actual selling price and the y-axis should have the predicted values. Use the appropriate functions to add the line $y = x$ to your plot and standardize the range of both axes.

```r
# Create an R squared plot of model performance
ggplot(home_test_results, aes(x = selling_price, y = .pred)) +
  geom_point(alpha = 0.5) +
  geom_abline(color = 'blue', linetype = "dashed") +
  coord_obs_pred() +
  scale_x_continuous(labels = scales::label_currency()) +
  scale_y_continuous(labels = scales::label_currency()) +
  labs(x = 'Actual Home Selling Price', y = 'Predicted Selling Price') +
  theme_bw()
```

Note

From the plot, you can see that your model tends to over-predict selling prices for homes that sold for less than $400,000, and under-predict for homes that sold for $600,000 or more. This indicates that you will have to add more predictors to your model or that linear regression may not be able to model the relationship as well as more advanced modeling techniques!

1.8 Complete model fitting process with `last_fit()`

In this exercise, you will train and evaluate the performance of a linear regression model that predicts `selling_price` using all the predictors available in the `home_sales` tibble.

This exercise will give you a chance to perform the entire model fitting process with `tidymodels`, from defining your model object to evaluating its performance on the test data.

Earlier in the chapter, you created an `rsample` object called `home_split` by passing the `home_sales` tibble into `initial_split()`. The `home_split` object contains the instructions for randomly splitting `home_sales` into training and test sets.

The `home_sales` tibble, and `home_split` object have been loaded into this session.

Instructions

- Use the `linear_reg()` function to define a linear regression **specification**. Use the `lm` engine.

```
# Define a linear regression specification
linear_model <- linear_reg() |>
  set_engine("lm") |>
  set_mode("regression")
```

- Train your linear regression object with the `last_fit()` function. In your model formula, use `selling_price` as the outcome variable and all other columns as predictor variables. Create a tibble with the model's predictions on the test data.

```
# Train linear_model with last_fit()
linear_fit <- linear_model |>
  last_fit(selling_price ~ ., split = home_split)

# Collect predictions and view results
predictions_df <- linear_fit |>
  collect_predictions()
predictions_df |>
  head() |>
  kable()
```

.pred	id	.row	selling_price	.config
397707.5	train/test split	3	411000	Preprocessor1_Model1
440709.5	train/test split	9	425000	Preprocessor1_Model1
487982.5	train/test split	10	535000	Preprocessor1_Model1
586699.0	train/test split	14	559900	Preprocessor1_Model1
469003.7	train/test split	15	552321	Preprocessor1_Model1
561843.3	train/test split	17	485000	Preprocessor1_Model1

- Create an R^2 plot of the model's performance. The x-axis should have the actual selling price and the y-axis should have the predicted values.

```
# Make an R squared plot using predictions_df
ggplot(predictions_df, aes(x = selling_price, y = .pred)) +
  geom_point(alpha = 0.5) +
  geom_abline(color = 'blue', linetype = "dashed") +
  coord_obs_pred() +
```

```
  scale_x_continuous(labels = scales::label_currency()) +
  scale_y_continuous(labels = scales::label_currency()) +
  labs(x = 'Actual Home Selling Price', y = 'Predicted Selling Price') +
  theme_bw()
```

Note

You have created your first machine learning pipeline and visualized the performance of your model. From the R^2 plot, the model still tends to over-predict selling prices for homes that sold for less than $400,000 and under-predict for homes at $600,000 or more, but it is a slight improvement over your previous model with only two predictor variables.

References

Frick, Hannah, Fanny Chow, Max Kuhn, Michael Mahoney, Julia Silge, and Hadley Wickham. 2024. *Rsample: General Resampling Infrastructure*. https://rsample.tidymodels.org.

Kuhn, Max, and Davis Vaughan. 2025. *Parsnip: A Common API to Modeling and Analysis Functions*. https://github.com/tidymodels/parsnip.

Kuhn, Max, and Hadley Wickham. 2024. *Tidymodels: Easily Install and Load the Tidymodels Packages*. https://tidymodels.tidymodels.org.