What is feature engineering?

FEATURE ENGINEERING IN R

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What is feature engineering?

Feature engineering is the art and science of

- creating,
- transforming,
- extracting, and
- selecting

variables to improve model performance and interpretability.

Height of an object as a function of time

```
# A tibble: 100 × 2
    time height
   <dbl>  <dbl>
 1 0        0
 2 0.101    3.85
 3 0.202   17.7
 4 0.303   15.1
 5 0.404   20.0
 6 0.505   32.6
 7 0.606   30.8
 8 0.707   26.6
```

Why engineer features?

We create a simple regression model of height

```
lr_height <- lm(height ~ time,
                data = height)
```

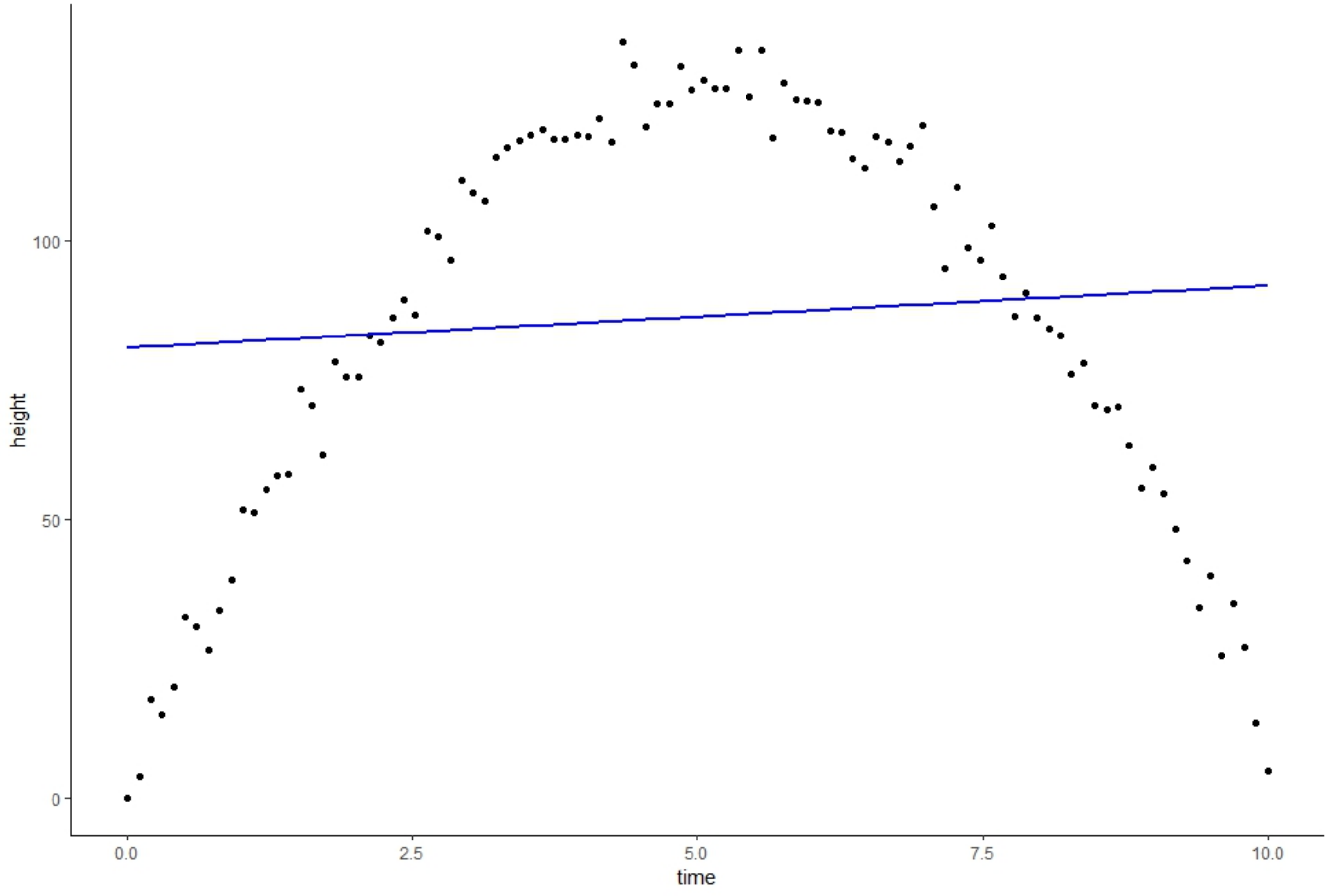
and graph it to assess accuracy by sight.

```
df <- height %>%
bind_cols(lr_pred = predict(lr_height))

df %>%
  ggplot(aes(x = time, y = height)) +
  geom_point() +
  geom_line(aes(y = lr_pred),
            color = "blue", lwd = .75)+
    theme_classic()
```

Our model fails miserably to represent the data!

Linear regression of height *vs.* time.



Using mutate()

The height of an object follows a parabolic path given by the following formula:

$$y(t) = y_0 + v_0 t - \frac{g}{2}t^2.$$

Where y represents the height of the object at time t, and y_0, v_0, and g are, respectively, the initial height, velocity, and acceleration due to gravity.

We can fit our model, recognizing the dependence of height on both time and the square of time.

`mutate()` takes a data frame as a first argument and the definition of a new variable to be added to the data frame.

```
df_2 <- df %>% mutate(time_2 = time^2)
```

```
# A tibble: 100 × 4
   time height lr_pred time_2
  <dbl>  <dbl>   <dbl>  <dbl>
1 0        0      80.8 0
2 0.101    3.85   80.9 0.0102
3 0.202   17.7    81.0 0.0408
4 0.303   15.1    81.1 0.0918
```

Predict using the engineered feature

We create another regression model, using our new feature along with the original one.

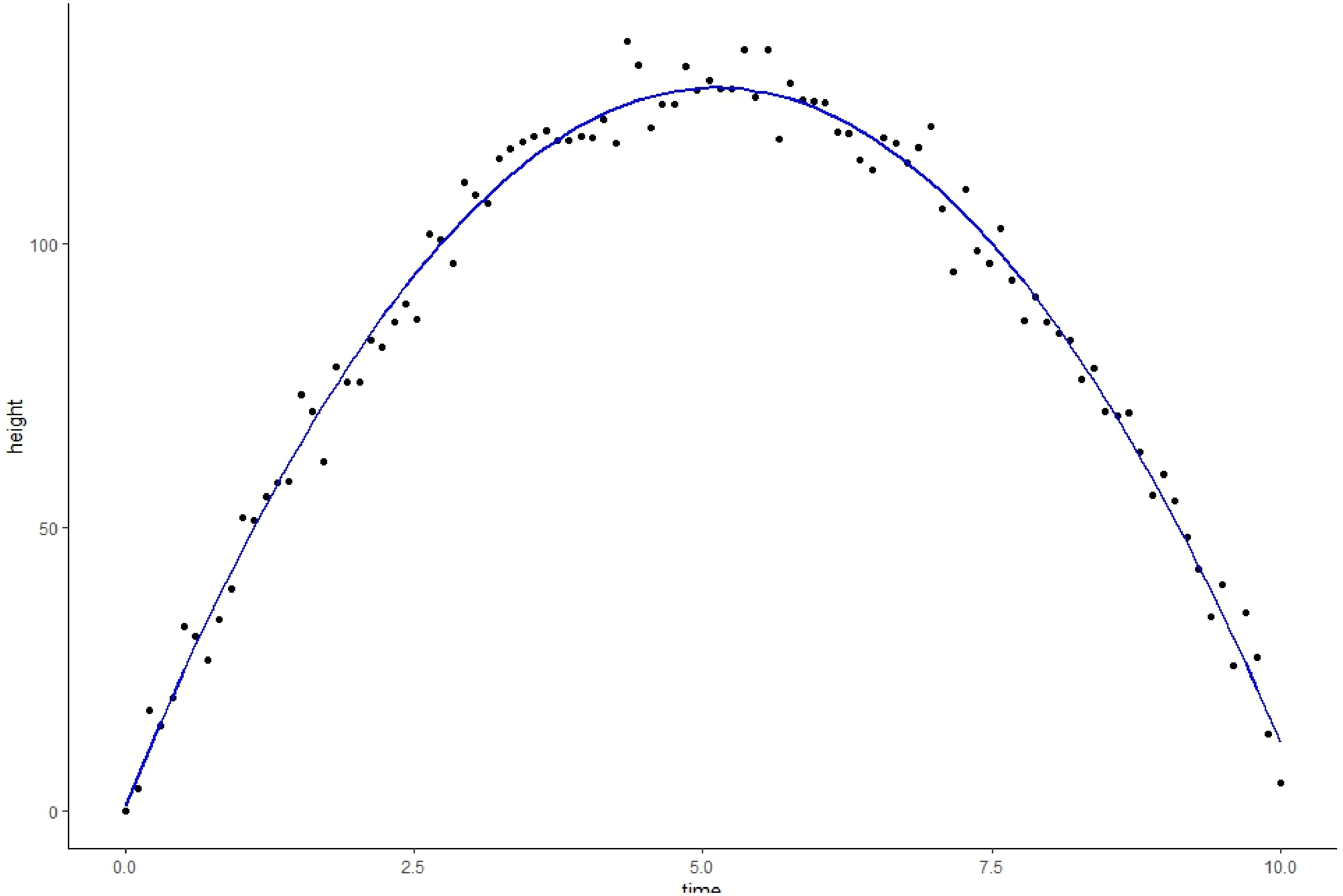
```
lr_height_2 <-
lm(height ~ time + time_2, data = df_2)
```

And graph our new prediction.

```
df_2 <- df_2 %>%
    bind_cols(lr2_pred = predict(lr_height_2))
df_2 %>%
  ggplot(aes(x = time, y = height)) +
  geom_point() +
  geom_line(aes(y = lr2_pred),
      col = "blue", lwd = .75) +
  theme_classic()
```

That is an impressive improvement without resorting to a different model.

Height vs. time and time_2



Let's practice!

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Creating new features using domain knowledge

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The importance of domain knowledge

Domain knowledge enables us to identify and create relevant and useful features for a particular model or task.

Feature engineering is about creating new input features from existing ones.

Examples of domain knowledge:

- **Financial:** The critical determinants of bankruptcy
- **Medical:** Pre-existing conditions relevant to a specific treatment
- **Marketing:** Distinguishing features of a consumer group

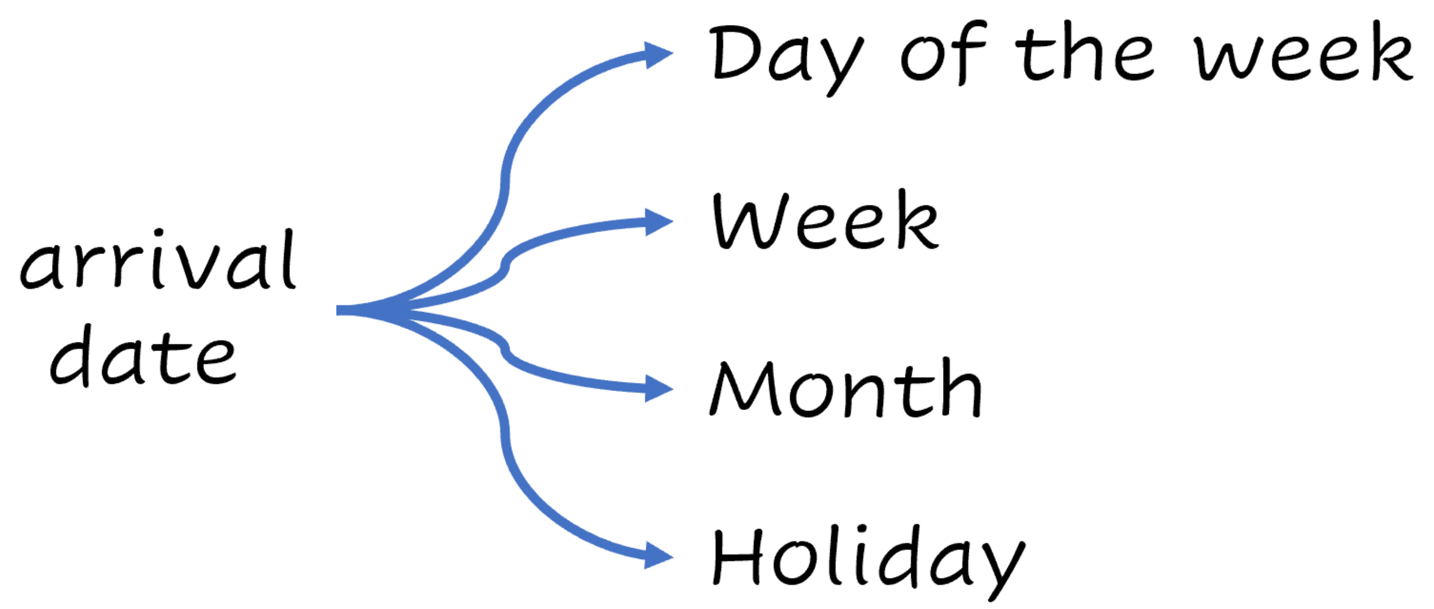
Creating variables based on professional experience

We want to predict hotel cancellations based on the following feature vector:

```r
features <-
c("IsCanceled", "LeadTime",
  "arrival_date",
  "StaysInWeekendNights",
  "StaysInWeekNights",
  "PreviousCancellations",
  "PreviousBookingsNotCanceled",
  "ReservedRoomType",
  "AssignedRoomType","BookingChanges",
  "DepositType","CustomerType",
  "ADR","TotalOfSpecialRequests")
```

Features form raw data

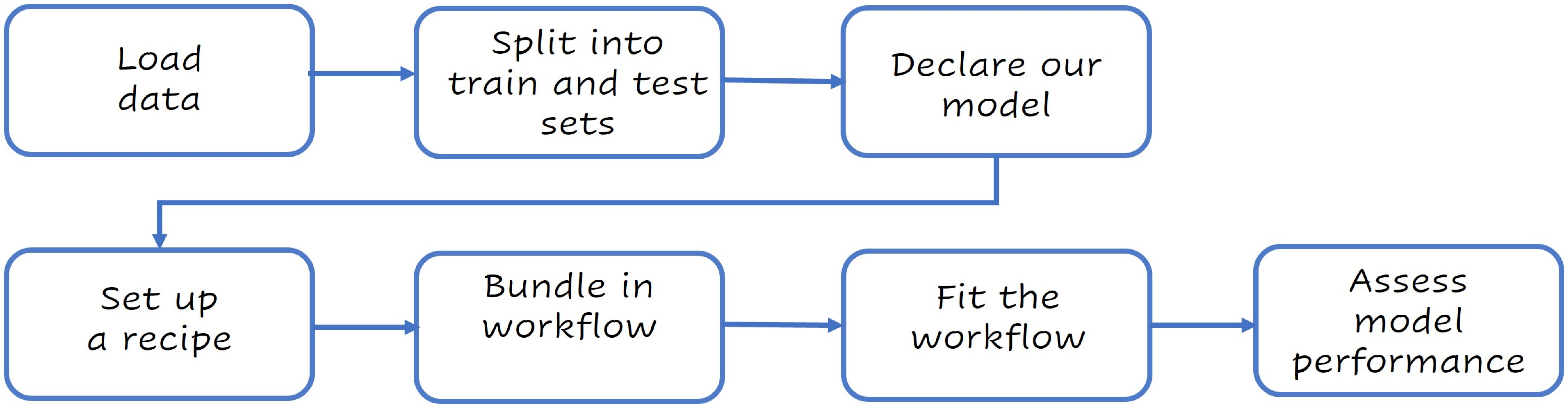
We can generate informative features from `arrival_date`.



But this becomes tedious quickly. We need to automate it!

The tidymodels framework

We'll use a workflow based on `tidymodels` , a collection of packages for modeling and machine learning using `tidyverse` principles (1) with emphasis on feature engineering.



We can learn more at **www.tidymodels.org**

[1] [Tidyverse guiding principles.](https://design.tidyverse.org/unifying-principles.html)

Setting up our data for analysis

Let's start by getting our data ready.

```
cancelations <-
  cancelations %>%
  mutate(across(where(is_character),as.factor))
```

```
set.seed(123)
split <- cancellations %>%
    initial_split(
    strata = "IsCanceled")
train <- training(split)
test <- testing(split)
```

The prop parameter can be used to change the train/test data split (the default is 3/4).

```
initial_split(data, prop = 3/4, strata = NULL)
```

Verify that `train` and `test` sets exhibit similar proportions of canceled reservations.

```
train %>%
  select(IsCanceled) %>% table() %>%
  prop.table()

IsCanceled
        0         1
0.5826946 0.4173054
```

```
test %>%
  select(IsCanceled) %>% table() %>%
  prop.table()

IsCanceled
        0         1
0.5827788 0.4172212
```

Building a workflow

Declare our model

```
lr_model <- logistic_reg()
```

Build a recipe

```
lr_recipe <-
  recipe(IsCanceled ~., data = train) %>%
  update_role(Agent, new_role = "ID" ) %>%
  step_date(arrival_date,
      features = c("dow", "week", "month")) %>%
  step_holiday(arrival_date,
      holidays = timeDate::listHolidays("US")) %>%
  step_rm(arrival_date) %>%
  step_dummy(all_nominal_predictors())
```

Print `lr_recipe`

```
Recipe
Inputs:

      role #variables
        ID          1
   outcome          1
 predictor         13

Operations:

Date features from arrival_date
Holiday features from arrival_date
Variables removed arrival_date
Dummy variables from all_nominal_predictors()
```

Building a workflow

Bundle the model and the recipe into a `workflow` object.

```
lr_workflow <-
  workflow()%>%
  add_model(lr_model)%>%
  add_recipe(lr_recipe)
```

Fit the workflow

```
lr_fit <-
  lr_workflow %>%
  fit(data = train)
```

Building a workflow

We can use `tidy(lr_fit)` to summarize our model.

```
# A tibble: 65 × 5
   term                        estimate std.error statistic   p.value
   <chr>                          <dbl>     <dbl>     <dbl>     <dbl>
 1 (Intercept)                 -1.92     0.228        -8.43 3.57e- 17
 2 LeadTime                     0.00414  0.000268     15.4  1.16e- 53
 3 StaysInWeekendNights         0.0860   0.0382        2.25 2.45e-  2
 4 StaysInWeekNights            0.0804   0.0185        4.34 1.40e-  5
 5 PreviousCancellations        2.39     0.147        16.2  2.45e- 59
 6 PreviousBookingsNotCanceled -0.440    0.0450       -9.77 1.45e- 22
 7 BookingChanges              -0.449    0.0463       -9.69 3.18e- 22
 8 ADR                          0.0104   0.000782     13.2  4.85e- 40
 9 TotalOfSpecialRequests      -0.727    0.0316      -23.0  5.29e-117
10 arrival_date_week            0.0245   0.0171        1.43 1.53e-  1
# … with 55 more rows
```

Assessing model performance

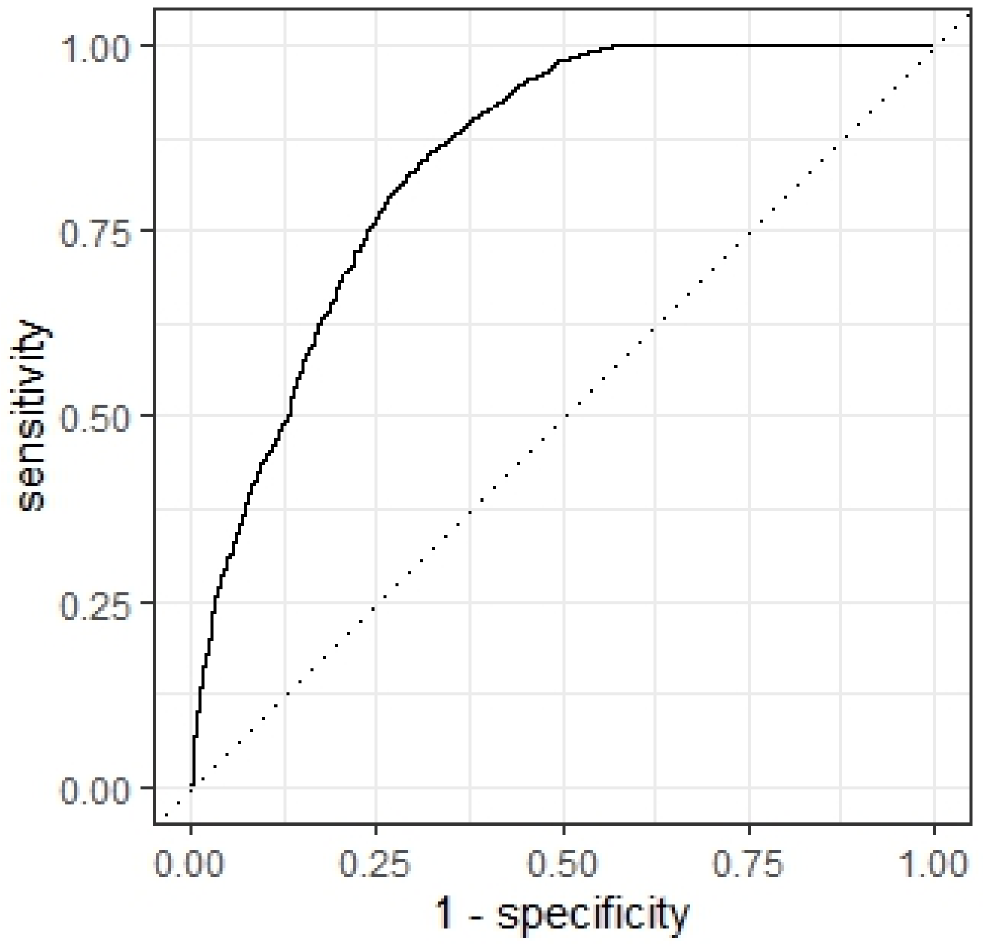
We can now assess our model's performance.

```
lr_aug <- lr_fit %>% augment(test)

bind_rows(
  lr_aug %>%
  roc_auc(truth = IsCanceled,.pred_0),
  lr_aug %>%
  accuracy(truth = IsCanceled,.pred_class))
```

```
# A tibble: 2 × 3
  .metric  .estimator .estimate
  <chr>    <chr>          <dbl>
1 roc_auc  binary         0.842
2 accuracy binary         0.782
```

```
lr_aug %>%
  roc_curve(truth = IsCanceled, .pred_0) %>%
  autoplot()
```



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Increasing the information content of raw data

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Dealing with raw data

A typical dataset with missing values

Col_1	Col_2	...	Col_n
Data	Data	Data	NA
NA	Data	Data	Data
Data	NA	Data	Data
Data	NA	Data	Data
Data	Data	Data	NA

Values as factors

Col_1
Factor_1
Factor_2
Factor_4
Factor_3
Factor_2

Dealing with raw data

Dataset with imputed values

Col_1	Col_2	...	Col_n
Data	Data	Data	Data
Data	Data	Data	Data
Data	Data	Data	Data
Data	Data	Data	Data
Data	Data	Data	Data

Factors represented as dummy variables

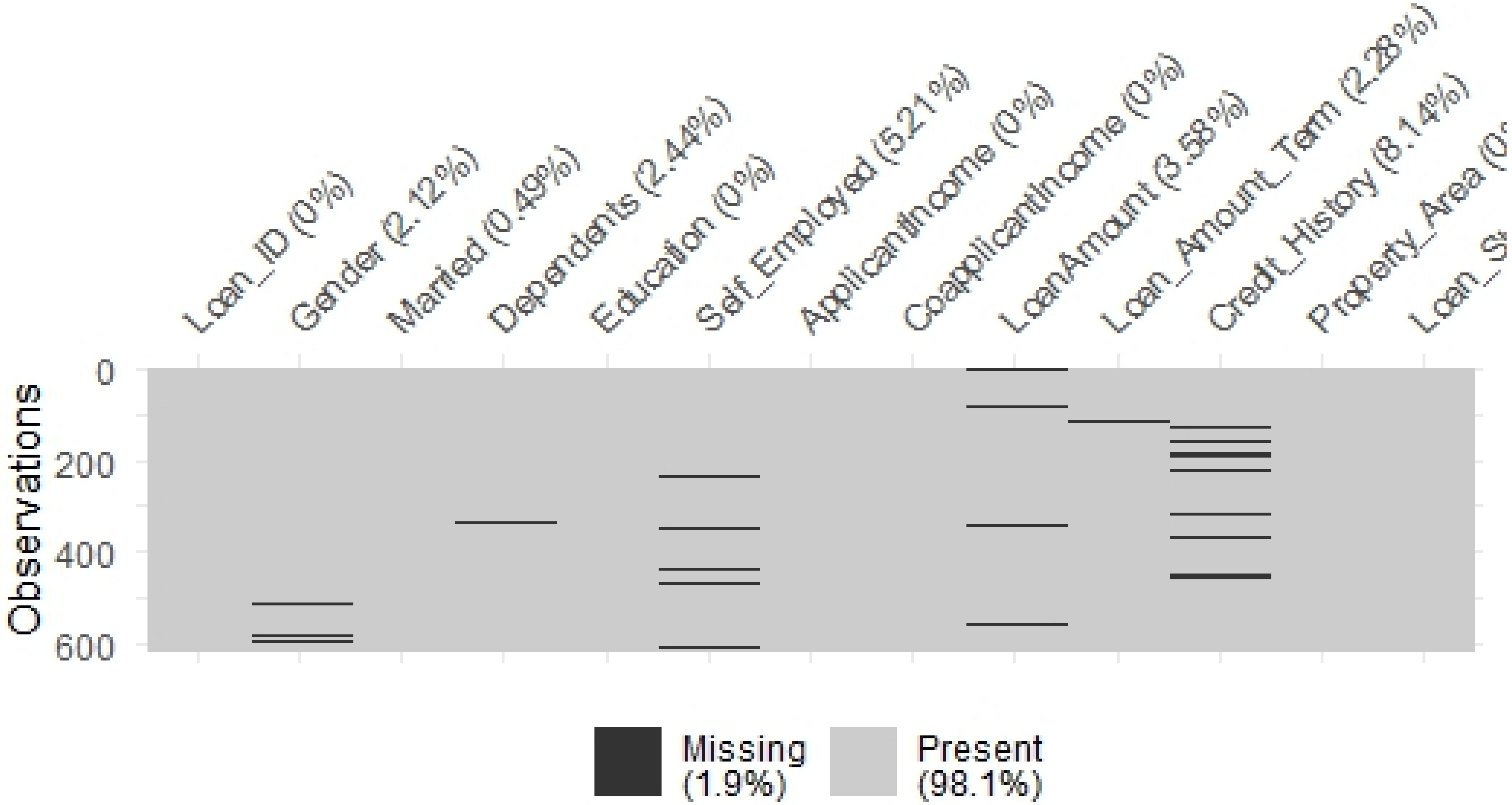
Factor_2	Factor_3	Factor_4
0	0	0
1	0	0
0	0	1
0	1	0
1	0	0

The loans dataset

```
# A tibble: 614 × 13
   Loan_ID  Gender Married Dependents Educa…¹ Self_…² Appli…³ Coapp…? LoanA…? Loan_…?
   <fct>    <fct>  <fct>   <fct>      <fct>   <fct>     <dbl>   <dbl>   <dbl>   <dbl>
 1 LP001002 Male   No      0          Gradua… No         5849       0      NA     360
 2 LP001003 Male   Yes     1          Gradua… No         4583    1508     128     360
 3 LP001005 Male   Yes     0          Gradua… Yes        3000       0      66     360
 4 LP001006 Male   Yes     0          Not Gr… No         2583    2358     120     360
 5 LP001008 Male   No      0          Gradua… No         6000       0     141     360
 6 LP001011 Male   Yes     2          Gradua… Yes        5417    4196     267     360
 7 LP001013 Male   Yes     0          Not Gr… No         2333    1516      95     360
 8 LP001014 Male   Yes     3+         Gradua… No         3036    2504     158     360
 9 LP001018 Male   Yes     2          Gradua… No         4006    1526     168     360
10 LP001020 Male   Yes     1          Gradua… No        12841   10968     349     360
# … with 604 more rows, 3 more variables: Credit_History <dbl>, Property_Area <fct>,
#   Loan_Status <fct>, and abbreviated variable names ¹?Education, ²?Self_Employed,
#   ³?ApplicantIncome, ??CoapplicantIncome, ??LoanAmount, ??Loan_Amount_Term
# ? Use `print(n = ...)` to see more rows, and `colnames()` to see all variable names
```

Missing values

We can visually identify missing values in `loans` using `vis_miss(loans)` from the package `naniar`.

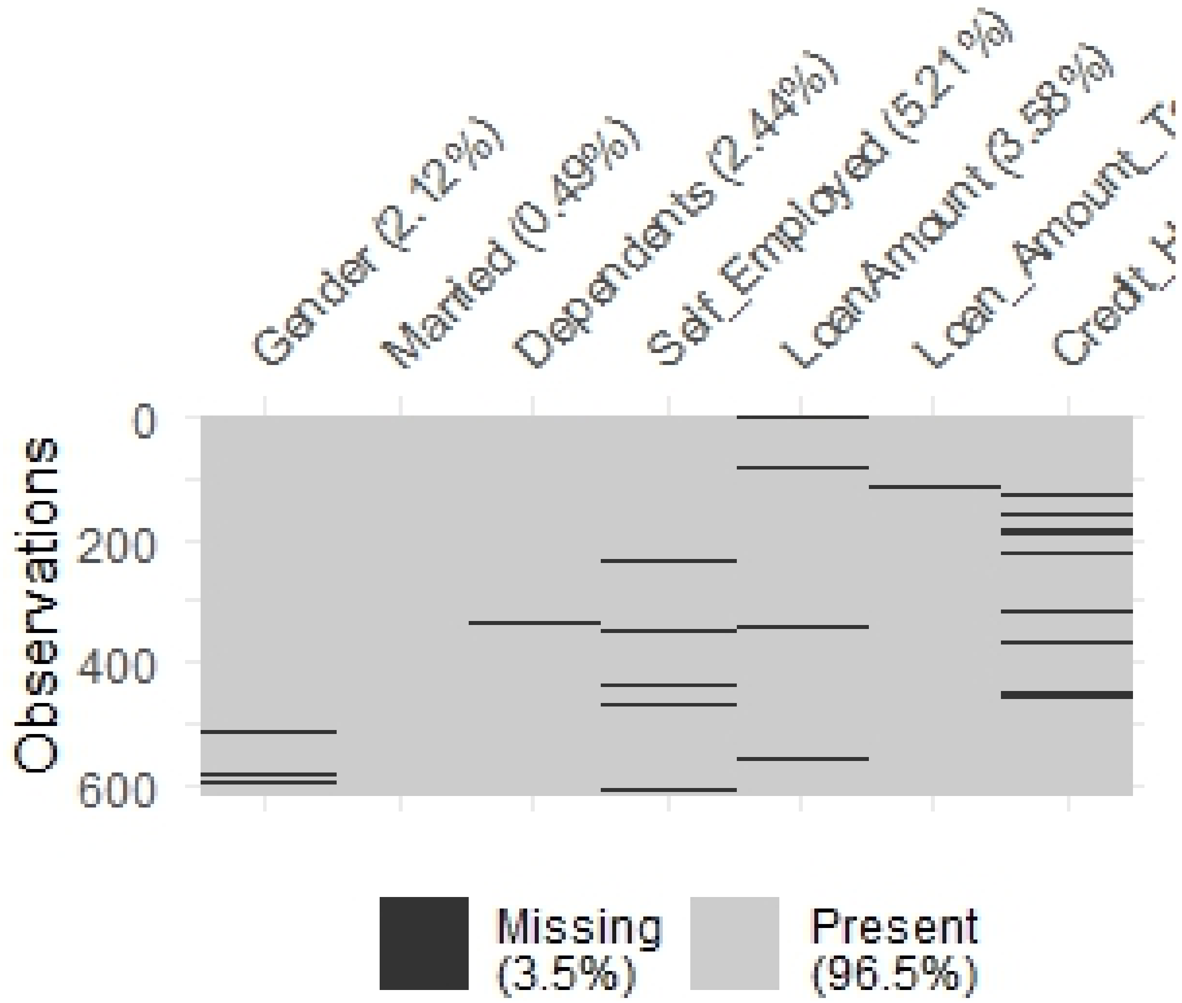


Missing values

We can zoom the table by selecting only the columns with missing values.

```
loans %>%
select(Gender,
       Married,
       Dependents,
       Self_Employed,
       LoanAmount,
       Loan_Amount_Term,
       Credit_History) %>%
  vis_miss()
```

A closer view of missing values



Missing values and dummy variables

We can address missing values and create dummy variables in the same recipe.

```
lr_recipe <-
  recipe(Loan_Status ~.,
         data = train) %>%
  update_role(Loan_ID,
              new_role = "ID" ) %>%
  step_impute_knn(all_predictors()) %>%
  step_dummy(all_nominal_predictors())
```

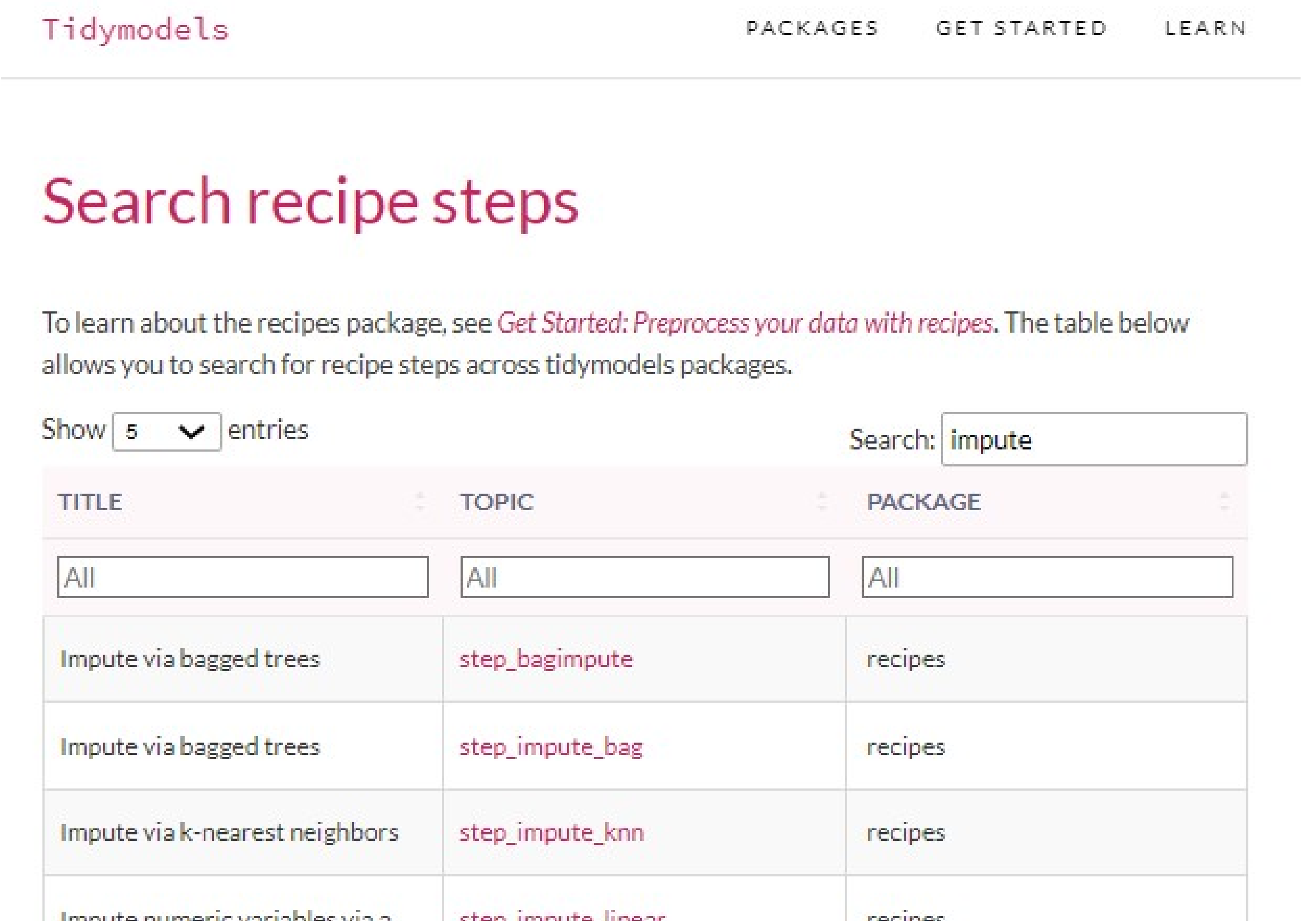
Print the recipe

```
lr_recipe
```

```
Recipe

Inputs:

      role #variables
        ID          1
   outcome          1
 predictor         30

Operations:

K-nearest neighbor imputation for all_predictors()
Dummy variables from all_nominal_predictors()
```

Finding the right recipe step

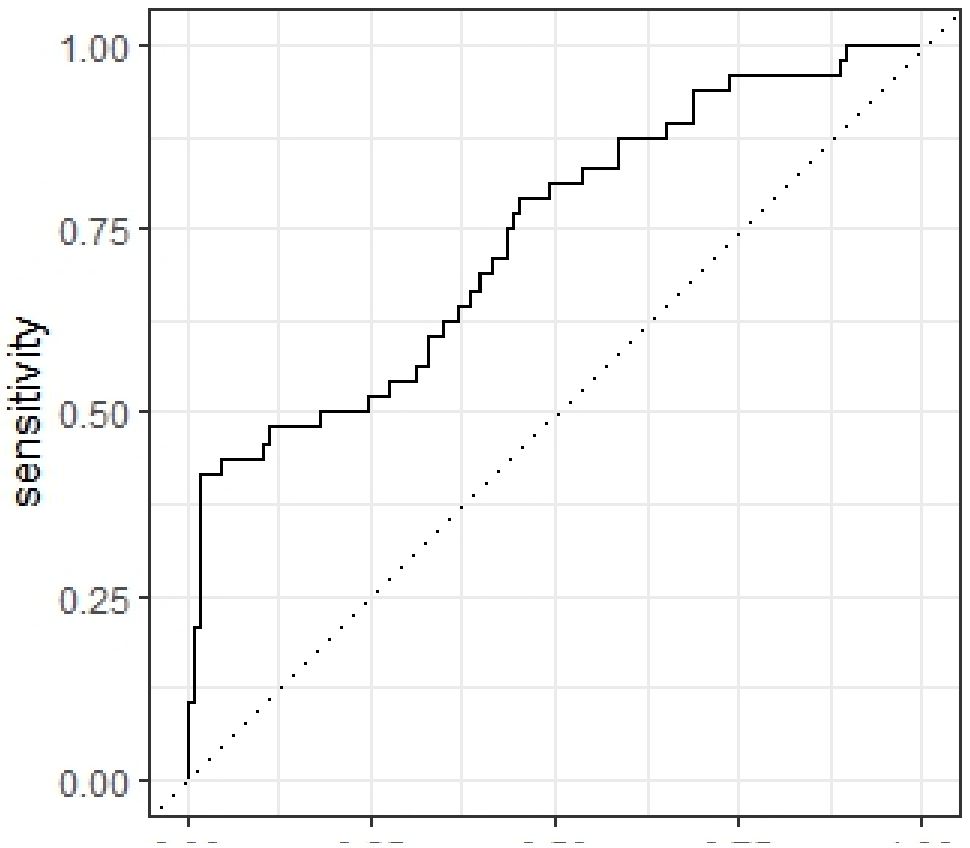
We can find other imputation methods and all recipe steps in the `tidymodels` documentations at **www.tidymodels.org/find/recipes**



Fitting and assessing our model

```
# Fit
lr_fit <-
  lr_workflow %>% fit(data = train)
lr_aug <-
  lr_fit %>% augment(test)
# Assess
lr_aug %>%
  roc_curve(truth = Loan_Status, .pred_N) %>%
  autoplot()

bind_rows(lr_aug %>%
            roc_auc(truth = Loan_Status,
                    .pred_N),
          lr_aug %>%
            accuracy(truth = Loan_Status,
                     .pred_class))
```

```
# A tibble: 2 × 3
  .metric  .estimator .estimate
  <chr>    <chr>          <dbl>
1 roc_auc  binary         0.738
2 accuracy binary         0.792
```



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