MACHINE LEARNING IN THE TIDYVERSE

Logistic Regression Models

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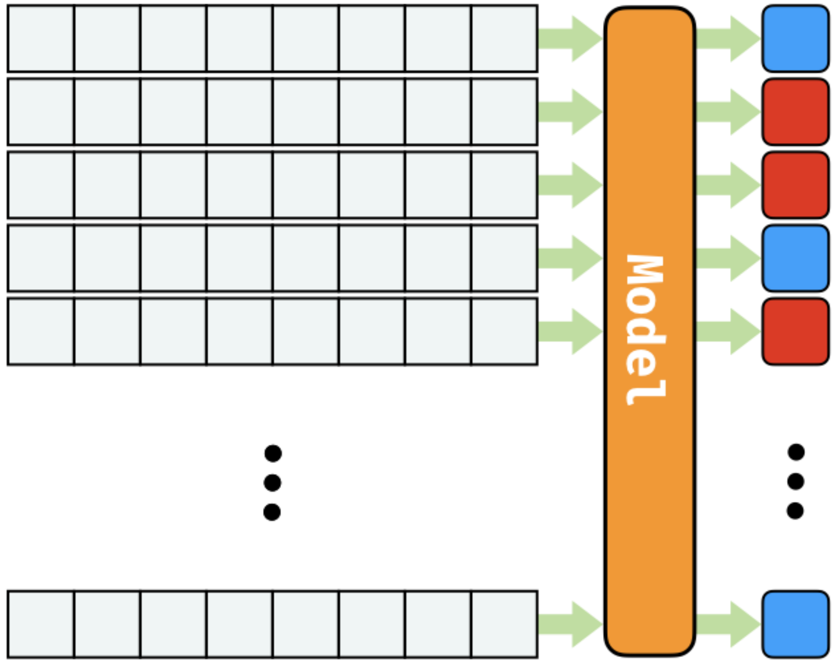
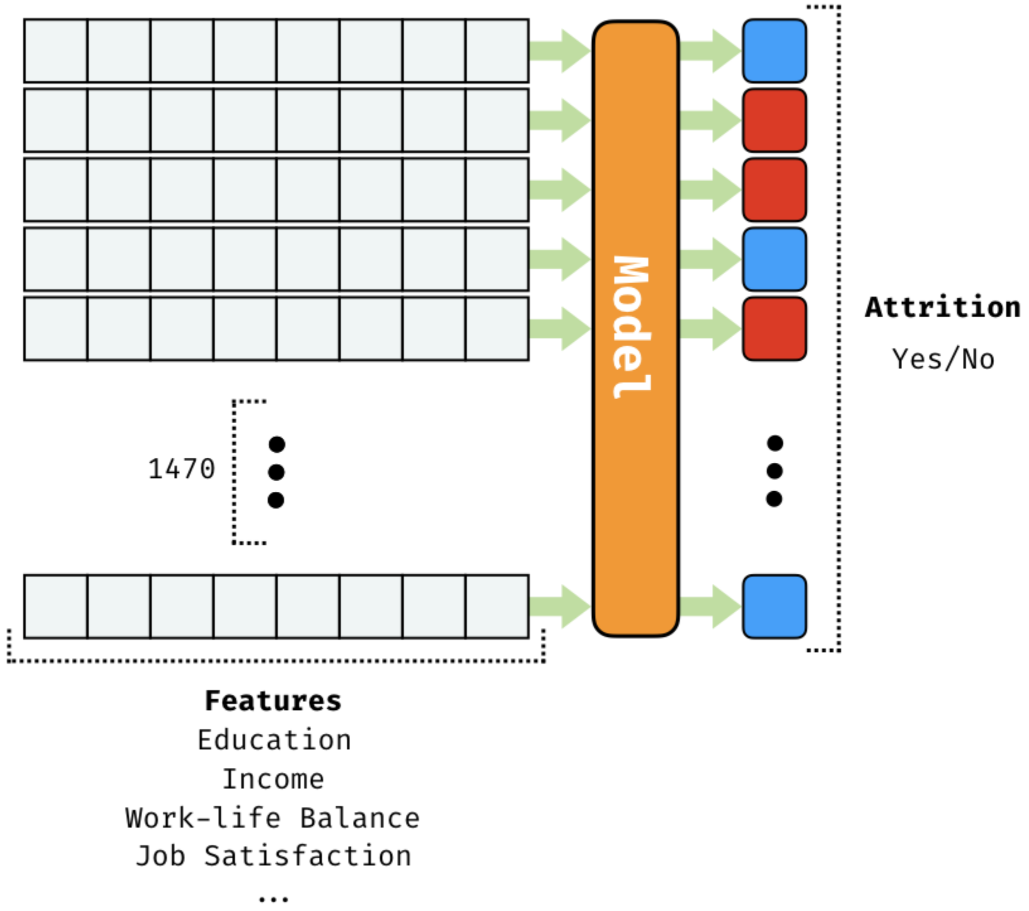
Binary Classification



The attrition Dataset



Logistic Regression

```
glm(formula = ___, data = ___, family = "binomial")
```

glm()

```
head(cv_data)
# A tibble: 5 x 4
  splits       id    train                          validate
* <list>       <chr> <list>                         <list>
1 <S3: rsplit> Fold1 <data.frame [882 × 31]> <data.frame [221 × 31]>
2 <S3: rsplit> Fold2 <data.frame [882 × 31]> <data.frame [221 × 31]>
3 <S3: rsplit> Fold3 <data.frame [882 × 31]> <data.frame [221 × 31]>
4 <S3: rsplit> Fold4 <data.frame [883 × 31]> <data.frame [220 × 31]>
5 <S3: rsplit> Fold5 <data.frame [883 × 31]> <data.frame [220 × 31]>

cv_models_lr <- cv_data %>%
  mutate(model = map(train, ~glm(formula = Attrition~.,
                                 data = .x, family = "binomial")))
```

MACHINE LEARNING IN THE TIDYVERSE

Time to Practice

MACHINE LEARNING IN THE TIDYVERSE

Evaluating Classification Models

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Ingredients for Performance Measurement

1) Actual `attrition` classes
2) Predicted `attrition` classes
3) A metric to compare 1) & 2)

1) Prepare Actual Classes

attrition	class
Yes	**TRUE**
No	**FALSE**

```
validate$Attrition

[1] No   No   No   No   No   Yes No   Yes No   No   No   No   No   No   No   No   No   Yes Yes
[25] No   No   Yes No   Yes No   Yes No   No   No   Yes No   No   No   No   No   No   No   No

validate_actual <- validate$Attrition == "Yes"
validate_actual
[1] FALSE FALSE FALSE FALSE FALSE  TRUE FALSE  TRUE FALSE FALSE FALSE FALSE FALS
[17] FALSE  TRUE  TRUE FALSE FALSE FALSE FALSE FALSE FALSE FALSE  TRUE FALSE  TR
```

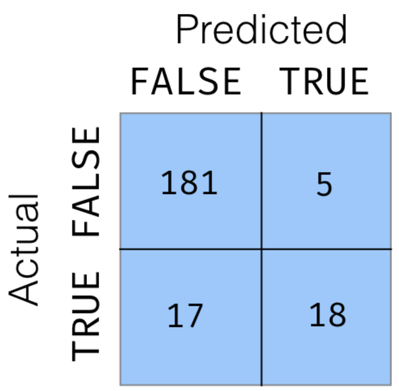
2) Prepare Predicted Classes

P(attrition)	class
> 0.5	**TRUE**
≤ 0.5	**FALSE**

```
validate_prob <- predict(model, validate, type = "response")
validate_prob
[1] 0.324 0.012 0.077 0.001 0.104 0.940 0.116 0.811 0.261 0.027 0.065 0.060

validate_predicted <- validate_prob > 0.5
validate_predicted
[1] FALSE FALSE FALSE FALSE FALSE  TRUE FALSE  TRUE FALSE FALSE FALSE FALSE
```

3) A metric to compare 1) & 2)

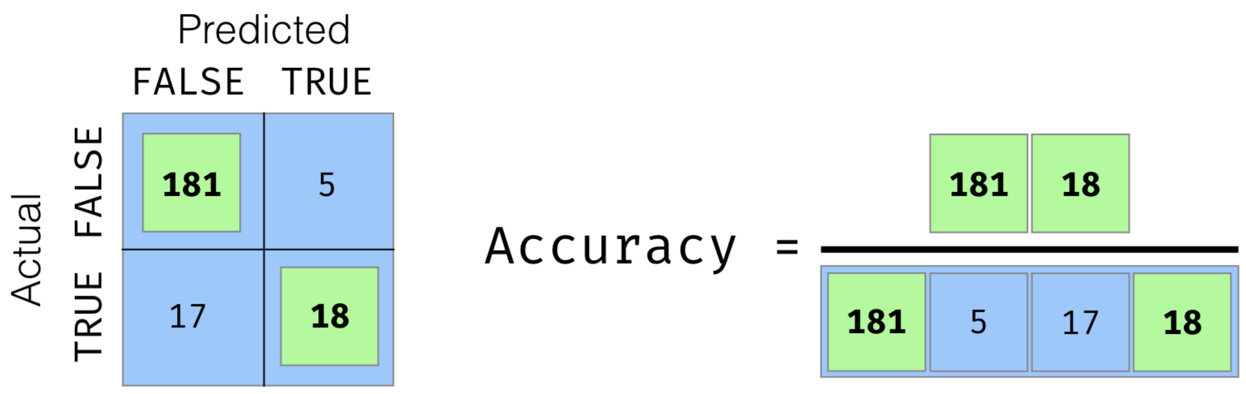


		Predicted	
		FALSE	TRUE
Actual	FALSE	181	5
	TRUE	17	18

```
table(validate_actual, validate_predicted)

               validate_predicted
validate_actual FALSE TRUE
          FALSE   181    5
          TRUE     17   18
```

3) Metric: Accuracy

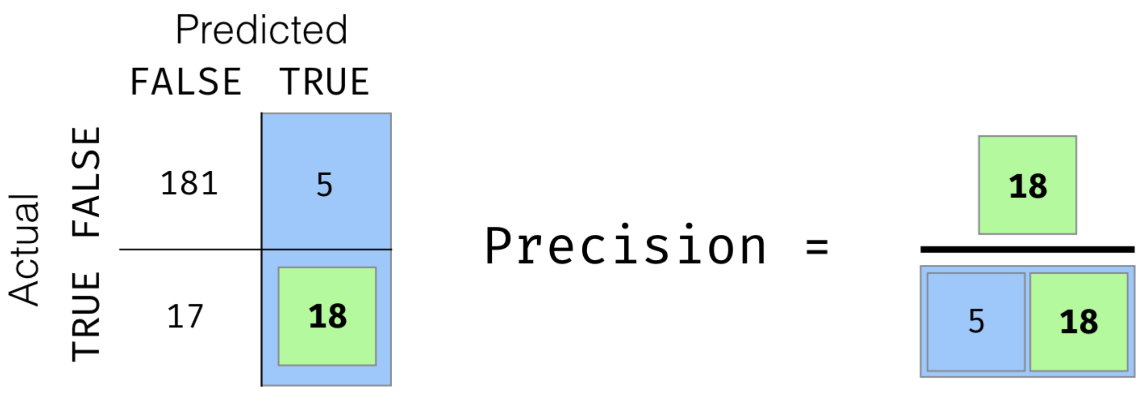


		Predicted	
		FALSE	TRUE
Actual	FALSE	181	5
	TRUE	17	18

$$\text{Accuracy} = \frac{\boxed{181}\,\boxed{18}}{\boxed{181}\,\boxed{5}\,\boxed{17}\,\boxed{18}}$$

```
accuracy(validate_actual, validate_predicted)
[1] 0.9004525
```

3) Metric: Precision

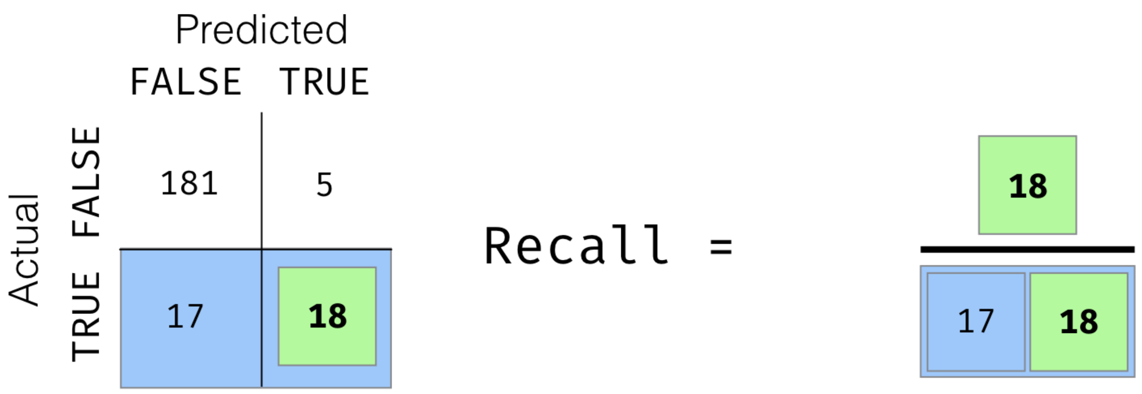


		Predicted	
		FALSE	TRUE
Actual	FALSE	181	5
	TRUE	17	18

$$\text{Precision} = \frac{\boxed{18}}{\boxed{5}\,\boxed{18}}$$

```
precision(validate_actual, validate_predicted)
 [1] 0.7826087
```

3) Metric: Recall



		Predicted	
		FALSE	TRUE
Actual	FALSE	181	5
	TRUE	17	18

```
recall(validate_actual, validate_predicted)
[1] 0.5142857
```

MACHINE LEARNING IN THE TIDYVERSE

Let's practice!

MACHINE LEARNING IN THE TIDYVERSE

Classification With Random Forests

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ranger() for Classification

```
cv_tune <- cv_data %>%
  crossing(mtry = c(2, 4, 8, 16))

cv_models_rf <- cv_tune %>%
  mutate(model = map2(train, mtry, ~ranger(formula = Attrition~.,
                                           data = .x, mtry = .y,
                                           num.trees = 100, seed = 42)))
```

1) Prepare Actual Classes

attrition	class
Yes	**TRUE**
No	**FALSE**

```
validate$Attrition

  [1] No  No  No  No  No  Yes No  Yes No  No  No  No  No  No  No  No  No  Yes Ye
 [25] No  No  Yes No  Yes No  Yes No  No  No  Yes No  No  No  No  No  No  No  No

validate_actual <- validate$Attrition == "Yes"
validate_actual
[1] FALSE FALSE FALSE FALSE FALSE  TRUE FALSE  TRUE FALSE FALSE FALSE FALSE FALS
[17] FALSE  TRUE  TRUE FALSE FALSE FALSE FALSE FALSE FALSE FALSE  TRUE FALSE  TR
```

2) Prepare Predicted Classes

P(attrition)	class
Yes	**TRUE**
No	**FALSE**

```
validate_classes <- predict(rf_model, rf_validate)$predict
validate_classes
[1] No   No   No   No   No   Yes No   No   No   No   No   No   No   No
[29] No   No   No   No   No   No   No   No   No   No   No   No   No   N

validate_predicted <- validate_classes == "Yes"
validate_predicted
[1] FALSE FALSE FALSE FALSE FALSE  TRUE FALSE FALSE FALSE
[19]  TRUE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
```

MACHINE LEARNING IN THE TIDYVERSE

Build the Best Attrition Model

MACHINE LEARNING IN THE TIDYVERSE

Recap: Machine Learning in the Tidyverse

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Chapter 1 - The List Column Workflow

1 Make a **list column**

`nest()`

2 Work with **list columns**

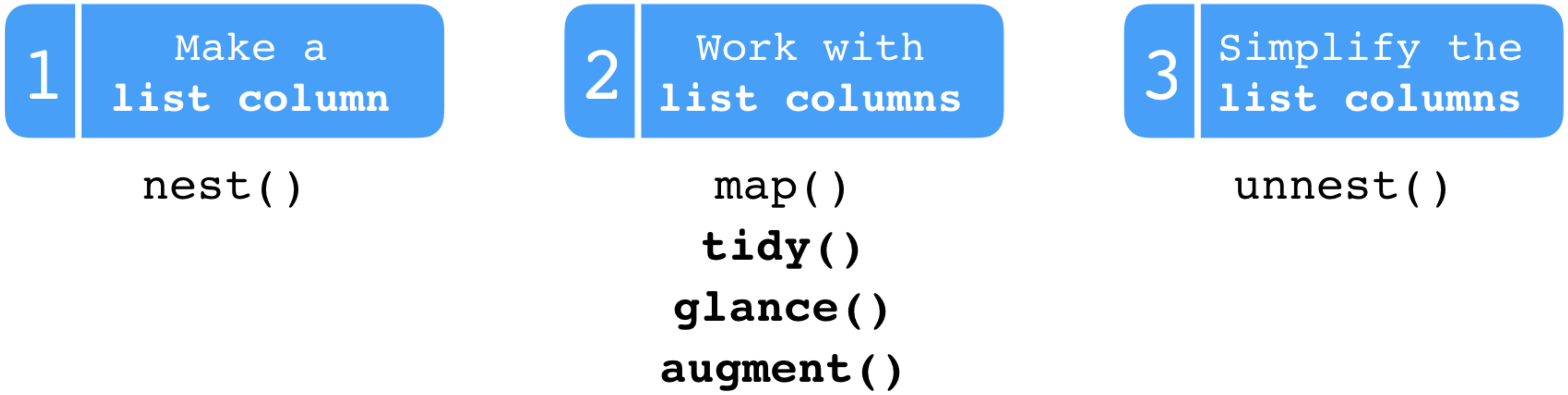
`map()`

3 Simplify the **list columns**

`unnest()`

`map_*()`

Chapter 2 - Explore Multiple Models With broom



1 Make a **list column**

nest()

2 Work with **list columns**

map()

tidy()

glance()

augment()

3 Simplify the **list columns**

unnest()

Chapter 3 - Build, Tune & Evaluate Regression Models

1 Make a list column

`nest()`

`initial_split()`

`vfold_cv()`

`crossing()`

2 Work with list columns

`map()`

`training()`

`testing()`

`lm()`

`ranger()`

`mae()`

3 Simplify the list columns

`unnest()`

`map_dbl()`

Chapter 4 - Build, Tune & Evaluate Classification Models

1 Make a list column

nest()
initial_split()
vfold_cv()
crossing()

2 Work with list columns

map()
training()
testing()
glm()
ranger()
recall()

3 Simplify the list columns

unnest()
map_dbl()

MACHINE LEARNING IN THE TIDYVERSE

Congratulations!