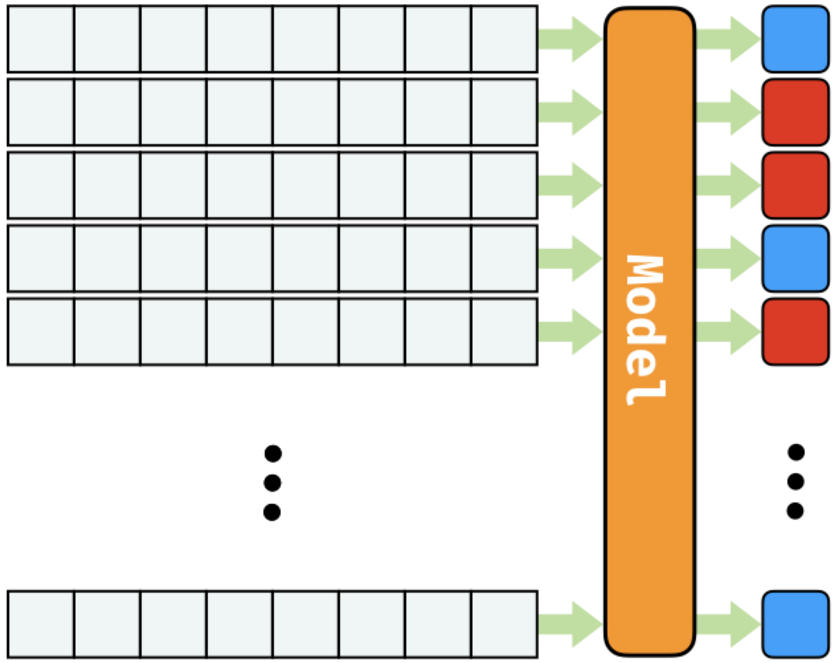
MACHINE LEARNING IN THE TIDYVERSE

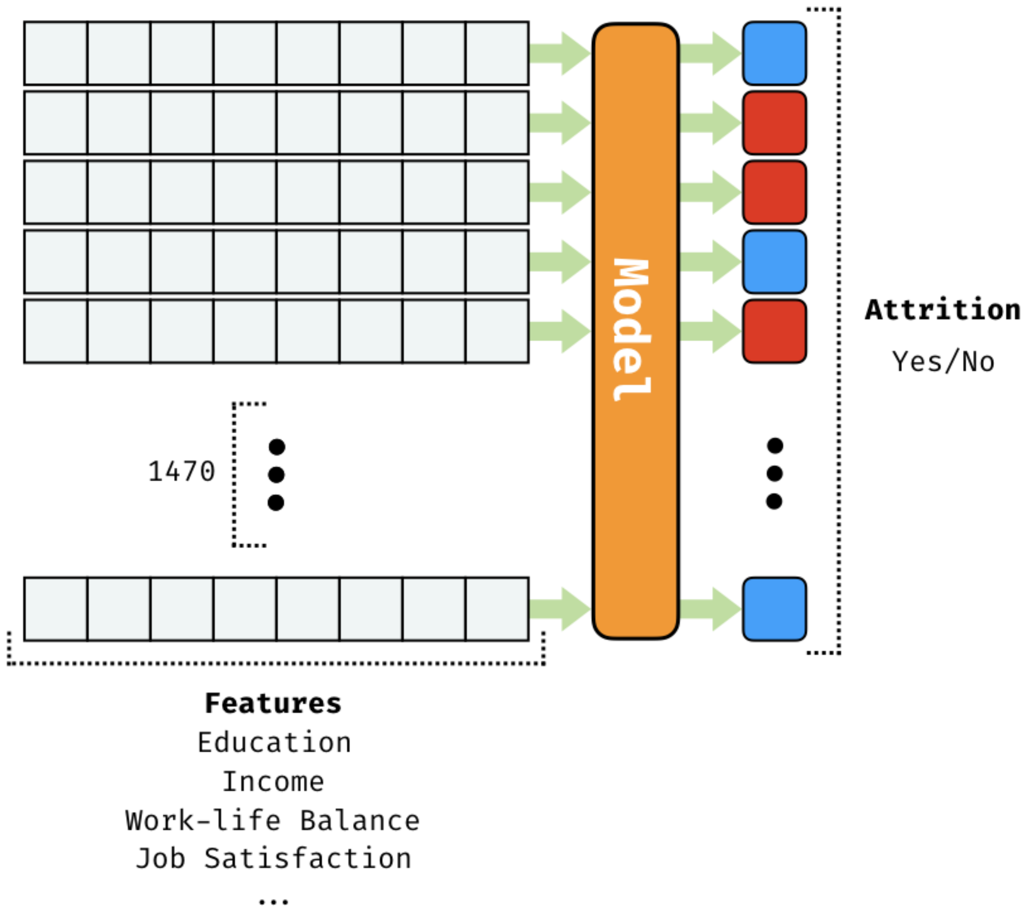
Logistic Regression Models

Dmitriy (Dima) Gorenshteyn
Lead Data Scientist,
Memorial Sloan Kettering Cancer Center

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

Dmitriy (Dima) Gorenshteyn
Lead Data Scientist,
Memorial Sloan Kettering Cancer Center

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  TF
```

2) Prepare Predicted Classes

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

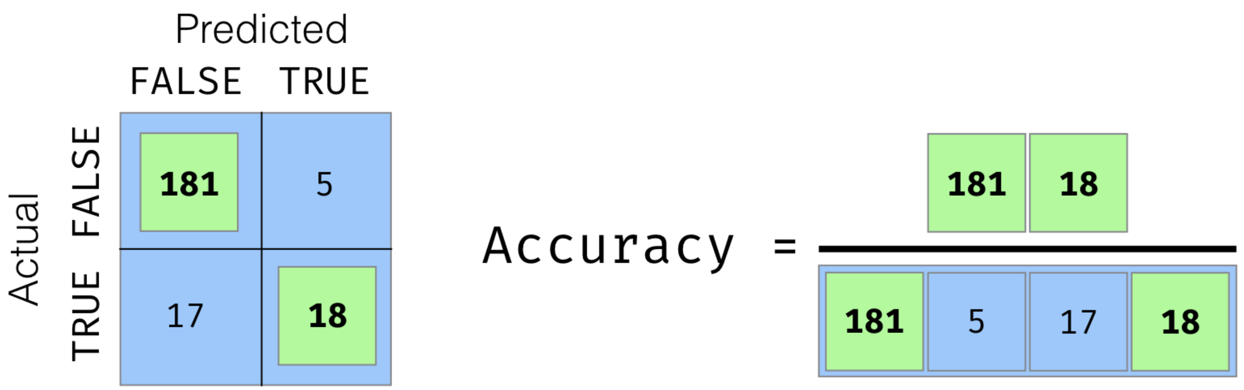
```
validate_prob <- predict(model, validate, type = "response")
validate_prob
[1] 0.324 0.012 0.077 0.001 0.104 0.940 0.116 0.811 0.261 0.027 0.065 0.060

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

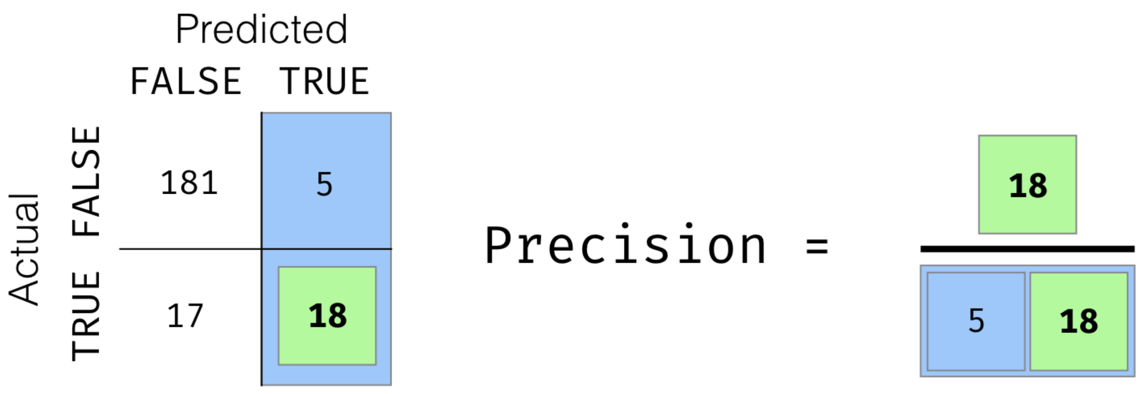
```
table(validate_actual, validate_predicted)

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

3) Metric: Accuracy



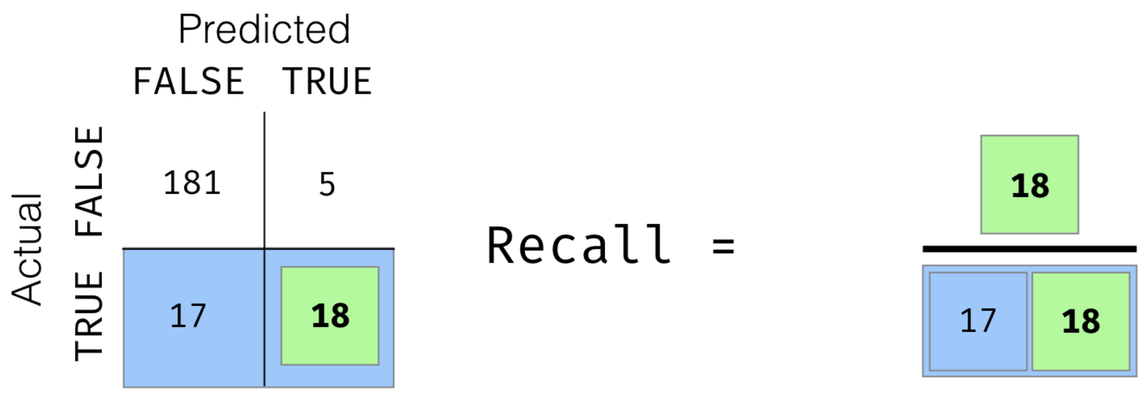

```
accuracy(validate_actual, validate_predicted)
[1] 0.9004525
```

3) Metric: Precision




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

3) Metric: Recall




```
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

Dmitriy (Dima) Gorenshteyn
Lead Data Scientist,
Memorial Sloan Kettering Cancer Center

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  Nc

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  TF
```

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

Dmitriy (Dima) Gorenshteyn
Lead Data Scientist,
Memorial Sloan Kettering Cancer Center

Chapter 1 - The List Column Workflow

1 Make a **list column**	2 Work with **list columns**	3 Simplify the **list columns**
`nest()`	`map()`	`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!