

# Computational Social Science

## Supervised Machine Learning

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# Plan

1. Course updates
2. Classification algorithms
3. Intro to machine learning in R

# Course updates

## Homework

- ▶ Homework 3 was due yesterday
- ▶ Homework 4 on supervised machine learning released next week

# Recap

- ▶ Supervised learning optimizes for predictive accuracy (focus on  $\hat{Y}$  not  $\hat{\beta}$ )
- ▶ Problems of over and under-fitting
  - ▶ Out-of-sample validation and cross-validation
  - ▶ Regularization
- ▶ Evaluating model performance
  - ▶ Precision, recall, F1, ROC/AUC

# Recap

- ▶ Given some outcome  $Y$  and a matrix of features  $X$ , we want to find a function  $Y = f(X)$  that best predicts the outcome

# Recap



# Recap

## Predicting penguins

- ▶  $Y = 1$  if the bird is a penguin, otherwise  $Y = 0$
- ▶  $X$  is a matrix including information on birds including their diet, wingspan, coloring, locations, etc.
  - ▶ Some of the information will be useful (e.g. ability to fly) but other information will be less meaningful (e.g. coloring)
- ▶ Goal is to find  $f(X)$  to predict whether a given bird is a penguin
- ▶ The quality of the prediction will depend on both the information contained in  $X$  and the properties of the function  $f()$ .

# Classification algorithms

- ▶ Logistic regression
- ▶ Support vector machines (SVM)
- ▶ Decision trees and random forests
- ▶ Neural networks
- ▶ And many others



# Machine learning in R

## Tidymodels

- ▶ `tidymodels` is a set of packages designed to use tidy principles to conduct machine-learning.
  - ▶ See <https://www.tidymodels.org/packages/> for a list of packages.

Pre-Process → Train → Validate



Source: tidymodels tutorial.

# Machine learning in R

## Loading tidymodels

The `tidymodels` package loads all of the sub-packages, as well as the `tidyverse` packages. We're going to be using a sample of data from the General Social Survey (GSS). The goal will be to predict whether a respondent has a college degree (or higher) as a function of their survey responses.

```
library(tidyverse)
library(tidymodels)
data <- read_csv("../data/2018_gss_sample.csv")
```

```
table(data$degree)
```

```
##
##      0      1
## 1568   710
```

# Machine learning in R

## Data cleaning

```
colnames(data)
```

```
## [1] "age"      "sex"      "race"     "sibs"     "paeduc"   "maeduc"  
## [7] "family16" "fund16"   "incom16"  "relig16"  "mawrkgrw" "othlang"  
## [13] "born"     "parborn"  "granborn" "zodiac"   "degree"
```

```
data <- data %>%  
  mutate(across(-c(age, sibs), as.factor))
```

# Machine learning in R

## Splitting data

We can use the `initial_split` command to create a train-test split, where 20% of the data are held-out for testing.

```
set.seed(987123)
data_split <- initial_split(data, prop = 0.8)
print(data_split)

## <Training/Testing/Total>
## <1822/456/2278>
```

# Machine learning in R

## Viewing the traing data

```
data_split %>% training() %>% head()
```

```
## # A tibble: 6 x 17
```

```
##   age sex  race  sibs paeduc maeduc family16 fund16 incom16 reli
```

```
##   <dbl> <fct> <fct> <dbl> <fct> <fct> <fct> <fct> <fct> <fct>
```

```
## 1    86 0    1      4 12    12    1      1      3      1
```

```
## 2    34 1    1      1 14    14    1      2      3      2
```

```
## 3    22 0    2      8 12    18    5      2      1      1
```

```
## 4    58 0    1      4 8     12    1      2      5      2
```

```
## 5    68 1    1      4 5     12    1      3      3      1
```

```
## 6    43 0    1     12 0      0    1      2      1      2
```

```
## # i 6 more variables: othlang <fct>, born <fct>, parborn <fct>, gran
```

```
## #   zodiac <fct>, degree <fct>
```

# Machine learning in R

## Pre-processing using recipe

We will use the recipes package to pre-process the data.

```
data_recipe <- training(data_split) %>%  
  recipe(degree ~ .) %>%  
  step_scale(all_numeric_predictors(), -all_outcomes()) %>%  
  step_dummy(all_factor_predictors(), -all_outcomes()) %>%  
  prep()
```

```
data_recipe
```

# Machine learning in R

## Extracting data from recipe

The previous chunk only applied these transformations to the training data. We want to also modify the test data so that they are the same dimensions. We can apply the recipe to the new data using the `bake` command. We also want to load the training data using the `juice` command. This extracts the data directly from the recipe.

```
data_testing <- data_recipe %>%  
  bake(testing(data_split))  
  
data_training <- juice(data_recipe)
```

# Machine learning in R

## Fitting a model

ML models in R exist across a range of different packages and `parsnip` gives them a standardized syntax. We define the model, choose the package (in this case `randomForest`), then use `fit` to train the model.

```
library(randomForest)
rf <- rand_forest(trees = 1000, mode = "classification") %>%
  set_engine("randomForest") %>%
  fit(degree ~ ., data = data_training)
```



# Machine learning in R

## Making predictions (in-sample)

```
preds <- predict(rf, data_training)
train_preds <- bind_cols(data_training, preds) %>%
  select(degree, .pred_class)
head(train_preds)
```

```
## # A tibble: 6 x 2
##   degree .pred_class
##   <fct>   <fct>
## 1 0      0
## 2 0      0
## 3 0      0
## 4 1      1
## 5 0      0
## 6 0      0
```

# Machine learning in R

## Calculating metrics (in-sample)

```
precision <- train_preds %>% precision(truth=degree, estimate = .pred_c  
recall <- train_preds %>% recall(truth=degree, estimate = .pred_class)  
print(bind_rows(precision, recall))
```

```
## # A tibble: 2 x 3  
##   .metric .estimator .estimate  
##   <chr>    <chr>      <dbl>  
## 1 precision binary      0.952  
## 2 recall   binary      0.998
```

# Machine learning in R

## Making predictions (out-of-sample)

```
preds <- predict(rf, data_testing)
test_preds <- bind_cols(data_testing, preds) %>%
  select(degree, .pred_class)
```

# Machine learning in R

## Calculating metrics (out-of-sample)

```
precision <- test_preds %>% precision(truth=degree, estimate = .pred_cl  
recall <- test_preds %>% recall(truth=degree, estimate = .pred_class)  
print(bind_rows(precision, recall))
```

```
## # A tibble: 2 x 3  
##   .metric .estimator .estimate  
##   <chr>    <chr>      <dbl>  
## 1 precision binary      0.765  
## 2 recall   binary      0.925
```

# Machine learning in R

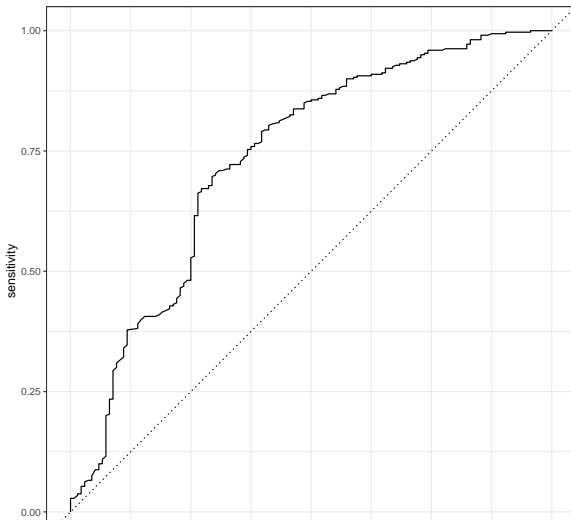
## Calculating metrics: Predicted probabilities

We can also extract the predicted probabilities by adding an argument to the predict function.

```
probs <- rf %>%  
  predict(data_testing, type = "prob") %>%  
  bind_cols(data_testing)  
head(probs %>% select(degree, .pred_0, .pred_1) %>% bind_cols(preds))  
  
## # A tibble: 6 x 4  
##   degree .pred_0 .pred_1 .pred_class  
##   <fct>    <dbl>    <dbl> <fct>  
## 1 1      0.595    0.405 0  
## 2 0      0.899    0.101 0  
## 3 0      0.527    0.473 0  
## 4 1      0.346    0.654 1  
## 5 1      0.41     0.59  1  
## 6 0      0.653    0.347 0
```

# Machine learning in R

## Calculating metrics: ROC



# Machine learning in R

## Calculating metrics: AUC

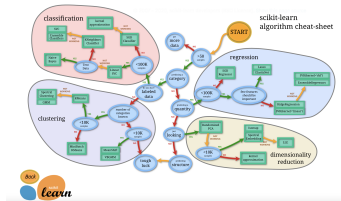
```
probs %>% roc_auc(degree, .pred_0)

## # A tibble: 1 x 3
##   .metric .estimator .estimate
##   <chr>   <chr>      <dbl>
## 1 roc_auc binary      0.734
```

# Machine learning in R

## Alternatives

- ▶ Python has a more developed ML ecosystem than R.
  - ▶ `scikit-learn` provides a suite of tools for most machine-learning tasks except deep-learning, which requires specialized libraries.



Source: scikit-learn documentation. See this tutorial for how to run scikit-learn using R.



# Machine learning in R

## Next week

- ▶ Supervised machine learning to perform text classification
- ▶ Cross-validation, parameter searches, and model comparison
- ▶ Data quality and predictive performance