

# Classification Metrics



# Setup

# Setup

## Modeling steps:

1. **Clean** the data
  - What do we do about NA's?
  - Convert categorical variables to **factors**
2. Establish a **model**
  - Or **many** models to try?
  - Do we need to **tune** any hyperparameters?
3. Establish a **recipe**
  - Or **many** recipes to try?
  - How will we **transform** our variables?
  - Categorical to **dummy** variables? (but not the response!)
  - (data = full dataset)
4. Make **workflows**

1. Send the workflow to cross validation for **model selection**
  - For comparing different *models*
  - For *tuning*
  - For comparing different *recipes*
2. Send your **final model** to cross-validation for **final metrics**
  - why do we cross-validate for final metrics?
3. Fit the **final model** on the **full dataset** - this is your finished product!

# Setup

```
ins <- read_csv("https://www.dropbox.com/s/bocjjyo1ehr5auz/insurance.csv?dl=1")

ins <- ins %>%
  mutate(
    smoker = factor(smoker)
  ) %>%
  drop_na()

knn_mod <- nearest_neighbor(neighbors = 5) %>%
  set_engine("kkn") %>%
  set_mode("classification")

knn_recipe <- recipe(smoker ~ age + bmi + charges,
  data = ins)

knn_wflow <- workflow() %>%
  add_recipe(knn_recipe) %>%
  add_model(knn_mod)

cvs <- vfold_cv(ins, v = 5)

knn_fit <- knn_wflow %>%
  fit_resamples(cvs)
```

# Metric 1: Accuracy

# Accuracy

What percent of our guesses were correct?

```
knn_fit %>% collect_metrics()
```

```
## # A tibble: 2 x 5
##   .metric .estimator mean      n std_err
##   <chr>    <chr>    <dbl> <int>   <dbl>
## 1 accuracy binary    0.965     5 0.00359
## 2 roc_auc  binary    0.992     5 0.00417
```



# Accuracy

The problem: Consider this data.

```
##      [1] "B" "B" "B" "B" "B" "B" "B" "B" "B" "B" "B" "B" "B" "B" "B"
##      [19] "B" "B" "B" "B" "B" "B" "B" "A" "B" "B" "B" "B" "B" "B" "B"
##      [37] "B" "B" "B" "B" "B" "B" "B" "B" "B" "B" "B" "B" "B" "B" "B"
##      [55] "A" "B" "B" "B" "B" "B" "B" "B" "B" "B" "B" "B" "B" "B" "B"
##      [73] "B" "B" "B" "B" "B" "B" "B" "B" "B" "B" "B" "B" "B" "B" "B"
##      [91] "B" "B" "B" "B" "B" "B" "B" "B" "B" "B" "B" "B" "B" "B" "B"
```

If I guess "B" every time, I'll have 98% accuracy!

## Metric 2: ROC

# ROC

**ROC** = "receiver operating characteristic" (ew)

**FALSE Positive Rate** = (how many A's did we say were B)/(how many did we say were "B" total)

*How many did we misclassify as B?*

**True Positive Rate** = (how many B's did we say were B)/(how many B's are there total)

*How many true B's did we miss?*

# ROC

**ROC** = plots TP and FP across many **decision boundaries**

First, find the probability that the model assigns each observation for the **first** category of your categorical variable. (Generally, this is alphabetical:)

```
knn_final_fit <- knn_wflow %>%  
  fit(ins)  
  
ins <- ins %>%  
  mutate(  
    prob_nonsmoker = predict(knn_final_fit, ins, type = "prob")$.pred_no  
  )
```

# ROC

```
ins %>%  
  roc_curve(truth = smoker, prob_nonsmoker) %>%  
  autoplot()
```

# ROC

**GOOD:** The ROC curve is way above the line (we can achieve a really good TP rate without sacrificing FP rate)

**MEDIUM:** The ROC curve is on the line (FP/TP is a trade-off)

**BAD:** The ROC curve is way below the line (we can't have good TP without bad FP)

**ROC-AUC** is the **area under the curve** - large values are good!

Try it!

Open **Activity-Classification-2.Rmd** again

Go to

Scroll down to the list of metrics

As a group, research **one** of the metrics that we haven't discussed in class, and compute it for some of your models.