Lesson 15: Model Building

With an emphasis on prediction

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Learning Objectives

1. Understand the place of LASSO regression within association and prediction modeling for binary outcomes.
2. Recognize the process for `tidymodels`
3. Understand how penalized regression is a form of model/variable selection.
4. Perform LASSO regression on a dataset using R and the general process for classification methods.

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Some important definitions

- **Model selection**: picking the "best" model from a set of possible models
  - Models will have the same outcome, but typically differ by the covariates that are included, their transformations, and their interactions
  - "Best" model is defined by the research question and by how you want to answer it!

- **Model selection strategies**: a process or framework that helps us pick our "best" model
  - These strategies often differ by the approach and criteria used to the determine the "best" model

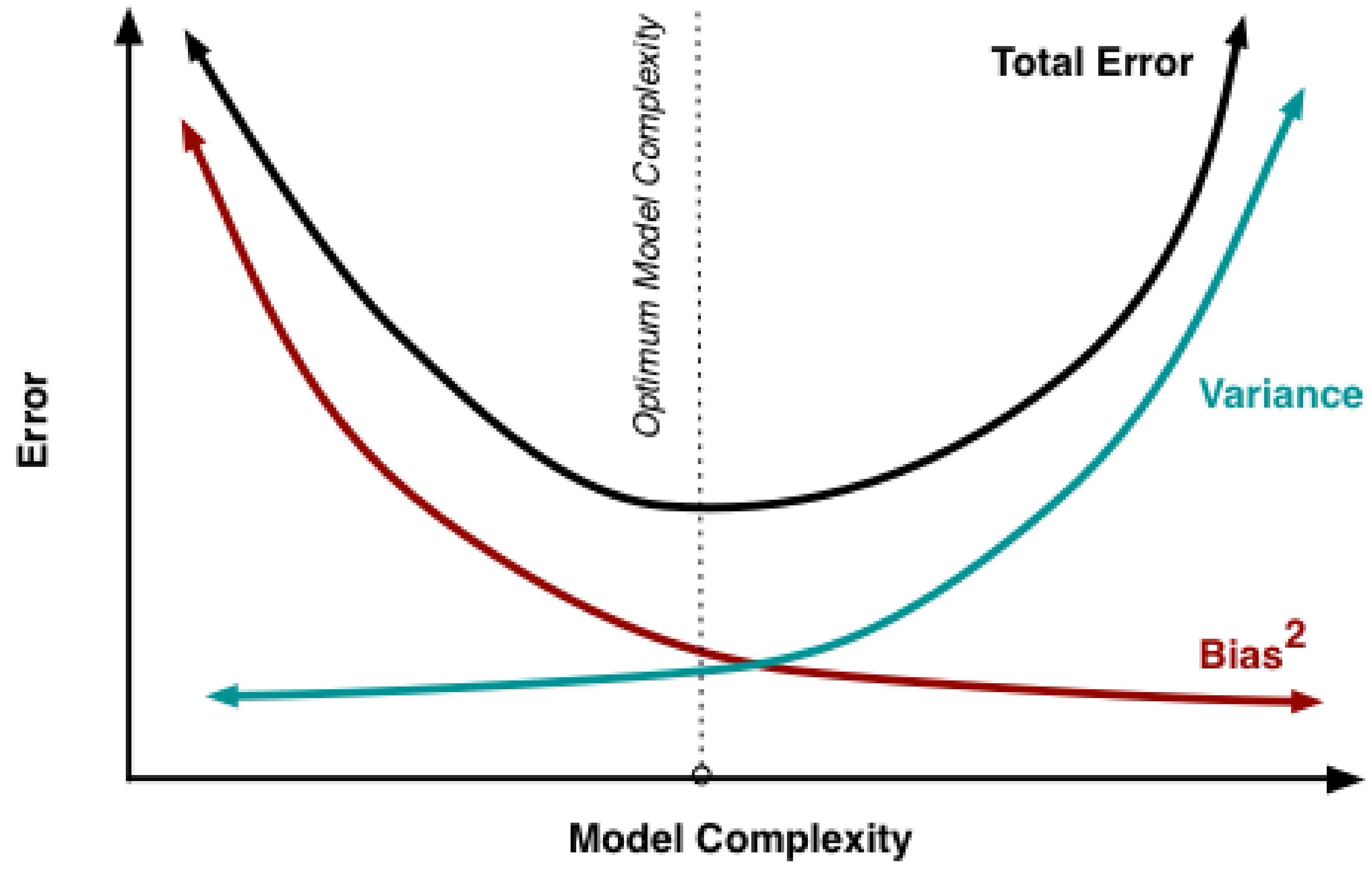
- **Overfitting**: result of fitting a model so closely to our *particular* sample data that it cannot be generalized to other samples (or the population)

Bias-variance trade off

- Recall from 512/612: MSE can be written as a function of the bias and variance

$$MSE = \text{bias}\left(\widehat{\beta}\right)^2 + \text{variance}\left(\widehat{\beta}\right)$$

  - **We no longer use MSE in logistic regression to find the best fit model, BUT the idea between the bias and variance trade off holds!**
- For the same data:
  - More covariates in model: less bias, more variance
    - Potential overfitting: with new data does our model still hold?
  - Less covariates in model: more bias, less variance
    - More bias bc more likely that were are not capturing the true underlying relationship with less variables



Source: http://scott.fortmann-roe.com/docs/BiasVariance.html

The goals of association vs. prediction

Association / Explanatory / One variable's effect

- **Goal:** Understand one variable's (or a group of variable's) effect on the response after adjusting for other factors
- Mainly interpret odds ratios of the variable that is the focus of the study

Prediction

- **Goal:** to calculate the most precise prediction of the response variable
- Interpreting coefficients is not important
- Choose only the variables that are strong predictors of the response variable
  - Excluding irrelevant variables can help reduce widths of the prediction intervals

Model selection strategies for *categorical* outcomes

Association / Explanatory / One variable's effect

- Selection of potential models is tied more with the research context with some incorporation of prediction scores
- Pre-specification of multivariable model
- Purposeful model selection
  - "Risk factor modeling"
- Change in Estimate (CIE) approaches
  - Will learn in Survival Analysis (BSTA 514)

Prediction

- Selection of potential models is fully dependent on prediction scores
- Logistic regression with more refined model selection
  - Regularization techniques (LASSO, Ridge, Elastic net)
- Machine learning realm
  - Decision trees, random forest, k-nearest neighbors, Neural networks

Before I move on…

- We CAN use purposeful selection from last quarter in **any** type of generalized linear model (GLM)
  - This includes logistic regression!
- The best documented information on purposeful selection is in the Hosmer-Lemeshow textbook on logistic regression
  - Textbook in student files is linked here
  - Purposeful selection starts on page 89 (or page 101 in the pdf)
- I will not discuss purposeful selection in this course
  - Be aware that this is a tool that you can use in any regression!

Okay, so prediction of categorical outcomes

- **Classification:** process of predicting categorical responses/outcomes
  - Assigning a category outcome based on an observation's predictors

- Note: we've already done a lot of work around predicting probabilities within logistic regression
  - Can we take those predicted probabilities one step further to predict the binary outcome??

- Common classification methods (good site on brief explanation of each)
  - Logistic regression
  - Naive Bayes
  - k-Nearest Neighbor (KNN)
  - Decision Trees
  - Support Vector Machines (SVMs)
  - Neural Networks

Logistic regression is a classification method

- But to be a good classifier, our logistic regression model needs to built a certain way

- Prediction depends on type of variable/model selection!
  - This is when it can become machine learning

- So the big question is: how do we select this model??
  - Regularized techniques, aka penalized regression

Poll Everywhere Question 1

Learning Objectives

1. Understand the place of LASSO regression within association and prediction modeling for binary outcomes.

2. Recognize the process for `tidymodels`

3. Understand how penalized regression is a form of model/variable selection.

4. Perform LASSO regression on a dataset using R and the general process for classification methods.

Before I get really into things!!

- `tidymodels` is a great package when we are performing prediction
- One problem: it uses very different syntax for model fitting than we are used to…
- `tidymodels` syntax dictates that we need to define:
    - A model
    - A recipe
    - A workflow

`tidymodels` with GLOW

To fit our logistic regression model with the interaction between age and prior fracture, we use:

```
# model
model = logistic_reg()
# recipe
recipe = recipe(fracture ~ priorfrac + age_c, data = glow1) %>%
              step_dummy(priorfrac) %>%
              step_interact(terms = ~ age_c:starts_with("priorfrac"))
# workflow
workflow = workflow() %>% add_model(model) %>% add_recipe(recipe)

fit = workflow %>% fit(data = glow1)
```

term	estimate	std.error	statistic	p.value	conf.low	conf.high
(Intercept)	−1.376	0.134	−10.270	0.000	−1.646	−1.120
age_c	0.063	0.015	4.043	0.000	0.032	0.093
priorfrac_Yes	1.002	0.240	4.184	0.000	0.530	1.471
age_c_x_priorfrac_Yes	−0.057	0.025	−2.294	0.022	−0.107	−0.008

Same as results from previous lessons

```r
glow_m3 = glm(fracture ~ priorfrac + age_c + priorfrac*age_c,
              data = glow1, family = binomial)
```

```r
tidy(glow_m3, conf.int = T) %>% gt() %>%
  tab_options(table.font.size = 35) %>%
  fmt_number(decimals = 3)
```

term	estimate	std.error	statistic	p.value	conf.low	conf.high
(Intercept)	−1.376	0.134	−10.270	0.000	−1.646	−1.120
priorfracYes	1.002	0.240	4.184	0.000	0.530	1.471
age_c	0.063	0.015	4.043	0.000	0.032	0.093
priorfracYes:age_c	−0.057	0.025	−2.294	0.022	−0.107	−0.008

Interaction model:

$$\text{logit}\left(\widehat{\pi}(\mathbf{X})\right) = \widehat{\beta}_0 \quad + \widehat{\beta}_1 \cdot I(\text{PF}) \quad + \widehat{\beta}_2 \cdot Age \quad + \widehat{\beta}_3 \cdot I(\text{PF}) \cdot Age$$
$$\text{logit}\left(\widehat{\pi}(\mathbf{X})\right) = -1.376 \quad + 1.002 \cdot I(\text{PF}) \quad + 0.063 \cdot Age \quad - 0.057 \cdot I(\text{PF}) \cdot Age$$

- Reminder of main effects and interactions

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Penalized regression

- **Basic idea:** We are running regression, but now we want to **incentivize our model fit to have less predictors**
  - Include a **penalty to discourage too many predictors** in the model

- Also known as *shrinkage* or *regularization* methods

- Penalty will reduce coefficient values to zero (or close to zero) if the predictor does not contribute much information to predicting our outcome

- We need a tuning parameter that determines the amount of shrinkage called lambda/λ
  - How much do we want to penalize additional predictors?

Poll Everywhere Question 2

Three types of penalized regression

Main difference is the type of penalty used

Ridge regression

- Penalty called L2 norm, uses sqaured values
- Pros
  - Reduces overfitting
  - Handles $p > n$
  - Handles collinearity
- Cons
  - Does not shrink coefficients to 0
  - Difficult to interpret

Lasso regression

- Penalty called L1 norm, uses absolute values
- Pros
  - Reduces overfitting
  - Shrinks coefficients to 0
- Cons
  - Cannot handle $p > n$
  - Does not handle multicollinearity well

Elastic net regression

- L1 and L2 used, best of both worlds
- Pros
  - Reduces overfitting
  - Handles $p > n$
  - Handles collinearity
  - Shrinks coefficients to 0
- Cons
  - More difficult to do than other two

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Overview of the process

1. Split data into training and testing datasets

2. Perform our classification method on training set
    - This is where we will use penalized regression!

3. Measure predictive accuracy on testing set

Example to be used: GLOW Study

- From GLOW (Global Longitudinal Study of Osteoporosis in Women) study

- **Outcome variable:** any fracture in the first year of follow up (FRACTURE: 0 or 1)

- ~~**Risk factor/variable of interest:** history of prior fracture (PRIORFRAC: 0 or 1)~~
- ~~**Potential confounder or effect modifier:** age (AGE, a continuous variable)~~
  - ~~Center age will be used! We will center around the rounded mean age of 69 years old~~

- Crossed out because we are no longer attached to specific predictors and their association with fracture
  - Focused on **predicting fracture with whatever variables we can!**

Step 1: Splitting data

- **Training:** act of creating our prediction model based on our observed data
  - Supervised: Means we keep information on our outcome while training

- **Testing:** act of measuring the predictive accuracy of our model by trying it out on *new* data

- When we use data to create a prediction model, we want to test our prediction model on *new* data
  - Helps make sure prediction model can be applied to other data **outside of the data that was used to create it!**

- So an important first step in prediction modeling is to *split our data* into a **training set** and a **testing set**!

Step 1: Splitting data

Training set

- Sandbox for model building
- Spend most of your time using the training set to develop the model
- Majority of the data (usually 80%)

Testing set

- Held in reserve to determine efficacy of one or two chosen models
- Critical to look at it once at the end, otherwise it becomes part of the modeling process
- Remainder of the data (usually 20%)

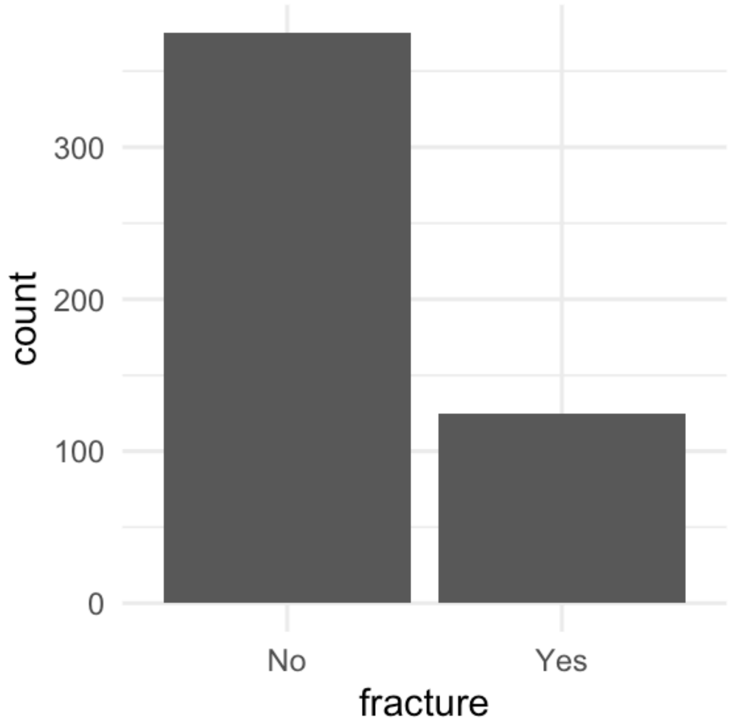
- Slide content from Data Science in a Box

Poll Everywhere Question 3

Step 1: Splitting data

- When splitting data, we need to be conscious of the proportions of our outcomes
  - Is there imbalance within our outcome?
  - We want to randomly select observations but make sure the proportions of No and Yes stay the same
  - We **stratify** by the outcome, meaning we pick Yes's and No's separately for the training set

```
ggplot(glow1, aes(x = fracture)) + geom_bar()
```



- Side note: took out `bmi` and `weight` bc we have multicollinearity issues
  - Combo of I hate these variables and my previous work in the LASSO identified these as not important

```
glow = glow1 %>%
    dplyr::select(-sub_id, -site_id, -phy_id, -age, -bmi, -weight)
```

Step 1: Splitting data

- From package `rsample` within `tidyverse`, we can use `initial_split()` to create training and testing data
  - Use `strata` to stratify by fracture

```
glow_split = initial_split(glow, strata = fracture, prop = 0.8)
glow_split
```

```
<Training/Testing/Total>
<400/100/500>
```

- Then we can pull the training and testing data into their own datasets

```
glow_train = training(glow_split)
glow_test = testing(glow_split)
```

Step 1: Splitting data: peek at the split

```
glimpse(glow_train)
```

```
Rows: 400
Columns: 10
$ priorfrac <fct> No, No, Yes, No, No, Yes, No, Yes, Yes, No, No,
No, No, No, …
$ height    <int> 158, 160, 157, 160, 152, 161, 150, 153, 156, 166,
153, 160, …
$ premeno   <fct> No, No, No, No, No, No, No, No, No, No, No, Yes,
No, No, No,…
$ momfrac   <fct> No, No, Yes, No, No, No, No, No, No, No, Yes, No,
No, No, No…
$ armassist <fct> No, No, Yes, No, No, No, No, No, No, No, No, No,
Yes, No, No…
$ smoke     <fct> No, No, No, No, No, Yes, No, No, No, No, Yes, No,
No, No, No…
$ raterisk  <fct> Same, Same, Less, Less, Same, Same, Less, Same,
Same, Less, …
$ fracscore <int> 1, 2, 11, 5, 1, 4, 6, 7, 7, 0, 4, 1, 4, 2, 2, 7,
2, 1, 4, 5,…
$ fracture  <fct> No, No, No, No, No, No, No, No, No, No, No, No,
No, No, No, …
$ age_c     <dbl> -7, -4, 19, 13, -8, -2, 15, 13, 17, -11, -2, -5,
-1, -2, 0, …
```

```
glimpse(glow_test)
```

```
Rows: 100
Columns: 10
$ priorfrac <fct> No, No, No, No, No, No, No, No, Yes, Yes, No, No,
No, No, No…
$ height    <int> 167, 162, 165, 158, 153, 170, 154, 171, 142, 152,
166, 154, …
$ premeno   <fct> No, No, No, Yes, No, Yes, Yes, Yes, Yes, No, No,
No, No, No,…
$ momfrac   <fct> No, No, No, No, No, Yes, No, No, Yes, No, No, No,
No, No, No…
$ armassist <fct> Yes, No, Yes, No, Yes, No, Yes, No, No, No, No,
No, No, No, …
$ smoke     <fct> Yes, Yes, No, No, No, No, No, No, No, No, No, No,
No, No, No…
$ raterisk  <fct> Same, Less, Less, Greater, Same, Same, Same, Same,
Same, Sam…
$ fracscore <int> 3, 1, 5, 1, 8, 3, 7, 1, 6, 7, 0, 2, 0, 0, 1, 2, 2,
8, 4, 3, …
$ fracture  <fct> No, No, No, No, No, No, No, No, No, No, No, No,
No, No, No, …
$ age_c     <dbl> -13, -10, 3, -8, 17, 0, 6, -5, 1, 17, -11, -6,
-10, -12, -6,…
```

Step 2: Fit LASSO penalized logistic regression model

- Using Lasso penalized regression!
- We can simply set up a penalized regression model

```r
lasso_mod = logistic_reg(penalty = 0.001, mixture = 1) %>%

            set_engine("glmnet")
```

- `glmnet` takes the basic fitting of `glm` and adds penalties!
  - In `tidymodels` we set an engine that will fit the model
- `mixture` option let's us pick the penalty
  - `mixture = 0` for Ridge regression
  - `mixture = 1` for Lasso regression
  - `0 < mixture < 1` for Elastic net regression

Step 2: Fit LASSO: Main effects

```
glow_rec_main = recipe(fracture ~ ., data = glow_train) %>%
  step_dummy(priorfrac, premeno, momfrac, armassist, smoke, raterisk)
glow_workflow_main = workflow() %>%
      add_model(lasso_mod) %>% add_recipe(glow_rec_main)
glow_fit_main = glow_workflow_main %>% fit(glow_train)
```

Step 2: Fit LASSO: Main effects: Identify variables

```
library(vip)
vi_data_main = glow_fit_main %>%
    pull_workflow_fit() %>%
    vi(lambda = 0.001) %>%
    filter(Importance != 0)
vi_data_main
```

```
# A tibble: 9 × 3
  Variable         Importance Sign
  <chr>                 <dbl> <chr>
1 raterisk_Greater     0.559  POS
2 momfrac_Yes          0.542  POS
3 priorfrac_Yes        0.493  POS
4 raterisk_Same        0.438  POS
5 smoke_Yes            0.376  NEG
6 premeno_Yes          0.285  POS
7 fracscore            0.197  POS
8 armassist_Yes        0.146  POS
9 height               0.0382 NEG
```

- Looks like age is removed!

Step 2: Fit LASSO: Main effects + interactions

- We want to include interactions in our regression
- The main effect model will be our starting point
  - Otherwise, we may drop main effects but not their interactions
  - Cannot do that: see hierarchy principle
- I remove `age_c` from this section because main effects did not include it

```
glow_rec_int = recipe(fracture ~ ., data = glow_train) %>%
  update_role(age_c, new_role = "dont_use") %>%

  step_dummy(priorfrac, premeno, momfrac, armassist, smoke, raterisk) %>%

  step_interact(terms = ~ all_predictors():all_predictors())

glow_workflow_int = workflow() %>%
      add_model(lasso_mod) %>% add_recipe(glow_rec_int)

glow_fit_int = glow_workflow_int %>% fit(glow_train)
```

Step 2: Fit LASSO: Identify interactions

```
vi_data_int = glow_fit_int %>%
      pull_workflow_fit() %>%
      vi(lambda = 0.001) %>%
      filter(Importance != 0)
vi_data_int
```

```
# A tibble: 34 × 3
   Variable                              Importance Sign
   <chr>                                      <dbl> <chr>
 1 smoke_Yes                                   4.29 NEG
 2 smoke_Yes_x_raterisk_Greater                3.89 POS
 3 smoke_Yes_x_raterisk_Same                   3.14 POS
 4 premeno_Yes_x_smoke_Yes                     3.00 NEG
 5 momfrac_Yes_x_armassist_Yes                 2.82 NEG
 6 priorfrac_Yes_x_premeno_Yes                 2.50 NEG
 7 priorfrac_Yes                               1.82 POS
 8 armassist_Yes_x_smoke_Yes                   1.44 POS
 9 premeno_Yes_x_raterisk_Greater              1.31 POS
10 momfrac_Yes_x_smoke_Yes                     1.17 POS
# ℹ 24 more rows
```

- This is where things got a little annoying for me…

Step 2: Fit LASSO: Identify interactions

- I combed through the column names of the results to find the interactions

```r
vi_data_int$Variable
```

```
 [1] "smoke_Yes"                           "smoke_Yes_x_raterisk_Greater"
 [3] "smoke_Yes_x_raterisk_Same"           "premeno_Yes_x_smoke_Yes"
 [5] "momfrac_Yes_x_armassist_Yes"         "priorfrac_Yes_x_premeno_Yes"
 [7] "priorfrac_Yes"                       "armassist_Yes_x_smoke_Yes"
 [9] "premeno_Yes_x_raterisk_Greater"      "momfrac_Yes_x_smoke_Yes"
[11] "priorfrac_Yes_x_momfrac_Yes"         "priorfrac_Yes_x_armassist_Yes"
[13] "premeno_Yes_x_armassist_Yes"         "momfrac_Yes_x_raterisk_Same"
[15] "priorfrac_Yes_x_raterisk_Greater"    "armassist_Yes_x_raterisk_Greater"
[17] "fracscore_x_momfrac_Yes"             "priorfrac_Yes_x_smoke_Yes"
[19] "premeno_Yes_x_raterisk_Same"         "fracscore_x_priorfrac_Yes"
[21] "fracscore_x_premeno_Yes"             "raterisk_Same"
[23] "fracscore"                           "fracscore_x_raterisk_Greater"
[25] "armassist_Yes_x_raterisk_Same"       "fracscore_x_smoke_Yes"
[27] "height"                              "momfrac_Yes_x_raterisk_Greater"
[29] "priorfrac_Yes_x_raterisk_Same"       "fracscore_x_raterisk_Same"
[31] "height_x_raterisk_Greater"           "height_x_premeno_Yes"
[33] "height_x_fracscore"                  "height_x_armassist_Yes"
```

Step 2: Fit LASSO: Identify interactions

- I combed through the column names of the results to find the interactions
  - I used ChatGPT to help me because I'm pretty new to `tidymodels`: let's view what I asked

```
interactions = vi_data_int %>% filter(grepl("_x_", Variable))

interaction_terms = ~ (all_predictors()^2) - #Makes interactions b/w all predictors
                        fracscore:starts_with("premeno") - # Removes this interaction
                        height:starts_with("premeno") -
                        height:starts_with("smoke") -
                        height:starts_with("momfrac")
```

Step 2: Fit LASSO: Create recipe and fit model (from LASSO)

- This is not the typical procedure for LASSO, but the `tidymodels` framework for interactions did not let me keep all main effects when looking at my interactions

```
glow_rec_int2 = recipe(fracture ~ ., data = glow_train) %>%
  update_role(age_c, new_role = "dont_use") %>%

  step_dummy(priorfrac, premeno, momfrac, armassist, smoke, raterisk) %>%

  step_interact(terms = interaction_terms)

log_model = logistic_reg()

glow_workflow_int2 = workflow() %>%
      add_model(log_model) %>% add_recipe(glow_rec_int2)

glow_fit_int2 = glow_workflow_int2 %>% fit(glow_train)
```

Step 2: Fit LASSO: Look at model fit

```r
print(tidy(glow_fit_int2), n=60)
```

```
# A tibble: 42 × 5
   term                            estimate std.error statistic p.value
   <chr>                              <dbl>     <dbl>     <dbl>   <dbl>
 1 (Intercept)                        3.09     10.3      0.300   0.764
 2 height                            -0.0415    0.0637  -0.652   0.515
 3 fracscore                         -2.92      2.15    -1.36    0.175
 4 priorfrac_Yes                     15.1       8.61     1.75    0.0793
 5 premeno_Yes                       -0.805     1.14    -0.709   0.478
 6 momfrac_Yes                       -1.71      1.74    -0.984   0.325
 7 armassist_Yes                     18.5      10.7      1.73    0.0838
 8 smoke_Yes                        -22.8     838.      -0.0272  0.978
 9 raterisk_Same                     16.0      10.1      1.59    0.112
10 raterisk_Greater                   1.13      9.16     0.123   0.902
11 height_x_fracscore                 0.0215    0.0136   1.58    0.113
12 height_x_priorfrac_Yes            -0.0825    0.0531  -1.55    0.120
13 height_x_armassist_Yes            -0.114     0.0645  -1.77    0.0762
14 height_x_raterisk_Same            -0.0940    0.0623  -1.51    0.131
15 height_x_raterisk_Greater          0.00238   0.0563   0.0423  0.966
16 fracscore_x_priorfrac_Yes         -0.373     0.177   -2.10    0.0353
17 fracscore_x_momfrac_Yes            0.608     0.313    1.94    0.0520
18 fracscore_x_armassist_Yes         -0.111     0.178   -0.626   0.531
19 fracscore_x_smoke_Yes              0.604     0.564    1.07    0.284
20 fracscore_x_raterisk_Same         -0.257     0.209   -1.23    0.217
21 fracscore_x_raterisk_Greater      -0.318     0.212   -1.50    0.133
22 priorfrac_Yes_x_premeno_Yes       -2.72      1.06    -2.56    0.0104
```

```
23 priorfrac_Yes_x_momfrac_Yes        -1.35        1.35     -1.00    0.317
24 priorfrac_Yes_x_armassist_Yes       1.45        0.820     1.76    0.0779
25 priorfrac_Yes_x_smoke_Yes          -0.329       1.68     -0.196   0.845
26 priorfrac_Yes_x_raterisk_Same       0.122       0.837     0.146   0.884
27 priorfrac_Yes_x_raterisk_Greater    0.838       0.916     0.915   0.360
28 premeno_Yes_x_momfrac_Yes           0.304       1.58      0.192   0.848
29 premeno_Yes_x_armassist_Yes         1.73        0.923     1.87    0.0615
30 premeno_Yes_x_smoke_Yes            -3.98        1.84     -2.17    0.0300
31 premeno_Yes_x_raterisk_Same         0.716       1.16      0.620   0.535
32 premeno_Yes_x_raterisk_Greater      1.71        1.19      1.44    0.150
33 momfrac_Yes_x_armassist_Yes        -3.60        1.43     -2.52    0.0118
34 momfrac_Yes_x_smoke_Yes             2.73        2.67      1.02    0.307
35 momfrac_Yes_x_raterisk_Same         1.87        1.33      1.41    0.160
36 momfrac_Yes_x_raterisk_Greater      0.730       1.33      0.548   0.583
37 armassist_Yes_x_smoke_Yes           1.58        1.67      0.948   0.343
38 armassist_Yes_x_raterisk_Same       0.690       0.893     0.774   0.439
39 armassist_Yes_x_raterisk_Greater   -0.247       0.975    -0.253   0.800
40 smoke_Yes_x_raterisk_Same          19.5       838.        0.0232  0.981
41 smoke_Yes_x_raterisk_Greater       20.0       838.        0.0239  0.981
42 raterisk_Same_x_raterisk_Greater   NA          NA        NA      NA
```

Poll Everywhere Question 4

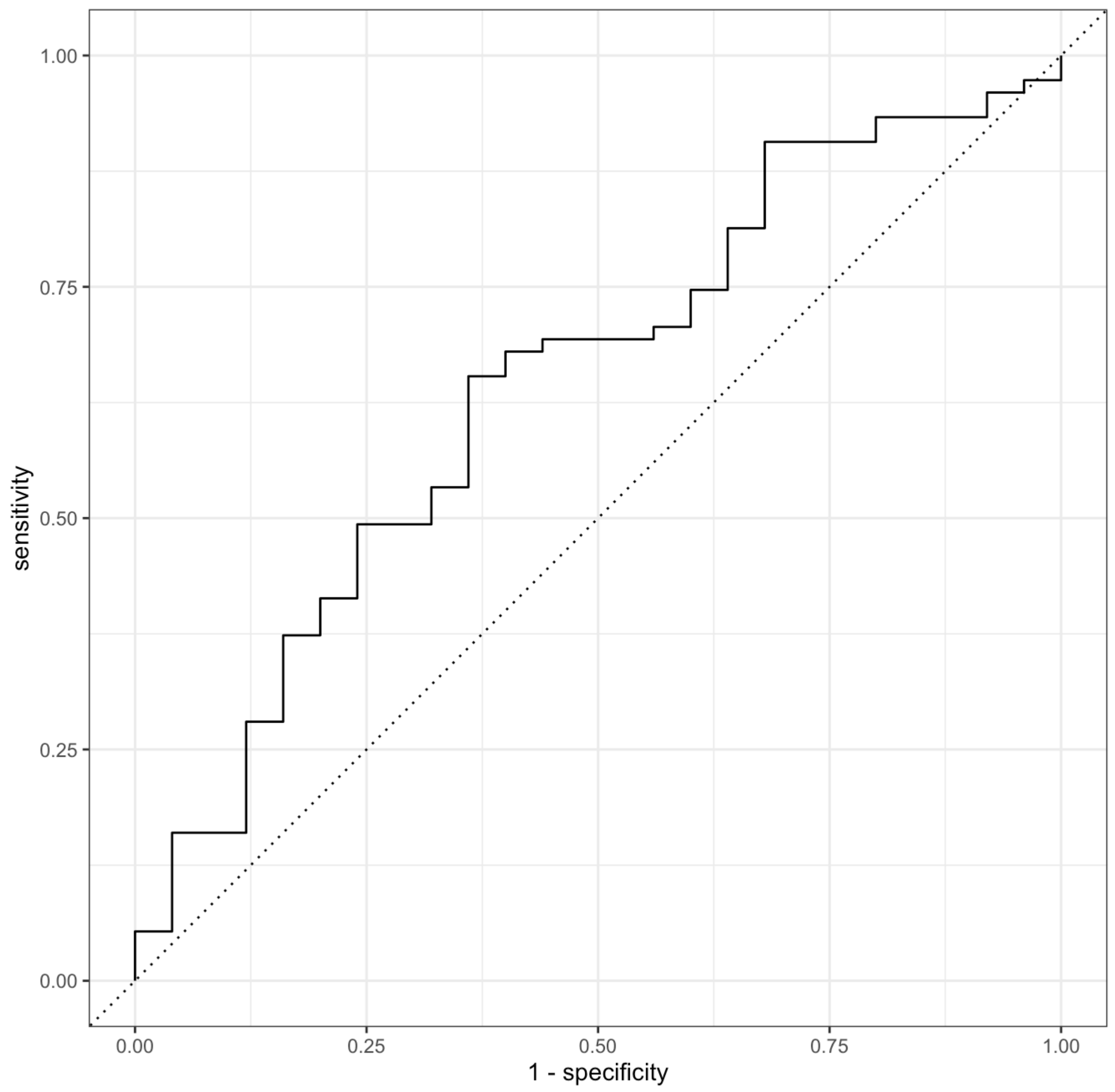
Step 3: Prediction on testing set

```
glow_test_pred = predict(glow_fit_int2, new_data = glow_test, type = "prob") %>%
    bind_cols(glow_test)
```

```
glow_test_pred %>%
  roc_auc(truth = fracture,
                 .pred_No)
```

```
# A tibble: 1 × 3
  .metric .estimator .estimate
  <chr>   <chr>          <dbl>
1 roc_auc binary         0.644
```

```
glow_test_pred %>%
  roc_curve(truth = fracture, .pred_No) %>%
  autoplot()
```



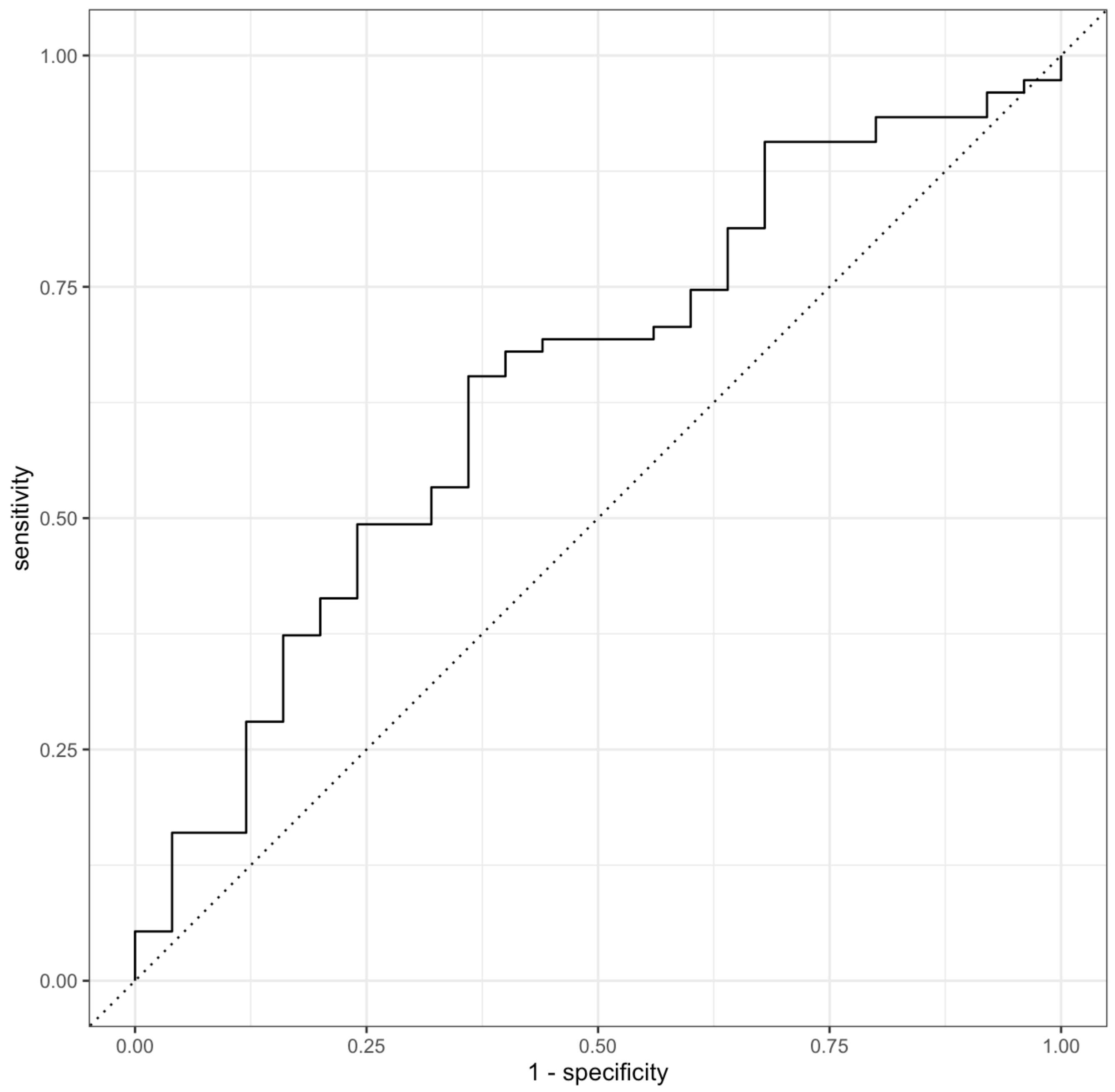
Step 3: Prediction on testing set

```
glow_test_pred = predict(glow_fit_int2, new_data = glow_test, type = "prob") %>%
    bind_cols(glow_test)
```

```
glow_test_pred %>%
  roc_auc(truth = fracture,
                   .pred_No)
```

```
glow_test_pred %>%
  roc_curve(truth = fracture, .pred_No) %>%
  autoplot()
```

```
# A tibble: 1 × 3
  .metric .estimator .estimate
  <chr>   <chr>          <dbl>
1 roc_auc binary         0.644
```

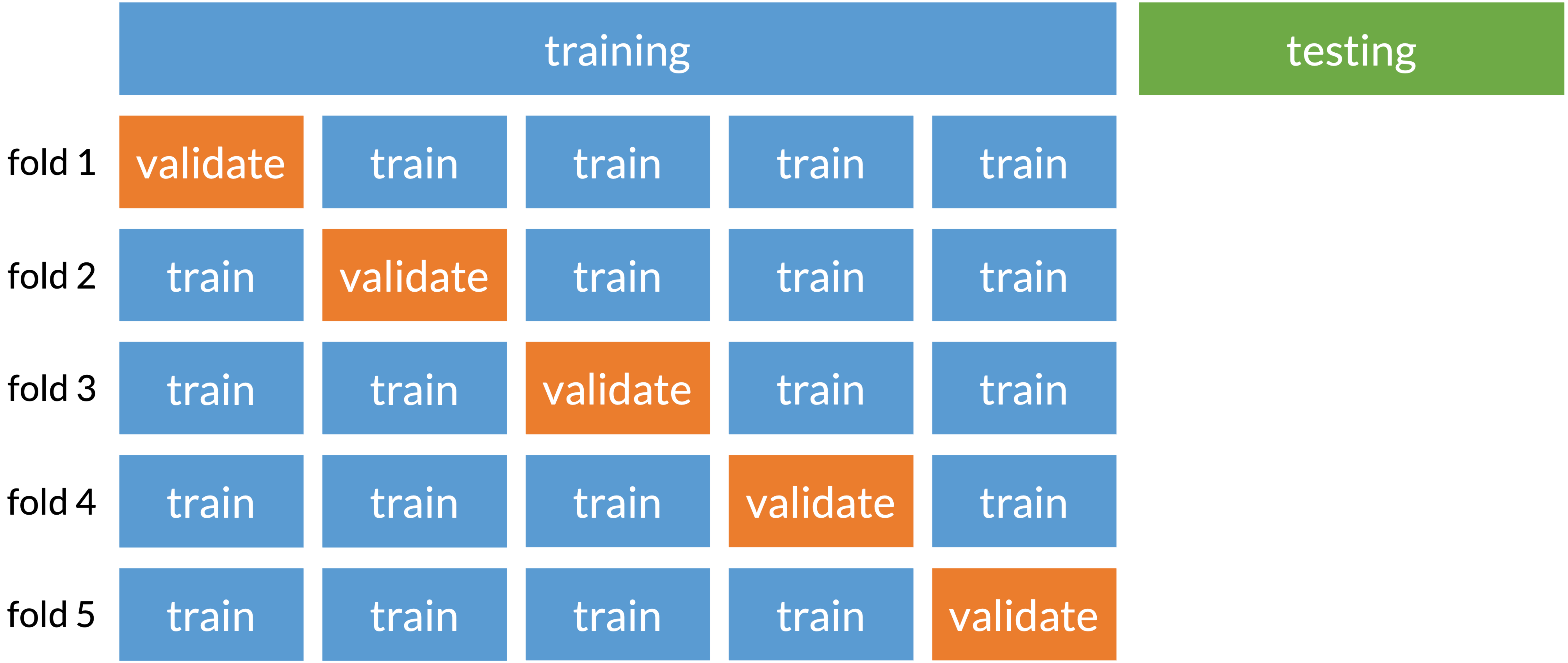


Why is this AUC worse than the one we saw with prior fracture, age, and their interaction?

- Only 1 training and testing set: can overfit training and perform poorly on testing
- We did not tune our penalty
- Our testing set only has 100 observations!

Cross-validation (specifically k-fold)

- Prevents overfitting to one set of training data
- Split data into folds that train and validate model selection
- Basically subsection of training and testing (called validating) before truly testing on our original testing set



Solutions / Resources (beyond our class right now)

- Use a tuning parameter for our penalty
  - Basically, we need to figure out what the best penalty is for our model
  - We use the training set to determine the best penality
  - Videos that includes tuning parameter with LASSO
    - TidyTuesday video on LASSO with interactions
- Cross-validation
  - Under Cross validation within Data Science in a Box
- For complete video of machine learning with **LASSO**, **cross-validation**, and **tuning parameters**
  - See "Unit 5 - Deck 4: Machine learning" on this Data Science in a Box page
    - Video goes through an example with more complicated data, but can be followed with our work!

Summary

- Revisited model selection techniques and discussed how a binary outcome can be treated differently than a continuous outcome
- Discussed association vs prediction modeling
- Discussed classification: a type of machine learning!
- Introduced penalized regression as a classification method
- Performed penalized regression (specifically LASSO) to select a prediction model
- Process presented today has major flaws
  - We did not tune our parameter
  - We did not perform cross validation

For your Lab 4

- You can use purposeful selection, like we did last quarter
  - If you want to focus on **association** modeling!
  - A good way to practice this again if you struggled with it previously

- You can try out LASSO regression
  - If you want to focus on **prediction** modeling!
  - And if you want to stretch your R coding skills