Lesson 14: 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. Understand how penalized regression is a form of model/variable selection.
3. Set up prediction model building steps and split data into training and testing sets.
4. Perform LASSO regression on a dataset using R and the general process for classification methods.

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Some important definitions

more like variable selection → which vars to include in model

- **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

tied to OLS: $\sum_{i=1}^{n} \varepsilon_i^2$

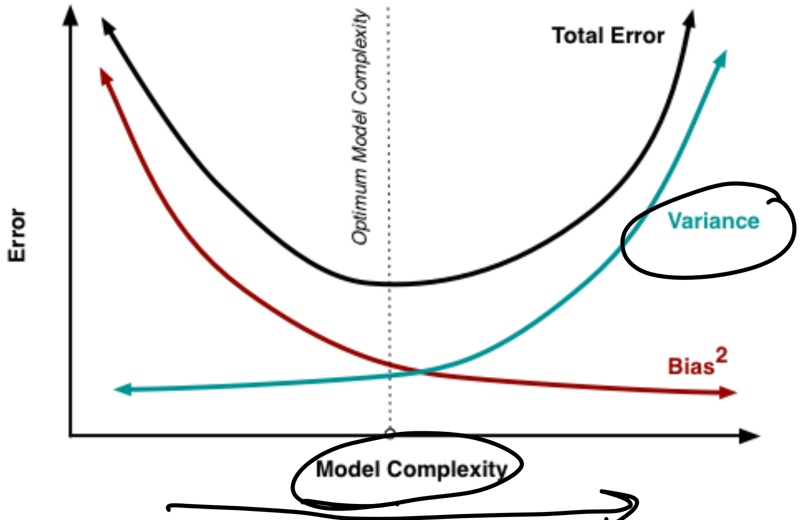
- Recall from 512/612: MSE can be written as a function of the bias and variance of coefficient estimates

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

$\hookrightarrow \hat{\beta}$ vs β $\qquad \hookrightarrow SE_{\hat{\beta}}$

- **No longer use MSE in logistic regression, BUT the idea between the bias and variance trade off holds!**
- For the same data, if our model has…
  - More covariates: less bias, more variance of coef. estimates
    - Potential overfitting: with new data does our model still hold?
  - Less covariates: more bias, less variance of coef. estimates
    more stable estimate of $\hat{\beta}$
    $\hat{\beta}$ not as close β $\quad$ ($\downarrow SE_{\hat{\beta}}$)
    - More bias bc more likely that were are not capturing the true underlying relationship with less variables

↓ vars ↓ flex ↑ stable



\# covariates, interaction

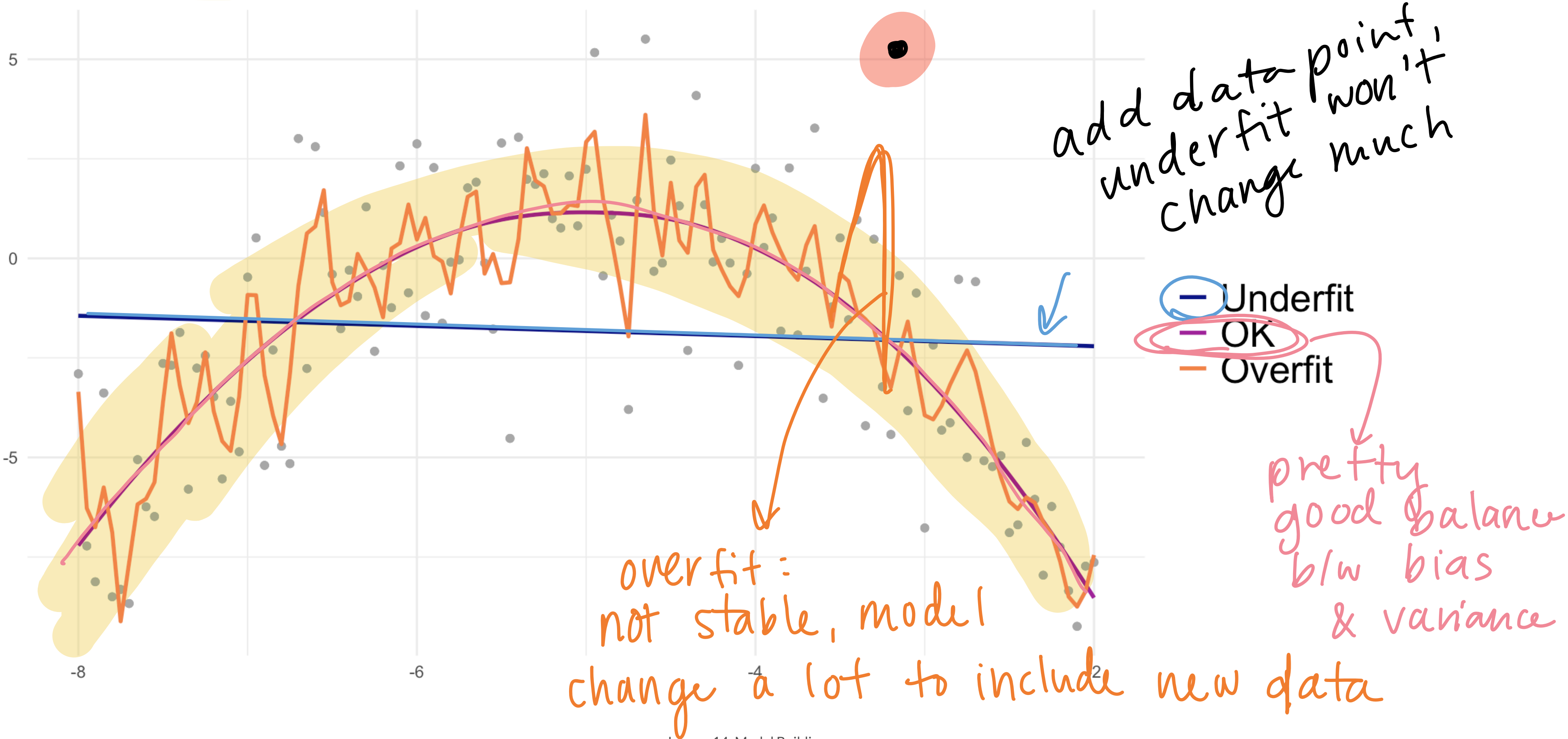
Source: http://scott.fortmann-roe.com/docs/BiasVariance.html

Think of it as a balance between **flexibility** and **stability** of our model

↑ variables ↑ flexible to current data ↓ stable

Visual of overfitting and underfitting data

From Data Science in a Box:



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
  - Think relationship between variables (outcome and predictor)
- Mainly interpret odds ratios of the variable that is the focus of the study

---

- Research question: How is food insecurity associated with household income?

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

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- Research question: How well can we predict food insecurity? What are the biggest conributing factors?

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

support relationship we want to investigate

- Pre-specification of multivariable model
- Purposeful model selection
  - "Risk factor modeling"

BSTA 512/612

- Change in Estimate (CIE) approaches
  - Will learn in Time to Event 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 lesson
  - Be aware that this is a tool that you can use in any regression!
  - You can follow my process for linear regression in Lesson 14 in BSTA 512/612

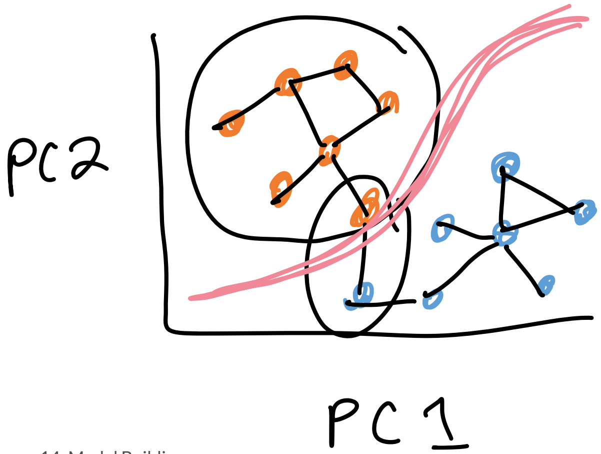
Okay, so prediction of categorical outcomes

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

covariates
independ vars } X's

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



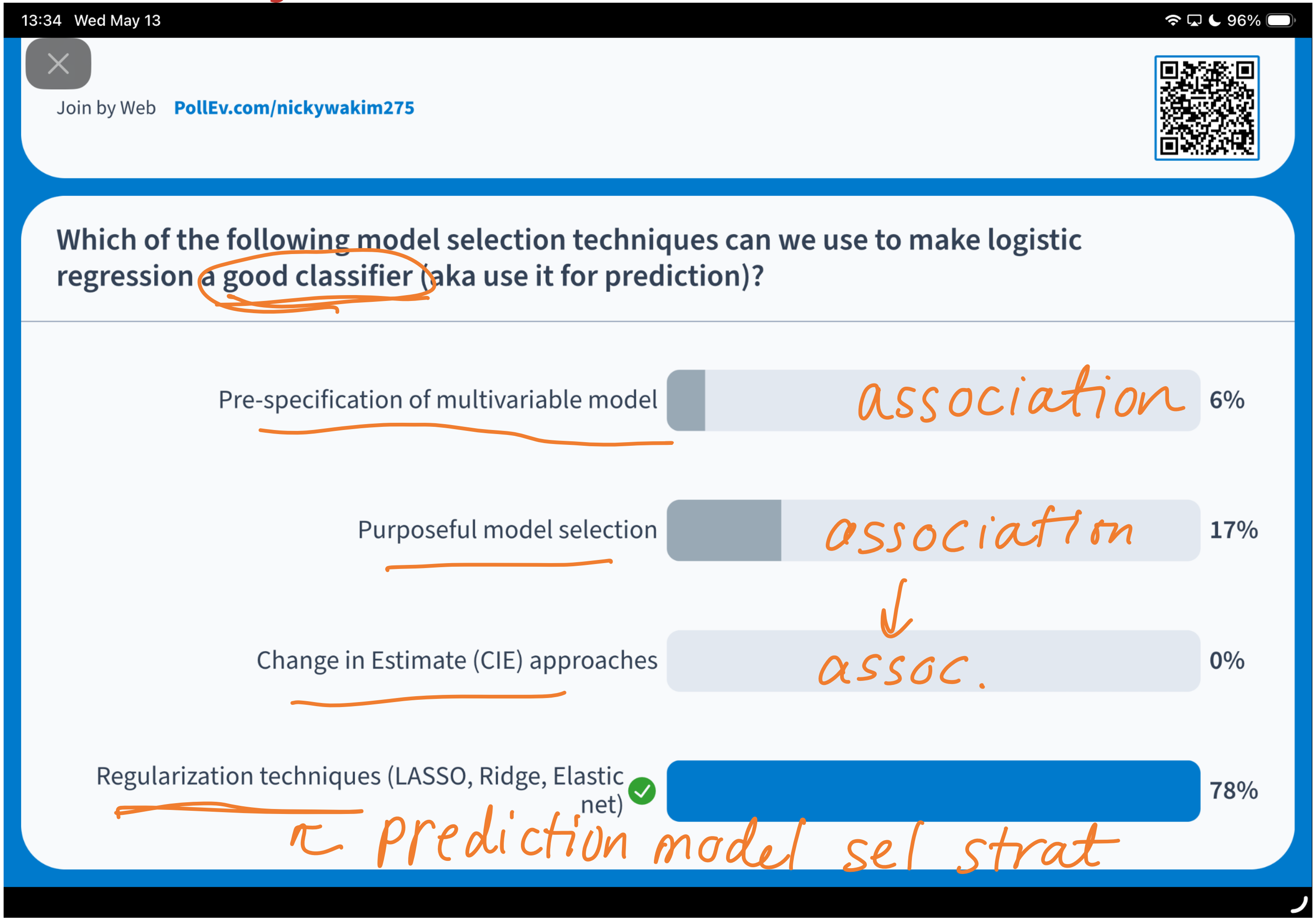
Logistic regression can be a classification model

- But to be a **good classifier**, our logistic regression model needs to…
  - be **built a certain way**
  - have **good potential predictors**

- 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



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Penalized regression

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

↳ leads to overfitting

minimum # predictors that still predict well

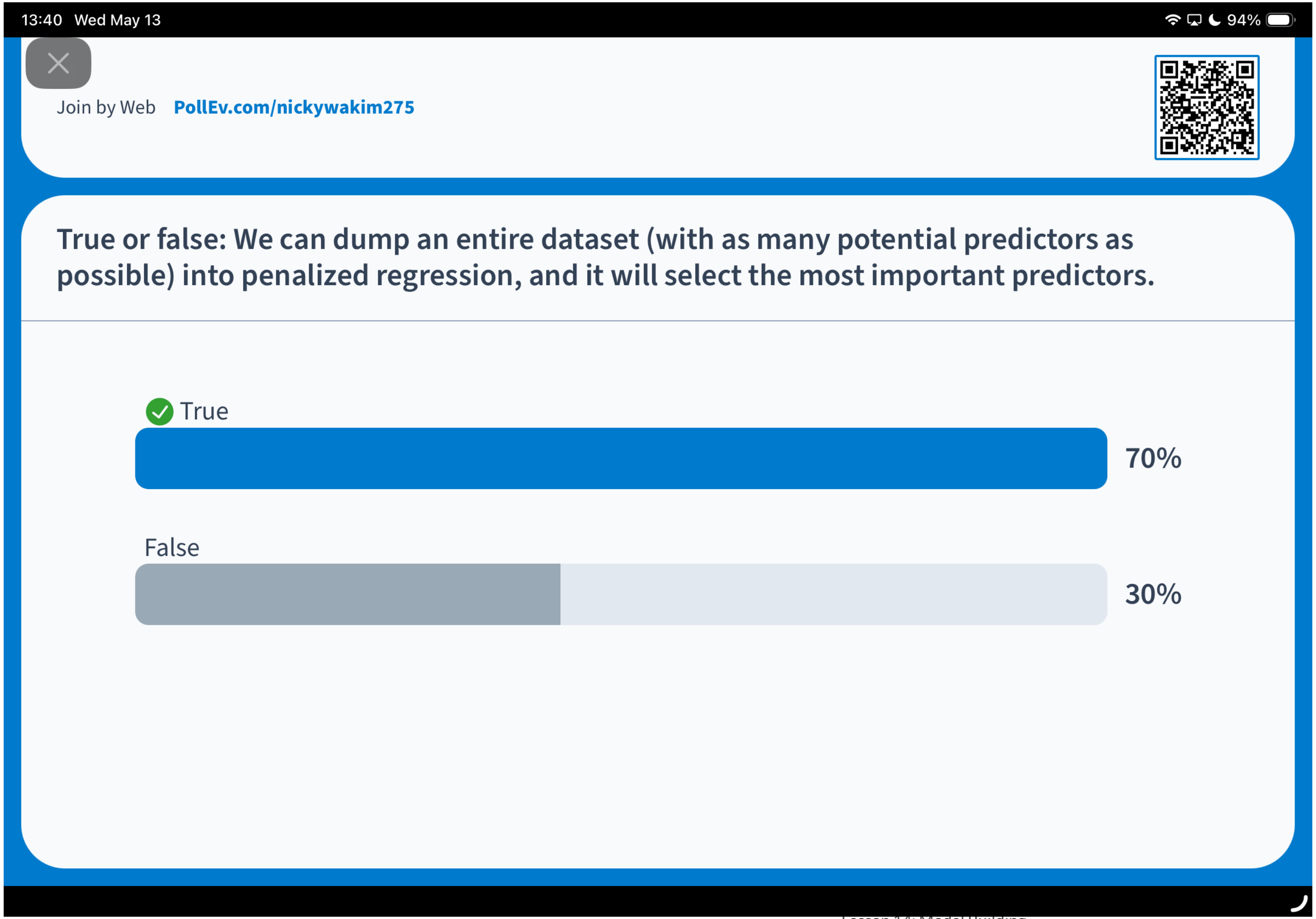
- Also known as *shrinkage* or *regularization* methods
  - "Shrinks" some coefficient estimates to 0

- 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?

optimize # pred & opt penalty

Poll Everywhere Question 2



Three types of penalized regression

Main difference is the type of penalty used

Ridge regression

- Penalty called L2 norm, uses squared values
- Pros
  - Reduces overfitting
  - Handles $p > n$ # predictors > sample size
  - 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

well see in proj

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

The `glmnet()` and `cv.glmnet()` functions

- We are familiar with `glm()` for fitting generalized linear models

- For penalized regression, we use `glmnet()` and `cv.glmnet()`
  - Can fit many types of outcomes (binary, continuous, count, etc.)
  - Can fit Lasso, Ridge, and Elastic net regression
  - Can include interactions and transformations of predictors
  - Input and output of the function are a little rigid (not very `tidyverse` compliant)

- Difference between the two functions:
  - `glmnet()` fits the model for a sequence of lambda values
  - `cv.glmnet()` performs cross-validation to find the optimal lambda

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Overview of predicton model building steps

1. Split data into training and testing datasets

2. Build classification model using 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!**

Let's look at our data

```
glimpse(glow1)
```

```
Rows: 500
Columns: 16
$ sub_id    <int> 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 1…
$ site_id   <int> 1, 4, 6, 6, 1, 5, 5, 1, 1, 4, 6, 1, 6, 1…
$ phy_id    <int> 14, 284, 305, 309, 37, 299, 302, 36, 8, …
$ priorfrac <fct> No, No, Yes, No, No, Yes, No, Yes, Yes, …
$ age       <int> 62, 65, 88, 82, 61, 67, 84, 82, 86, 58, …
$ weight    <dbl> 70.3, 87.1, 50.8, 62.1, 68.0, 68.0, 50.8…
$ height    <int> 158, 160, 157, 160, 152, 161, 150, 153, …
$ bmi       <dbl> 28.16055, 34.02344, 20.60936, 24.25781, …
$ premeno   <fct> No, No, No, No, No, No, No, No, No, No, …
$ momfrac   <fct> No, No, Yes, No, No, No, No, No, No, No,…
$ armassist <fct> No, No, Yes, No, No, No, No, No, No, No,…
$ smoke     <fct> No, No, No, No, No, Yes, No, No, No, No,…
$ raterisk  <fct> Same, Same, Less, Less, Same, Same, Less…
$ fracscore <int> 1, 2, 11, 5, 1, 4, 6, 7, 7, 0, 4, 3, 1, …
$ fracture  <fct> No, No, No, No, No, No, No, No, No, No, …
$ age_c     <dbl> -7, -4, 19, 13, -8, -2, 15, 13, 17, -11,…
```

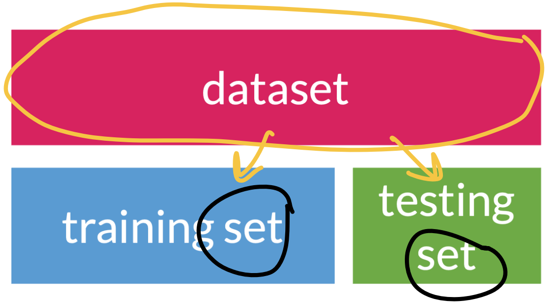
Step 1: Splitting data

Step 2

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

Step 3

- **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%)

iterative process

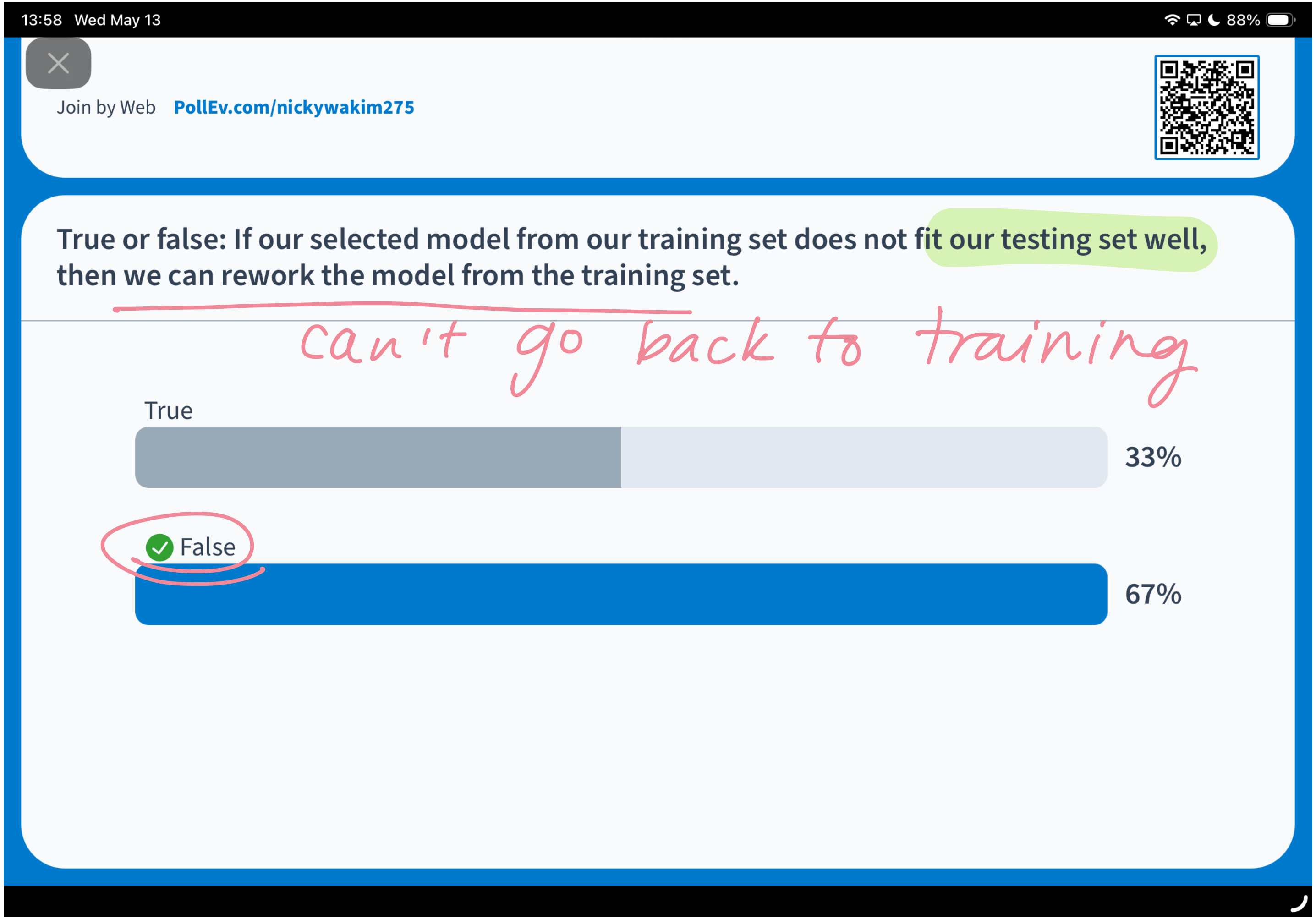
Testing set

- 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%)

final step

- Slide content from Data Science in a Box

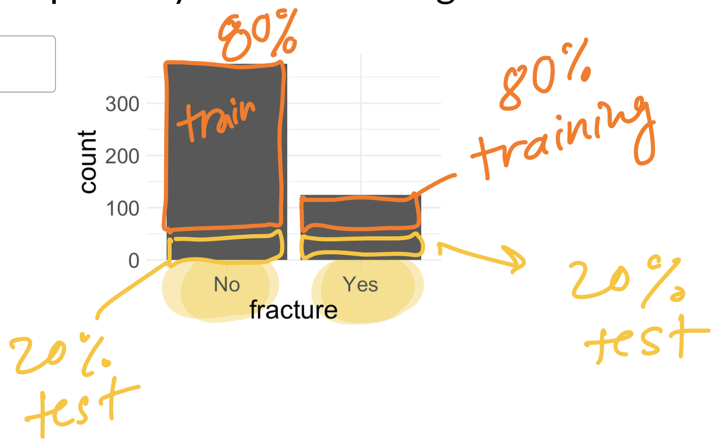
Poll Everywhere Question 3



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

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



- Side note: I took out some variables

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

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
  - Use `prop` to set the proportion of training data

80% training

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

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

even Yes/No b/w training & test

- 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

```r
glimpse(glow_train)
```

```
Rows: 400
Columns: 9
$ 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, …
$ 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, …
```

LASSO on this

```r
glimpse(glow_test)
```

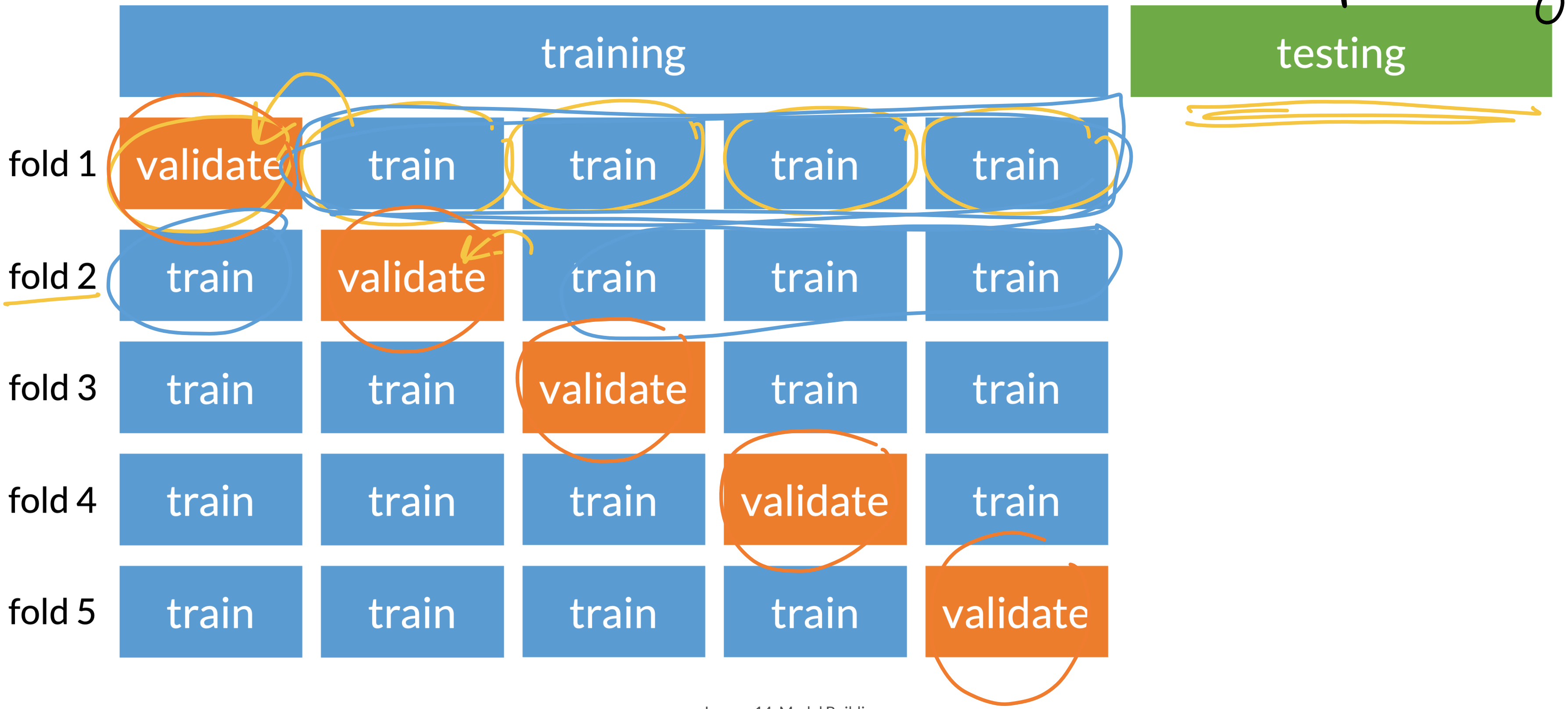
```
Rows: 100
Columns: 9
$ priorfrac <fct> No, No, No, No, No, No, No, Yes, Yes, No, No, No,
No, No, No…
$ height    <int> 167, 162, 165, 170, 154, 160, 171, 142, 152, 166,
154, 163, …
$ premeno   <fct> No, No, No, Yes, Yes, No, Yes, Yes, No, No, No, No,
Yes, No,…
$ momfrac   <fct> No, No, No, Yes, No, No, No, Yes, No, No, No, No,
Yes, No, N…
$ armassist <fct> Yes, No, Yes, No, Yes, Yes, No, No, No, No, No, No,
Yes, No,…
$ smoke     <fct> Yes, Yes, No, No, No, No, No, No, No, No, No, No,
Yes, No, N…
$ raterisk  <fct> Same, Less, Less, Same, Same, Less, Same, Same,
Same, Same, …
$ fracture  <fct> No, No, No, No, No, No, No, No, No, No, No, No, No,
No, No, …
$ age_c     <dbl> -13, -10, 3, 0, 6, -3, -5, 1, 17, -11, -6, -10,
-10, 0, -12,…
```

test model on this

Cross-validation (specifically k-fold)

cv.glmnet()
↳ giving optimal pred & optimal penalty

- Prevents overfitting to one set of training data
- Split **training set** into folds that train and validate model selection
- We can train and validate several times within the **training set**



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Unfortunately... `cv.glmnet()` needs a specific input for the data

1,2 0,1

```
y_train = as.numeric(glow_train$fracture) - 1 # glmnet needs numeric outcome
# x_train = glow_train %>% select(-fracture) %>% as.matrix()
f = as.formula(fracture ~ .)
f
```

fracture ~ priorfrac + age_c

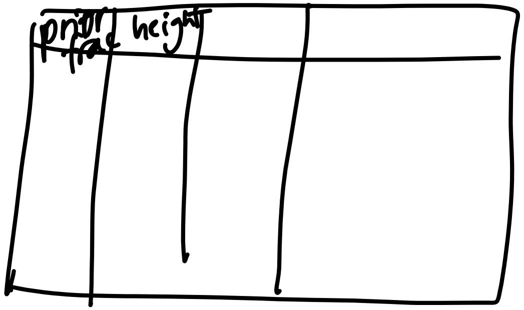
```
fracture ~ .
```

→ all predictors

```
x_train = model.matrix(f, data = glow_train)[, -1]
glimpse(x_train)
```

→ matrix of predictors given formula & data

```
num [1:400, 1:9] 0 0 1 0 0 1 0 1 1 0 ...
- attr(*, "dimnames")=List of 2
 ..$ : chr [1:400] "1" "2" "3" "4" ...
 ..$ : chr [1:9] "priorfracYes" "height" "premenoYes" "momfracYes" ...
```



Overview of predicton model building steps

1. Split data into training and testing datasets

y_train

2. Build classification model using training set

x_train

- This is where we will use penalized regression!

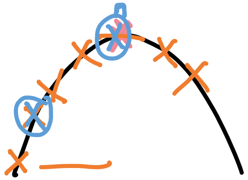
3. Measure predictive accuracy on testing set

Step 2: Fit LASSO penalized logistic regression model

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

```r
library(glmnet)
glow_fit <- cv.glmnet(
  y = y_train,
  x = x_train,
  family = "binomial",
  alpha = 1, # 1 for LASSO
  thresh = 1e-12
  )
```

setting stop



- cv.glmnet uses cross validation and finds the best penalty (lambda)
- alpha option let's us pick the penalty
  - alpha = 0 for Ridge regression
  - alpha = 1 for Lasso regression
  - 0 < alpha < 1 for Elastic net regression

Step 2: Fit LASSO: Coefficient estimates (*kinda*)

- We can look at the coefficient estimates of the model at the best lambda w/ shrinkage in model
- "Best lambda" is `lambda.min` in the output of `cv.glmnet()`

```
beta = coef(glow_fit, s = "lambda.min", x = x_train, y = y_train)
beta
```

```
10 x 1 sparse Matrix of class "dgCMatrix"
                 lambda.min
(Intercept)      3.87740705
priorfracYes     0.76550436
height          -0.03648382
premenoYes       0.28439319
momfracYes       0.79923255
armassistYes     0.26670345
smokeYes        -0.23118903
rateriskSame     0.41350772
rateriskGreater  0.64369667
age_c            0.03397730
```

```
lambda = glow_fit$lambda.min
lambda
```

```
[1] 0.00198163
```

λ

Step 2: Fit LASSO: Main effects: Identify variables

```
1 library(vip)
2 vi(glow_fit, lambda = glow_fit$lambda.min)
```

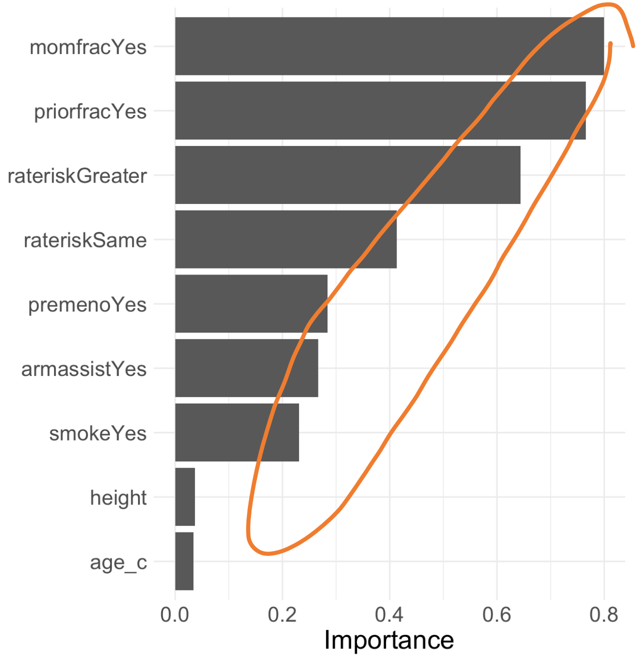
```
# A tibble: 9 × 3
  Variable          Importance Sign
  <chr>                  <dbl> <chr>
1 momfracYes            0.799  POS
2 priorfracYes          0.766  POS
3 rateriskGreater       0.644  POS
4 rateriskSame          0.414  POS
5 premenoYes            0.284  POS
6 armassistYes          0.267  POS
7 smokeYes              0.231  NEG
8 height                0.0365 NEG
9 age_c                 0.0340 POS
```

fracture

away from fracture

Looks like nothing is removed! (Importance would be 0)

```
1 vip(glow_fit,
2     lambda = glow_fit$lambda.min,
3     num_features = 20) +
4   theme(text = element_text(size=20))
```



STOP!

- Going to run another model!
- Just wanted to demonstrate the process with an set of main effects
- NOW we will include interactions in our model
    - More typical in prediction

Step 2: Fit LASSO: Main effects *+ interactions*

- Typically, we want to include interactions in our prediction model

$X_1 \times X_1$

$X_1 \times X_2 \quad X_1 \times X_3, \ldots$

```
f = as.formula(fracture ~ .^2) # formula for main effects and interactions
x_train_int = model.matrix(f, data = glow_train)[, -1]
glow_fit_int <- cv.glmnet(
  y = y_train,
  x = x_train_int,
  family = "binomial",
  alpha = 1,
  thresh = 1e-12
  )
```

priorfrac momfrac ——— priorfrac × momfrac

Step 2: Fit LASSO interaction model: Coefficient estimates (*kinda*)

```
beta_int = coef(glow_fit_int, s = "lambda.min", exact = TRUE, x = x_train, y = y_train)
lambda_int = glow_fit_int$lambda.min
lambda_int
```

```
[1] 0.0202826
```

```
beta_int
```

```
45 x 1 sparse Matrix of class "dgCMatrix"
                             lambda.min
(Intercept)                2.0850976952
priorfracYes               0.4943898067
height                    -0.0225868202
premenoYes                 .
momfracYes                 .
armassistYes               .
smokeYes                   .
rateriskSame               .
rateriskGreater            .
age_c                      .
priorfracYes:height        .
priorfracYes:premenoYes    .
priorfracYes:momfracYes    .
priorfracYes:armassistYes  0.3544339464
priorfracYes:smokeYes      .
priorfracYes:rateriskSame  .
```

```
priorfracYes:rateriskGreater  .
priorfracYes:age_c            .
height:premenoYes             .
height:momfracYes             0.0004091542
height:armassistYes           .
height:smokeYes               .
height:rateriskSame           .
height:rateriskGreater        0.0016221169
height:age_c                  0.0001517309
premenoYes:momfracYes         .
premenoYes:armassistYes       .
premenoYes:smokeYes           .
premenoYes:rateriskSame       .
premenoYes:rateriskGreater    0.4755109044
premenoYes:age_c              .
momfracYes:armassistYes       .
momfracYes:smokeYes           .
momfracYes:rateriskSame       1.1275503167
momfracYes:rateriskGreater    0.1980126090
momfracYes:age_c              .
armassistYes:smokeYes         .
armassistYes:rateriskSame     0.2851098186
armassistYes:rateriskGreater  .
armassistYes:age_c            .
smokeYes:rateriskSame         .
smokeYes:rateriskGreater      .
smokeYes:age_c                0.0027159535
```

Step 2: Fit LASSO interaction model: Variable importance

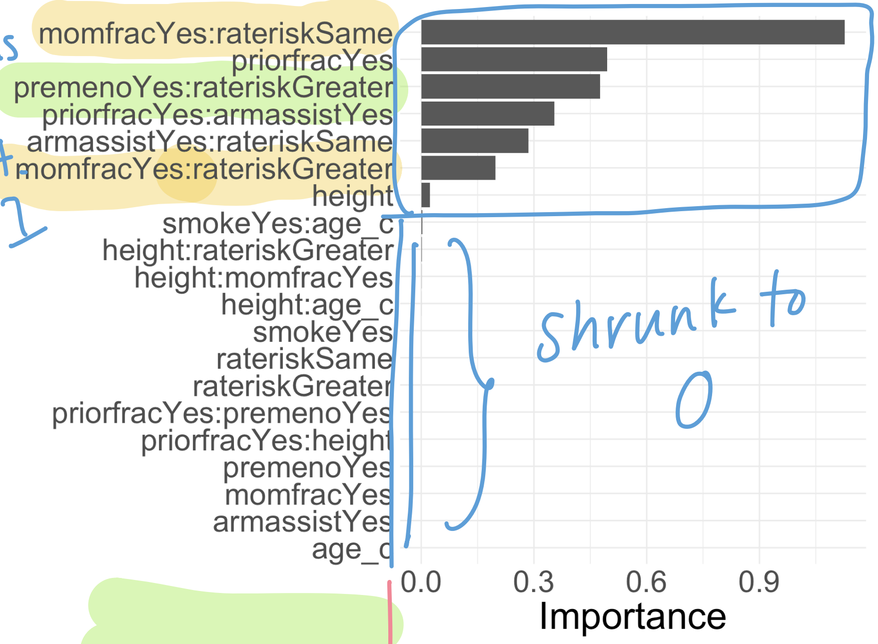
```r
vi(glow_fit_int,
   lambda = lambda_int)
```

```
# A tibble: 44 × 3
   Variable                    Importance Sign
   <chr>                            <dbl> <chr>
 1 momfracYes:rateriskSame       1.13     POS
 2 priorfracYes                  0.494    POS
 3 premenoYes:rateriskGreater    0.476    POS
 4 priorfracYes:armassistYes     0.354    POS
 5 armassistYes:rateriskSame     0.285    POS
 6 momfracYes:rateriskGreater    0.198    POS
 7 height                        0.0226   NEG
 8 smokeYes:age_c                0.00272  POS
 9 height:rateriskGreater        0.00162  POS
10 height:momfracYes             0.000409 POS
# ℹ 34 more rows
```

leads to fract Y=1

0

```r
vip(glow_fit_int,
    lambda =lambda_int,
    num_features = 20) +
  theme(text = element_text(size=30))
```



Step 2: Fit LASSO interaction model: Coefficient estimates (*for real*)

- Very specific way we can extract the exact coefficient estimates
- This uses the values in `beta_int` to calculate coefficient estimates conditional on fact that those variables were selected

```
library(selectiveInference)
out = fixedLassoInf(
  x_train_int,
  y_train,
  beta_int,
  lambda_int,
  family="binomial"
  )
```

} from cv.glmnet

Step 2: Fit LASSO interaction model: Coefficient estimates (*for real*)

```
1 out
```

```
Call:
fixedLassoInf(x = x_train_int, y = y_train, beta = beta_int,
    lambda = lambda_int, family = "binomial")

Testing results at lambda = 0.020, with alpha = 0.100

 Var   Coef Z-score P-value LowConfPt UpConfPt LowTailArea UpTailArea
   1  0.647   1.840   0.220    -0.750    1.568       0.049      0.050
   2 -0.044  -2.173   0.347    -0.073    0.092       0.050      0.050
  13  0.311   0.686   0.311    -1.427    2.970       0.050      0.050
  19 -0.002  -0.303   0.244    -0.211    0.056       0.050      0.050
  23  0.003   1.456   0.294    -0.007    0.012       0.050      0.050
  24  0.000   1.985   0.025     0.000    0.002       0.050      0.050
  29  0.786   1.642   0.194    -0.757    1.695       0.049      0.049
  33  1.972   1.967   0.191    -7.231   34.991       0.050      0.050
  34  0.888   0.881   0.286   -12.816   34.850       0.050      0.050
  37  0.715   1.919   0.364    -1.632    1.335       0.050      0.049
  42  0.052   0.955   0.929    -3.202    0.033       0.050      0.050

Note: coefficients shown are full regression coefficients
```

We can "tidy" the output and transform to ORs

- Use `tibble` to make tidy and take exponential of coefficients

```
lasso_inference_df <- tibble(
  term       = names(out$vars),
  estimate   = exp(out$coef0),
  std.error = out$sd,
  statistic = out$z,
  p.value    = out$pv,
  conf.low   = exp(out$ci[,1]),
  conf.high = exp(out$ci[,2])
)
```

variable names

to get estimated OR

CI's for ORs

We can “tidy” the output and transform to ORs

```
1 lasso_inference_df
```

OR LCI OR UCI OR

```
# A tibble: 11 × 7
   term                     estimate std.error statistic p.value conf.low conf.high
   <chr>                       <dbl>     <dbl>     <dbl>   <dbl>    <dbl>     <dbl>
 1 priorfracYes                1.91  0.352         1.84  0.220   4.72e-1   4.80e 0
 2 height                      0.956 0.0205       -2.17  0.347   9.29e-1   1.10e 0
 3 priorfracYes:armassi…       1.36  0.453         0.686 0.311   2.40e-1   1.95e 1
 4 height:momfracYes           0.998 0.00534      -0.303 0.244   8.10e-1   1.06e 0
 5 height:rateriskGreat…       1.00  0.00205       1.46  0.294   9.93e-1   1.01e 0
 6 height:age_c                1.00  0.0000923     1.98  0.0250  1.00e+0   1.00e 0
 7 premenoYes:rateriskG…       2.20  0.479         1.64  0.194   4.69e-1   5.45e 0
 8 momfracYes:rateriskS…       7.18  1.00          1.97  0.191   7.23e-4   1.57e15
 9 momfracYes:rateriskG…       2.43  1.01          0.881 0.286   2.72e-6   1.37e15
10 armassistYes:rateris…       2.05  0.373         1.92  0.364   1.95e-1   3.80e 0
11 smokeYes:age_c              1.05  0.0543        0.955 0.929   4.07e-2   1.03e 0
```

in proj, do not need to do this

Poll Everywhere Question 4

Overview of predicton model building steps

1. Split data into **training** and **testing** datasets

2. Build classification model using **training set**
   - This is where we will use penalized regression!

3. Measure predictive accuracy on **testing set**

Step 3: Prediction on testing set

L12: Assessing fit

```
f = as.formula(fracture ~ .^2) # formula for main effects and interactions
x_test_int = model.matrix(f, data = glow_test)[, -1]
glow_test_pred <- predict(glow_fit_int, newx = x_test_int,
                          s = "lambda.min", type = "response")
```

input diff b/c glmnet

model

use best λ

pred.prob (not logit)

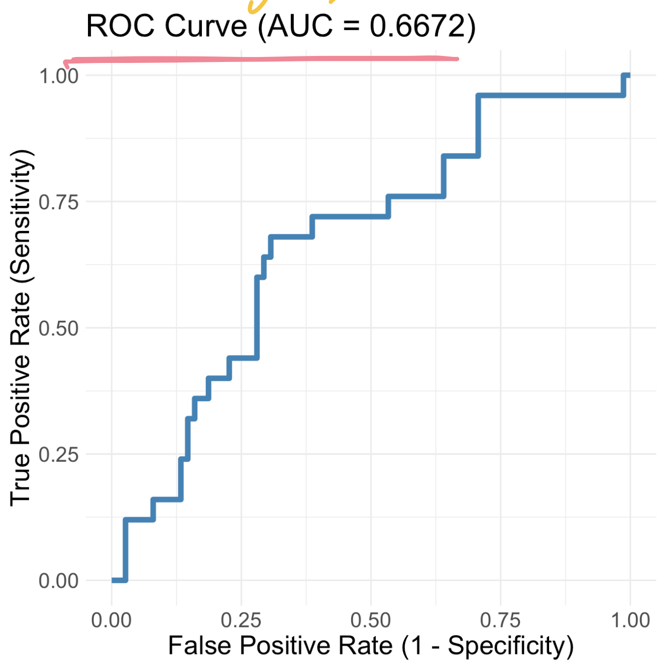
▶ Code

```
library(pROC)
roc_glow = roc(as.numeric(glow_test$fractur
               glow_test_pred)
auc(roc_glow)
```

obs

pred

```
Area under the curve: 0.6672
```



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

- Did not split training and testing before
- Our testing set only has 100 observations!
- None of these things really predict fracture?

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
- More info on `glmnet` function
- Performing 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 switch methods if you want!
- You can use purposeful selection, like we did last quarter
  - If you want to focus on **association** modeling!
  - But you will need to include at least one interaction!!
  - 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