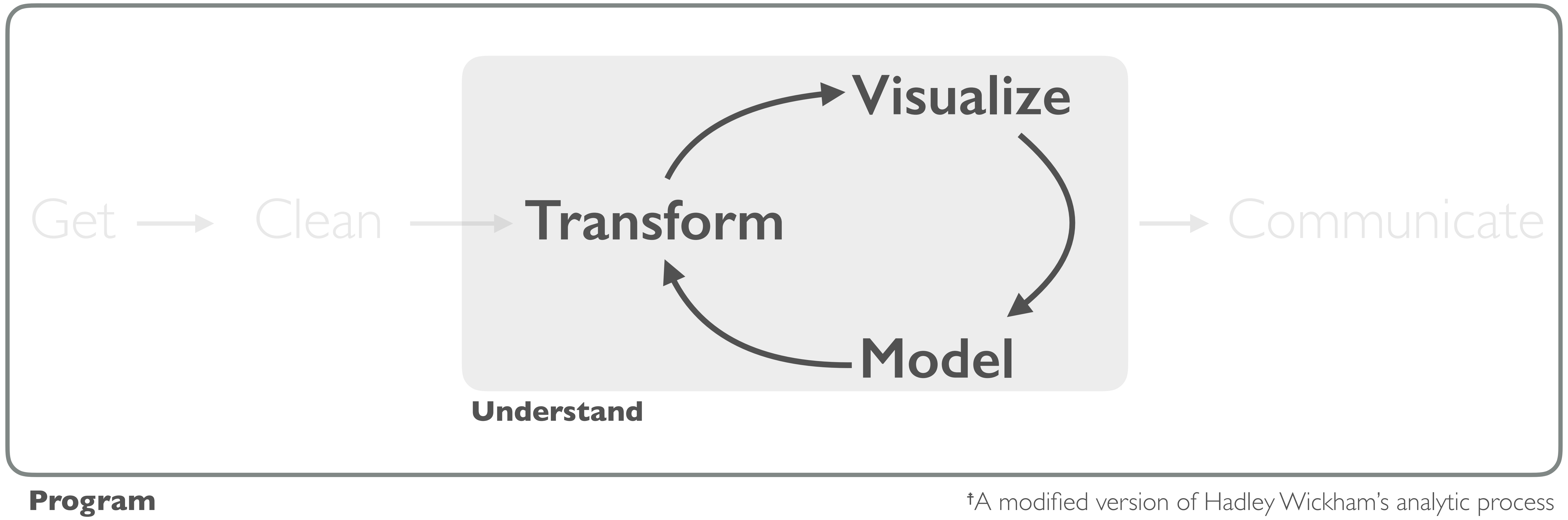
PREDICTIVE MODELING



†A modified version of Hadley Wickham's analytic process


What society thinks I do
What my friends think I do
What other computer scientists think I do
amc
What mathematicians think I do
What I think I do
Source on Save
# Load required pkgs
library(randomForest)
library(xgboost)
What I actually do

PREDICTIVE MODELING

- Text data can be used for predictive modeling much like more traditional data.
- Can be used for both classification and regression problems
- Caveats
  - Must be ***cleaned*** and ***tidied*** (document term matrix)
  - Technique must be able to handle the ***curse of dimensionality***
  - Technique must be able to handle ***sparsity***

PREREQUISITES

PACKAGE PREREQUISITE

```
library(tidyverse)          # data wrangling & plotting
library(tidytext)           # text manipulation
library(glmnet)             # elastic net modeling
library(pROC)               # ROC curve / AUC
```

DATA PREREQUISITE

```
# Click-bait news headlines
url <- "https://raw.githubusercontent.com/kwartler/text_mining/master/all_3k_headlines.csv"
headlines <- read_csv(url)

headlines
# A tibble: 3,000 x 4
   headline                             url                                       site        y
   <chr>                                <chr>                                     <chr>   <int>
 1 Mom Sentenced To 6 Years In Prison Fo… http://dailybuzzlive.com/mom-sentenced-to… dailyb…      1
 2 "The Most Shocking '\x98Jerry Springe… http://dailybuzzlive.com/the-most-shockin… dailyb…      1
 3 America''s Self-Inflicted Defense Woes http://www.activistpost.com/2016/08/ameri… activi…      1
 4 "A Man Spots A Reckless Driver, When … http://dailybuzzlive.com/a-man-spots-a-re… dailyb…      1
 5 Tim Cook Asks FBI To Withdraw Order T… http://www.buzzfeed.com/johnpaczkowski/ap… buzzfe…      1
 6 Police Union Threatens Not To Patrol … http://www.buzzfeed.com/salvadorhernandez… buzzfe…      1
 7 Ed Rendell: Clinton's Speech Was Pres… http://www.buzzfeed.com/christophermassie… buzzfe…      1
```

DATA PREP

Preparing for the modeling process

GENERALIZABILITY

- **Generalizability**: the confidence that a model will perform similarly on unobserved data.
- The difference between a descriptive vs. predictive capability

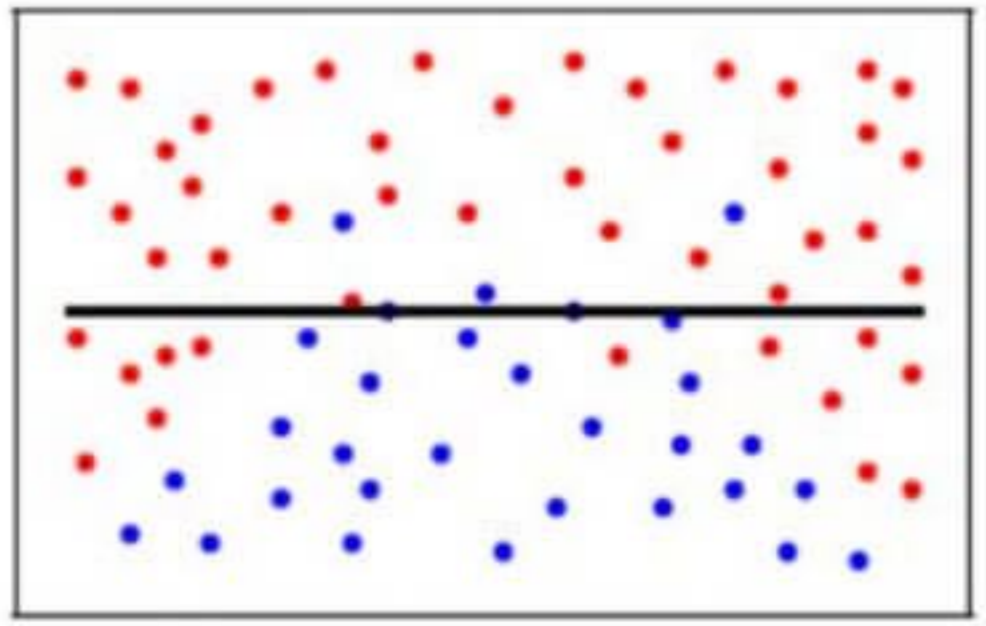
A more generalizable model gives us greater confidence in future accuracy

BIAS VS. VARIANCE

Bias

- Wrong model assumptions
- Model restrictions on hyperparameters
- Error due to model specification

Underfitting



BIAS vs. VARIANCE

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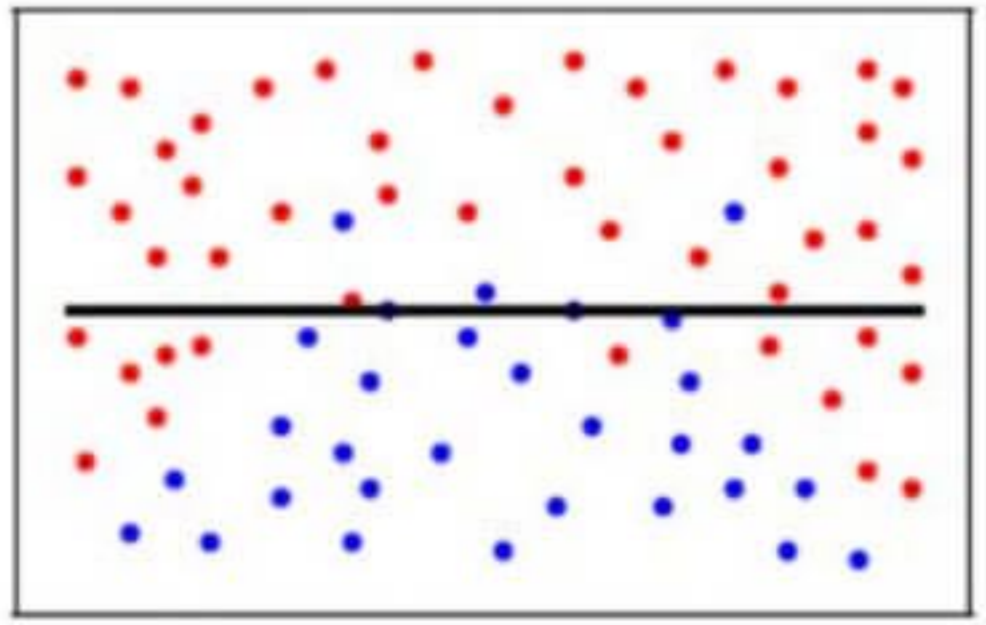
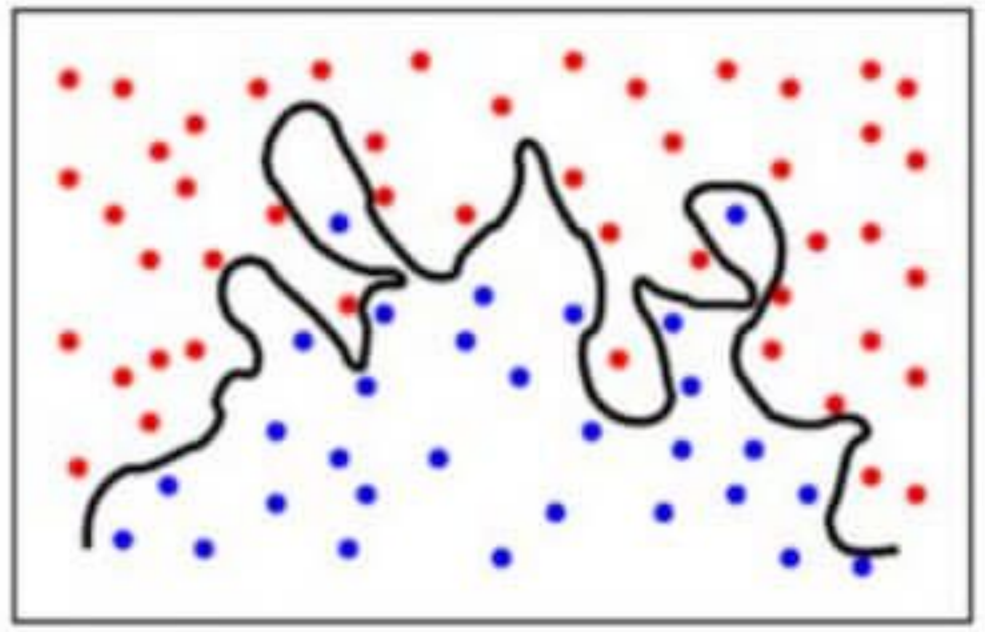
Variance

- Model over adapts to training data
- Hyperparameters overly tuned to training data
- Error due to the sampling of training set

Underfitting



Overfitting



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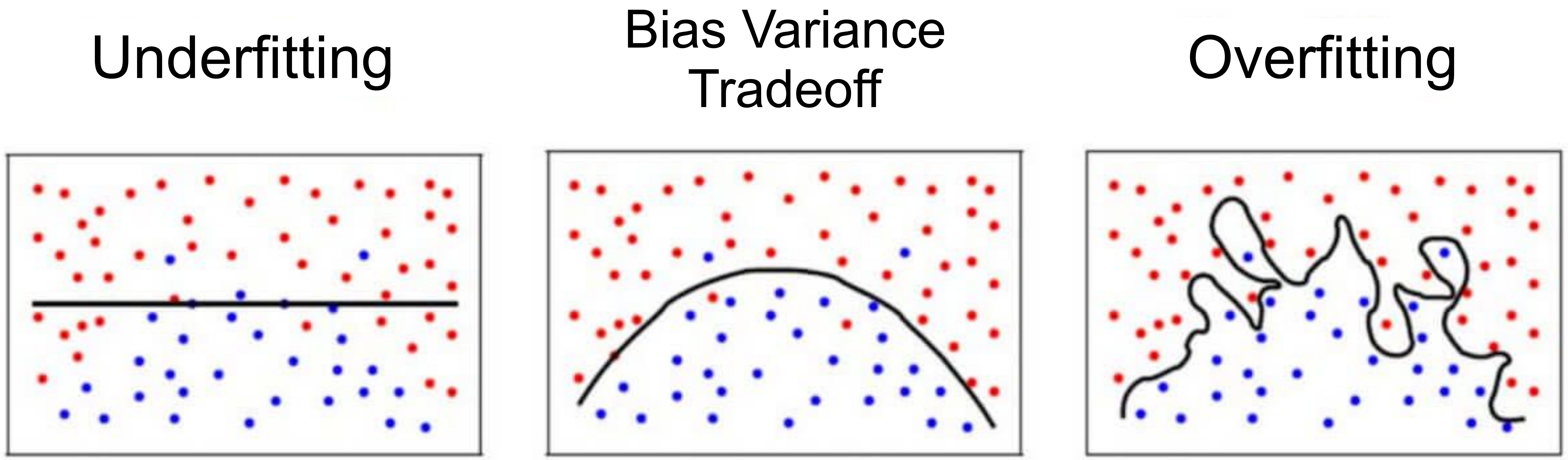
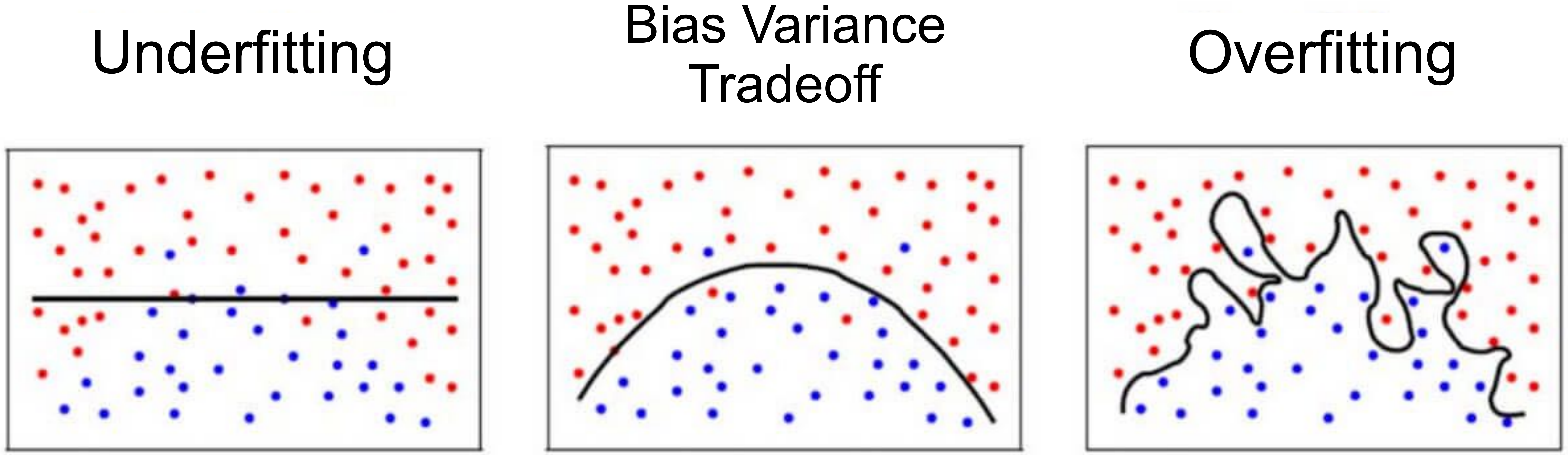


BIAS VS. VARIANCE

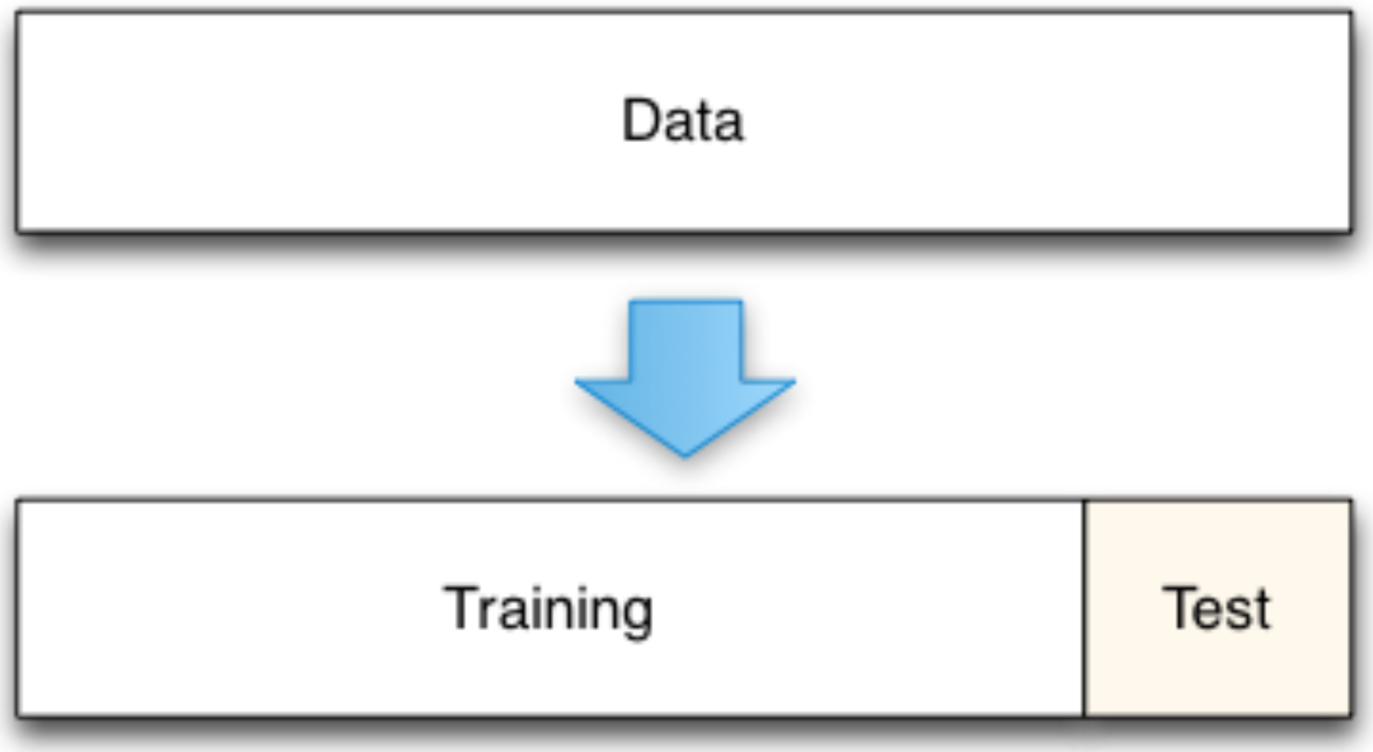
Resampling

- The more adaptable our modeling techniques become, the greater the importance to use advanced resampling methods to minimize overfitting…***aka over-confident predictions***



BASIC TRAIN/TEST SPLIT

- At a minimum, always use a training-test split to assess out-of-sample accuracy.
- Typical: 70/30
  - Dependent on size of data set



<u>Disadvantages</u>

- Model can overfit to training data
- Single test set provides only a single insight into predictive performance

ESTABLISHING TRAINING VS. TESTING SETS

```r
# assign about 70% to training and 30% to test
set.seed(123)

headlines <- headlines %>%
  mutate(partition = sample(
    x = c("Train", "Test"),
    size = 3000,
    prob = c(.7, .3),
    replace = TRUE)
   )
```

`set.seed` provides reproducibility

Next, create a `partition` variable

- sample from `x`
- 3000 times (length of data set)
- 70% from Train, 30% from Test

CLEAN AND TIDY DATA

```
# assign about 70% to training and 30% to test
headlines_tidy <- headlines %>%
  unnest_tokens(word, headline) %>%
  anti_join(stop_words) %>%
  count(url, partition, y, word) %>%
  mutate(id = paste(url, partition, sep = "_"))

headlines_tidy
# A tibble: 18,647 x 6
  url              partition      y word      n id
  <chr>            <chr>      <int> <chr> <int> <chr>
1 http://21stce… Train          1 anti      1 http://21stce…
2 http://21stce… Train          1 gove…     1 http://21stce…
3 http://21stce… Train          1 inst…     1 http://21stce…
4 http://21stce… Train          1 lead…     1 http://21stce…
5 http://21stce… Train          1 obama     1 http://21stce…
6 http://21stce… Train          1 opin…     1 http://21stce…
7 http://21stce… Train          1 party     1 http://21stce…
```

This is performing the same tidying process you've seen.

However, we add one step where we combine the url & partition:

id: http://21stcenturywire…_Train

We will use this later!

CONVERT TO A DOCUMENT TERM MATRIX

```
# convert to a DTM matrix
headlines_matrix <-  headlines_tidy %>%
  cast_dtm(id, word, n) %>%
  as.matrix()
```

To model we need to have our data in a DTM style but as a matrix object.

Now we're ready to create our training & testing splits

TRAINING SPLIT

```
train.x <- headlines_matrix %>%
  as_data_frame() %>%
  mutate(id = row.names(headlines_matrix)) %>%
  filter(str_detect(id, "_Train")) %>%
  select(-id) %>%
  as.matrix() %>%
  Matrix::Matrix(sparse = TRUE)

train.y <- headlines_tidy %>%
  filter(partition == "Train") %>%
  distinct(id, y) %>%
  .$y

train.x[1:5, 1:5]
5 x 5 sparse Matrix of class "dgCMatrix"
     anti government instructs leader obama
[1,]    1          1         1      1     1
[2,]    .          .         .      .     .
[3,]    .          .         .      .     .
```

Create training feature set, which is in the form of a sparse matrix… computationally efficient!

Create response variable vector

YOUR TURN!

You created the training split, now can you do the same thing to create the test split?

TESTING SPLIT

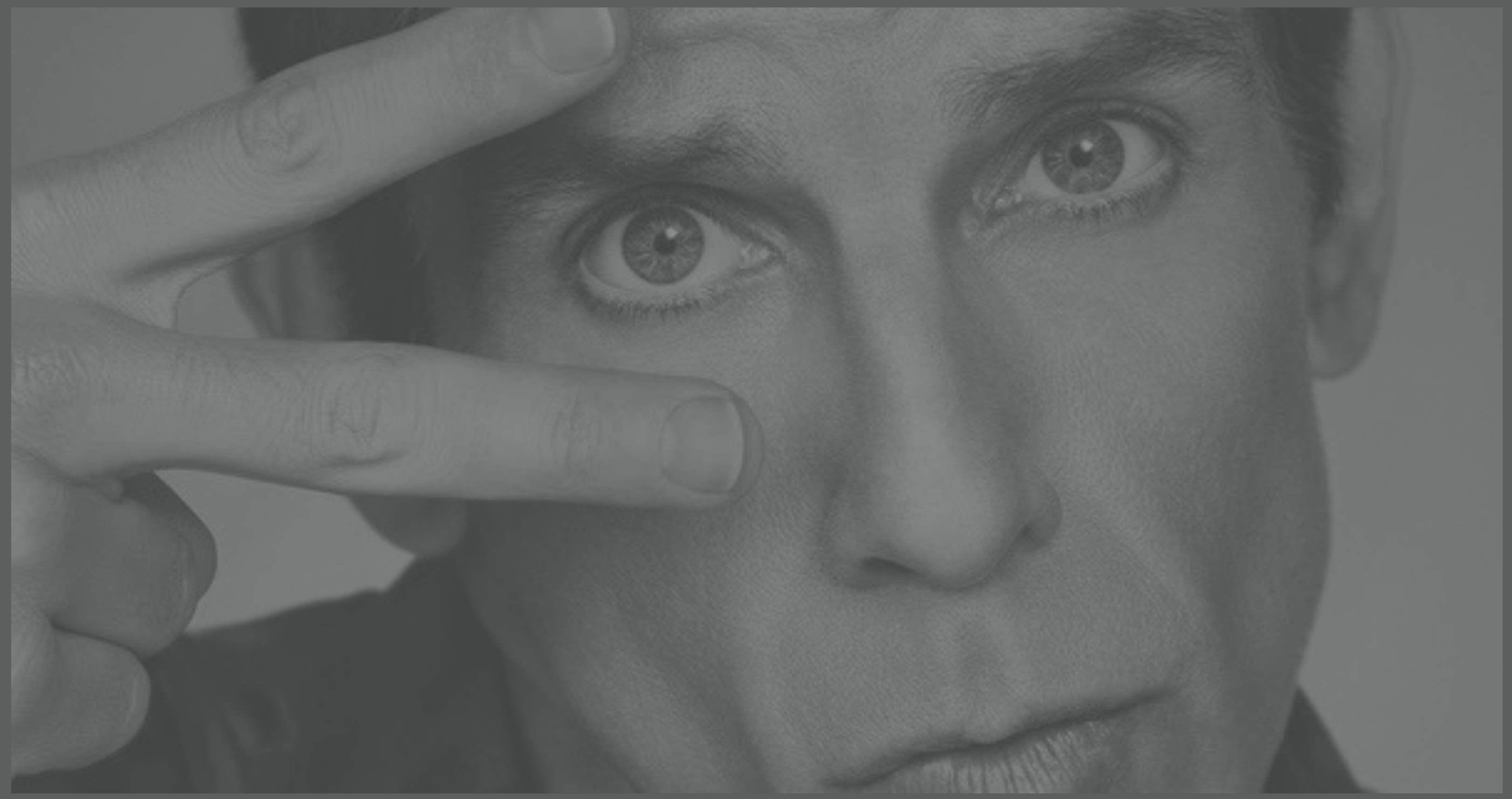
```
test.x <- headlines_matrix %>%
  as_data_frame() %>%
  mutate(id = row.names(headlines_matrix)) %>%
  filter(str_detect(id, "_Test")) %>%
  select(-id) %>%
  as.matrix() %>%
  Matrix::Matrix(sparse = TRUE)

test.y <- headlines_tidy %>%
  filter(partition == "Test") %>%
  distinct(id, y) %>%
  .$y

test.x[1:5, 1:5]
5 x 5 sparse Matrix of class "dgCMatrix"
     anti government instructs leader obama
[1,]    .          .         .      .     1
[2,]    .          .         .      .     .
[3,]    .          .         .      .     .
[4,]    .          .         .      .     .
[5,]    .          .         .      .     .

dim(test.x)
[1]  890 7149

table(test.y)
  0   1
450 440
```

Create testing feature set, which is in the form of a sparse matrix… computationally efficient!

Create response variable vector

MODELING

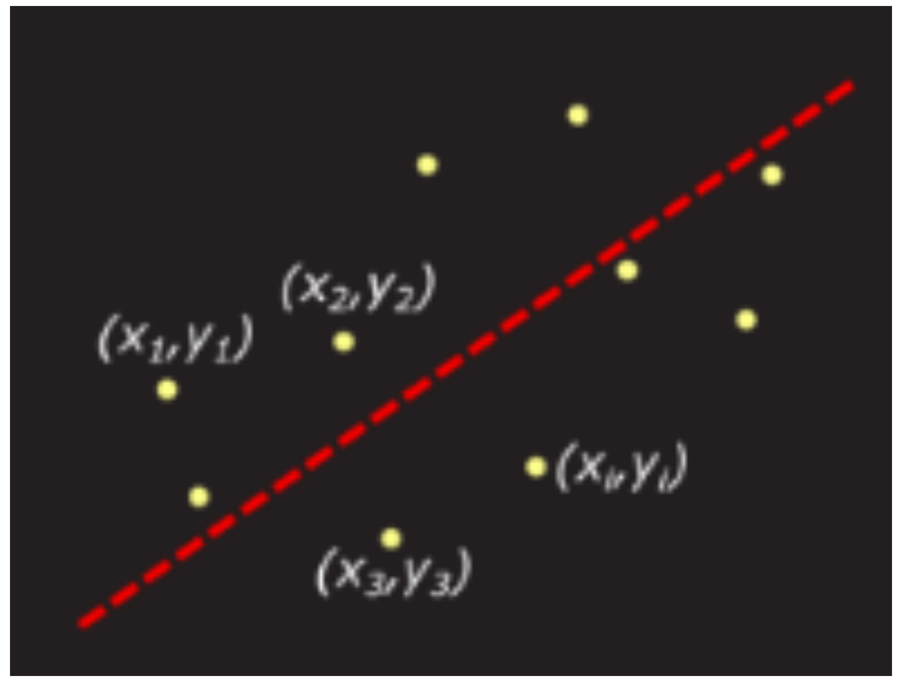
Regularized regression: Ridge, Lasso, & Elastic Nets

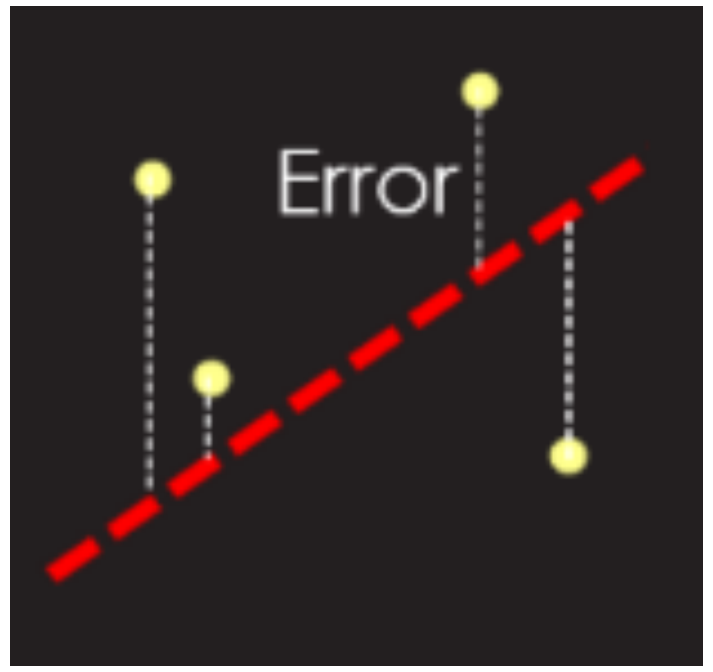


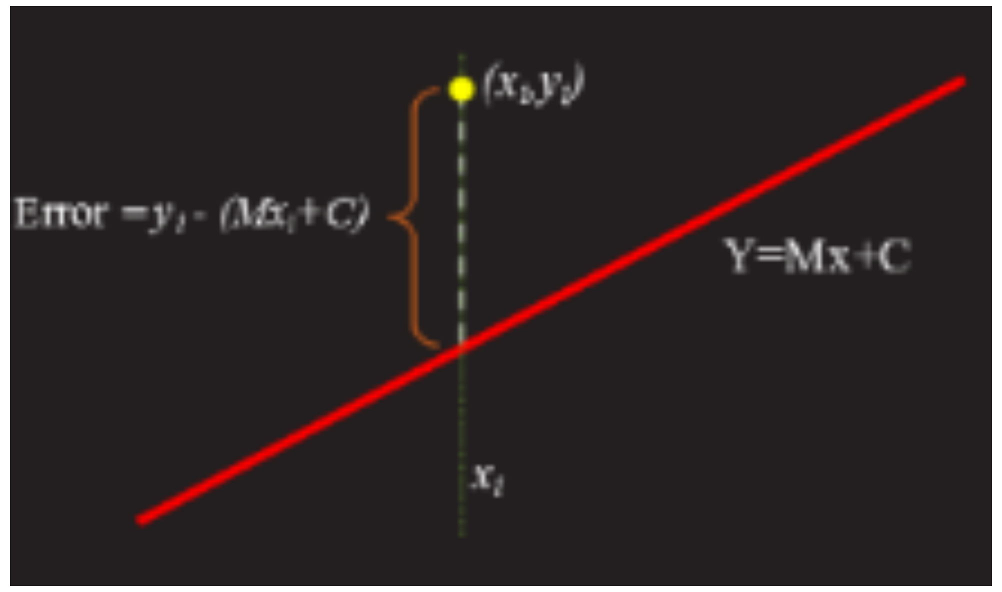
LINEAR REGRESSION

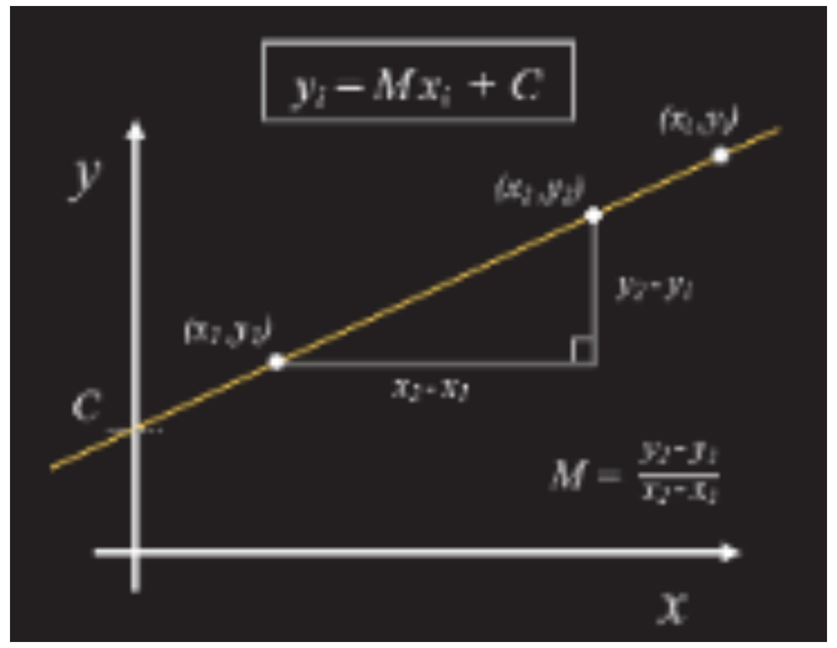
Goal of linear regression is to fit a line to the data that minimizes total squared error

Minimize RSS: $$\mathrm{RSS} = \sum_{i=1}^{n}\left(y_i - \beta_0 - \sum_{j=1}^{p}\beta_j x_{ij}\right)^2$$









LINEAR REGRESSION

Goal of linear regression is to fit a line to the data that minimizes total squared error

- Assumptions:
  - Linear relationship
  - Multivariate normality
  - No or little multicollinearity
  - No autocorrelation
  - Homoscedastic (constant variance in residuals)
  - $p < n$ (there is no unique solution when $p > n$

LINEAR REGRESSION

Goal of linear regression is to fit a line to the data that minimizes total squared error

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  - Homoscedastic (constant variance in residuals)
  - $p < n$ (there is no unique solution when $p > n$ ✔

Two problems we run into with text
Both cause serious problems with model stability & reliability

REGULARIZED REGRESSION

- Three **shrinkage methods** have been developed to resolve these (and other) concerns: <u>*Lasso*</u>, <u>*Ridge regression*</u>, <u>*Elastic nets*</u>.
- **Constrains** or **regularizes** the coefficient estimates, or equivalently, that **shrinks** the coefficient estimates towards zero.
- It may not be immediately obvious why such a constraint should improve the fit, but it turns out that shrinking the coefficient estimates can significantly reduce their variance.

REGULARIZED REGRESSION

- Three **shrinkage methods** have been developed to resolve these (and other) concerns: *Lasso*, *Ridge regression*, *Elastic nets*.

- **Constrains** or **regularizes** the coefficient estimates, or equivalently, that **shrinks** the coefficient estimates towards zero.

  - Lasso minimizes: $\mathrm{RSS} + \lambda \sum_{j=1}^{p} |\beta_j|.$

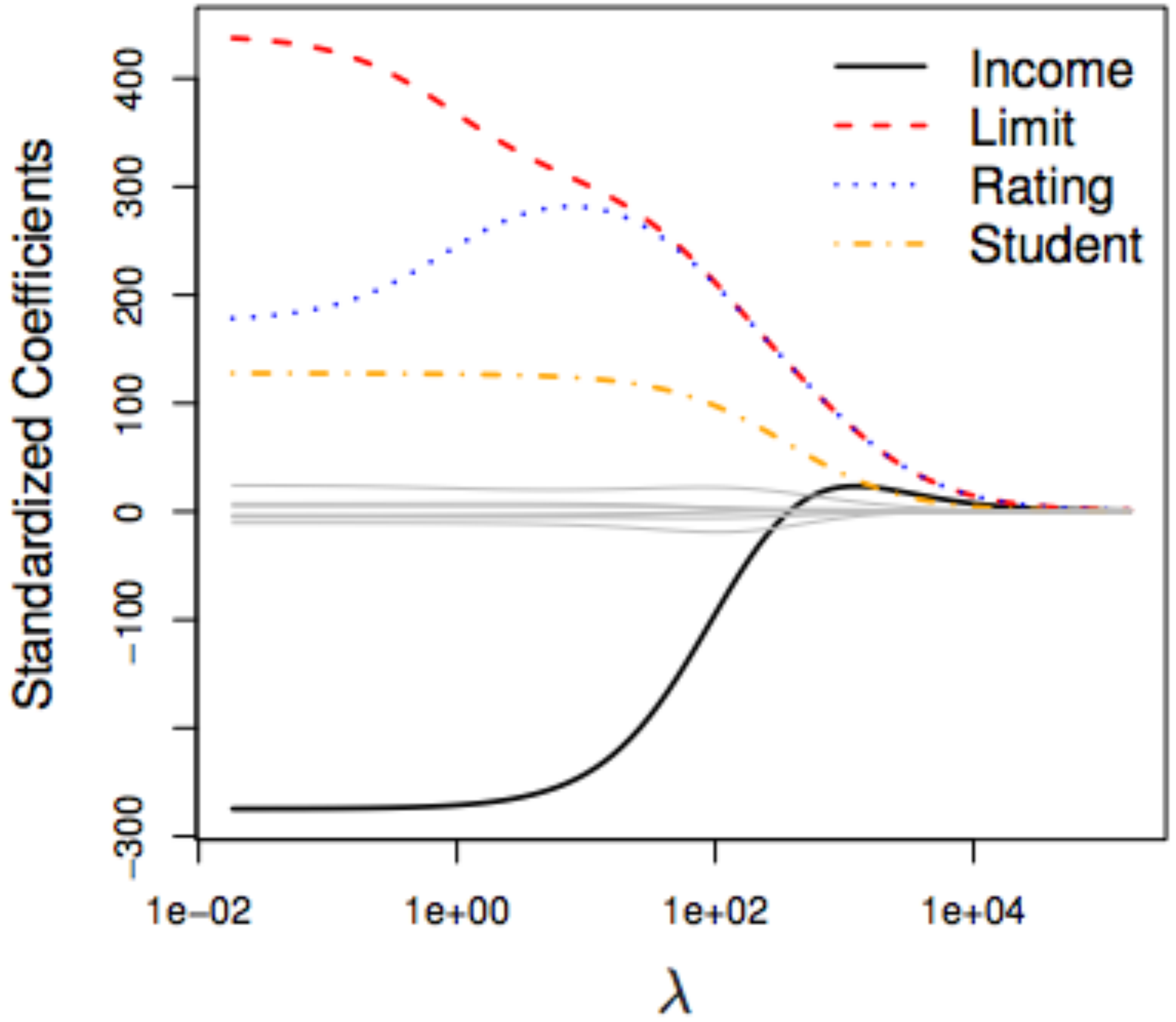
  - Ridge minimizes: $\mathrm{RSS} + \lambda \sum_{j=1}^{p} \beta_j^2.$

lambda (λ) becomes a tuning parameter:

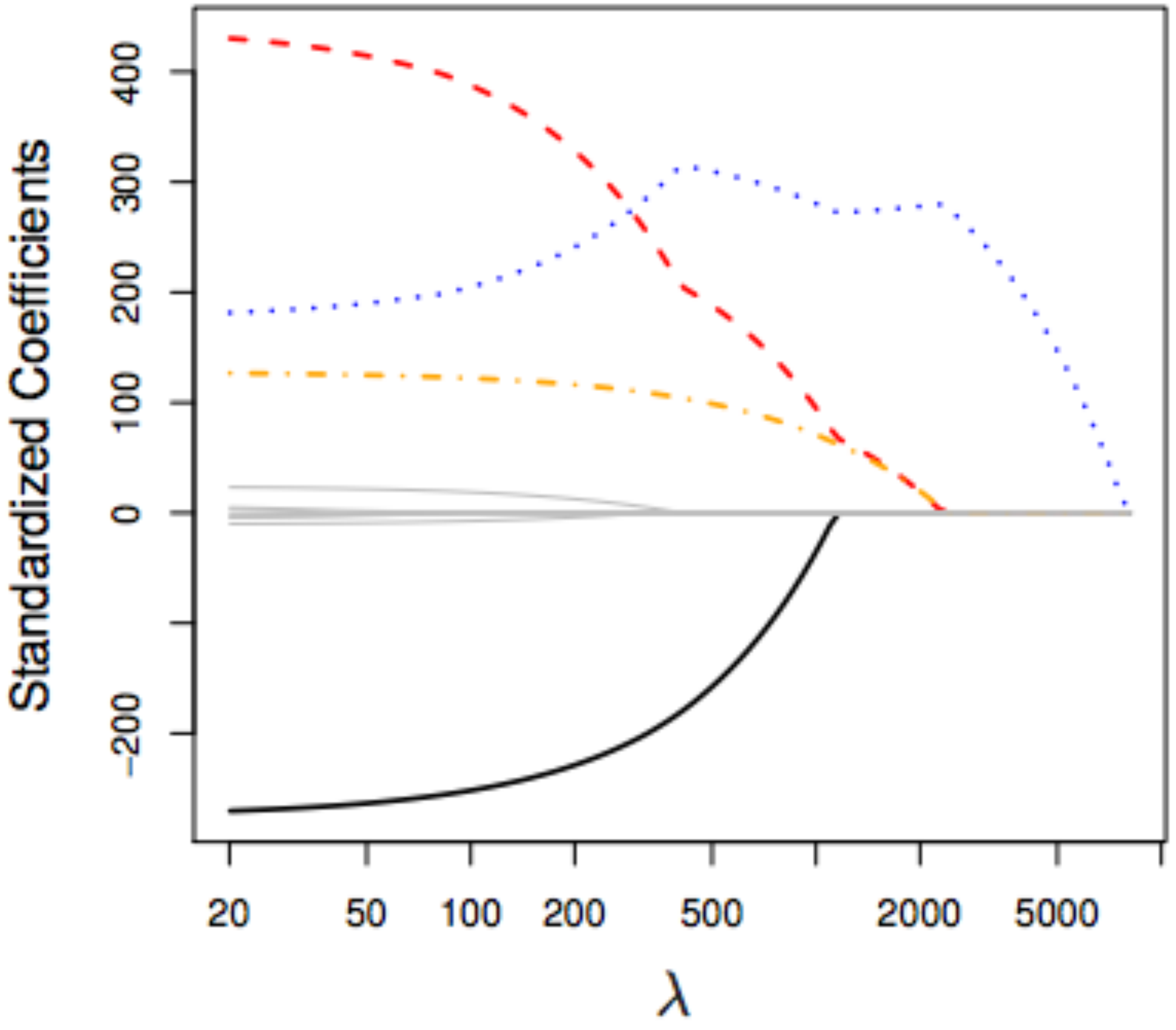
- $\lambda \cong 0$: equates to OLS regression
- $\lambda \cong \infty$: equates to the mean as all coefficients are forced to 0

REGULARIZED REGRESSION

Ridge Regression



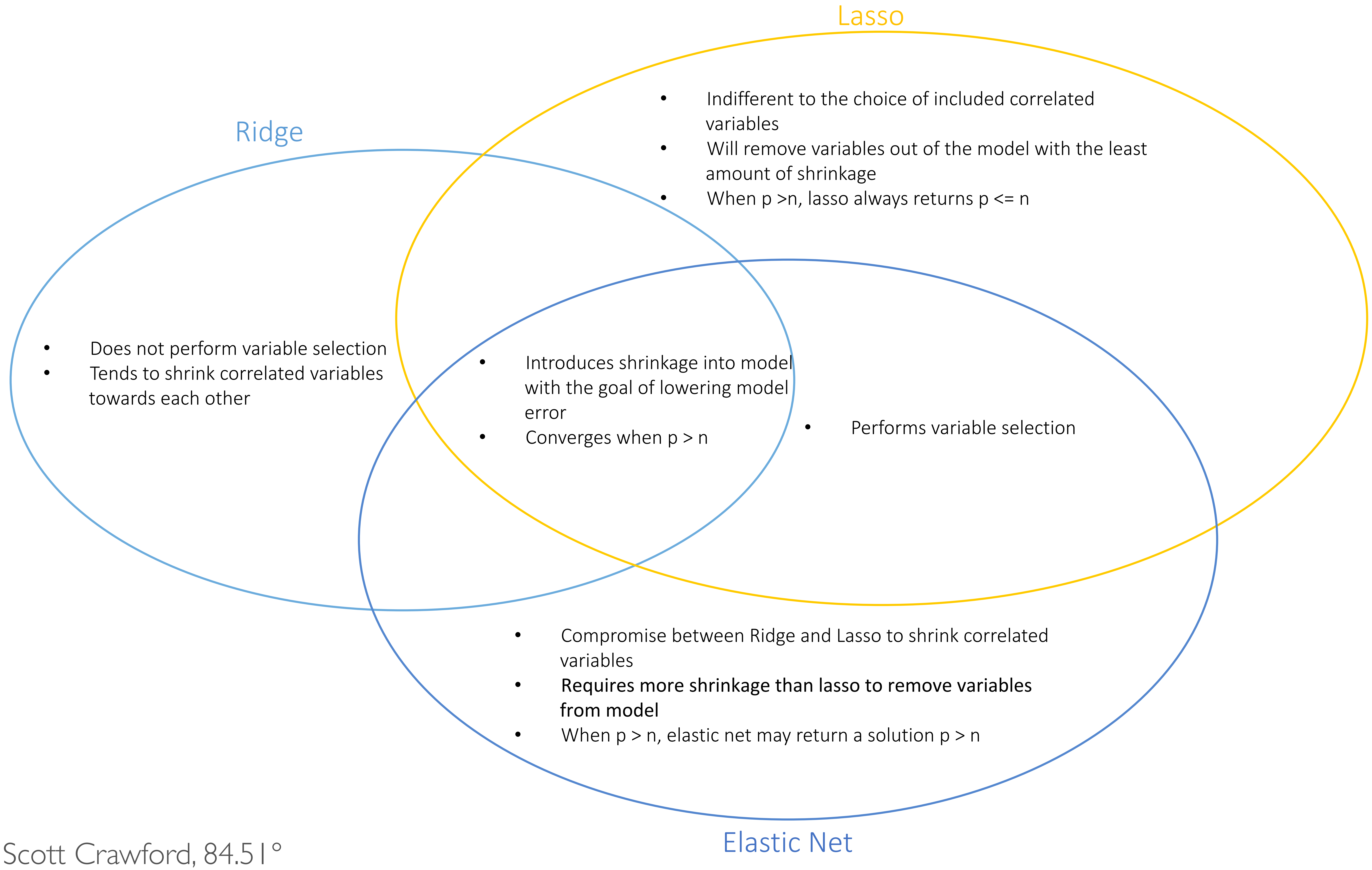
Lasso Regression



REGULARIZED REGRESSION

Elastic Net

REGULARIZED REGRESSION



Source: Mike Payne & Scott Crawford, 84.51°

REGULARIZED REGRESSION

Q: When do I use one versus the other?

When to use Ridge:

- You have reason to believe all coefficients should be kept in the model.
- You want correlated variables to be shrunk towards each other.
- Lower error rate than Lasso and Elastic Net

When to use Lasso:

- Perform variable selection - You have reason to believe a small subset of variables should be included in the final model
- p >> n
- Highly correlated variables that can be "arbitrarily" dropped
- Lower error rate than Ridge and Elastic Net

When to use Elastic net:

- A balance between the effects of Ridge and Lasso
- p >> n but okay with a solution p > n
- Lower error rate than Ridge and Lasso
- This is currently the most popular version of regularized regression

Source: Mike Payne & Scott Crawford, 84.51°

REGULARIZED REGRESSION

Q: When do I use one versus the other?

A: Most of the time *try them all*!

When to use Ridge:

- You have reason to believe all coefficients should be kept in the model.
- You want correlated variables to be shrunk towards each other.
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When to use Lasso:

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Source: Mike Payne & Scott Crawford, 84.51°

IMPLEMENTATION

```r
set.seed(123)

cv.lasso <- cv.glmnet(
  x = train.x,
  y = as.factor(train.y),
  alpha = 1,
  family = "binomial",
  nfolds = 10,
  type.measure = "class"
)
```

`set.seed` provides reproducibility

IMPLEMENTATION

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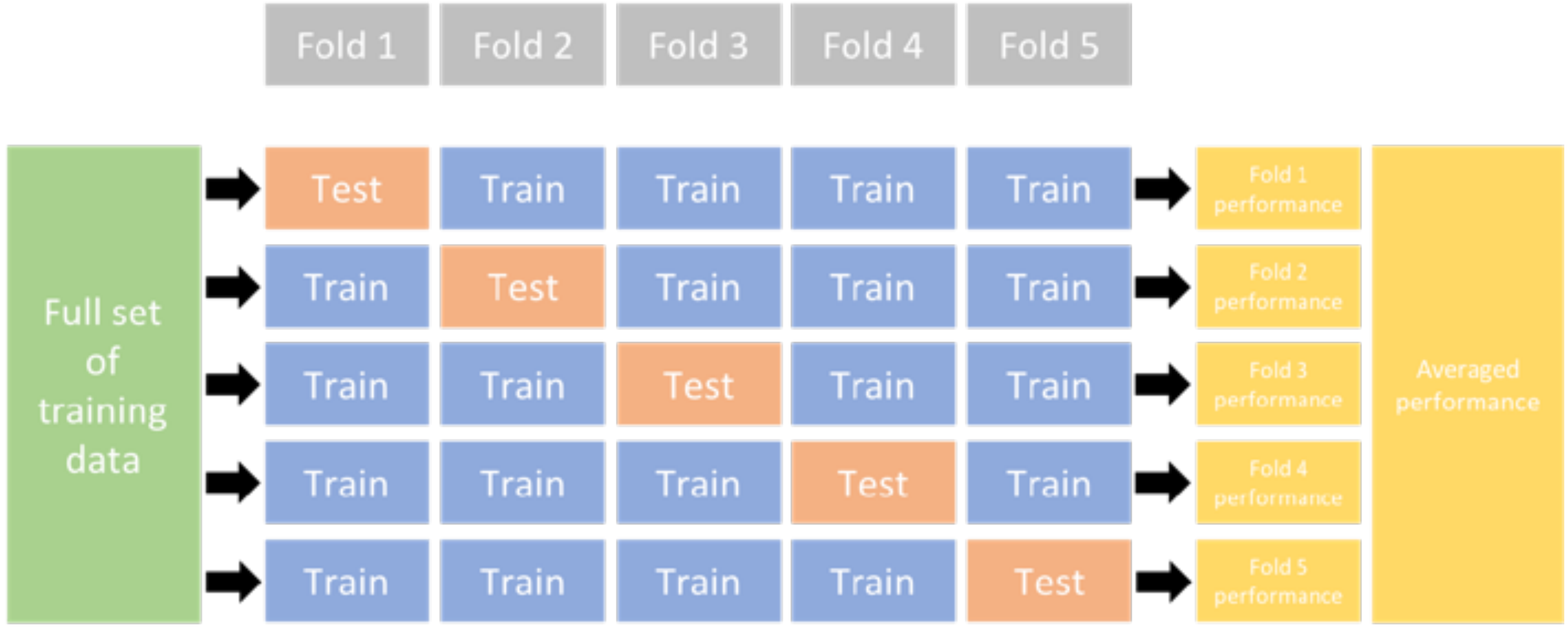
  nfolds = 10,
  type.measure = "class"
)
```

`cv.glmnet` provides built-in cross validation.

There is an equivalent `glmnet` function w/o built-in cv.

We use `nfolds` to tell the model how many cv folds to apply.



Source: Brandon Greenwell, Ascend Innovations

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)
```

`x` & `y` feed in our training and response data.

When performing classification we want our response to be encoded `as.factor`

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set.seed(123)

cv.lasso <- cv.glmnet(
  x = train.x,
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)
```

`alpha` is the parameter that tells it which of the regularization methods to use:

- `alpha = 1`: Lasso
- `alpha = 0`: Ridge
- `0 < alpha < 1`: Elastic net

IMPLEMENTATION

```
set.seed(123)

cv.lasso <- cv.glmnet(
  x = train.x,
  y = as.factor(train.y),
  alpha = 1,
  family = "binomial",
  nfolds = 10,
  type.measure = "class"
)
```

`family` describes the distribution of the y response variable.

Many to choose from but most common:

- `gaussian`: continuous
- `binomial`: binomial for two level classification

IMPLEMENTATION

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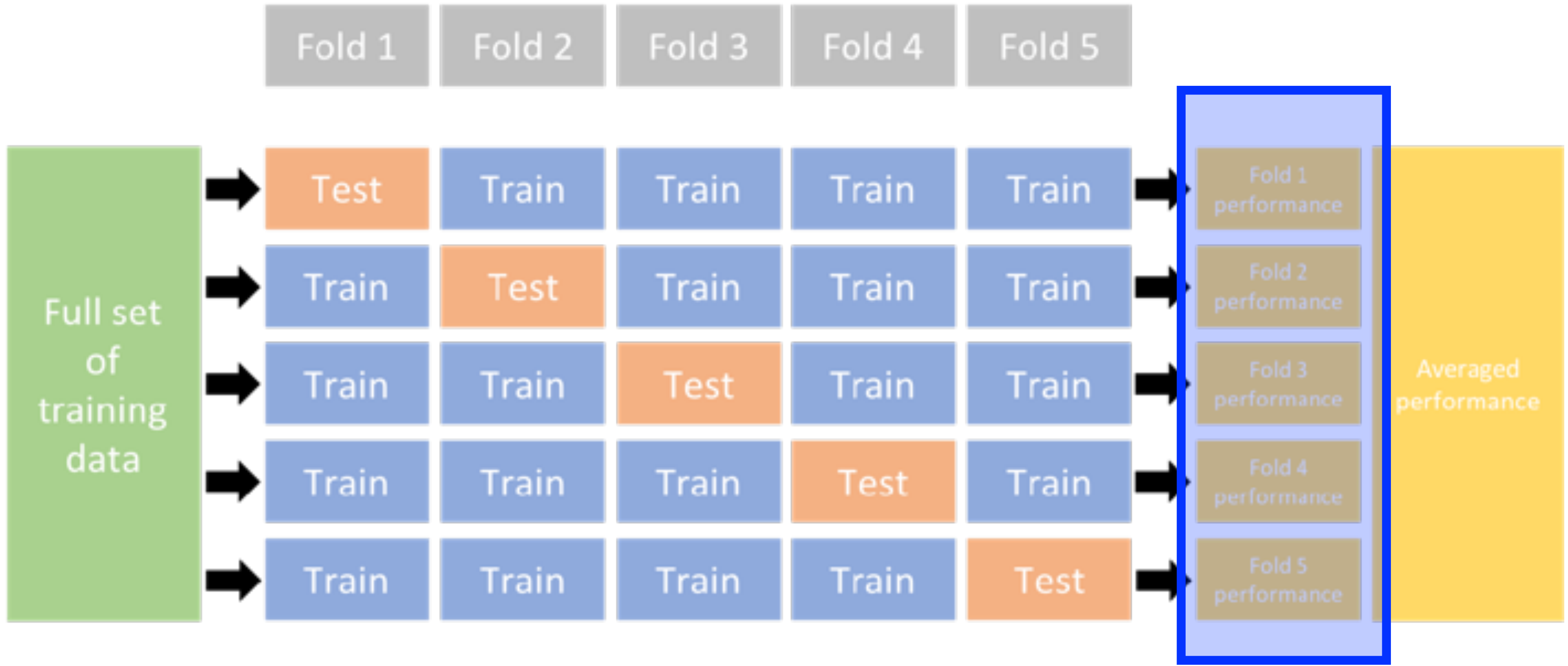
  x = train.x,
  y = as.factor(train.y),
  alpha = 1,
  family = "binomial",
  nfolds = 10,
  type.measure = "class"
)
```

`type.measure` states the performance measure used during the cv process:

- `class`: minimize misclassification rate
- `AUC`: maximize area under the curve
- `MSE`: minimize mean squared error
- `class`: minimize absolute square error



ASSESSMENT

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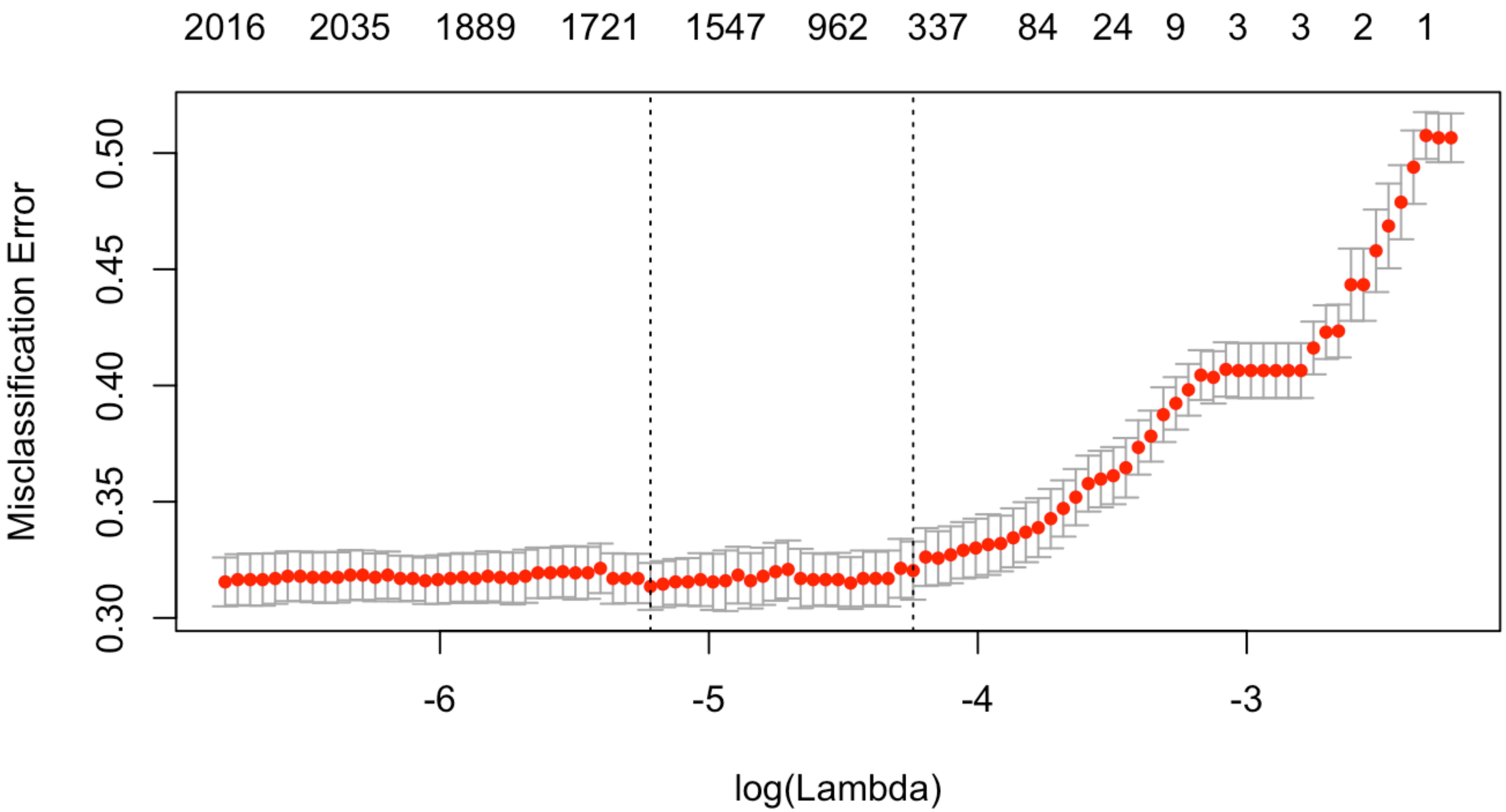
  x = train.x,
  y = as.factor(train.y),
  alpha = 1,
  family = "binomial",
  nfolds = 10,
  type.measure = "class"
)

plot(cv.lasso)
```

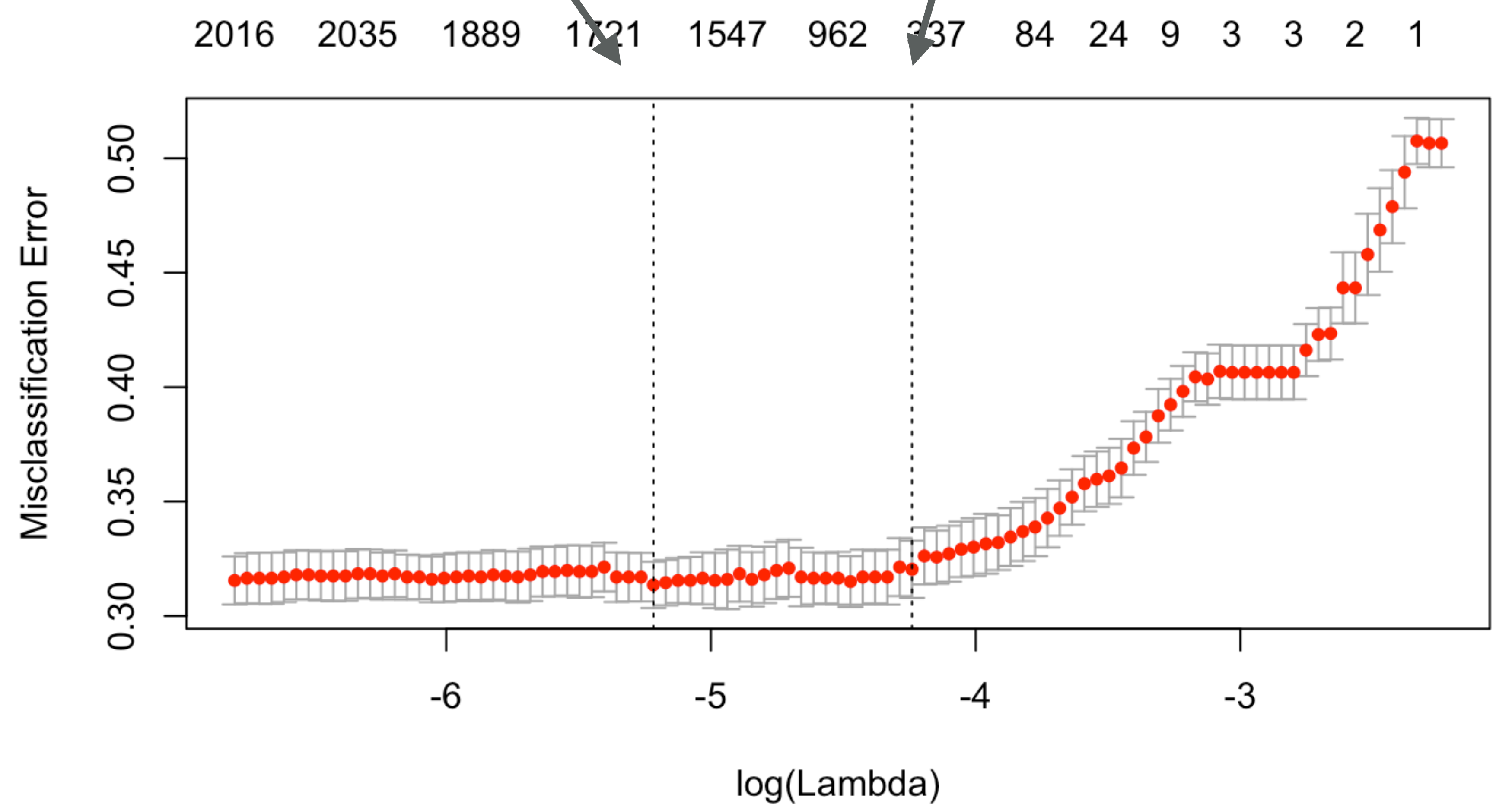


ASSESSMENT

```
# predict lasso
pred.lasso <- predict(
  cv.lasso,
  train.x,
  type = "class",
  s = cv.lasso$lambda.1se
)
```

To get predictions we feed predict:

- `cv.lass`: model
- `train.x`: new feature set
- `type`: prediction type (class or probability)
- `s`: `lambda.min` or `lambda.1se`



ASSESSMENT

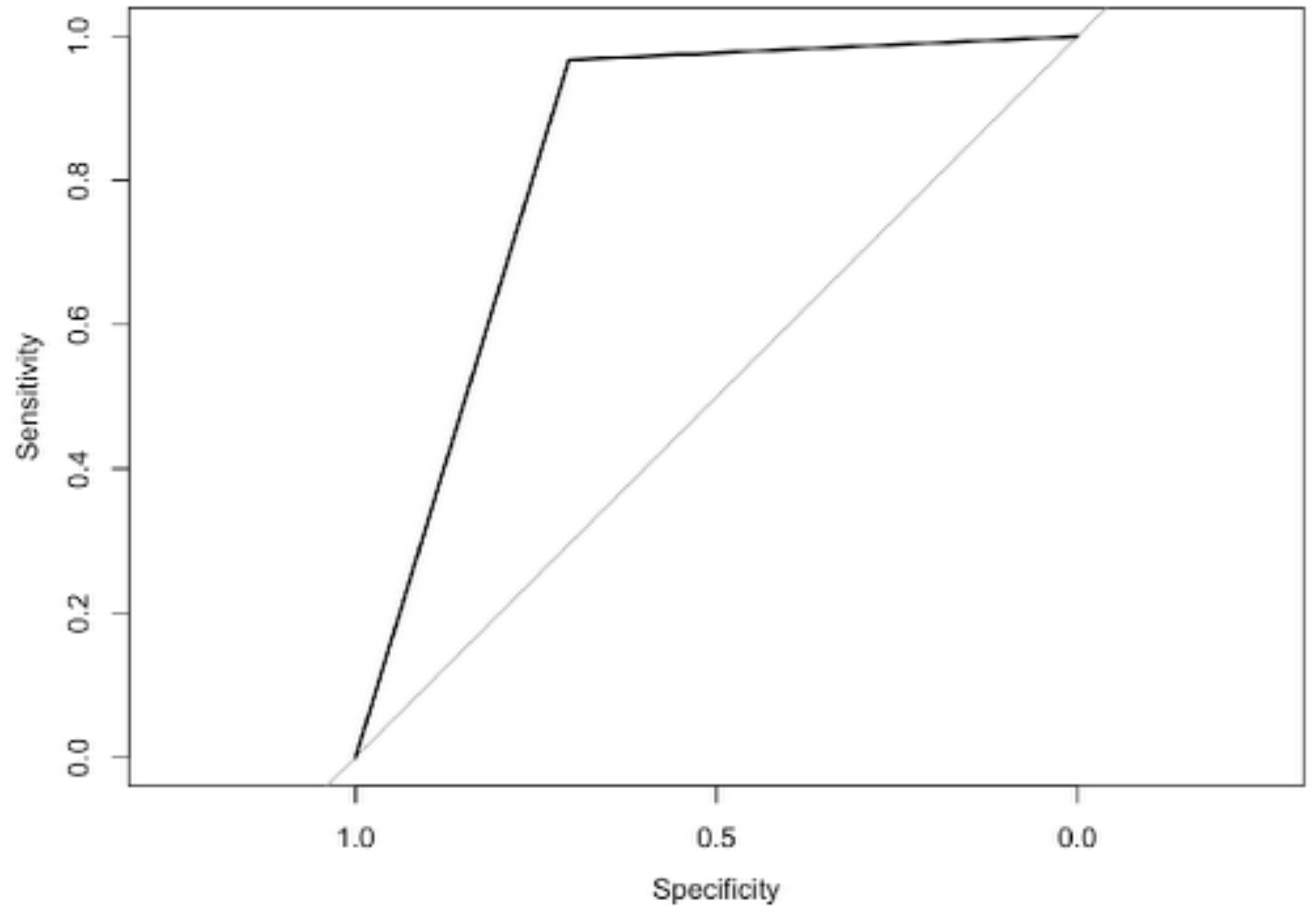
```
# predict lasso
pred.lasso <- predict(
  cv.lasso,
  train.x,
  type = "class",
  s = cv.lasso$lambda.1se
)

auc.lasso <- roc(train.y, as.numeric(pred.lasso))
auc.lasso
Area under the curve: 0.8359

plot(auc.lasso)
```

We can assess the area under the curve with `pROC::roc`

- Provides us with how well the model balances:
  - True positives
  - True negatives



ASSESSMENT

```
# confusion matrix
confusion <- table(pred.lasso, train.y)
confusion
          train.y
pred.lasso   0   1
         0 731  33
         1 307 986

# overall accuracy
sum(diag(confusion)) / sum(confusion)
[1] 0.8347107
```

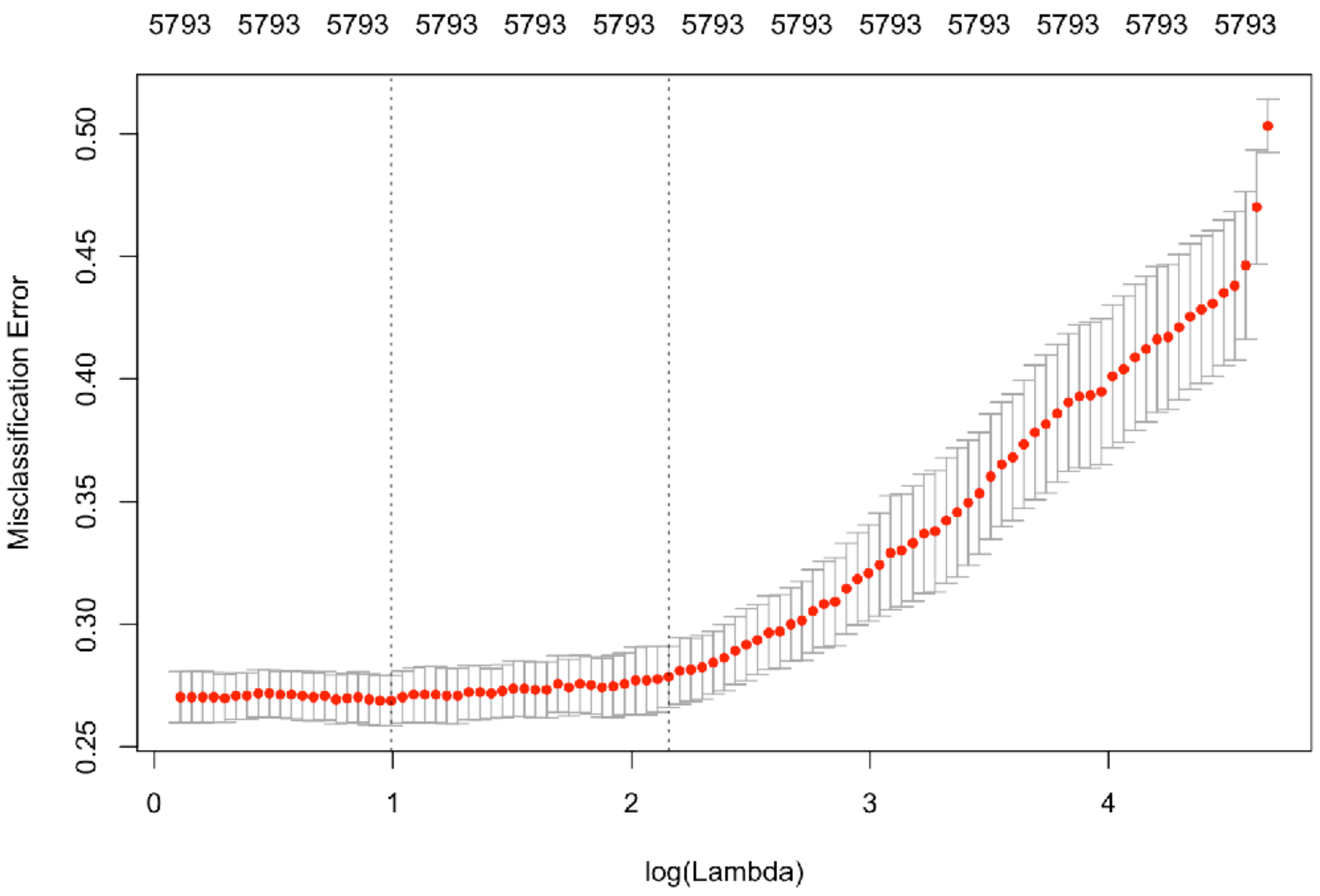
We can also the confusion matrix

YOUR TURN 1!

Apply a Ridge regression model (hint: alpha = ?) to the same training data and plot the misclassification rate. Which range of lambdas performs the best?

SOLUTION

```r
# apply Ridge model
set.seed(123)

cv.ridge <- cv.glmnet(
  x = train.x,
  y = as.factor(train.y),
  alpha = 0,
  family = "binomial",
  nfolds = 10,
  type.measure = "class"
)

# plot misclassification error
plot(cv.ridge)
```

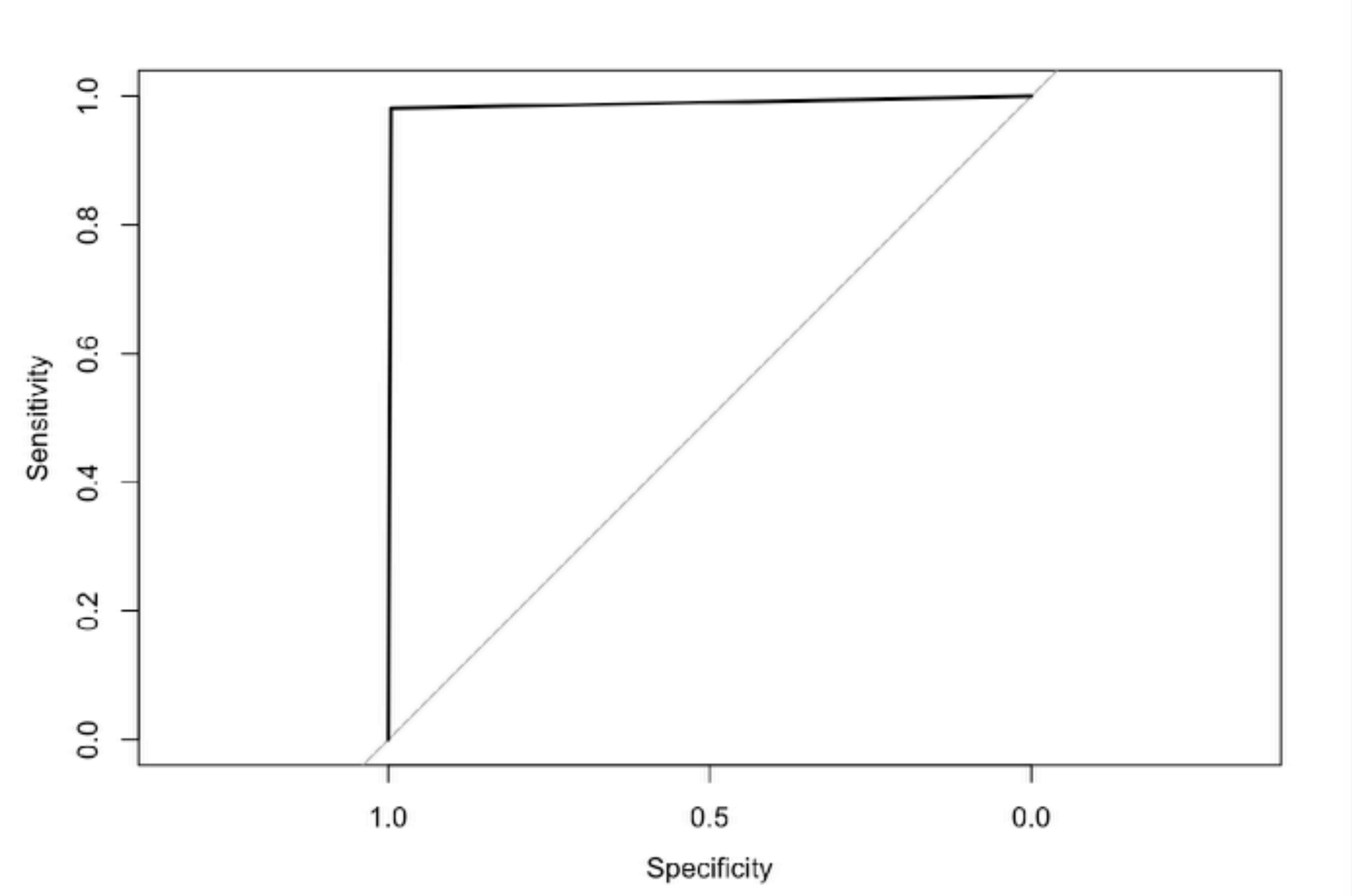


YOUR TURN 2!

Now get the predictions for the `train.x` *data using* `s = cv.ridge$lambda.1se`*. What is the area under the curve? Can you create the confusion matrix?*

SOLUTION

```
# predict ridge
pred.ridge <- predict(cv.ridge, train.x, type = "class", s = cv.ridge$lambda.1se)

# area under the curve
auc.ridge <- roc(train.y, as.numeric(pred.ridge))
auc.ridge
Data: as.numeric(pred.ridge) in 1038 controls (train.y 0) < 1019 cases (train.y 1).
Area under the curve: 0.9888

plot(auc.ridge)
```



ELASTIC NET

```
# Let's assess how an elastic net compares
```

We can apply an elastic net model by choosing `0 < alpha < 1`

But what value do we pick?

ELASTIC NET

```r
# Let's assess how an elastic net compares
tuning <- expand.grid(
  alpha    = seq(0, 1, by = .01),
  accuracy = NA
)

head(tuning)
  alpha accuracy
1  0.00       NA
2  0.01       NA
3  0.02       NA
4  0.03       NA
5  0.04       NA
6  0.05       NA
```

We can apply an elastic net model by choosing `0 < alpha < 1`

1. Let's create a tuning grid

ELASTIC NET

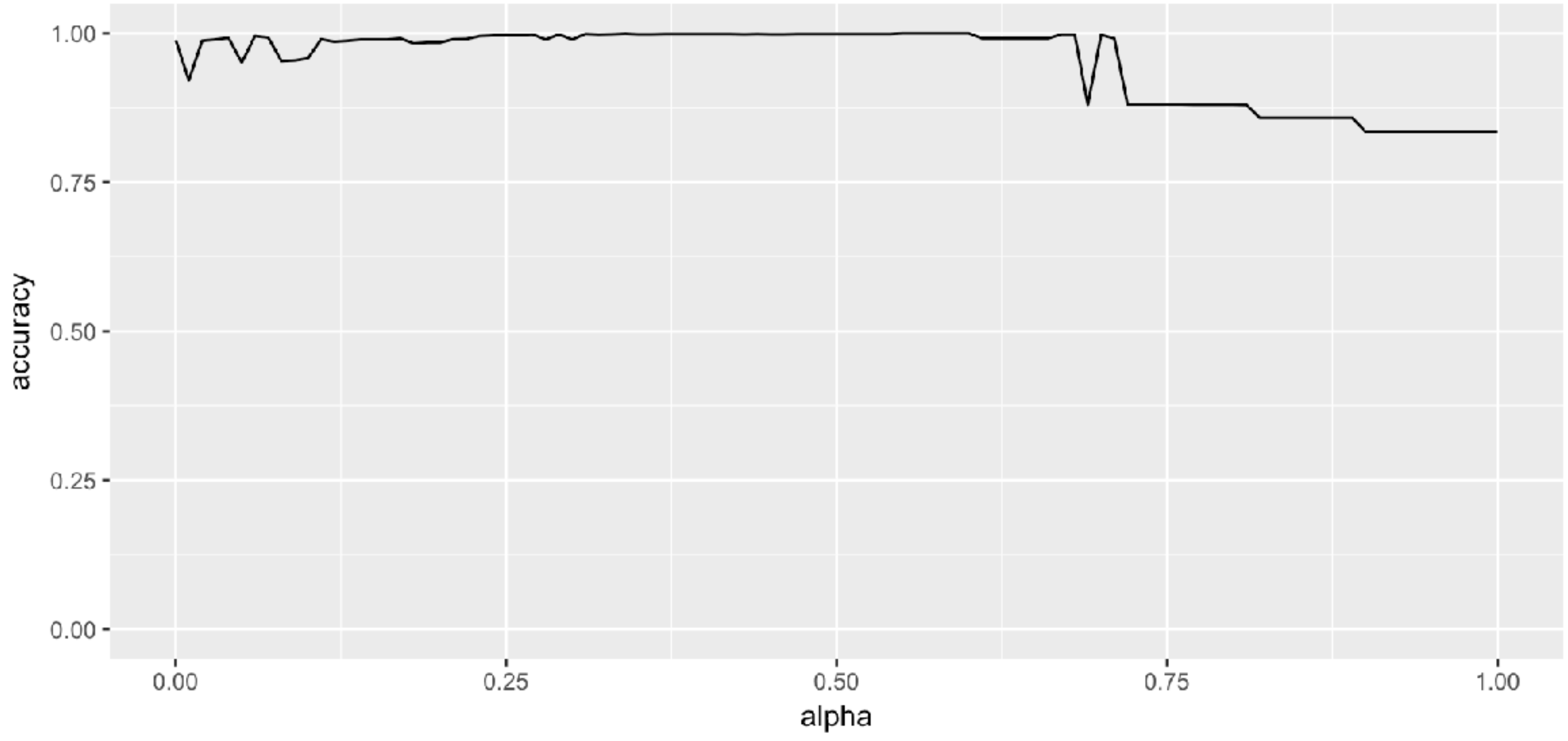
```
# Let's assess how an elastic net compares
for(i in seq_along(tuning$alpha)) {

  set.seed(123)

  cv <- cv.glmnet(
    x = train.x,
    y = as.factor(train.y),
    alpha = tuning$alpha[i],
    family = "binomial",
    nfolds = 10,
    type.measure = "class"
  )

  pred <- predict(cv, train.x, type = "class", s = cv$lambda.1se)
  confusion <- table(pred, train.y)
  tuning$accuracy[i] <- sum(diag(confusion)) / sum(confusion)
}
```

We can apply an elastic net model by choosing `0 < alpha < 1`

1. Let's create a tuning grid
2. Now we'll loop through each alpha value, apply a glmnet model, compute the accuracy and add that value into our tuning grid.

ELASTIC NET

```r
# Let's assess how an elastic net compares
ggplot(tuning, aes(alpha, accuracy)) +
  geom_line() +
  ylim(c(0, 1))
```



We can apply an elastic net model by choosing `0 < alpha < 1`

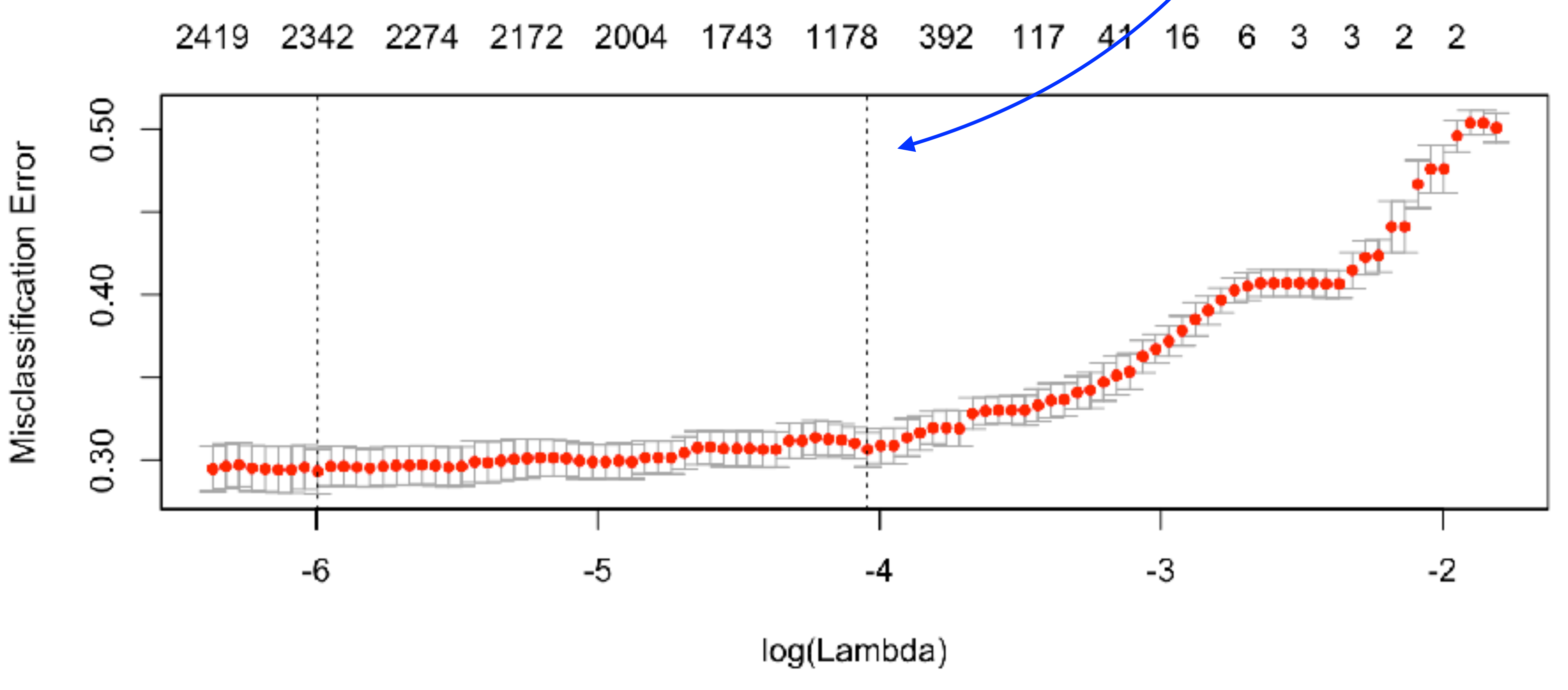
1. Let's create a tuning grid
2. Now we'll loop through each alpha value, apply a glmnet model, compute the accuracy and add that value into our tuning grid.
3. Now we can plot our results across all alpha values.

ELASTIC NET

```
# let's apply an elastic net with alpha = .65
cv <- cv.glmnet(
  x = train.x,
  y = as.factor(train.y),
  alpha = .65,
  family = "binomial",
  nfolds = 10,
  type.measure = "class"
)
```

Let's apply an elastic net with `alpha = .65`

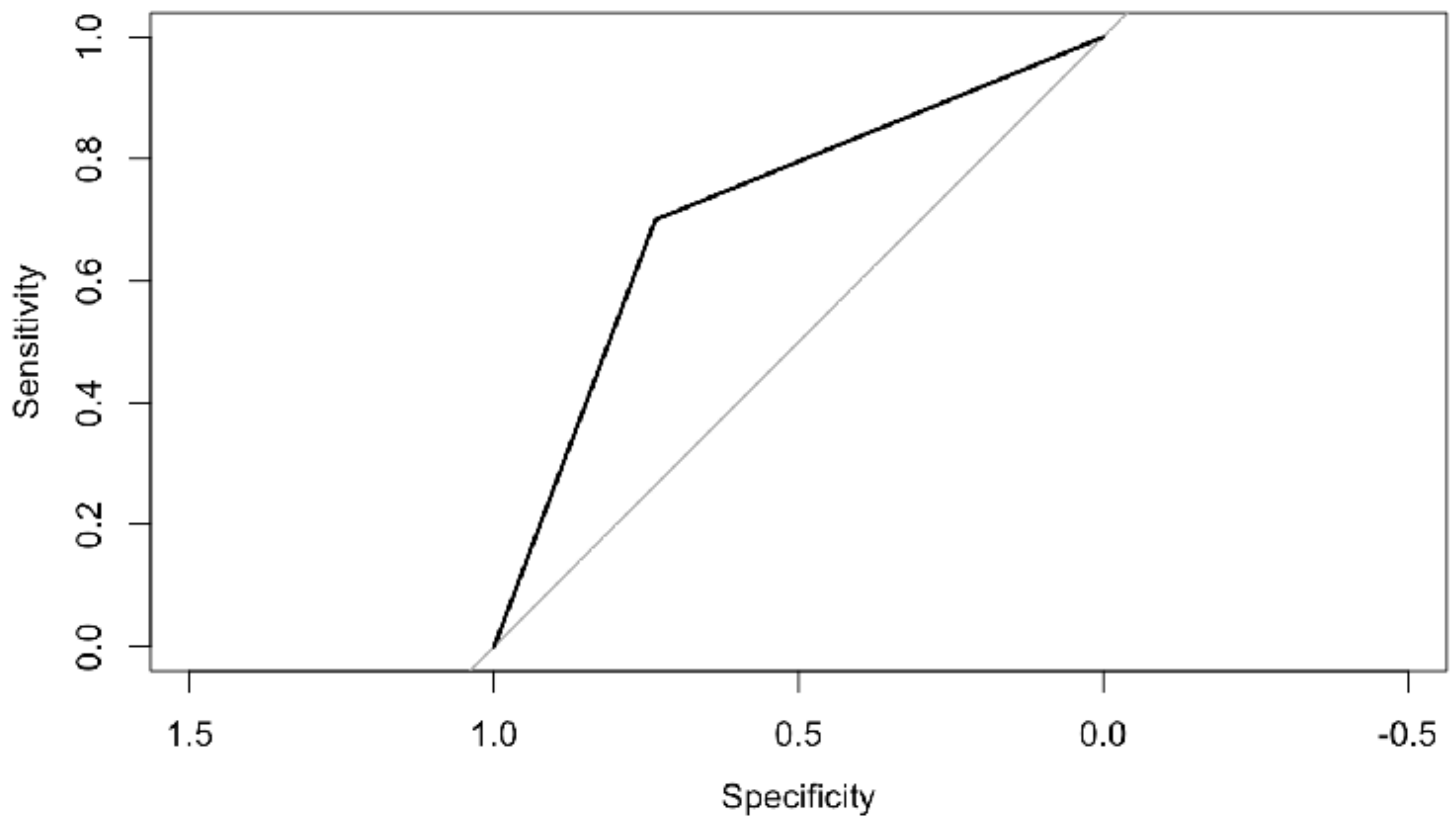
We can reduce our feature set down to about 1000 if we wanted/needed to.



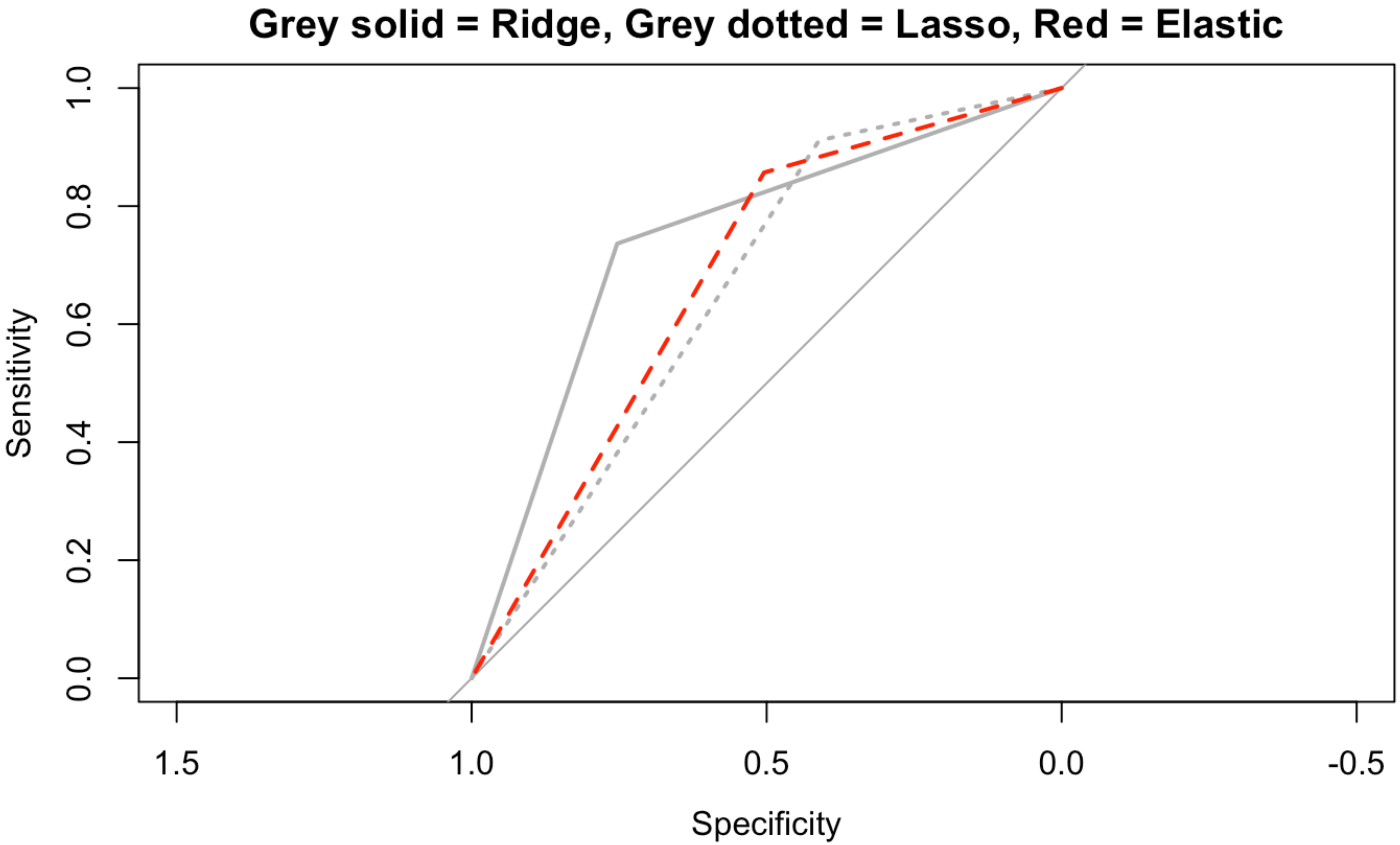
ELASTIC NET

```
# Now let's predict…but with our test set
pred.test <- predict(
  cv,
  test.x,
  type = "class",
  s = cv$lambda.min
)

auc <- roc(test.y, as.numeric(pred.test))
auc
Data: as.numeric(pred.test) in 450 controls (test.y 0) <
440 cases (test.y 1).
Area under the curve: 0.7178

plot(auc)
```

Now let's assess how well our model generalizes to an unseen data set (`test.x`)



ELASTIC NET


Grey solid = Ridge, Grey dotted = Lasso, Red = Elastic
Sensitivity
0.0
0.2
0.4
0.6
0.8
1.0
1.5
1.0
0.5
0.0
-0.5
Specificity

UNDERSTANDING THE RESULTS

So we found a decent model, now how do we understand the results?

UNDERSTANDING THE RESULTS

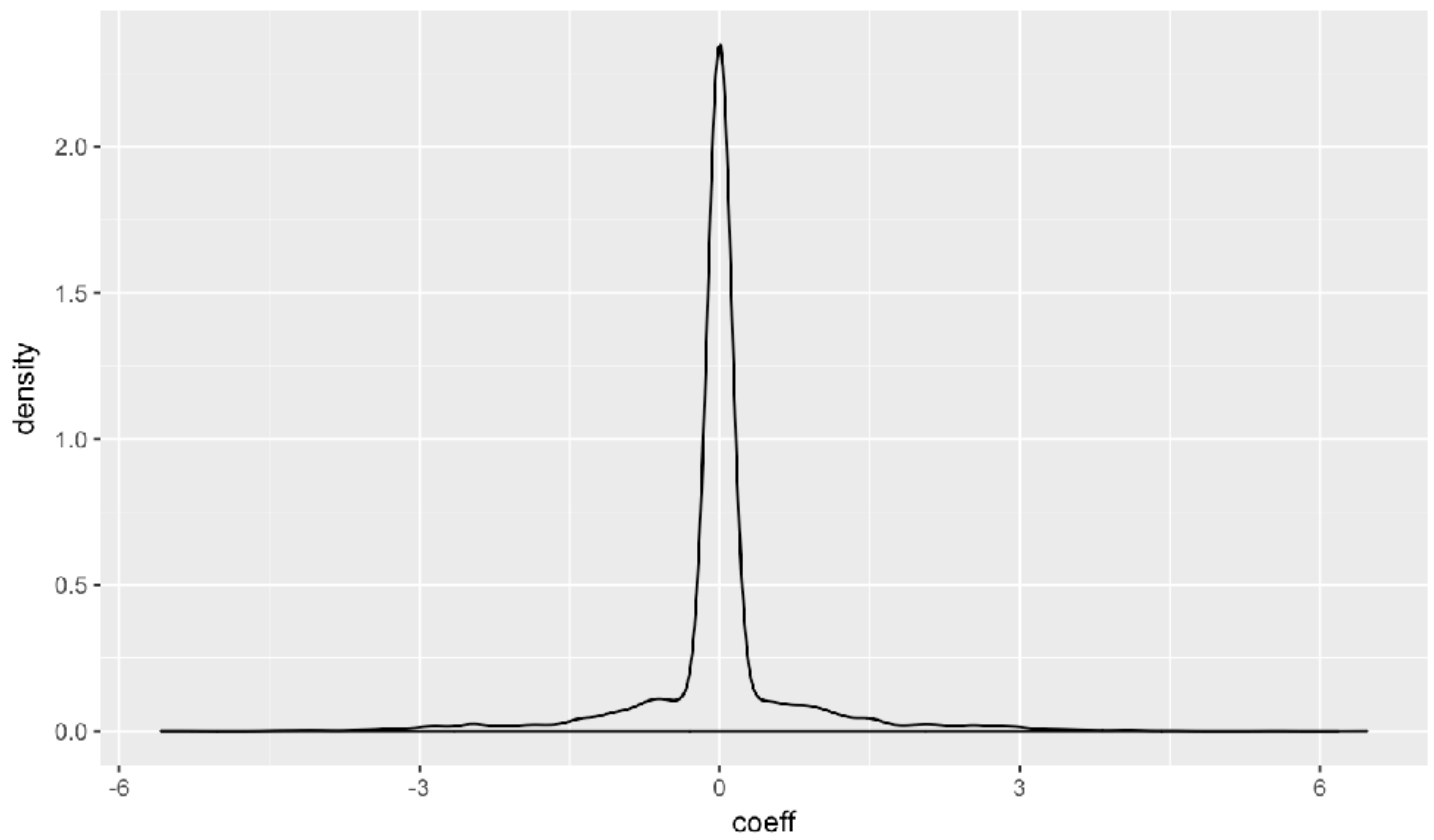
```
# finding the most impactful words
glmnet.coef <- as.matrix(coef(cv, s = "lambda.min"))
glmnet.coef <- tibble(
  words = row.names(glmnet.coef),
  coeff = glmnet.coef[, 1]
) %>%
  arrange(desc(coeff)) %>%
  mutate(words = fct_inorder(words))

glmnet.coef
# A tibble: 7,150 x 2
   words     coeff
   <fct>     <dbl>
 1 overthrow  6.47
 2 pummel     5.55
 3 u.k        4.54
 4 doug       4.54
```

We can extract each feature (word) and the coefficient

UNDERSTANDING THE RESULTS

```
# finding the most impactful words
summary(glmnet.coef$coeff)
     Min.   1st Qu.    Median      Mean   3rd Qu.      Max.
-5.581671  0.000000  0.000000  0.006956  0.000000  6.472727

ggplot(glmnet.coef, aes(coeff)) +
  geom_density()
```

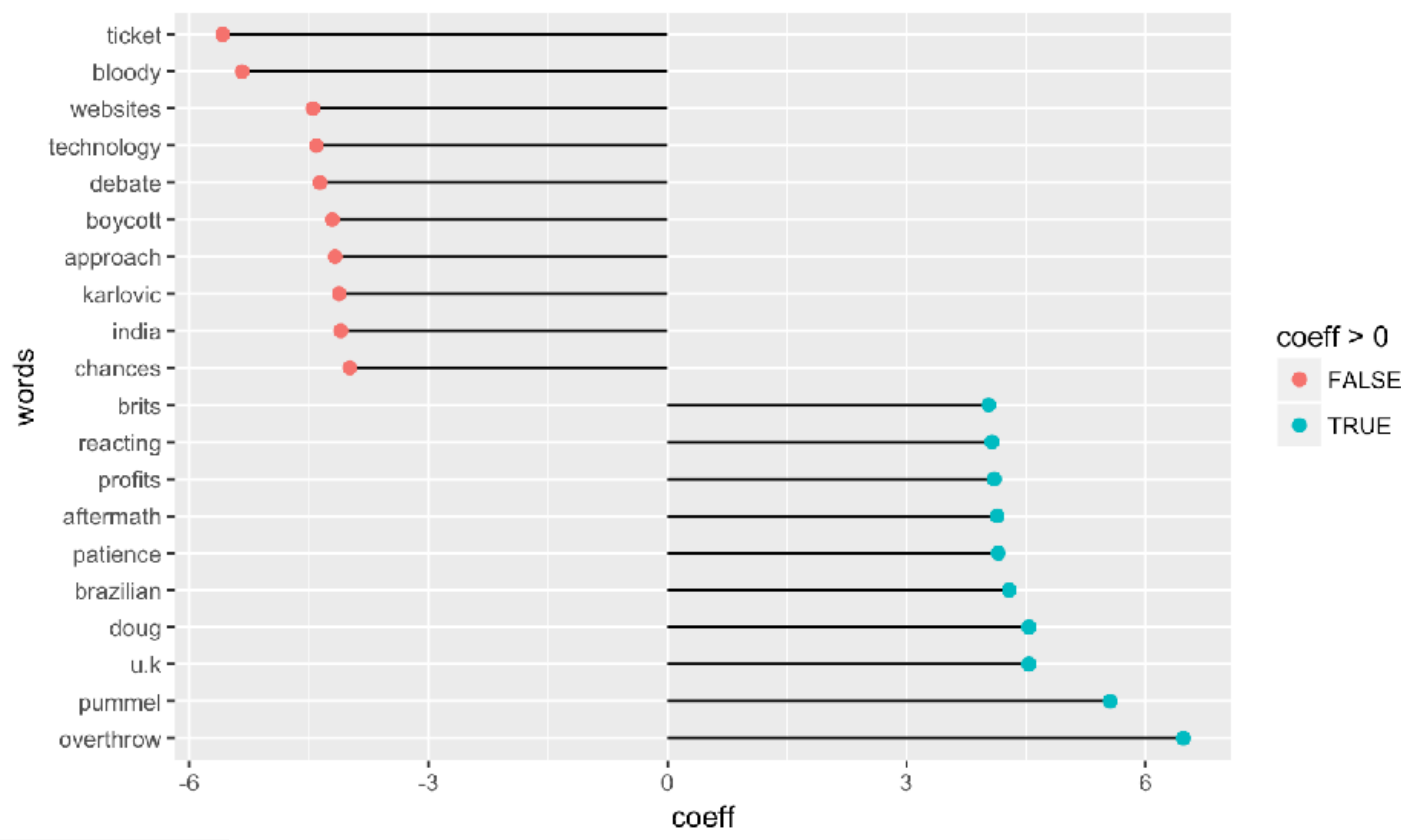
We see that many of the features have coefficients that have been shrunk to zero



UNDERSTANDING THE RESULTS

```
# top 10 positive and negative words
rbind(
  top_n(glmnet.coef, 10),
  top_n(glmnet.coef, -10)
) %>%
  ggplot(aes(x = coeff, y = words)) +
  geom_segment(aes(yend = words, xend = 0)) +
  geom_point(aes(color = coeff > 0), size = 2)
```

We can look at the top 20 influential words



UNDERSTANDING THE RESULTS

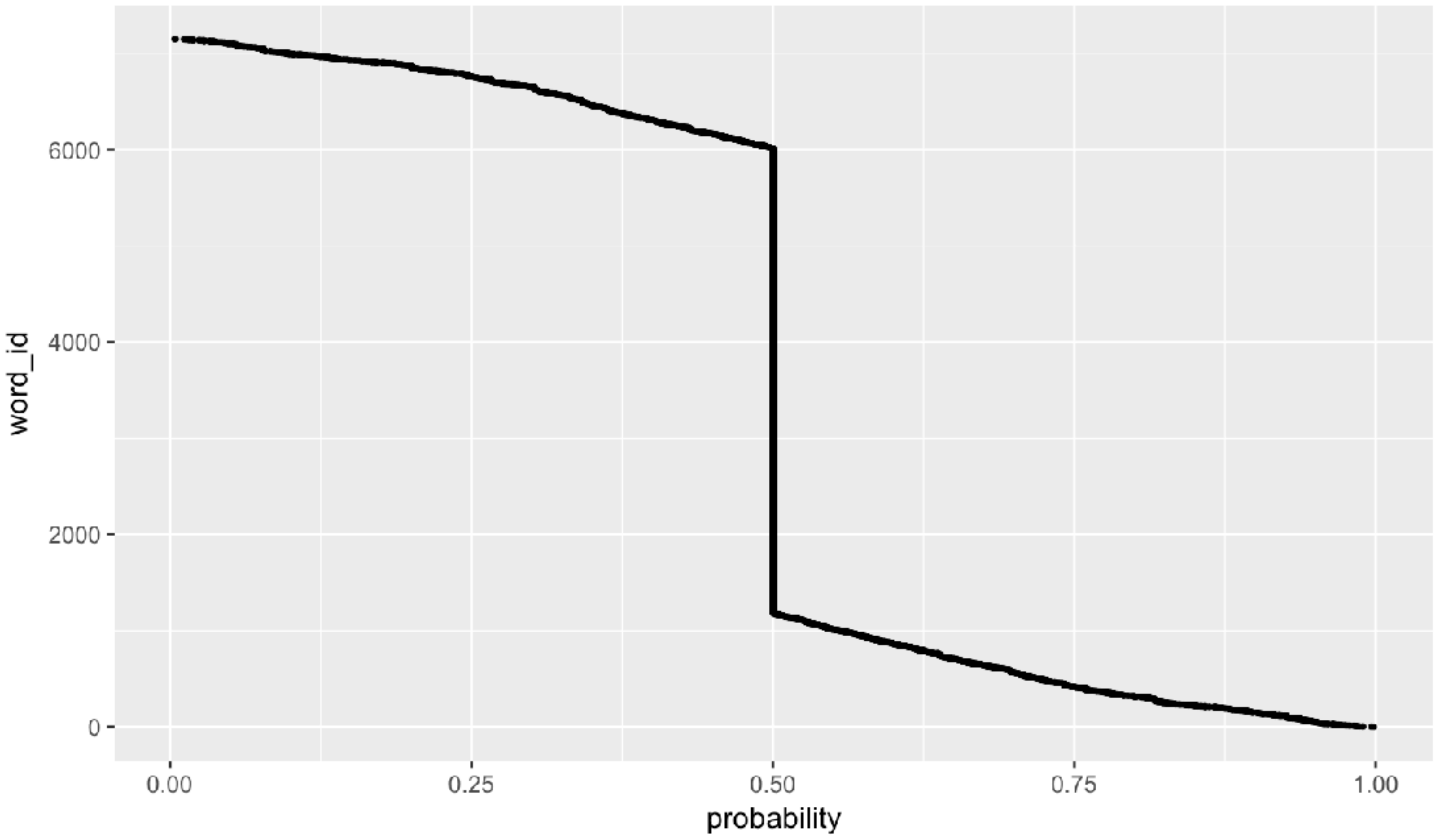
```
# convert to probabilities
glmnet_coef <- glmnet.coef %>%
  mutate(
    probability = arm::invlogit(coeff),
    word_id     = row_number(words)
    )

glmnet_coef
# A tibble: 7,150 x 4
   words     coeff probability word_id
   <fct>     <dbl>       <dbl>   <int>
 1 overthrow  6.47       0.998       1
 2 pummel     5.55       0.996       2
 3 u.k        4.54       0.989       3
 4 doug       4.54       0.989       4
 5 brazilian  4.29       0.986       5
 6 patience   4.15       0.984       6
```

Let’s compute the probabilities

UNDERSTANDING THE RESULTS

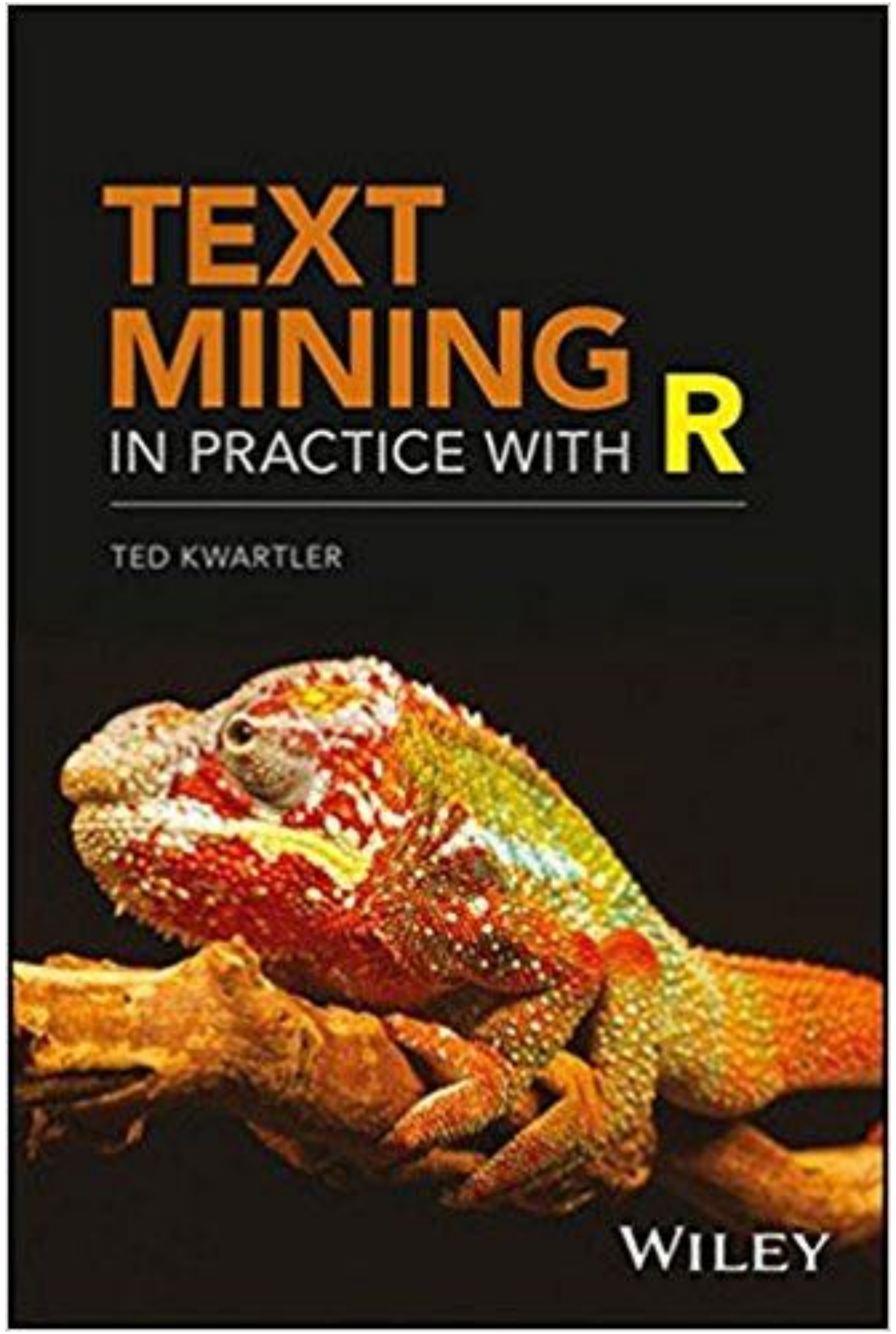
```r
# plot word probability distributions
ggplot(glmnet_coef, aes(probability, word_id)) +
  geom_point(size = .5)
```

Let's visualize the probabilities



SO LITTLE TIME!

LEARN MORE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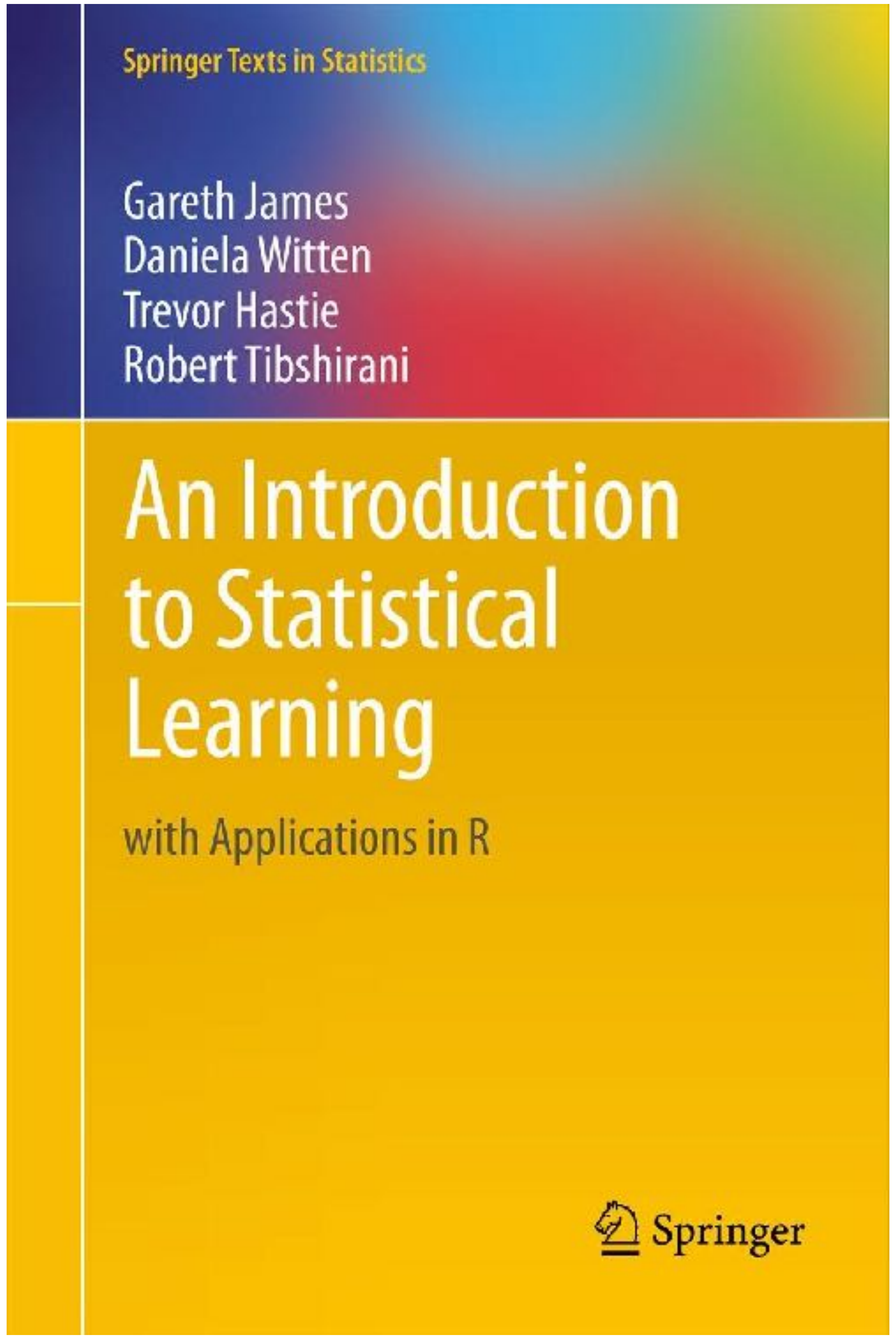
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Gareth James
Daniela Witten
Trevor Hastie
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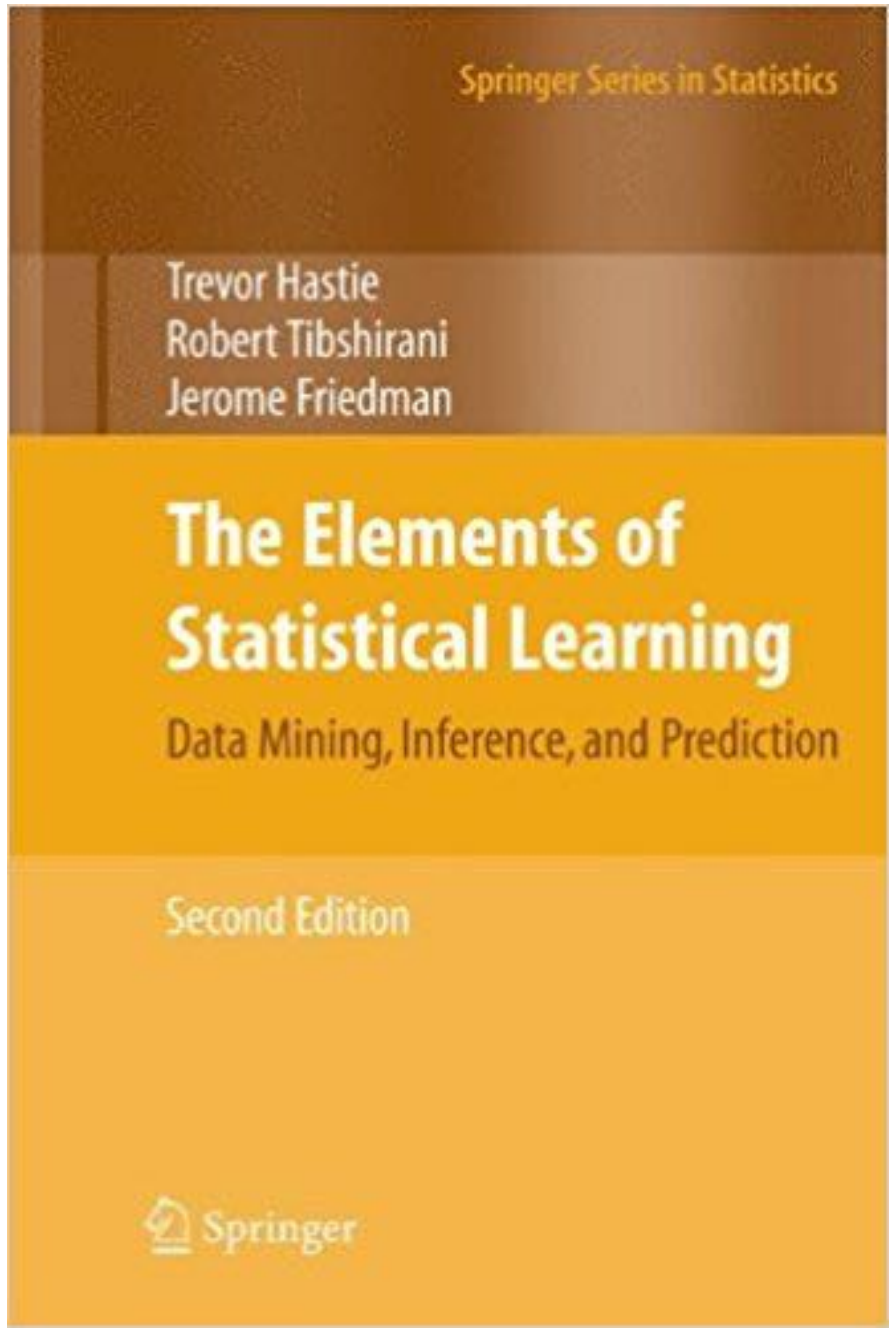
Springer Series in Statistics
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Jerome Friedman
The Elements of Statistical Learning
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WHAT TO REMEMBER

FUNCTIONS TO REMEMBER

Operator/Function	Description
`Matrix::Matrix`	Create a sparse matrix
`glmnet::cv.glment`	Compute a cross validated regularized regression model (Ridge: `alpha = 0`; Lasso: `alpha = 1`; Elastic net: `0 < alpha < 1`)
`pROC::roc`	Create a ROC curve and compute area under the curve
`predict`	Predict response values for a new feature set