Classification

Part 3

Prof. Bisbee

Vanderbilt University

Slides Updated: 2024-03-16

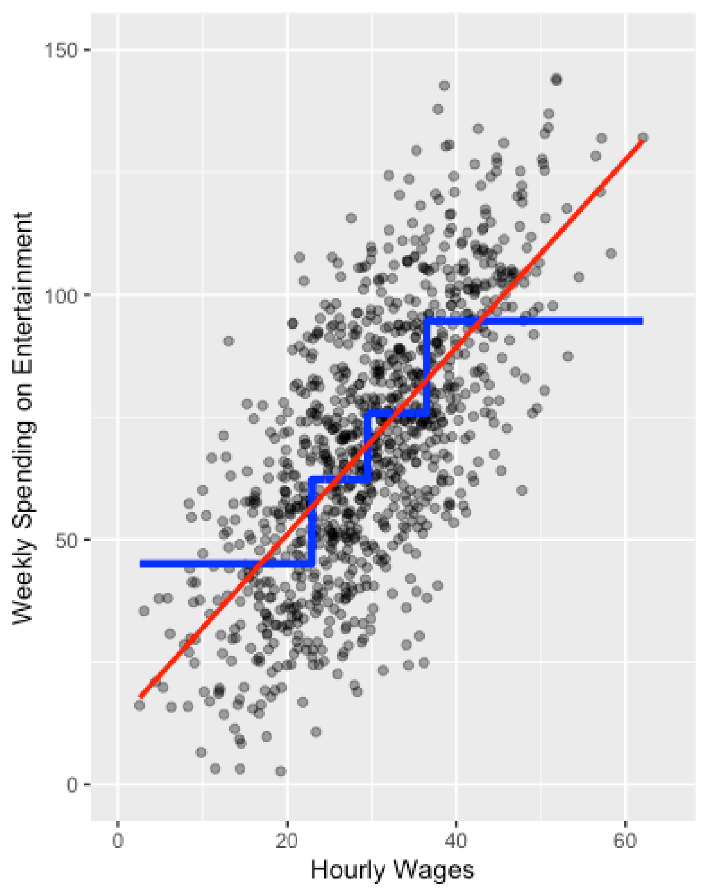
Agenda

1. Recap of regression and classification

2. Introducing (some) machine learning algorithms

What is regression?

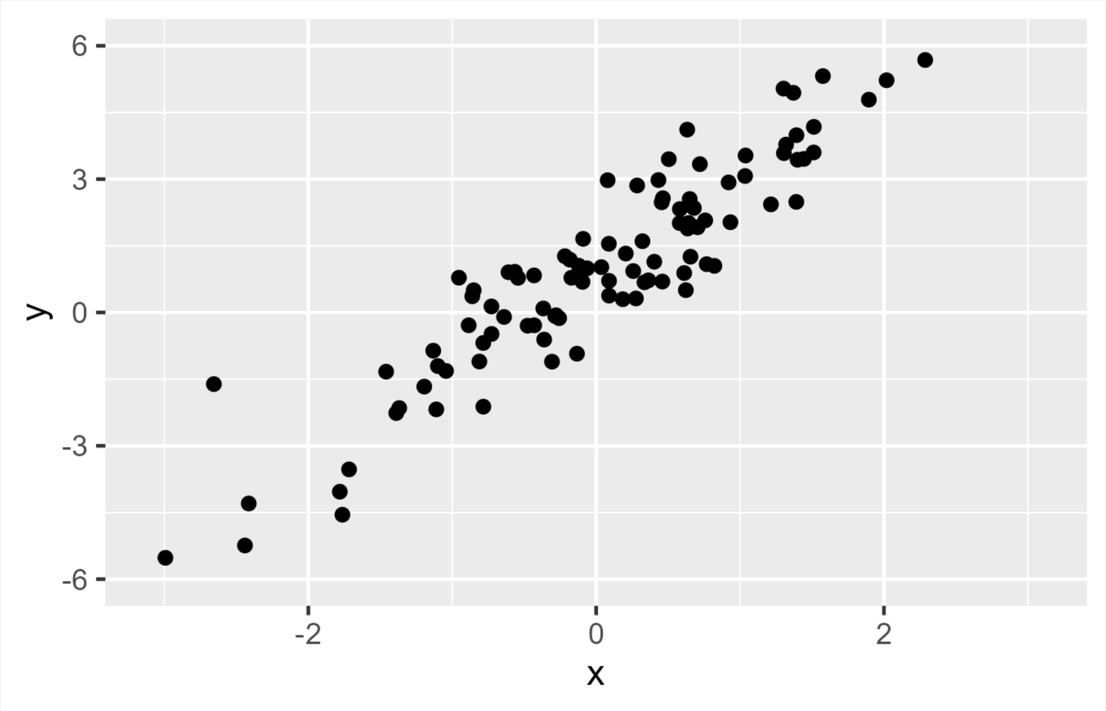
- Conditional means for continuous data



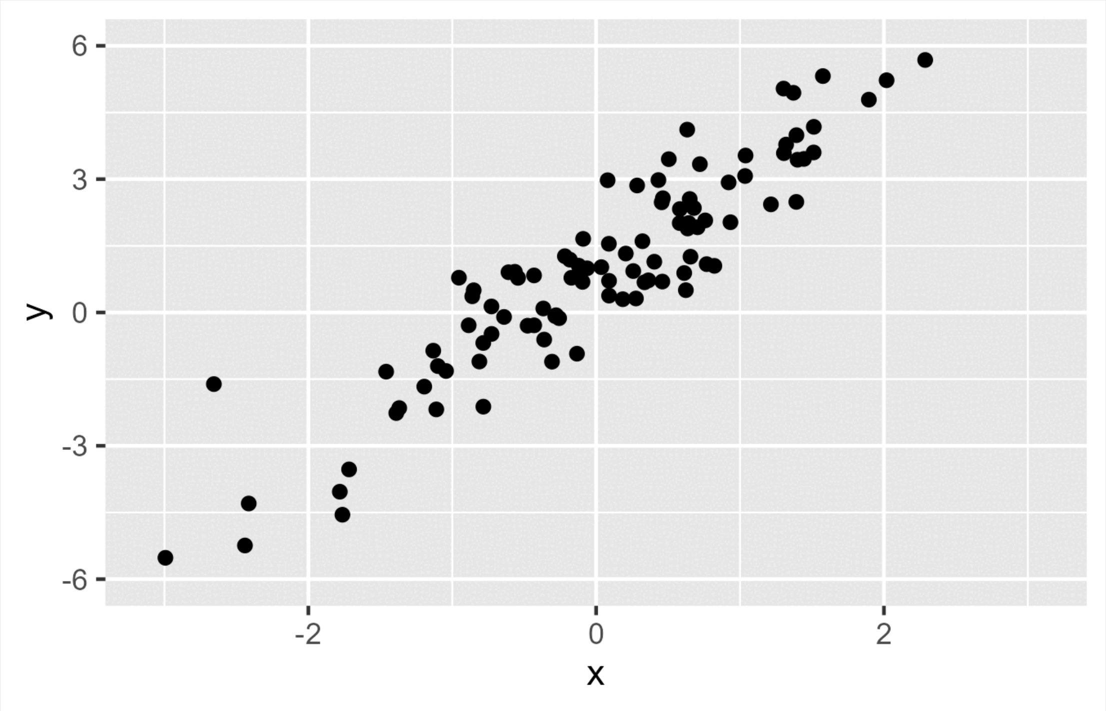
Regression

- Calculating a **line** that minimizes mistakes *for every observation*
  - NB: could be a curvey line! For now, just assume straight
- Recall from geometry how to graph a straight line
- $Y = a + bX$
  - a: the "intercept" (where the line intercepts the y-axis)
  - b: the "slope" (how much Y changes for each increase in X)
- (Data scientists use α and β instead of a and b b/c nerds)
- Regression analysis simply chooses the best line
  - "Best"?
  - The line that minimizes the mistakes (the **line of best fit**)

Visual Intuition



Visual Intuition

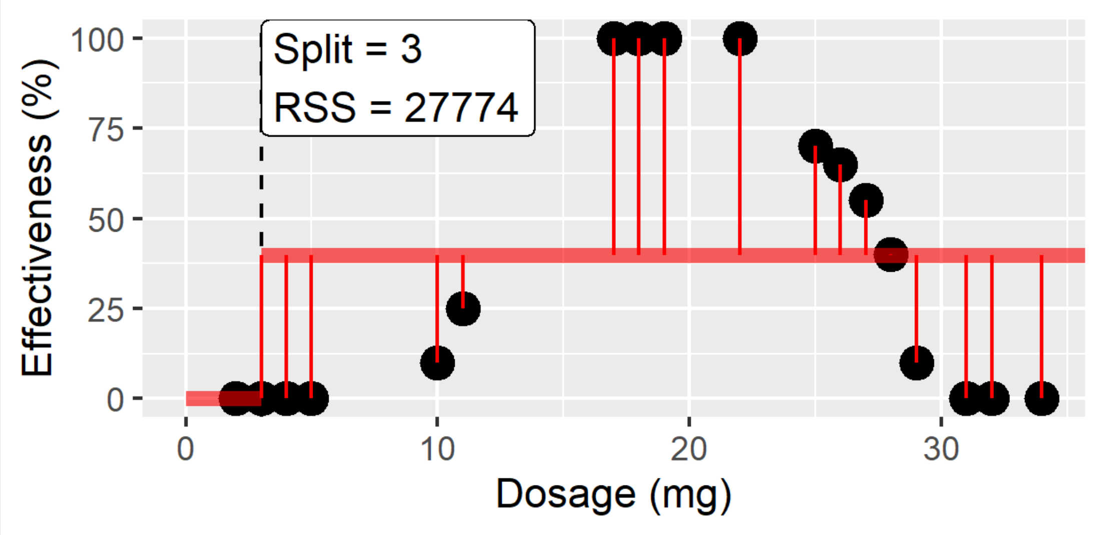


Two Camps Revisited

- Regression is great for **theory testing**
  - Results tell us something **meaningful** about our theory
- But if all we care about is **prediction**...?
  - Want to test every possible predictor (and combinations)
  - Don't care about **relationships**
  - Just care about **accuracy**
- Algorithms can save us time!
  - Random Forests
  - LASSO

Random Forests

- Identify the best "partition" (split) that divides the data



- In `R`: `ranger`
  - `formula = Y ~ .`

Random Forests

```r
require(tidyverse)
require(scales)
require(tidymodels)
fn <-
read_rds('C:/Users/bisbeejh/Dropbox/2024_spring/DS1000_S2024/data/fn_cl
```

Research Question

- What predicts whether you win at Fortnite?

```
form.perf <- 'won ~ hits + assists + accuracy + head_shots +
damage_to_players'

form.games <- 'won ~ eliminations + revives + distance_traveled +
materials_gathered'

form.context <- 'won ~ mental_state + startTime + gameIdSession'

form.full <- 'won ~ hits + assists + accuracy + head_shots +
damage_to_players + eliminations + revives + distance_traveled +
materials_gathered + mental_state + startTime + gameIdSession'
```

Comparing models

```
m.perf <- lm(as.formula(form.perf),fn)
summary(m.perf)
```

```
## 
## Call:
## lm(formula = as.formula(form.perf), data = fn)
## 
## Residuals:
##     Min      1Q  Median      3Q     Max 
## -0.7905 -0.2756 -0.1563  0.3429  1.0078 
## 
## Coefficients:
##                     Estimate Std. Error t value Pr(>|t|)
## (Intercept)        8.788e-02  3.768e-02   2.332 0.019893
## hits               6.962e-04  1.001e-03   0.695 0.487053
## assists            3.445e-02  1.020e-02   3.377 0.000764
## accuracy          -4.164e-01  1.081e-01  -3.850 0.000126
## head_shots        -4.808e-03  3.149e-03  -1.527 0.127057
## damage_to_players  4.728e-04  5.713e-05   8.275 4.31e-16
## 
## (Intercept)       *  
## hits
```

Comparing models

```
m.games <- lm(as.formula(form.games),fn)
summary(m.games)
```

```
##
## Call:
## lm(formula = as.formula(form.games), data = fn)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -1.0107 -0.2320 -0.1275  0.2028  0.9583
##
## Coefficients:
##                      Estimate Std. Error t value Pr(>|t|)
## (Intercept)         4.171e-02  2.210e-02   1.888 0.059397
## eliminations        1.151e-02  9.765e-03   1.178 0.238921
## revives             6.993e-02  1.809e-02   3.865 0.000119
## distance_traveled   1.805e-04  1.755e-05  10.287  < 2e-16
## materials_gathered -2.550e-06  3.515e-05  -0.073 0.942186
##
## (Intercept)        .
## eliminations
## revives            ***
```

Comparing models

```
m.context <- lm(as.formula(form.context),fn)
summary(m.context)
```

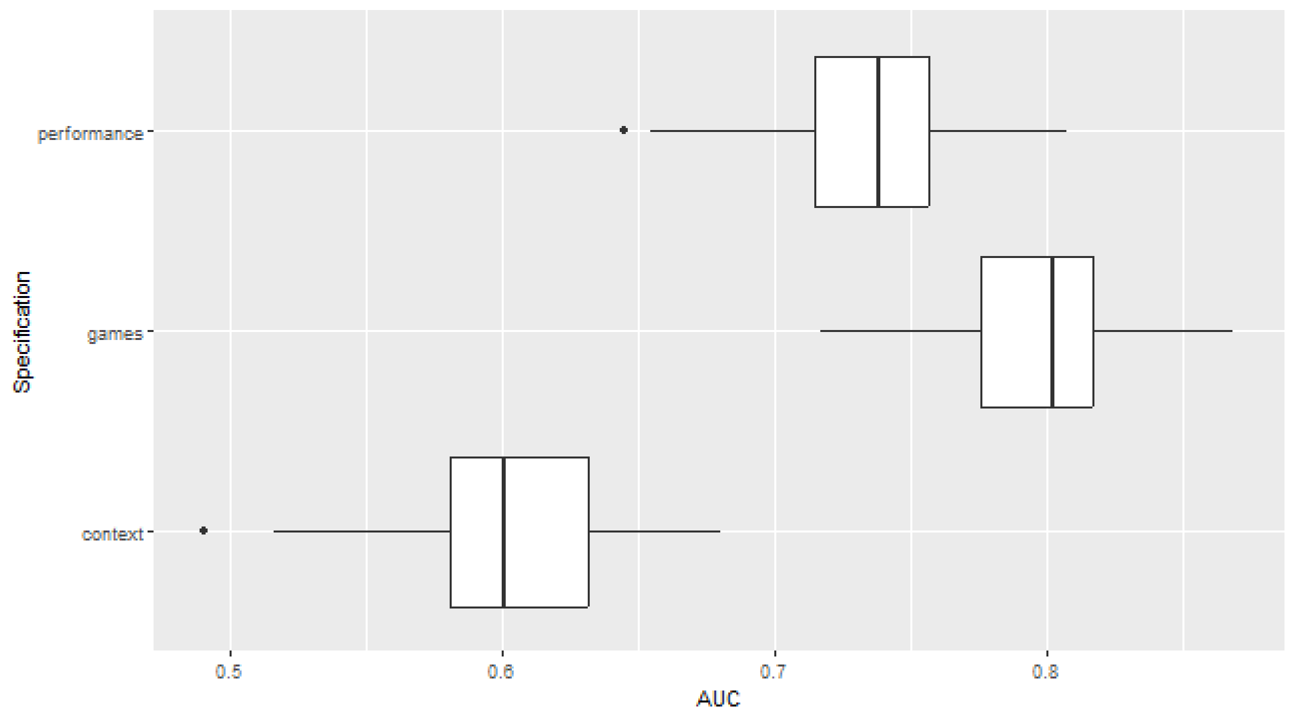
```
##
## Call:
## lm(formula = as.formula(form.context), data = fn)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -0.4698 -0.3258 -0.2340  0.5857  0.8553
##
## Coefficients:
##                      Estimate Std. Error t value Pr(>|t|)
## (Intercept)         9.027e+01  2.987e+01   3.022  0.00258
## mental_statesober   1.368e-01  2.933e-02   4.663 3.56e-06
## startTime          -5.672e-08  1.881e-08  -3.015  0.00264
## gameIdSession       1.460e-03  1.463e-03   0.998  0.31863
##
## (Intercept)        **
## mental_statesober ***
## startTime          **
## gameIdSession
```

Evaluate Model Fit

```r
cvRes <- NULL
for(i in 1:100) {
  inds <- sample(1:nrow(fn),size = round(nrow(fn)*.8),replace = F)
  train <- fn %>% slice(inds)
  test <- fn %>% slice(-inds)

  # Train
  mTmp.perf <- lm(as.formula(form.perf),train)
  mTmp.games <- lm(as.formula(form.games),train)
  mTmp.context <- lm(as.formula(form.context),train)

  # Test
  toEval <- test %>%
    mutate(prob.p = predict(mTmp.perf,newdata = test),
           prob.g = predict(mTmp.games,newdata = test),
           prob.c = predict(mTmp.context,newdata = test),
           truth = factor(won,levels = c('1','0')))

  auc.p <- roc_auc(toEval,truth,prob.p) %>%
    mutate(model = 'performance')

  auc.g <- roc_auc(toEval,truth,prob.g) %>%
    mutate(model = 'games')
```

Evaluate Model Fit

```
cvRes %>%
  ggplot(aes(x = .estimate,y = model)) +
  geom_boxplot() + labs(x = 'AUC',y = 'Specification')
```



Random Forests

```
require(ranger) # Fast random forests package
```

```
## Warning: package 'ranger' was built under R version 4.3.3
```

```
rf.f <- ranger(formula = as.formula(form.full),data = fn)

toEval <- fn %>%
  mutate(prob_won = rf.f$predictions) %>%
  mutate(truth = factor(won,levels = c('1','0')))

roc_auc(toEval,truth,prob_won)
```

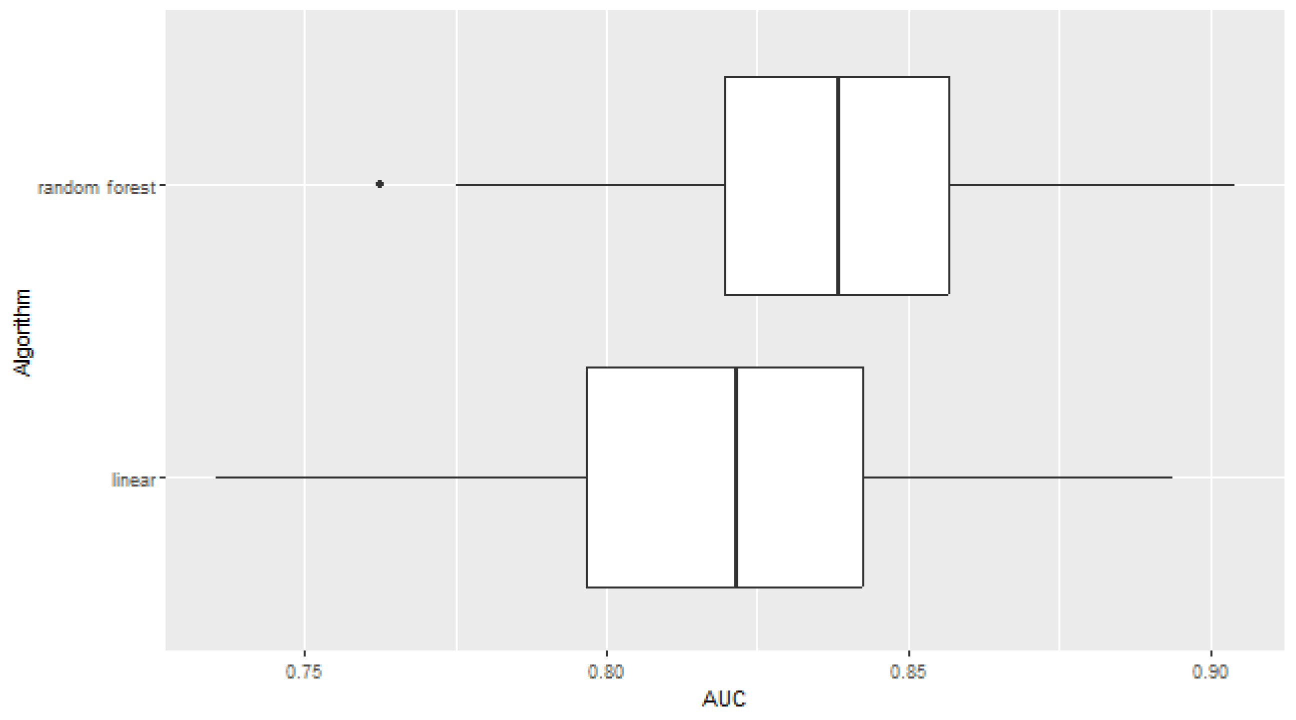
```
## # A tibble: 1 × 3
##   .metric .estimator .estimate
##   <chr>   <chr>          <dbl>
## 1 roc_auc binary         0.838
```

Random Forest Comparison

```
cvRes <- NULL
for(i in 1:100) {
  inds <- sample(1:nrow(fn),size = round(nrow(fn)*.8),replace = F)
  train <- fn %>% slice(inds)
  test <- fn %>% slice(-inds)

  # Train
  mLM.f <- lm(as.formula(form.full),train)
  mRF.f <- ranger(as.formula(form.full),train)

  # Test
  # NEED TO RUN PREDICTION ON RF FIRST
  tmpPred <- predict(mRF.f,test)

  toEval <- test %>%
    mutate(prob.lm = predict(mLM.f,newdata = test),
           prob.rf = tmpPred$predictions,
           truth = factor(won,levels = c('1','0')))

  auc.lm <- roc_auc(toEval,truth,prob.lm) %>%
    mutate(model = 'linear')

  auc.rf <- roc_auc(toEval,truth,prob.rf) %>%
```

Random Forest Comparison

```
cvRes %>%
  ggplot(aes(x = .estimate,y = model)) +
  geom_boxplot() + labs(x = 'AUC',y = 'Algorithm')
```



What matters most?

- Random Forests are particularly suitable for investigating **variable importance**
  - I.e., which X predictors are most helpful?
- A few options, but we rely on **permutation tests**
  - Idea: run the best model you have, then re-run it after "permuting" one of the variables
  - "Permute" means randomly reshuffle...breaks relationship
  - How much **worse** is the model when you break a variable?

Variable Importance

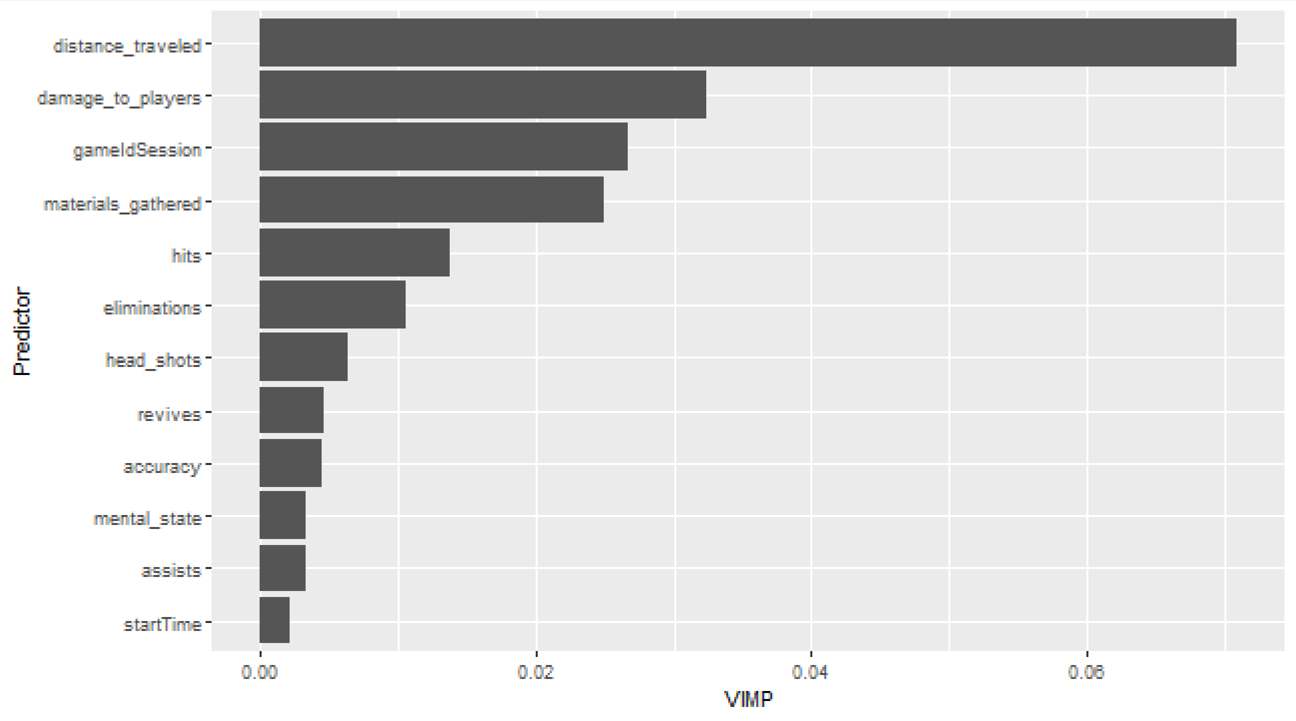
- In `ranger()`, use `importance = "permutation"`

```
rf.full <- ranger(formula = as.formula(form.full),data = fn %>%
                    mutate(mental_state = ifelse(mental_state ==
'sober',1,0)),importance = 'permutation')

rf.full$variable.importance
```

```
##               hits            assists           accuracy
##        0.013744542        0.003357181        0.004465332
##         head_shots  damage_to_players       eliminations
##        0.006363476        0.032384850        0.010595106
##            revives  distance_traveled materials_gathered
##        0.004715412        0.070833478        0.025052451
##       mental_state          startTime      gameIdSession
##        0.003392765        0.002135140        0.026763760
```

Variable Importance

```
toplot <- data.frame(vimp = rf.full$variable.importance,
                     vars = names(rf.full$variable.importance))

toplot %>%
  ggplot(aes(x = vimp,y = reorder(vars,vimp))) +
  geom_bar(stat = 'identity') + labs(x = 'VIMP',y = 'Predictor')
```



LASSO

- "Least Absolute Shrinkage and Selection Operator"
- Concept: Make it hard for predictors to matter
  - Practice: λ penalizes how many variables you can include
  - $\sum_{i=1}^{n}(y_i - \sum_j x_{ij}\beta_j)^2 + \lambda \sum_{j=1}^{p} |\beta_j|$
  - Minimize the errors, but penalize for each additional predictor
  - You *could* kitchen-sink a regression and get super low errors
  - LASSO penalizes you from throwing everything into the kitchen sink
- In `R`, need to install a new package! `install.packages('glmnet')`

```r
require(glmnet)
```

```
## Warning: package 'glmnet' was built under R version 4.3.2
```

LASSO

- Function doesn't use formulas
- Give it the raw data instead, divided into Y (outcome) and X (predictors)

```
rhsVars <- str_split(gsub('won ~ ','',form.full),' \\+ ')[[1]]
fn <- fn %>%
  drop_na(all_of(rhsVars))
Y <- fn$won
X <- fn %>% select(all_of(rhsVars)) %>%
  mutate(mental_state = ifelse(mental_state == 'sober',1,0),
         startTime = as.numeric(startTime))
```

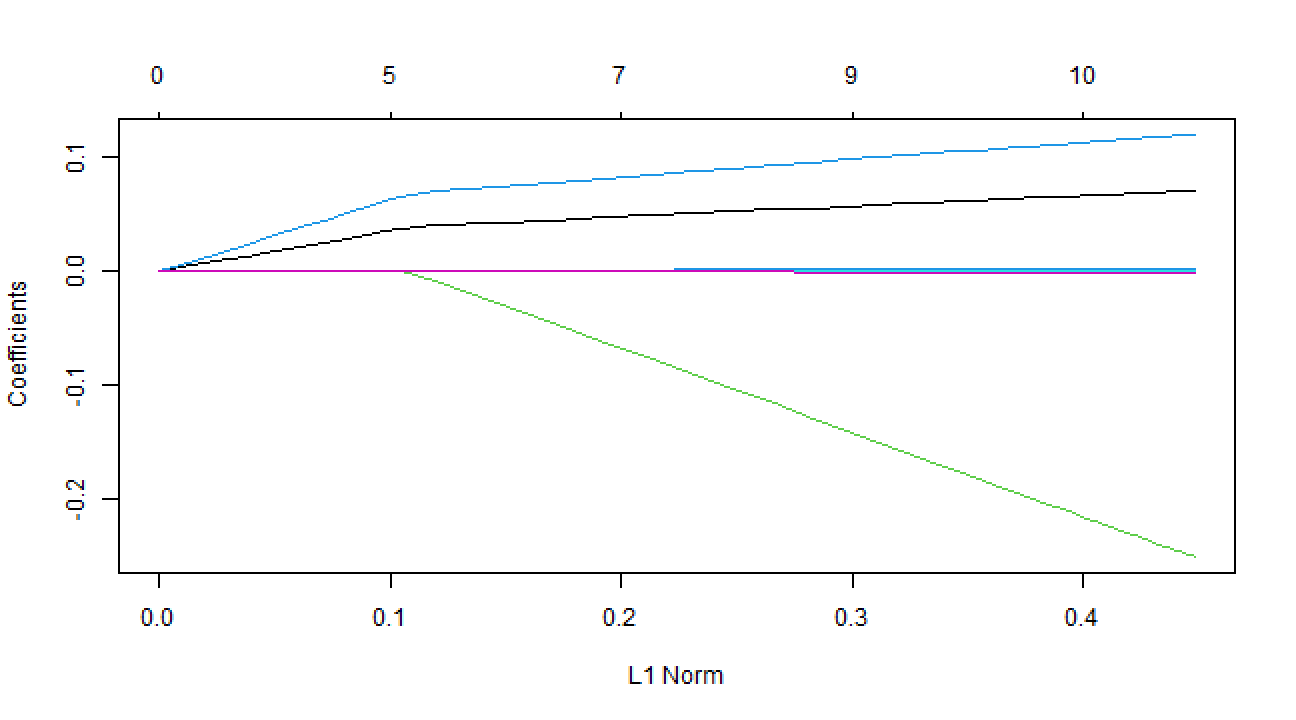
LASSO

- Now estimate!

```
lassFit <- glmnet(x = as.matrix(X),
                  y = as.matrix(Y))
```

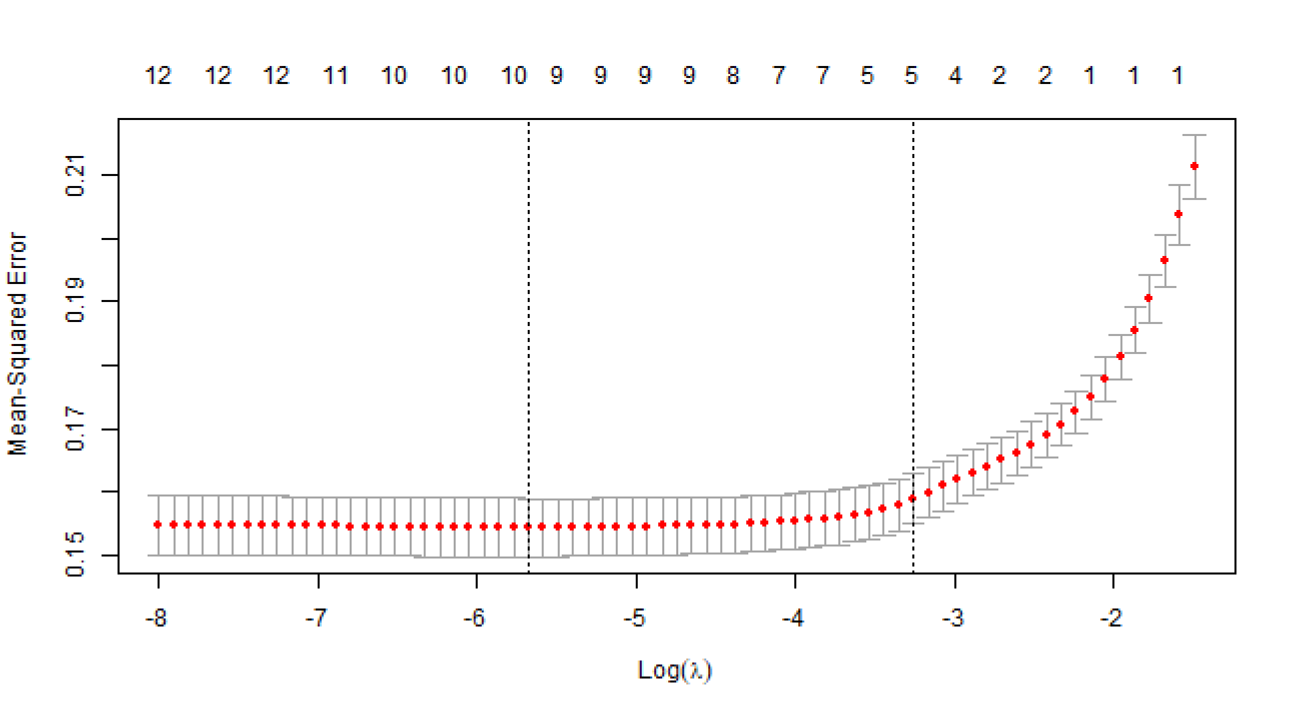
LASSO

```
plot(lassFit)
```



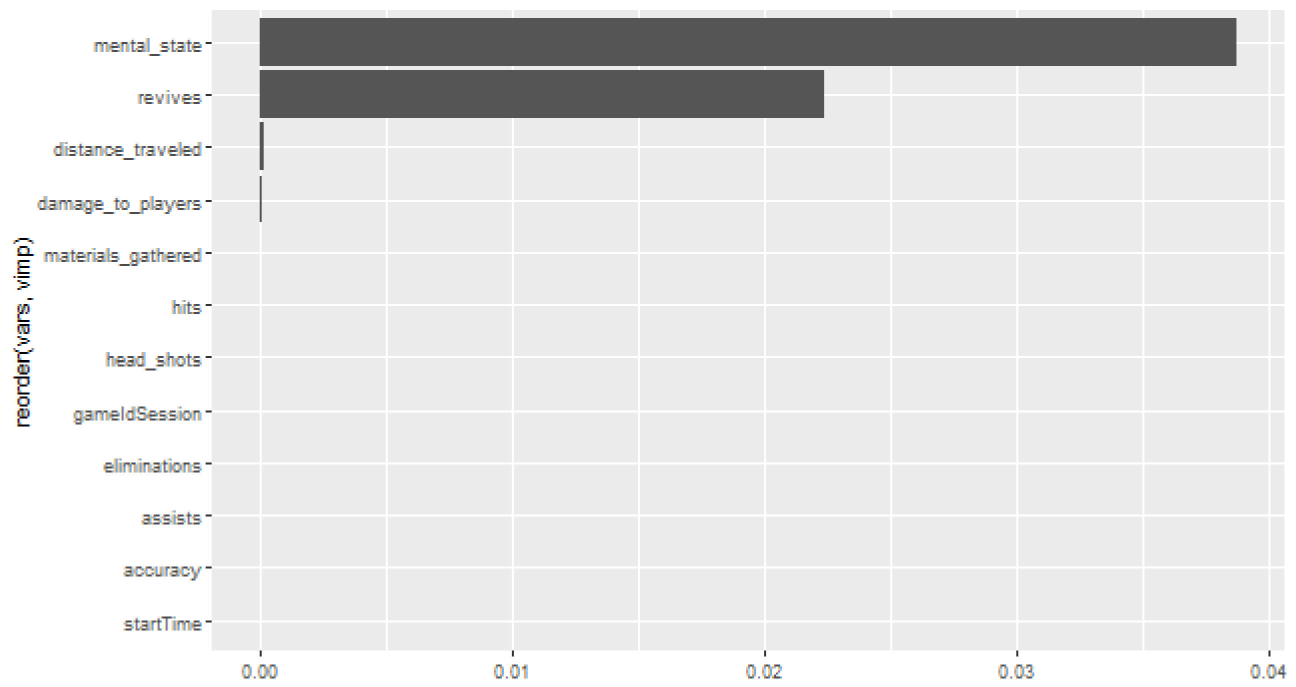
Has its own CV!

```
cv.lassFit <- cv.glmnet(x = as.matrix(X),y = as.matrix(Y))

plot(cv.lassFit)
```



Variable Importance

```
best <- cv.lassFit$glmnet.fit$beta[,cv.lassFit$index[2,]]
vimpLass <- data.frame(vimp = best,
                       vars = names(best))
vimpLass %>%
  ggplot(aes(x = vimp,y = reorder(vars,vimp))) +
  geom_bar(stat = 'identity')
```



Conclusion

- Lots of powerful tools out there!
- Make sure to take **more classes** on these topics!
- Go to Brightspace and take the **16th** quiz
- **Homework:**
    - Problem Set 9 (due 2024-03-29 by 11:59PM)
    - HW 17