MS&E 226 Project

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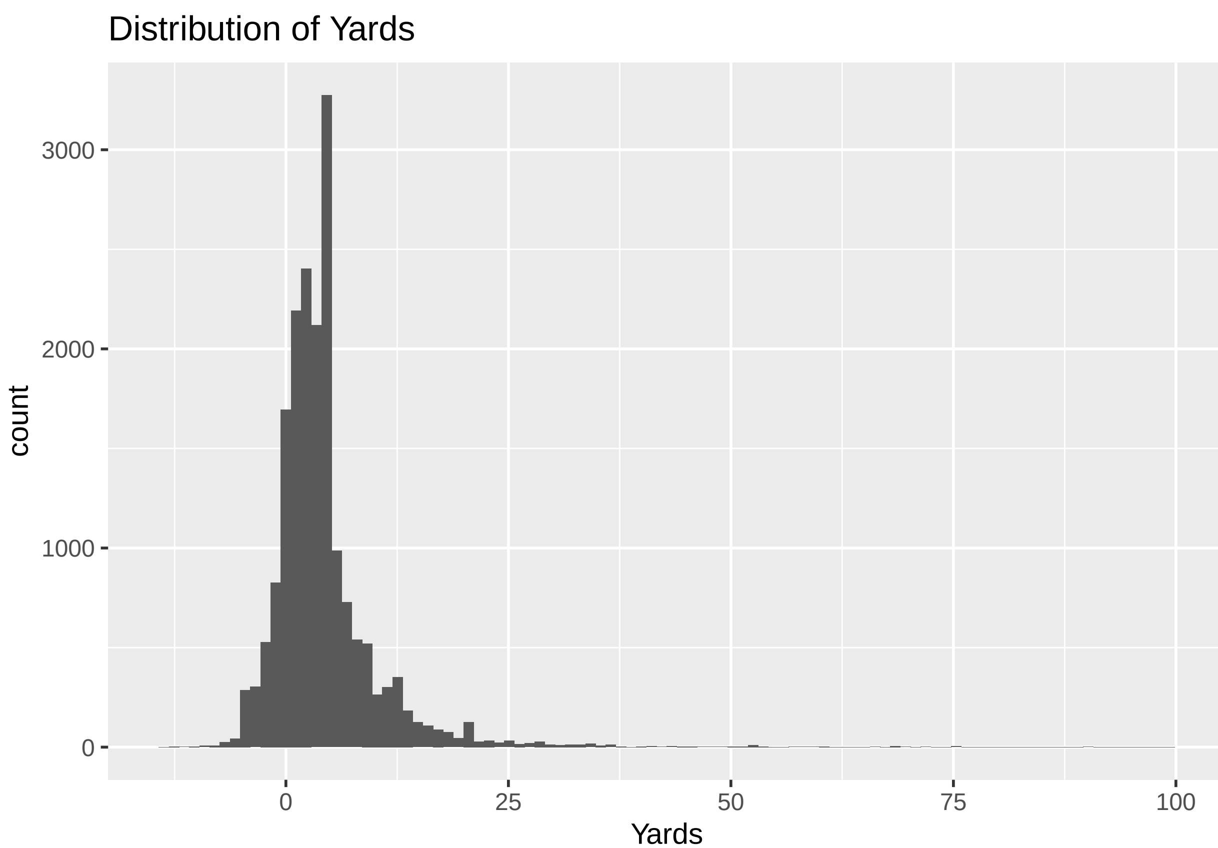
IMPORT DATA AND SPLIT INTO TRAIN AND HOLDOUT

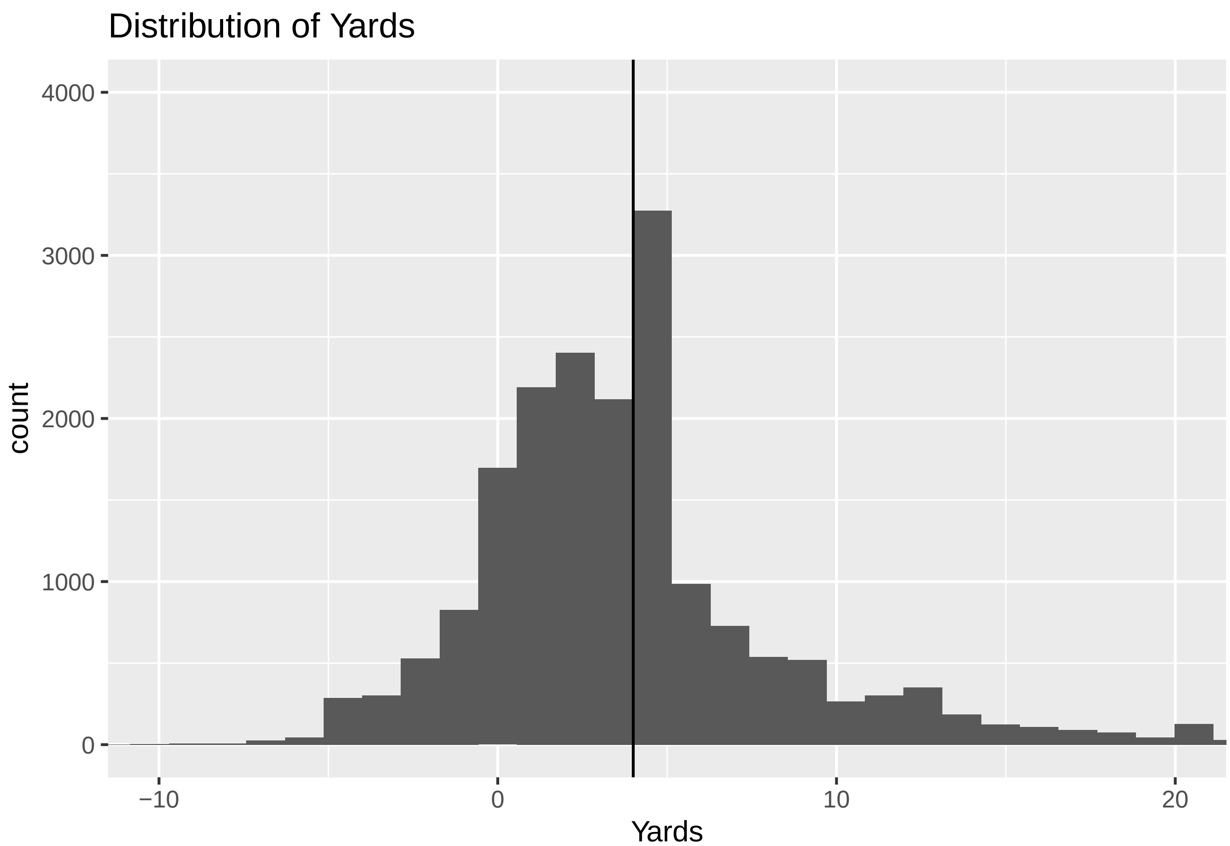
```
NFL_DATA <- read.csv(file = "train.csv", header = TRUE, sep=",")
NFL_DATA_Run_Observations <- NFL_DATA[(NFL_DATA$NflIdRusher == NFL_DATA$NflId)    , ]

# split 80:20 for training:test
set.seed(123)
training_data = sample(nrow(NFL_DATA_Run_Observations), size = nrow(NFL_DATA_Run_Observations) * 0.8)
NFL_DATA_Train = NFL_DATA_Run_Observations[training_data, ]
NFL_DATA_Holdout = NFL_DATA_Run_Observations[-training_data, ] # holdout is remaining indices
#View(NFL_DATA_Train)
```

DATA EXPLORATION OF OUTCOME VARIABLE

```
# Explore distribution of the continuos response variable we are predicting. (Yards/carry)
ggplot(data = NFL_DATA_Train) +
  geom_histogram(mapping = aes(x = Yards), bins = 100) +
  ggtitle("Distribution of Yards")
```



```r
# Zoom into specifically -10 to 20 yards
ggplot(data = NFL_DATA_Train) +
  geom_histogram(mapping = aes(x = Yards), bins = 100) +
  coord_cartesian(xlim=c(-10,20), ylim=c(0, 4000)) +
  geom_vline(xintercept = 4) +
  ggtitle("Distribution of Yards")
```




```r
# 2, 3, 4, 5 yards in particular are the peaks

# What percentage of runs result in > 10 yards? 0.0956517
More_Than_10 = NFL_DATA_Train[(NFL_DATA_Train$Yards > 10), ]
Percentage_Over_10 =  nrow(More_Than_10) / nrow(NFL_DATA_Train)
Percentage_Over_10
```

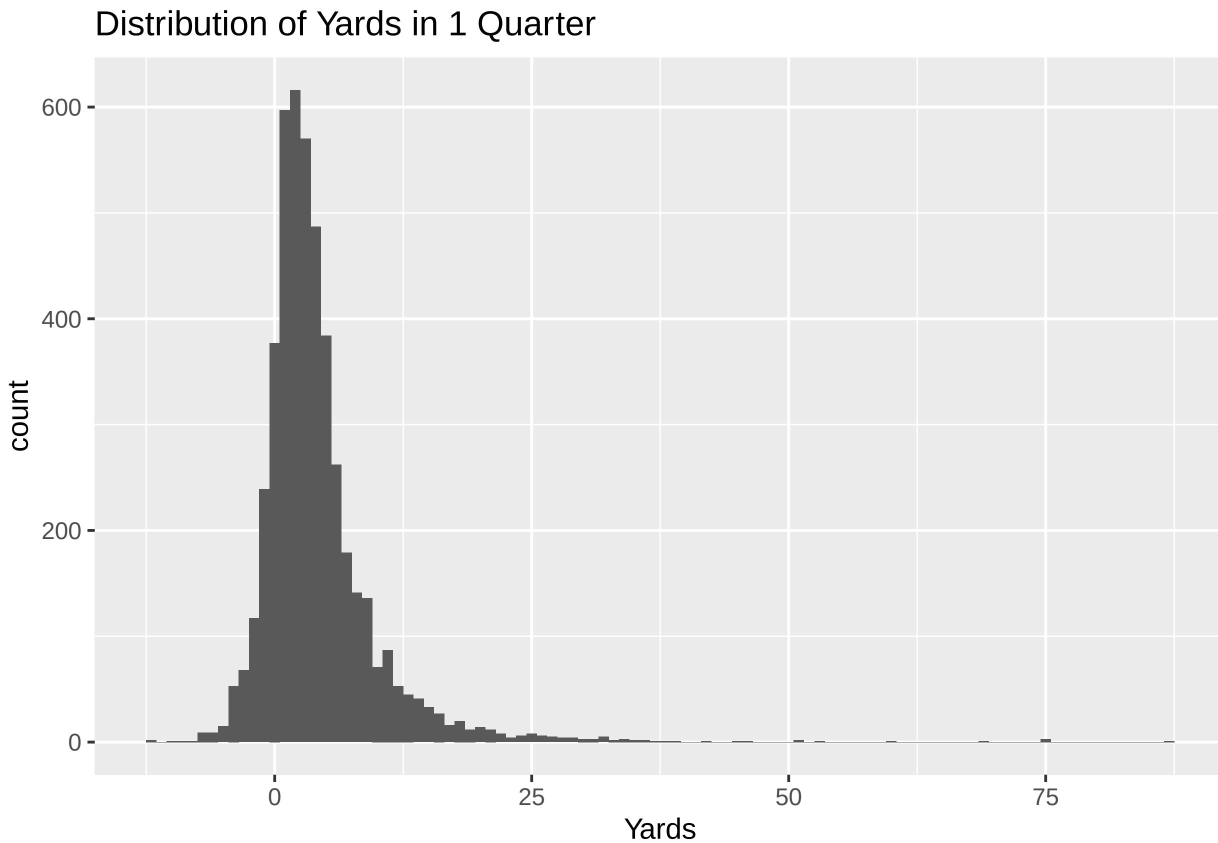
```
## [1] 0.095652
```

```r
# What Percentage of runs is < 0 yards? 0.1101101
Less_Than_0 = NFL_DATA_Train[(NFL_DATA_Train$Yards < 0), ]
Percentage_under_0 =  nrow(Less_Than_0) / nrow(NFL_DATA_Train)
Percentage_under_0
```

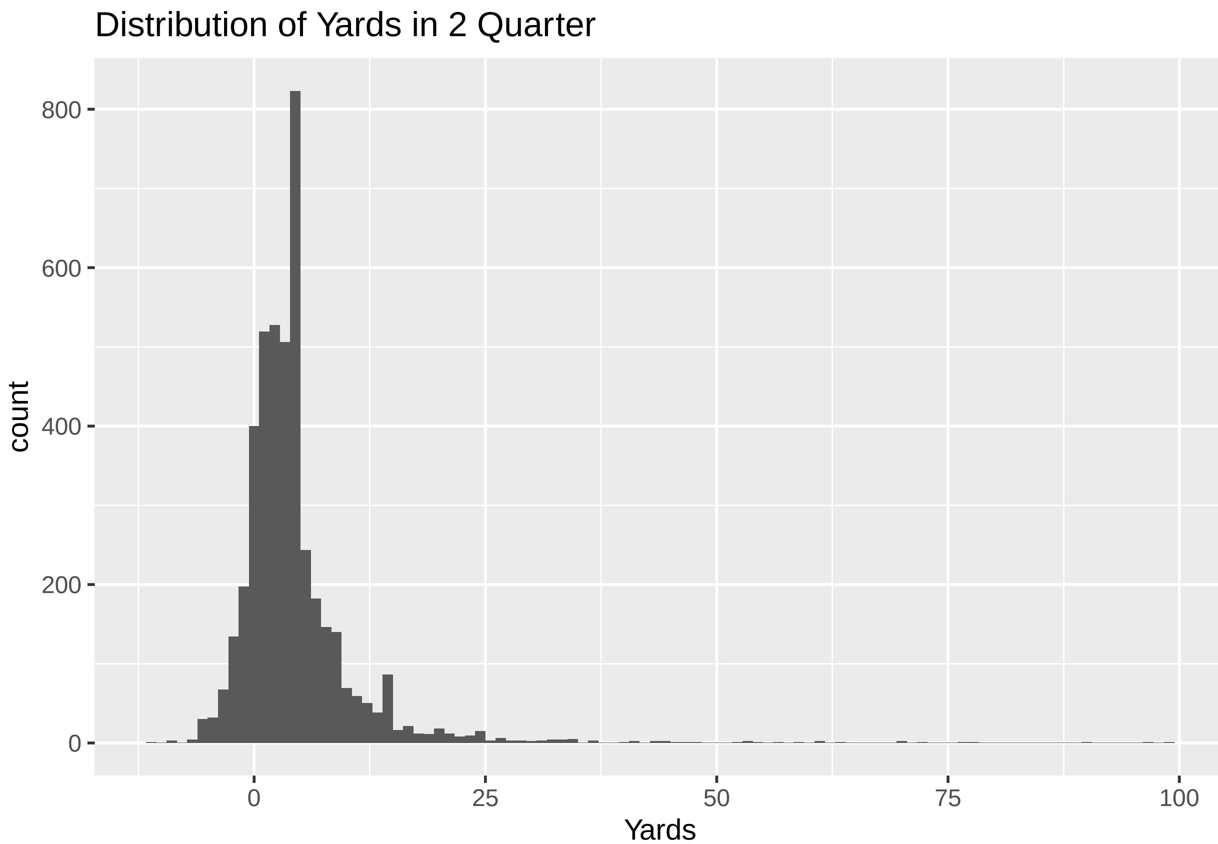
```
## [1] 0.11011
```

```r
# See if there is difference in run yard by quarter

# FACTOR QUARTER
NFL_DATA_Train$Quarter = factor(NFL_DATA_Train$Quarter)

# First quarter
```

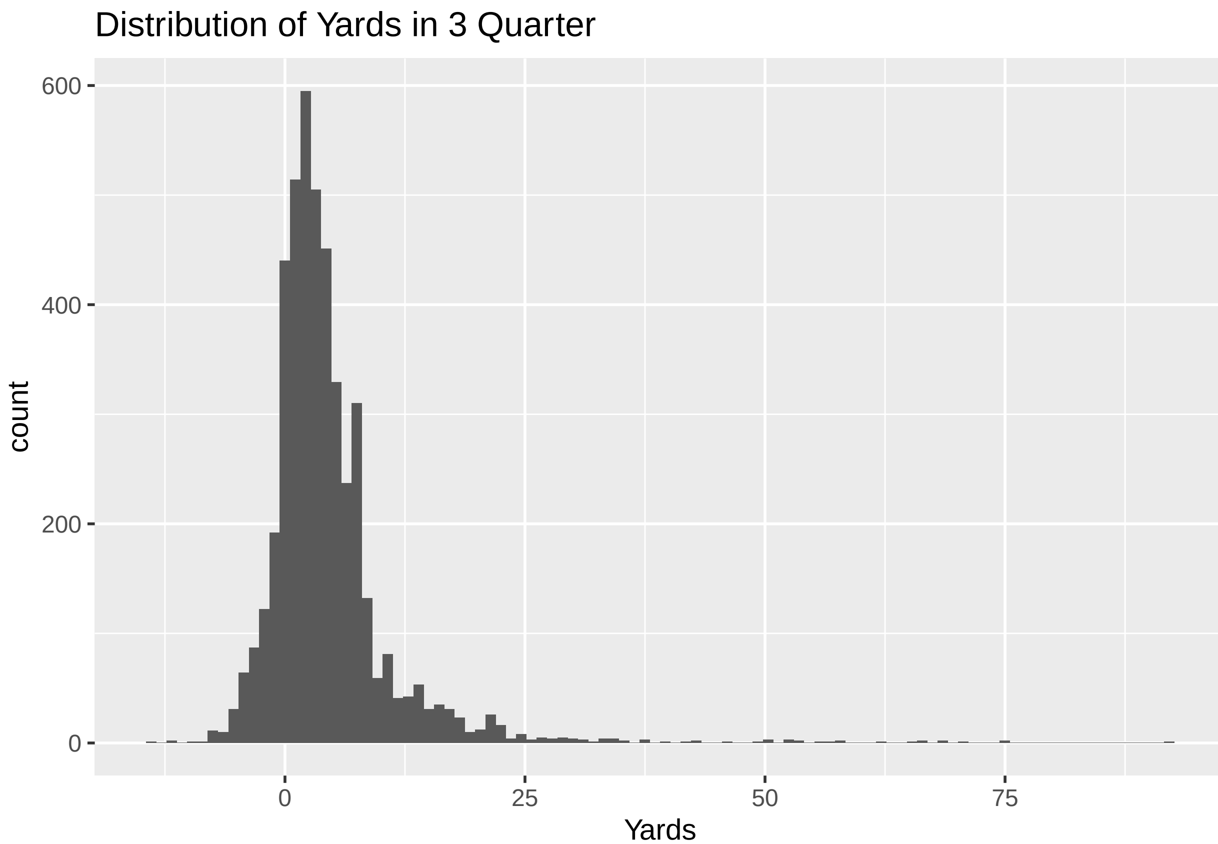
```r
ggplot(data = NFL_DATA_Train[(NFL_DATA_Train$Quarter == 1), ]) +
  geom_histogram(mapping = aes(x = Yards), bins = 100) +
  ggtitle("Distribution of Yards in 1 Quarter")
```




```r
# Second quarter
ggplot(data = NFL_DATA_Train[(NFL_DATA_Train$Quarter == 2), ]) +
  geom_histogram(mapping = aes(x = Yards), bins = 100) +
  ggtitle("Distribution of Yards in 2 Quarter")
```

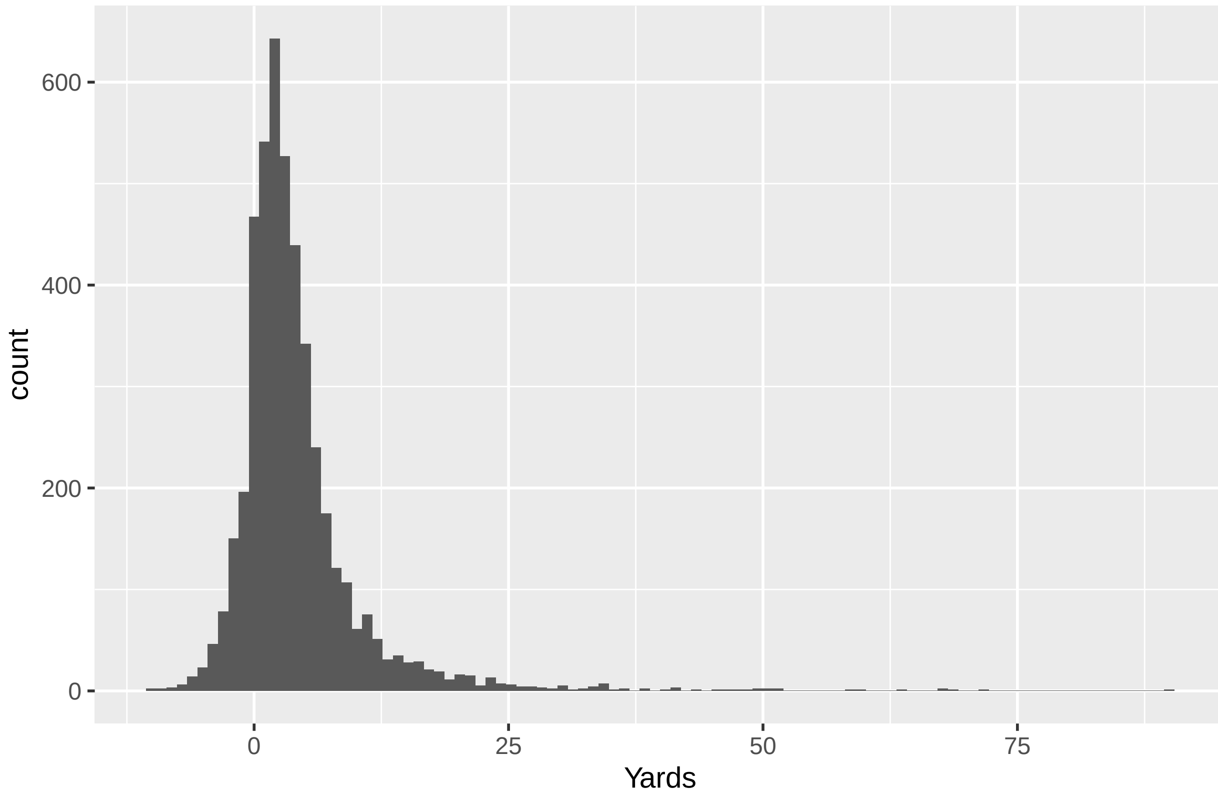



```
# Third quarter
ggplot(data = NFL_DATA_Train[(NFL_DATA_Train$Quarter == 3), ]) +
  geom_histogram(mapping = aes(x = Yards), bins = 100) +
  ggtitle("Distribution of Yards in 3 Quarter")
```




```r
# Fourth quarter
ggplot(data = NFL_DATA_Train[(NFL_DATA_Train$Quarter == 4), ]) +
  geom_histogram(mapping = aes(x = Yards), bins = 100) +
  ggtitle("Distribution of Yards in 4 Quarter")
```

Distribution of Yards in 4 Quarter



DATA EXPLORATION

```
# Plot 3d of X and Y position, and yards gotten
plot_ly(
  NFL_DATA_Train, x = ~X, y = ~Y, z = ~Yards, color = ~PossessionTeam) %>%
  add_markers() %>%
  layout(
    scene = list(xaxis = list(title = 'X'),
                 yaxis = list(title = 'Y'),
                 zaxis = list(title = 'Yards'))
  )
```

```
## Warning in RColorBrewer::brewer.pal(N, "Set2"): n too large, allowed maximum for palette Set2 is 8
## Returning the palette you asked for with that many colors

## Warning in RColorBrewer::brewer.pal(N, "Set2"): n too large, allowed maximum for palette Set2 is 8
## Returning the palette you asked for with that many colors
```

```
# Plot 3d of down and distance, and yards gotten
plot_ly(
  NFL_DATA_Train, x = ~Distance, y = ~Down, z = ~Yards, color = ~PossessionTeam) %>%
  add_markers() %>%
  layout(
    scene = list(xaxis = list(title = 'Distance'),
                 yaxis = list(title = 'Down'),
```

```
                 zaxis = list(title = 'Yards'))
)
```

```
## Warning in RColorBrewer::brewer.pal(N, "Set2"): n too large, allowed maximum for palette Set2 is 8
## Returning the palette you asked for with that many colors

## Warning in RColorBrewer::brewer.pal(N, "Set2"): n too large, allowed maximum for palette Set2 is 8
## Returning the palette you asked for with that many colors
```

DATA MANIPULATION AND CLEANING

Adding the covariates that we want to include, and modififying the dataframe

```
NFL_DATA_TRAIN_Modified <- NFL_DATA_Train

# Function to take the difference in time from the dataframe
timeDifference <- function(time) {
  num <- gsub("[:]", "" , str_sub(time, 12, 19), perl=TRUE)
  hr <- ifelse(str_sub(num, 1, 2) == "00", 24, as.numeric(str_sub(num, 1, 2)))
  min <- as.numeric(str_sub(num, 3, 4))
  sec <- as.numeric(str_sub(num, 5, 6))
  newTime <- 3600*hr + 60 * min + sec
  return(newTime)
}
# Add Time_Difference between the snap and the handoff
NFL_DATA_TRAIN_Modified$TimeDifference <-
  timeDifference(NFL_DATA_TRAIN_Modified$TimeHandoff) - timeDifference(NFL_DATA_TRAIN_Modified$TimeSnap)

# Add the Difference in Score by home score - visitor score
# Difference in Score (Pair with which team is winning (HomeScore-AwayScore))
NFL_DATA_TRAIN_Modified$HomeScoreAdvantage <-
  NFL_DATA_TRAIN_Modified$HomeScoreBeforePlay - NFL_DATA_TRAIN_Modified$VisitorScoreBeforePlay

# Add the age of the running player

# Change the birth dates to strings
NFL_DATA_TRAIN_Modified$PlayerBirthDate = as.character(NFL_DATA_TRAIN_Modified$PlayerBirthDate)
# Grab the Year for each of the running player
Birth_Year = str_sub(NFL_DATA_TRAIN_Modified$PlayerBirthDate, 7, 11)
# Grab Month of each running player
Birth_Month = str_sub(NFL_DATA_TRAIN_Modified$PlayerBirthDate, 1, 2)
# If Born in July (07) Have lived 5/12 of a year. ie (12 - (Birth_Month)) / 12
How_Much_Of_Year_Lived = (12 - as.numeric(Birth_Month)) / 12
Years_Lived = NFL_DATA_TRAIN_Modified$Season - as.numeric(Birth_Year)
Total_Years_Lived = Years_Lived + How_Much_Of_Year_Lived
NFL_DATA_TRAIN_Modified$PlayerAge = Total_Years_Lived

# Change HEIGHT to inches and continuous
Feet = as.numeric(str_sub(NFL_DATA_TRAIN_Modified$PlayerHeight, 1, 1))
Inches = as.numeric(str_sub(NFL_DATA_TRAIN_Modified$PlayerHeight, 3, 4))
Heights = (Feet * 12) + Inches
NFL_DATA_TRAIN_Modified$PlayerHeight = Heights
```

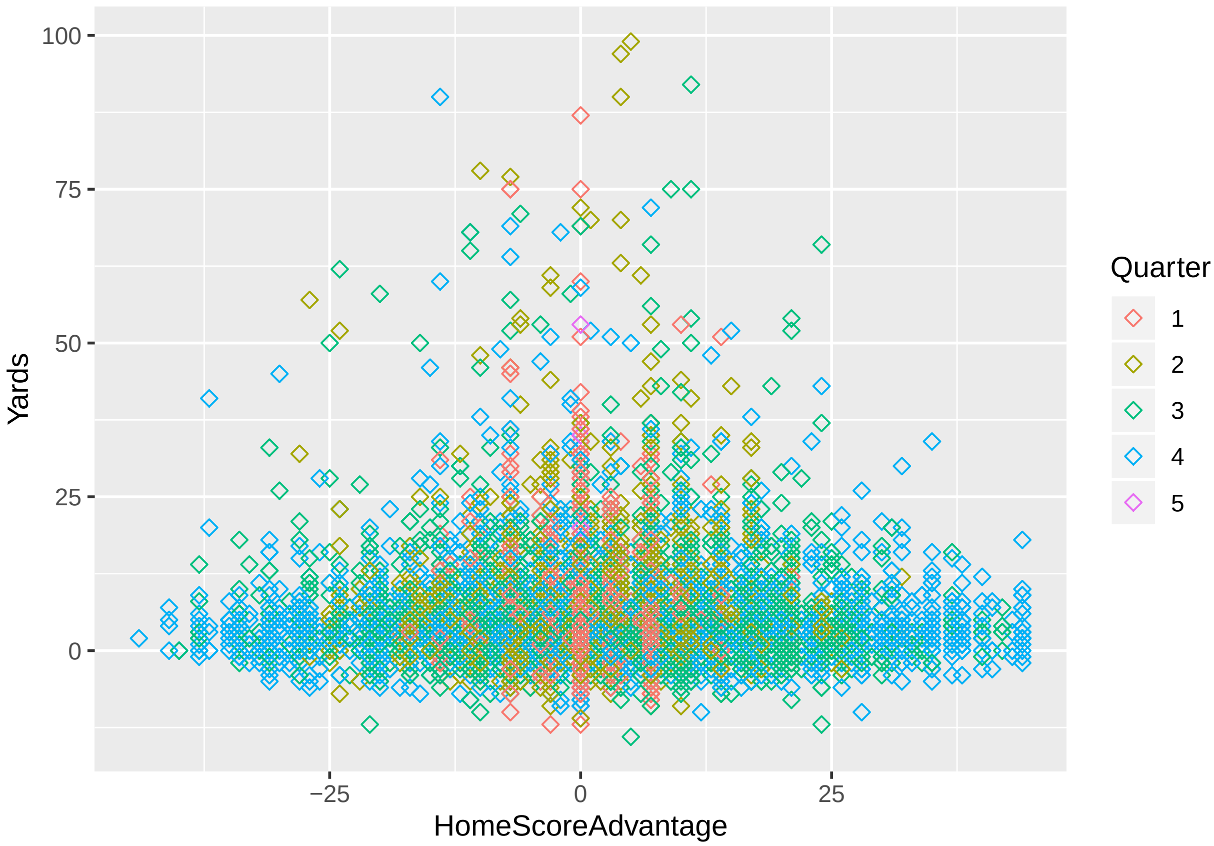
```r
# Changes GAMECLOCK to Seconds.

NFL_DATA_TRAIN_Modified$GameClock = as.numeric(NFL_DATA_TRAIN_Modified$GameClock)

# FACTORING VARIABLES INTO CATEGORICAL

# Factor OFFENSE FORMATION
NFL_DATA_TRAIN_Modified$OffenseFormation = factor(NFL_DATA_TRAIN_Modified$OffenseFormation)

# DEFENDERS IN BOX (Need Categorical and Ordinal)
NFL_DATA_TRAIN_Modified$DefendersInTheBox = factor(NFL_DATA_TRAIN_Modified$DefendersInTheBox)
```

MORE EXPLORATION WITH NEW/FACTORED COVARIATES (Still before Analyzing Techniques)

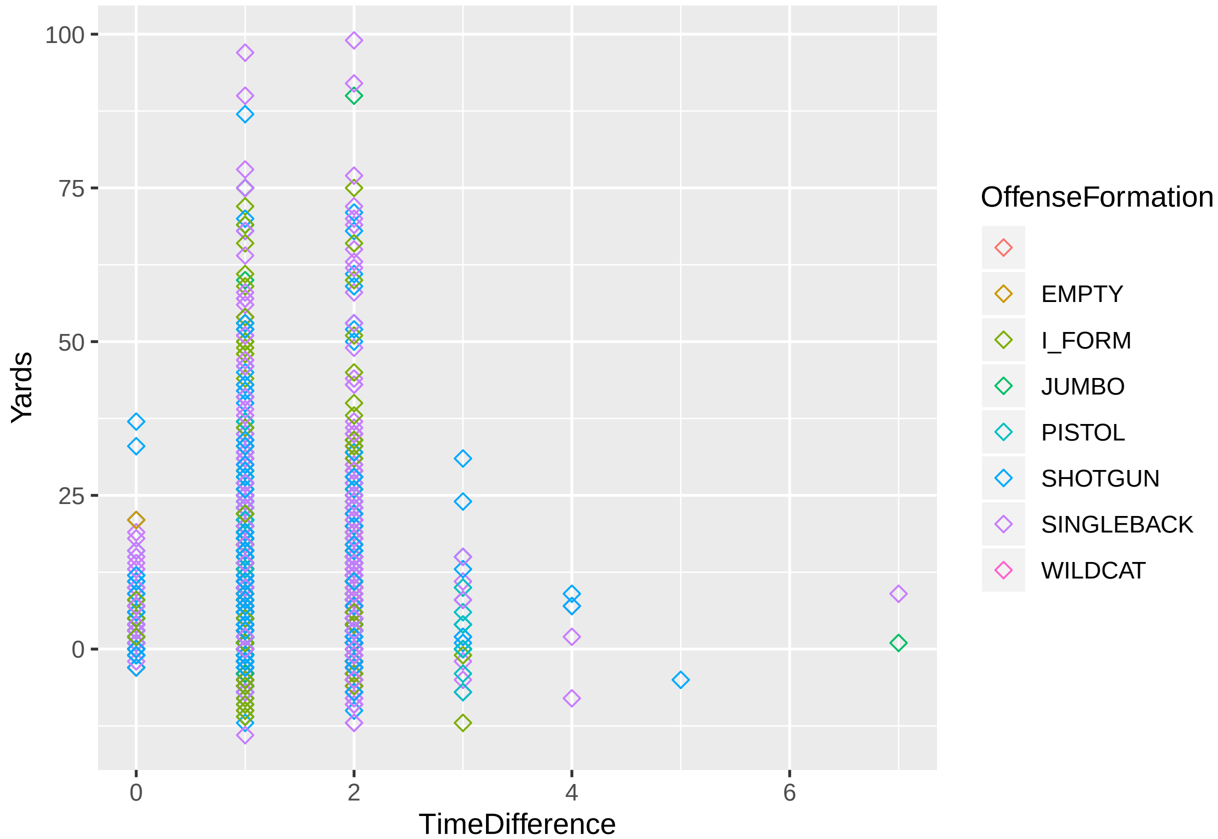
```r
# Plot 3d of offense formation and defenders in box, and yards gotten. More defenders, less yards
# Might be ok, might only need 2 yards, same for 4th down
plot_ly(
  NFL_DATA_TRAIN_Modified, x = ~OffenseFormation, y = ~DefendersInTheBox, z = ~Yards, color = ~Possessi
  add_markers() %>%
  layout(
    scene = list(xaxis = list(title = 'OffenseForm'),
                 yaxis = list(title = 'DefendInBox'),
                 zaxis = list(title = 'Yards'))
)
```

```
## Warning: Ignoring 2 observations

## Warning in RColorBrewer::brewer.pal(N, "Set2"): n too large, allowed maximum for palette Set2 is 8
## Returning the palette you asked for with that many colors

## Warning in RColorBrewer::brewer.pal(N, "Set2"): n too large, allowed maximum for palette Set2 is 8
## Returning the palette you asked for with that many colors
```

```r
# Yards vs. Difference in Score, Color = Quarter
ggplot(NFL_DATA_TRAIN_Modified, aes(x=HomeScoreAdvantage, y=Yards, color = Quarter )) +
  geom_point(size=2, shape=23)
```




```
# Difference in score spreads out depending on the quarter (makes sense)
# Overtime looks to have highest average yards
# 4th quarter more run plays

# Time between handoff and yards, color = offense style
ggplot(NFL_DATA_TRAIN_Modified, aes(x=TimeDifference, y=Yards, color = OffenseFormation)) +
  geom_point(size=2, shape=23)
```




```
# GameClock, Quarter, Yards
plot_ly(
  NFL_DATA_TRAIN_Modified, x = ~GameClock, y = ~Quarter, z = ~Yards, color = ~factor(DefendersInTheBox)
  add_markers() %>%
  layout(
    scene = list(xaxis = list(title = 'Game Clock'),
                 yaxis = list(title = 'Quarter'),
                 zaxis = list(title = 'Yards'))
  )
```

```
## Warning in RColorBrewer::brewer.pal(N, "Set2"): n too large, allowed maximum for palette Set2 is 8
## Returning the palette you asked for with that many colors

## Warning in RColorBrewer::brewer.pal(N, "Set2"): n too large, allowed maximum for palette Set2 is 8
## Returning the palette you asked for with that many colors
```

REFACTOR DEFENDER IN BOX TO INCLUDE ORDINALITY

```
# Leaving them unordered was for graphs above, to look good
NFL_DATA_TRAIN_Modified$DefendersInTheBox = factor(NFL_DATA_TRAIN_Modified$DefendersInTheBox, order = TI
```

SELECTION OF COVARIATES FOR ANALYSIS

```
# Drop columns that are collinear, or we think are not critical to our model
NFL_DATA_TRAIN_Filtered = select(NFL_DATA_TRAIN_Modified,
                                 -GameId, -PlayId, -Team, -S, -A, -Dis,
                                 -Orientation, -Dir, -DisplayName, -JerseyNumber,
                                 -YardLine, -FieldPosition, -HomeScoreBeforePlay,
                                 -VisitorScoreBeforePlay, -NflId, -TimeHandoff,
                                 -TimeSnap, -PlayerBirthDate, -PlayerCollegeName, -Location,
                                 -WindSpeed, -WindDirection, -StadiumType, -Turf,-GameWeather,
# Turf and stadium type all captured in stadium
# View(NFL_DATA_TRAIN_Filtered) # drop game weather, captured in Week, and Stadium. Also too many missi
```

NOW THAT HAVE SELECTED COVARIATES. MORE DATA CLEANING, FACTORING, ETC...

```
# Need to count how many NA / Empty cells there are for each column
# summary(NFL_DATA_TRAIN_Filtered)  # changed empty to NA when reading in file
# GameWeather, Temperature, Humidy all have missing or NA data
# sum(is.na(NFL_DATA_TRAIN_Filtered$GameWeather))
# sum(NFL_DATA_TRAIN_Filtered$GameWeather == "")

# Factor the DOWNS, Ordinally
NFL_DATA_TRAIN_Filtered$Down = factor(as.numeric(NFL_DATA_TRAIN_Filtered$Down), order = TRUE, levels =

# Player WEIGHT
NFL_DATA_TRAIN_Filtered$PlayerWeight = as.numeric(NFL_DATA_TRAIN_Filtered$PlayerWeight)

# Factor POSITION
NFL_DATA_TRAIN_Filtered$Position = factor(NFL_DATA_TRAIN_Filtered$Position)

# factor POSITION
NFL_DATA_TRAIN_Filtered$Position = factor(NFL_DATA_TRAIN_Filtered$Position)

# factor SEASON
NFL_DATA_TRAIN_Filtered$Season = factor(NFL_DATA_TRAIN_Filtered$Season)


# DATA CLEANING (REMOVING NA'S, and observations that happen less than 3 times)
# This was causing issues where one fold has a factor but another fold does not

# Need to delete a row within a column if there is just 1 special case. (Minimun 3 observations)

# DefensePersonnel (reduces observations by 11)
NFL_DATA_TRAIN_Filtered = NFL_DATA_TRAIN_Filtered[unsplit(table(NFL_DATA_TRAIN_Filtered$DefensePersonne

# Same for OffensePersonnel (reduces by 18 observations)
NFL_DATA_TRAIN_Filtered = NFL_DATA_TRAIN_Filtered[unsplit(table(NFL_DATA_TRAIN_Filtered$OffensePersonne

# Same for Position
```

```r
NFL_DATA_TRAIN_Filtered = NFL_DATA_TRAIN_Filtered[unsplit(table(NFL_DATA_TRAIN_Filtered$Position), NFL_I

# Same for Defenders In the Box
NFL_DATA_TRAIN_Filtered = NFL_DATA_TRAIN_Filtered[unsplit(table(NFL_DATA_TRAIN_Filtered$DefendersInTheBo

# Same for Offense Formation
NFL_DATA_TRAIN_Filtered = NFL_DATA_TRAIN_Filtered[unsplit(table(NFL_DATA_TRAIN_Filtered$OffenseFormatior

# Need to remove NA Rows: Still 16,758 observations out of ~18,000
NFL_DATA_TRAIN_Filtered_Final <- na.omit(NFL_DATA_TRAIN_Filtered)
# View(NFL_DATA_TRAIN_Filtered_Final)
```

BEGINNING OF ANALYSIS

Regression with all Covariates

```r
NFL_Train_Total_Model = lm(Yards ~ ., data=NFL_DATA_TRAIN_Filtered_Final)
NFL_Train_Total_Model.cv = cvFit(NFL_Train_Total_Model, data=NFL_DATA_TRAIN_Filtered_Final, y=NFL_DATA_T
NFL_Train_Total_Model.cv # RMSE= 6.388  # May have collinearity
```

```
## 10-fold CV results:
##    CV
## 6.573
```

```r
NFL_Train_Total_Model$coefficients
```

```
##                                  (Intercept)
##                                   4.36400296
##                                            X
##                                   0.00136289
##                                            Y
##                                   0.01324105
##                                   Season2018
##                                   0.25591227
##                                     Quarter2
##                                   0.24042162
##                                     Quarter3
##                                   0.24208899
##                                     Quarter4
##                                   0.13308696
##                                     Quarter5
##                                   1.18448991
##                                    GameClock
##                                   0.00027695
##                            PossessionTeamATL
##                                   0.52279214
##                            PossessionTeamBLT
##                                   1.78413256
##                            PossessionTeamBUF
##                                   0.27577077
##                            PossessionTeamCAR
##                                   0.94340163
```

```
##                                     PossessionTeamCHI
##                                            0.28630036
##                                     PossessionTeamCIN
##                                           -1.03309945
##                                     PossessionTeamCLV
##                                            1.20458119
##                                     PossessionTeamDAL
##                                            0.76922709
##                                     PossessionTeamDEN
##                                            0.84305634
##                                     PossessionTeamDET
##                                            0.39927663
##                                      PossessionTeamGB
##                                            0.59790966
##                                     PossessionTeamHST
##                                            0.93271280
##                                     PossessionTeamIND
##                                            1.13432263
##                                     PossessionTeamJAX
##                                            0.64910649
##                                      PossessionTeamKC
##                                            0.74554290
##                                      PossessionTeamLA
##                                            0.88134301
##                                     PossessionTeamLAC
##                                            1.12016728
##                                     PossessionTeamMIA
##                                            0.66096948
##                                     PossessionTeamMIN
##                                            0.68265047
##                                      PossessionTeamNE
##                                            0.52885765
##                                      PossessionTeamNO
##                                            1.47683784
##                                     PossessionTeamNYG
##                                            0.73977295
##                                     PossessionTeamNYJ
##                                            0.47931667
##                                     PossessionTeamOAK
##                                            0.80688463
##                                     PossessionTeamPHI
##                                            0.81505089
##                                     PossessionTeamPIT
##                                            0.98387679
##                                     PossessionTeamSEA
##                                            0.00523551
##                                      PossessionTeamSF
##                                            1.09890839
##                                      PossessionTeamTB
##                                            0.03094075
##                                     PossessionTeamTEN
##                                            1.28413364
##                                     PossessionTeamWAS
##                                            0.14761205
```

```
##                                      Down.L
##                                 -0.49376306
##                                      Down.Q
##                                 -0.47586885
##                                      Down.C
##                                 -0.24474125
##                                    Distance
##                                  0.06705364
##                       OffenseFormationI_FORM
##                                 -0.45031458
##                        OffenseFormationJUMBO
##                                 -0.15875945
##                       OffenseFormationPISTOL
##                                 -0.33596008
##                      OffenseFormationSHOTGUN
##                                 -0.38570103
##                   OffenseFormationSINGLEBACK
##                                 -0.32342080
##                      OffenseFormationWILDCAT
##                                 -0.56743232
##             OffensePersonnel0 RB, 2 TE, 3 WR
##                                  0.95596500
##             OffensePersonnel0 RB, 3 TE, 2 WR
##                                 -2.03306037
##        OffensePersonnel1 RB, 0 TE, 3 WR,1 DB
##                                 11.46310616
##             OffensePersonnel1 RB, 0 TE, 4 WR
##                                  2.78450477
##        OffensePersonnel1 RB, 1 TE, 2 WR,1 DB
##                                  7.04022435
##        OffensePersonnel1 RB, 1 TE, 2 WR,1 DL
##                                  1.62058401
##             OffensePersonnel1 RB, 1 TE, 3 WR
##                                  3.03476877
##        OffensePersonnel1 RB, 2 TE, 1 WR,1 DB
##                                  4.00775212
##        OffensePersonnel1 RB, 2 TE, 1 WR,1 DL
##                                  3.71319993
##        OffensePersonnel1 RB, 2 TE, 1 WR,1 LB
##                                  6.94399691
##             OffensePersonnel1 RB, 2 TE, 2 WR
##                                  2.98552445
##        OffensePersonnel1 RB, 3 TE, 0 WR,1 DL
##                                  2.99541932
##        OffensePersonnel1 RB, 3 TE, 0 WR,1 LB
##                                  5.06695308
##             OffensePersonnel1 RB, 3 TE, 1 WR
##                                  2.84947963
##             OffensePersonnel1 RB, 4 TE, 0 WR
##                                  2.87175018
##       OffensePersonnel2 QB, 1 RB, 0 TE, 3 WR
##                                  3.29414301
##       OffensePersonnel2 QB, 1 RB, 1 TE, 2 WR
##                                  3.30885850
```

```
##      OffensePersonnel2 QB, 1 RB, 2 TE, 1 WR
##                                  1.70215731
##      OffensePersonnel2 QB, 2 RB, 1 TE, 1 WR
##                                  7.03294294
##            OffensePersonnel2 RB, 0 TE, 3 WR
##                                  3.63855112
##            OffensePersonnel2 RB, 1 TE, 2 WR
##                                  3.38905662
##            OffensePersonnel2 RB, 2 TE, 1 WR
##                                  3.66270453
##            OffensePersonnel2 RB, 3 TE, 0 WR
##                                  2.43564786
##            OffensePersonnel3 RB, 0 TE, 2 WR
##                                  2.64966017
##            OffensePersonnel3 RB, 1 TE, 1 WR
##                                  2.70186985
##            OffensePersonnel3 RB, 2 TE, 0 WR
##                                  3.50371553
##      OffensePersonnel6 OL, 1 RB, 0 TE, 3 WR
##                                  3.58936284
## OffensePersonnel6 OL, 1 RB, 1 TE, 1 WR,1 DL
##                                  1.91550695
##      OffensePersonnel6 OL, 1 RB, 1 TE, 2 WR
##                                  2.38036923
## OffensePersonnel6 OL, 1 RB, 2 TE, 0 WR,1 DL
##                                  3.55171043
## OffensePersonnel6 OL, 1 RB, 2 TE, 0 WR,1 LB
##                                  4.07472385
##      OffensePersonnel6 OL, 1 RB, 2 TE, 1 WR
##                                  3.36056987
##      OffensePersonnel6 OL, 1 RB, 3 TE, 0 WR
##                                  3.57372879
##      OffensePersonnel6 OL, 2 RB, 0 TE, 2 WR
##                                  5.09858830
## OffensePersonnel6 OL, 2 RB, 1 TE, 0 WR,1 DL
##                                  3.01072723
##      OffensePersonnel6 OL, 2 RB, 1 TE, 1 WR
##                                  3.60057607
##      OffensePersonnel6 OL, 2 RB, 2 TE, 0 WR
##                                  4.06041580
##      OffensePersonnel7 OL, 1 RB, 0 TE, 2 WR
##                                  3.14554063
##      OffensePersonnel7 OL, 1 RB, 2 TE, 0 WR
##                                  3.62122212
##      OffensePersonnel7 OL, 2 RB, 0 TE, 1 WR
##                                  4.48123748
##                        DefendersInTheBox.L
##                                 -6.96017364
##                        DefendersInTheBox.Q
##                                  1.58359080
##                        DefendersInTheBox.C
##                                 -0.56595335
##                        DefendersInTheBox^4
##                                  0.22197237
```

```
##                          DefendersInTheBox^5
##                                   0.55012865
##                          DefendersInTheBox^6
##                                  -0.04065856
##                          DefendersInTheBox^7
##                                  -0.07257713
##                          DefendersInTheBox^8
##                                   0.06691407
##            DefensePersonnel0 DL, 5 LB, 6 DB
##                                  -1.90367142
##            DefensePersonnel1 DL, 3 LB, 7 DB
##                                  -1.63831555
##            DefensePersonnel1 DL, 4 LB, 6 DB
##                                  -1.64102659
##            DefensePersonnel1 DL, 5 LB, 5 DB
##                                  -0.43307818
##            DefensePersonnel2 DL, 2 LB, 7 DB
##                                   3.41441670
##            DefensePersonnel2 DL, 3 LB, 6 DB
##                                  -0.96370024
##            DefensePersonnel2 DL, 4 LB, 5 DB
##                                  -1.12173181
##            DefensePersonnel2 DL, 5 LB, 4 DB
##                                  -2.24849996
##            DefensePersonnel3 DL, 1 LB, 7 DB
##                                  -2.76827913
##            DefensePersonnel3 DL, 2 LB, 6 DB
##                                  -1.28256756
##            DefensePersonnel3 DL, 3 LB, 5 DB
##                                  -1.29077009
##            DefensePersonnel3 DL, 4 LB, 4 DB
##                                  -1.12210347
##            DefensePersonnel3 DL, 5 LB, 3 DB
##                                  -0.58904955
##            DefensePersonnel4 DL, 1 LB, 6 DB
##                                  -0.70220371
##            DefensePersonnel4 DL, 2 LB, 5 DB
##                                  -1.11749447
##            DefensePersonnel4 DL, 3 LB, 4 DB
##                                  -1.37702947
##            DefensePersonnel4 DL, 4 LB, 3 DB
##                                  -2.34898232
##            DefensePersonnel5 DL, 1 LB, 5 DB
##                                  -2.26531078
##            DefensePersonnel5 DL, 2 LB, 4 DB
##                                  -0.92526644
##      DefensePersonnel5 DL, 3 LB, 2 DB, 1 OL
##                                  -3.48683503
##            DefensePersonnel5 DL, 3 LB, 3 DB
##                                  -3.00113451
##            DefensePersonnel5 DL, 4 LB, 2 DB
##                                  -2.11957449
##            DefensePersonnel5 DL, 5 LB, 1 DB
##                                  -3.31938419
```

```
##            DefensePersonnel6 DL, 2 LB, 3 DB
##                                 -3.18296116
##            DefensePersonnel6 DL, 3 LB, 2 DB
##                                 -3.12072944
##            DefensePersonnel6 DL, 4 LB, 1 DB
##                                 -3.00687073
##                          PlayDirectionright
##                                 -0.02558475
##                                PlayerHeight
##                                 -0.02678516
##                                PlayerWeight
##                                 -0.00018641
##                                  PositionFB
##                                  0.32109939
##                                  PositionHB
##                                  2.45225873
##                                  PositionQB
##                                 -0.60699802
##                                  PositionRB
##                                  0.48727282
##                                  PositionTE
##                                  2.33283997
##                                  PositionWR
##                                  2.64722612
##                             HomeTeamAbbrATL
##                                 -0.34076403
##                             HomeTeamAbbrBAL
##                                 -0.17950982
##                             HomeTeamAbbrBUF
##                                  0.26056064
##                             HomeTeamAbbrCAR
##                                  0.45528471
##                             HomeTeamAbbrCHI
##                                 -0.19392233
##                             HomeTeamAbbrCIN
##                                  0.35223469
##                             HomeTeamAbbrCLE
##                                 -0.03682803
##                             HomeTeamAbbrDAL
##                                  0.11077453
##                             HomeTeamAbbrDEN
##                                 -0.46466064
##                             HomeTeamAbbrDET
##                                 -0.06176218
##                              HomeTeamAbbrGB
##                                 -0.13296029
##                             HomeTeamAbbrHOU
##                                 -0.28582071
##                             HomeTeamAbbrIND
##                                 -0.16448220
##                             HomeTeamAbbrJAX
##                                  0.12239543
##                              HomeTeamAbbrKC
##                                 -0.18233362
```

```
##                                  HomeTeamAbbrLA
##                                      0.06118917
##                                 HomeTeamAbbrLAC
##                                     -0.20257936
##                                 HomeTeamAbbrMIA
##                                     -0.13993846
##                                 HomeTeamAbbrMIN
##                                      0.09406523
##                                  HomeTeamAbbrNE
##                                      0.83606442
##                                  HomeTeamAbbrNO
##                                     -0.14217071
##                                 HomeTeamAbbrNYG
##                                      0.17937087
##                                 HomeTeamAbbrNYJ
##                                      0.38781682
##                                 HomeTeamAbbrOAK
##                                      0.14923110
##                                 HomeTeamAbbrPHI
##                                      0.12023634
##                                 HomeTeamAbbrPIT
##                                     -0.00804839
##                                 HomeTeamAbbrSEA
##                                      0.37715297
##                                  HomeTeamAbbrSF
##                                     -0.31175042
##                                  HomeTeamAbbrTB
##                                      0.34331602
##                                 HomeTeamAbbrTEN
##                                      0.14974627
##                                 HomeTeamAbbrWAS
##                                      0.18317262
##                              VisitorTeamAbbrATL
##                                      0.11926127
##                              VisitorTeamAbbrBAL
##                                     -1.22593702
##                              VisitorTeamAbbrBUF
##                                     -0.14853578
##                              VisitorTeamAbbrCAR
##                                     -0.22602736
##                              VisitorTeamAbbrCHI
##                                     -0.21665419
##                              VisitorTeamAbbrCIN
##                                     -0.46257061
##                              VisitorTeamAbbrCLE
##                                      0.02072874
##                              VisitorTeamAbbrDAL
##                                     -0.05521551
##                              VisitorTeamAbbrDEN
##                                     -0.01958155
##                              VisitorTeamAbbrDET
##                                     -0.12727400
##                               VisitorTeamAbbrGB
##                                      0.03796966
```

```
##                           VisitorTeamAbbrHOU
##                                  -1.29096177
##                           VisitorTeamAbbrIND
##                                  -0.51274503
##                           VisitorTeamAbbrJAX
##                                   0.26487852
##                            VisitorTeamAbbrKC
##                                  -0.04753699
##                            VisitorTeamAbbrLA
##                                   0.65637090
##                           VisitorTeamAbbrLAC
##                                  -0.41161468
##                           VisitorTeamAbbrMIA
##                                  -0.03750437
##                           VisitorTeamAbbrMIN
##                                  -0.28207140
##                            VisitorTeamAbbrNE
##                                   0.32397861
##                            VisitorTeamAbbrNO
##                                  -0.56852449
##                           VisitorTeamAbbrNYG
##                                  -0.28675035
##                           VisitorTeamAbbrNYJ
##                                  -0.38133070
##                           VisitorTeamAbbrOAK
##                                  -0.02212047
##                           VisitorTeamAbbrPHI
##                                  -0.08990205
##                           VisitorTeamAbbrPIT
##                                  -0.52749840
##                           VisitorTeamAbbrSEA
##                                   0.01376558
##                            VisitorTeamAbbrSF
##                                  -0.13122065
##                            VisitorTeamAbbrTB
##                                   0.07175978
##                           VisitorTeamAbbrTEN
##                                  -0.52592300
##                           VisitorTeamAbbrWAS
##                                   0.53538537
##                                         Week
##                                  -0.01288763
##                                  Temperature
##                                  -0.00513192
##                                     Humidity
##                                  -0.00685989
##                               TimeDifference
##                                   0.21244143
##                           HomeScoreAdvantage
##                                  -0.00937183
##                                    PlayerAge
##                                  -0.05285723
```

What if we always predicted the mean of yards? (Just Intercept Term)

```
NFL_Train_Total_Model1 = lm(Yards ~ 1, data=NFL_DATA_TRAIN_Filtered_Final)
NFL_Train_Total_Model1.cv = cvFit(NFL_Train_Total_Model1, data=NFL_DATA_TRAIN_Filtered_Final, y=NFL_DAT
NFL_Train_Total_Model1.cv # RMSE= 6.4191
```

```
## 10-fold CV results:
##     CV
## 6.5943
```

Forward Stepwise Regression

```
min_model = NFL_Train_Total_Model1
max_model = NFL_Train_Total_Model
stepwise_model = step(min_model, direction='forward', scope=max_model)
```

```
## Start:  AIC=63218
## Yards ~ 1
```

```
summary(stepwise_model)
```

```
##
## Call:
## lm(formula = Yards ~ 1, data = NFL_DATA_TRAIN_Filtered_Final)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -18.28  -3.28  -1.28   1.72  94.72
##
## Coefficients:
##             Estimate Std. Error t value            Pr(>|t|)
## (Intercept)   4.2793     0.0509      84 <0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 6.59 on 16757 degrees of freedom
```

```
# Ultimately, this is saying that the extra info we gain is not worth the complexity
```

Backward Stepwise Regerssion

```
backward_step = step(max_model, direction='backward')
backward_step
```

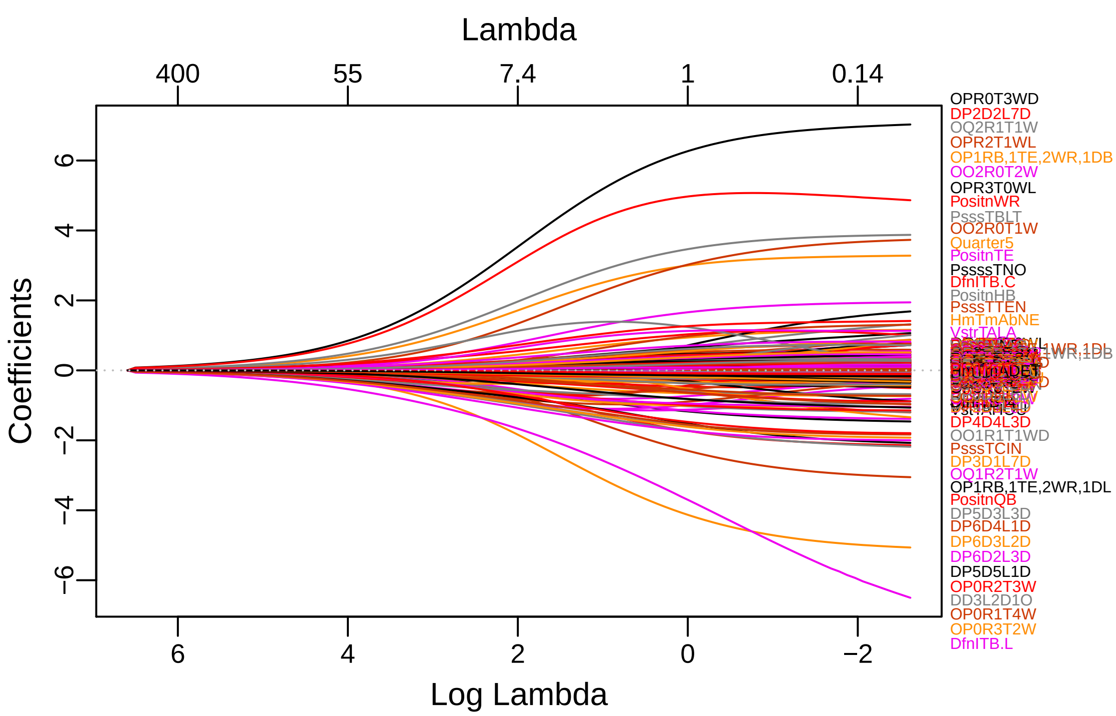
```
backward_step.cv = cvFit(backward_step, data=NFL_DATA_TRAIN_Filtered_Final, y=NFL_DATA_TRAIN_Filtered_F
backward_step.cv # RMSE= 6.5386 # Best Model so far
```

```
## 10-fold CV results:
##     CV
## 6.5386
```

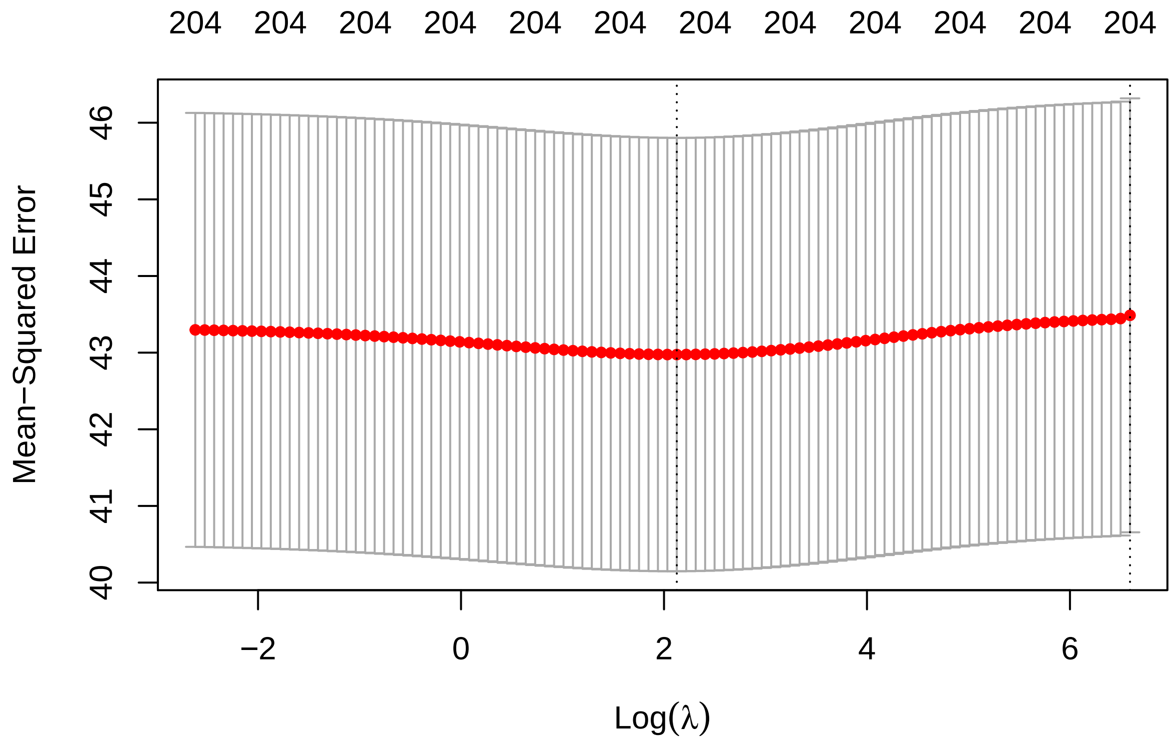
Ridge Regression

```r
library(glmnet)
## NORMALIZE Continouous Covariates # Will have to normalize defenders in box if we make continuous
Standardized_NFL_TRAIN = NFL_DATA_TRAIN_Filtered_Final
Standardized_NFL_TRAIN$X = scale(Standardized_NFL_TRAIN$X)
Standardized_NFL_TRAIN$Y = scale(Standardized_NFL_TRAIN$Y)
Standardized_NFL_TRAIN$GameClock = scale(Standardized_NFL_TRAIN$GameClock )
Standardized_NFL_TRAIN$Distance = scale(Standardized_NFL_TRAIN$Distance)
Standardized_NFL_TRAIN$PlayerHeight = scale(Standardized_NFL_TRAIN$PlayerHeight)
Standardized_NFL_TRAIN$PlayerWeight = scale(Standardized_NFL_TRAIN$PlayerWeight)
Standardized_NFL_TRAIN$Week = scale(Standardized_NFL_TRAIN$Week)
Standardized_NFL_TRAIN$Temperature = scale(Standardized_NFL_TRAIN$Temperature)
Standardized_NFL_TRAIN$Humidity = scale(Standardized_NFL_TRAIN$Humidity)
Standardized_NFL_TRAIN$TimeDifference = scale(Standardized_NFL_TRAIN$TimeDifference)
Standardized_NFL_TRAIN$HomeScoreAdvantage = scale(Standardized_NFL_TRAIN$HomeScoreAdvantage )
Standardized_NFL_TRAIN$PlayerAge = scale(Standardized_NFL_TRAIN$PlayerAge)

# Ridge Regression
# Ridge alpha = 0
x = model.matrix(Yards~. , Standardized_NFL_TRAIN)
y = Standardized_NFL_TRAIN$Yards
ridge_mod = glmnet(x, y, alpha = 0)
# install.packages("plotmo")
plot_glmnet(ridge_mod, label = TRUE)
```

```
## Warning in TeachingDemos::spread.labs(beta[iname, ncol(beta)], mindiff =
## 1.2 * : Maximum iterations reached
```




```r
cvfit = cv.glmnet(x, y, alpha = 0)
plot(cvfit)
```




```r
bestlam = cvfit$lambda.min # = 4.9384
```

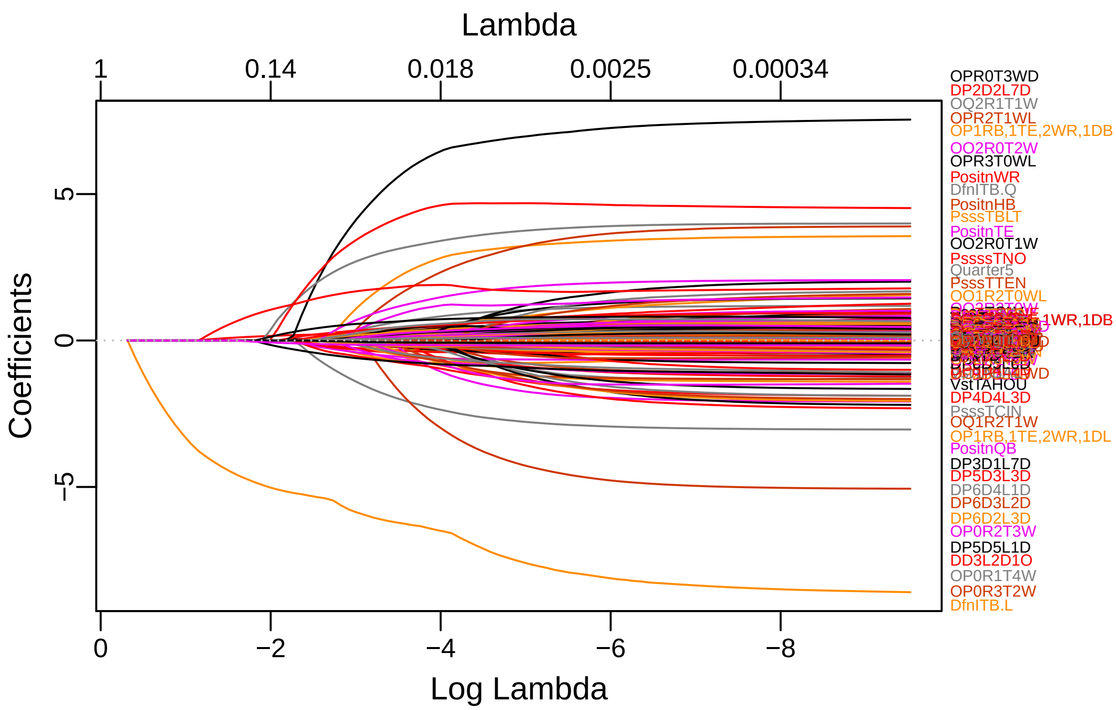
Get coefficients when log lamda is 10.098

```r
y_predicted <- predict(cvfit, s = bestlam, newx = x) # same x, in sample prediction
ridge_RMSE = sqrt(mean((y_predicted - y)^2))
# ridge_RMSE # = 6.3333
#coef(ridge_mod)[,4.9384] # Best is again basically forcing all the betas to 0. Just predict mean
```

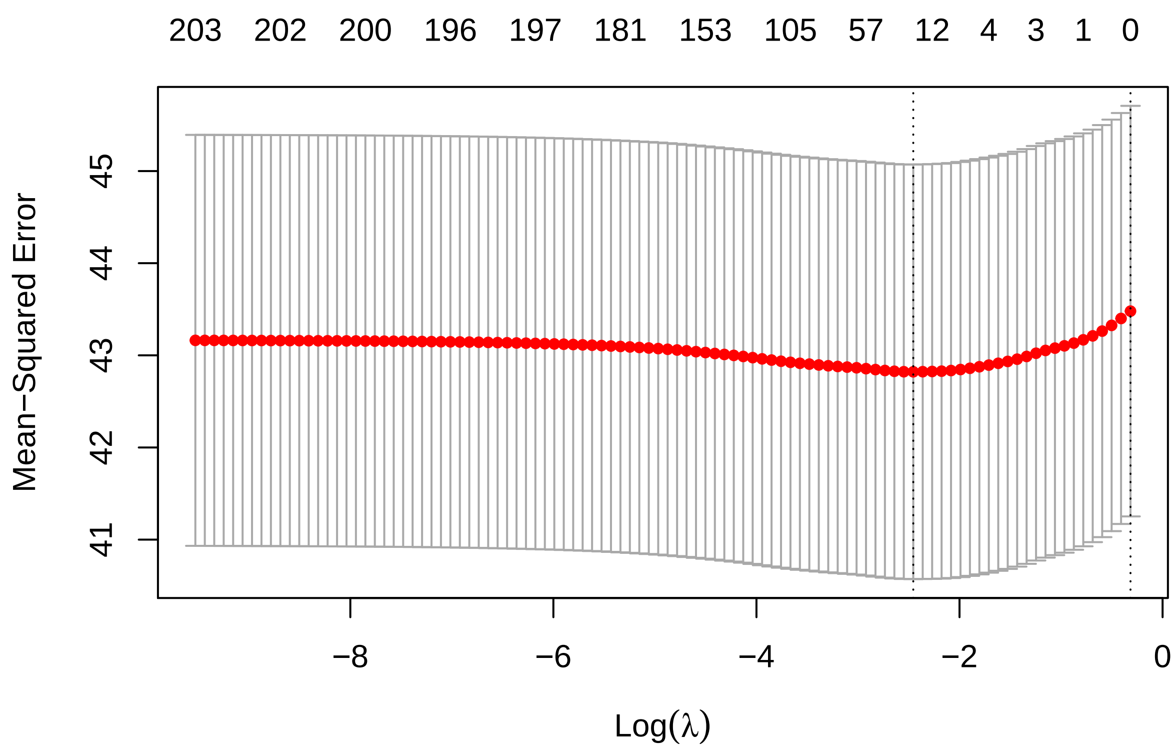
Lasso Regression

```r
lasso_mod= glmnet(x, y, alpha = 1)
# coef(lasso_mod)[,50]
plot_glmnet(lasso_mod, label = TRUE)
```

```
## Warning in TeachingDemos::spread.labs(beta[iname, ncol(beta)], mindiff =
## 1.2 * : Maximum iterations reached
```




```r
cvfit_lasso = cv.glmnet(x, y, alpha = 1)
plot(cvfit_lasso)
```




```r
bestlam_lasso = cvfit_lasso$lambda.min # = 0.046056
```

```r
y_predicted_lasso <- predict(cvfit_lasso, s = bestlam_lasso, newx = x) # same x, in sample prediction
lasso_RMSE = sqrt(mean((y_predicted_lasso - y)^2))
lasso_RMSE # = 6.3349
```

```
## [1] 6.5326
```

```
out = glmnet(x, y, alpha = 1) # Fit ridge regression model on full dataset
#predict(out, type = "coefficients", s = bestlam_lasso)[1:80,] # Display coefficients using lambda chos
```

Classification. Outcome Variable: NFL Yards >= distance. (Whether or not they get a first down)

With all Covariates

```
NFL_Train_Total_Model_c <- NFL_DATA_TRAIN_Filtered_Final
NFL_Train_Total_Model_c$FirstDown <- ifelse(
  NFL_Train_Total_Model_c$Yards >= NFL_Train_Total_Model_c$Distance, 1, 0)
NFL_Train_Total_Model_c$FirstDown <-
  factor(NFL_Train_Total_Model_c$FirstDown)
NFL_Train_Total_Model_c <- select(NFL_Train_Total_Model_c, -Yards) #remove colinear response variable f
```

Implementing Cross-Fold Validation for Classification

```
set.seed(122)
f <- createFolds(y=NFL_Train_Total_Model_c$FirstDown, k=10)
train_fold <- function (i) {
  NFL_Train_Total_Model_c[-unlist(f[i]),]
}

test_fold <- function (i) {
  NFL_Train_Total_Model_c[unlist(f[i]),]
}
```

Baseline model

```
accuracyR <- c()

for (i in 1:10) {
  glm_Model = glm(FirstDown ~ ., data=train_fold(i),
                             family = binomial)
  predict_result <- predict(glm_Model, newdata=test_fold(i), type="response")
  predict_logit <- ifelse(predict_result > 0.5, 1, 0)
  t <- table(predict_logit, test_fold(i)$FirstDown)
  accuracyR[i] = (t[1,1]+t[2,2])/dim(test_fold(i))[1]
}
cat("Mean accuracy of 10-fold validation is: ", mean(accuracyR), "\n")
```

```
## Mean accuracy of 10-fold validation is:  0.81585
```

```
#print(mean(accuracyR)) #0.81585
confusionMatrix(test_fold(i)$FirstDown, factor(predict_logit))
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    0    1
##          0 1233   82
##          1  226  134
##
##                Accuracy : 0.816
##                  95% CI : (0.797, 0.834)
##     No Information Rate : 0.871
##     P-Value [Acc > NIR] : 1
##
##                   Kappa : 0.363
##
##  Mcnemar's Test P-Value : 0.000000000000000369
##
##             Sensitivity : 0.845
##             Specificity : 0.620
##          Pos Pred Value : 0.938
##          Neg Pred Value : 0.372
##              Prevalence : 0.871
##          Detection Rate : 0.736
##    Detection Prevalence : 0.785
##       Balanced Accuracy : 0.733
##
##        'Positive' Class : 0
##
```

Why you don't use in-prediction error - biased -lower error or higher accuracy

```
  glm_Model = glm(FirstDown ~ ., data=NFL_Train_Total_Model_c,
                               family = binomial)
  predict_result <- predict(glm_Model, newdata=NFL_Train_Total_Model_c, type="response")
  predict_logit <- ifelse(predict_result > 0.5, 1, 0)
  t <- table(predict_logit, NFL_Train_Total_Model_c$FirstDown)
  accuracyR = (t[1,1]+t[2,2])/dim(NFL_Train_Total_Model_c)[1] #0.82438
```

#Penalized Logistic Regression #Ridge error in prediction

Lasso

```
lasso_mod= glmnet(x, y, alpha = 1)
```

SVM

have to use parallelSVM since SVM from e1071 would time out.

```
accuracyR <- c()
for (i in 1:10) {
  parallel_svm = parallelSVM(FirstDown ~ ., data=train_fold(i),
                             numberCores=3,
                             kernel="radial", cost = 1, gamma = 0.05)
```

```
  predict_result <- predict(parallel_svm,
                            newdata=test_fold(i), type="response")
  t <- table(predict_result, test_fold(i)$FirstDown)
  accuracyR[i] = (t[1,1]+t[2,2])/dim(test_fold(i))[1]
}
cat("Mean accuracy of 10-fold validation is: ", mean(accuracyR))
```

```
## Mean accuracy of 10-fold validation is:  0.81328
```

```
#print(mean(accuracyR)) #0.81483
confusionMatrix(test_fold(i)$FirstDown, factor(predict_result))
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    0    1
##          0 1250   65
##          1  240  120
##
##                Accuracy : 0.818
##                  95% CI : (0.799, 0.836)
##     No Information Rate : 0.89
##     P-Value [Acc > NIR] : 1
##
##                   Kappa : 0.345
##
##  Mcnemar's Test P-Value : <0.0000000000000002
##
##             Sensitivity : 0.839
##             Specificity : 0.649
##          Pos Pred Value : 0.951
##          Neg Pred Value : 0.333
##              Prevalence : 0.890
##          Detection Rate : 0.746
##    Detection Prevalence : 0.785
##       Balanced Accuracy : 0.744
##
##        'Positive' Class : 0
##
```

Ada

```
accuracyR <- c()
dat <- NULL
for (i in 1:10) {
  ada_fits <- ada(FirstDown ~ ., data = train_fold(i), iter = 50,
                  type="discrete", loss="exponential", nu=1)
  predict_ada <- predict(ada_fits, newdata=test_fold(i))
  t <- table(predict_ada, test_fold(i)$FirstDown)
  accuracyR[i] = (t[1,1]+t[2,2])/dim(test_fold(i))[1]
}
cat("Mean accuracy of 10-fold validation is: ", mean(accuracyR))
```

```
## Mean accuracy of 10-fold validation is:  0.81066
```

```r
#print(mean(accuracyR)) #0.81251
confusionMatrix(test_fold(i)$FirstDown, factor(predict_ada))
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    0    1
##          0 1237   78
##          1  247  113
##
##                Accuracy : 0.806
##                  95% CI : (0.786, 0.825)
##     No Information Rate : 0.886
##     P-Value [Acc > NIR] : 1
##
##                   Kappa : 0.307
##
##  Mcnemar's Test P-Value : <0.0000000000000002
##
##             Sensitivity : 0.834
##             Specificity : 0.592
##          Pos Pred Value : 0.941
##          Neg Pred Value : 0.314
##              Prevalence : 0.886
##          Detection Rate : 0.739
##    Detection Prevalence : 0.785
##       Balanced Accuracy : 0.713
##
##        'Positive' Class : 0
##
```