Predicting Player Rating in FIFA

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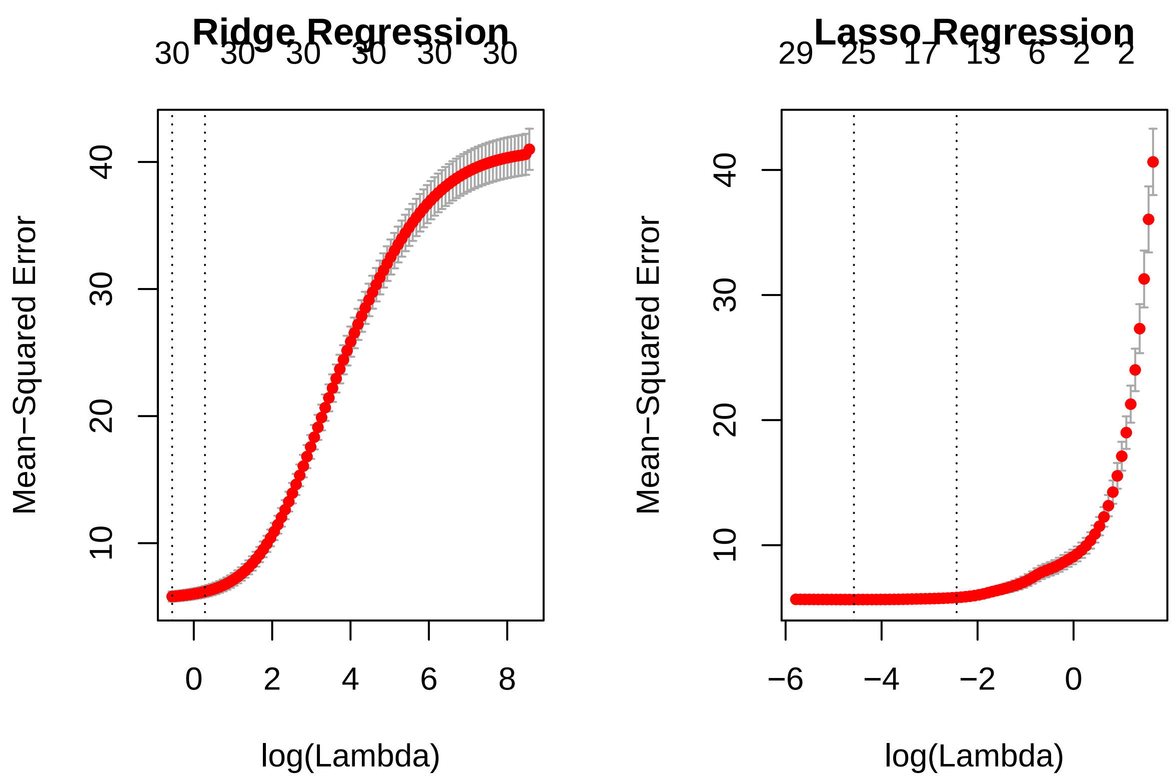
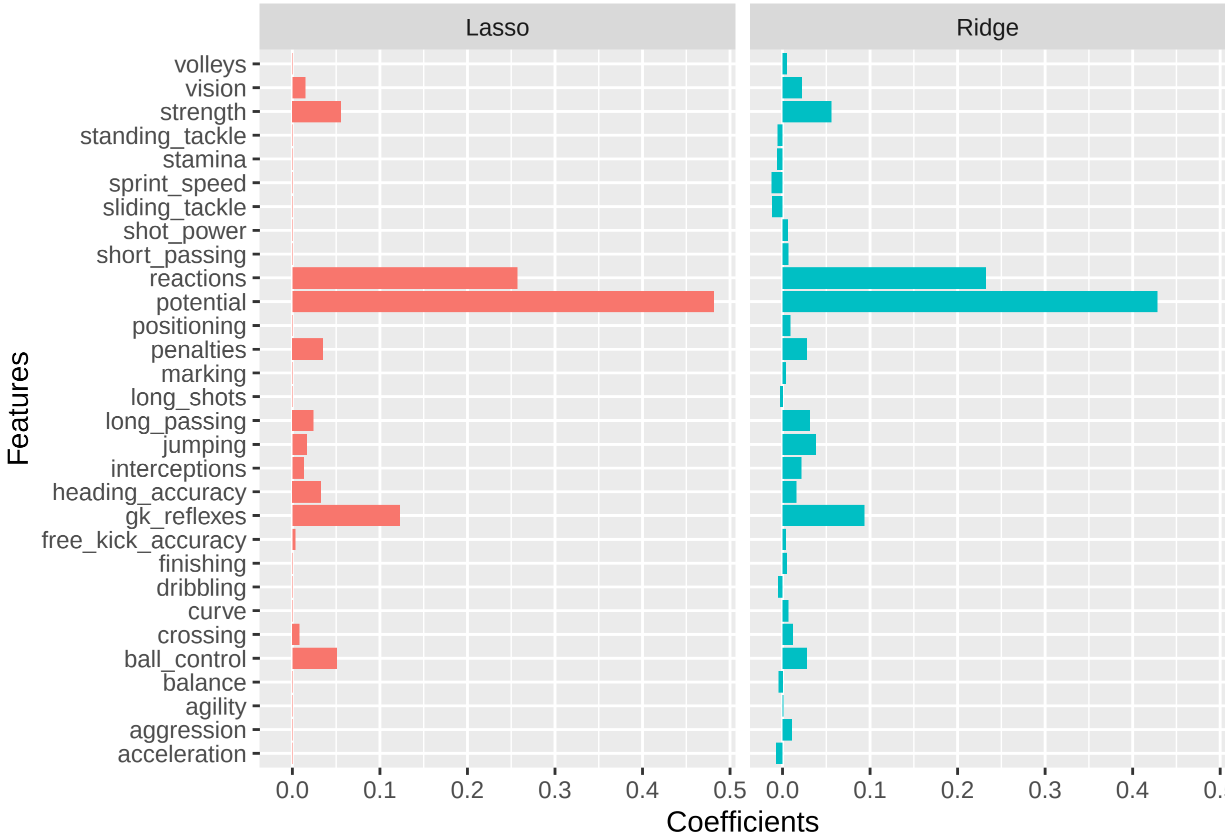



```
##                 MSE      MSPE
## Ridge   23.708457 21.546089
## LASSO    8.787523  8.515476
## RidgeCV  5.990798  5.825613
## LASSOCV  5.604834  5.616913
```



Lasso
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Features
volleys
vision
strength
standing_tackle
stamina
sprint_speed
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Variables

- player_name: The name of the player
- finishing: The accuracy of shots using foot, inside the penalty area
- dribbling: The ability to kepp possesion of the ball.
- ball_control: The ability to keep your ball under your feet with velocity.
- reactions: How quickly a player respinds a situation.
- stamina: Determine the rate at which a player will tire during a game.
- interceptions: The ability to intercepts a pass where the ball is going and stop it from going there.
- marking: The ability to track and defend an opposing player.
- overall_rating: The rating of the player based on all attributes.
- heading_accuracy: The accuracy of he player either a pass or a shot by using head.
- curve: The ability to shoot the ball in a curved shape.
- acceleration: Increase in the rate of speed of a player.
- balance: The ability to maintain balance after a physical challenge.
- strength: The ability to win a physical challenge.
- positioning: The ability to read the game offensively, get into good positions, make effective runs, and avoid getting caught offside.
- standing_tackle:The ability of the player to time standing tackles so that they win the ball rather than give away a foul.
- potential: A peak in overall rating that a player could reach.
- short_passing: The ability to perform a pass in short distance.
- free_kick_accuracy: The accuracy of a direct free kick on goal.(Free kick: an unimpeded kick of the stationary ball awared to one side as a penalty for a foul by the other side)
- sprint_speed: The maximum speed over a short distance of a player.
- shot_power: How hard can the player hits the ball when taking a shot at goal.
- long_shots: The accuracy of shots from outside of the penalty area.
- vision: The player's awareness of the position of his team mates & opponents around him.

- sliding_tackle: The ability of the player to time sliding tackles so that they win the ball rather than give away a foul.
- crossing: The accuracy of the player crosses the ball.
- volleys: The accuracy of a player strike or hit the ball at goal before it touches the ground.
- long_passing: The ability to perform a long pass in the air and on the ground to his teammate.
- agility: The ability of a player to move or turn in game.
- jumping: The vertical distance of a player can jump from the ground.
- aggression: The frequency & aggression of jostling, tackling & slide tackling.
- penalties: The ability to take penalties.
- gk_reflexes: The ability to react a ball in movement at goal by the goal keeper.

R-Code

```
knitr::opts_chunk$set(echo = TRUE)
setwd("/Users/Raymond/Desktop/Raymond Tan/HW/4B/STAT444/soccer-rating-prediction/data")
soccer.raw <- read.table("rating_potential.csv",sep = " ",na.strings = "NA")
library(glmnet)
library(data.table)
library(ggplot2)
library(MASS)
library(rpart)
library(gridExtra)
set.seed(123)
mse <- function(y,yhat) {
  return( mean( (y - yhat)^2 ))
}


soccer <- soccer.raw
soccer$player_name <- NULL
soccer$set <- ifelse(runif(n=nrow(soccer)) > 0.85,yes = 1,no = 2)
#Split data into training set and testing set
soccer.train <- soccer[which(soccer$set == 1),]
soccer.test <- soccer[which(soccer$set ==2),]
soccer.train$set <- NULL
soccer.test$set <- NULL
soccer.train.x <- soccer.train[,2:length(soccer.train)]
soccer.test.x <- soccer.test[,2:length(soccer.test)]

ridge.info <- c()
ridge.cv.info <- c()

lass.info <- c()
lass.cv.nfo <- c()

#Fit ridge model
ridge_model <- glmnet(as.matrix(soccer.train.x),soccer.train$overall_rating,alpha = 0)

#Calculate MSE and MSPE for ridge model
train.pred <- as.matrix(cbind(const=1,soccer.train.x)) %*% coef(ridge_model)
test.pred <- as.matrix(cbind(const=1,soccer.test.x)) %*% coef(ridge_model)
ridge_model.mse <- mse(train.pred,soccer.train$overall_rating)
```

```r
ridge_model.mspe <- mse(test.pred,soccer.test$overall_rating)
ridge.info <- c(ridge_model.mse,ridge_model.mspe)

#Fit Lasso model
lasso_model <- glmnet(as.matrix(soccer.train.x),soccer.train$overall_rating,alpha = 1)
train.pred <- as.matrix(cbind(const=1,soccer.train.x)) %*% coef(lasso_model)
test.pred <- as.matrix(cbind(const=1,soccer.test.x)) %*% coef(lasso_model)
lasso_model.mse <- mse(train.pred,soccer.train$overall_rating)
lasso_model.mspe <- mse(test.pred,soccer.test$overall_rating)
lasso.info <- c(lasso_model.mse,lasso_model.mspe)


#Fit model with cross validation
ridge_model <- cv.glmnet(as.matrix(soccer.train.x),soccer.train$overall_rating,alpha = 0,nfolds = 5)
lasso_model <- cv.glmnet(as.matrix(soccer.train.x),soccer.train$overall_rating,alpha = 1,nfolds = 5)

best_lambda.ridge <- ridge_model$lambda.1se
best_lambda.lasso <- lasso_model$lambda.1se
par(mfrow=c(1,2))
plot(ridge_model,main = "Ridge Regression")
plot(lasso_model,main = "Lasso Regression")
ridge_coeff <- ridge_model$glmnet.fit$beta[,ridge_model$glmnet.fit$lambda == best_lambda.ridge]
lasso_coeff <- lasso_model$glmnet.fit$beta[,lasso_model$glmnet.fit$lambda == best_lambda.lasso]

train.pred <- predict(ridge_model,as.matrix(soccer.train.x),s = "lambda.1se")
test.pred <- predict(ridge_model,as.matrix(soccer.test.x),s = "lambda.1se")
ridge_model.cv.mse <- mse(train.pred,soccer.train$overall_rating)
ridge_model.cv.mspe <- mse(test.pred,soccer.test$overall_rating)
ridge.cv.info <- c(ridge_model.cv.mse,ridge_model.cv.mspe)

train.pred <- predict(lasso_model,as.matrix(soccer.train.x),s = "lambda.1se")
test.pred <- predict(lasso_model,as.matrix(soccer.test.x),s = "lambda.1se")
lasso.cv.mse <- mse(train.pred,soccer.train$overall_rating)
lasso.cv.mspe <- mse(test.pred,soccer.test$overall_rating)
lasso.cv.info <- c(lasso.cv.mse,lasso.cv.mspe)

err <- as.table(rbind(ridge.info,lasso.info,ridge.cv.info,lasso.cv.info))
colnames(err) <- c("MSE","MSPE")
rownames(err) <- c("Ridge","LASSO","RidgeCV","LASSOCV")


err
#Compare Coefficients:
coeff <- data.table(Lasso = lasso_coeff,Ridge = ridge_coeff)
coeff[,Features :=names(ridge_coeff)]
to_plot <- melt(data = coeff,id.vars = 'Features',variable.name = 'Model',value.name = 'Coefficients')
 ggplot(to_plot,aes(x=Features,y=Coefficients,fill=Model)) + coord_flip() + geom_bar(stat = 'identity')
```