Predicting Atlanta Falcons NFL Receiver Touchdowns with Regression Modelling

Bhargav Ashok

2025-05-04

Installing packages

Loading our Atlanta Falcons Data

```
Atlanta_Falcons_data <- read_excel("Atlanta_Falcons_data.xlsx")
head(Atlanta_Falcons_data)
```

```
## # A tibble: 6 x 18
##      Rk Player      From    To     G Pos      AV   Tgt   Rec `Ctch%`   Yds `Y/R`
##   <dbl> <chr>      <dbl> <dbl> <dbl> <chr> <dbl> <dbl> <dbl>   <dbl> <dbl> <dbl>
## 1     1 Julio Jon~  2011  2020   135 WR      119  1320   848   0.642 12896  15.2
## 2     2 Roddy Whi~  2005  2015   171 WR      107  1377   808   0.587 10863  13.4
## 3     3 Terance M~  1994  2001   126 WR       67   989   573   0.579  7349  12.8
## 4     4 Alfred Je~  1975  1983   110 WR       61    NA   360  NA      6267  17.4
## 5     5 Andre Ris~  1990  1994    78 WR       53   463   423  NA      5633  13.3
## 6     6 Jim Mitch~  1969  1979   155 TE       47    NA   305  NA      4358  14.3
## # i 6 more variables: TD <dbl>, Lng <dbl>, `Y/Tgt` <dbl>, `R/G` <dbl>,
## #   `Y/G` <dbl>, Fmb <dbl>
```

Preparing our data, cleaning and training

Here, we are cleaning our data with the tidyr package and then splitting our data into a trained and tested set.

```
vars_needed <- c("TD", "Tgt", "Rec", "Ctch%", "Yds")
clean_df    <- Atlanta_Falcons_data %>% drop_na(all_of(vars_needed))

set.seed(123)
n       <- nrow(clean_df)
train_i <- sample(n, 0.8*n)
train_df <- clean_df[ train_i, ]
test_df  <- clean_df[-train_i, ]
```

fiting our Model (regular MLR)

Next, we fit our model using the equation: Y = (beta)0 + (beta)1X1 + (Beta)2X2 + … + (Beta)nXn + error (assuming normal distribution)

```r
mlr_fit <- lm(TD ~ Tgt + Rec + `Ctch%` + Yds, data = train_df)
summary(mlr_fit)
```

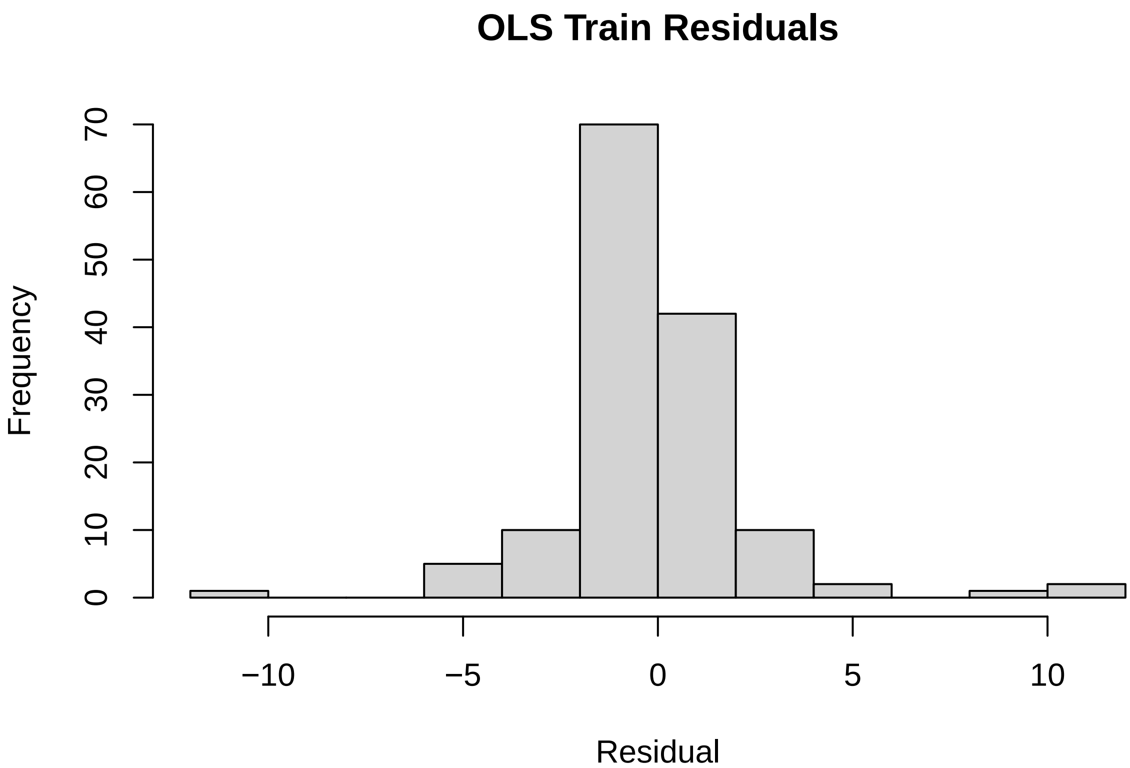
```
##
## Call:
## lm(formula = TD ~ Tgt + Rec + `Ctch%` + Yds, data = train_df)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -10.4458  -0.7242  -0.1969   0.7605  10.6716
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept) -0.3606742  0.7621684  -0.473   0.6368
## Tgt          0.0312459  0.0135714   2.302   0.0228 *
## Rec         -0.0044023  0.0176458  -0.249   0.8034
## `Ctch%`      0.5479172  1.0636249   0.515   0.6073
## Yds          0.0020808  0.0008571   2.428   0.0165 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.423 on 138 degrees of freedom
## Multiple R-squared:  0.9028, Adjusted R-squared:  0.8999
## F-statistic: 320.3 on 4 and 138 DF,  p-value: < 2.2e-16
```

The summary statistics are displayed above. Note the coefficients for the MLR equation and the adjusted R-squared Value.

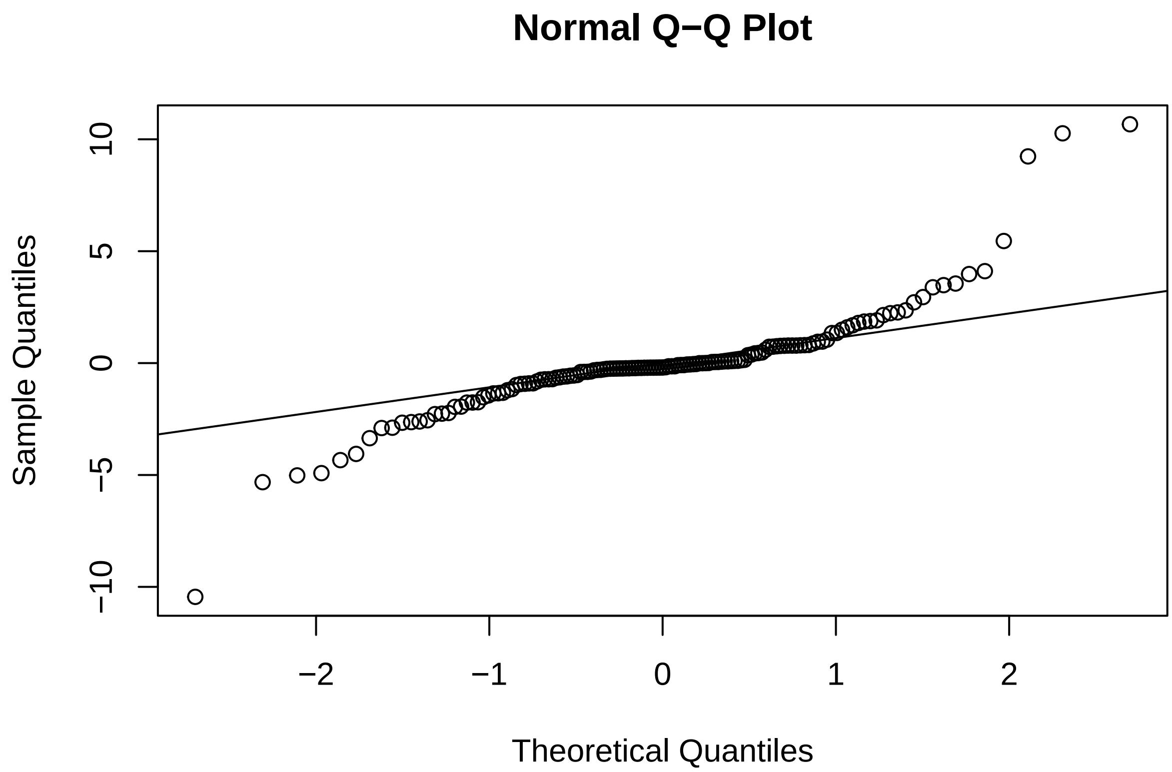
MLR fit data display (looking at model data)

Then, we display plots for our fitted data

```r
hist(resid(mlr_fit), main="OLS Train Residuals", xlab="Residual")
```




```r
qqnorm(resid(mlr_fit)); qqline(resid(mlr_fit))
```



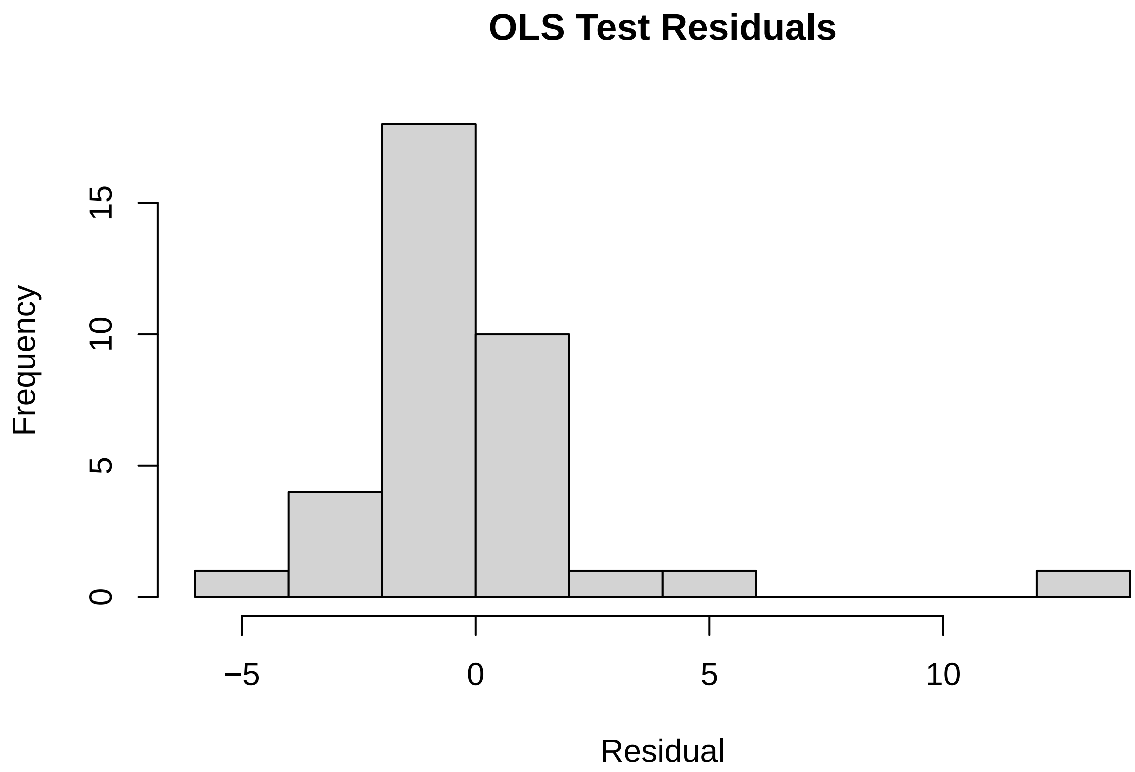

```r
vif(mlr_fit)
```

```
##        Tgt        Rec    `Ctch%`        Yds
## 110.938423  76.817866   1.126715  32.696953
```

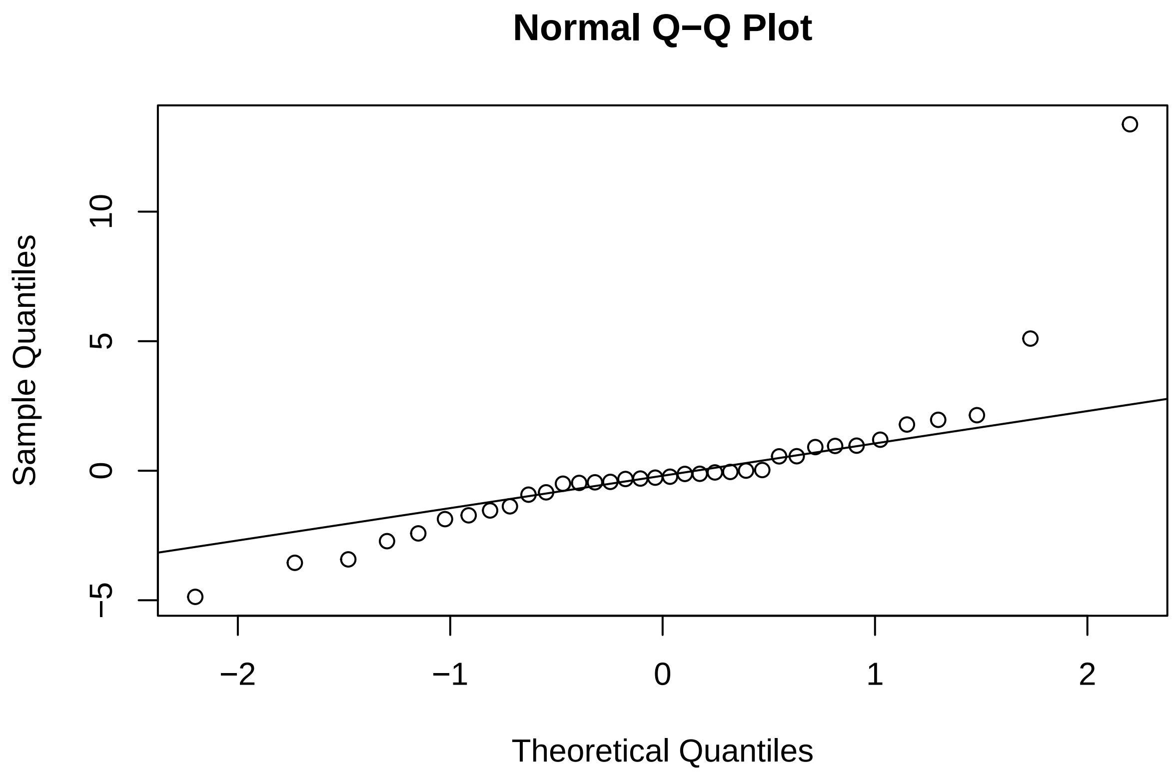
test data display (looking at unseen test data)

After that, we look at our unseen test data plots

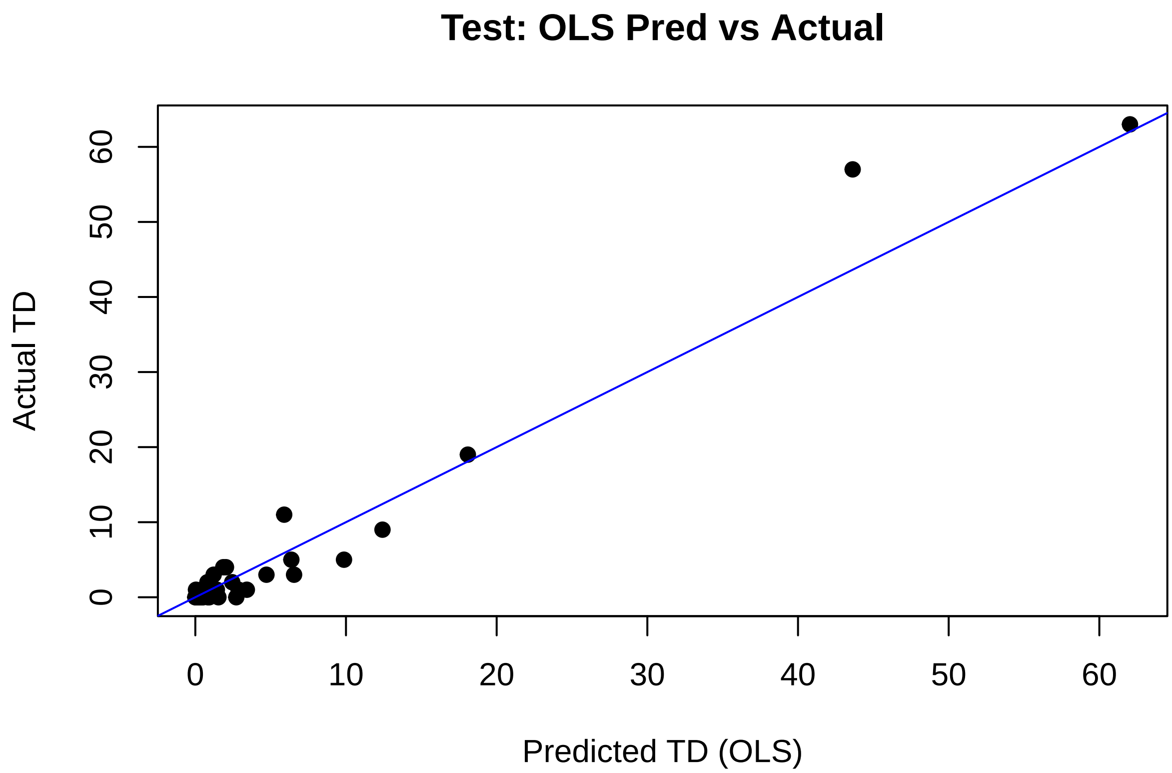
```r
test_df$pred_ols  <- predict(mlr_fit, newdata = test_df)
resid_test_ols    <- test_df$TD - test_df$pred_ols

# Plots
hist(resid_test_ols, main="OLS Test Residuals", xlab="Residual")
```




```
qqnorm(resid_test_ols); qqline(resid_test_ols)
```




```r
plot(
  test_df$pred_ols, test_df$TD,
  xlab="Predicted TD (OLS)", ylab="Actual TD",
  main="Test: OLS Pred vs Actual", pch=19
)
abline(0,1,col="blue")
```



We see the linear regression line on our predicted test data above.

Using Cross validation + Ridge/Lasso Regression

After looking at our model and our VIF (Variance Inflation Factor, which shows how standardized our data is in terms of multicollinearity), we see that the VIF > 10, which indicates high multicollinearity. This is not ideal for this scenario because the variables need to be standardized to account for the number inflation in multicollinearity. Due to this, we need to switch to a new type of regression model for even more accurate results. We use a technique called K-folds cross validation, where the data is split into multiple subsets and is iterated more than once in order to account for the multicollinearity inflation which is indicated above, as well improving the model to see how accurately it can predict unseen data points. We use the glmnet package for this.

```
# Prepare matrices
x_train <- model.matrix(TD~Tgt+Rec+`Ctch%`+Yds, train_df)[,-1]
y_train <- train_df$TD
x_test  <- model.matrix(TD~Tgt+Rec+`Ctch%`+Yds, test_df)[,-1]
y_test  <- test_df$TD

# Ridge
cv_ridge  <- cv.glmnet(x_train,y_train,alpha=0)
best_ridge<- cv_ridge$lambda.min
ridge_mod <- glmnet(x_train,y_train,alpha=0,lambda=best_ridge)
test_df$pred_ridge <- as.numeric(predict(ridge_mod,x_test))

# Lasso
```

```r
cv_lasso  <- cv.glmnet(x_train,y_train,alpha=1)
best_lasso<- cv_lasso$lambda.min
lasso_mod <- glmnet(x_train,y_train,alpha=1,lambda=best_lasso)
test_df$pred_lasso <- as.numeric(predict(lasso_mod,x_test))

# RMSE
cat("Ridge RMSE:",  rmse(y_test, test_df$pred_ridge), "\n")
```

```
## Ridge RMSE: 3.52247
```

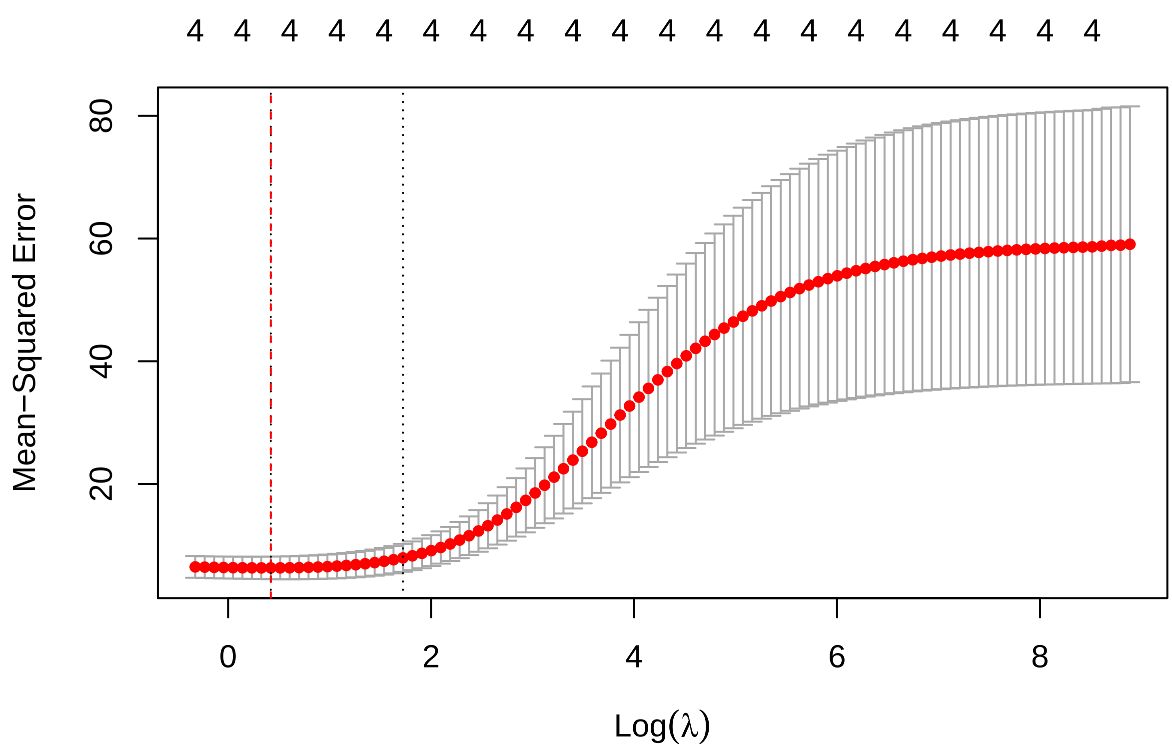
```r
cat("Lasso RMSE:",  rmse(y_test, test_df$pred_lasso), "\n")
```

```
## Lasso RMSE: 3.975591
```

We do a Cross Validation of Ride and lasso regression to see which one is more accurate. As we can see, Ridge regression has a lower RMSE which is more accurate for our model, so we will plot the Cross validation curve.

Plotting Ridge regression

```r
plot(cv_ridge)
abline(v=log(best_ridge),col="red",lty=2)
```

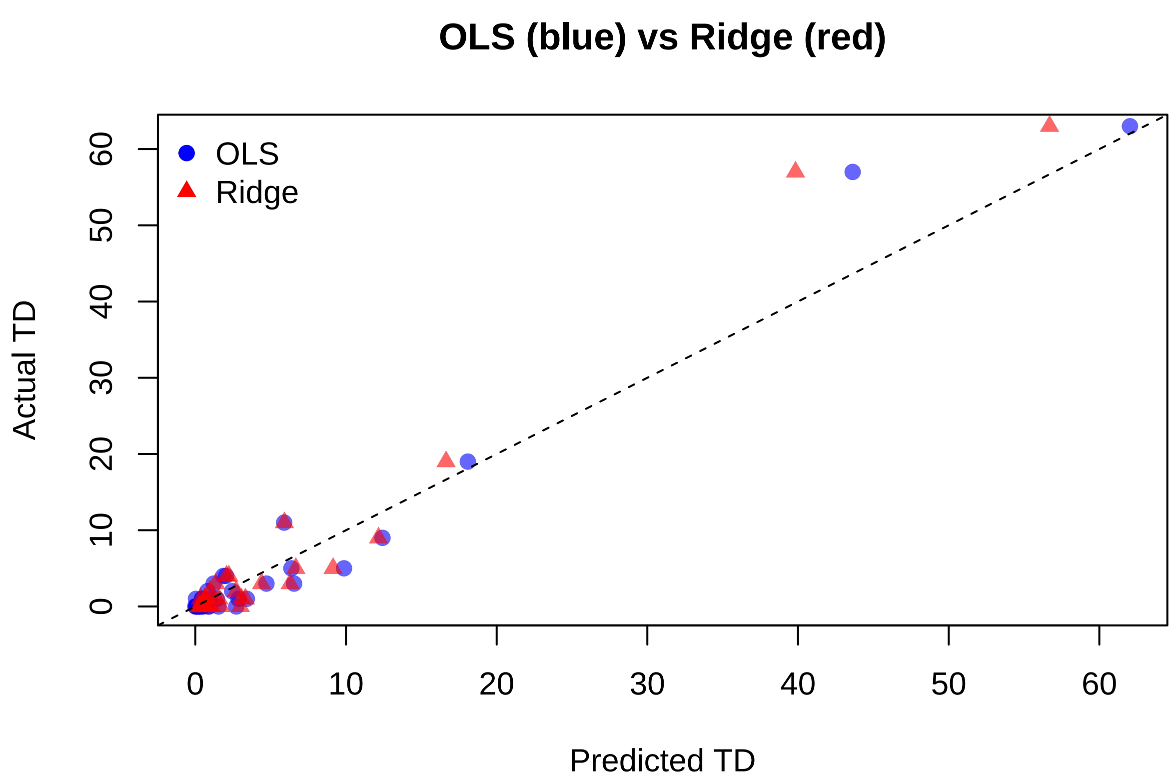


The cross validation ridge plot is shown above. According to "https://bookdown.org/ssjackson300/Machine-Learning-Lecture-Notes/choosing-lambda.html":

"What is plotted is the estimated CV MSE for each value of (log)
lambda on the x-axis. The dotted line on the far left indicates the value of
lambda which minimizes CV error. The dotted line roughly in the middle of the
x-axis indicates the 1-standard-error lambda- recall that this is the maximum value that
lambda can take while still falling within the on standard error interval of the minimum-CV lambda. The second line of code has manually added a dot-dash horizontal line at the upper end of the 1-standard deviation interval of the MSE at the minimum-CV lambda to illustrate this point further". These plots can change with randomization according to our seed number.

Plotting our Comparison graph between MLR and Ridge Regression MLR

```r
plot(test_df$pred_ols, test_df$TD,
     xlim = range(c(test_df$pred_ols,test_df$pred_ridge)),
     ylim = range(c(test_df$pred_ols,test_df$pred_ridge)),
     xlab="Predicted TD", ylab="Actual TD",
     main="OLS (blue) vs Ridge (red)", pch=19, col=rgb(0,0,1,0.6))
points(test_df$pred_ridge, test_df$TD, pch=17, col=rgb(1,0,0,0.6))
abline(0,1,lty=2)
legend("topleft", legend=c("OLS","Ridge"), pch=c(19,17),
       col=c("blue","red"), bty="n")
```



Finally, we can compare our MLR Ordinary Least Squares Regression (Linear Regression) Model with our Cross-Validated, Ridge Regression Model visually.