Fantasy Football Team

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9/21/2016

Player analysis and selection for the week of 09.19.2016

QB Analysis - Pull Player Data

QB Analysis

Cam Newton - Summary Passing Data

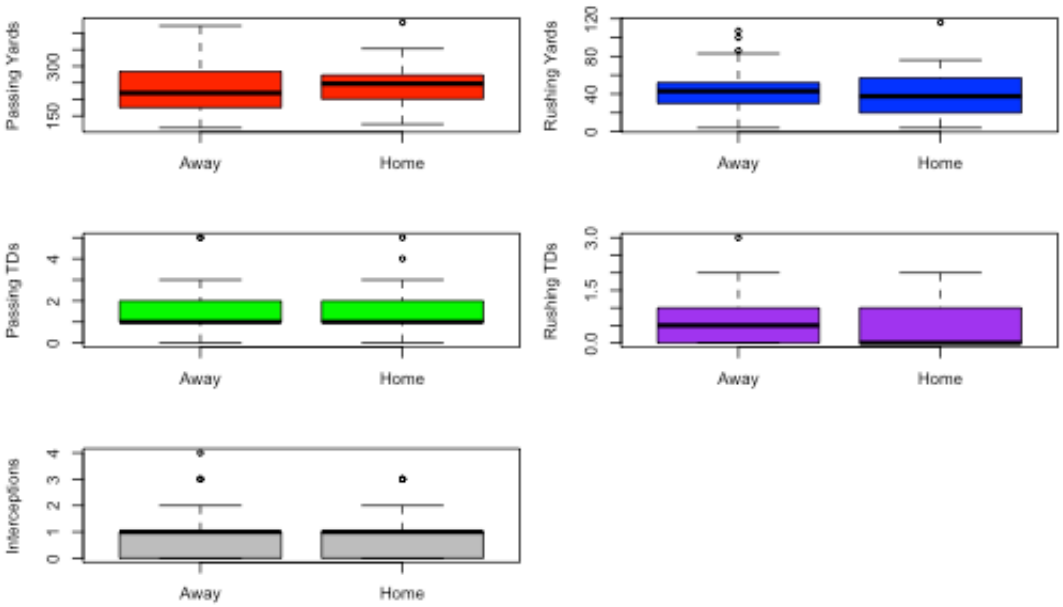
Newton Yards Summary

```
##  Location       Opp      Def.Rank.Yds      PassYds          PassTD
##  Away:42   ATL    :11   Min.   : 1.00   Min.   :114.0   Min.   :0.000
##  Home:42   NOR    :11   1st Qu.:10.00   1st Qu.:194.0   1st Qu.:1.000
##            TAM    : 8   Median :18.00   Median :231.5   Median :1.000
##            MIN    : 4   Mean   :18.63   Mean   :235.4   Mean   :1.488
##            SEA    : 4   3rd Qu.:28.00   3rd Qu.:277.0   3rd Qu.:2.000
##            ARI    : 3   Max.   :32.00   Max.   :432.0   Max.   :5.000
##            (Other):43
##       Int            RushYds           RushTD
##  Min.   :0.0000   Min.   :  4.00   Min.   :0.0000
##  1st Qu.:0.0000   1st Qu.: 23.75   1st Qu.:0.0000
##  Median :1.0000   Median : 39.00   Median :0.0000
##  Mean   :0.8333   Mean   : 40.67   Mean   :0.5476
##  3rd Qu.:1.0000   3rd Qu.: 53.25   3rd Qu.:1.0000
##  Max.   :4.0000   Max.   :116.00   Max.   :3.0000
##
```

Exploratory data analysis

Location analysis

```
par(mfrow = c(5,2), mar = c(4,4,1,1))
plot(CNdf$Location, CNdf$PassYds, ylab = "Passing Yards", col = "red")
plot(CNdf$Location, CNdf$RushYds, ylab = "Rushing Yards", col = "blue")
plot(CNdf$Location, CNdf$PassTD, ylab = "Passing TDs", col = "green")
plot(CNdf$Location, CNdf$RushTD, ylab = "Rushing TDs", col = "purple")
plot(CNdf$Location, CNdf$Int, ylab = "Interceptions", col = "grey")
```

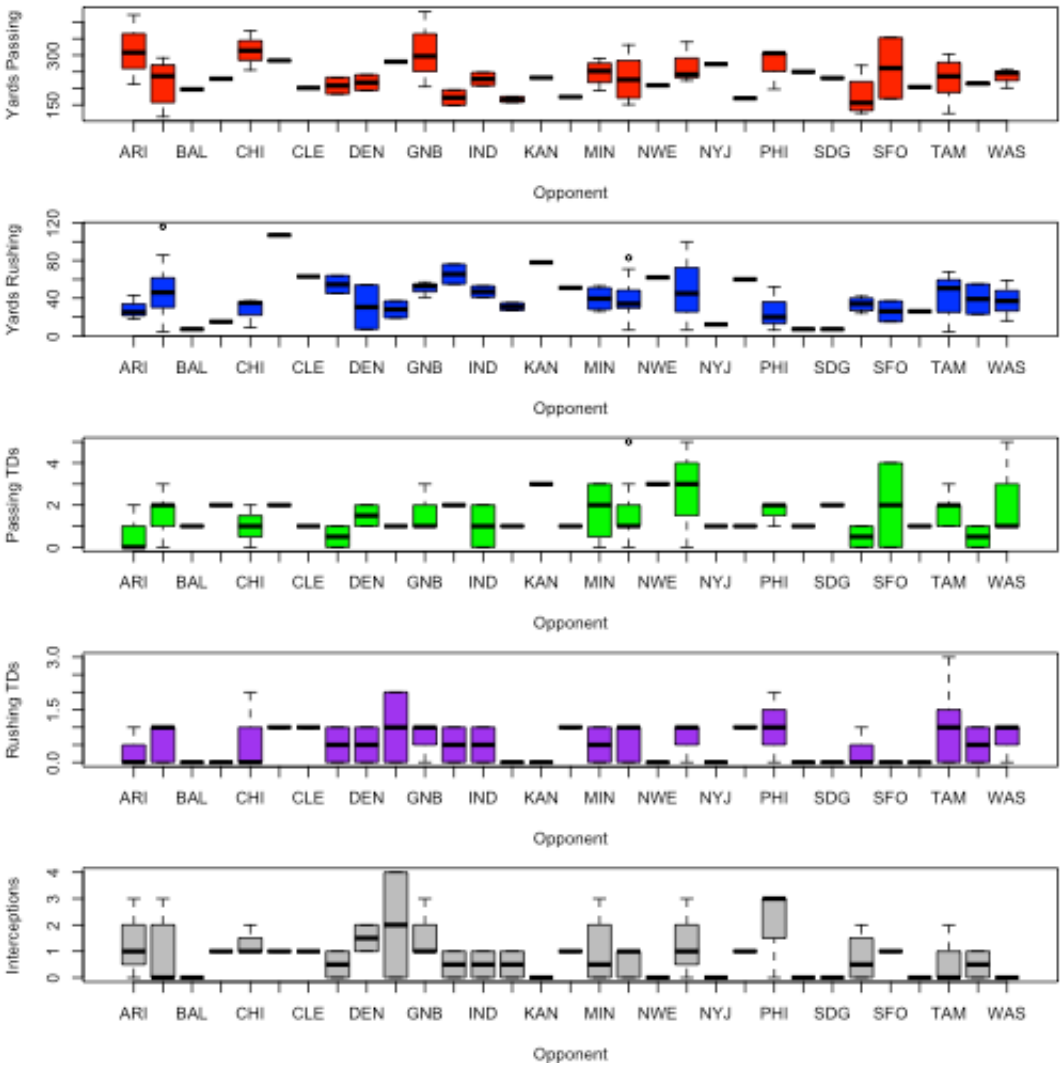


plot of chunk unnamed-chunk-63

Opponent Analysis

Opponent vs. Pass Yards

```
par(mfrow = c(5,1), mar = c(4,4,1,1))
plot(CNdf$Opp, CNdf$PassYds, ylab = "Yards Passing", xlab = "Opponent", col = "red")
plot(CNdf$Opp, CNdf$RushYds, ylab = "Yards Rushing", xlab = "Opponent", col = "blue")
plot(CNdf$Opp, CNdf$PassTD, ylab = "Passing TDs", xlab = "Opponent", col = "green")
plot(CNdf$Opp, CNdf$RushTD, ylab = "Rushing TDs", xlab = "Opponent", col = "purple")
plot(CNdf$Opp, CNdf$Int, ylab = "Interceptions", xlab = "Opponent", col = "grey")
```

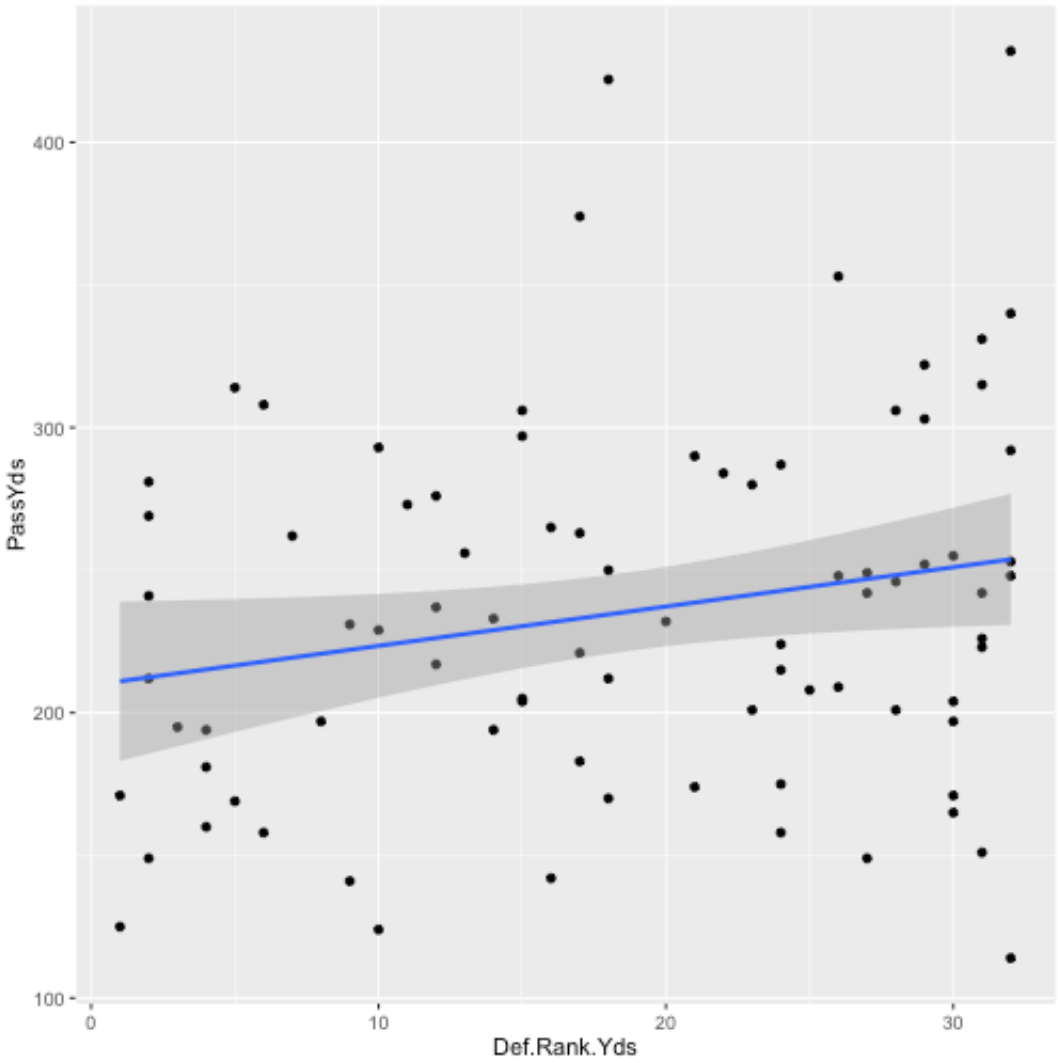


plot of chunk unnamed-chunk-64

Defensive Ranking Analysis

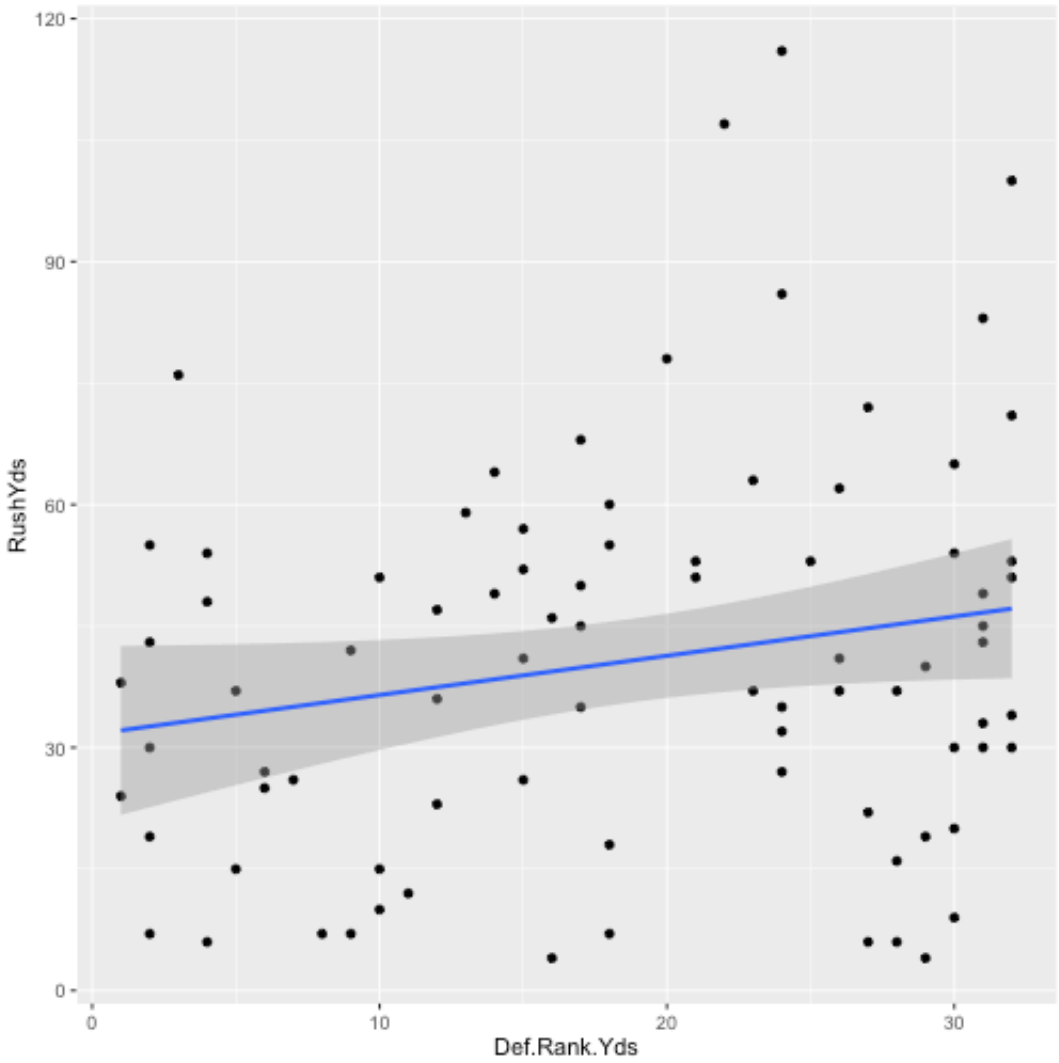
Defense rank vs. Pass Yards

```
library(ggplot2)
par(mfrow = c(5,2), mar = c(4,4,1,1))
qplot(Def.Rank.Yds,PassYds, data = CNdf) + geom_smooth(method = "lm")
```



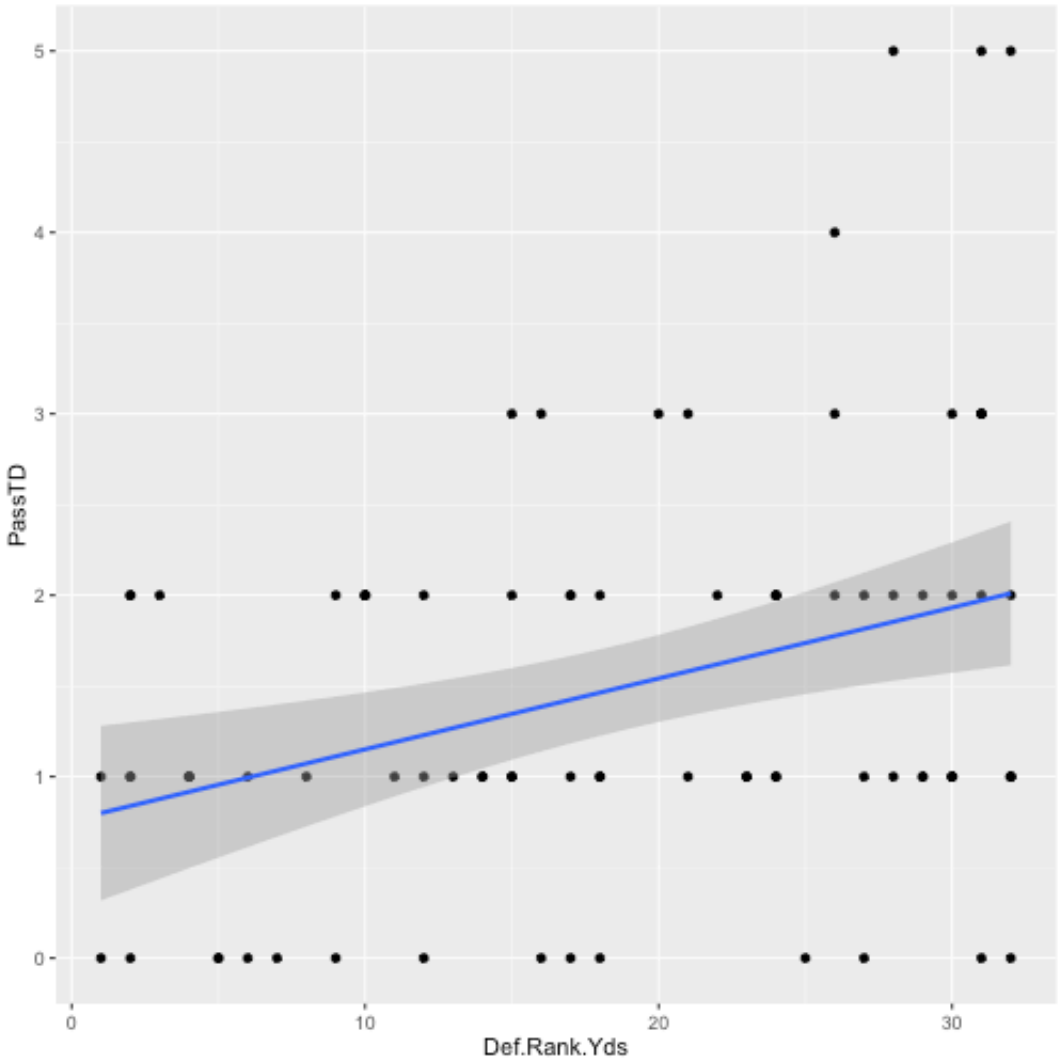
plot of chunk unnamed-chunk-65

```
qplot(Def.Rank.Yds, RushYds, data = CNdf) + geom_smooth(method = "lm")
```



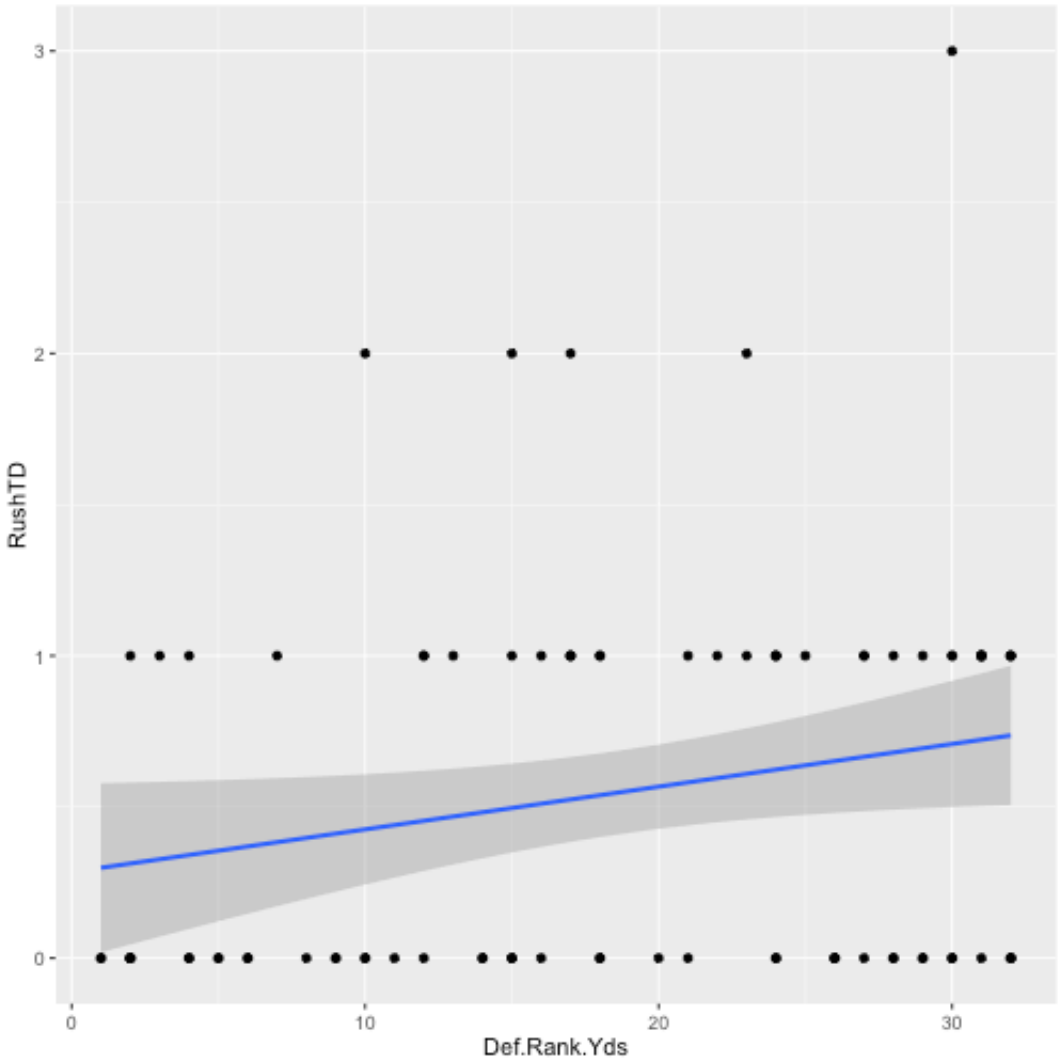
plot of chunk unnamed-chunk-65

```
qplot(Def.Rank.Yds, PassTD, data = CNdf) + geom_smooth(method = "lm")
```



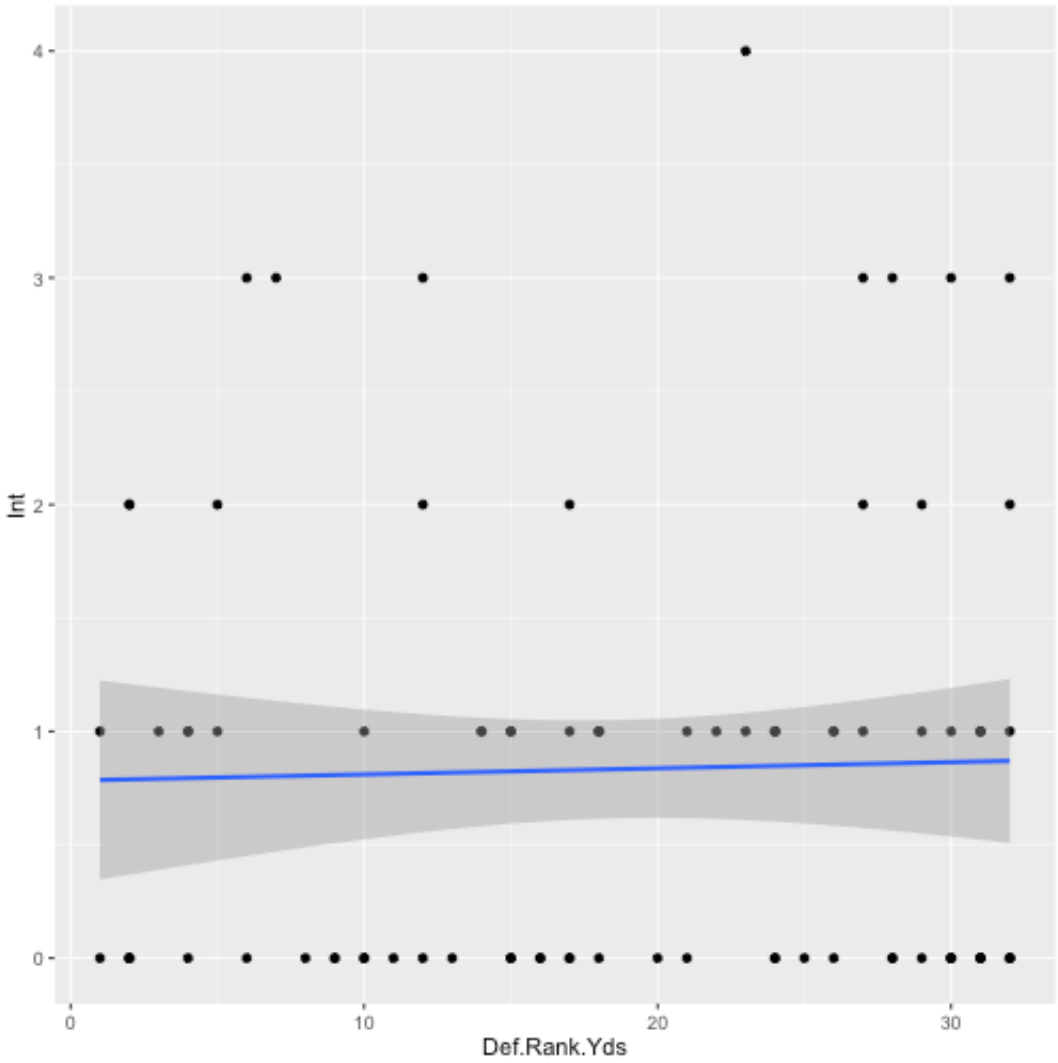
plot of chunk unnamed-chunk-65

```
qplot(Def.Rank.Yds, RushTD, data = CNdf) + geom_smooth(method = "lm")
```



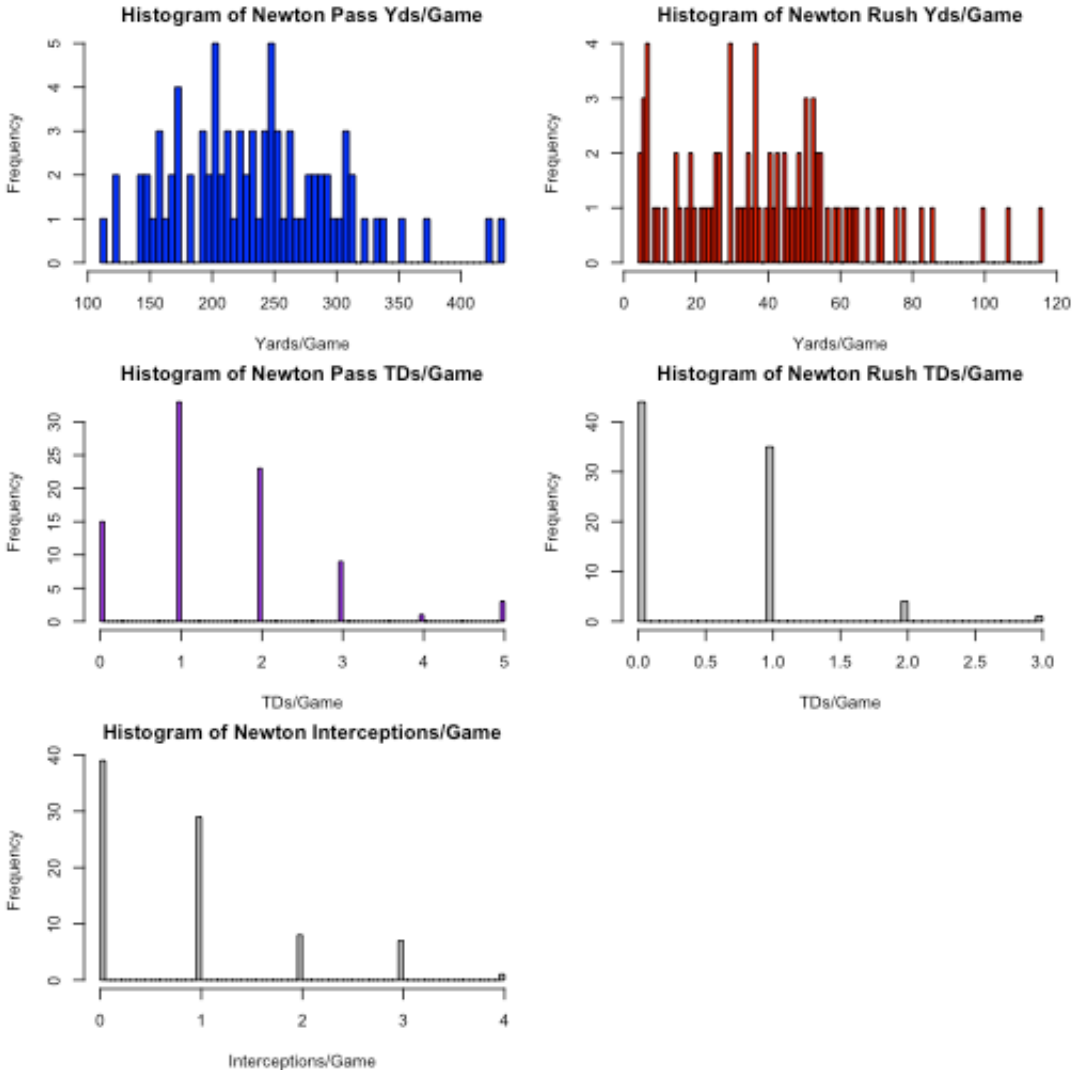
plot of chunk unnamed-chunk-65

```
qplot(Def.Rank.Yds, Int, data = CNdf) + geom_smooth(method = "lm")
```



plot of chunk unnamed-chunk-65

Newton Yards LSE



Linear model fitting

Model fitting vs. Location

Pass Yds vs. Location

```
##                Estimate Std. Error    t value     Pr(>|t|)
## (Intercept)  231.476190   10.01434 23.1144679 1.146648e-37
## LocationHome   7.785714   14.16242  0.5497447 5.839887e-01
```

Prediction interval using a linear model

```
##        fit      lwr      upr
## 1 231.4762 100.8408 362.1116
## 2 231.4762 100.8408 362.1116
## 3 231.4762 100.8408 362.1116
## 4 231.4762 100.8408 362.1116
## 5 231.4762 100.8408 362.1116
## 6 231.4762 100.8408 362.1116
```

Rush Yds. vs. Location

```
CNfitRushYdsLoc<- lm(RushYds ~ Location, data = CNdf)
summary(CNfitRushYdsLoc)$coefficients
```

```
##                Estimate Std. Error    t value     Pr(>|t|)
## (Intercept)  42.809524   3.719746 11.5087210 8.455620e-19
## LocationHome -4.285714   5.260516 -0.8146947 4.176069e-01
```

Prediction interval using a linear model

```
##        fit       lwr    upr
## 1 42.80952 -5.713951 91.333
## 2 42.80952 -5.713951 91.333
## 3 42.80952 -5.713951 91.333
## 4 42.80952 -5.713951 91.333
## 5 42.80952 -5.713951 91.333
## 6 42.80952 -5.713951 91.333
```

Pass TDs. vs. Location

```
##                Estimate Std. Error   t value     Pr(>|t|)
## (Intercept)  1.4285714  0.1792766 7.9685335 8.064972e-12
## LocationHome 0.1190476  0.2535354 0.4695503 6.399225e-01
```

Prediction interval using a linear model

```
##        fit        lwr      upr
## 1 1.428571 -0.9100618 3.767205
## 2 1.428571 -0.9100618 3.767205
## 3 1.428571 -0.9100618 3.767205
## 4 1.428571 -0.9100618 3.767205
## 5 1.428571 -0.9100618 3.767205
## 6 1.428571 -0.9100618 3.767205
```

Rush TDs vs. Location

```
##                Estimate Std. Error  t value     Pr(>|t|)
## (Intercept)   0.6190476 0.09991424  6.19579 2.207786e-08
## LocationHome -0.1428571 0.14130007 -1.01102 3.149811e-01
```

Prediction interval using a linear model

```
##         fit       lwr      upr
## 1 0.6190476 -0.684317 1.922412
## 2 0.6190476 -0.684317 1.922412
## 3 0.6190476 -0.684317 1.922412
## 4 0.6190476 -0.684317 1.922412
## 5 0.6190476 -0.684317 1.922412
## 6 0.6190476 -0.684317 1.922412
```

Model fitting vs. opponent

Pass Yards vs. opponent data

```
CNfitPassYds<- lm(PassYds ~ Opp, data = CNdf)
summary(CNfitPassYds)$coefficients
```

```
##                 Estimate Std. Error      t value     Pr(>|t|)
## (Intercept)  314.0000000   37.57596  8.356406770 3.029459e-11
## OppATL       -96.6363636   42.39140 -2.279621941 2.668241e-02
## OppBAL      -117.0000000   75.15192 -1.556846484 1.254588e-01
## OppBUF       -85.0000000   75.15192 -1.131042318 2.631294e-01
## OppCHI         0.3333333   53.14043  0.006272688 9.950187e-01
## OppCIN       -30.0000000   75.15192 -0.399191406 6.913562e-01
## OppCLE      -113.0000000   75.15192 -1.503620963 1.386149e-01
## OppDAL      -106.0000000   59.41281 -1.784127080 8.012798e-02
## OppDEN       -96.5000000   59.41281 -1.624228898 1.102602e-01
## OppDET       -33.5000000   59.41281 -0.563851483 5.752335e-01
## OppGNB        -2.6666667   53.14043 -0.050181502 9.601664e-01
## OppHOU      -142.0000000   59.41281 -2.390057032 2.043314e-02
## OppIND       -86.0000000   59.41281 -1.447499329 1.536467e-01
## OppJAX      -147.5000000   59.41281 -2.482629663 1.624279e-02
## OppKAN       -82.0000000   75.15192 -1.091123177 2.801543e-01
## OppMIA      -140.0000000   75.15192 -1.862893229 6.802323e-02
## OppMIN       -67.0000000   49.70832 -1.347862847 1.834357e-01
## OppNOR       -80.4545455   42.39140 -1.897897853 6.316179e-02
## OppNWE      -105.0000000   75.15192 -1.397169922 1.681848e-01
## OppNYG       -45.6666667   53.14043 -0.859358227 3.940132e-01
## OppNYJ       -41.0000000   75.15192 -0.545561589 5.876562e-01
## OppOAK      -144.0000000   75.15192 -1.916118750 6.075031e-02
## OppPHI       -44.3333333   53.14043 -0.834267475 4.078749e-01
## OppPIT       -64.0000000   75.15192 -0.851608333 3.982631e-01
## OppSDG       -83.0000000   75.15192 -1.104429557 2.743958e-01
## OppSEA      -137.5000000   49.70832 -2.766136441 7.791241e-03
## OppSFO       -53.0000000   59.41281 -0.892063540 3.763912e-01
## OppSTL      -110.0000000   75.15192 -1.463701823 1.491815e-01
## OppTAM       -85.1250000   44.06172 -1.931949189 5.871932e-02
## OppTEN       -99.5000000   59.41281 -1.674723061 9.988019e-02
## OppWAS       -79.6666667   53.14043 -1.499172381 1.397623e-01
```

Prediction interval using a linear model

```
##   fit      lwr      upr
## 1 204 19.38727 388.6127
## 2 204 19.38727 388.6127
## 3 204 19.38727 388.6127
## 4 204 19.38727 388.6127
## 5 204 19.38727 388.6127
## 6 204 19.38727 388.6127
```

Rush Yards vs. opponent data

```
CNfitRushYds<- lm(RushYds ~ Opp, data = CNdf)
summary(CNfitRushYds)$coefficients
```

```
##                Estimate Std. Error     t value    Pr(>|t|)
## (Intercept)  28.6666667   13.64632  2.10068854 0.040441916
## OppATL       20.4242424   15.39512  1.32666952 0.190306056
## OppBAL      -21.6666667   27.29264 -0.79386486 0.430814227
## OppBUF      -13.6666667   27.29264 -0.50074552 0.618623480
## OppCHI       -1.6666667   19.29881 -0.08636111 0.931504803
## OppCIN       78.3333333   27.29264  2.87012679 0.005882711
## OppCLE       34.3333333   27.29264  1.25797046 0.213916617
## OppDAL       25.8333333   21.57673  1.19727775 0.236525971
## OppDEN        1.8333333   21.57673  0.08496810 0.932606909
## OppDET       -0.6666667   21.57673 -0.03089749 0.975467352
## OppGNB       21.6666667   19.29881  1.12269445 0.266627522
## OppHOU       36.8333333   21.57673  1.70708635 0.093658926
## OppIND       18.3333333   21.57673  0.84968099 0.399324437
## OppJAX        2.3333333   21.57673  0.10814122 0.914292038
## OppKAN       49.3333333   27.29264  1.80756921 0.076350104
## OppMIA       22.3333333   27.29264  0.81829147 0.416854747
## OppMIN       10.8333333   18.05238  0.60010542 0.550993345
## OppNOR       11.7878788   15.39512  0.76568908 0.447257940
## OppNWE       33.3333333   27.29264  1.22133055 0.227365995
## OppNYG       21.6666667   19.29881  1.12269445 0.266627522
## OppNYJ      -16.6666667   27.29264 -0.61066527 0.544031201
## OppOAK       31.3333333   27.29264  1.14805071 0.256103198
## OppPHI       -2.6666667   19.29881 -0.13817778 0.890623575
## OppPIT      -21.6666667   27.29264 -0.79386486 0.430814227
## OppSDG      -21.6666667   27.29264 -0.79386486 0.430814227
## OppSEA        4.8333333   18.05238  0.26773934 0.789939195
## OppSFO       -2.6666667   21.57673 -0.12358996 0.902107454
## OppSTL       -2.6666667   27.29264 -0.09770644 0.922533973
## OppTAM       14.0833333   16.00173  0.88011329 0.382771364
## OppTEN       10.3333333   21.57673  0.47891110 0.633971877
## OppWAS        8.6666667   19.29881  0.44907778 0.655206533
```

Prediction interval using a linear model

```
##   fit       lwr      upr
## 1  26 -41.04511 93.04511
## 2  26 -41.04511 93.04511
## 3  26 -41.04511 93.04511
## 4  26 -41.04511 93.04511
## 5  26 -41.04511 93.04511
## 6  26 -41.04511 93.04511
```

Pass TDs vs. opponent data

```
CNfitPassTD<- lm(PassTD ~ Opp, data = CNdf)
summary(CNfitPassTD)$coefficients
```

```
##               Estimate Std. Error    t value   Pr(>|t|)
## (Intercept)  0.6666667  0.7240525  0.9207436 0.36135643
## OppATL       0.7878788  0.8168413  0.9645432 0.33915419
## OppBAL       0.3333333  1.4481049  0.2301859 0.81883347
## OppBUF       1.3333333  1.4481049  0.9207436 0.36135643
## OppCHI       0.3333333  1.0239648  0.3255320 0.74606017
## OppCIN       1.3333333  1.4481049  0.9207436 0.36135643
## OppCLE       0.3333333  1.4481049  0.2301859 0.81883347
## OppDAL      -0.1666667  1.1448274 -0.1455823 0.88480338
## OppDEN       0.8333333  1.1448274  0.7279117 0.46987138
## OppDET       0.3333333  1.1448274  0.2911647 0.77206183
## OppGNB       1.0000000  1.0239648  0.9765961 0.33320583
## OppHOU       1.3333333  1.1448274  1.1646588 0.24937274
## OppIND       0.3333333  1.1448274  0.2911647 0.77206183
## OppJAX       0.3333333  1.1448274  0.2911647 0.77206183
## OppKAN       2.3333333  1.4481049  1.6113013 0.11305415
## OppMIA       0.3333333  1.4481049  0.2301859 0.81883347
## OppMIN       1.0833333  0.9578314  1.1310272 0.26313568
## OppNOR       0.9696970  0.8168413  1.1871301 0.24046994
## OppNWE       2.3333333  1.4481049  1.6113013 0.11305415
## OppNYG       2.0000000  1.0239648  1.9531921 0.05608525
## OppNYJ       0.3333333  1.4481049  0.2301859 0.81883347
## OppOAK       0.3333333  1.4481049  0.2301859 0.81883347
## OppPHI       1.0000000  1.0239648  0.9765961 0.33320583
## OppPIT       0.3333333  1.4481049  0.2301859 0.81883347
## OppSDG       1.3333333  1.4481049  0.9207436 0.36135643
## OppSEA      -0.1666667  0.9578314 -0.1740042 0.86252511
## OppSFO       1.3333333  1.1448274  1.1646588 0.24937274
## OppSTL       0.3333333  1.4481049  0.2301859 0.81883347
## OppTAM       1.0833333  0.8490268  1.2759708 0.20752953
## OppTEN      -0.1666667  1.1448274 -0.1455823 0.88480338
## OppWAS       1.6666667  1.0239648  1.6276601 0.10952809
```

Prediction interval using a linear model

```
##   fit       lwr      upr
## 1   1 -2.557309 4.557309
## 2   1 -2.557309 4.557309
## 3   1 -2.557309 4.557309
## 4   1 -2.557309 4.557309
## 5   1 -2.557309 4.557309
## 6   1 -2.557309 4.557309
```

Rush TDs vs. opponent data

```
CNfitRushTD<- lm(RushTD ~ Opp, data = CNdf)
summary(CNfitRushTD)$coefficients
```

```
##                Estimate Std. Error    t value  Pr(>|t|)
## (Intercept)  0.33333333  0.4123706  0.8083343 0.4225117
## OppATL       0.21212121  0.4652168  0.4559620 0.6502801
## OppBAL      -0.33333333  0.8247413 -0.4041671 0.6877162
## OppBUF      -0.33333333  0.8247413 -0.4041671 0.6877162
## OppCHI       0.33333333  0.5831802  0.5715787 0.5700237
## OppCIN       0.66666667  0.8247413  0.8083343 0.4225117
## OppCLE       0.66666667  0.8247413  0.8083343 0.4225117
## OppDAL       0.16666667  0.6520152  0.2556177 0.7992355
## OppDEN       0.16666667  0.6520152  0.2556177 0.7992355
## OppDET       0.66666667  0.6520152  1.0224710 0.3112025
## OppGNB       0.33333333  0.5831802  0.5715787 0.5700237
## OppHOU       0.16666667  0.6520152  0.2556177 0.7992355
## OppIND       0.16666667  0.6520152  0.2556177 0.7992355
## OppJAX      -0.33333333  0.6520152 -0.5112355 0.6113095
## OppKAN      -0.33333333  0.8247413 -0.4041671 0.6877162
## OppMIA       0.66666667  0.8247413  0.8083343 0.4225117
## OppMIN       0.16666667  0.5455151  0.3055216 0.7611657
## OppNOR       0.21212121  0.4652168  0.4559620 0.6502801
## OppNWE      -0.33333333  0.8247413 -0.4041671 0.6877162
## OppNYG       0.33333333  0.5831802  0.5715787 0.5700237
## OppNYJ      -0.33333333  0.8247413 -0.4041671 0.6877162
## OppOAK       0.66666667  0.8247413  0.8083343 0.4225117
## OppPHI       0.66666667  0.5831802  1.1431573 0.2581108
## OppPIT      -0.33333333  0.8247413 -0.4041671 0.6877162
## OppSDG      -0.33333333  0.8247413 -0.4041671 0.6877162
## OppSEA      -0.08333333  0.5455151 -0.1527608 0.8791670
## OppSFO      -0.33333333  0.6520152 -0.5112355 0.6113095
## OppSTL      -0.33333333  0.8247413 -0.4041671 0.6877162
## OppTAM       0.66666667  0.4835474  1.3786996 0.1737790
## OppTEN       0.16666667  0.6520152  0.2556177 0.7992355
## OppWAS       0.33333333  0.5831802  0.5715787 0.5700237
```

Prediction interval using a linear model

```
##            fit       lwr      upr
## 1 9.992007e-16 -2.025999 2.025999
## 2 9.992007e-16 -2.025999 2.025999
## 3 9.992007e-16 -2.025999 2.025999
## 4 9.992007e-16 -2.025999 2.025999
## 5 9.992007e-16 -2.025999 2.025999
## 6 9.992007e-16 -2.025999 2.025999
```

Interceptions vs. opponent data

```
CNfitInt<- lm(Int ~ Opp, data = CNdf)
summary(CNfitInt)$coefficients
```

```
##                   Estimate Std. Error       t value  Pr(>|t|)
## (Intercept)  1.333333e+00  0.6136355  2.172843e+00 0.0342835
## OppATL      -4.242424e-01  0.6922742 -6.128243e-01 0.5426133
## OppBAL      -1.333333e+00  1.2272710 -1.086421e+00 0.2822092
## OppBUF      -3.333333e-01  1.2272710 -2.716053e-01 0.7869807
## OppCHI      -2.195188e-15  0.8678116 -2.529567e-15 1.0000000
## OppCIN      -3.333333e-01  1.2272710 -2.716053e-01 0.7869807
## OppCLE      -3.333333e-01  1.2272710 -2.716053e-01 0.7869807
## OppDAL      -8.333333e-01  0.9702429 -8.588915e-01 0.3942684
## OppDEN       1.666667e-01  0.9702429  1.717783e-01 0.8642661
## OppDET       6.666667e-01  0.9702429  6.871132e-01 0.4950072
## OppGNB       3.333333e-01  0.8678116  3.841079e-01 0.7024352
## OppHOU      -8.333333e-01  0.9702429 -8.588915e-01 0.3942684
## OppIND      -8.333333e-01  0.9702429 -8.588915e-01 0.3942684
## OppJAX      -8.333333e-01  0.9702429 -8.588915e-01 0.3942684
## OppKAN      -1.333333e+00  1.2272710 -1.086421e+00 0.2822092
## OppMIA      -3.333333e-01  1.2272710 -2.716053e-01 0.7869807
## OppMIN      -3.333333e-01  0.8117634 -4.106287e-01 0.6830003
## OppNOR      -6.969697e-01  0.6922742 -1.006783e+00 0.3186137
## OppNWE      -1.333333e+00  1.2272710 -1.086421e+00 0.2822092
## OppNYG      -9.243760e-17  0.8678116 -1.065180e-16 1.0000000
## OppNYJ      -1.333333e+00  1.2272710 -1.086421e+00 0.2822092
## OppOAK      -3.333333e-01  1.2272710 -2.716053e-01 0.7869807
## OppPHI       6.666667e-01  0.8678116  7.682159e-01 0.4457684
## OppPIT      -1.333333e+00  1.2272710 -1.086421e+00 0.2822092
## OppSDG      -1.333333e+00  1.2272710 -1.086421e+00 0.2822092
## OppSEA      -5.833333e-01  0.8117634 -7.186002e-01 0.4755435
## OppSFO      -3.333333e-01  0.9702429 -3.435566e-01 0.7325390
## OppSTL      -1.333333e+00  1.2272710 -1.086421e+00 0.2822092
## OppTAM      -8.333333e-01  0.7195514 -1.158129e+00 0.2520036
## OppTEN      -8.333333e-01  0.9702429 -8.588915e-01 0.3942684
## OppWAS      -1.333333e+00  0.8678116 -1.536432e+00 0.1303815
```

Prediction interval using a linear model

```
##            fit       lwr      upr
## 1 6.661338e-16 -3.014824 3.014824
## 2 6.661338e-16 -3.014824 3.014824
## 3 6.661338e-16 -3.014824 3.014824
## 4 6.661338e-16 -3.014824 3.014824
## 5 6.661338e-16 -3.014824 3.014824
## 6 6.661338e-16 -3.014824 3.014824
```

Model fitting vs. defensive rank

Pass Yards vs. Defensive Rank

```
##                Estimate Std. Error   t value     Pr(>|t|)
## (Intercept)  209.684496 14.6329907 14.329572 4.863700e-24
## Def.Rank.Yds   1.378596  0.6917944  1.992783 4.961161e-02
```

Prediction interval using a linear model

```
##        fit      lwr      upr
## 1 223.4705 95.84432 351.0966
## 2 223.4705 95.84432 351.0966
## 3 223.4705 95.84432 351.0966
## 4 223.4705 95.84432 351.0966
## 5 223.4705 95.84432 351.0966
## 6 223.4705 95.84432 351.0966
```

Rush Yards vs. Defensive Rank

```
##               Estimate Std. Error  t value     Pr(>|t|)
## (Intercept)  31.636691   5.461463 5.792714 1.236875e-07
## Def.Rank.Yds  0.484676   0.258198 1.877149 6.405391e-02
```

Prediction interval using a linear model

```
##        fit       lwr      upr
## 1 36.48345 -11.15038 84.11728
## 2 36.48345 -11.15038 84.11728
## 3 36.48345 -11.15038 84.11728
## 4 36.48345 -11.15038 84.11728
## 5 36.48345 -11.15038 84.11728
## 6 36.48345 -11.15038 84.11728
```

Pass TDs vs. Defensive Rank

```
##                Estimate Std. Error  t value    Pr(>|t|)
## (Intercept)  0.76030700 0.25208857 3.016031 0.003409254
## Def.Rank.Yds 0.03906339 0.01191783 3.277728 0.001535963
```

Prediction interval using a linear model

```
##        fit       lwr      upr
## 1 1.150941 -1.047727 3.349609
## 2 1.150941 -1.047727 3.349609
## 3 1.150941 -1.047727 3.349609
## 4 1.150941 -1.047727 3.349609
## 5 1.150941 -1.047727 3.349609
## 6 1.150941 -1.047727 3.349609
```

Rush TDs vs. Defensive Rank

```
##                Estimate Std. Error  t value   Pr(>|t|)
## (Intercept)  0.28453388  0.1464728 1.942571 0.05550046
## Def.Rank.Yds 0.01412087  0.0069247 2.039202 0.04465064
```

Prediction interval using a linear model

```
##         fit        lwr     upr
## 1 0.4257425 -0.8517653 1.70325
## 2 0.4257425 -0.8517653 1.70325
## 3 0.4257425 -0.8517653 1.70325
## 4 0.4257425 -0.8517653 1.70325
## 5 0.4257425 -0.8517653 1.70325
## 6 0.4257425 -0.8517653 1.70325
```

Interceptions vs. Defensive Rank

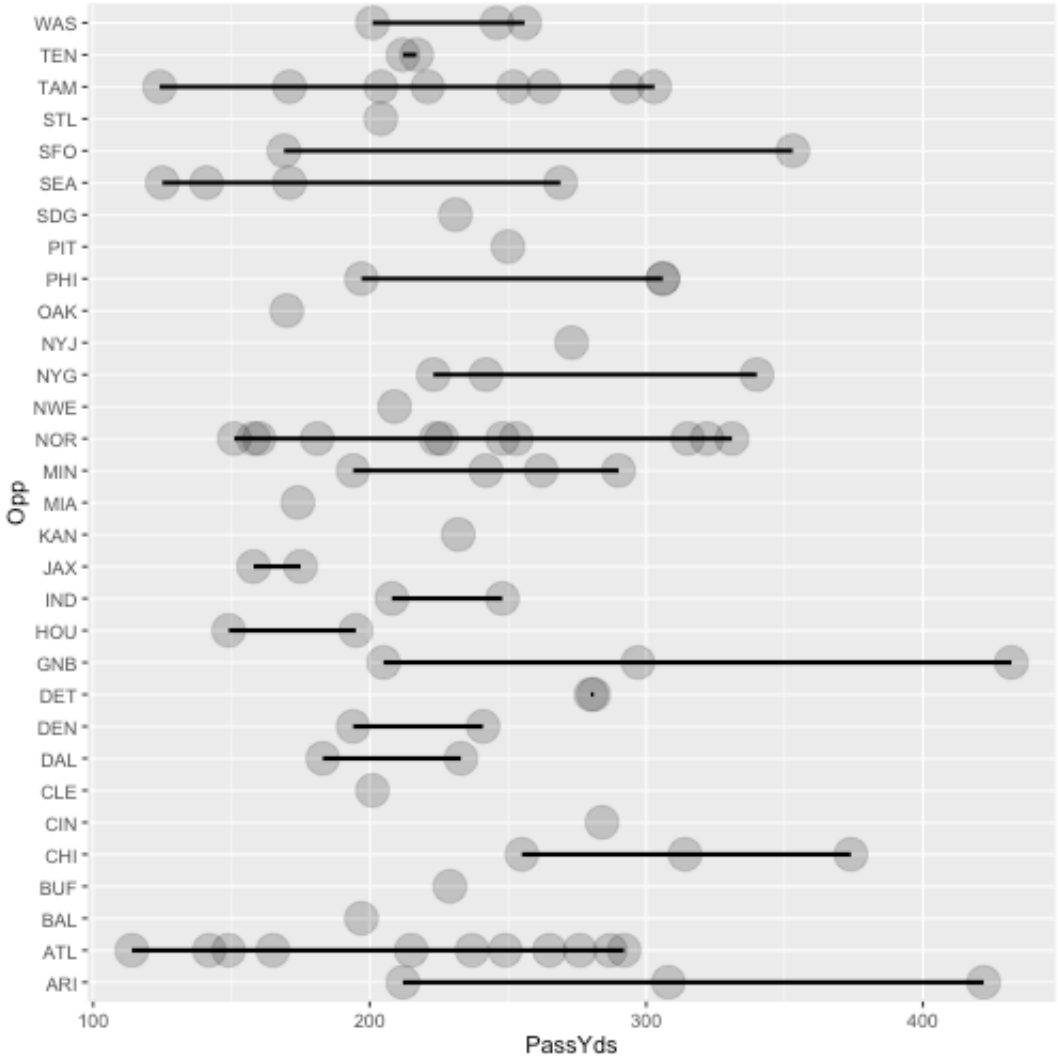
```
##                 Estimate Std. Error   t value    Pr(>|t|)
## (Intercept)  0.782843304 0.22988339 3.4053930 0.001025241
## Def.Rank.Yds 0.002710008 0.01086805 0.2493556 0.803709321
```

Prediction interval using a linear model

```
##         fit       lwr      upr
## 1 0.8099434 -1.195055 2.814942
## 2 0.8099434 -1.195055 2.814942
## 3 0.8099434 -1.195055 2.814942
## 4 0.8099434 -1.195055 2.814942
## 5 0.8099434 -1.195055 2.814942
## 6 0.8099434 -1.195055 2.814942
```

Newton Pass Yards Plot of Data Yards against opponents

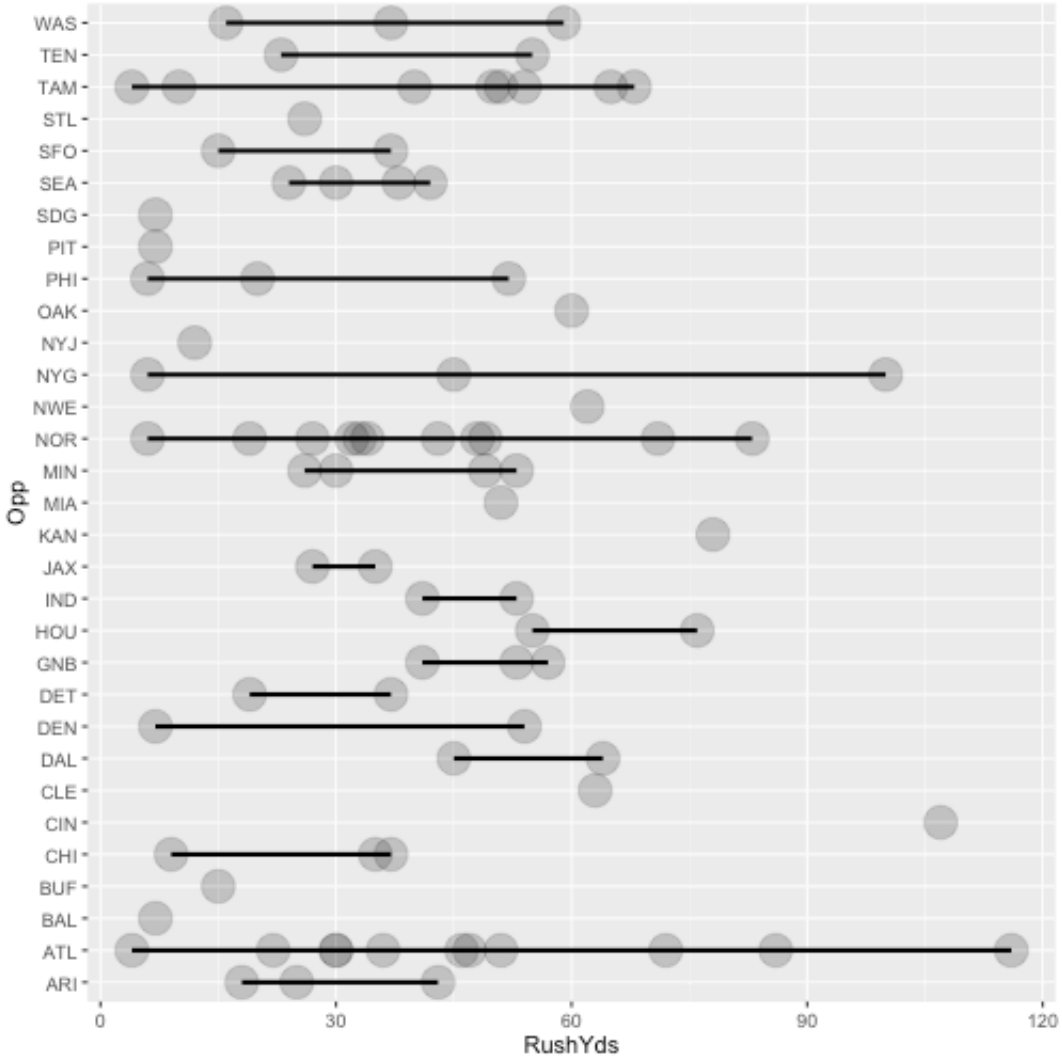
```
## Warning in qt((1 - level)/2, df): NaNs produced

## Warning in qt((1 - level)/2, df): NaNs produced

## Warning in qt((1 - level)/2, df): NaNs produced

## Warning in qt((1 - level)/2, df): NaNs produced

## Warning in qt((1 - level)/2, df): NaNs produced

## Warning in qt((1 - level)/2, df): NaNs produced

## Warning in qt((1 - level)/2, df): NaNs produced

## Warning in qt((1 - level)/2, df): NaNs produced
```



plot of chunk unnamed-chunk-94

Newton Rush Yards Plot of Data Yards against opponents

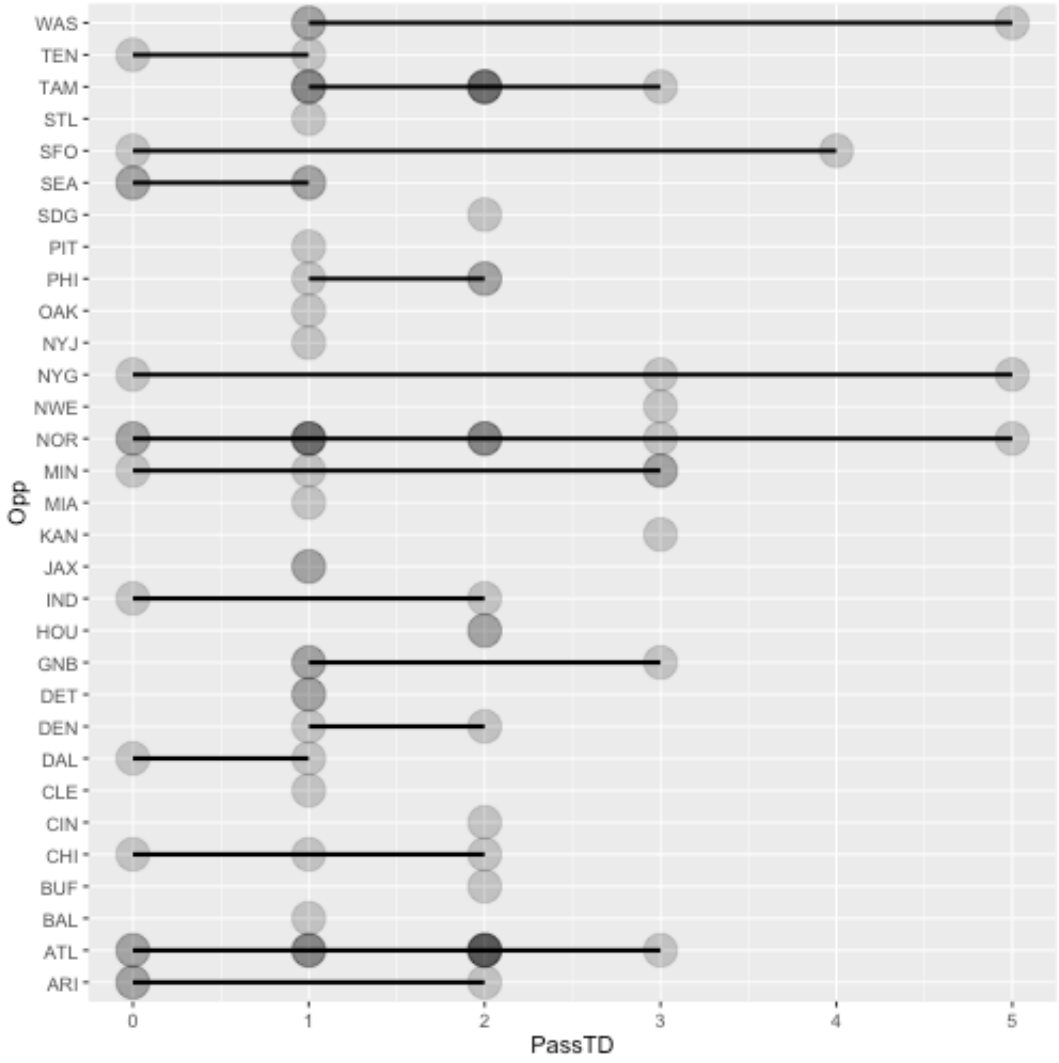
```
## Warning in qt((1 - level)/2, df): NaNs produced

## Warning in qt((1 - level)/2, df): NaNs produced

## Warning in qt((1 - level)/2, df): NaNs produced

## Warning in qt((1 - level)/2, df): NaNs produced

## Warning in qt((1 - level)/2, df): NaNs produced

## Warning in qt((1 - level)/2, df): NaNs produced

## Warning in qt((1 - level)/2, df): NaNs produced

## Warning in qt((1 - level)/2, df): NaNs produced
```



plot of chunk unnamed-chunk-95

Newton TDs Plot of Data Yards against opponents

```
## Warning in qt((1 - level)/2, df): NaNs produced

## Warning in qt((1 - level)/2, df): NaNs produced

## Warning in qt((1 - level)/2, df): NaNs produced

## Warning in qt((1 - level)/2, df): NaNs produced

## Warning in qt((1 - level)/2, df): NaNs produced
```



plot of chunk unnamed-chunk-96

Machine Learning Alogorithm (Pass Yards)

Data Splitting

In this data splitting action, I am splitting the data into 60% training set and 40% testing set.

```
##  Location       Opp      Def.Rank.Yds      PassYds          PassTD
##  Away:42   ATL    :11   Min.   : 1.00   Min.   :114.0   Min.   :0.000
##  Home:42   NOR    :11   1st Qu.:10.00   1st Qu.:194.0   1st Qu.:1.000
##            TAM    : 8   Median :18.00   Median :231.5   Median :1.000
##            MIN    : 4   Mean   :18.63   Mean   :235.4   Mean   :1.488
##            SEA    : 4   3rd Qu.:28.00   3rd Qu.:277.0   3rd Qu.:2.000
##            ARI    : 3   Max.   :32.00   Max.   :432.0   Max.   :5.000
##            (Other):43
##       Int            RushYds           RushTD
##  Min.   :0.0000   Min.   :  4.00   Min.   :0.0000
##  1st Qu.:0.0000   1st Qu.: 23.75   1st Qu.:0.0000
##  Median :1.0000   Median : 39.00   Median :0.0000
##  Mean   :0.8333   Mean   : 40.67   Mean   :0.5476
##  3rd Qu.:1.0000   3rd Qu.: 53.25   3rd Qu.:1.0000
##  Max.   :4.0000   Max.   :116.00   Max.   :3.0000
##
```

```
## [1] 52  8
```

```
## [1] 32  8
```

K-Fold Cross Validation

We will then use the K-Fold process to cross-validate the data by splitting the training set in to many, smaller data sets.

Here, I am creating 10 folds and setting a random number seed of 32323 for the study. Each fold has approximately the same number of samples in it.

```
set.seed(32323)
Passfolds <- createFolds(y=CNdf$PassYds,k=10,list=TRUE,returnTrain=TRUE)
sapply(Passfolds,length)
```

```
## Fold01 Fold02 Fold03 Fold04 Fold05 Fold06 Fold07 Fold08 Fold09 Fold10
##     74     75     76     76     76     76     75     76     76     76
```

```
Passfolds[[1]][1:10]
```

```
##  [1]  1  2  3  4  5  7  8  9 10 11
```

Machine learning alogorithm decisioning

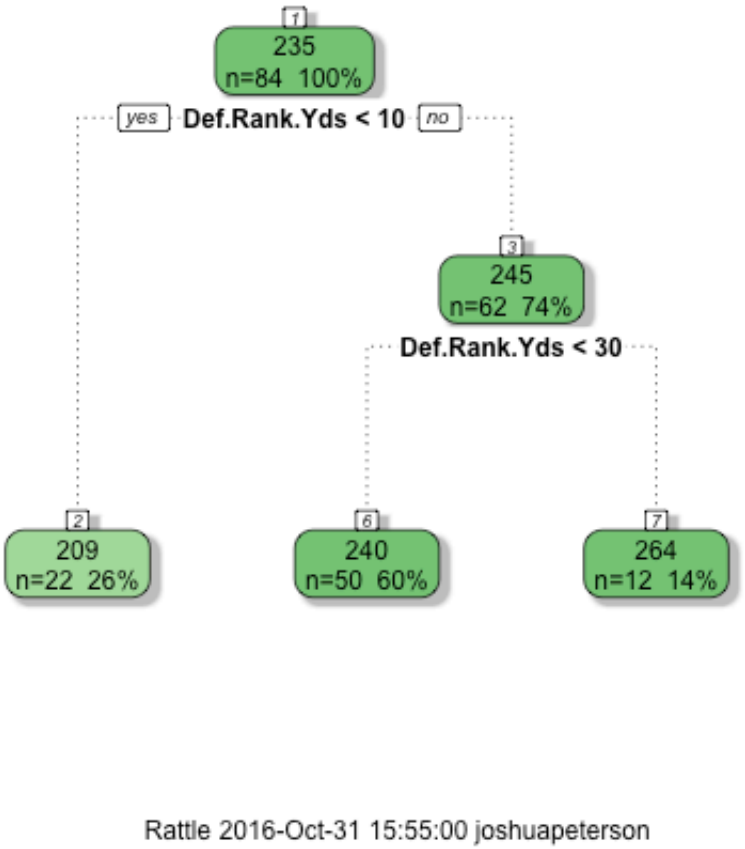
First I wanted to determine the optimal machine learning model to use. The first test I used the Decision Tree approach. I followed up by testing the Random Forest approach.

Machine learning using Decision Trees

The first task was to determine model fit.

Next, construct a Decision Tree graph

```
fancyRpartPlot(modelFitPass)
```



plot of chunk unnamed-chunk-100

Machine Learning Alogorithm (Rush Yards)

Data Splitting

In this data splitting action, I am splitting the data into 60% training set and 40% testing set.

```
##  Location       Opp      Def.Rank.Yds      PassYds          PassTD
##  Away:42   ATL    :11   Min.   : 1.00   Min.   :114.0   Min.   :0.000
##  Home:42   NOR    :11   1st Qu.:10.00   1st Qu.:194.0   1st Qu.:1.000
##            TAM    : 8   Median :18.00   Median :231.5   Median :1.000
##            MIN    : 4   Mean   :18.63   Mean   :235.4   Mean   :1.488
##            SEA    : 4   3rd Qu.:28.00   3rd Qu.:277.0   3rd Qu.:2.000
##            ARI    : 3   Max.   :32.00   Max.   :432.0   Max.   :5.000
##            (Other):43
##       Int            RushYds           RushTD
##  Min.   :0.0000   Min.   :  4.00   Min.   :0.0000
##  1st Qu.:0.0000   1st Qu.: 23.75   1st Qu.:0.0000
##  Median :1.0000   Median : 39.00   Median :0.0000
##  Mean   :0.8333   Mean   : 40.67   Mean   :0.5476
##  3rd Qu.:1.0000   3rd Qu.: 53.25   3rd Qu.:1.0000
##  Max.   :4.0000   Max.   :116.00   Max.   :3.0000
##
```

```
## [1] 52  8
```

```
## [1] 32  8
```

We will then use the K-Fold process to cross-validate the data by splitting the training set in to many, smaller data sets.

Here, I am creating 10 folds and setting a random number seed of 32323 for the study. Each fold has approximately the same number of samples in it.

```
set.seed(32323)
Passfolds <- createFolds(y=CNdf$RushYds,k=10,list=TRUE,returnTrain=TRUE)
sapply(Passfolds,length)
```

```
## Fold01 Fold02 Fold03 Fold04 Fold05 Fold06 Fold07 Fold08 Fold09 Fold10
##     74     75     76     75     76     76     76     76     76     76
```

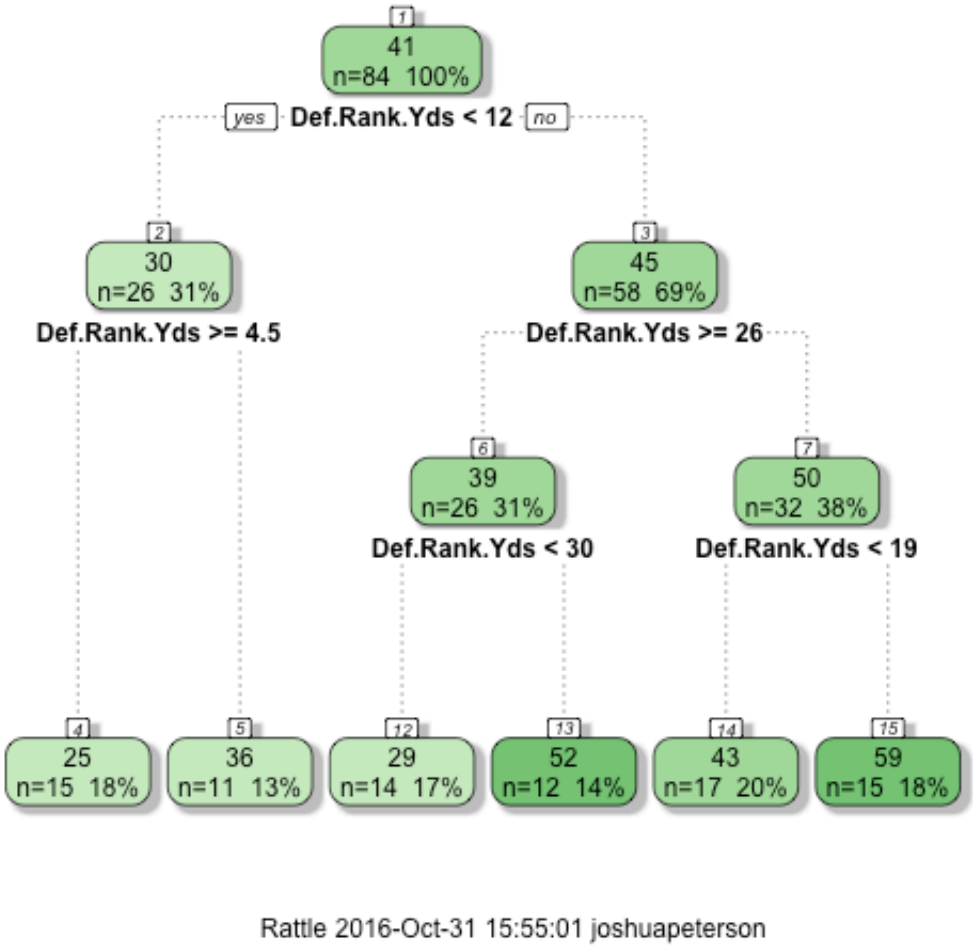
```
Passfolds[[1]][1:10]
```

```
##  [1]  1  2  3  5  6  8  9 10 11 12
```

Decision tree model fit Rush Yards Defense Rank.

Pass Yards decision tree graph

```
fancyRpartPlot(modelFitRush)
```



plot of chunk unnamed-chunk-104

Machine learning using Decision Trees

The first task was to determine model fit.

Output from Decision Tree Model vs. Yards Passing

Current week (9) opponent L.A. Rams (formerly St. Louis Rams). The defense is currently ranked # 10 according to www.pro-football-reference.com.

According to the model, there is a 60% chance that Cam Newton will pass for 240 yards. This takes in to account defense rank ONLY. There is an 18.0% chance Cam will rush for 25 yards. Once again this takes in to account defense rank ONLY.

We will now use the LM model for prediction (Pass Yds)

```
##        1        2        3        4        5        6        7        8
## 195.5174 195.5174 195.5174 195.5174 195.5174 195.5174 195.5174 195.5174
##        9       10       11       12       13       14       15       16
## 195.5174 195.5174 195.5174 195.5174 195.5174 195.5174 195.5174 195.5174
##       17       18       19       20       21       22       23       24
## 195.5174 195.5174 195.5174 195.5174 195.5174 195.5174 195.5174 195.5174
##       25       26       27       28       29       30       31       32
## 195.5174 195.5174 195.5174 195.5174 195.5174 195.5174 195.5174 195.5174
##       33       34       35       36       37       38       39       40
## 195.5174 195.5174 195.5174 195.5174 195.5174 195.5174 195.5174 195.5174
##       41       42       43       44       45       46       47       48
## 195.5174 195.5174 195.5174 195.5174 195.5174 195.5174 195.5174 195.5174
##       49       50       51       52       53       54       55       56
## 195.5174 195.5174 195.5174 195.5174 195.5174 195.5174 195.5174 195.5174
##       57       58       59       60       61       62       63       64
## 195.5174 195.5174 195.5174 195.5174 195.5174 195.5174 195.5174 195.5174
##       65       66       67       68       69       70       71       72
## 195.5174 195.5174 195.5174 195.5174 195.5174 195.5174 195.5174 195.5174
##       73       74       75       76       77       78       79       80
## 195.5174 195.5174 195.5174 195.5174 195.5174 195.5174 195.5174 195.5174
##       81       82       83       84
## 195.5174 195.5174 195.5174 195.5174
```

Predicted passing points

```
##        1        2        3        4        5        6        7        8
## 7.820694 7.820694 7.820694 7.820694 7.820694 7.820694 7.820694 7.820694
##        9       10       11       12       13       14       15       16
## 7.820694 7.820694 7.820694 7.820694 7.820694 7.820694 7.820694 7.820694
##       17       18       19       20       21       22       23       24
## 7.820694 7.820694 7.820694 7.820694 7.820694 7.820694 7.820694 7.820694
##       25       26       27       28       29       30       31       32
## 7.820694 7.820694 7.820694 7.820694 7.820694 7.820694 7.820694 7.820694
##       33       34       35       36       37       38       39       40
## 7.820694 7.820694 7.820694 7.820694 7.820694 7.820694 7.820694 7.820694
##       41       42       43       44       45       46       47       48
## 7.820694 7.820694 7.820694 7.820694 7.820694 7.820694 7.820694 7.820694
##       49       50       51       52       53       54       55       56
## 7.820694 7.820694 7.820694 7.820694 7.820694 7.820694 7.820694 7.820694
##       57       58       59       60       61       62       63       64
## 7.820694 7.820694 7.820694 7.820694 7.820694 7.820694 7.820694 7.820694
##       65       66       67       68       69       70       71       72
## 7.820694 7.820694 7.820694 7.820694 7.820694 7.820694 7.820694 7.820694
##       73       74       75       76       77       78       79       80
## 7.820694 7.820694 7.820694 7.820694 7.820694 7.820694 7.820694 7.820694
##       81       82       83       84
## 7.820694 7.820694 7.820694 7.820694
```

We will now use the LM model for prediction (Rush Yds)

```
##        1        2        3        4        5        6        7        8
## 24.73227 24.73227 24.73227 24.73227 24.73227 24.73227 24.73227 24.73227
##        9       10       11       12       13       14       15       16
## 24.73227 24.73227 24.73227 24.73227 24.73227 24.73227 24.73227 24.73227
##       17       18       19       20       21       22       23       24
## 24.73227 24.73227 24.73227 24.73227 24.73227 24.73227 24.73227 24.73227
##       25       26       27       28       29       30       31       32
## 24.73227 24.73227 24.73227 24.73227 24.73227 24.73227 24.73227 24.73227
##       33       34       35       36       37       38       39       40
## 24.73227 24.73227 24.73227 24.73227 24.73227 24.73227 24.73227 24.73227
##       41       42       43       44       45       46       47       48
## 24.73227 24.73227 24.73227 24.73227 24.73227 24.73227 24.73227 24.73227
##       49       50       51       52       53       54       55       56
## 24.73227 24.73227 24.73227 24.73227 24.73227 24.73227 24.73227 24.73227
##       57       58       59       60       61       62       63       64
## 24.73227 24.73227 24.73227 24.73227 24.73227 24.73227 24.73227 24.73227
##       65       66       67       68       69       70       71       72
## 24.73227 24.73227 24.73227 24.73227 24.73227 24.73227 24.73227 24.73227
##       73       74       75       76       77       78       79       80
## 24.73227 24.73227 24.73227 24.73227 24.73227 24.73227 24.73227 24.73227
##       81       82       83       84
## 24.73227 24.73227 24.73227 24.73227
```

Predicted rushing points

```
##        1        2        3        4        5        6        7        8
## 2.473227 2.473227 2.473227 2.473227 2.473227 2.473227 2.473227 2.473227
##        9       10       11       12       13       14       15       16
## 2.473227 2.473227 2.473227 2.473227 2.473227 2.473227 2.473227 2.473227
##       17       18       19       20       21       22       23       24
## 2.473227 2.473227 2.473227 2.473227 2.473227 2.473227 2.473227 2.473227
##       25       26       27       28       29       30       31       32
## 2.473227 2.473227 2.473227 2.473227 2.473227 2.473227 2.473227 2.473227
##       33       34       35       36       37       38       39       40
## 2.473227 2.473227 2.473227 2.473227 2.473227 2.473227 2.473227 2.473227
##       41       42       43       44       45       46       47       48
## 2.473227 2.473227 2.473227 2.473227 2.473227 2.473227 2.473227 2.473227
##       49       50       51       52       53       54       55       56
## 2.473227 2.473227 2.473227 2.473227 2.473227 2.473227 2.473227 2.473227
##       57       58       59       60       61       62       63       64
## 2.473227 2.473227 2.473227 2.473227 2.473227 2.473227 2.473227 2.473227
##       65       66       67       68       69       70       71       72
## 2.473227 2.473227 2.473227 2.473227 2.473227 2.473227 2.473227 2.473227
##       73       74       75       76       77       78       79       80
## 2.473227 2.473227 2.473227 2.473227 2.473227 2.473227 2.473227 2.473227
##       81       82       83       84
## 2.473227 2.473227 2.473227 2.473227
```

We will now use the LM model for prediction (Pass TDs)

```
##         1         2         3         4         5         6         7
## 0.8045535 0.8045535 0.8045535 0.8045535 0.8045535 0.8045535 0.8045535
##         8         9        10        11        12        13        14
## 0.8045535 0.8045535 0.8045535 0.8045535 0.8045535 0.8045535 0.8045535
##        15        16        17        18        19        20        21
## 0.8045535 0.8045535 0.8045535 0.8045535 0.8045535 0.8045535 0.8045535
##        22        23        24        25        26        27        28
## 0.8045535 0.8045535 0.8045535 0.8045535 0.8045535 0.8045535 0.8045535
##        29        30        31        32        33        34        35
## 0.8045535 0.8045535 0.8045535 0.8045535 0.8045535 0.8045535 0.8045535
##        36        37        38        39        40        41        42
## 0.8045535 0.8045535 0.8045535 0.8045535 0.8045535 0.8045535 0.8045535
##        43        44        45        46        47        48        49
## 0.8045535 0.8045535 0.8045535 0.8045535 0.8045535 0.8045535 0.8045535
##        50        51        52        53        54        55        56
## 0.8045535 0.8045535 0.8045535 0.8045535 0.8045535 0.8045535 0.8045535
##        57        58        59        60        61        62        63
## 0.8045535 0.8045535 0.8045535 0.8045535 0.8045535 0.8045535 0.8045535
##        64        65        66        67        68        69        70
## 0.8045535 0.8045535 0.8045535 0.8045535 0.8045535 0.8045535 0.8045535
##        71        72        73        74        75        76        77
## 0.8045535 0.8045535 0.8045535 0.8045535 0.8045535 0.8045535 0.8045535
##        78        79        80        81        82        83        84
## 0.8045535 0.8045535 0.8045535 0.8045535 0.8045535 0.8045535 0.8045535
```

Predicted rushing points

```
##        1        2        3        4        5        6        7        8
## 3.218214 3.218214 3.218214 3.218214 3.218214 3.218214 3.218214 3.218214
##        9       10       11       12       13       14       15       16
## 3.218214 3.218214 3.218214 3.218214 3.218214 3.218214 3.218214 3.218214
##       17       18       19       20       21       22       23       24
## 3.218214 3.218214 3.218214 3.218214 3.218214 3.218214 3.218214 3.218214
##       25       26       27       28       29       30       31       32
## 3.218214 3.218214 3.218214 3.218214 3.218214 3.218214 3.218214 3.218214
##       33       34       35       36       37       38       39       40
## 3.218214 3.218214 3.218214 3.218214 3.218214 3.218214 3.218214 3.218214
##       41       42       43       44       45       46       47       48
## 3.218214 3.218214 3.218214 3.218214 3.218214 3.218214 3.218214 3.218214
##       49       50       51       52       53       54       55       56
## 3.218214 3.218214 3.218214 3.218214 3.218214 3.218214 3.218214 3.218214
##       57       58       59       60       61       62       63       64
## 3.218214 3.218214 3.218214 3.218214 3.218214 3.218214 3.218214 3.218214
##       65       66       67       68       69       70       71       72
## 3.218214 3.218214 3.218214 3.218214 3.218214 3.218214 3.218214 3.218214
##       73       74       75       76       77       78       79       80
## 3.218214 3.218214 3.218214 3.218214 3.218214 3.218214 3.218214 3.218214
##       81       82       83       84
## 3.218214 3.218214 3.218214 3.218214
```

We will now use the LM model for prediction (Rush TDs)

```
##           1           2           3           4           5           6
## -0.05003085 -0.05003085 -0.05003085 -0.05003085 -0.05003085 -0.05003085
##           7           8           9          10          11          12
## -0.05003085 -0.05003085 -0.05003085 -0.05003085 -0.05003085 -0.05003085
##          13          14          15          16          17          18
## -0.05003085 -0.05003085 -0.05003085 -0.05003085 -0.05003085 -0.05003085
##          19          20          21          22          23          24
## -0.05003085 -0.05003085 -0.05003085 -0.05003085 -0.05003085 -0.05003085
##          25          26          27          28          29          30
## -0.05003085 -0.05003085 -0.05003085 -0.05003085 -0.05003085 -0.05003085
##          31          32          33          34          35          36
## -0.05003085 -0.05003085 -0.05003085 -0.05003085 -0.05003085 -0.05003085
##          37          38          39          40          41          42
## -0.05003085 -0.05003085 -0.05003085 -0.05003085 -0.05003085 -0.05003085
##          43          44          45          46          47          48
## -0.05003085 -0.05003085 -0.05003085 -0.05003085 -0.05003085 -0.05003085
##          49          50          51          52          53          54
## -0.05003085 -0.05003085 -0.05003085 -0.05003085 -0.05003085 -0.05003085
##          55          56          57          58          59          60
## -0.05003085 -0.05003085 -0.05003085 -0.05003085 -0.05003085 -0.05003085
##          61          62          63          64          65          66
## -0.05003085 -0.05003085 -0.05003085 -0.05003085 -0.05003085 -0.05003085
##          67          68          69          70          71          72
## -0.05003085 -0.05003085 -0.05003085 -0.05003085 -0.05003085 -0.05003085
##          73          74          75          76          77          78
## -0.05003085 -0.05003085 -0.05003085 -0.05003085 -0.05003085 -0.05003085
##          79          80          81          82          83          84
## -0.05003085 -0.05003085 -0.05003085 -0.05003085 -0.05003085 -0.05003085
```

Predicted rushing TD points

```
##          1          2          3          4          5          6
## -0.3001851 -0.3001851 -0.3001851 -0.3001851 -0.3001851 -0.3001851
##          7          8          9         10         11         12
## -0.3001851 -0.3001851 -0.3001851 -0.3001851 -0.3001851 -0.3001851
##         13         14         15         16         17         18
## -0.3001851 -0.3001851 -0.3001851 -0.3001851 -0.3001851 -0.3001851
##         19         20         21         22         23         24
## -0.3001851 -0.3001851 -0.3001851 -0.3001851 -0.3001851 -0.3001851
##         25         26         27         28         29         30
## -0.3001851 -0.3001851 -0.3001851 -0.3001851 -0.3001851 -0.3001851
##         31         32         33         34         35         36
## -0.3001851 -0.3001851 -0.3001851 -0.3001851 -0.3001851 -0.3001851
##         37         38         39         40         41         42
## -0.3001851 -0.3001851 -0.3001851 -0.3001851 -0.3001851 -0.3001851
##         43         44         45         46         47         48
## -0.3001851 -0.3001851 -0.3001851 -0.3001851 -0.3001851 -0.3001851
##         49         50         51         52         53         54
## -0.3001851 -0.3001851 -0.3001851 -0.3001851 -0.3001851 -0.3001851
##         55         56         57         58         59         60
## -0.3001851 -0.3001851 -0.3001851 -0.3001851 -0.3001851 -0.3001851
##         61         62         63         64         65         66
## -0.3001851 -0.3001851 -0.3001851 -0.3001851 -0.3001851 -0.3001851
##         67         68         69         70         71         72
## -0.3001851 -0.3001851 -0.3001851 -0.3001851 -0.3001851 -0.3001851
##         73         74         75         76         77         78
## -0.3001851 -0.3001851 -0.3001851 -0.3001851 -0.3001851 -0.3001851
##         79         80         81         82         83         84
## -0.3001851 -0.3001851 -0.3001851 -0.3001851 -0.3001851 -0.3001851
```

Total predicted points using linear regression models

```
##        1        2        3        4        5        6        7        8
## 13.21195 13.21195 13.21195 13.21195 13.21195 13.21195 13.21195 13.21195
##        9       10       11       12       13       14       15       16
## 13.21195 13.21195 13.21195 13.21195 13.21195 13.21195 13.21195 13.21195
##       17       18       19       20       21       22       23       24
## 13.21195 13.21195 13.21195 13.21195 13.21195 13.21195 13.21195 13.21195
##       25       26       27       28       29       30       31       32
## 13.21195 13.21195 13.21195 13.21195 13.21195 13.21195 13.21195 13.21195
##       33       34       35       36       37       38       39       40
## 13.21195 13.21195 13.21195 13.21195 13.21195 13.21195 13.21195 13.21195
##       41       42       43       44       45       46       47       48
## 13.21195 13.21195 13.21195 13.21195 13.21195 13.21195 13.21195 13.21195
##       49       50       51       52       53       54       55       56
## 13.21195 13.21195 13.21195 13.21195 13.21195 13.21195 13.21195 13.21195
##       57       58       59       60       61       62       63       64
## 13.21195 13.21195 13.21195 13.21195 13.21195 13.21195 13.21195 13.21195
##       65       66       67       68       69       70       71       72
## 13.21195 13.21195 13.21195 13.21195 13.21195 13.21195 13.21195 13.21195
##       73       74       75       76       77       78       79       80
## 13.21195 13.21195 13.21195 13.21195 13.21195 13.21195 13.21195 13.21195
##       81       82       83       84
## 13.21195 13.21195 13.21195 13.21195
```

Outcome: Cam Newton's predicted point total for Week 9 against the LA Rams is 13.21 points. NFL.com is predicting that Cam's point total will be 15.44 points

```
##
##
## processing file: QB_ML_Experiment_2016.Rmd
```

```
## Error in parse_block(g[-1], g[1], params.src): duplicate label 'Points'
```