Final Project FIFA 19 Analysis

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Purpose

We are investigating here and running statistical analysis on soccer data. As a longtime sports fan, statistics are now the name of the game and I was interested in seeing how electronic players held up to their real world counterparts, and whether there is easily detected bias to the ratings systems which ultimately are objective.

We'll be using a number of packages in our analysis, including:

- ggplot2, a graphing package.
- pastecs, statistical analysis.
- dplyr, for data cleaning.

Our Data

Our data comes to us from Kaggle. More specifically, we have three data sets we are looking at:

- Kaggle – FIFA 19 Ultimate Team https://www.kaggle.com/stefanoleone992/fifa-19-fifa-ultimate-team
- Kaggle – FIFA 19 Player Database https://www.kaggle.com/karangadiya/fifa19/
- Kaggle – World Cup Players https://www.kaggle.com/djamshed/fifa-world-cup-2018-players

All of these are related to soccer (or Football, as those across the pond would insist on it being called.) The first two datasets are from FIFA 19 by Electronic Arts, the juggernaut that has seen over 20 million units sold to date alone. While it does face competition from Pro Evolution Soccer, FIFA is still the undisputed champion of the simulated soccer world.

Our last dataset concerns the 2018 World Cup. We were interested in how simulated soccer royalty compared to real world soccer royalty.

To begin with, let's import our data.

```
fifaUltimate <- read.csv("fifa19ultimate.csv", header = TRUE)
fifaGame <- read.csv("fifagamedata.csv", header = TRUE)
worldCup <- read.csv("wc2018-players.csv", header = TRUE)
worldCup <- worldCup[-c(5)]
```

Cleaning the data.

Some preliminary analysis of our data and the form it comes to us.

```
fifaUltimateNA <- fifaUltimate[complete.cases(fifaUltimate), ]
fifaGameNA <- fifaGame[complete.cases(fifaGame), ]
worldCupNA <- worldCup[complete.cases(worldCup), ]

badFifaUltimate <- nrow(fifaUltimate) - nrow(fifaUltimateNA)
badFifaGame <- nrow(fifaGame) - nrow(fifaGameNA)
badWorldCup <- nrow(worldCup) - nrow(worldCupNA)

badFifaUltimate * 100 / nrow(fifaUltimate)

## [1] 100

badFifaGame * 100 / nrow(fifaGame)

## [1] 0.3295436

badWorldCup * 100 / nrow(worldCup)

## [1] 0
```

For the ultimate data:

- There is not a single complete entry in the entire 18831 rows of data.
- That being said, there are 95 variables and the vast majority have almost every column.
- Missing fields are NA.

For the FIFA data:

- Only 0.33% of the rows are missing any data. There are 18207 rows!
- There are 89 variables tracked.
- Missing results are marked NA. There are only 60 total incomplete rows.

For the World Cup data:

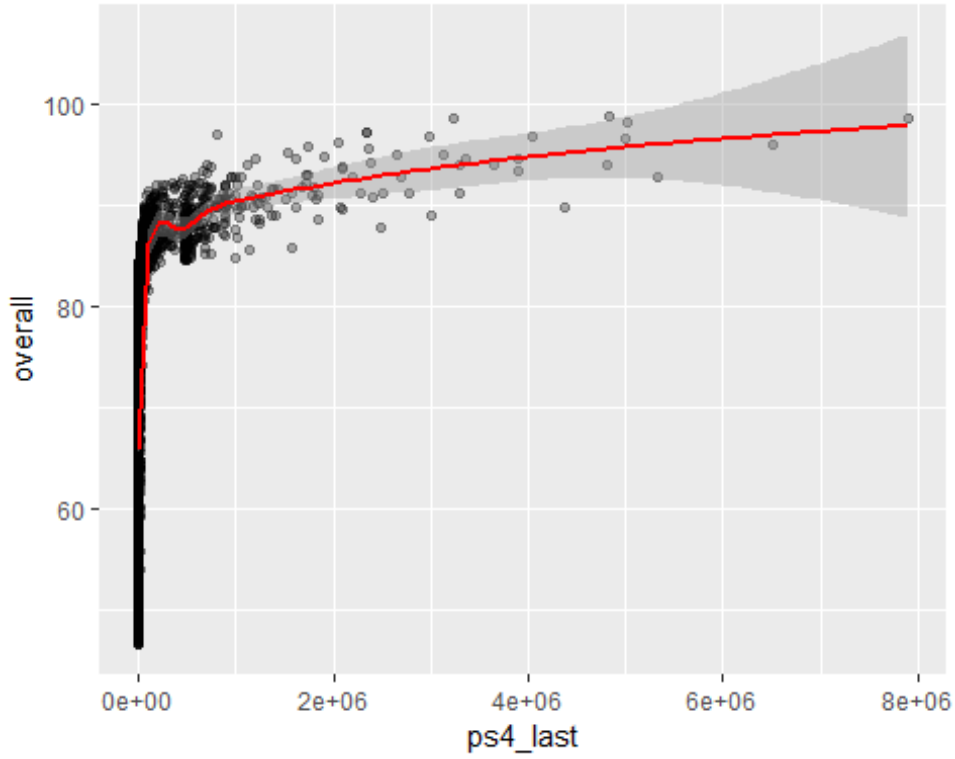
- Confirmed list of player names and birth date by country.
- Dataset has been curated based on FIFA records. This is the only complete data set we have – there is no missing data.
- Data is from official rosters provided by FIFA.
- No information on how it was originally collected. Small enough data set it could be done by hand.
- There are 10 variables tracked and 736 observations.

Preliminary Analysis

We will now take a look at scatterplots of our data.

```
ggplot(subset(fifaUltimate, ps4_last > 0), aes(x = ps4_last, y = overall)) +
  geom_point(position = "jitter", alpha = 0.3) +
  geom_smooth(col = "red")
```

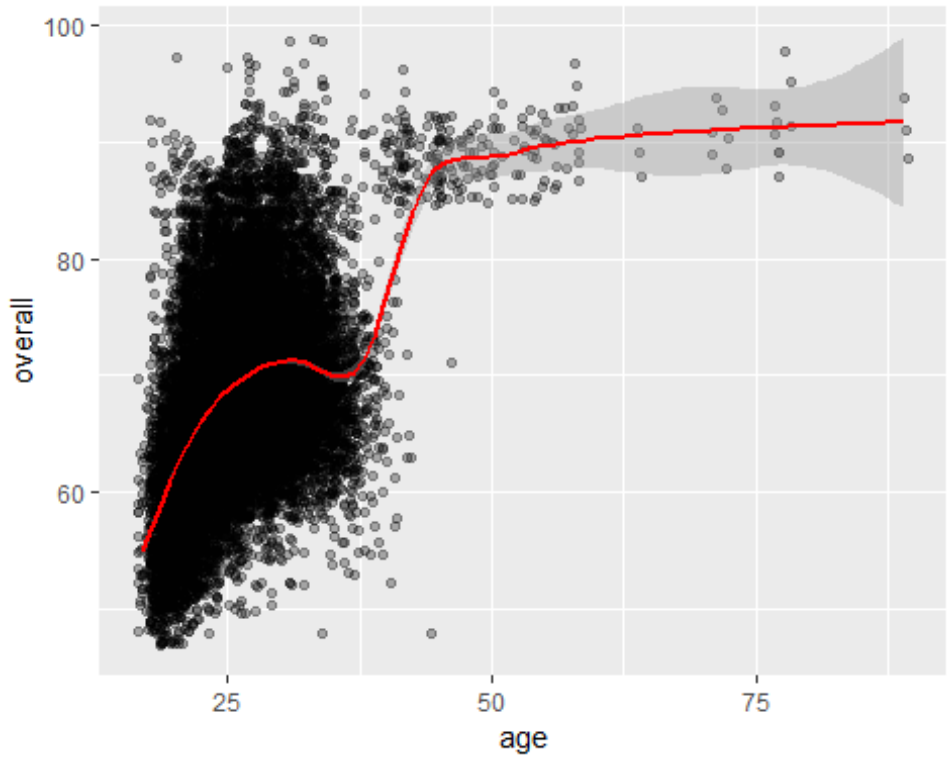
```
## `geom_smooth()` using method = 'gam' and formula 'y ~ s(x, bs = "cs")'
```



This graph charts the last sale price of the card on the PS4 versus the overall rating.

```
ggplot(fifaUltimate, aes(x = age, y = overall)) +
  geom_point(position = "jitter", alpha = 0.3) +
  geom_smooth(col = "red")
```

```
## `geom_smooth()` using method = 'gam' and formula 'y ~ s(x, bs = "cs")'
```



This graph shows the Ultimate rating versus age. Some of the players are "legacy" in that they are famous players from the past and it shows the overall age.

```
round(stat.desc(fifaUltimate$overall, basic = FALSE), digits = 3)
```

```
##       median         mean      SE.mean CI.mean.0.95          var
##       67.000       68.201        0.059        0.116       66.311
##      std.dev     coef.var
##        8.143        0.119
```

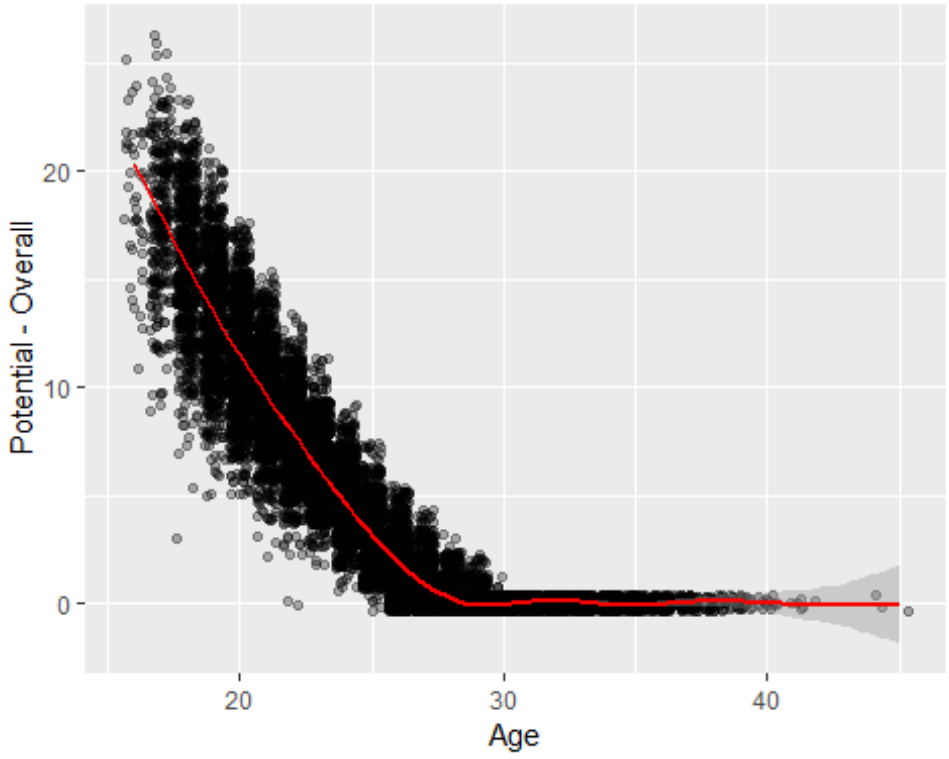
A look at our distribution of overall ratings.

```
ggplot(fifaGame, aes(x = Age, y = Overall)) +
  geom_point(position = "jitter", alpha = 0.3) +
  geom_smooth(col = "red")
```

```
## `geom_smooth()` using method = 'gam' and formula 'y ~ s(x, bs = "cs")'
```

Same age versus overall plot, but this time for the FIFA stats.

```
ggplot(fifaGame, aes(x = Age, y = Potential - Overall)) +
  geom_point(position = "jitter", alpha = 0.3) +
  geom_smooth(col = "red")

## `geom_smooth()` using method = 'gam' and formula 'y ~ s(x, bs = "cs")'
```

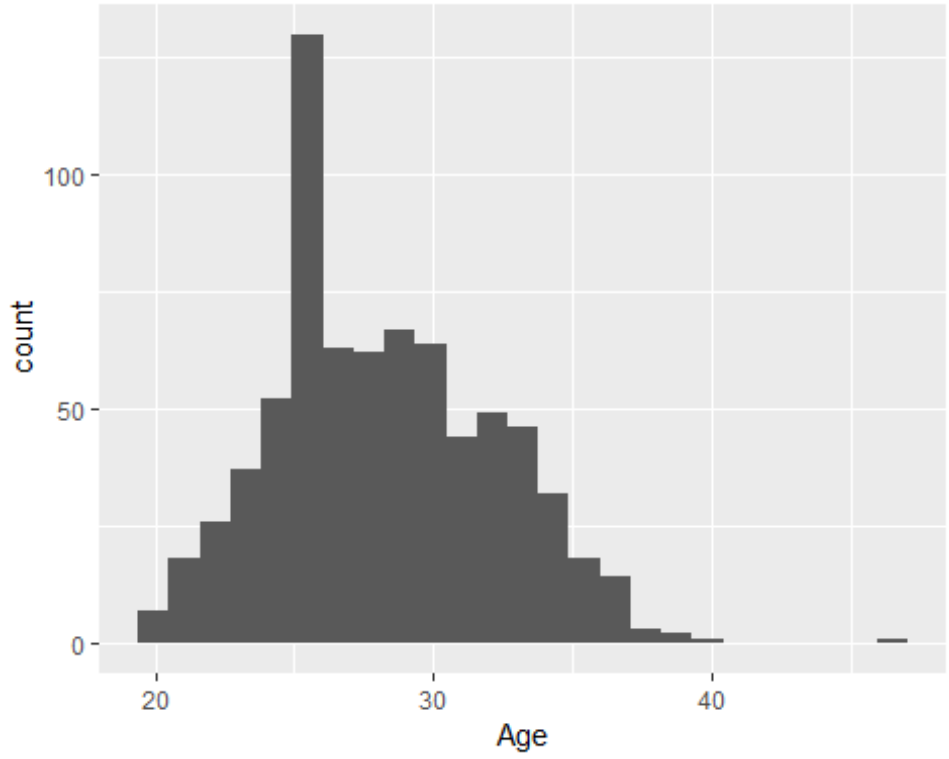


This graph is a measure of age versus room for growth i.e. $ potential - overall$.

```
round(stat.desc(fifaGame$Overall, basic = FALSE), digits = 3)
```

```
##       median         mean      SE.mean CI.mean.0.95          var
##       66.000       66.239        0.051        0.100       47.733
##      std.dev     coef.var
##        6.909        0.104
```

```
bw <- 2 * IQR(worldCup$Age) / length(worldCup$Age)^(1/3)
ggplot(worldCup, aes(x = Age)) +
  geom_histogram(binwidth = bw)
```



A histogram of the ages of players in the most recent World Cup.

```
round(stat.desc(worldCup$Age, basic = FALSE, norm = TRUE), digits = 3)
```

```
##       median         mean      SE.mean CI.mean.0.95          var
##       28.000       28.236        0.146        0.286       15.582
##      std.dev     coef.var     skewness     skew.2SE     kurtosis
##        3.947        0.140        0.262        1.453       -0.106
##     kurt.2SE   normtest.W   normtest.p
##       -0.295        0.984        0.000
```

```
cleanFifaGame <- subset(fifaGame, select = c("Name", "Age", "Overall",
"Potential", "Club","Position", "Height", "Weight", "Crossing", "Finishing",
"HeadingAccuracy" , "ShortPassing" , "Volleys" , "Dribbling" , "Curve",
"FKAccuracy", "LongPassing" , "BallControl" , "Acceleration" , "SprintSpeed"
, "Agility" , "Reactions", "Balance" , "ShotPower" , "Jumping" , "Stamina" ,
"Strength" , "LongShots", "Aggression" , "Interceptions" , "Positioning",
"Vision" , "Penalties" , "Composure", "Marking" , "StandingTackle" ,
"SlidingTackle" , "GKDiving" , "GKHandling", "GKKicking", "GKPositioning",
"GKReflexes"))
cleanFifaGameNA <- cleanFifaGame[complete.cases(cleanFifaGame), ]

head(cleanFifaGameNA)
```

```
##                Name Age Overall Potential               Club Position
## 1          L. Messi  31      94        94       FC Barcelona       RF
## 2 Cristiano Ronaldo  33      94        94           Juventus       ST
```

```
## 3         Neymar Jr  26      92        93 Paris Saint-Germain       LW
## 4            De Gea  27      91        93   Manchester United       GK
## 5      K. De Bruyne  27      91        92     Manchester City      RCM
## 6         E. Hazard  27      91        91             Chelsea       LF
##   Height Weight Crossing Finishing HeadingAccuracy ShortPassing Volleys
## 1    5'7 159lbs       84        95              70           90      86
## 2    6'2 183lbs       84        94              89           81      87
## 3    5'9 150lbs       79        87              62           84      84
## 4    6'4 168lbs       17        13              21           50      13
## 5   5'11 154lbs       93        82              55           92      82
## 6    5'8 163lbs       81        84              61           89      80
##   Dribbling Curve FKAccuracy LongPassing BallControl Acceleration
## 1        97    93         94          87          96           91
## 2        88    81         76          77          94           89
## 3        96    88         87          78          95           94
## 4        18    21         19          51          42           57
## 5        86    85         83          91          91           78
## 6        95    83         79          83          94           94
##   SprintSpeed Agility Reactions Balance ShotPower Jumping Stamina Strength
## 1          86      91        95      95        85      68      72       59
## 2          91      87        96      70        95      95      88       79
## 3          90      96        94      84        80      61      81       49
## 4          58      60        90      43        31      67      43       64
## 5          76      79        91      77        91      63      90       75
## 6          88      95        90      94        82      56      83       66
##   LongShots Aggression Interceptions Positioning Vision Penalties
## 1        94         48            22          94     94        75
## 2        93         63            29          95     82        85
## 3        82         56            36          89     87        81
## 4        12         38            30          12     68        40
## 5        91         76            61          87     94        79
## 6        80         54            41          87     89        86
##   Composure Marking StandingTackle SlidingTackle GKDiving GKHandling
## 1        96      33             28            26        6         11
## 2        95      28             31            23        7         11
## 3        94      27             24            33        9          9
## 4        68      15             21            13       90         85
## 5        88      68             58            51       15         13
## 6        91      34             27            22       11         12
##   GKKicking GKPositioning GKReflexes
## 1        15            14          8
## 2        15            14         11
## 3        15            15         11
## 4        87            88         94
## 5         5            10         13
## 6         6             8          8
```

We've now cleaned up the FIFA stats as those will be the most useful. We kept just the most useful fields for our analysis. Now, we can begin!

What are some of the questions we might be looking to answer?

Electronic Arts has done their best to score over 19000 football players around the world. On their platform, all skills should in theory be ranked accordingly. The Overall score is an easy catch-all explanation of player skill, but how is that calculated? Is it the average of all scores? Is there a league that has, in general, a stronger overall player base than any other? If I was utilizing their Career mode, I would want to know the beginning set up that gave my future superstar the highest overall potentional!

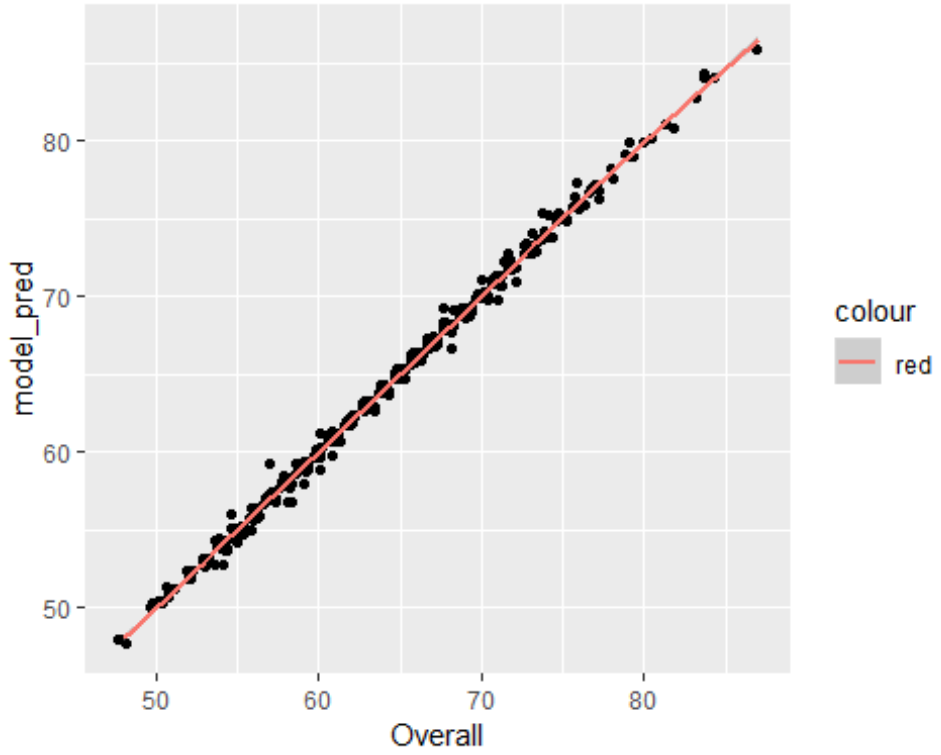
In order to address that,, we should look to address the following: which league has the highest overall skill rating, how exactly does FIFA weight the various skill measurements to determine overall rating, and how we can maximize the potential of our new recruits.

Our Model

Let's create our model. I'm going to split the data at this point as well, because I suspect that the model for goalkeepers is going to look significantly different than the model for all players, or just other position players.

```
cleanGK <- subset(cleanFifaGameNA, cleanFifaGameNA$Position == "GK")
cleanOthers <- anti_join(cleanFifaGameNA, cleanGK)

## Joining, by = c("Name", "Age", "Overall", "Potential", "Club", "Position",
"Height", "Weight", "Crossing", "Finishing", "HeadingAccuracy",
"ShortPassing", "Volleys", "Dribbling", "Curve", "FKAccuracy", "LongPassing",
"BallControl", "Acceleration", "SprintSpeed", "Agility", "Reactions",
"Balance", "ShotPower", "Jumping", "Stamina", "Strength", "LongShots",
"Aggression", "Interceptions", "Positioning", "Vision", "Penalties",
"Composure", "Marking", "StandingTackle", "SlidingTackle", "GKDiving",
"GKHandling", "GKKicking", "GKPositioning", "GKReflexes")

gkTest <- cleanGK %>% sample_frac(.2)
gkTrain <- anti_join(cleanGK, gkTest)

## Joining, by = c("Name", "Age", "Overall", "Potential", "Club", "Position",
"Height", "Weight", "Crossing", "Finishing", "HeadingAccuracy",
"ShortPassing", "Volleys", "Dribbling", "Curve", "FKAccuracy", "LongPassing",
"BallControl", "Acceleration", "SprintSpeed", "Agility", "Reactions",
"Balance", "ShotPower", "Jumping", "Stamina", "Strength", "LongShots",
"Aggression", "Interceptions", "Positioning", "Vision", "Penalties",
"Composure", "Marking", "StandingTackle", "SlidingTackle", "GKDiving",
"GKHandling", "GKKicking", "GKPositioning", "GKReflexes")

offenseTest <- cleanOthers %>% sample_frac(.2)
offenseTrain <- anti_join(cleanOthers, offenseTest)

## Joining, by = c("Name", "Age", "Overall", "Potential", "Club", "Position",
"Height", "Weight", "Crossing", "Finishing", "HeadingAccuracy",
"ShortPassing", "Volleys", "Dribbling", "Curve", "FKAccuracy", "LongPassing",
"BallControl", "Acceleration", "SprintSpeed", "Agility", "Reactions",
```

```
"Balance", "ShotPower", "Jumping", "Stamina", "Strength", "LongShots",
"Aggression", "Interceptions", "Positioning", "Vision", "Penalties",
"Composure", "Marking", "StandingTackle", "SlidingTackle", "GKDiving",
"GKHandling", "GKKicking", "GKPositioning", "GKReflexes")

overallModel <- glm(Overall ~ Age + Crossing + Finishing + HeadingAccuracy +
ShortPassing + Volleys + Dribbling + Curve + FKAccuracy + LongPassing +
BallControl + Acceleration + SprintSpeed + Agility + Reactions + Balance +
ShotPower + Jumping + Stamina + Strength + LongShots + Aggression +
Interceptions + Positioning + Vision + Penalties + Composure + Marking +
StandingTackle + SlidingTackle + GKDiving + GKHandling + GKKicking +
GKPositioning + GKReflexes, data = cleanFifaGameNA)

gkModel <-glm(Overall ~ Age + Crossing + Finishing + HeadingAccuracy +
ShortPassing + Volleys + Dribbling + Curve + FKAccuracy + LongPassing +
BallControl + Acceleration + SprintSpeed + Agility + Reactions + Balance +
ShotPower + Jumping + Stamina + Strength + LongShots + Aggression +
Interceptions + Positioning + Vision + Penalties + Composure + Marking +
StandingTackle + SlidingTackle + GKDiving + GKHandling + GKKicking +
GKPositioning + GKReflexes, data = gkTrain)

offenseModel <- glm(Overall ~ Age + Crossing + Finishing + HeadingAccuracy +
ShortPassing + Volleys + Dribbling + Curve + FKAccuracy + LongPassing +
BallControl + Acceleration + SprintSpeed + Agility + Reactions + Balance +
ShotPower + Jumping + Stamina + Strength + LongShots + Aggression +
Interceptions + Positioning + Vision + Penalties + Composure + Marking +
StandingTackle + SlidingTackle + GKDiving + GKHandling + GKKicking +
GKPositioning + GKReflexes, data = offenseTrain)

gkTest$model_pred <- round(predict(gkModel, gkTest, type = "response"))

offenseTest$model_pred <- round(predict(offenseModel, offenseTest, type =
"response"))

ggplot(gkTest, aes(x = Overall, y = model_pred)) +
  geom_jitter() +
  geom_smooth(aes(color = "red"))

## `geom_smooth()` using method = 'loess' and formula 'y ~ x'
```

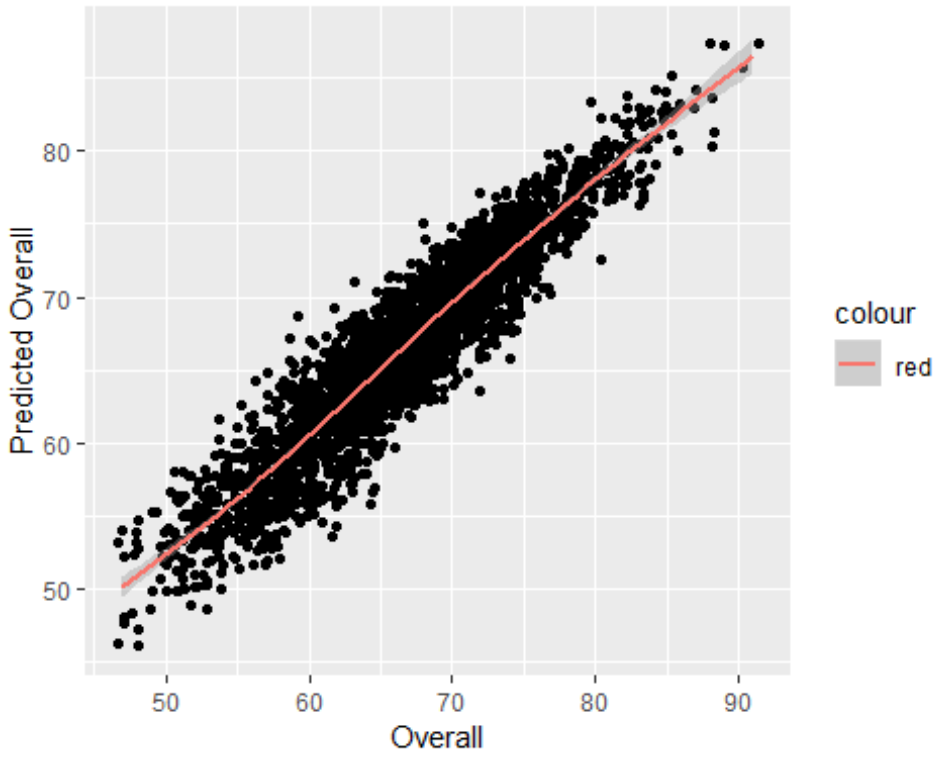


Wow, our model for goalkeepers looks really, really nice. There are a few outliers but for the most part the model looks very good at predicting the overall grade. It looks like there might not be as much nudge factor as expected.

Here's the same graph but for the test set of regular players:

```
ggplot(offenseTest, aes(x = Overall, y = model_pred)) +
  geom_jitter() +
  geom_smooth(aes(color = "red"))+
  ylab("Predicted Overall")
```

```
## `geom_smooth()` using method = 'gam' and formula 'y ~ s(x, bs = "cs")'
```



Overall a pleasing graph. I added some jitter due to the number of datapoints but generally there is an overall trend.

What variables are most significant? We have all of our data on the same scale so this analysis is slightly easier.

```
summary(gkModel)
```

```
##
## Call:
## glm(formula = Overall ~ Age + Crossing + Finishing + HeadingAccuracy +
##     ShortPassing + Volleys + Dribbling + Curve + FKAccuracy +
##     LongPassing + BallControl + Acceleration + SprintSpeed +
##     Agility + Reactions + Balance + ShotPower + Jumping + Stamina +
##     Strength + LongShots + Aggression + Interceptions + Positioning +
##     Vision + Penalties + Composure + Marking + StandingTackle +
##     SlidingTackle + GKDiving + GKHandling + GKKicking + GKPositioning +
##     GKReflexes, data = gkTrain)
##
## Deviance Residuals:
##      Min        1Q    Median        3Q       Max
## -1.54487  -0.26869  -0.01792   0.26840   1.50250
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)      8.346e-01  9.813e-02   8.505  < 2e-16 ***
## Age             -2.701e-03  2.062e-03  -1.310   0.1904
```

```
## Crossing         -3.229e-03  2.489e-03  -1.297   0.1948
## Finishing        -3.947e-03  3.140e-03  -1.257   0.2090
## HeadingAccuracy   1.656e-04  2.327e-03   0.071   0.9433
## ShortPassing      3.927e-04  1.461e-03   0.269   0.7881
## Volleys           1.463e-03  2.852e-03   0.513   0.6081
## Dribbling         3.040e-04  2.382e-03   0.128   0.8985
## Curve            -8.983e-04  2.282e-03  -0.394   0.6939
## FKAccuracy       -2.725e-03  2.058e-03  -1.324   0.1856
## LongPassing      -3.849e-04  1.409e-03  -0.273   0.7847
## BallControl      -9.169e-04  1.714e-03  -0.535   0.5927
## Acceleration      1.278e-03  1.455e-03   0.878   0.3798
## SprintSpeed       5.763e-04  1.425e-03   0.404   0.6859
## Agility          -5.519e-04  9.248e-04  -0.597   0.5508
## Reactions         1.101e-01  1.466e-03  75.076  < 2e-16 ***
## Balance           3.704e-04  9.411e-04   0.394   0.6940
## ShotPower         5.322e-03  1.322e-03   4.026 5.93e-05 ***
## Jumping          -1.506e-03  9.457e-04  -1.592   0.1115
## Stamina          -1.117e-03  1.277e-03  -0.874   0.3821
## Strength         -8.127e-04  8.204e-04  -0.991   0.3220
## LongShots        -2.509e-05  2.872e-03  -0.009   0.9930
## Aggression        8.417e-04  1.197e-03   0.703   0.4821
## Interceptions     3.054e-03  1.945e-03   1.570   0.1166
## Positioning      -5.149e-03  2.948e-03  -1.746   0.0809 .
## Vision            8.195e-04  7.554e-04   1.085   0.2781
## Penalties         3.000e-04  1.413e-03   0.212   0.8319
## Composure         1.603e-03  8.548e-04   1.875   0.0609 .
## Marking          -4.823e-04  1.498e-03  -0.322   0.7475
## StandingTackle    8.399e-04  3.070e-03   0.274   0.7844
## SlidingTackle     4.154e-04  2.987e-03   0.139   0.8894
## GKDiving          2.117e-01  2.733e-03  77.475  < 2e-16 ***
## GKHandling        2.151e-01  2.345e-03  91.734  < 2e-16 ***
## GKKicking         4.960e-02  1.662e-03  29.848  < 2e-16 ***
## GKPositioning     2.075e-01  2.266e-03  91.567  < 2e-16 ***
## GKReflexes        2.097e-01  2.616e-03  80.137  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for gaussian family taken to be 0.1051547)
##
##     Null deviance: 93236.26  on 1619  degrees of freedom
## Residual deviance:   166.57  on 1584  degrees of freedom
## AIC: 986.19
##
## Number of Fisher Scoring iterations: 2

summary(offenseModel)

##
## Call:
## glm(formula = Overall ~ Age + Crossing + Finishing + HeadingAccuracy +
```

```
##     ShortPassing + Volleys + Dribbling + Curve + FKAccuracy +
##     LongPassing + BallControl + Acceleration + SprintSpeed +
##     Agility + Reactions + Balance + ShotPower + Jumping + Stamina +
##     Strength + LongShots + Aggression + Interceptions + Positioning +
##     Vision + Penalties + Composure + Marking + StandingTackle +
##     SlidingTackle + GKDiving + GKHandling + GKKicking + GKPositioning +
##     GKReflexes, data = offenseTrain)
##
## Deviance Residuals:
##      Min        1Q    Median        3Q       Max
## -11.0625   -1.6495   -0.0432    1.6076   10.8006
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)     10.5567530  0.3458387  30.525  < 2e-16 ***
## Age              0.0583794  0.0065084   8.970  < 2e-16 ***
## Crossing         0.0067719  0.0029048   2.331 0.019752 *
## Finishing        0.0303307  0.0035554   8.531  < 2e-16 ***
## HeadingAccuracy  0.0875119  0.0031353  27.912  < 2e-16 ***
## ShortPassing     0.1073836  0.0056594  18.974  < 2e-16 ***
## Volleys         -0.0046531  0.0030880  -1.507 0.131875
## Dribbling        0.0079945  0.0046647   1.714 0.086588 .
## Curve            0.0058707  0.0030584   1.920 0.054935 .
## FKAccuracy       0.0086442  0.0027070   3.193 0.001410 **
## LongPassing     -0.0149297  0.0039644  -3.766 0.000167 ***
## BallControl      0.1625651  0.0059796  27.187  < 2e-16 ***
## Acceleration     0.0477304  0.0045726  10.438  < 2e-16 ***
## SprintSpeed      0.0340296  0.0041919   8.118 5.17e-16 ***
## Agility         -0.0008424  0.0034821  -0.242 0.808846
## Reactions        0.2685227  0.0045647  58.826  < 2e-16 ***
## Balance         -0.0163480  0.0030838  -5.301 1.17e-07 ***
## ShotPower        0.0209864  0.0033419   6.280 3.50e-10 ***
## Jumping          0.0024485  0.0022967   1.066 0.286395
## Stamina          0.0103999  0.0026428   3.935 8.36e-05 ***
## Strength         0.0398028  0.0029535  13.477  < 2e-16 ***
## LongShots       -0.0218054  0.0034420  -6.335 2.45e-10 ***
## Aggression      -0.0032853  0.0024290  -1.353 0.176229
## Interceptions   -0.0034589  0.0034978  -0.989 0.322746
## Positioning     -0.0490919  0.0033449 -14.677  < 2e-16 ***
## Vision          -0.0399565  0.0036763 -10.869  < 2e-16 ***
## Penalties        0.0078018  0.0030352   2.570 0.010169 *
## Composure        0.1388401  0.0038834  35.753  < 2e-16 ***
## Marking          0.0345941  0.0027791  12.448  < 2e-16 ***
## StandingTackle   0.0280537  0.0051862   5.409 6.44e-08 ***
## SlidingTackle   -0.0215724  0.0047697  -4.523 6.16e-06 ***
## GKDiving         0.0061678  0.0071661   0.861 0.389425
## GKHandling       0.0046242  0.0072611   0.637 0.524239
## GKKicking       -0.0027113  0.0070230  -0.386 0.699457
## GKPositioning   -0.0154661  0.0072236  -2.141 0.032289 *
## GKReflexes       0.0105602  0.0071758   1.472 0.141146
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for gaussian family taken to be 6.249683)
##
##     Null deviance: 591428  on 12906  degrees of freedom
## Residual deviance:  80440  on 12871  degrees of freedom
## AIC: 60319
##
## Number of Fisher Scoring iterations: 2
```

For goalkeepers, there are 5 variables that have quite an effect on the overall score:

1. GKHandling
2. GKDiving
3. GKReflexies
4. GKPosition
5. Reactions

For regular players, it is slightly different:

1. Reactions
2. Ball Control
3. Composure
4. Short Passing
5. Heading Accuracy

Reactions is important for both sets of players, but that is it.

```
gkTest <- mutate(gkTest, differential = (model_pred - Overall))
offenseTest <- mutate(offenseTest, differential = (model_pred - Overall))

overachievingOffense <- subset(offenseTest, differential < 0)
overachievingGK <- subset(gkTest, differential < 0)

underachievingOffense <- subset(offenseTest, differential > 2)
underachievingGK <- subset(gkTest, differential > 2)
```

There are 15 Goalkeepers who had ranked slightly higher than the model predicts and 1327 regular players. this corresponds to 3.704% of the goalkeepers and 41.122% of the regular players. Yikes! However, if we look at it a different way:

```
overachievingOffense.2 <- subset(overachievingOffense, abs(differential) >=
2)
overachievingGK.2 <- subset(overachievingGK, abs(differential) >= 2)

overachievingOffense.5 <- subset(overachievingOffense, abs(differential) >=
5)
```

There are now 0 goalkeepers that are 2 or more points away from their expected, and 860 regular players. So it seems goalkeepers are spot on but players are a little trickier!

However, 122 players are 5 or more points higher than the model predicts.

So who are the players we would find most desirable? Those would be the players that have an overall rating higher than our model predicts. They are more than the sum of their parts, basically.

We'll now look at the top 6 players per position, based on them being better than the model predicts.

```
overachievingOffense <-
overachievingOffense[order(overachievingOffense$differential),]

overachievingGK <- overachievingGK[order(overachievingGK$differential),]

print("Central Attacking Midfielder:")

## [1] "Central Attacking Midfielder:"

head(select(subset(overachievingOffense,overachievingOffense$Position ==
"CAM"), Name, Overall, differential))

##              Name Overall differential
## 300  Z. Jovanovic      64           -8
## 2402     N. Silva      74           -8
## 1178     Carlitos      64           -7
## 167     E. LÃ³pez      72           -6
## 723     L. BÃ©nes      69           -6
## 775        RÃ©gis      74           -6

print("Center Back:")

## [1] "Center Back:"

head(select(subset(overachievingOffense,overachievingOffense$Position ==
"CB"), Name, Overall, differential))

##             Name Overall differential
## 2290 R. Schlegel      62           -8
## 79     T. Davies      62           -6
## 119   J. Trtovac      61           -6
## 405   S. Ngezana      64           -6
## 518    G. Hanley      72           -6
## 935     T. Baack      58           -6

print("Central Defensive Midfielder:")

## [1] "Central Defensive Midfielder:"
```

```
head(select(subset(overachievingOffense,overachievingOffense$Position ==
"CDM"), Name, Overall, differential))
```

```
##                Name Overall differential
## 1615  S. AscacÃ-bar      78           -5
## 189         L. Fejsa      82           -4
## 2395 Markel Bergara      77           -4
## 24       J. McCarthy      77           -3
## 2088       S. Marreh      67           -3
## 2397     N. Pelaitay      62           -3
```

```
print("Center Forward:")
```

```
## [1] "Center Forward:"
```

```
head(select(subset(overachievingOffense,overachievingOffense$Position ==
"CF"), Name, Overall, differential))
```

```
##              Name Overall differential
## 596  Luis Alberto      82           -4
## 1027      B. Kuwas      74           -4
## 637     Toni Villa      73           -3
## 160     G. Caprari      73           -2
## 2710     J. Vargas      67           -2
```

```
print("Center Midfield:")
```

```
## [1] "Center Midfield:"
```

```
head(select(subset(overachievingOffense,overachievingOffense$Position ==
"CM"), Name, Overall, differential))
```

```
##              Name Overall differential
## 900     N. KeÃ¯ta      83           -5
## 786  Unai LÃ³pez      75           -4
## 2603    B. Halimi      69           -4
## 203   P. Galdames      70           -3
## 226    J. Fuentes      68           -3
## 325     A. GrgiÄ‡      68           -3
```

```
print("Left Attacking Midfield:")
```

```
## [1] "Left Attacking Midfield:"
```

```
head(select(subset(overachievingOffense,overachievingOffense$Position ==
"LAM"), Name, Overall, differential))
```

```
##                Name Overall differential
## 1771     D. Buitrago      72           -8
## 782  Leordinho Paes      72           -3
## 1791         H. Abe      68           -2
## 2910  Paulolettinho      71           -1
```

```r
print("Left Back:")
```

```
## [1] "Left Back:"
```

```r
head(select(subset(overachievingOffense,overachievingOffense$Position ==
"LB"), Name, Overall, differential))
```

```
##                Name Overall differential
## 1454          Elbis      62           -5
## 431      Bai Jiajun      68           -4
## 777      Jordi Alba      87           -4
## 1464    Y. Armougom      59           -4
## 1498     J. Pendant      63           -4
## 1632 RaÃºl Llorente      69           -4
```

```r
print("Left Center Back:")
```

```
## [1] "Left Center Back:"
```

```r
head(select(subset(overachievingOffense,overachievingOffense$Position ==
"LCB"), Name, Overall, differential))
```

```
##              Name Overall differential
## 88          O. Ba      65           -6
## 480  F. Fontanini      72           -6
## 337     G. Nauber      68           -5
## 1591    A. Sedlar      67           -5
## 2942   G. Valsvik      69           -5
## 2968    A. El-Abd      67           -5
```

```r
print("Left Center Midfielder:")
```

```
## [1] "Left Center Midfielder:"
```

```r
head(select(subset(overachievingOffense,overachievingOffense$Position ==
"LCM"), Name, Overall, differential))
```

```
##               Name Overall differential
## 247       K. Kampl      83           -4
## 1933 Fran Villalba      69           -4
## 2064 E. FernÃ¡ndez      68           -4
## 2861    C. Pinares      71           -4
## 1576   F. VÃ¡zquez      82           -3
## 2171   L. Torreira      82           -3
```

```r
print("Left Forward:")
```

```
## [1] "Left Forward:"
```

```r
head(select(subset(overachievingOffense,overachievingOffense$Position ==
"LF"), Name, Overall, differential))
```

```
##               Name Overall differential
## 202 Jonathan Viera      82           -3
```

```
print("Left Midfielder:")
```

```
## [1] "Left Midfielder:"
```

```
head(select(subset(overachievingOffense,overachievingOffense$Position ==
"LM"), Name, Overall, differential))
```

```
##                 Name Overall differential
## 661        S. Boufal      77           -7
## 82   Felipe Anderson      83           -6
## 816        J. Aquino      77           -6
## 1664        E. Frear      63           -6
## 2452         D. Gray      76           -6
## 2797        T. Usami      74           -6
```

```
print("Left Striker:")
```

```
## [1] "Left Striker:"
```

```
head(select(subset(overachievingOffense,overachievingOffense$Position ==
"LS"), Name, Overall, differential))
```

```
##              Name Overall differential
## 2678 M. Balotelli      83           -6
## 166       Douglas      72           -3
## 266     Marc Gual      70           -2
## 380    Santi Mina      80           -2
## 454          Mata      76           -2
## 1284    L. Pratto      78           -2
```

```
print("Left Wing:")
```

```
## [1] "Left Wing:"
```

```
head(select(subset(overachievingOffense,overachievingOffense$Position ==
"LW"), Name, Overall, differential))
```

```
##                Name Overall differential
## 1452           Isco      88           -8
## 2867     L. Insigne      88           -7
## 41   Y. Konoplyanka      79           -4
## 521     H. St Clair      56           -4
## 956   A. Al Qahtani      64           -4
## 1407      J. Ngando      60           -4
```

```
print("Left Wing Back:")
```

```
## [1] "Left Wing Back:"
```

```r
head(select(subset(overachievingOffense,overachievingOffense$Position ==
"LWB"), Name, Overall, differential))
```

```
##             Name Overall differential
## 2673  B. PittÃ³n      68           -3
## 1742 M. Pedersen      68           -2
## 2951 D. Lafferty      67           -2
## 1988       Mossa      71           -1
## 2150     R. Tait      67           -1
## 3218   L. Carole      72           -1
```

```r
print("Right Attacking Midfield:")
```

```
## [1] "Right Attacking Midfield:"
```

```r
head(select(subset(overachievingOffense,overachievingOffense$Position ==
"RAM"), Name, Overall, differential))
```

```
##                 Name Overall differential
## 1665      Y. Cabrera      69           -6
## 2562     J. Cuadrado      84           -3
## 2747 Emerson Avintes      71           -2
```

```r
print("Right Back:")
```

```
## [1] "Right Back:"
```

```r
head(select(subset(overachievingOffense,overachievingOffense$Position ==
"RB"), Name, Overall, differential))
```

```
##                  Name Overall differential
## 3174        J. Risdon      72           -5
## 157         T. Rieder      63           -4
## 758    A. Wan-Bissaka      74           -4
## 1580       Liu Boyang      54           -4
## 393         V. Salazar      71           -3
## 968  IvÃ¡n RodrÃ-guez      68           -3
```

```r
print("Right Center Back:")
```

```
## [1] "Right Center Back:"
```

```r
head(select(subset(overachievingOffense,overachievingOffense$Position ==
"RCB"), Name, Overall, differential))
```

```
##                 Name Overall differential
## 1319       B. N'Gala      62           -8
## 1543         M. Rahn      65           -8
## 627  Manuel da Costa      71           -6
## 664   G. Margreitter      74           -6
## 939      O. Gonzalez      73           -6
## 1512    S. Takahashi      62           -6
```

```
print("Right Center Midfielder:")
```

```
## [1] "Right Center Midfielder:"
```

```
head(select(subset(overachievingOffense,overachievingOffense$Position ==
"RCM"), Name, Overall, differential))
```

```
##               Name Overall differential
## 1969       Canales      80           -7
## 988  Pablo Sarabia      82           -4
## 1737  Sergi Darder      79           -4
## 2331     J. Clasie      76           -3
## 2586       F. Gino      66           -3
## 3085     Javi Lara      70           -3
```

```
print("Right Forward:")
```

```
## [1] "Right Forward:"
```

```
head(select(subset(overachievingOffense,overachievingOffense$Position ==
"RF"), Name, Overall, differential))
```

```
##                    Name Overall differential
## 766          Zhang Xizhe      72           -4
## 2840 D. Moberg Karlsson      69           -4
## 3148          G. Notsuda      66           -1
```

```
print("Right Midfielder:")
```

```
## [1] "Right Midfielder:"
```

```
head(select(subset(overachievingOffense,overachievingOffense$Position ==
"RM"), Name, Overall, differential))
```

```
##                   Name Overall differential
## 2070      Lucas Moura      83           -7
## 1944 Ã\201lvaro JimÃ©nez      74           -6
## 2793        S. Kaneko      70           -6
## 2937       B. AlÄ±cÄ±      73           -6
## 206            J. Ibe      74           -5
## 533          O. Romero      76           -5
```

```
print("Right Striker:")
```

```
## [1] "Right Striker:"
```

```
head(select(subset(overachievingOffense,overachievingOffense$Position ==
"RS"), Name, Overall, differential))
```

```
##                 Name Overall differential
## 2527     M. BolaÃ±os      73           -6
## 1120    K. Schindler      72           -4
## 2159         Deulofeu      80           -4
```

```
## 503       K. Billiat      75           -3
## 2642        N. Citro      68           -3
## 179  Z. IbrahimoviÄ‡      85           -2

print("Right Wing:")

## [1] "Right Wing:"

head(select(subset(overachievingOffense,overachievingOffense$Position ==
"RW"), Name, Overall, differential))

##                Name Overall differential
## 1354  F. El Mellali      66           -6
## 2980    R. Sterling      86           -6
## 1425      R. Nelson      70           -5
## 2237     C. Musonda      75           -5
## 78     Kuki Zalazar      64           -4
## 125  Lucas VÃ¡zquez      83           -4

print("Right Wing Back:")

## [1] "Right Wing Back:"

head(select(subset(overachievingOffense,overachievingOffense$Position ==
"RWB"), Name, Overall, differential))

##              Name Overall differential
## 2993 Pablo Maffeo      78           -4
## 3076  Johannesson      70           -3
## 51     M. Doherty      75           -2
## 925      A. Amade      58           -2
## 279    R. Laursen      65           -1
## 1508  D. Sundgren      69           -1

print("Striker:")

## [1] "Striker:"

head(select(subset(overachievingOffense,overachievingOffense$Position ==
"ST"), Name, Overall, differential))

##               Name Overall differential
## 2511   K. Sierhuis      68           -5
## 346    S. Demhasaj      64           -4
## 1378  B. Gschweidl      64           -4
## 1802     C. Huanca      58           -4
## 2116 Tiago Marques      64           -4
## 3224 L. FernÃ¡ndez      74           -4

head(select(overachievingGK, Name, Overall, differential))

##                 Name Overall differential
## 20          K. Navas      87           -1
```

```
## 110        J. Weaver      54           -1
## 151        M. Hassen      71           -1
## 159 Pablo CacharrÃ³n      58           -1
## 165        T. Masuda      61           -1
## 169     W. Yarbrough      68           -1
```

Analysis

Overall, how accurate was our model? Here we will define inaccuracy as +- 2 points from predicted.

For regular players:

```
accuracyOffense <- (1 - ((nrow(underachievingOffense) +
nrow(overachievingOffense.2)) / nrow(offenseTest))) * 100
```

For goalkeepers:

```
accuracyGK <- (1 - ((nrow(underachievingGK) + nrow(overachievingGK)) /
nrow(gkTest))) * 100
```

The model is accurate for 96.3% of Goalkeepers in our test set, and 58.6% of players in our regular set. Still, when one considers the implication none of our players are more than 9 points off from prediction so it is actually a pretty decent model despite being off by 2 points for 40% of players.

Conclusions

Based on our analysis, the overall skill is a fairly linear relationship between the different skills measured in our players. While there are some outliers, given a set of skills we can reasonably predict within a few points where that player will lie. While the initial analysis of players may have its own set of biases, once a player is graded their skills are weighted equally across the board. Goalkeepers in particular adhere fairly strictly to this.

We have now identified the top 5 skills for both sets of players in order to maximize your overall gains.These are the skills you should focus on to have the greatest overall effect.

This analysis is solely limited to FIFA 19. We may be able to improve the accuracy of the model by controlling for player position, something that we did not do other than by splitting out the goalkeepers.

Overall, I was impressed with how much of a relationship existed that was quantifiable. I was worried initially that there would be some liberties taken with scoring. I was pleasantly surprised to find that was not the case.