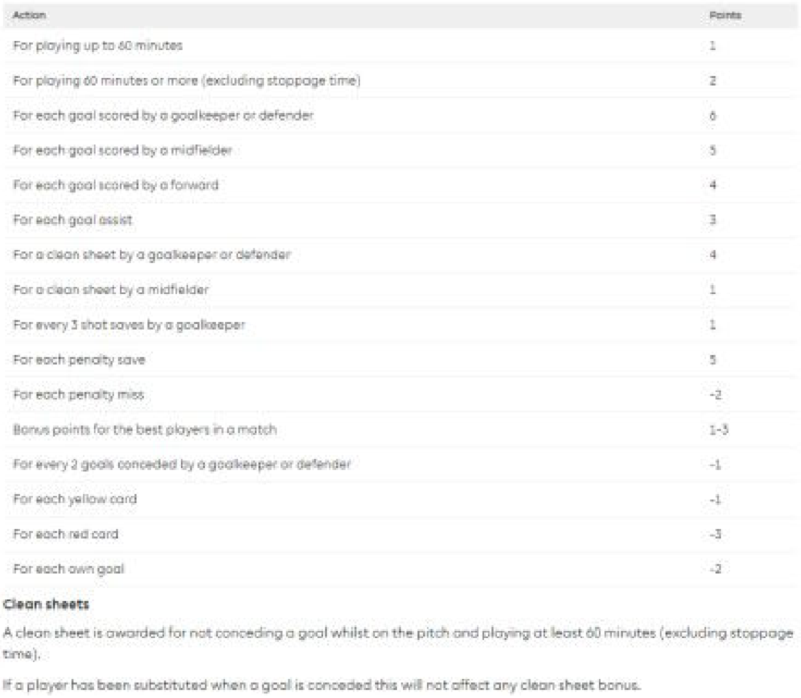
Now that the estimate of the score is created its time to work out what each players impact is. Below is a summary of the current scoring in the fantasy premier league



Action	Points
For playing up to 60 minutes	1
For playing 60 minutes or more (excluding stoppage time)	2
For each goal scored by a goalkeeper or defender	6
For each goal scored by a midfielder	5
For each goal scored by a forward	4
For each goal assist	3
For a clean sheet by a goalkeeper or defender	4
For a clean sheet by a midfielder	1
For every 3 shot saves by a goalkeeper	1
For each penalty save	5
For each penalty miss	-2
Bonus points for the best players in a match	1-3
For every 2 goals conceded by a goalkeeper or defender	-1
For each yellow card	-1
For each red card	-3
For each own goal	-2

Clean sheets

A clean sheet is awarded for not conceding a goal whilst on the pitch and playing at least 60 minutes (excluding stoppage time).

If a player has been substituted when a goal is conceded this will not affect any clean sheet bonus.

Most of the points are in 4 areas minutes played, goals scored, assists and goals conceded. The points are also different for the different positions a player might play so that will have to be taken into account

Goals Scored Points

First part is to predict the amount of goals a player might score. I decided that player level xG90 is the best metric to use and is readily available for the model. My particular source is the understat R package. This links directly to the understat website and allows the download of by player expected goal data

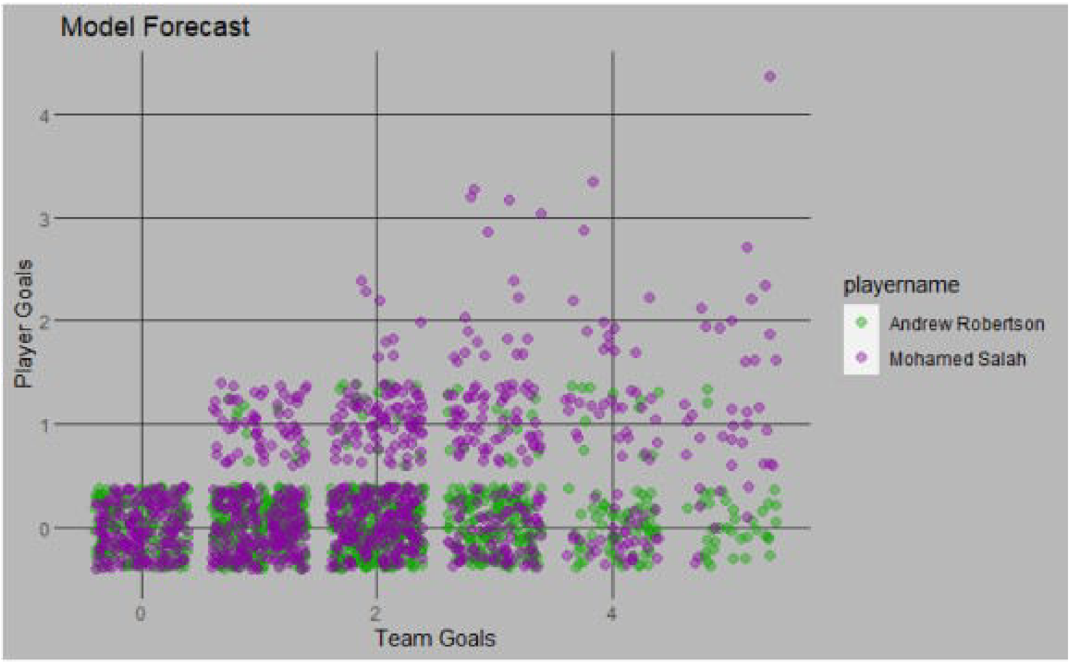
```
## this code downloads the whole xg data for 2019
twenty19 <- get_team_players_stats(team_name = "Arsenal" ,year = 2019) %>%
    bind_rows(get_team_players_stats(team_name = "Bournemouth" ,year = 2019))
%>%
    bind_rows(get_team_players_stats(team_name = "Burnley" ,year = 2019)) %>%
    bind_rows(get_team_players_stats(team_name = "Chelsea" ,year = 2019)) %>%
    bind_rows(get_team_players_stats(team_name = "Crystal Palace" ,year =
2019)) %>%
    bind_rows(get_team_players_stats(team_name = "Everton" ,year = 2019)) %>%
    bind_rows(get_team_players_stats(team_name = "Newcastle United" ,year =
2019)) %>%
    bind_rows(get_team_players_stats(team_name = "Leicester" ,year = 2019))
%>%
    bind_rows(get_team_players_stats(team_name = "Liverpool" ,year = 2019))
%>%
    bind_rows(get_team_players_stats(team_name = "Manchester City" ,year =
2019)) %>%
    bind_rows(get_team_players_stats(team_name = "Manchester United" ,year =
2019)) %>%
    bind_rows(get_team_players_stats(team_name = "Sheffield United" ,year =
2019)) %>%
    bind_rows(get_team_players_stats(team_name = "Southampton" ,year = 2019))
%>%
    bind_rows(get_team_players_stats(team_name = "Norwich" ,year = 2019)) %>%
    bind_rows(get_team_players_stats(team_name = "Brighton" ,year = 2019)) %>%
    bind_rows(get_team_players_stats(team_name = "Aston Villa" ,year = 2019))
%>%
    bind_rows(get_team_players_stats(team_name = "Tottenham" ,year = 2019))
%>%
    bind_rows(get_team_players_stats(team_name = "Watford" ,year = 2019)) %>%
    bind_rows(get_team_players_stats(team_name = "Wolverhampton Wanderers"
,year = 2019)) %>%
    bind_rows(get_team_players_stats(team_name = "West Ham" ,year = 2019))
```

I downloaded the data for 2017 and 2918 as well and then calculated each players overall xg90 as I think that will vary a lot therefore I am using the players xg90 over all the data. Therefore for this part of the model I will use the goals the team are predicted to score and the players xg90 with the thought being that if the players team was only to score one goal in the match the player wit the highest xG ratIng will be the ones most likely to score the goal.

```
## As always im using the tidymodels suite of packages and fitting a simpe
random forest

goals_split <- initial_split(goals, prop = 0.8, strata = goals_scored)
goals_train <- training(goals_split)
goals_test <- testing(goals_split)
goal_for <- rand_forest() %>%
                set_mode("classification") %>%
                set_engine("ranger") %>%
                  fit(goals_scored ~ ., goals_train)
```

Now I have a model that gives a prediction of how many goals a player might score. All I have to do is apply the model to the 10000 runs of the match for each player and it will have whether the player scored or not and if they scored ore then 1. Running the goal prediction model to for one match over 10000 times gives to following results for 2 Liverpool players



Most of the time the goals are scored by Salah as his expected goals per 90 is a lot higher then then Andrew Robertson’s. This expanded over 10000 versions of the match can be used to feed the model and calculate the points for goals scored.

Assists Points

Calculating assists points is pretty similar to goal scored points. Its a separate model that uses the estimate how many goals the players team will score and then the players xA per 90. The code is exactly the same as the code used for the goal expectation just with the new data for xA used instead of expected goals.

Minutes played points

This part of the point prediction is a relatively low amount of points available but is needed because the chance of a player playing is important as you want to maximise your team in getting the most amount of minutes possible.

```
## got each players last 5 matches average minutes played using the rollmean
function from the zoo package then put it into a category if the player went
onto play more then  60 minutes

s16min <- season16 %>% group_by(playername) %>%
                              mutate(rollmin = zoo::rollmean(minutes, 5, fill
= NA)) %>%
                              mutate(mins = if_else(minutes > 60, ">60",
"<60")) %>%
                                ungroup() %>%
                                select(mins, rollmin)



s17min <- season17 %>% group_by(playername) %>%
                              mutate(rollmin = zoo::rollmean(minutes, 5, fill
= NA)) %>%
                              mutate(mins = if_else(minutes > 60, ">60",
"<60")) %>%
                                ungroup() %>%
                                select(mins, rollmin)



s18min <- season18 %>% group_by(playername) %>%
                              mutate(rollmin = zoo::rollmean(minutes, 5, fill
= NA)) %>%
                              mutate(mins = if_else(minutes > 60, ">60",
"<60")) %>%
                                ungroup() %>%
                                select(mins, rollmin)



min_dat <- s16min %>% bind_rows(s17min) %>%
                              bind_rows(s18min) %>%
                                  filter(!is.na(rollmin))

min_dat$mins <- as.factor(as.character(min_dat$mins))
```

Once the data to train the model on was created I then followed a similar formula to the assist points and the goals scored.

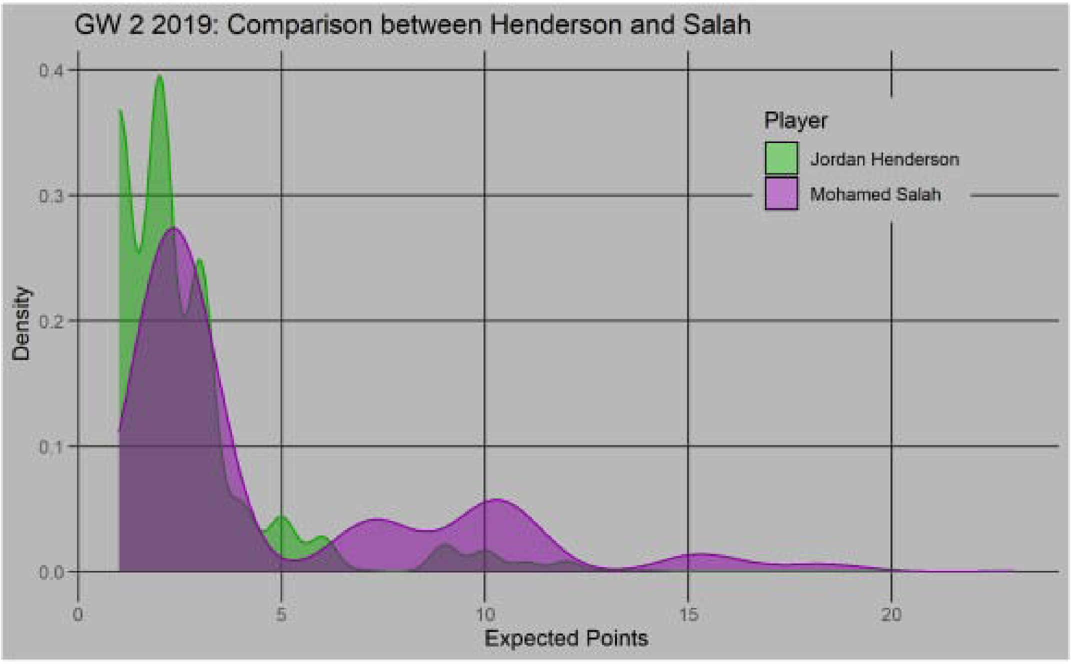
```
min_split <- initial_split(min_dat, prop = 0.9, strata = mins) # split the
data regime


min_train <- training(min_split) ## training split

min_test <- testing(min_split) ## testing split


## fitted a logistic regression model as there are only 2 categoires
min_mod <- logistic_reg() %>%
                set_engine("glm") %>%
                        fit(mins ~. , min_train)
```

As there are only two categories whether the player is likely to play more then 60 minutes or not which is the key part for getting the minutes played points. This also impacts the points the player will receive for clean sheets and the model will only give the full points for clean sheets if they are predicted to play more then 60 minutes.



There’s the final model output for a random game week from 2019 comparing Mo Salah and Jordan Henderson. Obviously this game Salah is more then likely to score more points. It also looks more like the distribution of all the points.