Principal Component Analysis of Premier League football data

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https://github.com/daniel-finnan/football_pca

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This is a Principal Component Analysis (PCA) intended to carry out an exploratory analysis of statistics from the Premier League. It uses data from the past 6 seasons, as well as the current unfinished 23/24 season. The goal (pun intended) is to discover links between the variables and identify similarities between the individuals. Data for the current season is dated 4 January, with all but four teams having played 20 games.

The approach is based on data for a team in a given season, focused on long-term performance, rather than on a match-by-match basis. It includes variables from the league table, plus more detailed variables, such as the number of times a team has hit the woodwork, or number of own goals. In total, we have 38 quantitative variables covering 140 teams across 7 seasons, ideal for dimensionality reduction.

The data has been scraped from an online source using Python, with code available in the scraping folder of this repository.

This analysis is also available in pdf format.

First, we'll load the libraries we need.

```
library(FactoMineR)
library(factoextra)
library(ggplot2)
library(corrplot)
library(reshape2)
library(dplyr)
library(tibble)
library(rmarkdown)
library(car)

# Turn off scientific notation
options(scipen = 999)
```

Data preparation

Read the data from the csv file we created during Python scraping and create an index row.

```
data <- read.table("pl_data.csv",
                   header=TRUE, sep=";", dec=".")
rownames(data) <- data$Idx
```

Adjust Everton

It is necessary to add back the 10 points deducted from Everton over breaking financial rules. We also need to adjust the positions in the table. This is important because the sanction has no direct impact on the team's performance statistics.

```r
data["EVE2023_24", "Points"] <- 26
data["EVE2023_24", "Position"] <- 13

# Fulham, Crystal Palace, Nottingham Forest & Brentford need to drop a table position
data[c("FUL2023_24", "CRY2023_24", "NFO2023_24", "BRE2023_24"), "Position"] <-
  data[c("FUL2023_24", "CRY2023_24", "NFO2023_24", "BRE2023_24"), "Position"] + 1
```

Categories

Categorise the teams into *Top 4*, *Top Half*, *Bottom Half* and *Relegated*, corresponding to qualification to the UEFA Champions League, the bottom 3 relegated teams, and the rest split between the top and bottom halves of the table.

```r
data$Category <-  ifelse(data$Position >= 1 & data$Position <= 4, "Top_4",
                  ifelse(data$Position >= 5 & data$Position <= 10, "Top_Half",
                  ifelse(data$Position >= 11 & data$Position <= 17, "Bottom_Half",
                  ifelse(data$Position >= 18 & data$Position <= 20, "Relegated", ""))))
```

Subsets

Active and supplementary individuals Teams from past seasons are our active individuals and the current season contains our supplementary individuals.

```r
data.active <- data[data$Season %in% c('2017_18', '2018_19', '2019_20', '2020_21',
                                       '2021_22', '2022_23'), ]
data.supp <- data[data$Season == '2023_24', ]
```

Variables We group the variables according to their characteristics.

```r
# List of all our variables
knitr::kable(colnames(data), caption = 'List of variables', col.names = c('Variable'))
```

Table 1: List of variables

Variable
Idx
Short_name
Position
Played
Won
Drawn
Lost
Goals_For

Variable
Goals_Conceded
Goal_Difference
Points
Yellow_Cards
Red_Cards
Shots
Shots_On_Target
Hit_Woodwork
Goals_From_Header
Goals_From_Penalty
Goals_From_Freekick
Goals_From_Inside_Box
Goals_From_Outside_Box
Goals_From_Counter_Attack
Offsides
Clean_Sheets
Saves
Blocks
Interceptions
Tackles
Last_Man_Tackles
Clearances
Headed_Clearances
Own_Goals
Penalties_Conceded
Goals_Conceded_From_Penalty
Passes
Through_Balls
Long_Passes
Backwards_Passes
Crosses
Corners_Taken
Season
Category

```r
# Split the variables into categories
general <- c(
  "Won",
  "Lost",
  "Goals_For",
  "Yellow_Cards",
  "Red_Cards")

attack <- c(
  "Shots",
  "Shots_On_Target",
  "Hit_Woodwork",
  "Goals_From_Header",
  "Goals_From_Penalty",
  "Goals_From_Freekick",
  "Goals_From_Inside_Box",
  "Goals_From_Outside_Box",
```

```r
  "Goals_From_Counter_Attack",
  "Offsides")

defence <- c(
  "Clean_Sheets",
  "Goals_Conceded",
  "Saves",
  "Blocks",
  "Interceptions",
  "Tackles",
  "Last_Man_Tackles",
  "Clearances",
  "Headed_Clearances",
  "Own_Goals",
  "Penalties_Conceded",
  "Goals_Conceded_From_Penalty")

team_play <- c(
  "Passes",
  "Through_Balls",
  "Long_Passes",
  "Backwards_Passes",
  "Crosses",
  "Corners_Taken")

# Putting all the variables into one large vector
all_vars <- c(general, attack, defence, team_play)

# We're not interested in variables related to outcomes, i.e. Wins, Losses.
all_vars <- all_vars[! all_vars %in% c('Won', 'Lost')]

# Add the category variable we created
all_vars <- c(all_vars, 'Category')

# Create a vector for supplementary quantitative variables
supp_vars <- c('Won', 'Lost', 'Drawn', 'Points', 'Goal_Difference')

# Note: Goals For is not a sum of types of goals in attack category, so we'll leave it in.
```

Analysis of variance

Given that our supplementary individuals are only part way through the season we will compare the variance, grouping by season. We suspect that some of our variables are low frequency occurrences, e.g. *Red Cards*, that won't have the same variance unless we have a sample of an entire season. It is also possible that some of our variables aren't normally distributed. We therefore run both Levene's test and Barlett's test for only the active individuals, i.e. the last six complete seasons, and with the active and supplementary individuals, including the current, unfinished season. Levene's test is less sensitive to departures from the normal distribution.

```r
# Take out the Category variable
all_vars <- all_vars[! all_vars %in% c('Category')]
col_nums <- match(all_vars, names(data.active))
```

```r
# First test for data without 2023/24 season
p_values_levene_active <- c()
p_values_barlett_active <- c()
for (i in col_nums) {
  var_test_levene_active <- leveneTest(data.active[,i] ~ data.active$Season)
  var_test_barlett_active <- bartlett.test(data.active[,i] ~ data.active$Season)
  p_values_levene_active <- c(p_values_levene_active, var_test_levene_active[1,3])
  p_values_barlett_active <- c(p_values_barlett_active, var_test_barlett_active$p.value)
}
# Next test for all data including 2023/24 season
p_values_levene_with_supp <- c()
p_values_barlett_with_supp <- c()
col_nums <- match(all_vars,names(data))
for (i in col_nums) {
  var_test_levene_with_supp <- leveneTest(data[,i] ~ data$Season)
  var_test_barlett_with_supp <- bartlett.test(data[,i] ~ data$Season)
  p_values_levene_with_supp <-
    c(p_values_levene_with_supp, var_test_levene_with_supp[1,3])
  p_values_barlett_with_supp <-
    c(p_values_barlett_with_supp, var_test_barlett_with_supp$p.value)
}

result_var <- data.frame(all_vars, p_values_levene_active, p_values_barlett_active,
                         p_values_levene_with_supp, p_values_barlett_with_supp)
knitr::kable(
  result_var,
  col.names = c(
    'Variable',
    'p-value Levene\'s Test (active)',
    'p-value Barlett\'s Test (active)',
    'p-value Levene\'s Test (active & supp.)',
    'p-value Barlett\'s Test (active & supp.)'
    ),
  caption = "Equality of variance across seasons")
```

Table 2: Equality of variance across seasons

Variable	p-value Levene's Test (active)	p-value Barlett's Test (active)	p-value Levene's Test (active & supp.)	p-value Barlett's Test (active & supp.)
Goals_For	0.9955905	0.9572639	0.9986970	0.9705449
Yellow_Cards	0.3399992	0.1960549	0.1191555	0.0541656
Red_Cards	0.7937712	0.9059329	0.0186474	0.0467544
Shots	0.8663386	0.7538935	0.9038174	0.8433726
Shots_On_Target	0.9484813	0.7461899	0.9220180	0.8014703
Hit_Woodwork	0.5447619	0.6293745	0.6489046	0.6797470
Goals_From_Header	0.6517935	0.6823331	0.3264908	0.4503763
Goals_From_Penalty	0.9758674	0.9369802	0.3419765	0.4060741
Goals_From_Freekick	0.2868602	0.1250603	0.1595176	0.1061669
Goals_From_Inside_Box	0.9764355	0.9360190	0.9898292	0.9626992
Goals_From_Outside_Box	0.5121779	0.4605865	0.5236051	0.5209465
Goals_From_Counter_Attack	0.7642042	0.2929498	0.8716523	0.0443325
Offsides	0.1235039	0.1749159	0.0626217	0.0808906

Variable	p-value Levene's Test (active)	p-value Barlett's Test (active)	p-value Levene's Test (active & supp.)	p-value Barlett's Test (active & supp.)
Clean_Sheets	0.7791743	0.4151258	0.8636720	0.5351277
Goals_Conceded	0.6605901	0.4922396	0.7765413	0.6209010
Saves	0.8810719	0.9430708	0.7781633	0.8559776
Blocks	0.9853524	0.9882893	0.9915402	0.9904116
Interceptions	0.0145180	0.0138629	0.0286917	0.0263362
Tackles	0.5864739	0.7007722	0.6715628	0.8088480
Last_Man_Tackles	0.4115447	0.4686153	0.0321501	0.0929970
Clearances	0.3846646	0.3998411	0.3716857	0.4071761
Headed_Clearances	0.7080492	0.4412628	0.7669477	0.5660520
Own_Goals	0.0905144	0.1994313	0.1039059	0.0839191
Penalties_Conceded	0.3615165	0.4844947	0.4338137	0.4630899
Goals_Conceded_From_Penalty	0.7131947	0.4441343	0.3440294	0.1433620
Passes	0.9955674	0.9359083	0.9960662	0.9720742
Through_Balls	0.0175478	0.0003351	0.0360526	0.0007602
Long_Passes	0.7288465	0.3971123	0.5585881	0.4027520
Backwards_Passes	0.9938562	0.9853229	0.9789966	0.9547053
Crosses	0.3884246	0.2978525	0.5234988	0.4126462
Corners_Taken	0.7888063	0.9109110	0.8748960	0.9292224

There are several variables that have sufficient evidence at the 5% level for different variances for both Barlett's test and Levene's test when we compare the active versus active and supplementary individuals. These include:

- *Red Cards*
- *Interceptions*
- *Through Balls*

Furthermore, the following variables at the 10% level for both tests:

- *Offsides*
- *Last Man Tackles*

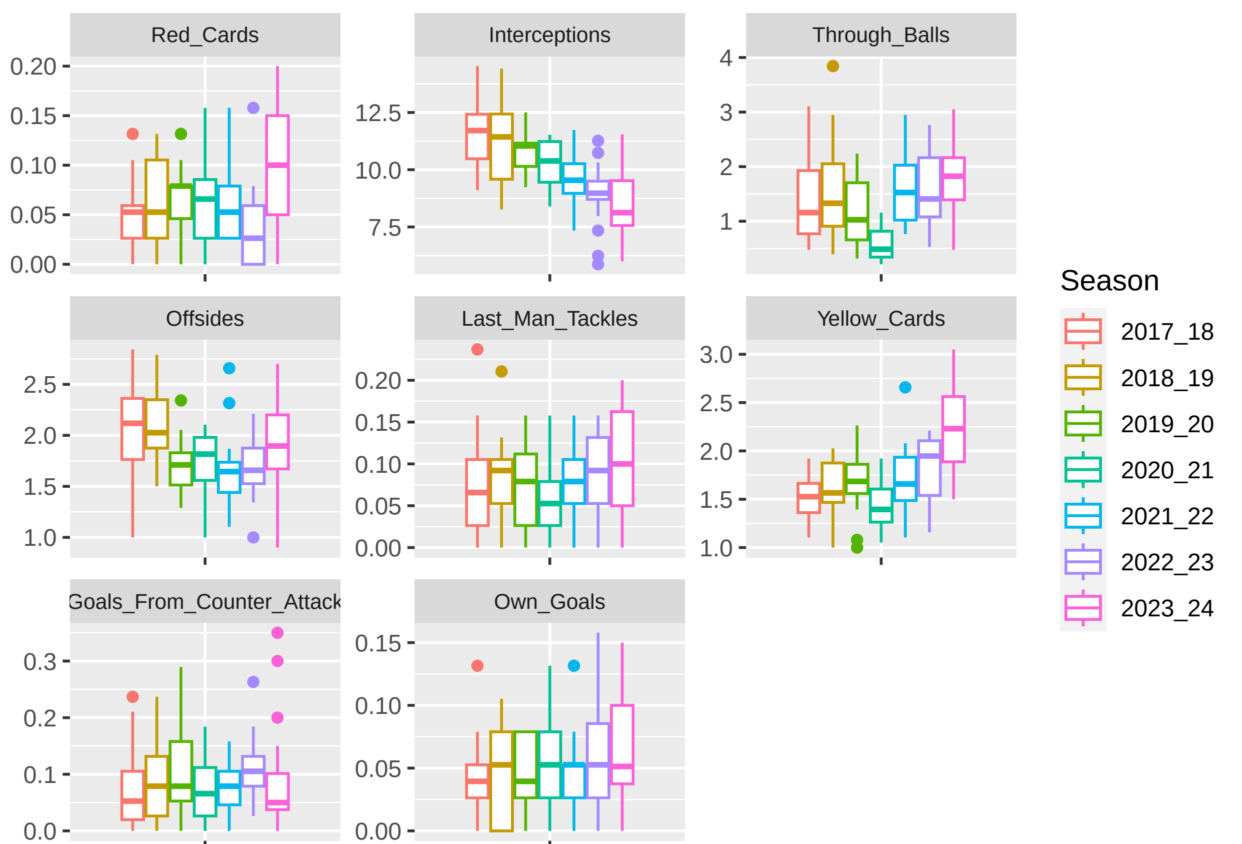
And, these for just Barlett's test at the 10% level:

- *Yellow Cards*
- *Goals From Counter Attack*
- *Own Goals*

This indicates that it is not valid to compare these variables between active and supplementary individuals. We can confirm this with a visual inspection.

```
# Reshape data for plots

# Only those variables with different variances plus Season
diff_vars <- c(
  "Red_Cards",
  "Interceptions",
  "Through_Balls",
  "Offsides",
```

```r
  "Last_Man_Tackles",
  "Yellow_Cards",
  "Goals_From_Counter_Attack",
  "Own_Goals",
  "Season"
  )

data.diff_vars <- data[, diff_vars]

melt(data.diff_vars, id = "Season") %>%
  ggplot(., aes(x = variable, y = value, color = Season)) +
    geom_boxplot() +
    facet_wrap(vars(variable), scales="free", nrow = 3, ncol = 3) +
    theme(
      strip.text = element_text(size = 8),
      axis.text.x=element_blank(),
      axis.title.x=element_blank(),
      axis.title.y = element_blank())
```



The boxplots show some evidence of more dispersion in the interquartile range (IQR) for the incomplete 2023/24 season compared to prior seasons. This is particularly pronounced for variables such as *Red Cards* and *Last Man Tackles*. We also note much higher maximum values for *Goals From Counter Attack*. It is clear that the reduced number of games we're looking at distorts these measures.

There are also a few variables which demonstrate unequal variance for just the active individuals. This suggests there could be an inherent, or a structural change in the variance over seasons. This impacts the following variables:

For both tests at the 5% level

- *Interceptions*
- *Through Balls*

For Levene's test at the 10% level

- *Own Goals*

Referring back to the boxplots, *Interceptions* appear to be decreasing almost every season with the IQR moving lower and the median reducing.

For *Own Goals*, the boxplots appear to indicate a vague trend, with a slight increase in the median and IQR. This variable is also another low frequency measure. In the last full season Brighton and Hove Albion scored the most own goals with 6 or 0.16 times per game. If we take the full sample of 7 seasons, then 21 teams have never scored a single own goal over the course of a season.

Through Balls is a bit more puzzling because we notice a big difference for the 2020/21 season. This was the Covid-19 impacted season with many games played behind closed doors. Liverpool registered the highest number for the season with 44 and Crystal Palace the lowest with 8. If we compare that to the season before, Manchester City recorded 85 and Watford 12. Likewise for the season after, Liverpool made 112 through balls and West Ham United 29. We could question whether a lack of fans at stadiums resulted in a change to the style of play. Although there are also suggestions that through balls are becoming rarer across European football in general, according to The Athletic. All the same, it is clear *Through Balls* in 2020/21 is an outlier.

Periodic changes to the Premier League rules could explain some of these structural changes. Notably, Video Assistant Referee (VAR) was introduced in the 2019/20 season, which ties into the downward trend for *Interceptions*. But rule changes don't immediately provide any explanation for the different variances for the *Own Goals* or *Through Balls* variables. We also note that Barlett's test for *Own Goals* doesn't show sufficient evidence for a difference in variance when considering only the active individuals.

We therefore exclude 8 variables from further inclusion in our analysis. Some of these are obviously low frequency measures that are not adequately captured for an incomplete season. Others demonstrate structural changes in the variance over each season perhaps because of rule changes, peculiarities such as Covid-19, or just the way in which the game is played.

```
# Update our variables of interest, removing those we don't want
remove_vars <- c(
  "Red_Cards",
  "Interceptions",
  "Through_Balls",
  "Offsides",
  "Last_Man_Tackles",
  "Yellow_Cards",
  "Goals_From_Counter_Attack",
  "Own_Goals")
adj_vars <- all_vars[! all_vars %in% remove_vars]
```

Descriptive statistics

Given the number of variables, we'll examine the extremes of the active individuals by looking at the 5 lowest and highest means and standard deviations.

```r
averages <- data.active[, adj_vars] %>%
  apply(., 2, mean)
n_avgs <- length(averages)
sorted_avg_low <- sort(averages, decreasing = FALSE)
lowest_avg_5 <- sorted_avg_low[1:5]
sorted_avg_high <- sort(averages, decreasing = TRUE)
highest_avg_5 <- sorted_avg_high[1:5]

std_dev <- data.active[, adj_vars] %>%
  apply(., 2, sd)
n_std_dev <- length(averages)
sorted_std_dev_low <- sort(std_dev, decreasing = FALSE)
lowest_std_dev_5 <- sorted_std_dev_low[1:5]
sorted_std_dev_high <- sort(std_dev, decreasing = TRUE)
highest_std_dev_5 <- sorted_std_dev_high[1:5]

knitr::kable(lowest_avg_5,
             col.names = c('Variable','Mean'),
             caption = "5 lowest means")
```

Table 3: 5 lowest means

Variable	Mean
Goals_From_Freekick	0.0258772
Goals_From_Penalty	0.1035088
Goals_Conceded_From_Penalty	0.1035088
Penalties_Conceded	0.1407895
Goals_From_Outside_Box	0.1822368

```r
knitr::kable(lowest_std_dev_5,
             col.names = c('Variable','SD'),
             caption = "5 lowest standard deviations")
```

Table 4: 5 lowest standard deviations

Variable	SD
Goals_From_Freekick	0.0270751
Goals_Conceded_From_Penalty	0.0586689
Goals_From_Penalty	0.0621373
Penalties_Conceded	0.0664737
Goals_From_Header	0.0973791

Goals From Freekick, *Goals From Penalty*, *Goals Conceded From Penalty* and *Penalties Conceded* have the lowest means and the least variability. These are rarer actions in a game, that happen more infrequently and vary little according to the team. These are also all actions resulting from intervention in games by the referee.

```r
knitr::kable(highest_avg_5,
             col.names = c('Variable','Mean'),
             caption = "5 highest means")
```

Table 5: 5 highest means

Variable	Mean
Passes	458.08553
Backwards_Passes	69.86096
Long_Passes	58.36842
Clearances	20.49978
Crosses	18.08531

```
knitr::kable(highest_std_dev_5,
             col.names = c('Variable','SD'),
             caption = "5 highest standard deviations")
```

Table 6: 5 highest standard deviations

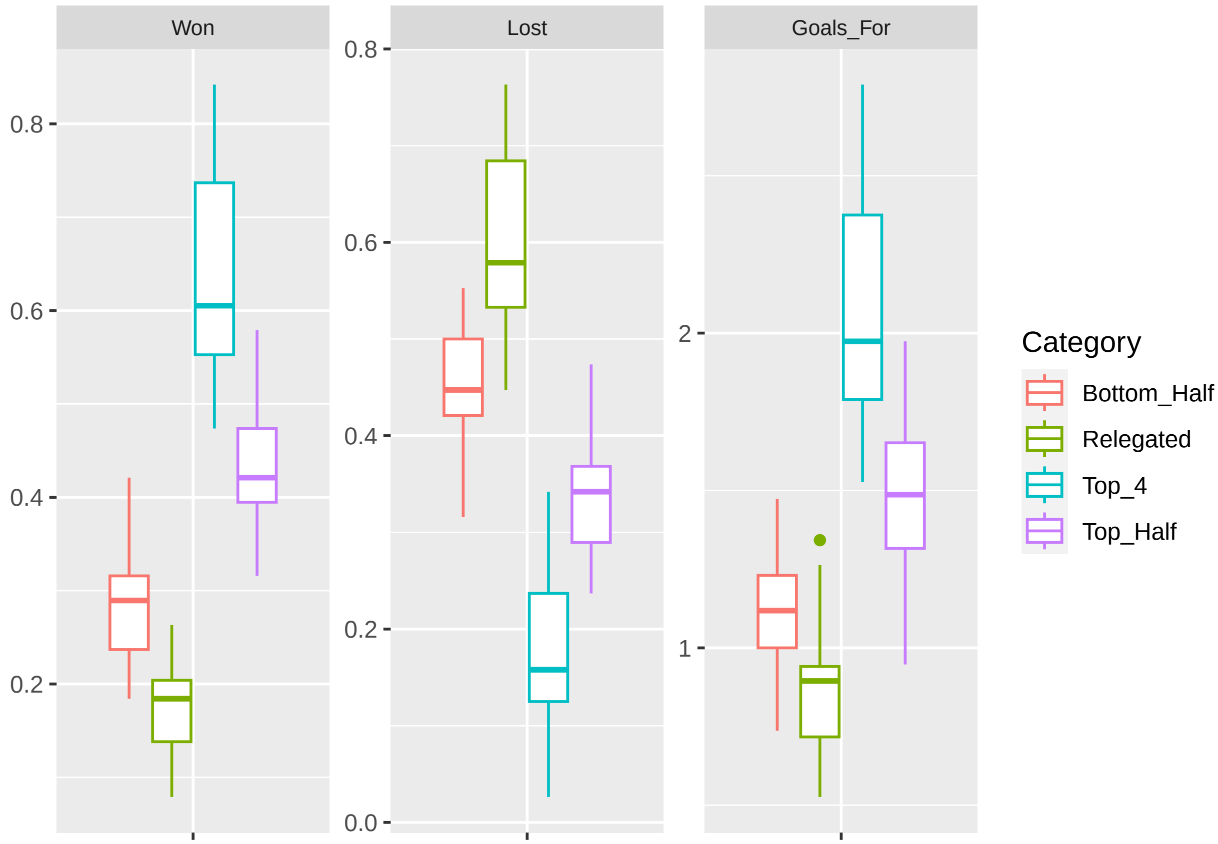
Variable	SD
Passes	99.77413
Backwards_Passes	16.22843
Long_Passes	7.69768
Clearances	4.50207
Crosses	2.41891

Passes, *Backwards Passes*, *Long Passes*, *Clearances* and *Crosses* have the highest means and most variability. These are commonly occurring actions in a game but can vary significantly according to the team. These are all elements of team play, except *Clearances* which is a defensive characteristic.

Boxplots

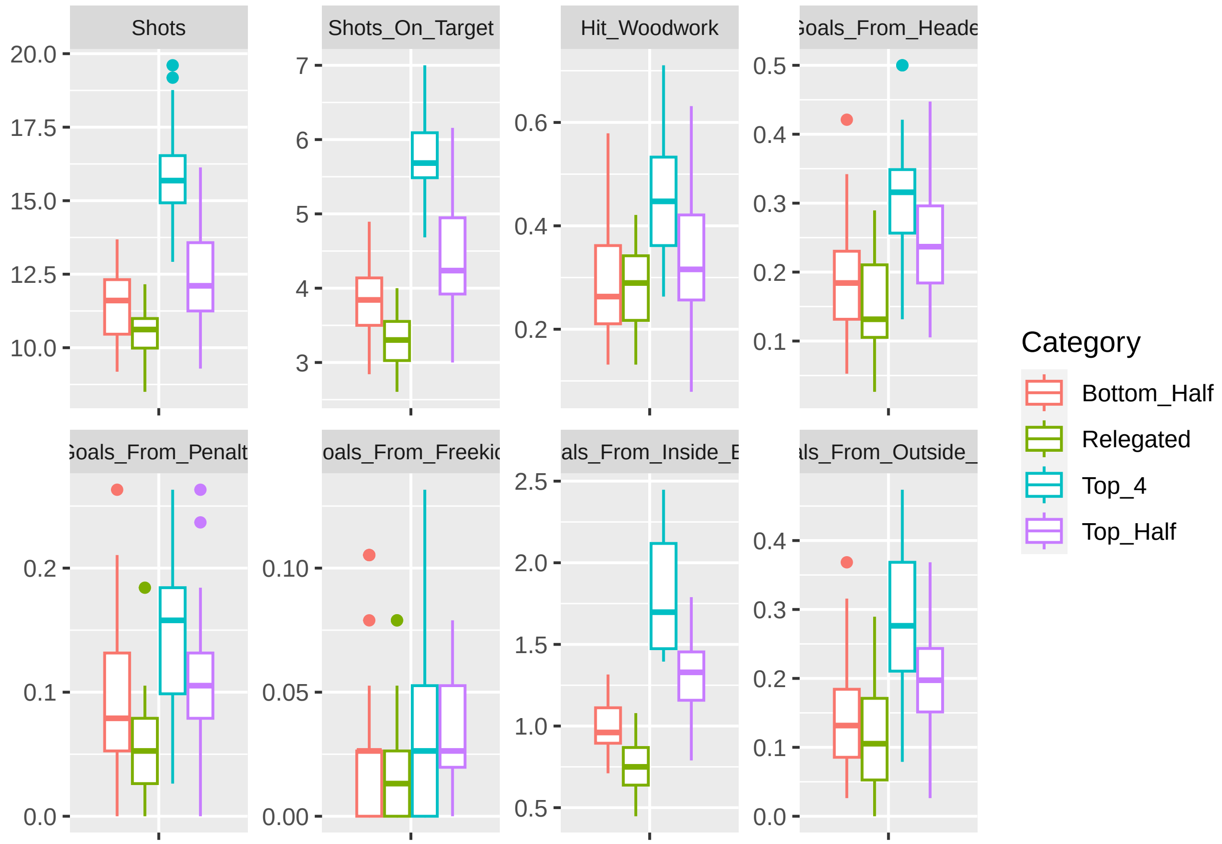
We can further analyse the spread of the variables according to category using boxplots.

```
# Update our variables of interest, removing those we don't want, adding category
general_adj <- c(general[! general %in% remove_vars], 'Category')
attack_adj <- c(attack[! attack %in% remove_vars], 'Category')
defence_adj <- c(defence[! defence %in% remove_vars], 'Category')
team_play_adj <- c(team_play[! team_play %in% remove_vars], 'Category')

# Function for making boxplots
create_boxplot <- function(arg_category, arg_nrow, arg_ncol) {
  melt(data.active[, arg_category], id = "Category") %>%
    ggplot(., aes(x = variable, y = value, color = Category)) +
      geom_boxplot() +
      facet_wrap(vars(variable), scales="free", nrow = arg_nrow, ncol = arg_ncol) +
      theme(
        strip.text = element_text(size = 8),
        axis.text.x=element_blank(),
        axis.title.x=element_blank(),
        axis.title.y = element_blank())
}
create_boxplot(general_adj, 1, 3)
```



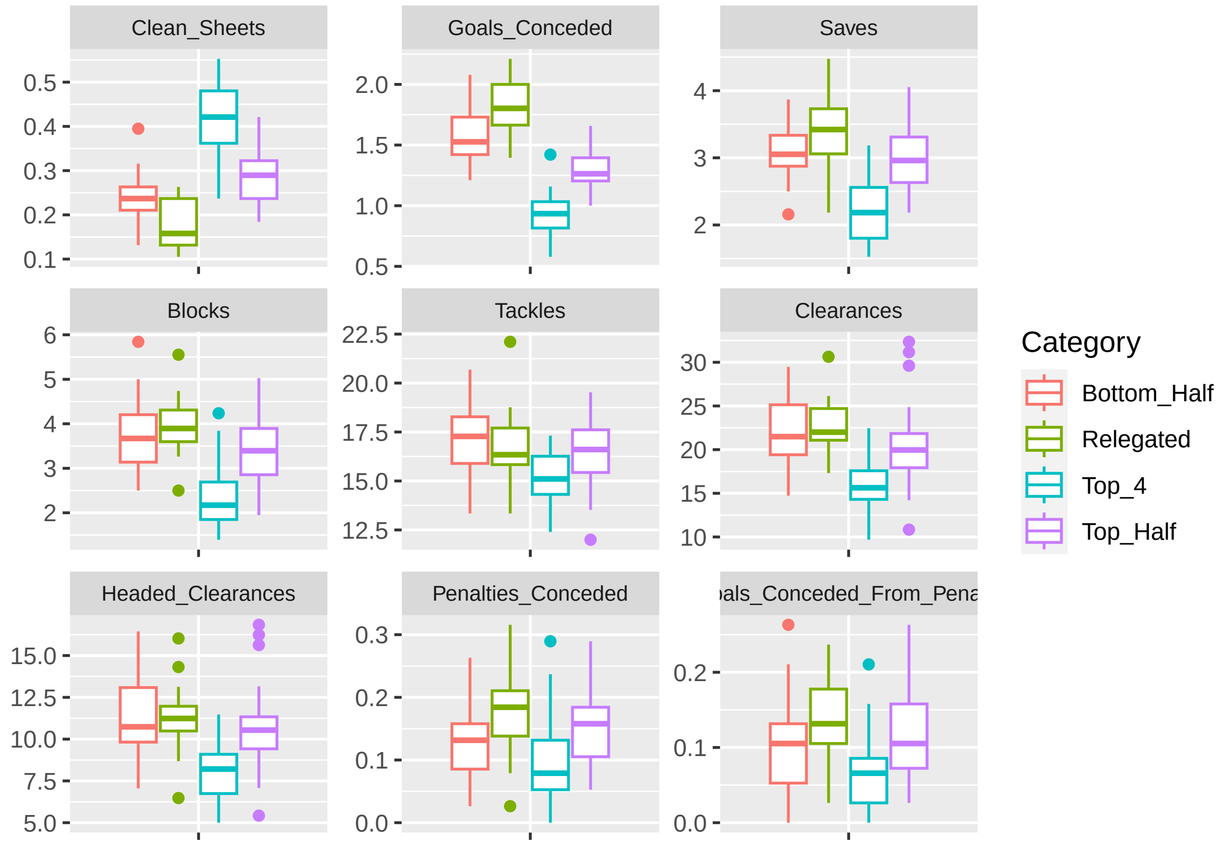
No surprise for the general variables. The boxplots are as expected across the categories.

```
create_boxplot(attack_adj, 2, 4)
```



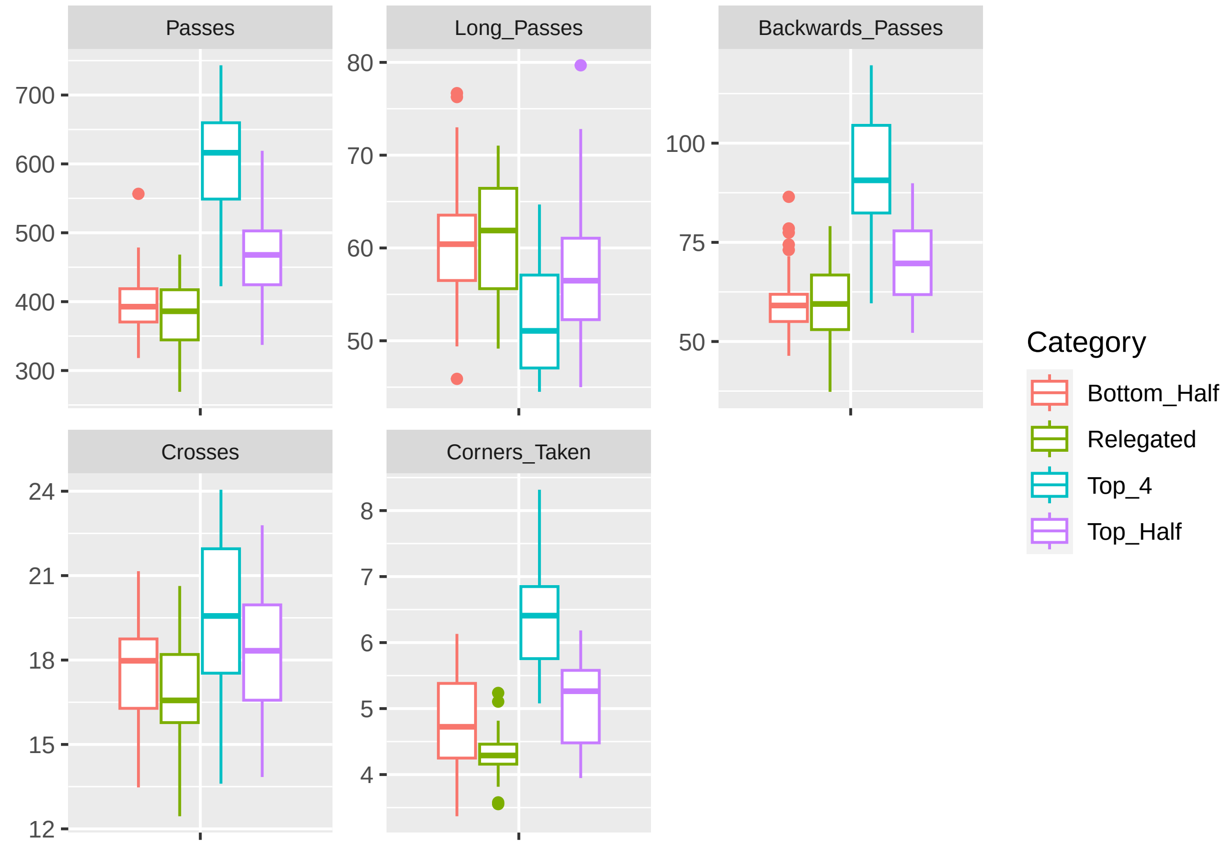
For attack, the variables also have medians and IQR dispersion that you would expect across the different categories. Although for *Hit Woodwork*, *Goals From Penalty* and *Goals From Freekick* some of the categories show similar medians and IQR. This somewhat fits in to our calculations for the means and standard deviations, with these variables being infrequent events in a game, therefore less representative across the different categories.

```
create_boxplot(defence_adj, 3, 3)
```



It is interesting with the defensive variables that the median for *Saves* is very similar for *Bottom Half* and *Top Half* teams, although dispersion of the IQR is a little greater for *Top Half* teams. It is also the case for *Blocks*, which again shows similarity between *Top Half* and *Bottom Half* teams. The *Tackles* variable demonstrates very similar medians and IQRs for both *Top Half*, *Bottom Half* and *Relegated teams*. The *Penalties Conceded* and *Goals Conceded From Penalty* breaks from the norm across the categories, with *Top Half* and *Relegated* teams closer in the median and IQR.

```
create_boxplot(team_play_adj, 2, 3)
```

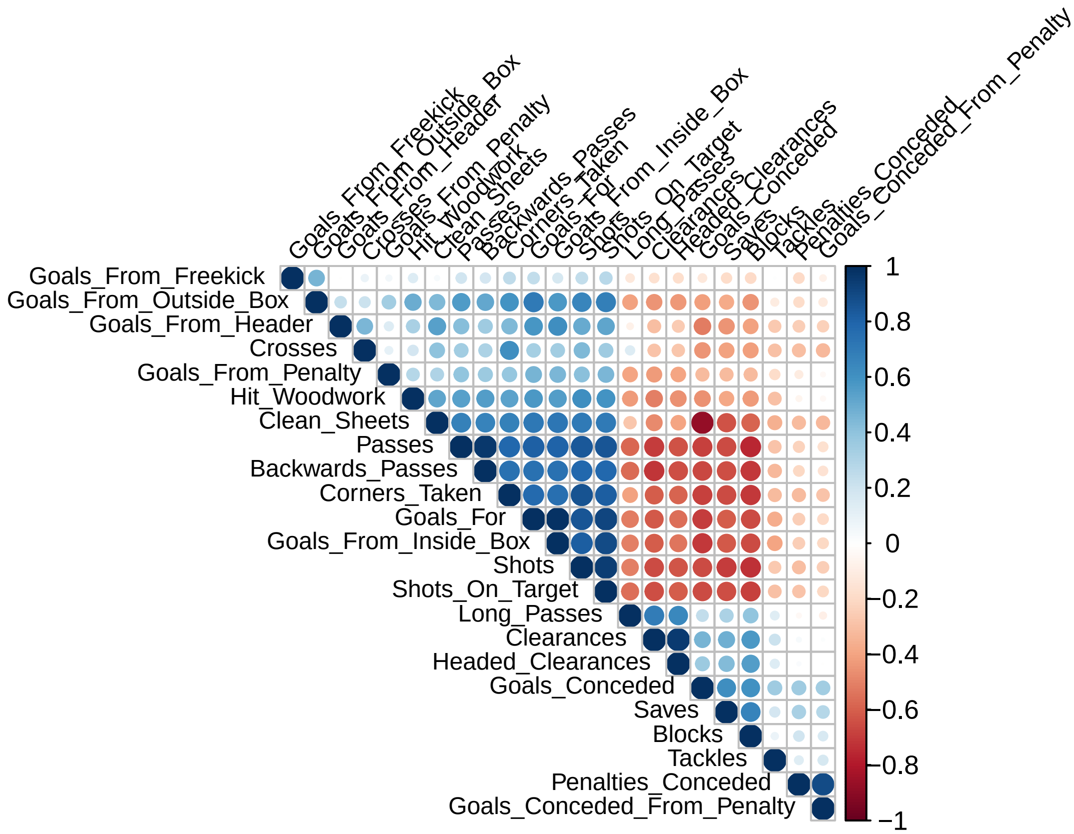


Looking at the team play category, the *Passes* variable demonstrates the least dispersion in the IQR for *Bottom Half* teams, with *Relegated* teams having a lower median, but more dispersion. *Long Passes* has the highest median values for the *Relegated* category, followed by *Bottom Half* teams, perhaps demonstrating a 'hit and hope' tactic for struggling clubs. *Backwards Passes* has the highest medians for *Top 4* and *Top Half* clubs, probably stemming from the use of back passes by the best performing teams to retain possession. *Crosses* and *Corners Taken* appear quite predictable across the categories, although we see that the IQR dispersion is very small for relegated teams in *Corners Taken*, illustrating how difficult it is for this category of team to force play into the final third of the field and be awarded a corner.

Correlation matrix

The sheer number of variables makes analysing correlations difficult hence the use of PCA. Nevertheless, we can try to identify particularly pertinent correlations between the variables.

```
cor.mat.all <- cor(data.active[, adj_vars])
corrplot(cor.mat.all, type="upper", order="hclust", method = 'circle',
         tl.col="black", tl.srt=45, tl.cex=0.75, number.cex=0.75)
```



The attacking variables tend to be negatively correlated with defensive variables. For instance, as a team has an increasing value for *Shots* it has a decreasing number of *Saves* or *Blocks*. *Goals From Freekick* are not strongly correlated with any other variable, maybe because these are more of a freak occurence and might go against the run of play.

Within the defensive variables, *Tackles* don't have a particularly strong correlation with any other variables, but they do appear to follow the same trend. For example, *Tackles* are negatively correlated with *Goals For*. So, if you are tackling more, you are scoring less goals since you are more likely to be on the back foot. And there is a positive correlation with *Goals Conceded*, suggesting that even though you are tackling more, this is not successful in defending against goals from your opponents.

The team play attributes align themselves either with attacking or defensive variables. *Passes* are positively correlated with attacking variables and negatively with defensive ones. *Long Passes* are negatively correlated with attacking variables like *Goals For* or *Shots*, backing up the theory that this is part of a 'hit and hope' tactic for struggling clubs. *Backwards Passes* also support the suggestion that this is part of a strategy used by stronger attacking teams for maintaining possession, with a positive correlation to attacking variables. *Crosses* have a positive correlation with *Corners Taken*, which makes sense given that the ball will often be played short to another player who then crosses it. Or, a team is attacking a lot down the wing with the aim of providing crosses, and therefore forcing lots of corners. *Corners Taken* are also more strongly correlated, positively to attacking, and negatively to defensive variables than *Crosses*. This again supports the hypothesis that weaker attacking teams find it harder to force corners, with stronger teams winning more corners because of their dominance around their opponents 18-yard box.

PCA

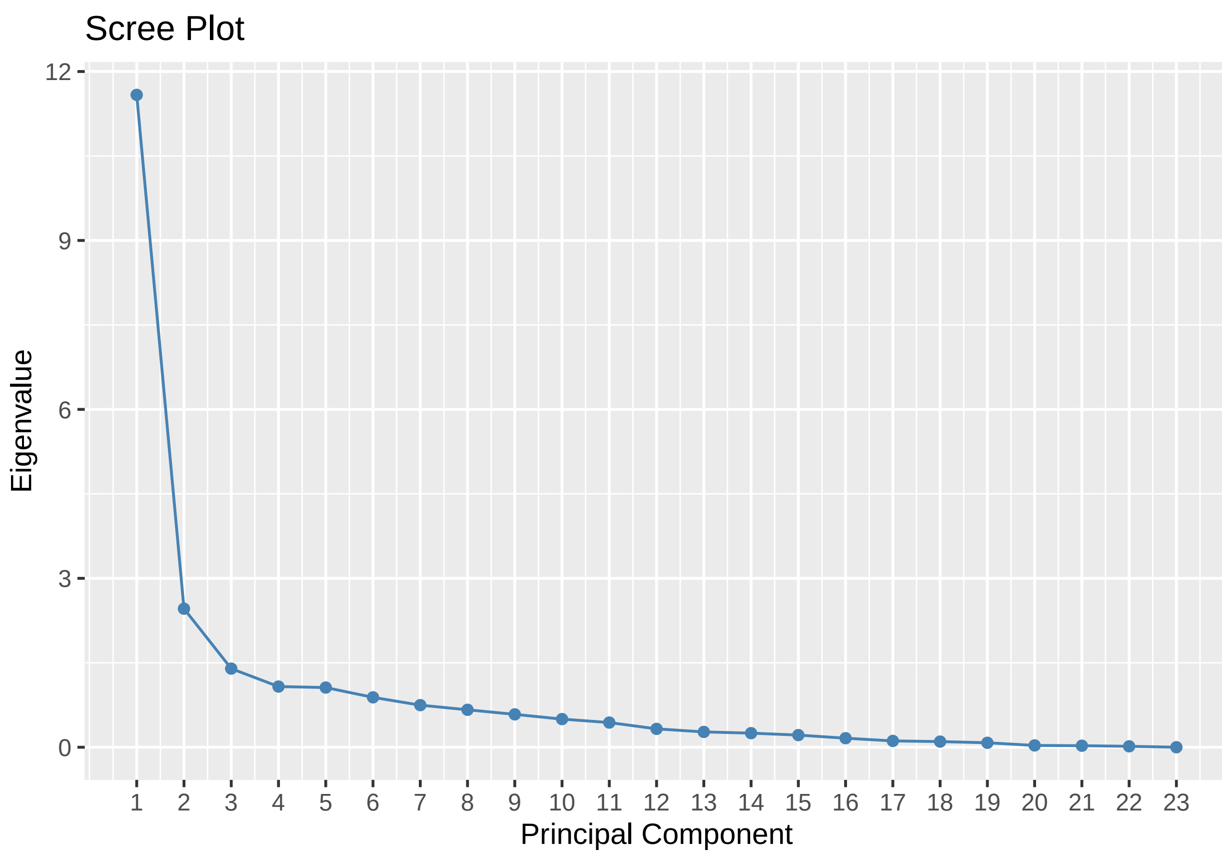
Time to run the PCA, initially with same number of components as variables.

```r
# Number of variables
p <- length(adj_vars)
active_vars <- c(adj_vars, 'Category')
result.pca <- PCA(data.active[, active_vars], scale.unit = TRUE, ncp = p, graph = FALSE,
                  quali.sup = 'Category')
eigenvalues <- result.pca$eig
knitr::kable(eigenvalues, caption = "Eigenvalues")
```

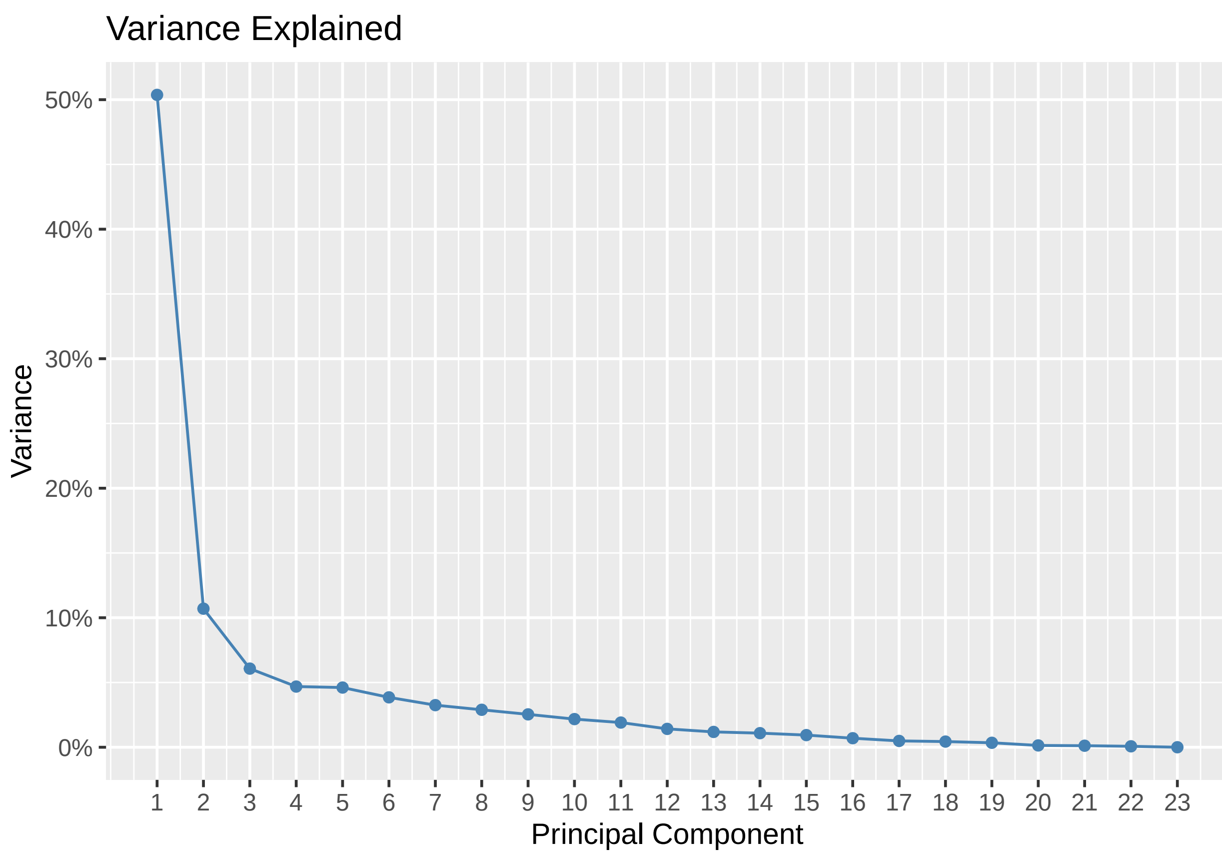
Table 7: Eigenvalues

	eigenvalue	percentage of variance	cumulative percentage of variance
comp 1	11.5850313	50.3697011	50.36970
comp 2	2.4608282	10.6992531	61.06895
comp 3	1.3966885	6.0725586	67.14151
comp 4	1.0779401	4.6866963	71.82821
comp 5	1.0603971	4.6104222	76.43863
comp 6	0.8861750	3.8529347	80.29157
comp 7	0.7479887	3.2521248	83.54369
comp 8	0.6655176	2.8935548	86.43725
comp 9	0.5842241	2.5401048	88.97735
comp 10	0.5001868	2.1747250	91.15208
comp 11	0.4386702	1.9072619	93.05934
comp 12	0.3263722	1.4190095	94.47835
comp 13	0.2724804	1.1846972	95.66304
comp 14	0.2506092	1.0896054	96.75265
comp 15	0.2160610	0.9393956	97.69204
comp 16	0.1607242	0.6988009	98.39085
comp 17	0.1126559	0.4898083	98.88065
comp 18	0.1007790	0.4381695	99.31882
comp 19	0.0794713	0.3455273	99.66435
comp 20	0.0323461	0.1406352	99.80499
comp 21	0.0275157	0.1196336	99.92462
comp 22	0.0170096	0.0739550	99.99857
comp 23	0.0003278	0.0014251	100.00000

```r
# Scree plot
# Make the matrix play with ggplot
df <- data.frame(component=1:nrow(eigenvalues), eigenvalues=eigenvalues[, 1],
                 variance=eigenvalues[, 2])
# Eigenvalues
ggplot(data = df, aes(x=component, y=eigenvalues)) +
  geom_line(color="steelblue") +
  geom_point(color="steelblue") +
  labs(title="Scree Plot",x="Principal Component", y = "Eigenvalue") +
  scale_x_continuous(breaks=df$component)
```




```r
# Variance
ggplot(data = df, aes(x=component)) +
  geom_line(aes(y = variance), color="steelblue") +
  geom_point(aes(y = variance), color="steelblue") +
  labs(title="Variance Explained",x="Principal Component", y = "Variance") +
  scale_x_continuous(breaks=df$component) +
  scale_y_continuous(labels = scales::percent_format(scale = 1)) +
  expand_limits(y = 50)
```



Number of components

We must decide on the number of principal components, m, to retain. There is a lot written on this part of the PCA methodology, so we'll refer to an authority on the subject.

"It is crucial to know how small m can be taken without serious information loss," according to I.T. Jolliffe, Principal Component Analysis. There are various rules or guidelines.

If we follow Kaiser's rule, we keep principal components with an eigenvalue > 1, therefore 5 components.

Cattel's criteria looks for the "elbow" in the scree plot, "the point beyond which the scree graph defines a more-or-less straight line," says Jolliffe. In our case, this would signal the use of 2 principal components. Although Jolliffe is somewhat critical of this method, owing to the degree of subjectivity.

Jolliffe also discusses choosing a cutoff in terms of the cumulative percentage of total variance, suggesting a value between 70% and 90%. If we use a 70% cutoff, we are driven towards 4 principal components, providing a cumulative variance of 71%. The upper bounds, a 90% cutoff, leads to 10 principal components, with a cumulative variance of 91%.

Given that we don't have a consensus with these different criteria, we choose 3 principal components since it provides a middle ground between Cattel's criteria and Jolliffe's lower bound cutoff.

Interpretation of the principal components

```
# Number of components
p <- 3
```

```r
# Re-run PCA
result.pca <- PCA(data.active[, active_vars], scale.unit = TRUE, ncp = p, graph = FALSE,
                  quali.sup = 'Category')
# Store the values so we can construct individual dataframes
coord <- result.pca$var$coord
cos2 <- result.pca$var$cos2
contrib <- result.pca$var$contrib
# This is our cutoff of interest, number of variables (minus 1 for Category)
num_vars <- length(adj_vars) - 1
contrib_cutoff <- 100/num_vars
```

We only interpret the variables that play a significant role contributing to the component and use a simple framework for verbally describing the strength of correlations.[1]

Value	Description
0.00-0.19	Very weak
0.20-0.39	Weak
0.40-0.59	Moderate
0.60-0.79	Strong
0.80-1.0	Very strong

Note: We're using the excellent `FactoMineR` package by Sebastien Le, Julie Josse and Francois Husson, which labels the principal components as `Dim.1`, `Dim.2`, etc. To avoid confusion we'll use the nomenclature *PC1*, *PC2,* etc in discussion.

```r
dim1 <- data.frame(coord[, 'Dim.1'], cos2[, 'Dim.1'], contrib[, 'Dim.1'])
names(dim1) <- c('coord', 'cos2', 'contrib')
dim1_cutoff <- subset(dim1, contrib > contrib_cutoff)
dim1_cutoff <- dim1_cutoff[order(dim1_cutoff$coord, decreasing = TRUE), ]
knitr::kable(dim1_cutoff)
```

PC1

	coord	cos2	contrib
Shots_On_Target	0.9338941	0.8721582	7.528319
Shots	0.9313257	0.8673676	7.486968
Goals_For	0.9191252	0.8447911	7.292092
Passes	0.9117317	0.8312547	7.175248
Goals_From_Inside_Box	0.9047963	0.8186564	7.066502
Corners_Taken	0.8853995	0.7839322	6.766768
Backwards_Passes	0.8730367	0.7621931	6.579120
Clean_Sheets	0.7970204	0.6352415	5.483295
Saves	-0.7410877	0.5492110	4.740695
Clearances	-0.7548651	0.5698213	4.918599
Blocks	-0.7804774	0.6091450	5.258035
Goals_Conceded	-0.7824303	0.6121971	5.284380

[1] Evans (1996)

Several of the variables are very strongly correlated with *PC1*. *Shots On Target*, *Shots*, *Goals For*, *Passes*, and *Goals From Inside Box* all have a positive correlation > 0.9 and high quality representation, according to the cos^2 value. Notably, almost all of these variables represent the outcome of an attempt on goal, with the exception of *Passes*, although this variable is positively correlated to attacking characteristics.

Next, we have *Corners Taken* and *Backwards Passes*, which are also very strongly correlated and are all variables relating to team play. These have a correlation > 0.87 and high values for cos^2. *Clean Sheets* have a strong positive correlation and is the first variable of note related to defence. We recall that *Clean Sheets* are positively correlated to our attacking variables.

For negative correlations, these are slightly weaker, but nevertheless still strongly correlated for *Saves*, *Clearances*, *Blocks* and *Goals Conceded*. The quality of representation is lower than the top positively correlated variables.

Overall, this component contains important information relating to a number of different characteristics spanning both attack, defence and team play. If we put aside the team play variables, the attacking variables are all focused on attempts on goal, while the defensive variables are all about action resulting from a dangerous attack. We can interpret this component as providing a measure of attack versus defence. We'll dub this component *attack-defence balance*.

```
dim2 <- data.frame(coord[, 'Dim.2'], cos2[, 'Dim.2'], contrib[, 'Dim.2'])
names(dim2) <- c('coord', 'cos2', 'contrib')
dim2_cutoff <- subset(dim2, contrib > contrib_cutoff)
dim2_cutoff <- dim2_cutoff[order(dim2_cutoff$coord, decreasing = TRUE), ]
knitr::kable(dim2_cutoff)
```

PC2

	coord	cos2	contrib
Goals_Conceded_From_Penalty	0.7618897	0.5804760	23.588643
Penalties_Conceded	0.7221273	0.5214678	21.190745
Clearances	-0.4042695	0.1634339	6.641417
Headed_Clearances	-0.4234157	0.1792809	7.285387
Crosses	-0.4676450	0.2186919	8.886922
Long_Passes	-0.5768155	0.3327161	13.520493

Goals Conceded From Penalty and *Penalties Conceded* are strongly positively correlated to *PC2*. The quality of representation is somewhat middling.

The next four most important variables for the component are *Clearances*, *Headed Clearances*, *Crosses* and *Long Passes*, which are all moderately negatively correlated. They are split between defensive and team play characteristics. The quality of representation here is all on the bottom end of the scale.

Recalling our descriptive statistics, the variables related to penalties have some of the lowest means and dispersion, while *Long Passes*, *Clearances* and *Crosses* have the highest means and most variability. While if we go back to our boxplots from earlier, the *Top 4* tend to have a higher value for *Crosses* and *Relegated* the most number of *Long Passes*.

The first two variables obviously relate to the result of disciplinary action in the box, and the last four could be all seen as variables relating to aerial action (in the sense that the ball is likely to be in air). We could conclude, given the positive and negative correlation to the component, that this all relates to foul play. For instance, a clearance or a cross that results in a foul in the box and leads to a penalty. But unfortunately the variables that might most help us here with interpretation, Red Cards and Yellow Cards, have been removed from the analysis. So we'll go with a bit a more generic label: *Misconduct*.

```r
dim3 <- data.frame(coord[, 'Dim.3'], cos2[, 'Dim.3'], contrib[, 'Dim.3'])
names(dim3) <- c('coord', 'cos2', 'contrib')
dim3_cutoff <- subset(dim3, contrib > contrib_cutoff)
dim3_cutoff <- dim3_cutoff[order(dim3_cutoff$coord, decreasing = TRUE), ]
knitr::kable(dim3_cutoff)
```

PC3

	coord	cos2	contrib
Penalties_Conceded	0.4323933	0.1869639	13.386230
Goals_From_Header	0.3630486	0.1318043	9.436913
Goals_Conceded_From_Penalty	0.3218543	0.1035902	7.416842
Tackles	-0.3910431	0.1529147	10.948377
Goals_From_Outside_Box	-0.3953946	0.1563369	11.193396
Goals_From_Freekick	-0.6973508	0.4862982	34.817940

The first three variables are weak to moderately positively correlated to *PC3*. *Penalties Conceded* and *Goals Conceded From Penalty* are defensive attributes, while *Goals From Header* is an attacking variable. They have a poorer quality representation.

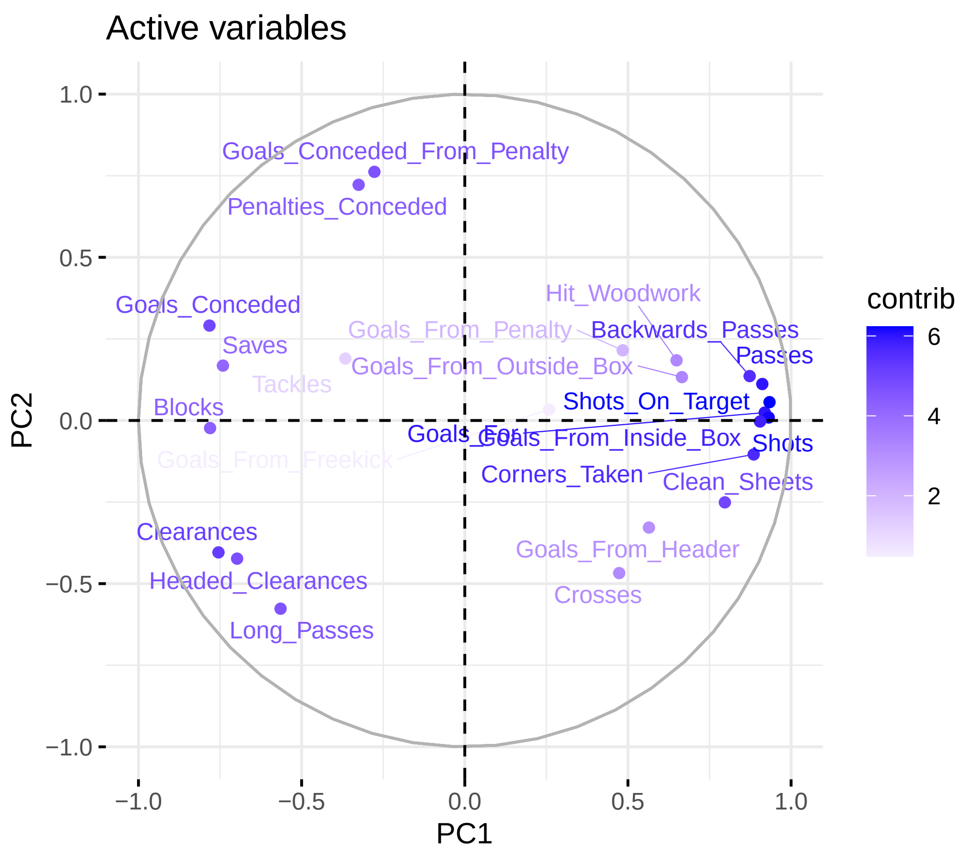
The next three: *Tackles*, *Goals From Outside Box* and *Goals From Freekick*, are a mixture of defensive and attacking variables. *Tackles* and *Goals From Outside Box* are weakly negatively correlated, while *Goals From Freekick* is strongly negatively correlated. The quality of representation is poor, except for *Goals From Freekick* which is moderate.

All of these variables have very low means and little dispersion, except for *Tackles*. The two most important variables here are *Goals From Freekick* and *Penalties Conceded*, which are both the result of some kind of refereeing decision. But with the others it is difficult to form a clear interpretation of what this component represents. We've got both goals resulting from a refereeing decision and those in free play, plus we've got attacking and defensive characteristics. Together there is no coherent explanation for *PC3*, therefore we deem this one not interpretable.

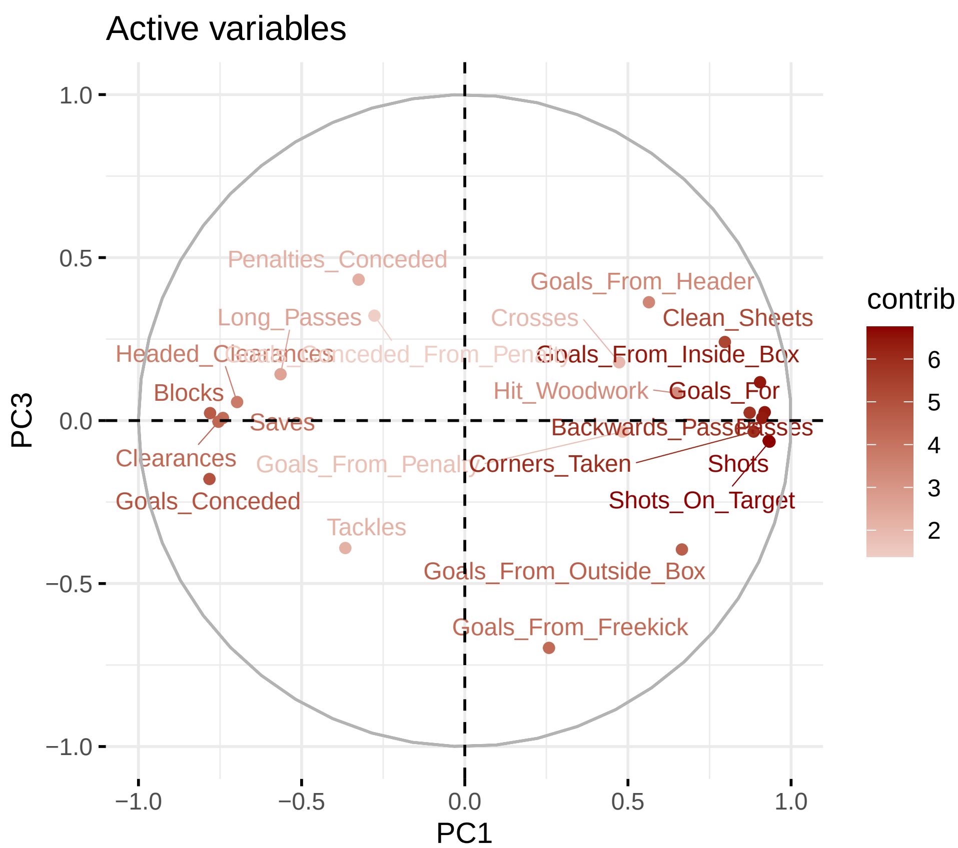
```r
# Vector with indexes of supplementary individuals
supp_idx <- which(rownames(data) == data.supp$Idx)

# Vector with active and supplementary variables
pca_all_vars <- c(active_vars, supp_vars)

# Rerun PCA (including supplementary individuals and supplementary quantitative variables)
result.pca <- PCA(data[, pca_all_vars], scale.unit = TRUE, ncp = p, graph = FALSE,
                  quanti.sup = supp_vars, quali.sup = 'Category', ind.sup = supp_idx)
```

Graphical representation The `factoextra` package by Alboukadel Kassambara and Fabian Mundt has some really nice functionality for customising visualisations. We can begin by projecting the active variables onto the principal components.

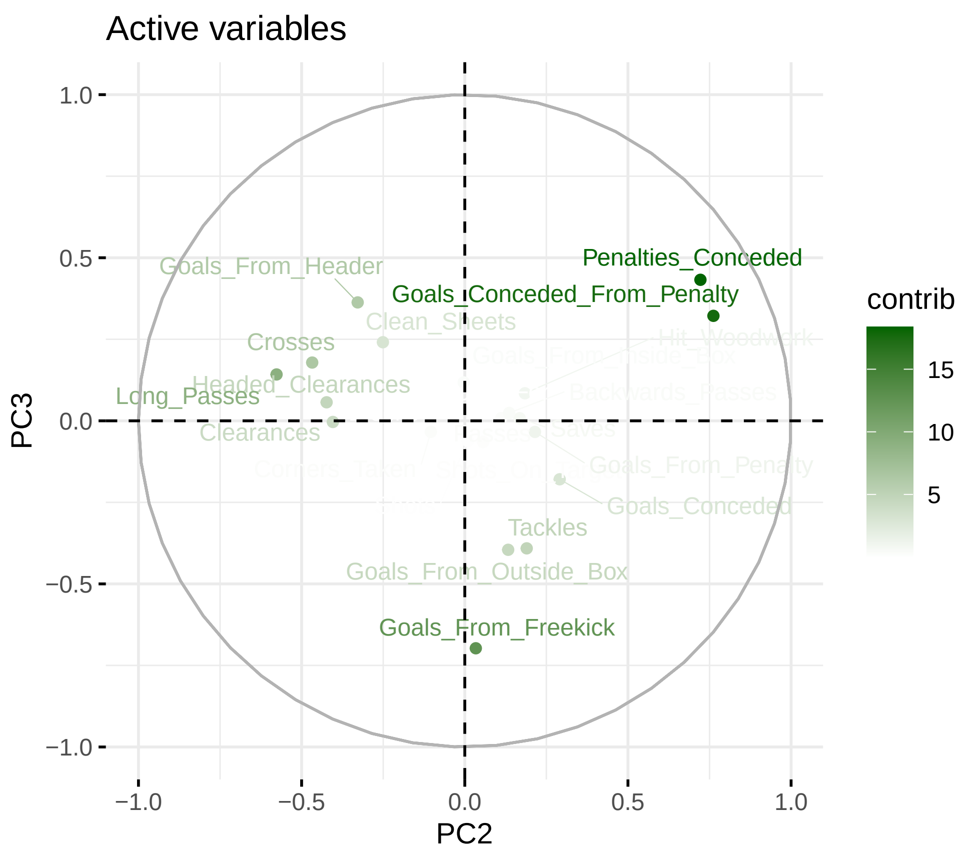
```
fviz_pca_var(result.pca, axes = c(1,2), repel = TRUE, labelsize = 3,
             geom = c("point", "text"), col.var="contrib", invisible = "quanti.sup") +
  scale_color_gradient2(low="grey", high="blue") +
  labs(title ="Active variables", x = "PC1", y = "PC2")
```




```
fviz_pca_var(result.pca, axes = c(1,3), repel = TRUE, labelsize = 3,
             geom = c("point", "text"), col.var="contrib", invisible = "quanti.sup") +
  scale_color_gradient2(low="grey", high="darkred") +
  labs(title ="Active variables", x = "PC1", y = "PC3")
```



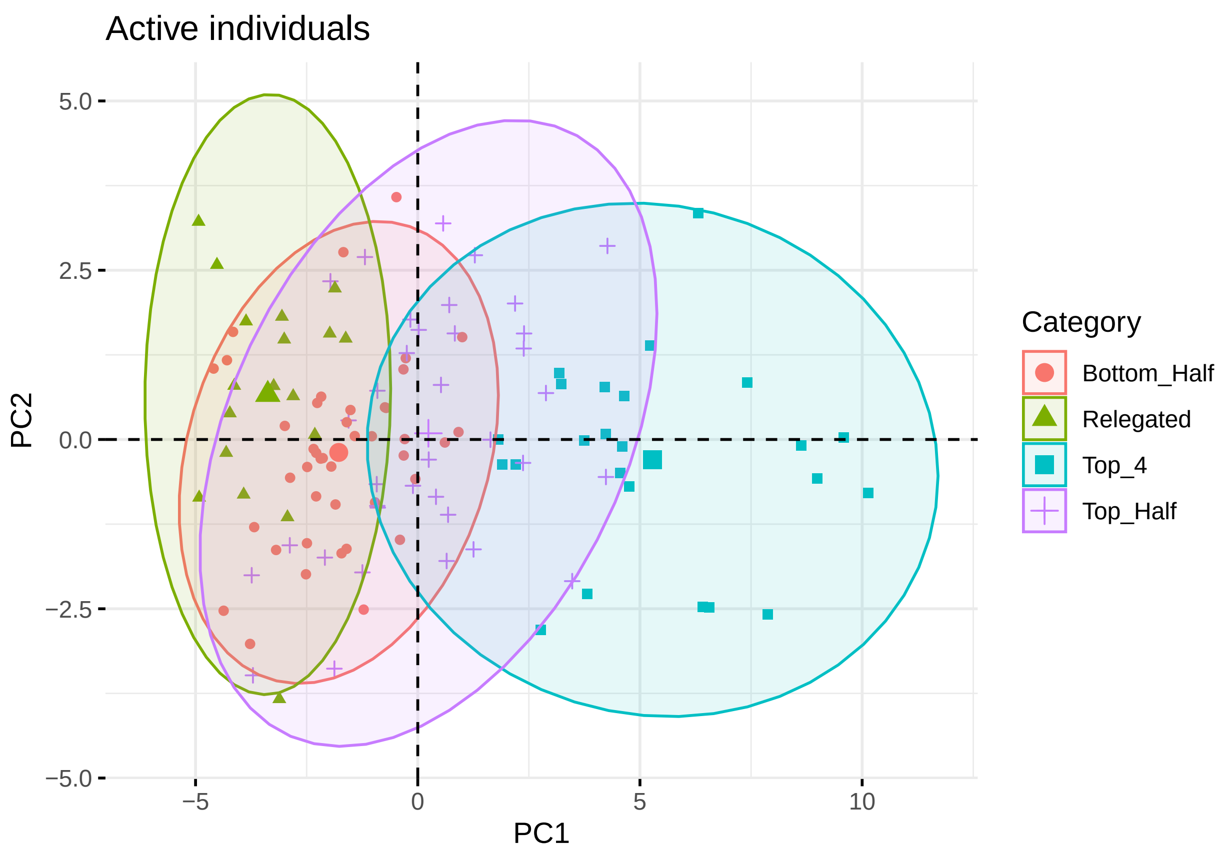

```r
fviz_pca_var(result.pca, axes = c(2,3), repel = TRUE, labelsize = 3,
             geom = c("point", "text"), col.var="contrib", invisible = "quanti.sup") +
  scale_color_gradient2(low="grey", high="darkgreen") +
  labs(title ="Active variables", x = "PC2", y = "PC3")
```



We can see a visual representation of our variables on the various PCs. For example, *Shots*, *Shots On Target* and *Goals For* are all well represented on the positive part of *PC1*, contrasted with *Blocks*, *Saves* and *Goals Conceded* which are also well represented and reside in the negative area. The lighter shaded variables are less well represented, corresponding with a contribution that fell below the threshold when we interpreted the PCs. We see that few variables are well represented on *PC3*.

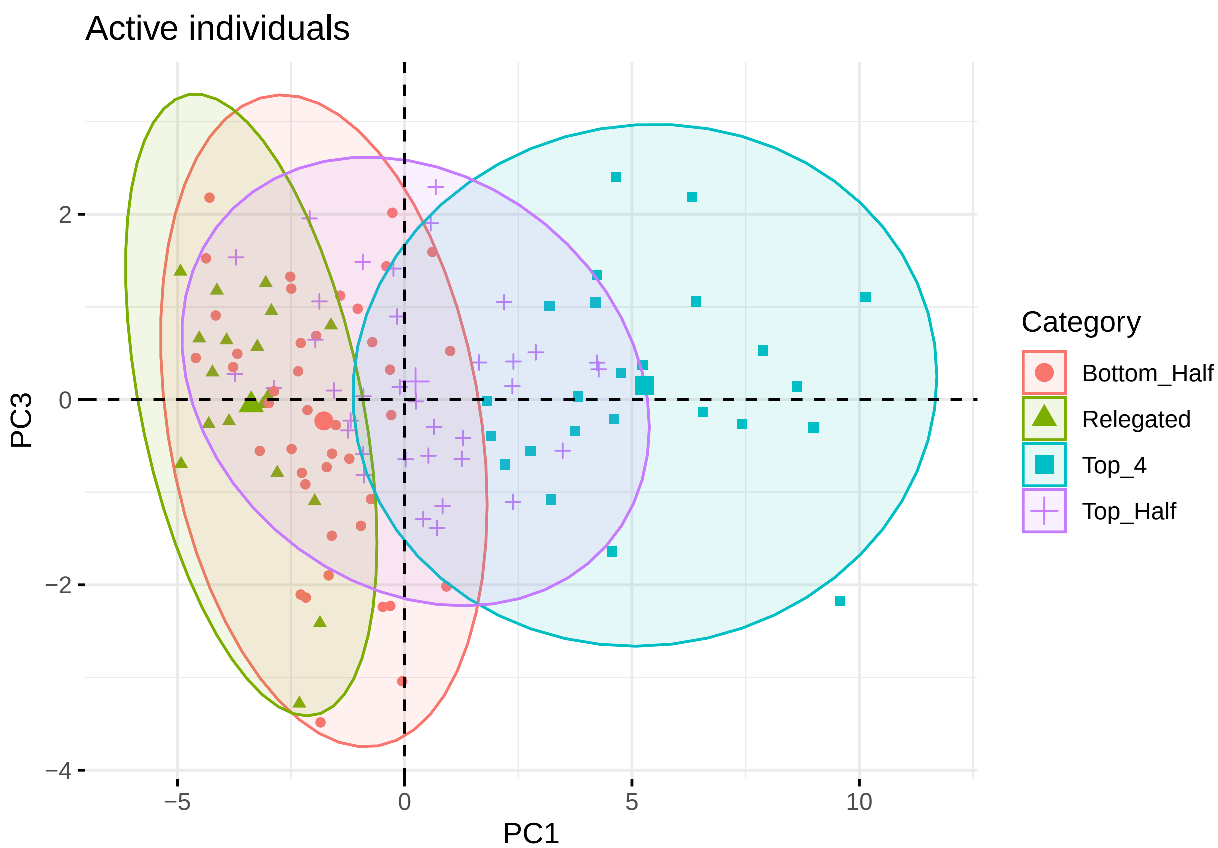
Active individuals Next, we can project the teams from past seasons onto the PCs.

```
fviz_pca_ind(result.pca,
             axes = c(1, 2),
             label = 'none',
             habillage = 'Category',
             addEllipses = TRUE,
             invisible = "ind.sup"
             ) +
  labs(title ="Active individuals", x = "PC1", y = "PC2")
```



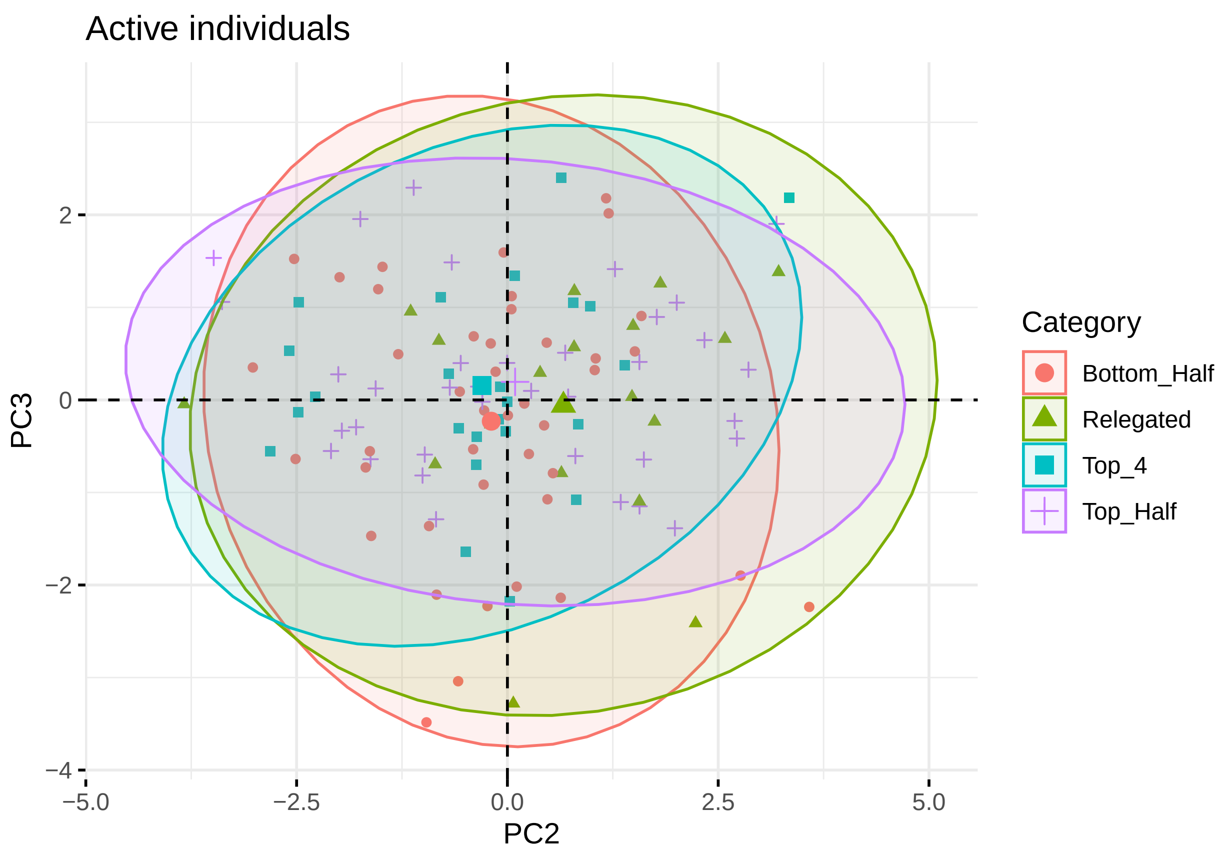
The first graph demonstrates that the different categories of team indeed occupy different areas on the PCs, but this only appears relevant for the category in terms of *PC1*. *Top 4* teams reside in both the positive and negative range of *PC2*. The same goes for *Top Half*, *Bottom Half* and *Relegated* teams. The distribution for these categories across *PC2* appears somewhat equal. And for *PC1* the clustering of different categories has some overlap, which we see with the concentration ellipses. This overlap appears more significant for the *Top Half*, *Bottom Half* and *Relegated* teams.

```
fviz_pca_ind(result.pca,
             axes = c(1, 3),
             label = 'none',
             habillage = 'Category',
             addEllipses = TRUE,
             invisible = "ind.sup"
             ) +
  labs(title ="Active individuals", x = "PC1", y = "PC3")
```



The second graph showing *PC1* and *PC3* again appears to indicate that *PC1* is relevant to the categories, but not *PC3*.

```
fviz_pca_ind(result.pca,
             axes = c(2, 3),
             label = 'none',
             habillage = 'Category',
             addEllipses = TRUE,
             invisible = "ind.sup"
             ) +
  labs(title ="Active individuals", x = "PC2", y = "PC3")
```



Finally, with the third graph of *PC2* and *PC3*, we seem to lose all relevance to the categories. The individuals of different categories appear to be a big jumble.

Link between categories and PCs We can go further in exploring the link between the different categories of teams and the components using the `dimdesc` function. This calculates the square correlation ratio between the coordinates of the individuals on the component and the category.

```
result.dimdesc <- dimdesc(result.pca, proba = 1, axes = 1:3)

PCs <- c('PC1', 'PC2', 'PC3')
corr_ratio <- c(result.dimdesc$Dim.1$quali[1],
                result.dimdesc$Dim.2$quali[1],
                result.dimdesc$Dim.3$quali[1])
p_values <- c(result.dimdesc$Dim.1$quali[2],
              result.dimdesc$Dim.2$quali[2],
              result.dimdesc$Dim.3$quali[2])
df_corr_ratio <- data.frame(PCs, corr_ratio, p_values)
knitr::kable(df_corr_ratio, caption = "Category square correlation ratio")
```

Table 12: Category square correlation ratio

PCs	corr_ratio	p_values
PC1	0.7263426	0.0000000
PC2	0.0404575	0.1861598

PCs	corr_ratio	p_values
PC3	0.0252002	0.3957487

```r
df_corr1 <- data.frame(result.dimdesc$Dim.1$category)
df_corr2 <- data.frame(result.dimdesc$Dim.2$category)
df_corr3 <- data.frame(result.dimdesc$Dim.3$category)
knitr::kable(df_corr1, caption = "PC1")
```

Table 13: PC1

	Estimate	p.value
Category=Top_4	5.1908751	0.0000000
Category=Top_Half	0.1468367	0.6176107
Category=Bottom_Half	-1.8703055	0.0000155
Category=Relegated	-3.4674064	0.0000022

```r
knitr::kable(df_corr2, caption = "PC2")
```

Table 14: PC2

	Estimate	p.value
Category=Relegated	0.5982320	0.0519660
Category=Top_Half	0.0255529	0.6789212
Category=Bottom_Half	-0.2570774	0.3314303
Category=Top_4	-0.3667075	0.2975810

```r
knitr::kable(df_corr3, caption = "PC3")
```

Table 15: PC3

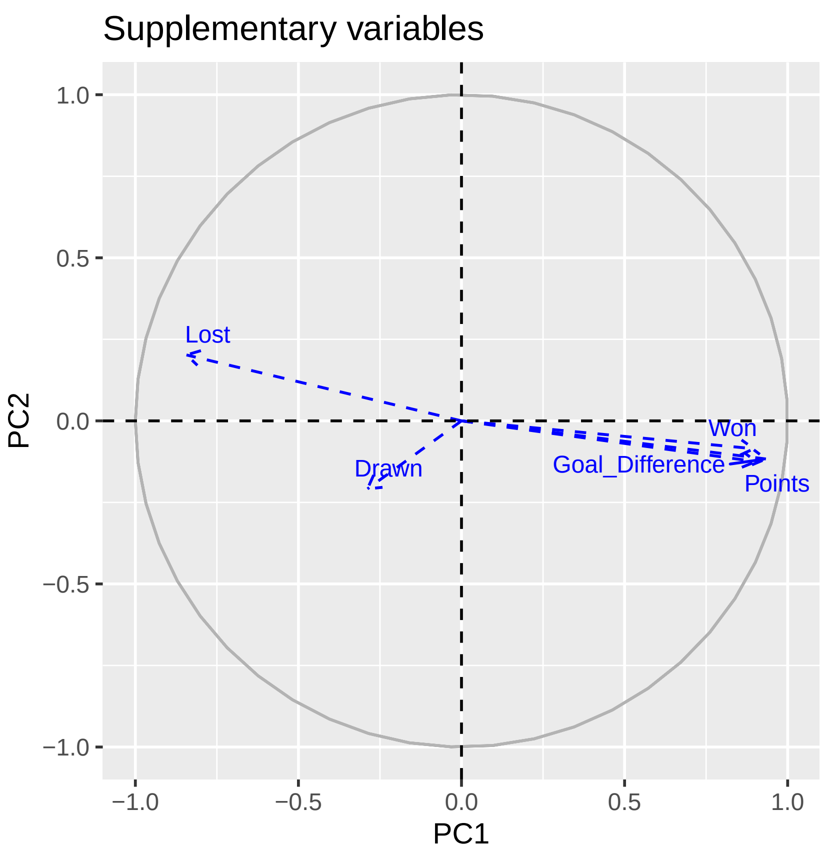
	Estimate	p.value
Category=Top_Half	0.1798061	0.2404090
Category=Top_4	0.1389675	0.4792741
Category=Relegated	-0.0735111	0.8220114
Category=Bottom_Half	-0.2452624	0.1194968

The category of team is highly significant for *PC1* with a p-value of $< 0.01\%$. However, for *PC2* and *PC3* we only have sufficient evidence at the 20% and 40% level. We can therefore say that overall *PC1* is linked with the category of team.

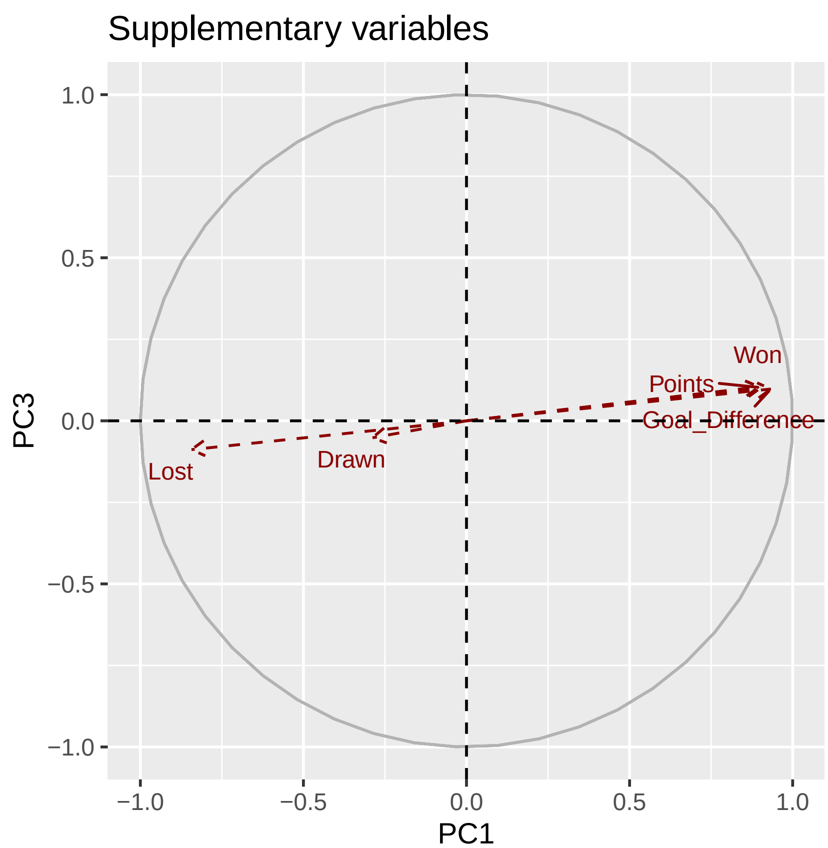
If we look at the specific categories for *PC1* we see that the estimates indicate that *Top 4* and *Top Half* teams have positive values, and *Bottom Half* and *Relegated* teams negative values. This fits into our graphical representation. The p-values are highly significant for all the categories of team except for *Top Half*. We also saw this in the first plot, with *Top Half* teams overlapping with the three other categories. So we can be confident that there is a link between *Top 4*, *Bottom Half* and *Relegated* teams with *PC1*, but not *Top Half* teams. And not for any links between the category of team and *PC2* or *PC3*.

Supplementary variables We can now look at the additional variables we didn't incorporate. Recall that these all relate to the outcome of games.

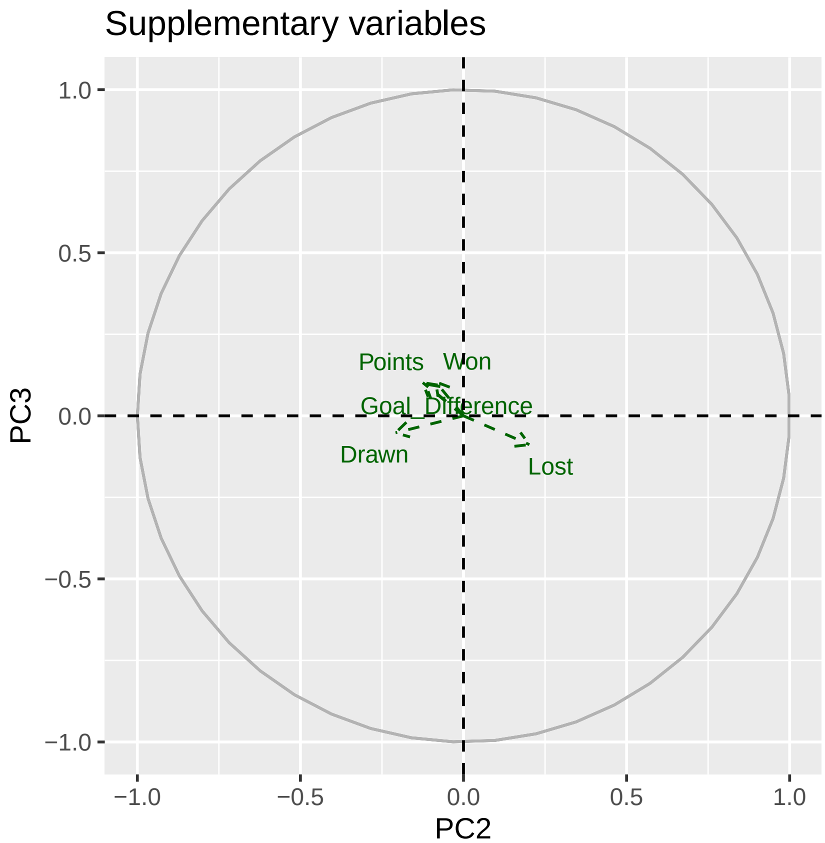
```
fviz_pca_var(result.pca, axes = c(1,2), repel = TRUE, labelsize = 3,
             label= "quanti.sup", col.quanti.sup = "blue", invisible = "var") +
  labs(title ="Supplementary variables", x = "PC1", y = "PC2")
```




```
fviz_pca_var(result.pca, axes = c(1,3), repel = TRUE, labelsize = 3,
             label= "quanti.sup", col.quanti.sup = "darkred", invisible = "var") +
  labs(title ="Supplementary variables", x = "PC1", y = "PC3")
```




```r
fviz_pca_var(result.pca, axes = c(2,3), repel = TRUE, labelsize = 3,
             label= "quanti.sup", col.quanti.sup = "darkgreen", invisible = "var") +
  labs(title ="Supplementary variables", x = "PC2", y = "PC3")
```



On the first plot, we see that *Lost* is negative on *PC1*, compared to games *Won*, *Goal Difference* and *Points*, which are firmly in positive territory. For *PC1*, the variable *Lost* has a positive value, while *Won*, *Goal Difference* and *Points* are negative. The *Drawn* variable is somewhat of an outlier and is clearly not well represented on either component. The projection of these supplementary variables underlines our interpretation of *PC1* as a measure of *attack-defence balance*, especially since *Goal Difference* aligns so strongly with the component.

It is a similar story for the second plot, particularly with *PC1*. But none of the variables show significant coordinates for *PC3*. Finally, with the third plot we see that none of the variables are well represented on either *PC2* or *PC3*. This once again underlines the importance of *PC1*.

We can look at this more closely using the results from the `PCA` function.

```
df_supp_cos2 <- data.frame(result.pca$quanti.sup$cos2[, c('Dim.1', 'Dim.2', 'Dim.3')])
knitr::kable(df_supp_cos2, col.names = c('PC1', 'PC2', 'PC3'), caption = "cos2")
```

Table 16: cos2

	PC1	PC2	PC3
Won	0.8037415	0.0072973	0.0108389
Lost	0.7111895	0.0408435	0.0078011
Drawn	0.0831302	0.0434608	0.0027149
Points	0.8145459	0.0155890	0.0103511
Goal_Difference	0.8711129	0.0136445	0.0095198

```r
df_supp_cor <- data.frame(result.pca$quanti.sup$cor[, c('Dim.1', 'Dim.2', 'Dim.3')])
knitr::kable(df_supp_cor, col.names = c('PC1', 'PC2', 'PC3'), caption = "cor")
```

Table 17: cor

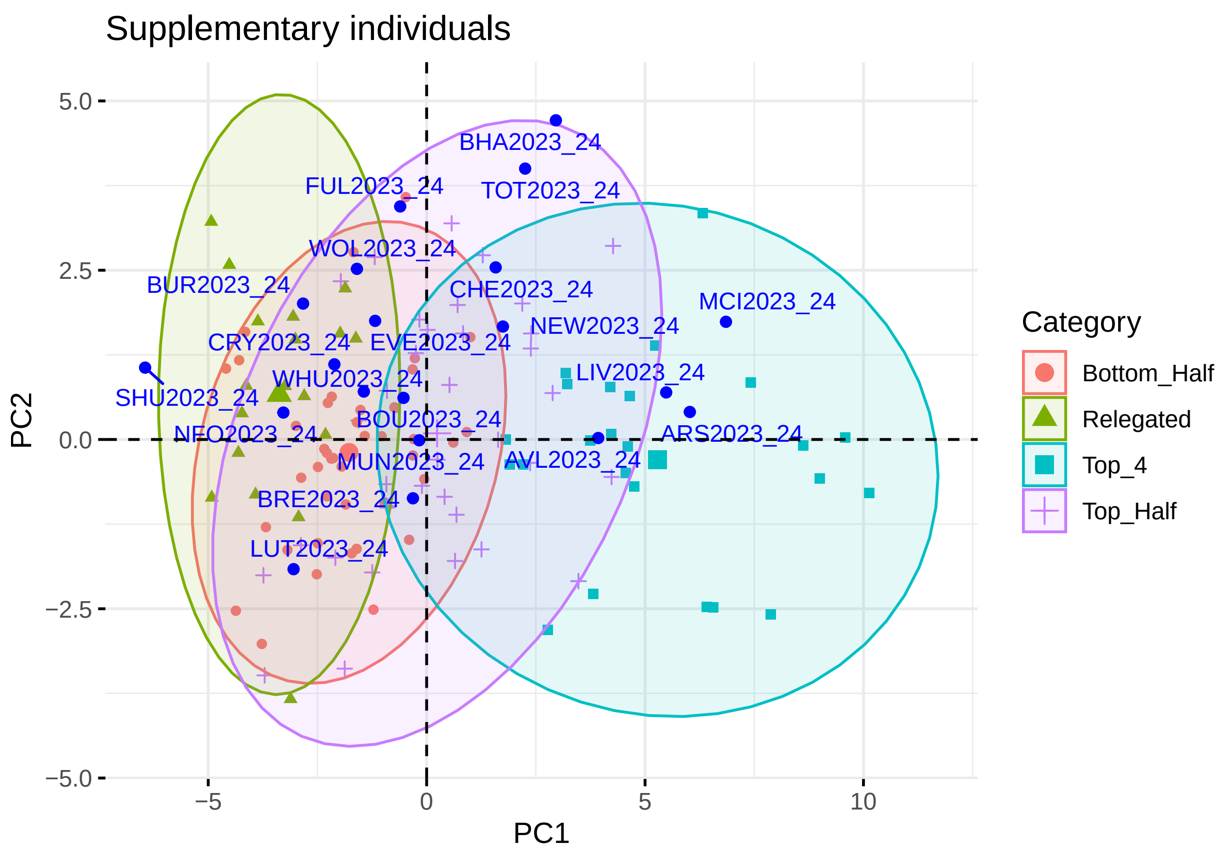
	PC1	PC2	PC3
Won	0.8965163	-0.0854240	0.1041099
Lost	-0.8433205	0.2020977	-0.0883237
Drawn	-0.2883231	-0.2084726	-0.0521043
Points	0.9025219	-0.1248558	0.1017403
Goal_Difference	0.9333343	-0.1168096	0.0975695

Firstly, dealing with the values for cos^2, we can see that only *PC1* has high quality representations for almost all the supplementary variables. The *Drawn* variable is the exception and doesn't have a high quality of representation. For *PC2* and *PC3*, the variables are poorly represented.

All these variables also have either a strong or very strong correlation with *PC1*, except for the *Drawn* variable, which is weakly correlated. As we previously saw visually, *Won*, *Points* and *Goal Difference* are positively correlated with *PC1* and the *Lost* variable is negatively correlated.

Supplementary individuals We start by projecting the supplementary individuals (the teams in the current, unfinished season) onto a plot of *PC1* and *PC2*. Despite being mostly interested in the first component, we'll retain the second component for visual consistency.

```r
fviz_pca_ind(result.pca,
             axes = c(1, 2),
             label = 'none',
             habillage = 'Category',
             addEllipses = TRUE,
             repel = TRUE,
             labelsize = 3
             ) +
  labs(title ="Supplementary individuals", x = "PC1", y = "PC2")
```



Manchester City, Arsenal, Liverpool and Aston Villa are all located around teams from previous seasons classified as *Top 4*. Other teams sneak into the edges of the concentration ellipse, but these are placed in the overlap with *Top Half* teams and are also close to the overlap with *Bottom Half* teams.

Next, Brighton and Hove Albion, Tottenham, Newcastle United, Chelsea, Manchester United and Brentford find themselves in the *Top Half* category. We notice that Brighton and Tottenham appear to be breaking new teritory in their placement in the upper echelons of the ellipse compared to past seasons given their placement on *PC2*. We interpreted *PC2* as *Misconduct* earlier and if we look at the number of cards they've been given, they've both got more than 50 *Yellow Cards*, the fourth and fifth most in the season so far. In terms of *Red Cards*, Tottenham is joint top with the most players sent off, while Brighton is joint third. However, the other teams with most *Red Cards*, Burnley and Liverpool aren't as high up on *PC2*, perhaps undermining our interpretation of this component.

The *Bottom Half* follows with Bournemouth, Fulham, Everton, West Ham United, Wolverhampton Wanderers, Crystal Palace and Burnley in the *Bottom Half*. These are all quite tightly clustered together.

Finally, Luton Town, Nottingham Forest and Sheffield United in the *Relegated* category. Sheffield United appear to be setting a record in the negative territory they occupy on *PC1*, no prior team has a worse value.

We've already seen that our *Top Half* category isn't strongly linked to the first component, but we'll also look at the coordinates for each supplementary individual in more detail. We will sort the teams based on their coordinates on *PC1*, categorise them as such, and compare them to the actual position in the table.

```
df_ind.sup <- data.frame(result.pca$ind.sup$coord[,'Dim.1'])
names(df_ind.sup) <- 'Dim.1'
df_ind.sup$Idx <- row.names(df_ind.sup)
df_ind.sup <- df_ind.sup[order(df_ind.sup$Dim.1, decreasing = TRUE), ]
df_ind.sup$position <- c(1:20)
```

```r
df_ind.sup$category <-  ifelse(df_ind.sup$position >= 1
                               & df_ind.sup$position <= 4, "Top_4",
                        ifelse(df_ind.sup$position >= 5
                               & df_ind.sup$position <= 10, "Top_Half",
                        ifelse(df_ind.sup$position >= 11
                               & df_ind.sup$position <= 17, "Bottom_Half",
                        ifelse(df_ind.sup$position >= 18
                               & df_ind.sup$position <= 20, "Relegated", ""))))
df_orig <- data.supp[, c('Idx', 'Position', 'Category')]
df_joined <- inner_join(df_ind.sup, df_orig, by='Idx')
df_joined <- df_joined[,c(2,1, 3, 4, 5, 6)]
knitr::kable(df_joined, align = 'c', row.names = FALSE, caption = "First PC",
             col.names = c('Team', 'Coordinates', 'Component position',
                           'Component category', 'Actual position', 'Actual category'))
```

Table 18: First PC

Team	Coordinates	Component position	Component category	Actual position	Actual category
MCI2023_24	6.8520362	1	Top_4	3	Top_4
ARS2023_24	6.0248489	2	Top_4	4	Top_4
LIV2023_24	5.4838616	3	Top_4	1	Top_4
AVL2023_24	3.9279583	4	Top_4	2	Top_4
BHA2023_24	2.9590124	5	Top_Half	7	Top_Half
TOT2023_24	2.2551408	6	Top_Half	5	Top_Half
NEW2023_24	1.7460943	7	Top_Half	9	Top_Half
CHE2023_24	1.5800975	8	Top_Half	10	Top_Half
MUN2023_24	-0.1710533	9	Top_Half	8	Top_Half
BRE2023_24	-0.3135018	10	Top_Half	17	Bottom_Half
BOU2023_24	-0.5298838	11	Bottom_Half	12	Bottom_Half
FUL2023_24	-0.6052148	12	Bottom_Half	14	Bottom_Half
EVE2023_24	-1.1795743	13	Bottom_Half	13	Bottom_Half
WHU2023_24	-1.4379610	14	Bottom_Half	6	Top_Half
WOL2023_24	-1.5960260	15	Bottom_Half	11	Bottom_Half
CRY2023_24	-2.1122093	16	Bottom_Half	15	Bottom_Half
BUR2023_24	-2.8286802	17	Bottom_Half	19	Relegated
LUT2023_24	-3.0462466	18	Relegated	18	Relegated
NFO2023_24	-3.2798172	19	Relegated	16	Bottom_Half
SHU2023_24	-6.4454758	20	Relegated	20	Relegated

Although not in the correct order, the teams in *Top 4* category are consistent with the actual table standings.

However, in the *Top Half* category, Brentford would be classified as a Top Half team, yet they are currently 16th in the table, or 17th in the table if we adjust Everton back to their original position before the sanctions against them. The confusion here appears to be with West Ham United, who according to our categories are a *Bottom Half* team, but in fact, are firmly in the *Top Half*, currently sitting in 6th place.

The *Relegated* teams, according to *PC1*, are Luton Town, Nottingham Forest and Sheffield United. The problem here is that Nottingham Forest are not currently languishing in a relegation spot, they are 16th or 15th (without Everton adjustment).

Overall, *PC1* isn't doing too bad a job of linking the category in which the teams in the current season would be placed. 80% of the teams are categorised correctly. We must also remember that we are projecting an incomplete season onto a component based on past seasons. So we could argue that if the teams maintained the same the trajectory for the season, then the final table might more closely resemble the standings obtained here.

Conclusion

We initially learnt that we can use a majority of the variables from our data to analyse an incomplete season with just over half the games played, according to our analysis of variance. Our brief analysis of the underlying correlations underline that the best form of defence is attack, with a clear link between positive and negative correlations, and certain team play variables aligned towards attack or defence. *PC1* revealed itself to be one of the most interesting components and it highlights a very clear structure related to the balance of attack and defence for a team, which is interrelated. And this is intrinsically linked to the outcome of games, the points gained and the goal difference. It is also clearly linked to the category for the final position in the table, except for *Top Half* teams. However, matches *Drawn* is not linked to *PC1* and it is of interest that traditional bookmakers also have difficulty in predicting drawn games. Our interpretation of *PC2* and *PC3* remains questionable, and it is perhaps pertinent to examine additional components.

Opportunities for furthering this analysis could come from linking the PCA with prediction models. Given the structure of *PC1* it could be relevant to group the variables into a separate PCA for attack, defence, etc. This is kind of along the lines of what Opta does with Expected Goals For and Expected Goals Against, gathering attacking and defending characteristics into a single measure. This point also brings us to the possibility of applying PCA to individual games rather than data gathered over an entire season. Because we converted the variables into per game measures, we could project variables from single games these onto components generated from a season. And finally, it would be interesting to revisit the variables we actually included in the analysis. We are missing vital measures such as percentage of possession. But also, we included all the variables gathered and it may be of use to exclude certain variables such as the goals scored or conceded, focusing on attributes indirectly linked to outcomes in order to get a more nuanced view of the quality of teams.