ML Final Project: Analysis

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```
library(tidyverse)
library(dendextend)
library(factoextra)
library(GGally)
library(ggfortify)
library(ggrepel)
library(gridExtra)
library(knitr)
library(mclust)
library(NbClust)
library(rgl)

# set for reproducible results
set.seed(14)

# clear variables
rm(list = ls())

# set working directory

opts_knit$set(root.dir = normalizePath('..'))

# define file name for analysis
filename <- 'Data/season_stats_clean.csv'
```

Research Question: Are there underlying patterns of groupings between NBA team compensation vs. overall team skillsets?

Data Cleaning

The data cleaning was done in separate R scripts. https://github.com/joemarlo/ML-NBA Steps: * Filtered data to the 2016 - 2017 season * Assigned player to one team based on the most minutes he played for, including stats across all teams played for * Scraped player salaries and RPM data from ESPN website, using fuzzy matching on player names to join to the main dataset * Scaled/Transformed data using cube root (shown below)

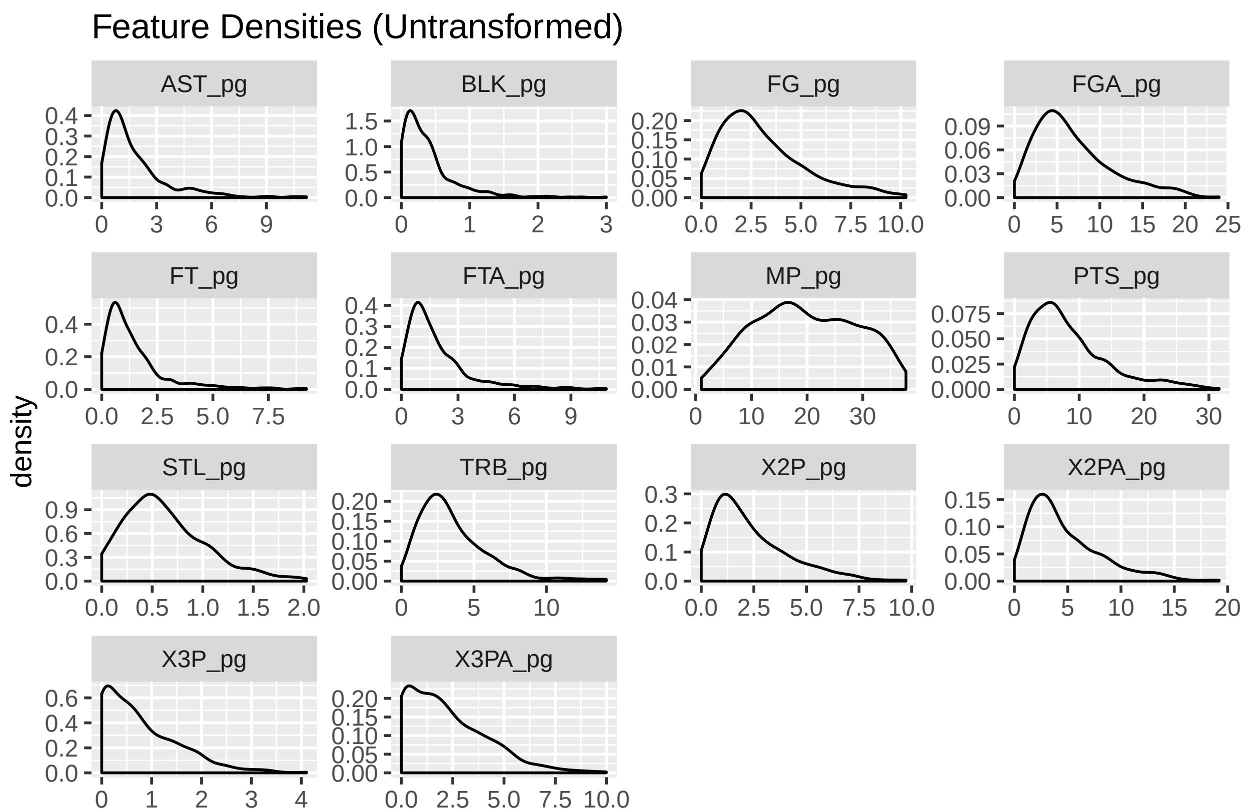
Exploratory Data analysis

```
# load data
nba <- read.csv(filename)
```

```
# replace NA values in RPM column with 0s
nba$RPM[is.na(nba$RPM)] <- 0
```

We decided to use the 14 features in our analysis (on a per game basis) because they provide a good balance of offensive (e.g Pts, Ast) and defensive stats (e.g. Reb, Blk). Additionally, advanced statistics such as VORP and PER utilize a combination of these 'base' statistics in their calculations. So, by using these base statistics between offensive and defensive metrics, this is more likely to provide more balanced groupings between those who are more offensive and those who are better at defense.

```
# plot distributions of key per game stats
features_pg <- grep('_pg', names(nba), value = TRUE)
nba_feat <- nba[ , features_pg]

nba_feat %>%
  pivot_longer(cols = everything()) %>%
  ggplot(aes(x = value)) +
  geom_density() +
  facet_wrap(~name, scales = "free") +
  labs(title = 'Feature Densities (Untransformed)',
       x = '')
```



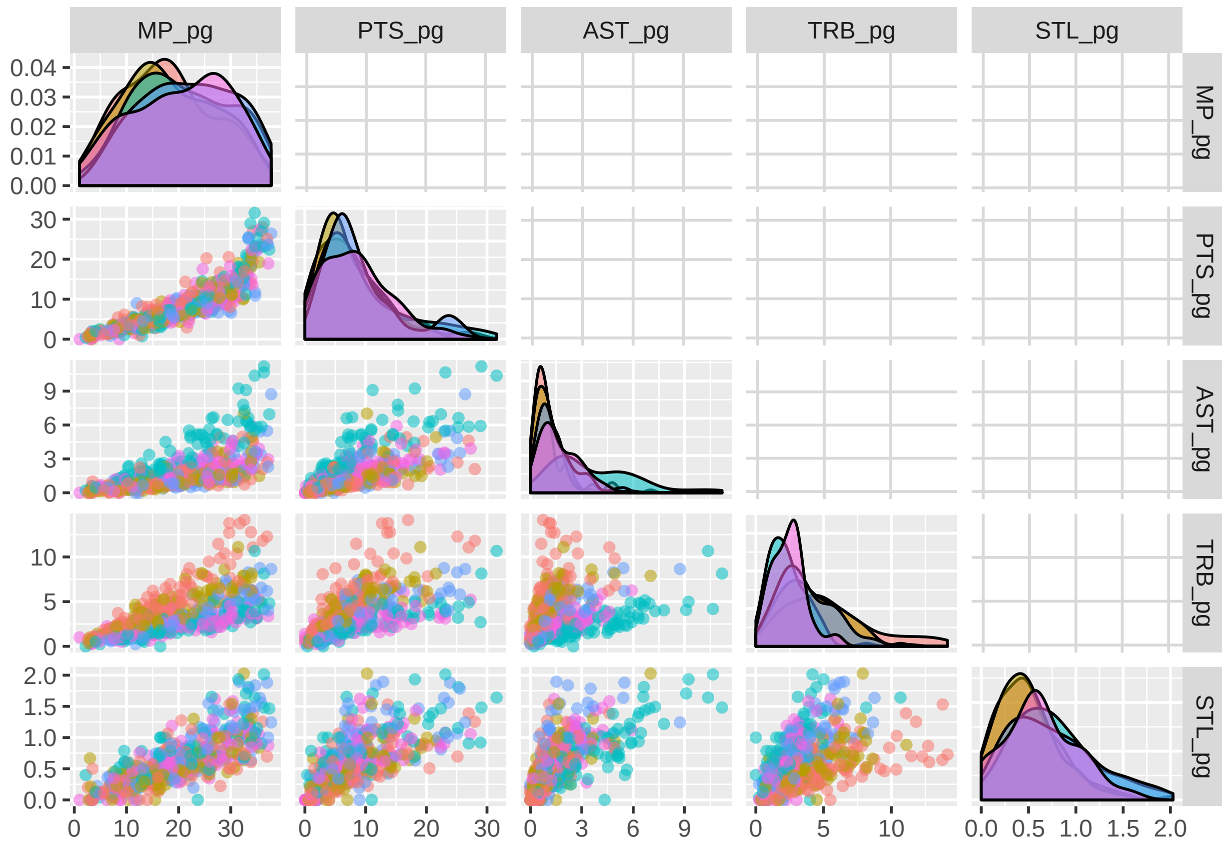
Variance was calculated to determine if we need to scale the data

```
# calculate variance
round(apply(nba_feat, MARGIN = 2, FUN = var), 2)
```

```
##   MP_pg   FG_pg  FGA_pg  X3P_pg X3PA_pg  X2P_pg X2PA_pg   FT_pg  FTA_pg
##   82.07    4.67   20.49    0.57    3.76    3.23   11.89    2.04    2.99
##  TRB_pg  AST_pg  STL_pg  BLK_pg  PTS_pg
##    5.89    3.11    0.17    0.17   36.72
```

```
# look at pairs plots for key stats
feat_plot <- c('MP_pg', 'PTS_pg', 'AST_pg', 'TRB_pg',
```

```
                'STL_pg', 'BLK_pg')
nba_feat_plot_pos <- nba[ , feat_plot]
ggpairs(nba_feat_plot_pos,
        columns = 1:(length(names(nba_feat_plot_pos)) - 1),
        progress = FALSE,
        mapping = ggplot2::aes(colour = nba$Pos, alpha = 0.4),
        upper = list(continuous = wrap('cor', size = 0))
)
```



Most of the features such as points and assists look like they exhibit a negative binomial distribution. If we look at the pairs plot, it looks like there are clear groupings by position.

Run PCA to inspect if there are any groupings

Before running any clustering algorithms, we will perform Principal Component Analysis to determine if there are any potential clusters. We first scaled the data because the ranges of the data can be different. A good example is minutes and blocks per game - Most players will have more minutes per game than blocks per game.

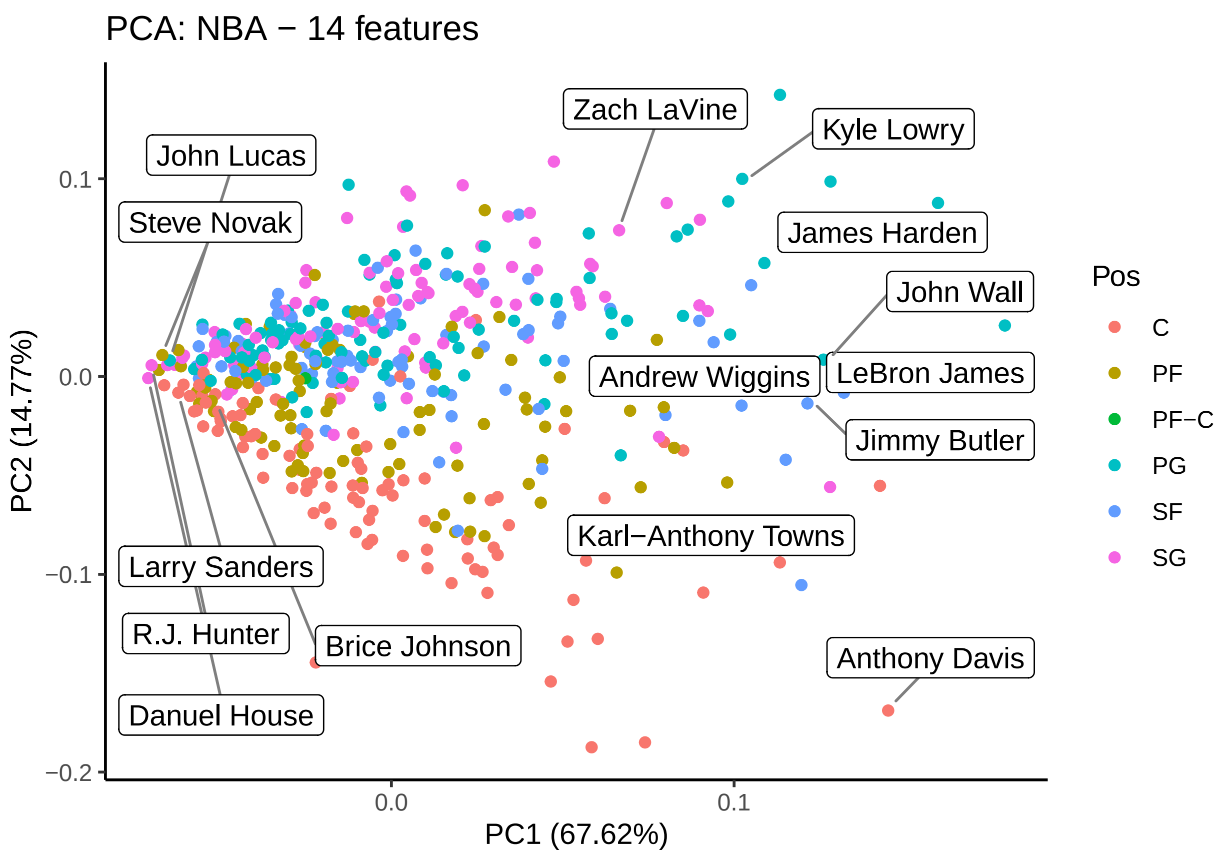
```
nba_feat_sc <- scale(nba_feat)

# run PCA
# princomp() uses spectral decomposition
# prcomp() uses singular value decomposition
nba_pca <- prcomp(nba_feat_sc)
summary(nba_pca)
```

```
## Importance of components:
##                           PC1    PC2     PC3     PC4     PC5     PC6
## Standard deviation     3.0767 1.4379 0.88672 0.80819 0.63364 0.52061
## Proportion of Variance 0.6762 0.1477 0.05616 0.04666 0.02868 0.01936
## Cumulative Proportion  0.6762 0.8239 0.88002 0.92667 0.95535 0.97471
##                            PC7     PC8     PC9    PC10    PC11      PC12
## Standard deviation     0.46651 0.29741 0.16765 0.10779 0.09065 2.849e-15
## Proportion of Variance 0.01555 0.00632 0.00201 0.00083 0.00059 0.000e+00
## Cumulative Proportion  0.99026 0.99658 0.99858 0.99941 1.00000 1.000e+00
##                             PC13      PC14
## Standard deviation     2.194e-15 1.597e-15
## Proportion of Variance 0.000e+00 0.000e+00
## Cumulative Proportion  1.000e+00 1.000e+00
```

```r
# create plot PCA data function
plot_pca <- function(object, frame = FALSE, x = 1, y = 2,
                     data, colour, title, label) {
  # plots data in PCA space
  # object = PCA or K-Means object
  # x = which PC for x-axis (1, 2, ,3, etc..)
  # y = which PC for y-axis (1, 2, 3, etc..)
  # object: PCA or K-means object
  # data = underlying data
  p <- autoplot(nba_pca, x = x, y = y, data = nba, colour = colour, frame = frame) +
        ggtitle(title) +
        # center title
        theme(plot.title = element_text(hjust = 0.5)) +
        geom_label_repel(aes(label = label),
                        box.padding   = 0.35,
                        point.padding = 0.5,
                        segment.color = 'grey50') +
        theme_classic()
  return(p)
}
```

Since 2 components make up 83% of the cumulative variance, we will plot these

```r
# Labels: Players who played more than 36 min per game or less than 3 min per game
labels_pca <- ifelse(nba$MP_pg >= 36 | nba$MP_pg <= 3,
                    as.character(nba$Player), '')
title_pca <- paste0('PCA: NBA - ', ncol(nba_feat) ,' features')

# Plot first two components with positions
plot_pca(nba_pca, data = nba, colour = 'Pos',
         label = labels_pca, title = title_pca
          )
```



Observations Based on the PCA plot, it looks like there are natural grouping based on position from the colors coding. For example, the centers are on the bottom diagonal, point guards are near the top, and SF/PFs are in the middle. It is also noticable that the stars and superstars are on the right-side of the cluster. Since this looks like a fan, we can also say that the stars are placed more towards the 'tips' of the fan. So, we will hypothesize that there may also be clusters from left to right, where the right-most are the top players, and the left side are the lower performing players.

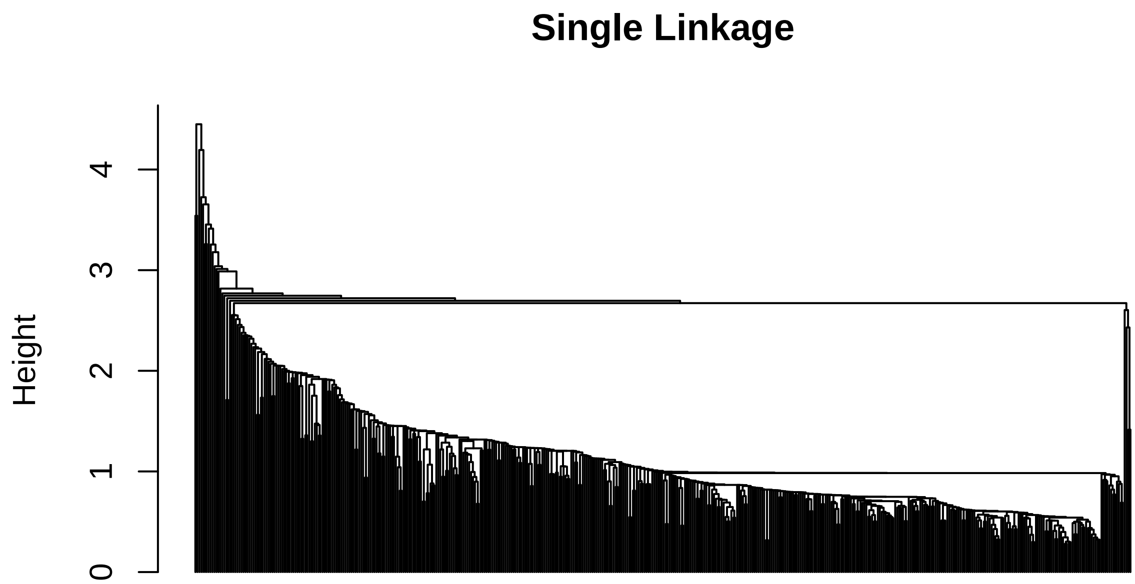
Clustering

Hierarchical clustering

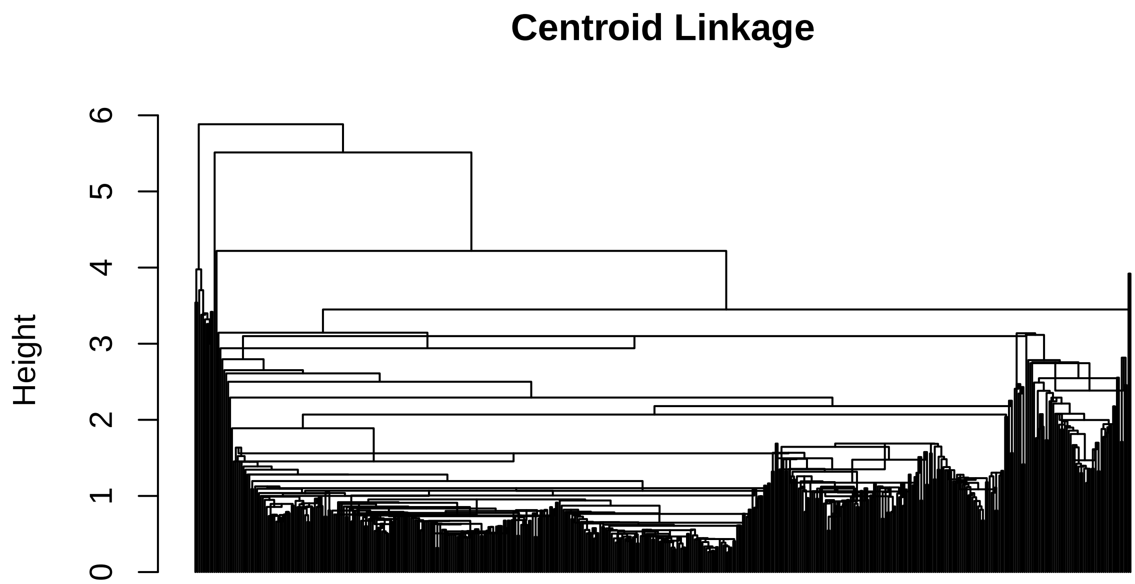
The first method of clustering we will try is hierarchical clustering. The dendrogram can help provide a visual aid in the number of clusters we can start to use.

```
# distance matrix for features
nba_dist_sc <- dist(nba_feat_sc, method = 'euclidean')

# try single, centroid, and ward (D2) linkage hier clustering
hcl_single <- hclust(d = nba_dist_sc, method = 'single')
hcl_centroid <- hclust(d = nba_dist_sc, method = 'centroid')
hcl_ward <-  hclust(d = nba_dist_sc, method = 'ward.D2')
```

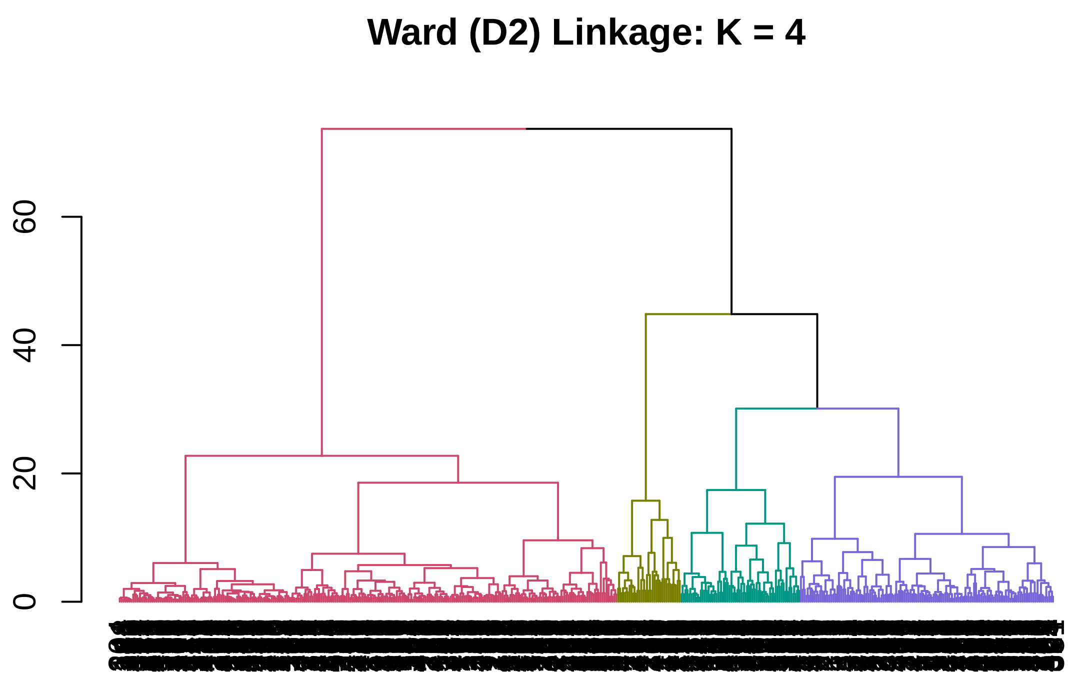
```
# nearest neighbors method
plot(hcl_single, hang = -1, main = 'Single Linkage',
     labels = FALSE, xlab = '', sub = '')
```




```r
# groups centroid
plot(hcl_centroid, hang = -1, main = 'Centroid Linkage',
     labels = FALSE, xlab = '',  sub = '')
```

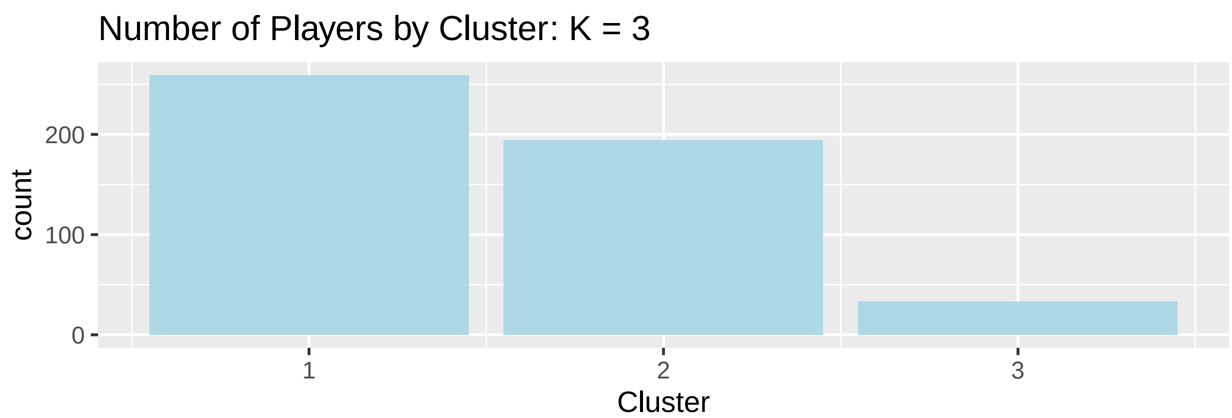


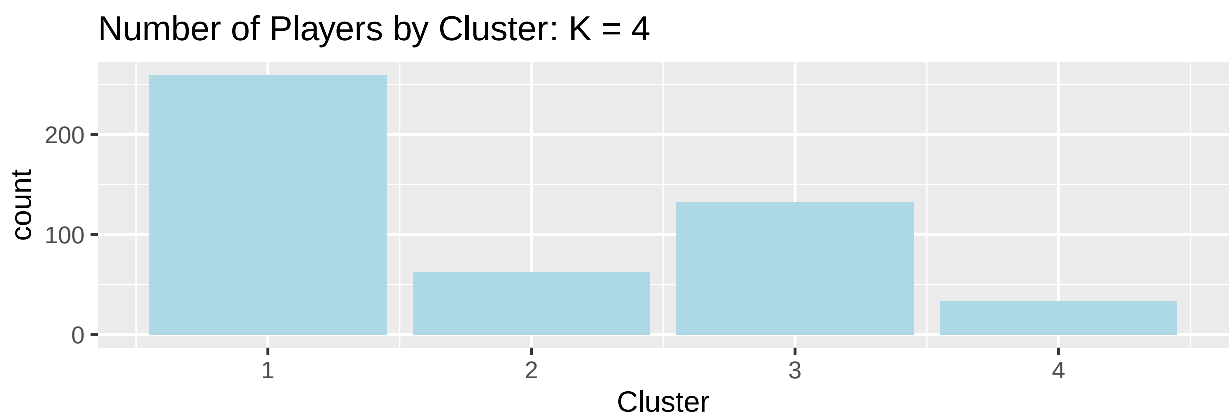

```r
# Ward's minimum variance method,
# with dissimilarities are squared before clustering
dend <- as.dendrogram(hcl_ward)
hcl_k <- 4
dend_col <- color_branches(dend, k = hcl_k)
plot(dend_col, main = paste0('Ward (D2) Linkage: K = ', hcl_k))
```



Since the Ward dendrogram seems to be the best among the three, we will look at its distribution for 3 and 4 clusters. We chose these initial groupings because this is a good number of initial clusters to group NBA players.

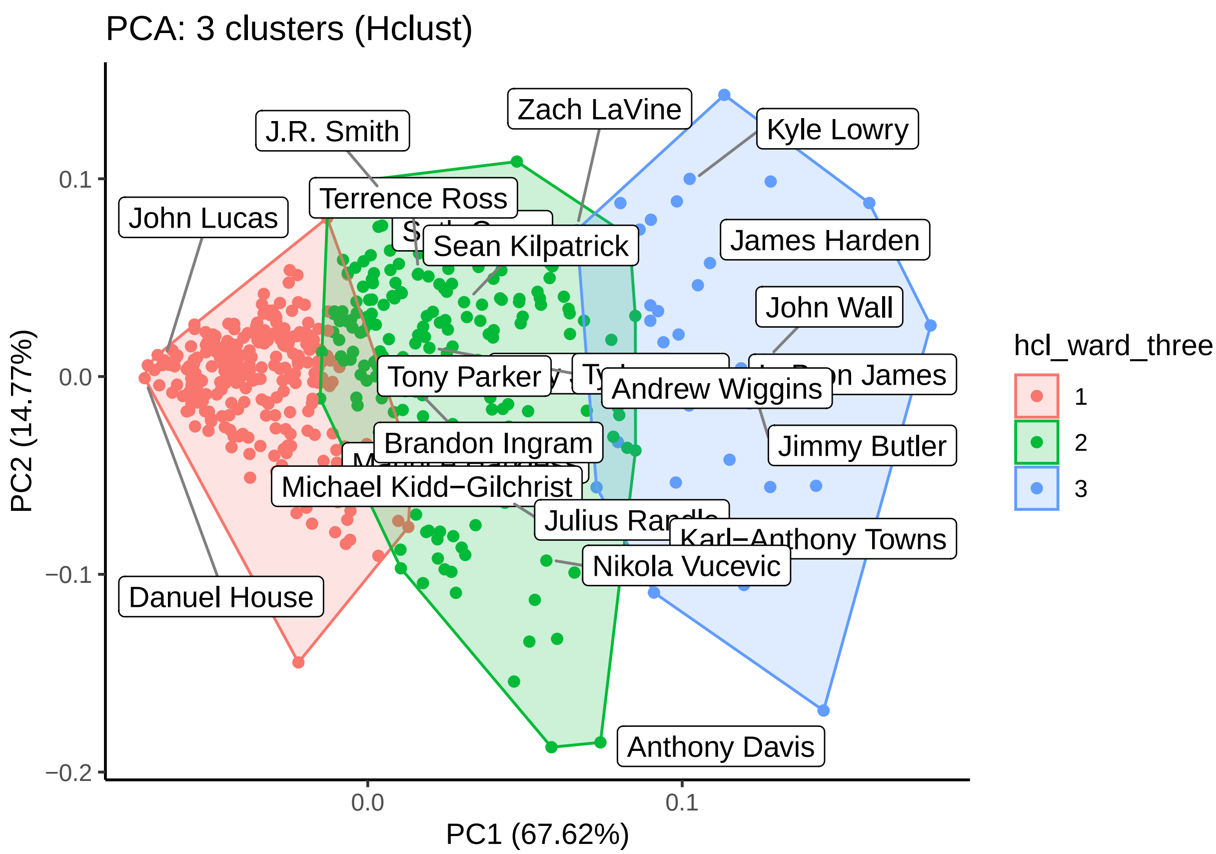
```
# add cluster labels to main data
nba$hcl_ward_labs_three <- cutree(hcl_ward, k = 3)
nba$hcl_ward_labs_four <- cutree(hcl_ward, k = 4)

# plot frequencies
p_one <- ggplot(data = nba, aes(x = hcl_ward_labs_three)) +
          geom_bar(fill = 'lightblue') +
          ggtitle('Number of Players by Cluster: K = 3') +
          xlab('Cluster')
p_two <- ggplot(data = nba, aes(x = hcl_ward_labs_four)) +
          geom_bar(fill = 'lightblue') +
          ggtitle('Number of Players by Cluster: K = 4') +
          xlab('Cluster')

# combine
cowplot::plot_grid(p_one, p_two, nrow = 2)
```

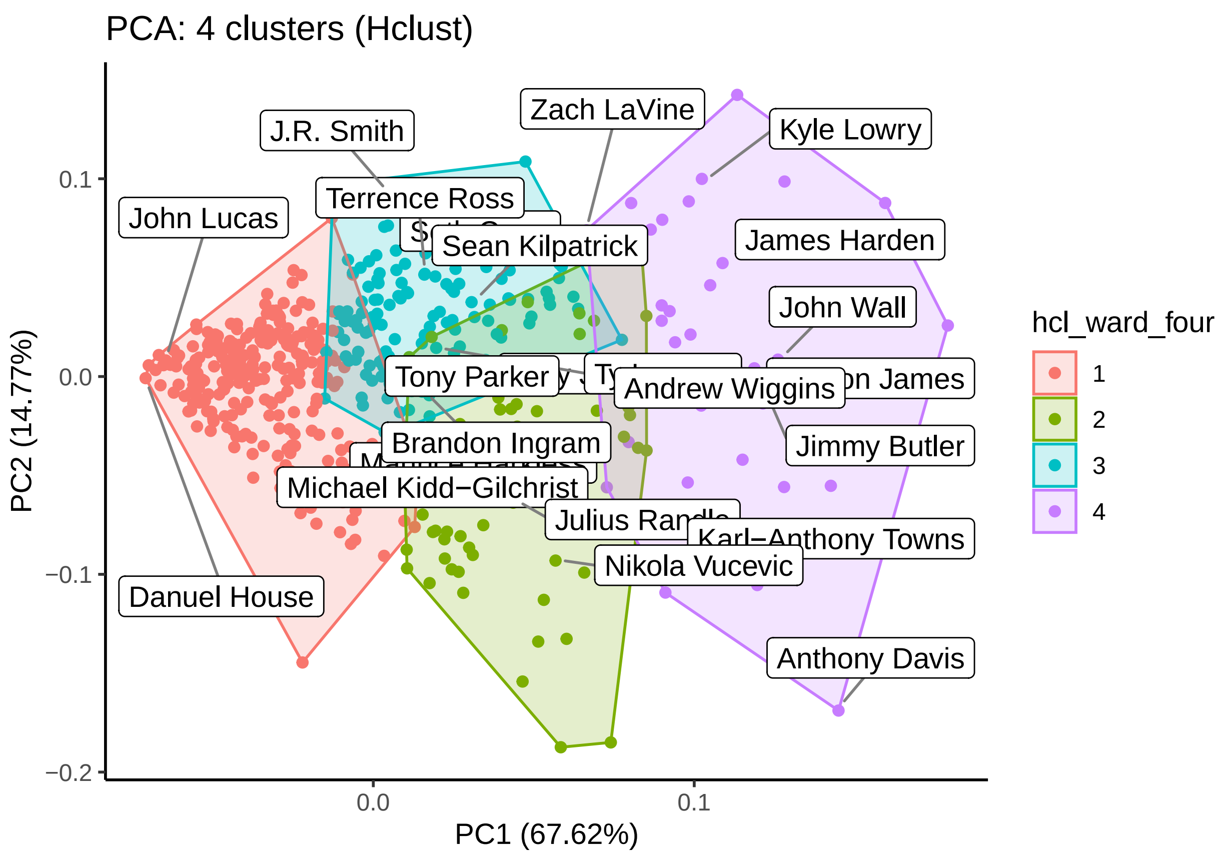




Visualizing clusters in PCA space

```
# add labels to data
nba$hcl_ward_three <- factor(cutree(hcl_ward, k = 3))
nba$hcl_ward_four <- factor(cutree(hcl_ward, k = 4))

# player names to include in plot
hcl_labels <- ifelse(nba$MP_pg >= 36 | nba$MP_pg <= 2.5 |
                     (nba$MP_pg >= 28.8 & nba$MP_pg <= 29) |
                     (nba$MP_pg >= 25 & nba$MP_pg <= 25.2),
                     as.character(nba$Player), '' )

# elements to loop over
hcl_labs <- names(nba %>% select(tail(names(.), 2)))
hcl_ks <- c(3, 4)

# plot hclust labels superimposed over PCA
for (i in seq_along(hcl_labs)) {
  p <- plot_pca(nba_pca, frame = TRUE,
                data = nba, colour = hcl_labs[i],
                title = paste0('PCA: ', hcl_ks[i], ' clusters (Hclust)'),
                label = hcl_labels
  )

  print(p)
}
```


PCA: 3 clusters (Hclust)
J.R. Smith
Zach LaVine
Kyle Lowry
John Lucas
Terrence Ross
Sean Kilpatrick
James Harden
John Wall
Tony Parker
Andrew Wiggins
Jimmy Butler
Brandon Ingram
Michael Kidd−Gilchrist
Karl−Anthony Towns
Nikola Vucevic
Danuel House
Anthony Davis
0.1
0.0
−0.1
−0.2
PC2 (14.77%)
0.0
0.1
PC1 (67.62%)
hcl_ward_three
1
2
3

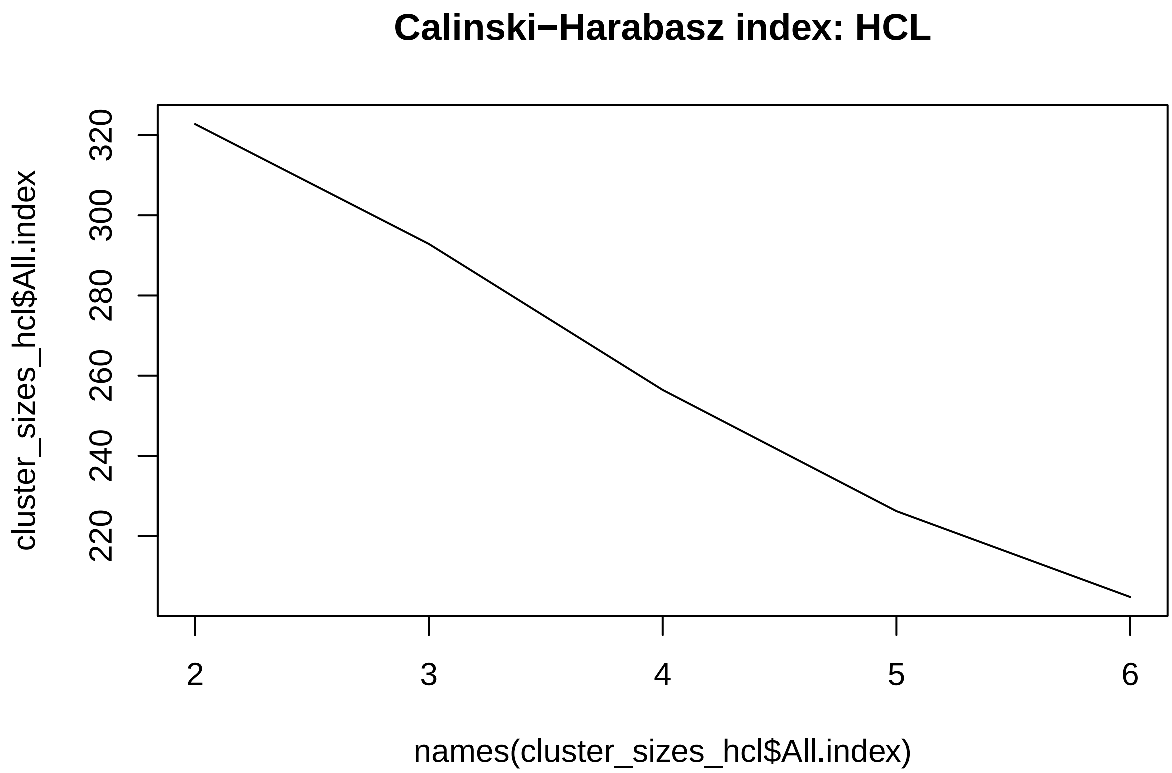


Visually, it looks like the four cluster solution may be able to give us more actionable insights vs the 3-cluster method. The average stats by cluster shows pretty clear separation among the groups. Group 4 are the stars, followed by group 2, 3, and then 4. The main difference between groups 2 and 3 is that group 2 looks to contain more players who tend to have more rebound and blocks per game.

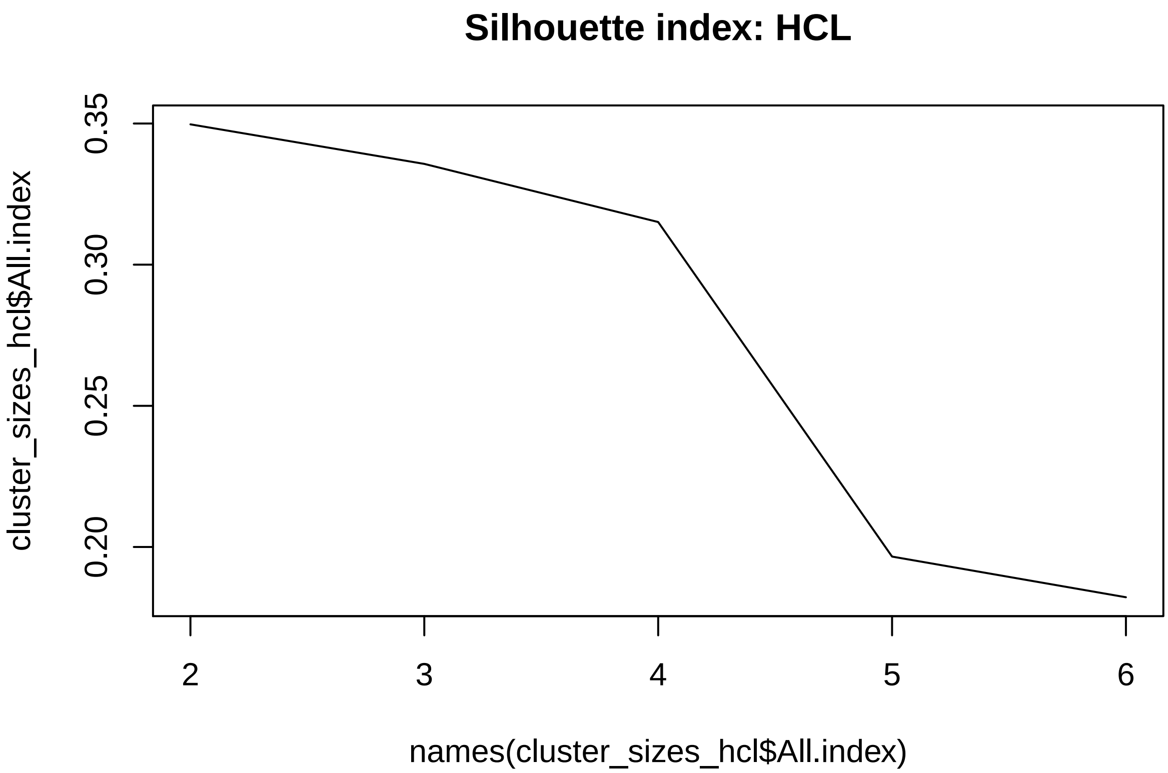
Optimize number of clusters

Methods: Calinski-Harabasz index and Scott

```
# get optimal cluster sizes
cluster_sizes_hcl <- NbClust(data = nba_feat_sc,
                             # it will likely be harder to interpret clusters
                             # past this amount
                             max.nc = 6,
                             method = 'ward.D2',
                             index = 'ch')

# plot C(G)
plot(names(cluster_sizes_hcl$All.index),
     cluster_sizes_hcl$All.index,
     main = 'Calinski-Harabasz index: HCL',
     type = 'l')
```




```r
# get optimal cluster sizes
cluster_sizes_hcl <- NbClust(data = nba_feat_sc,
                             # it will likely be harder to interpret clusters
                             # past this amount
                             max.nc = 6,
                             method = 'ward.D2',
                             index = 'silhouette')

# plot C(G)
plot(names(cluster_sizes_hcl$All.index),
     cluster_sizes_hcl$All.index,
     main = 'Silhouette index: HCL',
     type = 'l')
```



Among the different hierarchical clustering methods, the Ward method seems to be the best. The dendogram looks the most structured and the distribution of players in each cluster is more balanced. Hierarchical clustering could seem like a potential fit if we want the better players to be in a more 'select' group. Although the CH index indicates 2 clusters is optimal, we need to look at the practicality as well. 3 clusters may hav differences between groups of players. But, it is possible that NBA front offices will likely need more differentation when grouping player performance. Looking at the 4 cluster solutions and stats, the blue cluster tends to have more players who rebound, block more shots and tend to be more efficient (based on PER). So, these clusters seem to have decent separation from each other. We will now try K-Means clustering too see if that works better.

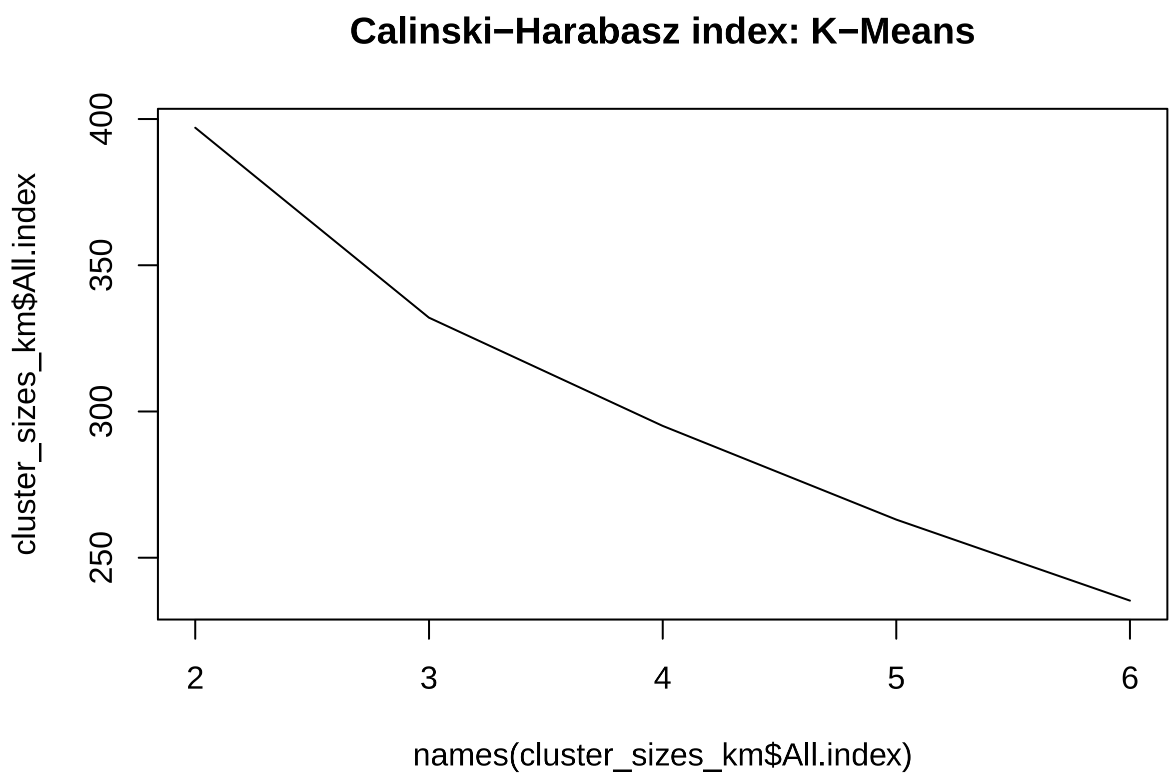
K-Means

Optimize number of clusters

Method: Calinski-Harabasz index

```
# get optimal cluster sizes
cluster_sizes_km <- NbClust(data = nba_feat_sc,
                            # it will likely be harder to interpret clusters
                            # past this amount
                            max.nc = 6,
                            method = 'kmeans',
                            index = 'ch')

# plot C(G)
plot(names(cluster_sizes_km$All.index),
     cluster_sizes_km$All.index,
```

```
      main = 'Calinski-Harabasz index: K-Means',
      type = 'l')
```




```
# get optimal cluster sizes
cluster_sizes_km <- NbClust(data = nba_feat_sc,
                            # it will likely be harder to interpret clusters
                            # past this amount
                            max.nc = 6,
                            method = 'kmeans',
                            index = 'silhouette')

# plot C(G)
plot(names(cluster_sizes_km$All.index),
     cluster_sizes_km$All.index,
     main = 'Silhouette index: K-Means',
     type = 'l')
```

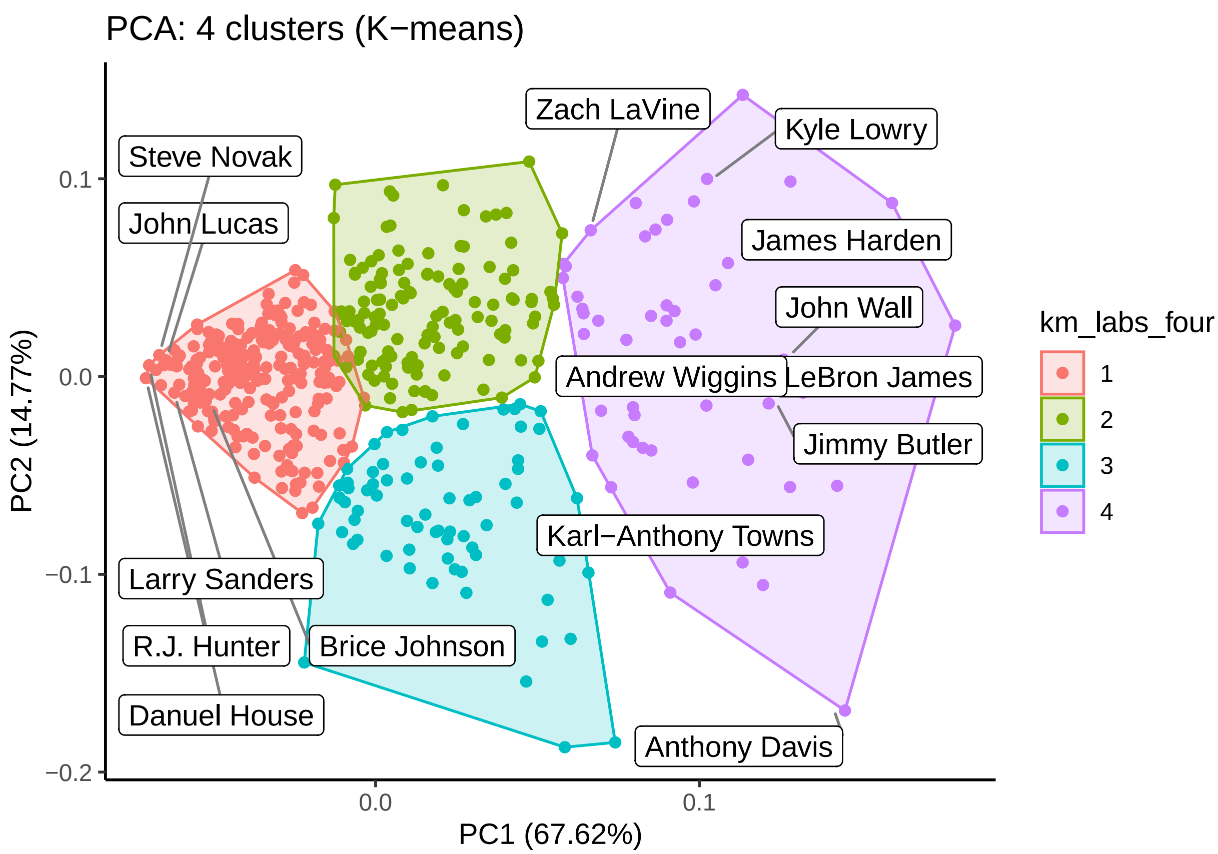
The optimization methods tell us that 2 clusters is best, but we will need more groups for meaningful and interesting separation among players. The silhouette index shows that there is a distinct drop off after 4 clusters.

K-means clustering with 4 groups

```
km_k <- 4
km_four <- kmeans(x = nba_feat_sc,
            centers = km_k,
            nstart = 100,
            algorithm = 'Hartigan-Wong')
```

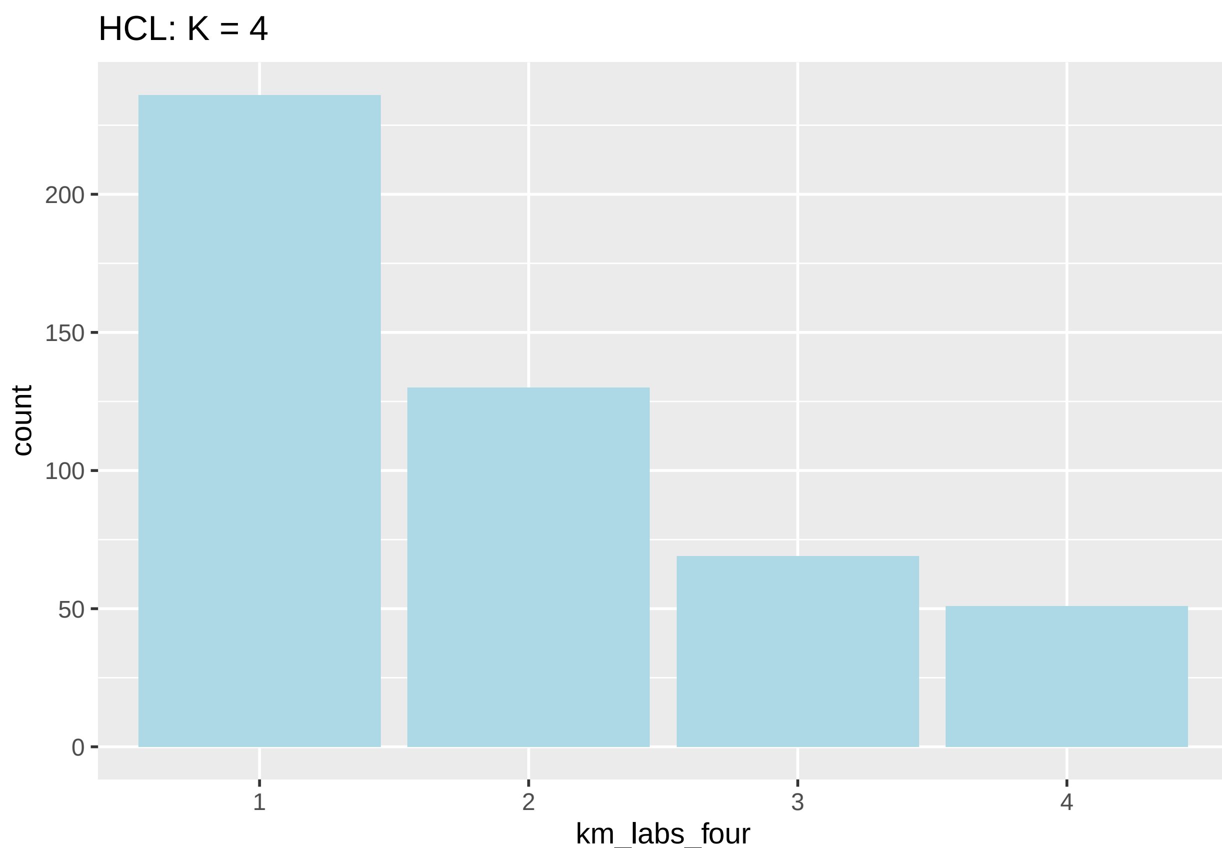
```
nba$km_labs_four <- factor(km_four$cluster)
```

```
# plot k-means clusters in PC space
# Labels: Players who played more than 36 min per game or less than 3 min per game
km_labels <- ifelse(nba$MP_pg >= 36 | nba$MP_pg <= 3,
                    as.character(nba$Player), '' )

plot_pca(km_five, data = nba, frame = TRUE, colour = 'km_labs_four',
          title = paste0('PCA: ', km_k, ' clusters (K-means)'),
          label = km_labels)
```



There is clean separation in the 4-cluster plot. We will now see how these clusters are separated by inspecting features within each group.

```
# get distribution of players in each cluster
ggplot(data = nba,
       aes(x = km_labs_four)) +
       geom_bar(fill = 'lightblue') +
       ggtitle('HCL: K = 4')
```



Describe why distribution is not balanced

It looks like the clusters are somewhat interpretable. Clusters to the right seem to indicate star players, while clusters to the left indicate lower performing players. However, the question becomes if 5 clusters is meaningful. Based on the averages for each cluster, there is not much difference between clusters 2 and 4. Additionally, it looks like there is room to better balance the number of players in each cluster and create more separation between clusters.

```
# averages by cluster
nba_km_avg <- data.frame(nba
                          %>% select(km_labs_four, MP_pg, PTS_pg, TRB_pg,
                                     AST_pg, BLK_pg, STL_pg, VORP, PER, RPM)
                          %>% group_by(km_labs_four)
                          %>% summarise_all(list(mean))
                          )
nba_km_avg
```

```
##   km_labs_four    MP_pg   PTS_pg   TRB_pg    AST_pg    BLK_pg    STL_pg
## 1            1 12.24558  3.94709 2.129925 0.8788919 0.2354097 0.3548853
## 2            2 25.61995 10.30825 3.484223 2.5209841 0.2885179 0.8214061
## 3            3 24.96591 10.29999 7.010810 1.6435808 0.9473312 0.7868895
## 4            4 33.85906 21.82156 5.724658 4.7255814 0.6158290 1.1623242
##          VORP      PER        RPM
## 1 -0.06694915 10.18941 -1.9458898
## 2  0.50153846 12.75308 -0.8625385
## 3  1.26811594 17.09710  0.3679710
## 4  3.19215686 21.29020  2.5100000
```

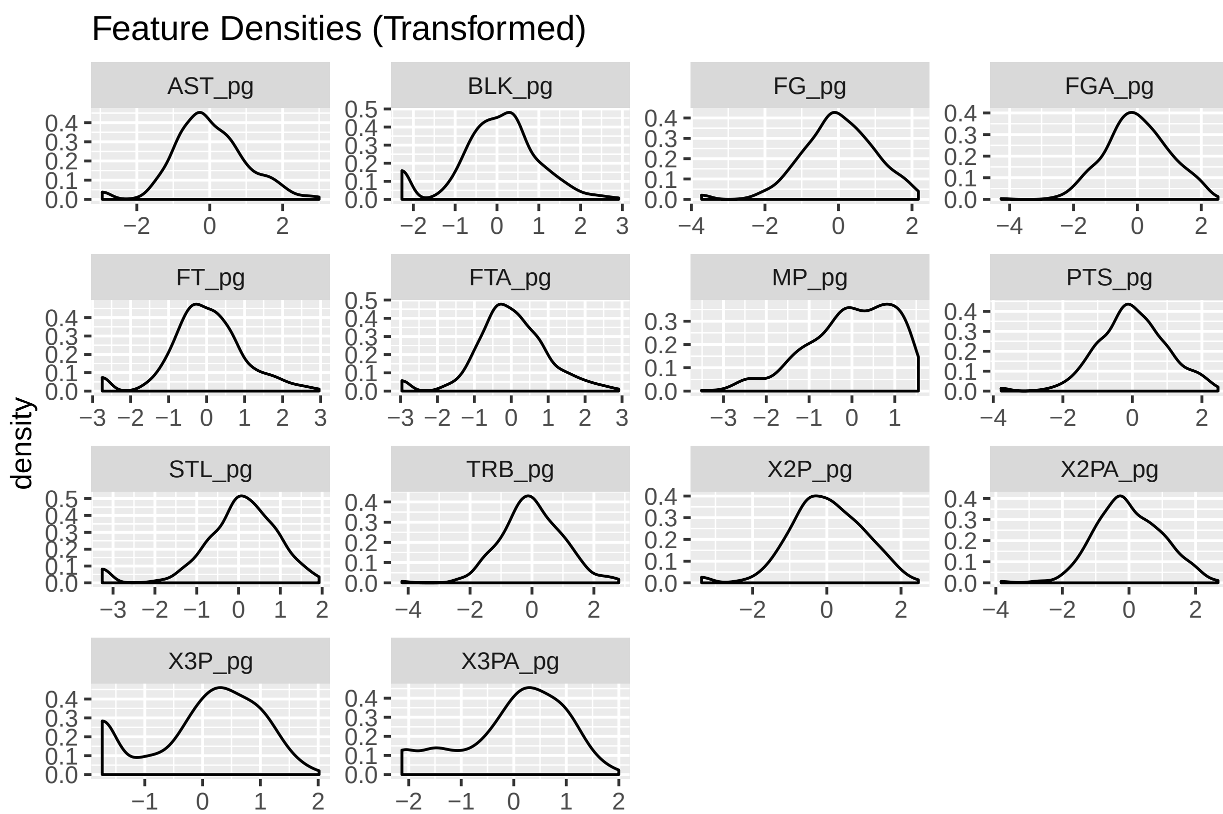
Observations Although the CH index indicates that the optimal number of clusters is 2, this seems too low of a number to meaningfully break out the NBA players into groups. It is also important to note that the CH index is a heuristic method. So although CH is a good approach to look for the number of clusters, it is important to combine this with our practical goal of looking for underlying patterns in the players. Thus, I think a more reasonable number to understand the data is with 3 - 4 clusters, which show the second and third best partitions based on the CH index. We will look at both and determine which one is a better fit for our goal.

Based on the plot, cluster distributions, and group averages, it looks like 4 clusters is optimal. One main reason is that there is more separation vs 4 clusters, which can provide more value when bucketing players by overall skillsets. Across the statistics, it looks like the clusters are broken out into the following: Best players (2), Good players with more assists, i.e. guards (1), good players who rebound and block more, .e.g forwards (4), and Low-performing players (3). We will now try model-based clustering as a third method.

Model-Based Clustering

```r
# transform features
nba_feat_cr <- (nba_feat) ^ (1/3)
# scale transformed features
nba_feat_cr_sc <- scale(nba_feat_cr)
```

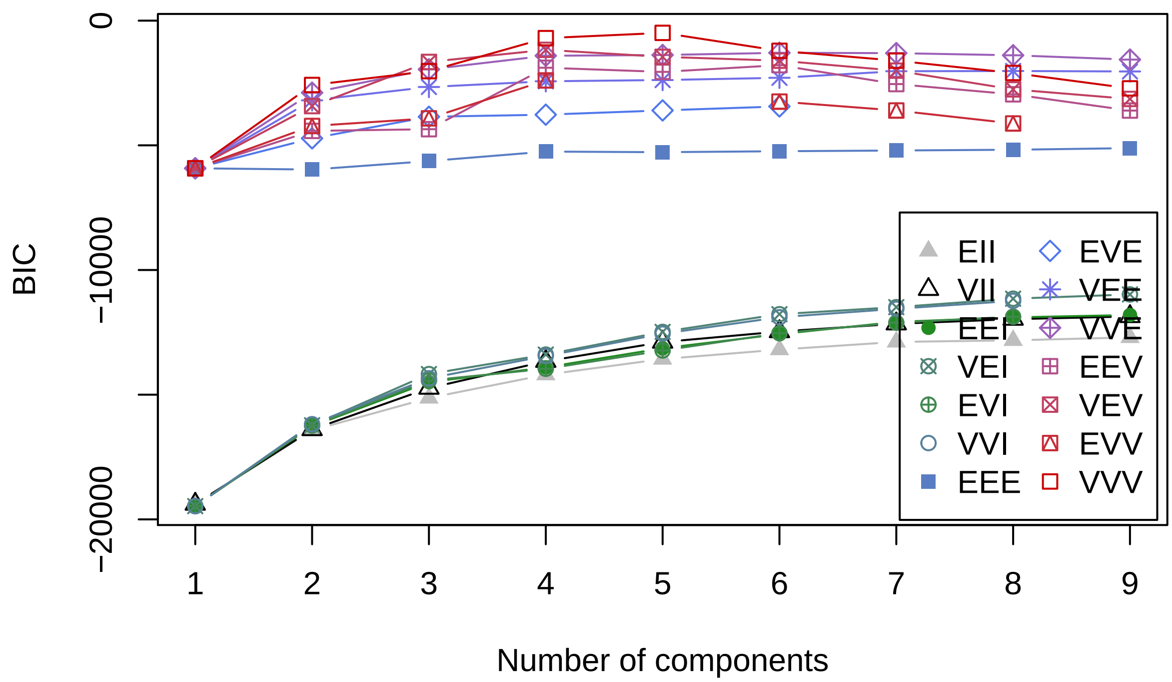
```r
# plot transformed variables
nba_feat_cr_sc %>% as_tibble() %>%
  pivot_longer(cols = everything()) %>%
  ggplot(aes(x = value)) +
  geom_density() +
  facet_wrap(~name, scales = "free") +
  labs(title = 'Feature Densities (Transformed)',
       x = '')
```



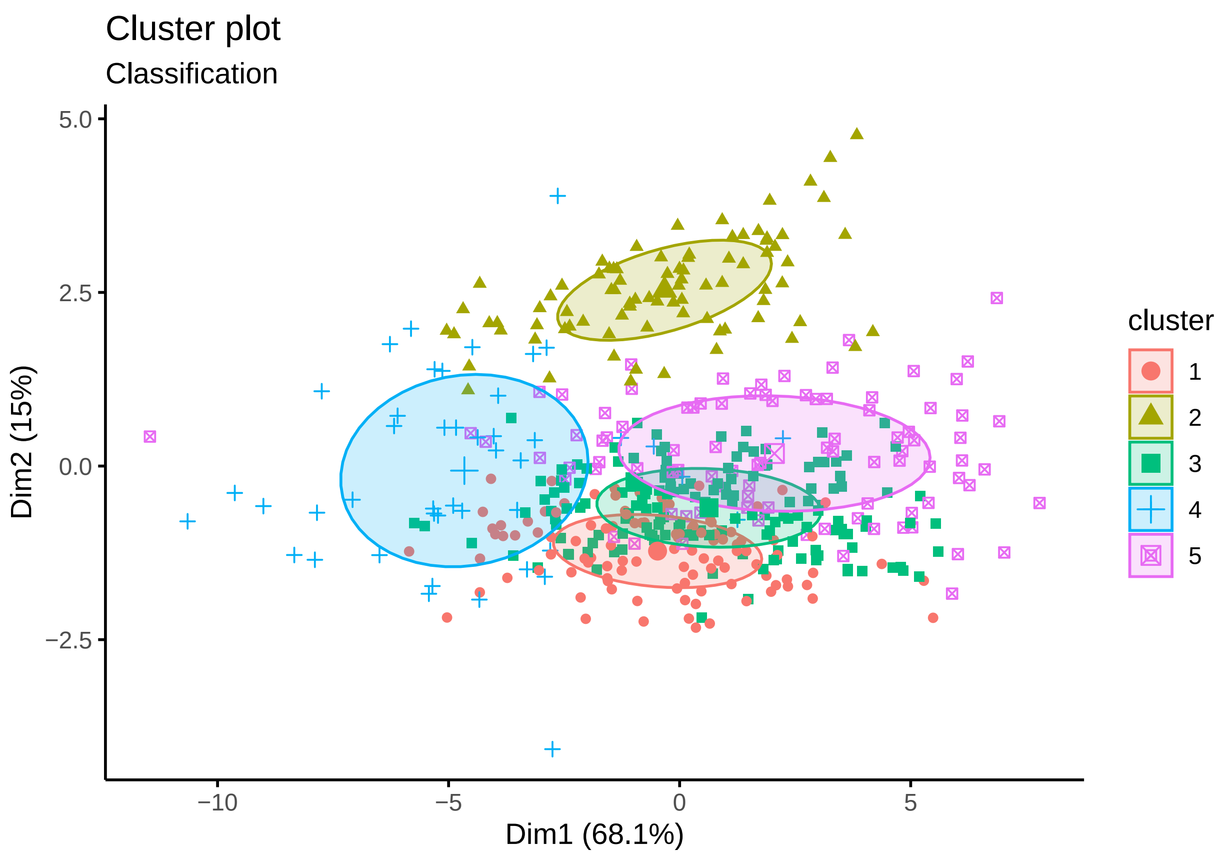

```r
# run model
player_clust.mcl <- Mclust(nba_feat_cr_sc)
summary(player_clust.mcl)
```

```
## ----------------------------------------------------
## Gaussian finite mixture model fitted by EM algorithm
## ----------------------------------------------------
##
## Mclust VVV (ellipsoidal, varying volume, shape, and orientation) model
## with 5 components:
##
##  log-likelihood   n  df       BIC       ICL
##        1607.448 486 599 -490.6436 -505.4606
##
## Clustering table:
##   1   2   3   4   5
## 106  84 160  45  91
```

```r
plot(player_clust.mcl, what = "BIC")
```




```
# plot results
fviz_mclust(player_clust.mcl, "classification", geom = "point")
```




```
# add cluster labels to plot
nba$mcl_labs <- player_clust.mcl$classification
```

Compare methods between Clusters

We will now compare crosstab solutions

```
# run crosstabs between cluster methods
xtab_hcl_km <- xtabs(~nba$hcl_ward_four + nba$km_labs_four)
xtab_hcl_mcl <- xtabs(~nba$hcl_ward_labs_four + nba$mcl_labs)
xtab_km_mcl <- xtabs(~nba$km_labs_four + nba$mcl_labs)

xtab_hcl_km
```

```
##                   nba$km_labs_four
## nba$hcl_ward_four   1   2   3   4
##                 1 231   4  24   0
##                 2   0   8  42  12
##                 3   5 118   3   6
##                 4   0   0   0  33
```

```
xtab_hcl_mcl
```

```
##                        nba$mcl_labs
## nba$hcl_ward_labs_four  1  2  3  4  5
##                      1 55 60 75 41 28
##                      2  0 24 12  1 25
##                      3 48  0 63  3 18
```

```
##                       4   3   0 10   0 20
```

```
xtab_km_mcl
```

```
##                  nba$mcl_labs
## nba$km_labs_four  1  2  3  4  5
##                 1 52 40 74 41 29
##                 2 51  0 63  2 14
##                 3  0 44  7  2 16
##                 4  3  0 16  0 32
```

Between HCL and KM, the maximum possible agreement between clusters is 87% (424 / 486). Between HCL and MCL, the maximum possible agreement between clusters is 30% (148 / 486). Between KM and MCL, the maximum possible agreement between clusters is 41% (201 / 486).

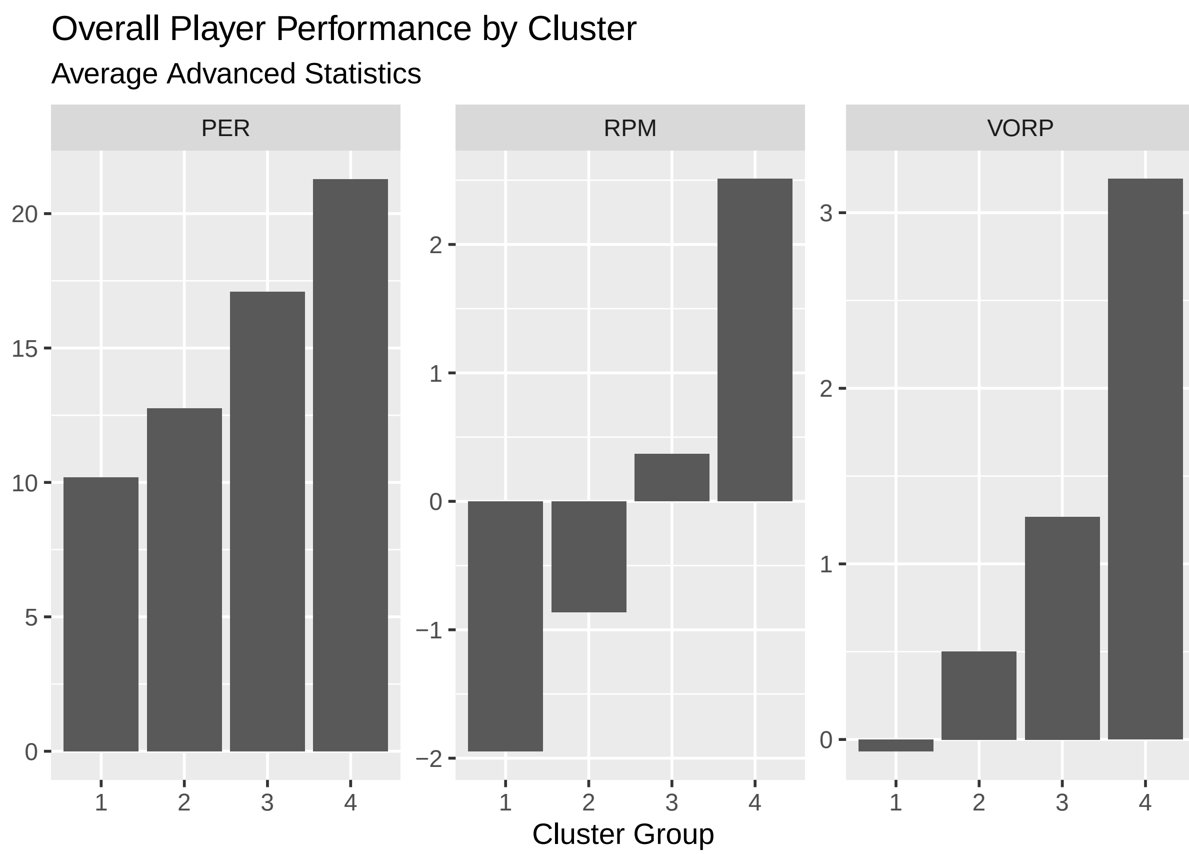
Based on the analysis, MCL tends to group players by position, whereas HCL and KM tend to cluster based on overall player statistics. This conclusion was reached based on inspecting distributions of player positions across the clustering methods. Because we are looking at player statistics and team compensation, the model-based clustering is not an ideal fit for this purpose.

Final Cluster selection

K-Means (4 clusters) was the optimal solution. Comparing the HCL and KM cluster plots (per above) reveals the K-Means produces clearer separation of players based on overall skillsets.

Inspection of clusters suggest that groupings separate players by skillsets. We validated this by comparing the clusters against advanced statistics. PER, VORP, and RPM are advanced statistics commonly used to assess general player performance. None of these statistics were used in the cluster modeling.

```
# plot averages by cluster
nba_km_avg %>%
  select(km_labs_four, VORP, PER, RPM) %>%
  pivot_longer(cols = c("VORP", "PER", "RPM")) %>%
  ggplot(aes(x = km_labs_four, y = value)) +
  geom_col() +
  facet_wrap(~name, scales = 'free') +
  labs(title = 'Overall Player Performance by Cluster',
       subtitle = 'Average Advanced Statistics',
       x = 'Cluster Group',
       y = '')
```

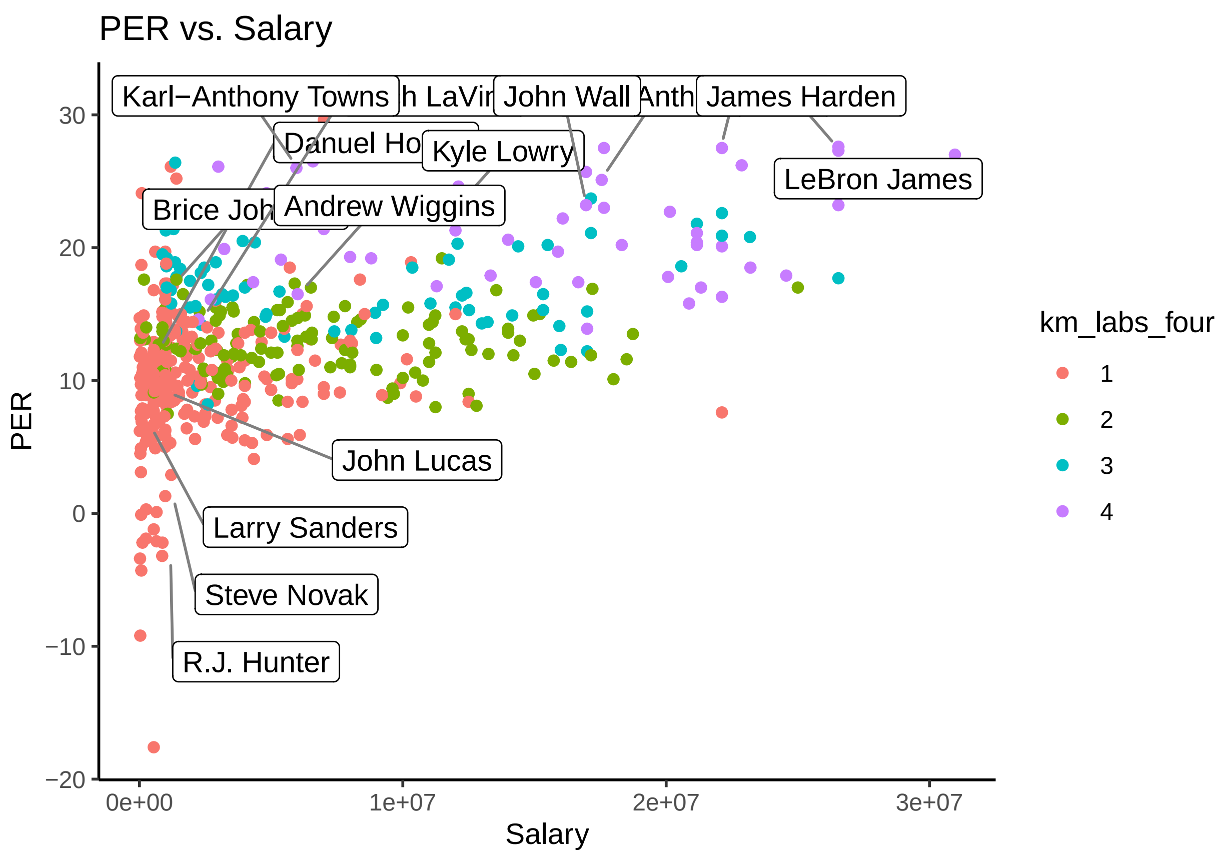


Post-Cluster Analysis

We will now look at different statistics and demographics to see how the clustering lines up

Clusters vs. Player Salaries

```r
# salary vs. advanced stats, overlayed with clusters

# cluster label to use
cl_label <- "km_labs_four"

# plot PER vs. salary
ggplot(data = nba, aes(x = Salary, y = PER)) +
  geom_point(aes_string(color = cl_label)) +
  geom_label_repel(aes(label = labels_pca),
                   box.padding   = 0.35,
                   point.padding = 0.5,
                   segment.color = 'grey50') +
  ggtitle('PER vs. Salary') +
  theme_classic()
```




```
# Highest Paid players in Lowest Tier
head(data.frame(nba
          %>% select(Player, G, MP_pg, Tm,
                     Salary, PER, cl_label)
          %>% filter(km_labs_four == 1)
          %>% arrange(desc(Salary))
          ))
```

```
##              Player  G    MP_pg  Tm   Salary  PER km_labs_four
## 1 Chandler Parsons 34 19.85294 MEM 22116750  7.6            1
## 2    Miles Plumlee 45 10.75556 MIL 12500000  8.4            1
## 3     Amir Johnson 80 20.10000 BOS 12000000 15.0            1
## 4  Mirza Teletovic 70 16.18571 MIL 10500000  8.8            1
## 5     Al Jefferson 66 14.10606 IND 10314532 18.9            1
## 6       Alec Burks 42 15.54762 UTA 10154495 11.6            1
```

```
# Lowest Paid players in highest tier
head(data.frame(nba
          %>% select(Player, G, MP_pg, Tm, Salary, PER, cl_label)
          %>% filter(km_labs_four == 4)
          %>% arrange(Salary)
          ))
```

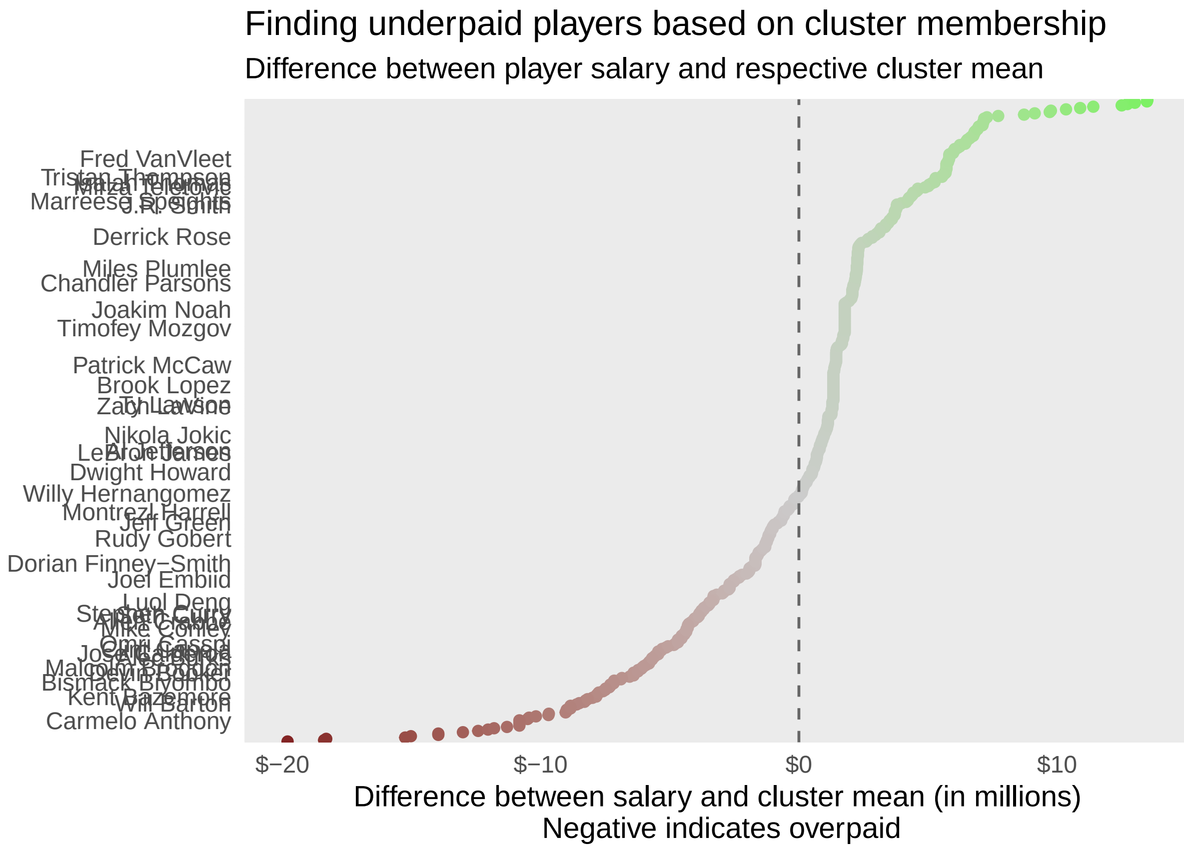
```
##                   Player  G    MP_pg  Tm  Salary  PER km_labs_four
## 1          Devin Booker 78 35.00000 PHO 2223600 14.6            4
## 2           Zach LaVine 47 37.21277 MIN 2240880 14.6            4
## 3       Dennis Schroder 79 31.45570 ATL 2708582 16.1            4
```

```
## 4 Giannis Antetokounmpo 80 35.56250 MIL 2995421 26.1            4
## 5         C.J. McCollum 80 34.95000 POR 3219579 19.9            4
## 6    Kristaps Porzingis 66 32.78788 NYK 4317720 17.4            4
```

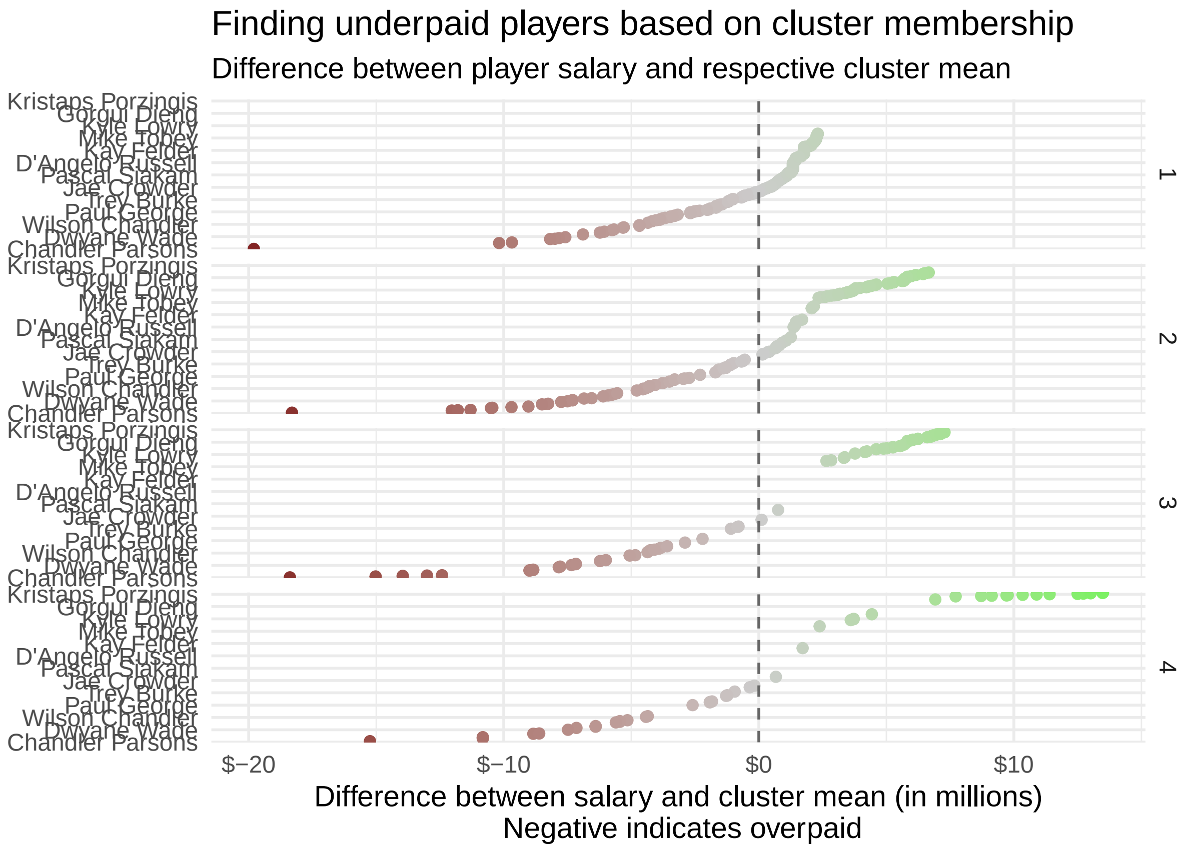
Observations There is potential to update salaries based on player tiers. For example, Chandler Parsons was paid 22M but is considered a low tier player, and is paid more than the high tier players such as Steph Curry (12M) and Kawhi Leonard (17.6M).

George to break out chart by cluster

```
nba %>%
  group_by(km_labs_four) %>%
  mutate(Clust_Salary = mean(Salary)) %>%
  ungroup() %>%
  mutate(Salary_diff = (Clust_Salary - Salary) / 1000000) %>%
  ggplot(aes(x = reorder(Player, Salary_diff), y = Salary_diff, color = Salary_diff)) +
  geom_point() +
  geom_hline(yintercept = 0,
             linetype = "dashed",
             color = "grey40") +
  scale_x_discrete(labels = players.to.show) +
  scale_y_continuous(labels = scales::dollar) +
  scale_color_gradient2(mid = "grey80", high = "green") +
  labs(title = "Finding underpaid players based on cluster membership",
       subtitle = "Difference between player salary and respective cluster mean",
       x = "",
       y = "Difference between salary and cluster mean (in millions)\n Negative indicates overpaid") +
  coord_flip() +
  theme_minimal() +
  theme(legend.position = "none")
```




```r
#
nba %>%
  group_by(km_labs_four) %>%
  mutate(Clust_Salary = mean(Salary)) %>%
  ungroup() %>%
  mutate(Salary_diff = (Clust_Salary - Salary) / 1000000) %>%
  ggplot(aes(x = reorder(Player, Salary_diff), y = Salary_diff, color = Salary_diff)) +
  geom_point() +
  geom_hline(yintercept = 0,
             linetype = "dashed",
             color = "grey40") +
  scale_x_discrete(breaks = function(x) x[c(TRUE, rep(FALSE, 40 - 1))]) +
  scale_y_continuous(labels = scales::dollar) +
  scale_color_gradient2(mid = "grey80", high = "green") +
  labs(title = "Finding underpaid players based on cluster membership",
       subtitle = "Difference between player salary and respective cluster mean",
       x = "",
       y = "Difference between salary and cluster mean (in millions)\n Negative indicates overpaid") +
  coord_flip() +
  theme_minimal() +
  theme(legend.position = "none") +
  facet_grid(km_labs_four~.)
```



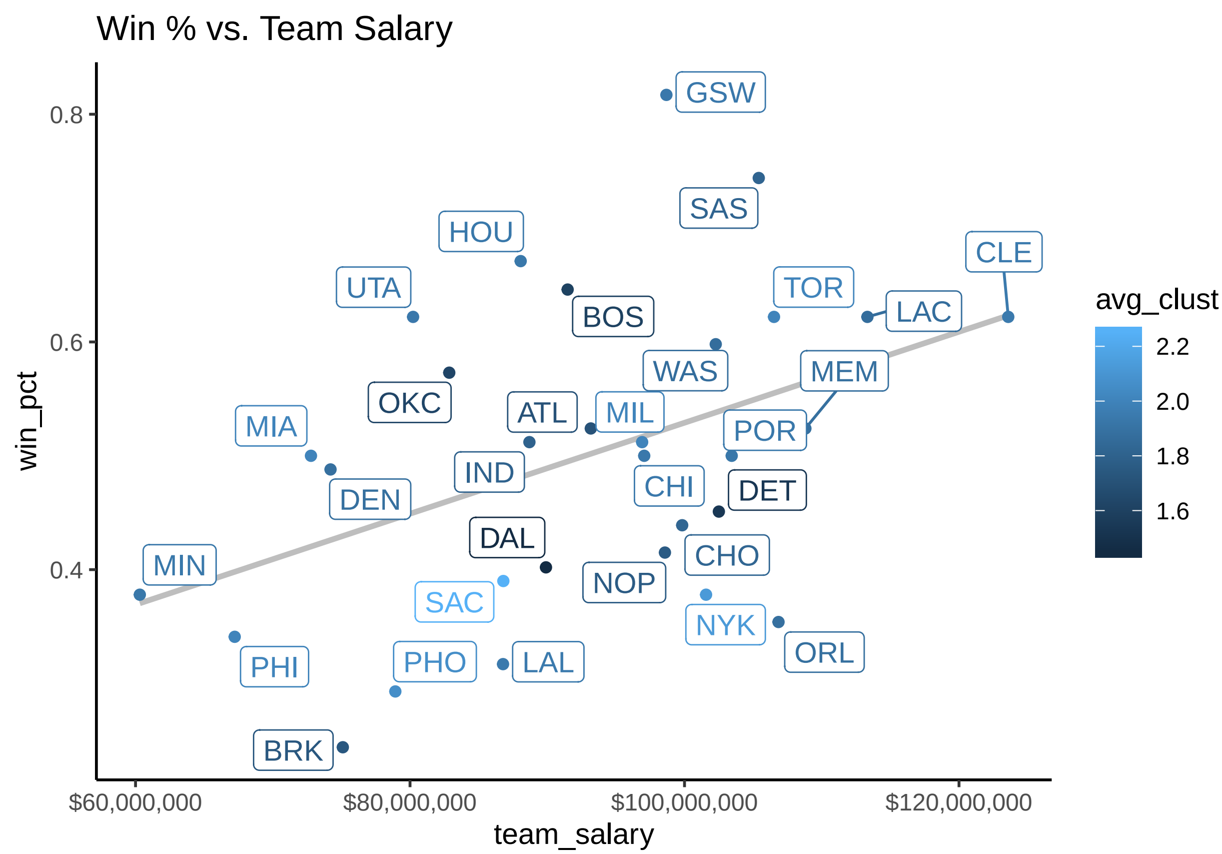
Team Compensation and Performance vs clusters

```
# convert labels to numeric
nba$cl_lab_numeric <- as.numeric(nba[ , cl_label])
nba_team <- data.frame(nba
                       %>% select(Tm, Salary, win_pct, cl_lab_numeric)
                       %>% group_by(Tm)
                       %>% summarise(team_salary = sum(Salary),
                                     win_pct = mean(win_pct),
                                     avg_clust = mean(cl_lab_numeric))
                       )

# order by descnding average cluster label
arrange(nba_team, desc(avg_clust))
```

```
##     Tm team_salary win_pct avg_clust
## 1  SAC    86799609   0.390  2.250000
## 2  NYK   101570502   0.378  2.125000
## 3  PHO    78930157   0.293  2.055556
## 4  MIA    72782449   0.500  2.000000
## 5  MIL    96913241   0.512  2.000000
## 6  PHI    67225712   0.341  2.000000
## 7  TOR   106521470   0.622  2.000000
## 8  CLE   123591014   0.622  1.941176
## 9  LAL    86775415   0.317  1.941176
## 10 CHI    97064073   0.500  1.933333
```

```
## 11 GSW    98681493   0.817  1.933333
## 12 UTA    80223193   0.622  1.933333
## 13 HOU    88062247   0.671  1.928571
## 14 MIN    60311572   0.378  1.928571
## 15 POR   103439444   0.500  1.928571
## 16 DEN    74208517   0.488  1.882353
## 17 MEM   108808118   0.524  1.882353
## 18 ORL   106849160   0.354  1.882353
## 19 LAC   113327068   0.622  1.866667
## 20 WAS   102276673   0.598  1.866667
## 21 CHO    99830531   0.439  1.823529
## 22 SAS   105410231   0.744  1.812500
## 23 IND    88698690   0.512  1.800000
## 24 NOP    98573436   0.415  1.761905
## 25 BRK    75102568   0.244  1.736842
## 26 ATL    93172774   0.524  1.705882
## 27 OKC    82858524   0.573  1.625000
## 28 BOS    91484921   0.646  1.600000
## 29 DET   102503259   0.451  1.533333
## 30 DAL    89904500   0.402  1.450000
```

```r
# plot
ggplot(nba_team,
       aes(x = team_salary, y = win_pct, color = avg_clust)) +
  geom_smooth(method = 'lm', formula = y ~ x, se = FALSE, color = 'gray') +
  geom_point() +
  scale_x_continuous(labels = scales::dollar_format()) +
  geom_label_repel(label = nba_team$Tm) +
  ggtitle('Win % vs. Team Salary') +
  theme_classic()
```




```r
# Inspect some teams
teams_sample <- c('NYK', 'GSW', 'BOS')

teams_sample_list <- list(rep(NA, length = length(teams_sample)))
for (i in seq_along(teams_sample)) {
  teams_sample_list[[i]] <- nba[nba$Tm == teams_sample[i],
                                c('Player', 'PER', cl_label)]
}

# change index to see different teams
teams_sample_list[[2]]
```

```
##                Player  PER km_labs_four
## 82          Ian Clark 13.1            1
## 98      Stephen Curry 24.6            4
## 119      Kevin Durant 27.6            4
## 164    Draymond Green 16.5            3
## 211    Andre Iguodala 14.4            2
## 235      Damian Jones  5.3            1
## 268 Shaun Livingston 10.1            1
## 270      Kevon Looney 13.4            1
## 285     James Michael 13.0            1
## 286     Patrick McCaw  8.6            1
## 293      JaVale McGee 25.2            1
## 344     Zaza Pachulia 16.1            3
## 427     Klay Thompson 17.4            4
```

```
## 443 Anderson Varejao  9.4            1
## 457       David West 16.6            1
```

Observations Although a team can have better players on average clusters, there are many variables at play here. A team can be better on average but poor management or coaching can affect a team's overall performance, e.g. NYK. Interestingly, GSW did not have the highest average cluster rating, because their bench is not very strong. This speaks to the strong influence that starter players can have on team performance. Another interesting note is that teams can play well even if they do not have many all-stars or a strong overall team, e.g BOS. This could be driven by great coaching and team chemistry. It is important to note that items such as injuries could greatly influence win %, even if players have high ratings.

Although there is a correlation between overall team salary and win %, it is interesting that average player rating does not necessarily align with overall win %.