# Analysis on Soccer Player Attributes

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# Executive Summary

The purpose of this project is to study player attributes of a European soccer database from Kaggle.com. The database consists of eight tables, sqlite_sequence, Player_Attributes, Player, Match, League, Country, Team and Team Attributes. The database was populated with more than 25,0000 matches from 2008 to 2016 seasons, 10,000 players, and 11 European countries with their lead championship. Players' and teams' attributes are sourced from EA Sports' FIFA video game series (https://sofifa.com/).

Research Questions:
The research questions for this project are:

1. What attributes set the players apart?
2. Which player attribute contributes most to a player's overall rating?

Data Cleaning:
Data analysis was conducted in Python using various libraries/modules such as, sqlite3, pandas, principal component analysis from scikit-learn, matplotlib, and seaborn. Data from the Player and the Player_Attributes tables were queried with an inner join query on the player identification number from the FIFA application programming interface (API). Queried data comprises of 183929 rows and 50 columns. Data was then cleaned so that records with missing or null data in any column was removed. Duplicated data, if any, was removed. Final dataset consists of 10898 rows and 50 columns. 38 columns of attributes with numeric data were identified for principal component and further analysis.

Data Exploration and Analysis:
Principal component analysis was conducted. Results shows that the first three principal components out of 38 dimensions, PC1, PC2 and PC2, explain 43.9%, 15.7% and 8.9%, respectively, which only explained a total of 68.5% of the variance in the dataset. Loading scores of all player attributes in each of the three principal components show that no one single player attribute contributes significantly more than any other attributes to these three principal components. Various charts indicate that there are two distinct (large and small) subgroups of players in the dataset. Created scatter plots, distribution plots, joinplots and correlation coefficient analysis explained the clusters and substantiated the answers to the research questions.

Conclusions:

1. The following attributes set players apart into subgroups: gk_diving, gk_reflexes, gk_handling, gk_positioning, and ball control. The first four attributes pertain to goalkeeper position while ball control relate to more to non_goalkeepers. Goalkeepers score relatively high in the goalkeeping attributes, but low in ball control, while the rest of players score in the opposite way. Thus, players were set into one small subgroup of goalkeepers and one large group of the rest of the players. Gk_kicking, a goalkeeping attribute further divided the larger subgroup into two: some players in the back field had high scores in gk_kicking that had a moderate positive linear correlation to their ball control scores.
2. Considering all players, reactions attribute had a strong positive linear correlation with overall rating, thus contributes most to the rating. The higher the reactions score, the higher the overall rating of the player.
3. However, at the subgroup level, for the goalkeeper subgroup, gk_diving, gk_handling, gk_positioning and gk_reflexes attributes had very strong positive linear correlation with overall rating and contribute most to the players' rating. For the rest of the players, reactions attribute had a strong correlation and contributed most to their overall rating.

Appendix A shows information and sources of data. Appendix B presents all the Python scripts used for data queries, cleaning, exploration and analysis and their outputs.

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# Introduction

This purpose of this project is to study player attributes of a European soccer database from Kaggle.com. The database consists of eight tables, sqlite_sequence, Player_Attributes, Player, Match, League, Country, Team and Team Attributes. The database was populated with more than 25,0000 matches from 2008 to 2016 seasons, 10,000 players, and 11 European countries with their lead championship. Players' and teams' attributes are sourced from EA Sports' FIFA video game series (https://sofifa.com/).

To be attain great team performance, individual soccer player typically undertakes intensive drills to master specific skills for his dedicated position(s). In addition to basic skills, specialized training may focus in attack, defensive, mentality, movement, power or goalkeeping attributes. When highly skillful soccer players work together as a team in a strategic team formation, the likelihood to win a game may increase significantly.

In the dataset, each soccer player was given an overall rating and potential score, along with scores for the following numeric attributes: crossing, finishing, heading accuracy, short passing, volleys, dribbling, curve, free kick accuracy, long passing, ball control, acceleration, sprint speed, agility, reactions, balance, shot power, jumping, stamina, strength, long shots, aggression, interceptions, positioning, vision, penalties, marking, standing tackle, sliding tackle, gk_diving, gk_handling, gk_kicking, gk_positioning and gk_reflexes.

## Research questions

The research questions for this project are:

1. What attributes set players apart?
2. Which player's attribute contributes most to a player's overall rating?

## Intended Audience

The intended audience for this project are: soccer fans and FIFA video game players.

# Reference


1. Database source: https://www.kaggle.com/hugomathien/soccer/data
2. Original data sources:
    a. http://football-data.mx-api.enetscores.com/ : scores, lineup, team formation and events
    b. http://sofifa.com/ : players and teams attributes from EA Sports FIFA games. *FIFA series and all FIFA assets property of EA Sports*
3. Merriam-Webster – Visual Dictionary Online: "player positions" http://www.visualdictionaryonline.com/sports-games/ball-sports/soccer/player-positions.php
4. Video from Bing.com: "Soccer Goalie Diving Drills": https://www.bing.com/videos/search?q=soccer+goalie+diving+drills&view=detail&mid=95069C368876787EAEBE95069C368876787EAEBE&FORM=VIRE
5. Wikipedia.org: "Association Football Positions" https://en.wikipedia.org/wiki/Association_football_positions
6. YouTube video series: "StatQuest: Principal Component Analysis (PCA), Step-by-Step" https://www.youtube.com/playlist?list=PLblh5JKOoLUIcdlgu78MnlATeyx4cEVeR
7. YouTube video: "Top 10 BEST Longest Goals by Goalkeepers" https://www.youtube.com/watch?v=QUp6OyrHoMc

8. footy4Kids: "Goalkeeper coaching for U12 and up" http://www.footy4kids.co.uk/soccer-drills/goalkeeping/goalkeeper-coaching-for-u12-and-up/

## Methodology and Analysis Approach

The methodology for this study basically is first to explore, clean up, analyze, visualize the data and then draw conclusions and attempt to find answers to the research questions. This study was conducted in Python using various libraries/modules such as, sqlite3, pandas, principal component analysis from scikit-learn, matplotlib, and seaborn. The steps below were taken to reach the findings and conclusions:

1. Database was downloaded from https://www.kaggle.com/hugomathien/soccer/data
2. Table structures and field datatypes were explored. Tables from the downloaded sqlite database were exported and previewed.
3. Using IO tools from pandas library, read_sql and to_csv, the Player and the Player_Attributes tables were queried with an inner join SQL on the player identification number from the FIFA application programming interface (API). Queried data was saved to a csv file.
4. Queried data comprises of 183929 rows and 50 columns. Data was then cleaned so that records with missing or null data in any column was removed. Duplicated data, if any, was removed. Final dataset consists of 10898 rows and 50 columns.
   <u>Lessons Learned:</u>
   a. I was surprise to find that a huge number of rows (players) were dropped till I read from the data source webpage and noted that the administrator of the database was not able to source quite some players' attributes from FIFA and have those fields blank.
   b. Data does not lie.
5. Identified thirty-eight (38) columns of players' attributes in numeric format for principal component analysis (PCA). Ran PCA to identify players' attributes that explained the most variance, to help reduce dimensions before further analysis. .
   <u>Lessons Learned:</u>
   a. Loading scores from PCA did not support dimension reduction. At this time, a decision had to be made to how to proceed. Additional data exploration was needed to decide where to zoom in for further analysis. Since it did not go as what I expected, I turned to other tools to use and approach to take.
   b. I created a series of charts using a programming loop, which allowed exploration systematically on each attribute.
   c. Additionally, adding color in the scatter plots for each point added a third dimension and presented a third attribute in the charts. The added information was easier on human eyes when compared to adding a z-axis for the third attribute.
   d. Joint plots provided distribution of player variables that were presented in a scatter plot. These techniques provided valuable information as how to proceed with data analysis to get to the bottom to find answers to the research questions.
   e. Scatter plot matrix contains all the pairwise scatter plots of the variables on a single page in a matrix format. This was very useful to help roughly determine whether there was a linear correlation between multiple variables.
6. Conducted further data exploration and visualization with scatter plots matrix, scatter plots, distribution plots and joint plots.
7. Identified clusters with further analysis.

8. Calculated correlation coefficient matrix for all attributes. Located attributes with strong correlation coefficient with overall rating. This was repeated for the goalkeeper subgroup and for the rest of the players. Correlated attributes were identified. Created scatter plots for the correlated attributes for visual confirmation.
9. Draw conclusions based on findings.

# Findings

## Principal Component Analysis

Figure 1 presents the Scree Plot of all the principal components from the 38 numeric attributes of the final, cleanup dataset of soccer players. PCA results shows that the first three principal components, PC1, PC2 and P32, out of 38 dimensions explain 43.9%, 15.7% and 8.9% of variance, respectively. This is a total of 68.5% of all variance.

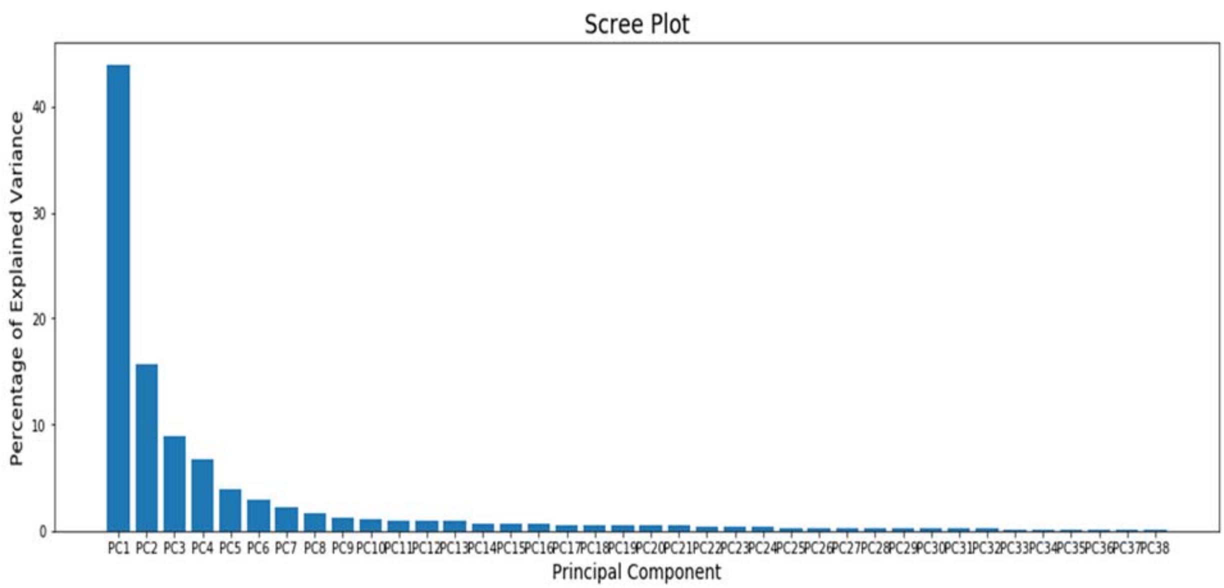



*Figure 1. Scree Plot: Percentage of Explained Variance*

Table 1 below lists the loading scores of player attributes in the first principal component. Loading scores of all player attributes in the first three principal components show that no one single player attribute contributes significantly more than any other attributes to the variance. None the less, the ball Control attribute was the leading attribute that explained the most variance. Considering the players as one group, overall rating has a low loading score in the PC1 dimension.

*Table 1. Loading Scores of Player Attributes in the First Principal Component, PC1*

| Player Attributes | Loading Scores | Player Attributes | Loading Scores | Player Attributes | Loading Scores |
|---|---|---|---|---|---|
| ***ball_control*** | ***0.233895*** | gk_positioning | 0.193662 | gk_kicking | 0.121982 |
| dribbling | 0.226609 | volleys | 0.193077 | reactions | 0.105162 |
| short_passing | 0.220168 | finishing | 0.191773 | aggression | 0.087644 |
| crossing | 0.213529 | acceleration | 0.185480 | ***overall_rating*** | ***0.083033*** |
| Curve | 0.211442 | penalties | 0.183370 | potential | 0.080174 |
| long_shots | 0.211257 | sprint_speed | 0.182038 | interceptions | 0.071469 |
| positioning | 0.204851 | long_passing | 0.177636 | standing_tackle | 0.065230 |
| shot_power | 0.199655 | agility | 0.168734 | sliding_tackle | 0.059237 |
| vision | 0.197614 | stamina | 0.158548 | marking | 0.052163 |
| gk_diving | 0.196600 | balance | 0.153811 | strength | 0.028138 |
| free_kick_accuracy | 0.196366 | height | 0.134852 | age | 0.005573 |
| gk_reflexes | 0.195234 | heading_accuracy | 0.132158 | jumping | 0.001561 |
| gk_handling | 0.195011 | weight | 0.125473 | | |

## Visualization

### Research Question: What attributes set the players apart?

From the findings above, it was decided not to reduce any dimension for further analysis. Scatter plots were created using data from the first three principal components: PC1 versus PC2 and PC1 versus PC3. Two distinct clusters were noted. The largest variation is seen in the first principal component dimension, PC1.

To find out what player attribute(s) plays a part in distinguishing the players into the subgroups, color was added in the plots for one player attribute at a time for all 38 attributes (lighter hue indicates higher scores). Scatter plots in Figures 2 through 6 indicate that goalkeeper attributes play a part in separating the players into the two clusters. It is reasonable to believe that the smaller subgroup shown on the right of the scatter plots consist of goalkeepers, who score higher in goalkeepers attributes (lighter hue). There are two reasons: a) Each team usually designates only one player as the goalkeeper, hence makes goalkeepers a small subgroup in the dataset. b) Goalkeepers, who focus their training in goalkeeping skills, should score higher in these attributes.

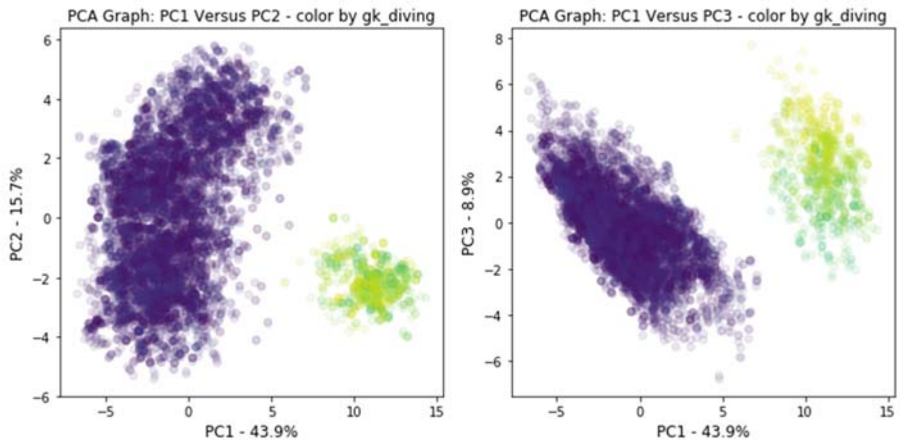



*Figure 2. Scatter Plots of PC1 Versus PC2 and PC1 Versus PC3 – Colored by gk_diving*

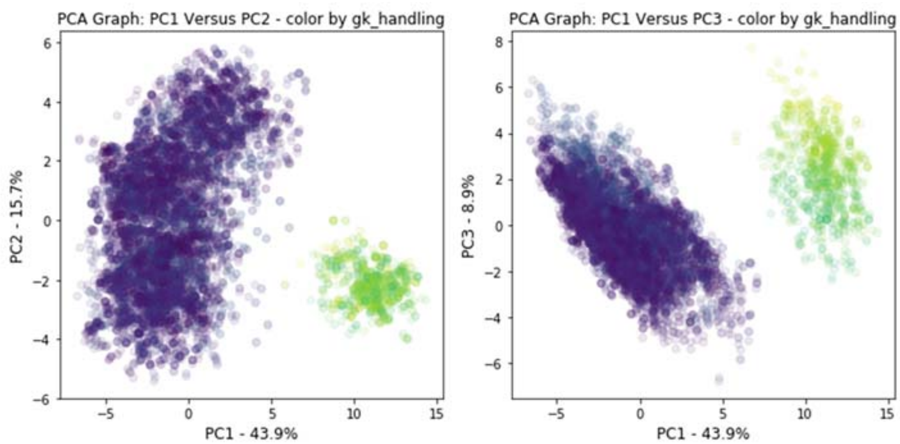



*Figure 3. Scatter Plots of PC1 Versus PC2 and PC1 Versus PC3 – Colored by gk_handling*

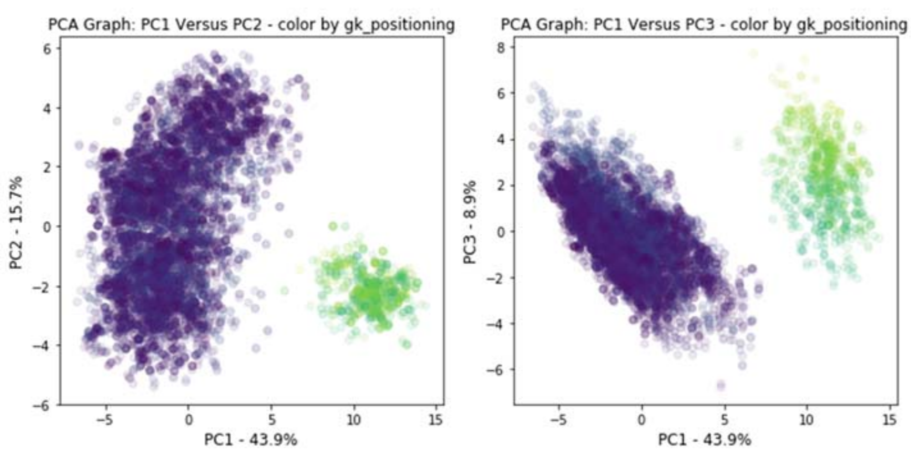



*Figure 4. Scatter Plots of PC1 Versus PC2 and PC1 Versus PC3 – Colored by gk_positioning*

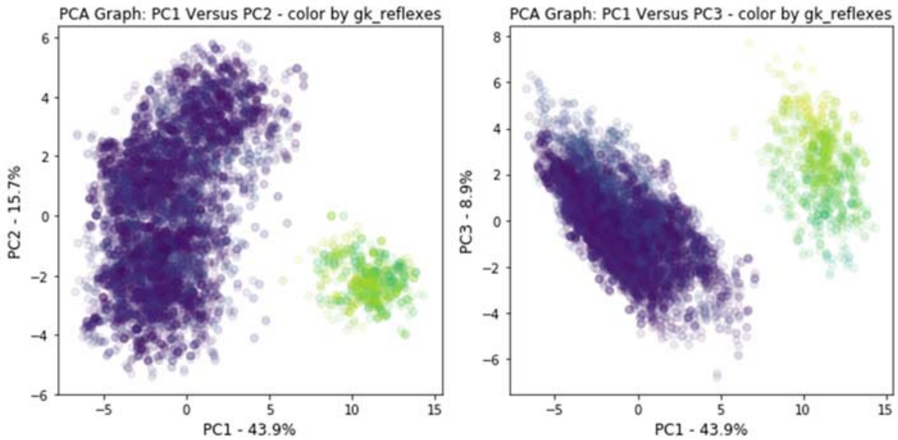



*Figure 5. Scatter Plots of PC1 Versus PC2 and PC1 Versus PC3 – Colored by gk_reflexes*

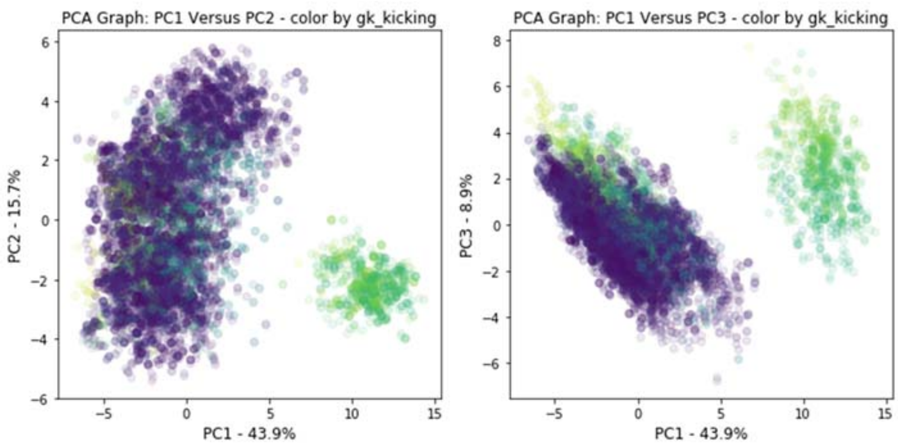



*Figure 6. Scatter Plots of PC1 Versus PC2 and PC1 Versus PC3 – Colored by gk_kicking*

Ball control attribute, with the highest loading score of 0.2339 in the first principal component, explains the most variance in the x-axis, PC1 dimension. Figure 7 below indicates that the small subgroup of goalkeepers on the right scores lower (darker hue) in the ball control attribute than the rest of the players (larger subgroup on the left). This attribute also set the players apart.

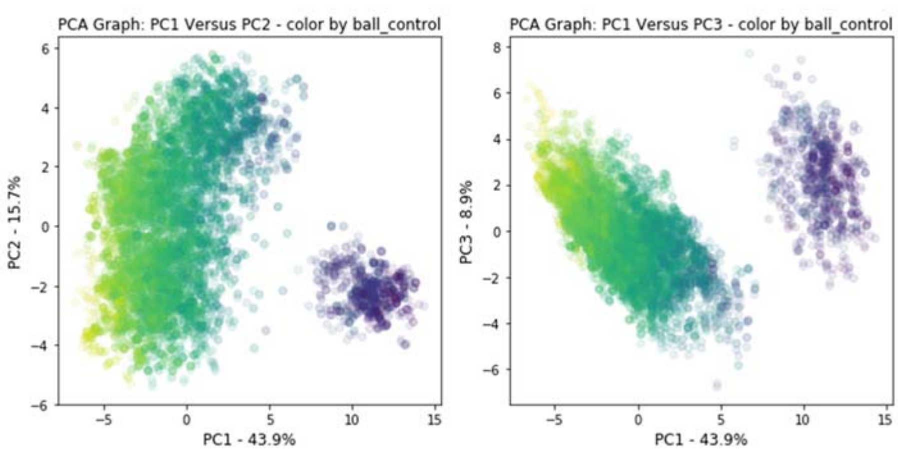



*Figure 7. PC1 Versus PC2 and PC1 Versus PC3 – Colored by Ball Control*

Figure 8 shows the distribution plots of all players attributes: age, height, weight, overall_rating, potential, crossing, finishing, heading_accuracy, short_passing, volleys, dribbling, curve, free_kick_accuracy, long_passing, ball_control, acceleration, sprint_speed, agility, reactions, balance, shot_power, jumping, stamina, strength, long_shots, aggression, interceptions, positioning, vision, penalties, marking, standing_tackle, sliding_tackle, gk_diving, gk_handling, gk_kicking, gk_positioning, gk_reflexes. It presents further evidence of separation of the players into subgroups by a few player attributes.

The distribution plots below show a small subgroup of players with relatively higher scores in gk_diving, gk_handling, gk_kicking, gk_positioning and gk_reflexes goalkeeping attributes (yellow highlight below and Figure 9) but with relatively low scores in ball control attribute (red highlight below and Figure 10). This reaffirms that goalkeeping and ball control attributes set the soccer players (goalkeepers) apart from the rest of players. This conclusion agrees with findings from the scatter plots in PC1 versus PC2 and PC1 versus PC3, in which a smaller subgroup is associated with lighter hue for relatively higher scores in goalkeeping attributes (Figures 2 through 6) and with darker hue for lower scores in ball control attribute (Figure 7).

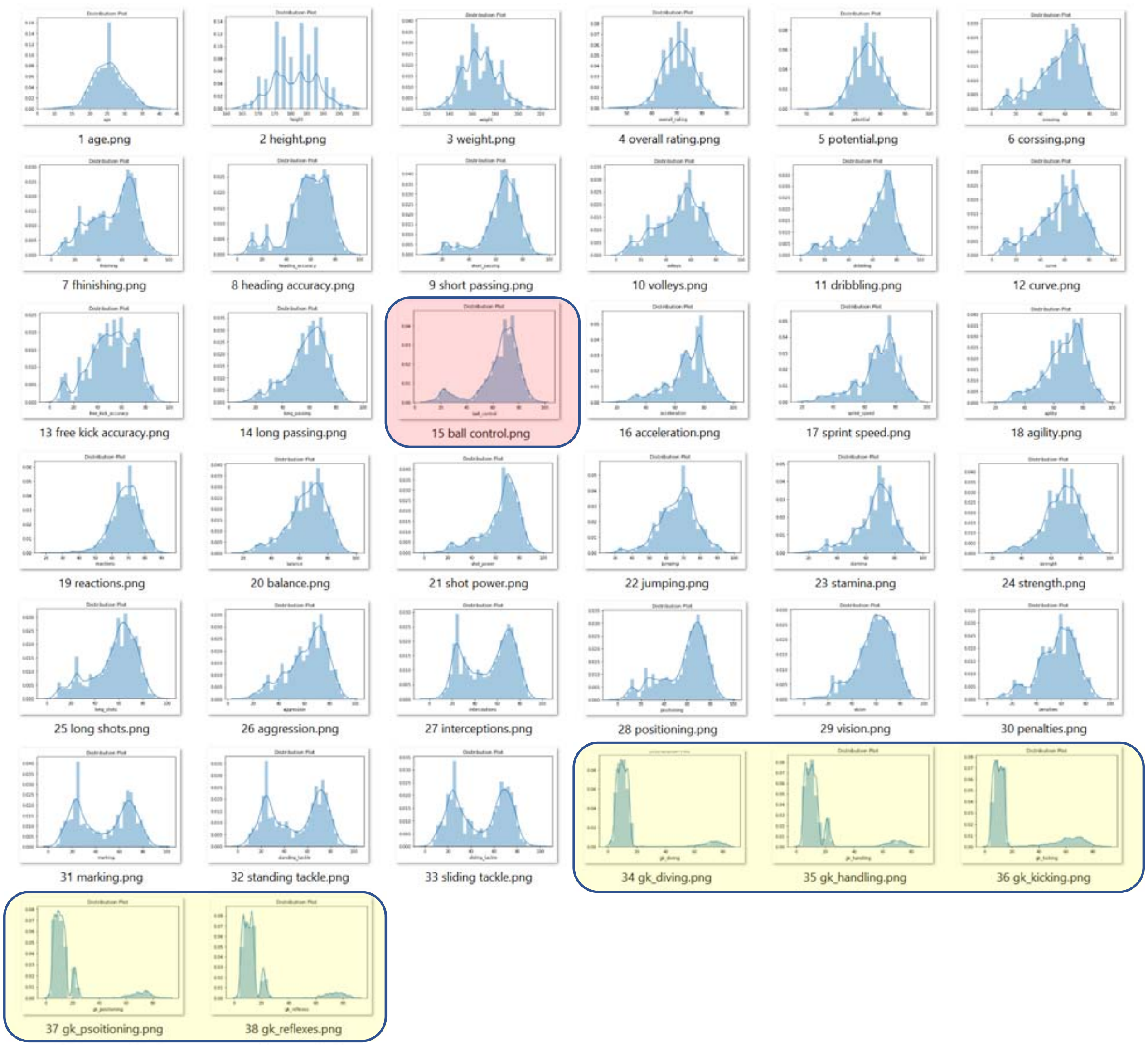



*Figure 8. Distribution Plots of All Player Attributes*

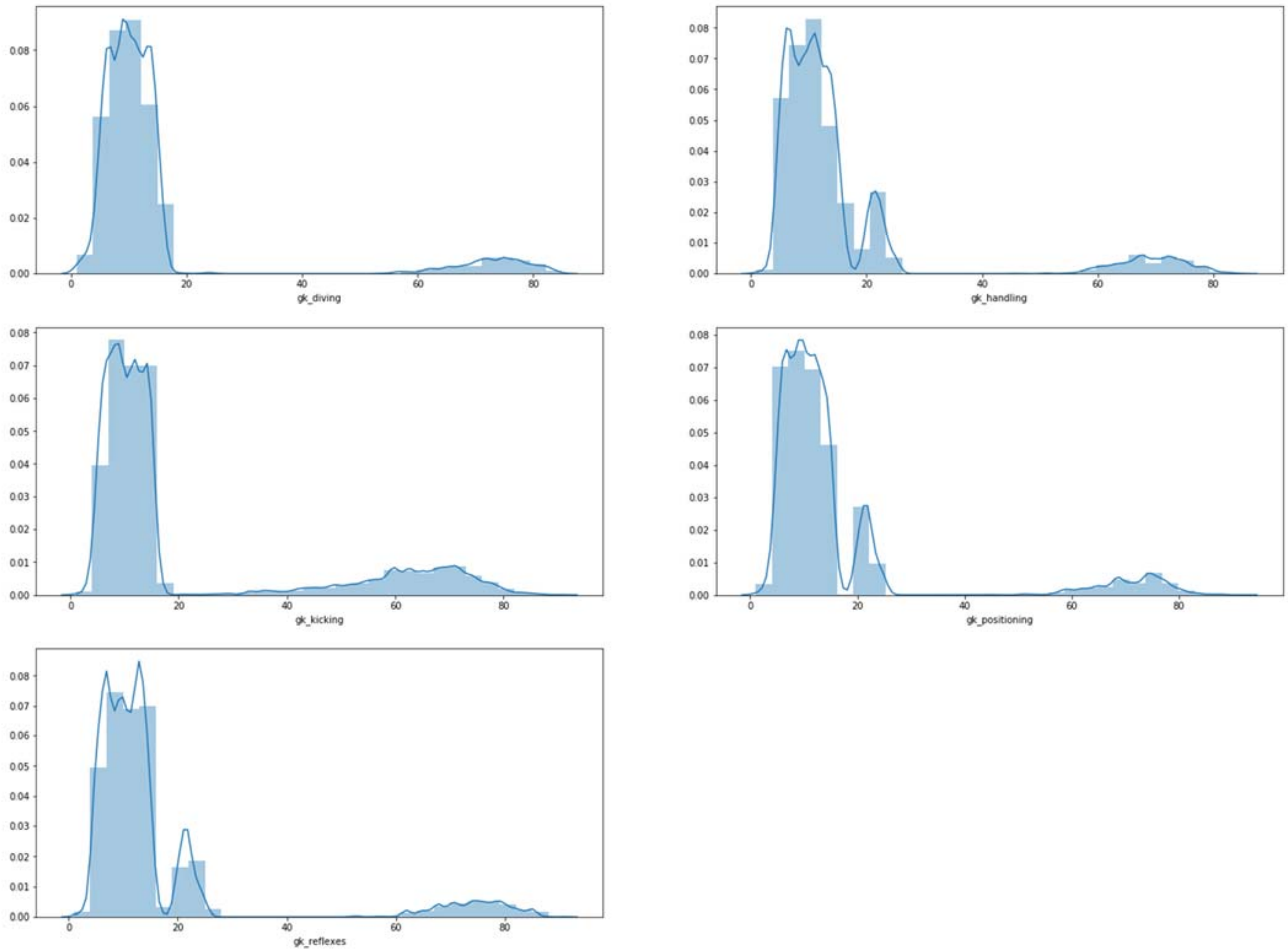



*Figure 9. Distribution Plots of Soccer Players by Goalkeeping Attributes: Diving, Handling, Kicking, Positioning and Reflexes*

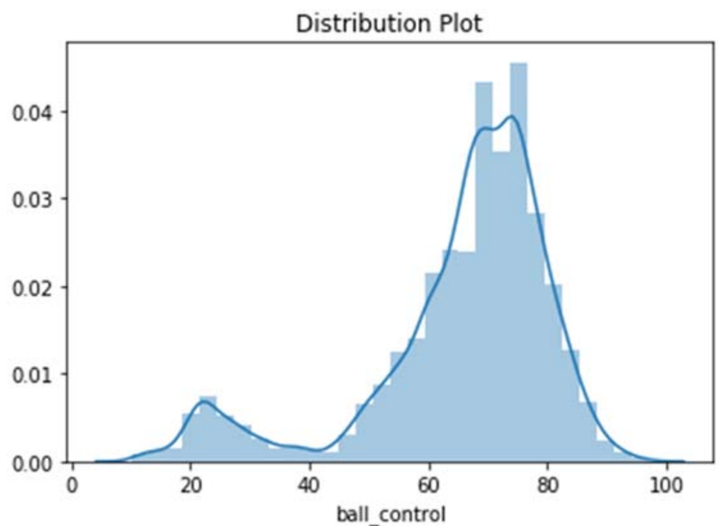



*Figure 10. Distribution Plots of Soccer Players by Ball Control Attribute*

### *Visualization in Ball Control Attribute Versus Goalkeeping Attributes*

With the findings from above, jointplots were created using ball control attribute against the five goalkeeping attributes (see Figures 11 through 15). These scatter plots joint with distribution plots visualize goalkeepers as the smaller subgroup (top left) and non-goalkeepers as the larger subgroup (bottom).

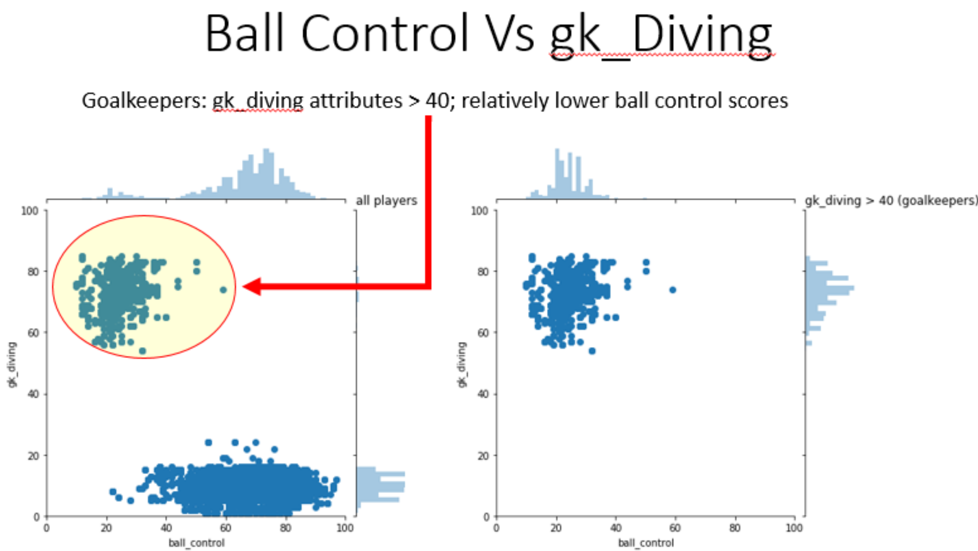



*Figure 11. Jointplot: Ball Control Attribute Versus gk_Diving Attribute*

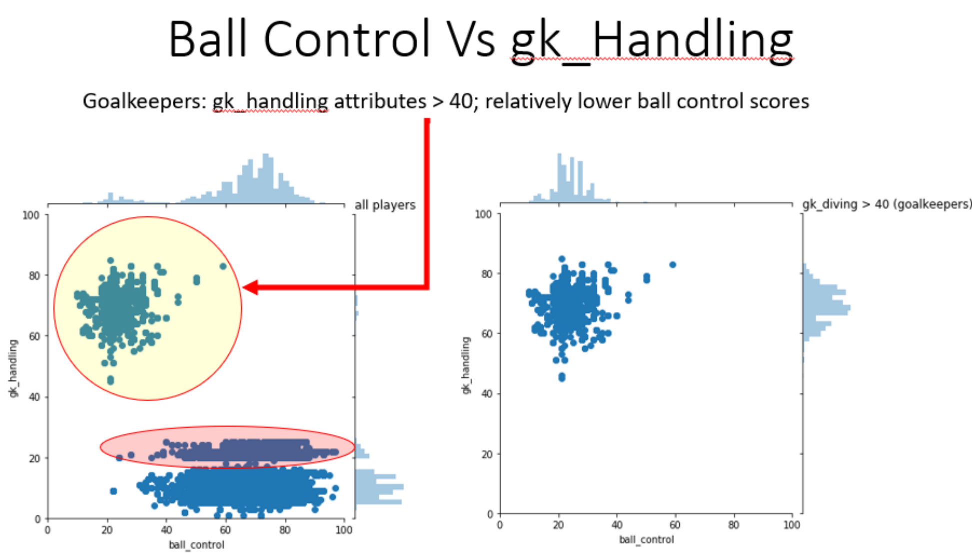



*Figure 12. Jointplot: Ball Control Attribute Versus gk_Handling Attribute*

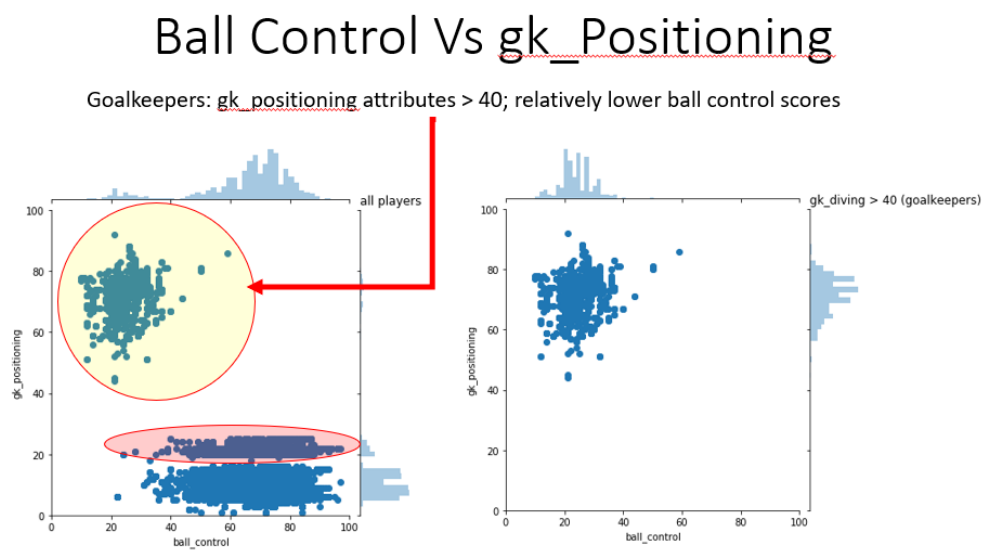



*Figure 13. Jointplot: Ball Control Attribute Versus gk_Positioning Attribute*

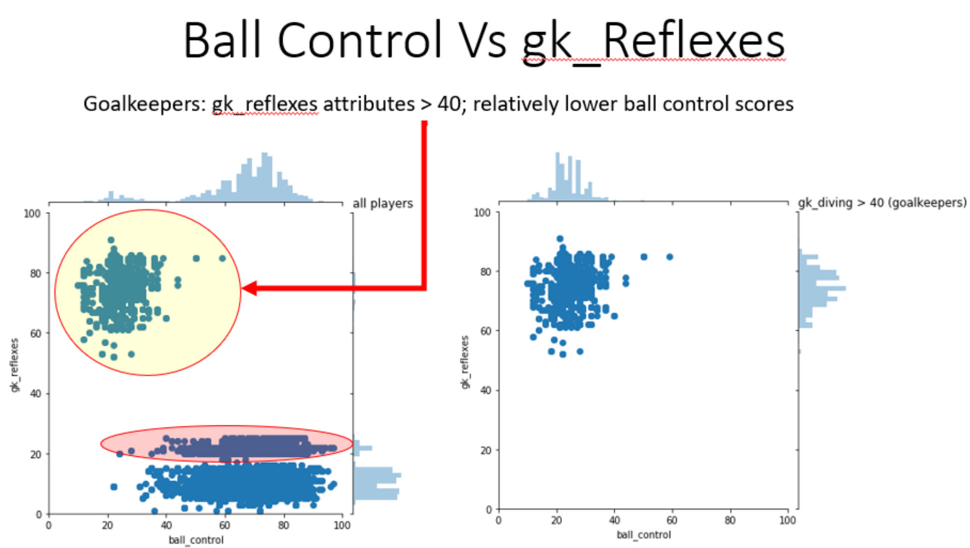



*Figure 14. Jointplot: Ball Control Attribute Versus gk_Reflexes Attribute*

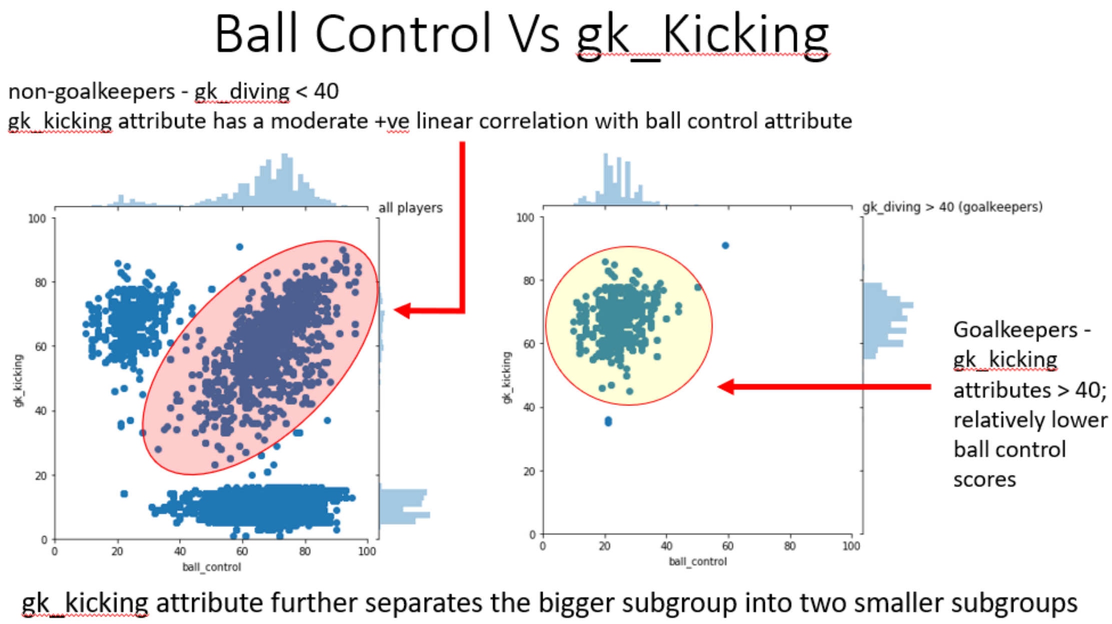



*Figure 15. Jointplot: Ball Control Attribute Versus gk_Kicking Attribute*

### *Side Notes: gk_Kicking Attribute*

Noted in Figure 15, non-goalkeepers were further split apart into two subgroups by gk_kicking attribute. The group highlighted in red had a moderate positive linear correlation between their scores in gk_kicking attribute and their scores in ball control attribute. This is not surprising as there may be some common techniques that are pertinent to both attributes that are important for certain player positions. Similar logic goes for other attribute pairs, such as: acceleration and sprint speed attributes (correlation coefficient = 0.9129), and ball control and dribbling (0.9273). It would be interesting to conduct further analysis to find out whether the players highlighted red in Figures 12 through 14 are the same group of players highlighted red in Figure 15.

## Research Question: Which player attribute contributes most to a player's overall rating?

### *All Players*

Correlation coefficient matrix was generated for all 38 player attributes. Table 2 below lists the correlation coefficients between overall rating and all other player attributes. Overall rating and potential has the highest correlation coefficient, 0.7840. Since the potential score may be considered some sort of rating similar to overall rating, the second highest correlation coefficient is considered. Overall rating has a strong positive correlation coefficient of 0.7248 with the reactions attribute (see highlighted).

*Table 2. Correlation Coefficient between Overall Rating and All Numeric Attributes*

| | overall_rating | | overall_rating | | overall_rating |
|---|---|---|---|---|---|
| age | 0.3826 | long_passing | 0.4300 | interceptions | 0.2373 |
| height | 0.0259 | ball_control | 0.3726 | positioning | 0.2782 |
| weight | 0.0351 | acceleration | 0.2137 | vision | 0.3992 |
| overall_rating | 1.0000 | sprint_speed | 0.2184 | penalties | 0.3373 |
| potential | 0.7840 | agility | 0.2211 | marking | 0.1106 |
| crossing | 0.2911 | reactions | 0.7248 | standing_tackle | 0.1456 |
| finishing | 0.2694 | balance | 0.1094 | sliding_tackle | 0.1159 |
| heading_accuracy | 0.2403 | shot_power | 0.3703 | gk_diving | 0.0501 |
| short_passing | 0.4161 | jumping | 0.2112 | gk_handling | 0.0373 |
| volleys | 0.2908 | stamina | 0.2487 | gk_kicking | 0.0795 |
| dribbling | 0.2991 | strength | 0.2404 | gk_positioning | 0.0361 |
| curve | 0.2987 | long_shots | 0.3267 | gk_reflexes | 0.0437 |
| free_kick_accuracy | 0.3048 | aggression | 0.2615 | | |

For a visual confirmation, a scatter plot of the reactions attribute against overall rating with trendline was created. Figure 20 shows a strong positive linear correlation. Figure 21 presents the correlation relationship with hue for two categorical attributes, defensive work rate and attacking work rate. Both plots show strong positive linear correlation within each subcategory by defensive work rate and by attacking work rate.

```
All Players
                reactions  overall_rating
reactions         1.00000         0.72483
overall_rating    0.72483         1.00000
```

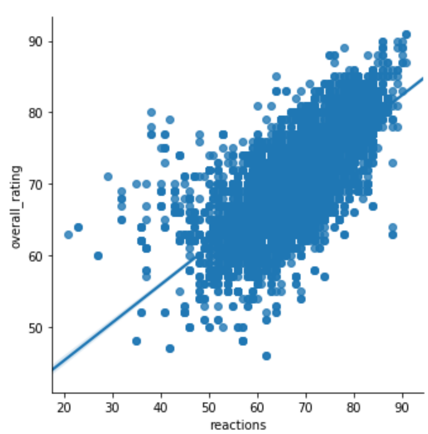



*Figure 20. Scatter Plot of Reactions Attribute Against Overall Rating*

|  | reactions | overall_rating |
|---|---|---|
| reactions | 1.000000 | 0.725001 |
| overall_rating | 0.725001 | 1.000000 |

|  | reactions | overall_rating |
|---|---|---|
| reactions | 1.00000 | 0.72456 |
| overall_rating | 0.72456 | 1.00000 |

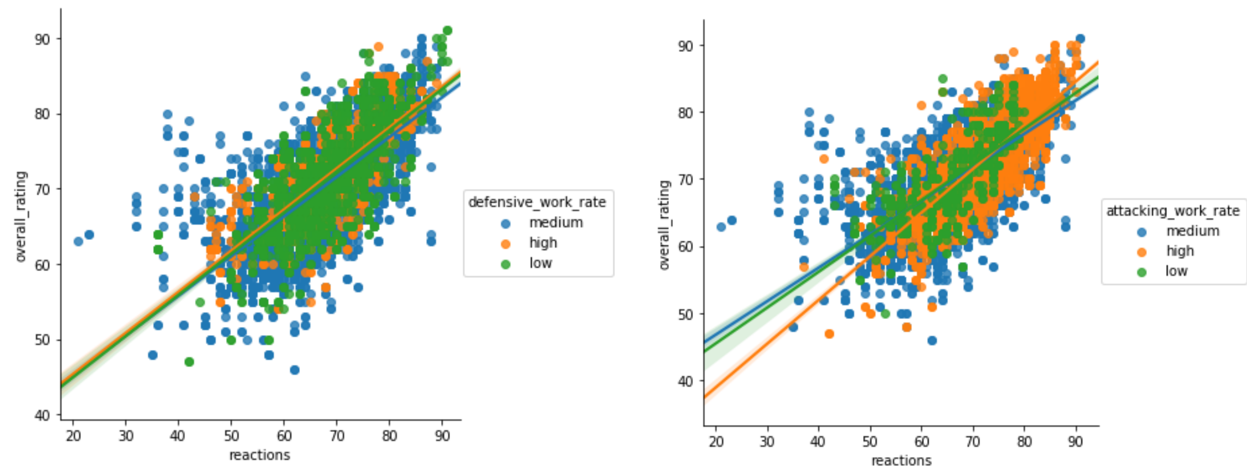



*Figure 21. Scatter Plot of Reactions Attribute Against Overall Rating with Hue by Defensive Work Rate and Attacking Work Rate*

### *Correlation Coefficients in Subgroups*

However, there are two distinct subgroups in the dataset (goalkeepers and the rest players). Hence, the correlation of overall rating with player attributes is further evaluated in each subgroup separately. Tables 3 and 4 list the correlation coefficients between overall rating and all numeric attributes for the goalkeeper subgroup and the rest players, respectively. Highlighted numbers indicate strong positive correlation.

*Table 3. Correlation Coefficient between Overall Rating and All Numeric Attributes - Goalkeeper Subgroup*

|  | **overall_rating** |  | **overall_rating** |  | **overall_rating** |
|---|---|---|---|---|---|
| age | 0.4274 | long_passing | 0.0919 | interceptions | 0.0655 |
| height | -0.0283 | ball_control | 0.2050 | positioning | -0.0385 |
| weight | -0.0251 | acceleration | 0.3000 | vision | 0.1784 |
| overall_rating | 1.0000 | sprint_speed | 0.2066 | penalties | -0.0169 |
| potential | 0.7805 | agility | 0.3076 | marking | 0.0523 |
| crossing | 0.0837 | reactions | 0.5609 | standing_tackle | 0.1062 |
| finishing | 0.0037 | balance | -0.0955 | sliding_tackle | 0.1638 |
| heading_accuracy | -0.0007 | shot_power | 0.1054 | gk_diving | 0.8979 |
| short_passing | 0.1165 | jumping | 0.4408 | gk_handling | 0.8281 |
| volleys | 0.1428 | stamina | 0.0990 | gk_kicking | 0.6697 |
| dribbling | 0.0882 | strength | 0.2180 | gk_positioning | 0.8632 |
| curve | 0.0373 | long_shots | 0.0251 | gk_reflexes | 0.8778 |
| free_kick_accuracy | 0.0166 | aggression | 0.1304 |  |  |

*Table 4. Correlation Coefficient between Overall Rating and All Numeric Attributes - Non_Goalkeeper Subgroup*

| | overall_rating | | overall_rating | | overall_rating |
|---|---|---|---|---|---|
| age | 0.3814 | long_passing | 0.5553 | interceptions | 0.2728 |
| height | 0.0257 | ball_control | 0.6467 | positioning | 0.3837 |
| weight | 0.0368 | acceleration | 0.2624 | vision | 0.5061 |
| overall_rating | 1.0000 | sprint_speed | 0.2825 | penalties | 0.4523 |
| potential | 0.7848 | agility | 0.2420 | marking | 0.1299 |
| crossing | 0.4089 | reactions | 0.7595 | standing_tackle | 0.1708 |
| finishing | 0.3494 | balance | 0.1471 | sliding_tackle | 0.1333 |
| heading_accuracy | 0.3741 | shot_power | 0.5300 | gk_diving | 0.0717 |
| short_passing | 0.6655 | jumping | 0.1947 | gk_handling | 0.0059 |
| volleys | 0.3779 | stamina | 0.3278 | gk_kicking | 0.0744 |
| dribbling | 0.4587 | strength | 0.2426 | gk_positioning | -0.0088 |
| curve | 0.4103 | long_shots | 0.4491 | gk_reflexes | 0.0254 |
| free_kick_accuracy | 0.4056 | aggression | 0.3122 | | |

## Visual Confirmation of Correlation in Subgroups

Scatter plots with trendlines were created for visual confirmation of correlation relationship between overall rating and correlated variables for each subgroup separately.

### Non_Goalkeeper Subgroup

Figure 22 shows a stronger positive linear correlation between player reactions attribute and overall rating for non-goalkeeper subgroup alone, <u>thus confirms that reactions attribute contributes most to the players' overall rating.</u>

```
Non_Goalkeepers: gk_diving < 50
                 reactions  overall_rating
reactions         1.000000        0.759507
overall_rating    0.759507        1.000000
```

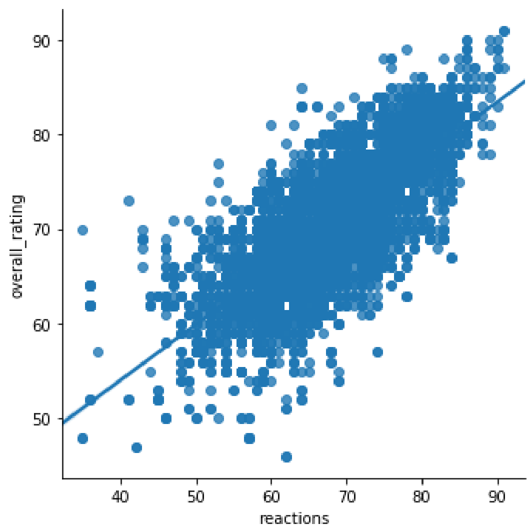



*Figure 22. Non_Goalkeepers Subgroup: Scatter Plot of Reactions Attribute Against Overall Rating*

## Goalkeeper Subgroup

Figures 23 and 24 present the visual confirmation that gk_diving, gk_reflexes, gk_positioning and gk_handling attributes have a strong positive linear correlation with overall rating. The last goalkeeping attribute, gk_kicking, and reactions attribute only had a moderate positive linear correlation with overall rating (Figure 25).

```
Goalkeepers Only: gk_diving > 50
                gk_diving  overall_rating
gk_diving        1.000000        0.897919
overall_rating   0.897919        1.000000
```

```
Goalkeepers Only: gk_diving > 50
                gk_reflexes  overall_rating
gk_reflexes        1.000000        0.877756
overall_rating     0.877756        1.000000
```

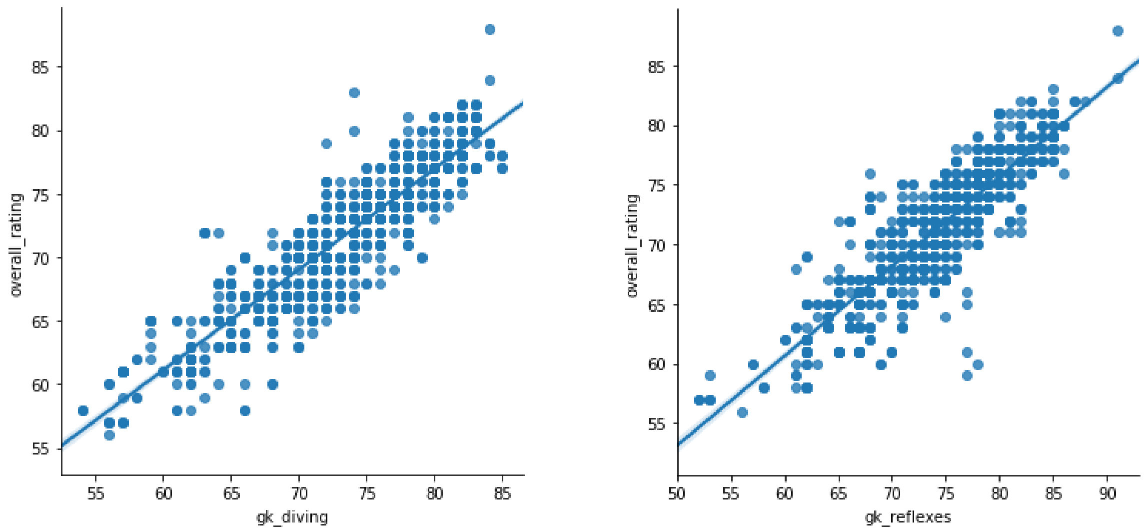



Figure 23. Goalkeeper Subgroup: Scatter Plots of gk_Diving (Left) and gk_Reflexes (Right) Attributes Against Overall Rating

```
Goalkeepers Only: gk_diving > 50
                gk_positioning  overall_rating
gk_positioning        1.000000        0.863162
overall_rating        0.863162        1.000000
```

```
Goalkeepers Only: gk_diving > 50
                gk_handling  overall_rating
gk_handling        1.000000        0.828148
overall_rating     0.828148        1.000000
```

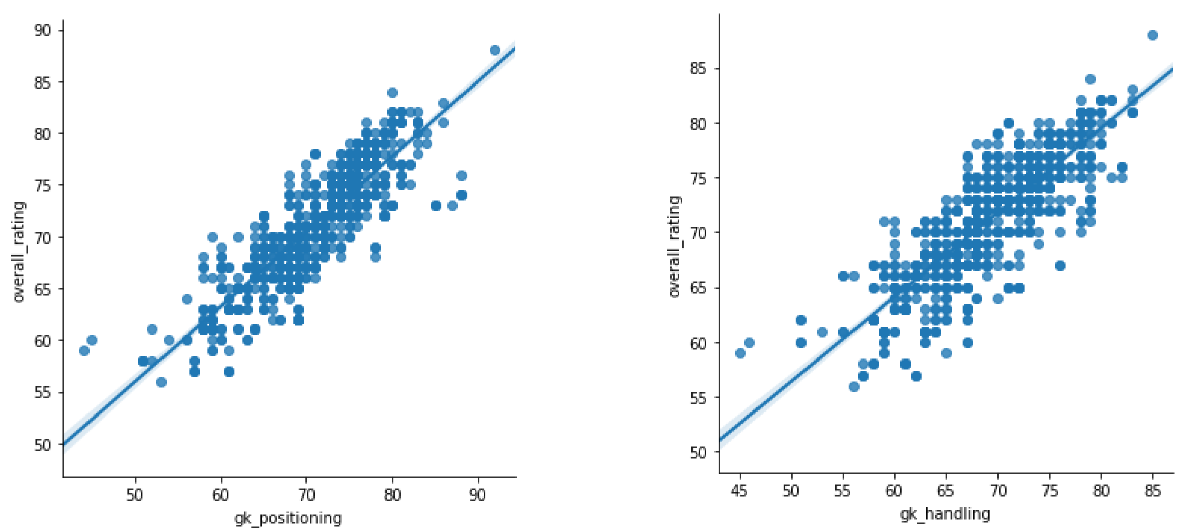
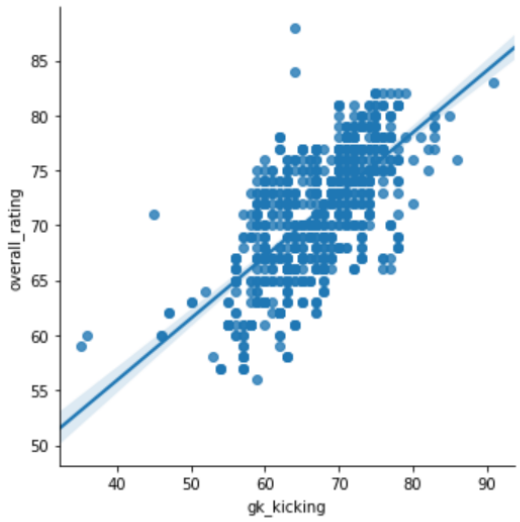



Figure 24. Goalkeeper Subgroup: Scatter Plots of gk_Positioning (Left) and gk_Handling (Right) Attributes Against Overall Rating

```
Goalkeepers Only: gk_diving > 50
               gk_kicking  overall_rating
gk_kicking       1.000000        0.669727
overall_rating   0.669727        1.000000
```

```
Goalkeepers Only: gk_diving > 50
                reactions  overall_rating
reactions         1.00000         0.56092
overall_rating    0.56092         1.00000
```



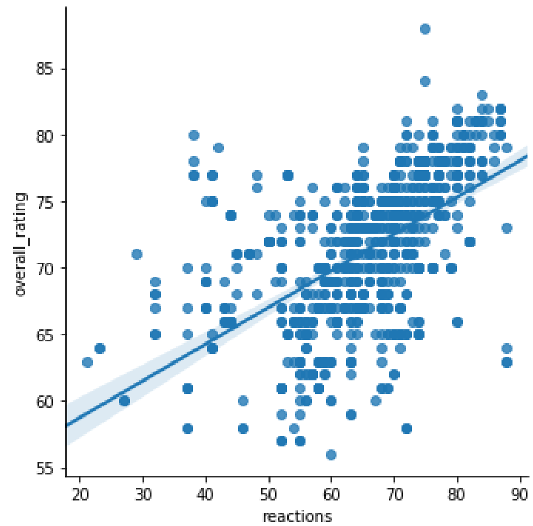




Figure 25. Goalkeeper Subgroup: Scatter Plots of gk_Kicking (Left) and Reactions (Right) Attributes Against Overall Rating

# Conclusions and Answers to Research Questions

## Research Question: What attributes set the players apart?

Four of the five goalkeeping attributes and ball control attribute separated the players apart:

a) a small subgroup of 930 goalkeepers, who have relatively high scores in goalkeeping attributes, gk_diving, gk_handling, gk_positioning, and gk_reflexes, but low in ball control, and
b) a larger subgroup of the rest of the 9968 players, whose scores relatively low in the goalkeeping attributes, but high in ball control.

With gk_kicking attribute and ball control attribute, players were, however, divided into three apparent subgroups:

a) one small subgroup of 930 goalkeepers, who have relatively high scores in gk_kicking, but low in ball control,
b) one slightly larger subgroup of 1413 players, whose scores in gk_kicking (>= 20) had a moderate positive linear correlation to their ball control scores, and
c) one much larger subgroup of the rest of 8556 players, whose score in gk_kicking (< 20) had no correlation with their ball control scores.

Typically, soccer players concentrate their drills on the skills they need for their positions. Drills for goalkeepers are very different from other players because their position requires them to use primarily their hands to block the soccer ball from entering the goal. They typically divert the direction of the soccer away from the goal or take control of the soccer with their hands. Goalkeepers drills typically specialize in collecting balls, jumping to divert or collect overhead balls, goal positioning to the attacking angle, diving for balls, ball distribution once collected, and so on. Specialized training brings special attributes that separate them apart from other players.

According to soccer game rules, if the offensive team kicks the ball out of the field, play is restarted with a goal kick. The goal kick can be taken by any player, rather than limited to the goalkeeper. So, it is not uncommon to have full back teammates to take the goal kick. This explains why there is a slightly larger subgroup of players who score well in gk_kicking and ball control.

### Research Question: Which player attribute contributes most to a player's overall rating?

For all players in the dataset, reactions attribute with the strongest correlation coefficient (0.724830) contributes most to a player's overall rating.

When evaluating in subgroup levels, the answer is different for each group. For goalkeeper subgroup, gk_diving (corr coeff. = 0.897919), gk_reflexes (corr coeff. = 0.877756), gk_positioning (corr coeff. = 0.863162) and gk_handling (corr coeff. = 0.828148) goalkeeping attributes have very strong positive linear correlation with and contribute most to the players overall rating. For the rest of the players as the larger subgroup, reactions (corr coeff. = 0.759507) has a strong positive linear correlation with and contributes most to players' overall rating.

## Limitation and Future Study

The limitation of this project is that the database does not contain player's position or team formation information for any game. So, to validate the answers to the research questions, such information will have to be obtained from other source, such as sofifa.com. Figure 26 shows the players and team formation of the soccer team, Liverpool, for 2018. Figure 27 presents attributes of a player from the team and similar players of other teams and their overall rating and potential scores.

As shown in Figure 28 there are various modern soccer team formations. Gray, blue, yellow and red dots represent players in goalkeeping, defensive, midfield, and attacking positions at the goal and in the back field, midfield and forefront. The number of players in the back, midfield and forward varies in different formations. But there is always only one goalkeeper. The drills of players may vary slightly based on their positions in the team formation. These team formation factors will affect the scores of various attributes for each player. However, there is a tactical theory in football, Total Football (Dutch: *totaalvoetbal*), in which any outfield player can take over the role of any other player in a team. The theory requires players to be comfortable in multiple positions; hence, it places high technical and physical demands on them. For teams that embrace this theory, players are likely to have attributes across positions. If player position and team formation information is available, the study may be bring to a whole new level for the future.

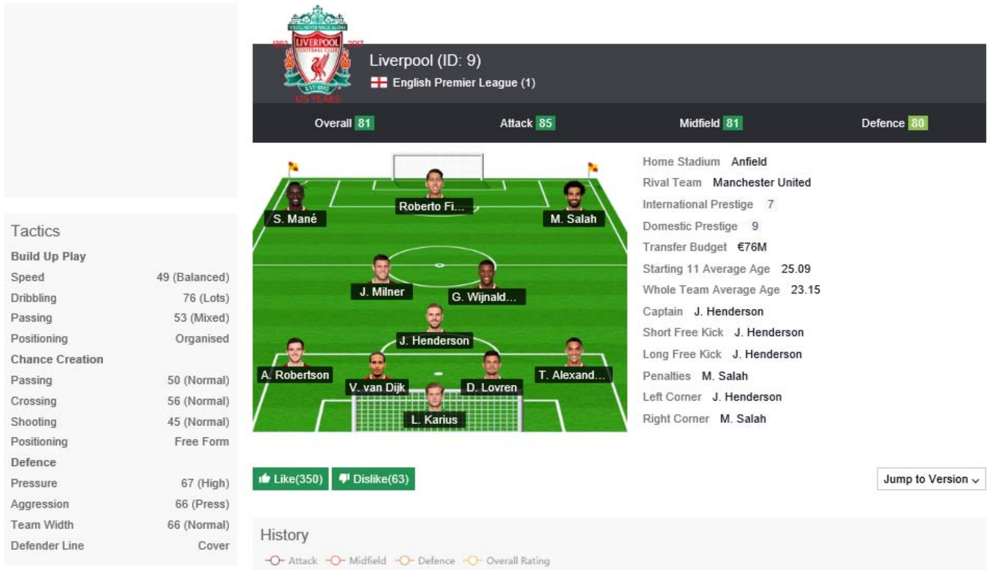



*Figure 26. Players and Team Formation of Soccer Team, Liverpool, for 2018.*

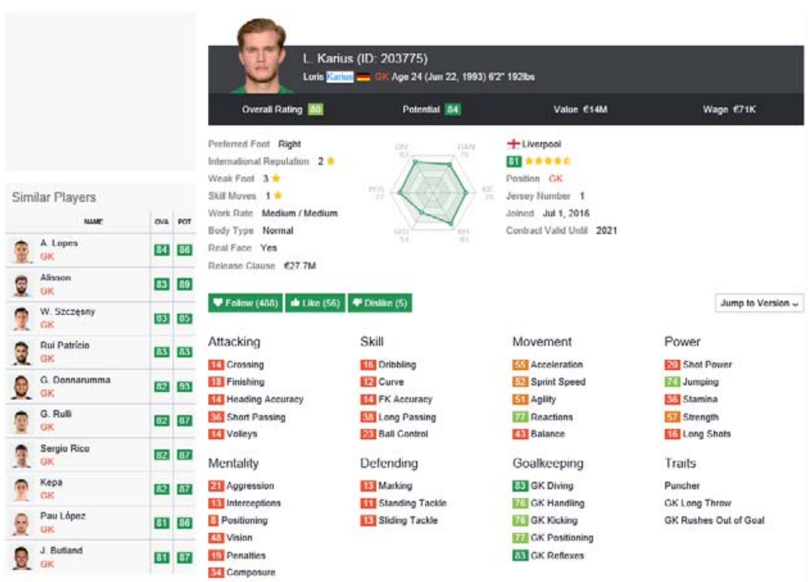



*Figure 27. Attributes of a Player from the Soccer Team, Liverpool and Similar Players with Overall Rating and Potential*

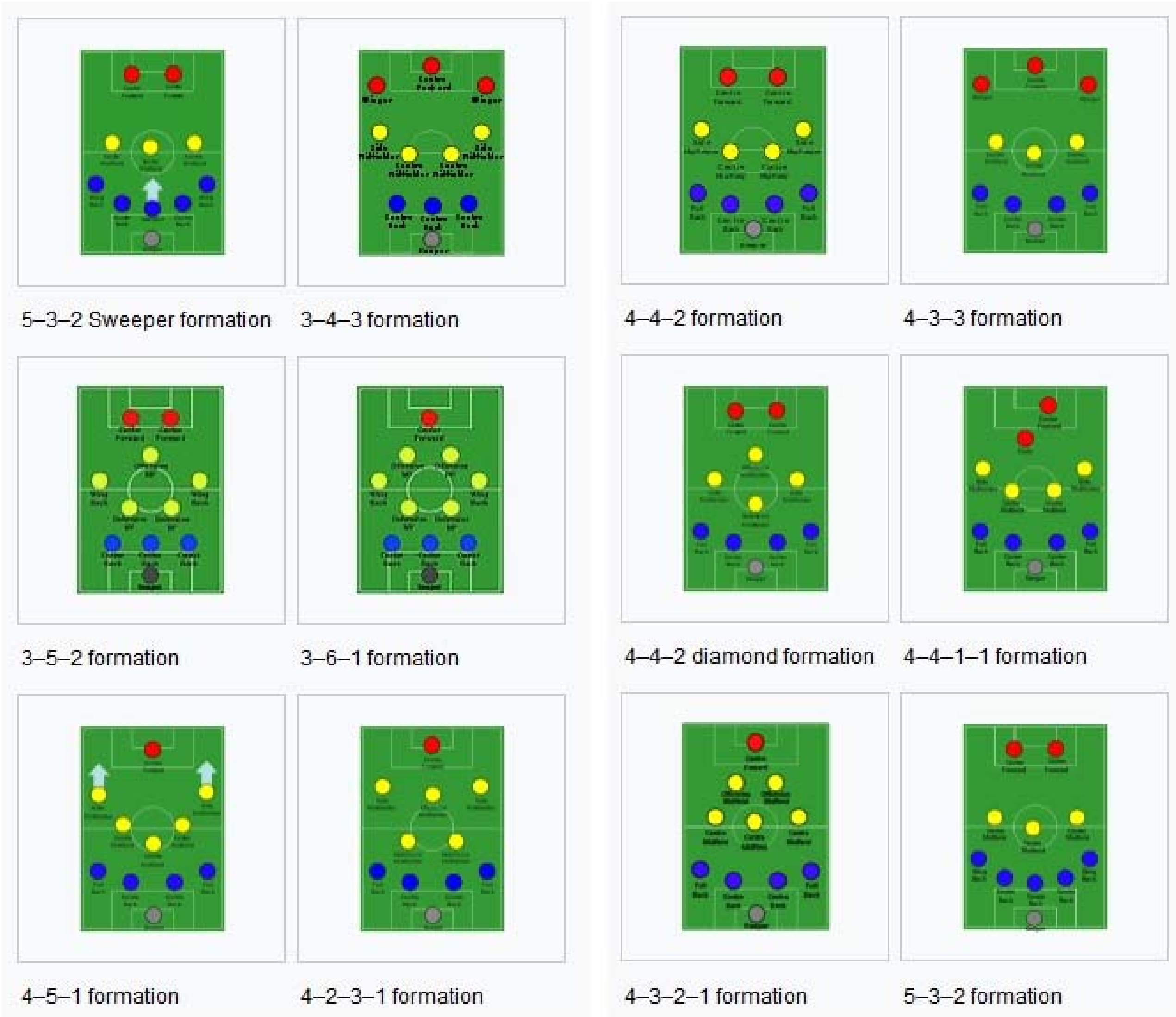



*Figure 28. Examples of Modern Soccer Team Formations*

# APPENDIX A: Source of Data

Data for this project was downloaded from this website: https://www.kaggle.com/hugomathien/soccer

The following presents brief information of the database in SQLite3 format:

- +25,000 matches
- +10,000 players
- 11 European Countries with their lead championship
- Seasons 2008 to 2016
- Players and Teams attributes sourced from EA Sports FIFA video game series [#]
- Team line up with squad formation (X, Y coordinates)
- Betting odds from up to 10 providers
- Detailed match events (goal types, possession, corner, cross, fouls, cards etc...) for +10,000 matches

  **16th Oct 2016: New table containing teams attributes from FIF !*

[#] Original data source for players and teams attributes tables: http://sofifa.com/ : players and teams attributes from EA Sports FIFA games. *FIFA series and all FIFA assets property of EA Sports.* Foreign keys "api_id" for players and matches are the same as the original data sources.

# APPENDIX B: Jupyter Notebook - Python Codes and Outputs

# Import required libraries, fetch data from database into pandas.DataFrame and format data type for PCA

In [3]:
```
import numpy as np
import sqlite3
import matplotlib.pylab as plt
import datetime as DT
import seaborn as sns
np.set_printoptions(precision=5)
import pandas as pd  # data processing, CSV file I/O (e.g. pd.read_csv)
#### import the PCA library from scikit learn library
from sklearn.decomposition import PCA
from mpl_toolkits.mplot3d import Axes3D  # didn't get to use this
%matplotlib inline

# Normalizing (scaling) the data is VERY important - indeed can be importa
nt to many machine
# learning algorithms.  Take the original features and scale them so that
they all have zero
# mean and unit variance
from sklearn import preprocessing

## pandas actually has a command to read_sql or read_sql_query and return
a pandas.DataFrame
## coerce_float=True argument to force float data type
## Need to FIRST connect to the database by creating a connection object c
alled conn.
conn = sqlite3.connect('database.sqlite')

# create a cursor object using the conn object method
# The cursor object has methods for accessing the data
# c = conn.cursor()  # this is not needed for the pd.read_sql IO tool

# Get the database table list from information in the sqlite_master table
# Follow convention to type SQL commands in all caps

# preview all tables in the database
print ('======')
print ('Tables in the database')
# Set the execute SQL command, Fetch and print all table names and info, a
nd
# return a pandas DataFrame
df_tables = pd.read_sql("""SELECT * FROM sqlite_master WHERE type='table';
""", conn)
print('df_tables shape: ', df_tables.shape)
print(df_tables)
print ('======')
print('Player_Attributes table:')
print(df_tables.sql[1]) # get sql that CREATE the Player_Atrribtues table
print ('======')
```

```
print('Player table:')
print(df_tables.sql[2]) # get sql that CREATE the Player table
print ('======')
print ('Player table')
df_Player = pd.read_sql("""SELECT * FROM Player """, conn)
print('df_Player.shape:', df_Player.shape)
print(df_Player.columns)
print(df_Player.head())
print ('======')
print ('Player_Attributes table')
df_Player_Attributes = pd.read_sql("""SELECT * FROM Player_Attributes""",
conn)
print('df_Player_Attributes.shape:', df_Player_Attributes.shape)
print(df_Player_Attributes.columns)
print(df_Player_Attributes.head())
print ('======')

# acquire data from database using pd.read_sql_query(sql, , ,)
# build SQL to SELECT all columns from both Player and Player_Attributes t
ables
# for rows reocrds w/ matching player_fifa_api_id
sql="SELECT * FROM Player INNER JOIN Player_Attributes ON Player.player_fi
fa_api_id=Player_Attributes.player_fifa_api_id;"
df_all_col=pd.read_sql_query(sql, conn, coerce_float=True, params=None, pa
rse_dates=['birthday','date'], chunksize=None)
# calculate age of player at the time attributes were collected
df_all_col['age'] = (df_all_col.date - df_all_col.birthday).astype('timede
lta64[Y]')

#Tally total score per player attribute category
df_all_col['total_attack'] = df_all_col.crossing + df_all_col.finishing +
df_all_col.heading_accuracy + \
                                df_all_col.short_passing + df_all_col.voll
eys
df_all_col['total_skill'] = df_all_col.dribbling + df_all_col.curve + df_a
ll_col.free_kick_accuracy + df_all_col.long_passing + \
                                df_all_col.ball_control
df_all_col['total_movement'] = df_all_col.acceleration + df_all_col.sprint
_speed + df_all_col.agility + \
                                df_all_col.reactions + df_all_col.balance
df_all_col['total_power'] = df_all_col.shot_power + df_all_col.jumping + d
f_all_col.stamina + df_all_col.strength + \
                            df_all_col.long_shots
df_all_col['total_mentality'] = df_all_col.aggression + df_all_col.interce
ptions + df_all_col.positioning + \
                                df_all_col.vision + df_all_col.penalties
df_all_col['total_defending'] = df_all_col.marking + df_all_col.standing_t
ackle + df_all_col.sliding_tackle
df_all_col['total_goalkeeping'] = df_all_col.gk_diving + df_all_col.gk_han
dling + df_all_col.gk_kicking + \
                                    df_all_col.gk_positioning + df_all_col
.gk_reflexes
print('df_all_col.columns: ', df_all_col.columns) # print column labels fo
r all columns from both tables
print('df_all_col.shape:', df_all_col.shape)
print(df_all_col.info())
```

```
# identify non_numeric and numeric columns of interest and create two list
s of column labels
non_numeric_col=['player_fifa_api_id', 'player_api_id','player_name', 'bir
thday', 'date', \
                 'preferred_foot', 'attacking_work_rate', 'defensive_work_
rate']
numeric_col = ['age', 'height', 'weight','overall_rating', 'potential','cr
ossing', 'finishing', \
               'heading_accuracy','short_passing', 'volleys', 'dribbling',
 'curve', \
               'free_kick_accuracy', 'long_passing', 'ball_control', 'acce
leration', \
               'sprint_speed', 'agility', 'reactions', 'balance', 'shot_po
wer', 'jumping', \
               'stamina', 'strength', 'long_shots', 'aggression', 'interce
ptions', 'positioning',\
               'vision', 'penalties', 'marking', 'standing_tackle', 'slidi
ng_tackle', 'gk_diving', \
               'gk_handling', 'gk_kicking', 'gk_positioning', 'gk_reflexes
']
numeric_few_col = ['age', 'height', 'weight','overall_rating', 'potential'
, 'total_attack', 'total_skill', \
                   'total_movement', 'total_power', 'total_mentality', 'to
tal_defending', 'total_goalkeeping']
```

```
======
Tables in the database
df_tables shape:  (8, 5)
    type               name           tbl_name  rootpage  \
0  table    sqlite_sequence    sqlite_sequence         4   
1  table  Player_Attributes  Player_Attributes        11   
2  table             Player             Player        14   
3  table              Match              Match        18   
4  table             League             League        24   
5  table            Country            Country        26   
6  table               Team               Team        29   
7  table    Team_Attributes    Team_Attributes         2   

                                                 sql  
0             CREATE TABLE sqlite_sequence(name,seq)  
1  CREATE TABLE "Player_Attributes" (\n\t`id`\tIN...  
2  CREATE TABLE `Player` (\n\t`id`\tINTEGER PRIMA...  
3  CREATE TABLE `Match` (\n\t`id`\tINTEGER PRIMAR...  
4  CREATE TABLE `League` (\n\t`id`\tINTEGER PRIMA...  
5  CREATE TABLE `Country` (\n\t`id`\tINTEGER PRIM...  
6  CREATE TABLE "Team" (\n\t`id`\tINTEGER PRIMARY...  
7  CREATE TABLE `Team_Attributes` (\n\t`id`\tINTE...  
======
Player_Attributes table:
CREATE TABLE "Player_Attributes" (
        `id`    INTEGER PRIMARY KEY AUTOINCREMENT,
        `player_fifa_api_id`    INTEGER,
        `player_api_id` INTEGER,
        `date`  TEXT,
        `overall_rating`        INTEGER,
        `potential`     INTEGER,
        `preferred_foot`        TEXT,
```

```
        `attacking_work_rate`   TEXT,
        `defensive_work_rate`   TEXT,
        `crossing`      INTEGER,
        `finishing`     INTEGER,
        `heading_accuracy`      INTEGER,
        `short_passing` INTEGER,
        `volleys`       INTEGER,
        `dribbling`     INTEGER,
        `curve` INTEGER,
        `free_kick_accuracy`    INTEGER,
        `long_passing`  INTEGER,
        `ball_control`  INTEGER,
        `acceleration`  INTEGER,
        `sprint_speed`  INTEGER,
        `agility`       INTEGER,
        `reactions`     INTEGER,
        `balance`       INTEGER,
        `shot_power`    INTEGER,
        `jumping`       INTEGER,
        `stamina`       INTEGER,
        `strength`      INTEGER,
        `long_shots`    INTEGER,
        `aggression`    INTEGER,
        `interceptions` INTEGER,
        `positioning`   INTEGER,
        `vision`        INTEGER,
        `penalties`     INTEGER,
        `marking`       INTEGER,
        `standing_tackle`       INTEGER,
        `sliding_tackle`        INTEGER,
        `gk_diving`     INTEGER,
        `gk_handling`   INTEGER,
        `gk_kicking`    INTEGER,
        `gk_positioning`        INTEGER,
        `gk_reflexes`   INTEGER,
        FOREIGN KEY(`player_fifa_api_id`) REFERENCES `Player`(`player_fifa
_api_id`),
        FOREIGN KEY(`player_api_id`) REFERENCES `Player`(`player_api_id`)
)
======
Player table:
CREATE TABLE `Player` (
        `id`    INTEGER PRIMARY KEY AUTOINCREMENT,
        `player_api_id` INTEGER UNIQUE,
        `player_name`   TEXT,
        `player_fifa_api_id`    INTEGER UNIQUE,
        `birthday`      TEXT,
        `height`        INTEGER,
        `weight`        INTEGER
)
======
Player table
df_Player.shape: (11060, 7)
Index(['id', 'player_api_id', 'player_name', 'player_fifa_api_id', 'birthd
ay',
       'height', 'weight'],
      dtype='object')
```

```
   id  player_api_id         player_name  player_fifa_api_id  \
0   1         505942  Aaron Appindangoye              218353
1   2         155782     Aaron Cresswell              189615
2   3         162549         Aaron Doran              186170
3   4          30572       Aaron Galindo              140161
4   5          23780        Aaron Hughes               17725

              birthday  height  weight
0  1992-02-29 00:00:00  182.88     187
1  1989-12-15 00:00:00  170.18     146
2  1991-05-13 00:00:00  170.18     163
3  1982-05-08 00:00:00  182.88     198
4  1979-11-08 00:00:00  182.88     154
======
Player_Attributes table
df_Player_Attributes.shape: (183978, 42)
Index(['id', 'player_fifa_api_id', 'player_api_id', 'date', 'overall_ratin
g',
       'potential', 'preferred_foot', 'attacking_work_rate',
       'defensive_work_rate', 'crossing', 'finishing', 'heading_accuracy',
       'short_passing', 'volleys', 'dribbling', 'curve', 'free_kick_accura
cy',
       'long_passing', 'ball_control', 'acceleration', 'sprint_speed',
       'agility', 'reactions', 'balance', 'shot_power', 'jumping', 'stamin
a',
       'strength', 'long_shots', 'aggression', 'interceptions', 'positioni
ng',
       'vision', 'penalties', 'marking', 'standing_tackle', 'sliding_tackl
e',
       'gk_diving', 'gk_handling', 'gk_kicking', 'gk_positioning',
       'gk_reflexes'],
      dtype='object')
   id  player_fifa_api_id  player_api_id                 date  overall_rat
ing  \
0   1              218353         505942  2016-02-18 00:00:00             6
7.0
1   2              218353         505942  2015-11-19 00:00:00             6
7.0
2   3              218353         505942  2015-09-21 00:00:00             6
2.0
3   4              218353         505942  2015-03-20 00:00:00             6
1.0
4   5              218353         505942  2007-02-22 00:00:00             6
1.0

   potential preferred_foot attacking_work_rate defensive_work_rate  cross
ing  \
0       71.0          right              medium              medium      4
9.0
1       71.0          right              medium              medium      4
9.0
2       66.0          right              medium              medium      4
9.0
3       65.0          right              medium              medium      4
8.0
4       65.0          right              medium              medium      4
8.0
```

```
      ...       vision  penalties  marking  standing_tackle  sliding_tackl
e  \
0     ...         54.0       48.0     65.0             69.0             69.
0
1     ...         54.0       48.0     65.0             69.0             69.
0
2     ...         54.0       48.0     65.0             66.0             69.
0
3     ...         53.0       47.0     62.0             63.0             66.
0
4     ...         53.0       47.0     62.0             63.0             66.
0

   gk_diving  gk_handling  gk_kicking  gk_positioning  gk_reflexes
0        6.0         11.0        10.0             8.0          8.0
1        6.0         11.0        10.0             8.0          8.0
2        6.0         11.0        10.0             8.0          8.0
3        5.0         10.0         9.0             7.0          7.0
4        5.0         10.0         9.0             7.0          7.0

[5 rows x 42 columns]
======
df_all_col.columns:  Index(['id', 'player_api_id', 'player_name', 'player_
fifa_api_id', 'birthday',
       'height', 'weight', 'id', 'player_fifa_api_id', 'player_api_id', 'd
ate',
       'overall_rating', 'potential', 'preferred_foot', 'attacking_work_ra
te',
       'defensive_work_rate', 'crossing', 'finishing', 'heading_accuracy',
       'short_passing', 'volleys', 'dribbling', 'curve', 'free_kick_accura
cy',
       'long_passing', 'ball_control', 'acceleration', 'sprint_speed',
       'agility', 'reactions', 'balance', 'shot_power', 'jumping', 'stamin
a',
       'strength', 'long_shots', 'aggression', 'interceptions', 'positioni
ng',
       'vision', 'penalties', 'marking', 'standing_tackle', 'sliding_tackl
e',
       'gk_diving', 'gk_handling', 'gk_kicking', 'gk_positioning',
       'gk_reflexes', 'age', 'total_attack', 'total_skill', 'total_movemen
t',
       'total_power', 'total_mentality', 'total_defending',
       'total_goalkeeping'],
      dtype='object')
df_all_col.shape: (183929, 57)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 183929 entries, 0 to 183928
Data columns (total 57 columns):
id                     183929 non-null int64
player_api_id          183929 non-null int64
player_name            183929 non-null object
player_fifa_api_id     183929 non-null int64
birthday               183929 non-null datetime64[ns]
height                 183929 non-null float64
weight                 183929 non-null int64
id                     183929 non-null int64
```

```
player_fifa_api_id     183929 non-null int64
player_api_id          183929 non-null int64
date                   183929 non-null datetime64[ns]
overall_rating         183142 non-null float64
potential              183142 non-null float64
preferred_foot         183142 non-null object
attacking_work_rate    180748 non-null object
defensive_work_rate    183142 non-null object
crossing               183142 non-null float64
finishing              183142 non-null float64
heading_accuracy       183142 non-null float64
short_passing          183142 non-null float64
volleys                181265 non-null float64
dribbling              183142 non-null float64
curve                  181265 non-null float64
free_kick_accuracy     183142 non-null float64
long_passing           183142 non-null float64
ball_control           183142 non-null float64
acceleration           183142 non-null float64
sprint_speed           183142 non-null float64
agility                181265 non-null float64
reactions              183142 non-null float64
balance                181265 non-null float64
shot_power             183142 non-null float64
jumping                181265 non-null float64
stamina                183142 non-null float64
strength               183142 non-null float64
long_shots             183142 non-null float64
aggression             183142 non-null float64
interceptions          183142 non-null float64
positioning            183142 non-null float64
vision                 181265 non-null float64
penalties              183142 non-null float64
marking                183142 non-null float64
standing_tackle        183142 non-null float64
sliding_tackle         181265 non-null float64
gk_diving              183142 non-null float64
gk_handling            183142 non-null float64
gk_kicking             183142 non-null float64
gk_positioning         183142 non-null float64
gk_reflexes            183142 non-null float64
age                    183929 non-null float64
total_attack           181265 non-null float64
total_skill            181265 non-null float64
total_movement         181265 non-null float64
total_power            181265 non-null float64
total_mentality        181265 non-null float64
total_defending        181265 non-null float64
total_goalkeeping      183142 non-null float64
dtypes: datetime64[ns](2), float64(44), int64(7), object(4)
memory usage: 80.0+ MB
None
```

# data cleaning

In [7]:
```
df_all_col.replace(r'\s+', np.nan, regex=True, inplace = True)
df_all_col.dropna(axis=0, how='any', inplace=True)  #drop row (sample) wit
h any NA entry
df_all_col.sort_values('player_name',axis=0, inplace=True)
df_all_col.drop_duplicates(inplace=True)
df_all_col.to_csv('df_all_col.csv')

print ('df_all_col.shape: ', df_all_col.shape)
print(df_all_col.shape)
print(df_all_col.info())
print(df_all_col.head())
print(df_all_col.tail())
print(df_all_col['defensive_work_rate'][0:60]) # need more data cleaning f
or col before ploting
print ('======')

df_unscaled_data = df_all_col[numeric_col]
print('df_unscaled_data.columns:', df_unscaled_data.columns)
print('df_unscaled_data.shape:', df_unscaled_data.shape)
print('df_unscaled_data.info: ', df_unscaled_data.info())
```

```
df_all_col.shape:  (10898, 57)
(10898, 57)
<class 'pandas.core.frame.DataFrame'>
Int64Index: 10898 entries, 1045 to 183615
Data columns (total 57 columns):
id                     10898 non-null int64
player_api_id          10898 non-null int64
player_name            10898 non-null object
player_fifa_api_id     10898 non-null int64
birthday               10898 non-null datetime64[ns]
height                 10898 non-null float64
weight                 10898 non-null int64
id                     10898 non-null int64
player_fifa_api_id     10898 non-null int64
player_api_id          10898 non-null int64
date                   10898 non-null datetime64[ns]
overall_rating         10898 non-null float64
potential              10898 non-null float64
preferred_foot         10898 non-null object
attacking_work_rate    10898 non-null object
defensive_work_rate    10898 non-null object
crossing               10898 non-null float64
finishing              10898 non-null float64
heading_accuracy       10898 non-null float64
short_passing          10898 non-null float64
volleys                10898 non-null float64
dribbling              10898 non-null float64
curve                  10898 non-null float64
free_kick_accuracy     10898 non-null float64
long_passing           10898 non-null float64
ball_control           10898 non-null float64
acceleration           10898 non-null float64
sprint_speed           10898 non-null float64
agility                10898 non-null float64
reactions              10898 non-null float64
balance                10898 non-null float64
```

```
shot_power             10898 non-null float64
jumping                10898 non-null float64
stamina                10898 non-null float64
strength               10898 non-null float64
long_shots             10898 non-null float64
aggression             10898 non-null float64
interceptions          10898 non-null float64
positioning            10898 non-null float64
vision                 10898 non-null float64
penalties              10898 non-null float64
marking                10898 non-null float64
standing_tackle        10898 non-null float64
sliding_tackle         10898 non-null float64
gk_diving              10898 non-null float64
gk_handling            10898 non-null float64
gk_kicking             10898 non-null float64
gk_positioning         10898 non-null float64
gk_reflexes            10898 non-null float64
age                    10898 non-null float64
total_attack           10898 non-null float64
total_skill            10898 non-null float64
total_movement         10898 non-null float64
total_power            10898 non-null float64
total_mentality        10898 non-null float64
total_defending        10898 non-null float64
total_goalkeeping      10898 non-null float64
dtypes: datetime64[ns](2), float64(44), int64(7), object(4)
memory usage: 4.8+ MB
None
      id  player_api_id player_name  player_fifa_api_id   birthday  height
  \
1045  67          40938        Abel               17880 1978-12-22   177.8

1046  67          40938        Abel               17880 1978-12-22   177.8

1047  67          40938        Abel               17880 1978-12-22   177.8

1048  67          40938        Abel               17880 1978-12-22   177.8

1049  67          40938        Abel               17880 1978-12-22   177.8


      weight    id  player_fifa_api_id  player_api_id        ...
\
1045     165  1046               17880          40938        ...

1046     165  1047               17880          40938        ...

1047     165  1048               17880          40938        ...

1048     165  1049               17880          40938        ...

1049     165  1050               17880          40938        ...


     gk_positioning  gk_reflexes   age total_attack total_skill  \
1045           13.0         10.0  31.0        311.0       319.0
```

```
1046           20.0          20.0  31.0        307.0       318.0
1047           20.0          20.0  30.0        305.0       316.0
1048           20.0          20.0  28.0        298.0       311.0
1049            8.0          12.0  28.0        288.0       335.0

     total_movement  total_power  total_mentality  total_defending  \
1045          375.0        355.0            351.0            219.0
1046          375.0        355.0            372.0            216.0
1047          377.0        357.0            372.0            221.0
1048          372.0        355.0            370.0            221.0
1049          366.0        346.0            356.0            212.0

      total_goalkeeping
1045               42.0
1046              143.0
1047              143.0
1048              141.0
1049              102.0

[5 rows x 57 columns]
           id  player_api_id player_name  player_fifa_api_id   birthday  \
183611  11055         532766        Zizo              222537 1996-01-10
183612  11055         532766        Zizo              222537 1996-01-10
183613  11055         532766        Zizo              222537 1996-01-10
183614  11055         532766        Zizo              222537 1996-01-10
183615  11055         532766        Zizo              222537 1996-01-10

        height  weight      id  player_fifa_api_id  player_api_id  \
183611  175.26     148  183661              222537         532766
183612  175.26     148  183662              222537         532766
183613  175.26     148  183663              222537         532766
183614  175.26     148  183664              222537         532766
183615  175.26     148  183665              222537         532766

              ...         gk_positioning  gk_reflexes   age total_attack
\
183611        ...                   11.0          8.0  19.0        250.0

183612        ...                   11.0          8.0  18.0        248.0

183613        ...                   11.0          8.0  18.0        247.0

183614        ...                   11.0          8.0  18.0        247.0

183615        ...                   11.0          8.0  11.0        247.0


       total_skill total_movement  total_power  total_mentality  \
183611       297.0          337.0        253.0            285.0
183612       296.0          334.0        238.0            271.0
183613       281.0          335.0        235.0            233.0
183614       281.0          335.0        235.0            233.0
183615       281.0          335.0        235.0            233.0

        total_defending  total_goalkeeping
183611            148.0               43.0
183612            144.0               43.0
```

```
183613            101.0                 43.0
183614            101.0                 43.0
183615            101.0                 43.0

[5 rows x 57 columns]
1045         o
1046         o
1047         o
1048         o
1049         o
1315    medium
1314    medium
1306    medium
1307    medium
1308    medium
1309    medium
1310    medium
1311    medium
1316    medium
1317    medium
1318    medium
1319    medium
1320    medium
1321    medium
1322    medium
1313    medium
1312    medium
2444    medium
2445    medium
2443    medium
2446    medium
2447    medium
2450    medium
2448    medium
2449    medium
2541    medium
2542    medium
2543    medium
2544    medium
2545    medium
2546    medium
2547    medium
3145    medium
3152    medium
3141    medium
3142    medium
3143    medium
3144    medium
3151    medium
3146    medium
3147    medium
3148    medium
3140    medium
3150    medium
3139    medium
3149    medium
3154    medium
```

```
3156    medium
3165    medium
3153    medium
3157    medium
3158    medium
3159    medium
3160    medium
3155    medium
Name: defensive_work_rate, dtype: object
======
df_unscaled_data.columns: Index(['age', 'height', 'weight', 'overall_ratin
g', 'potential', 'crossing',
       'finishing', 'heading_accuracy', 'short_passing', 'volleys',
       'dribbling', 'curve', 'free_kick_accuracy', 'long_passing',
       'ball_control', 'acceleration', 'sprint_speed', 'agility', 'reactio
ns',
       'balance', 'shot_power', 'jumping', 'stamina', 'strength', 'long_sh
ots',
       'aggression', 'interceptions', 'positioning', 'vision', 'penalties'
,
       'marking', 'standing_tackle', 'sliding_tackle', 'gk_diving',
       'gk_handling', 'gk_kicking', 'gk_positioning', 'gk_reflexes'],
      dtype='object')
df_unscaled_data.shape: (10898, 38)
<class 'pandas.core.frame.DataFrame'>
Int64Index: 10898 entries, 1045 to 183615
Data columns (total 38 columns):
age                   10898 non-null float64
height                10898 non-null float64
weight                10898 non-null int64
overall_rating        10898 non-null float64
potential             10898 non-null float64
crossing              10898 non-null float64
finishing             10898 non-null float64
heading_accuracy      10898 non-null float64
short_passing         10898 non-null float64
volleys               10898 non-null float64
dribbling             10898 non-null float64
curve                 10898 non-null float64
free_kick_accuracy    10898 non-null float64
long_passing          10898 non-null float64
ball_control          10898 non-null float64
acceleration          10898 non-null float64
sprint_speed          10898 non-null float64
agility               10898 non-null float64
reactions             10898 non-null float64
balance               10898 non-null float64
shot_power            10898 non-null float64
jumping               10898 non-null float64
stamina               10898 non-null float64
strength              10898 non-null float64
long_shots            10898 non-null float64
aggression            10898 non-null float64
interceptions         10898 non-null float64
positioning           10898 non-null float64
vision                10898 non-null float64
penalties             10898 non-null float64
```

```
marking                 10898 non-null float64
standing_tackle         10898 non-null float64
sliding_tackle          10898 non-null float64
gk_diving               10898 non-null float64
gk_handling             10898 non-null float64
gk_kicking              10898 non-null float64
gk_positioning          10898 non-null float64
gk_reflexes             10898 non-null float64
dtypes: float64(37), int64(1)
memory usage: 3.2 MB
df_unscaled_data.info:  None
```

## Preprocess data and conduct PCA - principal component analysis

In [9]:

```
scaled_data = preprocessing.scale(df_unscaled_data) #center and scale the
data
print('scaled data:')
print (scaled_data)  # preview scaled data

# create a PCA object.
# sklean uses this PCA object that can be trained using one dataset and ap
plied to another dataset
pca = PCA()
print(type(pca))
# do PCA math, calculate loading scores and the variation each PCA account
s for
pca.fit(scaled_data)
# generate coordinates for a PCA graph based on the loading scores and the
 scaled data
pca_data = pca.transform(scaled_data)
```

```
scaled data:
[[ 1.20435 -0.50782 -0.12955 ... -0.64338 -0.19821 -0.36672]
 [ 1.20435 -0.50782 -0.12955 ...  2.36822  0.20348  0.18149]
 [ 0.98217 -0.50782 -0.12955 ...  2.36822  0.20348  0.18149]
 ...
 [-1.68402 -0.88666 -1.24685 ... -0.64338 -0.31297 -0.47637]
 [-1.68402 -0.88666 -1.24685 ... -0.64338 -0.31297 -0.47637]
 [-3.2393  -0.88666 -1.24685 ... -0.64338 -0.31297 -0.47637]]
<class 'sklearn.decomposition.pca.PCA'>
```

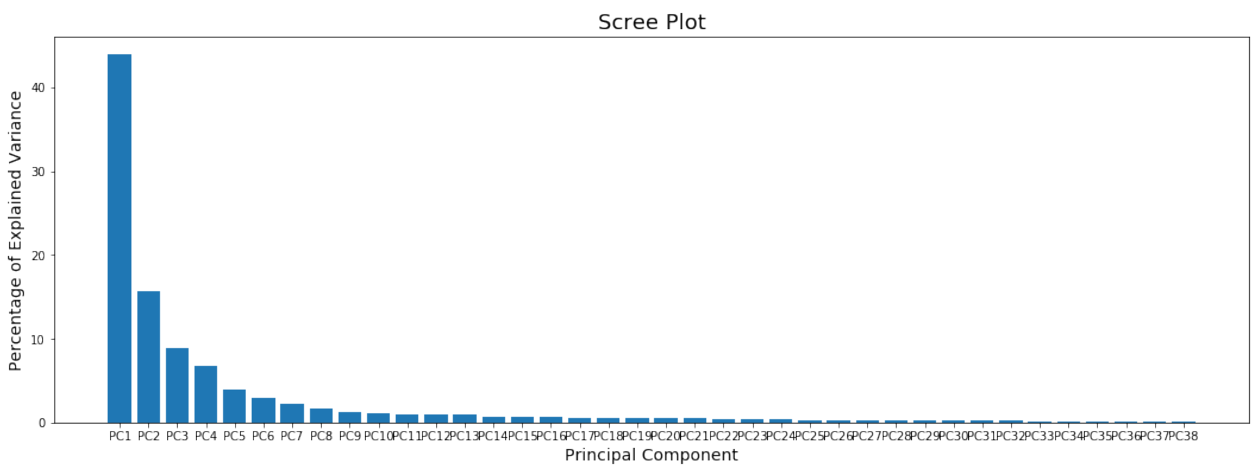
## Present Explained Variance, Scree Plot and Principal Components Scatter Matrix

In [11]:

```
# pca.explained_variance_ratio_ is <class 'numpy.ndarray'>.
# It calculates the percentage of variance that each principal component a
ccoutns for
per_var = np.round(pca.explained_variance_ratio_*100, decimals =1)
print('=======================')
print('percent of explained variance: ')
print(per_var)
PC_labels = ['PC'+ str(x) for x in range(1,len(per_var)+1)] # labels for t
```

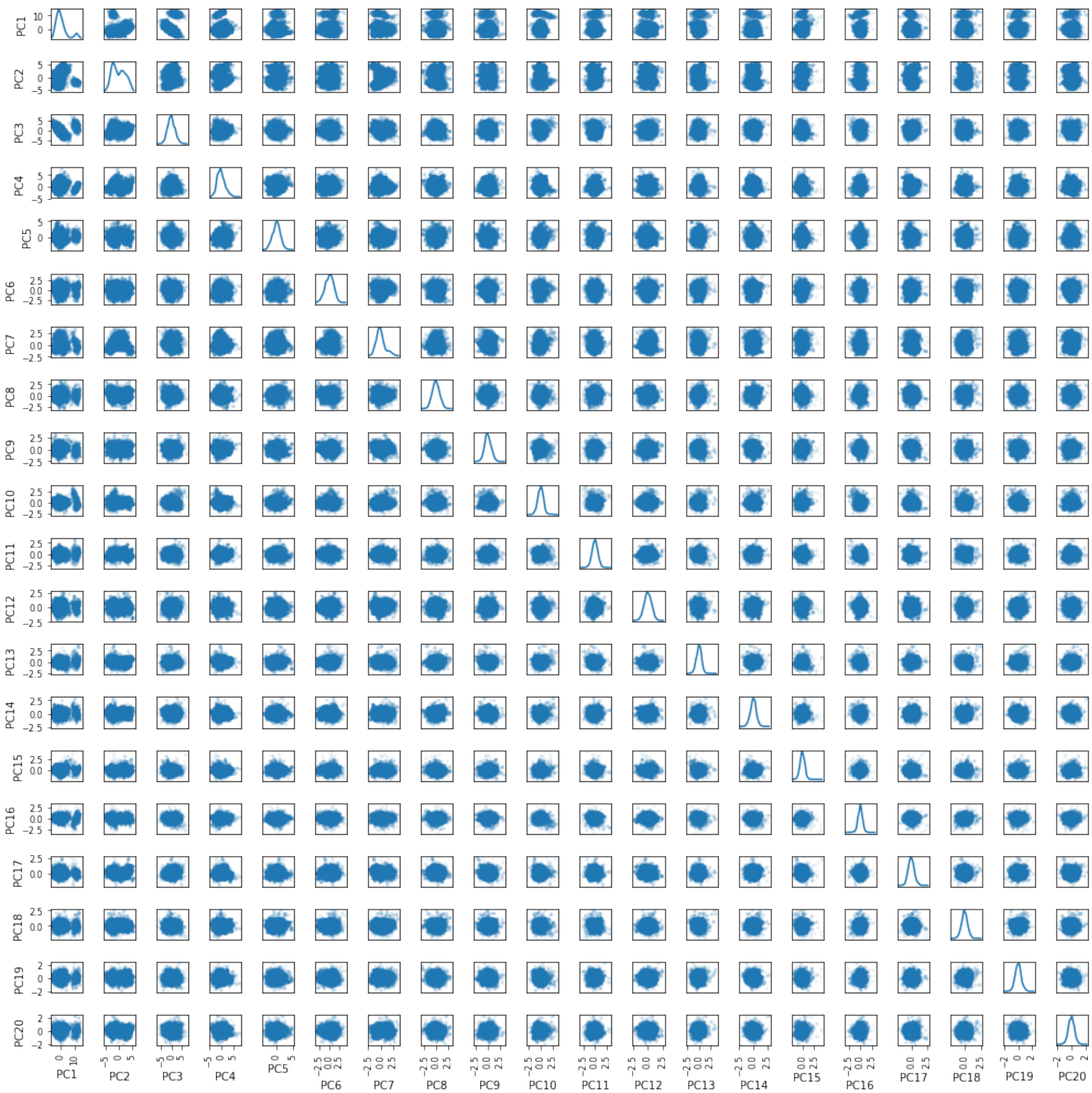
```
he Scree Plot: PC1, PC2 ...
print(' ')
print('=======================')

# create Scree Plot
plt.figure(figsize=(18, 6))
plt.bar(x=range(1, len(per_var)+1), height=per_var, tick_label=PC_labels)
plt.ylabel('Percentage of Explained Variance', fontsize='14')
plt.xlabel('Principal Component', fontsize='14')
plt.title('Scree Plot', fontsize='18')
plt.show()
plt.close()

# put pca_data with DataFrame with PC_labels
pca_df = pd.DataFrame(pca_data, index=None, columns=PC_labels)
print(pca_df.head()) # preview transformed and scaled
print('=======================')


print('Principal Components Scatter Matrix')
df_pc_matrix= pca_df[['PC'+ str(x) for x in range(1,21)]] # scatter matrix
 for PC1, PC2, ..., PC15
pd.plotting.scatter_matrix(df_pc_matrix, alpha=0.1, figsize=(14, 14), diag
onal='kde',range_padding =0.1)
plt.tight_layout()
plt.show()
plt.close()
```

```
=======================
percent of explained variance:
[43.9 15.7  8.9  6.8  3.9  3.   2.2  1.7  1.3  1.1  1.   1.   0.9  0.7
  0.7  0.7  0.6  0.6  0.5  0.5  0.5  0.4  0.4  0.4  0.3  0.3  0.3  0.3
  0.2  0.2  0.2  0.2  0.1  0.1  0.1  0.1  0.1  0.1]

=======================
```




```
        PC1       PC2       PC3       PC4       PC5       PC6       PC7  \
0 -2.640114  1.968095  0.650296 -1.085030  0.432893 -0.997913 -0.036752
1 -1.974144  1.547071  1.945571 -1.698880  0.785256 -0.431110  2.178955
2 -1.998243  1.632706  1.964671 -1.818000  0.655679 -0.269227  2.168876
3 -1.777293  1.508709  1.666837 -1.760435  0.469343 -0.019567  2.297794
4 -2.056297  0.869395  0.466741 -1.179464  0.879790 -0.124301  2.485314
```

```
        PC8       PC9      PC10    ...          PC29      PC30      PC31  \
0 -0.345769 -0.212905  0.717640    ...     -0.243024 -0.082784 -0.287740
1 -0.524871  0.683914  0.138753    ...     -0.313755 -0.136859 -0.142348
2 -0.553466  0.642269  0.157086    ...     -0.304040  0.008732 -0.030220
3 -0.364947  0.543994  0.246732    ...     -0.335973  0.075856  0.170031
4  0.184533  0.201187 -0.439294    ...     -0.316171  0.099965  0.113237

       PC32      PC33      PC34      PC35      PC36      PC37      PC38
0 -0.044248 -0.119196 -0.127400 -0.024028  0.054763  0.303422  0.202196
1 -0.096422 -0.082920  0.120610  0.091425 -0.042255  0.005217 -0.040199
2 -0.022378 -0.068867  0.080547  0.128276  0.035120  0.007889 -0.050469
3  0.044900 -0.031943  0.052600  0.120342  0.048383  0.012409 -0.034910
4  0.045786 -0.056746  0.502708  0.322174 -0.167724 -0.178028 -0.046963

[5 rows x 38 columns]
======================
Principal Components Scatter Matrix
```



# Take a Look at the Loading Scores of PC1, PC2 and PC3 to determine which feature has the largest influence in each principal component

In [12]:
```
loading_scores_PC1 = pd.Series(pca.components_[0],index=numeric_col)
loading_scores_PC1_sorted = loading_scores_PC1.abs().sort_values(ascending
=False)
print('Sorted PC1 Loading Scores (abs)')
print('PC1 sorted components: ', loading_scores_PC1_sorted.index)
print(loading_scores_PC1_sorted)
print('=======')

loading_scores_PC2 = pd.Series(pca.components_[1],index=numeric_col)
loading_scores_PC2_sorted = loading_scores_PC2.abs().sort_values(ascending
=False)
print('Sorted PC2 Loading Scores (abs)')
print('PC2 sorted components: ', loading_scores_PC2_sorted.index)
print(loading_scores_PC2_sorted)
print('=======')

loading_scores_PC3 = pd.Series(pca.components_[2],index=numeric_col)
loading_scores_PC3_sorted = loading_scores_PC3.abs().sort_values(ascending
=False)
print('Sorted PC3 Loading Scores (abs)')
print('PC3 sorted components: ', loading_scores_PC3_sorted.index)
print(loading_scores_PC3_sorted)
```

```
Sorted PC1 Loading Scores (abs)
PC1 sorted components:  Index(['ball_control', 'dribbling', 'short_passing
', 'crossing', 'curve',
       'long_shots', 'positioning', 'shot_power', 'vision', 'gk_diving',
       'free_kick_accuracy', 'gk_reflexes', 'gk_handling', 'gk_positioning
',
       'volleys', 'finishing', 'acceleration', 'penalties', 'sprint_speed'
,
       'long_passing', 'agility', 'stamina', 'balance', 'height',
       'heading_accuracy', 'weight', 'gk_kicking', 'reactions', 'aggressio
n',
       'overall_rating', 'potential', 'interceptions', 'standing_tackle',
       'sliding_tackle', 'marking', 'strength', 'age', 'jumping'],
      dtype='object')
ball_control          0.233895
dribbling             0.226609
short_passing         0.220168
crossing              0.213529
curve                 0.211442
long_shots            0.211257
positioning           0.204851
shot_power            0.199655
vision                0.197614
gk_diving             0.196600
free_kick_accuracy    0.196366
gk_reflexes           0.195234
gk_handling           0.195011
gk_positioning        0.193662
volleys               0.193077
```

```
finishing            0.191773
acceleration         0.185480
penalties            0.183370
sprint_speed         0.182038
long_passing         0.177636
agility              0.168734
stamina              0.158548
balance              0.153811
height               0.134852
heading_accuracy     0.132158
weight               0.125473
gk_kicking           0.121982
reactions            0.105162
aggression           0.087644
overall_rating       0.083033
potential            0.080174
interceptions        0.071469
standing_tackle      0.065230
sliding_tackle       0.059237
marking              0.052163
strength             0.028138
age                  0.005573
jumping              0.001561
dtype: float64
=======
Sorted PC2 Loading Scores (abs)
PC2 sorted components:  Index(['marking', 'standing_tackle', 'sliding_tack
le', 'interceptions',
       'aggression', 'strength', 'heading_accuracy', 'agility', 'height',
       'weight', 'finishing', 'stamina', 'volleys', 'balance',
       'gk_positioning', 'gk_handling', 'acceleration', 'gk_reflexes',
       'positioning', 'gk_diving', 'jumping', 'dribbling', 'age', 'curve',
       'gk_kicking', 'sprint_speed', 'long_passing', 'penalties', 'long_sh
ots',
       'vision', 'short_passing', 'free_kick_accuracy', 'overall_rating',
       'shot_power', 'crossing', 'reactions', 'potential', 'ball_control']
,
      dtype='object')
marking              0.360160
standing_tackle      0.357693
sliding_tackle       0.351805
interceptions        0.323485
aggression           0.310414
strength             0.269961
heading_accuracy     0.231016
agility              0.172402
height               0.171104
weight               0.151075
finishing            0.149702
stamina              0.122820
volleys              0.117505
balance              0.116588
gk_positioning       0.116035
gk_handling          0.111481
acceleration         0.109991
gk_reflexes          0.108521
positioning          0.108035
```

```
gk_diving             0.108023
jumping               0.103647
dribbling             0.086999
age                   0.083970
curve                 0.080749
gk_kicking            0.079368
sprint_speed          0.075460
long_passing          0.073430
penalties             0.069148
long_shots            0.061820
vision                0.061094
short_passing         0.060972
free_kick_accuracy    0.047318
overall_rating        0.043017
shot_power            0.028401
crossing              0.025229
reactions             0.019854
potential             0.011417
ball_control          0.011066
dtype: float64
=======
Sorted PC3 Loading Scores (abs)
PC3 sorted components:  Index(['overall_rating', 'potential', 'reactions',
 'gk_kicking', 'gk_reflexes',
       'gk_positioning', 'gk_handling', 'age', 'gk_diving', 'strength',
       'weight', 'jumping', 'vision', 'height', 'long_passing', 'penalties
',
       'shot_power', 'long_shots', 'free_kick_accuracy', 'volleys',
       'interceptions', 'short_passing', 'positioning', 'finishing', 'bala
nce',
       'aggression', 'sliding_tackle', 'sprint_speed', 'marking',
       'acceleration', 'curve', 'standing_tackle', 'ball_control', 'stamin
a',
       'agility', 'crossing', 'heading_accuracy', 'dribbling'],
      dtype='object')
overall_rating        0.456070
potential             0.370266
reactions             0.361309
gk_kicking            0.263859
gk_reflexes           0.243520
gk_positioning        0.243479
gk_handling           0.242146
age                   0.232184
gk_diving             0.222118
strength              0.169583
weight                0.150248
jumping               0.133864
vision                0.130572
height                0.128780
long_passing          0.127784
penalties             0.104386
shot_power            0.071653
long_shots            0.066604
free_kick_accuracy    0.062229
volleys               0.062204
interceptions         0.062061
short_passing         0.057178
```

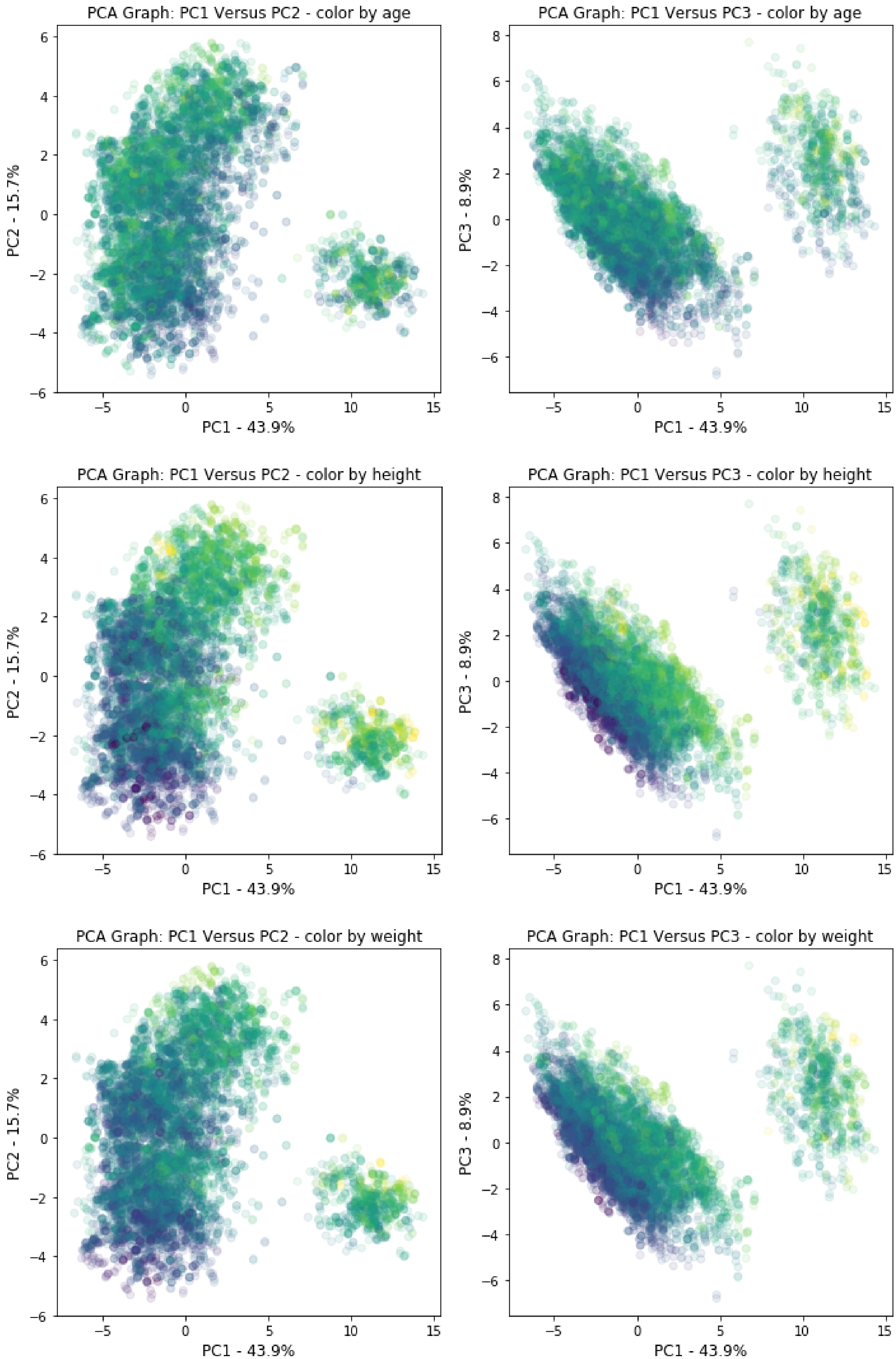
```
positioning          0.056740
finishing            0.054228
balance              0.054159
aggression           0.051947
sliding_tackle       0.038316
sprint_speed         0.036239
marking              0.036117
acceleration         0.033763
curve                0.032351
standing_tackle      0.025389
ball_control         0.020478
stamina              0.017236
agility              0.011974
crossing             0.010881
heading_accuracy     0.006203
dribbling            0.001945
dtype: float64
```

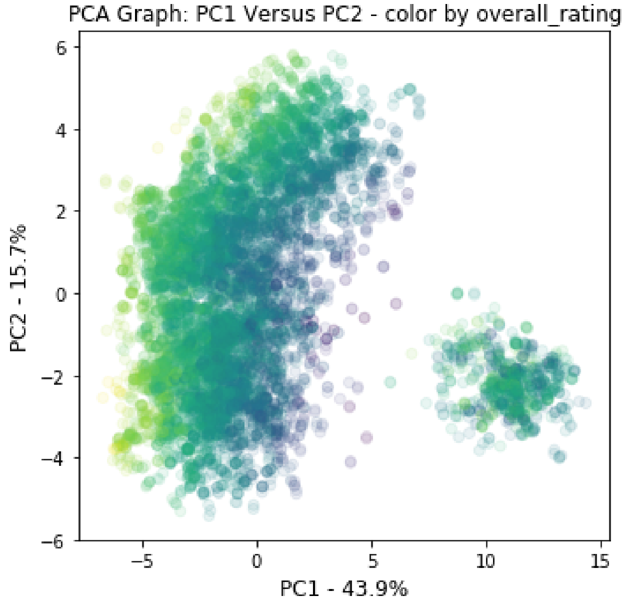
## Present graphs pertinent to the first three principal componets:

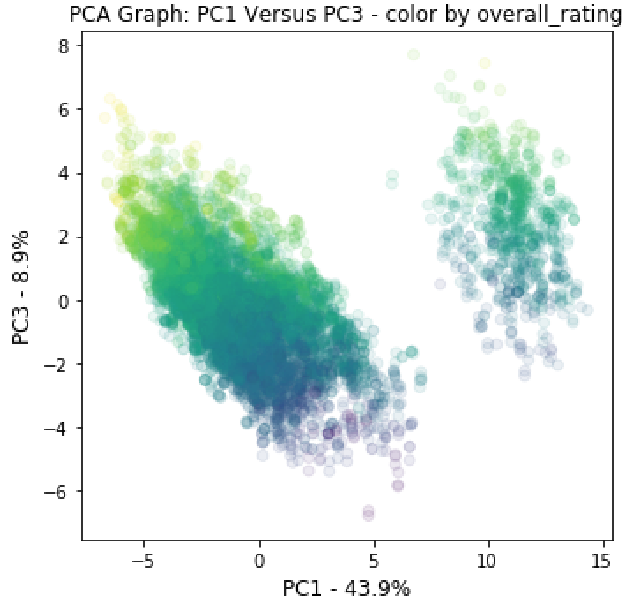
Note: When plotting PC1 versus PC2 AND PC1 versus PC3, two clusters are displayed.

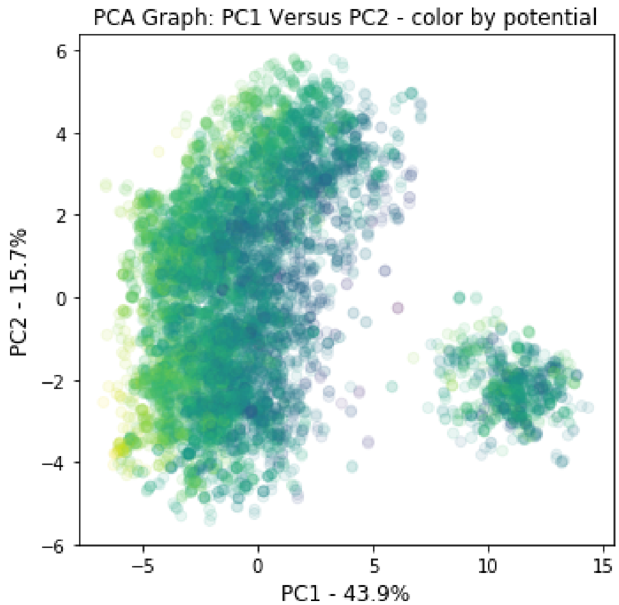
Next, we will visualize further in PC1, PC2 and PC3.

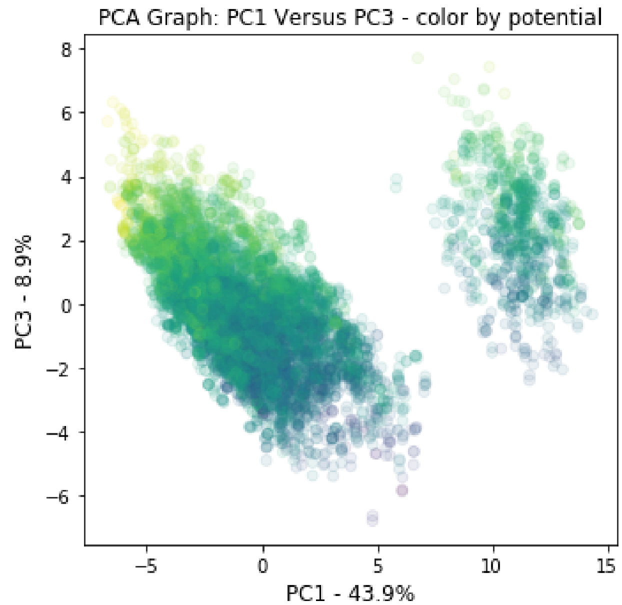
In [13]:
```
# draw PCA 2D plot: PC1 Vs PC2 and PC1 Vs PC3
def color_plot (i):
    plt.figure(figsize=(10, 5))
    plt.subplot(1,2,1)

    plt.scatter(pca_df.PC1, pca_df.PC2, c=scaled_data[:,i], alpha=0.1)
    plt.title("PCA Graph: PC1 Versus PC2 - color by " + numeric_col[i], fo
ntsize='12')
    plt.xlabel('PC1 - {0}%'.format(per_var[0]), fontsize='12')
    plt.ylabel('PC2 - {0}%'.format(per_var[1]), fontsize='12')
    plt.tight_layout()

    plt.subplot(1,2,2)
    plt.scatter(pca_df.PC1, pca_df.PC3, c=scaled_data[:,i], alpha=0.1)
    plt.title("PCA Graph: PC1 Versus PC3 - color by " + numeric_col[i], fo
ntsize='12')
    plt.xlabel('PC1 - {0}%'.format(per_var[0]), fontsize='12')
    plt.ylabel('PC3 - {0}%'.format(per_var[2]), fontsize='12')
    plt.tight_layout()
    plt.show()
    plt.close()

for j in range(0,38):
    color_plot (j)
```

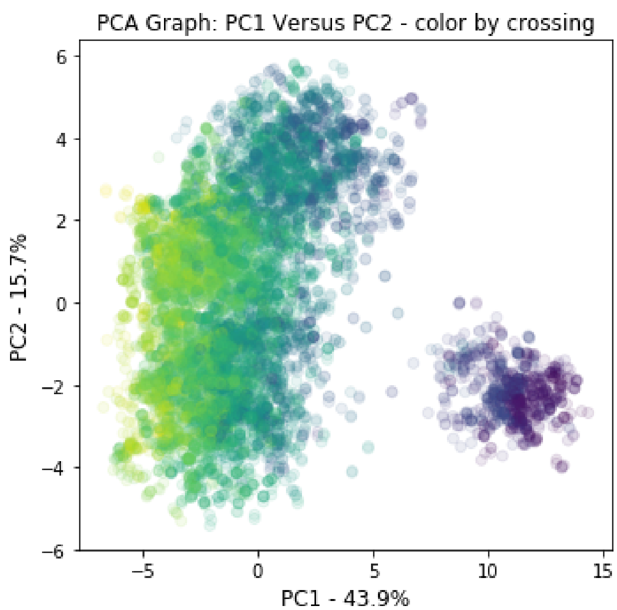

PCA Graph: PC1 Versus PC2 - color by age
PCA Graph: PC1 Versus PC3 - color by age
PCA Graph: PC1 Versus PC2 - color by height
PCA Graph: PC1 Versus PC3 - color by height
PCA Graph: PC1 Versus PC2 - color by weight
PCA Graph: PC1 Versus PC3 - color by weight
PC1 - 43.9%
PC2 - 15.7%
PC3 - 8.9%

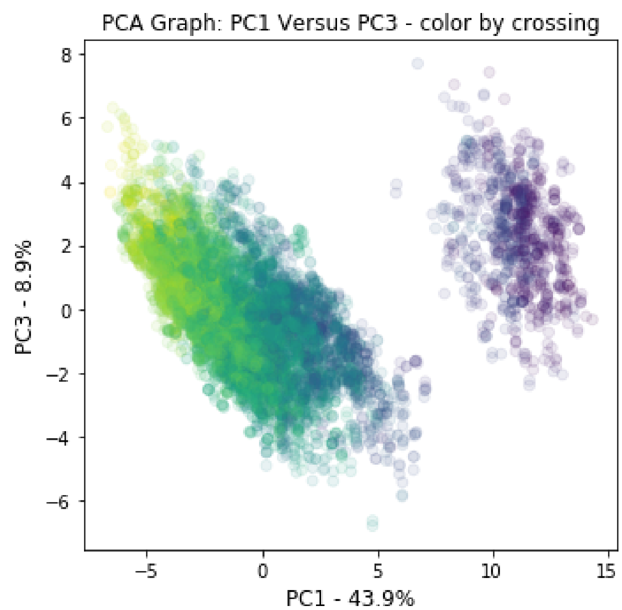

PCA Graph: PC1 Versus PC2 - color by overall_rating
PC2 - 15.7%
PC1 - 43.9%

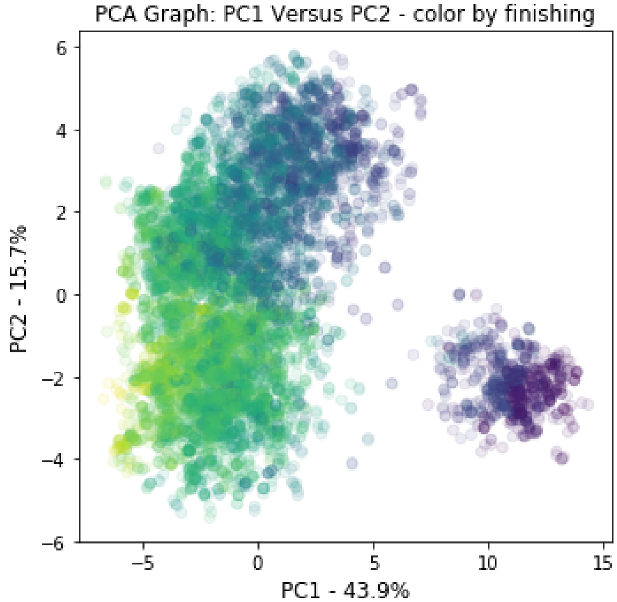

PCA Graph: PC1 Versus PC3 - color by overall_rating
PC3 - 8.9%
PC1 - 43.9%

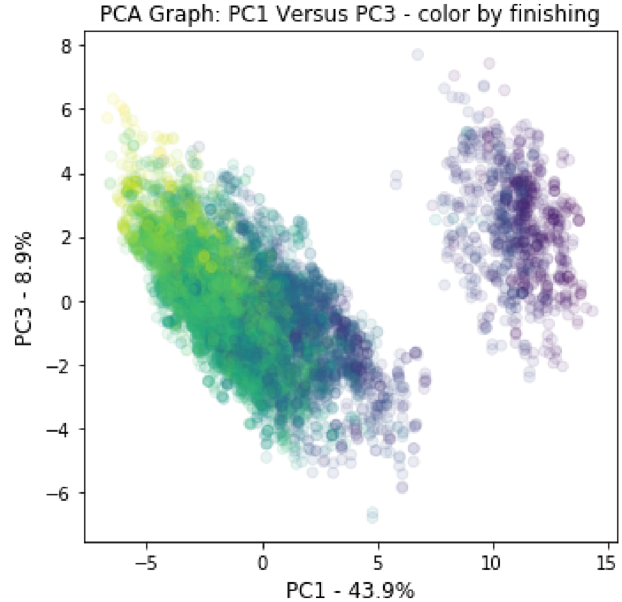

PCA Graph: PC1 Versus PC2 - color by potential
PC2 - 15.7%
PC1 - 43.9%

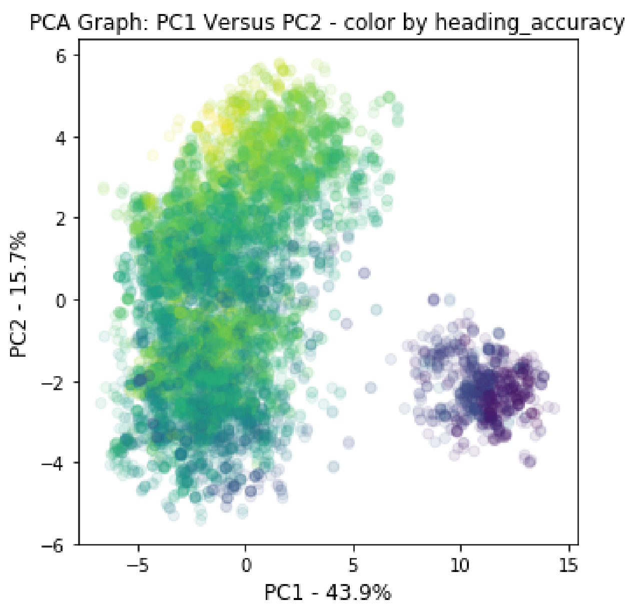

PCA Graph: PC1 Versus PC3 - color by potential
PC3 - 8.9%
PC1 - 43.9%

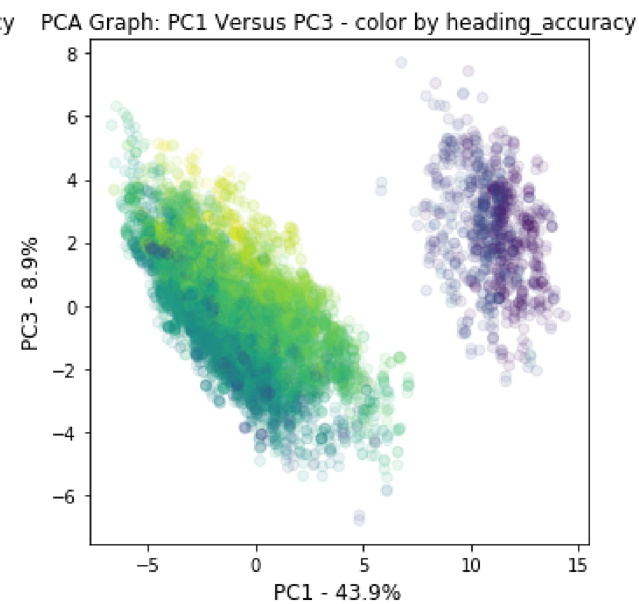

PCA Graph: PC1 Versus PC2 - color by crossing
PC2 - 15.7%
PC1 - 43.9%

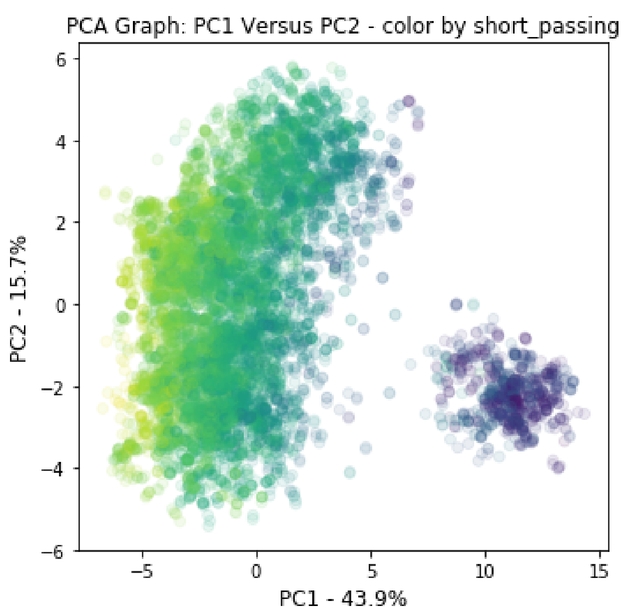

PCA Graph: PC1 Versus PC3 - color by crossing
PC3 - 8.9%
PC1 - 43.9%

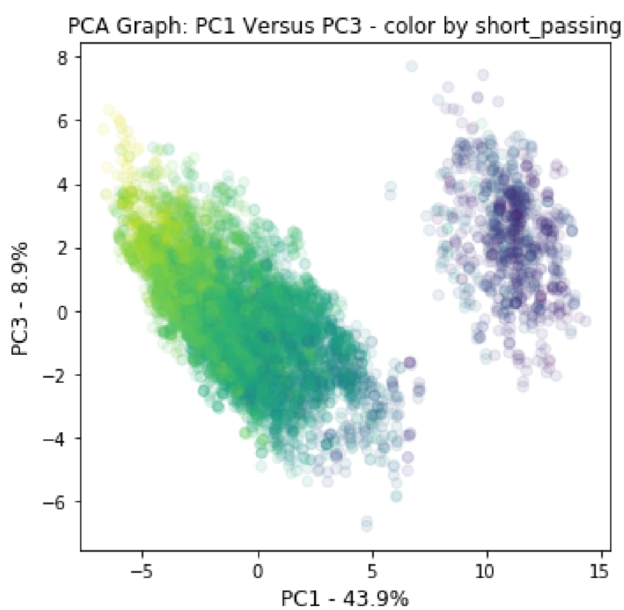

PCA Graph: PC1 Versus PC2 - color by finishing
PC2 - 15.7%
PC1 - 43.9%

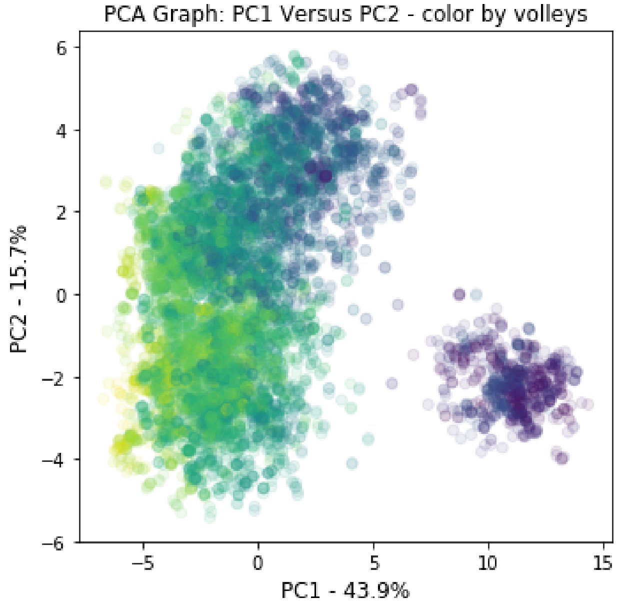

PCA Graph: PC1 Versus PC3 - color by finishing
PC3 - 8.9%
PC1 - 43.9%

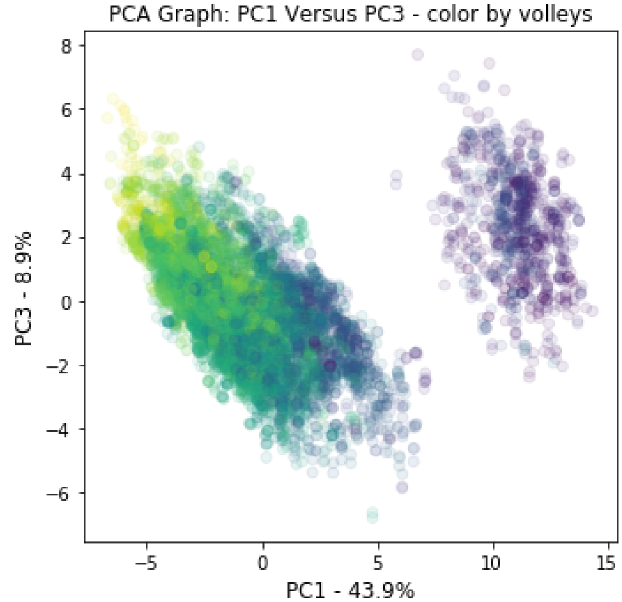

PCA Graph: PC1 Versus PC2 - color by heading_accuracy
PC2 - 15.7%
PC1 - 43.9%

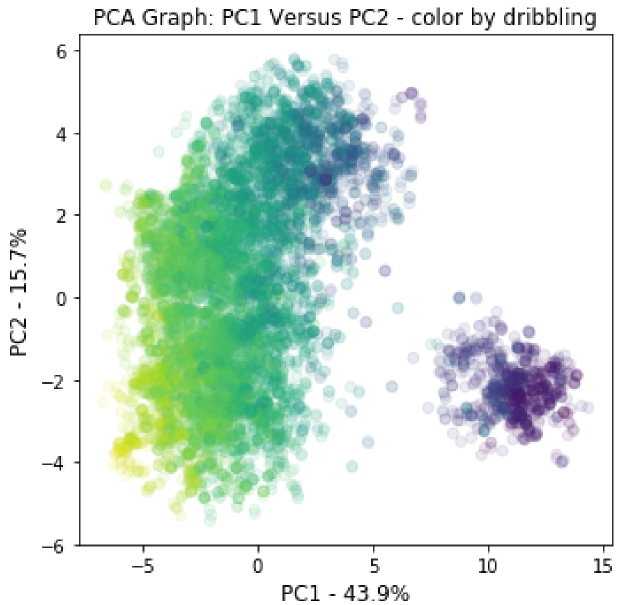

PCA Graph: PC1 Versus PC3 - color by heading_accuracy
PC3 - 8.9%
PC1 - 43.9%

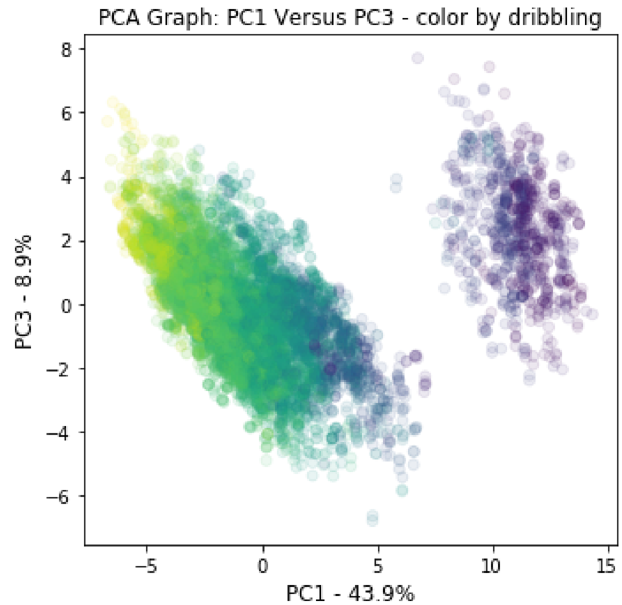

PCA Graph: PC1 Versus PC2 - color by short_passing
PC2 - 15.7%
PC1 - 43.9%

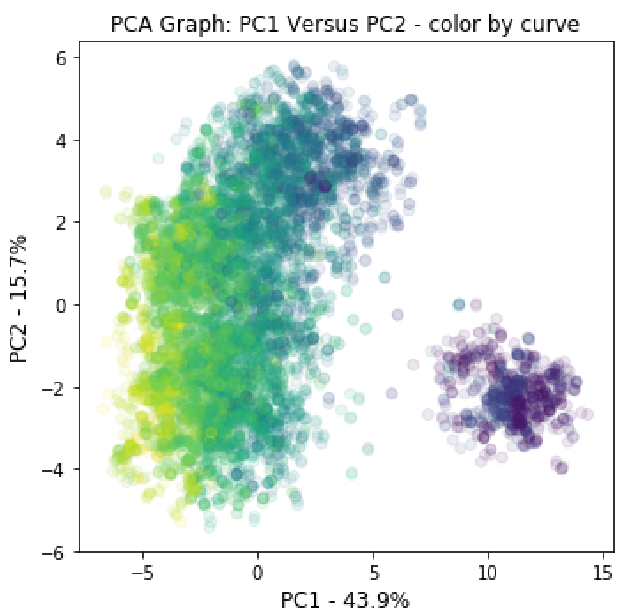

PCA Graph: PC1 Versus PC3 - color by short_passing
PC3 - 8.9%
PC1 - 43.9%

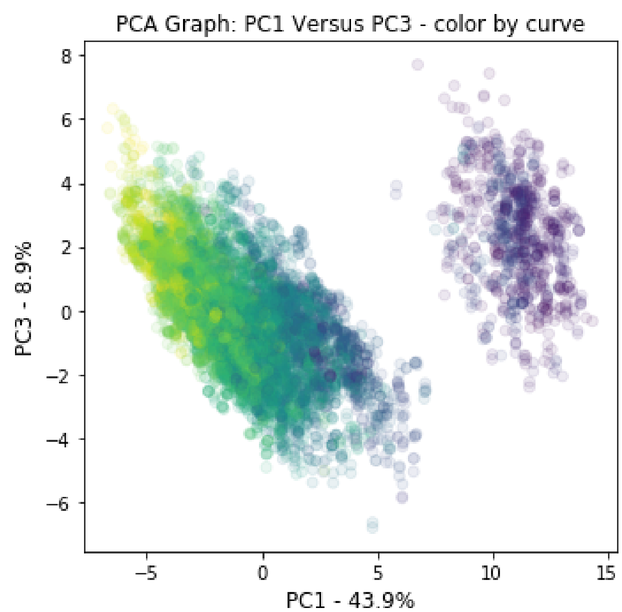

PCA Graph: PC1 Versus PC2 - color by volleys
PC2 - 15.7%
PC1 - 43.9%

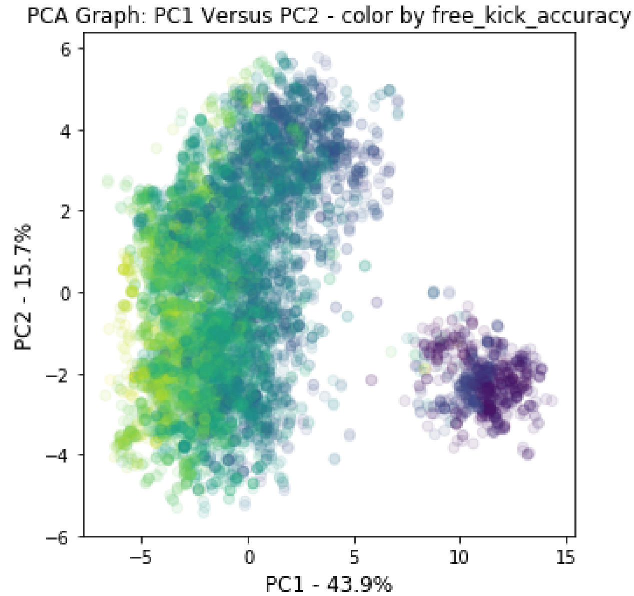

PCA Graph: PC1 Versus PC3 - color by volleys
PC3 - 8.9%
PC1 - 43.9%

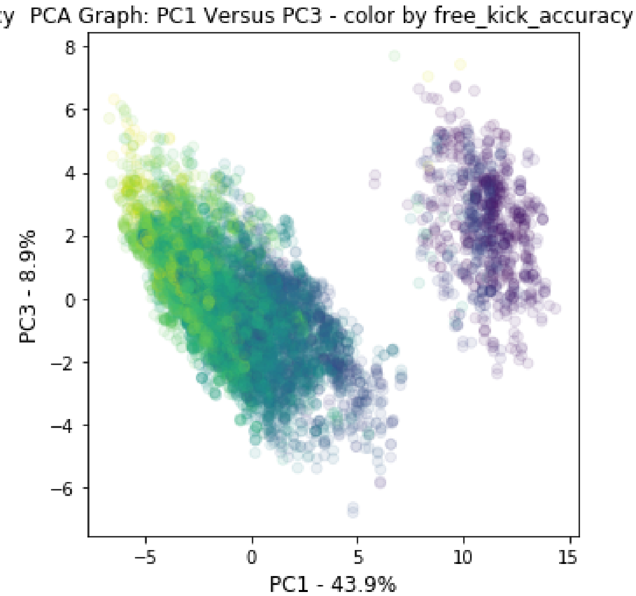

PCA Graph: PC1 Versus PC2 - color by dribbling
PC2 - 15.7%
PC1 - 43.9%

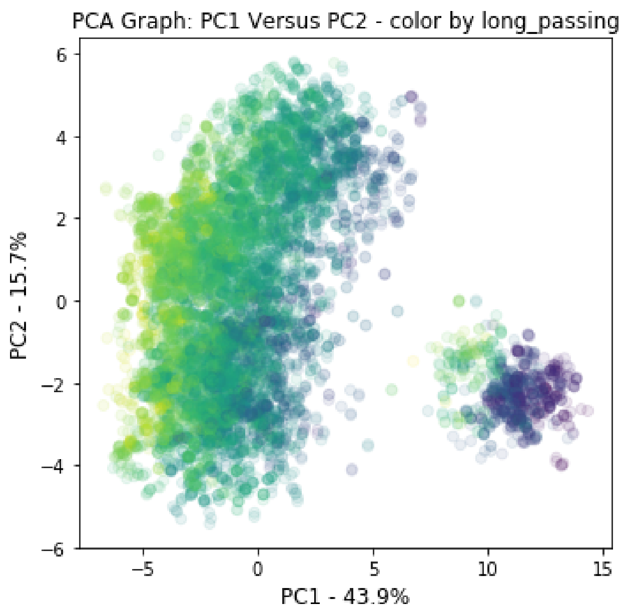

PCA Graph: PC1 Versus PC3 - color by dribbling
PC3 - 8.9%
PC1 - 43.9%

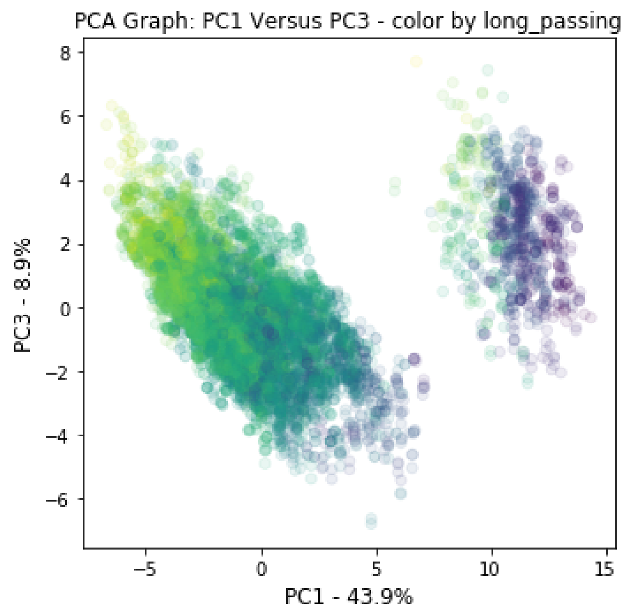

PCA Graph: PC1 Versus PC2 - color by curve
PC2 - 15.7%
PC1 - 43.9%

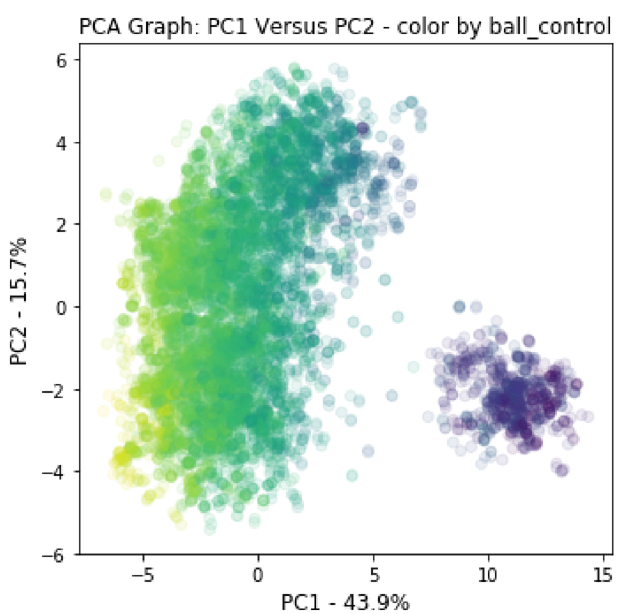

PCA Graph: PC1 Versus PC3 - color by curve
PC3 - 8.9%
PC1 - 43.9%

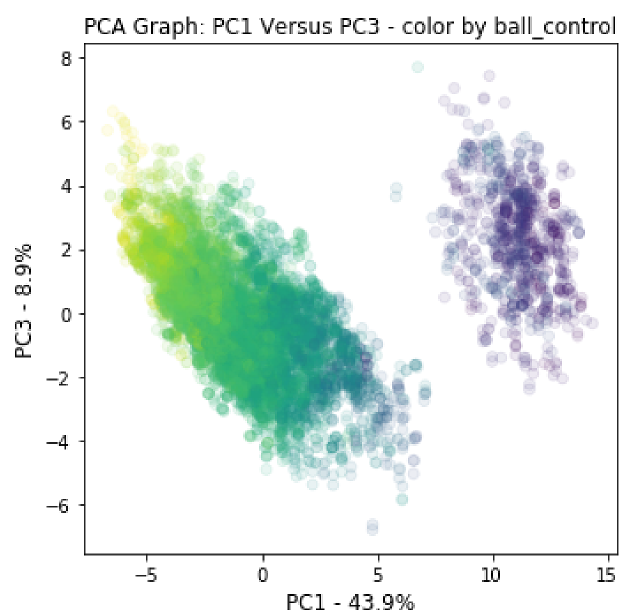

PCA Graph: PC1 Versus PC2 - color by free_kick_accuracy
PC1 - 43.9%
PC2 - 15.7%

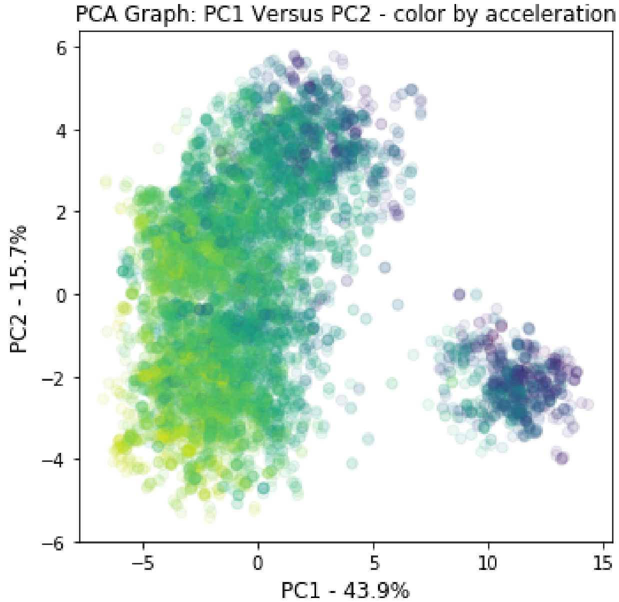

PCA Graph: PC1 Versus PC3 - color by free_kick_accuracy
PC1 - 43.9%
PC3 - 8.9%

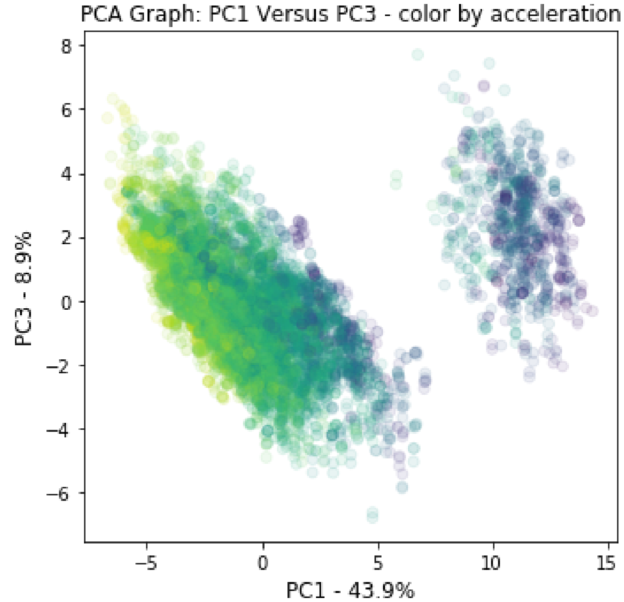

PCA Graph: PC1 Versus PC2 - color by long_passing
PC1 - 43.9%
PC2 - 15.7%

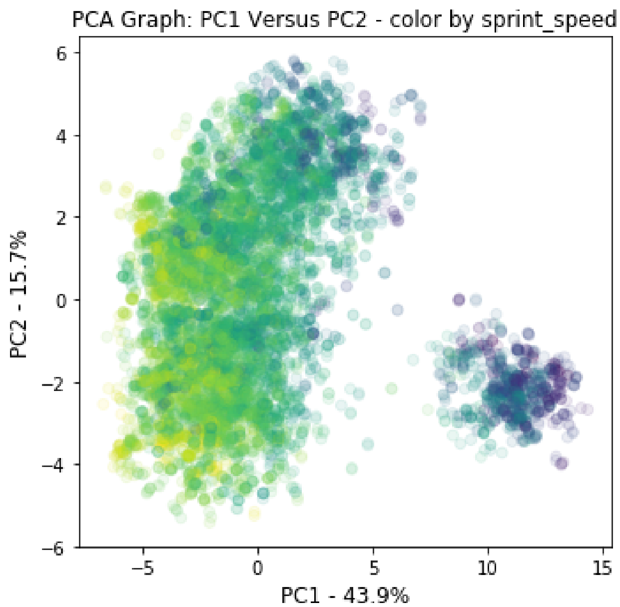

PCA Graph: PC1 Versus PC3 - color by long_passing
PC1 - 43.9%
PC3 - 8.9%

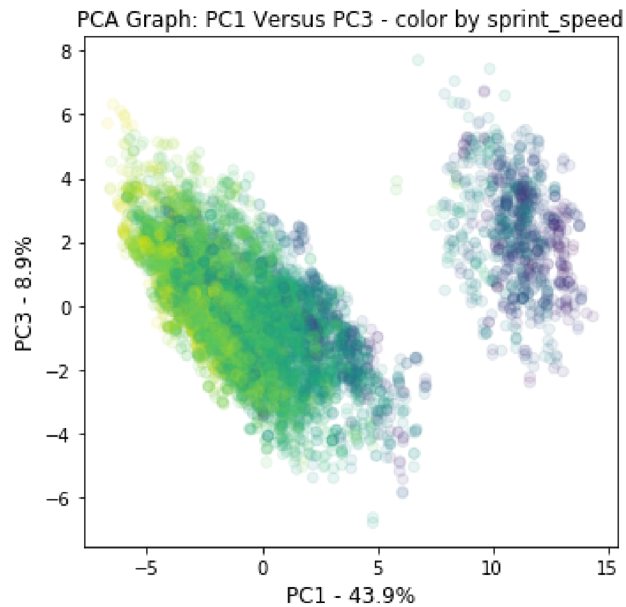

PCA Graph: PC1 Versus PC2 - color by ball_control
PC1 - 43.9%
PC2 - 15.7%

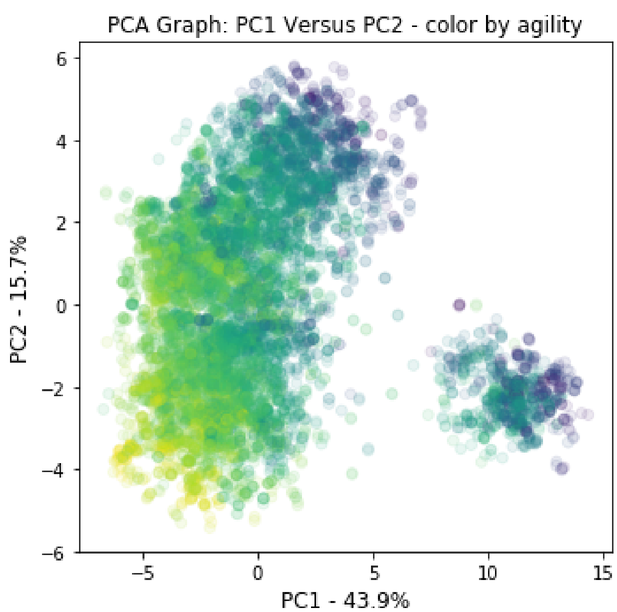

PCA Graph: PC1 Versus PC3 - color by ball_control
PC1 - 43.9%
PC3 - 8.9%

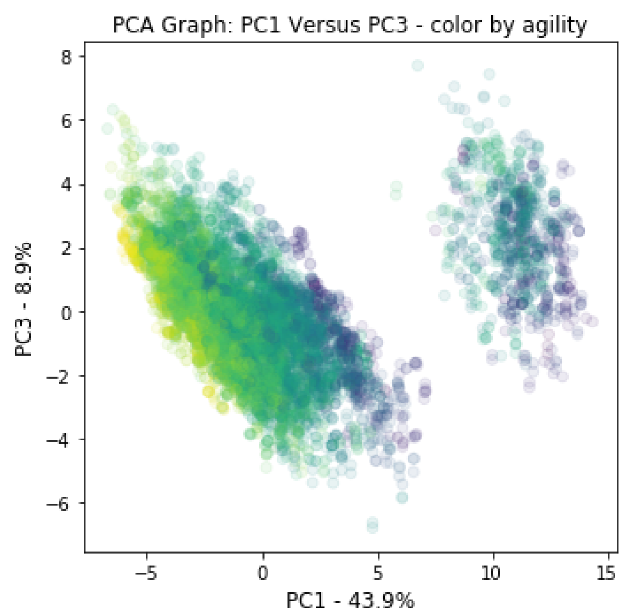

PCA Graph: PC1 Versus PC2 - color by acceleration
PC2 - 15.7%
PC1 - 43.9%

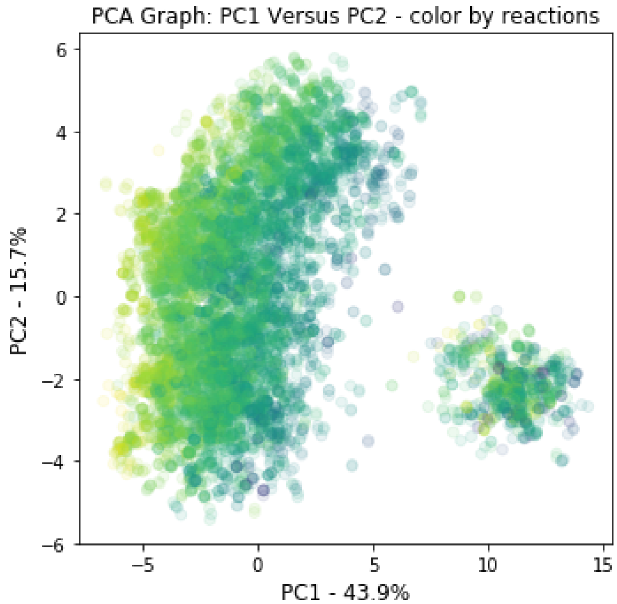

PCA Graph: PC1 Versus PC3 - color by acceleration
PC3 - 8.9%
PC1 - 43.9%

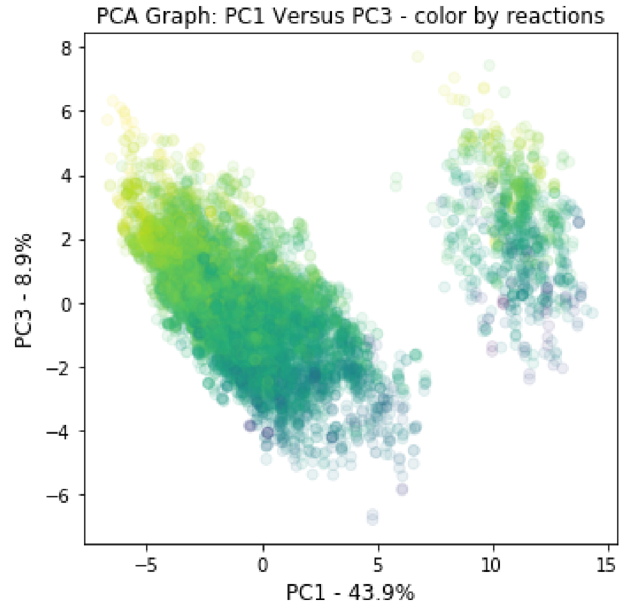

PCA Graph: PC1 Versus PC2 - color by sprint_speed
PC2 - 15.7%
PC1 - 43.9%

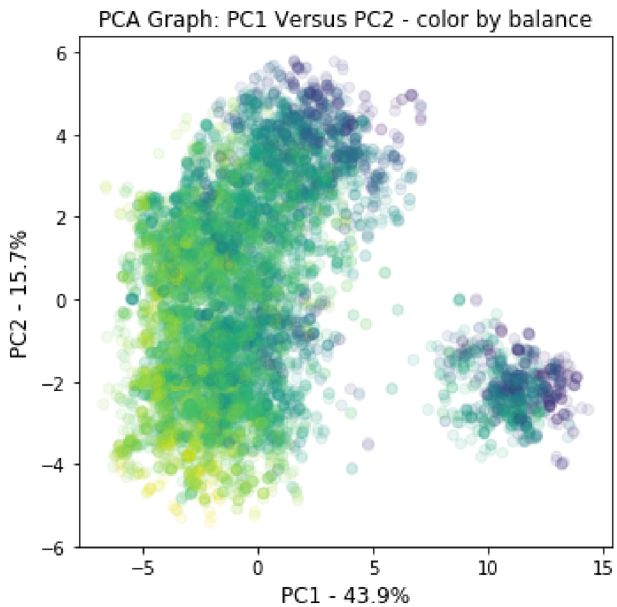

PCA Graph: PC1 Versus PC3 - color by sprint_speed
PC3 - 8.9%
PC1 - 43.9%

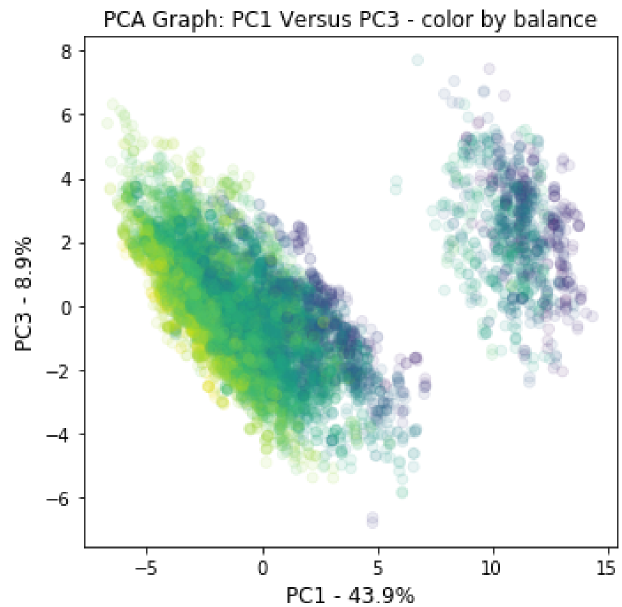

PCA Graph: PC1 Versus PC2 - color by agility
PC2 - 15.7%
PC1 - 43.9%

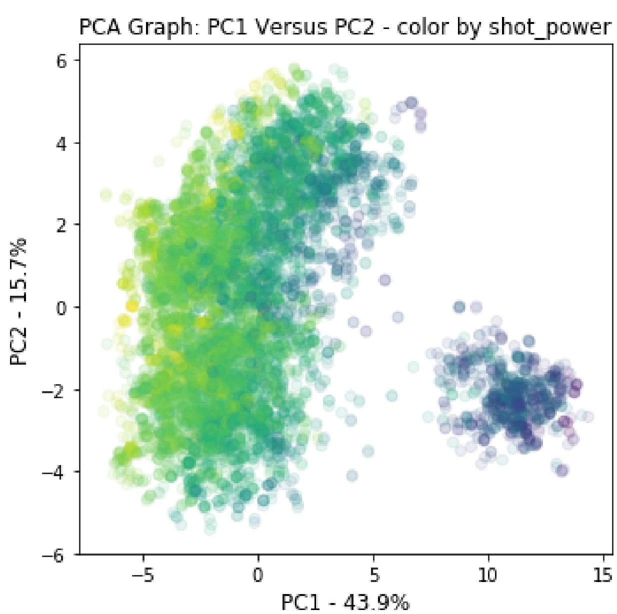

PCA Graph: PC1 Versus PC3 - color by agility
PC3 - 8.9%
PC1 - 43.9%

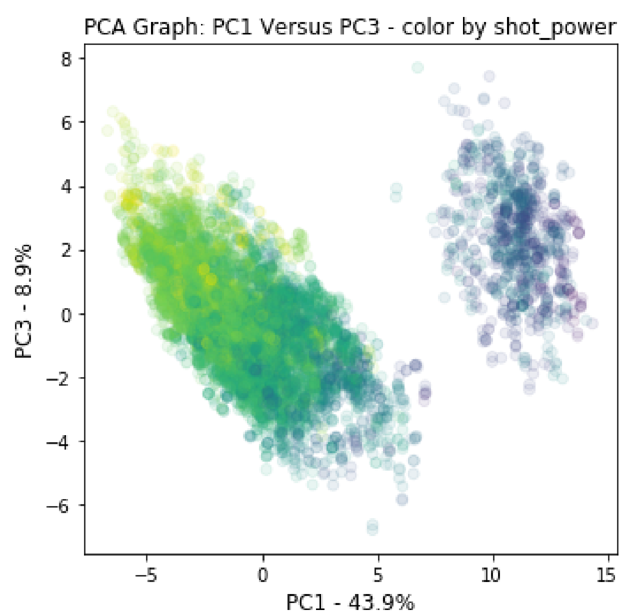

PCA Graph: PC1 Versus PC2 - color by reactions
PC2 - 15.7%
PC1 - 43.9%

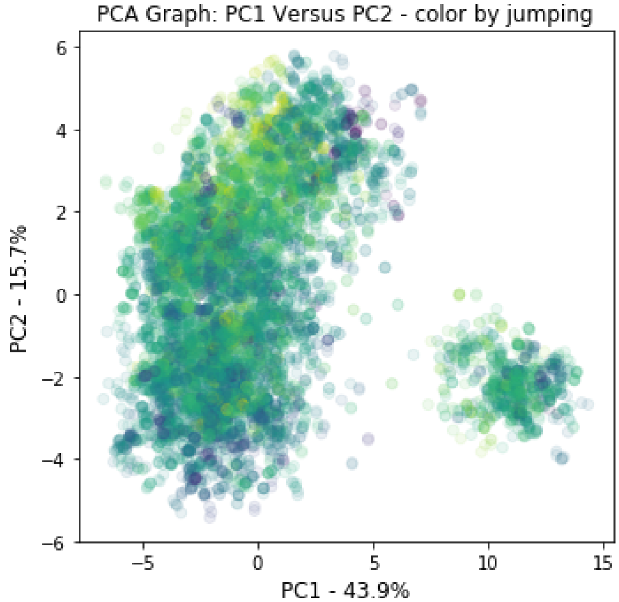

PCA Graph: PC1 Versus PC3 - color by reactions
PC3 - 8.9%
PC1 - 43.9%

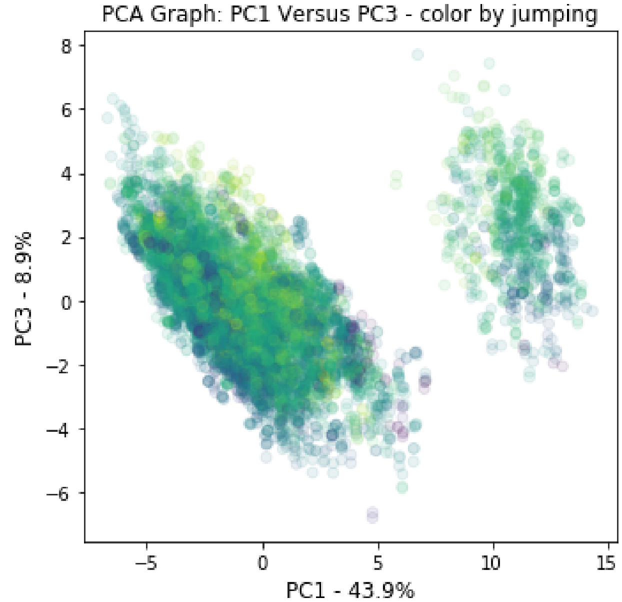

PCA Graph: PC1 Versus PC2 - color by balance
PC2 - 15.7%
PC1 - 43.9%

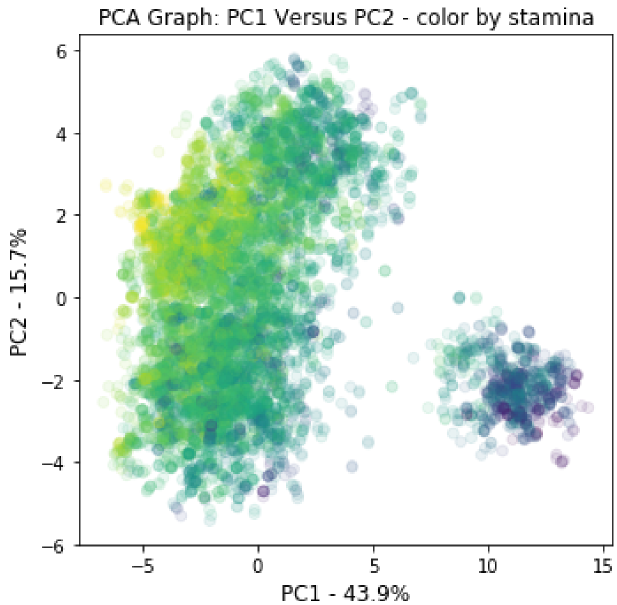

PCA Graph: PC1 Versus PC3 - color by balance
PC3 - 8.9%
PC1 - 43.9%

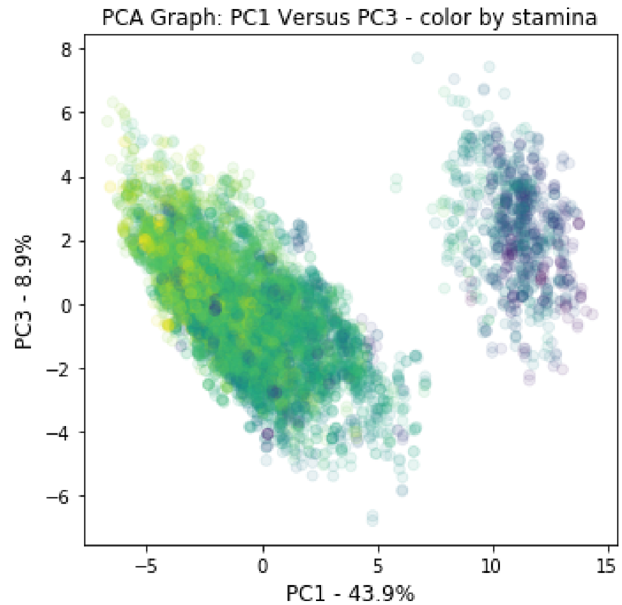

PCA Graph: PC1 Versus PC2 - color by shot_power
PC2 - 15.7%
PC1 - 43.9%

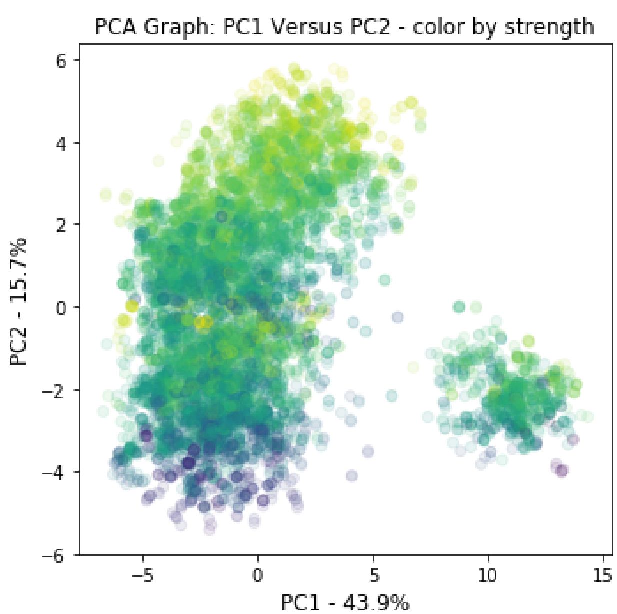

PCA Graph: PC1 Versus PC3 - color by shot_power
PC3 - 8.9%
PC1 - 43.9%

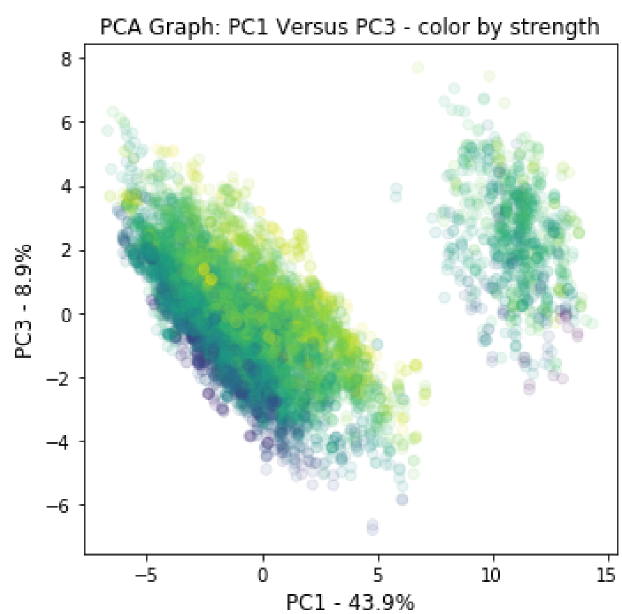

PCA Graph: PC1 Versus PC2 - color by jumping
PC2 - 15.7%
PC1 - 43.9%
6
4
2
0
−2
−4
−6
−5
0
5
10
15

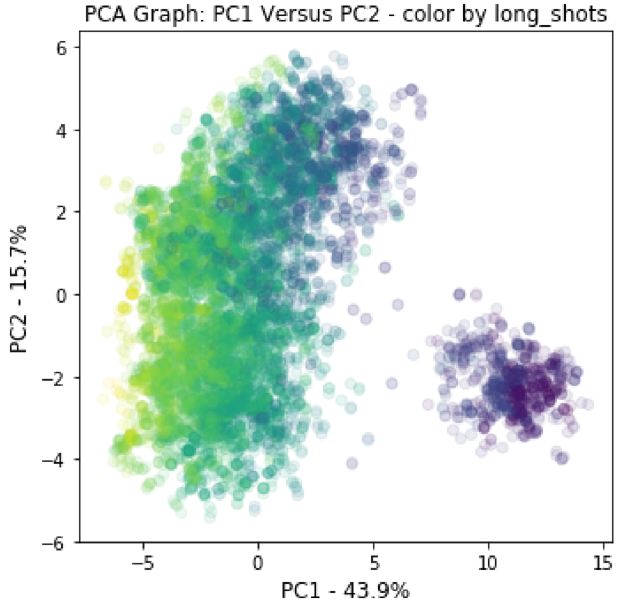

PCA Graph: PC1 Versus PC3 - color by jumping
PC3 - 8.9%
PC1 - 43.9%
8
6
4
2
0
−2
−4
−6
−5
0
5
10
15

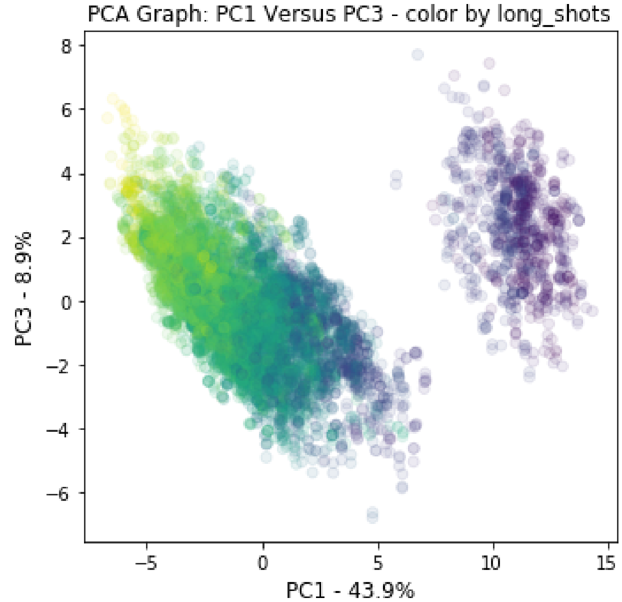

PCA Graph: PC1 Versus PC2 - color by stamina
PC2 - 15.7%
PC1 - 43.9%
6
4
2
0
−2
−4
−6
−5
0
5
10
15

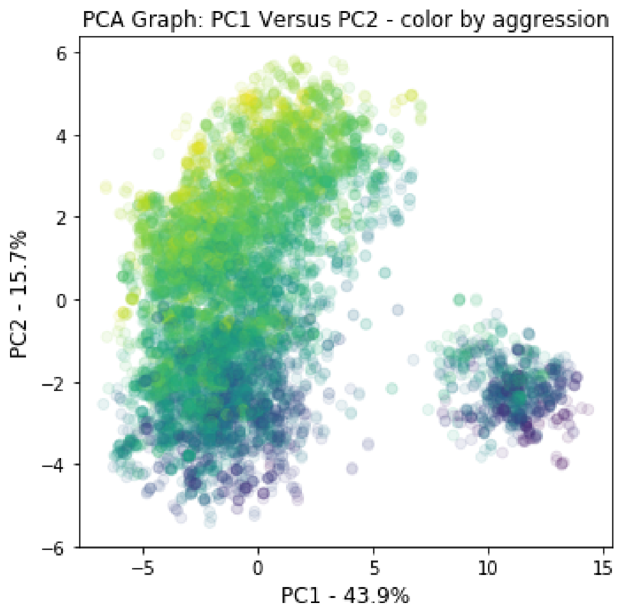

PCA Graph: PC1 Versus PC3 - color by stamina
PC3 - 8.9%
PC1 - 43.9%
8
6
4
2
0
−2
−4
−6
−5
0
5
10
15

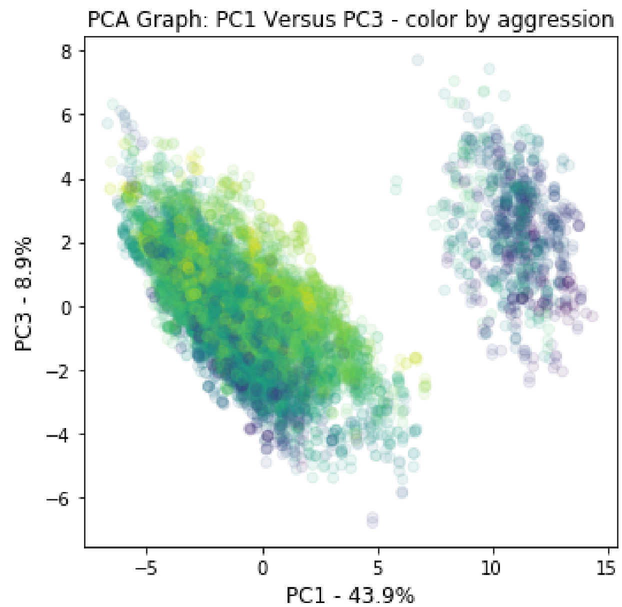

PCA Graph: PC1 Versus PC2 - color by strength
PC2 - 15.7%
PC1 - 43.9%
6
4
2
0
−2
−4
−6
−5
0
5
10
15

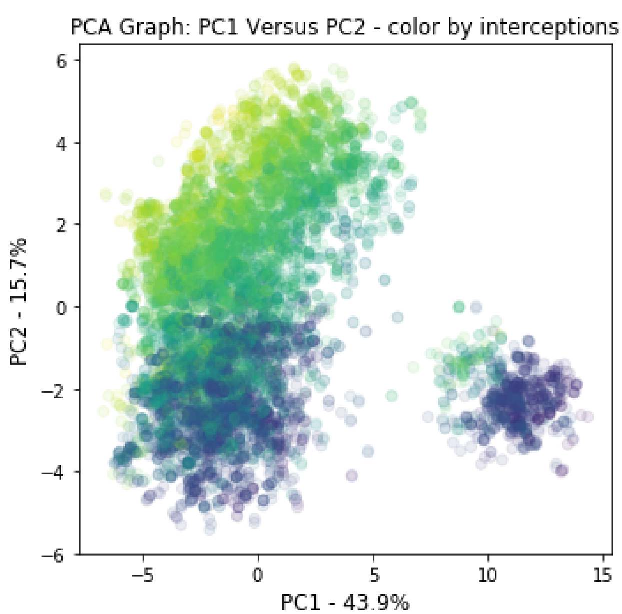

PCA Graph: PC1 Versus PC3 - color by strength
PC3 - 8.9%
PC1 - 43.9%
8
6
4
2
0
−2
−4
−6
−5
0
5
10
15

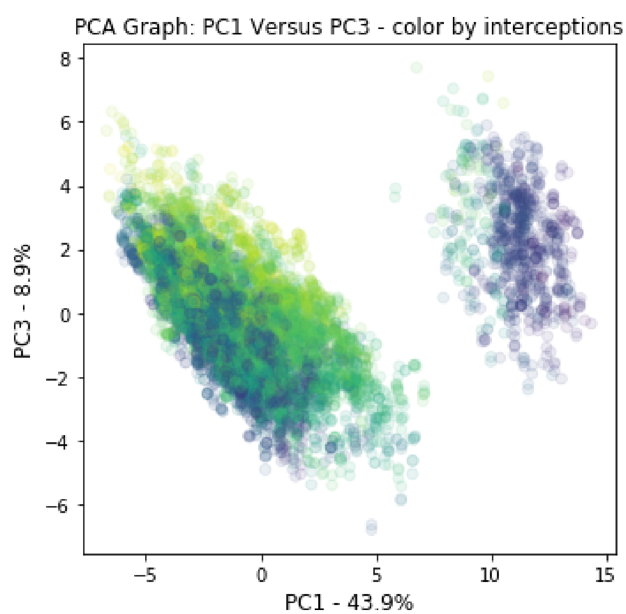

PCA Graph: PC1 Versus PC2 - color by long_shots
PC2 - 15.7%
PC1 - 43.9%

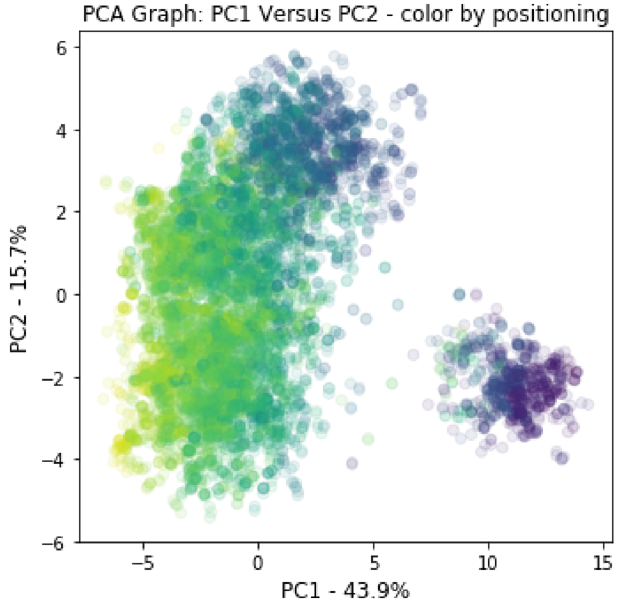

PCA Graph: PC1 Versus PC3 - color by long_shots
PC3 - 8.9%
PC1 - 43.9%

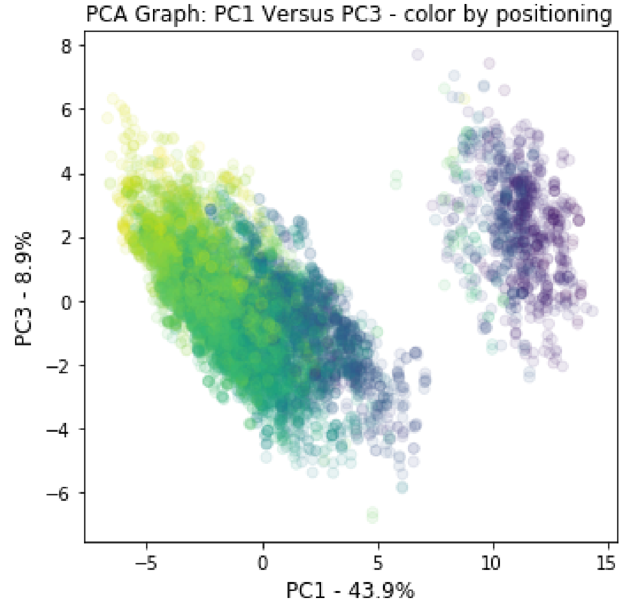

PCA Graph: PC1 Versus PC2 - color by aggression
PC2 - 15.7%
PC1 - 43.9%

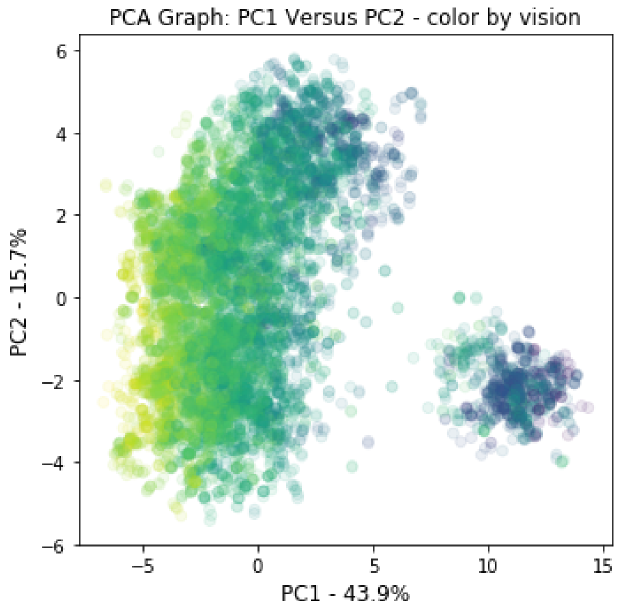

PCA Graph: PC1 Versus PC3 - color by aggression
PC3 - 8.9%
PC1 - 43.9%

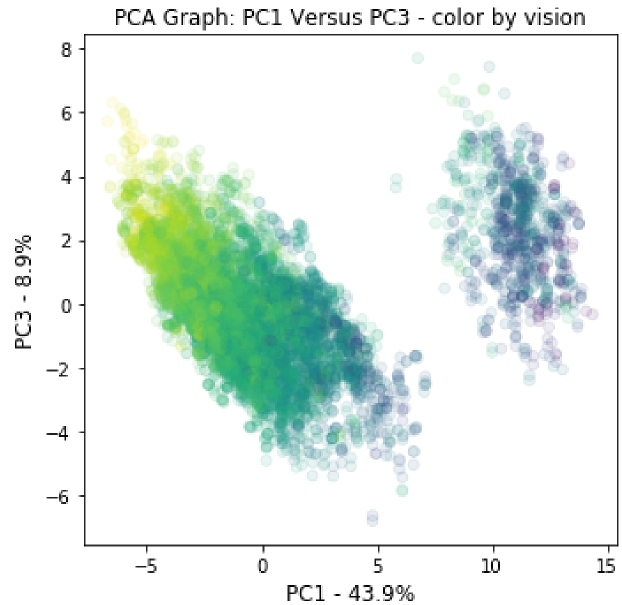

PCA Graph: PC1 Versus PC2 - color by interceptions
PC2 - 15.7%
PC1 - 43.9%

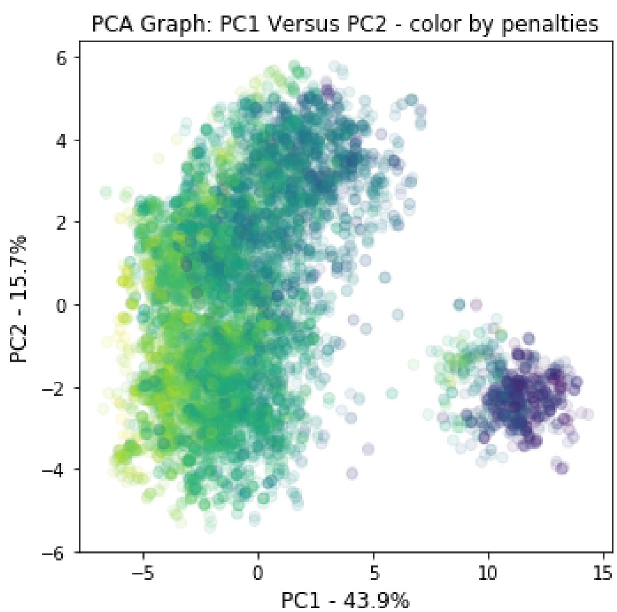

PCA Graph: PC1 Versus PC3 - color by interceptions
PC3 - 8.9%
PC1 - 43.9%

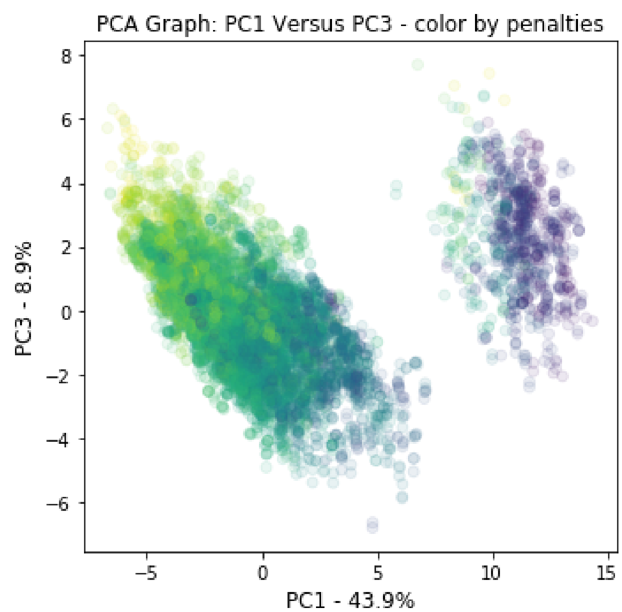

PCA Graph: PC1 Versus PC2 - color by positioning
PC2 - 15.7%
PC1 - 43.9%

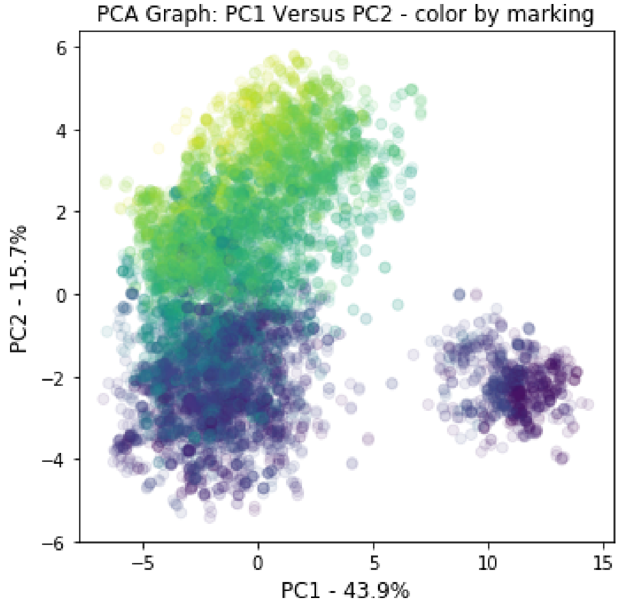

PCA Graph: PC1 Versus PC3 - color by positioning
PC3 - 8.9%
PC1 - 43.9%

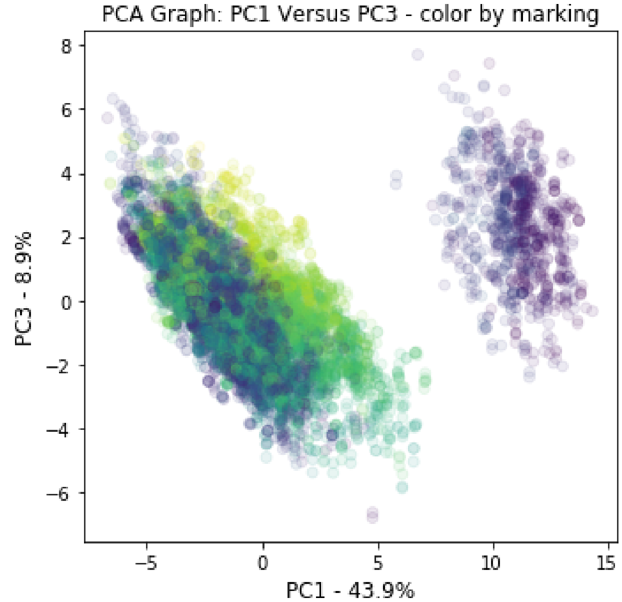

PCA Graph: PC1 Versus PC2 - color by vision
PC2 - 15.7%
PC1 - 43.9%

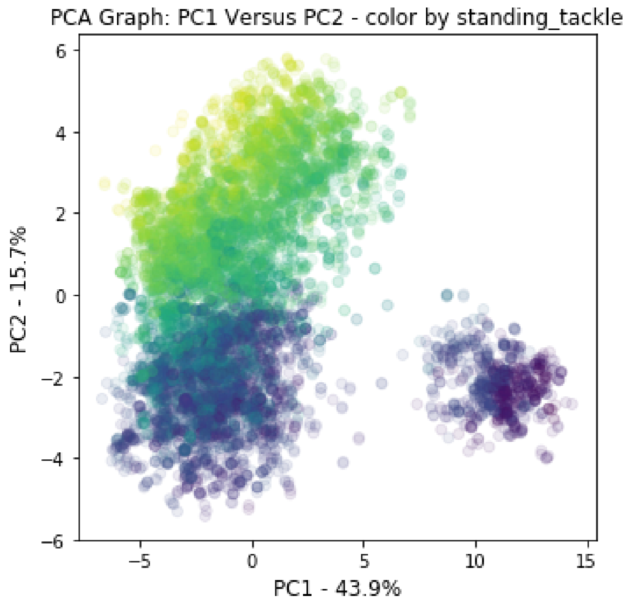

PCA Graph: PC1 Versus PC3 - color by vision
PC3 - 8.9%
PC1 - 43.9%

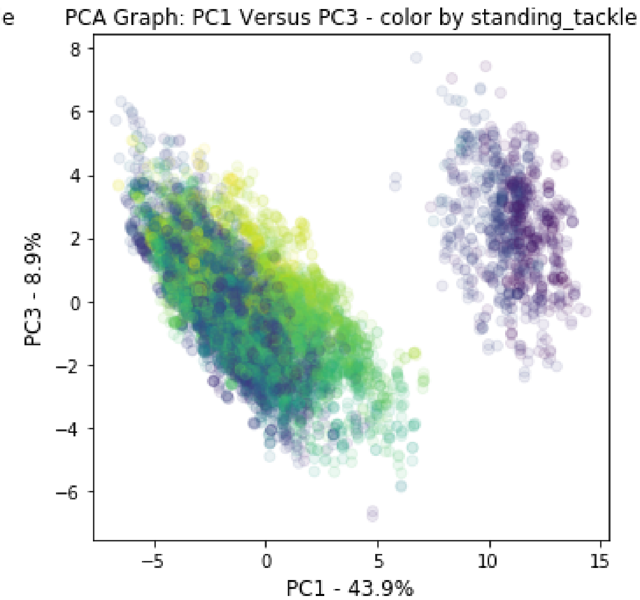

PCA Graph: PC1 Versus PC2 - color by penalties
PC2 - 15.7%
PC1 - 43.9%

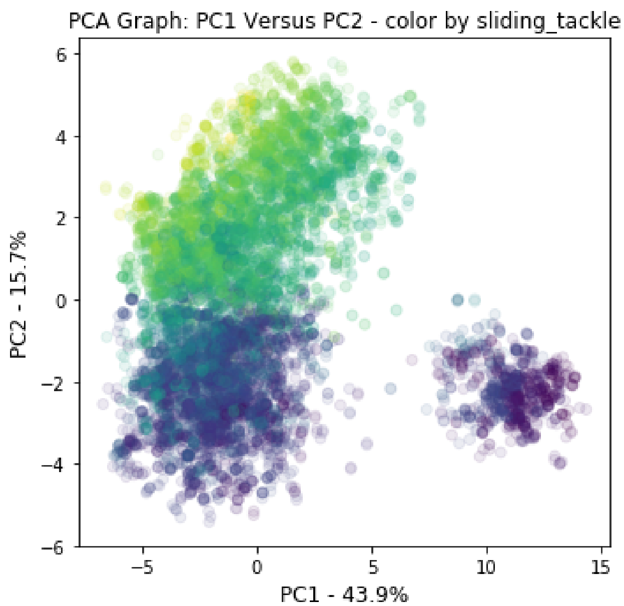

PCA Graph: PC1 Versus PC3 - color by penalties
PC3 - 8.9%
PC1 - 43.9%

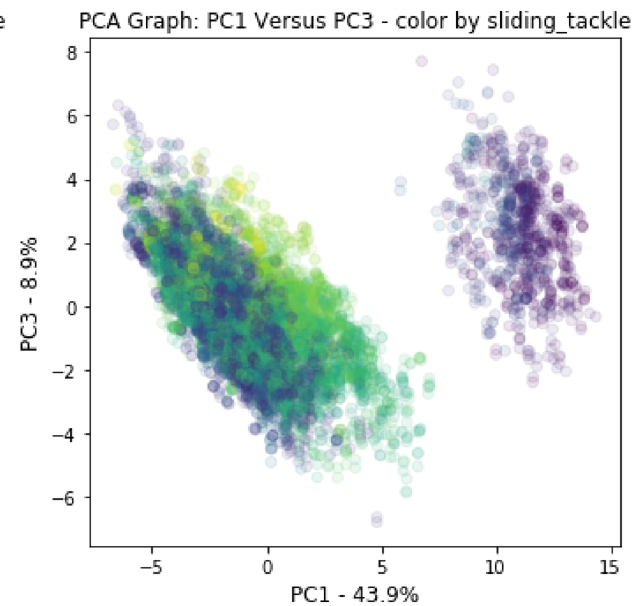

PCA Graph: PC1 Versus PC2 - color by marking
PC2 - 15.7%
PC1 - 43.9%

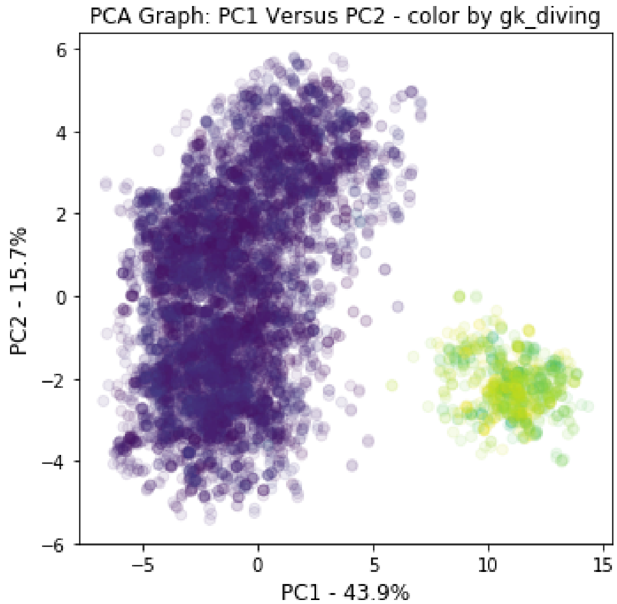

PCA Graph: PC1 Versus PC3 - color by marking
PC3 - 8.9%
PC1 - 43.9%

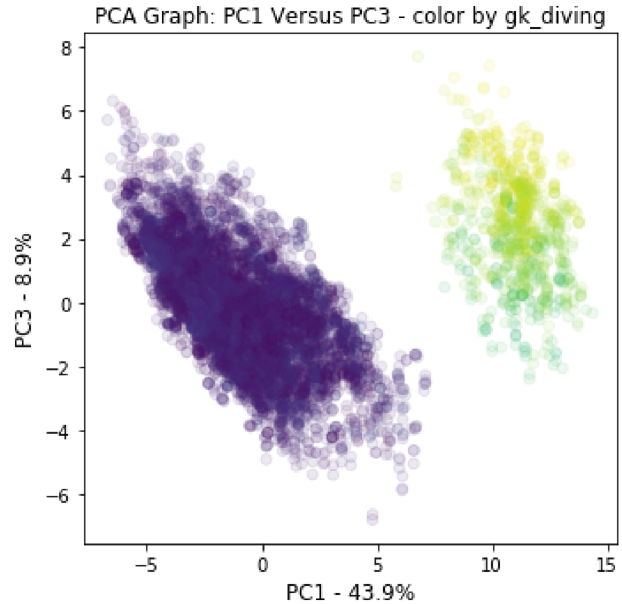

PCA Graph: PC1 Versus PC2 - color by standing_tackle
PC2 - 15.7%
PC1 - 43.9%

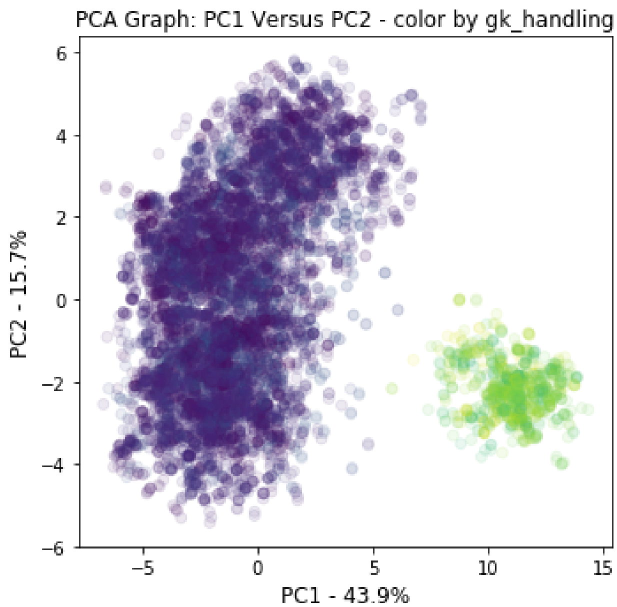

PCA Graph: PC1 Versus PC3 - color by standing_tackle
PC3 - 8.9%
PC1 - 43.9%

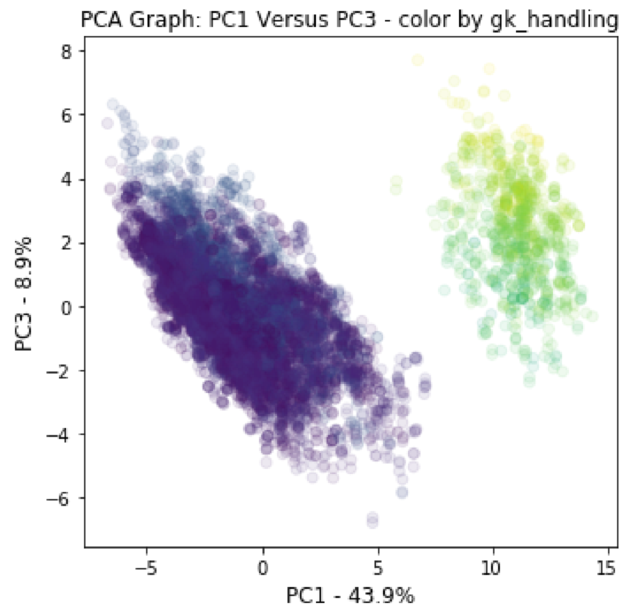

PCA Graph: PC1 Versus PC2 - color by sliding_tackle
PC2 - 15.7%
PC1 - 43.9%

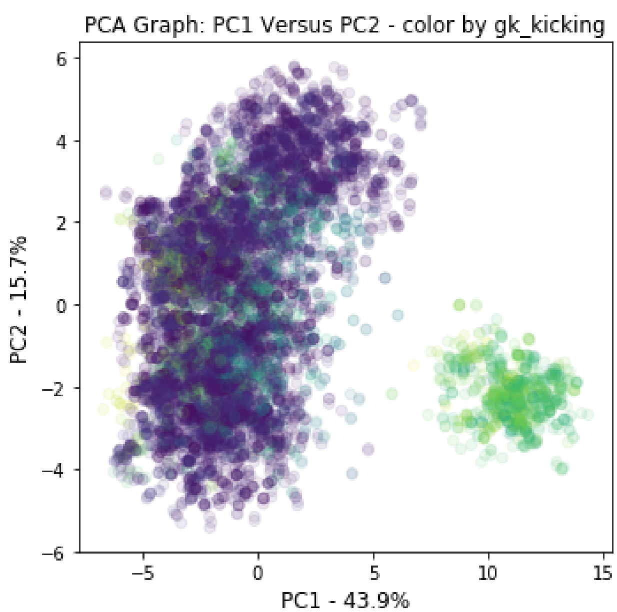

PCA Graph: PC1 Versus PC3 - color by sliding_tackle
PC3 - 8.9%
PC1 - 43.9%

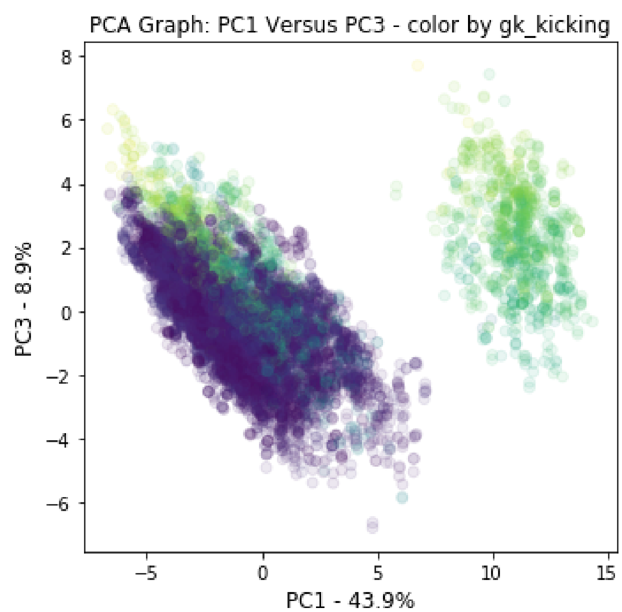

PCA Graph: PC1 Versus PC2 - color by gk_diving
PC2 - 15.7%
PC1 - 43.9%

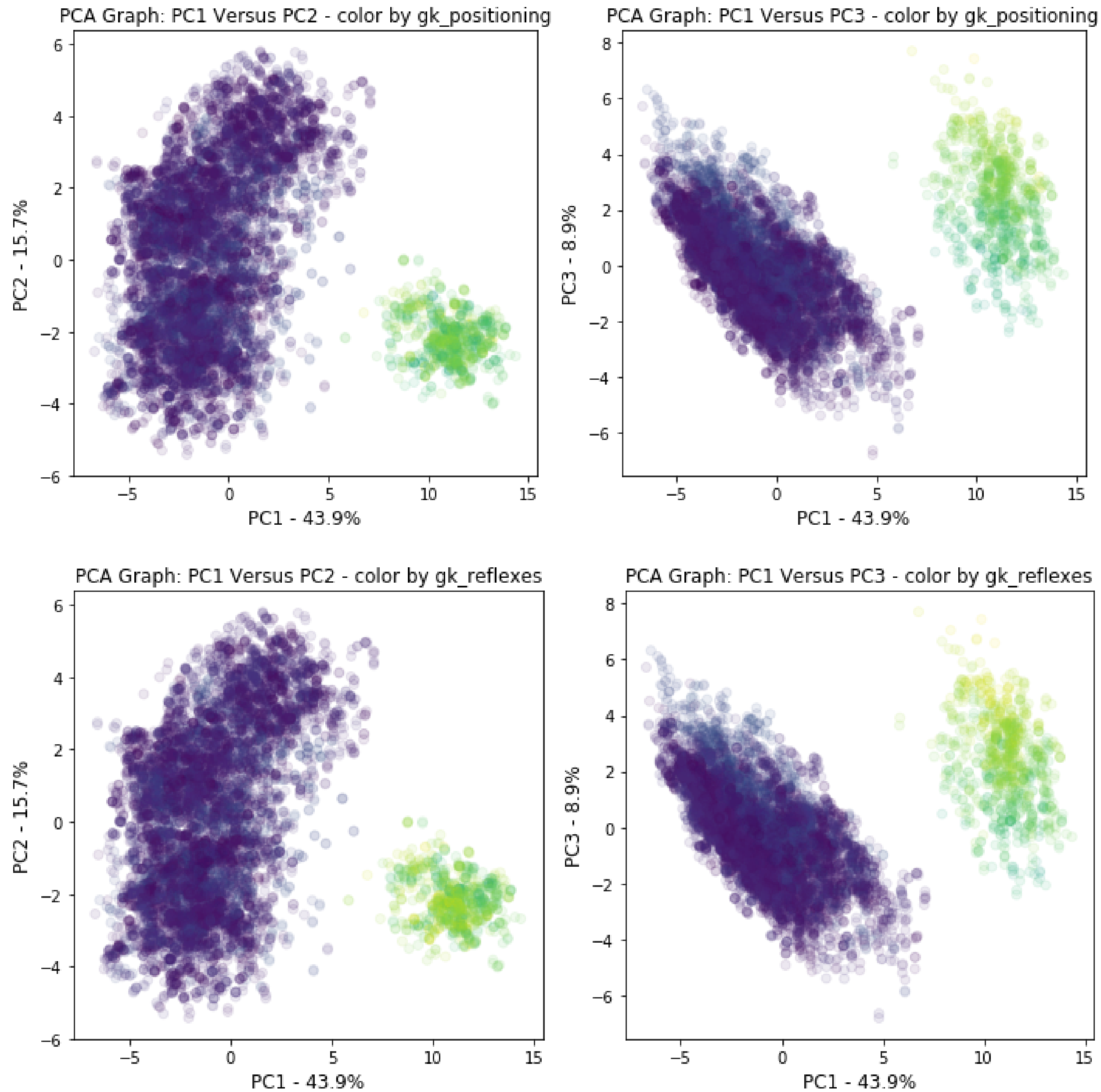

PCA Graph: PC1 Versus PC3 - color by gk_diving
PC3 - 8.9%
PC1 - 43.9%


PCA Graph: PC1 Versus PC2 - color by gk_handling
PC2 - 15.7%
PC1 - 43.9%


PCA Graph: PC1 Versus PC3 - color by gk_handling
PC3 - 8.9%
PC1 - 43.9%


PCA Graph: PC1 Versus PC2 - color by gk_kicking
PC2 - 15.7%
PC1 - 43.9%


PCA Graph: PC1 Versus PC3 - color by gk_kicking
PC3 - 8.9%
PC1 - 43.9%

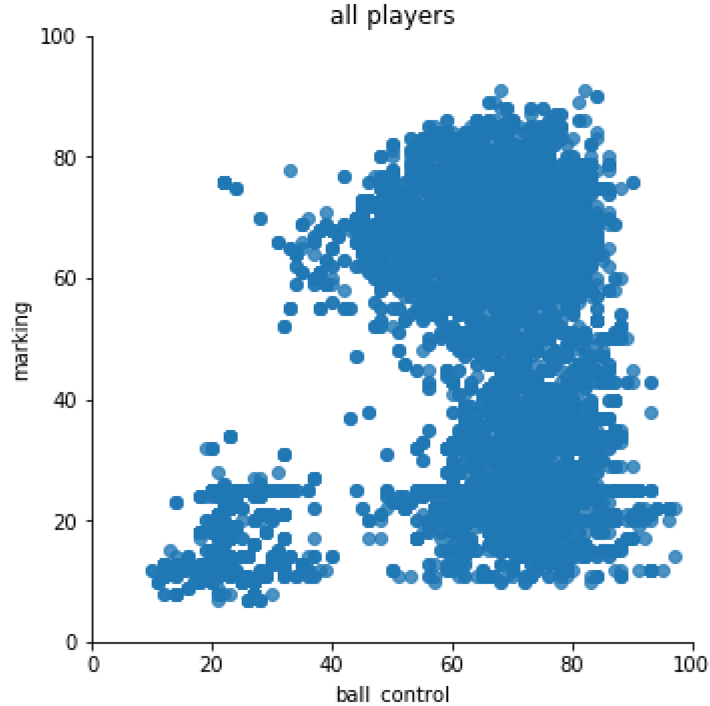


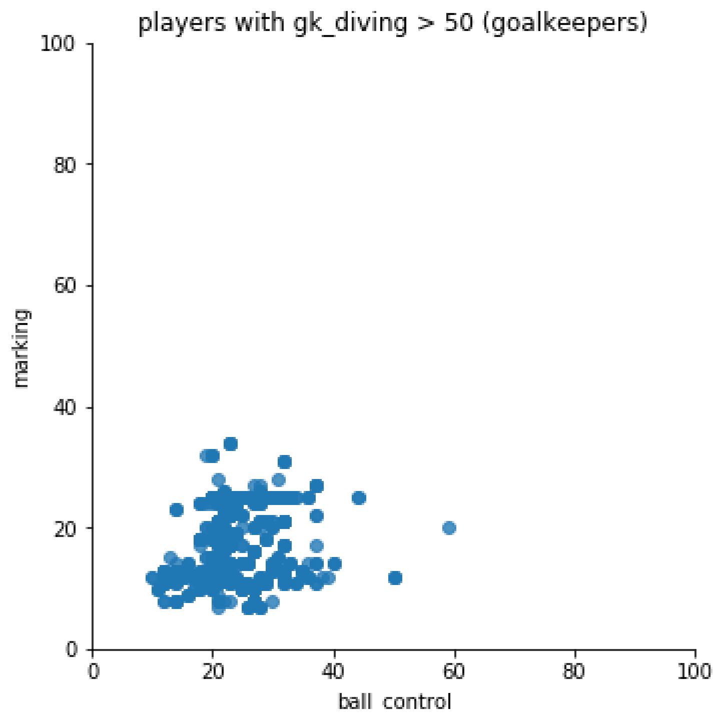

In [8]:
```
#'attacking_work_rate', 'defensive_work_rate']
#plt.title('players with gk_diving > 50 (goalkeepers)')
# create scatter plot with ball control (highest loading score in PC1) against marking (highest loading score in PC2)
def plot (df_all, df_sub, hue_col):
    # first plot
    vis1=sns.lmplot(x='ball_control', y='marking',  hue=hue_col, sharex=False, data=df_all, scatter=True, fit_reg=False, units=None, order=1, legend=True)
    plt.title('all players')
    plt.xlim(0,100)
    plt.ylim(0,100)
    plt.show()
    plt.close()
    # second plot: goalkeepers only
    vis2=sns.lmplot(x='ball_control', y='marking',  hue=hue_col, sharex=False, data=df_sub, scatter=True, fit_reg=False, units=None, order=1, legend=True)
```

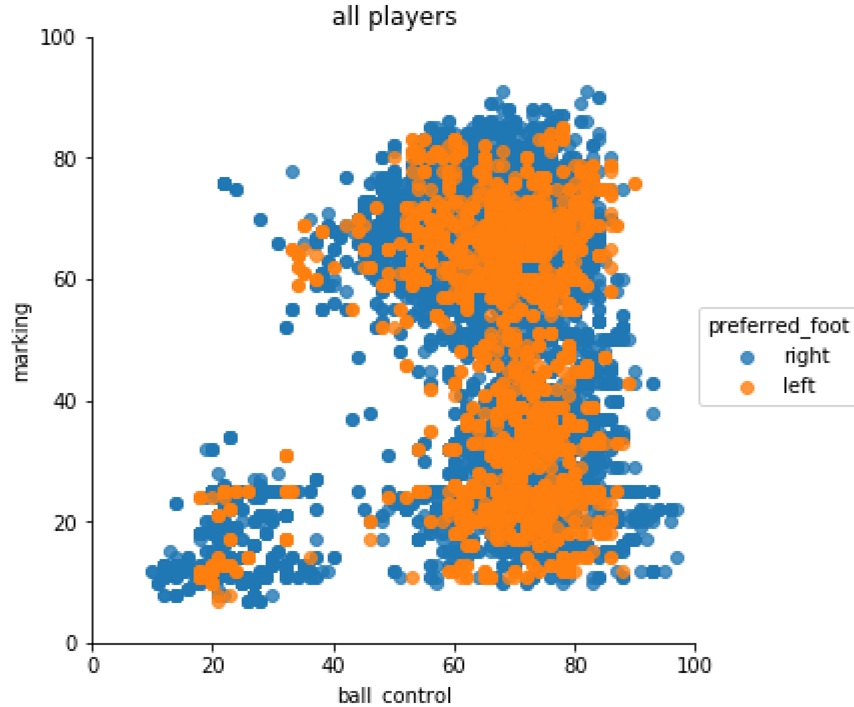
```
    plt.title('players with gk_diving > 50 (goalkeepers)')
    plt.xlim(0,100)
    plt.ylim(0,100)
    plt.show()
    plt.close()

print('gk_diving > 50 (goalkeepers)')
df_goalkeepers=df_all_col.loc[df_all_col['gk_diving']>50]
#print(df_goalkeepers.head())
plot(df_all_col, df_goalkeepers, None)

# color by lefty and righty
plot(df_all_col, df_goalkeepers, 'preferred_foot')
# plot lefty only
print('plot preferred left foot')
df1=df_all_col.loc[df_all_col['preferred_foot']=='left']
df2=df_goalkeepers.loc[df_goalkeepers['preferred_foot']=='left']
plot(df1,df2,None)

# color by 'attaching_work_rate'
df3=df_all_col[df_all_col['attacking_work_rate'].isin (['low','medium','hi
gh'])]
df4=df_goalkeepers[df_goalkeepers['attacking_work_rate'].isin (['low','med
ium','high'])]
plot(df3, df4, 'attacking_work_rate')

#plot jointplot with goal keeper attributes:
#'gk_diving', 'gk_handling', 'gk_kicking', 'gk_positioning', 'gk_reflexes'
def joint_plot (df, title) :
    vis=sns.jointplot(x='ball_control',y='gk_diving', data=df, xlim=(0,100
), ylim=(0,100), stat_func=None)
    plt.title(title, loc='left')
    plt.show()
    plt.close()
    vis=sns.jointplot(x='ball_control',y='gk_handling', data=df, xlim=(0,1
00), ylim=(0,100), stat_func=None)
    plt.title(title, loc='left')
    plt.show()
    plt.close()
    vis=sns.jointplot(x='ball_control',y='gk_kicking', data=df, xlim=(0,10
0), ylim=(0,100), stat_func=None)
    plt.title(title, loc='left')
    plt.show()
    plt.close()
    vis=sns.jointplot(x='ball_control',y='gk_positioning', data=df, xlim=(
0,100), ylim=(0,100), stat_func=None)
    plt.title(title, loc='left')
    plt.show()
    plt.close()
    vis=sns.jointplot(x='ball_control',y='gk_reflexes', data=df, xlim=(0,1
00), ylim=(0,100), stat_func=None)
    plt.title(title, loc='left')
    plt.show()
    plt.close()


    vis=sns.jointplot(x='marking',y='gk_diving', data=df, xlim=(0,100), yl
```

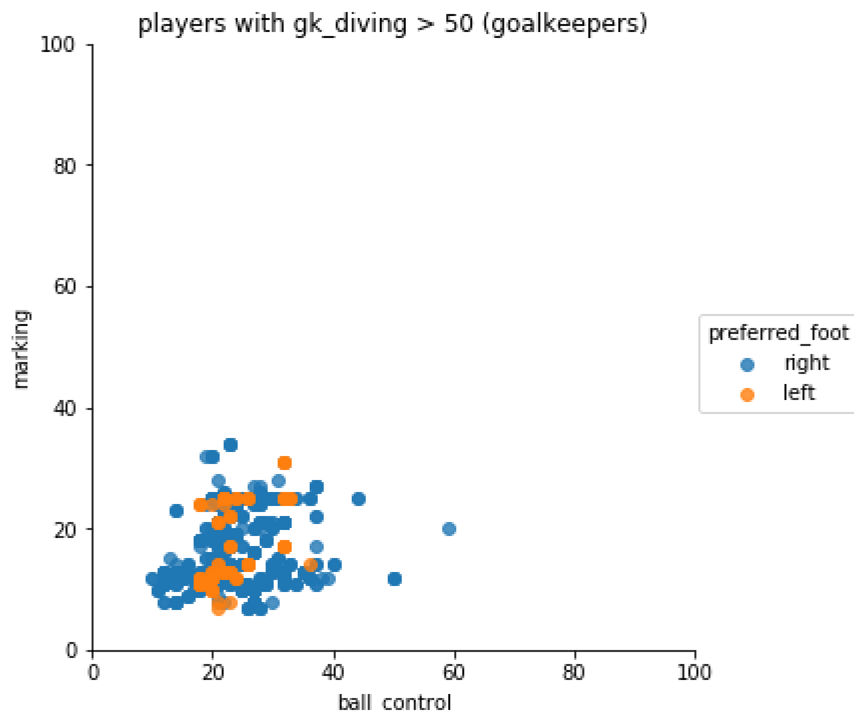
```
im=(0,100), stat_func=None)
    plt.title(title, loc='left')
    plt.show()
    plt.close()
    vis=sns.jointplot(x='marking',y='gk_handling', data=df, xlim=(0,100), 
ylim=(0,100), stat_func=None)
    plt.title(title, loc='left')
    plt.show()
    plt.close()
    vis=sns.jointplot(x='marking',y='gk_kicking', data=df, xlim=(0,100), y
lim=(0,100), stat_func=None)
    plt.title(title, loc='left')
    plt.show()
    plt.close()
    vis=sns.jointplot(x='marking',y='gk_positioning', xlim=(0,100), ylim=(
0,100), data=df, stat_func=None)
    plt.title(title, loc='left')
    plt.show()
    plt.close()
    vis=sns.jointplot(x='marking',y='gk_reflexes', xlim=(0,100), ylim=(0,1
00), data=df, stat_func=None)
    plt.title(title, loc='left')
    plt.show()
    plt.close()

'''
    vis=sns.jointplot(x='dribbling',y='gk_diving', data=df, xlim=(0,100), 
ylim=(0,100), stat_func=None)
    plt.title(title, loc='left')
    plt.show()
    plt.close()
    vis=sns.jointplot(x='dribbling',y='gk_handling', data=df, xlim=(0,100)
, ylim=(0,100), stat_func=None)
    plt.title(title, loc='left')
    plt.show()
    plt.close()
    vis=sns.jointplot(x='dribbling',y='gk_kicking', data=df, xlim=(0,100),
 ylim=(0,100), stat_func=None)
    plt.title(title, loc='left')
    plt.show()
    plt.close()
    vis=sns.jointplot(x='dribbling',y='gk_positioning', xlim=(0,100), ylim
=(0,100), data=df, stat_func=None)
    plt.title(title, loc='left')
    plt.show()
    plt.close()
    vis=sns.jointplot(x='dribbling',y='gk_reflexes', xlim=(0,100), ylim=(0
,100), data=df, stat_func=None)
    plt.title(title, loc='left')
    plt.show()
    plt.close()
'''

# df_goalkeepers=df_all_col.loc[df_all_col['gk_diving']>40]
joint_plot (df_all_col, 'all players')
joint_plot (df_goalkeepers, 'gk_diving > 50 (goalkeepers)')
```

```
gk_diving > 50 (goalkeepers)
```

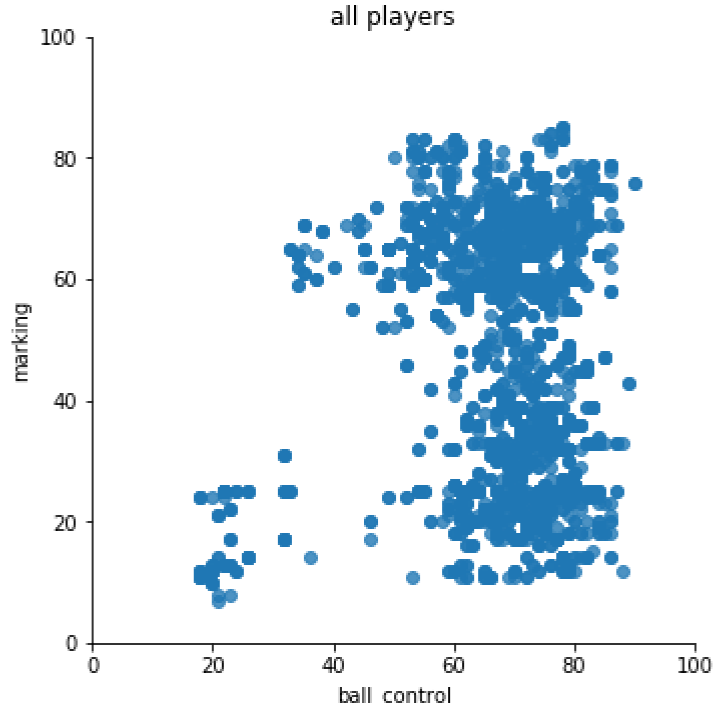


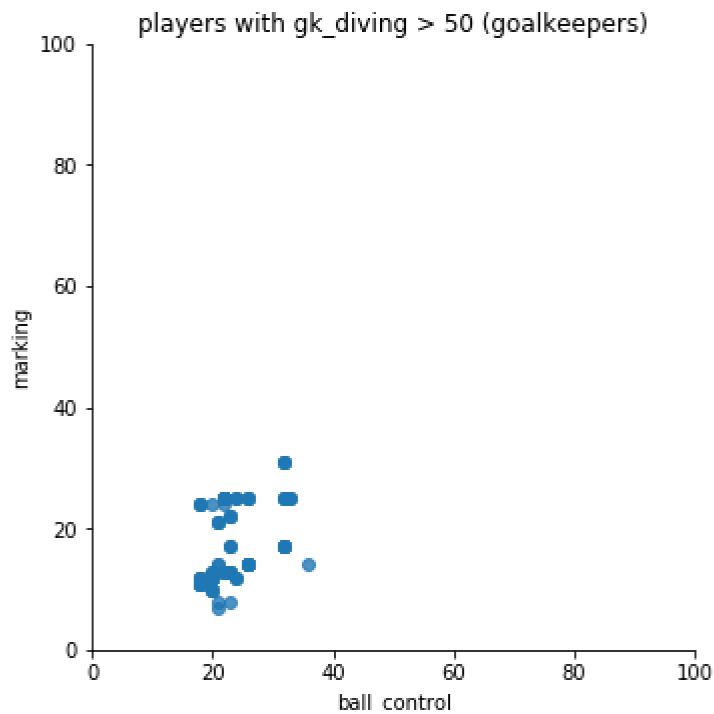



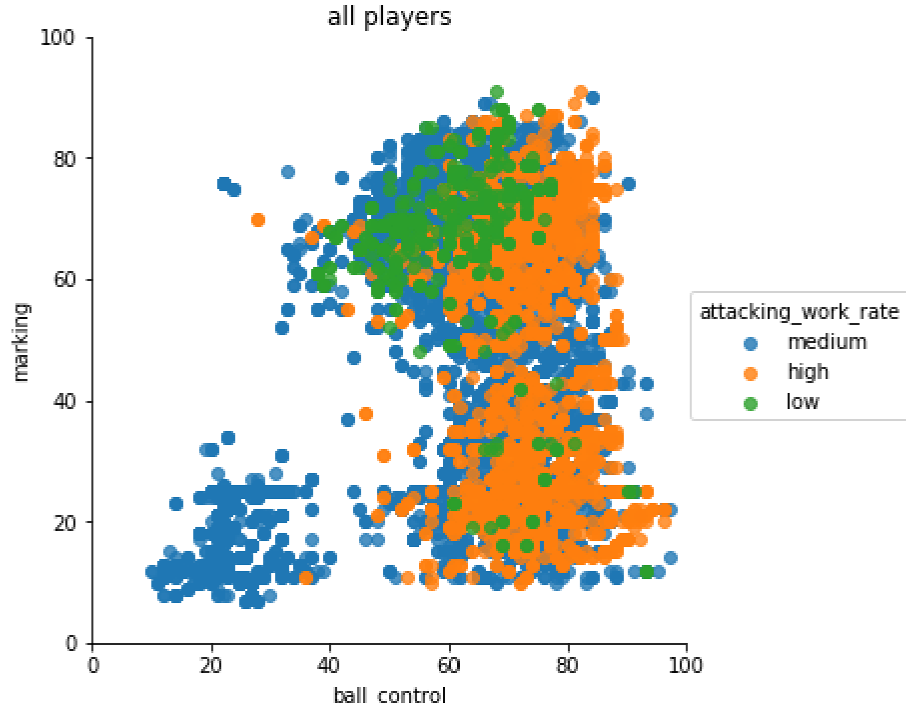


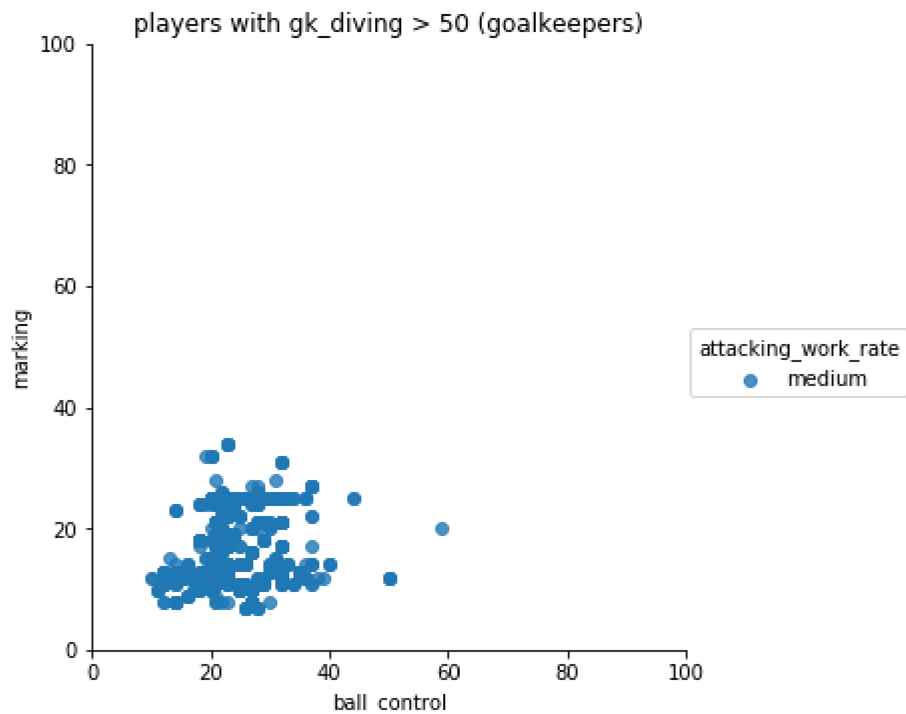



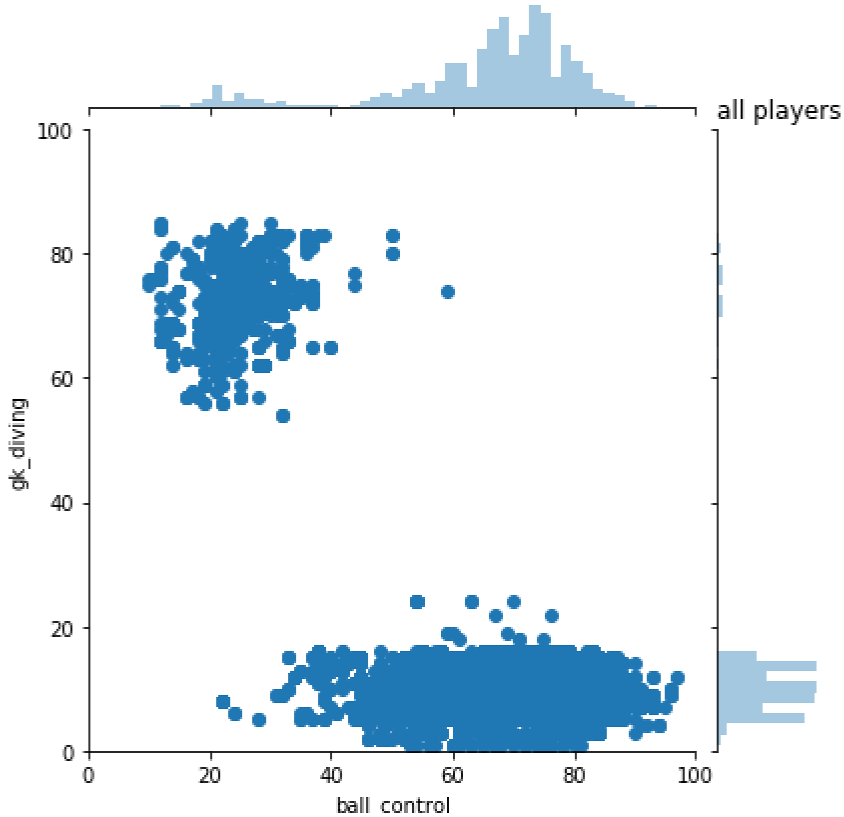

plot preferred left foot

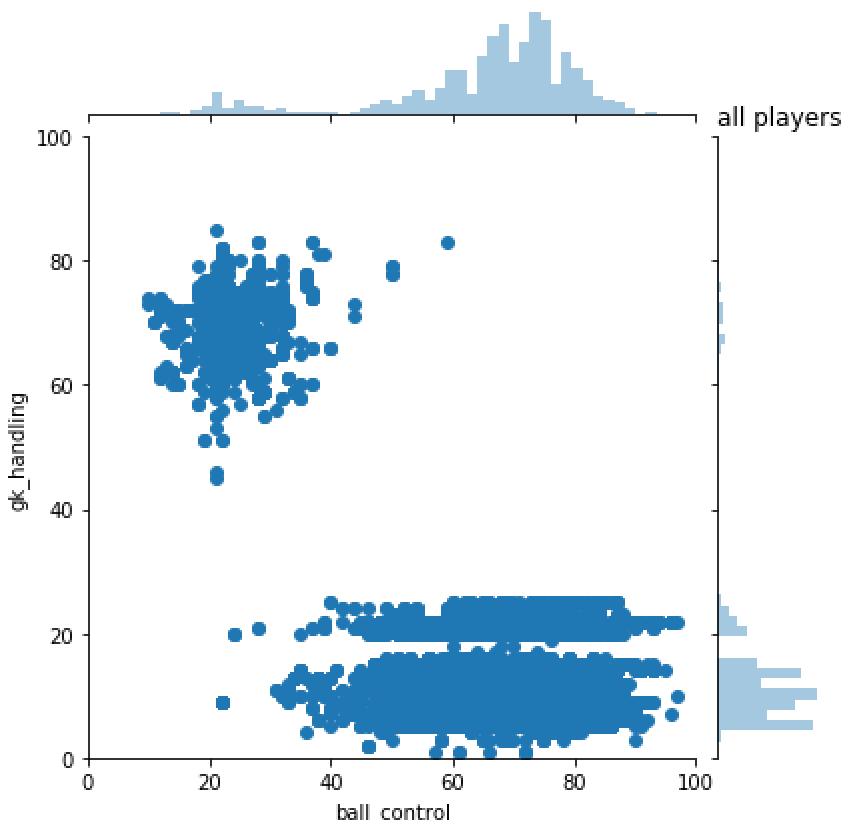

all players
100
80
60
40
20
0
marking
0
20
40
60
80
100
ball_control

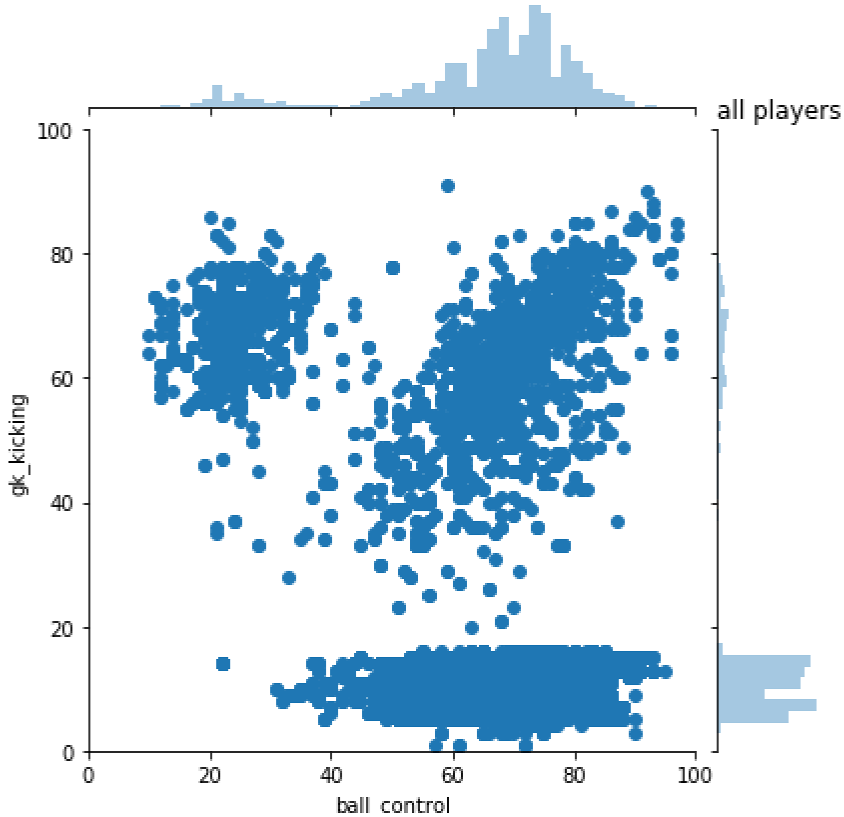

players with gk_diving > 50 (goalkeepers)
100
80
60
40
20
0
marking
0
20
40
60
80
100
ball_control

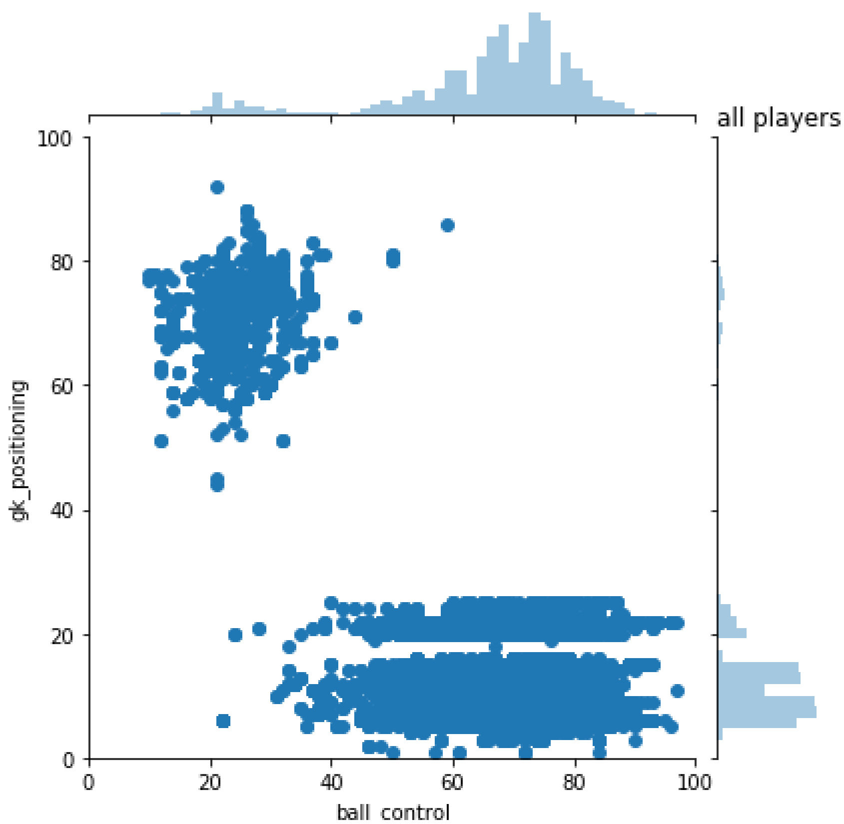

all players
100
80
60
40
20
0
0
20
40
60
80
100
marking
ball_control
attacking_work_rate
medium
high
low

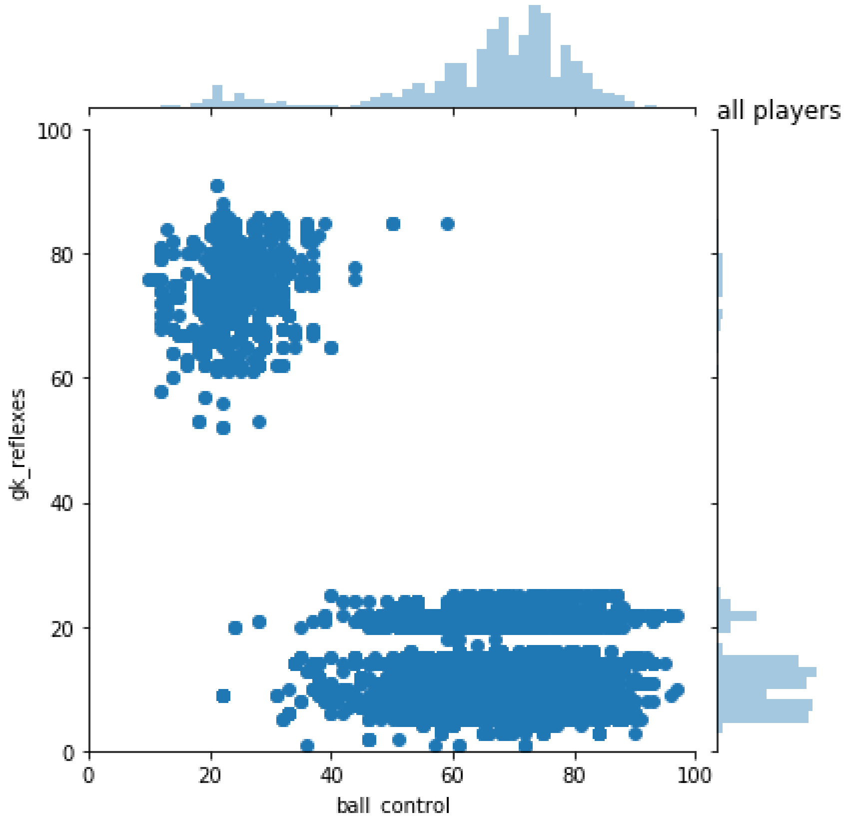

players with gk_diving > 50 (goalkeepers)
100
80
60
40
20
0
0
20
40
60
80
100
marking
ball_control
attacking_work_rate
medium

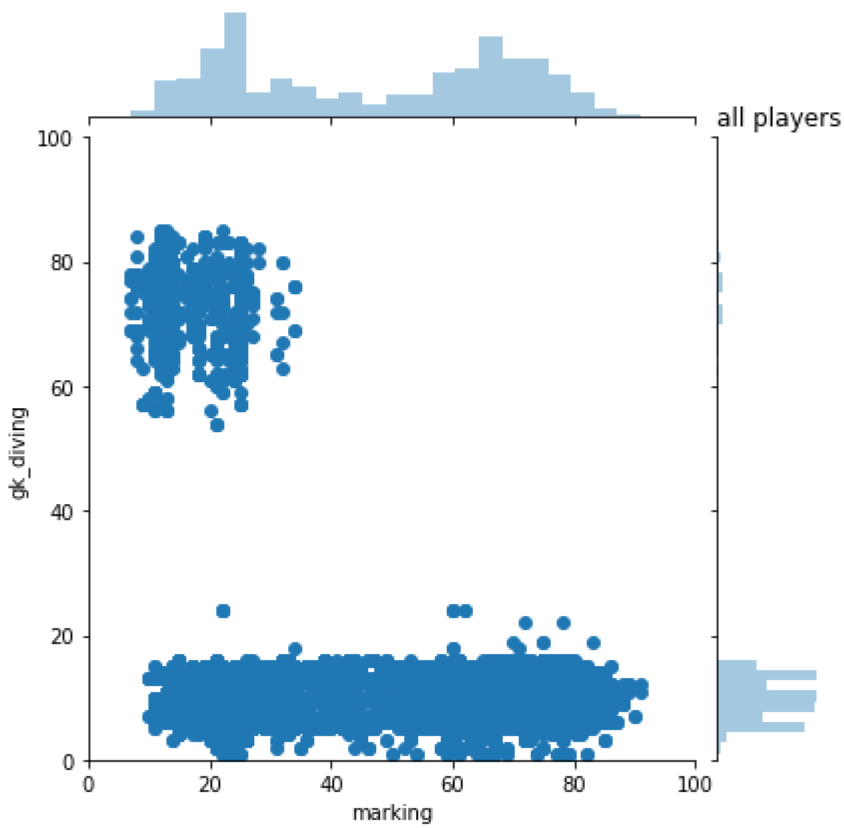

all players
100
80
60
40
20
0
gk_diving
0
20
40
60
80
100
ball_control

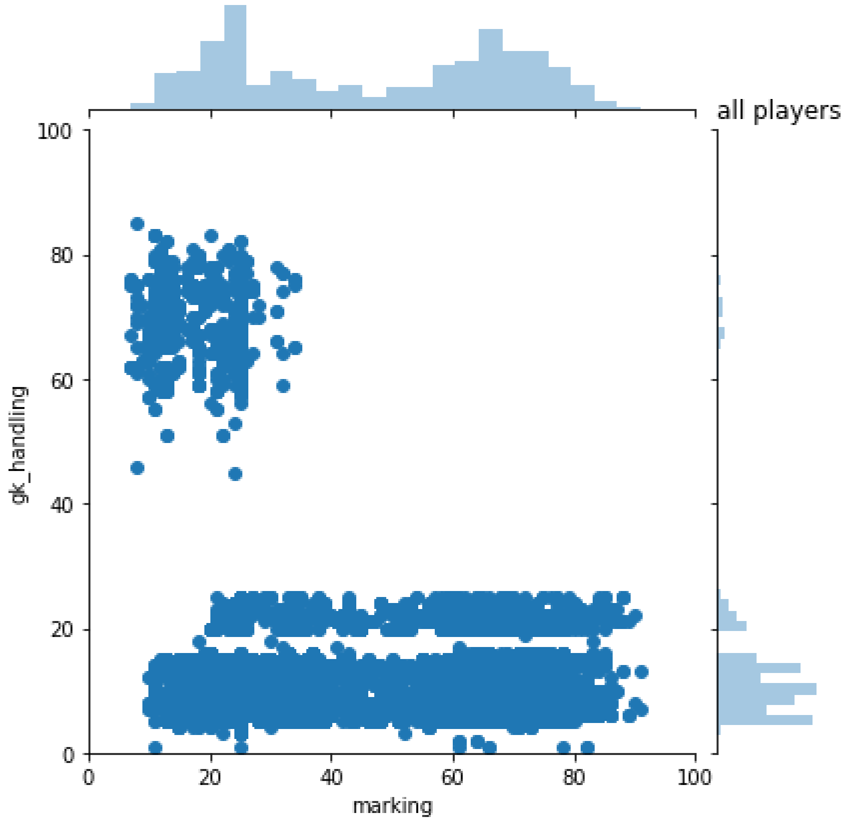

all players
100
80
60
40
20
0
gk_handling
0
20
40
60
80
100
ball_control

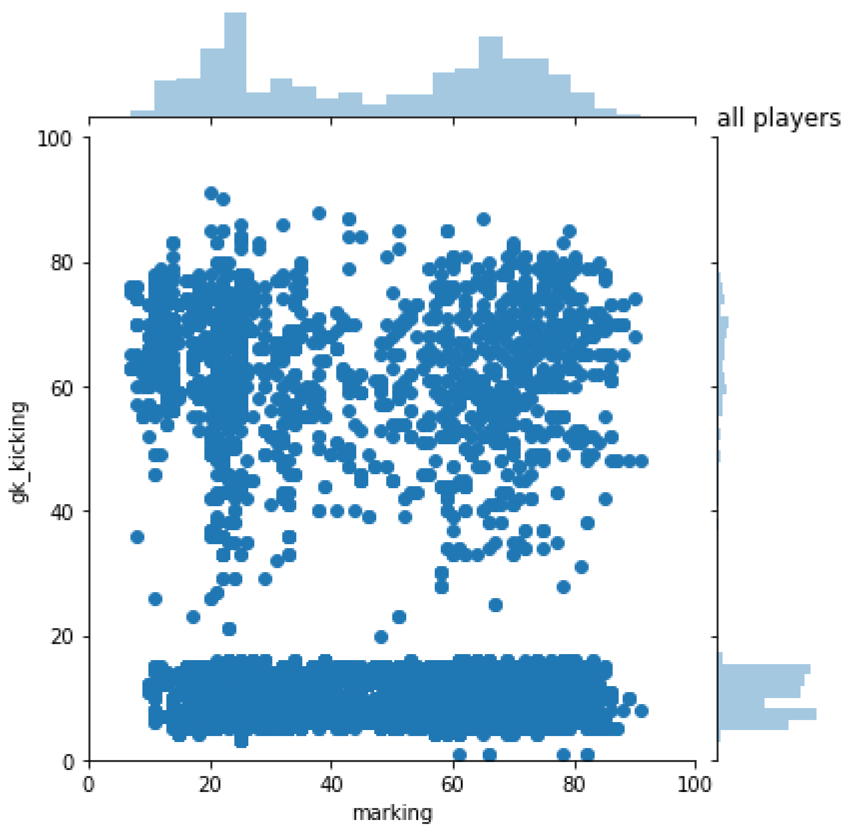

all players
gk_kicking
ball_control
0
20
40
60
80
100

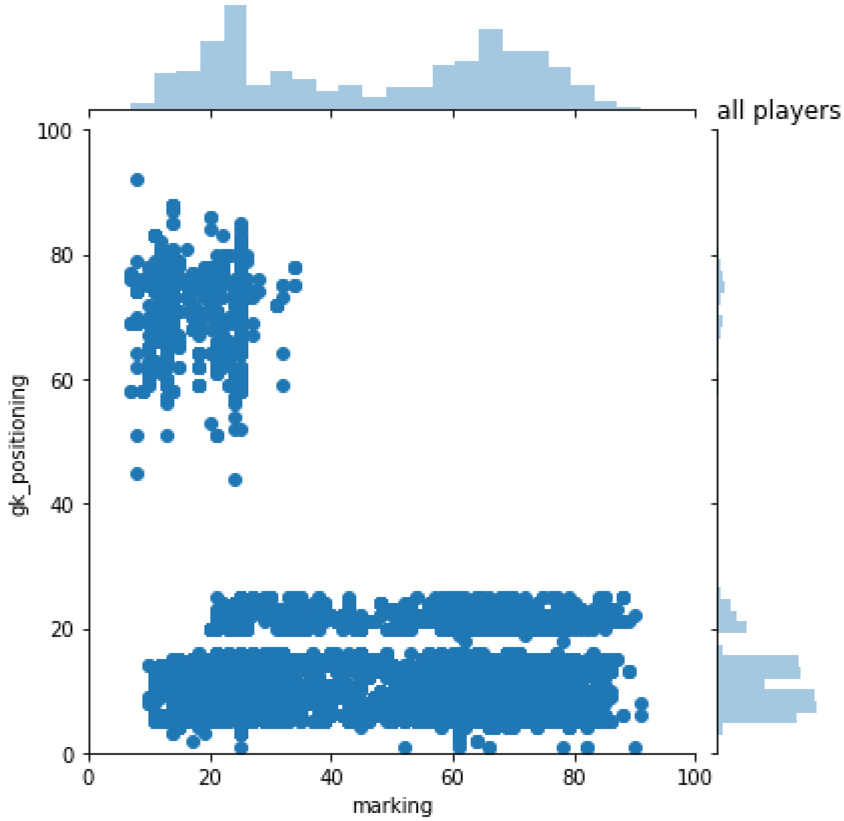

all players
gk_positioning
ball_control
0
20
40
60
80
100

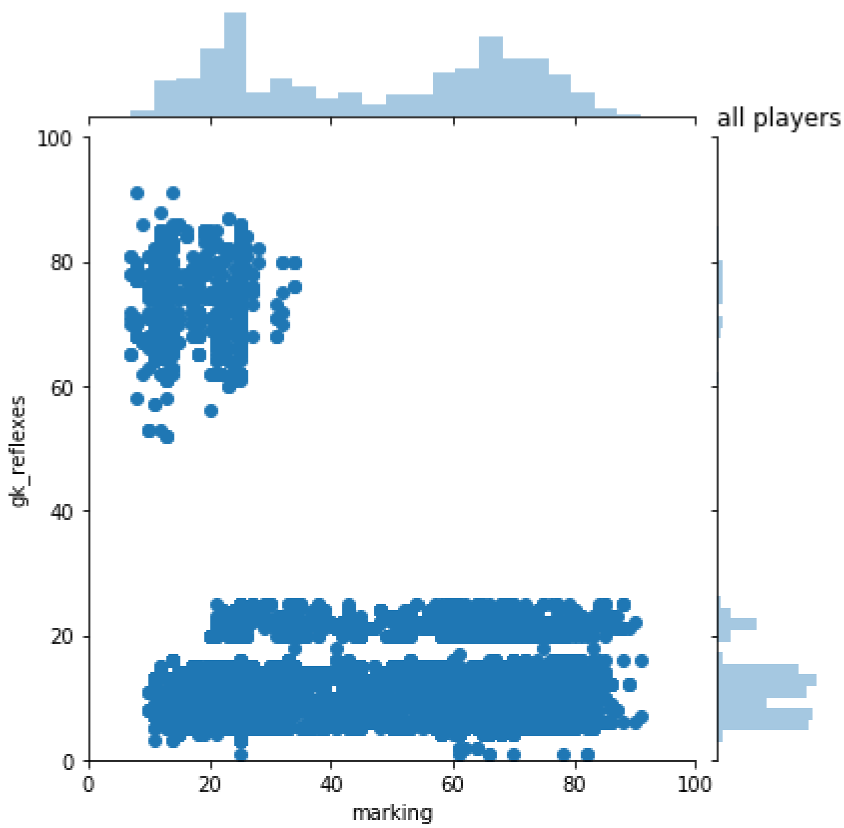

all players
gk_reflexes
ball_control
0
20
40
60
80
100

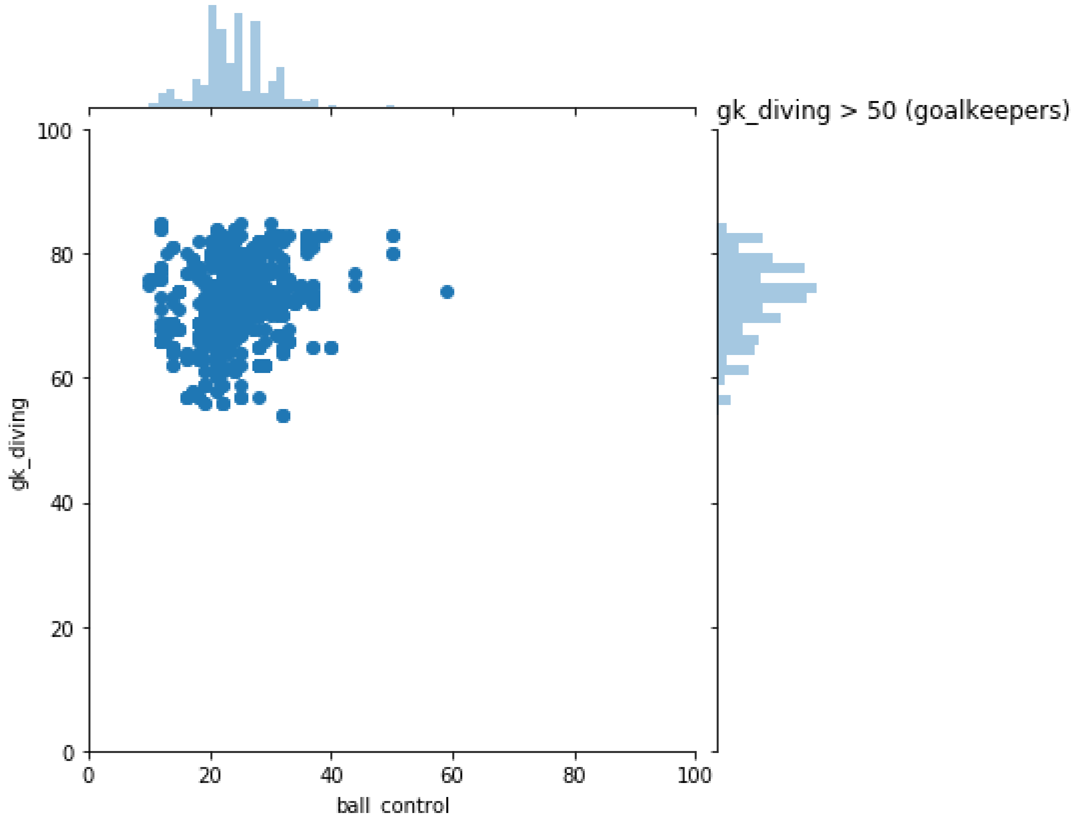

all players
gk_diving
marking
0
20
40
60
80
100

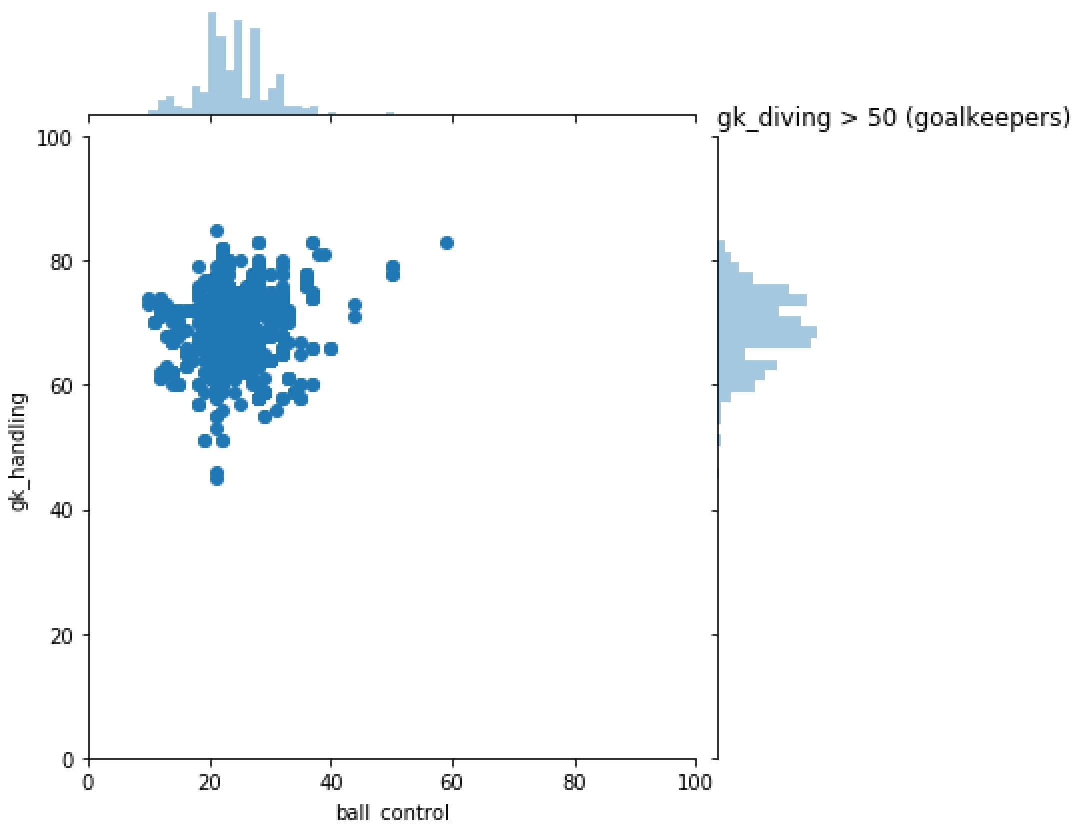

all players
gk_handling
marking
0
20
40
60
80
100

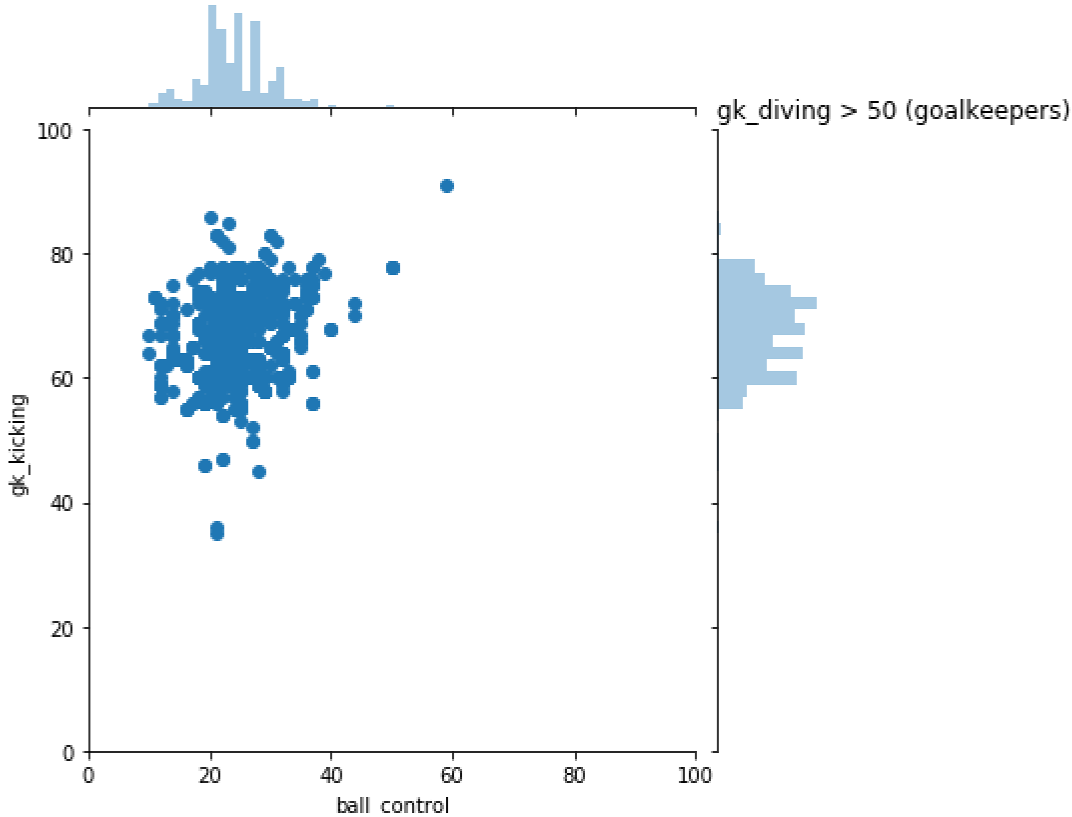

all players
gk_kicking
marking
0
20
40
60
80
100

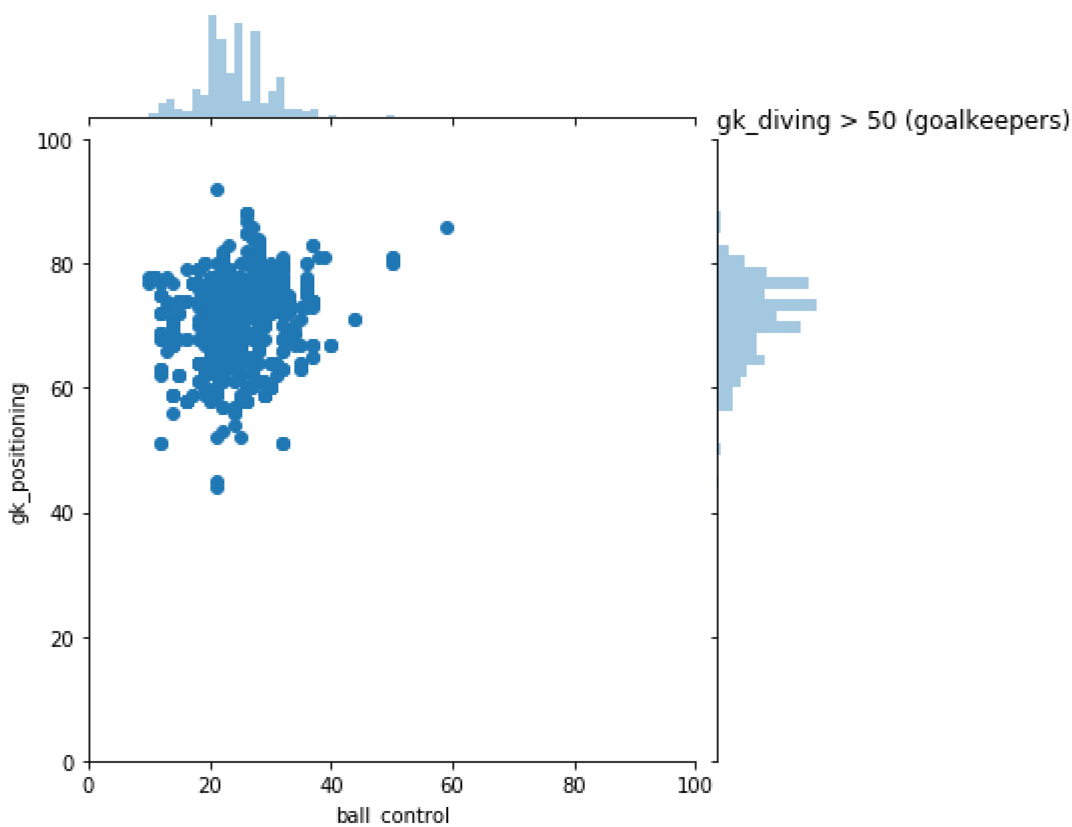

all players
gk_positioning
marking
0
20
40
60
80
100

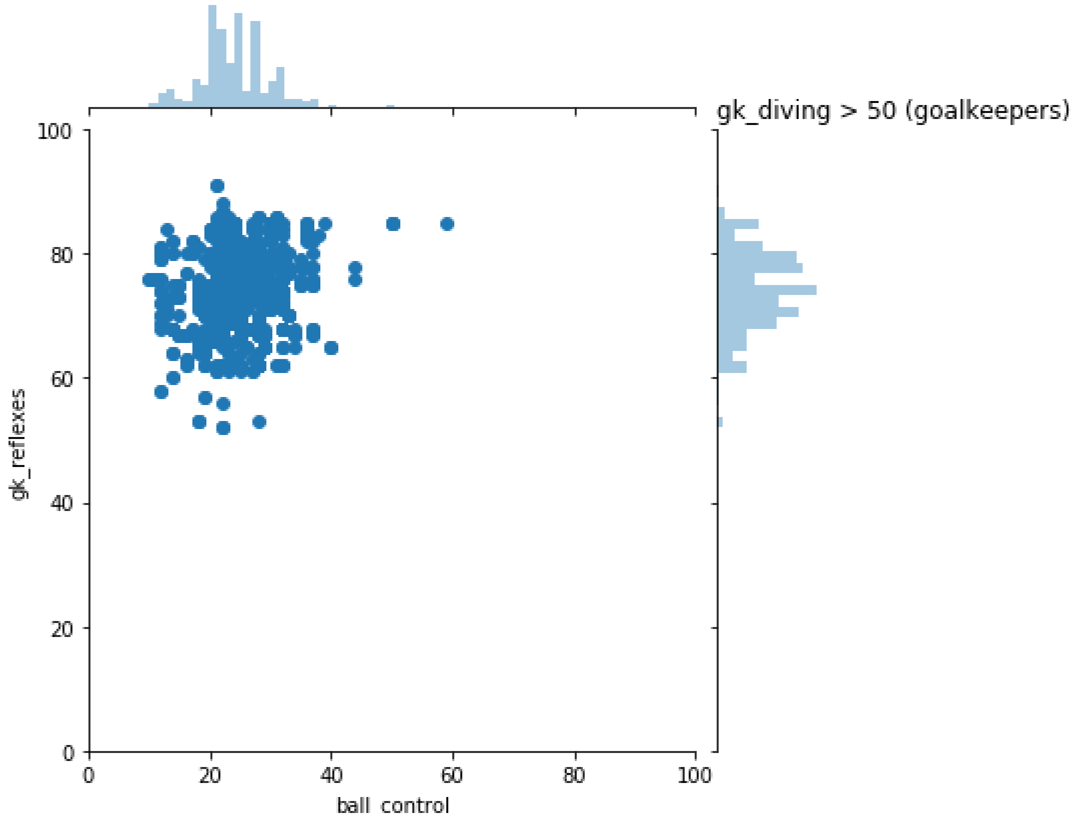

all players
gk_reflexes
marking
0
20
40
60
80
100

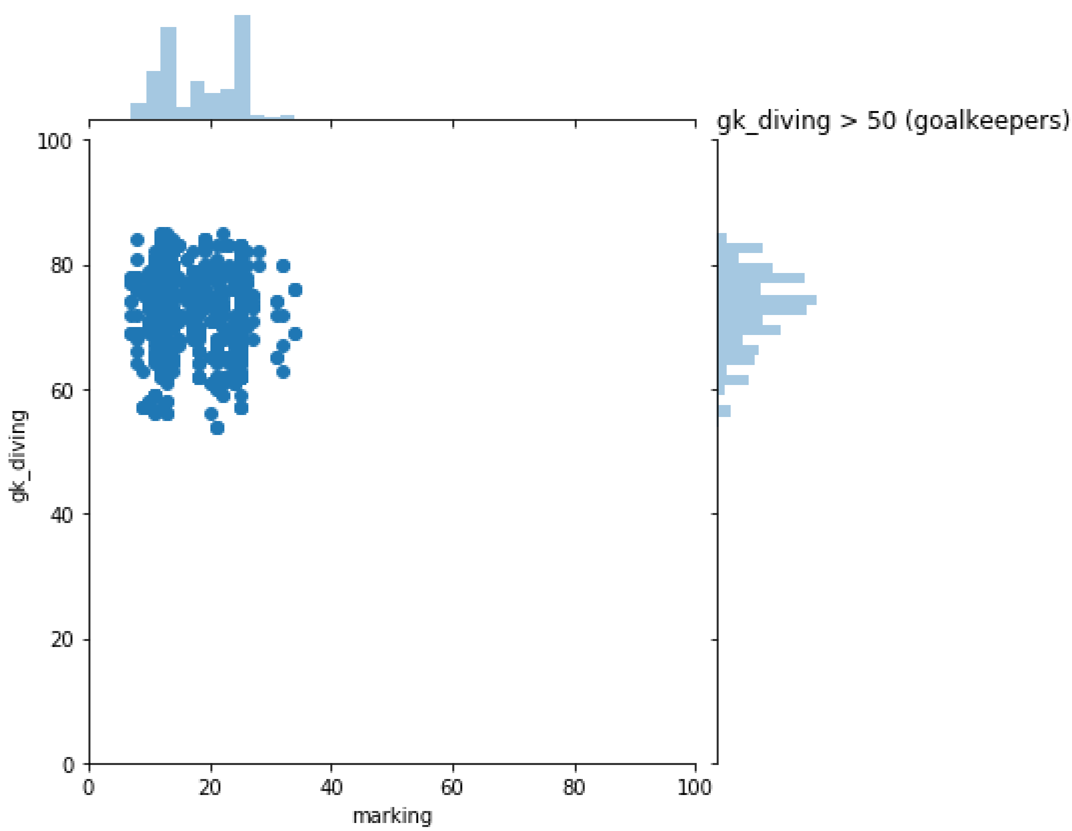

gk_diving > 50 (goalkeepers)
gk_diving
ball_control
0
20
40
60
80
100

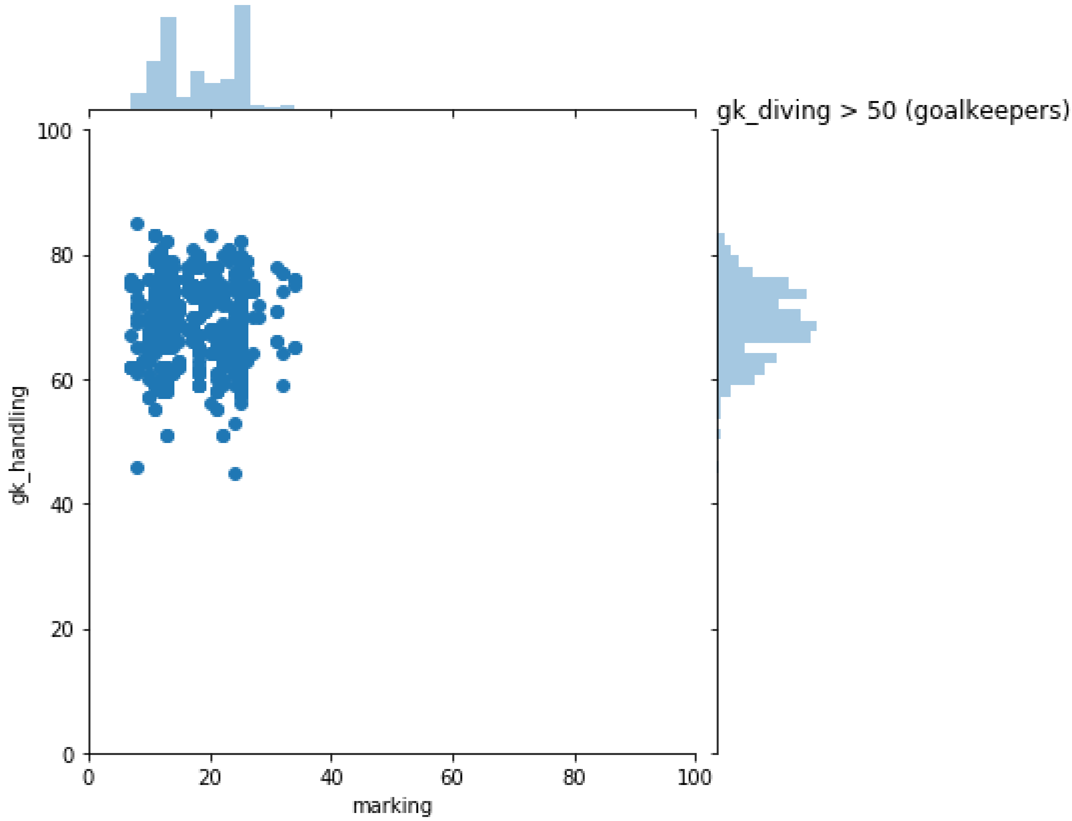

gk_diving > 50 (goalkeepers)
gk_handling
ball_control
0
20
40
60
80
100

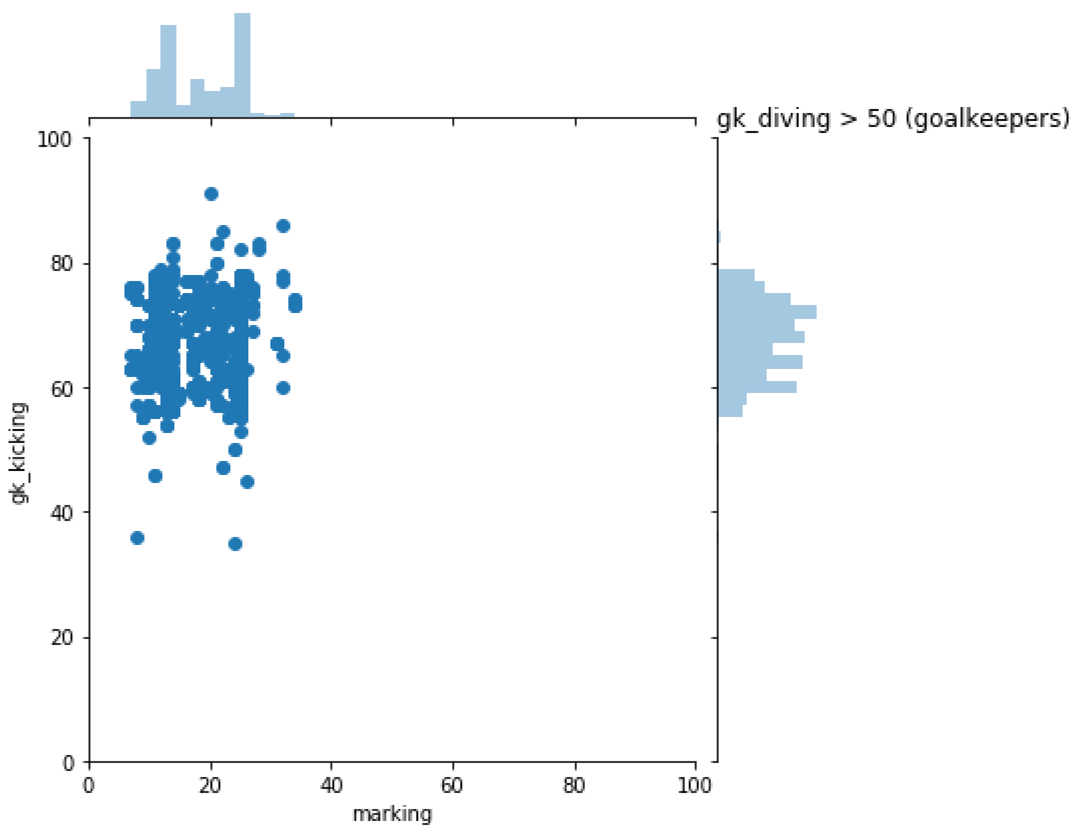

gk_diving > 50 (goalkeepers)
gk_kicking
ball_control
0
20
40
60
80
100

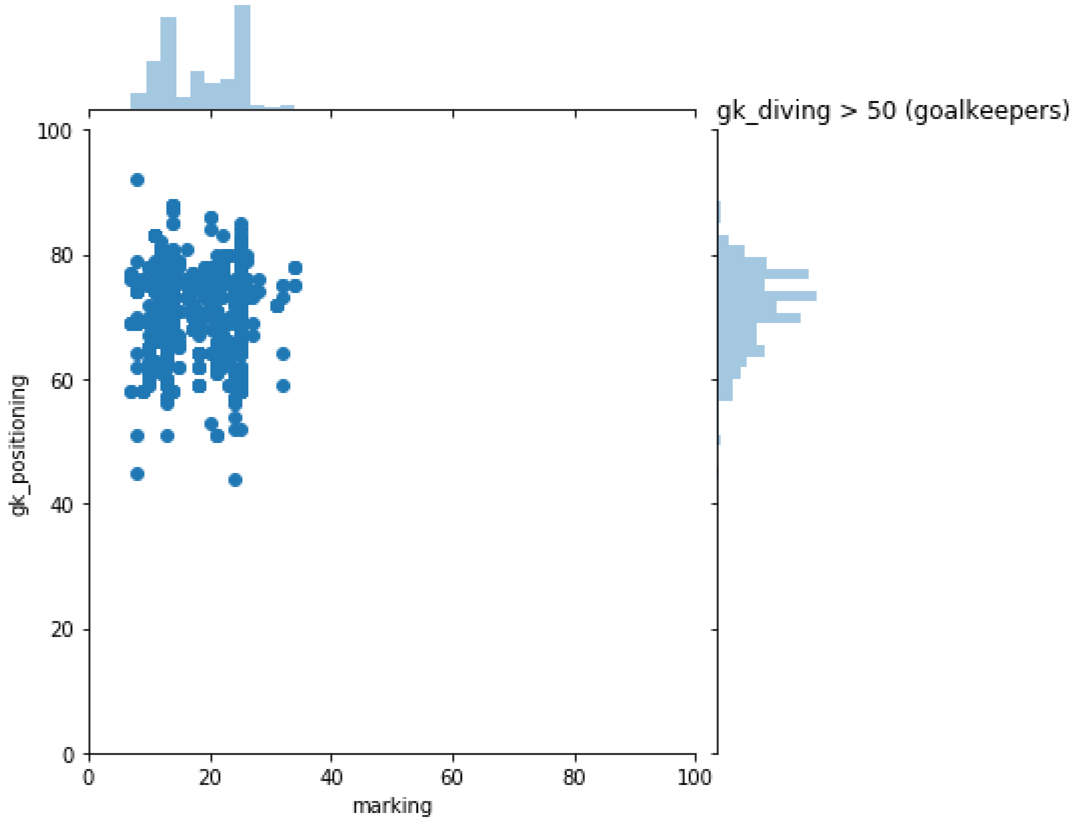

gk_diving > 50 (goalkeepers)
gk_positioning
ball_control
0
20
40
60
80
100

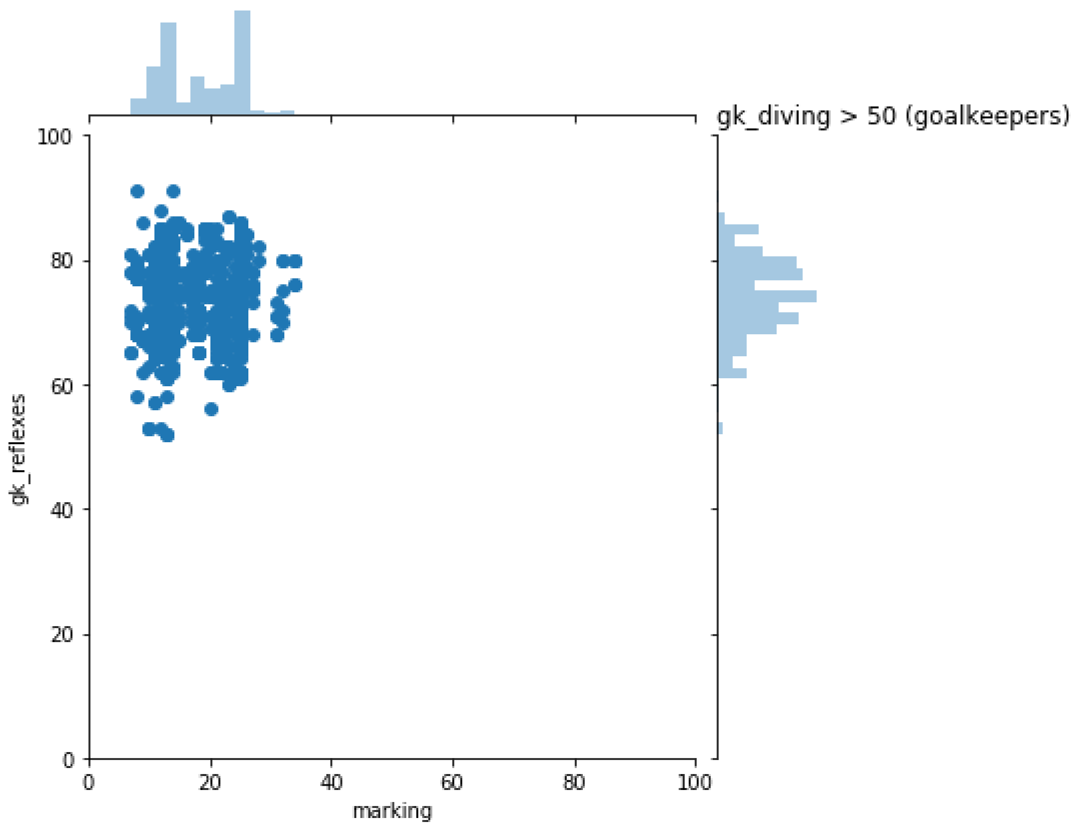

gk_diving > 50 (goalkeepers)
gk_reflexes
ball_control
0
20
40
60
80
100


gk_diving > 50 (goalkeepers)
gk_diving
marking
0
20
40
60
80
100


gk_diving > 50 (goalkeepers)
gk_handling
marking
0
20
40
60
80
100

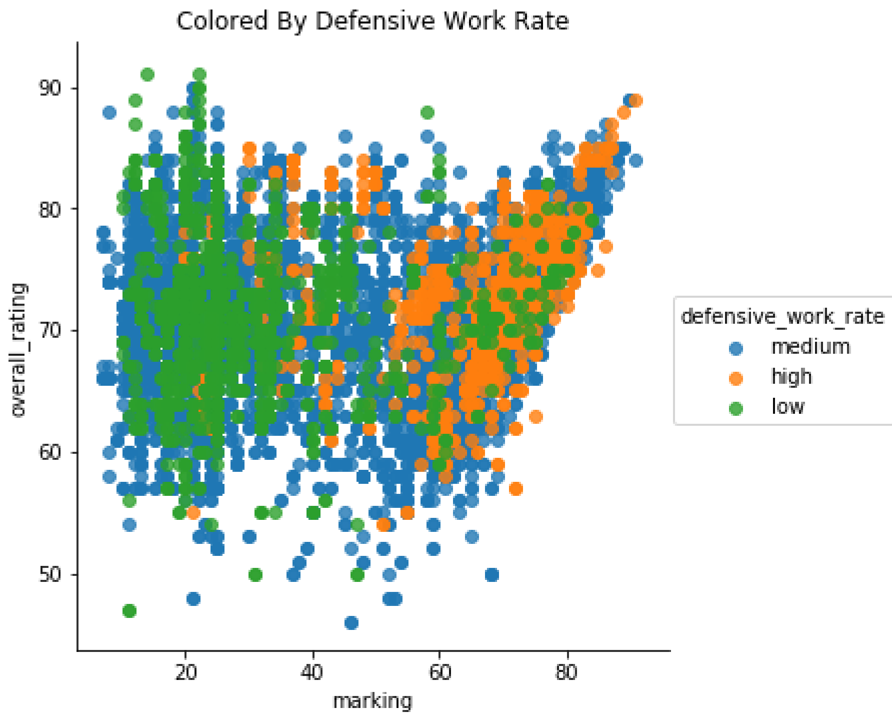

gk_diving > 50 (goalkeepers)
gk_kicking
marking
0
20
40
60
80
100

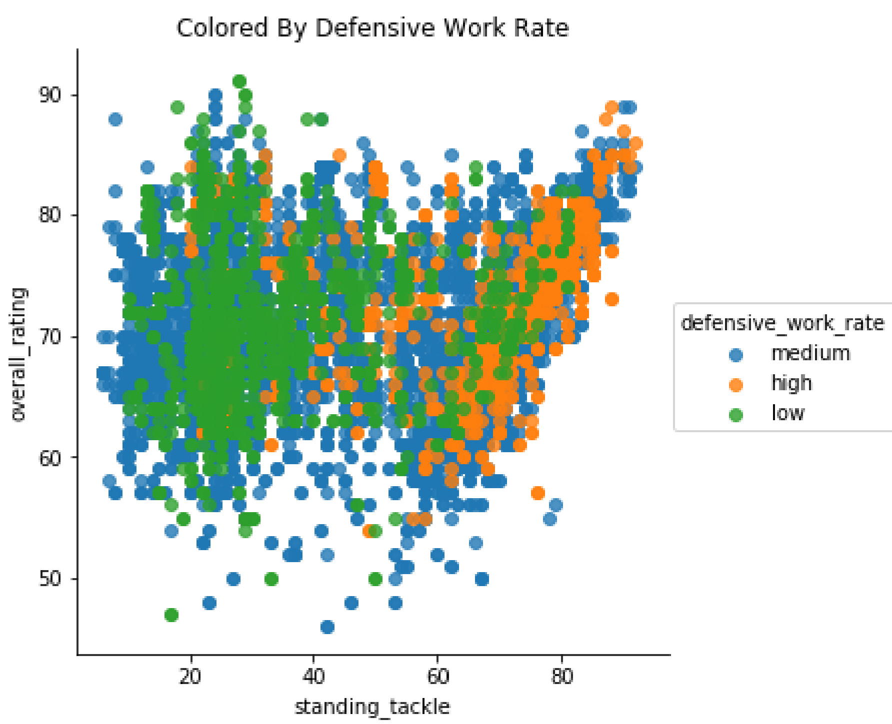


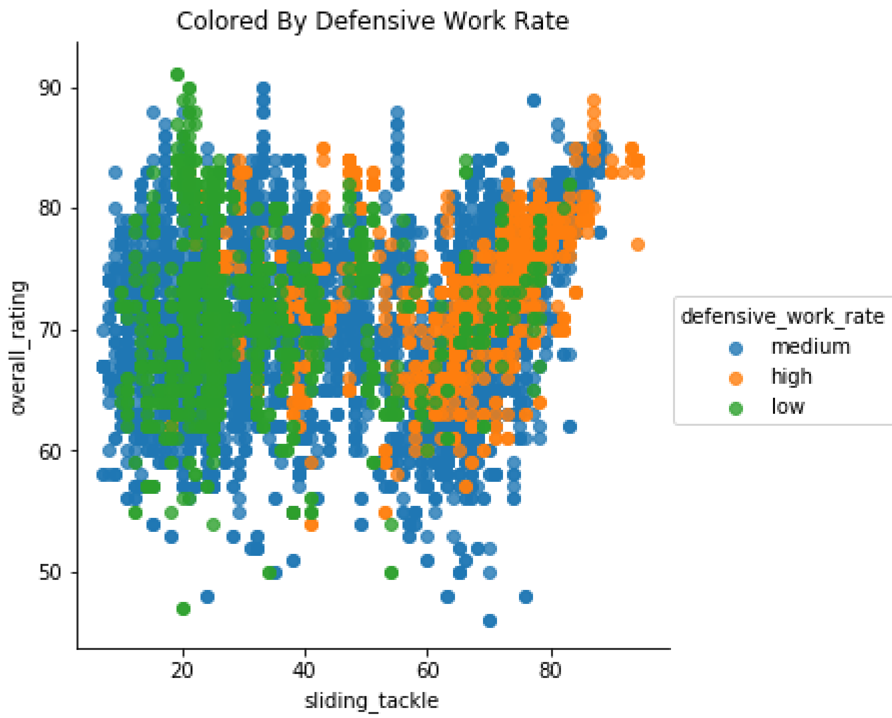



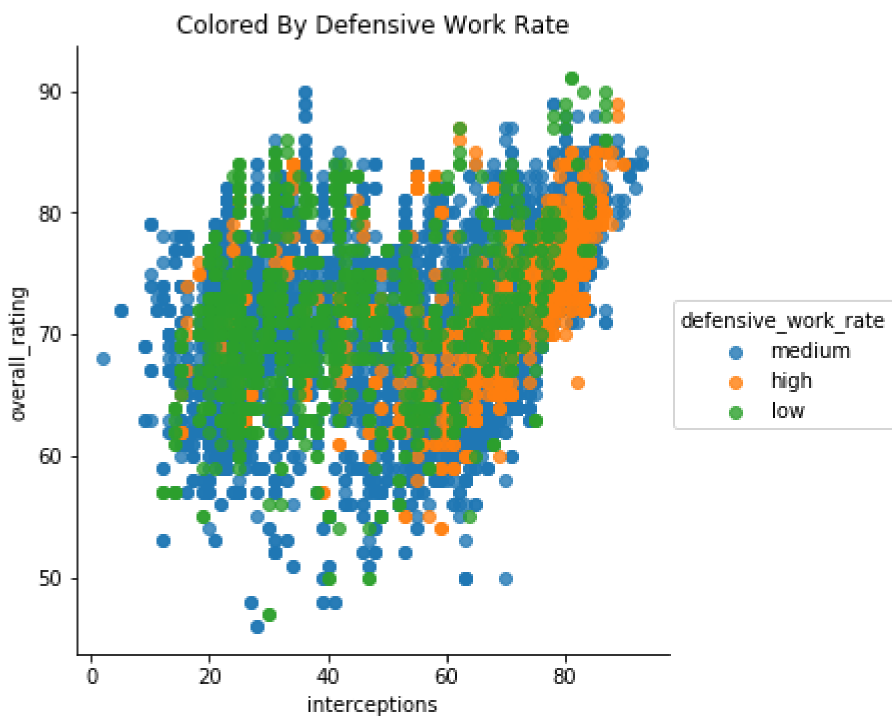

In [42]:
```
import seaborn as sns
df1=df_all_col[df_all_col['defensive_work_rate'].isin (['low','medium','hi
gh'])]
df2=df_all_col[df_all_col['defensive_work_rate'].isin (['high'])]
df3=df_all_col[df_all_col['defensive_work_rate'].isin (['medium'])]
```

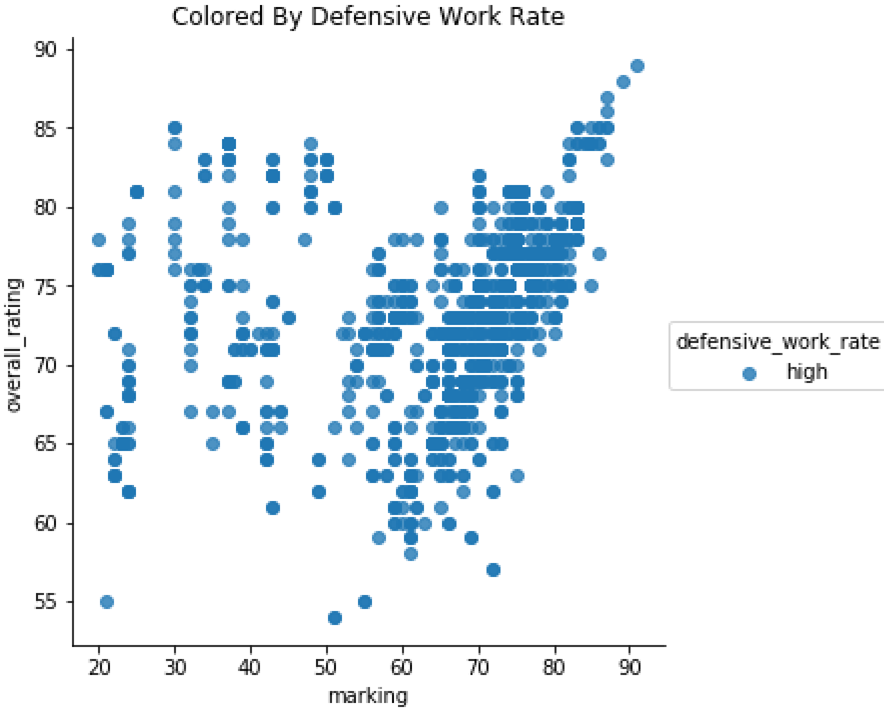
```
df4=df_all_col[df_all_col['defensive_work_rate'].isin (['low'])]

def lmplot (df):
    vis=sns.lmplot(x='marking', y='overall_rating',  hue='defensive_work_r
ate', sharex=False, data=df, \
                   scatter=True, fit_reg=False, units=None, order=1, legen
d=True)
    plt.title('Colored By Defensive Work Rate')
    plt.show()
    plt.close()

    vis=sns.lmplot(x='standing_tackle', y='overall_rating',  hue='defensiv
e_work_rate', sharex=False, data=df, \
                   scatter=True, fit_reg=False, units=None, order=1, legen
d=True)
    plt.title('Colored By Defensive Work Rate')
    plt.show()
    plt.close()

    vis=sns.lmplot(x='sliding_tackle', y='overall_rating',  hue='defensive
_work_rate', sharex=False, data=df, \
                   scatter=True, fit_reg=False, units=None, order=1, legen
d=True)
    plt.title('Colored By Defensive Work Rate')
    plt.show()
    plt.close()

    vis=sns.lmplot(x='interceptions', y='overall_rating',  hue='defensive_
work_rate', sharex=False, data=df, \
                   scatter=True, fit_reg=False, units=None, order=1, legen
d=True)
    plt.title('Colored By Defensive Work Rate')
    plt.show()
    plt.close()

lmplot(df1) #color by 'defensive_work_rate'].isin (['low','medium','high']
)
lmplot(df2) #color by 'defensive_work_rate'].isin (['high'])
lmplot(df3) #color by 'defensive_work_rate'].isin (['medium'])
lmplot(df4) #color by 'defensive_work_rate'].isin (['low'])
```

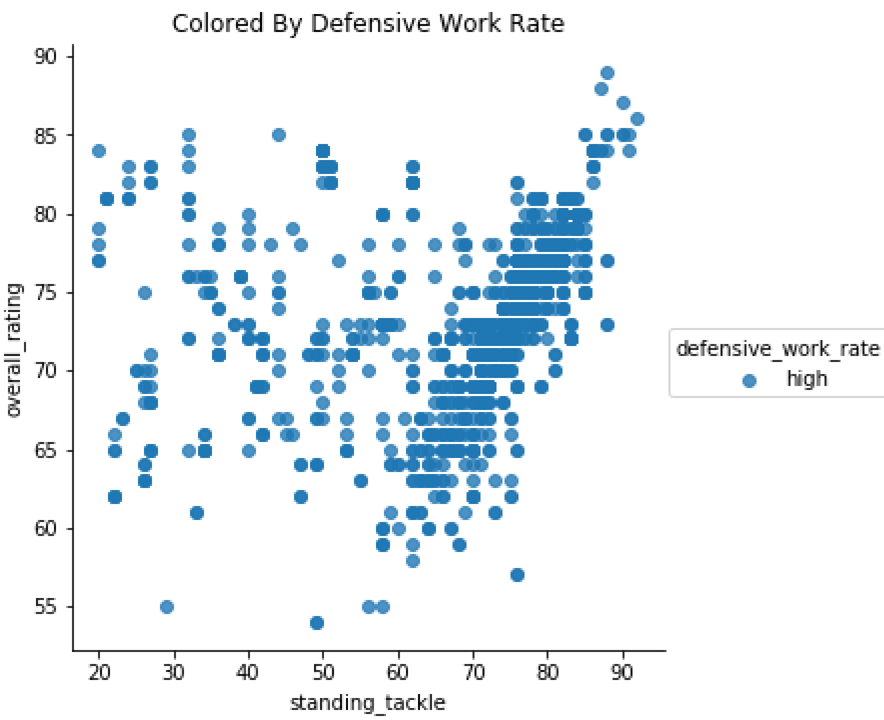

Colored By Defensive Work Rate
overall_rating
marking
90
80
70
60
50
20
40
60
80
defensive_work_rate
medium
high
low

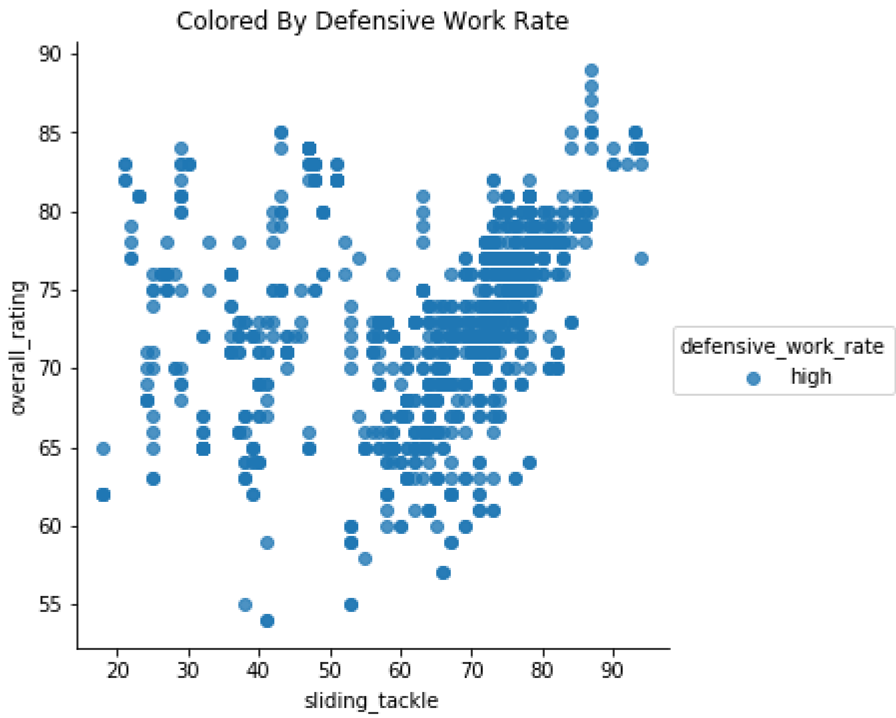

Colored By Defensive Work Rate
overall_rating
standing_tackle
90
80
70
60
50
20
40
60
80
defensive_work_rate
medium
high
low

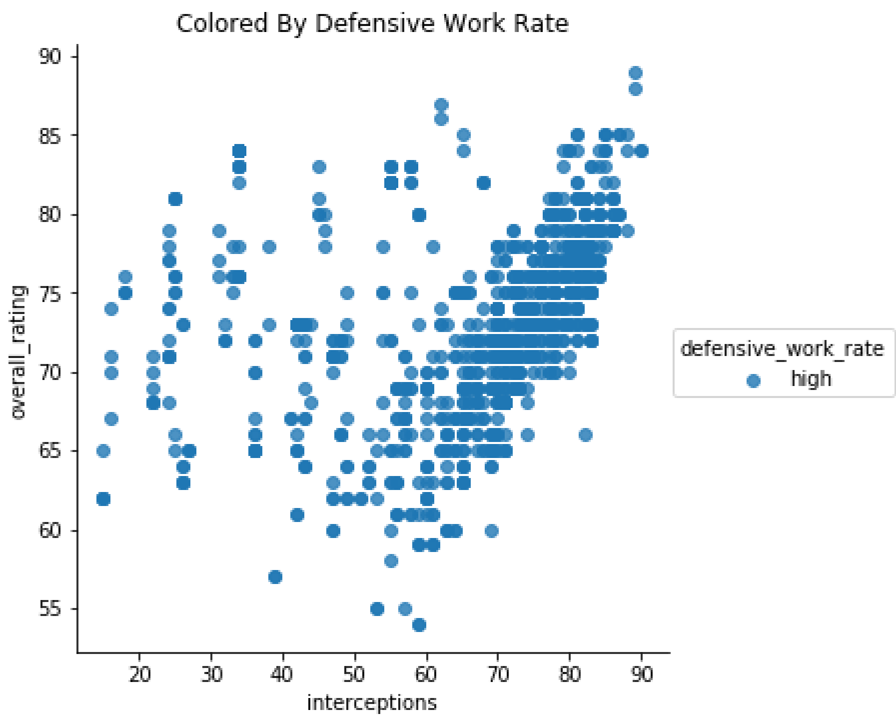

Colored By Defensive Work Rate
overall_rating
sliding_tackle
defensive_work_rate
medium
high
low

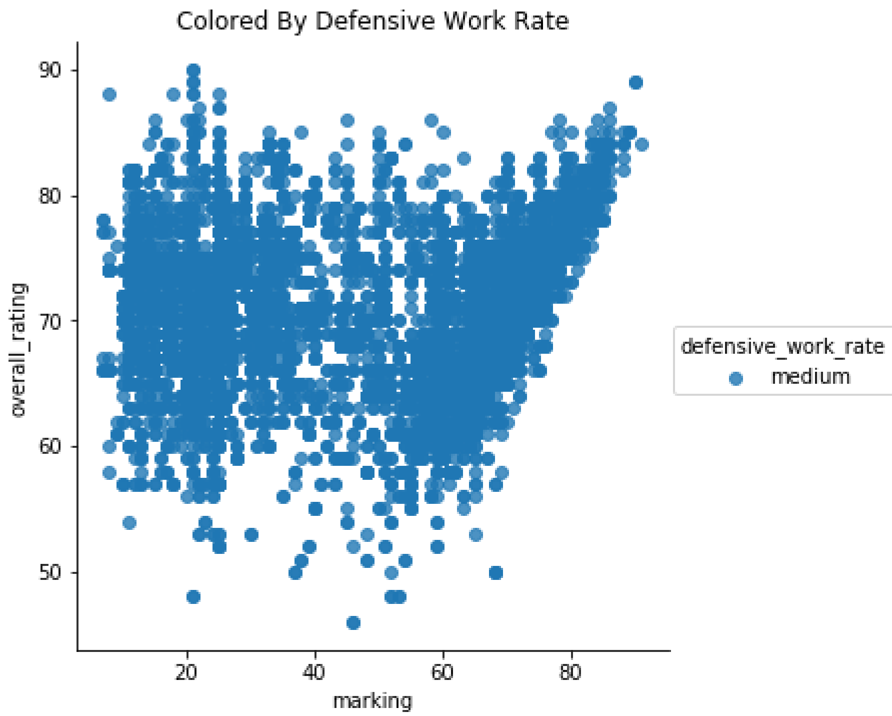

Colored By Defensive Work Rate
overall_rating
interceptions
defensive_work_rate
medium
high
low

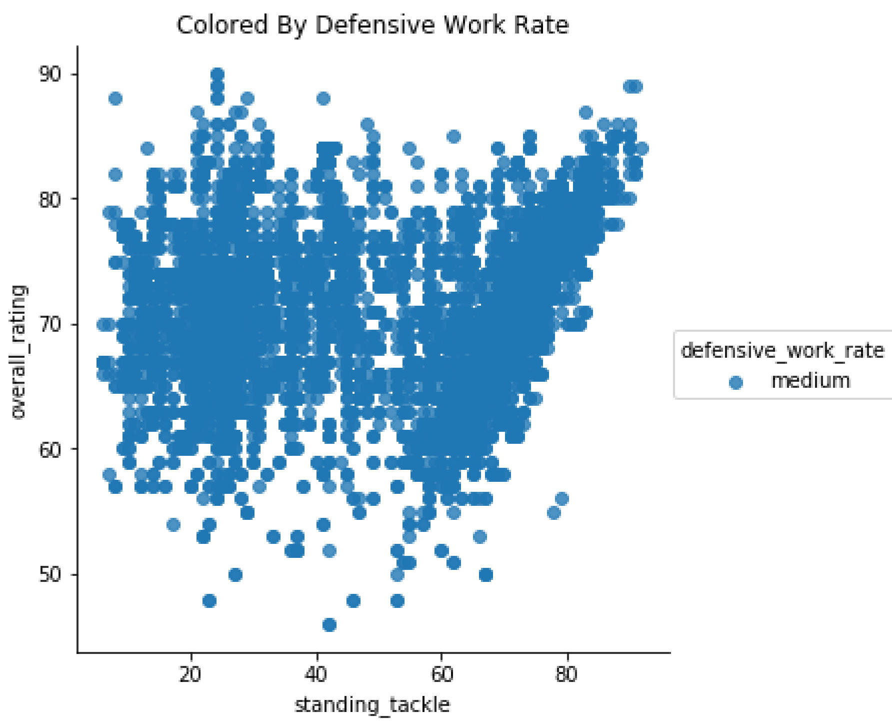

Colored By Defensive Work Rate
overall_rating
90
85
80
75
70
65
60
55
20
30
40
50
60
70
80
90
marking
defensive_work_rate
high

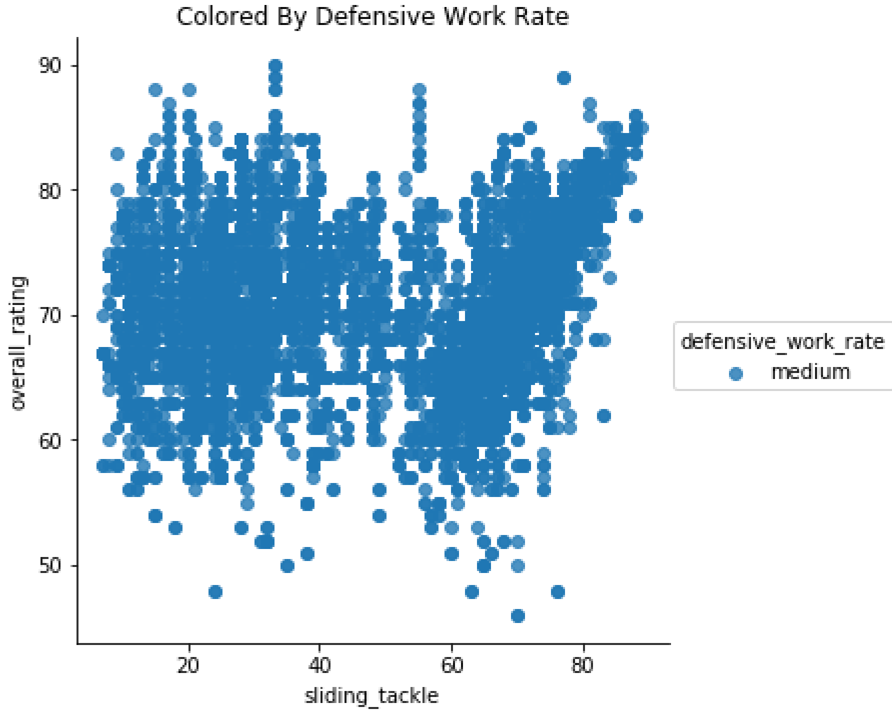

Colored By Defensive Work Rate
overall_rating
90
85
80
75
70
65
60
55
20
30
40
50
60
70
80
90
standing_tackle
defensive_work_rate
high

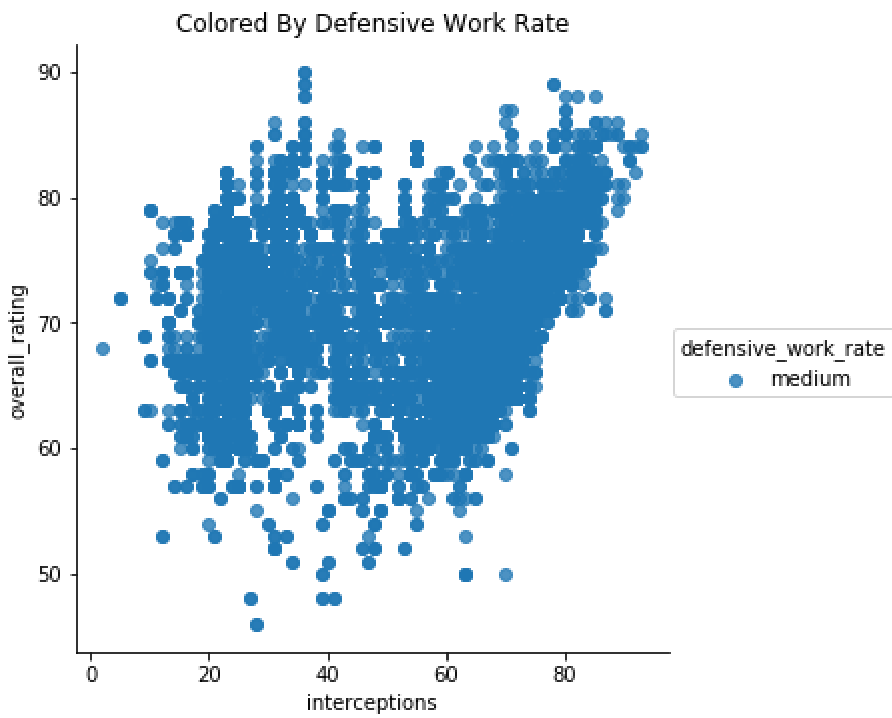

Colored By Defensive Work Rate
overall_rating
sliding_tackle
defensive_work_rate
high

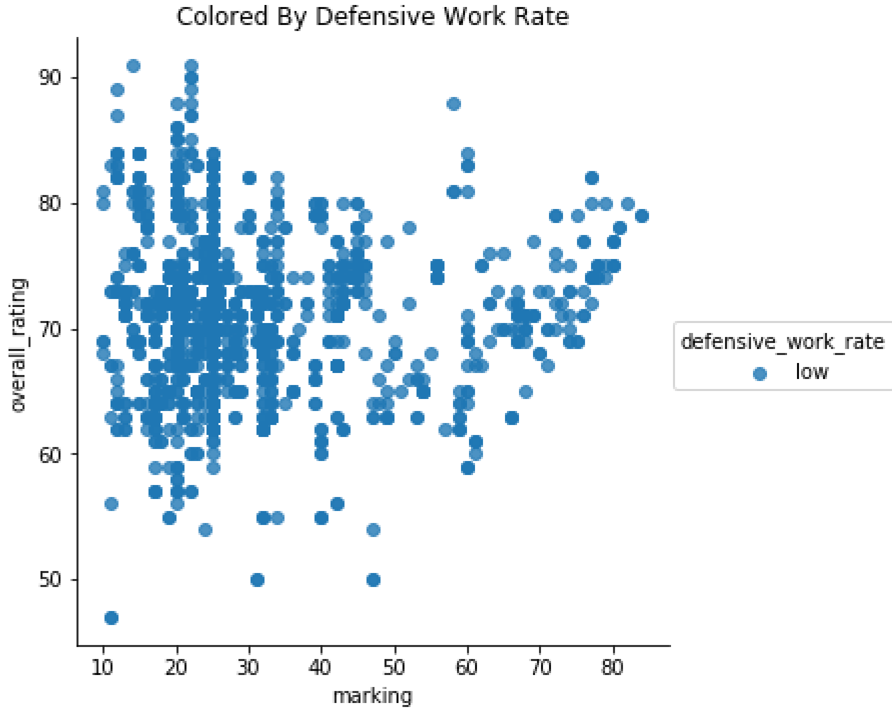

Colored By Defensive Work Rate
overall_rating
interceptions
defensive_work_rate
high

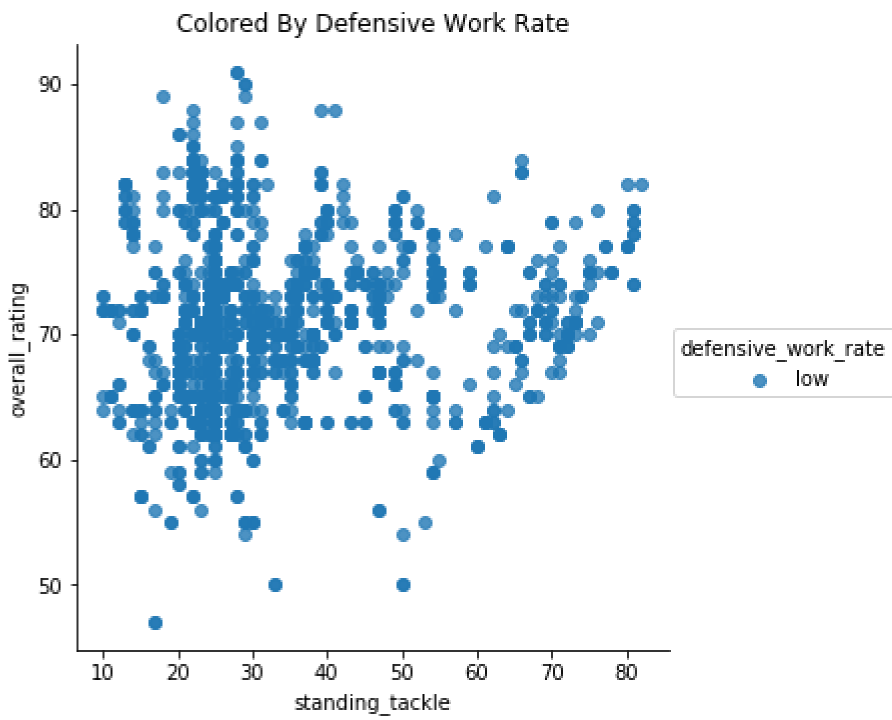

Colored By Defensive Work Rate
90
80
70
60
50
overall_rating
20
40
60
80
marking
defensive_work_rate
medium

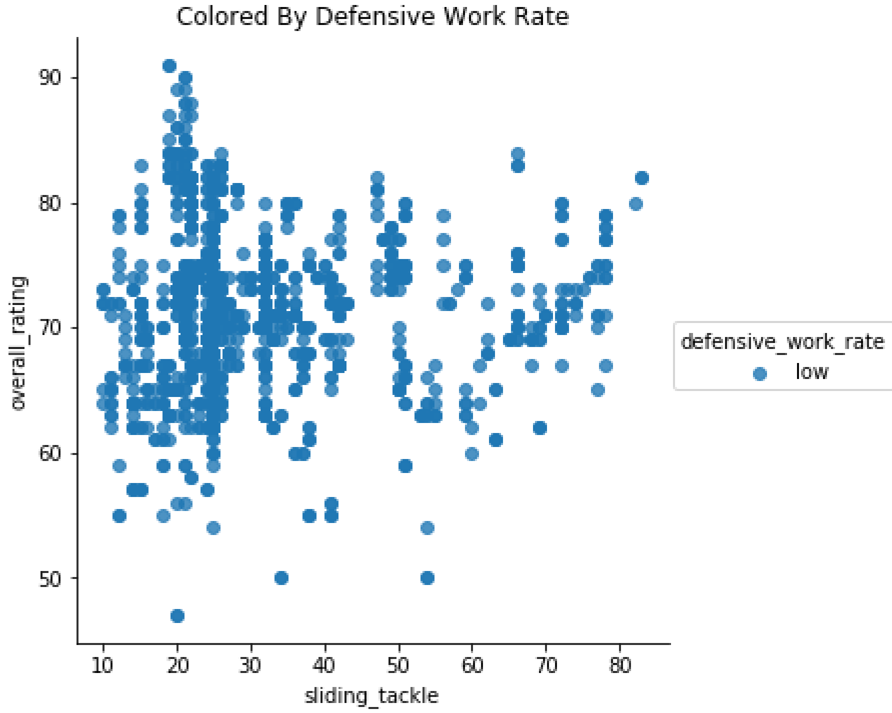

Colored By Defensive Work Rate
90
80
70
60
50
overall_rating
20
40
60
80
standing_tackle
defensive_work_rate
medium

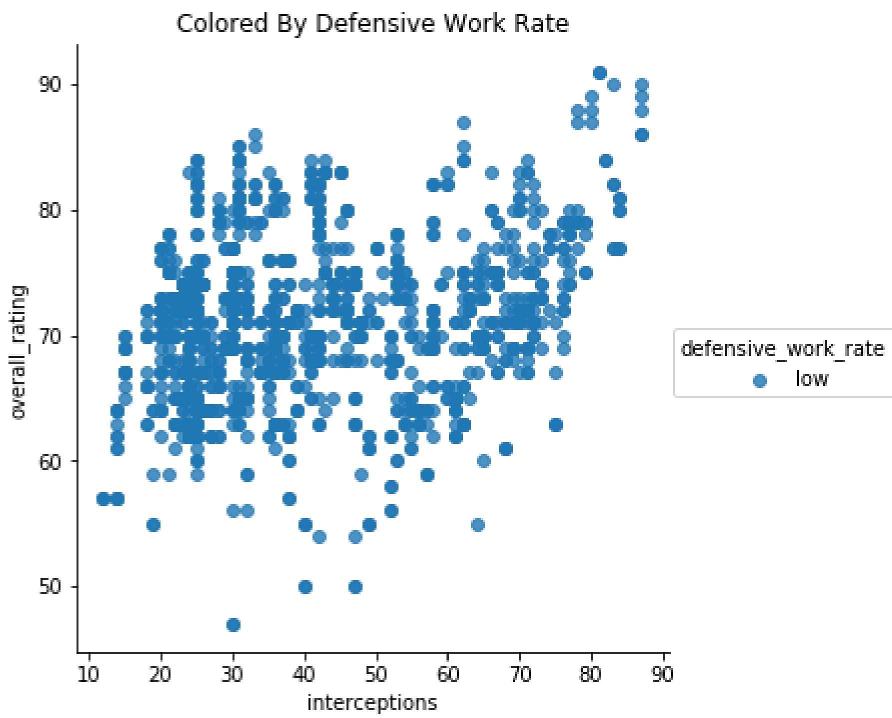

Colored By Defensive Work Rate
overall_rating
sliding_tackle
defensive_work_rate
medium
90
80
70
60
50
20
40
60
80


Colored By Defensive Work Rate
overall_rating
interceptions
defensive_work_rate
medium
90
80
70
60
50
0
20
40
60
80

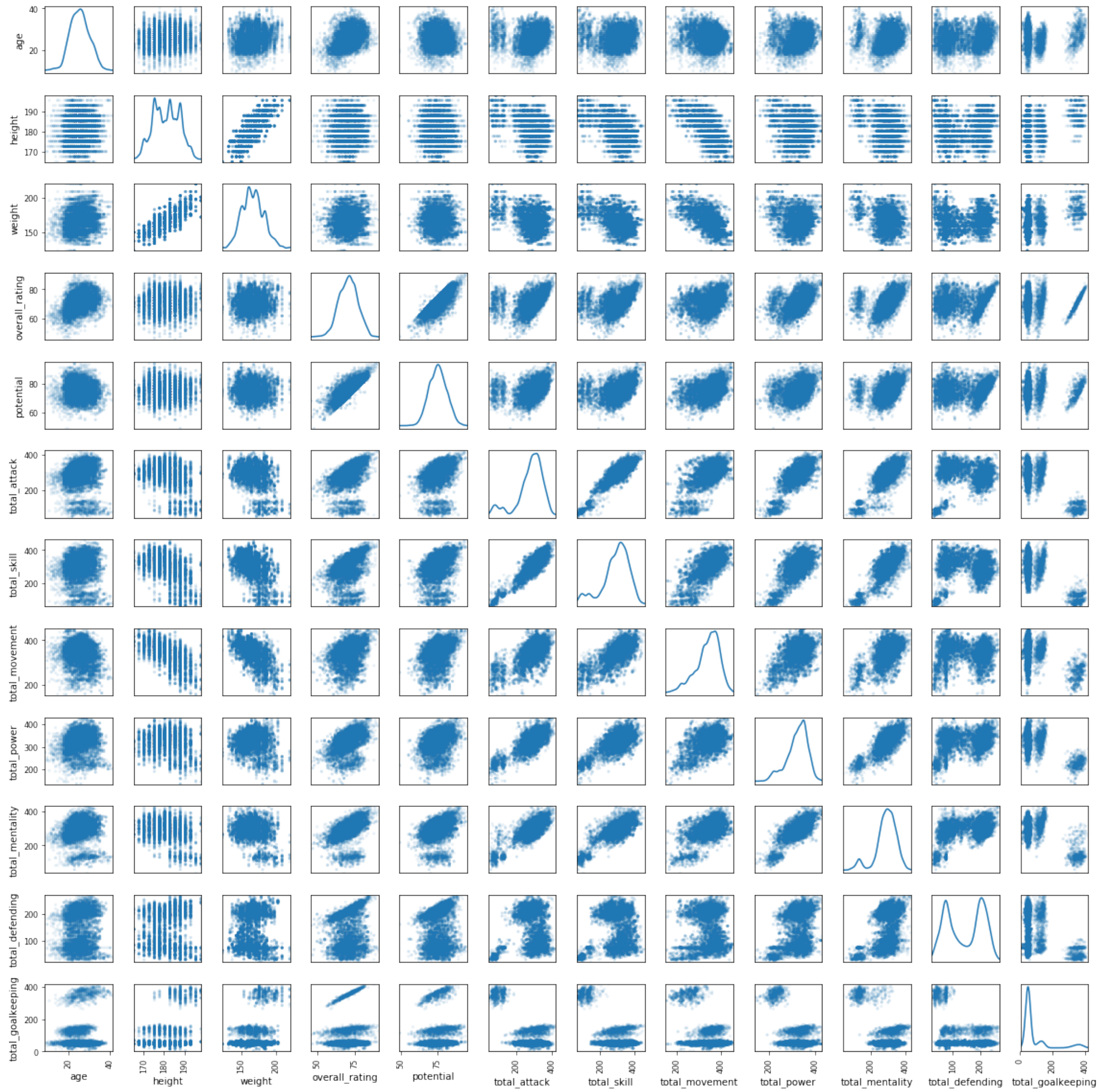

Colored By Defensive Work Rate
overall_rating
90
80
70
60
50
10
20
30
40
50
60
70
80
marking
defensive_work_rate
low


Colored By Defensive Work Rate
overall_rating
90
80
70
60
50
10
20
30
40
50
60
70
80
standing_tackle
defensive_work_rate
low




In [4]:
```
df_totals=df_all_col[numeric_few_col]
pd.plotting.scatter_matrix(df_totals, alpha=0.1, figsize=(16, 16), diagona
l='kde',range_padding =0.01)
plt.tight_layout()
plt.show()
plt.close()

total_cols = numeric_few_col + ['player_fifa_api_id', 'player_name']
df_t=df_all_col[total_cols]
df_t.to_csv('player_total_score_per_attributes_category.csv')
print(df_t.shape)
print (df_t.head())
```



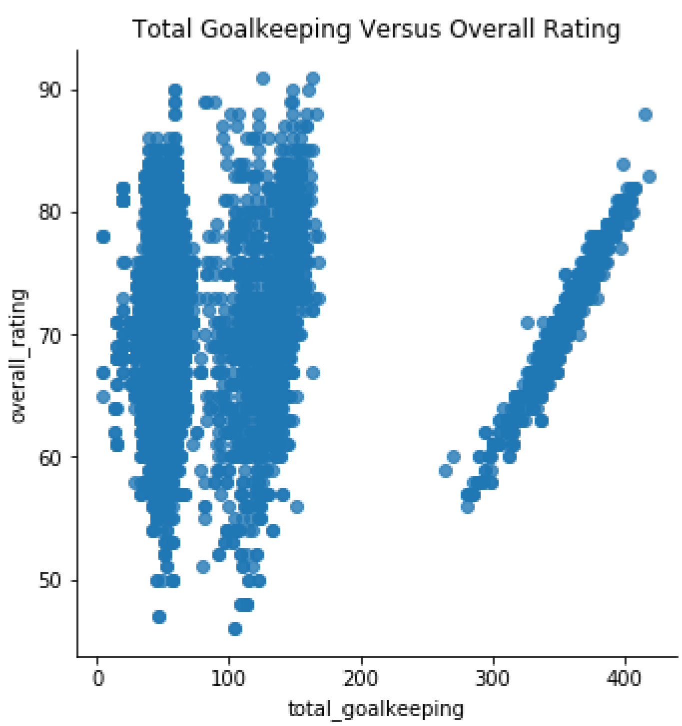

```
(10898, 15)
       age  height  weight  overall_rating  potential  total_attack  \
1045  31.0   177.8     165            73.0       75.0         311.0
1046  31.0   177.8     165            72.0       75.0         307.0
1047  30.0   177.8     165            73.0       75.0         305.0
1048  28.0   177.8     165            73.0       75.0         298.0
1049  28.0   177.8     165            70.0       72.0         288.0

      total_skill  total_movement  total_power  total_mentality  \
1045        319.0           375.0        355.0            351.0
1046        318.0           375.0        355.0            372.0
1047        316.0           377.0        357.0            372.0
1048        311.0           372.0        355.0            370.0
1049        335.0           366.0        346.0            356.0

      total_defending  total_goalkeeping  player_fifa_api_id  \
1045            219.0               42.0               17880
1046            216.0              143.0               17880
1047            221.0              143.0               17880
```

```
1048           221.0              141.0                17880
1049           212.0              102.0                17880

      player_fifa_api_id player_name
1045               17880        Abel
1046               17880        Abel
1047               17880        Abel
1048               17880        Abel
1049               17880        Abel
```

In [16]:

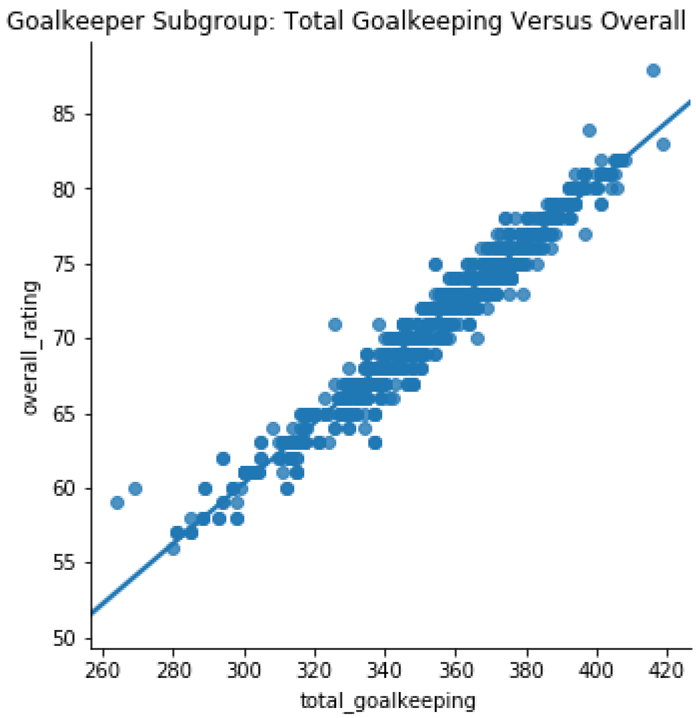
```
# Total Goalkeeping
vis=sns.lmplot(x='total_goalkeeping', y='overall_rating',  hue = None, sha
rex=False, data=df_totals, \
               scatter=True, fit_reg=False, units=None, order=1, legend=Tr
ue)
plt.title('Total Goalkeeping Versus Overall Rating')
plt.show()
plt.close()

df_totals_gk = df_totals[df_totals['total_goalkeeping'] > 250]
corr_gk=df_totals_gk[['total_goalkeeping','overall_rating']].corr()
print ('A Closer Look at the Goalkeeper Subgroup on the Far Right')
print(' total_goalkeeping > 250 ')
print(' ')
print('Strong Positive Linear Correlation: ')
print(corr_gk)

vis=sns.lmplot(x='total_goalkeeping', y='overall_rating',  hue = None, sha
rex=False, data=df_totals_gk, \
               scatter=True, fit_reg=True, units=None, order=1, legend=Tru
e)
plt.title('Goalkeeper Subgroup: Total Goalkeeping Versus Overall Rating')
plt.show()
plt.close()

# Total Mentality
vis=sns.lmplot(x='total_mentality', y='overall_rating',  hue = None, share
x=False, data=df_totals, \
               scatter=True, fit_reg=False, units=None, order=1, legend=Tr
ue)
plt.title('Total Mentality Versus Overall Rating')
plt.show()
plt.close()

df_totals_non_gk = df_totals[df_totals['total_goalkeeping'] < 250]
corr_mentality=df_totals_non_gk[['total_mentality','overall_rating']].corr
()
print ('A Closer Look at the Non_goalkeeper Subgroup on the Far Right')
print(' total_goalkeeping < 250')
print(' ')
print ('Moderate Positive Linear Correlation: ')
print(corr_mentality)

vis=sns.lmplot(x='total_mentality', y='overall_rating',  hue = None, share
x=False, data=df_totals_non_gk, \
               scatter=True, fit_reg=True, units=None, order=1, legend=Tru
e)
```

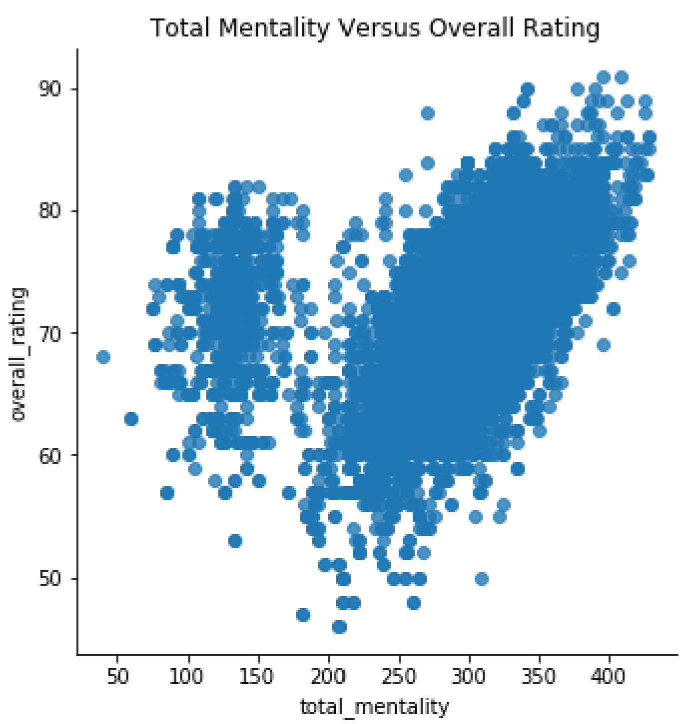
```
plt.title('Non_Goalkeeper Subgroup: Total Mentality Versus Overall Rating'
)
plt.show()
plt.close()

# Total Atack
vis=sns.lmplot(x='total_attack', y='overall_rating',  hue = None, sharex=F
alse, data=df_totals, \
               scatter=True, fit_reg=False, units=None, order=1, legend=Tr
ue)
plt.title('Total Attack Versus Overall Rating')
plt.show()
plt.close()

df_totals_non_gk = df_totals[df_totals['total_goalkeeping'] < 250]
corr_attack=df_totals_non_gk[['total_attack','overall_rating']].corr()
print ('A Closer Look at the Non_goalkeeper Subgroup on the Far Right')
print(' total_goalkeeping < 250')
print(' ')
print ('Moderate Positive Linear Correlation: ')
print(corr_attack)

vis=sns.lmplot(x='total_attack', y='overall_rating',  hue = None, sharex=F
alse, data=df_totals_non_gk, \
               scatter=True, fit_reg=True, units=None, order=1, legend=Tru
e)
plt.title('Non_Goalkeeper Subgroup: Total Attack Versus Overall Rating')
plt.show()
plt.close()
```



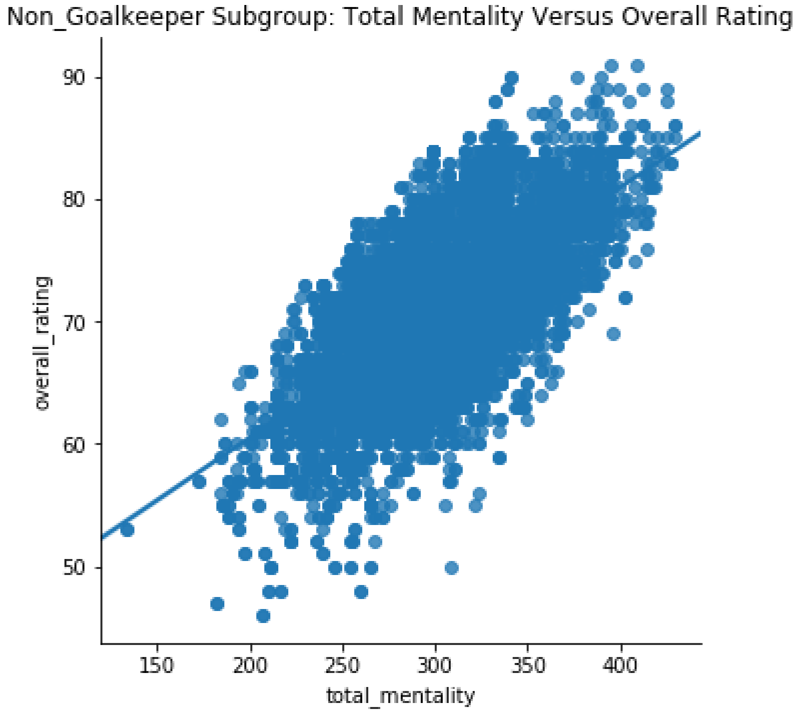

```
A Closer Look at the Goalkeeper Subgroup on the Far Right
 total_goalkeeping > 250

Strong Positive Linear Correlation:
                   total_goalkeeping  overall_rating
```

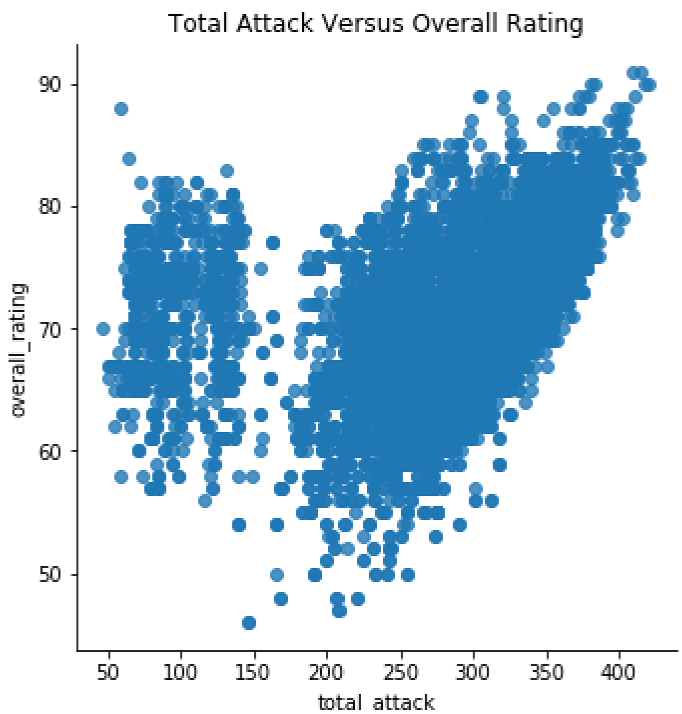
```
total_goalkeeping          1.000000       0.978269
overall_rating             0.978269       1.000000
```



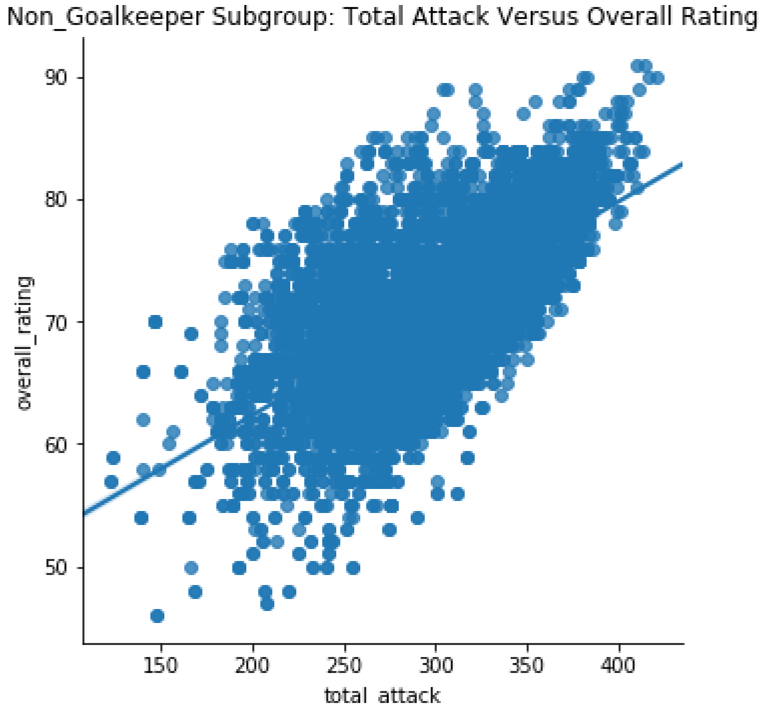




```
A Closer Look at the Non_goalkeeper Subgroup on the Far Right
 total_goalkeeping < 250

Moderate Positive Linear Correlation:
                 total_mentality  overall_rating
total_mentality          1.00000         0.67607
overall_rating           0.67607         1.00000
```




```
A Closer Look at the Non_goalkeeper Subgroup on the Far Right
 total_goalkeeping < 250

Moderate Positive Linear Correlation:
                total_attack  overall_rating
total_attack        1.000000        0.628757
overall_rating      0.628757        1.000000
```




## Interpret correlation coefficient

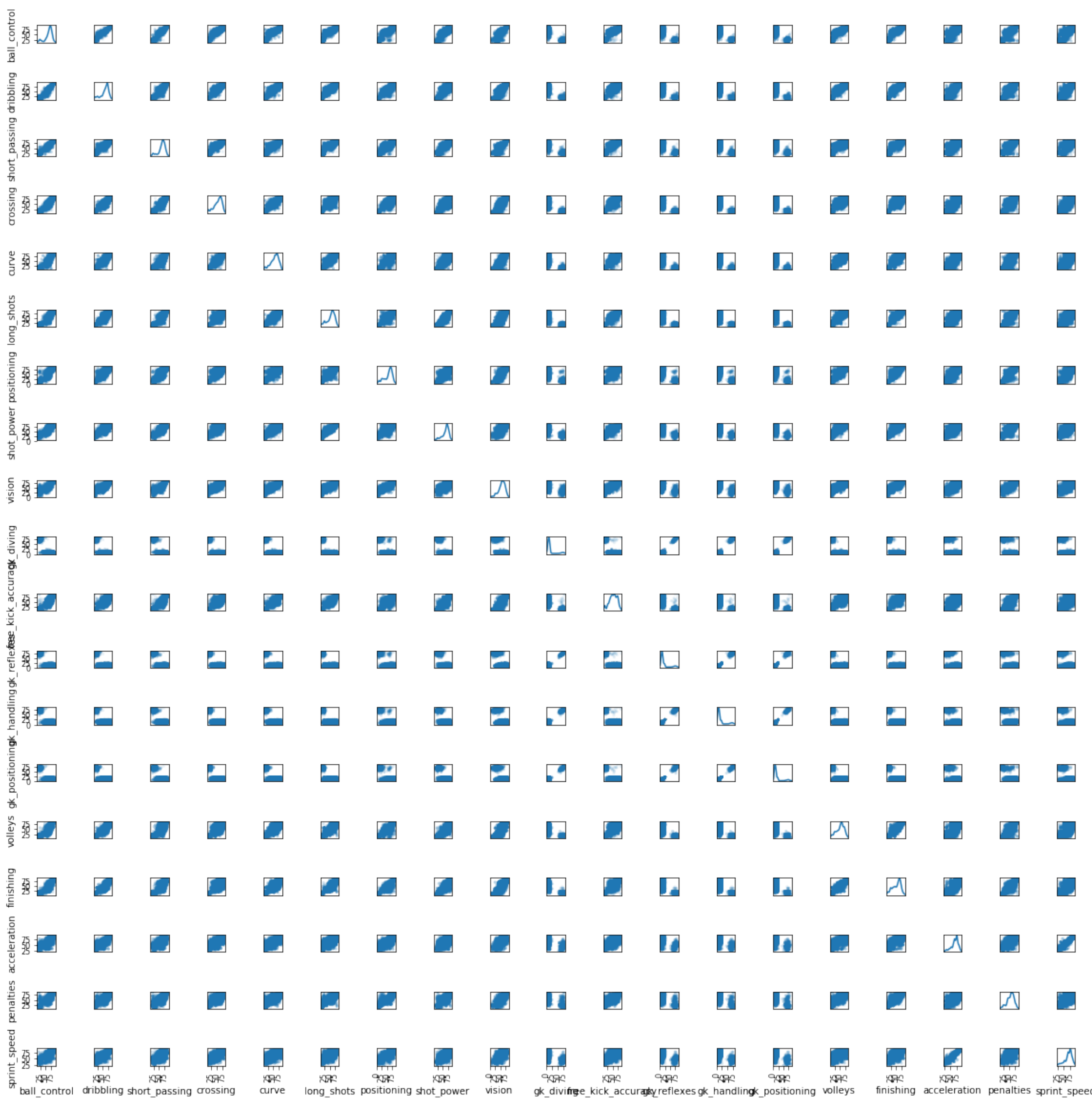
Exactly –1. A perfect downhill (negative) linear relationship
• –0.70. A strong downhill (negative) linear relationship
• –0.50. A moderate downhill (negative) relationship
• –0.30. A weak downhill (negative) linear relationship
• 0. No linear relationship

In [9]:
```
# save correlation coefficient for dataset to csv
df_corr = df_unscaled_data.corr()
df_corr.to_csv('df_corr.csv')

df_gk=df_unscaled_data.loc[df_unscaled_data['gk_diving']>50]
df_gk_corr = df_gk.corr()
df_gk_corr.to_csv('df_gk_corr.csv')

df_non_gk=df_unscaled_data.loc[df_unscaled_data['gk_diving']<50]
df_non_gk_corr = df_non_gk.corr()
df_non_gk_corr.to_csv('df_non_gk_corr.csv')
```

In [31]:
```
print('Unscaled Data Scatter Matrix 1')
print('PC1 sorted components: ', loading_scores_PC1_sorted.index[0:19])
#col_of_interest = ['ball_control', 'dribbling', 'short_passing', 'crossin
g', 'curve','long_shots', 'positioning', 'shot_power', 'vision', 'gk_divin
g','free_kick_accuracy', 'gk_reflexes', 'gk_handling']
col_of_interest = loading_scores_PC1_sorted.index[0:19]
df_col_of_interest= df_unscaled_data[col_of_interest] # scatter matrix for
 columns of interest


pd.plotting.scatter_matrix(df_col_of_interest, alpha=0.1, figsize=(16, 16)
```

```
, diagonal='kde',range_padding =0.01)
plt.tight_layout()
plt.show()
plt.close()
```

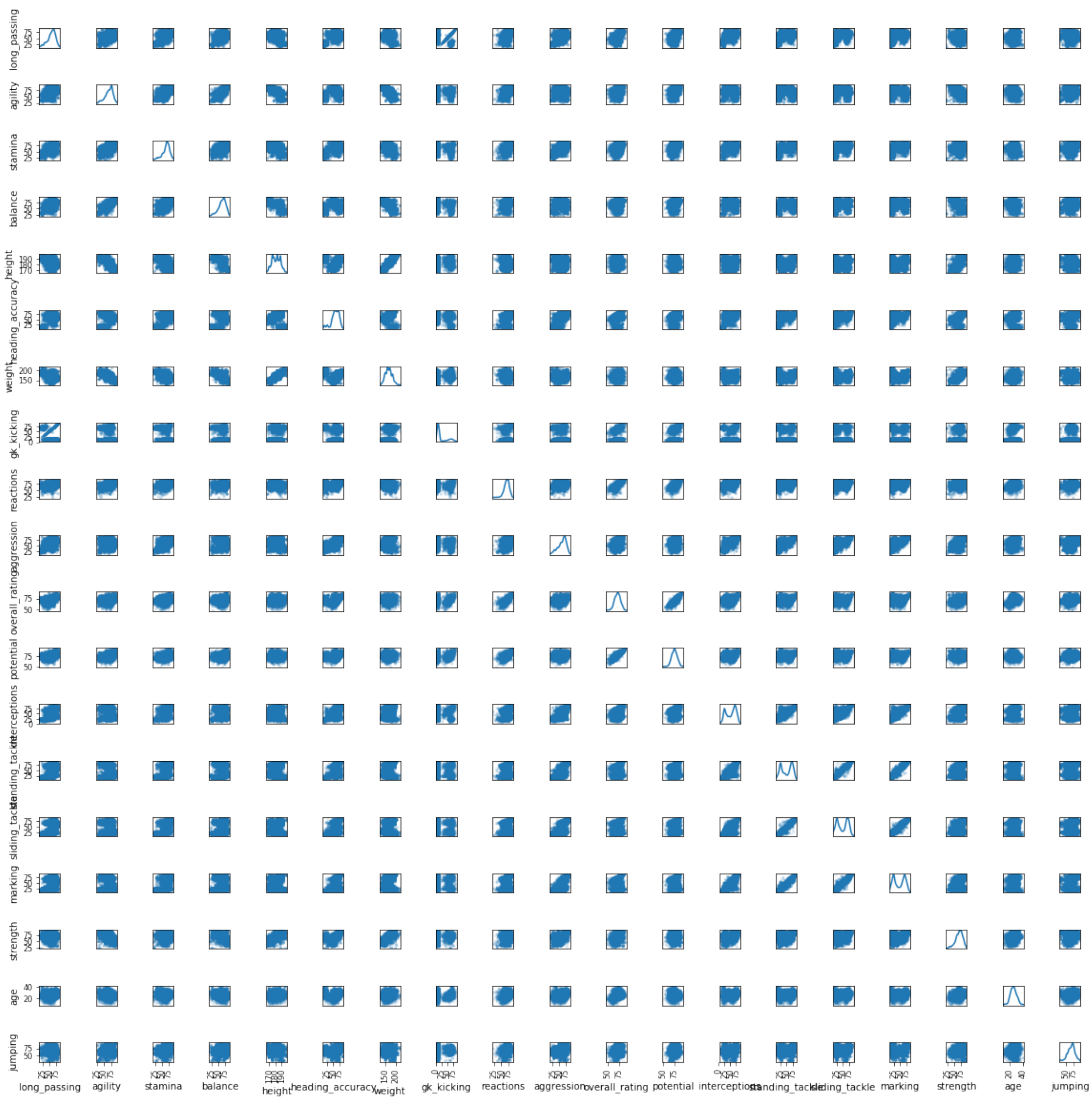
```
Unscaled Data Scatter Matrix 1
PC1 sorted components:  Index(['ball_control', 'dribbling', 'short_passing
', 'crossing', 'curve',
       'long_shots', 'positioning', 'shot_power', 'vision', 'gk_diving',
       'free_kick_accuracy', 'gk_reflexes', 'gk_handling', 'gk_positioning
',
       'volleys', 'finishing', 'acceleration', 'penalties', 'sprint_speed'
],
      dtype='object')
```




In [39]:
```
print('Unscaled Data Scatter Matrix 2')
print('PC1 sorted components: ', loading_scores_PC1_sorted.index[19:38])
#col_of_interest = ['ball_control', 'dribbling', 'short_passing', 'crossin
g', 'curve','long_shots', 'positioning', 'shot_power', 'vision', 'gk_divin
```

```
g','free_kick_accuracy', 'gk_reflexes', 'gk_handling']
col_of_interest = loading_scores_PC1_sorted.index[19:38]
df_col_of_interest= df_unscaled_data[col_of_interest] # scatter matrix for
 columns of interest

pd.plotting.scatter_matrix(df_col_of_interest, alpha=0.1, figsize=(16, 16)
, diagonal='kde',range_padding =0.01)
plt.tight_layout()
plt.show()
plt.close()
```

```
Unscaled Data Scatter Matrix 2
PC1 sorted components:  Index(['long_passing', 'agility', 'stamina', 'bala
nce', 'height',
       'heading_accuracy', 'weight', 'gk_kicking', 'reactions', 'aggressio
n',
       'overall_rating', 'potential', 'interceptions', 'standing_tackle',
       'sliding_tackle', 'marking', 'strength', 'age', 'jumping'],
      dtype='object')
```

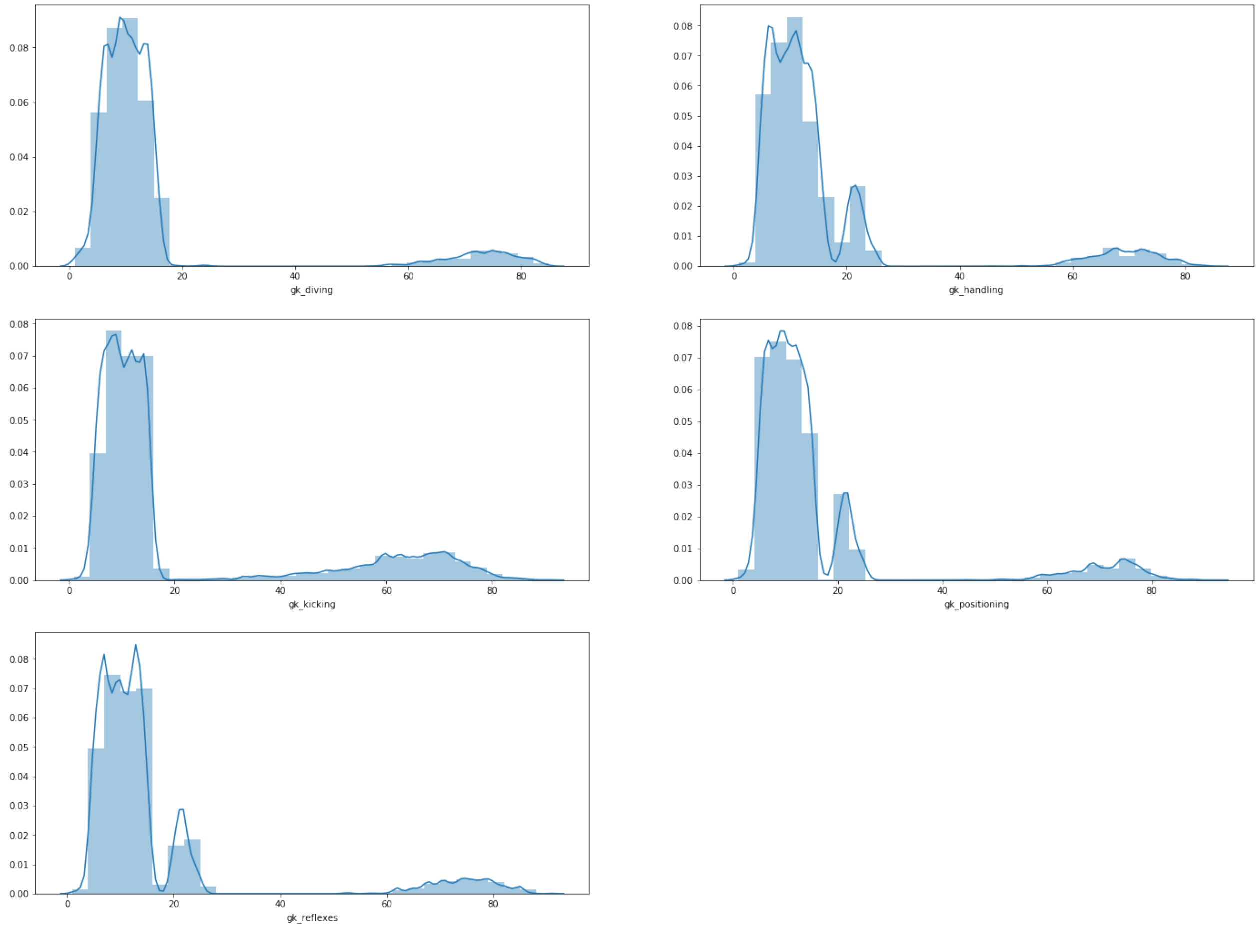


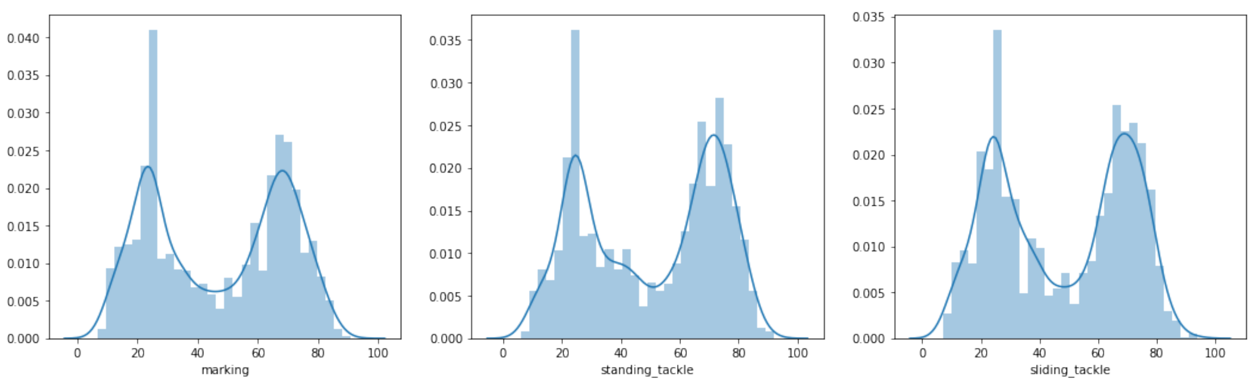
In [36]:
```
# create distribution plot for all features

final_col = ['player_fifa_api_id','preferred_foot','attacking_work_rate',
'defensive_work_rate'] + numeric_col
print(final_col)
df_final=df_all_col[final_col]
'''
df_final=def_all_col['player_fifa_api_id', 'preferred_foot', 'attacking_wo
rk_rate', 'defensive_work_rate', 'age', \
                     'height', 'weight', 'overall_rating', 'potential', 'c
rossing', 'finishing', 'heading_accuracy', \
                     'short_passing', 'volleys', 'dribbling', 'curve', 'fr
ee_kick_accuracy', 'long_passing', \
                     'ball_control', 'acceleration', 'sprint_speed', 'agil
ity', 'reactions', 'balance', 'shot_power', \
                     'jumping', 'stamina', 'strength', 'long_shots', 'aggr
ession', 'interceptions', 'positioning', \
                     'vision', 'penalties', 'marking', 'standing_tackle',
'sliding_tackle', 'gk_diving', 'gk_handling', \
                     'gk_kicking', 'gk_positioning', 'gk_reflexes']
'''
print(df_final.head())
print(len(final_col))
df_final.to_csv("df_final.csv")

# distplot for goalkeeping attributes
fig = plt.figure(figsize=(24,18))
ax1 = fig.add_subplot(321)
ax2 = fig.add_subplot(322)
ax3 = fig.add_subplot(323)
ax4 = fig.add_subplot(324)
ax5 = fig.add_subplot(325)
vis1=sns.distplot (df_all_col['gk_diving'], bins=30, ax=ax1)
vis2=sns.distplot (df_all_col['gk_handling'], bins=30, ax=ax2)
vis3=sns.distplot (df_all_col['gk_kicking'], bins=30, ax=ax3)
vis4=sns.distplot (df_all_col['gk_positioning'], bins=30, ax=ax4)
vis5=sns.distplot (df_all_col['gk_reflexes'], bins=30, ax=ax5)
plt.show()
plt.close()

# distplot for defending attributes
fig = plt.figure(figsize=(18,5))
ax6 = fig.add_subplot(131)
ax7 = fig.add_subplot(132)
ax8 = fig.add_subplot(133)
vis6=sns.distplot (df_all_col['marking'], bins=30, ax=ax6)
vis7=sns.distplot (df_all_col['standing_tackle'], bins=30, ax=ax7)
vis8=sns.distplot (df_all_col['sliding_tackle'], bins=30, ax=ax8)
plt.show()
plt.close()

#  distplot
for i in range (4,42) :
    sns.distplot (df_all_col[final_col[i]], bins=30)
    plt.title('Distribution Plot')
    plt.show()
```

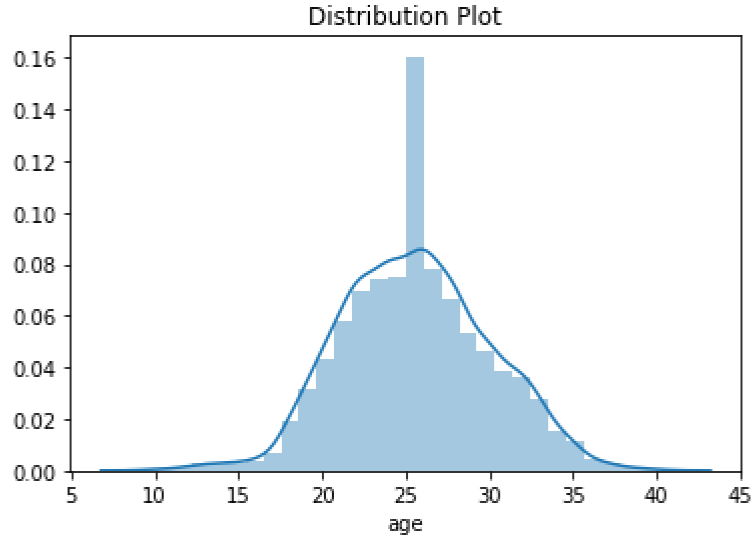
```
plt.close()
```

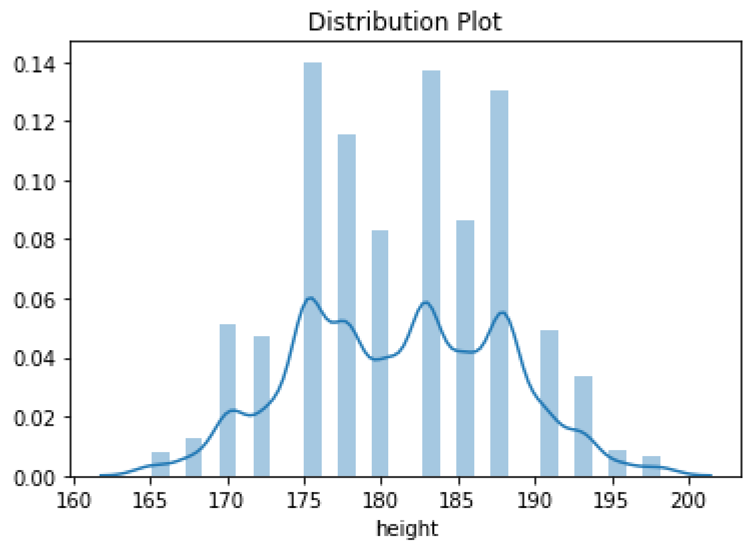
```
['player_fifa_api_id', 'preferred_foot', 'attacking_work_rate', 'defensive
_work_rate', 'age', 'height', 'weight', 'overall_rating', 'potential', 'cr
ossing', 'finishing', 'heading_accuracy', 'short_passing', 'volleys', 'dri
bbling', 'curve', 'free_kick_accuracy', 'long_passing', 'ball_control', 'a
cceleration', 'sprint_speed', 'agility', 'reactions', 'balance', 'shot_pow
er', 'jumping', 'stamina', 'strength', 'long_shots', 'aggression', 'interc
eptions', 'positioning', 'vision', 'penalties', 'marking', 'standing_tackl
e', 'sliding_tackle', 'gk_diving', 'gk_handling', 'gk_kicking', 'gk_positi
oning', 'gk_reflexes']
      player_fifa_api_id  player_fifa_api_id preferred_foot  \
1045               17880               17880          right
1046               17880               17880          right
1047               17880               17880          right
1048               17880               17880          right
1049               17880               17880          right

     attacking_work_rate defensive_work_rate   age  height  weight  \
1045                None                   o  31.0   177.8     165
1046                None                   o  31.0   177.8     165
1047                None                   o  30.0   177.8     165
1048                None                   o  28.0   177.8     165
1049                None                   o  28.0   177.8     165

      overall_rating  potential     ...       vision  penalties  marking
\
1045            73.0       75.0     ...         75.0       66.0     73.0

1046            72.0       75.0     ...         75.0       75.0     72.0

1047            73.0       75.0     ...         75.0       75.0     74.0

1048            73.0       75.0     ...         75.0       76.0     74.0

1049            70.0       72.0     ...         75.0       83.0     70.0


      standing_tackle  sliding_tackle  gk_diving  gk_handling  gk_kicking
 \
1045             74.0            72.0        7.0          5.0         7.0

1046             72.0            72.0        9.0         20.0        74.0

1047             75.0            72.0        9.0         20.0        74.0

1048             75.0            72.0        9.0         20.0        72.0

1049             70.0            72.0        9.0         10.0        63.0


      gk_positioning  gk_reflexes
1045            13.0         10.0
1046            20.0         20.0
1047            20.0         20.0
1048            20.0         20.0
1049             8.0         12.0
```

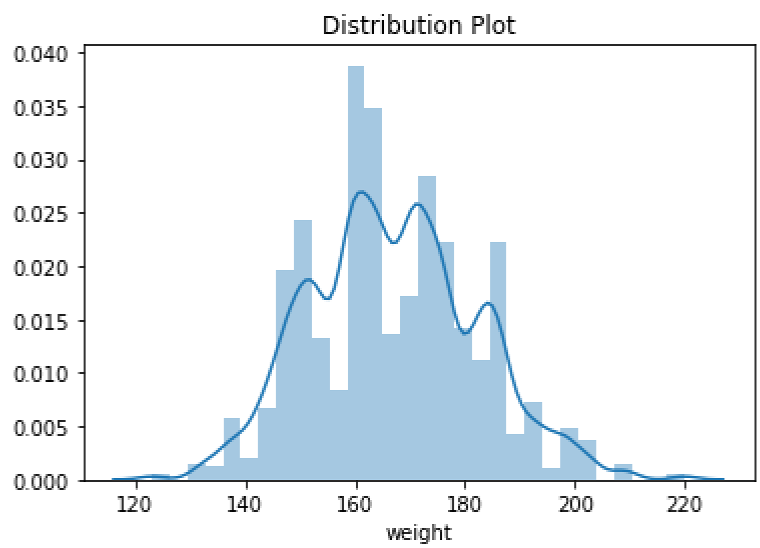
```
[5 rows x 43 columns]
42
```

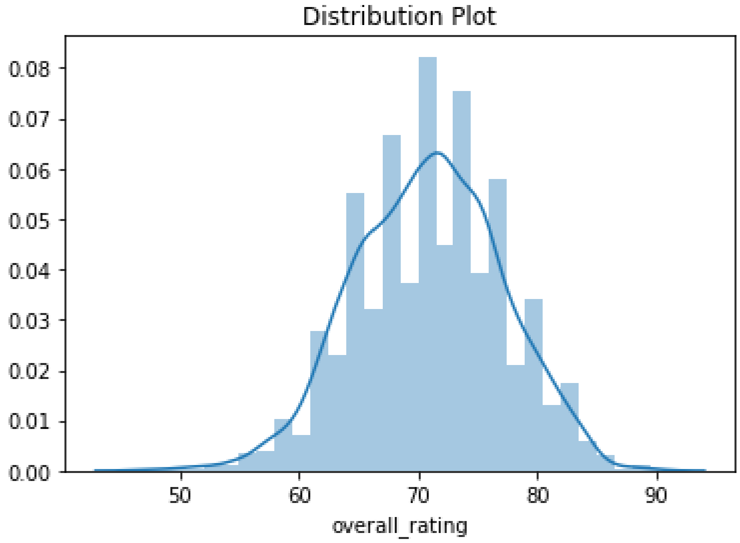


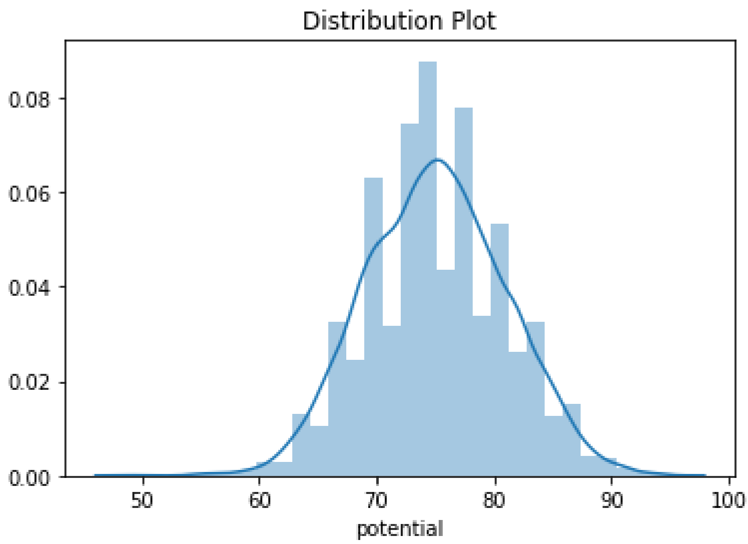



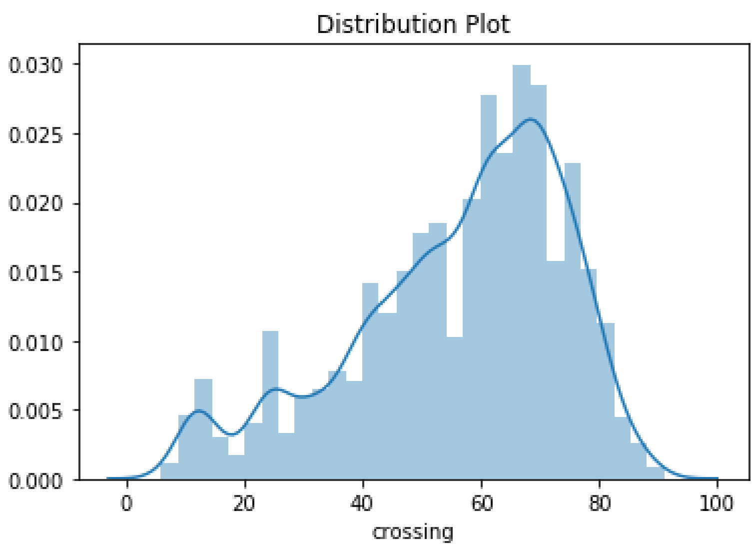

Distribution Plot
0.16
0.14
0.12
0.10
0.08
0.06
0.04
0.02
0.00
5
10
15
20
25
30
35
40
45
age

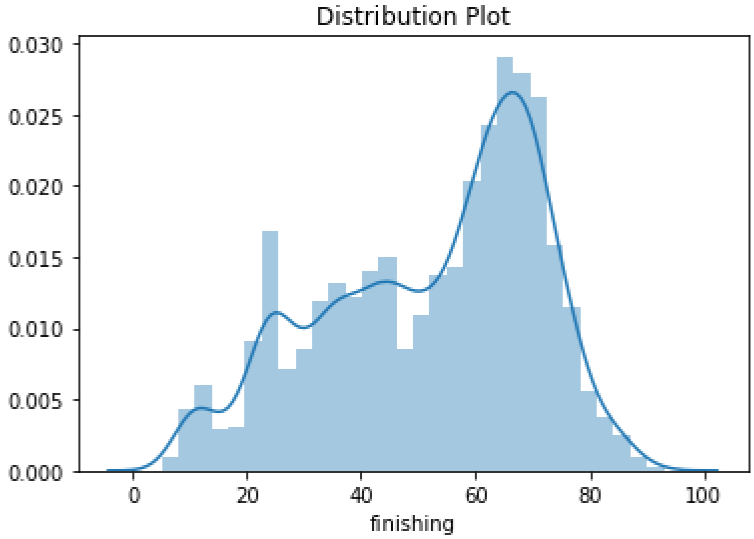

Distribution Plot
0.14
0.12
0.10
0.08
0.06
0.04
0.02
0.00
160
165
170
175
180
185
190
195
200
height

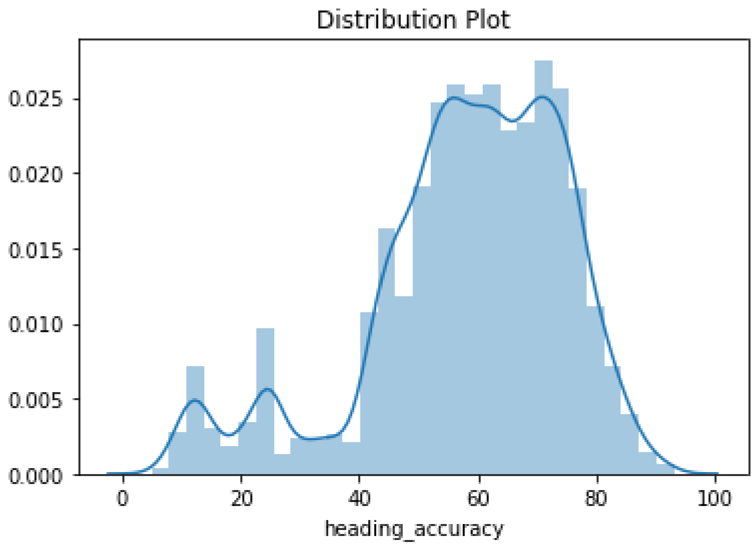

Distribution Plot
0.040
0.035
0.030
0.025
0.020
0.015
0.010
0.005
0.000
120
140
160
180
200
220
weight

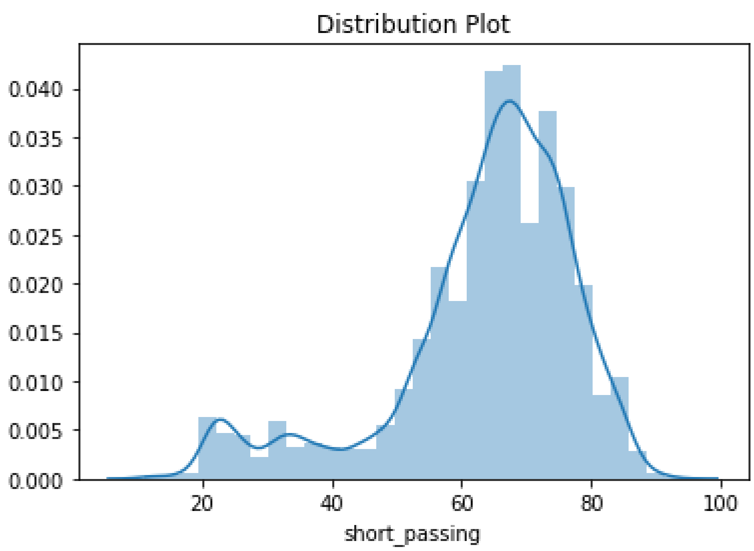

Distribution Plot
0.08
0.07
0.06
0.05
0.04
0.03
0.02
0.01
0.00
50
60
70
80
90
overall_rating

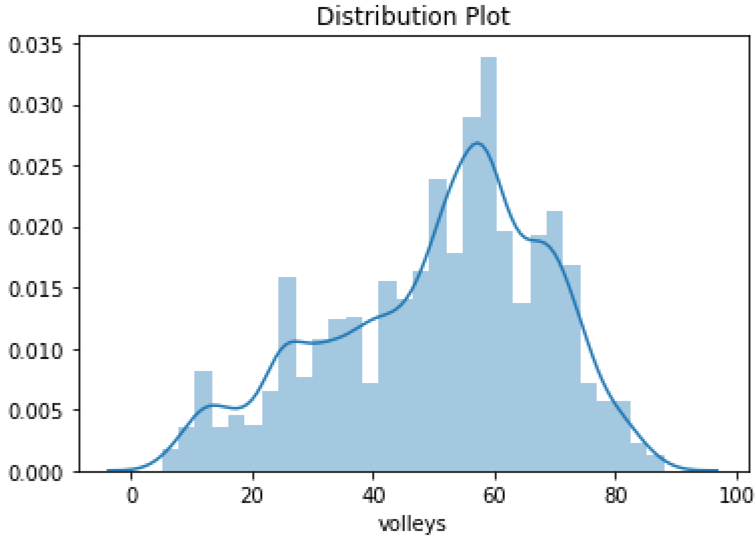

Distribution Plot
0.08
0.06
0.04
0.02
0.00
50
60
70
80
90
100
potential

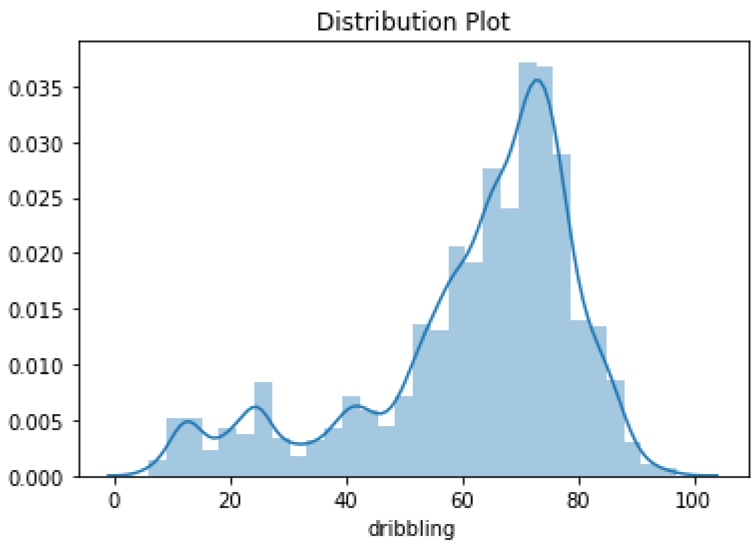

Distribution Plot
0.030
0.025
0.020
0.015
0.010
0.005
0.000
0
20
40
60
80
100
crossing

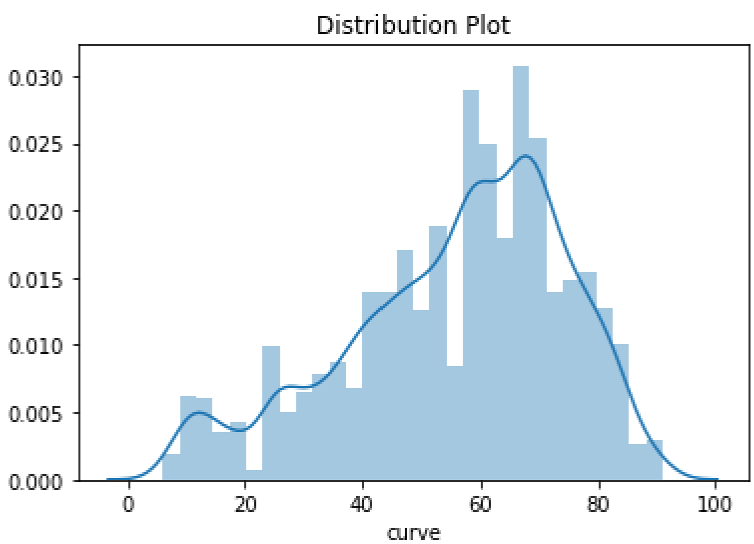

Distribution Plot
0.030
0.025
0.020
0.015
0.010
0.005
0.000
0
20
40
60
80
100
finishing

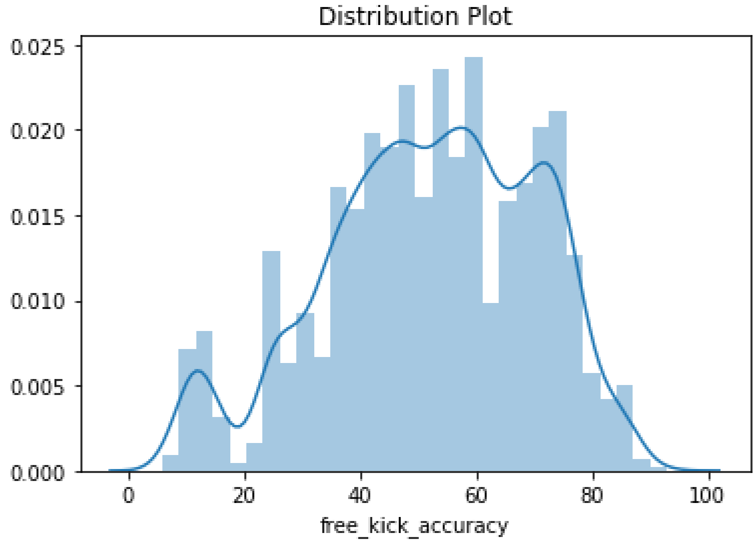

Distribution Plot
0.025
0.020
0.015
0.010
0.005
0.000
0
20
40
60
80
100
heading_accuracy

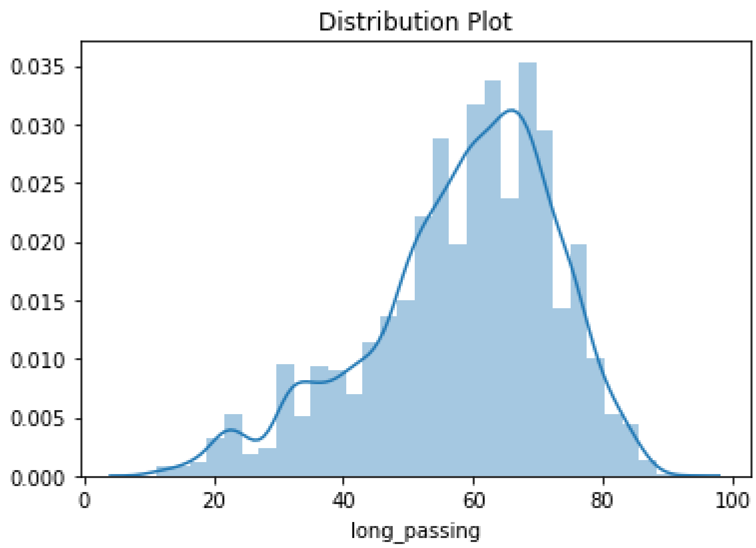

Distribution Plot
0.040
0.035
0.030
0.025
0.020
0.015
0.010
0.005
0.000
20
40
60
80
100
short_passing

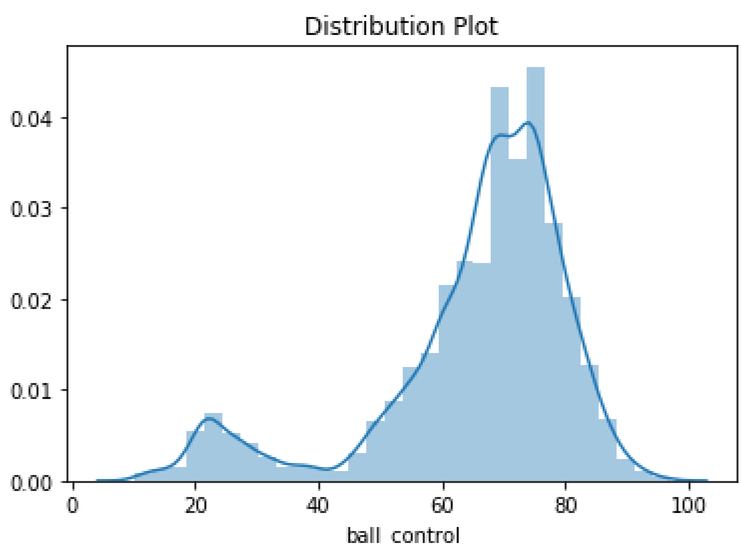

Distribution Plot
0.035
0.030
0.025
0.020
0.015
0.010
0.005
0.000
0
20
40
60
80
100
volleys

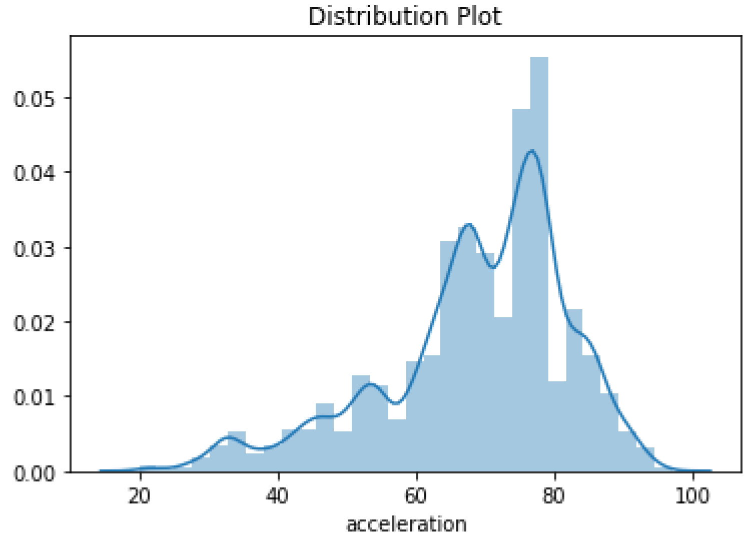

Distribution Plot
0.035
0.030
0.025
0.020
0.015
0.010
0.005
0.000
0
20
40
60
80
100
dribbling

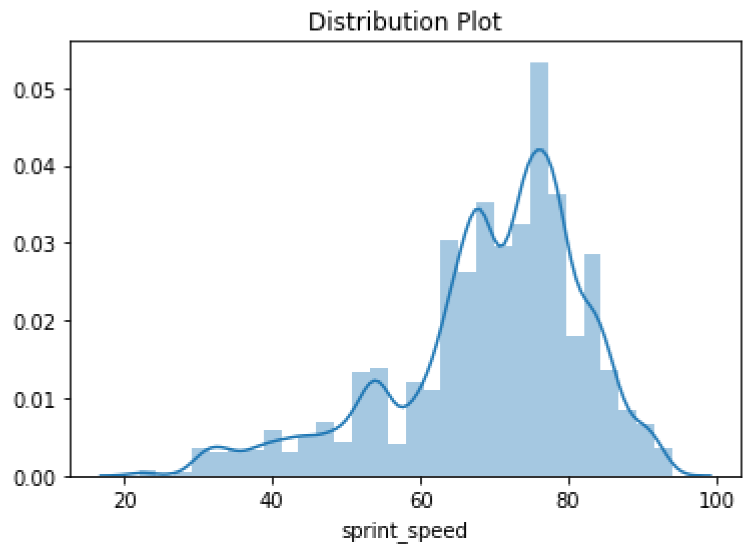

Distribution Plot
0.030
0.025
0.020
0.015
0.010
0.005
0.000
0
20
40
60
80
100
curve

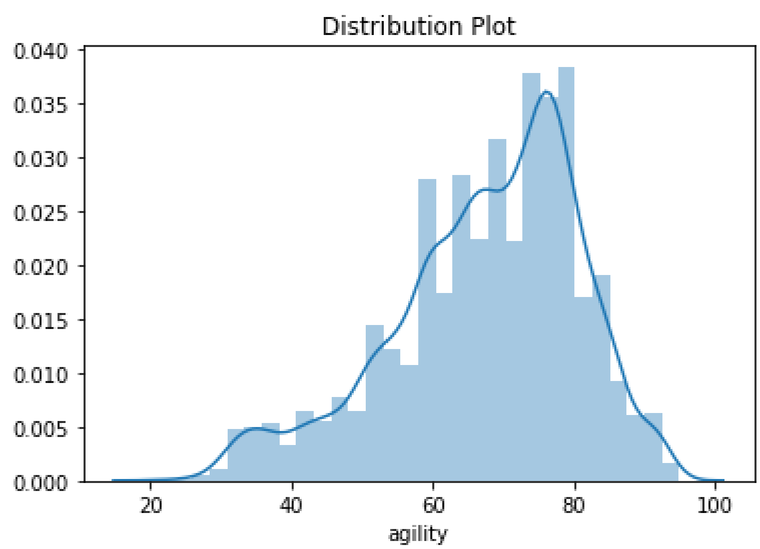

Distribution Plot
0.025
0.020
0.015
0.010
0.005
0.000
0
20
40
60
80
100
free_kick_accuracy

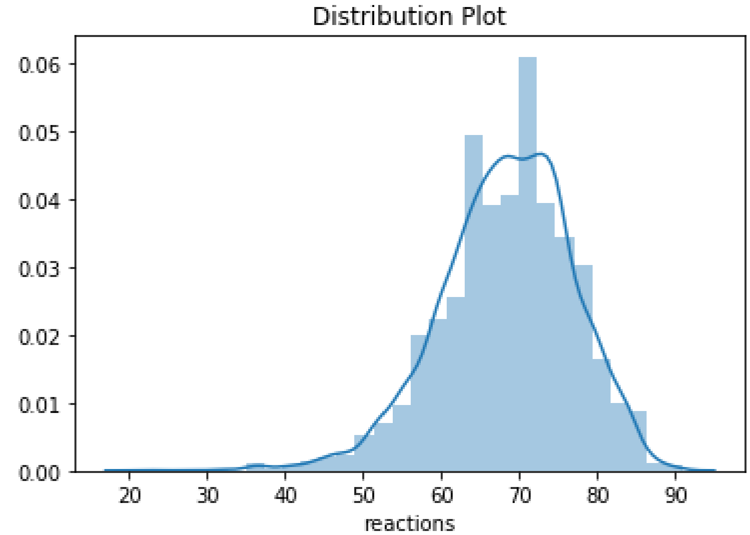

Distribution Plot
0.035
0.030
0.025
0.020
0.015
0.010
0.005
0.000
0
20
40
60
80
100
long_passing

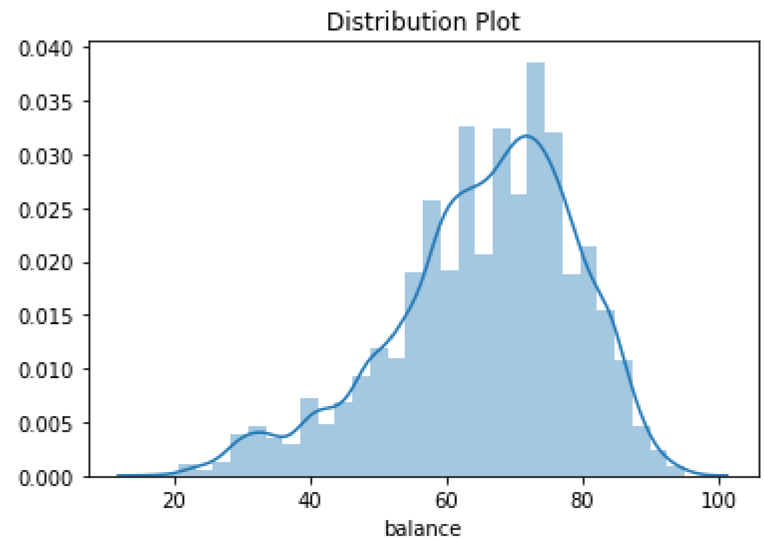

Distribution Plot
0.04
0.03
0.02
0.01
0.00
0
20
40
60
80
100
ball_control

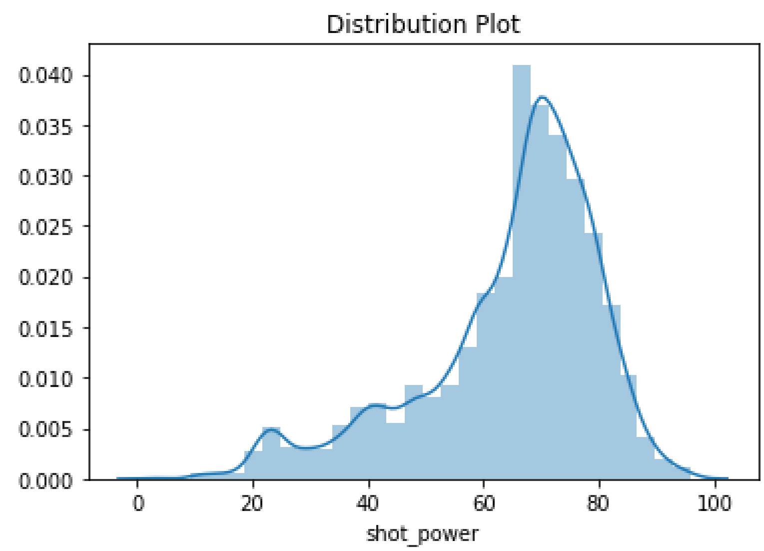

Distribution Plot
0.05
0.04
0.03
0.02
0.01
0.00
20
40
60
80
100
acceleration

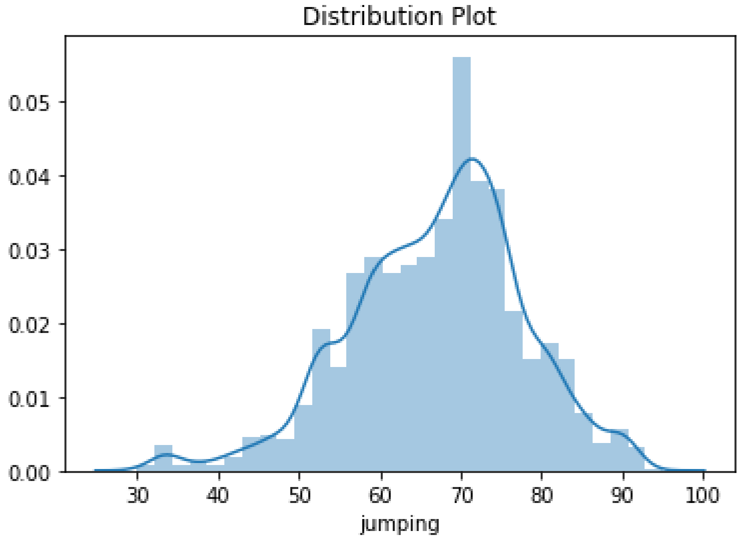

Distribution Plot
0.05
0.04
0.03
0.02
0.01
0.00
20
40
60
80
100
sprint_speed

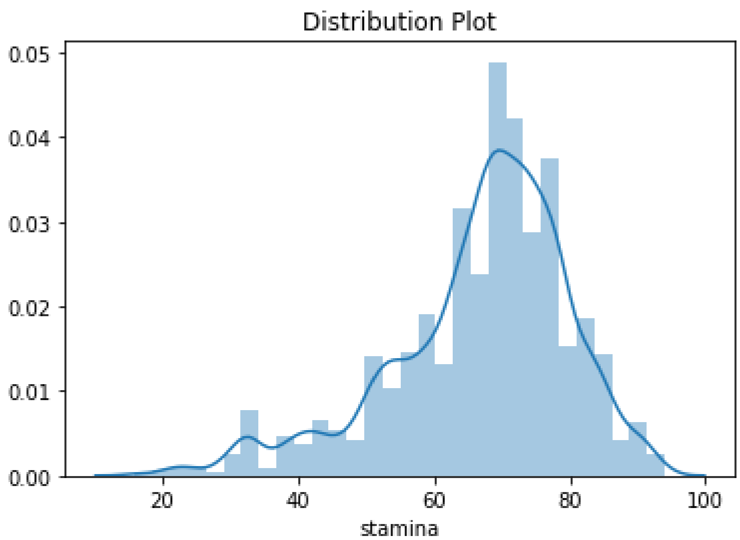

Distribution Plot
0.040
0.035
0.030
0.025
0.020
0.015
0.010
0.005
0.000
20
40
60
80
100
agility

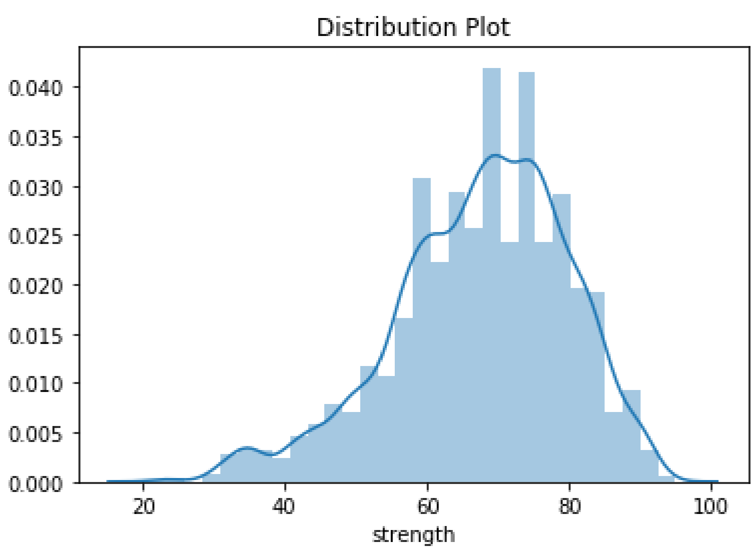

Distribution Plot
0.06
0.05
0.04
0.03
0.02
0.01
0.00
20
30
40
50
60
70
80
90
reactions


Distribution Plot
0.040
0.035
0.030
0.025
0.020
0.015
0.010
0.005
0.000
20
40
60
80
100
balance


Distribution Plot
0.040
0.035
0.030
0.025
0.020
0.015
0.010
0.005
0.000
0
20
40
60
80
100
shot_power


Distribution Plot
0.05
0.04
0.03
0.02
0.01
0.00
30
40
50
60
70
80
90
100
jumping


Distribution Plot
0.05
0.04
0.03
0.02
0.01
0.00
20
40
60
80
100
stamina


Distribution Plot
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0.035
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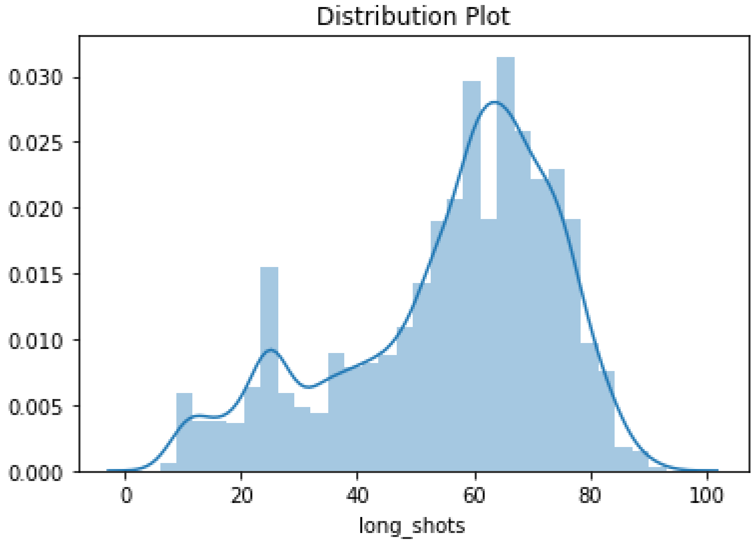
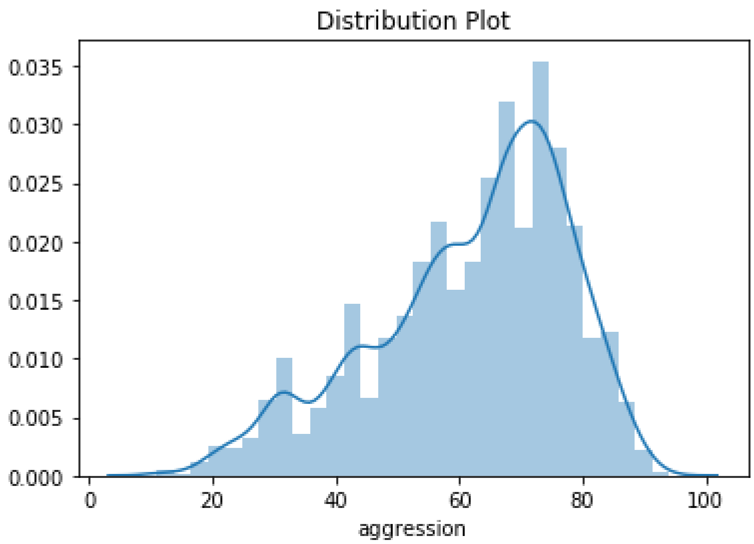
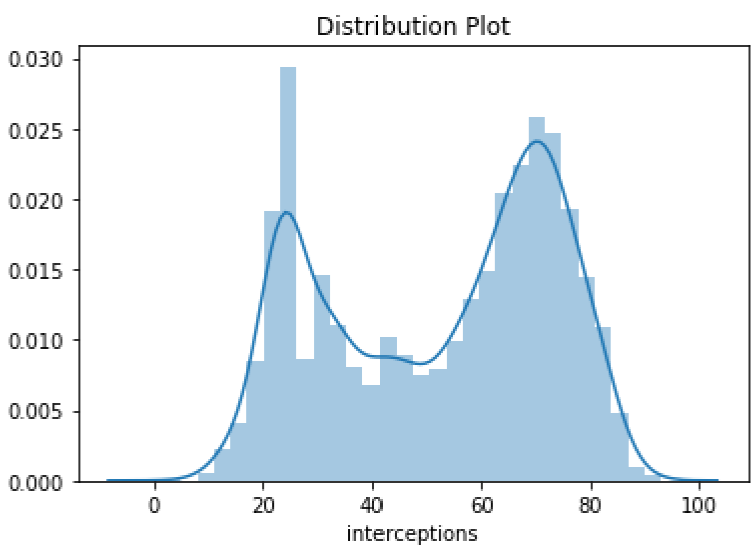
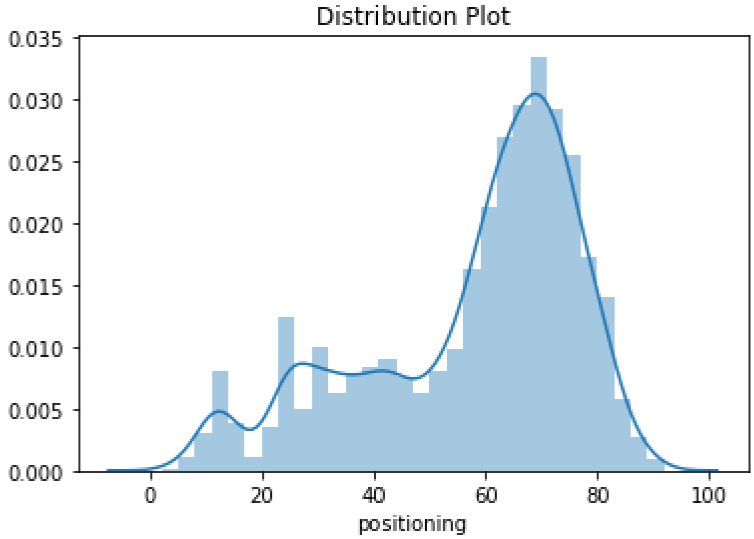
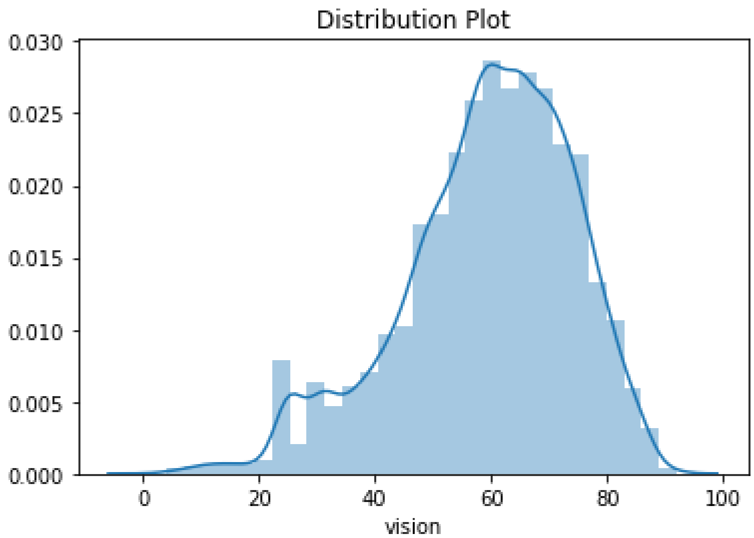
0.025
0.020
0.015
0.010
0.005
0.000
20
40
60
80
100
strength


Distribution Plot
0.030
0.025
0.020
0.015
0.010
0.005
0.000
0
20
40
60
80
100
long_shots


Distribution Plot
0.035
0.030
0.025
0.020
0.015
0.010
0.005
0.000
0
20
40
60
80
100
aggression


Distribution Plot
0.030
0.025
0.020
0.015
0.010
0.005
0.000
0
20
40
60
80
100
interceptions


Distribution Plot
0.035
0.030
0.025
0.020
0.015
0.010
0.005
0.000
0
20
40
60
80
100
positioning


Distribution Plot
0.030
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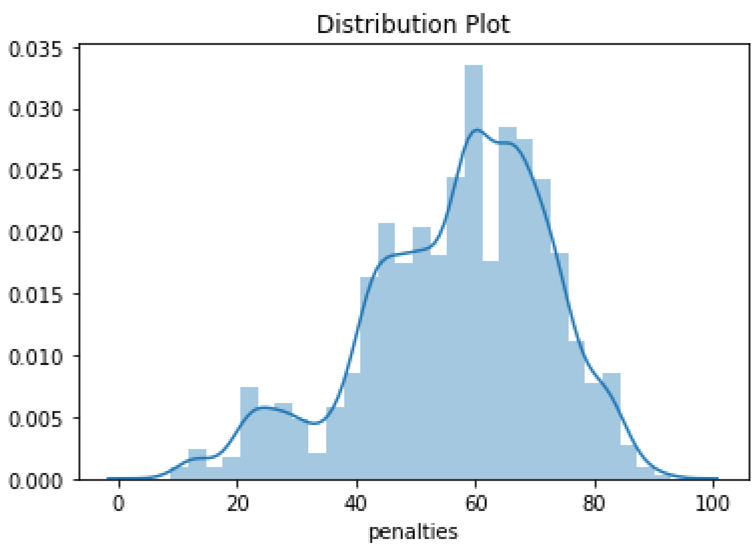
0.020
0.015
0.010
0.005
0.000
0
20
40
60
80
100
vision


Distribution Plot
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0.030
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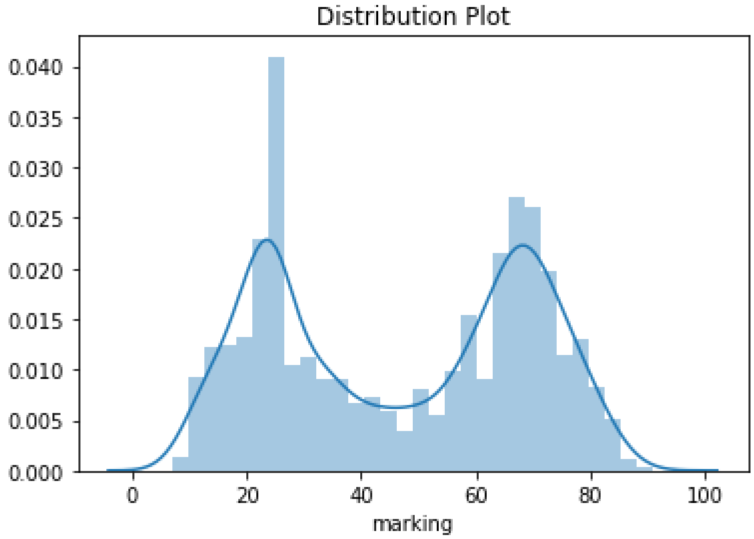
0.020
0.015
0.010
0.005
0.000
0
20
40
60
80
100
penalties


Distribution Plot
0.040
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0.025
0.020
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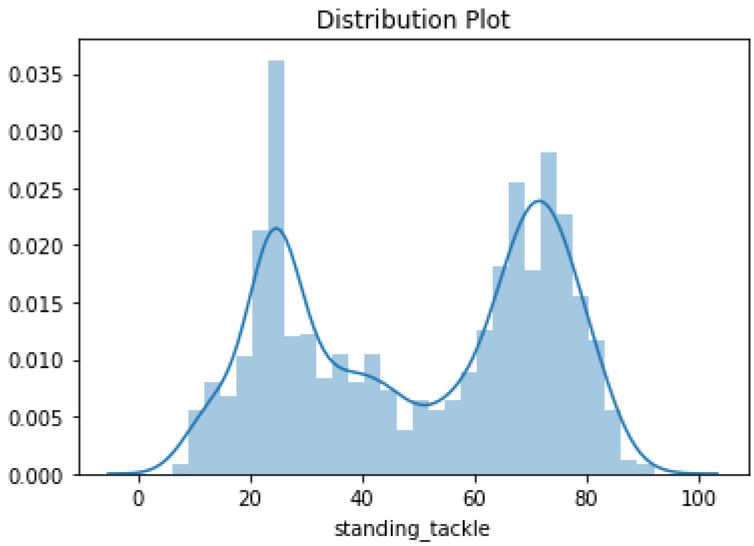
0.010
0.005
0.000
0
20
40
60
80
100
marking


Distribution Plot
0.035
0.030
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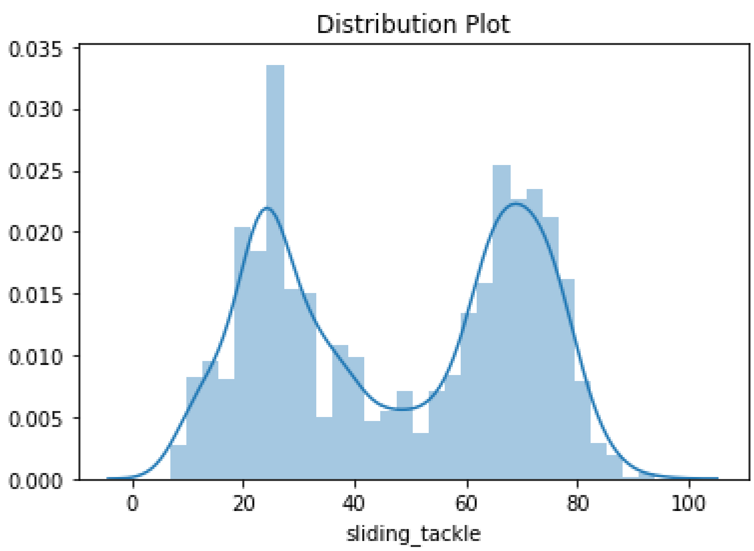
0.020
0.015
0.010
0.005
0.000
0
20
40
60
80
100
standing_tackle


Distribution Plot
0.035
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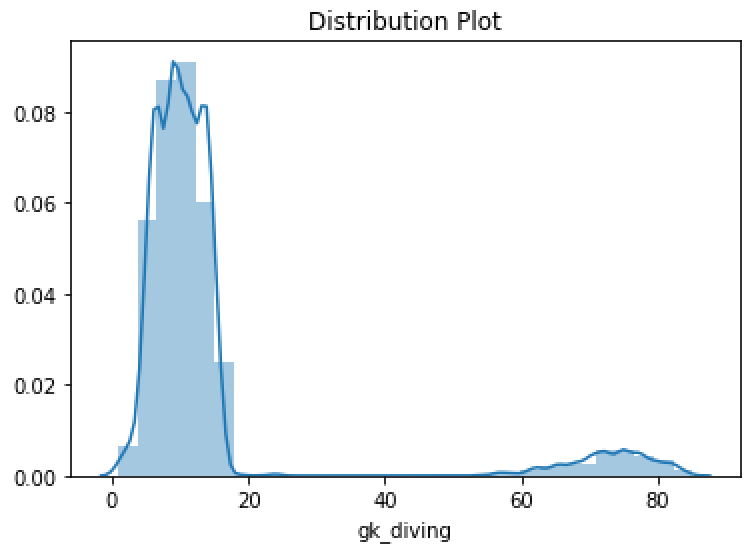
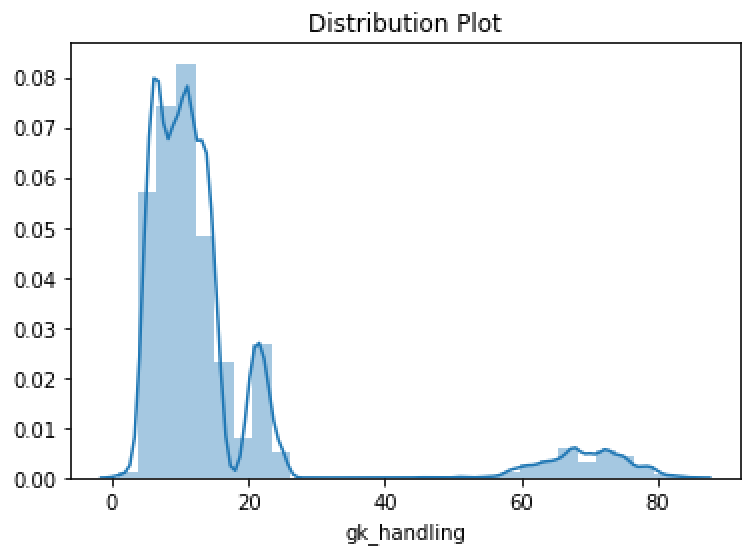
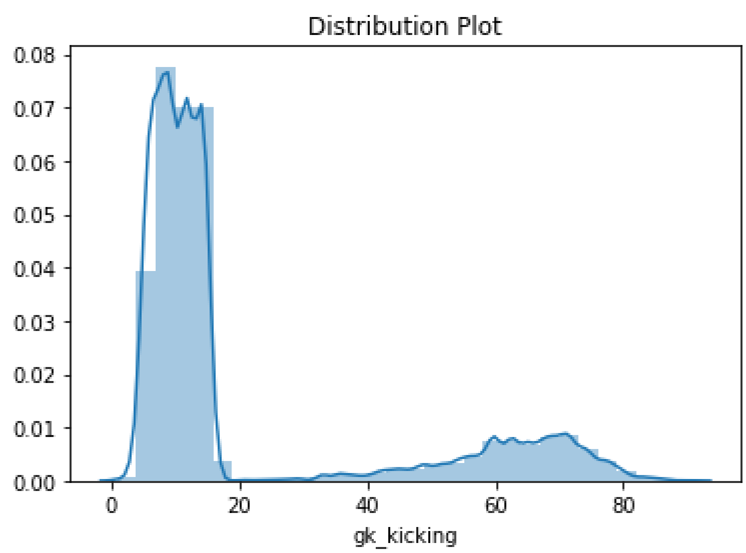
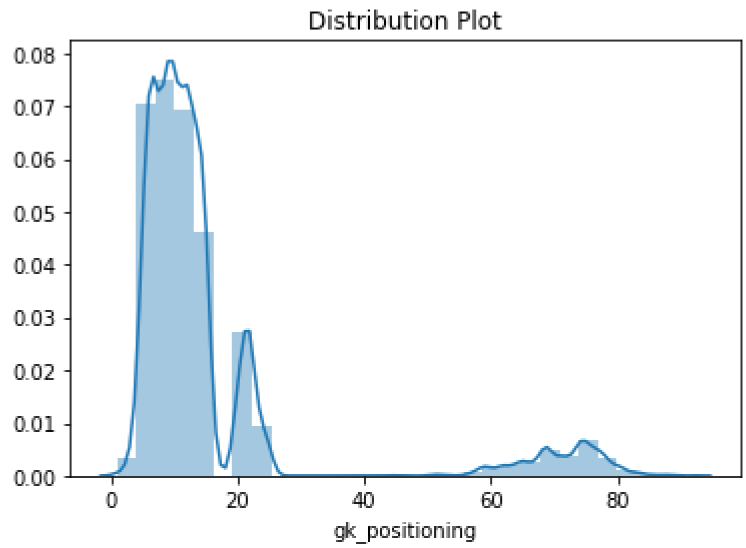
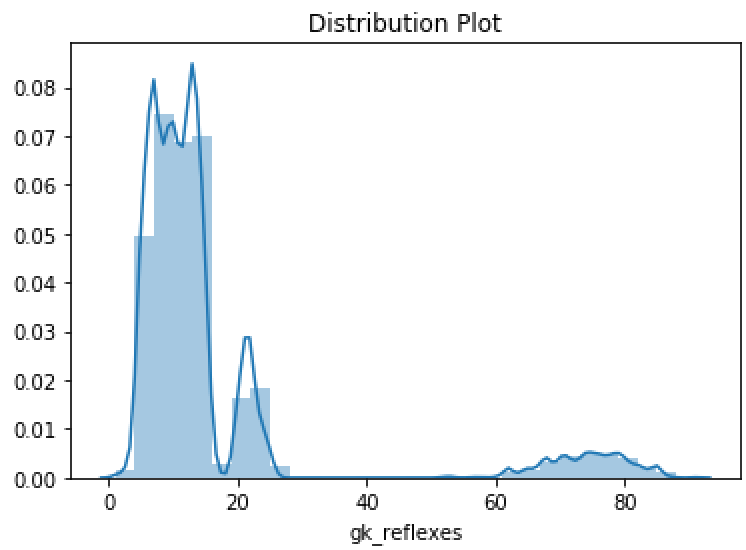
0.025
0.020
0.015
0.010
0.005
0.000
0
20
40
60
80
100
sliding_tackle


Distribution Plot
0.08
0.06
0.04
0.02
0.00
0
20
40
60
80
gk_diving


Distribution Plot
0.08
0.07
0.06
0.05
0.04
0.03
0.02
0.01
0.00
0
20
40
60
80
gk_handling


Distribution Plot
0.08
0.07
0.06
0.05
0.04
0.03
0.02
0.01
0.00
0
20
40
60
80
gk_kicking



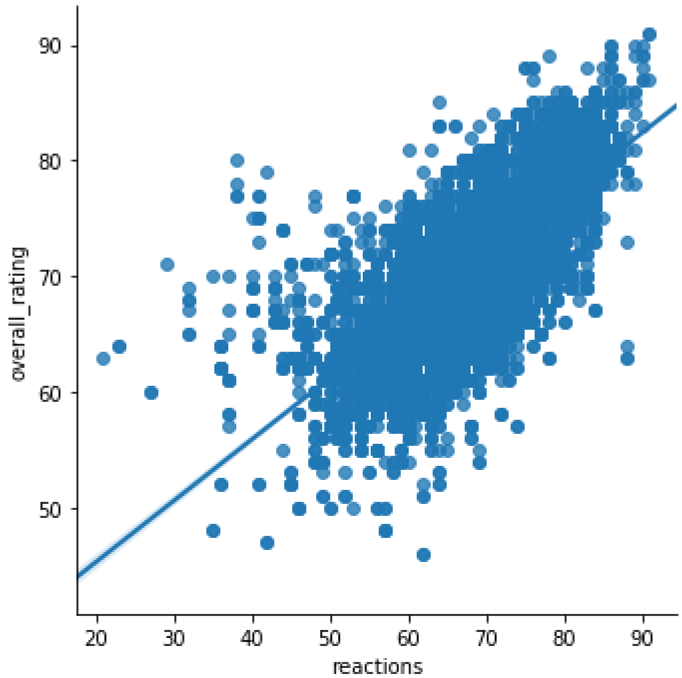

In [15]:

```
####
def print_corr (x_attribute, y_attribute, df, title):
    corr15=df[[x_attribute, y_attribute]].corr()
    print(title)
    print(corr15)
    vis15=sns.lmplot( x=x_attribute, y=y_attribute, hue=None, sharex=False
, data=df, scatter=True, fit_reg=True, units=None, order=1, legend=True)
    plt.show()
    plt.close()
###

print('A Closer Look at Overall Rating Versus Reactions Attributes')
print(' ')
print_corr('reactions', 'overall_rating', df_all_col, 'All Players')

# hue: attacking work rate
df11=df_all_col[df_all_col['attacking_work_rate'].isin (['low','medium','h
igh'])]
corr11=df11[['reactions','overall_rating']].corr()
print(corr11)
vis11=sns.lmplot( x='reactions', y='overall_rating', hue='attacking_work_r
ate', sharex=False, data=df11, scatter=True, fit_reg=True, units=None, ord
```

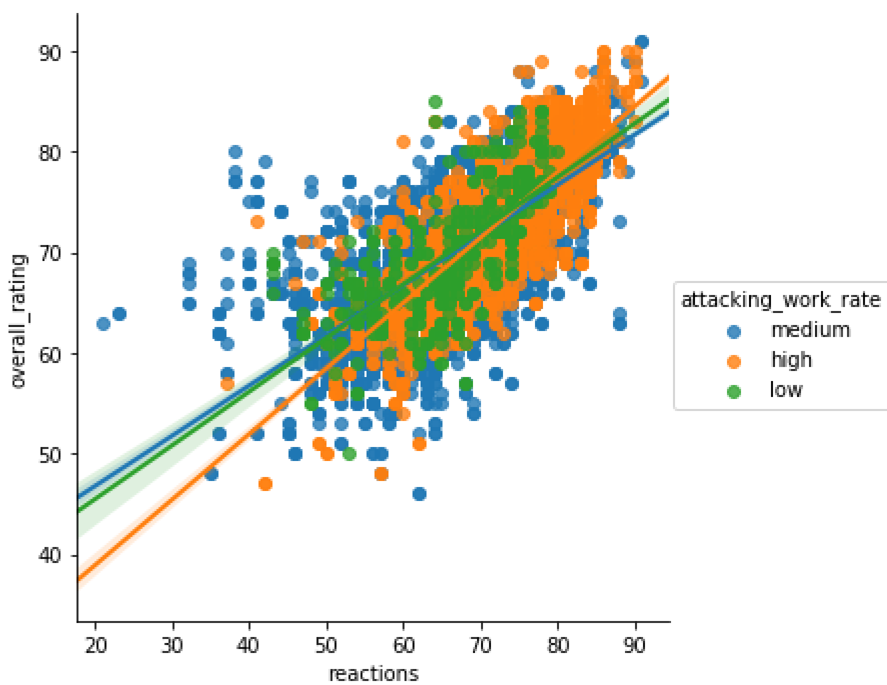
```
er=1, legend=True)
plt.show()

# hue: defensive work rate
df12=df_all_col[df_all_col['defensive_work_rate'].isin (['low','medium','h
igh'])]
corr12=df12[['reactions','overall_rating']].corr()
print(corr12)
vis12=sns.lmplot( x='reactions', y='overall_rating', hue='defensive_work_r
ate', sharex=False, data=df12, scatter=True, fit_reg=True, units=None, ord
er=1, legend=True)
plt.show()

df_goalkeepers=df_all_col[df_all_col['gk_diving'] > 50] # goalkeepers
df_non_goalkeepers=df_all_col[df_all_col['gk_diving'] < 50] # non_goalkeep
ers



##### Subgroups

print ('#######')
print ('  ')
print ('Non_Goalkeeper Subgroup')
print ('  ')
#df_non_goalkeepers=df_all_col[df_all_col['gk_diving'] < 50] # non_goalkee
pers
print_corr ('reactions','overall_rating', df_non_goalkeepers, 'Non_Goalkee
pers: gk_diving < 50')

print ('#######')
print ('  ')
print ('Goalkeeper Subgroup')
print ('  ')
#df_goalkeepers=df_all_col[df_all_col['gk_diving'] > 50] # goalkeepers
# strongest correlation
print_corr ('gk_diving','overall_rating',df_goalkeepers, 'Goalkeepers Only
: gk_diving > 50')
# 2nd strongest correlation
print_corr ('gk_reflexes','overall_rating',df_goalkeepers, 'Goalkeepers On
ly: gk_diving > 50')
# 3rd strongest correlation
print_corr ('gk_positioning','overall_rating',df_goalkeepers, 'Goalkeepers
 Only: gk_diving > 50')
# 4th strongest correlation
print_corr ('gk_handling','overall_rating',df_goalkeepers, 'Goalkeepers On
ly: gk_diving > 50')
# 5th strongest correlation
print_corr ('gk_kicking','overall_rating',df_goalkeepers, 'Goalkeepers Onl
y: gk_diving > 50')
# 6th strongest correlation
print_corr ('reactions','overall_rating', df_goalkeepers, 'Goalkeepers Onl
y: gk_diving > 50')
```

```
A Closer Look at Overall Rating Versus Reactions Attributes

All Players
                reactions  overall_rating
```

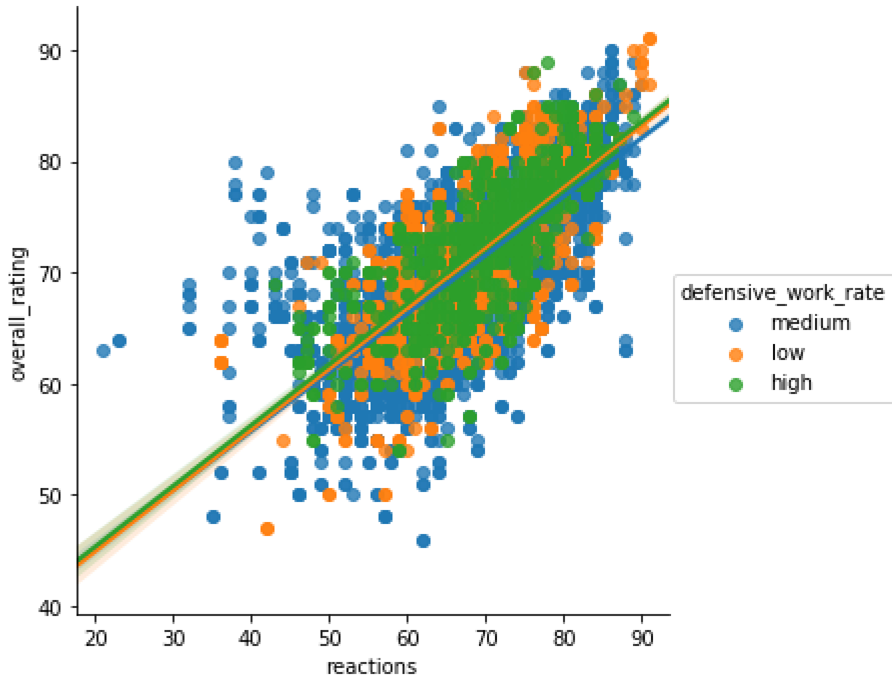
```
reactions         1.00000          0.72483
overall_rating    0.72483          1.00000
```



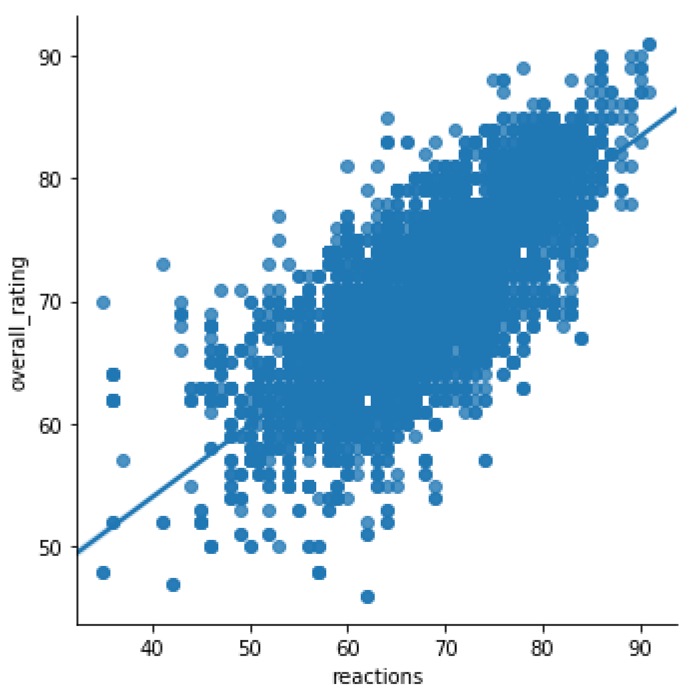

```
                reactions  overall_rating
reactions         1.00000          0.72456
overall_rating    0.72456          1.00000
```




```
                reactions  overall_rating
reactions        1.000000        0.725001
overall_rating   0.725001        1.000000
```

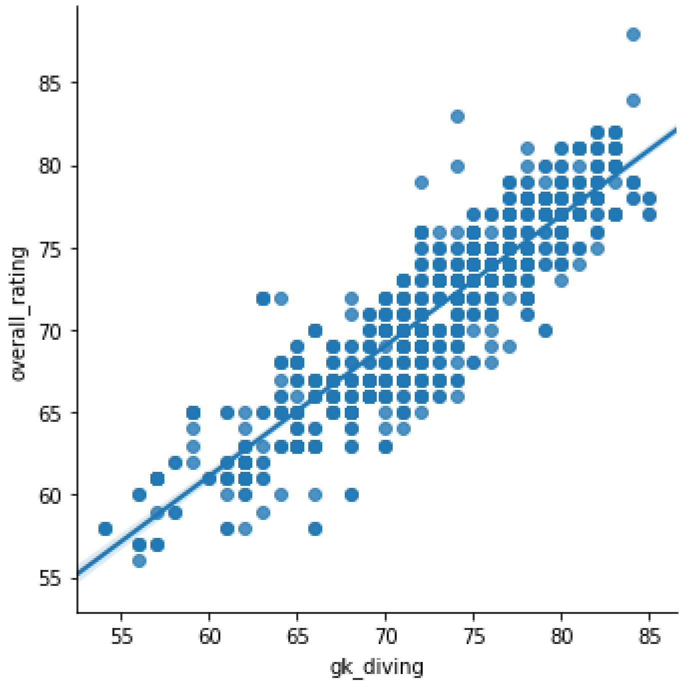



```
#######

Non_Goalkeeper Subgroup

Non_Goalkeepers: gk_diving < 50
                reactions  overall_rating
reactions        1.000000        0.759507
overall_rating   0.759507        1.000000
```

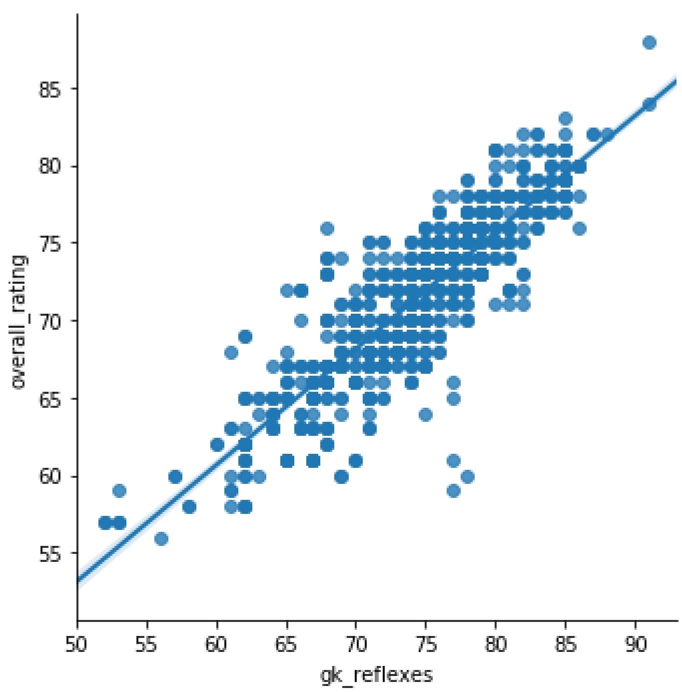



```
#######

Goalkeeper Subgroup

Goalkeepers Only: gk_diving > 50
                gk_diving  overall_rating
```

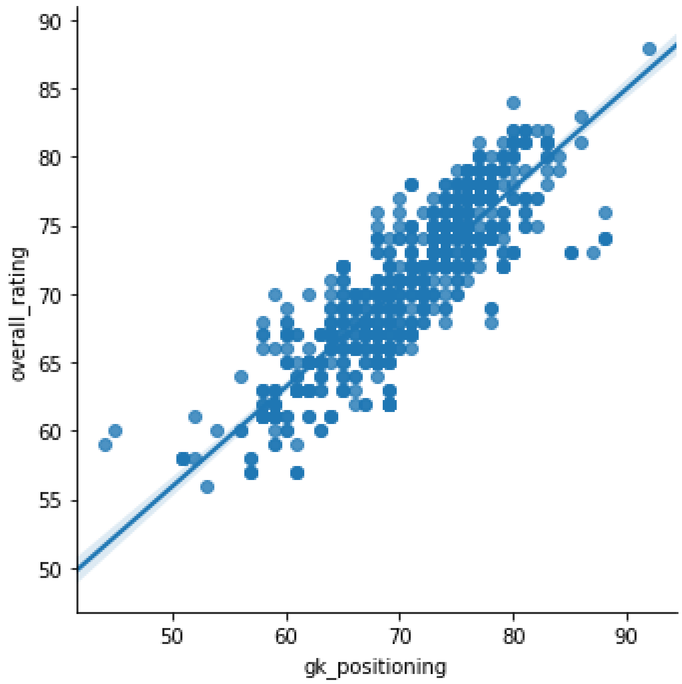
```
gk_diving        1.000000         0.897919
overall_rating   0.897919         1.000000
```



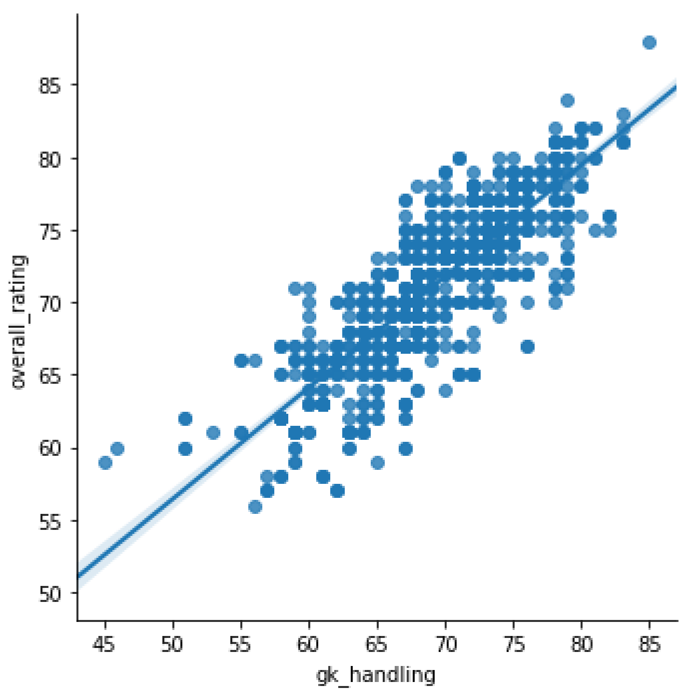

```
Goalkeepers Only: gk_diving > 50
                 gk_reflexes  overall_rating
gk_reflexes         1.000000        0.877756
overall_rating      0.877756        1.000000
```



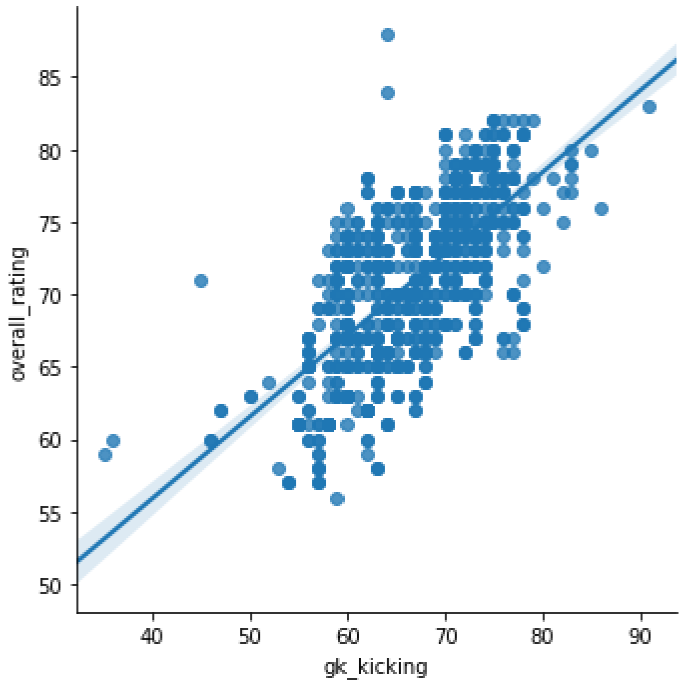

```
Goalkeepers Only: gk_diving > 50
                 gk_positioning  overall_rating
gk_positioning         1.000000        0.863162
overall_rating         0.863162        1.000000
```




```
Goalkeepers Only: gk_diving > 50
                gk_handling  overall_rating
gk_handling        1.000000        0.828148
overall_rating     0.828148        1.000000
```




```
Goalkeepers Only: gk_diving > 50
                gk_kicking  overall_rating
gk_kicking        1.000000        0.669727
overall_rating    0.669727        1.000000
```




```
Goalkeepers Only: gk_diving > 50
                reactions  overall_rating
reactions         1.00000         0.56092
overall_rating    0.56092         1.00000
```