APPLIED MACHINE LEARNING WITH FIFA

An Approach to Predict Soccer Player Evaluation and Valuation Metrics Using the FIFA18 Data Set

Lucas Newman, Rohith Selvarajan, Megharjun Srinivasa

The University of Texas at Dallas | Team 3

ML for FIFA

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1 Executive Summary

The purpose of this study was to gain insights into the world of Soccer. Specifically, to better understand the following questions: what makes a good player, what determines if a talented young prospect will amount to a good player, and what determines a player's value on the transfer market. Our intentions are that this study is the first of several, and that it serves as a basis for future exploration into the world of Soccer via Machine Learning and Deep Learning. The data for our study revolves around the FIFA 18 video game by EA Sports. In our dataset the main target variables were overall rating, potential rating, and metrics related to player value, whereas our explanatory features were ratings on a multitude of features having to deal with player skill, athleticism, intelligence and physicality.

In this analysis we were successfully able to get insights into what makes a good player and what determines their market value. We conducted dimensionality reduction with PCA and tuned lasso regression. Additionally we successfully created enhanced value models by position and conducted regression analysis on value and the elasticity of value. An enhanced and reduced value model that eliminates collinearity with feature engineering, and interaction terms as well as out performs the original model was created. We identified the optimal classification methods to predict a players overall rating. Also we came up with our own algorithm to rank features and used GridSearchCV for hyperparameter tuning. Players were clustered based on basic features. The implications of our results can help train AI systems on what to look for when scouting players, and help clubs financially structure contracts based on player attributes.

2 Motivations & Background

The purpose of this study was to gain insights into the world of Soccer. Specifically, to better understand the following questions: what makes a good player, what determines if a talented young prospect will amount to a good player, and what determines a player's value on the transfer market. Our intentions are that this study is the first of several, and that it serves as a basis for future exploration into the world of Soccer via Machine Learning and Deep Learning. The decision to use data from the FIFA video game stemmed from several factors. For example, such data was highly accessible from a multitude of sources. Moreover, by having this easily accessible data, there can be standardization between our modeling and future modeling along with others who decide to explore this topic. The origins of FIFA datasets online usually come from the scraping of sites such as sofifa.com and futwiz.com. Additionally, compared to other publicly available data regarding soccer, the FIFA data set has many more features. These extensive features are also ideal for answering and modeling the questions we seek to answer. Lastly, the current nature of artificial intelligence is highly tuned towards performing in a simulated world, such as a video game. The data for our study revolves around the FIFA 18 video game by EA Sports. Specifically, our dataset is the merging of 2 existing data sets on Kaggle, and both of these datasets web-scraped from sofifa.com. The link to this Kaggle dataset is provided here: https://www.kaggle.com/kevinmh/fifa-18-more-complete-player-dataset. This data set revolves around capturing numerous metrics for all the players in FIFA 18 and provides a vast array of metrics to quantify target variables such as player value, player potential, and player overall rating. However, for the purposes of this project this data had to be somewhat altered and cleaned. The second data set is: https://www.kaggle.com/thec03u5/fifa-18-demo-player-dataset and certain attributes of that data set such as definitive position status and value in terms of millions of euros was merged with the first dataset. Extensive data cleaning, scraping, and creation was done to create a FIFA data lake. As this is not the purpose of this analysis, we will not delve too deeply into the procedure of how we conducted this. However, to reference how this was done please visit: https://github.com/Lucasnewman5732/FIFA_Analytics. Lastly, for parts of our analysis we segmented the data by position group. Specifically, the position groups were: forwards, wingers, center midfielders, full backs, center backs, and goal keepers.

3 Data Description

In our dataset the main target variables were overall rating, potential rating, and metrics related to player value. These metrics were: "eur_value" a players value in euros on the transfer market, "Value (M)" their value in millions of euros, and "ln_value" the natural log of their value. Overall rating is essentially the grade on how good a player is, while the potential rating is the grade on what their ceiling is estimated to be.

Overall and potential are ratings (of integer type) on a scale of 0-100 and were treated as numerical data during regression and, as categorical data during classification. All the variables used for value were treated as numerical variables (of float type). The descriptive variables were "Name" (player names), "ID" (the unique player ID from sofifa.com), "club" (the team the player plays on), "club_id" (a unique ID for the club created via cat-coder), "league" (the league a player plays in), and "league_id" (a unique ID created for each league via cat-coder). The explanatory variables used were "age", "height_cm", "weight_kg" and all the features in the figure below:

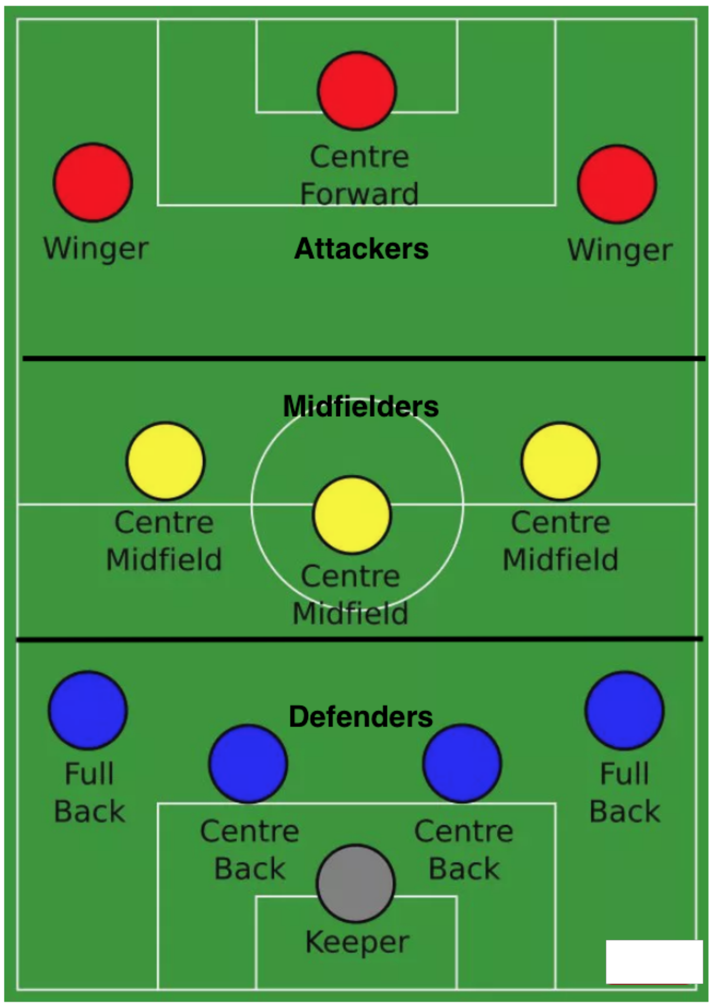
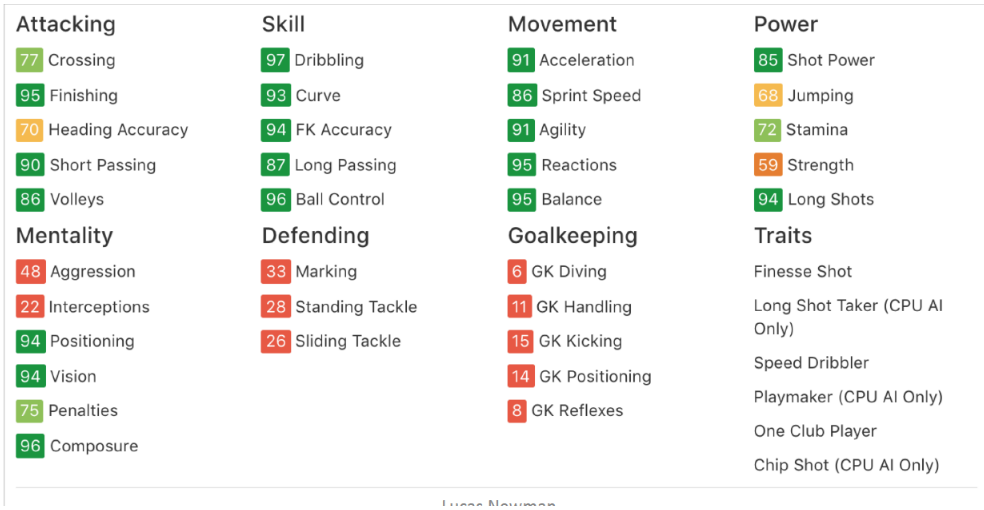

Centre
Forward
Winger
Attackers
Winger
Midfielders
Centre
Midfield
Centre
Midfield
Centre
Midfield
Defenders
Full
Back
Full
Back
Centre
Back
Centre
Back
Keeper

image1



4 Data Import, Transformations & Preliminary Analysis

The libraries utilized in this study are:

```
In [1]: from IPython.core.interactiveshell import InteractiveShell
        InteractiveShell.ast_node_interactivity = "all"
        #Import all the libraries needed
        import numpy as np
        import random
        import matplotlib.pyplot as plt
        import pandas as pd
        from mpl_toolkits.mplot3d import Axes3D
        import statsmodels.formula.api as smf
        from statsmodels.formula.api import *
        from statsmodels.formula.api import ols
        from scipy.stats import t
        from scipy.interpolate import *
        from matplotlib.pyplot import *
        from scipy.stats import *
        import statsmodels.api as sm
        from sympy import symbols, diff
        import math
        import sklearn
        import os
        import seaborn as sns
        from sklearn.preprocessing import StandardScaler
        from sklearn.linear_model import Ridge
        from sklearn.model_selection import train_test_split
        from sklearn.linear_model import LinearRegression
        from sklearn.linear_model import Ridge
        from sklearn.cluster import KMeans
        from matplotlib.ticker import PercentFormatter
```

```
from numpy import linspace
from sklearn.decomposition import PCA
from sklearn.preprocessing import scale
from statsmodels.multivariate.pca import PCA
from sklearn.decomposition import PCA
from sklearn.metrics import r2_score
from math import sqrt
from sklearn.metrics import mean_squared_error
from sklearn import metrics
from sklearn.model_selection import cross_val_score
from sklearn.linear_model import LassoCV
from sklearn.linear_model import RidgeCV
from sklearn.metrics import mean_squared_error, accuracy_score
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.model_selection import cross_validate
from sklearn.model_selection import GridSearchCV
from sklearn import metrics
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import train_test_split
from sklearn.model_selection import KFold
from sklearn.model_selection import ShuffleSplit
from sklearn.metrics import recall_score
from statsmodels.graphics.api import abline_plot
%matplotlib inline
```

Data Frame creations: Here we transform our original dataset to add ln_value as well as divide it up into the position groups we want, and lastly we create a dataframe that will be the basis of our analysis.

```
In [19]: complete_df= pd.read_csv("full_fifa18_data.csv", encoding= "utf-8",  index_col=0)
```

```
In [20]: #DF for centerbacks
         CB=pd.read_csv("center_backs.csv", encoding= "utf-8",  index_col=0)

         #df for full backs
         FB=pd.read_csv("full_backs.csv", encoding= "utf-8",  index_col=0)

         #df for goal keepers
         GK=pd.read_csv("goal_keepers.csv", encoding= "utf-8",  index_col=0)

         #df for center mids
         CM=pd.read_csv("center_mids.csv", encoding= "utf-8",  index_col=0)
         #df for wingers
         W=pd.read_csv("wingers.csv", encoding= "utf-8",  index_col=0)
         # DF for forwards
         F=pd.read_csv("forwards.csv", encoding= "utf-8",  index_col=0)
```

```
In [22]: lnVal=pd.DataFrame(((complete_df["eur_value"]/100000)+1).apply(np.log))
         lnVal.columns = ['ln_value']
```

```
complete = pd.concat([lnVal, complete_df], axis=1)

#We now have a column with ln(eur_value/100,000)+1 so we can then calculate elasticity
#Note we had to add 1 because there were some values = 0 and ln(0) is undefined. This u
#that were equal to zero will now be 1 and ln(1)=0
```

In [23]:
```
clubs = complete['club'].unique().tolist()
#len(clubs)
club_df=complete.copy()
club_df = complete.assign(id=(complete['club']).astype('category').cat.codes)
club_ids = club_df['id'].unique().tolist()
#len(club_ids)
club_df=club_df.reset_index()
complete=club_df.copy()
#Note "'ID' is player ID and 'id' is team ID"
#club_df.to_csv("EncodedDF_withLnVal")
#writer = pd.ExcelWriter('output.xlsx')
#club_df.to_excel(writer,'EncodedDF_withLnVal')
data = complete.assign(id=(complete['league']).astype('category').cat.codes)
data=data.reset_index()
#complete.isnull().any(axis=0)
#complete.isnull().sum(axis=0)
```

In [24]:
```
complete.head()
```

Out[24]:
```
       ID  ln_value                Name  Value (M) Position  Overall  \
0   20801  6.862758   Cristiano Ronaldo       95.5       ST       94
1  158023  6.957497            L. Messi      105.0       RW       93
2  190871  7.115582              Neymar      123.0       LW       92
3  176580  6.878326           L. Suárez       97.0       ST       92
4  167495  6.415097            M. Neuer       61.0       GK       92

   Potential                    full_name                 club  special ...   \
0         94  C. Ronaldo dos Santos Aveiro       Real Madrid CF     2228 ...
1         93                  Lionel Messi         FC Barcelona     2158 ...
2         94    Neymar da Silva Santos Jr.  Paris Saint-Germain     2100 ...
3         92                  Luis Suárez         FC Barcelona     2291 ...
4         92                 Manuel Neuer     FC Bayern Munich     1493 ...

   prefers_gk foot_Left foot_Right  att_rate_High  att_rate_Low  \
0           0         0          1              1             0
1           0         1          0              0             0
2           0         0          1              1             0
3           0         0          1              1             0
4           1         0          1              0             0

  att_rate_Medium  defend_rate_High  defend_rate_Low  defend_rate_Medium   id
0               0                 0                1                   0  467
```

```
1                1                 0                0                    1  220
2                0                 0                0                    1  433
3                0                 0                0                    1  220
4                1                 0                0                    1  223

[5 rows x 189 columns]
```

Here we create various feature lists for easier use later.

```
In [26]: # use complete.columns
```

```
In [25]: card_attr=['pac', 'sho', 'pas','dri', 'defend', 'phy' , 'gk_handling',
                      'international_reputation', 'skill_moves',
                'weak_foot', 'att_rate_High','att_rate_Low', 'att_rate_High',
                     'defend_rate_High','defend_rate_Low']
         descriptive=['club','age', 'league', 'height_cm', 'weight_kg']

         overall_target = ['Overall']
         potential_target=['Potential']
         value_target=['Value (M)']
         ln_value=['ln_value']
         eur_value=['eur_value']
         card_attr=['pac', 'sho', 'pas','dri', 'defend', 'phy' , 'reactions',
                      'international_reputation', 'skill_moves',
                'weak_foot', 'att_rate_High','att_rate_Low', 'att_rate_High',
                     'defend_rate_High','defend_rate_Low']
         attribute_profile=['age', 'height_cm', 'weight_kg', 'crossing', 'finishing', 'heading_a
                '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', 'composure', 'marking', 'standing_tackle',
                'sliding_tackle', 'gk_diving', 'gk_handling', 'gk_kicking',
                'gk_positioning', 'gk_reflexes']
         targets=['Overall','Potential', 'Value (M)', 'ln_value', 'eur_value']
         gk=['age','height_cm', 'weight_kg','gk_diving', 'gk_handling', 'gk_kicking',
                'gk_positioning', 'gk_reflexes' ]

         all_attr=['pac', 'sho', 'pas','dri', 'defend', 'phy' ,
                      'international_reputation', 'skill_moves', 'weak_foot','age', 'height_cm',
                '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', 'composure', 'marking', 'standing_tackle',
                'sliding_tackle', 'gk_diving', 'gk_handling', 'gk_kicking',
                'gk_positioning', 'gk_reflexes', 'att_rate_Low', 'att_rate_High',
                     'defend_rate_High','defend_rate_Low', 'age']
```

```
model_1=['Value (M)', 'age', 'height_cm', 'weight_kg', 'crossing', 'finishing', 'headin
       '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', 'composure', 'marking', 'standing_tackle',
       'sliding_tackle', 'gk_diving', 'gk_handling', 'gk_kicking',
       'gk_positioning', 'gk_reflexes']
```

Here we obtain some basic statistics on our descriptvie variables, target variables, and explanatory variables using the pandas describe method.

```
In [27]: explanatory=complete[descriptive]
         player_card=complete[card_attr]
         numeric_metrics=complete[attribute_profile]
         targets=complete[targets]
         explanatory.describe().transpose()
         numeric_metrics.describe().transpose()
         player_card.describe().transpose()
         targets.describe().transpose()
```

Out[27]:

	count	mean	std	min	25%	50%	75%	max
age	17739.0	25.160494	4.593598	16.0	22.0	25.0	28.0	47.0
height_cm	17739.0	181.277299	6.690376	155.0	177.0	181.0	186.0	205.0
weight_kg	17739.0	75.428660	6.996046	49.0	70.0	75.0	80.0	110.0

Out[27]:

	count	mean	std	min	25%	50% \
age	17739.0	25.160494	4.593598	16.0	22.0	25.0
height_cm	17739.0	181.277299	6.690376	155.0	177.0	181.0
weight_kg	17739.0	75.428660	6.996046	49.0	70.0	75.0
crossing	17739.0	49.911156	18.453203	5.0	38.0	54.0
finishing	17739.0	45.401601	19.484576	2.0	30.0	48.0
heading_accuracy	17739.0	52.430746	17.413967	4.0	45.0	56.0
short_passing	17739.0	58.435650	14.864880	10.0	53.0	62.0
volleys	17739.0	43.317493	17.749621	4.0	30.0	44.0
dribbling	17739.0	55.189300	18.978161	2.0	48.0	61.0
curve	17739.0	47.432437	18.480019	6.0	34.0	49.0
free_kick_accuracy	17739.0	43.264558	17.602919	4.0	31.0	42.0
long_passing	17739.0	52.578274	15.488822	7.0	42.0	56.0
ball_control	17739.0	58.245955	16.757686	8.0	53.0	63.0
acceleration	17739.0	64.704155	14.900734	11.0	56.5	67.0
sprint_speed	17739.0	64.942556	14.624438	11.0	57.0	68.0
agility	17739.0	63.437849	14.782087	14.0	55.0	65.0
reactions	17739.0	62.011387	9.115870	28.0	56.0	62.0
balance	17739.0	63.842719	14.102522	11.0	56.0	66.0
shot_power	17739.0	55.785614	17.384971	3.0	46.0	60.0
jumping	17739.0	64.938441	11.882673	13.0	58.0	66.0
stamina	17739.0	63.387339	15.897549	12.0	57.0	67.0
strength	17739.0	65.384069	12.599453	12.0	58.0	66.0

long_shots	17739.0	47.354811	19.286402	3.0	33.0	52.0
aggression	17739.0	55.937539	17.448138	11.0	44.0	59.0
interceptions	17739.0	46.678223	20.683786	4.0	26.0	52.0
positioning	17739.0	49.763346	19.448665	2.0	38.0	55.0
vision	17739.0	53.132533	14.371729	10.0	43.0	55.0
penalties	17739.0	49.026439	15.813347	5.0	39.0	50.0
composure	17739.0	58.012120	12.883032	5.0	51.0	60.0
marking	17739.0	44.200406	21.590332	4.0	22.0	48.0
standing_tackle	17739.0	47.543661	21.835268	4.0	26.0	54.0
sliding_tackle	17739.0	45.645358	21.489983	4.0	24.0	52.0
gk_diving	17739.0	16.735611	17.803344	1.0	8.0	11.0
gk_handling	17739.0	16.517391	17.026730	1.0	8.0	11.0
gk_kicking	17739.0	16.388748	16.623162	1.0	8.0	11.0
gk_positioning	17739.0	16.503749	17.141628	1.0	8.0	11.0
gk_reflexes	17739.0	16.866791	18.099374	1.0	8.0	11.0

	75%	max
age	28.0	47.0
height_cm	186.0	205.0
weight_kg	80.0	110.0
crossing	64.0	90.0
finishing	62.0	95.0
heading_accuracy	65.0	94.0
short_passing	68.0	92.0
volleys	57.0	91.0
dribbling	68.0	97.0
curve	62.0	92.0
free_kick_accuracy	57.0	93.0
long_passing	64.0	93.0
ball_control	69.0	95.0
acceleration	75.0	96.0
sprint_speed	75.0	96.0
agility	74.0	96.0
reactions	68.0	96.0
balance	74.0	96.0
shot_power	69.0	94.0
jumping	73.0	95.0
stamina	74.0	95.0
strength	74.0	98.0
long_shots	63.0	92.0
aggression	69.0	96.0
interceptions	64.0	92.0
positioning	64.0	95.0
vision	64.0	94.0
penalties	61.0	92.0
composure	67.0	96.0
marking	63.0	92.0
standing_tackle	66.0	92.0

```
sliding_tackle       64.0   91.0
gk_diving            14.0   91.0
gk_handling          14.0   91.0
gk_kicking           14.0   95.0
gk_positioning       14.0   91.0
gk_reflexes          14.0   90.0
```

Out[27]:

```
                            count       mean        std   min   25%   50%  \
pac                       17739.0  67.800440  10.971605  21.0  61.0  68.0
sho                       17739.0  53.595637  13.819056  14.0  44.0  56.0
pas                       17739.0  57.650375  10.437276  24.0  51.0  59.0
dri                       17739.0  62.696488  10.366483  24.0  57.0  64.0
defend                    17739.0  49.495744  17.111116  12.0  34.0  52.0
phy                       17739.0  64.874965   9.619584  27.0  59.0  66.0
reactions                 17739.0  62.011387   9.115870  28.0  56.0  62.0
international_reputation  17739.0   1.123682   0.404942   1.0   1.0   1.0
skill_moves               17739.0   2.319578   0.748182   1.0   2.0   2.0
weak_foot                 17739.0   2.949884   0.662293   1.0   3.0   3.0
att_rate_High             17739.0   0.260048   0.438673   0.0   0.0   0.0
att_rate_Low              17739.0   0.050172   0.218306   0.0   0.0   0.0
att_rate_High             17739.0   0.260048   0.438673   0.0   0.0   0.0
defend_rate_High          17739.0   0.160043   0.366656   0.0   0.0   0.0
defend_rate_Low           17739.0   0.087660   0.282808   0.0   0.0   0.0

                           75%   max
pac                       75.0  96.0
sho                       64.0  93.0
pas                       65.0  95.0
dri                       70.0  96.0
defend                    64.0  90.0
phy                       72.0  92.0
reactions                 68.0  96.0
international_reputation   1.0   5.0
skill_moves                3.0   5.0
weak_foot                  3.0   5.0
att_rate_High              1.0   1.0
att_rate_Low               0.0   1.0
att_rate_High              1.0   1.0
defend_rate_High           0.0   1.0
defend_rate_Low            0.0   1.0
```

Out[27]:

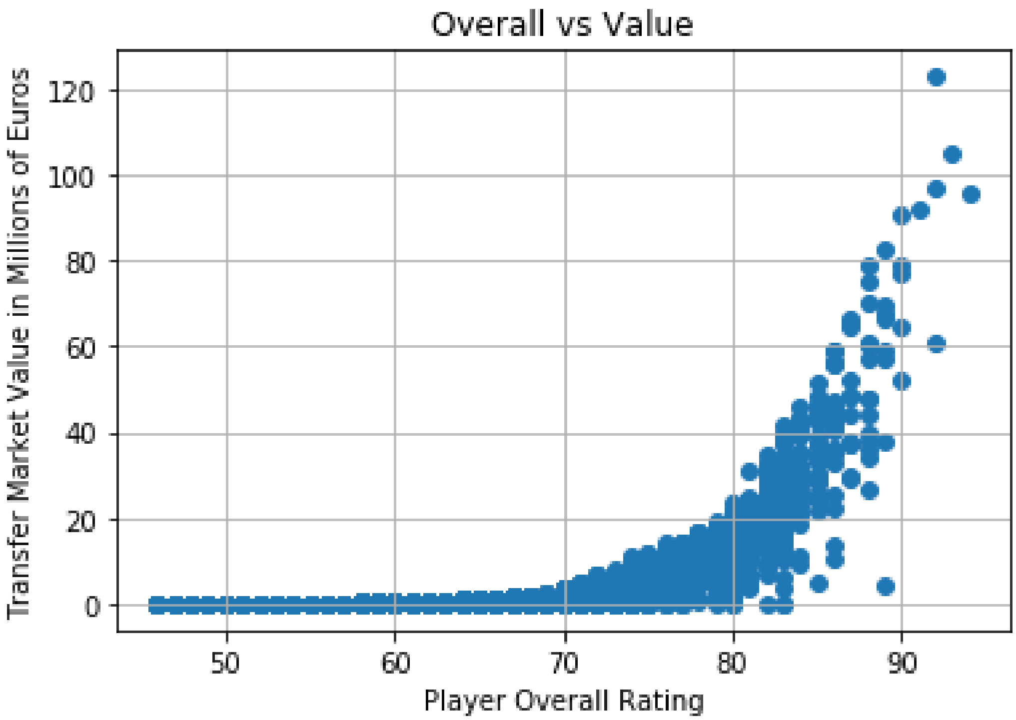
```
             count          mean           std   min            25%  \
Overall    17739.0  6.631687e+01  6.940958e+00  46.0      62.000000
Potential  17739.0  7.121923e+01  6.103628e+00  46.0      67.000000
Value (M)  17739.0  2.405757e+00  5.382428e+00   0.0       0.325000
ln_value   17739.0  2.309136e+00  1.236539e+00   0.0       1.446919
eur_value  17739.0  2.414659e+06  5.394812e+06   0.0  325000.000000
```

```
                  50%           75%           max
Overall       66.000000  7.100000e+01  9.400000e+01
Potential     71.000000  7.500000e+01  9.400000e+01
Value (M)      0.700000  2.100000e+00  1.230000e+02
ln_value       2.079442  3.091042e+00  7.115582e+00
eur_value 700000.000000  2.100000e+06  1.230000e+08
```

As seen above we have data on 17739 different players and there are no null values in our data. Summary statistics are provided above for many different features. For example in regards to overall rating the lowest rating is a 46, the mean is 67, the maximum is 94 and there is a standard deviation about 7. For some exploratory analysis on how these features relate to each other and the kinds of distributions they have we will create several visualizations.

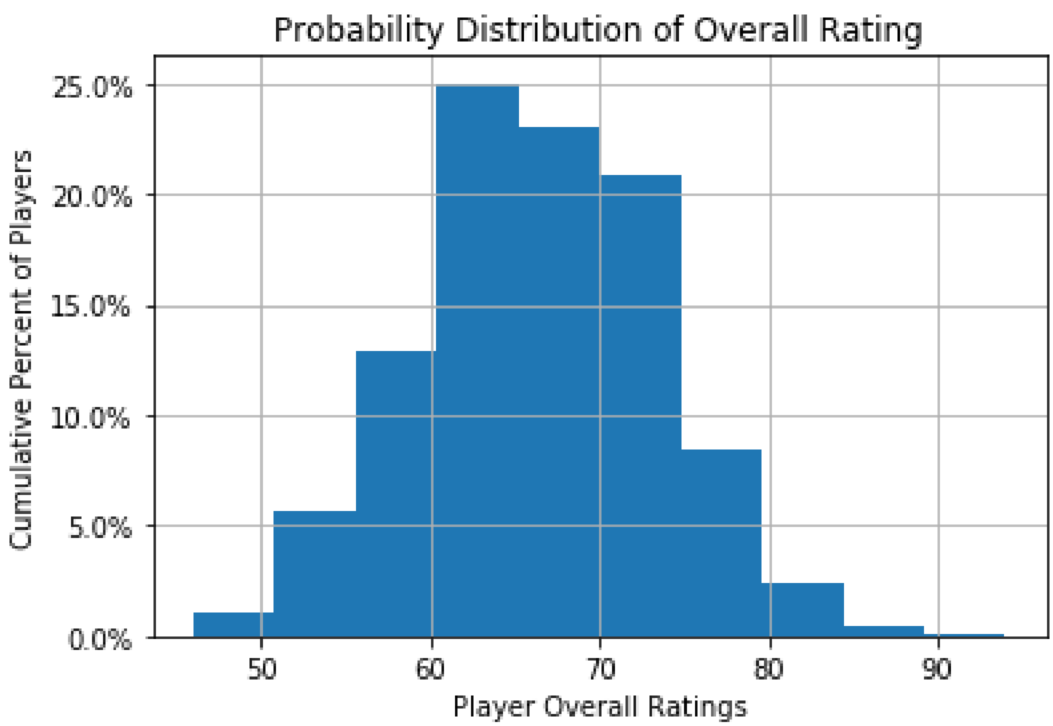
```
In [28]: fig,ax=plt.subplots()

         Overall=complete['Overall']
         Value=complete['Value (M)']
         ax.scatter(Overall,Value)
         plt.xlabel('Player Overall Rating')
         plt.ylabel('Transfer Market Value in Millions of Euros')
         plt.title('Overall vs Value')

         plt.grid(True)
```

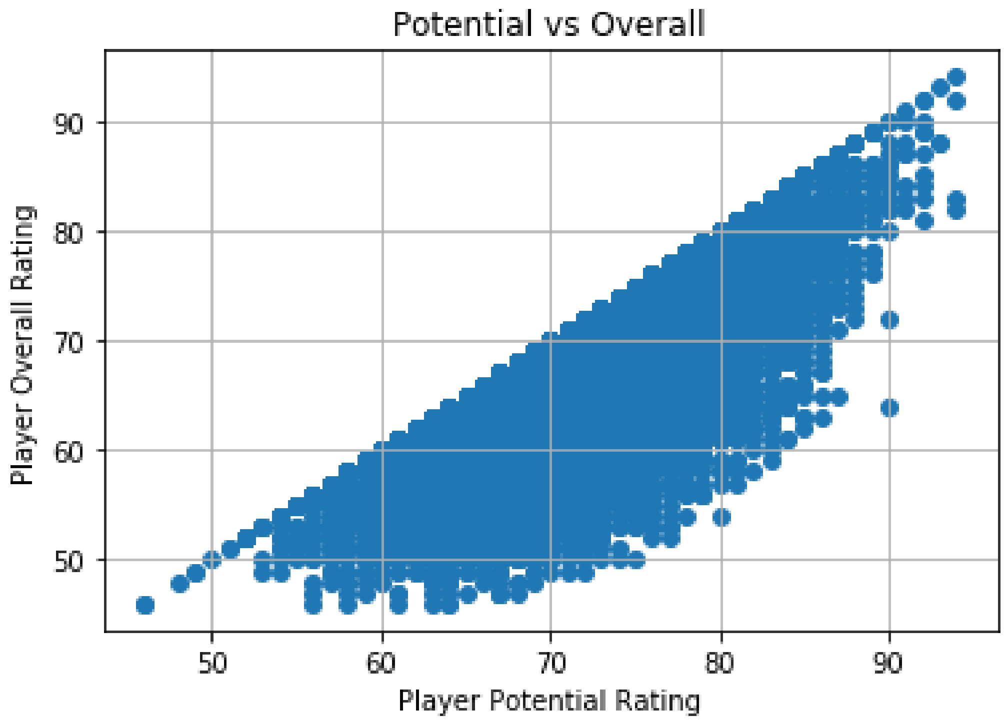
```
Out[28]: <matplotlib.collections.PathCollection at 0x1c22b78080>

Out[28]: Text(0.5, 0, 'Player Overall Rating')

Out[28]: Text(0, 0.5, 'Transfer Market Value in Millions of Euros')

Out[28]: Text(0.5, 1.0, 'Overall vs Value')
```



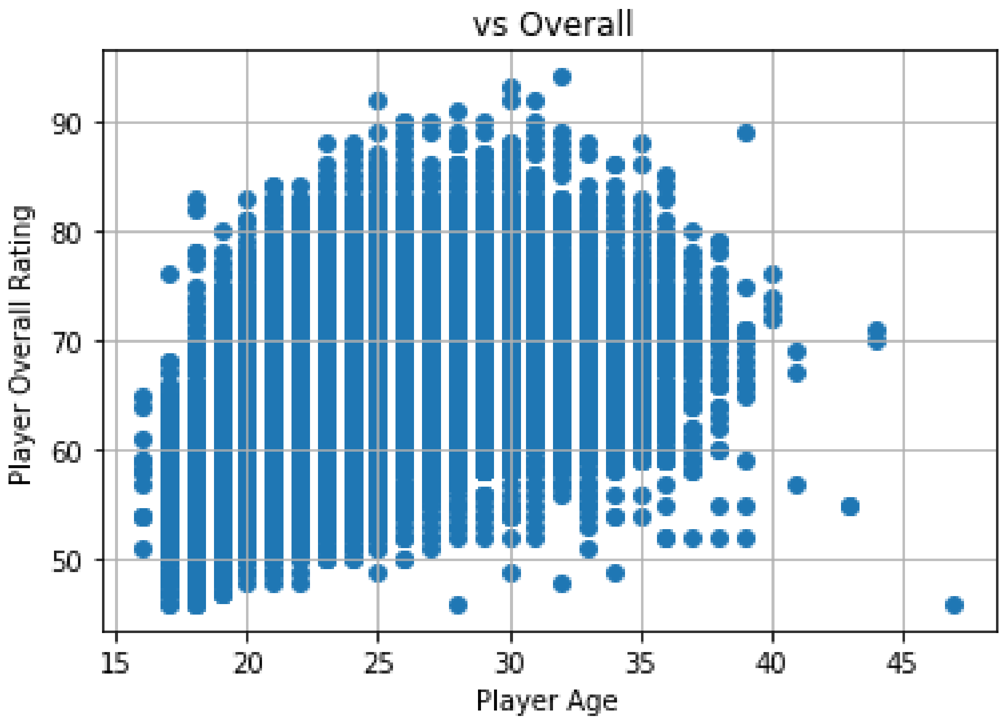

```
In [29]: from matplotlib.ticker import PercentFormatter
         data = np.array(complete[overall_target])


         plt.hist(data, weights=np.ones(len(data)) / len(data))

         plt.xlabel("Player Overall Ratings")
         plt.ylabel(" Cumulative Percent of Players ")
         plt.title("Probability Distribution of Overall Rating")
         plt.gca().yaxis.set_major_formatter(PercentFormatter(1))
         plt.grid(True)



         fig,ax=plt.subplots()

         Overall=complete['Overall']
         Potential=complete['Potential']
         ax.scatter(Potential,Overall)
         plt.xlabel('Player Potential Rating')
         plt.ylabel('Player Overall Rating')
         plt.title('Potential vs Overall')

         plt.grid(True)
```

```
Out[29]: (array([0.01093635, 0.05704944, 0.12926321, 0.25007047, 0.23056542,
                 0.20841085, 0.0844467 , 0.02407126, 0.00456621, 0.0006201 ]),
          array([46. , 50.8, 55.6, 60.4, 65.2, 70. , 74.8, 79.6, 84.4, 89.2, 94. ]),
          <a list of 10 Patch objects>)

Out[29]: Text(0.5, 0, 'Player Overall Ratings')

Out[29]: Text(0, 0.5, ' Cumulative Percent of Players ')

Out[29]: Text(0.5, 1.0, 'Probability Distribution of Overall Rating')

Out[29]: <matplotlib.collections.PathCollection at 0x1c22a6d048>

Out[29]: Text(0.5, 0, 'Player Potential Rating')

Out[29]: Text(0, 0.5, 'Player Overall Rating')

Out[29]: Text(0.5, 1.0, 'Potential vs Overall')
```

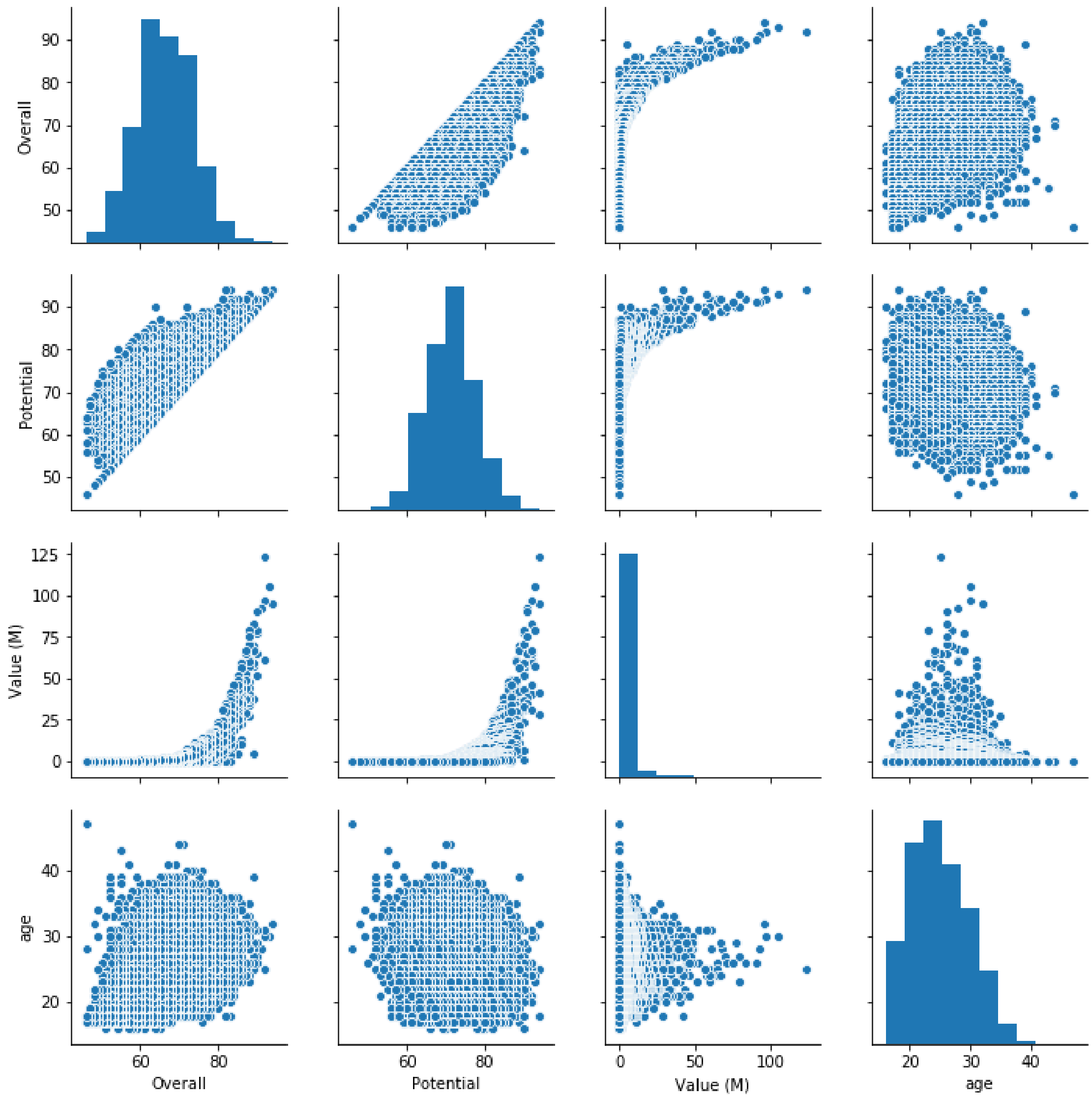





```
In [30]: fig,ax=plt.subplots()

         Age=complete['age']
         Overall=complete['Overall']
         ax.scatter(Age,Overall)
         plt.xlabel('Player Age')
         plt.ylabel('Player Overall Rating')
         plt.title(' vs Overall')

         plt.grid(True)

Out[30]: <matplotlib.collections.PathCollection at 0x11bf54588>

Out[30]: Text(0.5, 0, 'Player Age')

Out[30]: Text(0, 0.5, 'Player Overall Rating')

Out[30]: Text(0.5, 1.0, ' vs Overall')
```




```
In [32]: sns.pairplot(complete[['Overall', 'Potential', 'Value (M)', 'age']])

Out[32]: <seaborn.axisgrid.PairGrid at 0x1c22a42080>
```

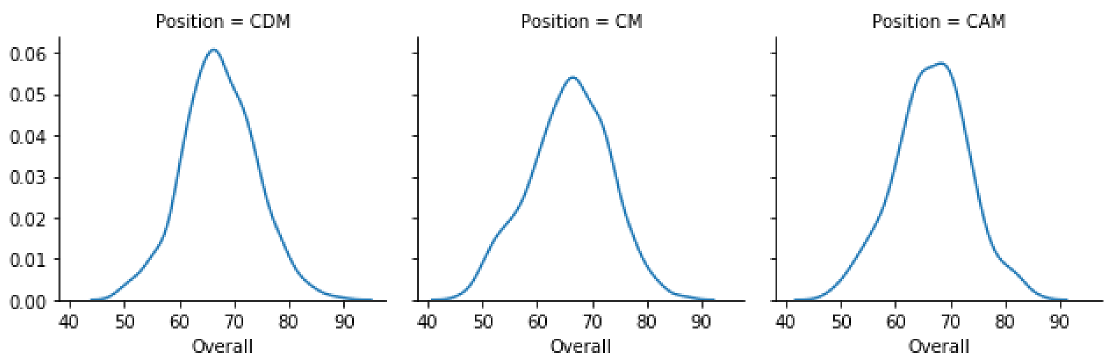


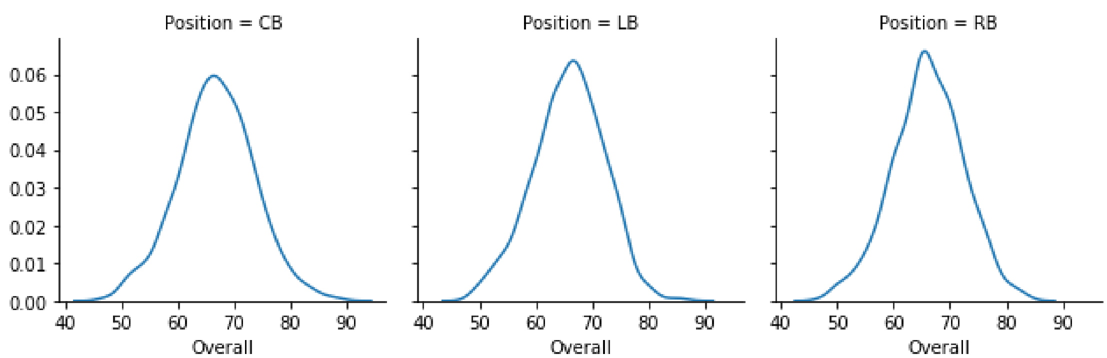
In [33]:
```
#Distribution of Overall by Position
# center mids
cm = complete[complete['Position'].isin(['CM', 'CDM', 'CAM'])]
cm = sns.FacetGrid(cm, col="Position")
cm.map(sns.kdeplot, "Overall")

#defenders
defend=complete[complete['Position'].isin(['CB', 'RB', 'LB'])]
defend = sns.FacetGrid(defend, col="Position")
defend.map(sns.kdeplot, "Overall")

#wingers
wing=complete[complete['Position'].isin(['LM', 'RM', 'LW', 'RW'])]
```

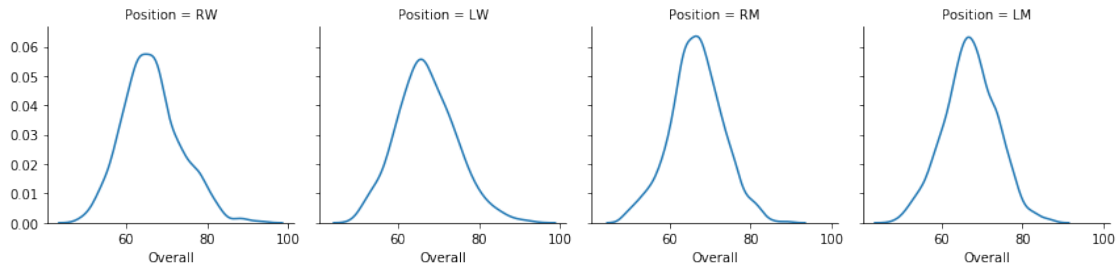
```
wing=sns.FacetGrid(wing, col="Position")
wing.map(sns.kdeplot, "Overall")

#goalies and forwards
gk_and_forwards=complete[complete['Position'].isin(['GK', 'CF', 'ST'])]
gk_and_forwards = sns.FacetGrid(gk_and_forwards, col="Position")
gk_and_forwards.map(sns.kdeplot, "Overall")
```

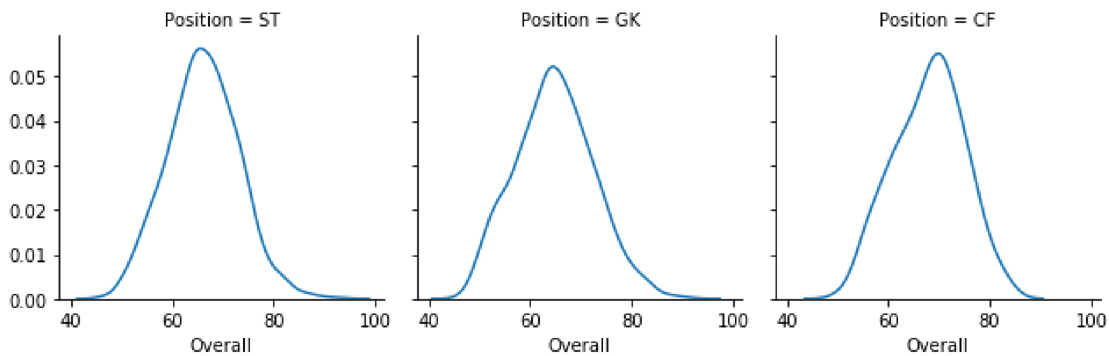
```
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/scipy/stats/stats.py:1713: FutureWarnin
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```

```
Out[33]: <seaborn.axisgrid.FacetGrid at 0x10a49b390>

Out[33]: <seaborn.axisgrid.FacetGrid at 0x1c50ab6898>

Out[33]: <seaborn.axisgrid.FacetGrid at 0x1c4ecf7f98>

Out[33]: <seaborn.axisgrid.FacetGrid at 0x1c228a28d0>
```





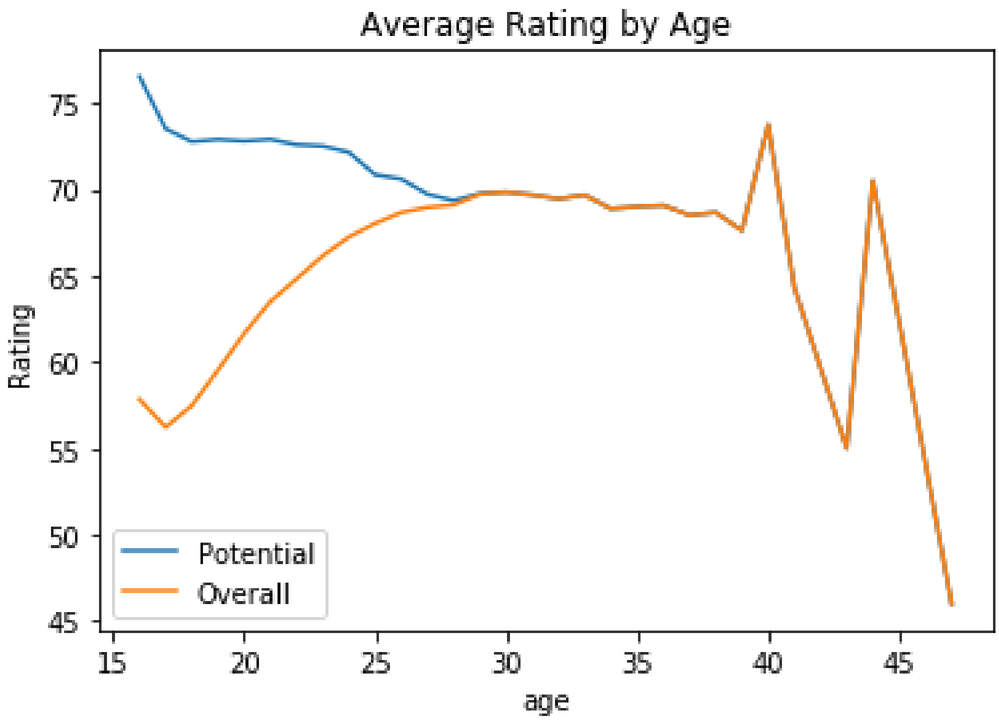




In [34]:
```
age_pot = complete.groupby(['age'])['Potential'].mean()
age_ovr = complete.groupby(['age'])['Overall'].mean()

df_pot_ovr_age = pd.concat([age_pot, age_ovr], axis=1)

ax = df_pot_ovr_age.plot()
ax.set_ylabel('Rating')
ax.set_title('Average Rating by Age')
```

Out[34]:
```
Text(0, 0.5, 'Rating')
```

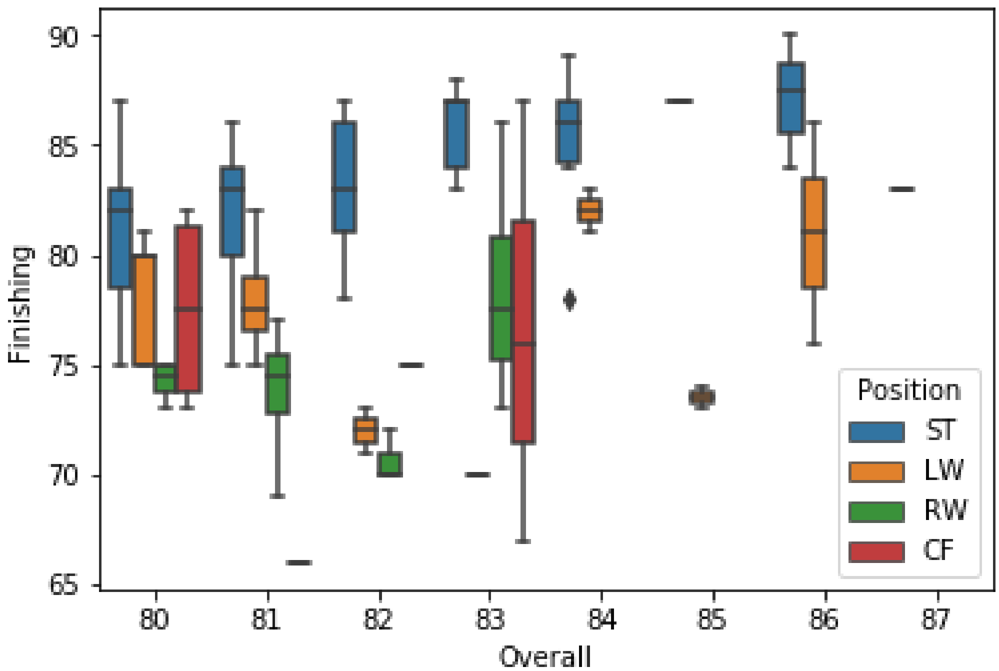
Out[34]:
```
Text(0.5, 1.0, 'Average Rating by Age')
```



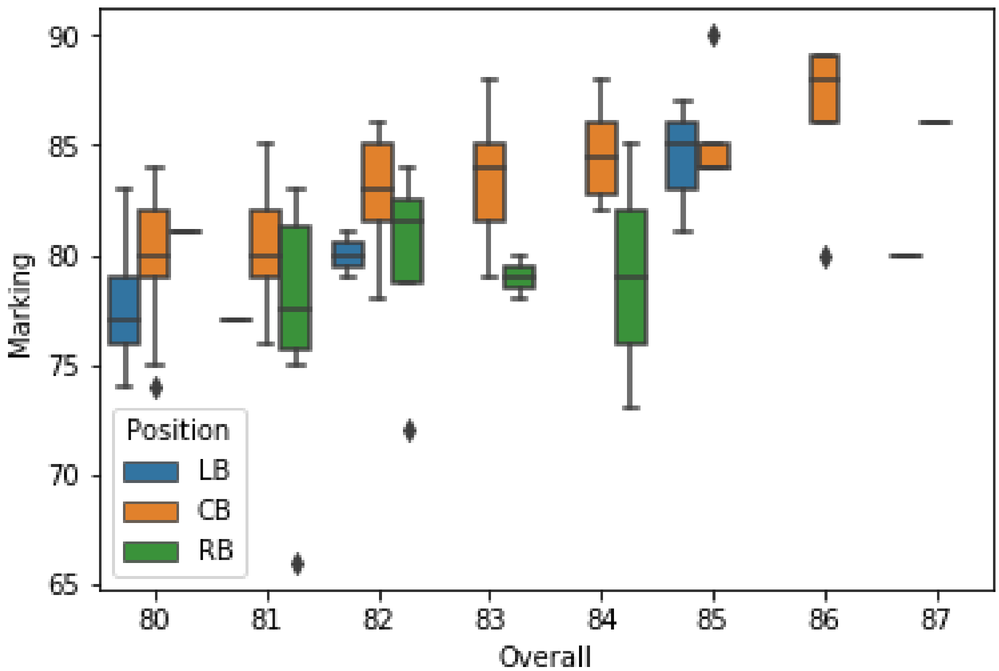

```
In [35]: #Finishing by Forwards
         #where the range of overall is between 80 and 88
         fin = (complete
                 .loc[complete['Position'].isin(['ST', 'CF', 'RW', 'LW'])]
                 .loc[:, ['Value', 'Overall', 'finishing', 'Position']]
             )
         fin = fin[fin["Overall"] >= 80]
         fin = fin[fin["Overall"] < 88]
         fin['Finishing'] = fin['finishing'].astype(float)

         sns.boxplot(x="Overall", y="Finishing", hue='Position', data=fin)
```

```
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/pandas/core/indexing.py:1472: FutureWar
Passing list-likes to .loc or [] with any missing label will raise
KeyError in the future, you can use .reindex() as an alternative.

See the documentation here:
https://pandas.pydata.org/pandas-docs/stable/indexing.html#deprecate-loc-reindex-listlike
  return self._getitem_tuple(key)
```

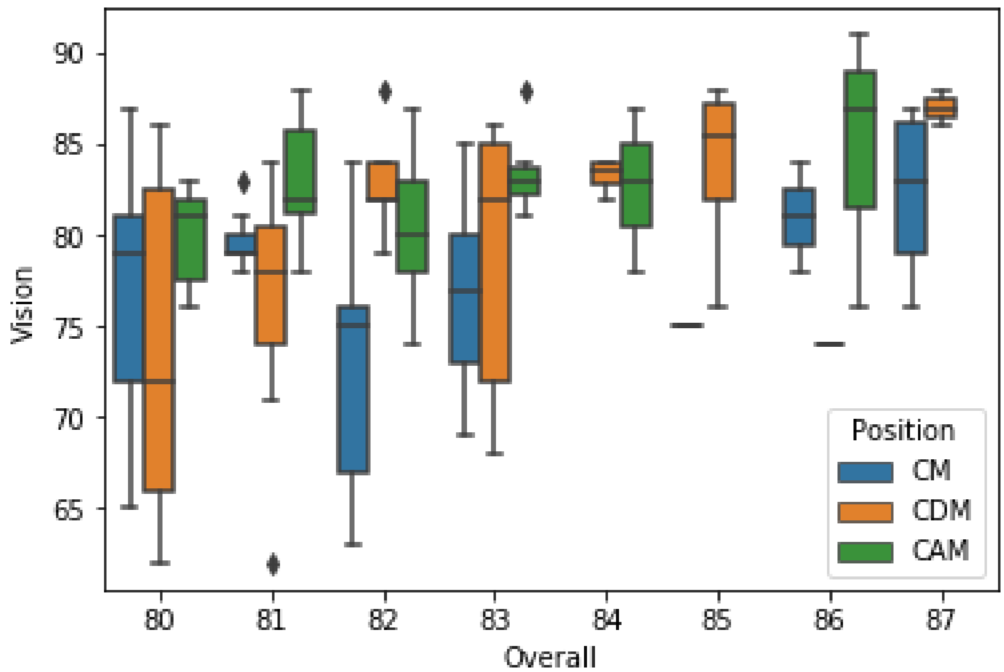
```
Out[35]: <matplotlib.axes._subplots.AxesSubplot at 0x1c4d020ef0>
```




```
In [36]: #Marking by Defenders
         #where the range of overall is between 80 and 88
         fin = (complete
                  .loc[complete['Position'].isin(['RB', 'LB', 'CB'])]
                  .loc[:, ['Value', 'Overall', 'marking', 'Position']]
             )
         fin = fin[fin["Overall"] >= 80]
         fin = fin[fin["Overall"] < 88]
         fin['Marking'] = fin['marking'].astype(float)

         sns.boxplot(x="Overall", y="Marking", hue='Position', data=fin)

Out[36]: <matplotlib.axes._subplots.AxesSubplot at 0x1c4ba044a8>
```

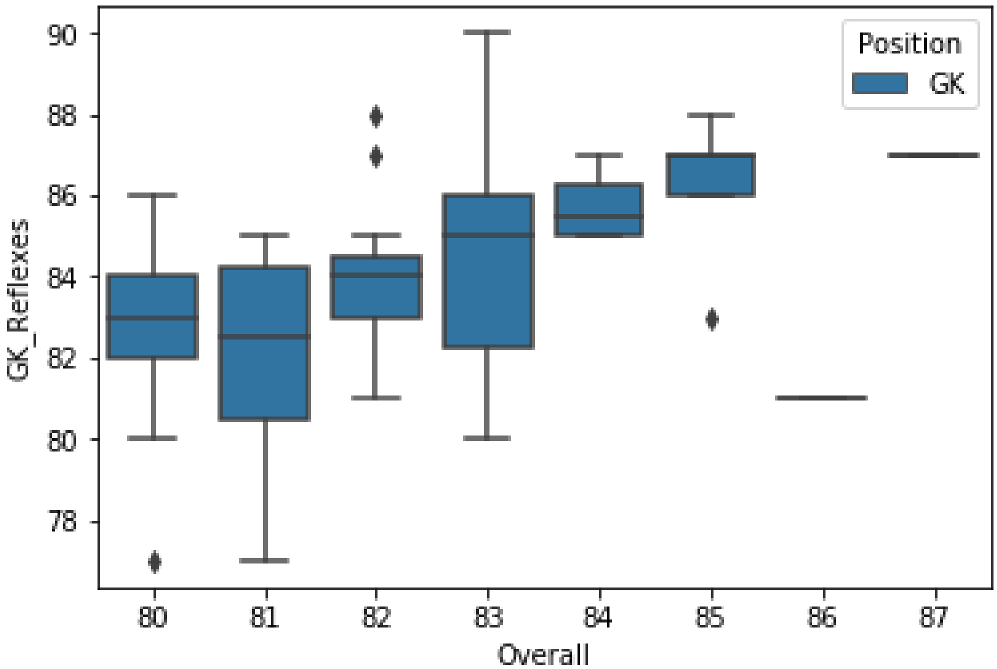



```
In [37]: #Vision by Center Mids
         #where the range of overall is between 80 and 88
         fin = (complete
                  .loc[complete['Position'].isin(['CM', 'CDM', 'CAM'])]
                  .loc[:, ['Value', 'Overall', 'vision', 'Position']]
             )
         fin = fin[fin["Overall"] >= 80]
         fin = fin[fin["Overall"] < 88]
         fin['Vision'] = fin['vision'].astype(float)

         sns.boxplot(x="Overall", y="Vision", hue='Position', data=fin)

Out[37]: <matplotlib.axes._subplots.AxesSubplot at 0x1c537cc1d0>
```

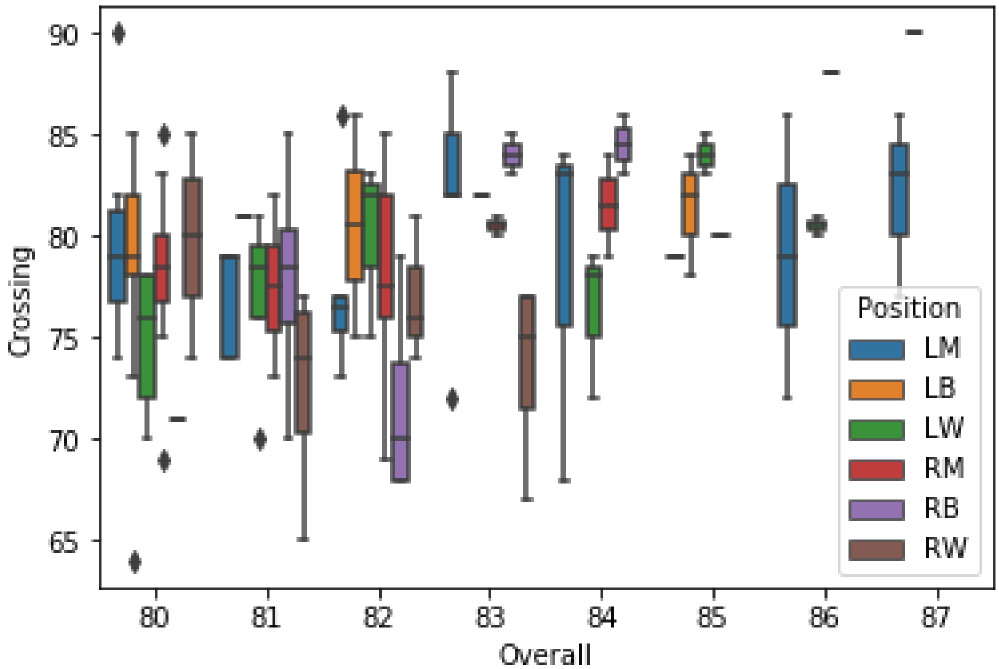



```
In [38]: #GK Reflexes
         #where the range of overall is between 80 and 88
         fin = (complete
                   .loc[complete['Position'].isin(['GK'])]
                   .loc[:, ['Value', 'Overall', 'gk_reflexes', 'Position']]
              )
         fin = fin[fin["Overall"] >= 80]
         fin = fin[fin["Overall"] < 88]
         fin['GK_Reflexes'] = fin['gk_reflexes'].astype(float)

         sns.boxplot(x="Overall", y="GK_Reflexes", hue='Position', data=fin)
```

```
Out[38]: <matplotlib.axes._subplots.AxesSubplot at 0x1c539745f8>
```



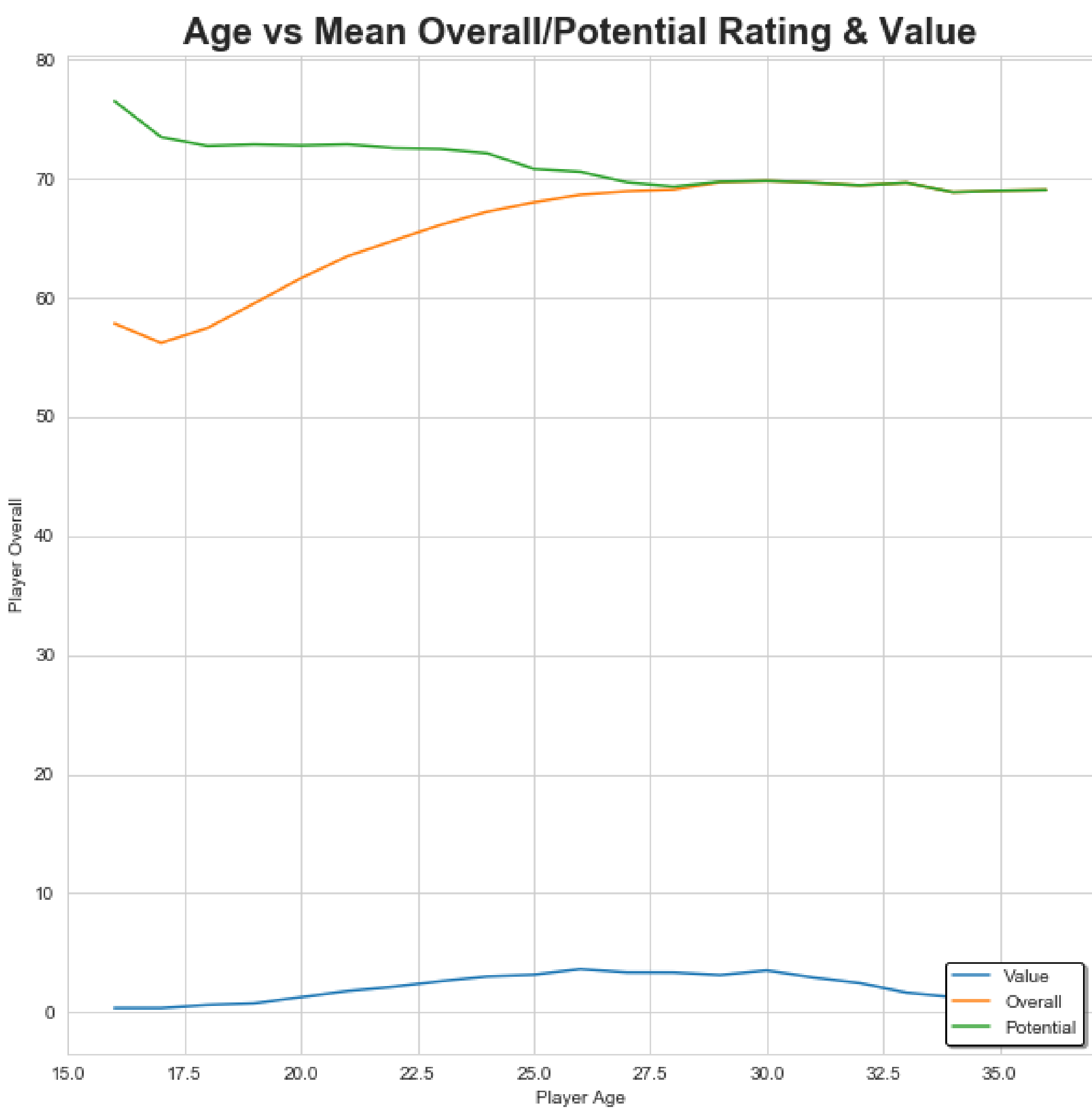

```
In [39]: #Crossing by Wide Players
         #where the range of overall is between 80 and 88
         fin = (complete
                   .loc[complete['Position'].isin(['LB', 'RB', 'LW', 'RW', 'LM', 'RM'])]
                   .loc[:, ['Value', 'Overall', 'crossing', 'Position']]
               )
         fin = fin[fin["Overall"] >= 80]
         fin = fin[fin["Overall"] < 88]
         fin['Crossing'] = fin['crossing'].astype(float)

         sns.boxplot(x="Overall", y="Crossing", hue='Position', data=fin)

Out[39]: <matplotlib.axes._subplots.AxesSubplot at 0x1c53b5b5c0>
```



In [42]:
```
# Selecting players with age smaller then 36
complete36 = complete.loc[complete['age'] <= 36]
# Selecting unique ages from DF
age = complete36.sort_values("age")['age'].unique()
# Selecting average Overall from DF
ovr = complete36.groupby("age")["Overall"].mean().values
# Selecting average potential from DF
potential = complete36.groupby("age")["Potential"].mean().values
# Selecting average value from DF
value=complete36.groupby("age")["Value (M)"].mean().values


plt.figure()
plt.figure(figsize=(10,10))
plt.title('Age vs Mean Overall/Potential Rating & Value', fontsize=20, fontweight='bold
plt.xlabel('Player Age', fontsize=10)
plt.ylabel('Player Overall', fontsize=10)
sns.set_style("whitegrid")
plt.plot(age, value, label="Value")
plt.plot(age, ovr, label="Overall")
plt.plot(age, potential, label="Potential")
plt.legend(loc=4, prop={'size': 10}, frameon=True,shadow=True, facecolor="white", edgec
plt.show()
```

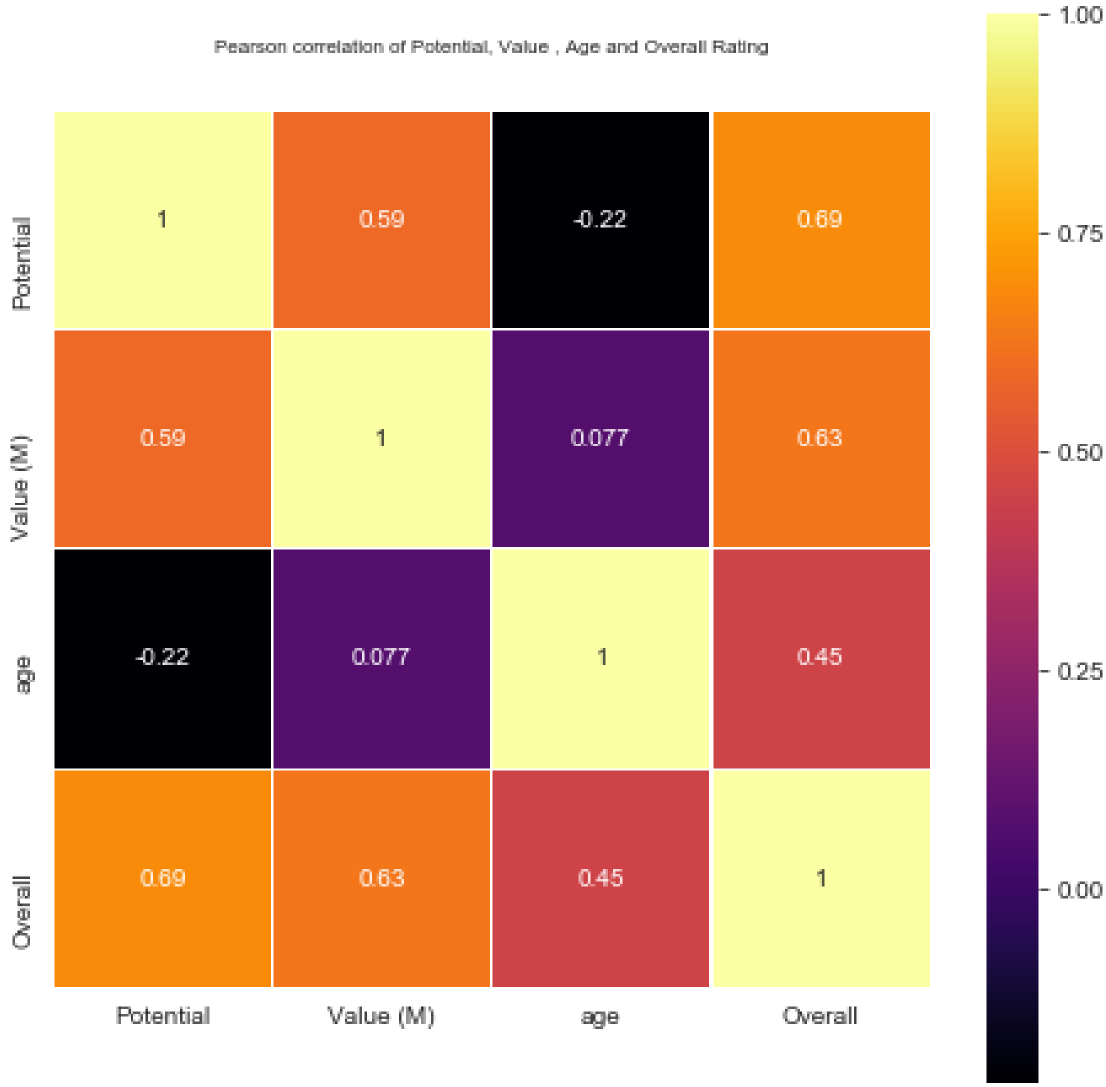
Out[42]: <Figure size 432x288 with 0 Axes>

```
Out[42]: <Figure size 720x720 with 0 Axes>

Out[42]: Text(0.5, 1.0, 'Age vs Mean Overall/Potential Rating & Value')

Out[42]: Text(0.5, 0, 'Player Age')

Out[42]: Text(0, 0.5, 'Player Overall')

Out[42]: [<matplotlib.lines.Line2D at 0x1c579b8128>]

Out[42]: [<matplotlib.lines.Line2D at 0x1c577b9898>]

Out[42]: [<matplotlib.lines.Line2D at 0x1c579cc828>]

Out[42]: <matplotlib.legend.Legend at 0x1c579ccb70>

<Figure size 432x288 with 0 Axes>
```



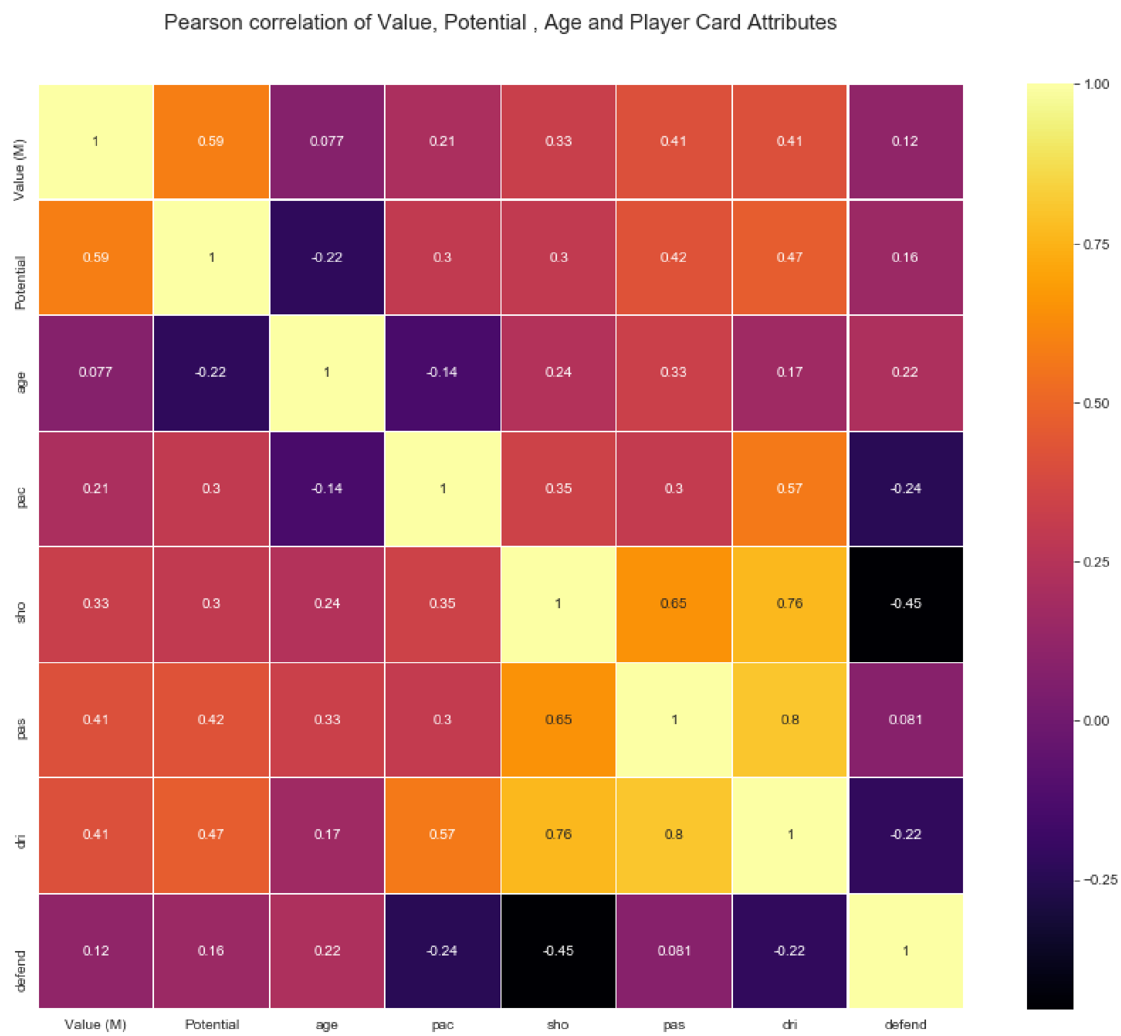
```
In [43]: #correlation of age with target variables
         corr_variables = complete[["Potential", "Value (M)","age", "Overall"]]
         colormap = plt.cm.inferno
         plt.figure(figsize=(8,8))
         plt.title('Pearson correlation of Potential, Value , Age and Overall Rating',
                   y=1.05, size=8)
         sns.heatmap(corr_variables.corr(),linewidths=0.1,vmax=1.0,
                     square=True, cmap=colormap, linecolor='white', annot=True)
```

```
Out[43]: <Figure size 576x576 with 0 Axes>

Out[43]: Text(0.5, 1.05, 'Pearson correlation of Potential, Value , Age and Overall Rating')

Out[43]: <matplotlib.axes._subplots.AxesSubplot at 0x1c5436b5c0>
```



```
In [44]: #correlation of basic features with value and potential
         corr_variables = complete[["Value (M)", "Potential", "age","pac", "sho", "pas", "dri",
         colormap = plt.cm.inferno
         plt.figure(figsize=(16,12))
         plt.title('Pearson correlation of Value, Potential , Age and Player Card Attributes',
                   y=1.05, size=15)
         sns.heatmap(corr_variables.corr(),linewidths=0.1,vmax=1.0,
                     square=True, cmap=colormap, linecolor='white', annot=True)
```

```
Out[44]: <Figure size 1152x864 with 0 Axes>

Out[44]: Text(0.5, 1.05, 'Pearson correlation of Value, Potential , Age and Player Card Attribut

Out[44]: <matplotlib.axes._subplots.AxesSubplot at 0x1c5436b5f8>
```

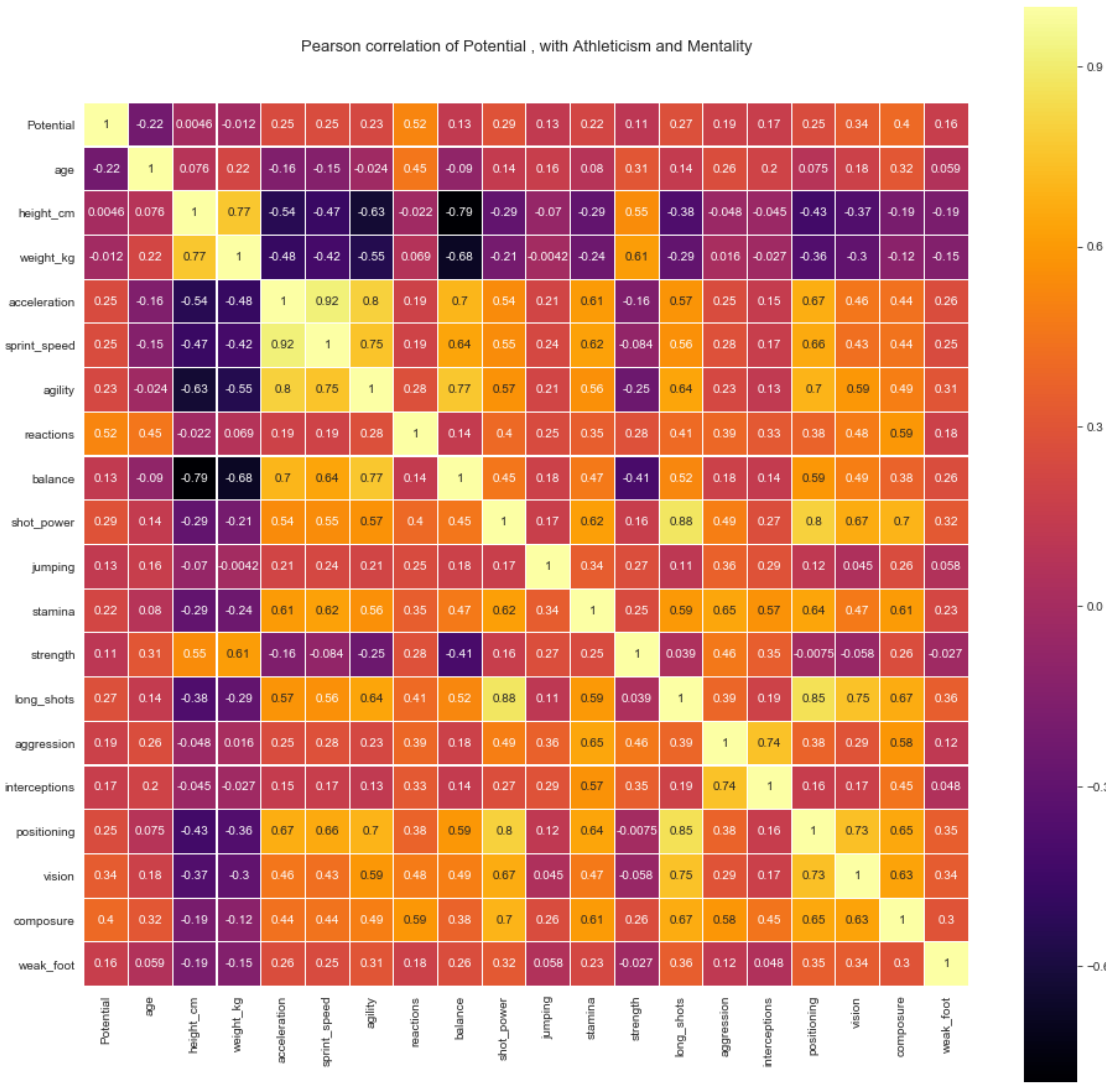


```
In [45]: #correlation of all features with potential
         features=['Potential','age', 'height_cm', 'weight_kg', 'acceleration', 'sprint_speed',
                'agility', 'reactions', 'balance', 'shot_power', 'jumping', 'stamina',
                'strength', 'long_shots', 'aggression', 'interceptions', 'positioning',
                'vision',  'composure', 'weak_foot']
         corr_variables=complete[features]
         colormap = plt.cm.inferno
         plt.figure(figsize=(16,16))
         plt.title('Pearson correlation of Potential , with Athleticism and Mentality',
                   y=1.05, size=13)
         sns.heatmap(corr_variables.corr(),linewidths=0.1,vmax=1.0,
                     square=True, cmap=colormap, linecolor='white', annot=True)
```

```
Out[45]: <Figure size 1152x1152 with 0 Axes>
```

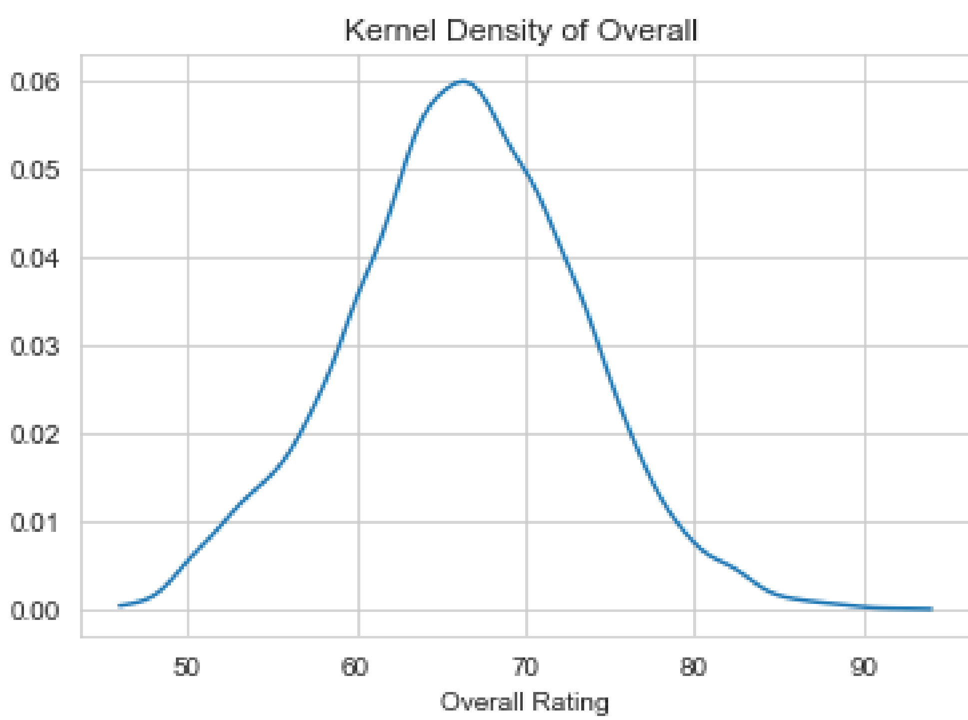
```
Out[45]: Text(0.5, 1.05, 'Pearson correlation of Potential , with Athleticism and Mentality')
```

```
Out[45]: <matplotlib.axes._subplots.AxesSubplot at 0x1c57b3c978>
```

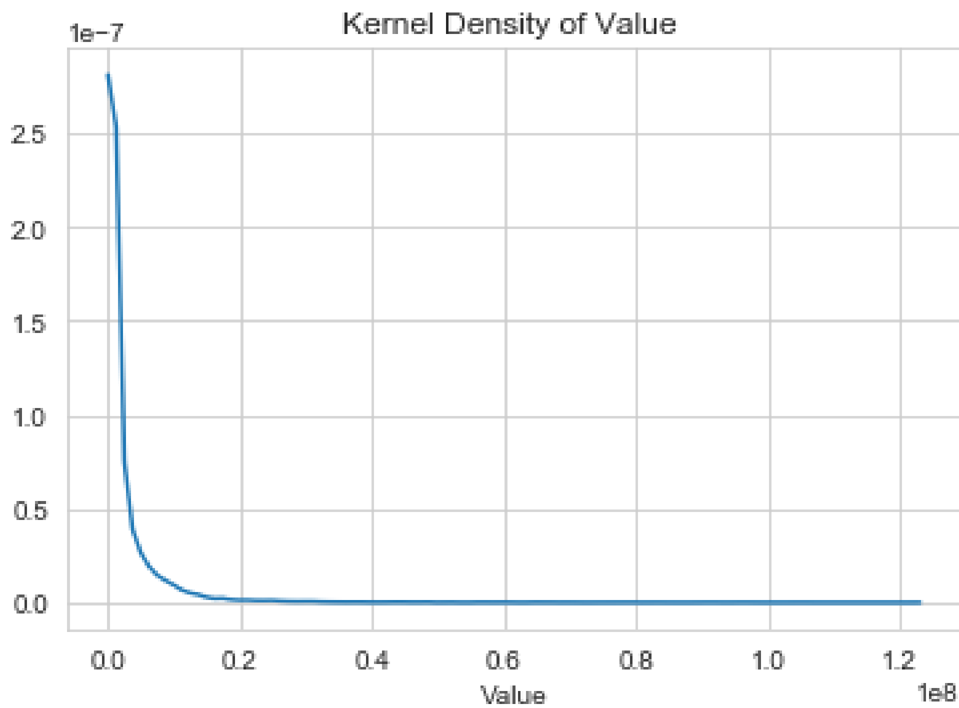


```
In [47]: #Kernel Density of Overall Rating
         from numpy import linspace
         #Kernel Density Estimator
         x= complete.Overall
         kde = gaussian_kde(x)
         dist_space = linspace(min(x), max(x), 100)
         plt.xlabel('Overall Rating')
         plt.plot(dist_space, kde(dist_space))
         plt.title("Kernel Density of Overall ")
         plt.show()

         #Kernel Density of Value
         x= complete.eur_value
         kde = gaussian_kde(x)
         dist_space = linspace(min(x), max(x), 100)
         plt.xlabel('Value')
         plt.plot(dist_space, kde(dist_space))
         plt.title("Kernel Density of Value ")
         plt.show()
```

```
Out[47]: Text(0.5, 0, 'Overall Rating')

Out[47]: [<matplotlib.lines.Line2D at 0x1c583fcb00>]

Out[47]: Text(0.5, 1.0, 'Kernel Density of Overall ')
```



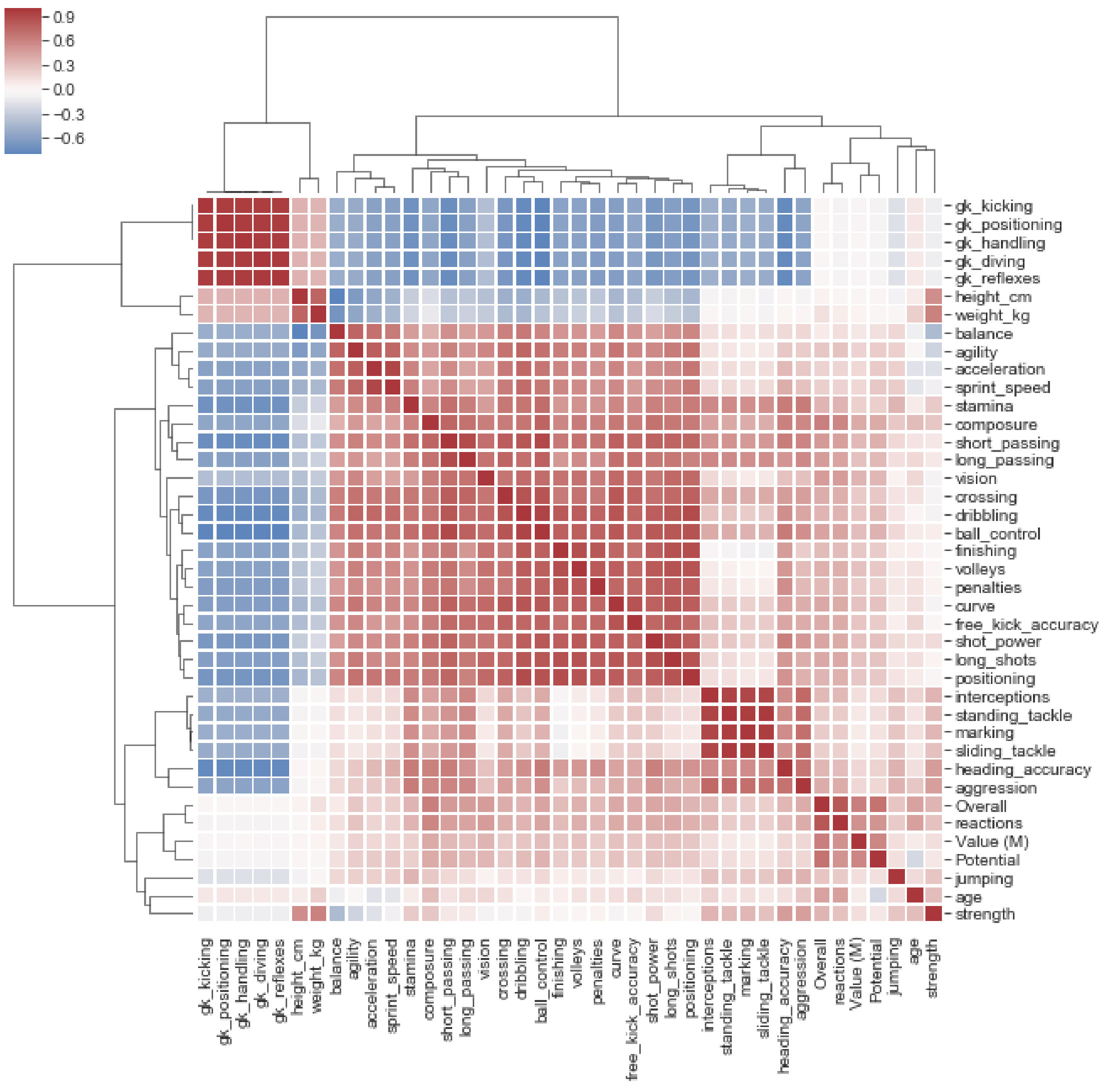
```
Out[47]: Text(0.5, 0, 'Value')

Out[47]: [<matplotlib.lines.Line2D at 0x1c58311e48>]

Out[47]: Text(0.5, 1.0, 'Kernel Density of Value ')
```




```
In [48]: #Cluster Map of Features
         #Heatmap: show the correlation between similar features.
         # Select a subset of the df
         used_variables = ['Overall', 'Potential',
                'Value (M)', 'age', 'height_cm', 'weight_kg', 'crossing', 'finishing', 'heading_
                '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', 'composure', 'marking', 'standing_tackle',
                'sliding_tackle', 'gk_diving', 'gk_handling', 'gk_kicking',
                'gk_positioning', 'gk_reflexes']
         used_columns = (complete.columns.get_level_values(None).isin(used_variables))
         df = complete.loc[:, used_columns]
```

```
# Draw the full plot
plt.figure(figsize=(16,16))
sns.clustermap(df.corr(), center=0, cmap="vlag", linewidths=.75)
```

```
Out[48]: <Figure size 1152x1152 with 0 Axes>

Out[48]: <seaborn.matrix.ClusterGrid at 0x1c5851c048>

<Figure size 1152x1152 with 0 Axes>
```



5 Applied Statistical Modeling & Learning

Unsupervised Dimensionality Reduction

We begin our analysis with some unsupervised dimmensionality reduction to determine the effect of omitting models from our models.

```
In [49]: #Our Model
         X = complete[attribute_profile]
         y_overall=complete[overall_target]

         #Exploring PCA
         from sklearn.preprocessing import StandardScaler
         sc = StandardScaler()
         X_std=sc.fit_transform(X)
         cov_mat = np.cov(X_std.T)
         eig_vals, eig_vecs = np.linalg.eig(cov_mat)
         print('Eigenvectors \n%s' %eig_vecs)
         print('\nEigenvalues \n%s' %eig_vals)
         eigen_val=pd.DataFrame(eig_vals)
         eigen_vec=pd.DataFrame(eig_vecs)



         X.shape
         from sklearn.decomposition import PCA
         from sklearn.preprocessing import scale
         dta = scale(X)
         pca = PCA(n_components=37)
         pca.fit(dta)
         #The amount of variance that each PC explains
         var= pca.explained_variance_ratio_
         var
         var.shape
         vardf=pd.DataFrame(var)
         vardf.head()
         #Cumulative Variance explains
         var1=np.cumsum(np.round(pca.explained_variance_ratio_, decimals=3)*100)
         print("\n\nThe cumulative variance explained is:" ,var1)

         plt.plot(var1)
         plt.xlabel('Variables', fontsize=12)
         plt.ylabel('Cumulative Variance Explained', fontsize=12)
         plt.grid(True)
```

```
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/preprocessing/data.py:625: Data
  return self.partial_fit(X, y)
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/base.py:462: DataConversionWarn
  return self.fit(X, **fit_params).transform(X)


Eigenvectors
[[ 2.02843901e-02  9.07376824e-02 -3.40142262e-01 ...  2.42955802e-02
```

```
  -1.16424396e-02 -4.04252606e-03]
 [-1.08675532e-01  1.87911306e-01 -2.51570216e-01 ... -3.54745880e-03
   2.23471915e-02 -1.00085395e-02]
 [-9.25594563e-02  1.80874719e-01 -3.08824513e-01 ... -4.21718616e-03
  -1.04913863e-02  6.34894219e-04]
 ...
 [-1.93941797e-01 -7.20250238e-02 -1.72165656e-01 ... -1.29811679e-02
  -8.06386989e-02 -8.79592893e-01]
 [-1.94269416e-01 -6.98741900e-02 -1.75710490e-01 ... -5.79467503e-03
   2.15473095e-02  2.89958666e-01]
 [-1.94987564e-01 -7.14351566e-02 -1.72916920e-01 ... -1.48850521e-02
   1.23052410e-02  1.80696323e-01]]

Eigenvalues
[19.17893005  5.34862594  3.09351964  2.07877653  1.34781746  0.82207439
  0.56756527  0.45652984  0.36115814  0.34090087  0.28259051  0.25185916
  0.24481632  0.23815146  0.22931382  0.21347939  0.20367806  0.19309225
  0.18120016  0.15351432  0.13732522  0.13266879  0.12788955  0.10892294
  0.09439369  0.08856606  0.07864995  0.0752148   0.07123754  0.06404232
  0.02458609  0.02710978  0.03110194  0.03207754  0.04326229  0.03854864
  0.03889521]
```

```
Out[49]: (17739, 37)
```

```
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/ipykernel_launcher.py:21: DataConversio
```

```
Out[49]: PCA(copy=True, iterated_power='auto', n_components=37, random_state=None,
           svd_solver='auto', tol=0.0, whiten=False)
```

```
Out[49]: array([0.51832024, 0.14454931, 0.08360393, 0.05617998, 0.03642545,
                0.02221697, 0.01533874, 0.01233795, 0.00976048, 0.00921302,
                0.00763715, 0.00680662, 0.00661628, 0.00643616, 0.00619732,
                0.00576939, 0.0055045 , 0.00521842, 0.00489703, 0.0041488 ,
                0.00371128, 0.00358544, 0.00345628, 0.0029437 , 0.00255104,
                0.00239354, 0.00212555, 0.00203272, 0.00192523, 0.00173078,
                0.00116919, 0.00105116, 0.0010418 , 0.00086691, 0.00084055,
                0.00073266, 0.00066445])
```

```
Out[49]: (37,)
```

Out[49]:

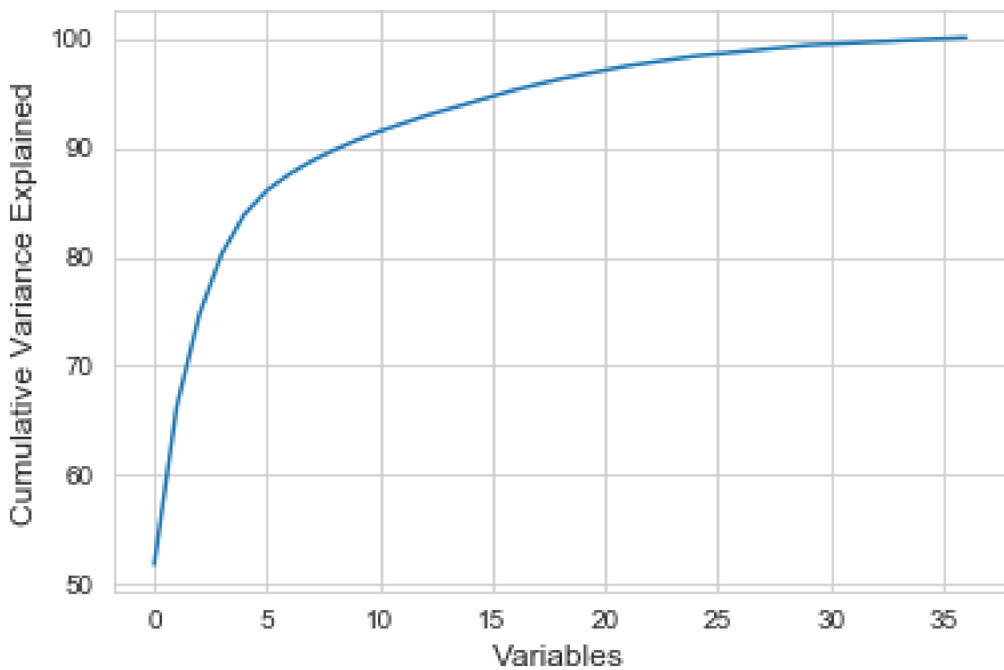
	0
0	0.518320
1	0.144549
2	0.083604
3	0.056180
4	0.036425

```
The cumulative variance explained is: [ 51.8  66.3  74.7  80.3  83.9  86.1  87.6  88.8  89.8  90
  92.9  93.5  94.1  94.7  95.3  95.8  96.3  96.7  97.1  97.5  97.8  98.1
  98.4  98.6  98.8  99.   99.2  99.4  99.5  99.6  99.7  99.8  99.9 100.
 100.1]
```

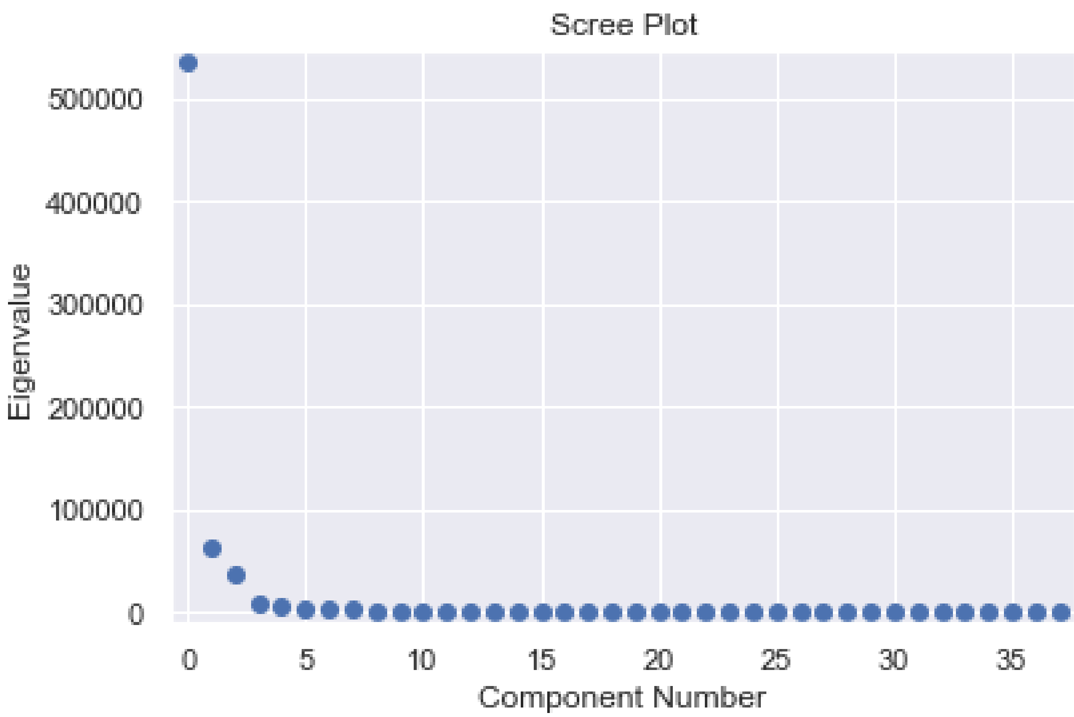
```
Out[49]: [<matplotlib.lines.Line2D at 0x1c58432c18>]
```

```
Out[49]: Text(0.5, 0, 'Variables')
```

```
Out[49]: Text(0, 0.5, 'Cumulative Variance Explained')
```




```
In [50]: #Scree Plot
         dta=pd.concat([y_overall, X], axis=1)
         #scree plot
         from statsmodels.multivariate.pca import PCA
         %matplotlib inline
         import seaborn as sns; sns.set()
         #Plotting a scree plot
         pca_model = PCA(dta.T, standardize=True, demean=True)
         fig = pca_model.plot_scree(log_scale=False)
```



We see that we can explain the vast majority of the variance in our model with roughly 5 varibles, but to account for more than 90% of the cumulative explained variance roughly 10 variables is needed.

6 Regression Analysis of Overall Rating

Regression on Overall Rating with Player Attributes:OLS and Robust Regression

Here we test one of our most important assumptions needed for our model: Overall is an aggregated calculation that is based on all of the player features in our attribute_profile. This assumption is key for our positional value analysis we will conduct later. Thus, we regress our attribute_profile on overall rating and treat overall rating as a numerical variable.

```
In [51]: #We account for heteroskedacity by using Whites Robust Standard Errors
         #define a basic model for overall and the full attribute profile
         X = complete[attribute_profile]
         X=sm.add_constant(X)
         y_overall=complete[overall_target]

         #Assuming a heteroskedastic model compute the regression results
         OLS_model = sm.OLS(y_overall,X)
         OLS_results=OLS_model.fit(cov_type='HC0')
         print(OLS_results.summary())
```

```
                            OLS Regression Results
==============================================================================
```

Dep. Variable:	Overall	R-squared:	0.846
Model:	OLS	Adj. R-squared:	0.845
Method:	Least Squares	F-statistic:	2560.
Date:	Thu, 06 Dec 2018	Prob (F-statistic):	0.00
Time:	16:32:10	Log-Likelihood:	-42966.
No. Observations:	17739	AIC:	8.601e+04
Df Residuals:	17701	BIC:	8.630e+04
Df Model:	37		
Covariance Type:	HC0		

	coef	std err	z	P>|z|	[0.025	0.975]
const	7.6296	1.169	6.527	0.000	5.339	9.921
age	0.0464	0.006	7.399	0.000	0.034	0.059
height_cm	-0.0029	0.006	-0.465	0.642	-0.015	0.009
weight_kg	0.0289	0.005	5.483	0.000	0.019	0.039
crossing	0.0161	0.003	5.834	0.000	0.011	0.022
finishing	0.0271	0.003	7.920	0.000	0.020	0.034
heading_accuracy	0.0965	0.003	31.748	0.000	0.091	0.102
short_passing	0.0769	0.005	15.270	0.000	0.067	0.087
volleys	0.0009	0.003	0.311	0.756	-0.005	0.007
dribbling	0.0143	0.004	3.210	0.001	0.006	0.023
curve	0.0109	0.003	3.916	0.000	0.005	0.016
free_kick_accuracy	0.0071	0.003	2.838	0.005	0.002	0.012
long_passing	-0.0163	0.004	-4.591	0.000	-0.023	-0.009
ball_control	0.1549	0.006	27.538	0.000	0.144	0.166
acceleration	0.0351	0.004	8.442	0.000	0.027	0.043
sprint_speed	0.0356	0.004	9.203	0.000	0.028	0.043
agility	-0.0035	0.003	-1.114	0.265	-0.010	0.003
reactions	0.2889	0.004	69.374	0.000	0.281	0.297
balance	-0.0138	0.003	-4.223	0.000	-0.020	-0.007
shot_power	0.0180	0.003	5.847	0.000	0.012	0.024
jumping	0.0070	0.002	3.189	0.001	0.003	0.011
stamina	0.0092	0.003	3.451	0.001	0.004	0.014
strength	0.0281	0.003	9.351	0.000	0.022	0.034
long_shots	-0.0200	0.003	-6.214	0.000	-0.026	-0.014
aggression	-0.0003	0.002	-0.144	0.885	-0.005	0.004
interceptions	0.0083	0.003	2.446	0.014	0.002	0.015
positioning	-0.0539	0.003	-16.388	0.000	-0.060	-0.047
vision	-0.0102	0.003	-3.412	0.001	-0.016	-0.004
penalties	0.0007	0.003	0.250	0.802	-0.005	0.006
composure	0.1031	0.003	30.108	0.000	0.096	0.110
marking	0.0035	0.004	0.839	0.402	-0.005	0.012
standing_tackle	0.0402	0.005	8.093	0.000	0.030	0.050
sliding_tackle	-0.0165	0.005	-3.396	0.001	-0.026	-0.007
gk_diving	0.0740	0.006	12.079	0.000	0.062	0.086
gk_handling	0.0828	0.006	13.140	0.000	0.070	0.095
gk_kicking	0.0371	0.006	6.334	0.000	0.026	0.049

```
gk_positioning         0.0755      0.006      12.473      0.000       0.064       0.087
gk_reflexes            0.0718      0.006      11.884      0.000       0.060       0.084
==============================================================================
Omnibus:                       60.633   Durbin-Watson:                   1.682
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               80.414
Skew:                           0.021   Prob(JB):                     3.45e-18
Kurtosis:                       3.327   Cond. No.                     1.99e+04
==============================================================================

Warnings:
[1] Standard Errors are heteroscedasticity robust (HC0)
[2] The condition number is large, 1.99e+04. This might indicate that there are
strong multicollinearity or other numerical problems.
```

Our model gives us an R-squared of about 85%, thus we can proceed with this critical assumption. On running this model we recieve a warning that we may suffer from multicollinearity, which is an issue we will resolve later. By using the statsmodels library we can also get easy access to informatio for hypothesis testing, variable significance and confidence intervals.

```
In [52]: #Robust Linear Regression
         rlm_model = sm.RLM(y_overall, X, M=sm.robust.norms.HuberT())
         rlm_results = rlm_model.fit()
         print(rlm_results.summary2())
```

```
                   Results: Robust linear model
===================================================================
Model:                  RLM                 Df Residuals:    17701
Dependent Variable:     Overall             Norm:            HuberT
Date:                   2018-12-06 16:39    Scale Est.:      mad
No. Observations:       17739               Cov. Type:       H1
Df Model:               37                  Scale:           2.6092
-------------------------------------------------------------------
                    Coef.  Std.Err.    z     P>|z|   [0.025  0.975]
-------------------------------------------------------------------
const               7.5849   1.1347   6.6846 0.0000  5.3610  9.8088
age                 0.0453   0.0059   7.6195 0.0000  0.0336  0.0569
height_cm          -0.0026   0.0062  -0.4229 0.6724 -0.0149  0.0096
weight_kg           0.0263   0.0053   4.9975 0.0000  0.0160  0.0366
crossing            0.0165   0.0028   5.9115 0.0000  0.0110  0.0219
finishing           0.0269   0.0034   7.9567 0.0000  0.0202  0.0335
heading_accuracy    0.0969   0.0029  33.5600 0.0000  0.0913  0.1026
short_passing       0.0782   0.0048  16.3196 0.0000  0.0688  0.0876
volleys             0.0019   0.0030   0.6569 0.5112 -0.0039  0.0077
dribbling           0.0112   0.0042   2.6696 0.0076  0.0030  0.0194
curve               0.0111   0.0029   3.8294 0.0001  0.0054  0.0168
free_kick_accuracy  0.0063   0.0026   2.4458 0.0145  0.0013  0.0114
long_passing       -0.0170   0.0036  -4.7749 0.0000 -0.0240 -0.0100
```

```
ball_control         0.1606    0.0050   31.8418 0.0000  0.1507   0.1705
acceleration         0.0355    0.0040    8.9502 0.0000  0.0277   0.0433
sprint_speed         0.0367    0.0037    9.8428 0.0000  0.0294   0.0440
agility             -0.0023    0.0030   -0.7545 0.4505 -0.0082   0.0036
reactions            0.2862    0.0039   74.2447 0.0000  0.2786   0.2937
balance             -0.0136    0.0032   -4.3124 0.0000 -0.0198  -0.0074
shot_power           0.0185    0.0030    6.2162 0.0000  0.0127   0.0243
jumping              0.0063    0.0022    2.9201 0.0035  0.0021   0.0105
stamina              0.0075    0.0025    2.9871 0.0028  0.0026   0.0123
strength             0.0299    0.0029   10.2412 0.0000  0.0242   0.0356
long_shots          -0.0231    0.0032   -7.3156 0.0000 -0.0293  -0.0169
aggression          -0.0003    0.0023   -0.1452 0.8846 -0.0048   0.0041
interceptions        0.0083    0.0032    2.5712 0.0101  0.0020   0.0146
positioning         -0.0536    0.0032  -16.8008 0.0000 -0.0598  -0.0473
vision              -0.0116    0.0029   -4.0205 0.0001 -0.0172  -0.0059
penalties            0.0006    0.0028    0.2275 0.8200 -0.0049   0.0061
composure            0.1048    0.0031   34.3429 0.0000  0.0988   0.1108
marking              0.0003    0.0041    0.0830 0.9338 -0.0077   0.0083
standing_tackle      0.0423    0.0049    8.7186 0.0000  0.0328   0.0519
sliding_tackle      -0.0159    0.0047   -3.3782 0.0007 -0.0251  -0.0067
gk_diving            0.0732    0.0061   12.0278 0.0000  0.0613   0.0852
gk_handling          0.0823    0.0061   13.4157 0.0000  0.0703   0.0944
gk_kicking           0.0400    0.0056    7.0900 0.0000  0.0289   0.0510
gk_positioning       0.0769    0.0060   12.7559 0.0000  0.0651   0.0888
gk_reflexes          0.0727    0.0060   12.0342 0.0000  0.0609   0.0845
===================================================================
```

Here we conduct robust linear regression with Hubers Maximum likelihood estimation to compare the confidence intervals of our features to those we obtained in OLS.

Regression on Overall Rating with Player Attributes: Fitting L1 and L2 Regularization

In [60]:
```
#Ridge Regression
from sklearn.linear_model import Ridge
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import Ridge
X = complete[attribute_profile]
y=complete[overall_target]
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.3,random_state=0)
#fitting several ridge regressions with various sizes of alpha
lr = LinearRegression()
lr.fit(X_train, y_train)
rr_small= Ridge(alpha=0.1)
rr_small.fit(X_train, y_train)
ridge = Ridge(alpha=1)
ridge.fit(X_train, y_train)
```

```python
rr10 = Ridge(alpha=10) #  comparison with alpha value
rr10.fit(X_train, y_train)
train_score=lr.score(X_train, y_train)
test_score=lr.score(X_test, y_test)
Ridge_train_score = ridge.score(X_train,y_train)
Ridge_test_score = ridge.score(X_test, y_test)
Ridge_train_score10 = rr10.score(X_train,y_train)
Ridge_test_score10 = rr10.score(X_test, y_test)
small_ridge_train_score10 = rr_small.score(X_train,y_train)
small_ridge_test_score10 = rr_small.score(X_test, y_test)
#evaluating the three ridge regressions
ysmall_prediction=rr_small.predict(X_test)
yregular_prediction = ridge.predict(X_test)
ylarge_prediction=ridge.predict(X_test)
from sklearn.metrics import r2_score
r2_small=r2_score(y_test, ysmall_prediction)
r2_regular=r2_score(y_test, yregular_prediction)
r2_large=r2_score(y_test, ylarge_prediction)
print("The R-Squared of the small alpha model is :" ,r2_small)
print("\nThe R-Squared of the default alpha model is :" ,r2_regular)
print("\nThe R-Squared of the large alpha model is :" ,r2_large)
ridge_coef=ridge.coef_
cols=np.array(X.columns)
cols=cols.reshape(37,1)
ridge_coef=ridge_coef.reshape(37,1)
coefs=np.concatenate((cols, ridge_coef), axis=1)
coefs=pd.DataFrame(coefs)
intercept=ridge.intercept_

#From this lets conclude we use the default alpha=1
y_prediction = ridge.predict(X_test)
predictedy=np.concatenate([y_prediction,X_test],axis=1)
predicted=pd.DataFrame(predictedy)
predicted.columns=['Overall','age', 'height_cm', 'weight_kg', 'crossing', 'finishing',
       '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', 'composure', 'marking', 'standing_tackle',
       'sliding_tackle', 'gk_diving', 'gk_handling', 'gk_kicking',
       'gk_positioning', 'gk_reflexes']
#predicted.head()
#predicted.describe().transpose()
#y_test.describe()

#Get the Root Mean Squar Error
from math import sqrt
from sklearn.metrics import mean_squared_error
```

```
RMSE_test=sqrt(mean_squared_error(y_true=y_test,y_pred=y_prediction))
print("Root Mean Square Error of test set is:" ,RMSE_test)

y_train_prediction = ridge.predict(X_train)
RMSE_train=sqrt(mean_squared_error(y_true=y_train,y_pred=y_train_prediction))
print("The RMSE of the training data is:" ,RMSE_train)

#K-folds cross validation
from sklearn import metrics
from sklearn.model_selection import cross_val_score
scores=cross_val_score(ridge,X,y,cv=5)
scores
```

```
Out[60]: LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None,
                  normalize=False)

Out[60]: Ridge(alpha=0.1, copy_X=True, fit_intercept=True, max_iter=None,
            normalize=False, random_state=None, solver='auto', tol=0.001)

Out[60]: Ridge(alpha=1, copy_X=True, fit_intercept=True, max_iter=None,
            normalize=False, random_state=None, solver='auto', tol=0.001)

Out[60]: Ridge(alpha=10, copy_X=True, fit_intercept=True, max_iter=None,
            normalize=False, random_state=None, solver='auto', tol=0.001)

The R-Squared of the small alpha model is : 0.8458129413678996

The R-Squared of the default alpha model is : 0.8458129475728042

The R-Squared of the large alpha model is : 0.8458129475728042
Root Mean Square Error of test set is: 2.7094674196860966
The RMSE of the training data is: 2.7360819852825267


Out[60]: array([-0.42136809, -3.19847964, -5.93214499, -4.62180961, -0.53326892])
```

```
In [62]: #Utilizing Lasso Regression
         from sklearn.linear_model import Lasso

         #default alpha=1
         lasso = Lasso().fit(X_train, y_train)
         print("Training set score: {:.2f}".format(lasso.score(X_train, y_train)))
         print("Test set score: {:.2f}".format(lasso.score(X_test, y_test)))
         print("Number of features used:", np.sum(lasso.coef_ != 0))

         # we increase the default setting of "max_iter",
         # otherwise the model would warn us that we should increase max_iter.
         lasso001 = Lasso(alpha=0.01, max_iter=100000).fit(X_train, y_train)
         print("\n\nTraining set score: {:.2f}".format(lasso001.score(X_train, y_train)))
```

```python
print("Test set score: {:.2f}".format(lasso001.score(X_test, y_test)))
print("Number of features used:", np.sum(lasso001.coef_ != 0))

#decrease alpha further
lasso00001 = Lasso(alpha=0.0001, max_iter=1000000).fit(X_train, y_train)
print("\n\nTraining set score: {:.2f}".format(lasso00001.score(X_train, y_train)))
print("Test set score: {:.2f}".format(lasso00001.score(X_test, y_test)))
print("Number of features used:", np.sum(lasso00001.coef_ != 0))
y_prediction = lasso.predict(X_test)
RMSE_test=sqrt(mean_squared_error(y_true=y_test,y_pred=y_prediction))
print("Root Mean Square Error of test set is:" ,RMSE_test)
r2=r2_score(y_test, y_prediction)
print("The R-Squared of the Model is :" ,r2)

#This r-square is lower because when conducting lasso regression for alpha =1
#we actually reduce the number of features we have from 37 to 25

#What would happen if we increased alpha above 1?
#Lets try for alpha =5 and alpha=10

lasso5 = Lasso(alpha=5, max_iter=1000000).fit(X_train, y_train)
print("Training set score for 5: {:.2f}".format(lasso5.score(X_train, y_train)))
print("Test set score for 5: {:.2f}".format(lasso5.score(X_test, y_test)))
print("Number of features used:", np.sum(lasso5.coef_ != 0))

lasso10 = Lasso(alpha=10, max_iter=1000000).fit(X_train, y_train)
print("Training set score for 10: {:.2f}".format(lasso10.score(X_train, y_train)))
print("Test set score for 10: {:.2f}".format(lasso10.score(X_test, y_test)))
print("Number of features used:", np.sum(lasso10.coef_ != 0))

#Let us try alpha=8
lasso8 = Lasso(alpha=8, max_iter=1000000).fit(X_train, y_train)
print("Training set score for 8: {:.2f}".format(lasso8.score(X_train, y_train)))
print("Test set score for 8: {:.2f}".format(lasso8.score(X_test, y_test)))
print("Number of features used:", np.sum(lasso8.coef_ != 0))
#This model is a good trade off between a relatively good prediction score while being
#so lets use alpha=8
y_prediction2 = lasso8.predict(X_test)
lasso_coef=lasso8.coef_
cols=np.array(X.columns)
cols=cols.reshape(37,1)
lasso_coef=lasso_coef.reshape(37,1)
coefs=np.concatenate((cols, lasso_coef), axis=1)
coefs=pd.DataFrame(coefs)
intercept=lasso8.intercept_
print(intercept)
print(coefs)
```

```
Training set score: 0.84
Test set score: 0.84
Number of features used: 26


Training set score: 0.85
Test set score: 0.85
Number of features used: 37


Training set score: 0.85
Test set score: 0.85
Number of features used: 37
Root Mean Square Error of test set is: 2.738414237577749
The R-Squared of the Model is : 0.8425008087308197
Training set score for 5: 0.80
Test set score for 5: 0.80
Number of features used: 15
Training set score for 10: 0.72
Test set score for 10: 0.72
Number of features used: 5
Training set score for 8: 0.75
Test set score for 8: 0.75
Number of features used: 10
[29.00742928]
                     0           1
0                  age           0
1            height_cm           0
2            weight_kg           0
3             crossing           0
4            finishing           0
5     heading_accuracy           0
6         short_passing   0.0164898
7              volleys           0
8            dribbling           0
9                curve           0
10  free_kick_accuracy           0
11        long_passing   0.0142212
12        ball_control   0.0183834
13        acceleration           0
14        sprint_speed           0
15             agility           0
16           reactions    0.410776
17             balance          -0
18          shot_power  0.00196838
19             jumping           0
20             stamina           0
21            strength    0.028935
```

```
22          long_shots           0
23          aggression           0
24       interceptions           0
25         positioning           0
26              vision           0
27           penalties           0
28           composure    0.105276
29             marking           0
30      standing_tackle          0
31       sliding_tackle          0
32           gk_diving  0.00535716
33         gk_handling           0
34          gk_kicking           0
35       gk_positioning  0.0103647
36         gk_reflexes   0.0406695
```

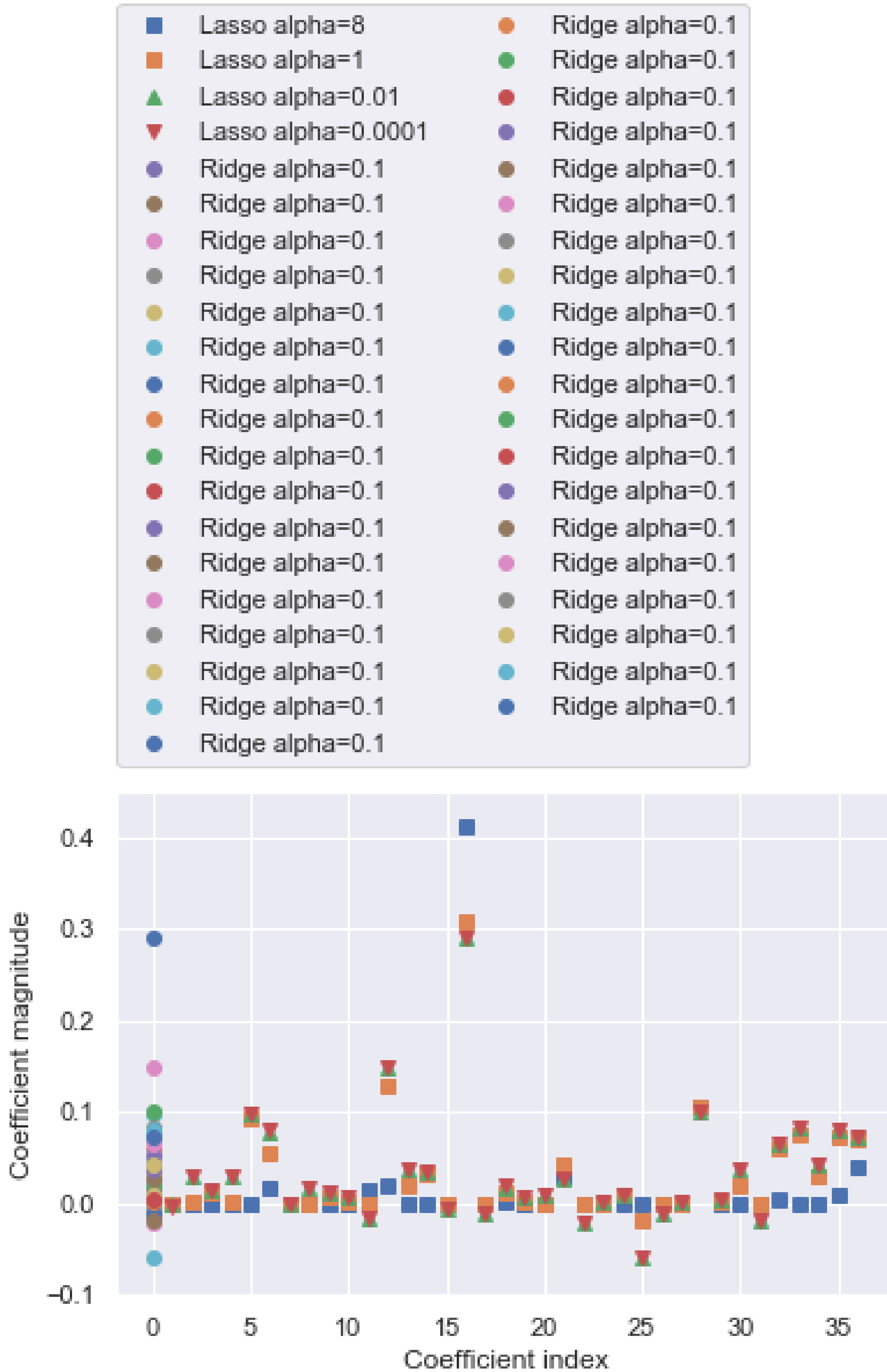
Comparing Ridge and Lasso:

```
In [63]: plt.plot(lasso8.coef_, 's', label="Lasso alpha=8")
         plt.plot(lasso.coef_, 's', label="Lasso alpha=1")
         plt.plot(lasso001.coef_, '^', label="Lasso alpha=0.01")
         plt.plot(lasso00001.coef_, 'v', label="Lasso alpha=0.0001")


         plt.plot(ridge.coef_, 'o', label="Ridge alpha=0.1")
         plt.legend(ncol=2, loc=(0, 1.05))
         plt.ylim(-0.1, 0.45)
         plt.xlabel("Coefficient index")
         plt.ylabel("Coefficient magnitude")
```

```
Out[63]: [<matplotlib.lines.Line2D at 0x1c534ea6a0>]

Out[63]: [<matplotlib.lines.Line2D at 0x1c53524c88>]

Out[63]: [<matplotlib.lines.Line2D at 0x1c534eaa90>]

Out[63]: [<matplotlib.lines.Line2D at 0x1c534eab70>]

Out[63]: [<matplotlib.lines.Line2D at 0x1c534eaeb8>,
          <matplotlib.lines.Line2D at 0x1c534f2588>,
          <matplotlib.lines.Line2D at 0x1c534f2710>,
          <matplotlib.lines.Line2D at 0x1c534f2898>,
          <matplotlib.lines.Line2D at 0x1c534f2a20>,
          <matplotlib.lines.Line2D at 0x1c534f2c18>,
          <matplotlib.lines.Line2D at 0x1c58425a58>,
          <matplotlib.lines.Line2D at 0x1c534f2e80>,
          <matplotlib.lines.Line2D at 0x1c534fc048>,
          <matplotlib.lines.Line2D at 0x1c534fc1d0>,
```

```
 <matplotlib.lines.Line2D at 0x1c534fc358>,
 <matplotlib.lines.Line2D at 0x1c534fc4e0>,
 <matplotlib.lines.Line2D at 0x1c534fc668>,
 <matplotlib.lines.Line2D at 0x1c534fc7f0>,
 <matplotlib.lines.Line2D at 0x1c58ef47f0>,
 <matplotlib.lines.Line2D at 0x1c534fcb00>,
 <matplotlib.lines.Line2D at 0x1c534fcc88>,
 <matplotlib.lines.Line2D at 0x1c534fce10>,
 <matplotlib.lines.Line2D at 0x1c534fcf98>,
 <matplotlib.lines.Line2D at 0x1c534f9160>,
 <matplotlib.lines.Line2D at 0x1c534f92e8>,
 <matplotlib.lines.Line2D at 0x1c534f9470>,
 <matplotlib.lines.Line2D at 0x1c534f95f8>,
 <matplotlib.lines.Line2D at 0x1c534f9780>,
 <matplotlib.lines.Line2D at 0x1c534f9908>,
 <matplotlib.lines.Line2D at 0x1c534f9a90>,
 <matplotlib.lines.Line2D at 0x1c534f9c18>,
 <matplotlib.lines.Line2D at 0x1c534f9da0>,
 <matplotlib.lines.Line2D at 0x1c534f9f28>,
 <matplotlib.lines.Line2D at 0x1c534f70f0>,
 <matplotlib.lines.Line2D at 0x1c534f7278>,
 <matplotlib.lines.Line2D at 0x1c534f7400>,
 <matplotlib.lines.Line2D at 0x1c534f7588>,
 <matplotlib.lines.Line2D at 0x1c534f7710>,
 <matplotlib.lines.Line2D at 0x1c534f7898>,
 <matplotlib.lines.Line2D at 0x1c534f7a20>,
 <matplotlib.lines.Line2D at 0x1c534f7ba8>]
```

```
Out[63]: <matplotlib.legend.Legend at 0x1c534f24a8>

Out[63]: (-0.1, 0.45)

Out[63]: Text(0.5, 0, 'Coefficient index')

Out[63]: Text(0, 0.5, 'Coefficient magnitude')
```


Lasso alpha=8
Lasso alpha=1
Lasso alpha=0.01
Lasso alpha=0.0001
Ridge alpha=0.1
0.4
0.3
0.2
0.1
0.0
−0.1
0
5
10
15
20
25
30
35
Coefficient magnitude
Coefficient index

7 Positional Value Modeling

Positional Value Modeling: Procedure

This approach to finding a value model for this position is based on the assumption that the main determinant to market value is a players overall rating. The approach to find a model that describes value for this position with a reduced number of features is the following: To gain basic insights we conduct simple OLS with robust SE on Overall for this position group with all attributes in the "attribute_profile" list. Then to reduce the amount of variables that matter we fit a lasso regression model on overall. The reason we fit our lasso on overall and not value is that by doing so on overall we see what few features actually make good players, at a given position, good. We compute pearson correlations on the lasso reduced model.When doing lasso regression, we use cross-validation to find the correct alpha to use. After this we choose all the features with a non-zero coefficient, and regardless if their coefficient is non-zero, we include non-soccer attributes such as Age, weight, and height. Since multicollinearity is likely, we conduct ridge regression on the non-zero coefficients from the lasso model. We use cross validation to also choose the correct alpha for our ridge regression. We then evaluate the reduced model performance, and compare it to the model performance of all the attributes on Value.

We conduct gradient boosting regression with grid search cross validation on our lasso reduced model to rank feature importance for a position with respect to value. We then use interaction terms to combine highly correlated features and further reduce our model. Lastly, we re-estimate our own reduced value model we created and compare it to the original model.

Positional Value Modeling: Goal Keeper

8 Goal Keeper

In [70]:
```
data=GK
lnVal=pd.DataFrame((data["Value (M)"]+1).apply(np.log))
lnVal.columns = ['ln_value']
gk_dta = pd.concat([lnVal, data], axis=1)
#Model definition
data=gk_dta
x=data[attribute_profile]
X=sm.add_constant(x)
y1=data[overall_target]
y2=data[value_target]
y3=data[ln_value]


OLS_model = sm.OLS(y1,X)
OLS_results=OLS_model.fit(cov_type='HC0')
#print(OLS_results.summary())
OLS_model2 = sm.OLS(y2,X)
OLS_results2=OLS_model2.fit(cov_type='HC0')
print("\n\nThe adjusted R-squared for the original gk value model is:" ,OLS_results2.rs
print("\nThe model AIC is: " ,OLS_results2.aic)
#Lasso Regression
X_train,X_test,y_train,y_test=train_test_split(x,y1,test_size=0.3,random_state=0)
```

```
lr = LinearRegression()
lr.fit(X_train, y_train)

#Lasso Fit (Overall)
lasso = Lasso(alpha=1.0, max_iter=1000000).fit(X_train, y_train)

from sklearn.linear_model import LassoCV
from sklearn.preprocessing import StandardScaler
X_std = sc.fit_transform(x)
regr_cv = LassoCV(alphas=np.arange(1,9999.999))
# Fit the linear regression
model_cv = regr_cv.fit(X_std, y1)
print("The alpha we should use for lasso regression is:" ,model_cv.alpha_)
#Lasso Coefficients
y_prediction = lasso.predict(X_test)
lasso_coef=lasso.coef_
cols=np.array(x.columns)
cols=cols.reshape(37,1)
lasso_coef=lasso_coef.reshape(37,1)
coefs=np.concatenate((cols, lasso_coef), axis=1)
coefs=pd.DataFrame(coefs)
intercept=lasso.intercept_
print(intercept)
print(coefs)
```

```
The adjusted R-squared for the original gk value model is: 0.4098131400144627

The model AIC is:  10499.852855029098
```

```
Out[70]: LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None,
                  normalize=False)
```

```
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/preprocessing/data.py:625: Data
  return self.partial_fit(X, y)
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/base.py:462: DataConversionWarn
  return self.fit(X, **fit_params).transform(X)
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/linear_model/coordinate_descent
  y = column_or_1d(y, warn=True)
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/model_selection/_split.py:2053:
  warnings.warn(CV_WARNING, FutureWarning)
```

```
The alpha we should use for lasso regression is: 1.0
[2.07617322]
                   0          1
0                age          0
```

```
1             height_cm           0
2             weight_kg           0
3              crossing          -0
4             finishing           0
5      heading_accuracy          -0
6         short_passing           0
7               volleys           0
8             dribbling           0
9                 curve           0
10   free_kick_accuracy           0
11         long_passing           0
12         ball_control           0
13         acceleration           0
14         sprint_speed           0
15              agility           0
16            reactions    0.111601
17              balance          -0
18           shot_power           0
19              jumping           0
20              stamina           0
21             strength           0
22           long_shots           0
23           aggression           0
24        interceptions           0
25          positioning           0
26               vision  0.00040904
27            penalties           0
28            composure  0.00131157
29              marking           0
30       standing_tackle         -0
31        sliding_tackle         -0
32            gk_diving    0.198543
33          gk_handling    0.206887
34           gk_kicking   0.0436979
35       gk_positioning    0.213626
36          gk_reflexes    0.207669
```

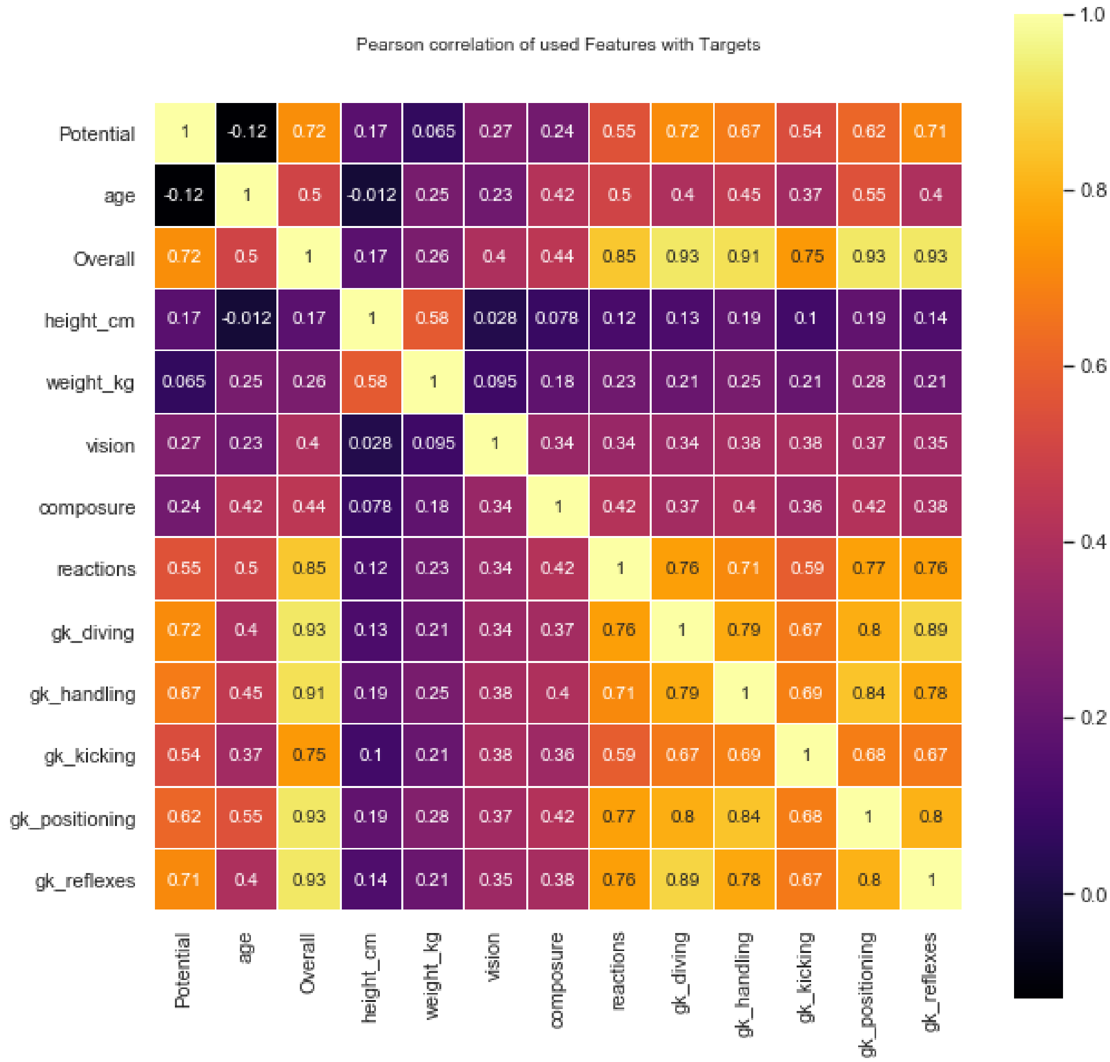
```
In [71]: #Correlation between GK features
         #Heatmap: show the correlation between similar features.
         # Select a subset of the df
         used_variables = ['Potential','age','Overall','height_cm', 'weight_kg', 'vision', 'comp
                         'gk_handling', 'gk_kicking','gk_positioning', 'gk_reflexes']
         corr_variables = gk_dta[used_variables]
         colormap = plt.cm.inferno
         plt.figure(figsize=(10,10))
         plt.title('Pearson correlation of used Features with Targets',
                   y=1.05, size=10)
```

```
sns.heatmap(corr_variables.corr(),linewidths=0.1,vmax=1.0,
            square=True, cmap=colormap, linecolor='white', annot=True)
```

Out[71]: <Figure size 720x720 with 0 Axes>

Out[71]: Text(0.5, 1.05, 'Pearson correlation of used Features with Targets')

Out[71]: <matplotlib.axes._subplots.AxesSubplot at 0x1c57ea4f28>



In [72]:
```
#Reduced Model
features=lasso.coef_
np.nonzero(features)
gk_features_used=['age','height_cm', 'weight_kg','vision', 'composure', 'reactions' ,'g
                  'gk_handling', 'gk_kicking','gk_positioning', 'gk_reflexes']
```

```
data=gk_dta
x=data[gk_features_used]
X=sm.add_constant(x)
y1=data[overall_target]
y2=data[value_target]
x.shape
#Finding the best alpha for ridge regression for value
x=data[gk_features_used]
y2=data[value_target]
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import RidgeCV
scaler = StandardScaler()
X_std = scaler.fit_transform(x)
regr_cv = RidgeCV(alphas=np.arange(0.001,9999.999))
# Fit the linear regression
model_cv = regr_cv.fit(X_std, y2)
model_cv.alpha_
print("The alpha we should use for ridge regression is:" ,model_cv.alpha_)
#Finding the best alpha for ridge regression for  elasticity of value
x2=data[gk_features_used]
y3=data[ln_value]
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import RidgeCV
scaler = StandardScaler()
X_std2 = scaler.fit_transform(x2)
regr_cv2 = RidgeCV(alphas=np.arange(0.001,9999.999))
# Fit the linear regression
model_cv2 = regr_cv.fit(X_std2, y3)
model_cv2.alpha_
print("The alpha we should use for ridge regression is:" ,model_cv2.alpha_)
```

Out[72]: (array([16, 26, 28, 32, 33, 34, 35, 36]),)

Out[72]: (1997, 11)

```
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/preprocessing/data.py:625: Data
  return self.partial_fit(X, y)
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/base.py:462: DataConversionWarn
  return self.fit(X, **fit_params).transform(X)
```

Out[72]: 43.00099999999999

```
The alpha we should use for ridge regression is: 43.00099999999999
```

```
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/preprocessing/data.py:625: Data
  return self.partial_fit(X, y)
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/base.py:462: DataConversionWarn
```

```
  return self.fit(X, **fit_params).transform(X)
```

```
Out[72]: 17.000999999999998
```

```
The alpha we should use for ridge regression is: 17.000999999999998
```

```
In [73]: #Ridge regression for value
         X_train,X_test,y_train,y_test=train_test_split(x,y2,test_size=0.3,random_state=0)
         lr = LinearRegression()
         lr.fit(X_train, y_train)
         #Ridge fit
         ridge = Ridge(alpha=43.001)
         ridge.fit(X_train, y_train)
         y_prediction = ridge.predict(X_test)
         ridge_coef=ridge.coef_
         cols=np.array(x.columns)
         cols=cols.reshape(11,1)
         ridge_coef=ridge_coef.reshape(11,1)
         ridge_coefs=np.concatenate((cols, ridge_coef), axis=1)
         ridge_coefs=pd.DataFrame(ridge_coefs)
         ridge_intercept=ridge.intercept_
         print(ridge_intercept)
         print(ridge_coefs)
```

```
Out[73]: LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None,
                  normalize=False)
```

```
Out[73]: Ridge(alpha=43.001, copy_X=True, fit_intercept=True, max_iter=None,
            normalize=False, random_state=None, solver='auto', tol=0.001)
```

```
[-13.14542092]
                  0            1
0               age    -0.237331
1         height_cm   -0.0300758
2         weight_kg    0.0201663
3            vision   0.00894544
4         composure    0.0325005
5         reactions    0.0331193
6         gk_diving     0.057807
7       gk_handling     0.146235
8        gk_kicking  0.000906135
9    gk_positioning    0.0668935
10      gk_reflexes    0.0620717
```

```
In [74]: #Ridge regression for elasticity
         X_train,X_test,y_train,y_test=train_test_split(x,y2,test_size=0.3,random_state=0)
```

```
lr = LinearRegression()
lr.fit(X_train, y_train)
#Ridge fit
ridge = Ridge(alpha=17.01)
ridge.fit(X_train, y_train)
y_prediction = ridge.predict(X_test)
ridge_coef=ridge.coef_
cols=np.array(x.columns)
cols=cols.reshape(11,1)
ridge_coef=ridge_coef.reshape(11,1)
ridge_coefs=np.concatenate((cols, ridge_coef), axis=1)
ridge_coefs=pd.DataFrame(ridge_coefs)
ridge_intercept=ridge.intercept_
print(ridge_intercept)
print(ridge_coefs)
```

```
Out[74]: LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None,
                  normalize=False)
```

```
Out[74]: Ridge(alpha=17.01, copy_X=True, fit_intercept=True, max_iter=None,
            normalize=False, random_state=None, solver='auto', tol=0.001)
```

```
[-13.12306795]
                  0            1
0               age    -0.237615
1         height_cm   -0.0302307
2         weight_kg    0.0202533
3            vision    0.0089393
4         composure    0.0325238
5         reactions    0.0331278
6         gk_diving    0.0577731
7       gk_handling     0.146363
8        gk_kicking  0.000856266
9    gk_positioning     0.066962
10      gk_reflexes    0.0620545
```

```
In [77]: #Model Eval for value
         X_train,X_test,y_train,y_test=train_test_split(x,y2,test_size=0.3,random_state=0)
         lr = LinearRegression()
         lr.fit(X_train, y_train)
         #Ridge fit
         ridge = Ridge(alpha=43.001)
         ridge.fit(X_train, y_train)
         Ridge_train_score = ridge.score(X_train,y_train)
         Ridge_test_score = ridge.score(X_test, y_test)
         y_prediction = ridge.predict(X_test)
         print("The training and test scores respectively are: " ,Ridge_train_score, "and" ,Ridg
         from math import sqrt
```

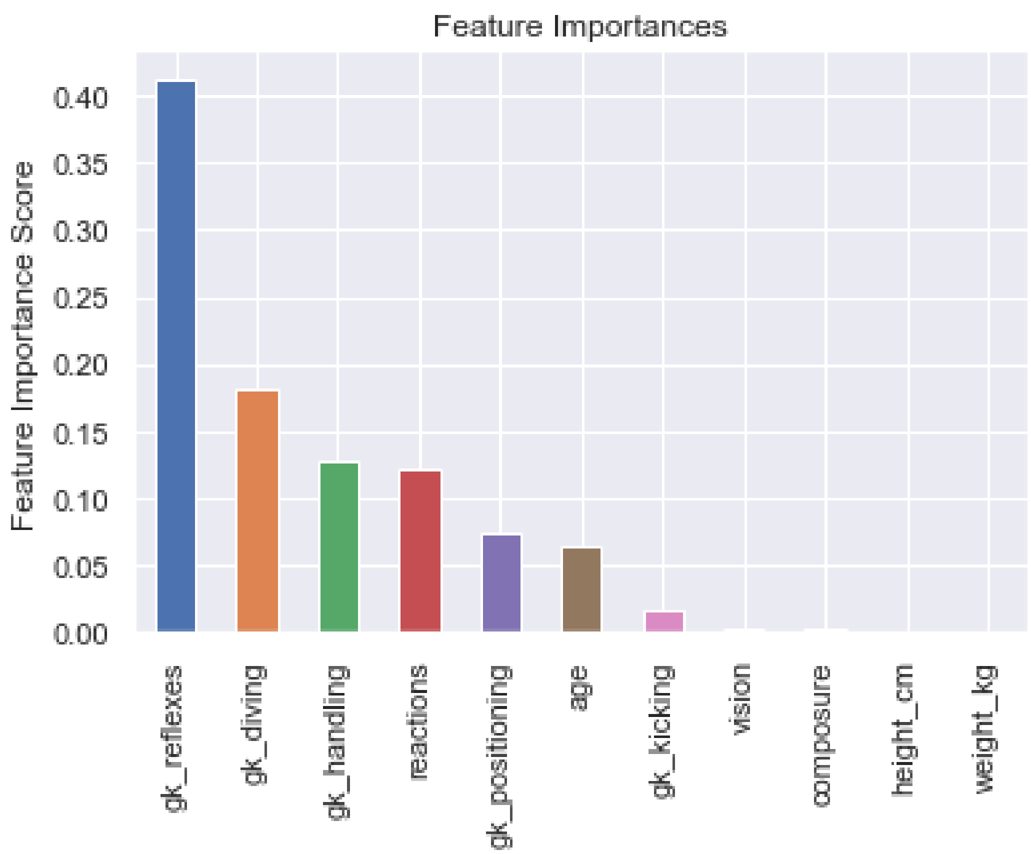
```
        from sklearn.metrics import mean_squared_error
        RMSE_test=sqrt(mean_squared_error(y_true=y_test,y_pred=y_prediction))
        print("\n Root Mean Square Error of test set is:" ,RMSE_test)
        from sklearn import metrics
        from sklearn.model_selection import cross_val_score
        scores=cross_val_score(ridge,x,y2,cv=5)
        print("\n K-folds cross validation scores:" ,scores)
```

```
Out[77]: LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None,
                  normalize=False)

Out[77]: Ridge(alpha=43.001, copy_X=True, fit_intercept=True, max_iter=None,
            normalize=False, random_state=None, solver='auto', tol=0.001)

The training and test scores respectively are:  0.4172929600398208 and 0.3783843942205314

 Root Mean Square Error of test set is: 3.9606127253424033

 K-folds cross validation scores: [-3.33025712e-01 -1.78110273e+01 -7.33523812e+01 -1.63418222e+
 -1.09703462e+04]
```

```
In [82]: #Gradient Boosting Regression on the Reduced Model for Value
        from sklearn.metrics import mean_squared_error, accuracy_score
        from sklearn.ensemble import GradientBoostingRegressor
        from sklearn.model_selection import cross_validate
        from sklearn.model_selection import GridSearchCV
        from sklearn import metrics
        from sklearn.model_selection import cross_val_score
        from sklearn.model_selection import train_test_split
        from sklearn.model_selection import KFold
        from sklearn.model_selection import ShuffleSplit
        from sklearn.metrics import recall_score
        gk_reduced=['Value (M)','age','height_cm', 'weight_kg','vision', 'composure', 'reaction
                       'gk_handling', 'gk_kicking','gk_positioning', 'gk_reflexes']
        dta=GK[gk_reduced]

        def modelfit(alg, dtrain, features, performCV=True, printFeatureImportance=True, cv_fol
            #Fit the algorithm on the data

            alg.fit(dtrain[features],dtrain["Value (M)"] )

            #Predict training set:
            dtrain_predictions = alg.predict(dtrain[features])

            #Perform cross-validation:
            cv_score =  cross_val_score(alg, dtrain[features], dtrain["Value (M)"], cv=cv_folds
                                                        scoring='neg_mean_squared_error')
            cv_score = np.sqrt(np.abs(cv_score))
```

```
    #Print model report:
    print ("\nModel Report")
    print ("RMSE : %.4g" % np.sqrt(metrics.mean_squared_error(dtrain["Value (M)"], dtra
    print ("CV Score : Mean - %.4g | Std - %.4g | Min - %.4g | Max - %.4g" % (np.mean(c
                                                                                np.std(cv_
                                                                                 np.max(cv

    if printFeatureImportance:
        feat_imp = pd.Series(alg.feature_importances_, features).sort_values(ascending=
        feat_imp.plot(kind='bar', title='Feature Importances')
        plt.ylabel('Feature Importance Score')

features = [i for i in dta.columns if i != "Value (M)"]
target = "Value (M)"
gbm0 = GradientBoostingRegressor(random_state=7)
modelfit(gbm0, dta, features)
```

```
Model Report
RMSE : 0.3608
CV Score : Mean - 1.42 | Std - 3.253 | Min - 0.06488 | Max - 11.13
```

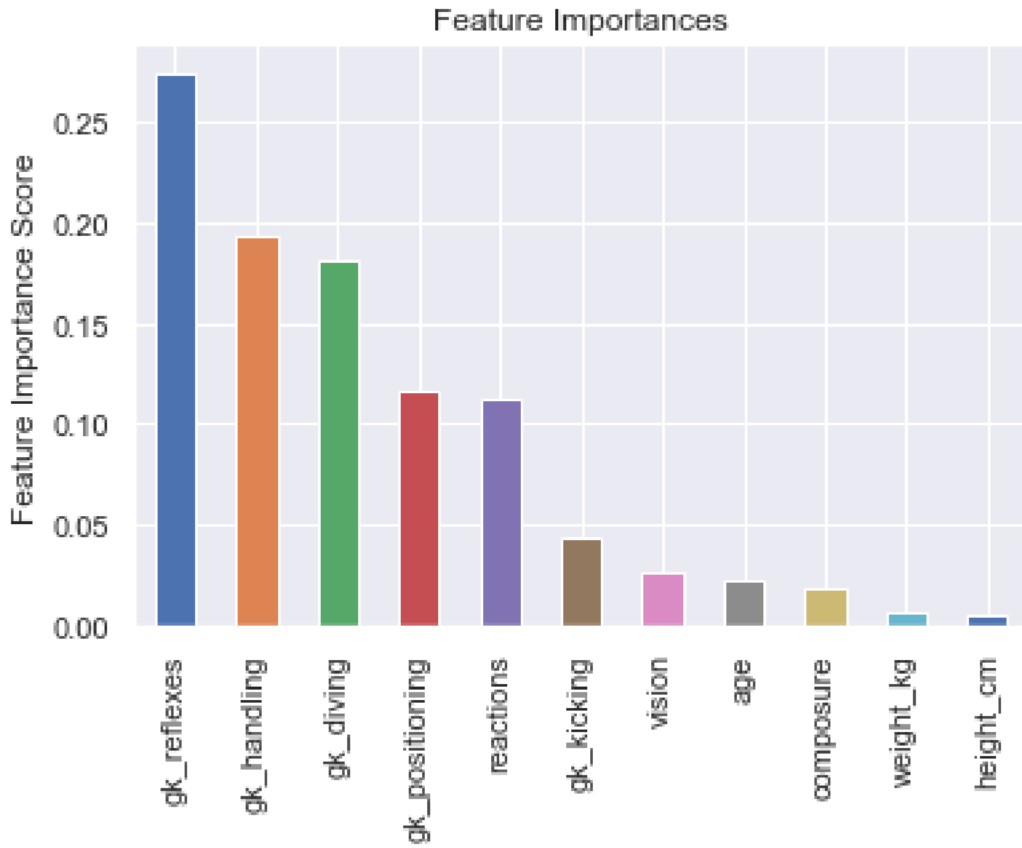


```
In [83]: #Feature Ranking with GridSearch CV
         estimators = [x for x in range(700,750,10)]
         param_test1 = {'n_estimators':estimators}
         gsearch1 = GridSearchCV(estimator = GradientBoostingRegressor(learning_rate=0.1, min_sa
                                            min_samples_leaf=50,max_depth=8,max_features='sqrt',
                                 param_grid = param_test1, scoring='neg_mean_squared_error',n_job
         gsearch1.fit(dta[features],dta["Value (M)"])

         gsearch1.score, gsearch1.best_params_, gsearch1.best_score_
         modelfit(gsearch1.best_estimator_, dta, features)
```

```
Out[83]: GridSearchCV(cv=10, error_score='raise-deprecating',
                estimator=GradientBoostingRegressor(alpha=0.9, criterion='friedman_mse', init=No
                      learning_rate=0.1, loss='ls', max_depth=8,
                      max_features='sqrt', max_leaf_nodes=None,
                      min_impurity_decrease=0.0, min_impurity_split=None,
                      min_samples_leaf=50, min_sa...       subsample=0.8, tol=0.0001, validation
                      warm_start=False),
                fit_params=None, iid=False, n_jobs=4,
                param_grid={'n_estimators': [700, 710, 720, 730, 740]},
                pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
                scoring='neg_mean_squared_error', verbose=0)
```

```
Out[83]: (<bound method BaseSearchCV.score of GridSearchCV(cv=10, error_score='raise-deprecating
                 estimator=GradientBoostingRegressor(alpha=0.9, criterion='friedman_mse', init=N
                       learning_rate=0.1, loss='ls', max_depth=8,
                       max_features='sqrt', max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=50, min_sa...       subsample=0.8, tol=0.0001, validatio
                       warm_start=False),
                 fit_params=None, iid=False, n_jobs=4,
                 param_grid={'n_estimators': [700, 710, 720, 730, 740]},
                 pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
                 scoring='neg_mean_squared_error', verbose=0)>,
          {'n_estimators': 730},
          -12.52598819477318)
```

```
Model Report
RMSE : 1.388
CV Score : Mean - 1.465 | Std - 3.222 | Min - 0.1063 | Max - 11.06
```




```
In [84]: #Create our New Model with Interaction Terms
         data=gk_dta
         x=data[attribute_profile]
         X=sm.add_constant(x)
         y1=data[overall_target]
         y2=data[value_target]
         y3=data[ln_value]
         data=gk_dta
         def gk_skills (row):
             return row['gk_reflexes'] * row['gk_handling'] * row['gk_diving'] *row['gk_position
         def gk_ath_ment (row):
             return row['acceleration'] *row['jumping'] *row['reactions'] * row['strength'] *row

         def gk_attack (row):
             return row['long_passing'] * row['ball_control'] *row['short_passing']
         def gk_phy (row):
             return row['height_cm'] * row['weight_kg']


         data['gk_skills'] = data.apply(gk_skills, axis=1)
```

```
data['gk_ath_ment']= data.apply(gk_ath_ment, axis=1)
data['gk_attack']= data.apply(gk_attack, axis=1)
data['gk_phy']= data.apply(gk_phy, axis=1)
features=['age', 'gk_skills', 'gk_ath_ment' , 'gk_attack', 'gk_phy']
x=data[features]
#We must now scale the features
x =pd.DataFrame(scaler.fit_transform(x))
x.columns= ['age', 'gk_skills', 'gk_ath_ment' , 'gk_attack', 'gk_phy']
#We have now addressed the issue of endogenity by including interaction terms
X=sm.add_constant(x)
y1=data[overall_target]
y2=data[value_target]
y3=data[ln_value]
mod=sm.OLS(y1,X)
res=mod.fit(cov_type='HC0')
yhat = res.fittedvalues
OLS_model = sm.OLS(y2,X)
OLS_results=OLS_model.fit(cov_type='HC0')
print(OLS_results.summary())
print(res.aic)
#Plot of y-hat for y-true on the reduced model for overall rating
from statsmodels.graphics.api import abline_plot
fig, ax = plt.subplots()
ax.scatter(yhat, y1)
line_fit = sm.OLS(y1, sm.add_constant(yhat, prepend=True)).fit()
abline_plot(model_results=line_fit, ax=ax)


ax.set_title('New Model fit to Overall')
ax.set_ylabel('Observed values')
ax.set_xlabel('Fitted values');
```

```
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/preprocessing/data.py:625: Data
  return self.partial_fit(X, y)
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/base.py:462: DataConversionWarn
  return self.fit(X, **fit_params).transform(X)


                            OLS Regression Results
==============================================================================
Dep. Variable:              Value (M)   R-squared:                       0.600
Model:                            OLS   Adj. R-squared:                  0.599
Method:                 Least Squares   F-statistic:                     55.22
Date:                Thu, 06 Dec 2018   Prob (F-statistic):           7.35e-54
Time:                        18:11:18   Log-Likelihood:                -4841.2
No. Observations:                1997   AIC:                             9694.
Df Residuals:                    1991   BIC:                             9728.
Df Model:                           5
```

```
Covariance Type:                  HC0
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const          1.5912      0.061     26.021      0.000       1.471       1.711
age           -1.2719      0.138     -9.209      0.000      -1.543      -1.001
gk_skills      3.4156      0.242     14.137      0.000       2.942       3.889
gk_ath_ment    0.3327      0.149      2.228      0.026       0.040       0.625
gk_attack      0.1957      0.190      1.031      0.302      -0.176       0.568
gk_phy        -0.0385      0.069     -0.560      0.575      -0.173       0.096
==============================================================================
Omnibus:                     2605.953   Durbin-Watson:                   0.955
Prob(Omnibus):                  0.000   Jarque-Bera (JB):           689484.372
Skew:                           6.965   Prob(JB):                         0.00
Kurtosis:                      92.957   Cond. No.                         2.54
==============================================================================

Warnings:
[1] Standard Errors are heteroscedasticity robust (HC0)
8961.799760791433
```

Not only have we addressed issues of multicollinearity but we have increased the r-squared form 38% to 60% with our new model.

Positional Value Modeling: Center Back

9 Center Backs

In [85]:
```
data=CB
lnVal=pd.DataFrame((data["Value (M)"]+1).apply(np.log))
lnVal.columns = ['ln_value']
cb_dta = pd.concat([lnVal, data], axis=1)

data=cb_dta
x=data[attribute_profile]
X=sm.add_constant(x)
y1=data[overall_target]
y2=data[value_target]
y3=data[ln_value]
#OLS for Overall
OLS_model = sm.OLS(y1,X)
OLS_results=OLS_model.fit(cov_type='HC0')
print("The R-squared for the attributes with overall is:" ,OLS_results.rsquared_adj)
OLS_model2 = sm.OLS(y2,X)
OLS_results2=OLS_model2.fit(cov_type='HC0')
print("\n\nThe adjusted R-squared for the original CB value model is:" ,OLS_results2.rs
print("\nThe model AIC is: " ,OLS_results2.aic)

#Lasso Regression
X_train,X_test,y_train,y_test=train_test_split(x,y1,test_size=0.3,random_state=0)
lr = LinearRegression()
lr.fit(X_train, y_train)

#Lasso Fit (Overall)
#lasso = Lasso(alpha=1.0, max_iter=1000000).fit(X_train, y_train)

from sklearn.linear_model import LassoCV
from sklearn.preprocessing import StandardScaler
X_std = scaler.fit_transform(x)
regr_cv = LassoCV(alphas=np.arange(1,9999.999))
# Fit the linear regression
model_cv = regr_cv.fit(X_std, y1)
print("The alpha we should use for lasso regression is:" ,model_cv.alpha_)

#Lasso Coefficients
y_prediction = lasso.predict(X_test)
lasso_coef=lasso.coef_
cols=np.array(x.columns)
cols=cols.reshape(37,1)
lasso_coef=lasso_coef.reshape(37,1)
coefs=np.concatenate((cols, lasso_coef), axis=1)
coefs=pd.DataFrame(coefs)
intercept=lasso.intercept_
print("the intercept is:" ,intercept)
```

```
print(coefs)
coefs.columns
```

```
The R-squared for the attributes with overall is: 0.9767396881639706


The adjusted R-squared for the original CB value model is: 0.5190537115283163

The model AIC is:  18373.33296177382
```

```
Out[85]: LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None,
                  normalize=False)
```

```
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/preprocessing/data.py:625: Data
  return self.partial_fit(X, y)
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/base.py:462: DataConversionWarn
  return self.fit(X, **fit_params).transform(X)
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/linear_model/coordinate_descent
  y = column_or_1d(y, warn=True)
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/model_selection/_split.py:2053:
  warnings.warn(CV_WARNING, FutureWarning)
```

```
The alpha we should use for lasso regression is: 1.0
the intercept is: [2.07617322]
                    0         1
0                 age         0
1           height_cm         0
2           weight_kg         0
3            crossing        -0
4           finishing         0
5    heading_accuracy        -0
6       short_passing         0
7             volleys         0
8           dribbling         0
9               curve         0
10  free_kick_accuracy        0
11       long_passing         0
12       ball_control         0
13       acceleration         0
14       sprint_speed         0
15            agility         0
16          reactions  0.111601
17            balance        -0
18         shot_power         0
19            jumping         0
20            stamina         0
21           strength         0
```

```
22          long_shots           0
23          aggression           0
24       interceptions           0
25         positioning           0
26              vision  0.00040904
27           penalties           0
28           composure  0.00131157
29             marking           0
30      standing_tackle         -0
31       sliding_tackle         -0
32           gk_diving    0.198543
33         gk_handling    0.206887
34          gk_kicking   0.0436979
35      gk_positioning    0.213626
36         gk_reflexes    0.207669
```

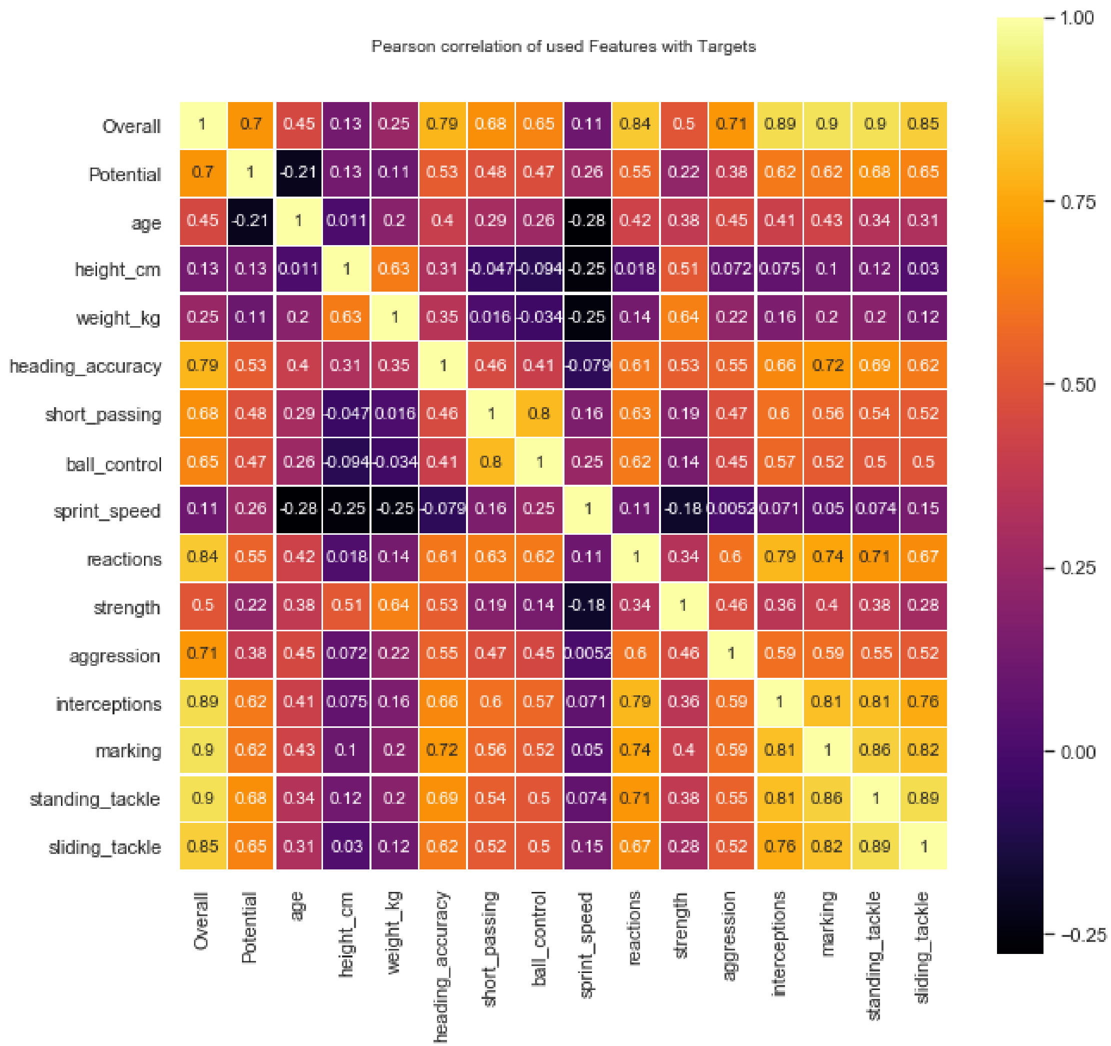
Out[85]: RangeIndex(start=0, stop=2, step=1)

In [86]:
```
#Pearson Correlation
used_variables = ['Overall','Potential','age','height_cm', 'weight_kg','heading_accurac
               'sprint_speed', 'reactions','strength', 'aggression',
                'interceptions', 'marking', 'standing_tackle', 'sliding_tackle']
corr_variables = data[used_variables]
colormap = plt.cm.inferno
plt.figure(figsize=(10,10))
plt.title('Pearson correlation of used Features with Targets',
          y=1.05, size=10)
sns.heatmap(corr_variables.corr(),linewidths=0.1,vmax=1.0,
            square=True, cmap=colormap, linecolor='white', annot=True)
```

Out[86]: <Figure size 720x720 with 0 Axes>

Out[86]: Text(0.5, 1.05, 'Pearson correlation of used Features with Targets')

Out[86]: <matplotlib.axes._subplots.AxesSubplot at 0x1c589b1a20>



In [87]:
```
#Preparing a ridge model
features=lasso.coef_
indices=np.nonzero(features)
np.take(features, indices)
cb_features_used=['age','height_cm', 'weight_kg','heading_accuracy', 'short_passing' ,'
               'sprint_speed', 'reactions','strength', 'aggression',
                 'interceptions', 'marking', 'standing_tackle', 'sliding_tackle']

data=cb_dta
x=data[cb_features_used]
X=sm.add_constant(x)
y1=data[overall_target]
y2=data[value_target]
y3=data[ln_value]
x.shape
```

```
#Finding the best alpha for ridge regression for value
x=data[cb_features_used]
y2=data[value_target]

from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import RidgeCV
scaler = StandardScaler()
X_std = scaler.fit_transform(x)
regr_cv = RidgeCV(alphas=np.arange(0.001,9999.999))
# Fit the linear regression
model_cv = regr_cv.fit(X_std, y2)
model_cv.alpha_
print("The alpha we should use for ridge regression is:" ,model_cv.alpha_)
```

```
Out[87]: array([[0.11160108, 0.00040904, 0.00131157, 0.19854295, 0.2068868 ,
                 0.04369794, 0.2136255 , 0.20766875]])

Out[87]: (3589, 14)

/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/preprocessing/data.py:625: Data
  return self.partial_fit(X, y)
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/base.py:462: DataConversionWarn
  return self.fit(X, **fit_params).transform(X)


Out[87]: 52.00099999999999

The alpha we should use for ridge regression is: 52.00099999999999
```

```
In [89]: #Fitting ridge regression to the reduced model
         #Note we use the suggested alpha of 52.01
         X_train,X_test,y_train,y_test=train_test_split(x,y2,test_size=0.3,random_state=0)
         lr = LinearRegression()
         lr.fit(X_train, y_train)
         #Ridge fit: Finding out what alpha to use for ridge
         ridge = Ridge(alpha=52.01)
         ridge.fit(X_train, y_train)
         y_prediction = ridge.predict(X_test)
         ridge_coef=ridge.coef_
         cols=np.array(x.columns)
         ridge_coef=ridge.coef_
         cols=np.array(x.columns)
         cols=cols.reshape(14,1)
         ridge_coef=ridge_coef.reshape(14,1)
         ridge_coefs=np.concatenate((cols, ridge_coef), axis=1)
         ridge_coefs=pd.DataFrame(ridge_coefs)
         ridge_intercept=ridge.intercept_
```

```
print(ridge_intercept)
print(ridge_coefs)
#Model Evaluation for Value
X_train,X_test,y_train,y_test=train_test_split(x,y2,test_size=0.3,random_state=0)
Ridge_train_score = ridge.score(X_train,y_train)
Ridge_test_score = ridge.score(X_test, y_test)
y_prediction = ridge.predict(X_test)
print("The training and test scores respectively are: " ,Ridge_train_score, "and" ,Ridg
from math import sqrt
from sklearn.metrics import mean_squared_error
RMSE_test=sqrt(mean_squared_error(y_true=y_test,y_pred=y_prediction))
print("\n Root Mean Square Error of test set is:" ,RMSE_test)
from sklearn import metrics
from sklearn.model_selection import cross_val_score
scores=cross_val_score(ridge,X,y2,cv=5)
print("\n K-folds cross validation scores:" ,scores)
```

Out[89]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None,
         normalize=False)
```

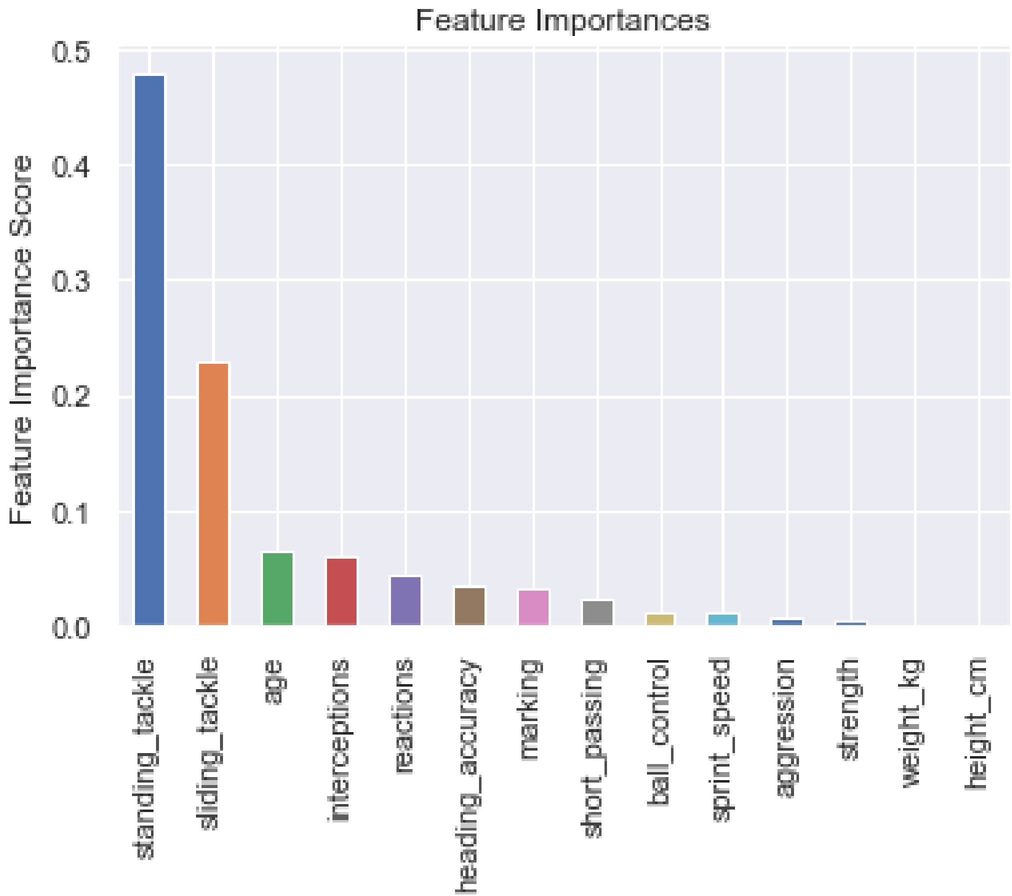
Out[89]:
```
Ridge(alpha=52.01, copy_X=True, fit_intercept=True, max_iter=None,
   normalize=False, random_state=None, solver='auto', tol=0.001)
```

```
[-30.75542114]
                   0           1
0                age   -0.232848
1          height_cm   0.0225915
2          weight_kg   0.0279878
3   heading_accuracy    0.050792
4      short_passing -0.00277465
5       ball_control   0.0193687
6       sprint_speed   0.0180922
7          reactions     0.10354
8           strength  0.00691043
9         aggression   0.0016774
10     interceptions   0.0663203
11           marking -0.00227414
12    standing_tackle    0.099245
13     sliding_tackle    0.142504
The training and test scores respectively are:  0.5197743531127669 and 0.48786044848023613

 Root Mean Square Error of test set is: 3.3666170779309024

 K-folds cross validation scores: [-5.16298889e-01 -6.92960691e+00 -4.90664710e+01 -8.46186913e+
 -2.73683812e+03]
```

In [90]:
```
#Gradient Boosting Regression
cb_reduced=['Value (M)','age','height_cm', 'weight_kg','heading_accuracy', 'short_passi
```

```
                 'sprint_speed', 'reactions','strength', 'aggression',
                  'interceptions', 'marking', 'standing_tackle', 'sliding_tackle']
dta=CB[cb_reduced]
def modelfit(alg, dtrain, features, performCV=True, printFeatureImportance=True, cv_fol
    #Fit the algorithm on the data

    alg.fit(dtrain[features],dtrain["Value (M)"] )

    #Predict training set:
    dtrain_predictions = alg.predict(dtrain[features])

    #Perform cross-validation:
    cv_score =  cross_val_score(alg, dtrain[features], dtrain["Value (M)"], cv=cv_folds
                                                scoring='neg_mean_squared_error')
    cv_score = np.sqrt(np.abs(cv_score))

    #Print model report:
    print ("\nModel Report")
    print ("RMSE : %.4g" % np.sqrt(metrics.mean_squared_error(dtrain["Value (M)"], dtra
    print ("CV Score : Mean - %.4g | Std - %.4g | Min - %.4g | Max - %.4g" % (np.mean(c
                                                                             np.std(cv_
                                                                              np.max(cv

    if printFeatureImportance:
        feat_imp = pd.Series(alg.feature_importances_, features).sort_values(ascending=
        feat_imp.plot(kind='bar', title='Feature Importances')
        plt.ylabel('Feature Importance Score')




features = [i for i in dta.columns if i != "Value (M)"]
target = "Value (M)"
gbm0 = GradientBoostingRegressor(random_state=7)
modelfit(gbm0, dta, features)
```

```
Model Report
RMSE : 0.649
CV Score : Mean - 1.516 | Std - 2.867 | Min - 0.1413 | Max - 10.02
```

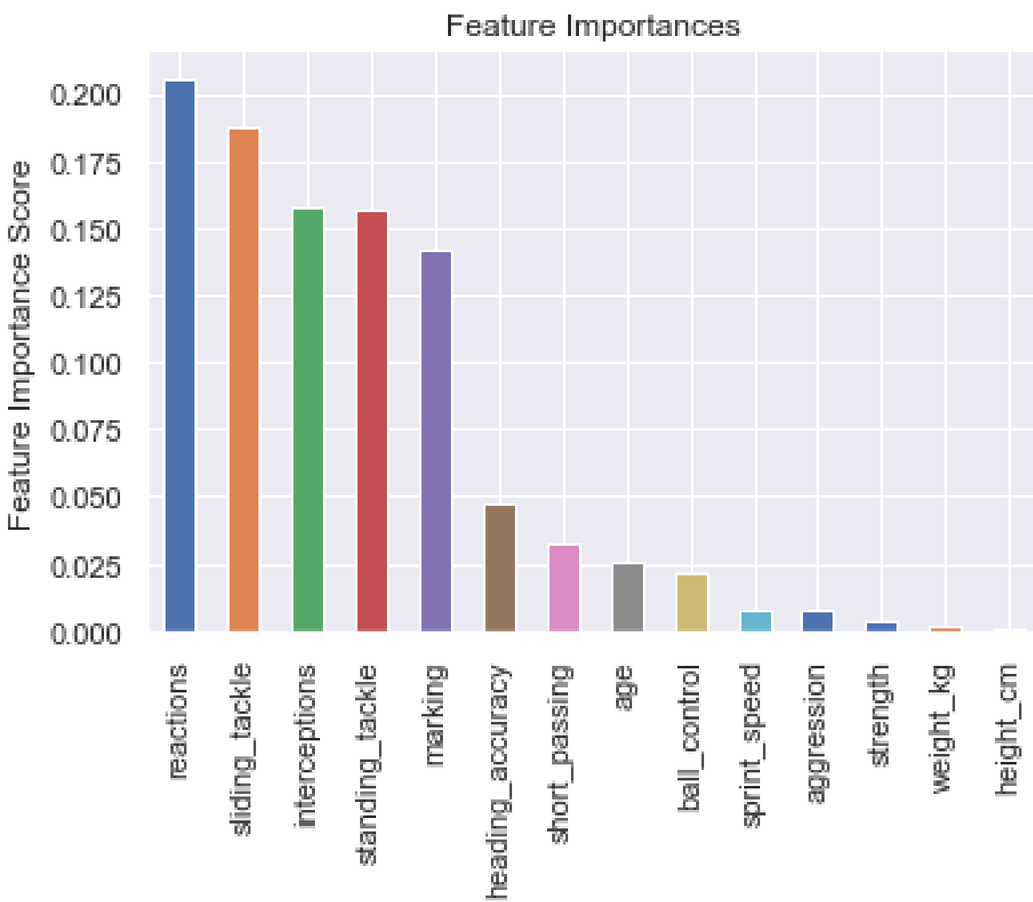



```
In [91]: #Tuning with GridSearch
         estimators = [x for x in range(700,750,10)]
         param_test1 = {'n_estimators':estimators}
         gsearch1 = GridSearchCV(estimator = GradientBoostingRegressor(learning_rate=0.1, min_sa
                                     min_samples_leaf=50,max_depth=8,max_features='sqrt',
                               param_grid = param_test1, scoring='neg_mean_squared_error',n_job
         gsearch1.fit(dta[features],dta["Value (M)"])

         gsearch1.score, gsearch1.best_params_, gsearch1.best_score_
         modelfit(gsearch1.best_estimator_, dta, features)

Out[91]: GridSearchCV(cv=10, error_score='raise-deprecating',
                estimator=GradientBoostingRegressor(alpha=0.9, criterion='friedman_mse', init=No
                      learning_rate=0.1, loss='ls', max_depth=8,
                      max_features='sqrt', max_leaf_nodes=None,
                      min_impurity_decrease=0.0, min_impurity_split=None,
                      min_samples_leaf=50, min_sa...       subsample=0.8, tol=0.0001, validation
                      warm_start=False),
                fit_params=None, iid=False, n_jobs=4,
```

```
             param_grid={'n_estimators': [700, 710, 720, 730, 740]},
             pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
             scoring='neg_mean_squared_error', verbose=0)
```

```
Out[91]: (<bound method BaseSearchCV.score of GridSearchCV(cv=10, error_score='raise-deprecating
                  estimator=GradientBoostingRegressor(alpha=0.9, criterion='friedman_mse', init=N
                        learning_rate=0.1, loss='ls', max_depth=8,
                        max_features='sqrt', max_leaf_nodes=None,
                        min_impurity_decrease=0.0, min_impurity_split=None,
                        min_samples_leaf=50, min_sa...       subsample=0.8, tol=0.0001, validatio
                        warm_start=False),
                  fit_params=None, iid=False, n_jobs=4,
                  param_grid={'n_estimators': [700, 710, 720, 730, 740]},
                  pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
                  scoring='neg_mean_squared_error', verbose=0)>,
          {'n_estimators': 740},
          -11.265483305113396)
```

```
Model Report
RMSE : 0.7678
CV Score : Mean - 1.487 | Std - 3.009 | Min - 0.1217 | Max - 10.44
```



In [92]:
```
#New CB Model
#Create our New Model with Interaction Terms
data=cb_dta
def cb_skills (row):
    return row['interceptions'] * row['marking'] * row['standing_tackle'] *row['sliding
def cb_ath (row):
    return row['sprint_speed'] *row['jumping'] *row['reactions'] * row['strength']

def cb_mentality (row):
    return row['aggression'] * row['composure'] * row['reactions']
def cb_attack (row):
    return row['short_passing'] * row['ball_control'] *row['heading_accuracy']
def cb_phy (row):
    return row['height_cm'] * row['weight_kg']


data['cb_skills'] = data.apply(cb_skills, axis=1)
data['cb_ath']= data.apply(cb_ath, axis=1)
data['cb_mentality']= data.apply(cb_ath, axis=1)
data['cb_attack']= data.apply(cb_attack, axis=1)
data['cb_phy']= data.apply(cb_phy, axis=1)
features=['age', 'cb_skills', 'cb_ath', 'cb_mentality', 'cb_attack', 'cb_phy']
x=data[features]
#We must now scale the features
x =pd.DataFrame(scaler.fit_transform(x))
x.columns= ['age', 'cb_skills', 'cb_ath' ,'cb_mentality', 'cb_attack', 'cb_phy']
#We have now addressed the issue of endogenity by including interaction terms
X=sm.add_constant(x)
y1=data[overall_target]
y2=data[value_target]
y3=data[ln_value]
mod=sm.OLS(y1,X)
res=mod.fit(cov_type='HC0')
yhat = res.fittedvalues
OLS_model = sm.OLS(y2,X)
OLS_results=OLS_model.fit(cov_type='HC0')
print(OLS_results.summary())
print(res.aic)
#Plot of y-hat for y-true on the reduced model for overall rating
from statsmodels.graphics.api import abline_plot
fig, ax = plt.subplots()
ax.scatter(yhat, y1)
line_fit = sm.OLS(y1, sm.add_constant(yhat, prepend=True)).fit()
abline_plot(model_results=line_fit, ax=ax)
```

```
        ax.set_title('New Model fit to Overall')
        ax.set_ylabel('Observed values')
        ax.set_xlabel('Fitted values');
```

```
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/preprocessing/data.py:625: Data
  return self.partial_fit(X, y)
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/base.py:462: DataConversionWarn
  return self.fit(X, **fit_params).transform(X)
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/statsmodels/base/model.py:1532: ValueWa
  'rank is %d' % (J, J_), ValueWarning)
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:              Value (M)   R-squared:                       0.659
Model:                            OLS   Adj. R-squared:                  0.658
Method:                 Least Squares   F-statistic:                     149.5
Date:                Thu, 06 Dec 2018   Prob (F-statistic):          1.53e-144
Time:                        18:24:15   Log-Likelihood:                -8550.3
No. Observations:                3589   AIC:                         1.711e+04
Df Residuals:                    3583   BIC:                         1.715e+04
Df Model:                           5
Covariance Type:                  HC0
================================================================================
                   coef    std err          z      P>|z|      [0.025      0.975]
--------------------------------------------------------------------------------
const            2.1994      0.044     50.277      0.000       2.114       2.285
age             -1.1025      0.058    -19.109      0.000      -1.216      -0.989
cb_skills        3.1551      0.140     22.526      0.000       2.881       3.430
cb_ath           0.2648      0.034      7.888      0.000       0.199       0.331
cb_mentality     0.2648      0.034      7.888      0.000       0.199       0.331
cb_attack        0.4746      0.087      5.426      0.000       0.303       0.646
cb_phy           0.2298      0.047      4.938      0.000       0.139       0.321
==============================================================================
Omnibus:                     3431.379   Durbin-Watson:                   0.721
Prob(Omnibus):                  0.000   Jarque-Bera (JB):           237718.354
Skew:                           4.441   Prob(JB):                         0.00
Kurtosis:                      41.868   Cond. No.                     1.24e+16
==============================================================================

Warnings:
[1] Standard Errors are heteroscedasticity robust (HC0)
[2] The smallest eigenvalue is 7.22e-29. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.
14218.162652910798
```

Our new model is an improvement over the lasso reduced model as the score has improved from 48% to 66%.

Positional Value Modeling: Full Back

10 Full Backs

In [93]:
```
data=FB
lnVal=pd.DataFrame((data["Value (M)"]+1).apply(np.log))
lnVal.columns = ['ln_value']
fb_dta = pd.concat([lnVal, data], axis=1)

data=fb_dta
x=data[attribute_profile]
X=sm.add_constant(x)
y1=data[overall_target]
y2=data[value_target]
y3=data[ln_value]
#OLS for Overall
OLS_model = sm.OLS(y1,X)
OLS_results=OLS_model.fit(cov_type='HC0')
print("The R-squared for the attributes with overall is:" ,OLS_results.rsquared_adj)
OLS_model2 = sm.OLS(y2,X)
OLS_results2=OLS_model2.fit(cov_type='HC0')
print("\n\nThe adjusted R-squared for the original CB value model is:" ,OLS_results2.rs
```

```
print("\nThe model AIC is: " ,OLS_results2.aic)

#Lasso Regression
X_train,X_test,y_train,y_test=train_test_split(x,y1,test_size=0.3,random_state=0)
lr = LinearRegression()
lr.fit(X_train, y_train)

#Lasso Fit (Overall)
lasso = Lasso(alpha=1.0, max_iter=1000000).fit(X_train, y_train)

from sklearn.linear_model import LassoCV
from sklearn.preprocessing import StandardScaler
X_std = scaler.fit_transform(x)
regr_cv = LassoCV(alphas=np.arange(1,9999.999))
# Fit the linear regression
model_cv = regr_cv.fit(X_std, y1)
print("The alpha we should use for lasso regression is:" ,model_cv.alpha_)
lasso = Lasso(alpha=1.0, max_iter=1000000).fit(X_train, y_train)
#Lasso Coefficients
y_prediction = lasso.predict(X_test)
lasso_coef=lasso.coef_
cols=np.array(x.columns)
cols=cols.reshape(37,1)
lasso_coef=lasso_coef.reshape(37,1)
coefs=np.concatenate((cols, lasso_coef), axis=1)
coefs=pd.DataFrame(coefs)
intercept=lasso.intercept_
print("the intercept is:" ,intercept)
print(coefs)
```

```
The R-squared for the attributes with overall is: 0.9211686117206395


The adjusted R-squared for the original CB value model is: 0.49884282137975655

The model AIC is:  19821.193103331858
```

```
Out[93]: LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None,
                  normalize=False)
```

```
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/preprocessing/data.py:625: Data
  return self.partial_fit(X, y)
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/base.py:462: DataConversionWarn
  return self.fit(X, **fit_params).transform(X)
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/linear_model/coordinate_descent
  y = column_or_1d(y, warn=True)
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/model_selection/_split.py:2053:
```

```
  warnings.warn(CV_WARNING, FutureWarning)


The alpha we should use for lasso regression is: 1.0
the intercept is: [9.83169515]
                    0            1
0                 age            0
1           height_cm            0
2           weight_kg            0
3            crossing    0.0296561
4           finishing   0.00264624
5    heading_accuracy    0.0724916
6       short_passing    0.0911999
7             volleys            0
8           dribbling            0
9               curve            0
10  free_kick_accuracy           0
11        long_passing  0.000705052
12        ball_control   0.0838473
13        acceleration  0.00947536
14        sprint_speed   0.0627873
15             agility           0
16           reactions     0.14768
17             balance          -0
18          shot_power  0.00867427
19             jumping  5.82115e-05
20             stamina   0.0440155
21            strength   0.0189905
22          long_shots           0
23          aggression   0.0030194
24       interceptions     0.08341
25         positioning          -0
26              vision           0
27           penalties  0.00482689
28           composure   0.0455749
29             marking   0.0405975
30      standing_tackle  0.0696805
31       sliding_tackle  0.0745425
32           gk_diving           0
33         gk_handling          -0
34          gk_kicking           0
35      gk_positioning          -0
36         gk_reflexes           0
```

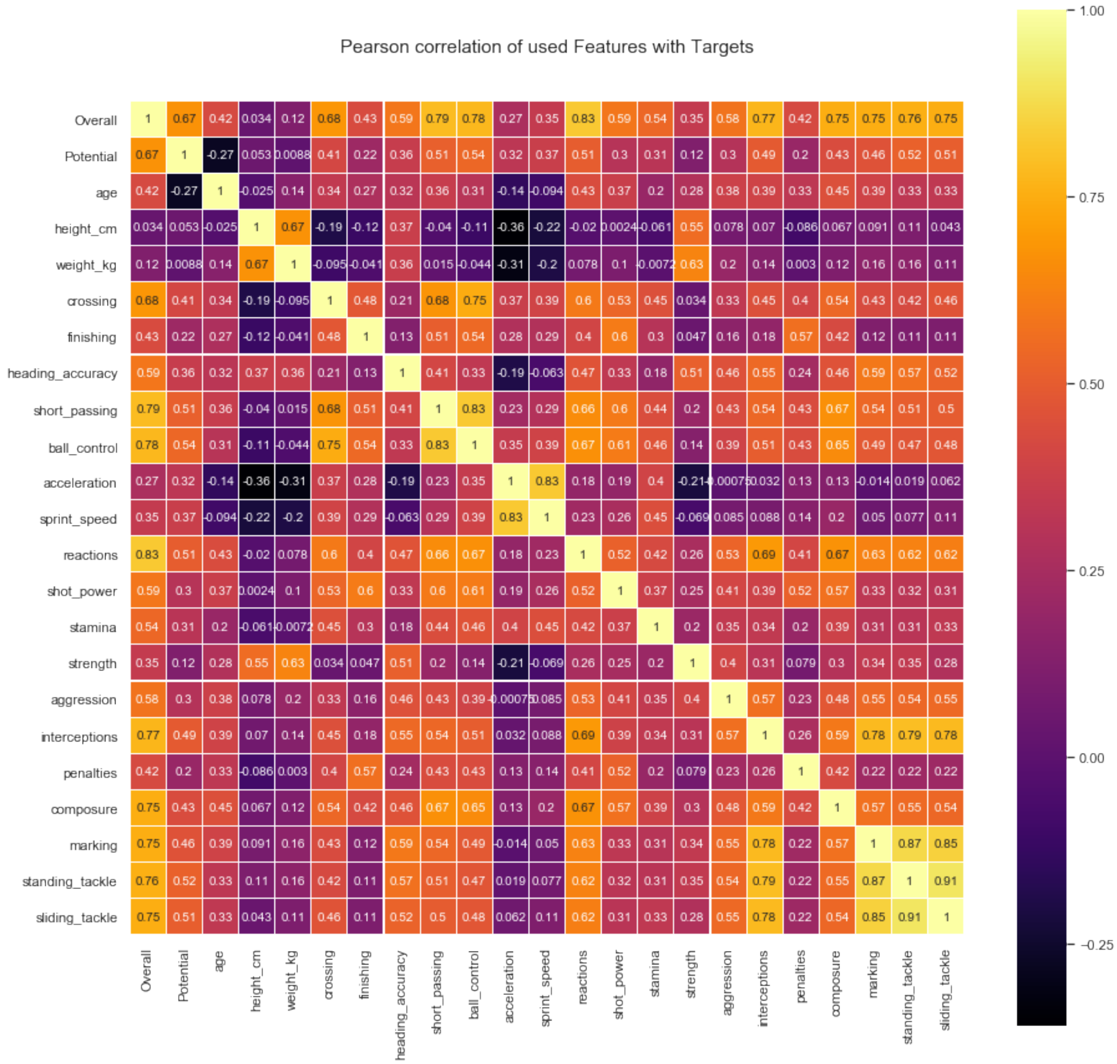
```
In [94]: used_variables = ['Overall','Potential',  'age', 'height_cm', 'weight_kg', 'crossing', 
                'short_passing', 'ball_control', 'acceleration', 'sprint_speed','reactions',  's
                'strength',  'aggression', 'interceptions', 'penalties', 'composure', 'marking',
```

```
corr_variables = data[used_variables]
colormap = plt.cm.inferno
plt.figure(figsize=(15,15))
plt.title('Pearson correlation of used Features with Targets',
          y=1.05, size=15)
sns.heatmap(corr_variables.corr(),linewidths=0.1,vmax=1.0,
            square=True, cmap=colormap, linecolor='white', annot=True)
```

Out[94]: <Figure size 1080x1080 with 0 Axes>

Out[94]: Text(0.5, 1.05, 'Pearson correlation of used Features with Targets')

Out[94]: <matplotlib.axes._subplots.AxesSubplot at 0x1c599d6eb8>




```
In [95]: #Preparing a ridge model
         features=lasso.coef_
```

```
indices=np.nonzero(features)
np.take(features, indices)
fb_features_used=['age', 'height_cm', 'weight_kg', 'crossing', 'finishing', 'heading_ac
       'short_passing',
        'ball_control', 'acceleration', 'sprint_speed',
       'reactions',  'shot_power', 'stamina',
       'strength',  'aggression', 'interceptions',
        'penalties', 'composure', 'marking', 'standing_tackle',
       'sliding_tackle']

data=fb_dta
x=data[fb_features_used]
X=sm.add_constant(x)
y1=data[overall_target]
y2=data[value_target]
y3=data[ln_value]
x.shape
#What alpha should we use
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import RidgeCV
scaler = StandardScaler()
X_std = scaler.fit_transform(x)
regr_cv = RidgeCV(alphas=np.arange(0.001,9999.999))
# Fit the linear regression
model_cv = regr_cv.fit(X_std, y2)
model_cv.alpha_
print("The alpha we should use for ridge regression is:" ,model_cv.alpha_)
#Fitting ridge regression to the reduced model
#Note we use the suggested alpha of 47.01
X_train,X_test,y_train,y_test=train_test_split(x,y2,test_size=0.3,random_state=0)
lr = LinearRegression()
lr.fit(X_train, y_train)
#Ridge fit: Finding out what alpha to use for ridge
ridge = Ridge(alpha=47.01)
ridge.fit(X_train, y_train)
y_prediction = ridge.predict(X_test)
ridge_coef=ridge.coef_
cols=np.array(x.columns)
ridge_coef=ridge.coef_
cols=np.array(x.columns)
cols=cols.reshape(21,1)
ridge_coef=ridge_coef.reshape(21,1)
ridge_coefs=np.concatenate((cols, ridge_coef), axis=1)
ridge_coefs=pd.DataFrame(ridge_coefs)
ridge_intercept=ridge.intercept_
print(ridge_intercept)
print(ridge_coefs)
```

```
Out[95]: array([[2.96560690e-02, 2.64623865e-03, 7.24915843e-02, 9.11999457e-02,
                7.05052413e-04, 8.38472739e-02, 9.47535938e-03, 6.27873387e-02,
                1.47680244e-01, 8.67427415e-03, 5.82115337e-05, 4.40155481e-02,
                1.89904876e-02, 3.01940311e-03, 8.34099959e-02, 4.82689489e-03,
                4.55749094e-02, 4.05975224e-02, 6.96804861e-02, 7.45425449e-02]])

Out[95]: (4443, 21)

/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/preprocessing/data.py:625: Data
  return self.partial_fit(X, y)
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/base.py:462: DataConversionWarn
  return self.fit(X, **fit_params).transform(X)


Out[95]: 47.00099999999999

The alpha we should use for ridge regression is: 47.00099999999999


Out[95]: LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None,
                  normalize=False)

Out[95]: Ridge(alpha=47.01, copy_X=True, fit_intercept=True, max_iter=None,
            normalize=False, random_state=None, solver='auto', tol=0.001)

[-12.58034089]
                   0           1
0                age   -0.232369
1          height_cm  -0.0245367
2          weight_kg  0.00689697
3           crossing   0.0159733
4          finishing   0.0234055
5    heading_accuracy   0.0274091
6       short_passing  0.00803264
7       ball_control   0.0119604
8       acceleration -0.00351722
9       sprint_speed   0.0125693
10         reactions    0.103654
11        shot_power  -0.0019431
12           stamina   0.0220401
13          strength   0.0164439
14        aggression  -0.0104205
15     interceptions   0.0453487
16         penalties   0.0097418
17         composure   0.0261696
18           marking  -0.0276853
19    standing_tackle   0.0610693
20     sliding_tackle   0.0507346
```

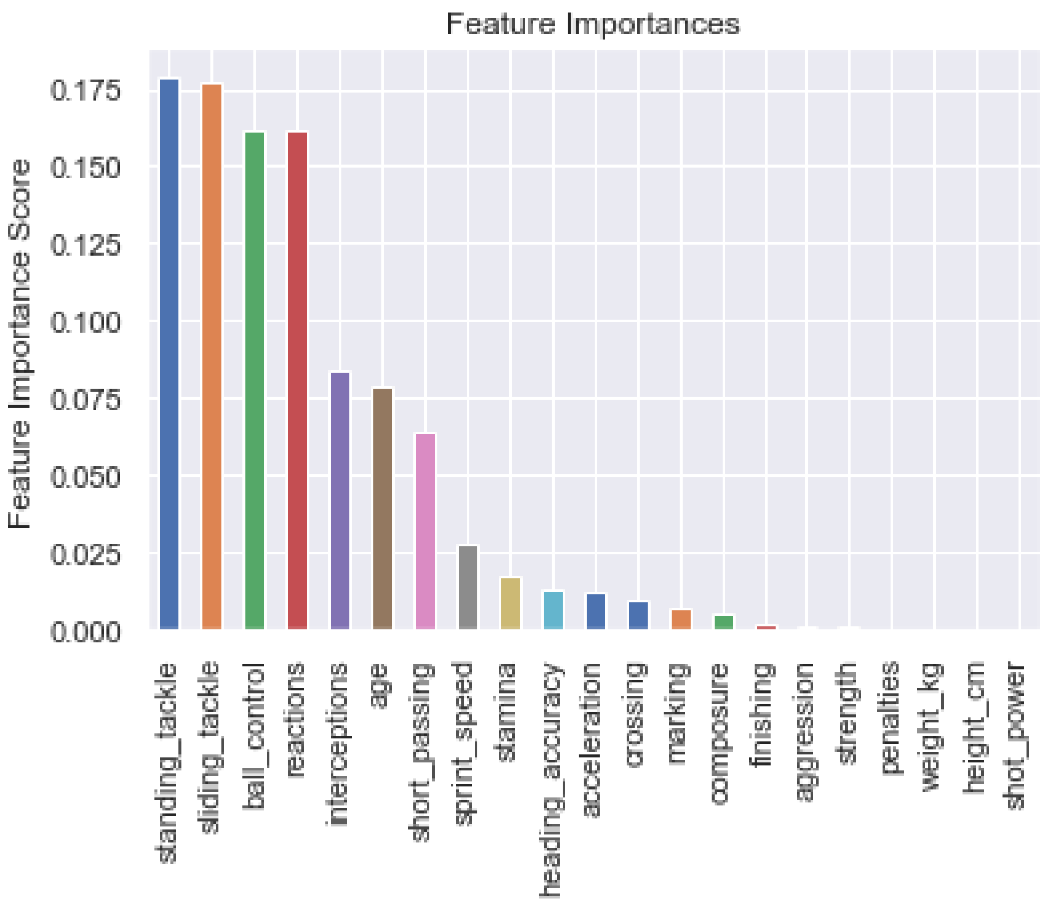
```
In [96]: #Model Evaluation for Value
         X_train,X_test,y_train,y_test=train_test_split(x,y2,test_size=0.3,random_state=0)
         Ridge_train_score = ridge.score(X_train,y_train)
         Ridge_test_score = ridge.score(X_test, y_test)
         y_prediction = ridge.predict(X_test)
         print("The training and test scores respectively are: " ,Ridge_train_score, "and" ,Ridg
         from math import sqrt
         from sklearn.metrics import mean_squared_error
         RMSE_test=sqrt(mean_squared_error(y_true=y_test,y_pred=y_prediction))
         print("\n Root Mean Square Error of test set is:" ,RMSE_test)
         from sklearn import metrics
         from sklearn.model_selection import cross_val_score
         scores=cross_val_score(ridge,X,y2,cv=5)
         print("\n K-folds cross validation scores:" ,scores)
```

```
The training and test scores respectively are:  0.5115982923524287 and 0.4666374868435317

 Root Mean Square Error of test set is: 2.397975080927799

 K-folds cross validation scores: [  0.40175035 -30.27929944   0.47428942 -23.25740157   0.16927
```

```
In [98]: #Gradient Boosting Regression
         FB=FB

         fb_reduced=['Value (M)',  'age', 'height_cm', 'weight_kg', 'crossing', 'finishing', 'he
                'short_passing',
                 'ball_control', 'acceleration', 'sprint_speed',
                'reactions',  'shot_power', 'stamina',
                'strength',  'aggression', 'interceptions',
                 'penalties', 'composure', 'marking', 'standing_tackle',
                'sliding_tackle']
         dta=FB[fb_reduced]
         def modelfit(alg, dtrain, features, performCV=True, printFeatureImportance=True, cv_fol
             #Fit the algorithm on the data

             alg.fit(dtrain[features],dtrain["Value (M)"] )

             #Predict training set:
             dtrain_predictions = alg.predict(dtrain[features])

             #Perform cross-validation:
             cv_score =  cross_val_score(alg, dtrain[features], dtrain["Value (M)"], cv=cv_folds
                                                         scoring='neg_mean_squared_error')
             cv_score = np.sqrt(np.abs(cv_score))

             #Print model report:
             print ("\nModel Report")
```

```
        print ("RMSE : %.4g" % np.sqrt(metrics.mean_squared_error(dtrain["Value (M)"], dtra
        print ("CV Score : Mean - %.4g | Std - %.4g | Min - %.4g | Max - %.4g" % (np.mean(c
                                                                                  np.std(cv_
                                                                                  np.max(cv

        if printFeatureImportance:
            feat_imp = pd.Series(alg.feature_importances_, features).sort_values(ascending=
            feat_imp.plot(kind='bar', title='Feature Importances')
            plt.ylabel('Feature Importance Score')

    features = [i for i in dta.columns if i != "Value (M)"]
    target = "Value (M)"
    gbm0 = GradientBoostingRegressor(random_state=7)
    modelfit(gbm0, dta, features)
```

```
Model Report
RMSE : 0.5426
CV Score : Mean - 0.7949 | Std - 0.6018 | Min - 0.169 | Max - 2.077
```

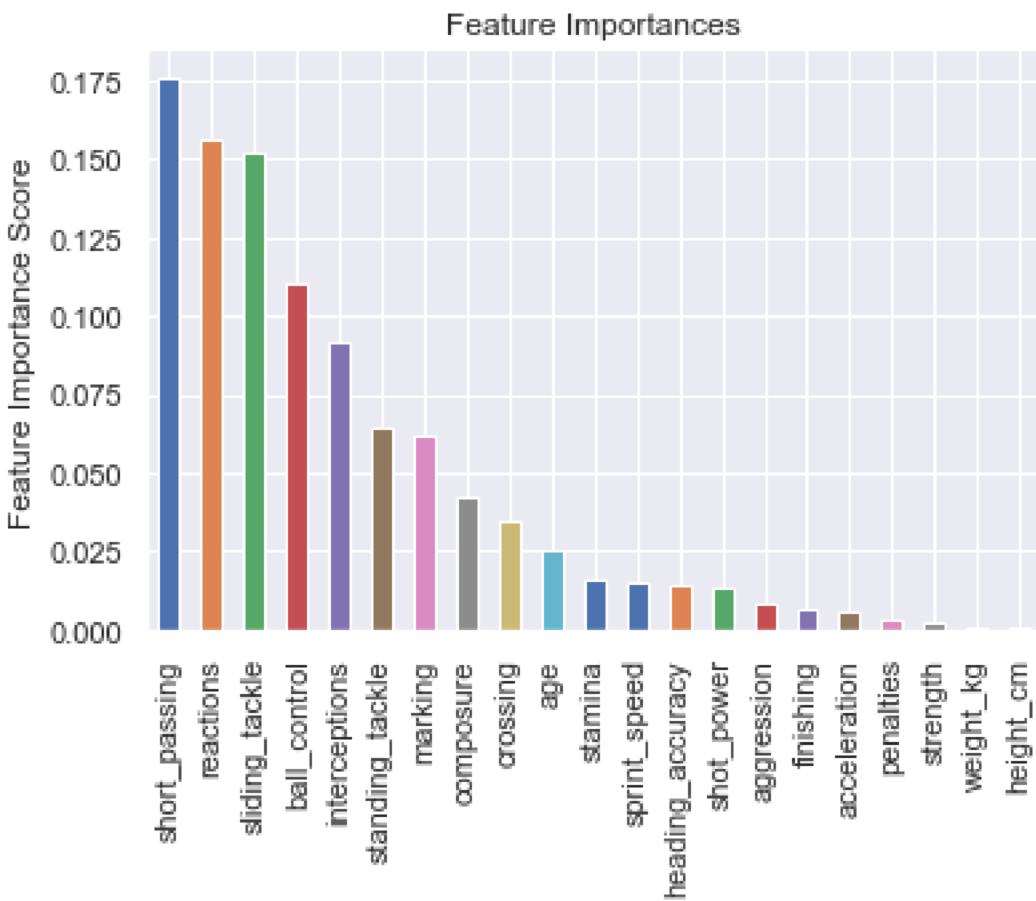


```
In [99]: #Tuning with GridSearch
         estimators = [x for x in range(700,750,10)]
         param_test1 = {'n_estimators':estimators}
         gsearch1 = GridSearchCV(estimator = GradientBoostingRegressor(learning_rate=0.1, min_sa
                                  min_samples_leaf=50,max_depth=8,max_features='sqrt',
                             param_grid = param_test1, scoring='neg_mean_squared_error',n_job
         gsearch1.fit(dta[features],dta["Value (M)"])

         gsearch1.score, gsearch1.best_params_, gsearch1.best_score_
         modelfit(gsearch1.best_estimator_, dta, features)
```

```
Out[99]: GridSearchCV(cv=10, error_score='raise-deprecating',
                estimator=GradientBoostingRegressor(alpha=0.9, criterion='friedman_mse', init=No
                      learning_rate=0.1, loss='ls', max_depth=8,
                      max_features='sqrt', max_leaf_nodes=None,
                      min_impurity_decrease=0.0, min_impurity_split=None,
                      min_samples_leaf=50, min_sa...       subsample=0.8, tol=0.0001, validation
                      warm_start=False),
                fit_params=None, iid=False, n_jobs=4,
                param_grid={'n_estimators': [700, 710, 720, 730, 740]},
                pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
                scoring='neg_mean_squared_error', verbose=0)
```

```
Out[99]: (<bound method BaseSearchCV.score of GridSearchCV(cv=10, error_score='raise-deprecating
                 estimator=GradientBoostingRegressor(alpha=0.9, criterion='friedman_mse', init=N
                       learning_rate=0.1, loss='ls', max_depth=8,
                       max_features='sqrt', max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=50, min_sa...       subsample=0.8, tol=0.0001, validatio
                       warm_start=False),
                 fit_params=None, iid=False, n_jobs=4,
                 param_grid={'n_estimators': [700, 710, 720, 730, 740]},
                 pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
                 scoring='neg_mean_squared_error', verbose=0)>,
          {'n_estimators': 740},
          -1.088927946286219)
```

```
Model Report
RMSE : 0.5156
CV Score : Mean - 0.7734 | Std - 0.7005 | Min - 0.1454 | Max - 2.315
```



In [100]:
```
#MODEL CREATION
data=FB
lnVal=pd.DataFrame((data["Value (M)"]+1).apply(np.log))
lnVal.columns = ['ln_value']
fb_dta = pd.concat([lnVal, data], axis=1)
fb_dta.head()
data=fb_dta
#Create our New Model with Interaction Terms
data=fb_dta
def fb_skills_off (row):
    return row['short_passing'] * row['ball_control'] * row['crossing']
def fb_skills_def (row):
    return row['sliding_tackle']*row['standing_tackle']*row['marking']
def fb_ath_ment (row):
    return row['sprint_speed'] *row['stamina'] *row['composure'] *row['reactions']*row


def fb_phy (row):
    return row['height_cm'] * row['weight_kg']
```

```
data=fb_dta
data['fb_skills_off'] = data.apply(fb_skills_off, axis=1)
data['fb_skills_def'] = data.apply(fb_skills_def, axis=1)
data['fb_ath_ment']= data.apply(fb_ath_ment, axis=1)
data['fb_phy']= data.apply(fb_phy, axis=1)
features=['age', 'fb_skills_off', 'fb_skills_def', 'fb_ath_ment', 'fb_phy']
x=data[features]
#We must now scale the features
x =pd.DataFrame(scaler.fit_transform(x))
x.columns= ['age', 'fb_skills_off', 'fb_skills_def', 'fb_ath_ment','fb_phy']
#We have now addressed the issue of endogenity by including interaction terms
X=sm.add_constant(x)
y1=data[overall_target]
y2=data[value_target]
y3=data[ln_value]
mod=sm.OLS(y1,X)
res=mod.fit(cov_type='HC0')
yhat = res.fittedvalues
OLS_model = sm.OLS(y2,X)
OLS_results=OLS_model.fit(cov_type='HC0')
#results of new model on value
print(OLS_results.summary())
print(res.aic)
OLS_model2 = sm.OLS(y3,X)
OLS_results2=OLS_model2.fit(cov_type='HC0')
#results for new model on value elasticity
print(OLS_results2.summary())
#Plot of y-hat for y-true on the reduced model for overall rating
from statsmodels.graphics.api import abline_plot
fig, ax = plt.subplots()
ax.scatter(yhat, y1)
line_fit = sm.OLS(y1, sm.add_constant(yhat, prepend=True)).fit()
abline_plot(model_results=line_fit, ax=ax)


ax.set_title('New Model fit to Overall')
ax.set_ylabel('Observed values')
ax.set_xlabel('Fitted values');
```

```
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/preprocessing/data.py:625: Data
  return self.partial_fit(X, y)
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/base.py:462: DataConversionWarn
  return self.fit(X, **fit_params).transform(X)


                            OLS Regression Results
==============================================================================
```

```
Dep. Variable:              Value (M)   R-squared:                       0.616
Model:                            OLS   Adj. R-squared:                  0.616
Method:                 Least Squares   F-statistic:                     215.7
Date:                Thu, 06 Dec 2018   Prob (F-statistic):          1.65e-206
Time:                        18:36:57   Log-Likelihood:                -9297.1
No. Observations:                4443   AIC:                         1.861e+04
Df Residuals:                    4437   BIC:                         1.864e+04
Df Model:                           5
Covariance Type:                  HC0
=================================================================================
                    coef    std err          z      P>|z|      [0.025      0.975]
---------------------------------------------------------------------------------
const             1.7616      0.029     59.870      0.000       1.704       1.819
age              -0.8706      0.040    -21.947      0.000      -0.948      -0.793
fb_skills_off     0.5490      0.068      8.102      0.000       0.416       0.682
fb_skills_def     0.8221      0.066     12.522      0.000       0.693       0.951
fb_ath_ment       1.5694      0.104     15.061      0.000       1.365       1.774
fb_phy            0.1773      0.030      5.830      0.000       0.118       0.237
==============================================================================
Omnibus:                     4689.268   Durbin-Watson:                   0.721
Prob(Omnibus):                  0.000   Jarque-Bera (JB):           563766.965
Skew:                           5.058   Prob(JB):                         0.00
Kurtosis:                      57.249   Cond. No.                         3.71
==============================================================================

Warnings:
[1] Standard Errors are heteroscedasticity robust (HC0)
18603.142824683324
                            OLS Regression Results
==============================================================================
Dep. Variable:               ln_value   R-squared:                       0.831
Model:                            OLS   Adj. R-squared:                  0.830
Method:                 Least Squares   F-statistic:                     3715.
Date:                Thu, 06 Dec 2018   Prob (F-statistic):               0.00
Time:                        18:36:57   Log-Likelihood:                -456.87
No. Observations:                4443   AIC:                             925.7
Df Residuals:                    4437   BIC:                             964.1
Df Model:                           5
Covariance Type:                  HC0
=================================================================================
                    coef    std err          z      P>|z|      [0.025      0.975]
---------------------------------------------------------------------------------
const             0.7266      0.004    180.606      0.000       0.719       0.735
age              -0.1900      0.005    -40.488      0.000      -0.199      -0.181
fb_skills_off     0.1877      0.010     18.307      0.000       0.168       0.208
fb_skills_def     0.2209      0.010     21.131      0.000       0.200       0.241
fb_ath_ment       0.3014      0.008     37.476      0.000       0.286       0.317
fb_phy            0.0478      0.005     10.193      0.000       0.039       0.057
```

```
==============================================================================
Omnibus:                      940.386   Durbin-Watson:                   1.370
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             5090.062
Skew:                           0.904   Prob(JB):                         0.00
Kurtosis:                       7.922   Cond. No.                         3.71
==============================================================================

Warnings:
[1] Standard Errors are heteroscedasticity robust (HC0)
```

As shown above the created model has eliminated the collinearity and improved the model. Positional Value Modeling: Center Mid

11 Center Midfielders

In [101]:
```
data=CM
lnVal=pd.DataFrame((data["Value (M)"]+1).apply(np.log))
lnVal.columns = ['ln_value']
cm_dta = pd.concat([lnVal, data], axis=1)

data=cm_dta
x=data[attribute_profile]
X=sm.add_constant(x)
```

```python
y1=data[overall_target]
y2=data[value_target]
y3=data[ln_value]
#OLS for Overall
OLS_model = sm.OLS(y1,X)
OLS_results=OLS_model.fit(cov_type='HC0')
print("The R-squared for the attributes with overall is:" ,OLS_results.rsquared_adj)
OLS_model2 = sm.OLS(y2,X)
OLS_results2=OLS_model2.fit(cov_type='HC0')
print("\n\nThe adjusted R-squared for the original CB value model is:" ,OLS_results2.r
print("\nThe model AIC is: " ,OLS_results2.aic)
#Lasso Regression
X_train,X_test,y_train,y_test=train_test_split(x,y1,test_size=0.3,random_state=0)
lr = LinearRegression()
lr.fit(X_train, y_train)

#Lasso Fit (Overall)
lasso = Lasso(alpha=1.0, max_iter=1000000).fit(X_train, y_train)

from sklearn.linear_model import LassoCV
from sklearn.preprocessing import StandardScaler
X_std = scaler.fit_transform(x)
regr_cv = LassoCV(alphas=np.arange(1,9999.999))
# Fit the linear regression
model_cv = regr_cv.fit(X_std, y1)
print("The alpha we should use for lasso regression is:" ,model_cv.alpha_)
lasso = Lasso(alpha=1.0, max_iter=1000000).fit(X_train, y_train)
#Lasso Coefficients
y_prediction = lasso.predict(X_test)
lasso_coef=lasso.coef_
cols=np.array(x.columns)
cols=cols.reshape(37,1)
lasso_coef=lasso_coef.reshape(37,1)
coefs=np.concatenate((cols, lasso_coef), axis=1)
coefs=pd.DataFrame(coefs)
intercept=lasso.intercept_
print("the intercept is:" ,intercept)
print(coefs)
```

```
The R-squared for the attributes with overall is: 0.8953641207295303


The adjusted R-squared for the original CB value model is: 0.46045033958288306

The model AIC is:  48960.15443371765
```

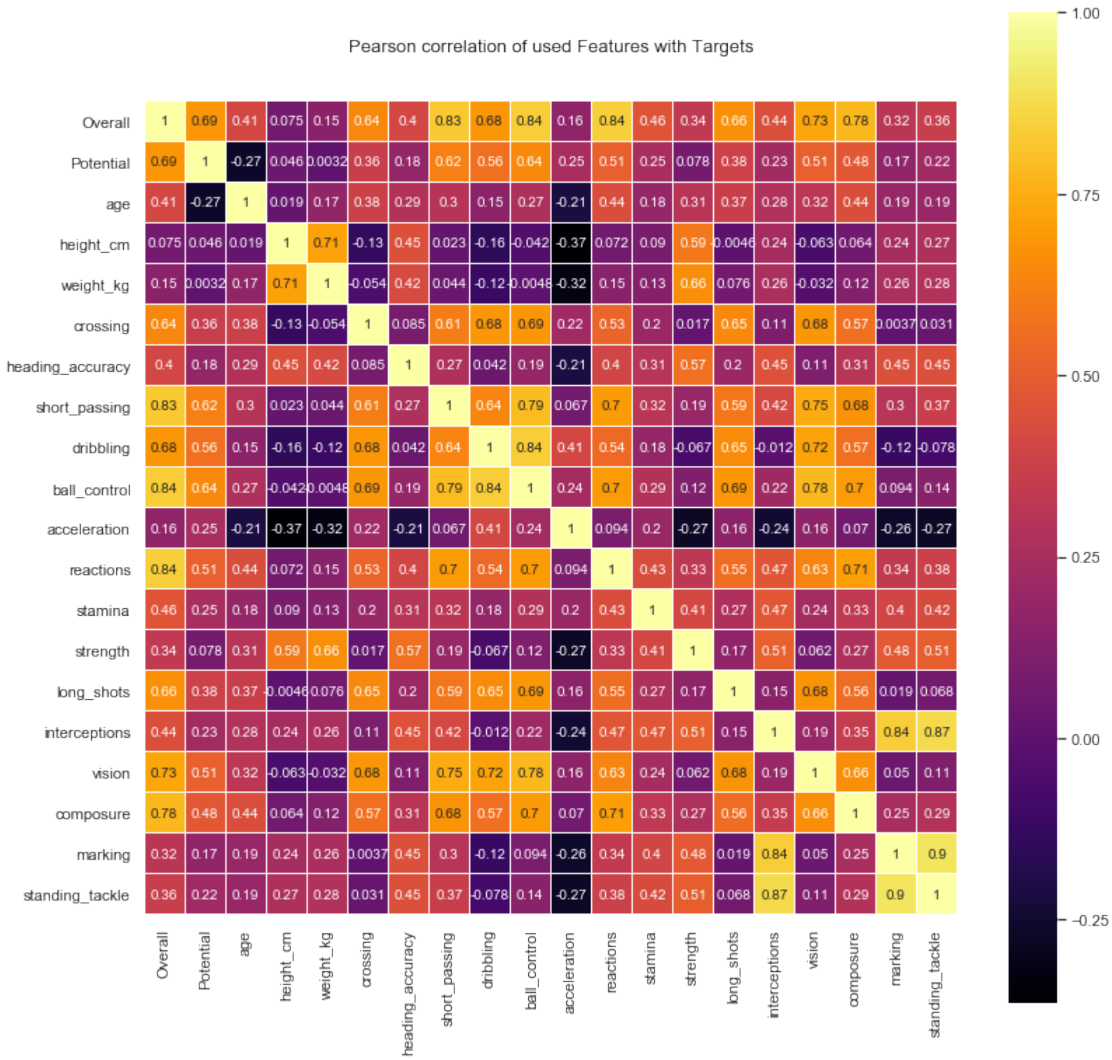
```
Out[101]: LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None,
                   normalize=False)
```

```
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/preprocessing/data.py:625: Data
  return self.partial_fit(X, y)
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/base.py:462: DataConversionWarn
  return self.fit(X, **fit_params).transform(X)
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/linear_model/coordinate_descent
  y = column_or_1d(y, warn=True)
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/model_selection/_split.py:2053:
  warnings.warn(CV_WARNING, FutureWarning)


The alpha we should use for lasso regression is: 1.0
the intercept is: [6.91522968]
                    0           1
0                 age           0
1           height_cm          -0
2           weight_kg           0
3            crossing   0.0204125
4           finishing  0.00998851
5    heading_accuracy   0.0431929
6       short_passing    0.194018
7             volleys          -0
8           dribbling  0.00547681
9               curve           0
10  free_kick_accuracy          0
11        long_passing          0
12        ball_control   0.203133
13        acceleration  0.0261684
14        sprint_speed  0.0111252
15             agility          0
16           reactions   0.200533
17             balance         -0
18          shot_power          0
19             jumping          0
20             stamina  0.0376082
21            strength  0.0314665
22          long_shots  0.0207321
23          aggression  0.00614993
24       interceptions  0.0108572
25         positioning         -0
26              vision  0.00419401
27           penalties  0.00809233
28           composure  0.0915333
29             marking  0.00131498
30      standing_tackle 0.00335376
31       sliding_tackle         0
32           gk_diving          0
33         gk_handling          0
34          gk_kicking          0
```

```
35      gk_positioning          0
36        gk_reflexes           0
```

```
In [102]: used_variables =['Overall','Potential','age', 'height_cm', 'weight_kg', 'crossing', 'h
                 'short_passing', 'dribbling',
                  'ball_control', 'acceleration',
                  'reactions',  'stamina',
                 'strength', 'long_shots',  'interceptions',
                 'vision',  'composure', 'marking', 'standing_tackle']
          corr_variables = data[used_variables]
          colormap = plt.cm.inferno
          plt.figure(figsize=(13,13))
          plt.title('Pearson correlation of used Features with Targets',
                    y=1.05, size=13)
          sns.heatmap(corr_variables.corr(),linewidths=0.1,vmax=1.0,
                      square=True, cmap=colormap, linecolor='white', annot=True)
```

```
Out[102]: <Figure size 936x936 with 0 Axes>

Out[102]: Text(0.5, 1.05, 'Pearson correlation of used Features with Targets')

Out[102]: <matplotlib.axes._subplots.AxesSubplot at 0x1c532a89e8>
```




```
In [103]: features=lasso.coef_
          indices=np.nonzero(features)
          np.take(features, indices)
          cm_features_used=['age', 'height_cm', 'weight_kg', 'crossing', 'heading_accuracy',
                 'short_passing', 'dribbling',
                  'ball_control', 'acceleration',
                  'reactions',  'stamina',
                 'strength', 'long_shots',  'interceptions',
                 'vision',  'composure', 'marking', 'standing_tackle']
          #Finding the best alpha for ridge regression for value
          x=data[cm_features_used]
          y2=data[value_target]

          from sklearn.preprocessing import StandardScaler
          from sklearn.linear_model import RidgeCV
```

```
scaler = StandardScaler()
X_std = scaler.fit_transform(x)
regr_cv = RidgeCV(alphas=np.arange(0.001,9999.999))
# Fit the linear regression
model_cv = regr_cv.fit(X_std, y2)
model_cv.alpha_
print("The alpha we should use for ridge regression is:" ,model_cv.alpha_)
x.shape
#Fitting ridge regression to the reduced model
#Note we use the suggested alpha of 55.01
X_train,X_test,y_train,y_test=train_test_split(x,y2,test_size=0.3,random_state=0)
lr = LinearRegression()
lr.fit(X_train, y_train)
#Ridge fit: Finding out what alpha to use for ridge
ridge = Ridge(alpha=55.01)
ridge.fit(X_train, y_train)
y_prediction = ridge.predict(X_test)
ridge_coef=ridge.coef_
cols=np.array(x.columns)
ridge_coef=ridge.coef_
cols=np.array(x.columns)
cols=cols.reshape(18,1)
ridge_coef=ridge_coef.reshape(18,1)
ridge_coefs=np.concatenate((cols, ridge_coef), axis=1)
ridge_coefs=pd.DataFrame(ridge_coefs)
ridge_intercept=ridge.intercept_
print(ridge_intercept)
print(ridge_coefs)
```

```
Out[103]: array([[0.02041246, 0.00998851, 0.04319294, 0.19401826, 0.00547681,
                  0.20313274, 0.0261684 , 0.01112518, 0.20053299, 0.03760819,
                  0.03146648, 0.0207321 , 0.00614993, 0.01085724, 0.00419401,
                  0.00809233, 0.09153333, 0.00131498, 0.00335376]])
```

```
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/preprocessing/data.py:625: Data
  return self.partial_fit(X, y)
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/base.py:462: DataConversionWarn
  return self.fit(X, **fit_params).transform(X)
```

```
Out[103]: 55.00099999999999
```

```
The alpha we should use for ridge regression is: 55.00099999999999
```

```
Out[103]: (8471, 18)
```

```
Out[103]: LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None,
                   normalize=False)
```

```
Out[103]: Ridge(alpha=55.01, copy_X=True, fit_intercept=True, max_iter=None,
             normalize=False, random_state=None, solver='auto', tol=0.001)
```

```
[-29.44659204]
                   0          1
0                age  -0.315486
1          height_cm -0.0191657
2          weight_kg  0.0294251
3           crossing 0.00663918
4   heading_accuracy  0.0253147
5      short_passing   0.210048
6          dribbling  0.0276017
7       ball_control  0.0747416
8       acceleration  0.0244876
9          reactions   0.188915
10           stamina   0.013117
11          strength  0.0143285
12        long_shots -0.0167068
13     interceptions 0.00766452
14            vision 0.00727878
15         composure  0.0688174
16           marking -0.0525116
17   standing_tackle   0.025667
```

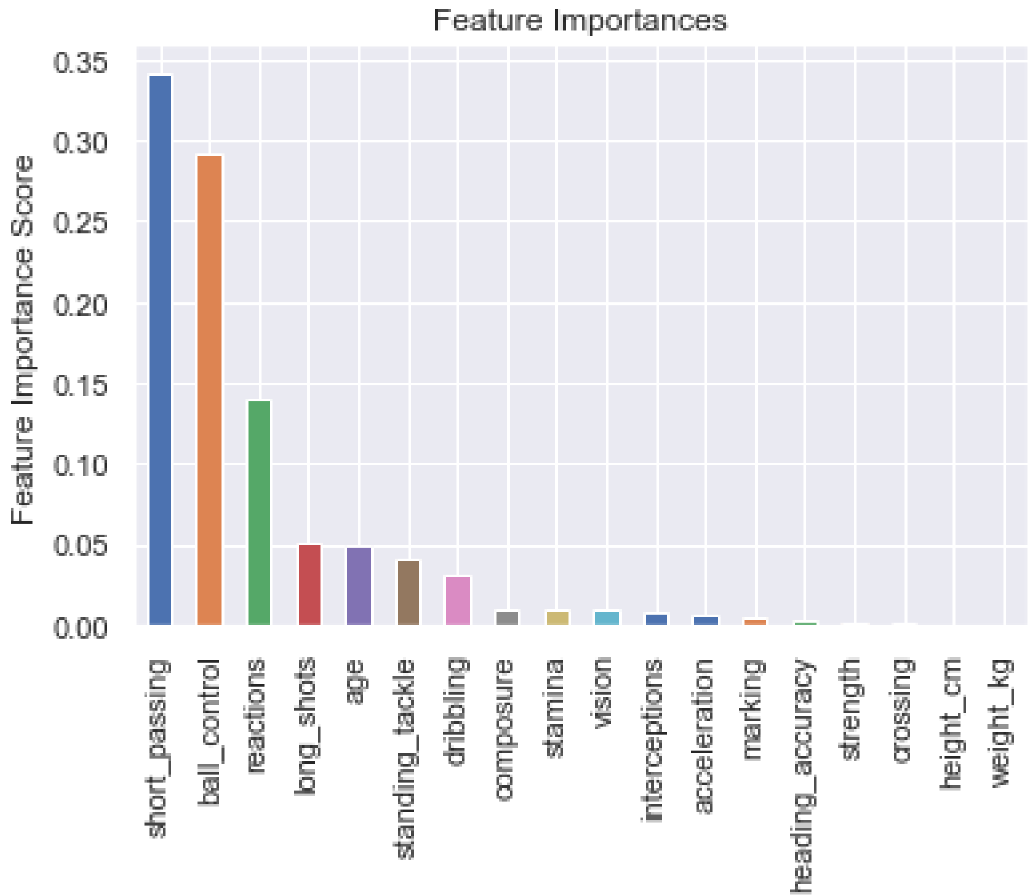
```
In [104]: #Model Evaluation for Value
          X_train,X_test,y_train,y_test=train_test_split(x,y2,test_size=0.3,random_state=0)
          Ridge_train_score = ridge.score(X_train,y_train)
          Ridge_test_score = ridge.score(X_test, y_test)
          y_prediction = ridge.predict(X_test)
          print("The training and test scores respectively are: " ,Ridge_train_score, "and" ,Rid
          from math import sqrt
          from sklearn.metrics import mean_squared_error
          RMSE_test=sqrt(mean_squared_error(y_true=y_test,y_pred=y_prediction))
          print("\n Root Mean Square Error of test set is:" ,RMSE_test)
          from sklearn import metrics
          from sklearn.model_selection import cross_val_score
          scores=cross_val_score(ridge,X,y2,cv=5)
          print("\n K-folds cross validation scores:" ,scores)
```

```
The training and test scores respectively are:  0.45178550541072693 and 0.4611055075784981

 Root Mean Square Error of test set is: 4.372830190504617

 K-folds cross validation scores: [  0.42382554 -81.09512036   0.44096329   0.45005531  -8.69297
```

```
In [105]: #Gradient Boosting Regression
```

```
cm_reduced=['Value (M)','age', 'height_cm', 'weight_kg', 'crossing', 'heading_accuracy
       'short_passing', 'dribbling',
        'ball_control', 'acceleration',
        'reactions',  'stamina',
       'strength', 'long_shots',  'interceptions',
       'vision',  'composure', 'marking', 'standing_tackle']
dta=data[cm_reduced]

def modelfit(alg, dtrain, features, performCV=True, printFeatureImportance=True, cv_fo
    #Fit the algorithm on the data

    alg.fit(dtrain[features],dtrain["Value (M)"] )

    #Predict training set:
    dtrain_predictions = alg.predict(dtrain[features])

    #Perform cross-validation:
    cv_score =  cross_val_score(alg, dtrain[features], dtrain["Value (M)"], cv=cv_fold
                                                    scoring='neg_mean_squared_error')
    cv_score = np.sqrt(np.abs(cv_score))

    #Print model report:
    print ("\nModel Report")
    print ("RMSE : %.4g" % np.sqrt(metrics.mean_squared_error(dtrain["Value (M)"], dtr
    print ("CV Score : Mean - %.4g | Std - %.4g | Min - %.4g | Max - %.4g" % (np.mean(
                                                                              np.std(cv
                                                                               np.max(c
    if printFeatureImportance:
        feat_imp = pd.Series(alg.feature_importances_, features).sort_values(ascending
        feat_imp.plot(kind='bar', title='Feature Importances')
        plt.ylabel('Feature Importance Score')



features = [i for i in dta.columns if i != "Value (M)"]
target = "Value (M)"
gbm0 = GradientBoostingRegressor(random_state=7)
modelfit(gbm0, dta, features)
```

```
Model Report
RMSE : 1.03
CV Score : Mean - 1.111 | Std - 0.8587 | Min - 0.2661 | Max - 2.905
```



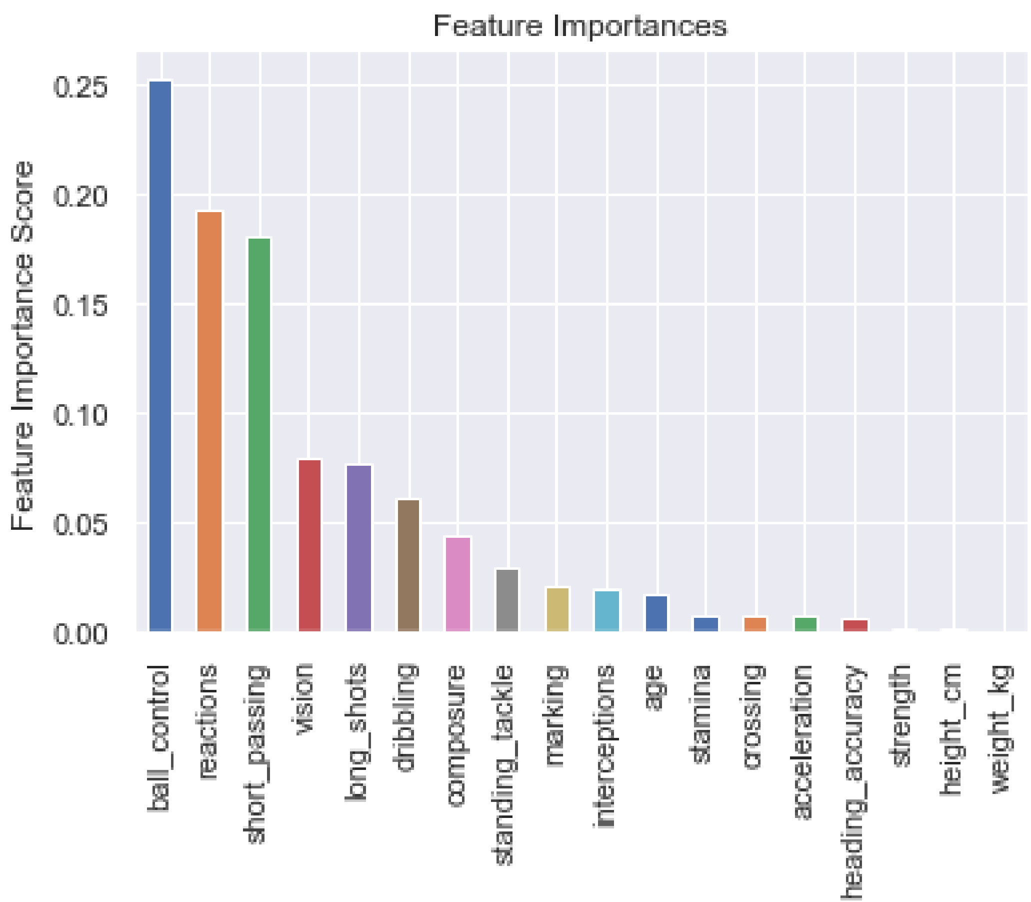
In [106]:
```
#Tuning with GridSearch
estimators = [x for x in range(700,750,10)]
param_test1 = {'n_estimators':estimators}
gsearch1 = GridSearchCV(estimator = GradientBoostingRegressor(learning_rate=0.1, min_s
                                  min_samples_leaf=50,max_depth=8,max_features='sqrt',
                        param_grid = param_test1, scoring='neg_mean_squared_error',n_jo
gsearch1.fit(dta[features],dta["Value (M)"])

gsearch1.score, gsearch1.best_params_, gsearch1.best_score_
modelfit(gsearch1.best_estimator_, dta, features)
```

Out[106]:
```
GridSearchCV(cv=10, error_score='raise-deprecating',
       estimator=GradientBoostingRegressor(alpha=0.9, criterion='friedman_mse', init=N
             learning_rate=0.1, loss='ls', max_depth=8,
             max_features='sqrt', max_leaf_nodes=None,
             min_impurity_decrease=0.0, min_impurity_split=None,
             min_samples_leaf=50, min_sa...       subsample=0.8, tol=0.0001, validatio
             warm_start=False),
       fit_params=None, iid=False, n_jobs=4,
```

```
             param_grid={'n_estimators': [700, 710, 720, 730, 740]},
             pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
             scoring='neg_mean_squared_error', verbose=0)
```

```
Out[106]: (<bound method BaseSearchCV.score of GridSearchCV(cv=10, error_score='raise-deprecatin
               estimator=GradientBoostingRegressor(alpha=0.9, criterion='friedman_mse', init=
                     learning_rate=0.1, loss='ls', max_depth=8,
                     max_features='sqrt', max_leaf_nodes=None,
                     min_impurity_decrease=0.0, min_impurity_split=None,
                     min_samples_leaf=50, min_sa...       subsample=0.8, tol=0.0001, validati
                     warm_start=False),
               fit_params=None, iid=False, n_jobs=4,
               param_grid={'n_estimators': [700, 710, 720, 730, 740]},
               pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
               scoring='neg_mean_squared_error', verbose=0)>,
           {'n_estimators': 740},
           -2.372786498292478)
```

```
Model Report
RMSE : 0.889
CV Score : Mean - 1.118 | Std - 1.06 | Min - 0.1824 | Max - 3.193
```



In [107]:
```
#MODEL CREATION

#Create our New Model with Interaction Terms
data=CM
lnVal=pd.DataFrame((data["Value (M)"]+1).apply(np.log))
lnVal.columns = ['ln_value']
cm_dta = pd.concat([lnVal, data], axis=1)
cm_dta.head()
data=cm_dta
def cm_skills_off (row):
    return row['short_passing'] * row['ball_control'] * row['long_shots'] *row['dribbl
def cm_skills_def (row):
    return row['standing_tackle']*row['marking']
def cm_ath_ment (row):
    return row['stamina'] * row['acceleration'] *row['composure'] *row['reactions'] *



def cm_phy (row):
    return row['height_cm'] * row['weight_kg']


data['cm_skills_off'] = data.apply(cm_skills_off, axis=1)
data['cm_skills_def'] = data.apply(cm_skills_def, axis=1)
data['cm_ath_ment']= data.apply(cm_ath_ment, axis=1)
data['cm_phy']= data.apply(cm_phy, axis=1)

features=['age', 'cm_skills_off', 'cm_skills_def', 'cm_ath_ment', 'cm_phy']
x=data[features]
#We must now scale the features
x =pd.DataFrame(scaler.fit_transform(x))
x.columns= ['age', 'cm_skills_off', 'cm_skills_def', 'cm_ath_ment', 'cm_phy']
#We have now addressed the issue of endogenity by including interaction terms
X=sm.add_constant(x)
y1=data[overall_target]
y2=data[value_target]
y3=data[ln_value]
mod=sm.OLS(y1,X)
res=mod.fit(cov_type='HC0')
yhat = res.fittedvalues
OLS_model = sm.OLS(y2,X)
OLS_results=OLS_model.fit(cov_type='HC0')
#results of new model on value
print(OLS_results.summary())
OLS_model2 = sm.OLS(y3,X)
```

```python
OLS_results2=OLS_model2.fit(cov_type='HC0')
#results for new model on value elasticity
print(OLS_results2.summary())
print(res.aic)
#Plot of y-hat for y-true on the reduced model for overall rating
from statsmodels.graphics.api import abline_plot
fig, ax = plt.subplots()
ax.scatter(yhat, y1)
line_fit = sm.OLS(y1, sm.add_constant(yhat, prepend=True)).fit()
abline_plot(model_results=line_fit, ax=ax)


ax.set_title('New Model fit to Overall')
ax.set_ylabel('Observed values')
ax.set_xlabel('Fitted values');
```

```
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/preprocessing/data.py:625: Data
  return self.partial_fit(X, y)
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/base.py:462: DataConversionWarn
  return self.fit(X, **fit_params).transform(X)


                            OLS Regression Results
==============================================================================
Dep. Variable:              Value (M)   R-squared:                       0.578
Model:                            OLS   Adj. R-squared:                  0.578
Method:                 Least Squares   F-statistic:                     337.8
Date:                Thu, 06 Dec 2018   Prob (F-statistic):               0.00
Time:                        18:47:16   Log-Likelihood:                -23419.
No. Observations:                8471   AIC:                         4.685e+04
Df Residuals:                    8465   BIC:                         4.689e+04
Df Model:                           5
Covariance Type:                  HC0
=================================================================================
                    coef    std err          z      P>|z|      [0.025      0.975]
---------------------------------------------------------------------------------
const             2.9211      0.042     70.004      0.000       2.839       3.003
age              -1.1676      0.047    -25.104      0.000      -1.259      -1.076
cm_skills_off     2.6849      0.125     21.527      0.000       2.440       2.929
cm_skills_def    -0.4403      0.082     -5.381      0.000      -0.601      -0.280
cm_ath_ment       2.6390      0.151     17.521      0.000       2.344       2.934
cm_phy            0.3485      0.048      7.251      0.000       0.254       0.443
==============================================================================
Omnibus:                     9573.454   Durbin-Watson:                   0.745
Prob(Omnibus):                  0.000   Jarque-Bera (JB):          1500961.550
Skew:                           5.667   Prob(JB):                         0.00
Kurtosis:                      67.219   Cond. No.                         3.65
==============================================================================
```

```
Warnings:
[1] Standard Errors are heteroscedasticity robust (HC0)
                            OLS Regression Results
==============================================================================
Dep. Variable:               ln_value   R-squared:                       0.793
Model:                            OLS   Adj. R-squared:                  0.793
Method:                 Least Squares   F-statistic:                     4110.
Date:                Thu, 06 Dec 2018   Prob (F-statistic):               0.00
Time:                        18:47:16   Log-Likelihood:                -3498.2
No. Observations:                8471   AIC:                             7008.
Df Residuals:                    8465   BIC:                             7051.
Df Model:                           5
Covariance Type:                  HC0
=================================================================================
                    coef    std err          z      P>|z|      [0.025      0.975]
---------------------------------------------------------------------------------
const             0.9222      0.004    232.102      0.000       0.914       0.930
age              -0.1603      0.004    -38.835      0.000      -0.168      -0.152
cm_skills_off     0.5110      0.008     67.173      0.000       0.496       0.526
cm_skills_def     0.0425      0.006      6.867      0.000       0.030       0.055
cm_ath_ment       0.2878      0.008     34.597      0.000       0.271       0.304
cm_phy            0.0441      0.004     10.181      0.000       0.036       0.053
==============================================================================
Omnibus:                     1231.245   Durbin-Watson:                   1.511
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            18634.013
Skew:                          -0.090   Prob(JB):                         0.00
Kurtosis:                      10.264   Cond. No.                         3.65
==============================================================================

Warnings:
[1] Standard Errors are heteroscedasticity robust (HC0)
41525.51401839299
```

As shown above the created model improved the score and solved the collinearity problem. Positional Value Modeling: Wingers

12 Wingers

```
In [108]: data=W
          lnVal=pd.DataFrame((data["Value (M)"]+1).apply(np.log))
          lnVal.columns = ['ln_value']
          W_dta = pd.concat([lnVal, data], axis=1)

          data=W_dta
          x=data[attribute_profile]
          X=sm.add_constant(x)
          y1=data[overall_target]
          y2=data[value_target]
          y3=data[ln_value]
          #OLS for Overall
          OLS_model = sm.OLS(y1,X)
          OLS_results=OLS_model.fit(cov_type='HC0')
          print("The R-squared for the attributes with overall is:" ,OLS_results.rsquared_adj)
          OLS_model2 = sm.OLS(y2,X)
          OLS_results2=OLS_model2.fit(cov_type='HC0')
          print("\n\nThe adjusted R-squared for the original CB value model is:" ,OLS_results2.r
          print("\nThe model AIC is: " ,OLS_results2.aic)
```

```
#Lasso Regression
X_train,X_test,y_train,y_test=train_test_split(x,y1,test_size=0.3,random_state=0)
lr = LinearRegression()
lr.fit(X_train, y_train)

#Lasso Fit (Overall)
lasso = Lasso(alpha=1.0, max_iter=1000000).fit(X_train, y_train)

from sklearn.linear_model import LassoCV
from sklearn.preprocessing import StandardScaler
X_std = scaler.fit_transform(x)
regr_cv = LassoCV(alphas=np.arange(1,9999.999))
# Fit the linear regression
model_cv = regr_cv.fit(X_std, y1)
print("The alpha we should use for lasso regression is:" ,model_cv.alpha_)
lasso = Lasso(alpha=1.0, max_iter=1000000).fit(X_train, y_train)
#Lasso Coefficients
y_prediction = lasso.predict(X_test)
lasso_coef=lasso.coef_
cols=np.array(x.columns)
cols=cols.reshape(37,1)
lasso_coef=lasso_coef.reshape(37,1)
coefs=np.concatenate((cols, lasso_coef), axis=1)
coefs=pd.DataFrame(coefs)
intercept=lasso.intercept_
print("the intercept is:" ,intercept)
print(coefs)
```

```
The R-squared for the attributes with overall is: 0.9482678210525392


The adjusted R-squared for the original CB value model is: 0.4663801039643096

The model AIC is:  39714.73444436689
```

```
Out[108]: LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None,
                   normalize=False)
```

```
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/preprocessing/data.py:625: Data
  return self.partial_fit(X, y)
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/base.py:462: DataConversionWarn
  return self.fit(X, **fit_params).transform(X)
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/linear_model/coordinate_descent
  y = column_or_1d(y, warn=True)
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/model_selection/_split.py:2053:
  warnings.warn(CV_WARNING, FutureWarning)
```

```
The alpha we should use for lasso regression is: 1.0
the intercept is: [5.93441979]
                    0           1
0                 age           0
1           height_cm           0
2           weight_kg           0
3            crossing   0.0800667
4           finishing   0.0207548
5    heading_accuracy   0.0299778
6       short_passing    0.127622
7             volleys           0
8           dribbling    0.113739
9               curve           0
10  free_kick_accuracy          0
11        long_passing  0.00250001
12        ball_control   0.175502
13        acceleration  0.0511156
14        sprint_speed  0.0377649
15             agility          0
16           reactions   0.125395
17             balance          0
18          shot_power          0
19             jumping  0.00194869
20             stamina  0.0354372
21            strength  0.00806433
22          long_shots  0.0121247
23          aggression  0.00117876
24       interceptions  0.00255774
25         positioning  0.0583953
26              vision  0.0151737
27           penalties  0.00629393
28           composure  0.0316954
29             marking          0
30      standing_tackle 8.01611e-05
31       sliding_tackle 0.000733575
32           gk_diving          0
33         gk_handling          0
34          gk_kicking         -0
35      gk_positioning          0
36         gk_reflexes         -0
```

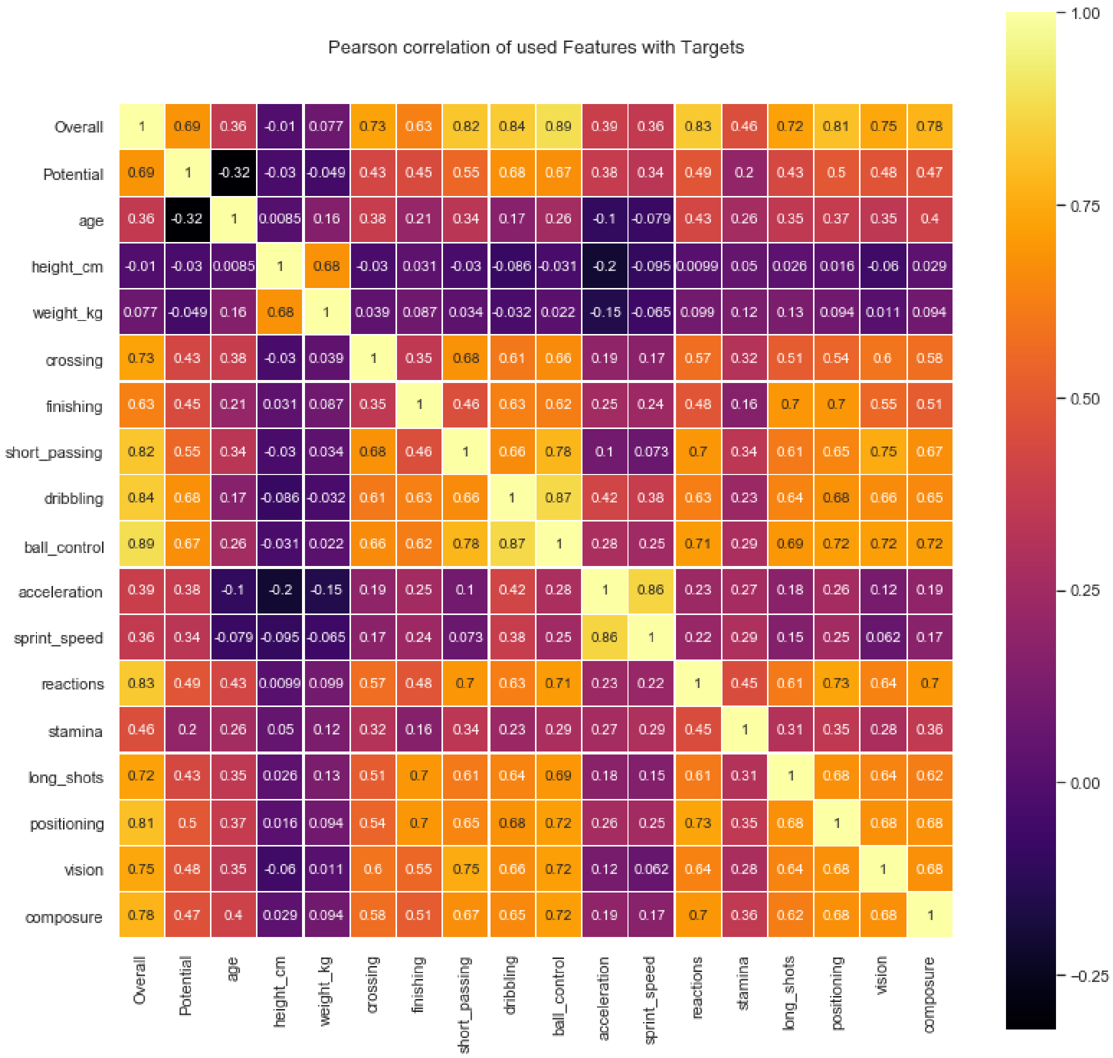
```
In [109]: used_variables = ['Overall','Potential','age', 'height_cm', 'weight_kg', 'crossing', '
                  'short_passing', 'dribbling', 'ball_control', 'acceleration', 'sprint_speed',
                  'reactions',  'stamina',
                  'long_shots', 'positioning',
                  'vision',  'composure']
          corr_variables = data[used_variables]
```

```
colormap = plt.cm.inferno
plt.figure(figsize=(13,13))
plt.title('Pearson correlation of used Features with Targets',
          y=1.05, size=13)
sns.heatmap(corr_variables.corr(),linewidths=0.1,vmax=1.0,
            square=True, cmap=colormap, linecolor='white', annot=True)
```

Out[109]: <Figure size 936x936 with 0 Axes>

Out[109]: Text(0.5, 1.05, 'Pearson correlation of used Features with Targets')

Out[109]: <matplotlib.axes._subplots.AxesSubplot at 0x11be61198>



In [110]:
```
features=lasso.coef_
indices=np.nonzero(features)
```

```python
np.take(features, indices)
w_features_used=['age', 'height_cm', 'weight_kg', 'crossing', 'finishing',
       'short_passing', 'dribbling', 'ball_control', 'acceleration', 'sprint_speed',
       'reactions',  'stamina',
       'long_shots', 'positioning',
       'vision',  'composure']
#Finding the best alpha for ridge regression for value
x=data[w_features_used]
y2=data[value_target]

from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import RidgeCV
scaler = StandardScaler()
X_std = scaler.fit_transform(x)
regr_cv = RidgeCV(alphas=np.arange(0.001,9999.999))
# Fit the linear regression
model_cv = regr_cv.fit(X_std, y2)
model_cv.alpha_
print("The alpha we should use for ridge regression is:" ,model_cv.alpha_)
x.shape
#Fitting ridge regression to the reduced model
#Note we use the suggested alpha of 79.01
X_train,X_test,y_train,y_test=train_test_split(x,y2,test_size=0.3,random_state=0)
lr = LinearRegression()
lr.fit(X_train, y_train)
#Ridge fit: Finding out what alpha to use for ridge
ridge = Ridge(alpha=79.01)
ridge.fit(X_train, y_train)
y_prediction = ridge.predict(X_test)
ridge_coef=ridge.coef_
cols=np.array(x.columns)
ridge_coef=ridge.coef_
cols=np.array(x.columns)
cols=cols.reshape(16,1)
ridge_coef=ridge_coef.reshape(16,1)
ridge_coefs=np.concatenate((cols, ridge_coef), axis=1)
ridge_coefs=pd.DataFrame(ridge_coefs)
ridge_intercept=ridge.intercept_
print(ridge_intercept)
print(ridge_coefs)
```

Out[110]:
```
array([[8.00666953e-02, 2.07547591e-02, 2.99778029e-02, 1.27622375e-01,
        1.13738671e-01, 2.50001130e-03, 1.75502420e-01, 5.11155599e-02,
        3.77649071e-02, 1.25394551e-01, 1.94868733e-03, 3.54371854e-02,
        8.06433388e-03, 1.21246975e-02, 1.17875974e-03, 2.55774399e-03,
        5.83953203e-02, 1.51737182e-02, 6.29393383e-03, 3.16954496e-02,
        8.01610996e-05, 7.33574595e-04]])
```

```
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/preprocessing/data.py:625: Data
```

```
  return self.partial_fit(X, y)
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/base.py:462: DataConversionWarn
  return self.fit(X, **fit_params).transform(X)
```

```
Out[110]: 79.00099999999999
```

```
The alpha we should use for ridge regression is: 79.00099999999999
```

```
Out[110]: (6685, 16)
```

```
Out[110]: LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None,
                   normalize=False)
```

```
Out[110]: Ridge(alpha=79.01, copy_X=True, fit_intercept=True, max_iter=None,
             normalize=False, random_state=None, solver='auto', tol=0.001)
```

```
[-37.96628836]
                 0          1
0              age  -0.338955
1        height_cm  0.0354684
2        weight_kg -0.0150212
3         crossing  0.0405286
4        finishing  0.0567221
5    short_passing  0.0972522
6        dribbling  0.0548051
7     ball_control    0.12961
8     acceleration  0.0501735
9     sprint_speed -0.0163293
10       reactions   0.141411
11         stamina  0.0124369
12      long_shots -0.0305993
13     positioning  0.0484458
14          vision  0.0315826
15       composure   0.065729
```

```
In [111]: #Model Evaluation for Value
          X_train,X_test,y_train,y_test=train_test_split(x,y2,test_size=0.3,random_state=0)
          Ridge_train_score = ridge.score(X_train,y_train)
          Ridge_test_score = ridge.score(X_test, y_test)
          y_prediction = ridge.predict(X_test)
          print("The training and test scores respectively are: " ,Ridge_train_score, "and" ,Rid
          from math import sqrt
          from sklearn.metrics import mean_squared_error
          RMSE_test=sqrt(mean_squared_error(y_true=y_test,y_pred=y_prediction))
          print("\n Root Mean Square Error of test set is:" ,RMSE_test)
          from sklearn import metrics
```

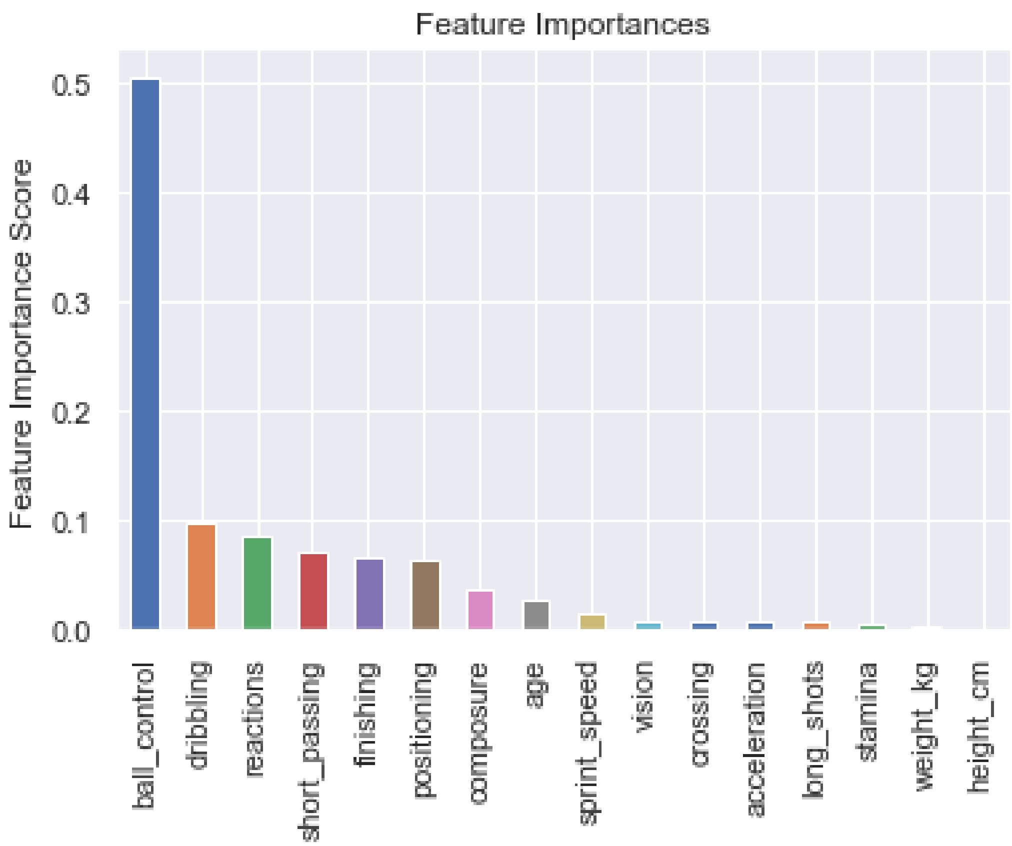
```
from sklearn.model_selection import cross_val_score
scores=cross_val_score(ridge,X,y2,cv=5)
print("\n K-folds cross validation scores:" ,scores)
```

```
The training and test scores respectively are:  0.44352486274701625 and 0.5149970405114312

 Root Mean Square Error of test set is: 4.00026697162954

 K-folds cross validation scores: [  0.43742721  -8.6296417    0.50575815 -11.95888424   0.35889
```

```
In [112]: #GBT
          #Gradient Boosting Regression


          w_reduced=['Value (M)', 'age', 'height_cm', 'weight_kg', 'crossing', 'finishing',
                 'short_passing', 'dribbling', 'ball_control', 'acceleration', 'sprint_speed',
                 'reactions',  'stamina',
                 'long_shots', 'positioning',
                 'vision',  'composure']
          dta=data[w_reduced]
          def modelfit(alg, dtrain, features, performCV=True, printFeatureImportance=True, cv_fo
              #Fit the algorithm on the data

              alg.fit(dtrain[features],dtrain["Value (M)"] )

              #Predict training set:
              dtrain_predictions = alg.predict(dtrain[features])

              #Perform cross-validation:
              cv_score =  cross_val_score(alg, dtrain[features], dtrain["Value (M)"], cv=cv_fold
                                                          scoring='neg_mean_squared_error')
              cv_score = np.sqrt(np.abs(cv_score))

              #Print model report:
              print ("\nModel Report")
              print ("RMSE : %.4g" % np.sqrt(metrics.mean_squared_error(dtrain["Value (M)"], dtr
              print ("CV Score : Mean - %.4g | Std - %.4g | Min - %.4g | Max - %.4g" % (np.mean(
                                                                                     np.std(cv
                                                                                      np.max(c
              if printFeatureImportance:
                  feat_imp = pd.Series(alg.feature_importances_, features).sort_values(ascending
                  feat_imp.plot(kind='bar', title='Feature Importances')
                  plt.ylabel('Feature Importance Score')



          features = [i for i in dta.columns if i != "Value (M)"]
```

```
target = "Value (M)"
gbm0 = GradientBoostingRegressor(random_state=7)
modelfit(gbm0, dta, features)
```

```
Model Report
RMSE : 0.9378
CV Score : Mean - 1.408 | Std - 0.8006 | Min - 0.3983 | Max - 2.681
```

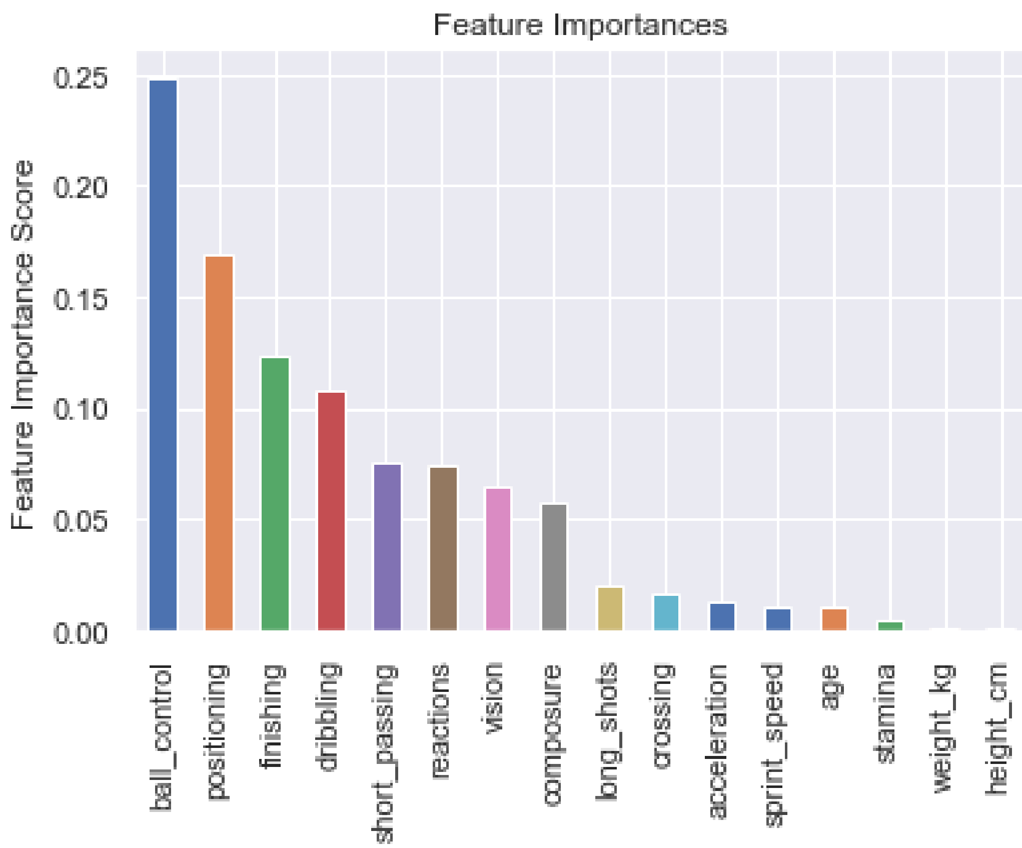



```
In [113]: estimators = [x for x in range(700,750,10)]
          param_test1 = {'n_estimators':estimators}
          gsearch1 = GridSearchCV(estimator = GradientBoostingRegressor(learning_rate=0.1, min_s
                                              min_samples_leaf=50,max_depth=8,max_features='sqrt',
                                  param_grid = param_test1, scoring='neg_mean_squared_error',n_jo
          gsearch1.fit(dta[features],dta["Value (M)"])

          gsearch1.score, gsearch1.best_params_, gsearch1.best_score_
          modelfit(gsearch1.best_estimator_, dta, features)

Out[113]: GridSearchCV(cv=10, error_score='raise-deprecating',
                 estimator=GradientBoostingRegressor(alpha=0.9, criterion='friedman_mse', init=N
```

```
                     learning_rate=0.1, loss='ls', max_depth=8,
                     max_features='sqrt', max_leaf_nodes=None,
                     min_impurity_decrease=0.0, min_impurity_split=None,
                     min_samples_leaf=50, min_sa...       subsample=0.8, tol=0.0001, validatio
                     warm_start=False),
               fit_params=None, iid=False, n_jobs=4,
               param_grid={'n_estimators': [700, 710, 720, 730, 740]},
               pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
               scoring='neg_mean_squared_error', verbose=0)
```

Out[113]:
```
(<bound method BaseSearchCV.score of GridSearchCV(cv=10, error_score='raise-deprecatin
              estimator=GradientBoostingRegressor(alpha=0.9, criterion='friedman_mse', init=
                     learning_rate=0.1, loss='ls', max_depth=8,
                     max_features='sqrt', max_leaf_nodes=None,
                     min_impurity_decrease=0.0, min_impurity_split=None,
                     min_samples_leaf=50, min_sa...       subsample=0.8, tol=0.0001, validati
                     warm_start=False),
              fit_params=None, iid=False, n_jobs=4,
              param_grid={'n_estimators': [700, 710, 720, 730, 740]},
              pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
              scoring='neg_mean_squared_error', verbose=0)>,
 {'n_estimators': 740},
 -3.4767927712485758)
```

```
Model Report
RMSE : 1.151
CV Score : Mean - 1.456 | Std - 1.165 | Min - 0.2721 | Max - 3.746
```



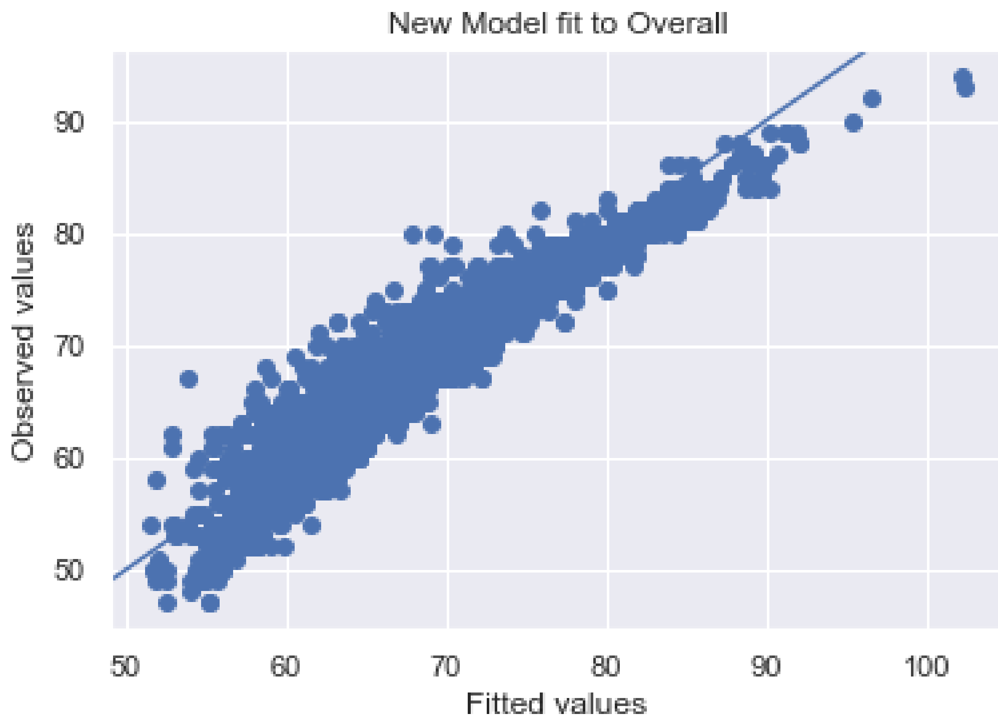
In [114]:
```
#MODEL CREATION

#Create our New Model with Interaction Terms

def w_skills (row):
    return row['short_passing'] * row['ball_control']  *row['dribbling']
def w_skills_off (row):
    return row['positioning']*row['finishing']
def w_ath_ment (row):
    return row['stamina'] * row['acceleration'] *row['sprint_speed']*row['composure']

#def w_mentality (row):
    #return row['composure'] *row['reactions'] * row['vision']

def w_phy (row):
    return row['height_cm'] * row['weight_kg']


data['w_skills'] = data.apply(w_skills, axis=1)
data['w_skills_off'] = data.apply(w_skills_off, axis=1)
```

```
data['w_ath_ment']= data.apply(w_ath_ment, axis=1)
#data['w_mentality']= data.apply(w_ath, axis=1)
data['w_phy']= data.apply(w_phy, axis=1)
features=['age', 'w_skills', 'w_skills_off', 'w_ath_ment',  'w_phy']
x=data[features]
#We must now scale the features
x =pd.DataFrame(scaler.fit_transform(x))
x.columns=['age', 'w_skills', 'w_skills_off', 'w_ath_ment', 'w_phy']
#We have now addressed the issue of endogenity by including interaction terms
X=sm.add_constant(x)
y1=data[overall_target]
y2=data[value_target]
y3=data[ln_value]
mod=sm.OLS(y1,X)
res=mod.fit(cov_type='HC0')
yhat = res.fittedvalues
OLS_model = sm.OLS(y2,X)
OLS_results=OLS_model.fit(cov_type='HC0')
#results of new model on value
print(OLS_results.summary())
OLS_model2 = sm.OLS(y3,X)
OLS_results2=OLS_model2.fit(cov_type='HC0')
#results for new model on value elasticity
print(OLS_results2.summary())
print(res.aic)
#Plot of y-hat for y-true on the reduced model for overall rating
from statsmodels.graphics.api import abline_plot
fig, ax = plt.subplots()
ax.scatter(yhat, y1)
line_fit = sm.OLS(y1, sm.add_constant(yhat, prepend=True)).fit()
abline_plot(model_results=line_fit, ax=ax)


ax.set_title('New Model fit to Overall')
ax.set_ylabel('Observed values')
ax.set_xlabel('Fitted values');
```

```
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/preprocessing/data.py:625: Data
  return self.partial_fit(X, y)
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/base.py:462: DataConversionWarn
  return self.fit(X, **fit_params).transform(X)


                            OLS Regression Results
==============================================================================
Dep. Variable:              Value (M)   R-squared:                       0.601
Model:                            OLS   Adj. R-squared:                  0.601
Method:                 Least Squares   F-statistic:                     240.9
```

```
Date:                Thu, 06 Dec 2018   Prob (F-statistic):          3.06e-237
Time:                        20:44:24   Log-Likelihood:                -18863.
No. Observations:                6685   AIC:                         3.774e+04
Df Residuals:                    6679   BIC:                         3.778e+04
Df Model:                           5
Covariance Type:                  HC0
================================================================================
                   coef    std err          z      P>|z|      [0.025      0.975]
--------------------------------------------------------------------------------
const            3.1022      0.050     62.372      0.000       3.005       3.200
age             -1.1215      0.055    -20.209      0.000      -1.230      -1.013
w_skills         2.4689      0.126     19.569      0.000       2.222       2.716
w_skills_off     0.3022      0.081      3.729      0.000       0.143       0.461
w_ath_ment       2.8084      0.209     13.455      0.000       2.399       3.218
w_phy            0.2306      0.048      4.770      0.000       0.136       0.325
==============================================================================
Omnibus:                     8926.764   Durbin-Watson:                   0.548
Prob(Omnibus):                  0.000   Jarque-Bera (JB):          3249589.748
Skew:                           7.372   Prob(JB):                         0.00
Kurtosis:                     110.000   Cond. No.                         3.50
==============================================================================

Warnings:
[1] Standard Errors are heteroscedasticity robust (HC0)
                            OLS Regression Results
==============================================================================
Dep. Variable:               ln_value   R-squared:                       0.881
Model:                            OLS   Adj. R-squared:                  0.881
Method:                 Least Squares   F-statistic:                     7349.
Date:                Thu, 06 Dec 2018   Prob (F-statistic):               0.00
Time:                        20:44:25   Log-Likelihood:                -980.83
No. Observations:                6685   AIC:                             1974.
Df Residuals:                    6679   BIC:                             2015.
Df Model:                           5
Covariance Type:                  HC0
================================================================================
                   coef    std err          z      P>|z|      [0.025      0.975]
--------------------------------------------------------------------------------
const            0.9536      0.003    278.243      0.000       0.947       0.960
age             -0.1408      0.004    -38.874      0.000      -0.148      -0.134
w_skills         0.4566      0.007     62.177      0.000       0.442       0.471
w_skills_off     0.0994      0.007     14.001      0.000       0.085       0.113
w_ath_ment       0.2985      0.007     42.892      0.000       0.285       0.312
w_phy            0.0283      0.004      7.349      0.000       0.021       0.036
==============================================================================
Omnibus:                     1446.349   Durbin-Watson:                   1.453
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            16604.855
Skew:                          -0.704   Prob(JB):                         0.00
```

```
Kurtosis:                      10.592   Cond. No.                         3.50
==============================================================================

Warnings:
[1] Standard Errors are heteroscedasticity robust (HC0)
27407.84573999451
```



As shown above the created model improved the score and solved the collinearity problem. Positional Value Modeling: Forwards

13 Forwards

```
In [115]: data=F
          lnVal=pd.DataFrame((data["Value (M)"]+1).apply(np.log))
          lnVal.columns = ['ln_value']
          f_dta = pd.concat([lnVal, data], axis=1)

          data=f_dta
          x=data[attribute_profile]
          X=sm.add_constant(x)
          y1=data[overall_target]
          y2=data[value_target]
          y3=data[ln_value]
```

```
#OLS for Overall
OLS_model = sm.OLS(y1,X)
OLS_results=OLS_model.fit(cov_type='HC0')
print("The R-squared for the attributes with overall is:" ,OLS_results.rsquared_adj)
OLS_model2 = sm.OLS(y2,X)
OLS_results2=OLS_model2.fit(cov_type='HC0')
print("\n\nThe adjusted R-squared for the original CB value model is:" ,OLS_results2.r
print("\nThe model AIC is: " ,OLS_results2.aic)
#Lasso Regression
from sklearn.linear_model import LinearRegression
X_train,X_test,y_train,y_test=train_test_split(x,y1,test_size=0.3,random_state=0)
lr = LinearRegression()
lr.fit(X_train, y_train)

#Lasso Fit (Overall)
lasso = Lasso(alpha=1.0, max_iter=1000000).fit(X_train, y_train)


from sklearn.linear_model import LassoCV

from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
X_std=scaler.fit_transform(X)
regr_cv = LassoCV(alphas=np.arange(1,9999.999))
# Fit the linear regression
model_cv = regr_cv.fit(X_std, y1)
print("The alpha we should use for lasso regression is:" ,model_cv.alpha_)
lasso = Lasso(alpha=1.0, max_iter=1000000).fit(X_train, y_train)
#Lasso Coefficients
y_prediction = lasso.predict(X_test)
lasso_coef=lasso.coef_
cols=np.array(x.columns)
cols=cols.reshape(37,1)
lasso_coef=lasso_coef.reshape(37,1)
coefs=np.concatenate((cols, lasso_coef), axis=1)
coefs=pd.DataFrame(coefs)
intercept=lasso.intercept_
print("the intercept is:" ,intercept)
print(coefs)
```

```
The R-squared for the attributes with overall is: 0.9688747358983668


The adjusted R-squared for the original CB value model is: 0.4357079026258578

The model AIC is:  21638.390672754944
```

```
Out[115]: LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None,
```

```
                   normalize=False)

/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/preprocessing/data.py:625: Data
  return self.partial_fit(X, y)
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/base.py:462: DataConversionWarn
  return self.fit(X, **fit_params).transform(X)
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/linear_model/coordinate_descent
  y = column_or_1d(y, warn=True)
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/model_selection/_split.py:2053:
  warnings.warn(CV_WARNING, FutureWarning)


The alpha we should use for lasso regression is: 1.0
the intercept is: [5.85079122]
                    0           1
0                 age           0
1           height_cm           0
2           weight_kg           0
3            crossing  0.00477795
4           finishing    0.113041
5    heading_accuracy   0.0426845
6       short_passing   0.0806355
7             volleys  0.00835998
8           dribbling    0.058005
9               curve  0.00328322
10  free_kick_accuracy  0.00273747
11       long_passing 0.000808266
12       ball_control    0.154566
13       acceleration   0.0246743
14       sprint_speed   0.0358264
15            agility           0
16          reactions   0.0884776
17            balance          -0
18         shot_power   0.0846525
19            jumping           0
20            stamina  0.00624438
21           strength   0.0321246
22         long_shots   0.0197307
23         aggression  0.00271808
24      interceptions           0
25        positioning    0.132097
26             vision           0
27          penalties           0
28          composure   0.0437402
29            marking           0
30     standing_tackle           0
31      sliding_tackle           0
32          gk_diving          -0
```

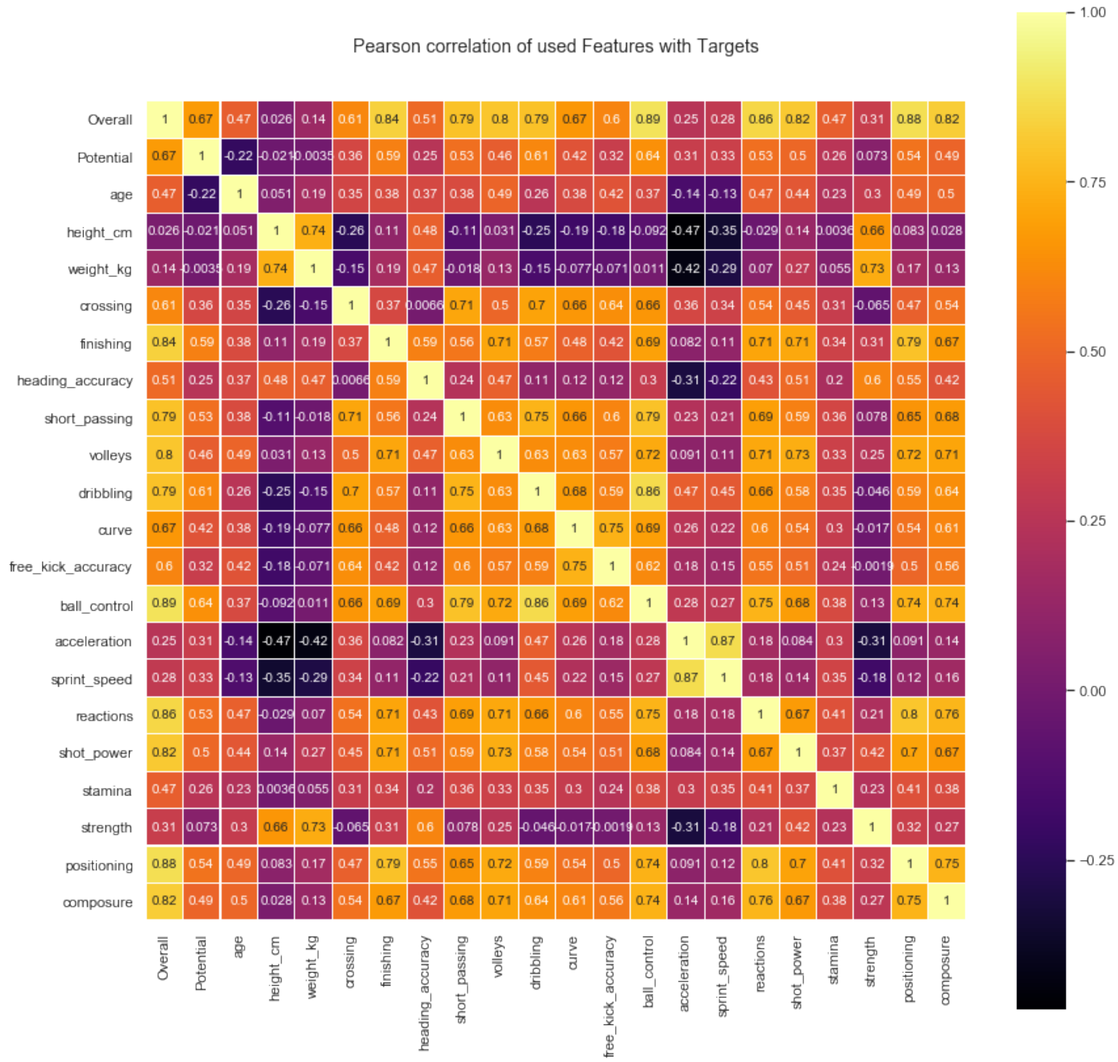
```
33        gk_handling          -0
34         gk_kicking          -0
35     gk_positioning           0
36        gk_reflexes           0
```

```
In [116]: used_variables = ['Overall','Potential','age', 'height_cm', 'weight_kg', 'crossing', '
                 'short_passing', 'volleys', 'dribbling', 'curve', 'free_kick_accuracy',
                  'ball_control', 'acceleration', 'sprint_speed','reactions',  'shot_power',  's
                 'strength',  'positioning','composure']
          corr_variables = data[used_variables]
          colormap = plt.cm.inferno
          plt.figure(figsize=(14,14))
          plt.title('Pearson correlation of used Features with Targets',
                    y=1.05, size=14)
          sns.heatmap(corr_variables.corr(),linewidths=0.1,vmax=1.0,
                      square=True, cmap=colormap, linecolor='white', annot=True)
```

```
Out[116]: <Figure size 1008x1008 with 0 Axes>
```

```
Out[116]: Text(0.5, 1.05, 'Pearson correlation of used Features with Targets')
```

```
Out[116]: <matplotlib.axes._subplots.AxesSubplot at 0x1c5abca588>
```




```
In [117]: features=lasso.coef_
          indices=np.nonzero(features)
          np.take(features, indices)
          f_features_used=['age', 'height_cm', 'weight_kg', 'crossing', 'finishing', 'heading_ac
                 'short_passing', 'volleys', 'dribbling', 'curve', 'free_kick_accuracy',
                  'ball_control', 'acceleration', 'sprint_speed','reactions',  'shot_power',  's
                 'strength',  'positioning','composure']
          #Finding the best alpha for ridge regression for value
          x=data[f_features_used]
          y2=data[value_target]

          from sklearn.preprocessing import StandardScaler
          from sklearn.linear_model import RidgeCV
          scaler = StandardScaler()
```

```
X_std = scaler.fit_transform(x)
regr_cv = RidgeCV(alphas=np.arange(0.001,9999.999))
# Fit the linear regression
model_cv = regr_cv.fit(X_std, y2)
model_cv.alpha_
print("The alpha we should use for ridge regression is:" ,model_cv.alpha_)
x.shape
#Fitting ridge regression to the reduced model
#Note we use the suggested alpha of 70.01
X_train,X_test,y_train,y_test=train_test_split(x,y2,test_size=0.3,random_state=0)
lr = LinearRegression()
lr.fit(X_train, y_train)
#Ridge fit: Finding out what alpha to use for ridge
ridge = Ridge(alpha=70.01)
ridge.fit(X_train, y_train)
y_prediction = ridge.predict(X_test)
ridge_coef=ridge.coef_
cols=np.array(x.columns)
ridge_coef=ridge.coef_
cols=np.array(x.columns)
cols=cols.reshape(20,1)
ridge_coef=ridge_coef.reshape(20,1)
ridge_coefs=np.concatenate((cols, ridge_coef), axis=1)
ridge_coefs=pd.DataFrame(ridge_coefs)
ridge_intercept=ridge.intercept_
print(ridge_intercept)
print(ridge_coefs)
```

```
Out[117]: array([[0.00477795, 0.11304053, 0.0426845 , 0.0806355 , 0.00835998,
                  0.05800503, 0.00328322, 0.00273747, 0.00080827, 0.15456563,
                  0.02467427, 0.03582643, 0.08847755, 0.08465247, 0.00624438,
                  0.03212463, 0.01973069, 0.00271808, 0.13209683, 0.04374019]])
```

```
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/preprocessing/data.py:625: Data
  return self.partial_fit(X, y)
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/base.py:462: DataConversionWarn
  return self.fit(X, **fit_params).transform(X)
```

```
Out[117]: 70.00099999999999
```

```
The alpha we should use for ridge regression is: 70.00099999999999
```

```
Out[117]: (3518, 20)
```

```
Out[117]: LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None,
                   normalize=False)
```

```
Out[117]: Ridge(alpha=70.01, copy_X=True, fit_intercept=True, max_iter=None,
             normalize=False, random_state=None, solver='auto', tol=0.001)
```

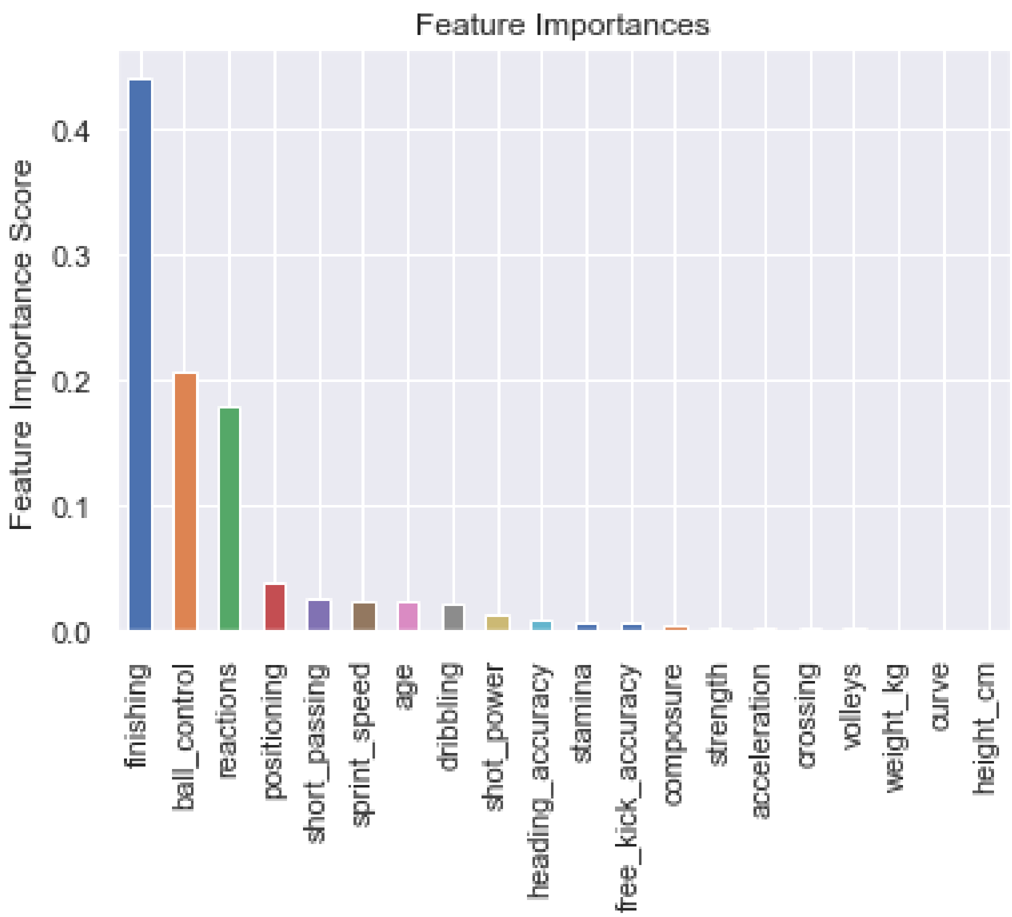
```
[-31.65342991]
                     0           1
0                  age   -0.385521
1            height_cm  -0.00154746
2            weight_kg    0.0106391
3             crossing  -0.00520718
4            finishing     0.224509
5     heading_accuracy  -0.00814832
6        short_passing    0.0660498
7              volleys   0.00332663
8            dribbling  0.000975116
9                curve    0.0178649
10  free_kick_accuracy    0.0191103
11        ball_control    0.0787713
12        acceleration    0.0109136
13        sprint_speed    0.0159083
14           reactions     0.152425
15          shot_power    -0.043562
16             stamina    0.0180914
17            strength    0.0180124
18         positioning    0.0455791
19           composure    0.0708274
```

```
In [118]: #Model Evaluation for Value
          X_train,X_test,y_train,y_test=train_test_split(x,y2,test_size=0.3,random_state=0)
          Ridge_train_score = ridge.score(X_train,y_train)
          Ridge_test_score = ridge.score(X_test, y_test)
          y_prediction = ridge.predict(X_test)
          print("The training and test scores respectively are: " ,Ridge_train_score, "and" ,Rid
          from math import sqrt
          from sklearn.metrics import mean_squared_error
          RMSE_test=sqrt(mean_squared_error(y_true=y_test,y_pred=y_prediction))
          print("\n Root Mean Square Error of test set is:" ,RMSE_test)
          from sklearn import metrics
          from sklearn.model_selection import cross_val_score
          scores=cross_val_score(ridge,X,y2,cv=5)
          print("\n K-folds cross validation scores:" ,scores)
```

```
The training and test scores respectively are:  0.44459314787396115 and 0.4051721153012315

 Root Mean Square Error of test set is: 5.640307227386972

 K-folds cross validation scores: [-3.26845515e-02 -1.81054077e+01 -9.75911635e+01 -3.14055837e+
 -1.22471176e-01]
```

In [119]:
```
#GBT
#Gradient Boosting Regression


f_reduced=['Value (M)','age', 'height_cm', 'weight_kg', 'crossing', 'finishing', 'head
       'short_passing', 'volleys', 'dribbling', 'curve', 'free_kick_accuracy',
        'ball_control', 'acceleration', 'sprint_speed','reactions',  'shot_power',  's
       'strength',  'positioning','composure']
dta=data[f_reduced]
def modelfit(alg, dtrain, features, performCV=True, printFeatureImportance=True, cv_fo
    #Fit the algorithm on the data

    alg.fit(dtrain[features],dtrain["Value (M)"] )

    #Predict training set:
    dtrain_predictions = alg.predict(dtrain[features])

    #Perform cross-validation:
    cv_score =  cross_val_score(alg, dtrain[features], dtrain["Value (M)"], cv=cv_fold
                                            scoring='neg_mean_squared_error')
    cv_score = np.sqrt(np.abs(cv_score))

    #Print model report:
    print ("\nModel Report")
    print ("RMSE : %.4g" % np.sqrt(metrics.mean_squared_error(dtrain["Value (M)"], dtr
    print ("CV Score : Mean - %.4g | Std - %.4g | Min - %.4g | Max - %.4g" % (np.mean(
                                                                              np.std(cv
                                                                               np.max(c
    if printFeatureImportance:
        feat_imp = pd.Series(alg.feature_importances_, features).sort_values(ascending
        feat_imp.plot(kind='bar', title='Feature Importances')
        plt.ylabel('Feature Importance Score')


features = [i for i in dta.columns if i != "Value (M)"]
target = "Value (M)"
gbm0 = GradientBoostingRegressor(random_state=7)
modelfit(gbm0, dta, features)
```

```
Model Report
RMSE : 0.8192
CV Score : Mean - 1.575 | Std - 2.469 | Min - 0.1849 | Max - 8.807
```



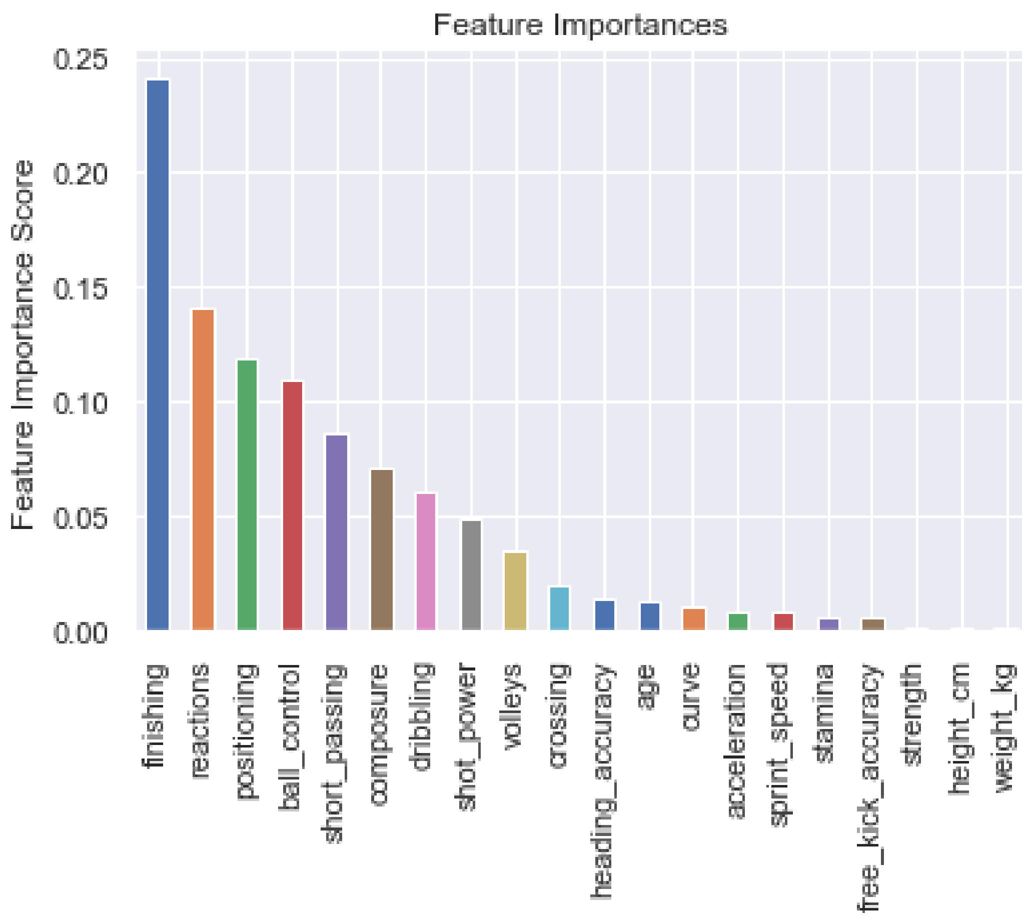
In [120]:
```
estimators = [x for x in range(700,750,10)]
param_test1 = {'n_estimators':estimators}
gsearch1 = GridSearchCV(estimator = GradientBoostingRegressor(learning_rate=0.1, min_s
                                  min_samples_leaf=50,max_depth=8,max_features='sqrt',
                        param_grid = param_test1, scoring='neg_mean_squared_error',n_jo
gsearch1.fit(dta[features],dta["Value (M)"])

gsearch1.score, gsearch1.best_params_, gsearch1.best_score_
modelfit(gsearch1.best_estimator_, dta, features)
```

Out[120]:
```
GridSearchCV(cv=10, error_score='raise-deprecating',
       estimator=GradientBoostingRegressor(alpha=0.9, criterion='friedman_mse', init=N
             learning_rate=0.1, loss='ls', max_depth=8,
             max_features='sqrt', max_leaf_nodes=None,
             min_impurity_decrease=0.0, min_impurity_split=None,
             min_samples_leaf=50, min_sa...       subsample=0.8, tol=0.0001, validatio
             warm_start=False),
       fit_params=None, iid=False, n_jobs=4,
```

```
             param_grid={'n_estimators': [700, 710, 720, 730, 740]},
             pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
             scoring='neg_mean_squared_error', verbose=0)
```

```
Out[120]: (<bound method BaseSearchCV.score of GridSearchCV(cv=10, error_score='raise-deprecatin
               estimator=GradientBoostingRegressor(alpha=0.9, criterion='friedman_mse', init=
                     learning_rate=0.1, loss='ls', max_depth=8,
                     max_features='sqrt', max_leaf_nodes=None,
                     min_impurity_decrease=0.0, min_impurity_split=None,
                     min_samples_leaf=50, min_sa...       subsample=0.8, tol=0.0001, validati
                     warm_start=False),
               fit_params=None, iid=False, n_jobs=4,
               param_grid={'n_estimators': [700, 710, 720, 730, 740]},
               pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
               scoring='neg_mean_squared_error', verbose=0)>,
          {'n_estimators': 730},
          -12.245103361932717)
```

```
Model Report
RMSE : 1.312
CV Score : Mean - 1.81 | Std - 2.995 | Min - 0.1426 | Max - 10.45
```



In [121]:

```
#MODEL CREATION

#Create our New Model with Interaction Terms

def f_skills (row):
    return row['short_passing'] * row['crossing'] *row['dribbling'] *row['ball_control
def f_skills_off (row):
    return row['positioning']*row['finishing']*row['volleys']*row['heading_accuracy']*
def f_ath_ment (row):
    return row['acceleration'] *row['sprint_speed']*row['strength'] *row['composure']

def f_phy (row):
    return row['height_cm'] * row['weight_kg']


data['f_skills'] = data.apply(w_skills, axis=1)
data['f_skills_off'] = data.apply(w_skills_off, axis=1)
data['f_ath_ment']= data.apply(w_ath_ment, axis=1)
```

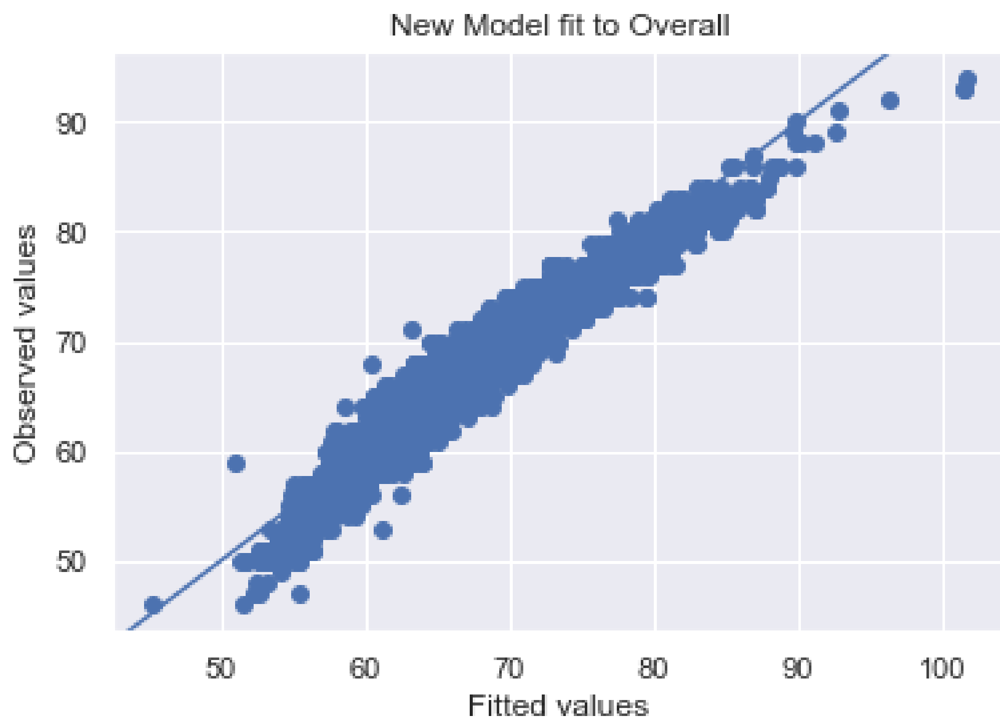
```
data['f_phy']= data.apply(w_phy, axis=1)
features=['age', 'f_skills', 'f_skills_off', 'f_ath_ment',  'f_phy']
x=data[features]
#We must now scale the features
x =pd.DataFrame(scaler.fit_transform(x))
x.columns=['age', 'f_skills', 'f_skills_off', 'f_ath_ment', 'f_phy']
#We have now addressed the issue of endogenity by including interaction terms
X=sm.add_constant(x)
y1=data[overall_target]
y2=data[value_target]
y3=data[ln_value]

mod=sm.OLS(y1,X)
res=mod.fit(cov_type='HC0')
yhat = res.fittedvalues
OLS_model = sm.OLS(y2,X)
OLS_results=OLS_model.fit(cov_type='HC0')
#results of new model on value
print(OLS_results.summary())
OLS_model2 = sm.OLS(y3,X)
OLS_results2=OLS_model2.fit(cov_type='HC0')
#results for new model on value elasticity
print(OLS_results2.summary())
print(res.aic)
#Plot of y-hat for y-true on the reduced model for overall rating
from statsmodels.graphics.api import abline_plot
fig, ax = plt.subplots()
ax.scatter(yhat, y1)
line_fit = sm.OLS(y1, sm.add_constant(yhat, prepend=True)).fit()
abline_plot(model_results=line_fit, ax=ax)


ax.set_title('New Model fit to Overall')
ax.set_ylabel('Observed values')
ax.set_xlabel('Fitted values');
```

```
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/preprocessing/data.py:625: Data
  return self.partial_fit(X, y)
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/base.py:462: DataConversionWarn
  return self.fit(X, **fit_params).transform(X)
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:              Value (M)   R-squared:                       0.578
Model:                            OLS   Adj. R-squared:                  0.577
Method:                 Least Squares   F-statistic:                     125.3
Date:                Thu, 06 Dec 2018   Prob (F-statistic):          2.21e-122
```

```
Time:                        20:55:49   Log-Likelihood:                -10290.
No. Observations:                3518   AIC:                         2.059e+04
Df Residuals:                    3512   BIC:                         2.063e+04
Df Model:                           5
Covariance Type:                  HC0
================================================================================
                   coef    std err          z      P>|z|      [0.025      0.975]
--------------------------------------------------------------------------------
const            2.9884      0.076     39.309      0.000       2.839       3.137
age             -1.4008      0.091    -15.344      0.000      -1.580      -1.222
f_skills         0.8866      0.181      4.885      0.000       0.531       1.242
f_skills_off     1.9764      0.148     13.318      0.000       1.686       2.267
f_ath_ment       3.3632      0.405      8.298      0.000       2.569       4.158
f_phy            0.7721      0.100      7.690      0.000       0.575       0.969
==============================================================================
Omnibus:                     4489.631   Durbin-Watson:                   0.539
Prob(Omnibus):                  0.000   Jarque-Bera (JB):          1070366.257
Skew:                           6.842   Prob(JB):                         0.00
Kurtosis:                      87.350   Cond. No.                         3.70
==============================================================================

Warnings:
[1] Standard Errors are heteroscedasticity robust (HC0)
                            OLS Regression Results
==============================================================================
Dep. Variable:               ln_value   R-squared:                       0.877
Model:                            OLS   Adj. R-squared:                  0.877
Method:                 Least Squares   F-statistic:                     3573.
Date:                Thu, 06 Dec 2018   Prob (F-statistic):               0.00
Time:                        20:55:49   Log-Likelihood:                -562.58
No. Observations:                3518   AIC:                             1137.
Df Residuals:                    3512   BIC:                             1174.
Df Model:                           5
Covariance Type:                  HC0
================================================================================
                   coef    std err          z      P>|z|      [0.025      0.975]
--------------------------------------------------------------------------------
const            0.9087      0.005    189.829      0.000       0.899       0.918
age             -0.1745      0.005    -32.942      0.000      -0.185      -0.164
f_skills         0.3067      0.009     33.537      0.000       0.289       0.325
f_skills_off     0.3772      0.010     37.179      0.000       0.357       0.397
f_ath_ment       0.2143      0.009     22.909      0.000       0.196       0.233
f_phy            0.0834      0.006     14.355      0.000       0.072       0.095
==============================================================================
Omnibus:                      737.491   Durbin-Watson:                   1.323
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             6258.434
Skew:                          -0.755   Prob(JB):                         0.00
Kurtosis:                       9.357   Cond. No.                         3.70
```

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

Warnings:
[1] Standard Errors are heteroscedasticity robust (HC0)
13883.08945311086
```



As shown above the created model improved the score and solved the collinearity problem.

14 Classifying Overall Rating and Position

```
In [3]: #Features Lists
        descriptive=['club','age', 'league', 'height_cm', 'weight_kg']

        overall_target = ['Overall']
        potential_target=['Potential']
        value_target=['Value (M)']
        ln_value=['ln_value']
        eur_value=['eur_value']
        club=['club_id']
        basic_attr=['Overall', 'Potential','age', 'pac', 'sho', 'pas','dri', 'defend', 'phy' , '
                     'international_reputation', 'skill_moves',
               'weak_foot', 'att_rate_High','att_rate_Low', 'att_rate_High',
                    'defend_rate_High','defend_rate_Low']
```

```
attribute_profile=['Potential','league_id','age', 'height_cm', 'weight_kg', 'crossing',
       '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', 'composure', 'marking', 'standing_tackle',
       'sliding_tackle', 'gk_diving', 'gk_handling', 'gk_kicking',
       'gk_positioning', 'gk_reflexes']
all_attr=['Overall','Potential', 'Value (M)',
         'league_id','age', 'height_cm', 'weight_kg', 'crossing', 'finishing', 'heading_
       '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', 'composure', 'marking', 'standing_tackle',
       'sliding_tackle', 'gk_diving', 'gk_handling', 'gk_kicking',
       'gk_positioning', 'gk_reflexes']
targets=['Overall','Potential', 'Value (M)', 'ln_value', 'eur_value']
data=pd.read_csv("Full_DF.csv")
```

Classifying Player Position with k-NN Classification

In [132]:
```
#Model Creation
y=data[['Position']].copy()
X=data[attribute_profile].copy()

# Splitting the dataset into the Training set and Test set
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.3, random_stat
# Feature Scaling
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)

# Fitting K-NN to the Training set
from sklearn.neighbors import KNeighborsClassifier
classifier = KNeighborsClassifier(n_neighbors = 15, metric = 'minkowski', p = 2)
classifier.fit(X_train, y_train)

# Predicting the Test set results
y_pred = classifier.predict(X_test)

# Making the Confusion Matrix
from sklearn.metrics import confusion_matrix
import seaborn as sns
mat = confusion_matrix(y_test, y_pred)
sns.heatmap(mat, square=True, annot=True, cbar=False)
```

```
plt.xlabel('predicted value')
plt.ylabel('true value');
#algorithm score
print(classifier.score(X_test, y_test))
from sklearn import metrics
from sklearn.model_selection import cross_val_score
CVscores=cross_val_score(classifier, X, y, cv=5)
print(CVscores)
```

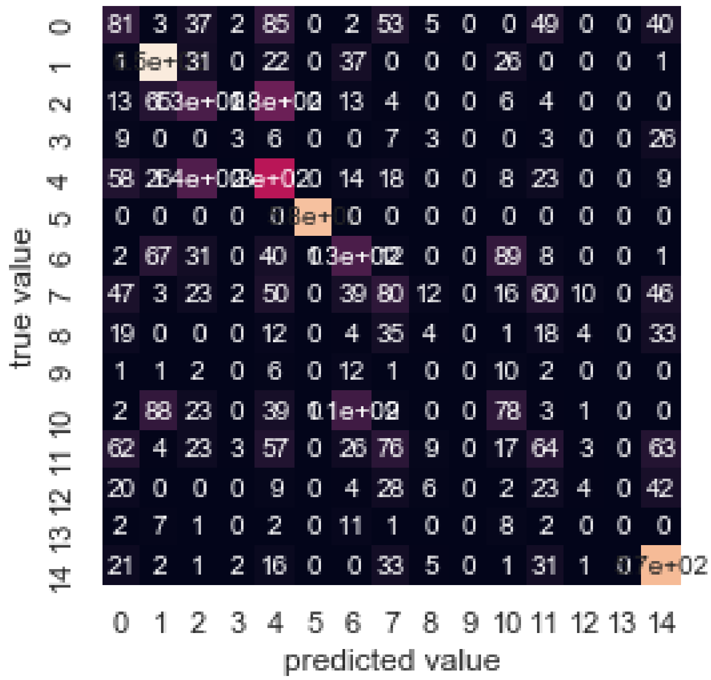
```
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/preprocessing/data.py:625: Data
  return self.partial_fit(X, y)
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/base.py:462: DataConversionWarn
  return self.fit(X, **fit_params).transform(X)
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/ipykernel_launcher.py:12: DataConversio
  if sys.path[0] == '':
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/ipykernel_launcher.py:17: DataConversio
```

```
Out[132]: KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski',
                     metric_params=None, n_jobs=None, n_neighbors=15, p=2,
                     weights='uniform')

Out[132]: <matplotlib.axes._subplots.AxesSubplot at 0x1c5ac43ac8>

Out[132]: Text(0.5, 12.5, 'predicted value')

Out[132]: Text(89.18, 0.5, 'true value')
```

```
0.5028184892897407
```

```
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/model_selection/_validation.py:
  estimator.fit(X_train, y_train, **fit_params)
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/model_selection/_validation.py:
  estimator.fit(X_train, y_train, **fit_params)
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/model_selection/_validation.py:
  estimator.fit(X_train, y_train, **fit_params)
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/model_selection/_validation.py:
  estimator.fit(X_train, y_train, **fit_params)
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/model_selection/_validation.py:
  estimator.fit(X_train, y_train, **fit_params)
```

```
[0.4635314  0.50676056 0.48830657 0.49083733 0.52230378]
```



Classifying Overall Rating: Random Forrest

```
In [133]: #Model Creation
          y=data[['Overall']].copy()
          X=data[attribute_profile].copy()
          # Splitting the dataset into the Training set and Test set
          from sklearn.model_selection import train_test_split
          X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.3, random_stat
          # Feature Scaling
          from sklearn.preprocessing import StandardScaler
          sc = StandardScaler()
          X_train = sc.fit_transform(X_train)
          X_test = sc.transform(X_test)
          # Fitting Random Forest Classification to the Training set
          from sklearn.ensemble import RandomForestClassifier
          classifier = RandomForestClassifier(n_estimators = 100, criterion = 'gini')
          classifier.fit(X_train, y_train)
          predictions = classifier.predict(X_test)
          from sklearn.metrics import confusion_matrix
          cm = pd.DataFrame(confusion_matrix(y_test, predictions))
          cm.head()
          #Import scikit-learn metrics module for accuracy calculation
          from sklearn import metrics

          # Model Accuracy, how often is the classifier correct?
```

```python
print("Accuracy:",metrics.accuracy_score(y_test, predictions))
from sklearn.metrics import mean_squared_error
RMSE_test=sqrt(mean_squared_error(y_true=y_test,y_pred=predictions))
print("Root Mean Square Error of test set is:" ,RMSE_test)
from sklearn import metrics
from sklearn.model_selection import cross_val_score
CVscores=cross_val_score(classifier, X, y, cv=5)
print(CVscores)
fig,ax=plt.subplots()
predicted=predictions
true=y_test
ax.scatter(predicted,true)
plt.xlabel('Predicted Overall')
plt.ylabel('True Overall')
plt.title('Predicted vs True')
plt.grid(True)
```

```
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/preprocessing/data.py:625: Data
  return self.partial_fit(X, y)
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/base.py:462: DataConversionWarn
  return self.fit(X, **fit_params).transform(X)
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/ipykernel_launcher.py:11: DataConversio
  # This is added back by InteractiveShellApp.init_path()
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/ipykernel_launcher.py:15: DataConversio
  from ipykernel import kernelapp as app
```

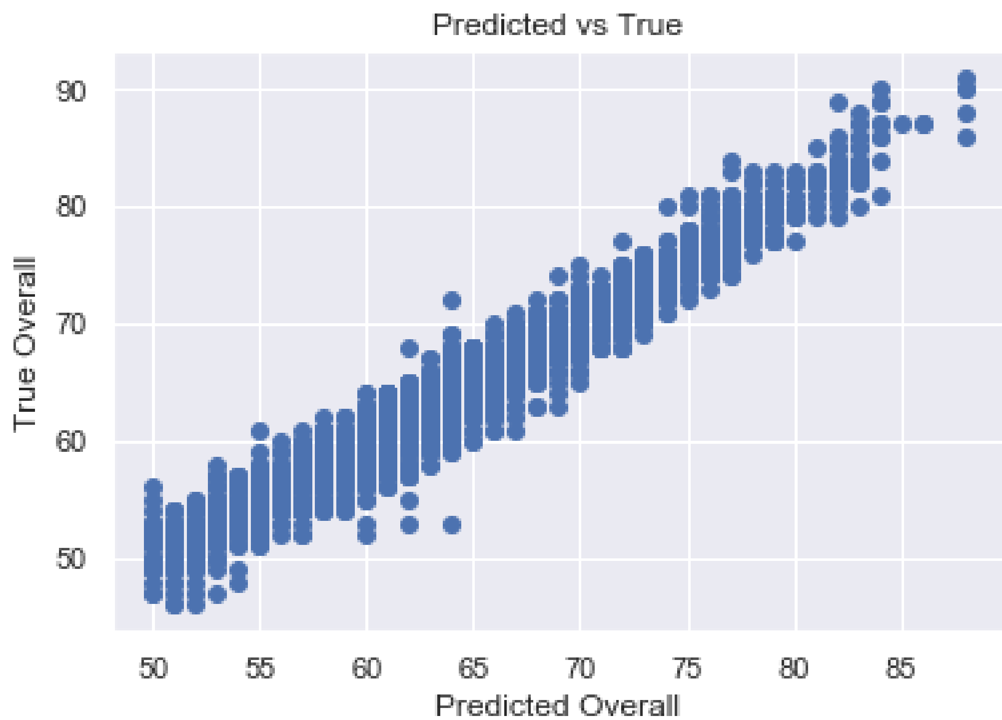
```
Out[133]: RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
                      max_depth=None, max_features='auto', max_leaf_nodes=None,
                      min_impurity_decrease=0.0, min_impurity_split=None,
                      min_samples_leaf=1, min_samples_split=2,
                      min_weight_fraction_leaf=0.0, n_estimators=100, n_jobs=None,
                      oob_score=False, random_state=None, verbose=0,
                      warm_start=False)
```

Out[133]:

	0	1	2	3	4	5	6	7	8	9	...	36	37	38	39	40	41	42	43	\
0	0	0	0	0	0	2	1	0	0	0	...	0	0	0	0	0	0	0	0	
1	0	0	0	0	2	1	1	1	0	0	...	0	0	0	0	0	0	0	0	
2	0	0	0	0	1	2	1	0	1	0	...	0	0	0	0	0	0	0	0	
3	0	0	0	0	6	6	3	1	1	0	...	0	0	0	0	0	0	0	0	
4	0	0	0	0	5	8	9	6	0	0	...	0	0	0	0	0	0	0	0	

	44	45
0	0	0
1	0	0
2	0	0
3	0	0
4	0	0

```
[5 rows x 46 columns]

Accuracy: 0.43987222848553176
Root Mean Square Error of test set is: 1.478074760667067


/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/model_selection/_split.py:652:
  % (min_groups, self.n_splits)), Warning)
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/model_selection/_validation.py:
  estimator.fit(X_train, y_train, **fit_params)
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/model_selection/_validation.py:
  estimator.fit(X_train, y_train, **fit_params)
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/model_selection/_validation.py:
  estimator.fit(X_train, y_train, **fit_params)
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/model_selection/_validation.py:
  estimator.fit(X_train, y_train, **fit_params)
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/model_selection/_validation.py:
  estimator.fit(X_train, y_train, **fit_params)


[0.42173061 0.41880101 0.43843336 0.45122986 0.43893454]


Out[133]: <matplotlib.collections.PathCollection at 0x1c58ac5dd8>

Out[133]: Text(0.5, 0, 'Predicted Overall')

Out[133]: Text(0, 0.5, 'True Overall')

Out[133]: Text(0.5, 1.0, 'Predicted vs True')
```



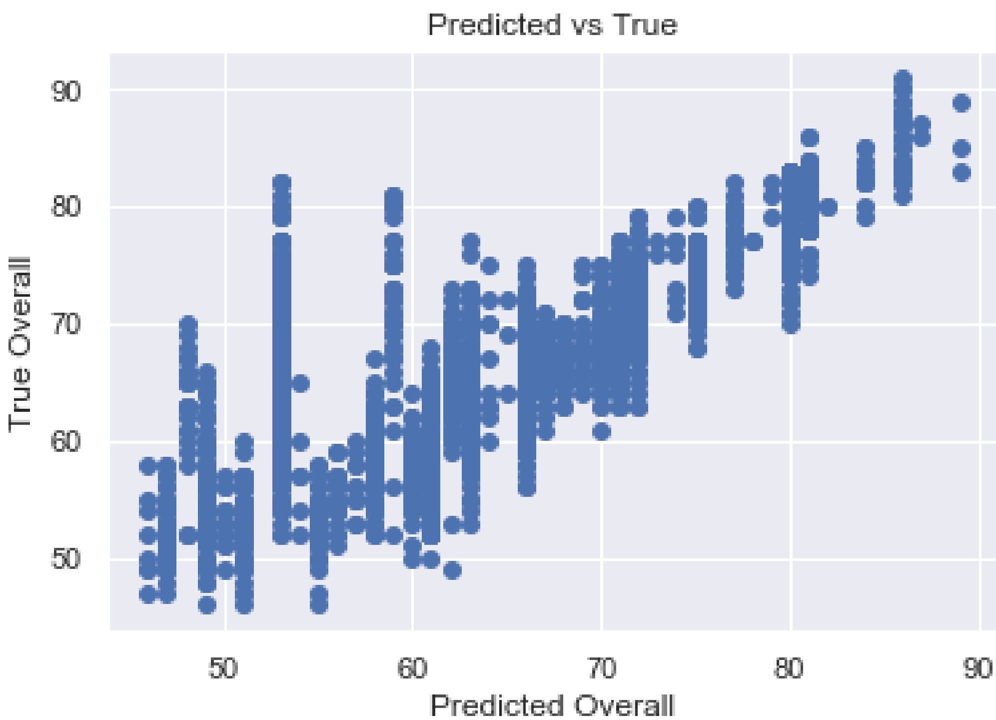
Classifying Overall Rating: Bayesian Classification

```
In [125]: #Model Creation
          y=data[['Overall']].copy()
          X=data[attribute_profile].copy()
          # Splitting the dataset into the Training set and Test set
          from sklearn.model_selection import train_test_split
          X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.3, random_stat
          # Feature Scaling
          from sklearn.preprocessing import StandardScaler
          sc = StandardScaler()
          X_train = sc.fit_transform(X_train)
          X_test = sc.transform(X_test)
          from sklearn.naive_bayes import GaussianNB
          classifier= GaussianNB()
          classifier.fit(X_train, y_train)

          # Predicting the Test set results
          y_pred = classifier.predict(X_test)

          # Making the Confusion Matrix
          from sklearn.metrics import confusion_matrix
          cm = pd.DataFrame(confusion_matrix(y_test, predictions))
          #Import scikit-learn metrics module for accuracy calculation
```

```python
from sklearn import metrics

# Model Accuracy, how often is the classifier correct?
print("Accuracy:",metrics.accuracy_score(y_test,y_pred))
from sklearn.metrics import mean_squared_error
RMSE_test=sqrt(mean_squared_error(y_true=y_test,y_pred=y_pred))
print("Root Mean Square Error of test set is:" ,RMSE_test)

fig,ax=plt.subplots()
predicted=y_pred
true=y_test
ax.scatter(predicted,true)
plt.xlabel('Predicted Overall')
plt.ylabel('True Overall')
plt.title('Predicted vs True')
plt.grid(True)
```

```
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/preprocessing/data.py:625: Data
  return self.partial_fit(X, y)
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/base.py:462: DataConversionWarn
  return self.fit(X, **fit_params).transform(X)
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/ipykernel_launcher.py:11: DataConversio
  # This is added back by InteractiveShellApp.init_path()
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/utils/validation.py:761: DataCo
  y = column_or_1d(y, warn=True)
```

```
Out[125]: GaussianNB(priors=None, var_smoothing=1e-09)

Accuracy: 0.11724915445321307
Root Mean Square Error of test set is: 5.25817843325294

Out[125]: <matplotlib.collections.PathCollection at 0x1c58a0da90>

Out[125]: Text(0.5, 0, 'Predicted Overall')

Out[125]: Text(0, 0.5, 'True Overall')

Out[125]: Text(0.5, 1.0, 'Predicted vs True')
```



Classifying Overall Rating: Support Vector Machine

```
In [5]: #Model Creation
        y=data[['Overall']].copy()
        X=data[attribute_profile].copy()


        # Splitting the dataset into the Training set and Test set
        from sklearn.model_selection import train_test_split
        X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.3, random_state
        # Feature Scaling
        from sklearn.preprocessing import StandardScaler
        sc = StandardScaler()
        X_train = sc.fit_transform(X_train)
        X_test = sc.transform(X_test)
        # Fitting SVM to the Training set
        from sklearn.svm import SVC
        classifier = SVC(kernel = 'linear', random_state = 0)
        classifier.fit(X_train, y_train)
        # Predicting the Test set results
        y_pred = classifier.predict(X_test)

        # Making the Confusion Matrix
        from sklearn.metrics import confusion_matrix
```

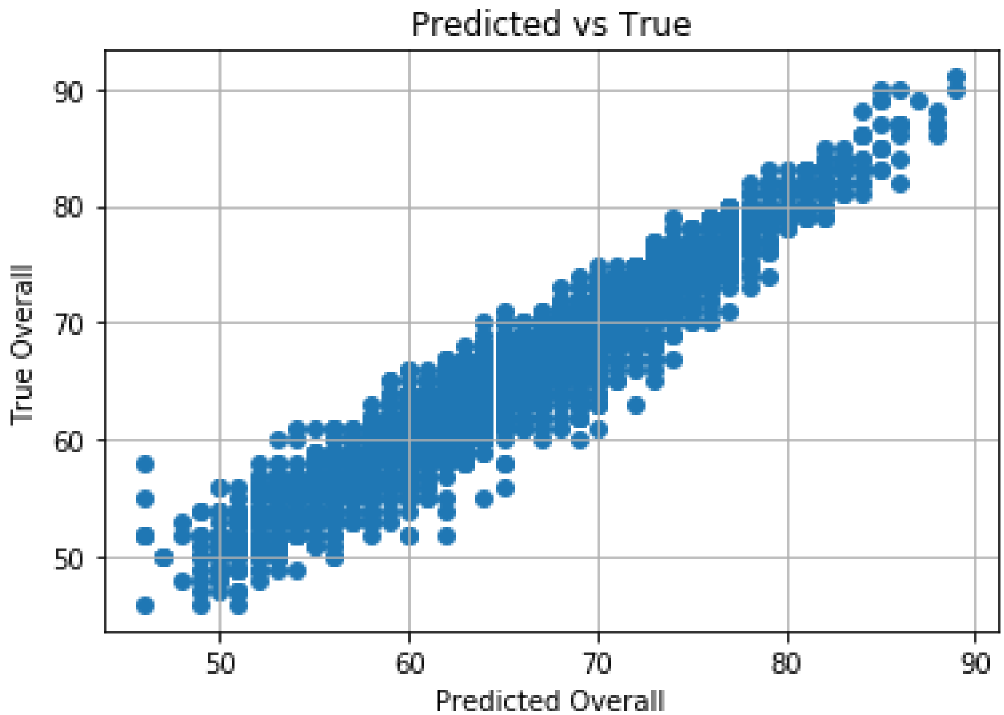
```
cm = pd.DataFrame(confusion_matrix(y_test, y_pred))
#Import scikit-learn metrics module for accuracy calculation
from sklearn import metrics

# Model Accuracy, how often is the classifier correct?
print("Accuracy:",metrics.accuracy_score(y_test,y_pred))
from sklearn.metrics import mean_squared_error
RMSE_test=sqrt(mean_squared_error(y_true=y_test,y_pred=y_pred))
print("Root Mean Square Error of test set is:" ,RMSE_test)
from sklearn import metrics
from sklearn.model_selection import cross_val_score
#CVscores=cross_val_score(classifier, X, y, cv=5)
#print(CVscores)
fig,ax=plt.subplots()
predicted=y_pred
true=y_test
ax.scatter(predicted,true)
plt.xlabel('Predicted Overall')
plt.ylabel('True Overall')
plt.title('Predicted vs True')
plt.grid(True)
```

```
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/preprocessing/data.py:625: Data
  return self.partial_fit(X, y)
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/base.py:462: DataConversionWarn
  return self.fit(X, **fit_params).transform(X)
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/ipykernel_launcher.py:13: DataConversio
  del sys.path[0]
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/utils/validation.py:761: DataCo
  y = column_or_1d(y, warn=True)
```

```
Out[5]: SVC(C=1.0, cache_size=200, class_weight=None, coef0=0.0,
          decision_function_shape='ovr', degree=3, gamma='auto_deprecated',
          kernel='linear', max_iter=-1, probability=False, random_state=0,
          shrinking=True, tol=0.001, verbose=False)
```

```
Accuracy: 0.22904922961292748
Root Mean Square Error of test set is: 1.996709054915415
```

```
Out[5]: <matplotlib.collections.PathCollection at 0x104ea3c88>

Out[5]: Text(0.5, 0, 'Predicted Overall')

Out[5]: Text(0, 0.5, 'True Overall')

Out[5]: Text(0.5, 1.0, 'Predicted vs True')
```



Classifying Overall Rating: Kernel SVM

```
In [128]: #Model Creation
          y=data[['Overall']].copy()
          X=data[attribute_profile].copy()


          # Splitting the dataset into the Training set and Test set
          from sklearn.model_selection import train_test_split
          X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.3, random_stat
          # Feature Scaling
          from sklearn.preprocessing import StandardScaler
          sc = StandardScaler()
          X_train = sc.fit_transform(X_train)
          X_test = sc.transform(X_test)

          # Fitting Kernel SVM to the Training set
          from sklearn.svm import SVC
          classifier = SVC(kernel = 'rbf', random_state = 0)
          classifier.fit(X_train, y_train)

          # Predicting the Test set results
          y_pred = classifier.predict(X_test)

          # Making the Confusion Matrix
```

```
from sklearn.metrics import confusion_matrix
cm = pd.DataFrame(confusion_matrix(y_test, predictions))


#Import scikit-learn metrics module for accuracy calculation
from sklearn import metrics

# Model Accuracy, how often is the classifier correct?
print("Accuracy:",metrics.accuracy_score(y_test,y_pred))
from sklearn.metrics import mean_squared_error
RMSE_test=sqrt(mean_squared_error(y_true=y_test,y_pred=y_pred))
print("Root Mean Square Error of test set is:" ,RMSE_test)
from sklearn import metrics
from sklearn.model_selection import cross_val_score
#CVscores=cross_val_score(classifier, X, y, cv=5)
#print(CVscores)
fig,ax=plt.subplots()
predicted=y_pred
true=y_test
ax.scatter(predicted,true)
plt.xlabel('Predicted Overall')
plt.ylabel('True Overall')
plt.title('Predicted vs True')
plt.grid(True)
```

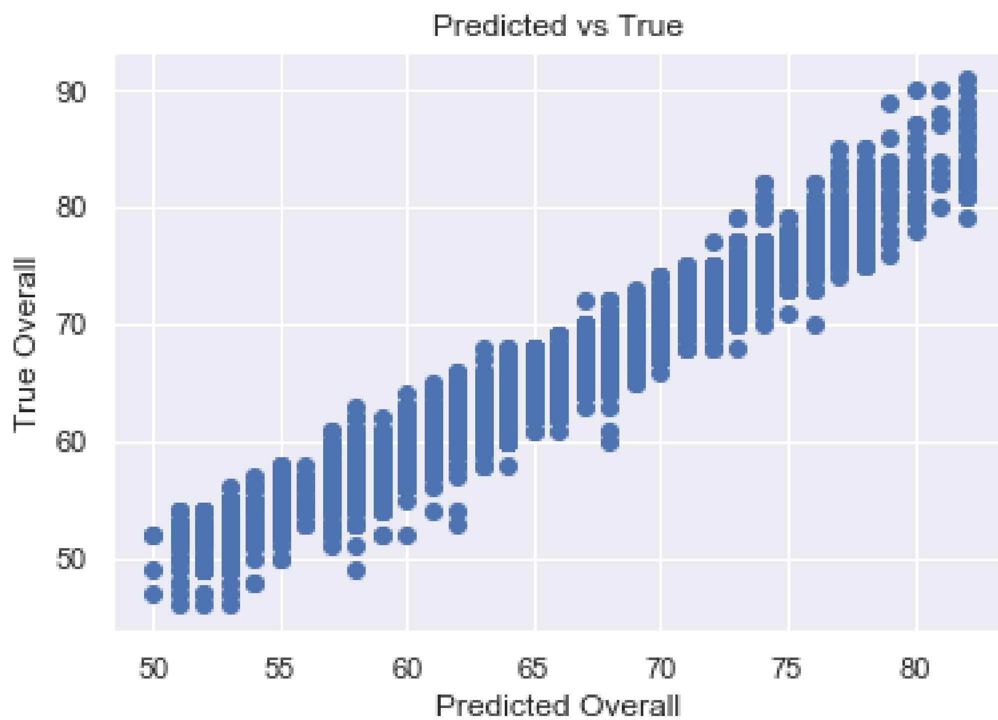
```
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/preprocessing/data.py:625: Data
  return self.partial_fit(X, y)
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/base.py:462: DataConversionWarn
  return self.fit(X, **fit_params).transform(X)
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/ipykernel_launcher.py:13: DataConversio
  del sys.path[0]
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/utils/validation.py:761: DataCo
  y = column_or_1d(y, warn=True)
```

```
Out[128]: SVC(C=1.0, cache_size=200, class_weight=None, coef0=0.0,
            decision_function_shape='ovr', degree=3, gamma='auto_deprecated',
            kernel='rbf', max_iter=-1, probability=False, random_state=0,
            shrinking=True, tol=0.001, verbose=False)
```

```
Accuracy: 0.2856069146937242
Root Mean Square Error of test set is: 1.715974857226964
```

```
Out[128]: <matplotlib.collections.PathCollection at 0x1c53dac128>

Out[128]: Text(0.5, 0, 'Predicted Overall')

Out[128]: Text(0, 0.5, 'True Overall')
```

Out[128]: Text(0.5, 1.0, 'Predicted vs True')



Classifying Overall Rating: Logistic Regression

In [129]:
```
#Model Creation
y=data[['Overall']].copy()
X=data[attribute_profile].copy()


# Splitting the dataset into the Training set and Test set
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.3, random_stat
# Feature Scaling
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
# Fitting Logistic Regression to the Training set
from sklearn.linear_model import LogisticRegression
classifier = LogisticRegression(random_state = 0)
classifier.fit(X_train, y_train)
# Predicting the Test set results
y_pred = classifier.predict(X_test)

# Making the Confusion Matrix
```

```python
from sklearn.metrics import confusion_matrix
cm = pd.DataFrame(confusion_matrix(y_test, predictions))


#Import scikit-learn metrics module for accuracy calculation
from sklearn import metrics

# Model Accuracy, how often is the classifier correct?
print("Accuracy:",metrics.accuracy_score(y_test,y_pred))
from sklearn.metrics import mean_squared_error
RMSE_test=sqrt(mean_squared_error(y_true=y_test,y_pred=y_pred))
print("Root Mean Square Error of test set is:" ,RMSE_test)

fig,ax=plt.subplots()
predicted=y_pred
true=y_test
ax.scatter(predicted,true)
plt.xlabel('Predicted Overall')
plt.ylabel('True Overall')
plt.title('Predicted vs True')
plt.grid(True)
```

```
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/preprocessing/data.py:625: Data
  return self.partial_fit(X, y)
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/base.py:462: DataConversionWarn
  return self.fit(X, **fit_params).transform(X)
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/ipykernel_launcher.py:13: DataConversio
  del sys.path[0]
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/linear_model/logistic.py:433: F
  FutureWarning)
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/utils/validation.py:761: DataCo
  y = column_or_1d(y, warn=True)
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/linear_model/logistic.py:460: F
  "this warning.", FutureWarning)
```

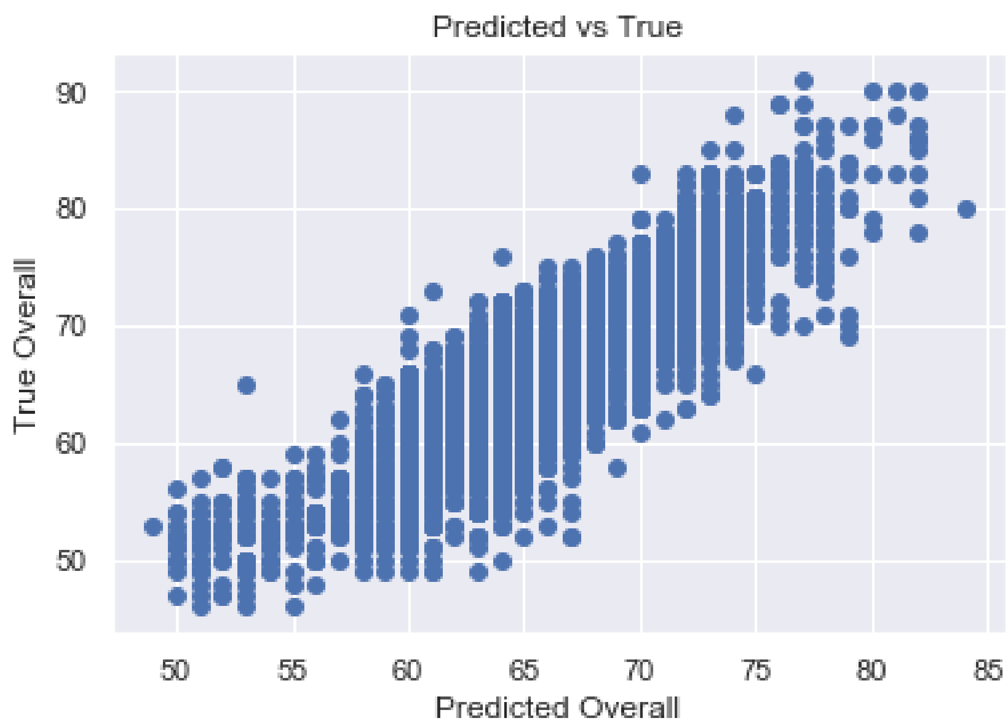
```
Out[129]: LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
                    intercept_scaling=1, max_iter=100, multi_class='warn',
                    n_jobs=None, penalty='l2', random_state=0, solver='warn',
                    tol=0.0001, verbose=0, warm_start=False)
```

```
Accuracy: 0.11649755730928223
Root Mean Square Error of test set is: 3.657550760389424
```

```
Out[129]: <matplotlib.collections.PathCollection at 0x1c5b16c208>
```

```
Out[129]: Text(0.5, 0, 'Predicted Overall')
```

```
Out[129]: Text(0, 0.5, 'True Overall')

Out[129]: Text(0.5, 1.0, 'Predicted vs True')
```



Classifying Overall Rating: Linear Discriminant Analysis Classifier

```
In [130]: #Model Creation
          y=data[['Overall']].copy()
          X=data[attribute_profile].copy()


          # Splitting the dataset into the Training set and Test set
          from sklearn.model_selection import train_test_split
          X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.3, random_stat
          # Feature Scaling
          from sklearn.preprocessing import StandardScaler
          sc = StandardScaler()
          X_train = sc.fit_transform(X_train)
          X_test = sc.transform(X_test)
          # Fitting LDA Classification to the Training set
          from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
          classifier = LinearDiscriminantAnalysis(solver='svd', tol=0.0001)
          classifier.fit(X_train, y_train)
          # Predicting the Test set results
          y_pred = classifier.predict(X_test)
```

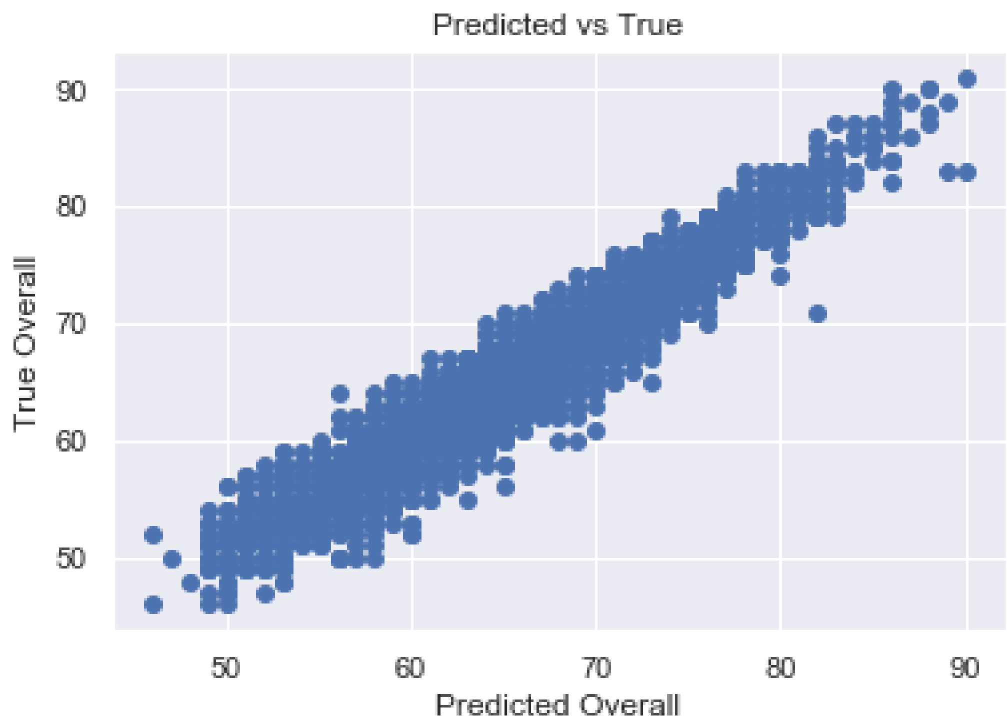
```
# Making the Confusion Matrix
from sklearn.metrics import confusion_matrix
cm = pd.DataFrame(confusion_matrix(y_test, predictions))


#Import scikit-learn metrics module for accuracy calculation
from sklearn import metrics

# Model Accuracy, how often is the classifier correct?
print("Accuracy:",metrics.accuracy_score(y_test,y_pred))
from sklearn.metrics import mean_squared_error
RMSE_test=sqrt(mean_squared_error(y_true=y_test,y_pred=y_pred))
print("Root Mean Square Error of test set is:" ,RMSE_test)

fig,ax=plt.subplots()
predicted=y_pred
true=y_test
ax.scatter(predicted,true)
plt.xlabel('Predicted Overall')
plt.ylabel('True Overall')
plt.title('Predicted vs True')
plt.grid(True)
```

```
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/preprocessing/data.py:625: Data
  return self.partial_fit(X, y)
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/base.py:462: DataConversionWarn
  return self.fit(X, **fit_params).transform(X)
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/ipykernel_launcher.py:13: DataConversio
  del sys.path[0]
/Users/lucasnewman/anaconda3/lib/python3.6/site-packages/sklearn/utils/validation.py:761: DataCo
  y = column_or_1d(y, warn=True)
```

```
Out[130]: LinearDiscriminantAnalysis(n_components=None, priors=None, shrinkage=None,
                        solver='svd', store_covariance=False, tol=0.0001)
```

```
Accuracy: 0.21984216459977451
Root Mean Square Error of test set is: 2.0376482822999695
```

```
Out[130]: <matplotlib.collections.PathCollection at 0x1c5b17ca58>

Out[130]: Text(0.5, 0, 'Predicted Overall')

Out[130]: Text(0, 0.5, 'True Overall')

Out[130]: Text(0.5, 1.0, 'Predicted vs True')
```



Classifying Overall Rating: Clasifier Performance Conclusion

The two best performing models for classifying Oveall rating were Random Forrest Classification and Kernel SVM.

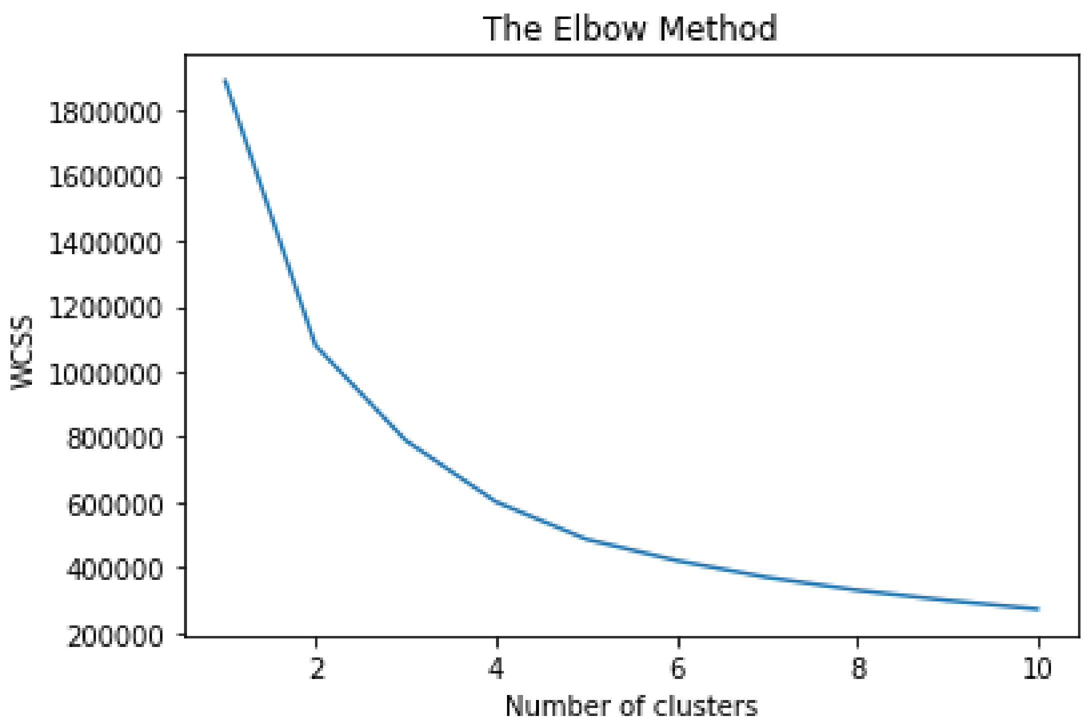
Clustering Basic Attributes

```
In [5]: data=pd.read_csv("Full_DF.csv")
        #Model Creation
        #y=data[['Overall']].copy()
        X=data[['Overall', 'Potential', 'age']].copy()



        # Splitting the dataset into the Training set and Test set
        #from sklearn.model_selection import train_test_split
        #X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.3, random_state
        # Feature Scaling
        #from sklearn.preprocessing import StandardScaler
        #sc = StandardScaler()
        #X_train = sc.fit_transform(X_train)
        #X_test = sc.transform(X_test)
        #The Elbow Method for Finding Ideal # of Clusters
        from sklearn.cluster import KMeans
        wcss = []
        for i in range(1, 11):
```

```
        kmeans = KMeans(n_clusters = i, init = 'k-means++', random_state = 42)
        kmeans.fit(X)
        wcss.append(kmeans.inertia_)
    plt.plot(range(1, 11), wcss)
    plt.title('The Elbow Method')
    plt.xlabel('Number of clusters')
    plt.ylabel('WCSS')
    plt.show()
    #The Elbow method above shows that about 3 Clusters is appropriate
    from sklearn.cluster import KMeans
    kmeans = KMeans(n_clusters = 3, init = 'k-means++', random_state = 42)
    y_kmeans = kmeans.fit_predict(X)
    kmeans.labels_
    cluster_centers=kmeans.cluster_centers_
    score=kmeans.score(X)
    y_kmeans
```

```
Out[5]: KMeans(algorithm='auto', copy_x=True, init='k-means++', max_iter=300,
            n_clusters=1, n_init=10, n_jobs=None, precompute_distances='auto',
            random_state=42, tol=0.0001, verbose=0)

Out[5]: KMeans(algorithm='auto', copy_x=True, init='k-means++', max_iter=300,
            n_clusters=2, n_init=10, n_jobs=None, precompute_distances='auto',
            random_state=42, tol=0.0001, verbose=0)

Out[5]: KMeans(algorithm='auto', copy_x=True, init='k-means++', max_iter=300,
            n_clusters=3, n_init=10, n_jobs=None, precompute_distances='auto',
            random_state=42, tol=0.0001, verbose=0)

Out[5]: KMeans(algorithm='auto', copy_x=True, init='k-means++', max_iter=300,
            n_clusters=4, n_init=10, n_jobs=None, precompute_distances='auto',
            random_state=42, tol=0.0001, verbose=0)

Out[5]: KMeans(algorithm='auto', copy_x=True, init='k-means++', max_iter=300,
            n_clusters=5, n_init=10, n_jobs=None, precompute_distances='auto',
            random_state=42, tol=0.0001, verbose=0)

Out[5]: KMeans(algorithm='auto', copy_x=True, init='k-means++', max_iter=300,
            n_clusters=6, n_init=10, n_jobs=None, precompute_distances='auto',
            random_state=42, tol=0.0001, verbose=0)

Out[5]: KMeans(algorithm='auto', copy_x=True, init='k-means++', max_iter=300,
            n_clusters=7, n_init=10, n_jobs=None, precompute_distances='auto',
            random_state=42, tol=0.0001, verbose=0)

Out[5]: KMeans(algorithm='auto', copy_x=True, init='k-means++', max_iter=300,
            n_clusters=8, n_init=10, n_jobs=None, precompute_distances='auto',
            random_state=42, tol=0.0001, verbose=0)
```

```
Out[5]: KMeans(algorithm='auto', copy_x=True, init='k-means++', max_iter=300,
            n_clusters=9, n_init=10, n_jobs=None, precompute_distances='auto',
            random_state=42, tol=0.0001, verbose=0)

Out[5]: KMeans(algorithm='auto', copy_x=True, init='k-means++', max_iter=300,
            n_clusters=10, n_init=10, n_jobs=None, precompute_distances='auto',
            random_state=42, tol=0.0001, verbose=0)

Out[5]: [<matplotlib.lines.Line2D at 0x1c1e355710>]

Out[5]: Text(0.5, 1.0, 'The Elbow Method')

Out[5]: Text(0.5, 0, 'Number of clusters')

Out[5]: Text(0, 0.5, 'WCSS')
```




```
Out[5]: array([1, 1, 1, ..., 0, 0, 0], dtype=int32)

Out[5]: array([1, 1, 1, ..., 0, 0, 0], dtype=int32)
```

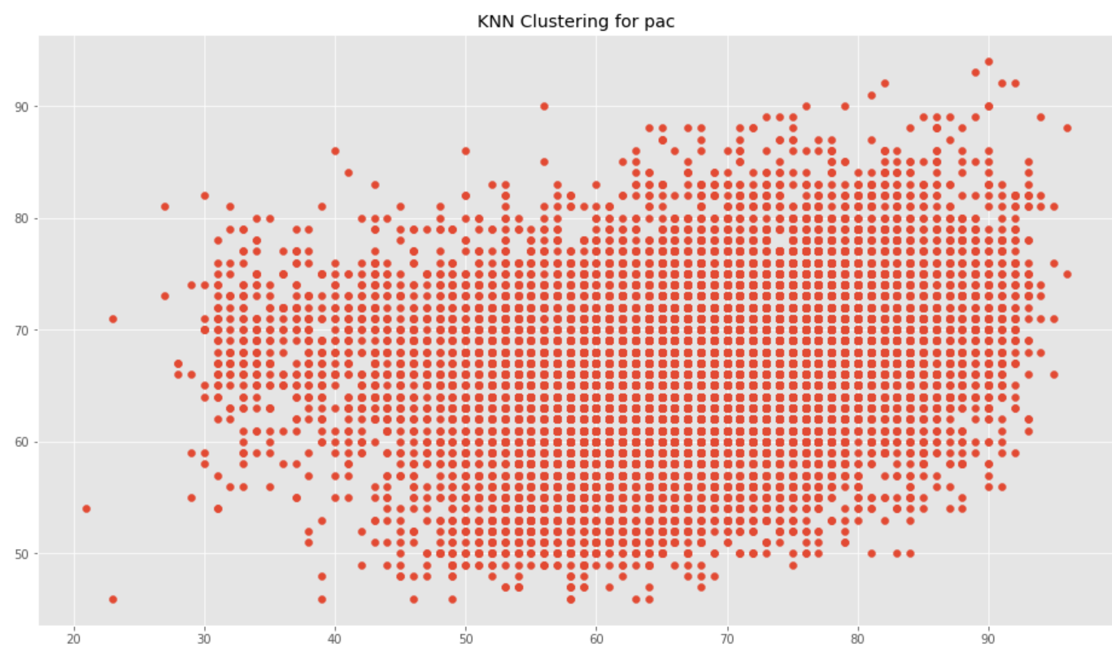
```
In [6]: #clustering basic features
        import numpy as np
        import pandas as pd
        %matplotlib inline
        from matplotlib import pyplot as plt
```

```python
plt.rcParams['figure.figsize'] = (16, 9)
plt.style.use('ggplot')
from matplotlib.colors import ListedColormap
from sklearn.neighbors import KNeighborsClassifier
from sklearn import datasets, linear_model
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.cluster import KMeans
from sklearn import metrics
from scipy.spatial.distance import cdist
import tkinter as tk
import statsmodels.api as sm
fifa_data_orig = pd.read_csv('full_fifa18_data.csv')
#Creating the KNN Dataset with Attributes
clustData = fifa_data_orig.copy()
clustDep = clustData['Overall']
knnFeatures = clustData[['pac', 'sho', 'dri', 'pas', 'defend', 'phy', 'reactions']]
print(knnFeatures[0:5])

#K Nearest Neighbor
knnModel = KNeighborsClassifier(n_neighbors = 4)
#Running the model with testing data
knnModel.fit(knnFeatures, clustDep)
#Prediction using the testing data
y_pred = knnModel.predict(knnFeatures)
x_min, x_max = knnFeatures.min() - 1, knnFeatures.max() + 1
y_min, y_max = knnFeatures.min() - 1, knnFeatures.max() + 1
#xx, yy = np.meshgrid(np.arange(x_min, x_max), np.arange(y_min, y_max))
plt.scatter(knnFeatures['pac'], clustDep)
#plt.xlim(x_min(), x_max())
#plt.ylim(y_min(), y_max())

#Plotting KNN
plt.title("KNN Clustering for pac")
plt.show()

plt.scatter(knnFeatures['sho'], clustDep)
plt.title("KNN Clustering for sho")
plt.show()

plt.scatter(knnFeatures['dri'], clustDep)
plt.title("KNN Clustering for dri")
plt.show()

plt.scatter(knnFeatures['pas'], clustDep)
plt.title("KNN Clustering for pas")
plt.show()
```

```
plt.scatter(knnFeatures['defend'], clustDep)
plt.title("KNN Clustering for defend")
plt.show()

plt.scatter(knnFeatures['phy'], clustDep)
plt.title("KNN Clustering for phy")
plt.show()

plt.scatter(knnFeatures['reactions'], clustDep)
plt.title("KNN Clustering for reactions")
plt.show()
```

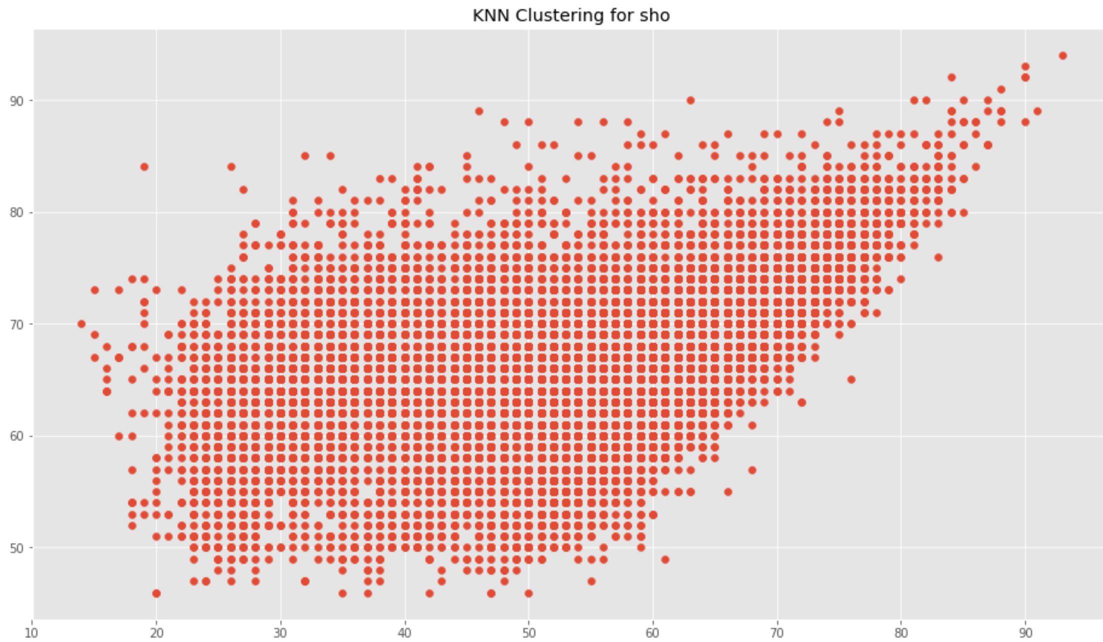
```
   pac  sho  dri  pas  defend  phy  reactions
0   90   93   90   82      33   80         96
1   89   90   96   86      26   61         95
2   92   84   95   79      30   60         88
3   82   90   87   79      42   81         93
4   91   90   89   95      60   91         85
```

```
Out[6]: KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski',
                     metric_params=None, n_jobs=None, n_neighbors=4, p=2,
                     weights='uniform')

Out[6]: <matplotlib.collections.PathCollection at 0x1c1fb0c198>

Out[6]: Text(0.5, 1.0, 'KNN Clustering for pac')
```



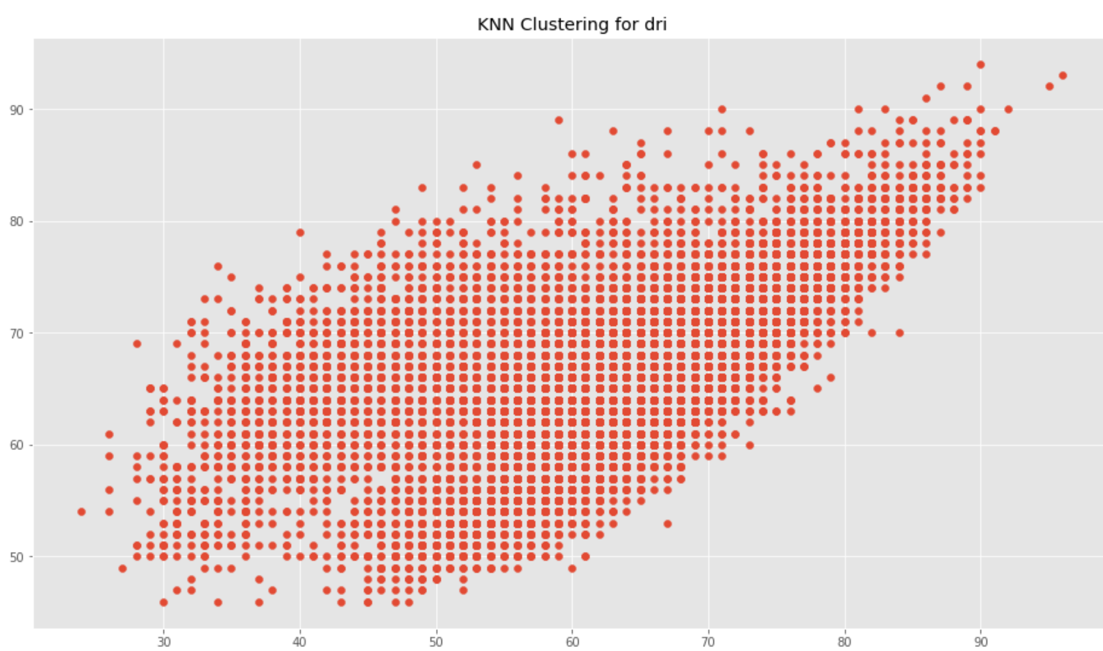
Out[6]: <matplotlib.collections.PathCollection at 0x1c1fe13438>

Out[6]: Text(0.5, 1.0, 'KNN Clustering for sho')



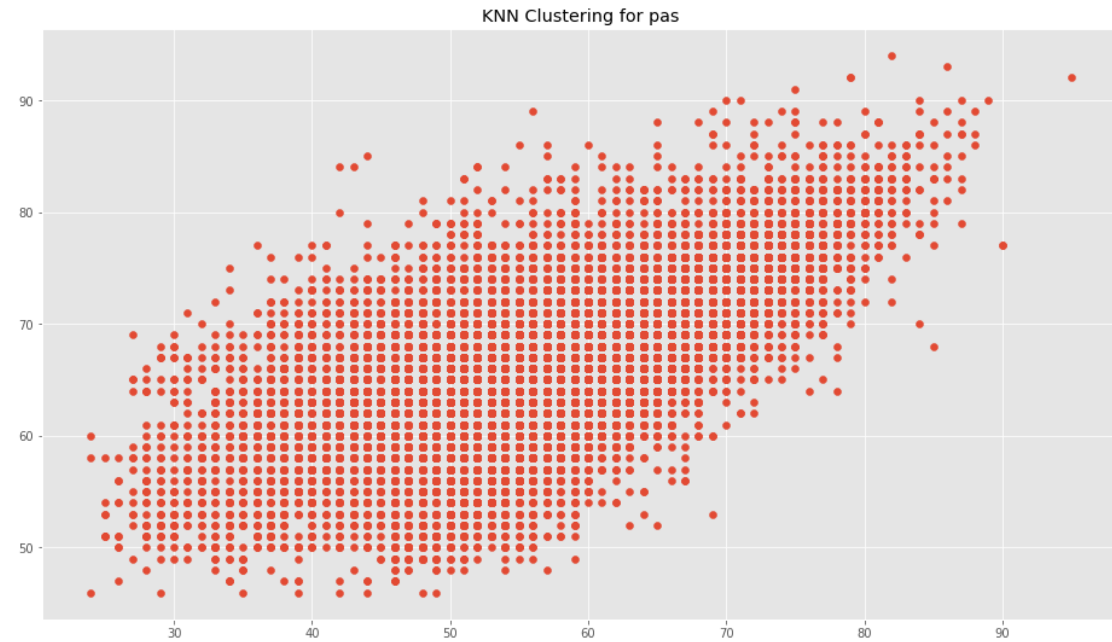
Out[6]: <matplotlib.collections.PathCollection at 0x1c2099db70>

Out[6]: Text(0.5, 1.0, 'KNN Clustering for dri')



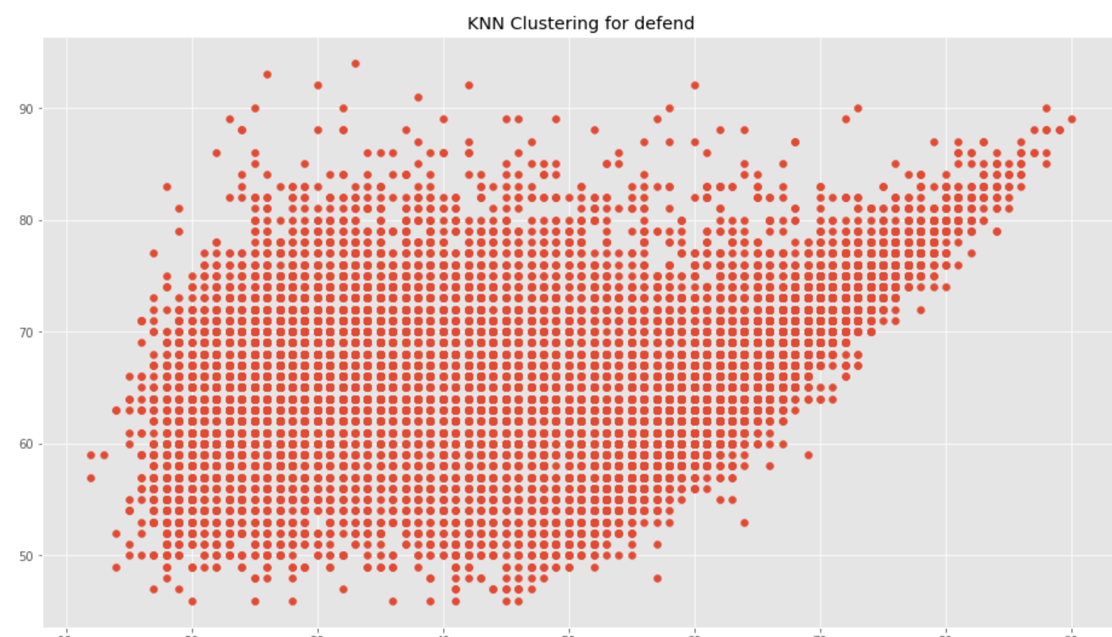
```
Out[6]: <matplotlib.collections.PathCollection at 0x1c2183c4a8>
```

```
Out[6]: Text(0.5, 1.0, 'KNN Clustering for pas')
```



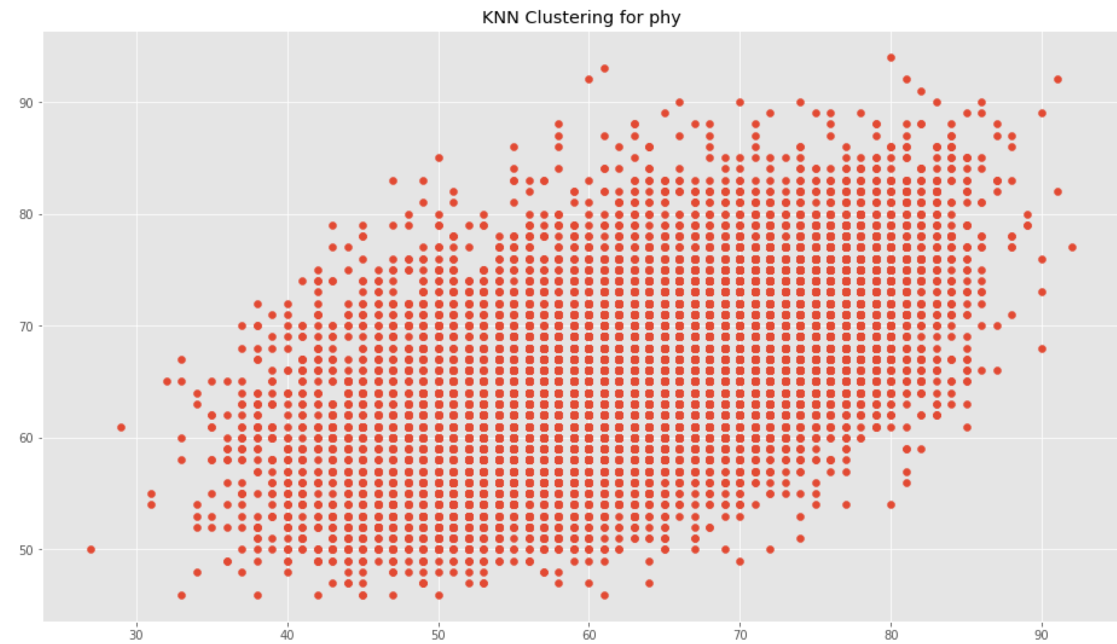

```
Out[6]: <matplotlib.collections.PathCollection at 0x1c224fcda0>
```

```
Out[6]: Text(0.5, 1.0, 'KNN Clustering for defend')
```



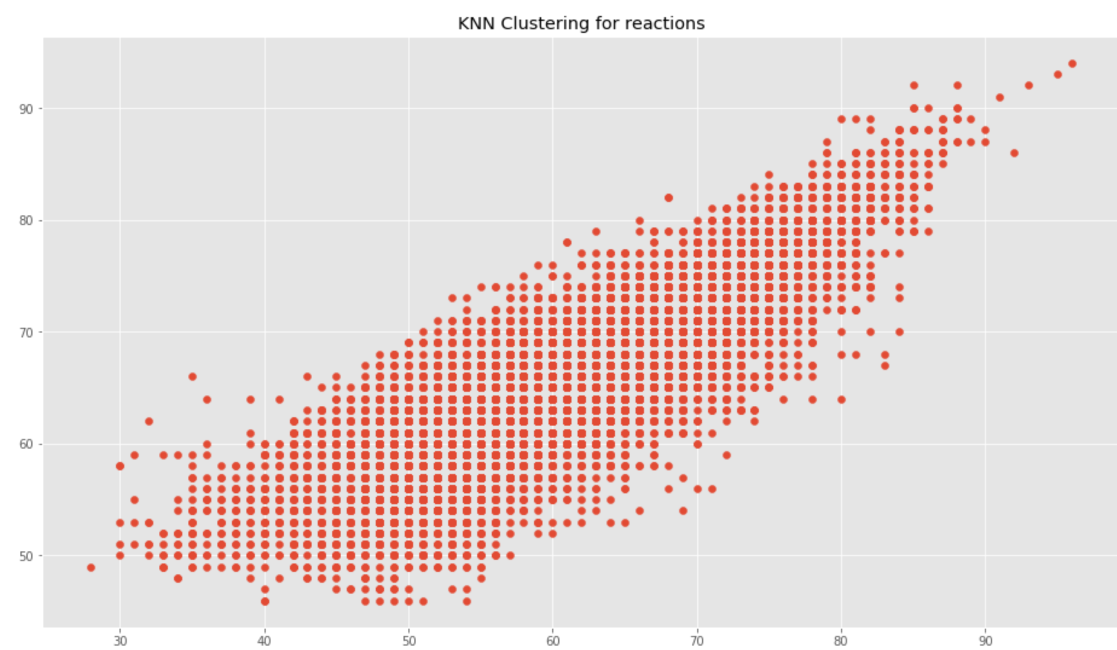
Out[6]: <matplotlib.collections.PathCollection at 0x1c225ad240>

Out[6]: Text(0.5, 1.0, 'KNN Clustering for phy')



Out[6]: <matplotlib.collections.PathCollection at 0x1c23888b38>

Out[6]: Text(0.5, 1.0, 'KNN Clustering for reactions')



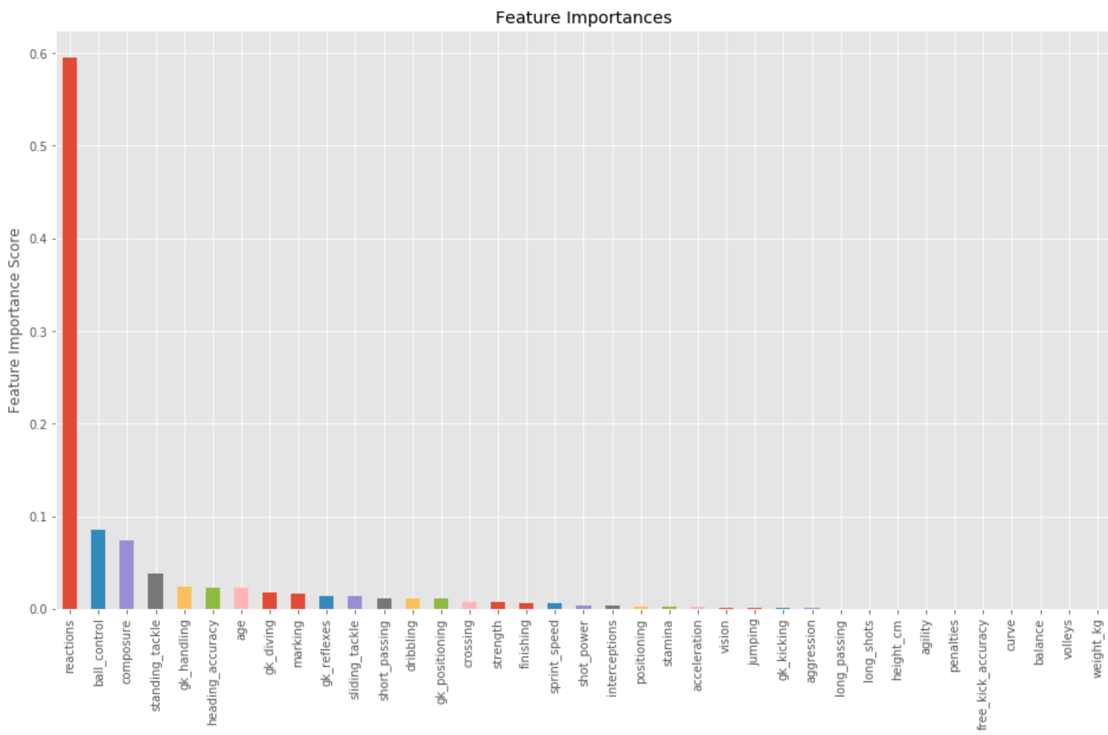
Feature Ranking for Overall & Potential with Gradient Boosting Machines and Hyperparameter Tuning with Grid Search

Overall Rating Feature Ranking

```
In [9]: from sklearn.metrics import mean_squared_error, accuracy_score
        from sklearn.ensemble import GradientBoostingRegressor
        from sklearn.model_selection import cross_validate
        from sklearn.model_selection import GridSearchCV
        from sklearn import metrics
        from sklearn.model_selection import cross_val_score
        from sklearn.model_selection import train_test_split
        from sklearn.model_selection import KFold
        from sklearn.model_selection import ShuffleSplit
        from sklearn.metrics import recall_score
        gb_model_overall=['Overall','age', 'height_cm', 'weight_kg', 'crossing', 'finishing', 'h
               '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', 'composure', 'marking', 'standing_tackle',
               'sliding_tackle', 'gk_diving', 'gk_handling', 'gk_kicking',
               'gk_positioning', 'gk_reflexes']
        dta=data[gb_model_overall]

        #Algorithm Design
        def modelfit(alg, dtrain, features, performCV=True, printFeatureImportance=True, cv_fold
            #Fit the algorithm on the data

            alg.fit(dtrain[features],dtrain["Overall"] )

            #Predict training set:
            dtrain_predictions = alg.predict(dtrain[features])

            #Perform cross-validation:
            cv_score =  cross_val_score(alg, dtrain[features], dtrain["Overall"], cv=cv_folds,
                                                       scoring='neg_mean_squared_error')
            cv_score = np.sqrt(np.abs(cv_score))

            #Print model report:
            print ("\nModel Report")
            print ("RMSE : %.4g" % np.sqrt(metrics.mean_squared_error(dtrain["Overall"], dtrain_
            print ("CV Score : Mean - %.4g | Std - %.4g | Min - %.4g | Max - %.4g" % (np.mean(cv
                                                                                  np.std(cv_s
                                                                                   np.max(cv_

            if printFeatureImportance:
                feat_imp = pd.Series(alg.feature_importances_, features).sort_values(ascending=F
```

```
        feat_imp.plot(kind='bar', title='Feature Importances')
        plt.ylabel('Feature Importance Score')
    #Gradient Boosting Regressor Fit
    features = [i for i in dta.columns if i != "Overall"]
    target = "Overall"
    gbm0 = GradientBoostingRegressor(random_state=7)
    modelfit(gbm0, dta, features)
```

```
Model Report
RMSE : 1.521
CV Score : Mean - 2.333 | Std - 1.408 | Min - 1.442 | Max - 5.53
```

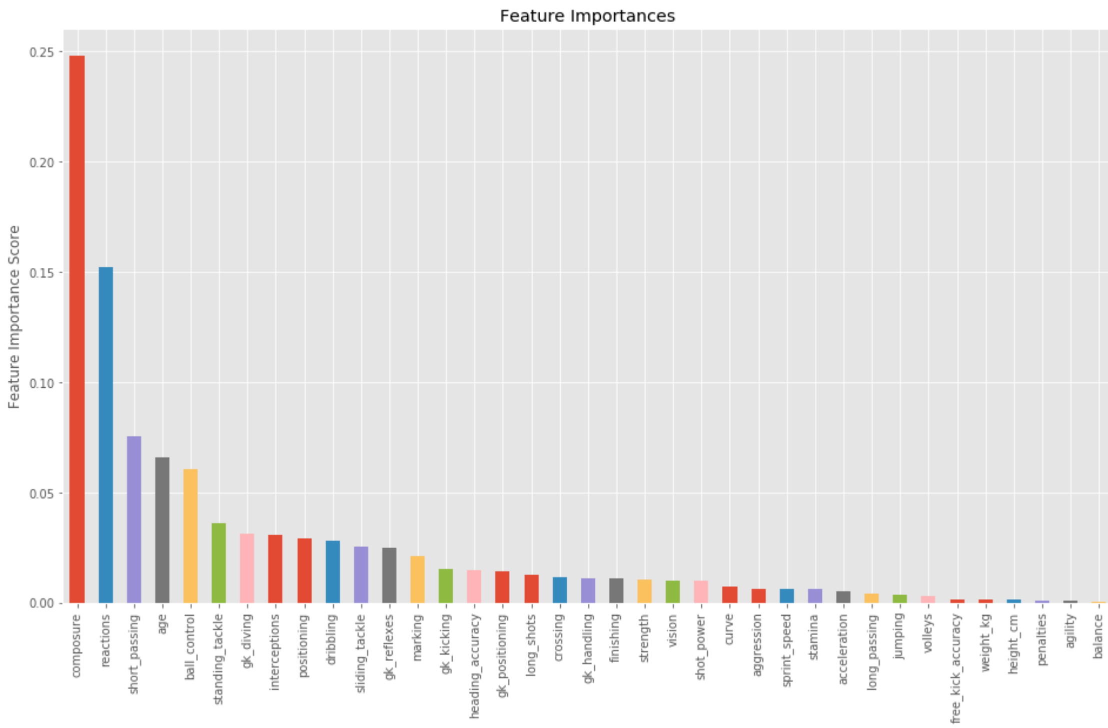



```
In [10]: #Tuning with GridSearch
         #Hyperparameter tuning of estimators with GridSearch
         estimators = [x for x in range(700,750,10)]
         param_test1 = {'n_estimators':estimators}
         gsearch1 = GridSearchCV(estimator = GradientBoostingRegressor(learning_rate=0.1, min_sa
                                          min_samples_leaf=50,max_depth=8,max_features='sqrt',
                                 param_grid = param_test1, scoring='neg_mean_squared_error',n_job
         gsearch1.fit(dta[features],dta["Overall"])

         gsearch1.score, gsearch1.best_params_, gsearch1.best_score_
         modelfit(gsearch1.best_estimator_, dta, features)
```

```
Out[10]: GridSearchCV(cv=10, error_score='raise-deprecating',
                estimator=GradientBoostingRegressor(alpha=0.9, criterion='friedman_mse', init=No
                      learning_rate=0.1, loss='ls', max_depth=8,
                      max_features='sqrt', max_leaf_nodes=None,
                      min_impurity_decrease=0.0, min_impurity_split=None,
                      min_samples_leaf=50, min_sa...       subsample=0.8, tol=0.0001, validation
                      warm_start=False),
                fit_params=None, iid=False, n_jobs=4,
                param_grid={'n_estimators': [700, 710, 720, 730, 740]},
                pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
                scoring='neg_mean_squared_error', verbose=0)
```

```
Out[10]: (<bound method BaseSearchCV.score of GridSearchCV(cv=10, error_score='raise-deprecating
                 estimator=GradientBoostingRegressor(alpha=0.9, criterion='friedman_mse', init=N
                       learning_rate=0.1, loss='ls', max_depth=8,
                       max_features='sqrt', max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=50, min_sa...       subsample=0.8, tol=0.0001, validatio
                       warm_start=False),
                 fit_params=None, iid=False, n_jobs=4,
                 param_grid={'n_estimators': [700, 710, 720, 730, 740]},
                 pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
                 scoring='neg_mean_squared_error', verbose=0)>,
          {'n_estimators': 740},
          -3.4734194554188926)
```

```
Model Report
RMSE : 0.6862
CV Score : Mean - 1.591 | Std - 0.971 | Min - 0.9888 | Max - 3.673
```

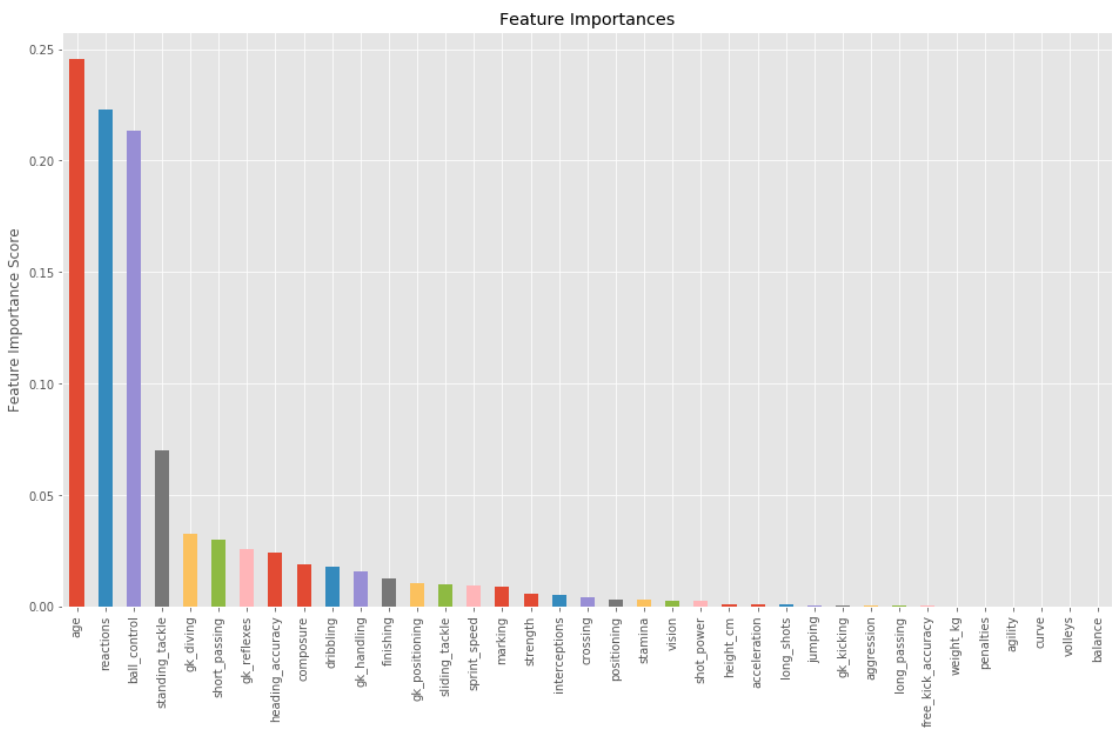


Potential Rating Feature Ranking

```
In [11]: gb_model_potential=['Potential','age', 'height_cm', 'weight_kg', 'crossing', 'finishing
                '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', 'composure', 'marking', 'standing_tackle',
                'sliding_tackle', 'gk_diving', 'gk_handling', 'gk_kicking',
                'gk_positioning', 'gk_reflexes']

         dta=data[gb_model_potential]
         #Algorithm Design
         def modelfit(alg, dtrain, features, performCV=True, printFeatureImportance=True, cv_fol
             #Fit the algorithm on the data

             alg.fit(dtrain[features],dtrain["Potential"] )

             #Predict training set:
             dtrain_predictions = alg.predict(dtrain[features])

             #Perform cross-validation:
             cv_score =  cross_val_score(alg, dtrain[features], dtrain["Potential"], cv=cv_folds
                                                        scoring='neg_mean_squared_error')
             cv_score = np.sqrt(np.abs(cv_score))
```

```
    #Print model report:
    print ("\nModel Report")
    print ("RMSE : %.4g" % np.sqrt(metrics.mean_squared_error(dtrain["Potential"], dtra
    print ("CV Score : Mean - %.4g | Std - %.4g | Min - %.4g | Max - %.4g" % (np.mean(c
                                                                              np.std(cv_
                                                                               np.max(cv

    if printFeatureImportance:
        feat_imp = pd.Series(alg.feature_importances_, features).sort_values(ascending=
        feat_imp.plot(kind='bar', title='Feature Importances')
        plt.ylabel('Feature Importance Score')
#Gradient Boosting Regressor Fit
features = [i for i in dta.columns if i != "Potential"]
target = "Potential"
gbm0 = GradientBoostingRegressor(random_state=7)
modelfit(gbm0, dta, features)
```

```
Model Report
RMSE : 2.241
CV Score : Mean - 2.903 | Std - 1.351 | Min - 1.908 | Max - 5.954
```



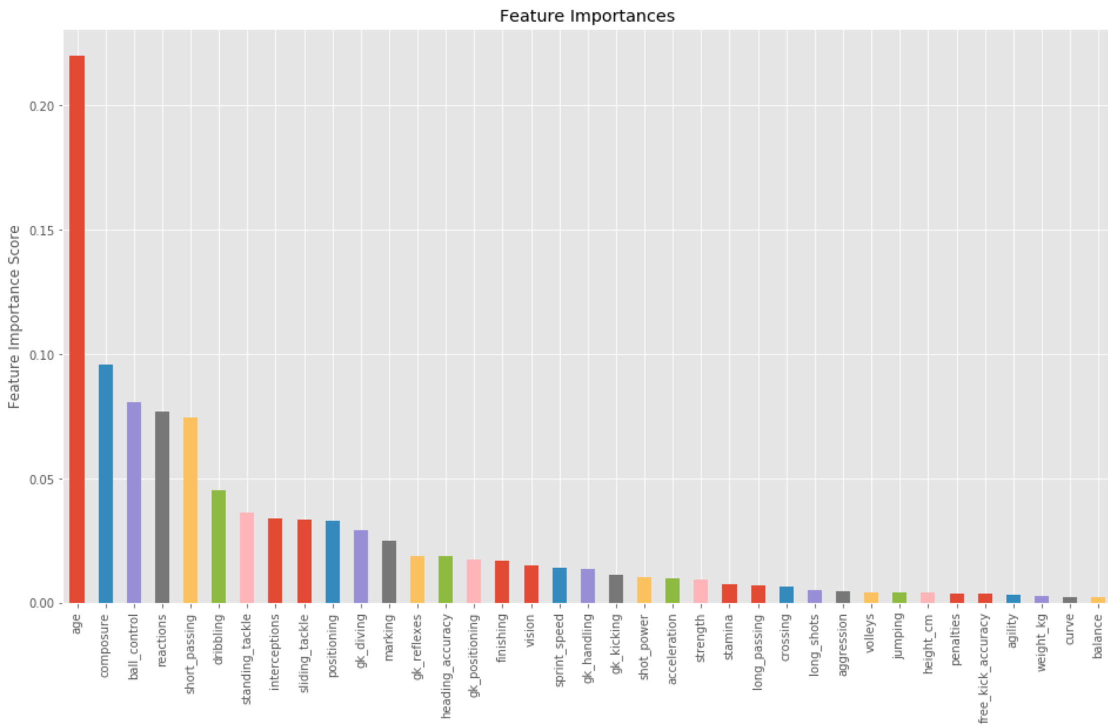

```
In [12]: #Hyperparameter tuning of estimators with GridSearch
         estimators = [x for x in range(700,750,10)]
```

```
param_test1 = {'n_estimators':estimators}
gsearch1 = GridSearchCV(estimator = GradientBoostingRegressor(learning_rate=0.1, min_sa
                                    min_samples_leaf=50,max_depth=8,max_features='sqrt',
                        param_grid = param_test1, scoring='neg_mean_squared_error',n_job
gsearch1.fit(dta[features],dta["Potential"])

gsearch1.score, gsearch1.best_params_, gsearch1.best_score_
modelfit(gsearch1.best_estimator_, dta, features)
```

Out[12]:
```
GridSearchCV(cv=10, error_score='raise-deprecating',
       estimator=GradientBoostingRegressor(alpha=0.9, criterion='friedman_mse', init=No
             learning_rate=0.1, loss='ls', max_depth=8,
             max_features='sqrt', max_leaf_nodes=None,
             min_impurity_decrease=0.0, min_impurity_split=None,
             min_samples_leaf=50, min_sa...       subsample=0.8, tol=0.0001, validation
             warm_start=False),
       fit_params=None, iid=False, n_jobs=4,
       param_grid={'n_estimators': [700, 710, 720, 730, 740]},
       pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
       scoring='neg_mean_squared_error', verbose=0)
```

Out[12]:
```
(<bound method BaseSearchCV.score of GridSearchCV(cv=10, error_score='raise-deprecating
        estimator=GradientBoostingRegressor(alpha=0.9, criterion='friedman_mse', init=N
              learning_rate=0.1, loss='ls', max_depth=8,
              max_features='sqrt', max_leaf_nodes=None,
              min_impurity_decrease=0.0, min_impurity_split=None,
              min_samples_leaf=50, min_sa...       subsample=0.8, tol=0.0001, validatio
              warm_start=False),
        fit_params=None, iid=False, n_jobs=4,
        param_grid={'n_estimators': [700, 710, 720, 730, 740]},
        pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
        scoring='neg_mean_squared_error', verbose=0)>,
 {'n_estimators': 740},
 -6.040395972594995)
```

```
Model Report
RMSE : 1.244
CV Score : Mean - 2.289 | Std - 0.8957 | Min - 1.55 | Max - 4.226
```



Here we use Gradient boosting regression to come up with a preliminary feature ranking for both overall and potential. We then use GridSearch Hyperparameter tuning to ehnance our model and thus re-rank the features.

15 Findings & Implications

Results: Regression on Overall Rating

Most importantly our model gives us an R-squared of about 85%, thus we can proceed with this critical assumption that our features are highly correlated with overall rating. OLS regression with Robust SE was used on all players to see which features were statistically significant at alpha =5%. We used robust regression with Huber's Maximum likelihood estimation and comparison of statistically significant features and confidence intervals with results from OLS. As ridge regression is good in dealing with collinearity, we conduct ridge regression with a weight=1 and observed the change in coefficients and intercept. We conducted lasso regression with various [U+FFFD][U+FFFD] as a means of feature reduction. Using L1 and L2 regularization helped us in dealing with collinearity. The results of our various regression models were as follows: OLS model R-squared results: 0.845 Ridge with α=1 R-square results=0.845 Lasso with α=1 R-square results=0.845 Lasso with α=8 and reduced features=0.8 All of our regressions showed that the 5 most important features in determining overall rating independent of position in order are: reactions, composure, heading accuracy, short passing, and goal keeper handling. This was determined by the magnitude of the coefficients and z-statistics at alpha=5%. However, it doesn't make too much sense to evaluate these features independent of position, which is why when we create our value models, we must segment players by position.

Results: Positional Value Modeling

This approach to finding a value model for this position is based on the assumption that the main determinant to market value is a players overall rating. The approach to find a model that describes value for this position with a reduced number of features is the following: To gain basic insights we conduct simple OLS with robust SE on Overall for this position group with all attributes in the "attribute_profile" list. Then to reduce the number of variables that matter we fit a lasso regression model on overall. The reason we fit our lasso on overall and not value is that by doing so on overall we see what few features actually make good players, at a given position, good. We compute pearson correlations on the lasso reduced model.When doing lasso regression, we use cross-validation to find the correct alpha to use. After this we choose all the features with a non-zero coefficient, and regardless if their coefficient is non-zero, we include non-soccer attributes such as Age, weight, and height. Since multicollinearity is likely, we conduct ridge regression on the non-zero coefficients from the lasso model. We use cross validation to also choose the correct alpha for our ridge regression. We then evaluate the reduced model performance, and compare it to the model performance of all the attributes on Value.

We conduct gradient boosting regression with grid search cross validation on our lasso reduced model to rank feature importance for a position with respect to value. We then use interaction terms to combine highly correlated features and further reduce our model. Lastly, we re-estimate our own reduced value model we created and compare it to the original model.

Our goal was to come up with a reduced value model by position that reduces the number of features, eliminates collinearity between the remaining features, ranks the features by importance (with respect to value), and is an improvement in predictive power compared to the original model. We successfully achieved this goal using the procedure above for all positions. For goal keepers it was determined the 3 most important features are goal keeper reflexes, handling and diving, and our reduced model had an r-squared of 0.6. For centerbacks the most important features were reactions, sliding tackle, and interceptions and our reduced model had an r-square of about 0.66. For full backs the most important featues were short passing, reactions and sliding tackles, and our reduced model produced an r-square of about 0.62. For center midfielders, our most important features were ball control, reactions, short passing, and vision, and our reduced model had an r-squared of about 0.58. For wingers, we determined the most important featues as ball control, positioning, finishing, and dribbling. Our reduced model for wingers had an r-squared of about 0.60. For forwards our most important features were finishing, reactions, positioning, and ball control. Our reduced model for forwards produced an r-squared of about 0.58. In conclusion our value models reduced the number of features with lasso regression, ranked the feature importance with gradient boosting regression and fabricated new models with no collinearity issues by creating interaction terms between highly correlated features. Lastly, where the original value models had r-squared values around 0.35-0.40, our models we created had r-squared values between 0.57-0.66, and were thus able to improve the ability to model value by position.

Results: Analysis of Classification Methods

Our purpose in using classification methods was to predict a players position, given an attribute profile, and to treat overall rating as a categorical variable and test several methods to determine which models would be best at predicting overall rating. For predicting player position we used k-NN classification, and had success in predicting position. When scoring the model we obtained a score of 0.502. This model may be of value in the future as AI gets more involved in the world of soccer scouting, an AI system could predict the best positional fit for a young player based on the attributes they have. For predicting overall rating we treated overall as a categorical variable with 100 different categories (0-100). The reason for doing this was to analyze how closely a players rating could be predicted compared to when we treated overall as a numeric variable and conducted regression. In classifying overall rating we used several models: random forrest, bayesian classification, support vector machines, kernel SVM, logistic regression and LDA classification. When we scored our models we often recived low scores, as a result of including 100 different classes, thus we also included the root mean square so we could compare our classification models to our regression models, as well as a confusion matrix. The purpose of doing this was to identify the two best models for predicting overall rating when we treat that as a category, so that we could expand upon these models in the future. Our two models that performed the best were random forrest and kernel SVM. Random forrest had an accuracy score of 0.439 and RMSE of about 1.5, while kernel SVM had an accuracy score of 0.286 and RMSE 1.716. Our least performant model was bayesian classification with an accuracy score of 0.117 and an RMSE of 5.258.

When we changed overall to a categorical variable this became a non-linear problem. Some reasons random forrest performed so well was random forrest is oowerful and accurate, good performance on many problems, including non linear problems. Some reasons why kernel SVM performed well were, kernel SVM has high performance on nonlinear problems, and is not biased by outliers, or not sensitive to overfitting.

Results: Analysis of Clustering Methods

We utilized k-means clustering to identify clusters of basic attributes. We chose k-mens because it is simple to understand, easily adaptable, works well on small or large datasets, is fast, efficient and performant. However, the one big challenge for k-means is you have to identify how many clusters you need. To do so we used the elbow method and found that the ideal amount of clusters was about 4. The basic attributes that we clustered were pace, shooting, dribbling, passing, defending, physicality, and reactions. The results obtained from doing this is shown below

```
In [14]: fifa_data_orig = pd.read_csv('full_fifa18_data.csv')
         #Creating the KNN Dataset with Attributes
         clustData = fifa_data_orig.copy()
         clustDep = clustData['Overall']
         knnFeatures = clustData[['pac', 'sho', 'dri', 'pas', 'defend', 'phy', 'reactions']]
         print(knnFeatures[0:5])
         knnModel = KNeighborsClassifier(n_neighbors = 4)
         #Running the model with testing data
         knnModel.fit(knnFeatures, clustDep)
         y_pred = knnModel.predict(knnFeatures)
         x_min, x_max = knnFeatures.min() - 1, knnFeatures.max() + 1
         y_min, y_max = knnFeatures.min() - 1, knnFeatures.max() + 1
```

```
   pac  sho  dri  pas  defend  phy  reactions
0   90   93   90   82      33   80         96
1   89   90   96   86      26   61         95
2   92   84   95   79      30   60         88
3   82   90   87   79      42   81         93
4   91   90   89   95      60   91         85
```

```
Out[14]: KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski',
                    metric_params=None, n_jobs=None, n_neighbors=4, p=2,
                    weights='uniform')
```

Implications

Our findings provided can provide a basis for training AI systems on what to look for by position when trying to scout players. The ultimate goal is to move towards a system that can scout players more efficiently and identify young up and coming prospects before curent human scouts could. Our findings also shed financial insight to clubs so that they can understand how to better structure player contracts and proposals they may make for players on the transfer market, given a set of attributes by a player at a position.

16 Conclusion

In this analysis we were successfully able to get insights into what makes a good player and what determines their market value. We conducted dimensionality reduction with PCA and tuned lasso regression. Additionally we successfully created enhanced value models by position and conducted regression analysis on value and the elasticity of value. An enhanced and reduced value model that eliminates collinearity with feature engineering, and interaction terms as well as out performs the original model was created. We identified the optimal classification methods to predict a players overall rating. Also we came up with our own algorithm to rank features and used GridSearchCV for hyperparameter tuning. Players were clustered based on basic features. The implications of our results can help train AI systems on what to look for when scouting players, and help clubs financially structure contracts based on player attributes.

Future Methods

Some future methods we intend on exploring are: Conduct further modeling with classification algorithms as opposed to seeing which model just performs best. The primary focus of our future analysis will be regarding the development of a recommender system that recommends players to teams based on team style, budget, and current players on a team. Specifically we will explore alternating least squares as a recommender system. We will seek to use deep learning and reinforcement learning to identify future top prospects faster than scouts can so that a competitive advantage will be achieved.

17 Appendix

To see how the data cleaning and prep was done please visit: https://github.com/Lucasnewman5732/Lucas-Newman-5732/blob/master/FIFA_DATA_Preprocessing_Clear

For reference to a data file needed please visit: https://www.kaggle.com/lucasnewman5732/buan6340projec

18 References

[1] Kumar, Gunjan. (2013). Machine Learning for Soccer Analytics. 10.13140/RG.2.1.4628.3761. [2] VanderPlas, J. T. (2017). Python Data Science Handbook: Essential Tools for Working with Data. Sebastopol, CA: OReilly Media. [3] Mu¨ller, A. C., & Guido, S. (2017). Introduction to Machine Learning with Python: A Guide for Data Scientists. Beijing: OReilly. [4] Hastie, T., Tibshirani, R., & Friedman, J. H. (2017). The Elements of Statistical Learning: Data Mining, Inference, and Prediction. New York, NY: Springer. [6] Mitchell, T. M. (2017). Machine learning. New York: McGraw Hill.