Expected Player and Team Performance Based on FIFA 2019 Ratings Part 1

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Summary of Research Questions:

1) Using the ratings for various attributes assigned to all players in the roster for the officially-licensed video game FIFA 2019, which players have the top overall ratings for different aspects of the game such as shooting, dribbling, passing, defending, goalkeeping, etc. across various leagues from different countries? Which are the best teams in the Premier League as predicted from the FIFA 2019 data? Does this prediction hold true when compared to the actual results from league data?
    a) Result:
        i) Lionel Messi was the player with the highest Overall Skill and the highest Overall Passing, Cristiano Ronaldo with the highest Overall Shooting, Giorgio Chiellini with the highest Overall Defending, and Manuel Neuer with the best Overall Goalkeeping.
        ii) The top 3 teams in the Premier League according to their ratings from FIFA 2019 are Manchester City, Chelsea, and Tottenham Hotspur. The best Premier League teams in real life (as determined through their performance in the 2018/19 season) are Manchester City, Liverpool, and Chelsea. Although the FIFA 2019 data for a team is not an *exact* predictor of the team's performance in real life, the results demonstrate that the predictions from our analysis were *mostly* accurate for the top teams but not accurate for the teams in the lower half of the table.
2) Using a set of sample attributes, what overall rating and monetary value might a future player receive as determined by a Machine Learning algorithm? Which attributes have the most effect on determining a player's value and wages?
    a) Result:
        i) For a player with the same attribute ratings as Lionel Messi, our machine learning algorithm predicted a value of €116,907,256.
        ii) The attributes that have the most effect on determining a player's value are GKReflexes (for goalkeepers) and Skill Moves.
3) How do players of different nationalities compare across certain key attributes such as dribbling, passing, etc.?
    a) Result:
        i) For players in the FIFA 19 dataset who have a general overall rating of at least 75 (and are thus likely to actually be considered for their respective national teams), players from Portugal have the highest overall skill, those from Wales have the highest overall shooting and passing, those from

Poland have the highest overall defending, and those from spain are the best at goalkeeping.

4) Does the homogeneity of a team in the Premier League based on the nationalities of its players have an effect on the team's performance in the Premier League?
    a) Result:
        i) The homogeneity of a team (as determined by the team's calculated homogeneity index*) has no discernible effect on its performance in real life.
5) How accurately do the overall ratings of players based on their nationality (with data from FIFA 2019) portend the success of a certain country in international tournaments such as the FIFA World Cup?
    a) Result:
        i) The overall ratings of players based on their nationality (with data from FIFA 2019) do a poor job of predicting the country's performance in international tournaments like the FIFA World Cup.

Motivation and Background:

Be it in the United Kingdom, where FIFA 19 opened at number one in the software sales chart, or in Japan where 155641 copies were sold in less than three months, FIFA by EA Sports is one of the most popular video games in the world available on most major gaming platforms all over the world. As such, the player ratings in the video game hugely affect the perceived popularity and quality of certain players, which in turn affects the revenue generated by clubs from merchandise sales and ticket sales. A player's merchandising power and brand value can definitely affect their transfer value, which has critical real-world ramifications on club revenue. The data from FIFA 19, then, can be used to perform various kinds of introspective analyses which can determine how accurately these ratings reflect player performance and quality in real life. Results from these analyses could allow for determining the accuracy of the rating system currently being used by EA and could perhaps offer suggestions that can improve the algorithm used to define player ratings as well as the transfer values associated with players.

Dataset:

1) Data containing all kinds of different attributes for all the players in the FIFA 2019 roster; 89 columns and 18208 rows: https://www.kaggle.com/karangadiya/fifa19
2) Website containing a dataset about real-life game-day statistics for several seasons across leagues: https://sports-statistics.com/sports-data/soccer-datasets/ **Out of all the datasets listed on the website, we will be using the English Premier League from the 2018/19 season.
3) Data containing information about each fixture in the 2018 FIFA World Cup: https://gitlab.com/djh_or/2018-world-cup-stats/blob/master/world_cup_2018_stats.csv

Challenge Goals:

We chose three different challenge goals for this project. The first was the use of Multiple Datasets. In addition to our primary FIFA 19 dataset, we created DataFrames from two additional datasets containing real-world data for comparison in exploring several of our research questions. The 2018 World Cup data and league/specific stats for the England Premier league (#2 and #3 above) were utilized in our analysis of research questions #1, #4, and #5. We also imported a fourth dataset, available from the GeoPandas library ('naturalearth_lowres'), to provide geometry data for all countries around the globe and implement geospatial data visualizations for research question #3 after merging it with various filtered DataFrames.

Our second and third challenge goals were to implement a Machine Learning model and to use a New Library. Both goals were met through our work on research question #2. We imported Keras/Tensorflow to allow us to implement a Convolutional Neural Network model, looking at many features from our primary FIFA 19 dataset, and predicting values for players' monetary worth based on various combinations of those features.

Methodology:

First research question:

In order to determine which players from the FIFA 2019 dataset were the best at different aspects of the game such as shooting, dribbling, etc. we decided to create 5 "overall" categories that merged some of the attributes related to an overarching category; given that there are approximately 37 rated attributes for each player, we believed it would be much more efficient to group some of these attributes into "overall" categories for the sake of comparison. For instance, attributes in the FIFA 2019 such as dribbling, ball control, vision, free-kick accuracy, reactions, positioning, balance, agility, acceleration, etc. are largely dependent on a player's individual skill and as such, for each player, a new attribute called "Overall Skill" was created which was essentially the average of all the aforementioned attributes. The most skillful players, then, were considered to be those that had the highest rating for "Overall Skill". A similar process was followed for other aspects of the game as well, namely for finding a player's "Overall Shooting", "Overall Passing", "Overall Defending", and "Overall Goalkeeping" (which was done on a filtered list of players consisting solely of goalkeepers in the game). The specific attributes from the FIFA 2019 dataset considered for each overall category were:

Overall Skill: Dribbling, BallControl, Acceleration, Agility, Reactions, Balance, Positioning, FKAccuracy, Vision

Overall Shooting: Finishing, Volleys, Curve, ShotPower, LongShots, Composure, Penalties

Overall Passing: Crossing, ShortPassing, Curve, LongPassing, Vision, FKAccuracy

Overall Defending: HeadingAccuracy, Jumping, Strength, Aggression, Interceptions, Marking, StandingTackle, SlidingTackle

Overall Goalkeeping: GKDiving, GKHandling, GKKicking, GKPositioning, GKReflexes, ShortPassing

While making these categories for no reason other than the discretion of the programmer does definitely add bias to the result, we believed that the added bias was worth the insights into the dataset such an analysis would provide and that comparing players based on every single attribute for which they have a rating would be quite inefficient and not as insightful. In order to decide which team performed the best in real life, we tallied up each team's wins and draws in the 2018/19 season (based on our Premier League dataset). To determine the number of points each team received, we assigned 3 points for a win and 1 point for a draw (just like the point system employed in real life. We then ranked each team based on their final points tally to create essentially the final premier league standings for the 2018/19 season so that we could compare it with FIFA 19's predictions of the best teams.

<u>Second research question:</u>

We created two complex neural networks to help predict the player's value based on certain features. The first model we created was the attribute model. This model takes in 38 features such as passing scores, shooting, dribbling and goalkeeping. This model was trained on 70 percent of the data in FIFA2019.csv dataset. The second model called the overall model is less accurate since it only uses four parameters (Overall skill, Overall Shooting, Overall). These features were created for research question 1. The models are saved on an absolute path so they do not need to be trained every time. To show how each feature affects the predicted value we took a constant set of features and went to the first feature and ran the model for multiple values of the feature. We then took these values and plotted them on a line plot. We did this for every feature for both models.

<u>Third research question:</u>

In order to find the answer to our research question, we first decided to only analyze the countries officially ranked in the top 20 by FIFA (a governing body responsible for International Football, not the video game). This allowed us to significantly reduce the number of players in consideration for the analysis. Our next step, as previously stated, was to only analyze players whose general overall rating was high enough to be realistically considered for their national team. After some deliberation, our group decided on a general overall cutoff of 75 – as such, the players whose overall shooting, skill, etc. was analyzed were those who had a general overall of 75 or above. This once again cut down on the number of players in consideration for the analysis, making our analysis a little more efficient. Our final step was to analyze the different overall ratings for each player remaining under consideration and group the players by country, thus allowing us to determine players from which country were the best at a certain category. One key decision that we made was to only analyze those players for a certain category whose position made it necessary for them to be proficient in that category. For example, when analyzing players from which nationality were the best at defending, we only analyzed those players who were defenders according to their position; after all, it would be unreasonable to

judge a defender based on his attacking prowess. Players were grouped into four categories based on their position as follows:
Attack – LS, ST, RS, LW, RW, LF, CF, RF, LAM, CAM, RAM
Midfield – LM, LCM, CM, RCM, RM, LDM, CDM, RDM, LAM, CAM, RAM, LWB, RWB
Defense – LWB, LB, LCB, CB, RCB, RB, RWB, LDM, CDM, RDM
Goalkeepers – GK
The specific categories considered for evaluating a certain skill were:
Overall Skill – Attack, Midfield
Shooting Overall – Attack
Passing Overall – Attack, Midfield, Defense
Defending Overall – Defense
Goalkeeping – Goalkeepers

Fourth research question:

To analyze the diversity of a team we created an homogeneity index for each team. The homogeneity index of a certain team was considered to be the maximum possible homogeneity of a certain team based on the nationalities of the players. To illustrate how the homogeneity index was calculated, consider a team of 11 players consisting of 5 Brazilian players, 2 Spanish players, 3 French players, and 1 German player. In this case, the maximum homogeneity of the team (the most players of a single nationality that can play together) would be 5 (Brazilian, in this case) out of a total 11, so 5/11 which is ~$0.\overline{45}$. The same procedure was followed and a homogeneity index calculated for each team in the Premier League, thus allowing us to directly compare our results with the Premier League standings calculated for Research Question 1.

Fifth research question:

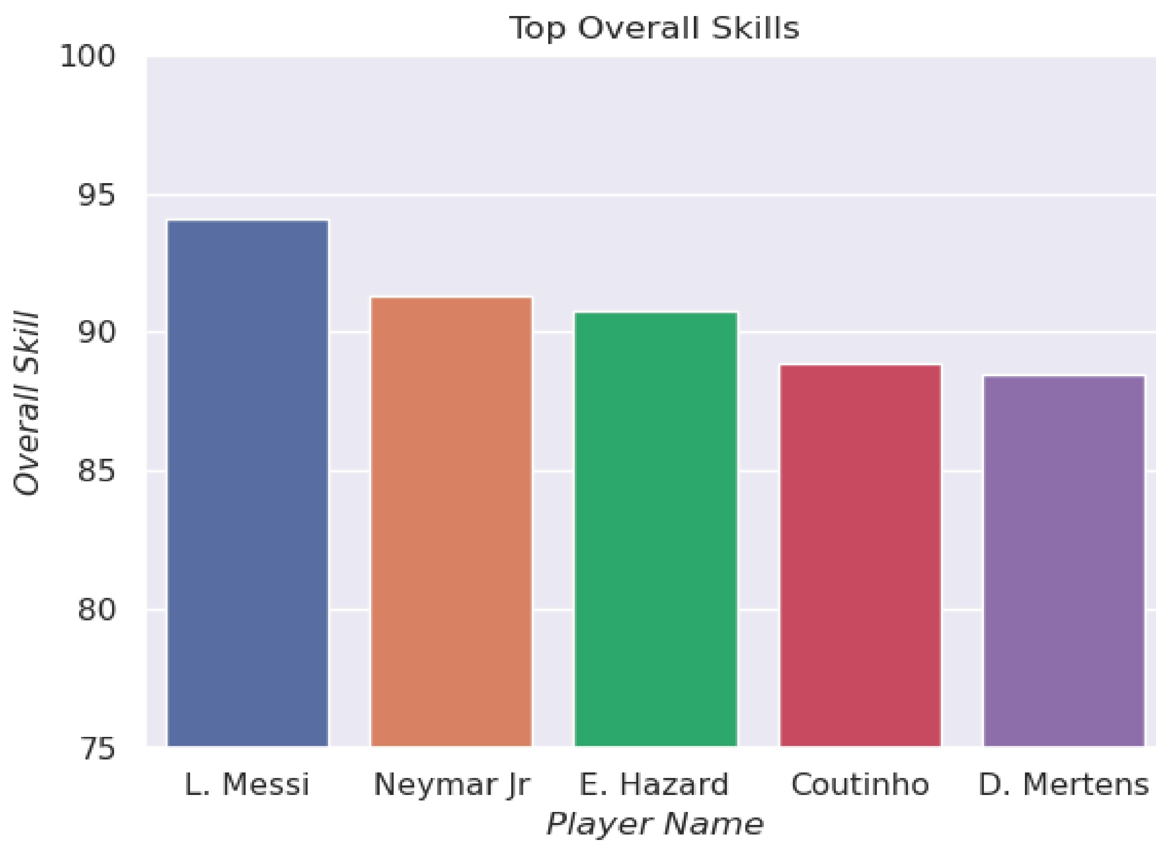
We used our data from research question 3 and modified it to create a composite overall score for national teams. We then analyzed the World Cup dataset to see how accurately a national team's overall score as determined from the FIFA 2019 dataset reflects the team's performance in the World Cup. We followed a procedure similar to the one we used to calculate the number of points each team in the Premier League received in the 2018/19 season: we tallied up the total wins and draws of each national team that played in the 2018 FIFA World Cup, awarding three points for a win and one point for a draw. Naturally, the teams that progressed further into the tournament ended up having more points than those that got eliminated in the earlier stages. To compare the best teams as determined by their performance in the 2018 FIFA World Cup with their predicted performance as determined by the average overall ratings of its players, we then focused only on those players in the FIFA 2019 dataset whose national team actually participated in the 2018 FIFA World Cup. We then decided to calculate the average overall rating of the top 20 players for each national team (as the top 20 or so players of each nationality are generally sent for prestigious international competitions like the World Cup).

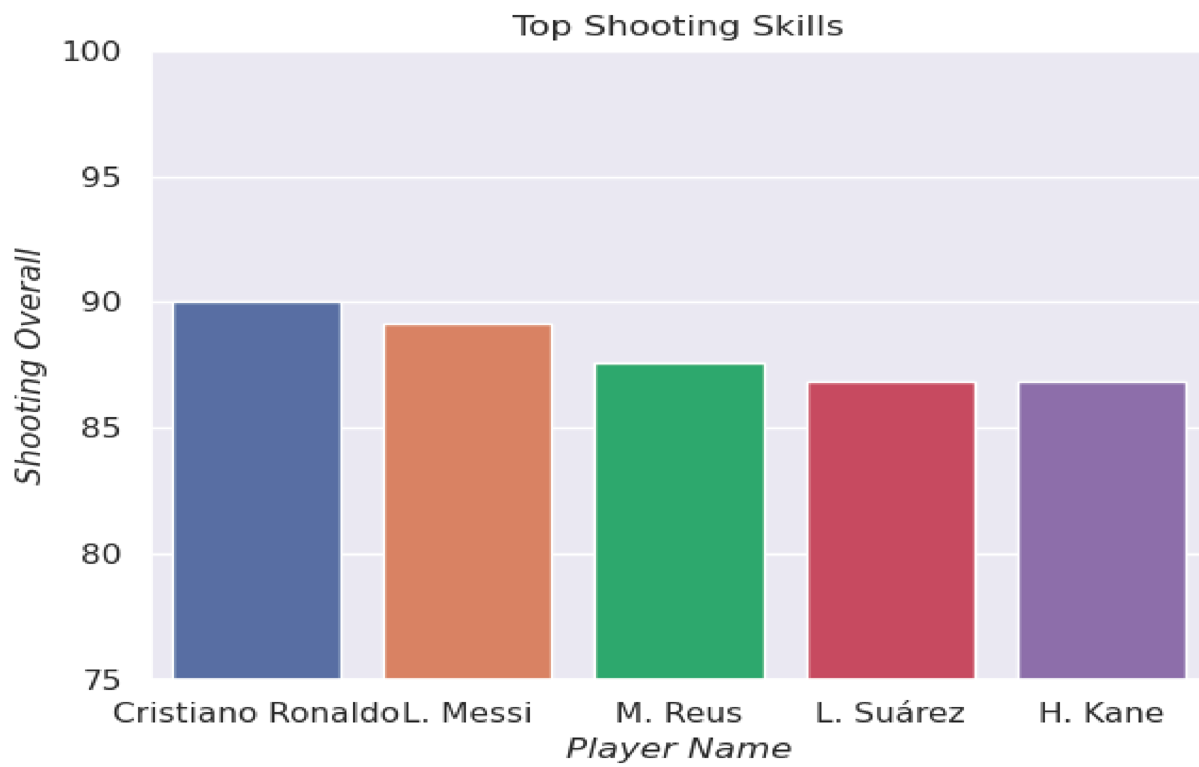
Results

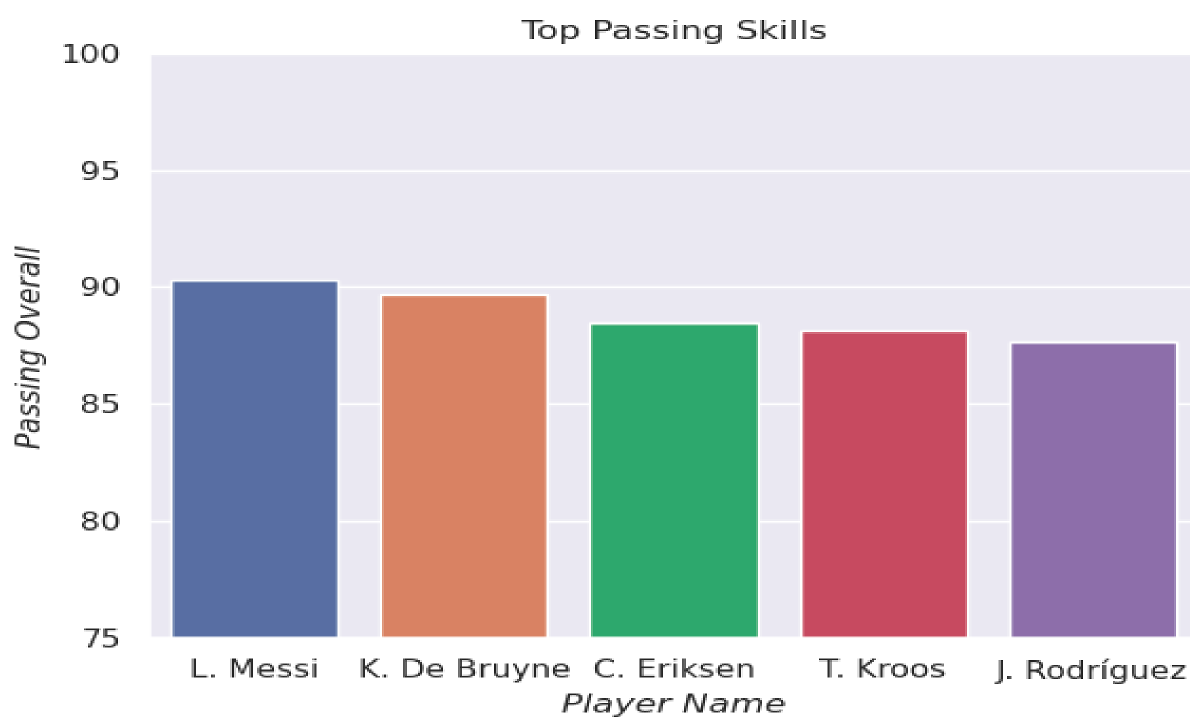
Research Question 1:

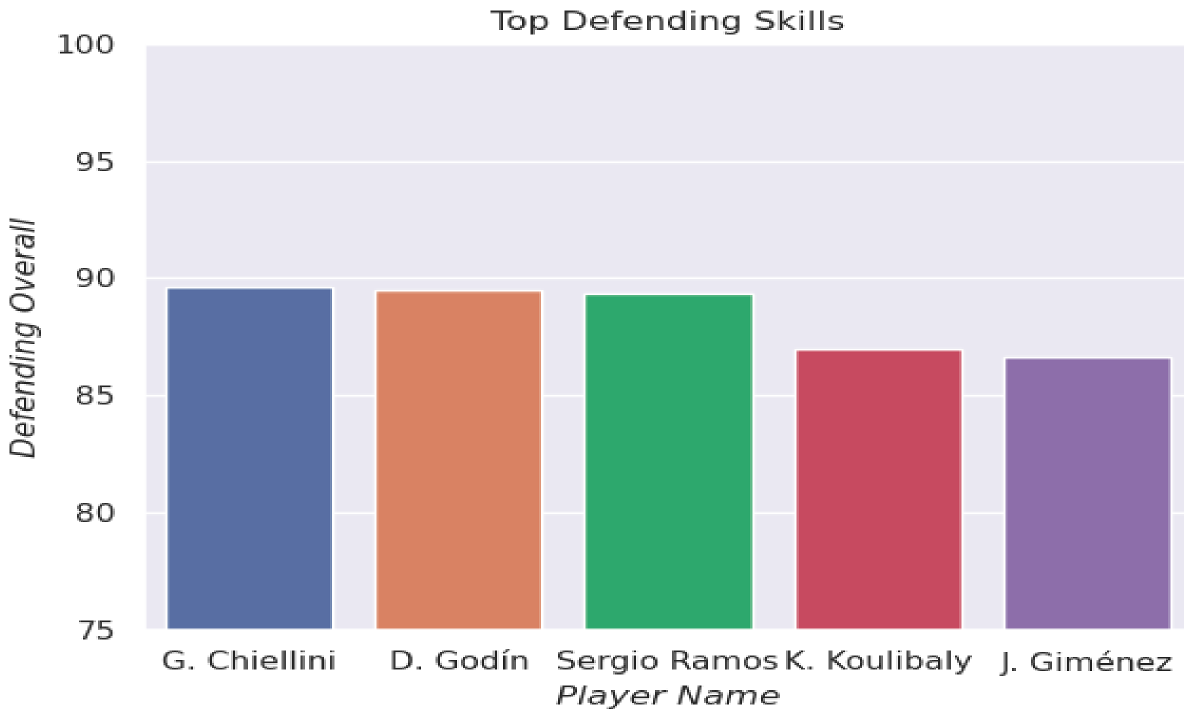
The following were the top 5 players for each aforementioned category:

Rank	Skill	Shooting	Passing	Defending	Goalkeeping
1	L. Messi (94.111)	C. Ronaldo (90.000)	L. Messi (90.333)	G. Chiellini (89.625)	M. Neuer (82.666)
2	Neymar Jr. (91.333)	L. Messi (89.143)	K. De Bruyne (89.666)	D. Godín (89.500)	D. De Gea (82.333)
3	E. Hazard (90.777)	M. Reus (87.571)	C. Eriksen (88.500)	Sergio Ramos (89.375)	Ederson (80.166)
4	Coutinho (88.888)	L. Suárez (86.857)	T. Kroos (88.166)	K. Koulibaly (87.000)	M. ter Stegen (78.500)
5	D. Mertens (88.444)	H. Kane (86.857)	J. Rodríguez (87.666)	J. Giménez (86.625)	J. Pickford (77.666)




Top Shooting Skills
100
95
90
85
80
75
Shooting Overall
Cristiano Ronaldo
L. Messi
M. Reus
L. Suárez
H. Kane
Player Name


Top Passing Skills
100
95
90
85
80
75
Passing Overall
L. Messi
K. De Bruyne
C. Eriksen
T. Kroos
J. Rodríguez
Player Name

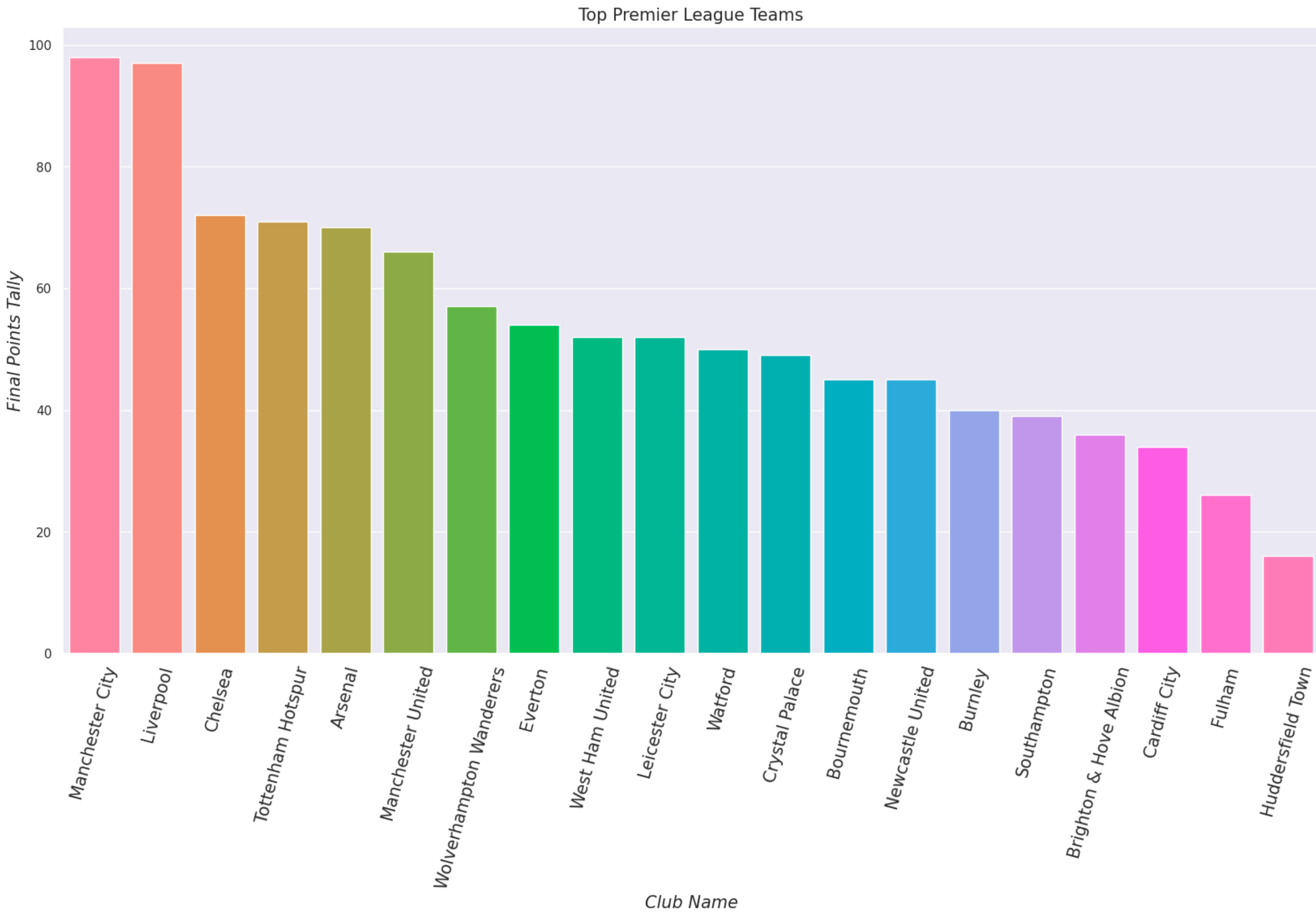

Top Defending Skills
100
95
90
85
80
75
Defending Overall
G. Chiellini
D. Godín
Sergio Ramos
K. Koulibaly
J. Giménez
Player Name


Top Goalkeeping Skills
100
95
90
85
80
75
Goalkeeping
M. Neuer
De Gea
Ederson
M. ter Stegen
J. Pickford
Player Name

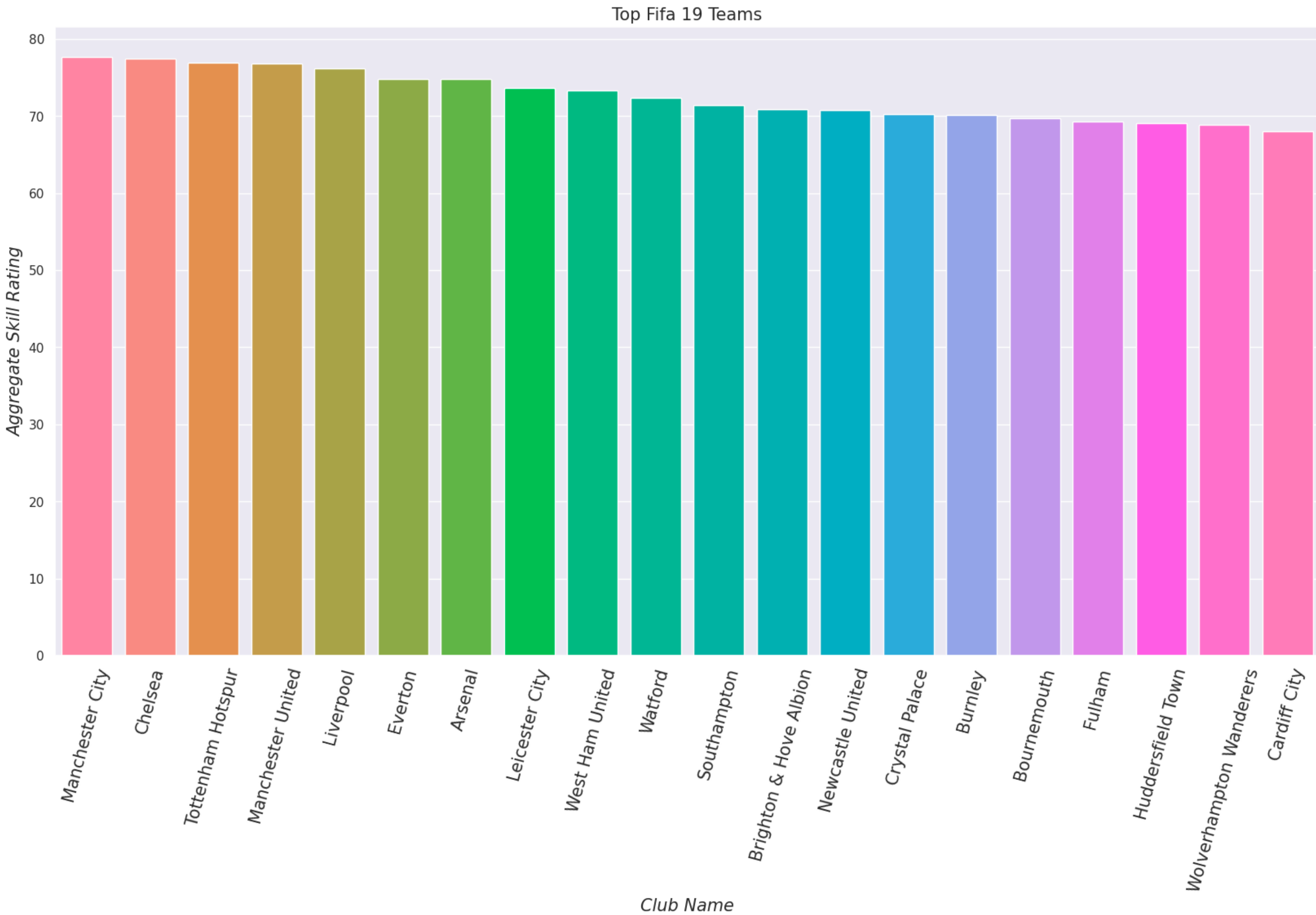
The results outlined in the visualization above mostly lined up with our expectations, especially for the top-rated players in each category. Some of the other players that were ranked outside the top three were a *little* surprising especially as their performances in the actual season weren't too noteworthy; however, that is a totally expected result as a player's FIFA rating is by no means a fool-proof indicator of his performance in real life. Furthermore, the "best" players from each category were decided based on criteria that we ourselves designed; as such, simply changing our criteria (such as the attributes considered for each broader category) would generate a new list of top players and as such, the list we have currently generated is not an end-all-be-all when it comes to determining the best players in FIFA 19 even though it does provide an interesting look into the ways in which FIFA 19 rates players.

We employed a somewhat similar strategy to identify the best teams in the Premier League according to FIFA 19 – the overall ratings of each player (from the "Overall" column in the original dataset, NOT the "Overall" ratings that we created) in a team were averaged to create an "overall" rating for the team, and teams from the Premier League were then ranked based on their respective overall ratings, the results from which can be seen in the visualization below.

Best Teams in Real Life (obtained using real results from Premier League 2018/19)	Best Teams in FIFA 2019 (as determined through overall of each player in the team)
1) Manchester City (98 Points) 2) Liverpool (97 Points) 3) Chelsea (72 Points) 4) Tottenham Hotspur (71 Points) 5) Arsenal (70 Points) 6) Manchester United (66 Points) 7) Wolverhampton Wanderers (57 Points) 8) Everton (54 Points) 9) Leicester City (52 Points) 10) West Ham United (52 Points) 11) Watford (50 Points) 12) Crystal Palace (49 Points) 13) Bournemouth (45 Points) 14) Newcastle United (45 Points) 15) Burnley (40 Points) 16) Southampton (39 Points) 17) Brighton & Hove Albion (36 Points) 18) Cardiff City (34 Points) 19) Fulham (26 Points) 20) Huddersfield Town (16 Points)	1) Manchester City (77.690) 2) Chelsea (77.483) 3) Tottenham Hotspur (76.931) 4) Manchester United (76.800) 5) Liverpool (76.166) 6) Everton (74.793) 7) Arsenal (74.766) 8) Leicester City (73.586) 9) West Ham United (73.300) 10) Watford (72.370) 11) Southampton (71.379) 12) Brighton & Hove Albion (70.900) 13) Newcastle United (70.759) 14) Crystal Palace (70.276) 15) Burnley (70.179) 16) Bournemouth (69.690) 17) Fulham (69.250) 18) Huddersfield Town (69.103) 19) Wolverhampton Wanderers (68.828) 20) Cardiff City (68.000)



Top Premier League Teams
Final Points Tally
100
80
60
40
20
0
Manchester City
Liverpool
Chelsea
Tottenham Hotspur
Arsenal
Manchester United
Wolverhampton Wanderers
Everton
West Ham United
Leicester City
Watford
Crystal Palace
Bournemouth
Newcastle United
Burnley
Southampton
Brighton & Hove Albion
Cardiff City
Fulham
Huddersfield Town
Club Name

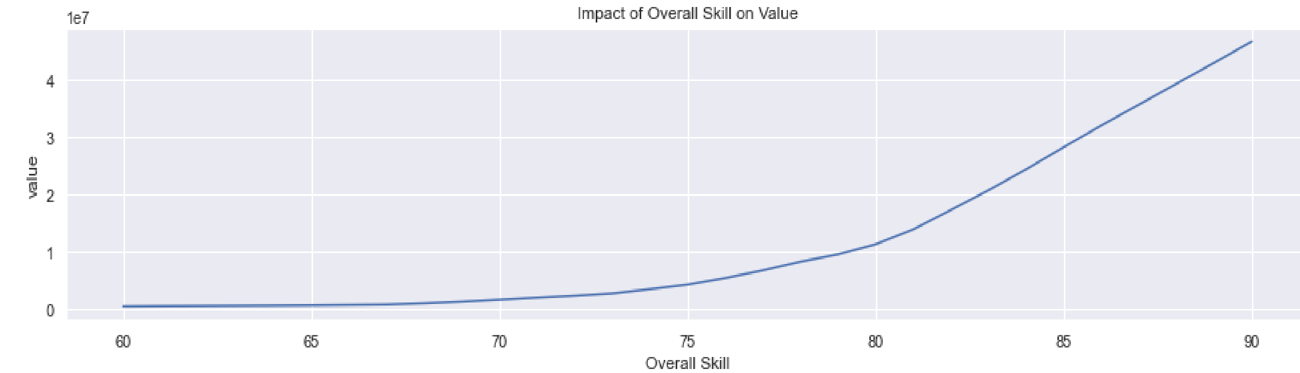


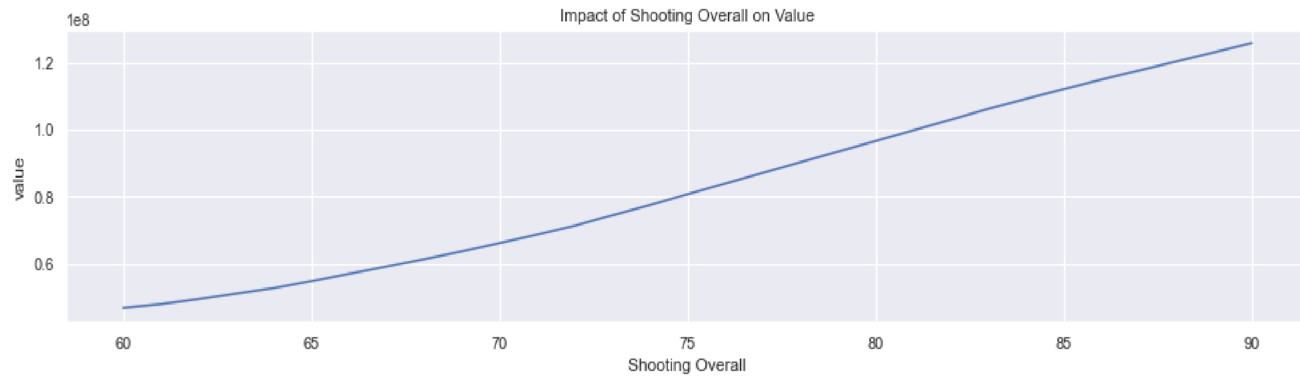
The results, once again, followed a similar pattern: FIFA 19's predictions of the very top teams were very close to the results from real life. For instance, Manchester City had the highest overall team rating in FIFA 2019 and they were also the ones that won the Premier League that season. For some other clubs like Chelsea and Tottenham Hotspur, too, the FIFA 19 data provided a good indication of their success in the 2018/19 season (even though the rankings were not *exact*, they were pretty close). However, the predictions for teams in the bottom half of the Premier League were nowhere as accurate as those for the top teams in the Premier League. One possible explanation for this discrepancy is that EA (the company responsible for developing the game) doesn't spend as much time on deciding and evaluating the ratings for players from bottom-half teams as they do on deciding the player ratings from upper-half (and as such, more financially lucrative and more likely to be scrutinized) teams. The upper-half teams like Manchester City, Liverpool, Chelsea, etc. often feature some of the most popular players in the game whose ratings are scrutinized by hundreds and thousands of fans who play the game. As a result, to avoid coming under fire, EA spends more time evaluating what rating to give the more popular players (and consequently, the more popular teams). Another reason why there might be a discrepancy between the two rankings is our methodology for ranking the best teams in the

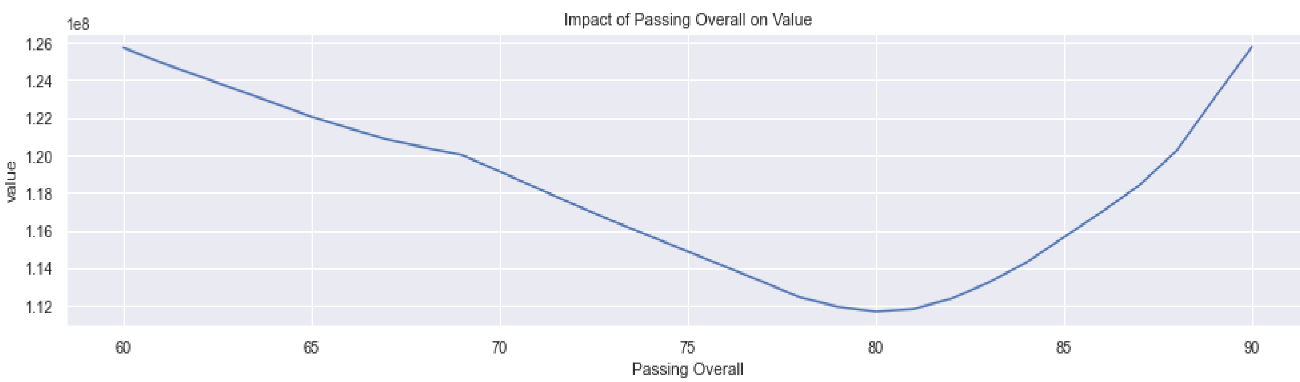
dataset. Even though a team's entire player roster is featured in the FIFA 19 dataset and was used to determine a team's overall rating, only 11 of those players (not including substitutions) actually participate in any given game; therefore, only those players are directly responsible for a team's success in real life. By including the entire roster in our analysis, our methodology would incorrectly predict the success of a team whose roster features a lot of players (many of whom have low overall ratings and don't actually play during the season) but still has an extremely strong playing 11.
*** The table shown above was created for clarity so that it would be easier for the reader to compare results – while the actual information in the visualizations comes straight from our program, we thought that manually creating a table in which we could place results would make it easier for the grader to simultaneously see and compare results that originate from different parts of our program. The same tabular data is also present in the csv files created in our code.

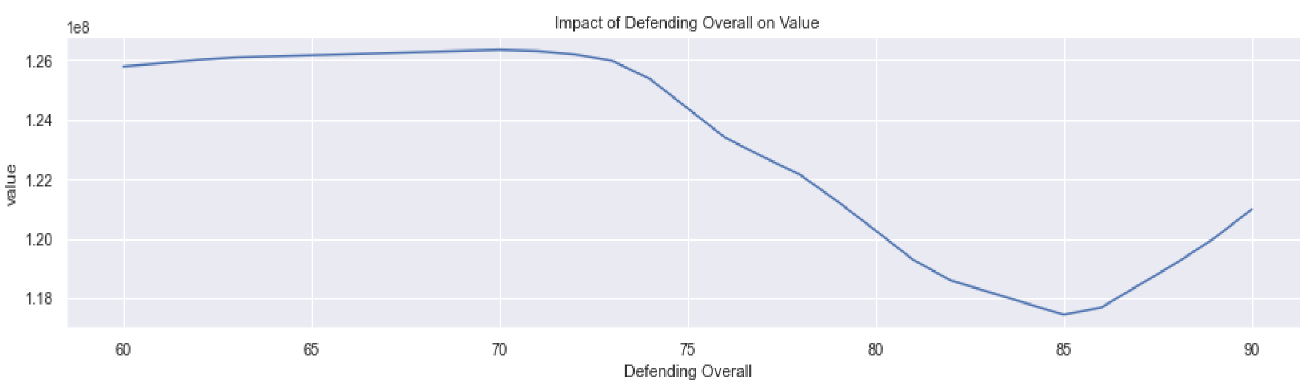
<u>Research Question 2:</u>
Having created the two models , described in the methodology section, we were able to calculate the test and train errors for the models. Due to the randomness of training the accuracy fluctuates a little but for one instance the error for the overall model is €4,045,506.52 and the attribute model has an error of €3,009,521.73. These errors may seem high but due to some players like Messi getting 105M euros it can be tolerated. However it just shows that the model is not very good for calculating lower valued players. We also wanted to analyze the impact of each parameter on the predicted value. To do this we created two visualizations one showing how increasing the parameter for each of attributes affects the value predicted and one visualization just showing which attributes at the final value changed the prediction. The first visualization had 38 plots for the attribute model and 4 for the overall model so they were split into 5 figures total.

Overall Model features:

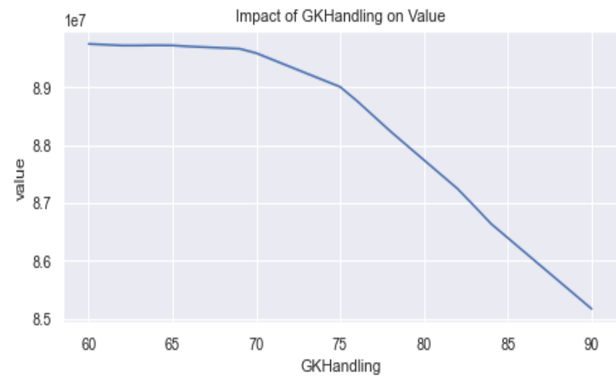


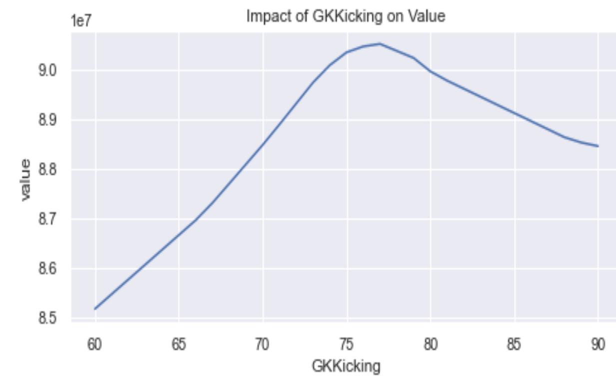


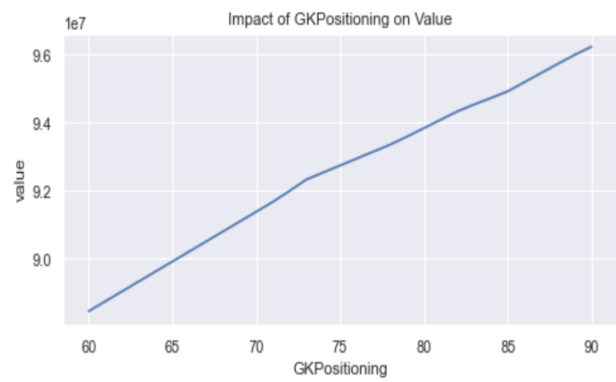


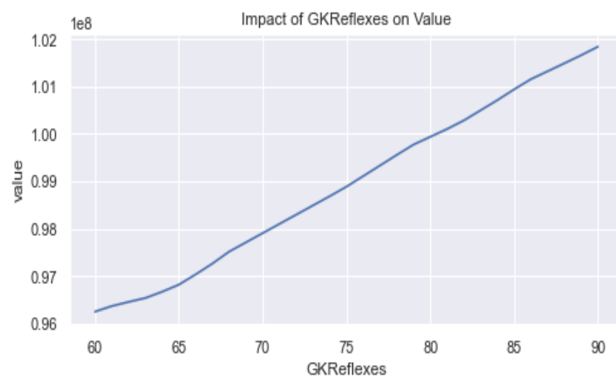


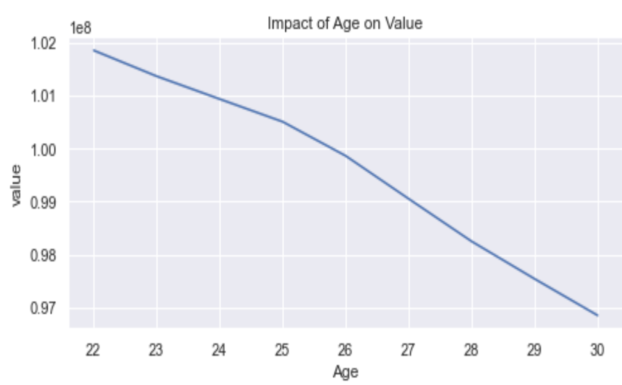
Attribute Model features:

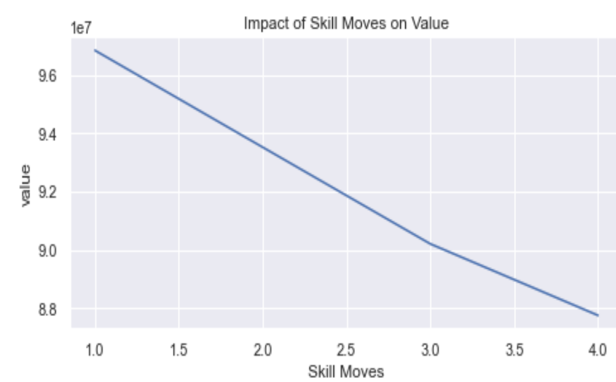


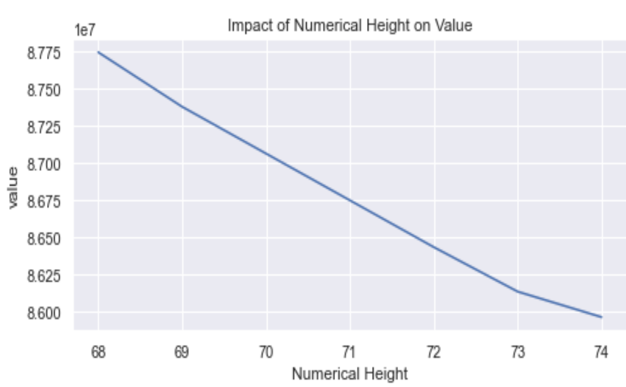


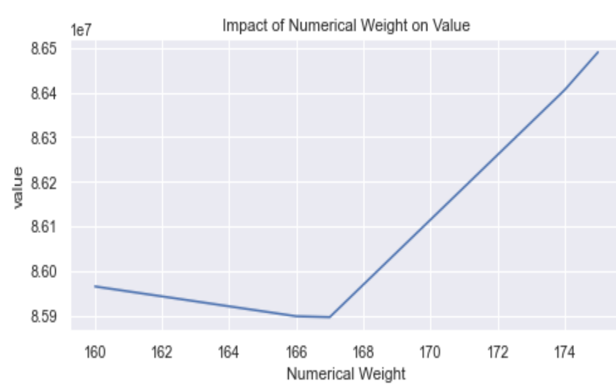


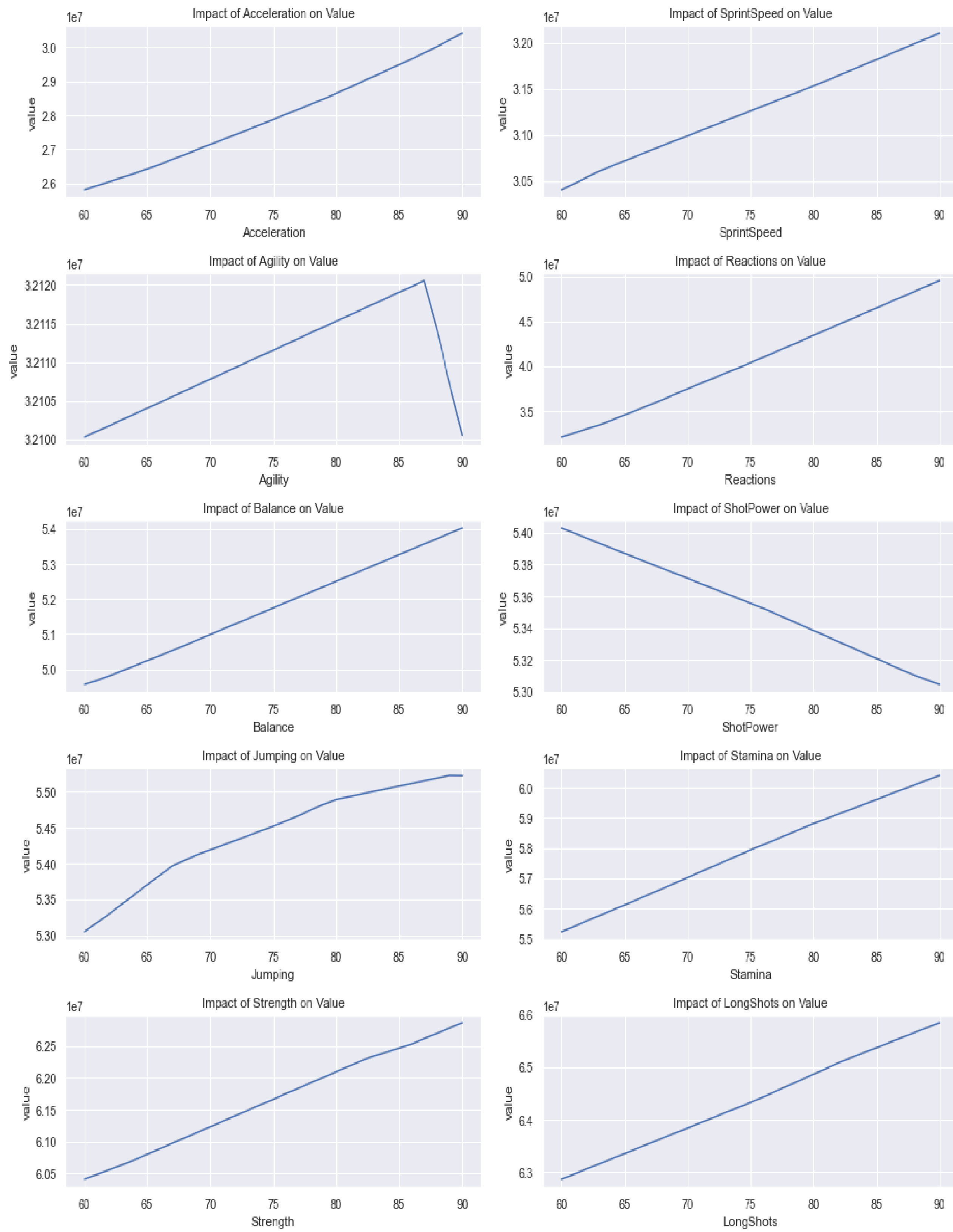












Impact of Acceleration on Value
1e7
value
3.0
2.9
2.8
2.7
2.6
60 65 70 75 80 85 90
Acceleration
Impact of SprintSpeed on Value
1e7
value
3.20
3.15
3.10
3.05
60 65 70 75 80 85 90
SprintSpeed
Impact of Agility on Value
1e7
value
3.2120
3.2115
3.2110
3.2105
3.2100
60 65 70 75 80 85 90
Agility
Impact of Reactions on Value
1e7
value
5.0
4.5
4.0
3.5
60 65 70 75 80 85 90
Reactions
Impact of Balance on Value
1e7
value
5.4
5.3
5.2
5.1
5.0
60 65 70 75 80 85 90
Balance
Impact of ShotPower on Value
1e7
value
5.40
5.38
5.36
5.34
5.32
5.30
60 65 70 75 80 85 90
ShotPower
Impact of Jumping on Value
1e7
value
5.50
5.45
5.40
5.35
5.30
60 65 70 75 80 85 90
Jumping
Impact of Stamina on Value
1e7
value
6.0
5.9
5.8
5.7
5.6
5.5
60 65 70 75 80 85 90
Stamina
Impact of Strength on Value
1e7
value
6.25
6.20
6.15
6.10
6.05
60 65 70 75 80 85 90
Strength
Impact of LongShots on Value
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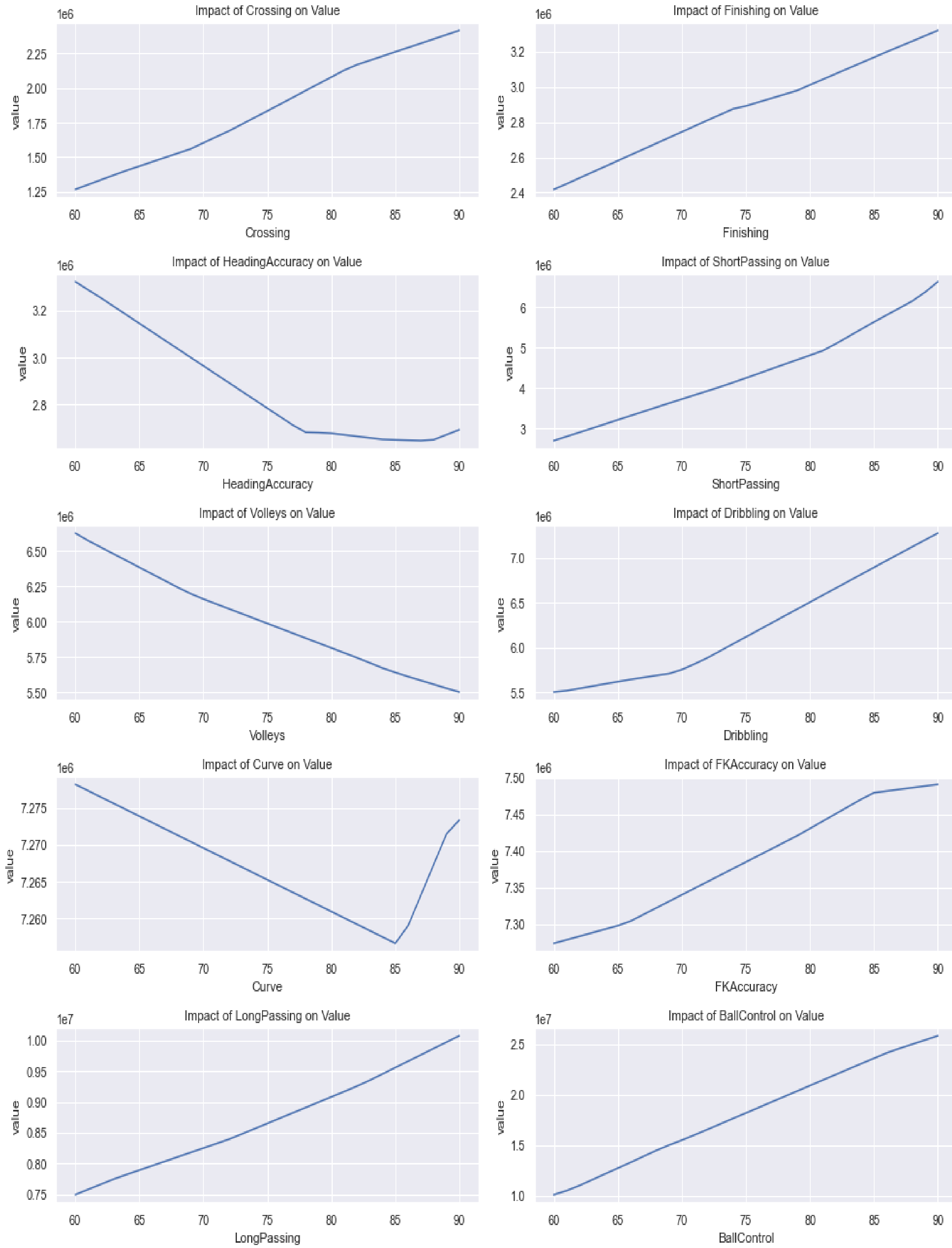
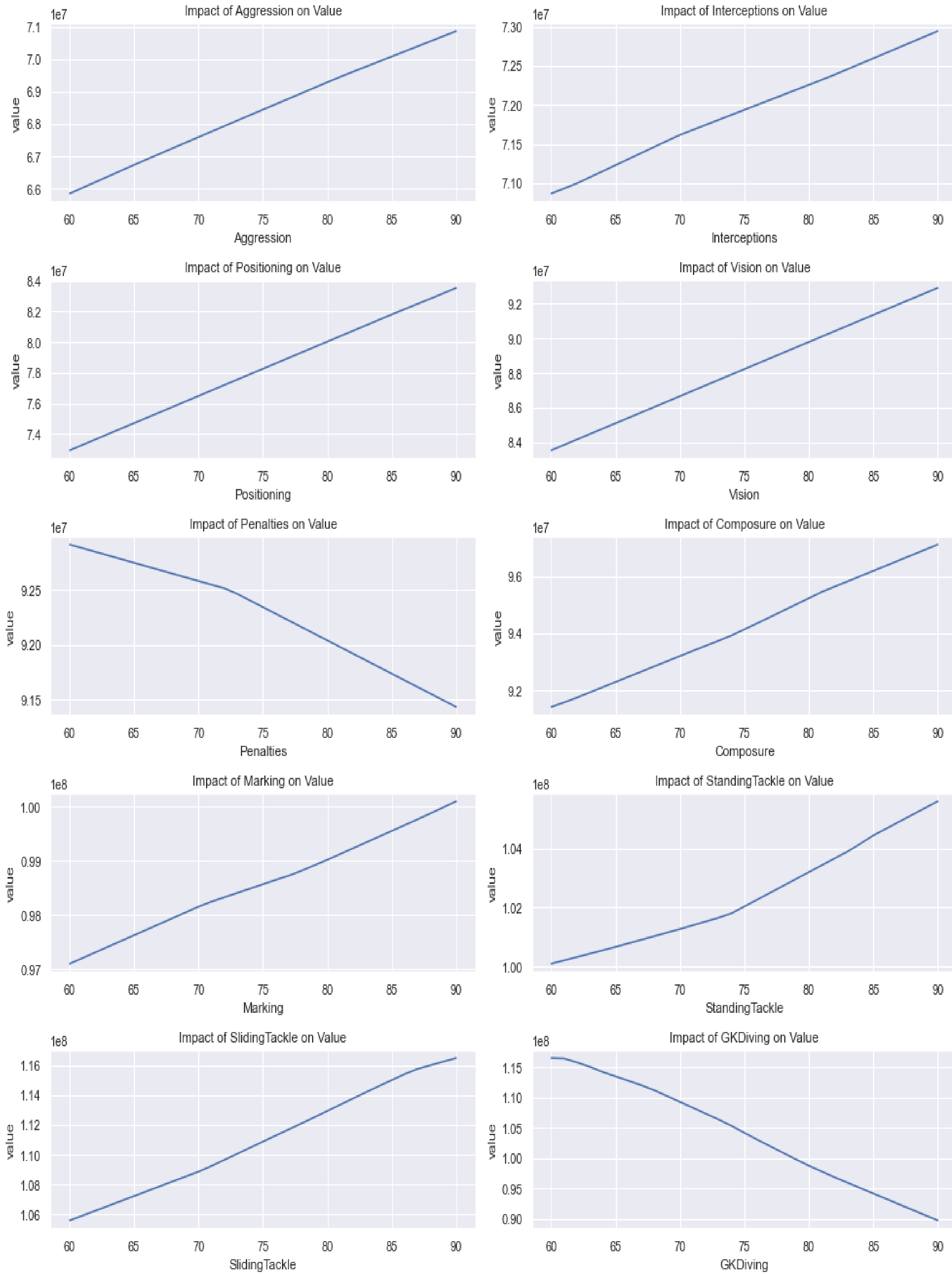
value
6.6
6.5
6.4
6.3
60 65 70 75 80 85 90
LongShots


Impact of Crossing on Value
1e6
value
Crossing
Impact of Finishing on Value
1e6
value
Finishing
Impact of HeadingAccuracy on Value
1e6
value
HeadingAccuracy
Impact of ShortPassing on Value
1e6
value
ShortPassing
Impact of Volleys on Value
1e6
value
Volleys
Impact of Dribbling on Value
1e6
value
Dribbling
Impact of Curve on Value
1e6
value
Curve
Impact of FKAccuracy on Value
1e6
value
FKAccuracy
Impact of LongPassing on Value
1e7
value
LongPassing
Impact of BallControl on Value
1e7
value
BallControl


Impact of Aggression on Value
Impact of Interceptions on Value
Impact of Positioning on Value
Impact of Vision on Value
Impact of Penalties on Value
Impact of Composure on Value
Impact of Marking on Value
Impact of StandingTackle on Value
Impact of SlidingTackle on Value
Impact of GKDiving on Value
value
Aggression
Interceptions
Positioning
Vision
Penalties
Composure
Marking
StandingTackle
SlidingTackle
GKDiving
1e7
1e8

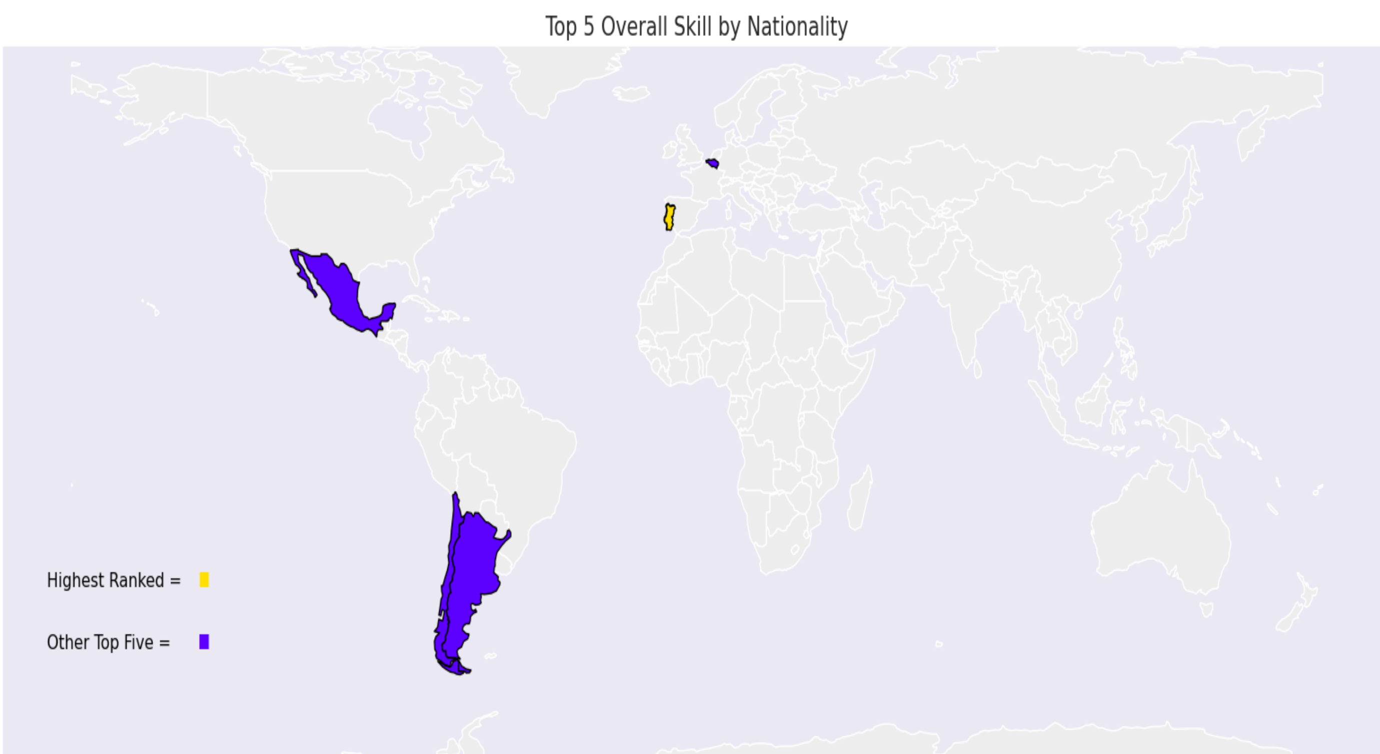
As we expected, the visuals that we got from our machine learning model contained some extremely surprising results. We expected that for almost every single attribute, an increase in the rating for that attribute would lead to an increase in the player's monetary value, and even though the degree to which the monetary value might be different across attributes, we did expect to see a positive trend for nearly every attribute. As is evident from the visualizations above, that is not the case. It is a little difficult to specifically pinpoint what aspect of our code is causing these discrepancies as we trained a neural network on the FIFA 19 dataset and, by design, a neural network is a "blackbox" model in that it is not possible to understand the exact rationale behind the neural network's decision. However, there are a few reasons we could think of which could explain the negative correlations in some of the graphs above. Consider the GKDiving attribute, for example. As the rating for the GKDiving attribute increases, the monetary value plummets. Such a result seems extremely counterintuitive: after all, the better a goalkeeper is at diving to stop the ball, the better his monetary value should be, right? The catch is, our neural network was trained on *all* players and not simply goalkeepers. In fact, some of the highest rated and most financially valuable players in the game are not goalkeepers but are still assigned ratings for their goalkeeping abilities. As these extremely valuable non-goalkeeper players have very low ratings for their GKDiving abilities, our neural network probably thinks that having a low GKDiving rating is better for the player's financial value. However, while that may intuitively make sense, the same rationale does not hold true for other goalkeeping attributes such as GKPositioning or GKReflexes. Another caveat in comparing players' monetary values based on change in a single attribute is that it doesn't take into account the effect that a player's other attributes is having on his monetary value, especially for players who are specialists at a certain skill. Consider the result for penalties – according to our machine learning model, as a player's penalty rating increases his monetary value decreases. A possible reason why this might be happening is that the dataset on which our neural network was trained contains "penalty specialists": players who are very good at taking penalties but perhaps not as good at other aspects of the game. In such a scenario, a player will have a very high penalty rating while having poor ratings for many other attributes, thus having a lower monetary value than players whose penalty rating may not be as strong but are good at a lot of other things. In short, we have no solid explanation for why the neural network is behaving the way it does. With that being said, the neural network does function as we expected for a majority of the other attributes: for instance, as demonstrated by our "overall model", an increase in a player's 'overall skill' or 'shooting overall' does have a positive affect on his monetary value, as expected. Even for some of the individual attribute graphs for attributes like age or sprint speed or acceleration, the machine learning model does a very good job of predicting the overall trend in monetary value as the attribute ratings change.

Research Question 3:

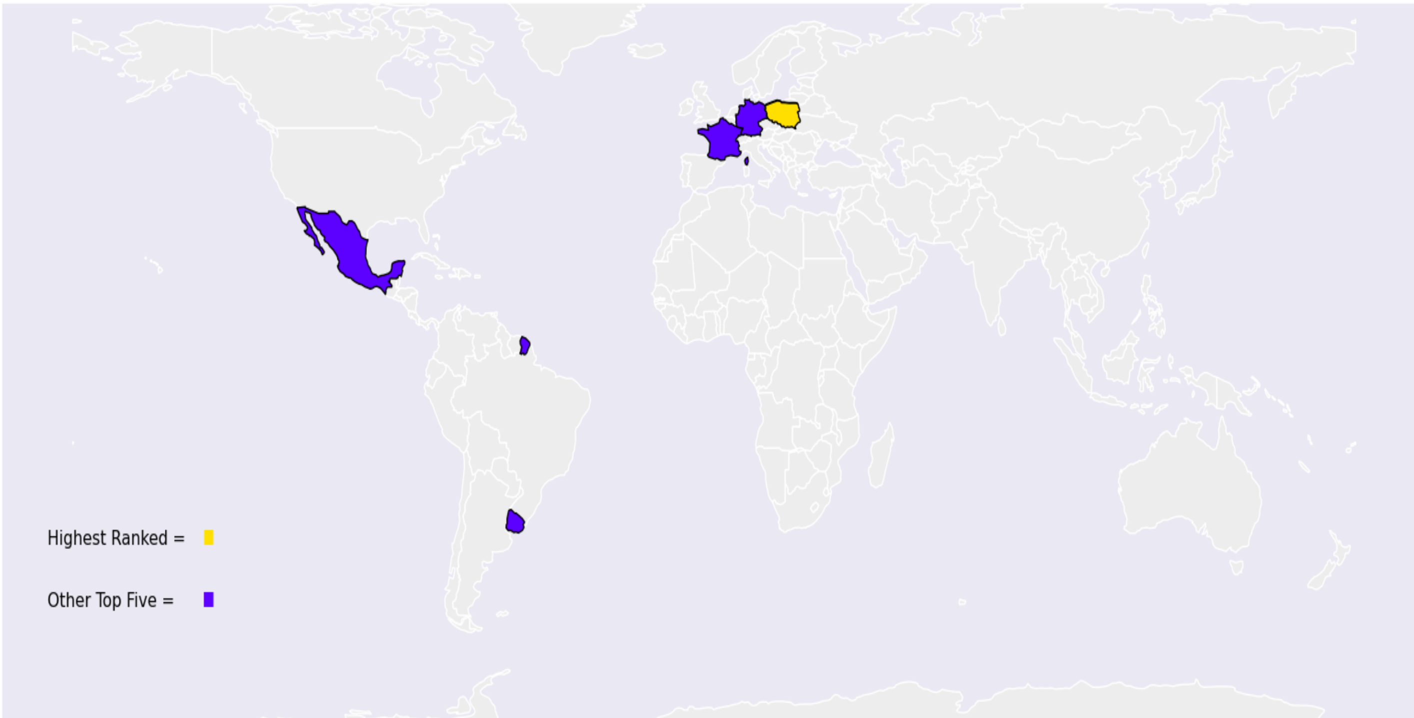
The goal of research question 3 was to identify which national teams have the highest overall ratings for the same categories we defined in research question 1 (such as Overall Skill, Shooting Overall, etc.). The trick with making an effective analysis that could answer our research question was to identify the fact that not all players of a particular national team are actually selected for their national team and as such should be excluded from our analysis.

Skill	Shooting	Passing	Defending	Goalkeeping
Portugal (75.766)	Wales (78.714)*	Wales (70.250)*	Poland (81.938)	Chile (71.666)
Mexico (74.924)	Poland (78.190)	Chile (69.341)	Belgium (78.738)	Germany (71.042)
Belgium (74.681)	France (75.461)	Belgium (69.070)	Senegal (77.821)	France (70.666)
Chile (74.625)	Mexico (75.020)	Portugal (68.885)	Croatia (77.417)	Belgium (70.600)
Wales (74.472)*	Uruguay (74.648)	Spain (68.382)	Uruguay (76.682)	Italy (70.513)
Argentina (74.369)	Germany (74.625)	Switzerland (68.321)		

*Since the geometry for Wales in our geographical dataset is considered a part of the geometry of the UK, we decided not to include Wales in our plots. In cases where Wales was a part of the top 5, we decided to plot the top 5 NOT including Wales. As a result, our visualizations below can sometimes show the 6th best country if Wales is a part of the top 5.

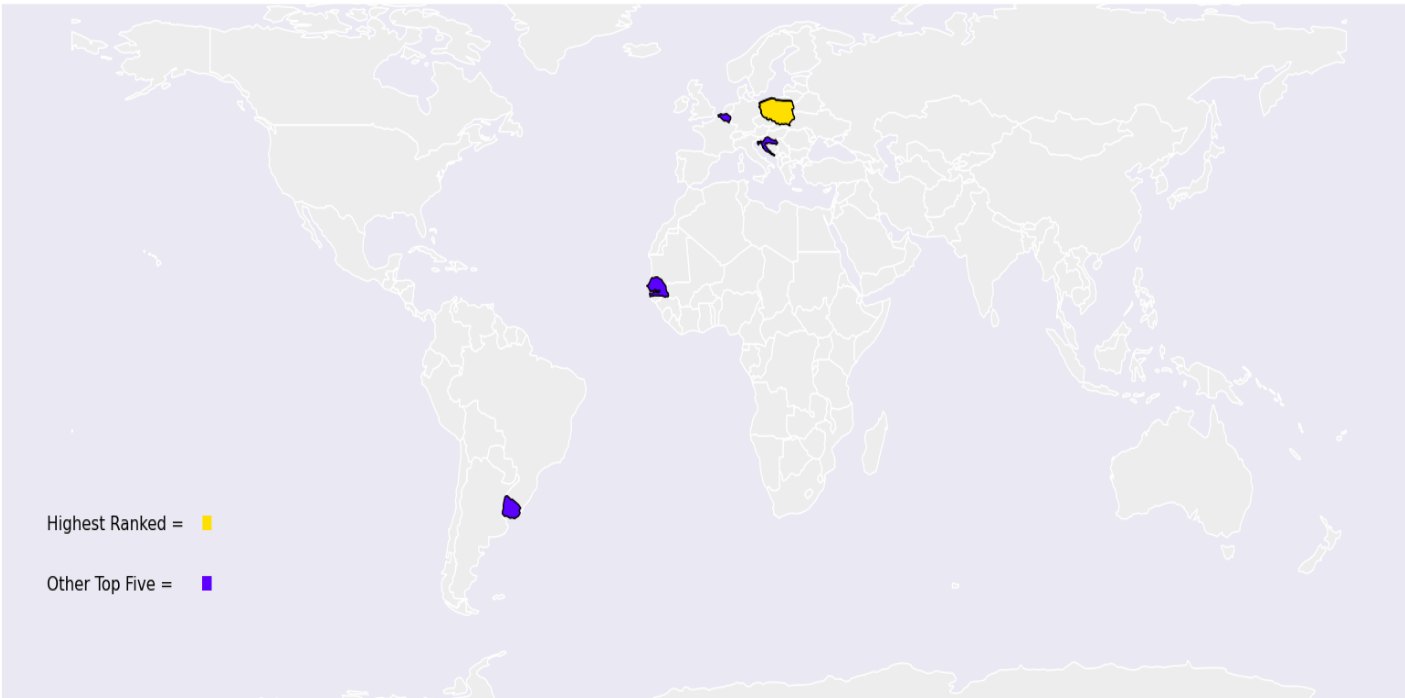


Top 5 Shooting by Nationality

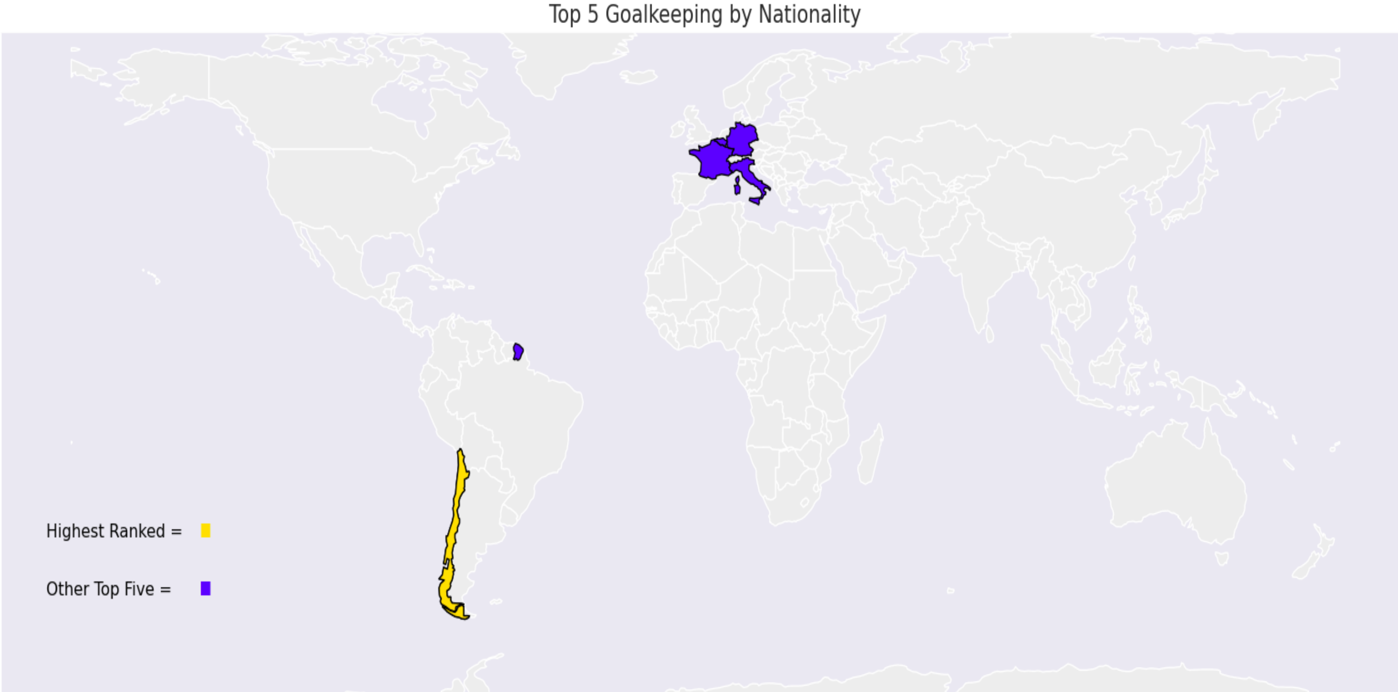


Top 5 Passing by Nationality

Top 5 Defending by Nationality



Top 5 Goalkeeping by Nationality



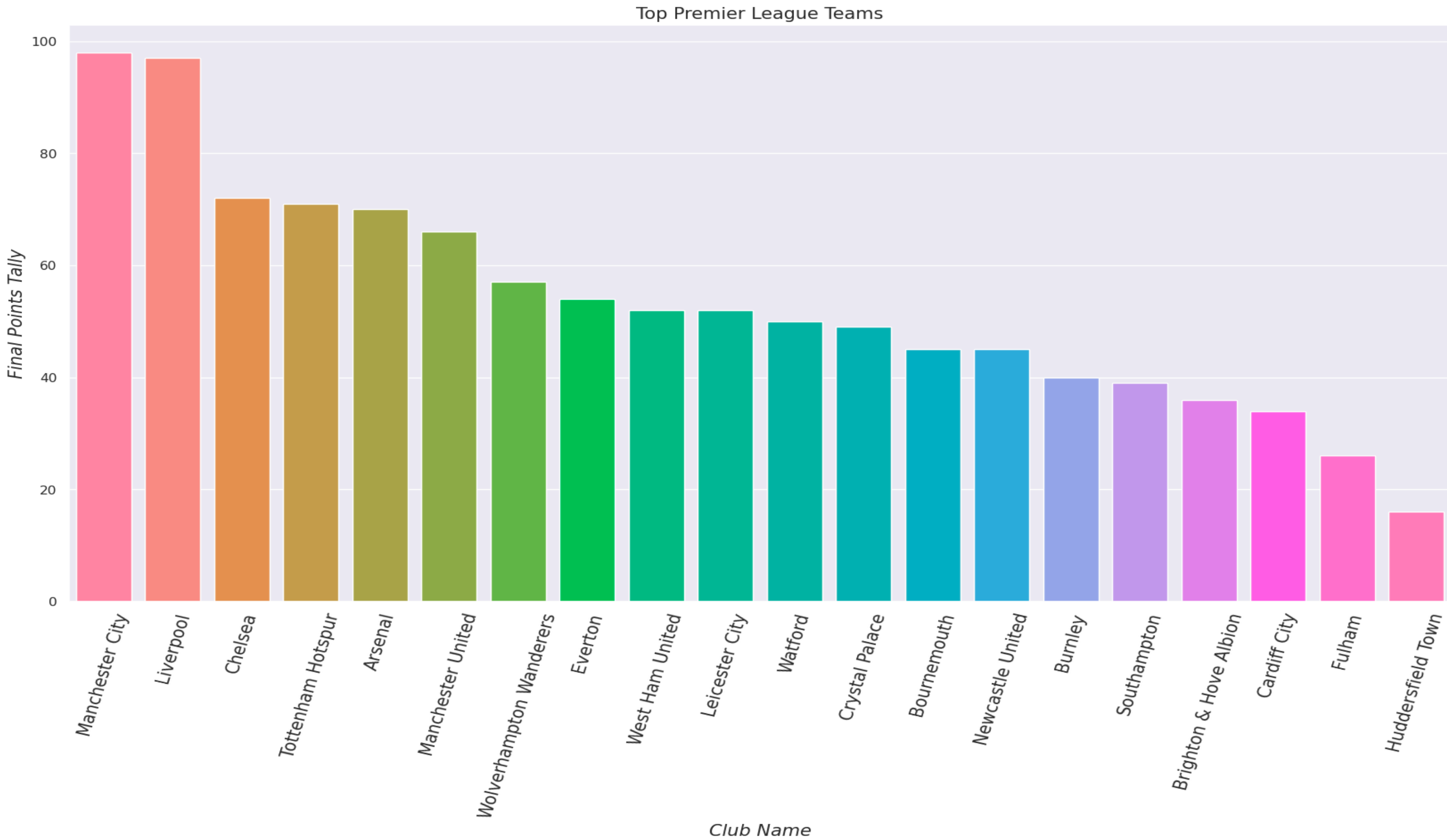
Some of the results we got from our analysis were extremely surprising. A lot of the lower-ranked national teams actually had high overalls for a certain skill. For instance, Wales (ranked 18 by FIFA) topped the Shooting and Passing skills (according to FIFA 19). Poland (ranked 19 by FIFA) topped the Defending skill. On the other hand, some of the other higher ranked teams such as Brazil, Germany, Argentina, France, England, Spain, etc. could not be found in the top 5 for a lot of the skills. A major explanation for this unexpected result is our methodology for determining the best national teams. A lot of the decisions we made while deciding which players to include in our analysis at various points – such as when deciding the overall cutoff or the positions considered for each skill – were arbitrary (logical and thoughtful, but arbitrary nevertheless) and simply tweaking those decisions a little bit completely changes which nationalities are the best for certain skills. An important reason why the lower ranked national teams doing very well in our analysis is our overall cutoff of 75 – each national team has a different number of players that fit our decided criteria which is not the case in real life. Take Wales, for example. There are only 6 players that have an overall of 75 or above, indicating that there is a high discrepancy in the overalls of the top welsh players and the remaining welsh players. On the other hand, Brazil has 187 players that have an overall of 75 or above. Thus, the analysis for Wales is going to be based on just 6 players while that for Brazil is going to be based on 187 players, thus illustrating why Wales is more likely to top the charts according to the criteria we have set forth. To better illustrate this result, consider two hypothetical teams A and B with 11 players each. Team A has 1 player rated 90 while everyone else in the team is rated 10. Team B has all of its players rated 80. According to our criteria, Team A will have a higher average overall rating of 90 (as only the player rated 90 will be considered for analysis) while Team B will have an average rating of 80 and will thus be rated lower (even though it has more players that fit our criteria and is more likely to better than Team A in real life).
**The tabular visualization above was created for better comparison clarity using the data generated in the csv files from the code.

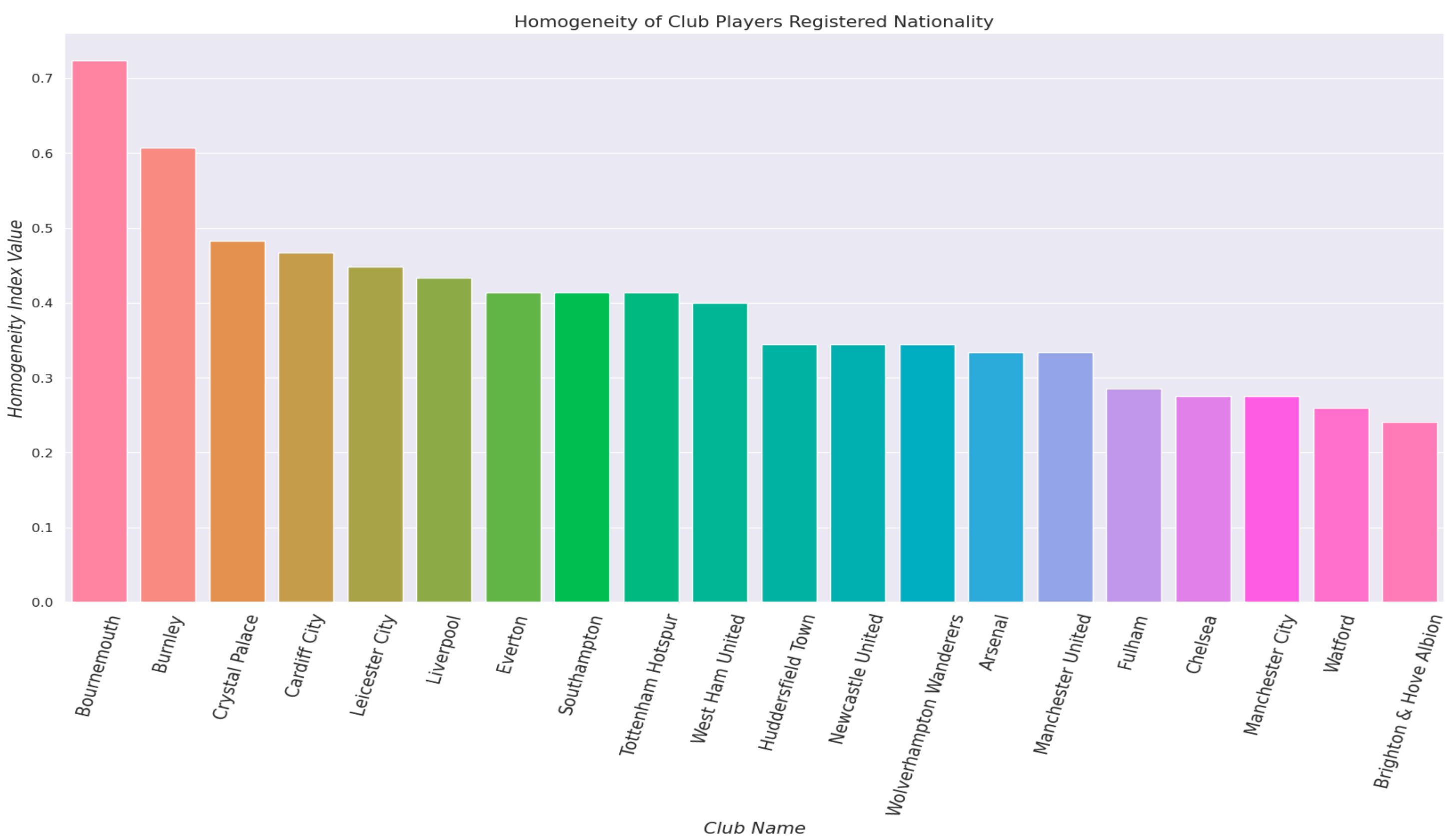
Research Question 4:

The goal of research question 4 was to identify whether the homogeneity of a team (based on its calculated homogeneity index) in the Premier League had an effect on the team's performance in real life. The following were the detailed rankings based on homogeneity index.:

Best Teams in Real Life (obtained using real results from Premier League 2018/19)	Most Homogenous Teams (based on their Homogeneity Index)
1. Manchester City (98 Points) 2. Liverpool (97 Points) 3. Chelsea (72 Points) 4. Tottenham Hotspur (71 Points) 5. Arsenal (70 Points) 6. Manchester United (66 Points) 7. Wolverhampton Wanderers (57 Points) 8. Everton (54 Points) 9. Leicester City (52 Points) 10. West Ham United (52 Points) 11. Watford (50 Points) 12. Crystal Palace (49 Points) 13. Bournemouth (45 Points) 14. Newcastle United (45 Points) 15. Burnley (40 Points) 16. Southampton (39 Points) 17. Brighton & Hove Albion (36 Points) 18. Cardiff City (34 Points) 19. Fulham (26 Points) 20. Huddersfield Town (16 Points)	1. Bournemouth (0.724) 2. Burnley (0.607) 3. Crystal Palace (0.483) 4. Cardiff City (0.466) 5. Leicester City (0.448) 6. Liverpool (0.433) 7. Everton (0.414) 8. Southampton (0.414) 9. Tottenham Hotspur (0.414) 10. West Ham United (0.4) 11. Huddersfield Town (0.345) 12. Newcastle United (0.345) 13. Wolverhampton Wanderers (0.345) 14. Arsenal (0.333) 15. Manchester United (0.333) 16. Fulham (0.286) 17. Chelsea (0.276) 18. Manchester City (0.276) 19. Watford (0.259) 20. Brighton & Hove Albion (0.241)

**The tabular visualization above was created for better comparison clarity using the data generated in the csv files from the code.

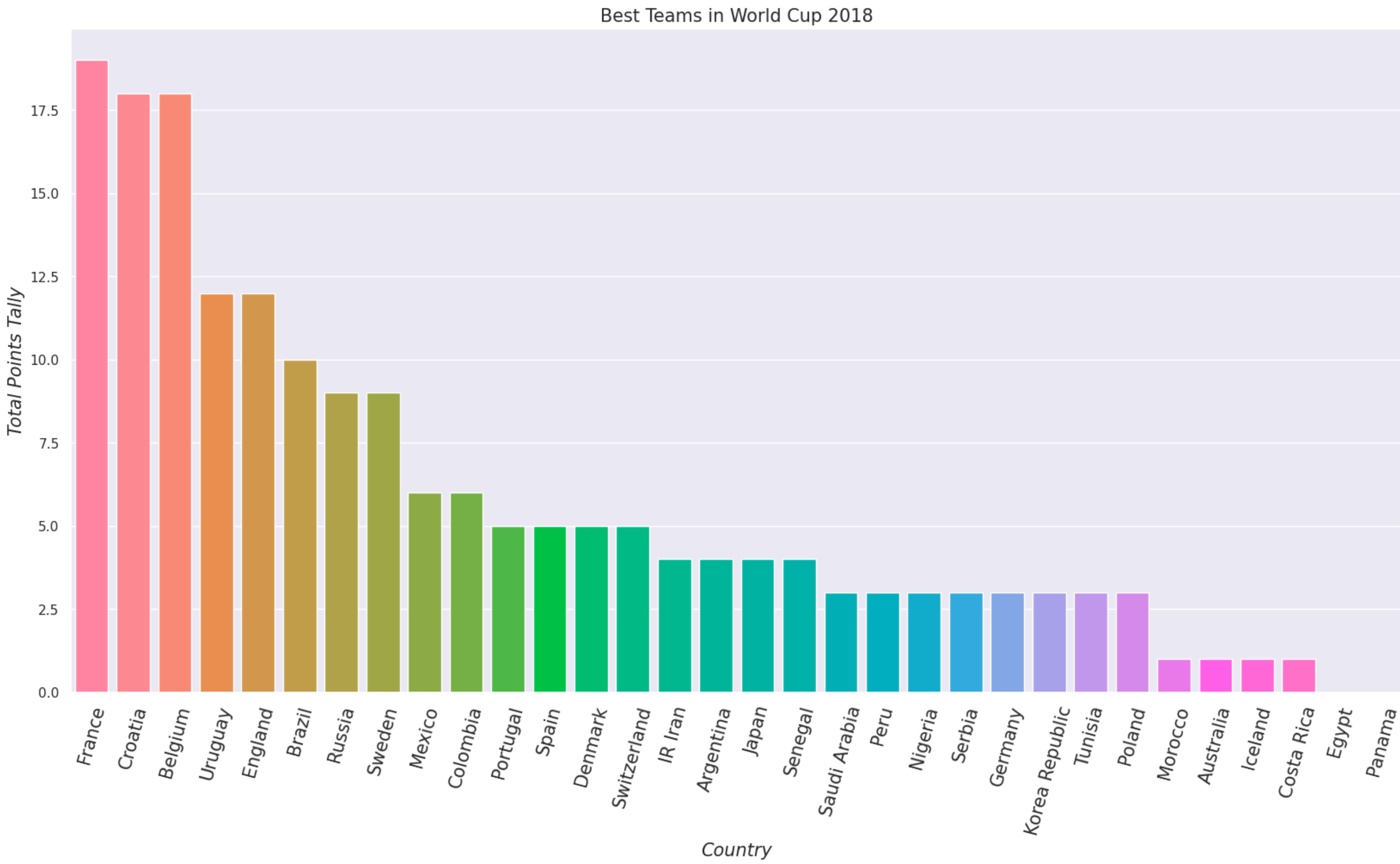

Top Premier League Teams
Final Points Tally
0
20
40
60
80
100
Manchester City
Liverpool
Chelsea
Tottenham Hotspur
Arsenal
Manchester United
Wolverhampton Wanderers
Everton
West Ham United
Leicester City
Watford
Crystal Palace
Bournemouth
Newcastle United
Burnley
Southampton
Brighton & Hove Albion
Cardiff City
Fulham
Huddersfield Town
Club Name

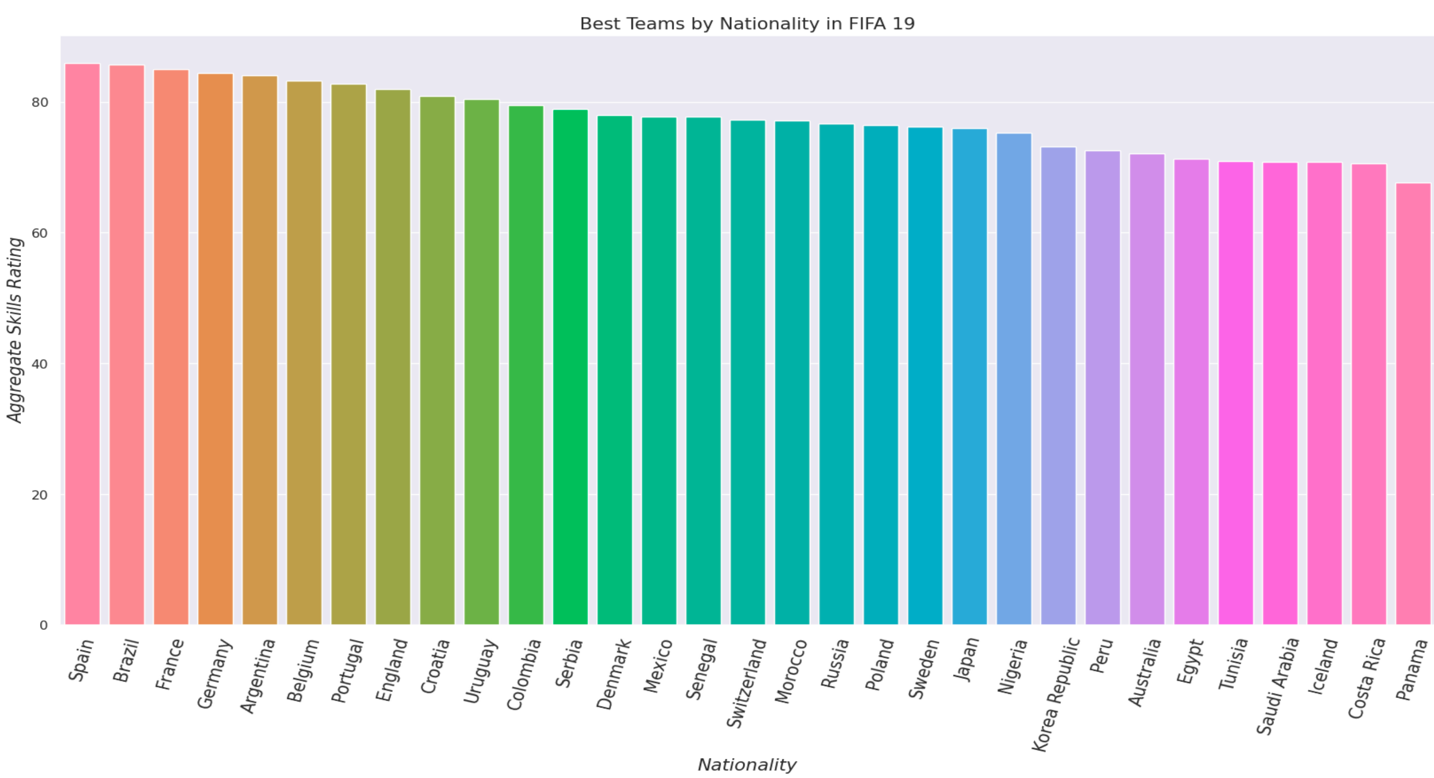

Homogeneity of Club Players Registered Nationality
Homogeneity Index Value
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
Bournemouth
Burnley
Crystal Palace
Cardiff City
Leicester City
Liverpool
Everton
Southampton
Tottenham Hotspur
West Ham United
Huddersfield Town
Newcastle United
Wolverhampton Wanderers
Arsenal
Manchester United
Fulham
Chelsea
Manchester City
Watford
Brighton & Hove Albion
Club Name

As can be seen from the table above, there is no direct correlation between the homogeneity of a team and its success in real life. Manchester City, for instance, had a homogeneity index of just 0.276 but finished at the top while Liverpool, which had a higher homogeneity index of 0.433, also finished at the top. This lack of correlation can be interpreted in a few different ways. The direct and most obvious conclusion, based simply on the analysis above, would be to say that a team's homogeneity has no effect on a team's success, and while such a conclusion is definitely supported by the data, it misses a few external factors that the homogeneity index fails to take into account. The purpose of exploring this particular research question was to essentially determine whether a player's nationality shapes his style of play (possession-based, counter-attacking, etc.) in such a way that players of the same nationalities – and thus of the same playing style –gel together better than those of different nationalities, thus affecting the overall team performance. One flaw with this approach is that a player's style of play is dependent more on the academy in which he was trained rather than his nationality. Quite often, a club's academy scouts and recruits young talent from all across the world, ingraining in them the club's playing philosophy. Players from different nationalities, then, might still share the same style of play if they were trained in the same academy. FC Barcelona's famous La Masia Academy, for example, is known for training its players in a fast-paced possession-based game style; these players encompass youngsters from all around the world, not just those from Spain. Additionally, many of these players are recruited by international academies at a very young age; their footballing development, then, is largely dependent on their academy and not their nationality. Another important reason why homogeneity may not play a large role in success is because most of the financially stronger clubs may not consider a player's nationality when buying him, rather focusing on his skill and position. Teams like Manchester City or Manchester United, some of the richest clubs in the world, do not rely only on players from their own academy – they often have the financial muscle to recruit the best players from other clubs and academies. To conclude, a lot of factors go into defining "homogeneity" and our analysis highlights that homogeneity in play-style cannot be linked directly with homogeneity through nationality.

<u>Research Question 5:</u>

The primary goal of Research Question 5 was similar to that of the second half of Research Question 1, to decide which teams were the best based on the average overall ratings of their players. However, instead of finding out the best teams in the Premier League, we were now evaluating the best teams that participated in the 2018 FIFA World Cup. Even though the video game says FIFA "19", it is actually released in 2018 and is meant to represent the 2018-19 season, and as such our analysis is valid.


Best Teams in World Cup 2018
Total Points Tally
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
France
Croatia
Belgium
Uruguay
England
Brazil
Russia
Sweden
Mexico
Colombia
Portugal
Spain
Denmark
Switzerland
IR Iran
Argentina
Japan
Senegal
Saudi Arabia
Peru
Nigeria
Serbia
Germany
Korea Republic
Tunisia
Poland
Morocco
Australia
Iceland
Costa Rica
Egypt
Panama
Country


Best Teams by Nationality in FIFA 19
Aggregate Skills Rating
0
20
40
60
80
Spain
Brazil
France
Germany
Argentina
Belgium
Portugal
England
Croatia
Uruguay
Colombia
Serbia
Denmark
Mexico
Senegal
Switzerland
Morocco
Russia
Poland
Sweden
Japan
Nigeria
Korea Republic
Peru
Australia
Egypt
Tunisia
Saudi Arabia
Iceland
Costa Rica
Panama
Nationality

As is readily apparent from the visualizations, the best teams as predicted by FIFA 19 are not exactly the same as those that performed the best in the 2018 World Cup. This is a fairly expected result as a team's overall rating as determined by a video game is in no way a definitive indicator of all the factors that go into a team's success, such as the chemistry between the players, the quality of management, the "luck" involved in each game, etc. Unlike the Premier League, the World Cup follows a completely different format – countries are placed in "groups" and must play each country in their group. The top two teams from each group proceed to the knockout stages of the competition, a concept which is non-existent in the Premier League. Since the World Cup follows a different format and is much shorter in time than the Premier League (the Premier League lasts for almost ¾ of a year), the impact that each single game has in the World Cup is much more than that in the Premier League. As such, in a one-off game, the "overall" ratings of the teams involved may not necessarily reflect the outcome of the game even though it can provide insights into which team has better skilled players; after all, the ratings for FIFA 19 are determined by the player's performance over the course of the entire previous season, so the ratings may or may not hold true for individual knockout games in the world cup. Additionally, the chemistry between players in a team also has a major impact on the team's performance in real life. Players usually spend most of the year training and playing for their respective clubs; as such, they are used to the play-style of their club as well as that of their club teammates. However, for international tournaments, players of the same nationality but from different clubs often have to play together with little past experience/training. This lack of chemistry between players can have a huge role in deciding how well the team as a whole plays, and the individual ratings of players themselves do not matter as much (after all, it is the entire team that wins/loses, not a single individual).

Work Plan:

1. Get top players for each category (such as shooting, goalkeeping, and passing) - ½ day
2. Create Neural Network to predict overall rating and/or value - 2 days
3. Analyze Machine Learning model using various statistical tests such as mean squared error, t-test, etc. – ½ day
4. Analyze machine learning model to identify the features that have the largest impact on a player's estimated price – 1 day
5. Plot the relationship between the change in a certain attribute and the expected price as determined by the Machine learning model – ½ day
6. Find out the best teams in different leagues by aggregating overall ratings for the players in the teams and compare the results of the actual leagues (by calculating the wins for each team in each league) to the predicted results. – ½ day
7. Given the best players for each attribute (such as shooting, passing, etc.), group the players by their nationality and compare different nationalities for different attributes. – ½ day.

8. Present the aforementioned data using geographical visualization for each attribute – ½ day.
9. Create a homogeneity index for each soccer league to compare the diversity of each team and see if there is a relationship between diversity and performance of the team in their respective league. – ½ day
10. Plot the relationship between the homogeneity of different teams and the number of wins they have in their respective league. – ½ day
11. Compare the ratings of players from each nationality to performance in international competitions like the World Cup 18. - 1 day
    Total days: 8 days

We were able to follow this work plan and had time left over to add on extra features such as testing our machine learning models on a single player such as Lionel Messi. The plan was very flexible and we were able to do multiple tasks on one day by splitting up the work. Ultimately we took about 8 days all together but we were able to complete the basics fairly quickly and were able to spend some time cleaning up our code.

Testing:

Since most of the project was focused on creating visualizations we could not use assert statements or smaller data files instead we wrote our results to csv files and compared them with the data visualizations. For example, in research question three when we made a csv of the rankings of all countries but we only plotted the top 5. To check if the data visualization was accurately plotting the right countries we compared the results to what was there in the csv. We did this with each diagram in research questions 1,3,4 and 5.
For the machine learning model we used the mean squared error of the test set to check the accuracy of the model on new data. We trained the model on 70% of the data in FIFA2019.csv and used the 30% to validate the results. To further understand the model we converted the mean squared error from the scaled form to euros to see what was the average uncertainty of the values printed out. We saw that the model was off about 3 million euros, which considering the high values of certain players, was accurate enough for our purposes. Another way we tested out the model was to look at each feature and its effect on the value predicted. We demonstrated this with line plots but we also created a dictionary and printed it out to compare only the maximum value each feature could output as shown below. Lastly we demonstrated that both models can predict a player's value by printing out the predicted value for Lionel Messi, a famous soccer player, and compared it to his actual value.

```python
def main():
    visualize_models()
    print("Testing models on one soccer player\n")
    test_model_on_players()
    print("")
    print("Testing importance of each feature on overall model:\n")
    overall_features_in_order = sorted(_o_features_max_value.items(), key=lambda x:
                                x[1], reverse=True)
    print(overall_features_in_order)
    print("")
    print("Testing importance of each feature on attribute model:\n")
    attribute_features_in_order = sorted(_a_features_max_value.items(), key=lambda x:
                                x[1], reverse=True)
    print(attribute_features_in_order)
```

```
In [9]: runfile('C:/Users/davse/Documents/ml_visualization.py', wdir='C:/Users/davse/Documents')
Testing models on one soccer player

Lionel Messi actual:['€110.5M'] overall model:[[42758796.]] attribute model: [[1.07304856e+08]]

Testing importance of each feature on overall model:

[('Overall Skill', 43023720.0), ('Shooting Overall', 43023720.0), ('Passing Overall', 43023720.0), ('Defending Overall', 43023720.0)]

Testing importance of each feature on attribute model:

[('GKReflexes', 137984510.0), ('Skill Moves', 133170180.0), ('Numerical Weight', 133146950.0), ('Numerical Height', 132527010.0), ('Age',
130585690.0), ('GKKicking', 129692670.0), ('Composure', 129412870.0), ('Marking', 126145656.0), ('SlidingTackle', 125237880.0),
('GKPositioning', 124888380.0), ('StandingTackle', 124862710.0), ('Penalties', 116834550.0), ('GKHandling', 116625870.0), ('GKDiving',
114619500.0), ('Vision', 111703016.0), ('Positioning', 105045190.0), ('Aggression', 98749390.0), ('LongShots', 97928720.0), ('Strength',
96888580.0), ('Interceptions', 96375320.0), ('Stamina', 85801750.0), ('Jumping', 84314060.0), ('ShotPower', 83458056.0), ('Reactions',
82380270.0), ('Balance', 80184010.0), ('Agility', 55181860.0), ('SprintSpeed', 53136210.0), ('Acceleration', 45543332.0), ('BallControl',
37724360.0), ('LongPassing', 24698186.0), ('Dribbling', 23356678.0), ('FKAccuracy', 17510440.0), ('Curve', 17392458.0), ('ShortPassing',
13351035.0), ('Volleys', 13054199.0), ('Finishing', 11407254.0), ('Crossing', 9963577.0), ('HeadingAccuracy', 9506811.0)]
```

Collaboration:

We didn't have help from other students (other than Tas). We used online documentation for pandas, seaborn and tensorflow to help with the respective data visualizations and ml. To help with ml we used an online course (https://www.udemy.com/course/linear-regression-with-artificial-neural-network/) to learn about the tensorflow keras library and how to create a neural network for regression models; topics we didn't learn in class.