Predicting Overall Player Ratings in FIFA 19

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1 INTRODUCTION

FIFA 19 is an extremely popular and successful video game based on real-world soccer. The game lets players take control of their favorite athletes and teams, allowing players to compete in mock matchups against AI, friends, or other players online. In order to make the game as realistic as possible, EA (the developer and publisher of the game) creates an extensive profile of each athlete featured in the game using data collected from their real-life performances. Most noticeably, every athlete is assigned an overall rating (out of 100), which acts as a holistic measure of the given athlete's abilities. In addition to the overall rating, EA also assigns ratings for specific skills such as crossing, finishing, heading accuracy, etc. for each athlete.

As a long-time fan of the game and a member of the FIFA community, I (like many other fans) was curious how EA decides to assign the overall rating of each athlete. For example, members of the community often disagree with the ratings assigned to any given player, feeling that many of the most famous players are often overrated while solid (but less famous) players are often underrated. In fact, many fans believe that the overall ratings of the most famous players are manually tuned up. Although EA has given fans a glimpse into their data collection and assignment process, they have largely kept fans in the dark about how they generate the all-important overall ratings. Ultimately, this is what drove me to pursue my final project: I wanted to see whether fans' concerns were merited and what stats EA focuses on when assigning overall ratings.

2 THE DATA

I used a FIFA 19 data set found on kaggle in order to complete my project [1].

2.1 Data Set Features

Overall, the data set contains 18,208 data points and 89 features. Each data point represents a player while each feature represents a different part of a given player's profile.

An important thing to note is that not every feature in a player's profile is relevant to his overall rating (nor should they be). For example, some of these 89 features include such descriptors as the athlete's nationality, the URL associated with a picture of the athlete's face, the URL associated with a picture of the athlete's home country's flag, etc. While all of this information is useful in the

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game itself, it is irrelevant for our purposes. As a result, it became necessary to parse the data in some sensible way and extract only the relevant features.

2.2 Parsing Methodology

While examining the data, it became clear that only 35 of the 89 features describe the specific skill ratings associated with a given player (all of which are out of 100, like the overall rating). These 35 features are what I ended up focusing on while implementing my algorithm. The game itself separates these 35 features into 7 categories: shooting, physical, goalkeeping, defending, pace, passing, and dribbling. A breakdown of what specific features are associated with which category is summarized in Table 1.

Shooting	Physical	Goalkeeping	Defending	Pace	Passing	Dribbling
Finishing	Aggression	Diving	Heading	Acceleration	Crossing	Agility
Long shots	Jumping	Handling	Interceptions	Spring speed	Curve	Balance
Penatlies	Stamina	Kicking	Marking		Free kick	Ball control
Positioning	Strength	Positioning	Sliding tackle		Long passing	Composure
Shot power		Reflexes	Standing tackle		Short passing	Dribbling
Volleys		Speed			Vision	Reactions

Table 1. The 7 categories of the 35 skill features

Additionally, while examining the data, it became clear that certain features are dependent on a player's position. For example, notice that one of the 7 categories is goalkeeping, which is a category that is (or should be) only relevant for the ratings of goalkeepers. Thus, I also divided the overall data set into 4 smaller categorized data sets depending on a player's position: goalkeepers, midfielders, forwards, and defenders. A breakdown of what specific positions are associated with which category is summarized in Table 2.

Goalkeepers	Midfielders	Forwards	Defenders
GK	CAM	ST	CB
	CDM	RW	LB
	CM	RF	LWB
	LM	LW	RB
	RM	LF	RWB
		CF	

Table 2. The 4 categorized data sets and their associated positions

3 ALGORITHM IMPLEMENTATION

I ultimately decided to use a GP regressor with a dot product kernel to predict overall ratings. I implemented all of this using Python and the scikit-learn library.

3.1 Why the Dot Product Kernel

I experimented with several different kernels before ultimately settling on the dot product kernel. For example, I tried using a RBF kernel as well, but the RBF kernel GP produced worse results and took much longer to train. Thus, it just made practical sense to use the dot product kernel and I ended up using it for the duration of my project.

From an intuitive standpoint, I believe the choice of a dot product kernel also makes the most amount of sense: a linear relationship between a player's skill ratings and his overall rating makes much more sense than any other possible relationship (something that practical trials confirmed).

3.2 Choice of Features by Data Set

As mentioned previously, I divided the overall data set into 4 smaller data sets depending on the players' positions. This meant I had to train and test 4 separate GPs, but it also meant that I needed to figure out which of the 7 skill categories would be most relevant for each data set.

Ultimately, my choices came as a result of a mixture of common sense and experimentation: I first used common sense to pick out which feature categories seemed most relevant for the given position, then experimented with a combination of these categories until I got the best results. The categories I ended up assigning for each data set is summarized in Table 3.

Goalkeepers	Midfielders	Forwards	Defenders
Goalkeeping	Pace	Pace	Pace
	Shooting	Shooting	Passing
	Passing	Passing	Defending
	Dribbling	Dribbling	Physical
	Defending		
	Physical		

Table 3. The 4 categorized data sets and their associated feature categories

The critical thing to observe is that no player is good in every skill category and only certain skill categories are relevant for a given position. For example, it makes sense that forwards do not need to be good at goalkeeping or defending to be good forwards. It also makes sense that defenders do not need to be prolific shooters or dribblers to be good defenders. However, midfielders pose a challenge: midfielders in soccer must be a jack-of-all-trades, meaning the best midfielders are good at both defending and attacking. While certain midfielders might specialize in attacking and others might specialize in defending, they must generally be good at both. Thus, I considered every category except goalkeeping to predict the overall ratings of midfielders, meaning the midfielders GP considers the most amount of features.

4 PREDICTION RESULTS

Overall, the GPs performed admirably and their results are summarized in Table 4.

Goalkeepers	Midfielders	Forwards	Defenders
(0.467, 0.489)	(1.177, 1.206)	(0.945, 0.965)	(0.797, 0.825)

Table 4. The GPs' median absolute errors obtained from a 10-fold cross validation, of the format: (training error, testing error)

Considering that these errors are on a scale of 100, I am happy with the results that I got. As shown in the table above, the goalkeepers regressor had the best performance while the midfielders regressor had the worst performance. From a logical standpoint, though, I believe these results make sense. More specifically, it makes sense that goalkeepers are the easiest to predict on as they only have one skill category relevant to their overall rating. Conversely, it also makes sense that midfielders are the hardest to predict on as I had to widen the considered features considerably to account for the versatile nature of the position.

4.1 Discrepancies with Prior Beliefs

As mentioned in my introduction, a big part of the reason I chose to pursue this final project is because I was curious whether fans' complaints were merited: are famous players overrated while less famous players with solid skills are underrated?

As a long-time fan of the FIFA games, I had sided with other fans in presuming that the most famous players are overrated. In fact, I originally believed that the most famous players (like Messi and Ronaldo) would pose a difficult challenge as I thought their overall ratings would vary widely from what the GP would predict. However, these concerns ended up being unmerited.

In fact, when examining the players with the largest discrepancy between their predicted rating and their overall rating, the GPs seem to make mistakes for good and bad players alike. Although the game does not seem to grossly overrate famous players, famous players do indeed show a general trend of being overrated, as shown in Table 5.

Player	Predicted overall rating	True overall rating
L. Messi	90.90	94
Cristiano Ronaldo	92.21	94
De Gea	89.95	91
Sergio Ramos	89.06	91
K. De Bruyne	90.22	91
K. Mbappe	86.67	88
J. Henderson	80.64	82
L. Modric	88.89	91
V. van Dijk	85.87	86
G. Buffon	86.94	88
E. Hazard	90.16	91

Table 5. Some of the most famous players' predicted overall ratings compared to their assigned overall ratings

5 CONCLUSION

Overall, I had a great time with this project and thought it was a ton of fun. Although I had originally believed that EA tends to grossly overrate extremely famous players, it seems like they only do so a little bit. And now, thanks to this project, I can also brag to my friends that I know what features EA focuses on when they construct the overall rating of a player.

REFERENCES

[1] https://www.kaggle.com/karangadiya/fifa19/