MMR/Rank Simulation Analysis Report

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Table of Contents

Introduction

In this report, we go over an analysis on our MMR/Rank Simulation project. Our project attempted to simulate MMR and rank distributions in a video games competitive ladder.

Defining MMR

Elo was a ranking system originally developed for chess, which handled one-on-one competitive games. League of Legends (LoL), the game our model was based on, employed the elo rating system during its first season. On the other hand, MMR is Matchmaking Rating, a rating score that many video games use to replace the elo rating. A player's MMR decides what other users this player should be matched against. It is a number hidden from the player and is only used behind the scenes. After its first season, LoL developed more complicated system using MMR to allow for better matchmaking in the system, as the elo rating system is obsolete for multiplayer games, which usually feature a game-size of five-versus-five or more ("What is LOL MMR…"). MMR has many different factors that affect the gains and losses for winning and losing. It takes into account the average of the match for both teams, which our model follows, and how the player compares to this number. A player who is considered the worst member on the team, and the team is favored to lose, will gain a lot more MMR than a player who was favored to win and considered the best player on the team.

Other Simulations for MMR

For most competitive multiplayer video games, there are third-party websites that keep track of player data to simulate the MMR for the player, without accessing the actual MMR kept in the databases of video game companies. These websites allow the users to enter their in-game usernames, then return an estimate of their MMR based on their current rank and the rank of their past teammates. These websites serve as another real-life application for our current simulation.

Sensitivity Test

With the myriad of different variables and factors that play a role in our simulation, testing for changes in these variables is a must. In this section, we'll be looking at the different affects certain changes have in our overall simulation and how they apply to the real world.

Team Size Sensitivity

Competitive video games have a variety of different team sizes, whether it is 5 for League of Legends, 6 for Overwatch, or 1 to 3 for Rocket League. By using our simulation, we can find out if different team sizes affect how much the players' personal skills matter for their MMR.

First, we ran a regression on MMR versus skill factors with the team size set to 5. The results of our regression can viewed in Table 1. Each individually altered skill changes MMR by different amounts. Coefficients are different from one another because of the way the importance of skill factors is implemented.

Next, we ran the same regression with the team size set to 2. The results of this regression can be viewed in Table 2. When we changed team size to two, the coefficients of each skill factor increased by a noticeable amount.

Table 1: Regression of MMR vs Skills with Team Size 5

Dependent Variable: MMR	
Constant	127.89
(X_0)	(26.50)
Communication	30.27**
(X_1)	(1.37)
Tilt	18.64**
(X_2)	(0.93)
Internet	21.79**
(X_3)	(2.80)
Leadership	31.84**
(X_4)	(1.08)
GameKnowledge	30.17**
(X_5)	(1.12)
ReactionTimes	10.07**
(X_6)	(0.83)
Early_Game	42.82**
(X_7)	(1.03)
Late_Game	43.46**
(X_8)	(0.94)
Mechanics	51.76**
(X_9)	(1.11)

Table 2: Regression of MMR vs SKills with Team Size 2

Dependent Variable: MMR	
Constant	-152.12
(X_0)	(42.97)
Communication	51.74**
(X_1)	(1.93)
Tilt	32.16**
(X_2)	(1.50)
Internet	30.56**
(X_3)	(4.05)
Leadership	49.74**
(X_4)	(1.42)
GameKnowledge	51.03**
(X_5)	(1.37)
ReactionTimes	17.02**
(X_6)	(1.17)
Early_Game	65.97**
(X_7)	(1.43)
Late_Game	66.34**
(X_8)	(1.53)
Mechanics	80.70**
(X_9)	(1.62)

As we decreased team size, the more a player's skill mattered toward the MMR increase. This change can be explained by our implementation of determining the winning team. A team's individual skills are summed together with multipliers and random noise being taken into account. This aggregation of skill is then compared to the other team's aggregation of skill. The team with the higher number wins. By decreasing the size of a team, a single player's skills plays a larger role in that aggregation of skill. In a team of size 5 with every player having an aggregate skill of 10, then the total skill for that team would be 50. A single player would only account for 20% of that total skill. If we were to decrease the team size to two, then the total team skill would become 20. The same player with aggregate skill of 10 then becomes 50% of that total skill.

These results can also be seen in actual video games. In games with larger team sizes, such as Overwatch with team size of six, it can be hard for players to stand out and help determine the outcome of the game. Even if the player is the best on their team, they must overcome the mistakes of five of their teammates while also battling the skill level of six opponents. In games such as Rocket League with team sizes of three or lower, it is much easier for a player to overtake a game and single handedly win as they have less teammates to cover for and less opponents to worry about. With games where team size is one, skill becomes a direct reflection of your MMR.

Default MMR Sensitivity

In our simulation, a test ran with all players starting at a default MMR of 1500, resulted in the average of our bell curve sitting around 1550-1600. From that average, the players worse and better than the average then moved along the tails, getting thinner the farther away they got from the average. Figure 1 shows these results. If we change the default MMR to 1700, the bell curve average sits around 1750, as seen in Figure 2. From this we can infer that average MMR is relative to what the default MMR is for each player.

Figure 1: MMR Distribution with Default MMR of 1500

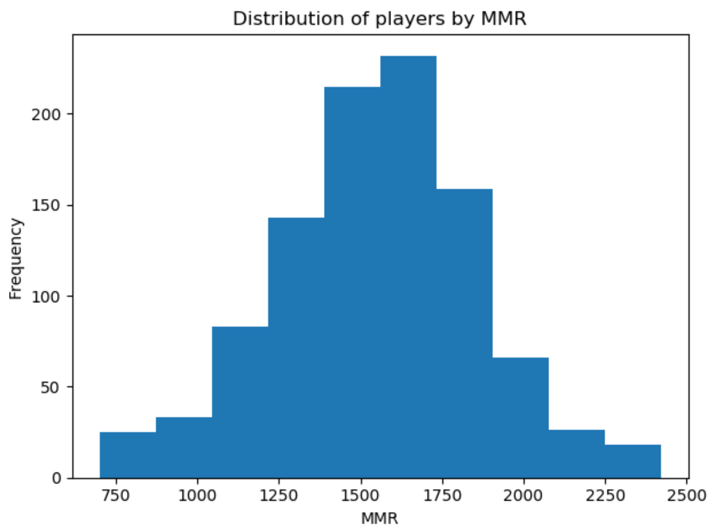
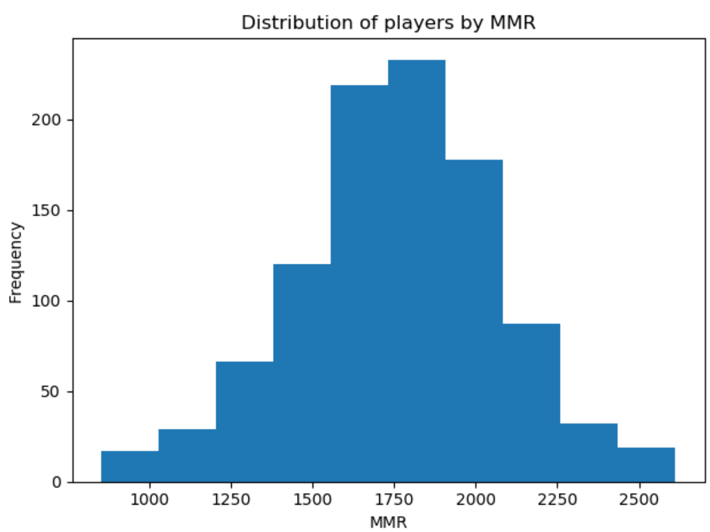


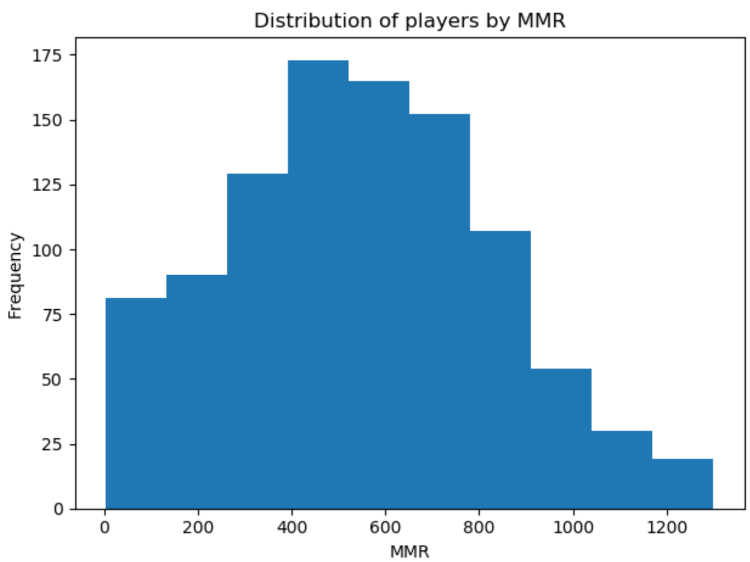
Figure 2: MMR Distribution with Default MMR of 1700



In both of these examples, neither tail reached our MMR limits of 0 and 2800. Because of this, players of certain skills are better matched, as there is a separation between their MMR. Those with well below average skills will always be placed with those with the same well below average skills, as they will be the farthest away from the MMR average.

Now what if the default MMR of our simulation was placed in an extreme place such as 500. Looking at Figure 3, we can see that a default MMR of 500 still has an MMR average relative to the default MMR at around 550. However, our distribution fails to follow the normal distribution as the lowest MMR tiers begin to clump up with players due to our lower cap 0. Because of this clumping, there is not as much separation between players of varying skills. A player with well below average skill would still be placed in games with players just below average skill. This can cause frustration in many of the players who feel everyone they play is simply better than them.

Figure 3: MMR Distribution with Default MMR of 500



This scenario is seen in many video game ranking ladders. For example, Rainbow Six Siege, a first-person shooter game developed by Ubisoft, suffers from an inconsistent variety of skill in players on the lower ends of their rank ladder. An article from PC Gamer states that one of the biggest problems that Rainbow Six Siege suffers from in their ranking system is, "Uneven matchmaking that allows high-level players to stomp the less skilled" (Park). Although we don't know exactly how Rainbow Six Siege determines a new player's starting MMR, the default MMR may be a cause for this problem. A solution for this could be to raise the default MMR for new players, so that the different skill levels can spread out more.

Skill Factor Sensitivity

In our simulation, the skills that determine which team wins each have a multiplier attached to them. These multipliers are our way of quantifying importance of each skill factor. In the simulation's current state, the multipliers have a range of 1-5, with 1 being skills having the least amount of impact on the game, while skills with a multiplier of 5 being skills we believe to be the most important. The "reaction time" skill is the only skill with multiplier 1; and the "mechanics" skill, which is how well the player physically plays the game, is the only skill we have with a multiplier of 5.

Each of these skills can be used to predict a player's MMR. As seen in Table 1, each skill has its own coefficient on how much an increase in skill will affect MMR. Figure 4 demonstrates a scatter plot of a player's reaction time compared to their MMR. Backed by the small coefficient in the regression, it can be seen that reaction time is not the best descriptor for MMR. Figure 5 is a scatter plot of a player's mechanics compared to their MMR. In contrast to the scatter plot for reaction time, this scatter plot shows a slight upwards trend in MMR as mechanic skill increases but still has some large variation. These two results are to be expected with how we used different multipliers in our simulation.

Figure 4: MMR vs. Reaction Times

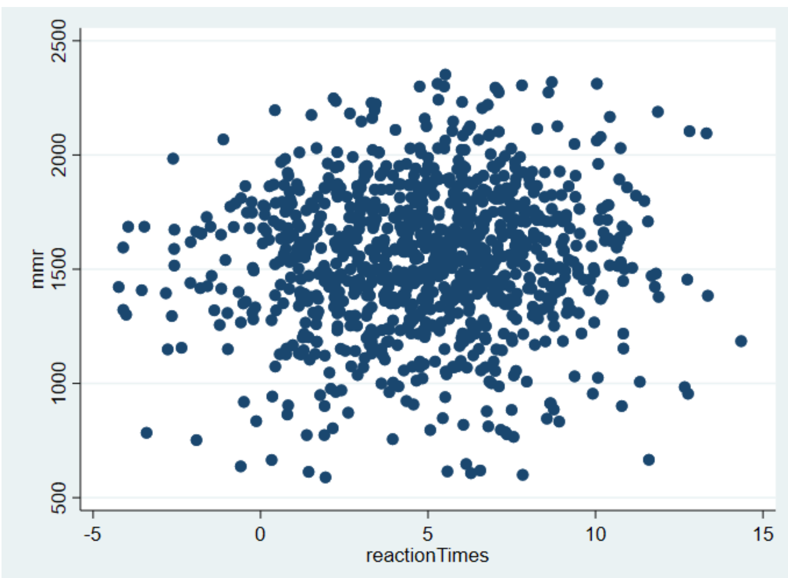
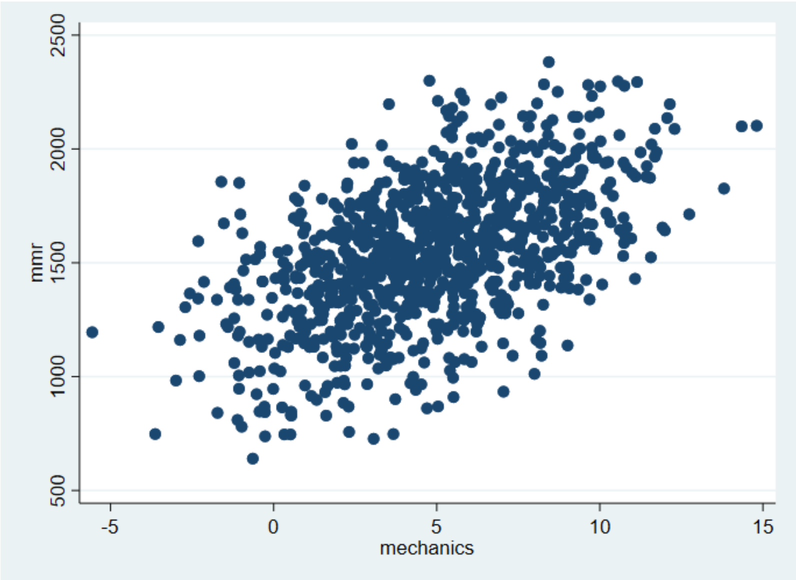


Figure 5: MMR vs Mechanics



Now let's observe what happens when we increase the multiplier of mechanics. Figure 6 shows a simulation run with the mechanic's multiplier changed to 20. Compared to the earlier scatter plot, this graph shows a large decrease in variation of the points. Almost all of the points group towards an upwards trend line. This shows that as we increase the importance of a certain skill, it then becomes a better explanatory variable for MMR. Because the importance of mechanics increases, other skill factors begin to lose significance. Viewing Table 3, we can see that the coefficients of other variables have decreased to about half of what they were in Table 1. As the importance of mechanics increases, it begins to overshadow the other skill factors.

Figure 6: MMR vs Mechanics with Multiplier 20

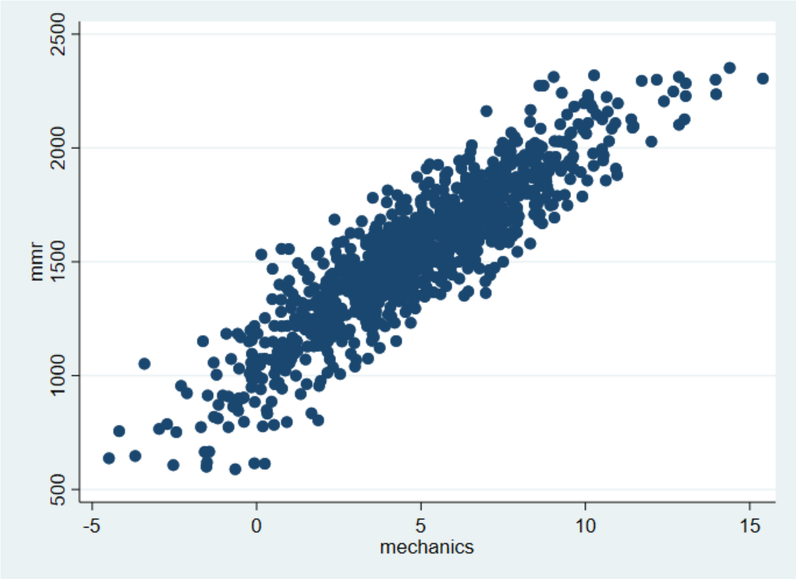


Table 3: Regression of MMR vs SKills with Mechanics Multiplier 20

Dependent Variable: MMR	
Constant	571.362
(X_0)	(26.04)
Communication	13.36**
(X_1)	(1.61)
Tilt	9.13**
(X_2)	(1.06)
Internet	7.73**
(X_3)	(2.97)
Leadership	12.40**
(X_4)	(1.10)
GameKnowledge	14.26**
(X_5)	(0.97)
ReactionTimes	4.68**
(X_6)	(0.90)
Early_Game	20.40**
(X_7)	(0.94)
Late_Game	18.86**
(X_8)	(1.07)
Mechanics	94.70**
(X_9)	(1.31)

This changing of importance in our simulation can be applied to real video games. In games such as League of Legends, many aspects of the game are more important than others. By increasing importance of a certain skill, players with that skill will tend to win more games as their mastery of such skill has become more important towards a team's victory, and vice versa can be said for decreasing the importance of a certain skill. For example, what items you buy for your character are vital to winning a game in League of Legends. Purchasing items that play to the strengths of the character you are playing can be the difference between winning and losing. However, League of Legends has a recommendation list for what items to purchase for each character. Along with this, the internet has many resources to view what the best players are buying. This has caused the mastery of the skill of purchasing correct items to be easily achieved by just about anyone. If League of Legends were to remove the recommendations and the online resources were to disappear, the importance of knowing what to buy increases. Players that know what is the best thing to buy will begin to see themselves winning more games. Developers can use this thought of mind to make changes to their games.

References

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Park, Morgan. "Rainbow Six Siege's revamped Ranked mode doesn't address its worst problems." *PCGAMER*, 18 Feb. 2019. https://www.pcgamer.com/rainbow-six-sieges-revamped-ranked-mode-doesnt-address-its-worst-problems/