Tyler Newman

Wadhwa

Econ 123CW

3 June 2021

Is Persistence Enough?

Introduction & Background

In Malcolm Gladwell's 2008 book, Outliers, he claims that anyone who practices a given task for 10,000 hours will master that skill; if someone were to practice the same skill, eventually they would become a master at it. Gladwell's claim is based on *The Role of Deliberate Practice in the Acquisition of Expert Performance*, a study conducted by K. Anders Ericsson, Ralf Th. Krampe, and Clemens Tesch-Romer and published in 1993. While Gladwell cites from this study that continued practice, or rather time is the most important part in finding success and mastery in a skill, he forgets to mention Ericsson et. al.'s emphasis on the importance of deliberate practice. In the abstract of the study, they state, "Individual differences, even among elite performers, are closely related to assessed amounts of deliberate practice." They both agree on how significant time is, but while Gladwell claims that as long as you practice the skill for the arbitrary 10,000 hours, this study makes it clear that the hours spent must be meaningful and full of purposeful practice to achieve mastery. The goal of this paper is to learn if there is statistical proof that even after practicing an activity for 10,000 hours, it would not necessarily mean that a person has become a master at that skill. In this study, the win rates and out-of-game player statistics will be used to compare the role continuous playing has on a player's performance at the game. Does anyone have the ability to reach the highest levels of play if they can put in 10,000 hours?

In 2020, Jeffrey R. Young had the opportunity to interview Ericsson where he asked for his opinion on Gladwell's interpretation of his research. One of the main takeaways is that Gladwell did not emphasize the importance of a teacher that will guide a student towards the deliberate practice that leads to mastering a skill. When a student is paired with a teacher who can design a practice regiment perfect for them and ask "what would be the next step for [them[student]] to develop and improve." Ericsson thinks this is important because without a teacher helping a student and changing their schedule to encourage growth, the student is likely to "stall out" and never increase their skill mastery even with continued hours of practice. The website mobalytics.gg - a subscription-based business that offers coaching for users to help them improve their skills at League of Legends - was able to test Ericsson's conclusion in 2018 when they used their user's data to analyze the impact of their coaching service on the improvement in a player's abilities. Their model used data on the number of times Mobalytic's different platforms were checked and when coaching advice was used by a player and compared it with actual increases in a players League Points and/or Rank. The research showed players who used their Mobalytic subscription had a 42.6% chance of climbing out of their current rank, which is works as great advertising for a business promoting the importance of their coaching system for players who have reached their skill plateau.

Interestingly, other research concludes that while deliberate practice may play a role in mastering a skill, it may not account for all growth by that person. Michael Miller (2018) cites the meta-analysis conducted by Brooke Macnamara (2016) that deliberate practice only predicts 20 - 25% of the variance in people's mastery of different skills. Whether this is gaming, music, or sports, Mcnamara concluded there must be other variables than practicing that effect a person's overall mastery. She concluded that these variables would include things like the age at which a person began a skill and a person's genetics; however, because we will not be focusing on the individual player's genetic makeup and personal traits, we will be focusing on how well continuous play effects that 20 - 25% variance window. Do people genuinely become masters at the game as they put more time and energy into the game? Do people who play specific champions have a higher chance at climbing and being better with more time?

This paper will be using data from League of Legends players who are at least have an account level of 50 and have played at least 50 games of Ranked Solo: 5x5. League of Legends is a Multi-player Online Battle Arena (MOBA) game that puts 5 players together to destroy the opposing team's base. Players choose a character, pick a lane, and must cooperate with their team to find victory. A major part of the dichotomy of making online games is balancing the game across different skill levels of players. Riot Ghostcrawler, a game developer for League of Legends, has even acknowledged the difficulty and great lengths that have to be taken to balance the game for these different levels of players in his article */DEV: BALANCE FRAMEWORK UPDATE* (2020). This study can provide evidence for how game designers should balance their games and what type of learning curve they should implement for new players. One of League's (as well as other online games) biggest discouragement of new players and a growing player base is the difficulty for people to get into the game. In */DEV: NEW PLAYER EXPERIENCE* (2018), Ghostcrawler addresses growing concerns of the barriers to entry for new players when they try to start the game. While he mainly focuses on fixing their tutorial to provide a better learning experience for players, I think it is more important for the game to recognize the best tips for new players to grow and give them that information/ lead them towards learning those tips naturally. Being able to track how players increase their ability by playing more games and by playing a single champion more, we can create a visual learning curve that game designers and balancers can use to improve their decisions when making changes to their game.

Model & Data

Much of research in this area is either done through meta-analysis when the researcher is trying to see the effects of continued practice over time because their goal is to see if practice makes perfect in all types of skills. While research done on games and League of Legends specifically are focused on predicting which team will win by using in-game statistics like gold per minute, first-blood, dragons killed, etc. lends itself well to logistic regression, our model focuses on how important individual details of a players account (games played, rank, account level) will lend itself better towards a standard multivariate model using OLS coefficients, ex:

$$yi = \beta 0 + k \sum j=1\ \beta j \cdot xij + ui$$

Given this model, this paper will use a model with 5 different variables that are accessible through Riot's API that give information about a player's account and how much they play. Win Rate will be the independent value that we use as the value our coefficients will try to predict. In Ghostcrawler's article on game balance, he makes it clear that the goal is that a player who is in their correct rank for their skill level will not have an absurdly high win rate. This is because as a player's win rate comes to about 50%, they are reaching a skill threshold where the game has placed them into the tier where people who have about the same skill level are also around within that tier. League of Legends has an inaccessible hidden statistic called MMR that is based on a player's win rate in their tier. Because of MMR's opacity, the best statistic usable for judging whether a player is increasing in mastery is to test the win rate. To do this the model will test the impact of the interaction between tier and games played on the win rate of the player (along with the other statistics). Mobalytics cared more about reporting if a player was increasing their tier because that is what is important to their user base. While increasing win rate and increasing rank are similar and tied together, they do not report on the same thing especially as more games are required to tier up as players reach higher tiers of play. The model is below.

$$\text{Win Rate} = \beta\_0 + \beta\_1{*}\text{Tier} + \beta\_2{*}\text{Rank} + \beta\_3{*}\text{League Points} - \beta\_4{*}\text{Account Level} - \beta\_5{*}\text{Account Level}^2 - \beta\_6{*}\text{games played} + \beta\_7{*}\text{Tier}{*}\text{games played} + \beta\_8{*}\text{combined champion mastery}$$

Tier and Rank refer to the categorical descriptions given to a player on the ranked ladder. It goes from Iron to Challenger, increasing with prestige and difficulty as you climb. Those who come closer to Challenger are deemed as pros/ the best at the game as near the top only about 2% of the whole player base falls into this realm. The model treats these categorical variables as factors in the model - counting up as prestige climbs. I expect these to be positive variables as a better tier and a better rank should align with a better win rate as it takes a player to win a majority of the time to reach these ranks.

League Points are the score between ranks. 100 is required to reach the next tier, and at higher ranks of play, a greater number of League Points makes a big difference compared to lower players. Because of this, League Points should have a positive relationship to win rate as they increase with wins. The more points you have, the more likely you have a positive win rate (+ 50%).

Account Levels are the individual levels of a player's account which is more so correlated with total playtime rather than any type of proficiency in the game. I hypothesize that there is a learning curve that wins rate increases with for level, but at a certain point, things even out towards 0 and growth stops. I predict that account level has a negative effect linearly and quadratically because the higher a players level, the more games they will have played and if they are playing more games without any coaching that would change their playstyle, they will reach their tier where they are around players of similar level and their win rate will decrease towards 50%. This of course is similar to games played as games played measure how many games have been played by a player, and if that number continues to go up the player will reach a point where they are unable to climb any further no matter how many games they play. In the end, each game will harm their win rate.

Champion Mastery is a player’s combined score of all champions played. Champion mastery is a metric that shows how much time a player has spent playing different characters. While having a low champion mastery could be good as it points towards a player understanding their champion well and one-tricking, having a higher mastery should be positively correlated with win rate as knowing more about different champions increases a player’s knowledge of the game and adds towards their overall mastery.

These variables that make up the dataset are all available details given by Riot’s API that have been shaped together using a python wrapper called Riot Watcher. Using Riot Watcher it is possible to attain all variables except for win rate. Win rate is found by attaining the total wins of a player, dividing it by total games played, and rounding it down to two decimal places. The dataset was then exported as a CSV and ran as a multi-variate linear model in R.

Empirical Results

When running this model, it originally was tainted by players who were smurfing. Smurfing is when a player who has a higher ranked or higher level account creates a lower leveled account to play. They do this because they can easily win against lower-tiered players and have an account with a high tier, but a low account level. To account for this, 1907 data points were removed because they either played less than 50 games or they were under the level of 50. The model predicted without accounting for smurfing is below in Figure 1.

Figure 1:

```
Call:
lm(formula = winrate ~ tier.order + rank.order + leaguePoints +
    summoner.level + games + champion.mastery, data = cleanedset

Residuals:
     Min       1Q   Median       3Q      Max
-0.50229 -0.03986  0.00014  0.04390  0.45699

Coefficients:
                   Estimate Std. Error t value Pr(>|t|)
(Intercept)       4.738e-01  3.237e-03 146.372  < 2e-16 ***
tier.order.L      1.246e-01  3.266e-03  38.147  < 2e-16 ***
tier.order.Q     -6.362e-02  3.037e-03 -20.944  < 2e-16 ***
tier.order.C      1.966e-02  2.982e-03   6.593 4.78e-11 ***
tier.order^4      6.506e-03  2.990e-03   2.176  0.02962 *
tier.order^5     -2.463e-03  2.979e-03  -0.827  0.40853
rank.order.L      2.791e-02  2.465e-03  11.325  < 2e-16 ***
rank.order.Q      7.369e-03  2.434e-03   3.028  0.00248 **
rank.order.C     -1.208e-02  2.435e-03  -4.961 7.27e-07 ***
leaguePoints      1.769e-04  4.214e-05   4.198 2.74e-05 ***
summoner.level   -3.050e-06  2.537e-05  -0.120  0.90433
games             2.422e-06  8.738e-06   0.277  0.78162
champion.mastery  2.844e-05  1.986e-05   1.432  0.15227
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.08502 on 4876 degrees of freedom
Multiple R-squared:  0.3373,    Adjusted R-squared:  0.3356
F-statistic: 206.8 on 12 and 4876 DF,  p-value: < 2.2e-16
```

Because the model is meant to predict the win rate percentage (games won to games played), variables have coefficients with powers to the -1 power or less as they will directly move the win rate up and down per unit increase of each. Running the model yields the summary results below in Figure 2.

Figure 2:

```
Call:
lm(formula = winrate ~ nosmurfstier.order + nosmurfsrank.order +
    leaguePoints + summoner.level + summoner.level^2 + games +
    nosmurfstier.order * games + champion.mastery, data = nosmurfs)

Residuals:
      Min        1Q    Median        3Q       Max
-0.248546 -0.023749  0.000182  0.026484  0.290085

Coefficients:
                           Estimate Std. Error t value Pr(>|t|)
(Intercept)               4.807e-01  2.617e-03 183.639  < 2e-16 ***
nosmurfstier.order.L      1.231e-01  3.739e-03  32.925  < 2e-16 ***
nosmurfstier.order.Q     -5.758e-02  3.604e-03 -15.976  < 2e-16 ***
nosmurfstier.order.C      2.114e-02  3.730e-03   5.666 1.60e-08 ***
nosmurfstier.order^4     -5.543e-05  3.726e-03  -0.015  0.98813
nosmurfstier.order^5     -3.204e-03  3.509e-03  -0.913  0.36141
nosmurfsrank.order.L      1.421e-02  1.861e-03   7.637 2.98e-14 ***
nosmurfsrank.order.Q     -1.236e-03  1.801e-03  -0.686  0.49282
nosmurfsrank.order.C     -2.693e-03  1.774e-03  -1.518  0.12908
leaguePoints              9.443e-05  3.142e-05   3.006  0.00267 **
summoner.level            3.909e-06  1.717e-05   0.228  0.81987
games                     2.825e-05  6.992e-06   4.040 5.48e-05 ***
champion.mastery          2.591e-05  1.354e-05   1.914  0.05575 .
nosmurfstier.order.L:games -1.771e-04  1.637e-05 -10.819  < 2e-16 ***
nosmurfstier.order.Q:games  8.944e-05  1.492e-05   5.994 2.30e-09 ***
nosmurfstier.order.C:games -2.110e-05  1.711e-05  -1.233  0.21749
nosmurfstier.order^4:games -1.952e-05  1.727e-05  -1.130  0.25839
nosmurfstier.order^5:games  1.424e-05  1.490e-05   0.956  0.33929
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.04876 on 2964 degrees of freedom
Multiple R-squared:  0.4072,	Adjusted R-squared:  0.4038
F-statistic: 119.8 on 17 and 2964 DF,  p-value: < 2.2e-16
```

An immediate takeaway is also that summoner level and champion mastery are not significant in predicting the win rate of a player. This is most likely due to these variables holding no reasonable effect on how well a player performs. As previously explained, both of these variables provide the chance for both positive and negative increases, and it may be found unsurprising that they end up having no significant effect on the model.

Variables that did have significant effects are a player's ranked tier, a player's ranked rank, a player's league points, the total games played by a player, and the interaction between a player's rank and their total games played. Out of all of these significant variables, a player's ranked tier has the greatest influence on a player's win rate with a coefficient of 1.231e-01. Most likely this is due to players who played up into their preferred rank easily with a high win rate and then stopped playing the game as much. Further development of this model would need more data to find players who are actively playing and trying to tier up. Surprisingly, total games played have a positive correlation, albeit small, of 2.825e-05; although, this is the opposite when looking at the interaction between ranked tiers and total games played as it is negative at -1.771e-04. Important to note is that the adjusted R-squared of the model is 0.4038 meaning more variables need to be found to help explain more of the variance of player's win rates, and given that the adjusted is smaller than the regular R-squared, there were unimportant variables included in this model, to begin with.

The following figures are pair graphs of the dependent variable along with some of the variables. These graphs show a common trend, that the overall average of players comes out around 50%. In figure 3, the data shows that players of each tier on average have a 50% win rate in that tier. Figure 4 and figure 5 also detail that as the number of games and the higher the player's level, the more likely the player starts to average around 50%. As mentioned above, some players do stop playing the game after reaching the rank they want and this could be affecting these stats. And finally, figure 6 is simply a histogram of the player's win rates which shows that of all players there is an average of a little over 50%.

Figure 3:

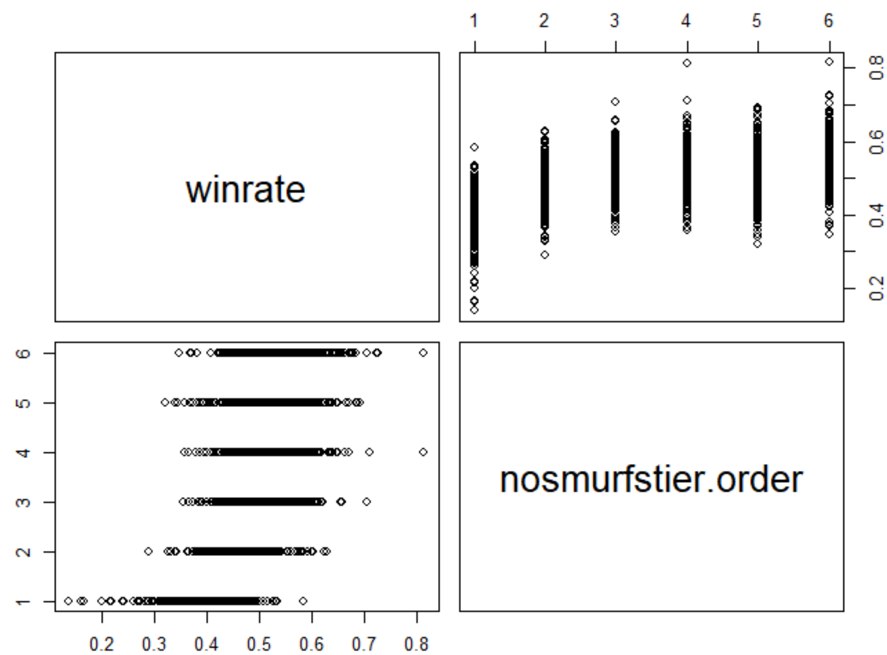


Figure 4:

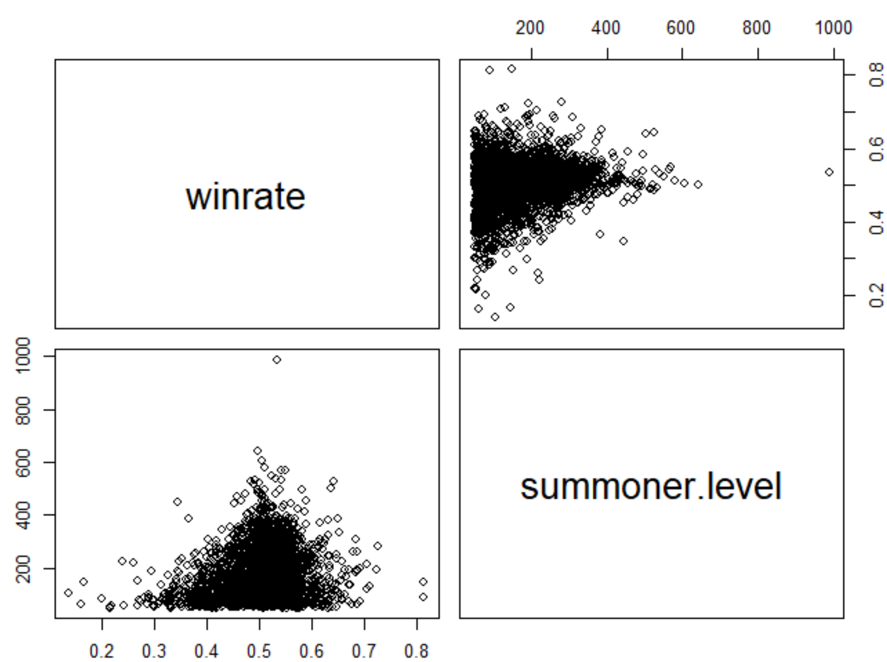


Figure 5:

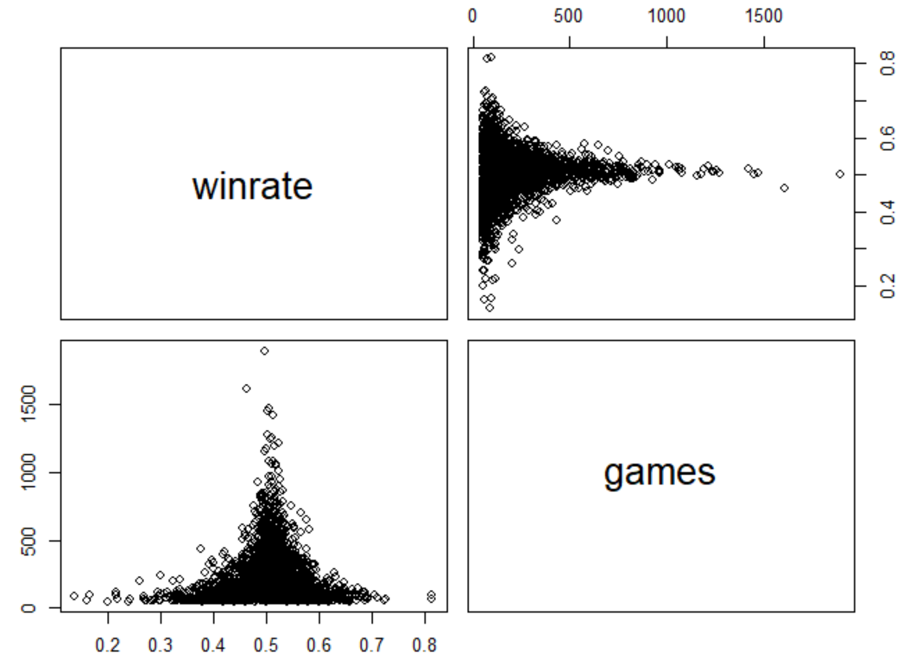
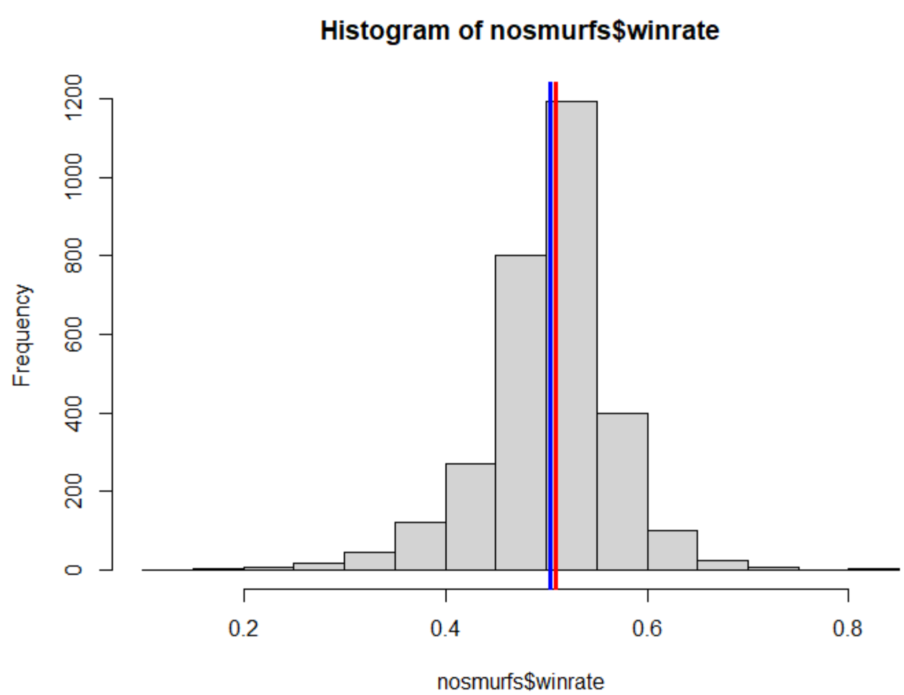


Figure 6:



Conclusion

It should come as no surprise that if a player is a higher tier, they should have a higher win rate. Players in higher tiers are better than players of lower tiers, and this is reflected well in the higher coefficient assigned to the player's tier. However, this is adjusted by the interaction between a higher amount of games played and a player's tier. As a player tries to climb, they will play more and more games and if they do not get there quickly they will have played many more games than another who reached the same tier with a higher win rate. This points to a negative correlation between playing more games with the intent of climbing and the player's overall win rate and accounts for why we see in the figures of the pairs above that everything always comes back to around a 50% win rate.

But this is okay! This is in line with how Ghostcrawler and other developers want to balance their game. Having the opportunity to have an equal chance of winning every day that you play adds the incentive to get better and try harder in your game. If a player wants to win, on average they should be with a team that has equal chances of winning on either side, and if that player decides to try harder, and become a better player, they can be the difference that wins the game. The chances of winning are in the player's hands, and it is on them to work harder for their wins and progression.

This model could be improved to account for other variables, and we could look into the genetics and individual details of players to account for more differences in play, but in the end, the win rates would be the same. What would be more important in the future is to look into individual games and see how important in-game statistics are towards winning a game. In what ways does a player need to take control of the game to push that 50% chance of winning forward?

References

Ericsson, K. Anders. “Deliberate Practice and Acquisition of Expert Performance: A General Overview.” *Academic Emergency Medicine*, vol. 15, no. 11, 2008, pp. 988–994., doi:10.1111/j.1553-2712.2008.00227.x.

Ghostcrawler. “/Dev: New Player Experience.” */Dev: New Player Experience – League of Legends*, 2018, nexus.leagueoflegends.com/en-us/2018/05/dev-new-player-experience/.

Gladwell, Malcolm. *Outliers: The Story of Success*. Back Bay Books, 2013.

Macnamara, Brooke N., et al. “The Relationship Between Deliberate Practice and Performance in Sports.” *Perspectives on Psychological Science*, vol. 11, no. 3, 2016, pp. 333–350., doi:10.1177/1745691616635591.

Miller, Michael. “The Great Practice Myth: Debunking the 10,000 Hour Rule • Six Seconds.” *Six Seconds*, 22 Feb. 2021, www.6seconds.org/2020/01/25/the-great-practice-myth-debunking-the-10000-hour-rule/.

Mobalytics. “Research: Climbing Stats in Ranked League of Legends.” *Mobalytics*, 13 Nov. 2020, mobalytics.gg/lol-ladder-research/.

R. Young, Jeffrey. “Researcher Behind '10,000-Hour Rule' Says Good Teaching Matters, Not Just Practice - EdSurge News.” *EdSurge*, EdSurge, 24 July 2020, www.edsurge.com/news/2020-05-05-researcher-behind-10-000-hour-rule-says-good-teaching-matters-not-just-practice.

Summoner's Rift, Team. “/Dev: Balance Framework Update.” *League of Legends*, na.leagueoflegends.com/en-us/news/dev/dev-balance-framework-update/.