An Analysis of Video Game Player Performance: The Presence of Tilt

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***Abstract*—This study aims to determine if the phenomenon known as 'tilt' exists. Professional player match history data was used to visually identify trends where tilt may be present. Preliminary findings suggest that tilt may exist among professional players. The results of this study could potentially be used to help professional *League of Legends* players optimize future performance by adjusting practice or competitive match schedules based on time passed since last win or loss. Though these preliminary are encouraging, further analysis would be required before making any definitive claims.**

I. Introduction

In recent years, the competitive gaming industry (known as eSports) has grown to become a very large and prosperous area of interest to investors, marketing teams, entrepreneurs, and more. For example, in 2013, more than 71 million people in the United States watched or participated in eSports [3]. In 2014, *Dota 2's* world championship event known as *The International* boasted a prize pool of almost $10 million USD with about $5 million going to the first place team [4]. With the stakes so high, players, coaches, analysts, and team managers alike have a vested interest in optimizing player performance.

In competitive gaming, when a player consistently performs badly for a significant period of time, it can be said that the player may be 'on tilt.' This is a phrase that originally developed during the age of pinball cabinets but it is most prominently used in the family of card games known as poker [2]. When a player is on tilt, he or she may be frustrated with their own performance or luck. As a result, the player tends to make irrational decisions which leads to additional poor performance and frustration.

II. Area of Focus

In this data analysis, indicators of future player performance were explored and identified. In particular, the duration since the last win or loss was found to potentially be a indicator of player performance. Further analysis with additional data of various player skill levels would be needed to further confirm this statement, but preliminary findings suggest this might be the case.

Initially, there were two concerns which I believed would deserve some special attention. First, pros may have a calmer composure and may be friendlier, less irritable, etc regardless of whether they are winning or losing simply due to their exposure to competing many times, experiencing many losses, etc. In contrast, average players may tend to be much more irritable when they are losing because they are worried about their ranking decreasing. Second, if two friends are playing together, they may be less likely to become irritable due to bad performance. Instead, they may try to enjoy the game and avoid damaging a friendship over a game. These factors could possibly skew results into having less 'tilting' effect and would need to be taken into consideration.

In my analysis, I only considered Challenger tier (highest rank in the game) players. As we'll see in the results and findings section, they might not be so immune to 'tilt', despite their professional exposure. The comparison of playing with friends versus random players and associated performance was not investigated.

III. Purposefulness

ESports players are constantly practicing to gain a competitive edge. However, if the player is on tilt, he or she is likely not performing as well as he or she could, and the result is less beneficial practice sessions. This is essentially time being wasted due to frustration. If coaches or teams plan out their practice schedule effectively, they may be able to avoid frustration and a number of unnecessary losses.

IV. Data Collection and Analysis

The analysis focuses on performance of players of the game entitled *League of Legends*. *League of Legends* is currently the most popular game in the world with 27 million daily players and 67 million monthly players as of January of 2014 [5]. At the time of writing, this is the most up-to-date data (publicly available) regarding the size of the game's playerbase.

Riot Games has provided a public developer's API for obtaining post-game stats of each match. Data was obtained via HTTP requests to a RESTful API. Specifically, the match history of ten of the top League of Legends players in North America was collected, a total of 6502 matches.

V. Implementation

Data collection and scrubbing was the first major task. I began with collecting 10 League of Legends players account names from the Challenger tier ladder . I then obtained their account IDs via calls to the developer API.

With the IDs, I then obtained the match history data from the developer API. However, the API limited output to 15 matches at a time. To account for this, I had to let a script run for quite some period of time which would continuously call the API and update the current index passed to the API (incrementing 15 at a time), all while checking to be sure I didn't exceed the developer key request limit. The results were then stored in MongoDB.

The responses contained much more information than I needed, so I needed to do some scrubbing to make processing easier. The matches data was scrubbed so that each line of the resulting scrubbed file would represent one match. The name of the player, win status (0 or 1), time since last win in seconds, and time since last loss in seconds were recorded. At this point, the data was ready for graphing and analysis. A sample of this scrubbed data is shown in Figure 1.

I used a web service, Plotly [1], and their Python wrapper to build the necessary graphs for analysis.

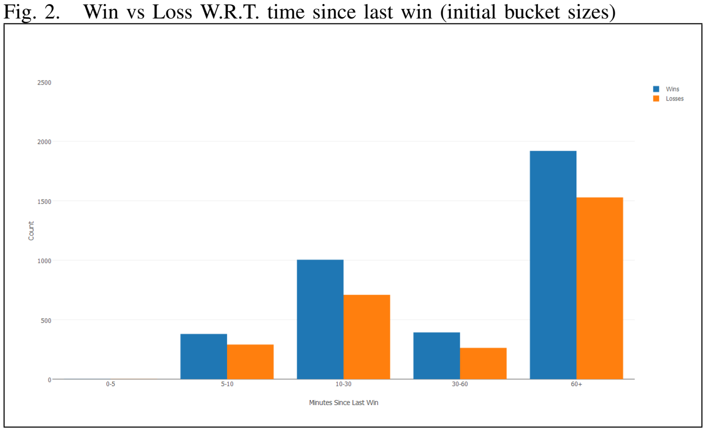
Fig. 1. Scrubbed Sample Data

```
name win timeSinceWin timeSinceLoss
bjergsen 0 -1 -1
bjergsen 1 -1 498
bjergsen 1 679 2991
bjergsen 1 1023 6107
bjergsen 0 509657 518108
bjergsen 0 511781 659
bjergsen 0 514648 471
bjergsen 1 939882 422776
bjergsen 1 4314 428846
bjergsen 0 501 431288
bjergsen 0 169046 166820
bjergsen 0 171281 548
bjergsen 1 346026 172809
bjergsen 1 445 175344
bjergsen 1 458 177797
```

VI. Results and Other Findings

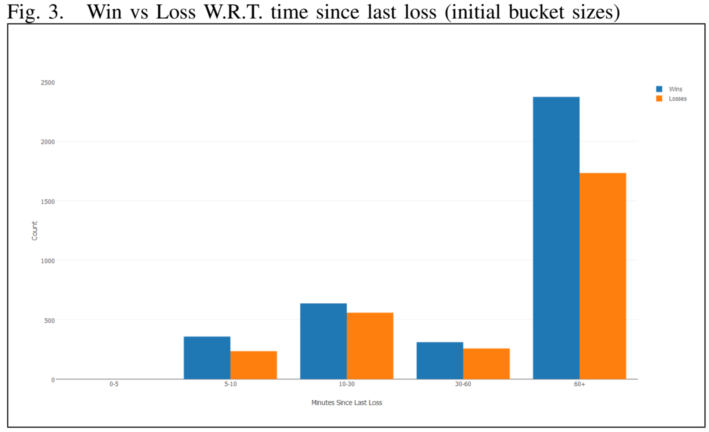
I started by taking a look at the number of minutes that had passed since the last loss and/or win. That is, the time between the end of the last win (or loss) and the start of the current match. Theoretically, the greater this time is, the more likely the player got up, grabbed a drink, went out for food, etc in between games.

Fig. 2. Win vs Loss W.R.T. time since last win (initial bucket sizes)



In Figure 2, there doesn't seem to be much correlation between win rates and times since last win or loss. The only seemingly noticeable observation is that there are more wins than losses. However, this is expected since these are professional players. The number of wins should always be higher than the number of losses.

Fig. 3. Win vs Loss W.R.T. time since last loss (initial bucket sizes)

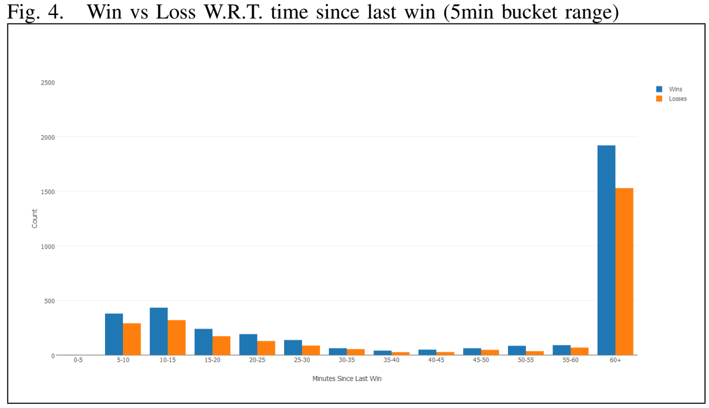


In Figure 3, I graph the same wins and losses, but with respect to time since last loss, as opposed to time since last win. If tilt does exist, then one would expect more losses just after a loss, and more wins after a significant amount of time has passed after a loss - this would be the "cool down" period. For the first time, we see there might be some kind of interesting trend if we look at the last time bucket of Figure 3. When comparing the "60+" columns of Figure 2 to Figure 3, we can see that the difference between wins and losses has grown (significantly more wins).

Additionally, the difference between wins and losses for the "10-30" minute bucket with respect to last win is clearly larger than the difference for the same bucket with respect to the last loss. If tilt exists, this would make sense if we assume that ten to thirty minutes is a relatively short period of time. I.e. this supports the proposition that immediately following a loss, players tend to lose more and immediately following a win, players tend to win more. Note that when I say "win more" I mean win more than usual with respect to fraction of wins to losses. I do not mean more wins than losses, as this would not prove anything since pro players, on average, win significantly more than they lose, anyway.

At this point, it is difficult to say if any trend really exists with these observations.

Fig. 4. Win vs Loss W.R.T. time since last win (5min bucket range)



Just to ensure there were no patterns being hidden due to the large time ranges, Figure 4 and 5 depict the same data as

Fig. 5. Win vs Loss W.R.T. time since last loss (5min bucket range)

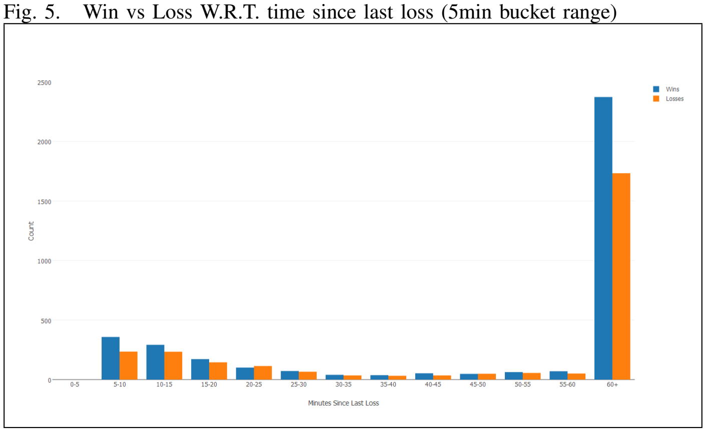
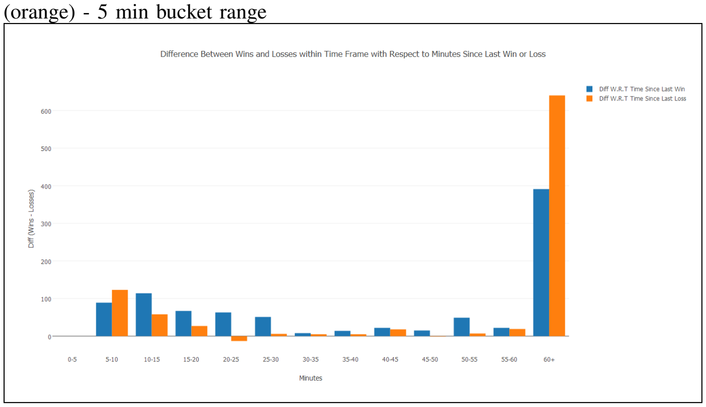


Figure 2 and 3 respectively, but with smaller bucket ranges (5 minutes each). Unfortunately, not much information could be gathered from this, except that 5 minute ranges were perhaps a bit too small for our limited sample size.

There were a few groups that looked like there might be some hint at increased time resulted in more wins compartively to losses, but it wasn't clear. That's when I decided to graph out the difference between the total wins and losses in each time bucket. I used blue for difference with respect to the amount of time passed since last win and orange for difference with respect to the amount of time passed since last loss. Initially, not much seemed to be revealed using bucket of 5 minutes. But, when expanding to a larger view of 30 minute buckets across 2 hours, the results seemed to be promising

Fig. 6. Difference W.R.T time since last win (blue) and time since last loss (orange) - 5 min bucket range

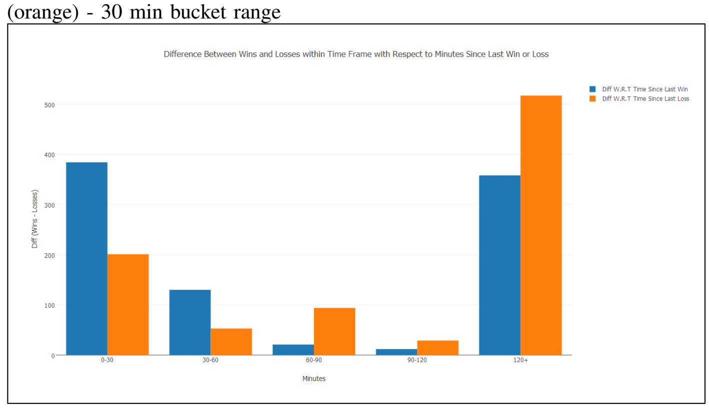


At this point, it is difficult to find trends, likely due to the natural domination of wins vs losses exhibited by professional players (who have high win rates regardless of tilt or other factors). To account for this, we need some sort of mechanism to bring out the changes of win versus loss magnitude. In Figure 6, I graph the differences between wins and losses with respect to the amount of time since the last win or loss.

To understand Figure 6, I will give an example. Time since last game is defined as the time between the last game's end and the beginning of the current game. Assume a player P and a match M which started at time T and P also won the game. Also assume Player P's last win was 58 minutes ago and P's last loss was 7 minutes ago. Thus, M would increment the number of wins in the 55-60 minutes since last win range by one, and increment the number of wins in the 5-10 minute range since last loss by one. Because this is a graph of the difference between wins and losses, this means the current game in question would increase the magnitude of both the blue bar for the "55-60" bucket and the orange bar of the "5-10" bucket by one. Also, it is worth mentioning that the total of all blue bars should be approximately equal to the total of all orange bars. There should only be a small difference due to the lack of a previous win or loss toward the beginning of each player's match history, as represented in the scrubbed data by "-1"s (Figure 1).

Unfortunately, all that can be gathered from this is that a significant portion of the matches occur at least sixty minutes after the previous game, and that maybe we should take a look at time ranges beyond sixty minutes. It also appears that our time ranges (buckets) may be too small for our sample data since we have a variety of fluctuations from one bucket to the next. In Figure 7, I try to account for this by switching to thirty minute intervals.

Fig. 7. Difference W.R.T time since last win (blue) and time since last loss (orange) - 30 min bucket range



In Figure 7, we can see a much more obvious trend arising. Immediately following a win, players tend to have a significantly higher win to loss difference. As time progresses, this difference shrinks and then levels out, but doesn't reach as high as it did during the first thirty minutes following a win. Conversely, following a loss, we can see that player tended to win significantly less than normal. As time progressed after a loss, players seemed to win signficantly more, especially in the two hours and beyond bucket. Again, this seems to support the notion that tilt might exist, where a loss causes players to, on average, lose more games if no break is taken before continuing with the next game. While this is only a preliminary finding with limited sample size, there does seem to be some clear evidence of a relationship here.

VII. Limitations and Future Improvements

One of the primary limitations of this study was that the match history of only professional players were considered. Professional players may be calmer and more tilt-resistant than casual gamers. An interesting extension would be to identify if poor performance has a stronger influence among casual League of Legends players, resulting in much larger differences in wins and losses after a win or loss.

The 6502 matches used in this study only reflected the play patterns of ten professional gamers. To obtain a more representative result, we should really consider the games of hundreds, thousands, or maybe even tens of thousands of players.

This analysis only focused on visual representation and identification of trends. A more convincing argument could be obtained if a more numerical analysis was carried out - e.g. ANOVA, etc. Additionally, this could be extended to predict player performance, as opposed to just simply identifying trends.

Finally, the idea of ”uplift”, the opposite of tilt, could be investigated. That is, does good performance and winning result in higher win rates immediately afterward (on average).

Finally, does tilt have a cascading effect. That is, does a player who is on tilt cause other players to go on tilt (via complaining, verbal abuse, etc in game) and as a result, spiral out of control, causing exponentially many other players to go ”on tilt” and begin losing as well? Similarly, does the notion of ’uplift’ exist (the opposite of tilt)? If so, does it exhibit this cascading effect? That is, can a winning player positively influence his or her teammates resulting in higher win rates, similarly causing exponentially many other players to be ”uplifted” and begin winning more?

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