# An Exploratory Study in Survival Rates of Online Game Players

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All code and the data used in this project can be found here:
https://github.com/yangz3/DOTA2-Player-Survival-Rate-Analysis

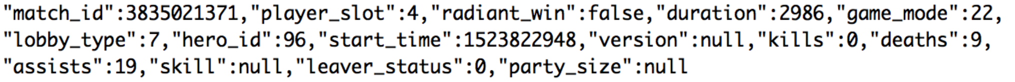
## Introduction

With the advances in computer and Internet, gaming online becomes a common part of everyday life. People play online games together with friends, or in most cases with strangers for entertainment. In fact, NBC News reported that there were mover 1 billion hours of League of Legends played in a month in 2012 [1]. That was only one game among many others with even more popularity.

As a result, we are interested in what makes people want to play the game. Or in other words, what makes a player decide to stay in community and keep playing. And what would make the player quit the game. One of the most intuitive approaches is to compare between games with different designs, and compare the user playing time. We can then investigate the effect of design factors and the interactions between them on a user's playing time. However, this would require reliable and uniformed sources from multiple games, which is beyond our reach. Instead, we focus on one game – Defense of the Ancients (DotA) 2, and compare between players. Specifically, we want to investigate what happened in the games that made a DotA player decided to not play the game anymore. Equivalently, it will also inform us what will make a player keep playing the game.

## Data structure

Our data comes from the OpenDotA website, where we can get access to over a million DotA players data ever since their first game. We downloaded 35352 players' data (https://www.dropbox.com/s/cbraofsl18oavyr/download.tar.gz?dl=0). Each player has one json file which contains all games that player was ever involved. Each game has a data point in the json file, formatted as follows:



```
"match_id":3835021371,"player_slot":4,"radiant_win":false,"duration":2986,"game_mode":22,
"lobby_type":7,"hero_id":96,"start_time":1523822948,"version":null,"kills":0,"deaths":9,
"assists":19,"skill":null,"leaver_status":0,"party_size":null
```

Where we have the match id, the player's side, game result, game duration, game mode, lobby type, hero id, game start time, version, number of kills, number of deaths, number of assists, skill, leaver status, and party size. A full document of these data can be found here [2].

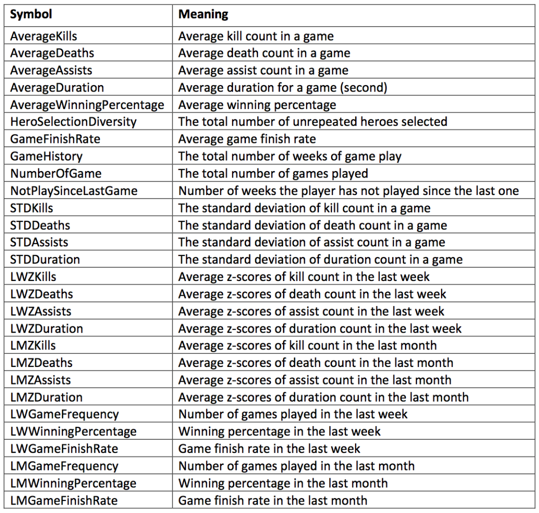
## Analysis plan

To process the data, we first removed data from players who have played for shorter than two months. These players were often new to the game and thus were unstable and can be unpredictable when it comes to why they quitted the game. To better model the population, we removed data points from these players from the data set.

We then calculate the performance dependent variables – one set of variables for each player. Specifically, the performance dependent variables include average kills, average deaths, average assists, average game duration, average winning percentage, hero selection diversity (i.e., we counted the number of unrepeated heroes selected by that user), average game finish rate, game frequency (i.e., number of games per week), game history (i.e., total number of weeks playing DotA2), number of games (i.e., total number of games played), number of weeks not played since the last game.

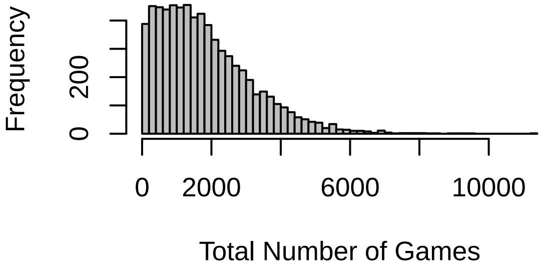
We also want to pay attention to that player's last period of game play before she quitted the game. For example, we calculated Z-scores of performance characteristics (e.g., kills/deaths/assists) of the player against her average performance throughout her entire gaming history. We also calculated the average performance characteristics of the player's last period of game play such as winning percentage, game finish rate, and game frequency. In our data processing, we defined the last week and the last month as the last period of game play. The above characteristics are calculated for the last week and the last month respectively.

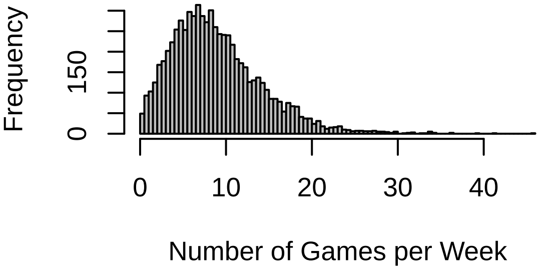
Table 1. shows all dependent variables we calculated:

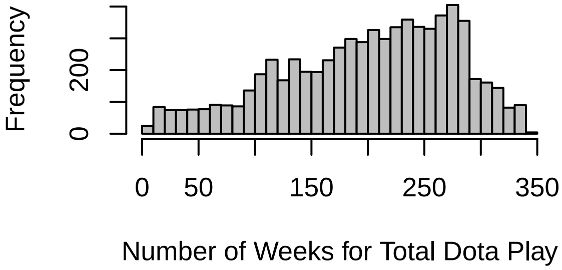


| Symbol | Meaning |
|---|---|
| AverageKills | Average kill count in a game |
| AverageDeaths | Average death count in a game |
| AverageAssists | Average assist count in a game |
| AverageDuration | Average duration for a game (second) |
| AverageWinningPercentage | Average winning percentage |
| HeroSelectionDiversity | The total number of unrepeated heroes selected |
| GameFinishRate | Average game finish rate |
| GameHistory | The total number of weeks of game play |
| NumberOfGame | The total number of games played |
| NotPlaySinceLastGame | Number of weeks the player has not played since the last one |
| STDKills | The standard deviation of kill count in a game |
| STDDeaths | The standard deviation of death count in a game |
| STDAssists | The standard deviation of assist count in a game |
| STDDuration | The standard deviation of duration count in a game |
| LWZKills | Average z-scores of kill count in the last week |
| LWZDeaths | Average z-scores of death count in the last week |
| LWZAssists | Average z-scores of assist count in the last week |
| LWZDuration | Average z-scores of duration count in the last week |
| LMZKills | Average z-scores of kill count in the last month |
| LMZDeaths | Average z-scores of death count in the last month |
| LMZAssists | Average z-scores of assist count in the last month |
| LMZDuration | Average z-scores of duration count in the last month |
| LWGameFrequency | Number of games played in the last week |
| LWWinningPercentage | Winning percentage in the last week |
| LWGameFinishRate | Game finish rate in the last week |
| LMGameFrequency | Number of games played in the last month |
| LMWinningPercentage | Winning percentage in the last month |
| LMGameFinishRate | Game finish rate in the last month |

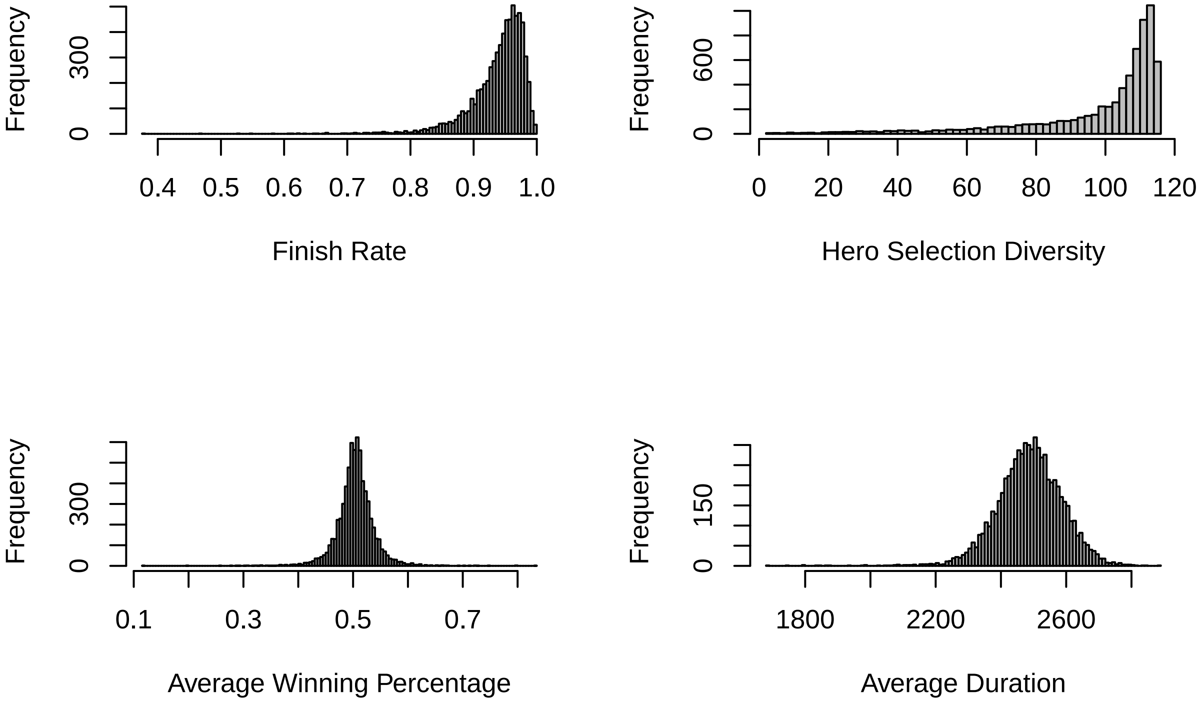
To tell the data summary story, we first plot histograms of the first 20% exploratory data. The histograms are plotted below.



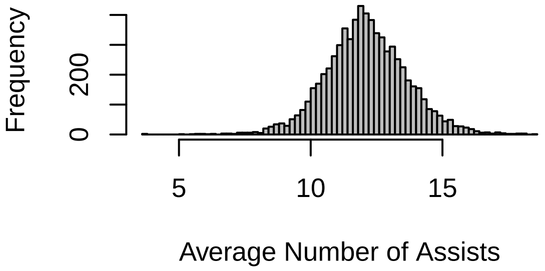


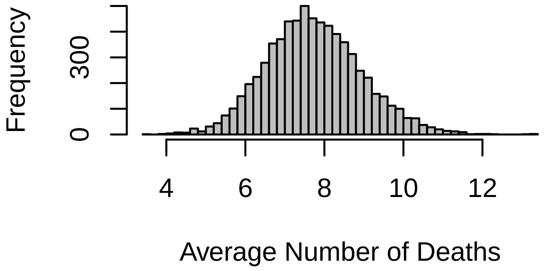


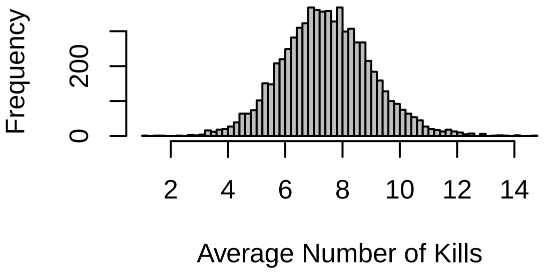
We can see from these plots that the total number of games played by each player and the number of games per week are more like normal distributions however with only one tail on the right. The mojority of players play 0-3000 games in our samples, while most of the players play 3-15 games every week. This indicates a log transformation might be needed for these dependent variables. However, for the number of weeks for the total DotA play, we did not see a normal distribution.

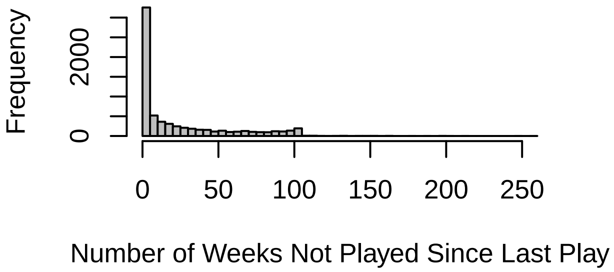


From the above histograms we can see clearly a normal distribution for the average winning percentage and average duration. In fact, the DotA2 platform automatically adjust the game difficulty for a player through e.g., matching the player with opponents with different levels to control the winning percentage to be 50%. The finish rate and the hero selection diversity have also normal distributions but the right tails are limited by the upper boundary. As we can see that most of the players have a game finish rate between 85% to 100%. And most of the players have used more than 100 heroes during her game play history.









From the above plots we can clearly see normal distributions of game performance including average number of assists, deaths and kills. Most players have average number of assists ranging from 10-15, while 6-10 for deaths, and roughly the same for kills.

Since most of the players are still active in the game, so we see most players have not played for less than 5 weeks. We set a threshold to 48 weeks (i.e., 4 months). If a player has not played for longer than 4 months, she is counted as an inactive player. This threshold is selected based on experience, for e.g., an international travel or an internship might be roughly 3 months where a player might not be able to play during that period, but able to after. Inevitably, we have an imbalanced data set. We counted the number of active players and the number of inactive players in the exploratory data set and the result is shown in the following table:

| Quitted? | Frequency |
|---|---|
| no | 5461 |
| yes | 1419 |

To avoid having an imbalanced data set, we randomly down sampled the active player to match the number of the inactive players and move on to the next stage.

The most intuitive model is merely using winning percentage as the independent variable. A player might lose interests in the game simply because she lost to many games, which can be reflected in the winning percentage. So we first build logistic regressions based on average winning percentage, last week winning percentage, last month winning percentage, and the difference between average and last week winning percentage, and the difference between average and last month winning percentage. We set a threshold of 50% on the probability outputted by the model to predict if a player is inactive. We calculate the prediction accuracies which are show in the table below:

| Model | Accuracy |
|---|---:|
| average WP | 0.5345314 |
| last week WP | 0.5056378 |
| last month WP | 0.5084567 |

| Model | Accuracy |
|---|---|
| average WP - last week WP | 0.5010571 |
| average WP - last month WP | 0.4982382 |

This result indicates that the winning percentage along cannot well predict if a user is likely to quit the game since the prediction accuracy is almost the same as prior possibility (i.e. 50%). We then select more independent variables, build the following model and evaluate their accuracies. Specifically, we build logistic regression models based on 1) only last period statistics, 2) only all period statistics, 3) combined statistics (all statistics). The prediction performance is shown in the table below:

| Model | Accuracy |
|---|---|
| only last period stats | 0.5429880 |
| only all period stats | 0.8002114 |
| combined | 0.8097252 |
| combined and reduced | 0.8090204 |

Since not all independent variables can explain the dependent variable well, we reduced the number of independent variables and selected the ones that are significant in the summary of the model using the combined all period stats and last period stats independent variable set. This model is shown as follows, where p(x) is the possiblity for a player to quit the game:

$$log(\frac{p(x)}{1-p(x)}) = \beta_0 + (\beta_1 * AverageAssists) + (\beta_2 * AverageDuration) + (\beta_3 * log(NumberOfGame) +$$

$$(\beta_4 * log(GameFrequency)) + (\beta_5 * GameHistory) + (\beta_6 * HeroSelectionDiversity) + (\beta_7 * STDKills) +$$

$$(\beta_8 * STDAssists) + (\beta_9 * LWZKills) + (\beta_{10} * LWZAssists) + (\beta_{11} * LMZAssists) + (\beta_{12} * DiffLMGameFrequency)$$

We also run a predicion evaluation using the exploritary data and the result is shown in the above table. As we can see the prediction accuracy of this model is roughtly as good as the all combined model. So we selected this model to move on to the validation phase.

```
folds <- rep(1:5, length.out = nrow(second_60))
set.seed <- 200
folds <- sample(folds)
accuracy <- c(0,0,0,0,0)

 for(i in 1:5){
    train <- filter(second_60, folds != i)

    down_train <- downSample(x = train[, colnames(train)],
                         y = factor(train$Active))

    test <- filter(second_60, folds == i)
    down_train$ActiveNumeric <- (down_train$Active == FALSE)*1
    test$ActiveNumeric <- (test$Active == FALSE)*1

    glm_all_reduced <- glm(ActiveNumeric ~ AverageAssists+ AverageDuration +
    log(NumberOfGame) + log(GameFrequency) + GameHistory +  HeroSelectionDiversity +
    STDKills + STDAssists + LWZKills + LWZAssists + LMZAssists + DiffLMGameFrequency,
    data = down_train, family = binomial(link = "logit"))
    valid_p <- predict(glm_all_reduced, type = "response", newdata = test)
    y_pred <- ifelse(valid_p > 0.5, FALSE, TRUE)
    y_act <- test$Active
    accuracy[i] <- mean(y_pred == y_act)
 }

  mean(accuracy)
```

```
## [1] 0.8093325
```

```
  sd(accuracy)
```

```
## [1] 0.006341297
```

The 5-fold cross-validation shows an average predication accuracy of 0.858 with a standard deviation of 0.005.

Finally, we combine the exploratory and the validation dataset to train a final model, while using the rest 20% of all data points as the test set. The result is shown as follows.

```
combined_80 <- rbind(first_20,second_60)

down_train <- downSample(x = combined_80[, colnames(combined_80)],
                         y = factor(combined_80$Active))
test <- third_20

down_train$ActiveNumeric <- (down_train$Active == FALSE)*1

test$ActiveNumeric <- (test$Active == FALSE)*1

glm_all_reduced <- glm(ActiveNumeric ~ AverageAssists+ AverageDuration +
log(NumberOfGame) + log(GameFrequency) + GameHistory +  HeroSelectionDiversity +
STDKills + STDAssists + LWZKills + LWZAssists + LMZAssists + DiffLMGameFrequency,
data = down_train, family = binomial(link = "logit"))

    test_pred <- predict(glm_all_reduced, type = "response", newdata = test)
    y_pred <- ifelse(test_pred > 0.5, FALSE, TRUE)
    y_act <- test$Active
    accuracy <- mean(y_pred == y_act)

    library(caret)
    library(e1071)
    confusionMatrix(data=table(y_pred, y_act))
```

```
## Confusion Matrix and Statistics
##
##         y_act
## y_pred  FALSE TRUE
##   FALSE  1187  959
##   TRUE    324 4409
##
##                Accuracy : 0.8135
##                  95% CI : (0.8041, 0.8226)
##     No Information Rate : 0.7803
##     P-Value [Acc > NIR] : 7.311e-12
##
##                   Kappa : 0.5273
##  Mcnemar's Test P-Value : < 2.2e-16
##
##             Sensitivity : 0.7856
##             Specificity : 0.8213
##          Pos Pred Value : 0.5531
##          Neg Pred Value : 0.9315
##              Prevalence : 0.2197
##          Detection Rate : 0.1726
##    Detection Prevalence : 0.3120
##       Balanced Accuracy : 0.8035
##
##        'Positive' Class : FALSE
##
```

We achieved an accuracy of 0.816. We also calculated the confusion matrix and the result indicates a false positive rate of 0.213 where inactive players are predicted as active players. The false negative rate is 0.176 where active players are predicted as inactive players.

```r
summ <- summary(glm_all_reduced)$coefficients[1:13,c(1)]
kable(summ, row.names = T, digits = 3,
      caption = "Logistic Model Coefficient Table")
```

Table 4: Logistic Model Coefficient Table

| | x |
|---|---:|
| (Intercept) | 33.246 |
| AverageAssists | -0.082 |
| AverageDuration | -0.006 |
| log(NumberOfGame) | -1.407 |
| log(GameFrequency) | 1.137 |
| GameHistory | -0.015 |
| HeroSelectionDiversity | -0.002 |
| STDKills | -0.432 |
| STDAssists | -0.839 |
| LWZKills | 0.046 |
| LWZAssists | 0.326 |
| LMZAssists | 0.146 |
| DiffLMGameFrequency | 0.027 |

The above coefficient table can be used to draw insight, to see if certain independent variables correlate the possibility of quitting the game. Independent variables that have positive coefficients indicate a positive correlation, while negative coefficients indicate negative correlation with the quitting possibility.

The result indicates that players perform more assists and longer average duration per game are less likely to quit the game. It is also true if the player played more games. However, if the player played the game too often, it is more likely that this player will quit the game.

In addition, longer game history, higher hero selection diversity, higher variance in kills and assists all indicate a less possibility of game quitting. This might because the diversity and the variance made the player find the game more interesting and challenging.

Finally, we found more kills, assists in the last week, more assists in the last month, and less game play frequency in the last month all indicate a higher possibility of game quitting.

## Limitation

Though we got a model that can predict the chance of players quitting the game fairly well, we are aware of the statistical inference and the causality problems that our current model might have. For example, the players we sampled using the Open DotA API might not be randomly sampled, and they can for sure not represent players of other online games. When it comes to the causality, we might also have reverse causality problem between the Number of Game variable and the possibility of quitting the game. A player might decide to stay in the game because she has played so many games. Or it is also possible that the decision to stay in the game causes a higher number of game played.

In addition, there are for sure other factors that are missed from this data analysis. For example, this model missed the dynamics between players in the game such as conversations, and fine-grained activities. There are also effect from game platforms. For example, a platform tends to match a player with opponents with higher level after the player's winning percentage is higher than 50%. These missed factors merit further investigation in future.

## Reference

[1] NBC News. https://www.nbcnews.com/tech/tech-news/league-legends-players-log-1- billion-hours-month-flna1C6423906

[2] OpenDotA API Documentation https://docs.opendota.com/#