Understanding players' motivation on leaving a match based on their previous experience

Chaima Jemmali
PhD student in Computer Science
College of Computer and Information Science
Northeastern University
jemmali.c@husky.neu.edu

Borna Fatehi
Master student in Game Science and Design
College of Arts, Media and Design
Northeastern University
fatehi.b@husky.neu.edu

Abstract

Players retention and churn analysis has been subject of major studies in game related papers. Based on the nature of the game, the study of players' retention can vary significantly. In this paper we are studying the reasons a player might leave a match based on his previous experiences on the same game. We used the data collected from DotA and performed feature selection and linear models to find important features affecting the number of matches left. Our obtained model could explain most of the data and we found out that players' past experience can affect the ratio in which they leave a match.

Keywords: Match Left, Game Analytics, DotA Game

1- Introduction

Game Analytics are different from Data analytics in a way that the predictions should be able to fit in the context of the game. As games increase in complexity, interpretability has become a larger issue. Different methods have different strength and weaknesses and it's important to understand which ones work better with a certain type of data.

Player's retention has been one of the fields that has been attracting researchers in game analytics field. There are multiple factors involved in player's retention and researchers have been studying some of them with the various data they had. In other words, player's retention can be investigated through multiple aspects. Chat log data, the amount of time required in an MMO game or other game elements and mechanics can have direct effect on player's retention. In this work, we consider player's background and stats in the game to predict matches left in a MOBA game. We believe that matches left can be a strong predictor for player's churn and has not been studied before.

In this paper, we are looking into data from DotA-licious, to find patterns between people who leave a match. This means that we are not looking into churn or player stopping playing the game but rather at how many matches in the game do they leave. Based on information collected throughout all the games played by a player, we are looking into reasons for them to do so. We believe that the more matches left, the higher chance of quitting the game. Understanding the reasons behind the games left can help with players' retention. To achieve our goal, we used multiple different models; linear models and applied step forward feature selection applied all the variables in DotA-Licious data to understand the important variables in leading the players' decision on leaving a match. We found that players' experience is a big factor in our prediction, especially specific factors like number of deaths and creeps killed.

2- Previous Work

Players' retention has been an active research topic in game analytics. There are multiple factors involved in player's retention and different studies have been made with various data sets. While many papers have studied churn and players' retention none of them have considered the numbers of games left in a Multiplayer Online Battle Arena (MOBA) like DotA (Defense of the Ancients). Some of these studies' findings can be very relevant to our case. Shores et al. [1] looked at how toxic behavior in some deviant players can affect other players' experience and might lead them to stop laying the game. They used chat log data in league of legend to understand the player's reason to leave the game.

Tyack et al.[2] looked at team compositions and how playing with friends or strangers affect play possibilities and allow more variety. Social factors seem to affect playing, however, leaving or stop playing didn't seem to be affected by social factors and a large variety of reasons: the most important being time constraints as MOBAs takes a lot of time from other activities or playing other games. This confirms the challenges behind predicting games left since many of the reasons can be completely unrelated to the game itself.

Edge [3] shows that player satisfaction and therefore retention is closely related to their perceived locus of control. Players have a goal while playing a game and locus of control in that case accounts for both the feasibility of the goal and whether expected progress toward a selected goal is being achieved. This applies in our case as the goal the player wants to achieve in each game of DotA is winning that single game, a player leaving that game might think the team has no chance of winning.

Drachen et al. [4] weren't looking at churn but used interesting models in their study; K-means, Principle Component Analysis, Non-negative Matrix /factorization and Archetypal Analysis on World of Warcraft data collected over five years to predict players leveling up over time. While, their prediction is different from ours, the format of the data used is very similar to ours.

In this study we are looking at the player's game stats to find any correlation between the past experience with the game and the frequency in which they leave a match.

3- Methods

3-1- Data

The data we are using is data collected from Dota-Licious, a DotA platform that punishes leavers and tracks players' stats down to every creepkill. The platform was created for the more serious players. Defense of the Ancients or DotA is a 5v5 Moba game. Players, compete in two teams of five players against each other. Each team has its own base and region that occupies the map, and the goal for each team is to destroy a base called the Ancient of the opposing team. Players will engage in fights with other heroes and other NPC enemies to earn gold, level up and buy items. A match usually last around 30 minutes. The data collected[1] represents the summation of each player's stats across all games played between April 2010 until February 2012 and it involves originally 84,320 players.

3-2- Data Pre-processing

3-2-1- Data Cleaning

Before using data, we needed to perform some cleaning actions. First we removed all the observations containing N/A or null column along with observations which had zero on the total number of games played.

In our analysis we used the average numbers instead of total numbers. These average numbers were the calculation of total number of each variable divided by the total number of games played. As an example, Average Kills is the average of kills a player had during all his/her game sessions. In this way variables can be compared between players meaningfully despite player's having different number of games played in total.

We have also performed a manual feature selection to consider only important variables that are meaningful to our predictions. Reducing dimension by excluding unimportant features can decrease the variance without increasing much bias. Features discarded are described below:

- Most Played: Name of heroes they played most with
- Most Won: Name of heroes they mostly won with
- Last Active: Their last active session
- Language: selected language chosen
- Last Reset: Last time they reset the game
- Status: Online/Offline at the time the data was collected
- Date Capture: The date their data was captured
- Player ID: The unique ID of each player
- Position: newbie, administrator, sr. member, etc.
- Level 6 After, Level 11 After
- Daily Rank
- Posts Per Day'

We used our game knowledge and step forward feature selection in deciding on which variables to leave out. The position has been laid out since there were not variability on it and the rest was not relevant to our prediction.

3-2-2- Adding new dimension

We defined the variable "unwillingness" and calculated it for each player. This variable is the ratio of total games left on total games left plus games lost. This variable can show the ratio in which a player who is close to lose a match actually leave the game. We assume that the game is well balanced so that all the heroes can compete against each other during all time frames of a match and players can compete meaningfully until the last minute when they actually lose a game. So when they leave the game it shows they have lost their hope to struggle against their opponent in that match.

The “willingness” is simply “1-unwillingness” which shows how willing a player is to continue a lost game until they actually lose or change the outcome of a match to win that match. Based on this variable, we can have some estimation on the player’s retention as if a player leaves the game more often they are more in danger of losing their retention. The closer the willingness is to 1, the more games the player stayed until they lost the game and their left games is close to zero.

3-2-3- Removing new generated NAs

The unwillingness variable, in some cases, doesn't generate a number because of the division by zero for the players who had zero number of games left and zero number of games lost; The players who won all the matches they played. We excluded these players out of our data because a) we could not use them to predict the willingness and b) we were interested in understanding the reason behind people leaving the game and since these players never left any game they were not of interest.

3-2-4- Removing variables with strong correlations

Kills per minute and average kills had strong correlation of .92. So one of them can be representative of kills a player had and we decided to choose average kills to maintain consistency with the rest of the features. Also we excluded average time since a) there were not much variability among players’ average time and most of the average time were around 2500 seconds or 42 minute and b) There is a correlation between the willingness and average time. In fact, willingly players have more average time spent since they remain in a match until the last minute and on the opposite, unwillingly players average playing time is short. When we use linear modeling with inclusion of average time, the average time will get the most weight in the prediction. So we excluded that to understand other related factors rather than those were quite obvious.

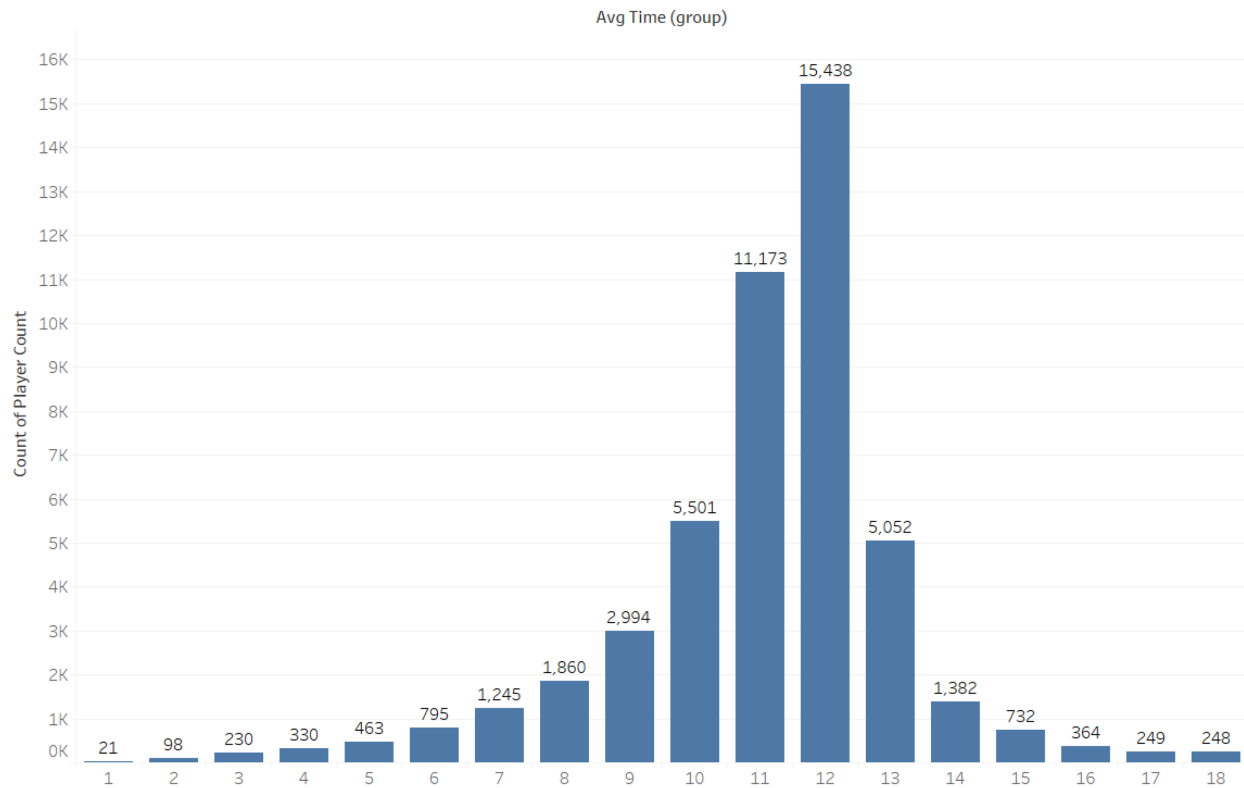

Figure 1 - Number of observations which lay on each average time groups. Each group is consisting of 200 seconds time interval

The range of average time in our data set was between 223 and 5700 in seconds. Each group in the above chart is the interval of 200 in average time except for last group. So group 1 have the average time between 223 and 400, group 2 have the average time between 400 and 600 and so forth. The last group has the average time of more than 3600. The X axis in the above chart shows the groups and the Y axis shows the total number of observations which lay on each group. It can be understood that the chart is bell shaped and most of the observations lay between groups of 10 to 13 which is identical to the time interval between 2000 and 2800 and most of them are in group 12 which is the interval of 2400 to 2600. So most of the game sessions took about 42 minutes in average.

3-3- Models

Since our problem is a regression problem, we had to use regression algorithms. Also as we have mentioned earlier we are trying to find inference rather than prediction. We used forward feature selection and manually removed less important variables from the linear model obtained. Then we grouped our data to test and train and used the validation set approach to validate the model obtained.

4- Results

We performed the forward feature selection for predicting the willingness among all the features on the player data. The linear model obtained shows the important features in predicting the result.

Coefficients	Estimate	T value	P value	Significance
Average Kills	1.71e-02	26.969	< 2e-16	***
Average Neutrals Killed	3.03e-03	26.461	< 2e-16	***
Skill Level	4.47e-02	17.84	< 2e-16	***
Average Raxs Destroyed	-1.47e-01	-22.775	< 2e-16	***
Points	-2.58e-04	-19.418	< 2e-16	***
Average Couriers Killed	-2.36e-01	-11.821	< 2e-16	***
Longest WinSteak	2.74e-03	6.628	3.43E-11	***
Current WinSteak	6.78e-03	7.246	4.36E-13	***
Average Tower Destroyed	-7.35e-02	-19.57	< 2e-16	***
Won Rate	6.60e-02	9.125	< 2e-16	***
StatsReset	-8.49e-03	-7.071	1.56E-12	***
Average Deaths	-2.39e-03	-43.605	< 2e-16	***
Average Creeps Killed	2.39e-03	43.605	< 2e-16	***
Average Assists	-1.73e-10	-3.308	0.000941	***
Average Creeps Denied	-4.90e-10	-3.119	0.001813	**
Referrals	-1.75e-03	-1.547	0.121779	

Residual Standard Error: 0.2248
Multiple R-squared: 0.2018
F-Statistic: 793.5

As it can be seen in the above result there are still lots of variables for predicting the willingness. Also the model can only explain about %20 of the whole data set. By looking at the t-values we realized that some of the variables have more effect on the prediction. So we used only important ones and ignored the rests to see if we get an enhanced result. The important features are:

- Creeps Killed
- Deaths (Negative)
- Kills
- Neutral Kills
- Skill Level
- Raxs Destroyed (Negative)
- Tower Destroyed (Negative)
- Points (Negative)

It is notable that we used the threshold of 15 for t-values to select the important features. We applied polynomial for these selected features and the best result obtained was when applying the polynomial of degree 2 to the death variable.

Coefficients	Estimate	T value	P value	Significance
Average Kills	9.01e-03	19.114	< 2e-16	***

Average Neutrals Killed	1.91e-03	21.743	< 2e-16	***
Skill Level	7.13e-02	44.093	< 2e-16	***
Average Raxs Destroyed	-1.90e-02	-3.918	< 2e-16	***
Points	-9.68e-05	-9.71	8.93e-05	***
Average Tower Destroyed	-2.25e-02	-7.958	< 2e-16	***
Poly(Average Deaths, 1)	-2.40e+06	-40.147	1.78e-15	***
Poly(Average Deaths, 2)	-3.36e+01	-189.716	< 2e-16	***
Average Creeps Killed	1.68e-03	40.147	< 2e-16	***

Residual Standard Error: 0.1724
Multiple R-squared: 0.5304
F-Statistic: 6303

The model improved significantly and now it can predict %53 of the data. By applying the filtering in the new features but this time with threshold of 30 for t-values we see that there are only three of these variables that are in fact important for predicting the willingness:

- Death
- Creeps Killed
- Skill Level

Below the linear model obtained from using only these three features is shown

Coefficients	Estimate	T value	P value	Significance
Poly(Average Deaths, 1)	-3.08e+06	-78.03	<2e-16	***
Poly(Average Deaths, 2)	-3.44e+01	-196.72	<2e-16	***
Average Creeps Killed	2.15e-03	78.03	<2e-16	***
Skill Level	7.18e-02	47.88	<2e-16	***

Residual Standard Error: 0.174
Multiple R-squared: 0.5213
F-Statistic: 13680

This model can explain %52 of the results with very few features. The model can be explained as follows:

“The players who had more creeps killed and more skill level but less death in average, are more willing to continue a match until the end even when they actually are close to lose that match”

Validation

We divided our data set by random sampling to two equal size of train and set, and performed validation set approach for validating our model. The test MSE of 0.03020275 shows that our model is predicting the test data quietly accurate.

5- Discussion

The R-squared obtained from result can only explain %52 of the data. This can be due to the fact that players might leave a match frequently when they are really close to their loosing no matter how much experienced they are and also there might be other non in-game reasons for leaving a match. For example, a power outage or low internet speed or other reasons might lead a player to leave a match no matter how experienced and professional a player might be. If we divide the data into two groups that one group leave the game for in-game reason (players feel real close to their loose and they leave) and out of game reasons by chance, meaning that there is an equal chance that each games leaving lie on either group, our model is predicting pretty much well However, as we have mentioned earlier we removed the average time people spent on the game because there was not much variability on it meaning that people spent an equal time on average on every game sessions. This might exclude the players who left the game by non in-game reasons to some extent but the statement still persists.

We selected the features using certain threshold for the t-values to select only important features which can explain most of the data. Although the selected features can explain good chunk of data, the importance of the other variables in influencing the willingness should not be ignored. The thresholds are calculated by including and excluding features by importance to see if the inclusion or exclusion can have indeed a significant impact on the obtained result. The final three selected features are the important features which excluding each one of them can impact the final result significantly.

Having creeps killed as a factor for predicting the willingness can give insight about the strategy of the willingly players who continue the game. It can reveal that players who focus their attention on killing the creeps are the ones who will continue the game until the end. The more a player kills a creep the more he gains gold and he/she then can therefore use those golds for power ups and improvements for his/her hero. The stronger they become during a match the more willingly they will be to continue that match.

6- Conclusion

In this paper we studied the player's degree of leaving a match based on the previous gaming experience on the same game based on the game data collected from 2010 to 2012 on dota-licious.

We determined the important features which are impactful in predicting the degree of willingness which one might have during a match. The degree of willingness is defined as to what extent a player is willing to continue a match although he/she might feel that they are close to lose that match and is calculated as follows:

$$Willingness = 1 - Unwillingness = 1 - \frac{Games\ Left}{Games\ Lost + Games\ left}$$

Then we showed that the willingness of the players can be explained by their previous gaming experience on the same game and the more they are experienced and skilled the more they are willing to continue a match and struggle to change the result of the game even if they are close to lose that match. The important features for predicting the willingness are number of deaths, creeps killed and skill level. The former has negative correlation with the willingness while the two latter have positive meaning that the reason the players become unwilling to continue a game are due to their high number of deaths and low number of creeps killed and low skill level.

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