# An Analysis of Online Match-Based Games

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***Abstract*—Online match-based games, such as the online versions of the board game of chess, have already captured a global audience of tens of millions of players. Through a unique combination of characteristics, a relatively short duration—often "coffee-break" minutes instead of hours of continuous gameplay—, weak correlation between matches, and clear emphasis on winning, match-based games may serve a unique segment of the global player population. Although this segment of the gaming population may later become consumers of more sophisticated Massively Multiuser Virtual Environment (MMVE) systems, few previous studies have focused on the characteristics of online match-based games. Complementing them, in this work we collect and analyze information corresponding to 5 online match-based game datasets, totaling over 170 million matches played by a population of 1.3 million unique gamers over 14 years. Our analysis focuses on workload characteristics, win ratio, and player evolution. Studies such as ours may guide the multi-disciplinary field of MMVE design by providing new understanding of player lifetime and behavior. For example, we find a correlation between the interactivity of match-based games and the retention of players over both long and short term, that friendship does not always help to perform better in games, and that in match-based games each player explores tens of different play strategies over time.**

## I. INTRODUCTION

Many of today's online games are match-based, that is, they are repeatedly played by sides contesting for a clear winning goal during relatively short intervals of play. Spanning several genres, including Real-Time Strategy (RTS), First-Person Shooters (FPS), action-sport, and traditional board games, online match-based games currently entertain tens of millions of players world-wide through a unique combination of design features. Thus, understanding the characteristics of online match-based games may lead not only to improving current online game organization and architecture, but also, as player demands naturally become more sophisticated, in designing a new generation of match-based MMVEs, for example, for training purposes. Although a rich body of online gaming knowledge already exists, specifically about player behavior [1], [2], network traffic [3], [4], and meta-gaming activity [5], [6], few previous studies [7], [8] have focused on match-based games. Complementing these studies, we present in this work an analysis of the workload, competition, and player evolution in match-based online games.

We focus in this work on match-based online games for four main reasons. Our first reason is that many popular games are based on matches. We conjecture that the concept of a match, rather than only the genre or gameplay rules, is an important reason for the success of these games. In contrast to the much-studied MMORPG games, for which a few successful games attract a large majority of the players, many successful online match-based games exist. Successful match-based games include titles across many genres, from the RTS game Defense of the Ancients (DotA) to the Free Internet Chess Server (FICS) version of the traditional board game of chess. Intra-genre, match-based games offer numerous examples of successful variants. For example, DotA coexists with successful games such as League of Legends; and FICS supports several successful variants of chess, including standard (Western) chess, close variants such as "blitz", and variants with significant rule-changes such as "bughouse". Thus, by conducting a match-based analysis, our study has the potential of characterizing a wide variety of inter- and intra-genre games although using only a few game datasets.

Our second reason is that understanding the characteristic of online match-based games can facilitate the design of other MMVEs, including collaborative tools and serious games for learning, skill training, and problem solving. To achieve their goals, serious games may need their users to repeatedly complete tasks in preset or dynamic scenarios. Serious game designers may learn from successful match-based games how to keep their players engaged. Moreover, several types of serious games have similar properties with existing match-based games, for example, games for military training and FPS games. The in-game behavior of players in FPS games, to some extent reflects the players' intrinsic weaknesses, such as slow reaction or ability to decide correctly. Finding these weaknesses may help the military training games to enhance the skills of trainees.

Our third reason is that many match-based games, including chess, have a real-world correspondent. Thus, our findings may later be correlated with the "ground truth" of real-world investigations, thus alleviating a common problem of socially oriented gaming studies, and our results may be used to design better games that cross the boundary from virtual to real. For an example of correlation between online and real-world communities, we refer to a previous analysis of bridge communities [9].

Our fourth reason is that traditional game organization and architecture may need to adapt to the socio-technical characteristics of online match-based games with a massive number of players that are both socially and geographically diverse. Designing and deploying online games that scale with the number and location of players, without service disruption, remains an important challenge in systems research. Because the population of online games fluctuates long and short term [3], [6], [10], game providers have to schedule the workloads

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efficiently, trying to both minimize costs and improve player experience. Although techniques for cluster [11], super- [12], and, more recently, cloud computing [10] exist, the workloads of match-based games may require new approaches. Winning matches may be an important motive for players to keep returning to a game, a motive that does not play a role in open-ended games such as MMORPGs. Supporting the concept of match, for example through match-aware rating mechanisms and matchmaking algorithms, is a multi-disciplinary challenge across machine learning and data processing systems. Last, the end of a match is a well-defined moment of progress for player experience, which facilitates the analysis of player evolution and, in turn, may enable new designs for gameplay and online game systems. Evaluating changes in the behavior of players can also be used to identify early the signs that precede player departure [6], [13], to detect cheaters [14], and to support advertisers.

Our main contribution is a study of online match-based games, inter- and intra-genre. Our study aims at providing an initial, broad view of the class of match-based games, and does not aim at being exhaustive. Specifically, we:

1. Collect 5 datasets corresponding to online match-based games (Section II). These datasets include information of over 1.3 million players, who have played over 170 million matches over a cumulative period of over a decade.
2. Investigate the question: *Are the workloads of online match-based games and other online games similar?* (Section III).
3. Investigate three questions related to winning in match-based games (Section IV). *How is the win ratio progressing with the duration of gameplay?* We also investigate how friendship, another common motivator in massive online games, is correlated with winning: *Are the win ratio and friendship correlated?* Last: *Is the winning predicted well by current rating systems?*
4. Answer two questions related to the long-term behavior of players (Section V). First: *How do player lifetime and match play correlate with the number of friends?* We also look at the in-game strategy: *How many strategies do players explore?*

## II. Datasets

In this section we introduce the datasets we have collected: 2 datasets from an RTS game (DotA), 2 Go datasets, and 1 chess dataset. DotA is a team versus team (each team can have 5 members at most) mod for the RTS game Warcraft III. Go and chess are popular board games played by two players move-by-move. Table I shows a summary of these datasets, in it, # Players, # Matches, and AvgWR are the number of players, the number of matches, and the average win ratio of all players, respectively.

TABLE I
Summary of datasets.

| Trace | Period | # Players | # Matches | AvgWR |
|---|---|---|---|---|
| Dota-League | 2006/07-2011/03 | 61,198 | 3,744,753 | 0.495 |
| DotAlicious | 2010/04-2012/02 | 62,495 | 625,692 | 0.468 |
| KGS | 2000/02-2009/03 | 832,247 | 27,420,576 | 0.530 |
| DGS | 2001/09-2007/07 | 7,780 | 158,835 | 0.485 |
| FICS | 1997/11-2011/09 | 361,645 | 142,582,678 | 0.411 |

### A. DotA

We have two DotA datasets: Dota-League and DotAlicious-Gaming (DotAlicious). Dota-League was one of the most popular DotA platforms in Europe for 6 years, until it was shut down in November 2011. Besides serving normal players, it also hosted a number of DotA tournaments. DotAlicious is a newer DotA platform, with servers geographically distributed over North America and Europe. For each match, information such as: the nicknames of the players, the countries from which they are playing, the start and end times, the match result, and friendship between players is included. In Dota-League, the match start and end times were only available from November 2008 onwards, for 1,470,786 matches. For both of the datasets, we filtered out invalid matches such as matches with a duration of zero seconds.

### B. Go

The KGS Go Server (KGS) and the Dragon Go Server (DGS) are our sources of Go data. After its launch in 2000, KGS became one of the largest Go servers in the world. KGS is a real-time server that enables two online players to simultaneously play against each other in real time. DGS was founded in 2001, and is a turn-based server, in which players do not need to be online at the same time: the server will show the last move to the opponent when he logs in to the server again. The start and end times, the player nicknames along with their skill levels, and the match result are recorded for each match.

### C. Chess

Our chess dataset contains the data from FICS, which was established in 1995. FICS is one of the oldest and largest online chess servers. The FICS dataset is the largest among these 5 datasets. In this dataset, both standard chess matches and variant chess matches are collected. Each match record includes the match type, the nicknames and ratings of the players, the start date (before January 2009) or start time (from January 2009), every move, and the match result.

## III. Analysis of Workload Characteristics

Provisioning resources is an essential task for online gaming operators. Using the least possible resources to support the workloads generated by players brings maximum profits. However, inadequate provisioning may result in idle resources or the departure of players. In this subsection, we discuss three characteristics of the workloads of match-based games.

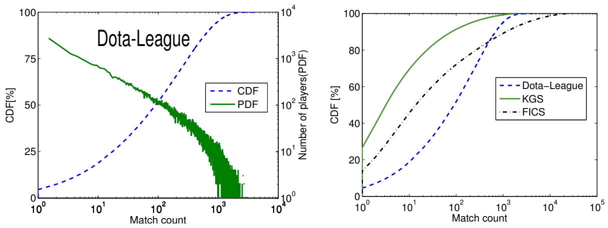



Fig. 1. Match count per player for Dota-League, KGS, and FICS.

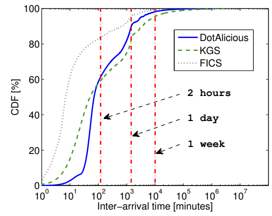



Fig. 2. CDF of inter-arrival time.

### *A. Match count per player*

Figure 1 depicts the match count (total number of matches played) per player of Dota-League, KGS, and FICS. The Cumulative Distribution Function (CDF) is depicted against the left vertical axis. The Probability Distribution Function (PDF) is depicted against the right axis and only for the Dota-League dataset in Figure 1 (left). The right vertical axis and the horizontal axis are log-scale. Since there is a number of computer players (bots) existing in KGS and FICS servers, we filter out the top 0.5% "players" in terms of their match count, assuming these are all bots. The filtered data are used in the following analysis.

Although the number of board game players is larger, a significant portion of them play only a few matches: about 25% of KGS players and about 15% of FICS players participated in only one match. However, this value is much lower for Dota-League (3%). The match count per player of match-based games is heterogeneous. The median values of the match count in Dota-League, KGS, and FICS are 91, 4, and 15, while the 99.5% quartiles are 1,945, 1,908, and 23,396, respectively. Nearly half of the online board game players participate in less than 15 matches.

The match count per player follows a long tail distribution, where the maximum value can be over a hundred times larger than the median value. We fit the match count per player against the power-law, log-normal, weibull, exponential, normal, and gamma distributions using the maximum likelihood estimation technique. The best-fitting distribution has the smallest Akaike information criterion with correction (AICc) [15]. The match count per player can be best fitted, for KGS and FICS, using the power-law distribution. For Dota-League, the log-normal distribution is the best fit.

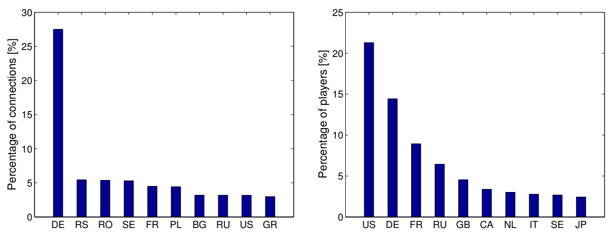
### *B. Inter-arrival time distribution*

We define the (match) inter-arrival time as the duration between the start times of two consecutive matches of a player. The inter-arrival times of a player represent his frequency of playing matches. Figure 2 shows the CDF of inter-arrival times across all the players of DotAlicious, KGS, and FICS. Over 80% of the inter-arrival times are less than one day and over 95% of the inter-arrival times are less than one week in these datasets. This indicates that a large percentage of players comes back to play shortly after their last match; this is similar to MMORPG EVE Online [6]. The distribution of the inter-arrival times peaks at 47 minutes. Given the average duration of DotA matches (41 minutes), it means players tend to play two consecutive DotA matches. The inter-arrival time of DotA matches is longer than for World of Warcraft (median 20 minutes) [16]. As players are very likely to be continuously playing in successive matches, it could be beneficial to build a highly-efficient P2P-based MMVE using the DotA players' own computers as servers.

### *C. Geographic distribution of connections and players*

International use can be a metric to measure the success of online games. Many of the popular games, such as World of Warcraft, Starcraft, etc., are catering to subscribers from all over the world. One of the problems in serving players from different countries is how to deploy geographically distributed game servers while keeping a reasonable quality of experience for all players (see [10] and references within). Investigating the geographic distribution of game workloads can support addressing this problem.

For each match in DotAlicious, the countries where the players connect from are recorded. We count connections from each country, over all matches. Figure 3 shows the geographic distribution of connections in DotAlicious and that of the players of DGS[1]. The workloads of games are not equally distributed, since the top 10 countries account for a majority of the connections or the players. For DotAlicious, probably because nearly half of the European game servers are located in Germany, there are significantly more connections from Germany than from other countries. For both of these games, the top 10 countries are located in North America and Europe, which should therefore be key areas in resource deployment. For comparison, Feng et al. [17] analyzed the distribution of online FPS players, and also found that most players are located in North America, Europe, and Asia.




(a) DotAlicious (b) DGS

Fig. 3. Geographic distribution of connections and players.

[1]Data from http://www.dragongoserver.net/statistics.php?stats=1, 2012-06-27

## IV. Analysis of Win Ratio

A big skill gap between players in a match can result in a disappointing experience. The more skillful players may lack challenge; the less skillful players may give up. Most of the match-based games have implemented a rating system to help players recognize their skill level and find proper opponents. The quality of rating system affects an elementary metric for match-based game players, the win ratio, defined as the percentage of wins of the total of wins and losses. In this section, we study the correlations between winning and several other characteristics, including the amount of played matches, friendship, and current rating systems.

### A. Win ratio vs. match count

Intuitively, playing more matches should lead to better gaming skills and thus higher win ratios. Figure 4 shows the average win ratio versus the match count for Dota-League, KGS, and FICS. We normalize the match count based on the maximum values observed for each game. We then slice the normalized match count range into 100 bins and calculate the average win ratio for each bin.

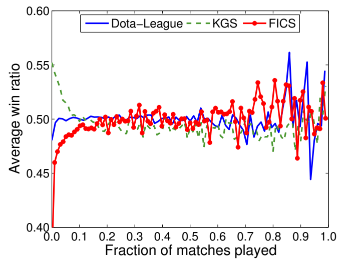



Fig. 4. Average win ratio over fraction of matches played.

For beginning players (range [0.0-0.1] in the horizontal axis), the evolution trends of the win ratios of KGS and FICS are opposite. The reason may be that, when registering in these games, players are suggested to fill in their skill levels. However, the default value of KGS is low, while that of FICS is a median value. Thus, beginners in KGS whose actual skill level may be higher, will play with less skillful players and gain a higher win ratio, and vice-versa for FICS. Beyond this starting zone, the win ratio fluctuates around 0.5. Thus, there is no direct correlation between win ratio and match count (with the correlation coefficient $R = 0.1108$, p-value $P = 0.3342$). For advanced players (range [0.7-1.0]), the fluctuation is larger, which might be caused by the different types of players. People with longer player lifetime may be professional players or hardcore players with varying skill levels.

### B. Win ratio vs. friendship

In many types of competitions, team-spirit and cooperation with friends have great effect on the success. In the gaming field, we can also find friendship and cooperation between players in many different types of games, for example in online bridge [9]. In this subsection, we analyze the impact of friendship on win ratios in DotA.

We find two kinds of relationships between players in Dota-League and DotAlicious. In Dota-League, players have a friend list called "buddy link", whereas in DotAlicious players can be a member of a clan with maximum 8 members. We consider both the buddy link and the clan membership as friendship. Figure 5 illustrates the performance of players, for 3 equally sized win ratio ranges. In this figure, friend matches refer to the matches players play with their friends in the same team. WRa is the win ratio of all matches; WRf is the win ratio of matches played with a friend. Benefiting players are players whose WRf is higher than their WRa. Since the fraction of players whose WRa is less than 0.2 or more than 0.8 is very small, we eliminate these players as outliers and focus on the WRa range from 0.2 to 0.8. The vertical axis is used to represent the fraction of friend matches, the fraction of benefiting players, average WRa and average WRf.

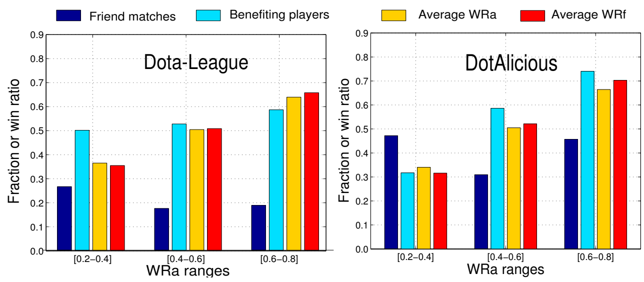



Fig. 5. Performance of players for different win ratio ranges.

According to the "Friend matches" bars, more than half of the players play individually; also, players in Dota-League play less games with friends than players in DotAlicious. The reason is probably that the Dota-League matchmaking assigns players randomly, without guarantee to be in the same team with a friend. With the increase of win ratio, more players perform better in matches with their friends and improve their win ratios ("Benefiting players" bars). On average (bars "Average WRa" and "Average WRf"), the players with higher WRa (ranges [0.4-0.6] and [0.6-0.8]) win more matches when they play with friends in a team. However, the increase of the average win ratio is small (under 0.05). Surprisingly, the players with lower WRa (range [0.2-0.4]) lose more matches when they cooperate with friends. To some extent, it implies that DotA is not a beginner-friendly game: beginners can't help each other to higher win ratios. For comparison, Ducheneaut et al. [18] found that cooperation helps players to level up in World of Warcraft; Mason and Clauset [19] found that in Halo: Reach, teams composed of friends, on average, win more games than teams composed of strangers.

### C. Winning prediction of current rating systems

As we mentioned at the beginning of this section, game operators may design or implement their own rating systems. In this subsection, we discuss the existing rating systems in DGS and FICS, and analyze the winning probability (WP) of a player in a match according to the skill level given by the rating systems. The DGS and FICS servers implement the

TABLE II

THE WINNING PROBABILITY BY SKILL GAPS.

| DGS | | | | FICS | | | |
|---|---|---|---|---|---|---|---|
| Gap | # Matches | % | WP | Gap | # Matches | % | WP |
| 2 | 389 | 1.0 | 0.499 | 2 | 1,675,560 | 1.2 | 0.502 |
| 5 | 588 | 1.5 | 0.524 | 4 | 1,821,258 | 1.3 | 0.505 |
| 11 | 1,300 | 3.2 | 0.518 | 10 | 5,094,868 | 3.7 | 0.509 |
| 25 | 2,970 | 7.4 | 0.484 | 22 | 10,019,375 | 7.4 | 0.521 |
| 57 | 6,283 | 15.6 | 0.534 | 49 | 20,980,110 | 15.4 | 0.545 |
| 129 | 11,950 | 29.6 | 0.550 | 108 | 35,523,732 | 26.1 | 0.597 |
| 290 | 9,130 | 22.6 | 0.617 | 238 | 38,386,954 | 28.2 | 0.696 |
| 652 | 5,349 | 13.3 | 0.710 | 520 | 19,009,291 | 14.0 | 0.838 |
| 1,467 | 1,962 | 4.9 | 0.787 | 1,137 | 3,365,828 | 2.5 | 0.932 |
| 3,299 | 448 | 1.1 | 0.821 | 2,487 | 227,260 | 0.2 | 0.994 |
| Total | 40,369 | 100.0 | 0.591 | Total | 136,104,236 | 100.0 | 0.648 |

EGF[1] and Glicko[2] systems, which are both based on the Elo[3] rating system, to measure the skill of players, respectively.

We define the winning probability for a specific skill gap as the fraction, from the matches between players whose skill rating differs by the gap, of the matches where the winner is the player with higher skill rating, based on the rating before the match. In general, if the skill gap is less than 100 in DGS or less than 200 in FICS, the skill levels of the two players are very similar. We logarithmically assign the skill gap value into 10 bins based on the maximum skill gaps of DGS and FICS (3,299 and 2,487, respectively). Table II presents the change of winning probability from the lowest to the highest skill gap. After filtering out abnormal matches (such as draws, matches with handicap[4] in DGS, etc.), we obtain 40,369 cleaned DGS matches and 136,104,236 FICS matches.

When the skill gap is small (under 100), the winning probability of the higher skill player is around the expected value of 0.5. As the skill gap increases, the higher skill players have higher probability to win matches. When the skill gap is high enough, there is still a probability for the lower skill player to win the match, especially in DGS. The reason may be that a number of players play casually in online board games, and the amount of DGS matches is not as large as that of FICS. The percentage of matches with large skill gaps (over 500) is over 16%, which indicates that players in those matches may not have a good gaming experience and that the board game operators should improve the quality of their matchmaking systems.

## V. Analysis of Player Behavior and Evolution

Due to the large variety of available games, players have many choices. The selection can be influenced by both the content of games and the quality of the offered service. Retaining players with longer player lifetime (from the first time till the last time a player has been seen) can yield more revenue for game companies. In this section, we analyze how the player lifetime interacts with the number of in-game friends, and in-game play strategy.

### A. Player lifetime and match count vs. number of friends

We have discussed the influence of friendship on the performance of players in matches (Section IV-B). We now study how the friendship affects player lifetime in DotA-League.

Figure 6 illustrates that players with more friends generally stick to the game longer (left vertical axis) and play more matches (right vertical axis). The friendship does have a strong correlation with player lifetime ($R = 0.8412$, $P < 0.01$). Thus, it would be a good idea for the game operators to maintain players by reminding players to make more friends and by providing convenient services to support social interaction. Unlike Facebook, where users have on average of about 130 friends, most players here have at most 60 friends.

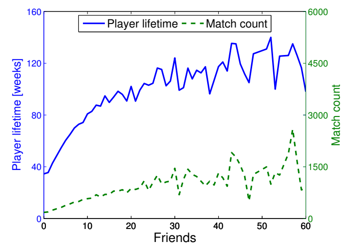



Fig. 6. Number of friends with player lifetime and match count.

### B. Player lifetime vs. play strategy

Predicting player lifetime is an important task for a game company, because if a company can predict how long the player's game lifetime will be, it can both leverage some methods to prolong player lifetime and better market in-game or side products. Although lifetime prediction has been researched for the past 5 years, only a small fraction of these studies have taken into account the players' in-game behavior.

We study the number of strategies players use in DotA-licious and FICS. In DotAlicious, the in-game characters of players are called "heroes". Different heroes represent different types of strategies. In FICS, for simplicity, the first move of a player in a match represents a strategy. There are over 100 available strategies in our DotAlicious dataset and 20 available strategies in FICS.

Figure 7 shows the average number of strategies used by players with different lifetimes. The horizontal axis shows the lifetime of players, and the percentage of matches using the top $n$ strategies--by match count--is depicted against the left vertical axis, while the right vertical axis shows the number of strategies used. The value of $n$ is 3 and 1 in DotAlicious and FICS, respectively. In general, there is a positive correlation between player lifetime and the number of used strategies ($R = 0.8789$, $P < 0.01$): the longer the player lifetime is, the more strategies he will have used. The top $n$ strategies account for a large majority of matches, which indicates that players are conservative. According to Figure 7, if the amount of available strategies is larger, players may spend more time

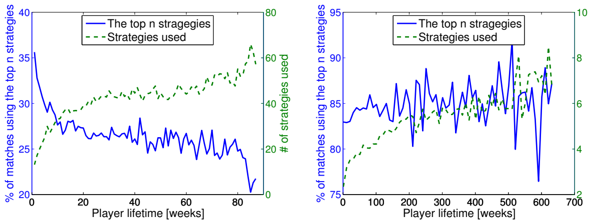
[1]http://senseis.xmp.net/?FIDETitlesAndEGFGoRatings

[2]http://senseis.xmp.net/?GlickoRating

[3]http://senseis.xmp.net/?EloRating

[4]http://senseis.xmp.net/?Handicap

in exploring all the strategies. As for the game operators, they may need to provide (better) awards to encourage players to try new strategies.




(a) DotAlicious (b) FICS

Fig. 7. The evolution of play strategy with player lifetime.

## VI. Related Work

Our work complements the large body of MMVE data analysis by focusing on match-based game data.

User behavior analysis is closest to our work. Previous research efforts have focused on arrival of players, in-game behavior, social network, and cheat-detection. Feng et al. [17] investigate the geographic distribution of game servers and players. For the arrival and departure of players, Chen et al. [13] and Chambers et al. [6] try to predict player departure based on network latency and session times, respectively. For in-game behavior, Suznjevic et al. [1] classify players' actions into different categories and analyze the session length, inter-session time, and network consumption for different categories. Balint et al. [9] analyze the user behavior, social network and play style of bridge communities. For cheat-detection, Pao et al. [14] use a machine learning technique to identify bots based on a user's trajectory. We have compared our results with selected results from these previous studies throughout this work.

The network not only affects an MMVE user's experience, but also affects the design of an MMVE system. Previous work has also investigated the network traffic of MMVE [3], [4], [20] and the network traffic of FPS games [7], [8].

## VII. Conclusion and Future Work

The concept of matches underlies many online games with large, socially and geographically diverse populations. To facilitate the design and implementation of online match-based games, we have conducted for these games a comparative analysis of workloads, win ratio, and player behavior and evolution. Our study, which is based on long-term datasets collected from several online match-based games, has lead to the following key observations:

1. The workloads of online match-based games and other online games are similar in several aspects. For example, a large majority of match inter-arrival times is less than one week, most players are North American or European, etc.
2. The win ratio of players is not directly correlated to how many matches they have played.
3. Friendship does not always improve the in-game performance of players.
4. Current rating systems predict the winning probability well, but existing match-making systems need improvement.
5. There is a positive correlation between player lifetime and the number of friends.
6. Players explore more play strategies over time, especially if the game offers many strategic choices.

For the future, we plan to extend our work in three directions: further analyzing the rich datasets and investigate more data correlations, building models for the lifetime of players, and understanding the similarities between online and real-world behavior of players.

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