Online-offline activities and game-playing behaviors of avatars in a massive multiplayer online role-playing game

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received 29 July 2009; accepted in final form 3 November 2009
published online 3 December 2009

PACS 87.23.Ge – Dynamics of social systems
PACS 89.65.-s – Social and economic systems
PACS 89.75.-k – Complex systems

Abstract – Massive multiplayer online role-playing games (MMORPGs) are very popular in China, which provides a potential platform for scientific research. We study the online-offline activities of avatars in an MMORPG to understand their game-playing behavior. The statistical analysis unveils that the active avatars can be classified into three types. The avatars of the first type are owned by game cheaters who go online and offline in preset time intervals with the online duration distributions dominated by pulses. The second type of avatars is characterized by a Weibull distribution in the online durations, which is confirmed by statistical tests. The distributions of online durations of the remaining individual avatars differ from the above two types and cannot be described by a simple form. These findings have potential applications in the game industry.

Introduction. – According to the Statistical Reports on the Internet Development in China released by China Internet Network Information Center, the past twelve years have witnessed a sharp increase in the number of Chinese netizens from 0.63 million on 31 October 1997 to 338 million on 16 July 2009. Till June 2009, the size of netizens playing massive multiplayer online games (MMOGs) is 78.55 million. The MMOGs in mainland China include two types, i.e., the massive multiplayer online role-playing game (MMORPG) and the large-scale casual game, both having about 49 million users. An MMOG is an online virtual world, where avatars can live and interact with one another in a somewhat realistic manner. The huge number of users in MMOGs has raised many open academic problems and attracted vast interest of academics from diverse angles of view, especially since the pioneering work done by Edward Castronova, who traveled in a virtual world called “Norrath” and performed a preliminary analysis of its economy [1]. Particularly, virtual worlds have great potential for research in social, behavioral, and economic sciences [2].

There are several studies based on different virtual worlds [3–13]. In this letter, we investigate the online-offline activities and game-playing behaviors of the avatars inhabiting a server of a massive multiplayer online role-playing game operated by Shanghai Shanda Interactive Entertainment Ltds, which is the leader of China’s MMORPG industry and runs dozens of online games. We will show that the statistical properties of the online-offline activities of individual avatars allow us to classify avatars and identify game cheaters. The game session durations of some multiplayer networked games (say, Quake and Half-Life) are found to be exponentially distributed [14]. Alternatively, Chang and Feng argued that the durations can be fitted with a Weibull distribution through their analysis on several online games [15].

Description and preprocessing of the data. – Our data are online-offline logs recorded during the time period from 1 September 2007 to 31 October 2007 of an
MMORPG server run by Shanda Interactive Entertainment Ltd. There is one log file for each day. Each entry contains three pieces of information: the masked avatar ID, its login time, and its logout time. The resolution of the time stamps is 1 second. During the recording time period, there were 19843 avatars who entered the game. For security sake, the true avatar IDs have been encrypted in numbers from 1 to 19843.

For each avatar, we collect all the associated entries, whose timestamp is 1 second. During the recording time period, there were 19843 avatars who entered the game.

An entry is written to the log file when an avatar goes offline. Therefore, the entries in a log file are arranged according to an increasing order of logoff moments. For security sake, the true avatar IDs have been encrypted into numbers from 1 to 19843.

We adopt the strategy of removing the offline entry by mapping A as an offline-online activity. For the above cases, we will record the action that one avatar enters map B from map A as an offline-online activity. For the above cases, we adopt the strategy of removing the offline entry by merging the two entries \( \{ t^{on}_i, t^{off}_i \} \) and \( \{ t^{on}_{i+1}, t^{off}_{i+1} \} \) into one \( \{ t^{on}_i, t^{off}_{i+1} \} \). It is possible that the offline duration associated with an inter-map transfer of an avatar is greater than 0 if there is a heavy network traffic. For the online durations, all \( \tau \) values are non-negative and there are 52442 online durations (about 0.4% of the total sample) that are equal to 0. The online durations with \( \tau = 0 \) are excluded from further analysis.

Collective behaviors. – The instant number of online avatars per second can be constructed according to the online-offline data, whose statistical properties have been investigated [16]. It was found that the online avatar number exhibits one-day periodic behavior and clear intraday pattern, the fluctuation distribution of the online avatar numbers has a leptokurtic non-Gaussian shape with power law tails, the increments of online avatar numbers after removing the intraday pattern are uncorrelated and the associated absolute values have long-term correlation, and both time series exhibit multifractal nature [16]. Some of these properties are relevant to the traffic of the server and the profit of the MMORPG company.

In this section, we will investigate the collective behaviors of individual avatars based on their gaming activities. Three quantities are studied. For each player, we define two quantities, one is total online times \( t \) and the other is total online session duration \( T \), and then take the whole population as a sample to make a description of the collective activities.

\[
N^{on} = \sum_{j=1}^{19843} n_j^{on} \quad \text{and} \quad N^{off} = \sum_{j=1}^{19843} n_j^{off},
\]

Defining that \( N^{on} = \sum_{j=1}^{19843} n_j^{on} \) and \( N^{off} = \sum_{j=1}^{19843} n_j^{off} \), it follows immediately that

\[
N^{on} = N^{off} + 19843.
\]

We have calculated the online and offline duration sequences of all the 19843 avatars and find that \( N^{on} = 14393332 \) and \( N^{off} = 14373489 \), which is consistent with eq. (6). On average, each avatar plays about 12 sessions each day.

Preprocessing the data is necessary. We find that there are 41845 offline durations (about 0.3% of the total sample) that are negative, which can be attributed to recording errors introduced by the system. There are also 1221811 offline durations (about 8.5% of the total sample) that equal to zero. The observation of \( \eta = 0 \) is nothing but a consequence of the data recording rule that the log file will record the action that one avatar enters map B from map A as an offline-online activity. For the above cases, we adopt the strategy of removing the offline entry by merging the two entries \( \{ t^{on}_i, t^{off}_i \} \) and \( \{ t^{on}_{i+1}, t^{off}_{i+1} \} \) into one \( \{ t^{on}_i, t^{off}_{i+1} \} \). It is possible that the offline duration associated with an inter-map transfer of an avatar is greater than 0 if there is a heavy network traffic. For the online durations, all \( \tau \) values are non-negative and there are 52442 online durations (about 0.4% of the total sample) that are equal to 0. The online durations with \( \tau = 0 \) are excluded from further analysis.

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Distribution of the number of gaming sessions of individual avatars. For each avatar, we count the number \( m \) of gaming sessions that he/she played during the two-month time period under investigation. The sequence has 19843 data points. The empirical probability density function \( p(m) \) of individual gaming session number \( m \) is illustrated in fig. 2. One can observe that there is a power law behavior between \( p(m) \) and \( m \):

\[
p(m) \approx m^{-\alpha m+1}, \quad \text{for } m \geq m_{\min},
\]
where the power law exponent can be approximatively obtained by the following equation based on the maximal likelihood estimation [17]:

$$\alpha_m = N_m \sum_{j=1}^{N_m} \ln \frac{m_j}{m_{\text{min}} - 0.5},$$  \hfill (8)

where $N_m$ is the number of $m$ that are no less than $m_{\text{min}}$. By setting $m_{\text{min}} = 1$, eq. (8) gives that the tail exponent $\alpha_m = 0.39$. The Kolmogorov-Smirnov test confirms that the distribution can model the data with high statistical significance. For comparison, we also plot the Lévy distribution with the corresponding power law exponent $\alpha_m = 0.39$ [18]. The small distance between the empirical distribution and the Lévy curve indicates that the numbers of sessions are approximately distributed according to a Lévy distribution.

The very small value of $\alpha_m$ indicates that the decay of the distribution is very slow. The daily online number is no more than 10 for 97.1% of the avatars and is no more than 1 for 85.2% of the avatars. In addition, we notice that the fluctuation at the tail of the distribution $p(m)$ is high and the occurrence of large $m$ values seems to be greater than the prediction of the $p(m)$ function. The maximal value of the $m$ sequence is 187812 (Avatar ID: 4636), which means that the avatar went online and offline 128.3 times per hour! The evolution of the daily number $m(t)$ of game sessions played by this avatar 4636 is illustrated in the right axis of fig. 3. We also show in the left axis the evolution of daily number $m(t)$ of game sessions for avatar 16577 for comparison.

Figure 4 shows the occurrence $O(\tau)$ of the online duration $\tau$ for avatar 4636. There are two spikes in fig. 4 located at around $\tau = 20$ and 28. We observe that $O(20) = 134544$ and $O(28) = 30302$, which amounts to 71.6% and 16.1% of the number of online durations. The inset shows the associated $\tau$ sequence. A clear change of cheating behavior from $\tau \approx 20$ to $\tau \approx 28$ is observed, which happened on 14 October 2007.

Figure 2: Empirical probability density function $p(m)$ of the number of sessions $m$ of 19843 individual avatars. The dashed line is a Lévy distribution with exponent 0.39.

Fig. 3: Evolution of the daily number of game sessions played by two typical avatars 4636 (right axis) and 16577 (left axis).

Distribution of the total time spent by individual avatars. An important measure of the avatar game-playing behavior is the total time he/she spends, which can be calculated as follows:

$$T_j = \sum_{i=1}^{m_j} \tau_i,$$ \hfill (9)

where is the sum of all session durations of avatar $j$. The size of the $T_j$ series is 19843. The maximal total time is 1142 hours (Avatar ID: 4636), which means that the avatar was active in the game 18.7 hours per day.

Figure 5 depicts the probability density function $p(T)$ of the total time $T$ for the whole population. One can observe that there is a power law behavior in the tail of $p(T)$:

$$p(T) \approx T^{-(\alpha_T + 1)}, \quad \text{for } T \geq T_{\text{min}}.$$ \hfill (10)

The tail exponent $\alpha_T$ can also be determined by maximal likelihood estimation using eq. (8), where the argument $m$ is replaced by $T$. By setting $T_{\text{min}} = 500$, eq. (8) gives that the tail exponent $\alpha_T = 0.35$. It is interesting to note that the tail exponent $\alpha_T$ of the total time $T_j$ is very close to the power law exponent of the session number $m_j$.

Distribution of the durations of individual sessions. We put all the online durations $\tau_i$ of all the avatars together as a whole sample and investigate its distribution.
The size of the whole sample is 13092371. Figure 6 shows the empirical distribution density $p(\tau)$ of the online durations $\tau$ in log-log scales. The most striking feature of fig. 6 is the occurrence of many spikes, which locate at $\tau = 2, 12, 20, 25, 28, 44, 71, 87, 300, 505, 600, 614, 1200, 1500, 1800, 2000, 2411, 3000, 3600, 5000, 6000, 614, 1200, 1500, 1800, 2000, 2411, 3000, 3600, 5000, and 10000. These spikes are outliers that are markedly greater than the normal level. For some of the spikes, its neighbors are also greater than the normal level. These spikes indicate the abnormal behavior of some players, which are usually related to game cheaters. This observation can be used to identify game cheaters.

Consider the spike at $\tau = 5000$. There are 466 game sessions with $\tau = 5000$. We find that there are 15 avatars (IDs: 339, 3797, 5542, 5954, 6148, 6886, 7044, 7767, 10217, 11436, 15611, 15613, 17733, 18075, 18246) whose online duration sequences have at least one point being $\tau = 5000$. The occurrence of $\tau = 5000$ is 1 for all the avatars except for avatars 15611 and 15613, whose occurrences are 233 and 220, respectively. Figure 7 shows the occurrence $O(\tau)$ of the online duration $\tau$ for avatar 15611. We find that there are two spikes in fig. 7 located at $\tau = 3600$ and 5000, whose occurrences are $O(\tau) = 137$ and 233. We also observe that $O(3601) = 60$ and $O(5001) = 165$. Note that the size of the online duration sequence of this avatar is 1115. Hence the proportion of the occurrence of these four $\tau$ values is 53.36%. The inset shows the associated $\tau$ sequence. A clear change of cheating behavior from $\tau = 5000$ to $\tau = 3600$ is observed, which happen on 10 October 2007. For avatar 15613, very similar behavior is observed and a change of cheating from $\tau = 5000$ to $\tau = 3600$ happened on 12 October 2007. The striking similarity of the behavior of the two avatars implies that their host players might be closely related. In summary, as shown in fig. 4 and fig. 7, there are bursts or pulses in the histogram of the occurrence of some fixed online durations $\tau$. These avatars are impossible to be operated by humans. Rather, they are controlled by some robots, whose host players are game cheaters.

**Online duration distributions for individual avatars.** - Now we turn to study the online-offline behaviors of individual avatars, which are of potential interest and ultra importance in the identification of game cheaters, the detection of server traffic, the understanding of the game-playing patterns of players, and the design and improvement of online games.

Owning to the consideration of commercial applications and statistics of the results, we are more interested in active avatars when investigating their game-playing patterns at the level of individual avatars. There are numerous avatars whose total numbers $m$ of online sessions are small. For instance, the proportions of avatars with $m \leq 1$, $m \leq 2$, $m \leq 10$, $m \leq 50$ and $m \leq 100$ are 27.8%, 43.2%, 66.4%, 83.6% and 88.9%, respectively. Although an avatar with $m = 50$ is not inactive, it is hard to construct its empirical distribution $p(\tau)$ with sufficient statistics. In addition, according to the 7th Online Game Research Report (2007) and the 8th Online Game Industry Research Report (2008)\(^1\), about 92% players spent more than one hour in playing online games every day. Combining these two facts, we exclude from our

\(^1\)http://china.17173.com/2007/irc1717131220.rar (in Chinese), accessed on 1 December 2009.
analysis the avatars who were online for no more than 30 days or whose daily cumulative online durations were less than half an hour. This results in 947 avatars remaining. According to the regular behavior of the program-controlled avatars, we filter out 258 robot avatars that were too active from the entire population. Finally, there are 689 avatars remaining for further analysis.

**Weibull distributions.** In order to check if these active avatars share the same online-offline behavior, we determine the empirical complementary cumulative distribution $C(\tau)$ of each avatar. Our eye-balling gives us the impression that most distributions have fat tails, which could be modeled by the Weibull distribution [19,20]

$$C(\tau) = \exp\left(-\left(\frac{\tau}{\tau_0}\right)^b\right),$$

where $\tau_0$ is the characteristic time, and $b < 1$ is the exponent. It follows immediately that

$$\ln\left[1/C(\tau)\right] = \left(\frac{\tau}{\tau_0}\right)^b,$$

which means that $\ln[1/C(\tau)]$ scales as a power law with respect to $\tau$. Weibull distributions are ubiquitous in many fields [19–21]. For instance, the intertrade durations are found to have Weibull distributions in both emerging and developed markets [22–24]. Figure 8 shows the dependence of $\ln[1/C(\tau)]$ as a function of $\tau$ for three avatars. All the three curves exhibit power laws with the scaling ranges spanning about three orders of magnitude, which is the graphic evidence that the distribution of the online durations for individual avatars of this type is Weibull.

In order to identify the avatars whose online durations conform to the Weibull distribution, we design an approach to classify the avatars based on statistical tests. For each avatar, its empirical distribution of online durations is fitted to a Weibull formula by means of the maximum likelihood estimation (MLE) method. The fitted formula is then converted to its cumulative form $F(\tau)$. We then investigate whether the sample of online durations is drawn from the “theoretical” distribution $F(\tau)$ from the best MLE fit. The null model is that the data can be modeled by a Weibull distribution. We can perform the Kolmogorov-Smirnov (KS) test [25,26] for this purpose. The Kolmogorov-Smirnov statistic (KS statistic), which measures the distance between the empirical cumulative distribution function of the sample and the cumulative distribution function of the best fit, is defined as

$$\text{KS} = \max(|F_{\text{emp}} - F|),$$

where $F_{\text{emp}}$ is the cumulative distribution function of the empirical sample and $F$ is the cumulative distribution function from the best MLE fit. Alternatively, the Cramérvon Mises criterion can also be used for judging the goodness-of-fit of the probability distribution compared with a given distribution [27], which is given by

$$C_M^2 = n \int_{-\infty}^{+\infty} \left[F(\tau) - F^*(\tau)\right]^2 dF(\tau).$$

In one-sample applications, the function can be described as follows [28,29],

$$C_M^2 = \frac{1}{12n} + \sum_{i=1}^{n} \left[\frac{2i-1}{2n} - F(\tau_i)\right]^2,$$

where $n$ is the sample size. If the KS (or CvM) statistic is less than a critical value, the null hypothesis cannot be rejected.

At the significant level of 1%, we find that there are 489 avatars whose online durations can be well modeled by the Weibull distribution. Figure 9 presents the histogram of the fitted exponent $b$ for the 489 avatars. There is one value of $b$ (ID: 5483) that is greater than 1, which corresponds to a sub-exponential distribution decaying faster than exponential. We find that the distribution is mono-modal and $b = 0.68 \pm 0.12$.

**Other distributions.** For the avatars whose online durations do not follow Weibull distributions, we cannot find a simple form for the online duration distribution. Figure 10 illustrates the survival distributions of $\tau$ for three typical avatars in log-log scales. It seems that the first-order derivative is not continuous for avatars 13755 and 18096, since there are clear kinks in the $C(\tau)$ curves.
show correspondingly the plots of $\ln [1/C(\tau)]$ vs. $\tau$.

For avatar 19750, the $C(t)$ curve looks like a Weibull truncated with a power law tail. However, statistical tests shows that it is neither a Weibull distribution nor a power-law-tailed distribution. The inset of fig. 10 shows correspondingly the curves of $\ln [1/C(\tau)]$ with respect to $\tau$ for the three avatars. No evident power law regime is observed in the three curves, which confirms that the online durations of these avatars do not follow Weibull distributions.

**Conclusion.** In summary, we have studies the online-offline activities and game-playing behaviors of avatars in a massive multiplayer online role-playing game based on the log files recorded during the time period from 1 September 2007 to 31 October 2007. We found that the number of game sessions and total time of online durations of individual avatars are distributed according to a power law, with large bursts in both tails. In addition, the distribution of the online durations of all avatars as a whole sample is decorated by sharp spikes. These phenomena are signals of game cheaters who used robots to control their avatars, which can be identified by the abnormal pulses in the distribution of online durations for individual avatars. In addition, we also found that there are a group of normal avatars whose online durations are distributed as Weibulls. These findings have potential applications in the online game industry.

Our finding that the online durations of many normal avatars are distributed according to a Weibull distribution adds new evidence that human dynamics is not a simple Poisson process [30]. However, the Weibull behavior cannot be explained by existing models based on priority queue [30], cascading on homogeneous Poisson process [31], or adaptive interest [32].

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This work was partly supported by the Program for New Century Excellent Talents in University (Grant No. NCET-07-0288).

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