

Analyses of a Virtual World

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Abstract We present an overview of a series of results obtained from the analysis of human behavior in a virtual environment. We focus on the massive multiplayer online game (MMOG) *Pardus* which has a worldwide participant base of more than 400,000 registered players. We provide evidence for striking statistical similarities between social structures and human-action dynamics in real and virtual worlds. In this sense MMOGs provide an extraordinary way for accurate and falsifiable studies of social phenomena. We further discuss possibilities to apply methods and concepts developed in the course of these studies to analyse oral and written narratives.

1 Introduction

Quantitative approaches in social sciences and humanities have benefited greatly from the introduction of advanced information technologies. These allow one to accumulate and store a huge amount of data, as well as to enable its effective processing. Computer-based communication technologies have led to the formation

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of virtual societies, and these societies have themselves become the subjects of research. In this Chapter, we demonstrate some results obtained through analyses of human behavior in a Massive multiplayer online game (MMOG) (Castronova 2005). Playing such games has become one of the largest collective human activities in the world; at present hundreds of millions of people participate in such activities including, for example, approximately 10 million who are registered for the most popular MMOG *World of Warcraft* (Statista 2015). In turn, the records of activity of players in MMOGs provide extraordinary opportunities for quantitative analyses of social phenomena with levels of accuracy that approach those of the natural sciences. The results we discuss below were obtained from a series of analyses of the MMOG *Pardus*. Since it was launched in 2004, the *Pardus* game served as a unique testing ground to measure different observables that characterize inhabitants of the virtual world and in this way to obtain clues also on complex social processes taking place in the real¹ world (Szell and Thurner 2010, Szell et al. 2010, Szell et al. 2012, Thurner et al. 2012, Shell and Thurner 2013, Klimek and Thurner 2013, Corominas-Murtra et al. 2014, Fuchs and Thurner 2014, Fuchs et al. 2014, Sinatra and Szell 2014).

The reasons for the appearance of a chapter on a multiplayer online world in a book devoted to complexity-science approaches to oral and written narratives may not be obvious at first sight. Comparative mythology, folktales and epic literature which are the main issues in this book have little to do with the virtual world of *Pardus*. However, a more careful comparison reveals a number of common features and potentially transferrable analytical tools. In both cases, one treats narrative or virtual characters in a manner similar to how sociologists treat real social groups, with an aim to quantify properties of such groups. See e.g. Stiller et al. (2003), Mac Carron and Kenna (2012), Mac Carron and Kenna (2013) and references therein. In such studies, quantitative analyses put comparison and classification of different narratives on a solid basis. A similar goal is pursued by the analysis of actions of virtual characters (players) of an MMOG.

Although the societies of an MMOG and of a narrative are to some extent mirrors of the real world, they reflect it in different ways. In an MMOG, each individual is the character controlled by a player (i.e., an avatar or graphical representation of the user). In a narrative, the individual is a character in a story. The narrative is created with the intention to be perceived by a reader and it carries a personal contribution of a writer. Life in an MMOG evolves as a complex system and is driven by numerous interactions between players. Here we discuss some results of analyses of the virtual world and methods used to obtain them which, we hope, might be also useful in future analyses of the world of narratives. Moreover, analysis of life in a synthetic world serves as a tool to learn more about human behavior in the real world.

We discuss the application of complex-network concepts to uncover the diversity of social interactions in a society. We pay particular attention to how multidimensional graphs, wherein nodes may be connected by more than one type of edge or link,

¹ We use the word “real” due to lack of a better term. Certainly human behavior, emotions, and decisions in online worlds are as “real” as in the offline world – they might only be biased differently depending on the context.

contribute to the formation of different interconnected *multiplex* networks. We demonstrate how one can test traditional social-dynamical hypotheses which apply to virtual societies too, bringing to the fore intrinsic similarities between virtual and real worlds. In addition, we analyse the evolution of social networks in time through a first analysis of dynamical features of multi-level human activity (sequences of human actions of different types). This study of multi-level human activity in Section 3 can be seen as a dynamic counterpart to static multiplex network analysis presented in the following section.

2 Database and Networks

Pardus is a browser-based MMOG played since September 2004. It is an open-ended game with no explicit winning purpose and a worldwide player base of more than 400,000 registered participants (Pardus 2015, Szell and Thurner 2010). The game has a science fiction setting and each player controls one character. The characters act within a virtual world, making up their own goals and interacting with the social environment which is self-organized. The game features three different universes: *Orion*, *Artemis*, and *Pegasus*. Each universe has a fixed start date but no scheduled end date. The results we discuss here concern the *Artemis universe*, selected for study because it has most active players and because its data set is most complete. *Artemis* was opened on June 10, 2007 and at the time of this study was inhabited by several thousand active characters.

Each character in the game is a pilot who owns a spacecraft, travels in the universe and is able to perform a number of activities of different types, such as communication, trade, attack, establishing or breaking friendships or enmities, etc. Since we focus on social features, we make use of records about the following activities of each character in the game:

- sending private messages from one player to another (communication, C);
- attacking other players or their belongings (attack, A);
- trading or giving gifts (trade, T);
- indicating friends by adding their names to a friend list (F);
- indicating enemies by adding their names to an enemy list (E);
- removing friends from the friend list (D);
- removing enemies from the enemy list (X);
- placing a bounty on other players (B).

The overall number of actions performed by the characters during 1,238 consecutive days of observation was $N = 8,373,209$ [for a detailed description of the database see Szell and Thurner (2010), Mryglod et al. (2015)].

A straightforward way of mapping the *Pardus* society onto a complex network is to associate nodes with individual characters. A link between two nodes represents an action that took place between the corresponding pair of characters. Every action type (from the above list) is directed; it is initiated by one character and directed

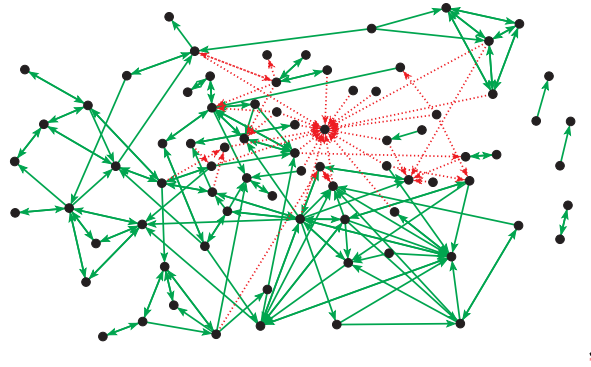


Fig. 1 Friendship (green, solid) and enemy (red, dashed) relations on day 445 between 78 randomly selected game characters. The diagram is taken from Szell and Thurner (2010). An animated evolution of this network can be seen at: <http://www.youtube.com/user/complexsystemsvienna>

towards another. Given the different possible actions, one arrives at a set of directed networks where links in each network correspond to actions of certain types. We define the in- and out- degrees as the number of incoming and outgoing links that a given node has, and we denote these by k^{in} and k^{out} respectively. When we don't specify whether we are dealing with in- or out-degrees, or if it doesn't matter (when the network is not directed), we use the generic symbol k for the degree instead. Data are available with a one-second resolution, making possible a refined analysis of dynamical features of the virtual society. With the data on activities of each player to hand, one can construct networks of social interactions at each instant in time and follow their evolution.

As an example, in Fig. 1 we show networks of friendship and enemy relations on the 445th day (01 September 2008) between 78 randomly selected characters. One can measure the basic network properties, track their evolution over time (Szell and Thurner 2010) and quantify correlations between properties of networks of different types (Szell et al. 2010). In Fig. 2 we show several features of the communication (C), friendship (F), and enemy (E) networks, measured during the same day in the virtual world. We display three measures: the cumulative degree distribution $P(k)$, the clustering coefficient $C(k)$ and the mean degree $k^{\text{nn}}(k)$. The first of these, $P(k)$, is the probability that the degree k_i of a randomly selected node i is at least as large as a given value k ($k_i \geq k$). The second measure, $C(k)$, is defined in the following manner. One first forms the ratio of the number of links which *actually* exist between i 's neighbours and the number of all *possible* links between them. If node i has k_i neighbours, each of these can be linked to $k_i - 1$ other neighbours of node i . The total number of potential links between i 's neighbours is therefore $k_i(k_i - 1)/2$, having divided by two to deal with the overcounting induced by each link being shared by two nodes. If y_i is the actual number of links between the neighbours of node i , then we define the clustering of the i th node to be

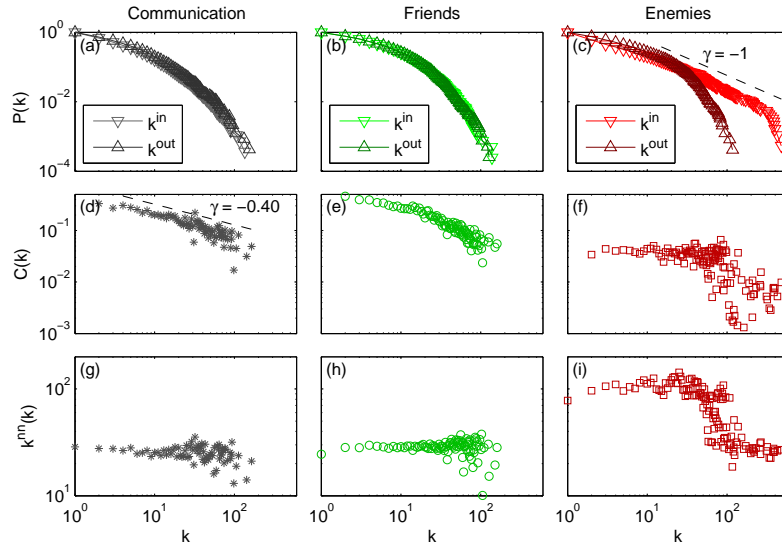


Fig. 2 Cumulative degree distributions of (a) communication (C), (b) friendship (F) and (c) enemy (E) networks; clustering coefficient C as a function of degree k for the (d) C, (e) F and (f) E networks; nearest neighbor degree k^{nn} versus degree of the (g) C, (h) F, and (i) E networks. Fits to power laws ($\sim k^\gamma$) are indicated by dashed lines, when appropriate. All distributions are shown as for 2008-09-01, the picture is taken from Szell and Thurner (2010).

$$C_i = \frac{2y_i}{k_i(k_i - 1)}. \quad (1)$$

Taking the average of the C_i 's over all nodes for which $k_i = k$ gives the mean clustering $C(k)$. This is the average clustering associated with nodes of degree k . The third and final measure in Fig. 2, $k^{nn}(k)$, is the mean degree of the nearest neighbours of nodes which themselves have degree k . These and other basic network properties of the *Pardus* society are discussed in detail in Szell and Thurner (2010) and further analyzed in numerous publications (Szell et al. 2010, Szell et al. 2012, Thurner et al. 2012, Shell and Thurner 2013, Klimek and Thurner 2013, Corominas-Murtra et al. 2014, Fuchs and Thurner 2014, Fuchs et al. 2014, Sinatra and Szell 2014, Mryglod et al. 2015).

Fig.2 tells us that there are a number of characteristics that distinguish networks of different types. Each plot is on a double-logarithmic scale so that any power-laws present would show up as straight-line segments. For example, comparing the properties of the communication, friendship, and enemy networks, one finds that only in the latter case can the cumulative node degree distribution be approximated by a power law. This is evidenced in Fig.2c where the fit indicates that $P(k) \sim k^\gamma$ with $\gamma = -1$. The corresponding plots for the communication and friendship cases, Fig.2a and Fig.2b, respectively, are evidently not described by power-laws.

Fig. 2d and Fig. 2e show that the clustering coefficients $C(k)$ for the communication and friendship networks exhibit clear downward trends as k increases, whereas Fig. 2f shows that the clustering coefficients are to a large extent independent of k for the enemy networks, at least for large values of k . That the same can be said about the degrees k^{in} is evident from Figs. 2g to i.

These observations can be complemented by examining the behavior of the *linking probability* $p(k)$ as function of the degree k (not shown in Fig. 2). This is the probability of a new node connecting to an existing node with degree k . By fitting it with a power-law function of the type $p(k) \sim k^\alpha$, we can try to understand how the network grows as new nodes are added. If α is positive, it means that new nodes prefer to attach to nodes which have higher degrees. In the case where $\alpha = 1$, which signals a linear dependency, this phenomenon is known as *preferential attachment*. The following values for the exponents have been reported for in-degrees: $\alpha \simeq 0.62$ for the friendship and $\alpha \simeq 0.90$ for the enemy network. We refer to Szell et al. (2010a) for further discussions on this topic.

These quantitative observations are important because they allow one to conclude that there are intrinsic differences in the network formation processes for the C, F and E networks. In particular, in a typical preferential-attachment mechanism, links attach to nodes according to how many links these nodes already have; high-degree nodes receive more new neighbours than their low-degree counterparts. The resulting node degree distribution decays as a power law, the linking probability increases linearly with k (i.e. $\alpha = 1$) and the clustering coefficient $C(k)$ is uniform as a function of k (Barabási and Albert 1999). None of these three properties holds for the communication or friendship networks, but all are roughly satisfied for the enemy network. This suggests that the preferential attachment scenario is mainly relevant for the latter. In other words, the more enemies a character has, the more likely they are to accrue more enemies but the same is not true for friends or for communication.

The above discussion around Fig. 2 focuses on the differences between the various network types. There are similarities too. The following common features have been observed for *Pardus* networks of different types (Szell and Thurner 2010): (i) their average node degrees grow over time; (ii) the mean shortest path length decreases with time; (iii) networks such as communication, trade and friendship, are reciprocal (individuals tend to reciprocate connections); (iv) but networks such as enmity, attack and bounty are not. Properties (i) and (ii) signal that the network becomes more dense as time evolves while properties (iii) and (iv) show that networks with positive connotations tend to be reciprocal while those with negative connotations are not.

The example network shown in Fig. 1 is a part of a multiplex network (Wasserman and Faust 1994), that consists of a set of characters that are joined by different types of links, corresponding to different types of social relations (recorded as different actions, in the case of the *Pardus* game). It is well established by now that multiplexity plays an essential role in network organization. Indeed, an interplay between different social relations, expressed as an interaction of links of different types, may lead to new levels of complexity. To quantify the relations between

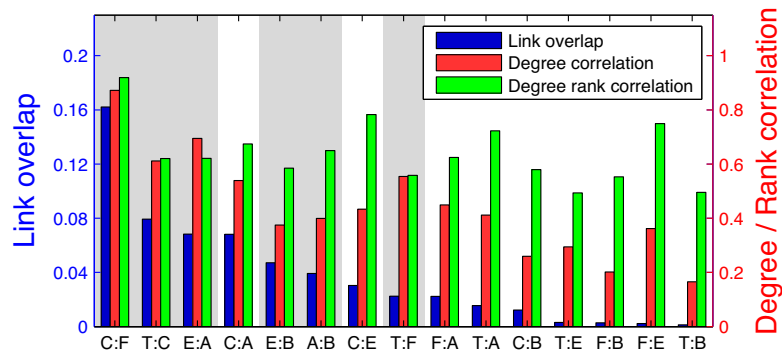


Fig. 3 Link overlap, degree correlation, and degree rank correlation for different pairs of networks. Pairs of equal connotation (positive-positive or negative-negative) are marked with a gray background. See Szell et al. (2010) for more explanations, where from the picture has been taken.

multiplex network layers, a thorough analysis for the *Pardus* society has focused on the *link overlap* and correlations between node degrees between the different network layers (Szell et al. 2010).

The *link overlap* quantifies the interaction between two networks by measuring the tendency that edges are simultaneously present in both networks. It is defined by the so-called *Jaccard coefficient*, which is a similarity score between two sets of elements. It is defined as the size of the intersection of the sets divided by the size of their union. It is therefore a global measure which ranges in size from zero (no overlap) to 1 (100% overlap).

The correlation between node degrees (or their ranks), on the other hand, measures the extent to which degrees of agents in one type of network correlate with degrees of the same agents in the other one. If the correlation between node degrees in two different networks is close to 1, players who have many links in one network have many links in the other one and vice versa. In Fig. 3 we show these quantities for different links pairs of networks. One sees that pairs of the same connotation (positive-positive or negative-negative) typically have high overlaps, whereas this is not the case for pairs of opposite connotation. Moreover, low values of the degree correlations indicate that hubs in one network are not necessarily hubs in another. This demonstrates the tendency of individuals to play different roles in different networks.

Properties of the multiplex network vary for different types of players. A recent analysis of gender-specific differences has shown (Shell and Thurner 2013) that females and males manage their social networks in substantially different ways. In particular, on the individual level, females perform better economically and are less inclined to take risks than males. Males reciprocate friendship requests from females faster than vice versa and hesitate to reciprocate hostile actions of

females. On the network level, females have more communication partners, who are themselves less connected than partners of males. Cooperative links between males are under-represented, reflecting competition for resources among males.

Analysis of the *Pardus* universe also allows one to quantify to what extent classical sociological hypotheses hold up in a virtual world. Such analyses recently enabled us to propose two approximate social laws in communication networks (Szell and Thurner 2010). These findings were made in the course of testing Granovetter's *Weak Ties Hypothesis* (Granovetter 1973), which suggests casual acquaintanceships link communities in an essential way. This means that weak links are important to hold the network together - it is the weak links, not the strong ones, that tend to form the ties between distinct sets of nodes. To explain this quantitatively, we require three new concepts. Firstly, the *overlap* O is the fraction of common neighbours between two neighbouring nodes; if A and B represent the sets of neighbours of two nodes, the overlap is the number of nodes in that A and B have in common ($A \cap B$) divided by the total number in A and B taken together ($A \cup B$). This is a local measure, distinct from the global link overlap discussed earlier. Secondly, the *link-betweenness centrality*, b , is the ratio of the number of shortest paths between two nodes that contain a given link to the total number of shortest paths between these nodes. Thirdly we need the *weight* w of a link joining two nodes. This is also a local quantity. For the communication network, the weight of a link between two nodes corresponds to the number of private messages sent between two individuals these nodes represent.

The stronger the connection between two individuals, the more similar is their local environment, and vice versa. Therefore we expect that the overlap is an increasing function of weight. Analysis of the structure of communication networks in the *Pardus* world has indeed revealed that, on average, the overlap O related to the weight w of a link joining two given nodes increases as

$$O(w) \sim \sqrt[3]{w}. \quad (2)$$

To understand how this connects with Granovetter's hypothesis, consider two sets of nodes: one set involving Node A and one including Node B. If the set of nodes connected to Node A is very distinct from the set of nodes connected to Node B, then the overlap O between the two sets is low (it is zero if they are completely distinct). If O is small, Eq.(2) tells us that w is also a small number. This means that the weight w between nodes A and B is small on average. This low weight corresponds to the notion of casual relationship. Thus Eq.(2) quantifies Granovetter's hypothesis - it tells us that light-weight relationships are essential to bind distinct sets of nodes.

Another way to quantify the Weak Ties Hypothesis is to check the behavior of the overlap O as a function of link-betweenness centrality, b . If the hypothesis is valid, shortest connections between two sets of nodes are forced to go through the weak links that connect them. In other words, low overlap corresponds to high betweenness. The obtained dependency was indeed found to be a decreasing function of the explicit form

$$O(b) \sim \frac{1}{\sqrt{b}}, \quad (3)$$

which supports the hypothesis.

Other social hypotheses that were tested and confirmed for the *Pardus* networks concern triadic closure and network densification (Granovetter 1973). The triadic closure conjecture follows balance considerations (Heider 1946) and reflects the property among three nodes A, B, and C in a social network, that if node pairs A-B and A-C are linked by strong ties, there tends to be a weak or strong tie between the node pair B-C. The phenomenon of triadic closure (Rapoport, 1953) states that individuals are driven to reduce the cognitive dissonance caused by the absence of a link in the (unclosed) triad. Because of this the triad in which there exist strong ties between all three subjects A, B and C should appear in a higher than expected frequency. Network densification (i.e. shrinking of its diameter and growing of average degrees with a span of time) is an aging effect that has been observed recently in many growing networks (Leskovec et al. 2007). Observation of similar effects for *Pardus* networks serves as one more argument about universal features of this phenomenon. It is worth noting one feature known in the real world that is also reflected in the virtual society. It concerns the number of people with whom one can maintain stable social relationships, given humans' limited cognitive capacities. This is the so-called "Dunbar" number (Dunbar, 1993). See also Kenna and Berche (2010) for a mathematical basis for the upper limit of group sizes. A prominent feature of the plots in Fig. 2 is that the maximal out-degree of networks represented there is limited by $k^{\text{out}} \simeq 150$, a value conjectured to be the maximal number of stable relationships humans can comfortably maintain (Dunbar 1993).²

Results discussed so far give a quantitative description of the *Pardus* society based on a network perspective. We argued how networks of different social interactions arise and evolve, how they interact with one another, what are the observables that describe their properties and what are their implications for life in a virtual world. Although dynamical features of network evolution were also analyzed here, we did not address so far the question of temporal structure of human actions. We now ask if there exist regularities that govern temporal behavior of characters in a virtual world and if so, do they resemble those in the real world? Some answers to this question will be given in the following section.

3 Human Multi-Level Activity

The lives of humans can be viewed as sequences of different actions. Some of these are performed on a regular basis; others have strong stochastic components. Some actions are performed frequently; others are carried out sporadically. One associated quantity of interest is the time-lapses between such events - the "inter-event" times. Many early models which were used to study the inter-event time distribution of human action sequences were based on the assumption that such actions are performed randomly in time. In the simplest cases, these are described statistically

² Editors' note: See Robin Dunbar's chapter in this volume.

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Player 8 ... CC C CT CCBCCCCCCC CCCCC C C CC ...
Player 676 ... FFFF CCCCC CFFCCCCC CC FCTCCCEE ...
Player 784 ... AAAAAAAAAA T T T T T T CCC CC ...
Player 910 ... CFC C C C TT TTTT FT CC C CT E T ...

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Fig. 4 Short segment of action sequences, performed by four players. Different actions are shown by different letters as explained in section 2.

by a Poisson process. This assumption suggests that times between actions of the same individual are independent and distributed exponentially. Models of such kind are still being used, however there appears to be an accumulation of evidence that distribution functions characterizing sequences of different human actions in time are highly non-trivial [see Barabási (2005), Oliveira and Barabási (2005), Vazquez et al. (2006), Malmgren et al. (2009), Goh and Barabási (2008), Wu et al. (2010), Jo et al. (2012), Yasseri et al. (2012a), Yasseri et al. (2012b) and references therein]. An inhomogeneous bursty distribution of human actions influences their temporal statistics and often is associated with power laws. Such conclusions were made on the basis of observing different types of single human action such as writing letters, checking out books in libraries, writing e-mails, web browsing, and many more. Analysis of temporal features of the performance of actions of different types, which we call a multi-level human activity, still remains an open challenge. The main problem here is the obvious difficulty in accessing reliable and statistically relevant databases of records of various forms of human activity.

The clear advantage of our data set on the multi-level activity of characters in the *Pardus* world is that it is based on the analysis of behavior of thousands of characters across several years, and that it concerns various types of actions. In this sense it can be considered as the dynamic counterpart of static multiplex network analysis. The main outcome of this study is given in this section. The interested reader is referred to Mryglod et al. (2015) for a more extensive report.

Fig. 4 shows four segments of action sequences, performed by four *Pardus* players. Different actions are shown by different letters as explained at the beginning of section 2. The times for each action have been recorded which allows us to analyze peculiarities of temporal behavior of each player during the whole observation time (for the results shown below it is equal to 1238 days since 10 June 2007 when the *Artemis universe* was opened). Further, we can assemble a general picture of temporal behavior of all players. Below we concentrate on the statistics of inter-event times τ , i.e. the time intervals between two consecutive actions of the same player. In Fig. 5 we show the distribution functions of the inter-event time τ for all actions³ of all players who performed at least 50 actions, considering players with fewer actions being not representative. As it can be seen from Figs. 5a, b, the distributions follow approximate power laws, the numerical value of the exponent

³ Here we take into account all actions as listed at the beginning of section 2, discarding for technical reasons the 'bounties' B.

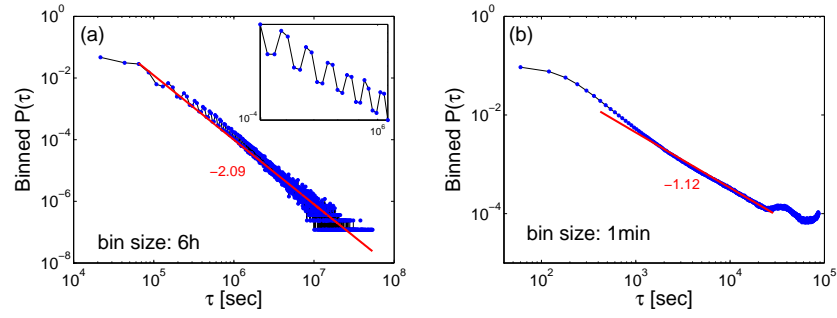


Fig. 5 Distribution of the inter-event times τ for all players who performed at least 50 actions. (a) entire observation period (1,238 days), bin size is 6 hours=21,600 sec. (b) first 24 hours, bin size is 1 min. Inset: same as (a) for six days. Circadian rhythms are clearly visible. The picture is taken from Mryglod et al. (2015).

depending on the chosen bin size. A prominent feature of the plots is that they manifest a fine structure: one observes regular patterns of various periodicity when the plots are considered on a smaller scale. The emergence of periodic patterns is known to be an inherent feature of human activity (Jo et al. 2012, Yasseri et al. 2012a, Malmgren et al. 2009). In our case it can be naturally explained by circadian and active working day cycles as well as by peculiarities of performing different actions (Mryglod et al. 2015).

The power-law behavior of inter-event time distribution functions signals the bursty nature of human dynamics (Barabási 2005, Oliveira and Barabási 2005). One of the variables that is used to quantify burstiness is the so-called burstiness index (Goh and Barabási 2008), B , defined as (Jo et al. 2012, Yasseri et al. 2012b)

$$B \equiv \frac{\sigma - m}{\sigma + m}, \quad (4)$$

where m and σ represent the average inter-event time and the standard deviation, respectively. As follows from definition in Eq. (4), a value of $B \approx -1$ characterizes regular patterns. Random Poisson process with a fixed event rate yields $B \approx 0$. In Fig. 6 we show several action streams of individual players with different values of burstiness. Panels (a), (b), and (c) display action streams where B is maximal, minimal, and close to zero. We find that the average value of burstiness for all actions of all players is $\bar{B} \approx 0.53$. This feature of the virtual world can be compared with the burstiness values characterizing real world activities of mobile communication $\bar{B} \approx 0.2$ (Jo et al. 2012), and Wikipedia editing⁴ $\bar{B} \sim 0.6$ (Yasseri et al. 2012b). Note that, similar to the real world, the burstiness is action-specific in the virtual world too. We find that burstiness of attacks has larger values than for communication. This illustrates the intuitive understanding of the nature of

⁴ In this case, the events correspond to consequent edits of Wikipedia articles.

these actions: attacks (A) appear highly clustered within short time intervals, while communication (C) is more uniformly distributed over time.

Another inherent feature of the multi-level human activity in the *Pardus* world is that time distributions found there are action-specific: each type of actions has a particular and characteristic distribution. This fact is far from trivial, the claim being that the decay of the inter-event time distributions might serve as a distinguishing feature of action type. Similar to physics, where one can classify life times of unstable elements by decay constants that uniquely characterize each element, one can quantify the decay of action-specific inter-event time distributions by the decay constants that uniquely characterize different types of actions too. Leaving the detailed discussion of this fact to a separate publication (Mryglod et al. 2015) where the inverse cumulative distributions $P(\geq \tau)$ of inter-event times were analyzed and the numerical values of the decay constants can be found, we mention here, that the overall behavior of players is characterized by three different time scales: (i) an immediate reaction (τ does not exceed several minutes), (ii) an early day (τ is less than 8 hours), (iii) a late day (τ is between 8 and 24 hours). At long times (more than several months) an exponential cut off becomes apparent, whereas for very short times (time scale (i)) all distributions have a similar tendency to decay very fast: the short inter-event times are typical for most of the actions. The scales (ii) and (iii) bring about specific features of different actions and allow to classify them. We found that on scale (ii) the inverse cumulative distributions of inter-event times of every specific action are best approximated by a power law:

$$P(\geq \tau) \sim \tau^{-\alpha}, \quad (5)$$

while on scale (iii) the decay is of exponential form:

$$P(\geq \tau) \sim \exp(-\tau/\tau_0). \quad (6)$$

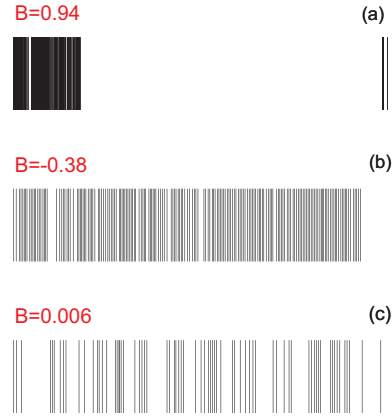


Fig. 6 Action streams of three players, each with different values of burstiness B . Lines mark times of executed actions, the distance between lines is the inter-event time.

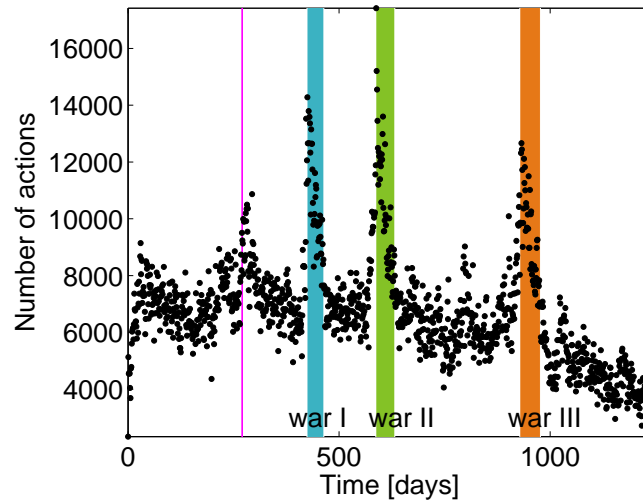


Fig. 7 Numbers of actions per day of all types over time. There are four pronounced peaks in the player activity that corresponds to specific events that happened in the virtual world during the observation period: the three coloured vertical stripes indicate war periods, the thin vertical line indicates the introduction of a major new game feature.

Constants α and τ_0 allow to discriminate between actions of different type and to quantify them in the unique way.

Before finishing this chapter we comment on the global dynamics and activity patterns that can be observed in the *Pardus* world. In Fig. 7 we show how actions are distributed over time. One can see four pronounced peaks in the players' activities. They correspond to specific events that happened in the virtual world during the observation period: the three coloured vertical stripes in the figure indicate war periods, the vertical line indicates the introduction of a major new game feature. Besides an obvious conclusion about the increase of activity during war periods, changes in action-specific dynamics are observed (e.g., intensification of attacks and communication). Another question of interest was to check whether the changes in player activity might serve as precursors of coming wars (or precursors of the end of war). Interaction and coexistence of different social relations are important to describe conflicts in social systems (Bohorquez et al. 2009, Lim et al. 2007, Clauset and Gleditsch 2012). Assuming that a war in a virtual world emerges and finishes as a result of a complex process of social interaction, it is tempting to ask about details of early and late stages of this process. Our attempts to use cross-correlation analysis for finding potential lead effects of player activity patterns on the onset of war have not (yet) lead to conclusive answers (Mryglod et al. 2015).

4 Conclusions and Outlook

To what extent is the behavior of characters in a virtual world similar to human behavior in the real world? To answer this question, one has to compare quantitative behavioral features in both worlds. Results obtained in the analysis of player behavior in the MMOG *Pardus* provide solid evidence for the existence of certain similarities of social structure and human dynamics in the real and the virtual worlds. These similarities concern certain types of social networks, their growth patterns, the validity of major sociological hypotheses, gender specific dynamics, etc. In this sense, MMOGs provide an extraordinary opportunity for an accurate analyses of social phenomena and falsifiable hypotheses.

Let us return to the question about the comparison of social activities in a virtual world and in the (written or oral) narrative. Two properties of the virtual society are obvious: (i) its structure changes over time, (ii) every element of the society (every character) acts in time. To what extent might the study of these properties be useful for similar analyses of narratives? In section 2 we have shown how property (i) is covered within the network formalism. In addition, one may use inter-event time distributions to quantify property (ii). To this end, the application of a multi-level human activity formalism may be useful, as outlined in section 3. In the analysis of social networks of narratives, usually the resulting static networks of all acting characters are studied (Mac Carron and Kenna 2012). In principle, one can get access to their evolution too, introducing the time-line via counts of narrative subunits [pages or chapters (Mac Carron and Kenna 2013), or appearance of new actors (Dunbar 1993)]. In this sense, property (i) is accessed in the narrative analysis too. We are not aware of analyses of property (ii) for a narrative. Although such a problem statement might be interesting, its realisation, besides obvious difficulties in introducing a coherent and self-consistent time line, will meet difficulties of separating dynamics caused by the evolution of a subject and a style of presentation.

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