Multirelational organization of large-scale social networks in an online world

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The capacity to collect fingerprints of individuals in online media has revolutionized the way researchers explore human society. Social systems can be seen as a nonlinear superposition of a multitude of complex social networks, where nodes represent individuals and links capture a variety of different social relations. Much emphasis has been put on the network topology of social interactions, however, the multidimensional nature of these interactions has largely been ignored, mostly because of lack of data. Here, for the first time, we analyze a complete, multirelational, large social network of a society consisting of the 300,000 odd players of a massive multiplayer online game. We extract networks of six different types of one-to-one interactions between the players. Three of them carry a positive connotation (friendship, communication, trade), three a negative (enmity, armed aggression, punishment). We first analyze these types of networks as separate entities and find that negative interactions differ from positive interactions by their lower reciprocity, weaker clustering, and fatter-tail degree distribution. We then explore how the interdependence of different network types determines the organization of the social system. In particular, we study correlations and overlap between different types of links and demonstrate the tendency of individuals to play different roles in different networks. As a demonstration of the power of the approach, we present the first empirical large-scale verification of the long-standing structural balance theory, by focusing on the specific multiplex network of friendship and enmity relations.

complex networks | multiplex relations | quantitative sociology

Human societies can be regarded as large numbers of locally interacting agents, connected by a broad range of social and economic relationships. These relational ties are highly diverse in nature and can represent, e.g., the feeling a person has for another (friendship, enmity, love), communication, exchange of goods (trade), or behavioral interactions (cooperation or punishment). Each type of relation spans a social network of its own. A systemic understanding of a whole society can only be achieved by understanding these individual networks and how they influence and coconstruct each other. The shape of one network influences the topologies of the others, as networks of one type may act as a constraint, an inhibitor, or a catalyst on networks of another type of relation. For instance, the network of communications poses constraints on the network of friendships, trading networks are usually constrained to positively connoted interactions such as trust, and networks representing hostile actions may serve as a catalyst for the network of punishments. A society is therefore characterized by the superposition of its constitutive socioeconomic networks, all defined on the same set of nodes. This superposition is usually called multiplex, multirelational, multimodal, or multivariate network (see Fig. 1). The study of small-scale multiplex networks has a long tradition in the social sciences (1) and has been applied to areas such as homophily in social networks (2), the effect of combined interactions on an agent's behavior (3), and the nontrivial interrelation between family and business networks (4). Multiplexity is thought to play an important role in the organization of large-scale networks. For example, the existence of different link types between agents explains the overlap of community structures observed in social networks, where nodes may belong to several communities, each associated to one different type of interaction (5, 6). Methodological work on multiplex networks includes the development of multiplex community detection (7), clustering (8), and other network analysis algorithms (9). The role of multiple relation types in measured social networks has recently been investigated across communication media (10), in an online game (11), as well as in ecological networks (12).

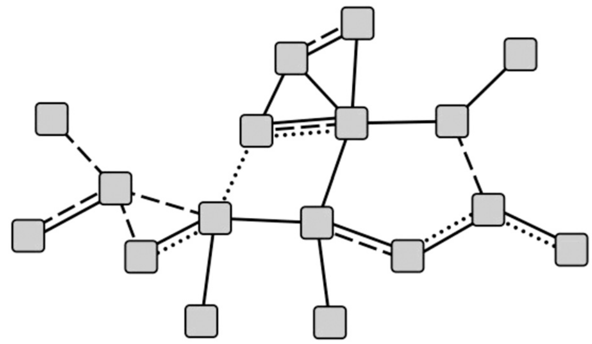

Fig. 1. Multiplex networks consist of a fixed set of nodes connected by different types of links. This multirelational aspect is usually neglected in the analysis of large social networks. In our MMOG dataset, six types of social links can exist between any two players, representing their friendship or enmity relations, their exchanged private messages, their trading activity, their one-to-one aggressive acts against each other (attacks), and their placing of head money (bounties) on other players as, e.g., means of punishment.

Traditional methods of social science, such as small-scale questionnaire-based approaches, get more and more replaced by automated methods of data collection which allow for entirely different scales of analysis (13–15). This change of scale has opened new perspectives and has the potential to radically transform our understanding of social dynamics and organization (16). The empirical verification of social theories such as the strength of weak ties (17, 18) become possible with hitherto unthinkable levels of precision. However, this large-scale perspective suffers from the drawback of a relatively coarse-grained representation of social processes taking place between individuals and of blindness in respect to the existence of different types of social interactions. For example, in most works on e-mail (19) or mobile phone networks (17, 20), the existence and weight of a link is

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determined by the volume of information exchanged between two individuals. Although nodes can be generally well characterized (age, sex, zip code, etc.), the corresponding type of interaction (e.g., family or work interaction) is usually unavailable in the data and can only be inferred from behavioral patterns (21). Moreover, research on large social networks has focused on single types of interaction only, e.g., phone or e-mail communication, and has ignored the wide spectrum of human interactions in real life (2). Whenever interdependencies and feedbacks between multiple relational interactions are significant, an aggregate representation of the different network types or the representation of one single type will lead to a biased and misleading characterization of the organization of the system.

The following work is an attempt toward fully characterizing the multiplex nature of a large-scale social system. To this end, we analyze coherent data from a complete society consisting of about 300,000 players of a massive multiplayer online game (MMOG) (22). Having become extremely popular over the past years, there exists a multitude of large-scale online games—often played by thousands, sometimes even millions. These games offer the possibility to experience alternative lives in which players can engage in different types of social interactions, ranging from establishing friendships and economic relations to the formation of groups, alliances, fighting, and even waging of war (18). Practically all actions of all players can be recorded in log files. The booming popularity of MMOGs opens previously unthinkable potentials for data-driven, quantitative socioeconomic research (23) and enables, e.g., economic surveys (24), studies on group dynamics (25), or large-scale social network analyses and the testing of classical sociological hypotheses (18).

The data allow the nature of one-to-one interactions between players to be identified; the topological properties of the corresponding networks—defined on the same set of agents—can be studied. We show that different types of interactions are characterized by distinct connectivity patterns. Exploring the interdependence of the different networks reveals how multiplexity shapes the organization of the system at different levels, from the stability of local motifs to the global overlap between the networks. Moreover, the existence of positively and negatively connoted interactions between players, e.g., through declared friendship or enmity, allows the organization of the system to be analyzed from the point of view of signed networks (1). Within this framework, it becomes possible to experimentally verify structural balance (26), a long-standing theory in social psychology (27) proposed for understanding emergence of conflict and tension in social systems (28). The central idea behind structural balance is that some configurations of signed motifs, i.e., local "building blocks" of networks containing positive and/or negative ties, are socially and psychologically more stable than others and are therefore more likely to be present in human societies. By measuring the dynamics and abundance of signed triads (sets of three nodes connected by positive or negative links), we perform a large-scale validation of structural balance and provide insights indispensable for a realistic modeling of conflicts.

Results

Nature of the Various Networks. Different types of connectivity patterns may signal different organization principles behind the formation of networks (29, 30). Statistical properties of the six networks, when considered as separated entities, are collected in Table 1. We get the following results.

Positive links are highly reciprocal, negative links are not. Table 1 shows that networks with a positive connotation [friendship, private messages (PMs), and trades] are strongly reciprocal (31) (*SI Text*), in the sense that node pairs have a high tendency to form bidirectional connections, whereas networks with a negative connotation (enmity, attack, and bounty) all show significantly smaller reciprocity. Low reciprocation in enemy networks may partially be explained by deliberate refusal of reciprocation to demonstrate aversion by total lack of response (18). For attack networks, it may originate from the asymmetry in the strength of the players (a strong player is more likely to attack a weaker player to secure a win). Asymmetry in negative relations is confirmed in the correlations between node in-degrees and out-degrees. Positive links are almost balanced in the in- and out-degrees, $\rho \sim 1$, whereas negative links show an obvious suppression in doing to others what they did to you.

Power-law degree distributions indicate aggressive actions. Studying cumulative in- and out-degree distributions, we find pronounced power-law distributions for aggressive behavior, i.e., attacking (out-degree for attacks), being declared an enemy (in-degree for enmity), and punishing/being punished (out- and in- degree for bounty). Power laws are absent for positive (friendship, communication, trade) and passive links (being attacked) (see Fig. 2). This discrepancy in degree distributions hints at qualitatively different link-growth/rewiring processes taking place in positive tie networks compared to the negative ones. For example, the classic network growth model of preferential attachment (32) leads to a power-law degree distribution. As we have shown in ref. 18, the growth of enemy networks is well characterized by this model, but not the growth of friend networks.

Positive links cluster. From Table 1 it is clear that the positively connoted links show higher clustering coefficients than negatively connoted ones. High values of the clustering coefficient are expected for positive interactions due to their cohesive nature and the benefits of dense subgraphs for better performance (33). The significantly lower values of clustering for negative

Table 1. Single network properties

		Positive ties			Negative ties			
		Friends	PMs	Trades	Enemies	Attacks	Bounties	Envelope (all αs)
Directed	N_α	4,313	5,877	18,589	2,906	7,992	2,980	18,819
	L_α^{dir}	31,929	185,908	796,733	21,183	57,479	5,096	967,205
	r_α	0.68	0.84	0.57	0.11	0.13	0.20	0.59
	$\rho(k_\alpha^{\mathrm{in}},k_\alpha^{\mathrm{out}})$	0.88	0.98	0.93	0.11	0.64	0.31	0.95
Undirected	$L_\alpha^{\mathrm{undir}}$	21,118	107,448	568,923	20,008	53,603	4,593	679,404
	$\bar{k}_\alpha$	9.79	36.57	61.21	13.77	13.41	3.08	72.20
	C_α	0.25	0.28	0.43	0.03	0.06	0.01	0.42
	$C_\alpha/C_\alpha^{\mathrm{rand}}$	109.52	45.71	131.95	6.13	37.27	13.88	109.93

Properties of directed networks: number of nodes N_α (connected to at least one link), number of directed links L_α^{dir}, reciprocity r_α, and in-degree/out-degree correlation $\rho(k_\alpha^{\mathrm{in}},k_\alpha^{\mathrm{out}})$. Greek indices mark network types. Properties of the corresponding undirected networks: number of undirected links $L_\alpha^{\mathrm{undir}}$, average degree $\bar{k}_\alpha$, clustering coefficient C_α, and ratio to the corresponding random graph clustering $C_\alpha/C_\alpha^{\mathrm{rand}}$. The networks, when considered as separate entities, present distinct types of organization depending on the nature of the interactions. Positively (negatively) connoted links present high (low) values of r_α, $\rho(k_\alpha^{\mathrm{in}},k_\alpha^{\mathrm{out}})$, and C_α.

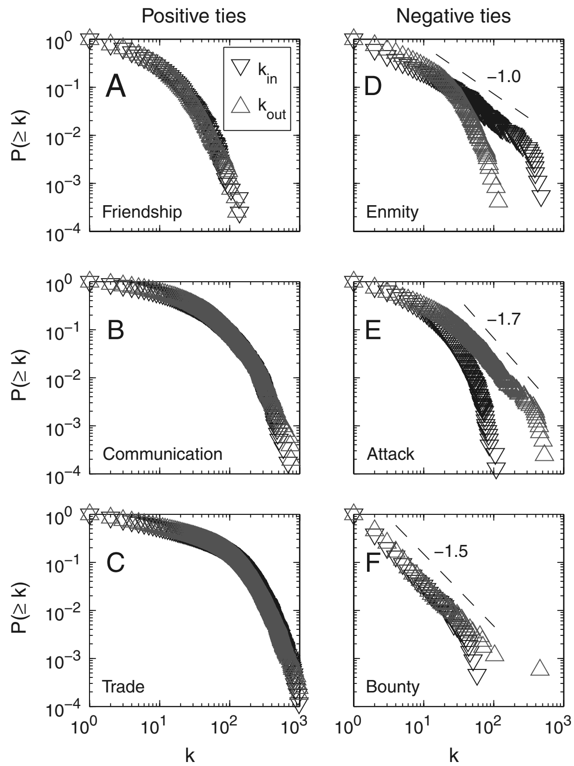

Fig. 2. Cumulative in-degree and out-degree distributions for the six types of networks spanning the same set of agents: (*A*) friendship, (*B*) communication, (*C*) trade, (*D*) enmity, (*E*) attack, and (*F*) bounty. Note the differences between in- and out-degree distributions and the presence of power laws (with cutoffs) for negatively connoted interactions (*Right Column*), which are absent for positive ties (*Left Column*). It is immediately clear that topological properties of social networks depend strongly on the nature of their ties. Ignoring this multirelational composition can lead to loss of essential information.

values suggests that mechanisms such as triadic closure (34) are not dominant for negative interactions (see *SI Text* for a confirmation) and has its origin in the balance of signed motifs (see below).

The independent analysis of the different networks reveals distinct types of organization which depend on the nature of the links. It is crucial to account for these distinct topological properties in models for the dynamics of cooperation and conflict in human societies. To demonstrate the danger of not differentiating between types of interactions, we include data on the envelope network (as defined in *Materials and Methods*) in Table 1. Neglecting the nature of social ties and mixing different interactions (even within the same dataset) results in gross misrepresentation of the system, in this case at least by losing the typical low reciprocity and clustering observed in negative tie subnetworks.

For a detailed analysis of the time evolution of single network properties on the same dataset (first 445 days in the Artemis game universe), refer to ref. 18. There several "aging" or "maturing" effects were reported, such as a decrease of the clustering coefficient and reciprocity in friend networks over time.

Network–Network Interactions. Due to strong interactions between different social relations, a next level of complexity enters when considering the coexistence of different types of links (35). From now on, we only focus on undirected versions of the networks, as defined in *Materials and Methods*. To quantify the resulting interdependencies between pairs of networks, we follow two approaches.

On one hand, we focus on the link overlap between networks and calculate the Jaccard coefficient $J_{\alpha\beta}$ between two different sets of links α and β. On the other hand, we compute correlations $\rho(k_\alpha,k_\beta)$ between node degrees in different networks (see *SI Text*). These coefficients measure to which extent degrees of agents in one type of network correlate with degrees of the same agents in another one. If $\rho(k_\alpha,k_\beta)$ is close to one, players who have many (few) links in network α have many (few) links in network β. Note that both measures might be affected by different network sizes or average degrees. To account for this possibility, we additionally compute correlations $\rho(\mathrm{rk}(k_\alpha),\mathrm{rk}(k_\beta))$ between rankings of node degrees, where rk represents rank. Overlap and correlation quantities provide complementary insights into the organization of social structures. In Fig. 3, for all pairs of networks, the three measures are shown. Note that no causal directions can be implied and that all correlations are positive. From highest to smallest overlap (from left to right), Fig. 3 provides the following conclusions:

Communication–friendship. The pronounced overlap implies that friends tend to talk *with each other*. The equally pronounced correlation attests that players who communicate with many (few) others tend to have many (few) friends. The former result was already reported in ref. 18, where a high fraction of communication partners was shown to be friends.

Trade–communication. The high overlap shows that trade partners have a tendency to communicate with each other, whereas the high correlations shows a tendency of communicators being traders.

Enmity–attack. The high overlap shows that enemies tend to attack each other, or that attacks are likely to lead to enemy markings. The high correlations imply that aggressors or victims of aggression tend to be involved in many enemy relations.

Communication–attack. The relatively high overlap shows that there is a tendency for communication taking place between players who attack each other. The relatively high correlation implies that players who communicate with many (few) others tend to attack or be attacked by many (few) players. Aggression is not anonymous, but accompanied by communication.

Enmity–bounty and attack–bounty. Similar to enmity–attack.

Communication–enmity. Similar to communication–attack.

Trade–friendship. Similar to trade–communication, however with a smaller overlap. It is more difficult for traders to become friends than to just communicate.

Friendship–attack. The low overlap shows that attacks tend to *not* take place between friends, or that fighting players do *not* tend to become friends. The relatively high correlations mean that players with many (few) friends attack or are attacked by many (few) others.

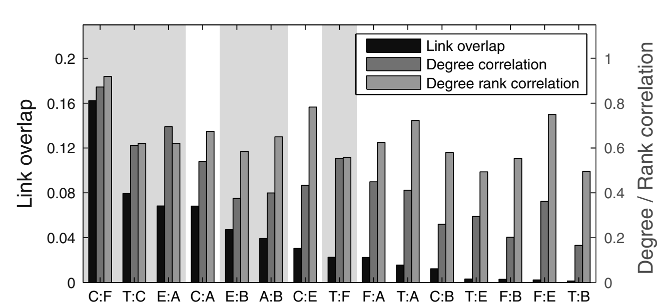

Fig. 3. Link overlap (Jaccard coefficient), degree correlation $\rho(k_\alpha,k_\beta)$, and degree rank correlation $\rho(\mathrm{rk}(k_\alpha),\mathrm{rk}(k_\beta))$ for all pairs of networks (ordered by link overlap). E, enmity; F, friendship; A, attack; T, trade; C, communication; and B, bounty. Pairs of equal connotation (positive–positive or negative–negative) are marked with a gray background. These pairs have high overlaps, whereas oppositely connotated pairs have lower overlaps. The various relations are organized in a nontrivial way, suggesting that agents play very different roles in different relational networks.

Trade–attack. Similar to friendship–attack.

Communication–bounty. Similar to communication–attack and communication–enmity, however with much smaller overlap and degree correlations.

Trade–enmity. For this and all other interactions, overlap vanishes. Players who trade with each other almost never become enemies and vice versa.

Friendship–bounty. Similar to communication–bounty.

Friendship–enmity. The degree (rank) correlation is substantial, suggesting that players who are socially active tend to establish both positive as well as negative links. However, the vanishing overlap shows the absence of ambivalent relations. Friends are never enemies.

Trade–bounty. This interaction shows the smallest values for all three properties, which could be due to substantial differences in network sizes. The relatively small correlation may suggest that players who are experienced in trade have a tendency to *not* act out negative sentiments by spending money on bounties.

The exact values of the two correlation measures have to be interpreted with some caution. High values might be biased by, e.g., the time a player spent in the game or by ignoring link weights for the number of exchanged private messages or traded money. Nevertheless, low values of $\rho(k_\alpha,k_\beta)$ indicate that hubs in one network are not necessarily hubs in another (see, e.g., the trade–enmity case), suggesting that agents play very different roles in different relational networks. For example, agents can be central for flows of information but peripheral for flows of goods (36) In the *SI Text*, we give further relations between above network–network measures and study their evolutions in time (see Figs. S1 and S2).

Large-Scale Empirical Test of Structural Balance. In the following, we assign $+(-)1$ to a positively (negatively) connoted link. All friendship links have a value of $+1$, all enemy links -1. Social balance focuses on signed triads where the sign of a triad is the product of the signs of its three links.

Social balance theory—in its strong form (28)—claims that positive triads are "balanced" whereas negative triads are "unbalanced" (see Fig. 4). Unbalanced triads are sources of stress and therefore tend to be avoided by agents when they update their personal relationships. From a physics point of view, the resulting dynamics can be viewed as an energy minimization process which may lead to jammed states (37) due to a rugged energy landscape (38). There is a "weak formulation" of structural balance (39) which postulates that triads with exactly two positive links are underrepresented in real networks, whereas the three other kinds of triads should be much more abundant. In the weak formulation, only situations where "the friend of my friend is my enemy" are unstable, whereas in the strong form of structural balance, "the enemy of my enemy is my enemy" is also unstable (see Fig. 4).

To test social balance, we focus on the multiplex network of friendship and enmity interactions. The number of different types of triads are labeled N_Δ. They are compared to the expected number of such triads in a null model (reshuffled signs of links, N_Δ^{rand}; see *SI Text*). In Fig. 4, a standard measure of statistical deviation, the z score (see *SI Text*), shows that $+++$ and $+--$ triads are heavily overrepresented, whereas $++-$ triads are heavily underrepresented with respect to pure chance. Triads of type $---$ are underrepresented to a lesser degree than the three other types, favoring the weak formulation of structural balance over Heider's original formulation of balance theory. It is obvious that triads are characterized by different levels of stability. The robustness of these results is further confirmed by examining the time evolution of the number of triads in friendship/enmity networks over all 445 days (Fig. 5).

A detailed dynamical analysis of our data further reveals that a vast majority of changes in the network are due to the creation of new positive and negative links, not due to switching of existing links from plus to minus or vice versa. We illustrate this dominance of link destruction and creation over sign switching on the dynamics of the following triadic structures. Let us define a *wedge* as a signed undirected triad with two links, i.e., a triad with one link missing (a "hole"). There are three possible wedge types: $++$, $+-$, or $--$. We measure day-to-day transitions from wedges to other possible triadic structures. In the vast majority of all cases (>99.9%), a wedge stays unchanged. In case of change, most often a hole is closed by either a positive or a negative link (see Fig. S3). The removal of a link is less frequent; sign switches almost never occur. This result is in marked contrast with many dynamical models of structural balance (37) which assume that a given social network is fully connected from the start and that only the link signs are the relevant dynamical parameters, which evolve to reduce stress in the system. Our observation underpins that network sparsity and growth are fundamental properties and they need to be incorporated in any reasonable model of dynamics of positive and antagonistic forces in social systems. In full agreement with the results shown in Figs. 4 and 5, wedges of type $++$ close preferentially (about 7 times more likely) with a positive link, and wedges of type $+-$ close preferentially (about 11 times more likely) with a negative link. There is no clear sign preference in the closure of type $--$ wedges. For details see *SI Text* and Figs. S3–S5.

We collect empirical transition rates in a transition matrix M_{STC}, which we use in a simple dynamical model for signed triadic closure (STC) (see *SI Text*). This STC model applies M_{STC} on a daily state vector of signed wedges. These wedges are closed or left unchanged according to the elements of M_{STC}. With this model, we are able to reproduce the empirical observations to a reasonable extent (see Fig. 5 *Right*).

	+ + +	+ + −	+ − −	− − −
Strong formulation of balance	B	U	B	U
Weak formulation of balance	B	U	B	B
N_Δ	26,329	4,428	39,519	8,032
N_Δ^{rand}	10,608	30,145	28,545	9,009
z	71	-112	47	-5

Fig. 4. Different types of signed triads, balanced (B) or unbalanced (U) according to the strong or weak formulation of structural balance. We show the number of each type of triad N_Δ in the friendship–enmity multiplex network, the expected number N_Δ^{rand} of such triads when averaged over 1,000 sign randomizations, and the corresponding z score (see *SI Text*). Triads $+++$ and $+--$ are overrepresented; $++-$ triads are underrepresented with extraordinary significance.

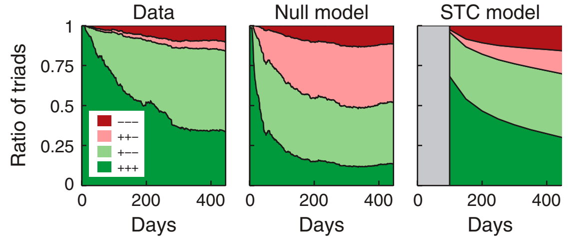

Fig. 5. Ratio of signed triad types over time. (*Left*) Measured in the data. (*Center*) Expected in the random null model (see *SI Text*). (*Right*) Simulation of STC with a model based on wedge transition rates (see *SI Text*). Initial condition: Measured network of day 100. All ratios measured in the data deviate significantly from ratios in the null model, except for the $---$ triads. The STC model reproduces the observed ratios considerably better.

Discussion

Most empirical studies of large-scale social networks focus on node properties (5), for instance, to uncover the topological centrality of social agents or patterns of homophily between agents (40), while being blind to the multiple nature of the links connecting agents. In many social systems, however, a proper description of multiplexity is essential to capture the stress caused by different forces acting on social agents and therefore to uncover the principles shaping the large-scale organization of social interactions. For instance, the interaction and coexistence of multiple relations are crucial to describe the emergence of conflict in social systems (41–43) or the development of trust in commercial networks (44).

Our work begins to quantitatively measure the multidimensionality of human relationships. Its results shed light on macroscopic implications of interaction types: Relations driven by aggression lead to markedly different systemic characteristics than relations of a nonaggressive nature. Network–network interactions reveal a nontrivial structure of this multidimensionality and how humans play very different roles in different relational networks. The richness of the dataset allows the effect of multiple relations on the structure and stability of a large-scale social network to be explored, thereby providing a first empirical basis for the modeling of multiplex complex networks. Future research perspectives include different generalizations of structural balance theory, e.g., to a larger set of social relations, to the case of weighted and/or directed networks or to larger motifs, an extension of the concept of modularity for multiplex (7) or signed (45) networks but also dynamical aspects, for instance, the dynamics of noncooperative organizations (46).

Materials and Methods

Social Network Data from the Online Game "Pardus." The dataset contains practically all actions of all players of the MMOG Pardus since 2004 when the game went online (18). Pardus is an open-ended game with a worldwide player base of more than 300,000 people. Players live in a virtual, futuristic universe in which they explore and where they interact with others in a multitude of ways to achieve their own goals (22). Here we focus on one of the three separate game *universes*, Artemis, in which $N = 18{,}819$ players have interacted with at least one other player over the first 445 consecutive days of this universe's existence.

Players typically engage in various economic activities to accumulate wealth. Communication between any two players can take place directly, by using a one-to-one, e-mail-like, PM system (see *SI Text*), or indirectly, by meeting in built-in chat channels or online forums. Social and economical decisions of players are often strongly influenced and driven by social factors such as friendship, cooperation, and conflict. Conflictual relations may result in aggressive acts such as attacks, fights, revenge, or even destruction of another player's means of production or transportation. Under certain conditions, hostile acts may degenerate into large-scale conflicts between different factions of players—wars.

The dataset contains longitudinal and relational data allowing for an almost complete and dynamical mapping of multiplex relations of an entire society. The data are free of interviewer effects because agents are not conscious of their actions being logged. Measurement errors which usually affect reliability of survey data (47) are practically absent. The longitudinal aspect of the data allows for the analysis of dynamical aspects such as the emergence and evolution of network structures. Finally, it is possible to extract multiple social relationships between a fixed set of humans. We focus on the following set of six types of one-to-one interactions between players (for details, see *SI Text*): friendship and enmity relations, PM communication, trades, attacks, and revenge/punishment through head money (bounties). We label these networks by Greek indices: $\alpha = 1$ refers to friendship networks, …, $\alpha = 6$ to bounties. We focus on one-to-one interactions only (without projections as, e.g., used in refs. 48 and 49) and discard indirect interactions such as mere participation in a chat.

Friendship and enmity networks are taken as snapshots at the last available day 445. All other networks are aggregated over time, meaning that whenever a link existed within day 1 and 445, it is counted as a link. For simplicity, we use unweighted, directed networks. Further, we define undirected networks as follows: A link exists between nodes *i* and *j* if there exists at least one directional link between those nodes. We construct triads [motifs of three connected nodes (1)] from undirected links. For a combined analysis of the whole system, we define an *envelope network* which is composed of the set of all links of *all* interaction types. In the envelope network, a link from *i* to *j* exists if it exists in at least one of the six relational networks.

Network Measures. The statistical properties of the six networks have been studied as separate entities using the following notations and measures. N_α is the number of nodes in the network type α, and $L_\alpha^{\mathrm{dir(undir)}}$ is the number of (un)directed links. Reciprocity is labeled by r_α, and $\rho(k_\alpha^{\mathrm{in}}, k_\alpha^{\mathrm{out}})$ is the correlation of in- and out-degrees within the α network. Average degree, clustering coefficient, and clustering coefficient with respect to the corresponding random graph are marked by $\bar{k}_\alpha$, C_α, and $C_\alpha / C_\alpha^{\mathrm{rand}}$, respectively. For more details, see the *SI Text*.

Network Interactions. For network–network interactions, we compute the Jaccard coefficient which measures the interaction between two networks by measuring the tendency that links simultaneously are present in both networks. $J_{\alpha\beta}$ is a similarity score between two sets of elements and is defined as the size of the intersection of the sets divided by the size of their union (50), $J_{\alpha\beta} \equiv |\alpha \cap \beta| / |\alpha \cup \beta|$. Related similarity measures, such as the cosine similarity measure lead to comparable results. The correlation measures used are described in detail in the *SI Text*.

The legal department of the Medical University of Vienna has attested the innocuousness of the used anonymized data.

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