Social Architecture and the Emergence of Power Laws in Online Social Games

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ABSTRACT
This paper explores the concept of the "social architecture" of games, and tests the theory that it is possible to analyse game mechanics based on the effect they have on the social behaviour of the players.

Using tools from Social Network Analysis, these studies confirm that social activity in games reliably follows a power distribution: a few players are responsible for a disproportionate amount of social interactions. Based on this, the *scaling exponent* is highlighted as a simple measure of sociability that is constant for a game design. This allows for the direct comparison of social activity in very different games. In addition, it can act as a powerful analytical tool for highlighting anomalies in game designs that detrimentally affect players' ability to interact socially.

Although the social architectures of games are complicated systems, SNA allows for quantitative analysis of social behaviours of players in meaningful ways, which are to the benefit of game designers.

Keywords
Social Games, Social Network Analysis, Social Architecture, Power Laws, Online Communities, Facebook, Game Design

INTRODUCTION
The term "Social Architecture" is originally from the political and economic sciences and is used to describe the collection of formal structures and systems in a society that together define and support the community within a nation (Wright 2005, 2006). This same term also neatly describes the formal structures in social software that define and support the social activity within a community of users (Gent 2009), and the patterns of social interactions with games (Yee 2009).

In the case of games, the definition of social interactions are very broad, including chatting, trading, fighting, gifting and any number of potentially subtle forms of between-player communication.

The social architecture of a game is partly defined by the way the game mechanics encourage interaction between players (e.g. trading, competition, cooperation),

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supporting interfaces for interaction (chat, guilds), second-order effects of mechanics (e.g. downtime) and also the social context (existing relationships) of play. Together, this complex social architecture defines the larger patterns of social interactions that occur during play.

Importantly, in the development of both governance and game systems, the social architecture is something that must be carefully designed, and made up of many constituent parts that work in concert together. For such applications to be effective and provide engaging user experiences, the fundamental social structures, and interactions they allow or encourage must be considered and designed with care and attention. Creators of games that attempt to harness these social aspects cannot just be game designers but must be "social architects" (Rollings et al 2003, p500).

The social architecture appears to be based on a central assumption that, given the same starting conditions, the interplay of game mechanics in a given context has a deterministic effect on the social behaviour of the game players. These changes are both direct, in the type of communication players engage in, and indirect in the broader long term affect game mechanics may have on the culture of a game community. The key argument is that all game mechanics affect social behaviour in some way, regardless of the context of the mechanic in the game. Similarly, different combinations of similar mechanics may also profoundly affect the resulting social patterns observed in play. Therefore, the social architectures of games (and, indeed, social systems in general (Kim 2000)) must be considered holistically as organic systems.

Pervasiveness of Social Architectures

Formal social mechanics are ubiquitous on the social web. While we have long been able to discuss the relative merits of *Star Wars* and *Star Trek* on bulletin boards, chat rooms and forums, now more complex social mechanics give us further options for a social interaction on the Internet. From basic features such as the ability to create profiles, to functions such as "friending" or "following", the implicit aspects of inter-personal relationships are becoming more explicit. In games, social mechanics often take a more central role - interaction is not simply through direct communication and often involves more complex patterns. Players may be able to engage in trading, aggression, cooperation, thievery and politics. Zagal et al (2000) propose that social interaction in games may be stimulated (such as through the trading mechanic used in *The Settlers of Catan* (Kosmos 1995)) or spontaneous (such as chatting during a *Quake* (id Software 1996) deathmatch) in nature. While this model effectively describes direct social interactions that are stimulated by a game design, some (even non-social) mechanics may also have indirect, second-order effects on the social interaction in a game - Subtle changes in seemingly unrelated mechanics and user interface might have profound knock-on effects in the wider social environment of the system.

Yee (2009), for instance, provides compelling examples of the various factors that together make a social architecture in massively multiplayer games (MMOGs). In comparing the mechanisms of character death in World of Warcraft (WoW; Blizzard 2004) and Everquest (EQ; Verant Interactive 1999), Yee theorises that the emergence of altruistic behaviour in the social community is a result of differences in the mechanics employed in EQ and WoW. Death in EQ forces players to retrieve their corpse in order to regain items, while WoW allows players to reclaim them automatically. In EQ, it became common for players to help the recently deceased – despite there being no reward for doing so:

"It is not simply that EQ provides players with tools with which to offer assistance, but these tools are readily available at a low cost … a five second spell at minimal cost to the provider can save another player an hour of painful and dangerous corpse retrieval" (Yee 2009)

In summary, the aggregation of the mechanics of every aspect of a given social game – regardless of the extent of which a given mechanic is intended to have social effects – together defines the abstract "social architecture" for that game.

POWER LAWS IN SOCIAL GAMES

Social Network Analysis (SNA) is a set of tools designed to be able to analyse social effects in complex systems (e.g. Wasserman et al 1994). It allows quantitative analysis of social architectures, like games, even where the different architectures of various systems are very different. One of the most reliable findings of Social Network Analysis of social systems is that the distribution of connections and social activity follows a power law.

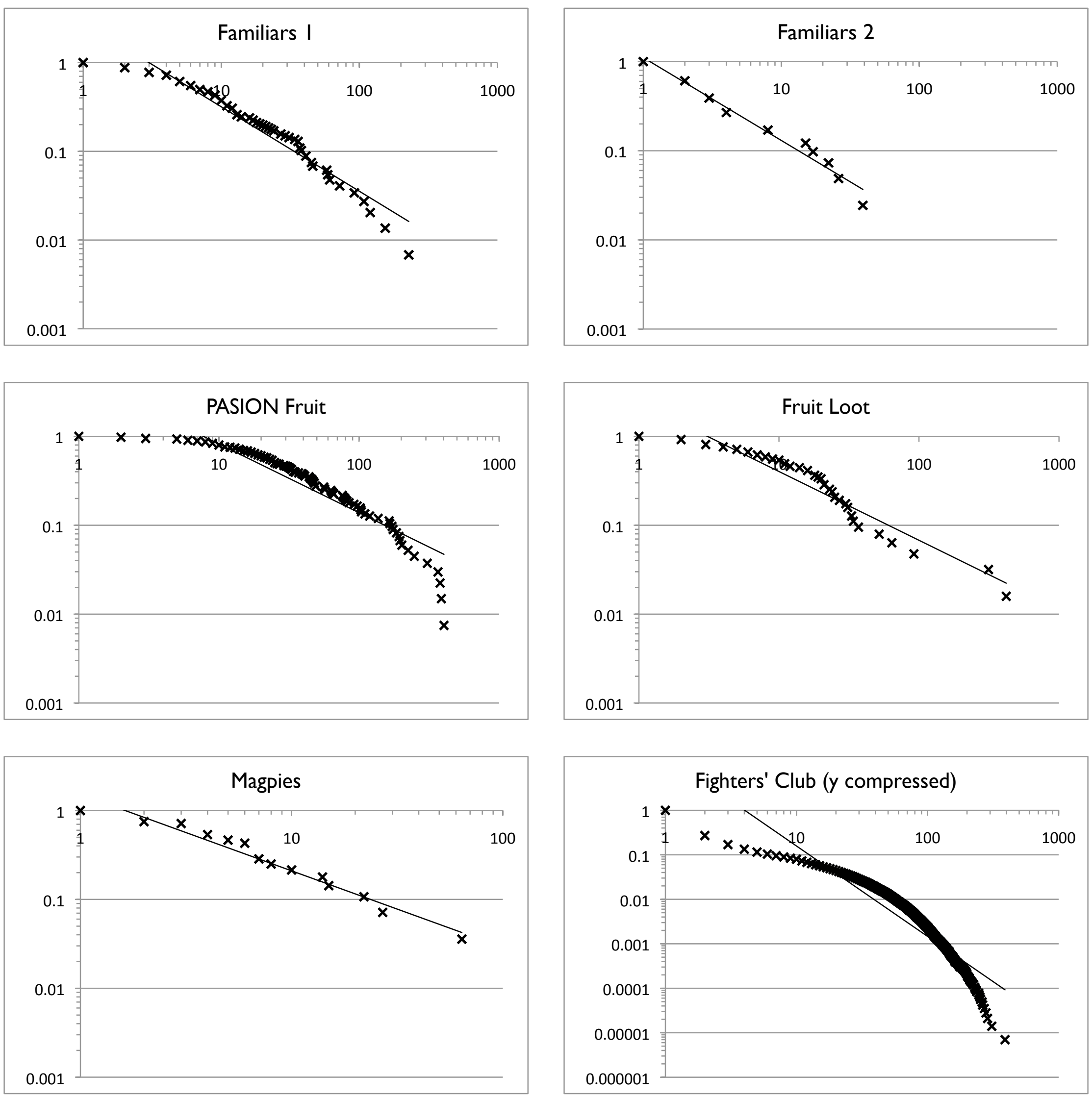

Figure 1 - Power-law of social activity in several social games
(Data Sources: Kirman 2009a, 2009b, 2010, Nazir et al 2008)

This means a few of the most active members are responsible for a disproportionate amount of activity and connections within a social system. Along with the distribution of wealth (Pareto 1897), population of cities (Zipf 1949) and usage of words in a language (Zipf 1935), studies of major social computing applications (e.g. Golder et al 2007) have consistently reported these networks are scale free or scale invariant (Barabási et al 1999).

In the context of online games, Koster (2003, p98) talks about this same effect emerging in the community of *Ultima Online* (UO; Origins, 1997) around the social interactions of murder. The mean number of murders committed by each player is 2. In 2003, however, the top player had murdered over 14,000 other players, compared to a meagre 2,000 by the next best (or worst?). If that player had been playing UO since the day of the game's release in 1997, they would have committed on average more than 6 murders every day. This serves to underline the disproportionate amount of social interactions engaged in between players in the social systems of a game - the low mean of 2 highlights that the vast majority of players had not been nearly so murderous in their play-style.

The same analyses were conducted for six data sets gathered from the interaction data taken from the server-logs of social games (Nazir et al 2008, Kirman et al 2009a). The data for particular kinds of social interaction was used dependent on the game design. For example, in *Fighters' Club*, the social interaction is initiating a fight with another player. In *Familiars 1*, this interaction is a comment on a player's in-game blog. In *PASION Fruit*, this interaction is a gift of an in-game resource to another player. Importantly, whatever forms the social interactions take (e.g. message, gift, headshot, …), the analysis yields similar results.

In every single case, without exception, the same pattern was found. The power law distribution of activity apparently applies universally to social interactions within games (see figure 1). That social activity in games should reliably follow a power-law should not be surprising, since it has been demonstrated that contributions to Web2.0 sites such as *Wikipedia* and *Digg* also show these patterns (Wilkinson 2008). However this finding suggests that the communities of games are partly built using real-world social forces.

In scale free networks, the cumulative distribution of activity is characterized by a decay following a power-law:

$$P(k) \approx k^{-\alpha}$$

In other words, it is extremely common that in social computing systems, including games, the probability of a user having more than k connections (e.g. friends) in a system is based on the scaling exponent α, which is constant for each system. Hence, regardless of the finer details of implementation and popularity, the social activity between members of a large user-base follows simple and predictable mathematical patterns.

Determinism in Social Architectures

Social network analysis is primarily useful in mining the complex relationship networks that are built during social play (Nazir et al 2008, Kirman et al 2009b). If social network analysis is to be useful in comparative studies between games, we are forced to make a fundamental assumption: that the social architecture of a game has a deterministic effect on the social behaviour of the players. That is, the same game mechanics, played in the same social context, should result in identical macroscopic patterns of social behaviour.

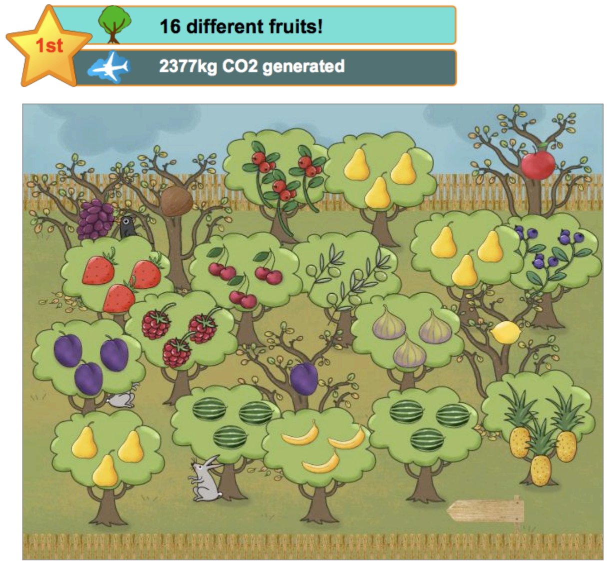

Figure 2 - The PASION Fruit and Fruit Loot social mechanics were identical

The inclusion of social context is crucial – although we can play the political game Diplomacy both online and off, the social patterns of interactions between the players is modified based on this change in context.

With this assumption, we are able to reliably compare games that may have very different mechanics, based on the patterns of the social interactions between the players. The network analyses of the games provides a holistic picture of the social architecture of the game, that is unaffected by the idiosyncrasies of individual players.

Evidence for Deterministic Scaling

When comparing two or more different games, the results of social network analysis are only a reliable tool if they describe the social behaviour as a function of the social architecture, rather than that of the players. In other words, the game design itself is the independent variable in the comparison, since the players' behaviour is assumed to be completely predictable even with different (but comparable) groups of individuals.

In order to test this assumption, data gathered during the operation of two social games was analysed. These two games had identical social mechanics, and therefore social architectures. The central difference between the games was in the presentation of some feedback metrics, which are out of the scope of this paper. However, since the core mechanics of the games were identical yet the *players were different*, we can assume that any similarity in patterns of social interactions is caused by the common architecture rather than the individual players.

PASION Fruit and Fruit Loot were two games with identical mechanical designs. The common goal for players was to build up virtual gardens with collections of diverse fruit trees. Each player was assigned a certain type of "home fruit" based on their location. In order to collect more fruit for their garden, players needed to receive them from other players. There were no formal trading mechanisms included in the game – the central social interaction was instead through gifting. Players could send each other gifts of fruit trees that they had previously collected or grown. Since there was no room for formal trading, a culture of gifting developed among the social community of the game, where players exchanged comments based on the fruit they wanted or could provide to each other.

Both games were simultaneously opened to the public in a concurrent trial lasting 11 weeks, starting in mid-January 2010. Initially, a handful of participants were recruited in Italy and the UK and asked to play the game. Since registration was publicly open, the player-base was permitted to grow as a natural viral, or snowballing, effect as would be experienced by a typical social game.

The purpose of the trial was to investigate personal patterns of social behaviour based on social feedback received in each game. However since the social mechanics employed in both games were identical, the data gathered can be used as an opportunity to examine the hypothesis of determinism in social architecture. If the macroscopic patterns of social interactions were different, it would suggest that individual players have a significant impact on the wider social patterns of the game. If both sets of patterns are similar, it suggests that the social patterns are not influenced by idiosyncrasies of the users themselves.

At the conclusion of the trial, the PASION Fruit condition recorded 140 active users who had between them generated 1875 interactions (gifts of fruit) between one another. The Fruit Loot condition gathered 408 interactions between 70 users

Network Analysis of the interactions in both conditions showed that the cumulative function of player activity between users in both conditions followed a power distribution with similar exponent of decay (α=0.773 in best fit, with R^2=0.843 in the PASION Fruit condition and α=0.774, R^2=0.907 in the Fruit Loot condition). In other words, a random player that interacted with k or more different users in the system in both games had a probability of $\approx k^{-0.77}$.

The similarity in exponent, despite differences in community size, shows that the patterns of social interactions were close across both conditions. Players at similar levels of activity interacted with a similar number of co-players. This result provides evidence to support the core assumption of theories of social architectures in games – That the social architectures of games have a deterministic effect on the social behaviour of the players. Despite having different groups of players in each game, the patterns of social interactions between the players are almost identical at the macroscopic level.

∝-RCHITECTURE

Understanding the social architecture of games is challenging, since it is the result of a combination of mechanical game design, social context, user interface and technical implementation factors. The interaction mechanisms of a game directly affect the social activity of the players. For example, if a game requires a lot of social interactions in order for players to achieve success (as in gifting games such as PASION Fruit and Fruit Loot), it is expected that the user activity will increase. Similarly, if the process of using the interface to interact with another user is quick, the users can be more socially active in a shorter time period.

Social Network Analysis can give hundreds of interesting and curious statistics (Wasserman 1994) about the social activity of players within a game, and it can be very illuminating for designers to explore these analyses for the benefit of future works. However, each of these statistics is tightly coupled to the specific mechanics of that particular system. By contrast, the scaling exponent (α) is a single value that represents the holistic view of the social architecture of a system. It allows us to directly compare systems without the complexities of individual details of implementation.

The Scaling Exponent

"Scaling" happens at a level that isn't affected by the whims of individual players, or even by levels of activity or game popularity. Given the evidence above, it is a reasonable assumption that, for example, different "realms" (game instances) in World of Warcraft will show very similar patterns of social behaviour. Similarly, we can imagine that an exact re-implementation of Farmville would show almost exactly the same value for α. This is because α has emerged from the movement of users through the architecture of the system, and not through popularity or exposure. This makes α an ideal tool for supporting comparative studies of social behaviour in social games, both large and small.

Of course, there are caveats – α requires a minimum level of activity in order to be reliable. Also, it would be rash to rely on α alone as an evaluation of a system. Despite this, in this paper we assert that it represents a powerful tool for generating fast evaluative and quantitative insights into the nature of online social architectures which in turn can give us a better understanding of the user experience when engaging with social games.

For instance, it can be used to measure the effect of changes in a system on the social architecture over time – "Did feature X change the social behaviours of the players?" rather than "Did feature X get used?" For example, following Yee's (2009) ideas around player death, implementing more permanent death mechanics into any given MMOG may result in surprising second-order effects in the social architecture of the system as may be quantifiably observed through changes in the exponent.

Scaling as an indicator of architecture

The holistic effect of the social architecture on activity can be observed by the difference in the scaling exponent (α) between different games. If the exponent is high, and therefore the graph sharp, this shows that it is rarer for players to be more socially active than in a similar games with a lower scaling exponent. This is an indicator of the differences in social architecture between the games.

Figure 3 visualises this by plotting the best-fit scaling exponent for several social games over typical ranges of k. The values for scaling exponents are taken from peer-reviewed publications of social network analyses of a variety of social games, as described in Table 1. This allows us to calculate the probability of players in each game that are socially active above a certain level. For example, in PASION Fruit, based on the scaling exponent we can reliably predict that there is a 2.1% probability that a random new user will interact with 100 or more other players during their player lifetime (i.e. $100^{-0.843}$). These examples also show that the social environment of PASION Fruit is more promiscuous, in that a higher proportion of players interact more widely within the game, compared to players of Fighters' Club. Since the scaling exponent acts as a constant for a given social architecture, we can make direct comparisons even though the mechanical designs of the games may be very different.

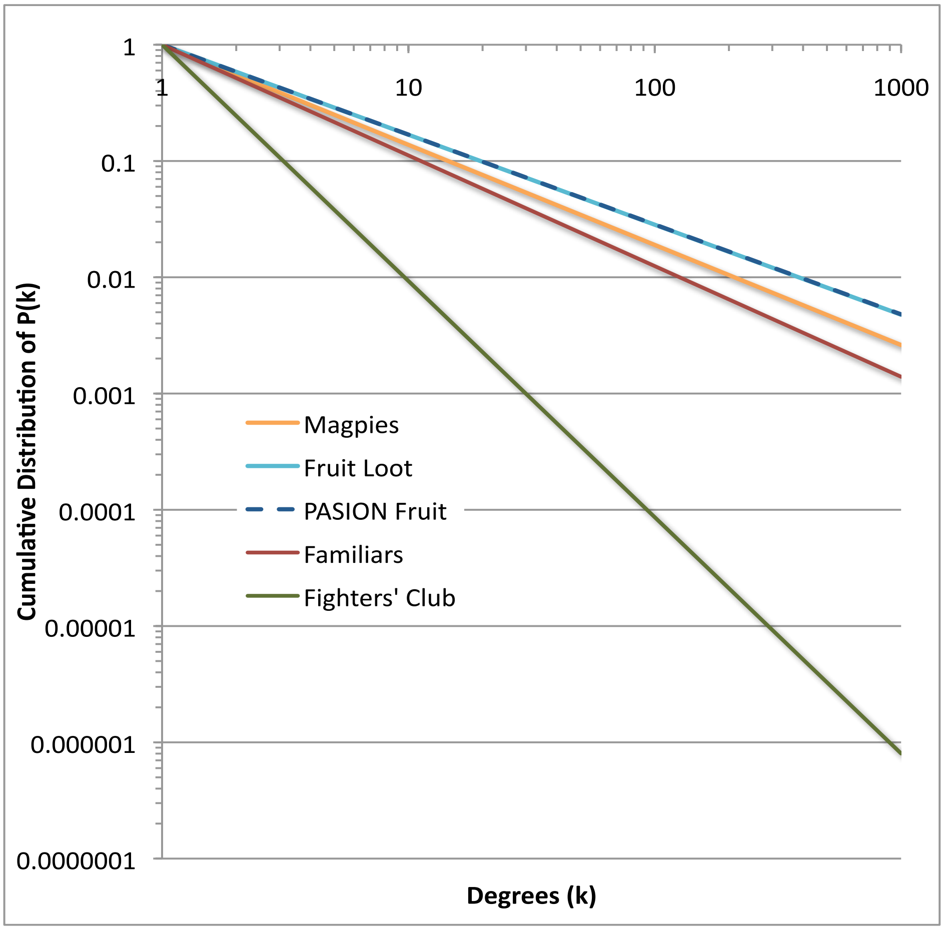

Figure 3 – Comparison of Scaling Trajectories in Social Games

These comparisons do not make judgement about the users themselves, but instead are based on the structure of the varying social architectures on which the services exist. For example, the nature of social interaction in PASION Fruit - quick and frequent gifts – implies there is less commitment required for choosing to interact with someone. The cost of sending gifts to other players is very low; therefore this can partially explain the apparent general promiscuity of the users.

Game	**α**	**R^2**
PASION Fruit	0.773	0.843
Fruit Loot	0.774	0.907
Magpies (Kirman 2010)	0.861	0.962
Familiars (Kirman 2009b)	0.952	0.932
Fighters' Club (Nazir et al 2008)	2.032	0.874

Table 1 - Comparison of best-fit scaling exponents

A higher scaling exponent, as seen for Fighters' Club, should not necessarily be considered a negative pattern by itself - it is dependent on the intentions of the game design. If higher activity levels (therefore a lower scaling exponent) were expected from players based on this design, then a high exponent may be an indicator that there is some issue with the implementation or user interface that is affecting the players' ability to interact.

The key point is that scaling appears to be universal across games with very different mechanisms (and motivations) for social interactions among their players. The scaling exponent changes based on the differences in social architecture and social context, however the macroscopic view of interactions appears to follow the same patterns.

SCALING AND HIGHLIGHTING USABILITY ISSUES

The friends network in social network service Facebook does not exactly follow a power-law (Golder et al 2007), instead it follows a multi-scaled distribution i.e. users with more than 250 friends are dramatically more rare. Given the reliability of the power-law in other systems, this is an indicator that there is either a technical issue that makes adding new friends more difficult past this point, or that there is some other reason why 250 is an interesting number of friends.

Multi-scaling occurs where there is more than one scaling exponent at different levels of k in the same network, and Broad-scaling occurs where after a point, the tail of a single-scale network decays at an exponential or Gaussian rate (Amaral et al 2000).

Changes in scaling are a symptom of a hindrance in the process for preferential attachment (Barabási 2003) in a network (in other words, how the network grows). According to Amaral et al (2000), this hindrance can be a result of two factors:

(i) Aging of Vertices - if a node in the network "dies" they are no longer available for connection in the network. For example, in the social network of movie actors (Watts 2003), if a popular actor dies during an active part of their career (e.g. River Phoenix, Heath Ledger), they will not be available to expand the network in the normal pattern. If this happens regularly it can lead to broad scaling effects in the network.

(ii) Limited Capacity or Increased Cost of Attachment - Where nodes in the network have a hard limit to the number of connections they can maintain. For example, the distribution of flight routes to different airports follows a power law. However above a certain limit, airports are challenged to physically expand any further to cope with new routes.

These hindrances also affect the social networks in social games. If the network of a social game shows multi-scaling, it is an indicator of an anomaly within some part of the social architecture.

In the Facebook game Hugged (Nazir et al 2008), the cumulative distribution of player activity shows multi-scaling. Figure 4 shows the cumulative distribution of k (degrees). The social graph shows multi-scaling, with the range $k \leq 15$ having scaling exponent $\alpha = 0.9669$ and at $k > 15$ having a sharp phase change with $\alpha = 4.1581$.

The cause of this multi-scaling is due to a specific problem in the social architecture of the application. Hugged allows users to select one of a range of "Hugs" (e.g. Friendly

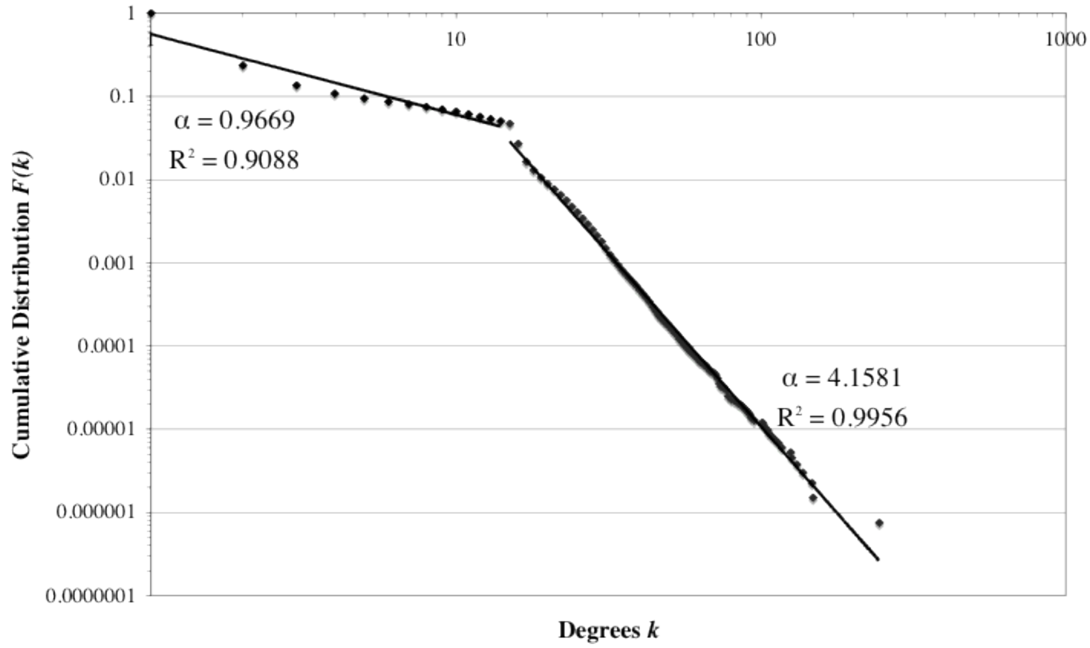

Figure 4 - Emergence of Multi-Scaling in a Social Game

hugs, Birthday hugs, Sexy hugs, etc.) and send them to a choice of their Facebook friends. However, the Facebook API used by Hugged limits the number of application notifications a user may make to friends within a 24-hour period to 15 (at the time of the sample). A single hug request to up to 15 players would place that player in the first scale of users. To appear in the second scale (i.e. interact with more than 15 other players) would require the player to re-visit the game after the 24 hour enforced wait. The emergence of multi-scaling shows that players are more unlikely than expected to revisit in order to interact with more than 15 friends at a time.

In other words, given the first scaling exponent as a constant for the game, we would predict that players with more than 15 connections within 24 hours would be much more common than appears to be the case.

This anomaly is an issue within the social architecture – in this case the API-imposed limits are an example of an increased cost of attachment in the form of an enforced wait between interactions that prevents all but the most determined users from interacting with their network as much as they would like. In order to correct it, the developers of Hugged (i.e. Nazir et al 2008) would need to find a way around the API. Without this restriction, that is a part of the social architecture of the game, the social network of Hugged would likely become single-scaled.

This is just one example of how the patterns in the scaling of activity in social games can be used to highlight specific user experience issues in social architectures. This is especially true for issues that affect the most active users and can be difficult to spot when using traditional sampling methodologies.

The most active users are the most rare – the average user would have a low number of social interactions (e.g. 2.2 in Hugged). Although this user interface issue only affects a minority of players, these are the players that maintain the integrity of the social networks built during play. Without these "hardcore" users, the network of players would collapse, leaving sometimes large numbers of less active players disconnected from the social network (Kirman et al 2009b).

Limits to Scaling

Theoretically it may be impossible for games based on social interactions to be classed as purely Scale Free (or scale invariant) networks. There is a likely threshold, above which the scaling starts to decay at an exponential rate (i.e. broad-scaling). This would be observed as a "dipping tail" in the plot of the cumulative distribution function.

Systems such as the World Wide Web (Barabási 2003) have been shown to be purely scale-free, because there is no practical limit to the number of links that can exist to, or from a web page. However, when dealing with social relationships, the anthropologist Dunbar (1992) theorises that there is a limit to the capabilities of primates to maintain relationships related to the size of the neo-cortex. Dunbar's Number is "about 150" and represents the theoretical maximum number of simultaneous relationships humans have the capability to maintain.

This theory of "the Social Brain" has compelling evidence, and the effects can readily be observed in real human social behaviour. 150 is about the size of Hutterite and Amish communities (Dunbar 1998), the size of military Company level units, and even the average size of Christmas cards networks (Hill et al 2003).

This number happens to coincide with the threshold that appears in the networks of interactions in social games, and in online social networks generally (e.g. Orkut (Ahn et al 2007)). The game designer Raph Koster (2003) points out that sizes of player guilds in Ultima Online has a "knee" at around 150 - this size of guild is disproportionately popular in the sample.

The emergence of Dunbar's number in social connections made within games has little evidence at this point, and may not fully explain the thresholds to player interactions, Dunbar's arguments raise the possibility of limits to the volume of social interactions a player may be able to create. Although we can reasonably expect a website to have large numbers of links across the web, for a human player engaging in social interactions in a game, there is an upper limit to the cognitive and practical abilities of the species. There is an unknown biological limit that will affect a social network of humans to scale indefinitely.

DISCUSSION

In large social games, where there may be thousands of users and tens of thousands of interactions, untangling the complex web of interactions relies on complex tools like social network analysis. These tools can expose many surprising and unintuitive features. It gives a glimpse beyond the perspective of the interactions of individuals with software, exposing the patterns and behaviours of users as fundamentally social beings.

Although it can make for interesting visualisations, the practical value of social network analysis as an evaluative tool for game design and player experience is easily overlooked. This paper presents one of the simplest statistics from network analysis – the scaling exponent - and argues that it can be used to evaluate and quantify the abstract nature of the “Social Architecture” of social games. The contribution of this paper is not in improving the statistical methodology behind social network analysis. Instead the focus is clarifying the importance of selecting a few, important metrics that give genuine value to the evaluation and further refinement of social games.

Real-world examples of the value of this approach have been provided. Despite the relatively large range of different low-level game mechanics between social games, social activity within social games reliably follows a power distribution. By using the scaling exponent as a quantifiable and reliable expression of the social architecture, we are able to perform new comparative analyses to better understand the impact of game mechanics on the patterns of interactions between players of social games. These analyses can not only help identify previously obscured issues with the social architecture based on multi-scaling effects, but also enable comparative analyses between games of radically different forms. The purpose of this paper is to highlight the genuine value of applying social network analysis to support the design and evaluation of social games.

Future Work

This paper has concentrated on one particular metric, the scaling exponent, to describe social activity in games. Social Network Analysis is a group of tools designed for use with complex network data. Although these tools enjoy great success in the analysis of other systems, use of the tools to analyse the graphs of player interaction in game studies is limited.

Through analysis of several social games, this paper has confirmed that the social behaviour of players in games follows similar patterns to those seen in other social systems. This means that although the complicated weave of social interaction in games poses analytical problems, it is susceptible to deeper investigation using these tools.

In particular, the scaling exponent is a statistic based on the macroscopic view of social behaviour of game players. Additional indices, such as centrality and reciprocity, can give many more insights about the finer patterns of social interactions that may occur between players of games. This paper has only scratched the surface of the possibilities of SNA as a quantitative tool to support game design analysis.

This paper has also focused on the analysis of the social interaction in games of a particular genre of casual web-based games. This is due to the availability of large amounts of server data for social interactions. Koster (2003) and the Virtual Worlds Exploratorium (e.g. Kawale 2009) have performed similar research on Massively Multiplayer Games such as UO and EQ2. Published results suggest these games show similar patterns but the commercially sensitive nature of these data makes direct comparison more difficult.

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