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DOI
10.1017/9781316422823.013

Publication date
2018

Document Version
Accepted author manuscript

Published in
Social Interactions in Virtual Worlds

Citation (APA)
Kuipers, F., Märtens, M., van der Hoeven, E., & Iosup, A. (2018). The Power of Social Features in Online Gaming. In K. Lakkaraju, G. Sukthankar, & R. T. Wigand (Eds.), *Social Interactions in Virtual Worlds: An Interdisciplinary Perspective* (pp. 313-336). Cambridge University Press. https://doi.org/10.1017/9781316422823.013

Title

The Power of Social Features in Online Gaming

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Keywords

Online social gaming, Quality of Experience, interaction graphs, toxicity.

Abstract

Within the vast and rich field of online gaming, a new generation of Online Social Games (OSGs) is emerging that have in common a core of social interaction, sometimes explicit, other times implicit. This common core of social experience promises to become at least as important as the experience derived from the game-world itself. In this chapter, we consider the social side of OSGs and provide the following contributions:

1. We motivate the importance of taking social features into account to improve the quality of experience in online gaming.
2. We discuss the various dimensions of (player experience in) OSGs.
3. We describe a social network analysis methodology for identifying relations in OSGs and indicate how this methodology could be used to improve the game-play experience.
4. We also consider and illustrate how certain "social" behaviour, like toxicity, is negative and may harm the game-play experience, if not adequately addressed.
5. We mention several directions for future research to put the power of social features in OSGs to good use.

1. Introduction

The online gaming industry is thriving. It entertains millions of players (50% of the online population of the USA, with similar numbers reported in most developed countries), in a global market of tens of billions of dollars per year. For example, Riot's League of Legends alone is said to attain over 1 billion dollars in revenues[1] yearly, but it is not the only game with revenues of this order of magnitude. Besides entertainment, the techniques developed first for online gaming are also increasingly used in enterprise training and evaluation, for example using complex simulations that require cooperation across multiple continents and advanced visualisations [8]; in the evacuation of large-scale disaster areas [9]; and in education [1], for example in Massive Open Online Courses. But the techniques that power new games and related applications are less introverted than ever. Online Games (OGs), from the smartphone game Bounden [12] that tries to breach the social fence that prevents us from interacting with strangers, to the decade-running World of Warcraft, which beyond individual training incentivizes players to socialize and do activities together [13], are indicating that future OGs will increasingly be social—indeed, online games will increasingly have social features, and thus be truly Online *Social* Games (OSGs). In this chapter, we focus on how to identify, quantify, and possibly leverage such social features in OSGs.

[1] http://goo.gl/bBKggU (gamasutra.com, Sep. 2015)

Social game-features have not simply been designed and developed; they are the complex, emergent or only partially engineered consequences of how the player population interacts with each other, inside and outside the particular game. Without social game-features, the market success of recent online games would not have been obtained. For example, Multiplayer Online Battle Arena (MOBA) games [17] have become increasingly popular and captivate their player base by virtue of complex game mechanics and competitive nature, but also through the mechanisms they offer so that players communicate, connect and socialise with each other while and especially beyond gaming. MOBA games, such as League of Legends, are typically played in independent matches, e.g., a 5vs5 or 6vs6 format, in which the players of each team need to closely cooperate in their attempt to win from the other team. Collaboration is driven by communication, frequently by voice or text-based chats of predefined phrases that can be sent quickly. The competition between teams can be so sophisticated and suspenseful that professional gaming (eSport) is getting more momentum, as tens of millions of spectators gather online or offline for the purpose of watching [18]. Considering this wide diversity of social game-features, *in this chapter we focus on understanding patterns of social interactions within the game. Which social features emerge or are designed to emerge in games? How are they emerging in practice?* This leads to numerous detailed research questions, for example: *how do teams and groups form in MOBA games?*

The presence of social game-features is not in itself enough to attract the interest of the market; at the extreme, only quantifying their relationship to player retention and spending can do this. Since the number of players and revenues has grown tremendously over the past few years, with estimates often exceeding hundreds of millions of active users online [6][15][16], as a result, so has the number of online games. For a game operator, the latter means that competition is fierce and player retention is key. In other words, the players of the online game should continuously have a good *game-play experience*; else they may leave for another game operator or even trigger through their social ties departures of large groups of players to a different game operator. In the field of multimedia, this type of experience-related performance metric is called Quality of Experience (QoE) [3], which reflects the quality of the application/service as perceived by the user. QoE can be influenced by several aspects, such as human preconditions, social aspects, system-oriented Quality of Service (QoS) like network delay and CPU/GPU processing power, and the quality of the content at the source. Considering for example MOBA games, which, by nature, demand intricate strategies to be executed in collaboration, players who contribute are valued and praised, and in some games (e.g., Overwatch) voted for. The opposite also happens. When team members do not follow game etiquette (either deliberately or not) or place their own interest in front of that of the team (for example by stealing kills or resources, or focusing on personal stats instead of winning), this may result in diminished game-experience and even loss of the match. Given the intensity of the game, players who, in the eyes of their team members, misbehave may be criticized via the communication channels that were meant to coordinate the team effort, causing conflict within the team. Such conflicts bear the risk to escalate rapidly resulting in verbal assaults, shifting the focus of the players from the actual game towards harassing each other by means of profanity and harsh insults. The impact on the game-experience can be dramatic, as the social features meant to foster a friendly atmosphere of collaboration are corrupted by players to create a toxic environment. This is but one example to illustrate that QoE not only stands to gain from social features in OSGs, but that social misbehaviour may cause deep player dissatisfaction, which may ultimately trigger them to leave the game, either for that single match or even forever. *We identify in this chapter ways to measure positive and negative aspects of QoE for online games with social game-features.*

Understanding and learning about the nature of social interactions in games is essential to improve game design for future online social games. Rich social relationships and networks could be used to improve gaming services, such as team formation and game population retention, which are important for the user experience and the commercial value of the companies who run these games. Anti-social behaviour in games may only be combated, if it can be detected, quantified and the corresponding triggers are understood. Social features might even be used to run games much more efficiently, reducing operational costs and opening the market to even more high-quality games created by indie game developers and small-and-medium sized game studios.

We identify in this chapter a common core of social interaction, sometimes explicit, other times implicit, but always strong and important for the game-play experience. We believe this common core will lead to a unified theory of useful social game-features, one in which the social experience will be at least as important as the experience derived from the game-world itself. In this direction, *this chapter discusses ways to leverage social game-features in OSGs.*

To summarize, the main contribution of this work is five-fold:

1. We motivate the importance of taking social game-features into account to improve the quality of experience in online gaming. Because we consider for this chapter a general audience, we also explain the key terms and concepts used in this work, in Section 2.
2. We propose a socially aware model for future OSGs, in Section 3. The model we propose is general and focuses on three core pillars of modern gaming operations: game-world management, game-data processing, and game-content generation.
3. Also in Section 3, we survey methods for identifying social features in future OSGs and present examples, selected from our previous work, of using these methods in practice for today's OSGs. We also propose a new framework for identifying meaningful social relationships in online games.
4. We survey methods for using the social power in future OSGs and in Section 4 present examples, selected from our own work, of using these methods in practice for today's OSGs.
5. We identify and analyse several directions for future research in socially aware OSGs, in Section 5.

2. Background

The social aspects of online gaming may differ per gaming genre, so we start by enumerating the different gaming genres that exist. Unfortunately, there is no standard classification of gaming genres, and different organizations may use their own taxonomies and definitions. We have opted to classify games based on the amount of simultaneous players and to consider only games in which multiple players may interact (otherwise, the *in-game* social component is missing). We make a first coarse, high-level classification, to distinguish between (1) Multiplayer Online Games (MOGs) and (2) Massively Multiplayer Online Games (MMOGs), and subsequently subdivide these two classes into various gaming genres.

MOGs are multiplayer games in which players play against and with each other in teams. These games admit only a limited amount of players per match (i.e., a single *game instance*). Typically, teams within such a match comprise 2 to 64 online players. However, while the amount of players in a match is modest, the number of concurrent matches may easily be thousands.

We further identify several MOG subgenres:

- **MOBA**, already described in Section 1: In MOBAs, each player controls in real-time an in-game representation (*avatar*), and (usually two) equally-sized teams of players have as objective the conquest of the opponent's main building or trophy. The game includes many tactical and strategic elements, from the team operation to the management of resources. Example games are: League of Legends, Dota 2 and Heroes of the Storm.
- **Sports**: Sports games represent simulations of various types of popular physical sports. For example, soccer is a popular online sports game, which even offers online tournaments. This genre is of high pace, because it requires real-time interaction and consequently low network delays. The most prominent examples are the soccer games from the FIFA series.
- **Fighting**: Fighting games are similar to sports game, but may also feature fantasy elements. They resemble a 1-on-1 combat by use of martial arts and combinations of moves. Example games are: Street Fighter, Super Smash Bros and Tekken.
- **Real-time Strategy (RTS)**: An RTS game is generally played in a context of war and involves commanding troops, maintaining operational bases and managing a war economy to succeed in the battle against one or more opponents. Opposed to MOBAs, RTS games have a stronger focus on strategic elements and tactical fights with whole armies, rather than with a single avatar. Examples include Starcraft II and Warcraft III.
- **Traditional turn-based strategy (TTBS):** TTBS games are traditional strategy games, such as chess and go, which have been played with the same rules for many (thousands of) years. In the age of the Internet, they have adapted to allow for large numbers of game instances to occur simultaneously.

MMOGs offer a virtual game-world that is populated by over thousands of users simultaneously, allowing them to interact through (often self-created and much-tuned) characters with the in-game world or with other players.
We may discriminate several subgenres:

- **Massively Multiplayer Online Role-playing Game (MMORPG)**: This genre features a usually massively-large game-world in which player and non-player characters meet each other, interact, trade and sometimes fight each other. To advance in the game, players level up their in-game character by completion of missions and quests, usually by teaming up with other players to overcome those challenges. Examples include World of Warcraft, Guild Wars 2 and EVE Online.
- **Massively Multiplayer First-Person Shooter (MMFPS)**: A player in an MMFPS game owns a weapon and tries to shoot as many rivals (other players) as possible. Several playing modes may be possible, including teaming up.
- **Massively Multiplayer Online Social Game (MMOSG)**: In MMOSGs, players build their own cities or farms. Like in reality, this may involve trading with or buying goods from others. This genre is explicitly designed to interact with your friends and the community. Examples include Farmville 2 and Clash of Clans.

The above classification is neither exhaustive nor unique, in the sense that some subgenres might also be played in both a MOG and MMOG setting.

To operate a MOG or MMOG requires considerable *gaming infrastructure* (*datacentres* hosting tens to hundreds of powerful *servers*). In recent years, *cloud-operated games* have emerged as a form of always-online gaming. Among the many options for cloud-operated games [19], *cloud gaming* offers users the ability to stream games to their computer from a server operated by the game provider. Consequently, all the game genres mentioned above could also appear as cloud games.

Since, in cloud games, all the processing and rendering is done by the service provider and streamed over the internet to the end-user, there is no need to download the complete gaming software for each game nor does one need high-end gaming hardware. Instead, a game-client suffices to, in principle, enjoy multiple games. Clearly, cloud gaming places extra stringent demands on the network QoS, since it requires sending the complete screen (server to client) and commands (client to server) in real-time and on the gaming infrastructure of the game operators.

3. Identifying and Quantifying Social Features in OSGs

Because social features are only partially engineered and may appear as complex emergent behaviour of the local interactions between players, identifying and quantifying them is challenging. In this section, we present a model for social features that will be helpful for this challenge.

3.1. A General Model of OSGs

Three main pillars

An OSG platform typically consists of the following three pillars:

1. *Game-World Management*, which comprises game hosting, and the management of players and in-game objects in the virtual game-world. Moreover, the OSG infrastructure and management should be scalable to serve millions of players online, match elastically the number of players, be always available, be consistent and have low latency.
2. *Game-Data Processing* is a selection of methods and tools to analyse game status and history. Clearly, the massive numbers of players in the game-world collectively generate massive amounts of data: user interactions, uploaded screenshots and videos, social networking, etc. Analysing the data can help the system designers understand player behaviour and gain insight into system operation, thus allowing them to build better games for the players and to operate games more efficiently.
3. *Game-Content Generation*. Game-content, from bits such as textures to abstract puzzles and even entire game designs, is at the core of the entertainment value of games. Until the early 2000s, manual labour ensured that the quality and quantity of game content matched the demands of the playing community, but this is not scalable due to the exponential growth in number of users and production costs. Hence, there is an increasing need for procedural generation of game-content at a massive scale to provide players new incentives to keep on engaging with each other and the game.

The game-world management pillar provides in-game data to the game-data processing pillar and uses content produced by the game-content generation pillar. However, not all of the requirements listed for these three pillars are being met today. Challenges remain in procedural generation of content, harnessing cloud-computing platforms for scalability, and leveraging social data and relationships to improve the game-play experience. In this chapter, the focus is exclusively on the social aspects of online gaming.

Dimensions of social interaction

In addition to the three gaming pillars, we present and exemplify three dimensions of social interaction:

1. Explicit versus implicit social ties.
2. Inside the Game-World versus outside.
3. Long lasting game-world versus short-lived matches.

We provide some examples to illustrate how the three social dimensions could manifest in online gaming:

- Forms of explicit association are easiest to detect and include the formation of clans and guilds.
- Players who have played/won/lost/conducted other activities together form an entire implicit social network with various characteristics that may be useful in improving, for example, the way players are matched to other players for a particular match.
- Explicit community work outside a single game or a set of related/unrelated games is facilitated through Online Meta-Gaming Networks (OMGNs). OMGNs are Internet-based communities of online gaming players that extend in-game functionality by focusing on the relationship between game sessions, on what happens in the meantime between game sessions, and on the relationship between games. Also other means of communication, like SMS, may be used to coordinate outside of a game, for example to obtain a high chance of being teamed up with friends.
- A long lasting game-world may lead to different relationships than brief possibly repeated encounters in short-lived instances of multiple matches.

Given that these three dimensions for social interaction in online gaming exist, the question is how to turn them to good use to improve overall performance and game-play experience. For instance, for a social network game such as FarmVille, it might be more efficient to place a group of friends who interact frequently on the same server, which requires solving the question of how to use the explicit or implicit social structure of games to provision and allocate the system's resources.

In terms of QoE, a new model is needed that should consider the effect of QoS parameters as well as social aspects. While a QoE model has been developed for telephony in the past, it has already proved difficult to find one for online multimedia services, like video-on-demand, and will be even more challenging when other elements, like social ties, play a role.

3.2. Identifying emergent social networks using interaction graphs

In this section, we describe a graph model, presented in our previous work [4], which is able to capture social relationships of a variety of types and strengths. In [4], we have applied our model to game-data and in this section we will summarize the results to show how one could leverage those networks to improve QoE.

Data:

One of the three gaming pillars is Game-Data Processing, which obviously requires game-data to begin with. There are a number of, e.g. competitive and privacy, reasons why obtaining game-data, if you are not the game operator, is challenging. Many details of the "internals" of the game infrastructure and player information are shielded from the public. Yet, some data, like statistics, are published on websites and can be obtained by APIs or web scraping. Other means to gather data are monitoring the game-related network traffic and actually playing the game personally or by the usage of bots. In order to facilitate research on online gaming, the Game-Trace Archive was created to provide an open access to related data [14].
For our work on identifying implicit online social gaming networks [4], we collected data corresponding to long-term activity of communities playing DotA (the Dota-League and the DotAlicious communities), StarCraft II, and World of Tanks, which we made available in the Game Trace Archive [14]. At the time these datasets were crawled, the four online communities offered each player a profile webpage that displayed information on friends and clan membership. Also individual webpages per match were published that contained the start and end times of the

match, the player list, the outcome of the match (i.e., which team had won, or whether there was a draw, or if the match was aborted) and game-specific information. To reduce the effect of possible temporary webpage or network outages, each webpage was crawled at least twice and matches with zero duration were filtered out. The four types of datasets comprise:

(i) Friendship data from Dota-League;
(ii) Clan membership data from DotAlicious;
(iii) User skill levels from Dota-League and DotAlicious;
(iv) Match data for all four communities.

The four datasets together include both explicit as well as implicit social gaming information. As such, we may use tools from social network analysis, like the use of graphs to represent user relationships even if they manifest implicitly via user interactions. Such social network studies often extract graphs based on a single, domain-specific, and usually threshold-based rule for mapping relationships to links. However, gaming involves relationships in various domains that normally do not exist in regular social networks, for example, winning together and competing with each other. Hence, to study user relationships in MOGs, all of these domains and social perspectives need to be carefully examined and compared. In [4], two types of graph-based models were used to represent user relationships in MOGs, namely:

Friendship graph:

The friendship graph is obtained from the friendship data of Dota-League. If two players, represented as nodes in the graph, have indicated that they are friends, a link in the graph is connecting those two nodes. Since friendship is mutual and the data did not indicate any intensity in friendship, the friendship graph is undirected and unweighted.

Interaction graph:

In the social network analysis of, for example Facebook [11], an interaction graph is used to represent interaction between two users. Similarly, in the context of OSGs, a link between two nodes could reflect some form of interaction between the corresponding two nodes/players. However, unlike in the Facebook study by Wilson et al. [11], in which all interactions are assumed to be homogeneous, many different types of interactions are captured in the game-data. The five types of interactions that were studied and for which interaction graphs were extracted are the following:

(1) SM: two players played in the Same Match;
(2) SS: two players played on the Same Side of a match;
(3) OS: two players played on Opposite Sides of a match;
(4) MW: two players of a Match Won together;
(5) ML: two players of a Match Lost together.

To study the social relationships in OSG interaction graphs one could consider various graph metrics, e.g.:

- Network size (the number of non-isolated nodes in a graph)
- Nodal degree (the number of a node's neighbours)
- Distance (the length of a shortest path between two nodes)
- Diameter (the largest distance between any two nodes)
- Clustering coefficient (the fraction of pairs of its neighbours that are linked)
- Assortativity (the average Pearson Ranking Correlation Coefficient (PRCC) of the degree between pairs of connected nodes)

Interaction graphs could be directed or undirected and weighted or unweighted. In [4], the choice was made not to use link weights to capture the interaction strength, because many graph metrics are only defined for unweighted graphs. Instead, a threshold-based rule was applied, to discard interactions of low strength and to include only the interactions with sufficient strength to pass the thresholds into the graph. Two mapping thresholds were considered: the period t of effect for a user interaction, and the minimum number n of interactions that need to have occurred between two users for a relationship to exist. For example, in an SM graph with t equal to one week, and n equal to ten, a link between two players exists only if the data contains at least one week in which they played at least ten games together. Indeed, the values for t and n, in this case, govern the strength of relationships reflected in the interaction graph and are important parameters. For example, both a small value of t and a large value of n would induce a graph of strong relationships.

The five above-mentioned interaction graphs are undirected and unweighted. They also differ in detail, since both SS and OS constitute sub-classes of SM, and both MW and ML on their turn require players to have played on the same side (SS). Consequently, for the same values of t and n, there are fewer relationships in the SM graph than in the SS and OS graphs, which in turn have fewer relationship constraints than the ML and MW graphs. Note that the list of considered interaction graphs is not exhaustive and, in principle, can handle more complex types of interaction. For example, playing against each other at least ten times during winter, while also located in the same country. Moreover, the thresholds themselves could act both as lower and upper bound. For example, we could focus on moderately interacting players (the majority of an MOG's population) by specifying, as threshold, a maximum number of interactions between two players. If two players exceed the threshold, then they are not connected by a link in the interaction graph.

Summary of analysis results:

The analysis in [4] of the four gaming communities and their various interaction graphs revealed similarities, but also differences in the social relationships and preferences amongst players. The differences indicate that an interaction graph analysis should not only be conducted per gaming genre, but also per game design within a particular genre. A proper analysis could serve as a reference to game designers and MOG community administrators in adjusting their designs to increase QoE. For example, players in StarCraft II appeared to prefer competing (by playing on the opposite side) with their rivals. Possibly, this community is more driven by trying to retaliate or redeem oneself after a previously lost match. MOG communities that are similar to StarCraft II could leverage such knowledge by organizing tournaments or publishing player ranks, to promote the activity level of their players, all in an attempt to increase the competitiveness of the environment.

The study in [4] compared the various interaction graphs based on several graph metrics. One noteworthy metric is that of triadic closure. A closed triad is defined to be a group of three nodes that are all connected to each other. It is known, from psychology, that triadic closure is more likely to manifest with positive (a friend of my friend is likely to be a friend) rather than negative relationships (an enemy of my enemy is less likely to be an enemy). Typically, in social networks, only positive relationships are present and negative relationships could not be studied. On the contrary, in OSG networks both kinds of relationships occur, since prosocial and enmity relationships are strongly expressed. We therefore tested in [4], whether positive triadic closure is indeed more pronounced than negative triadic closure. In this context, playing on the same side

(SS) was assumed to indicate a positive relationship and playing on the opposite side (OS) a negative relationship (although also friends might enjoy playing against each other).

Indeed, the SS graphs for Dota-League, StarCraft II, and World of Tanks reflected higher triadic closure than the OS graphs. For DotAlicious, the differences between the triadic closures for both its SS and OS graphs were less pronounced. One possible reason is that the clan feature provided in DotAlicious diminishes the significance of playing on the opposite side as a negative relationship. It remains for future work on other datasets to establish whether this conjecture is valid. In Section 3.5, we will closely investigate "toxicity" as a more pronounced form of negative relationship.

3.3. Identifying emergent social networks using the Attribute-Role-Action framework

We describe in this section the *Attribute-Role-Action* (ARA) framework, which we see as a richer framework for identifying emergent social networks than what we have introduced in Section 3.2; unlike the framework from Section 3.2, the ARA framework still requires much work before it can be applied automatically in practice.

The core objective of the ARA framework is that a simple set of techniques should be able to extract complex social relationships from either implicit or explicit, but fine-grained game-data. Relations may be identified by not only measuring in-game interaction graphs (as in Section 3.2), but also by analysing indirectly related data. These data consist both of the player in-game fine-grained actions, such as conducting in-game raids or chatting in-game together, and of out-of-game actions related to forming and maintaining relationships, such as discussing over non-game channels. Data related to these *actions* can be further detailed per social *role* played during the action, from friend or enemy, to selfish behaviour (being a "pugger") or being a same-party member. Roles can be defined as detailed as needed, for example enabling the expression of degrees of social roles, from a guild leader known by all guild members, to a social manager of a guild activity, to a relatively distant party member known by few. Because roles can be infinitely many, creating a set of techniques addressing them all would be impractical without some form of clustering. We propose that a small set of *attributes* exhibited by roles could expose the dimensions used by any role, and thus be addressed by specific techniques with a wide applicability.

Table 1 summarizes an example of an ARA framework. Its three main columns, "Role Attributes", "Role", and "Actions", correspond to the three main dimensions of the ARA framework. The 15 Roles are diverse, ranging from the supportive "friend" to the all-seeing, but otherwise inactive, "spectator." The "Role Attributes" describe whether the actions are performed by players with a friendly or hostile view on the acting player, or with cooperative or competitive attitudes; the attributes may indicate an equal (transitive relationship) or unequal role; may indicate that the role is superficial and thus perhaps inconsequential in the long run; may indicate a socio-emotional role (such as support) or task-oriented role (such as relationship by belonging to the same guild); and whether the role is informally or formally specified. The "Actions" included in Table 1 are also diverse, from being included in the friend or ignore list, to indicating an action that negatively affects the player.

Role Attributes												Role	Action																		
friendly	hostile	cooperative	competitive	equal	unequal	intense	superficial	socioemotional	task-oriented	informal	formal		friend list	ignore list	in party	in raid	in guild	whisper chat	party chat	raid chat	guild chat	seeing (near)	trading	giving	group leader	in combat focus target negative	in combat focus target positive	out of combat focus target	party decline	guild decline	world
+		+		+		+		+		+		friend	+	-	+	+	+	+				+	+	+			+	+	-	-	-
+		+		+		+		+		+		guildie		-	+	+	+					+	+	+			+	+	-	-	-
+		+		+		+		+			+	social manager (guild)		-		+	+				+								-	-	-
+		+		+		+			+	+		party member	+	-	+												+		-		
+		+		+		+			+		+	management (guild)		-		+	+			+	+								-	-	-
+		+		+			+		+	+		pugger		-	+	+			+	+									-		
+		+		+			+		+		+	pug leader	+	-	+	+			+	+					+				-		
+		+			+	+		+		+		elitist (negative)		+	-											+			+		+
+		+			+	+			+		+	guild leader		-		+	+			+	+				+				-	-	-
+			+	+		+		+				rival	+	-	+									-		+		+			+
+			+	+		+			+			enemy arena team		-												+					
	+	+										temporarily same goal		-												-	+				
	+		+									world pvper														+	-				+
	+		+									scammer	-	+									+			+	-				
+	+					+	+	+		+	+	spectator			+	+	+	+	+	+	+	+							+		+

Table 1. Example of an Attribute-Role-Action framework in practice. Symbols denote importance.

Table 1 already combines practical knowledge that: (i) Roles such as "friend" and "guildie" (belonging to the same guild), and even "social manager" of a guild, are with respect to our dimensions very similar, and thus may be addressed by similar techniques; (ii) Attributes such as "friendly" and "cooperative" are highly correlated but not identical, as sometimes cooperative players may even be hostile to each other outside a specific action; (iii) many of the negative Roles, and in Table 1 the rows between "rival" and "scammer", have fewer Attributes and Actions terms, and thus may be easier to service; (iv) Actions with strong chance of decreasing game-play experience, such as "party decline", may be countered by techniques that increase presence of Attributes such as "friendly" and "cooperative"; the same happens for Actions with high pro-social consequences such as "giving"; (v) Actions with visceral reaction, such as "in combat focus target" may be triggered by both established rivalries and temporary roles.

To conclude, we see the ARA framework and the example in Table 1 as first steps towards defining a more fine-grained socially aware gaming model.

3.4. Quantifying QoE using user action graphs and MOS scores

Although increasing QoE is the ultimate goal, at the moment even measuring QoE for games is difficult. A common way to capture the users' perception of a service is by asking feedback from a panel of users and subsequently computing a Mean Opinion Score (MOS). Individual users from the panel are asked to rate a certain service by using a 5-point scale (ITU-T P.800), where the scale runs from 1 (meaning "bad") to 5 ("excellent"). The final MOS score reflects the average of the users' assessments. Despite the frequent usage of such a panel-based method, it has obvious disadvantages: it is costly and takes a lot of time. This methodology is therefore mostly used in an attempt to derive an objective QoE model that, based for instance on QoS measurements, is calibrated to accurately reflect the subjective MOS score. Several models and tools are already available to objectively quantify the QoE of video or audio, e.g., see [3], but not much QoE work has targeted the field of OSGs. Moreover, the few available models that do attempt to measure the QoE of online games primarily focus on the effects of the QoS parameters on the QoE, e.g., see [2], [7], [10], but ignore other important aspects, such as the influence of social ties on the QoE.

The user action graph

To capture the social side of playing behaviour and experience, E. Dias [20], under our supervision, investigated a Massively Multiplayer Online Social Game (MMOSG) called MagicLand, which unfortunately is no longer available. In order to conduct that investigation, three classes of metrics were defined: (1) game-play metrics, (2) social metrics, and (3) performance metrics, each of which will be illustrated below.

Relevant game-play metrics for MagicLand were:

- *Skill level*: Very skilled players may experience a game differently in comparison to novices.
- *Time to level up*: A measure reflecting how difficult it is to advance in a game.
- *Actions*: For example, planting, harvesting, buying some assets, etc. By considering *actions per minute*, one could also study a player's involvement in a game. Inactive players may indicate a lack of enjoyment, while overly active could point to inexperienced players just clicking around. Both extremes may imply a low QoE.
- *Goals completed*: This metric to some extent depends on skill, time to level up, and actions per minute, and reflects player engagement.

Relevant social metrics for MagicLand were:

- *Friend visits*: The number of friend visits during a game session.
- *Visit times*: The time a player spends visiting his/her friends.
- *Friend requests*: One may solicit help from friends to complete certain goals.

- *Gifting*: The act of helping friends by giving them certain items.

Relevant performance metrics for MagicLand included (obtaining traces on) network and server performance.

We will briefly explain how to combine these various metrics in order to reach an OSG QoE model:

1) The first stage is data collection. In order to validate the QoE model, we need to collect both objective data, reflected by the game-play, social and performance metrics, as well as subjective data, obtained via a questionnaire and reflected in a MOS score.
2) The second stage consists of correlating the objective and subjective data to determine which gaming metrics influence the QoE most and in what way.
3) In the last stage this information is used to create a model that is able to determine the overall QoE of an OSG without any subjective input.

The work in [20] on MagicLand was not conducted with a large enough test panel to draw significant conclusions and to develop a QoE model for MagicLand. It however did lead to the following observation: *Playing with friends leads to a higher QoE and faster level-up times, but this mostly holds for experienced players and not as much for the novices.*
In the following section, we will illustrate that social (mis)behaviour can also have a negative effect on the QoE.

3.5. Identifying in-game toxicity using natural language processing

In this section, we will summarize our main findings from [5], which used natural language processing (NLP) to detect profanity, or so-called toxicity, in the chat-logs of a game. Toxicity is a clear example of a negative form of social behaviour and could seriously affect a player's game-play experience.

Data:

The chat data used in [5] was crawled from the DotAlicious platform, one of the DotA communities studied in Section 3.2. The dataset comprised both the all-chat as well as the ally-chat logs. All-chat communication is accessible to all players of the match, while the ally-chat (which accounted for nearly 90% of all chat communication) is only visible by allied players (players in the same team). Unfortunately, the DotAlicious site is no longer available, and we cannot release the data publicly in order to protect the privacy of the players, especially when dealing with such a sensitive topic as personal insults. Some of the data may be available upon request.

Extracting meaning from data using Natural Language Processing:

The data obtained from DotAlicious contained all chat logs for 10,305 matches of DotA. The logs were tokenized into single words by white-space splitting, maintaining the information of the corresponding sender. Contrary to standard practice in the field of NLP, our tokenizer kept symbols like exclamation marks attached to words and regarded different capitalizations as different tokens. This was done as different capitalization and symbols like smileys are frequently used to emphasize statements and carry thus valuable information about the sentiment of the corresponding sender. Since the chats took place while playing fast-paced matches, the spelling of the words leaves much to be desired for and also contains many abbreviations and game-specific commands. In general, the used language rarely follows any grammatical structures, but is rather elliptic and extremely abbreviated, often consisting of technical slang-terms not found in standard dictionaries. This is another reason why standard procedures (for example part-of-speech tagging and spelling correction) are largely inapplicable. While different languages appeared, English was the dominant language in the corpus.

After the tokenization process, we attached labels to each word, marking it for example as profanity, technical term, smiley, stop word or expression of laughter. To assign a label to a word, three different classes of rules were considered:

1) Pattern: the word includes or starts with certain symbols.
2) List: the word appears a pre-defined list (dictionary).
3) Letterset: the set of letters of the word equals the set of letters of a word from a pre-defined list.

The letterset rules have been particularly useful to alleviate the impact of bad spelling. For example, a commonly used insult is the word "noob", which is somehow derived from "newbie" and used to typify a player as such. Many different ways of stating "noob" were found in the corpus, e.g. "NOOOOOOOOb", "nooobbbbb" and "noonb", pointing to deliberate and unintentional misspellings of the word. Considering lettersets allows classifying all those words to a same class, as long as no other meaningful recombination of the letters appears in the corpus. The text-corpus analysed in [5] consisted of 7,042,112 words, of which 286,654 were distinct.

What is toxicity and how to detect it?

Toxicity has not been established as a well-defined term in literature yet, but is frequently used to refer to all forms of displeasing anti-social behaviour of players. Part of this behaviour is language used for verbal assault and harassment of other players. For our purposes, we interpret it as the act of sending a chat message with the aim to insult another player within the same team.

While the extraction of profane words and insults (via list and letterset rules) might give an idea about the atmosphere of the particular match, the detection of profanity is not sufficient. A highly competitive game as DotA may trigger strong emotions that result into swearing, which is an expression of an immediate dissatisfaction, but not necessarily meant to hurt a teammate. In fact, people might sympathize with a swearing person, in case he was the victim of an unfortunate event. Thus, we found that in order to detect toxicity, considering the context is crucial.

One way of taking the context into account is the use of *n*-grams. An *n*-gram is a contiguous sequence of *n* words that appear in a temporal context. That context could comprise all words sent by a single player no more than 1 second before and/or after a word labelled as profane. As such, in [5], for all players who participated in at least 10 matches, the 100 most frequently used *n*-grams for *n* = 1, 2, 3, 4 that contained at least one profane word were retrieved and analysed manually to determine which of them were toxic. The rule for toxicity was that the corresponding *n*-gram could be understood as an insult directed towards another person "you noob" and not some self-referential humour: "I am so noob".

Results analysis:

Out of the 10,305 matches analysed in [5], 6,528 matches contained at least one toxic remark. As our selection of toxicity was conservative and very strict to avoid false positives, the total amount of toxic remarks was modest and generally no more than 5 toxic remarks were made per match. The maximum amount of toxic remarks registered for a single match was 22.

To investigate potential causes or triggers for toxicity, toxicity was further evaluated against:

- The win-rate for each player, i.e. the amount of matches won divided by the amount of matches played in total;

- The expected game-outcome;
- In-game events like kills of player characters.

The results in [5] indicated that, surprisingly, there seems to be no strong linear correlation between the win-rate and the level of toxicity. Profanity and toxicity seem to be used regardless of success in the game. To gain deeper insights, analysing the distribution of toxicity over all matches is not insightful, but the distribution and usage of toxicity within the matches paints a different and more intuitive picture. Considering the progress of the game, the team that will lose is observed to use more toxic remarks on average in the later stages of the match in comparison to the opposing winning team. A possible explanation is that the level of toxicity increases with the frustration experienced in the face of a more and more inevitable defeat.

As indicated, frustration may spark toxic behaviour and certain game events may be at the root of that frustration. One obvious game-event players try to avoid is that of their avatar (temporarily) being killed. To test whether such kill events were indeed triggers of toxicity, the data were analysed to examine whether each of the 16,950 detected toxic remarks were preceded by a kill-event taking place not more than 10 seconds before the actual remark. For comparison, an equivalent amount of 16,950 random chat-lines were used as a null-model to analyse whether there have been any kill-events in the same time window. As expected, toxic remarks turned out to be indeed more frequently preceded by kill-events than random remarks, roughly by a factor of two.

The methodology described above can be adapted to other MOBAs and possibly even games of different genres, as long as protected textual chat communication within teams is a social feature. As language (and corresponding insults) used by players may be strongly game-dependent, one would need to redefine the list and pattern rules for word labelling according to the specific terms used in the game under consideration.

4. Using Social Features in Future Online Social Games

There are many possible applications of social features, as defined in this chapter, for OSGs. We discuss several such applications.

4.1. Match recommendation in Online Social Games based on interaction graphs

Match recommendation in a MOG community can be seen as an attempt to predict player pairs that are likely to form gaming relationships in the future. Match recommendation often includes two types of predictions: (1) predicting new relationships between players who previously had no relationships at all, and (2) predicting renewed relationships between players who have interacted in the past.

In multiplayer games, your “click” with fellow players may have a big influence on your QoE. Consequently, good matchmaking algorithms should help to improve user experience, and hence, the commercial value of MOGs. For example, in Dota-League, players could only join a waiting queue, and, only when there were enough players, teams were formed considering the skill levels of the players in the game. Although such an approach enforces balanced matches, it does not take into account the social relationships of players. As a possible consequence, many of the games in Dota-League were aborted at the very beginning of the match. Instead, the findings of McGonigal [6] and our own research have pointed out that matches played by players with strong social ties are enjoyed to a higher extent than those played together with players to which one has weak or no social ties. We therefore believe that matchmaking in OSGs stands to gain by including predictions on which player pairs are likely to "click" and form social gaming relationships in the future. A socially aware match recommendation algorithm was devised in [4] as follows: For all players who are online and have not been assigned to a match, we compute their connected components based on the interaction graphs extracted with a large value for threshold n. Those components are ranked in decreasing order of their size, and then all players from the same component are assigned to the same match as long as it does not exceed the permissible match size. Otherwise the component is split, assuring that the number of players per part equals the match size, and the same methodology is applied. Such an algorithm could be made more advanced, by also including other features like location and the toxicity profile of players, but in [4] we have shown that even such a simple algorithm can already increase the QoE.

4.2. Social climate engineering for Online Social Games

The toxicity detection method we have developed in our previous work [5] is based on contextual information to distinguish simple swearing from deliberate insults. While already effective, it could also serve as a building block for a monitoring system that can be used together with player reports to identify toxic players. Clearly, giving such players incentives to prevent further toxicity from happening is important, but there are also other emotional states expressed by the players that are worth monitoring and which have been part of our work as well. For example, encouraging and motivating behaviour should be helpful to improve team spirit and cope with difficult situations. Kindness and forgiveness may motivate fellow players to not give up and continue giving their best effort.

By using standard supervised learning methods on TF-IDF features (term-frequency inverse-document-frequency) over the used words by the players towards their allies, predictions about the game outcome were already possible to 0.7 accuracy after two-thirds of a match were over. While cause and effect need to be more carefully examined, this could mean that the language used by the players is critical for success.

Refining the prediction methods towards QoE measures rather than match outcome could provide a "barometer" of the emotional state of the corresponding players. Understanding what factors make a match enjoyable will provide feedback for game designers to balance the competitiveness of the game in favour of an improved experience.

In fact, our analysis supports the hypothesis that toxicity is mainly fuelled by the inherent competitiveness (i.e., killing each other) of the MOBA game under consideration, while being seemingly uncorrelated to the actual outcome of a match. Consequently, if players can be successful despite being toxic, they need a different incentive to cease insulting and to behave more pleasantly. Possibly, the matchmaking systems that ensemble the teams could be altered to take toxicity into account to avoid creating a social powder keg. Although preventing toxicity entirely seems to be a utopia, controlling it to some degree would ensure a much more positive game-experience.

Possible in-game mechanism to combat toxicity could also consist of awareness campaigns that target at toxic players with the goal to rehabilitate them. While winning in a difficult competitive match might still be the main reason for players to engage with the game, there exist cosmetic aspects, i.e. items that decorate and dress in-game avatars that are highly desirable by a large sub-population of players. In fact, cosmetic items are a considerate source of income for the game developing company. This proves that there can be artificial incentives created that influence player behaviour despite the prospect of game success.

Future games might use these or similar incentives to steer the social behaviour between players into a more positive direction, without taking the edge from the competitiveness. Understanding under which circumstances toxic and friendly behaviour arises will be the first step (trigger-condition) of such a future system.

4.3. Scaling games with socially aware techniques

Scaling the game-world to operate well for large amounts of units and/or players is not trivial. All entities in the game-world might be able to interact with one another. Processing all the actions (interactions) that entities want to execute requires an increasing amount of processing power as the number of entities and actions increases. This load needs to be partitioned to achieve scalability. If all entities can interact with all other entities at any time, and if they need to know the state of all other entities, then the servers handling those entities would quickly be overwhelmed by the amount of information generated by an increasing entity count. Two related techniques are commonly used to achieve scalability in practice: *interest management* [21] tries to disregard information that is less relevant or even entirely irrelevant, and *load partitioning* [24] tries to divide the information-management problems across the participating processing nodes and player machines. The use of both of these techniques is currently oblivious to social features. We encourage focusing on socially aware techniques for scaling games, along the following directions:

First, many interest-management techniques already exist [21][22][23], but it would be interesting to extend their filtering of in-game information with filtering of non-friends, inclusion of information for arbitrarily distant acquaintances, and other social features. Such criteria could be prime candidates to filter for information that is arbitrarily relevant to the player, in that the social features could be linked to the likeliness of interaction or even their potential impact on game-play experience.

Second, load partitioning leads to similar opportunities as interest management, but with different techniques [24][25]. The current approaches in practice, in both commercial games such as Runescape and community gaming platforms such as OpenRA, assume that either contiguous areas (*zone-based partitioning*) or largely fixed sets of in-game objects (*object-based partitioning*) are leading to most of the interaction, and should thus be handled by one server each. This idea could be extended by including social features in the partitioning process, for example by clustering by social features when deciding the set of in-game objects to be assigned to a server.

5. Conclusion & Directions for Future Research

The convergence of technological and social networks, if understood and managed, creates opportunities for better system design, and also for better user experience. Implicit social relationships between users, such as direct communication, direct exchange of data, and acting together can be seen as strong social relationships (ties) between users. However, social behaviour could also be social misbehaviour (toxicity), leading to reduced game-play experience. In order to put the power of social features in OSGs to good use, much research still needs to be conducted:

- There is a need for a QoE model to objectively capture the user's game-play experience. This includes tools to capture the social aspect in gaming and to translate those into an experience score.
- There are challenges in properly defining and measuring toxicity. Once that is possible across game genres, one should investigate what are its short-term effects, for instance on

the QoE, but also what are its long-term effects, for example, is it "contagious"? Moreover, given that toxicity is unwanted behaviour, how could a game operator best deal with it?

- While, in this chapter, we mostly considered the social behaviour and relationships in online gaming, there is still much research to be done on how to leverage such information. For instance, social ties may bring about certain "social" workload patterns, which might be used by a data centre scheduler to improve overall network and system performance.

ACKNOWLEDGEMENTS

The key findings as summarized in this chapter could not have been presented here without the instrumental work of our many collaborators, whom we thank: Ruud van de Bovenkamp, Emanuel Dias, Dick Epema, Adele Lu Jia, and Siqi Shen.

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