A Framework to Infer Player Experience and Inform Customized Content Generation in Gameful Systems

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Abstract
Being able to monitor player behaviors is of particular importance in gameful systems, which are dynamic by nature and require real-time interventions. In these contexts, the designer should be assisted to avoid delivering a static and monotonous experience. As a consequence, the game should be able to adapt to the player that is interacting with it, to give the best UX possible, and avoid an abandonment. The aim of this project is to gain insights on the impact the game has on players by analyzing how they interact with the system and with the community of players. The outcomes will give information on player experience and profile. In turn, this knowledge will lead and assist the generation of customized content for each player and continuously improves its generation strategy.

CCS Concepts
•Human-centered computing → HCI theory, concepts and models; Empirical studies in HCI;

Author Keywords
Gameful System, Game Analytics, Player Profiling, Player Social Network, PCG-Games

Context and Motivation
It has been widely proven that player individual preferences [38] influence the impact that a game has on her, in terms

of participation, retention and engagement. Therefore, the promised land would be a game that self-adapts its mechanics according to the user currently playing it. Researchers have been addressing the task of modelling players since Bartle's work [1], by developing theoretical frameworks and taxonomies. However, only in the last decades the main focus fell on the study of in-game behaviors, rather than on player types determined through self-assessments. Despite some works (e.g. [19, 3]) have investigated how to gather and structure in-game behaviors, these approaches are context-dependent and, thus, difficult to generalize.
It also remains unclear how to automatically convert the knowledge gained from the extracted player behaviors into personalized game mechanics. In addition, the main focus has been on profiling players without considering the social context and the influence that they exert on one another through social game mechanics, such as competing, cooperating and collaborating.
Finally, the vast majority of works have been conducted on entertainment games, leaving the serious games and the gamified systems domains to be further investigated.

Research Questions

1. Can we use gameplay data to estimate the goodness of each player's experience?
2. Can we extract in-game behaviors from gameplay data so as to exploit them to inform an algorithm that generates tailored content?
3. Can we model players in-game social interaction in a social network and evaluate players' social value employing social network analysis metrics?

Related Works

Gameful systems employ elements proper of games contextualized in non-entertainment application domains to foster motivation [20, 34]. The individual's personal inner motivation [13, 29] and intention [12] guide the process of behavior change, leading to a positive influence [16, 20]. The elements that drive the behaviors of users are highly heterogeneous. While some players are motivated by achievements, some benefit from social mechanics, and some by a hybrid approach [44, 14]. Nevertheless, the majority of the implementations are focused on the usage of points, badges and leaderboards [8]. A great supporter in building intrinsic motivation in performing the task in question is relatedness [45], due to the need people have to feel in connection with other human beings [7, 24]. This sense of community, which lead to higher commitment [15, 31], can be achieved through games [36, 39]. In fact, preliminary empirical studies showed that cooperative game mechanics have positive effects in many domains [2, 6, 37, 6]. Thus, Kovisto et al. [23] manifested the need of diversifying the use of gameful affordances.
It must be taken into account, however, that not all players manifest the same needs and preferences, hence the need of player modeling [40]. Players taxonomies are mostly theory-driven approaches (e.g, [32, 28, 11]), which are likely to miss relevant features since they were built upon abstraction [30]. Moreover, these methods often rely on the usage of questionnaires. In first instance, answers are likely to be biased either because players have a wrong perception of themselves or because they have the desire to please their interlocutor [9]. In contrast, game metrics, which measures quantitatively some attributes that occur in the game context [9], are the most objective measure. This objectivity led to a massive use of those metrics to assist design and development of games [22]. Gameplay data is extremely insightful when measuring the player experience is the purpose [9], and can be easily retrieved through automatic logging system [22]. Gameplay-based PEM [43] is driven by the assumption that player experience can be extrapolated from real-time actions. Being able to monitor

players' in-game behaviours gives immediate feedback on how they interact with the game, without biases that are intrinsic in more subjective methods [35]. Even though log files are a gold mine [18], they must be treated carefully, and particular attention must be payed to how this data should be interpreted. Many studies aimed at analyzing the behavior that players assumed in the game so as to understand the way they interacted with it (e.g., [19, 42, 27, 3]). However, most of these works are conducted offline with aggregated data, without considering that players tend to change their in-game behaviour during their gameplay [9]. Procedural Contend Generation (PCG) allows to dynamically generate game content of heterogeneous nature [17], according to the players taken into consideration. The strength of this approach lies in the fact that, through these mechanisms, a highly personalized game can be developed containing time and cost of production. In the literature are present many games that use PCG for different purposes, such as keeping the players entertained [5, 21], adjust the difficulty level to avoid frustration and/or boredom [10, 25] or tune the system according to players' knowledge [46, 47]. Nevertheless, an abstract framework considering players identity at 360 degrees lacks.

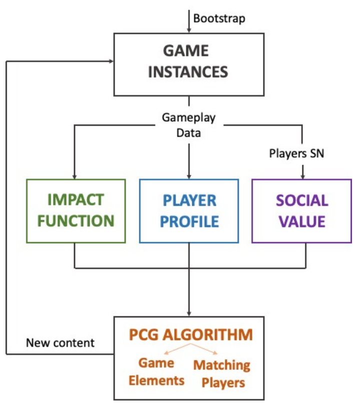

Figure 1: Framework's modules and flow.

Contribution

The main contribution will be the development of a framework (Figure1) that continuously monitors how players interact with the game, to inform the strategy used to deploy personalized content. The target is to enhance players' experience and retention [33]. The framework will fine-tune its generation strategy by evaluating the impact of each deployed content on each player through an impact function. The framework will be built of the modules:

1. **Impact Function** – general-purpose and domain-independent metric to evaluate the impact that the game has on players to assess the goodness of the decision in the following iteration. This function is particularly relevant in the serious games and gameful systems domains, since it could be used to evaluate the impact of the game using an indicator that measures the "ulterior motive" in play (e.g., in a Persuasive Game for Health the measure of interest would be a health-based indicator).
2. **Player Profile** – module to extract player behaviors from gameplay data, so as to build player profiles that are constantly updated during the game. The goal is to continue to define abstract behaviors, building on our preliminary work [26]. These abstract behaviors can be associated to concrete indicators in the game, by the designer, and continuously monitored.
3. **Social Value** – module to build and analyze the Player Social Network (SN), derived from their in-game interactions. The analysis will be aimed at understanding the structure of the SN [41] and the social identity of players (e.g. are they influencers [4] or influenced?), to inform matchmaking algorithms.

The modules will be used as black boxes by a PCG algorithm that: (1) deploys personalized game mechanics using the player profiles, and (2) matches players according to their profiles and social values. The algorithm will be designed in a reinforcement-learning-fashion, in that it will iteratively evaluate the effectiveness of its choice by measuring the value of the impact function and, then, it will optimize its decision strategy accordingly. The gameplay will be seen as divided into subsequent timeframes, at the end of which the customized content will be evaluated, and new content will be generated for the following iteration.
Additional values are intrinsic in our domain, in that it is a (1) long-term (six months) (2) on-the-field gamified system

that (3) employs game elements tailored to its users, moving towards well-defined research needs in the field [23].

Research Approach and Methods

The use case scenario is a long-lasting open-world gameful system (Play&Go, Figure2) active in the city of Trento and Rovereto (Italy). The game motivates players to track their movement in the city and pushes them to improve their performance through weekly challenges. Players can also choose to compete or cooperate with others through multiplayer challenges. Every year we host a 6-month edition of the game, during which we gather gameplay data. Since the game is designed and developed in our lab, we can intervene in the design so as to (1) learn from past editions and (2) study interesting phenomena, research-wise.
The idea is to define a general framework that tailors and adapts the game elements according to each players' preferences and needs. Then, the framework will be evaluated in our use case scenario. The framework is built of independent modules (Figure1), each requiring modular studies on in-game behaviors and multiplayer game elements (through the study of the player network). This framework will work dynamically at run-time with gameplay data and will improve the goodness of the customized game element, generated by analyzing individual and social in-game behaviors. The evaluation of the content will be performed through an impact function, which allows the designer to specify the relevant indicators in her application domain. Then, at each iteration, the function will evaluate the impact of the game on each player, in terms of the specified indicator. The value will improve the decision strategy used to generate customizable content. In the use case scenario, the automatically generated contents are challenges that have the purpose to foster an improvement (or maintenance) of players behaviors, in terms of sustainable mobility. These challenges can be either individual or multiplayer. However, the framework is designed to be domain-independent.

Dissertation Status and Next Steps

The first year of my PhD has been mostly dedicated on the study of the state of the art and the definition of the research questions, together with a preliminary study, on the ongoing (at the time) edition of the game. In this preliminary study we focused on RQ2, by suggesting a set of abstract behaviors, retrievable from gameplay data (*Player Profile* module in Figure1). We also assessed that it is impossible to label them as belonging to one dominant player type [26]. This analysis led the design of the following edition of Play&Go, in which some more sophisticated game mechanics have been introduced, such as a levelling system, unlockable content and the possibility of choosing personal challenges. Moreover, social game elements have been implemented. In the meantime, the framework (Figure1), which will be the main contribution of my doctoral project, has been designed. During this second year, the main focus has been the definition and evaluation of a general-purpose, domain-independent and customizable function to evaluate the impact that the system has on its players (RQ1). The outcome of this work, which is currently under review, will be exploited in the module of the framework aimed at evaluating the impact that the generated content has on each player (*Impact Function* module in Figure1), to inform the decision strategy employed by the generator itself. We are currently designing the new edition of the game, applying the lessons learned from the analysis of the previous editions and introducing the framework so as to understand its validity. The last year will be dedicated to the analysis of the Player Social Network and the matchmaking algorithm (RQ3), as long as the evaluation of the framework itself, which will be (partially) conducted during my visiting period at the Graz University of Technology.

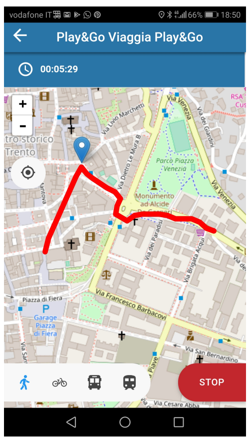

Figure 2: Play&Go screenshot https://play.google.com/store/apps/details?id=it.smartcommunitylab.viaggiatrento.playgo&hl=e

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