Player Modeling

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Abstract

Player modeling is the study of computational models of players in games. This includes the detection, modeling, prediction and expression of human player characteristics which are manifested through cognitive, affective and behavioral patterns. This chapter introduces a holistic view of player modeling and provides a high level taxonomy and discussion of the key components of a player's model. The discussion focuses on a taxonomy of approaches for constructing a player model, the available types of data for the model's input and a proposed classification for the model's output. The chapter provides also a brief overview of some promising applications and a discussion of the key challenges player modeling is currently facing which are linked to the input, the output and the computational model.

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1 Introduction

Digital games are dynamic, *ergodic* media (i.e., a user interacts with and alters the state of the medium). They are designed to be highly engaging and embed rich forms of user interactivity. Collectively, the human-computer interaction (HCI) attributes of digital games allow for high levels of player incorporation [9]. As such, they yield dynamic and complex emotion manifestations which cannot be captured trivially byf standard methods in affective computing or cognitive modeling research. The high potential that games have in affecting players is mainly due to their ability of placing the player in a continuous mode of interaction, which develops complex cognitive, affective and behavioral responses. The study of the player in games may not only contribute to the design of improved forms of HCI, but also advance our knowledge of human experiences.

Every game features at least one user (i.e., the player), who controls an avatar or a group of miniature entities in a virtual/simulated environment [9]. Control may vary from the relatively simple (e.g., limited to movement in an orthogonal grid) to the highly complex (e.g., having to decide several times per second between hundreds of different possibilities in a highly complex 3D world). The interaction between the player and the game context is

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of prime importance to modern game development, as it breeds unique stimuli which yield emotional manifestations to the player. Successful games manage to elicit these emotions in a manner that is appreciated by the player, and which form the main reason that the player is willing to engage in the game [50].

The primary goal of player modeling and player experience research is to understand how the interaction with a game is experienced by individual players. Thus, while games can be utilized as an arena for eliciting, evaluating, expressing and even synthesizing experience, we argue that one of the main aims of the study of players in games is the understanding of players' cognitive, affective and behavioral patterns. Indeed, by the nature of what constitutes a game, one cannot dissociate games from player experience.

This chapter focuses on experience aspects that can be detected from, modeled from, and expressed in games with human players. We explicitly exclude the modeling of non-player characters (NPCs), as in our view, player modeling involves a *human player* in the modeling process. We also make a distinction between *player modeling* [10, 26] and *player profiling*. The former refers to modeling complex *dynamic* phenomena during gameplay interaction, whereas the latter refers to the categorization of players based on *static* information that does not alter during gameplay — that includes personality, cultural background, gender and age. We will mainly focus on the first, but will not ignore the second, as the availability of a good player profile may contribute to the construction of reliable player models.

In summary, player modeling — as we define it in this chapter — is the study of computational means for the modeling of player cognitive, behavioral, and affective states which are based on data (or theories) derived from the interaction of a human player with a game [78]. Player models are built on *dynamic* information obtained during game-player interaction, but they could also rely on *static* player profiling information. Unlike earlier studies focusing on taxonomies of *behavioral* player modeling — e.g., via a number of different dimensions [58] or direct/indirect measurements [56] — we view player modeling in a holistic manner including cognitive, affective, personality and demographic aspects of the player. Moreover, we exclude approaches that are not directly based on human-generated data or not based on empirically-evaluated theories of player experience, human cognition, affect or behavior. The chapter does not intend to provide an inclusive review of player modeling studies under the above definition, but rather a high-level taxonomy that explores the possibilities with respect to the modeling approach, the model's input and the model's output.

The rest of this chapter provides a taxonomy and discussion of the core components of a player model which are depicted in Figure 1. That includes the computational model itself and methods to derive it as well as the model's input and output. The chapter illustrates a few promising applications of player modeling and ends with a discussion on open research questions for future research in this field.

2 Computational Model

Player modeling is, primarily, the study and use of artificial and computational intelligence (AI and CI) techniques for the construction of computational models of player behavior, cognition and emotion, as well as other aspects beyond their interaction with a game (such as their personality and cultural background). Player modeling places an AI umbrella to the multidisciplinary intersection of the fields of user (player) modeling, affective computing, experimental psychology and human-computer interaction.

One can detect behavioral, emotional or cognitive aspects of either a human player or

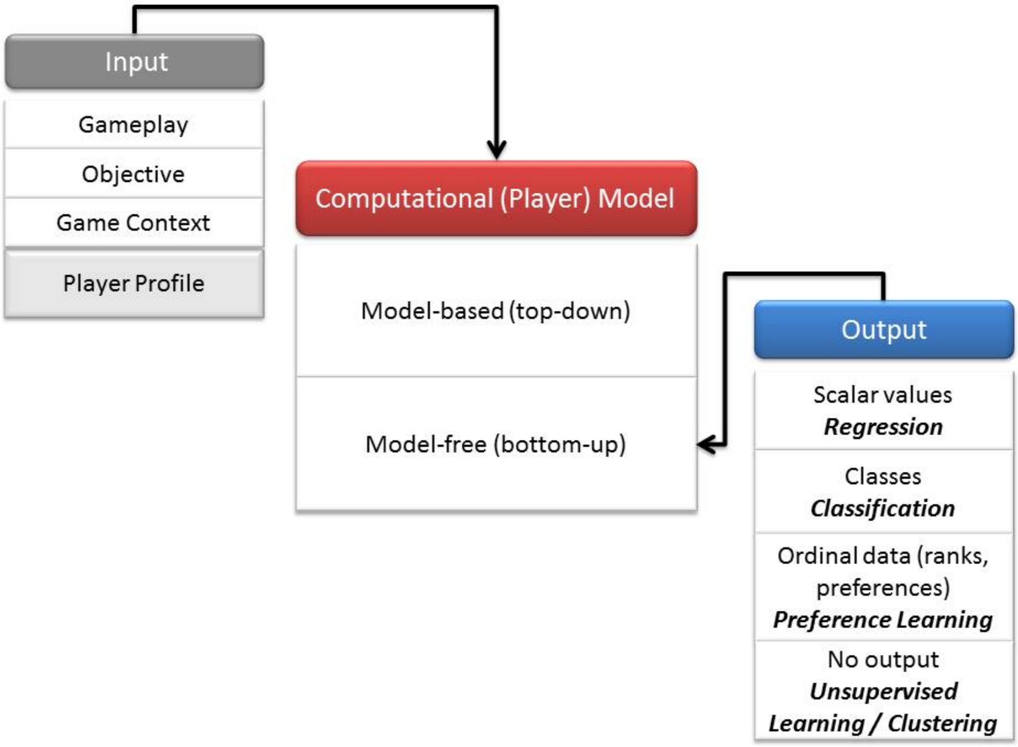

Figure 1 Player Modeling: the core components.

a non-player character (NPC). In principle, there is no need to model an NPC, for two reasons: (1) an NPC is coded, therefore a perfect model for it exists in the game's code, and is known by the game's developers; and (2) one can hardly say that an NPC possesses actual emotions or cognition. However, NPC modeling can be a useful testbed for player modeling techniques, by comparing the model discovered with the actual coded one. More interestingly, it can be an integral component of adaptive AI that changes its behavior in response to the dynamics of the opponents [6]. Nevertheless, while the challenges faced in modeling NPCs are substantial, the issues raised from the modeling of human players define a far more complex and important problem for the understanding of player experience.

By clustering the available approaches for player modeling, we are faced with either *model-based* or *model-free* approaches [80] as well as potential hybrids between them. The remaining of this section presents the key elements of both model-based and model-free approaches.

2.1 Model-based (Top-down) Approaches

According to a *model-based* or top-down [80] approach a player model is built on a theoretical framework. As such, researchers follow the modus operandi of the humanities and social sciences, which hypothesize models to explain phenomena, usually followed by an empirical phase in which they experimentally determine to what extent the hypothesized models fit observations.

Top-down approaches to player modeling may refer to emotional models derived from emotion theories (e.g., cognitive appraisal theory [21]). Three examples are: (1) the emotional dimensions of arousal and valence [19], (2) Frome's comprehensive model of emotional response to a single-player game [22], and (3) Russell's circumplex model of affect [51], in which emotional manifestations are mapped directly to specific emotional states (e.g., an increased heart rate of a player may correspond to high arousal and therefore to excitement). Model-based approaches can also be inspired by a general theoretical framework of behavioral analysis and/or cognitive modeling such as usability theory [30], the belief-desire-intention (BDI) model, the cognitive theory by Ortony, Clore, & Collins [47], Skinner's model [57], or Scherer's theory [53]. Moreover, theories about user affect exist that are driven by game design, such as Malone's design components for 'fun' games [40] and Koster's theory of 'fun' [35], as well as game-specific interpretations of Csikszentmihalyi's concept of Flow [14]. Finally, several top-down difficulty and challenge measures [2, 28, 45, 59, 60, 70, 75] have been proposed for different game genres as components of a player model. In all of these studies, difficulty adjustment is performed based on a player model that implies a direct link between challenge and 'fun'.

Note, however, that even though the literature is rich in theories on emotion, caution is warranted with the application of such theories to games (and game players), as most of them have not been derived from or tested on ergodic media such as games. Calleja [9], for instance, reflects on the inappropriateness of the concepts of 'flow', 'fun' and 'magic circle' (among others) for games.

2.2 Model-free (Bottom-up) Approaches

Model-free approaches refer to the construction of an unknown mapping (model) between (player) input and a player state representation. As such, model-free approaches follow the modus operandi of the exact sciences, in which observations are collected and analyzed to generate models without a strong initial assumption on what the model looks like or even what it captures. Player data and annotated player states are collected and used to derive the model. Classification, regression and preference learning techniques adopted from machine learning or statistical approaches are commonly used for the construction of a computational model. Data clustering is applied in cases where player states are not available.

In model-free approaches we meet attempts to model and predict player actions and intentions [64, 65, 76] as well as *game data mining* efforts to identify different behavioral playing patterns within a game [15, 43, 61, 62, 72]. Model-free approaches are common for facial expression and head pose recognition since subjects are asked to annotate facial (or head pose) images of users with particular affective states (see [55] among others) in a crowd-sourcing fashion. The approach is also common in studies of psychophysiology in games (see [68, 79] among others).

2.3 Hybrid Approaches

The space between a completely model-based and a completely model-free approach can be viewed as a continuum along which any player modeling approach might be placed. While a completely model-based approach relies solely on a theoretical framework that maps a player's responses to game stimuli, a completely model-free approach assumes there is an unknown function between modalities of user input and player states that a machine learner (or a statistical model) may discover, but does not assume anything about the structure of this function. Relative to these extremes, the vast majority of the existing works on player modeling may be viewed as hybrids between the two ends of the spectrum, containing elements of both approaches.

3 Input

The model's input can be of three main types: (1) anything that a human player is doing in a game environment gathered from *gameplay* data (i.e., behavioral data); (2) *objective* data collected as bodily responses to game stimuli such as physiology and body movements; and (3) the *game context* which comprises of any player-agent interactions but also any type of game content viewed, played, and/or created. The three input types are detailed in the remainder of this section. We also discuss static information on the player (such as personality and gender) that could feed a player model.

3.1 Gameplay Input

The main assumption behind the use of behavioral (gameplay-based) player input is that player actions and real-time preferences are linked to player experience as games may affect the player's cognitive processing patterns and cognitive focus. In the same vein, cognitive processes may influence player experience. One may infer the player's present experience by analyzing patterns of his interaction with the game, and by associating his emotions with context variables [12, 24]. Any element derived from the interaction between the player and the game forms the basis for gameplay-based player modeling. This includes detailed attributes of the player's behavior (i.e., game metrics) derived from responses to system elements (i.e., NPCs, game levels, or embodied conversational agents). Game metrics are statistical spatio-temporal features of game interaction [17]. Such data is usually mapped to levels of cognitive states such as attention, challenge and engagement [12]. In addition, both general measures (such as performance and time spent on a task) and game-specific measures (such as the weapons selected in a shooter game — e.g., in [25]) are relevant.

A major problem with interpreting such behavioral player input is that the actual player experience is only indirectly observed by measuring game metrics. For instance, a player who has little interaction with a game might be thoughtful and captivated, or just bored and busy doing something else. Gameplay metrics can only be used to approach the likelihood of the presence of certain player experiences. Such statistics may hold for player populations, but may provide little information for individual players. Therefore, when one attempts to use pure gameplay metrics to make estimates on player experiences and make the game respond in an appropriate manner to these perceived experiences, it is advisable to keep track of the feedback of the player to the game responses, and adapt when the feedback indicates that the player experience was gauged incorrectly.

3.2 Objective Input

Games can elicit player emotional responses which, in turn, may affect changes in the player's physiology, reflect on the player's facial expression, posture and speech, and alter the player's attention and focus level. Monitoring such bodily alterations may assist in recognizing and synthesizing the player's model. As such, the objective approach to player modeling incorporates access to multiple modalities of player input.

Within objective player modeling, a number of real-time recordings of the player may be investigated. Several studies have explored the interplay between physiology and gameplay by investigating the impact of different gameplay stimuli to dissimilar physiological signals. Such signals are usually obtained through electrocardiography (ECG) [79], photoplethysmography [68, 79], galvanic skin response (GSR) [41, 49], respiration [68], electroencephalography (EEG) [44], electromyography (EMG) and pupillometry [7]. In addition to physiology one may track the player's bodily expressions (motion tracking) at different levels of detail and infer the real-time affective responses from the gameplay stimuli. The core assumption of such input modalities is that particular bodily expressions are linked to basic emotions and cognitive processes. Motion tracking may include body posture [52] and head pose [55], as well as gaze [4] and facial expression [48].

While such objective multimodal measurements are usually more meaningful than the gameplay inputs discussed in the previous subsection, a major problem with most of them is that they are viewed by the player as invasive, thus affecting the player's experience with the game. This affect should be taken into account when interpreting measurements.

3.3 Game Context Input

In addition to both gameplay and objective input, the game's context is a necessary input for player modeling. Game context refers to the real-time parameterized state of the game. Player states are always linked to game context; a player model that does not take context into account runs a high risk of inferring erroneous states for the player. For example, an increase in galvanic skin response (GSR) can be linked to a set of dissimilar high-arousal affective states such as frustration and excitement; thus, the cause of the GSR increase (e.g., a player's death or level completion) needs to be fused within the GSR signal and embedded in the model.

3.4 Player Profile Information

Differences between players lead to different playing styles and preferences. Player profile information includes all the information about the player which is static and it is not directly (nor necessarily) linked to gameplay. This may include information on player personality (such as expressed by the Five Factor Model of personality [13]), culture dependent variables, and general demographics such as gender and age. Such information may be used as static model input and could lead to the construction of more accurate player models.

A typical way of employing player profile information is the stereotype approach [34]. The approach attempts to (automatically) assign a player to a previously defined subgroup of the population, for which key characteristics have been defined. Each subgroup is represented by a stereotype. After identifying to which subgroup the player belongs, the game can choose responses appropriate for the corresponding stereotype. This approach has been used by Yannakakis & Hallam [73] and by Thue [63]. They define stereotypes in terms of a player's gaming profile, rather than the gamer's characteristics outside the realm of gaming.

Van Lankveld et al [69, 71] look beyond pure gaming behavior, attempting to express a player's personality profile in terms of the Five Factor Model. While they achieve some success in modeling players in terms of the five factors, they notice that gameplay behavior not necessarily corresponds to "real life" behavior, e.g., an introverted person may very well exhibit in-game behavior that would typically be assigned to an extroverted person. Therefore, we can recognize two caveats which should be taken into account when aiming to use a real-life personality profile of a player to construct a model of the player inside a game: (1) the player's behavior inside the game not necessarily corresponds to his real-life behavior and vice versa; and (2) a player's real-life profile not necessarily indicates what he appreciates in a game.

4 Output

The model's output is usually a set of particular *player states*. Such states can be represented as a class, a scalar (or a vector of numbers) that maps to a player state — such as the emotional dimensions of arousal and valence or a behavioral pattern — or a relative strength (preference). The output of the model is provided through an annotation process which can either be driven by self-reports or by reports expressed indirectly by experts or external observers [80]. However, there are instances where reports on player states are not available; output then must be generated by unsupervised learning (see [15, 17] among others).

The most direct way to annotate a player state is to ask the players themselves about their playing experience and build a model based on these annotations. Subjective player state annotations can be based on either a player's free-response during play or on forced data retrieved through questionnaires. Free-response naturally contains richer information about the player's state, but it is often unstructured, even chaotic, and thus hard to analyze appropriately. Forcing players to self-report their experiences using directed questions, on the other hand, constrains them to specific questionnaire items which could vary from simple tick boxes to multiple choice items. Both the questions and the answers provided may vary from single words to sentences. Questionnaires can either involve elements of the player experience (e.g., the Game Experience Questionnaire [29]), or demographic data and/or personality traits (e.g., a validated psychological profiling questionnaire such as the NEO-PI-R [13]).

Alternatively, experts or external observers may annotate the player's experiences in a similar fashion. Third-person annotation entails the identification of particular player states (given in various types of representation as we will see below) by player experiences and game design experts (or crowd-sourced via non-experts). The annotation is usually based on the triangulation of multiple modalities of player and game input, such as the player's head pose, in-game behavior and game context [55]. Broadly-accepted emotional maps such as the Facial Action Coding System [18] provide common guidelines for third-person emotion annotation.

Three types of annotations (either forced self-reports or third-person reports) can be distinguished. The first is the *rating*-based format [41], which labels player experience states with a scalar value or a vector of values (found, for instance, in the Game Experience Questionnaire [29]). The second is the *class*-based format, which asks subjects to pick a user state from a particular representation which could vary from a simple boolean question (*was that game level frustrating or not? is this a sad facial expression?*) to a user state selection from, for instance, the Geneva Emotion Wheel [54]. The third is the *preference*-based format, which asks subjects to compare an experience in two or more variants/sessions of the game [77] (*was that level more engaging that this level? which facial expression looks happier?*). A recent comparative study has exposed the limitations of rating approaches over ranking questionnaire schemes (e.g., pairwise preference) which include increased order of play and inconsistency effects [74].

Beyond annotated player states or player profiles (such as personality traits), player models may be constructed to predict attributes of gameplay (e.g., in [39, 65] among others) or objective manifestations of the experience [3].

5 Applications

In this section we identify and briefly illustrate a few promising, and certainly non inclusive, applications of player modeling to game design and development, that range from adapting the challenge during the game to personalizing the purchasing model in free-to-play games.

5.1 Adaptive Player Experience and Game Balancing

As already mentioned in section 2.1 there exist several theoretical frameworks investigating the relationship between experience and game interaction that have been either built with primarily games in mind (e.g. the player immersion model of Calleja [9]; the theory of 'fun' of Koster [35]) or derived from other fields (e.g. psychology) and domains and tailored to games (e.g. the theory of flow [14] adopted for games [11]). Essentially what unifies all these theories is that ultimate player experience is achieved when elements of the game (mechanics, storyline, challenges) are in some sort of right balance with the general skills of the player. A common, but rather simplistic, approach to balance between game challenges and different player skills in order to match a broader range of players consists of providing a small, predefined set of difficulty levels which the player can pick from. A more sophisticated approach consists of adapting the game's challenge in response to the actions of the players and to the state of the game environment; relevant examples of this approach are the *AI director* [8] of *Left 4 Dead* (Valve, 2008) and the *race script* [23] framework used in *Pure* (Black Rock Studio, 2008).

Most of the game balancing approaches currently used rely on simple in-game statistics to estimate the state of the players and make strong assumptions on what kind of experience the players are looking for in the game (e.g., the basic assumption behind the AI director in *Left 4 Dead* is that players enjoy dramatic and unpredictable changes of pace). While, in general, such assumptions hold for a large number of players (as the designers usually have a good idea of their players), they are not universally applicable and may actually exclude large groups of potential players that would be willing to play a game if it would offer an experience more to their liking. Reliable player modeling techniques have the potential to adapt the challenge level of a game (and other gameplay elements) in a manner that suits each individual player [75, 1].

5.2 Personalized Game Content Generation

Procedural content generation (PCG) aims to deliver a large amount of game content algorithmically with limited memory resources. Nowadays PCG is mainly used to cut the development cost and, at the same time, to face the increasing expectations of players in terms of game content. Recently, the problem of automating the generation of high-quality game content has attracted considerable interest in the research community (see [78] and the corresponding chapter in this volume). In particular, research showed that search algorithms can be combined successfully with procedural content generation to discover novel and enjoyable game content [38, 66, 67]. Accordingly, the automation of content creation offers an opportunity towards realizing player model-driven procedural content generation in games [80]. The coupling of player modeling with PCG approaches may lead to the automatic generation of personalized game content.

Player models may also inform the generation of computational narrative (viewed here as a type of game content [80]). Predictive models of playing behavior, cognition and affect can drive the generation of individualised scenarios in a game. Examples of the coupling between player modeling and interactive narrative include the affect-driven narrative systems met in *Façade* [42] and *FearNot!* [5], the emotion-driven narrative building system in *Storybricks* (Namaste Entertainment, 2012), and the affect-centred game narratives such as the one of *Final Fantasy VII* (Square Product, 1997).

5.2.1 Towards Believable Agents

Human player models can inform and update believable agent architectures. Behavioral, affective and cognitive aspects of human gameplay can improve the human-likeness and believability of any agent controller — whether that is ad-hoc designed or built on data derived from gameplay. While the link between player modelling and believable agent design is obvious and direct the research efforts towards this integration within games is still sparse. However, the few efforts made on the imitation of human game playing for the construction of believable architectures have resulted in successful outcomes. Human behavior imitation in platform [46] and racing games [31] have provided human-like and believable agents while similar approaches for developing *Unreal Tournament* bots (e.g. in [33]) recently managed to pass the Turing test in the 2k BotPrize competition.

5.3 Playtesting Analysis and Game Authoring

While aiming at creating a particular game *experience*, designers can only define and alter the game *mechanics* [11, 27] (i.e., game rules) that, in turn, will affect the playing experience. From the mechanics arise the *game dynamics*, i.e., *how* the game is actually played. The dynamics lead to *game aesthetics*, i.e., what the player experiences during the game.

Even when a game is tested specifically to determine whether it provides the desired player experience, it is usually difficult to identify accurately which are the specific elements of the mechanics that work as intended. Player modeling, which yields a relationship between player state, game context, and in-game behavior, may support the analysis of playtesting sessions and the identification of what appeals to a particular player, and what does not (see [15, 43, 72] among many).

Player modeling provides a multifaceted improvement to game development as it does not only advance the study of human play and the enhancement of human experience. Quantitative testing via game metrics — varying from behavioral data mining to in-depth low scale studies — is improved as it complements existing practices [78].

Finally, user models can enhance authoring tools that, in turn, can assist the design process. The research field that bridges user modeling and AI-assisted design is in its infancy and only a few example studies can be identified. Indicatively, designer models have been employed to personalise mixed-initiative design processes [37, 36]. Such models drive the procedural generation of designer-tailored content.

5.4 Monetization of Free-to-Play Games

Recent years have seen an increasing number of successful free-to-play (F2P) games on diverse platforms, including Facebook, mobile devices and PC. In F2P games, playing the game itself is free. Revenues come from selling additional contents or services to the players with in-game *microtransactions* [20]. In order to be profitable, these games require developers to constantly monitor the purchasing behavior of their players [20]. Player modeling may improve the understanding of the players behavior [16] and help with the identification of players who are willing to pay. In addition, the information provided by player modeling might be used to customize the market content and mechanisms, eventually leading to increased profits.

6 The Road Ahead: Challenges and Questions

In this section we list a number of critical current and future challenges for player modeling as well as promising research directions, some of which have been touched upon in the previous sections.

- Regardless of the line of research in player modeling chosen, the biggest obstacle right now is lack of proper and rich data publicly available to the researchers. What is required is a rich multimodal corpus of gameplay and player data as well as player descriptions. Such a corpus must include detailed gameplay data for several games for a large number of players, including actions, events, locations, timestamps as well as biometrical data, that are trivial to obtain in large volumes (e.g., camera images and eye-tracking). Demographic data for the players must be available, as well as player information in the form of several questionnaires and structured interview data. Not all this data needs to be available for every subject in the database; several large datasets of gameplay data already exist, and it would be beneficial to include those in the database too.
- The use of procedural content generation techniques for the design of better games has reached a peak of interest in commercial and independent game development [78], which is showcased by successful (almost entirely procedurally generated) games such as *Minecraft* (Mojang, 2011) and *Love* (Eskil Steenberg, 2010). Future games, in general, are expected to contain less manual and more user-generated or procedurally-generated content, as the cost of content creation and the content creation bottleneck are key challenges for commercial game production. As the number of games that are (partially or fully) automatically generated grows, the challenge of modeling players in never-ending open worlds of infinite replayability value increases substantially.
- Nowadays, several modalities or player input are still implausible within commercial game development. For instance, existing hardware for physiological measurements requires the placement of body parts (e.g., head or fingertips) to the sensors, making physiological signals such as EEG, respiration and skin conductance rather impractical and highly intrusive for most games. Modalities such as facial expression and speech could be technically plausible in future games: even though the majority of the vision-based affect-detection systems currently available cannot operate in real-time [81], the technology in this field is rapidly evolving [32].

  On a positive note, recent advances in sensor technology have resulted in low-cost unobtrusive biofeedback devices appropriate for gaming applications. In addition, top game developers have started to experiment with multiple modalities of player input (e.g., physiological and behavioral patterns) for the personalization of experience of popular triple-A games such as *Left 4 Dead* (Valve, 2008) [1]. Finally, recent technology advances in gaming peripherals such as the PrimeSense camera showcase a promising future for multimodal natural interaction in games.
- Comparing model-based and model-free approaches to player modeling, we note that model-based inherently contains argumentation and understanding for the choices of the model, which model-free lacks. However, practice shows that model-based approaches often fail to encompass relevant features because of a lack of insight of the model builders. The model-free approach has the advantage of automatically detecting relevant features; however, it is also prone to detecting meaningless relationships between user attributes, game context and user experience. In computer games an extensive set of features of player behavior can be extracted and measured. At the same time there is, usually, lack of insight in what these features actually mean, at least at present. Therefore, in the current state of research, model-free approaches seem most suitable. Domain-specific knowledge, feature extraction and feature selection are necessary to achieve meaningful models of players .
- As mentioned before, player characteristics within a game environment may very well differ from the characteristics of the player when dealing with reality. Thus, validated personality

models such as psychology's Five Factor Model might not fit well to game behavior. An interesting direction in player modeling research is to determine a fundamental personality model for game behavior; such a model will have some correspondence with the Five Factor Model, but will also encompass different characteristics. Moreover, the behavioral clues that can be found in game behavior may be considerably different from those that can be found in reality.

- Experience has shown that diligent application of data mining techniques may provide insight into group behaviors. However, it remains difficult to make predictions about individuals. As such, player models can usually only give broad and fuzzy indications on how a game should adapt to cater to a specific player. One possible solution is to define several possible player models and classify an individual player as one of them (the stereotyping approach). Then, when gameplay is going on, the model can be changed in small steps to fit the player better. I.e., the player model is not determined as a static representation of the player, used to determine how the game should be adapted; rather it is a dynamic representation of a group of players, that changes to highlight the general characteristics of a specific player, and drives the game adaptation dynamically. In our view, this step-wise approach to game adaption by means of player modeling has the potential to lead to quick, good results in creating games that offer a personalized form of engagement to the player.

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