



MODELAGEM DE JOGADORES COM PROVENIÊNCIA

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Orientador: Geraldo Xexéo

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This thesis presents an overview about Player Modeling

Abstract of Dissertation presented to COPPE/UFRJ as a partial fulfillment of the requirements for the degree of Master of Science (M.Sc.)

PLAYER MODELING WITH PROVENANCE

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This thesis presents an overview about Player Modeling and shows how Provenance can help while building such models.

Player Modeling is inherently associated with games in general. In this context, some questions come to the mind when modeling a player - the foremost question is: what is a player model? A second possible question can be: what kind of input is used to model a player?... going on: what processes are involved while building a player model? A possible question to close the loop: what is the purpose\outcome of building player models after all?

This work was conceived because the author has a true appreciation for electronic games and specifically in how mapping\modeling player motivations, preferences and actions can change the outcome for both players and game creators\developers.

We live in the big data boom era and as such we have plenty of raw data to explore. Game session logs can be explored in many different ways. This data hides gems that can improve player entertainment while maximizing game creators budget.

All in all what the player wants is a engaging game with balanced characteristics, that is, not too easy and not too hard; not too short and not too long, etc. At the same time, game developers want to create those engaging games of course. To be able to create such games, the use of player models can be of high value and that's what this thesis discuss in a more deep level.

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List of Abbreviations

AI	Artificial Intelligence, p. 1
DARPA	Defense Advanced Research Projects Agency, p. 5
HCI	Human Computer Interaction, p. 4
NPC	Non-Player Character, p. 7

Chapter 1

Introduction

Player Modeling is currently a very relevant topic in game Artificial Intelligence (AI) research.

The term “player model” is nebulous, and a broad spectrum of possible definitions have been used in various publications [2]. While many people have described player modeling and discussed its importance, the definition and usage of the idea has grown over time, with no single clear definition or scope.

The practice of trying to understand players through analyzing their interactions with the games they play is becoming more and more common and important. Under the labels “player modeling”, “game data mining” and “game analytics”, researchers from various fields (game studies, game design, computational intelligence and statistical machine learning) are bringing learning algorithms and statistical techniques to bear on the logs of (usually multiple, sometimes huge numbers of) players playing games.

The most important goal for almost every existing game is entertainment [3] and this is achieved with a combination of items like graphics, story (in some game genres) and AI. Entertainment is a subjective concept and, in order to know how much a game entertains a player, some general metrics are evaluated. One of the most important metrics is immersion, which is generally related to how absorbing and engaging a game is. Two common approaches to achieve immersion are the use of stunning graphics and the development of a good AI system. While graphics are responsible for initially “seducing” the players, AI is responsible for keeping them interested and engaged in the game. The aesthetic elements were the industry’s main concern for a long time since they are more attractive. It’s easier to convince a customer to buy a game because it “looks good” than because it has a complex AI that is much harder to be presented in marketing events. However this scenario is starting to change. Game AI is receiving increasing attention since it helps keeping the player engaged to the game.

The successful design of player experience can make the difference between a

game that engages players for extended periods of time and a game that contains content — whether that is mechanics, levels, maps or narrative plots — that fail to elicit appropriate experience patterns and rich affective experiences to its users [4].

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, 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 [5].

Basically, player modeling consists in modeling the player characteristics and behaviors during the game in order to improve some game aspect. A more formal definition, discussed in [1, 6], considers player modeling as “an abstract description of the current state of a player at a moment. This description can be done in several ways like satisfaction, knowledge, position and strategy”.

In summary, player modeling 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 [7].

TODO: mention the methodology, as well as its scope and significance;

Chapter 2

Literature Review

In this work player modeling is applied to electronic games. What follows is a brief background information about the main topics discussed in this work.

2.1 Games

2.1.1 What is a Game?

The existence of a discussion about what a game is, or whether some activity is actually a game may surprise those who stumble upon it for the first time. However, while studying games, it is important to understand what we are analyzing or what we are creating. For this, it is better that the concept of what defines a “game” is plain clear and that we know how far we are moving away from an “ideal game” when we are creating a new game [8].

Based on various definitions of games found in the literature and repeated in several introductory articles and also in the observation and detailed analysis of what happens when we play, the following definition of what a game is, can serve as a beacon for our study:

Games are social and cultural voluntary activities, meaningful, strongly absorbing, non-productive, that use an abstract world with real-world negotiated effects, and whose development and final outcome is uncertain, where one or more players or teams of players, interactively and quantitatively modify the state of an artificial system, possibly in pursuit of conflicting goals, by means of decisions and actions, some with the capacity to disrupt the opponent, being the whole process regulated, oriented and limited by accepted rules, and thereby obtaining a psychological reward, usually in the form of entertainment, amusement, or a sense of victory over an adversary or challenge.

The reason for having a definition of what a game is is not to create a barrier between games and not games. What we want is to delimit in a fluid way what we consider a game. We may think that this definition is a big “or” of requisites. Thus, something totally ceases to be a game only when all conditions are broken [8].

2.1.2 Game Potential

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 [5].

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 of prime importance to modern game development, as it breeds unique stimuli which yield emotional manifestations to the player.

The study of the player in games may not only contribute to the design of improved forms of Human Computer Interactions (HCI), but also advance our knowledge about human experiences.

2.1.3 Game Industry

According to the Global Games Market Report [10] the gaming market has now 2.2 billion gamers across the globe with an expectation of generating \$116 billion in game revenues in 2017 [11].

It is a competitive market especially in terms of gameplay, which is something largely determined by the quality of a game’s AI. A game with a large variety of unique agent behaviors has a competitive advantage to a game with a few hand coded expert systems. In addition to being a preferred investment to developers it’s also a viable option on current hardware. Due to hardware advancements, processor cycles are easier to come by and memory is cheap.

2.2 Artificial Intelligence

2.2.1 History

Can machines think? This is the main question regarding artificial intelligence (AI).

In the first half of the 20th century, science fiction familiarized the world with the concept of artificially intelligent robots. It began with the “heartless” Tin man from the Wizard of Oz. By the 1950s, we had a generation of scientists, mathematicians, and philosophers with the concept of artificial intelligence (or AI) culturally assimilated in their minds. One such person was Alan Turing, a young British polymath who explored the mathematical possibility of artificial intelligence. Turing suggested that humans use available information as well as reason in order to solve problems and make decisions, so why can’t machines do the same thing? This was the logical framework of his 1950 paper, *Computing Machinery and Intelligence* [12] in which he discussed how to build intelligent machines and how to test their intelligence.

From that point on, computers needed to fundamentally change. Before 1949 computers lacked a key prerequisite for intelligence: they couldn’t store commands, only execute them. In other words, computers could be told what to do but couldn’t remember what they did. With advancements in this area, AI flourished from 1957 to 1974. Computers could store more information and became faster, cheaper, and more accessible. Machine learning algorithms also improved and people got better at knowing which algorithm to apply to their problems.

Initial successes, as well as the advocacy of leading researchers convinced government agencies such as the Defense Advanced Research Projects Agency (DARPA) in the United States to fund AI research at several institutions. The government was particularly interested in a machine that could transcribe and translate spoken language as well as high throughput data processing.

In the 1980’s, AI was reignited by two sources: an expansion of the algorithmic toolkit, and a boost of fun “deep learning” techniques got popularized which allowed computers to learn using experience. Expert systems which mimicked the decision making process of a human expert were also introduced. The program would ask an expert in a field how to respond in a given situation, and once this was learned for virtually every situation, non-experts could receive advice from that program.

During the 1990s and 2000s, many of the landmark goals of artificial intelligence had been achieved. In 1997, reigning world chess champion and grand master Gary Kasparov was defeated by IBM’s Deep Blue, a chess playing computer program. In the same year, speech recognition software was implemented on Windows. This was another great step forward but in the direction of the spoken language interpretation endeavor. It seemed that there wasn’t a problem machines couldn’t handle.

We haven’t gotten any smarter about how we are coding artificial intelligence, so what changed? It turns out, the fundamental limit of computer storage that was holding us back 30 years ago was no longer a problem. , which estimates that the memory and speed of computers doubles every year, had finally caught up and in many cases, surpassed our needs. It offers a bit of an explanation to the roller

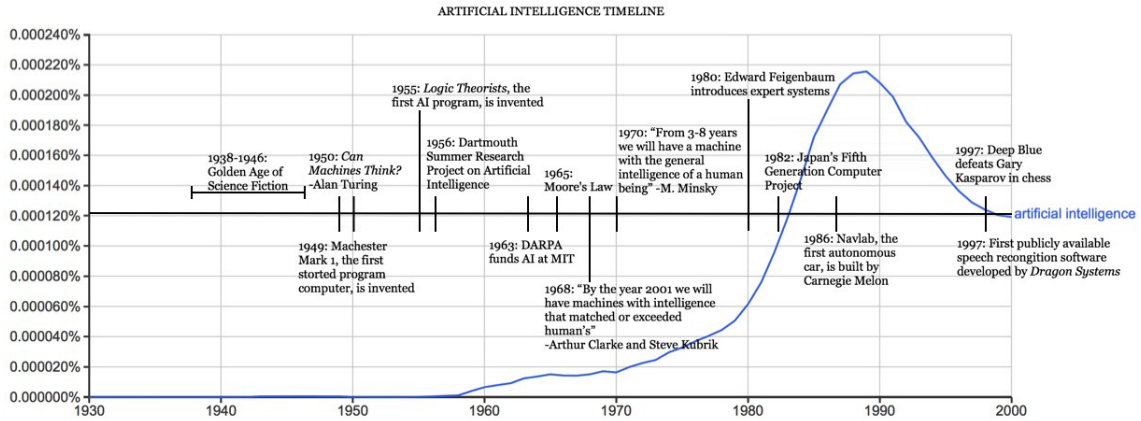


Figure 2.1: Artificial Intelligence Timeline

coaster of AI research; we saturate the capabilities of AI to the level of our current computational power (computer storage and processing speed), and then wait for Moore's Law to catch up again.

We now live in the age of "big data" an age in which we have the capacity to collect huge sums of information too cumbersome for a person to process. The application of artificial intelligence in this regard has already been quite fruitful in several industries such as technology, banking, marketing, and entertainment. We've seen that even if algorithms don't improve much, big data and massive computing simply allow artificial intelligence to learn through brute force. There may be evidence that Moore's law is slowing down a tad, but the increase in data certainly hasn't lost any momentum. Breakthroughs in computer science, mathematics, or neuroscience all serve as potential outs through the ceiling of Moore's Law.

So, what is in store for the future? In the immediate future, AI language is looking like the next big thing. In fact, it's already underway. Today when we call a company, most of the time we directly spoke with a human. These days, machines are even calling us! One could imagine interacting with an expert system in a fluid conversation, or having a conversation in two different languages being translated in real time. We can also expect to see driverless cars on the road in the near future. In the long term, the goal is general intelligence, that is a machine that surpasses human cognitive abilities in all tasks. Even if the capability is there, the ethically would serve as a strong barrier against fruition. When that time comes (but better even before the time comes), we will need to have a serious conversation about machine policy and ethics, but for now, we'll allow AI to steadily improve and run amok in society [13].

2.2.2 AI in Player Modeling

Over the last years, with the increase in computers' processing power, AI is receiving more attention as a fundamental feature and new techniques are constantly being proposed. One approach that is gaining attention is Player Modeling. It intends to understand and model players' characteristics and behaviors during the game. This modeling allows games to customize their AI to specific players, making the game experience more interesting. Among the players characteristics that can be modeled are preferences and knowledge [1].

In a scenario in which AI is gradually receiving more attention from the game industry and lots of gameplay data are available for processing, customization is a feature that will become very relevant in the next years. Mainly because it is able to increase players' immersion and consequently the players' entertainment. A technique that may be underneath customization is player modeling.

Among the several AI approaches, Player Modeling is gaining importance as an alternative for making games more adaptable and consequently, more challenging.

For the experienced player, the AI is never good enough. It needs to keep challenging the player, to adapt to the player and if possible learn from the player.

2.3 Player Modeling

Player models are built on dynamic information obtained during game-player interaction\sessions, but they could also rely on static player profiling information [5]. The core components of a player model are depicted in Figure 2.2. It includes the computational model itself and methods to derive it as well as the model's input and output.

It's trivial to detect behavioral, emotional or cognitive aspects of either a human player or 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.

By clustering the available approaches for player modeling, we are faced with either model-based or model-free approaches as well as potential hybrids between them [5].

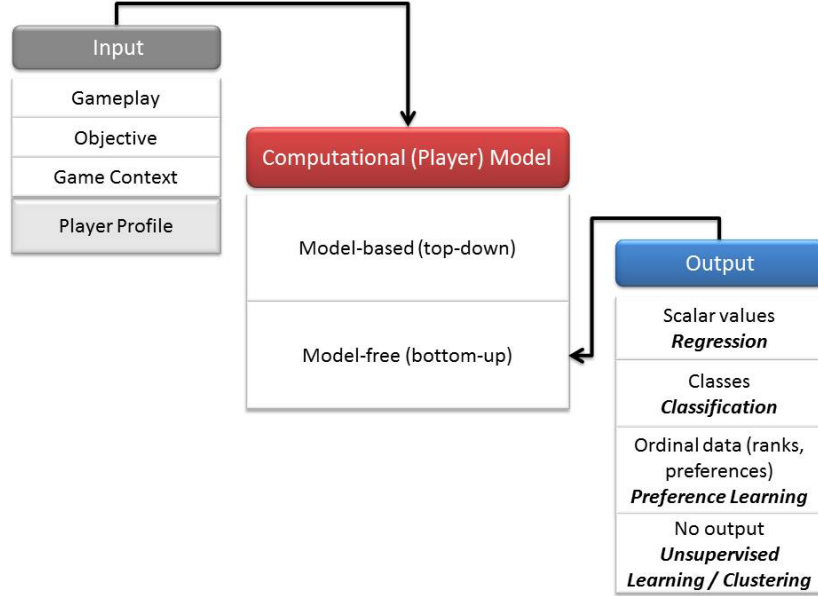


Figure 2.2: Player Model components

2.3.1 Top-down (model-based)

A top-down approach is based and built on a theoretical framework such as the usability theory [14]. Researchers follow the *modus operandi* of the humanities and social sciences, which hypothesize models to explain phenomena, usually followed by an empirical phase¹ in which they experimentally determine to what extent the hypothesized models fit.

Moreover, there are theories that are driven by game design, such as Malone's design components for 'fun' games [16] and Koster's theory of fun [17].

Several top-down difficulty and challenge measures 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' [5].

2.3.2 Bottom-up (model-free)

A model-free approach refers to the construction of an unknown mapping or model between player input and a player state representation. Researchers 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

¹Empirical means based on, concerned with, or verifiable by observation or experience rather than theory or pure logic. A naive observer might indeed conjecture that science owes its special status because it pays close attention to observed phenomena (the empirical data) and draws whatever conclusions these phenomena inductively warrant (empirical confirmation) [15].

and used to derive the model. In a later stage, classification, regression and preference learning techniques adopted from machine learning or statistical approaches are commonly used for the construction of a computational model [5]. In model-free approaches we meet attempts to model and predict player actions and intentions. Data mining efforts are put into use to identify different behavioral playing patterns within a game.

2.3.3 Hybrids

The space between a model-based and a 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 learning algorithm (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 [5].

2.3.4 Taxonomies

Taxonomies are important guiders that show us available paths to follow. They try to define, name and then group similar characteristics and features of the studied subject. As such, [1] defines a possible taxonomy for player modeling.

Table 2.1: Player Modeling Taxonomy Summary by [1]

Description	Categories	Goals	Applications	Methods	Implementation
Knowledge	Online Tracking	Collaboration	Speculation in Search	Action Modeling	Explicit
Position	Online Strategy Recognition	Adversarial	Tutoring	Preference Modeling	Implicit
Strategy	Off-line Review	Storytelling	Training	Position Modeling	
Satisfaction			Substitution	Knowledge Modeling	

This taxonomy can be explained through a set of questions related to a research in player modeling. The following questions are going to be used as a guideline since answering them implies in an advance in the understanding of the project at hand.

1. What the model is going to describe?

2. When is the data going to be processed?
 - (a) if the data is processed and attempts to predict actions are made all the time, this is called online tracking;
 - (b) if the data is processed in batches during the game while observing a set of actions, this is called online strategy recognition;
 - (c) if the whole game data is processed afterwards, this is called an off-line review.
3. What is the expected goal\outcome with Player Modeling?
4. What gameplay activity the model is going to improve?
5. What models are going to be used to generate an understanding about the agent?
6. What is the interface between the algorithms and the game in which the model is going to be used?
 - (a) if the source code is available, program it explicitly;
 - (b) if the platform only offers scripting languages or other interfaces, program it implicitly.

Chapter 3

Methodology

A methodology chapter, explaining how the research has been designed and why the research methods/population/data collection and analysis being used have been chosen.

Chapter 4

Results

A findings chapter, outlining the findings of the research itself.

Chapter 5

Analysis and Discussion

An analysis and discussion chapter, analyzing the findings and discussing them in the context of the literature review (this chapter is often divided into two—analysis and discussion).

Chapter 6

Conclusions

The goal of your conclusion isn't to introduce any new ideas, but to sum up everything you've written. Specifically, your conclusion should accomplish three major goals:

1. Restate the main idea of your essay, or your thesis statement
2. Summarize the sub-points of your essay
3. Leave the reader with an interesting final impression

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Appendix A

Demos

Notes

■ TODO: mention the methodology, as well as its scope and significance; . . . 2