AIIDE 2012 Doctoral Consortium
AAAI Technical Report WS-12-18

Creating Model-Based Adaptive Environments Using Game-Specific and Game-Dependent Analytics

Brent Harrison
North Carolina State University
Raleigh, North Carolina 27606

Abstract

My research involves creating and evaluating adaptive game environments using player models created using data-driven techniques and algorithms. I hypothesize that I will be able to change parts of a game to elicit certain behaviors from players, and that these changes will also result in an increase of engagement and/or intrinsic motivation.

Introduction

The goal of my research is to show that game analytics can be used in a variety of different game environments to model players and that those models can be used to adapt games to encourage/discourage certain types of behavior. I hypothesize that these changes will also increase player engagement and/or intrinsic motivation. To make progress towards this goal there are three research questions that I must address:

1. Can game analytics be used to model player behavior and if so, what are the techniques to do so?
2. How can we use these models of player behavior to change different game environments to elicit a desired response in the player?
3. Do these changes elicit the desired response in players?

To this end, I have chosen to study two different game environments: a simple one and a complex one. The simple environment is a flash game based on the board game *Scrabble* (Figure 1), and the complex environment is a quest-based adventure game named *Sidequest: The Game* (SQ:TG) (Figure 2). To answer the first question, I will design algorithms to model player behavior based only on data. To answer the second question, I will create techniques to procedurally adapt content in real time and then integrate these adaptions into one system. To address the final question, I will evaluate the effect that each adaption had on players.

Motivation

Recent research has made it clear that there are different aspects of gameplay that appeal to different players (Bartle 1996). Therefore, game designers create games that include

Figure 1: A flash game based on the board game *Scrabble*

different types of gameplay to appeal to a wide audience. An effect of this type of design is that games can become quite large and contain content that some players may never see.

Figure 2: A screenshot of Sidequest: The Game

In response to this, there has been an increasing interest in *adaptive* video games. An adaptive video game is a video game that changes itself based on the player that is currently playing it. Examples of adaptive games include games that alter the difficulty of the game to produce challenging experiences and games that guide the player towards content that they will enjoy. Currently, there has been little work done on using data to create adaptive game environments. This goal of this work is to show that data-driven algorithms can be used during both the model creation stage and the game adaption stage to make an adaptive game environment.

Related Work

Since my research takes place in three phases, I will present work related to each phase below. Each section will provide a brief, illustrative sample of the work done in this field.

Player Modeling

One technique that is used to generate player models is to use player feedback. These techniques were used by Richard Bartle (1996) to create his taxonomy of four player types and by Nick Yee (2006) to determine player motivations in online games. Another strategy for creating player models is to use prior knowledge to inform the creation process. The models used in the *PaSSAGE* system (Thue, Bulitko, and Spetch 2008) use an author-informed mapping from actions onto predefined player types in order to determine which actions certain users will prefer.

The techniques that I propose to create player models differ from these techniques in that focus only on the data produced during gameplay. While some of the features that I will use to create these models are chosen based on intuition, my methods will differ from previous methods (such as the techniques proposed by Thue *et al.*) in that I make no assumptions about how these features will affect different types of players. I would, however, examine gameplay data to determine how different types of players interact with different features and use that to create my models.

There have been several advancements in the area of data-driven player modeling. Drachen *et al* (2009) used self-organizing maps to determine that four classes of players exist in *Tomb-Raider: Underworld* by examining a set of game-specific analytics. Recently, Zook *et al* (2012) used matrix factorization to model and predict player performance in training simulations.

Game Adaption

Perhaps the most common form of game adaption is dynamic difficulty adjustment (DDA). Hagelback and Johansson (2009) showed that players enjoyed playing against bots with DDA since they produced closer games. A famous example of difficulty scaling can be found in *Left 4 Dead* (2009). *Left 4 Dead* employs an AI director controls the number of enemies spawned in order to induce certain responses from the players during gameplay.

The PaSSAGE system (Thue, Bulitko, and Spetch 2008) presents content to a player based on that player's *type*. It is important to note that while PaSSAGE uses data to make these adaptions, the models on which their adaptions are based are constructed using knowledge engineering.

The work that I am doing will incorporate aspects of DDA as well as aspects of player preference based game adaption. My main contribution to this area will be the creation of a purely data-driven system that integrates several types of adaption as well as showing the effects that these adaptions have on actual players.

Constructing Player Models

One of the questions that I will address through my research is whether game analytics can be used to create models of player behavior. To answer this question, I must be able to discover patterns of behavior that exist in the game environments that I am studying. In this research, I am defining a player model as a computational model that describes a trend or pattern present in the way people play games.

Table 1: Examples of game-specific and game-independent analytics in simple and complex game environments. Also included is the example game that I am using for each.

	Specific	Independent
Simple(*Scrabble*)	Game Score, Word Length, Word Played	Mouse Clicks, Mouse Position
Complex(SQ:TG)	Goals Completed, Number of Kills, Number of Deaths	Mouse Clicks, Mouse Position

In order to create these models, I must examine several aspects, or features, of gameplay. I have chosen to divide these features into two categories:

- Game-independent features
- Game-specific features

Game-independent features are features that exist in almost every video game. An example of these types of features are those that deal with input devices. Since most games have a way to interact with the game environment, these types of features are considered independent of the type of game being played. Game-specific features are features that cannot be separated from the game that they are found in. Examples of these include the words a user has played in *Scrabble* or the quests a player has completed in SQ:TG. A table containing examples of these features can be found in Table 1.

There are several reasons that I have chosen to examine these two classes of gameplay features. One reason to study game-independent features is that the resultant models could be applicable to other games. A reason for using game-specific features is that they are likely to increase the accuracy of the models they are used to create since game-specific features can be used to create a more detailed description of a player's behavior during a game session. By considering these two types of features together, we get a more accurate description of a player's behavior.

To create these models, I must identify predictive trends that exist in these features. For SQ:TG, I have explored using correlation networks to identify sets of quests that are likely to be completed together (2011). Using this information, I can predict which quests a player is likely to complete in real-time. For *Scrabble*, I have created a naive Bayesian model to calculate the probability that a player will quit the game prematurely (2012).

Game Adaption

Once we have these models of human behavior in games, I will develop techniques that use these models to adapt each game in order to elicit certain behavioral responses in players. There are two hypotheses that I will test concerning these adaptions. The first of these is that changing certain aspects of the game environment will result in a predictable change in the player's behavior. The second is that these adaptions will result in a more engaging/intrinsically motivating experience than in a non-adaptive game environment.

The adaptions made can be divided into two classes:

- Facilitative: Adaptions that encourage certain behavior
- Inhibitive: Adaptions that discourage certain behavior

Examples of behaviors we would want to facilitate might include players completing certain quests in SQ:TG or players playing certain types of words in *Scrabble*, whereas behaviors we would want to inhibit include players quitting the game early or abandoning quests. In order to inhibit or facilitate these behaviors, the system must influence certain game features. The features that the system will influence correspond to those that were used to create the models being used. For example, assume we have a model that indicates that a high amount of player deaths leads to that player abandoning the current quest in SQ:TG and that we want to inhibit this behavior. The system should encourage the player to finish this quest by lowering the number of player deaths. The system will accomplish this by affecting certain aspects of gameplay (such as the number of enemies present).

The feeling the player is in control of the game environment is a central to intrinsic motivation (Ryan and Deci 2000) and flow (Csikszentmihalyi 1992). Therefore, forcing the player to exhibit certain behaviors will result in low engagement and intrinsic motivation. As such, the system must be able to inhibit/facilitate behavior while remaining minimally intrusive. I have chosen to account for this by using an *adaption parameter*. The value of this parameter will determine how much control the system can have on the game world. Lower values of this parameter mean that the system can only make subtle changes to the environment whereas higher values indicate that more noticeable changes can be made. If subtle changes to the game do not have their intended effect, then the value of the parameter will increase, giving the system more environmental control.

To maximize an adaption's effect on the user, changes to the environment must be made as soon as possible. One possible method of solving this problem is continuously calculating the probability that a player belongs to any given player model. Game adaption can be made when this probability rises above a predetermined confidence threshold.

Evaluation

To determine whether the adaptions made to the game had the desired effect, I will perform an evaluation using both the simple and complex game environments. Each of these experiments will be carried out independently of one another. Both of these experiments will be done using a between subjects, full-factorial experimental design. Since each game will be published online, possible participants will be directed to a website where they will be, upon consent, randomly placed into an experimental group and then presented with the corresponding game to play. Upon completion of the game, they will be presented with an exit survey.

In both game environments (*Scrabble* and SQ:TG), the effect that adaptions have on both qualitative and quantitative metrics will be tested. For each game, participants will be placed into one of four possible experimental groups:

- No Adaption: The game contains no adaptions
- Game-Independent Model-Based Adaptions Only
- Game-Dependent Model-Based Adaptions Only
- Game-Independent and Game-Dependent Model-Based Adaptions

As you can see, the only differences between these groups are the types of adaptions made, which will be determined by the player models that the system is allowed to use.

The quantitative metrics that we will study are determined by the behaviors that we are seeking to inhibit or facilitate. If we want to discourage players from quitting games of *Scrabble* before they were completed, for example, then the quantitative metric that we would examine would be the number of games that were ended early.

For these experiments, we will look at two qualitative metrics describing user state. The first of these is *intrinsic motivation*. Intrinsic motivation is defined as motivation based in the inherent satisfactions derived from action (Ryan and Deci 2000). To test this, we will use a subset of the questions available from the intrinsic motivation inventory.

The second qualitative metric that we want to study is engagement. The game engagement questionnaire (Brockmyer et al. 2009) is a questionnaire that attempts to measure several aspects of player engagement in order to create a unified idea of a player's engagement during a game. Using this questionnaire, I plan to measure the differences in player engagement across all experimental groups.

Progress and Future Work

Currently, I have implemented the non-adaptive version of *Scrabble* and done an initial round of data collection using it. SQ:TG is still being implemented. I have also made significant progress in the model creation phase of my research and have started implementing adaptions for *Scrabble*. My progress and future work will be discussed in greater detail for each phase of my research below.

Constructing Player Models

In *Scrabble*, I have created a model that examines a set of game-specific variables in order to determine the probability that a player will end the game prematurely using how much each feature deviates from the expected value of that feature (2012). This model was created using a naive Bayesian probability model in which we calculated the conditional probability of the current player ending the game early given the player's last three actions.

I have also designed a technique that I will use to determine which quests a player will complete in SQ:TG. This technique was designed by examining achievements in World of Warcraft (WoW) (2011). This technique involves finding groups of achievements that are likely to be completed together by finding cliques in the correlation network of all achievements. I feel that this technique will transition nicely into SQ:TG using quests instead of achievements

Future work in this phase of research will involve determining how to incorporate game-independent analytics into these models of player behavior. My current thought is that I can use a technique similar to the deviation-based ones used to predict when players will quit in *Scrabble*.

Game Adaption

At the moment, no adaptions have been implemented, although I have several ideas for how I want to proceed with this phase. One possible direction to take in *Scrabble* is to alter the game such that observed features begin to approach the expected values for those features. The idea behind this adaption is that changing these values should discourage the player from ending the game early, which should result in an increase in engagement/intrinsic motivation.

There are several possible ways in which I can leverage the information of which quests a player will complete in SQ:TG. One option is that we guide the player to this game content either by using in-game textual cues of where these quests can be found, or by moving the non-player characters (NPCs) that give out these quests closer to the player. The reasoning behind this type of change is that we would increase intrinsic motivation by making the player aware that they have option to complete the objectives that they want to complete. Another option is to force the player to experience other content instead. My intuition behind this type of adaption is that players may be more challenged by new experiences and, therefore, have a more engaging experience.

Perhaps the main area that needs to be expanded on here is how the adaptive parameter will be used. For certain adaptions, such as controlling the difference between player and computer scores in *Scrabble*, the role of the adaptive parameter is easy to implement. The system will be allowed to cause a change in this value proportional to the value of the adaptive parameter. For adaptions such as controlling what quests the player completes in SQ:TG, the application of the adaption parameter is less obvious. Currently, my plan is to implement a series of thresholds and specify what aspects of the game the system can control at each threshold.

Evaluation

I have determined my experimental design and have a set of proposed sampling techniques. I have also determined the questionnaires that I want to use to measure engagement and intrinsic motivation. I have also proposed a technique for choosing the quantitative metrics that I will study.

I want to explore other possible measurement tools for measuring engagement and intrinsic motivation. I want to ensure that these two questionnaires measure what I want to measure and are reliable tools for measurement. I also want to verify if there are tools that exist that are more appropriate given the questions that I am asking.

Conclusion

By the end of my Doctoral research, I will have shown that player models can be constructed procedurally by looking at both game-specific and game-independent analytics in both simple and complex game environments. These models are an improvement over previous model creation techniques that are based on prior knowledge or user studies in that they focus on trends that are actually observed during gameplay. In addition, these models can then be used as a basis for creating adaptive game environments. By the end of my Doctoral research, I will have made the following contributions:

- Designing algorithms to find trends of player behavior using both game-specific and game-independent analytics
- Creating methods to adapt various game environments which integrate both models created using game-specific analytics and models using game-independent analytics
- An evaluation of if each adaption was able to successfully inhibit or facilitate desired quantitative behaviors and the effects that these adaptions had on engagement and intrinsic motivation

By using these model-based adaptions, I believe that game designers will be able to create vast amounts of content while maintaining an engaging experience.

References

Bartle, R. 1996. Hearts, clubs, diamonds, spades: Players who suit MUDs. *Journal of MUD research* 1(1):19.

Booth, M. 2009. The ai systems of left 4 dead. In *Keynote, Fifth Artificial Intelligence and Interactive Digital Entertainment Conference (AIIDE09)*.

Brockmyer, J.; Fox, C.; Curtiss, K.; McBroom, E.; Burkhart, K.; and Pidruzny, J. 2009. The development of the game engagement questionnaire: A measure of engagement in video game-playing. *Journal of Experimental Social Psychology* 45(4):624–634.

Csikszentmihalyi, M. 1992. *Optimal experience: Psychological studies of flow in consciousness*. Cambridge Univ Pr.

Drachen, A.; Canossa, A.; and Yannakakis, G. 2009. Player modeling using self-organization in Tomb Raider: Underworld. In *Computational Intelligence and Games, 2009. CIG 2009. IEEE Symposium on*, 1–8. IEEE.

Hagelback, J., and Johansson, S. 2009. Measuring player experience on runtime dynamic difficulty scaling in an rts game. In *Computational Intelligence and Games, 2009. CIG 2009. IEEE Symposium on*, 46 –52.

Harrison, B., and Roberts, D. 2011. Using sequential observations to model and predict player behavior. In *Proceedings of the Sixth International Conference on the Foundations of Digital Games, New York, NY, USA*.

Harrison, B., and Roberts, D. 2012. When players quit (playing scrabble). In *Proceedings of the Eighth Annual AAAI Conference on Artificial Intelligence and Interactive Digital Entertainment*.

Ryan, R., and Deci, E. 2000. Intrinsic and extrinsic motivations: Classic definitions and new directions. *Contemporary educational psychology* 25(1):54–67.

Thue, D.; Bulitko, V.; and Spetch, M. 2008. PaSSAGE: A Demonstration of Player Modeling in Interactive Storytelling. *Artificial Intelligence and Interactive Digital Entertainment (Palo Alto, CA, USA) AIIDE* 8.

Yee, N. 2006. Motivations for play in online games. *CyberPsychology & Behavior* 9(6):772–775.

Zook, A.; Lee-Urban, S.; Drinkwater, M.; and Riedl, M. 2012. Skill-based mission generation: A data-driven temporal player modeling approach. In *Proceedings of the 7th International Conference on Foundations of Digital Games*.