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Computer-Aided Game Design: Doctoral Consortium Research Abstract

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Abstract

Artificial intelligence can model and predict how humans will react to game systems. Using models of human-like imperfect play, one can estimate how quantitative changes to a game will impact a player's qualitative experience. I discuss my research to use artificial intelligence to automatically play, analyze, and design certain classes of games. Not only does it generate new content quickly and effectively, this research also provides some insights into why humans find some games more difficult than others, and how player skill measurably improves over time.

1 Introduction

Games, regardless if they are played with cards, tokens, dice, or computers, must be carefully designed and tuned to provide a positive experience for players. Typically this design process is guided by a human game designer's intuition and experience. However, using quantitative metrics and artificial intelligence, computer-aided tools can provide designers some insight about how players of varied skill might perceive their games.

The general focus of my research is to better understand how artificial intelligence can be used to model and predict how humans will react to game systems, and to use algorithms to enhance human creativity with computational creativity [Wiggins, 2006]. By incorporating simple models of the kinds of choices, errors, and imperfect play that humans are likely to make, we can estimate how quantitative changes to the design of a game will impact a qualitative human experience.

By modeling humans using artificial intelligence, my goal is not to significantly outperform humans at tasks like playing games [Campbell *et al.*, 2002; Silver *et al.*, 2016] or designing games [Browne and Maire, 2010; Cook and Colton, 2011; Togelius and Schmidhuber, 2008], but to ultimately improve our understanding of human behavior. With computer-aided game design tools, game designers can make new games quicker and cheaper, and game players can have more content that is tuned to their specific, unique preferences. Additionally, a better understanding of how precise systems can be adjusted to suit human tastes and abilities has the potential to create machines that are easier, more productive, and more enjoyable to use. I believe this kind of research can leverage computational intelligence to improve our quality of life.

2 Contributions

To date, I have made several recent contributions in the field of applying artificial intelligence to game design.

Given a set of rules and adjustable parameters, I led a research project to discover how algorithms can procedurally adjust various parameters of a game to have a measurable impact on human player experience [Isaksen *et al.*, 2015a][1]. Typically, a game designer will set some rules and parameters, play test the game with human participants, evaluate the results of the play test, adjust the rules and parameters, and repeat the process – iterating around the loop until the game is acceptable to players and designers.

Our team automated this process by creating AI agents that play *Flappy Bird* [Nguyen, 2013][2], making the same types of errors that humans make in simple minimal one-button games. In particular, we modeled human *precision*, which is the motor skill accuracy at which someone can precisely perform an action at a predicted time in the future, and *actions per second*, which calculates how fast a human can repeatedly perform an action [Magill and Anderson, 2007]. By constraining the AI agent to function within this model, we were able to measure how effectively the computer could play any variant of the game. By automating the play test process, this allowed us to repeat the process tens of thousands of times over a range of input parameters, using a Monte Carlo simulation to generate a histogram of expected scores.

To analyze these histograms, I used *survival analysis*, a statistical technique commonly used in medical trials, for insurance risk calculation, and to study the lifetime of mechanical parts [Lee and Wang, 2013]. To my knowledge, this was the first time that survival analysis had been used for the analysis of games. By equating the final score of a simulated agent with a lifetime – since in Flappy Bird the longer the player stays alive the higher their score – we were able to assume constant game difficultly to fit exponential distributions to the resulting histograms. The decay rate of the exponential is thereby related to game difficulty: the higher the probability of achieving low scores, the higher the difficulty of a game.

[1]This paper won the Best Paper in Artificial Intelligence and Game Technology award at *Foundations of Digital Games* 2015.

[2]*Flappy Bird* is one of the most popular mobile games of all time, and is remarkable for being so simple and difficult when most mobile games are tuned to be easy to play for casual audiences.

Given our human-like AIs and the ability to estimate the difficulty of any game variant, we used our algorithm to (1) search for unique games of a particular difficulty, (2) sample the space of all possible games to understand how different parameters related to game difficulty, and (3) create games that are far in parameter space from the original game [Isaksen *et al.*, 2015b]. By maximizing the minimum parameter distance between all pairs of a finite number of playable, unique games, we were also able to use a genetic optimizer to discover four interesting and unique variants without any human input.

I was able to further examine the role of simulation and survival analysis to better understand games of changing difficulty, and how learning affects the difficulty of a game [Isaksen and Nealen, 2015]. In this work, we again used human-like AIs to simulate games under differing dynamic rule changes to show how the *hazard rate* [Rinne, 2014] – the likelihood that a player will fail given they have already achieved a certain score without failing – is an effective way to understand how humans might perceive the difficulty of a game. In this work, I also showed that the initial skill level of a player has a significant impact on the type of experience they may have with a game – advanced players might find encouragement in the early stages of a game while novice users might find negative feedback where they are increasingly unlikely to achieve higher scores. Furthermore, by modeling different rates of learning and skill acquisition [Lane, 1987] into our AI agents, we were able to predict the effective difficulty of a specific game as players improve over time.

Extending beyond action games, we have demonstrated the utility of artificial intelligence for evaluating strategies for novel combinatorial games. Given a novel game we designed to ensure that the scores of the two players remains close at all times, we tested different simple heuristics that humans would be likely to try, simulating how agents using these heuristics would perform against each other and might switch strategies and heuristics to adapt to the opponent [Isaksen *et al.*, 2015c].

3 Directions for Future Work

Moving beyond my previously published contributions, I am interested in improving more areas of game design with quantitative reasoning and modeling with artificially intelligent agents, especially AIs that can learn and improve.

One question I am currently addressing revolves around understanding how novice players first learn how to play a new game. Successful games typically have simple heuristics that make it easy for new players to learn and play better than randomly, but have layers of more sophisticated heuristics that can be applied as players get better at the game. We have recently completed a study using genetic algorithms to generate simple, human-usable heuristics for playing a well-known single player game.

I am also interested in exploring methods for automatically tuning specific areas of game design. For example, adjusting the number of cards or dice, costs of units, or scoring systems used in a game is a non-trivial process. When predicting how humans perceive the outcome of randomness, this can't be modeled with the same type of human error in precision as I used in action games, but requires more sophisticated models that incorporate local representativeness. For action games that combine strategy and dexterity, finding the right balance of parameters to improve overall experience becomes a multiple dimensional problem which my collaborators and I will tackle with similar approaches to this existing work.

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