Interactive Bayesian Optimization for Game Mechanics

Abstract

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Game design often involves a final phase of substantial finetuning of game assets. Paradigmatic examples include varying the settings of player-controlled character movement parameters, altering opponent combat statistics, or varying low-level parameters around movement and collision of game objects. Tuning is often a time-consuming and expensive process for several reasons:

- 1. parameter values must be set to (globally) optimal values, requiring search over a large space
- 2. evaluation of a setting cannot be done analytically or via simulation but requires costly (in terms of time and money) direct human evaluation
- 3. quality of a set of parameters may be difficult to specify on a global scale, but instead be relative to other sets of parameters

Interactive Bayesian optimization (closely related to active learning (Settles 2012) and sequential experimental design (Chaloner and Verdinelli 1995)) approaches can address these issues through optimization of design objectives that are expensive to evaluate (?). Employing non-parametric models (here Gaussian Processes) we demonstrate the application of interactive Bayesian optimization to two cases studies of game design tuning in a shoot-em-up game: (1) optimizing player controls to player preferences and (2) adjusting enemy design parameters to enforce a desired level of player behavior.

For control optimization we demonstrate how a preference-learning approach can provide potential control settings to be tested and evaluated against the previous set of controls. Bayesian optimization affords automatic exploration-exploitation trade-offs that enable rapidly (globally) optimizing controls to player preferences via pairwise preference feedback. For enemy design optimization we demonstrate how a designer-specified objective function for player performance statistics can guide building a regression model from enemy parameter settings to desired design features.

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First, we discuss related work in game tailoring and adaptation. Second, we motivate and describe our interactive Bayesian optization appraoch, detailing the Gaussian process regression and preference learning models. Third, we describe our shoot-em-up game and describe two empirical human studies demonstrating the efficacy of our approch. We conclude by discussing extensions and the range of applications of this modeling approach.

Related Work

(Yu and Trawick 2011) uses SVM, hard to AL on this (Hunicke and Chapman 2004) ad hoc

(Yannakakis and Hallam 2009) (Yannakakis, Maragoudakis, and Hallam 2009) GP pref model employed, not found best. however, we use more sophisticated kernel fn in order to better adjust fit parameters across dimensions and get back information on relative importance of dimensions

(Bakkes, Spronck, and van Lankveld 2012)

Gaussian Processes

Gaussian Process Regression

(Rasmussen and Williams 2006)

Gaussian Process Preference Learning

(Chu and Ghahramani 2005) (Brochu 2010)

Active Learning

(Settles 2012)

Experiment

Game Domain Methods Results

Discussion Acknowledgments References

Bakkes, S. C.; Spronck, P. H.; and van Lankveld, G. 2012. Player Behavioural Modelling for Video Games. *Entertainment Computing* in press:1–9.

Brochu, E. 2010. *Interactive Bayesian optimization: learning user preferences for graphics and animation*. Ph.D. Dissertation, University of British Columbia.

Chaloner, K., and Verdinelli, I. 1995. Bayesian experimental design: A review. *Statistical Science* 10 (3):273–304.

Chu, W., and Ghahramani, Z. 2005. Preference learning with gaussian processes. In *Proceedings of the 22nd International Conference on Machine learning*, 137–144. ACM.

Hunicke, R., and Chapman, V. 2004. AI for dynamic difficulty adjustment in games. In *Proceedings of the AAAI Workshop on Challenges in Game Artificial Intelligence*.

Rasmussen, C. E., and Williams, C. K. 2006. *Gaussian processes for machine learning*, volume 1. MIT press Cambridge, MA.

Settles, B. 2012. *Active learning*, volume 6. Morgan & Claypool Publishers.

Yannakakis, G. N., and Hallam, J. 2009. Real-time game adaptation for optimizing player satisfaction. *IEEE Transactions on Computational Intelligence and AI in Games* 1(2):121–133.

Yannakakis, G. N.; Maragoudakis, M.; and Hallam, J. 2009. Preference learning for cognitive modeling: a case study on entertainment preferences. *IEEE Transactions on Systems, Man and Cybernetics, Part A: Systems and Humans* 39(6):1165–1175.

Yu, H., and Trawick, T. 2011. Personalized procedural content generation to minimize frustration and boredom based on ranking algorithm. In *Seventh Artificial Intelligence and Interactive Digital Entertainment Conference*.