A Machine Learning Facility for Adapting Competitive Game Strategies to Players' Proficiency

Daisuke Takeuchi, Univ.Nanzan
Masami Noro, Univ.Nanzan
Atsushi Sawada, Univ.Nanzan

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Introduction

Player modeling is an important issue in the design of game AI, and the importance of considering the player's situation in this context is emphasized.

Temporal Maturity -The player learn strategies as they play the game and become more proficient and advanced over time.

The purpose of this study:
・Propose a mechanism for predicting the temporal maturity of players and switching their game strategies.

The goal of this study:
・Propose a mechanism to predict a player's temporal maturity and to switch strategies dynamically.
・Design an architecture to dynamically switch game strategies based on the prediction results.

Introduction

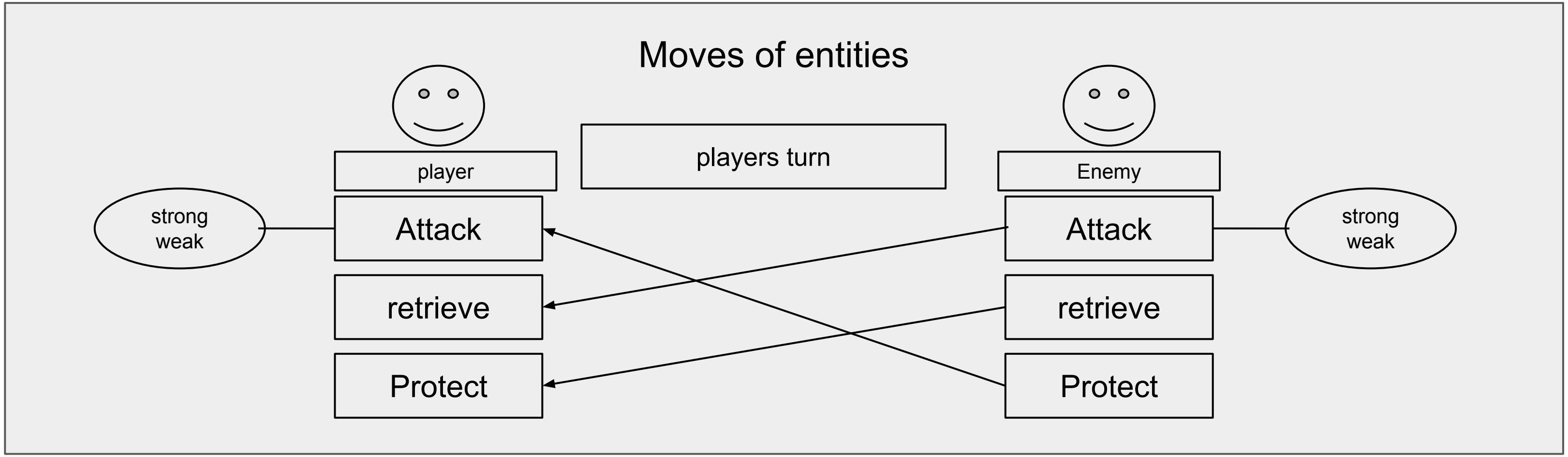
The subject of this study was a turn-based RPG.

The rules of the game were defined as follows.

・The HP(Hit-Point) of Player and CPU is 100pt at start.

・saelect action each other alternately and HP of both changes accordingly.

・They take turns selecting actions until their HP get 0.



Introduction

Temporal proficiency is the change in proficiency over time.

Use LSTM(Long Short-Term Memory) to predict temporal mastery.

*LSTM can learn and predict (regression, classification) time-series data, and examples include sentiment analysis, speech recognition, and language modeling.

outlook

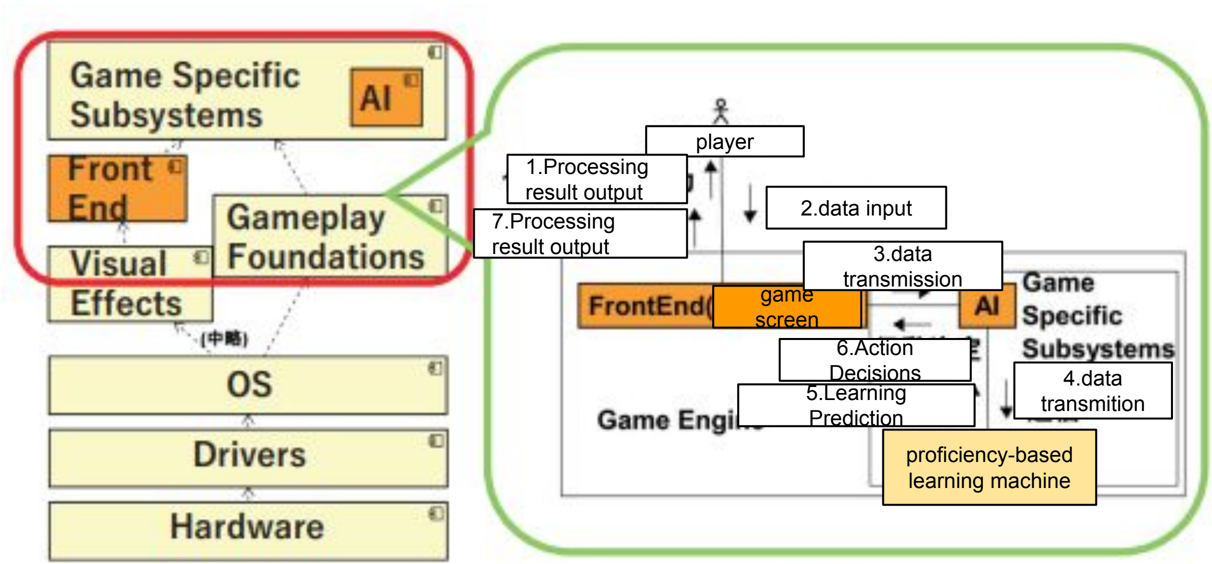
The following technical issues will be addressed in this study.

1. design of game engine architecture with integrated proficiency prediction mechanism

2. detailed design of the proficiency prediction mechanism

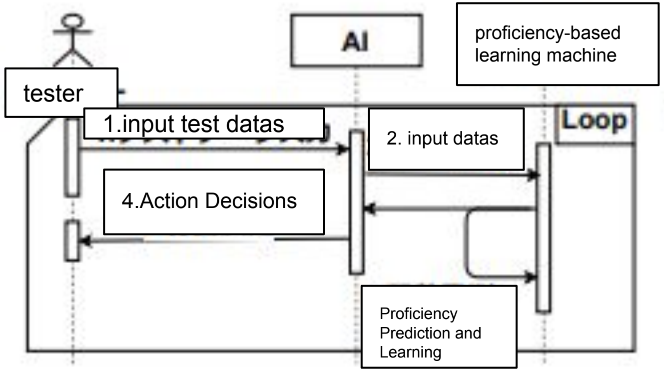
3. validation

Design of learning mechanism

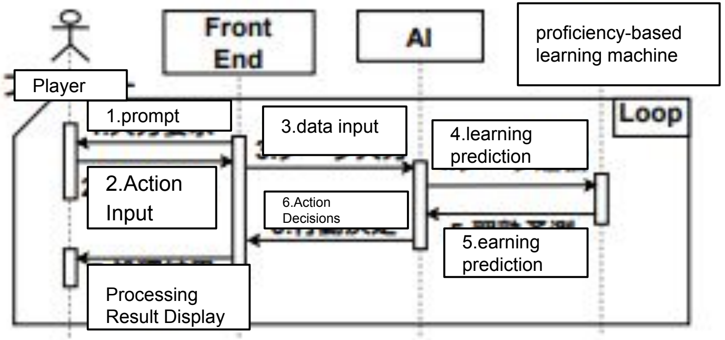


Position of this system in the game engineering architecture

Design of learning mechanism



dynamic behavior of component in learning



dynamic behavior of component in using

Design of learning mechanism

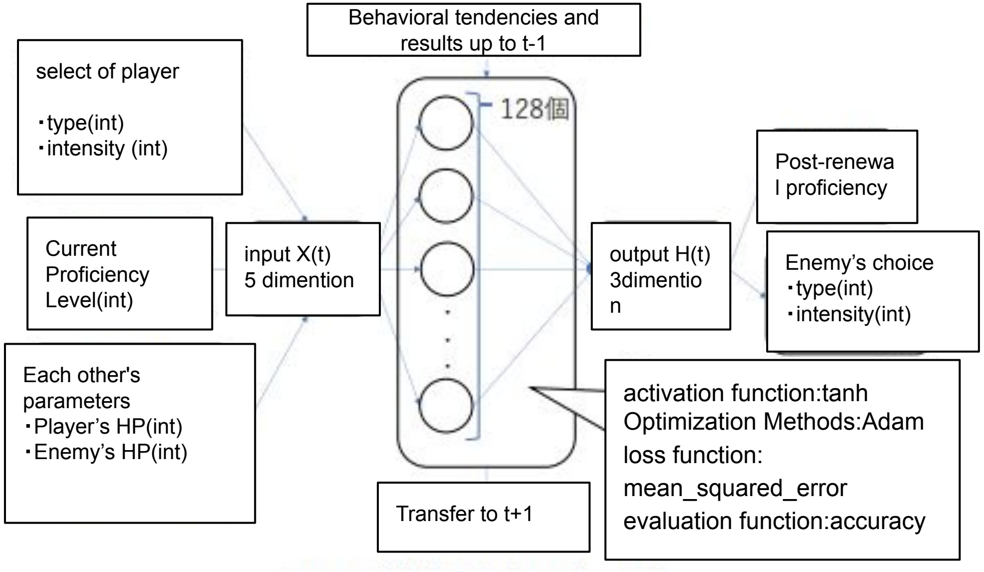
Data used to predict temporal proficiency

kind of data	exlanation
behavioral trend	Array of recording of the player's chosen actions (array) : Type of action (int) , strength (int)
result	result of player (win: +1, lose: -1)

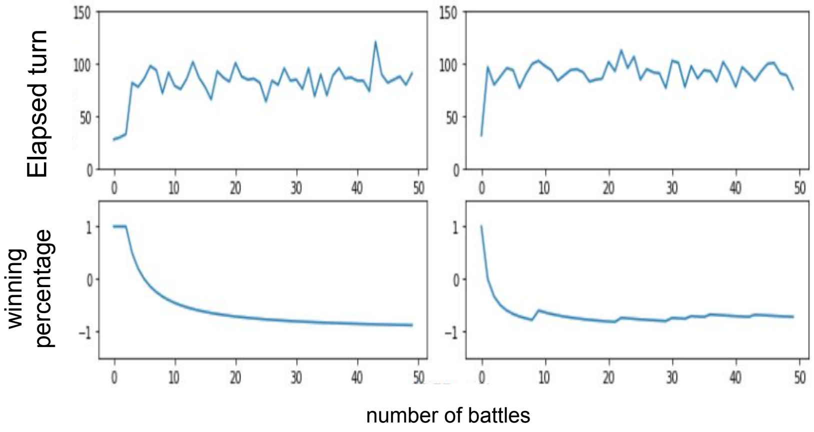
Player proficiency can be thought of as manifested in changes in the way they play and in their wins and losses.

LSTM Design

t : number of turns which increase according to play time.

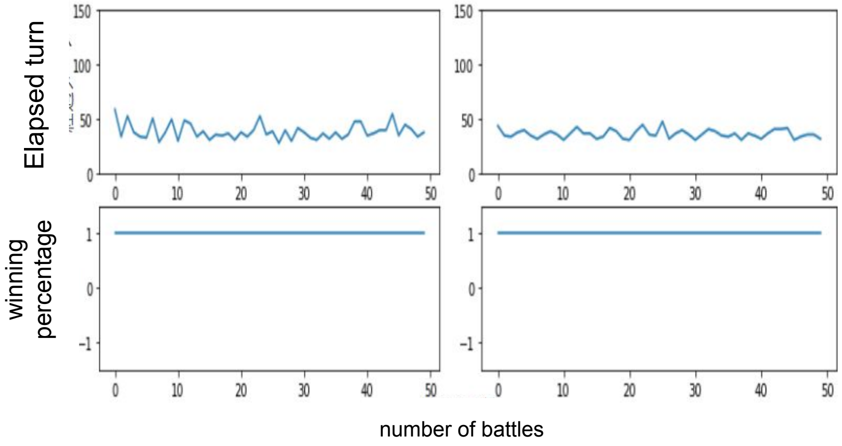


Validation



Elapsed turns and win rates

Players that have high learning level



Elapsed turns and win rates

players that have low learning level/

experimental results

[high learning level player]

・The number of turns required to settle the case oscillates at a high value.

・Player's win rate decreased.

-> The learner is able to change the strategy of the game in order to increase the difficulty level accordingly.

[low learning level player]

・The number of turns required to settle a low percentage oscillates.

・Players kept winning.

-> The learner can predict that the player's proficiency will not increase and can change the strategy of the game to decrease the difficulty.

Conclusion

The purpose of this study is to propose a mechanism that predicts the player's proficiency and switches actions, and to confirm its effectiveness. and to confirm the effectiveness of this mechanism. And Experimental evaluations showed that these idea are generally valid.

The learning machine is simple design because it has few dimensionality of input vectors and no weight.

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