UCSM-DNN: User and Card Style Modeling with Deep Neural Networks for Personalized Game AI

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Abstract

This paper tries to resolve long waiting time to find a matching person in player versus player mode of online sports games, such as baseball, soccer and basketball. In player versus player mode, game playing AI which is instead of player needs to be not just smart as human but also show variety to improve user experience against AI. Therefore a need to design game playing AI agents with diverse personalized styles rises. To this end, we propose a personalized game AI which encodes user style vectors and card style vectors with a general DNN, named UCSM-DNN. Extensive experiments show that UCSM-DNN shows improved performance in terms of personalized styles, which enrich user experiences. UCSM-DNN has already been integrated into popular mobile baseball game: MaguMagu 2021 as personalized game AI.

Introduction

Deep neural networks (DNN) and reinforcement learning have shown significant performance improvements on player versus player (PvP) contents, which able to win human experts in various complex games (Silver et al. 2016; Vinyals et al. 2019). However, winning is not the only ultimate goal of designing a game AI. From game product life cycle point of view, how to improve user experiences is the essential purpose to design a game AI. In most of PvP contents, normally the size of user matching pool is decreasing continuously, which results in increased waiting time. To reduce user matching time, most game developers have provided AI matching to users. However, users who want to play PvP contents expect to play against similar level users who show their own playing styles, not AI which shows rigid playing style only. To meet these users expectations, it is essential to design a personalized game AI (PGA) that could replace the specific user, especially in most of online sports games, such as baseball, soccer and basketball.

Typical method to make user specific or group specific model is transfer learning (Torrey and Shavlik 2010), which is useful to generate target specific DNN based on pre-trained DNN with general domain training data. For example, (Khaustov, Bogdan, and Mozgovoy 2019) proposed team specific approach which try to learn ball passing patterns in soccer from real matches. All above mentioned approaches have *scalability* issue: if there are N users, we should fine-tune N DNNs models. Therefore, transfer learning is not suitable to make PGA agents for online games which has numerous users e.g. more than 10,000 daily active users.

The goal of this paper is to design a PGA with a single DNN, which is not just human-like but also shows the user specific playing style. To this regard, we propose a personalized game AI which encodes user styles and card styles with a general DNN, named UCSM-DNN. UCSM-DNN provides improved user experiences in PvP contents and ultimately benefits to long term product life cycle of online sports games.

UCSM-DNN

Fig. 1 shows the overall architecture of UCSM-DNN. Different from transfer learning approach, our model can generate various user specific PGA agents with a single DNN only. The PGA agent decides which pitch to throw, where to throw, whether swing or not and where to swing in *MaguMagu 2021* (Netmarble 2020). The inputs of the USCM-DNN consist of three components: game features extracted from raw log data, user style modeling (USM) and card style modeling (CSM).

As shown in Fig. 1, the core idea of USM is defined as user style vector (USV), which encodes playing styles of specific users. We define style projection function of USV as $S : \mathbb{L} \to \mathbb{S}$, where $\mathbb{L}$ represents raw log data set and $\mathbb{S}$ represents *style vector feature space*. If two users have similar playing styles, then their USV should be close in style vector feature space.

Style vector feature space $\mathbb{S}$ consisted of two types of USV to represent not only special cases but also general cases: binary USV ($\mathrm{x_b}$) and distribute USV ($\mathrm{x_d}$). Binary USV $\mathrm{x_b}$ differentiates playing styles of users in special conditions, such as *throw fastball or curveball* under the situation of *two strikes*. We define binary USV $\mathrm{x_b}$ as follows:

$$x_i \in \mathrm{x_b},\ x_i = \begin{cases} 1, & \text{if } p(a_i|c_i) \geq t_i \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

where c_i, a_i, t_i and $p(a_i|c_i)$ represents game condition, action, threshold and conditional probability of a user takes action a_i given condition c_i.

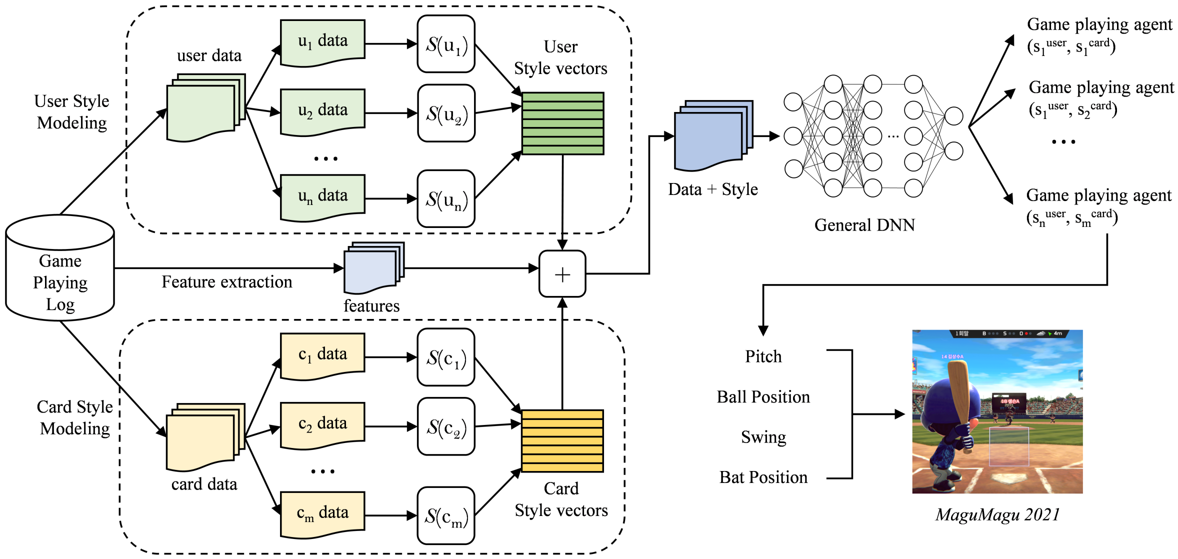

Figure 1: The system overview of UCSM-DNN

On the other hand, distribute USV $\mathrm{x_d}$ represents playing styles of general conditions, such as *choose a pitch type* based on the probability of given playing log data. We define distribute USV $\mathrm{x_d}$ using probability distribution of a_i as follows:

$$x_j \in \mathrm{x_d},\ x_j = p(a_j),\ \sum_{j=1}^{m} x_j = 1 \tag{2}$$

where $p(a_i)$ represents probability that a user take action a_i.

Card style encodes playing style of users who use specific cards. Cards which player controls in game also affect users' playing styles as well. As shown in Fig. 1, we define card style vector (CSV) which represents playing styles of users who use that specific card. Similar with USV, we define style projection function CSV $S(c_j)$ where c_j represents game playing log data with card j was used.

We integrate UCSM-DNN as SDK on mobile phone for *MaguMagu 2021*. UCSM-DNN SDK only costs 112K parameters for DNN, 488KB memory usage for 1,000 users and 2,000 cards, and the average inference time is less than 30ms measured in Samsung Galaxy S9.

Experiment

To evaluate the performance of UCSM-DNN, we make a metric to measure quantitatively how PGA agents can simulate various playing styles. If two users have similar playing styles, the outputs of UCSM-DNN should be similar. Also, if two users have different playing styles, the outputs of UCSM-DNN that uses their style vectors should be different. We define distinguishability of playing styles (DPS) as follows:

$$\mathrm{DPS} = \frac{1}{|\mathcal{D}|}\sum_{i,j\in\mathcal{D}} \mathrm{MSE}(o_i, o_j) - \frac{1}{|\mathcal{S}|}\sum_{i,j\in\mathcal{S}} \mathrm{MSE}(o_i, o_j) \tag{3}$$

where $\mathcal{S}$ represents set of pair consists of similar users and $\mathcal{D}$ represents set of pair consists of different users in terms of playing styles. The larger first term is, the more different styles for users with different playing styles. And the smaller second term is, the more similar styles for users with similar playing styles. We evaluate UCSM-DNN using game play log of 4,950 user pairs for 4 weeks.

models	pitch	ball pos	swing	bat pos
UCSM-DNN	**.0197**	**.0088**	**.0959**	**.0847**
USM only	.0045	.0071	.0613	.0707
CSM only	.0093	.0003	.0445	.0751
w/o style vector	.0080	.0019	.0392	.0028
weighted random	.0034	.0005	.0192	.0084
uniform random	.0010	.0005	.0335	.0007

Table 1: Experimental results using DPS

The larger DPS is, the more personalized model is. For example in pitching case, the DPS of UCSM-DNN increased 246.3% compare to w/o style vectors. As we can see from Table 1, when considering both USM and CSM, we archived the best performance for designing PGA agents in terms of personalized styles.

Conclusions

In this paper, we have presented a PGA method based on user and card style modeling with single DNN only. Extensive experiments confirm the useful behaviour of UCSM-DNN in terms of modeling user specific personalized styles. UCSM-DNN already in live service as PGA agents to the famous online baseball game: *MaguMagu 2021*. We hope the methodology developed in this paper could help to increase the product life cycle of various online sports games.

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