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Experimental study for a computational model in ITS to predict the learners' state

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Abstract: Cognitive architecture plays essential role in Intelligent Tutoring System (ITS). For effective learning support, dynamic model subserving the function of the prediction of learners' states should be incorporated. In this paper, we proposed a neural network-based architecture in progress that can incorporate the dynamic model to generate the prediction of leaners' perceptual states when categorical ambiguous stimulus and the instruction of category were given.

Keywords: cognitive architecture, intelligent tutoring system, neural network

1. Introduction

Cognitive architecture in the research field of artificial intelligence in education and learning have demonstrated its importance as a role of learner model in Intelligent Tutoring System (ITS) (Anderson et al, 09). As is well known that domain modelling, tutor modelling and learner modelling are essential role of ITS construction (Nkambou et al, 10), sophisticated learner model plays crucial role not only to estimate learner states but also to generate acute "prediction" for the learner states. Estimation of learner states has long been one of the most important issues in ITS. Bayesian approach has been adopted for knowledge-state estimation (e.g. Bayesian Knowledge Tracing), and affective tutors have been proposed that can estimate leaners' mental states (Ammar et al,10). Estimation of mental states can be achieved with various physiological data (D'Mello et al, 2007), and intelligent mentoring system (IMS) incorporates mental states of learners. Machine learning approach including deep neural network came to realize the acute prediction the learner mental states from physiological data and the estimation results are used for teachers' pedagogical decision making (Matsui et al, 19). On the other hand, "how to predict the learners' states" can remain crucial issues to optimize the pedagogical decision making of ITS. The selection of teaching actions should be optimized with predictions of how the action will affect the state of the learner (e.g. to encourage the learner, a teacher considers how his/her action effects on the learner's mental states). To predict the learners' state and utilize it for the decision making, learner model should incorporate the dynamics of learning-related states including emotion. In this paper, our in-progress neural model incorporating the dynamics of leaner's states as the neural network model is proposed.

2. Proposed model for prediction of learner's perceptual states

In this article, we considered the simple situation where learner is provided with categorically ambiguous (including perceptually ambiguous like Rubin's vase) stimuli as educational material and with the perspective as the instruction such as "See this stimulus as the face." Fig.1 shows the protype of proposed neural model for prediction of learners' perceptual states. The model contains of three modules: (1) Gate module, (2) Attractor network module, and (3) Perspective controller module. Gate module is a module that pay attention to a part

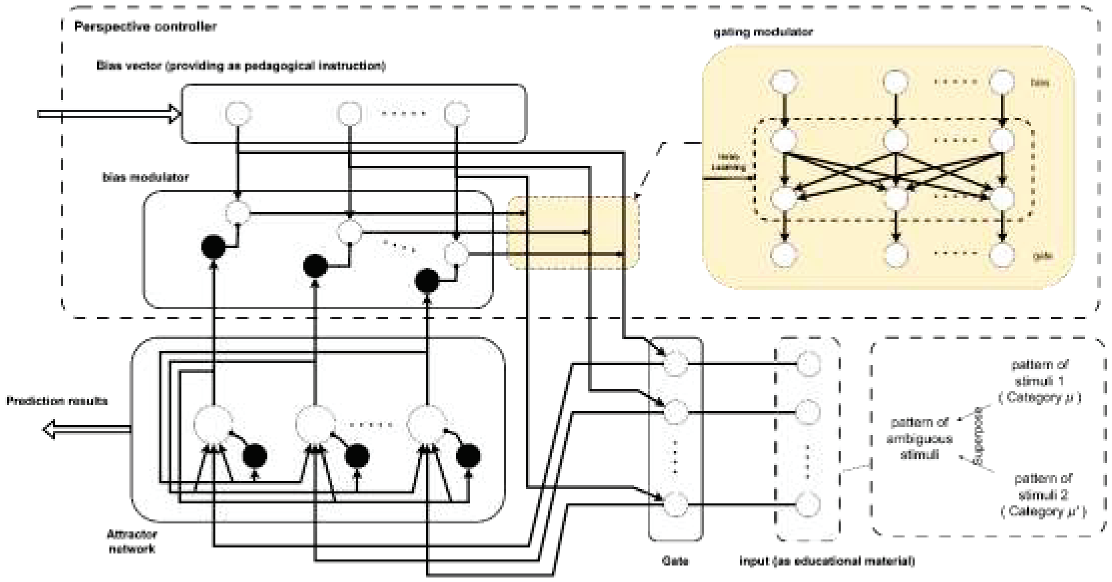

Figure 1. The proposed neural network model. Blank circles and filled circles indicate the excitatory and inhibitory neurons, respectively.

of input. We construct the attractor network module based on the model of Inferior Temporal cortex proposed by [Matsumoto et al 03]. The output of this module indicates the prediction of learner's perceptual states. Perspective controller module is a key module to realize the perspective-based perception. This module consists of three elements: (1) bias vector and (2) gating modulator and (3) bias modulator. Bias vector represents a perspective that is provided as the pedagogical instruction. Gating modulator is feed-forward neural network that modulate gate pattern and its neural connectivity is updated based on the prediction error from bias modulator. Bias modulator computes a prediction error between the excitatory neurons of attractor network module and bias vector. The whole model is a part of model of learners to incorporate the dynamic states of the learner.

3. Simulation and results

The purpose of the simulations was to test whether output pattern (i.e. prediction) can be generated in line with the bias vector (instruction) when an ambiguous stimulus (created by superposing two stimuli belonging to different categories) input. The input was given as an n-dimensional vector. The pattern $\xi^{\mu,\nu}$ represents stimuli belonging to category μ. According to [Matsumoto et al., 03], 15 stimuli (3 elements × 5 categories) were generated and the elements belonging to same category correlated with each other at 0.3. We adopted $\xi^{1,3}$ and $\xi^{4,2}$ as inputs and the connectivity of the gating module was trained before ambiguous stimuli was input. In the simulation, ambiguous stimuli H^{ext} is given as $H^{ext} = \alpha\xi^{1,3} + (1-\alpha)\xi^{4,2}$ ($\alpha \sim 0.456$) and bias vector is given as $\xi^{1,3}$ or $\xi^{4,2}$.

Figure 2 shows the transaction of overlap $m^{\mu,\nu}(t)$ (the distance between $\xi^{u,v}$ and neural activity of attractor network, ref. (Matsumoto, 05)) and prediction error. *Left-Up* shows the transaction when a bias vector was given as $v_{bias} = \xi^{1,3}$, and *Right-Up* shows the transaction when a bias vector was given as $v_{bias} = \xi^{4,2}$. The results indicated that in case of $v_{bias} = \xi^{4,2}$, the model predicted that the learner's perceptual state converged to $\xi^{4,2}$ in accordance with the perspective. On the other hand, it predicted the perceptual state converged to $\xi^{4,2}$ in case of $v_{bias} = \xi^{1,3}$. This inappropriate prediction was ascribed to failure of learning manner in gate module. In learning phase of the gating module, the stimuli were input from $\xi^{1,3}$ to $\xi^{4,2}$ and its connectivity can be adjusted to make it easier to perceive the input as $\xi^{4,2}$. This phenomenon should be related to catastrophic forgetting (French 1999). Since learners do not study all learning content at the same time, it is necessary to devise ways to describe the learner model as a neural network model.

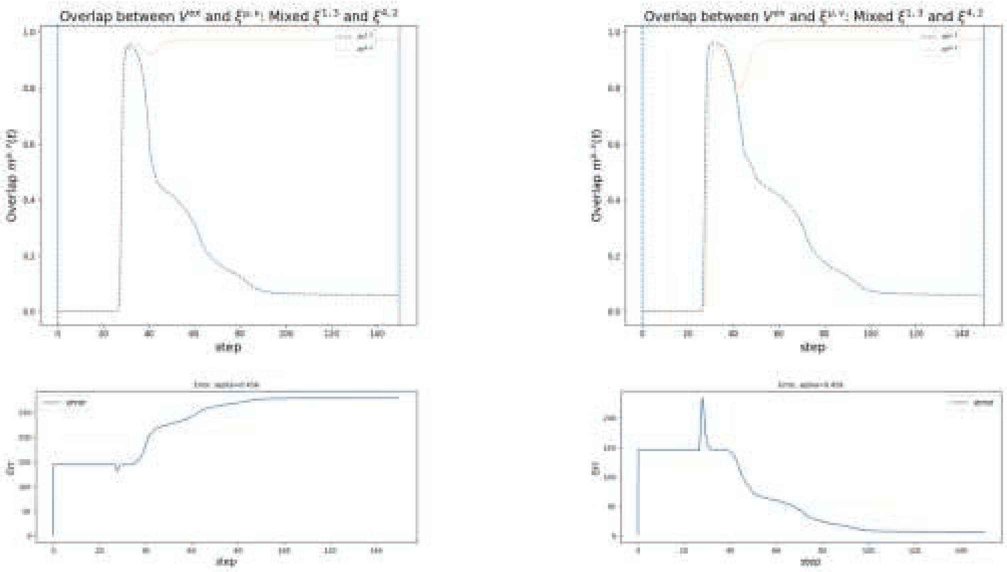

Figure 3. Transaction of overlap $m^{\mu,\nu}(t)$ and prediction error $\varepsilon(t)$: (Left) $\xi^{1,3}$ was given as bias vector, (Right) $\xi^{4,2}$ was given as bias vector.

4. Summary and limitation

In this study, we proposed the necessity of prediction module into the cognitive architecture of learner model in ITS. The neural network model that can predict the learner's states of perception was constructed. It also remains important issues other than the refinement of the model: (1) how to generate bias vectors, (2) validity evaluation of the model (e.g. alignment to subject's response in psychological experiments), and (3) the design of interaction between the proposed model and other component of ITS for effective learning support (e.g. adaptive feedback (Yamamoto 23)).

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