International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING

IJISAE

ISSN:2147-6799 www.ijisae.org Original Research Paper

Bayesian Continual Learning for Cognitive Artificial Intelligence

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Submitted: 10/09/2022 **Accepted:** 20/12/2022

Abstract: Currently, most research on artificial intelligence (AI) is focused on the AI that can make optimal decisions. The optimal AI systems aim to minimize the misclassification rate in classification and mean squared error in regression. As the research on AI that extends beyond human intelligence to emotion is progressing, the interests of cognitive AI that can imitate human thinking and emotion increase. So, we proposed a continual learning model to construct the cognitive AI. In this paper, we define cognitive AI as an extended concept to include not only optimal decision but also rational decision that mimics human emotions. Human learning follows a lifelong learning process in which human existing intelligence or knowledge is continuously updated by new experiences throughout life. So, we study on a continual learning method based on Bayesian inference with Markov Chain Monte Carlo for making cognitive AI. To verify the performance of the proposed method, we carry out simulation study and make experiments using machine learning data.

Keywords: *Bayesian inference, Cognitive artificial intelligence, Continual learning, Human thinking and emotion*

1. Introduction

Compared to traditional symbolic artificial intelligence (AI), current connectionist AI has made remarkable progress using advanced machine learning algorithms [1-7]. The connectionist AI based on deep learning has shown the performance beyond human intelligence [8,9]. We call this optimal AI in this paper. The optimal AI aims to minimize the misclassification rate and mean squared error (MSE) in classification and regression respectively. For example, using deep learning algorithms, the optimal AI provides better performance than human in image recognition problems [5,10]. AlphaGo was a representative example of optimal AI [9]. This is a case in which optimal AI surpassed human intelligence in the Go game. As the optimal AI develops, we will also require AI to have human thinking intelligence that goes beyond optimal decision-making. This is because optimal AI does not consider human thinking and emotion. In this paper, we study on the AI that can consider human thinking. We call this cognitive AI. Of course, various cognitive architectures for AI had been introduced [11-18], but we research the scope of cognitive AI limited to imitate human thinking. The learning procedure of human thinking follows a lifelong (continual) learning process in which human existing intelligence or knowledge is continuously updated by diverse experiences throughout life. So, we propose a continual learning model to construct our cognitive AI. We combine Bayesian inference with continual learning in the proposed model. In addition, we apply the Markov Chain Monte Carlo (MCMC) to Bayesian computing for our Bayesian continual learning model. We study on new approach to build an imitation machine that thinks and behaviours like human. This is updated by learning and experiencing various cases (data) over time. Also, the learning model has been called as continual (or lifelong) learning [19,20]. The continual machine learning is similar to human thinking procedure because its learning is dependent on n tasks over time [21-24]. That is, in continual learning, the model that has learned n-th data set is updated with the existing model parameters by learning only the new data when the $(n+1)$-th data is given. Whenever new data is observed, the parameters of existing model are updated by learning only the new data without relearning the entire data from 1st to $(n+1)$-th data sets. This learning is similar to the process of human lifelong learning and acquiring updated knowledge.

2. Research Background

2.1. Cognitive Artificial Intelligence

Cognitive science is to study human mind [1]. The study of mind is a field that requires interdisciplinary studies, such as mathematical statistics, computer science, physics, psychology, etc. [12,25-27]. As research on AI is actively progressing, the interdisciplinary research with cognitive science is becoming more important [5,14-18]. Minsky (1985) explained the intelligence for machine and human by agent and agency [28]. He also introduced the machine intelligence with thinking, feeling and emotion [29]. Therefore, cognitive science has been dealing with AI as one of its major research fields [1,11]. But now, most AI researchers are focused on development of AI systems with the highest accuracy in classification and regression tasks. The optimal AI systems have gone beyond human intelligence in various fields such as the Go game [9]. In contrast, the development of cognitive AI is still in the early stages of research [27,30]. Ahmad (2017) proposed a brain inspired cognitive AI to encourage the development of AI for cognitive thinking intelligence [14]. In addition, Sumari and Ahmad (2017) introduced the knowledge-growing system (KGS) as the origin of the cognitive AI [15]. They built the KGS by human

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information processing and social science perspectives as well as psychological and mathematical perspectives [15]. Sereati et al. (2020) studied on a cognitive AI device as an intelligent processor based on human thinking emulation [17]. Lastly, Kelley and Twyman (2020) articulated a cognitive framework for artificial general intelligence (AGI) [18]. They illustrated the emotional model based on the independent core observed model with considering morals and ethics [18]. Compared to various existing studies on cognitive AI, the cognitive AI proposed in this paper is defined from a slightly different perspective. A detailed explanation of this is dealt with in section 3.

2.2. Continual Lifelong Learning

Humans have the ability to continuously acquire experiences, organize them, transfer them into knowledge, and remember them [6]. This is called lifelong or continual learning. In machine learning tasks, as new data is added to existing model learned for the previously data, the explanatory power of the previous data decreases. This phenomenon is catastrophic forgetting. Continual learning was proposed to solve the problem of catastrophic forgetting. In general, the continual learning methods are divided into memory-based, structure-based and regularization-based approaches. First, memory-based methods reduce forgetting by saving the previous experiences explicitly and implicitly [19,23]. Next, structure-based methods use modules to perform localized inferences [20,22,24]. Lastly structure-based methods assume that the capacity of data learning is fixed, and control the changes of parameters not to reduce the model performance [21]. In our research, we apply the concept of continual learning to Bayesian inference model for cognitive AI.

3. Proposed Method

3.1. Bayesian inference and learning for cognitive AI

We propose a method to build cognitive AI that imitates human thinking and emotion. In this paper, we try to provide an imitation machine to represent human thinking and behaviors as a computational model. we consider the cognitive AI as AI that thinks and behaves with optimal value and rational cognitive areas in Figure 1.

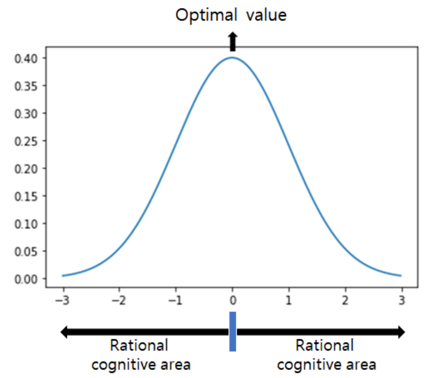

Fig. 1. Concept of our cognitive AI.

The concept of our cognitive AI is based on probability distribution. For example, the cognitive AI thinks and behaves using the random numbers extracted from Gaussian distribution in Figure 1. The probability of optimal value (mean) is the largest. The cognitive AI is most affected by the optimal value. However, since random numbers can be generated even in the rational cognitive areas, the values generated according to the probability of Gaussian distribution are slightly different each time. The thinking and behavior of AI using this result can change every time. Therefore, unlike optimal AI that always uses only the optimal value, our cognitive AI is a method that imitates human thinking and behavior. To construct our cognitive AI, we propose a model of Bayesian continual learning using Bayesian inference with continual learning. First, we consider Bayesian inference model. Bayesian inference has been applied to various fields of cognitive science [31,32]. Perfors et al. (2011) proposed Bayesian framework based on probability to understand human mind [31]. They focused on Bayesian statistical learning for human mind modeling [32]. Recently, Jun (2021) proposed a machine that imitates human thinking using Bayesian learning and boosting [10]. We now develop Bayesian computational model for human cognition using the MCMC. Based on the previous belief (prior), human mind draws decision-making by learning from some observed data (likelihood). That is, human combines likelihood of observed data (experience) with prior belief to update the belief about given domain. This updated belief is defined as a posterior distribution. So, the likelihood efficiently connects prior and posterior using new observed data. We also consider Bayesian inference for building cognitive AI, and combine Bayesian inference with continual learning. We use Bayesian computing based on Markov chain simulation to construct the proposed method. Bayesian inference basically has a learning process by prior, likelihood, and posterior [33-35]. Our research begins with Bayes' theorem in (1) [33].

$$P(H_i|D) = \frac{P(D|H_i)P(H_i)}{\sum_{j=1}^{k} P(D|H_j)P(H_j)} \quad (1)$$

Where H_i is ith hypothesis in the set of k hypotheses, and D is observed data. Therefore, we apply the learning process of Bayesian inference to build cognitive AI. Figure 2 shows Bayesian learning process for cognitive AI.

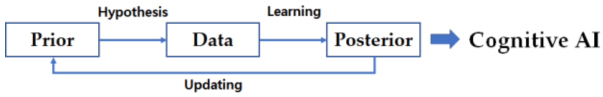

Fig. 2. Bayesian learning process for cognitive AI.

Given a domain for decision making by human thinking and emotion, prior represents hypothesis of domain knowledge. That is, prior is initial belief about given domain without new observed data (experiences). Humans have new experiences through new observed data under the hypothesis that represents prior belief in a given domain. The prior is changed into posterior by the experience. The machine uses the posterior for behavior of cognitive AI.

3.2. Bayesian continual learning for cognitive AI

In Using the Bayesian inference and learning in section 3.1, we construct Bayesian continual learning for cognitive AI that thinks like human. The proposed method consists of three steps as follows.

(Step 1) Initialization

(1-1) Defining model and initializing parameter, $Y = f(X;\ \theta_0)$

(1-2) Determining prior distribution based on θ_0
(1-3) Representing data and parameter update
$\theta_{new} = \theta_{pre} + \alpha f(x_1, x_2, \dots, x_n; \theta_{curr})$
(1-4) Considering tasks and separating them,
$T = (task_1, task_2, \dots, task_n)$

(Step 2) Training
(2-1) Defining and updating parameter according to tasks
$\hat{\theta}_i$: estimated parameter using data of $task_i$
θ_{i-1}: parameter knowledge using data from $task_1$ to $task_{i-1}$

$$\theta_i = (\hat{\theta}_i + \theta_{i-1})/2$$

(2-2) Building final model and parameter
θ_{final}: final updated parameter using all tasks
(2-3) Constructing posterior based on θ_{final}

(Step 3) Application
(3-1) Predicting Y for given X using posterior distribution
(3-2) Performing decision using random sampling from posterior distribution
(3-3) Applying sample to cognitive AI for imitating human behaviors

First, we initialize model parameter and separate the data into n tasks for continual learning. Next, we train the tasks for updating the parameter. We also use MCMC computing for Bayesian continual learning [33]. Lastly, we apply the results of training step to cognitive AI for imitating human thinking and behavior. Figure 3 shows MCMC modeling and continual learning to explain the proposed Bayesian continual learning.

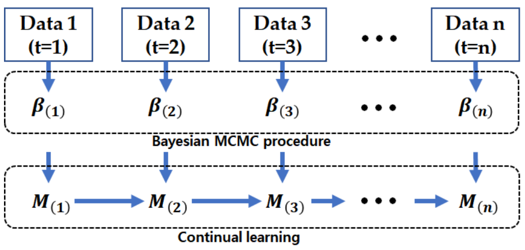

Fig. 3. Bayesian continual learning for cognitive AI.

The parameter $\beta_{(i)}$ is estimated through MCMC for *n* data sets representing human experiences over time. A continual learning model $M_{(i)}$ is determined for parameter estimated from each data (task). Because there is no previous continual model, the first Bayesian continual learning model $M_{(1)}$ is defined as (2).

$$M_{(i)} = \beta_{(i)}, \ i = 1 \tag{2}$$

That is, $M_{(1)}$ is equal to $\beta_{(1)}$. From the second data set, the Bayesian continual learning model is determined as shown in (3).

$$M_{(i)} = average(M_{(i-1)}, \beta_{(i)}), \ i = 2,3,\dots,n \tag{3}$$

The model of *i*th data $M_{(i)}$ is obtained as average of $M_{(i-1)}$ and $\beta_{(i)}$. $M_{(n)}$ is the Bayesian continual learning model that has trained using all data. Finally, we apply $M_{(n)}$ to cognitive AI.

4. Experiments and Results

4.1. Experimental result using UCI machine learning data

To illustrate how our proposed method can be applied to practical domain, we made an experiment using the UCI machine learning data [36]. We used the data set of online shoppers purchasing intention which consists of 18 variables and 12,330 observations. In this experiment, the output variable is *Revenue*, and the input variables are *Informational*, *ProductRelated_Duration*, and *PageValues*. So, we constructed linear model using MCMC, and showed the trace plots of warm-up to approximation and posterior distribution plots of model parameters in Figure 4.

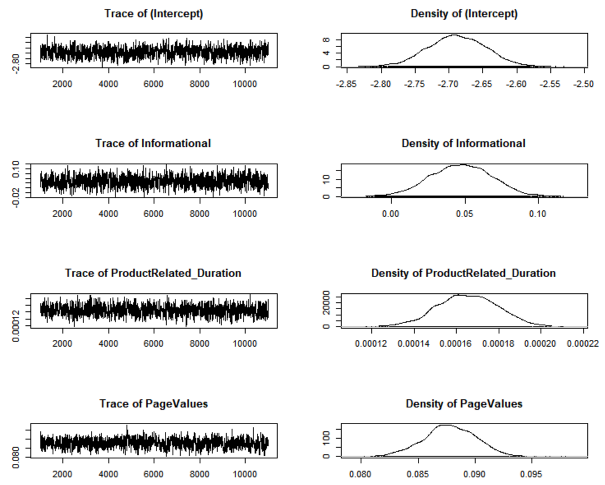

Fig. 4. Trace and posterior distribution plots for parameters.

We set the sample size for warm-up (burn-in) to be 1,000 by the trace plots of Figure 4. We confirmed this decision was appropriate, because all the trace plots of parameters are stable since the sample size 1,000. We also found the characteristics of parameter distribution through the posterior distribution plots. Table 1 shows the parameter comparison of optimal and cognitive AI models.

Table 1. Comparison of parameters of optimal and cognitive AI models

Parameter	Optimal AI	Cognitive AI		
		N=10,000	N=15,000	N=20,000
Intercept (b_0)	-2.689000 (-2.771422, -2.607383)	-2.688298 (-2.770123, -2.606428)	-2.686647 (-2.766919, -2.605542)	-2.687852 (-2.768973, -2.606055)
Info. (b_1)	0.047260 (0.004322, 0.089139)	0.047293 (0.005457, 0.087082)	0.046978 (0.005062, 0.086909)	0.047055 (0.004313, 0.088950)
Prod. (b_2)	0.000165 (0.000138, 0.000193)	0.000165 (0.000137, 0.000193)	0.000165 (0.000138, 0.000192)	0.000165 (0.000138, 0.000194)
Page. (b_3)	0.087750 (0.083265, 0.092363)	0.087800 (0.083136, 0.092171)	0.087804 (0.083126, 0.092293)	0.087825 (0.083144, 0.092324)

We built linear model of response variable (*Revenue*) and three explanatory variables (*Info. Prod.* and *Page.* for *Informational*, *ProductRelated_Duration*, and *PageValues* respectively) as follows.

$$Revenue = b_0 + b_1 Info. + b_2 Prod. + b_3 Page.$$

In Table 1, we illustrate the point and interval estimations of model parameters. Each parameter by traditional linear modeling is estimated as only one value. We call this approach optimal AI modeling in this paper. In the optimal AI modeling, the estimated results of points and intervals are only one values respectively. The estimated values of optimal AI are not changed. Therefore, we use only the same conclusion estimated as the optimal value. However, humans do not always perform the same optimal behavior. Human behavior does not deviate significantly from optimal, but, humans may behave slightly differently in some cases. In this paper, we proposed a cognitive AI modeling that can imitate such human cognitive behavior. From the results of cognitive AI according to sample size (N) in Table 1, we can provide diverse values for point and interval estimations. Using these results, we can make machines to imitate the human cognitive behaviors.

4.2. Continual learning result based on Bayesian inference

We separated the data of online shoppers purchasing intention of section 4.1 into 5 data sets for continual learning in Bayesian inference and computing for cognitive AI. The 12,330 observations were divided into 5 data sets randomly. Each data set consists of 2,466 observations and is used for a phase. Table 2 shows the Bayesian learning results at each phase.

Table 2. Bayesian learning results at each phase

Parameter	Phase 1	Phase 2	Phase 3	Phase 4	Phase 5
Intercept (b_0)	-2.7613	-2.8328	-2.5728	-2.6375	-2.6875
Info. (b_1)	0.1003	0.0399	-0.0128	0.0254	0.0702
Prod. (b_2)	0.0002	0.0002	0.0001	0.0001	0.0002
Page. (b_3)	0.0909	0.0917	0.0824	0.0840	0.0924

In Phase 1, we use first separated data set for Bayesian learning with MCMC. In Phases 2 to 5, we performed Bayesian learning using the remaining four separated data sets as in Phase 1. We found that there is a slight difference in the analysis results by phase. This means that Bayesian learning provides a learning method for cognitive AI, because the learning outcomes for decision-making are different each time. For example, the parameter value of b1 (Info.) became negative in phase 3, unlike the results of the other phases, where all of the values were positive. The results in Table 2 may show slightly different values. We found that it is possible to imitate various human thoughts using the result of Table 2. Next, we illustrate Bayesian continual learning results up to each phase using the previous results in Table 3.

Table 3. Bayesian continual learning results up to each phase

Parameter	Up to 2	Up to 3	Up to 4	Up to 5
Intercept (b_0)	-2.7971	-2.6849	-2.6612	-2.6754
Info. (b_1)	0.0701	0.0287	0.0270	0.0486
Prod. (b_2)	0.0002	0.0002	0.0001	0.0002
Page. (b_3)	0.0913	0.0869	0.0854	0.0889

In the column of Up to 2, the parameter values are calculated as the average of the parameter values of Phases 1 and 2 in Table 2. For example, the b_0 value (-2.7971) of Up to 2 is average of b_0 values of Phases 1 and 2 (-2.7613 and -2.8328). Also, the parameters of Up to 3 are calculated as average of the parameter values of Up to 2 and Phase 3 of Table 2. The parameters of Up to 4 and Up to 5 are calculated in the same way. We found that the results of Bayesian continual learning in Table 3 is similar to the results of cognitive AI in Table 1. By our proposed method, we found that the Bayesian continual learning model has little difference compared to the model that uses all the data at once. Therefore, the proposed Bayesian continual learning model can be used for cognitive AI that can imitate human behavior updated by new observed data (experience) over life.

5. Conclusions

Most machine learning methods are focused on optimal decision-making models. They provide the highest accuracy in classification and the smallest mean square error in regression problems. Therefore, existing machine learning methods have limitations in building models for cognitive AI. In this paper, we proposed a machine learning model to build the cognitive AI that imitates human thinking and behavior. Our cognitive AI is different to the optimal AI that performs optimal decisions in various fields such as AlphaGo. Humans often do not make optimal decisions in some cases. They also make decisions emotionally. That is, they do not always make the same decisions on the same problems. In our research, we proposed Bayesian continual learning model to make a machine that mimics human decision-making based on optimality and emotionality. First, using Bayesian learning method, we implemented a cognitive learning model, not the optimal AI that always makes optimal decisions. Next, we used continual learning model to improve cognitive ability through given experiences over time for imitating human thinking. To illustrate how the proposed method could be applied to practical domain, we carried out experiments using real machine learning data from UCI machine learning repository.

In our paper, we showed an approach to make the cognitive AI that imitates human thinking using the experimental results of regression problem with numeric data. We expect our research contributes to diverse area of cognitive AI. Actually, human thinks and behaviors using the experiences on diverse data type such as text and sound. So, we will develop more advanced Bayesian continual learning models to deal with text and sound data for making the cognitive AI to imitate human thinking and behaviors more precisely in our future works.

Conflicts of Interest

The authors declare no conflict of interest.

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