Deep Multi-agent Attentional Learning for Cognitive Attention Analysis in Educational Context

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Abstract

Recent development of sensing systems allows massive sensory data to be generated continuously, which makes complex human learning possible. In response to increasing concerns about education issues, we bridge students' EEG signals to their cognitive attention status in the educational context. We consider two inherent characteristics of human mental attention, the spatially-temporally varying salience of features and the relations between individual features. Based on these, we propose a multi-agent spatial-temporal attention model. The spatial-temporal attention mechanism helps intelligently select informative channels and their active periods. And the multiple agents in the proposed model represent physiological phenomenon with collective globally selected single features. With a joint goal, the agents share gained information and coordinate their selection policies to learn the optimal attention analysis model.

1 Introduction

Detecting students' attention in class provides key information to teachers to capture and retain students' attention. An attentive student will naturally be more open to obtaining knowledge than a bored or frustrated student. Currently, there is no standard method for estimating attention, many approaches have been developed to solve the problem. A lot of vision-based solutions have been proposed to detect facial expressions [Asteriadis *et al.*, 2011]. However, their use raises privacy issues, requires more computing power, and their accuracy is influenced by factors such as lighting conditions, camera positions, and background interference. Other researchers [Xu *et al.*, 2012] detect eye movement trajectories with eye trackers. However, the system can be quite expensive and long term use may cause eye injuries. Since mental attention is difficult to measure using self-report instruments, past researchers [Patsis *et al.*, 2013] employed electroencephalography (EEG) as a tool to measure changes in attention states. Their methods are based on hand-crafted features for statistical machine learning models. Recently, deep learning has experienced massive success in modeling high-level abstractions from complex data, and there is a growing interest in developing deep learning for EEG analysis [Zhang *et al.*, 2018]. Despite this, these methods still lack sufficient justification. In this work, following our previous work [Chen *et al.*, 2019], we consider two inherent characteristics of human mental attention and EEG features and exploit them to improve the analysis performance.

The first characteristic of human mental attention is the spatially-temporally varying salience of features. Human mental attention states can be represented as a sequence of multi-channel EEG data. However, only a subset of channels are particularly informative for recognizing certain mental status [Narayanan and Bertrand, 2019]. Irrelevant features often influence the recognition and undermine the performance. In addition, we assume that the significance of data changes over time. Therefore, we propose a spatial-temporal attention method to select salient channels and their active periods that are indicative of the true mental status.

The second characteristic of human mental attention considered in this paper is the relations between individual channels. When multiple adjacent and non-adjacent channels are selected, we explore their relations by capturing the global interconnections. Multiple agents select informative channels independently based on both their local observations and the information shared by each other. Each agent can individually learn an efficient selection policy by trial-and-error. After a sequence of selections and information exchanges, a joint decision on recognition is made. The selection policies are incrementally coordinated during training since the agents share a common goal which is to minimize the loss caused by false recognition.

2 The Proposed Method

2.1 Problem Statement

We now detail the human mental analysis problem on multi-channel sensory data. Each input sample $(\mathbf{x}, y)$ consists of a 2-d vector $\mathbf{x}$ and a label y. Let $\mathbf{x} = [\mathbf{x}^0, \mathbf{x}^1, ...\mathbf{x}^K]$ where K denotes the time window length and $\mathbf{x}^i$ denotes the multi-channel EEG vector collected at the point i in time. Suppose that $\mathbf{x}^i = (x_0^i, x_1^i, ...x_P^i)$, where P denotes the number of channels of the EEG devices. Therefore, $\mathbf{x} \in R^{K \times P}$ and $y \in [1, ..., C]$. C represents the number of mental status classes. The goal of the proposed model is to predict y.

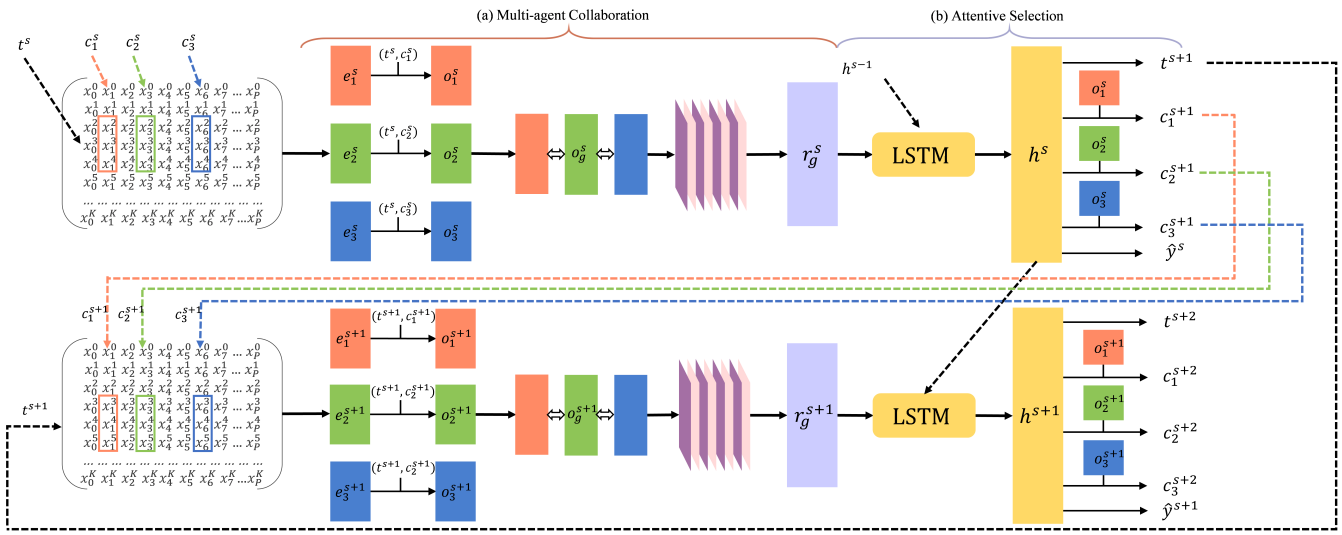

Figure 1: The overview of the proposed model. At each step s, three agents a_1, a_2, a_3 individually select channels and obtain observations o_1^s, o_2^s, o_3^s from the input $\mathbf{x}$ at (t^s, c_1^s), (t^s, c_2^s) and (t^s, c_3^s). The agents then exchange and process the gained information to get the representation r_g^s of the shared observation. And they decide the next channels again. Based on a sequence of observations after an episode, the agents jointly make the classification. Red, green and blue denote the workflows that are associated with a_1, a_2, a_3, respectively. Other colors denote the shared information and its representations.

2.2 Model Structure

The overview of the model structure is shown in Figure 1. At each step s, the agents select an active period together and individually select informative channels from the input $\mathbf{x}$. These agents share their information and independently decide the salient channels at the next step. The channels are determined spatially and temporally. After several steps, the final classification is jointly conducted by the agents based on a sequence of the observations. Each agent can incrementally learn an efficient decision policy over episodes. But by having the same goal, which is to jointly minimize the recognition loss, they collaborate with each other and learn to align their behaviors such that it achieves their common goal.

Multi-agent Collaboration.

Suppose that we employ H agents $a_1, a_2, ...a_H$ (we assume $H = 3$ in this paper for simplicity). The workflows of a_1, a_2, a_3 are shown in red, green and blue in Figure 1.

At each step s, each agent locally observes a small patch of $\mathbf{x}$, which includes data from a specific channel in its active period. Let the observations be e_1^s, e_2^s, e_3^s as Figure 1 shows. They are extracted from $\mathbf{x}$ at locations (t^s, c_1^s), (t^s, c_2^s) and (t^s, c_3^s), respectively, where t denotes the selected active period and c denote the channel. The model encodes the region around (t^s, c_i^s) $(i \in \{1, 2, 3\})$ with high resolution but uses a progressively lower resolution for points further from (t^s, c_i^s) in order to remove noises and avoid information loss. We then further encode the observations into higher level representations. With regard to each agent a_i $(i \in \{1, 2, 3\})$, the observation e_i^s and the location (t^s, c_i^s) are linear transformed independently, parameterized by θ_e and θ_{tc}, respectively. Next, the summation of these two parts is further transformed with another linear layer parameterized by θ_o The whole process can be summarized as the following equation:

$$\begin{aligned} o_i^s &= f_o(e_i^s, t^s, c_i^s; \theta_e, \theta_{tc}, \theta_o) \\ &= L(L(e_i^s) + L(concat(t^s, c_i^s))) \quad i \in \{1, 2, 3\}, \end{aligned} \tag{1}$$

where $L(\bullet)$ denotes a linear transformation and $concat(t^s, c_i^s)$ represents the concatenation of t^s and c_i^s. Each linear layer is followed by a rectified linear unit (ReLU) activation. Therefore, o_i^s contains information from "what" (e_i^s), "where" (c_i^s) and "when (t^s)".

Making multiple observations not only avoids the system processing the whole data at a time but also maximally prevents the information loss from only selecting one region of data. Furthermore, multiple agents make observations individually so that they can represent mental status by extracting the relations between the selected channels. The model can explore various combinations of channels to recognize mental status during learning.

Then we are interested in the collaborative setting where the agents communicate with each other and share the observations they make. So we get the shared observation o_g^s by concatenate o_1^s, o_2^s, o_3^s together so that o_g^s contains all the information observed by three agents. A convolutional network is further applied to process o_g^s and extract the informative spatial relations. The output is then reshaped to be the representation r_g^s so that r_g^s represents the mental status to be identified with multiple channels selected from motions on different body positions.

Attentive Selection.

In this section, the details about how to select channels and active period attentively are introduced. We first introduce the episodes in this work. The agents incrementally learn the attentive selection policies over episodes. In each episode, following the bottom-up processes, the model attentively selects

data regions and integrates the observations over time to generate dynamic representations, in order to determine effective selections and maximize the rewards, i.e., minimize the loss. Based on this, LSTM is appropriate to build an episode as it incrementally combines information from time steps to obtain final results. As can be seen in Figure 1, at each step s, the LSTM module receives the representation r_g^s and the previous hidden state h^{s-1} as the inputs. Parameterized by θ_h, it outputs the current hidden state h^s:

$$h^s = f_h(r_g^s, h^{s-1}; \theta_h) \tag{2}$$

Now we introduce the selection module. The agents select salient channels and an active period at each step. At the step s, three agents control $c_1^{s+1}, c_1^{s+1}, c_3^{s+1}$ independently based on both the hidden state h^s and their individual observations o_1^s, o_2^s, o_3^s so that the individual decisions are made from the overall observation as well. t^{s+1} is jointly decided based on h^s only since it is a common selection. The decisions are made by the agents' selection policies which are defined by Gaussian distribution stochastic process:

$$c_i^{s+1} \sim P(\cdot \mid f_l(h^s, o_i^s; \theta_{c_i})) \;\; i \in \{1, 2, 3\}, \tag{3}$$

and

$$t^{s+1} \sim P(\cdot \mid f_t(h^s; \theta_t)) \tag{4}$$

The purpose of stochastic selections is to explore more kinds of selection combinations such that the model can learn the best selections during training.

To align the agents' selection policies, we assign the agents a common goal that correctly recognizing mental status after a sequence of observations and selections. They together receive a positive reward if the recognition is correct. Therefore, at each step s, a prediction $\hat{y}^s$ is made by:

$$\hat{y}^s = f_y(h^s; \theta_y) = softmax(L(h^s)) \tag{5}$$

The agents receive a delayed reward R after each episode. $R = 1$ if $\hat{y}^S = y$ and 0 otherwise. The target of optimization is to coordinate all the selection policies by maximizing the expected value of the reward $\bar{R}$ after several episodes.

2.3 Training and Optimization

This model involves parameters that define the multi-agent collaboration and the attentive selection. The parameters $\Theta = \{\theta_e, \theta_{tc}, \theta_o, \theta_g, \theta_h, \theta_{c_i}, \theta_t, \theta_y\}$ ($i \in \{1, 2, 3\}$). The parameters for classification can be optimized by minimizing the cross-entropy.

However, selection policies that are mainly defined by θ_{c_i} ($i \in \{1, 2, 3\}$) and θ_t are expected to select a sequence of channels. The parameters are thus non-differentiable. In this view, we deploy a Partially Observable Markov Decision Process (POMDP) to solve the optimization problem. Suppose $e^s = (e_1^s, e_2^s, e_3^s)$, $ct^s = (c_1^s, c_2^s, c_3^s, t^s)$, We consider each episode as a trajectory $\tau = \{e^1, ct^1, y^1; e^2, ct^2, y^2; ..., e^S, ct^S, y^S\}$. Our goal is to learn the best selection policy Π that maximizes $\bar{R}$. Specifically, Π is decided by Θ. Thus we need to find out the optimized $\Theta^* = \arg\max_{\Theta}[\bar{R}]$. One common way is gradient ascent. Following the REINFORCE rule [Williams, 1992]:

$$\nabla_\Theta \bar{R} \approx \frac{1}{M} \sum_{i=1}^{M} R^{(i)} \sum_{s=1}^{S} \nabla_\Theta log\Pi(y^{(i)} | \tau_{1:s}^{(i)}; \Theta), \tag{6}$$

where M denotes the number of Monte Carlo samples and y_i is the correct label for the ith sample. Therefore, the overall optimization can be summarized as maximizing $\bar{R}$ and minimizing the classification loss.

3 Conclusion

This work introduces a multi-agent attentional model for human mental attention analysis with EEG signals. we first propose a selective attention mechanism for extracting the spatially-temporally varying salience of EEG channels. Then, multi-agent is proposed to capturing interconnections of features from single channels. The agents' cooperate intelligently by aligning their actions to achieve the common analysis target.

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