Simple Probabilistic Data-driven Model for Adaptive BCI Feedback

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Keywords: Adaptive BCI, Probabilistic model

Abstract

Due to abundant signal and user variability among others, BCIs remain difficult to control. To increase performance, adaptive methods are a necessary means to deal with such a vast spectrum of variable data. Typically, adaptive methods deal with the signal or classification corrections (adaptive spatial filters [1], co-adaptive calibration [2], adaptive classifiers [3]). As such, they do not necessarily account for the implicit alterations they perform on the feedback (in real-time), and in turn, on the user, creating yet another potential source of unpredictable variability. Namely, certain user's personality traits and states have shown to correlate with BCI performance, while feedback can impact user states [4]. For instance, altered (biased) feedback was distorting the participants' perception over their performance, influencing their feeling of control, and online performance [5]. Thus, one can assume that through feedback we might implicitly guide the user towards a desired state beneficial for BCI performance. An adaptive, Active (Bayesian) Inference model was proposed as a way to develop entirely adaptive BCI as it can include different dynamics of signal and user variabilities by relying on user and task models [6]. In a simple case (one level of adaptation), by inferring dynamic user reactions to feedback, it can adapt the feedback in order to maximise performance. However, Active Inference demands explicit conceptions of user and task models specific to each case, and its current implementation seems to necessitate high computational power, making it sub-optimal for real-time BCI.

Simple Probabilistic Model

If we wish to maximise performance by influencing the user through dynamic feedback while accounting for user's reactions, we could achieve that with a simple probabilistic, adaptive model, as follows. Given a finite number of possible feedback or actions $a = 1,2..n$, $a(r)$ per run $r = 1,..m,$ each action creates a corresponding user's reaction or observation $o_a(r) \in R$ as online performance. Next to the observations and actions, the model primarily contains: (i) the priors about the user k_a which are static but different for each action; (ii) the confidence about priors α which is a constant value (same for each action), and (iii) an exploration/exploitation parameter $w(r)$ that is a function of time but is the same for each action. The priors, if available, prescribe the best first action for a specific user type (e.g., a certain feedback for a certain personality trait). Otherwise they prescribe equal probabilities to each first action k_a = p($\frac{1}{n}$). After every new run r, the model keeps the observation (online performance) from the previous run and each time calculates the new weighted average per action $\mu_a(r)$, with given parameters: $\mu_a(r) = w(r)\mu_a(o_a(r\text{-}1)) + \alpha k_a$. The model transforms the new mean vector of actions: $\mu(\boldsymbol{r}) = [\mu_a(r)] = [\mu_1(r), \mu_2(r).., \mu_n(r)]$ into probabilities using a softmax function $\sigma(\mu(\boldsymbol{r}))$; resulting as a vector of probabilities to select one of n future actions: $[P(a(r+1))] = P(\sigma(\mu(\boldsymbol{r})))$. Thus, this model is not deterministic, which leaves a slight chance for the least probable action to be chosen, thus enabling exploration.

Real dataset

We tested our adaptive model offline on real data from 30 participants from [5]. In that study, participants were separated into 3 groups, each receiving one out of three possible feedback (actions) as: positive bias, negative bias, and no bias. Authors also collected personality traits, states and calibration performance of participants, and divided the participants into high and low scores depending on whether their scores were above or below the median value. As no participant received all 3 actions, to be able to test our adaptive model, we simulated virtual participants as follows. One virtual participant contained data from 3 actual participants (one from each group) such that all 3 of them shared at least 2 personality traits or calibration performance. For instance, if 3 participants had high scores on anxiety and low scores on calibration performance, then they would create one virtual participant. This way we expect to minimise the individual differences and homogenise the reactions to feedback, simulating a real participant. We managed to create 48 virtual participants. As the experiment in [5] was performed over two sessions, then the *average online performance* (observations per run per action) from the first session served to train our model's priors as *training data*. On the other hand, we randomly picked *average online performance* from the runs of the second session, to serve as *testing data*. The priors prescribe the best action (here, a bias type) for a specific user (given personality trait or calibration performance scores). Thus, priors are calculated as the normalized mean of *training data* per action of all real participants who share one trait. That is, if one virtual participant pairs low anxiety and high extroversion, we would first calculate the average of *training data* for each trait separately and then average them together to fit our virtual user. As result, our prior is different for each action, which enables one specific first action (bias) to be chosen for a user type.

Model comparisons

As depicted in **Figure 1** below, for 48 virtual users and 20 repetitions, we compare the following models:

(i) Adaptive model without priors – called *ModelAdaptive*,
(ii) Adaptive model with wrong priors, i.e., prescribing the worst first actions for each virtual user – *ModelAdaptive+AntiPriors*,
(iii) Adaptive model with correct priors – *ModelAdaptive+Priors*,
(iv) Static model performing always positive bias – *ModelFixed_positive*,
(v) Static model performing always negative bias – *ModelFixed_negative*,
(vi) Static model performing always realistic feedback – *ModelFixed_nobias*,
(vii) Static model with priors for all participants – *ModelPriors*,
(viii) Static model with wrong priors for all – *ModelAntiPriors*,
(ix) Model performing completely random action without priors – *ModelRandom.*

Results

1-way ANOVA (independent variable: model, dependent variable: performance) with FDR correction showed significant increase of performance ($p<0.05$) of the ModelAdaptive+Priors when compared to all other models.

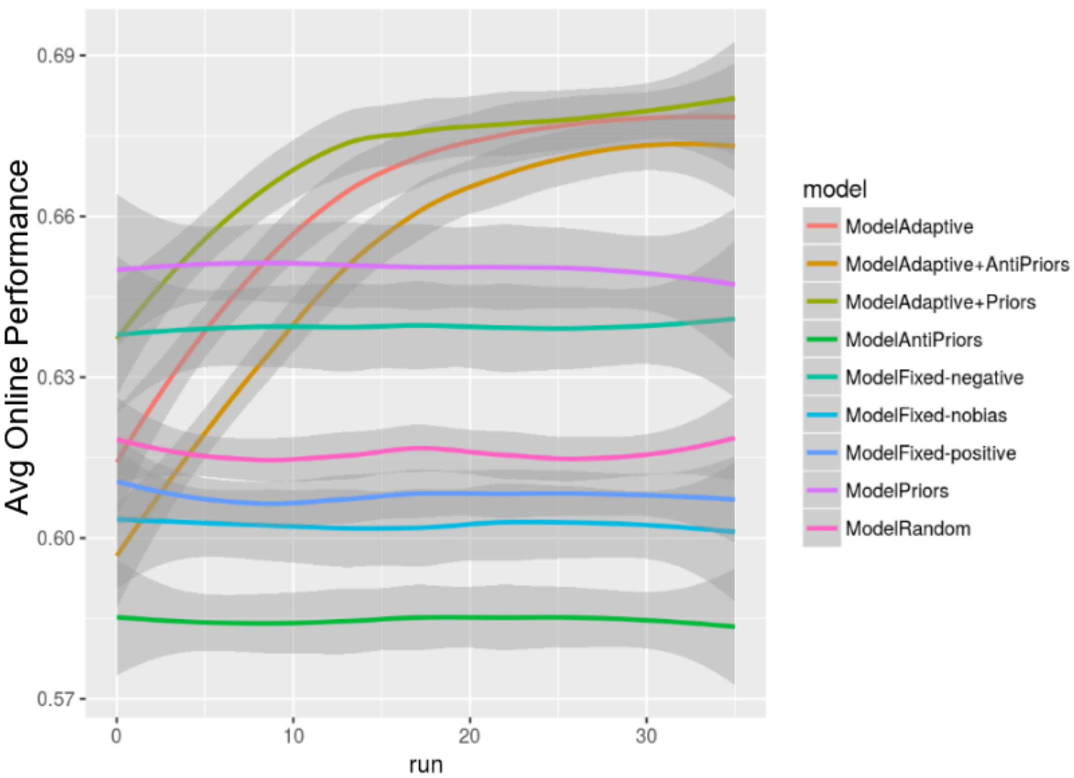

Fig.1. Evolution of models over 40 runs for 48 virtual participants and 20 repetitions, for online performance. We can observe that the adaptive model with priors reaches the highest performance, and that naturally the static model with wrong priors performs the worst.

Discussion

We are aware that this method has 2 flaws. First, the virtual users are not real, and second, the observations i.e., reactions to feedback are not consecutive but randomly picked from the testing dataset. However, those are common drawbacks of most offline methods. This adaptive model promises great potential as it is intuitive, simple to implement, fairly flexible and resilient to wrong priors. In the future, we plan to test this model online.

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