Using EEG in Knowledge Tracing

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ABSTRACT

Knowledge tracing (KT) is widely used in Intelligent Tutoring Systems (ITS) to measure student learning. Inexpensive portable electroencephalography (EEG) devices are viable as a way to help detect a number of student mental states relevant to learning, e.g. engagement or attention. This paper reports a first attempt to improve KT estimates of the student's hidden knowledge state by adding EEG-measured mental states as inputs. Values of *learn*, *forget*, *guess* and *slip* differ significantly for different EEG states.

Keywords

EEG, knowledge tracing, Logistic regression.

1. Introduction

Knowledge tracing (KT) is widely used in Intelligent Tutoring Systems (ITS) to measure student learning. In this paper, we improve KT's estimates of students' hidden knowledge states by incorporating input from inexpensive EEG devices. EEG sensors record brainwaves, which result from coordinated neural activity. Patterns in these recorded brainwaves have been shown to correlate with a number of mental states relevant to learning, e.g. workload [1], associative learning [2], reading difficulty [3], and emotion [4]. Importantly, cost-effective, portable EEG devices (like those used in this work) allow us to collect longitudinal data, tracking student performance over months of learning.

Prior work on adding extra information in KT includes using student help requests as an additional source of input [5] and individualizing student knowledge [6]. Here we use students' longitudinal EEG signals as input to dynamic Bayes nets to help trace their knowledge of different skills. An EEG-enhanced student model allows unobtrusive assessment in real time. The ability to detect learning while it occurs instead of waiting to observe future performance could accelerate instruction dramatically. Current EEG is much too noisy to detect learning reliably on its own. However, as this paper shows, adding EEG to KT may allow better detection of learning than using KT alone.

2. Approach

KT is a Hidden Markov Model using a binary latent variable ($K^{(i)}$) to model whether a student knows the skill at step i. It estimates the hidden variable from its observations ($C^{(i)}$'s) in previous steps of whether the student applied the skill correctly. KT usually has 4 (sometimes 5) probabilities as parameters: initial knowledge (L_0), learning rate (t), forgetting rate (f) (usually assumed to be zero, but not in this paper), guess rate (g), and slip rate (s). We add another observed variable ($E^{(i)}$), representing the EEG measured mental state estimated from EEG signals and time-aligned to the student's performance at step i.

EEG-derived signals are often described as a type of measure of human mental states. For example, NeuroSky uses EEG input to derive proprietary attention and meditation measures claimed to indicate focus and calmness [7]. We hypothesize that a student may have a higher learning rate t and/or a lower slip rate s when focusing or calm at a given step. Thus EEG-KT, shown in Figure 1, extends KT by adding variable $E^{(i)}$ computed from EEG input.

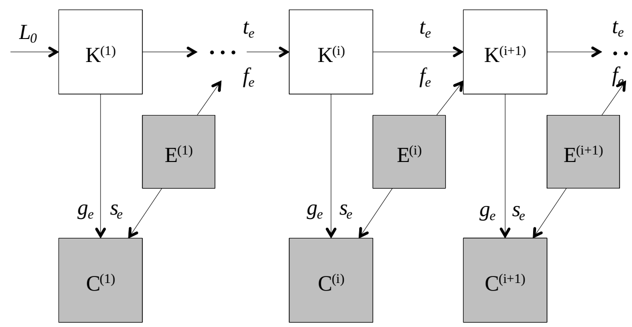

Figure 1. EEG-KT uses a binary EEG measure in KT

3. Evaluation and Results

To evaluate this approach, we compare EEG-KT to the original KT on a real data set. Our data comes from children 6-8 years old who used Project LISTEN's Reading Tutor at their primary school during the 2013-2014 school year [8]. We measure the growth of oral reading fluency by labeling a word as fluent if it was accepted by the automatic speech recognizer (ASR) as read correctly without hesitating or clicking on it for help.

EEG raw signals are collected by NeuroSky BrainBand at 512 Hz, and are denoised as in Chang et al. [3]. We use NeuroSky's proprietary algorithm to generate 4 channels: signal quality, attention, meditation, and rawwave. We then use Fast Fourier Transform to generate 5 additional channels from rawwave: delta, theta, alpha, beta, and gamma. In total, excluding signal quality, we obtain 8 EEG measures. We also compute a confidence-of-fluency (Fconf) metric as our 9th EEG measure by using training pipeline similar to [9]. It pre-balances the data by under-sampling, computes the average and variance of each channel's values over each word's duration as 16 features, and trains Gaussian Naïve Bayes classifiers to predict fluency (61.8% accurate, significantly above chance with $p < 0.05$ in Chi-squared test). We compute Fconf as Pr(fluent | 16 features) – Pr(disfluent | 16 features).

We normalize each of the 9 measures within student, discretize it as a binary variable (TRUE if above zero; FALSE otherwise), and use it to fit an EEG-KT model. We also evaluate Rand-KT, which replaces EEG with randomly generated values from a Bernoulli distribution. We use EM algorithms to estimate the parameters, and implement the models in Matlab Bayesian Net Toolkit for Student Modeling (BNT-SM) [10, 11].

The data has 6,313 observations from 12 students, with 83% labeled as fluent. We use leave-1-student-out cross-validation (CV), which trains word-specific models on 11 out of 12 students and tests on the remaining single student. To maintain enough data for EM to estimate the parameters, we keep 4 students who have many more than 500 observations in the training data and cross-validate only the other 8 students. We use AUC (area under the curve) to assess model prediction, as shown in Table 1. Fconf-KT and Theta-KT beat KT, but not significantly. The other 7 models did worse than KT, the bottom 5 significantly so.

Table 1. AUC scores by 8-fold CV

(underlined if p <0.05 in pair[1]ed t-test comparison to KT)

Models	AUC	Models	AUC
Fconf-KT	0.6613	Gamma-KT	0.6317
Theta-KT	0.6568	RAW-KT	0.6275
KT	**0.6479**	MED-KT	0.6230
ATT-KT	0.6435	Delta-KT	0.6224
Alpha-KT	0.6429	Rand-KT	0.6146
Beta-KT	0.6355		

Table 2 reports the estimated parameters for the two most interpretable EEG measures, meditation and attention. Students in a meditative state according to EEG were significantly less likely to forget, guess, or slip. Students in an attentive state according to EEG were significantly less likely to forget or slip.

Table 2. Avg. estimated parameters in EEG-KT across words

(underlined if $p < 0.05$ in paired t-test across high/low state)

	Meditation		Attention	
Parameters	High	Low	High	Low
t_e	0.32	0.33	0.38	0.43
f_e	0.10	0.25	0.15	0.30
g_e	0.53	0.62	0.55	0.56
s_e	0.03	0.07	0.03	0.08

4. Conclusion and Future Directions

To improve KT's estimates of students' hidden knowledge states, we tried adding different binary EEG measures as an input. This simple approach produced significantly different estimates of forgetting, guessing, and slip rates according to the attention and meditation indicators, but did not improve model fit significantly. Our subsequent approach achieved much higher accuracy (AUC .7665) by using logistic regression to merge EEG measures [12].

With months of data and many words per minute, fluency development offers a rich domain for studying EEG-enriched KT, but it can apply to other types of learning as well. Another future direction is to analyze its practical impact on learning. As Beck and Gong [13] pointed out, tiny improvements in predictive accuracy don't matter -- actionable intelligence does. We want to estimate the possible speedup in learning from using EEG to detect it as it occurs rather than wait to see it in later performance.

5. Acknowledgements

This work was supported in part by the National Science Foundation under Cyberlearning Grant IIS1124240. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the National Science Foundation.

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