Predicting Learning by Analyzing Eye-Gaze Data of Reading Behavior

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ABSTRACT

Researchers have highlighted how tracking learners' eye-gaze can reveal their reading behaviors and strategies, and this provides a framework for developing personalized feedback to improve learning and problem solving skills. In this paper, we describe analyses of eye-gaze data collected from 16 middle school students who worked with Betty's Brain, an open-ended learning environment, where students learn science by building causal models to teach a virtual agent. Our goal was to test whether newly available consumer-level eye trackers could provide the data that would allow us to probe further into the relations between students' reading of hypertext resources and building of graphical causal maps. We collected substantial amounts of gaze data and then constructed classifier models to predict whether students would be successful in constructing correct causal links. These models predicted correct map-building actions with an accuracy of 80% (F1 = 0.82; Cohen's kappa $\kappa = 0.62$). The proportions of correct link additions are in turn directly related to learners' performance in Betty's Brain. Therefore, students' gaze patterns when reading the resources may be good indicators of their overall performance. These findings can be used to support the development of a real-time eye gaze analysis system, which can detect students reading patterns, and when necessary provide support to help them become better readers.

Keywords

Eye-Gaze Data Analysis; Computer-Based Learning Environment; Reading Behavior; Classification.

1. INTRODUCTION

In a number of computer-based learning environments (CBLEs), students are expected to learn and refresh their domain knowledge from resources (typically in text or hypertext form with figures), then to construct solutions to assigned problems based on their learned knowledge. Such environments are known to help students develop cognitive skills and strategic reasoning processes, and, therefore, help students not only learn the domain content but prepare them for future learning [2, 3, 5, 17, 30-32]. However, because of the open-ended nature of these environments, novice learners often have difficulties in making progress toward their goals and completing their solutions. Therefore, the ability to track and understand learners' performance and behaviors is important for their overall success, so that relevant personalized feedback and instruction can be provided to them as necessary. However, tracking students' reading behaviors with sufficient precision and accuracy in computer-based learning environments is a non-trivial task.

Use of technologies, such as eye tracking devices can provide behavioral metrics that researchers can use to study learners basic cognitive processes and other information processing skills during reading [12, 27, 28, 35]. For educational research and applications, use of eye-tracking data has mainly focused on studying the effects of instructional strategies on eye-gaze behavior [21]. Some of these studies focus on learning how students' spatial contiguity [16], attention level [23] and viewing behavior [1] affect the cognitive processes that mediate learning outcomes. Conati et al. [7] have reviewed previous studies that modeled students' cognitive, metacognitive and affective states in intelligent learning environments using eye-gaze data. For example, Bondareva, et al. [4] assessed student learning from eye-gaze data during interaction with MetaTutor, an intelligent CBLE designed to develop self-regulated learning skills when generating summaries after reading about complex science topics. The MetaTutor study reported 78% classification accuracy on student learning based on the features extracted by gaze data alone. Similar results were reported by Kardan and Conati [18], in modeling students' learning with interactive simulations.

Peterson, et al. [25] report that learners' eye-gaze and pupil dilation data were used to predict performance and learning gains in ChemTutor, designed to teach chemistry. Hutt, et al. [14] studied students' mind wandering using eye-gaze on specific areas of interest (AOI) [10]. All of these results show that eye-tracking devices help to track learners' reading behaviors in CBLEs. Most of this research has relied upon expensive research-grade eye-tracking devices appropriate primarily for lab settings. However, newly available consumer-level eye-trackers are relatively inexpensive and have recently been deployed in classroom environments [14]. Our goal in this study is to run an initial proof of concept case study to demonstrate that these consumer-grade eye-tracking devices with sampling rates less than 90 Hz can effectively predict learners' behaviors in CBLEs.

In the research reviewed above [1, 4, 7, 16, 18, 22, 23], eye gaze features were extracted using global gaze features computed across broad Areas of Interest (AOI) that do not differentiate between more fine-grained screen contents. For example, the features extracted in [4] are based on predefined window position in the learning environment. This can be a limiting factor in CBLEs, where students are expected to learn by combining information from multiple hypertext resources. In Betty's Brain, a CBLE developed by our group [3, 24], students build a causal map to teach their agent, using hypertext resources that span multiple pages. Students are expected to find, read, and interpret sentences that provide information about entities and causal relations between entities, and add the link(s) to the current causal model. Extracting students' eye-gaze features as they read these hypertext resources would require a different AOI for each hypertext resource page. To address this challenge we propose a methodology to extract eye-gaze features that are directly related to content in each of the hypertext resource pages.

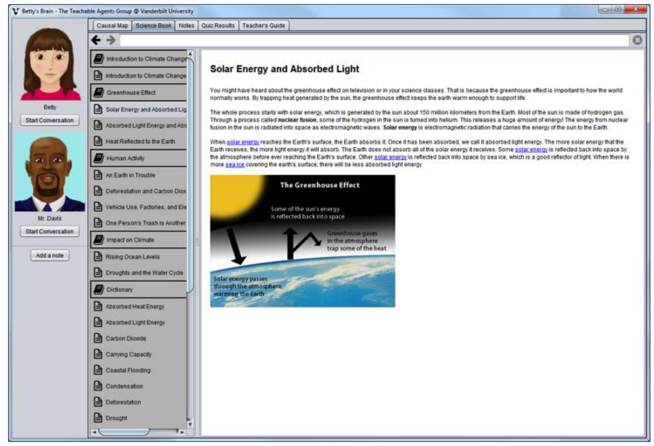
The proposed methodology was applied to eye-gaze data collected from middle school students who worked on Betty's Brain learning environment. The features extracted from the eye-gaze data were then used to construct classifier models that predict learners' model building effectiveness given their reading characteristics. For our study, we were able to predict learner performance in causal map building with an accuracy of 80% (F1 = 0.82; Cohen's kappa κ = 0.62). The learned classifier model was then used to classify learners reading behavior and directly related to learners' performance on map building action in Betty's Brain. These findings can be used to support the development of a real-time eye-gaze analysis system to provide personalized feedback and adaptive instructions.

The rest of the paper is organized as follows. Section 2 describes the learning environment. Section 3 describes the proposed methodology to extract content based eye-gaze features from learning environment with multiple hypertext resources. Section 4 describes the experimental design, data collection, methodology to preprocess the data and train the classifiers to predict learning based on features extracted solely from eye-gaze data. The results are reports in section 5. Conclusions, limitations and future work are discussed in section 6.

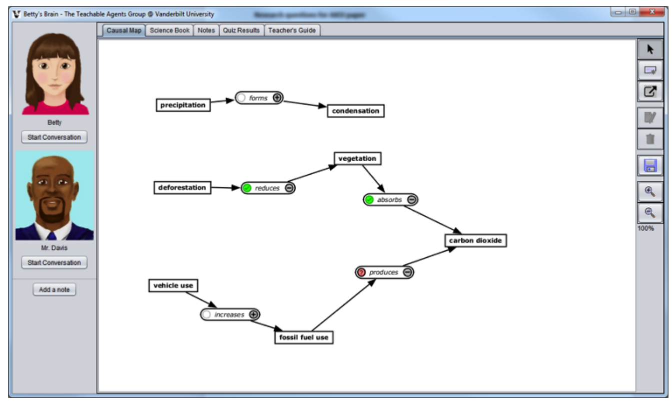
2. BACKGROUND: THE BETTY'S BRAIN LEARNING ENVIRONMENT

The Betty's Brain learning environment [24] assigns learners the task of teaching a science topic to a teachable agent named Betty by constructing a visual causal map consisting of a set of entities connected by directed causal links. As students build their map, they can ask Betty questions, and can answer them and explain her answers. The students' goal is to teach Betty a causal map that matches a hidden expert model of the topic.

Students' activities are categorized into three primary action types: (1) reading hypertext resources on the science topic (*READ*), (2) building the causal map (*BUILD*), and (3) assessing (*ASSESS*) the correctness of the map [8]. Students iterate among these activities until they have taught Betty a correct model. In this paper, we study learners' information acquisition processes primarily as reading the hypertext resources that describe the science topic under study (*e.g., human causes and effects of climate change*) by breaking it down into a set of subtopics. Each sub-topic describes a system or a process (*e.g., the greenhouse effect*) in terms of entities (*e.g., absorbed heat energy*) and causal relations among these entities (*absorbed heat energy increases the average global temperature*). As students read about the topic, they extract the causal relations between entities and construct the causal map to teach Betty. Figures 1 illustrates the Betty's Brain *READ* (set of hypertext resources) and *BUILD* interfaces.



(a)



(b)

Figure 1. Betty's Brain system showing (a) *READ* (Science resources) and (b) *BUILD* (Causal Map) Interfaces

Students can assess their own understanding and success in teaching Betty by:

1. Querying Betty using a template for asking *cause-effect* questions. A second pedagogical "mentor" agent, *Mr. Davis,* helps grade Betty's answers by comparing them against the expert model.
2. Asking Betty to take a quiz, which helps them evaluate the current state of the map.

In addition to the three major actions (*READ*, *BUILD*, and *ASSESS*), students can also take *NOTES* on information from the science book, and *CONVERSE* with Betty or Mr. Davis. Students' interactions with the environment are recorded, in log files with associated timestamps.

Student performance in the Betty's Brain environment is measured by their current "map score", which is computed as the difference between the number of correct and incorrect links present in the student's map at any point of time. Depending on the edit actions performed by the student, map score can increase, decrease, or remain the same. Map score patterns vary among students and display their individual learning behaviors.

Students' learning behaviors in Betty's Brain are modeled according to a cognitive/metacognitive task model [19]. Their interactions with the system are mapped to particular skills (for example, reading hypertext resources is mapped to an information acquisition skill), which are then interpreted in terms of the overall learning objectives. A sequential combination of skills, performed in a context, is interpreted as a problem solving strategy. Researchers have employed a combination of analytics methods [34] and exploratory sequence mining techniques for detecting and characterizing students' metacognitive processes [20] in the Betty's Brain environment. Betty's Brain has been shown to significantly improve student learning, as measured by gains observed from pre- to post-tests. [9, 19, 20, 24, 34].

An important component that governs students' learning and causal reasoning processes in Betty's Brain is their ability to interpret the information provided in the hypertext resources and convert it into efficient causal links. However, this information extraction and interpretation procedure cannot be captured completely from our log files. The use of eye tracking devices can help us track the reading behaviors of students and provide more insight into this procedure. Hence, our goal in this work is to use eye tracking devices in classrooms to better understand students' learning behaviors as they interact with Betty's Brain in authentic settings. In the next section, we describe our proposed methodology to extract eye-gaze features that are directly related to content in each of the hypertext resources.

3. METHODOLOGY TO EXTRACT EYE-GAZE FEATURES

The steps involved in extracting content based eye-gaze features from hypertext resources in an open-ended learning environment are shown in Figure 2. In order to extract features, we first align the log data (in Figure 2(a)) from the learning environment and raw data (b) from the eye-tracking device. Then the Area of Interest (AOI) from each section of the hypertext resources (key file) are aligned, and used to extract the content based eye-gaze features. The details of log data and the key file are described below.

Students' interactions with the learning environment are stored with timestamps, in log files. This includes all student activities such as Read, Build, Notes, and Assess actions. To extract the content based eye-gaze features, we define the bounding box coordinates [x, y] of three AOI regions: a) the title, b) the image c) the sentence that explains the causal relationship between entities. The AOI positions vary for each resource page, hence a key file is created with start and end positions of AOI region of each hypertext resource in the learning environment. Table 1 shows a sample key file with details of AOIs for a science resource page *"Solar Energy and Absorbed Light"* [33]. The sentence *"The more solar energy that the Earth receives, the more light energy it will absorb."* describes the causal relationship between the two entities *"Solar energy" and "Absorbed light energy"* that is relevant for the causal model. The [x, y] coordinates of starting position and ending position of the AOIs are identified, for a display with screen resolution of 1600*900, and recorded in the key file.

The raw data from the eye-tracking device contains eye-gaze position on the display represented as [x, y] coordinates with the timestamp for each sample. The number of samples per second are based on the sampling rate of the eye-tracking device. The timestamp in the log data and raw data from eye-tracking are used to align and combine them for further analyses. Using the aligned data and position of AOIs from the key file, the eye-gaze information on AOIs is extracted and then used to extract content based eye-gaze features. Eye movements while reading are measured by fixations (duration of gaze focused on the same point) and saccades (movement of gaze between two fixations) [27, 28]. In this study, we used four frequently used [15, 29] measures of fixation, and two frequently used measures based on saccades as the features as summarized in Table 2. The features are computed for each of the three AOIs discussed above and also for the total page, thus providing a minimum of 4 x 4 = 16 content-based eye-gaze features for each hypertext resource page. Some of the hypertext resources contained multiple sentences that explain the causal relationship between entities.

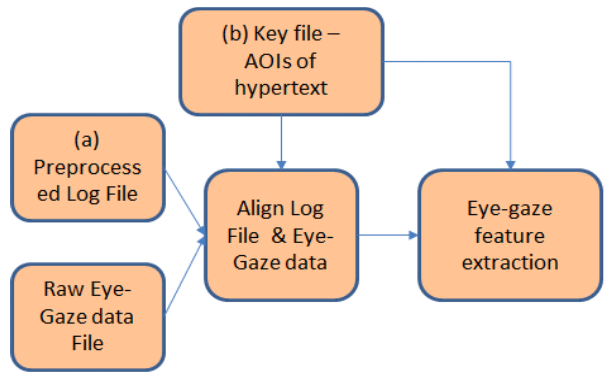


Figure 2: Algorithm to Extract Content Based Eye-Gaze Features from Multiple Hypertext Resources

Table 1: Sample Key file with AOIs for a resource page

AOI	Starting position in [x, y] coordinates	Ending position in [x, y] coordinates
Image	[415,350]	[810,640]
Title	[417,120]	[734, 145]
Causal Relation	[416, 281]	[1330,305]
Entities	*Solar energy*	*Absorbed light energy*
Causal Relationship between entities	*The more solar energy that the Earth receives, the more light energy it will absorb.*	

4. EXPERIMENTAL METHODOLOGY

The analysis presented in this paper is based on a recent study of Betty's Brain. The data was collected from eighteen 6th grade students from two classrooms of a middle school in Nashville, Tennessee, USA.

Students used the Betty's Brain system to learn about the causes and effects of climate change. The students' goal was to develop a causal map containing 22 concepts and 25 links representing the greenhouse effect *(e.g. solar energy, absorbed light energy)*, human activities affecting global climate change *(e.g. deforestation,* *vehicle use)*, and impacts on climate *(e.g. sea ice, ocean level, drought).* The hypertext resources were organized into one introductory page, three pages covering the greenhouse effect, four pages covering human activities, and two pages covering impacts on climate. Additionally, a glossary section provided a description of some of the concepts, one per page. The complete resources were made up of 31 hypertext pages.[1]

Table 2: Description of eye-gaze features

Feature	Description
Fixation Count	Total number of fixations counted in a page
Average Fixation Duration in milliseconds	Mean of fixation duration on a page (i.e., Gaze duration mean)
Fixations Count on AOI	Total number of fixations counted in an AOI
Average Fixation Duration on AOI	Mean of fixation duration on AOI
Relative Saccade angle in degrees	The relative angle between two consecutive saccades.
Saccade Amplitude	The size of the saccade measured in degrees or mins of arc

4.1 Study Procedure

The study was conducted over seven school days, with students participating in the study for one 60-minute class period each day. On day 1, students completed the pretest. On day 2, students worked with Betty's Brain introduction topic to get hands-on training on how to identify causal relation with reading text passages. During the second day, we also trained the students on how to calibrate the eye tracker and helped them to create their eye-tracking profile on the laptop. In this study, we used nine Tobii 4c eye-tracking device to collect students' eye-gaze data. The eye trackers were attached to the laptop computer just below the screen using magnetic strips. Students calibrated using the inbuilt Tobii Eye Tracking software[2] that displays on-screen instructions followed by a six point calibration sequence, where the points appear on the screen and disappear when students fixated on each point. Students worked on Betty's Brain climate change topic for four class periods (day 3-6). During these periods, students first selected their eye-tracking profile and calibrated their gaze points using nine-point calibration without the help of researchers. On the last day, students completed the post-test that was identical to the pre-test.

4.2 Data Collection

To extract content based eye-gaze features we combined data from the Tobii 4c eye-tracking devices with log data from Betty's Brain system as they worked on the Climate change topic on days 3-6 of the study.

4.3 Validation of Eye-Tracking Data

Researchers helped the students to set up and calibrate the eye-tracking device during the training day (second session) for a total of 18 students. However, we are not able to use the data from two students' due to continuous calibration failure; hence we used the eye-gaze data collected from 16 students' in this analysis.

On an average, eye gaze data were obtained for 53.3% of the entire duration that each student interacted with the learning environment. The reason for the loss of data can be attributed to students' a) focus on the keyboard while taking notes and typing labels for keywords, b) interaction with other students and c) focus on the teacher or researcher during instructions. To assess the degree to which the proportion of data collected was caused by stable individual differences between students; we correlated the average proportion of data collected over days 1 & 3 for each student with the average duration of data collected over days 2 & 4. This correlation was very strong ($r = 0.89$), demonstrating that factors causing variation in the amount of data collected for each student were strongly affected by individual differences between students. However, given the noisy classroom environment, the overall amount of eye-gaze data collected for 16 of the 18 students was a promising sign that consumer-level eye trackers could be useful in this setting.

4.4 Data Analysis and Methodology

We processed the eye-gaze data using pygaze analyzer, an open-source toolbox for eye-tracking [8] to extract fixation and saccades. The key file, as shown in table 1, is developed based on AOIs in ten hypertext resources. Eye-gaze features as described in table 2 are extracted using the data collected from 16 students.

To predict learners' performance in the map building activity using only the eye gaze data, we considered the map-building activities (*ADD, EDIT and DELETE* causal links) that were immediately followed by a supported[3] by hypertext Read actions [34]. The research methodology to model learners' performance using eye-gaze data on hypertext resources during Read action is shown in Figure 3. The eye-gaze features extracted during each Read action, and performance on the subsequent supported Build actions were used as a labeled data to train and validate the classifier. The trained classifier was then applied on eye-gaze features extracted during all Read actions to classify the learner's reading behavior on hypertext resources as effective or ineffective. The average number of effective and ineffective Read actions over a session were then used to model learners' performance on causal map building actions in the same session.

5. RESULTS

In this section, we first describe the results of eye-gaze feature extraction and performance of the classifier trained using labeled data. Then the analysis of modeling learners' performance using reading behavior is discussed.

[1] The Betty's Brain system can be downloaded from https://wp0.vanderbilt.edu/oele/software/

[2] The Tobii Eye Tracking software was downloaded from https://tobiigaming.com/getstarted/

[3] The two sequential actions Read → Build, is considered supported, only if the information acquired in Read action is used in the Build action.

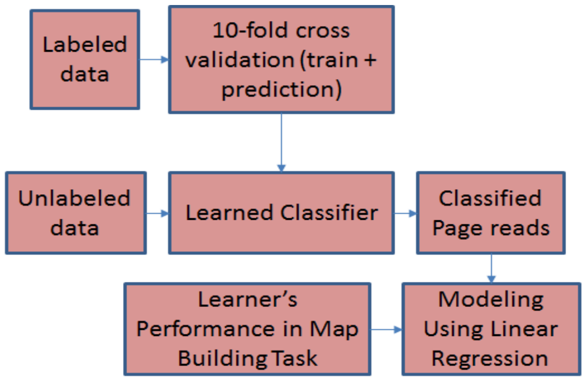


Figure 3: Research Methodology to Predict Learning from learner's Reading Behavior

We extracted eye-gaze features during 160 Read actions that were immediately followed and supported by Build actions from 16 student's log and eye-tracking data. Out of 160 eye-gaze features, 36 (22%) were removed due to insufficient eye-gaze data (total duration of eye-gaze on page < 1 millisecond). Of the remaining 124 eye-gaze features collected during Read actions, 104 Build actions were correct, resulting in an increased map score, and only 20 edit actions resulted in a decrease in performance. In order to develop a classifier model using this imbalanced dataset we used Synthetic Minority Over-sampling Technique (SMOTE) algorithm [6], to up-sample the minority data (incorrect edits). SMOTE is used to avoid overfitting when replicating the minor samples during up-sampling. In SMOTE, a subset of data is taken from the minority class to create a synthetic similar instances which are then added to the original dataset.

We used the Gradient tree boosting algorithm [11] for predicting map edit action. In this algorithm, many classification models are trained sequentially, and the loss function of each model is minimized using a gradient descent method. In this analysis, we used decision trees as the classification model for gradient boosting. We used Rapidminer [13] for implementing upsampling and Gradient tree boosting. The classification results using 10 fold cross-validation are shown in Table 3.

The gradient tree boosting algorithm predicted the correctness of map edit action with an accuracy of 80.83%, Cohen's kappa κ = 0.62, and F1 Score = 0.82.

Table 3: Predicting Performance on Map Edit Actions.

	Actual		
Predicted	**Map Edit (+)**	**Map Edit (-)**	**Class Precision**
Map Edit (+)	79	15	84.04%
Map Edit (-)	25	89	78.07%
Class Recall	75.96%	85.58%	

The trained gradient tree boosting classifier was then used to classify learners' reading behavior as effective or ineffective using eye-gaze data during from all of the Read actions. We extracted 1987 eye-gaze features during Read actions of all students. Out of 1987 Reading behaviors extracted, 329 (16.5%) were classified as ineffective and rest were classified as effective. Without applying any up sampling technique, for each student, we computed the number of effective and ineffective read actions per session. To model learners' performance in map building actions using their reading behavior on hypertext resources, we used a linear regression with the net change in map scores per session as a dependent variable. The regression statistics are described in Table 4.

Table 4: Regression Statistics

Multiple R	0.515
R Square	0.262
Adjusted R Square	0.229
Standard Error	3.675
Observations	49

Learner's performance in the map building task could be predicted from a number of effective and effective Read actions by using the following formula:

*Performance = 0.17 * # of effective page Read actions + 0.21 * # of Ineffective Page Read actions - 1.46; R = 0.51.*

The correlation value, *R*, indicates a moderate degree of correlation between the independent variable (Number of effective and ineffective read actions) and dependent value (Performance in the map building actions).

The results of classifier models trained using the imbalanced data show that prediction of learners' performance for each link-creation event, only using content-based eye-gaze features, was significantly greater than chance (Kappa score κ = 0.62, and F1 Score = 0.82). The results of the linear regression model indicate the ability to predict learner's performance on map building tasks based on their reading behaviors observed during Read actions.

6. CONCLUSIONS, LIMITATIONS AND FUTURE WORK

Our goals in this research were threefold: (1) to test the effectiveness of using consumer-level eye-tracking devices in a noisy classroom environment; (2) to extract the content level eye-gaze features during learners reading hypertext resources in the learning environment; and (3) to predict the learner's performance based on their reading behavior. In this study, we collected eye-gaze data from 16 middle school student while working on Betty's Brain learning environment in a noisy classroom environment. We proposed a methodology to extract content level eye-gaze features and applied it to the data collected from our study. The extracted features were able to predict learner's performance in map building task with an F1 score of 0.82. These results show the ability to track and predict learner's performance that can be used to provide real-time feedback and adaptive instructions to them.

The present study has two limitations. First, we were able to extract only 124 eye-gaze features during the reading task to train the classifier to predict learning. Also, the eye-gaze features extracted were imbalanced necessitating use of an upsampling technique to train and validate the classifier. Second, we were able to collect eye-tracking data only for 54% of the entire duration that student's interaction with the learning environment in the real classroom setting due to the unstructured nature of the environment.

In addition to collecting more data in our future studies, we propose to analyze students' learning behaviors not only from their reading behaviors, but also from learner's other interactions with the system, such as analyzing the quiz answers and interactions with the two virtual agents in the system -- the Mentor, Mr. Davis, and the Teachable Agent, Betty. The goal is to derive more precise information of the coherence relations between actions (see [34]). We also propose to implement real-time eye-gaze analysis to provide personalized feedback based on learner's reading behavior.

7. ACKNOWLEDGMENTS

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