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An Automated Object-Task Mining Model for Providing Students with Real Time Performance Feedback

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Abstract

This paper proposes an automated learning system that provides students with real time performance feedback during engineering laboratory assignments by discovering associations between objects that students interact with, and the manner of interaction. Technological advancements in computer vision and machine learning techniques are creating opportunities for STEM researchers to integrate commercial, off-the-shelf technologies in the design and development of automated learning systems in STEM classrooms. In this work, the authors employ the Microsoft Kinect to serve as the computer vision system to observe objects in the laboratory environment and how students utilize those objects. Machine learning metrics are utilized to quantify the veracity of the object-student associations generated by the proposed automated feedback system.

The knowledge gained from this research has broad impacts within engineering education and beyond, as researchers seek novel technology solutions that have the potential to transform the manner in which students learn and receive feedback, towards more customized modes of STEM education delivery.

1. Introduction

Each year, Universities spend millions of dollars constructing new laboratory facilities or maintaining existing ones [1]. However, these laboratory facilities are typically only available to students during “normal working hours”, as the time constraints of instructors and teaching assistants limit the availability of these resources. Furthermore, due to the instructor/student ratio in a typical engineering classroom/laboratory, it is challenging for students to get one-on-one instruction on demand, if they are faced with challenges while performing engineering laboratory tasks. Figure 1 presents the fundamental challenge of customizing laboratory instruction to satisfy students’ needs:

Scenario 1: The student to instructor ratio: This scenario results when the number of students is greater than the number of instructors or teaching assistants available to help provide customized feedback for each student. Given student (i), (j), (k), and only one instructor, the challenges of providing students with individual feedback increases, as the heterogeneity of students’ queries increases. Due to time and distance constraints, it therefore becomes infeasible for a single instructor to simultaneously provide feedback to students (i), (j) and (k) in a timely manner that would address their concerns. This may present challenges and learning biases amongst different student characteristic types such as introverts and extroverts [2].

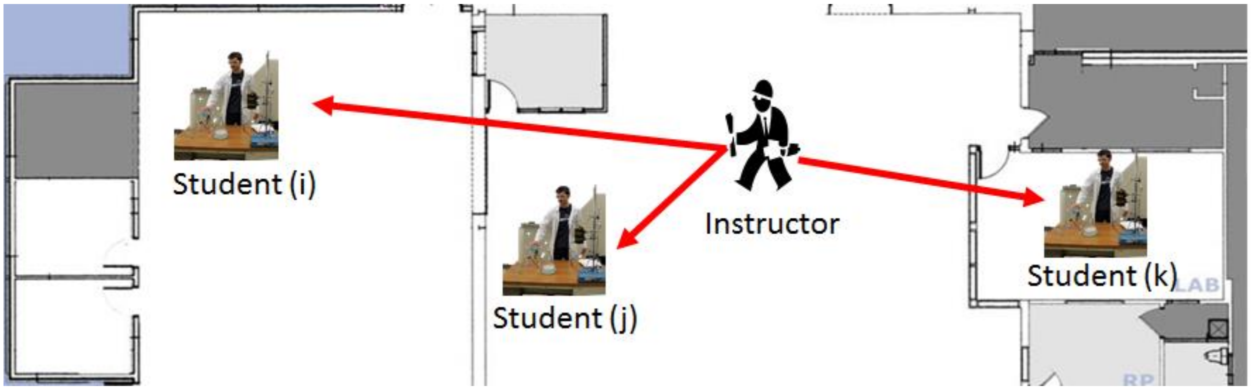


Figure 1: Typical Challenges Facing Students and Instructors During Engineering Design Laboratories

Scenario 2: Student interest availability, instructor/laboratory facility unavailability: In many engineering laboratories, students are not allowed to work without direct supervision from a teaching assistant or instructor. Unfortunately, many engineering laboratory facilities are based on the schedules of the instructor, teaching assistant or university, and may be misaligned with students' schedules. For example, certain engineering and science majors are known to work and study at night such as Computer Science students [3]. However, if their work hours are not aligned with that of their instructors, they are forced to adjust their schedules and miss out on work productivity.

In scenarios 1 and 2, the fundamental challenge is balancing cost of learning with value attained. For the student, paying for an individual instructor, solely catering to their every needs may enhance their learning and productivity, but may be infeasible due to the tremendous financial burden that that would impose. For the instructor, catering to each student's question at any time period, would be fulfilling, as the instructor will be assured that each student grasped a concept. However, such level of customization would require a tremendous amount of time, that would ultimately delay the completion of course content and extend the length of the course offerings to time periods that may not be acceptable to students.

Hence the fundamental research question is: *how can educators achieve student specific customization in a cost effective, timely manner?*

To answer the above research question, the authors of this work propose an automated learning system that is constructed using off-the-shelf components and open source machine learning algorithms to achieve real time student feedback on certain laboratory specific tasks. A successful integration of automated learning systems into undergraduate engineering education has the potential to expand the availability of laboratory facilities by providing students with real time performance feedback, comparable to that of an instructor or teaching assistant. However, in the context of engineering education, there exists a knowledge gap in terms of whether the integration of these automated learning systems would have a meaningful impact in enhancing students' performance during laboratory activities. In order for automated learning systems to provide meaningful performance feedback to students, they must themselves acquire knowledge about the laboratory environments. Specifically, automated learning systems must be able to detect objects within a laboratory environment that students may use during laboratory activities. This would enable the automated learning systems to provide feedback to students while they use these objects.

This paper is organized as follows: this section provides an overview of the concepts motivating this research. Section 2 presents research works most closely related to this research. Section 3 presents the methodology of automated learning systems. Section 4 presents the application and results from this study and Section 5 concludes that paper.

2. Literature Review

2.1 Co-robots and Automated Learning Systems

The term co-robots refers to a class of robots that work side by side with humans, rather than being completely autonomous and isolated [4]. The term "robot" is used broadly to represent that which is not human, ranging from a physical hardware system to a machine learning algorithms. In this work, the use of the term Automated Learning System focuses on the "brains" of a co-robot system. This represents the configurable hardware component, based on a wide range of existing robotic technologies[5]. Automated Learning Systems are gaining interest in both research and application domains ranging from autonomous self-driving vehicles [6,7] to adaptive personal assistants with real time voice interactions [8–10]. Several challenges have been outlined in order for co-learning systems to be seamlessly integrated in the social fabric of modern society [11]; 1) *Dynamic Spaces* [5,12–15] (i.e., the ability of co-learning systems to successfully navigate and adapt to the fluid nature of environments that humans interact in), 2) *Social Learning* [16–19](i.e., the ability of co-learning systems to continuously learn about human behavior and their surrounding environment), 3) *Sustainability* [20,21] (i.e., the ability of co-learning systems to remain relevant to the interests of their human counterparts by either updating their behavior or functionality), *4) Affect and Social Signal Awareness* [22–24] (i.e., the ability of co-learning systems to infer meaning from human facial, body movement, etc. expressions), 5) *Social Norms* [25–28] (i.e., the ability of co-learning systems to abide by the constraints of society and minimize deviations from them) and 6) *Societal Issues* [29–33] (i.e., the ability of co-learning systems to mitigate the societal concerns such as sensor data acquisition, data privacy, knowledge dissemination, etc. that may result due to the ability of co-learning systems to sense, gather data and generate models that could be used to both enhance or potentially harm humans).

Beyond simply existing, automated learning systems have the potential to provide tangible learning benefits to individuals. For example, robots have also been developed to help students with autism enhance their social interaction skills [34]. Recent initiatives such as the RoboPlay at the

University of California Davis continue to explore the creativity of K-12 students through workshops such as UC Davis C-STEM Day [35,36].

2.2 Educational Data Mining

Data is generated throughout the pedagogical process of learning, from homework and quizzes to student surveys and assessments. With the abundance of data in the education domain, there has been an expansion of data mining/machine learning approaches for making sense of education data. The term *educational data mining* has emerged as the novel application of data mining techniques to educational data in order to understand the factors that influence students' learning[37]. There have been a wide range of researchers that have proposed data mining driven techniques for modeling education data[38]. Mostow et al. propose an educational data mining tool to browse student interactions [39]. Merceron et al. propose a visualization tool that enables instructors to discover pedagogically relevant patterns by mining and visualizing students' on-line exercise work [40]. Online platforms such as Massively Open Online Courses (MOOCs) have increased the size and availability of educational related data [41]. Text mining algorithms have been proposed by several authors in an attempt to quantify students' sentiments, relating to a specific educational topic of interest [41,42].

While there exist extensive research on educational related data, existing methodologies are limited in their ability to provide students with real time feedback relating to their task performance or understanding of critical engineering laboratory assignments. Through the proposed automated feedback system, this research aims to fill this research gap.

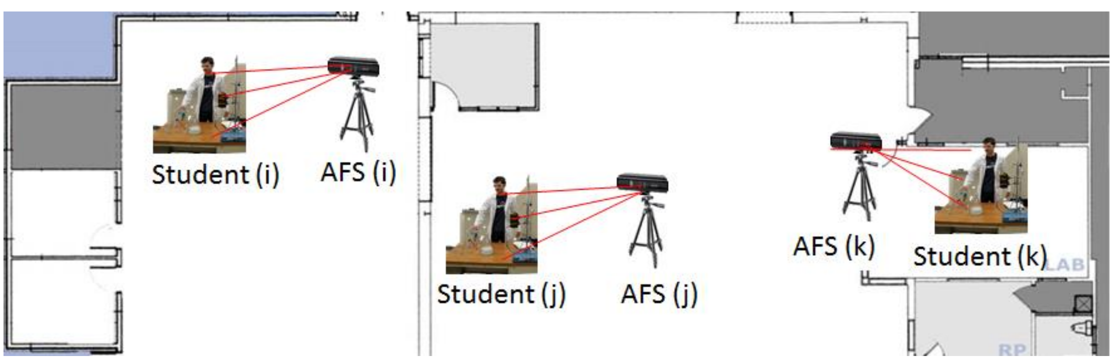


Figure 2: Proposed Automated Feedback System for Customized Student Feedback

3. Research Methodology

The automated feedback system (AFS) presented in Figure 2 provides students with real time performance feedback during engineering laboratory assignments by discovering associations between objects that students interact with, and the manner in which students interact with those objects. The components needed to create the ASF are commercial, off-the-shelf, with the two primary components being a i) depth-vision system (e.g., Microsoft Kinect) and ii) a machine learning processing unit and feedback visualization system (e.g., a tablet). Machine learning metrics are employed to quantify the veracity of the object-student associations generated by automated learning systems. Based on this feedback, automated learning systems provide feedback to students, whenever their association with an object deviates from the history of associations with that object.

3.1: Conceptual Outline of Automated Feedback System

The proposed automated feedback system for engineering laboratories includes three steps as seen in Figure 3: 1) Laboratory Data Acquisition, 2) Data Mining Association Model Generation and Validation 3) Student Anomaly Detection and Visualization. The components of the AFS are low cost, off-the-shelf components that can be purchased at a local hardware store or online. Due to the relatively low cost nature of the proposed system, it is assumed that an AFS can be assembled and placed at each station in the laboratory where students work and require feedback. The components of the AFS will now be explained in detail.

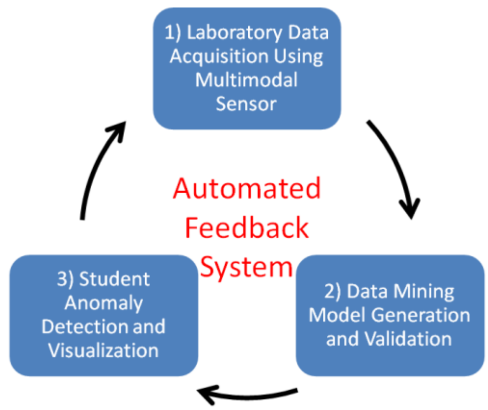


Figure 3: Components of the Automated Feedback System

3.2 Step 1: Laboratory Data Acquisition Using Multi-modal Sensor

Multimodal sensors such as the Microsoft Kinect, Asus Xtion Live [43], Primesense Carmine [44], etc., coupled with OpenCV [45], are capable of capturing multiple data streams including video (RBG), depth and skeletal data. For this work, the skeletal data in Figure 4 is the most relevant, as it will be used to data mine associations between different joints on a human body (red circles in Figure 4) and actions that students are performing.

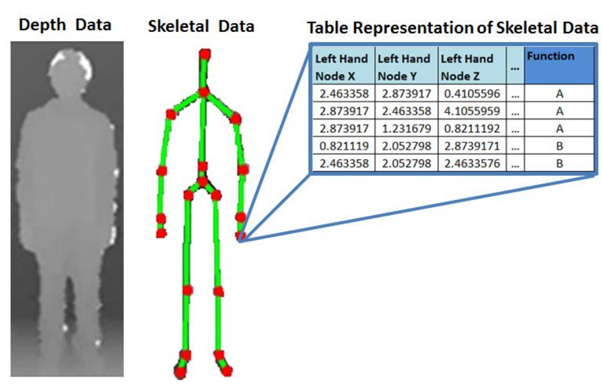


Figure 4: Multi-modal data acquisition

The skeletal data is transformed into numeric XYZ values for each of the joints, as seen in Figure 4, with a new data sample captured once every q milliseconds, depending on the hardware capabilities. For example, for the Left Hand Node in Figure 4, the first instance of data captured is 2.4634 (Left Hand Node X), 2.8739 (Left Hand Node Y) and 0.4105 (Left Hand Node Z), representing the 3D position of that particular joint at an instant in time. On the far right of the table in Figure 4, the function is provided that represents the action that a student was engaged in. The model would first have to be trained in order to have ground truth data pertaining to functions that students perform using objects. By capturing skeletal data across multiple students, the automated learning system can determine, through data mining, when statistical anomalies exist from a student's action that deviates from the history of actions associated with a given function.

3.3: Step 2: Data Mining Model Generation and Validation

Both *supervised* and *unsupervised* machine learning algorithms can be employed to enable the AFS to learn patterns from students' actions during laboratory activities. *Unsupervised machine learning* discovers patterns within an unlabeled data set through techniques such as clustering [46–48] and association rule mining [49–54]. In the case of the AFS, *unsupervised* machine learning algorithms will be needed in the absence of a class/predictor variable. For example, if a student is performing a set of actions that are unknown to the AFS and have not yet been provided by an instructor, the AFS will discover how this student's actions relates to other functions, without knowing what the function actually is. *Supervised machine learning* on the other hand utilizes training data to develop a model that predicts/classifies unseen instances of data. This is achieved by employing techniques such as Decision Tree Induction [55], Bayesian Inference [56–58], Support Vector Machines [59,60] etc. The AFS will utilize *supervised machine learning* algorithms in scenarios where the functions that students are performing (e.g., hammering a nail) are known by the AFS, with the objective of determining what appropriate skeletal body positions result in a safe use of the hammer. Both *Unsupervised Learning* and *Supervised Learning* are employed by the AFS, depending on the scenario being investigated.

Figure 5: Example setup of AFS with visual feedback for students

3.4: Step 3: Student Anomaly Detection and Visualization

Section 3.3 will result in the generation of a data mining model of students' skeletal joint locations, as they perform specific functions in the classroom (e.g., using a hammer). Based on the machine learning models, if there is a deviation that exists with one student (compared to the baseline), then feedback will be provided using a visual feedback display such as that presented in Figure 5. The predictive validity of the resulting machine learning models is measured by well-established metrics such as %Accuracy, Root Mean Squared Error, Precision, Recall, etc. including *n*-fold cross validation techniques [61].

Instead of providing students with raw statistical values pertaining to the validity of the AFS's predictive model, the visual display can simply showcases their skeletal body data, or video representation, which can be used to identify what areas of the body were inconsistent with previous joint-function associations.

4: Application: An Automated Feedback System for Engineering Design Laboratories

4.1. Overview of Engineering Laboratory Assignment

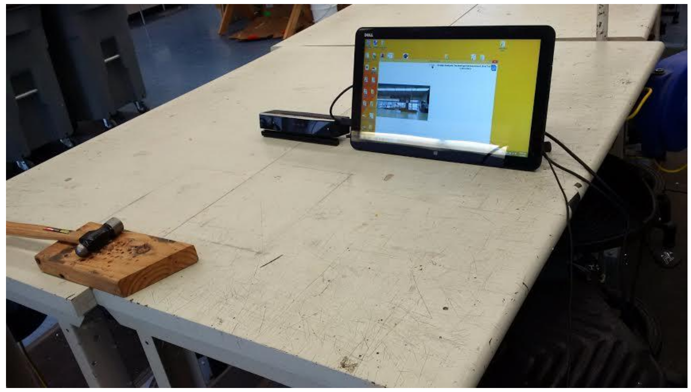


Figure 6 :Experimental Setup of AFS

To demonstrate the real world application of the proposed AFS in engineering laboratory environments, the authors conducted a set of experiments to test the skeletal data acquisition and subsequent data mining knowledge discovery components of this research. Data was collected in one of the engineering laboratory/workshops at Penn State University. As can be seen in Figure 6, the AFS consists of two major components; The multimodal sensing system (i.e., Microsoft Kinect in this paper) and the visual display feedback system that is connected to the Kinect, are used to process the raw data captured by the Kinect for machine learning purposes, as well as provide relevant visual feedback to both students and instructors.

In the scenario presented in Figure 6, the student is preparing to utilize the hammer. Based on the joint associations of the students' skeletal data (Figure 4), the objective of the AFS is to detect patterns in the manner in which a student moves while performing an action (e.g., Hammering) and detect anomalous patterns in that action at another instant in time. Anomalous patterns could be as a results of:

- A student utilizing a new object (e.g., screw driver, instead of a hammer)
- A student utilizing the same object but to achieve a new function (e.g., hammer used to remove a nail, rather than hammer it)
- A student utilizing the same object but in a manner that is not consistent to previous usage

4.2 Outline of Data Acquisition

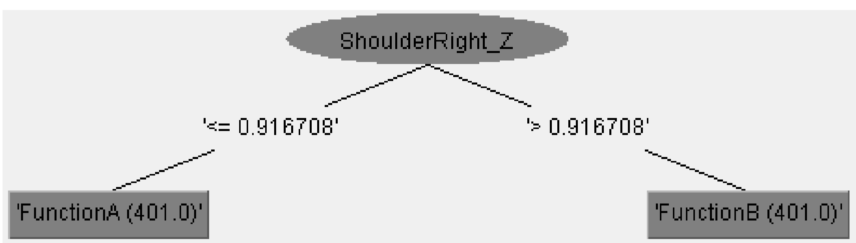
A total of 802 instances of data was collected relating to two functions. The data set contained 226 attributes representing different characteristics of the data. I.e., XYZ position, velocity and acceleration data was collected for each of the nodes, as seen in Figure 4. The data acquisition involves two scenarios; one in which the hammer was used to simulate hammering a small nail and the second in which the hammer was used to simulate hammering a metal part for shaping purposes (Figure 6). Without knowing what the object at hand is, the AFS should be able to detect that these two activities are different and classify them as individual events (supervised learning approach). In the event that the functions are unknown, unsupervised learning seeks to determine whether these two actions would fall under separate clusters. The Microsoft Kinect captures data at a rate of one instance/33 milliseconds, with the data stored on the hard drive of the tablet system (Figure 6).

4.3 Results and Discussion

For the supervised learning model, the J48 classifier was employed using the Weka software package [62]. The decision tree in Figure 7 indicates that out of the 226 data points representing a wide range of joint characteristics, the Z co-ordinate value of the right shoulder (ShoulderRight_Z in Figure 7) was shown the be the strongest attribute for predicting which of the functions was being performed by a student. The resulting decision rule is of the form:

- If ShoulderRight_Z<=0.916808 meters, relative to the fixed position of the AFS, THEN Function A (e.g., hammering a small nail) is being performed
- If ShoulderRight_Z>0.916708 meters, relative to the fixed position of the AFS, THEN Function B (e.g., hammering a large metal object) is being performed

This prediction could also be used to determine when a student was performing an anomalous action. I.e., if the instructor has determined that students should be hammering a small nail but they are instead, hammering a large object, this would show up as an anomaly in the AFS system and provide feedback to the student to adjust accordingly.



Correctly Classified Instances	801	99.8753 %
Incorrectly Classified Instances	1	0.1247 %
Kappa statistic	0.9975	
Mean absolute error	0.0012	
Root mean squared error	0.0353	
Relative absolute error	0.2494 %	
Root relative squared error	7.0622 %	
Total Number of Instances	802	
=== Detailed Accuracy By Class ===		
TP Rate FP Rate Precision Recall F-Measure ROC Area Class		
0.998 0 1 0.998 0.999 0.999 FunctionA		
1 0.002 0.998 1 0.999 0.999 FunctionB		

Weighted Avg. 0.999 0.001 0.999 0.999 0.999 0.999
=== Confusion Matrix ===
a b <-- classified as
400 1 | a = FunctionA
0 401 | b = FunctionB

Figure 7: Decision Tree Model of Student Joint Associations

For unsupervised learning, where the AFS is unsure about the class/predictor variable, unsupervised clustering algorithms can be employed. For example, in Figure 8, it can be seen that for the same ShoulderRight_Z joint, there exists two separate clusters; one in the far left in blue (i.e., associated with Function A) and one in the far right in red (associated with Function B). While the blue clusters seem to be homogenous, it can be seen that the second cluster has some heterogeneity, including a mix of blue and red. However, red points are dominating this cluster. This indicates that while this skeletal joint attribute is a good discriminating feature, there exists some impurity in the cluster assignment.

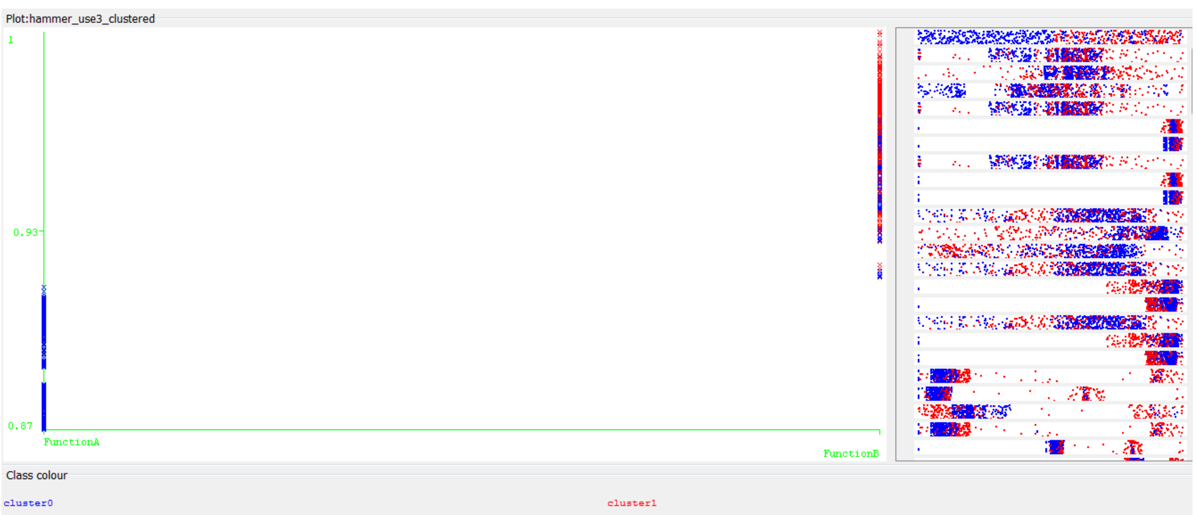


Figure 8: K-means clustering of Joint Actions

Depending on the instructor's objectives during an engineering laboratory assignment, all or a subset of these results could be provided to students in real time using the AFS' visual display, shown in Figure 6. Alternatively, the instructor could choose to only provide students with intervention content whenever there is an anomalous event detected.

5: Conclusions and Path forward

This paper proposes an automated feedback system (AFS) that provides students with real time performance feedback during engineering laboratory assignments by discovering associations between objects that students interact with, and the manner in which students interact with those objects. The AFS proposed in this work utilizes commercial, off-the-shelf hardware to demonstrate the feasibility of such as system being implemented in a typical laboratory setting. In this work, the authors employ the Microsoft Kinect to serve as the computer vision system. Using skeletal data pertaining to students' body language poses during laboratory assignments, the AFS discovers joint-associations using both supervised (when the function being performed is known a priori) and unsupervised (when the function being performed is not known a priori) machine learning algorithms to make statistical inferences about students' actions. Using the visual display of the AFS, student feedback can be provided in real time in cases intervention may be relevant in correcting students' actions.

The knowledge gained from this research has broad impacts within engineering education and beyond, as researchers seek novel technology solutions that have the potential to transform the manner in which students learn and receive feedback, towards more customized modes of STEM education delivery that is cost effective and scalable.

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