Actualize: A Personalized and Adaptive Learning Project

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Abstract— Personalized and adaptive learning in e-learning systems is becoming more prevalent as we see a rise in students participating in remote learning. Our research aims to identify Learning Management System (LMS) requirements in an online e-learning setting for programming languages education and identify a suitable algorithm, including machine learning, to enable personalized and adaptive learning. Actualize is the name of our LMS, and it can provide personalized and adaptive learning for students in an e-learning environment. It can record, analyze, and track students' behavior and actions to maintain an accurate student model and intelligently deliver learning resources and adaptive assessments. Pedagogies with personalized and adaptive learning provide students with learning materials and assessments curated to their needs and preferences for optimized learning. Students whose learning preferences are catered to find their learning experiences more enjoyable and engage more deeply with their resources while learning at their own pace and level of interest. Much research has been done in developing systems that identify or predict learning styles and learning paths; however, there are very few examples of personalized and adaptive learning for programming language education, the focus of our work.

I. Introduction

With the increasing demand for STEM-related jobs, we look to the future of education and consider the emerging pedagogies that will enable students to meet those needs [7]. Technology in education, such as personalized and adaptive learning systems, enables student learning according to their preferences and needs and allows educators to monitor students' progress and provide timely feedback and intervention when adequate [5]. Under personalized and adaptive learning, students learn according to their desired learning style: the preferred way of using one's ability to learn [10]. The student's learning preferences and previous knowledge are accommodated as they progress through any course by way of their learning path; a learning path is the learning materials and assessments that students interact with to reach the courses' learning objectives [2]. One implementation of personalized and adaptive learning in online e-learning utilizes an LMS that can leverage data from students, such as their preferences, in an algorithm with machine learning to deliver personalized and adaptive learning paths [12]. This is also the approach selected for our research.

A course of diverse students requires equally diverse learning materials that can meet the needs of every student. Learning content is often fragmented; that is, learning resources are many, varied in modality, and in many cases are better suited for certain learners over others [8]. Systematic and efficient assigning of the learning content to the appropriate individuals has always been a problem in e-learning [2]. While some learning resources can be put to good use, finding them can be a hindrance due to availability issues; other resources are inappropriate to the requirements of the learning activities [1]. Students who learn from inadequate materials, due to their learning preferences or the provided brevity or over saturation of the knowledge can become disinterested in their learning.

Actualize is a personalized and adaptive learning LMS that can help students learn programming languages. Our research focuses on a Python learning course prototype, though Actualize can eventually support personalized and adaptive learning of any programming language. Unlike in standardized education, a personalized path helps students be more attentive, enthusiastic, and more involved in the educational process. It better helps to address and recognize individual students' needs [4]. Our project vision is that students can select their learning preferences to make their learning paths more engaging and their learning resources more effective. A student, or learner, is modeled so that through their preferences, personality, behavior, and knowledge factors, the LMS can provide learning materials in line with their preferences to learn more effectively and progress better [4].

This article will discuss related works that use learner models and works that implement personalized learning paths. We will then introduce our research with Actualize and detail our implementation goals and required resources. The conclusion and our reference readings will follow these sections.

II. Related work

This section gives an overview of related work and studies in the e-learning environments, personalized and adaptive learning, and learner modeling techniques. The significance of these works and their relation to our research are explained in the appropriate sections below.

The basis of personalized and adaptive learning is nurturing a learning strategy or experience by utilizing resources and adapting them to benefit students based on their previous knowledge and learning ability or preference [4]. Personalized and adaptive learning uses two key concepts to accomplish this: learning content personalization and learning path personalization [11]. We will first explore learning content personalization.

In an e-learning environment and within personalized and adaptive learning, content personalization refers to delivering specific learning resources to a student over other resources of the same subject [7]. The delivery of these learning resources depends on the e-learning environment's ability to identify students' learning styles effectively. Some of the work that has been done to detect learning styles in e-learning systems relies on machine learning techniques. A data-driven approach [10] predicts the students' learning style using extracted data and classifying learner attributes and behaviors, and the classifiers were implemented using trained machine language algorithms.

The second key concept of personalized and adaptive learning is the learning path. A high-quality learning path can optimize the effectiveness of learning content, and it can be identified by a learning path recommendation model [2]. Multiple learning paths can exist for an e-learner; however, in personalized and adaptive learning, the most appropriate learning path considers the learners' preferences, previous knowledge, and learning needs to accomplish a learning objective.

A research study detailed a strategy [11] that employed data mining technologies to develop a learner model that included the learners' basic information, personality character, learning strategy character, and learning behavior character. This system uses rule-based analysis to develop a personalized learning strategy.

The above research helps us understand the requirements of a personalized and adaptive learning framework. Personalized and adaptive learning provides learning paths to students based on their learning styles [6]. There have been many research studies into strategies to identify learning styles and learning paths [13]. While we also rely on analyzing student activity data, we propose to let the students freely select their own learning style at any time so that they may receive personalized learning paths on their needs. This approach also promotes student engagement and satisfaction with their own educational path.

III. Actualize: a vision for intelligent learning

A. Overview

The Actualize project is our vision for a personalized and adaptive learning LMS deployment in an online e-learning environment. Actualize was designed for programming languages education. For our research, we designed a prototype course that would teach the fundamentals of the Python language. This section will discuss the concepts and requirements that set the foundation for our system, the fundamental basis for its functionality, and the implementation requirements to bring forth our vision. This section also includes the diagrams that we created to help illustrate concepts, relationships, and logical flows of various components of our system.

Within the Python course, the curriculum defines a list of student learning objectives. Student learning objectives outline all the knowledge students are expected to acquire, and it is verified through knowledge assessments. The advancement of students' knowledge and its assessment relies on the resources provided within the course content. Course content includes learning resources, such as lessons, slides, videos, exercises, etc., and course content also includes assessment resources, such as homework, quizzes, and tests. The course instructor maintains all course content resources; that is, the teacher can create, add, edit, link, remove, import from other courses, or receive shared resources from other courses/instructors.

B. System Framework

Personalized and adaptive learning from the Actualize LMS relies on the students learning preferences and the personalization of learning resources. **Figure 1** shows how the LMS utilizes student data to determine what course resources to provide them with. The Actualize Python course depends on learning resources of a multimodal nature; that is, the included course content appeals to diverse learning preferences. Additionally, there are equally diverse knowledge assessment resources. Naturally, students are not required to study all learning resources and complete all learning assessment exercises; it is the role of the Actualize LMS to deliver learning resources and assess students' knowledge intelligently; as a personalized and adaptive learning system, it can identify the most relevant course materials depending on the student [3]. **Figure 2** shows how some learning resources are incompatible with certain students (marked with "x"), while other resources are not as effective as others (marked with "?" and check mark respectively); an adaptive learning process replaces the guesswork with intelligent automation.

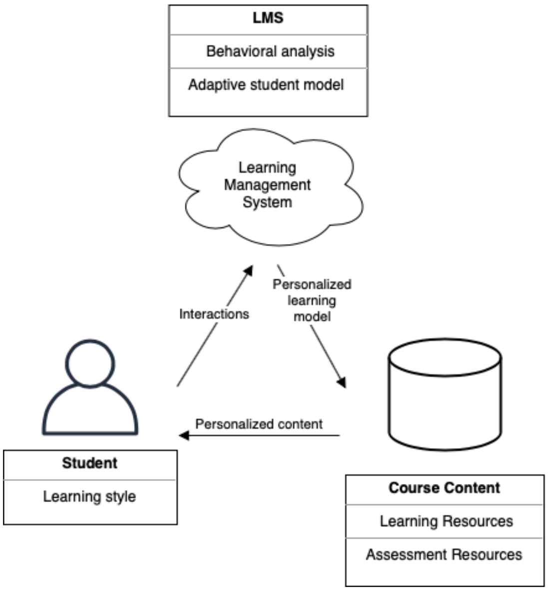

Figure 1: Personalized and adaptive learning overview.

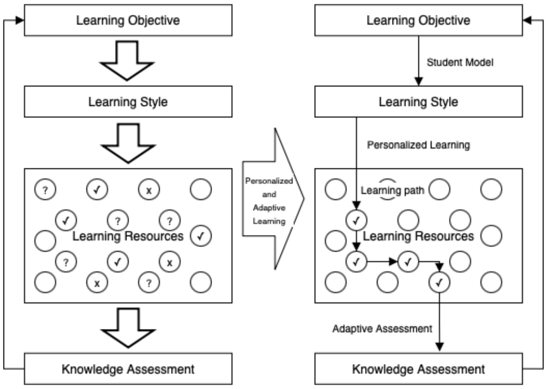

Figure 2: Traditional learning and personalized and adaptive learning comparison.

To begin the Actualize Python course, a student must enroll in the course and create a student profile (or avatar). During enrollment, the student will participate in a questionnaire that outlines their learning preferences. The multimodal nature of the course resources allows for students to have more than one mode of learning. The Actualize LMS builds a student model from the data. The student model is required for the LMS to identify the appropriate learning path. A learning path is the learning resource and assessment methods that the student will have to complete to reach a student learning objective.

Data for the student model is continually collected based on the activities and behaviors of the student within the Actualize LMS. Some data that the system can use is how long the student takes to accomplish certain tasks, assessment results, and learning system interactions and behaviors; an intelligent "monitoring" agent studies students' activity and generates feedback to the student model [9]. **Figure 3** shows an example of data kept in the student model; a student model helps the Actualize LMS remain flexible and adaptive to the students' needs. The Actualize LMS employs an algorithm that uses the student model as input to deliver personalized and adaptive learning paths.

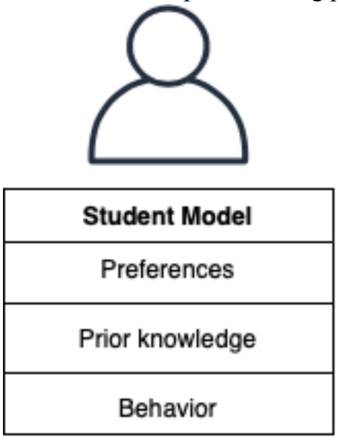

Figure 3: The student model.

C. Algorithm and Machine Learning

The algorithm that Actualize relies on has multiple parts, and we will explain it further in this section. The algorithm's objective, as shown in **Figure 4**, is to deliver a learning path that will provide a student with personalized and adaptive learning by utilizing the course learning resources and assessment resources to complete all student learning objectives. The first part to consider is the collection of student data to process a detailed student model.

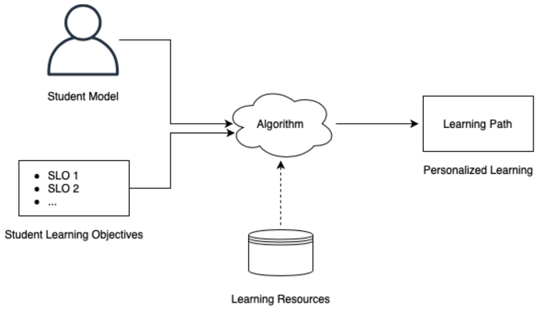

Figure 4: Personalized and adaptive learning algorithm

Preliminary data for the student model is first created when students open their accounts and select their learning preferences. As students spend time studying and learning within the LMS, intelligent agents collect data to refine the individual student models. The term "intelligent agent" refers to an autonomous program that operates in a designated environment and processes data or events to achieve a single or limited set of goals [9].

One example of an intelligent agent within the LMS is a "learning quality score" evaluation agent that could record the number of times students opened learning materials for reference during or after homework and assessments; the intelligent agent would determine that a learning resource is of low quality if students cannot correctly answer questions as they attempt to reach a student learning objective. Another example would be a "study interest" monitoring agent that would determine if the amount of time a student spent looking at study materials confirms that the material is of interest and accommodating to the targeted preferences. Since intelligent agents tend to be very specialized, combinations of them can be used to achieve higher-level goals; for example, the two previously described agents can be used in conjunction to help identify learning resources that are both accommodating to students preferences and of high quality.

Actualize relies on multiple intelligent agents to accomplish a wide array of goals (**Figure 5**). Information necessary for the student models can describe how the students respond to course resources that match or conflict with their preferences. The aggregation of student model data can also reveal if students prefer lessons with either detailed knowledge or broad overviews, what level of difficulty is best suited for assessment purposes, what category of modality can accommodate a student when they desire alternative learning resources, lesson format preferences, assessment question preferences, and much more. This leads to the next part of the algorithm, using the student model to deliver personalized and adaptive learning content.

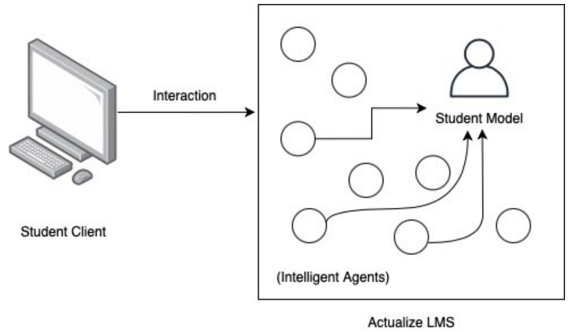

Figure 5: User actions analyzed by a corresponding intelligent agent or agents.

The implementation of intelligent agents can help Actualize learn about the students; the next step is to identify the course resources best suited for each student based on the data on hand. This part of the algorithm relies on decision tree algorithms and supervised machine learning. One of the roles of the course educator is the monitoring of continued satisfactory progress. As the LMS collects and develops student models, it is then tasked with delivering learning resources that adhere to learning preferences, and a decision tree algorithm can identify these resources. The course resources contain metadata that allows the algorithm to identify the modalities that each resource can accommodate and the modality information of the resource. Additional information would also include the difficulty, estimated study time for study resources, and the estimated completion time for assessment questions. The LMS would organize course resources within a tree data structure. Individual lessons, examples, exercises, grouped materials, or assessment questions would be the leaves, and each higher level would be the category or course module that they belong to.

D. Learning Paths

Traversing a tree that includes all the course resources would rely on the student model data to make appropriate selections. The quality of these selections could be a further metadata inclusion through a supervised machine learning execution. As more data is collected within the course and future courses, the LMS can use machine learning to identify the most effective resources for certain learning preferences and weed out ineffective resources for elimination or improvement. The course educator would supervise the machine learning implementation to approve or modify the data according to their interpretation of the course outcomes and the course structure and logistics.

As students spend time studying, learning, and taking part in knowledge assessments, the LMS gains valuable insights into their behaviors. **Figure 6** shows how the LMS behaves as students, who may have different learning preferences, interact with their lessons and assessments and how learning paths can evolve. The intelligent agents work to provide the algorithm and machine learning with data to deliver personalized and adaptive learning paths.

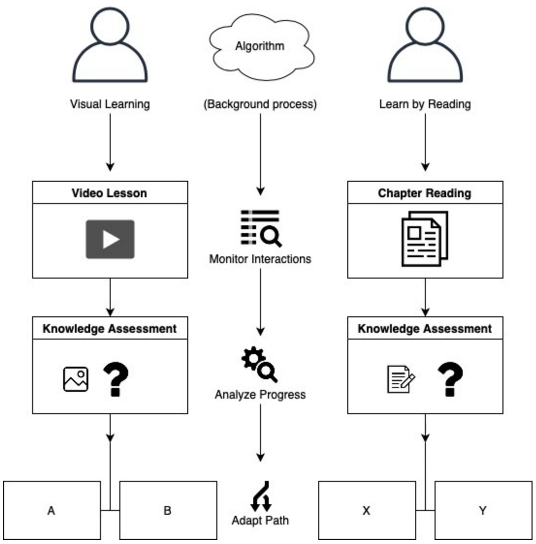

Figure 6: Adaptive learning paths

E. Student Experience

Students enrolled in an Actualize course enjoy a learning experience custom-tailored to their needs and preferences. By freely selecting their modal preferences, students have the power to engage with the learning experiences that they prefer. As students proceed through a course, the accuracy and effectiveness of their learning materials and the quality of their knowledge assessments increase and adapts to their knowledge and skill level.

F. Teacher Experience

In an Actualize learning environment teachers have the roles of both educator and administrator. They have the ability to see a detailed overview of the entire course, where they can monitor the students' progress and identify struggling students so that they can offer them aid like remediation or additional studying opportunities. Teachers can also add material to the course like learning and assessment content.

IV. Conclusion

Actualize is our vision for a personalized and adaptive learning LMS deployment in an online Python education environment. In essence, a student model is continuously refined within the Actualize LMS, and in return, it intelligently delivers learning resources and assessment resources. The scope of our work outlines the requirements necessary to begin scaffolding such a system and shares the key foundations of a working implementation. Our research taught us the concepts and details behind personalized and adaptive learning; we learned about learning style detection and adaptation, and we learned about learning path delivery and personalization. We also explored the concepts and applications of intelligent agents and machine learning. Our next steps are to follow our leads and design the algorithm and machine learning to make the project a functioning example.

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