A mobile expert system for tutoring multiple languages using machine learning

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Abstract—Towards the creation of a mobile expert tutoring system that teaches multiple languages, we have incorporated machine learning approaches into a sophisticated mobile system. The mobile system provides adaptivity to user needs based on the creation of user models. The resulting superset that consists of all user/student models is further processed by two machine learning approaches in order to create user model clusters and to provide sophisticated data as stereotypes for new potential users.

Index Terms—mobile assisted language learning, machine learning, k-means algorithm, user modeling, stereotypes.

I. INTRODUCTION

The advent of the mobile era has provided people with a wide range of easily accessible services on many subject areas. Over the last century, our world has witnessed major improvements in the areas of transportation and telecommunications. As a result, personal, professional, social, and economic considerations all point to the advantages of learning foreign languages [11]. Language learning can be assisted by computer systems that provide direct customized instruction or feedback to students whilst performing a task. Such systems lie in the field of Intelligent Tutoring Systems (ITS). ITSs are primarily expert systems, which tend to be more complex in their basic structure, being in a sense a combination of subject matter expert, students-result-analysis-and-interpretation expert as well as expert tutor. The incorporation of an expert advisor and an expert assistant on error diagnosis and proneness procedures in a system, accentuates the emulation of the decision-making ability of a human expert. The classical architecture of an intelligent tutoring system is composed of four elements [9], that are related: the Domain model, the Student Model, the Teaching Model and the User Interface. The Domain Model handles all content to be taught by the system. The Student Model offers information about the behavior and the knowledge of the student and should be able to perform detection to the students’ errors. The Teaching Model incorporates the knowledge of the system, consisting of a system of rules, which selects the content to be displayed and monitors the use of the student, and provides assistance when necessary. Finally, User Interface is the model that interacts directly with the student.

Considering the scientific area of ITSs, there is an increasing interest in the use of computer-assisted foreign language instruction [17]. Especially, in cases where these systems offer the possibility of learning multiple languages at the same time, the students may further benefit from this educational process [18]. The need for tutoring systems that may provide user interface friendliness and also individualized support to errors via a student model is even greater when students are taught more than one foreign languages simultaneously [11]. Student modeling may include modeling of students’ skills and declarative knowledge and can perform individualized error diagnosis of the student. The integration of mobile technologies into learning and teaching has been more gradual, as educators have sought to understand how to use these tools to support various kinds of learning [10], such as multiple language learning. Moreover, clustering large data sets, such as students’ characteristics, is a significant aspect in language learning [8].

Assisting the educational process through the use of mobile devices led to the wide spread research field of mobile learning. Correspondingly, creating mobile learning environments for the needs of foreign language learning has created the quite recent area of Mobile-Assisted Language Learning (MALL), where the educational process is assisted or enhanced through the use of handheld mobile devices. Such devices include smartphones and the well-known Personal Digital Assistants (PDAs). MALL can be visualized as a subset of both Mobile Learning (m-learning) and Computer-assisted language learning (CALL). Through MALL systems, students have the ability to access language learning materials, test their knowledge, as well as to communicate with their teachers and peers at any time and at any place.

Our system’s mobile learning facilities may expand e-learning by confining the difficulties posed by place and time. Simultaneously, it may provide students with opportunities to learn and take in educational content in their everyday life. In mobile learning, students have the possibility of being on the move while keeping their smartphones, a fact that can act as a learning environment by itself connecting the students to courses, online resources, learning activities and communication features. The smartphone can interact with surrounding devices, either used by other students or embedded in everyday objects, which ameliorate the educational procedure [7]. In the case of language learning, it is yet better to use mobile technologies.
In view of the above, in this paper we have developed a multilingual mobile-assisted language learning system which is the application of MALL in a multiple language learning environment. The prototype system combines an attractive multimedia interface and is adaptive to individual student needs in mobile learning. The communication between the system and its potential users as students is accomplished through the use of web services. The incorporation of machine learning techniques (k-means algorithm), which is well known for their efficiency in clustering large data sets, promotes the educational procedure, by partitioning each student’s characteristic to clusters. In this way, our system promotes the educational process by ameliorating the user modeling using machine learning techniques in order to provide individualized educational instruction over mobile phones.

The paper is organized as follows. First, we present the related work, concerning mobile language learning in section 2. In section 3, we discuss our system’s architecture. Following, we discuss in depth about the stereotypes with K-means clustering algorithm in section 4. Finally, in section 5, we come up with a discussion about the usability of our mobile expert system for multiple language learning using machine learning techniques.

II. RELATED WORK

In this section we present related scientific work concerning mobile language learning.

In [13], the authors conducted a study, where three groups participated on the added value of mobile technology for learning English as a second language for primary school students. The results showed that the group which took the mobile phone home improved the most. Their conclusion is that formal school learning can be augmented by learning in an informal context, away from school. In [2], the authors conducted a research, which introduced mobile devices into an intensive reading course and allowed functions that are usually found only in the language laboratory to be easily and flexibly utilized in the general classroom. To enhance and improve the reading comprehension of English as a foreign language reader, a computer-assisted-language-learning (CALL) system for use on PDAs, integrating an instant translation mode, an instant translation annotation mode, and an instant multi-users shared translation annotation function was developed. The system promotes the educational procedure, by partitioning each student's characteristic to clusters. In this way, our system promotes the educational process by ameliorating the user modeling using machine learning techniques in order to provide individualized educational instruction over mobile phones.

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In [3], the authors investigated the response of English majors to a mobile learning platform (NCCU-MLP), developed at National Chengchi University, in which they were involved as participants. The goal of the NCCU-MLP is to improve the students’ English ability as well as to update the teachers’ understanding of how to use the technology. The purpose of this research was to investigate the responses of students to a mobile learning environment. The research involved 18 participants in a pilot study and 37 participants in a follow-up study who participated in a group activity involving mobile learning activities. The findings indicate a positive response from the participants regarding the content and procedures involved in the activity. In [20], the authors presented the IEEE LOM Standard, which is used for describing educational resources with metadata, it is beyond its scope to directly support the description of characteristics related with MALL. The authors targeted addressing this issue, that is, to propose an IEEE LOM Application Profile that can be used for tagging educational resources suitable for Language Learning and supported by Mobile and Wireless Devices. In [12], the authors investigated whether a context-sensitive and social-oriented approach to Mobile Assisted Language Learning (MALL) can be applied to the language learning context and how it is manifested. In order to carry out this investigation, the authors drew on literature on the development of identity in second language learning and the use of ethnographic approaches to data collection and interpretation. They reported on two case studies, involving learners of Icelandic and Serbian/Croatian, conducted over two years at a UK university. The paper concludes that the use of mobile technology enables language learners to use these devices as ‘a prosthesis of the self’ which allowed them to explore the perception of their L2 selves in a variety of day-to-day scenarios. In [5], the authors utilized three different educational environments for Iranian language learners. Government employees received continuous refreshment of their language skills in a non-formal mode using a combination of mobile web and short messaging. Two mobile games have been designed, which served as a platform for exercises, assignments and self-study in combination with schools and higher education. These games have shown that they can motivate the learners using an informal setting. The paper concludes that using m-learning within the informal framework of learning provides a ubiquitous tool that can powerfully help adult learners and students in Iran during their continuous lifelong learning. In [1], the authors presented the results of an initial study which compares the academic benefits of integrating podcasts into the curriculum against using them as a supplemental/review tool. The study’s findings indicated that when instructors use podcasts for multiple instructional purposes, students are more likely to use this technology and to report academic benefits. While the study was limited by small sample sizes and by some within-group variation in instructional techniques, the study provided initial evidence that podcast technology has the potential to provide greater benefits if it is used more than simply as a tool for reviewing. The study’s positive findings indicated that additional research to examine the effects of specific instructional uses of podcast technology is merited. In [16], the authors presented a computer-assisted language learning software for mobile devices (MAC), that was aimed to helping speakers acquire speech contrasts not native to their own language. The software is based on the high variability
phonetic training (HVPT) technique. An overview of the software is given, followed by results from an efficacy study. Two groups took place and used slightly different variations of the MAC software. Results showed that both groups showed significant but equivalent improvements. These results showed that the magnitude of improvement using mobile phones was similar to those obtained using fixed PCs. In [4], the authors presented M-CALL, a mobile computer-assisted language learning courseware for Korean language learners. M-CALL runs on a personal digital assistant with public wireless LAN for mobile learning. It consists of cyber pet game, mobile learning courseware, mobile learning system, and mobile tutoring. It provides various functions for Korean language learning. Currently, the prototype M-CALL was designed and partly implemented between mobile PDA and personal computer.

However, after a thorough investigation in the related scientific literature, we came up with the conclusion that the implementation of mobile-assisted language learning systems, supporting multilingual content in their domain of knowledge along with clustering of student’s characteristics, is a scientific subject that is not covered and needs much more research to reach maturity.

III. ARCHITECTURE

The prototype mobile multi-language learning system provides potential target users with the opportunity to obtain all the domain knowledge, namely the educational material and information, on their mobile devices through a simple process of point-and-connect using mobile communication network technology. Our proposed system is designed using the Client/Server model, which is proper for designing network-based systems and consists of three parts, as shown in Figure 1.

![Figure 1. Mobile Communication Network](image)

The system’s server is in charge of inquiring the database and then outputting the results into the client. The client aims to provide a portable and cooperative learning platform with tools set servicing mobile learners. Learner can construct a virtual learning world of him/herself. The most crucial classes in the application can be divided into four parts, as illustrated in Figure 2. The Knowledge Level represents the state of learning, which is in charge of rendering the related learning interfaces using the data stored in the client or in the server. Classes in other parts can search the state information through the classes in this part. The Intelligent Tutor creates the rules which decide how to change the Knowledge Level of a user. All the activities related to this class are targeted to adapt the curriculum to students’ needs, assist the students when needed and perform proneness and diagnosis to students’ errors. User modeler is responsible for acquiring and representing the necessary information about each student and updates the system’s belief for each student based on his/her interaction with the system. Furthermore, it involves the construction of a qualitative representation that accounts for student behavior in terms of existing background knowledge about a domain. In other terms, it can be ameliorated by the incorporation of machine learning techniques, namely of the k-means clustering algorithm, which is going to be described below.

![Figure 2. Mobile Client Design Model](image)

Our system uses a three-tier architecture, which includes the presentation tier, the logic tier and the data tier, as shown in Figure 3. Apart from the usual advantages of modular software with well-defined interfaces, the three-tier architecture is intended to allow any of the three tiers to be upgraded or replaced independently in response to changes in requirements or technology, a fact that is crucial for mobile applications. Typically, the user interface runs on a desktop PC and uses a standard graphical user interface, the functional process logic may consist of one or more separate modules running on an application server, and a database server contains the computer data storage logic. In particular, the presentation tier is the topmost level of the application. It displays information related to such tasks and results to an operation that the user is able to easily recognize and understand. Moreover, it communicates with other tiers by outputting results to the browser/client tier and all other tiers in the network. The logic tier is pulled out from the presentation tier and it controls our mobile application’s functionality by performing detailed processing. This tier coordinates the application, processes commands, makes logical decisions and evaluations and performs calculations. It also moves and processes data between the two surrounding layers. Finally, the data tier consists of database servers, where information is stored and retrieved. The information is then passed back to the logic tier for processing and then eventually back to the user. This tier keeps data neutral and independent from application servers or from the logic tier. Giving data its own tier also improves the scalability and performance of our system.
A. Incorporating machine learning

In order to define prototypical behaviors, so that any user is close to one of these, we classify the users’ characteristics into K classes and computing K typical clusters. For this reason, there is an emerging need of an unsupervised algorithm which can handle such data, generate a representative for each class, provide the best intrinsic K and have the ability to generalize to unknown users too. Thus, we choose to adapt the K-means algorithm, which provides more maturity in the corresponding user models and adaptivity in user interaction. The basic procedure for implementing the k-means clustering algorithm can be summarized as follows:

- Select K initial cluster centers.
- The K clusters are formed by associating each data point with its closest cluster center. The centroids of these K clusters become the new cluster center.
- The above procedure is repeated until the new cluster centers are the same as the previous ones.

This algorithm aims at minimizing an objective function J, typically a squared error function:

\[ J = \sum_{i=1}^{k} \sum_{j=1}^{n} d_{ij} = \sum_{i=1}^{k} \sum_{j=1}^{n} \left\| x_{i}^{(j)} - c_{j} \right\|^2 \]  

where \(d_{ij}\) is the distance measure between a data point \(x_{i}\) and the cluster center \(c_{j}\). \(J\) is an indicator of the distance of the n data points from their perspective cluster centers and it represents the compactness of the clusters created [6].

For the incorporation of the machine learning approach into the resulting mobile multilingual system (as shown in Figure 4), we make the following basic steps:

- For the initialization of the system the algorithmic techniques receive as input, pre-stored data or data from empirical studies. It uses two fundamental characteristics which tend to influence the educational procedure:
  - the age of students and
  - their level of knowledge in one of the foreign language taught.

These characteristics have been found quite significant in past language learning applications [15].

- Machine learning techniques are used as a next step in order to describe efficiently the circumstances that underlie the student’s actions in terms of their behavioral patterns and preferences.

- Based on the aforementioned characteristics, the system creates clusters of the already existing students. These clusters contain valuable information about their members, considering their behavior, their preferences and generally their interaction with the system.

Finally, when a new user is added to the system, by registration, the student’s initial characteristics (age, level of knowledge) are processed by the system’s machine learning mechanisms to classify the student in an existing student cluster. In this way, it can offer personalized advice for revision end error proneness concerning the taught languages, individualized navigation and adaptation to student’s needs.
IV. STEREOTYPES WITH K-MEANS CLUSTERING ALGORITHM

In k-means algorithm, the main parameter is the number k of clusters (stereotypes) used to partition the original data. In order to determine the optimal number of clusters, we ran the algorithm for k = 2, . . . , 9 without giving any initial value for the cluster centers, using the Euclidean distance and taking into account the number of vectors, which represents the user’s characteristics. To avoid the solution given for a given k being a local minima, because of the randomness of the original centers, k-means was run for each value of k 100 times and the solution used was the one that minimized the objective function J presented in the above equation. In order to determine how good the partition obtained was, for each user i we obtained an indication $\phi_i$ representing how similar the behavior of that user is with users of the same cluster compared with the behavior of users of all other clusters, formally [6]:

$$
\phi_i = \frac{\min(b_{i,m}, m = 1, \ldots, k) - d_i}{\max(d_i, \min(b_{i,m}, m = 1, \ldots, k))}
$$

(2)

where $\phi_i$ is a value ranging in $(-1, +1)$, $d_i$ is the average distance of user i to all the users of its own cluster, $b_{i,k}$ is the average distance of user i to all the users of cluster k, and m is the number of user stereotypes. A value of +1 indicates that the user is very distant to the rest of the clusters, a value of 0 or near 0 indicates that the user is not distinctive of that cluster, and a negative value that indicates that the user has probably been assigned to the wrong cluster. The quality of a partition, $q_k$, ($k = 2, \ldots, 9$), is obtained as the mean value of all the $\phi_i$ values of the system [6],

$$
q_k = \frac{1}{N} \sum_{i=1}^{N} \phi_i
$$

(3)

with N the number of users, 50 in our case. The following figure presents the evolution of the quality of the partitions obtained for the values of k tested. As can be seen the optimum partition, as we have measured the quality of a partition, is obtained with a value of k = 4. The following Voronoi diagram, illustrated in Figure 5, is a special kind of decomposition of a given space, determined by distances to a specified family of objects in the space and presents a representation of the four clusters produced and $\phi_i$ for each user within that clusters. We can observe that, from these clusters, the blue one is easily distinguishable with a high number of users and a high $\phi_i$ value for its elements, indicating well defined behavior of its users, while the green cluster has a low number of users included and lower $\phi_i$ values.

Figure 5. Voronoi Diagram

At this point, we have to emphasize the fact that the whole processing that is required by the machine learning approaches take place in the system’s server, while the output is sent to the mobile devices. A screenshot of the resulting output in a mobile device is illustrated in Figure 7 and represents the error diagnosis process that acts in the students’ evaluation section.
and shows the categorization of errors, indicated by different colors which correspond to different types of errors.

![Image of categorization of students' errors]

**Figure 7. Categorization of students’ errors**

**V. CONCLUSIONS AND FUTURE WORK**

In this paper, we have described a multilingual mobile multi-language learning application which combines attractiveness and user-friendliness and a framework that addresses the problem of clustering students in order to provide sophisticated and dynamic user models. Clustering is conducted by the k-means algorithm which takes as input, to initialize the process, two important students’ characteristics. Our approach to student modeling exploits the fact that educational systems have a large number of users and we use a machine learning reasoning mechanism that is based on recognized similarities between them. In this way, the K-means algorithm creates clusters based on pre-stored data and data from empirical studies. Finally, after determining in which cluster each new student belongs, the system can reason about this specific student, adapting its behavior to the student’s needs. The resulting adaptation emerges from the analysis of each cluster’s characteristics that derive from each cluster as a superset of already existing student models.

It is in our future plans to evaluate our mobile expert system in order to examine the degree of usefulness of the personalized learning offered in our system. Moreover, we are planning to further evaluate the system in terms of its usefulness of the multilingual support along with the efficiency of k-means clustering in the language learning process.

**REFERENCES**


