TRANSFORMER LANGUAGE MODEL-BASED MOBILE LEARNING SOLUTION FOR HIGHER EDUCATION

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ABSTRACT

Mobile learning or mLearning has become an essential tool in many fields in this digital era, among the ones educational training deserves special attention, that is, applied to both basic and higher education towards active, flexible, effective high-quality and continuous learning. However, despite the advances in Natural Language Processing techniques, mLearning still does not take full advantage of the great potential of the latter techniques. It is the case of the transformer language models distributed in chatbot form. Accordingly, this work presents a mLearning application based on OpenAI GPT-3 model, which enables user-friendly interactions. The proposed system was tested in two evaluation scenarios, and the experimental results endorse its appropriateness toward learning experience enhancement.

KEYWORDS

Higher Education, Intelligent Virtual Assistant, Mobile Learning, Natural Language Processing, User-Generated Content, Transformer Language Models

1. INTRODUCTION

Mobile learning or mLearning allows to gather knowledge and develop skills by exploiting mobile technologies. mLearning exploits all media types (audio, text, visual data, *etc.*) at any place and time (Crompton & Burke, 2018). Consequently, it has become an essential tool in this digital era, driven by the recent advances in communication networks, information technologies, and learning applications (Bai, 2019). All levels of education have been affected by digitalization which promotes practice-based learning instead of just offering theoretical knowledge. Particularly, mLearning has been extensively used in both basic and higher educational levels, being a critical component in the latter towards high-quality, active, and continuous education (Crompton & Burke, 2018). As a result, mLearning is established as a strategic tool to enhance university student capacities (Pinto et al., 2020). There exist several mobile technologies used in mLearning, such as eBooks, smartphones, tablets, etc. Among them, mobile phones are the most common devices due to their multi-task nature (audio, image, and video recording capabilities, and all kinds of educational software available) (Crompton & Burke, 2018; Hartley & Bendixen, 2019).

Its flexible and convenient nature (Pedro et al., 2018) is highly attractive to digital natives who seek a fully immersive learning experience. However, learning experience enhancement can only be achieved through well-designed learning solutions (Parsazadeh et al., 2018). Accordingly, consideration should be given to advanced mLearning approaches to ensure learning effectiveness. In this line, transformer language models are relevant to this work. They are intended to solve sequence-to-sequence tasks and handle long-term dependencies by relying on the self-attention mechanism based on the encoder-decoder architecture. More in detail, the input word embeddings enter the first encoder, and then they are transformed and propagated to the next encoder. The output is obtained after decoding. These models are the most advanced for Natural Language Generation and are distributed in a chatbot form (Brown et al. 2020). A chatbot is a conversational agent able to interact with users in a natural way using textual or voice-based interfaces in order to answer questions, establish a conversion on any topic or even perform a certain task. This technology has been applied in multiple domains, such as customer service and, especially to education and training (Tallyn et al., 2018). Users can benefit from the instant availability of mLearning applications and the ability to respond naturally using chatbots. Accordingly, this work contributes with a transformer language model-based mobile application which exploits Natural Language Processing (NLP) to enable user-friendly interactions to enhance mLearning acceptance of both educators and learners, inside and outside of the classroom.

The rest of the paper is organized as follows. Section 2 reviews relevant literature on mLearning to support the motivation of the present work. Section 3 presents the proposed solution, while Section 4 details the implementation decisions and displays the experimental results obtained. Finally, Section 5 concludes the article.

2. RELATED WORK

mLearning solutions are nowadays official tools in both classrooms and workplaces, but they are also relevant systems outside these environments, at homes for teleworking and remote education, respectively (Kumar Basak, 2018). They seek to provide new efficient ways of learning and also remove the existing limitations in the process with the ultimate objective of meeting the learner's needs. As previously mentioned, mLearning was originally developed as a way to save resources (money and time) while at the same time enabling high-quality, easier and faster learning. Learning processes involve challenging tasks such as comprehension, design, problem-solving, debugging, etc. (Malik et al., 2020). Thus, Technology Enhanced Learning (TEL) and Learning Analytics (LA) constitute relevant approaches for enhancing users' learning satisfaction in multimodal learning environments compared or combined with traditional methodologies (Mota et al., 2018).

The European Digital Agenda 2020[1] seeks to perform strategic ICT (Information and Communications Technology) research and innovation actions like promoting digital skills and inclusion. Among Good Practice Teaching (GPT) (Romero-Rodríguez et al., 2020), which involves cooperative work, knowledge, and self-regulation training along with the development of digital competence, educational chatbot solutions are appropriate. The latter solutions promote human-machine interaction and engagement (Smutny & Schreiberova, 2020). This is the case with the Ethnobot chatbot (Tallyn et al., 2018), which asks users ethnographic-related questions. However, the most advanced technology for chatbot design is the aforementioned language transformer models. Particularly, OpenAI, an Artificial Intelligence research and deployment company, provides three different models depending on the use case: GPT-3, oriented to NLP, Codex for programming users, and Content filter to detect whether a text may be confidential or insecure (Brown et al. 2020). However, none of them focus on the educational field.

In the particular case of Spain, mLearning has started to be applied to preschool and primary levels (Romero-Rodríguez, 2020). The results obtained show a positive increase in motivating the learners and improving their learning outcomes (Bai, 2019). However, there is still work to be done in digital competence development in Spain (Fuentes et al., 2019), even though it is the fifth country in the world regarding the number of smartphone and Internet users2. Therefore, the Instituto Nacional de Tecnologías Educativas y Formación del Profesorado (INTEF) indicated the necessity to promote the latter digital competence among students (Romero-Rodríguez, 2020) beyond Learning Management System (LMS) software (Antonova & Bontchev, 2020). LMS is very popular at higher levels (Abazi-Bexheti et al., 2018). Examples of LMS include Blackboard, Edmodo, Google Classroom, Moodle, Sakai, and Schoology. In this line, Andrei et al. (2019) presented the Open Virtual Mobility Learning Hub which combines different interactive learning methodologies in open-source frameworks like MOODLE. Learning apps are also very common, the second most popular category on Google Play (Singh & Suri, 2022). Take Duolingo, Quizlet, SoloLearn as representative examples.

Regarding prior research on mLearning, Mota et al. (2018) presented a framework to create applications with augmented reality, while Oyelere et al. (2018) developed MobileEdu focusing on computing education for university students following a blended learning approach, that is, combining mlearning and traditional face-to-face teaching (Nogueira & Paniago, 2022). Furthermore, Parsazadeh et al. (2018) presented a Jigsaw-based mLearning application that combines interactive and cooperative learning to promote peer and group interaction. More recently, Nazar et al. (2022) created an Android app to comprehend the concept of redox in Chemistry for university students. Other popular use cases include language (Brata et al., 2019) and

[1] Available at https://library.educause.edu/resources/2019/4/2019-horizon-report, January 2023.
[2] Available at https://compromiso.atresmedia.com/levanta-la-cabeza/quienes-somos/movimiento-uso-responsable-tecnologia_201901245c49b0f20cf238d4657881bc.html, January 2023.

code (Troussas et al., 2020; App Inventor and Scratch) learning. Accordingly, Liu (2022) developed an mLearning application to improve the English language among college students, which combines gamification and collaborative/competitive learning. More closely related to our work is the WeChat application developed by Ng et al. (2020), the most popular collaborative learning application used among Chinese students.

This work contributes to all the fundamental perspectives of mLearning: (contribution-i) cognitive (how the brain operates during learning), (c-ii) emotional (engagement, motivation, etc.), (c-iii) behavioral (outcomes of the learning process), and (c-iv) contextual (interaction and collaboration). Consequently, the proposed intelligent mobile application seeks learning optimization in a virtual and adaptive environment by exploiting NLP techniques over the content (c-i and c-iii). It also adapts the utterances to the emotional state of the users thanks to its sentiment analysis (SA) and empathetic module to prevent frustration and promote confidence (c-ii). Note that the latter feature is especially relevant since the emotional state of the learner is strongly related to the outcome of the learning process (Singh & Suri, 2022). Finally, the system uses an innovative communication approach with a transformer language model (c-iv).

3. PROPOSED METHOD

The proposed virtual learning assistant is depicted in Figure 1. In this figure, the conversational server and client application are illustrated. The solution is intended for both professors and students and was especially designed for the Spanish language, even though its adaptation to other languages may be considered straightforward. Thanks to the pre-trained model available, this solution will be able to accommodate any educational issue without prior training or additional information. The assistant provides automatic question generation and free dialogue functionalities. In the particular case of students, the virtual assistant enables doubts resolution.

3.1 Conversational Server

The conversational server is the core of the system and allows to automatically generate interactions with the users in the form of questions or free dialogue. The system utterances are enriched following a template-based approach to ensure that the human-machine interaction is satisfactory.

3.1.1 ML Model Selection Module

Once the request is received from the client, it is necessary to select the Machine Learning (ML) model to generate the system output. Accordingly, the model with a higher computational cost is selected. If the latter model is not available, that is, request errors are being produced, or there is a response time greater than 30 seconds, the next model based on higher computational cost is selected.

3.1.2 Playground Manager Module

The playgrounds in OpenAI are composed of templates that contextualize the dialogue in a specific area or topic and ensure that the system response is appropriate. Thus, this module allows to management of the available playgrounds and includes relevant features like personalization, empathy, and feedback.

Personalization stage. It detects the profile of the user (teacher or student), the conversation type (automatic question generation or free dialogue), and the area and topic of the conversation. The history of the interactions is also managed in this stage (maximum history of six utterances). Firstly, the users indicate their role, and since the words teacher or student (or synonyms of these words) may be absent, the system identifies the role with the following template in the playground, "*Si te dijese* [USER ROLE DEFINITION IN NATURAL LANGUAGE], *¿qué dirías que soy un profesor o un alumno? Contesta con una sola palabra*" (If I told you [USER ROLE DEFINITION IN NATURAL LANGUAGE], what would you say I am, a teacher or a student? Answer with one word). The system returns the role of the user, and only when "teacher" or "student" is identified the conversation continues. Otherwise, the system keeps asking the users about their roles. Then, the operation mode is detected using the following templates, "*Soy un/una docente. Si te dijese* [USER OPERATION MODE DEFINITION IN NATURAL LANGUAGE], *¿qué dirías que he elegido de las opciones disponibles: generar preguntas de examen, chat abierto? Contesta con una sola de las opciones de* *la lista*" (I am a teacher. If I told you [USER OPERATION MODE DEFINITION IN NATURAL LANGUAGE], what would you say I have chosen from the available options: exam question generation, free dialogue? Answer with only one of the options from the list) and "*Soy un/a estudiante, si te dijese* [USER OPERATION MODE DEFINITION IN NATURAL LANGUAGE], *¿qué dirías que he elegido de las opciones disponibles: generar preguntas de auto-evaluación, resolver dudas, chat abierto? Contesta con una sola de las opciones de la lista*" (I am a student, if I told you [USER OPERATION MODE DEFINITION IN NATURAL LANGUAGE], what would you say that I have chosen from the available options: generate self-assessment questions, resolve doubts, free dialogue? Answer with only one of the options from the list), for the teacher and student roles, respectively. Finally, if the question generation functionality was previously detected for the teacher or student role, it is time to infer the area and topic of the conversation. Accordingly, a similar template is used, "*Si te dijese* [USER AREA AND TOPIC DEFINITION IN NATURAL LANGUAGE], *¿a qué área y temática me refiero? Contesta siguiendo el siguiente formato, materia: A, tema: B*" (If I told you [USER AREA AND TOPIC DEFINITION IN NATURAL LANGUAGE], what area and topic am I referring to? Answer using the following format, area: A, topic: B).

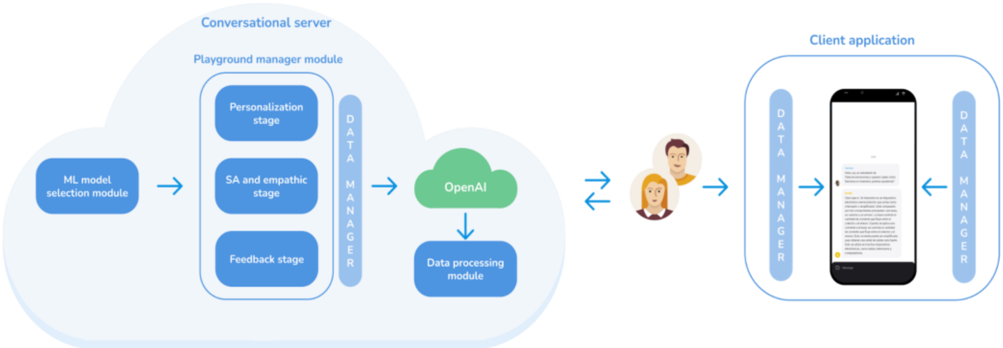

Figure 1. System scheme

SA and empathetic stage. The system generates sentences adapted to the state of mind of the users since it has been trained to follow this template "*El asistente es dinámico, nunca repite dos veces lo mismo, es creativo, es inteligente y muy amable*" (The assistant is dynamic, it never repeats the same thing twice, it is creative, intelligent and very kind). During the quiz with the students (system automatic question generation and user response), if three consecutive mistakes are made by the student, the assistant asks how the student feels. The latter response is analyzed using the template "*Si te digo* [USER STATE OF MIND DEFINITION IN NATURAL LANGUAGE] *dirías que estoy ¿triste o feliz?*" (If I told you [USER STATE OF MIND DEFINITION IN NATURAL LANGUAGE] would you say I am happy or sad?). If the emotion "tristeza" (sad) is detected, questions from a lower difficulty level will be presented to the student.

Feedback stage. The empathetic nature of the assistant defined in the previous stage is combined with the feedback provided to the users. The latter is possible thanks to the template "*Soy un/a estudiante y a la pregunta* [ASSISTANT QUESTION] *he contestado* [USER ANSWER]. *Dime si mi respuesta es 100% correcta, parcialmente correcta o no es correcta. Y explícame el porqué*" (I am a student and to the question [ASSISTANT QUESTION] I have answered [USER ANSWER]. Please tell me if my answer is 100% correct, partially correct or incorrect. And explain to me why).

Finally, for the utterances generation of the virtual assistant, there exist several additional playgrounds depending on the role and action previously chosen.

- **Exam question generation for the teacher role**. The template used is "*Soy un/a docente con conocimientos avanzados, necesitaría generar una pregunta para un examen de* [ASSISTANT AREA AND TOPIC DETECTED]" (I am a teacher with advanced knowledge, I would need to generate a question for an exam [ASSISTANT AREA AND TOPIC DETECTED]).
- **Self-assessment for the student role**. The template used is "*Soy un/a estudiante, necesitaría practicar para un examen de* [ASSISTANT AREA AND TOPIC DETECTED]. *Genérame una pregunta al respecto*" (I am a student, I would need to practice for a [ASSISTANT AREA AND TOPIC DETECTED] exam. Give me a question about it).

- **Doubts resolution for the student role**. The template used is “*Soy un/a estudiante. Necesitaría que me resolvieras esta pregunta* [USER QUESTION IN NATURAL LANGUAGE]” (I am a student. I need you to solve this question [USER QUESTION IN NATURAL LANGUAGE]).

3.1.3 Data Processing Module

Text processing is essential for personalization, SA, and empathetic stages. Thus, this module deletes symbols, URLs, and other non-alphanumeric content.

3.2 Data Manager

The main functionality of this module is to serve as an abstraction layer between the conversational server, the ML model selector, and the client application. Server-client data are sent and received in JSON format. In addition, JSON allows the status of the conversion to be established by identifying the type of interlocutor and the number of interactions, as well as the immediately preceding questions and conversations, thus, acting as an intermediate lazy cache.

3.3 Client Application

It serves as the system access interface for the end users. This module identifies the number of interactions that have been carried out in the free chat functionality. In addition, the cleaning of the user cache is performed when the user ends the conversation with the “terminate” command.

4. EXPERIMENTAL RESULTS

This section presents the implementation decisions. In the end, the evaluation results are discussed.

4.1 Conversational Server

This module was deployed as a Flask server (version 2.2.2) with a Gunicorn traffic balancer (version 20.1.0) using Python programming language (version 3.8).

4.1.1 ML Model Selection Module

For the generation of sentences, the system uses the GPT-3 transformer language model (version 3.5) provided by OpenAI.

4.1.2 Playground Manager Module

In order to either reduce the randomness of the response or guarantee the maximum dynamism of the dialogues, the *temperature* parameter was set as follows (0 and 1, respectively).

- **Personalization stage**. *Temperature* = 0.
- **SA and empathetic stage**. *Temperature* = 0 when using the templates to train the assistant and *Temperature* = 1 when generating empathetic interactions.
- **Feedback stage**. *Temperature* = 1.

4.1.3 Data Processing Module

Regular expressions are exploited to detect both symbols (“#”, “′”, “;”, “`”, “~”, “&”, “.”, “?”, “¿”, “!”, “¡”) and URLs (starting with http, https, pic, and www).

4.2 Data Manager

The Python http module is used for request management on the client side while, on the server, the Flask library. In addition, for the generation of requests against the transformer language model, the OpenAI Python library is used.

4.3 Client Application

The client has been designed using the cross-platform Flutter language; hence the proposed system is accessible from Windows, macOS, iOS, and Android as a native application or from a browser. For the design of the chat, the Flyer Chat library was used. A model-view-controller paradigm was followed.

4.4 Case Study

In our study, a total of 100 interactions have been manually annotated by two NLP experts. Particularly, two evaluation scenarios have been set.

Scenario 1. Five thematic areas with a single topic (history – World War II, biology – cellular and biochemistry, mathematics – differential equations, medicine – human anatomy, engineering – Python programming) and ten questions each have been generated using the assistant. The following evaluation questions were used, EQ1: Is the question generated by the assistant related to the area requested?, EQ2: Is the question useful for an exam?, EQ3: Are there any grammatical errors, or its construction is inconsistent?

Scenario 2. The answers to the questions generated for the previous scenarios are evaluated using, EQ4: Is the answer related to the question?, EQ5: Is the concept clearly explained to a student?, EQ6: Are there any grammatical errors, or its construction is inconsistent?

4.5 Annotation Results

Tables 1 and 2 show the results obtained for the first and second evaluation scenarios, respectively. Results are provided in terms of the percentage of affirmative answers to the evaluation questions. The values of the first evaluation scenario range from 92% to 100% for EQ1 and EQ2. Thus, the questions generated by the assistant are both within the area and topic of the dialogue and appropriate to be included in the exam. The number of grammatical and coherent errors is minimal (up to 6%). In the second evaluation scenario (see Table 2), the results obtained for EQ4 and EQ5 are even higher, between 94% and 100%. However, grammatical and coherence errors are more frequent (up to 14%). The latter fact is due to the greater difficulty in generating complete answers to the questions generated to be used in an exam (second scenario) compared to creating the questions themselves (first scenario).

Table 1. Percentage of affirmative answers of the two annotators for the first evaluation scenario

	EQ1	**EQ2**	**EQ3**
Annotator 1	98%	92%	4%
Annotator 2	96%	100%	6%

Table 2. Percentage of affirmative answers of the two annotators for the second evaluation scenario

	EQ4	**EQ5**	**EQ6**
Annotator 1	100%	94%	12%
Annotator 2	100%	98%	14%

5. CONCLUSION

There exist a variety of mLearning solutions that are being exploited in classrooms and workplaces as new efficient tools to meet the learner's needs while removing the existing limitations in the process, such as time and location constraints. The latter proliferation of mLeaning systems has been driven not only by private parties as the end users themselves but also by the European Digital Agenda 2020, and the Spanish INTEF to promote digital skills.

In this line, this work seeks to fully exploit the latest advances in NLP techniques in an intelligent virtual assistant based on the transformer language model GPT-3 by OpenAI. Our solution is composed of a conversational server and a client application. Among its most relevant features are the personalized and emphatic utterances along with the feedback provided during the dialogues with the users. Experimental results show that the questions generated by the assistant are both within the area and topic of the dialogue (up to 98 %), appropriate to be included in the exam (up to 100 %), and fully explanatory (100 %) to a student (98 %). The number of grammatical and coherent errors is minimal (up to 14 %). A real example of a conversation with the virtual assistant is shown in Figure 2. The user, in this case, is a student that wants to practice for a chemistry exam about redox reactions.

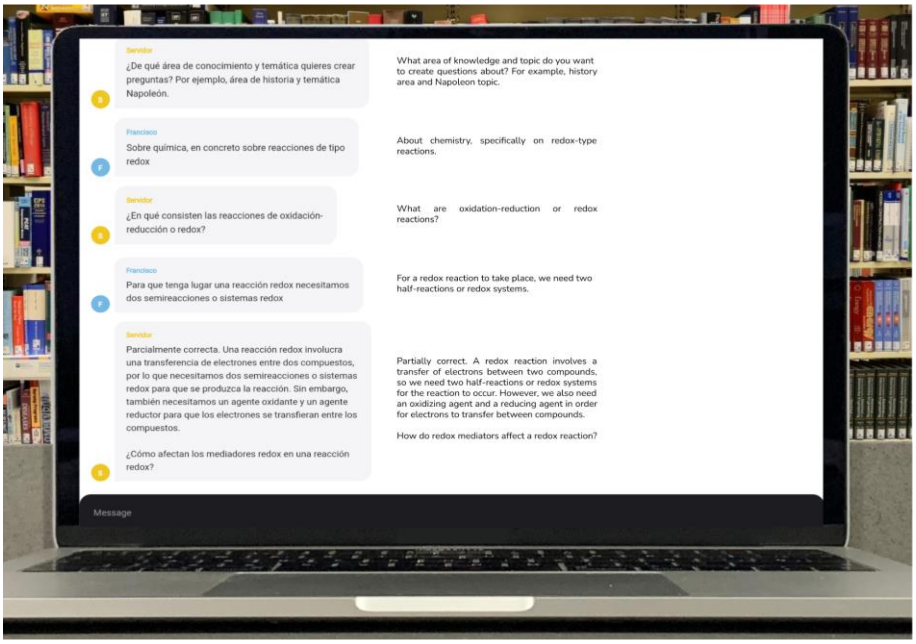

Figure 2. Integration of the system in a multiplatform application

In future work, the dialogues generated in the mobile application can be mined to recommend adjustments in learning methods. Other languages will be considered in the next versions of the assistant.

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