A Conversational Agent for Smart Schooling

A case study on K-12 dropout risk assessment

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Abstract. The goal of smart education is to utilize advanced technology in order to improve the teaching experience by establishing a stimulating and interactive atmosphere for learning. Conversational agents emerge as an aid for a smarter education. One of the possibilities to be explored is the building of tools that help predict and prevent student failure or dropout. This case study presents a research project that consists on the creation of a school platform for student interaction, in which a conversational agent, developed using Rasa, communicates with both the students and the class director and is able to assign a risk of academic failure, based on their answers to questionnaires scripted by a team of psychologists. XGBoost outperfomed AdaBoost, Decision Tree and Random Forest algorithms with an accuracy of 97%.

Keywords: Rasa · Academic Failure · Smart Education · Machine Learning · Conversational Agent.

1 Introduction

Smart cities aim to enhance sustainability, increase efficiency and improve the overall quality of life for citizens. These cities integrate information and communication technologies (ICT) and Internet of Things (IoT) devices which collect and analyze data from numerous sources and that data is later used to manage assets and resources efficiently, make informed decisions and provide better services to citizens [1].

In this context, smart schooling emerges with the goal of using digital tools to improve the teaching and learning experience. It is a mean for an engaging and interactive learning environment.

Conversational agents are a component of smart schooling as they can be a useful tool for building the student's tailored profile and contributing to their needs by providing information and assistance.

Recently, the issue of using conversational agents in educational environments increased with the emergence of chatGPT [2]. Among matters related to plagiarism and academic honesty, which are surpassed by benefits to both students and professors [3, 4], such as increasing student engagement and the facilitation of asynchronous communication [5], it may also help prevent school failure as proposed in this article.

However, in spite of this common agreement about the usefulness of conversational agents for educational purposes, the majority of research has been carried out with higher education or secondary students. Information on the profitability of these agents in the context of compulsory education is lacking.

Ethical Statement. Considering that the children are obviously underaged, the project and interaction plans were presented to their parents, and those who agreed were asked to sign an informed consent form. The scripts to be used by the conversational agent were written by a team of educational psychologist researchers who are working on the project alongside computer science researchers and a technology company. Further information about the team can be found on the project description subsection of this article. Students are aware that they are interacting with a chabot as they see an avatar and the agent presents itself in the first interaction. The class director and a psychologist are always present in the classroom at every testing moment. It is also important to note that the children are only able to interact with the chatbot in planned and controlled testing moments and never on any other occasions at the present time.

Document Structure. The case study report is divided into three main sections. First, a project description is provided. Additionally, a component view is shown. Subsequentely, the Education Intelligence and Conversational Agent modules are presented. This last section briefly refers to two examples of Rasa-based tutors in educational contexts. Following this, the outcomes are examined and a discussion is conducted, culminating in a conclusion.

2 The Case Study Report

A case study is a method to be used in this context, as, per definition, it provides thorough comprehension of a process, program, event, or activity [6] . These in-depth insights can generate hypotheses for future research [7]. The object of this case study report is to address a K-12 dropout risk assessment using a dialogue-based structure. The approach used is descriptive.

2.1 Project Description

This project seeks to collaborate with the public government initiative of avoiding school failure and dropout for K-12 students. The target is to create a set of warnings that help the class director recognize the dropout risk and enable them to act in a timely manner.

The team working on the project is multidisciplinary, consisting of: educational psychologist researchers, who are building the scripts, ensuring that the language used and conversation flow is appropriate for children of different ages and at different stages or their academic journey. These scripts will be followed by a team of computer science researchers in order to build the conversational agent. Meanwhile, the technology company, that works on developing software solutions in the Education and Training sectors, is in charge of the deployment of the agent.

Together, they are leveraging the strengths of each discipline to create a digital platform that will help identify those who may be at risk of academic failure and dropout.

2.2 Component View

Overall, the proposed solution is composed of two modules, Education Intelligence and Digital Assistant, which will interact with three involved actors (class director, student and the school platform), as represented in Figure 1.

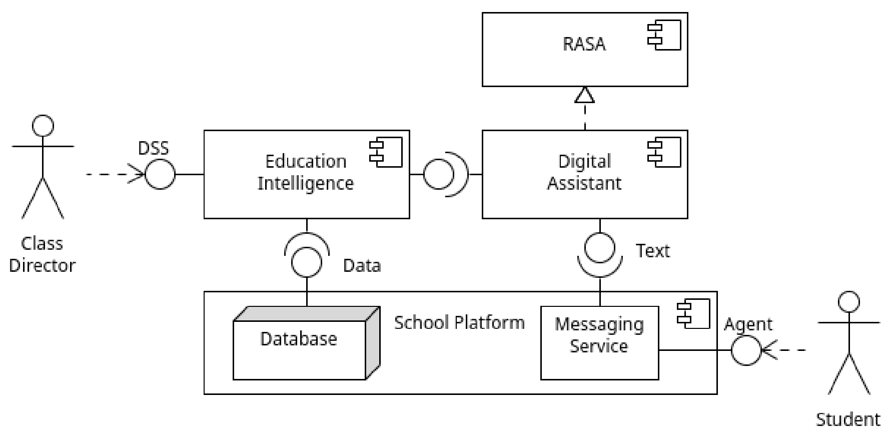

Fig. 1: Components diagram representing the platform integration with the involved actors.

The Education Intelligence component is responsible for processing the information obtained from both the school platform and the student in order to produce information of interest to the class director but also data that help refine the behavior of the Digital Assistant module.

The Digital Assistant module serves as an interaction support for the student.

The student provides subjective information about how they feel about their school experience while the school platform provides objective information such as grades and absences.

The primary purpose of this platform is to support the class director with monitoring school failure or droupout risk, which is possible through the combination of all these components.

2.3 Education Intelligence

Machine Learning was utilized to forecast a student's academic situation, which may have an impact on how to provide assistance to the student. To make this forecast, the Machine Learning model relied on the recent grades of the student in the subjects of Portuguese and Mathematics. Furthermore, in addition to these prerequisites, it also required the responses given by the students to the questionnaires from Rasa. Rasa is a widely used open source framework for building chat and voice-based AI assistants [8].

Prior to integrating the Machine Learning component with the Digital Assistant, it was necessary to investigate which algorithm was most suitable for classifying (and therefore predicting) a student's academic situation.

A team of psychologists created a survey for students to complete, which focused on their academic experiences. This survey was administered to students in different school years. Furthermore, in addition to the survey responses, the psychologists also had access to the students' grades in Portuguese and Mathematics for both the first and second terms. Moreover, based on each student's academic situation, the psychologists assigned a cluster to them.

This cluster identifies the academic situation of a particular student, see Table 1.

The dataset consisted of 845 entries and 123 columns. Among these entries, 422 were from primary school students and 423 were from middle students. Additionally, the dataset had a few null values and some missing data, so an initial pre-processing step was necessary.

The distribution of students among the clusters can be seen in Figure 2. It can be seen that the different clusters have a similar number of students.

It is also noted that one fourth of the total number of students are classified as being at high risk of academic failure, which can be a concerning number at first glance. However, the school from which this data was collected is known for its ability to deal with struggling students due to the fact that it is a semi-private school located in a remote area, where students struggle to find distractions, so

Table 1: Descriptions of each cluster.

Cluster	Description
Cluster 0	Indicates that the student has a high risk of academic failure;
Cluster 1	Suggests that the student is at a moderate risk of not succeeding academically;
Cluster 2	Indicates that the student is at a moderate level of risk, although less serious than cluster 1;
Cluster 3	Indicates that the student has a low level of risk and is therefore on a good path towards academic success;

it is possible that many of these students were transferred from other schools with this purpose, therefore explaining the high number of students at risk.

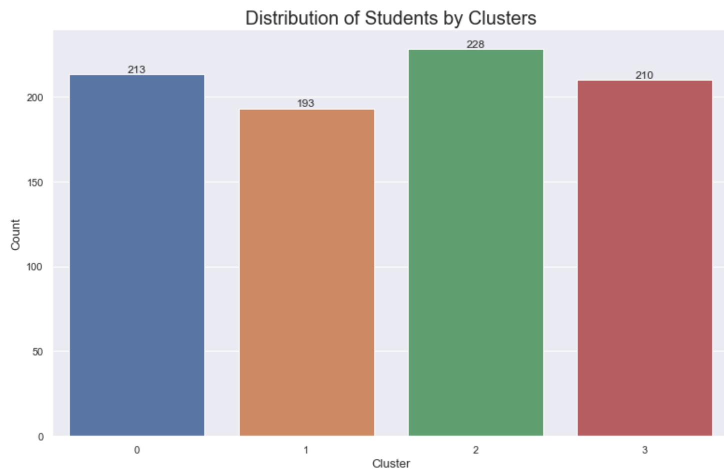

Fig. 2: Distribution of students among the clusters. See Table 1 for detailed explanation of each cluster.

Three studies were carried out, one for each dataset. The first dataset contained all the columns from the initial dataset.

The second dataset included the 13 columns that psychologists had identified as the most relevant for classifying the student's cluster. These columns included the student's most recent grades in Portuguese and Mathematics, their satisfaction with their grades, their perception of whether their grades reflected their abilities, their level of engagement in school, their short and long-term self-regulation skills, their motivation (two columns), their perception of the value of education, and their support from family, teachers, and peers.

The third dataset consisted of five columns. The columns are: the student's most recent grades in Portuguese and Mathematics, their satisfaction with their grades, their perception of whether their grades reflected their abilities, and their level of engagement in school.

Four algorithms were tested in addition to these three datasets. All of these algorithms had previously been studied as the most powerful in terms of academic situations [9]. The AdaBoost, DecisionTree, RandomForest, and XGBoost algorithms were applied.

A Grid Search Cross Validation was applied to optimize the hyperparameters of each algorithm, and the datasets were divided into 80% training and 20% testing in all algorithms. Based on the results presented in Table 2, we can conclude that the highest accuracy is achieved when using the XGBoost and Random Forest algorithms. The XGBoost algorithm achieved an accuracy of

0.9704 in both dataset 2 and dataset 3, while the Random Forest algorithm achieved its highest accuracy (0.9586) when using dataset 3. Generally speaking, dataset 3 performs better, and the best model for this dataset is XGBoost. Given these results, and in order to properly classify each student's cluster, it was identified that it is only necessary to use the information present in dataset 3 and the XGBoost algorithm.

Table 2: Results for each algorithm.

Algorithm	Dataset 1	Dataset 2	Dataset 3
AdaBoost	0.8698	0.8580	0.8817
Decision Tree	0.8817	0.9231	0.9527
XGBoost	**0.9645**	**0.9704**	**0.9704**
Random Forest	0.8935	0.9527	0.9586

2.4 Conversational Agent

Alongside Rasa there are other platforms that can be used for building chatbots, such as A.L.I.C.E. based chatbots (such as Pandora-bots). However, they differ in their features, approach and capabilities. [10] Rasa uses state-of-the-art Transformer-based architecture for abducting complex relationships between words [8]. .

DIET (Dual Intent and Entity Transformer) is a neural network architecture that handles both intents and entity extraction. It is able to learn with the tokens and sentence characteristics and is considerably faster to train and parallels large-scale pre-trained language models in performance. [11]

On the whole, Rasa is known for its Natural Language Processing versatility and learning capabilities, enhancing the "pattern matching" by extrapolating from instances. For that reason it is considered a good choice [12] considering this project's constraints. Therefore, the conversational agent used in this research project was developed using the Rasa framework.

For a reference, ArgueTutor is a Rasa-based tutor providing guidance on the writing process. It offers students adaptative and immediate feedback, theoretical knowledge and detailed guidance through their writing process. These features are integrated using rule-based trained chat intents following the architecture of Rasa NLU and Rasa Core. It has been tested by 55 students and researchers verified that by using ArgueTutor students wrote more convincing texts [13].

Another Rasa-based tutor embodied into a robot that helps children washing hands is worth of mentioning. This tutor was designed to to promote positive behavior change in children, specially in the task of hand hygiene. The robot gives feedback in real time to the children, to motivate them to maintain the quality of their hand-washing if they are doing it correctly, or to correct them in case they are not. And as for the conversational part, the robot can have conversations about hand hygiene and domain specific subjects, and for that it uses a combination of RASA, Google's Automatic Speech Recognition and Text-To-Speech engines [14].

Rasa Framework The general structure of a Rasa project consists of a rasa NLU, rasa rules, rasa stories, actions and domain.yml.

```
- rule: Say goodbye anytime the user says goodbye
  steps:
  - intent: goodbye
  - action: utter_goodbye
```

(a) Example of a rule.

```
class AskForMaterialAction(Action):
    def name(self) -> Text:
        return "action_ask_material"
    def run(self,
        dispatcher: CollectingDispatcher,
        tracker: Tracker,
        domain: DomainDict,
    ) -> List[EventType]:

        dispatcher.utter_message(image = "images/hello/student_with_good_grades/traz_o_material.png")
        dispatcher.utter_message(text=f"Brings school supplies.")
        dispatcher.utter_message(buttons=  [{"title" : "👍", "payload" : "👍"},
                                            {"title" : "👎", "payload" : "👎"}])
```

(b) Example of an action.

```
- intent: negate
  examples: |
    - I don't know
    - don't know
    - no idea
    - no
    - never
    - no way
    - none
    - don't care
    - doesn't matter
    - whatever
    - don't care!!
    - couldn't care less
    - not interested
```

(c) Example of an intent.

Fig. 3: NLU file.

- NLU: The NLU (Natural Language Understanding) is responsible for understanding the user's input and extracting relevant information such as user intent and entities.
- Rules: The rules file is used to define conditional statements that help to control the flow of a conversation.
- Stories: Rasa stories are pre-defined sequences of actions that represent a particular conversation flow. Stories allow developers to map out different conversation paths that the chatbot can take based on the user's input.
- Actions: Rasa actions are the specific tasks that the chatbot can perform in response to the user's input. Actions can include sending a message, making an API request, or accessing a database.
- Domain: The domain file defines the chatbot's vocabulary, actions, and responses. It includes all the intents, entities, actions, and templates that the chatbot needs to understand and respond to user input.

For this project there are a total of 502 actions, 63 intents, 10 rules and 4 stories.

Some actions are simple responses such as "hello" and "goodbye". The chatbot is also able to detect inappropriate words and redirect the conversation in case such words are detected, Moreover, it is also programmed to tell the students to ask the class director for help in case of confusion.

Since the target user of this conversational agent is K-12 students, it was decided that button-type answers as well as the use of emojis would be predominant. This means that in several interactions the user only has to select the button that matches their opinion or intention, for instance, in the questionnaire that is presented in the first activity, where the student has to select which answer applies most to the sentence shown, and the answers vary from "totally disagree" to "totally agree". When the chatbot asks the students how their week has been, a set of emojis varying from happy to sad are presented.

What is more, the chatbot has been developed in two languages: portuguese and english. Both versions share exactly the same characteristics and follows the same flow. The jokes presented by the chatbot were made sure to be equivalent and the language register is equal.

2.5 Realworld Experiments

A total of three activities have been fully developed and tested.

The first activity starts with the conversational agent presenting itself and asking the students to introduce themselves and say what their eye and hair colour is, as well as asking them for a characteristic that they like about themselves or others like about them, in order to establish a rapport with the students. It then moves on to a questionnaire also written by the team of psychologists involved in the project, which included asking students for their opinion regarding their own study habits (*e.g.,* "I always hand in my homework on time" and "After I finish my homework I revise to make sure it's correct"), their view of education (*e.g.,* "It's important for me to learn as much as I can" and "It's important for me to go to university") and their family and friends support (*e.g.,* "My parents are interesting in knowing about what goes on at school" and "My friends respect what I have to stay"). Then, the chatbot asks the students for their favorite free-time activities and gives information about how that activity can help them become a better student, for example, if a student says "doing sports", the chatbot will explain how that activity might require team work, just like doing a group project at school. It was through this activity that the educational psychologists were able to assign a cluster to the students, based on their answers from the questionnaires, as explained in section 2.3. In addition, this activity aims to show students that school can also be fun and they can take their daily routine and free time activities and apply their knowledge and strategies at school.

In the second activity, the chatbot greets the students, asks them how their week has been and tells them a joke in order to make them feel comfortable and at ease. Afterwards, a context-situation is presented in which a colleague is struggling at school and the student is asked for strategies that this colleague can use in order to improve his grade. Finally, a few strategies are analyzed in detail so that the students can understand how they can improve their own performance at school. It is important to note that this activity performs based on the assigned cluster. If the student has previously been classified as a high-risk student, certain strategies were discussed, whereas different strategies were analyzed if the student has been classified as low-risk. The goal is to help the students in predicting consequences.

The third activity consists of detailing these study strategies a bit further and showing possible outcomes of using or not using these strategies. What is more, a small exercise is also presented in which students have to try and organize a birthday party and, using these steps given by the students, the chatbot will explain how planning and doing things step by step can help them in the long term. This activity aims to use a real-life example to demonstrate to the students how they can apply these strategies at school in order to become better students and improve their grades.

3 Results and Discussion

Even though conversational agents can be a useful tool in educational contexts, information about its use in the field of education is scarce, especially at the ages of compulsory education. This also applies to the use of Rasa, which, in spite of its advantages, has not been fully explored in these contexts.

School failure and dropout is a serious issue to which not many tools have been developed in regards to prediction and prevention. Conversational agents can be a useful tool in this sense. Therefore, this case study report observed and gathered insights on the impact of a conversational agent in regards to K-12 dropout risk assessement.

Three tests were conducted in the first trimester of the present year and feedback was positive. Students adhesion was satisfactory and no major issues were reported. All tests were performed in a controlled environment in which the class director and a psychologist were present at all times. Parents of the children were previously informed and signed a consent form.

Through the conversational agent, it is possible to obtain a student's profile that refers to their risk perception. In order to do so, the student answers a questionnaire mediated by Rasa, and then these data go through a Machine Learning model that classifies the student. By predicting this information, it is possible to warn the class director who can then take action.

Nonetheless, a few setbacks were encountered at the beginning of the study. These included different opinions regarding the type of answers that students could provide, as researchers deemed necessary to have more textual input in order to correctly perform sentiment analysis and personality detection but psychologists reckoned that children at the ages of primary and secondary education do not have an entirely developed personality. What is more, psychologists focused mainly on the safe conduct of the experience for the children, arguing and infering appropriate conversation flows whereas computer science researchers' focal point ranges from data collection to data analysis and techniques used, which were limited for the sake of finding common ground for the project. In order to ensure that the interactions with the conversational agent were engaging and enjoyable it was decided that emojis and button-type answers would be often available which hindered the textual input necessary for a proper analysis.

Overall, the use of a conversational agent in such a platform has been favourable and the multidisciplinarity profitable. Children find this tool entertaining and engaging, which enables retrieval of important data much needed in order to build a Decision Support System (DSS) that will help detect chances of school failure or dropout in advance. Additionally, the use of this type of tools can be advantageous considering that it may help the teacher to keep up with unnoticed or hidden situations.

By signaling students at risk in a timmely manner, it is possible to warn the class director and further action can be taken, resulting in an accurate prediction and prevention of school failure and dropout. Future work can include focusing on what type of action can be taken once risk is predicted.

4 Conclusion

Smart education aims to use digital tools to improve the teaching experience by creating an engaging and interactive learning environment. In order to achieve intelligent education, conversational agents are an important factor as they provide a more interactive environment and, through the construction of the student's profile and other data, provide assistance to students when needed. However, the use of Rasa in educational contexts has not been fully explored, which was concluded by the difficulties in finding information on the topic.

This case study concluded that it is possible to obtain an accurate student's profile through the use of a conversational agent. It was found that XGBoost outperformed all other algorithms with an accuracy of 97%. Now, it is up to future work to develop a set of rules so that decisions can be made according to the student's academic situation. These rules may include actions such as notifying the teacher or the parents, among other actions aimed at preventing academic failure.

In the future, the plan is to develop a more comprehensive conversational agent that can provide broader responses and assess the sentiment and motivation behind them.

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