EvaTalk: A Chatbot System for the Brazilian Government Virtual School

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Abstract: EvaTalk is a complete chatbot system developed to attend users from *Escola Virtual de Governo* (EV.G), which is a Brazilian virtual school maintained by the federal government. The proposed architecture was based on a framework to build chatbots, but it was necessary to replace and adapt services to attend EV.G needs. The architecture is composed of the following modules: Interface for direct interaction; Artificial Intelligence to comprehend and process messages; Development to deal with the knowledge base; and Business Intelligence to analyze messages. The first version responded to questions related to Institutional Membership and chitchat. Still, it was noted that Eva needed more training data considering that the developers could not predict well user behavior. Therefore, it was necessary to change the conversational data examples and flows to match user behavior observed after release, which showed an increase in the chatbot's response confidence. The system relies mostly on the data collected through the data analysis tools to evolve.

1 INTRODUCTION

Escola Virtual de Governo (EV.G)[1] is a Brazilian virtual school that hosts free and open courses aimed at public servants in the areas of interest and responsibility of the federal public administration, providing unification of all government schools and allowing studies and analysis of the phenomenon of training in public administration (Teixeira and Pontes, 2017). EV.G is maintained by the Brazilian federal government trough the National School of Public Administration (Enap).

The number of enrollments in courses in this platform in 2018 was 442.719, increasing to 940.545 enrollments in 2019 according to its open information dashboard[2]. This growth raises a challenge to the customer service area. Currently, the support is made through a "Contact Us" page, in which the user can fill a form and have it sent to the support e-mail, where the staff can answer. Questions are related to procedures to engage or follow a course or even to become an EV.G partner to provide course material. The job of the human attendants is to identify the issue and send the appropriate solution from a collection of default answers, with step-by-step commands. This approach demands some human effort which grows together with the platform, which does not have all the financial resources to have as many attendants as needed.

To deal with the growth of EV.G and speed up the user support process, this work proposes a chatbot architecture to answer the frequently asked questions. Chatbots receive natural language from users and execute one or more related commands to engage in a conversation, being able to adapt to new information or new requests, if it employs machine learning (Radziwill and Benton, 2017). The proposed implementation makes use of open-source tools customized to attend EV.G's needs.

The development and implementation of a chatbot for the EV.G platform is expected to lower the demand for human support without necessarily extinguishing it and solve the most common user doubts. Also, it will have a good impact on the quality of service, because providing an answer quickly have an impact on the responsiveness factor, which is one of the variables to measure customer satisfaction (Purnamasari. et al., 2017). The chatbot's knowledge-base will be supplied with the messages previously sent by users through the "Contact Us" page and the standard

[1]https://www.escolavirtual.gov.br/
[2]https://emnumeros.escolavirtual.gov.br/indicadores/

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responses registered on a document used by the attendants when responding to emails. As a part of the personification of the chatbot, it was given the name Eva, and the system is called EvaTalk.

This paper is organized as follows: Section 2 presents other chatbot architectures developed for Portuguese speaking users; Section 3 raises requirements and specificities of Evatalk; Section 4 shows the designed architecture; Section 5 describes EvaTalk behaviour with real users; Section 6 proposes the next steps for improving the system; and Section 7 concludes the paper.

2 RELATED WORKS

Despite relying on recent areas of study, to answer Portuguese-written questions, some works developed chatbot systems that were composed mostly by three layers: user interface, natural language understanding, and a knowledge base. What presents relative inconsistency are the technologies used, as there are many tools and algorithms still under development for this purpose.

Avila et al. (2019) proposed a chatbot architecture to answer questions related to medicines prices. MediBot is contacted via Telegram and has a custom made module to understand natural language. It depends on external resources to load its knowledge base.

Fialho et al. (2013) created a conversational interface system that helps tourists to find answers about Monserrate. Its learning data demands some effort to create and maintain because it is defined by XML files that require long-winded syntax.

Ketsmur et al. (2019) developed a text-to-speech architecture for a smart home system and Mostaço et al. (2018) proposed one that retrieves information about agricultural sensor networks. Both are powered by IBM Watson, which is not open-source software and has a very limited free version.

However, none of the authors present ways of collecting massive data from the user to understand the users' behavior and help the evolving process of the chatbot by feeding it back collected data. Therefore, de Lacerda and Aguiar (2019) worked on an open-source framework that has the basic layers but also holds a data analytics module.

Even though the architecture shown in Figure 1 and proposed by de Lacerda and Aguiar (2019) is a complete chatbot system, it was a generalist implementation. Therefore, this work served as a starting point to EvaTalk, but it was necessary to modify and replace some services to create a system suitable for EV.G customer service.

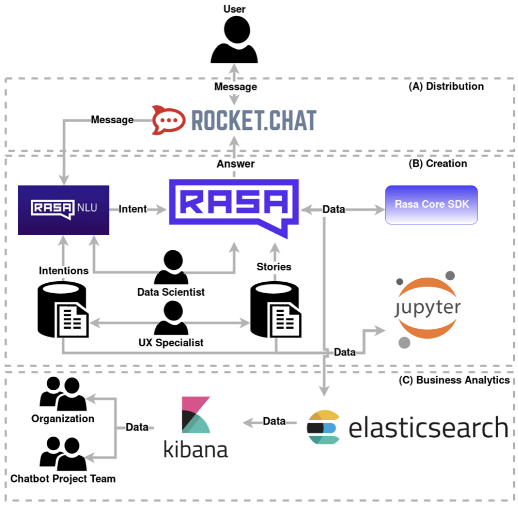

Figure 1: Chatbot System Architecture Proposed by de Lacerda and Aguiar (2019).

3 SYSTEM REQUIREMENTS

Recent studies revealed that users expect chatbots to behave as humans, but, at the same time, they also demand much more from it than from a human attendant, so it is important that it is evident for a user what are the chatbot features and limitations (Jenkins et al., 2007; Følstad et al., 2018). Therefore, Eva must not pretend to be a human but act as one. Also, it should provide to the user what are its capabilities, when convenient in a conversation.

Besides that, due to the emergence of a different language in computer-mediated interactions and, therefore, the occurrence of new discursive genres online (Giordan and Dotta, 2008), Eva should be able to understand terms outside standard Portuguese, as the chat environment implies the occurrence of shortcuts to speed communication, misspelling and acronyms (Varnhagen et al., 2010; Al-Sa'Di and Hamdan, 2005). These behaviors are already noticeable in emails received by EV.G'S customer service. The chatbot must be capable of receiving a sentence in the users' natural language and produce an adequate response if the subject of the conversation pertains to the chatbot's domain.

Regarding the content that the chatbot must answer, Table 1 lists the subjects that EV.G email receives questions about. At its final release, it must be able to answer to all of these subjects. Initially, as a release strategy, the chat widget will be exclusively available on the Institutional Membership page[3] of EV.G. Therefore, it will only answer questions re-

[3]https://www.escolavirtual.gov.br/adesao-institucional

lated to this page and chitchat, making use of data collected through the traditional customer service. This approach intends to provide a way to evaluate the architecture and the knowledge-base in an environment that presents a lower risk. Finally, EvaTalk must be compatible with EV.G's visual identity to manage customer service and have data analysis tools to identify problems and improve its training.

Table 1: Subjects Answered by EV.G's Customer Service.

Subject	Topics
Account	Sign up Sign in Edit personal data Delete account Change password Recover password
Certificates	Issue certificate Validate certificate Details
Courses	Course access Course availability Anticipate completion Studies program
Course Enrollment	Enroll in a course Proof of enrollment Validate proof of enrollment Re-enroll in a course Cancel enrollment
Institutional Membership	Categories Become a partner Statistics Course hosting Partners Offered services

4 ARCHITECTURE

Figure 2 shows the architecture designed for the EvaTalk system, which will be detailed later on in this paper. In addition to the basic layers used in chatbot systems, it has a layer to run data analysis. These layers will be called modules and were divided in the following way: Interface, Artificial Intelligence, Development and Business Intelligence.

In this architecture, the user interacts directly with the Interface Module, which receives messages and sends them to the Artificial Intelligence Module. Before being handled by the conversational intelligence tool, the message will pass through middlewares to be preprocessed. Then, the conversational intelligence tool sends the message's response back to the Interface Module, where it is displayed to the user. Both the message and the response are sent to the Business Intelligence Module where they will be indexed on data analysis tools and stored on a database. It all happens at running time, but the Development Module is modified before running time and it is where the developers will provide the knowledge-base data collected by the traditional customer service. When the system is up, this module will serve data to the training process made by the Artificial Intelligence Module.

4.1 Interface Module

An important part of a chatbot is its graphical interface because it is where users have direct interaction with the system. Some chatbot tools offer the capability to work with multiple endpoints for user interaction for the same bot, at the same time. Although its a possibility for the future, Evatalk is focused on using only one endpoint for chat conversations.

During the development of Evatalk, it was observed that some features where important to the user interface in this specific use case, such as the possibility to insert buttons on conversations to guide them, compatibility with the a markup language which enables formatted linking and image viewing.

The alternative chosen for EvaTalk was the use of a modified version of an open-source software called WebChat[4]. It has been customized to have visual identity compatibility with EV.G. The main advantages of WebChat are the ease of customization and the development of new features. It is also suitable for chatbots since other tools have more complex functioning to attend multiple channels of communication, which is not a goal for this work.

4.2 Artificial Intelligence Module

To achieve the expected user experience for Evatalk it is necessary to let the users express themselves trough Portuguese-written text. This implies the necessity of the chatbot being able to understand the users' natural language, deal with variations from standard Portuguese language, and maintain a coherent conversation flow, as per the requirements defined in Section 3.

For a chatbot, two parts are seem as needed for it to be able to engage in a conversation with the user: a Natural Language Understanding (NLU) processor and a dialogue management system. An NLU processor is responsible to convert user messages in their natural language to a machine-readable form, so that it can be processed in some further steps (Macherey

[4]https://github.com/botfront/rasa-webchat

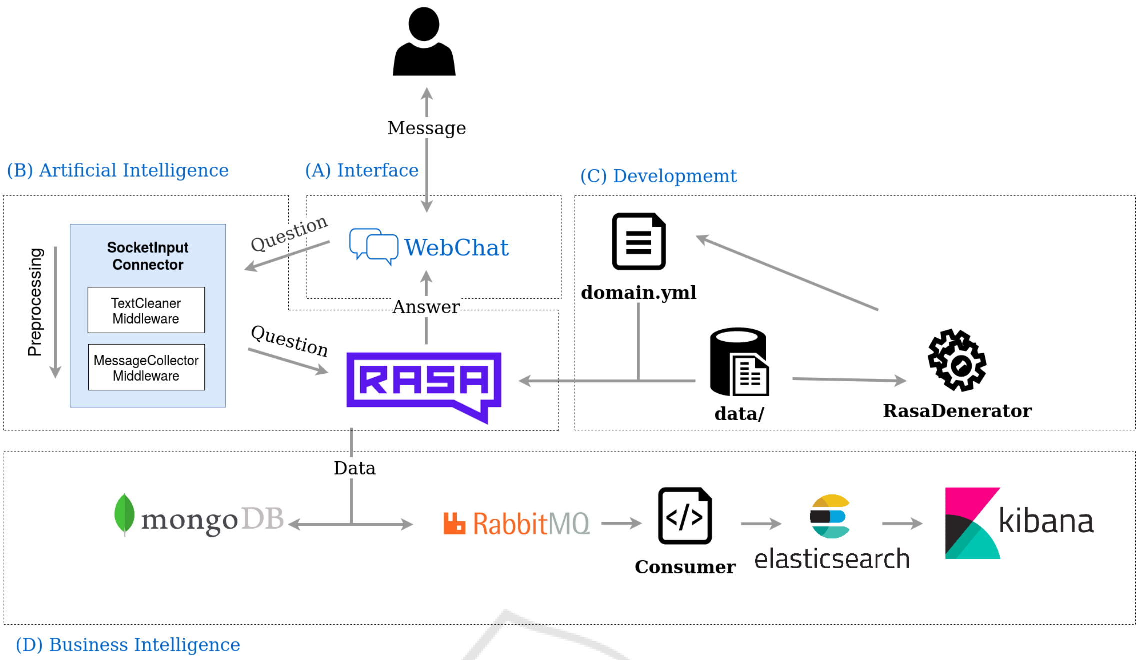

Figure 2: Evatalk's Architecture.

et al., 2001, p.1). A dialogue management system should receive the NLU processor's output and produce a response that fits the context of what the user said.

There are some tools capable of providing these components, for Evatalk project the Rasa[5] stack was chosen. Rasa is an open-source toolkit for building conversational systems, composed of Rasa NLU and Rasa Core (Bocklisch et al., 2017), which are its NLU processor and dialogue management system, respectively. Some factors that contributed to preferring Rasa are the ease of use due to human-readable training data formats; pre-defined pipelines for training; high flexibility in connection with external services; and an active community that can be useful for troubleshooting.

The choice of the technological stack for a chatbot influences in its training data format, because it needs to be compatible with the technology. Choosing Rasa introduced some concepts such as intents, stories, utterances, and a domain file. For Rasa, intents are variations of the same sentence that the user is expected to send in a conversation; stories describe the conversation flows; utterances are what the chatbot can say back to the user; and the domain file act as an index for all the actions available to the chatbot.

The integration with the Interface Module is made through a connector. There are standard connectors to some of the most popular interfaces and messaging services, with input and output channels. However, to deal with some situations presented in Section 3, it was necessary to develop a custom connector, which has an expandable architecture through a middleware implementation[6]. This middleware processing was developed to provide greater freedom when performing text preprocessing when compared to the standard method included in Rasa, as the middlewares process messages before they reach the NLU processor. It is also possible to access and modify data that goes beyond the message text, such as session identifiers.

Using the middleware approach, two middlewares were added to Evatalk. One of them is responsible for cleaning user messages by removing accents, punctuation and replacing common web acronyms for its standard spelling. The list of substitution rules changes based on the developer's analysis of the data collected on user interactions. This middleware requires that NLU training examples follow the same rules to increase precision. This is not an unexplored approach since Ferreira. et al. (2017) had to "remove and manually correct words or sentences that were grammatically incorrect" to process the text in his natural language processing.

Another middleware was implemented to collect user messages that were sent in a short period. The dialogue management system default behavior is to process each message as a First In First Out (FIFO) queue. This middleware awaits for a new user mes-

[5]https://rasa.com/

[6]https://gitlab.evg.gov.br/codigo-aberto/

sage before passing the collected messages ahead, be it to the next middleware or the chatbot. If a user sends two messages in a row and the first one has punctuation that indicates the end of the sentence, the middleware sends them separately to be processed. If the punctuation is not present, the middleware appends the second message to the first message and sends them as one.

4.3 Development Module

To manage the chatbot's content, developers will be manipulating files that contain response templates, conversation examples or training data for the NLU processor. These files require specific formatting that follows the guidelines defined by the chatbot's conversation management system and NLU processor. The domain file works as an index for Rasa and is the one that contains the responses' templates and maps all intents, stories, and actions that are described in other data files. This mapping requires good management and effort to keep it synced with the content in the data files.

To lower the number of errors related to content formatting, an open-source tool called Rasa Denerator[7] was added to Evatalk's system. It allows for developing content without referencing every data item in the domain file because it will be automatically created. As for the responses templates, they are defined in a separate file and Denerator will take care of appending them to the domain file generated. Thus, developers collected question examples from the customer service emailbox for each topic of Institucional Membership and placed at the data folder. The responses given through email were adapted to fit a chat environment.

4.4 Business Intelligence Module

Evatalk's dialogue management system outputs its conversational data in a specific format and already has some implemented compatibility layers with database management systems where it can be saved. To provide a way to store users conversations, MongoDB[8] was chosen as a database management system because of its compatibility with other technologies used in Evatalk and its document-based approach to saving data.

Data generated by the chatbot contains the user messages, the chatbot's responses and the classification made by the NLU processor such as the intention of the user. Collecting and analyzing users' data is part of the development process of Eva's content and EV.G as a platform. Since Evatalk's system is part of EV.G's user support process, platform issues can be identified through user interactions with the chatbot.

Besides that, the users interactions stored are also important to add aspects of the users' natural language to data and guide changes in conversational flows when it is clear that users are not reacting well to responses or having difficulties following the designed flow.

A data analysis tool was used to allow developers to see the bigger picture of the interactions between users and the chatbot. ElastichSearch[9] and Kibana[10] were chosen based on the previous study of de Lacerda and Aguiar (2019) which fit the requirements for Evatalk's system. These tools allowed the creation of dashboards with graphics and the extrapolation of the data collected from interactions.

One difficulty faced with these technological choices was consuming the data because of the specific data format of the interactions. To solve that, a Message Broker was used in conjunction with an evolution[11] of a consumer from de Lacerda and Aguiar (2019) work. The evolution includes modifications to make the consumer an independent service, adapt the data format, collect new data, and add support for recovering from failures using a database as a restoration point.

5 RESULTS

As expected, the Business Analysis module provided insights about the first months of the chatbot in production. Figure 3 shows the relation between number of messages and response confidence, weekly.

Initially, as part of initial testing, the chatbot had only Institutional Membership data and the first users were mostly professionals that were involved with EV.G. Therefore, they knew what to ask because they have been working in the area and, consequently, the confidence was high. Later, a substantial number of real users started to interact with the chat widget so that questions started to deviate from what developers initially inserted in the knowledge-base.

With real users, confidence started to get low and the chatbot team had to analyze stored conversations to understand the user behavior and update the knowledge-base. Apart from the daily process of including user messages that were not comprehended

[7] https://pypi.org/project/rasa-denerator/

[8] https://www.mongodb.com/

[9] https://www.elastic.co/

[10] https://www.elastic.co/products/kibana

[11] https://gitlab.evg.gov.br/codigo-aberto/

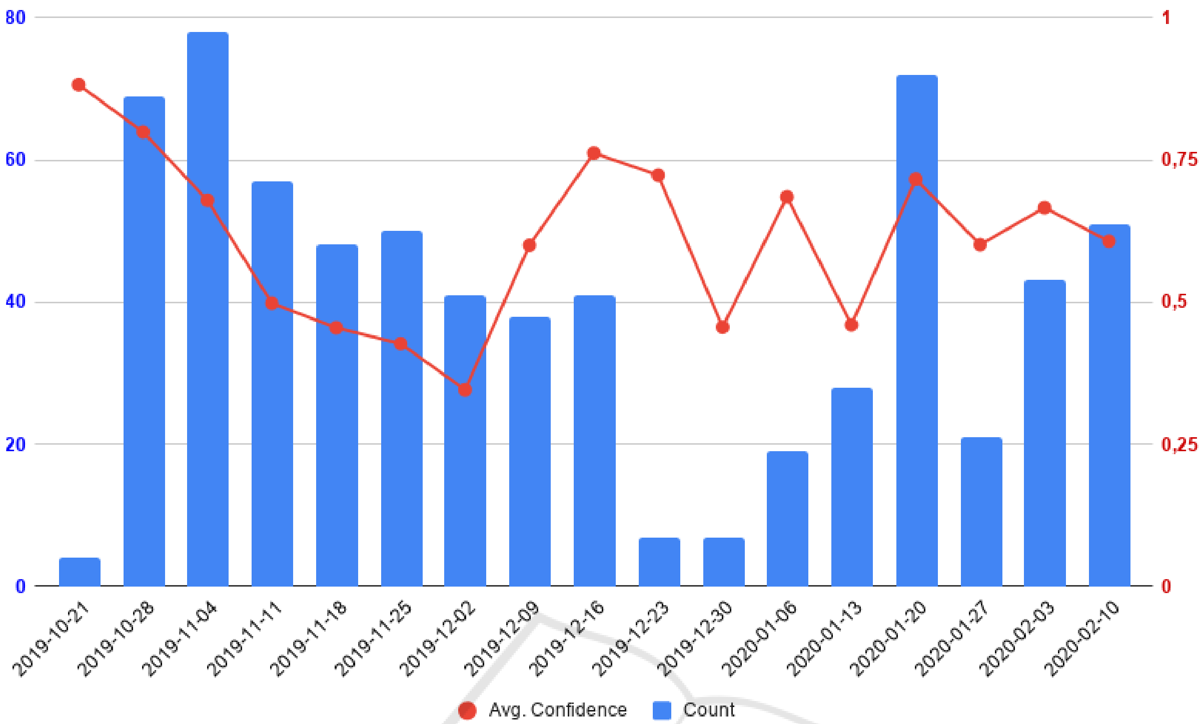

Figure 3: Weekly Number of Messages in Blue and Weekly Average Confidence in Red.

as new training data, because of the decrease in confidence scores, developers made a major change in conversational flows and the subjects that the chatbot was capable of responding.

Conversations showed that, even though the chat widget was only on the Institutional Membership page, users tended to ask about other subjects that were listed in Table 1. Also, users that asked about Institutional Membership only had an interest in the main topic, being that "Become a partner". Hence, developers started populating the knowledge-base with other subjects and their most asked topics, and also removed the topics that were not popular so that they would not influence the confidence score of other questions. These changes happened in the beginning of December 2019 and, as result, confidence started increase again.

At the end of the year, the chatbot received fewer messages, as users do not tend to access EV.G as much in this time of the year. Changes were really tested at the beginning of 2020, as user interactions increased and confidence scores maintained a great average week by week, indicating that conversational data modification was successful. Still, user interactions keep shaping the knowledge-base day by day, as we intend to get the confidence score higher and higher.

6 FUTURE WORKS

The work experience gathered with Evatalk creation showed the need for a system that allows non-technical staff to monitor and change the chatbot's content. For instance, pedagogues and linguists can contribute to the creation of content in ways that serve users more efficiently and also to take care of the language used to communicate with users, since the chatbot represents a government platform.

Also, since this work implemented a chatbot that answers simple questions, we hope that it will execute more complex tasks in the future, like issuing certificates and help users to find courses that fit their interests to attend to.

Lastly, future works include the addition of multi-language support, through automatic translations of user messages and chatbot content in a translator middleware. The objective of this middleware is to offer minimal chatbot support service to users who do not speak Portuguese.

7 CONCLUSIONS

EvaTalk chatbot system proved to be a promising tool to lower the demand for human customer service.

Some issues will still need human assistance, but Eva can deal with repetitive and mechanical questions, which are the main problem for EV.G customer service. Its first release was important to understand the complexity of user behavior and the need for evolving processes, that will require people from many fields of expertise.

Regarding the development and maintenance of the entire architecture, the main difficulty is that the area is constantly evolving and Eva's development team must always be prepared to update the tools and methods used to bring the most humanlike customer service, that is, the user leaves satisfied with the service provided and does not feel the need to communicate with a human. Although the initial content added to training data was raised by EV.G's team members, Eva's evolution depends substantially on data collected from user messages.

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