

**Modelo Classificador de Intenções com utilização de Redes Neurais Recorrentes:
um estudo de caso para auxiliar os estudantes com dúvidas nas funcionalidades do
AVA MOODLE**

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Resumo: Esta pesquisa apresenta um chatbot inteligente do IBM Watson para melhorar a participação do aluno no Moodle. Redes Neurais Recorrentes foram utilizadas para gerar um modelo e classificar as intenções de 48 alunos que interagiram com o assistente. Uma rede neural foi treinada e submetida aos critérios de avaliação e obteve 99,80% dos testes de precisão. O assistente virtual também demonstrou capacidade de colaborar nas atividades de atendimento ao aluno nas dúvidas frequentes sobre o uso do Moodle. Este estudo apresentou evidências ser viável implementar o chatbot para auxiliar dúvidas nestes contextos.

Palavras-chave: Assistente virtual, IBM Watson, Ambiente Virtual de Aprendizagem, Redes Neurais Recorrentes.

**Intent Classifier Model using Recurrent Neural Networks: a case study to
help students with doubts about the functionalities of AVA MOODLE**

Abstract: This survey features an intelligent IBM Watson chatbot to improve student participation in Moodle. Recurrent Neural Networks were used to generate a model and classify the intentions of 48 students who interacted with the assistant. A neural network was trained and submitted to the evaluation criteria and obtained 99.80% precision tests. The virtual assistant also demonstrated the ability to collaborate in student service activities. Infrequently asked questions about the use of Moodle. This study showed evidence that it is feasible to implement the chatbot to help with doubts in these contexts.

Keywords: Virtual assistant, IBM Watson, Virtual Learning Environment, Recurring Neural Networks.

1. Introduction

A chatbot (bot) is a virtual assistant designed to simulate a conversation using text messages, similar to the short message system (SMS). Chabot's try to simulate human activities, interacting and working with students in virtual environments (Leonhardt *et al.*, 2003). To (Huang; Zhou e Yang, 2007), usually the interaction with a chatbot starts at the introduction of a question or sentence, after the embedded software answers the question, makes a comment or starts a new topic. According to (Schlicht, 2018), a chatbot can be defined by two types: (I) based on rules, where his answers are predefined and he cannot process information or commands to the existing specifications. For this type of chatbot, intelligence is limited by the set of rules; (II) based on AI techniques, which learn interactions with students. These chatbots use Natural Language Processing (PLN) to provide accurate and dynamic responses. Different market segments are already investing in AI, including IBM. International Business Machines (IBM) has presented updates on its Artificial Cognition Web Platform, called Watson, which allows the development of applications for different business models, including chatbots (High, 2012). This article aims to present an intelligent chatbot, developed with the cognitive services of IBM Watson, to answer the frequent doubts of students.

2. Chatbot in the educational context

The Chabot's allow the collection and storage's of information exchanged with students for potential queries in the form of reports or analysis in decision making (Asher, 2017), (Silva *et al.*, 2018). In this sense, the use of chatbots enables IES a reduction in the number of queries doubts about Moodle. Technologies to develop Chabot's include platforms defined in the cloud, such as Microsoft Azure chat and Heroku. According to (Primo, 1998), after conducting a comparative study between different web platforms for the development of chatbot, he concluded that the platforms monitored in the cloud have chronicity of intelligence. According to (Kojouharov, 2017), one of the ways to build an intelligent robot is to create a response generation model in an open domain conversation. The domain understood by chatbot in the context of learning consists of a set of frequently asked questions about the use of Moodle in the response generation domain; a chatbot can take two approaches: Recovery-based uses a repository of presets and the generating chatbots generate new responses from models.

3. Platforms for chatbot development

A survey was carried out to identify the leading chatbot development platforms to meet the proposal's requirements: to support text messages, multiplatform and free, according to Table 1.

Table 1. Some platforms for chatbot development.

Features / Platform	Botpress	Dialogflow	Wit.ai	Lex	Chatfuel	IBM Watson
Open-source	X					
Customization required	X	X	X	X	X	X
Integrated with natural language processing	X	X	X	X		X
Content management	X	X			X	X
Integrates bot analysis	X	X			X	X
Custom analysis	X			X		X
Modular architecture	X			X		X
Extensible	X			X		X
Free nlp provider lock	X					X
Available on-premises	X					X
Available in the cloud	X	X	X	X	X	X
GUI for non-technicians	X	X	X	X	X	X
Extensible dialog management	X					X
SLA available	X					X
Voice Enabling		X				X
Support available	X					X
Multilingual	X	X			X	X
Role-based user access control	X	X		X	X	X
Built-in Human-in-Loop (HITL)	X					X
All message channels	X					X

The chatbot receives input and forwards it to the Application module that connects to the Conversation Service Module, a container for the dialogue flow and training data. This interprets the text, directs the flow of interaction, and gathers all the information necessary to answer or execute a student transaction. The Application module has the function of making the connection between the messaging services and Watson. Finally, the Analytic module is responsible for monitoring and recording and storing interactions made with students to identify unanswered questions successfully. The architecture is shown in Figure 1 below.

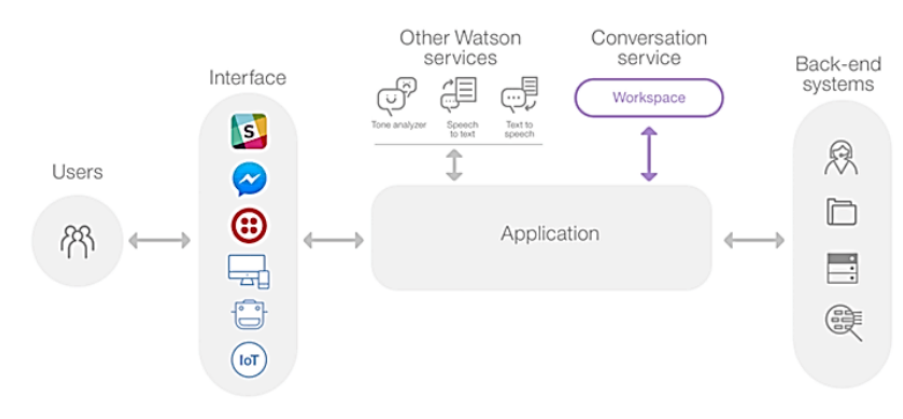


Figure 1. Watson Assistant architecture overview. Source: IBM (2019).

Then, the module for restarting the interaction is activated, and the chatbot offers to help with other questions, with: "Can I help you with anything else?" The conversation termination module is then activated, and the chatbot sends the message "At any time, you can call me," which makes it possible to restart a new interaction.

4. Methodology for the development of chatbot

Figure 2 shows the methodological procedures used for the development and implantation of the chatbot in the VLE.

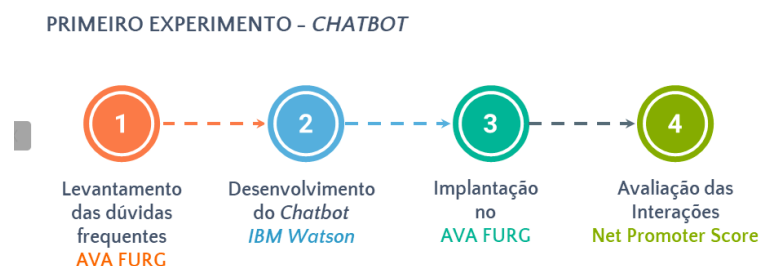


Figure 2. Methodological procedures for implanting the chatbot in the VLE.

4.1. Integration with VLE

As the following steps were necessary to integrate the chatbot through the Facebook Messenger interface to VLE-Moodle: 1) Creation of the API for the chatbot on Facebook, to obtain the access token, its function, and to use the Watson API to read, write or modify the chatbot page data. 2) connect the chatbot to Facebook Messenger. The Messenger platform sends events to the chatbot webhook to notify you when interactions occur.

4.1.1. Data collection and analysis

Chatbot's interactions with students took place over four weeks; interactions were collected and analyzed in three groups: correct answers; out of contextual questions, and wrong answers. Of 14 interactions: 6 answers were correct, 6 questions out of context, and 2 unanswered. Considering only the number of right and wrong answers, we have a percentage of 75% for the correct answers and 25% for the wrong answers, for a total of eight responses. Figure 3 shows the classification of interactions. Figure 3 shows the

classification of interactions.

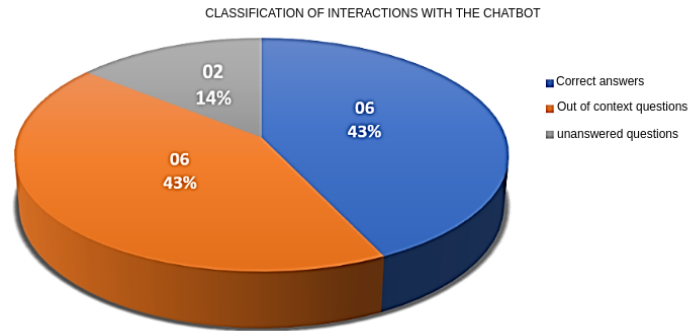


Figure 3. Classification of interactions with the chatbot.

Table 2 shows the answers separated and classified according to the categories analyzed: correct answers, incorrect answers, and out-of-context questions.

Table 2. Categorization of interactions.

Correct answers	Out of context questions	Unanswered questions
"Redefine password"	"Get off my screen, please"	"How to enroll in a course for the first time"
"Moodle Tutorials"	"I want to take a tutoring training course"	"I didn't change my password or user, I can't access"
"Log-in to Moodle"	"Good afternoon, is this course already formed?"	
"How to send message"	"When will my post-graduate classes return?"	
"Enroll in the discipline"	"I would like to know my number"	
"Submit task"	"How do I get a card?"	

Figure 4 below shows the number of users who interacted with the chatbot in the four weeks of use.

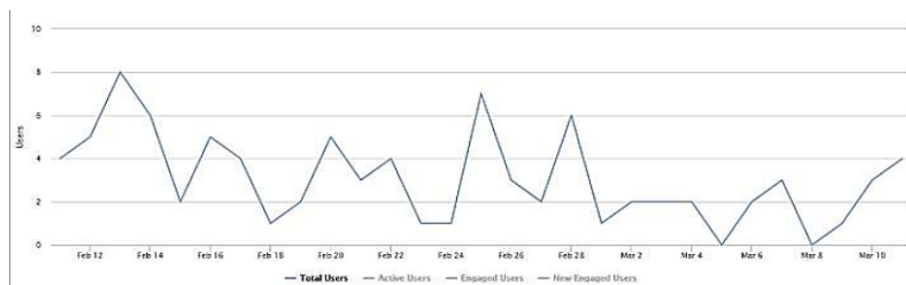


Figure 4. Some students were interacting with the chatbot in the four weeks.

4.1.2. IBM WATSON application

The student has access to the VLE Moodle Web Interface in the proposed architecture through a computer or mobile device. VLE adds the use of technologies such as HTML, CSS, JavaScript, and PHP. The application was hosted on the IBM Cloud, making it a full web service, a knowledge base was developed using the "Knowledge Data-Watson" module, to answer the questions prepared by the students, the chatbot uses the "Watson API" to integrate with the chosen channel, in this case, Facebook Messenger. The chatbot training was carried out by observing the closed contexts of the subjects defined in the first chatbot so that it was possible to repeat the questions of the conversations that did not obtain correct answers. Figure 5 shows the implemented chatbot.

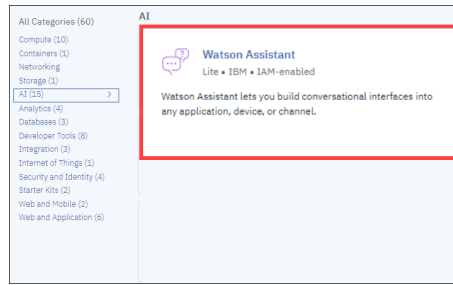


Figure 5. Chatbot creation panel

Figure 6 shows the intent configuration panel that the chatbot has been trained to recognize. In item 1, the name assigned to the node related to the context created is displayed. Item 2 shows an intention created; below, item 3 shows some examples of students' possible questions.



Figure 6. Defining chatbot intentions.

Figure 7 shows the intentions and responses created in the dialogue, in this phase, the chatbot was trained. In the end, the chatbot is ready to be used.

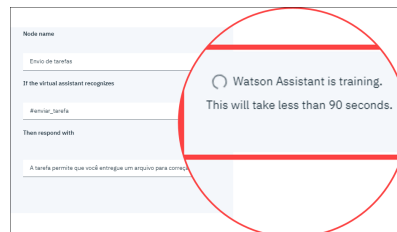


Figure 7. Chatbot training.

5. Intent classifier model

According to (Maheshwari, 2019), a text classification model, in general, consists of the following steps: training, resources vector, markers, machine learning algorithm.

5.1. Data preparation

Each intention contained in the data set was mapped to a real vector domain, according to (Lai *et al.*, 2015). For this experiment, the vectors had a size of 20, 3000 most relevant terms were selected from the total number, and finally, the number of terms in each revision of the variable, the limits were revised to 100 words, truncating lengthy revisions and filling shorter corrections with zero values. In the vectorization of intentions, the Keras library was used. Finally, the column named activity type was the training target, as it contains the categories of purposes registered on the teaching platform. Figure 8 shows the attributes contained in the dataset.

	id_site	code_module	code_presentation	activity_type	week_from	week_to
0	546943	AAA	2013J	resource	NaN	NaN
1	546712	AAA	2013J	oucontent	NaN	NaN
2	546998	AAA	2013J	resource	NaN	NaN
3	546888	AAA	2013J	uri	NaN	NaN
4	547035	AAA	2013J	resource	NaN	NaN

Figure 8. Stages for classification of intentions. Source: Open University Learning Analytics dataset

5.2. Proposed architecture

The architecture adopted in work is the recurrent neural networks, following the model (Segatto e Coury, 2006). 20 vectors form the first input layer to represent the 20 most relevant intentions. The second hidden layer comprises 14 nodes and houses the S2S layer, which uses 100 storage memory units. This layer is responsible for keeping the state of the time series. The output layer generates 20 output values, one for each class of intention. Table 3, below, presents an overview of the proposed RNN model.

Table 3. Overview of the proposed RNN model. Source: author.

Architecture	Layers	Nodes	F.Activation	F.Loss - EQM	Algorithm
S2S	3	20/14/20	Softmax	Cross-Entropy	ADAM
S2S: Step-By-Step Architecture MSE: Main Square Error ADAM: Adaptative Moment Estimation Algorithm					

5.3. RNN Training

The model has about 100 neurons in the first layer, totaling 1,000,000 parameters. The second layer presents 100 neurons concluding with 80,400 parameters. Finally, the third and last layer was applied to 20 neurons, leaving 1,082,420 parameters to be estimated. The classifier model used a supervised learning approach. The summary of training data can be seen in Figure 9.

Layer (type)	Output Shape	Params #
embedding_1 (Embedding)	(None, 100, 100)	1000000
spatial_dropout1d_1 (Spatial)	(None, 100, 100)	0
lstm_1 (LSTM)	(None, 100)	69400
dense_1 (Dense)	(None, 20)	2020
Total params: 1,082,420		
Trainable params: 1,082,420		
Non-trainable params: 0		

Figure 9. Model created for training the network.

The model was subjected to two tests: the first was adopted with the function = 0.001 and the second, with the function = 0.5. Finally, the Adaptive Moment Estimation Algorithm (Adam) was chosen to optimize the training, integrating the adaptive learning rate and the moment. In the experiments carried out, the data set was subdivided into two datasets: the first with 90% of the data used for training the artificial neural network. The other with 10% was reserved for testing and validating the network, according to the table 4.

Table 4. Dataset splitting.

Training	Test
5.727,0	637,0

The criteria for evaluating the results (Revocation, Precision, Failure, Precision) were in accordance with (Oliveira *et al.*, 2019).

6. Results

To understand the level of satisfaction of the students who interacted with the chatbot, the Net Promoter Score (NPS) methodology (Keiningham *et al.*, 2007) was used. Table 5 shows each degree of satisfaction classified according to the method.

Table 5. Categorization of interactions.

Classification zone	NPS
Excellence	between 76 and 100
Quality	between 51 and 75
Improvement	between 1 and 50
Review	between -100 and 0

At the end of the interactions with the chatbot, students were invited to evaluate the virtual assistant's service through a questionnaire. The quality of the chatbot responses reached an average of 3.85 points, on a scale of 1 to 5, with 1 representing "Terrible" and 5 representing "Great," the standard derivation was 0.84 points. With that, we realized that the students, for the most part, were satisfied with the virtual assistant's responses during an interaction performed. As for the level of satisfaction with the service provided by the chatbot, the results indicate that the 48 responses counted were obtained, 01 (2.08%) answered as "dissatisfied," and 15 (31.25%) were "delighted" with the service. The students were separated and classified according to the number of votes counted, as shown in Table 6.

Table 6. Categorization of interactions.

Evaluation	Level	Amount	Classification(%)
5	excellent	15	32,0
4	very good	23	48,0
3	good	-	-
2	reasonable	1	2,0
1	bad	-	-
0	terrible	-	-

48 students answered the survey. To obtain the NPS satisfaction level, it is necessary to calculate the difference between the Promoter and Detractor classification percentages. In this case, as the Detractor index was equaled to 0, evaluation with indexes 0 or 1 was not counted.

$$NPS = \frac{Promoters - Detractors}{Total} * 100$$

Calculating the NPS for this number of responses, the value of 76.60% is obtained. The calculation is shown below.

$$NPS = \frac{37 - 1}{47} * 100 = 76.60\%$$

With the NPS equal to 76.60%, the logo or the virtual assistant's attendance was classified as excellent, according to Table 7. Of these, 03 responses were selected, as they are relevant to the work. The first answer suggests a mandatory interaction with the chatbot at the user's first access to the VLE platform, a second answer that can change the interface. Finally, the last suggestion to expand the context of matters to which the assistant can respond. As the responses are selected in Table 6, follow and help improve chatbot.

The main performance measures in neural networks were used to validate the neural network: Accuracy, Precision, Recall, and F1 Score. In the graphs of Figure 10

Table 7. Chatbot improvement suggestions.

What are your suggestions for improving the chatbot?	
01	I think could criticize or create a simple design of the robot's image, but there is no reason to change it, the system works very well and seems to be more of an VLE guide than a "problem solver". I could suggest a mandatory first login interaction just to make it more famous and a reference to be a "problem solver".
02	It could have a better interface.
03	More varieties of subjects can be placed for the user who asks and answers their questions.

below, two performance tests of the network can be observed. Along with the iterations, the training algorithm's accuracy increases with each passing season and then stabilizes. The trained network (graph a) achieved the best training performance after executing 5 epochs when configured (graph b); the same network needed 19 epochs to converge and stabilize.

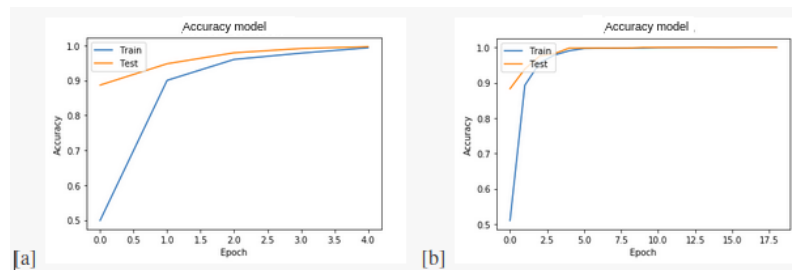


Figure 10. Validation accuracy of RNN.

The values selected by the optimization algorithm were as follows: 100% (above) and 99.9% (above); that is, the model displayed promising results in identifying the intentions present in the dataset. However, only with the accuracy value, it is not possible to affirm the quality of the network performance since the metric can classify false positives as correct, producing an inconsistent result. For this reason, other performance metrics were used, the values obtained in performance metrics. (Precision, Recall and F1 Score) show in Table 8.

Table 8. Metrics obtains - Training set

Function α	Accuracy	Precision	Recall	F1 Score
0,001	0.99800	0.82111	0.84279	0.83181
0,5	1.00000	0.83268	0.84712	0.83984

Then, the confusion matrix was generated using the values obtained with the performance metrics Table 8 and comparing with the values achieved by a neural network optimization algorithm. The generated matrix is shown in Table 9 below.

Table 9. Generate confusion matrix

	TP	TN
TP	2093	432
TN	388	2150
TP: True positive		
TN: True negative		

The lowest values obtained from the set of tests indicate that the accuracy of the model reached more than 83.0% of correct answers. The precision received more than 84.0%, the recall reached around 83.0% and F1 Score was around approximately 84.0%. The adjustments performed on the network change the function's values that suffer little

difference in the network, or those that lead to the conclusion that the margin of error reached is acceptable in both cases. The selected values can be shown in Table 10 below.

Table 10. Metrics obtained - Test set

Function α	Accuracy	Precision	Recall	F1 Score
0,001	0.83804	0.84361	0.82891	0.83619
0,5	0.99487	0.83767	0.81544	0.90953

The result of the interaction is shown in Figure 11. Example of one of the questions submitted to the bot: 1- "como me inscrevo em um curso pela primeira vez". Then, the chatbot identifies the student's intention: 2 - "Disciplinas" and return with the answer, 3, corresponding:

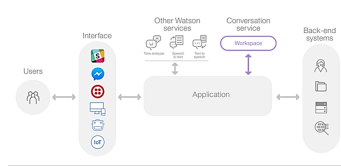


Figure 11. The panel of recognition of intentions.

Figure 12 below shows the chatbot interactions on the Facebook Messenger interface. In the tests performed, the visual assistant was able to adequately answer the questions not answered in the first interactions.

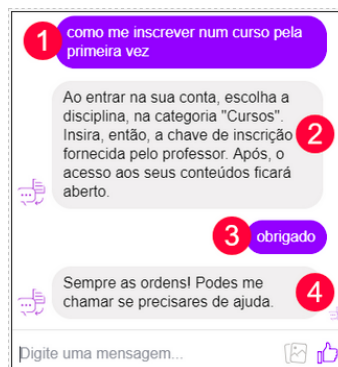


Figure 12. Chatbot integrated with Facebook Messenger

Regarding the interaction in the VLE, the results showed that the chatbot, in its scope, obtained satisfactory results in the identification of the student's intentions. Regarding the satisfaction of use by the students, he obtained the highest score in his evaluation. In the experiment that analyzed the efficiency of the RNN in the classification of intentions, the results demonstrated remarkable rates of correct answers.

7. Conclusion

This work presented the implementation of an IBM Watson intelligent educational conversation chatbot in the AVA Moodle integrated with MSN Messenger, to help in the use of the tools available to students at a public university in the south of the country in relation to the support material provided by teachers in the environment, using artificial intelligence techniques. As expected, the virtual assistant demonstrated the ability to collaborate in student service activities on frequently asked questions in the AVA Moodle, and the improvement to serve the academic community where the potential of these

applications in the educational scenario was viable, allows paradigms to be able to be gradually changed and bring the necessary improvements to the current context, where attendance has increased significantly in relation to remote activities, in this case it contributes to the waiting time for students, especially those who do not have previous knowledge. The project is currently submitted to the new criteria of evaluation tests, precision and increment with intentions of answers and option of the bot to interact in LIBRAS with deaf students.

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