Digital Service in Brazilian Large Collections: Proposed Mobile Solution Integrated to Chatbots applied to University Collections

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Abstract.

This article describes the initial process of developing a system for managing personalized service processes in the physical spaces of the library in higher education networks in Brazil, with its operation focused on accredited networks in the rental of books to the community. The development of the mobile customer service application, called chatbot, will assist on the evaluation process of libraries, based on artificial intelligence, with deep learning techniques and recurrent neural networks for the definition of the profile of the user. With the proposed tool an advanced analysis of emotions is performed to provide recommendations to the user about their tasks, according to the level of didactic instructions in the book. The implementations of the structures and the experiments to train the tool to learn the demands of the user were carried out. As contributions of this work it can be listed: the demonstration of the database treatment process with real information from the queries of a library for NLP (Natural Language Processing); the implementation of the web structure with the support of a chatbot to provide guidance for the user; the demonstration of experiments (and challenges faced) with tools based on Artificial Neural Networks in their use for learning about the profile of the user during the conversation with the chatbot; and an analysis of future feasibility of integration in literary services.

Keywords: University library, Chatbot, Virtual assistant, Natural language processing, Artificial Neural Networks.

1. Introduction

According to Hubner and Kuhn (2017), physical libraries are still very relevant in supporting teaching, research and extension even in Brazil. The university collections bring together major works, including: theses and dissertations, literary works, scientific articles, books, periodicals, artistic productions, dictionary, maps, among other documents integrating different areas of knowledge (Chowdhury & Chowdhury, 2003; Gleason,2018). In this scenario, a question becomes pertinent: with so much exposure, who has never been lost in the search for a book?

The service systems of university libraries have been reflecting on the quality of services provided, both in personalized service and in face-to-face service, extended to the academic community (faculty, students and employees) and the general community (community of other institutions, researchers, students of exchange and other visitors). Providing consultations, renewals, journal reservations and all other exposed materials for the dissemination of knowledge. According to Cristobal (2018), although the educational function is the most prevalent in university libraries, it is the quality and speed of access to information that retains customers and inspires new readers.

In this context of personalized service, intelligent agents are widely used tools, automatically and humanized, in applications designed to provide solutions similar to the actions proposed by humans. The development of a more robust chatbot is based on Artificial Intelligence, including several areas that are covered such as machine learning, deep learning and artificial neural networks. In the understanding and communication of the human with the machine, Natural Language Processing (NLP) is an aspect of artificial intelligence that manipulates human language (Kang et al., 2020)

The classic NLP processing models, from Deep Learning (machine learning), are trained with various texts aimed at pre-established rules of pre-programmed questions and answers. In this context it is possible to only receive input sentences from responses related to the training established. In other words, in the automatic system, the service menus are used as rules, where it is typed several numbers until the final objective (Kang et al., 2020). Among the techniques used, there is deep learning with neural networks, recurrent in the recognition of images and texts. This model tends to provide better performance, as it processes two tasks, encoding and decoding texts (Kang et al., 2020; Deng & Liu, 2018). The objective of deep learning, in addition to recording the history of the student in the database (date, time of access, their reading profile, age, course, subject, current period), is also to recommends based on the preference of a reading. Thus, the user profile is modeled, providing future accesses with more precision in the indication of the literary works.

When using personalized service, it is possible to present a summarized form of the classification of the researched work, estimated reading time, and guidance on its geolocation. Providing a virtual tour within the collection on the path to follow until the researched book. Thus, contemplating not only veterans, but mainly newcomers and the external public not familiarized with the academic space, the cataloging and ordering of books on the shelves. Generating an incredible experience using immersion and interaction features with directional icons and consequently, bringing more credibility to the institution. In the Brazilian scenario, it is possible to verify that other research have somehow addressed the aforementioned theme, such as García & Vieira (2010), who observed, after research, that the 2.0 libraries are using the web 2.0 tools in the composition of their services. The technologies with the highest incidence were in reference and information services, DSI-Information Dissemination and user service, and the most used tools were RSS (Really Simple Syndication), Blogs and chats.

Thus, the general objective of this research is to unite in a single platform the access to libraries for new features, maintaining a flow of spontaneous conversation, without the perception of artificiality, in a simple and quick access of its trajectory to meet the intellectual printed content through augmented virtual reality considering Brazilian context. Therefore, the aim is to: better understand the profile of readers when evaluating behavior to provide important information for targeting literary products and services; training a chatbot for the academic environment and projecting a three-dimensional scenario of intuitive directional movement in the location of works housed in the collections; development of a structure based on recurrent artificial neural networks to recommend readings by the profile of the user.

This study is justified by the demand for intelligent, useful and accessible tools for the academic society in the orientation and dissemination of scientific knowledge, through an element of paramount importance in this context: the library.

2. Theoretical foundation

The main concepts that supported the research to be presented in this article, and were previously mentioned are the NLP, the Data Analytics and Chabots, together with some new paradigms such as Library 2.0, or virtual library. The Library 2.0 represents the versions or generations, based on the changes in the service profile over time in relation to the computerization of the services and products offered. An idea of a participatory library, engaging the internet user to the space of content creation and collaboration in an online donation process (Leitão, 2013). In addition to the above concept, in relation to Machine Learning concepts, some techniques were relevant to the research, such as:

- **Deep Learning:** is a term widely used in machine learning, in order to solve problems that work with neural networks with many layers. This technique allows prediction from a large volume of structured or unstructured data (Deng & Liu, 2018).
- **Artificial Neural Network (ANN):** it works in a modeling with mathematical functions to understand complex problems in a set of characters and generate results (Abiodun et al., 2018).

To implement the solution, some development tools were used (Goyal et al., 2018):

- TensorFlow: is an open-source library for manipulating and creating multidimensional tensors in machine learning to decipher patterns.
- Seq2seq: The Sequence to Sequence neural network model consists of using a recurrent neural network, with an LSTM (Long Short Term Memory) to encode a sequence of words or characters in a source language into a fixed-length vector representation and , then decode from that representation using another ANN in the target language.
- Pandas (Python Data Analysis Library): library for manipulation and transformation of raw data into other data with 'slice and dice' indexing functionality, with aggregation and selection of data subsets in the application of Machine Learning algorithms.

- Bag of Words: Simplified textual representation technique, considering relevant words for its models, that is, more frequent words in the text according to the repetition limit criteria.
- Embedding Layer: Its objective function is to map words to real number vectors used in the last decoder process.

Such tools were used for the development and implementation of the proposed solution.

3. Methodology

For the experiment, it was used a dataset from a real customer and another custom corpus model in a conversation structure with simulated questions and answers pre-defined with approximately 2,000 records. The research method was structured in the following sequence:

Step 1: Modeling and implementation of the structure based on a Microsoft SQL Server relational database in the behavior of storing chatbot data, based on information mining from data frames. The service interface with the Angular platform, which connects the specialist agent to external systems.

Step 2: Implementation of the Seq2Seq model representing a sequence of events that occur to make recommendations for literary works and a targeted search for copies within the collection.

Step 3: Study of accuracy and measurement procedures in machine learning problems, especially in the case of classification.

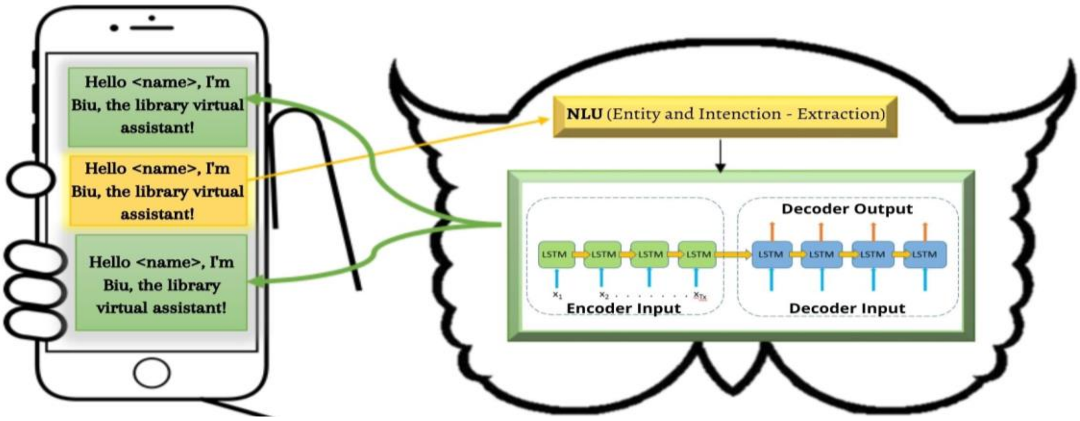
Thus, the application of the chat bot will be related to the management of literary works within university collections, considering that the peculiarities of the educational sector form readers and shape the world. Based on this definition, an expert agent named Biu, from the acronym University Library, was implemented with Recurring Neural Networks in order to improve the vocabulary of recognition and translation of contextualized texts for each node of the dialogue.

4. Results

4.1 Developed Structure and its Flow of Operation

Biu's basic task is to provide the best response to any interaction with the user, providing relevant, dynamic and very realistic information. Figure 1 presents the conceptual functioning of the intelligent agent using deep learning. More specifically, when a text input is provided, the processing is represented in a flowchart (see Figure 2), signaling the derivation of the request within the conversation flow, or, recognizing the intention of the user to change the context.

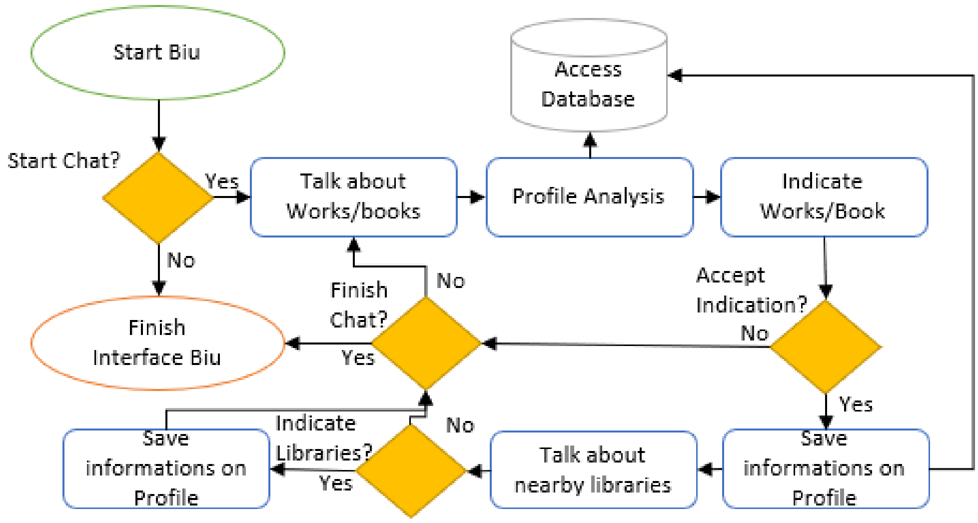
Figure 1: Biu dynamics analogy



Source: Authors, 2021.

For a fictitious dialogue to have more focus and relevance, the conversational agent needs to be able to understand the intentions of the message, see the unknown measurements (new context), and learn to deduce the desired results without having to redefine the algorithm with new response rules. As a solution, the assistant agent was developed with the concatenation of the Natural Language Processing areas and Deep Learning techniques.

Figure 2: Biu Flowchart



Source: Authors, 2021.

The development of Biu is defined in two distinct modules: an administrative module and a constructor module. These modules work separately but use self-produced data to perform their tasks. The administrative module aims to allow the manipulation of the internal database of the application, in addition to viewing the messages that Biu classified. These tasks are divided into 2 sub-modules: Database and ASPNET.Core Web API. The next module, constructor, has the objective function of applying all of Biu's learning techniques, including training. They are subdivided into: Data pre-processing, RNR construction, Seq2seq architecture, training and results.

4.2 Administrative Module

The implementation of the administrative module had a MySQL Server database to store data on books, authors and user profiles. For its operation in Biu, the ASP NET.Core Web API was applied, which operates in the integration of the database with the Biu backend in accessing data. Through RESTFull requests, with post methods, it requests data such as the number of books available in the collection, location and user profile data.

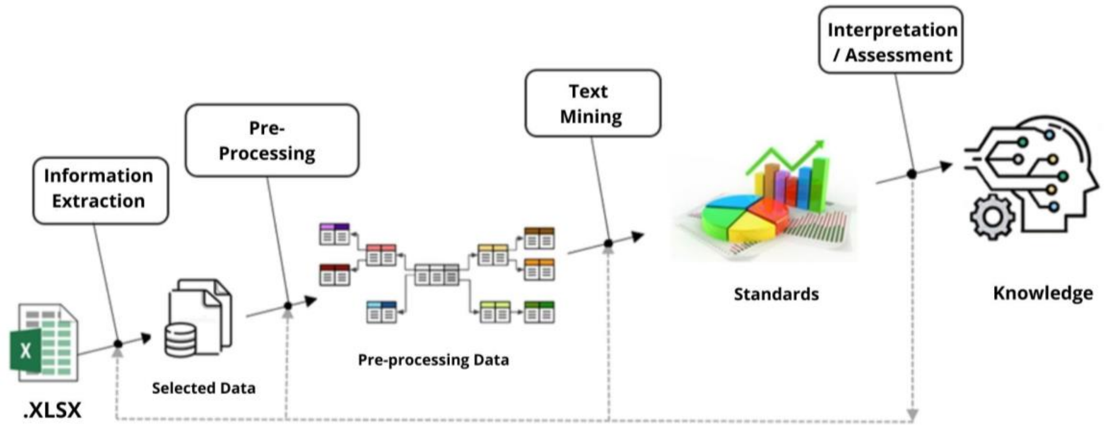
4.3 Builder Module

4.3.1 Data Pre-Processing

In the development of an artificial intelligence system, the access to a database is the foundation for training, and as the main process data pre-processing (PDD) represents the standardized form of data for learning the recurrent neural network.

Figure 3 represents the set of activities applied to Biu in through the knowledge flow. As the first corpus, a dataset from a real client was used, originating from the works available in the collection of UNIBH (University Center of Belo Horizonte), containing 23,413 records (rows) and 24 series (columns) containing semi-structured data with the extension .xlsx (Microsoft Excel file). However, the knowledge extracted from this data frame was effectively the datapoint: the book name, author and category.

Figure 3: Knowledge Extraction Processing



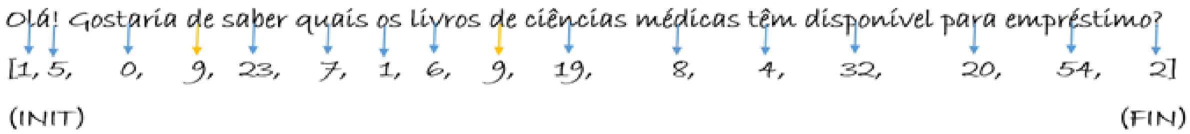
Source: Authors, 2021.

In the second dataset, the custom corpus model contains more than 100 conversation exchanges between two characters, with sampled conversation pairs in .TXT files with the following models: one IDs for each conversation line of the character who uttered the phrase and text of speech. Pre-processing starts with the normalization of data for learning, transforming unstructured texts into structured texts, through a script that configures the words into a more objective vocabulary for training. Basically, the concept used in conversational modeling involves word vectorization, entity recognition and intention classification. The last two being one of the ways to abstract the text for analysis, and the first technique that helps to reach this abstraction.

This weighting, defining the weights of each word within the context, used the intention classifier technique, simply assigning a weight to each word. Thus, when passing a certain text to the neural network, it will check which words are more likely to appear and thus consider it as output. Two lists are extracted, one with predictive attributes and another with expected responses. The text is separated into a list of words that make up this text to remove irrelevant terms in context, such as special characters and invalid or null data. Thus, making the vocabulary more objective for training the recurrent neural network. As a sign indicating the beginning and end of a sentence, <INIT> and <FIN> labels were assigned for the learning model to be able to identify, in sequence, when the prediction starts and ends. The optimization of training, due to memory space or processing execution time, in this case, the number of examples and attributes available for analysis can make the use of pattern extraction algorithms unfeasible.

The selection and removal of infrequent data was necessary with the creation of a quantitative variable to go through each word individually and check its relevance or repetitions within the data set. The reduction was to increase the number of values of certain attributes (number of times the word must appear in the text) in the count lower than 2 times. In other words, words that appear in the limit lower than 2 times in the text will not be considered for training the recurrent neural network, as it will not help much in the learning process of the algorithm. Another crucial step is the translation of textual values to an integer value, as the neural network does not understand a sentence but a number, that is, each word read will be replaced by a numerical value. This conversion, as a knowledge base, is the tokenization process that indicates the occurrence of words, in a sequence, with the implementation of a numerical index in each vocabulary, resulting in a sequence of words interconnected by space and by delimiting symbols, such as shows figure 4 below.

Figure 4: Representation of the tokenization process



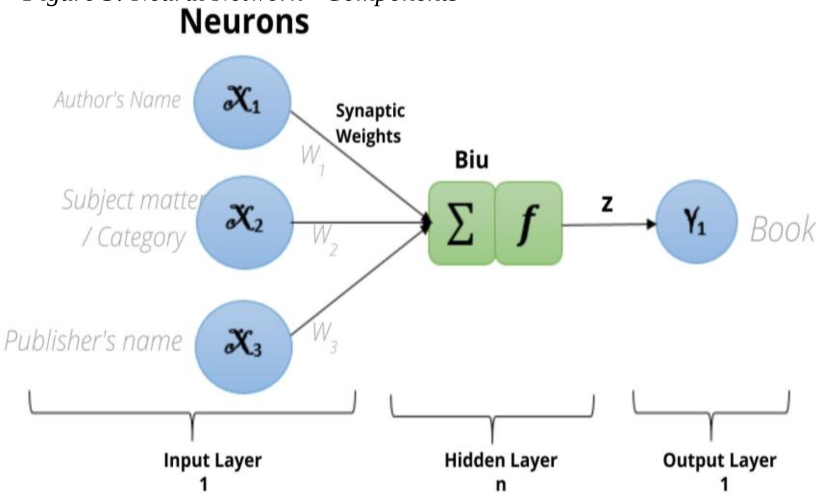
Translation: Helo! Would you like to know what medical science books are available for loan?
Source: Authors, 2021.

The delimiter symbols are assigned in the sentence to identify the beginning (INIT) and end (FIN) of the sentence and to indicate the Words irrelevant to the Limit <PIL> of occurrences as association to the text. The sample selected for processing was defined in 1,000 works of the real dataset. These were defined in three small blocks: within a limit of 70% for training and the remaining 30% for the final test of the model. Once the data standardization process is finished, the next step is to introduce it to the recurrent neural network.

4.3.2 Construction of Recurring Neural Networks

To create the network, using the TensorFlow library, a sequential model was instantiated, since Biu is working with time series (ordered). Then, a number of neurons with a repetition module of an LSTM (Long Short-Term Memory) were instantiated. In the network topology of Figure 5, it represents the node structure of the layered dialog.

Figure 5: Neural Network - Components



Source: Authors, 2021.

In this example, as a prediction of a book, three attributes or three characteristics are assigned on the network like (author name, subject and publisher) as a basis and as a result it is returned the characteristic which is the name of the expected book. These data have a temporal dependence. For the flow of a dialog, the reading of each sentence follows a sequence of words per word. In other words, to make a prediction it is necessary to consider seasonal events and verify the previous word to predict the later one.

The artificial synapse has the same objective as the human brain synapses, that is, it has the functional objective of transmitting information between neurons considering the highest degree of importance in the learning process of the neural network with its weights. These neurons have a softmax activation function, which forces the neural network to present the probability that the data represents the defined classes. The objective is to pass as parameter the output binary numbers so that the neural network learns the weight to make the automatic prediction. That way, when the model detects unknown measurements, it can infer from these data which book it is likely to represent.

That is, from an existing dataset, learn to deduce desired results without explicitly programming the rules for those results. The recurring neural network receives as input both current data parameters and previous processes in a loop. These repetitions allow the pertinent information to persist to proceed with the conversation. In other words, when at a new time (period between one access to another) the reader consults a specific book on a subject, the bot is able to indicate new works based on the history of consultations of the behavioral profile of the reader.

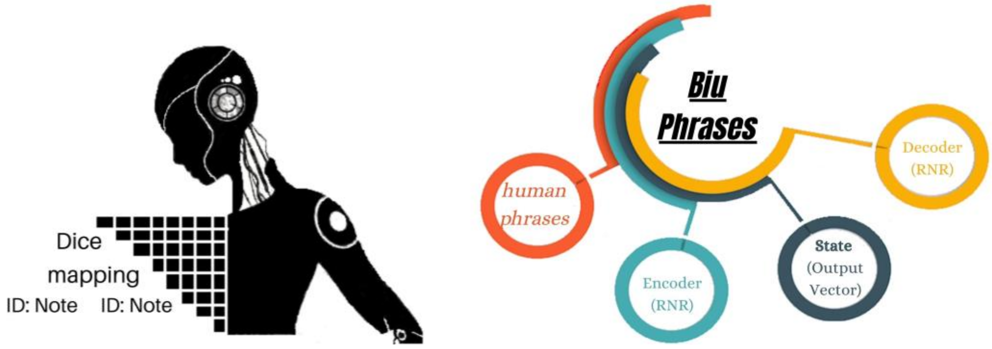
4.3.3 Seq2seq architecture

Biu's architecture uses recurrent Neural Networks with two LSTM neurons known as Encoder-Decoder, which models the relationship between sequence, being one network to encode and another to decode. In this step, with the instance of the TensorFlow library, placeholder tensors are created, in Portuguese empty space, which will be used during training with input (text) and output (text category) values. As an overview, they are undefined tensors, which will be given a value later. The idea of the Sequence-to-Sequence model is to use supervised deep learning techniques to process a data sequence as input into a domain-specific recurring network and have the ability to produce other data in another dimensional space aligned with each input token to the output.

In practice, it happens like this: when reading a sequence, a new point is created in a latent space with more dimensions that represents that sequence. From that point on, it is possible to generate a new network that starts from this principle to translate a new sentence into the same meaning. In the creation of Biu, in this phase, a collection of texts with a large volume of samples are passed as input, which are transformed into computational processes that use a dictionary collection (Python's native mapping). The mapping function converts data into key/value pairs, speeding up access to elements in the recommendation process. After collecting the data (where several people gave their ratings) an analysis procedure is applied to create the recommendation system, as a parameter, it creates a set of mapping rules with pairs of elements as in figure 6.

In fact, the model of automatic coders implemented through TensorFlow, known as an autoencoder, which applies backpropagation algorithms to adjust the weights in training to get the real value or the right answer, through a set of constraints that force the network to learn new ways to represent data by setting target values to equal inputs. A representation of the structure of a deep autoencoder, where the goal is to create a representation of the input in the output layer so that the two are as close (similar) as possible.

Figure 6: Data Mapping



ID = represents the user who gave the rating associated with the grade.
Note = represents the value of the user's assessment, which will feed the learning model.
Source: Authors, 2021.

However, the real use of automatic encoders is to determine a compressed version of the input data with the least amount of data loss. That is, the purpose is to find the best and relevant parameters for training a model where the dataset has a large number of parameters. In the Seq2Seq structure the input and output placeholder tensors are created as follows. As input, the human phases, previously treated in pre-processing, with approximately 8,583 records in which they are submitted to two recurrent neural networks. One of the networks has the function of encoding the input data on the network, in a vector representation capable of capturing the meaning and relevant information associated with them. The other network is responsible for receiving as input the vector formulated in the first network and using it to produce the sentence returned as the output of the network. That is, the encoder network, generating a new state (output vector) after reading the entire sequence to the last internal state, where it divides the input data into a compressed version, ensuring that important data is not lost, but the overall data size is significantly reduced. Then, this data is submitted to the decoding network that generates the final sentence of the chatbot. Before the data is passed to the LSTM encoder neurons, a new pre-processing is submitted, starting with the creation of placeholder tensor models to constantly feed the batch size (set of registers) of the input and output variables that are sent to the neural networks to do the training. As parameters, one of the integer types is passed with the IDs of the words for each one of the sentences, and another one of the matrix type with dimensions such as: number of lines (size of the register batches), and the column with the number of words inside the sentence at runtime. As the sentences are very dynamic, the number of words for each sentence can vary, with a maximum limit of 2 appearances in the largest pre-defined sentence previously, and the smaller sentences are added with a complement <PAD> to equal the size of the variables to be submitted to the learning process during each timestep:

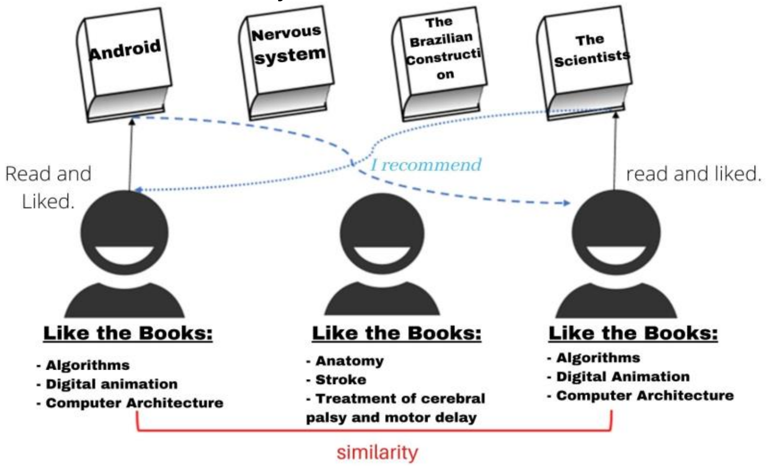
Entrada: Olá <PAD> <PAD> <PAD> - translation: Input: Hello <PAD> <PAD> <PAD>
Saída: Olá Tudo bem <PAD> - translation: Output: Hello All right <PAD>
Entrada: Tudo bem e você – translation: Entry: All right and you

If only those phrases mentioned above are inside the batch, the matrix dimensions are [3,4], in which 3 refers to batches and 4 to the number of words to be submitted to training. Two more placeholder tensors are created, one to define the learning rate and another to work with dropout techniques that aim to zero out some values of the input neuron. Thus, preventing overfit, which is when the neural network adapts too much to the training database and when in production, it can present poor results. The pre-processing of the target words (output) that precedes the Decoder function, consists of defining and dividing the batch size instead of feeding the neural network with each response, and the other is adding the identifier symbol at the beginning of each sentence, previously defined as <INIT>. The first pillar of the encoder neural network bed has the objective of receiving human sentences from the database and returning a vector defined as Output Vector. In addition to adding a hidden state for each word that will be used later in the decoder.

The network layer of the decoder performs the decoding of both the training database and the test database in an embedding matrix application (mapping words to real number vectors). By doing that, the data is in a format that the tensors can read. The decoder, in addition to the input, from the previous state, has an additional process, which generates a sequence, based on this compressed sentence, in order to return an output corresponding to the size of the input. It is at this moment that the matrix attention mechanisms with three-dimensional

arrangement related to the decoder cell are implemented, initializing the state with a zero value. However, a decoder layer has access to the encoder layer which adds an importance weight to each of the words and generates a context vector which will be returned to the decoder as an additional input. Or rather, this is where the memory-based filtering of the user profile takes place, through similarity between the keys and the outputs (real answers). Thus, the content that has the greatest degree of similarity with the behavior of the reader is recommended. In other words, before recommending a certain literary work to user 'A', the network filters the average of the best-rated content previously by a group of readers with the same behavior profile as the present user as in figure 7.

Figure 7: Recommendation System



Source: Authors, 2021.

In the last part of the decoder layer, where the dense neural networks are fully connected in the network, which are the final responses to be displayed by Biu, generates a probability for each of the words that exist in the output vector in the confidence of the function of softmax activation, which is also of the sigmoid type, used for sorting neural networks.

4.3.4 Biu Learning Process

The knowledge of Biu consists of learning how to adjust the synaptic weights of the output layer of each iteration so that the output vector approaches the expected value for the final answer. This adjustment is performed by the backpropagation optimization algorithm, which has an epoch number with stopping criteria. For initialization of weights, a standard deviation of 0.1 was assigned. This deviation shows how much variation or 'scatter' there is from the mean (or expected value). The number of epochs was set at 100 times that the network will undergo weight adjustment. Each epoch is the net equivalent of going through all 8,385 records previously handled, divided by the 32 batch number. The link between epoch and batch is that in training they are passed to the neural network. The batch has the size of 131 records, which are formed with 32 sentences to update the weights.

Another defined hyperparameter is the input values that the neural network will have that will later be submitted to embeddings. When setting the embeddings array size of the encoded with 8,583 as rows (organizational table) and of the related decoder with 512 as columns. In

the architecture of a recurrent neural network, Biu has three input layers that start with the learning value of 0.01. This value is adjusted according to the decay (gradient descent) value of 0.9 declared manually where at each epoch the value of learning is decremented. The dropout probability value is set to 0.5 in Biu. When defining the section in tensorflow, all variables or the entire tensorflow graph are assigned, so that it does not accumulate several objects in memory, which can generate memory overflow errors. The input layer receives, through the placeholder, tensor parameters defined with the default number of words of 25 positions and all the hyperparameters defined previously. The input layer receives, through the parameters of the placeholder, tensors defined with the number of words of 25 positions and all the hyperparameters defined previously. The dimensions of the input tensors are passed the ID referring to each word, represented by an embeddings layer matrix.

The training predictions are obtained by invoking the seq2seq model, passing as parameters: input placeholders with tensor reverse to fill the received sentence length tokens and output placeholder tensors with sequence length, that is, the size of answers, questions, matrix embeddings, the batch size and the ID of the words. So, the network will return the total amount of words. For problem-to-text error calculation, the Sequence Loss function separates the training prediction variables, the expected responses, and a matrix of weights to adjust the weights in the initial position. The model uses the Adam optimizer to update the new gradient values, from a a perturbation of values in the initial solution that makes it change its configuration and thus making it possible to explore a new feasible solution. Biu training consists of running an entire time and already testing the validation database, in order to evaluate the performance of the algorithm.

The time it will take and the error of each batch are returned to analyze how the algorithm is behaving. This is also the case with the validation base, where the average error for the validation is less than the minimum value that exists in the error validation list, which means that there have been improvements if there is no need to learn a little more. This first configuration proposed for validation with the tensorflow tool showed an irrelevant accuracy (below 0.5), being necessary to carry out the test in other versions and larger models, in order to verify the scalability of the results. Providing to the neural network training base a more textual data can help on improving the accuracy in the learning process (Above 0.5). A future study for optimizing the learning of Biu will be the validation in two aspects: analysis of characteristics (the number of input variables figured as of a relevant complexity for the experiment, so a validation of which characteristics are really important is required) and comparison of parameters, as in Santos et al. (2020) and tensorflow versions (such as TensorFlow 2.3). In addition to future learning experiments with the developed structure, the aim is to evaluate the possibility of implementing new tools for audio survey responses, mainly directing visually impaired people to locate the book within the collection. Integration with the google scholar API so that articles from the most diverse areas are also indicated. Price analysis of books and articles that are not included in the dataset.

5. Conclusion

During the project implementation, contributions were obtained, limitations and challenges were identified; and various future possibilities were glimpsed. A treatment of real data from queries to works of a real university library was demonstrated, as well as its

treatment for the use of NLP focused on supporting a chatbot directed to literary works, which represents a differential of the proposed work against the solutions already available in the literature.

As a demand for future research, the issue of incompatibility of tensorflow versions was observed, which figured as a limiting issue for the progress and success of the proposed project. In view of the time available for development, new research must be carried out within an adequate time frame. Finally, the structures developed, even with the learning period pending, allow for other aspects of contributions, such as integration with the google scholar API to also indicate articles from the most diverse areas, price evaluation and service to the disabled public, in Portuguese.

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