Building a Chatbot to Promote College Admissions

Bharath Kumar [1], Jagadeep H S [2], Srivathsa N [3], Shashank M [4], Ms. Suma N G [5]

Computer Science and Technology, Presidency University
Computer Science and Technology, Presidency University
Computer Science and Technology, Presidency University
Computer Science and Technology, Presidency University
Assistant Professor, Dept. of Computer Science & Engineering, Presidency University

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Abstract - Human participation makes university entry very difficult in Vietnam. Here is an article that introduced the chatbot to support the university admissions process by answering questions. Unlike the state of the art, where usually a bot is built, in this paper we use a developed bot on the Rasa platform. To that aim, we learned different ways in the understanding of natural language for good pipelines. We further developed and published a website to log in for training bots. The experimental results show that the pipelines using DIET with pre-training models are competitive.

Key Words : Examination Timetabling, Genetic Algorithms, Hybrid Genetic Algorithms, Local Search, Partition- Based Hybrid Algorithm, Priority-Based Hybrid Algorithm, Uncapacitated Examination Timetabling, Toronto Benchmark Instances, Graph Colouring, Memetic Algorithms, Solution Representations, Crossover Scheme, Saturation Degree Heuristic, Hyper-Heuristic Local Search.

1.INTRODUCTION

Artificial Intelligence in general, and Virtual assistants, as well as chatbots are becoming an integral part of customer interaction and, as such, have taken hold of the scientific communities' attention-. Conversational AI is aimed at creating intelligent "robots" that may perform an interactive conversation between humans and machines,. Categories: Task-Oriented Dialogue Systems; Discussion-Oriented Dialogue Systems; and Question-Answer Dialogue Systems. The first is based on user interaction, say reserving a table in restaurants or booking tickets for travels. Have a natural conversation with the reader. The other one is an NLP-based group where questions proposed by users will be responded to in clear and neat words. AI-powered bots have brought massive changes over e-commerce. For entrepreneurs, it was a fine means to connect buyers and consumers. The bots amplify user experience through round-the-clock customer service online. Intelligent communicators, due to the beneficence, find huge applications in areas related to insurance, education, entertainment, healthcare, e-commerce, or business intelligence. An intelligent voice assistant included with this application is Amazon Alexa, Apple Siri, Microsoft Cortana, IBM Watson bot, and Google Assistant.

In the case of enrollment, Vietnamese schools still rely on traditional ways of spreading propaganda and enrollment. One option, for example, involves just going to high school schools and teaching the wordings. This work is costly, full of labor, and cannot easily be effective during the recent COVID-19 Pandemic. Schools also put many other sources of information on their Web sites, but the information presented on their websites is mostly very incomplete. Social media, such as Facebook, can be an improved method to address questions on admission. Each school can have its fan page and address queries on the site itself. However, this is inefficient since it can't support and answer all queries promptly due to the inability of humans, so this approach has very poor support, leaving students and parents very dissatisfied. Above, we tried to solve the problem by creating an intelligent chatbot that answers questions about university admissions in Vietnam. In this process, first, we have created a database by collecting inputs from students, parents, and teachers. Humans collect data in order to train intelligent chatbots using the Rasa platform. We tested numerous pipelines to come up with the best combination. After training, the bot will be sent to support the access process. The main contributions of this article are three:

Questions and answers in Vietnamese, written for the login ID. This is human-added data, used to train intelligent chatbots. This information is also publicly available.

Authors investigated the Rasa platform for the development of chatbots; this consists of various functions, including target search, location name recognition, and feedback. Furthermore, it will enable us to evaluate various aspects in Rasa about how systems are combined that constitute the best ensembles in the development of a chatbot system.

Questions sharing and answers sharing around Rasa platform. On this FB host platform, there come up the research answers by the questions from Hung Yen University of Technology and Education.

2.RELATED WORK

Due to its increasing relevance in real life, the Q&A discussion creation field of intelligence has received significant attention. From its inception in the 1960s, Q&A has been a practical option since 2015, thanks to advances in deep learning and the availability of large datasets. Rasa is regarded as the most exceptional and potent idea for creating chatbots. Two major components of Rasa, an open concept, are natural language comprehension and conversation management. Distribution targets, resource extraction, and feedback are managed by the former while the latter is responsible for managing the next turn of the conversation based on the content. Rasa's ability to provide a flexible environment for pipeline development makes it an extension of our focus on building chatbots.

The area of research in Vietnam has been extensively conducted in English, but there are few studies that can be regarded as comparable. Nguyen and Shcherbakov suggest a Vietnamese seq2seq network for monitoring 'conversual intelligence' using the sequ2set protocol. Nguyen et al. employed a knowledge-based approach to create sanity robot, capable of solving mathematical problems at the high school level, in contrast to other methods. Secondary school students are given periodic instructions and automaticly by the system.

The most significant work for us, proposed by Nguyen and Shcherbakov, was a Vietnamese chatbot that utilized Rasa NLU and two pre-trained models, FastText and BERT, which achieved satisfactory results. Although we have a similar idea, our chatbot-based implementation of the Rasa framework differs in two significant ways from our previous system: firstly, we built an intelligent robot using Rash, but we cannot identify it specifically.

3. THE CHATBOT SYSTEM

A. Data Collection and Notes

Our chatbot system's data collection and preparation are explained here.

1. Over the last two years, data from fan pages and school websites were collected to construct the chatbot system. This information was used for testing purposes. There are no equipment available for us to do this, so we carry out the task by hand. Information and discussions on access are included in the archive.. By using 400 interviews and 8,500 questions and 6,500 answers, we were able to clean up the archive of questions that had not been answered. Data cleaning in the project was carried out to remove ambiguous and unclear questions, and then it used standard instructions like removing elementary numbers or characters.

2.Annotating the documents: Then, we annotated targets and connotations in NLU material of Rasa. It is said that at least 10 examples of each requirement have to be present to effectively train NLU. This takes lots of time in case it's done by hand.

Since now we actually used k-means just so that it generates the hypotheses of the target—actually putting into a small opinion piece against the written question is what happened. First and foremost, represent the problem as such, in TF-IDF. Continue afterwards by using the technique of Elbow in desire to find our optimized desire with respect to the amount given by k-Value. Specifically, we vary k-means from 100 to 1000, with a step of 20. We further sub-divide the input question into 200 hypotheses like in Figure 1. We shall be changing the intent of the group manually by deletion of duplicate intent instances therein. We are also adding instances in those thoughts which have lower frequency so that all items don't become disjoint. It will satisfy the target audience's needs for NLU training. Finally, we get a final dataset with 160 hypotheses having more than 10 instances for each hypothesis.

We take into consideration the quality of the target language as well by asking four Vietnamese annotators with data annotation and NLP background. Each author reads a total of 4127 examples of 160 hypotheses. Agreement is set to 1 if each model agrees with the annotations given in its label and 0 otherwise.

Rasa NLU, besides the recognition purpose, does need Name Recognition or NER. Because education policy predicts the next steps based on the connection between the goals and institutions. Therefore, we scored the locations of the input data. In this study, we consider five areas that students and parents ask about: location, size, organization, person and time. Using the same goal description process for all types of sites, the consistency of the site description was calculated as 0.80. Statistical data for location descriptions are given in Table 1.

Furthermore, we recounted the narratives that were based on the chatbot model. Consequently, the system can generalize interactions that have not been seen before. Initially, we created 160 storylines by using one objective and one action to create them. After that, we added multi-layered stories and events from real conversations to enhance the conversation's details. A total of 211 descriptions have been recorded.

B. Chatbot

The aim of this is to outline the process of deploying our chatbot on Rasa through automation. Rasa is an open-source software that enables the development of chatbots and offers several useful products for training and handling sessions at NLU, which are the main reasons we have chosen to collaborate with them.

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1) Rasa platform:

An illustration of the Rasa assistant and the human's interaction:.

- Upon receipt of the messages, the translator analyzes the language using a range of data types, including raw text and target entities.
- The message is sent to a tracker that continuously checks for changes in the session state.
- Machine learning and rules are utilized to handle events and determine the next steps in the conversation.
- The system chooses the most effective policy for the next step.
- Close the viewer's options during execution.
- A response is sent to the user for generation.

Rasa NLU and the Rasri Core are the two modules used to accomplish this. The query is analyzed by Rasa NLU, which extracts pre-defined entities, while Rasc Core chooses the chatbot's actions using a probabilistic model that relies on data from Rasa.

2) Natural Language Understanding (NLU):

NLU module interprets the user's intent, and converts redundant information into a structured output.elaboration. For example, ask_offer_letter is used to ask if someone living in Tandan can receive an acceptance letter. How? Tandan is the address, and the chatbot decides whether to contact the nearest office to retrieve the letter or report its status if it's not available. The NLU module is modeled after the DIET model for this research.

3) Negotiation management:

The next step in negotiation management is determined by three primary methods:
If the session matches the specified rule, RulePolicy can predict actions using rules.yml files.
Emersonates stories from training data and anticipates the next task by analyzing the matching stories in the stories. yml file during memeoization.index.pl?
EDPolicy : Machine learning for next action prediction

using probabilities.
The standardized system ensures that the chatbot performs effectively and improves overall user experience.

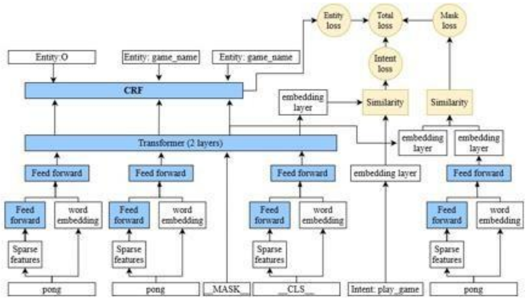


Figure 2. The DIET architecture for joint intent classification and NER [15].

C. Custom System Pipeline :

The pipeline is customized as an NLU product. The goal is to find the correct combination to build a robot.

Specifically, as shown in Table II, we define six pipelines with differences in tokenizers and feature generators, while sharing identifiers and checkpoints using DIET and session management.

- The first pipeline uses VN Core NLP for tokenization and employs regular expressions and enumeration vectors as features.
- The second pipeline replaces VNCoreNLP tokenization with whitespace tokenization.
- The third pipeline applies whitespace for tokenization and uses BERT for embedding (BERT's polyglot for Rasa).
- The fourth pipeline utilizes VNCoreNLP for tokenization and raw BERT polyglot for embedding.
- The fifth pipeline combines features from PhoBERT, regular expressions, and computed vectors to enable hidden agents.
- The last pipeline replaces PhoBERT with BERT (for Rasa).

4. SETTINGS AND EVALUATION METRICS

A. Settings

The dataset was split with an 80-20 ratio for training and test, respectively. 4-gram count features of the character are used (word frequency). The DIET classifier uses a two-layer transducer with relative supervision. For a vector, the size is 768 and it is trained 50 times. We trained the selected answer 100 times.? A method of fallback is employed by the pipeline to provide a solution.

Default of 0.5. Training all the pipelines was done with a single GeForce RTX 2080. Ti GPU.

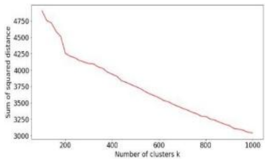
B. Evaluation Metrics

The main metrics applied for the assessment of the performance of the detection and NER tests were precision, recall, and F-score.

$$Precision = \frac{TP}{TP+FP}; \quad Recall = \frac{TP}{TP+FN}$$

$$F-score = \frac{2*P*R}{P+R}$$

• TP is the number of predicted models.



STATISTICS OF ENTITY ANNOTATION

NER	train	test	total
Location	193	41	234
Major	510	139	649
Organization	903	226	1129
Person	9	2	11
Time	102	39	141

For models with correct text, the number of patterns predicted as FP is 0.0%.
This is the number of samples that must be taken into account.
Despite the model's mistake in predicting, the label was actually accurate.

5. RESULTS AND DISCUSSION

Initially, the section highlights the comparison of six pipelines and the actual control of the discussion before publishing ablation studies and ultimately disclosing information about the system.
A. Preliminary Results.
1) NLU Output:

A) Pressure Results Distribution:

The use of the pipeline yields comparable outcomes.' For a precise comparison, the pipeline was trained using 5-fold cross-validation on the training data and then retrained on all datasets to forecast test outcomes.
The pipeline in position six is consistently superior to other positions in Table III. This outcome is due to two things: it employs a variety of operational methods, including BERT, regular expressions, and computed vectorized features, which enhances the representation of emotions. A tokenizer from Vietnam is also employed. Despite the fact that the sixth pipeline was the best, the fifth pipeline is the second best.? This is because both have similar elements except for the language structure. The reason why this is so? It is suggested by this observation that PhoBERT may be more advantageous for detection tasks.

Surprisingly, pipelines with basic functionality, like the first and second, yield positive outcomes. However, the third and fourth pipelines that use BERT (multi-language BER and Rasa-adapted Ber) are not as effective as the simpler ones. This outcome indicates that objective classification tasks require N-gram features.

Table III

THE PERFORMANCE OF PIPELINES FOR INTENT DETECTION.

Pipeline	Train set			Test set		
	Precision	Recall	F-score	Precision	Recall	F-score
1	96.5	96.3	96.0	85.9	85.4	84.5
2	96.6	96.4	96.2	86.1	85.6	84.7
3	92.3	92.1	91.1	81.1	81.5	79.6
4	92.6	92.7	91.7	81.4	81.1	79.2
5	97.5	97.4	97.2	86.2	85.9	85.0
6	**98.6**	**98.4**	**98.5**	**89.0**	**86.8**	**87.9**

b) Field extraction:

A comparison has been made between the performances of six pipelines on this NER task.

Table IV

THE PERFORMANCE OF PIPELINES FOR NER.

Pipeline	Train set			Test set		
	Precision	Recall	F-score	Precision	Recall	F-score
1	96.7	96.0	96.4	**93.7**	**93.0**	**93.3**
2	96.6	95.1	95.5	93.1	91.6	92.2
3	96.7	95.4	95.5	90.9	90.7	90.7
4	96.8	96.1	96.4	92.2	92.2	92.2
5	96.8	**96.2**	**96.5**	93.3	92.8	93.0
6	**97.1**	96.1	96.4	92.6	92.4	92.5

Table IV indicates that the sixth pipeline wasn't the most optimal one. The pipeline utilized for training under PhoBERT demonstrated impressive results. In the experimental setup, this was the first pipeline to use conventional materials successfully.. NER involves fewer training models, while DIET necessitates more extensive training, as shown in Table 1. Nonetheless, the pipelines are still of small size on both sides.

c) Contribution of Pre-learned Language Patterns.
By modifying the language model, we determined the contribution of pre-learned language patterns.

Pipeline (sixth pipeline) feature set.
It also redesigned the pipeline so it could calculate F-score for training and testing. Comparatives are presented for informational purposes only due to limited space.

Table V

THE CONTRIBUTION OF PRE-TRAINED LMS.

Pre-LM	Train set			Test set		
	Precision	Recall	F-score	Precision	Recall	F-score
XLNet [17]	97.3	96.3	96.8	84.6	80.8	82.7
GPT-2 [18]	93.4	91.6	92.5	82.8	79.6	81.2
PhoBERT [19]	97.5	97.4	97.2	86.2	85.9	85.0
RoBERTa [20]	97.0	96.4	96.7	86.0	85.2	85.6
DistilBERT [21]	96.8	96.0	96.4	86.7	83.9	85.3
BERT [22]	**98.6**	**98.4**	**98.5**	**89.0**	**86.8**	**87.9**

Table V demonstrates that the pipeline developed with BERT performs well in competition, while the Pipeline designed with PhoBERT is of significant size. It is evident that the weighted BERT adaptation for Rasa holds greater significance than other pre-trained language models. When PhoBERT was modified to Vietnamese, its performance improved.. Other pre-researched language models were less effective due to their small vocabulary.

d) Training data and accuracy:

We investigated whether the number of training examples affects the classification objectives. This involved dividing the training data into percentages. The data was reconstructed by the model to enable it to make predictions about the test set.

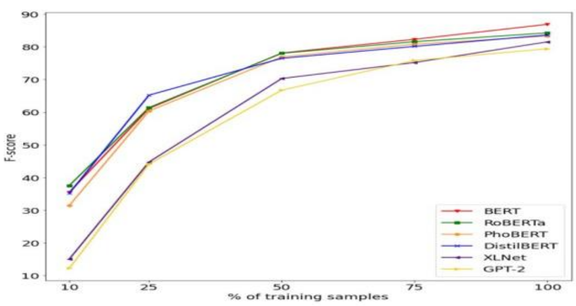


Figure 3. The performance of NLU with different training data sizes.

In Figure 3, NLU's performance is reflected in the number of training examples. The training data's 10% is indicative of a low F-score, but it rises significantly between 10% and 50%. Nevertheless, the benefit was negligible. In addition, BERT, PhoBERT, RoBERTA and Distil BERERT models also function similarly. Despite the use of previously researched LMs, pipelines with these features are consistently superior to those using GPT-2 and XLNet.

2) Negotiation Management:

The model demonstrates effectiveness in negotiation and prediction. Conversation outcomes were accurately reported based on Rasa's recommendation.

Table VI

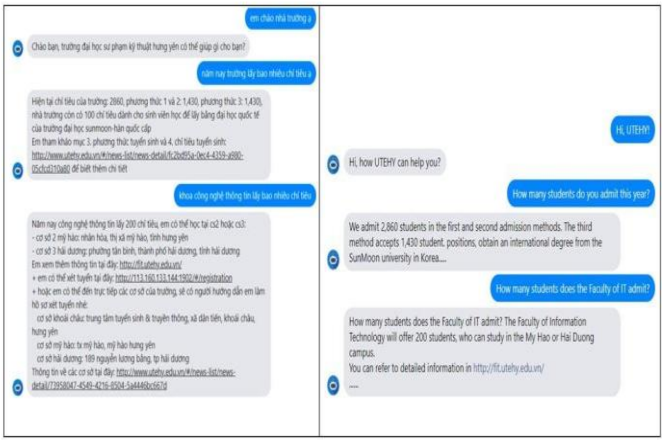
THE PERFORMANCE OF CONVERSATION AND ACTION PREDICTION.

Conversation	Action		
Accuracy	Precision	Recall	F-score
51.2	81.6	83.1	82.1

Table VI illustrates that creating dialogues is a challenging task for bots. This difficulty arises because the bot has only learned 211 stories. Additionally, crafting appropriate conversations is among the most complex tasks in chatbot development. We believe that adding more examples would significantly improve the quality of argument generation. On the other hand, the prediction performance is commendable as it aligns with the expected results indicated by the F-score in Table III.

B. Ablation Study

The study examined the ablation process in the sixth pipeline. To estimate the metric, all partitions were removed and the pipeline was reconstructed. As we already mentioned earlier, SVM (linear kernel, C=1.0, gamma=0.1) and CRF (L1 = 0, 12 = 1, with default features) were used as alternatives to DIET for detecting both target and location. F-scores were computed on the test set.



The role of each component in the pipeline is detailed and explained clearly in Table VII. The F-score is reduced when LM features and location mappers are not included. Why? For example, if the F-score is removed from 87.7 to 84.1 without considering any

Table VII

THE ABLATION STUDY FOR INTENT DETECTION.

Tokenizer		X X X X		
Featurizer (LM)		X X X		
Classifier (SVM+CRF)			X X	
Entity mapper				X
F-score	84.1	88.8	87.7	87.9

relationship with scores (the training NLU models are built on these two measures), the drop in FSC produces an overall reduction of about 3% over previous years due to the removal of LM features. Interestingly, the substitution of DIET with SVM and CRF led to a slight increase in the F-score. As previously noted, the training data set is relatively small and DIET necessitates a significant amount of quantitative data.

C. System

This system is On Facebook. It facilitates access to Hung Yen University of Technology and Education. Figure 4 displays the communication between students and robots. The results are similar. This image demonstrates that the robot can comprehend and respond to user inquiries accurately. As an illustration, the bot can grasp the system's intricacies when it detects the number of students accepted in 2022. And it can carry on like that.

6. CONCLUSIONS

This article presents a clever chatbot. It Upholds the admission process ofauniversities. We built the chatbot on the Rasa platform Here we assessed diverse pipelines We searched for the finest NLU component combination .The experiment results reveal three crucial points

First the chatbot uses DIET. An Explanation of NLU competition follows. Second, the chatbot's revenue lessens. Finally SVM and CRF yield better DIET results for NLU .The smaller Training data is a key factor.

From the Study we dispatched robots. These robots are headed to Hung Yen University of Science and Technology
.Their mission? To Support an admission process.

Upcoming endeavors will better a dataset. This dataset includes thoughts ,organizations and stories. Enhancing the quality of NLU Is another target .We also aim to advance the management dialogue. Our ultimate aim is to generate the correct response.

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