BUILDING AN ADMISSION QUESTION AND ANSWERING SYSTEM FOR CAN THO UNIVERSITY OF TECHNOLOGY

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ABSTRACT

The problem of developing a question-and-answering system is a challenging task in the field of Natural Language Processing. Natural language is inherently ambiguous, making it difficult to determine the semantic meaning of questions as well as identify the correct answers. In this research, we investigated a question-and-answering system based on the Rasa Framework. The system's model is capable of memorizing and accurately answering questions that it has encountered during the training phase. Additionally, the model can handle new questions during the testing phase by selecting an appropriate answer from the set of answers provided during training. The dataset used for training the model consisted of 720 questions and 136 intents, collected from the admission information of Can Tho University of Technology, students, and the Internet up to 2024. The answers to the questions were gathered from the university's admission experts. Based on the results, we proposed a question-and-answering process and developed a web-based admission question-and-answering system to replace advisors in responding to user inquiries online regarding the university's admission information. The system's experimental results demonstrated that the natural language understanding model achieved an accuracy of 97.4% on the test set and an expert-evaluated accuracy of 90.1%.

1. INTRODUCTION

Artificial Intelligence (AI), Machine Learning, and Deep Learning are becoming increasingly popular today. All these technologies are interconnected, with the shared goal of mimicking human intelligence. Applications in this field include logical reasoning, knowledge representation, planning, learning, natural language processing, and perception. Among these, question-and-answering systems are particularly widespread and represent one of the key application areas of AI.

Question-and-answering (QA) systems are a domain within computer science, operating in the fields of information retrieval and natural language processing. These systems process and respond to questions posed by humans in natural language. They are typically operated by computer programs that generate answers by querying a structured database containing relevant information or knowledge, often relied on a knowledge base. QA systems are designed to provide answers to a range of questions within a set of documents or to generate responses from a data source. These systems allow users to ask questions in natural language and then extract relevant answers, responding to the user’s queries accurately and almost in natural language, and instantly, rather than providing related document sets like traditional search engines. QA systems are increasingly attracting researchers and developers because users demand rapid and accurate answers. Moreover, the development and expansion of QA systems can enhance the efficiency and effectiveness of task processing within the system.

Many studies have been conducted on developing QA systems for customer information consultation and admissions.

Elnozahy et al (2019) have built an information extraction framework proposed as a part of the research project “LET’SeGA” to support educational institutions in selecting students for different programs. This would also help target specific student segments in marketing decisions for academic programs. In the proposed framework, an ontological model is created for universities’ data which is used to support students’ recruitment and retention ensuring students’ success after admission.

Phuc et al (2023) have built a system to automatically answer questions based on the content of text files using deep learning techniques. The system extracts information from the question, enters the keywords, and returns the relevant text using the BM25 algorithm. Given the text with the highest relevance, the deep learning model is trained to extract the corresponding answer. The RoBERTa model was selected with the highest training speed and accuracy and deployed to the system to evaluate the results.

Trung et al (2021) have built an AI-based chatbot where students can instantly get daily updates on curriculum, admission for new students, tuition fees, IELTS writing task II score, and the like. The chatbot was developed by Deep Learning models, which are already integrated into the Rasa framework. Their model can detect more than fifty types of questions from users' input with an accuracy of 97.1% on the test set. The chatbot was applied for National Economics University's official admission Fanpage on the Facebook platform, which is the most famous social network in Vietnam.

The application of QA systems for university admissions is currently receiving significant attention. Therefore, we conducted a study on an admissions QA system model and developed a web-based system to enhance the efficiency of automated responses to admissions inquiries at Can Tho University of Technology (CTUT) by using Rasa instead of the Pre-trained Transformer model (Khiem, 2023). This research follows a series of activities, including data collection, research application of the Rasa Framework in building the QA system, and finally, testing and evaluating the model in an application.

2. BACKGROUND

2.1 Natural language processing

Natural Language Processing (NLP) is a branch of AI that focuses on studying the interaction between computers and human natural language, in the form of speech or text. NLP has two branches: speech processing and text processing. Speech processing focuses on researching and developing algorithms and computer programs to process human language in the form of speech (audio data). Text processing, on the other hand, focuses on analyzing input text data such as text in files or text entered via the keyboard. Important applications of text processing include information retrieval, machine translation, automatic text summarization, and automatic spell-checking.

NPL is a computational technique that analyzes and represents text in a way that closely resembles human natural language, enabling its use in various fields and tasks.

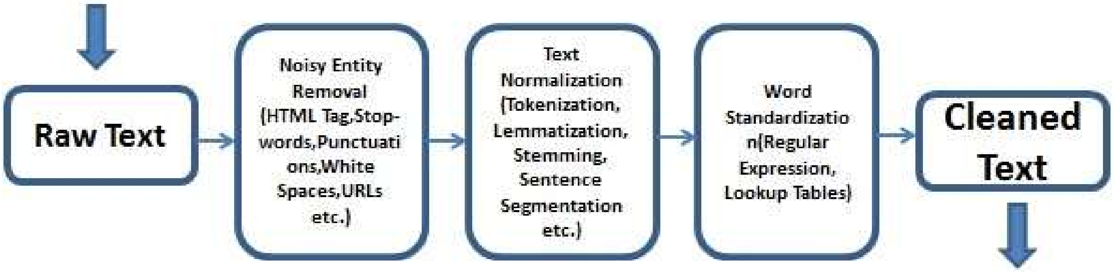


Figure 1. Text Cleaning Pipline

Source: https://www.linkedin.com/pulse/pre-processing-text-nlp-vanessa-afolabi

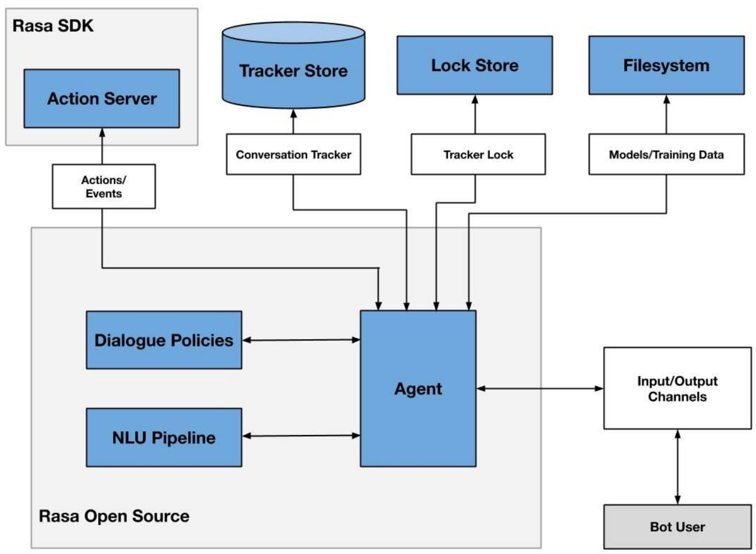


Figure 2. Architecture of Rasa

Source: Rasa, (2025).

2.2. Rasa

Rasa is an artificial intelligence system developed by Rasa Technologies, built on the Python programming language. The goal of Rasa is to provide developers with a powerful tool with many features for building automated chat applications between humans and machines.

One of the key features of Rasa is its focus on building chat applications based on reinforcement learning and deep learning models. This enables Rasa to create chat applications capable of understanding context and semantics, naturally interacting with users, almost like a human-to-human conversation.

Rasa 3.0 is a framework for building AI chatbots with a modular and scalable architecture. It consists of three main layers: NLU (Natural Language Understanding) for intent classification and entity extraction, Dialogue Management using rule-based and machine-learning policies, and Action Execution for custom responses and integrations. The new version enhances flexibility with a redesigned NLU pipeline, improved TED policy, better debugging tools, and simplified action handling. With support for rule-based and AI-driven conversations, Rasa 3.0 enables developers to create robust, context-aware virtual assistants that can run on-premise or integrate with external APIs.

Rasa allows users to fully control the NLP pipeline, without limitations like Dialogflow or GPT-4. It doesn't need to send data to the cloud like GPT-4 or Dialogflow, suitable for applications requiring high security. It can combine both hard law and deep learning AI, helping chatbots be both intelligent and better controlled than GPT-4.

Rasa can integrate advanced models such as BERT, GPT or Transformer-based models to enhance language understanding. It can improve the ability to combine NLP with computer vision and audio, helping to develop better multimodal chatbots.

3. ACHIEVED RESULTS

3.1. Dataset

The training dataset for the model consists of 720 questions collected from the admissions website of Can Tho University of Technology, students, admissions experts, and frequently asked questions about admissions on the Internet. Based on the admissions project and expert opinions, we developed 136 user intents related to the collected questions, which are presented in Table 1.

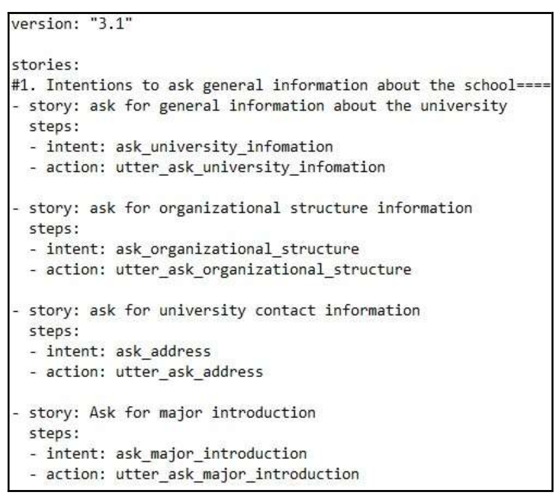
Table 1. Some user intent

No.	Question	Intent
1	Hello	hello
2	Information about the university	ask_university_infomation
3	Address of university	ask_address
4	Introduction to the majors being trained at the university	ask_major
5	Tuition fees of the majors	ask_tuition_free
6	Which unit provides admissions consulting?	ask_admission_ consulting
…	…	…
136	Bye	goodbye

3.2. Training data on Rasa

After constructing the questions, intents, and corresponding answers, we proceeded to create the question scenario for Rasa (stories) as shown in Figure 3.

Set up the configuration for the workflow pipeline in the config.yml file. In addition to allowing users to integrate external preprocessing tools, Rasa provides several language models such as MitieNLP, SpacyNLP, and WhitespaceTokenizer for tasks like tokenization and feature vectorization (language representation).



```
version: "3.1"

stories:
#1. Intentions to ask general information about the school====
- story: ask for general information about the university
  steps:
  - intent: ask_university_infomation
  - action: utter_ask_university_infomation

- story: ask for organizational structure information
  steps:
  - intent: ask_organizational_structure
  - action: utter_ask_organizational_structure

- story: ask for university contact information
  steps:
  - intent: ask_address
  - action: utter_ask_address

- story: Ask for major introduction
  steps:
  - intent: ask_major_introduction
  - action: utter_ask_major_introduction
```

Figure 3. Stories in Rasa

```
# Configuration for Rasa NLU.
language: vi
pipeline:
- name: WhitespaceTokenizer
- name: LanguageModelFeaturizer
  model_name: "bert"
  model_weight: "rasa/LaBSE"
  cache_dir: null
- name: RegexFeaturizer
- name: LexicalSyntacticFeaturizer
- name: CountVectorsFeaturizer
- name: CountVectorsFeaturizer
  analyzer: char_wb
  min_ngram: 1
  max_ngram: 4
- name: DIETClassifier
  epochs: 400
  constrain_similarities: true
- name: EntitySynonymMapper
  epochs: 100
  constrain_similarities: true
- name: FallbackClassifier
  threshold: 0.65
  ambiguity_threshold: 0.1
```

Figure 4. NLU pipeline

In the NLU pipeline, we configured the language for Vietnamese. For the tokenizer, we customized the WhitespaceTokenizer by using the underthesea library for Vietnamese instead of the default whitespace-based tokenization. The training model used was BERT (which supports Vietnamese).

Currently, Rasa supports several intent classifiers such as KeywordIntentClassifier, MitieIntentClassifier, SklearnIntentClassifier, and DIETClassifier. Among them, KeywordIntentClassifier is a keyword-matching method suitable for small datasets; the MitieIntentClassifier uses a linear multi-class SVM classification method, while the SklearnIntentClassifier uses a linear SVM method for intent classification; DIETClassifier (Dual Intent and Entity Transformer) is a classifier with a multitasking architecture, including both intent classification and entity recognition in a sentence. DIETClassifier is the most advanced method, improving upon previous methods and providing the best results in intent identification.

Additionally, Rasa provides the FallbackClassifier, which classifies a sentence into the nlu_fallback intent in case of ambiguous classification, meaning it uses the fallback_threshold confidence threshold to determine whether the sentence belongs to one of the existing intents or the nlu_fallback intent. In this research, we combined the DIETClassifier and the FallbackClassifier.

3.3. Experimental results

In this research, the metrics used to evaluate the Rasa NLU model and expert assessments of the answers corresponding to user input questions when deploying the program were Precision, Recall, F-measure (F1Score), and Accuracy.

- Accuracy: the ratio of correct predictions to the total number of predictions. It is a general metric but can be misleading if the data is imbalanced. The formula for calculating accuracy is as follows:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

- Precision: Precision measures the ratio of correct positive predictions to the total number of positive predictions. The formula for calculating precision is as follows:

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

- Recall: Recall measures the ratio of actual positive samples that the model correctly predicts. The formula for calculating recall is as follows:

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

- F1-Score: The harmonic mean between Precision and Recall, providing a comprehensive assessment of the model's performance, is particularly useful when there is an imbalance between classes. The formula for calculating the F-measure is as follows:

$$F1Score = 2\,x\,\frac{Precision\ x\ Recall}{Precision + Recall} \quad (4)$$

- Rasa NLU model Evaluation

Use the k-fold cross-validation method with k = 5 via the following command: *rasa test nlu --config configs/config.yml --cross-validation --runs 1 --folds 5 --out gridresults/config-bert*

The evaluation results on the test set for the intent classification classifier are as follows: Accuracy = 97,4%; F1-score = 96,9%; Precision: 97,2%.

```
2025-01-10 10:28:37 INFO     rasa.model_testing  - CV evaluation (n=5)
2025-01-10 10:28:37 INFO     rasa.model_testing  - Intent evaluation results
2025-01-10 10:28:37 INFO     rasa.nlu.test  - train Accuracy: 1.000 (0.000)
2025-01-10 10:28:37 INFO     rasa.nlu.test  - train F1-score: 1.000 (0.000)
2025-01-10 10:28:37 INFO     rasa.nlu.test  - train Precision: 1.000 (0.000)
2025-01-10 10:28:37 INFO     rasa.nlu.test  - test Accuracy: 0.974 (0.009)
2025-01-10 10:28:37 INFO     rasa.nlu.test  - test F1-score: 0.969 (0.011)
2025-01-10 10:28:37 INFO     rasa.nlu.test  - test Precision: 0.972 (0.018)
```

Figure 5. Results after evaluating with 5-fold cross validation

- Expert Evaluation

We developed the Admissions Question & Answering System website using the Flask Framework and connected it to Rasa via API for testing. We invited several admissions experts from the university to ask questions through the website's chat window. The results showed that 90.1% of the answers were correct according to the experts' queries. Incorrect answers occurred when users inputted questions with abbreviations not found in the thay_the_tu.txt file, spelling mistakes, or ambiguous words in the sentence. Additionally, for questions unrelated to admissions or not found in the database, the system would provide a default response like "Does the above information meet your requirements? If it does not meet the requirements, it is possible that the content you asked has not been updated. Please try asking the question in another way." The accuracy of the system when testing with admissions experts decreases due to incorrect spelling, questions not included in the training set, acronyms and so forth.

3.4. Admissions Question & Answering System

Based on the user's query behavior, we developed a process for answering user questions/queries as shown in Figure 6.

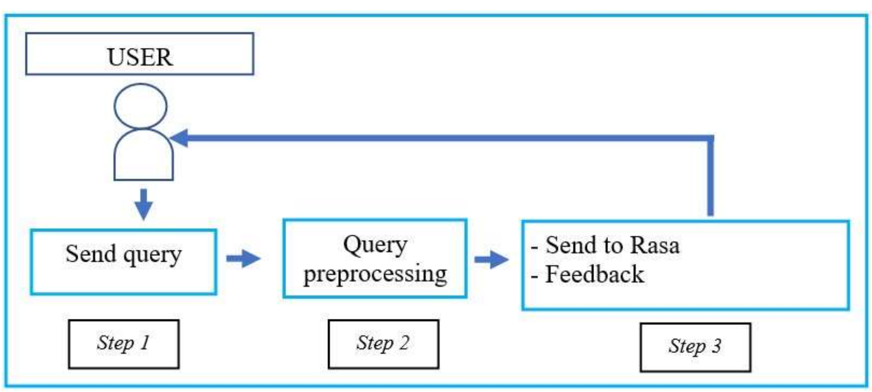


Figure 6. User Query Answering Process

The steps in the process shown in Figure 6 are carried out as follows:

- Step 1: The user enters a query in Vietnamese text.

- Step 2: Perform special character removal, normalize the Vietnamese sentence (such as tone marks, accents, and so on), and replace words (we created a file of replacement words to adjust the user's query to be closer to the queries used for training), remove extra spaces, tokenize using the underthesea library, remove stopwords (a stopword.txt file created by the authors based on the collected queries), and convert to lowercase.

- Step 3: Send the pre-processed query from Step 2 to Rasa via API and receive the response from Rasa. Display the content of the answer to the user's query on the interface.

An image of the system interface is shown in Figure 7.

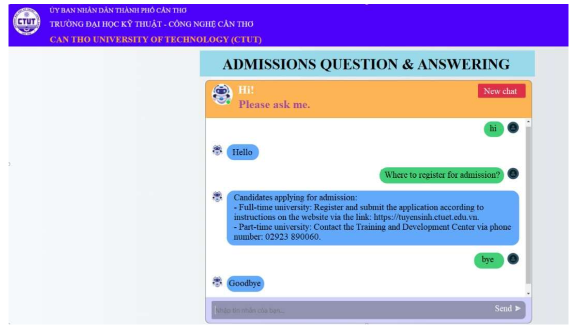
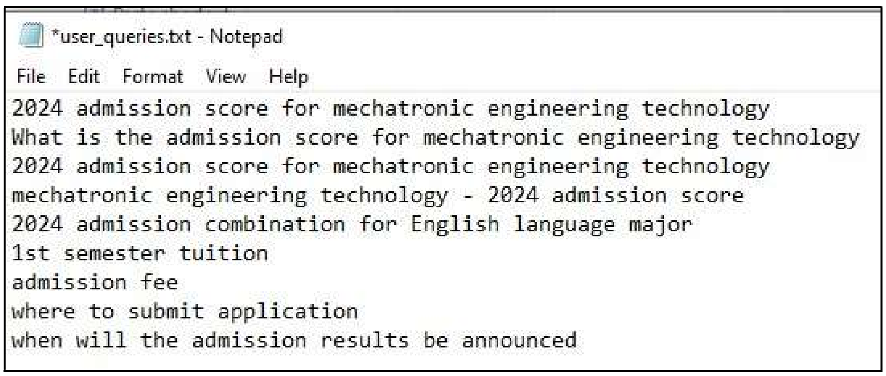


Figure 7. System Interface

To collect user query data on the deployed ADMISSIONS QUESTION & ANSWERING system, we designed a file to store the queries as shown in Figure 8.


*user_queries.txt - Notepad

File Edit Format View Help

```
2024 admission score for mechatronic engineering technology
What is the admission score for mechatronic engineering technology
2024 admission score for mechatronic engineering technology
mechatronic engineering technology - 2024 admission score
2024 admission combination for English language major
1st semester tuition
admission fee
where to submit application
when will the admission results be announced
```

Figure 8. User Query content on the Question & Answering System

Based on the collected query information, we supplemented the training data for Rasa to help the system answer user questions more effectively.

Some advantages when developing chatbots on Rasa compared to the Transformer-based Model: Rasa does not require large-scale neural network inference; It works well on low-resource environments like edge devices or enterprise servers; The maintains structured and predictable responses, which is crucial for enterprise chatbots (e.g., customer support); It is cheaper and easier to deploy on-premise, with no reliance on expensive API calls. It is very suitable for installation and operation on CTUT's server.

4. CONCLUSION

This research presented a method for building a question-and-answering system based on Rasa and illustrated the implementation for a specific domain, namely the admissions domain at Can Tho University of Technology. The implementation, along with the configured parameters, achieved quite good results. The natural language understanding model had an accuracy of 97.4%, and the accuracy according to expert evaluation was 90.1%.

Furthermore, we proposed a user query answering process and successfully built an admissions Question & Answering system on the web platform.

The experimental system produced good results when the input text was a complete Vietnamese sentence with proper syntax and minimal abbreviations. The development direction for the program should focus on further improving the Vietnamese preprocessing part such as updating stopword data and replacing word files. Additionally, the program needs to build a knowledge base to infer and suggest answers when the input message is not found in the predefined data set, rather than providing a default answer.

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XÂY DỰNG HỆ THỐNG HỎI ĐÁP TUYỂN SINH TẠI TRƯỜNG ĐẠI HỌC KỸ THUẬT - CÔNG NGHỆ CẦN THƠ

TÓM TẮT

Phát triển hệ thống hỏi đáp là một bài toán đầy thách thức trong lĩnh vực Xử lý ngôn ngữ tự nhiên. Trong nghiên cứu này, chúng tôi xây dựng hệ thống hỏi đáp tuyển sinh dựa trên Rasa có khả năng ghi nhớ và trả lời chính xác các câu hỏi gặp phải trong giai đoạn huấn luyện. Bộ dữ liệu dùng để huấn luyện gồm 720 câu hỏi và 136 ý định được thu thập từ thông tin tuyển sinh của Trường Đại học Kỹ thuật - Công nghệ Cần Thơ, sinh viên và Internet đến năm 2024. Thông tin các câu trả lời lấy từ các chuyên gia tuyển sinh của trường. Dựa trên kết quả thu thập, chúng tôi phát triển hệ thống hỏi đáp tuyển sinh dựa trên web để trả lời các câu hỏi trực tuyến của người dùng về thông tin tuyển sinh. Kết quả thử nghiệm của hệ thống chứng minh mô hình hiểu ngôn ngữ tự nhiên đạt độ chính xác 97,4% trên bộ kiểm tra và độ chính xác được chuyên gia đánh giá là 90,1%.

Từ khóa: *Hệ thống hỏi đáp, Rasa, xử lý ngôn ngữ tự nhiên*