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An Application of RASA Technology to Design an AI Virtual Assistant: A Case of Learning Finance and Banking Terms in Vietnamese*

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Abstract

Banking and finance is a broad term that incorporates a variety of smaller, more specialized subjects such as corporate finance, tax finance, and insurance finance. A virtual assistant that assists users in searching for information about banking and finance terms might be an extremely beneficial tool for users. In this study, we explored the process of searching for information, seeking opportunities, and developing a virtual assistant in the first stages of starting learning and understanding Vietnamese to increase effectiveness and save time, which is also an innovative business practice in Use-case Vietnam. We built the FIBA2020 dataset and proposed a pipeline that used Natural Language Processing (NLP) inclusive of Natural Language Understanding (NLU) algorithms to build chatbot applications. The open-source framework RASA is used to implement the system in our study. We aim to improve our model performance by replacing parts of RASA's default tokenizers with Vietnamese tokenizers and experimenting with various language models. The best accuracy we achieved is 86.48% and 70.04% in the ideal condition and worst condition, respectively. Finally, we put our findings into practice by creating an Android virtual assistant application using the model trained using Whitespace tokenizer and the pre-trained language m-BERT.

Keywords: Virtual Assistant, Natural Language Processing, Vietnamese, Natural Language Understanding, Finance and Banking, Smart Classroom

JEL Classification Code: G15, E22, O1

1. Introduction

As one of the disciplines in economics, trade, Banking, and Finance is a particularly appealing topic in the Vietnamese economic research community (Ho et al., 2020; Luc, 2018). Finance and Banking is a broad discipline related to all services and currency exchange transactions (Law, 2014). It is regarded as the lifeblood of business enterprise with the foundation of all kinds of economic activities and technology development. Moreover, it has been called "Fintech", which plays a vital role (Nguyen et al., 2020). Therefore, Finance and Banking have generated a large amount of specialized terminology that is very diversified and highly academic. Studying finance and banking with dense terminology creates great difficulties for people or enterprises who are

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both inside and outside of the sector and want to look for information or learn new knowledge in this domain.

Nowadays, understanding the terms and having extensive knowledge in the field of Banking and Finance is essential, not only for companies and businesses but also for each individual in the changing digital economy day by day. With the development of the Internet, it is easier for users to have more opportunities to research and learn than ever. People can use the Google tool to look up terminologies on the website/blog or forum whenever they want with internet-connected devices. However, many inadequacies remain, such as inconsistent explication in different media transports, time-waiting in searching for mainstream documents, or inflexible translation, which causes many obstacles for learners. We tried to create a new interactive dictionary model which is more intelligent and more effective.

Furthermore, there was a sharp development in research in the Artificial Intelligence (AI) field, especially Deep learning (Huang et al., 2020), Natural Language Processing, Speech Recognition technologies, virtual assistants or chatbots (Adamopoulou & Moussiades, 2020) gradually became an amazing technology trend. Since Siri was born in 2010, virtual assistants have constantly been developing in various ways, including familiar virtual assistants such as Siri, Google Assistant, HomePod Apple, and so on (De Barcelos Silva et al., 2020; Tulshan & Dhage, 2019). Because of the advantages of a virtual assistant's performance, including recognizing and distributing voice analysis, natural language processing, and others, a virtual assistant is known as a learning aid for Flexible and effective training (Gubareva & Lopes, 2020; Lupa-Wójcik, 2019; Page & Gehlbach, 2017). In Vietnam, because virtual assistants have difficulty solving compound words and multiple-meaning terms in the Vietnamese language, it has not been applied effectively to deal with learners' problems yet. We will propose an idea about a Vietnamese financial banking virtual assistant app in this paper. It is most likely an instant and effective learning tool for learners.

In this paper, we created a specific dataset and applied the RASA platform to build the model as a "Resolver" for our virtual assistant. We created a natural language understanding (NLU) and core model following the research of Bocklisch et al. (2017) and Gubareva and Lopes (2020), but the NLU model was enhanced for the Vietnamese language to achieve high accuracy. Finally, we concretize our research by building a virtual assistant application on the Android platform.

The remainder of this paper is organized as follows. Section 2 provides an overview of related works. Section 3 describes how we applied them to our research, including the way we built the dataset for our research and experiments. Section 4 is devoted to the evaluation research. In section 5, we explain how we deploy our assistant product. And finally, conclusions are drawn in section 6.

2. Research Background and Related Works

2.1. Virtual Assistant

In the context of education 4.0, Artificial intelligence-based research has been more interesting than ever, promoting many related works on universities to solve their student's issues. Besides, Dibitonto et al. (2018) have a finding that students prefer voice communication to get quick responses, but it does not integrate with informal social network sites such as Facebook, Instagram, etc. for learning.

In one of their previous works, Tamizharasi et al. (2020) used Support Vector Machine, which is a machine-learning algorithm to build a resolver for the medical chatbot dealing with their problems. However, machine learning algorithms indeed remain some limitations such as not incremental or interactive learning, poor transfer learning ability or reusability of modules, and so on. However, there was a growth of Open-source conversational AI tools that created cutting-edge innovation in interactive learning ability, understanding messages, classifying intents, and capturing key contextual information (Sharma & Joshi, 2020). Another previous research proposed a framework or used an open-source for building chatbots or virtual assistants (Campagna et al., 2017; Harms et al., 2019; Srivastava & Prabhakar, 2019). The virtual assistant was built as a chatbot also makes the system much more interactive and personal with conversational skills that empower the assistant to deliver information more effectively and friendly to users, as presented in the operational solution assistant system for foreign SMEs in Korea (Thai & Huh, 2021). Virtual assistants/chatbots will analyze and make guesswork depending on captured information and specific stories to deal with complex cases that machine learning algorithms have not yet done.

In our study, we will build a virtual assistant as a chatbot that can be much more interactive and personal than rule-based chatbots. It can understand the context and intent of complex conversations and attempt to provide more relevant responses.

2.2. Natural Language Processing (NLP) and Natural Language Understanding (NLU) Techniques in the Vietnamese Language

Natural language processing (NLP) is an important technique to enable computers to understand human language in both written and verbal forms. Natural language processing emphasizes machine learning and deep learning techniques to complete tasks, like language translation or question answering (Palmer, 2010). Natural Language Understanding (NLU) is the technique that deals with understanding the semantics of a specific text (Allen, 1988) and focusing on a machine's ability to understand the human language. NLU refers to how unstructured data is rearranged so that machines may "understand" and analyze it.

We will create a virtual assistant that can process unstructured text from peculiarities of the human language into machine-readable with NLP technique (in our context is Vietnamese) and perform a syntactic/semantic analysis. After that, we will use the NLU technique to understand natural languages and represent their semantics in a form that computers can interpret (Allen, 1988).

2.3. Knowledge domain of Finance and Banking

As one of the disciplines in the field of economics - trade, the banking and finance industry plays an important role in the field of trade and currency. Finance and Banking is a broad discipline that relates to all services and currency exchange transactions (Law, 2014). Disciplines and sectors related to banking and finance can be divided as follows:

Banking: knowledge in finance, banking, currency, credit management, capital and asset management, knowledge of money issued, credit term appraisal. Knowledge of modern financial and monetary management, corporate financial management, commercial banking, non-banking financial institutions, financial risk management tools, knowledge of financial, statistical, accounting, tax processes, insurance in banks and businesses.

Financial investment: in-depth knowledge of financial investment, market analysis and forecasting skills, financial investment skills; knowledge related to financial markets, risks, and how to manage the risks of investment instruments in the Financial Markets; management activities of financial market management agencies; state management of financial markets and financial investment; accounting process in financial investment; understand the State's regulations on financial markets and financial investment.

Corporate finance: in-depth knowledge of corporate financial management, financial appraisal of investment projects, analysis of corporate financial statements; capital mobilization, management and use operations; acquire knowledge related to accounting process, banking credit operations, valuation, securities; the State's regulations on enterprise management, the provisions of the tax law; Acquire additional knowledge about business - commercial law, tax policy.

Tax: tax theory, tax policies, tax laws; tax administration process of tax authorities, regulations on making tax declaration dossiers; knowledge related to tax accounting process; Additional knowledge on tax laws and international commitments.

International finance: knowledge of international finance, operations related to international finance such as international business (foreign currency trading, securities business, insurance business...), international trade, international investment, international payment, international credit, exchange rate; international financial processes, and operations, international investment project management processes, ODA project management, debt management, international accounting, financial management of multi-national companies.

In the scope of this research, we will build a knowledge dictionary about general terms which learners usually look for or search for in the fields of Finance and Banking.

3. Methodology

In this section, we will present how we applied the RASA platform to build a resolver model (NLU & Core model) for our virtual assistant. RASA is an open-source conversational AI Platform that supports building chatbots as well as virtual assistants based on natural language understanding (NLP). It is a combination of two modules:

RASA NLU has the responsibility for getting inputs, understanding the intent of the user, and finding the entities. This component internally uses Bag-of-Word (BoW) algorithm to find intent and Conditional Random Field (CRF) to find entities. It is almost decided that your chatbot/virtual assistant has the correct answer returning. Custom pipeline with other algorithms is usually applied in this model to find intent depending on your virtual assistant's different contexts of data.

RASA Core will take the output of RASA NLU (intent and entities) and apply Machine Learning models to generate reply messages for virtual assistants (Figure 1).

Our virtual assistant was created in our research. We try to optimize the model's performance by replacing some Vietnamese tokenizers and doing experiments on different language models. A customized pipeline for a specific dataset based on the Vietnamese language was proposed in our research. Besides, we also propose a method to handle out-of-scope questions in RASA determined by entities' confidence.

3.1. Preparing Dataset

For preparing a dataset for the development of an AI virtual assistant, we need to collect the most popular terms in the finance and banking sector. We crawled web data from the 3 biggest banks in Vietnam and extract terms related to finance and banking; we also screened terms from textbooks and handouts on finance and banking-related subject in the faculty of finance and banking. Reviewing lecturers on the subject, we selected 709 most popular original terms in some

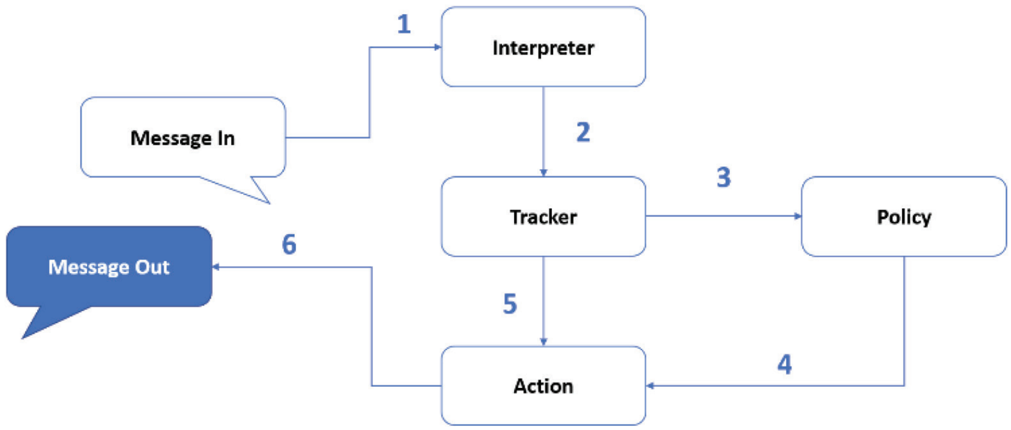

Figure 1: General Architecture of RASA Open-Source (Bocklisch et al., 2017)

Figure 2: Our Framework for Preparing the Dataset

sub-sector: financial market, financial instruments, securities, etc., based on the mentioned sources. Based on each found term, our team started to analyze and generate related frequently asked questions that students were often confused about. In parallel with this action, we did pre-research to look up answers to materials for the generated queries. Our team did a cross-checking on each other and final review by the lecturers of related subjects to ensure that answers were always correct in all cases. After collecting the dataset, we converted all samples to the format dataset of RASA. The framework for building the dataset is shown in Figure 2.

To serve students in our university, all of the samples in our dataset, which is called FIBA2020, were collected from academic material such as textbooks and lecture slides from the Department of Finance and Banking. Table 1 shows some samples of the FIBA2020 dataset.

3.2. Dataset Structure

To build the data set structure, we start by analyzing a simulated conversation between a student and a virtual assistant, as shown in Figure 3.

Indeed, each utterance always has an intent. The virtual assistant needs to understand the user's intent and extract needed information before giving the correct answer. We built the proper structure for our dataset based on RASA documentation (Bocklisch et al., 2017).

In our story example, the utterance's intent is asking definition, and the needed entity is the terminology "Appraised value" (giá trị thẩm định). Depending on the data training format of RASA, we built a structured dataset following the steps in Figure 4.

3.2.1. Building Intent

Intent detection (Balodis et al., 2018) is one of the main tasks of a dialogue system. The variety of user languages makes it difficult for virtual assistants to categorize intentions. Therefore, we should construct many questions that are the same purpose that represent one intent. These synonym questions are built by referencing from dictionary and Google search suggestions and reviewed by lecturers in the faculty of finance and banking. Namely, our dataset has six intents: definition, meaning, classification, characteristics, formula, operation defined under six intents: ask_dinhnghia(definition), ask_ynghia(meaning), ask_dacdiem(characteristics), ask_phanloai(classification), ask_congthuc(formula), ask_cachhoatdong(operation). The number of samples per intent is described in Figure 5.

3.2.2. Building Entity, Synonym

An entity is a piece of information extracted from the user's intent. In our research, entities are financial and banking terminologies. It will be extracted after the intent is classified. We defined 246 terms in the form of the entities in our dataset. In addition, we found that certain terms have different names and may be asked for multiple ways to refer

Table 1: Some Samples of the FIBA2020 Dataset

Term	Question	Answers
Externality (Ảnh hưởng ngoại lai)	What is externality? ("Ảnh hưởng ngoại lai là gì?")	Externality, in economics, is an effect caused by the activities of one economic entity and directly affects another economic entity. ("Ảnh hưởng ngoại lai, trong kinh tế học, là ảnh hưởng gây ra bởi hoạt động của một chủ thể kinh tế này và tác động trực tiếp tới chủ thể kinh tế khác")
Externality (Ảnh hưởng ngoại lai)	What is the harm of externality? ("Tác hại của ảnh hưởng ngoại lai?")	Externality is a type of failure, so it also takes a toll on social welfare, often associated with non-paying motorists. ("Ảnh hưởng ngoại lai là một loại thất bại thị trường nên nó cũng gây tổn thất phúc lợi xã hội, thường gắn liền với nạn kẻ đi xe không trả tiền.")
Externality (Ảnh hưởng ngoại lai)	What is the remedy for externality? ("Biện pháp khắc phục của ảnh hưởng ngoại lai")	Some solutions to overcome external influences: Pigou tax, Coase theorem. ("Một số giải pháp khắc phục ảnh hưởng ngoại lai: thuế Pigou, Định lý Coase.")
Externality (Ảnh hưởng ngoại lai)	What is the cause of externality? ("Nguyên nhân dẫn đến ảnh hưởng ngoại lai?")	Externality effects are caused by a disproportionate between private costs (or benefits) and social costs (or benefits); i.e. externality related to the interdependence of utility functions and (or) production functions. ("Ảnh hưởng ngoại lai là do sự không cân xứng giữa chi phí (hoặc lợi ích) tư nhân và chi phí (hoặc lợi ích) xã hội tạo nên; tức ảnh hưởng ngoại lai liên quan đến sự phụ thuộc lẫn nhau của các hàm lợi ích và (hoặc) các hàm sản xuất.")

Student	Hello! ("Chào bạn")
Virtual assistant	Hello, how can I help you? ("Xin chào, mình có thể giúp gì cho bạn?")
Student	What can you do? ("Bạn có thể làm được gì?")
Virtual assistant	Hihi, I'm very good at instructing you about finance and banking, just ask me! ("HiHi, mình rất giỏi các thuật ngữ ngân hàng, có gì bạn cứ hỏi mình nhé")
Student	Do you know what appraised value is? ("Bạn có biết giá trị thẩm định là gì không")
Virtual assistant	Appraised value is the dollar value assigned to asset for applicable tax purposes ("Giá trị thẩm định là giá trị đồng đô la gán cho một tài sản với mục đích đo thuế áp dụng")

Figure 3: Example of Conversation Between Virtual Assistant and Student

Figure 4: Data Structure Steps

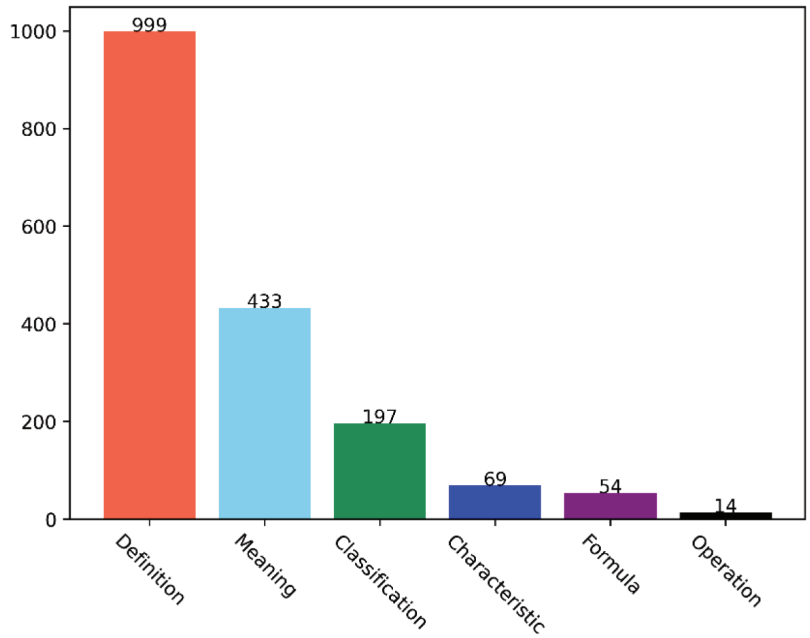

Figure 5: Intent Distribution on Dataset FIBA2020

to the same term. Hence, we used a synonyms map to solve that problem. For example, the term "net profit margin (biên lợi nhuận ròng)" also has the name "net profit ratio (tỷ suất lợi nhuận ròng)", so we defined "net profit ratio (tỷ suất lợi nhuận ròng)" as synonym to "net profit margin (biên lợi nhuận ròng)".

3.2.3. Building Stories

We researched to find out instances where the user might need help from a virtual assistant. We learned about how RASA creates the dialogue that shapes the story. In these cases, we find that asking a term randomly, asking related questions in a term, asking terms in one lesson, or asking a certain term that appears in the virtual assistant's answer. On that basis, the group has built 221 stories in training data to illustrate our cases.

3.3. Customized RASA Pipeline

In the RASA platform (Figure 6), incoming messages are processed by a sequence of components. These components are executed one after another in a so-called processing pipeline defined in config.yml:

pipeline:

- name: "Component A"
- name: "Component B"
- name: "Last Component"

For the assistant to return the desired response to the student, the user's utterance must go through a training process that includes many different components that are modelled as a pipeline. A pipeline is made up of components that are all the needed models for specific NLP operations such as pre-processing natural text, selecting features, entity Extractor, Intent Classifier, and persistence (Figure 6). They are executed consequently to process message input. RASA supports many pre-configured pipelines for the training process. Because of the specific features of the Vietnamese language, we have created customized pipelines, finetuned them, and done some experiments on the Vietnamese language dataset to find a proper model with high accuracy.

Nguyen, T. et al. has pointed out that the RASA pipeline can be customized to achieve higher effectiveness (Thi et al., 2021). In this paper, we did several experiments on eight pipelines, showed the best pipeline on our FIBA2020 dataset, and analysed each pipeline's impacts on the result.

Tokenizers: Tokenizer is one of the significant components in the RASA pipeline, it is used for text segmentation. For example, sentence "I want to know about offset Loan (Tôi muốn biết về vay bù đắp tài chính)" will be segmented into ["I" ("Tôi"), "want to" ("muốn"), "know about" ("hỏi về"), "loan" ("vay"), "offset" "bù đắp tài chính"]. This is an extremely necessary step before text feature extraction, this means a tokenizer will have a strong impact on the learning of the model. However, based on our observations, the RASA platform doesn't support a specific tokenizer for Vietnamese,

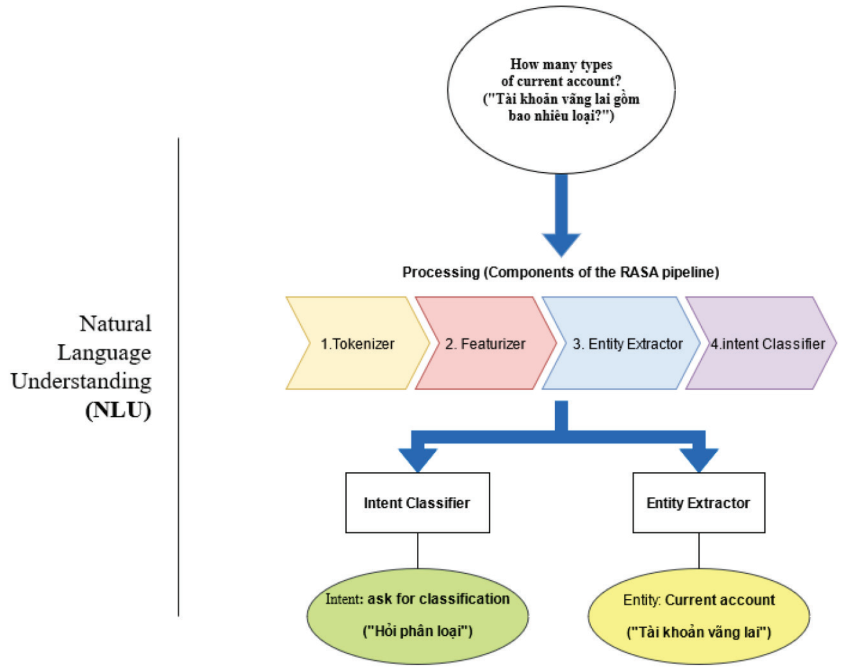

Figure 6: Structural Outline of the Pipeline

so we applied 3 tokenizers for Vietnamese: PyVi (0.1 Trung Tran 2020); Underthesea (1.3.1); VnCoreNLP (1.1.1 Dat Nguyen 2020.

The reason that we used these three tokenizers for text segmentation is that these are built especially for Vietnamese so that one sentence can be segmented based on the meaning of each word included, these are more suitable for the Vietnamese dataset.

In an attempt to find the best solution for our Virtual Assistant, we did experiments on these three tokenizers and the default Whitespace tokenizer of Rasa, the results are presented in Section 4.

Pretrained Language Model: This is a module that represents a sentence with a feature vector. All sentences are passed into a Featurizer that supports returning a set of feature vectors before doing tasks such as intent classification, entity recognition, and response selection. HFTransformersNLP is a utility component supported by RASA which relies on HuggingFace's Transformers library for the core implementation of the selected language model used as a featurizer. According to the RASA team, these language models are strict as a featurizer which means that their weights are not fine-tuned along with the training of downstream NLU components like DIETClassifier. In this paper, we used the bert-base-multilingual-uncased pre-trained language model as a featurizer because it is trained on 124 uncased languages including Vietnamese.

3.4. Handle Out of Scope Question

Our solution to handling out-of-scope questions is setting a threshold p. Suppose with any question q, the set of confidence scores mapping with entities is C_q, we propose an equation (1) that determines a valid question.

$$\text{valid}(q) = \begin{cases} 1, & \max C_q \geq p \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

In our research, we set .

4. Model Evaluation

To evaluate the effectiveness of the RASA model, we assess both models RASA NLU and RASA Core, specifically in the following sections.

4.1. RASA NLU

As mentioned in Section 3, the Rasa NLU model has the function of classifying the intent of the question and extracting terms. Therefore, we used Precision, Recall, and F-1 score as metrics. All metrics are calculated on single intent or entity and are averaged after. These will be described clearly in equations (2), (3), (4):

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

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

$$\text{F1} = 2 \times \frac{\text{Precesion} \times \text{Recall}}{\text{Precesion} + \text{Recall}} \quad (4)$$

Where TP is True Positive, intents or entities in question are predicted correctly; FP is False Positive, intents or entities in question are confused with other intent/entity; TN is True Negative, intents or entities in other questions are not confused with the considered question; FN is False Negative, intents or entities in other questions are confused with the considered question.

4.2. RASA Core

Because of the function of returning the answer to the user, we will create four specific test sets to observe the effectiveness of the Rasa Core model. In detail, we generated four test sets from the original dataset called A, B, C, and D by the rule that removes words from question samples. Percentage of removed words are respectively 0%, 20%, 40%, 60%. This attempt can show the effectiveness of the Rasa Core model in perfect condition and bad condition. We simply evaluate the RASA Core model by accuracy metric, the ratio of correct answers to the total. (Equation 5).

$$\text{Accuracy} = \frac{\text{Number of correct answers}}{\text{Total answers}} \quad (5)$$

4.3. Evaluation

In this section, we will report the result of our experiments to show the effectiveness of the RASA model (Tables 2, 3, & 4).

After experiments, we observed that in the process of intent and entity classification, all pipelines showed high results and the approximate performance when the difference is only 0.01 to 0.02%. (Table 2, Table 3). Vigorous differences are only shown when evaluating Rasa Core (Table 4). As mentioned in Section 4.2 above, we created four test sets under non-ideal conditions by reducing the percentages of words. The accuracy will generally decrease in proportion to the percentage of removed words at all pipelines. Pretrained language model m-Bert shows the best accuracy on Test set A (0% removed words) when using Underthesea as the tokenizer, which achieved 86.48%, higher than the default featurizer (85.35%). About tokenizers, Whitespace and Underthesea show higher results than the others. Although Underthesea + mBert achieved high accuracy on Test set A, it does not seem to give good results on non-ideal cases (Test sets B, C, D); whitespace does this better, according to Table 4. This can be explained that when using Whitespace, the sentence will be segmented by space, which means each word in the sentence will be featurized separately, leading to the model covering more situations. Because we will apply this research in real life by developing a virtual assistant application, the combination of Whitespace and m-Bert will be selected.

Table 2: Evaluation of Intent Classification (%)

Tokenizer \ Featurizer		Default	m-bert
Whitespace	Precision	88.76	88.77
	Recall	88.88	88.89
	F1	88.82	88.84
PiVy	Precision	88.76	88.77
	Recall	88.88	88.88
	F1	88.82	88.83
Underthesea	Precision	88.77	88.76
	Recall	88.88	88.88
	F1	88.83	88.82
VnCoreNLP	Precision	88.76	88.76
	Recall	88.88	88.88
	F1	88.82	88.82

Table 3: Evaluation of Intent Classification (%)

Tokenizer \ **Featurizer**		**Default**	**m-bert**
Whitespace	Precision	98.07	98.09
	Recall	98.81	98.82
	F1	98.30	98.32
PiVy	Precision	98.06	98.06
	Recall	98.80	98.82
	F1	98.30	98.30
Underthesea	Precision	98.06	98.07
	Recall	98.81	98.81
	F1	98.30	98.30
VnCoreNLP	Precision	98.06	98.06
	Recall	98.80	98.78
	F1	98.30	98.29

Table 4: Accuracy of RASA Core Model (%) ((%) (**Red**, **Blue**, **Green**, **Purple** Indicated the Best of Test Set A, Test Set B, Test Set C, Test Set D Respectively)

Tokenizer \ **Featurizer**		**Default**	***m*-bert**
Whitespace	Test set A	85.35	85.37
	Test set B	82.81	**84.22**
	Test set C	81.95	**81.99**
	Test set D	68.17	65.00
PiVy	Test set A	78.03	78.02
	Test set B	76.90	74.08
	Test set C	75.49	73.80
	Test set D	**70.42**	57.46
VnCoreNLP	Test set A	78.02	78.02
	Test set B	75.34	76.69
	Test set C	72.08	72.64
	Test set D	60.14	61.23
Underthesea	Test set A	81.40	**86.48**
	Test set B	79.72	74.65
	Test set C	78.02	70.42
	Test set D	70.14	70.00

5. Developing Virtual Assistant Application

5.1. Deploy AI Model

After training the model, we proceeded to deploy the model as a REST API for building Android apps called FIBA Virtual Assistant. Many cloud server services are used for deploying processes, including AWS, Heroku, etc. For the purpose of building a demo for evaluating the ability to apply this study in real life, we chose the Heroku cloud server to deploy the best model we achieved.

5.2. Voice Processing

Because the RASA model takes a text question as input and returns a text answer, we have to do voice processing in our application. It includes two components: speech-to-text (STT) and text-to-speech (TTS); we will describe more clearly the following:

Speech to text is the process of converting a user's natural speech to text. To apply this in FIBA, we employ a SpeechRecognizer library that supports the Vietnamese language.

Text to speech is the process of converting answer text to speech. Many services are supporting it, but we used API Text to Speech provided by Google Cloud.

6. Conclusion

Our contribution to this paper is creating the FIBA2020 dataset, which includes terms and their explanation related to Finance and Banking in the Vietnamese language. Using our dataset, we built a Rasa model and attempted to improve it by customizing Rasa pipelines. In detail, we added three Vietnamese tokenizers and a pre-trained language model m-Bert, which is trained in 124 languages, including Vietnamese. We did 8 experiments, analyzed the result, and selected a model that used Whitespace Tokenizer and m-Bert to build a virtual assistant application on Android. The best accuracy we achieved is 86.48 %, and 70.04% in the ideal condition and worst condition, respectively. Based on the research results, we create a virtual assistant that can provide valuable recommendations to users in keeping with the searching and understanding of Banking and Finance general terms and specialized fields. It is very useful for students who study major in finance and banking as well as any people who are a novice in this sector. We are planning to launch it freely for students to access and build it as an application for smart classroom environment

However, our research has only focused on collecting and constructing datasets about Banking and Finance in general terms in Vietnamese. For more specific applications in each bank and enterprise, it is necessary to cooperate with the bank and enterprise to build an extensive dataset and update the newest terms and services they provide. In this study, assessing the level of approval and performance of the virtual assistant is not discussed, so it has not yet evaluated the practical applicability of the system. Building virtual assistants friendly and making it easier for other developers who do not need strong technical knowledge to apply in different fields such as health care, social welfare, education, and insurance is our research's future work.

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