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An Ontology-Based Question Answering System for University Admissions Advising

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Abstract: Question-Answer systems are now very popular and crucial to support human in automatically responding frequent questions in many fields. However, these systems depend on learning methods and training data. Therefore, it is necessary to prepare such a good dataset, but it is not an easy job. An ontology-based domain knowledge base is able to help to reason semantic information and make effective answers given user questions. This study proposes a novel chatbot model involving ontology to generate efficient responses automatically. A case study of admissions advising at the International University–VNU HCMC is taken into account in the proposed chatbot. A domain ontology is designed and built based on the domain knowledge of university admissions using Protégé. The Web user interface of the proposed chatbot system is developed as a prototype using NetBeans. It includes a search engine reasoning the ontology and generating answers to users' questions. Two experiments are carried out to test how the system reacts to different questions. The first experiment examines questions made from some templates, and the second one examines normal questions taken from frequent questions. Experimental results have shown that the ontology-based chatbot can release meaningful and long answers. The results are analysed to prove the proposed chatbot is usable and promising.

Keywords: Ontology; chatbots; answer-question systems; domain knowledge base; admissions advising

1 Introduction

As known, social networks are very popular nowadays and data analysis jobs help much in enhancing marketing strategies [1,2]. In social network sites, automatic supports, e.g., interacting with customers or web users, are crucial and attracting more users. A chatbot is now not strange in social networks, it becomes a friend, a consultant, or an assistant answering problems in some specific fields. In other words, a chatbot is able to understand and communicate with people and perform specific tasks. In natural language processing, it is used in applications that offer automatic verbal interactions. For example, a chatbot [3] has been developed alongside an E-learning platform in order to answer questions relevant to course materials, and chitchat as well. This makes online classes more interesting, especially, nowadays, online courses/classes are very popular. Depending on different architectures, these smart entities can communicate in many ways, whether to provide instructions, answers to questions, or to entertain users.

According to [4], there are many types of chatbots, classified based on: the knowledge domain, the service provided, the goals, the input processing and response generation method, the human-aid, and the build method. Basing on the knowledge domain, a retrieval-based model can be used, in that, a domain ontology is able to be built for information retrieval since it is a powerful expression tool [5,6]. Some ontology-based chatbots have been built to support answering automatically questions in specific domains, e.g., shopping in e-commerce [7], drug information consultant in medical [8], and educational and professional orientation [9]. Theses chatbots help human much nowadays because of an overload of consultative jobs in many fields or being impracticable to access to a person in charge. In another way, the input processing and response generation methods take into account the generative models which are more human-like. In generative models, some usable methods are machine learning or deep learning, e.g., Recurrent neural network (RNN) [10], Long short-term memory (LSTM) [11], Qanats [12], Sequence-to-sequence (Seq2seq) [13], Hierarchical Recurrent Encoder–decoder (HRED) [14], SPHRED [15], XLNet [16], etc. Using generative models brings some positive achievements, for example, by improving the QANet model to be combined with the retrieval-based model, a hybrid model K-12 e-learning assistant chatbot [3] was built and better than a teacher counselling service. However, the generative model-based chatbots often return short answers and need to train a large dataset. This makes building a chatbot more difficult if training data is not enough at the beginning.

1.1 Problem Statement

As we can see, the generative model is more interesting and effective for open domain chatbots, but it requires a large amount of well-prepared question-answer data for training the model. In many cases, this kind of data is not available at the beginning, so domain data is necessary to be collected to construct a knowledge base for a chatbot model, e.g., an ontology-based chatbot. Therefore, this study concerns building a domain knowledge base for a closed domain chatbot, focusing on the case study of university admissions advising. Particularly, it proposes a chatbot model for admissions advising at the International University (IU) belonging to the Vietnam National University–Hochiminh City (VNU-HCMC). A domain ontology is constructed given the information of university admissions at the university admissions website of IU. Based on the domain ontology, we can make a response reasoner of the specified domain.

1.2 Objectives

The study focuses on building an ontology-based chatbot which can help response frequent questions of university admissions automatically. The source of the ontology is from the admissions information of the International University (VNU-HCMC). Moreover, the proposed chatbot model is developed dynamically so that it can be extended by adding more data into the ontology to enrich the knowledge base. In this manner, the performance of the chatbot will be improved significantly.

The following sections will present related work (Section 2), research methodology (Section 3), experimental results with evaluation (Section 4) and conclusions (Section 5).

2 Related Work

As mentioned in the Introduction Section, this section presents related techniques and the concerning chatbot models which are based on ontology.

2.1 Ontology

According to Antoniou et al. [5], Ontology is a fundamental Semantic Web technology, it defines the formal semantics of the terms used for describing data, and the relations between these terms. It is efficient to express the semantic information of knowledge bases in different domains. That is why ontology is used to represent semantic knowledge bases for automatic inference or information retrieval in a specific domain. OWL (Web ontology language, http://www.w3.org/TR/owl-features/) is a main Web ontology language which satisfies the requirements of building a domain ontology, including a well-defined syntax, a well-defined semantics, efficient reasoning support, sufficient expressive power, and convenience. Therefore, an ontology can be used efficiently in a search engine of a chatbot.

2.2 Existing Ontology-based Chatbot Models

Ontology is a solution for understanding what utterances are about. That is the reason the ontology-based chatbot models were born. It is also driven domain knowledge so that it can create domain-driven conversations. Ontology is used to store the domain knowledge and navigate through it [17]. Therefore, this ontology-based knowledge base can provide information for answer generation in dialogs. The benefit of the ontology-based approach is to "keep conversation memory explicitly throughout the conversation". Because of the benefits of ontology, it has been adopted into closed domain chatbots and provides very specific answers given questions.

There are many kinds of question answering systems (QAS) (known as chatbots) emerging [18]. Most QAS have three main subtasks: questions analysis, search of documents/database containing the answers, and extraction of answers. Their goal is to response users' questions in natural language using their own terminology. The databases used in QAS are able to be structured databases, unstructured free text, or semantic knowledge bases. In that, the ontology-based QAS use ontology to build semantic knowledge bases which can infer information semantically within the ontology-based domain knowledge in order to response user queries. The benefits of these systems are they do not require training data and the user does not need to learn the vocabulary or the structure of the ontology. Therefore, the user can ask questions in a natural way in a specific domain.

The ontology-based QAS have been developed in many fields, for example, an e-learning bot built by Clarizia et al. [19] allows dealing with students' questions of subjects in lectures. Its knowledge base is an ontology containing "users" and "learning objects" which is a collection of content items, practice items, and assessment items. It plays a role as an education support system for students. Experimental results show that the chatbot can furnish about 71% correct suggestions. On the other hand, ontology could help recommend interesting courses to the prospective students, for instance, in a personalized course recommendation system proposed by [20]. It combined collaborative-based filtering with content-based filtering by using ontology to map the course profiles and student profiles with job profiles. In that way, the system could produce recommendation results better than traditional collaborative-filtering methods considering only keyword similarity. In another application domain, such as medical, an ontology of drugs and their relevant information has been constructed for MediBot [8], which is Portuguese Speakers Drug. The knowledge base of the ontology is a combination of many data sources and expert knowledge. The bot is responsible for converting natural language to SPARQL query, processing the query, and sending a response to users.

Recently, an educational program counseling system [21] has been proposed using ontology. It has achieved higher performance than the Apache Lucene system using a keyword-based text search engine. University admissions counseling or advising is very crucial, nowadays, since many future students want to know how to choose a suitable major out of many majors at universities. Especially, admissions advising at Vietnamese universities is very time and labor-consuming. Advisors need to update admissions information regularly so that they can help future students to decide on the most suitable academic program. However, there has not been a QAS yet to support these jobs at Vietnam universities. Therefore, developing a QA system of advising university admissions is very significant at Vietnamese universities.

As known, the ontology-based model is limited to a specific knowledge domain, but able to be built from the real-world data sources with domain experts' support and achieve significant outcomes. Therefore, this study considers using ontology to build a QA system of admissions advising at the International University as a case study.

3 Research Methodology

The proposed chatbot framework, namely IUOntoBase Chatbot, consists of three steps: data preparation, ontology construction and reasoning (Fig. 1). The ontology construction is the main process step, an ontology of university admissions information is constructed for understanding input queries in natural language and reasoning relevant things in order to generate most suitable answers. The following subsections will give more details of the proposed framework.

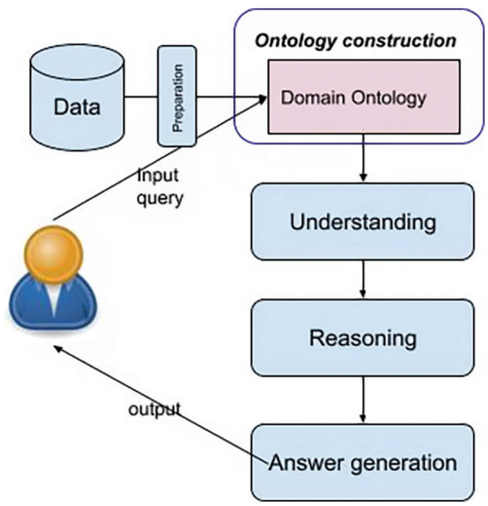

Figure 1: The proposed chatbot framework

3.1 Ontology Construction

As known, ontology is an expressive powerful expressive tool in semantic knowledge representation. Based on that, this study proposes building an ontology of a knowledge domain of university admissions as a case study. Particularly, the raw data is collected from the admissions website of the International University (https://tuyensinh.hcmiu.edu.vn/). It is cleaned to remove meaningless words, then analysed to construct ontology concepts and relationships among concepts in the preparation step before modelling a domain ontology.

To model the domain ontology, domain entities are first identified, and then data and object properties are added. Fig. 2 depicts the ontology model of the International University (IU), including Major, Unit, Employee, etc. This study focuses on the enrollment and academic advising, so the information on curricula is considered along with subjects.

The following is the definition of the domain ontology model, namely IUOnto.

Definition 1. (Domain ontology model of the International University) A domain ontology structure of IU is defined as a four-tuple: $O := <\mathbb{C}, \mathbb{R}_{sub}, \mathbb{P}, \mathbb{A}>$, where $\mathbb{C}$ represents classes and entities in the IU domain, $\mathbb{R}_{\mathbb{SUB}}$ describes SubClass-Of relationships, $\mathbb{P}$ represents properties defined in the ontology, and A represents axioms, such as, an instantiation axiom assigning an instance to a class, an assertion axiom assigning two instances by means of a property, a domain axiom for a property and a class, and a range axiom for a property value and an instance. In detail, $\mathbb{C}$ and $\mathbb{P}$ are further divided into sets:

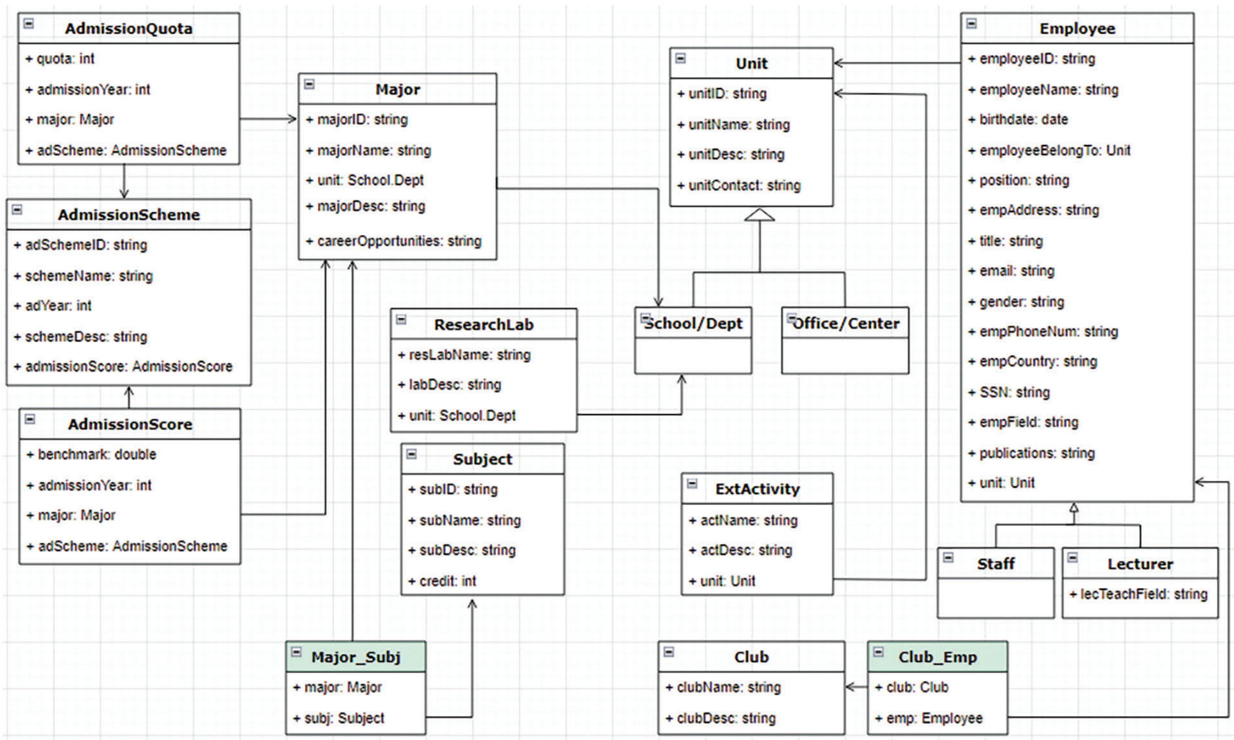

Figure 2: Ontology model of the International University

$\mathbb{C} = C \cup I$ comprises a set of domain classes (concepts) C, and a set of specific domain instances (of the concepts) I. The identified domain entities of university admissions are mainly majors, subjects, admissions schemes, admission quotas and scores of majors, and relevant ones, e.g., units, employees, research labs, clubs, and other activities. As shown in Fig. 2, there are 16 classes categorised into three groups: C_1 including classes without parents, e.g., School/Dept, Employee, Major, Subject; C_2 including association classes, e.g., Major_Subj and Club_Emp are association classes between the two connected classes Major–Subject and Club–Employee, respectively; C_3 including classes having sub-classes, e.g., Unit. $\mathbb{R}_{\mathbb{SUB}}$ comprises a set of the SubClass-Of relationships: School/Dept and Office/Center are the subclasses of Unit class; Staff and Lecturer are the subclasses of the Employee class.

$\mathbb{P} = R \cup A$ comprises a set R of object properties in classes (C), and a set A of data properties. For each major, there are admission scores and quotas with respect to admission schemes. Each unit manages a number of majors and employees as well as academic activities. Particularly, in IUOnto, the Major and Unit object properties in the AdmissionQuota and Employee classes refer to the corresponding Major and Unit classes, respectively, as Fig. 2. The adScheme is an AdmissionScheme object property of the AdmissionQuota and AdmissionScore classes. The object properties often have their own inverses to facilitate querying information from both sides. Each class has some data properties, e.g., Lecturer has the lecTeachField attribute with *string* type and the attributes inherited from the Employee class.

Based on IUOnto, the IU ontology is built using Protégé tool, as shown in Fig. 3.

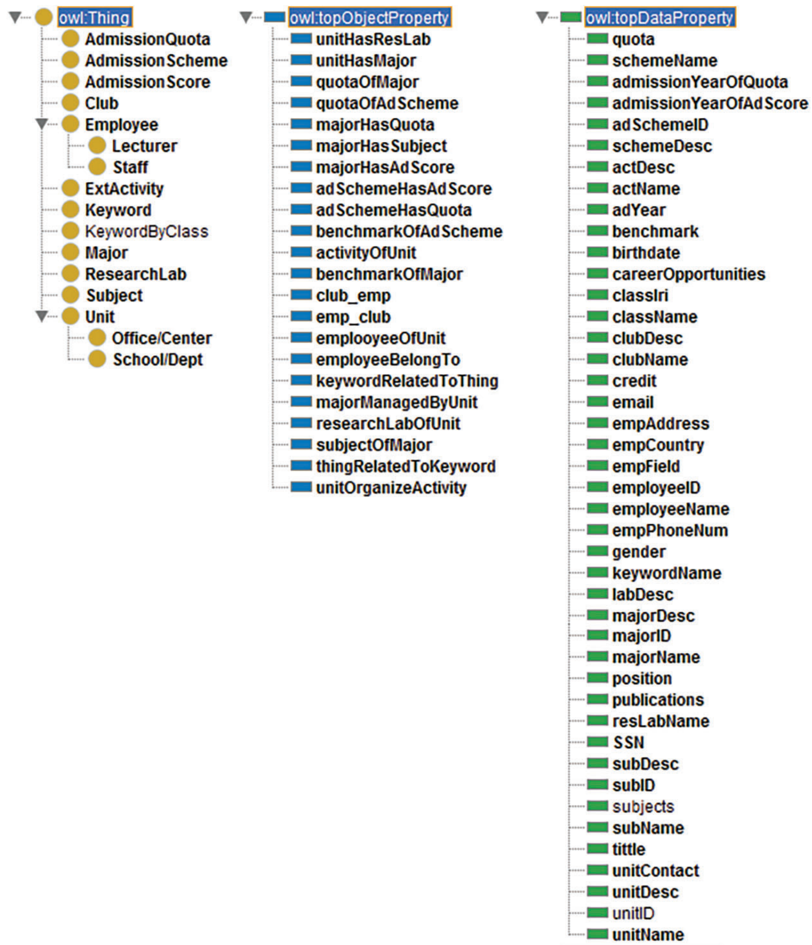

Figure 3: The admissions ontology of the International University

To quickly seek instances in the IU ontology, some keywords are added into each instance. Therefore, a multivalued keywordName property is added into the Thing class. Moreover, some keywords are commonly used in many instances, hence we have the Keyword class. Besides, keywords categorized in groups are presented by the KeywordByClass class.

From this ontology, we can construct a full ontology-based knowledge base by populating the data collected from the IU into the built ontology. For instances, Fig. 4 shows some instances of AdmissionScore and Subject classes. For classes that do not have a Name property, e.g., AdmissionScore, their IDs must be meaningful names.

Fig. 5 shows some keywords added into the instances of Major class. It is noted that the data values in the ontology are in Vietnamese, since the IU admissions data is in Vietnamese. In Fig. 5, the "Quản trị Kinh Doanh" (*Business Administration*) Major has some keywords "kinh doanh" (*business*), "quản trị" (*administration*), and "quản trị kinh doanh" (*business administration*).

Tab. 1 shows the metrics of IUOnto after populating the IU admissions data. Totally, there are 17 classes, 23 object properties, 44 data properties, 12552 axioms, and 1457 individuals created.

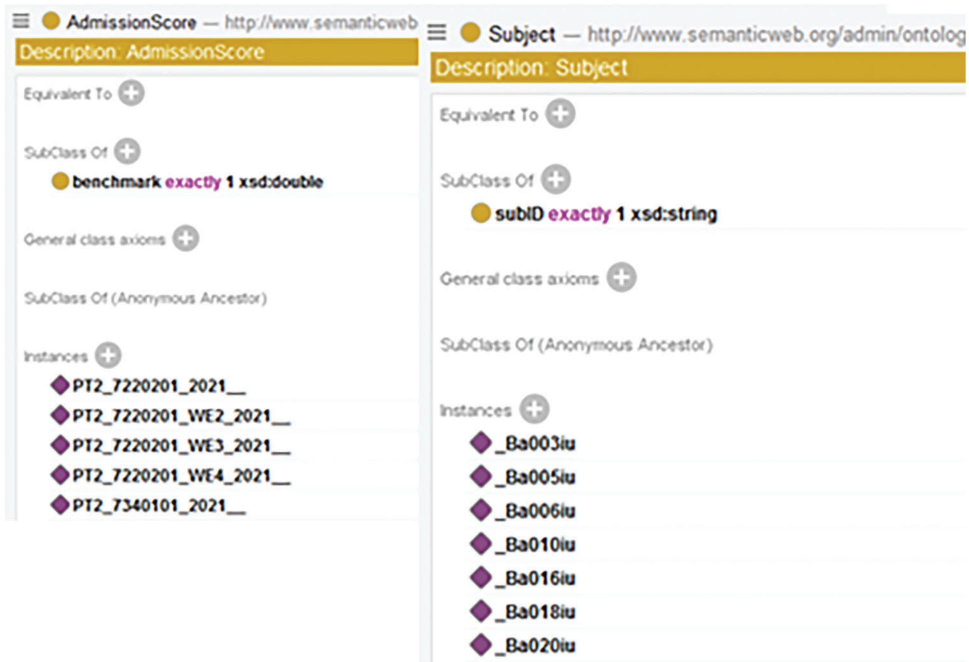

Figure 4: The partial instances of AdmissionScore and subject classes

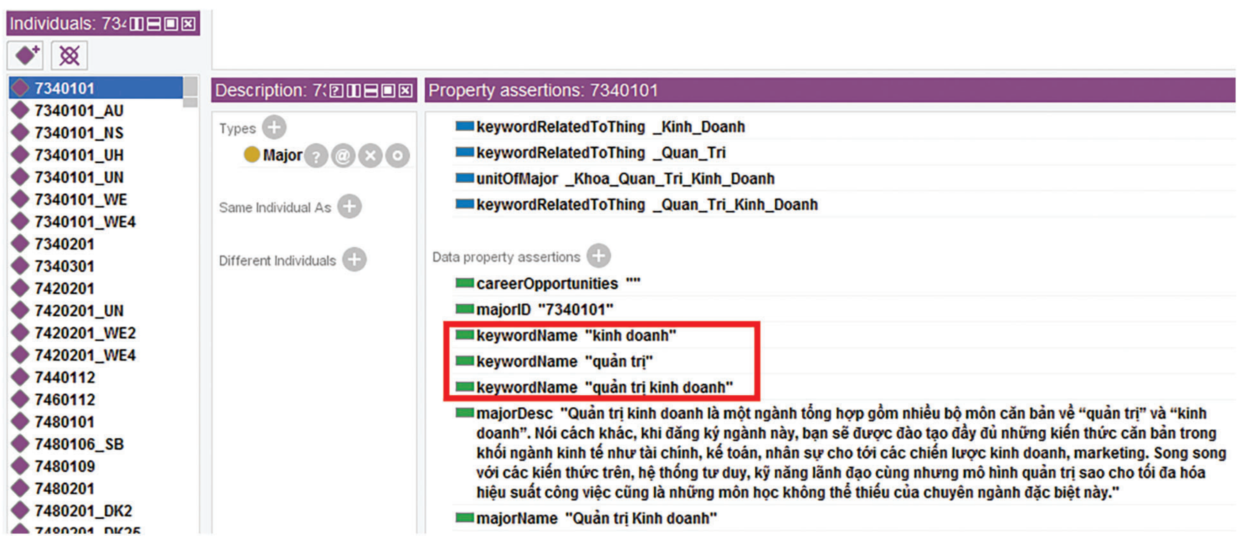

Figure 5: The partial instances of the major class and relevant keywords

3.2 Reasoning and Answer Generation

Based on the above ontology, the machine can reason information of instances so that it can understand the meaning of a keyword if that one is found in the list of keywords or instance names/IDs. By ontology reasoning, the IUOntoBase chatbot can generate answers to users' questions. Algorithm 1 presents how to generate answers given a question. Keywords from questions are extracted by using the VNcoreNLP library [22]. The output answer is the information or description of the returned instance.

Table 1: The metrics of IUOnto

Metrics		Object property axioms	
Axiom	12552	SubObjectPropertyOf	22
Logical axiom count	10954	InverseObjectProperties	11
Declaration axioms count	1538	DisjointObjectProperties	31
Class count	17	FunctionalObjectProperty	5
Object property count	23	InverseFunctionalObjectProperty	7
Data property count	44	ObjectPropertyDomain	22
Individual count	1457	ObjectPropertyRange	22
Annotation property count	2	**Data property axioms**	
Class axioms		SubDataPropertyOf	39
SubClassOf	21	DisjointDataProperties	1
DisjointClasses	48	FunctionalDataProperty	20
		DataPropertyDomain	39
		DataPropertyRange	39
		Individual axioms	
		ClassAssertion	1460
		ObjectPropertyAssertion	3168
		DataPropertyAssertion	5999
		Annotation axioms	
		AnnotationAssertion	60

Algorithm 1: Ontology-based answer generation

```
Input: A question from a user
Output: A set of relevant answers
Process:
Function ask (question)
{
Extract keywords in the given question by the VNCoreNLP library
List<string> userKeywords = extractKeywords(question);
Let relavantThings = {}; // a set of instances found by keywords (may be duplicated)
For each userKeyword in the user's question
    For each owlKeyword in the ontology
        If (userKeyword matches owlKeyword)
        {
            Get all instances {I} by owlKeyword;
```

(Continued)

Algorithm 1 (continued)

```
            relavantThings.add(I);
        }
    Group relevantThings by IRI to count the number of matches of each instance
    Sort the grouping result in descending order of the matching numbers;
    Return relevantThings with the most matches;
}
```

Algorithm 1 has shown that relevant things are returned if any userKeywords match owlKeywords. That means there is no response if not matched. There are 747 keywords which are typical and various in the domain of university admissions are added to the IUOnto. Therefore, the chatbot can response most questions related to the university admissions.

3.3 Prototyping

By the IUOntoBase chatbot framework, a QA system is implemented in Java. NetBeans is used to design and develop the Web interface of the chatbot using Spring Boot, the IU ontology population and reasoner. Fig. 6 shows the QA system framework. By using Protégé, the IU ontology is built and saved as an Ontology.owl file; Java classes of the IUOnto model are generated from the IUOnto model. To program the aforementioned IU ontology population and reasoner, Protege-OWL API is imported into the system so that new terms or admissions information can be updated, and queries can be automatically responses.

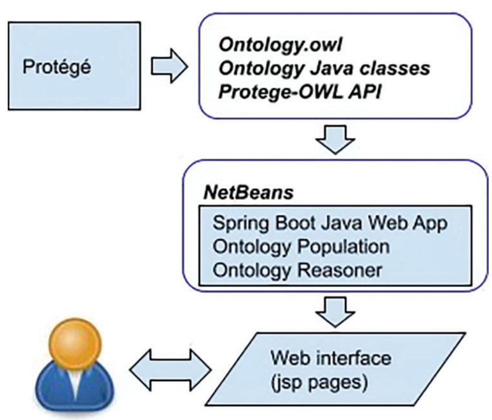

Figure 6: Integrated framework of the QA system

Since the IUOntoBase chatbot is used for admissions advising at IU, the used dataset is collected the IU admissions website. Given the IU data, the IU ontology is constructed. The programmes of 21 majors at IU along with their subjects are added into the ontology. The admission score and quota of each major are also modified. There are six admissions schemes, 12 schools/departments and 17 offices/centers appended into the ontology.

Some web interface pages of the chatbot are depicted in Figs. 7 and 8. User queries are input into the chat box, and responses are generated by the IUOntoBase chatbot. For example, two sequential questions are answered correctly in Figs. 7 and 8.

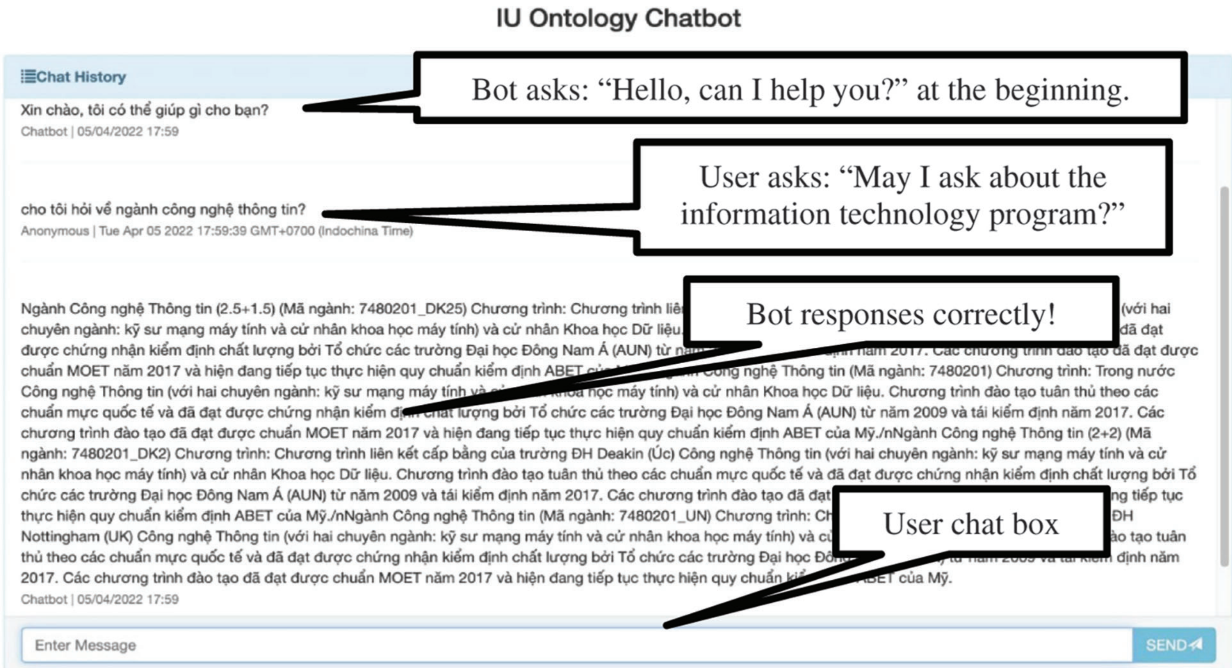

Figure 7: Web interface page of the chatbot

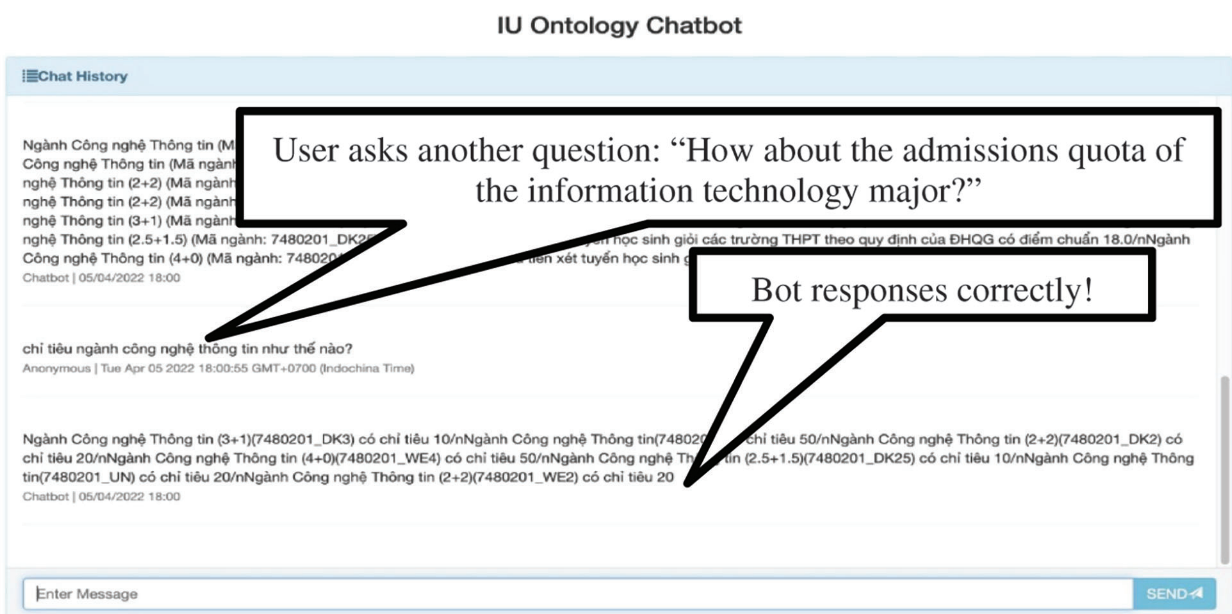

Figure 8: Web interface page of the chatbot (cont.)

The following presents experiments run on a MacBook Pro with 6-Core Intel Core i7 processor, 2.2 GHz and 16 GB of RAM.

4 Experimental Results and Evaluation

In this study, two experiments are carried out to validate the proposed chatbot model. Testing questions at different levels of difficulty are made for the experiments. According to [18], the evaluation criteria of responses are able to be the rates of satisfactory, correctness and usefulness represented by scores from 1 to 5. These metrics can be defined as follows by the Cambridge Dictionary:

Satisfactory: good or good enough for a particular need or purpose.

Correctness: the quality of being in agreement with the true facts or with what is generally accepted.

Usefulness: effective; helping you to do or achieve something.

The responses from the chatbot are remarked by domain experts who are in charge of developing the admissions advising website at the International University. The highest score (5) means the response is completely satisfied, correct or useful. The medium score (3) means somehow the response may give some acceptable, meaningful, useful information. The lowest score (0) means the response is completely not relevant or useful.

4.1 Experiment 1

In the first experiment, 78 questions covering nine topics in the IUOnto are made for evaluating the chatbot model. The templates of testing questions are: “May I ask about <major name>|<unit name>?”, “What is the admissions quota of <major name>?”, “What is the admissions score of <major name>?”. In that, 11 questions are medium, i.e., relatively related to the application domain, and the rest questions are directly related to the domain. Fig. 9 shows the evaluations of answers responded by the model.

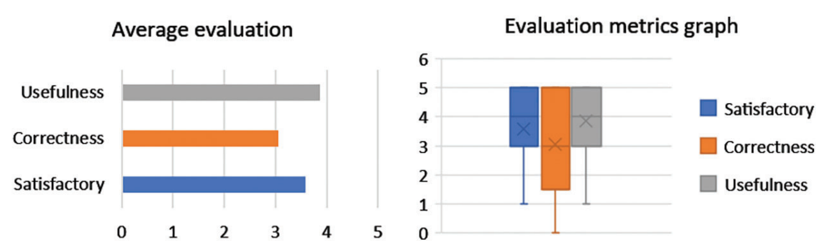

Figure 9: Evaluation metrics of the proposed model in experiment 1

As seen, the distributions of satisfactory, correctness and usefulness scores are left-skewed, and all means are greater than 3. It shows that most responses are satisfied, correct and useful. The scores of satisfactory and usefulness are quite high, greater than 3.5. Furthermore, the proportion of answers having scores equal or greater than 3 is considered as the acceptable evaluation rate. Fig. 10 shows the acceptable rates of satisfactory, correctness and usefulness are higher than 74%. The success rates (scores >= 4) of satisfactory and usefulness are higher than 70%.

Fig. 11 shows evaluation metrics for 11 medium questions, average evaluation scores are greater than 2.5, and the distributions of scores are also left-skewed. In that, the scores of satisfactory and usefulness are higher than 3. These results have proved that the performance of the proposed model is acceptable.

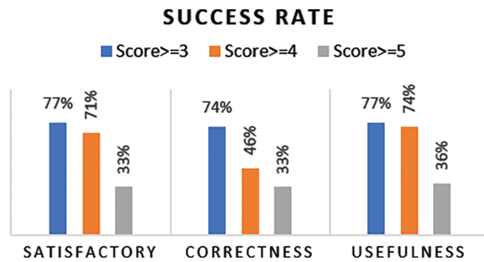

Figure 10: Successful evaluation rate of the proposed model in experiment 1

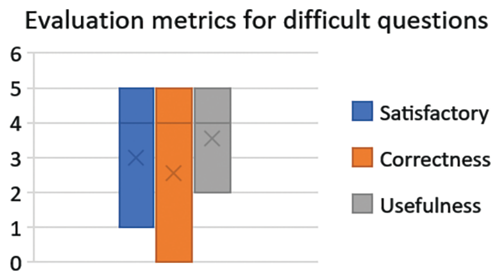

Figure 11: Evaluation metrics for difficult question in experiment 1

4.2 Experiment 2

For further validating the proposed models, a set of 16 questions related to the domain information in the learning sources are suggested as listed in Tab. 2. These questions were collected by the domain experts in the web team developing the admissions advising website at IU in 2021. These questions are frequent and typical when advising admissions at IU. These questions are classified at three level of difficulty: (1) Easy (directly related to the application domain), (2) Medium (relatively related to the application domain), (3) Difficult (not relevant much to the domain).

Table 2: Experimental questions at different difficulty levels

No.	Questions in Vietnamese (English)	Level
1	Các phương thức tuyển sinh năm 2021? *(Admissions schemes in 2021)*	1
2	Giới thiệu trung tâm dịch vụ công nghệ thông tin? *(Introduction to the center for information services)*	1
3	Làm thế nào lấy lại tài khoản email? *(How to get my email account back?)*	2
4	Cho tôi hỏi học phí trung bình là bao nhiêu? *(What is the average tuition fee?)*	3
5	Khoa quản trị kinh doanh đào tạo những ngành nào? *(What programs does the school of business administration offer?)*	1
6	Giới thiệu ngành quản trị kinh doanh? *(Introduction to business administration program)*	1
7	Chỉ tiêu tuyển sinh ngành quản trị kinh doanh. *(The admissions quota of the business administration major)*	1

(Continued)

Table 2 (continued)

No.	Questions in Vietnamese (English)	Level
8	Điểm chuẩn ngành quản trị kinh doanh. *(Admissions score of the business administration major.)*	1
9	Chỉ tiêu ngành công nghệ thông tin? *(The admissions quota of the information technology major)*	1
10	Điểm chuẩn ngành công nghệ thông tin năm 2021? *(Admissions score of the information technology major in 2021)*	1
11	Ngành ngôn ngữ anh ra trường làm gì? *(After graduating from an English linguistics program, what will a graduate be able to do?)*	2
12	Các ngành liên kết của khoa công nghệ thông tin? *(What are twinning programs at the school of computer science and engineering?)*	1
13	Hãy giới thiệu về thư viện của trường? *(Introduction to the library at the university)*	3
14	Phòng công tác sinh viên có chức năng gì? *(What are the functions of students services office)*	1
15	Ngành công nghệ thông tin có những chuyên ngành nào? *(What are the majors in the information technology program?)*	2
16	Trường có những hoạt động ngoại khóa nào dành cho sinh viên? *(What extracurricular activities does the university have for students?)*	3

Tab. 3 presents the evaluation scores of responses to the above questions in Experiment 2.

Table 3: The evaluations of the proposed chatbot in experiment 2

Q.No	Satisfactory	Correctness	Usefulness
1	5	5	5
2	5	5	5
3	4	3	5
4	0	0	0
5	3	2	4
6	4	4	5
7	5	5	5
8	5	5	5
9	5	5	5
10	5	5	5
11	3	3	4
12	5	5	5
13	0	0	0

(Continued)

Table 3 (continued)

Q.No	Satisfactory	Correctness	Usefulness
14	5	5	5
15	5	4	5
16	0	0	2
Avg	*3.6875*	*3.5*	*4.0625*

As shown in Tab. 3, the ontology-based chatbot model can provide most of the responses satisfied high, except for difficult questions (4, 13, 16). Moreover, the responses are meaningful and useful. Question 4 is challenging, Question 13 is out of domain, so the bot could not provide any answer. However, Question 16 has some relevant keywords, e.g., "extracurricular activities", hence the bot can reason and respond some useful information. This is reasonable in practice.

4.3 Evaluation and Discussion

In the context of the ontology model, the IUOnto contains essential concepts for university admissions, more variety than the ontology of educational program counseling built in [21] which has only the concepts of City/Capital, Program, DeptProgram and Type. Moreover, this ontology can be extended with more data so that more responses can be generated. Tab. 4 presents the features of the developed QA system compared with the existing educational program counseling system [21]. The developed system has similar features as the existing system, and is richer with more classes, object properties and data properties. Therefore, its inference ability is better, and its answers will be more information.

Table 4: Features of the educational program counseling system and the developed system

Feature	Educational program counseling system	The developed QA system
NLP query support	Yes	Yes
Extensibility	Yes	Yes
Interoperability	Yes	Yes
Inference engine	Yes	Yes
Exception handling	Yes	Yes
Consistency check	Yes	Yes
Search nature	Semantic-based	Semantic-based
Visualization	Yes	Yes
Class count	9	17
Object property count	19	23
Data property count	2	44
Language	English	Vietnamese

5 Conclusions

The ontology-based chatbot model can achieve high performance in answering questions in the learned application domain. The experimental results have shown the proposed chatbot framework is promising and acceptable. It can provide meaningful and long answers, while existing chatbots could not give long answers. Especially, this chatbot is useful for counseling educational programs for future students at Vietnamese universities. In the future, the reasoning algorithm of the chatbot will be improved to generate more accurate answers. A synonym database might be used to extend the ability to understand different words in queries.

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Conflicts of Interest: The authors declare that they have no conflicts of interest to report regarding the present study.

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