Lead Engagement by Automated Real Estate Chatbot

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***Abstract*— Recently, *automated chatbot* has been increasingly applied in real estate industry. Even though chatbots cannot fully replace the traditional relation between agents and home buyers, they can help to engage potential clients (or *leads*) in meaningful conversations, which is highly useful for lead capture.**

In this paper, we present an intelligent chatbot for this purpose. Various machine learning techniques, including multi-task deep learning technique for intent identification and frequent itemsets for conversation elaboration, have been employed in our system. Our chatbot has been deployed by CEO K35 GROUP JSC with daily updated data of real estate information at Hanoi and Ho Chi Minh cities, Vietnam.

Keywords—real estate chatbot, deep learning, frequent itemsets, lead capture

I. Introduction

Automated chatbot has been witnessed recently as an emerging trend for customer cares in various domains. Many *virtual assistants* have been introduced by major technology corporations such as Apple's Siri, Microsoft's Cortana or Amazon's Echo. Such developments are resulted from the recent achievement in research in artificial intelligence, especially machine learning.

In literature research, an intelligent chatbot is considered as a system consisting of various components [1], including *Natural Language Understanding* (NLU), *Dialog Manager* (DM) and *Natural Language Generation* (NLG). In [2,3], a complete chatbot system is introduced using an encoder-decoder neural network system for training data from past conversation. In [4], a system where NLU and DM are concurrently trained in a BiLSTM system.

Individual components of a chatbot system are also addressed in various works. In [5], *Hidden Markov Models* (HMM) and *Conditional Random Field* (CRF) is used to handle the *slot tagging* problem, a subproblem of NLU. In [6,7], *Convolutional Neural Network* (CNN) is used to classify intent and domain of the conversed texts, which are also subproblems of NLU. The accuracy of NLU is also increased by using RNN [8]. In [9], machine learning techniques are used to manage states of DM.

In this paper, we focus on using automated chatbot in the real estate industry. Today, real estate *agents* spend most of their time trying to generate *leads* (or potential customers). It is done by remarkably large human efforts for gathering property and customer details, responding to consumers with quotes, get approval and paperwork signed. *Chatbots* are a potential solution to all these hassles. By automatizing customers' inquiries, chatbots can create a valuable database of potential prospect profiles and very useful for *lead capture* by means of automatic conversation. Even though chatbots cannot fully replace the traditional relation between agents and home buyers, they can help to engage potential clients (or leads) in meaningful conversations, in a real-time manner.

In this paper, we present a chatbot system for real estate domain, which provides the following features:

- *Intent identification* (i.e. we can know the detailed requirements for the clients), which is done by a multi-task deep learning system.
- *Elaborating leading questions*, which consult client to clarify their initial requests.

Our system has been deployed by the CEO K35 GROUP JSC with the real dataset of real estate domain in Hanoi and Ho Chi Minh cities, which are updated in daily manner.

II. Illustrated Use-Cases The Chatbot at the Glance

A. Intent Identification

Figure 1 presents a typical conversation of our chatbot when discussing with a client. When the client states that he

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is looking for a house in District 1, the system then answers by a recommended list of suitable real estate.

In order to do so, our chatbot is able to *classify the intents* of the clients, as illustrated in Figure 2. Table 1 presents all of intents in the real estate domain that our chatbot can successfully handle.

Fig. 1. Recommendation of real estates from the requests

Fig. 2. Intents classification

TABLE I. The list of real estate intents

Label	Description
City	The city where the real estate is located
District	The district where the real estate is located
Street	The street where the real estate is located
Ward	The ward where the real estate is located
Area	The area where the real estate is located
Floor	Number of floors
Room	Number of rooms
Legal	Legal information related to the real estate (e.g. certificate of home ownership)
Orientation	The direction which the real estate is facing
Position	Whether the real estate is on a street or a lane
Potential	Potential usage of the real estate (e.g. to open a shop, a company office)
Price	Price of the real estate
Project	The project of the real estate belongs to (e.g. Sunrise city)
Type	The type of the real estate (e.g. land, apartment, villa, house)
Surrounding places	Places near the real estate (e.g. school, hospital, restaurant)
Surrounding characteristics	The characteristics of surrounding area (e.g. secured, quiet, populous)
Surrounding names	Name of the places near the real estate (e.g. Bach Khoa, Binh Dan)
Transaction type	Type of the transaction (e.g. buy, for rent, to rent, for sale)
Normal	Any others information that does not belong to the labels above

B. Generation of Leading Questions

Our chatbot is also able to generate *leading questions* to consult the clients for better understanding their intents from the initial requests. As illustrated in Figure 3, when a user states that he wants to buy a house in District 1, our system asks the users to see whether he wants the house for *street views*, *business*, *renting*, *nearby market* or *office usage*, since they are frequent intents when one is looking for a house in District 1.

Fig. 3. Leading question for client consultation

III. Intent Identification using Multi-task Learning

In order to perform the intent identification task, we follow the approach described in [10], whose architecture is described in Figure 4. Our main component is a Bi-GRU architecture for feature extraction, upgraded by the dense connection mechanism. We also combine word embedding with a Char-CNN layer to produce embedded information at character level.

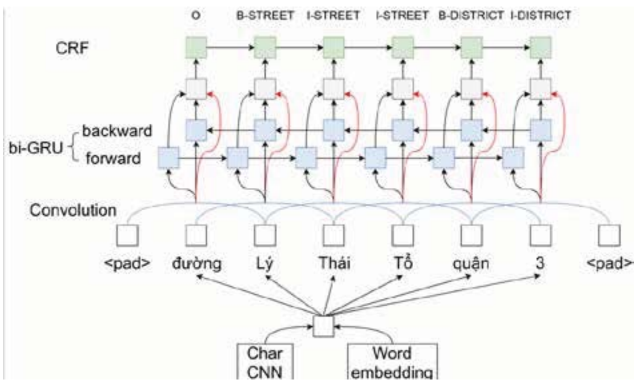

Fig. 4. Multi-task learning for sequense tagging

IV. Using Frequent Itemsets for Leading Questions Generation

In order to generate leading questions as previously discussed, we rely on the technique of mining frequent itemsets. In this case, the itemsets to be generated are ones of the intents based on the initial requirements provided by the users.

For example, let us consider the following information provided by the user:

"I want to buy a house in District 1"

Processing this sentence, our intent identification process can generate the set of initial intents as "*buy*", "*house*", "*District 1*".

Then, we treat our database of collected information of real estate as a transaction set and mine the frequent itemsets with high confidence scores which *contain those initial intents*. The rules can be illustrated as follows.

["*District 1*", "*street view*"]
["*District 1*", "*business*"]
["*District 1*", "*renting*"]
["*District 1*", "*nearby market*"]
["*District 1*", "*office usage*"]

For frequent itemsets implies the common interests when one considers buying a house in District 1. Hence, our chatbot can generate leading questions to ask whether the user is interested in those additional intents or not.

V. EXPERIMENTS

The accuracy of our chatbot heavily relies on its capability of intent identification. Thus, we conduct the corresponding experiment in this aspect. In our experiment, we use a dataset of around 10000 real estate advertisement collected from the website *mogi.vn*. Table II presents our experimental results, in which we employ various combination of deep learning technique. Overall, we enjoy F1 scores of over 85%, which is sufficient to be applied in practice.

TABLE II. Experimental results

	F1	**Precision**	**Recall**
BiGRU-CharCNN-CRF	85.6	85.3	85.8
BiGRU-CharCNN-CRK (+ skip)	85.8	85.7	85.8
BiGRU-CharCNN-CRF (+ WordCNN)	86.1	85.4	86.9
BiGRU-CharCNN-CRF (+ WordCNN + skip)	86.3	86.1	86.6

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