

A virtual companion for older adults using the Rasa Conversational AI framework

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Abstract. This position paper describes how the Rasa Conversational AI framework can be used to implement a variety of different use cases involving conversational support for older adults.

Keywords: Active and healthy ageing · Conversational AI · Rasa framework.

1 Introduction

This position paper describes how a set of use cases were implemented using the Rasa Conversational AI framework. The use cases were developed in the e-VITA project, which is a 3 year joint European (H2020) and Japanese (MIC) funded research project that addresses a wide range of domains within active and healthy ageing [1].¹

2 Related Work

There has been increasing interest in recent years in exploring how new developments in conversational AI can be applied to support active and healthy ageing. [2] presents a comprehensive state-of-the-art review, while [3] reports a month-long study of interactions between a virtual agent and older adults in their homes. [4] shows how dialogue technology can provide natural interaction, while [5] describes how information about the older adult's emotional status was extracted from an analysis of their verbal and non-verbal communication. [6] is an ongoing project in the Netherlands with the aim of improving the lives of older adults using voice technology. [7] reviews current work on virtual coaches, discussing theories and future research directions.

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3 The e-VITA virtual coach requirements

Requirements for the e-VITA virtual coach were gathered in a dynamic process of participatory design in real life settings involving interviews with older community-dwelling adults in Germany, Italy, France, and Japan. Based on the interviews a number of use cases were identified. The current work focuses on use cases associated with support of daily living, helping to perform tasks, and providing information.

4 The Rasa Conversational AI framework

Rasa is an open-source and customizable framework using state-of-the-art machine learning-based technologies that enable developers to create advanced conversational assistants [8]. The main concepts in Rasa are: intents, entities, responses, forms, slots, actions, and stories.

Intents and entities are extracted from the user's utterances using Rasa's Natural Language Understanding (NLU) module which uses machine learning-based technologies to classify the intents of the user's utterances and extract entities from the utterances. The developer provides examples of typical user utterances that are used to train the system and create an NLU model.

Responses are the system outputs and can take the form of text or speech as well as buttons, attachments, and other media. Forms are used to collect information from the user, for example, for the items required to make a flight booking. This information is stored in slots as key-value pairs e.g. *city:London*, acting as the system's memory and potentially influencing the system's future behaviour.

Actions specify what the system should do following a user's input, including making a response, making an external API call, or querying a database or other knowledge source. Actions defined by the developer are called *custom actions*.

Stories are declarative representations of the conversation flow and are used along with rules and a Transformer Embedding Dialogue (TED) policy to determine the next action that the system should take in the conversation. Knowledge Graph technology and Knowledge Bases are integrated in Rasa using specific knowledge-based actions that can supply content for the system's responses [9].

5 Use cases in the current work

This section describes how the use cases identified for the e-VITA virtual coach can be implemented using the Rasa framework. The code repository for the examples is available in [10] and a video recording of some interactions with the virtual coach that was developed in this work can be viewed in [11].

```

Your input -> Hi
Hi there! What is your first name?
Your input -> James
So James, what is your last name?
Your input -> Bond
Alright!
I can remember that your name is James Bond!
Hello James, How are you?

```

Fig. 1. Storing information about the user.

5.1 Storing information about the user

In an initial interaction with a user the virtual coach should ask for the user's name and other relevant information. In Rasa this can be done using a form in which there are required slots to store the user's first and last names. Fig.1 shows a simple example in which the coach requests the user's name at the beginning of an initial interaction and then uses this information in a subsequent exchange. Forms can also be used for more complex use cases to request and store useful details about the user, such as next-of-kin, carer, preferences, hobbies, etc. that will be useful in future encounters involving daily support.

5.2 Monitoring the user's emotional state

A virtual coach that provides daily support and companionship for an older adult should be able to engage in small talk (also known as chit-chat) in order to provide companionship as well as enabling the coach to obtain potentially important information about the user's well being. Fig.2 shows a simple example where the user says that they are feeling and on hearing this the chatbot asks for more information and then suggests playing some music.

In the e-VITA project an emotion detection system is being used to assess the user's emotional state based on analysis of their spoken utterances. Since the interactions in the current work were text-based, an approach using sentiment analysis was developed in which the user's utterance was submitted to the spaCy NLP sentiment analysis module `spacytextblob` which can be used as a pipeline component in the Rasa framework [13]. The sentiment analysis module returns a range of polarities where numbers above 0 indicate a positive emotional state and numbers below 0 indicate a negative emotional state. The coach can then respond in an appropriate way. For example, the coach's response to a

```

Your input -> I am super sad
Oh! I am sad to hear that. Would you like to tell me why? I am curious ...
Your input -> I feel so alone. I have no-one to talk to.
Oh. Life is like that sometimes. Music?
Your input -> yes
Ok, let's play your favorite tunes.

```

Fig. 2. Sentiment analysis in chat.

negative sentiment could be anything like asking to share feelings, music recommendations, jokes, etc., as shown in Fig. 2. The output could also be tailored to some aspect of the the user's personal profile that would help to formulate a response to a negative sentiment.

In the current work there were some situations where this approach did not work well. For example, for statements like *I don't feel so good* or *not bad*, the sentiment analysis module was unable to classify the correct sentiments and responded with confusing statements. More work is needed using more sophisticated NLU analysis to train the module on inputs such as these.

5.3 Helping the user perform a task

The virtual coach can help the user perform tasks such as sending an email or text message, making a phone call, or accessing a music API without having to interact with the complex functions of an app on a device such as a smartphone. In this use case a form can be used to elicit the values of the required slots. In Fig. 3 the system uses a custom action involving an email form with slots to elicit the recipient's email address, the subject of the email, and the text of the message. Having filled these slots a method is called to submit the values in the form to an email API.

5.4 Obtaining information from an external API

The virtual coach can get information such as weather updates, news, or sports results from an external API and output the information to the user. Fig. 4 shows an example where the user asks *what is the weather like?*. This utterance is classified as a `weather` intent that triggers a weather story that includes an action to extract the `city` – in this case, as the user has not specified the city, the default is set to *Belfast*. In other cases the coach could ask for the `city` and other slots such as `date` and `time`. The value for `city` is then submitted to a weather API using a custom action and a response is created showing the maximum and minimum temperature and the overall weather status of the city.

```

Your input -> send email
Please provide the email ID for the person you want to send an email to
Your input -> sheen2004@gmail.com
Please provide the subject for your email
Your input -> test subject
Please provide the message for your email
Your input -> test message 1
I have sent the email to sheen2004@gmail.com

```

Fig. 3. Sending a email.

```

Your input -> What is the weather like?
Weather is Clouds Temperature is minimum 15 Celcius and maximum is
17 Celcius In Belfast

```

Fig. 4. Query for weather information.

5.5 Accessing a knowledge source

In the e-VITA project a range of knowledge sources are used, including databases, internet resources, sensor information, emotion detection, common knowledge, and knowledge about the user. Rasa can maintain a knowledge base for data access. One way in which this can be done is to use an in-memory knowledge base in the form of a JSON file. The virtual coach in the current work makes use of an extract from a knowledge base developed in the e-VITA project in which there is an `object_type` called `diseases`, as shown in Fig. 5.

Fig. 6 shows an example of some sample utterances to query the knowledge base using the `query_knowledge_base` intent.

If the user's utterance is classified as an intent, an action is invoked within a story to access the knowledge base and retrieve a response, mapping the attribute name identified in the utterance (e.g. `symptoms`, `cure`) on to the attribute in the JSON knowledge base and retrieving its associated value as the coach's response as shown in Fig.7.

6 Conclusions and Future Work

A virtual coach can be of great assistance for older adults and the use cases described here are examples of how Conversational AI can be used to create such a virtual coach. Future technical work will extend the approach to sentiment analysis by integrating with an emotion detection

```
"disease": [  
  {  
    "id": 0,  
    "name": "Diabetes",  
    "definition": "Diabetes is a chronic long-lasting health condition  
      that affects how your body turns food into energy",  
    "cause": "Overweight, obesity, and physical inactivity",  
    "precaution": "Reduce your total carb intake, Exercise regularly, Quit smoking",  
    "doctor_type": "General Practitioner and Endocrinologist.",  
    "symptoms": "Hunger and fatigue, Peeing more often and being thirstier.",  
    "cure": "There are some medicines that can help with diabetes. But there  
      is no long term cure",  
    "suggest_diagnosis": "Contact General Practitioner",  
    "leads_to": "risk of heart disease, stroke, high blood pressure"  
  }  
]
```

Fig. 5. JSON code for diseases.

```
intent: query_knowledge_base  
examples: |  
- what [diseases>{"entity": "object_type", "value": "disease"} do you know about?  
- What are the [symptoms>{"entity": "attribute", "value": "symptoms"} of [Diabetes]  
  {"entity": "disease"}  
- do you know the [cure>{"entity": "attribute", "value": "cure"} of [Diabetes]  
  {"entity": "disease"}
```

Fig. 6. Utterances to query the knowledge base.

```
Your input -> What diseases do you know about?  
I found the following objects of type 'disease':  
1: Diabetes  
Your input -> What is the cure for Diabetes?  
There are some medicines that can help with diabetes. But there is no long term cure.  
Your input -> What are the symptoms of Diabetes?  
Hunger and fatigue, peeing more often and being thirstier ...
```

Fig. 7. Interactions with the diseases knowledge base.

system linked to a speech-based interface in order to detect emotional cues in acoustic parameters in the user's speech. The current knowledge base will be extended using knowledge graphs to enable more complex knowledge modelling covering a range of topics and to enable tailoring to individual users through personal profiles. The range of dialogues involving information retrieval is being extended using access to APIs such as Wikidata in different languages, and dialogues are being developed that will require multi-turn conversations about topics such as fall prevention, nutrition, and physical and cognitive exercise. The virtual coach will be tested in living labs and in the homes of older adults to ensure user acceptance and general usability.

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