# Conversational access of large-scale knowledge graphs

Delaram Javdani Rikhtehgar[1]

[1]University of Twente, Enschede, The Netherlands

**Abstract**

With the rapid advancement of semantic web technologies, various Knowledge Graphs have been created by various institutes and organizations to preserve data. What is challenging is how humans can intuitively access and learn from such large-scale knowledge. In this paper, to achieve a meaningful, engaging, and enjoyable interaction between visitors and large-scale knowledge graphs, we will propose a knowledge graph-based conversational agent that selects and packages user-interested information into narratives, models user interests, and takes initiative (e.g. answering user questions, providing recommendations, or requesting feedback or clarification) to convey knowledge. As an application, we will focus on the cultural heritage domain and create a museum guide.

**Keywords**

Knowledge Graphs, Conversational Agents User Modeling, Question Answering, Recommendation

## 1. Problem statement & Importance

In the past decades, with the progress of the semantic web, much effort has been made to preserve existing data into large-scale knowledge graphs (KGs) [1, 2, 3]. While this trend has many benefits, intuitively accessing and learning from such large-scale knowledge for the end-users is often challenging as KGs have different shapes and sizes, and exploring them is not usually simple and enjoyable for end-users and requires prior knowledge that most of them do not have. A great deal of research has been done to make this data accessible to end-users through conversational agents (CAs) [4, 5, 6]. However, designing these CAs is a very challenging process, as different parameters have to be considered, many of which have not been taken into account in previous work. E.g. current CAs based on KGs have designed conversations that are not human-like, lack meaningful interaction, and provide limited knowledge in answering user questions. In this research, we will explore how to make information in the KGs accessible to end-users through CA in an appealing and intuitive manner, so that the interaction between end-users and the KGs becomes meaningful and enjoyable. This includes selecting and packaging user-interested information (i.e. triples) into narratives, modeling user interest, and choosing suitable actions to convey knowledge.

While this could be a general-purpose approach, the focus of this research is on Cultural Heritage (CH) domain. As in other areas, more and more Cultural Heritage (CH) institutions, such as libraries, museums, galleries, and archives, have launched large-scale digitization

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d.javdanirikhtehgar@utwente.nl (D. J. Rikhtehgar)

processes that result in massive digital collections in the form of large-scale KGs. This not only ensures the long-term preservation of cultural artifacts in their digital form but also allows online instant access to the resources that otherwise require physical presence and fosters the development of applications like virtual exhibitions and online museums. We will describe how these KGs can be accessed by visitors through a conversational museum guide in a meaningful, engaging, and enjoyable interaction. The key contributions of this research are:

- Extracting triples from KGs, ordering and packaging them according to the interests of the visitors, and generating narratives from them.
- Modeling visitors' interests during the conversation for personalized and context-aware access to information.
- Forming a conversational museum guide that creates meaningful, engaging and enjoyable interaction between visitors and KGs based on its own initiatives.

## 2. Related work

Lately, knowledge graphs have been used for the representation of knowledge in ML-based chatbots in fields such as e-commerce [7], retrieving domain-specific context information [8], disaster support [9], or cross-language communication [10]. With explicitly modeled knowledge and the ability to connect to other KGs, integrating the KG with the chatbot helps enhance the "intelligence" of the conversational agent when the connection of different contextual information is require [11, 9, 12] or better detecting user intent [10]. KGs are also used in combination with social robotics (e.g. Furhat[1]) and conversational AI platform (e.g. Rasa[2]) [4] with the aim of providing high-quality information to users through accessing semantically rich KGs in various fields. The most well-known and widely used conversational AI platforms used in previous work are Dialogflow[3] [12, 13], Rasa [9, 10, 4], Flask[4] [11] and Watson assistance [8].

So far, there has not been much work exploring the use of KGs for museum guides. Varitimiadis et al. [6] surveyed sixteen developed museum chatbots and categorized them into five types based on the conversational skills and the engaging techniques used by the chatbot developers. One-third of these chatbots have some conversational skills and only three of them utilize KGs in certain ways to achieve human-like conversations. Machidon et al. [13] proposed an intelligent conversational agent (CA), implemented with Dialogflow, that assists users to explore the exhibits within Europeana[5] (Europe's digital cultural library, museum, and archive). They designed a ranking mechanism to rearrange the search results obtained from Europeana.

In summary, most chatbots do not offer human-like conversations, lack meaningful interaction, and do not provide the complete requested knowledge. They do not model the user's interest or give personalized recommendations. They do not have information ordering and packaging strategies, narrative generation capabilities, and suitable strategies to convey knowledge; they respond mainly through rule-based methods and are unable to answer factoid questions

[1]https://furhat.io/
[2]https://rasa.com/
[3]https://cloud.google.com/dialogflow
[4]https://flask.palletsprojects.com
[5]https://www.europeana.eu/en

beyond a set of questions. In this research, we plan to develop a KG-based conversational museum guide that is knowledgeable about the museum collections and takes the initiative of answering questions, offering recommendations and asking for feedback or clarifications. We also investigate how to formally model user interest and incorporate it into knowledge extraction and delivery.

## 3. Research Questions

Our basic assumption is that our conversational agent plays a role of a museum guide that guides the visitor through the collection and delivers as much knowledge about the collection as possible while keeping the visitor as engaged as possible. The agent focuses on the KGs about some specific exhibitions or CH institutions. Additionally, the agent can access some external KGs such as Europeana, Wikidata[6], or DBpedia[7] but such expeditions should be brief to keep the whole interaction as focused as possible.

The main research question of our work is ***"How to shape knowledge-centered human-machine conversations and meaning-making in an engaging and intuitive manner?"*** This question generates many other research questions which are described in the following:

- RQ1: How should the information in the KG be extracted according to the interests of the visitors? How should this information be arranged (i.e. size of the information, the order of the delivery, etc.) and presented to visitors?
  - The KG contains a lot of information, but to present this information in an **appealing and intuitive manner** to the visitor, it is necessary to extract an *as complete as possible* and *as concise as possible* subgraph containing the user's requested entities with their attributes and the entities that they are closely associated with. On the other hand, the user interest should be taken into account when ordering and packaging certain triples into a natural language response to **keep the user engaged**.
- RQ2: How to formally model user interests during the conversation so that user interests can be reasoned directly with knowledge extraction and delivery for personalized and context-aware access to the information?
  - To improve the user experience, it is necessary to model the user's interests during the interactions in order to extract user-specific information from the KG and to provide personalized recommendations. By formally representing user interest, the communication between the user and the knowledge graphs could become more **meaningful and seamless**.
- RQ3: How to form a conversational museum guide that creates meaningful, engaging, and enjoyable interaction between visitors and KGs based on its own initiatives?
  - The CA should be proactively involved in the conversation to meet the information needs of visitors by answering their questions, providing recommendations, or requesting feedback or clarification.

[6]https://www.wikidata.org/wiki/Wikidata:Main Page
[7]https://www.dbpedia.org/,

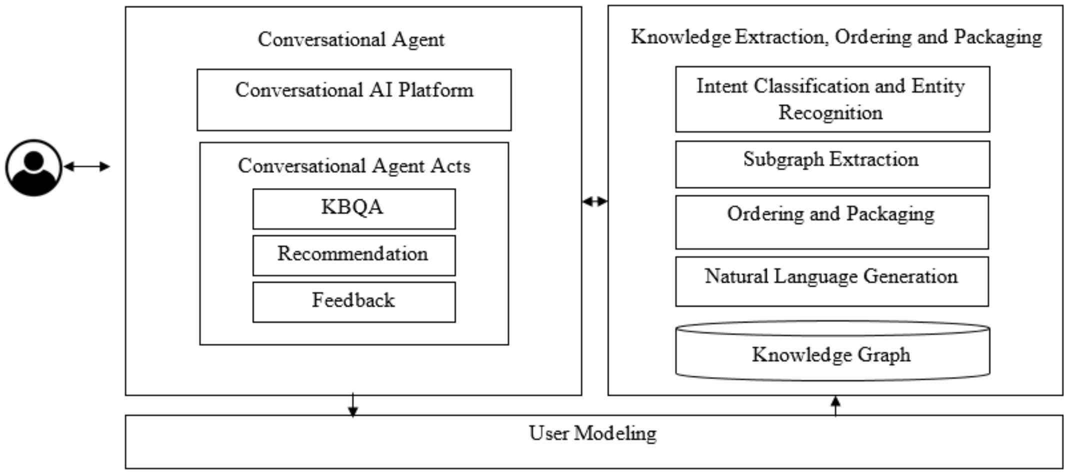


**Figure 1:** Proposed approach

# 4. Approach

The main idea behind our approach is to explore how KGs can be leveraged to create a museum guide with extended question-answering and recommendation capabilities based on user interest modelling. The proposed approach is shown in Figure 1. It comprises three main components which are Knowledge Extraction, Ordering and Packaging, Conversational Agent, and User Modeling.

## 4.1. Knowledge Extraction, Ordering and Packaging

This section is about our RQ1. We plan to extract knowledge from the KG for a user's requested information by generating as complete as possible and as concise as possible subgraphs and then order and package certain triples into natural language responses.

### 4.1.1. Intent Classification & Entity Recognition

Classifying intents is usually the first step in conversational systems. This process maps a user's requested information to a predefined class with the aim of facilitating the understanding of it. This classification helps identify user intention before generating SPARQL queries. Tokenization and part-of-speech tagging approaches will be used to extract information about different types of entities. Additionally, entity linking is needed to recognize whether the entities mentioned by the user are actual entities in the KG. We intend to handle both intent classification and entity recognition using Dual Intent Entity Transformer (DIET) [14]. We expect users to perform the following dialogue acts [15] (Note that the exact list of acts will be decided based on data collected from real conversations between visitors and museum guides):

- A request about the topic (e.g., I'd like to know about "The Night Watch").

- A request about an aspect (e.g., Could you tell me about its creator?).
- A request about a mentioned concept (e.g., Do you know more about Rembrandt?).
- A requests about an unmentioned concept (What is there to know about oil paint?).
- Provide positive feedback (e.g., That's quite interesting!).
- Provide negative feedback (e.g., That's pretty boring).
- Accept offer of information (e.g., I'd love to learn about its creator).
- Decline offer of information (e.g., Sorry, I'm not interested in that.).

#### 4.1.2. Subgraph Extraction

The main purpose is to create a series of queries to extract a subgraph from the KG containing information about the user request. We intend to generate SPARQL queries from the user request efficiently and query the KG to retrieve a sub-graph containing information about the user request. How to decide the boundary of such a subgraph, how complete and how concise such subgraph should be, etc. are the questions we want to address.

#### 4.1.3. Knowledge ordering and Packaging

Once the subgraph is extracted, we need to consider how to package multiple triples in the optimal order to generate short utterances, instead of generating a long text which is not suitable for conversations. The order of information should reflect the user's interest and the agent's own goal so that a sufficient amount of knowledge is transferred to the user in a personalized and engaging order.

#### 4.1.4. Natural Language Generation (NLG)

Generating natural language texts from a set of triplets is a challenging task in NLG [16, 17, 18]. We plan to use pre-trained language models [19] for this purpose.

### 4.2. User Modeling

In order to answer RQ2, we plan to formally model and represent user interests and incorporate them while extracting and delivering knowledge. Based on the Cultural Heritage KG, we will build a basic KG of user interests that will be updated and extended dynamically during the conversation. We intend to assign weights to the user's interest in each type of entity in the KG and dynamically update them as the user expresses interest in a particular entity. With such weighted information, the user interest KG can be incorporated into the knowledge extraction, ordering, and packaging step (see Section 4.1) that makes sure the extracted subgraph is of the most interest to the user and the knowledge is ordered and delivered in a more personalized manner.

### 4.3. Conversational Agent

This section is about our RQ3. The focus is on how to make the agent self-driven with its own purpose, decide which actions to take given the user's input, and not only answer questions, but also recommend or ask for feedback or clarification. Additionally, how to make sure the conversations are engaging and enjoyable.

#### 4.3.1. Conversational AI Platform

The conversational AI platform is used for managing interaction with the user. Dialogflow and Rasa are the most popular conversational AI platforms, that use advanced AI techniques and can integrate large sources of knowledge including KGs.

#### 4.3.2. Determining Conversational Agent's Acts

The conversational museum guide on top of the usual acts (e.g. greetings, ...) should have the ability to answer visitors' questions, make recommendations, or request feedback or clarification to satisfy visitors' information needs. Overall, we expect the CA to perform the following dialogue acts:

- Directly answer an info request ("The Night Watch" painting is ...).
- Provide related info (e.g., I do not know, but. . .).
- Ask for feedback (e.g., Do you find (info) interesting?).
- Offer to discuss topic (e.g., Want to learn about "The Night Watch"?).
- Offer to discuss aspect (e.g., Do you want to know about its creator?).
- Offer to discuss mentioned concept (e.g., I could say more about the Rembrandt?).

## 5. Evaluation

To the best of our knowledge, there is no available dataset containing conversations between users and CA in the museum domain. Therefore, we plan to interview museum guides to understand "What is the dialogue between visitors and guides", set up a small-scale data collection to record such dialogues, and potentially apply existing algorithms to recognize prototypical dialog acts in the museum context.

For evaluation, we plan to create a user study as an assessment approach. To make this evaluation interesting for the user, we plan to integrate our CA into a virtual reality environment with multi-modal input (e.g. user's utterances, eye-gaze, speech emotion) and output (e.g. text, voice). This work is in line with our previous work[8], a conversational museum guide in a web-based virtual exhibition based on a previous physical exhibition of the Het Rembrandthuis in Amsterdam.

One evaluation metric in the user studies could be asking users and domain experts to give a rating on a scale of 1 to 5, based on whether the information extracted from the KG is concise and complete and properly transformed into the natural language, whether the extracted information is interesting, whether users' interests been taken into account in the conversation, whether the CA's responses make sense with respect to the user's query, etc. Another evaluation could be a user study between our CA and an existing deployed chatbot (e.g. Google Arts[9] and Google

[8]https://www.hhai-conference.org/demos/pd_paper_3267/
[9]https://artsandculture.google.com/

Assistant[10]). Additionally, for evaluation of the generated text from the KG, we plan to calculate the BLEU score [20].

## 6. Expected Contributions and Preliminary Plans

To conclude, we have seen from the state-of-the-art approaches that research on KG-based conversational agents is still in its early stages. With this research, we intend to push this forward by proposing a KG-driven museum guide that takes initiative to create a meaningful, engaging, and enjoyable interaction between visitors and large-scale knowledge graphs. It particularly will have the ability to extract sub-graphs from a KG based on users' requested information, order and package information, generate natural language from KG, answer questions, model user interest, and make recommendations. In the future, we plan to integrate it into a virtual reality environment with multi-modal input for detecting user interest and multi-modal responses in virtual reality. Given this, we expect the outcome of this research to help shape knowledge-centered human-machine conversations and meaning-making in an engaging and intuitive manner.


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