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RECOMMENDER CHATBOT AS A TOOL FOR COLLABORATIVE BUSINESS INTELLIGENCE IN TOURISM DOMAIN

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Abstract. Nowadays big amounts of data are created by different sources. Big Data allows for expanding the analysis scope beyond the in-house data sources and taking into consideration publicly available data on the web and external sources. Collaborative Business Intelligence goes beyond the organization frame and collecting people in one virtual space in order to give their opinion concerning certain issue results in an opportunity to boost the decision-making process and make it more reasonable. In this research we focus on tourism domain. Tourists often search for information from different sources and compare found facts. This leads to spending significant amounts of time comparing descriptions and photos across different platforms before deciding. To overcome this challenge, the use of virtual assistants has become increasingly common. These virtual assistants can perform various functions beyond just comparing prices, such as comparing user reviews. We introduce a framework for a virtual assistant that incorporates the following crucial elements: a conversational unit, a task identification, data exploration component, and a recommendation model.

Keywords: Collaborative Business Intelligence, Tourism, Data Exploration, Chatbot.

1 Introduction

The decision-making process is a multifaceted endeavor that predominantly relies on the information accessible to the decision-maker. In today's contemporary society, we find ourselves amidst an era characterized by vast reservoirs of data across diverse domains. These data repositories hold considerable potential for facilitating decision preparation and execution. Nonetheless, these data are often collected and stored by disparate software systems, utilizing different formats, and presenting varying levels of accessibility and security. Moreover, data can be plagued by issues such as incompleteness, contradictions, and unreliability. To address the challenges associated with processing such extensive data volumes, the expertise of data analysts is sought. Business intelligence (BI) emerges as a valuable aid in deriving meaningful insights and shaping strategic decisions. By scrutinizing historical and current data, BI tools proficiently present outcomes through visually intuitive formats.

A substantial impediment in harnessing the full potential of accumulated data arises from the lack of direct communication between technical specialists,

decision-makers, and business process analysts. To overcome this hurdle, the adoption of a collaborative business intelligence (CBI) approach becomes imperative. However, organizing effective collaboration among potential users, decision-makers, and technical specialists in the realm of data analysis proves to be a complex task. To tackle these challenges, the BI4people project [1] has been established with the purpose of providing solutions.

The core objective of BI4people is to democratize the benefits of Business Intelligence, ensuring its accessibility to the widest possible audience. This is achieved through the implementation of a software-as-a-service model for the data warehousing process, encompassing the integration of diverse and disparate data sources, as well as intuitive analysis and data visualization [2]. The central concept revolves around uniting individuals within a virtual space, fostering their active participation by encouraging the exchange of comments and opinions for the collective benefit. Furthermore, the utilization of others' findings or insights fosters a collaborative approach to Business Intelligence, thus giving rise to what is known as Collaborative BI.

When it comes to planning their travels, tourists often find themselves scouring various sources of information, including Google Maps, feedback on booking sites, and conducting comparisons of the gathered facts. This process demands significant time and effort. Consequently, tourists aspire to make informed decisions based on the experiences of others. However, most tourists do not possess expertise in data analysis or the ability to make rational decisions. Therefore, they require a user-friendly tool that incorporates data visualization capabilities, offering potential solutions and ideas in a comprehensible manner.

2 Background

Data exploration plays a crucial role in the broader Business Intelligence (BI) process, encompassing the collection, identification, and analysis of data to unveil valuable insights and patterns. However, it is important to acknowledge that data analysis can be a daunting task for inexperienced users.

Collaborative BI entails employing collaborative tools and methodologies to bolster Business Intelligence (BI) processes. These tools can encompass a range of technologies, including social networks, brainstorming sessions, chat applications, and more, all aimed at facilitating knowledge sharing and collaboration among business users, analysts, and technical specialists. The underlying concept is that by harnessing the collective knowledge and expertise of a group, superior solutions can be generated, leading to enhanced decision-making compared to working in isolation.

Chatbots play a vital role in supporting users by providing information, searching data, and executing routine tasks. A chatbot is a computer program designed to simulate human conversation, utilizing text or voice interactions with users [3]. These intelligent agents are typically created with specific tasks in mind, aimed at providing information or performing designated functions. Notably, there exist chatbots and Conversational Agents (CAs) that enable users to execute complex data analysis tasks by combining commands within nested conversations [4, 5].

Chatbots offer numerous advantages for Collaborative Business Intelligence (CBI), including: 24/7 availability, personalization, and scalability. These advantages make chatbots invaluable tools within the CBI landscape, facilitating seamless communication, support, and personalized experiences for users engaging in data analysis and decision-making processes.

Thus, the research questions are following.

RQ1. Can a virtual assistant using a conversational interface help simplify the data exploration process for non-experienced users?

RQ2. What features of a virtual assistant are most helpful in assisting users who have limited knowledge of the domain and business intelligence?

RQ3. How can virtual assistants be designed to integrate in BI platform?

3 The State of the Art

In today's world, there exists variety of chatbots and recommender models. A well-known example of recommendation systems was considered when Netflix offered a prize for the recommendation algorithm of predicting movie ratings by users [6]. The prize was awarded in September (2009), after over three years of work.

There are many general purpose chatbots to help users in solving general problems. Ranoliya et al. designs a chatbot for university related FAQs [7]. They implement chatbot using Artificial Intelligence Markup Language (AIML) and Latent Semantic Analysis (LSA). Narducci et al. develop a Telegram chatbot, based on a conversational recommender system, which is able to provide personalized recommendations in the movie domain. They implement critiquing strategies for improving the recommendation accuracy as well [8].

Besides these, there are many specialized Chatbots for applications such as customer care, health care, medical diagnoses, etc. Mathew et al. proposes a chatbot for disease prediction and treatment recommendation to avoid the time-consuming method of visiting hospitals [9]. Similar to this research, Tode et al. developed a chatbot for medical purpose using deep learning to help poor and

needy people [10]. Preez et al. proposes an intelligent web-based voice recognition chat bot [11].

Now-a-days, many hotels, travel agencies, and airline companies are adopting Chatbots as a recent technology to help them boost their businesses. Ukpabi et al. explores chatbot adoption in tourism services [12]. Pillai et al. proposes AI-based chatbot for hospitality and tourism by extending the technology adoption model (TAM) with context-specific variables [13]. Nica et al. present foundation stones behind a chatbot for e-tourism that allows people textually communicate with the purpose of booking hotels, planning trips, and asking for interesting sights worth being visit [14]. They demonstrated how model-based reasoning can be used for enhancing user experience during a chat.

Since mobile technology has been widely used, therefore many researchers propose mobile based solution for tourism industry. Abowd et al. develop a mobile application, named Cyberguide, which provide a hand-held context-aware tour guide [15]. Similarly, Horozov et al. also used the location parameter as a key criterion for personalized POI recommendations in mobile environments [16]. Their application works with the physical entities such as restaurants and can be used in the context of restaurant recommender system. The research work of Zheng et al. is also based on user generated GPS traces for learning travel recommendations [17]. Zhiyang et al. develop a user-based collaborative filtering approach for generating tourist attraction recommendations as the list of preference attractions for the tourist [18].

Generally, there exist two major groups of recommendation systems. First group explores properties of the items recommended and named as Content-based systems. Second group, Collaborative filtering, considers similarity measure to recommend items/users and focus on the relationship between users and items. The items which are preferred by similar users are recommended.

4 Methods and Materials

Conversational agents (CAs) are computer programs designed to engage in natural conversations with human users. They can be categorized as either chatbots for informal chatting or task-oriented agents for providing users with specific information related to a task [19, 20]. CAs may use text-based input and output or more complex modalities such as speech. The handling of dialogue is a crucial component of any CA, which can range from simple template-matching systems to complex deep neural networks.

While chatbots and task-oriented agents are the primary categories for classifying CAs, other aspects such as input and output modalities, applicability,

and the agent's ability to self-learn could also be considered [21]. Chatbots can be classified into three main groups based on their response generation: pattern-based, information-retrieval, and generative. Task-oriented agents must provide precise and consistent answers to fact-based conversations on specific topics. The general pipeline depicts the various stages of processing as separate components (fig.1). The three basic components are natural language understanding (NLU), cognitive processing, and natural language generation (NLG). NLU involves identifying precisely what the user said or meant, while cognitive processing executes the dialogue policy to construct the knowledge required for the response using a knowledge base. NLG involves formulating the answer as a sentence.

In order to investigate the effectiveness of integrating a virtual assistant for data exploration, we have chosen to utilize a scenario focused on the analysis of tourist data. This scenario requires our virtual assistant to be equipped with a set of statistical commands as well as possess text analysis capabilities. The data exploration process entails a systematic examination and analysis of datasets with the goal of gaining insights, identifying patterns, and uncovering valuable information. This process typically involves several key steps, including data collection, data cleaning and preprocessing, descriptive statistics, data visualization, exploratory data analysis (EDA), hypothesis testing, and iterative refinement.

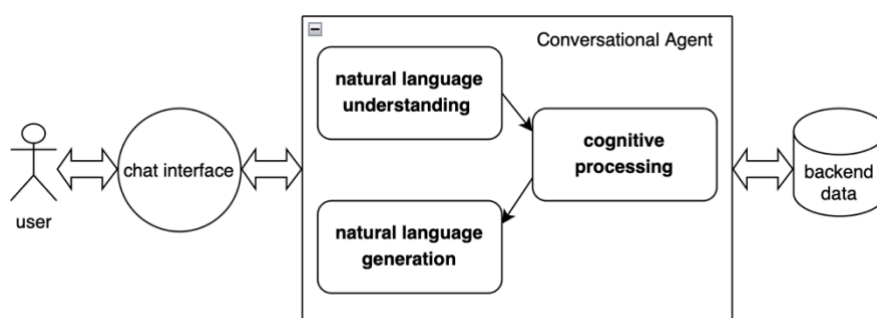


Fig. 1. The basic pipeline for conversational agent.

To organize and streamline these steps, we propose dividing them into distinct groups. The first group includes data collection and preprocessing, which involves tasks such as metadata creation and data cleaning. The second group focuses on data exploration, encompassing activities such as descriptive statistics, EDA, and hypothesis formulation. The third group centers around data visualization, allowing for effective representation and interpretation of the data. Lastly, the fourth group involves the collection of feedback, which facilitates the iterative improvement of the virtual assistant's performance. These groupings

align with the general framework established in the BI4People project [1]. While we specifically collect and clean touristic data for testing our ideas, it is important to note that the virtual assistant framework is designed to be applicable to datasets from a tourism domain. The domain plays a significant role in terms of vocabulary and the development of predefined behavior models within the assistant.

In various domains, such as data analysis or collaborative chats, users frequently engage in sequential interactions with entities known as "items". These interactions can occur over an extended period, and their characteristics evolve over time. As a result, a network of temporal connections is formed between users and items. Effectively recommending items in real-time and predicting changes in user behavior present significant challenges in these domains, necessitating further exploration and research. Representation learning has emerged as a powerful technique for capturing the evolving properties of users and items by generating low-dimensional embeddings.

The generation of dynamic embeddings poses several fundamental challenges for existing methods. Firstly, most current approaches only generate embeddings for users when they take actions, overlooking the temporal aspect of user behavior. Secondly, items exhibit both stationary properties that remain constant and time-evolving properties. However, existing methods often focus exclusively on either stationary or time-evolving properties, failing to capture the complete dynamics. Additionally, many methods rely on scoring all items for each user to predict user-item interactions, which becomes impractical for datasets with millions of items and users. These limitations highlight the need to address these challenges and develop more accurate and efficient techniques for real-time recommendations and predictions across diverse domains.

In this research, our focus lies in the task of tourist data exploration, where we aim to identify and generalize queries and commands as items. Our ultimate goal is to provide recommendations for non-expert users in the field of data exploration specifically in the tourist domain. As our research is in its early stages, we begin by investigating fundamental aspects to lay the groundwork for developing a recommender assistant framework.

5 Results

The scenario begins with loading the data into a dataframe. To ensure the dataset is ready for analysis, we conduct prior data loading, cleaning, and labeling procedures. An essential step in this process is creating metadata, which allows us to generate a set of initial data research questions that can be suggested to users

at the start. Additionally, metadata exploration enables us to construct a trace matrix, aiding in matching available data to users' queries. The next task involves transforming users' queries into commands that invoke relevant methods and return numerical data as answers. It is imperative to provide an explanation of the obtained data, and to accomplish this, we propose the utilization of an abstract semantic tree to identify commands and parameters, along with a prompt generator to convert data into plain text. While data visualization can be considered a separate task, it plays a vital role in presenting the results. Users are given the opportunity to comment or annotate the results, and the recommender unit can collect feedback. Encouraging users to provide feedback becomes the second important task for the virtual assistant.

The communication aspect of the virtual assistant is crucial, as it is responsible for understanding and generating dialogue with the user, maintaining context, and interacting with other software components. Current solutions offer a wide range of features and interfaces for implementing natural language chatting. However, our focus lies in supporting data exploration as the core task of the virtual assistant. Our main idea is to automatically generate data processing commands based on the text of the user's query. We identify two main challenges in this process: building a set of reference queries and implementing a set of basic commands. Consequently, there are two sets of items that users interact with within the system.

We have adopted an approach based on representation learning to tackle our research problem. Representation learning involves automatically acquiring meaningful and compact representations of data, typically in the form of low-dimensional vectors or embeddings. In our case, we create various types of embeddings, including user trajectories that capture user-item interactions, user features, and item features. Each interaction is associated with a feature vector that contains additional information such as textual content. By leveraging these embeddings, we can make predictions about user queries for new users or new interactions. Additionally, we can predict user behavior, enabling us to recommend relevant actions and data analysis approaches. This allows us to provide our users with new questions and different perspectives on the touristic data, enhancing their exploration experience in the domain.

6 Conclusion and Discussion

In order to generalize the discussed features of a virtual personal assistant, we propose the framework that outlines four essential components of a virtual personal assistant:

- Natural language conversation processing: This component is responsible for processing the dialogue between the user and the virtual assistant. The virtual assistant must accurately identify the user's intentions and execute the appropriate dialogue policy to construct a response. It then generates a response in natural language that is easily understandable by the user.
- Task identification: This component involves identifying the services that best match the user's needs based on natural language processing and semantic analysis of the input text. It also extracts relevant keywords for information retrieval, behavior annotation, and matching.
- Recommender model: This component is responsible for personalizing the experience based on the user's preferences, history, and behavior. It employs machine learning and artificial intelligence algorithms to learn from data exploration and user interactions.

Thus, the framework provides a comprehensive framework for developing a virtual assistant software by identifying the main modules necessary for facilitating the software creation.

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