Conversational Agents for Recommender Systems

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ABSTRACT

In my Ph.D. work, my objective is to improve the state of the art in Conversational Recommender Systems, by proposing a model that closely follows the process that people enact when searching for products and services. Rich user profiles are elicited using natural language dialogue. Item descriptions will be extracted from a combination of structured and unstructured data such as user reviews. Natural language explanations will ensure that users can quickly understand the reasoning behind the recommendations. Interactive explanation will then allow them to further compare several alternatives. This extended abstract presents the motivations of my work, it details the research plan, and the research questions. Finally, it shows some preliminary results, and outlines the next steps for my Ph.D. program.

CCS CONCEPTS

• **Information systems** → **Recommender systems**; **Information extraction**; • **Computing methodologies** → **Discourse, dialogue and pragmatics**; • **Theory of computation** → *Reinforcement learning*; *Active learning*.

KEYWORDS

conversational recommender systems, conversational agents, review-based recommender systems, interactive explanation, natural language processing

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1 INTRODUCTION AND MOTIVATIONS

Recent advancements in Deep Learning and Natural Language Processing caused the rise of Virtual Assistants such as Amazon Alexa, Apple Siri and Google Assistant. They are software agents that interact with users via voice or text, and can assist users in performing several everyday tasks, such as making appointments, searching the Web, or playing music. They have the potential of being an interesting new platform for providing personalized recommendations. Despite this, most Virtual Assistants still do not offer any recommendation capabilities. Research is currently investigating the idea of combining together Virtual Assistants and recommender systems [33, 37, 45]. The result of this combination is the creation of a new generation of Conversational Recommender Systems (CoRS), that can talk with a user to find interesting and useful items, much in the same way a sales agent or a friend would. Using natural language allows them to mimic the information-seeking process followed by people [19].

Of course, using Natural Language Processing to talk with users is not sufficient to faithfully replicate this process. It is also important to understand how people look for the products that they need. Every person has different goals, interests, and tasks in mind. Therefore, different people will be interested in different features. Most e-commerce platforms on the Web such as Amazon allow users to write reviews about the products that they purchased. These are text documents that represent each user's opinion on one or more aspects of the product. They are very useful for two reasons: first, they let us discover the features that represent a particular product. Second, they let us understand which features matter to users the most. Therefore, reviews are a promising candidate for extracting knowledge about both users and products. In fact, review-based recommender systems have been widely investigated in the literature [4]. These systems however have one major drawback: in order to generate recommendations, a user must have written some reviews beforehand. This is necessary in order to build the user's own profile. Natural language dialogues can help solve this limitation: instead of building the profile from the user's past reviews, we can directly ask the user to tell what he/she is looking for, and what are the most important features. In this way, even a user with no reviews can receive recommendations. The other advantage is that the recommendations will be based on what the user is currently looking for.

Another motivation for my work concerns the more ethical aspects of recommendation. The General Data Protection Regulation (GDPR) explicitly formulates the "right to an explanation" [10], i.e., the citizens' right to receive an explanation for algorithmic decisions. Recommender systems are with no doubt involved in this issue, because they apply AI techniques to support human decision-making. My Ph.D. work tackles the explainability problem via the introduction of natural language *interactive explanations*. This means that explanations can be a starting point for further interaction, allowing users to better compare different alternatives.

The objective of my Ph.D. research is to develop a novel system for conversational recommendation, that closely follows the way people interact with each other in order to find products that are relevant and useful. The system is characterized by the following features:

- It will combine together multiple information sources: technical features of the products, unstructured data (e.g. reviews), and conversational messages;

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- It will feature an optimal conversational strategy for *user profile elicitation*;
- It will exploit conversational strategies to perform interactive explanations.

2 RELATED WORK

Conversational Recommender Systems

Jannach et al. [15] contains a review of the state of the art in terms of Conversational Recommender Systems. CoRSs can be developed using many different input and output modalities, such as forms, graphical maps, or natural language. However, all CoRSs share some similarities: they guide the users through an interactive, human-like dialogue [17]. The conversational recommender process is iterative, and spans over multiple interaction turns. [5, 11, 15, 34] describe some variations of the conversational recommendation process. CoRSs have proven to be beneficial, as stated in [31], as they assist users in navigating complex product spaces [36]. The idea of combining recommender systems with virtual assistants was formulated in Rafailidis and Manolopoulous [33]. The authors sustain that there is currently a gap between the two technologies, which they summarize as a set of research questions. The objective of my Ph.D. work is to answer two of those questions: *"How can user preferences via conversations be modelled into machine learning models in recommendation systems?"* and *"To what extent can we provide explainable recommendations via conversations?"*. In the literature, there are already some proposals for modeling the conversational recommendation process using natural language. Bogers and Koolen [1] proposed the concept of *narrative-driven recommendation*. A narrative description of the current context and needs of the user is used to enhance the recommendation process. The task of learning the context of the recommendations is also very similar to the user background extraction phase described in [42]. Kang et al. [18] performed a study by observing natural language interactions between users and a movie recommender system. The objective of this study was to understand what types of queries are usually written. The authors discovered that users would either search for movies based on specific objective features (such as the genre, or the release year), subjective features (e.g. "movie with interesting characters"), or search a specific movie by name. The findings of this paper support the hypothesis that users may be interested in subjective qualities of the products that they are looking for. While the scope of [18] is limited to understanding the first stages of the interaction, the objective of my Ph.D. work is to model the entire recommendation process. Christakopoulou and Radlinski [6] developed a preference elicitation framework that identifies which questions should be asked to new users in order to quickly learn their preferences. The user profile is built by asking users to either rate specific items, or compare them against other items. The authors employed strategies based on Reinforcement Learning and Active Learning. Zhang et al. [45] introduces the *System Ask - User Responds* (SAUR) paradigm for conversational search. In the SAUR paradigm, the user initiates the task by providing an initial request. After this request, the system starts asking a series of questions. For each question, the user has to give more details about a specific *aspect* of the desired product. The question generation module is trained by converting user reviews into simulated conversations. An implementation of the paradigm is also presented, using *Personalized Multi-Memory Networks* (PMMN). A similar approach is described in Sun and Zhang [37] and Lei et al. [22]. Both papers present CoRSs that ask faceted questions to build the user profile. The question generation task is performed using Deep Reinforcement Learning techniques. One limitation of these works is that the interaction process is mostly *system-driven*. One objective of this Ph.D. is to investigate *mixed-initiative* models that allow both the user and the system to take control of the conversation.

Extracting data from text

Chen et al. [4] describes the state of the art regarding review-based recommender systems. Fundamentally, there are two approaches for exploiting user reviews for improving recommendations. The first approach is to learn *implicit* factors from reviews. This can be done by using factorization strategies on the reviews, in order to map each review into a multi-dimensional latent space. Recent models for learning latent representations are based on Deep Learning, such as DeepCoNN (Zheng et al. [46]), TransNets (Catherine et al. [3]), Li and Tuzhilin [23], and Shalom [35]. The second approach is to learn *explicit* factors from reviews. Explicit factors are also commonly known as *facets* or *aspects*, and describe some explicit characteristics of the products. The task of extracting facets is also called *Aspect-Based Sentiment Analysis* (ABSA). The most important advantage of facets is that they are naturally *intelligible*, and so they can be used for many tasks besides recommendation. For example, facets could be used to explain why a certain item was recommended (e.g. *"I suggest you this phone because users praise its battery life"*). Deep Learning has also been applied for the ABSA task. Some of the architectures that have been investigated are Convolutional Neural Networks (CNN) [44], Recurrent Neural Networks (RNN) [7], Long-Shorm Term Memory (LSTM) networks [9, 24, 25, 27]. In general, the literature strongly suggests that review-based recommender systems outperform those based on single ratings. However, they suffer from the limitations described in the Introduction. The aim of this Ph.D. is to alleviate this problem by changing the way the user profile is built: instead of exploiting a user's own reviews, data will be extracted from a natural language conversation. While some works such as [37] and [6] use some data extracted from reviews, there is little evidence in the literature regarding the combination of user reviews and natural language dialogues for the conversational recommender scenario.

Interactive natural language explanations for recommender systems

Tintarev and Mashtoff [39, 40] delineated the goals of explanation in a recommender system, which are: Transparency, Scrutabililty, Trust, Persuasiveness, Effectiveness, Efficiency, and Satisfaction. In 2017, Nunes and Jannach [29] released a systematic review of the explanation techniques for recommender systems. One interesting consideration from the review is that personalized explanations are often linked to improved transparency, persuasiveness and satisfaction, when compared to non-personalized explanations. Several works propose the use of opinion mining for generating rich explanations based on user-written reviews. Personalization is obtained by measuring the features that are most important to the current user. Liu et al. [26] proposes a generative explanation framework, that exploits the information from review data to generate natural language explanations for the decision of a text classification system. Similar contributions are made by Suzuki et al. [38] and Ouyang et al. [30], which both investigate the use of synthetic explanations generated from user reviews using deep neural networks. With synthetic explanations users can have a summarized view of all the opinions of the users, thus saving them from the burden of browsing hundreds of reviews.

Another possibility to make explanations more personalized is to give users the ability to interact with them. In this way, the explanation becomes a starting point for further interactions [29]. Interactive explanations can be seen as a form of user control in the context of explanations [16]. This can be achieved in many different ways: for example, users may respond to the explanation, allowing them to correct any wrong assumption made by the system. This kind of interactive explanation is connected with the scrutability goal. In fact, it is also sometimes referred to as "scrutable" interactive explanation [16]. There are several examples of scrutable interactive explanations, in which users are able to interactively respond to the explanation by changing the preferences or the weights [2, 14, 21, 43]. Interactive explanations improve the perceived usefulness [2], scrutability, transparency [21], efficiency and satisfaction. According to [29], three types of questions are commonly associated with interactive explanation: *what-if* (i.e. what would be recommended if different data were provided), *why* (i.e. why the system is asking for a specific input), and *why-not* (i.e. why a particular item was not recommended). To the best of our knowledge, there is little to no research regarding the integration of interactive explanation techniques in a CoRS that uses natural language. Therefore, one of the objectives of this Ph.D. is to fill this gap in the literature.

3 RESEARCH GOALS AND CURRENT STAGE OF THE THESIS

As stated in the Introduction, the main objective of this Ph.D. is to develop a novel conversational recommender system. This system interacts using natural language, and is inspired by the information seeking process that is actually followed by people when searching for the desired products and services. It will make use of natural language dialogue to iteratively navigate the product space and understand the user's needs. Information about users and items will be gathered from different information sources, which will allow us to achieve a multi-dimensional view of both user requirements and product descriptions. Natural language interactive explanations will also be considered, which will increase the transparency, persuasiveness and trust of the recommended items. They will also allow users to compare alternative products, and weigh their strengths and weaknesses. The desired outcome of this research is the automation of the task of searching for products and services. Instead of requiring users to manually analyze a list of candidates, and scan all their reviews, the system will automatically select the most appropriate products by asking the right questions. Natural language explanations will then summarize what people think of each product. The development of this system requires reaching several sub-goals, which will be discussed in the following paragraphs.

3.1 Building a user profile through conversation

Modeling an appropriate dialogue strategy for conversational recommendation is essential to generate good recommendations. This means finding a way to allow users to express their needs and wants in the most complete way possible. Intuitively, people who are helping someone find an item are inclined to ask about some characteristics that they are interested in (e.g. *"What is the price range?"*, or *"What do you use you phone for?"*, or *"Do you like Italian cuisine?"*). Alternatively, they can ask to rate some items to gauge their preferences and suggest items similar to those that are liked. Narrative-driven recommendation [1] is a fundamental part of this dialogue model. During the conversation, users can easily describe the context in which the recommendation is being requested, their preferences, and the typical tasks they are involved in. This short textual description, along with other structured and unstructured data sources will be used to construct a semantically rich user profile. After this step, the system will take initiative, and start asking questions to narrow the product space down to a small set of candidates. We will consider two types of questions: item-based and facet-based. Item-based questions will require that the user rate some items. From these ratings, the system will infer the user's preferences, and the features that matter the most. With facet-based questions, the system will directly ask the user to talk about the features that he/she is interested into. Examples of such questions are: *"What screen size would you like?"*, *"Are you interested in horror movies?"*. To select the most appropriate questions to ask during the conversation, we are investigating two strategies: Active Learning [41], and Reinforcement Learning. Active Learning has been already used in the area of recommender systems to select a small set of informative items that should be rated by the user. A comprehensive description of the state of the art for such techniques is described in [8]. Thus, Active Learning is a perfect fit for selecting item-based questions. However, we will also investigate whether it can be used for facet-based questions as well. We are also considering strategies based on Reinforcement Learning (RL), such as those used in [6] and [37]. These techniques are commonly used to find a sequence of actions that lets an agent transition from a starting state to a goal state by maximizing a utility function. It is straightforward to model the conversational recommendation task as such: each action is a question asked by the system, and the goal is to recommend an item that is useful for the user. Finally, past conversations will also be included in the user profile, in compliance with the iterative nature of CoRSs. To complete this sub-goal, we will answer the following Research Questions:

RQ1: Can Natural Language improve the quality of recommendations in a CoRS?

RQ2: Can Narrative-driven recommendation improve the quality of recommendations in a CoRS?

RQ3: Can item/facet-based questions improve the quality of recommendations in a CoRS?

3.2 Building item descriptions from multiple information sources

People who are looking for a product that can satisfy their needs are not only interested in objective features. In fact, they often look for products that exhibit some particular subjective qualities [18]. In accordance with this, our system will be able to handle both objective and subjective product features. While objective features can be easily obtained from product descriptions or Linked Open Data repositories such as Wikidata, the same cannot be said for subjective features. During my Ph.D. I am investigating techniques based on Deep Learning for extracting explicit factors from unstructured text such as user reviews. These factors represent the *facets* that are usually mentioned for a particular type of product (e.g. "battery life" and "screen" for phones, "mileage" and "comfort" for cars). With these techniques, facet-based ratings will be extracted from reviews, which will describe the quality of a product for different aspects, different tasks, or in different situations. This information will be incorporated into the product description. Also, these techniques will help discover new product facets. This step is also crucial for user profile elicitation: the newly discovered facets will determine the set of facet-based questions that will be asked by the system. The following Research Questions summarize this sub-goal:

RQ4: Can facet-based data extracted from unstructured text improve the quality of recommendations of a CoRS?

RQ5: Can Deep Learning models for extracting data from reviews also be applied to text messages sent to a CoRS?

3.3 Matching user profiles and item descriptions

For the actual recommendation process, a possible strategy is to map both user profiles and item descriptions into the same feature space. This is straightforward, because we can use the same objective and subjective features that were discovered in the previous steps. Given a set of d features, user profiles can be modeled as d-dimensional vectors, where each element represents the user's rating of a specific feature that was mentioned during the dialogue. Concretely, this vector will represent the aspects that matter to the user the most. Item descriptions will also be modeled as the d-dimensional vectors. In this case, each element represents either a specific technical feature of the product (e.g. the operating system of a phone, the genre of a song), or an aggregate of the users' opinion of a subjective feature of the product (e.g. the quality of the photos of a phone, or the quality of the service of a restaurant). Accordingly, this vector represents what the product is, and what are its strongest and weakest points. For the recommendation algorithm, I am investigating both Multi-Criteria [28] and Content-Based [13] algorithms, since both are able to deal with representing users and items as multi-dimensional vectors. The following Research Question summarizes this sub-goal:

RQ6: What is the best strategy for matching user profiles acquired through conversation and item descriptions acquired through technical features and subjective facets extracted from reviews?

3.4 Providing natural language interactive explanations

Natural language explanations can benefit from leveraging both technical features and subjective opinions. In fact, opinion mining can provide users with a quick overview of the most frequent observations made by reviewers, including issues that are frequently encountered. During this Ph.D., I will be researching two types of explanations: *feature-based* and *synthetic review generation*. Feature-based explanations leverage the matching between a user's profile vector and an item's description. This way, we can create a personalized explanation that justifies the recommendation with the features that the user is interested in. Synthetic review generation [30, 38] is also an interesting approach. The aim is to generate a paragraph that synthesizes the general opinion of the reviewers of a particular product. Additionally, I will be investigating techniques for *interactive explanation*. In fact, the advantage of using a dialogue is that the user can ask follow-up questions. For example, a user may not be convinced enough by the reasons given by the system, and thus he/she may ask for a more thorough explanation, e.g. "*What are the preferences that most influenced this recommendation?*", "*What would you recommend if I didn't specify X?*" Moreover, the user might be interested in understanding the differences between alternative options, and so he could ask why a particular item is more appropriate than another (e.g. "*Why do you recommend X over Y?*"). From the interactive comparison, some new insights might emerge: for instance, the user might discover new features that are relevant for making a decision, but he had not considered before. In order to complete this sub-goal, the following Research Questions must be answered:

RQ7: Can feature-based explanations improve the explanation goals of a CoRS?

RQ8: Can synthetic review generation improve the explanation goals of a CoRS?

RQ9: Can natural language interactive explanations improve the explanation goals of a CoRS?

4 PRELIMINARY EVALUATION

Since the proposed system is a combination of virtual assistants and recommender systems, it is imperative that its evaluation takes into account both perspectives. The evaluation of the recommendations can be performed using traditional metrics such as accuracy, Mean Average Precision, and nDCG. We will also consider metrics that go beyond accuracy, by taking into account the novelty and usefulness of the recommendations, and the user experience [20]. The conversational aspects of the system will be evaluated using metrics such as the interaction time, ratio of completed tasks, and ratio of recognition errors. The objective of these metrics is to assess the effectiveness and efficiency of the interaction in natural language. Due to the conversational nature of the proposed system, user studies are an essential tool for its evaluation. They will be performed to evaluate the user's subjective experiences that are expressed while using the system. Data will be collected using questionnaires, such as ResQue [32] and SASSI [12].

The first relevant result of my Ph.D. is the development of ConveRSE [13], a domain-independent framework for the development of conversational recommender systems that interact via natural language. Users can talk with ConveRSE by providing preferences to items that they like or dislike (e.g. *"I like The Matrix"*, or *"I love Jim Carrey, but I don't like Yes Man"*). The system generates recommendations using a content-based algorithm, namely the PageRank with Priors. Users can then give feedback to the recommended items (e.g. *"I love this movie"*, *"I like it, but I don't like the director"*), which is used to improve the following recommendations. A user study was conducted, which concluded that natural language interaction is able to improve the quality of recommendations and the interaction cost compared to a button-based CoRS interface, thus providing a positive answer to RQ1. This study also helped discover some of the obstacles that must be overcome when integrating natural language in a CoRS.

5 ONGOING WORK

In this abstract, I have presented the project of a Conversational Recommender System that leverages structured and unstructured information, natural language dialogues, and interactive explanation to improve the experience of providing personalized recommendations. Reaching this goal requires developing many components and overcoming several challenges. During the rest of my Ph.D. I will focus on answering the research questions described in Section 3. For this reason, I am conducting the following activities: (a) investigating strategies for eliciting narrative descriptions from users; (b) developing Active Learning and Reinforcement Learning strategies for selecting item-based and facet-based questions for user profile elicitation; (c) developing Aspect-Based Sentiment Analysis models for extracting facet-based ratings from unstructured text; (d) developing feature-based strategies for explaining recommendations; (e) developing models for generating synthetic reviews; (f) performing offline experiments to evaluate the performance of each approach; (g) performing online user experiments to assess the impact of each approach on the user experience. I will also perform a three-month internship at the Amazon Alexa Shopping Team, where I will apply the knowledge I acquired in the area of Conversational Search and Recommendation to solve problems in a real-world scenario.

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