Virtual Bartender: A Dialog System Combining Data-Driven and Knowledge-Based Recommendation

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Abstract

This research is about combination of data-driven and knowledge-based recommendations The research is made in an application scenario for whisky recommendation, where a guest chats with a recommender system. Preferences about taste are difficult to express and the knowledge about taste is tacit and thus can hardly be represented and used adequately. People or not aware of how to describe flavors in a standardized way and how to do a justified choice. This is because knowledge about taste is mainly tacit knowledge. To deal with this knowledge, data-driven recommendation is adequate. On the other hand, in particular experienced customers use knowledge about distilleries, locations and the distillery process to express their preferences and want to have arguments for the recommended products. This shows that a combination of data-driven and knowledge-based recommendations is appropriate in areas where tacit knowledge and explicit knowledge are available.

Introduction

A recommender system is a software tool and techniques providing suggestions for items to be of use to a user. The suggestions relate to various decision-making processes, such as what items to buy, what music to listen to, or what online news to read (Ricci et al., 2011, p. 1). Recommender systems play an important role in highly-rated Internet Sites such as Amazon.com, YouTube, Netflix, LinkedIn, Facebook, Tripadvisor, Last.fm and IMDb (Ricci et al, 2015). A lot of different products like books, movies, music etc. are recommended by recommender systems – but also social platforms use recommender systems for extending the social networks of friends or business contacts (Aggarwal, 2016).

Of significant difference to the application areas are scenarios, in which recommendations are made in a dialog between the recommender and the client. Think of a recommendation of a wine for a meal. Typical for these scenarios is that the context determines the recommendation (Adomavicius et al., 2011) or that there is not sufficient information about the client.

Recommendations can be made of data or knowledge. We analyze an application domain and show that a combination of data-driven and knowledge-based recommendation is most appropriate. We derive criteria for the combination of the two approaches depend on the availability of data, the type knowledge and the user interaction.

Literature Review

In the literature review we discuss several topics, which are of relevance for the design of a dialog-based recommender system. First we distinguish different types of recommender systems. Then we discuss the types of knowledge and there influence on the decision between data-driven and knowledge-based approaches.

Types of recommender systems

There are different types of recommender systems (Burke 2007). One distinction is between data-driven and knowledge-based techniques. Collaborative, content-based and demographic filtering are data-driven systems. Collaborative filtering generates recommendations using only information about rating profiles for different users. Content-based recommenders learn a classifier by combining the user's rating profiles with product features. A demographic recommender provides recommendations based on a demographic profile of the user. All of these data-driven tech-

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niques suffer from the cold-start problem or first rater problem. They need a certain amount of data to provide valuable results.

A knowledge-based recommender suggests products based on inferences about a user's needs and preferences. Knowledge-based recommenders are sometimes listed in a distinct category of content-based recommenders (Aggarwal, 2016, p. 16), but they can also contain explicit domain knowledge about *how* certain product features meet users' needs and preferences (Burke 2007). Thus, a criterion for the choice of data-driven and knowledge-based recommender systems is the availability of data and knowledge.

Use of Knowledge-based Systems

Besides technology-related problems like data availability or sparsity there are human factors such as the ideal interaction between recommender systems and humans and the acceptance of such systems (Jannach et al. 2011, p. 16). Not considering such human factors could lead to consumer preferring human rather than machine recommendation (Yeomans et al. 2008).

In a dialog-based situation the recommendation is created in collaboration between human and application. A user might ask for explanation of the recommendation, which requires the knowledge, on which the recommendation is based, to be represented in a way that is understandable by humans. This would be achieved by knowledge-based systems, in which knowledge is represented explicitly. Thus, in such a setting knowledge-based recommender systems seem to be preferable to data-driven methods, which are relying on statistics or represent the knowledge in subsymbolic way in neural networks.

Types of Knowledge

Building a knowledge-based system means to acquire-knowledge and represent it in a way that can be automatically executed. This process of creating a knowledge-base is called knowledge engineering.

From knowledge management we know that there are different types of knowledge (see Figure 1). A first distinction is between implicit and explicit knowledge. Implicit knowledge it in the mind of people, while explicit knowledge is externalized. For implicit knowledge a further distinction can be made between tacit knowledge and self-aware knowledge. Tacit knowledge has been introduced and deeply investigated by Polanyi (1966).

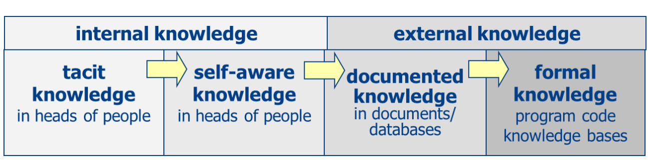

Figure 1 Types of Knowledge

Building a knowledge base from explicit knowledge simply means to transform it into a formal representation (Figure 2). Implicit knowledge first has be made explicit before it can be formally represented. One way to deal with tacit knowledge is to learn it from data instead of getting it from a human. For recommender systems, this means to apply data-driven approaches. Preferences of customer are extracted from data of buying behavior.

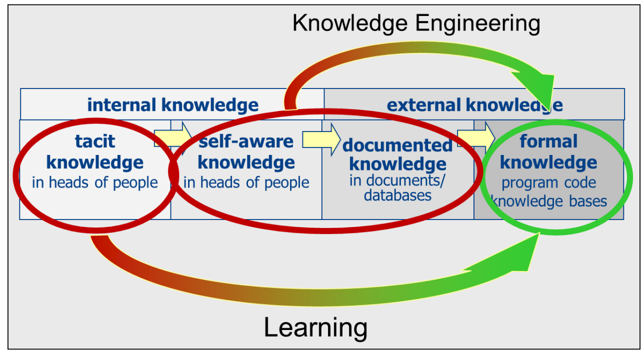

Figure 2 Knowledge Engineering and Learning

From this analysis we can see that in a dialog-based application knowledge-based recommender are preferable for the interaction between human and system. However, not all knowledge might be available in explicit form. The objective of this research is to examine how data-driven methods and knowledge-based approaches can be combined for recommender systems.

Application Scenario

Recommendation of items for which expertise is available but which on the other hand are hard to describe. For example, the taste of wine or whisky, or the smell of perfume are hard to describe. There is no standard vocabulary and the choice of the "right" product depends on personal preferences. On the other hand there are experts for these domains. For example, a wine expert can assess the quality and taste of a wine from the grapes, the region and the year. In our research we examine the recommendation of whisky. The vision is to develop a virtual bartender.

The choice of the appropriate whisky is mainly determined by the taste. To find out, how experts proceed when they recommend a whisky, we interviewed a professional bartender. The insights from the interview allowed drawing a brief procedure of a possible whisky recommendation conversation (see Figure 3): After a little bit of small talk, she tries to find out fast, how experienced the customer is. If the person is not experienced, she selects something sweet, that is lightly peated and not too expensive. If the customer is familiar with whisky, she asks for preferences then makes a recommendation. After tasting, the customer gives her a feedback, which influences the next recommendation.

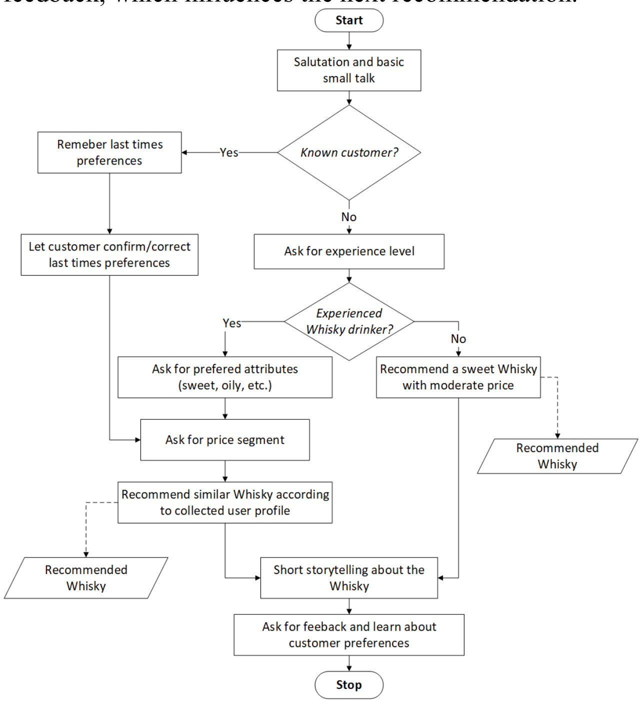

Figure 3 A whisky recommendation process

Describing the taste is difficult. To show this variety we analysed description of whiskies of the Scotch Malt Whisky Society. Here a few examples:

- "The palate is bathed in a sunshine glow of ***tropical fruits (banana, custard apple, monstera)*** – intensely sweet, mouth-watering and lip-smacking, but with Victory V's and ***salt and pepper crisps*** reminding us it has slept long in oak."
- "The air was filled with ***cinder toffee, raisins, dates, Brazil nuts, balsamic vinegar*** and a rich Malmsey ***Madeira wine***. On the palate we nibbled sweet, ***salty and spicy roasted party nuts*** whilst we chatted, sharing a laugh and a drink with friends."
- "We were foraging for berries in bushes, drank a cranberry orange prosecco cocktail and distilled sandalwood oil. On the palate neat it was just like a Caribbean black cake, a boozy rum-soaked fruit cake with a good dose of molasses, brown sugar and browning (burnt sugar) sauce. With water polished mahogany, sweet myrrh incense and salty liquorice were followed by zesty Indian lime pickle and extra dark honey vanilla cornbread."

There have been many approaches to cluster the taste of whisky. Over 400 aromatic and taste descriptors were identified and grouped into 12 sensory features, from which a taxonomy of the whisky tastes was developed (Wishart, 2000). However, the value of these characterizations is limited, as most consumers of whisky will have none or little understanding of the right term to describe their desired taste of whisky (Mead & Matarić, 2009).

To deal with the huge variety of tastes the Scotch Malt Whisky Society distinguishes 12 flavor profiles.

- young & spritely
- sweet, fruity and mellow
- spicy & sweet
- spicy & dry
- deep, rich & dried
- old & dignified
- light & delicate
- juicy, oak and vanilla
- oily & coasty
- lightly peated
- peated
- heavily peated

Each profile has a short description (see Figure 4).

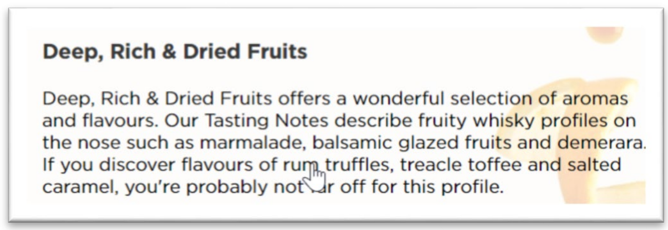

Figure 4 Description of a Flavor Profile (www.smw.org)

While it is hard to imagine that a system can deal with the huge variety of taste description, the classification into 12 profiles will not lead to successful results when recommending whiskies of rich and complex flavor.

During the recommendation process, the bartender tries to find out the preferences of the customer. The dialog is different depending on the knowledge of the customers. And here the expertise of the bartender comes in. Besides taking about taste, the bartender can apply her knowledge about distilleries and the distillation procedures. The character of whisky is quite complex as it is influenced by many factors such as the location of the distillery (quality of water source, regulations of the state, weather the cask will be exposed to), the grain recipe and the size and number of stills (Lapointe & Legendre, 1994). General knowledge about whisky regions give first hints about character of the whisky. For example, Lagavullin and Ardbeg are distilleries located on Islay (see Figure 5), and whiskies from Islay are typically smoky.

The bartender can also apply knowledge about the distillery process. For finishing, whiskies can be refilled in different casks. The former use of the casks, e.g. for sherry or port, changes the characteristic of the whisky flavor.

All this knowledge allows the bartender to have a conversation with the customer and to explain the recommendation to experienced customers.

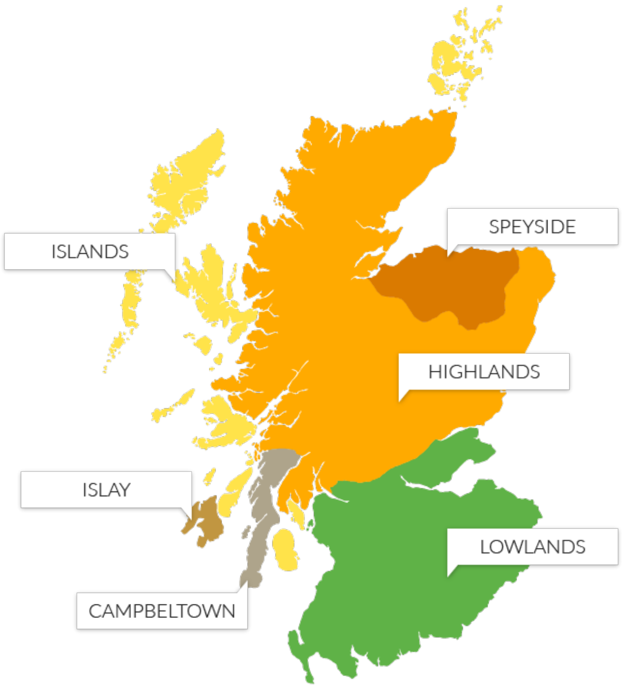

Figure 5 Whisky regions in Scotland

A dialog-based Whisky Recommender

The objective of our research was to analyze, which recommendation methods are appropriate for dialog-based recommender systems. According to Mead & Matarić (2009), the success of content-based recommendations normally depends on two important domain properties: (1) the items need to be described using well-defined features; and (2) users must have some understanding of these features and how they relate to their requirements.

From the analysis of the application scenario and from interviews with both experiences bartenders it turned out that a combination of data-driven and knowledge-based recommendation is most appropriate.

- Knowledge about taste cannot be articulated appropriately and thus is categorized as tacit knowledge. Tiwana (2000) already showed that it is inappropriate to make this knowledge explicit. Thus, collaborative and content-based filtering are used, which automatically determine fitting whiskies based on data.
- However, a recommender system has to take into consideration that a customer cannot express his/her preferences adequately. This is where knowledge-based recommendation is applied, which uses knowledge about typical tastes and preferences.
- Knowledge-based approaches are used by the chatbot to guide a conversation in order to get the missing user input. This input from the chat is essential to find out individual whisky preferences and taste. In particular experienced customers prefer to talk about their preferences and experiences and expect justified explanation of the recommendation.

The analysis of the knowledge, on which the recommendation is based, allowed us to assign recommendation methods to the different steps. These are indicated by different colours in the process model (Figure 6). Content-based recommendation is orange, collaborative filtering is yellow and knowledge-based recommendation is colored green. There are process steps, which could be processed with several or a different recommendation method. For example, the decision for inexperienced whisky drinker can be based only on other people's choices (collaborative) but also take into consideration attributes of appropriate whiskies based on guesses of the bartender (content-based). The most appropriate recommendation methods were chosen in the schema to get an impression how a combination of different recommendation methods could look like.

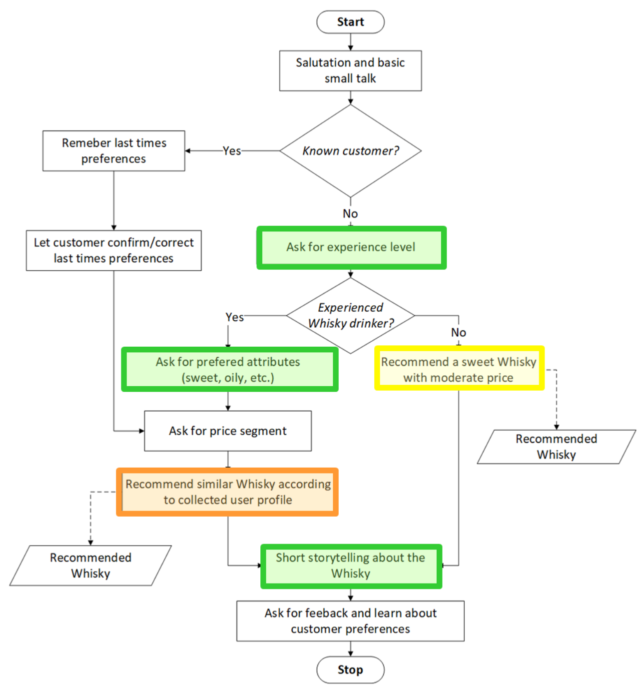

Figure 6 Recommender techniques in the Whisky recommendation process

Prototype Development

To validate the finding, we developed two versions of a chatbot. The first version is mainly focused on content-based filtering using only a simple knowledge base. For evaluation the whisky dataset according to Lapointe and Legendre (1994) was used which contains over 100 whiskies along 84 attributes. It has been adapted for the recommendation process by adding a price attribute and dropping some attributes that can hardly be expressed. In order to support the initial conversation, a background story has been included for each whisky in the dataset.

The chatbot was implemented with dialogflow. A webservice generates the user preference vector, calculates the similarity to each whisky in the dataset and updates the backend information. The next figure shows a sample dialog.

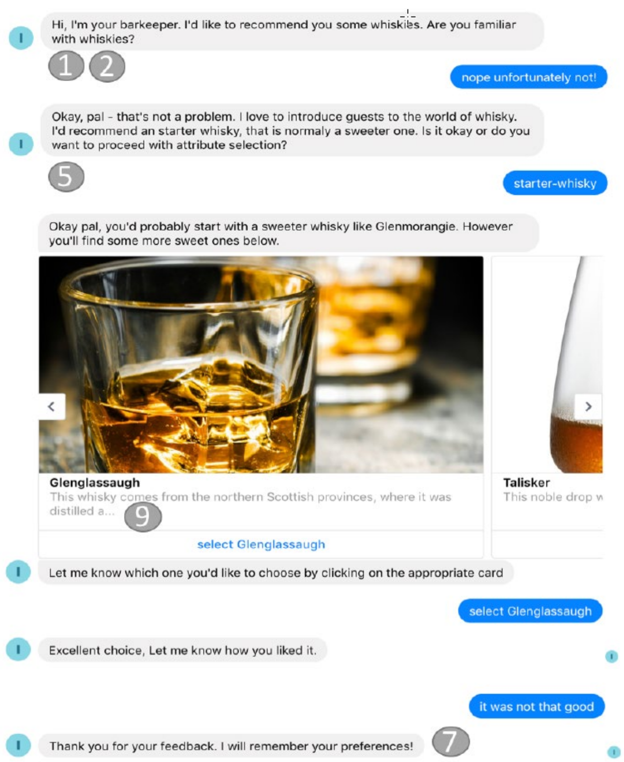

Figure 7 Screenshot of a recommendation dialog

This first prototype only uses a very simple knowledge base. In order to understand the appropriate combination of knowledge-based and data-driven recommendation, we developed a second prototype.

Two approaches for combining different recommender approaches in a hybrid system were examined. In the parallel combination the results of different recommender systems (called hybridization) are combined by calculating the *weighted averages*.

A sequential combination allows to apply different recommender systems for specific subtasks, using the output of one approach as input for the next one. This approach is key for the whisky recommendation, because knowledge-based and data-driven recommendations have different strength and exploit different types of knowledge. Furthermore, the decision for the sequential approach is underlined in combining the two strategies of *asking* and *proposing* in dialogue-based approaches (Viappiani et al., 2006): A chatbot combines knowledge-based recommendation (what we find out during the conversation by *asking*) with content-based recommendation (what we already know about the customer a for *proposing* something).

A conversation for a recommendation can consist of different communication fragments and questions. The knowledge-based approach allows for flexible conversation. Instead of asking each customer the same questions, the knowledge base guides the chatbot through the conversation fragments, depending on the knowledge that is already available about the customer. Figure 8 shows conversation flows for returning and new customers.

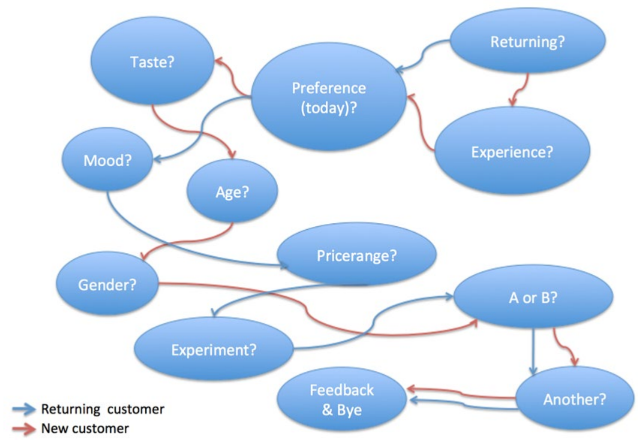

Figure 8 Communication flows of returning and new customers

The following showcase of the chatbot shows how content-based and knowledge-based recommendation are combined in this. If a customer starts chatting with the bot, it asks for the name and therefore knows, whether the person is returning or new. It then asks for today's preference. In the example of Figure 9, the customer wants to drink something smoky and the database returns 12 whiskies, which are smoky. As we know already, what other flavours the person likes (content-based), the bot can ask for the price range and if the person wants to try something completely different than last time or more similar to the drinking history. This reduces the number of matching whiskies and the customer can then choose between the top two whiskies. The feedback for the recommendation and customer's drinking history are saved in the database.

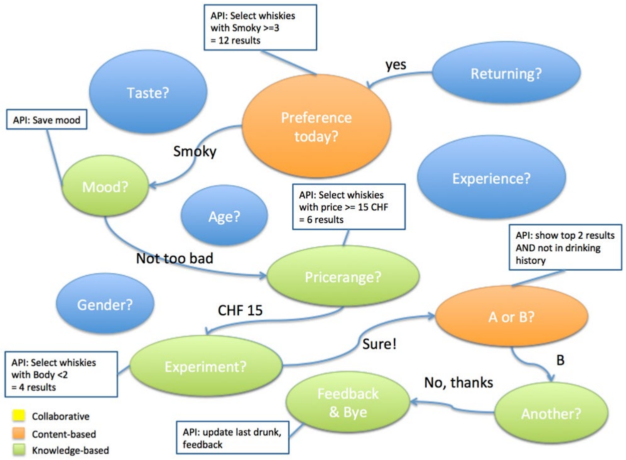

Figure 9 Conversation with a returning customer

Conclusion

Both chatbots were evaluated with experienced and unexperienced whisky drinkers. The research showed that for dialog-based representation a combination of data-driven and knowledge-based recommendation is appropriate. Knowledge is needed to have a conversation with a customer. In particular experienced customers want to express their preferences and want to have arguments for the recommended products. However, products like wine or whisky are difficult to express. People or not aware of how to describe flavors in a standardized way and how to do a justified choice. This is because knowledge about taste is mainly tacit knowledge. To deal with this knowledge, data-driven recommendation is more adequate.

Thus, a combination of knowledge-based and data-driven recommendation is useful for a conversational recommender system.

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