Personalization of Search Results using Interactive Intent Modeling

Antti Kangasrääsiö ANTTI.KANGASRAASIO@HIIT.FI
Helsinki Institute for Information Technology HIIT, Department of Computer Science, Aalto University

Dorota Głowacka DOROTA.GLOWACKA@HIIT.FI
Helsinki Institute for Information Technology HIIT, Department of Computer Science, University of Helsinki

Samuel Kaski SAMUEL.KASKI@HIIT.FI
Helsinki Institute for Information Technology HIIT, Department of Computer Science, Aalto University

Abstract

In interactive intent modeling the user participates in constructing a model of her search intent using an interactive user interface. This allows the user to iteratively refine the model used for personalizing her search results, even in the presence of high initial uncertainty of the search intent. This approach for personalization has been shown to be beneficial in exploratory information retrieval. This extended abstract summarizes the key results from past studies and suggests possibilities for the generalization of this approach.

1. Introduction

Personalization of search results relies primarily on the ability of the system to create a concise model of the information need or search intent of the user. By using this model, it is possible for the system to prioritize what information and search results to present to the user.[1]

One approach to constructing these types of models is to engage the user in a dialogue with the system. This way the model is constructed by starting from an initial rough model of the user's interests, and refining it using iterative adjustments. The initial model can be constructed, for example, based on the keyword query used by the user to explain her search intent. The refinements can be, for example, relevance feedback given to system-suggested search keywords.

[1]These choices have to be made given the limitations in in the amount of space that is available in the user interface, the limited cognitive resources of the user and and the response time requirements of an interactive system.

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This approach has some requirements that need to be fulfilled for it to be applied. First, there has to be a way for the system to visualize the current state of the personalization model to the user. This is related to the study of the *interpretability* of machine learning models (Rüping, 2006), open user models (Ahn et al., 2007) and information visualization in general. Second, there has to be a way for the user to make adjustments to said model. This is related to the study of *controllability* of interactive machine learning models (Kelley et al., 2008; Jameson & Schwarzkopf, 2002). There are other important considerations as well (Höök, 2000); for example, the *usability* of interactive systems should be considered. One example of an usability consideration is, that the user should be able to both predict the effects of her actions and to understand what happened because of her actions.

There are multiple benefits from this type of approach to constructing models for personalization. First, the approach works even when we have very little initial information of the user's interests (also known as the "cold start" problem (Lika et al., 2014)), as the user has the ability to refine the model until the performance is satisfactory. Second, by allowing the user to both see and interact with the model she is able to understand better how the personalization works, which may increase the trust to the system, and allows the user to make corrections to the model when needed (Kulesza et al., 2015).

In addition to our work, multiple other interactive search systems have been developed in the field of information retrieval and recommender systems as well (He et al., 2016). In the following section we summarize some main results from our previous research in using interactive intent modeling in the context of exploratory information retrieval. After that, we discuss the possible other application domains where this approach could be used as well.

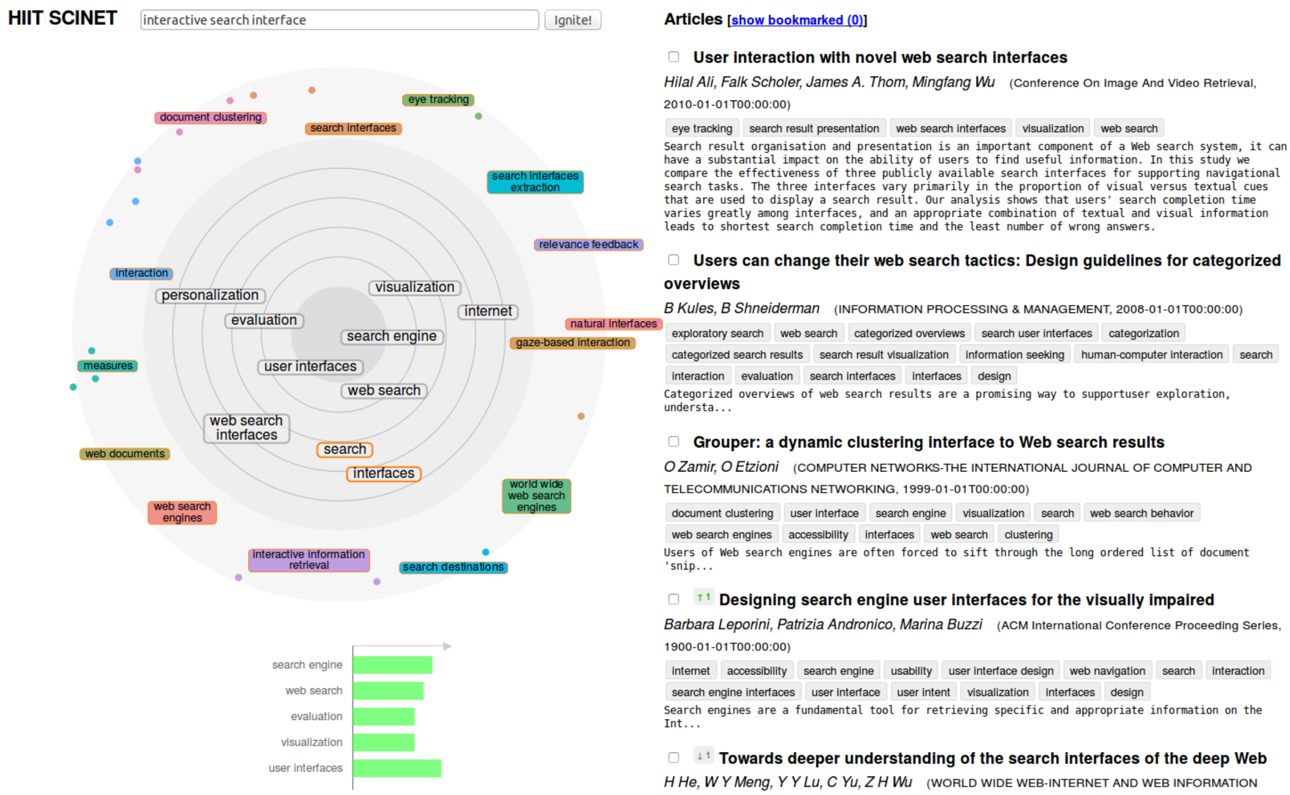

Figure 1. A characteristic example of the search interfaces used in our studies.

2. Main Results in Exploratory Search

2.1. General System Overview

The interactive search interfaces used in our studies generally resemble the interface shown in Figure 1. User initiated the search using the keyword search box on the top. The most relevant documents are displayed on the right side of the screen. On the left side, the user intent model is presented as a radar visualisation. In the radar, the most relevant keywords are displayed in the center of the radar. The more relevant the keyword currently is, the closer it is to the center. On the edge of the radar, keyword suggestions are shown. The user can adjust the model by moving keywords to new locations on the radar (i.e. provide relevance feedback to the keywords). In (Kangasrääsiö et al., 2016), an additional timeline interface was situated under the radar to display the user's history of relevance feedback.

2.2. Interactive Intent Modeling

In a typical interaction with an information retrieval system, the user expresses a specific information need, entered as a query, investigates the results returned by the search engine, and alters the query to direct the search to a chosen direction: a more specific subtopic or an alternative direction. As a result, users frequently have to carefully investigate the results to be able to reformulate their query.

In (Głowacka et al., 2013; Ruotsalo et al., 2013) we proposed that better support for search can be provided through learning from feedback on higher level representations of the data sets, such as topics or keywords, that are extracted from document features. This feedback enables applying machine learning techniques, such as reinforcement learning to improve relevance, novelty and diversity of results. This allows users to direct their search using the offered keyword cues at any point of time without getting trapped in a context, or having to provide tedious documentlevel relevance feedback, or relying on implicit feedback mechanisms that may take long to converge.

The resulting information access system couples reinforcement learning techniques with information visualization and interaction to boost exploratory search. The users can actively engage in an exploratory search loop where they manipulate article features, such as keywords, by dragging them within the exploratory view and thus providing relevance feedback to them. We found a suitable abstract level on which it is convenient for the users to direct their search (in our case, the document keywords are the navigation options users can use to direct their search), and use observed interaction together with binary feedback to feed reinforcement learning based optimization of further navigation options.

A task-based user study conducted with 20 participants comparing our system to a traditional query-based baseline indicates that our system significantly improves the effectiveness of information retrieval by providing access to more relevant and novel information without having to spend more time acquiring the information.

2.3. Controllability of Interactive Models

The controllability of interactive machine learning models studies the question: "*How to enable the user to achieve the kind of changes in the search model that the users wants to happen*". This is not always a trivial question to answer, as the mathematical models used in personalization can be quite complex, and small changes made by the user may have large and even unpredictable effects.

In (Kangasrääsiö et al., 2015) we presented an initial approach to solving this issue. The idea is that we require that the user model should always conform with the most recent feedback given by the user. For example, if the user feedback states that a certain keyword should have a certain relevance value, the model constructing algorithm will do it's best to make sure that the resulting user model agrees with this (even at the expense of making some older feedback fit worse to the resulting model).

The practical way we achieved this was an application of a control engineering feedback loop. We assumed that the target model state should be reachable by giving some finite sequence of feedback values to the keyword the user adjusted. We then iteratively gave suitable feedback to that keyword, until the resulting model state was within reasonable bounds of the goal state (if possible in limited number of steps). From the modeling perspective, this could also be interpreted as an automatic selection of the "weight" for the most recent user feedback. A benefit of this approach is that it is agnostic of the underlying user model formulation, requiring only the ability to give iterative feedback and observe the resulting model state.

In (Kangasrääsiö et al., 2015), in a user study with 10 participants, we noticed that improving the controllability contributed to improved task performance in information retrieval tasks with a narrow task specification (there was a clearly defined correct answer). However, in broader tasks (where more exploration was required and multiple correct answers existed) the user's performance was worse when they had more control. This finding is similar to that in (Ahn et al., 2007), where it was noticed that giving users full control over their user model is not always beneficial. Further research on when and how control should be given to the user, to yield maximum benefit, is still required.

2.4. Predictability of Interactive Models

The predictability of an interactive machine learning model refers to the ability of the user to *predict what essential changes will happen in the user model* as a consequence of the various actions the user has available for interacting with the model (before the user actually commits to these actions).[2] This is a complementary feature to controllability, although a controllable system also tends to be predictable, and vice versa. It is also clear that when the user model is complex, it is not trivial to guarantee that the model will change in predictable ways as a consequence of user actions.

In (Kangasrääsiö et al., 2015) we presented an initial approach to solving this issue. The idea is that when the user has partially committed to modifying a certain feature of the user model, we calculate multiple "*possible future models*". Each of these corresponds to one type of adjustment to the model feature at hand. For example, if the user would like to give relevance feedback to a certain search keyword, we could compute what would happen if the user would indicate that the keyword is 'relevant' or 'not relevant'. These possible future models are then used to visualize the effects of different actions before the user actually commits to the feedback. As these predictions need only be approximate, they can often be computed faster than full model updates.

The practical way we achieved this was to wait until the user indicated interest in giving feedback to certain search keyword. We then computed in the background two possible future models, by giving relevance feedback 1 (relevant) and 0 (not relevant) to the currently selected keyword. We then used these possible future models to calculate an interpolated approximation of what would happen if the user would give any kind of feedback to that particular keyword (relevance value between 1 and 0).

In (Kangasrääsiö et al., 2015), in a user study with 10 participants, we noticed that improving the predictability of the system improved the usability and perceived usefulness of the system. The users also reported that they were able to understand better how different features in the model were related to each other thanks to this feature. This finding is similar to that made in (Herlocker et al., 2000), where it was shown that by explaining the behavior of the recom-

[2] As updating the model and computing new personalized recommendations to the user may be an expensive operation, it is important to reduce the amount of unnecessary actions that the user will simply undo when she notices that the action did not have the effects she intended. Also, some systems may not support undoing of feedback actions.

mendation system to the users contributed to improved user acceptance of the system. It is still a research question how big of an effect the predictability of the system has to the task performance by itself.

2.5. Dealing with Drifting Intents and User Errors

In exploratory information retrieval, the user is often initially uncertain about her precise information need, and is learning while searching (Marchionini, 2006). As the user learns, her information need also evolves over time. If learning happens within a search session, this may cause part of the feedback the user gave earlier to become obsolete or erroneous. This is also known as *concept drift* (Gama et al., 2014). Another reason why feedback given to the system may be wrong is that the user could have made a mistake in giving the feedback and failed to notice that the feedback was not interpreted as she intended.

If obsolete and erroneous information is used in constructing the model of the current interest of the user, it is likely that the personalization performance will suffer. However, many systems simply assume that all of the recent information is relevant and equally accurate. This means that there is an implicit assumption that no concept drift or errors should exist in the observed data.

In (Kangasrääsiö et al., 2016; Kangasrääsiö et al., 2016) we present a Bayesian user model that is able to estimate the accuracy of each individual piece of user feedback. Based on these estimates, we can make suggestions to the user regarding what past feedback could be in need of revision. We also developed a timeline interface that allows the user to see her recent feedback history and and make changes to it if needed.

In (Kangasrääsiö et al., 2016), in a user experiment with 16 participants, we observed that this functionality made it easier for users to notice and correct mistakes in their feedback. The users also reported that it was easier for them to modify their query when the timeline interface functionality was enabled.

To the best of our knowledge, this was the first study where an interactive information retrieval user model took concept drift and errors explicitly into account in constructing the model and allowed the user to interactively adjust these inferences if needed.

3. Other Possible Application Domains

The applicability of interactive modeling rests on the assumption that the user can be made engaged in constructing a model of her interests. For example, in the case of exploratory information retrieval, the user can immediately observe the value of giving feedback to the search system if the quality of the results visibly improves as a consequence of these actions. In general, the situation should be such that the user feels rewarded from engaging in interaction with the system.

Another feature that is required of the system is an interpretable model of the user's interest. For example, in the case of information retrieval, our model estimates the relevance of various keywords, which makes it easy to be visualized to the user in an intuitive way. In general, it would be beneficial if the features of the model are conceptually simple for the user to understand, and that modifying, for example, the importance of the features, makes sense from the modeling standpoint.

We have identified two domains where this type of interaction could be applicable: natural search interfaces and Bayesian model prior elicitation.

Natural search interfaces
Our search engine was designed for finding scientific documents by giving feedback to keywords. In this application domain, this is a reasonable approach. However, there are multiple situations where there are more natural ways for the user to define her search interest (Hearst, 2011). One example of such interfaces is a interface that allows the user to find sport plays by sketching pictures of the players' positions on the field (Sha et al., 2016).

These types of situations are no different from the traditional setting, in the sense that a model of the user's interests needs to be constructed in order to make the personalized recommendations. While the type of interaction may be different from the traditional setting, the same principles of interactive construction of the model may still be applied, as the change in interaction modality should not, in general, have an effect on the uncertainty experienced by the user.

For example, in the case of sketching pictures of of the player's positions on a playing field, it may happen that some of the positions sketched at the beginning don't make sense together with the positions sketched later on in the search session. This could be, for example, because the user is not very familiar with the normal play patterns in the game. In this case, it could be useful if the system could ask the user for clarification, pointing out the most likely outliers in the player positions.

Inferring priors for Bayesian models
The performance of Bayesian machine learning models is often dependent on the proper selection of prior distribution parameters (also known as *hyperparameters*) for the model. Especially when there is small amount of observed data from a complex situation, such as in the filed of medicine, the use of reliable prior information from experts is important (Albert et al., 2012).

However, it is not easy for the experts to understand how changing these priors will affect the inferences made by the model. The experts may also have high uncertainty regarding some parts of the prior knowledge, and sometimes even experts can be mistaken in their understanding. If the search for the best prior information model could be formulated as a interactive model construction task, the experts could start with a rough model of the prior and refine it in small increments. This way the experts could also be able to understand better how the changes in the model priors affect the final inferences.

For example, when choosing the next value to try for a model parameter, approximate models could be quickly fitted using different values of the parameter, and the estimates could be visualized to the expert. This could potentially save considerable amount of time, as the expert could make more informed choices when trying out different parameter values.

4. Summary

In this extended abstract, we showed that interactive modeling of user's interests is an applicable approach in exploratory information retrieval. We presented some solutions for dealing with the controllability and predictability of these types of systems, as well as dealing with the changes in user's intent and errors in user feedback.

We also discussed possible new application domains for this type of paradigm, identifying two application domains where this type of approach could also be used: natural search interfaces and Bayesian model prior elicitation.

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