Perspectives on Bayesian Optimization for HCI

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Abstract
In this position paper we discuss optimization in the HCI domain based on our experiences with Bayesian methods for modeling and optimization of audio systems, including challenges related to evaluating, designing, and optimizing such interfaces. We outline and demonstrate how a combined Bayesian modeling and optimization approach provides a flexible framework for integrating various user and content attributes, while also supporting model-based optimization of HCI systems. Finally, we discuss current and future research direction and applications, such as inferring user needs and optimizing interfaces for computer assisted teaching.

Author Keywords
Bayes, Optimization, Gaussian process priors, Modeling

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H.5.m. [Information interfaces and presentation (e.g., HCI)]: Miscellaneous.

Introduction
In our work with audio based interfaces and optimization of those, we often find it beneficial to consider a simple conceptual view (Fig. 1) of the system consisting of the user(s), the interface (including any processing of content), the content itself (such as audio signals) and

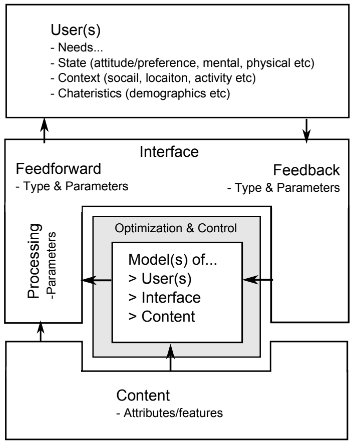

Figure 1: Conceptual overview of the HCI systems under consideration including a simplified flow of information with the flow from the model typically controlled by the optimization/control mechanism. Attributes describing a particular element is indicated with a - prefix, and these are typically used as either feature/co-variates or observations/regressors in the models.

models used to represent various aspects of the system.

The ultimate goal is to design and/or optimize any of the elements of the HCI system to fulfill the often implicit, uncertain, and dynamic needs of the user. This often requires a model which can tell to what extent the user's need is fulfilled given a certain configuration of the entire HCI system. This can be accomplished by taking into account observable variables such as content, user state and context as well as other user characteristics. Since the model is merely a model, and rarely perfect, it should be able to convey its uncertainty about predictions, and further be able to provide suggestions on how to improve itself by utilizing the interaction with the user. That is, the model should be able to represent knowledge of its own imperfections, which can be accomplished by taking into account the variables (such as feedback types and the presented content) which influences the model's performance measured e.g. by reduction of overall uncertainty.

This suggest two overall challenges where optimization has proven highly relevant for HCI. The first is in choosing and learning (*exploring*) a concrete, generalizable model of the system and user in an optimal fashion. The second is in *exploiting* such a model to optimize the system in order to fulfill the user's (and possibly the model's) needs.

Methodology

The methodology we have adopted — and subsequently contributed to — is often termed Bayesian optimization [1, 2, 8]. The core is a non-parametric Bayesian regression model based on Gaussian process priors, which takes any type of input representation via flexible covariance functions, and can include group structure by extending the hierarchical Bayesian formulation [4, 5]. The models has an inherent representation of uncertainty on both outputs (observations), parameters and inputs (features). A particular advantages is that this inherent representation of uncertainty can be exploited to perform simultaneous learning and optimization of the regression function using for example the so-called *Expected Improvement* [8] principle - or be used to learn a complete, generalizable user model by applying information theoretic measures of model improvement [7]. One downside of this modeling flexibility is the scalability, however, a lot of work has gone into reformulating the models and optimization for scalability, e.g. [5].

Optimizing Audio Interfaces

We have applied the methodology in a number of applications focusing on modeling audio and optimizing audio interfaces by extending the basic Bayesian optimization approach in various ways which are outlined in the following.

Hearing Devices

In [12, 9], the methodology was used to optimize a complex audio interface for hearing impaired users. The audio interface contains a signal processor with a multitude of parameters controlling the exact compensation of the hearing loss of the individual user. The first challenge in this case is that hearing impaired users are not only untrained listeners, but are typically also elderly uncertain users. Therefore, they can be very noisy assessing their internal criterion. For this reason, we introduced a novel relative feedback type and observation model for handling such inconsistencies, and with the Bayesian formulation, we easily included this observation models into the optimization. The optimization was further made more robust by including suitable priors/regularization on the model parameters. The second challenge is what criterion the user actually optimizes for, i.e. determining/defining the need of the user. The purpose of a hearing aid is to restore the user's speech understanding in the context of a noisy environment, while not being unpleasant in general, but the user will most of the time wear the device outside of this situation. This imposes constraints on the parameters that are optimized, the context we optimize in and on the user's criterion which in this case was contained to general preference. While fixed in the given study these aspects could potentially be modelled and elicited as part of an future, extended model.

Home Entertainment Systems
Audio interfaces is an important part of home entertainment systems and Smartphones but even though there is plenty of evidence for significant personal preferences e.g. in the frequency response of the audio system, few of the billions of audio systems are optimized for the individual listener. In [10] we examined to what extent a personalization procedure can be used to optimize the audio device by taking into account the parameter settings of the audio interface in the prior such that adjacent frequency bands are biased to have relatively similar settings. We biased the the user to focus on the overall quality of the sound. Using a particular fixed, graphical interface, the user was asked to report his/her preference of a particular example. The results showed that we could improve the procedure compared to simply trying out different configurations at random, but we could not show any signification effect of including the prior information.

Models of perception
Is not always a possibility to directly optimize the user's need without a representation of the user's understanding of a given aspect of the system. In [7] the framework was used to robustly elicit and model the users perception of the emotion expressed in music where exteded the basic framework with a pairwise comparisons for providing a robust user interaction and feedback. The experimentation was done by optimizing the exploration of the model, by sequentially choosing the content presented in the audio interface based on a information theoretic optimally criterion. We demonstrated how the learning rate of the model can be improved by selecting the optimal content (audio excerpts). The same study also emphasized the importance of modeling each user individually, but did take into account a explicit group structure in the optimization which can potentially lead to a future improvement in learning rate by transferring knowledge from one use to the other.

Perspectives & Future Work

The outlined approach is by no means the only way to model and optimize elements of HCI systems, however, we believe that the Bayesian optimization approach offers a natural way to incorporate and represent uncertainty of all the aspect of a modern HCI system. This allows for a relatively easy formulation of new extensions which naturally supports optimizing various aspect of the system. One such extension include inferring and utilizing group structure for directly optimizing and personalizing interfaces inline with modern services such as Netflix and Amazon. There is currently a great interest in extending the basic framework outlined here to efficiently representing and finding group structure [4, 3, 11].

A relatively unexplored application is the optimization of interfaces and the presented content to actively teach the user about a particular subject. There is an obvious optimality criterion (or user need), namely progress knowledge level about a given subject. The immediate challenge thus lies in choosing the interfaces, e.g. based on learning modalities, and the actual content/question presented. This has partly been explored within the outlined framework [6], and we see great potential for exploring this further for other applications in order teach users about the interface itself, but also about the content in a more engaging setting while ensuring an optimal increase in the skill level.

The greatest challenge—and opportunity—we see for optimization for HCI is to elicit and infer the state and needs of the user, and optimize the interface and content accordingly. While the user's need is very well defined in some applications, it seems to be a daunting task in others (e.g. music recommendation). However, given the emergence of modern sensor technology (including EEG, heart rate, location, etc.), we see a potential for incorporating such information into the already existing regression framework and in the near future be able to do real-time inference and optimization of user needs.

Summary

In this position paper, we have briefly described our existing work on optimization in the HCI domain, and provided examples and arguments for the benefits of a combined Bayesian modeling and optimization approach. The outlined approach is highly related to techniques and methods in control theory and reinforcement learning, and we see a productive collaboration with these and other communities for solving some of the open questions in HCI, such as robust, dynamic inference and optimization reveal user needs and state.

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