Bayesian Methods for Interaction and Design

Intended for researchers and practitioners in interaction design, this book shows how Bayesian models can be brought to bear on problems of interface design and user modelling. It introduces and motivates Bayesian modelling and illustrates how powerful these ideas can be in thinking about human–computer interaction, especially in representing and manipulating uncertainty. Bayesian methods are increasingly practical as computational tools to implement them become more widely available, and offer a principled foundation to reason about interaction design.

The book opens with a self-contained tutorial on Bayesian concepts and their practical implementation, tailored for the background and needs of interaction designers. The contributed chapters cover the use of Bayesian probabilistic modelling in a diverse set of applications, including improving pointing-based interfaces, efficient text entry using modern language models, advanced interface design using cutting-edge techniques in Bayesian optimisation, and Bayesian approaches to modelling the cognitive processes of users.

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Preface

Motivation

This edited book synthesises recent progress in applications of probabilistic methods in the area of human–computer interaction (HCI). HCI is a field concerned with the design and study of computing systems for human use. Most design efforts in HCI follow a human-centred (also known as user-centred) approach that considers the context of use and the abilities and needs of stakeholders. However, most existing human-centred methods prescribe resource-intensive design and evaluation methods. The prevailing paradigm relies extensively on trial and error and expensive empirical measurements.

HCI has recently revived its interest in using algorithmic approaches to drive design and evaluation [17]. *Computational interaction* is a topic area that studies algorithmic methods to optimise designs, adapt user interfaces, automate evaluation, and even explain and describe interaction through simulation of user interfaces and prediction of user actions on those interfaces. However, traditional computational modelling approaches in HCI [1], such as model human processor (MHP) [5], GOMS [11] and Fitts' law [15], ignore uncertainty. Statistical analysis methods commonly used in HCI tend towards a frequentist treatment of probability with its known shortcomings [3, 13].

This book aims to fill a gap in the literature and promote research on Bayesian methods in HCI. Bayesian methods, such as *Bayesian statistical analysis* [9] (statistics that use Bayesian interpretation of probability of events) and *uncertainty quantification (UQ)* [10] (the characterisation and computation of uncertainty and confidence for models and data in a principled statistical manner), have been adopted across a wide range of scientific and engineering research disciplines and fields (e.g. physics [16], nuclear safety and management [18], astronautical engineering [6], medicine and healthcare [2]). However, despite there being Bayesian approaches to a variety of related problems in science and engineering, applications in HCI are still nascent. Although there are already some examples of successful use of Bayesian methods in interaction design (e.g. supporting user modelling [4, 12], probabilistic interfaces [44], novel interactions [20, 21], design optimisation [8, 14], evaluation and statistical analysis [7, 13]), such methods are not yet widely adopted in the broader HCI community.

Outline

The chapters in this book expose the reader to Bayesian methods for interaction design and teach them how to apply such principled methods to their own research and practice. One of the main goals of this book is to bridge the gap between literature on theoretical Bayesian methods and practical applications in interaction and design and make Bayesian methods accessible to a broader HCI audience.

This book does so through a series of chapters split in four parts, beginning with an introduction to Bayesian methods and Bayesian statistics, followed by a section that illustrates applications of Bayesian inference to infer user intents in probabilistic interfaces. This is followed by a collection of chapters on Bayesian optimisation in the design of interfaces. The final section illustrates use of Bayesian methods in cognitive and user performance modelling and simulation.

Part I of this book explains the Bayesian treatment of probability and uncertainty through two chapters. Chapter 1 makes a case for Bayesian modelling and illustrates principles and applications of Bayesian inference on simple, tutorial-like examples relevant to interactive design. Chapter 2 explains Bayesian statistics and its application to interactive design evaluation. After reading Part I, the reader will have the foundational knowledge on how to apply the Bayesian method to interactive design with a road map for how to explore related, more advanced topics further.

Part II illustrates how to design user interfaces that can reduce the uncertainty about the user's goals and intentions using Bayesian inference. Chapters 3–6 show how to infer user goals and intentions for four different, fundamental interaction types: information search, pointing target selection, command selection and text entry. Chapter 7 then discusses how to combine forward (traditional ML) models with inverse (Bayesian) modelling in the context of touch sensing. Having read Part II, the reader will know how to implement probabilistic user interfaces that can reason about and act in response to inherently uncertain user behaviours.

The next part of the book, Part III, illustrates Bayesian optimisation approaches to design user interfaces that optimise for user preferences and abilities. User preferences for particular features of an interface or the interface as a whole are notoriously difficult to elicit and often require repeated, costly empirical user studies. The chapters in this part detail how to use Bayesian optimisation to efficiently reduce the search space of all possible interfaces to a few user-desired options. The methods covered in this section will give the reader new tools to optimise their user interface design in a principled way that goes beyond trial and error.

Finally, Part IV illustrates applications of Bayesian approaches to computational cognitive models that simulate human decision-making and physical actions. Such approaches provide a theoretical and methodological update to traditional computational modelling approaches in HCI. After reading these final chapters, the reader will be able to apply a probabilistic lens onto the user's decision-making and how their cognitive plans result in physical action.

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