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Types and states: Mixture and hidden Markov modelling for the cognitive sciences

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Authors
Speekenbrink, Maarten
Visser, Ingmar

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Types and states: Mixture and hidden Markov modelling for the cognitive sciences

Maarten Speekenbrink (m.speekenbrink@ucl.ac.uk)
Cognitive, Perceptual and Brain Sciences, University College London
Gower Street, London WC1E 6BT, United Kingdom

Ingmar Visser (i.visser@uva.nl)
Department of Developmental Psychology, University of Amsterdam
Weesperplein 4, 1018 XA Amsterdam, The Netherlands

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Objectives and scope

There are many situations in which one may encounter distinct *types* of entities, such as different animal species, and different *states* in which these entities may exist, for example motivational states like hunger. Cognition is sometimes also best understood in terms of discrete types and states. For example, aspects of cognitive development can be characterised as the acquisition of increasingly complex rules constituting different types of reasoning (Jansen, Raijmakers, & Visser, 2007). And rather than a gradually shifting trade-off, people may switch rapidly between distinct decision-making modes favouring either speed or accuracy (Dutilh, Wagenmakers, Visser, & van der Maas, 2011). The idea that cognitive processes are guided by qualitatively different strategies underlies a wide range of theories of word recognition, cognitive development, categorization, and decision making, to name but a few topics (for an overview, see e.g. Scheibehenne, Rieskamp, & Wagenmakers, 2013).

As the identity of cognitive types and states is generally not directly observable, appropriate statistical techniques are required to identify them. This tutorial will focus on mixture models (MMs) and hidden Markov models (HMMs), which are the foundation of such techniques. In MMs, a type or state (e.g., a cognitive strategy) is formalized as a probability distribution over observables. Because a dataset may contain different types, the overall distribution is a mixture of such individual component distributions. As the component distributions need not be of the same parametric family (e.g., Gaussian distributions can be mixed with other distributions), MMs allow for considerable flexibility in the definition of types and states. HMMs are a natural extension of MMs, allowing switches between states over time, making them particularly useful when people can switch between cognitive strategies during a task. In addition to identifying the different states, HMMs allow one to also focus on the process underlying state transitions.

While MMs and HMMs are widely used in fields such as computational biology (e.g., for DNA sequence analysis) and machine learning (e.g., for speech recognition and text classification), their use in the analysis of cognition and behaviour is relatively rare. This is unfortunate, as MMs and HMMs are ideally suited to test and explore important theoretical ideas in cognitive science. The objective of this tutorial is to provide researchers in cognitive science with an accessible introduction to MMs and HMMs and provide them with the necessary skills to apply them in their own research.

Outline of the tutorial

The tutorial is divided into two parts. The first part introduces the theory behind MMs and HMMs. The second part will be more practical, using a number of examples to show (a) how to apply MMs and HMMs with user-friendly and freely available software, (b) how to interpret these models, and (c) how the models can reveal aspects in the data which remain hidden with more traditional analyses. The first part of the tutorial will be delivered as a classroom style lecture. The second part will use a more hands-on approach with practical computer-based examples and exercises. The audience is encouraged to bring a laptop; all necessary software and material will be made available in advance.

Part I: Theory

Introduction to mixture models. This part will introduce the basic structure of MMs and the use of graphical and other techniques to determine whether MMs might be applicable.

Estimation. This part will provide an intuitive treatment of maximum likelihood estimation and introduce numerical optimization and Expectation-Maximization (EM), the two main methods for this type of estimation of MMs and HMMs. Practical issues such as starting values and local maxima will also be discussed.

Inference. This part will discuss methods for model selection and how to determine the number of components (i.e., types, or latent classes). We will also discuss methods to test parameters for significance and the use of posterior probabilities to determine the component to which a data point belongs.

Hidden Markov models. This part will introduce hidden Markov models as a direct extension of mixture models. We will then discuss how to generalize the previously discussed methods of estimation and inference to these models.

Part II: Practice

Introduction to `depmixS4` This part will introduce `depmixS4` (Visser & Speekenbrink, 2010), a flexible package to estimate MMs and HMMs in the `R` environment for statistical computing (R Development Core Team, 2010). The examples in the remainder of the tutorial will mainly use this package.

Examples of mixture models Examples will include the use of MMs to detect developmental stages in the liquid conservation task and the use of MMs to detect multiple learning strategies in a category learning task.

Examples of hidden Markov models Examples will include the use of HHMs to analyse speed-accuracy trade-offs and the use of HMMs to model response strategies in multiple cue learning.

Extensions This part will briefly discuss some extensions to basic MMs and HMMs, including the use of covariates to predict the identity of mixture components and states. We will also briefly discuss the use of Bayesian methods to estimate MMs and HMMs.

About the organizers

The organizers are the developers of `depmixS4` (Visser, Jansen, & Speekenbrink, 2010), a popular `R` package to estimate mixture and hidden Markov models. They are also the authors of an upcoming book on this topic (commissioned by Springer for their "UseR" series) and a recent tutorial on hidden Markov models (Visser, 2011). The organizers have extensive experience in the application of MMs and HMMs to research in developmental and cognitive science (e.g., Speekenbrink, Lagnado, Wilkinson, Jahanshahi, & Shanks, 2010; Visser et al., 2010). They can draw upon this experience to provide the audience with real examples and practical advice relevant to a cognitive science audience.

Justification

Theories which propose the existence of distinct types and states are widespread in the cognitive sciences. Traditional statistical analysis, such as t-tests and ANOVAs, or not applicable to test such ideas. MMs have been successfully used to test "toolbox models" of cognition (e.g., Scheibehenne et al., 2013) and HMMs to test discrete strategy switches (e.g. Speekenbrink et al., 2010; Jansen et al., 2007). This tutorial will provide cognitive scientists with the intuitive understanding and practical knowledge of these models necessary to apply them to their own research.

Intended audience

This tutorial will be mainly introductory and no specific prior background knowledge is required. While basic knowledge of probability and statistics will be helpful, treatment of the theoretical concepts will largely be conceptual. Familiarity with the `R` environment will be helpful in general, but by making the commands and code available, previous experience is no requirement to follow and replicate the results of the practical examples.

Requirements

Participants would ideally bring a laptop to the tutorial. The required software (`R` and `depmixS4`) is open source and freely and easily obtainable. `R` is available for all major platforms and can be downloaded from `http://www.r-project.org`. The `depmixS4` package can be downloaded from `http://cran.r-project.org/web/packages/depmixS4/` or installed from within `R` through the command `install.packages('depmixS4')`.

Contact details

Maarten Speekenbrink, Cognitive, Perceptual and Brain Sciences, University College London, Gower Street, London WC1E 6BT, England, UK. Tel: +44 20 7679 8548. Email: m.speekenbrink@ucl.ac.uk

Ingmar Visser, Department of Developmental Psychology. Weesperplein 4, 1018 XA Amsterdam, The Netherlands. Tel: +31 20 5256723, Email: I.Visser@uva.nl.

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