Bayesian Estimation of Evidence Accumulation Architectures in Neuroscience and Cognition

http://www.tascl.org/estes.html

A summer school supported by the **William K. and Katherine W. Estes Fund** for
Advanced Training in Mathematical and Computational Modeling for Psychological Science

Sponsored by the Boston University Department of Psychological and Brain Sciences

The 5-day workshop will be offered in the week prior to the 2016 Psychonomics conference (Monday 7th – Friday 11th November) at Boston University on the Charles River Campus.

Places are limited and attendance is by application sent to Anna Finlay, anna.finlay@utas.edu.au
Deadline for Applications: 26th September.

Organizing Committee and Presenters

Prof. Andrew Heathcote
Universities of Tasmania & Newcastle, Australia

Prof. Scott D. Brown
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Dr. Brandon Turner
The Ohio State University

Dr. Dora Matzke University of Amsterdam

Dr. Maxim Bushmakin
Northeastern University

Prof. Marc Howard
Boston University

This workshop is suitable for researchers ranging from those experienced with conventional evidence accumulation modeling (as advanced models will be covered) to those new to models of this type. It is desirable to have some experience with cognitive modeling in general (we recommend http://sites.uci.edu/cmmc/ and the related book), particularly Bayesian methods to fit such models (we recommend, http://bayescourse.socsci.uva.nl/ and the related book), as is experience with R (we recommend http://health.adelaide.edu.au/psychology/ccs/teaching/lsr/).

The workshop is free, but students will be responsible for their own living costs. We recommend students look into accommodation in the region of the Charles River Campus area early. Entry into the workshop is by a maximum 1-page application. Your application should describe academic qualifications, relevant prior experience, and research interests and email contact details. Students can bring a dataset for analysis by evidence accumulation modeling, and if so should describe the data set and the research question it addresses in the application. On the final day of the workshop students will make a presentation about their data set or a data set supplied to students.

Background and Course Outline

The idea that rapid decisions are made by accumulating a threshold amount of evidence has been successfully used and applied in two frameworks: (1) random-walk and diffusion models, and (2) racing accumulator models. Arguably, the most successful models within these two frameworks are the drift-diffusion model (DDM; Ratcliff & McKoon 2008), and the linear-ballistic accumulator (LBA; Brown & Heathcote, 2008) model, respectively. The mathematical tractability of the LBA, combined with new sampling methods equipped to handle its highly correlated parameters (DE-MCMC; Turner, Sederberg, Brown & Steyvers, 2013), has made (hierarchical) Bayesian estimation practical. The Bayesian approach has important advantages, such as providing better ways to address model complexity issues (Pitt & Myung, 2002), ensuring viable parameter estimation in sparse data environments, and enabling the assessment of group- and individual-level differences through hierarchical modeling (Shiffrin, Lee, Kim & Wagenmakers, 2008).

Over the last year we have written a suite of functions in the R programming language, called Dynamic Models of Choice (DMC), which lets users apply the Bayesian approach to data from experiments with complex factorial designs while requiring only limited programming experience. Most recently we have also made available fast routines for computing the LBA and DDM likelihood in an R package (Singmann, Gretton, Brown & Heathcote, 2015), and incorporated Bayesian DDM estimation in DMC. We have successfully taught one-day workshops on using the non-hierarchical version of DMC as part of a Model-based Neuroscience Summer School in Amsterdam (June, 2015, to be repeated and expanded in 2016 and 2017), and as a Cognitive Science Conference Tutorial in Pasadena (July, 2015). In November 2015, we presented a 2-day workshop in Taiwan teaching the full hierarchical version of DMC.

The William K. and Katherine W. Estes Fund summer school significantly expands the scope of the training we will offer beyond using existing models to:
1) Analyse a data set from a standard (n-choice) paradigm brought along by workshop attendees.
2) Perform model-based neuroscience analyses (Forstmann & Wagenmakers, 2015).
3) Develop new models to accommodate specialized tasks and cognitive processing architectures.

The first two days of the workshop will introduce DMC in both non-hierarchical and hierarchical settings, with a mixture of lectures and hands-on analyses of example data sets for standard n-choice tasks. The morning of Day 3 will address (1), enabled by a large team of expert organizers who can assist students individually to get them started on their analyses; this will be revisited during day four (with more practical advice and help offered by the team), and students will present their results on the final day of the workshop, with the aim of producing publication-quality analyses. Attendees will be given access to updates (see http://www.tascl.org/dmc.html, including testimonials from students of past DMC events).

With respect to (2) our team has been at the forefront of evidence-accumulation model-based neuroscience (Cassey et al., 2014; Mittner et al., 2014; Turner et al., 2015). We will discuss these and other approaches and implement simultaneous estimation of behavioral and neural data (either as a covariate or as a dependent variable) in DMC. With respect to (3) we have already implemented in DMC the go/no go task with the LBA and DDM, providing an example of integration over unobserved responses. We have also built on the stop-signal task work of Matzke et al. (2013) and Logan et al. (2014; "special" race models of choice as well as stopping) in implementing a special stop-signal race model in DMC, including "trigger failure" (Matzke et al., in press). We will use this model to illustrate a cognitive architecture based on mixtures of different numbers of racing accumulators, and will also implement and discuss models of the redundant-target task race model of Eidels et al. (2010; addressing tasks and race architectures for complex contingent choices). The later part of Day 3, all of Day 4 will be dedicated to (2) and (3).

Students should bring laptops and with access to the Internet through eduroam organized through their home institution. All exercises are in the R language and will be carried out through a browser giving access to RStudio on Amazon Web Services so no software need me installed beyond a current browser. For those not familiar with R we recommend working though Dan Navarro's free introductory textbook (http://health.adelaide.edu.au/psychology/ccs/teaching/lsr/) and practicing exercises using RStudio to become familiar with that interface (https://www.**rstudio**.com/).

Following is a detailed timetable including specific readings, session titles, and session instructors. We recommend the background reading given in the reference list at the end of this document.

Day 1: Individual Estimation with DMC

Time/Instructor	Activity
9.30am - 10.30am **Scott Brown**	Lecture 1: *Evidence Accumulation Models* We examine why evidence accumulation models are useful and the details of three models, the LBA, DDM and LNR. **Reading:** *Donkin, Brown & Heathcote, (2011)*
10.30am - 11.00am	Morning Tea Break
11.00am - 12.00pm **Andrew Heathcote**	Practical 1: *Simulating & exploring the DDM, LBA & LNR.* Introduction to the structure of DMC (dynamic models of choice), an R software system for Bayesian estimation of evidence accumulation models. Demonstrations of the setup of a model and simulation of data for a single subject and exploring the LNR model. Independent work running code to explore the LBA and DDM models.
12.00pm - 1.00pm	Lunch Break
1.00pm - 2.00pm **Dora Matzke**	Lecture 2: *Very Basic Bayes* Introduction to Bayesian estimation, and prior and posterior distributions, including how to specify priors and how to examine posteriors. **Reading:** *Wagenmakers, Morey, & Lee (2015).*
2.00pm - 2.30pm **Andrew Heathcote**	Practical 2: *Priors and posteriors* How to specify and plot a prior. How priors vary on different parameter scales. How priors and likelihoods are combined to get posterior likelihoods. Independent work specifying different priors.
2.30pm - 3.00pm	Afternoon Tea Break
3.00pm - 3.30pm **Brandon Turner**	*Lecture 3: DEMCMC* Markov Chain Monte-Carlo (MCMC) Sampling using Differential Evolution (DEMCMC). **Reading:** *Turner, Sederberg, Brown, Steyvers (2013).*
3.30pm - 4.30pm **Andrew Heathcote**	Practical 3: *Sampling* (**continued overnight as homework**) Demonstration of how to sample a single LNR subject and how to test whether samples are good, refining samples and plotting how well the model fits the data (posterior predictives). Independent work on sampling a single LBA and DDM subject. Demonstration of model selection methods.
4:30pm – 5.00pm **Scott Brown**	*Lecture 4: Plotting RT distributions and fits.* DMC makes some choices on these issues, but there are other approaches, which we overview in this lecture.

Day 2: Hierarchical Estimation with DMC

Time	Activity
9.00am - 9.30am **Full team**	Q&A: *Homework and other activates from Day 1*
9.30am - 10.30am **Brandon Turner**	*Lecture 5: Hierarchical Models* An overview of hierarchical models, posterior predictives and model selection. An overview of the algorithm for sampling a hierarchical model.
10.30am - 11.00am	Morning Tea Break
11.00am - 12.30pm **Andrew Heathcote**	*Practical 4: Specifying & Sampling Hierarchical Models* Demonstration of sampling from multiple LNR subjects independently and hierarchically. Independent work on sampling hierarchical LBA and DDM. Demonstration of model selection and posterior predictives for hierarchical models.
12.30pm - 1.30pm	Lunch Break
1.30pm - 2.30pm **Andrew Heathcote**	*Lecture 6: Plausible Value Correlations & Advanced Factorial Models* Real experimental designs are often complicated, using several factors and covariates. In this lecture we show how to use DMC in such complicated designs.
2.30pm - 3.00pm **Andrew Heathcote**	*Practical 5: Reading in and fitting data* Demonstration of how to read in data files and set up a model for a two-factor design with a covariate.
3.00pm - 3.30pm	Afternoon Tea Break
3.30pm – 4.30pm **Full Team**	Q & A: *Applying DMC to your data* Open discussion of the data bought by students. **Homework: start working on your own data.**

Day 3: Inhibition and Contingent Choice with DMC

Time	Activity
9.30am - 10am **Full Team**	Q & A: *Applying DMC to your data* Open discussion of the data bought by students.
10am-10:30am **Scott Brown**	*Lecture 7: How to Debug in R.* Although the workshop assumes basic knowledge of R this quick overview provides useful skills for using the advanced code required in more specialized models.
10.30am - 11.00am	Morning Tea Break
11.00pm - 12.30pm **Dora Matzke**	*Lecture 8: Go-NoGo and Stop Signal Paradigms* We discuss how to estimate models when some responses are withheld, focusing on the horse-race model of response inhibition, and a mixture-model extension for failures to trigger the stop response. **Readings**: Logan, Van Zandt, Verbruggen, & Wagenmakers (2014); Matzke, Dolan, Logan, Brown, & Wagenmakers (2013); Matzke, Love, & Heathcote (in press)
12:30pm – 1:30pm	Lunch Break
1:30pm – 3:00pm **Dora Matzke**	*Practical 7: Go-NoGo and Stop Signal Models in DMC* Using DMC to perform individual and hierarchical analysis of Go-NoGo and Stop-Signal models with extensions accounting for choice accuracy and trigger failure.

3.00pm - 3.30pm	Afternoon Tea Break
3.30pm - 4.00pm **Maxim Bushmakin**	Lecture 9: Complex Choice: We discuss how to use Logical-Rule and Coactive accumulator architectures to model contingent choice in the Redundant Target Paradigm with AND and OR instructions, including a mixture of trials where participants failure to follow instructions. **Reading:** Bushmakin, Eidels & Heathcote (submitted).
4.00pm - 5.00pm **Andrew Heathcote**	Practical 8. Individual and hierarchical fitting of redundant-target paradigm models with DMC.

Day 4: Model Based Neuroscience

Time	Activity
9.30pm - 10.30pm **Brandon Turner**	*Lecture 10: Linking Brain to Behavior.* There are many ways to link neural data to behavioral models. In this lecture we discuss several prominent approaches. **Reading:** *Turner, Forstmann, Love, Palmeri, Van Maanen (submitted).*
10.30am - 11.00am	Morning Tea Break
11.00pm - 12.00pm **Brandon Turner**	Lecture 11: Joint Modeling In this lecture we discuss one new strategy for modeling neural and behavioral data through hierarchical Bayesian modeling. **Reading:** *Turner, Forstmann, Wagenmakers, Brown, Sederberg, and Steyvers (2013).*
12.00pm – 12:30pm **Brandon Turner**	Practical 9: *Applying multiple neural covariates*. Here we demonstrate how to link multiple neural measures to cognitive models to boost predictive power using bespoke R code. **Reading:** *Turner, Rodriguez, Norcia, McClure, Steyvers (submitted).*
12.30pm - 1.30pm	Lunch Break
1.30pm – 3.00pm **Brandon Turner**	*Practical 10: Relating single-trial measures to BOLD activity.* Hands on demonstration of how to first estimate single-trial parameters of the LBA, then regress them against single-trial measures of the BOLD response using bespoke R code.
3.00pm - 3.30pm	Afternoon Tea Break
3.30pm - 4.30pm **Scott Brown**	*Lecture 12: Further approaches to model-based neuroscience.* We examine some alternative approaches to model-based neuroscience. **Readings:** *Cassey et al, (2014); van Ravenzwaaij et al. (submitted); Cassey et al. (submitted).*

Day 5: Multiple responses and student presentations.

Time	Activity
9.30am - 10.30am **Students**	Presentations
10.30am - 11.00am	Morning Tea Break
11.00pm - 12.30pm **Students**	Presentations
12.30pm - 1.30pm	Lunch Break

1.30pm – 3.00pm **Students**	Presentations
3.00pm - 3.30pm	Afternoon Tea Break
3.30pm - 4.30pm **Students**	Presentations

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