Workshop on Optimizing Experimental Designs: Theory, Practice, and Applications

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Background and Purpose

The accurate and efficient measurement of observations is at the core of empirical scientific research. To ensure measurement is optimal, and thereby maximize inference, there has been a recent surge of interest among researchers in the design of experiments that lead to rapid accumulation of information about the phenomenon under study with the fewest possible measurements.

Statisticians have contributed to this area by introducing methods of optimizing experimental design (OED: e.g., Atkinson & Donev, 1992; Lindley, 1956), which is related to active learning in machine learning (Cohn, Ghahramani & Jordan, 1996) and to computerized adaptive testing in psychometrics (van der Linden & Glass, 2000). The methodology involves adapting the experimental design in real time as the experiment progresses. Specifically, in OED, an experiment is run as a sequence of stages, or mini-experiments, in which the values of design variables (e.g., stimulus properties, task parameters, testing schedule) for the next stage are chosen based on the information (e.g., responses) gathered at earlier stages, so as to be maximally informative about the question of interest (i.e., the goal of the experiment).

OED has become increasing popular in recent years, largely due to the advent of fast computing, which has made it possible to solve more complex optimization problems, and as such is starting to reach everyday experimental scientists. A growing number of labs are applying OED across scientific fields, including cognitive psychology (Myung & Pitt, 2009; Cavagnaro, Myung, Pitt & Kujala, 2010), neuroscience (Lewi, Butera & Paninski, 2009), psychophysics (Lesmes, Jeon, Lu, & Dosher, 2006), systems biology (Kreutz & Timmer, 2009), astrophysics (Loredo, 2004), systems engineering (Allen, Yu & Schmitz, 2003), and clinical drug trials (Wathen & Thall, 2008). OED is not only a useful framework to enhance scientific research, but the underlying principles are also useful as a framework to understand how intelligent agents actively sample information to enhance their learning (e.g., Bramley, Lagnado & Speekenbrink, 2014; Nelson, 2005).

The purpose of the workshop is to introduce the principles underlying OED, illustrate how to apply OED in practice using widely and freely available software tools (e.g., R) to showcase applications of OED in areas such as cognitive psychology, education and assessment, and machine learning, and provide a platform to share work on OED.

Workshop Format

This full-day workshop will be organized around two specific goals: (1) to educate the cognitive science community about optimal experimental design (OED) and (2) to bring practitioners together who use it to share and showcase their latest work with the community. The first goal will be met in the morning session, which will include a 75-minute tutorial on the theoretical and computational foundations of OED given by Jay Myung and then another 75-minute hands-on session on the practical and implementation aspects of OED given by Maarten Speekenbrink. The second goal will be met in the afternoon, which will consist of six 30-minute invited presentations featuring example applications demonstrating the use of OED in various disciplines.

There will be a website with a workshop program, the titles and abstracts of all presentations, and recommended readings.

Target Audience

Graduate students, postdoctoral researchers, and scientists, who are new to OED and have workable knowledge of statistics on a graduate level. We anticipate that around 40-50 participants would attend the workshop.

Workshop Organizers

Jay Myung is Professor of Psychology at the Ohio State University. He received his PhD in 1990 in psychology at Purdue University and spent a year as a postdoc at the University of Virginia. His research interests in the fields of cognitive and mathematical psychology include optimal experimental design, Bayesian inference, model comparison, and neural networks. Homepage: http://faculty.psy.ohio-state.edu/myung/personal/.

Mark Pitt is Professor of Psychology at the Ohio State University. He received his PhD in 1989 in psychology at Yale University, twiddled his thumbs for a while, and then joined the faculty at OSU. His research interests are in model evaluation, design optimization, and in the field of language and spoken word recognition. Homepage: http://lpl.psy.ohio-state.edu/.

Maarten Speekenbrink is Lecturer in Mathematical Psychology at University College London. He received his PhD in 2005 in psychology at the University of Amsterdam, focusing on psychological methodology. Afterwards, he moved to UCL for a postdoctoral research position, where he was later appointed as lecturer. His research interests include optimal experimental design, statistics, computational modeling, learning, and decision making. Homepage: http://www.ucl.ac.uk/speekenbrink-lab/.

Presenters

The following invited speakers have confirmed their participation:

Daniel Cavagnaro
Dept. of Information Systems and Decision Sciences
California State University Fullerton, USA

Christopher DiMattina
Department of Psychology
Florida Gulf Coast University, USA

Woojae Kim
Department of Psychology
Ohio State University, USA

Jay Myung
Department of Psychology
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Center for Adaptive Behavior and Cognition
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Anna Rafferty
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Seoul National University, KOREA

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