Optimizing the Design of an Experiment using the ADOpy Package: An Introduction and Tutorial

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Introduction

Experimentation is one of the cores of cognitive science, whether one is interested in understanding the mechanisms underlying cognitive control or the neural basis of decision-making. Through accurate measurement in a well-thought-out experimental design, the goal is to obtain sufficiently noise-free data to make inferences about processing. The design of an experiment can be especially tricky, requiring consideration of many factors (e.g., what levels and how many levels of a variable should be presented, how many stimuli per level, etc.). The final design can sometimes result in only a subset of the design space (i.e., conditions) yielding interesting results, with the remaining data being minimally informative.

Advances in Bayesian statistics and machine learning offer algorithm-based ways to generate optimal and efficient experimental designs so as to minimize uninformative and wasted experimental trials (e.g., Cavagnaro, Myung, Pitt, & Kujala, 2010; Lesmes, Lu, Baek, & Dosher, 2010). In an optimized experiment, stimuli are selected adaptively and optimally (i.e., in an information theoretic sense; Lindley, 1956) on each trial by real-time data analysis of observed responses from earlier trials. What is being optimized is the values of the design variables that can be manipulated experimentally, such as the intensity of a stimulus in a psychophysics experiment or the monetary rewards and probability of occurrence in a preferential choice experiment. This is unlike a traditional experiment in which the design is fixed for all participants and stimulus presentation is either random or follows a predetermined schedule.

One such approach is referred to as Adaptive Design Optimization (ADO; Cavagnaro et al., 2010). ADO derives from optimal experimental design in statistics (Atkinson & Donev, 1992; Chaloner & Verdinelli, 1995) and active learning in machine learning (Cohn, Atlas, & Ladner, 1994; Settles, 2012). ADO is a general-purpose, algorithm-based method for autonomously conducting adaptive experiments that lead to rapid accumulation of information about the phenomenon of interest with the fewest number of trials. ADO can improve significantly the informativeness and efficiency of data collection (e.g., Cavagnaro et al., 2011 & 2016).

ADOpy

Expertise in statistics and computational modeling is required to use these machine-learning methods. To improve their accessibility to a wide range of researchers, we have developed an open-source Python package. The package, dubbed ADOpy, implements ADO for optimizing experimental designs. ADOpy is currently available on GitHub (https://github.com/adopy), with three pre-installed adaptive experimental tasks as of January 2019: (a) the slope and threshold estimation of the psychometric function (Kontsevich & Tyler, 1999); (b) the delay discounting experiment (Cavagnaro et al., 2016); and (c) the choice under risk and ambiguity experiment (Levy et al., 2010).

ADOpy is written using high-level semantic-based commands in a such way that the whole ADO procedure is broken into a set of meaningful function calls that can be easily edited and modified by users. Further and importantly, the package is user-friendly in that users can use the package without having to understand the computational details of the ADO algorithm. Additionally, the package is modular so that new models and/or experimental tasks can be easily added. Thus, only a modest amount of programming and modeling experience is required to use ADOpy.

The purpose of the proposed tutorial is to introduce ADOpy to cognitive scientists in a hands-on training environment, first providing a conceptual introduction to optimal experimental design and then walking through examples that demonstrate how to use methodology. The tutorial will be based on a manuscript (in preparation) to be submitted for publication in the near future.

Tutorial Format

This half-day tutorial will be organized into two 1.5-hour sessions with a 30-min coffee break between them. The first part, given by the first two authors, will consist of a general overview of the conceptual and statistical foundations of ADO (1 hour) and then 30 minutes to answer questions and set up for the tutorial session. After the break, the second 1.5 hours will be a tutorial on the ADOpy package, with hands-on training using concrete, work-through examples, run jointly by the third and fourth authors.

There will be a website with a program, a web link to the GitHub site, the abstracts and slides of all presentations, supplementary Python code to be used in the hands-on session and recommended readings.

Target Audience

Graduate students, postdoctoral researchers, and scientists, who are new to ADO and have workable knowledge of Bayesian statistics on a graduate level and also of basic Python programming.

Organizers/Presenters

Jay I. Myung is Professor of Psychology at the Ohio State University. He received a PhD in 1990 in psychology at Purdue University. His research interests in the fields of cognitive and mathematical psychology include computational cognition, optimal experimental design, Bayesian modeling, and model comparison. Homepage: https://faculty.psy.ohio-state.edu/myung/personal/

Mark A. Pitt is Professor of Psychology at the Ohio State University. He received his PhD in 1989 in psychology at Yale University. In addition to researching computational approaches to improving inference in experimentation, he researches questions in psycholinguistics, such as how listeners recognize spoken words. Homepage: http://lpl.psy.ohio-state.edu/.

Jaeyeong Yang is a second-year graduate student of psychology in the Department of Psychology at Seoul National University. He received a double major B.S. in psychology and computer science, and he wrote the *ADOpy* package in Python.

Woo-Young Ahn is Assistant Professor of Psychology at Seoul National University. He received a PhD in 2012 in clinical psychology at Indiana University and has published over 20 papers in journals such as *Cognitive Science, Proceedings of the National Academy of Sciences, Current Opinion in Behavioral Sciences, Journal of Mathematical Psychology,* and *Computational Psychiatry*. His research interests include decision neuroscience and computational psychiatry, and he developed the Bayesian modeling package *hBayesDM* (https://github.com/CCS-Lab/hBayesDM).

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