Applications of Instance-Based Learning Theory: Using the SpeedyIBL Library to Construct Computational Models

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1 INTRODUCTION

Making decisions in changing and uncertain situations is one of the great challenges facing humans. Although it is challenging, humans are arguably able to learn and adapt to changing conditions of choice. Therefore, understanding how humans make decisions in dynamic situations has become a long-standing goal of cognitive decision theory.

Instance-Based Learning Theory (IBLT) has emerged as a descriptive theory of experiential choice that can help explain decision making as a dynamic process, resulting from human interactions with the environment [5]. The theoretical process and mechanisms proposed in IBLT can be implemented computationally in models with diverse applications. These applications include binary choice tasks (e.g., [6]), dynamic supply chain inventory management (e.g., [7]), search and rescue and navigation scenarios (e.g., [9]), and dynamic allocation of limited resources (e.g., [1, 3]).

In this tutorial, we will introduce IBLT and its implementation in an open source library, *SpeedyIBL*, to demonstrate the capabilities of IBLT to handle a diverse taxonomy of individual and multi-agent decision making problems. The tutorial is designed to provide the theoretical and conceptual foundations of dynamic decision making and IBLT, and practical, hands-on sessions for the construction of IBL models using SpeedyIBL. Participants will be able to implement IBL models and demonstrate the emulated human decisions from their models. Participants will implement their models in Python using Google Colab, a free interactive online Jupyter notebook environment.

1.1 SpeedyIBL Library

The software we use for this tutorial is SpeedyIBL, an open source Python library developed by [10]. This library provides a computational implementation of IBLT proposed by [5]. SpeedyIBL leverages parallel computation with vectorization to accelerate the execution time of IBL models compared to those implemented with other IBL platforms (e.g., [8]).

2 LEARNING OBJECTIVES

- Gain familiarity with the approach taken by IBLT to model learning and decisions from experience.
- Understand how to create an IBL agent that learns to make decisions with the SpeedyIBL library, through an example of a binary choice task.
- Apply SpeedyIBL to solve a decision making tasks, the Iowa Gambling Task.
- Gain exposure to various applications of IBL models from the SpeedyIBL library.

3 PREREQUISITES AND AUDIENCE

This tutorial is an introductory course on cognitive modeling, and it provides hands-on experience in constructing IBL models for decision making tasks. It is intended for beginner modelers who would like to learn how to construct computational models of decision making with a general computational framework, SpeedyIBL. Before attending the tutorial, students should read the paper about the implementation of SpeedyIBL [10]. Having a basic background in Python programming will be beneficial, but is not required.

The tutorial will walk step-by-step through how to build IBL models using Google Colab, so it is appropriate for those with no prior experience in cognitive modeling or Python development notebooks. The instructors will send detailed instructions for any setup that is necessary prior to the tutorial.

4 TUTORIAL STRUCTURE

This 3-hour in-person tutorial is divided into three main sections followed by a concluding summary with a discussion of additional applications: the first section describes the theory behind the human decision making process through IBLT, the second introduces the SpeedyIBL library and the implementation of IBL models using a simple example of binary choice, the third section will dive into the hands-on implementation of IBL models, and finally, the tutorial will conclude with a summary and discussion of additional applications.

4.1 Section 1: Instance-Based Learning Theory

This section will provide the background and theoretical foundation for constructing computational models of decision making using SpeedyIBL. We will introduce Instance-Based Learning Theory (IBLT) [5], a comprehensive account of how humans make decisions based on experience during dynamic tasks. Many computational models based on IBLT (IBL models) have been constructed and demonstrated to be successful in explaining and predicting human decision making in a variety of contexts. In this section students will learn about the origins of IBLT, the major theoretical principles of the theory, and how the general theory can be applied to multiple decision tasks.

4.2 Section 2: Introduction to the SpeedyIBL Library with a Binary Choice Example

The second section of the tutorial will introduce the SpeedyIBL library. This library provides an advanced implementation of the theoretical components of IBLT, leveraging parallel computation with vectorization to speed up the execution time of IBL models.

We will cover how to install the library both online using a Jupyter Notebook, such as Google Colab, and locally where the attendants have their Python environment set up[1]. We will then discuss the technical details of defining and simulating an IBL agent. To illustrate the functionality concretely, we will walk through a simple example of a decision

[1]SpeedyIBL requires Python 3.7 or later.

making task: a binary choice task with repeated choices and feedback in the experimental paradigm of decisions from experience [4]. In this task, an agent makes multiple sequential decisions between two alternatives, each associated with a particular distribution of outcomes, with the goal of maximizing the overall outcomes over time.

4.3 Section 3: Building an IBL Model for the Iowa Gambling Task

Participants will proceed through a hands-on experience of building an IBL model using SpeedyIBL that expands from the example introduced in Section 2. Using provided instructions, participants will implement an agent that performs the Iowa Gambling Task [2]. The instructors will then walk through a viable solution.

5 STUDENT ASSESSMENTS

In the tutorial, the students will be presented with practical exercises. The exercises will be run in Google Colab, a free interactive online Jupyter notebook environment. They cover the content of how to create IBL agents for the binary choice task and the Iowa Gambling Task.

6 SUMMARY

In this tutorial we will introduce IBLT, a theory of human decisions from experience that has been shown to accurately explain and predict human decisions across a variety of tasks. We will provide students with open source software to develop IBL models, SpeedyIBL, a Python library which provides a computational implementation of IBLT. The tutorial will provide hands-on experience on how to use this library to build agents that complete decision making tasks. Students will start to simulate human decision making agents in binary choice tasks and then create IBL models in a task of increasing complexity, the Iowa Gambling Task. At the end of this tutorial, students will have acquired the background and theoretical information about IBLT, the ability to build IBL models for specific tasks to gain insights into human behavior, and will be exposed to the value of cognitive modeling for cognitive science generally.

7 INSTRUCTORS

Erin H. Bugbee is a Ph.D. student in Cognitive Decision Science at Carnegie Mellon University. She studies how humans learn and make sequential decisions from experience by building computational cognitive models of human decision making and through behavioral experimentation. She has previous teaching experience as a teaching assistant for many classes at Brown University and Carnegie Mellon University, and as an instructor at Amazon's Machine Learning University.

Thuy Ngoc Nguyen is an Assistant Professor in Computer Science at the University of Dayton. She holds a Ph.D. in Computer Science from the Free University of Bozen-Bolzano in Italy. Her research is centered around understanding how people learn to make decisions under uncertainty and how to design artificial intelligence systems that facilitate human decision making processes as well as are useful for humans to collaborate with when making joint decisions. She has teaching experience as a teaching assistant at Carnegie Mellon University, and as an instructor at the University of Massachusetts Lowell.

Cleotilde Gonzalez is Research Professor of Cognitive Decision Science and the founding director of the Dynamic Decision Making Laboratory at Carnegie Mellon University. She is the co-author and developer of Instance-Based Learning Theory.

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