Examining Conceptual Properties: Bayesian Inference in Human Concept Learning

Chelsea Zou
Binghamton University

Abstract

Understanding how humans generalize broad concepts from specific examples is a fundamental question in cognitive science. This study explores the potential application of Bayesian inference as a theoretical framework for human concept learning. Drawing parallels between human learning and Bayes theorem, this study investigates whether the number of observations during training can influence how well individuals are able to incorporate new information, update their prior knowledge, and correctly identify and understand conceptual properties of different number categories. Eight undergraduate participants engaged in a task examining four different concepts: even, odd, multiples of ten, and negative numbers. These tasks presented a small number of observations at first, followed by a larger set of observations belonging to each concept. Results indicate a significant improvement in accuracy, and decreased response times when participants are exposed to seven observations compared to three. Overall, these findings support the validity of the Bayesian framework in application to participant learning strategies of different concepts.

Keywords: concept learning, Bayesian inference, cognitive science, numerical concepts

Examining Conceptual Properties:

Bayesian Inference in Human Concept Learning

How exactly do humans learn and generalize broad concepts from specific examples? This has been a critical question to cognitive scientists studying the underlying processes of human learning, inference, and reasoning, and has sparked major explorations across different fields: from developmental psychology, to artificial intelligence research. Human concept learning is a complex cognitive process that hinges on our remarkable ability to identify and understand abstract ideas or categories based on a limited set of examples (Tenenbaum 1998). This process is rooted in the belief that individuals have the capacity to acquire and refine their understanding of concepts by observing new information, and updating their knowledge in light of this new information. Interestingly, some researchers within the field of computational cognition have drawn parallels between the processes of human learning and a fundamental concept in probability theory, known as Bayes theorem (Jacobs 2011).

The Bayesian framework proposes that learners employ a combination of their pre-existing knowledge and newly encountered examples to make educated estimates regarding the likelihood of an object or item belonging to a particular concept or category (Shi et al., 2010). This process enables individuals to make educated and efficient judgments about new information based on their accessible prior information (Goodman et al., 2008). To illustrate the general idea of Bayes Theorem, let P(A) be a prior probability or “prior knowledge" for some event A (e.g., the chance it will rain on any day in the month of October). Let P(B) be some new observation we receive (e.g., the air feels humid today). Using Bayes theorem, we can use these elements to update P(A|B), (e.g., the probability that it is raining, given that we observe the air feels humid) (Swinburne 2004). This subtle intersection between cognitive science and mathematics offers an exploratory yet compelling framework for unraveling the intricacies of concept learning.

In practice, the purpose of this study is to assess the potential application of Bayesian inference as a theoretical framework for human concept learning. As an example, consider a task where a learner is provided with a single image of a chicken egg as an instance of a particular concept they are asked to infer. Now, they must choose a test image belonging to the same concept: a block of cheese, a cryptogram, or a plant seed. It is difficult to choose because the participant can only base their inference on one observation, and multiple interpretations of the egg can lead to any one of the test images being correct (cheese: both are “dairy”; cryptogram: both can be “cracked”; seed: both can birth “life”). The small number of observations lead to a large inference space, thereby increasing the room for error. Now, consider that the learner is provided with two new observations belonging to the same category: a jug of milk and a can of yogurt. Now the learner can more confidently deduce that the concept is “dairy” and select the block of cheese as the correct answer from the test image set. Instead of images, the proposed experiment will be applied through a numbers game by leveraging the various properties of number concepts, such as even, odd, negative, etc. (Tenenbaum 1999).

The hypothesis is that as humans are provided with more examples belonging to a particular number concept, the accuracy to judge whether new examples of numbers not previously encountered before will increase, while the reaction time to judge will decrease. From this research, perhaps we can gain insight into whether or not there exists a statistical underpinning isomorphic to the inference engine of cognition.

Methods

Participants

A total of eight participants were recruited to complete the experiment. All of them were Binghamton University undergraduate students. Their involvement in the study was a voluntary component of their Cognition Lab coursework, and they were not compensated. All participants were assumed to have normal vision because the research presents visual number stimuli on a computer screen. Additionally, participants were required to possess standard motor skills as this enabled them to interact with the computer interface, which involved the task of clicking keyboard buttons to provide responses. The duration of each participant's engagement was approximately ten minutes.

Materials

The experiment was developed in Psychopy 2022 (Peirce, 2007). The materials needed for this study was access to the laptop that ran the Psychopy experiment. The training stimuli consisted of 40 numbers, ten numbers belonging to each of the four different concepts: even, odd, multiples of ten, and negative numbers. The testing stimuli consisted of a total of 144 numbers, with 12 sets of three grouped numbers for each concept. Each number was randomly generated under the criteria of the particular concept using a Python script.

Procedure

The experiment was designed to test the impact of the number of observations on participants' learning and cognitive processing of concept learning. The four concepts presented were distinct numerical categories: even, odd, multiples of ten, and negative numbers. The procedure of this experiment aims to understand how the number of observations and exposure to these instances of a particular concept during training influences participants' accuracy and response times.

Each participant underwent four different sessions, one for each concept. Each session was tested in two phases: the first training phase with a very limited number of observations provided, and the second training phase with a larger set of observations available. The first training phase presented a sequence of three different numbers that belong to the concept of the session. After displaying these three numbers sequentially for two seconds each, they were immediately tested with six questions. Each question showed a set of three numbers that may or may not have belonged to that concept, and they were asked use the [right arrow] and [left arrow] keys on the keyboard to answer “Yes” or “No” to the question: “Does this set of numbers belong to the same concept you saw during training”? After answering six of these types of questions, they moved on to the second phase of the session.

The second phase increased the number of observations to show a sequence of seven new numbers instead of three, for two seconds each. All of these displayed numbers belonged to the same concept from phase one. Again, during this second testing phase, they were asked another set of six questions in the same format as before, with different groups of numbers than the test questions from the first phase.

The independent variable in this experiment was the number of observations shown during training (so either three numbers or seven numbers). The dependent variable was the response time of each participant and accuracy of the “Yes/No” questions they answered. The hypothesis was that the accuracy should be higher in the second phase where they were shown seven new observations, than in the first phase, where they were only shown three observations. This is because an increased number of correct observations can potentially update the participant's knowledge closer to the true representation of the concept. The response time was hypothesized to be lower in the second phase than in the first, due to an increased confidence in the validity of their judgment.

Results

The results of the experiment are summarized below in Table 1. The average number of mistakes made with three observations was 4.75 out of six questions (SD = 3.15), approximately 20.8% accurate. After seven observations, the average number of mistakes made by the participants decreased to 2.5 out of six questions (SD = 2.65), approximately 58.3% accurate. The average reaction time in seconds, to answer the questions with three observations, across all eight participants was 1.83 seconds (SD = 0.61). After seven observations, the average reaction time also decreased to 1.23 seconds (SD = 0.39). A paired t-test was conducted for the accuracy between three observation and seven observation conditions, with $t(7) = 2.32$, $p < .05$, $d = 0.57$, as well as for reaction time with $t(7) = 1.12$, $p < .05$, $d = 0.34$, revealing a significant difference between the two conditions. However, it is also important to note the individual differences observed between participants. Table 2 reveals the accuracy and response times broken down per participant. Additionally, a visual representation of these results (Figure 1 and Figure 2) can be found under the Tables and Figures section below.

General Discussion

Overall, these results indicate that with an increased number of observations shown to the participants, the accuracy will increase and the reaction times will decrease, supporting the initial hypothesis. While this research aligns with the Bayesian framework's proposition that learners integrate prior knowledge with new observations to make informed judgments about conceptual categories, there are several limitations. For one, the sample size is small (N = 8). Although significance testing was employed to validate the findings, the limitation raises concerns about the generalizability of the findings to broader populations. The homogeneity of the participants in terms of age and educational background restricts the external validity of the results. Furthermore, as this study was done regarding a numerical task, individual differences in mathematical ability can bias results. Recognizing the potential impact of individual differences on study outcomes, future investigations may benefit from incorporating additional measures or controls to better account for how these variations could influence the observed patterns in accuracy and reaction times. Additionally, the experimental design poses a challenge to its ecological validity. In real-world scenarios, individuals often encounter concepts in a more complex and interconnected manner (Goodman et al., 2008). By isolating numerical concepts within a specific task, the study may not fully capture the intricacies of concept learning in more realistic and dynamic settings. Future research could address this limitation by incorporating more ecologically valid stimuli and tasks (Tenenbaum 1998), providing a more accurate representation of how individuals generalize concepts in everyday life.

Finally, there are some interesting questions that may arise from this research. The first question regards the transferability of Bayesian framework: To what extent can the Bayesian framework be applied to diverse conceptual domains beyond numerical categories? Investigating its effectiveness in areas such as language (Granito et al., 2015), object recognition (Logothetis 1996), or abstract concepts could provide a broader understanding of its applicability. Another question surrounds the memorability of Bayesian concept learning and long-term retention. For instance, examining participants' retention of numerical concepts over an extended period could reveal insights into the durability of knowledge acquired through Bayesian-informed learning. Some implications of these questions can contribute to works within educational settings

(Lundqvist 2014), where curricula could be designed to provide a varied and increased number of examples to enhance concept learning and optimize knowledge acquisition. Another impacted field is artificial intelligence (Ch 1997). Perhaps integrating computational Bayesian frameworks into machine learning models may enhance their ability to generalize and adapt to new information. Overall, the wide ranging interdisciplinary study of Bayesian concept learning offers promising avenues for future research and practical applications

References

Tenenbaum, J. (1998). Bayesian modeling of human concept learning. *Advances in neural information processing systems,* 11.

Goodman, N. D., Tenenbaum, J. B., Feldman, J., & Griffiths, T. L. (2008). A rational analysis of rule‐based concept learning. *Cognitive science*, 32(1), 108-154.

Shi, L., Griffiths, T. L., Feldman, N. H., & Sanborn, A. N. (2010). Exemplar models as a mechanism for performing Bayesian inference. *Psychonomic bulletin & review*, 17(4).

Swinburne, R. (2004). Bayes' theorem. *Revue Philosophique de la France Et de l*, *194*(2).

Tenenbaum, J. (1999). Rules and similarity in concept learning. *Advances in neural information processing systems*, 12.

Jacobs, R. A., & Kruschke, J. K. (2011). Bayesian learning theory applied to human cognition. *Wiley Interdisciplinary Reviews: Cognitive Science*, *2*(1), 8-21.

Peirce, J. W. (2007). PsychoPy—psychophysics software in Python. *Journal of neuroscience methods*, *162*(1-2), 8-13.

Ch, R., & MAP, M. (1997). Bayesian learning. *book: Machine Learning. McGraw-Hill Science/Engineering/Math*, 154-200.

Lundqvist, J. (2014). A review of research in educational settings involving children's responses. *Child Indicators Research*, *7*, 751-768.

Granito, C., Scorolli, C., & Borghi, A. M. (2015). Naming a lego world. The role of language in the acquisition of abstract concepts. *PloS one*, *10*(1), e0114615.

Logothetis, N. K., & Sheinberg, D. L. (1996). Visual object recognition. *Annual review of neuroscience*, *19*(1), 577-621.

Tables and Figures

Table 1: Descriptive Statistics Averaged Across Participants

Condition		Number of Mistakes Made	Response Time (seconds)
Three Observations	**Mean**	4.75	1.83
	SD	3.15	0.61
Seven Observations	**Mean**	2.5	1.23
	SD	2.65	0.39

Table 2: Descriptive Statistics For Each Participant

Participant	Number of Mistakes Made for Three Observations	Number of Mistakes Made for Seven Observations	Response Time for Three Observations (seconds)	Response Time for Seven Observations (seconds)
1	6	7	2.16	1.43
2	6	2	1.20	0.86
3	6	0	1.55	1.34
4	0	1	1.09	0.78
5	10	6	1.98	1.07
6	6	4	3.14	1.66
7	4	0	2.03	0.82
8	0	0	1.54	1.91

Figure 1: Results Across Participants

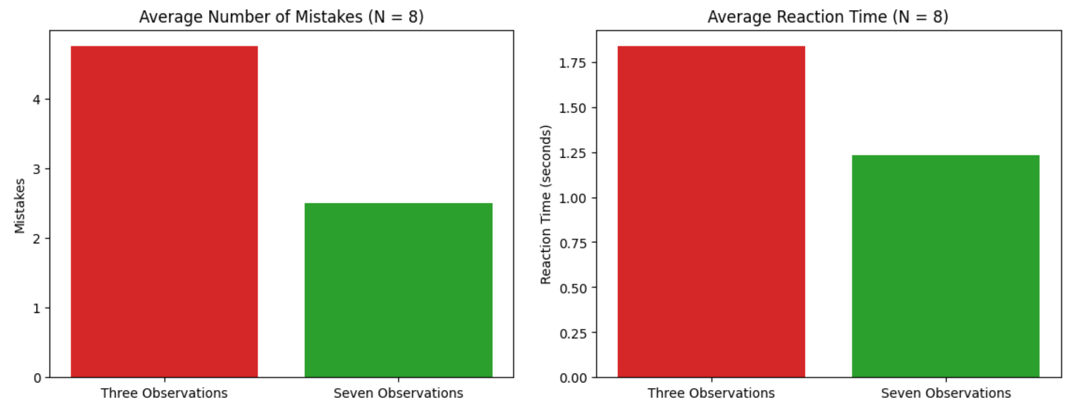

Figure 2: Results For Each Participant