Prerequisites

Experience with computational modeling is not required, but students should have some familiarity with basic math (algebra and probability).

Course requirements

All students are expected to post a short response to each reading on Canvas (in the Discussions section). Each student will also be responsible for leading the group discussion for 2-3 papers.

Office hours

By appointment (please email the instructor, gershman@fas.harvard.edu).

Lottery

In the event that the course is over-enrolled, there will be a lottery. Petitions will be accepted according to the following ordering: (i) Psychology and Program in Neuroscience graduate students; (ii) undergraduates who have taken PSY 1401; (iii) Psychology and AM Psych concentrators; (iv) everyone else.

Grading Rubric

94-100 A 90-93 A- 87-89 B+ 83-86 B

80-82 B- 77-79 C+ 73-76 C 70-72 C-

67-69 D+â€¨ 63-66 Dâ€¨ 60-62 D- Below 60 E (fail)

Academic Honor

You are expected to submit your own, original work for the exam and the final paper. Any misconduct will be reported, as is required by the college. Discussing your ideas with others and getting feedback on your work is encouraged, but you are required to cite any and all ideas that are not your own, and ensure that any assignments you turn in are your own writing and the result of your own research.

Accessibility

Any student needing academic adjustments or accommodations is requested to present their letter from the Accessible Education Office (AEO) and speak with the professor by the end of the second week of the term, (specific date). Failure to do so may result in the Course Headâ€™s inability to respond in a timely manner. All discussions will remain confidential, although AEO may be consulted to discuss appropriate implementation.

Schedule

Meeting 1: Foundational concepts
9/1/21 **note Wednesday meeting time**
â€¢ Jacobs, R.A., & Kruschke, J.K. (2011). Bayesian learning theory applied to human cognition. Wiley Interdisciplinary Reviews: Cognitive Science, 2, 8-21.
â€¢ LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. Nature, 521, 436-444.

Meeting 2: Associative learning
9/13/21
â€¢ Rescorla, R., & Wagner, A. R. (1972). A theory of Pavlovian conditioning: variations in the effectiveness of reinforcement and nonreinforcement. In A. Black & W. Prokasy (Eds.), Classical Conditioning II: Current research and theory (pp. 64â€"99). New York, NY: Appleton-Century-Crofts.
â€¢ Courville, A.C., Daw, N.D., & Touretzky, D.S. (2006). Bayesian theories of conditioning in a changing world. Trends in Cognitive Sciences, 10, 294-300.

Meeting 3: Attention in associative learning
9/20/21
â€¢ Pearce, J.M., & Hall, G. (1980). A model for Pavlovian learning: Variations in the effectiveness of conditioned but not of unconditioned stimuli. Psychological Review, 87, 532-552.
â€¢ Mackintosh, N.J. (1975). A theory of attention: Variations in the associability of stimuli with reinforcement. Psychological Review, 82, 276â€"298.

Meeting 4: How general are the laws of learning?
9/27/21
â€¢ Seligman, M.E. (1970). On the generality of the laws of learning. Psychological Review, 77, 406-418.
â€¢ Gallistel, C.R. (2000). The replacement of general-purpose learning models with adaptively specialized learning modules. The New Cognitive Neurosciences, 1179-1191.

Meeting 5: Reinforcement learning
10/4/21
â€¢ Schultz, W., Dayan, P., & Montague, P.R. (1997). A neural substrate of prediction and reward. Science, 275, 1593-1599.
â€¢ Daw, N.D., Niv, Y., & Dayan, P. (2005). Uncertainty-based competition between prefrontal and dorsolateral striatal systems for behavioral control. Nature Neuroscience, 8, 1704-1711.

Meeting 6: Causal learning
10/18/21
â€¢ Gopnik, A., Glymour, C., Sobel, D.M., Schulz, L.E., Kushnir, T., & Danks, D. (2004). A theory of causal learning in children: Causal maps and Bayes nets. Psychological Review, 111, 3-32.
â€¢ Bramley, N. R., Dayan, P., Griffiths, T. L., & Lagnado, D. A. (2017). Formalizing Neurathâ€™s ship: Approximate algorithms for online causal learning. Psychological review, 124, 301-338.

Meeting 7: Active learning
10/25/21
â€¢ Oaksford, M., & Chater, N. (1994). A rational analysis of the selection task as optimal data selection. Psychological Review, 101, 608-631.
â€¢ Gureckis, T. M., & Markant, D. B. (2012). Self-directed learning: A cognitive and computational perspective. Perspectives on Psychological Science, 7, 464-481.

Meeting 8: Social learning
11/1/21
â€¢ Shafto, P., Goodman, N.D., & Griffiths, T.L. (2014). A rational account of pedagogical reasoning: Teaching by, and learning from, examples. Cognitive Psychology, 71, 55-89.
â€¢ Toyokawa, W., Whalen, A., & Laland, K. N. (2019). Social learning strategies regulate the wisdom and madness of interactive crowds. Nature Human Behaviour, 3, 183-193.

Meeting 9: Category learning
11/8/21

â€¢ Kruschke, J. K. (1992). ALCOVE: An exemplar-based connectionist model of category learning. Psychological Review, 99, 22â€“44.
â€¢ Anderson, J.R. (1991). The adaptive nature of human categorization. Psychological Review, 98, 409-429.

Meeting 10: Origins of knowledge
11/15/21
â€¢ Saxe, A.M., McClelland, J.L., & Ganguli, S. (2019). A mathematical theory of semantic development in deep neural networks. Proceedings of the National Academy of Sciences, 116, 11537-11546.
â€¢ Piantadosi, S.T., Tenenbaum, J.B., & Goodman, N.D. (2012). Bootstrapping in a language of thought: A formal model of numerical concept learning. Cognition, 123, 199-217Z

Meeting 11: Learning to learn
11/22/21
â€¢ Kemp, C., Perfors, A., & Tenenbaum, J. B. (2007). Learning overhypotheses with hierarchical Bayesian models. Developmental science, 10, 307-321.
â€¢ Wang, J. X., Kurth-Nelson, Z., Kumaran, D., Tirumala, D., Soyer, H., Leibo, J. Z., ... & Botvinick, M. (2018). Prefrontal cortex as a meta-reinforcement learning system. Nature Neuroscience, 21, 860-868.

Meeting 12: Evolution and learning
11/29/21
â€¢ Paenke, I., Kawecki, T. J., & Sendhoff, B. (2009). The influence of learning on evolution: A mathematical framework. Artificial Life, 15, 227-245.
â€¢ Smith, K., Kirby, S., & Brighton, H. (2003). Iterated learning: A framework for the evolution of language. Artificial Life, 9, 371â€“386.