Sample Syllabus
Computational Cognitive Science
Winter
Professor: Steven Frankland
Winifred Raven 103
Office Hours: TBD

Synopsis

Human cognition is characterized by remarkable intellectual feats and equally frustrating failures. What general principles determine what minds can and can't achieve? In this course, we treat human cognition as computation and construct artificial systems to model some cognitive strengths and weaknesses. We will explore how computational systems can learn (or fail to learn), how they can remember (and forget), and ways they can select appropriate (or inappropriate) actions. We will cover basic principles and applications of neural networks, probabilistic models, and reinforcement learning, with readings drawn broadly from psychology, neuroscience, artificial intelligence, and computer science. Part of each 3 hr class (~50%) will be spent in lecture. The second part of each 3 hr class (~50%) will be spent working directly with computational models in active learning exercises that use neural networks for hands-on exploration.

Learning Objectives

- Understanding prominent theoretical approaches to the computational modeling of human cognition.
- Broad familiarity with important contributions from computer science, artificial intelligence/machine learning, psychology, and neuroscience.
- Practical competence in building and evaluating neural networks, using Python.
- Deeper understanding of what's possible for each cognitive system, given objectives and constraints.

Course Prerequisites and Recommendations

COSC 1, or equivalent experience. (if uncertain, ask instructor)
COGS 1 is recommended, though not required.
Prior experience with calculus, probability, and linear algebra may be helpful, but not required.

Grading
35% Final Project (~10 pg paper).
35% Weekly Lab Modeling Exercises
20% Brief Response Papers (2, of your choosing. ~1-2 pages)
10% Course Attendance/Participation

Active-learning exercises
Modeling will be done in Python, using numpy and pytorch. Each week, we will work through a jupyter notebook that explores some of the topics in lecture. In addition to the parts we complete jointly, there will be a small number of additional questions and modeling extensions to be submitted by the following week's class. These will be graded each week on a qualitative scale (i.e., 10/10 *excellent;* 8/10 *satisfactory;* 6/10 *completed, but lacking*; 0/10, not completed).

Possible Reference Books for Labs **-** not required reading, but helpful references.
Inside Deep Learning: Math, Algorithms, Models
PyTorch Pocket Reference: Building and Deploying Deep Learning Models

Final Project
~10 page paper (~2000 words). Choose one of two types of final project (other formats are possible; if you have an idea, talk to the instructor!). Due June 3rd.

- *Option 1. Proposal* (*no additional modeling necessary).* Identify a question/phenomenon of interest to you regarding human cognition that is amenable to computational modeling. Conduct literature review on extant models. Hypothesize a particular computational mechanism for the phenomenon (helpful to use images), consider alternatives, and propose a plan for how to evaluate your proposed mechanism with modeling and/or empirical data.

- *Option 2. Modeling Extensions* (additional *modeling necessary).* Take a question and model we have (or will have) explore(d) in class, and extend it in a new direction (e.g., new data, or new architecture, or new applications). Write-up your methods and results, with figures.

*Bonus points if submitted in LaTex CogSci Submission format.

Response Papers
The lab exercises will contain conceptual questions to consider. Over the course of the term, choose any **2 such questions** and respond with a ~1-2 page paper on each.

General Schedule of Topics

The first few weeks of the course cover important conceptual foundations of computational cognitive science. This includes an overview of different theoretical approaches (week 1), study of basic principles of learning in brains and machines, with a particular focus on resource constraints (week 2), fundamentals of learning without feedback (week 3), and learning over different time-periods (week 4).The second part of the course studies some core processes of interest to cognitive scientists. This includes perception (week 5), memory storage and retrieval (week 6), attention (week 7), action selection (week 8), and reasoning (week 9, no lab). We conclude by putting some of these pieces together to discuss strengths and limits of current large language models as models of human intelligence (no lab) (week 10).

More Specific Schedule

March 27th: Computational approaches to modeling cognition

- Readings:

  Newell, A. (1980). Physical symbol systems. Cognitive science, 4(2), 135-183.

  Favela, L. H. (2020). Dynamical systems theory in cognitive science and neuroscience. *Philosophy Compass*, *15*(8), e12695.

  Griffiths, T. L., Chater, N., Kemp, C., Perfors, A., & Tenenbaum, J. B. (2010). Probabilistic models of cognition: Exploring representations and inductive biases. Trends in cognitive sciences, 14(8), 357-364.

  McClelland, J. L., Botvinick, M. M., Noelle, D. C., Plaut, D. C., Rogers, T. T., Seidenberg, M. S., & Smith, L. B. (2010). Letting structure emerge: connectionist and dynamical systems approaches to cognition. Trends in cognitive sciences, 14(8), 348-356.

- Lab assignment**: Introduction to neural networks**.

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April 3rd: Learning in Brains and Machines

- Readings:

  Rumelhart, D. E., Hinton, G. E., & Williams, R. J. (1986). Learning representations by back-propagating errors. *nature*, *323*(6088), 533-536.

  Lillicrap, T. P., Santoro, A., Marris, L., Akerman, C. J., & Hinton, G. (2020). Backpropagation and the brain. *Nature Reviews Neuroscience*, *21*(6), 335-346.

Lieder, F., & Griffiths, T. L. (2020). Resource-rational analysis: Understanding human cognition as the optimal use of limited computational resources. *Behavioral and brain sciences*, *43*, e1.

Chater, N., Oaksford, M., Chater, N., & Oaksford, M. (1999). Ten years of the rational analysis of cognition. *Trends in cognitive sciences*, *3*(2), 57-65.

- Lab Assignment**: Gradient descent, Constrained Optimization**.

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April 10th: **Learning without a teacher**

- Readings

Sayood, K. (2017). Introduction to Data Compression. ***Chapter 1.***

Psych. Sims, C. R. (2018). Efficient coding explains the universal law of generalization in human perception. *Science*, *360*(6389), 652-656.

Hinton, G. E., & Zemel, R. (1993). Autoencoders, minimum description length and Helmholtz free energy. *Advances in neural information processing systems*, *6*.

- Lab. **Auto-encoders**

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April 17th: Learning on different time-scales.

- Readings

McClelland, J. L., McNaughton, B. L., & O'Reilly, R. C. (1995). Why there are complementary learning systems in the hippocampus and neocortex: insights from the successes and failures of connectionist models of learning and memory. *Psychological review*, *102*(3), 419.

Thrun, S., & Pratt, L. (1998). Learning to learn: Introduction and overview. In *Learning to learn* (pp. 3-17). Boston, MA: Springer US.

Rao, R. P., & Jiang, L. P. (2022). Predictive coding theories of cortical function. In *Oxford Research Encyclopedia of Neuroscience*.

Lake, B.M., Baroni, M. (2023). Human-like systematic generalization through a meta-learning neural network. Nature. https://doi.org/10.1038/s41586-023-06668-3

- Lab: **Prediction using Recurrent Neural Nets**

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April 24th: Perception

- Readings:

Olshausen, B. A., & Field, D. J. (1996). Emergence of simple-cell receptive field properties by learning a sparse code for natural images. *Nature*, *381*(6583), 607-609.

Kersten, D., Mamassian, P., & Yuille, A. (2004). Object perception as Bayesian inference. *Annu. Rev. Psychol.*, *55*, 271-304.

Kell, A. J., & McDermott, J. H. (2019). Deep neural network models of sensory systems: windows onto the role of task constraints. *Current opinion in neurobiology*, *55*, 121-132.

Zhuang, C., Yan, S., Nayebi, A., Schrimpf, M., Frank, M. C., DiCarlo, J. J., & Yamins, D. L. (2021). Unsupervised neural network models of the ventral visual stream. *Proceedings of the National Academy of Sciences*, *118*(3), e2014196118.

- Lab: **Convolutional Neural Nets.**

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May 1st: Memory

- Readings

Hopfield, J. J. (1982). Neural networks and physical systems with emergent collective computational abilities. *Proceedings of the national academy of sciences*, *79*(8), 2554-2558.

Graves, A., Wayne, G., Reynolds, M., Harley, T., Danihelka, I., Grabska-Barwińska, A., ... & Hassabis, D. (2016). Hybrid computing using a neural network with dynamic external memory. *Nature*, *538*(7626), 471-476.

Gallistel, C. R., & Balsam, P. D. (2014). Time to rethink the neural mechanisms of learning and memory. *Neurobiology of learning and memory*, *108*, 136-144.

- **Lab: Hopfield Networks**

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May 8th: Attention

- Readings

  Itti, L., & Koch, C. (2001). Computational modelling of visual attention. *Nature reviews neuroscience*, *2*(3), 194-203.

  Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., ... & Polosukhin, I. (2017). Attention is all you need. *Advances in neural information processing systems*, *30*.

  Lindsay, G. W. (2020). Attention in psychology, neuroscience, and machine learning. *Frontiers in computational neuroscience*, *14*, 29.

- **Lab: Transformers.**

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May 15th: Action Selection

- Readings

  Moerland, T. M., Broekens, J., Plaat, A., & Jonker, C. M. (2023). Model-based reinforcement learning: A survey. Foundations and Trends in Machine Learning, 16(1), 1-118.

  Mnih, V., Kavukcuoglu, K., Silver, D., Rusu, A. A., Veness, J., Bellemare, M. G., ... & Hassabis, D. (2015). Human-level control through deep reinforcement learning. nature, 518(7540), 529-533.

  Gurney, K., Prescott, T. J., & Redgrave, P. (2001). A computational model of action selection in the basal ganglia. I. A new functional anatomy. Biological cybernetics, 84, 401-410.

  Gopnik, A. (2020). Childhood as a solution to explore–exploit tensions. Philosophical Transactions of the Royal Society B, 375(1803), 20190502.

- **Lab: model-free learning (Q learning).**

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May 22nd: Reasoning

- Readings

  Chollet, F. (2019). On the measure of intelligence. *arXiv preprint arXiv:1911.01547*.

Blazek, P. J., & Lin, M. M. (2021). Explainable neural networks that simulate reasoning. *Nature Computational Science*, *1*(9), 607-618.

Webb, T., Holyoak, K. J., & Lu, H. (2023). Emergent analogical reasoning in large language models. *Nature Human Behaviour*, *7*(9), 1526-1541.

- No Lab (work on final projects, due June 3rd)

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May 29th: Exploring Large Language Models & Intelligence

- No Lab (work on final projects, due June 3rd)

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Academic Honor Principle

The faculty, administration, and students of Dartmouth College acknowledge the responsibility to maintain and perpetuate the principle of academic honor, and recognize that any instance of academic dishonesty is considered a violation of the Academic Honor Principle.

Religious Observances

Dartmouth has a deep commitment to support students' religious observances and diverse faith practices. Some students may wish to take part in religious observances that occur during this academic term. If you have a religious observance that conflicts with your participation in the course, please meet with me as soon as possible—before the end of the second week of the term at the latest—to discuss appropriate course adjustments.

Student Accessibility and Accommodations

Students requesting disability-related accommodations and services for this course are required to register with Student Accessibility Services (SAS; Apply for Services webpage; student.accessibility.services@dartmouth.edu; 1-603-646-9900) and to request that an accommodation email be sent to me in advance of the need for an accommodation. Then, students should schedule a follow-up meeting with me to determine relevant details such as what role SAS or its Testing Center may play in accommodation implementation. This process works best for everyone when completed as early in the quarter as possible. If students have questions about whether they are eligible for accommodations or have concerns about the implementation of their accommodations, they should contact the SAS office. All inquiries and discussions will remain confidential.

Mental Health and Wellness

There are a number of resources available to you on campus to support your wellness, including: the Counseling Center which allows you to book triage appointments online, the Student Wellness Center which offers wellness check-ins, and your undergraduate dean. The student-led Dartmouth Student Mental Health Union and their peer support program may be helpful if you would like to speak to a trained fellow student support listener. If you need immediate assistance, please contact the counselor on-call at (603) 646-9442 at any time. Please make me aware of anything that will hinder your success in this course.

Title IX

At Dartmouth, we value integrity, responsibility, and respect for the rights and interests of others, all central to our Principles of Community. We are dedicated to establishing and maintaining a safe and inclusive campus where all community members have equal access to Dartmouth's educational and employment opportunities. We strive to promote an environment of sexual respect, safety, and well-being. Through the Sexual and Gender-Based Misconduct Policy (SMP), Dartmouth demonstrates that sex and gender-based discrimination, sex and gender-based harassment, sexual assault, dating violence, domestic violence, stalking, etc., are not tolerated in our community.

For more information regarding Title IX and to access helpful resources, visit Title IX's website (sexual-respect.dartmouth.edu). As a faculty member, I am required to share disclosures of sexual or gender-based misconduct with the Title IX office.

If you have any questions or want to explore support and assistance, please contact the Title IX office at 603-646-0922 or TitleIX@dartmouth.edu. Speaking to Title IX does not automatically initiate a college resolution. Instead, much of their work is around providing supportive measures to ensure you can continue to engage in Dartmouth's programs and activities.