SYLLABUS: AM226_neural_computation_fall2021_syllabus.pdf

Prerequisite Problems: AM226_PS0_21F.pdf

Final Project Info: AM226_Final_Projects.pdf

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Please sign up for course Slack Channel.

Date	Topic	Reading and Notes
Sep 1	Introduction; Supervised Learning and the Perceptron	Slides: Introduction.pdf Lecture Notes: Supervised Learning and Perceptron.pdf Recommended Reading: Chapter 3 of Models of the Mind book introduces the history behind the McCulloch and Pitts model and the Perceptron algorithm.
Sep 8	Perceptron Learning Algorithm	Lecture Notes: Supervised Learning and Perceptron.pdf Recommended Reading: Hertz et al. (Introduction to the theory of neural computation) Chapter 5 (Note that a free online copy is available through the library. See the Library Reserves or this link: https://ebookcentral-proquest-com.ezp-prod1.hul.harvard.edu/lib/harvard-ebooks/reader.action?docID=5320059&ppg=112)
Sep 13	Perceptron Capacity and Cover's Counting Theorem; Purkinje Cells	Recommended Reading: Hertz *et al.*, Chapter 5 (Note that a free online copy is available through the library. See the Library Reserves or this link: https://ebookcentral-proquest-com.ezp-prod1.hul.harvard.edu/lib/harvard-ebooks/reader.action?docID=5320059&ppg=112) Lecture Notes: Supervised Learning and Perceptron.pdf Slides: Perceptrons_at_capacity_upload.pptx Recommended Reading: Cover's paper Recommended Reading: Emin Orhan's note on Cover's theorem Optional Tutorial: Tutorial on Gardner's Calculation
Sep 15	Purkinje cells at capacity; Maximum margin classifiers	Brunel *et al.*, (2004) Optimal Information Storage and the Distribution of Synaptic Weights: Perceptron versus Purkinje Cell (Available in Library Reserves) Barbour *et al.*, (2007) What can we learn from synaptic weight distributions? (Available in Library Reserves) Lecture Notes: MaxMargin-Kernel.pdf Andrew Ng's Lecture Notes on Support Vector Machines
Sep 20	Nonlinearly Separable Data; Kernel SVM;	Lecture Note: MaxMargin-Kernel.pdf Andrew Ng's Lecture Notes on Support Vector Machines Slides: Kernels_and_Cerebellar-like_architectures.pptx Further reading: Raymond JL, Medina JF. Computational principles of supervised learning in the cerebellum. Annual review of neuroscience. 2018 Jul 8;41:233-53. (Available in Library Reserves) Further reading: Cho, Y., & Saul, L. K. (2009). Kernel methods for deep learning. In *Advances in neural information processing systems* (pp. 342-350). Further reading: Babadi B, Sompolinsky H. Sparseness and expansion in sensory representations. Neuron. 2014 Sep 3;83(5):1213-26. (Available in Library Reserves) Further reading: Litwin-Kumar, Ashok, et al. "Optimal degrees of synaptic connectivity." *Neuron* 93.5 (2017): 1153-1164. (Available in Library Reserves)

Sep 22	Multilayer Neural Networks	Deep Learning Book Chapter 6 Lecture Note: Multilayer Networks and the Backpropagation Algorithm.pdf
Sep 27	Multilayer Neural Networks; Backpropagation algorithm and its biological plausibility;	Deep Learning Book Chapter 6 Lecture Note: Multilayer Networks and the Backpropagation Algorithm.pdf Optional reading: Whittington, J.C. and Bogacz, R., 2019. Theories of error back-propagation in the brain. *Trends in cognitive sciences*. Optional reading: Lillicrap, T.P., Cownden, D., Tweed, D.B. and Akerman, C.J., 2016. Random synaptic feedback weights support error backpropagation for deep learning. *Nature communications*, *7*, p.13276.
Sep 29	Learning with a global error signal	Lecture Note: Learning_with_a_global_error_signal.pdf.pdf Optional reading: Williams, Ronald J. "Simple statistical gradient-following algorithms for connectionist reinforcement learning." *Machine learning* 8.3-4 (1992): 229-256.
Oct 4	Actor-Critic-Experimenter Learning	Lecture Note: Learning_with_a_global_error_signal.pdf.pdf Slides: Actor_Critic_Experimenter_Learning.pdf Optional reading: Fiete, I.R., Fee, M.S. and Seung, H.S., 2007. Model of birdsong learning based on gradient estimation by dynamic perturbation of neural conductances. *Journal of neurophysiology*, *98*(4), pp.2038-2057.
Oct 6	Generalization in Deep Networks; Neural Tangent Kernel	Lecture Notes: NTK.pdf Optional reading: Canatar, Abdulkadir, Blake Bordelon, and Cengiz Pehlevan. "Spectral bias and task-model alignment explain generalization in kernel regression and infinitely wide neural networks." *Nature communications* 12.1 (2021): 1-12.
Oct 13	Generalization in Deep Networks; Rescorla-Wagner Rule	Slides: Generalization_in_NNs_AM226.pdf Slides: Reinforcement_Learning.pdf Optional reading: Dayan and Abbott; Chapter 9 (Links to an external site.) Optional reading: Daw and Tobler, 2014; Value Learning through Reinforcement: The Basics of Dopamine and Reinforcement Learning (Available in Library Reserves) Optional reading: Schultz, W., Dayan, P., Montague, P.R., 1997. A neural substrate of prediction and reward. Science. 275, 15931599. (Available in Library Reserves)
Oct 18	TD-Learning; Unsupervised Learning with Hebbian Plasticity	Slides: Reinforcement_Learning.pdf Slides: PCA_oja.pdf Optional reading: Hertz *et al.* Chapter 8
Oct 20	PCA Networks; Retinal Ganglion Cells; Natural Scene Statistics	Notes: PCA Networks and Redundancy Reduction.pdf Slides: Whitening_Theory.pdf Optional reading: Hertz *et al.* Chapter 8
Oct 25	Whitening theory of RGCs	Notes: PCA Networks and Redundancy Reduction.pdf Slides: Whitening_Theory.pdf Optional reading: Huang, Y., & Rao, R. P. (2011). Predictive coding. *Wiley Interdisciplinary Reviews: Cognitive Science*, *2*(5), 580-593. (Links to an external site.)Read this for more detail on another approach to efficient coding, called predictive coding, related to redundancy reduction. Optional reading: Natural Image Statistics: Chapter 5 Principal Components and Whitening, Read this if you want to learn more about natural image statistics and whitening theory

		Optional reading: Atick, J. J., & Redlich, A. N. (1992). What does the retina know about natural scenes?. *Neural computation*, *4*(2), 196-210. (Library Reserves) Full information theoretic treatment of redundancy reduction. Optional reading: Pitkow, X., & Meister, M. (2012). Decorrelation and efficient coding by retinal ganglion cells. *Nature neuroscience*, *15*(4), 628-635. and Abbasi-Asl, R., Pehlevan, C., Yu, B. and Chklovskii, D., 2016, November. Do retinal ganglion cells project natural scenes to their principal subspace and whiten them?. In *2016 50th Asilomar Conference on Signals, Systems and Computers* (pp. 1641-1645). IEEE. (Library Reserves) Tests of the whitening theory
Oct 27	Sparse Coding	Slides: Sparse_Coding.pptx Optional reading: Olshausen, B. A., & Field, D. J. (1997). Sparse coding with an overcomplete basis set: A strategy employed by V1?. *Vision research*, *37*(23), 3311-3325. (Library Reserves) and 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. (Library Reserves) Optional reading: Koulakov, A. A., & Rinberg, D. (2011). Sparse incomplete representations: a potential role of olfactory granule cells. *Neuron*, *72*(1), 124-136. (Library Reserves) This paper uses the sparse coding model to explain a circuit motif in the olfactory bulb Optional reading: Chettih, S. N., & Harvey, C. D. (2019). Single-neuron perturbations reveal feature-specific competition in V1. *Nature*, *567*(7748), 334-340. (Library Reserves) This paper tests a major prediction of the sparse coding model.
Nov 1	Population Coding	No lecture today. Please see this recorded lecture, and come to class if you have questions. https://harvard.zoom.us/rec/play/I1M12V8AL8poj_-anNW24TWGSxHYK0FSkAaiP4ycFZlz1_sEGi6RdbX0NRhOJO9WqU0Oqw7L4Vx7h2Pa.OWpIRmK0YFeDz_iN Slides: Neural_Coding_and_Decoding.pptx Lecture notes: Population_Coding.pdf Optional Reading: Dayan and Abbott, Chapter 1 has a good discussion of coding with spikes and Poisson processes
Nov 3	Statistical Estimation	Lecture notes: Population_Coding.pdf Optional Reading: Dayan and Abbott, Chapter 3 has a good discussion of statistical estimation
Nov 8	Fisher Information	Lecture notes: Population_Coding.pdf Optional Reading: Dayan and Abbott, Chapter 3 has a good discussion of statistical estimation
Nov 10	Noise Correlations	Lecture notes: Population_Coding.pdf Slides: Noise_Correlations.pdf Optional Reading: Rumyantsev, O.I., Lecoq, J.A., Hernandez, O., Zhang, Y., Savall, J., Chrapkiewicz, R., Li, J., Zeng, H., Ganguli, S. and Schnitzer, M.J., 2020. Fundamental bounds on the fidelity of sensory cortical coding. *Nature*, *580*(7801), pp.100-105. (Library reserves)
Nov 15	Hopfield Networks	Lecture notes: Hopfield Networks - 1.pdf Recommended Reading: Hertz et al. (Introduction to the theory of neural computation) Chapter 2 (Note that a free online copy is available through the library. See the Library Reserves or this link: https://ebookcentral-proquest-com.ezp-prod1.hul.harvard.edu/lib/harvard-ebooks/reader.action?docID=5320059&ppg=112)
Nov 17	Hopfield Networks	Lecture notes: Hopfield_Networks-II.pdf
Nov 22	Hopfield Networks; Line Attractors	Lecture Notes: Hopfield_Networks-II.pdf Lecture Notes: Line_Attractor.pdf Bonus lecture notes on how to train attractors: Hopfield_Networks-III.pdf Slides: Hopfield_Nets.pptx Neural-Integrators-Manifold-Attractors.pptx
Nov	Line Attractor;	Lecture Notes: Line_Attractor.pdf Lecture Notes: The Ring Attractor.pdf

29	Ring Attractor	Optional reading: Seung, H.S., 1996. How the brain keeps the eyes still. *Proceedings of the National Academy of Sciences*, *93*(23), pp.13339-13344.
Dec 1	Ring Attractor	Lecture Notes: The Ring Attractor.pdf Bonus lecture notes: Chaos.pdf Slides: Neural-Integrators-Manifold-Attractors.pptx Code: RingNetwork.m