APMTH 226: Neural Computation - Project Information

October 20, 2025

1 Basic Information

A major component of APMTH 226 is final projects. Some organizational matters:

- Projects can be done in groups of 1, 2 or 3. We expect project workload to reflect the number of people in the group. The amount of work expected per person is roughly two problem sets.
- Project proposals are due (Canvas upload) on November 14th midnight. We will try to give you feedback within a week.

  Project proposal format: Proposals should be one page maximum. Include project title, teammates, project idea and relevant references.
- A final report is due on December 14th midnight. For your final report, use the NeurIPS paper template with NeurIPS page limits: 8-pages of main text plus unlimited references. Don't feel obliged to fill all the 8-pages, but do provide sufficient detail and explanations. Readability is very important. You are allowed to submit supplementary information, but (as in NeurIPS) looking at supplementary material is at our discretion.
- You are strongly encouraged to seek our input during the TF hours and office hours. If these time slots are not sufficient, e-mail us to set up meetings.

Project content: We expect course projects to have some original contribution beyond what is already published. Take this as an opportunity to start something you will continue working on after the class is over. Here are three possible types of projects, but we are open to other suggestions and ideas:

- You can do original research. This can be in line with your thesis work.
- You can pick a research paper with appropriate theory content, reproduce an appropriate portion of its results, and extend it in some non-trivial way.
- You can do a literature review. If you chose this path, we expect you to add some of your own thinking. For example, you may chose to review Bayesian models of olfactory processing in rodents as a project. Besides presenting different models, you may compare and contrast them in light of experimental findings, and do some small calculation/simulation to elucidate the differences in their predictions.

FAQ

- Can we do a machine learning project? Yes, but it has to have a neural network component.
- Can we do a purely computational project? Yes.
- Can we do a purely theoretical project? Yes.

2 References for Project Ideas

Feel free to talk to us about formulating a project. Below are some references and ideas that may give you inspiration. You CAN propose a project that is not in the list. This list will be updated.

1. Olfaction Theory: We float in a sparse high dimensional world of olfactory signals. Biology appears to have converged on specialised neuronal circuitry in order to parse this unique datastream - the quest to understand the aims of this circuitry is an active research area. Theoretical underpinnings of this draw from the compressed sensing, high-dimensional statistics and random matrix theory literature. Some good papers: Krishnamurthy et al. Disorder and the neural representation of complex odors, Babadi and Sompolinsky Sparseness & Expansion in Sensory Representations, Litwin-Kumar et al. Optimal degrees of synaptic connectivity.

2. Balanced Networks. Researchers observed that excitation and inhibition in cortical circuits track each other to a degree that they almost cancel. This is called excitation-inhibition balance. What is the mechanism behind such balancing, what are its implications? See a recent review by Deneve and Machens, Efficient codes and balanced networks.

3. Theories of Error Back-Propagation in the Brain (Whittington and Bogacs, 2019). This paper reviews some of the approaches to biologically plausible implementations of the backpropagation algorithm

4. Kernels and neural networks; Deep learning as a Gaussian Process. There is a recent surge in literature elucidating parallels between neural networks and kernels. Neural Tangent Kernels provide interesting insights into the learning dynamics of deep networks.

5. Neural Scaling Laws. As discussed in class, this is a currently very active area.

6. Model collapse. What happens if we use data generated by LLMs to train further models?

7. Neural Manifolds. Researchers are finding the neural representations live in low-dimensional and non-linear "manifolds" all over the cortex. An interesting recent paper is Gallego *et al*, Cortical population activity within a preserved neural manifold underlies multiple motor behaviors, 2018.

8. Alternative learning rules for Hopfield network (Mezard, Nadal, and Toulouse Solvable models of working memories)

9. What can we learn from synaptic weights? (Barbour *et al.* 2007) The Gardner calculation has been used by many to explain properties of synaptic weight distributions. This paper is a good and early starting point.

10. Memory rehearsal (Wei and Koulakov Long-Term Memory Stabilized by Noise-Induced Rehearsal, Storkey papers)

11. Short term memory and noise induced diffusion (Burak and Fiete Fundamental limits on persistent activity in networks of noisy neurons. Shaham and Burak, Continuous parameter working memory in a balanced chaotic neural network)

12. Emergence of compositionality in neural networks (Yang *et al.*, Task representations in neural networks trained to perform many cognitive tasks)

13. Starting with the seminal paper by Sompolinsky, Crisanti and Sommers, Chaos in random neural networks 1988, many researchers studied the dynamical regimes, and especially chaos, in randomly connected neural networks. Always a hot topic!

14. Relation between structure and activity in neural networks (Ocker, Josic, Shea-Brown, and Buice Linking Structure and Activity in nonlinear spiking networks Hu, Brunton, Cain, Mihalas, Kutz and Shea-Brown Feedback through graph motifs relates structures and function in complex networks. Mastrogiuseppe and Ostojic. Linking connectivity, dynamics and computations in low-rank recurrent neural networks)

15. Path integration and neural dynamics (Ocko, Hardcastle, Giocomo, and Ganguli. Emergent elasticity in the neural code for space)

16. Generalization in over-parameterised neural networks (Advani and Saxe. High-dimensional dynamics of generalization error in neural networks. Goldt et al Dynamics of stochastic gradient descent for two-layer neural networks in the teacher-student setup).

17. How does depth improve learning in neural networks? (Saxe, McClelland, and Ganguli. A mathematical theory of semantic development in deep neural networks. Nye and Saxe Are Efficient Deep Representations Learnable?)

18. A normative approach to biologically-plausible unsupervised learning (Pehlevan and Chklovskii. Neuroscience-inspired online unsupervised learning algorithms.)

19. Pathway splitting (e.g. between ON neurons sensitive to luminance increments and OFF neurons sensitive to luminance decrements in retina) appears in many sensory systems. At what level of processing should this split occur? When should these pathways be symmetric? (Gjorgjieva, Sompolinsky, and Meister, Benefits of Pathway Splitting in Sensory Coding; Fitzgerald and Clark, Nonlinear circuits for naturalistic visual motion estimation; Roy *et al.*, Inter-mosaic coordination of retinal receptive fields)

20. Storage capacity of nonlinear networks. Gardner's capacity calculation can be extended to two-layer networks with treelike structure. How does activation function choice affect how capacity scales with hidden layer width? (Barkai, Hansel, and Sompolinsky 1992; Zavatone-Veth and Pehlevan 2021).

21. How can spiking networks simulate continuous dynamics? (Boerlin *et al* 2013, Masset *et al* 2022)[1]