Preparation for the Nordita Winter School on Physics and Machine Learning

The Organizing Committee

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This document outlines the background knowledge and technical skills expected of participants at the Nordita Winter School on Physics and Machine Learning. The material serves as a *"preschool"* guide, ensuring that participants are equipped to engage with the school's advanced content. The topics span essential prerequisites in machine learning, physics, and mathematics, as well as guidance on recommended readings and hands-on activities. By reviewing and practicing the concepts listed here, participants will be prepared for the school's theoretical and practical sessions.

TLDR – In case you have limited time for preparation, please prioritize the reading of Chapters 6 and 9 of Goodfellow (2016) together with the PyTorch "Learn the basics" tutorial.

1 Machine Learning Prerequisites

Concepts – We expect the students of the school to be familiar with the following concepts:

- **Multi-Layer Perceptrons (MLPs)**
  - **Key ideas:** Feed-forward neural networks, fully connected layers, activation functions, backpropagation.
  - **Suggested Reading:** Goodfellow, et al. (2016) *Deep Learning* - Chapter 6
  - **Alternatives:**
    - Prince (2024) *Understanding Deep Learning* - Chapter 4
    - Zhang, et al. (2023) *Dive into Deep Learning* - Chapter 5
- **Convolutional Neural Networks (CNNs)**
  - **Key ideas:** Filters, pooling, feature maps, and their role in image recognition.
  - **Suggested Reading:** Goodfellow, et al. (2016) *Deep Learning* - Chapter 9
  - **Alternatives:**
    - Prince (2024) *Understanding Deep Learning* - Chapter 10
    - Zhang, et al. (2023) *Dive into Deep Learning* - Chapter 7

Programming Skills – We expect that you have some basic familiarity with Python for numerical computing and visualization. Please also install the following Python libraries:

- Standard scientific stack: `NumPy`, `SciPy`, `Matplotlib`
- Notebook interface: `Jupyter` (or equivalent)
- Deep learning frameworks: `PyTorch`, `JAX`
- Quantum computing and hybrid quantum-classical ML: `PennyLane`, `Qiskit`

Neural Network Implementation – We expect you to be able to implement basic neural networks, ideally through `PyTorch` or `JAX`. You can practice with the following introductions:

- PyTorch *"Learn the Basics"*
- PyTorch *"60-minute Blitz"* (includes hands-on CNN exercise with CIFAR-10)
- JAX *"Quickstart"*

References

- Goodfellow, Bengio, Courville (2016) *Deep Learning.*
- Zhang, et al. (2023) *Dive into Deep Learning.*
- Prince (2024) *Understanding Deep Learning.*
- Michael Nielsen (2019), *Neural Networks and Deep Learning.*

2 Physics Prerequisites

We will assume you are familiar with the following:

Quantum Mechanics

- **Concepts**: Hilbert space formalism, unitary evolution, measurements, expectation values, Pauli matrices.
- **Suggested Reading**: *Introduction to Quantum Mechanics*, by David J. Griffiths

Statistical Physics

- **Concepts** – Canonical ensemble, Boltzmann-Gibbs distribution, partition function, free energy, and entropy, first-order and second-order phase transitions, order parameters, critical exponents, spontaneous symmetry breaking. Familiarity with fundamental models (e.g., Ising model) is beneficial.
- **Suggested Reading:** *Statistical mechanics: entropy, order parameters, and complexity*, by James Sethna

3 Mathematical Prerequisites

- **Concepts**
  - **Calculus:** Differentiation, integration, and basic concepts from multivariable calculus. This is essential for understanding optimization and backpropagation.
  - **Linear Algebra:** Vectors, matrices, eigenvalues, eigenvectors, and matrix decompositions. These concepts are crucial for understanding neural networks, dimensionality reduction, and optimization.
  - **Probability and Statistics:** Basic concepts of probability distributions, expectation, variance, and statistical inference. These concepts form the basis of many machine learning algorithms and statistical physics models.
- **Suggested Reading:** Goodfellow, et al. (2016) *Deep Learning* - Part I (from Chapter 2 to Chapter 4) is a good rehearsal of the mathematics useful for the school.

4 Other Reading

- Breiman (1995) *"Reflections after refereeing papers for NIPS"*
- Vinuesa, Brunton (2022) *"Enhancing computational fluid dynamics with machine learning"*

Further Reading (Optional)

- Zdeborová, Krzakala (2015). *"Statistical physics of inference: Thresholds and algorithms"* - Pedagogical review of connections between statistical physics and inference.
- Mehta et al. (2019). *"A high-bias, low-variance introduction to Machine Learning for physicists."* - A primer on ML techniques for physicists.
- Biswas et al. (2021). *"Machine learning and quantum computing: A perspective."* - Insights into the intersection of quantum computing and ML.