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Nota di contenuto	Chapter 1: Neutrinos: A Desperate Remedy -- Chapter 2. A Review of Neutrino Physics -- Chapter 3. The NOvA Experiment -- Chapter 4. Event Reconstruction -- Chapter 5. The 3-Flavor Analysis -- Chapter 6. A Long Short-Term Memory Neural Network -- Chapter 7. Domain Generalization by Adversarial Training -- Chapter 8. Conclusion.
Sommario/riassunto	This thesis presents significant advances in the use of neural networks to study the properties of neutrinos. Machine learning tools like neural networks (NN) can be used to identify the particle types or determine their energies in detectors such as those used in the NOvA neutrino experiment, which studies changes in a beam of neutrinos as it

propagates approximately 800 km through the earth. NOvA relies heavily on simulations of the physics processes and the detector response; these simulations work well, but do not match the real experiment perfectly. Thus, neural networks trained on simulated datasets must include systematic uncertainties that account for possible imperfections in the simulation. This thesis presents the first application in HEP of adversarial domain generalization to a regression neural network. Applying domain generalization to problems with large systematic variations will reduce the impact of uncertainties while avoiding the risk of falsely constraining the phase space. Reducing the impact of systematic uncertainties makes NOvA analysis more robust, and improves the significance of experimental results.
