1 Conclusion

We've successfully implemented a Restricted Boltzmann machine to solve the 1D Ising model, by clever usage of the NumPy library and Monte-Carlo sampling. We've shown that the RBM can be used to approximate the ground state energy of the Ising model, and that the model is capable of learning the ground state energy of the system. In our analysis, we found that the model is sensitive to it's hyperparameters, which is to be expected for any neural network - but we have also shown how important it is to have a large enough sample size for the Monte-Carlo sampler to properly traverse the spin-configuration landscape. The number of hidden units also play a crucial role in the learning process, where a too complex model will leave our RBM stuck trying to learn patterns that may not exist. We've also shown that the temperature of the system is an important parameter to consider, as the rate of convergence is affected by the temperature, and this further provides proof for why the temperature is usually ignored in RBM's for the Ising model (set to $T = 1$).

Adding long-range interactions changes the ground state energy, but the RBM is still capable of learning the ground state energy of the system. This is a promising result, as it shows that the RBM can be used to solve more complex systems than the simple Ising model. The 1D Ising model ground state is still the aligned spin-configuration, and even with the more complex Hamiltonian, our machine was successful in identifying this.

Further work could include implementing a 2D Ising model, where phase transitions are present, and the ground state is not as trivial to find. This would be a more challanging problem, but with our current results, there does not seem to be any reason for why the RBM would not be able to solve this problem as well.