

Simulating Quantum Systems with Neural Networks

- The goal is to find the ground state of quantum many body Hamiltonians.
 - This is QMA-Complete and thus we don't expect it to be efficiently solvable even on a quantum computer, without lower bounds on the spectral gap.
- Simulation is difficult because we do not have an efficient representation of the wave function in an exponentially growing Hilbert Space. To see this,

$$\Psi = \sum_{\text{spins}} \psi_{n_1 \dots n_N} |n_1 \dots n_N \rangle$$

- The coefficients $\psi_{n_1 \dots n_N}$ can, for no entanglement, be broken into:

$$\psi_{n_1 \dots n_N} = c_{n_1} \dots c_{n_N}$$

- With entanglement, this decomposition is not possible, and finding the coefficient values typically becomes exponentially hard with system size.



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Current Approaches

- Tensor Network Methods
 - Restrict the form of the wavefunction while preserving its “essential” features to focus on a specific corner of Hilbert Space.
 - Examples: MPS (very successful in 1D), PEPs (usually done only on 2d lattices)
 - Drawback:
 - Does not generally work well on systems defined on irregular graphs.
- Monte Carlo Methods
 - Sampling based approach that can work with non-sparse wave functions
 - Examples: path integral, projector, variational
 - Drawback:
 - Biased estimators and the sign problem



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Monte Carlo Approach

- Instead of calculating the coefficients exactly, we can sample from an “ansatz” distribution and optimize the parameters (called “ θ ” here) of this distribution based on the samples obtained.

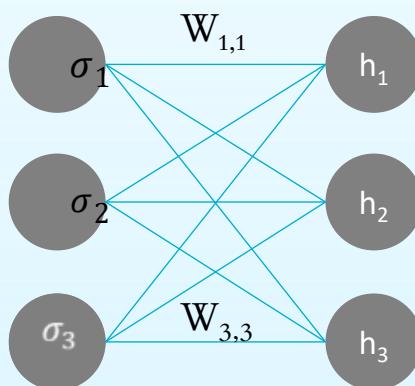
$$E(\theta) = \frac{\langle \psi(\theta) | H | \psi(\theta) \rangle}{\langle \psi(\theta) | \psi(\theta) \rangle} = \frac{\int |\psi(x, \theta)|^2 \frac{H\psi(x, \theta)}{\psi(x, \theta)} dx}{\int |\psi(x, \theta)|^2 dx}$$

- Where our local energy is defined as $\frac{H\psi(x, \theta)}{\psi(x, \theta)}$

Restricted Boltzmann Machine

- Idea: Try using various neural networks as ansätze for quantum wave functions.
- Advantages: Agnostic to the Hamiltonian graph, not quite as susceptible to the sign problem, neural networks are very well optimized.
- RBM Energy Example:

$$E = -\sum_j a_j \sigma_j - \sum_i b_i h_i - \sum_{ij} W_{ij} h_i \sigma_j$$



$$\psi(\sigma, \theta) = \sum_{\{h_i\}} e^{-E(\sigma, h)}$$

σ : Spin Configuration
 h : Hidden Spin Configuration $\{-1,1\}$
 a : Set of weights associated with σ
 b : Set of weights associated h
 W : weights connecting the visible and hidden vectors
 m : # of hidden units
 n : # of visible units

Carleo & Troyer, 2016,
<https://science.sciencemag.org/content/355/6325/602>.
 abstract



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Current Status and Why?

Testing on Transverse Field 3-regular 3-XORSAT Hamiltonian:

$$H_{XOR} = -(1-s) \sum_i \sigma_i^x - s \sum_{\langle i,j,k \rangle} J_{ijk} \sigma_i^z \sigma_j^z \sigma_k^z$$

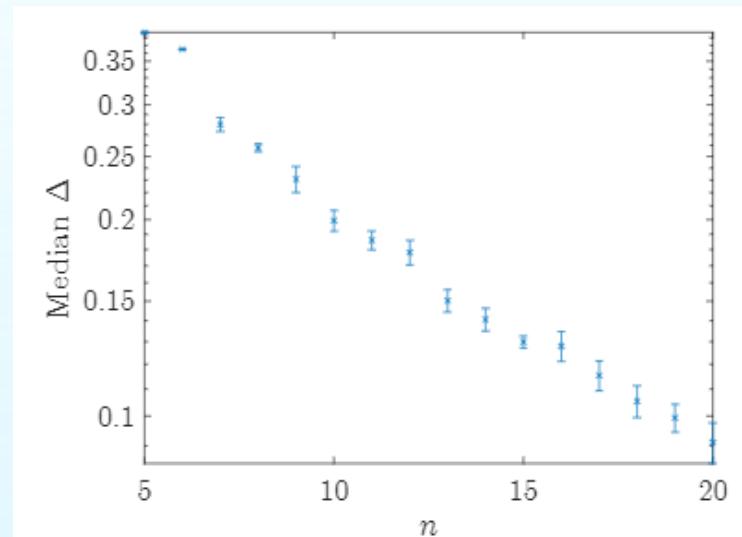
- 3-XORSAT are optimization problems where we have a group of variables (x) which belong to 3 groups and every group satisfies the constraint:

$$x_i \oplus x_j \oplus x_k = b_{ijk} \pmod{2}$$

$$x_a: \{0,1\}$$

$$b_{ijk} = \{0,1\}$$

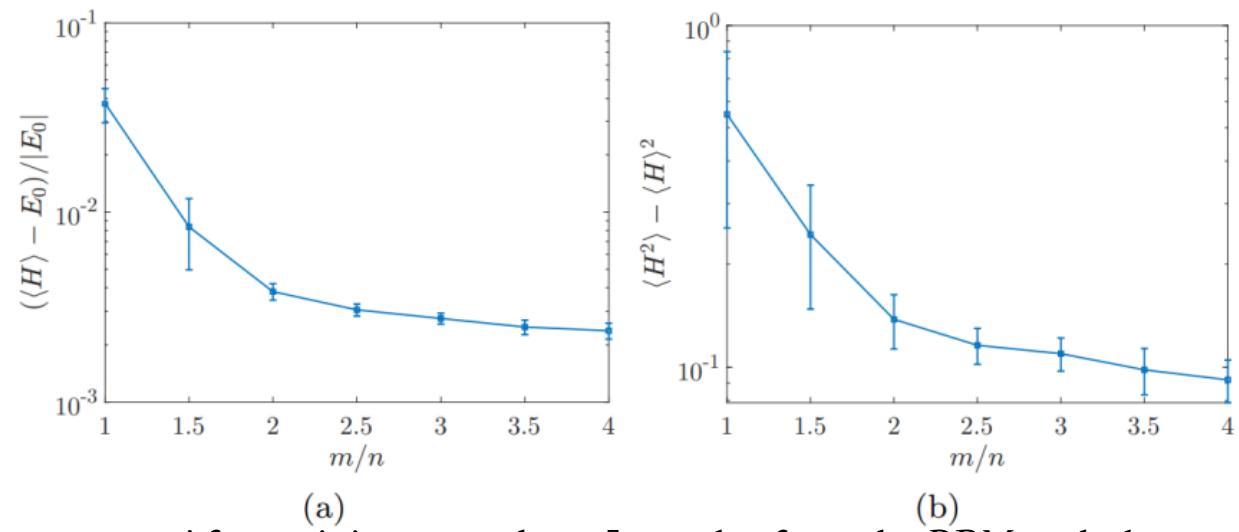
- This is a useful system to test this approach on for two reasons:
 - We randomly select the value of $b_{ijk} = \{0, 1\}$ and which triplets the spin sites belong to. This randomness acts a good way to test the neural network generally.
 - When $s = \frac{1}{2}$, the gap between the ground state and first excited state closes exponentially quickly meaning our neural network must become more accurate as the system size grows.



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Preliminary Results



After training, we take 10^7 samples from the RBM and plot the 95% confidence interval for the hidden unit to visible unit density (m/n) versus the Error and Variance

- We can see here that as we increase the ratio m/n , we obtain smaller Relative Error and Variance.
- There does, however, appear to be a saturation that requires further investigation.



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Future Work

- We see this project as in the beginning stages with much room for exploration such as:
 - Comparing the complexity of this XORSAT approach to other approaches
 - Benchmarking different Hamiltonians along with different system and parameter sizes
 - Identifying “bottlenecks” in training the networks (complex energy landscapes, unusual probability distributions, etc.)
 - Constructing the networks in different ways, i.e. more layers, convolutional layers, recurrent neural nets, etc.
 - Studying systems unsuitable for tensor methods
 - Studying systems that suffer from the sign problem
 - Time evolution as opposed to a ground state search
 - Comparing performance to quantum algorithms for the same problem



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References

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- The Performance of the Quantum Adiabatic Algorithm on Random Instances of Two Optimization Problems on Regular Hypergraphs, Farhi et al., 2012, <https://journals.aps.org/pra/abstract/10.1103/PhysRevA.86.052334>
- Barriers as a Reason for Hardness in Both Classical and Quantum Algorithms, Bellitti et al., 2021, arxiv:2102.00182

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Brief Example

$$H_{TFI} = -h \sum_i \sigma_i^x - \sum_{\langle i,j \rangle} \sigma_i^z \sigma_j^z$$

1. Propose a spin flip and accept the update with probability

$$P = \min(1, |\frac{\psi_{New}}{\psi_{Old}}|^2)$$

2. Sample the Local Energy:

$$\begin{aligned} E_{Loc} &= \frac{H_{TFI} \psi(\sigma, \theta)}{\psi(\sigma, \theta)} = -h \sum_i \frac{\sigma_i^x \psi(\sigma, \theta)}{\psi(\sigma, \theta)} - \sum_{\langle i,j \rangle} \frac{\sigma_i^z \sigma_j^z \psi(\sigma, \theta)}{\psi(\sigma, \theta)} \\ &= -h \sum_i \frac{\psi(\sigma_i^x, \theta)}{\psi(\sigma, \theta)} - \sum_{\langle i,j \rangle} v_i^z v_j^z \end{aligned}$$

3. Repeat as many times as necessary to sample the wavefunction distribution