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Exploring Spin Chain Models for Quantum Machine Learning

FUTURE GADGET LAB

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Problem Statement

- **The Goal:**

  Develop a quantum machine learning model that can learn the sine function from $[0, 2\pi]$ with $N=100$ discretization points

- **Core Problem:**

  How do complexity of quantum models, particularly spin chain models, affect their learning capabilities and accuracy?

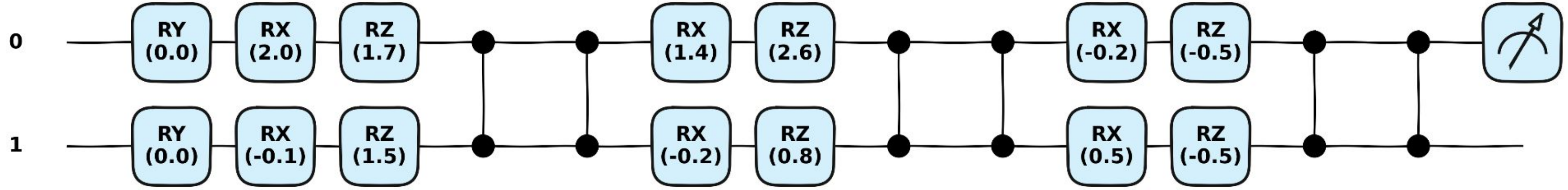
Proposed Solution

- **Toy Implementation:** A simple variational quantum model using a single qubit
- **Cost Functions:** *Mean Squared Error, Huber Loss, Quantile Loss, and Log cos-h*
- **Optimized Implementation-1:**
  - Closed Ising chain **(I)**
- **Optimized Implementation-2:**
  - An extended version with additional Heisenberg XXX interaction between alternate qubits **(H)**

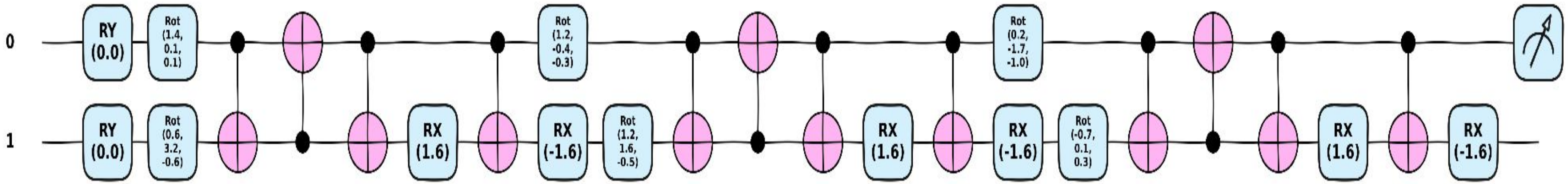
Implementation Details

- **Framework:** PennyLane
- **Implementation:**
  - Chain length for **I** and **H** = 2, 3, 4, 5
  - Cost functions: *Mean Absolute Error, Huber Loss*
- **Figures of merit:**
  - Loss
  - Accuracy

Circuit

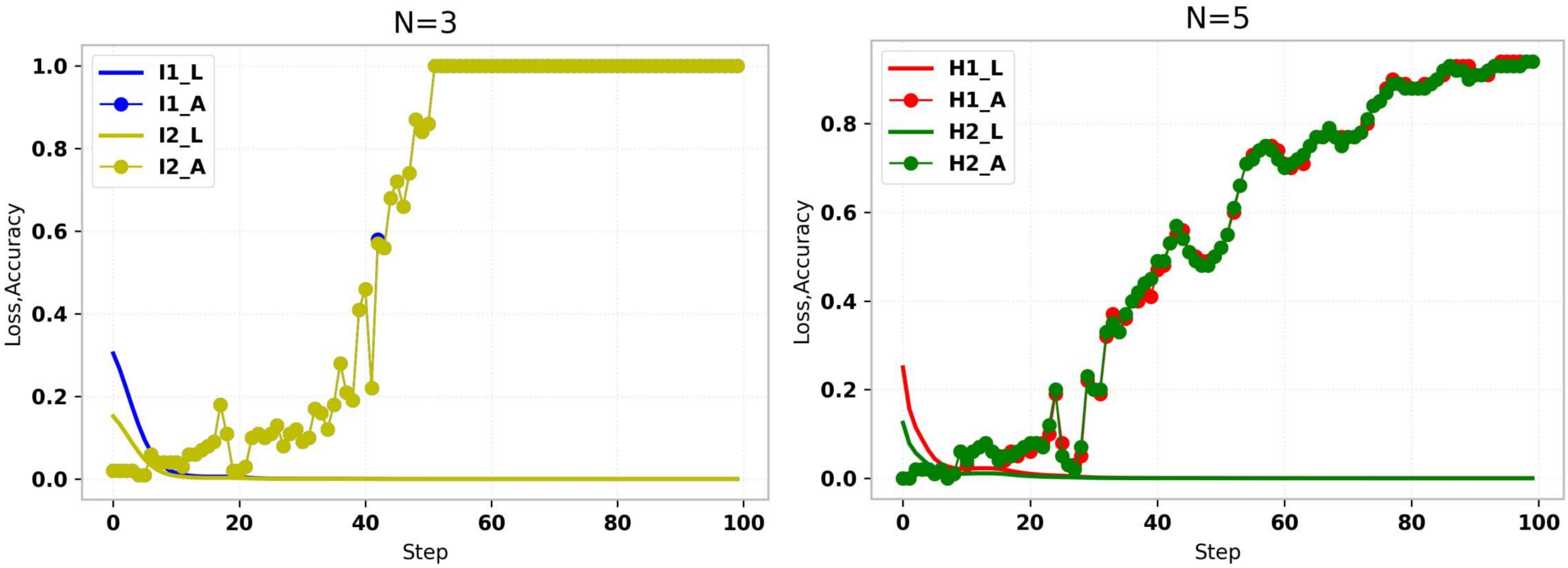


*(a) Circuit implementation for **I** with N=2 qubits*



*(b) Circuit implementation for **H** with N=2 qubits*

Figures of Merit



*Loss and Accuracy for **I, N=3** (left); **H, N=5** (right)*

Success and Metrics

- **Accuracy Results**: Both **I** and **H** models were able to learn the sine function with high accuracy, often reaching an accuracy of 1. However, the **I** model with N=3 qubits outperformed other configurations
- **Key Observations**: **I, N=3** showcased the balanced number of interactions required to reliably model the sine function without overfitting
- **Cost function optimization: Huber loss** struck a balance between the sensitivity to large errors and smooth gradient optimization

Future Scope

- **Extending the Analysis:** Including more qubits and exploring different types of interactions, such as long-range interactions in spin chains.
- **Phase Transition Study:** Effect of phase transitions within spin models on learning capabilities
- **Theoretical Framework:** Develop a theoretical framework to systematically study the global effect of model complexity on learning performance, providing a more comprehensive understanding of when and why complexity becomes detrimental

Conclusion

- We have demonstrated the effectiveness of the **Ising model with N=3 qubits** for learning the sine function, highlighting the importance of balanced model complexity. Huber Loss emerged the best cost function.
- Our findings suggest that careful consideration of model complexity and cost function selection is crucial in developing effective quantum machine learning models. While increasing complexity can enhance expressivity, it can also introduce challenges that may negate these benefits.
- Our work sets the stage for future investigations into the role of complexity in quantum models and the exploration of more sophisticated spin chain interactions

Acknowledgements

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