QCBM Documentation 3

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1 Model Description

Training Data: RELU + Sigmoid + Elu + Tanh Distribution
Pre-training: Particle number distribution
Number of qubits: 10
Number of Ancillas: 2
Loss Function: MMD Loss
Kernel: Gaussian RBF kernel
Accuracy: KL Divergence
Learning rate: 1.0
Optimizer: optax.adam

2 Observations

2.1 Uniform superposition Pre - Training (No Ancillas)

S.No	qcbm circuit	Layers	min KL Div	Model
1	RX + RZ + CNOT	$\geq 2 layers$	10^{-1}	Converges
2	RZ + IsingXY + IsingZZ	$\geq 2 layers$	10^{-1}	Converges

2.2 With ancillas

S.No	qcbm circuit	Layers	min KL Div	Model
1	RX + RZ + CNOT (No Pre-training)	$\geq 2 layers$	10^{-1}	Converges
2	RZ + IsingXY + IsingZZ (With pre-training)	$\geq 3 layers$	10^{-2}	Converges

2.3 No Pre - Training

S.No	qcbm circuit	Layers	min KL Div	Model
1	RX + RZ + CNOT	$\geq 2 layers$	10^{-2}	Converges
2	RZ + IsingXY + IsingZZ	-	inf	Doesn't Converge

3 Conclusion

Pre-training the model with particle number distribution, as expected only helps in the case of Ising entangling gates.

The performance of the circuit RZ + IsingXY + IsingZZ with the pre-training scheme of uniform superposition of all the possible particle number states leads to convergence upto the order of 10^{-1} less in KL divergence as that of fully entangled circuit i.e., RX + RZ + CNOT with same number of layers.

An improvement in the order 10^{-1} in KL divergence is found in the presence of ancillas for circuit with Ising Entangling gates.