

Unsupervised Generative Modeling Using Matrix Product States



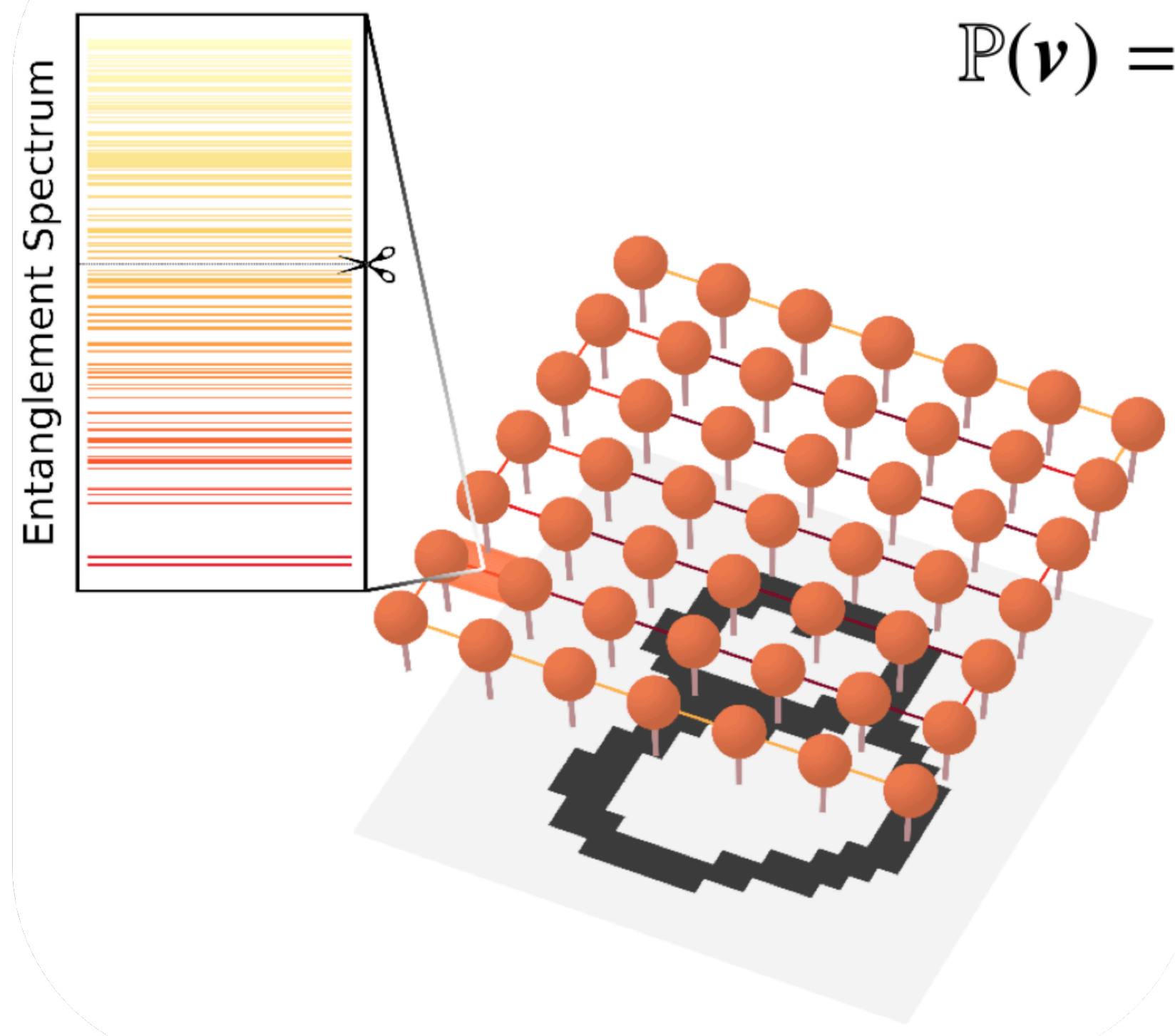
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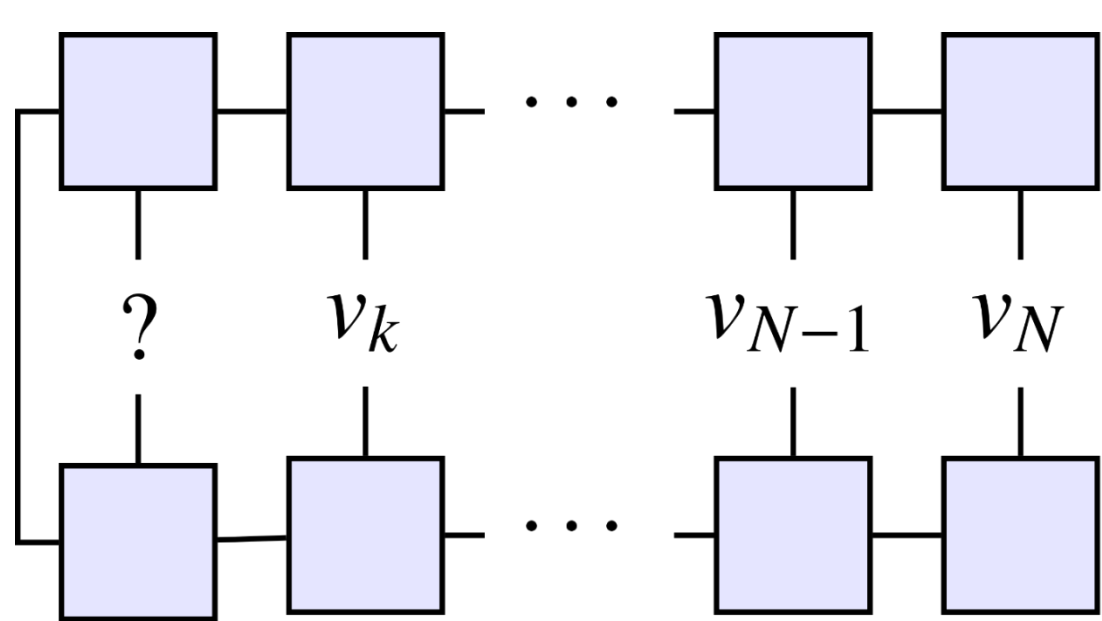
$$\mathbb{P}(\mathbf{v}) = \frac{|\Psi(\mathbf{v})|^2}{Z} = \left| \begin{array}{c} A^{(1)} \\ v_1 \end{array} \begin{array}{c} A^{(2)} \\ v_2 \end{array} \cdots \begin{array}{c} A^{(N)} \\ v_N \end{array} \right|^2$$

Modeling probability distribution of complex data using Born rule in quantum physics is a fresh approach to generative modeling in machine learning. Our model is based on Matrix Product States (MPS), a potent representation for entangled many-body quantum systems. Incorporating methods from both machine learning and physics like Density Matrix Renormalization Group (DMRG), it shows great potential in both learning and sampling on classical datasets like MNIST, compared to the conventional neural network approaches.

$$\mathcal{L} = -\frac{1}{|\mathcal{T}|} \sum_{\mathbf{v} \in \mathcal{T}} \ln \mathbb{P}(\mathbf{v})$$

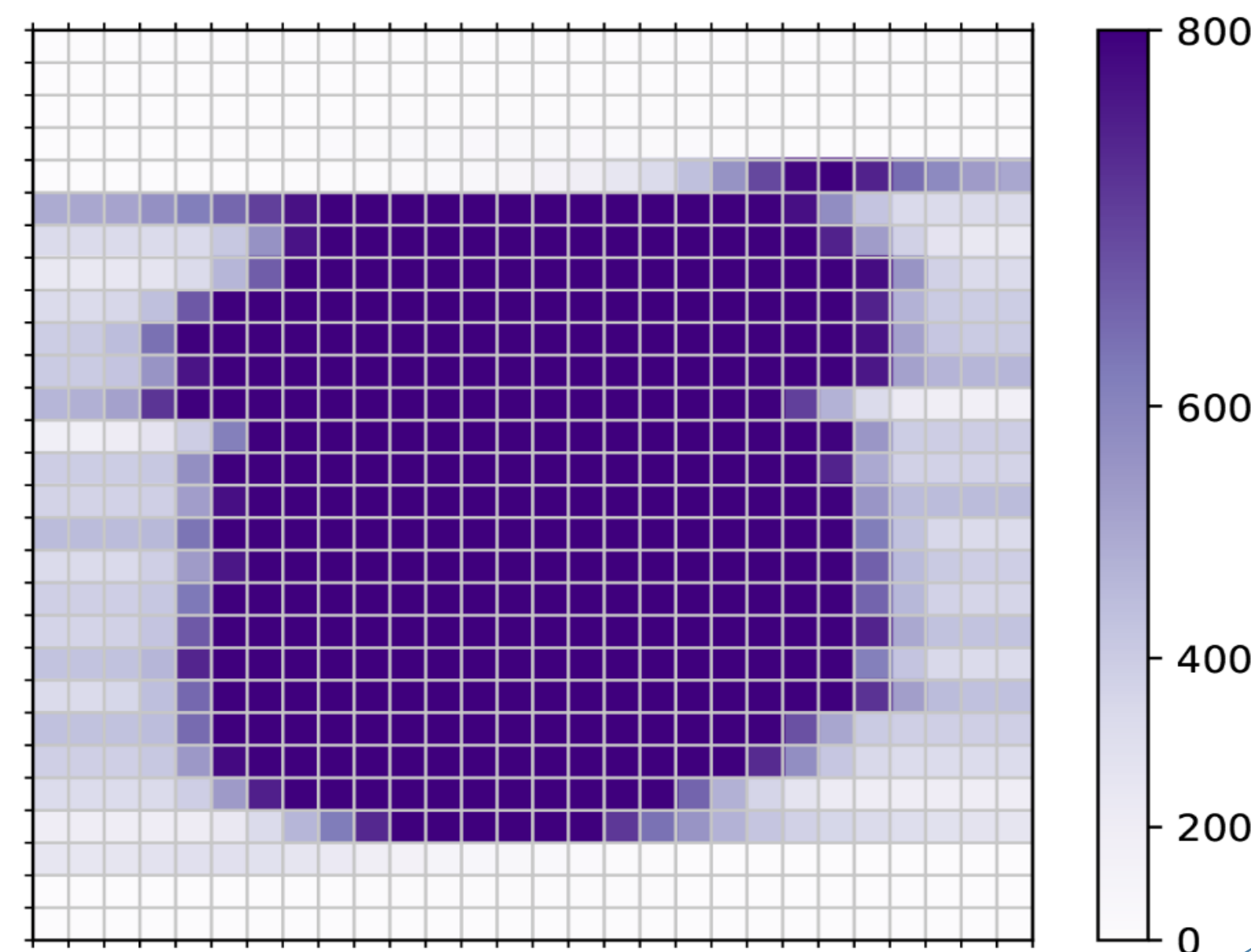
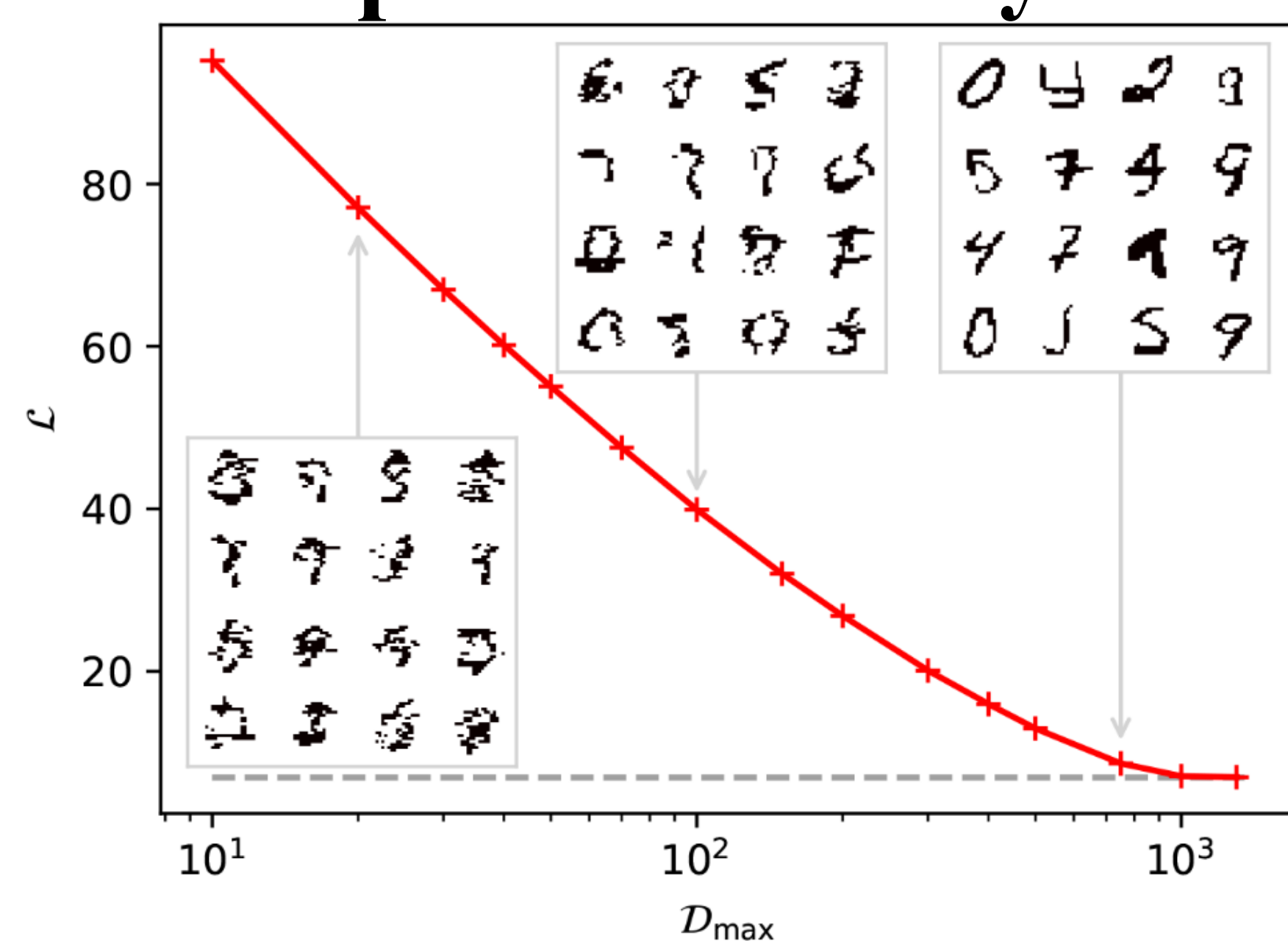
Features

1. Adaptive Adjustment of Expressibility
2. Efficient Computation of Exact Gradients and Log-likelihood
3. Efficient Direct Sampling

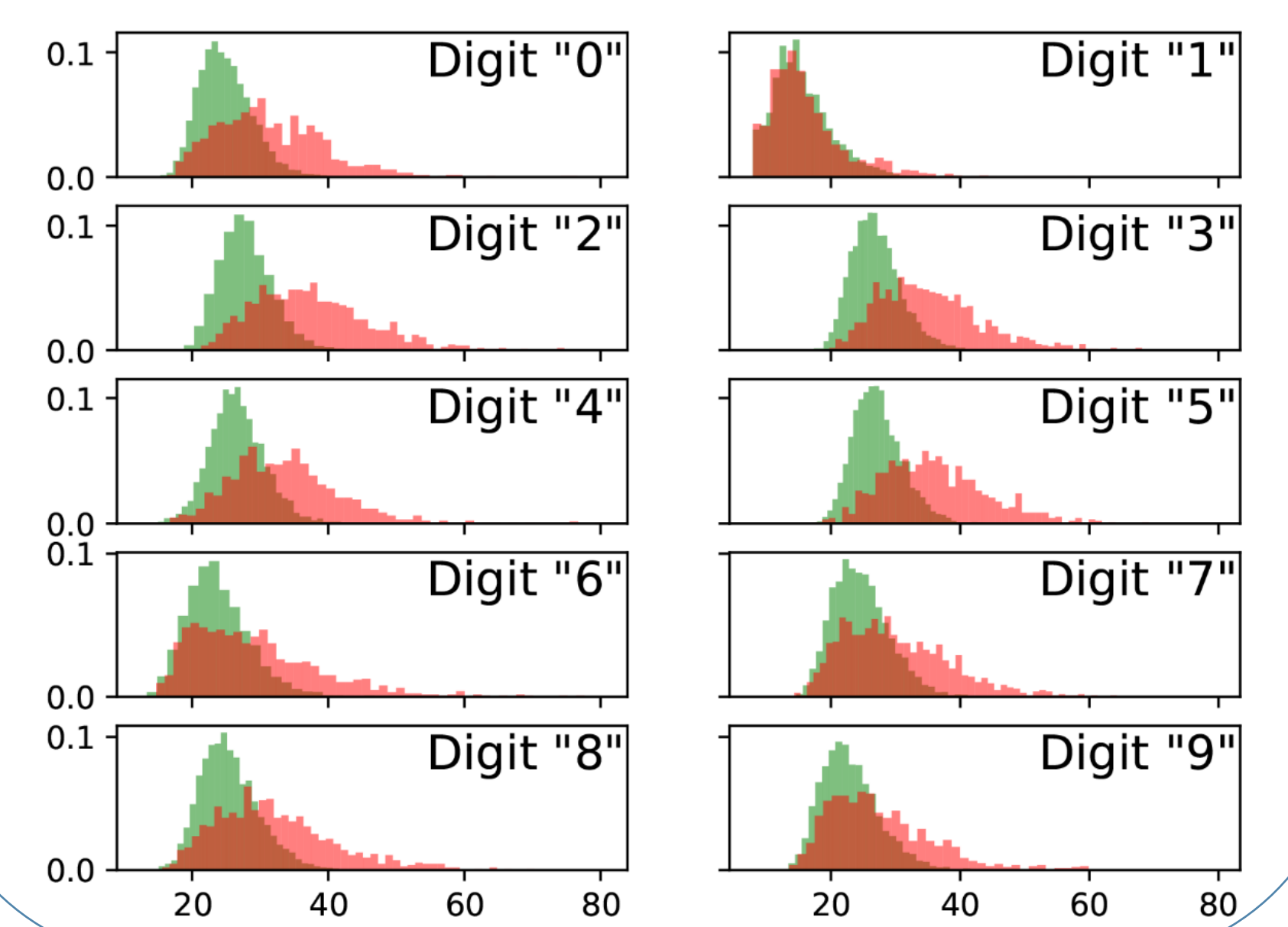
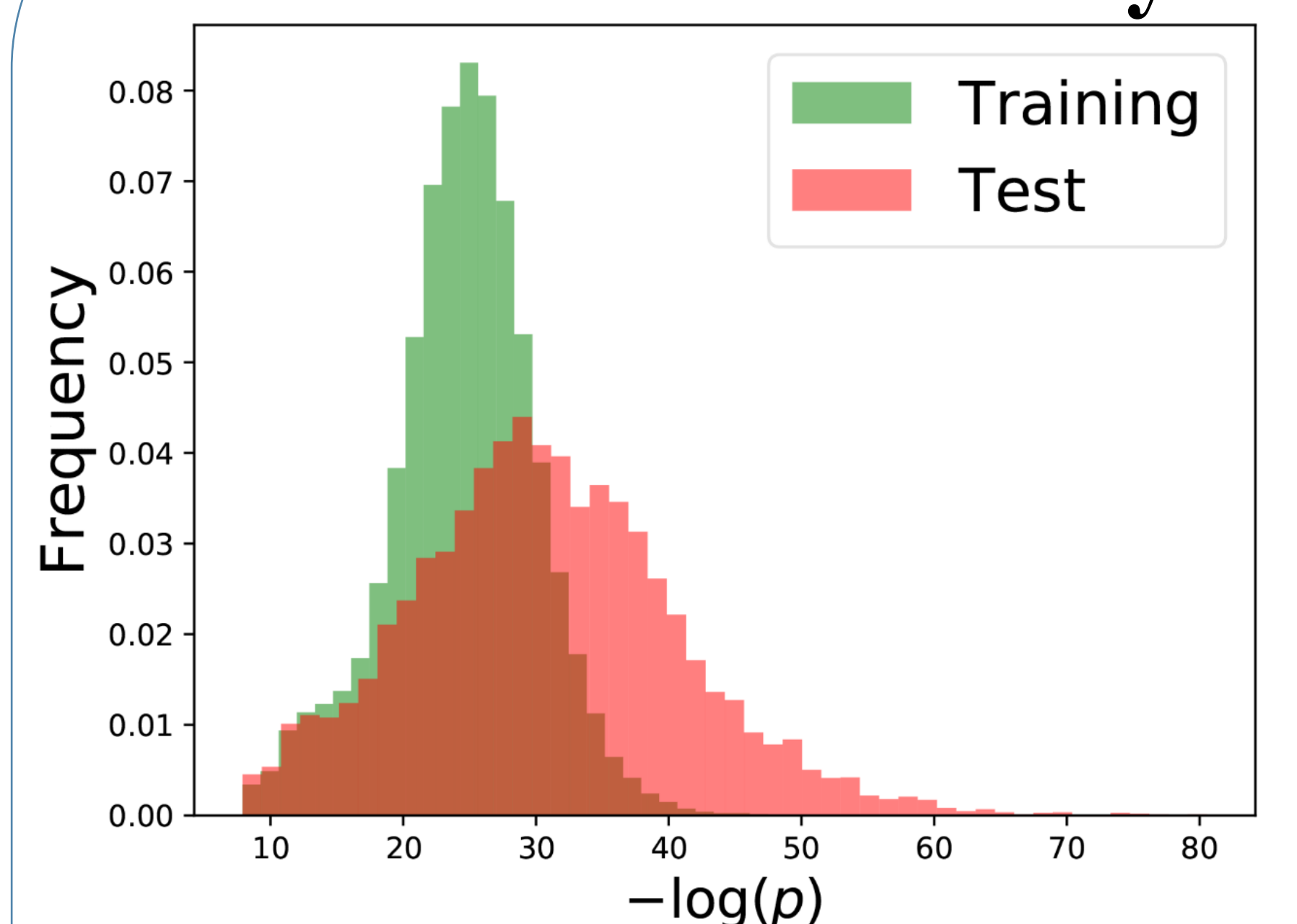


4. Theoretical Understanding of Expressive Power

Expressive Ability



Generalization Ability



Application



Column Reconstruction on Training Images

Column Reconstruction on Test Images

Outlook

- Language/time sequence modeling
- Born machines with stronger tensor network architectures, such as Tree, MERA and PEPS
- Realization on quantum computer

Paper, tutorial and codes at:

