MPS Pure state training

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The training scheme used here is that outlined in this paper from Lei Wang. The state is modeled as a pure-state MPS with unspecified bond dimension, defined on a system of size L. Samples are drawn from the ground-truth state Ψ in a sequence of random bases: at each measurement step, a set of L angles (θ, ϕ), randomly distributed across the unit sphere, is used to construct L random single-qubit unitaries that are applied to the ground-truth state; a single measurement is then taken in the z product basis. This procedure is repeated N times to construct a dataset consisting of applied unitaries and corresponding outcomes.

The MPSs are trained by stochastic gradient descent using the two-site update method described in the paper above: for a particular batch of data, the algorithm sweeps back and forth across the MPS, adjusting the local tensors at each bond in order to raise the log-likelihood assigned by the MPS to the observed data. At each update step, the local bond dimension of the MPS can be adjusted according to user-specified cutoffs; a regularization term proportional to the Renyi-2 entropy of the state when cut across each bond is applied.

1 Preliminary experiments

I trained MPS models on ground-truth states constructed as MPSs with fixed bond dimension and random-normal values in each tensor.

Figure 1 plots the fidelity of the trained model onto the ground truth state as a function of training set size; prior to saturation the behavior is approximately linear in the number of samples

In Figure 2 I plot the number of training samples required to acheive a fidelity of .99, as a function of system size; the dependence is surprisingly weak (I'm using a low bond dimension here so perhaps the targets are 'too easy').

I have made no attempts to optimize the training, which is done via vanilla SGD; in particular the hyperparameters were set by hand without any sort of cross-validation. There is significant variation across different random model seeds.

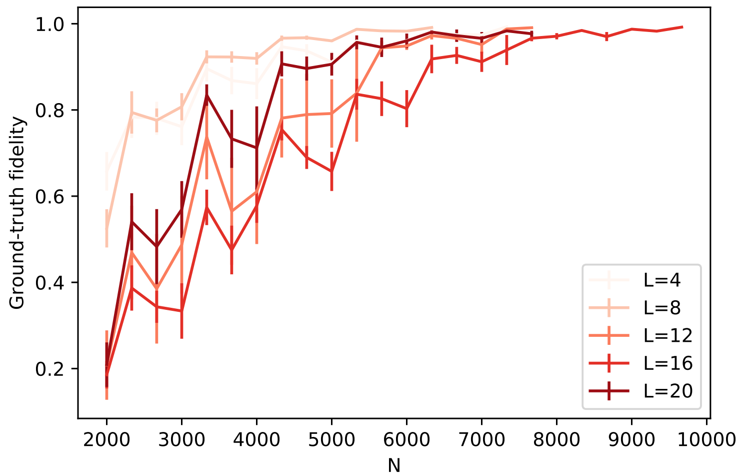

Figure 1: Fidelity onto ground-truth state for various system sizes. Error bars correspond to different random seeds.

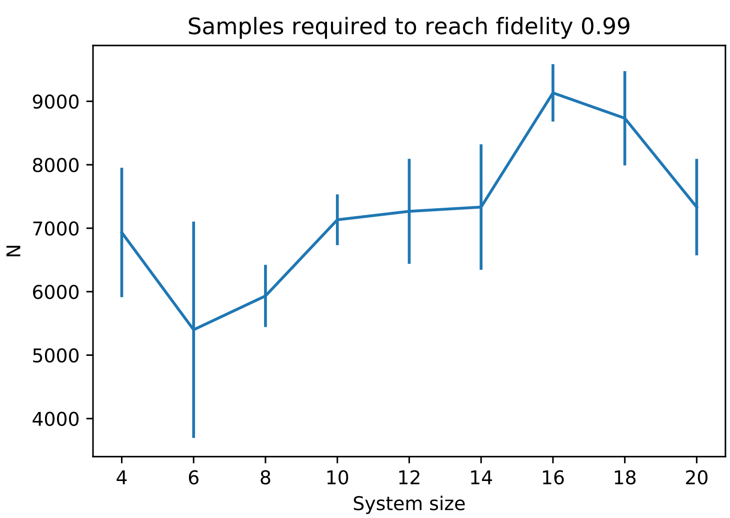

Figure 2: Number of samples required to acheive fidelity .99