

# AQER: A Scalable and Efficient Data Loader for Digital Quantum Computers

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## Abstract

Digital quantum computers promise computational capabilities beyond classical systems, but scarce qubits and limited coherence make data loading a persistent bottleneck. Approximate quantum loaders (AQLs) address this bottleneck by trading preparation fidelity for circuit complexity. We develop AQER, an AQL method that constructs loading circuits through maximal entanglement reduction. We first cast tensor-network, variational, and non-variational loaders into a unified optimization framework and derive information-theoretic bounds showing that AQL infidelity is controlled by the single-qubit entanglement entropy of the inverse-evolved target state. Guided by this result, AQER appends two-qubit blocks to reduce entanglement, analytically fits a product-state approximation, and refines all parameters. Experiments on classical image and language data, random-circuit states, and transverse-field Ising ground states up to 50 qubits show consistently lower infidelity with equal or fewer two-qubit gates than representative baselines.

## 1 Introduction

Digital quantum computers [1] promise to deliver computational capabilities that surpass classical systems in diverse fields, including quantum simulation, optimization, and machine learning [2, 3, 4]. Nevertheless, the available quantum resources, such as the number of high-quality qubits and the coherence time, remain severely constrained in the foreseeable future. This limitation underscores the need to improve the efficiency of the foundational modules of quantum computing: state preparation, quantum processing, and readout. Among these modules, efficient state preparation is a critical prerequisite for data-dependent quantum algorithms, because it constructs quantum gate sequences that encode classical or quantum inputs into quantum states [5, 6]. In the worst case, preparing an arbitrary quantum state within a provable error tolerance can require exponentially many gates or ancillary qubits [7, 8].

The approximate quantum loader (AQL) paradigm offers a practical direction for reducing this overhead. Rather than demanding exact preparation, an AQL constructs a shorter circuit whose output state is close enough to the target for downstream use. This relaxation is especially natural in quantum machine learning: small perturbations of input features often have negligible impact on classification accuracy [9], and certain quantum learning advantages can persist under imperfect state loading [10]. Existing AQL methods broadly fall into tensor-network approaches, which exploit low-entanglement representations such as matrix product states [11, 12, 13], and circuit-based approaches, which optimize a parameterized loader directly [14, 15, 16]. Despite these developments, most methods are either restricted to specific data structure or are heuristic, and the fundamental quantity governing AQL approximation error remains unclear.

This work addresses that gap by reformulating AQL as the joint search over circuit parameters and architecture that minimizes the infidelity  $1 - |\langle v_{\text{target}} | U(\boldsymbol{\theta}; \mathcal{A}) | \psi_{\text{product}} \rangle|^2$ , where  $U(\boldsymbol{\theta}; \mathcal{A})$  is the loading circuit and  $|\psi_{\text{product}}\rangle$  is an easily prepared product state. This unified view leads to a theory that identifies what AQL should optimize.

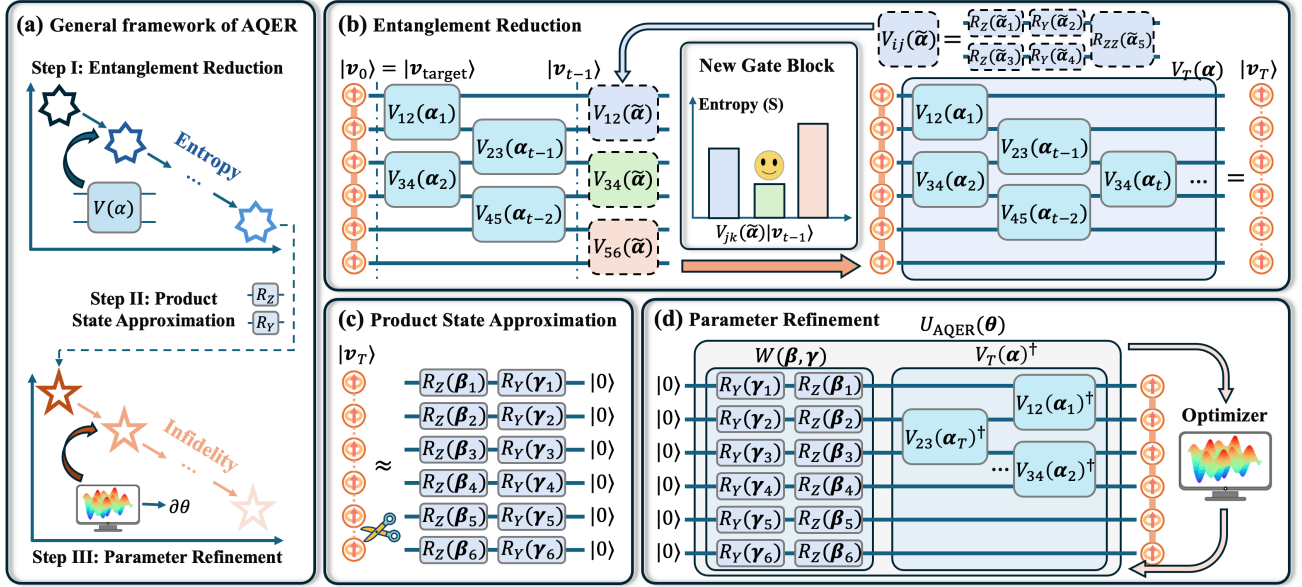


**Figure 1:** Workflow of AQER. The algorithm first reduces entanglement by appending two-qubit blocks, then computes a product-state approximation using single-qubit rotations, and finally refines all parameters against the infidelity loss.

**Theorem 1** (AQL error is controlled by inverse-evolved entanglement). *Let  $\mathcal{S}(|\psi\rangle) = \sum_{i=1}^N \mathcal{S}_{\{i\}}(|\psi\rangle)$  be the sum of single-qubit entanglement entropies. For any candidate circuit  $U$ , set  $S = \mathcal{S}(U^\dagger|v_{\text{target}}\rangle)$ . Then every product-state loader through  $U$  has infidelity at least an explicit function  $f_1(S)$ , while a product state constructible from local single-qubit reduced density matrices achieves infidelity at most an explicit function  $f_2(S)$ . In the low-entanglement regime,  $f_1(S) = \ln(2)S/(2N) + O(S^3)$  and  $f_2(S) = \ln(2)S/2 + O(S^3)$ .*

The theorem gives a concrete design principle: reducing the single-qubit entanglement of the inverse-evolved target state reduces the best achievable loading error, and the constructive upper bound explains why local reduced density matrices are enough to initialize a high-quality product-state approximation.

## 2 AQER

Motivated by this theory, AQER constructs the loading circuit by maximal entanglement reduction. Figure 1 summarizes the workflow. Step I iteratively appends parameterized two-qubit blocks  $V_{\mathcal{I}_t}(\alpha_t)$ , with gates of the form  $R_{ZZ}R_YR_Z$ , and chooses both the qubit pair  $\mathcal{I}_t$  and parameters  $\alpha_t$  to minimize  $\mathcal{S}$  of the transformed target. Step II uses the resulting low-entanglement state to build an explicit product-state approximation: single-qubit rotations  $R_Z(\beta_i)R_Y(\gamma_i)$  are obtained from local reduced density matrices without global numerical optimization. Step III fine-tunes all parameters in the full circuit  $U_{\text{AQER}}(\theta)$  by directly minimizing infidelity.

This design has two practical advantages. First, it is data-type agnostic: the same algorithm can load classical vectors, states from random quantum circuits, and quantum many-body states. For classical data, the target state and entanglement quantities are evaluated through classical simulation or tensor-network representations; for quantum data, the entanglement proxy can be estimated from local measurements. Second, AQER improves trainability. Because Step I moves the transformed target toward a product state, the Step III variational refinement starts in a lower-loss region rather than near the high-infidelity plateau typical of random initialization.

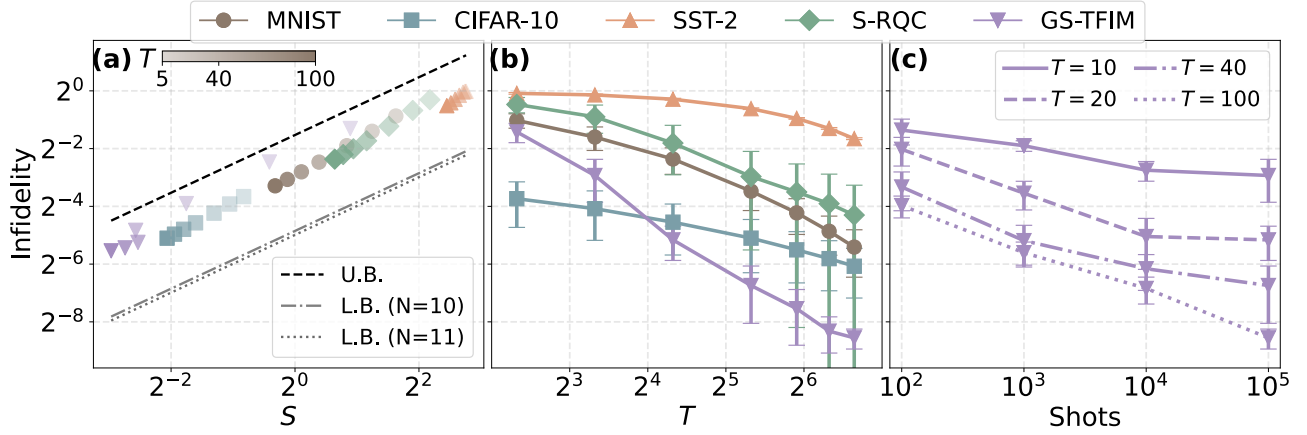


**Figure 2:** Empirical validation of the AQER mechanism. The panels show that lowering the inverse-evolved entanglement measure reduces infidelity, increasing the two-qubit gate budget improves loading accuracy across datasets, and more measurement shots stabilize large-system quantum-data loading.

### 3 Experiments

We evaluate AQER on both classical and quantum datasets. The classical benchmarks are MNIST, CIFAR-10, and SST-2 sentence embeddings, encoded using amplitude or compact complex encoding [17, 18, 19, 20]. The quantum benchmarks are random-quantum-circuit states and ground states of the one-dimensional transverse-field Ising model (TFIM) [21]. We compare against three representative loaders: a one-dimensional MPS method, a hardware-efficient circuit (HEC) loader, and automatic quantum circuit encoding (AQCE). The primary metrics are infidelity and the number of two-qubit gates  $G$ , since two-qubit gates dominate near-term circuit cost.

AQER achieves the best infidelity across all benchmark families with matched or smaller two-qubit gate counts. At  $G = 80$ , AQER obtains mean infidelities 0.034 on MNIST, 0.018 on CIFAR-10, 0.406 on SST-2, 0.067 on random-circuit states, and 0.003 on TFIM ground states; the strongest baselines at comparable gate counts give 0.051, 0.024, 0.518, 0.267, and 0.007, respectively. The improvement is most pronounced for highly entangled synthetic quantum data: for  $G \in \{40, 80\}$ , AQER reduces infidelity by more than 60% relative to AQCE. Figure 2 also confirms the theoretical mechanism: increasing the number of entanglement-reduction steps drives both the entanglement measure and the infidelity down, and the observed trend follows the linearized bounds implied by the theory.

We further test scalability and downstream utility. On GS-TFIM states with  $N = 50$  qubits, Step III optimization starts far below infidelity 1 and continues decreasing, indicating that entanglement reduction mitigates barren-plateau-like initialization. Across  $N \in \{20, 30, 40, 50\}$ , AQER maintains roughly constant infidelity when the number of entangling blocks grows linearly with  $N$ . For downstream physics, AQER-loaded TFIM states reproduce the magnetization signature of the ferromagnetic-to-paramagnetic transition near  $g/J = 1$ . For classical data, reconstructed images improve with larger gate budgets, and SST-2 quantum-kernel classification approaches the exact-loading error as the AQER circuit grows.

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