Cloning is as Hard as Learning for Stabilizer States*

Nikhil Bansal , Matthias C. Caro , and Gaurav Mahajan

Introduction. The *No-Cloning* theorem [WZ82; Die82] is a foundational result in quantum theory. It states: There is no unitary U such that $U(|\psi\rangle\,|0\rangle) = |\psi\rangle\,|\psi\rangle$ holds simultaneously for multiple non-orthogonal pure states $|\psi\rangle$. In words, for any set of states that contains at least two non-orthogonal states, the No-Cloning theorem rules out the existence of a hypothetical *one-fits-all* cloning map. We also have what one may call an *approximate No-Cloning* theorem [Wer98; KW99]: Approximately cloning arbitrary pure states requires as many copies as pure state tomography [Gro+10; BDK16; Haa+16; OW16; PSW25]. While this tells us that it is exponentially costly to clone pure states without any structural assumptions, imposing sufficiently stringent structure can make the cloning task easy. As a trivial example, any class of orthogonal states can be cloned perfectly from a single copy. Thus, there are two extremes: Approximate cloning is exponentially costly without structure, but even exact cloning becomes trivial with orthogonality structure.

In many areas of quantum computation and information, and in particular in quantum learning theory [AW17; AA24], we often consider neither of these extremes. Instead, we focus on classes of states that are structured yet sufficiently rich to exhibit non-trivial quantum behavior. Prominent examples include stabilizer states [Mon17], tensor network states [LLP10; Cra+10; LVV15; Ara+17; Bak+25], quantum example states [BJ95; AW17; Car+24; CNS26], and phase states [Aru+23]. However, whereas questions of learning such structured classes of states are well-studied, questions of (approximate) cloning under structural assumptions remain unexplored. This leads us to our first central question:

Can approximate cloning be easier than learning for structured classes of states?

In the asymptotic regime, as the number of cloned copies goes to infinity, [CY14] gave strong evidence that the answer to the above question should be negative. In contrast, a computational version of the question was raised in [Fef+26], and there is evidence [NZ24; BNZ25; ÇGS26] towards a positive answer. We, however, interpret the question in terms of sample complexity: Are there structured classes of states for which the sample complexity of approximate cloning is strictly smaller than that of learning? This motivates us to connect the modern perspective of quantum learning theory with the foundational question of cloning by proposing a structured version of the approximate cloning problem:

Definition 1: (Cloning of structured states – Informal) A class $\mathcal{S}$ of quantum states is said to admit a $(t, t+m, \epsilon)$-quantum cloning scheme if there exists a linear CPTP map $\Lambda_{\mathcal{S},t,m,\epsilon} : \mathcal{B}(\mathcal{H}^{\otimes t}) \to \mathcal{B}(\mathcal{H}^{\otimes t+m})$ such that

$$\sup_{\rho\in\mathcal{S}} \mathrm{d}_{\mathrm{TD}}\left(\Lambda_{\mathcal{S},t,m,\epsilon}(\rho^{\otimes t}), \rho^{\otimes t+m}\right) \leq \epsilon\,. \tag{1}$$

We call ϵ the error incurred by the cloning scheme.

In this work, we show that structured cloning with small constant error for stabilizer states requires a sample complexity scaling linearly in the number of qubits, matching their learning complexity. Given the prominent role of stabilizer states in quantum computing, our result can be viewed as an approximate No-Cloning theorem for practically relevant states. We prove this by relating cloning to a structured version of the recent classical sample amplification problem [Axe+20; Axe+24]: Given a dataset drawn from an unknown distribution from some known class, produce a larger dataset that looks like it consists of true samples. [Axe+20] proved that sample amplification can be strictly easier than learning. Taking motivation from the computational learning theory [Val84], which deals with learning a Boolean function f from data $\{(x_i, f(x_i))\}$, where the x_i are drawn i.i.d. from some known n-bit distribution $\mathcal{V}_n$, we ask whether such structured distributions $\{(\mathcal{V}_n, f)\}_{f\in\mathcal{F}}$, with $\mathcal{F}$ a Boolean function class, can be amplified more sample-efficiently than learned.

Main Results. Motivated by the above, we study two core questions in this work: First, is structured sample amplification easier than learning? And second, is structured quantum cloning easier than learning? We show that the two questions are related for specific structured classes of functions and states, and for those classes we give negative answers to both questions. Our results on sample amplification and cloning sample complexity lower bounds for different structured classes are highlighted and compared with learning sample complexities in Table 1.

*arXiv:2604.15269v1 gave a faulty proof for its claimed cloning results via random purification. The stabilizer state cloning bound holds, but it requires a different proof. This Extended Abstract represents the contents of an updated version of the paper that will soon appear on the arXiv.

Problem Instance (Classical/Quantum)	Learning (with small constant error)	Sample Amplification/Cloning (with small constant error)
n-bit parities	$\Theta(n)$	$\Omega(n)$ (This work)
$k_{\mathcal{F}}$-dimensional Boolean function subspace	$O(k_{\mathcal{F}})$	$\Omega(k_{\mathcal{F}})^*$ (This work) (*depending on properties of the code $C_{\mathcal{F}}$)
n-qubit stabilizer states	$\Theta(n)$ [Mon17]	$\Omega(n)$ (This work)

Table 1: **Overview of our main results:** A comparison between known sample complexity bounds for learning (with small constant error) and our new sample complexity lower bounds for amplification/cloning.

On the classical side, we develop a general lower bound on the optimal achievable error in structured sample amplification for any structured distribution class of the form $\mathcal{D} = \{(\mathcal{U}_n, f)\}_{f\in\mathcal{F}}$, with $\mathcal{F}$ a known Boolean function class. We then instantiate this bound for parity functions, and more generally for function classes that form a linear space.

Theorem 1: (Structured Sample Amplification Lower Bounds – Informal)

1. ***General lower bound:*** *Let $\mathcal{F}$ be a "symmetric[1]" class of Boolean functions on n bits. Let $b_{\mathcal{F}}$ be the teaching dimension [GK95] of $\mathcal{F}$. Sample amplification for $\mathcal{F}$ from $< b_{\mathcal{F}}$ samples incurs an error of at least half the probability that $b_{\mathcal{F}}$ uniformly random labeled examples uniquely identify the target function.*
2. ***Lower bound for parities:*** *Sample amplification for the class $\mathcal{F}_{\text{par}} = \{x \mapsto s \cdot x \mod 2\}_{s\in\mathbb{Z}_2^n}$ of n-bit parity functions from $< n$ samples incurs at least a constant error of 0.14.*
3. ***Lower bounds from coding theory:*** *Let $\mathcal{F}$ be some $k_{\mathcal{F}}$-dimensional linear subspace of all Boolean functions on n bits. Sample amplification for $\mathcal{F}$ from $< k_{\mathcal{F}}$ samples incurs an error of at least half the probability that a certain corresponding linear code corrects $k_{\mathcal{F}}$ random erasure errors minus an $O(k_{\mathcal{F}}^2/2^n)$ term.*

While sample amplification is strictly easier than learning for the unstructured class of all Boolean functions as a direct consequence of results from [Axe+20; Axe+24], Theorem 1 shows that structured sample amplification for particular classes of functions is as hard as learning. Thus, for certain structures, we have found classical "No Sample Amplification" results similar in spirit to quantum No-Cloning theorems.

On the quantum side, we make use of our lower bounds for structured sample amplification to derive optimal cloning lower bounds for different families of states. We first prove a general lower bound on the optimal achievable error for cloning a set of (mixed) states that "hide" unknown symmetry subgroups of a large (known) Abelian group. Here, we say that a state $\rho \in S$ "hides" a subgroup $H \leq G$ under some fixed unitary representation[2] μ if the elements of H leave the state invariant, i.e., $\operatorname{tr}(\rho\mu(h)) = 1, \forall h \in H$, and the elements not in H change the state significantly, i.e., $|\operatorname{tr}(\rho\mu(g))|$ is bounded away from 1 for all $g \in G \setminus H$. We then give our cloning lower bound for stabilizer states.

Theorem 2: (Structured Quantum Cloning Lower Bounds – Informal)

1. ***General lower bound****: Let G be a known Abelian group. Let S_α be a class of (mixed) n-qubit states that "hide" unknown symmetry subgroups $H \leq G$ of order α. Let p_H^t denote the probability of uniquely identifying H from t copies of a corresponding canonical H-hiding state σ_H. Then, cloning S_α from $< t$ copies incurs an error of at least $\frac{1}{2}\mathop{\mathbf{E}}_{H\leq G:|H|=\alpha}\left[p_H^t - p_H^{t-1}\right]$, where the expectation is uniform over subgroups $H \leq G$ of order α.*
2. ***Lower bound for stabilizer states****: Cloning for the class of pure n-qubit stabilizer states from $< \lfloor n/3 \rfloor$ copies incurs at least a constant error of 0.28 minus a term exponentially small in n.*

Approximate cloning is already known to be as hard as learning for the unstructured class of all pure states [Wer98; KW99]. Theorem 2 shows that the same is true for stabilizer states. Thus, imposing such structure does not separate cloning from learning in terms of sample complexity.

[1]Here, we call a function class symmetric if all its elements have the same minimum teaching sequence size and if obtaining a teaching sequence from random samples is equally likely for each function in the class.

[2]For point 1 in Theorem 2 below, we assume the representation μ to contain every irrep of G exactly once.

Techniques. We establish our sample amplification and cloning lower bounds with a common proof strategy, which highlights that the similarity between cloning and sample amplification is not merely superficial but can indeed be made technically rigorous. The unifying proof approach consists in constructing a distinguisher that can tell true samples/copies apart from amplified ones. In the case of stabilizer state cloning, our distinguisher runs an average-case optimal learner for the relevant state ensemble (which we choose to be a specific subclass of stabilizer states, see below) on the purported $t+1$ quantum copies. The distinguisher accepts precisely when the hypothesis produced by the learner equals the true state. Composing any t-to-$(t+1)$ quantum cloner with a $(t+1)$-copy learner gives a valid t-copy learner, so the cloning error must be lower bounded by the gap between the optimal average probabilities of learning from $t+1$ and from t genuine copies.

We analyse these probabilities for a specific subclass of stabilizer states. Concretely, within the class of $(3n)$-qubit stabilizer states, we consider the class $\mathrm{BiGraph}_{3n}$ of $(n, 2n)$-bipartite graph states of the form

$$|A\rangle = \frac{1}{\sqrt{2^{3n}}} \sum_{x\in\mathbb{Z}_2^n, y\in\mathbb{Z}_2^{2n}} (-1)^{x^T A y} |x\rangle|y\rangle\,, \tag{2}$$

which are indexed by their biadjacency matrices $A \in \mathbb{Z}_2^{n\times 2n}$. First, for $t = n-1$ copies, we upper bound the optimal average probability of learning an unknown state from $\mathrm{BiGraph}_{3n}$ via a dimension counting argument. Namely, for $t = n-1$, we show that the span of the states $|A\rangle^{\otimes n-1}$ has a dimension that is exponentially smaller than $|\mathrm{BiGraph}_{3n}|$, leading to an exponentially small optimal success probability of identifying an unknown state in $\mathrm{BiGraph}_{3n}$ from $n-1$ copies. For $t+1 = n$ copies, by contrast, applying Hadamard gates to the $2n$ qubits on one side of the bipartition and measuring in the computational basis produces independent samples $(x, x^{\mathsf{T}}A)$. These observed measurement outcomes uniquely determine A as soon as we see n linearly independent sampled vectors x, which among n samples happens with probability $\prod_{i=1}^{n}(1-2^{-i}) \geq 0.28$. This constant jump in learning success yields a constant cloning-error lower bound. Monotonicity of the cloning error together with a simple padding (to cover the cases of $(3n+1)$- and $(3n+2)$-qubit states) then leads us to the claimed $\Omega(n)$ lower bound for general n-qubit stabilizer state cloning with sufficiently small constant error.

Outlook. Our results on quantum cloning for particular classes of structured quantum states related to Abelian StateHSP problems, with stabilizer states as a concrete example, achieved via a novel connection between cloning and classical sample amplification, raise several natural follow-up questions, including:

- **Cloning hypergraph states:** A natural next class of states to explore cloning for are hypergraph states of order d [Ros+13], which also admit a description in terms of stabilizer operators that include Toffoli gates in addition to Paulis. These states can alternatively be thought of as phase states of degree-d polynomials over $\mathbb{Z}_2$ [Aru+23]. It is an intriguing question whether cloning hypergraph states can be related to sample amplification of low-degree polynomials, and whether such a connection can give rise to lower bounds. Beyond hypergraph states, the study of cloning for classes such as matrix product states, or output states of QNC^0 and QAC^0 circuits may be of interest.
- **Cloning against restricted distinguishers:** In the distinguisher-based perspective on cloning, we have not restricted the computational power of the distinguisher. Motivated by quantum cryptography [Wie83; JLS18; Fef+26; NZ24; BNZ25], it is natural to consider the task of cloning structured classes of states against polynomial-time adversaries. While our lower bounds for stabilizer state cloning immediately carry over to cloning against polynomial-time adversaries, it remains to explore the impact of imposing computational restrictions on the adversary for cloning other classes of quantum states. Specifically, it would be interesting to see whether cloning and learning can be separated for relevant classes of states in this computational model of cloning.
- **Average-case quantum cloning:** Our formulation of quantum cloning as well as our proven lower bounds are in a worst-case picture. In particular, to establish our stabilizer state cloning lower bound, we first restrict attention to a suitable subset of states; thus, the stabilizer result holds for a worst-case notion of cloning. In contrast, Werner's optimal cloning map for general pure states is optimal both in the worst case and in the average case [Wer98]. We conjecture that our worst-case lower bounds for cloning similarly extend to the average case.

Answering these open questions will help develop and understand quantum cloning, a fundamental feature of quantum information tailored to practically relevant quantum states, through the lens of modern quantum learning theory.

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