Redefining the Quantum Supremacy Baseline With a New Generation Sunway Supercomputer

Xin Liu,1 Chu Guo,2,∗ Yong Liu,1,1 Yuling Yang,1 Jiawei Song,1 Jie Gao,1 Zhen Wang,1 Wenzhao Wu,1 Dajia Peng,3 Pengpeng Zhao,1 Fang Li,1,† He-Liang Huang,2,4 Haohuan Fu,3,5 and Dexun Chen1

1National Supercomputing Center in Wuxi, Wuxi, Jiangsu, China
2Henan Key Laboratory of Quantum Information and Cryptography, Zhengzhou, Henan 450000, China
3Department of Earth System Science, Ministry of Education Key Laboratory for Earth System Modeling, Institute for Global Change Studies, Tsinghua University, Beijing 100084, China
4Shanghai Branch, CAS Centre for Excellence and Synergetic Innovation Centre in Quantum Information and Quantum Physics, University of Science and Technology of China, Hefei, Anhui 230026, China

(Dated: November 23, 2021)

A major milestone in the era of noisy intermediate scale quantum computers is quantum supremacy [Nature 574, 505 (2019)] claimed on the Sycamore quantum processor of 53 qubits, which can perform a random circuit sampling task within 200 seconds while the same task is estimated to require a runtime of 10,000 years on Summit. This record has been renewed with two recent experiments on the Zuchongzhi 2.0 (56 qubits) and Zuchongzhi 2.1 (60 qubits) quantum processors. On the other front of quantum supremacy comparison, there has also been continuous improvements on both the classical simulation algorithm as well as the underlying hardware. And a fair justification of the computational advantages for those quantum supremacy experiments would require to practically simulate the same problems on current top supercomputers, which is still in lack. Here we report the full-scale simulations of these problems on new generation Sunway supercomputer, based on a customized tensor network contraction algorithm. Our benchmark shows that the most challenging sampling task performed on Sycamore can be accomplished within 1 week, thus collapsing the quantum supremacy claim of Sycamore. Additionally, we show that the XEB fidelities of the quantum supremacy circuits with up to 14 cycles can be verified in minutes, which also provides strong consistency check for quantum supremacy experiments. Our results redefine quantum supremacy baseline using the new generation Sunway supercomputer.

INTRODUCTION

Ever since initially proposed in 1982 [1], quantum computers have long held the belief to be able to efficiently solve certain computational problems that are intractable for classical computers. After 40 years of theoretical and experimental developments [2–9], it has now come to the era of noisy intermediate scale quantum computers. A major experimental milestone achieved along this way is the quantum supremacy experiment conducted with the 53-qubit superconducting quantum processor, entitled as Sycamore, by Google in 2019 [11], which demonstrates that for the specific task of sampling from a random quantum circuit, Sycamore can be 109 times faster than the best classical supercomputer Summit. Recently this record has been renewed with the 56-qubit and 60-qubit quantum processors entitled as Zuchongzhi 2.0 and Zuchongzhi 2.1 respectively [12, 13]. The rapid evolution of quantum processors also enables quantum algorithms on a larger scale [14–19].

Quantum supremacy is a competition between the best quantum and classical computers and it is a continuous instead of a single-shot effort. Pushing this competition to its extreme would be beneficial for both fields. In fact, both the classical simulation algorithms as well as the classical computing hardware have been upgrading rapidly along with the development of quantum computers. On the classical simulation algorithm side, a work from Alibaba in 2020 proposes a slicing and subtree reconfiguration scheme to search for near optimal tensor contract orders under a fixed memory bound [20]. When used in combination with tensor network contraction (TNC) algorithm, they estimate that the most difficult sampling task on Sycamore, namely sampling from a random quantum circuit of 20 cycles (referred as Sycamore-20 afterwards), would only cost 19 days on Summit [20]. Instead of simulating exactly the same sampling task as performed on Sycamore, Ref. [21] shows that 2 million correlated exact amplitudes for Sycamore-20 can be computed with a 60-GPU cluster in 5 days, based on a customized big-head TNC algorithm. A similar strategy is also adapted and implemented on the new Sunway supercomputer with the runtime shortened to 304 seconds [22]. On the classical computing hardware side, highly efficient accelerators such as GPU and TPU have been upgrading rapidly and exascale computing systems are emerging. As an example, the new-generation NVIDIA A100 GPU has a 19.5-TFLOPS single-precision performance and a 312-TFLOPS half-precision performance.

At the time of writing, a full-scale simulation of the most difficult sampling tasks performed on those quantum processors, which integrates both novelties on the classical side, namely a state of the art TNC algorithm and a top supercomputer in the world, has not been reported. In this work, we report a highly efficient and full-scale implementation of a customized TNC algorithm on the new generation Sunway supercomputer. We demonstrate that the runtime to generate a perfect sample for Sycamore-20 is 440 seconds with single-precision arithmetic and 276 seconds with mixed-precision arithmetic. As a result, the most difficult sampling task performed on Sycamore, namely sampling 1 million bitstrings with 0.2% fidelity can be accomplished in 1 week, collapsing quantum supremacy claimed for Sycamore. Our results thus provide the quantum supremacy baseline for future bench-
mark.
Additionally, we verify three quantum supremacy circuits (defined as random quantum circuits with 12 cycles or above), namely Sycamore-12, Sycamore-14 and Zuchongzhi 2.0-12, by computing the exact amplitudes for 1 million experimentally generated bitstrings and then computing the cross benchmarking (XEB) fidelities for those circuits. The obtained values for XEB fidelities are slightly lower, but within errorbar, than those values estimated from the simplified variants used in the quantum supremacy experiments. Our result makes possible the real-time verification of large-scale quantum supremacy circuits which could become an indispensable tool for future development of quantum processors.

EFFICIENT IMPLEMENTATION OF A CUSTOMIZED TNC ALGORITHM

Mathematically, an $n$-qubit quantum state is represented as a rank-$n$ tensor, with $2^n$ entries of complex numbers, while single-qubit and two-qubit quantum gate operations can be represented as rank-2 and rank-4 tensors respectively. Applying a gate operation amounts to contracting the common tensor indices between the gate operation and the quantum state. This is the so-called Schrödinger algorithm with a time complexity $O(m2^n)$ and space complexity $O(2^n)$ for a quantum circuit with $m$ gate operations. For Sycamore-20, we have $n = 53$ and $m \approx 400$ (single-qubit gate is neglected since they can be absorbed into two-qubit gates) and thus the time complexity is $O(10^{18})$. Ideally, this could be accomplished within seconds on an exascale supercomputer! The real limitation is the memory cost to store the quantum state, which is about 68 petabytes if stored as single-precision complex numbers and is at least one order of magnitude larger than the memory size of state of the art supercomputers. The implementation of the Schrödinger algorithm up to now is thus limited within 45 qubits [23–26].

To simulate the Sycamore quantum processor or beyond, an algorithm to trade time for space has to be used. Here we note the work from IBM researchers that leverages secondary storage to overcome the memory issue, which however is a more of a theoretical proposal instead of actual implementation [27]. During the past two years the method of choice to simulate the Sycamore-like quantum processor has gradually converged to a specific type of TNC algorithm [20, 21, 28], which treats the gate operations, the initial quantum state as well as the target computational basis (which are both made of separable rank-1 tensors) as a whole tensor network. Contracting this tensor network results in the exact amplitude for this basis. Such tensor network contraction is in general an NP-hard problem, whose performance greatly relies on a properly devised tensor contraction order. TNC is often used in conjunction with a tensor index slicing scheme, which slices a number of tensor indices such that the original tensor network is equivalent to the summation of a bunch of smaller tensor networks. This technique is important in practice since the largest intermediate tensor during the contraction of the original tensor network could easily exceed the available amount of memory for large problems. As a result, the complexity of the original tensor network is that of each sliced tensor network times the total number of slices. Researchers from Alibaba propose an intertwined tensor slicing and subtree reconfiguration scheme to optimize the slicing and the tensor contraction order for the sliced tensor network altogether [20], whose strategy is also adopted in latest version of the package cotengra [29]. Currently, the tensor contraction order found for Sycamore-20 using different strategies are more or less of the same order of $10^{18}$ [20, 21, 29] and in this work we use cotengra to produce a near-optimal tensor contraction order for later computation.

Given a specific tensor contraction order, the performance of TNC then depends mostly on the performance of pair-wise tensor contraction. The new generation Sunway supercomputer is powered by the homegrown SW26010P CPU, each with a total of 96 GB memory and is further divided into 6 core groups, each with 64 cores. The single-precision and half-precision performances are 14 TFLOPS and 53 TFLOPS respectively, and the memory bandwidth is 307 GB/s. Unfortunately, we find in practice that the resulting TNC produced by cotengra (also similar for other approaches) is dominated by highly skewed tensor contractions, namely contraction between a very high-rank tensor and a very low-rank tensor, for which the floating point arithmetic complexity is essentially of the same order as the memory access complexity (both proportional to the size of the larger tensor). As a result the ultimate performance of the tensor contraction is limited by the memory bandwidth. Nevertheless, to make the most utilization of our CPU architecture, we propose a fused tensor permutation and multiplication algorithm to push the efficiency of skewed tensor contraction to its extreme.

Our full-scale implementation starts with a two-level parallelization scheme which demonstrates to be most efficient for Sycamore-20: the inner level consists of 6 core groups (a single CPU) which takes a single sliced tensor network as input and distributes each tensor contraction onto the 384 cores; the outer level distributes all the slices into different CPUs. The tensor index slicing is done with a maximally allowed intermediate tensor size of $2^{31}$ for single precision, which results in $2^{22}$ slices, and $2^{30}$ for mixed precision, which results in $2^{25}$ slices. For the highly skewed pair-wise tensor contraction performed inside each CPU between a high-rank tensor $A$ and a low-rank tensor $B$, we first store a copy of $B$ in the local data memory (LDM) of each CPU core (256 KB), and then we fetch the slices of $A$ into LDMs of cores and perform a local matrix multiplication in parallel. The central design principle is that $A$ and $B$ are only loaded into the LDMs once. The parallelization scheme as well as the major steps of the tensor network contraction algorithm are also shown in Fig. 1(b) (see Supplementary for more details).

In practice we find that for typical tensor networks generated for the quantum supremacy circuits, our implementation can reach a 0.63 TFLOPS single-precision efficiency for each
FIG. 1. (a) A rendered photo of the new generation Sunway supercomputer. (b) Demonstration of the two-level parallelization scheme. The tensor network on the left-most side is first sliced into many smaller tensor networks, each of which is distributed onto a single CPU. Then for each smaller tensor network the pair-wise tensor contractions are done with our fused tensor permutation and multiplication algorithm, which is further parallelized on the 384 cores of a single CPU.

CPU (which surpasses the memory bandwidth by a factor of 2 due to the existences of a few computational intensive tensor contractions). Compared to the commonly used package jax [30], there is an average speedup of more than 25x and a maximum speedup of more than 100x. The near optimal software implementation together with the unprecedented parallelization scale over 41,932,800 cores allow us to tackle those quantum supremacy circuits which are believed to be extremely difficult or impossible to simulate previously.

To this end we note that the TNC algorithm used here is in sharp comparison with the ones used in Ref. [31–34], where the tensors in the time direction are pre-contracted, resulting in a two-dimensional tensor network with the same geometry as the quantum processor. In the latter case it has been shown that the FLOPS efficiency could easily exceed 60% [22]. However for Sycamore-20, each tensor in the resulting two-dimensional tensor network is too large to be stored on a single CPU, making it impractical for quantum supremacy circuits with more than 14 cycles [11].

ESTABLISHING QUANTUM SUPREMACY BASELINE

The classical runtime of the quantum supremacy circuits are estimated by evaluating the runtime for generating one perfect sample (except in the case of Zuchongzhi 2.1 where sampling a single bitstring classically already becomes demanding). This is done by computing a batch of 64 amplitudes in a single run by leaving 6 qubits open and then per-

FIG. 2. Total runtime (green dashed line with circle) to simulate the same sampling task (producing 1 million bitstrings with the same XEB fidelity as the quantum processor) for quantum supremacy circuits on (a) Sycamore (b) Zuchongzhi 2.0 and (c) Zuchongzhi 2.1, based on extrapolation from the runtime to generate a single perfect sample. The x-axis $d$ denotes the number of cycles. For Sycamore and Zuchongzhi 2.0, we directly generate one perfect sample. While for Zuchongzhi 2.1, we estimate the time to generate a perfect sample from the runtime to compute a single slice using a single CPU. The blue rectangle marks the total runtime for Ref. [21] on 60 GPUs while the light blue rectangle marks the estimated total runtime for Alibaba [20] on Summit.
form frugal sampling, which could guarantee to produce one sample with probability close to 1 [20, 32]. Here we note that for TNC algorithm there is a very economic way to compute a correlated bunch of amplitudes in a single run by reusing the contraction outcome of a major portion of the tensor network, and iterate over the rest small portion. In this way, the overhead of computing a small bunch of correlated amplitudes is negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude. Moreover, it has been shown that to match the sampling outcomes negligible compared to computing a single amplitude.
after Sycamore, seem to indicate that classical computational capacity for simulating random quantum circuits is growing in pace with the quantum counterparts. This is partially due to that the new Zuchongzhi series quantum processors grow more in terms of the number of qubits but less of the gate operation fidelities [36], and that the classical simulation algorithm, especially TNC based algorithms and classical accelerators are also progressing rapidly.

Our results herald a renewed starting of the quantum-classical competition in terms of simulating quantum supremacy experiments in exascale systems. There is still plenty of space for optimization on the classical side. In the first place, the memory bandwidth and the half-precision performance are apparently bottlenecks for our simulations, which are only 20% and 17% of that of NVIDIA A100 GPU. Since our current approach is essentially bounded by the memory bandwidth, we expect an immediate 5x performance increase using other CPU architectures with higher memory bandwidths. A more intelligently devised tensor contraction order could certainly help, especially if the balance between computation and memory could be better taken into account. Additionally, it is recently shown that to compute a large number of uncorrelated amplitudes it is still possible to reuse a large number of intermediate tensors and easily gain a 20x performance increase [37]. We thus believe that in near term the time to classically simulate Sycamore-20 would be reduced by 2 orders of magnitude (about 1.5 hours).

This work is partially supported by National Key R&D Program of China (2017YFA0604500), and National Natural Science Foundation of China (U1839206). C. G acknowledges support from National Natural Science Foundation of China under Grants No. 11805279, No. 61833010, No. 12074117 and No. 12061131011. H.-L.H. acknowledges support from the Youth Talent Lifting Project (Grant No. 2020-JCJQ-QT-030), National Natural Science Foundation of China (Grant No. 11905294), China Postdoctoral Science Foundation, and the Open Research Fund from State Key Laboratory of High Performance Computing of China (Grant No. 201901-01).

* guochu604b@gmail.com  
† alexander_liu_99@163.com  
‡ 38349735@qq.com  
§ haohuan@tsinghua.edu.cn

[1] R. P. Feynman, International journal of theoretical physics 21, 467 (1982).
[2] P. W. Shor, in Proceedings 35th annual symposium on foundations of computer science (ieee, 1994) pp. 124–134.
[3] P. Krantz, M. Kjaergaard, F. Yan, T. P. Orlando, S. Gustavsson, and W. D. Oliver, Applied Physics Reviews 6, 021318 (2019).
[4] H.-L. Huang, D. Wu, D. Fan, and X. Zhu, Science China Information Sciences 63, 180501 (2020).
[5] S. Slussarenko and G. J. Pryde, Applied Physics Reviews 6, 041303 (2019).
[6] R. Blatt and C. F. Roos, Nature Physics 8, 277 (2012).
[7] C. D. Bruzewicz, J. Chiaverini, R. McConnell, and J. M. Sage, Applied Physics Reviews 6, 021314 (2019).
[8] J. Biamonte, P. Wittek, N. Pancotti, P. Rebentrost, N. Wiebe, and S. Lloyd, Nature 549, 195 (2017).
[9] S. McArdle, S. Endo, A. Aspuru-Guzik, S. C. Benjamin, and X. Yuan, Reviews of Modern Physics 92, 015003 (2020).
[10] J. Preskill, Quantum 2, 79 (2018).
[11] F. Arute, K. Arya, R. Babbush, D. Bacon, J. C. Bardin, R. Barends, R. Biswas, S. Boixo, F. G. Brandao, D. A. Buell, et al., Nature 574, 505 (2019).
[12] Y. Wu, W.-S. Bao, S. Cao, F. Chen, M.-C. Chen, X. Chen, T.-H. Chung, H. Deng, Y. Du, D. Fan, et al., Physical Review Letters 127, 180501 (2021).
[13] Q. Zhu, S. Cao, F. Chen, M.-C. Chen, X. Chen, T.-H. Chung, H. Deng, Y. Du, D. Fan, M. Gong, et al., Science Bulletin (2021).
[14] V. Haveliček, A. D. Córdoals, K. Temme, A. W. Harrow, A. Kandala, J. M. Chow, and J. M. Gambetta, Nature 567, 209 (2019).
[15] G. A. Quantum et al., Science (New York, NY) 369, 1084 (2020).
[16] S. McArdle, S. Endo, A. Aspuru-Guzik, S. C. Benjamin, and X. Yuan, Reviews of Modern Physics 92, 015003 (2020).
[17] M. P. Harrigan, K. J. Sung, M. Neeley, K. J. Satzinger, F. Arute, K. Arya, J. Atalaya, J. C. Bardin, R. Barends, S. Boixo, et al., Nature Physics 17, 332 (2021).
V. Saggio, B. E. Asenbeck, A. Hamann, T. Strömbärg, P. Schiansky, V. Dunjko, N. Friis, N. C. Harris, M. Hochberg, D. Engefeld, et al., Nature 591, 229 (2021).

X. Mi, M. Ippoliti, C. Quintana, A. Greene, Z. Chen, J. Gross, F. Arute, K. Arya, J. Atalaya, R. Babbush, et al., arXiv preprint arXiv:2107.13571 (2021).

C. Huang, F. Zhang, M. Newman, X. Ni, D. Ding, J. Cai, X. Gao, T. Wang, F. Wu, G. Zhang, et al., Nature Computational Science, 1 (2021).

F. Pan and P. Zhang, arXiv preprint arXiv:2103.03074 (2021).

Y. Liu, X. Liu, F. Li, H. Fu, Y. Yang, J. Song, P. Zhao, Z. Wang, D. Peng, H. Chen, et al., in Proceedings of the International Conference for High Performance Computing, Networking, Storage and Analysis (2021) pp. 1–12.

K. De Raedt, K. Michielsen, H. De Raedt, B. Trieu, G. Arnold, M. Richter, T. Lippert, H. Watanabe, and N. Ito, Computer Physics Communications 176, 121 (2007).

M. Smelyanskiy, N. P. Sawaya, and A. Aspuru-Guzik, arXiv:1601.07195 (2016).

T. Hänner and D. S. Steiger, in Proceedings of the International Conference for High Performance Computing, Networking, Storage and Analysis (2017) pp. 1–10.

E. Pednault, J. A. Gunnels, G. Nannicini, L. Horesh, T. Magerlein, E. Solomonik, and R. Wisnieff, arXiv:1710.05867 (2017).

E. Pednault, J. A. Gunnels, G. Nannicini, L. Horesh, and R. Wisnieff, arXiv preprint arXiv:1910.09534 (2019).

I. L. Markov and Y. Shi, SIAM Journal on Computing 38, 963 (2008).

J. Gray and S. Kouris, Quantum 5, 410 (2021).

J. Bradbury, R. Frostig, P. Hawkins, M. J. Johnson, C. Leary, D. Maclaurin, G. Necula, A. Paszke, J. VanderPlas, S. Wanderman-Milne, and Q. Zhang, “JAX: composable transformations of Python+NumPy programs,” (2018).

C. Guo, Y. Liu, M. Xiong, S. Xue, X. Fu, A. Huang, X. Qiang, P. Xu, J. Liu, S. Zheng, et al., Physical Review Letters 123, 190501 (2019).

B. Villalonga, S. Boixo, B. Nelson, C. Henze, E. Rieffel, R. Biswas, and S. Mandrà, npj Quantum Information 5, 1 (2019).

B. Villalonga, D. Lyakh, S. Boixo, H. Neven, T. S. Humble, R. Biswas, E. G. Rieffel, A. Ho, and S. Mandrà, Quantum Science and Technology 5, 034003 (2020).

C. Guo, Y. Zhao, and H.-L. Huang, Physical Review Letters 126, 070502 (2021).

I. L. Markov, A. Fatima, S. V. Isakov, and S. Boixo, arXiv:1807.10749 (2018).

A. Zlokapa, S. Boixo, and D. Lidar, arXiv preprint arXiv:2005.02464 (2020).

G. Kalachev, P. Panteleev, and M.-H. Yung, arXiv preprint arXiv:2108.05665 (2021).