
Accelerating Parallel Diffusion Model Serving with Residual Compression

Jiajun Luo*

Shenzhen International Graduate
School Tsinghua University
luo-jj24@mails.tsinghua.edu.cn

Yicheng Xiao*

Southern University of
Science and Technology
xiaoyc2022@mail.sustech.edu.cn

Jianru Xu

Southern University of
Science and Technology
12211830@mail.sustech.edu.cn

Yangxiu You

Jiangnan University
joesephyou@tencent.com

Rongwei Lu

Shenzhen International Graduate School
Tsinghua University
lurw24@mails.tsinghua.edu.cn

Chen Tang

The Chinese University of Hong Kong
chentang@link.cuhk.edu.hk

Jingyan Jiang

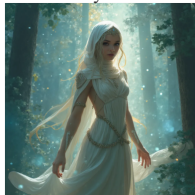
Shenzhen Technology University
jiangjingyan@sztu.edu.cn

Zhi Wang[†]

Shenzhen International Graduate School
Tsinghua University
wangzhi@sz.tsinghua.edu.cn

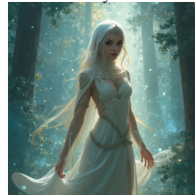
Original
Single-device

Latency: 23.16s



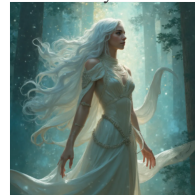
CompactFusion
Compression-based
fresh activations

FID = 3.263
Latency: 7.57s



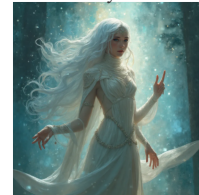
PipeFusion
Overlap-based
stale activations

FID = 6.722
Latency: 9.49s



DistriFusion
Overlap-based
stale activations

FID = 9.911
Latency: 8.05s



Prompt: *Ethereal fantasy concept art of an elf, magnificent, celestial, ethereal, painterly, epic, majestic, magical, fantasy art, cover art, dreamy.*



Prompt: *Romantic painting of a ship sailing in a stormy sea, with dramatic lighting and powerful waves.*

Figure 1: **CompactFusion** is a compression framework for parallel diffusion serving acceleration. Leveraging the intrinsic redundancy in diffusion models, CompactFusion transmits compressed step-wise residuals instead of full activation to significantly reduce communication volume and preserve fidelity, while prior works rely on stale activations for computation-communication overlap, leading to noticeable degradation. Setting: $4 \times L20$, FLUX-1.dev, 28-step, 1024×1024 resolution, 1-step warmup for all algorithms.

*Equal contribution.

[†]Corresponding author.

Abstract

Diffusion models produce realistic images and videos but require substantial computational resources, necessitating multi-accelerator parallelism for real-time deployment. However, parallel inference introduces significant communication overhead from exchanging large activations between devices, limiting efficiency and scalability. We present **CompactFusion**, a compression framework that significantly reduces communication while preserving generation quality. Our key observation is that diffusion activations exhibit strong temporal redundancy—adjacent steps produce highly similar activations, saturating bandwidth with near-duplicate data carrying little new information. To address this inefficiency, we seek a more compact representation that encodes only the essential information. CompactFusion achieves this via **Residual Compression** that transmits only compressed residuals (step-wise activation differences). Based on empirical analysis and theoretical justification, we show that it effectively removes redundant data, enabling substantial data reduction while maintaining high fidelity. We also integrate lightweight error feedback to prevent error accumulation. CompactFusion establishes a new paradigm for parallel diffusion inference, delivering lower latency and significantly higher generation quality than prior methods. On $4\times L20$, it achieves $3.0\times$ speedup while greatly improving fidelity. It also uniquely supports communication-heavy strategies like sequence parallelism on slow networks, achieving $6.7\times$ speedup over prior overlap-based method. CompactFusion applies broadly across diffusion models and parallel settings, and integrates easily without requiring pipeline rework. Portable implementation demonstrated on xDiT is publicly available at <https://github.com/Cobalt-27/CompactFusion>.

1 Introduction

Diffusion models are scaling rapidly both in size and in computation, outpacing the capacity of single accelerators. The model sizes have grown from 983M parameters in Stable Diffusion 1.5 [1] to more than 12B in FLUX.1 [2]. Meanwhile, diffusion models are significantly more computationally intensive than LLMs, with compute increasing faster than the model size [3]. As computational demand rises, single-GPU inference can no longer meet latency constraints, making multi-accelerator parallelism essential for practical deployment.

However, parallel paradigms introduce a new challenge: the increasing prominence of communication bottlenecks, stemming from the fact that interconnect bandwidth has not kept pace with the growth of the compute. From A100 to H100, FP16 FLOPS increases over $6\times$ ($312T \rightarrow 1,979T$), while NVLink bandwidth grows only $1.5\times$ and PCIe bandwidth simply doubles [4, 5]. In FLUX.1, standard patch parallelism transmits around 60 GB of activations per image per GPU, consuming over 45% inference time across $4\times L20$ with PCIe interconnects. As bandwidth lags behind, communication increasingly dominates inference cost, underscoring the need to reduce transmission overhead.

Previous works exploited the **Temporal Redundancy** [6] inherent in diffusion models, where adjacent inference steps produce highly similar activations, to mitigate the communication bottleneck and accelerate parallel inference. Methods like DistriFusion [7] and PipeFusion [8] adopt **Displaced Parallelism**, which reuses stale activations from previous steps to overlap communication with computation. Although this reduces visible latency, it introduces three fundamental limitations. **(1)** Displaced parallelism replaces current activations with outdated ones, leading to noticeable quality degradation. **(2)** Moreover, the core data volume remains unreduced, meaning communication-intensive strategies like sequence parallel [9] still transmit large activations. Consequently, their performance gains are fragile and collapse when the overlap window insufficiently masks communication costs. **(3)** It requires nontrivial rework of the model pipeline [10], which makes integration complex and limits generality across architectures.

We rethink how temporal redundancy should be exploited, and propose **Residual Compression** as a more fundamental solution. Instead of merely overlapping the transfer of redundant activations, we ask: **why transmit redundant data at all?** Diffusion activations change slowly over time with adjacent steps producing highly similar value; yet prior methods still transmit full activations, saturating interconnects with near-duplicate data carrying little new information. Our key observation

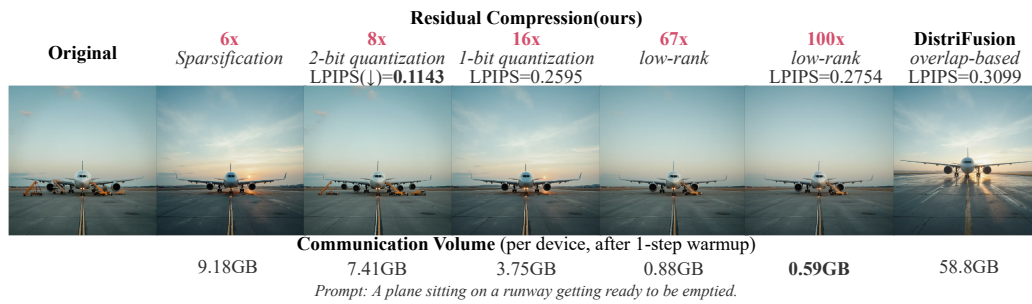


Figure 2: We introduce **Residual Compression** as a new paradigm for efficient parallel diffusion. It generalizes across compressors and sustains high quality even under $100.05\times$ compression. Setups: 4 devices, 1-step warmup.

is that removing redundant data should drastically reduce communication volume and resolve the communication bottleneck, while maintaining the quality. Thus, we seek a more compact representation that encodes only the essential change. Residual Compression achieves this by transmitting only compressed activation residuals (differences between time-steps), combined with a lightweight error feedback mechanism. Based on empirical analysis and theoretical justification, we show that it effectively removes redundant data, enabling substantial data reduction while maintaining high fidelity. We redefine how redundancy is addressed in parallel diffusion—not by hiding its transmission with overlap tricks, but by eliminating it at the source.

Residual compression surpasses previous overlap-based methods for following superiority:

- **Avoiding stale activations leads to higher quality.** Residual Compression works with current data, avoiding the quality degradation inherent in using stale activations in prior methods, yielding significantly higher fidelity. Under aggressive 2-bit quantization, residual compression achieves excellent quality, substantially outperforming state-of-the-art DistriFusion and PipeFusion in identical setups (Figure 1). Remarkably, even at extreme compression ratios of over $100\times$ (transmitting $< 1\%$ of the original data), our method maintains better quality than DistriFusion (Figure 2 and section 4.2).
- **A significant drop in data volume yields much lower latency.** Residual Compression significantly reduces data exchange, delivering superior end-to-end performance across diverse hardware configurations. It achieved $3\times$ speedup on $4\times H20$ (NVLink) and $4\times L20$ (PCIe) clusters (Figure 1), surpassing prior methods. Furthermore, it makes communication-intensive parallel strategies practical even in low-bandwidth environments, achieving $6.7\times$ speedup over DistriFusion on Ethernet-level bandwidth.
- **Residual compression is structurally decoupled from the parallel pipeline, enabling broad compatibility and easy adoption.** It operates entirely at the communication layer, without modifying model logic or parallel execution flow. The design generalizes across compression methods (Figure 2) and parallel strategies, and has been applied on large-scale image and video models such as FLUX.1 and CogVideoX, and integrated into frameworks including xDiT and distrifuser, with fewer than 20 lines of core code changed. In contrast, prior methods are tightly coupled with specific strategies and require substantial rework. By focusing exclusively on the transmission aspect, residual compression maintains a lightweight profile and exhibits deployment readiness.

CompactFusion implements residual compression as a portable system, supporting compression techniques including quantization [11], low-rank, and sparsity (as shown in Figure 2), with tunable ratios from $2\times$ to over $100\times$ while preserving high fidelity. It works with parallel strategies such as Patch Parallel and Ring Attention, and integrates into existing frameworks (xDiT, distrifuser) with minimal modification. We believe CompactFusion represents a promising paradigm shift in parallel diffusion acceleration.

2 Preliminaries on Parallelism

Parallelism is the art of distributing tasks across multiple devices, enabling accelerators to work collaboratively for improved latency and throughput. This distribution can occur across various

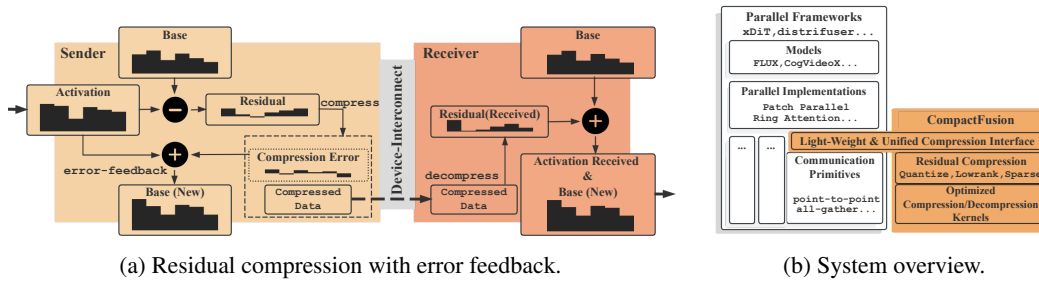


Figure 3: (a) CompactFusion prevents long-term error accumulation by adding feedback into residual compression. (b) By wrapping a few standard communication primitives with a unified compression interface, CompactFusion requires minimal change to the existing frameworks and can easily be integrated to new model structure.

dimensions: input token(patch) sequence(Sequence Parallel [9]), model layers (Pipeline Parallel [12]), intra-layer computation (Tensor/Expert Parallel [13, 14]), or data samples (Data Parallel [15]). Notably, many parallel strategies necessitate intensive inter-device communication [7] due to the partitioning of weights, activations, or inputs among devices, requiring data exchange for complete computation.

This work focuses on **Sequence Parallel** [9, 16, 17], which partitions the input sequence across devices and is used in recent works on parallel diffusion [7, 8] as well as in high-performance diffusion inference frameworks [10, 18]. It is by far the **most widely adopted parallel strategy** for diffusion models, as it is highly latency-friendly and well suited for real-time generation. A more detailed description of these strategies is provided in Appendix B.

To reduce perceived latency, prior works overlaps communication with computation by reusing stale activations [7, 8, 19], but suffers from quality degradation, complex pipeline rework, and unchanged (potentially large) communication volume, limiting its effectiveness.

3 Method

CompactFusion mitigates the communication bottleneck in parallel diffusion by leveraging residual compression (Sections 3.1 to 3.3) and practical system co-design (Section 3.4), achieving significant data reduction with minimal quality degradation.

3.1 Exploiting Temporal Redundancy via Residual Compression

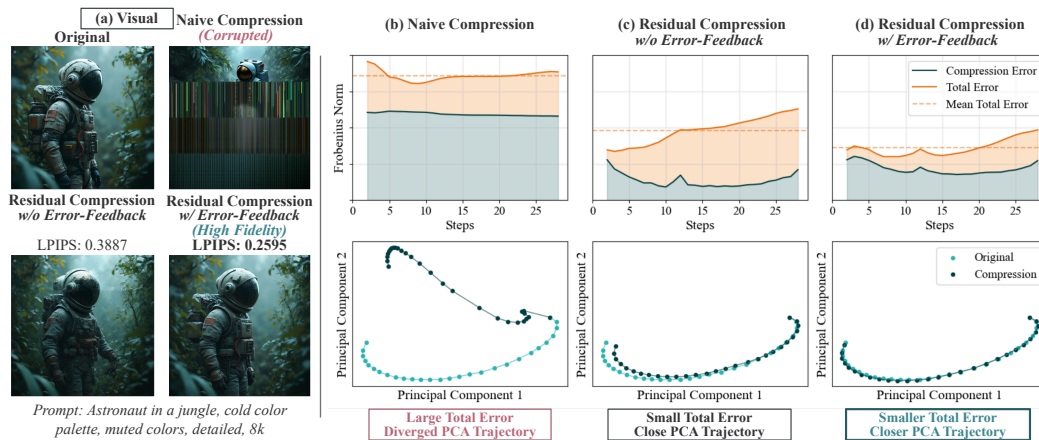


Figure 4: Comparison of strategies under 1-bit quantization: original (no compression), naive compression, residual compression with/without error feedback. Left: Visual Results, right: Error Analysis and PCA Trajectories (closer better) of activations over steps. We report two metrics: *Compression Error* (difference between input and output of compression) and *Total Error* (cumulative deviation from the uncompressed ground truth, lower is better). Setups: 4 devices, 1-step warmup.

Transmitting compressed residuals effectively eliminates redundancy from the data, lowering the communication volume while preserving fidelity. This efficiency stems from a key insight: diffusion models exhibit high temporal redundancy, with activations changing only minimally between steps. As a result, transmitting full activations often involves sending largely redundant information. By encoding only the meaningful differences, we can greatly reduce the volume of transmitted data. However, naively compressing high-dimensional activations still introduces substantial errors, often resulting in severe quality degradation or visual collapse (as shown in Figure 4(a)). Effectively leveraging temporal redundancy, therefore, requires more than simply reducing the amount of data—it demands meticulous design.

Our optimization builds on two observations. First, activations change gradually across steps, their step-wise residuals (differences from the previous result) having much smaller magnitude (as shown in Figure 5, residual norm is only a fraction of full activation norm). Second, compressing a smaller-magnitude signal typically induces proportionally less error. This makes the residual a more efficient compression target as it captures the essential change. We therefore propose residual compression: instead of transmitting the full activation, we transmit its compressed difference from the previous reconstruction and recover the current state by adding it back.

To verify this principle, we apply aggressive 1-bit binarization (detailed in Appendix D) to both naive (compressing full activation, Figure 4(b)) and residual compression (Figure 4(c)) over Ring Attention. Naive compression fails completely: the output is corrupted, with large errors. In contrast, residual compression yields clean reconstructions with much smaller error at each step, and the activation trajectory remains close to the uncompressed baseline throughout.

While the idea of transmitting differences exists in other contexts [20, 21], to the best of our knowledge, CompactFusion is the first to demonstrate its effectiveness on parallel inference, and also the first on diffusion models, enabling aggressive data reduction while preserving generation quality.

Limitation: Despite low per-step error, residual compression accumulates error over time. As shown in Figure 4(c), the total error grows over steps without correction, which requires a mechanism to prevent the accumulation of long-term error.

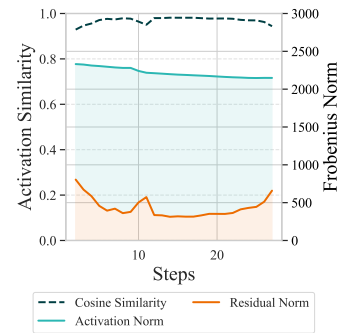


Figure 5: Adjacent-Step Activation Similarity and Activation/Residual Norm, on Flux.

3.2 Compensating Error Accumulation with Feedback

Residual compression significantly reduces per-step compression error by targeting smaller-magnitude signals. However, these small errors still accumulate over diffusion steps (curve for Total Error, Figure 4(c)). To eliminate long-term drift and preserve fidelity, CompactFusion integrates *Error Feedback*, a technique used in gradient compression [22, 23]. Rather than discarding the residual compression error at each step, we store it locally and add it to the next-step residual before compression, recirculating untransmitted information and systematically compensating for loss (illustrated in Figure 3a). This stabilizes reconstruction and prevents the compressed state from diverging from the original trajectory. Details are in Appendix H.

Problem Formulation. To understand how compression affects inference quality, we model diffusion as a sequence of transformations $a_t = f_t(a_{t-1})$, where a_t denotes the intermediate activation in a fixed layer and f_t captures the combined effect of one forward pass and scheduler update. Following relevant works [24, 25], we define a δ -compressor C_δ with $\delta \in (0, 1]$, satisfying $\mathbb{E} [\|C_\delta(z) - z\|^2] \leq (1 - \delta) \mathbb{E} [\|z\|^2]$ for $\delta \in (0, 1]$.

Assumptions. Our analysis relies on realistic assumptions grounded in empirical observations of diffusion behavior. First, the model exhibits strong local stability—captured by L -smoothness of each transformation f_t , i.e., $\|f_t(x) - f_t(y)\|^2 \leq L^2 \|x - y\|^2$, with $L < 1$. Second, activations evolve gradually over time due to temporal redundancy: the expected per-step change is much smaller in scale than the activations themselves, i.e., $\sigma_\Delta^2 \ll \sigma_a^2$. We also assume uncorrelated error terms where appropriate. The definitions and assumptions are elaborated in Appendix H.2 and Appendix H.3;

these properties are well-supported in practice—activation norms remain bounded, and residual magnitude is significantly smaller than that of activations (Figure 5).

Proposition 3.1 (Steady-State Error Bound). *Let v^{naive} and $v^{residual}$ denote the steady-state mean squared error upper bounds under naive compression and residual compression with error feedback, respectively. Then under the given assumptions, their ratio satisfies the bound*

$$\frac{v^{residual}}{v^{naive}} = \frac{\sigma_{\Delta}^2}{\sigma_a^2} \cdot \frac{1 - L^2}{1 - L^2 - (1 - \delta)(L^2 + 1)}.$$

See Appendix H for the proof. This ratio confirms that residual compression with feedback yields a significantly lower steady-state error, often by an order of magnitude or more. The result holds under a mild stability condition: $\delta > 1 - \frac{1-L^2}{L^2+1}$ which imposes a lower bound on the required compression quality. In contrast, Residual compression *without* error feedback fails to converge; its error grows linearly with time steps and does not admit a steady state bound.

Validation. We validate this theory empirically using 1-bit binarization. As shown in Figure 4(d), CompactFusion with error feedback maintains low cumulative deviation throughout the inference process, closely follows the original trajectory, and generates high-quality images.

Advantages. Residual compression with error feedback enables robust and accurate compression under aggressive settings, maintaining fidelity even with 1-bit quantization (16× compression).

3.3 Scaling Residual Compression to Extreme Ratios

We aim to push the boundary of residual compression, targeting over 100× compression ratio while preserving quality beyond state-of-the-art methods.

At extreme compression ratios, low-rank approximation is the only viable option. Quantization saturates at 1-bit (16×), and sparsification collapses under diffusion—at 100× sparsity, most values are never updated over typical 20–30 steps. In contrast, low-rank approximation provides a promising alternative: it retains full coverage of the coordinates while drastically reducing communication volume. Each activation or residual tensor $X \in \mathbb{R}^{n \times m}$ is approximated as $X \approx UV^T$, where $U \in \mathbb{R}^{n \times r}$ and $V \in \mathbb{R}^{m \times r}$, with $r \ll \min(n, m)$.

To make this feasible under real-time constraints, we adopt subspace iteration [26] (detailed in Appendix D), a faster alternative to SVD. While SVD offers optimality, it is approximately 60 times slower than the subspace iteration solution, far exceeding the ~5ms communication window and ~1ms compression budget in practice. In contrast, we adapt the subspace iteration from gradient compression [27], producing a usable approximation in milliseconds.

We improve low-rank compression by achieving a better tradeoff between precision and directional coverage. We observe that diffusion residuals are frequently high-rank, indicating that the activation changes span many directions across steps. However, each transmission is constrained to a low-rank subspace. We identify this high-rank/low-rank mismatch as a key bottleneck: the model attempts dense updates, but the compressor delivers sparse (in terms of subspace dimension) projections. To resolve this, we propose a strategic tradeoff—sacrificing accuracy (closeness to the optimal approximation) to expand rank coverage (number of dimensions covered per step). Concretely, we quantize the low-rank matrices with INT4, allowing higher per-step rank under the same transmission budget. This transforms the compressor into a subspace throughput machine, delivering broader coverage across update directions, even if each is less precise.

We empirically validate this strategy by comparing it with an alternative that improves approximation optimality through more subspace iterations (see Appendix F.1). Despite added quantization error, expanding rank coverage yields significantly better generation quality, confirming that directional breadth matters more than per-step accuracy under tight bandwidth constraints.

Notably, our approach maintains better visual fidelity over DistriFusion even at 100.05× compression on FLUX.1-dev.

3.4 System Co-Design for Efficiency and Usability

CompactFusion is co-designed for real-world deployment—translating algorithmic gains into measurable latency reduction with minimal integration cost.

Optimized Compression Kernels. We develop highly optimized GPU kernels for our compression techniques. Beyond efficient quantization and subspace iteration, we repurpose the concept of N:M sparsity [28] which originally used in weight pruning, and adapt it to activation compression via a N:M block sparsifier. Unlike standard TopK methods that suffer from sorting overhead and irregular memory access, our block sparsifier enables linear-time selection and GPU-friendly memory patterns. It is the only sparsifier design we found to yield practical on-device speedup.

Latency Hiding via Overlap. The framework runs compression kernel concurrently with communication primitives. By carefully integrating into Ring Attention pipeline, it effectively overlap the compression overhead with communication waits, minimizing its impact on latency.

Ease of Integration. CompactFusion benefits from the inherent modularity of Residual Compression, which cleanly separates compression from execution logic (Figure 3b). It wraps standard communication primitives without altering model code or parallel pipeline, and generalizes across strategies, compressors, and frameworks. In contrast, prior methods often entangle with specific parallel strategies and require substantial pipeline rework.

4 Experiments

4.1 Setups

Models. Our method works with off-the-shelf models, we evaluate it on the state-of-the-art FLUX.1-dev [2] for image generation, and on CogVideoX-2b [29] for video generation. We adhere to standard inference settings on xDiT, employing 28 steps for FLUX.1-dev and 50 steps for CogVideoX-2b.

Dataset. We test the image generation model using prompts in COCO Captions 2014 dataset [30] and video generation using prompts sampled from VBench [31].

Hardware. To demonstrate broad applicability, experiments are conducted on various hardware and interconnects: high-bandwidth NVLink (H20 clusters, bandwidth: 366 GB/s), standard PCIe (L20 clusters, bandwidth: 17.13 GB/s) and simulated lower-bandwidth Ethernet (A40 clusters using tc for traffic control), ensuring robustness evaluation under various deployment constraints.

Baselines. We apply CompactFusion to Sequence Parallelism, the most widely adopted strategy in parallel diffusion (Section 2), to reflect real-world deployment scenarios. We compare it with strong baselines from both industry and research, including **Patch Parallel** (all-gather KV) [18], **Ring Attention** (ring-style KV transfer) [9], **DeepSpeed-Ulysses** (all-to-all) [16], and **DistriFusion** (displaced patch parallel) [18]. We also include **PipeFusion** (displaced TeraPipe [32]) [8] as a baseline, though it is orthogonal to our method. We note that PipeFusion is not evaluated on video models as the xDiT does not support PipeFusion for video models (further discussed in Appendix C).

CompactFusion Variants. We showcase three CompactFusion variants over Sequence Parallel with Ring Attention. **Compact-1bit** and **Compact-2bit** apply 1-bit and 2-bit quantization, with 16 $\times$ and 8 $\times$ compression respectively. **Compact-Lowrank** shows the potential for extreme communication reduction, reaching 100.05 $\times$ compression on FLUX via rank-32 approximation and INT4.

Metrics. Following the relevant work, we adopt the standard evaluation metrics for image quality testing: Peak Signal Noise Ratio (PSNR), Learned Perceptual Image Patch Similarity (LPIPS) [33] and Fréchet Inception Distance (FID) [34]. We adopt the following metrics for video quality testing: Structural Similarity Index Measure (SSIM)[35], Peak Signal-to-Noise Ratio (PSNR), and Learned Perceptual Image Patch Similarity (LPIPS)[33]. We also conduct a human evaluation study to assess perceptual consistency from a human perspective (detailed in Appendix E.1).

4.2 Main Results

CompactFusion achieves lower latency while maintaining high visual fidelity. It consistently performs well across different generation models, including FLUX.1-dev for images and CogVideoX for videos. It is also robust across hardware setups—L20, H20, and A40—and across network conditions such as

NVLink, PCIe, and simulated Ethernet. These results are shown in Figure 6. Quantitative metrics across 3, 4, and 6-GPU scales are provided in Tables 1 and 2.

Notably, CompactFusion uniquely enables the widely adopted but communication-intensive sequence parallel over slow networks, achieving up to $6.7\times$ speedup over DistriFusion under Ethernet-level bandwidth conditions (Figure 7).

By directly eliminating redundant data, CompactFusion drastically reduces the transmission volume. In its low-rank variant, it sends less than 1% of the original activation data. Despite this, it still outperforms DistriFusion in generation quality, as shown in Table 1 (image) and Table 2 (video).

SP	DF	PF	1bit	2bit	Lowrank	SP	DF	1bit	2bit	Lowrank
Latency:						Latency:				
10.89s	8.05s	9.49s	7.46s	7.57s	10.60s	52.90s	39.93s	35.50s	35.54s	39.13s
FID ($\downarrow$):-	9.9113	6.7221	7.0819	3.2625	8.6817	LPIPS($\downarrow$): -	0.3624	0.3084	0.2373	0.3391
LPIPS ($\downarrow$):-	0.3099	0.2502	0.2595	0.1143	0.2754					
										
Prompt: A multi-colored parrot holding its foot up to its beak.						Prompt: A detailed wooden toy ship with intricately carved masts...				
										
Prompt: A kid wearing headphones and using a laptop.						Prompt: The camera follows behind a white vintage SUV...				
										
Prompt: A pair of parking meters reflecting expired times.						Prompt: A street artist, clad in a worn-out denim jacket...				
										
Prompt: A double decker bus driving down the street.						Prompt: An elderly gentleman, with a serene expression...				

Figure 6: Qualitative results. FID and LPIPS is computed against the original images. **SP** stands for Sequence Parallel using Ring Attention, **DF** for DistriFusion and **PF** for PipeFusion. **1bit**, **2bit** and **Lowrank** are our methods. We use 1-step warmup for CompactFusion/PipeFusion/DistriFusion.

Table 1: Quantitative evaluation on 4 GPUs. **w/ G.T.** means calculating the metrics with the ground-truth COCO images, while **w/ Orig.** means with the original model’s samples. Latency results on L20 (PCIe) and H20 (NVLink) are reported; speedup is calculated with respect to the single-device latency. Note that COCO-based metrics w/ G.T. may be uninformative. Its variations are small, and even disrupted outputs can score well [36].

Method	PSNR ($\uparrow$)		LPIPS ($\downarrow$)		FID ($\downarrow$)		Latency (s)		Speedup		Human Eval. ($\uparrow$)
	w/ Orig.	w/ G.T.	w/ Orig.	w/ G.T.	w/ Orig.		L20	H20	L20	H20	
Original(Single-device)							23.16	20.26	1.00	1.00	
Ring Attention	—	0.772	—	32.75	—		10.89	7.54	2.12	2.68	—
Patch Parallel							10.90	6.83	2.12	2.97	
DeepSpeed-Ulysses							9.13	6.70	2.54	3.02	
DistriFusion	21.63	0.761	0.310	33.12	9.91	8.05	8.05	2.88	2.52	0.25	
PipeFusion	23.42	0.766	0.250	32.36	6.72	9.49	9.07	2.44	2.23	0.56	
Compact-1bit(Ours)	22.90	0.767	0.260	33.20	7.08	7.46	6.86	3.10	2.95	0.47	
Compact-2bit(Ours)	29.54	0.772	0.114	33.09	3.26	7.57	6.70	3.06	3.02	0.84	
Compact-Lowrank(Ours)	22.85	0.769	0.275	33.07	8.68	10.60	11.99	2.18	1.69	0.38	

4.3 Ablation Studies

We perform targeted ablation studies to evaluate the contributions of core components and design choices in CompactFusion.

Warmup Step. Like displaced parallel, CompactFusion requires at least a 1-step warmup, where the uncompressed activation is used to initialize the base tensor for later residual computation (detailed in Appendix D). Figure 8 compares different methods and warmups. We observe that CompactFusion maintains stable and high visual quality with just a single warmup step, showing

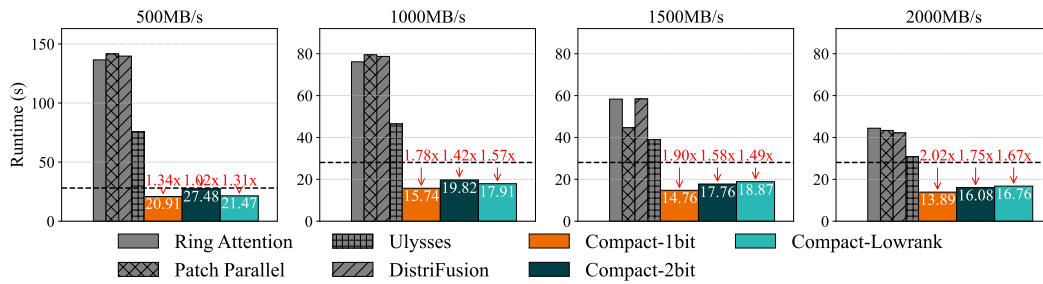


Figure 7: Measured latency of sequence parallel variants on $4 \times$ A40 GPUs under simulated Ethernet bandwidth. Horizontal dashed line indicates single-device latency. Only CompactFusion yields speedups, uniquely enabling efficient sequence parallelism over slow networks.

Table 2: Quantitative video generation evaluation on 3 GPUs and 6 GPUs. All metrics (SSIM, PSNR, LPIPS) are calculated with respect to the original samples. Latency results on L20 (PCIE) are reported; speedup is calculated against single-device latency.

Device	Method	SSIM ($\uparrow$)	PSNR ($\uparrow$)	LPIPS ($\downarrow$)	Latency (s)	Speedup
1	Original(Single-device)	—	—	—	122.42	—
3	Ring Attention	—	—	—	63.30	1.93x
	Patch Parallel	—	—	—	72.61	1.69x
	DeepSpeed-Ulysses	—	—	—	62.65	1.95x
	DistriFusion	0.842	24.13	0.220	60.75	2.01x
	Compact-1bit (Ours)	0.762	20.46	0.291	56.41	2.17x
	Compact-2bit (Ours)	0.832	24.37	0.217	56.73	2.16x
6	Compact-Lowrank (Ours)	0.728	19.64	0.320	60.98	2.01x
	Ring Attention	—	—	—	52.90	2.31x
	Patch Parallel	—	—	—	53.37	2.29x
	DeepSpeed-Ulysses	—	—	—	39.03	3.14x
	DistriFusion	0.703	18.09	0.362	39.93	3.07x
	Compact-1bit (Ours)	0.746	19.75	0.308	35.50	3.45x
	Compact-2bit (Ours)	0.813	23.26	0.237	35.54	3.45x
	Compact-Lowrank (Ours)	0.708	19.06	0.339	39.13	3.13x

little degradation compared to longer warmup. In contrast, baseline methods are more sensitive to warmup configuration. For more detailed results, please refer to Appendix F.3

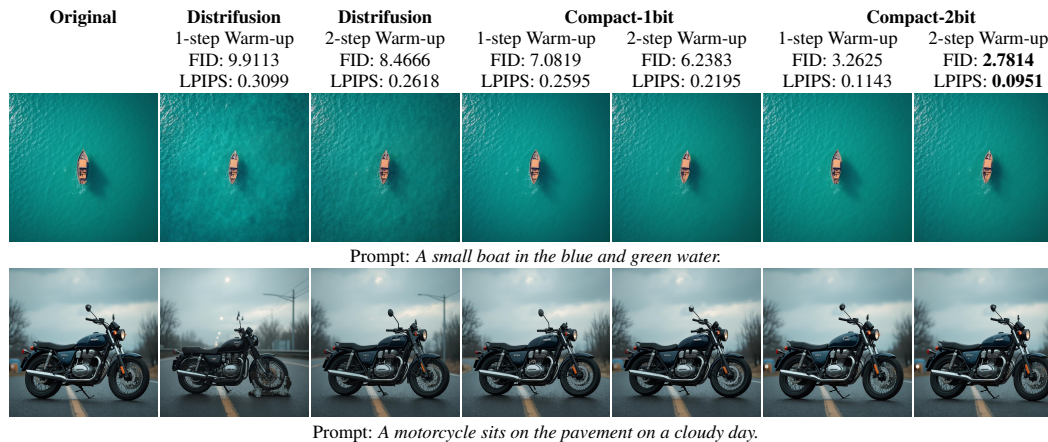


Figure 8: Impact of warmup steps on visual quality.

Effectiveness of Error Feedback. Error Feedback significantly improves quality. For Compact-1bit under 1-step warmup, it reduces FID from 19.23 to 7.08, lowers LPIPS from 0.389 to 0.260, and increases PSNR from 19.78 to 22.90. For more detailed results, please refer to Appendix F.2.

Performance on Patch Parallel and Ring Attention. CompactFusion supports both Patch Parallel and Ring Attention with minimal integration effort. On FLUX.1-dev and $4 \times$ L20, Compact-2bit

reduces latency from 10.90s to 8.08s on Patch Parallel (26% reduction), and from 10.89s to 7.71s on Ring Attention (29% reduction). In both settings, it delivers high-quality generation, significantly outperforming prior work across perceptual metrics.

5 Conclusion

CompactFusion accelerates parallel diffusion by eliminating temporal redundancy at the source. It transmits only compressed residuals with error feedback, preserving generation quality while significantly reducing communication. CompactFusion is designed as a modular, drop-in layer over standard communication primitives, and integrates seamlessly into existing frameworks. Extensive experiments show that it delivers consistent speedups across models, hardware, and networks. We offer a lightweight and efficient approach for diffusion inference at scale.

6 Acknowledgements

This work is supported in part by the National Key Research and Development Project of China (Grant No. 2023YFF0905502), National Natural Science Foundation of China (Grant No. 92467204 and 62472249), and Shenzhen Science and Technology Program (Grant No. JCYJ20220818101014030 and KJZD20240903102300001). This study is also supported in part by the Natural Science Foundation of Top Talent of SZTU(Grant No. GDRC202413).

We would like to express our sincere appreciation to the xDiT team for their comprehensive parallel diffusion framework, which served as the foundation for our experiments.

We thank all participants who contributed to the human evaluation survey. We also thank Zhengyi Su for helpful discussions and support on the theoretical analysis.

References

- [1] Robin Rombach, Andreas Blattmann, Dominik Lorenz, Patrick Esser, and Björn Ommer. High-resolution image synthesis with latent diffusion models. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 10684–10695, June 2022.
- [2] Black Forest Labs. Flux. <https://github.com/black-forest-labs/flux>, 2024.
- [3] Muyang Li, Yujun Lin, Zhekai Zhang, Tianle Cai, Xiuyu Li, Junxian Guo, Enze Xie, Chenlin Meng, Jun-Yan Zhu, and Song Han. SVDQuant: Absorbing Outliers by Low-Rank Components for 4-Bit Diffusion Models, March 2025. arXiv:2411.05007 [cs].
- [4] NVIDIA A100 GPUs Power the Modern Data Center.
- [5] NVIDIA H100 Tensor Core GPU.
- [6] Xibo Sun, Jiarui Fang, Aoyu Li, and Jinzhe Pan. Unveiling Redundancy in Diffusion Transformers (DiTs): A Systematic Study, November 2024. arXiv:2411.13588 [cs].
- [7] Muyang Li, Tianle Cai, Jiaxin Cao, Qinsheng Zhang, Han Cai, Junjie Bai, Yangqing Jia, Ming-Yu Liu, Kai Li, and Song Han. DistriFusion: Distributed Parallel Inference for High-Resolution Diffusion Models, July 2024. arXiv:2402.19481 [cs].
- [8] Jiannan Wang, Jiarui Fang, Aoyu Li, and PengCheng Yang. PipeFusion: Displaced Patch Pipeline Parallelism for Inference of Diffusion Transformer Models, May 2024. arXiv:2405.14430 [cs].
- [9] Shenggui Li, Fuzhao Xue, Chaitanya Baranwal, Yongbin Li, and Yang You. Sequence Parallelism: Long Sequence Training from System Perspective, May 2022. arXiv:2105.13120 [cs].
- [10] xdit-project/xDiT, May 2025.
- [11] Benoit Jacob, Skirmantas Kligys, Bo Chen, Menglong Zhu, Matthew Tang, Andrew Howard, Hartwig Adam, and Dmitry Kalenichenko. Quantization and Training of Neural Networks for Efficient Integer-Arithmetic-Only Inference. In *2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 2704–2713, Salt Lake City, UT, June 2018. IEEE.
- [12] Yanping Huang, Youlong Cheng, Ankur Bapna, Orhan Firat, Mia Xu Chen, Dehao Chen, HyoukJoong Lee, Jiquan Ngiam, Quoc V. Le, Yonghui Wu, and Zhifeng Chen. GPipe: Efficient Training of Giant Neural Networks using Pipeline Parallelism, July 2019. arXiv:1811.06965 [cs].
- [13] Deepak Narayanan, Mohammad Shoeybi, Jared Casper, Patrick LeGresley, Mostofa Patwary, Vijay Anand Korthikanti, Dmitri Vainbrand, Prethvi Kashinkunti, Julie Bernauer, Bryan Catanzaro, Amar Phanishayee, and Matei Zaharia. Efficient Large-Scale Language Model Training on GPU Clusters Using Megatron-LM, August 2021. arXiv:2104.04473 [cs].
- [14] Dmitry Lepikhin, HyoukJoong Lee, Yuanzhong Xu, Dehao Chen, Orhan Firat, Yanping Huang, Maxim Krikun, Noam Shazeer, and Zhifeng Chen. GShard: Scaling Giant Models with Conditional Computation and Automatic Sharding, June 2020. arXiv:2006.16668 [cs].
- [15] Samyam Rajbhandari, Jeff Rasley, Olatunji Ruwase, and Yuxiong He. ZeRO: Memory Optimizations Toward Training Trillion Parameter Models, May 2020. arXiv:1910.02054 [cs].
- [16] Sam Ade Jacobs, Masahiro Tanaka, Chengming Zhang, Minjia Zhang, Shuaiwen Leon Song, Samyam Rajbhandari, and Yuxiong He. DeepSpeed Ulysses: System Optimizations for Enabling Training of Extreme Long Sequence Transformer Models, October 2023. arXiv:2309.14509.
- [17] Jiarui Fang and Shangchun Zhao. USP: A Unified Sequence Parallelism Approach for Long Context Generative AI, July 2024. arXiv:2405.07719 [cs].
- [18] mit-han-lab/distrifuser, May 2025.
- [19] XiuYu Zhang, Zening Luo, and Michelle E. Lu. Partially Conditioned Patch Parallelism for Accelerated Diffusion Model Inference, December 2024. arXiv:2412.02962 [cs].
- [20] Jue Wang, Binhang Yuan, Luka Rimanic, Yongjun He, Tri Dao, Beidi Chen, Christopher Re, and Ce Zhang. Fine-tuning Language Models over Slow Networks using Activation Compression with Guarantees, March 2023. arXiv:2206.01299 [cs].

- [21] Yuhao Liu, Hanchen Li, Yihua Cheng, Siddhant Ray, Yuyang Huang, Qizheng Zhang, Kuntai Du, Jiayi Yao, Shan Lu, Ganesh Ananthanarayanan, Michael Maire, Henry Hoffmann, Ari Holtzman, and Junchen Jiang. Cachegen: Kv cache compression and streaming for fast large language model serving. In *Proceedings of the ACM SIGCOMM 2024 Conference*, ACM SIGCOMM '24, page 38–56, New York, NY, USA, 2024. Association for Computing Machinery.
- [22] Sai Praneeth Karimireddy, Quentin Rebjock, Sebastian U. Stich, and Martin Jaggi. Error Feedback Fixes SignSGD and other Gradient Compression Schemes, May 2019. arXiv:1901.09847 [cs].
- [23] Yujun Lin, Song Han, Huizi Mao, Yu Wang, and William J. Dally. Deep Gradient Compression: Reducing the Communication Bandwidth for Distributed Training, June 2020. arXiv:1712.01887 [cs].
- [24] Sebastian U. Stich. On Communication Compression for Distributed Optimization on Heterogeneous Data, December 2020. arXiv:2009.02388 [cs, stat].
- [25] Rongwei Lu, Jiajun Song, Bin Chen, Laizhong Cui, and Zhi Wang. DAGC: Data-Aware Adaptive Gradient Compression. In *IEEE INFOCOM 2023 - IEEE Conference on Computer Communications*, pages 1–10, May 2023. ISSN: 2641-9874.
- [26] G. W. Stewart. Simultaneous iteration for computing invariant subspaces of non-hermitian matrices. *Numerische Mathematik*, 25:123–136, 1975/76.
- [27] Thijs Vogels, Sai Praneeth Karimireddy, and Martin Jaggi. PowerSGD: Practical Low-Rank Gradient Compression for Distributed Optimization, February 2020. arXiv:1905.13727 [cs].
- [28] AoJun Zhou, Yukun Ma, Junnan Zhu, Jianbo Liu, Zhijie Zhang, Kun Yuan, Wenxiu Sun, and Hongsheng Li. Learning N:M Fine-grained Structured Sparse Neural Networks From Scratch, April 2021. arXiv:2102.04010 [cs].
- [29] Zhuoyi Yang, Jiayan Teng, Wendi Zheng, Ming Ding, Shiyu Huang, Jiazheng Xu, Yuanming Yang, Wenyi Hong, Xiaohan Zhang, Guanyu Feng, et al. Cogvideox: Text-to-video diffusion models with an expert transformer. *arXiv preprint arXiv:2408.06072*, 2024.
- [30] Xinlei Chen, Hao Fang, Tsung-Yi Lin, Ramakrishna Vedantam, Saurabh Gupta, Piotr Dollár, and C. Lawrence Zitnick. Microsoft COCO captions: Data collection and evaluation server. *CoRR*, abs/1504.00325, 2015.
- [31] Ziqi Huang, Yinan He, Jiashuo Yu, Fan Zhang, Chenyang Si, Yuming Jiang, Yuanhan Zhang, Tianxing Wu, Qingyang Jin, Nattapol Chanpaisit, Yaohui Wang, Xinyuan Chen, Limin Wang, Dahua Lin, Yu Qiao, and Ziwei Liu. Vbench: Comprehensive benchmark suite for video generative models, 2023.
- [32] Zhuohan Li, Siyuan Zhuang, Shiyuan Guo, Danyang Zhuo, Hao Zhang, Dawn Song, and Ion Stoica. TeraPipe: Token-Level Pipeline Parallelism for Training Large-Scale Language Models, September 2021. arXiv:2102.07988 [cs].
- [33] Richard Zhang, Phillip Isola, Alexei A. Efros, Eli Shechtman, and Oliver Wang. The unreasonable effectiveness of deep features as a perceptual metric, 2018.
- [34] Martin Heusel, Hubert Ramsauer, Thomas Unterthiner, Bernhard Nessler, and Sepp Hochreiter. Gans trained by a two time-scale update rule converge to a local nash equilibrium, 2018.
- [35] Zhou Wang, A.C. Bovik, H.R. Sheikh, and E.P. Simoncelli. Image quality assessment: from error visibility to structural similarity. *IEEE Transactions on Image Processing*, 13(4):600–612, 2004.
- [36] Jiarui Fang, Jinzhe Pan, Xibo Sun, Aoyu Li, and Jiannan Wang. xDiT: an Inference Engine for Diffusion Transformers (DiTs) with Massive Parallelism, November 2024. arXiv:2411.01738 [cs].
- [37] Cheng Lu, Yuhao Zhou, Fan Bao, Jianfei Chen, Chongxuan Li, and Jun Zhu. Dpm-solver: A fast ode solver for diffusion probabilistic model sampling in around 10 steps, 2022.

NeurIPS Paper Checklist

1. Claims

Question: Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope?

Answer: [Yes]

Justification: The claims made in the abstract and introduction accurately reflect the contributions. Claims clearly match our system design, empirical results and analysis.

Guidelines:

- The answer NA means that the abstract and introduction do not include the claims made in the paper.
- The abstract and/or introduction should clearly state the claims made, including the contributions made in the paper and important assumptions and limitations. A No or NA answer to this question will not be perceived well by the reviewers.
- The claims made should match theoretical and experimental results, and reflect how much the results can be expected to generalize to other settings.
- It is fine to include aspirational goals as motivation as long as it is clear that these goals are not attained by the paper.

2. Limitations

Question: Does the paper discuss the limitations of the work performed by the authors?

Answer: [Yes]

Justification: The discussion on limitations is provided in Appendix A.

Guidelines:

- The answer NA means that the paper has no limitation while the answer No means that the paper has limitations, but those are not discussed in the paper.
- The authors are encouraged to create a separate "Limitations" section in their paper.
- The paper should point out any strong assumptions and how robust the results are to violations of these assumptions (e.g., independence assumptions, noiseless settings, model well-specification, asymptotic approximations only holding locally). The authors should reflect on how these assumptions might be violated in practice and what the implications would be.
- The authors should reflect on the scope of the claims made, e.g., if the approach was only tested on a few datasets or with a few runs. In general, empirical results often depend on implicit assumptions, which should be articulated.
- The authors should reflect on the factors that influence the performance of the approach. For example, a facial recognition algorithm may perform poorly when image resolution is low or images are taken in low lighting. Or a speech-to-text system might not be used reliably to provide closed captions for online lectures because it fails to handle technical jargon.
- The authors should discuss the computational efficiency of the proposed algorithms and how they scale with dataset size.
- If applicable, the authors should discuss possible limitations of their approach to address problems of privacy and fairness.
- While the authors might fear that complete honesty about limitations might be used by reviewers as grounds for rejection, a worse outcome might be that reviewers discover limitations that aren't acknowledged in the paper. The authors should use their best judgment and recognize that individual actions in favor of transparency play an important role in developing norms that preserve the integrity of the community. Reviewers will be specifically instructed to not penalize honesty concerning limitations.

3. Theory assumptions and proofs

Question: For each theoretical result, does the paper provide the full set of assumptions and a complete (and correct) proof?

Answer: [Yes]

Justification: Assumptions and proof are provided in Section 3.1 and appendix H.

Guidelines:

- The answer NA means that the paper does not include theoretical results.
- All the theorems, formulas, and proofs in the paper should be numbered and cross-referenced.
- All assumptions should be clearly stated or referenced in the statement of any theorems.
- The proofs can either appear in the main paper or the supplemental material, but if they appear in the supplemental material, the authors are encouraged to provide a short proof sketch to provide intuition.
- Inversely, any informal proof provided in the core of the paper should be complemented by formal proofs provided in appendix or supplemental material.
- Theorems and Lemmas that the proof relies upon should be properly referenced.

4. Experimental result reproducibility

Question: Does the paper fully disclose all the information needed to reproduce the main experimental results of the paper to the extent that it affects the main claims and/or conclusions of the paper (regardless of whether the code and data are provided or not)?

Answer: [\[Yes\]](#)

Justification: Our code is publicly released, and we provide full experimental settings (Section 4 and appendix E).

Guidelines:

- The answer NA means that the paper does not include experiments.
- If the paper includes experiments, a No answer to this question will not be perceived well by the reviewers: Making the paper reproducible is important, regardless of whether the code and data are provided or not.
- If the contribution is a dataset and/or model, the authors should describe the steps taken to make their results reproducible or verifiable.
- Depending on the contribution, reproducibility can be accomplished in various ways. For example, if the contribution is a novel architecture, describing the architecture fully might suffice, or if the contribution is a specific model and empirical evaluation, it may be necessary to either make it possible for others to replicate the model with the same dataset, or provide access to the model. In general, releasing code and data is often one good way to accomplish this, but reproducibility can also be provided via detailed instructions for how to replicate the results, access to a hosted model (e.g., in the case of a large language model), releasing of a model checkpoint, or other means that are appropriate to the research performed.
- While NeurIPS does not require releasing code, the conference does require all submissions to provide some reasonable avenue for reproducibility, which may depend on the nature of the contribution. For example
 - (a) If the contribution is primarily a new algorithm, the paper should make it clear how to reproduce that algorithm.
 - (b) If the contribution is primarily a new model architecture, the paper should describe the architecture clearly and fully.
 - (c) If the contribution is a new model (e.g., a large language model), then there should either be a way to access this model for reproducing the results or a way to reproduce the model (e.g., with an open-source dataset or instructions for how to construct the dataset).
 - (d) We recognize that reproducibility may be tricky in some cases, in which case authors are welcome to describe the particular way they provide for reproducibility. In the case of closed-source models, it may be that access to the model is limited in some way (e.g., to registered users), but it should be possible for other researchers to have some path to reproducing or verifying the results.

5. Open access to data and code

Question: Does the paper provide open access to the data and code, with sufficient instructions to faithfully reproduce the main experimental results, as described in supplemental material?

Answer: [\[Yes\]](#)

Justification: We release our full codebase with detailed instructions, scripts for reproducing results. All used models and datasets are publicly available, and setup details are included in the paper.

Guidelines:

- The answer NA means that paper does not include experiments requiring code.
- Please see the NeurIPS code and data submission guidelines (<https://nips.cc/public/guides/CodeSubmissionPolicy>) for more details.
- While we encourage the release of code and data, we understand that this might not be possible, so “No” is an acceptable answer. Papers cannot be rejected simply for not including code, unless this is central to the contribution (e.g., for a new open-source benchmark).
- The instructions should contain the exact command and environment needed to run to reproduce the results. See the NeurIPS code and data submission guidelines (<https://nips.cc/public/guides/CodeSubmissionPolicy>) for more details.
- The authors should provide instructions on data access and preparation, including how to access the raw data, preprocessed data, intermediate data, and generated data, etc.
- The authors should provide scripts to reproduce all experimental results for the new proposed method and baselines. If only a subset of experiments are reproducible, they should state which ones are omitted from the script and why.
- At submission time, to preserve anonymity, the authors should release anonymized versions (if applicable).
- Providing as much information as possible in supplemental material (appended to the paper) is recommended, but including URLs to data and code is permitted.

6. Experimental setting/details

Question: Does the paper specify all the training and test details (e.g., data splits, hyperparameters, how they were chosen, type of optimizer, etc.) necessary to understand the results?

Answer: [\[Yes\]](#)

Justification: All experimental settings, including model setup, diffusion steps, and evaluation protocols, are described in the paper (Section 4 and appendix E).

Guidelines:

- The answer NA means that the paper does not include experiments.
- The experimental setting should be presented in the core of the paper to a level of detail that is necessary to appreciate the results and make sense of them.
- The full details can be provided either with the code, in appendix, or as supplemental material.

7. Experiment statistical significance

Question: Does the paper report error bars suitably and correctly defined or other appropriate information about the statistical significance of the experiments?

Answer: [\[No\]](#)

Justification: Following prior work, we do not report error bars or statistical significance tests for diffusion inference.

Guidelines:

- The answer NA means that the paper does not include experiments.
- The authors should answer "Yes" if the results are accompanied by error bars, confidence intervals, or statistical significance tests, at least for the experiments that support the main claims of the paper.
- The factors of variability that the error bars are capturing should be clearly stated (for example, train/test split, initialization, random drawing of some parameter, or overall run with given experimental conditions).

- The method for calculating the error bars should be explained (closed form formula, call to a library function, bootstrap, etc.)
- The assumptions made should be given (e.g., Normally distributed errors).
- It should be clear whether the error bar is the standard deviation or the standard error of the mean.
- It is OK to report 1-sigma error bars, but one should state it. The authors should preferably report a 2-sigma error bar than state that they have a 96% CI, if the hypothesis of Normality of errors is not verified.
- For asymmetric distributions, the authors should be careful not to show in tables or figures symmetric error bars that would yield results that are out of range (e.g. negative error rates).
- If error bars are reported in tables or plots, The authors should explain in the text how they were calculated and reference the corresponding figures or tables in the text.

8. Experiments compute resources

Question: For each experiment, does the paper provide sufficient information on the computer resources (type of compute workers, memory, time of execution) needed to reproduce the experiments?

Answer: [Yes]

Justification: We report GPU types, hardware configurations, and latency for results.

Guidelines:

- The answer NA means that the paper does not include experiments.
- The paper should indicate the type of compute workers CPU or GPU, internal cluster, or cloud provider, including relevant memory and storage.
- The paper should provide the amount of compute required for each of the individual experimental runs as well as estimate the total compute.
- The paper should disclose whether the full research project required more compute than the experiments reported in the paper (e.g., preliminary or failed experiments that didn't make it into the paper).

9. Code of ethics

Question: Does the research conducted in the paper conform, in every respect, with the NeurIPS Code of Ethics <https://neurips.cc/public/EthicsGuidelines>?

Answer: [Yes]

Justification: Our research complies with the NeurIPS Code of Ethics.

Guidelines:

- The answer NA means that the authors have not reviewed the NeurIPS Code of Ethics.
- If the authors answer No, they should explain the special circumstances that require a deviation from the Code of Ethics.
- The authors should make sure to preserve anonymity (e.g., if there is a special consideration due to laws or regulations in their jurisdiction).

10. Broader impacts

Question: Does the paper discuss both potential positive societal impacts and negative societal impacts of the work performed?

Answer: [Yes]

Justification: The societal impacts are provided in Appendix J.

Guidelines:

- The answer NA means that there is no societal impact of the work performed.
- If the authors answer NA or No, they should explain why their work has no societal impact or why the paper does not address societal impact.
- Examples of negative societal impacts include potential malicious or unintended uses (e.g., disinformation, generating fake profiles, surveillance), fairness considerations (e.g., deployment of technologies that could make decisions that unfairly impact specific groups), privacy considerations, and security considerations.

- The conference expects that many papers will be foundational research and not tied to particular applications, let alone deployments. However, if there is a direct path to any negative applications, the authors should point it out. For example, it is legitimate to point out that an improvement in the quality of generative models could be used to generate deepfakes for disinformation. On the other hand, it is not needed to point out that a generic algorithm for optimizing neural networks could enable people to train models that generate Deepfakes faster.
- The authors should consider possible harms that could arise when the technology is being used as intended and functioning correctly, harms that could arise when the technology is being used as intended but gives incorrect results, and harms following from (intentional or unintentional) misuse of the technology.
- If there are negative societal impacts, the authors could also discuss possible mitigation strategies (e.g., gated release of models, providing defenses in addition to attacks, mechanisms for monitoring misuse, mechanisms to monitor how a system learns from feedback over time, improving the efficiency and accessibility of ML).

11. Safeguards

Question: Does the paper describe safeguards that have been put in place for responsible release of data or models that have a high risk for misuse (e.g., pretrained language models, image generators, or scraped datasets)?

Answer: [NA]

Justification: This paper poses no such risks.

Guidelines:

- The answer NA means that the paper poses no such risks.
- Released models that have a high risk for misuse or dual-use should be released with necessary safeguards to allow for controlled use of the model, for example by requiring that users adhere to usage guidelines or restrictions to access the model or implementing safety filters.
- Datasets that have been scraped from the Internet could pose safety risks. The authors should describe how they avoided releasing unsafe images.
- We recognize that providing effective safeguards is challenging, and many papers do not require this, but we encourage authors to take this into account and make a best faith effort.

12. Licenses for existing assets

Question: Are the creators or original owners of assets (e.g., code, data, models), used in the paper, properly credited and are the license and terms of use explicitly mentioned and properly respected?

Answer: [Yes]

Justification: They are explicitly mentioned in the paper and further listed in Appendix I.

Guidelines:

- The answer NA means that the paper does not use existing assets.
- The authors should cite the original paper that produced the code package or dataset.
- The authors should state which version of the asset is used and, if possible, include a URL.
- The name of the license (e.g., CC-BY 4.0) should be included for each asset.
- For scraped data from a particular source (e.g., website), the copyright and terms of service of that source should be provided.
- If assets are released, the license, copyright information, and terms of use in the package should be provided. For popular datasets, paperswithcode.com/datasets has curated licenses for some datasets. Their licensing guide can help determine the license of a dataset.
- For existing datasets that are re-packaged, both the original license and the license of the derived asset (if it has changed) should be provided.

- If this information is not available online, the authors are encouraged to reach out to the asset's creators.

13. **New assets**

Question: Are new assets introduced in the paper well documented and is the documentation provided alongside the assets?

Answer: [\[Yes\]](#)

Justification: Our open-source codebase is well documented, with documentation provided alongside the code.

Guidelines:

- The answer NA means that the paper does not release new assets.
- Researchers should communicate the details of the dataset/code/model as part of their submissions via structured templates. This includes details about training, license, limitations, etc.
- The paper should discuss whether and how consent was obtained from people whose asset is used.
- At submission time, remember to anonymize your assets (if applicable). You can either create an anonymized URL or include an anonymized zip file.

14. **Crowdsourcing and research with human subjects**

Question: For crowdsourcing experiments and research with human subjects, does the paper include the full text of instructions given to participants and screenshots, if applicable, as well as details about compensation (if any)?

Answer: [\[Yes\]](#)

Justification: We include the instructions and the example in the appendix. We did not employ workers.

Guidelines:

- The answer NA means that the paper does not involve crowdsourcing nor research with human subjects.
- Including this information in the supplemental material is fine, but if the main contribution of the paper involves human subjects, then as much detail as possible should be included in the main paper.
- According to the NeurIPS Code of Ethics, workers involved in data collection, curation, or other labor should be paid at least the minimum wage in the country of the data collector.

15. **Institutional review board (IRB) approvals or equivalent for research with human subjects**

Question: Does the paper describe potential risks incurred by study participants, whether such risks were disclosed to the subjects, and whether Institutional Review Board (IRB) approvals (or an equivalent approval/review based on the requirements of your country or institution) were obtained?

Answer: [\[No\]](#)

Justification: The study posed no risk to participants, we did not seek IRB approval.

Guidelines:

- The answer NA means that the paper does not involve crowdsourcing nor research with human subjects.
- Depending on the country in which research is conducted, IRB approval (or equivalent) may be required for any human subjects research. If you obtained IRB approval, you should clearly state this in the paper.
- We recognize that the procedures for this may vary significantly between institutions and locations, and we expect authors to adhere to the NeurIPS Code of Ethics and the guidelines for their institution.
- For initial submissions, do not include any information that would break anonymity (if applicable), such as the institution conducting the review.

16. Declaration of LLM usage

Question: Does the paper describe the usage of LLMs if it is an important, original, or non-standard component of the core methods in this research? Note that if the LLM is used only for writing, editing, or formatting purposes and does not impact the core methodology, scientific rigorousness, or originality of the research, declaration is not required.

Answer: [NA]

Justification: The core method development in this research does not involve LLMs as any important, original, or non-standard components.

Guidelines:

- The answer NA means that the core method development in this research does not involve LLMs as any important, original, or non-standard components.
- Please refer to our LLM policy (<https://neurips.cc/Conferences/2025/LLM>) for what should or should not be described.

A Limitations

While CompactFusion offers strong compression with minimal quality loss, several practical limitations remain.

First, compression itself introduces overhead. Although our implementation overlaps compression with communication in Ring Attention, full overlap is not always achievable, especially on fast interconnects with limited idle time. This can reduce net gains. We believe further kernel optimizations and scheduling strategies can help bridge this gap.

Second, while our low-rank variant supports high compression ratio, the subspace iteration it relies on remains slower than quantization or sparsity. This limits its speedup under fast networks, though still valuable for bandwidth-limited settings like edge deployment.

B More Preliminaries

B.1 Sequence Parallelism

Sequence parallel enables multiple GPUs to collaboratively generate a single image or video sample, thereby reducing the latency per sample. During inference, an image or video frame is first divided into a sequence of patches (tokens). Sequence parallel partitions this sequence of patches across multiple devices so that each GPU is responsible for computing a section of it.

After the partition, however, inter-GPU communications are required. For FFN layers, communication is unnecessary—each patch (token) is processed independently, and all required data resides locally on the same device. But for attention layers, every patch must attend to all other patches across the full sequence, which introduces cross-device dependencies.

Different parallel strategies handle this communication differently:

Patch Parallel[7]. This strategy performs a single AllGather operation over all devices to collect the complete set of keys and values (Figure 9). Each GPU thus receives global K and V tensors before executing the attention computation. It may incur substantial communication overhead as the entire K, V matrices are transmitted every step.

Ring Attention[9]. Instead of a full AllGather, Ring Attention organizes the devices into a logical ring and performs a series of peer-to-peer exchanges. Each stage transmits only a shard of K, V and computes the corresponding partial result. Computation and communication are interleaved, offering partial overlap.

Ulysses[16]. Ulysses adopts a slightly different design, using two All-to-All operations to exchange the required data between devices.

We provide illustrative pseudocode in Algorithms 1 and 2.

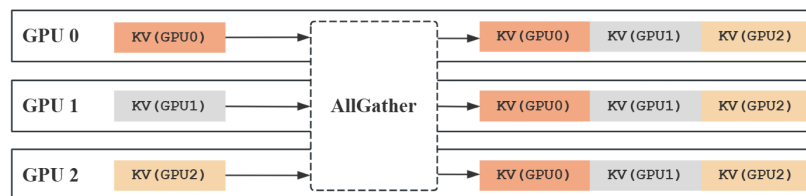


Figure 9: Illustration of Patch Parallel.

Algorithm 1 Patch Parallel

Input: Local tokens/features X_i on device i

- 1: $Q_i, K_i, V_i \leftarrow \text{ProjectQKV}(X_i)$
 - 2: $K_{\text{gathered}}, V_{\text{gathered}} \leftarrow \text{AllGather}(K_i, V_i)$
 - 3: $O_i \leftarrow \text{Attention}(Q_i, K_{\text{gathered}}, V_{\text{gathered}})$
 - 4: **return** O_i
-

Algorithm 2 Ring Attention

Input: Local tokens/features X_i on device i , total devices N

```
1:  $Q_i, K_i, V_i \leftarrow \text{ProjectQKV}(X_i)$ 
2: Initialize local output buffer:  $O_i \leftarrow 0$ 
3: for  $s = 0$  to  $N-1$  do
4:    $K^{(s)}, V^{(s)} \leftarrow \text{RingSendRecv}(K_i, V_i, s)$   $\triangleright$  receive shard from device  $(i-s) \bmod N$ 
5:    $O_i \leftarrow \text{Aggregate}(O_i, \text{AttentionPartial}(Q_i, K^{(s)}, V^{(s)}))$ 
6: end for
7: return  $O_i$ 
```

B.2 Displaced Patch Parallel (DistriFusion)

Patch Parallel performs a synchronous AllGather of K, V at every denoising step and waits immediately before attention, which leads to substantial blocking when the transfer payload is large. Displaced Patch Parallel [7] avoids this by adopting a *send-now, receive-later* schedule with a one-step displacement. In each iteration, the system launches a non-blocking communication for the *current* (K, V) but computes attention using the *previous* step's gathered (K, V) , thereby overlapping communication with computation. Each iteration waits on the handle from the earlier launch when those tensors are actually required. This schedule reduces latency at the cost of using stale keys and values, which can introduce quality drift.

C Discussion

Residual Compression and Displaced Parallelism. Residual compression and displaced parallelism are not mutually exclusive. They can potentially be combined to leverage the strengths of both. For example, integrating CompactFusion with PipeFusion may allow reducing the memory footprint needed to store base tensors for residual computation.

Exploiting Temporal Redundancy. Inspired by excellent prior work DistriFusion and PipeFusion, we revisit the core idea behind temporal redundancy. As the name suggests, this data is largely redundant. Rather than continuing to transmit it and try masking its communication cost, we believe the most effective approach is to eliminate it entirely from the communication path. CompactFusion follows this principle: it directly discards redundant data, leading to more efficient and scalable parallel diffusion.

Why PipeFusion is not evaluated on video models. To the best of our knowledge, xDiT is the most widely used parallel diffusion inference framework, actively maintained and widely adopted in both research and deployment. It originates from the official PipeFusion repository and inherits its core features. However, neither PipeFusion nor xDiT currently support video models such as CogVideoX. As a result, evaluating PipeFusion in this setting would require substantial reengineering. This is beyond the scope of our work and the capacity of us. We stress that the omission is due to technical constraints rather than intentional bias. Our goal remains fair and comprehensive comparison wherever feasible.

D Implementation Details

Warmup Implementation. Similar to displaced parallelism, CompactFusion requires at least one warmup step. It is used to initialize the uncompressed base tensor for residual calculation. Ablation studies show that CompactFusion is highly robust and achieves strong generation quality even with a single warmup step (Section 4.3). There are two practical ways to implement warmup: (1) running the warmup steps with parallelism but without compression; or (2) letting each device execute the warmup locally without any communication. The first method introduces some communication but is typically faster on PCIe and NVLink. However, it may become a bottleneck under extremely slow networks. The second method avoids communication but incurs slightly higher latency due to lack of parallelism. We adopt the first method in our experiments.

Quantization. We quantize an activation tensor $X \in \mathbb{R}^{N \times C}$ using element-wise multiplication between a quantized sign/value tensor and a scale matrix:

$$Q(X) = q(X) \odot (uv^\top),$$

where

- $q(X)$ is the element-wise quantized tensor (e.g., ± 1 for 1-bit, or $\{-2, -0.5, +0.5, +2\}$ for 2-bit),
- $\odot$ denotes the element-wise product,
- $u \in \mathbb{R}^{N \times 1}$, $v \in \mathbb{R}^{C \times 1}$ form a rank-1 approximation of the activation magnitude.

In practice, we estimate u and v as:

$$u_i = \frac{\frac{1}{C} \sum_j |X_{ij}|}{\frac{1}{NC} \sum_{i,j} |X_{ij}|}, \quad v_j = \frac{1}{N} \sum_i |X_{ij}|.$$

This yields a scale matrix where $(uv^\top)_{ij}$ reflects the product of the normalized token-wise and channel-wise means. All quantization operations are implemented in fused end-to-end Triton kernels for efficiency. We note that this scale estimation is heuristic and leaves substantial room for improvement.

Low-Rank Compression. We aim to approximate a matrix $A \in \mathbb{R}^{m \times n}$ with a low-rank decomposition of the form:

$$A \approx UV^\top, \quad \text{where } U \in \mathbb{R}^{m \times r}, V \in \mathbb{R}^{n \times r}.$$

To compute this approximation efficiently, we use a T -step subspace iteration [26]; subspace iteration was first used in gradient compression [27]:

Algorithm 3 Subspace Iteration (rank- r)

Input: $A \in \mathbb{R}^{m \times n}$, target rank r , iterations T

- 1: Randomly Sample Q and orthonormalize: $Q \leftarrow \text{orthogonalize}(Q)$.
 - 2: **for** $t = 1$ **to** T **do**
 - 3: $Z \leftarrow A^\top (A Q) \in \mathbb{R}^{n \times r}$
 - 4: $Q \leftarrow \text{orthogonalize}(Z)$
 - 5: **end for**
 - 6: $U \leftarrow A Q \in \mathbb{R}^{m \times r}$
 - 7: $U \leftarrow \text{orthogonalize}(U)$
 - 8: $V \leftarrow Q \in \mathbb{R}^{n \times r}$
 - 9: **return** U, V
-

Residual Base and Error Feedback. In CompactFusion, each transmitted tensor represents a residual, which is the change in activation relative to a stored base. The base is initialized with the uncompressed activation during the warm-up step and updated after every iteration. Compression introduces an error that is observable only on the sender side, since the receiver never sees the true residual before compression. Therefore, error feedback is applied at the sender: the previously accumulated error is added back to the next residual before compression, ensuring that lost information is gradually compensated over time.

Integration into Parallel Pipelines. CompactFusion integrates into existing parallel frameworks by simply wrapping standard communication primitives such as `send/recv` and `AllGather`. This modular design allows the same compression interface to be reused across different parallel strategies, ensuring compatibility with existing diffusion inference pipelines.

E More Experiment Details

E.1 Human Evaluation

To complement automated perceptual metrics (e.g., FID, LPIPS), we conducted a human evaluation study to assess how different parallel inference strategies affect generation quality.

We distributed an online questionnaire to colleagues and friends, asking them to compare images generated by five different parallelization methods. The goal was to identify which results were more visually consistent with the original reference image.

Directly ranking five images per question was found to be cognitively demanding and time-consuming, which discouraged participation. To simplify the task while still capturing ranking preference, we designed an alternative method. We randomly sampled 30 groups of images, and each participant answered 30 questions (15 of each type), with the following two instructions:

- Please select the two images that are *most* similar to the Reference Image.
- Please select the two images that are *least* similar to the Reference Image.

Each question displayed one reference image (generated by the original uncompressed model) and five test images produced by different parallel strategies (including DistriFusion, PipeFusion, and CompactFusion variants), as shown in Figure 10. The five options were randomly shuffled to avoid position bias. The prompts used for generation were randomly sampled from the COCO dataset.



Figure 10: Example from our human evaluation questionnaire. Participants are asked to select two images most (or least) similar to the reference image. Each set contains five outputs generated by different parallel inference methods, shown in random order.

We collected 20 valid responses in total. For each method, we compute the probability that its output falls into the more consistent subset (either selected as most similar, or not selected as least similar). This reflects how frequently a method produces perceptually closer results to the reference image.

We note that this evaluation involved no personal or sensitive information and posed no potential risks to participants.

E.2 More Setups

Models. The default scheduler used is DPM solver. [37]

Dataset. For evaluation, we randomly sample 5000 prompts from the image validation set and 200 video validation prompts.

F More Quantitative Results

This section provides more quantitative results for ablation study and some experiments we use to elaborate our methods.

F.1 Effect of Tradeoff between Rank and Precision

Table 3: Quantitative evaluation for Compact-Lowrank, Pure Lowrank with Iteration 2 and Pure Lowrank with Iteration 10.

Method	PSNR ($\uparrow$)		LPIPS ($\downarrow$)		FID ($\downarrow$)	
	w/ G.T.	w/ Orig.	w/ G.T.	w/ Orig.	w/ G.T.	w/ Orig.
Compact-Lowrank	9.89	22.85	0.769	0.275	33.07	8.68
Pure Lowrank 12 with Iteration=2	9.86	20.78	0.765	0.340	33.91	12.19
Pure Lowrank 8 with Iteration=2	9.84	20.11	0.762	0.361	34.68	13.97
Pure Lowrank 8 with Iteration=10	9.84	20.10	0.763	0.362	34.53	13.87

Compact-Lowrank uses rank 32 and applies INT4 quantization to the transmitted U and V , matching the communication cost of rank-8 FP16 methods. In contrast, the Pure Lowrank baselines use lower ranks (8 or 12) and do not quantize. As shown in Table 3, increasing the subspace iteration steps (from 2 to 10) brings negligible quality gains, while increasing the rank significantly improves generation quality. This highlights the importance of directional coverage over projection precision under tight bandwidth budgets.

F.2 Effect of the Error Feedback

Table 4: Quantitative evaluation for Compact-1bit with and without Error Feedback mechanism.

Method	PSNR ($\uparrow$)		LPIPS ($\downarrow$)		FID ($\downarrow$)	
	w/ G.T.	w/ Orig.	w/ G.T.	w/ Orig.	w/ G.T.	w/ Orig.
Compact-1bit (with Error Feedback)	9.80	22.90	0.767	0.260	33.20	7.08
Compact-1bit (without Error Feedback)	9.57	19.78	0.759	0.389	37.98	19.23

The results (Table 4) show that incorporating error feedback significantly improves performance across all metrics. Specifically, the Compact-1bit with Error Feedback variant achieves higher PSNR scores, lower LPIPS values, and notably better FID scores compared to the version without error feedback. This indicates that error feedback helps preserve perceptual and structural quality, making it a critical component for effective low-bit communication.

F.3 Effect of the Warmup steps

Table 5: Quantitative evaluation for WarmUp Steps

Method	PSNR ($\uparrow$)	LPIPS ($\downarrow$)		FID ($\downarrow$)		Latency (s)	
	w/ Orig.	w/ G.T.	w/ Orig.	w/ G.T.	w/ Orig.	L20	H20
DistriFusion WarmUp 1	21.62	0.760	0.309	33.12	9.91	8.05	6.86
DistriFusion WarmUp 2	23.37	0.762	0.261	33.11	8.46	8.38	6.93
Compact-1bit WarmUp 1	22.89	0.766	0.259	33.20	7.08	7.46	6.86
Compact-1bit WarmUp 2	24.48	0.768	0.219	33.26	6.23	7.63	6.92
Compact-2bit WarmUp 1	29.54	0.772	0.114	33.09	3.26	7.57	6.70
Compact-2bit WarmUp 2	31.02	0.772	0.095	33.11	2.78	7.71	6.89

Table 5 demonstrates that longer warm-up phases and higher-bit compression with error feedback improve visual quality.

Table 6: Human evaluation results. “Top-2 Count” refers to how often a method’s output was selected as one of the *most similar* images; “Bottom-2 Count” refers to how often it was selected as one of the *least similar* ones. “Final Score” reflects the probability of being placed in the more consistent group.

	PipeFusion	DistriFusion	Compact-Lowrank	Compact-1bit	Compact-2bit
Top-2 Count ($\uparrow$)	150	24	65	103	258
Top-2 Rate ($\uparrow$)	0.50	0.08	0.22	0.34	0.86
Bottom-2 Count ($\downarrow$)	113	173	139	119	56
Bottom-2 Rate ($\downarrow$)	0.38	0.58	0.46	0.40	0.18
Final Score ($\uparrow$)	0.56	0.25	0.38	0.47	0.84

F.4 Details on Human Evaluation Results

Compact-2bit method can exhibit high consistency and fidelity with regard to human perception (Table 6).

F.5 Temporal Stability Evaluation

Table 7: Temporal stability evaluation on CogVideoX (6 GPUs) following VBench [31] metrics.

Method	Temporal Flickering ($\uparrow$)	Motion Smoothness ($\uparrow$)
Original (No Compression)	0.9721	0.9817
DistriFusion	0.9658	0.9795
Compact-2bit	0.9644	0.9808
Compact-1bit	0.9661	0.9806
Compact-Lowrank	0.9623	0.9775

The results (Table 7) show that all CompactFusion variants maintain temporal stability comparable to or better than prior methods. The differences across metrics are minimal, indicating that compression introduces no noticeable degradation in temporal stability.

G More Qualitative Results

This section provides more qualitative results for FLUX.1-dev model and CogVideoX-2b model.

G.1 FLUX.1-dev Qualitative Results

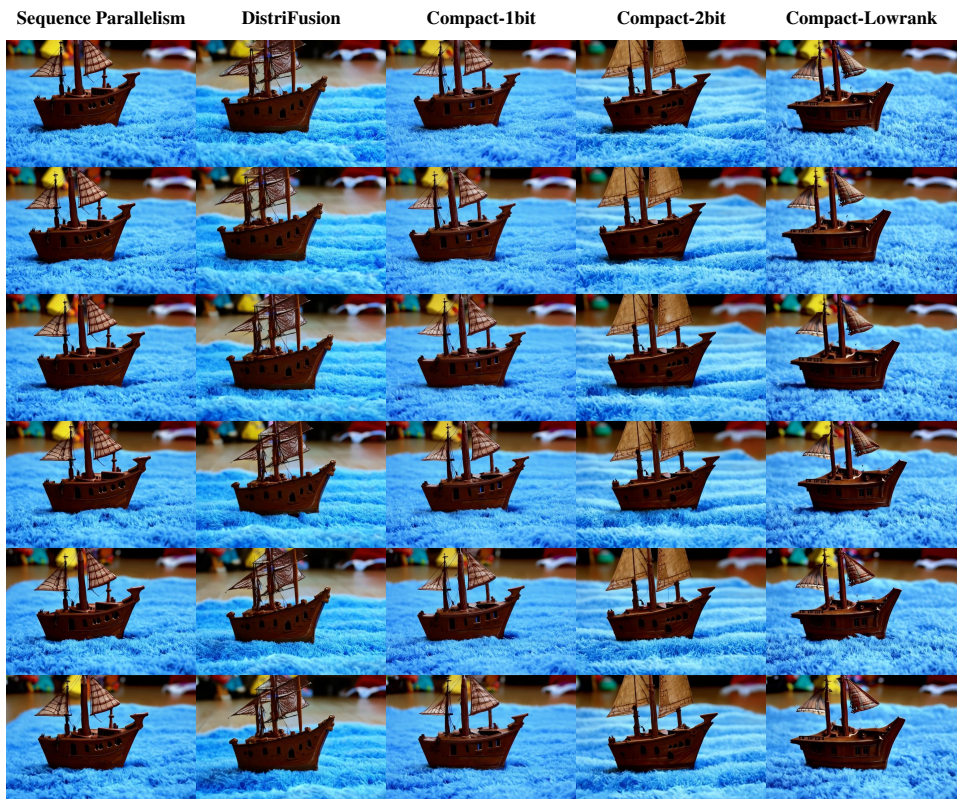
The supplementary qualitative results are shown in Table 8.

G.2 CogVideoX-2b Qualitative Results

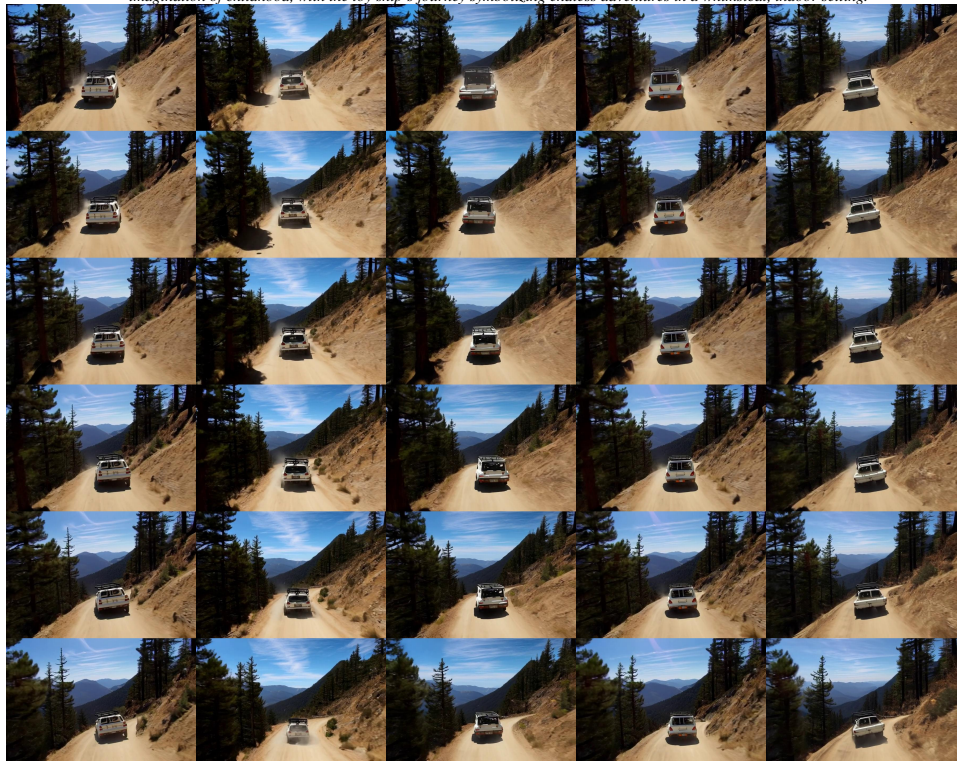
The supplementary qualitative results are shown in Table 9 and Table 10.



Table 8: Supplement Image Qualitative Results.

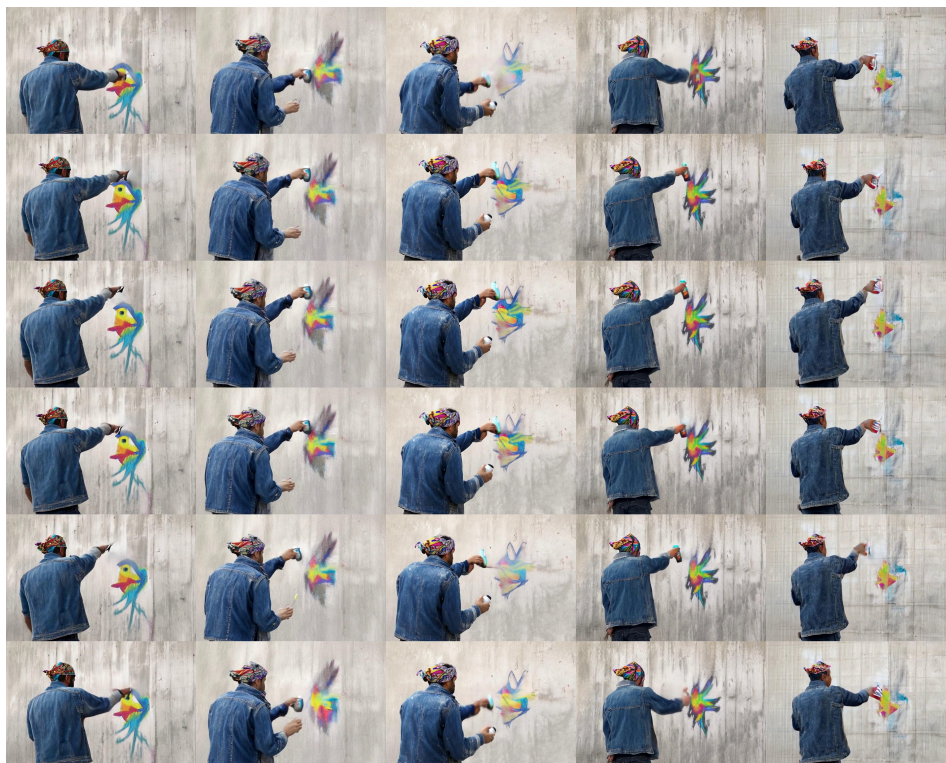


Prompt: A detailed wooden toy ship with intricately carved masts and sails is seen gliding smoothly over a plush, blue carpet that mimics the waves of the sea. The ship's hull is painted a rich brown, with tiny windows. The carpet, soft and textured, provides a perfect backdrop, resembling an oceanic expanse. Surrounding the ship are various other toys and children's items, hinting at a playful environment. The scene captures the innocence and imagination of childhood, with the toy ship's journey symbolizing endless adventures in a whimsical, indoor setting.



Prompt: The camera follows behind a white vintage SUV with a black roof rack as it speeds up a steep dirt road surrounded by pine trees on a steep mountain slope, dust kicks up from it's tires, the sunlight shines on the SUV as it speeds along the dirt road, casting a warm glow over the scene. The dirt road curves gently into the distance, with no other cars or vehicles in sight. The trees on either side of the road are redwoods, with patches of greenery scattered throughout. The car is seen from the rear following the curve with ease, making it seem as if it is on a rugged drive through the rugged terrain. The dirt road itself is surrounded by steep hills and mountains, with a clear blue sky above with wispy clouds.

Table 9: Supplement Video Qualitative Results (1/2).



Prompt: A street artist, clad in a worn-out denim jacket and a colorful bandana, stands before a vast concrete wall in the heart, holding a can of spray paint, spray-painting a colorful bird on a mottled wall.



Prompt: An elderly gentleman, with a serene expression, sits at the water's edge, a steaming cup of tea by his side. He is engrossed in his artwork, brush in hand, as he renders an oil painting on a canvas that's propped up against a small, weathered table. The sea breeze whispers through his silver hair, gently billowing his loose-fitting white shirt, while the salty air adds an intangible element to his masterpiece in progress. The scene is one of tranquility and inspiration, with the artist's canvas capturing the vibrant hues of the setting sun reflecting off the tranquil sea.

Table 10: Supplement Video Qualitative Results (2/2).

H Compression Error Analysis

H.1 Analysis Overview

This section provides detailed derivations for the steady-state expected squared error bounds for the Naive Compression and Residual Compression schemes discussed in the main paper. We also analyze a hypothetical residual compression scheme without error feedback to highlight the importance of the feedback mechanism.

H.2 Definitions

We consider a function f_t as a mapping from the previous state at step $t - 1$ to the current state at step t . Let a_t denote the true activation at step t , $\tilde{a}_t$ denote the reconstructed activation after compression at step t and a_t^* denote the activation get using the reconstructed activation from last step. All of these definitions target one specific layer. When warmup step is set to 1, the first step $\tilde{a}_1 = a_1$. $\{\tilde{a}_t\}_{t=1}^T$ will be the base that is stored locally in the case of residual compression. The general relationship can be expressed as

$$a_t = f_t(a_{t-1})$$

and

$$a_t^* = f_t(\tilde{a}_{t-1}), \quad a_t^* \xrightarrow{\text{compress \& decompress}} \tilde{a}_t.$$

Then, we can use $\{a_t\}_{t=0}^T$ to denote an ideal, uncompressed sequence that is generated iteratively by the above function.

The total error is defined as the sum of the compression error and the propagation error

$$\tilde{e}_t = \tilde{a}_t - a_t = (\tilde{a}_t - a_t^*) + (a_t^* - a_t) = e_t + \eta_t,$$

where $e_t = \tilde{a}_t - a_t^*$ is the compression error and $\eta_t = a_t^* - a_t = f_t(\tilde{a}_{t-1}) - f_t(a_{t-1})$ is the propagation error. In the following derivation, $\Delta a_t = a_t - a_{t-1}$ is used to refer to the residual of true activation.

H.3 Assumptions

We adopt the following assumptions for our error bound analysis:

Assumption 1 (L -Smoothness). The function f_t is L -smooth with $L < 1$

$$\|f_t(x) - f_t(y)\|^2 \leq L^2 \|x - y\|^2 \quad \forall x, y,$$

which implies that the process contracts over time, ensuring stability.

Assumption 2 (δ -Compressor). The compressor C_δ satisfies

$$\mathbb{E}[\|C_\delta(x) - x\|^2] \leq (1 - \delta)\mathbb{E}[\|x\|^2], \quad \delta \in (0, 1],$$

where δ measures the compression quality (higher δ indicates better fidelity).

Assumption 3 (Bounded True Residual Variance). The true residuals have bounded expected energy:

$$\mathbb{E}[\|\Delta a_t\|^2] \leq \sigma_\Delta^2,$$

where σ_Δ^2 is a finite constant.

Assumption 4 (Bounded Activation Variance). The target activations have bounded expected values:

$$\mathbb{E}[\|a_t^*\|^2] \leq \sigma_a^2,$$

where σ_a^2 is a finite constant.

Assumption 5 (Uncorrelated Errors (Simplification)). We assume certain terms are uncorrelated in expectation:

- $\mathbb{E}[\langle \Delta a_t, \tilde{e}_{t-1} \rangle] = 0$ (true residual uncorrelated with previous total error),
- $\mathbb{E}[\langle \delta f_t, \Delta a_t \rangle] = 0$ (perturbation effect uncorrelated with true residual),

- $\mathbb{E}[\langle \delta f_t, \tilde{e}_{t-1} \rangle] = 0$ (perturbation effect uncorrelated with previous total error),
- Compression error and propagation error are uncorrelated.

Here, $\delta f_t = f_t(a_{t-1} + \tilde{e}_{t-1}) - f_t(a_{t-1})$ is the perturbation effect due to the error in the input to f_t

H.4 Analysis Model and Scope

Throughout this analysis, we model the evolution of the system state using the reconstructed state from the previous step, i.e., $a_t^* = f_t(\tilde{a}_{t-1})$. This means the function f_t always operates on the potentially noisy state resulting from previous compression steps.

In practical parallel implementations, such as sequence parallelism, a device might compute attention using a combination of locally available, uncompressed ("fresh") Key/Value pairs and received Key/Value pairs that have undergone compression/decompression. Our analysis, by assuming the entire input context $\tilde{a}_{t-1}$ has passed through the compression cycle, simplifies the setup and likely provides a conservative upper bound on the error compared to such mixed-context scenarios. The core principles of error propagation and the benefits of compressing smaller residuals, however, remain applicable.

H.5 Error Analysis for Naive Compression

Proposition H.1. *Let v^{naive} denote the steady-state mean squared error upper bound under naive compression. Assuming the process has reached stationarity, the error satisfies the bound*

$$v^{\text{naive}} = \frac{(1 - \delta)\sigma_a^2}{1 - L^2}, \quad \text{provided } L < 1.$$

Proof.

In the naive scheme, $\tilde{a}_t = C_\delta(a_t^*)$. The total error $\tilde{e}_t = \tilde{a}_t - a_t$ is decomposed into compression error $e_t^{\text{naive}} = \tilde{a}_t - a_t^*$ and propagation error $\eta_t = a_t^* - a_t = f_t(\tilde{a}_{t-1}) - f_t(a_{t-1})$. Assuming these errors are uncorrelated (Assumption 5):

$$\mathbb{E}[\|\tilde{e}_t\|^2] = \mathbb{E}[\|e_t^{\text{naive}}\|^2] + \mathbb{E}[\|\eta_t\|^2].$$

Using the δ -compressor property (Assumption 2) and the bounded activation variance assumption (Assumption 4), we can bound the compression error by

$$\mathbb{E}[\|e_t^{\text{naive}}\|^2] = \mathbb{E}[\|C_\delta(a_t^*) - a_t^*\|^2] \leq (1 - \delta)\mathbb{E}[\|a_t^*\|^2] \leq (1 - \delta)\sigma_a^2.$$

Using the L -smoothness assumption (Assumption 1), we can bound the propagation error by

$$\mathbb{E}[\|\eta_t\|^2] = \mathbb{E}[\|f_t(\tilde{a}_{t-1}) - f_t(a_{t-1})\|^2] \leq L^2\mathbb{E}[\|\tilde{a}_{t-1} - a_{t-1}\|^2] = L^2\mathbb{E}[\|\tilde{e}_{t-1}\|^2].$$

Combining the terms yields the recurrence

$$\mathbb{E}[\|\tilde{e}_t\|^2] \leq (1 - \delta)\sigma_a^2 + L^2\mathbb{E}[\|\tilde{e}_{t-1}\|^2].$$

Letting v^{naive} as the steady-state error upper bound and assuming $\mathbb{E}[\|\tilde{e}_t\|^2] = \mathbb{E}[\|\tilde{e}_{t-1}\|^2]$ in steady state, we obtain:

$$v^{\text{naive}} = (1 - \delta)\sigma_a^2 + L^2v^{\text{naive}}.$$

Solving for v^{naive} gives the bound

$$v^{\text{naive}} = \frac{(1 - \delta)\sigma_a^2}{1 - L^2} \quad (\text{requires } L < 1),$$

where stability requires $L < 1$. □

H.6 Error Analysis for Residual Compression

Proposition H.2. Let v^{residual} denote the steady-state mean squared error upper bound for residual compression. Assuming the process has reached stationarity, the error is bounded by

$$v^{\text{residual}} = \frac{(1-\delta)\sigma_{\Delta}^2}{1-L^2-(1-\delta)(L^2+1)}, \quad \text{provided } L^2 + (1-\delta)(L^2+1) < 1.$$

Proof.

In the residual scheme, we let $\Delta a_t^* = a_t^* - \tilde{a}_{t-1}$, $\tilde{\Delta} a_t = C_{\delta}(\Delta a_t^*)$, and $\tilde{a}_t = \tilde{a}_{t-1} + \tilde{\Delta} a_t$. The total error is $\tilde{e}_t = e_t^{\text{residual}} + \eta_t$, where $e_t^{\text{residual}} = \tilde{a}_t - a_t^* = \tilde{\Delta} a_t - \Delta a_t^*$. Follow the assumption that e_t^{residual} and η_t are uncorrelated (Assumption 5), we can get

$$\mathbb{E}[\|\tilde{e}_t\|^2] = \mathbb{E}[\|e_t^{\text{residual}}\|^2] + \mathbb{E}[\|\eta_t\|^2].$$

Using the δ -compressor property (Assumption 2):

$$\mathbb{E}[\|e_t^{\text{residual}}\|^2] \leq (1-\delta)\mathbb{E}[\|\Delta a_t^*\|^2].$$

Since

$\Delta a_t^* = f_t(\tilde{a}_{t-1}) - \tilde{a}_{t-1} = [f_t(a_{t-1} + \tilde{e}_{t-1}) - f_t(a_{t-1})] + [f_t(a_{t-1}) - a_{t-1}] - \tilde{e}_{t-1} = \delta f_t + \Delta a_t - \tilde{e}_{t-1}$, where $\delta f_t = f_t(a_{t-1} + \tilde{e}_{t-1}) - f_t(a_{t-1})$ and $\Delta a_t = a_t - a_{t-1} = f_t(a_{t-1}) - a_{t-1}$. Applying the uncorrelatedness assumptions (Assumption 5), we can further bound $\mathbb{E}[\|\Delta a_t^*\|^2]$

$$\begin{aligned} \mathbb{E}[\|\Delta a_t^*\|^2] &= \mathbb{E}[\|\delta f_t\|^2] + \mathbb{E}[\|\Delta a_t\|^2] + \mathbb{E}[\|\tilde{e}_{t-1}\|^2] \\ &\leq L^2\mathbb{E}[\|\tilde{e}_{t-1}\|^2] + \sigma_{\Delta}^2 + \mathbb{E}[\|\tilde{e}_{t-1}\|^2] \quad (\text{using Assumption 1 and Assumption 3}) \\ &= (L^2 + 1)\mathbb{E}[\|\tilde{e}_{t-1}\|^2] + \sigma_{\Delta}^2. \end{aligned}$$

Thus, the compression error is bounded by

$$\mathbb{E}[\|e_t^{\text{residual}}\|^2] \leq (1-\delta)[(L^2 + 1)\mathbb{E}[\|\tilde{e}_{t-1}\|^2] + \sigma_{\Delta}^2].$$

The propagation error term is bounded exactly as in the naive case: $\mathbb{E}[\|\eta_t\|^2] \leq L^2\mathbb{E}[\|\tilde{e}_{t-1}\|^2]$.

Combining the bounds for compression and propagation errors:

$$\mathbb{E}[\|\tilde{e}_t\|^2] \leq (1-\delta)[(L^2 + 1)\mathbb{E}[\|\tilde{e}_{t-1}\|^2] + \sigma_{\Delta}^2] + L^2\mathbb{E}[\|\tilde{e}_{t-1}\|^2].$$

Letting v^{residual} as the steady-state error upper bound and assuming $\mathbb{E}[\|\tilde{e}_t\|^2] = \mathbb{E}[\|\tilde{e}_{t-1}\|^2]$ in steady state, we obtain:

$$v^{\text{residual}} = (1-\delta)(L^2 + 1)v^{\text{residual}} + (1-\delta)\sigma_{\Delta}^2 + L^2v^{\text{residual}}.$$

Solving yields the closed-form upper bound:

$$v^{\text{residual}} = \frac{(1-\delta)\sigma_{\Delta}^2}{1-L^2-(1-\delta)(L^2+1)},$$

where stability requires:

$$1-L^2 > (1-\delta)(L^2+1).$$

H.7 Analysis Without Error Feedback

Consider a hypothetical scheme where the true residual $\Delta a_t = a_t - a_{t-1}$ is compressed and added to the previous reconstruction: $\tilde{a}_t = \tilde{a}_{t-1} + C_{\delta}(\Delta a_t)$. The error $\tilde{e}_t = \tilde{a}_t - a_t$ evolves as:

$$\tilde{e}_t = (\tilde{a}_{t-1} + C_{\delta}(\Delta a_t)) - (a_{t-1} + \Delta a_t) = (\tilde{a}_{t-1} - a_{t-1}) + (C_{\delta}(\Delta a_t) - \Delta a_t) = \tilde{e}_{t-1} + \epsilon_t,$$

where $\epsilon_t = C_{\delta}(\Delta a_t) - \Delta a_t$ is the compression error on the true residual. If we assume ϵ_t are uncorrelated over time, the expected squared error (variance) accumulates:

$$\mathbb{E}[\|\tilde{e}_t\|^2] = \mathbb{E}[\|\tilde{e}_{t-1}\|^2] + \mathbb{E}[\|\epsilon_t\|^2] \leq \mathbb{E}[\|\tilde{e}_{t-1}\|^2] + (1-\delta)\sigma_{\Delta}^2.$$

This indicates that $\mathbb{E}[\|\tilde{e}_t\|^2]$ grows linearly with t and does not converge to a finite steady state, highlighting the necessity of the error feedback mechanism (implicit in using $\tilde{a}_{t-1}$ to compute the target a_t^* and the residual Δa_t^*) for stability.

H.8 Steady-State Error Bounds

We present the derived steady-state expected squared error bounds for naive compression (v^{naive}) and residual compression with error feedback (v^{residual}), based on the given assumptions. The results are as follows.

$$v^{\text{naive}} = \frac{(1 - \delta)\sigma_a^2}{1 - L^2}, \quad v^{\text{residual}} = \frac{(1 - \delta)\sigma_{\Delta}^2}{1 - L^2 - (1 - \delta)(L^2 + 1)}.$$

Provided the stability condition for residual compression is satisfied and given that, typically, $\sigma_{\Delta}^2 \ll \sigma_a^2$, the residual scheme offers a lower theoretical error bound (although a precise comparison requires evaluating all expressions, including denominators).

I License and Asset Attribution

We use two open-source implementations in our experiments:

- **xDiT(xfuser)** [10]: A parallel diffusion inference framework released under the Apache-2.0 license.
- **DistriFusion(distrifuser)** [18]: Released under the MIT license.

Both projects are publicly available, and we have properly credited their creators in the main text. We have respected all terms of their licenses, and all usage is compliant with their respective open-source agreements. No proprietary assets or restricted-use models were used in this work.

All remaining components of CompactFusion, including our compression modules and integration layers, are implemented independently.

J Broader Impacts

CompactFusion improves the efficiency of diffusion model inference by reducing communication overhead. This can lower deployment cost and enable generative models to run on a wider range of hardware.

These improvements may help democratize access to generative AI and reduce energy consumption in large-scale deployments. We do not foresee negative societal impacts from this work.