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Department of Electronic Engineering, Tsinghua University

INFINIGENCE
无问芯穹

Generative Model Compression and Acceleration

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2024.07

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NICS EFC

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AI-Generated Content (AIGC)

AIGC, which uses generative models to generate content that satisfies human instructions, aims to make the content creation process more efficient and accessible[1].

Language Generation

Large Language Models: LLaMA-2-7B[2]

Visual Generation

Video Diffusion Models: Sora[3]

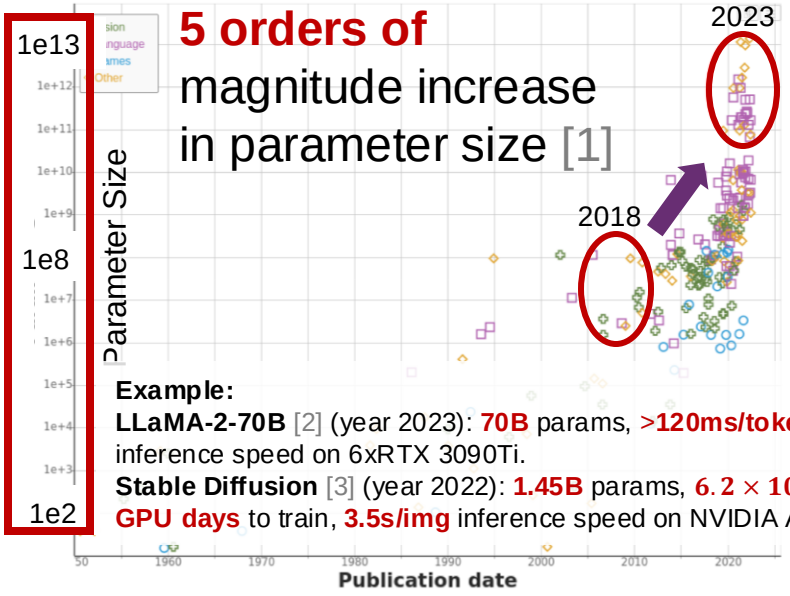
[1] Cao, Yihan, et al. "A comprehensive survey of ai-generated content (aigc): A history of generative ai from gan to chatgpt." *arXiv 2023*.
[2] Touvron, Hugo, et al. "Llama 2: Open foundation and fine-tuned chat models." *arXiv 2023*.
[3] Brooks, Peebles, et al., "Video generation models as world simulators." *2024*.

Trend of Generative Models

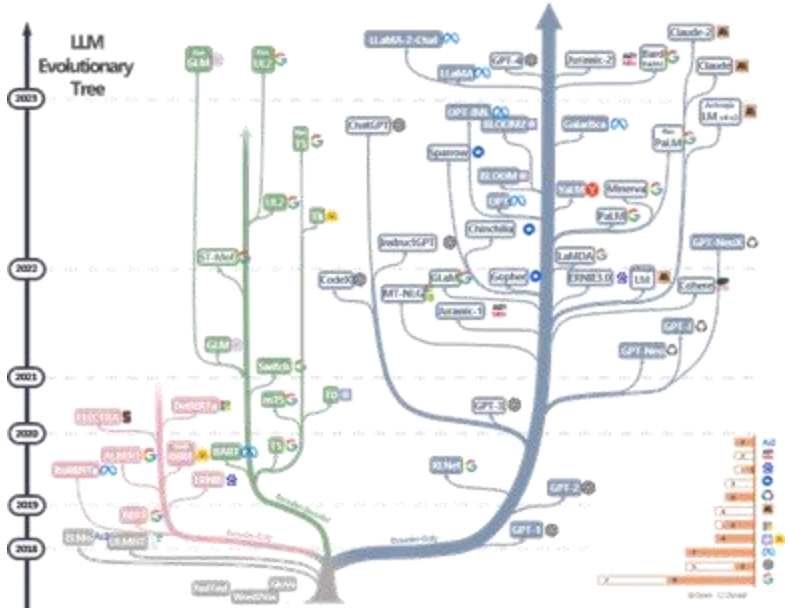
The size of generative models has being rapidly increased

2018 - 2023

5 orders of magnitude increase in parameter size [1]



Example:
LLaMA-2-70B [2] (year 2023): **70B** params, **>120ms/token** inference speed on 6xRTX 3090Ti.
Stable Diffusion [3] (year 2022): **1.45B** params, 6.2×10^3 **GPU days** to train, **3.5s/img** inference speed on NVIDIA A100.



[1] Villalobos et al. "Machine Learning Model Sizes and the Parameter Gap." arXiv preprint arXiv:2207.02852 (2022).
[2] Touvron, Hugo, et al. "Llama 2: Open foundation and fine-tuned chat models." *arXiv 2023*.
[3] Rombatch et al., High-Resolution Image Synthesis with Latent Diffusion Models, CVPR'22.
[4] Yang et al., "Harnessing the Power of LLMs in Practice: A Survey on ChatGPT and Beyond", *ACM Transactions on Knowledge Discovery from Data* (2023).

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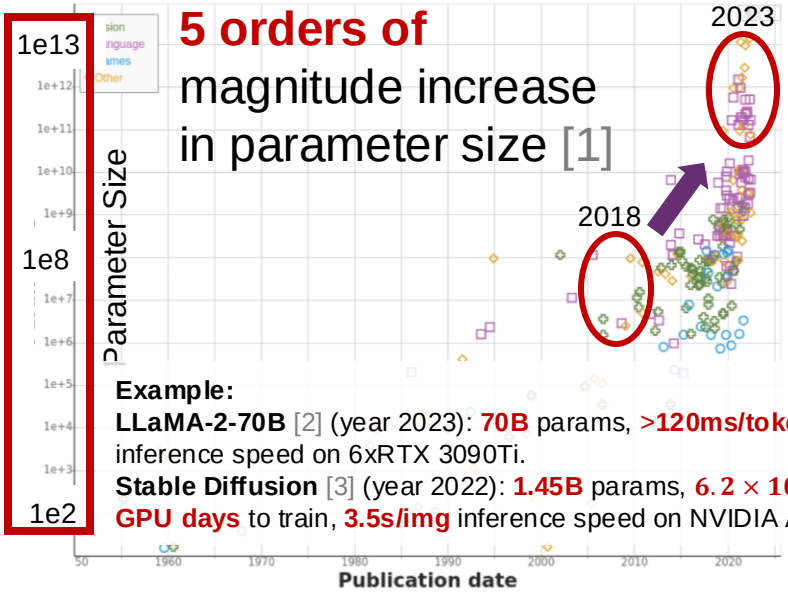

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OpenSora[4] requires **30s** and **18G VRAM** to generate one 2s video clip that contains 16 frames and has a resolution of 512x512.

[1] Villalobos et al. "Machine Learning Model Sizes and the Parameter Gap." arXiv preprint arXiv:2207.02852 (2022).
[2] Touvron, Hugo, et al. "Llama 2: Open foundation and fine-tuned chat models." *arXiv 2023*.
[3] Rombatch et al., High-Resolution Image Synthesis with Latent Diffusion Models, CVPR'22.
[4] https://github.com/hpcaitech/Open-Sora

Challenge and Research Goal

- As the model size is scaling up, the demands for computing power are increasing
- Due to real-time, usable, privacy and other application demands, physical limitations of the scenario, as well as cost control considerations, models need to be deployed on computing devices with limited computing power and low storage, and are required to run under low budgets.
- How to deploy “large” generative models and satisfy the application’s efficiency requirements while maintaining algorithmic performance?

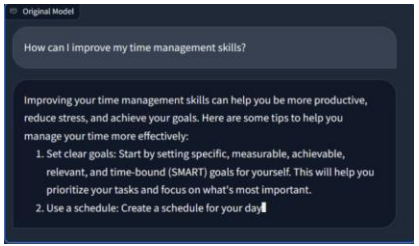
Our goal is to **improve the efficiency (e.g., latency, throughput, storage)** of generative models to satisfy the application requirement.

Research Overview

Research Goal：Efficient model inference for AIGC application

Application

Language Generation



Large Language Models
(e.g., LLaMA-2-7B)

Visual Generation

Diffusion Models
(e.g., Stable Diffusion 3)

Methodology: Hardware-aware algorithm-level and model-level optimization

Technique

Algorithm-level

Diffusion Timestep Compression — Tackling Many Timesteps of Diffusion

Non-Autoregressive Generation — Tackling Full Autoregressive Generation of LLMs

Model-level

Structure Design

Model Compression

Research Framework

Efficient Large Language Models

Overview

Survey
[TPAMI Submission]

Survey on efficient LLM inference techniques

Algorithm-level

SoT
[ICLR'24]

Parallel generation via prompting.
1.91~2.39x speed-up

Model-level

Sparse Attention

MoA
[NeurIPS Submission]

Decide the heterogeneous elastic rule of the attention span for each head.
5.5~6.7x throughput improvement

Pruning

EEP
[NeurIPS Submission]

Search the pruning pattern for MoE and use expert merging for finetuning.
48%~71% memory reduction, 1.11~1.40x speed-up, better performance

Quantization

LLM-MQ
[NeurIPS'23 Workshop]

Mixed-precision quantization.
2.8-bit quantization

QLLM-Eval
[ICML'24]

Evaluating the effect of quantization.
Providing knowledge and practical suggestions

Efficient Diffusion Models

Algorithm-level

Time Step Compression

LCSC
[ICLR Submission]

Linear combination of checkpoints.
15~23x training acceleration, 1.25~2x timestep compression

USF
[ICLR'24]

OMS-DPM
[ICML'23]

Search for optimal schedulers.
1.5~2x speed-up

Model-level

Quantization

MixDQ
[ECCV'24]

Mixed-precision quantization.
3x memory decrease, 1.5x speed-up

ViDiT-Q
[NeurIPS Submission]

Quantization for DiT.
2.5x memory improvement, 1.5x speed-up

Pruning & Sparse Attention

DiTFastAttn
[NeurIPS Submission]

Window & reused attention for DiT.
1.6x speed-up

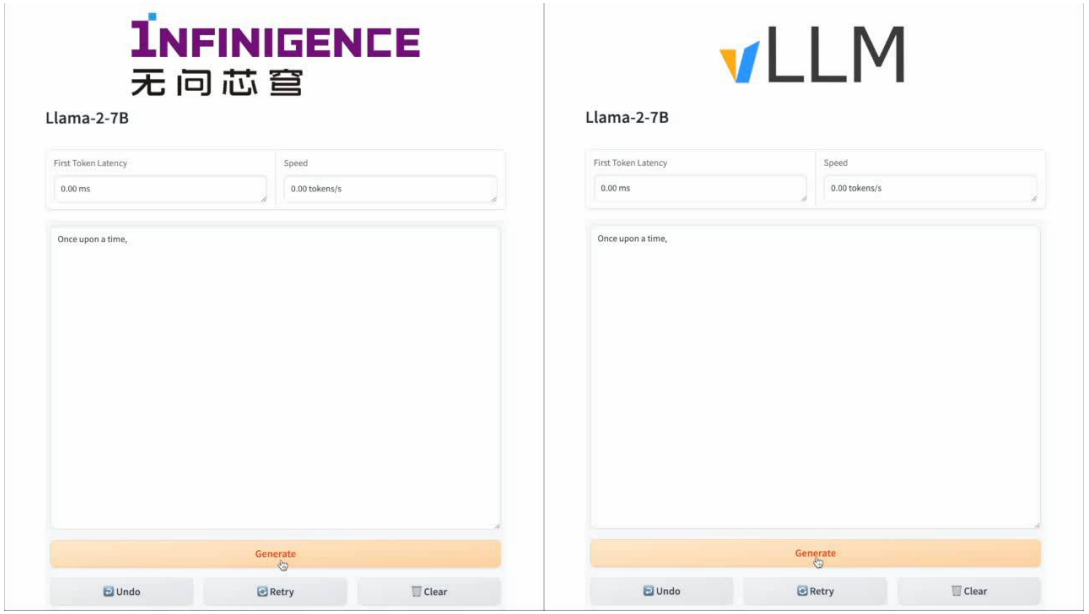
Fast Compression

FlashEval
[CVPR'24]

10x evaluation acceleration

Acceleration Demo: LLMs

Achieving 2× throughput improvement with operator optimization



LLaMA-2-7B on AMD MI210

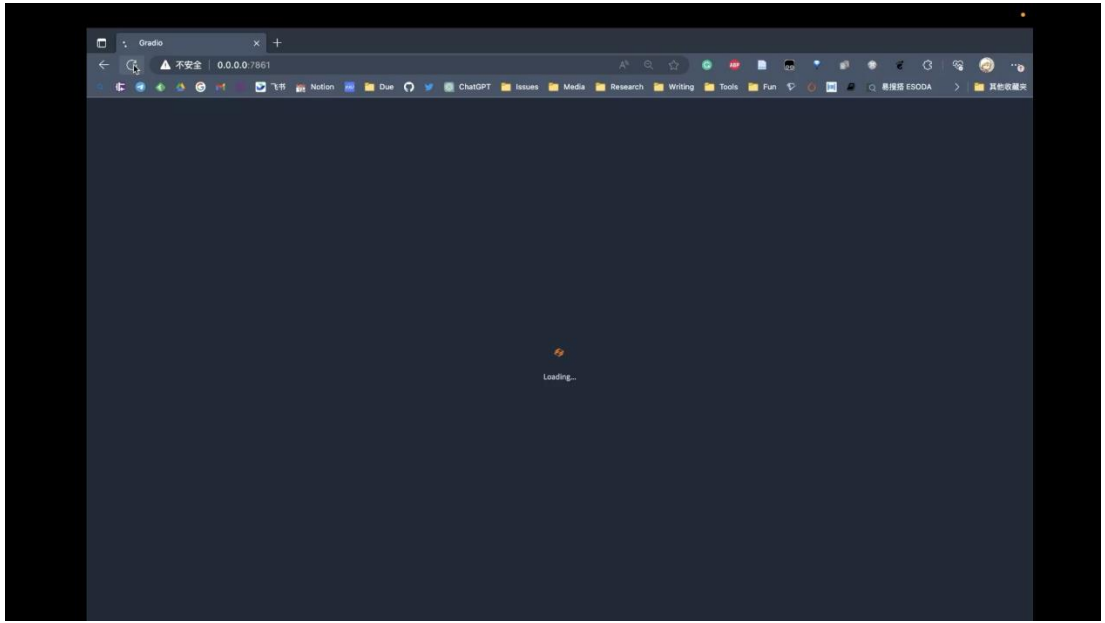
Before Acceleration (right):
39 tokens/s

After Acceleration (right):
79 tokens/s

No performance drop

Acceleration Demo: Diffusion Models

Achieving 6.9× end-to-end speed-up and reducing 1.5× memory usage with TensorRT deployment and diffusion step optimization



Stable Diffusion on a single NVIDIA A100 GPU

Before Acceleration (left):
11.7s latency, 11.9G VRAM

After Acceleration (right):
1.7s latency, 7.8G VRAM

Almost no performance drop

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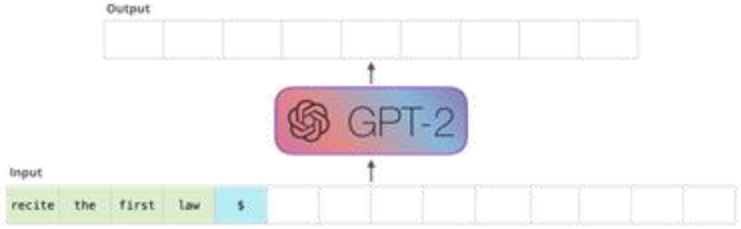
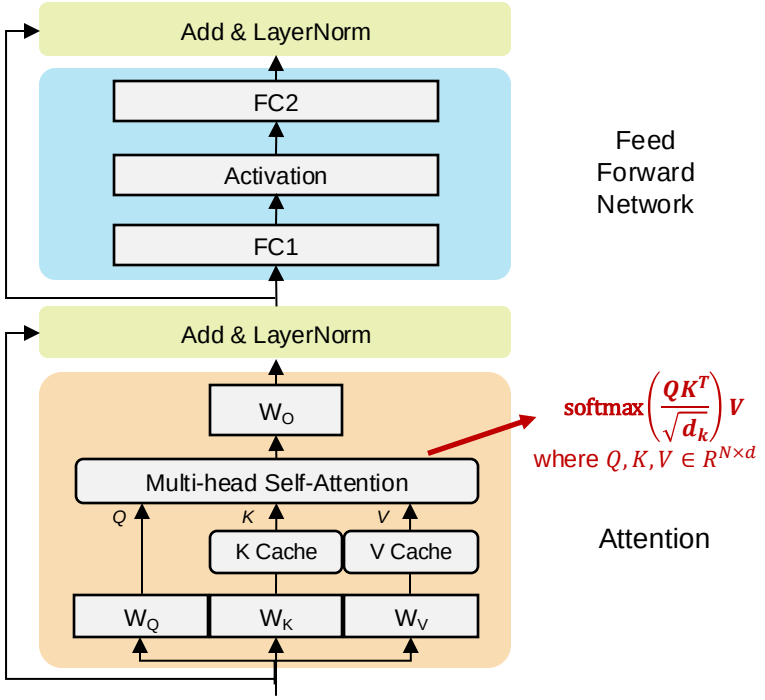
How LLMs do inference

- Most LLMs are based on the Transformer architecture[1].
- A Transformer block consists of :
  - Attention-Linear (generate matrix Q, K, V)
  - Multi-Head Attention
  - Feed Forward Network
  - Layer Norm
- A typical LLM inference process:



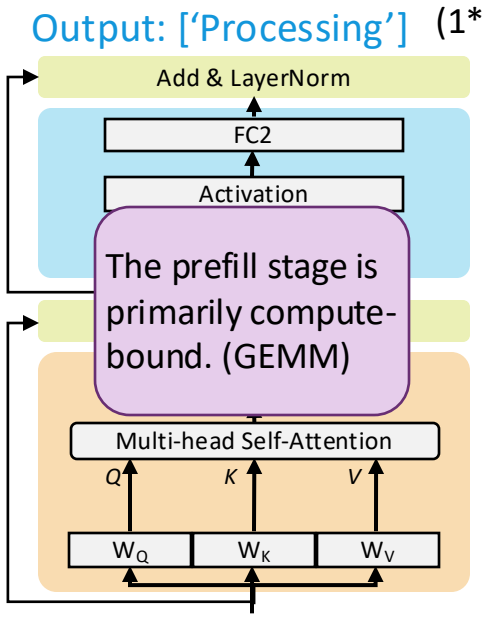
Example of Decoder's word-by-word translation



[1] Vaswani, Ashish, et al. "Attention is all you need." *NeurIPS 2023.*

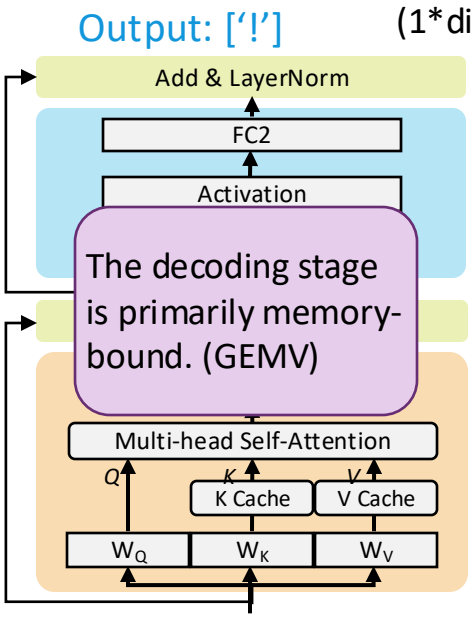
How LLMs do inference

- LLM Inference has two different stages:
- **Prefill Stage:** takes a prompt sequence to generate the key-value cache (KV Cache)



Prompt: ['I', 'like', ‘natural', ‘language’] (4*dim)

- **Decode Stage:** utilizes and updates the KV cache to generate tokens one by one, where the current token depends on all the previously tokens

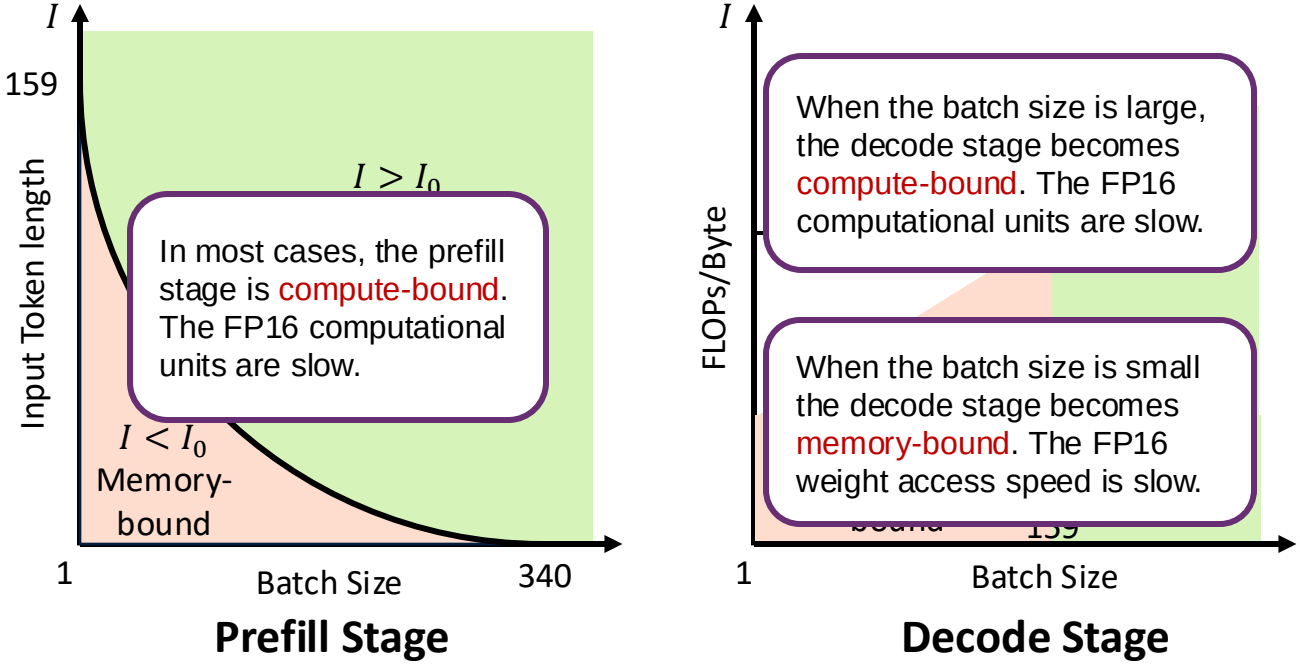


The memory overhead of KV Cache linearly grows

Prompt: [‘I’, ‘like’, ‘natural’, ‘language’, ‘Processing] (1*dim)

Efficiency Analysis of LLM Inference

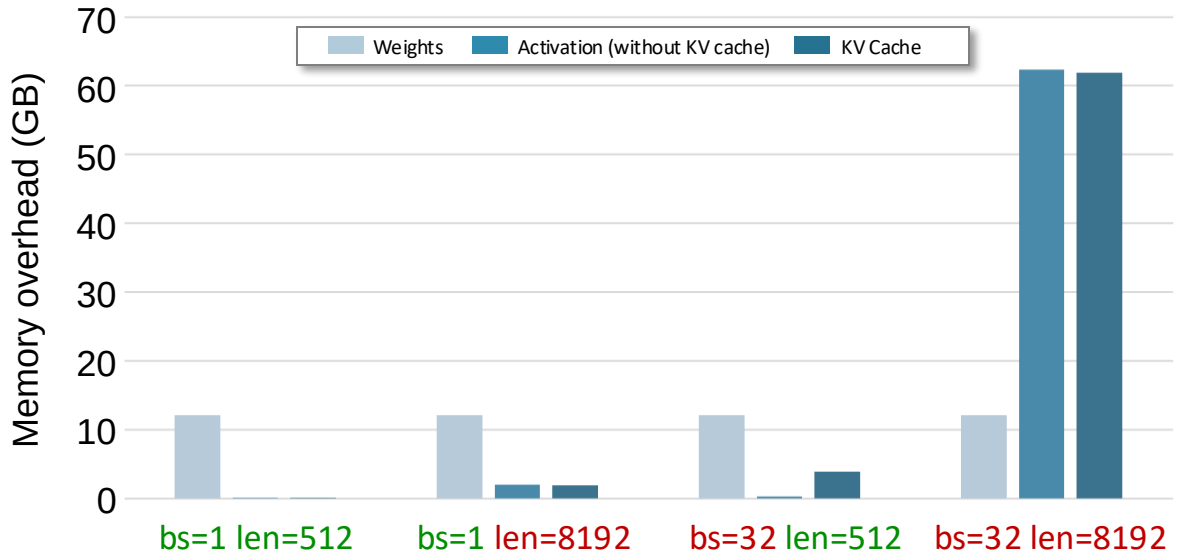
- Bottleneck Analysis of Computational Workloads
  - Take LLaMA3-70B as an example: 8192*8192 linear layer
  - A100 FP16 CUDA Core: I_0 =156 FLOPs/Byte



Efficiency Analysis of LLM Inference

- Bottleneck Analysis of Memory overhead (OPT-66B)
  - As the batch size and token length increase, the maximum memory overhead gradually shifts from weights to activations and the KV Cache.
  - Note: The main memory overhead for activations come from the O(n^2) attention matrix in the self-attention operation.

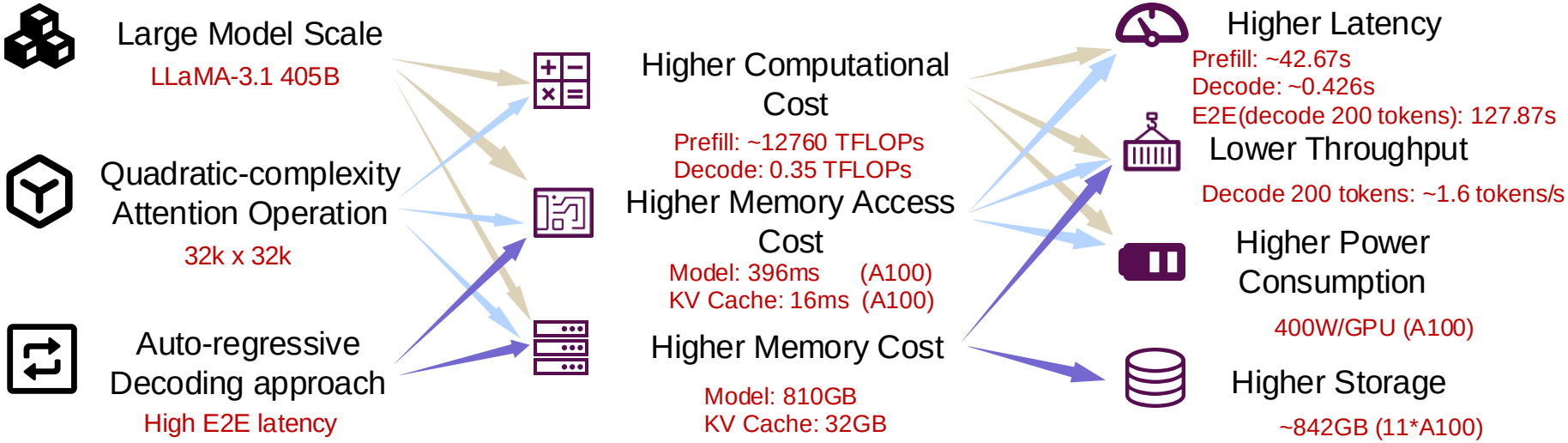
w.o. FlashAttention
(n is the input token length)



Efficiency Analysis of LLM Inference

- Root causes of inefficiency during LLM Inference
  - Model scale: A large number of weights and computations.
  - Attention operation: It has quadratic complexity *w.r.t.* input token length.
  - Decoding approach: Generate tokens one by one (fully sequential).

For example: Deploy LLaMA-3.1 405B in the cloud server



[1] Zhou, Zixuan, Ning, Xuefei, et al. "A Survey on Efficient Inference for Large Language Models." *arXiv 2024*.

Efficient Techniques for LLMs

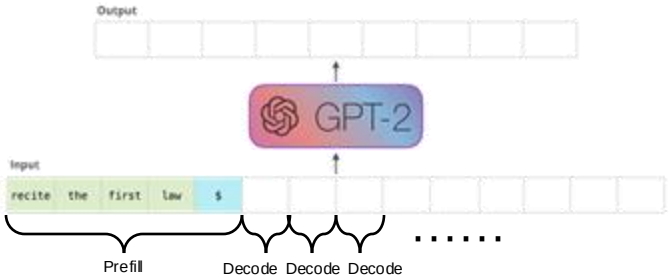
Directions to improve Large Language Models' efficiency

Prefill Stage

Reduce $t_{prefill}$, M_{weight}, M_{other_act}

Decode Stage

Reduce t_{decode}, M_{weight}, $M_{kv\ cache}$



Overall Cost

(for each request)

Total Latency: $t_{prefill} + t_{decode} * N_{token}$

Total Memory: $M_{weight} + M_{kv\ cache} + M_{other\_act}$

Overview of Efficient Techniques

Lower Latency | Lower Storage | Higher Throughput | Lower Power Consumption

What algorithm property?	Cause what?	Solutions
Model Scale	• Large computation • Large memory access • Large memory footprint	Data-level Optimization: Input Compression, Output Organization
Attention Operation	• Input-quadratic computation • Input-quadratic memory access • Input-quadratic memory footprint	Model-level Optimization: Structure Design, Model Compression
Decoding Approach	• Low arithmetic intensity (i.e., computation / memory access) cause under-utilization • Varying length -> Dynamically increasing KV cache cause fragmented memory, increasing both footprint and access	System-level Optimization: Inference Engine, Serving Framework

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Model Scale	• Large computation • Large memory access • Large memory footprint	• Prompt pruning • Soft prompt tuning • … → Input Compression • Output Organization → Output Organization
Attention Operation	• Input-quadratic computation • Input-quadratic memory access • Input-quadratic memory footprint	• Dynamic MoE • Low-complexity attention → Structure Design • Quantization • Sparse Attention • Weight Pruning → Model Compression • …
Decoding Approach	• Low arithmetic intensity (i.e., computation / memory access) cause under-utilization • Varying length -> Dynamically increasing KV cache cause fragmented memory, increasing both footprint and access	• Graph and Operator Optimization → Inference Engine • Speculative decoding • Memory Management → Serving Framework • Batching • …

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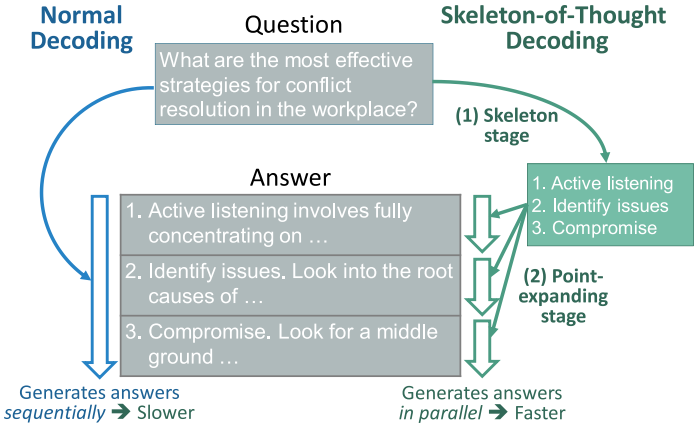
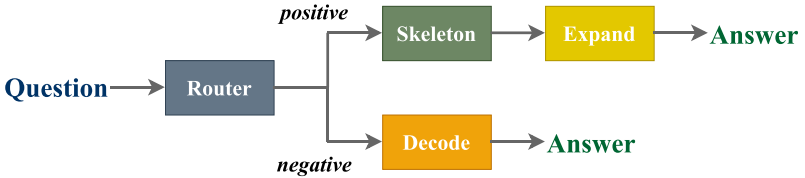
Skeleton-of-Thought (SoT)

- Skeleton-of-Thought (SoT) consists of two stages:
  (1) **Skeleton Stage**: Guide the LLM to output a concise skeleton of the answer.
  (2) **Point-expanding Stage**: Guide the LLM to expand on each point from the skeleton in parallel.
- SoT can improve the hardware utilization and decrease the end-to-end latency.





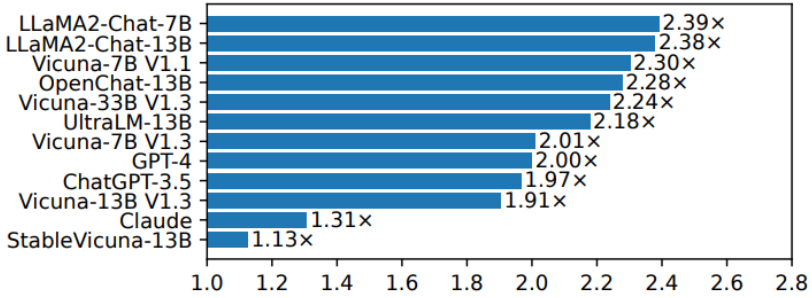
We further extend **SoT with router (SoT-R)** to make the overall solution more practical.

- The router first decides whether to apply the SoT decoding mode based on the user's prompt.

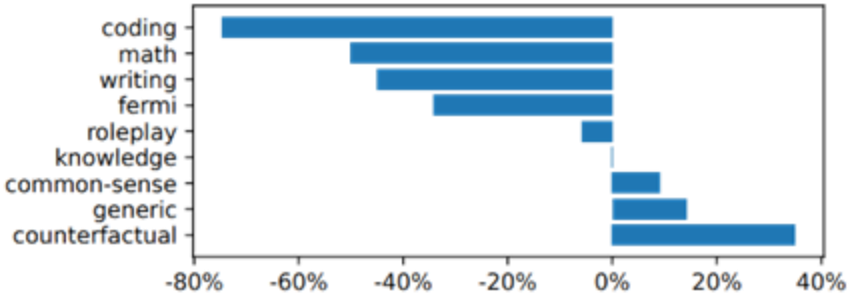
[1] Ning, Xuefei, et al. "Skeleton-of-Thought: Large Language Models Can Do Parallel Decoding." ***ICLR 2024*****.**

Skeleton-of-Thought (SoT)

- Overall evaluation framework
  - 12 fashion LLMs, including 9 open-source models and 3 API-based models
  - 2 evaluation frameworks: FastChat and LLMZoo
  - 3 evaluation datasets: Vicuna-80 and WizardLM
- Evaluation of efficiency and answer quality (on Vicuna-80)
  - SoT achieves up to 2.39× speed-ups and obtains more than 1.9× speed-ups on nine LLMs.
  - SoT can improve the diversity and relevance of the answer by explicitly organizing the content.



End-to-end speed-ups
on different LLMs

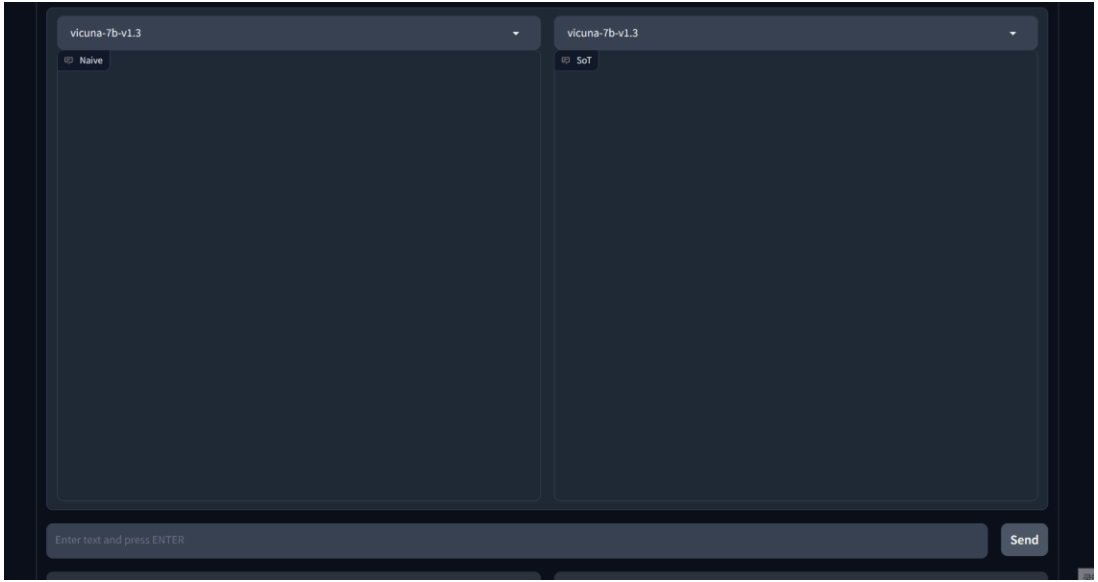


Answer Quality
on different question categories

[1] Ning, Xuefei, et al. "Skeleton-of-Thought: Large Language Models Can Do Parallel Decoding." ***ICLR 2024*****.**

Skeleton-of-Thought (SoT)

Accelerating LLM inference by up to 2.39× end-to-end speed-up *without* any changes to their model, system, or hardware



Vicuna-7B model on one A100 GPU: 2.1× end-to-end speed-up compared with sequential decoding

[1] Ning, Xuefei, et al. "Skeleton-of-Thought: Large Language Models Can Do Parallel Decoding." *ICLR 2024*.

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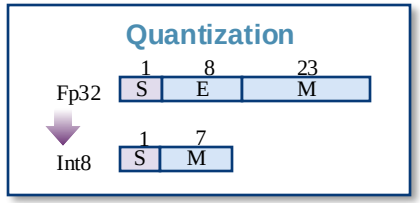
Quantization Technique

- Quantization is a promising technique to address the aforementioned efficiency issues.
  - Taking **signed uniform** quantization as an example, quantization parameters include

Scaling Factor, **Zero Point,** **Bitwidth**

$$x_{\text{int}} = \text{clip}\left(\left\lfloor \frac{x}{s_x} \right\rceil + z; q_{\min}, q_{\max}\right), \quad \text{where } q_{\max} = 2^{b-1} - 1, \; q_{\min} = -2^{b-1}$$



  - The Weight-Activation Quantization methods enable the utilization of low-precision Tensor Cores to mitigate the compute-bounded GEMM operators in the prefill stage.
  - The Weight-only Quantization methods prove effective to accelerate the memory-bounded GEMV operators in the decoding stage.
  - The KV Cache Quantization methods are necessary to alleviate the large memory overhead when handling tasks with long contexts or large batch sizes.

Mixed-precision Quantization (LLM-MQ)

Expected to accelerate linear operators by 1.9~2.7× speed-up via mixed-precision quantization and sparse outliers protection technique

- Assign high bit-width to high-sensitivity layers in order to minimize the change in model output.
  - Use first-order information to estimate the sensitivity:

$$\mathcal{L}(Q_b(\mathbf{W}_i)) \approx \mathcal{L}(\mathbf{W}) + \mathbf{g}_i^T(\mathbf{W}_i - Q_b(\mathbf{W}_i)),$$

  - For each layer, w

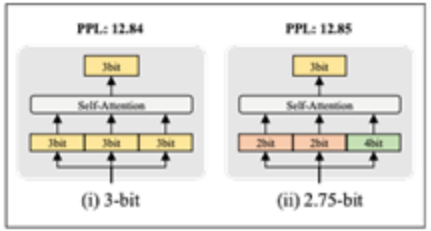
$$\min |\mathcal{L}(Q_b(\mathbf{W}_i))| \leq |\mathcal{L}(\mathbf{W}$$

  - We model the ab
    following integer

$$\arg\min_{c_{i,b}} \sum_i^N \sum_b c_{i,b} \cdot s_{i,b},$$

$$s.t. \sum_b c_{i,b} = 1, \quad \sum_i^N \sum_b c_{i,b} \cdot \mathcal{M}(Q_b(\mathbf{W}_i)) \leq \mathcal{B},$$

$$c_{i,b} \in \{0,1\}, b \in \{2,3,4\},$$



- For zero-shot understanding tasks:
  - When the average accuracy loss is around 0.1%, the model can be quantized to an average of 3.6 bits.
  - When the average accuracy loss is around 1%, the model can be quantized to an average of 2.8 bits.

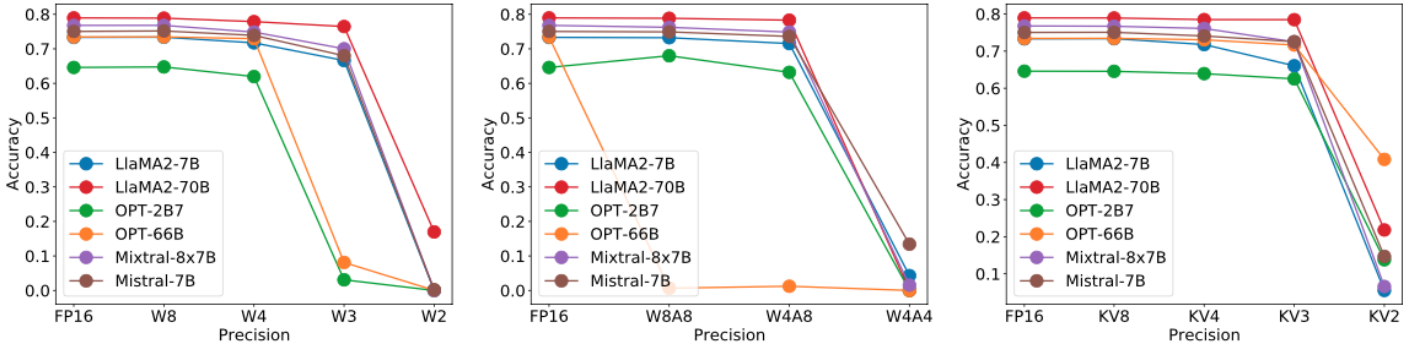
Does the accuracy on specific tasks sufficiently reflect the **effect of quantization** on LLMs?

							okqa	Avg. (↑)	Wiki (↓)
							0	65.08	7.89
							0	64.67	8.12
							0	63.23	9.26
							0	41.74	1056.33
							0	65.03	8.08
							0	64.02	8.81
							60	37.06	5e6
LLM-MQ (Ours)	4.0	79.49	76.31	69.30	58.50	41.20		64.96	8.03
	3.8	79.22	76.22	69.85	58.29	41.40		65.00	8.08
	3.6	79.05	75.88	69.77	58.59	42.20		65.10	8.23
	3.4	79.49	74.77	69.61	58.12	40.60		64.52	8.61
	3.2	79.33	75.12	67.96	57.87	41.60		64.38	8.43
	3.0	79.00	75.08	68.59	57.79	41.00		64.29	8.54
	2.8	78.73	74.32	67.96	57.95	41.20		64.03	8.83
	2.6	78.35	73.81	68.03	57.32	39.40		63.38	9.35
	2.4	77.31	72.93	68.59	54.63	40.00		62.69	10.03
	2.2	76.77	70.83	67.09	55.26	38.40		61.67	10.80
	2.0	75.84	68.32	65.51	54.29	37.20		60.23	12.17

[1] Li, Ning et. al., "LLM-MQ: Mixed-precision Quantization for Efficient LLM Deployment." *NeurIPS Workshop' 23*

Evaluating Quantized LLMs (QLLM Eval)

- Effects of Quantization on Tensor Types
  - The larger the model size, the higher the tolerance for Weight and KVcache Quantization, and the lower the tolerance for Activation Quantization.
  - The larger the model size, the fewer outliers in the Weight and KV Cache tensors, and the more outliers in the Activation tensors.

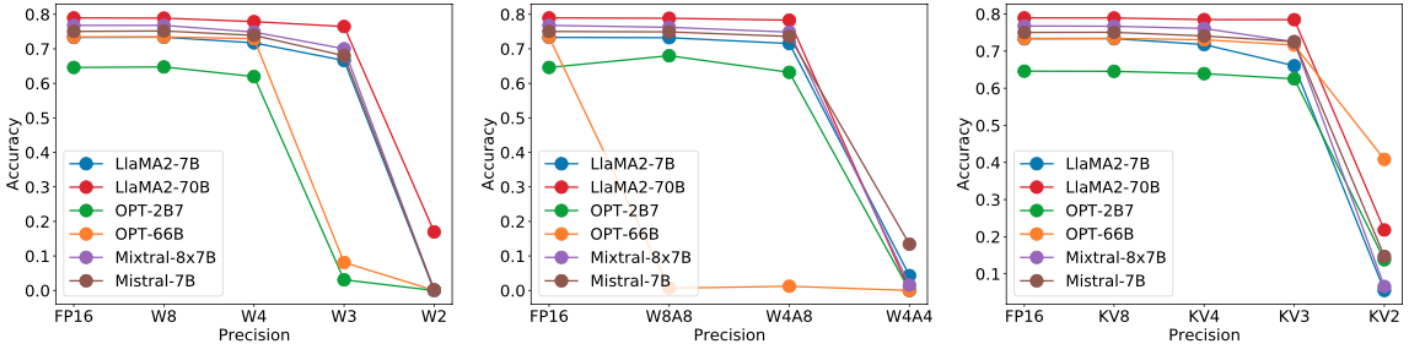


(a) Weight-only Quant. (b) Weight-Activation Quant. (c) KV Cache Quant.

[1] Li, Shiyao, Ning, Xuefei, et al. "Evaluating Quantized Large Language Models." *ICML2024*.

Evaluating Quantized LLMs (QLLM Eval)

- Effects of Quantization on Different LLMs
  - For the majority of models, the performance order of the quantized models is generally consistent with that of the original models.
  - Leveraging the Mixture-of-Experts (MoE) technique to increase the model size does not necessarily enhance the model's tolerance to quantization.

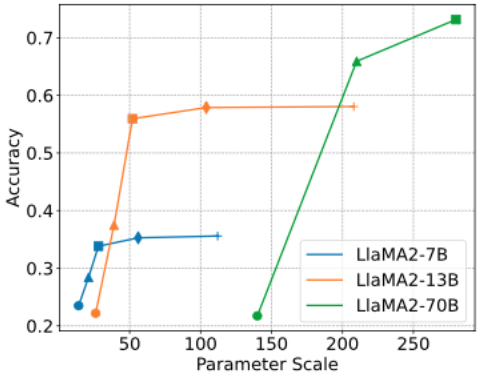


(a) Weight-only Quant. (b) Weight-Activation Quant. (c) KV Cache Quant.

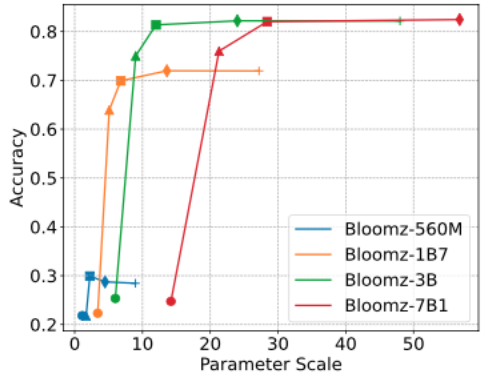
[1] Li, Shiyao, Ning, Xuefei, et al. "Evaluating Quantized Large Language Models." *ICML2024*.

Evaluating Quantized LLMs (QLLM Eval)

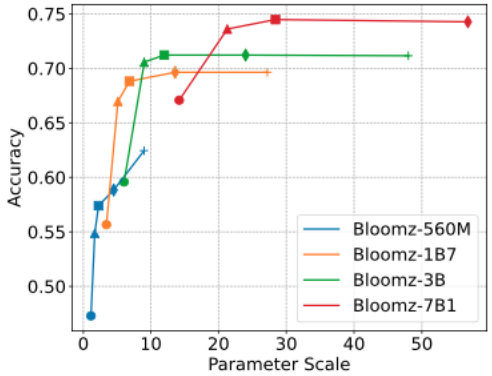
- Effects of Quantization on Different Tasks
  - For most cases, quantizing LLMs to W4, W4A8, and KV4 has negligible performance loss.



(a) Q-LlaMA2 families on the RACE task



(b) Q-Bloomz families on the RACE task

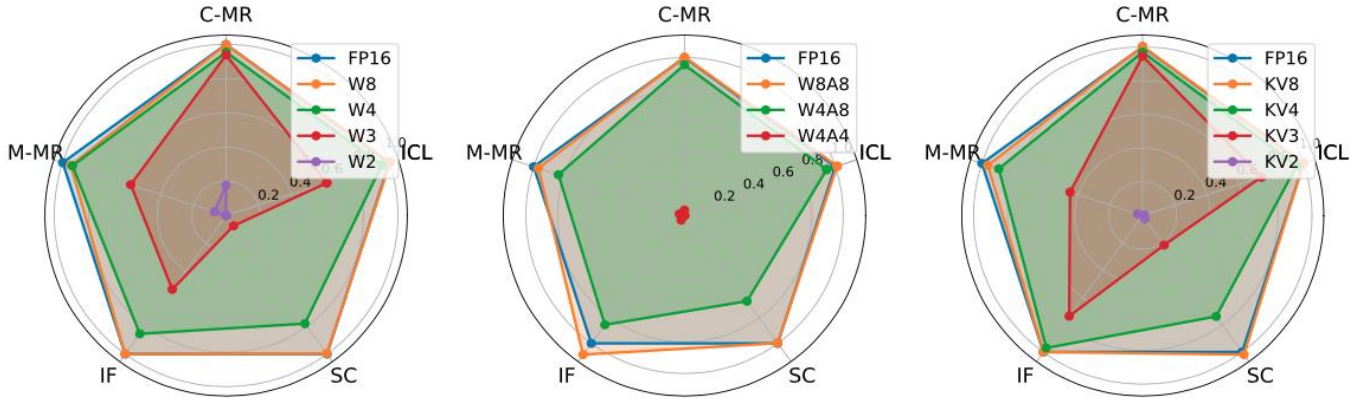


(c) Q-Bloomz families on the PIQA task

[1] Li, Shiyao, Ning, Xuefei, et al. "Evaluating Quantized Large Language Models." ***ICML2024*****.**

Evaluating Quantized LLMs (QLLM Eval)

- Effects of Quantization on Emergent Abilities
  - The tolerance to quantization varies across the four abilities, listed in descending order of tolerance: In-context Learning ~ Instruction Following > Multi-Step Reasoning ~ Self-calibration.

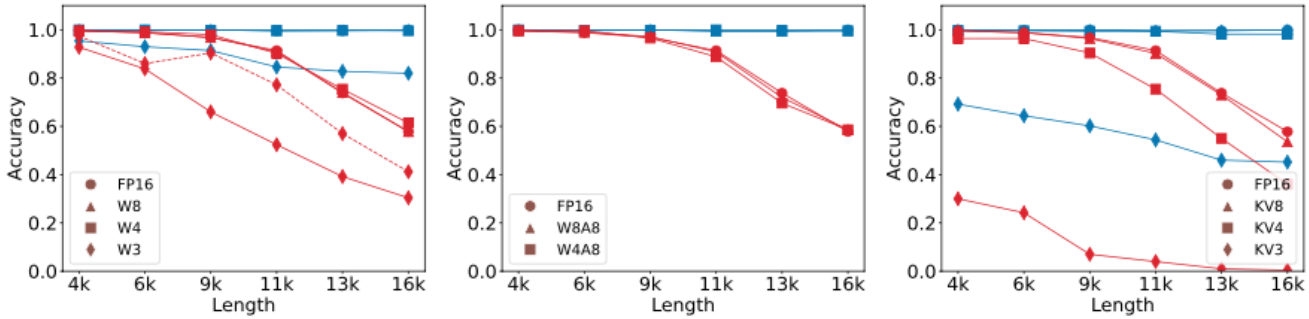


(a) Weight-only Quant. on LLaMA2-7B (b) Weight-Activation Quant. on LLaMA2-7B (c) KV Cache Quant. on LLaMA2-7B

[1] Li, Shiyao, Ning, Xuefei, et al. "Evaluating Quantized Large Language Models." ***ICML2024*****.**

Evaluating Quantized LLMs (QLLM Eval)

- Effects of Quantization on Long-Context Modeling Abilities
  - The performance of LLMs on lengthy texts (>4k) is more sensitive to weight-only and KV cache quantization than short texts (<4k).
  - For long-context tasks, most LLMs are more sensitive to KV Cache quantization than Weight-only and Weight-Activation Quantization.
  - For long-context tasks (>4K), we recommend applying W4, W4A8 and KV8.



(a) Weight-only Quant. (b) Weight-Activation Quant. (c) KV Cache Quant.

[1] Li, Shiyao, Ning, Xuefei, et al. "Evaluating Quantized Large Language Models." *ICML2024*.

Evaluating Quantized LLMs (QLLM Eval)

- Knowledge summary

Knowledge Level	Key Knowledge
Tensor-level	**1. Tensor type (Sec. 3.2)**: The larger the model, the higher the tolerance for Weight-only and KV Cache Quantization, while the tolerance for Activation Quantization is lower. **2. Tensor position (Sec. 3.2)**: The sensitivity to quantization varies significantly across different tensor positions due to their distinct data distributions.
Model-level	**1. (Sec. 3.3)** The relative rankings of quantized LLMs are generally consistent with those of the FP16 LLMs when the bit-width is higher than W4, W4A8, and KV4. **2. (Sec. 3.3)** Leveraging MoE to increase the model size can improve the model's performance but may not improve the tolerance to quantization.
Task-level	**1. Emergent abilities (Sec. 4)**: The tolerance of Multi-Step Reasoning and Self-Calibration to quantization is lower than that of Instruction-Following and In-Context Learning abilities. **2. Dialogue tasks (Sec. 6)**: As the bit-width decreases, sentence-level repetition occurs first, followed by token-level repetition, and token-level randomness. **3. Long-Context tasks (Sec. 7)**: The longer the text, the larger the performance loss caused by Weight and KV Cache quantization. Most LLMs are more sensitive to KV Cache Quantization than Weight-only and Weight-Activation Quantization.
Bit-width Recommendation	**1. Basic NLP tasks (Sec. 3)**: W4, W4A8, KV4, W8KV4. **2. Emergent (Sec. 4)**: W8, W8A8, KV8 ($<$ 13B); W4, W4A8, KV4 ($\geq$ 13B). **3. Trustworthiness (Sec. 5)**: W8, W8A8, KV8 ($<$ 7B); W4, W4A8, KV4 ($\geq$ 7B). **4. Dialogue (Sec. 6)**: W8, W8A8, KV4. **5. Long-Context (Sec. 7)**: W4, W4A8, KV4 (token $<$ 4K); W4, W4A8, KV8 (token $\geq$ 4K). *(Note: Within 2% accuracy loss on the evaluated tasks. The recommended quantization bit-width may not generalize to other LLMs or tasks)*

[1] Li, Shiyao, Ning, Xuefei, et al. "Evaluating Quantized Large Language Models." ***ICML2024*****.**

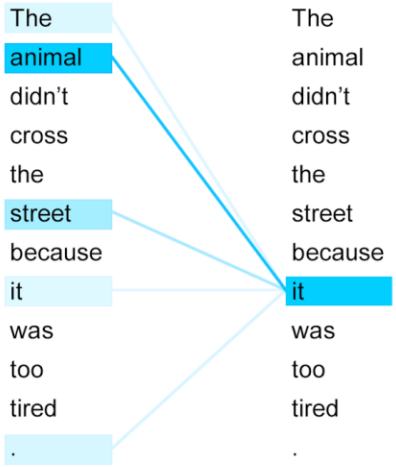
Overview of Efficient Techniques

Lower Latency | Lower Storage | Higher Throughput | Lower Power Consumption

What algorithm property?	Cause what?	Solutions
Model Scale	• Large computation • Large memory access • Large memory footprint	• Prompt pruning • Soft prompt tuning • … • Output Organization → Input Compression, Output Organization
Attention Operation	• Input-quadratic computation • Input-quadratic memory access • Input-quadratic memory footprint	• Dynamic MoE • Low-complexity attention • Quantization • **Sparse Attention** • Weight Pruning • … → Structure Design, Model Compression
Decoding Approach	• Low arithmetic intensity (i.e., computation / memory access) cause under-utilization • Varying length -> Dynamically increasing KV cache cause fragmented memory, increasing both footprint and access	• Graph and Operator Optimization • Speculative decoding • Memory Management • Batching • … → Inference Engine, Serving Framework

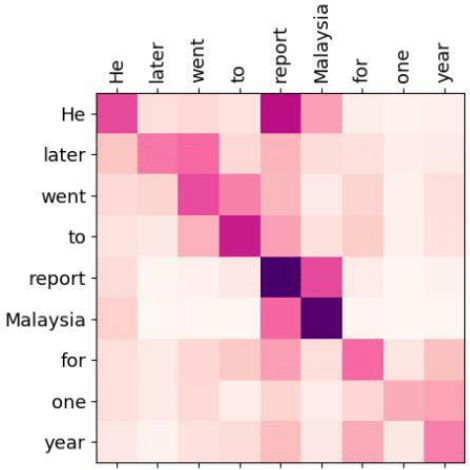
[1] Zhou, Zixuan, Ning, Xuefei, et al. "A Survey on Efficient Inference for Large Language Models." *TPAMI Submission*.

Attention Mechanism



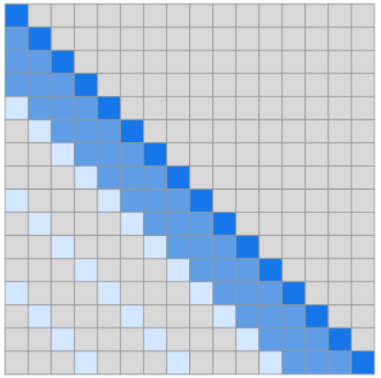
Attention Mechanism

each word "looks at" other words in the sentence to determine their **relevance** (attention value) to the current word.



Attention Matrix

Represents the **relevance** between word pairs with **matrix**, showing the the attention values.



Sparse Attention

Each word doesn't need to focus on all words, **only a few relevant** ones, such as nearby context.*

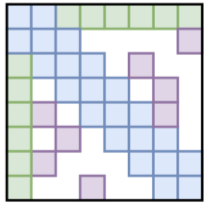
*Child, Rewon et al. "Generating Long Sequences with Sparse Transformers." *ArXiv* abs/1904.10509 (2019): n. pag.

Sparse Attention Methods

For language understanding models, like BERT

For generative large language models, like GPT

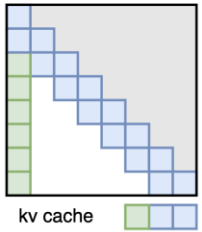
local global random



design the **unified static** mask to reduce attention computation **during prefill**

BigBird
2020.7

local global



design the **unified static** mask to reduce attention computation and KV-cache **during prefill and decode**

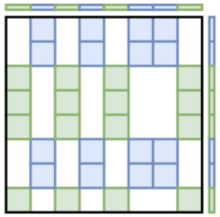
StreamingLLM
2023.9

static

dynamic

Reformer
2020.2

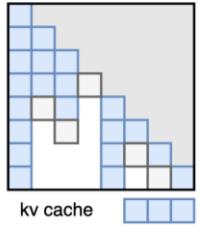
different buckets



compute attention within the same bucket, **dynamically** allocate tokens to a **unified** number of buckets **during prefill**

H2O
2023.6

preserved pruned



dynamically prune previous tokens at a **unified** ratio in the KV-cache **during decode**

[1] Kitaev, Nikita, Łukasz Kaiser, and Anselm Levskaya. "Reformer: The efficient transformer." arXiv preprint arXiv:2001.04451 (2020).
[2] Zaheer, Manzil, et al. "Big bird: Transformers for longer sequences." Advances in neural information processing systems 33 (2020): 17283-17297.
[3] Zhang, Zhenyu, et al. "H $_2$ O: Heavy-Hitter Oracle for Efficient Generative Inference of Large Language Models." arXiv preprint 2306.14048 (2023).
[4] Xiao, Guangxuan, et al. "Efficient Streaming Language Models with Attention Sinks." The Twelfth International Conference on Learning Representations.

The Local Context Problem

needle-in-a-haystack task

Below is a record of lines I want you to remember. For each line index, memorize its corresponding <REGISTER_CONTENT>.

long context

line funny-boy: REGISTER_CONTENT is <34836>
line cute-chicken: REGISTER_CONTENT is <28499>
…
line **lovely-dog**: REGISTER_CONTENT is **<28840>**
…
line small-bug: REGISTER_CONTENT is <23550>

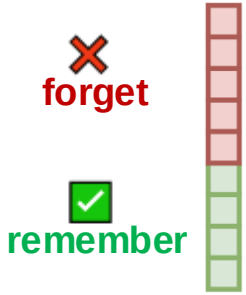
Tell me what is the <REGISTER_CONTENT> in line lovely-dog? I need the number.

The <REGISTER_CONTENT> is **<28840>** ✓

The <REGISTER_CONTENT> is **<23550>** ×

local attention, local context

local attention[1]
+ global attention on initial tokens

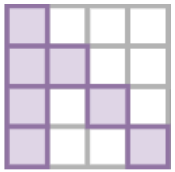


LLM **forgets** the context beyond the **attention span**

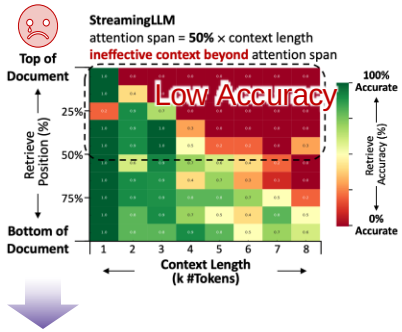
[1] Xiao, Guangxuan, et al. "Efficient Streaming Language Models with Attention Sinks." The Twelfth International Conference on Learning Representations.

Mixture of Attention (MoA)

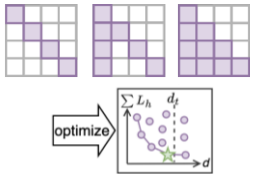
Improve the throughput of LLM inference by 5.5~6.7× via automatic sparse attention configurations for each attention layer and head.



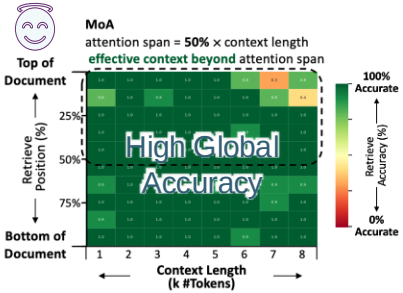
2024 SreamingLLM [1]
Unified Mask



Local attention overhead, **global** retrieval ability

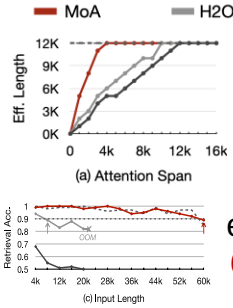


INFINIGENCE 无问芯穹 2024
Mixture of Attention [5]



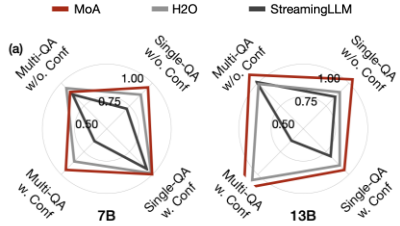
Size	Framework	Memory (GB) 4k	8k	16k	Throughput (tok/s) 4k	8k	16k
7B	FlashAttn2	28.5	44.4	76.3	134.6	66.9	32.9
	H2O	36.9	OOM	OOM	754.9	296.3	51.7
	MoA	**22.7**	**32.9**	**53.5**	**897.7**	**436.7**	**206.4**
13B	FlashAttn2	36.8	49.2	74.0	81.3	40.8	19.8
	H2O	40.4	77.9	OOM	330.2	138.2	37.4
	MoA	**32.0**	**39.6**	**55.0**	**471.5**	**222.6**	**108.3**

For 7B and 13B models at 50% sparsity, memory usage reduced by **1.2x-1.4x**; throughput increases by **5.5x-6.7x** over FlashAttention.



3.9x effective context length

effective at up to **60k** input length



At 50% sparsity, LV-Eval score impact **<5%** (36% for streamingLLM).

[1] Fu, Tianyu, Huang, Hoafeng, Ning, Xuefei, et al. "MoA: Mixture of Sparse Attention for Automatic Large Language Model Compression." *NeurIPS Submission*.

Mixture of Attention (MoA)

INFINIGENCE 无问芯穹

Step1: Dataset

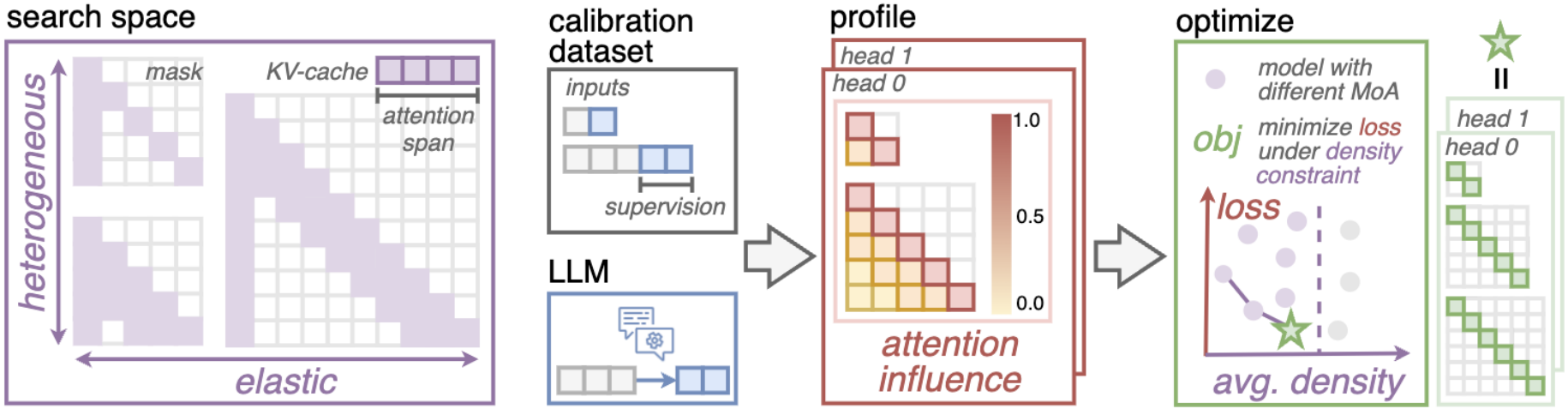
Construct calibration dataset using **long-contextual** MultiNews dataset along with **summarizations generated by original LLM.**

Step2: Profile

Automatically quantify the **influence** of different attention values in LLM on final prediction results, , producing **accuracy-density trade-offs** curves for all schemes.

Step3: Optimize

Select the **optimal elastic rule** for each attention head to **minimize the overall accuracy impact** at a given sparsity level across input lengths.



With the masks, large models can **skip** the corresponding attention **computations** and **KV-Cache**, achieving inference efficiency optimization **without needing additional training.**

Overview of Efficient Techniques

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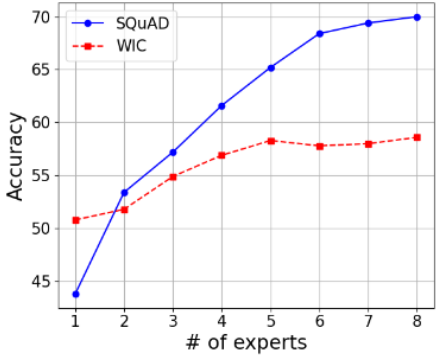
[1] Zhou, Zixuan, Ning, Xuefei, et al. "A Survey on Efficient Inference for Large Language Models." *TPAMI Submission*.

Efficient Expert Pruning (EEP)

Construct search space of expert merging and search for coefficients.
Can be used to prune active/total expert num.

Adjust number of active expert



Key Observations:

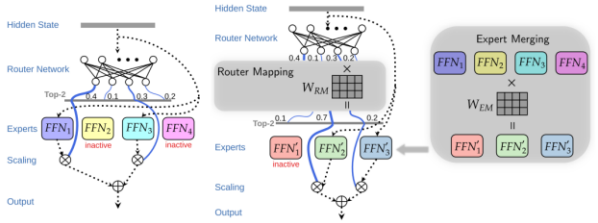
1. Inactive expert can benefit
2. Redundancy exists

Search Space

1. Weight Merging Matrix
2. Routing weights transformation

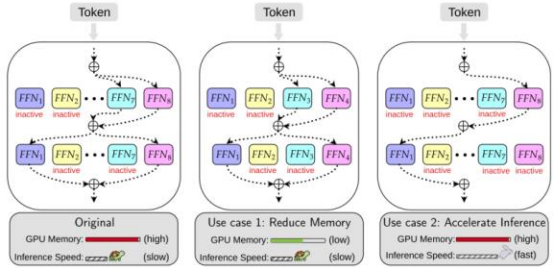
Search Process

1. Discrete (only prune)
2. Continuous (expert merging)



Use Cases

1. Reduce total expert
2. Reduce active expert



[1] Enshu Liu*, Junyi Zhu*, Zinan Lin+, Xuefei Ning+, et al. "Efficient Expert Pruning for Sparse Mixture-of-Experts Language Models: Enhancing Performance and Reducing Inference Costs " *NeurIPS Submission*.

Efficient Expert Pruning (EEP)

EEP prunes 75%/50% total/active expert while achieves comparable and even better performance. EEP can generalize well on OOD data.

Reduce Total Experts

Expert	Method	COPA	MultiRC	WIC	WSC	RTE	BoolQ	CB	ReCoRD	DROP	SQuAD	Avg.
Num=8	Full Model	89.0	83.0	51.8	63.5	73.2	77.4	51.7	50.3	30.6	53.4	62.4
Num=4	Random	63.8	49.4	37.6	43.3	45.1	50.2	38.7	35.1	27.4	58.3	44.9
	Frequency [37]	63.0	74.8	36.0	34.6	18.1	71.0	30.4	41.6	29.9	58.2	45.8
	Soft Activation [37]	73.0	30.6	51.4	37.5	41.9	40.4	17.9	36.8	33.3	10.2	37.3
	NAEE [34]	87.0	76.0	52.6	64.5	61.7	77.2	51.7	50.4	30.6	53.0	60.5
	EEP (Prune Only)	95.0	81.2	57.8	67.3	74.0	82.8	69.6	60.0	37.3	75.2	70.3
	EEP (Prune+Merge)	**99.0**	**84.6**	**65.0**	**73.1**	**76.9**	**84.8**	**75.0**	**63.6**	**39.7**	**80.6**	**74.2**
Num=2	Random	36.8	22.3	13.6	15.0	28.4	15.5	38.6	16.9	18.3	36.9	24.2
	Frequency [37]	51.0	17.6	8.8	1.9	48.4	30.6	35.7	10.4	14.9	9.2	24.9
	Soft Activation [37]	33.0	18.2	49.4	18.5	15.2	1.8	32.1	4.4	11.7	50.0	23.4
	NAEE [34]	75.0	42.4	48.4	49.0	54.5	49.8	19.6	42.0	31.2	58.2	47.0
	EEP (Prune Only)	76.0	63.8	51.8	63.5	64.3	70.6	58.9	47.2	37.1	64.0	59.7
	EEP (Prune+Merge)	**93.0**	**71.6**	**58.6**	**65.4**	**69.0**	**75.6**	**66.1**	**47.2**	**38.4**	**70.2**	**65.6**

Reduce Active Experts

Total	Active	Method	WIC	WSC	BoolQ	CB	SQuAD	Avg.
8	2	Full Model	51.8	63.5	77.4	51.7	53.4	59.6
	1	Full Model	50.8	48.1	66.0	48.2	43.8	51.4
	1.4∼1.5	Dyn [34]	50.0	59.6	72.8	46.4	44.8	54.7
	1	EEP	**59.2**	**70.2**	**79.0**	**66.1**	**51.8**	**65.3**
4	1	NAEE [34]	48.6	20.2	56.2	33.9	51.8	42.1
	1.4∼1.5	NAEE+Dyn [34]	43.4	61.5	36.2	53.6	53.4	49.6
	1	EEP	**55.8**	**70.2**	**74.4**	**64.3**	**72.0**	**67.3**

Generalization Test

Budget	Method	IID (50 val. sets)	OOD (7 unseen datasets)
Num=8	Full Model	60.7	72.6
Num=6	Random	53.0±9.6	64.6±10.0
	Frequency [37]	35.2	35.0
	Soft Activation [37]	54.3	65.6
	NAEE [34]	57.5	69.4
	EEP (Prune Only)	59.6	**71.4**
	EEP (Prune+Merge)	**61.8**	71.3
Num=4	Random	45.1±6.1	50.3±10.7
	Frequency [37]	26.6	25.2
	Soft Activation [37]	46.7	53.1
	NAEE [34]	53.5	63.6
	EEP (Prune Only)	55.4	62.4
	EEP (Prune+Merge)	**56.9**	**64.6**

Expert merging improves the performance of the pruned model

[1] Enshu Liu*, Junyi Zhu*, Zinan Lin+, Xuefei Ning+, et al. "Efficient Expert Pruning for Sparse Mixture-of-Experts Language Models: Enhancing Performance and Reducing Inference Costs " *NeurIPS Submission*.

Efficient Techniques for LLMs

Overall Cost (for each request)	Total Latency: $t_{prefill} + t_{decode} * N_{token}$ Total Memory: $M_{weight} + M_{kv\ cache} + M_{other\_act}$
SoT (Skeleton-of-Thought)	Total Latency: $t_{prefill} + t_{decode} * N_{token} / B$ Total Memory: $M_{weight} + M_{kv\ cache} + M_{other\_act}$
LLM-MQ (Mixed-precision quantization)	Total Latency: $t_{prefill} + t_{decode}\downarrow * N_{token}$ Total Memory: $M_{weight}\downarrow + M_{kv\ cache} + M_{other\_act}$
MoA (Mixture of Attention)	Total Latency: $t_{prefill} + t_{decode}\downarrow * N_{token}$ Total Memory: $M_{weight} + M_{kv\ cache}\downarrow + M_{other\_act}$
EEP (Efficient Expert Pruning)	Total Latency: $t_{prefill} + t_{decode}\downarrow * N_{token}$ Total Memory: $M_{weight}\downarrow + M_{kv\ cache} + M_{other\_act}$

目录 Contents

How DMs do inference

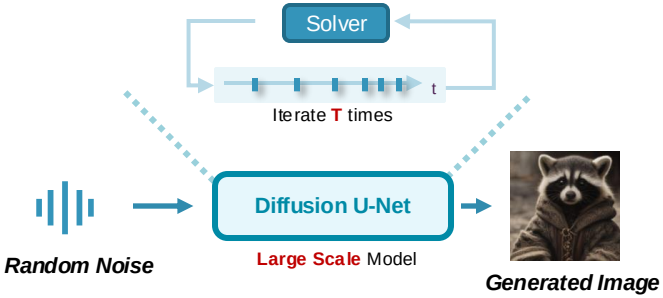
- Forward Process: Gradually add gaussian noise of different levels
- Backward Process: Gradually denoise the gaussian noise
- Intuition: the NN learns to predict the “noise” at each timestep.

[1] Ho, Jonathan et al. “Denoising Diffusion Probabilistic Models.” *ArXiv 2020*.

Efficiency Analysis of DM Inference

Current visual generation faces efficiency challenge

Large Param Size: 2.5B (SDXL)
Iterative NN Inference: 10-100x



Diffusion Model

Current SOTA
visual generation scheme

Latency Challenge:

SDXL 50 steps
on RTX3090: **30** s

Cannot Satisfy →

Image Editing
Needs **Fast (<1s)** Feedback

Memory Challenge:

SDXL model
9.7GB GPU Memory

Cannot Fit In →

Desktop GPU: RTX4070
8GB GPU Memory

Efficient Techniques for DMs

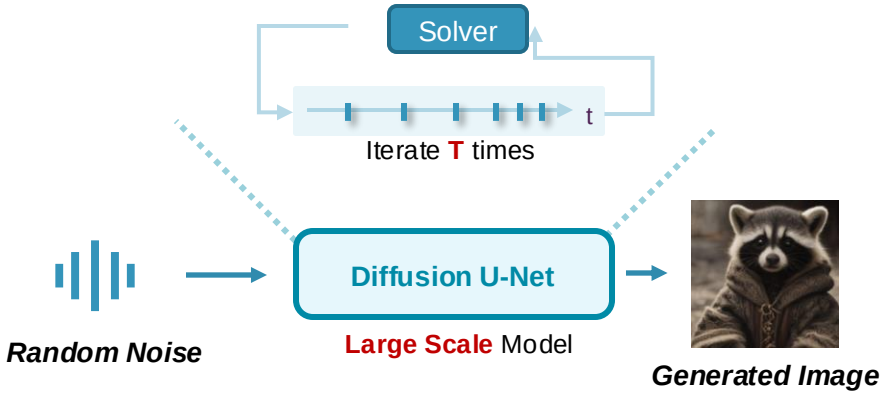
Directions to improve Diffusion Models' efficiency

Algorithm-level

Reduce $N_{timestep}$

Model-level

Reduce t_{model}, M_{weight}, M_{act}



Overall Cost

(for each iter)

Total Latency: $t_{model} * N_{timestep}$

Total Memory: $M_{weight} + M_{activation}$

Overview of Efficient Techniques

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We improve diffusion model's efficiency from Algorithm & Model & Data level

Latency Challenge:

Cannot Satisfy →

SDXL 50 steps on RTX3090: **30** s

Image Editing Needs **Fast (<1s)** Feedback

Memory Challenge:

Cannot Fit In →

SDXL model **9.7GB** GPU Memory

Desktop GPU: RTX4070 **8GB GPU Memory**

Algorithm-level

Time Step Compression

LCSC [ICLR Submission] — Linear combination of checkpoints. **15~23x training acceleration, 1.25~2x timestep compression**

USF [ICLR'24] **OMS-DPM** [ICML'23] — Search for optimal schedulers. **1.5~2x speed-up**

Model-level

Quantization

MixDQ [ECCV'24] — Mixed-precision quantization. **3x memory decrease, 1.5x speed-up**

ViDiT-Q [NeurIPS Submission] — Quantization for DiT. **2.5x memory improvement, 1.5x speed-up**

Pruning & Sparse Attention

DiTFastAttn [NeurIPS Submission] — Window & reused attention for DiT. **1.6x speed-up**

Fast Compression

FlashEval [CVPR'24]

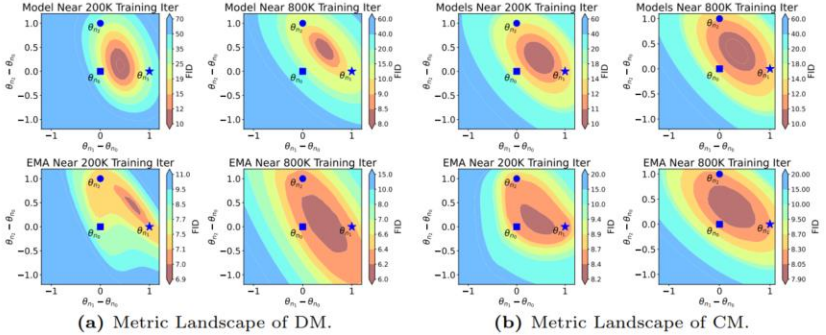
10x evaluation acceleration

Efficient Diffusion Models

Linear Combination of Saved Checkpoints (LCSC)

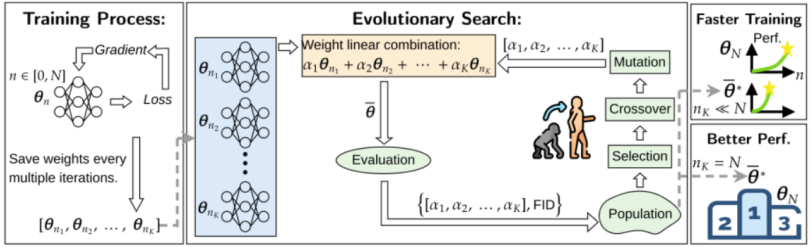
Achieving 15~23× training speed-up on Consistency Models and 1.25~1.7× inference speed-up on Diffusion Models

Motivation: Combination of checkpoints can improve the performance of CM/DM.



(a) Metric Landscape of DM. (b) Metric Landscape of CM.

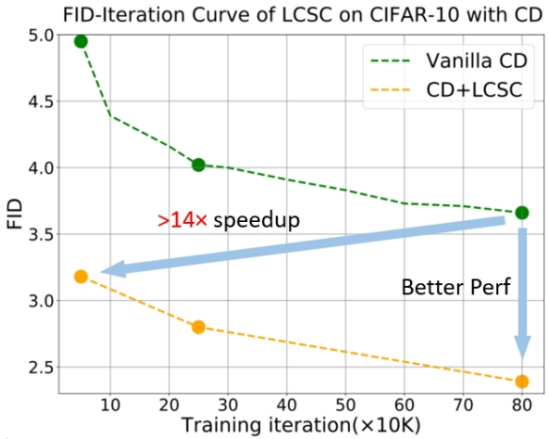
Methodology: Search the combination coefficients of saved checkpoints

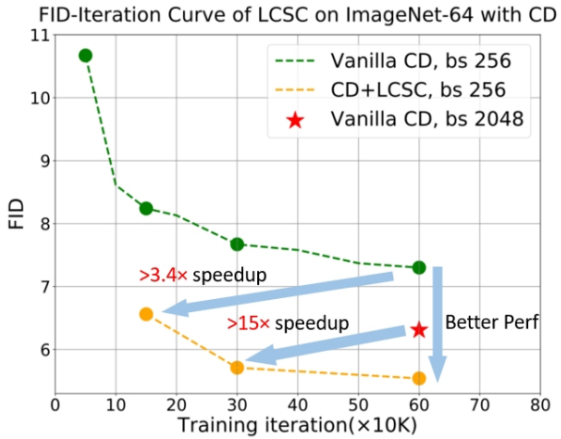


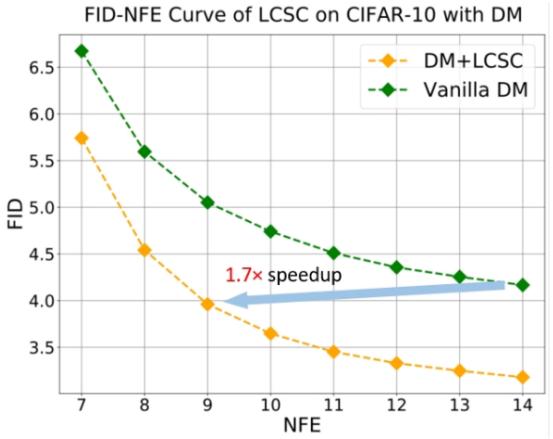
Use Case: accelerate training & enhancing converged models

[1] Liu, Enshu, et al. "Linear Combination of Saved Checkpoints Makes Consistency and Diffusion Models Better." *ICLR Submission*.

Linear Combination of Saved Checkpoints (LCSC)







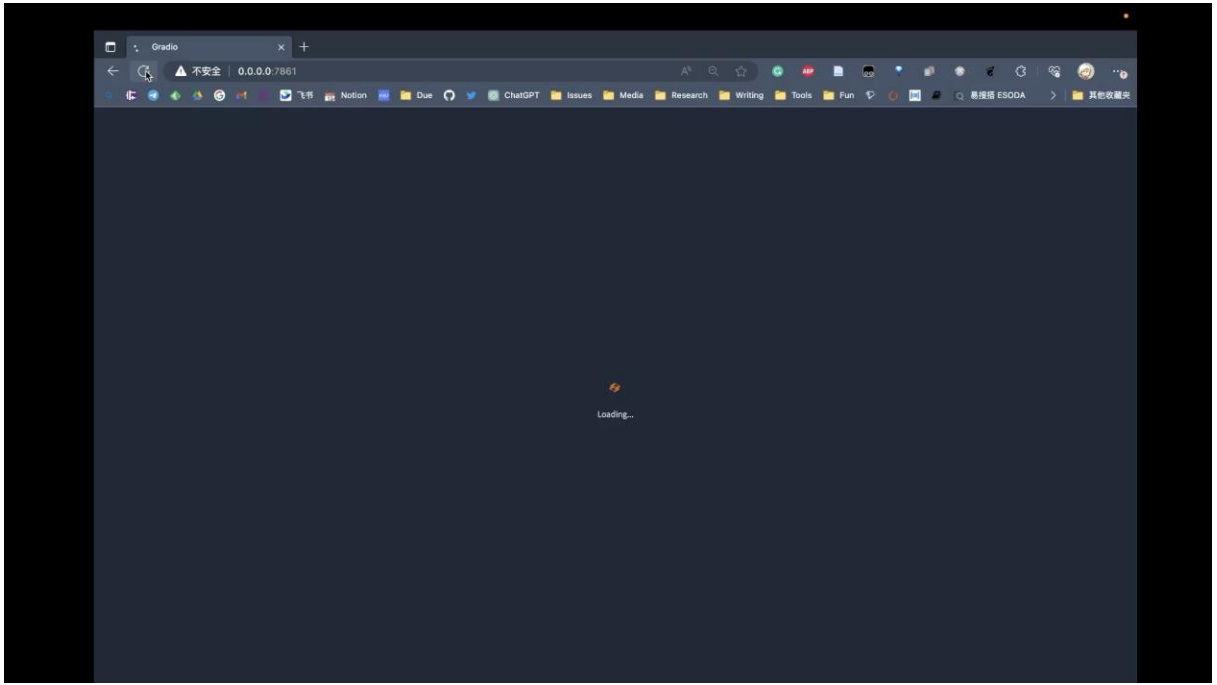
Baseline（FID=7.30）

Ours（FID=5.54）

[1] Liu, Enshu, et al. "Linear Combination of Saved Checkpoints Makes Consistency and Diffusion Models Better." *ICLR Submission*.

Optimizing the Model Schedule (OMS-DPM)

OMS-DPM + TensorRT Demo: 6.9× Latency Opt. & 1.5× Memory Opt.



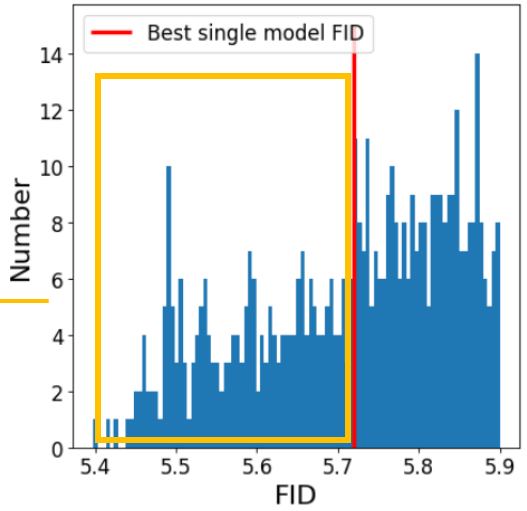
[1] Liu, Enshu, Ning, Xuefei, et al. "OMS-DPM: Optimizing the Model Schedule for Diffusion Probabilistic Models." *ICML2023.*

Optimizing the Model Schedule (OMS-DPM)

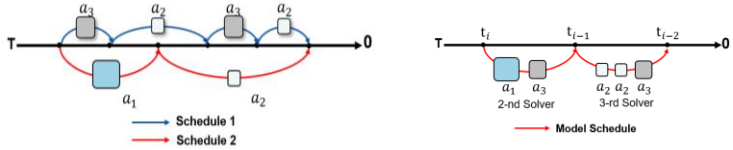
Achieving 2-5× speed-up on typical datasets and 2× speed-up on Text-to-Image generation

Motivation: Small models outperform large models at some timesteps

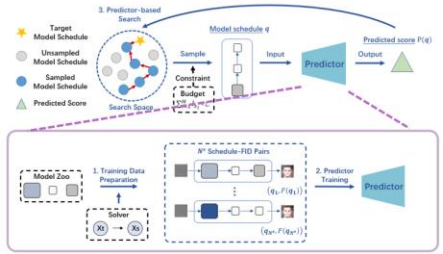
Mixing small and large models can possibly get better FID than only use large model



Methodology: Model Schedule & Predictor-based Search



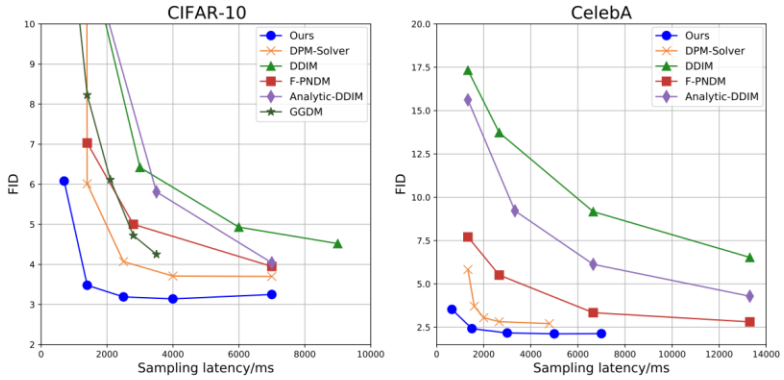
Model Schedule



Search Method

[1] Liu, Enshu, Ning, Xuefei, et al. "OMS-DPM: Optimizing the Model Schedule for Diffusion Probabilistic Models." *ICML2023.*

Optimizing the Model Schedule (OMS-DPM)



Baseline

Ours

[1] Liu, Enshu, Ning, Xuefei, et al. "OMS-DPM: Optimizing the Model Schedule for Diffusion Probabilistic Models." *ICML2023.*

Unified Sampling Framework (USF)

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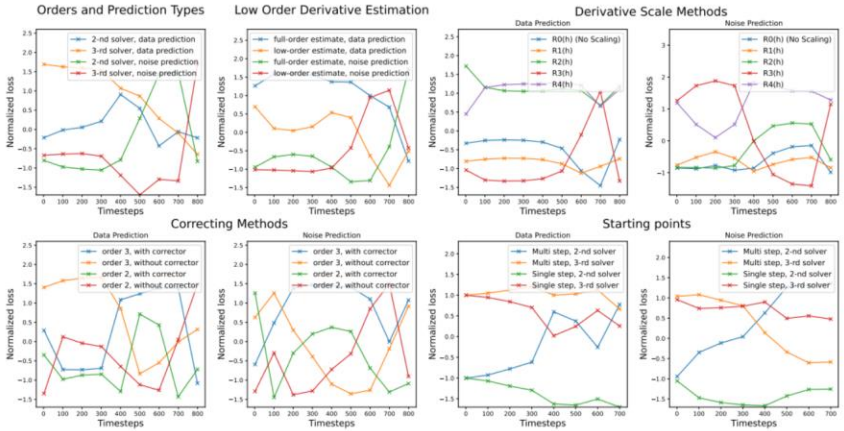
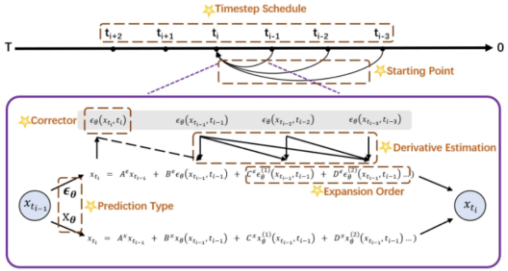
Achieving 2× speed-up on Text-to-Image generation and enables sampling with very low NFE

Motivation: Current solvers use sub-optimal strategies, cause poor quality with few NFE

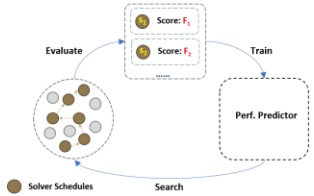


The ranking of all strategies changes over timestep

Methodology: A framework that unifies all exiting solvers and search based on it.



Method framework



Search method

Method	Prediction	Taylor order	Starting point	Scale	Corrector
DPM-Solver-2S	Noise	1,2	-1,-2	$\frac{h*(e^h-1)}{e^{h_{-1}}-h_{-1}}$	None
DPM-Solver-3S	Noise	1,2,2	-1,-2,-3	None	None
DPM-Solver++(2M)	Data	2	-1	$\frac{h*(1+e^{-h})}{e^{-h_{-1}}+h_{-1}}$	None
UniPC-2-$B_1(h)$	Noise/Data	2	-1	$\frac{h_{-1}}{e^{h_{-1}}-h_{-1}}$	UniC-2
UniPC-2-$B_2(h)$	Noise/Data	2	-1	$\frac{h_{-1}(e^h-1)}{e^{h_{-1}}-h_{-1}}$	UniC-2
UniPC-p ($p>2$)	Noise/Data	p	-1	None	UniC-p
DEIS-p (in the λ domain)	Noise	p	-1	None	None

USF unifies all solvers

[1] Liu, Enshu, Ning, Xuefei, et al. "A Unified Sampling Framework for Solver Searching of Diffusion Probabilistic Models." *ICLR2024.*

Unified Sampling Framework (USF)

Dataset	Method	NFE						
		4	5	6	7	8	9	10
CIFAR-10	Baseline-W(S)	255.21	288.12	32.15	14.79	22.99	6.41	5.97
	Baseline-W(M)	61.13	33.85	20.84	13.89	10.34	7.98	6.76
	Baseline-B	57.52	23.44	10.33	6.47	5.16	4.30	3.90
	Ours	**11.50**	**6.86**	**5.18**	**3.81**	**3.41**	**3.02**	**2.69**
CelebA	Baseline-W(S)	321.39	330.10	52.04	17.28	16.99	10.39	6.91
	Baseline-W(M)	31.27	20.37	14.18	11.16	9.28	8.00	7.11
	Baseline-B	26.32	8.38	6.72	6.72	5.17	4.21	4.02
	Ours	**12.31**	**5.17**	**3.65**	**3.80**	**3.62**	**3.16**	**2.73**
ImageNet-64	Baseline-W(S)	364.60	366.66	72.47	47.84	54.21	28.22	27.99
	Baseline-W(M)	93.98	69.08	50.35	40.99	34.80	30.56	27.96
	Baseline-B	76.69	61.73	42.81	31.76	26.99	23.89	24.23
	Ours	**33.84**	**24.95**	**22.31**	**19.55**	**19.19**	**19.09**	**16.68**
LSUN-Bedroom	Baseline-W(M)	44.29	24.33	15.96	12.41	10.87	9.99	8.89
	Baseline-B	22.02	17.99	12.43	10.79	9.92	9.11	8.52
	Ours	**16.45**	**12.98**	**8.97**	**6.90**	**5.55**	**3.86**	**3.76**
ImageNet-128	Baseline-W(M)	32.08	15.39	10.08	8.37	7.50	7.06	6.80
	Baseline-B	25.77	13.16	8.89	7.13	6.28	6.06	6.03
	Ours	**18.61**	**8.93**	**6.68**	**5.71**	**5.28**	**4.81**	**4.69**
ImageNet-256	Baseline-W(M)	80.46	54.00	38.67	29.35	22.06	16.74	13.66
	Baseline-B	51.09	27.71	17.62	13.19	10.91	9.85	9.31
	Ours	**33.84**	**19.06**	**13.00**	**10.31**	**9.72**	**9.06**	**9.06**

Results on typical datasets

Method	NFE						
	4	5	6	7	8	9	10
Baseline-W(S)	161.03	156.72	106.15	75.28	58.54	39.26	29.54
Baseline-W(M)	30.77	22.71	19.66	18.45	18.00	17.65	17.54
Baseline-B	24.95	20.59	18.80	17.83	17.54	17.42	17.22
Ours	**22.76**	**16.84**	**15.76**	14.77	**14.23**	**13.99**	**14.01**
Ours-500	24.47	17.72	15.71	**14.60**	14.47	14.15	14.27
Ours-250	23.84	18.27	17.29	14.90	15.50	14.12	14.31

Results on T2I task

Ours

Baseline

[1] Liu, Enshu, Ning, Xuefei, et al. "A Unified Sampling Framework for Solver Searching of Diffusion Probabilistic Models." *ICLR2024.*

Motivation: Diffusion Quantization

The text-to-image/video diffusion models are **memory-intensive**, and cannot be deployed on **Edge** Devices (Even Desktop GPU)

>

OPEN SORA

Open-SORA 2s Video
~10 GB Peak Memory

FP16 SDXL 512x512
9.7GB Peak Memory

Desktop GPU: RTX4070
8GB GPU Memory

Mobile: IPhone 14
6GB Memory

Solution: Model Quantization, **low-bit data** storing and computing, Reduce the memory cost

Mixed-precision Quantization (MixDQ)

Motivation: Few-step text-to-image diffusion models face additional challenge for quantization

FP16

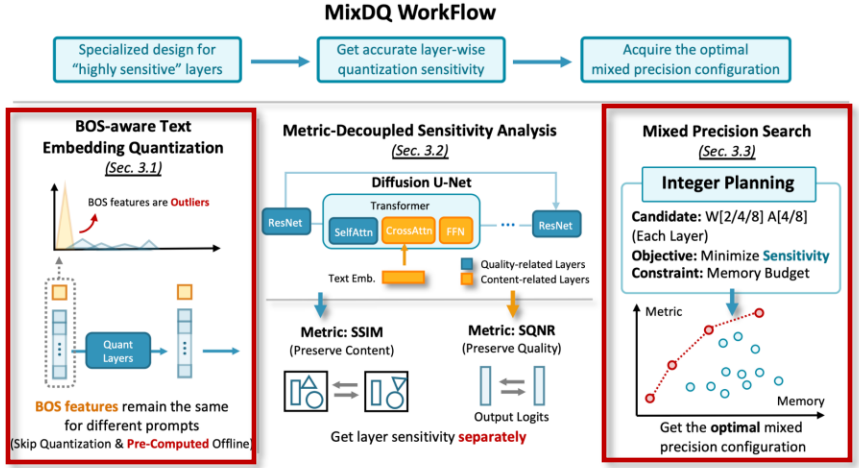
Q-Diff (W8A8)

"Two sheep are standing side by side behind a fence."

(* Adopting Q-Diffusion for 1-step SDXL-turbo model)

Solutions:

- BOS-aware Quantization Technique
  "Address Outliers in Text Embeddings"
- Mixed-precision Bit-width Allocation
  "Address over-sensitive layers"



[1] Zhao, Tianchen, Ning, Xuefei, et al. "MixDQ: Memory-Efficient Few-Step Text-to-Image Diffusion Models with Metric-Decoupled Mixed Precision Quantization." *ECCV2024.*

Mixed-precision Quantization (MixDQ)

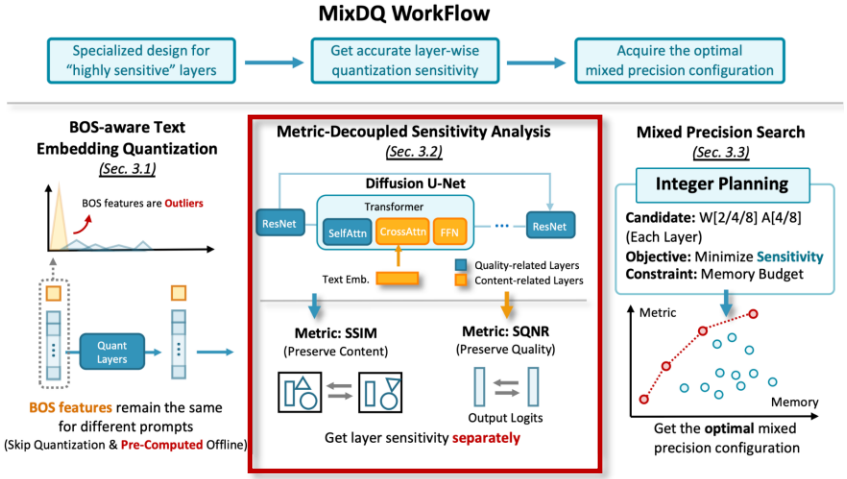
Motivation: Quantization affects both the image quality & content

FP | Content Changed Quality Retained | Content Retained Quality Changed

"A bicycle replica with a clock as the front wheel."

Solution:

- "Metric-decoupled" analysis and mixed precision



[1] Zhao, Tianchen, Ning, Xuefei, et al. "MixDQ: Memory-Efficient Few-Step Text-to-Image Diffusion Models with Metric-Decoupled Mixed Precision Quantization." *ECCV2024.*

Mixed-precision Quantization (MixDQ)

Experimental Results: MixDQ improves **both image quality & text alignment**
Achieves W4A8 with negligible loss(+0.5 FID), while baseline methods fail at W8A8 (+50 FID)

Model	Method	Bit-width (W/A)	*Storage Opt.*	*Compute Opt.*	FID(↓)	CLIP(↑)	IR(↑)
SDXL-turbo (1 step)	FP	16/16	-	-	17.15	0.2722	0.8631
	Naive PTQ	8/16	2×	1×	16.89	0.2740	0.8550
		4/16	4×	1×	301.49	0.1581	-2.2526
		8/8	2×	4×	103.96	0.1478	-1.7446
		4/8	4×	8×	358.894	0.1242	-2.2815
	Q-Diffusion	8/16	2×	1×	16.97	0.2735	0.8588
		4/16	4×	1×	22.58	0.2685	0.6847
		8/8	2×	4×	76.18	0.1772	-1.3112
		4/8	4×	8×	118.93	0.1662	-1.6353
	MixDQ(Ours)	4/16	4×	1×	17.23	0.2693	0.8254
		3.66/16	4.4×	1×	17.40	0.2682	0.7528
		8/8	2×	4×	17.03	0.2703	0.8415
		5/8	3.2×	8×	17.23	0.2697	0.8307
		4/8	4×	8×	17.68	0.2698	0.7822
LCM-lora (4 steps)	FP	16/16	-	-	25.56	0.2570	0.2122
	Naive PTQ	8/8	2×	4×	23.36	0.2548	0.0517
		4/8	4×	8×	87.36	0.2055	-1.6160
	Q-Diffusion	8/8	2×	4×	23.92	0.2561	0.1875
		4/8	4×	8×	57.73	0.2280	-1.1863
	MixDQ(Ours)	8/8	2×	4×	22.54	0.2552	0.1573
		4/8	4×	8×	33.48	0.2403	-0.6732

[1] Zhao, Tianchen, Ning, Xuefei, et al. "MixDQ: Memory-Efficient Few-Step Text-to-Image Diffusion Models with Metric-Decoupled Mixed Precision Quantization." *ECCV2024.*

Mixed-precision Quantization (MixDQ)

Practical 1.45× speed-up and 2× memory saving on Nvidia GPU
The 1st Open-source tool that achieves speedup and support few-step models

FP16 MixDQ W8A8

2x U-Net Memory Opt.: **4.8 GB -> 2.4 GB**

1.45x U-Net Latency Opt.: **36.1 ms -> 24.9 ms**

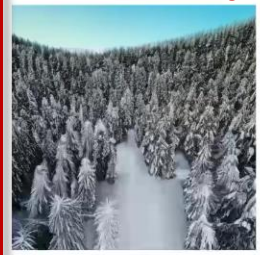
	Reduce VRAM	No Visual Degradation	Latency Speedup	Open Source	Support Few-step
Stable Diffusion WebUI - **FP8**	✓	✗	✗	✓	✗
Huggingface DiffusionFast: **Dynamic Quantization**	✓	✓	✗	✓	✗
Nvidia TensorRT: **Q-Diffusion PTQ**	✓	✓	✓	✗	✗
Ours: **MixDQ**	✓	✓	✓	✓	✓

[1] Zhao, Tianchen, Ning, Xuefei, et al. "MixDQ: Memory-Efficient Few-Step Text-to-Image Diffusion Models with Metric-Decoupled Mixed Precision Quantization." *ECCV2024.*

Video and Image DiT Quantization (ViDiT-Q)

Pioneer in DiT Quantization for Image and Video Generation

Nearly Identical



FP16

ViDiT-Q W8A8

Baseline W8A8

FP16

Baseline W8A8

Multiple Fins

Baseline W4A8

Blank Images

Blurred and Blank

FP16

Baseline W8A8

ViDiT-Q W8A8

Baseline W4A8

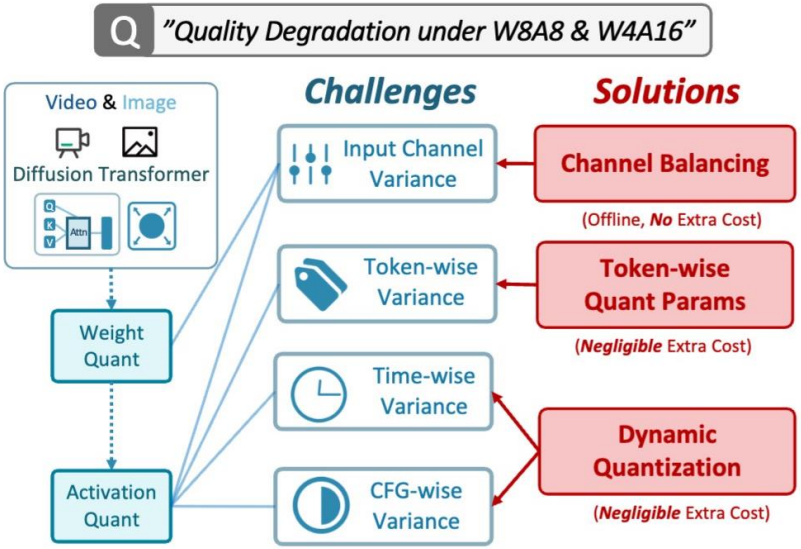
ViDiT-Q W4A8

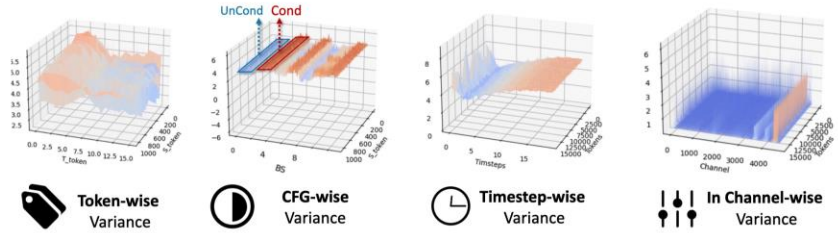
[1] Zhao, Tianchen, Fang Tongcheng, et al. "ViDiT-Q: Efficient and Accurate Quantization of Diffusion Transformers for Image and Video Generation" *NeurIPS Submission.*

Video and Image DiT Quantization (ViDiT-Q)

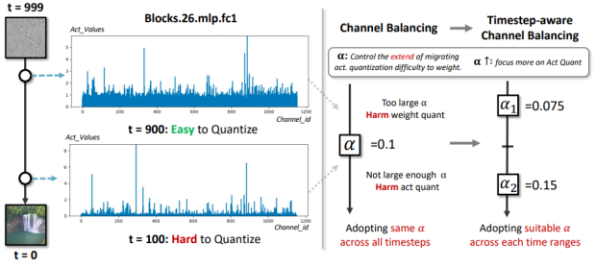
Motivation: DiT (Diffusion Transformers) have unique properties for quantization

Solution: Quantization scheme tailored for DiTs





Conclude **unique challenges of DiT** quantization "highly variant activation along different levels"



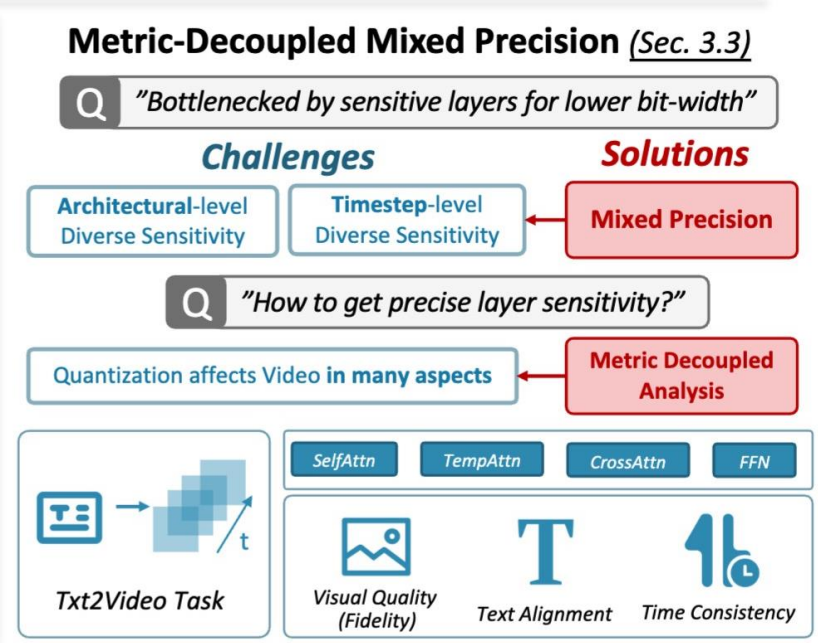
Specialized Technique: "Timestep-aware Channel Balancing"

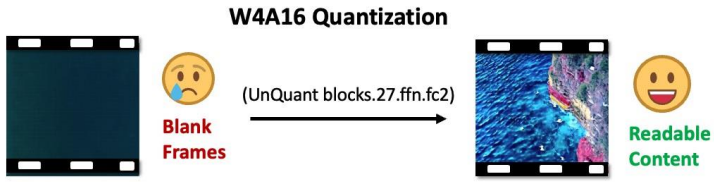
[1] Zhao, Tianchen, Fang Tongcheng, et al. "ViDiT-Q: Efficient and Accurate Quantization of Diffusion Transformers for Image and Video Generation" *NeurIPS Submission.*

Video and Image DiT Quantization (ViDiT-Q)

Motivation: Quantization affects many aspects of video generation

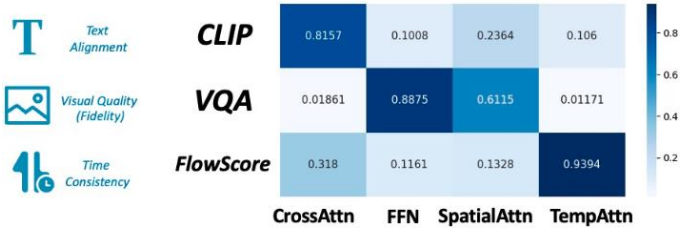
Solution: Metric-Decoupled analysis and mixed-precision





Evidence: Quantization are **"bottlenecked"** by some over-sensitive layers

Identify the "Quantization Bottleneck" Phenonmenon



Quantization's influence on **different aspects** have **strong correlation** with **layer types**

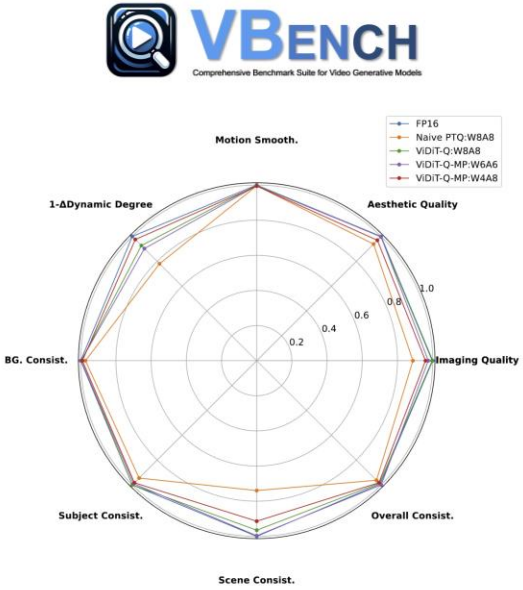
Use multiple metrics to find the sensitive layers

[1] Zhao, Tianchen, Fang Tongcheng, et al. "ViDiT-Q: Efficient and Accurate Quantization of Diffusion Transformers for Image and Video Generation" *NeurIPS Submission.*

Video and Image DiT Quantization (ViDiT-Q)

Achieve superior performance for multiple aspects

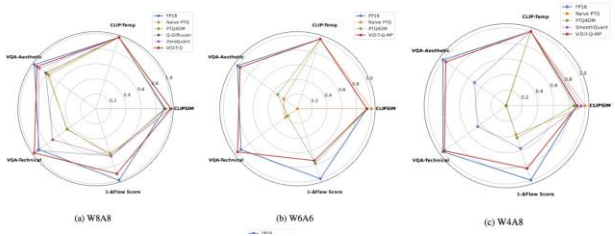
Comprehensive Benchmark



Similar performance with FP16

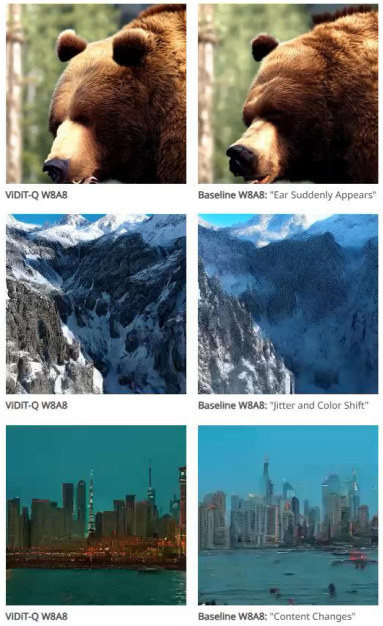
Multiple Metrics

Model	Method	Bit-width (W/A)	CLIPSIM	CLIP-Temp	VQA-Aesthetic	VQA-Technical	Flow Score.
STDiT	-	16/16	0.1797	0.9988	63.4014	50.4597	0.9751
	Naive PTQ	8/8	0.1956	0.9988	48.2358	25.5961	0.6081
	PTQ4DM [52]	8/8	0.1812	0.9984	50.0674	25.1344	0.6335
	Q-Diffusion [27]	8/8	0.1781	0.9987	51.6834	38.2680	0.6473
	ZeroQuant [69]	8/8	0.1938	0.9988	58.3127	51.5312	0.6442
	ViDiT-Q	8/8	0.1950	0.9991	60.7025	54.6361	0.8865
	Naive PTQ	6/6	0.1912	0.9964	14.6374	10.6919	33.611
	PTQ4DM [52]	6/6	0.1804	0.9977	20.9610	8.6566	0.7600
	ViDiT-Q-MP	6/6	0.1794	0.9983	60.8124	53.4413	1.2266
	Naive PTQ	4/8	0.2010	0.9986	0.1765	0.0863	1.5722
	PTQ4DM [52]	4/8	0.1727	0.9981	0.4781	0.2672	1.5298
	SmoothQuant [66]	4/8	0.1910	0.9989	31.9626	22.8467	0.5594
	ViDiT-Q-MP	4/8	0.1809	0.9989	60.6158	49.3838	1.1278



Outperform baseline quantization methods

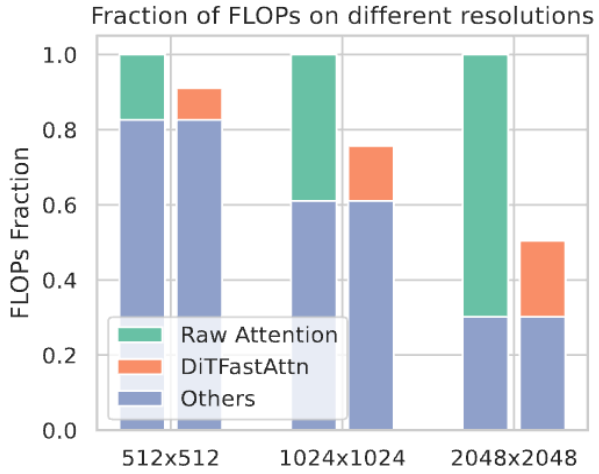
Qualitative Examples



[1] Zhao, Tianchen, Fang Tongcheng, et al. "ViDiT-Q: Efficient and Accurate Quantization of Diffusion Transformers for Image and Video Generation" ***NeurIPS Submission.***

Attention Compression (DiTFastAttn)

Reduce 73% FLOPs and 47% latency of attention (overall latency decrease by 32%) of DiT models on 2Kx2K generation.
Support both image generation and video generation.



Motivation:

1. Attention can be computationally costly, especially when processing a large number of tokens, as is the case in high-resolution image generation and long-form video generation tasks.

2. Diffusion Transformer (DiT) are emerging as a popular model for image and video generation tasks. There are some redundant computations involved in the generation process when using DiT models.

[1] Yuan Z, Lu P, Zhang H, et al. "DiTFastAttn: Attention Compression for Diffusion Transformer Models". NeurIPS *Submission.*

Attention Compression (DiTFastAttn)

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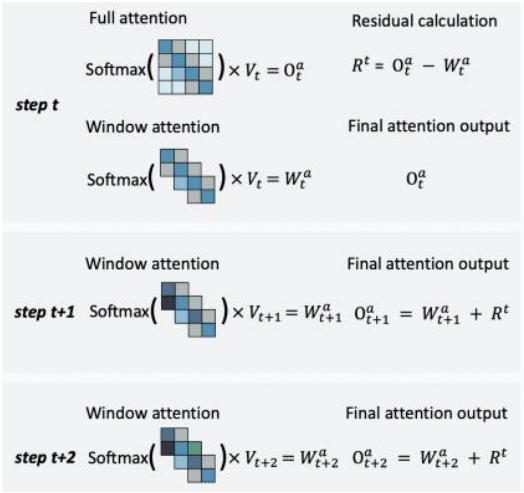
Method 1: Window attention with residual share

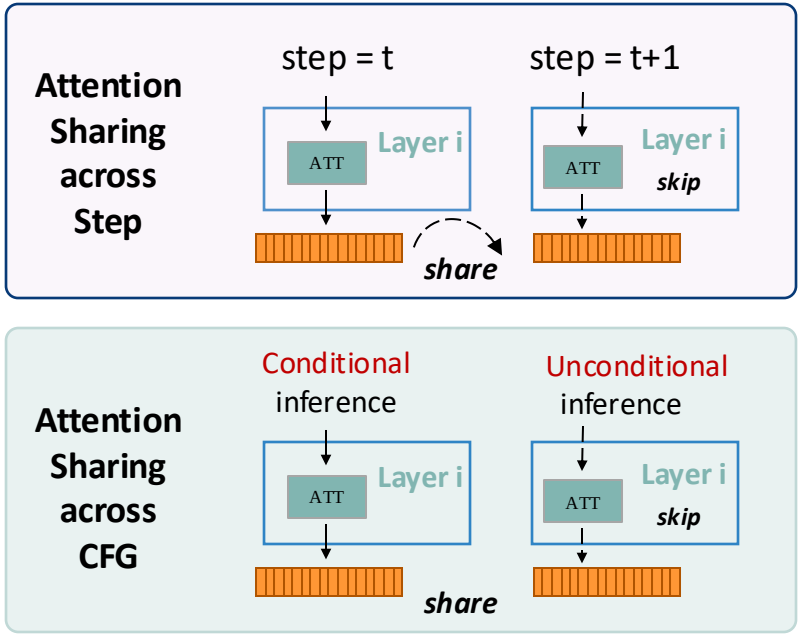
The changes in the attention output across different timesteps are primarily driven by a local attention window.



In each timestep, we only compute the local attention and then add the residual of previous global attention, without the need to recompute the full global attention.

Method 2 & Method 3:

Attention sharing across steps & CFG

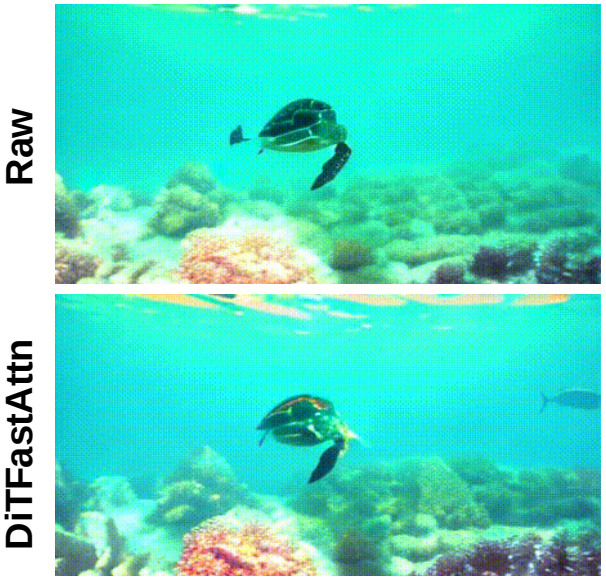


[1] Yuan Z, Lu P, Zhang H, et al. "DiTFastAttn: Attention Compression for Diffusion Transformer Models". NeurIPS *Submission.*

Attention Compression (DiTFastAttn)

Apply to 2K Image Generation
Experiments on PixArt-Sigma

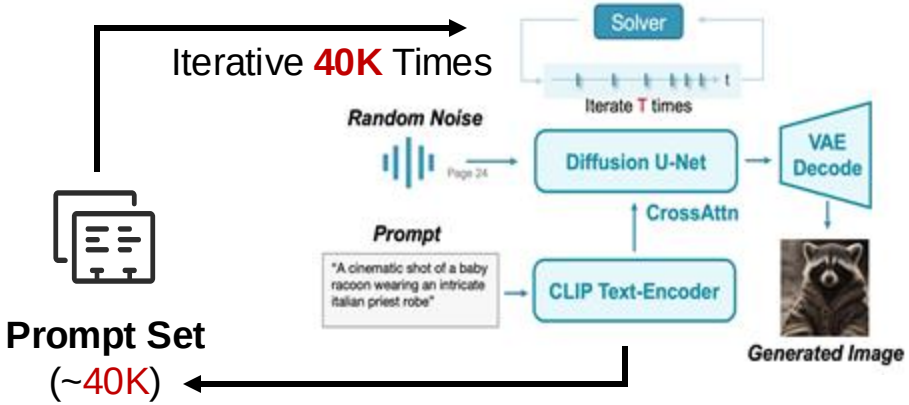
Apply to Video Generation
Experiments on OpenSORA



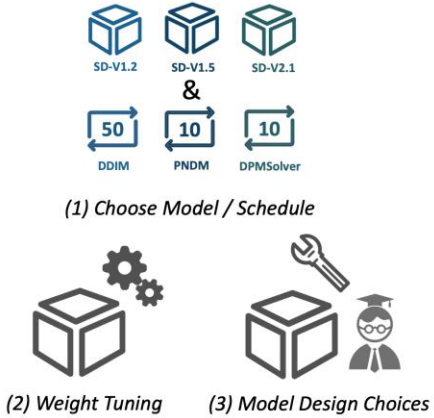
[1] Yuan Z, Lu P, Zhang H, et al. "DiTFastAttn: Attention Compression for Diffusion Transformer Models". NeurIPS *Submission.*

Faster Evaluation (FlashEval)

Motivation: Text-to-image Diffusion Evaluation is **slow,**
Many applications requires repeated evaluation



Evaluating SD v1.5 50 steps on
complete COCO cost **~50 GPU hours**

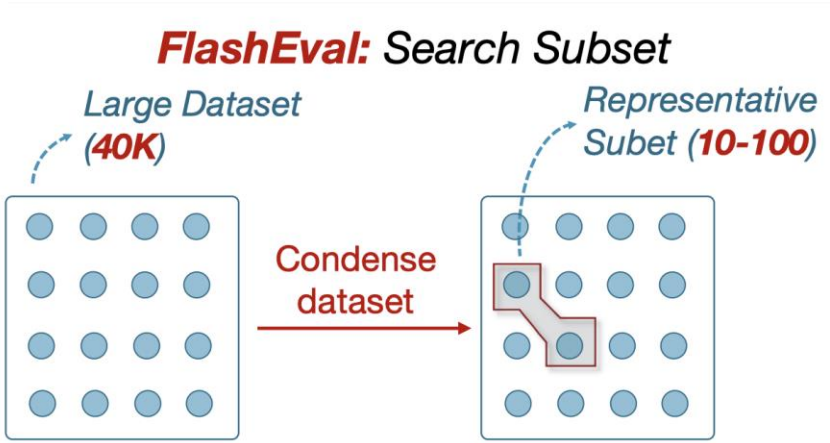


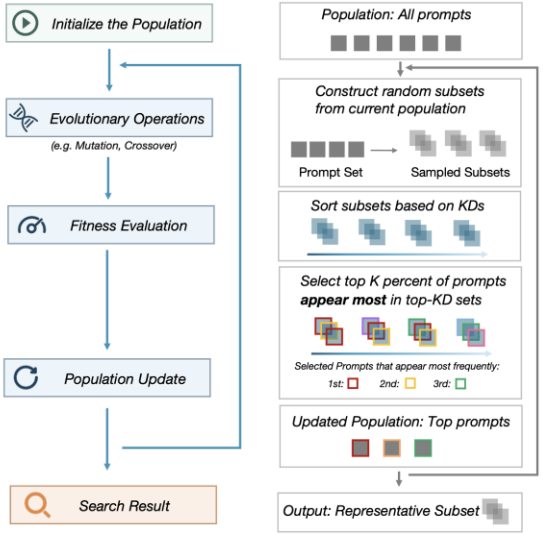
Many applications require
Repeated Evaluation

[1] Zhao, Lin, et al. "FlashEval: Towards Fast and Accurate Evaluation of Text-to-image Diffusion Generative Models." *CVPR2024.*

Faster Evaluation (FlashEval)

Methodology: Find “Representative Subset”, by Evolutionary-inspired searching





[1] Zhao, Lin, et al. “FlashEval: Towards Fast and Accurate Evaluation of Text-to-image Diffusion Generative Models.” ***CVPR2024.***

Faster Evaluation (FlashEval)

12 Model Variants
(Dreamlike, SD v1.2/1.5/2.1 and their 6/8 bit Quantized version)

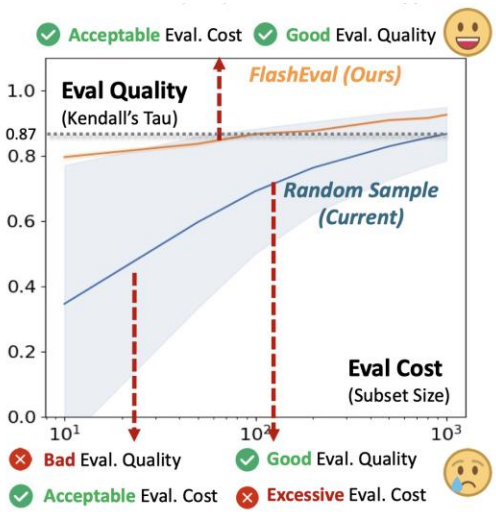
8 Schedules
(DDIM, DPMSolver, PNDM 10/20/50 Steps)

4 Metrics
(FID, ImageReward CLIPScore, HPS)

Diverse Evaluation Settings

models	item size	N'=50			N'=500		
	methods \sub-tasks	random	model variants	schedulers	random	model variants	schedulers
Train	RS	0.607±0.000	0.594±0.000	0.632±0.000	0.857±0.000	0.858±0.000	0.857±0.000
	B3-prompt	0.900	0.909	0.862	0.895	0.917	0.872
	B3-set	0.895±0.002	0.912±0.002	0.894±0.002	0.971±0.002	0.970±0.001	0.966±0.002
	Ours	**0.956±0.004**	**0.969±0.004**	**0.960±0.004**	**0.984±0.003**	**0.986±0.003**	**0.978±0.003**
Test	RS	0.597±0.000	0.588±0.000	0.560±0.000	0.829±0.000	0.826±0.000	0.827±0.000
	B3-prompt	0.729	0.784	0.810	0.805	0.822	0.851
	B3-set	0.750±0.014	0.680±0.021	0.721±0.013	0.875±0.007	0.836±0.008	0.863±0.008
	Ours	**0.851±0.004**	**0.800±0.008**	**0.850±0.005**	**0.906±0.003**	**0.899±0.004**	**0.909±0.003**

Our Searched **50-item** Subset have comparable evaluation quality with **Random-sampled 500**



Better Evaluation Eff-Perf Trade-off

[1] Zhao, Lin, et al. "FlashEval: Towards Fast and Accurate Evaluation of Text-to-image Diffusion Generative Models." ***CVPR2024.***

Efficient Techniques for DMs

Overall Cost
(for each iter)

Total Latency: $t_{model} * N_{timestep}$
Total Memory: $M_{weight} + M_{activation}$

LCSC & OMS-DPM & USF
(Schedule Optimization)

Total Latency: $t_{model} * N_{timestep} \downarrow$
Total Memory: $M_{weight} + M_{activation}$

MixDQ & ViDiT-Q
(Mixed-precision quantization)

Total Latency: $t_{model} \downarrow * N_{timestep}$
Total Memory: $M_{weight} \downarrow + M_{activation} \downarrow$

DiTFastAttn
(Attention Compression)

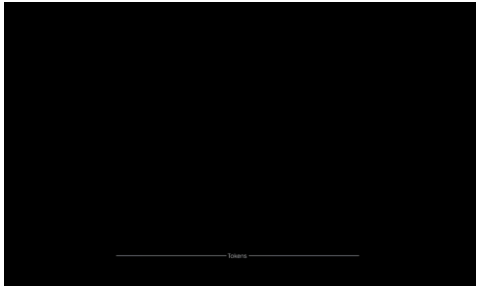
Total Latency: $t_{model} \downarrow * N_{timestep}$
Total Memory: $M_{weight} + M_{activation} \downarrow$

目录 Contents

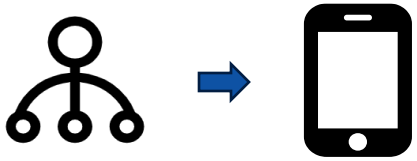
Future Scenarios

Language Generation

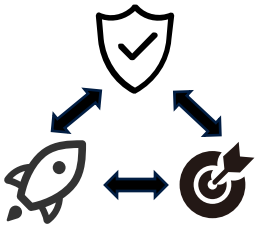
Agent and Multi-model Framework



Long Context LLMs

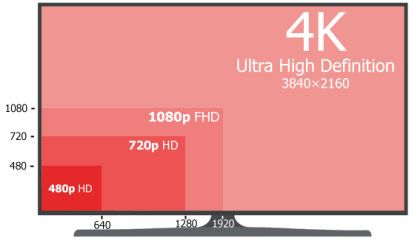


Edge Scenario Deployment



Security-Efficiency Synergy

Visual Generation



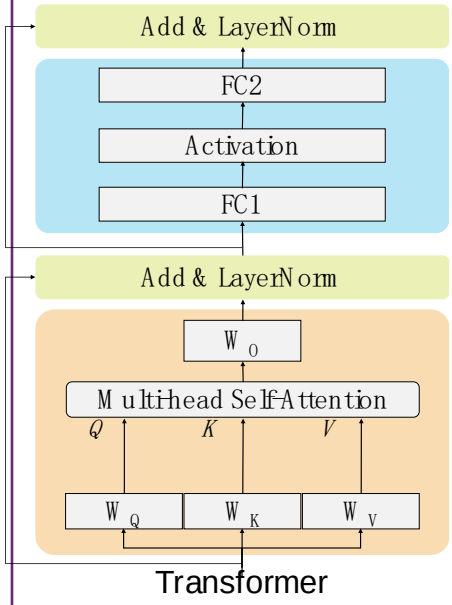
Spatial-Dimension:
High-resolution Generation

Temporal-Dimension:
Long Video Generation

Future Directions

Goal: higher generation quality + better controllability and interactivity

Unified Model Architecture



Efficiency Challenge:

Quadratic complexity in context length

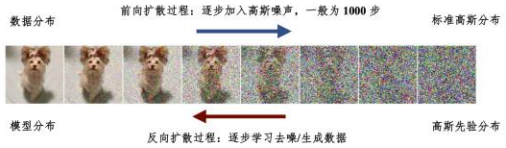
Unified Generation Approach

Auto-regressive Decoding

Efficiency Challenge:

Multiple generation steps

Diffusion



Research Summary

Overview

Survey
[TPAMI Submission]

Survey on efficient LLM inference techniques

Algorithm-level

SoT
[ICLR'24]

Parallel generation via prompting.
1.91~2.39x speed-up

Model-level

Sparse Attention

MoA
[NeurIPS Submission]

Decide the heterogeneous elastic rule of the attention span for each head.
5.5~6.7x throughput improvement

Pruning

EEP
[NeurIPS Submission]

Search the pruning pattern for MoE and use expert merging for finetuning.
48%~71% memory reduction,
1.11~1.40x speed-up,
better performance

Quantization

LLM-MQ
[NeurIPS'23 Workshop]

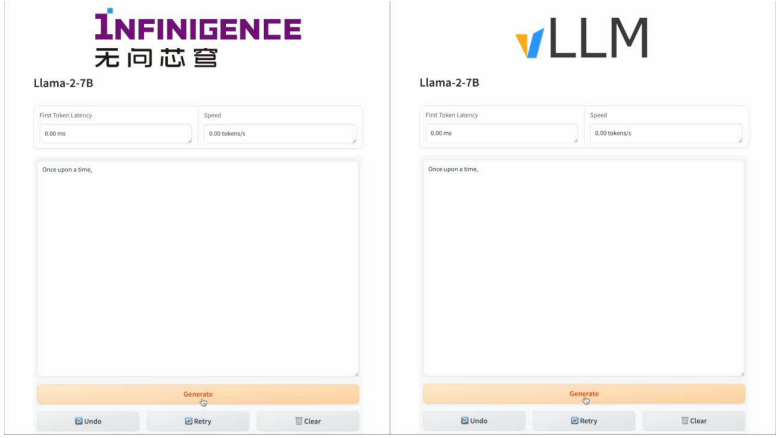
Mixed-precision quantization.
2.8-bit quantization

QLLM-Eval
[ICML'24]

Evaluating the effect of quantization.
Providing knowledge and practical suggestions

Efficient Large Language Models

Achieving 2× throughput improvement



LLaMA-2-7B on AMD MI210

Research Summary

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Algorithm-level

Time Step Compression

LCSC [ICLR Submission]

Linear combination of checkpoints.
15~23x training acceleration,
1.25~2x timestep compression

USF [ICLR'24]

OMS-DPM [ICML'23]

Search for optimal schedulers.
1.5~2x speed-up

Fast Compression

FlashEval [CVPR'24]

10x evaluation acceleration

Model-level

Quantization

MixDQ [ECCV'24]

Mixed-precision quantization.
3x memory decrease,
1.5x speed-up

ViDiT-Q [NeurIPS Submission]

Quantization for DiT.
2.5x memory improvement,
1.5x speed-up

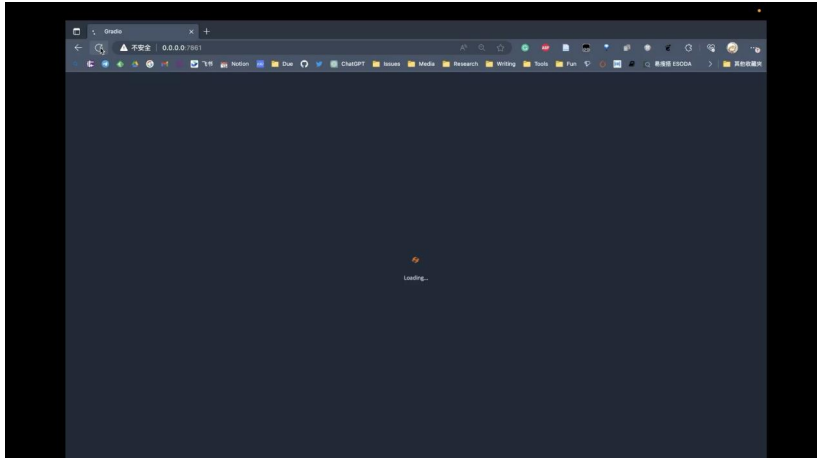
Pruning & Sparse Attention

DiTFastAttn [NeurIPS Submission]

Window & reused attention for DiT.
1.6x speed-up

Efficient Diffusion Models

Achieving 6.9× speed-up and reducing 1.5× memory



Stable Diffusion on a single NVIDIA A100 GPU

清華大學电子工程系
Department of Electronic Engineering, Tsinghua University

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Thank You !

新书：《高效深度学习：模型压缩与设计（全彩）》

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2024.07.11

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NICS EFC