LLM Optimization Libraries: Inference & Training Phases

2110572: Natural Language Processing Systems

Assoc. Prof. Peerapon Vateekul, Ph.D.
Department of Computer Engineering,
Faculty of Engineering, Chulalongkorn University

Credit: TA.Pluem & TA.Knight

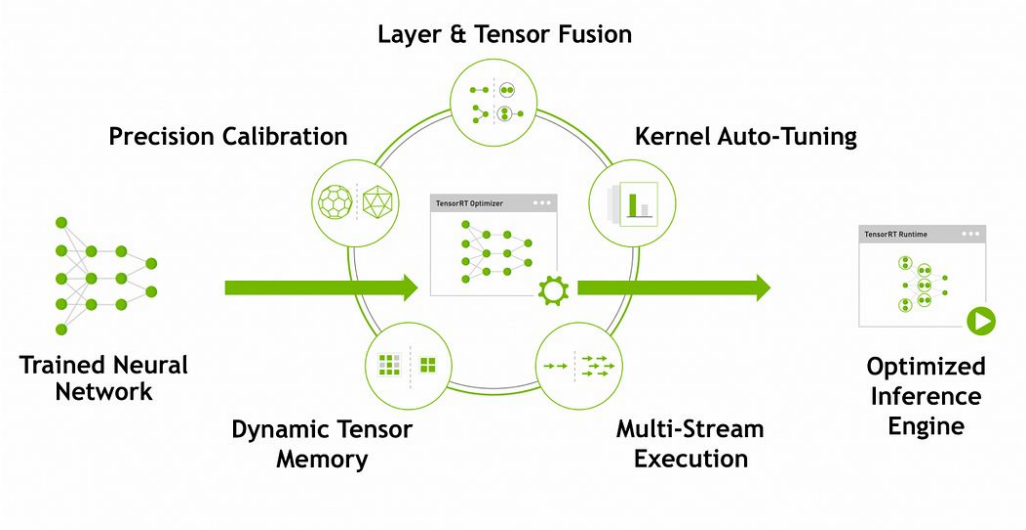
Outline

- Only inference
  - 1) TensorRT-LLM + Triton Inference Server [demo]
  - 2) NVIDIA Dynamo [resource]
- Supporting fine-tuning (training) & inference
  - 3) Unsloth (single GPU - free, but multiple GPUs - paid) [demo]
  - 4) DeepSpeed (multiple GPUs - all free, but more complicated than Unsloth) [resource]
- Conclusion

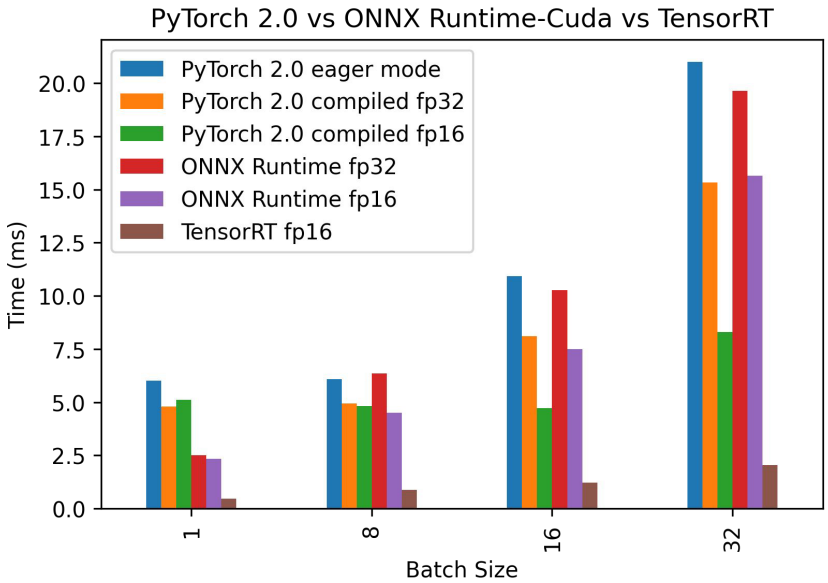
1) TensorRT-LLM + NVIDIA Triton Server [inference]

TensorRT: What is it?

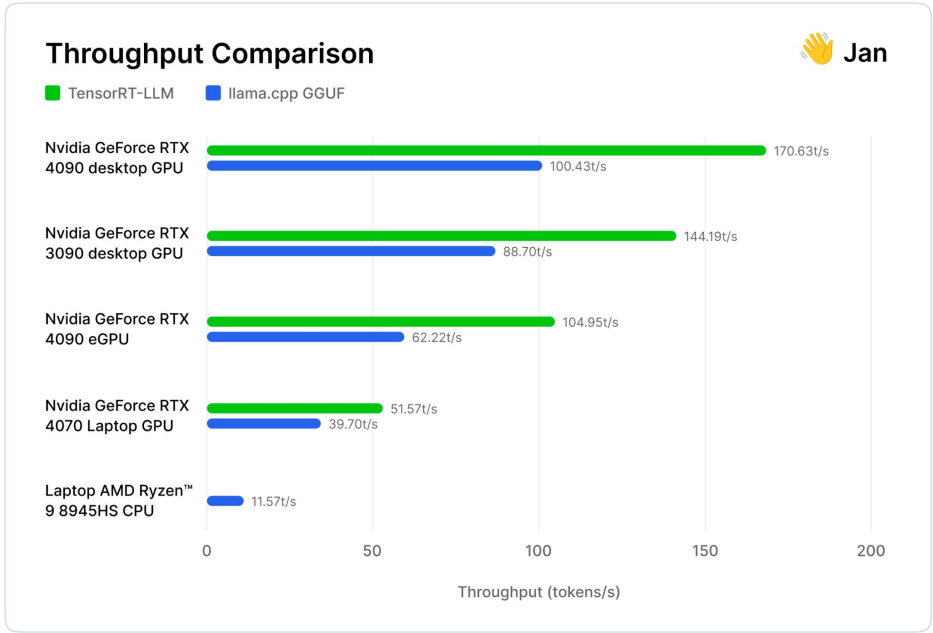
TensorRT is a library developed by NVIDIA for faster inference on NVIDIA GPUs. It is built on CUDA, NVIDIA's parallel programming model.



TensorRT: Its performance



a 3090Ti with a ResNet



Mistral 7b

TensorRT-LLM: Features

1. Quantization
2. In-flight Batching
3. Chunked Context
4. KV cache reuse
5. Speculative Sampling

BF16 stands for bfloat16 (short for Brain Floating Point 16-bit), a 16-bit floating point format primarily designed to speed up AI/ML training while maintaining accuracy close to 32-bit floating point (FP32).

```
12345 = 1.2345 × 10^4
```

- **Mantissa** = 1.2345
- **Exponent** = 4
- **Base** = 10 (in decimal)

Common Floating-Point Formats

Format	Total Bits	Size in Bytes	Description
FP32	32 bits	**4 bytes**	Standard for training, high precision
FP16	16 bits	2 bytes	Half-precision, used in mixed-precision training
BF16	16 bits	2 bytes	Similar dynamic range as FP32, lower precision
FP64	64 bits	8 bytes	Double-precision, not commonly used in DL

1. Quantization

TensorRT-LLM supports running LLMs on various numerical precision modes.

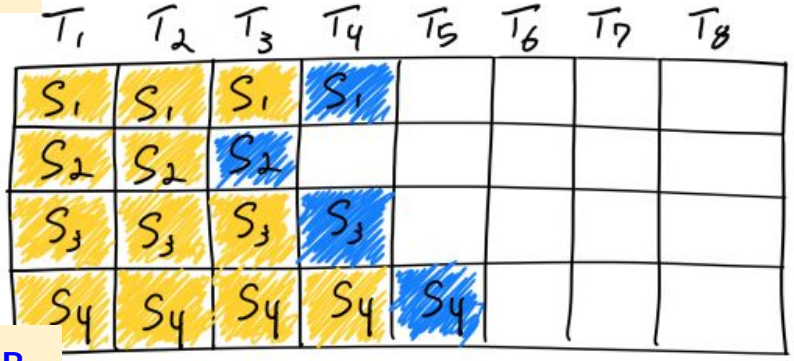
- FP32, FP16 and BF16
- INT8 SmoothQuant (W8A8) [1]: SmoothQuant: Accurate and Efficient Post-Training Quantization for Large Language Models [2024]
- INT4 and INT8 Weight-Only (W4A16 and W8A16)
- GPTQ and AWQ (W4A16) [2, 3]: (1) GPTQ: Accurate Post-Training Quantization for Generative Pre-trained Transformers [2022], (2) AWQ: Activation-aware Weight Quantization for LLM Compression and Acceleration [2023]
- FP8 (Hopper GPUs only)
- NVFP4 (Blackwell GPUs only)

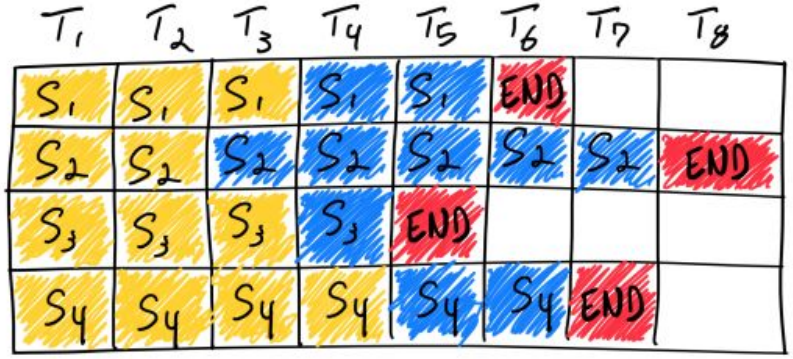
Term	Explanation
W	**Weights** bit precision (number of bits used to represent model weights)
A	**Activations** bit precision (number of bits used to represent inputs/outputs of layers)
W4A16	Weights are 4-bit, Activations are 16-bit
W8A16	Weights are 8-bit, Activations are 16-bit

[1] https://arxiv.org/abs/2211.10438
[2] https://arxiv.org/abs/2210.17323
[3] https://arxiv.org/abs/2306.00978

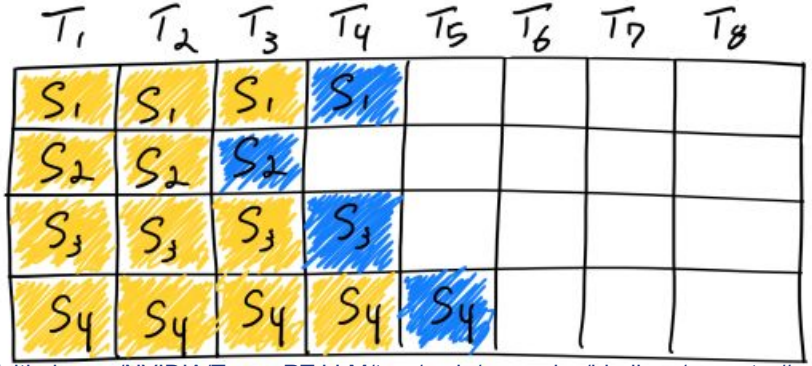
2. **In-flight Batching (IB)**; assume batch size = 4

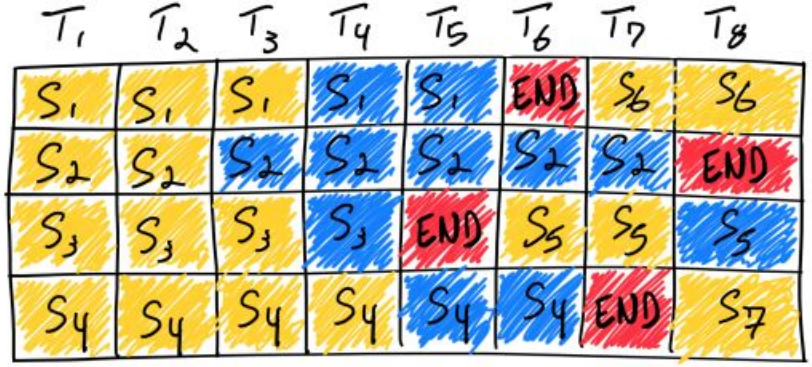
w/ IB





w/o IB



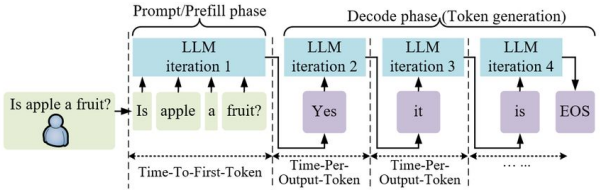


https://github.com/NVIDIA/TensorRT-LLM/tree/main/examples/bindings/executor#advanced-example

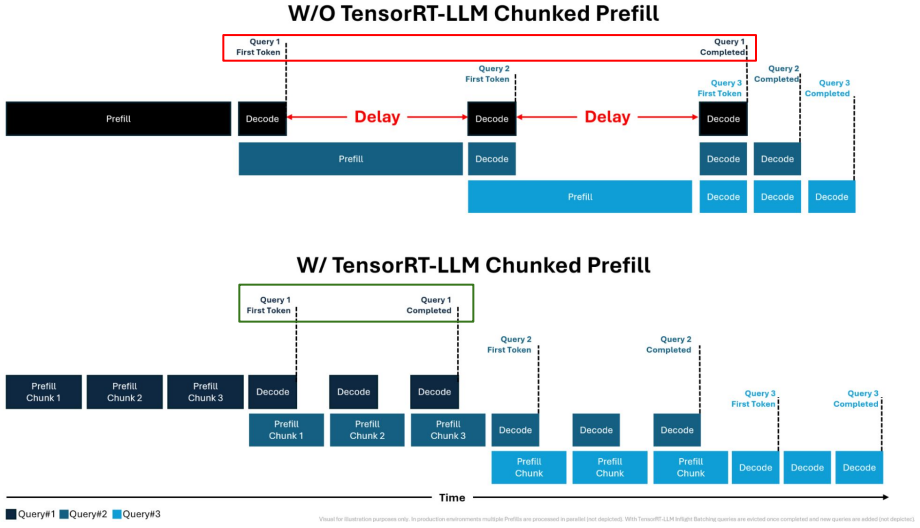
3. Chunked Context

The chunked context feature splits the context into several manageable chunks rather than processing all context tokens at once. Chunked prefill optimizes the initial embedding phase by batching prefill computations across requests, boosting GPU efficiency—especially with in-flight batching and variable-length inputs.

- Chunked context ensures long prompts won't cause Out-Of-Memory (OOM).
- Chunked prefill ensures many prompts can be processed efficiently.



Stage	Description	Characteristics
Prefill	Processes input tokens and computes KV cache.	Highly parallelized, efficient GPU utilization.
Decode	Generates output tokens one at a time based on previous tokens.	Sequential processing, potentially slower, memory-bound.

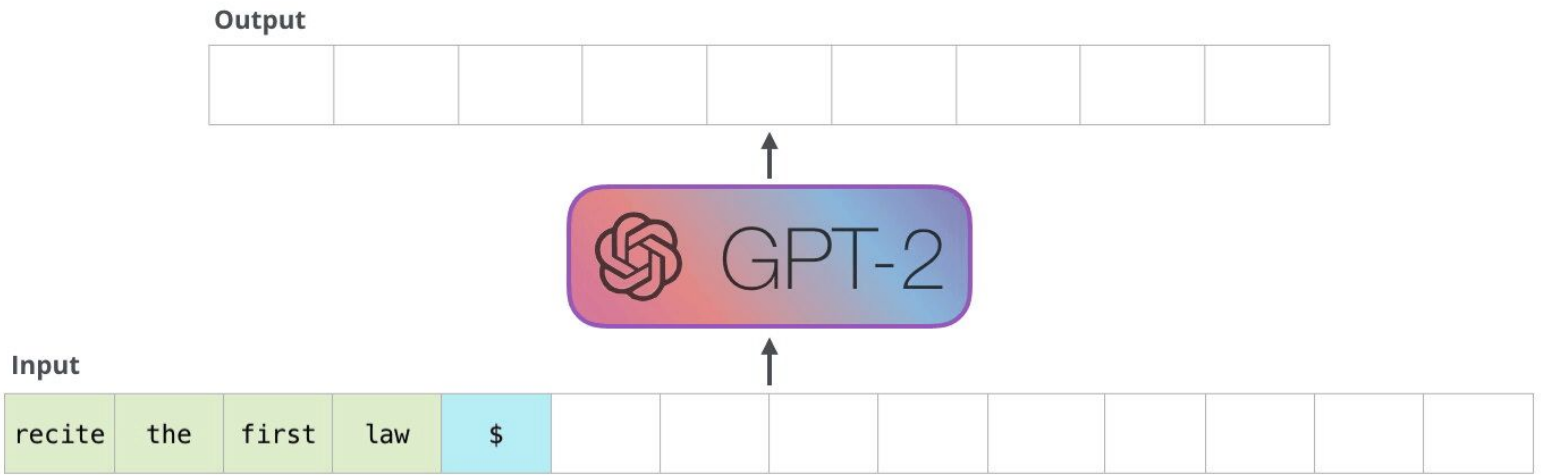


4. KV cache reuse

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

Reduces time-to-first-token by reusing KV cache from multiple requests with the same system prompts or multi-turn requests.

KV caching occurs during multiple token generation steps and only happens in the decoder (i.e., in decoder-only models like GPT, or in the decoder part of encoder-decoder models like T5). Models like BERT are not generative and therefore do not have KV caching.

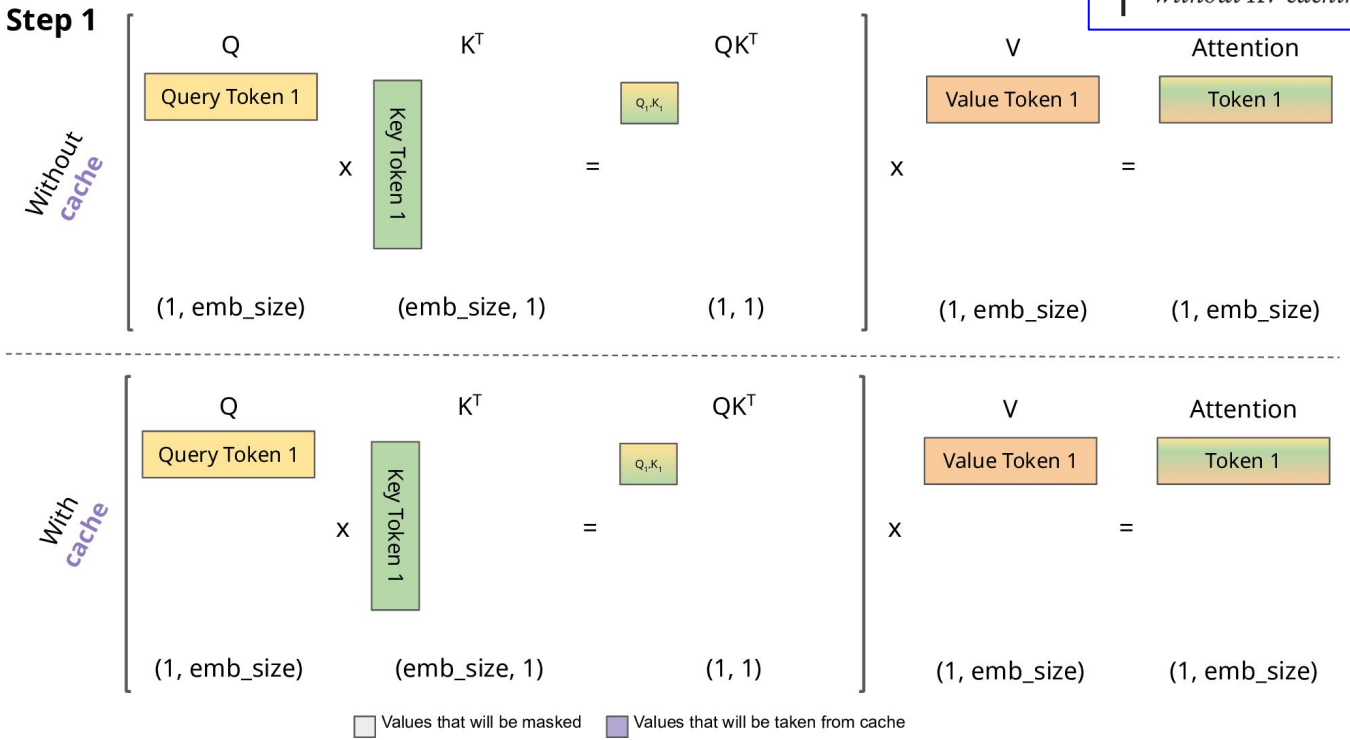


https://medium.com/@joaolages/kv-caching-explained-276520203249

4. KV cache reuse (cont.)

Reduces time-to-first-token by reusing KV cache from multiple requests with the same system prompts or multi-turn requests.

> *with KV caching: 11.885 +- 0.272 seconds*
> *without KV caching: 56.197 +- 1.855 seconds*

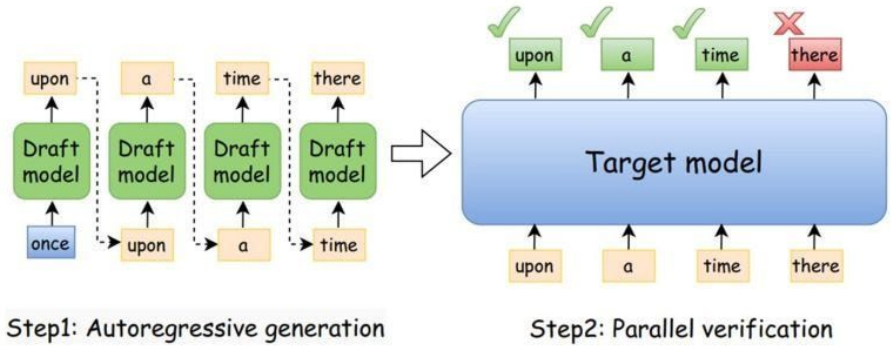


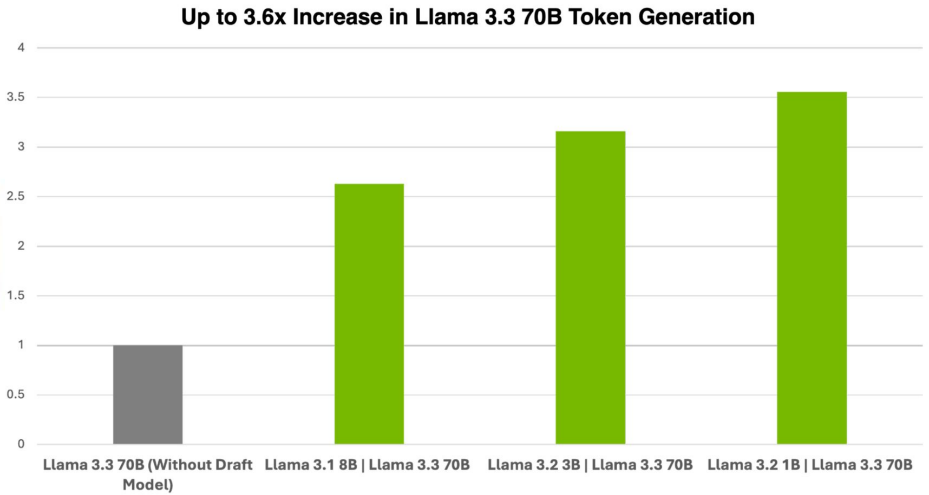
https://medium.com/@joaolages/kv-caching-explained-276520203249

5. Speculative Sampling

Speculative Sampling (or Speculative decoding) uses a smaller LM to predict multiple future tokens (draft tokens). The predicted continuation is then verified by the larger LLM we are hosting. If it is accepted, use the draft tokens as the output and continue generating the next token.

- Draft model = generator
- Target model = verifier





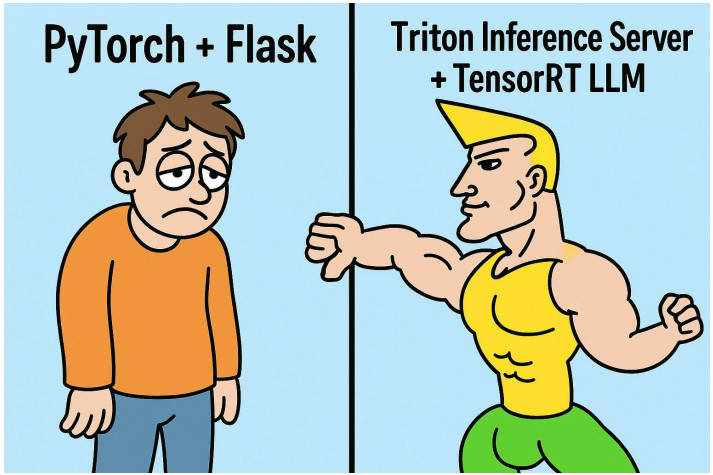
https://github.com/NVIDIA/TensorRT-LLM/blob/main/examples/draft_target_model/README.md
https://medium.com/@genai.works/speed-up-llm-inference-with-speculative-decoding-1fc79701e9d6

Draft model | Target model

Example (demo from lab's server)

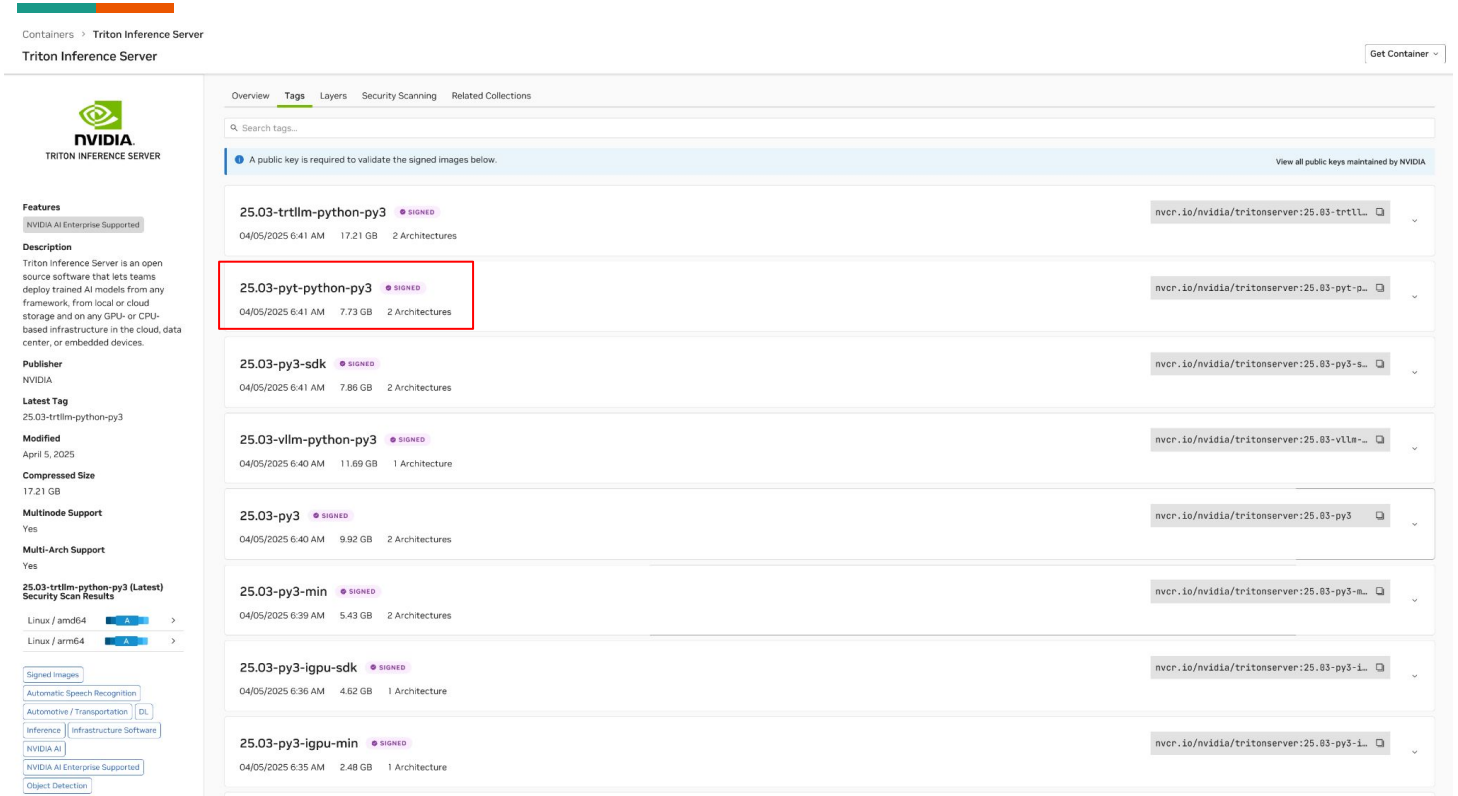
Objective: Deploy Qwen2.5 7B model using Triton Inference Server with TensorRT-LLM backend.

Required GPU with 24GB VRAM (at least 3090 or 4090)



Pull a Triton Inference Server from Nvidia NGC. This demo uses 25.03-pyt-python-py3.

Step 0: Load TensorRT-LLM docker



https://catalog.ngc.nvidia.com/orgs/nvidia/containers/tritonserver/tags

Step 1: Load model Qwen 7B

Download model weights

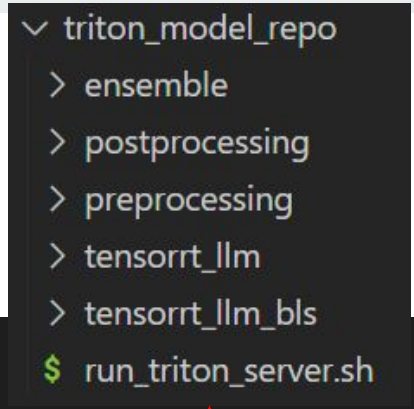
```
root@a156c29a2adf:/app/examples/qwen# git clone https://huggingface.co/Qwen/Qwen2.5-0.5B-Instruct ./tmp/Qwen2.5/0.5B
```

Step 2: Convert the model based on configuration

```
for model_size in 0.5 7; do
    python convert_checkpoint.py --model_dir ./tmp/Qwen2.5/${model_size}B/ --output_dir ./tllm_checkpoint_1gpu_fp16_${model_size}B --dtype float16
    trtllm-build --checkpoint_dir ./tllm_checkpoint_1gpu_fp16_${model_size}B --output_dir ./tmp/Qwen2.5/${model_size}B/trt_engines/fp16/1-gpu \
    --gemm_plugin float16 --max_seq_len 2048 --max_batch_size 8 --max_beam_width 1 --reduce_fusion enable --use_paged_context_fmha enable --multiple_profiles enable
done
```

```
# for SmoothQuant quantization
python3 convert_checkpoint.py --model_dir ./tmp/Qwen2.5/7B/ --output_dir ./tllm_checkpoint_1gpu_sq --dtype float16 --smoothquant 0.5
trtllm-build --checkpoint_dir ./tllm_checkpoint_1gpu_sq --output_dir ./engine_outputs --gemm_plugin int8
```

Step 3: Configure Triton server & Launch the server




```
ENGINE_DIR=/app/examples/qwen/tmp/Qwen2.5/7B/trt_engines/fp16/1-gpu
TOKENIZER_DIR=/app/examples/qwen/tmp/Qwen2.5/7B
MODEL_FOLDER=/triton_model_repo
TRITON_MAX_BATCH_SIZE=8
INSTANCE_COUNT=4
MAX_QUEUE_DELAY_MS=10000
MAX_QUEUE_SIZE=0
FILL_TEMPLATE_SCRIPT=/app/tools/fill_template.py
DECOUPLED_MODE=true
LOGITS_DATATYPE=TYPE_FP32
KV_CACHE_FREE_GPU_MEM_FRACTION=0.7
ENABLE_KV_CACHE_REUSE=true
BATCHING_STRATEGY=inflight_fused_batching
ENABLE_CHUNKED_CONTEXT=false

cp -R /app/all_models/inflight_batcher_llm/* ${MODEL_FOLDER}

python3 ${FILL_TEMPLATE_SCRIPT} -i ${MODEL_FOLDER}/ensemble/config.pbtxt triton_max_batch_size:${TRITON_MAX_BATCH_SIZE},logits_datatype:${LOGITS_DATATYPE}
python3 ${FILL_TEMPLATE_SCRIPT} -i ${MODEL_FOLDER}/preprocessing/config.pbtxt tokenizer_dir:${TOKENIZER_DIR},triton_max_batch_size:${TRITON_MAX_BATCH_SIZE},preprocessing_instance_count:${INSTANCE_COUNT}
python3 ${FILL_TEMPLATE_SCRIPT} -i ${MODEL_FOLDER}/tensorrt_llm/config.pbtxt triton_backend:tensorrtllm,triton_max_batch_size:${TRITON_MAX_BATCH_SIZE},decoupled_mode:${DECOUPLED_MODE},max_queue_delay_microseconds:${MAX_QUEUE_DELAY_MS},max_queue_size:${MA
python3 ${FILL_TEMPLATE_SCRIPT} -i ${MODEL_FOLDER}/postprocessing/config.pbtxt tokenizer_dir:${TOKENIZER_DIR},triton_max_batch_size:${TRITON_MAX_BATCH_SIZE},postprocessing_instance_count:${INSTANCE_COUNT},max_queue_size:${MAX_QUEUE_SIZE}
python3 ${FILL_TEMPLATE_SCRIPT} -i ${MODEL_FOLDER}/tensorrt_llm_bls/config.pbtxt triton_max_batch_size:${TRITON_MAX_BATCH_SIZE},decoupled_mode:${DECOUPLED_MODE},bls_instance_count:${INSTANCE_COUNT},logits_datatype:${LOGITS_DATATYPE}
python3 /app/scripts/launch_triton_server.py --world_size=1 --model_repo=/triton_model_repo --http_port=14524
```

Launch server in the last line!

These lines just fill the config files with your specified config.

Step 4: Start the demo

4.1) KV Caching (code): 9.45 sec → 8.86 sec

KV Caching

```
import time

start = time.time()
response = generate_text(api_url, model, prompts[0])
end = time.time()
print(f'{end - start:.2f} sec')

start = time.time()
response = generate_text(api_url, model, prompts[0])
end = time.time()
print(f'{end - start:.2f} sec')
```

```
9.45 sec
8.86 sec
```

4.2) In-flight Batching (code):
w/o IB 50.45 sec → w/ IB 9.72 sec (aync)

No inflight batching

```
import time

total_time = 0
for i, prompt in enumerate(prompts):
    start = time.time()
    response = generate_text(api_url, model, prompt)
    end = time.time()
    total_time += end - start
    print(f'Iteration {i}' , f'{end - start:.2f} sec')

print()
print(f"Total time: {total_time:.2f} sec")
```

With Inflight batching

```
import asyncio
import aiohttp
import time

async def agenerate_text(api_url, model, prompt, max_tokens=500, speculative_sampling=False, num_draft_tokens=5):
    data = {
        "text_input": prompt,
        "max_tokens": max_tokens,
        "bad_words": "",
        "stop_words": "",
    }

    if speculative_sampling:
        data["num_draft_tokens"] = num_draft_tokens
        data["use_draft_logits"] = False
        data["stream"] = False

    async with aiohttp.ClientSession() as session:
        async with session.post(f"{api_url}/v2/models/{model}/generate", json=data) as response:
            if response.status == 200:
                return await response.json()
            else:
                return {"error": await response.text()}
```

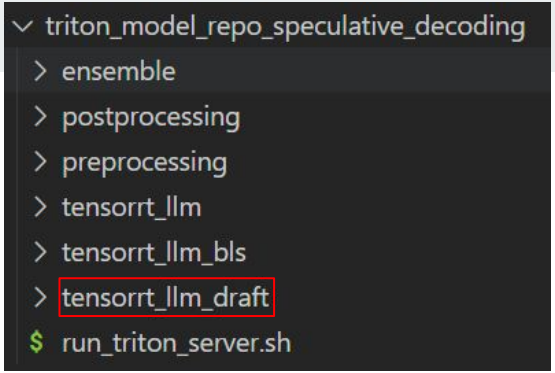
```
ENABLE_KV_CACHE_REUSE=true
BATCHING_STRATEGY=inflight_fused_batching
ENABLE_CHUNKED_CONTEXT=false
```

4.3) Chunk context (via configuration)
Doesn't improve

4.4) Speculative sampling (vida configuration)
Doesn't improve

Step 1: **Build a new engine** with speculative decoding mode specified.

```
# For Speculative Sampling
trtllm-build --checkpoint_dir ./tllm_checkpoint_1gpu_fp16_7B --output_dir ./tmp/Qwen2.5/7B/trt_engines/fp16/1-gpu-target \
    --gemm_plugin float16 --max_seq_len 2048 --max_batch_size 8 --max_beam_width 1 --reduce_fusion enable --use_paged_context_fmha enable --multiple_profiles enable
    --max_draft_len=10 --speculative_decoding_mode draft_tokens_external
```



4.4) Speculative sampling (cont.)

Step 2: Slightly modify Triton config: draft & target models

```
ENGINE_DIR=/app/examples/qwen/tmp/Qwen2.5/7B/trt_engines/fp16/1-gpu-target
DRAFT_ENGINE_DIR=/app/examples/qwen/tmp/Qwen2.5/0.5B/trt_engines/fp16/1-gpu
TENSORRT_LLM_DRAFT_MODEL_NAME="tensorrt_llm_draft"
TENSORRT_LLM_MODEL_NAME="tensorrt_llm"
TOKENIZER_DIR=/app/examples/qwen/tmp/Qwen2.5/7B
MODEL_FOLDER=/triton_model_repo_speculative_decoding
TRITON_MAX_BATCH_SIZE=4
INSTANCE_COUNT=4
MAX_QUEUE_DELAY_MS=10000
MAX_QUEUE_SIZE=0
FILL_TEMPLATE_SCRIPT=/app/tools/fill_template.py
DECOUPLED_MODE=false
LOGITS_DATATYPE=TYPE_FP32
KV_CACHE_FREE_GPU_MEM_FRACTION=0.4
ENABLE_KV_CACHE_REUSE=true
MAX_TOKEN_IN_PAGED_KV_CACHE=2048*8
DRAFT_GPU_DEVICE_IDS=0
ENABLE_CHUNKED_CONTEXT=false

cp -R /app/all_models/inflight_batcher_llm/* ${MODEL_FOLDER}
mkdir -p tensorrt_llm_draft
cp -R ${MODEL_FOLDER}/tensorrt_llm/* ${MODEL_FOLDER}/tensorrt_llm_draft
```

```
## Speculative sampling ###
sed -i 's/name: "tensorrt_llm"/name: "tensorrt_llm_draft"/g' ${MODEL_FOLDER}/tensorrt_llm_draft/config.pbtxt
python3 ${FILL_TEMPLATE_SCRIPT} -i ${MODEL_FOLDER}/tensorrt_llm_bls/config.pbtxt triton_max_batch_size:${TRITON_MAX_BATCH_SIZE},decoupled_mode:${DECOUPLED_MODE},bls_instance_count:${INSTANCE_CO
python3 ${FILL_TEMPLATE_SCRIPT} -i ${MODEL_FOLDER}/tensorrt_llm_draft/config.pbtxt triton_backend:tensorrtllm,triton_max_batch_size:${TRITON_MAX_BATCH_SIZE},decoupled_mode:${DECOUPLED_MODE},max
python3 /app/scripts/launch_triton_server.py --world_size=1 --model_repo=/triton_model_repo_speculative_decoding --http_port=14524 --tensorrt_llm_model_name "tensorrt_llm,tensorrt_llm_draft"
```

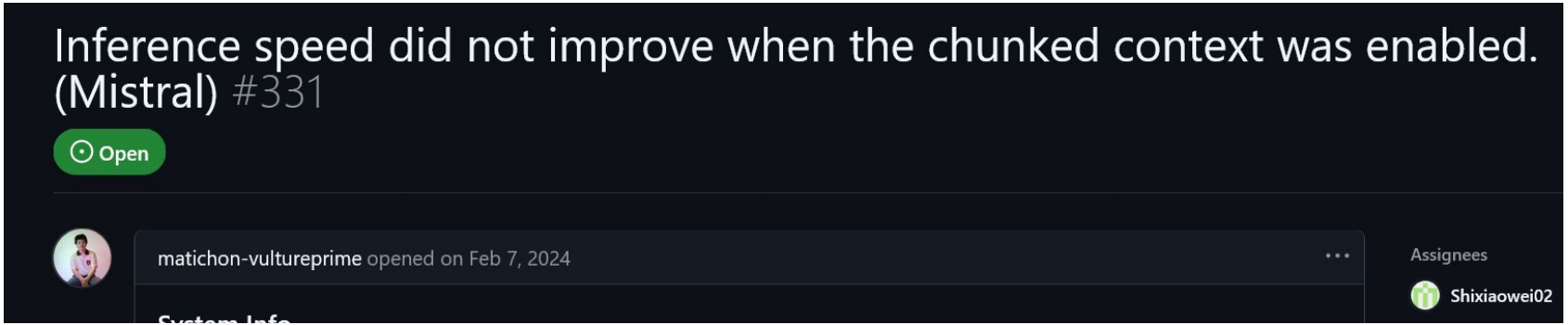
Add this into the BLS config

* BLS = Business logic script

```
,tensorrt_llm_model_name:${TENSORRT_LLM_MODEL_NAME},tensorrt_llm_draft_model_name:${TENSORRT_LLM_DRAFT_MODEL_NAME}
```

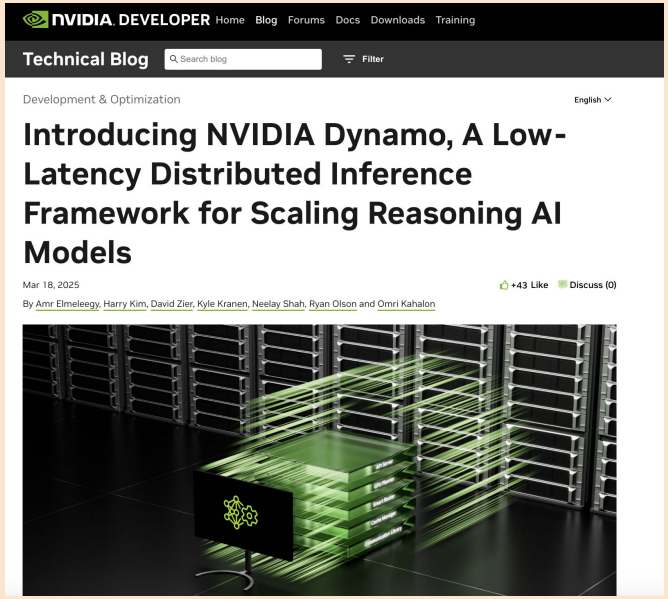
Must use KV cache (cannot disable KV cache option)

```
terminate called after throwing an instance of 'tensorrt_llm::common::TllmException'
  what():  [TensorRT-LLM][ERROR] Assertion failed: KV-cache-less is only supported for context (/workspace/tensorrt_llm/cpp/tensorrt_llm/plugins/gptAttentionPlugin/gptAttentionPlugin.cpp:1102)
1       0x7f47148f0bdd /usr/local/lib/python3.12/dist-packages/tensorrt_llm/libs/libnvinfer_plugin_tensorrt_llm.so(+0x8dbdd) [0x7f47148f0bdd]
```



2) NVIDIA Dynamo [inference]

LLMs: NVIDIA Triton Server → NVIDIA Dynamo



https://developer.nvidia.com/blog/introducing-nvidia-dynamo-a-low-latency-distributed-inference-framework-for-scaling-reasoning-ai-models/

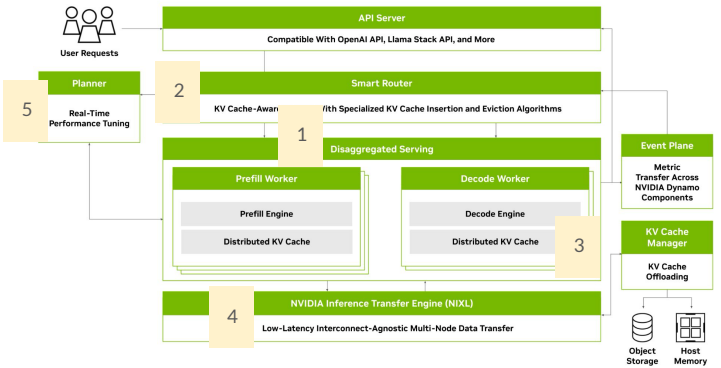
NVIDIA Dynamo

NVIDIA Dynamo is a high-throughput, low-latency inference framework designed for serving generative AI and reasoning models in **multi-node distributed environments**.

Dynamo is designed to be inference engine agnostic (**supports TRT-LLM, vLLM, SGLang or others**)

To enable large-scale distributed and disaggregated inference serving, Dynamo includes five key features.

1. Dynamo Disaggregated Serving
2. Dynamo Smart Router
3. Dynamo Distributed KV Cache Manager
4. NVIDIA Inference Transfer Library (NIXL)
5. Dynamo Planner



https://www.nvidia.com/en-us/ai/dynamo/

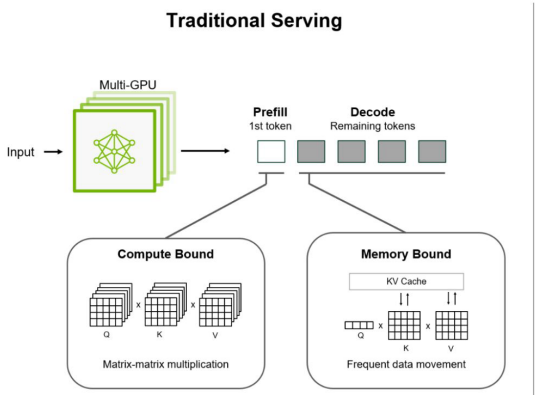
NVIDIA Triton Server vs. NVIDIA Dynamo

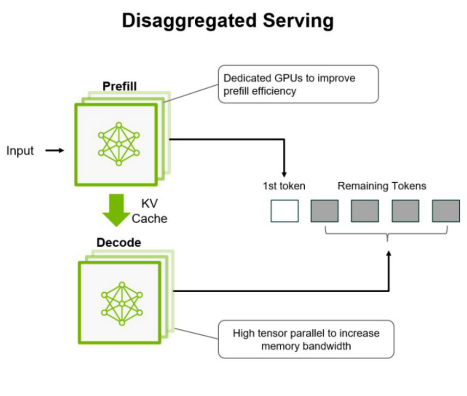
🧩 Key Differences Summary

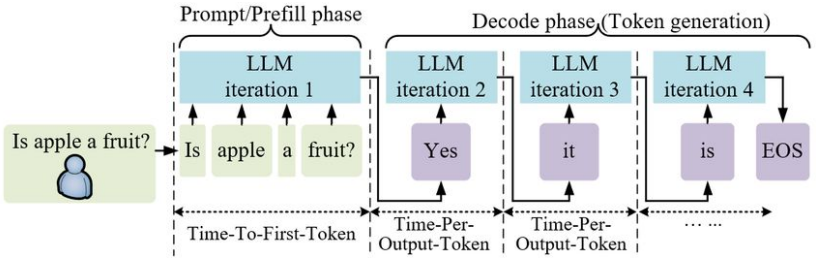
Feature	NVIDIA Triton Inference Server	NVIDIA DynaMo (Dynamic Model Orchestration)
Purpose	General model serving engine	Advanced LLM inference orchestrator
Built for	Multiple frameworks and use cases	High-throughput LLM serving
Model types	Any (CV, NLP, etc.)	LLMs (e.g., Mixtral, LLaMA, GPT-J, etc.)
Dynamic batching	✅ Yes	✅ More advanced (in-flight, priority aware)
Streaming support	✅ Yes (with TensorRT-LLM)	✅ Yes (optimized with memory paging)
KV cache & query routing	Basic via TensorRT-LLM backend	✅ Optimized (paged cache, preemption, scheduling)
Scale	Multi-GPU, multi-model	Multi-GPU, multi-node, dynamic orchestration
Framework integration	TensorFlow, PyTorch, ONNX, TensorRT, etc.	TensorRT-LLM, NIM, LLM-focused tools
When to use	General ML/AI serving	Scalable, multi-query LLM deployment

1. Dynamo Disaggregated Serving

Disaggregating these phases (prefill & decode) into specialized LLM engines allows for better hardware allocation, improved scalability, and overall enhanced performance.





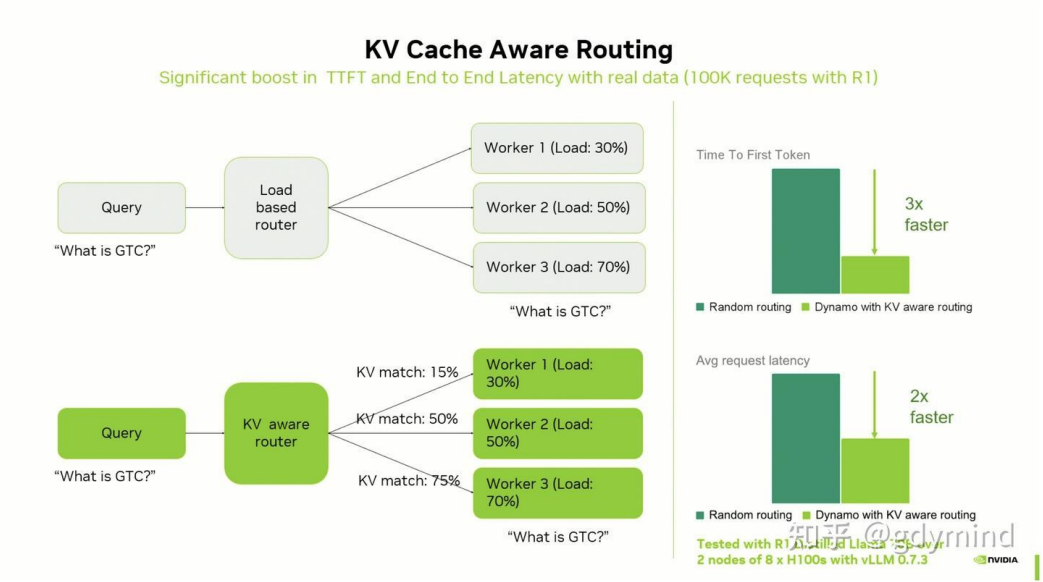


Stage	Description	Characteristics
Prefill	Processes input tokens and computes KV cache.	Highly parallelized, efficient GPU utilization.
Decode	Generates output tokens one at a time based on previous tokens.	Sequential processing, potentially slower, memory-bound.

https://github.com/ai-dynamo/dynamo/blob/main/docs/architecture.md

2. Dynamo Smart Router

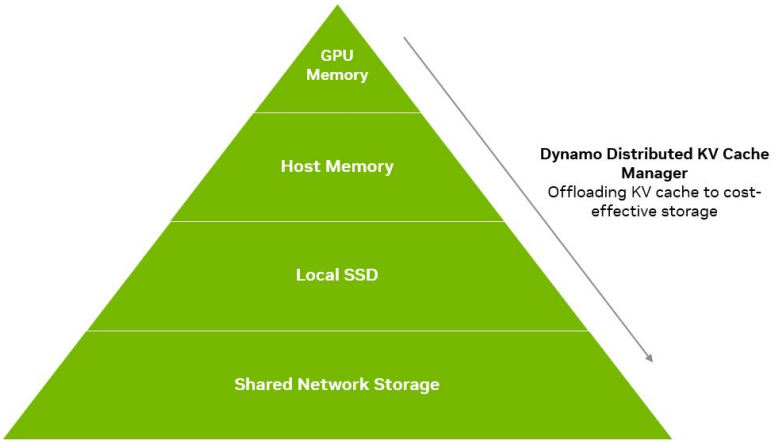
Providing optimized inference for large language models by intelligently directing requests to workers with the most relevant cached data while simultaneously load balancing based on utilization metrics.



https://developer.nvidia.com/blog/introducing-nvidia-dynamo-a-low-latency-distributed-inference-framework-for-scaling-reasoning-ai-models/

3. Dynamo Distributed KV Cache Manager

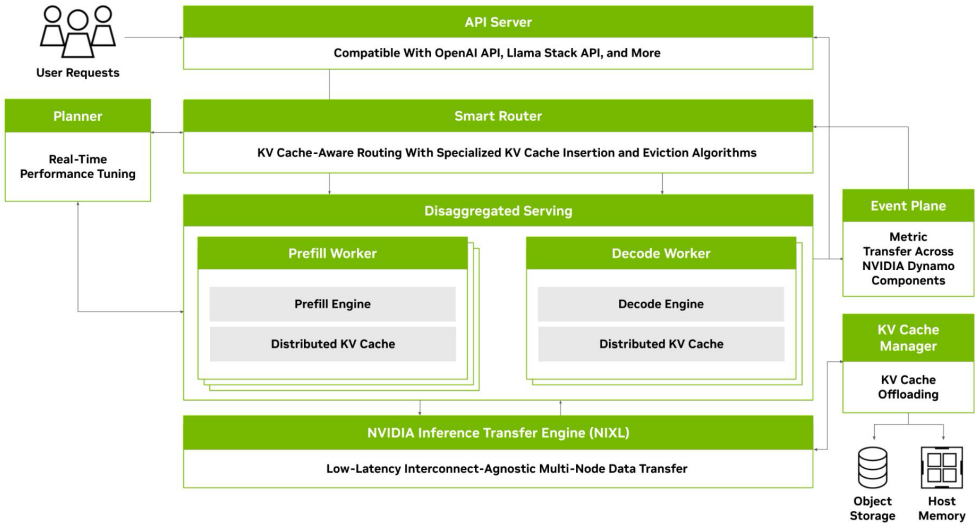
Enabling the offloading of older or less frequently accessed KV cache blocks to more cost-effective memory and storage solutions, such as CPU memory, local storage, or networked object or file storage.



https://developer.nvidia.com/blog/introducing-nvidia-dynamo-a-low-latency-distributed-inference-framework-for-scaling-reasoning-ai-models/

4. NVIDIA Inference Transfer Library (NIXL)

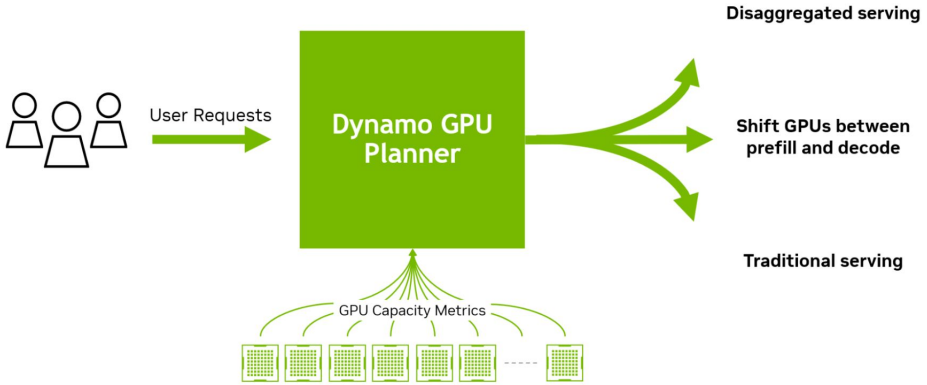
NIXL is designed to support inference frameworks by addressing their challenges while delivering high-bandwidth, low-latency point-to-point data transfers.



https://developer.nvidia.com/blog/introducing-nvidia-dynamo-a-low-latency-distributed-inference-framework-for-scaling-reasoning-ai-models/

5. NVIDIA Dynamo Planner

Ensuring that GPU resources are allocated efficiently across prefill and decode, adapting to fluctuating workloads while maintaining peak system performance.



https://developer.nvidia.com/blog/introducing-nvidia-dynamo-a-low-latency-distributed-inference-framework-for-scaling-reasoning-ai-models/

NVIDIA Dynamo's Performance

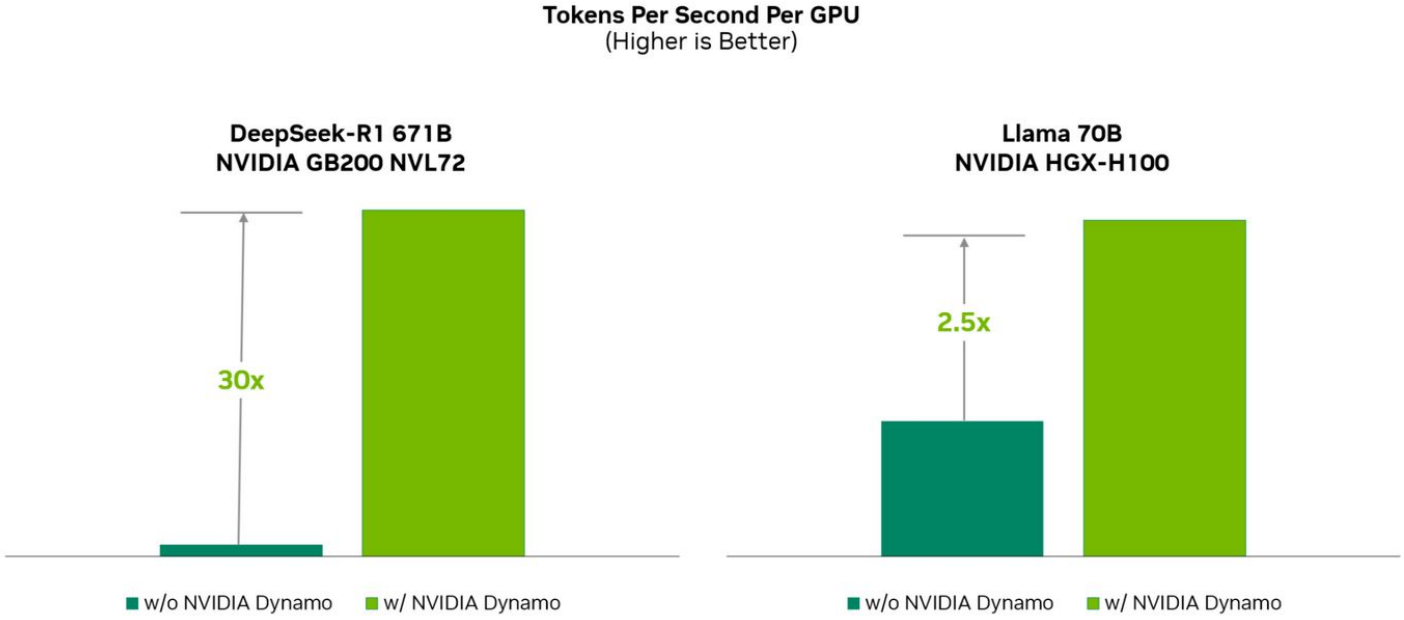
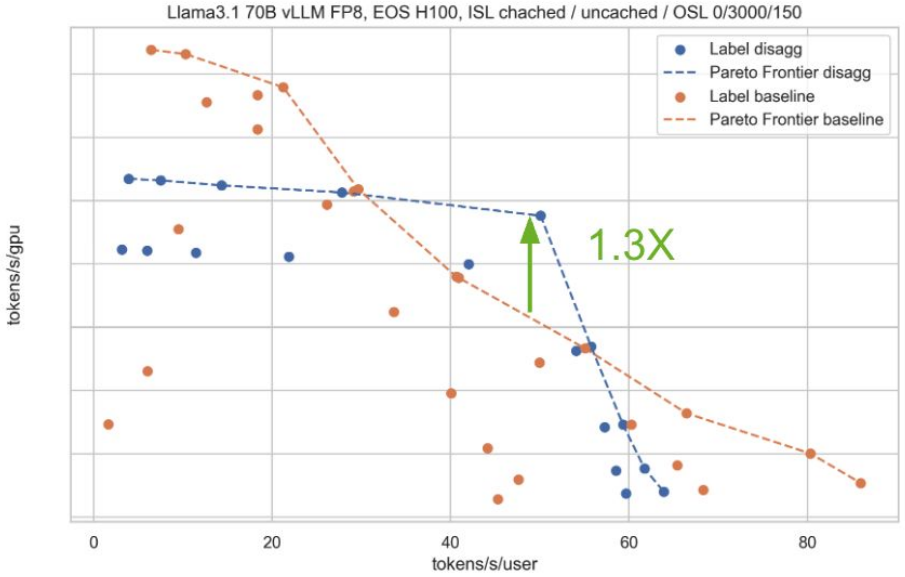


Figure 2. NVIDIA Dynamo delivers exceptional throughput performance when running DeepSeek-R1 671B model on NVIDIA GB200 NVL72 boosting performance by 30x. It more than doubles performance on the Llama 70B model running on NVIDIA Hopper GPUs

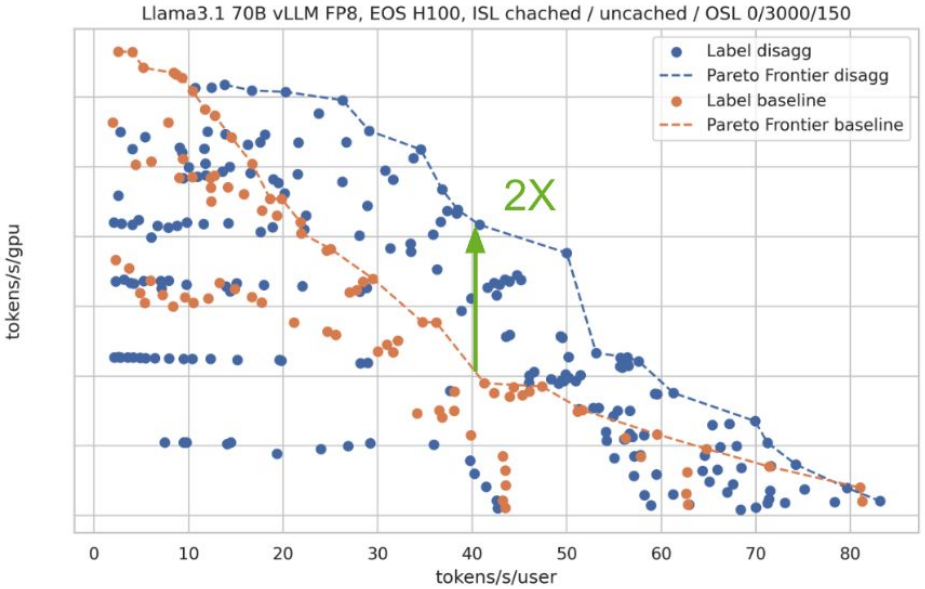
Left: TensorRT-LLM, FP4, ISL/OSL: 32K/8K. Without Dynamo: Inflight Batching, TEP16PP4DP4. With Dynamo: Disaggregated Serving, Context: EP4DP16, Generation: EP64DP3. Projected performance subject to change. Right: vLLM, FP8, ISL/OSL: 3K/50 . Without Dynamo: Inflight Batching, TP8DP2. With Dynamo: Disaggregated Serving, Context: TP2DP4, Generation: TP8.

NVIDIA Dynamo's Performance (cont.)

One Node



Two Nodes



oughput ความเร็วในการ inference (ความเร็ว per sec) → วัดแต่ละ user ได้ความเร็วเท่าไหร่
ามเร็ว per GPU → วัดแต่ละ GPU ได้ความเร็วเท่าไหร่

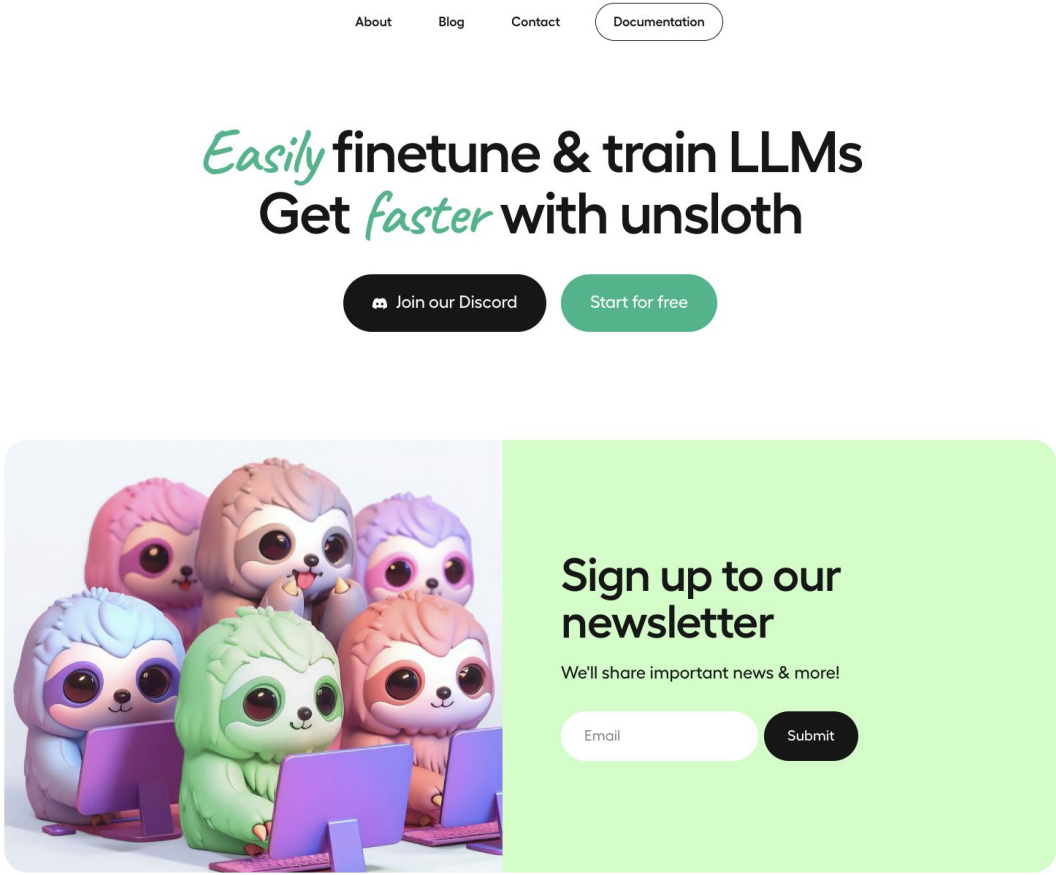
NVIDIA Dynamo

Github: https://github.com/ai-dynamo/dynamo

Examples: https://github.com/ai-dynamo/dynamo/blob/main/examples/llm/README.md

3) Unsloth
[fine-tune & inference]

https://unsloth.ai/

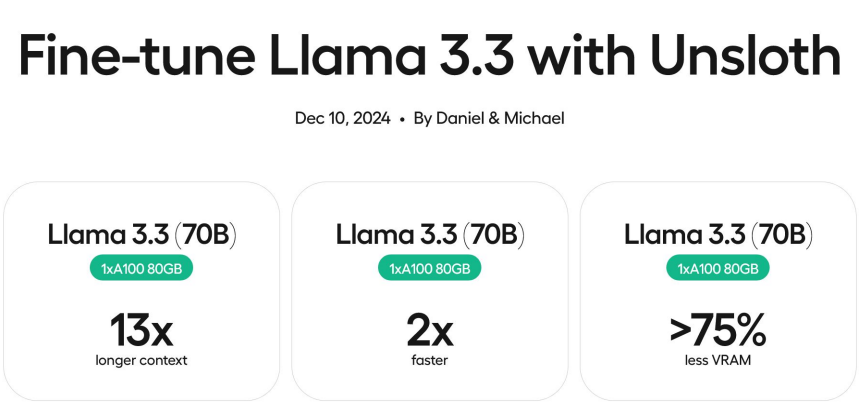


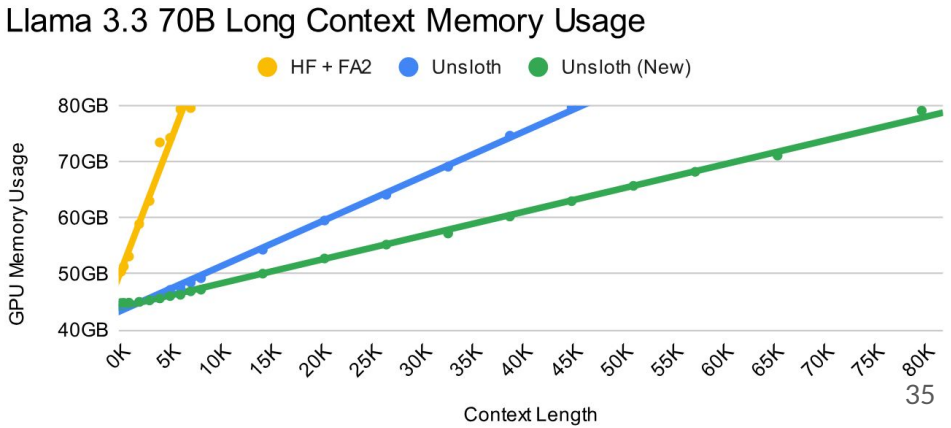
Unsloth: Less VRAM & Larger Batch Sizes

The unsloth library is a lightweight and high-performance fine-tuning framework for Large Language Models (LLMs). It's designed to make parameter-efficient fine-tuning (PEFT) — like LoRA (Low-Rank Adaptation) — fast, simple, and memory-efficient, especially on consumer hardware (like 8GB or 16GB VRAM GPUs).

It builds on top of Hugging Face Transformers + PEFT + BitsAndBytes.

It works by overwriting some parts of the modeling code with optimized operations. By manually deriving backpropagation steps and rewriting all Pytorch modules into Triton kernels.





Free on a single GPU, but not free for multiple GPUs!

Pricing

Free

Freeware of our standard version of unsloth

Get started

- Open-source
- Supports Mistral, Gemma
- Supports LLama 1, 2, 3
- Single GPU support
- Supports 4 bit, 16 bit LoRA

unsloth *Pro*

Unlock multi GPU support + 2.5x faster training + 20% less VRAM

Contact us

- 2.5x number of GPUs faster than FA2
- 20% less memory than OSS
- Multi GPU support
- Up to 8 GPUS support
- For any usecase

unsloth *Enterprise*

Unlock 30x faster training + multi-node support + 30% accuracy

Contact us

- 32x number of GPUs faster than FA2
- up to +30% accuracy
- 5x faster inference
- Supports full training
- All Pro plan features
- Multi-node support
- Customer support

Unsloth supports (1) many models, (2) many PEFT (LoRA) techniques, and (3) many hardware

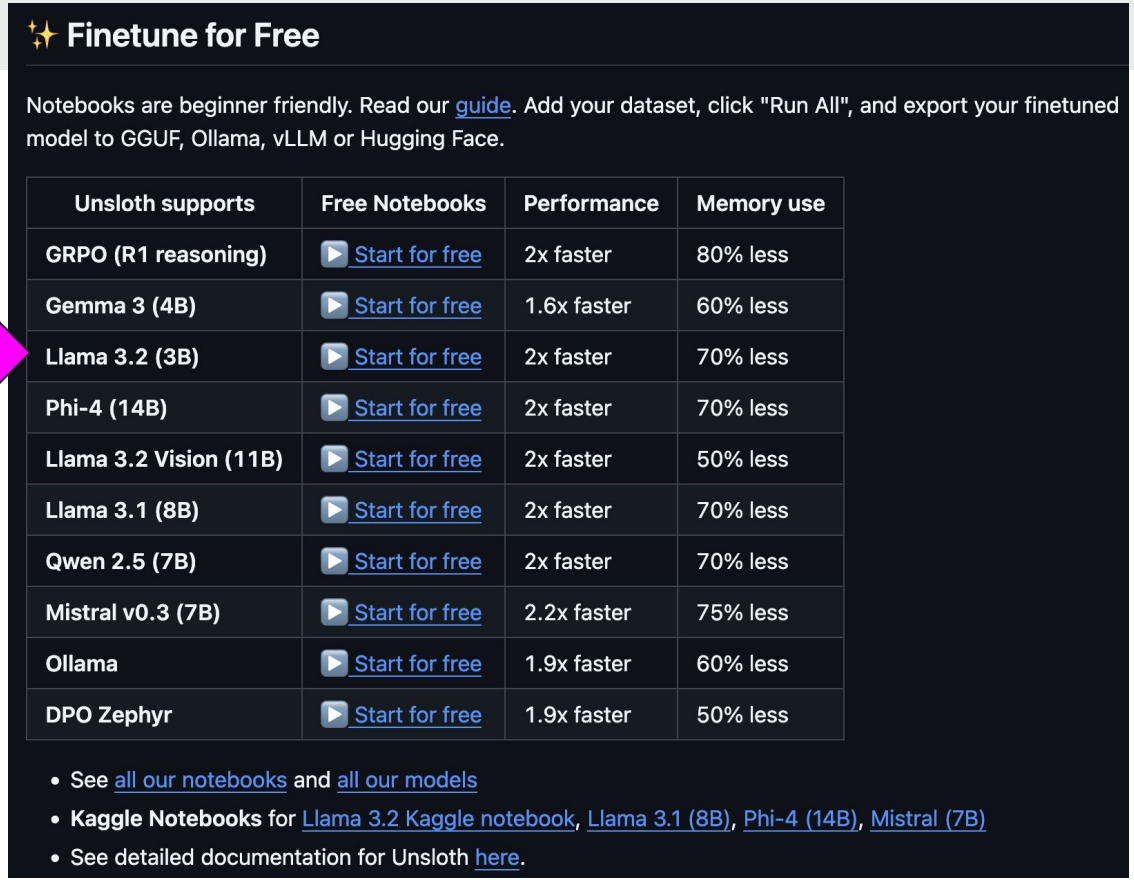
Unsloth.ai News

- 📣 NEW! EVERYTHING is now supported incuding: full finetuning, pretraining, ALL models (Mixtral, MOE, Cohere, Mamba) and all training algorithms (KTO, DoRA) etc. MultiGPU support coming very soon.

- Supports 4bit and 16bit QLoRA / LoRA finetuning via bitsandbytes.

- No change of hardware. Supports NVIDIA GPUs since 2018+. Minimum CUDA Capability 7.0 (V100, T4, Titan V, RTX 20, 30, 40x, A100, H100, L40 etc) Check your GPU! GTX 1070, 1080 works, but is slow.

Unsloth Notebook Examples



✨ Finetune for Free

Notebooks are beginner friendly. Read our guide. Add your dataset, click "Run All", and export your finetuned model to GGUF, Ollama, vLLM or Hugging Face.

Unsloth supports	Free Notebooks	Performance	Memory use
GRPO (R1 reasoning)	▶ Start for free	2x faster	80% less
Gemma 3 (4B)	▶ Start for free	1.6x faster	60% less
Llama 3.2 (3B)	▶ Start for free	2x faster	70% less
Phi-4 (14B)	▶ Start for free	2x faster	70% less
Llama 3.2 Vision (11B)	▶ Start for free	2x faster	50% less
Llama 3.1 (8B)	▶ Start for free	2x faster	70% less
Qwen 2.5 (7B)	▶ Start for free	2x faster	70% less
Mistral v0.3 (7B)	▶ Start for free	2.2x faster	75% less
Ollama	▶ Start for free	1.9x faster	60% less
DPO Zephyr	▶ Start for free	1.9x faster	50% less

- See all our notebooks and all our models
- **Kaggle Notebooks** for Llama 3.2 Kaggle notebook, Llama 3.1 (8B), Phi-4 (14B), Mistral (7B)
- See detailed documentation for Unsloth here.

https://colab.research.google.com/github/unslothai/notebooks/blob/main/nb/Llama3.2_(1B_and_3B)-Conversational.ipynb

We aim to fine-tune Llama3.2-3B in the conversational task (this code) on Colab!

Unsloth's performance on different tasks (accuracy)

Model	Average	IFEval	BBH	MATH	MMLU
unsloth/phi-4 16-bit	40.73 %	68.82 %	55.25 %	50.00 %	48.65 %
unsloth/phi-4 -unsloth-bnb-4bit Dynamic 4-bit	39.22 %	67.94 %	53.84 %	45.62 %	47.62 %
unsloth/phi-4 -bnb-4bit BnB 4-bit	39.06 %	67.30 %	53.54 %	46.07 %	47.29 %
microsoft/phi-4 Microsoft 16-bit	30.36 %	5.85 %	52.43 %	31.65 %	47.63 %

Unsloth on DeepSeek 671B (around 1.2TB) with different MoE bits

MoE Bits	Disk Size	Type	Quality	Link	Down_proj
1.58-bit	**131GB**	IQ1_S	Fair	Link	2.06/1.56bit
1.73-bit	**158GB**	IQ1_M	Good	Link	2.06bit
2.22-bit	**183GB**	IQ2_XXS	Better	Link	2.5/2.06bit
2.51-bit	**212GB**	Q2_K_XL	Best	Link	3.5/2.5bit

Comparison

W/O (No) Unsloth

- Batch size = 1
- Num train steps = 60

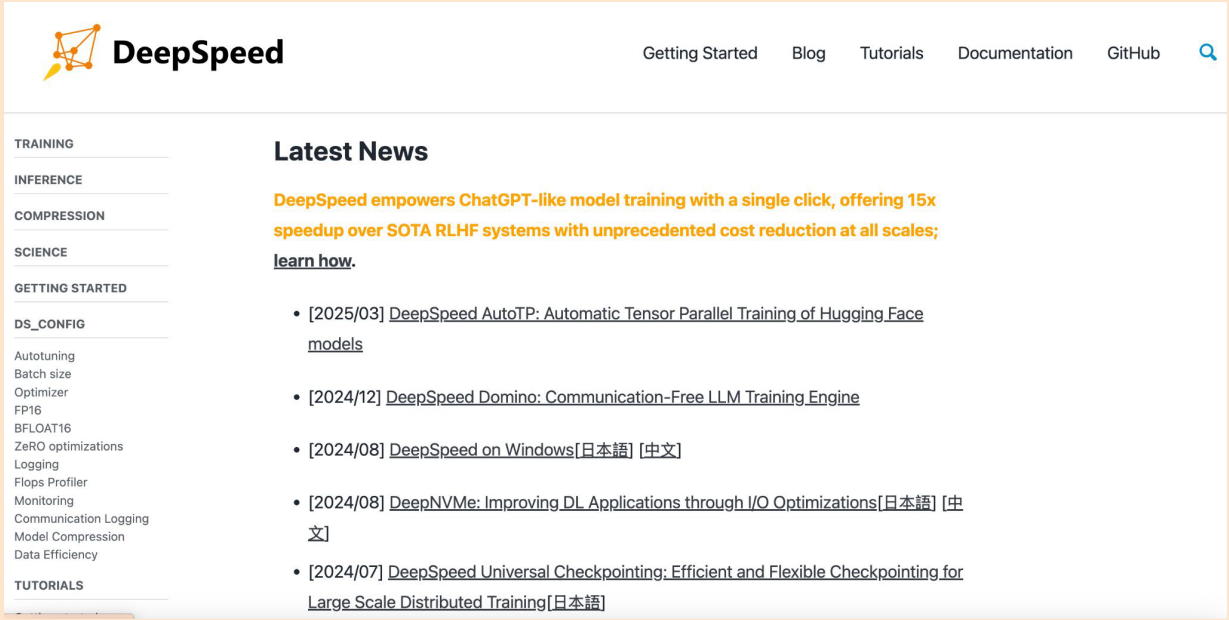
```
209.5694 seconds used for training.
3.49 minutes used for training.
Peak reserved memory = 14.244 GB.
Peak reserved memory for training = 12.035 GB.
Peak reserved memory % of max memory = 96.628 %.
Peak reserved memory for training % of max memory = 81.643 %.
```

W/ Unsloth

- Batch size = 2
- Num train steps = 60

```
437.6992 seconds used for training.
7.29 minutes used for training.
Peak reserved memory = 4.131 GB.
Peak reserved memory for training = 0.69 GB.
Peak reserved memory % of max memory = 28.024 %.
Peak reserved memory for training % of max memory = 4.681 %.
```

4) DeepSpeed [fine-tune & inference]

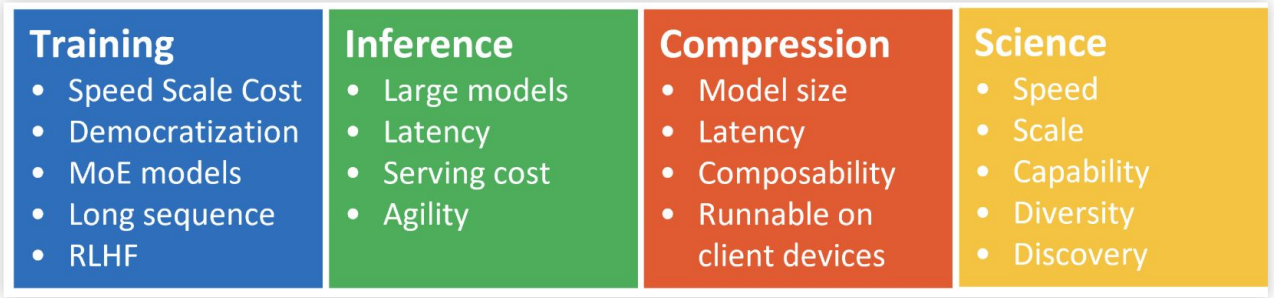


https://www.deepspeed.ai/

DeepSpeed: Extreme Speed and Scale for DL Training and Inference

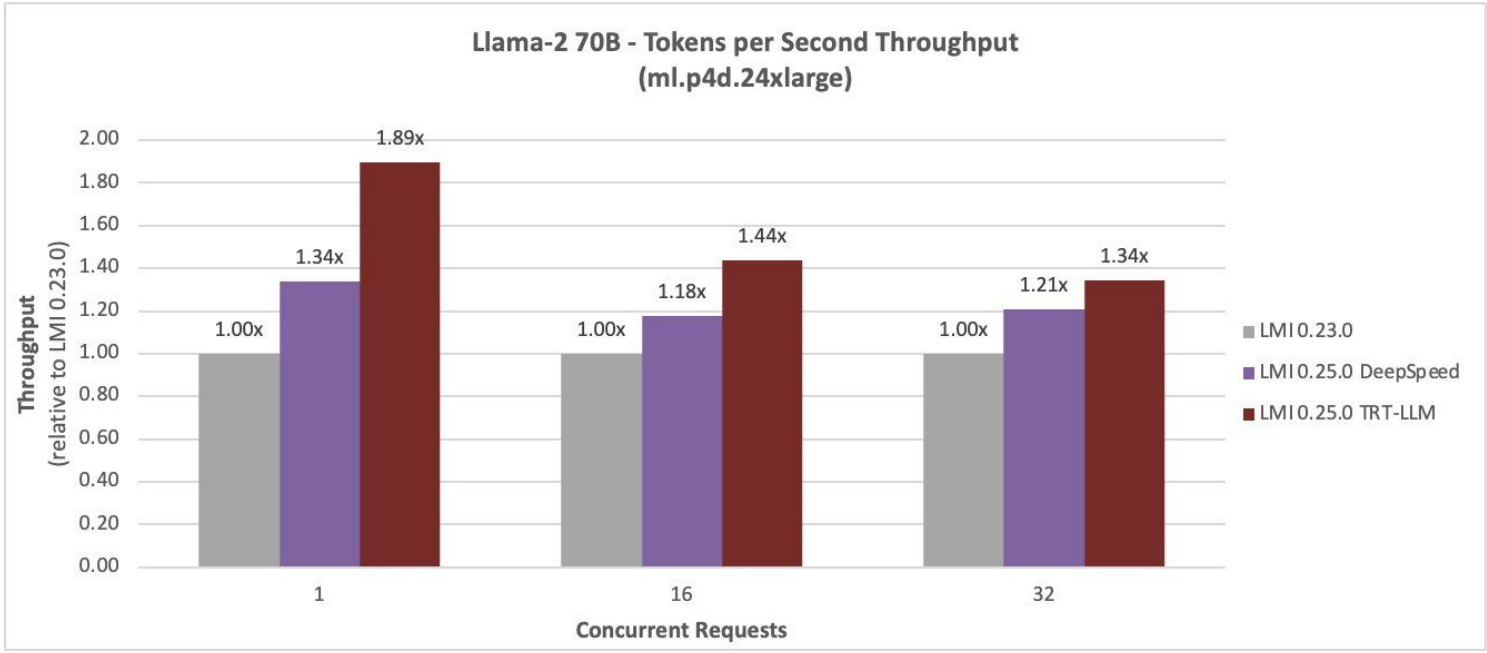
DeepSpeed is an open-source deep learning optimization library developed by Microsoft, designed to train and serve large-scale models efficiently — especially large language models (LLMs) like GPT, BERT, and others. It makes **distributed training (multiple GPUs)** and inference easy, efficient, and effective.

DeepSpeed has four innovation pillars:



DeepSpeed also supports inference, but TRT-LLM is better!

Amazon SageMaker launches a new version (0.25.0) of **Large Model Inference (LMI)** Deep Learning Containers that works with many frameworks like DeepSpeed, FastTransformer, TensorRT-LLM, vLLM.



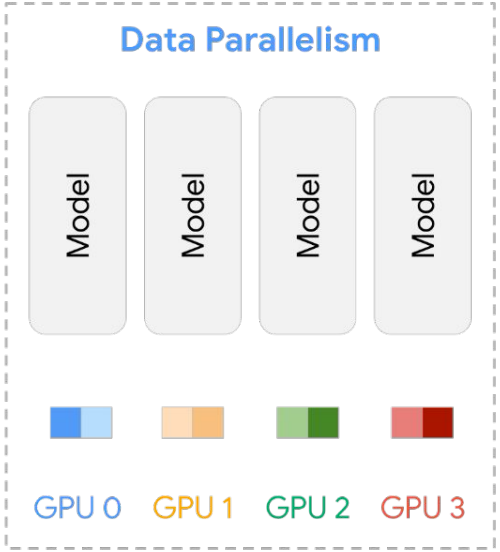
DeepSpeed Main Features

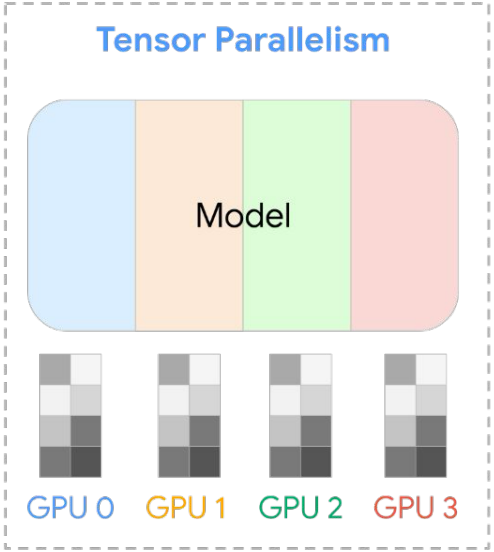
1. Data, Pipeline, and Model (with Megatron) parallelism
2. The Zero Redundancy Optimizer (ZeRO) [1]

Feature	Description
Zero Redundancy Optimizer (ZeRO)	Reduces memory usage to enable training huge models across GPUs
DeepSpeed-Inference	High-performance, low-latency inference engine (serving large models)
Model Parallelism	Splits one model across multiple GPUs or machines
Optimizer Offloading	Moves optimizer states to CPU or NVMe to save GPU memory
Mixed Precision (FP16/BF16)	Enables faster training with lower precision
LoRA + Quantization support	Fine-tune large models with reduced memory footprint
Megatron + DeepSpeed	Joint framework for extreme-scale training

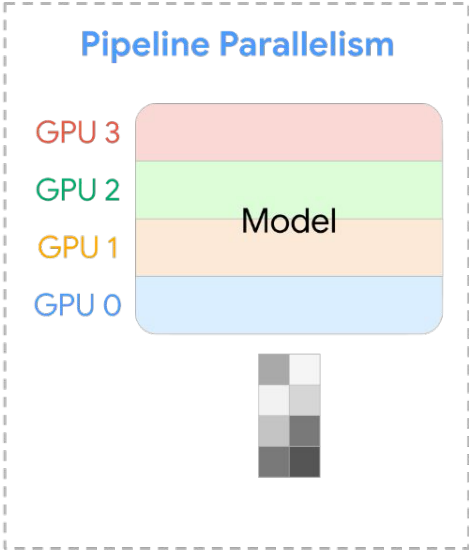
[1] https://arxiv.org/abs/1910.02054

DeepSpeed - (1) Model Parallelism - various modes





A single layer's computation is split across multiple GPUs.



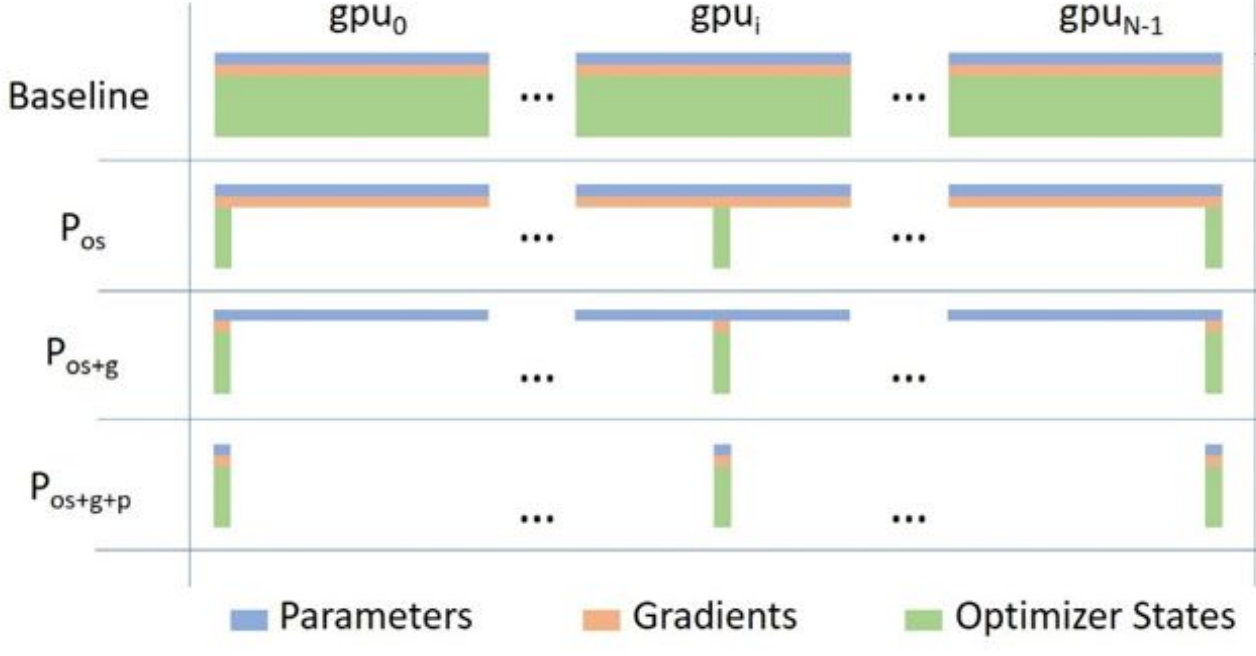
Splits the model across GPUs **by layers.** Each GPU processes a different stage of the model.

DeepSpeed - (2) Zero Redundant Optimizer (ZeRO)

Feature	ZeRO-1	ZeRO-2	ZeRO-3
Optimizer State Sharding	✅ Yes	✅ Yes	✅ Yes
Gradient Sharding	❌ No	✅ Yes	✅ Yes
Parameter Sharding	❌ No	❌ No	✅ Yes
Memory Savings	~4x	~8x	~16x+
Communication Overhead	Low	Moderate	High

DeepSpeed - (2) Zero Redundant Optimizer (ZeRO)

- Sharding: Parameters, Gradients, States
- Save memory consumption
- Reduce communication overhead



	Memory Consumption		Comm Volume
	Formulation	Specific Example K=12 Ψ=7.5B N_d=64	
Baseline	$(2+2+K)*\Psi$	120GB	1x
P_{os}	$2\Psi+2\Psi+\frac{K*\Psi}{N_d}$	31.4GB	1x
P_{os+g}	$2\Psi+\frac{(2+K)*\Psi}{N_d}$	16.6GB	1x
P_{os+g+p}	$\frac{(2+2+K)*\Psi}{N_d}$	1.9GB	1.5x

Trade-off overhead

DeepSpeed Resources

Github: https://github.com/deepspeedai/DeepSpeed

Transformers with DeepSpeed: https://huggingface.co/docs/transformers/deepspeed

Tutorial: https://www.deepspeed.ai/tutorials/

Conclusion

- **To optimize the inference model & self-use: TensorRT-LLM**
- To serve the application with a single GPU: NVIDIA Triton Server
- To serve the application with multiple GPUs: NVIDIA Dynamo

- To fine-tune the model on a single GPU: Unsloth
- To fine-tune a huge model that needs to be distributed into many GPUs: DeepSpeed