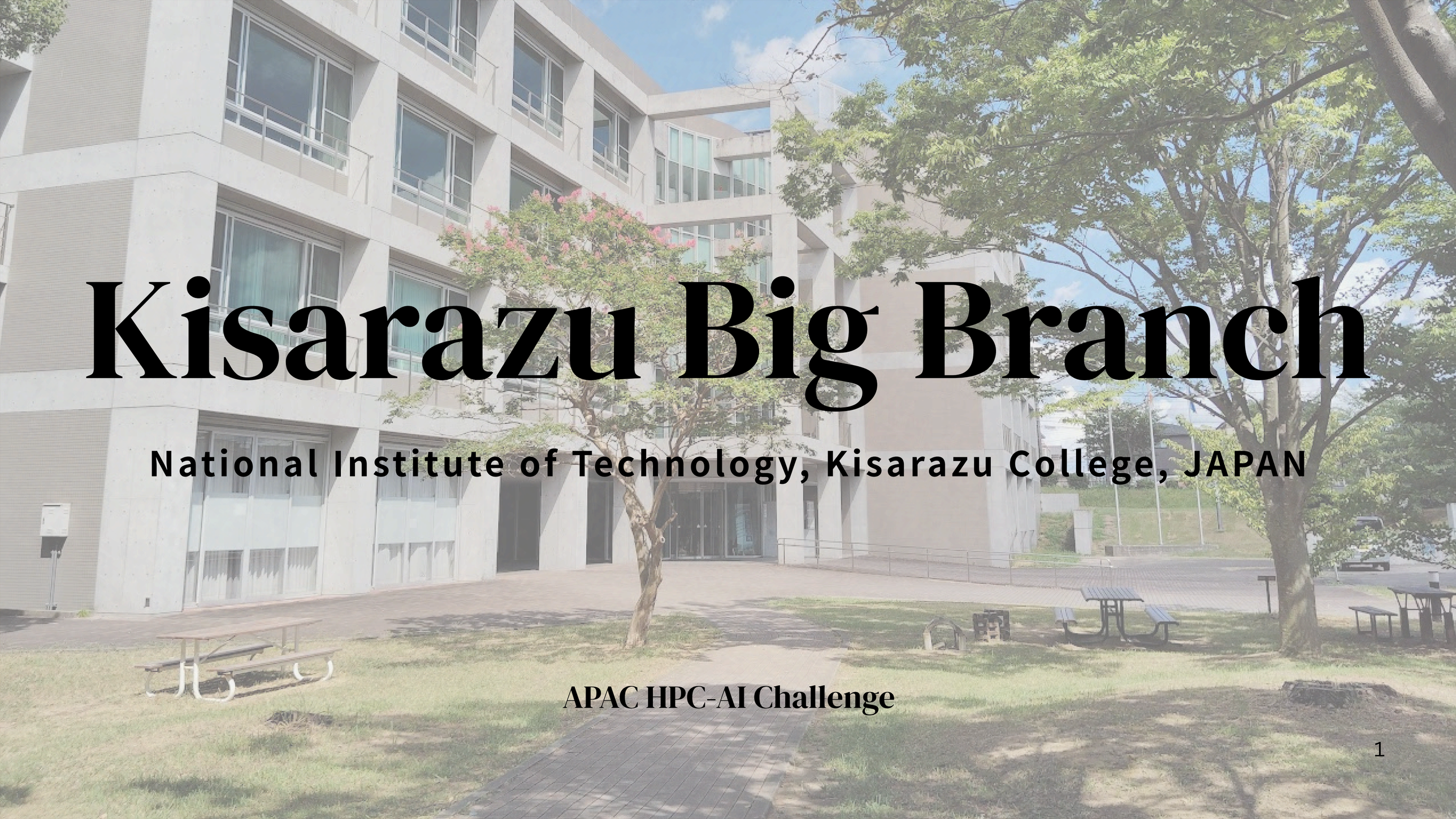

Kisarazu Big Branch

National Institute of Technology, Kisarazu College, JAPAN

APAC HPC-AI Challenge

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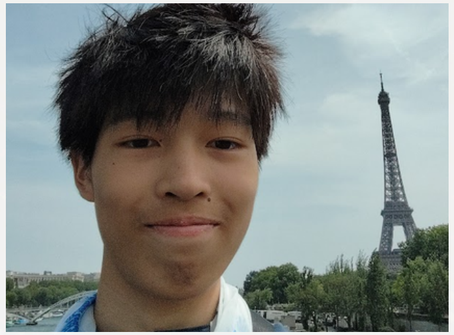
Our Team

Kisarazu Big Branch

Ochi Yuma (Leader)

I’m eating Kaya Toast

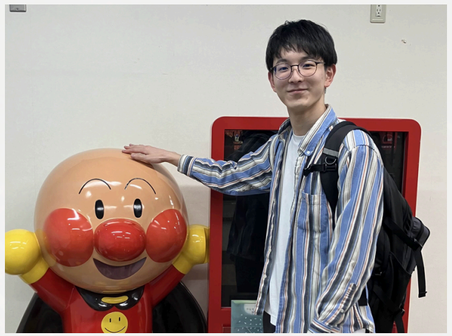


Tsuneki Hirotaka

Computer OTAKU

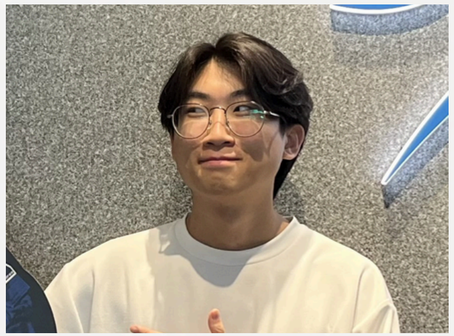
Akimoto Sora

Goodnight



Naito Masahiro

I like Anpanman



Isaac Yap Zhen Khai

That one foreigner on the team

Prof. Oeda Shinichi

Our Glorious Supreme Big Branch Supervisor

Objective: Maximizing throughput of DeepSeek 671B inference

Framework:

SGLang

Machine:

Aspire2a+

- 8x H100 / node
- 2 nodes access

Constraints:

No experimental features
(eg: torch.compile)

SGLang

A fast serving framework for large language models and vision language models

Features

- Fast Backend Runtime
- Flexible Frontend Language
- Extensive Model Support
- Active Community

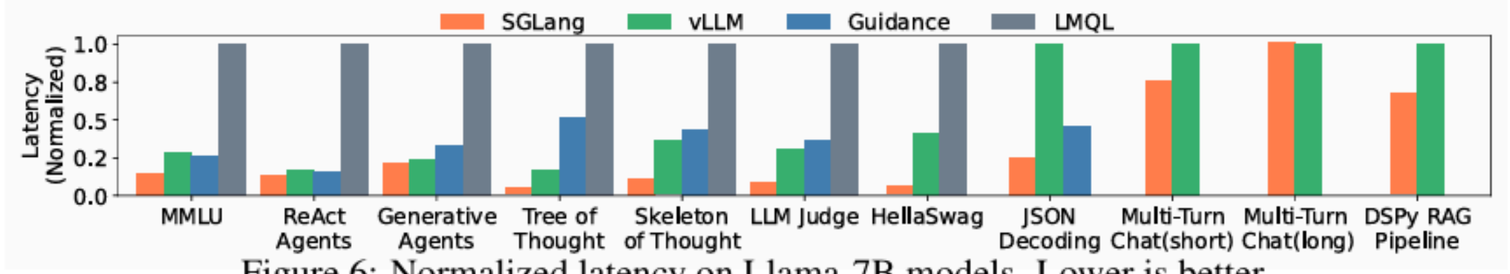


Figure 6: Normalized latency on Llama-7B models. Lower is better.

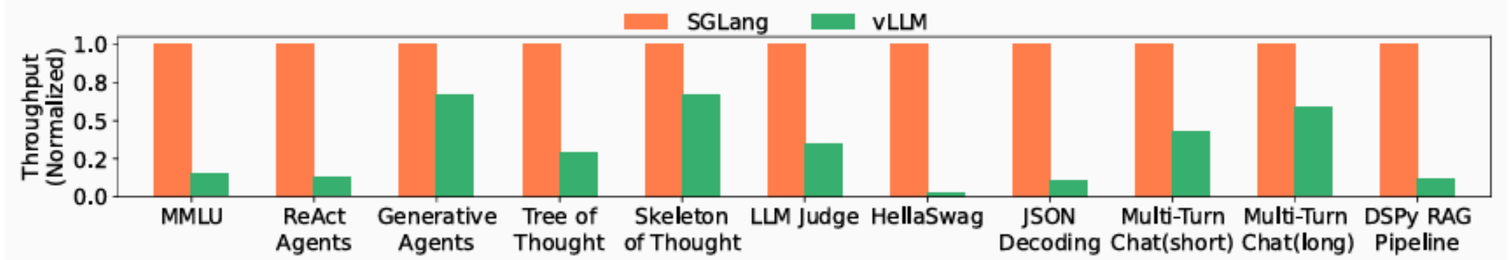


Figure 7: Normalized throughput on Mixtral-8x7B models with tensor parallelism. Higher is better.

https://arxiv.org/pdf/2312.07104

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DeepSeek R1

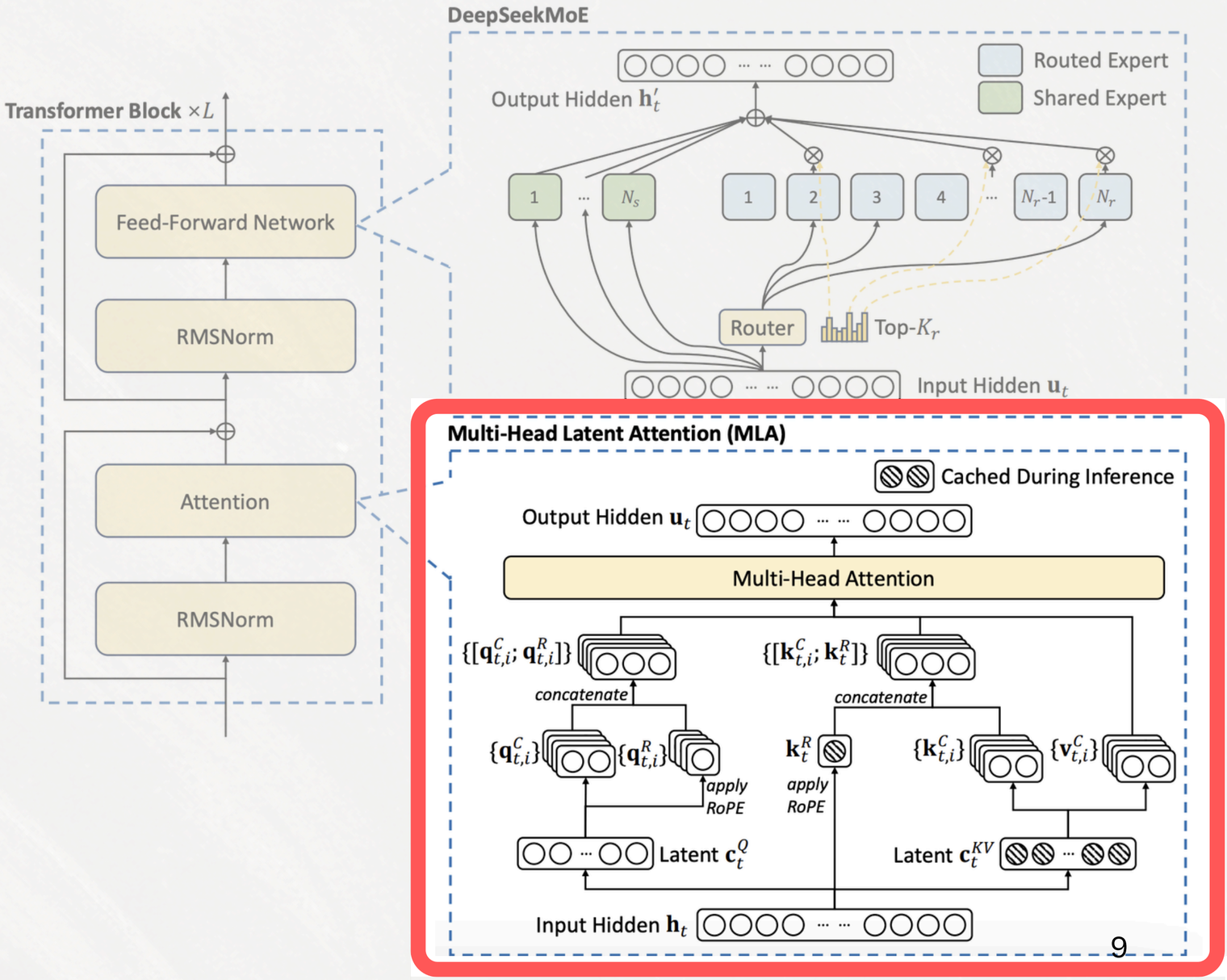
1. 671B parameters,
   37B active

2. Applied Reinforcement Learning during Training

3. Key features include
   - Multi-head Latent Attention (MLA)
   - Mixture of Experts (MoE)
   - Multi-Token Prediction (MTP)

Multi-head Latent Attention (MLA)

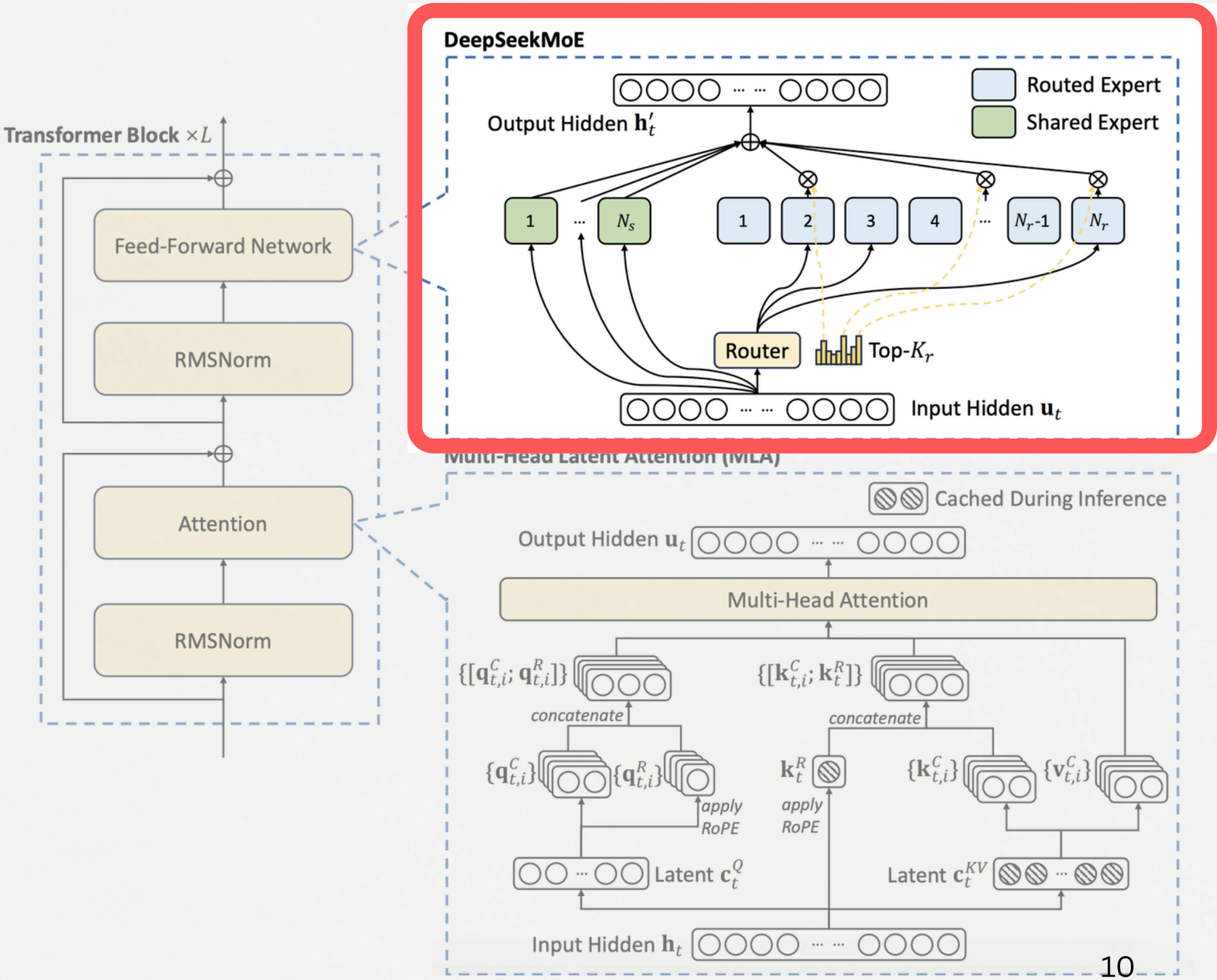
- Compresses KV cache into lower-dimensional latent space
- Boosts training and inference speed while significantly reducing memory usage



https://arxiv.org/pdf/2412.19437

Mixture of Experts (MoE)

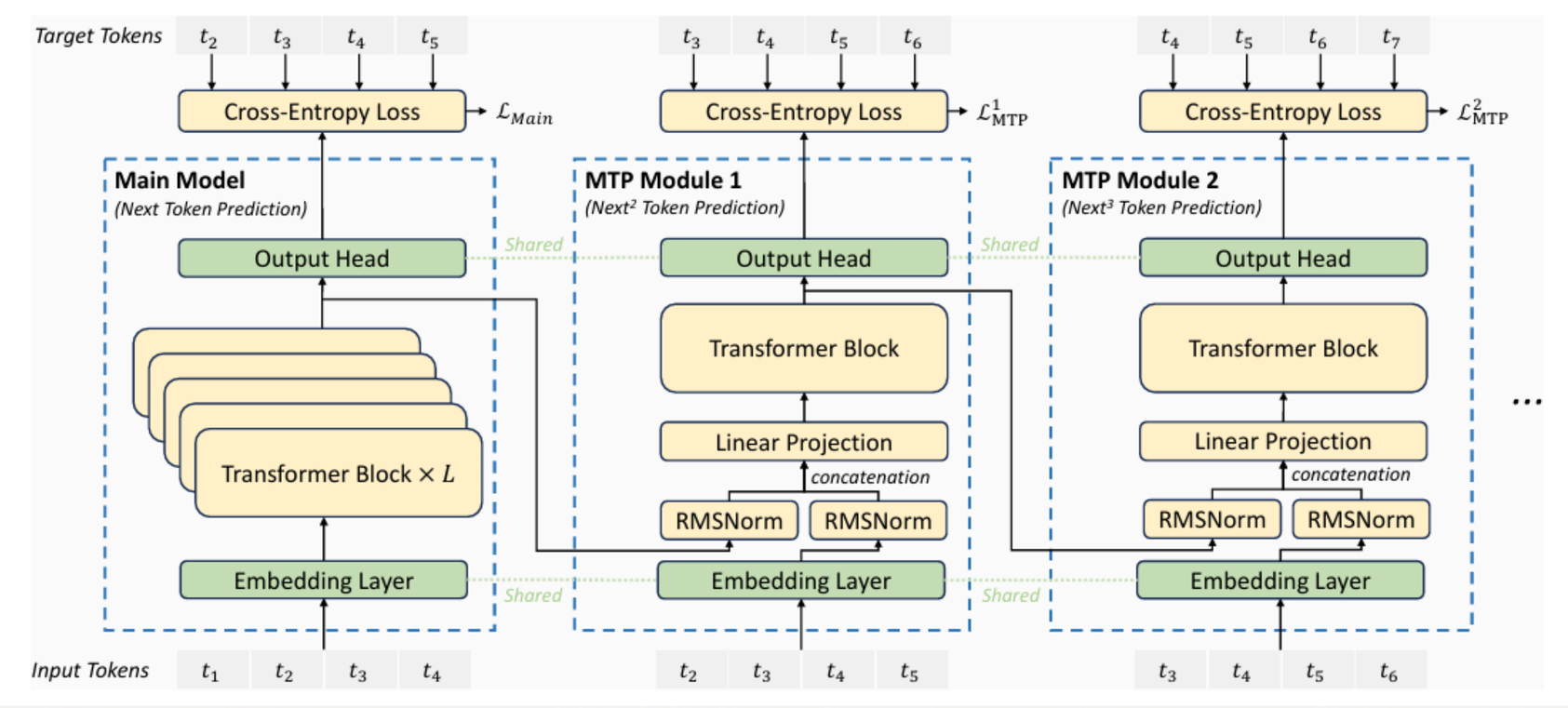
- Replaces FFN with certain number of NN (“experts”)
- Router determines which tokens are sent to which experts
- Efficient pretraining and faster inference owing to only partial usage of parameters



https://arxiv.org/pdf/2412.19437

Multi-Token Prediction (MTP)

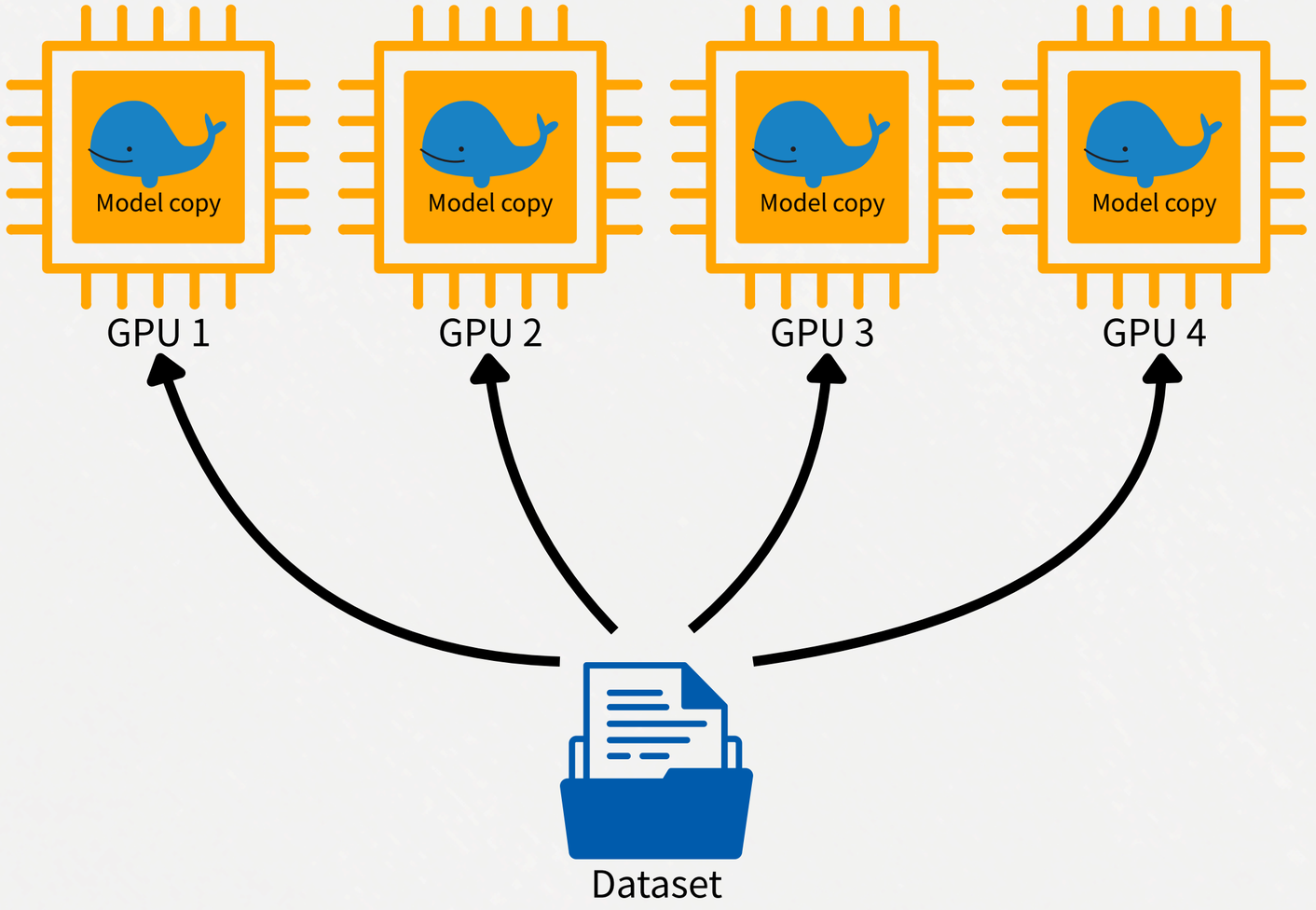
- Extends the prediction scope to multiple future tokens at each position.
- Allows speculative decoding to improve inference speed by predicting multiple tokens at once



https://arxiv.org/pdf/2412.19437

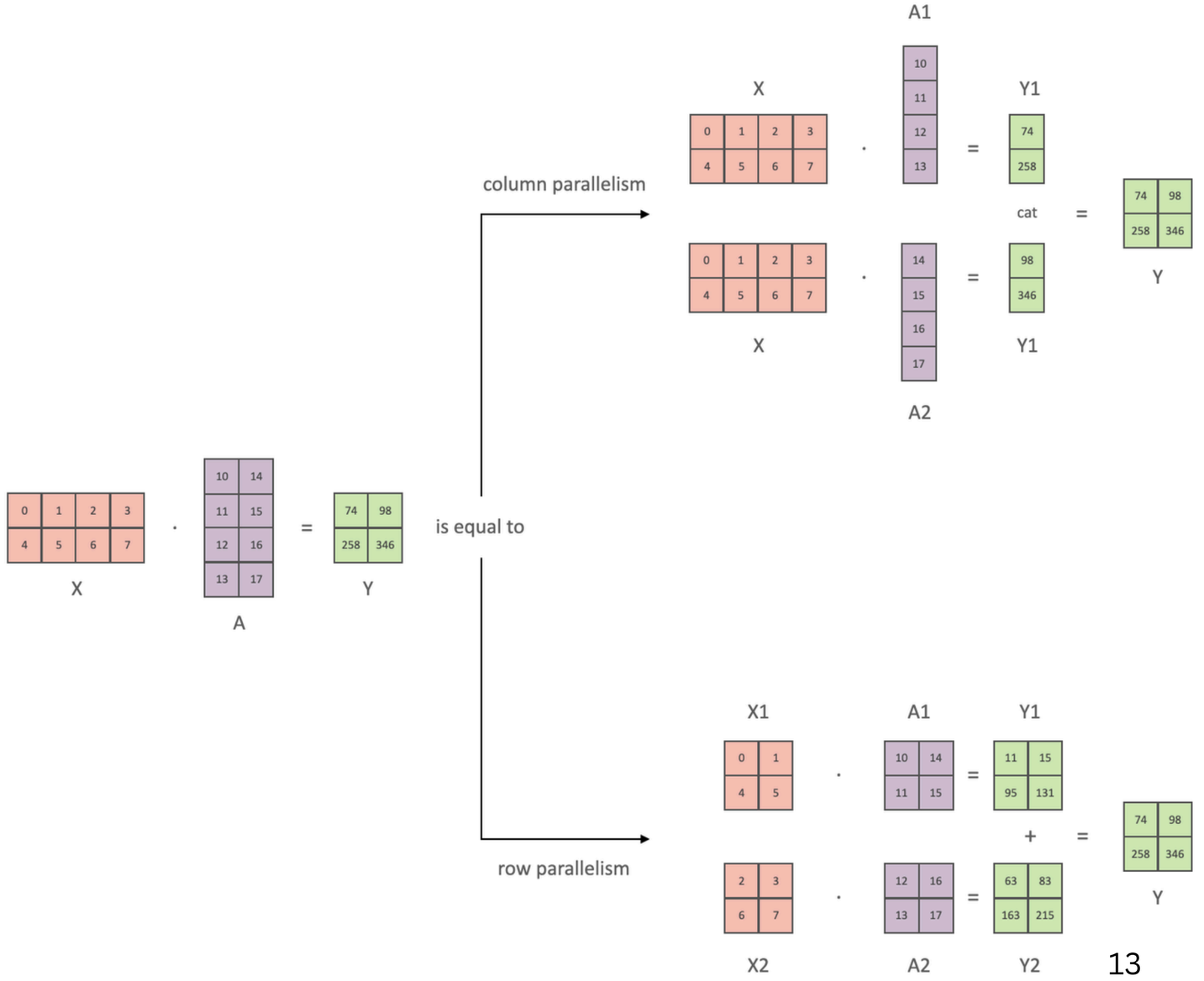
Data Parallelism (DP)

- Replicates model across GPUs
- Data batches are evenly distributed
- Computation workload is efficiently shared, leading to faster inference



Tensor Parallelism (TP)

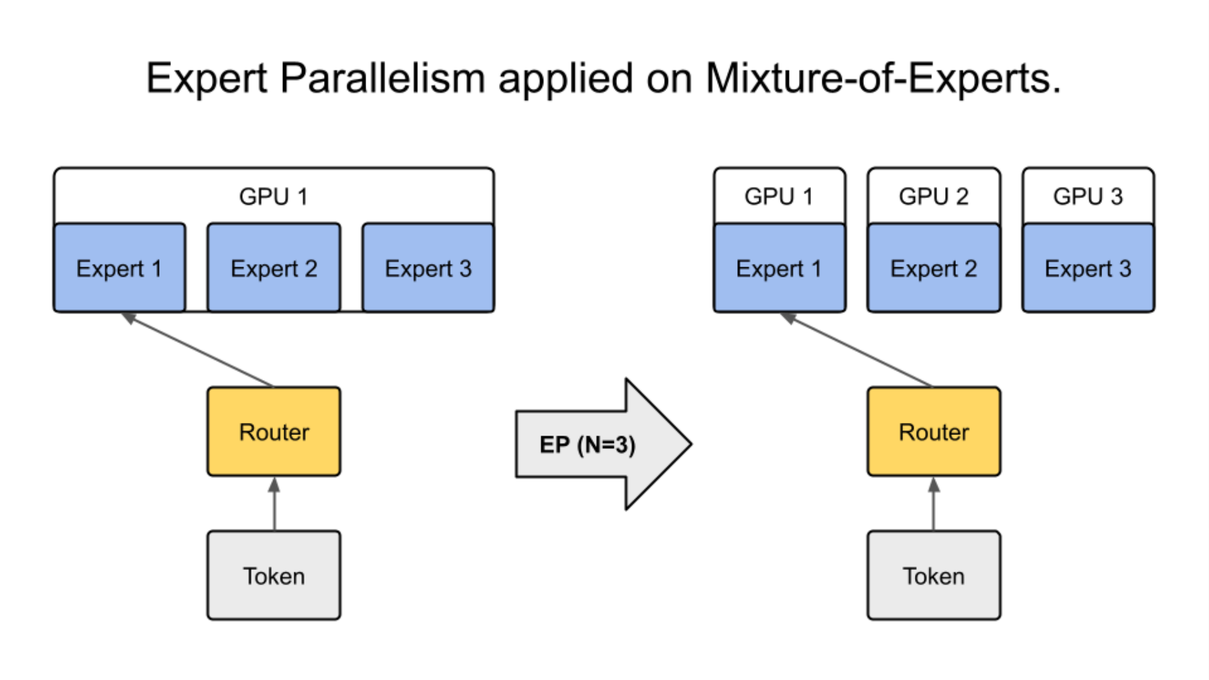
- Shards the model’s tensors across GPUs
- Enables large models that are not able to fit in one GPU to fit on multiple GPUs
- Increases overhead as inter-GPU communication is required



https://huggingface.co/docs/transformers/v4.15.0/parallelism

Expert Parallelism (EP)

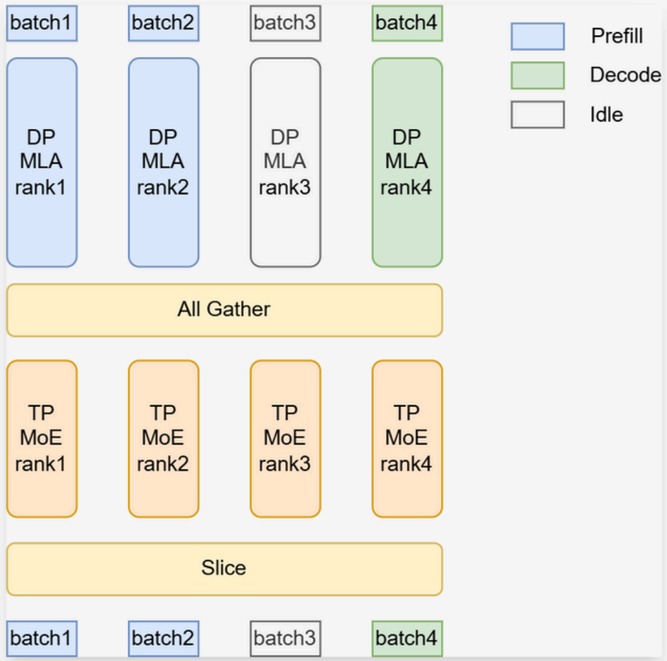
- Distributes whole MoE experts (that are not affected by TP) across GPUs
- Only applies to MoE layers and does not affect other layers



https://docs.nvidia.com/nemo-framework/user-guide/latest/nemotoolkit/features/parallelisms.html

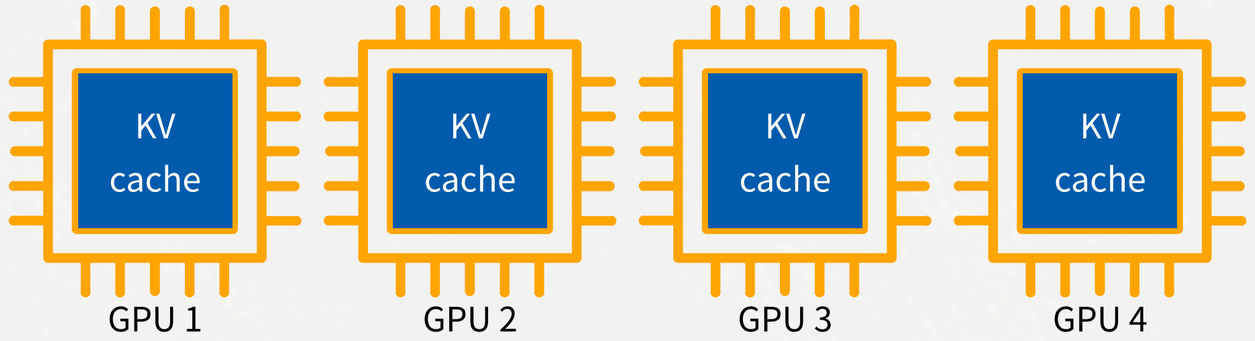
DP Attention

- DPs the attention across GPUs
- Splits the KV cache across GPUs, reducing memory usage

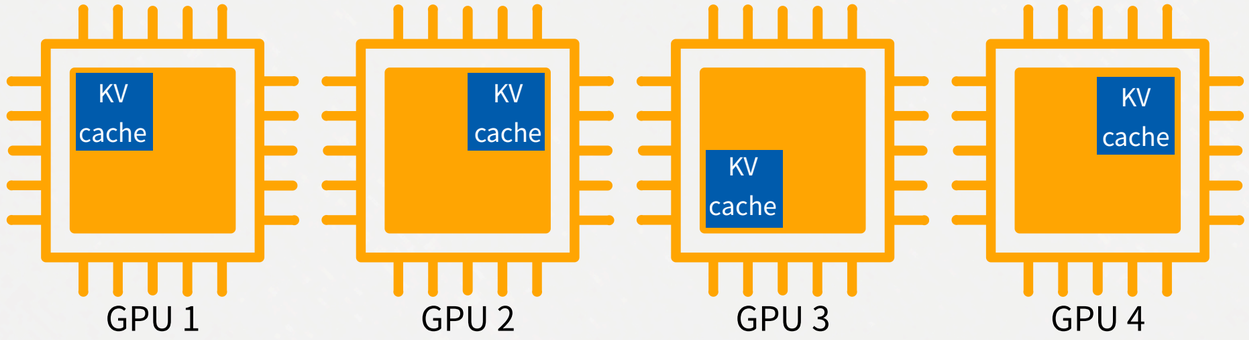


https://lmsys.org/blog/2024-12-04-sglang-v0-4/

Normal TP



DP Attention



- KV cache memory usage is reduced by sharding it across GPUs

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Our Baseline -Base 0-

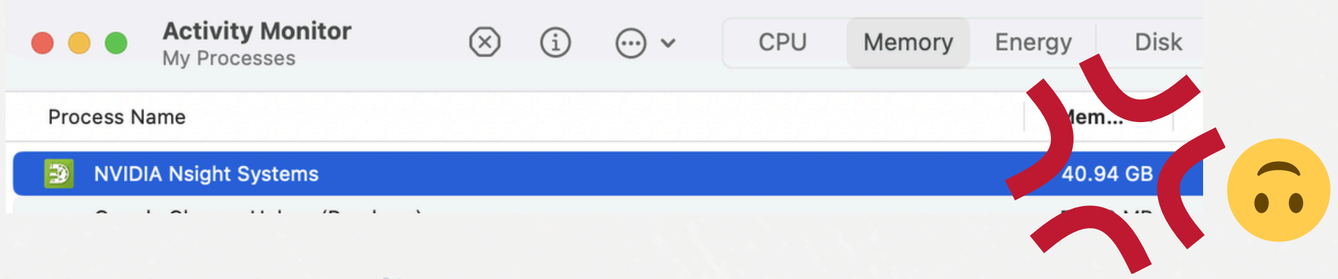
with example jobscript specified in task rules **(SGLang v0.4.10 used)**

- 6347.38 (tok/s)

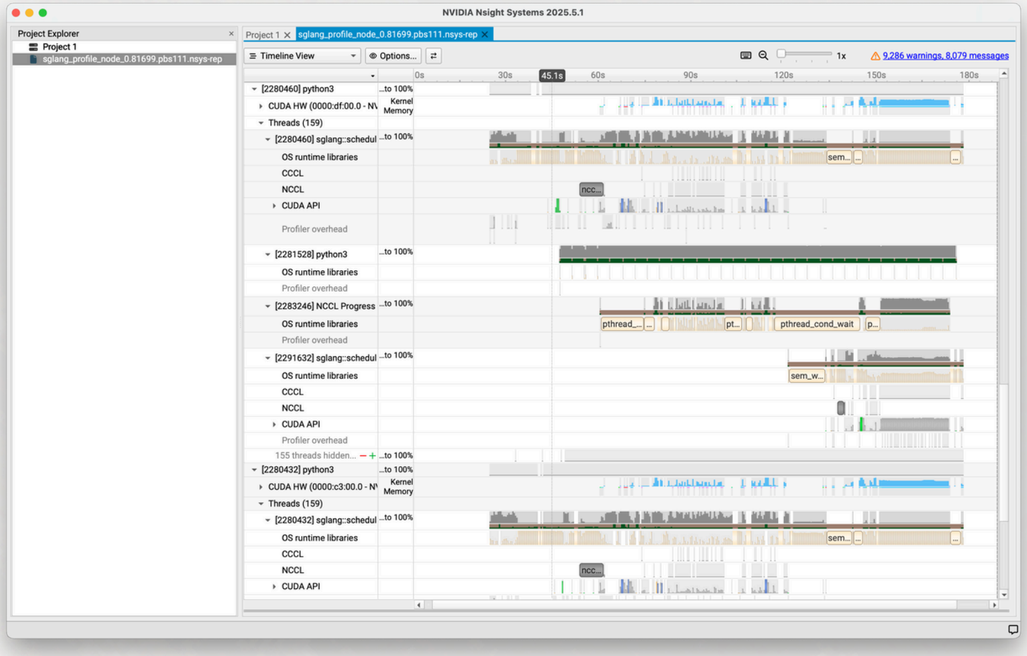
```
#!/bin/bash
#PBS -P 50000130
#PBS -l walltime=00:10:00
#PBS -l select=2:ncpus=112:ngpus=8:mpiprocs=2:mem=1880gb
#PBS -j oe
#PBS -m abe
#PBS -o output.txt
##PBS -l other=hyperthread

module load cuda/12.2.2 cudnn/12-9.3.0.75 nccl/12.6-2.22.3-1

NSYS_PATH="/home/users/industry/ai-hpc/apacsc11/scratch/nsys/target-linux-x64/nsys"

cd ${HOME}/ochi/solve

/usr/mpi/gcc/openmpi-4.1.7a1/bin/mpirun \
-hostfile ${PBS_NODEFILE} \
-map-by ppr:1:node:PE=112 -oversubscribe -use-hwthread-cpus \
-bind-to none --report-bindings -display-map \
-tag-output -output-filename ${HOME}/run/sglang.${PBS_JOBID} \
-x PATH \
-x NCCL_DEBUG=INFO \
bash -c "uv run python \
-m sglang.bench_offline_throughput \
--model-path /home/users/industry/ai-hpc/apacsc11/scratch/deepseek \
--dataset-path /home/users/industry/ai-hpc/apacsc11/scratch/sharegpt/ShareGPT_V3_unfiltered_cleaned_split.json \
--num-prompts 2000 --load-format dummy --seed 2025 --dtype bfloat16 \
--tp 16 --nnodes 2 --trust-remote-code \
--dist-init-addr \${DIST_INIT_ADDR}:5000 --node-rank \${OMPI_COMM_WORLD_RANK}"
```

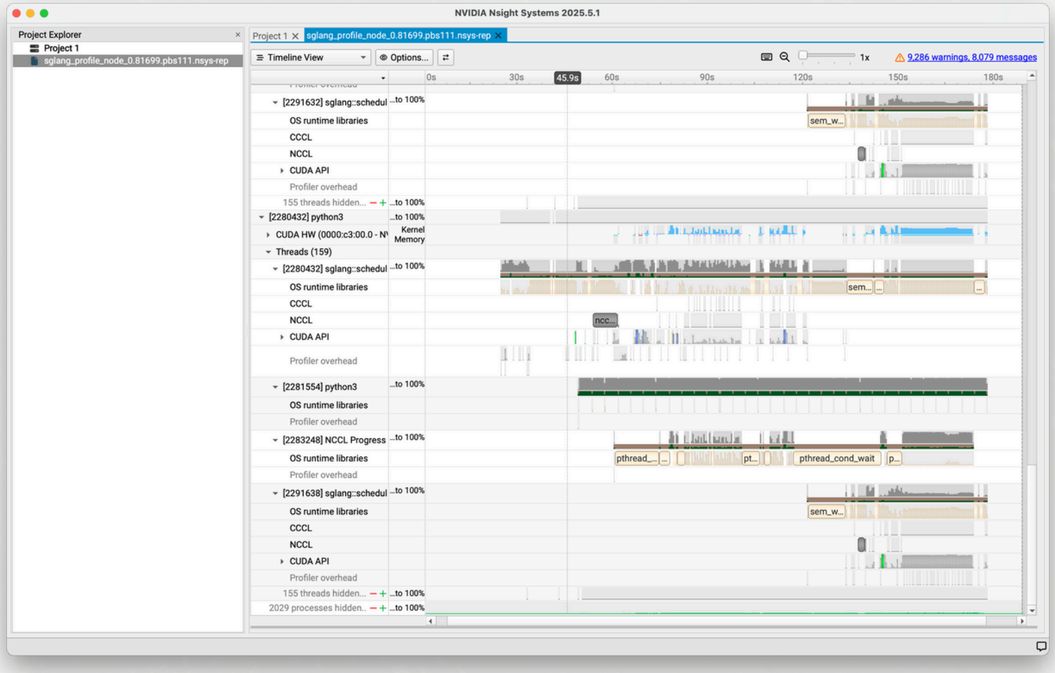
```
[1,0]<stdout>:#Input tokens: 626729
[1,0]<stdout>:#Output tokens: 388685
[1,0]<stdout>:#Input tokens: 4096
[1,0]<stdout>:#Output tokens: 256
[1,0]<stdout>:
[1,0]<stdout>:====== Offline Throughput Benchmark Result =======
[1,0]<stdout>:Backend:                                 engine
[1,0]<stdout>:Successful requests:                     2000
[1,0]<stdout>:Benchmark duration (s):                  159.97
[1,0]<stdout>:Total input tokens:                      626729
[1,0]<stdout>:Total generated tokens:                  388685
[1,0]<stdout>:Last generation throughput (tok/s):      21.19
[1,0]<stdout>:Request throughput (req/s):              12.50
[1,0]<stdout>:Input token throughput (tok/s):          3917.70
[1,0]<stdout>:Output token throughput (tok/s):         2429.68
[1,0]<stdout>:Total token throughput (tok/s):          6347.38
[1,0]<stdout>:-------------------------------------------------
~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~
                        Resource Usage on 2025-09-04 23:05:54.180
~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~
        JobId: 83373.pbs111
        Project: 50000130
        Exit Status: 0
~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~
        NCPUs: Requested(224), Used(224)
        CPU Time Used: 00:49:42
        Memory: Requested(3760gb), Used(37195476kb)
        Vmem Used: 19948242224kb
        Walltime: Requested(00:10:00), Used(00:06:05)
~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~
```

Profiling Results

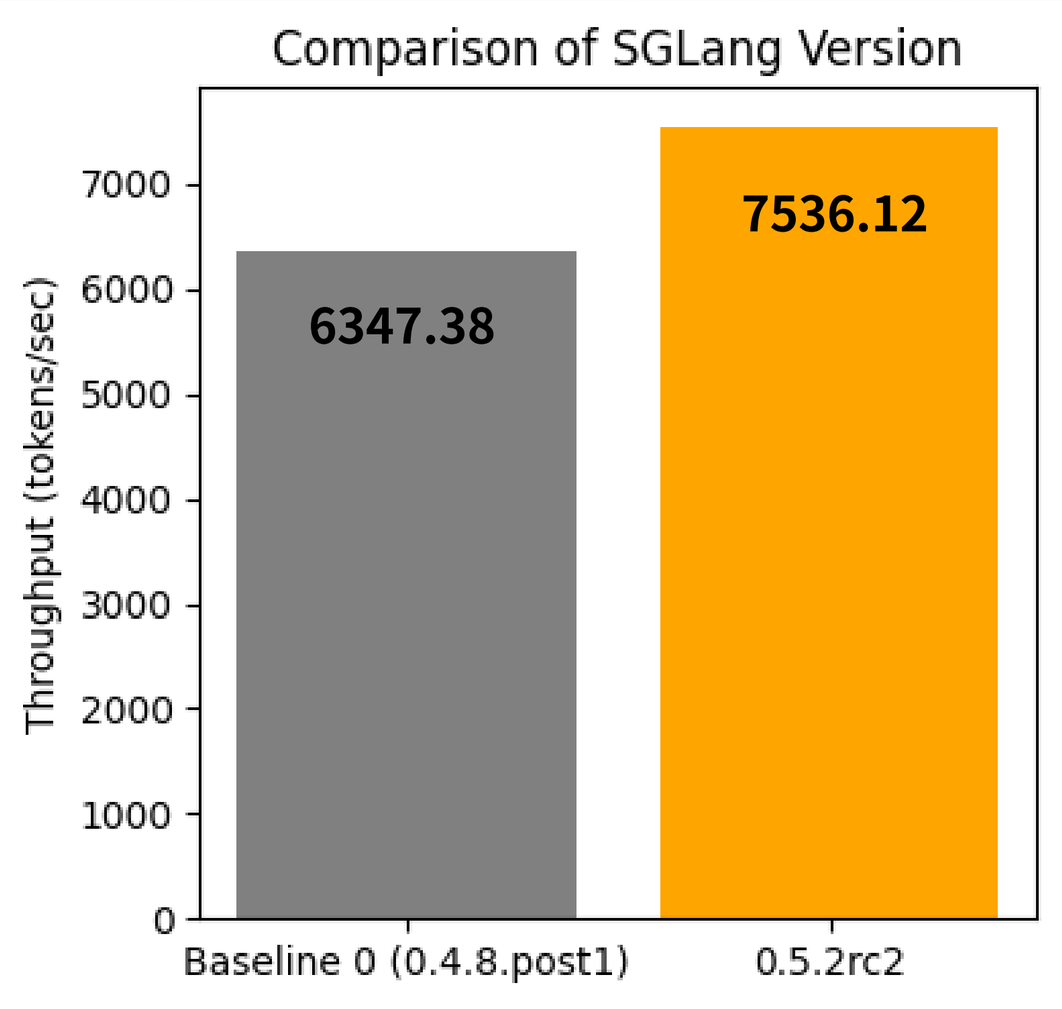


- Why profiling doesn't make sense for us
  - Too many factors, we couldn't identify where the bottlenecks are🤯.
  - Nsight Systems consumes too much memory (e.g., 40GB consumption for ONLY 200 requests profiling data, required is 2000)





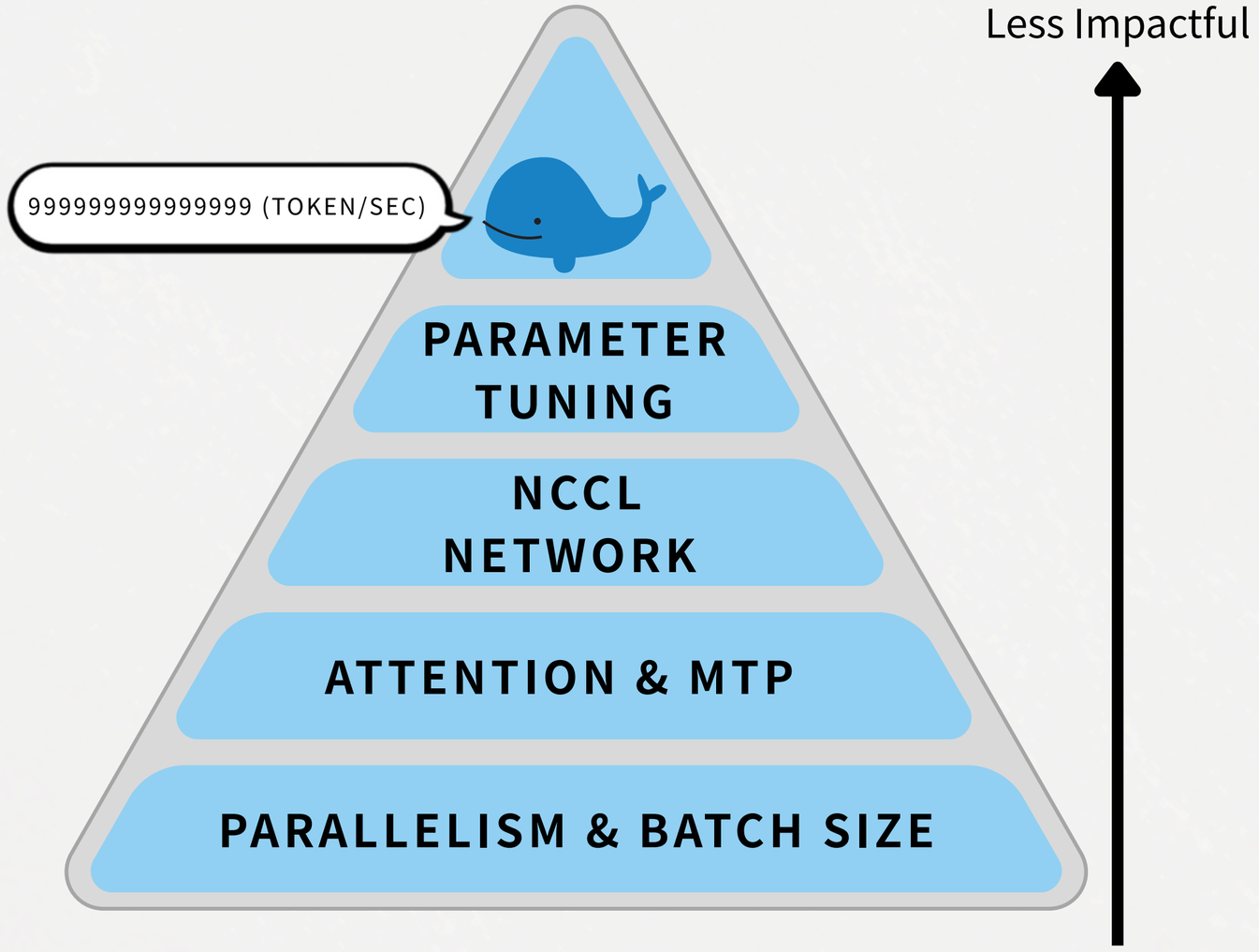
Updated SGLang → -Base 1-

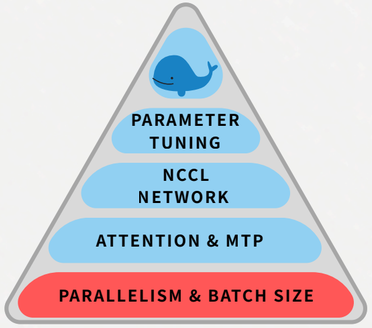


- Accelerating SGLang with Multiple Token Prediction (v0.4.10)
- SGLang HiCache: Fast Hierarchical KV Caching with Your Favorite Storage Backends (v0.5.2)

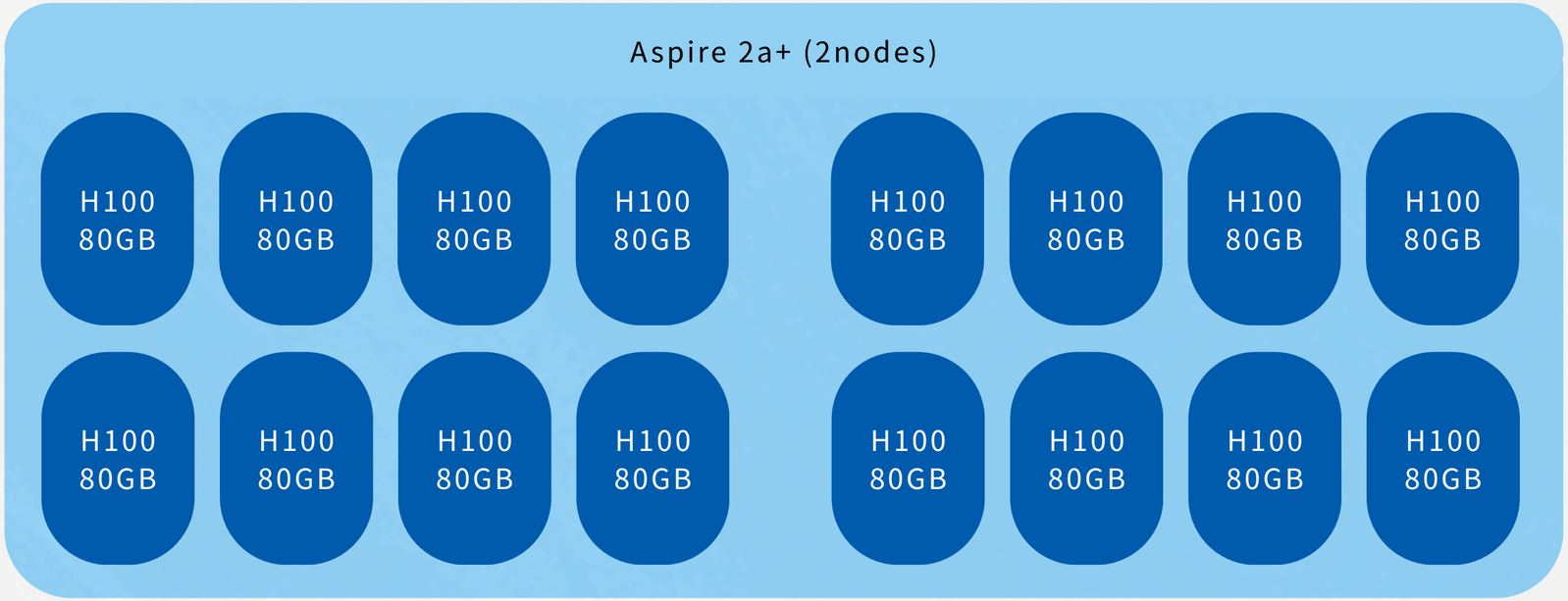
Inference Optimization Strategy

- Hierarchically classified optimization method by impactfulness
- In the absence of profiling, we scour logs to look for various pieces of information, such as GPU memory usage, number of cached tokens, etc.
- Our experiments and next steps are decided based heavily on our findings from logs





DP & TP Configuration

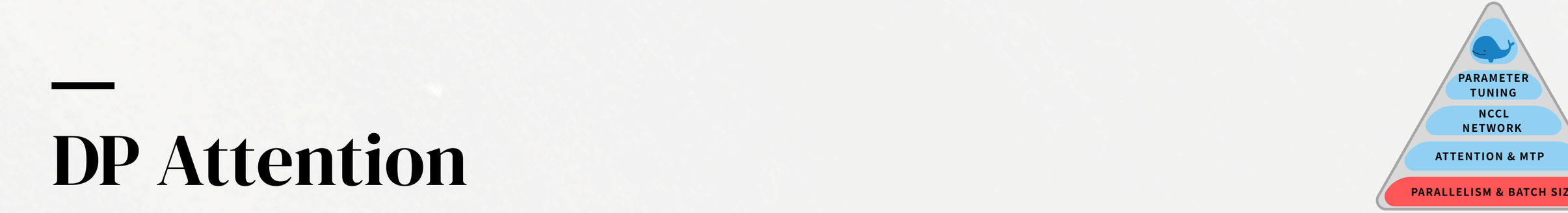


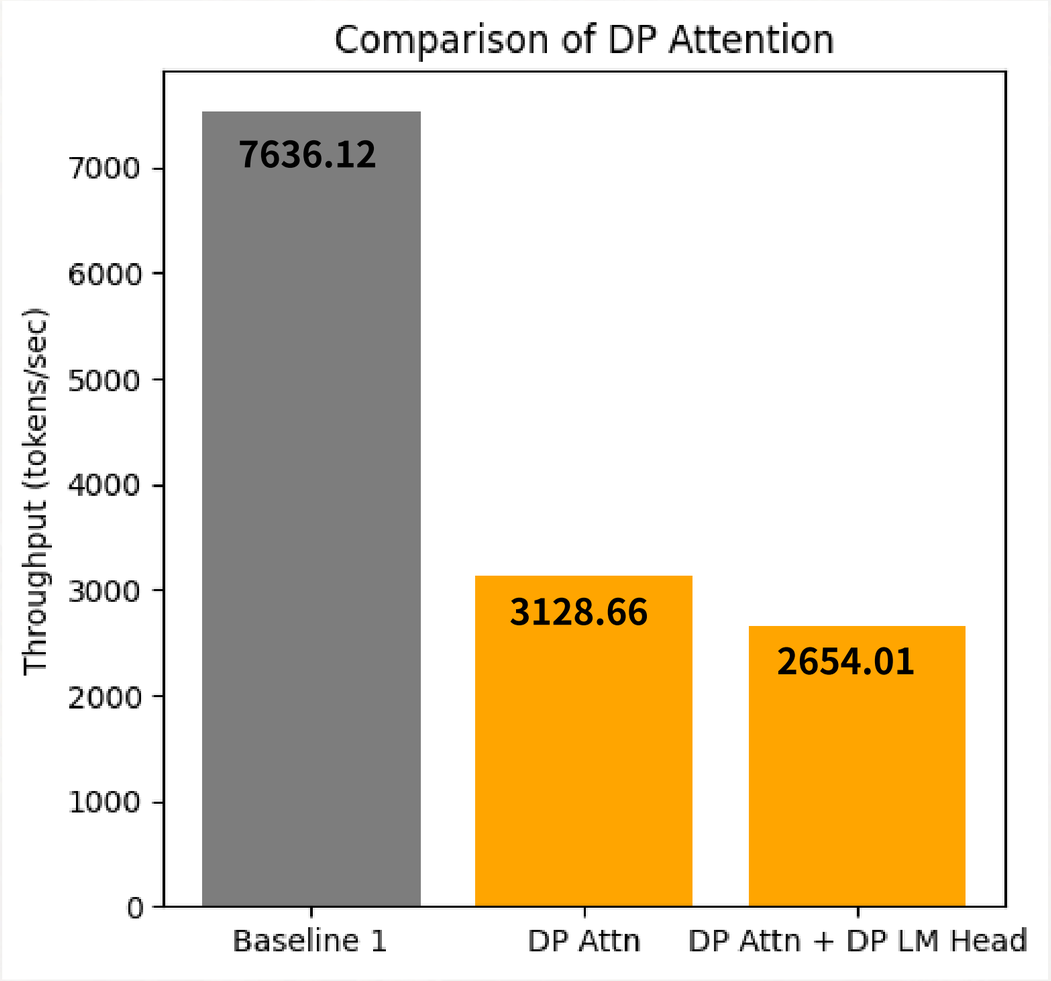
1,280GB (80GB x 16)

Up to 1,342GB

Only DP=1, TP=16 was possible

DP Attention





Our hypothesis:

- Increased inter-GPU communication overhead due to increased all-gather operations

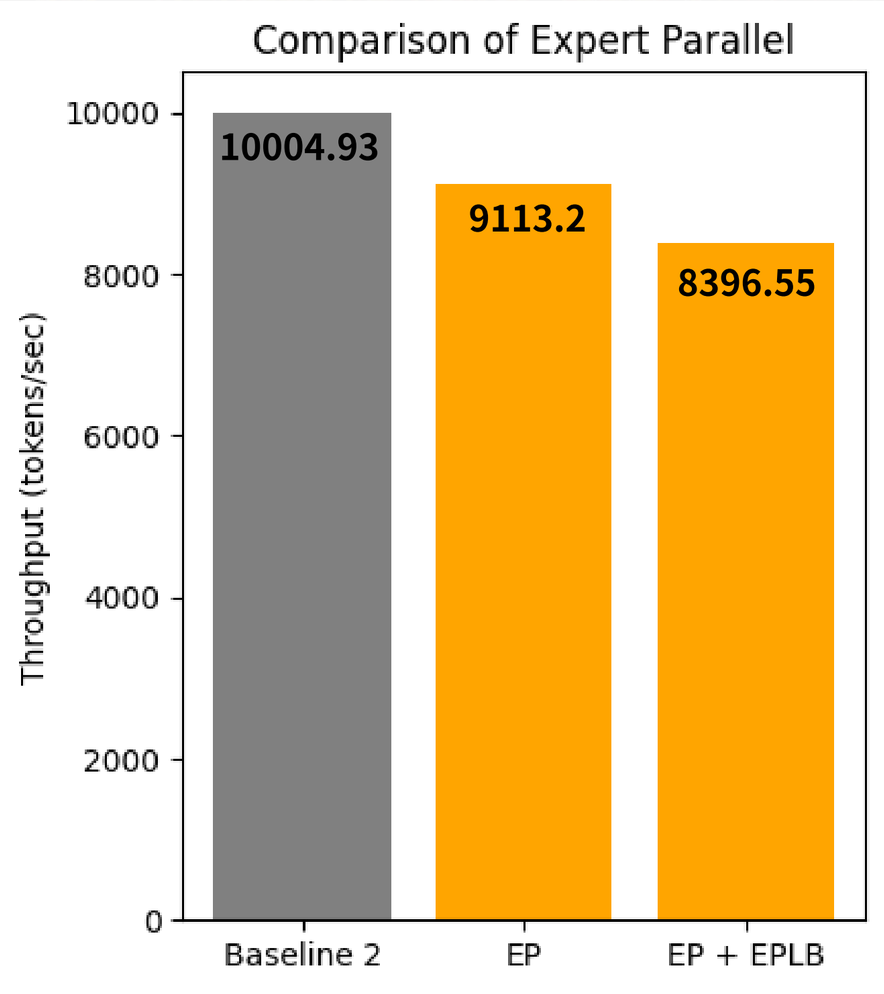
```
13 TP12] KV Cache is allocated. #tokens: 424274, KV size: 27.77 GB
13 TP1] KV Cache is allocated. #tokens: 424274, KV size: 27.77 GB
13 TP8] KV Cache is allocated. #tokens: 424274, KV size: 27.77 GB
13 TP10] KV Cache is allocated. #tokens: 424274, KV size: 27.77 GB
13 TP13] KV Cache is allocated. #tokens: 424274, KV size: 27.77 GB
```

Before DP Attention

```
TP13] KV Cache is allocated. #tokens: 214770, KV size: 14.06 GB
TP9] KV Cache is allocated. #tokens: 214770, KV size: 14.06 GB
TP15] KV Cache is allocated. #tokens: 214770, KV size: 14.06 GB
TP14] KV Cache is allocated. #tokens: 214770, KV size: 14.06 GB
TP12] KV Cache is allocated. #tokens: 214770, KV size: 14.06 GB
```

After DP Attention

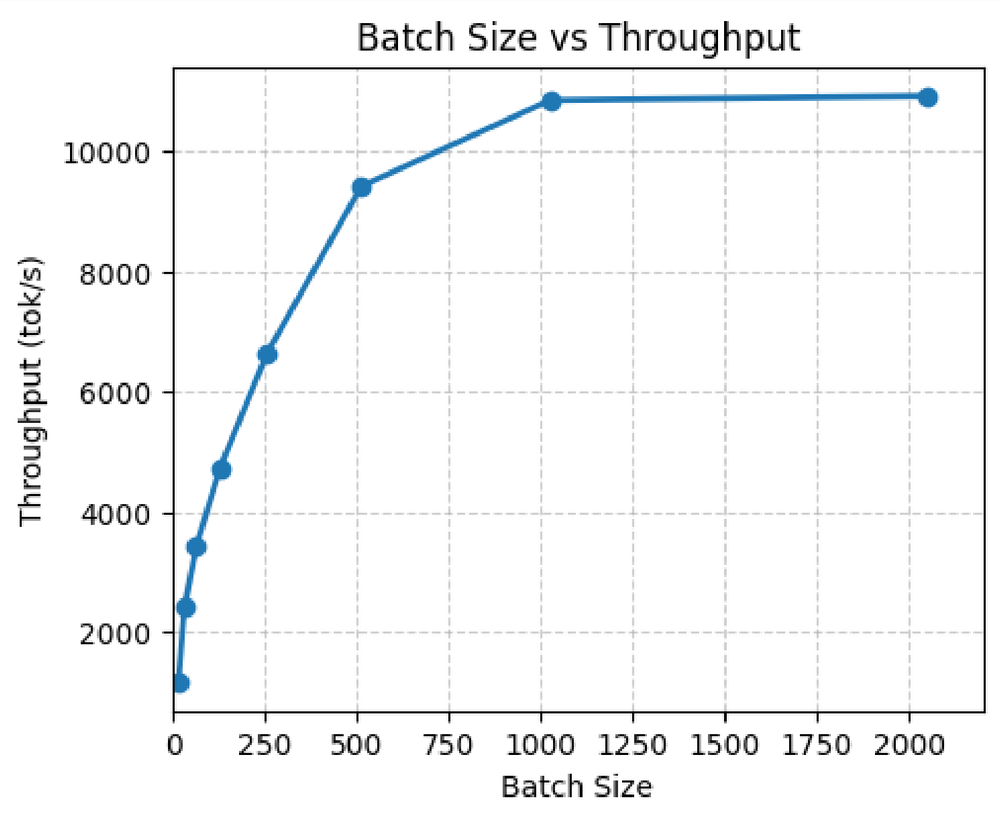
Expert Parallelism



Our hypothesis:

- Overhead introduced by EP and EPLB is more than the actual speedup
- EP may lead to GPU bottlenecks if only certain experts are preferred
- EPLB helps to curb this issue but itself introduces much overhead

Batch Size



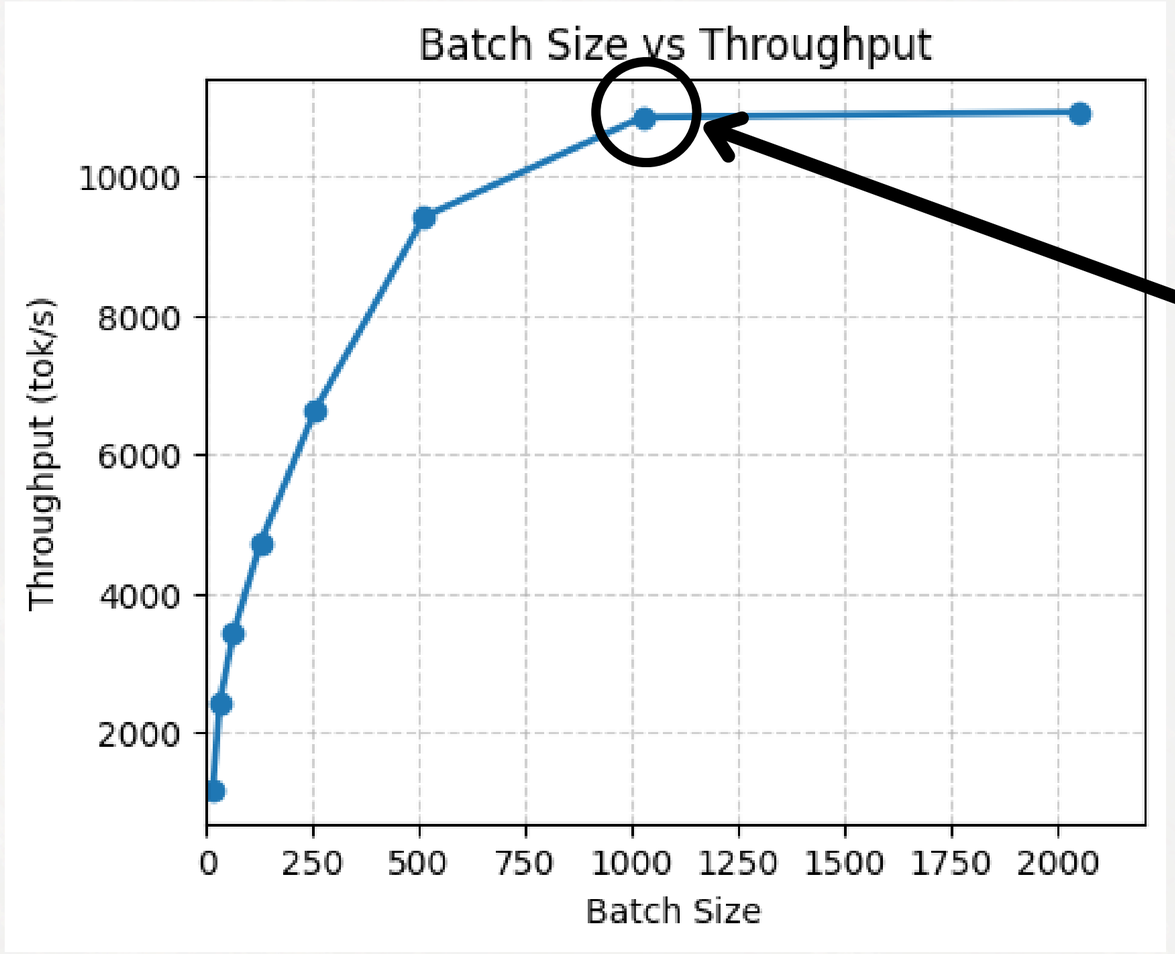
We observed that throughput increases with batch size

```
other_args.extend(
    [
        "--cuda-graph-max-bs",
        batch_size,
        "--mem-fraction-static",
        server_args.mem_fraction_static,
        "--tp-size",
        server_args.tp_size,
        "--max-running-requests",
        batch_size,
    ]
)
```

In SGLang, --max-running-requests and --cuda-graph-max-bs should be assigned the batch size

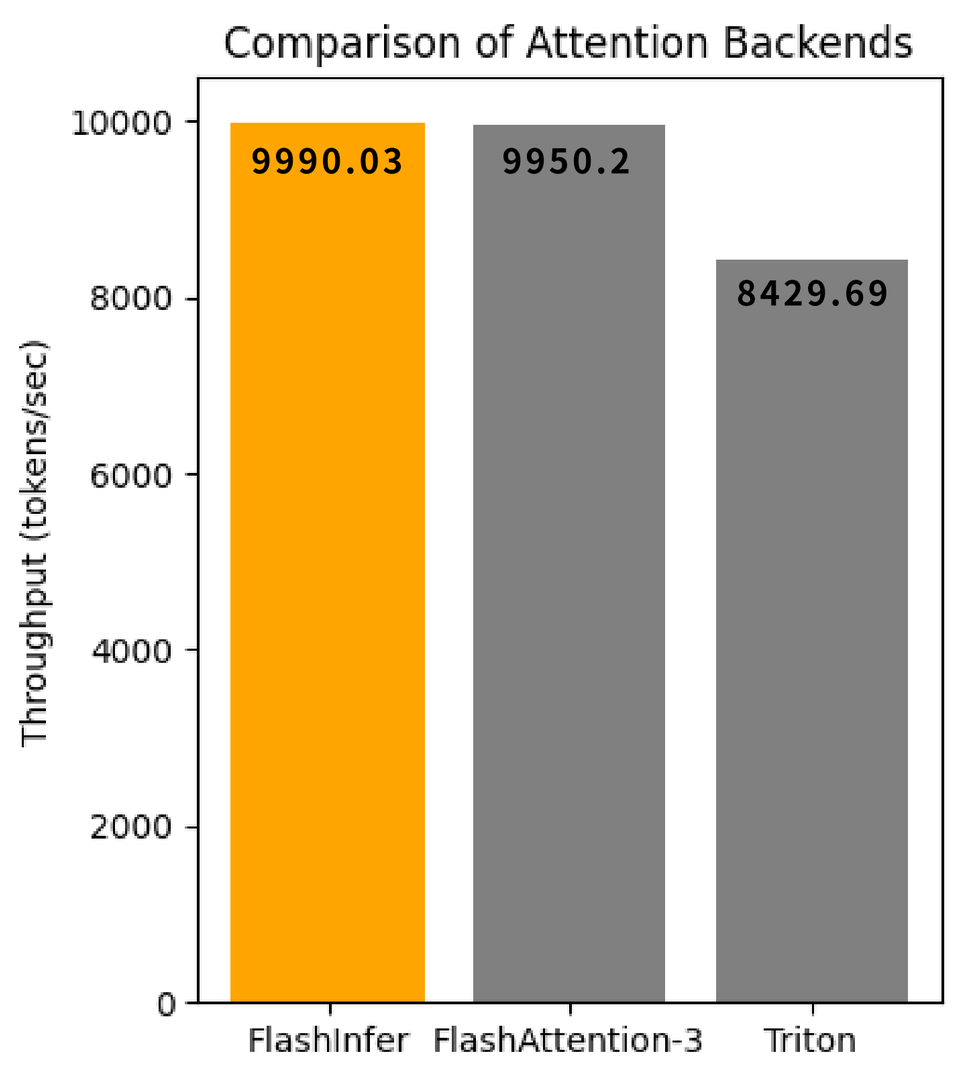
https://github.com/sgl-project/sglang/blob/main/scripts/playground/bench_speculative.py

Updating Our Baseline -Base 2-

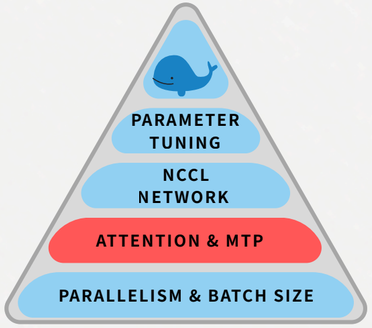


BS=1024, 10848.09(tok/s)

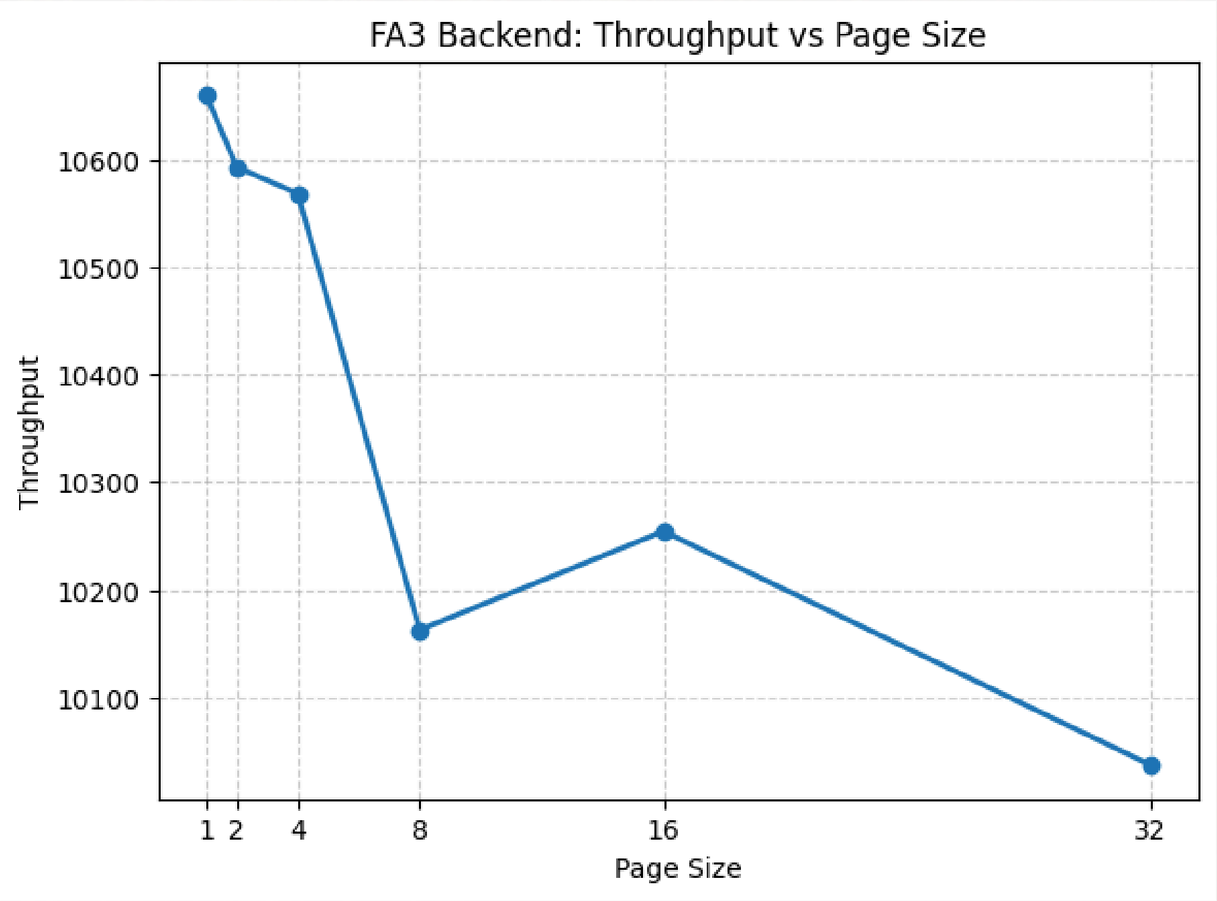
Attention Backend



- Flashinfer is optimized for inference and produced the highest throughput
- FlashAttention-3 was default
- Backends such as TRTLLM does not support Hopper GPU architechture



Page-size



Supporting matrix for different attention backends

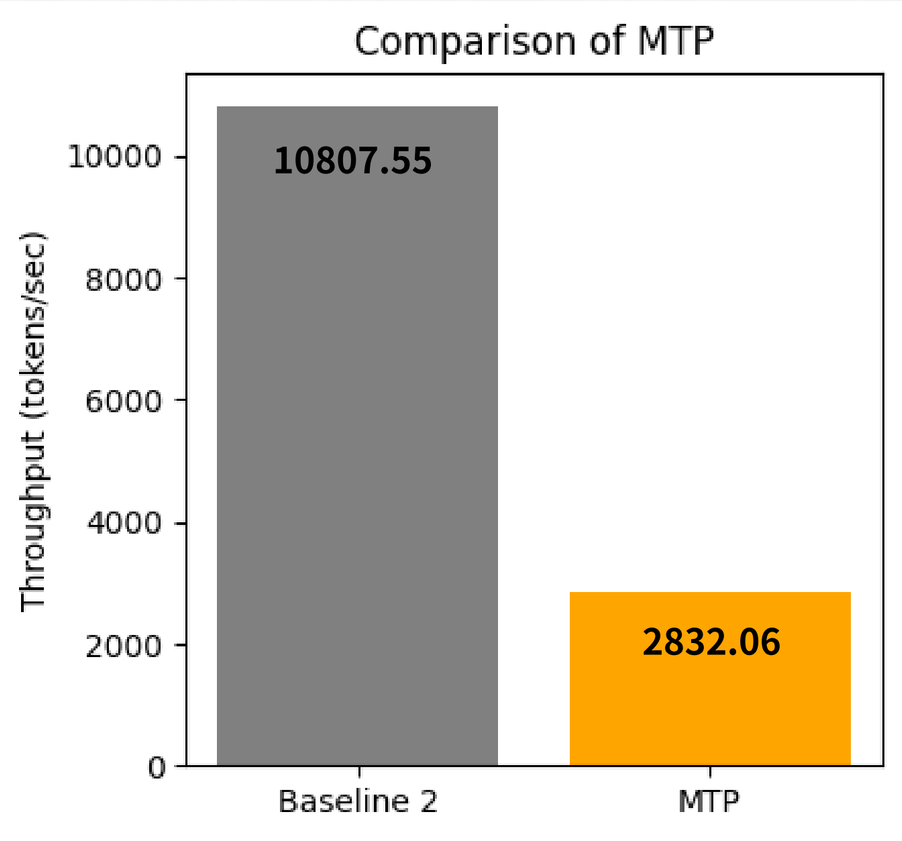
Backend	Page Size > 1	Spec Decoding	MLA	Sliding Window	MultiModal
FlashInfer	✗	✓	✓	✓	✓
FA3	✓	✓	✓	✓	✓
Triton	✗	✓	✓	✓	✗

https://docs.sglang.ai/advanced_features/attention_backend.html

Screenshot taken on Oct 9, actual website as since been recently updated

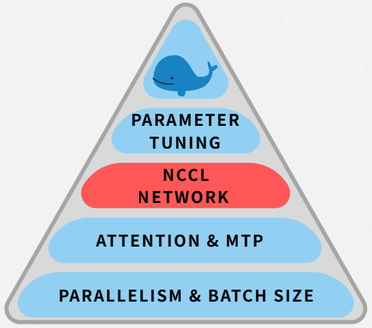
- FlashInfer does not support >1 page size, therefore FA3 was used
- We found that throughput drops as we increased page size

Multi Token Prediction



Hypothesis:

- After many tries, we discovered that we were required to decrease **--mem-fraction-static** from 0.8 down to 0.55 in order for it to work
- Due to that requirement, throughput was poor for any configuration of MTP parameters that we tried



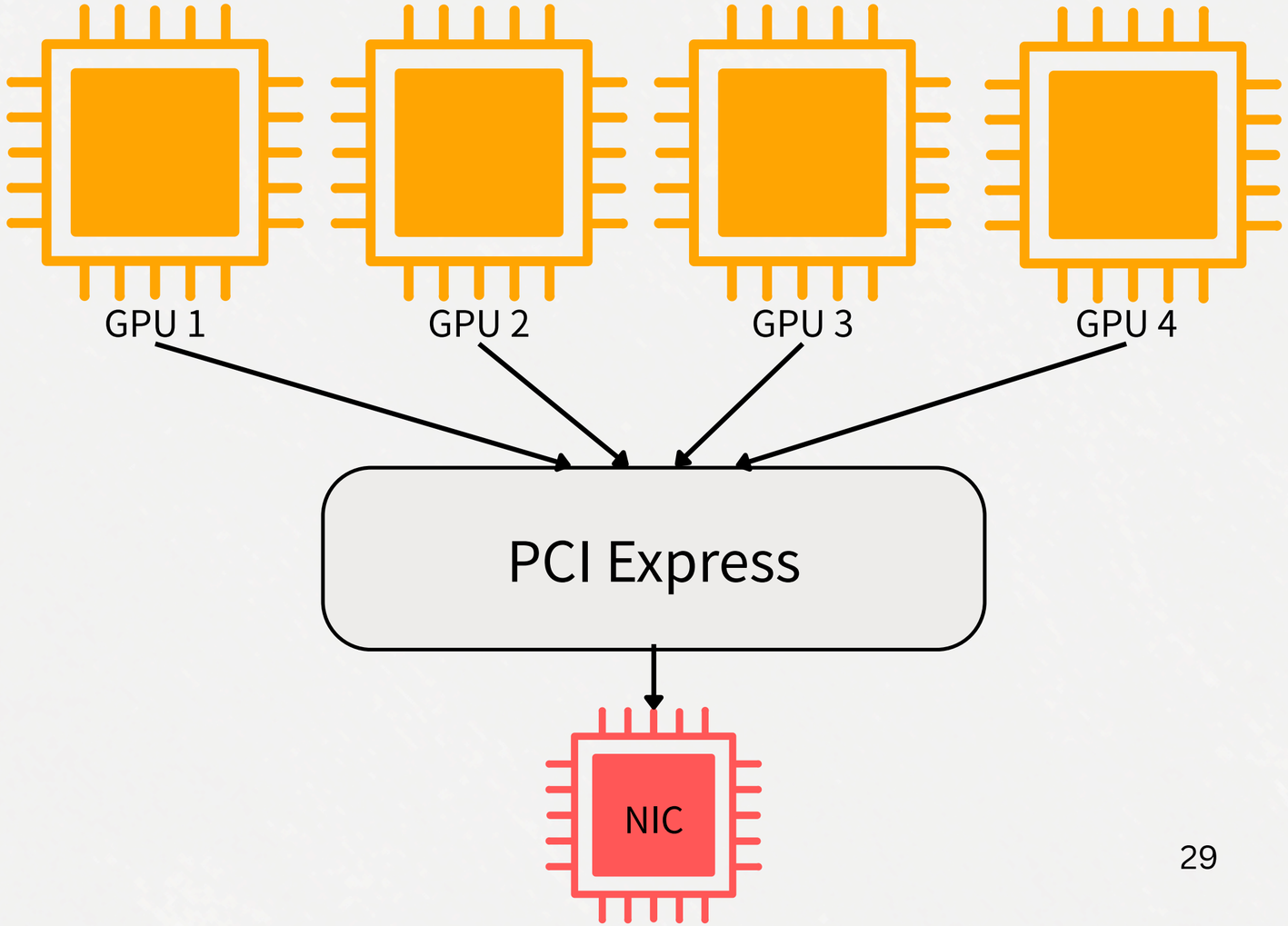
NCCL Tuning: GPUDirect RDMA

NVIDIA Collective Communication Library (NCCL)

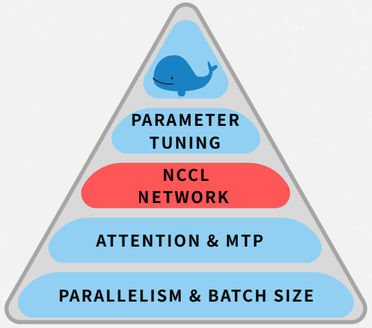
- Provide efficient multi-GPU and multi-node communication primitive
- Support GPU-to-GPU communication without through the CPU

GPUDirect RDMA

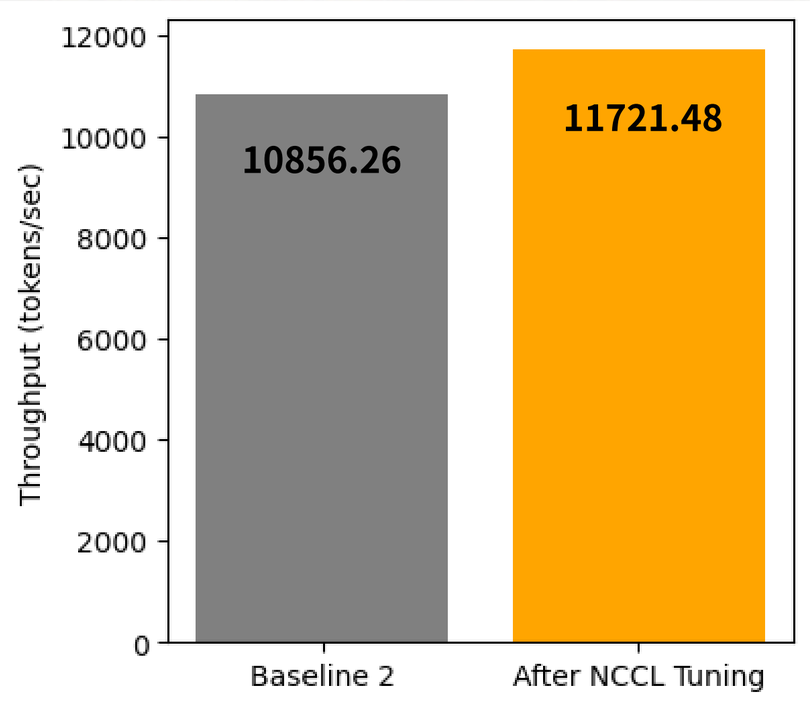
- Enables a direct path for data exchange between the GPU and network interfaces.



NCCL Tuning

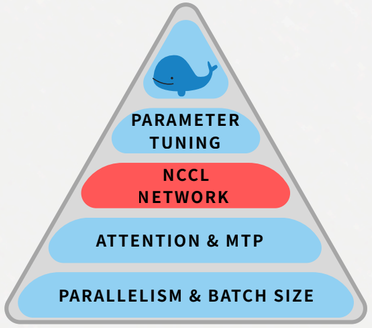


- We set env variables to tune NCCL, such as:
  - export NCCL_NET_GDR_LEVEL=SYS
  - export NCCL_NET_GDR_READ=1
  - ...




```
# Choose ONLY IB HCAs (adjust names to your node: mlx5_0..mlx5_11 are shown)
export NCCL_IB_HCA="mlx5_0,mlx5_1,mlx5_3,mlx5_4,mlx5_5,mlx5_6,mlx5_7,mlx5_9,mlx5_10,mlx5_11"
# Make NCCL stop trying to "fuse" different NIC types
export NCCL_NET_MERGE_LEVEL=LOC
# Prefer IB GID index 0 for IB (if your site uses a different index for RoCE/IB, set accordingly)
export NCCL_IB_GID_INDEX=0

export NCCL_NET_GDR_LEVEL=SYS
export NCCL_NET_GDR_READ=1
#export NCCL_PXN_DISABLE=1

export SGLANG_HACK_PD_DECODE_NUM_RESERVED_DECODE_TOKENS=2
export SGLANG_SET_CPU_AFFINITY=1
export SGL_ENABLE_JIT_DEEPGEMM=1
export MC_TE_METRIC=true

export NCCL_CROSS_NIC=0
export NCCL_P2P_NVL_DISABLE=0
export NCCL_SHM_DISABLE=0
export NCCL_IB_TC=0

export NCCL_ALGO=Tree,Ring,CollnetDirect,CollnetChain,NVLS,NVLSTree
export NCCL_NVLS_ENABLE=1
export NCCL_P2P_LEVEL=NVL
```

How we specified NCCL_IB_HCA

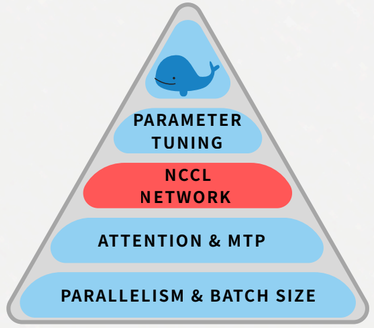



```
~/ochi/solve/aspire/r1/exp_tsune_00f$ grep -E 'hca_id|link_layer' ibv_devinfo
hca_id: mlx5_0
                link_layer:             InfiniBand
hca_id: mlx5_1
                link_layer:             InfiniBand
hca_id: mlx5_2
                link_layer:             Ethernet
hca_id: mlx5_3
                link_layer:             InfiniBand
hca_id: mlx5_4
                link_layer:             InfiniBand
hca_id: mlx5_5
                link_layer:             InfiniBand
hca_id: mlx5_6
                link_layer:             InfiniBand
hca_id: mlx5_7
                link_layer:             InfiniBand
hca_id: mlx5_8
                link_layer:             Ethernet
hca_id: mlx5_9
                link_layer:             InfiniBand
hca_id: mlx5_10
                link_layer:             InfiniBand
hca_id: mlx5_11
                link_layer:             InfiniBand
```

The **NCCL_IB_HCA** specifies which interfaces to use for communication.

Use only **InfiniBand devices** to force the node to use only InfiniBand.

```
export NCCL_IB_HCA="mlx5_0,mlx5_1,mlx5_3,mlx5_4,mlx5_5,mlx5_6,mlx5_7,mlx5_9,mlx5_10,mlx5_11"
```



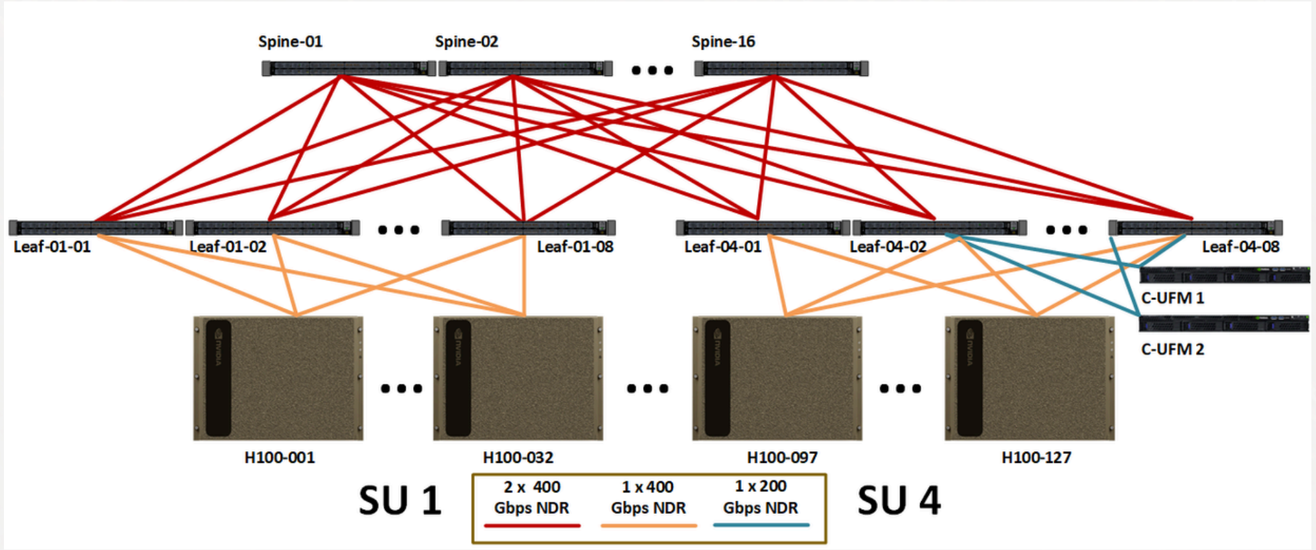
Variance between Nodes

DGX SuperPOD Architecture

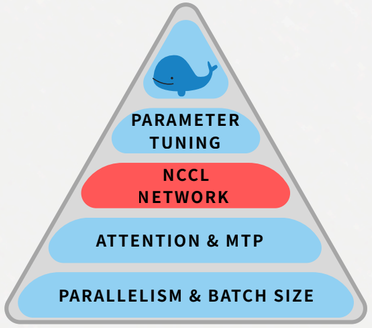
- Ensures optimal traffic routing and that performance is consistent across all portions of the fabric.

HOWEVER, in our experiments:

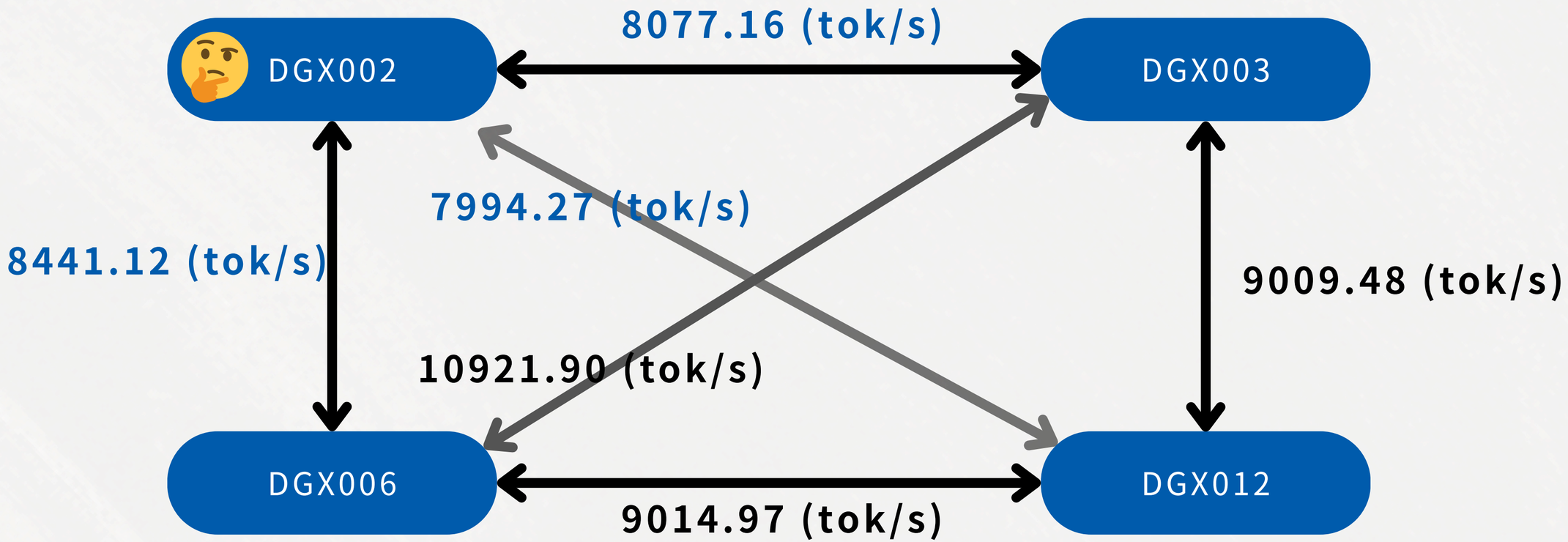
- Throughput of the same jobscript varies by around 1x~1.2x when executed multiple times
- We hypothesize that this is due to the allocation of different node combinations



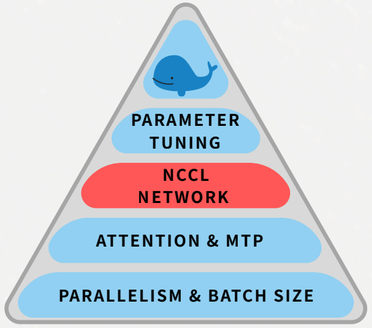
https://docs.nvidia.com/dgx-superpod/reference-architecture-scalable-infrastructure-h100/latest/network-fabrics.html



Variance between Nodes



DGX002 seems to be problematic



Patching to SGLang

- We increased warmup by:
  - increasing num_prompts to 512
  - increasing input, output lengths to 4096, 256 respectively
- This is clearly **non-destructive to the generation quality**

```
warmup_requests = sample_random_requests(
    input_len=256,
    output_len=16,
    num_prompts=min(bench_args.num_prompts, 16),
    range_ratio=1.0,
    tokenizer=tokenizer,
    dataset_path=bench_args.dataset_path,
)
```

sglang/benchmark_offline_throughput.py

PATCH

```
warmup_requests = sample_random_requests(
    input_len=4096,
    output_len=256,
    num_prompts=min(bench_args.num_prompts, 512),
    range_ratio=1.0,
    tokenizer=tokenizer,
    dataset_path=bench_args.dataset_path,
)
```

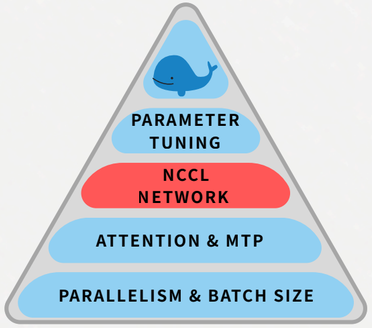
PATCHED sglang/benchmark_offline_throughput.py

- We also used input_requests (i.e. benchmark dataset) for warmup instead of warmup_requests, and the throughput increased even further

```
# Warm up
if not bench_args.skip_warmup:
    logging.info("\nWarmup...")
    throughput_test_once(
        backend_name=bench_args.backend,
        backend=backend,
        reqs=warmup_requests,
        ignore_eos=not bench_args.disable_ignore_eos,
        extra_request_body=extra_request_body,
        profile=False,
    )
    time.sleep(0.5)
```

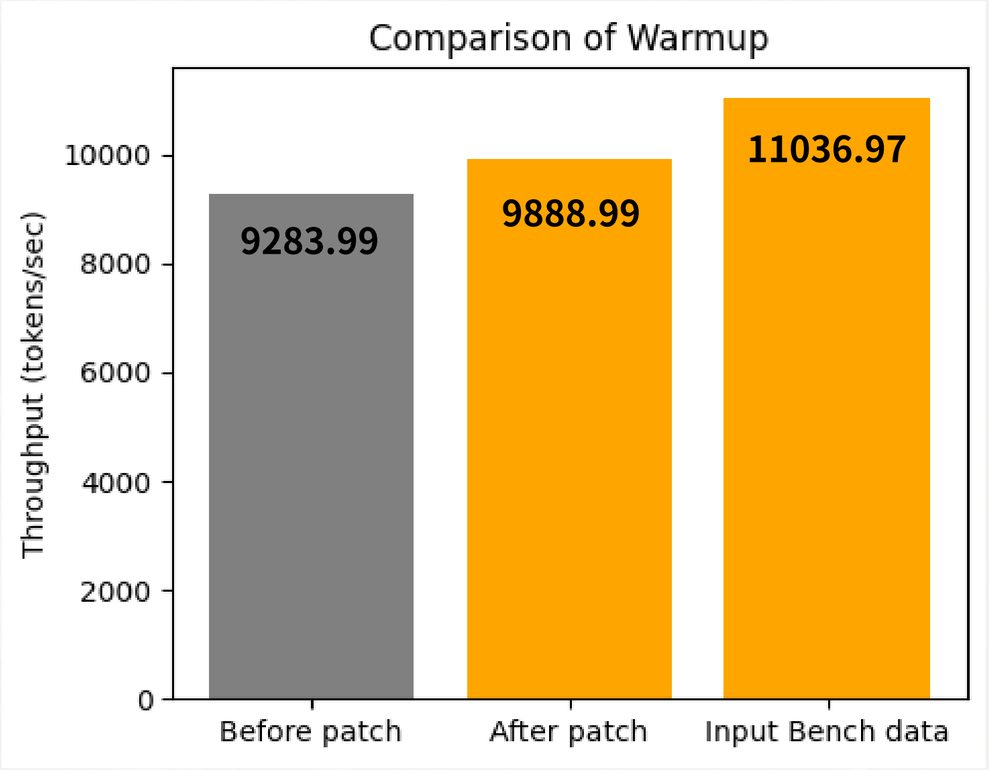
→ input_requests

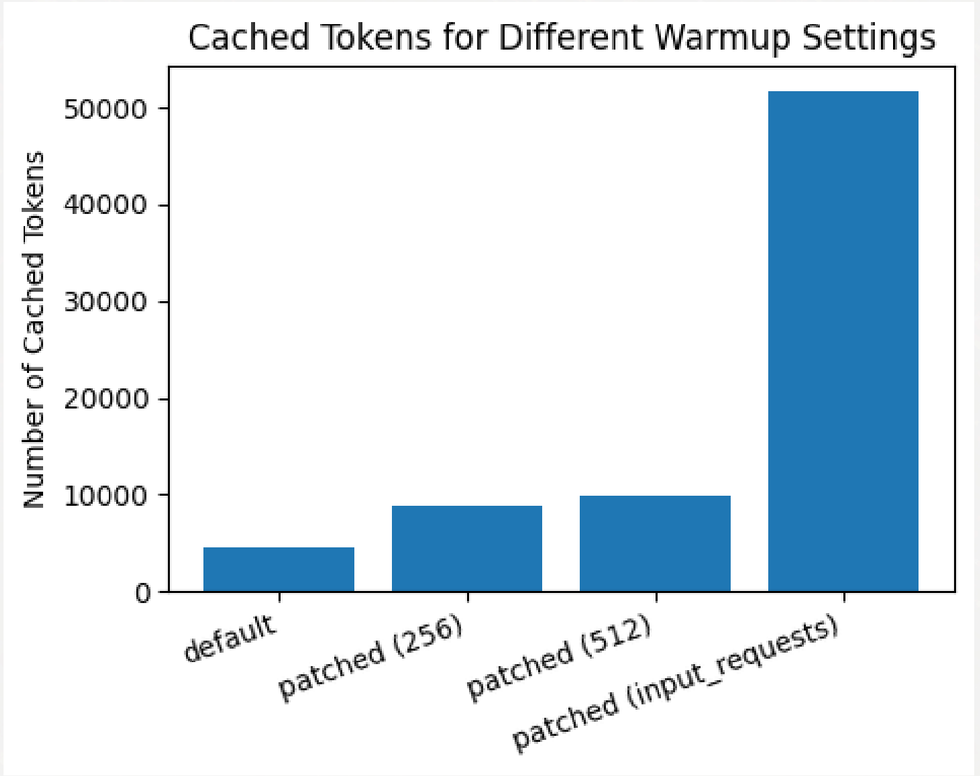
PATCHED sglang/benchmark_offline_throughput.py

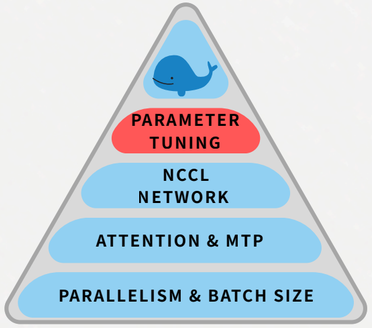


Patching to SGLang

- By warming up compute nodes with the same dataset, its KV cache can be prefilled before the actual benchmark, leading to faster inference

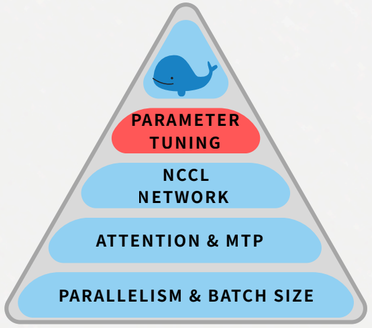






Other parameters

Changes	Description	Baseline	throughput (tokens/s)
--disable-radix-cache	Turns off RadixAttention prefix caching	10087.56 10399.40 10803.40	10807.55 10832.35 10904.22
--disable-overlap-schedule	Stops overlapping CPU scheduling work	10004.89 10855.00 10791.86	10806.71 10902.25 10822.39
--grammar-backend xgrammar	Offers faster JSON decoding performance	10004.93	7941.49



Final tuning

- At the end of optimization, we tuned --mem-fraction-static
- It specifies the GPU memory allocated to model weights and KV cache

--mem-fraction-static	Max GPU Memory Used (TB)	Throughput
0.80	1.14	9239.17
0.88	1.23	10152.85
0.89	OOM	-

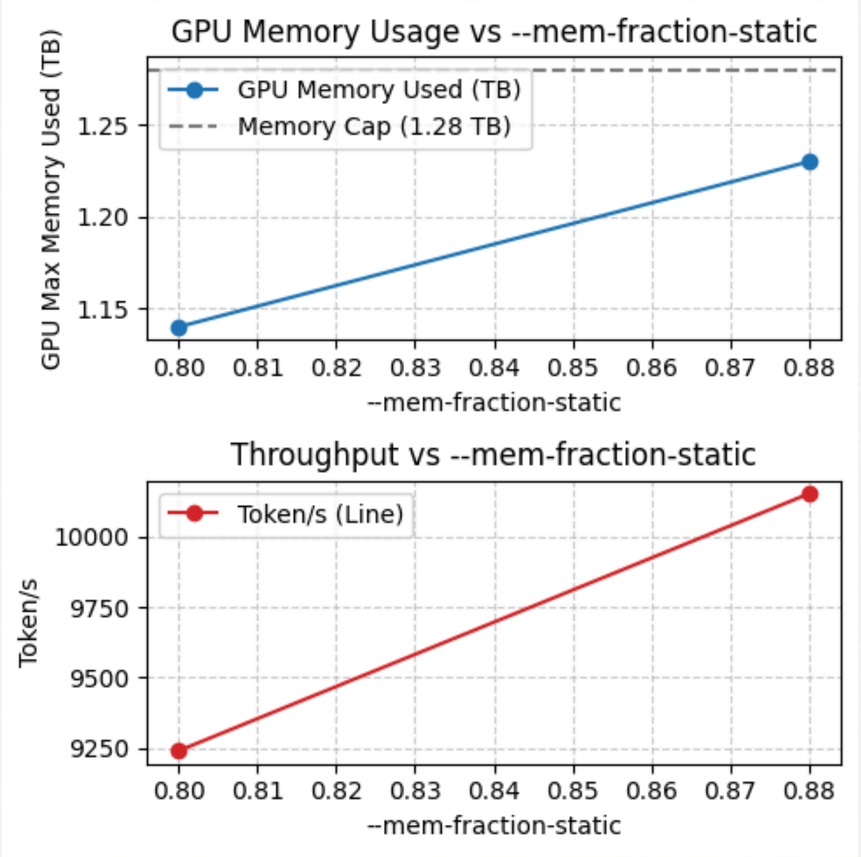
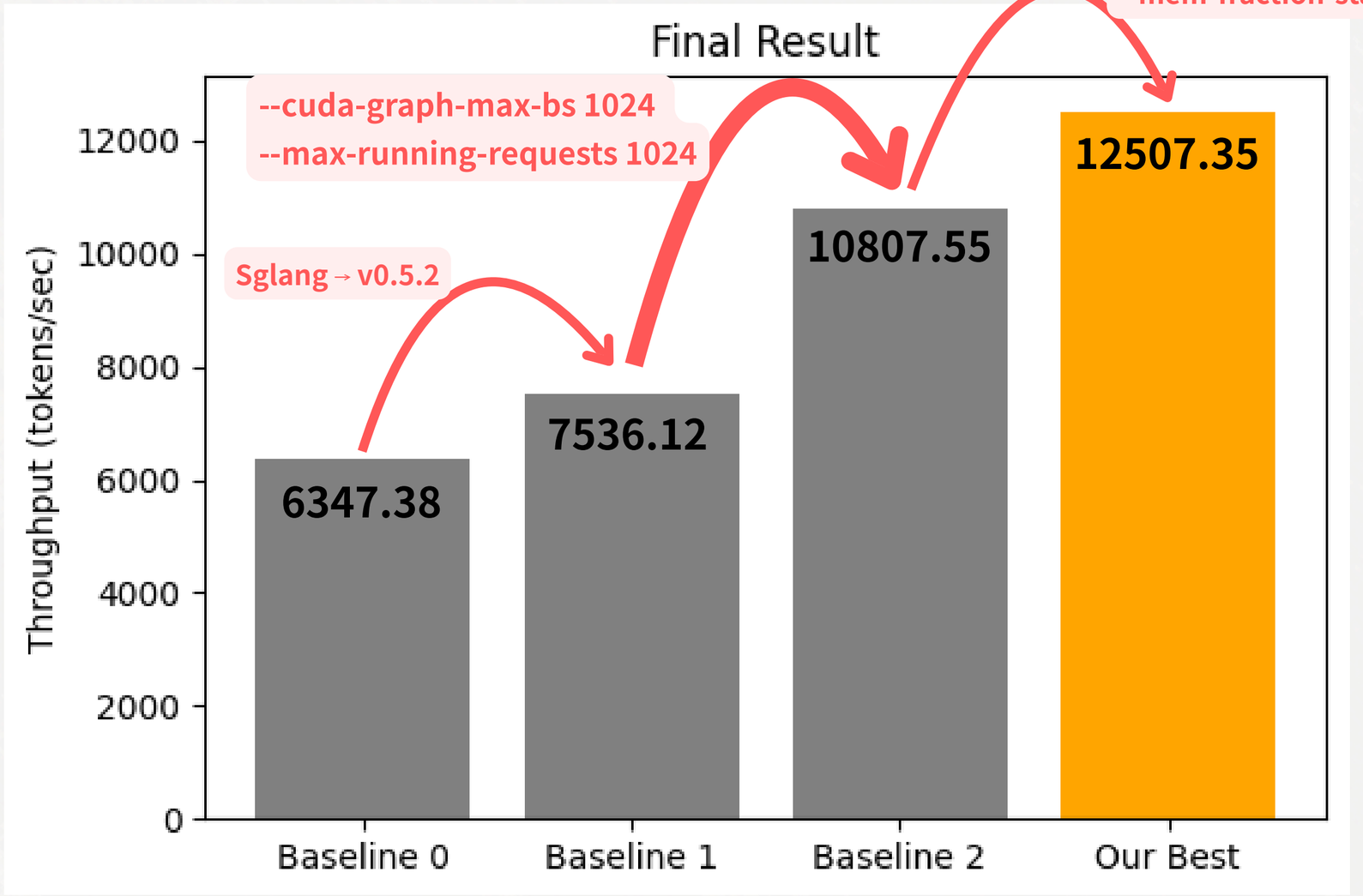


Table of Contents

Summary of Results



Acknowledgements

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The End

Thank You For Listening

APAC HPC-AI Challenge

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