Core C++ 2025

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From GPU Bottlenecks to Smooth Chat: Cost-Efficient Architectures for LLM Inference

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PLiOPS
EXTREME DATA PROCESSOR

OpenAI and NVIDIA Announce Strategic Partnership to Deploy 10 Gigawatts of NVIDIA Systems

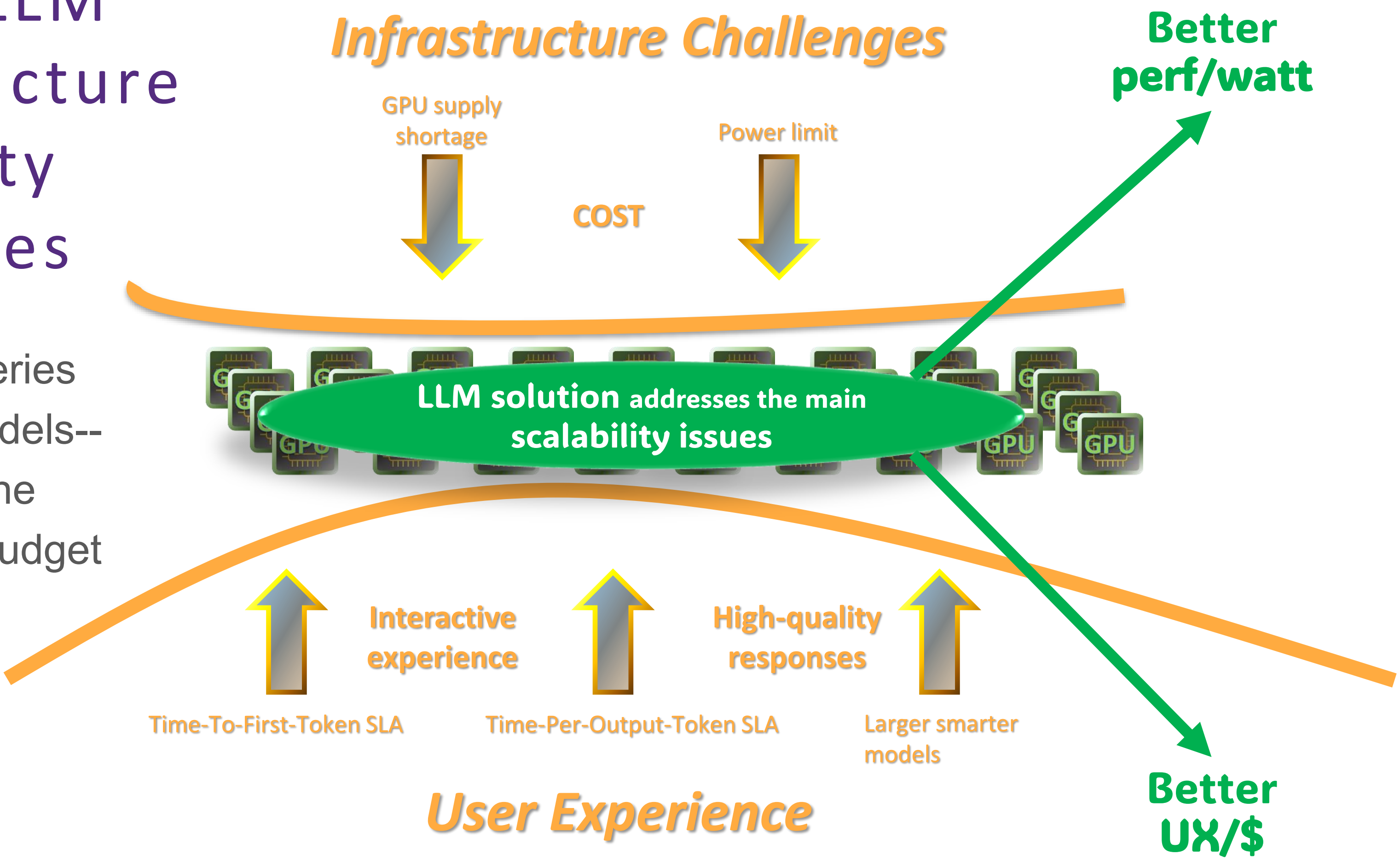
September 22, 2025

C++ Devs for LLM inference

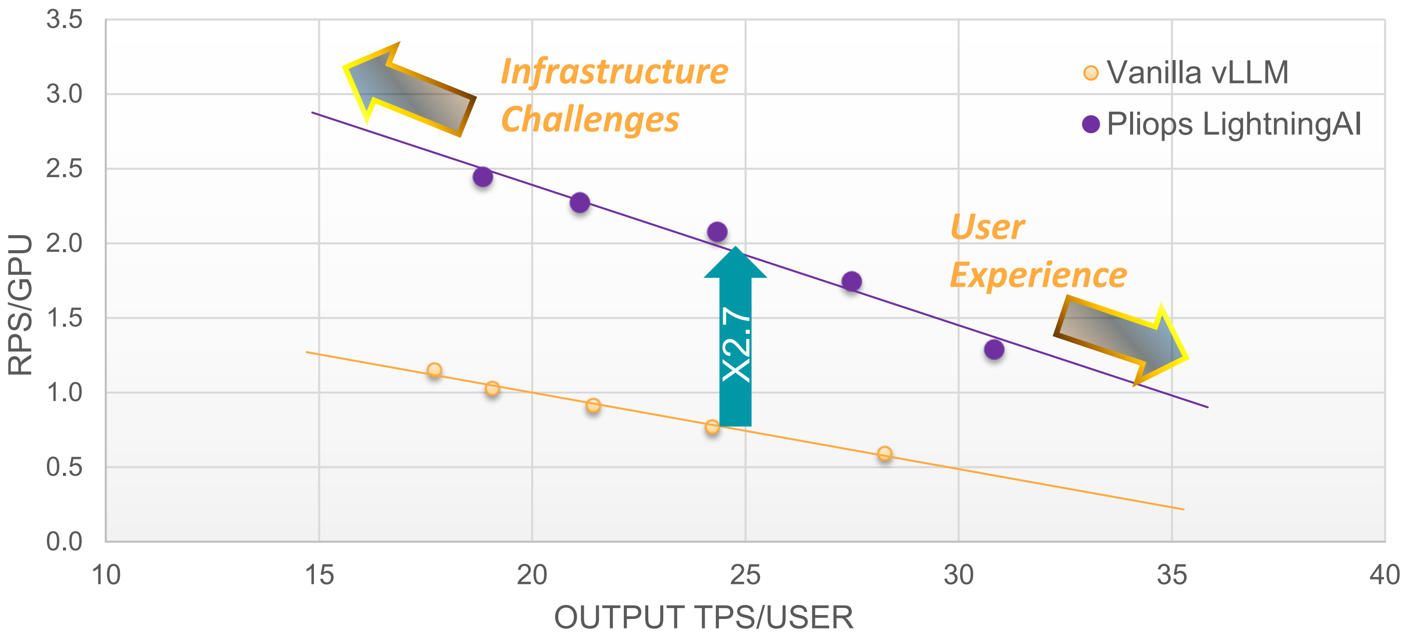
https://www.ted.com/talks/eric_schmidt_the_ai_revolution_is_underhyped

Solving LLM Infrastructure Scalability Challenges

Serve **MORE** queries with **LARGER** models-- **FASTER**, under the **SAME POWER** budget



System Efficiency vs User Experience Tradeoff



Setup:
- HW: 8* H100, PCIe Gen 5, Dell server
- Model: llama-3-70B, 8FP, GQA 8, TP 2
- Prompt: 100-3500, output: 64
- Different batch sizes

Agenda for Today's Talk

- ❑ Why prefill and KV-cache dominate E2E performance
- ❑ KV-cache Offloading: Shared KV-store approach (Disaggregated)
- ❑ Results, theoretical model and implications for system design

Popular LLM Applications w Repetitive Context

Chatbots

reuse early chat content as context for later chat input

Bug Fixing

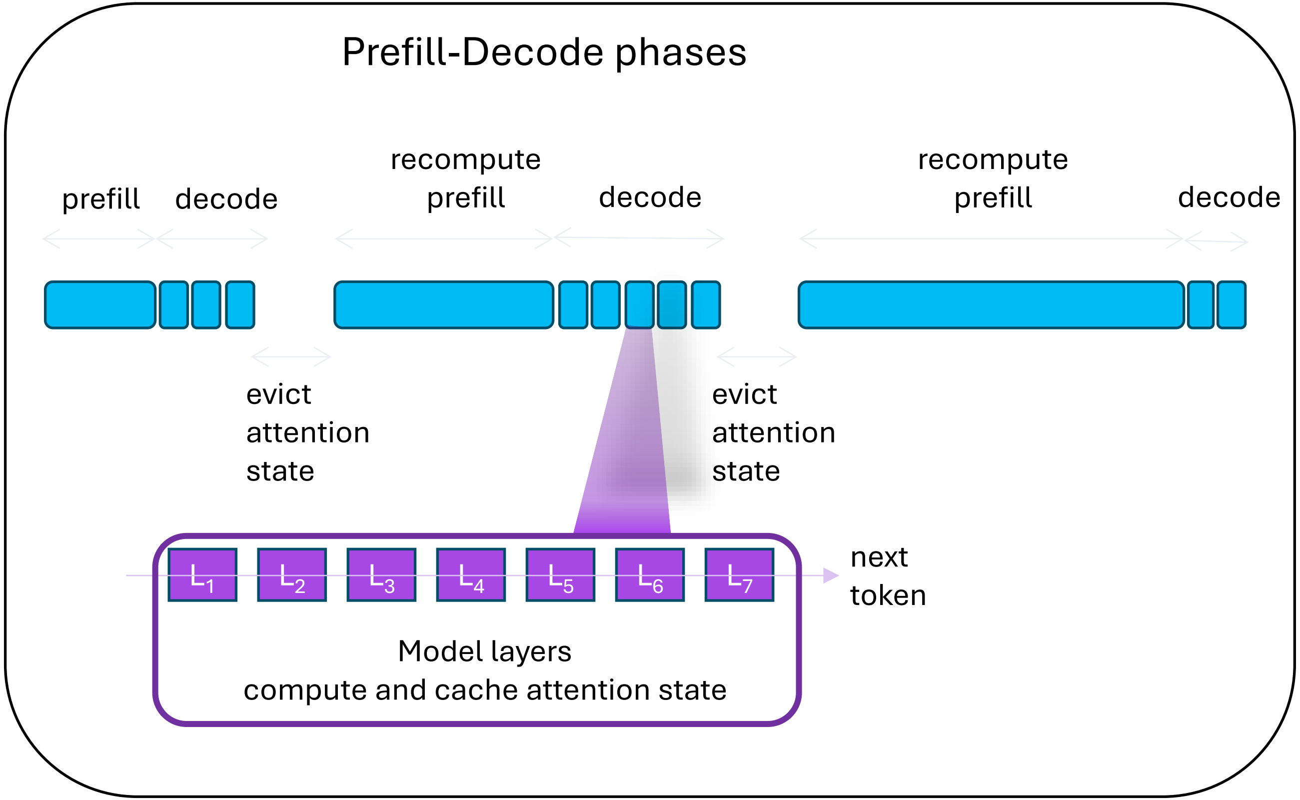
Frequently using entire code repository as context

Insights

Assistant and rec sys query large document sets

Repetitive computations * highly inefficient * up to 99% prefill cost * limit HBM bandwidth utilization and e2e performance

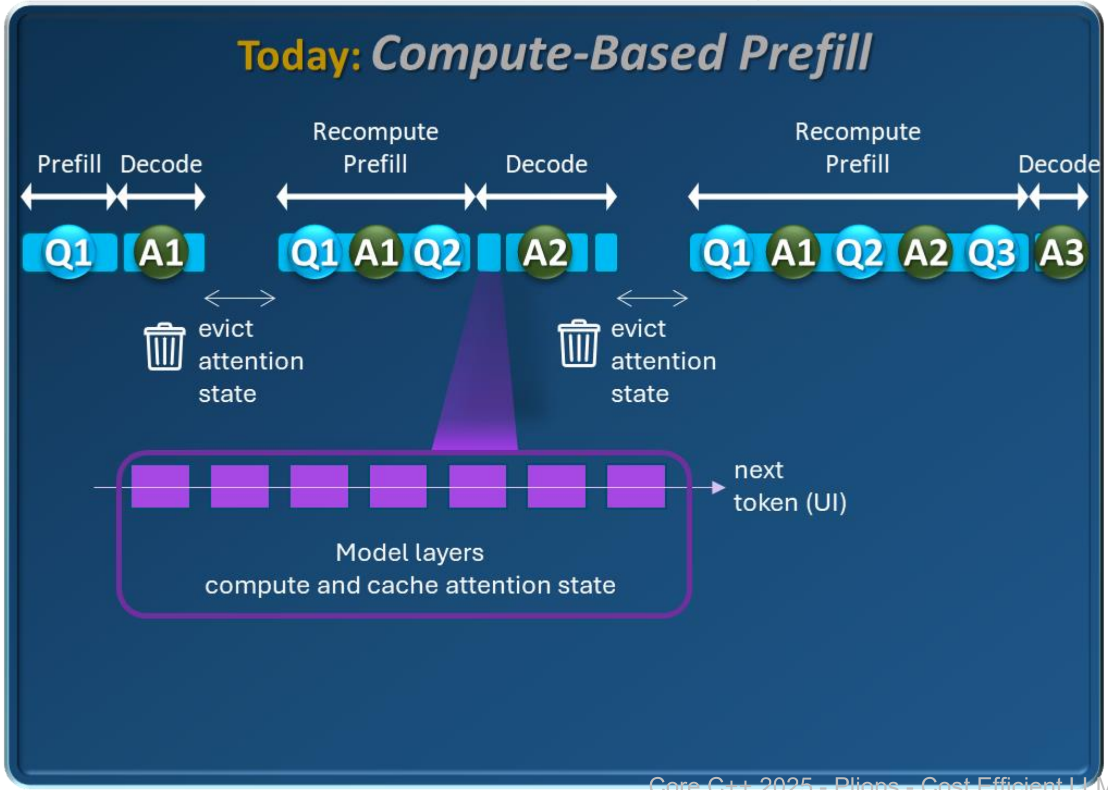
Prompt Computation vs. Token Generation



- Prefill phase (prompt)
  - All input tokens processed in parallel to generate the first output token
  - Time to first token (TTFT)
  - Compute bound
- Decode phase (token)
  - Serialized token generation
  - Time per output token (TPOT)
  - Memory bound

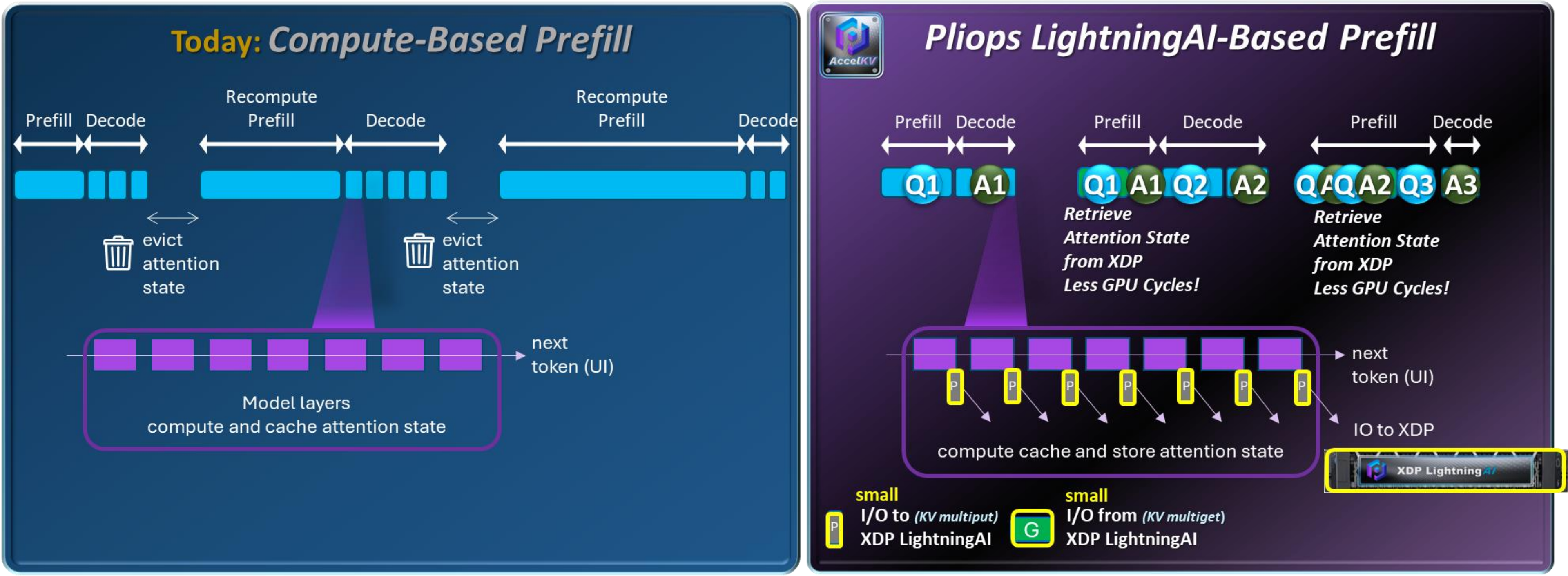
Multi-Turn Chats Evict KV-Cache Between Turns

Multi-turn conversation or multi-shot task agent prefill attention kv-cache based on expanding history



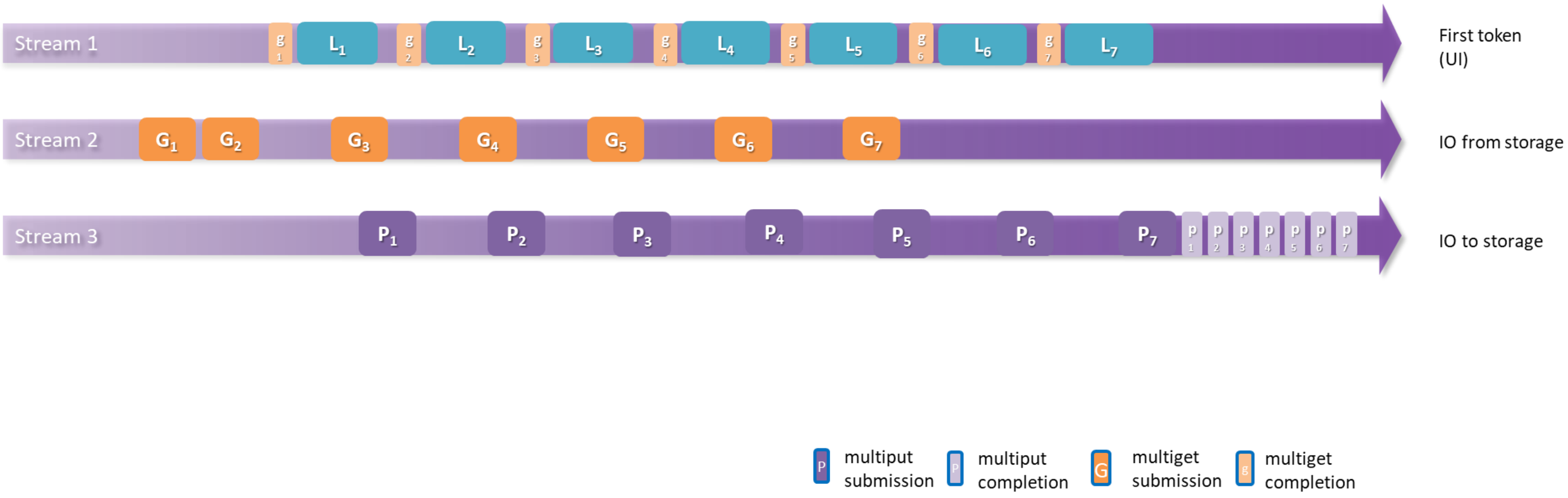
KV-Cache Offloading in a Nutshell

Multi-turn conversation or multi-shot task agent prefill attention kv-cache based on expanding history



IO-Compute Parallelism

Prefill attention KV-cache: (2) retrieve past (1) compute new interaction (3) store new

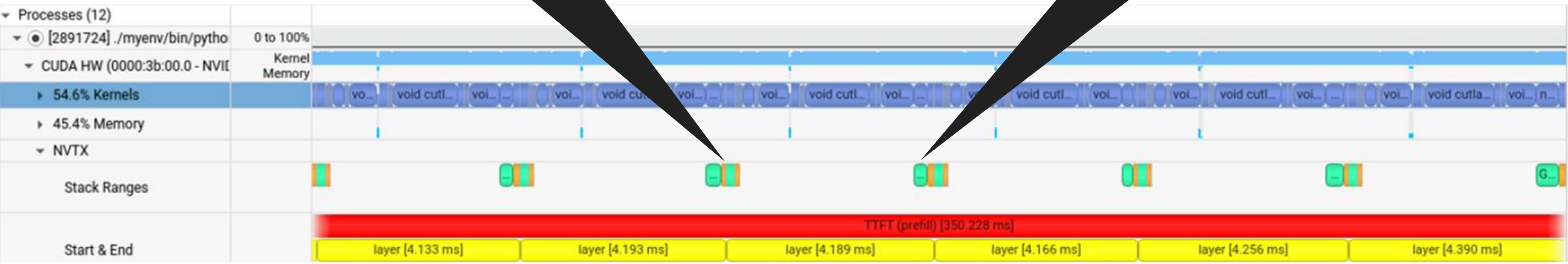


IO-Compute Parallelism – Nsight View

Layer wise pipelining: IOs execute in parallel with new prompt kv-cache computation

In orange: GPU-initiated Put-IOs of the previous layer

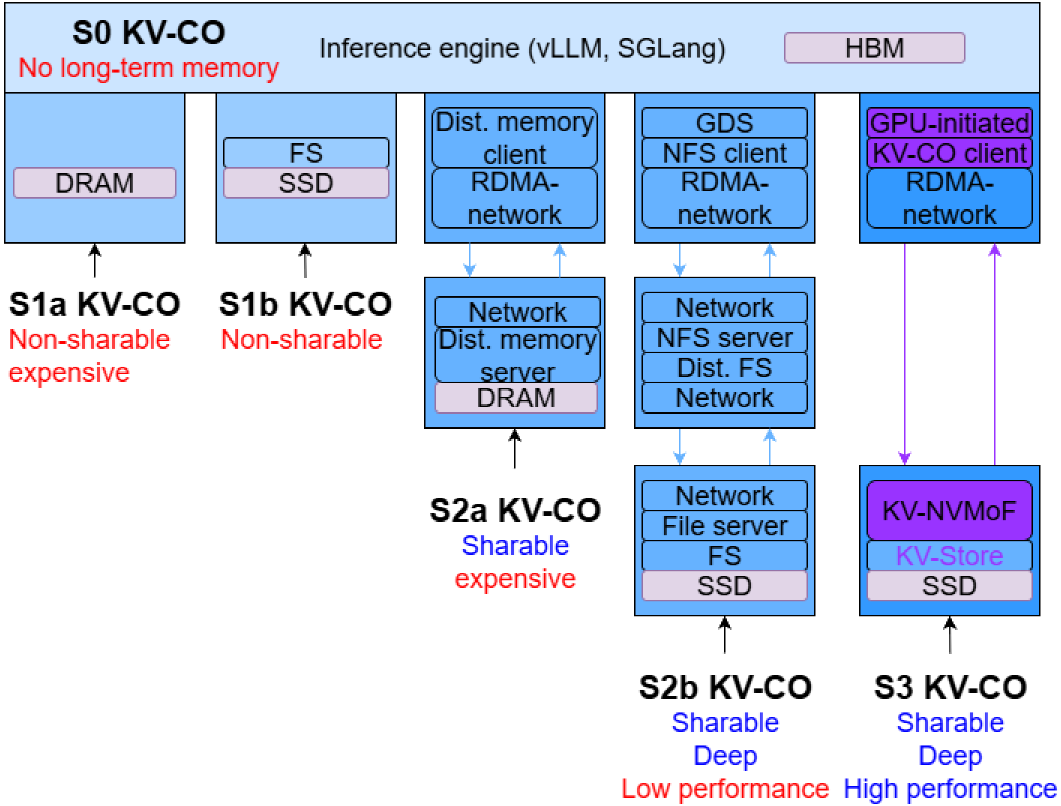
In green: GPU-initiated Get-IOs for the next layer



In yellow: compute current layer

Stratified classification of KV-cache offloading (KV-CO) Solutions

- **S0:** Simple but tiny capacity
- **S1:** extended capacity, remains non-sharable, incurs higher cost
- **S2:** sharable namespace and deep at the expense of performance or cost
- **S3:** sharable namespace and deep with improved performance



Prefill Speedup Analysis

Prefill Acceleration By KV-Cache Retrieval

- R - time to retrieve a token from storage
  - $R = |KV_{token}|/BW_{IO}$
- T - compute time per input token
  - $T = (2|model| + N_{in} \cdot O(\sqrt{|model|}))/TFLOPs(*)$
- Effective token acceleration $e = T/R$
- α – KV-cache fraction cached in storage
- N_{in} – number of input token

(*) approximate attention compute; assuming all GPU compute is utilized, not always true

Prefill Acceleration Analysis

- $TTFT^{V} = N_{in} \cdot T$
- Offloading writes the newly generated KV cache
  - Let **W** denote the write time of a single token KV
- Assuming IO and compute can be overlapped
  - At each layer prefetch next layer's KV cache and write the KV cache of the previous layer
  - $TTFT^{KV} = \max(\underbrace{\alpha \cdot N_{in} \cdot T/e}_{\text{IO time to fetch existing KV cache from storage}}, \underbrace{(1-\alpha) \cdot \boldsymbol{N_{in}} \cdot W}_{\text{IO time to write the new part of the prompt}}, \underbrace{(1-\alpha) \cdot \boldsymbol{N_{in}} \cdot T}_{\text{Compute time of the new part of the prompt}})$

Prefill Acceleration Analysis (Cont.)

- $TTFT^{KV} = \max(\alpha \cdot N_{in} \cdot T/e\ , (1-\alpha) \cdot N_{in} \cdot W, (1-\alpha) \cdot N_{in} \cdot T)$
  - When $W \leq T$ TTFT is not affected by write IOs
- $TTFT^{KV} = \max(\alpha \cdot N_{in} \cdot T/e\ , (1-\alpha) \cdot N_{in} \cdot T)$
- $TTFT^{V} = N_{in} \cdot T$

Insight
Write only need to match compute performance

Performance gain (speedup)

- compute-bound: x=$1/(1-\alpha)$
- IO-bound: x=e/α

Acceleration depends on read performance and hit rate

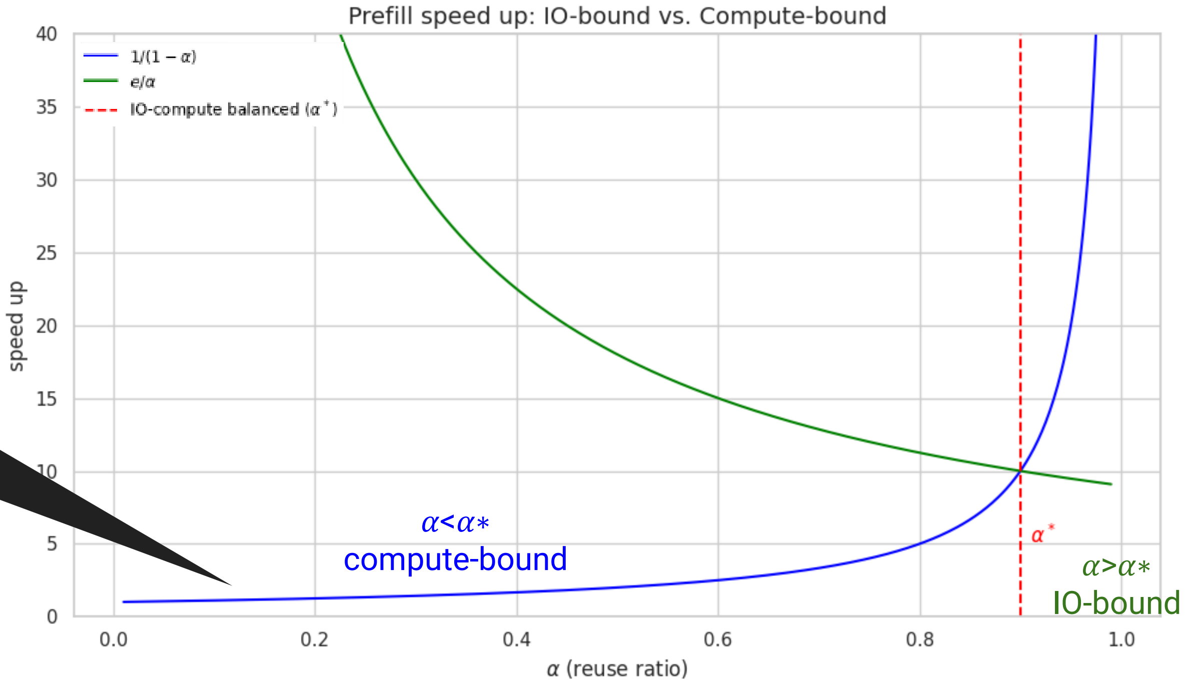
Prefill Acceleration Analysis (Cont.)

For example **e=9**

e is the acceleration from offloading (T/R)

Crossover point

$\alpha* = e/(1+e)$

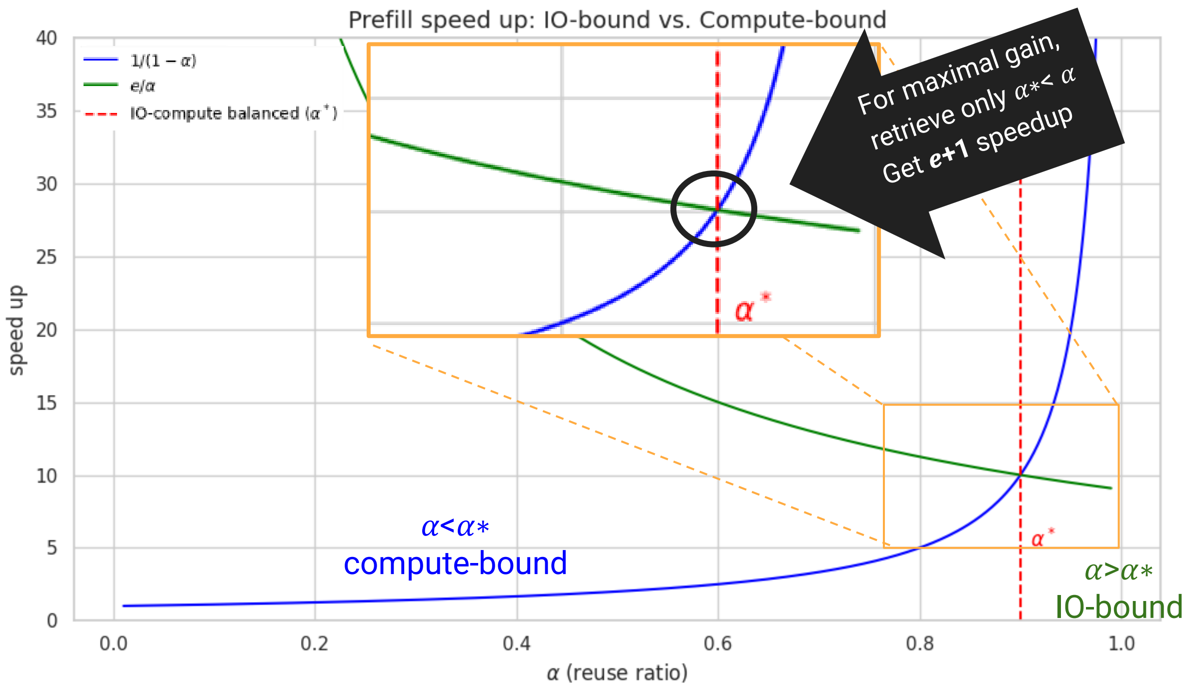


Insight
No advantage for higher IO speed! (HBM, DRAM)

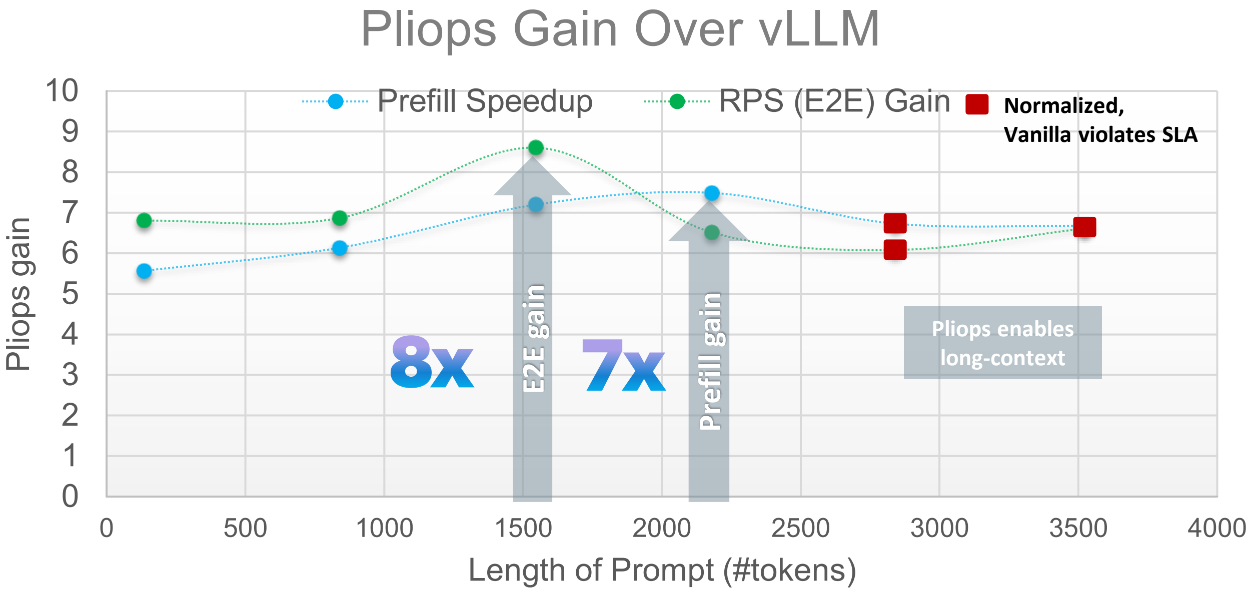
Prefill Acceleration Analysis (Cont.)

For example **e=9**
e is the acceleration from offloading (T/R)

Crossover point
$\alpha{*}=e/(1+e)$



Prefill Acceleration - Compute-Bound Example

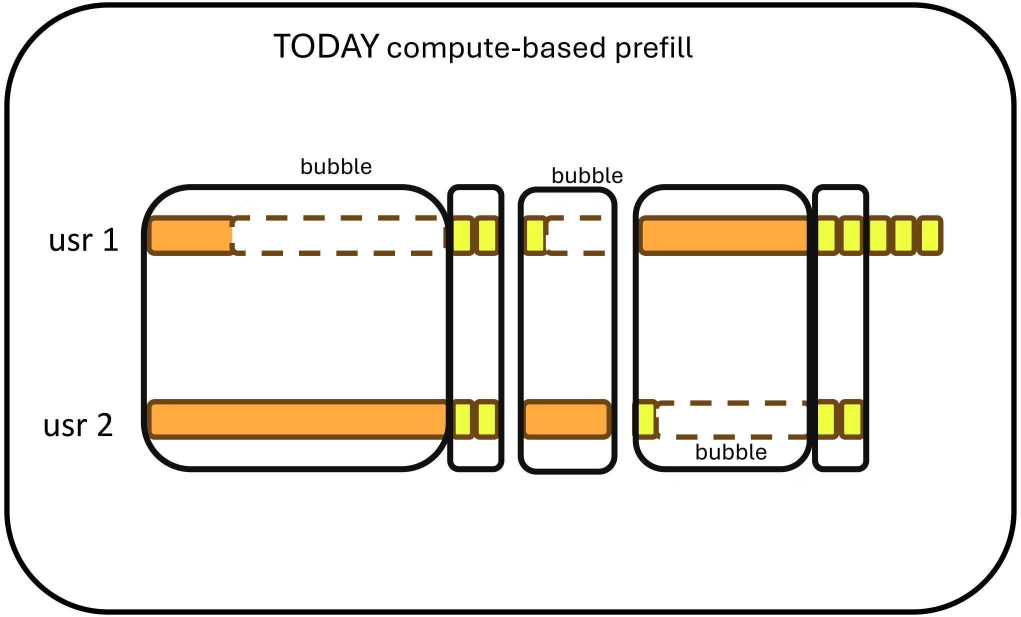


Replacing GPU compute with storage IO in prefill allows higher HBM BW efficiency in decode via larger batch size

- HW: H100 gen 5 Dell server
- Model: llama-3-70B, 8FP, GQA 8, TP 1
- SLA: TTFT 400ms, TPOT 40ms
- Prompt: 100-3500, output: 64
- Maximum batch size to meet SLA

End-to-End (E2E) Gain for Continuous Batching

Colocating Prefill and Decode

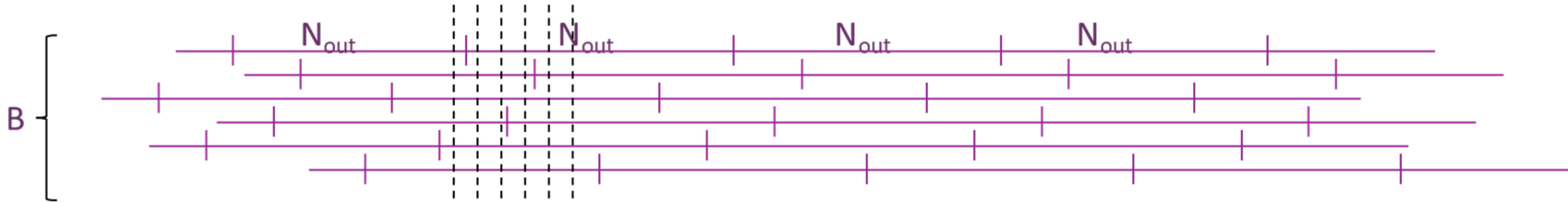


- In-flight batching (continuous)
- Decode "love" batches as it is memory bw bound

- Prefill-prefill interference
- Prefill-decode interference
- Creating "bubbles"


E2E Gain - Continuous Batching Analysis

- B – number of concurrent requests
- N_{out} – Average number of output tokens
- Number of concurrent prefills~ $Binom(B, 1/N_{out})$



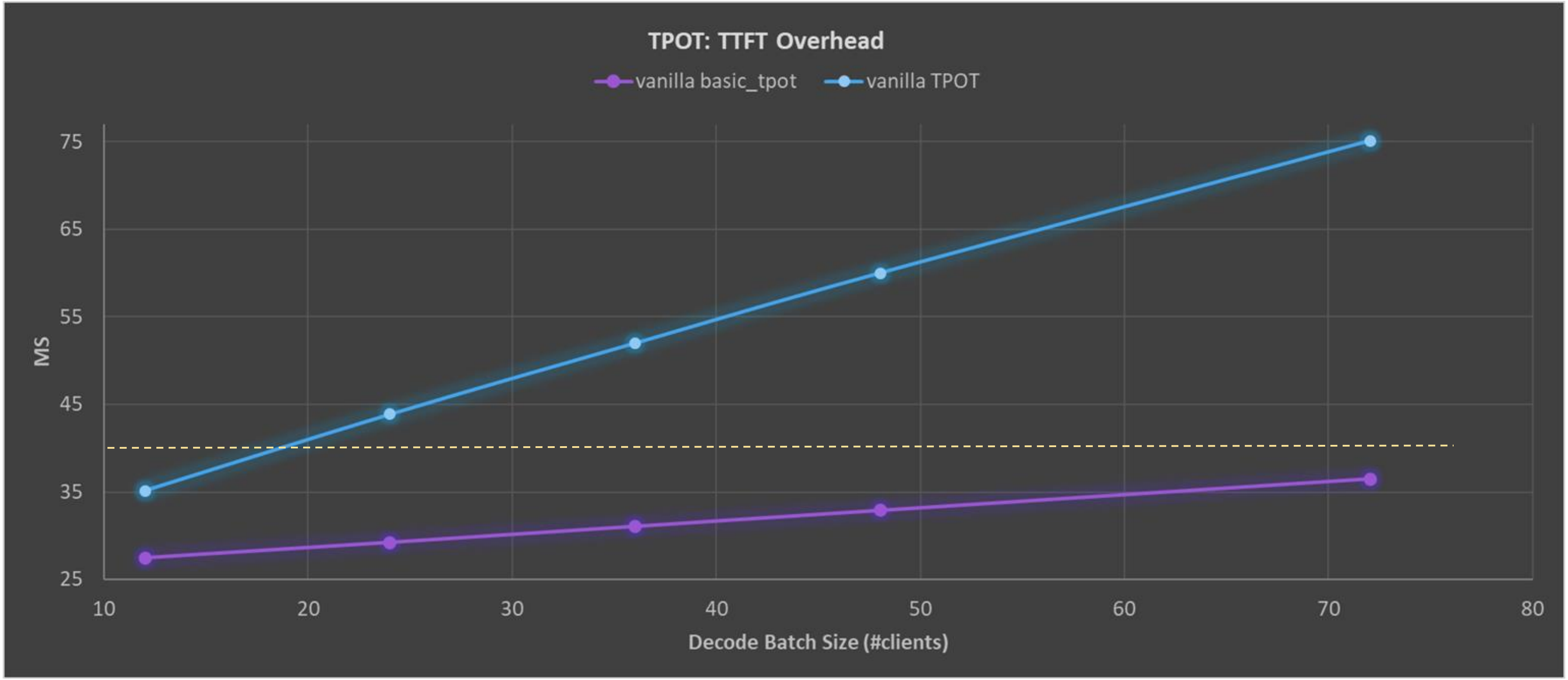
E2E Gain - Continuous Batching Analysis

- B – number of concurrent requests
- N_{out} – Average number of output tokens
- Number of concurrent prefills~ $Binom(B, 1/N_{out})$
- $\boldsymbol{E[TTFT(B)] = TTFT(1) + \ (B-1)/N_{out} \ \cdot TTFT(1) = (\ 1 + (B-1)/N_{out}) \cdot TTFT(1)}$
- $\boldsymbol{E[TPOT(B)] = TPOT(1) + (B-1) \cdot (TTFT(1)/N_{out} + |KV(1)|/BW_{HBM})}$
  - $|\boldsymbol{KV(1)}|$ is the average KV cache size of a single input prompt
  - $\boldsymbol{BW_{HBM}}$ is the memory BW

Expected number of additional simultaneous prefills in a prefill slot

Time to transfer a single prompt KV cache to compute engines

Measured TPOT Overhead for LlaMa-3-70B



Impact of Prefill Speedup on Decode Speedup

- $\boldsymbol{TPOT(B) \sim= TPOT(1)+(B-1)\cdot(\overbrace{TTFT(1)/N_{out}}^{\Delta P}+\overbrace{|KV(1)|/BW_{HBM}}^{\Delta H})}$
- $\mathrm{TPOT(B)} \leq \mathrm{SLA}_{\mathrm{TPOT}}$
- Maximal B to meet $\mathrm{SLA}_{\mathrm{TPOT}}$: $\lfloor(SLA_{TPOT} - TPOT(1))/(\Delta P+\Delta H)\rfloor$
- $\Delta P_{KV}=\Delta P/x$
- $B_{KV}/B_{vanilla} =(\Delta P + \Delta H)/(\Delta P_{KV} + \Delta H)$
  $=(\Delta P + \Delta H)/(\Delta P/x+ \Delta H)$
- When $x \rightarrow \infty$, $B_{KV}/B_{vanilla}= \mathbf{1}+\Delta P/\Delta H$

System is required to meet SLA

x is the speedup of the prefill using IO

Insight
TPS gain

Asymptotic E2E Gain Analysis

- TPS gain <= 1+ $\Delta P/\Delta H$ aim to maximize $\Delta P/\Delta H$

- $\Delta P = \boldsymbol{TTFT(1)/N_{out}}$, $\Delta H = |\boldsymbol{KV(1)}|/\boldsymbol{BW_{HBM}}$
  - $TTFT(1) = N_{in} \cdot \underbrace{(2|model|/TFLOPs}_{\text{“Model” Compute Time}} + \underbrace{N_{in} \cdot O(\sqrt{(|model|}\,)/TFLOPs))}_{\text{Attention Compute Time}}$

- $\Delta H = \underbrace{N_{in}\,|KV_{token}}_{|KV(1)|}|/\boldsymbol{BW_{HBM}}$

KV cache size of a single token

Asymptotic E2E Gain Analysis (Cont.)

TTFT(1) behaves differently in two distinct regimes

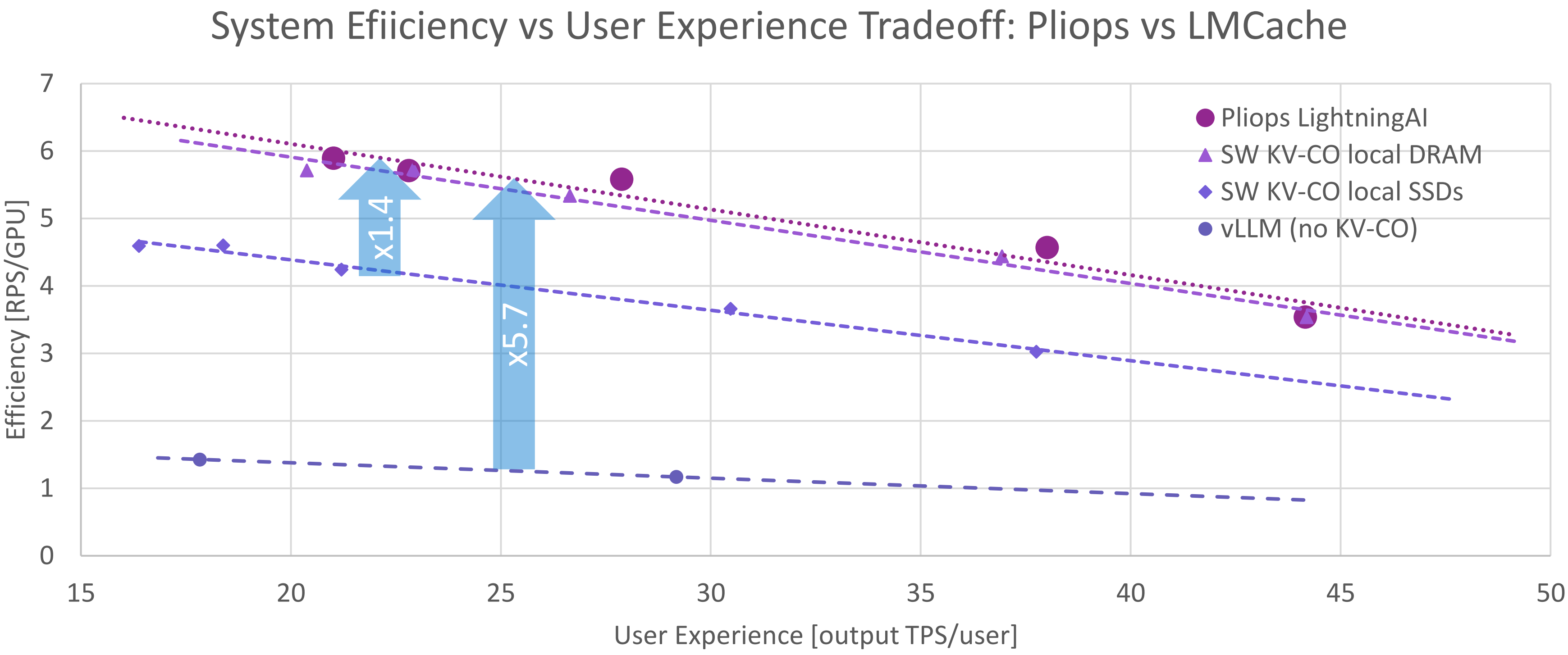
Model params
- Model size
- KV-cache compression (GQA, MQA, MLA)

GPU params
- Mem bw to compute ratio

App params
- in/out ratio

- Short prompt regime : $\Delta P/\Delta H \propto |model|/|KV_{token}| \cdot BW_{HBM}/TFLOPs \cdot 1/N_{out}$ $(N_{in} \ll 6d)$
- Long prompt regime : $\Delta P/\Delta H \propto \sqrt{|model|/|KV_{token}|} \cdot BW_{HBM}/TFLOPs \cdot N_{in}/N_{out}$ $(N_{in} >> 6d)$

Pliops/Local DRAM/Local SSD Efficiency Comparison



- HW: H100 gen 5 Dell server
- Model: Qwen3-14B, 16FP
- Prompt: 9600 (avg), 6.5 turns (avg)
- output: 80-120
- Different batch sizes

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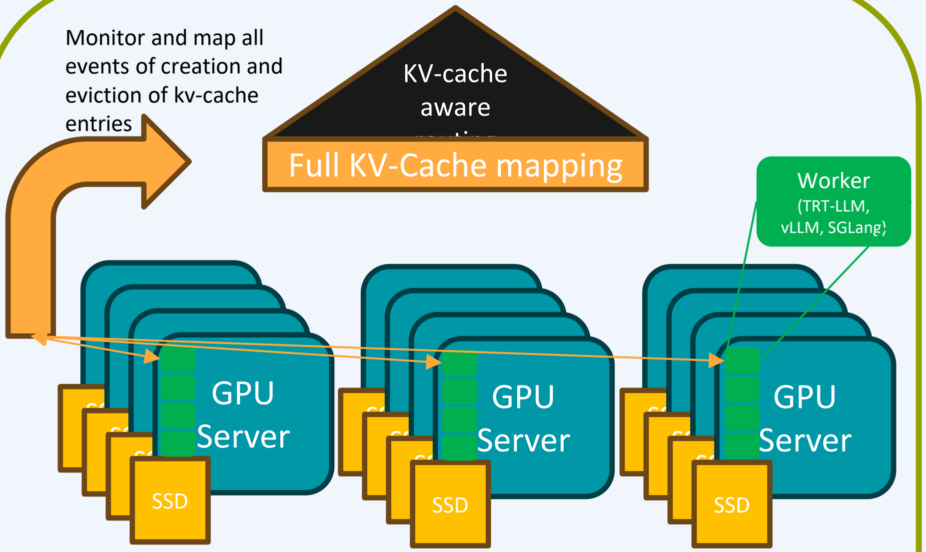
AI Factories
Data-Center Scale LLM Inference

Datacenter Scale LLM Inference Framework

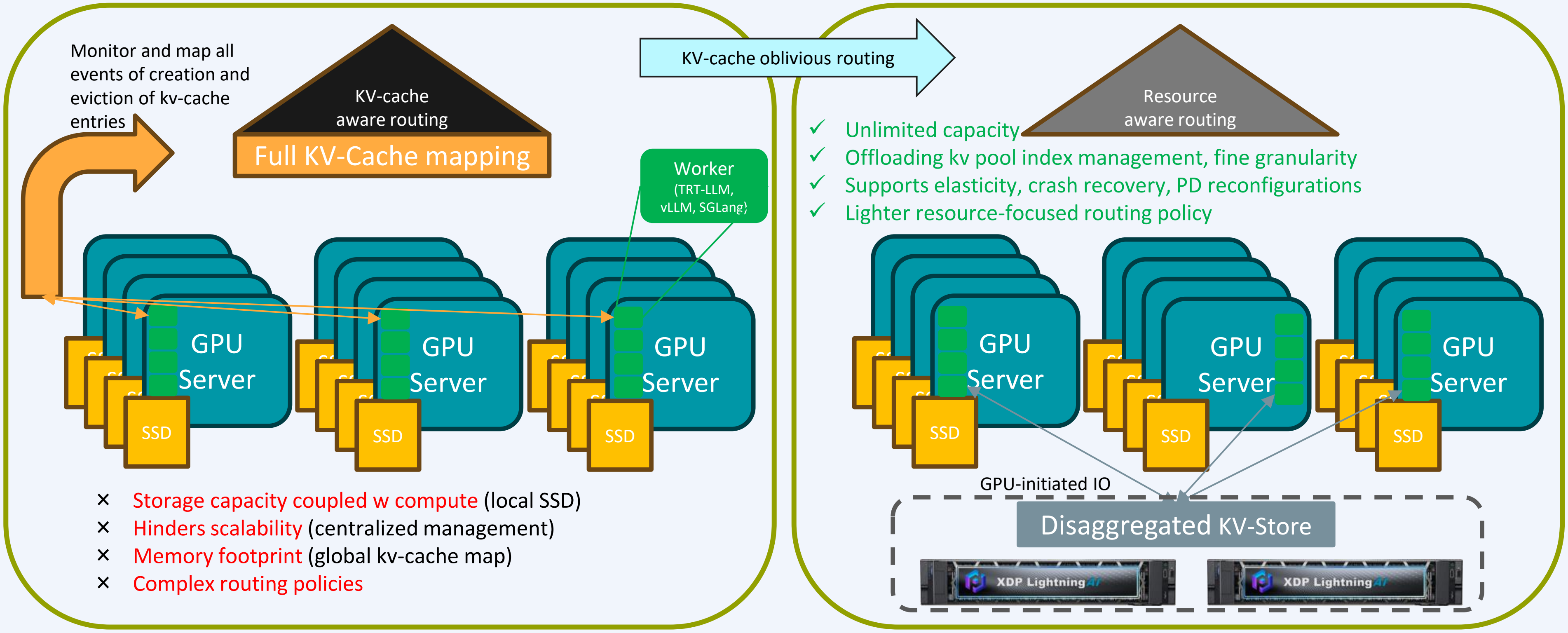


- × Storage capacity coupled w compute (local SSD)
- × Hinders scalability (centralized management)
- × Memory footprint (global kv-cache map)
- × Complex routing policies

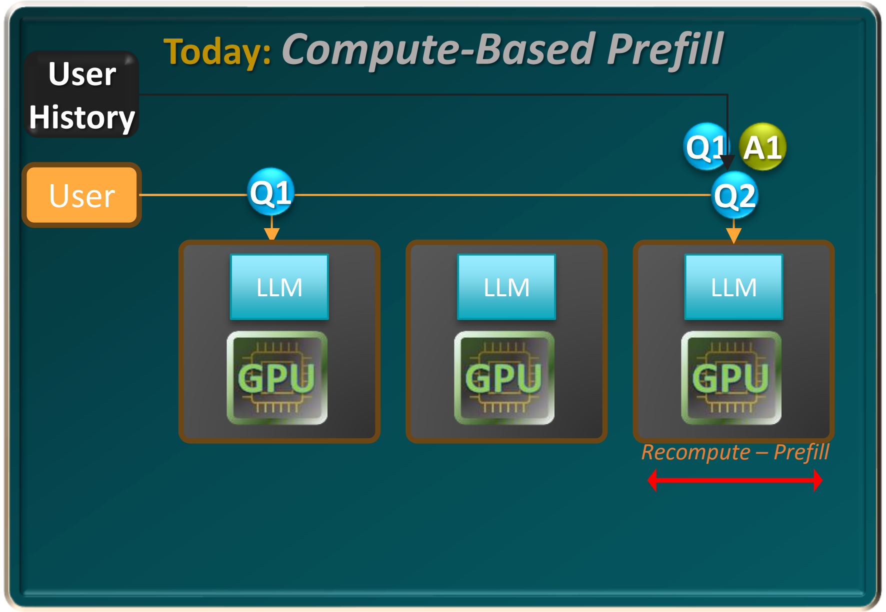
- Dynamo (Nvidia)
- llm-d (IBM/RedHat/Google)
- AIBrix (ByteDance)
- Production Stack (Tensor Mesh)

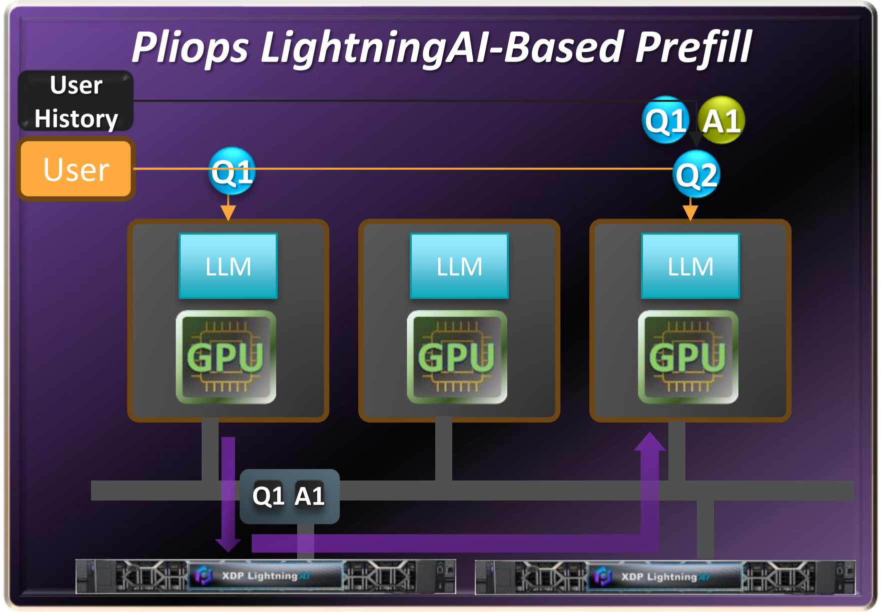
Support for Prefill-Decode Disaggregation (PDD)

Simplicity for Performance and Robustness

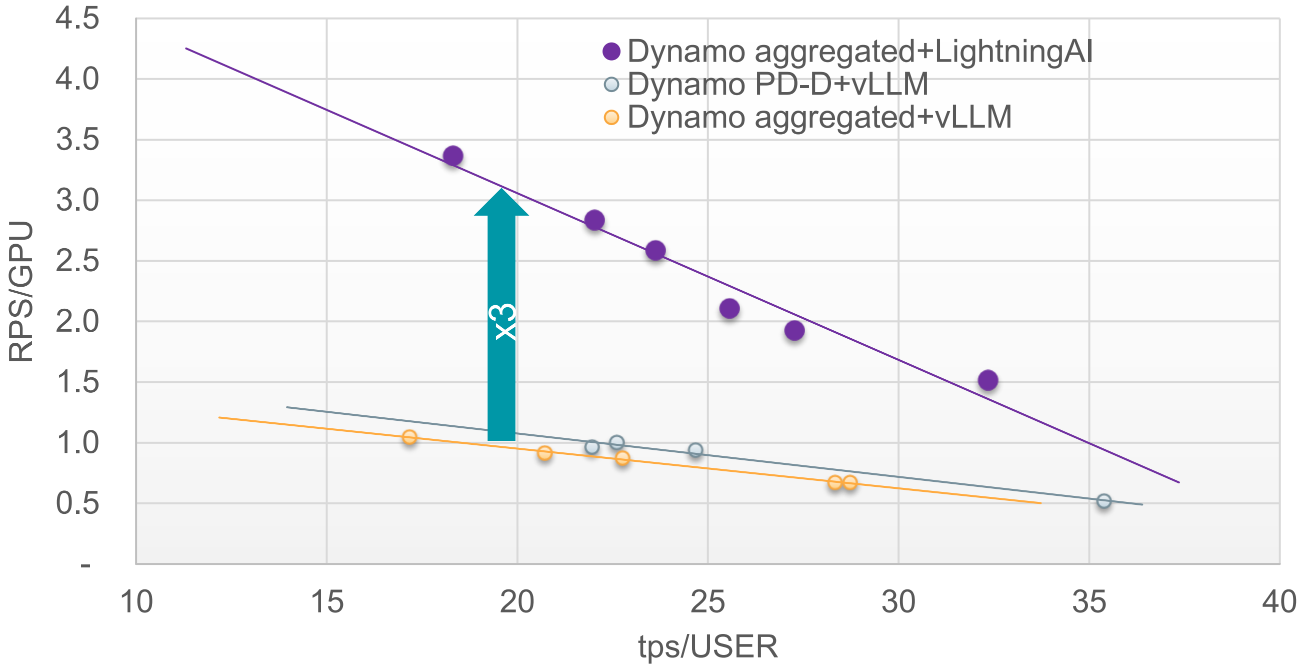


KV-Cache Offloading- System View





System Efficiency vs User Experience Tradeoff



- HW: H100 gen 5 Dell server
- Model: llama-3-70B, 8FP, GQA 8, TP 2
- Prompt: 2200, output: 170, turns: 15
- Different number of workers, clients

Summary & Conclusions

- ✓ KV-cache offloading increases efficiency and reduces cost while maintaining user experience constraints
- ✓ Throughput gains depend on the model, the GPU, and the workload
- ✓ In compute-bound cases, no benefit for faster-than-SSD memory
- ✓ Speedup depends mainly on read performance
- ✓ GPU-initiated IO achieves full IO-compute overlap with zero CPU overhead

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THANK YOU

QUESTION

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