LLM Inference Optimization

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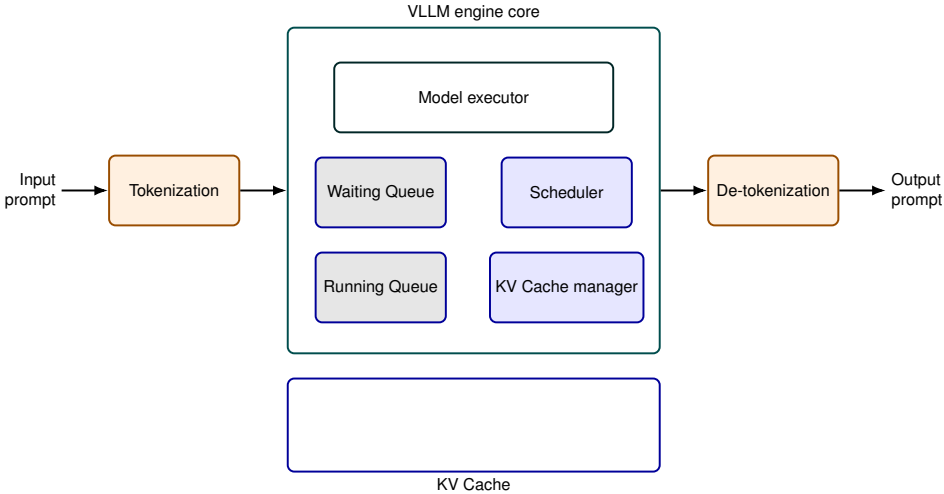
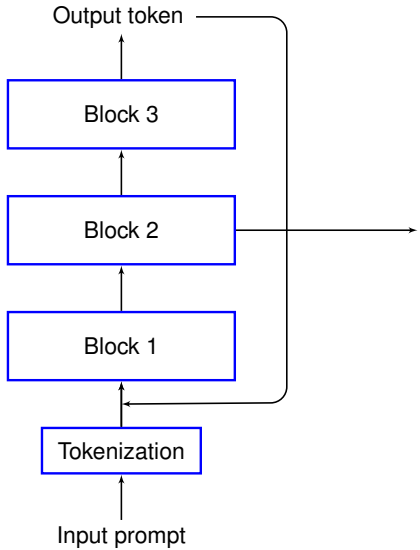
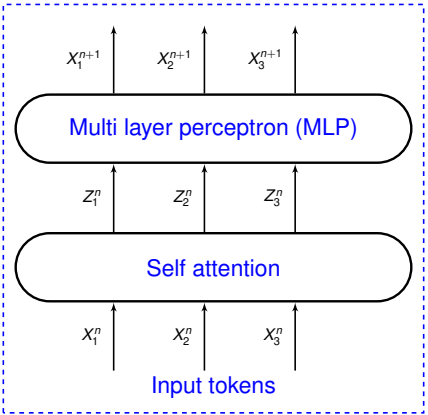
LLM inference server



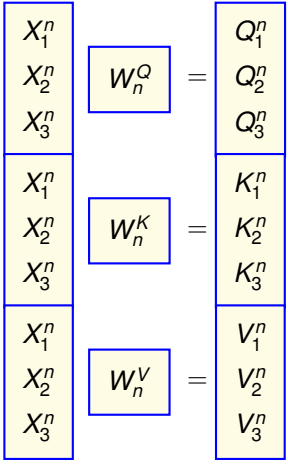
Processing pipeline





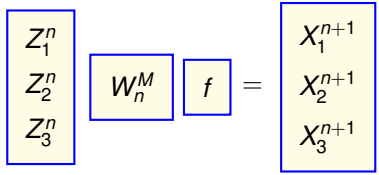
Processing at block n

Attention computations



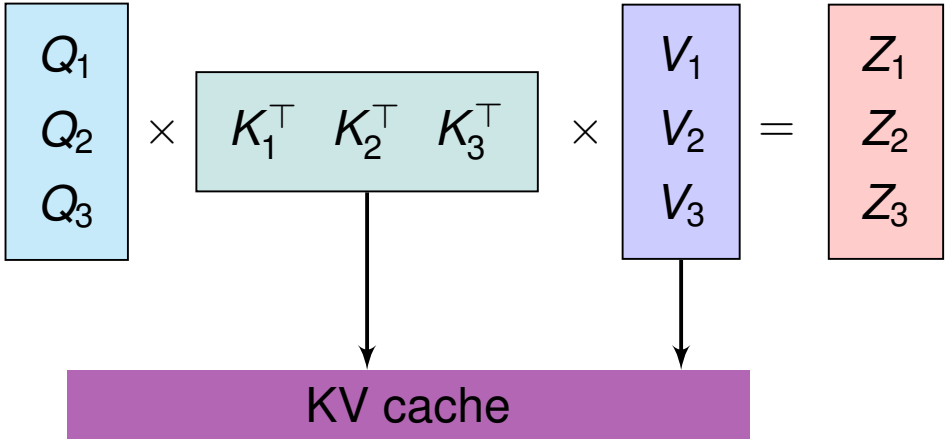
- $Z^n = \texttt{softmax}(Q_n K_n^\top) V_n$

MLP computations



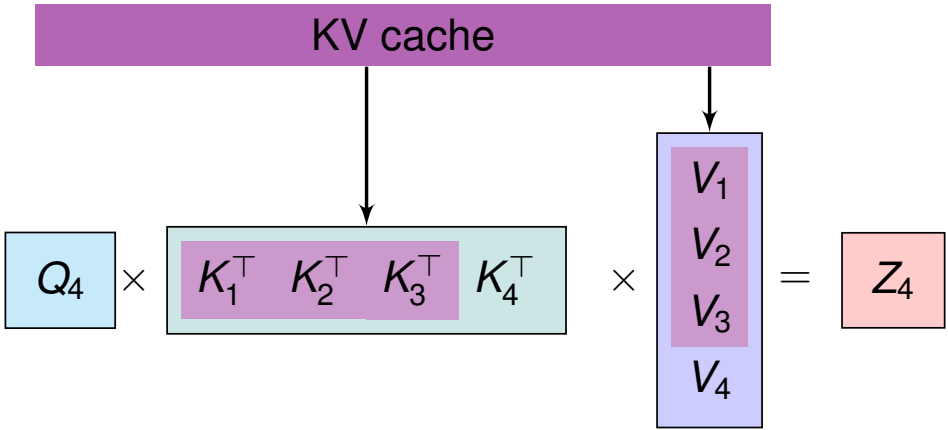
- $X^{n+1} = \texttt{MLP}(Z^n)$
- Prefill: Input tokens are *processed in parallel*
- Number of rows correspond to number of input tokens

Preprocessing with KV cache write



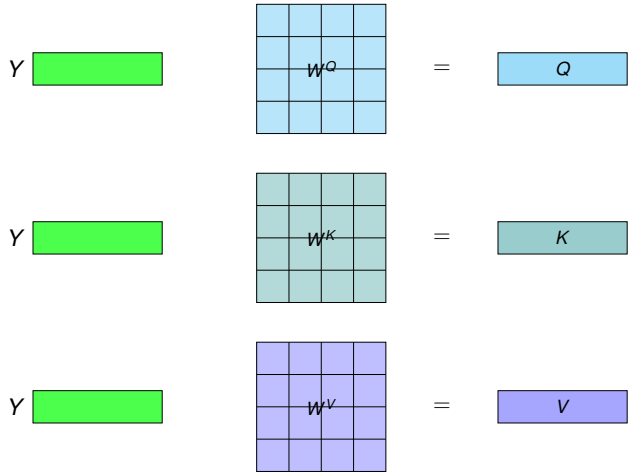
- (K, V) values stored in KV cache for subsequent decodes
- Output $Z \triangleq \text{softmax}\left(\frac{QK^\top}{\sqrt{d}}\right) V$ has the same number of rows

Postprocessing with KV cache read and write



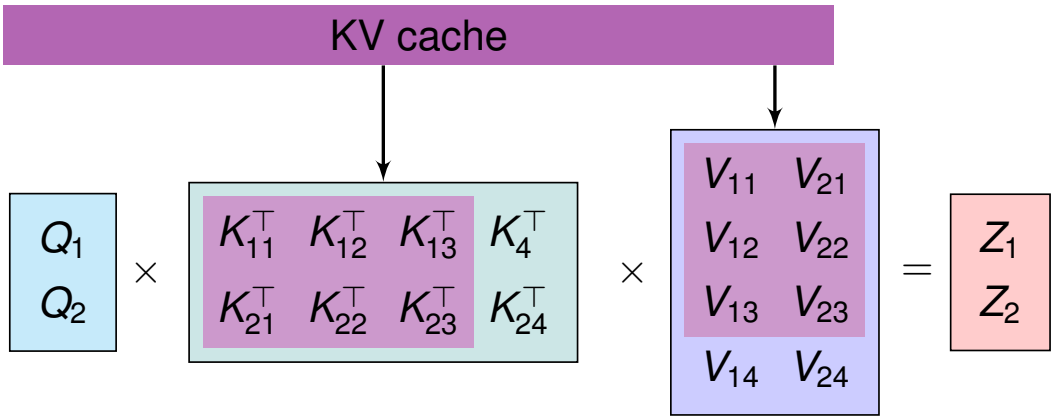
- Previously stored K, V values retrieved for each decode
- Output K, V values appended to previously stored K, V values in KV cache

Decode

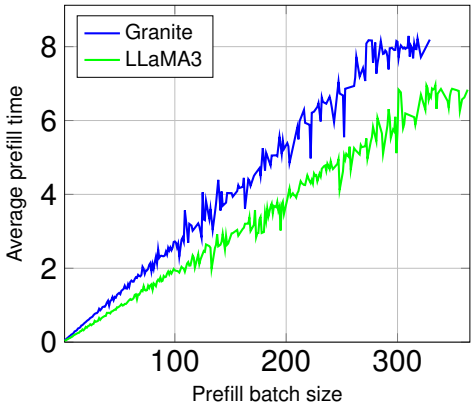


- Decode: Output tokens are *processed sequentially* from input tokens
- Underutilized compute capacity for each decode

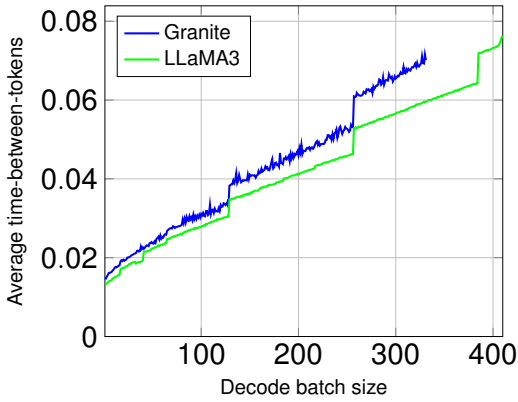
Continuous batching of decodes



Prefill and Decode times (ShareGPT dataset)



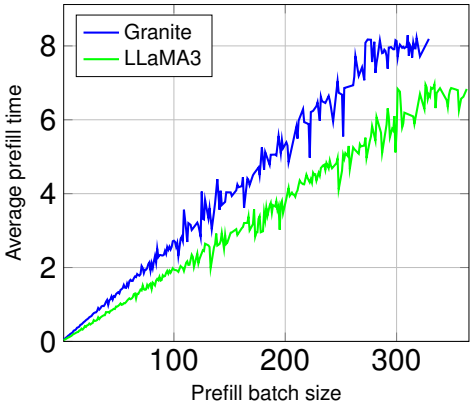
Prefill time

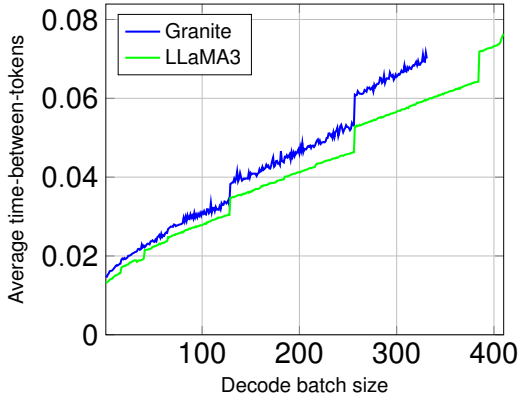


Decode time

Experiment setup: NVIDIA A100 (80GB) GPU, LLaMA and Granite 8GB models, vLLM V0

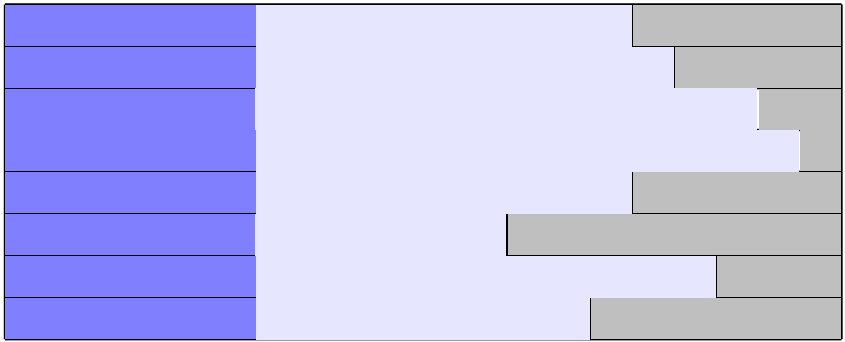
Prefill and Decode times





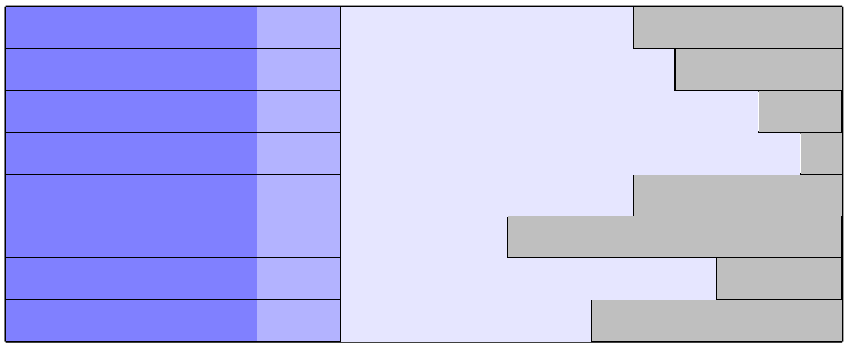
- Each prompt k has l_k input tokens
- Time to prefill K prompts is $c_p + t_p \sum_{k=1}^{K} l_k$
- Time to decode a batch of B tokens is $c_d + t_d B$

Prefilling prompts



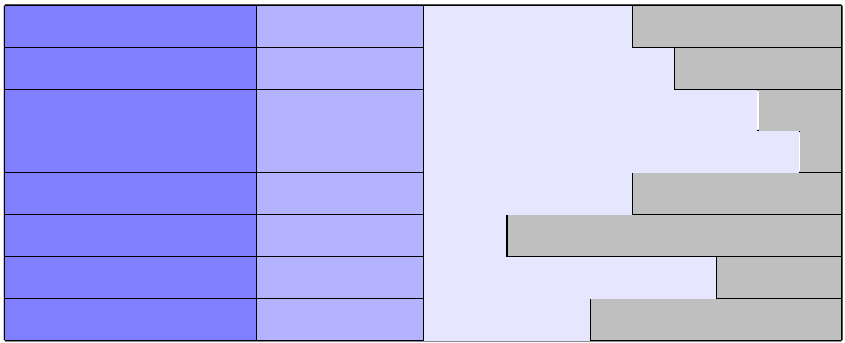
- Time to prefill B prompts is $c_p + t'_p \sum_{k=1}^{B} l_k \approx c_p + t_p B$

Decode for prefilled prompts



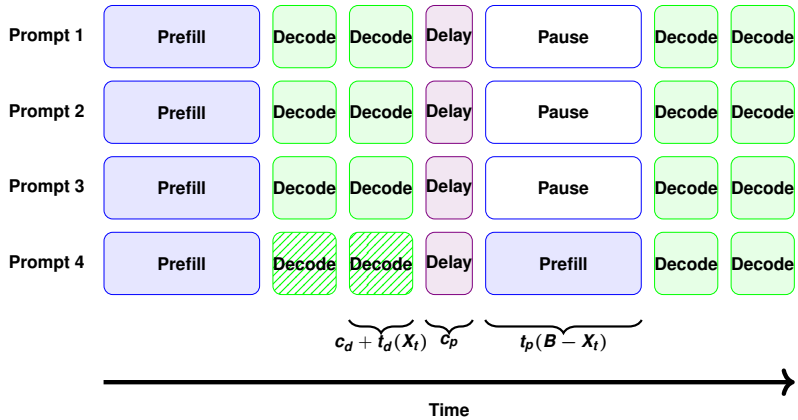
- Time to decode a batch of B tokens is $c_d + t_d B$

Decode for prefilled prompts



- Decode finishes for a prompt when the number of output tokens are generated
- This reduces the batch size

Alternating prefill and decode



Alternating prefill and decode

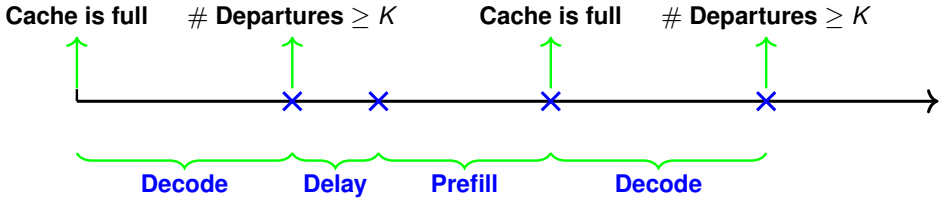
Default VLLM (v0) policy

- The inference engine alternates between prefill and decode phases
- Attempt a prefill whenever a prompt completes and there's a vacancy in the KV cache
- Switchover from decode to prefill incurs a fixed overhead

Observation

- Frequent prefills lead to larger switching delay and hence smaller throughput
- Infrequent prefills lead to smaller batch size and smaller throughput

Alternating prefill and decode: controlled transition



Key question

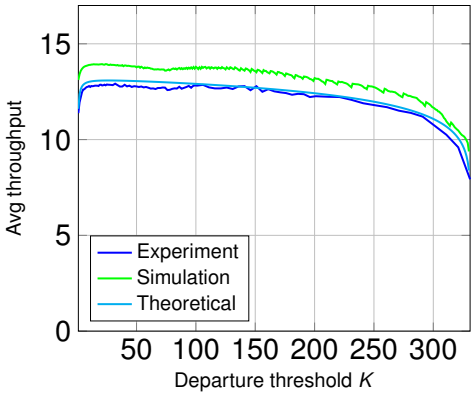
- What is the optimal departure threshold for average throughput maximization?

Analytical result

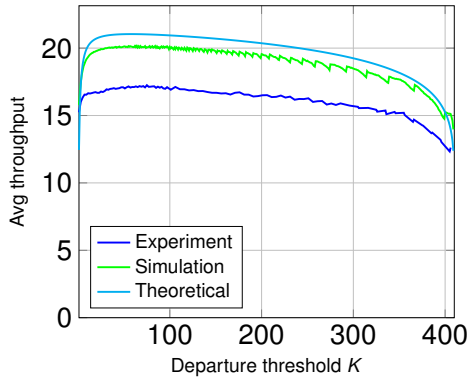
For constant input token length, geometrically distributed output token length with mean $1/\alpha$, and backlogged request queue

$$\rho(K)^{-1} \approx \frac{1}{K}\left(c_p + c_d \frac{\ln(1-\frac{K}{B})}{\ln(1-\alpha)}\right) + \frac{t_d}{\alpha} + \frac{t_p d_0}{N}.$$

Experimental validation



Granite



Llama

Figure: Performance metrics for different models with the ShareGPT dataset.

Conclusion

- Departure threshold-based scheduling algorithm.
- Analytical model for inference system, deduced closed form expression for throughput.
- Proved existence of optimal departure threshold that maximizes the system throughput.
- Characterization of LLM inference system to find the analytical model parameters.
- Experimental validation with vLLM inference server and NVIDIA A100 GPU.
- **Key outcome**: Proposed policy leads to 13% improvement in average throughput accompanied by 14% reduction in average prompt completion time.