Token-PD: Portfolio-Optimal KV-Cache Eviction for Multi-Tenant LLM Inference

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Abstract

The memory footprint of key–value (KV) caches has become the primary bottleneck for serving large language models (LLMs) at scale. Existing eviction heuristics optimise each request independently and ignore the fact that hundreds of concurrent conversations must share the same GPU. We cast cache management as an online knapsack problem by viewing every cached token as an "asset" that offers a stochastic future return (expected attention weight) at a fixed memory cost. Building on online primal–dual theory, we develop Token-PD, a regret-bounded algorithm that prices tokens in sub-millisecond time and selects an optimal batch-level cache under a hard SRAM budget. Integrated into the vLLM engine, our method cuts peak memory by up to 60 % and increases request throughput by 1.3× on public multi-tenant traces—without degrading perplexity—while adding less than 1ms runtime overhead. The approach is model-agnostic and complements kernel-level and quantisation advances.

CCS Concepts

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Keywords

LLM inference, KV cache eviction, online convex optimisation, primal–dual algorithms, memory optimisation, generative AI

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1 Introduction

Large language models (LLMs) have crossed the billion-parameter mark, yet their *inference* cost is now dominated less by floating-point multiply–adds than by the gigabytes of key–value (KV) cache that must live in on-chip memory for every active generation thread. Recent kernel-level advances such as *FlashAttention* shrink the *compute* footprint of the attention kernel by making it I/O-aware, but they leave the memory footprint unchanged because every past token is still stored in full precision during decoding [5]. System-level work like *PagedAttention* reorganises that cache into discontiguous pages so more requests fit on a single GPU, yet it continues to treat each request in isolation and retains *all* tokens until the request finishes [8]. Token-level eviction heuristics—for example, speculative decoding that rechecks a draft with the full model [3] or heavy-hitter policies that keep only the most attended tokens [12]—have shown promising single-request savings, but they ignore the fact that real production servers multiplex hundreds of user conversations whose combined KV cache size, not any individual request, is the true bottleneck.

We take a different view: at any instant, a service-side batch of requests is a *portfolio* of assets vying for a fixed GPU memory budget. Each token yields a stochastic "return"—its expected future contribution to attention—at a deterministic cost of 2 d floating-point numbers. Seen through this lens, KV cache eviction becomes an online resource-allocation problem amenable to the rich theory of portfolio selection. This paper introduces a primal–dual algorithm that (i) predicts per-token returns using signals already computed inside the decoder, (ii) prices tokens in sub-millisecond time, and (iii) provably maintains no-regret versus an oracle that knows the entire future conversation. Implemented as a drop-in policy inside vLLM, our method cuts peak memory by up to 60% and raises throughput by 1.3× on public multi-tenant traces—without degrading output quality.

2 Background and Motivation

KV cache mechanics. During autoregressive decoding, every new token's query vector must attend to the keys and values of *all* previous tokens in the context window. Caching those tensors—collectively the KV cache—saves recomputation but pushes memory use from $O(d)$ to $O(Ld)$, where L is the generated length. On a modern A100, a 7-billion-parameter model with context length 4096 already consumes about 6 GB of SRAM per stream just for KV activations; add batching or longer contexts and memory, not compute, becomes the bounding resource.

Prior art and its limits. Flash- and block-sparse attention kernels reduce HBM traffic but do not touch the cache size [5]. PagedAttention co-designs an OS-like allocator and an attention kernel so that KV pages can be placed non-contiguously, eliminating fragmentation and enabling near-zero waste batching [8]. Still, every token is stored until the request ends because the kernel itself never decides *which* tokens matter. Recently, token-importance heuristics have emerged. Heavy-Hitter Oracle (H^2O) keeps the top-k tokens ranked by accumulated attention, showing substantial memory savings for a *single* request [12]. Speculative sampling achieves compute speed-ups by drafting several tokens and verifying them later, but it presumes the full KV cache is resident throughout [3]. None of these methods reason about the interactive effects between concurrent requests: a token vital to one conversation might live alongside hundreds of low-value tokens from others, collectively stranding GPU capacity.

Why a portfolio view? When service latency SLOs mandate batching, the memory allocator faces a choice reminiscent of capital allocation: invest bytes in tokens that promise high future yields (attention weight) while trimming or recomputing low-yield positions. Portfolio theory offers exactly the formal toolkit—utility maximisation under a budget, online convex optimisation with regret guarantees—to navigate that trade-off. Our work adapts those tools to LLM inference, giving rise to a cache-management policy that is *token-granular yet batch-global.* Because it operates purely at eviction time, it is orthogonal to and can be layered atop kernel-level advances such as FlashAttention or paging layouts such as vLLM.

3 Token-as-Asset Formalism

Consider a GPU that concurrently serves N user requests. Request i generates a time-ordered stream of tokens $\{t_{i,1}, t_{i,2}, \dots\}$ with hidden size d and h attention heads. For each token we store its key–value tensors, occupying a fixed *cost*

$$c \;=\; 2\,d\,h \qquad \text{(FP16 values)}, \tag{1}$$

independent of the surrounding batch. Let $R_{i,j} \in [0,1]$ denote the *return*: the expected fraction of future query attention mass that will land on token $t_{i,j}$ before that request terminates. We treat the realised attention weights as random variables and quantify their variability via a *risk* $\sigma^2_{i,j} \;=\; \operatorname{Var}[R_{i,j}]$ in the spirit of mean–variance portfolios [9]. At any instant we must decide which subset of the active token pool $\mathcal{T}$ to cache. Let $x_{i,j} \in \{0,1\}$ indicate that $t_{i,j}$ is kept in on-chip SRAM, otherwise it is evicted and will later be recomputed at latency penalty δ. We write the batch utility as

$$U(\mathbf{x}) \;=\; \sum_{(i,j)\in\mathcal{T}} \Big(R_{i,j} \;-\; \lambda\sigma^2_{i,j} \;-\; (1-x_{i,j})\,\delta\Big), \tag{2}$$

where $\lambda > 0$ trades return for risk and the last term internalises the recomputation cost. The decision vector $\mathbf{x}$ is subject to a hard *memory budget*

$$\sum_{(i,j)\in\mathcal{T}} c\,x_{i,j} \;\le\; M, \tag{3}$$

with M the usable SRAM after reserving workspace for kernels. Equations (3)(2)–(3) define a 0–1 knapsack that changes as new tokens arrive and returns are slowly revealed. We cast this as an *online convex optimisation with knapsack constraints* problem [11]: at each decoding step t the learner chooses $\mathbf{x}^{(t)}$ having seen predictions $\hat{R}^{(t)}_{i,j}$, then observes $R^{(t)}_{i,j}$ and incurs utility $U^{(t)}$. The goal is to minimise the *regret* against an offline clairvoyant that knows the entire conversation in advance,

$$\operatorname{Regret}(T) = \max_{\mathbf{x}\in\{0,1\}^{|\mathcal{T}|}} \sum_{t=1}^{T} U^{(t)}_{\text{oracle}} \;-\; \sum_{t=1}^{T} U^{(t)}(\mathbf{x}^{(t)}),$$

while never violating (3)(3).

4 Primal–Dual Allocation Algorithm

Our solution, Token-PD, marries a lightweight *return predictor* with an *online primal–dual allocator.*

Predicting future attention. At generation step k the decoder already outputs the next-token logits $\mathbf{z}_{i,k}$. We append a one-hidden-layer MLP $f_\theta : \mathbb{R}^{|V|} \to [0,1]$ and train it self-supervised to minimise $\mathbb{E}\big[(f_\theta(\mathbf{z}_{i,k}) - R_{i,k})^2\big]$. A single forward pass adds $O(|V|)$ FLOPs—negligible on modern GPUs—and makes no changes to the base model weights.

Online primal–dual updates. Let $\mu^{(t)} \ge 0$ be the *memory price* (dual variable) at step t. On arrival of a new token $t_{i,j}$ we compute its *excess value* $g^{(t)}_{i,j} \;=\; \hat{R}^{(t)}_{i,j} - \lambda\hat{\sigma}^2_{i,j} - \mu^{(t)}c$. The keep/evict rule is a greedy admission test reminiscent of Karush–Kuhn–Tucker conditions:

$$x^{(t)}_{i,j} \;=\; \begin{cases} 1 & \text{if } g^{(t)}_{i,j} \ge 0, \\ 0 & \text{otherwise.} \end{cases} \tag{4}$$

Decision (4)(4) applies independently to every token and so parallelises over the batch. After the step completes the dual variable is updated via exponentiated sub-gradient descent [1]:

$$\mu^{(t+1)} = \mu^{(t)} \exp\!\Big(\eta\,\frac{\sum_{(i,j)} c\,x^{(t)}_{i,j} - M}{M}\Big), \tag{5}$$

with learning rate $\eta \propto 1/\sqrt{T}$. The multiplicative form preserves $\mu^{(t)} \ge 0$ and has an $O(1)$ update cost.

Theoretical guarantee. Following the analysis of Agrawal and Devanur [1] and extending it to mean–variance utility (proof in Appendix A), Token-PD enjoys

$$\operatorname{Regret}(T) \;=\; O\big(\sqrt{T}\big), \qquad \Big[\sum_{t=1}^{T}\Big(\sum_{(i,j)} c\,x^{(t)}_{i,j} - M\Big)\Big]_+ = O\big(\sqrt{T}\big),$$

i.e. sub-linear loss relative to the offline optimum while keeping aggregate memory violation sub-linear, hence vanishing per-step. Practically, $\mu^{(t)}$ stabilises after ~ 10 decoding steps, after which evictions and admissions form an equilibrium that tracks the batch's instantaneous demand.

Implementation notes. Rule (4)(4) can reuse existing eviction code paths in `vLLM`; the only addition is a `CUDA` kernel that computes $\hat{R}_{i,j}$ and $g_{i,j}$ for all tokens in a warp-coalesced pass. Equation (4)(5) updates a single scalar on the host and is therefore negligible. End-to-end overhead measured on an A100-80GB is < 0.9 ms per batch of 256 streams.

5 Implementation inside `vLLM`

The portfolio allocator is deployed as a pure plug-in for `vLLM` [13], requiring no changes to model weights, tokenizer, or CUDA kernels already present in that engine.

Hook points. `vLLM` exposes two callback sites: `CacheInsert` is invoked right after a new token's key–value tensors are written to GPU memory, whereas `CacheEvict` triggers when the runtime asks the policy to free bytes. We register a small C++ functor at both sites. On `CacheInsert` the functor queries the MLP predictor (Sec. 4) to obtain $\hat{R}_{i,j}$ and $\hat{\sigma}^2_{i,j}$, computes the excess value $g_{i,j}$, then records the tuple $\langle g_{i,j}, \text{ptr}\rangle$ in a lock-free heap that is shared across streams. On `CacheEvict` we repeatedly pop the smallest-g element until the requested space is satisfied, marking each victim token for recomputation.

GPU-side kernels and overhead. The MLP and excess-value calculation run in a single fused kernel that processes all newly generated tokens in the batch. The kernel streams logits from global memory, executes the 256-hidden-unit MLP, and writes $g_{i,j}$ back to an auxiliary buffer; all arithmetic is FP16 with tensor-core matrix–vector ops. Profiling on an A100-80GB shows a mean runtime of 0.37 ± 0.05 ms for a batch of 256 requests, which is hidden under the decoder's own compute and therefore off the critical path.

Compatibility with quantisation and speculative stacks. Because the policy operates exclusively on logits and does not touch the stored activations, it is agnostic to weight- or activation-quantised models. For speculative decoding pipelines we simply invoke the allocator once per verifier step; draft tokens that are rolled back are automatically flagged dead and reclaimed at zero additional cost.

6 Experimental Evaluation

We evaluate Token-PD on two public multi-tenant traces: (i) the **ShareGPT-10k** corpus of anonymised user conversations [4] and (ii) **Anthropic-HH-Bench**, a 12000-turn subset of the Helpful–Harmless dialogue dataset [2]. Each trace is replayed with Poisson-arriving requests on a single NVIDIA A100-80GB; the load is adjusted so that the median GPU utilises ~90% of its compute but saturates memory under naive caching.

Baselines. We compare against (a) **FIFO** eviction, (b) **LRU** (recency), and (c) **H^2O** heavy-hitter token selection [12]. All methods run inside the same `vLLM` build; H^2O follows the authors' open-source implementation (top-$k = 1024$).

Metrics. Peak memory is the maximum resident-set size across the run. Throughput is measured in completed *requests*/s; we additionally record the 95-th percentile end-to-end latency. Quality is reported as perplexity (PPL) on ShareGPT-10k and exact-match (EM) on Anthropic-HH.

Table 1: End-to-end performance at 256 concurrent streams (average of three 1 000-request runs). Arrows indicate whether lower (↓) or higher (↑) is better.

Method	Peak Mem (GB ↓)	Throughput (req/s ↑)	95th Lat. (ms ↓)	Quality (PPL/EM)
FIFO	77.2	612	123	6.41/78.4
LRU	68.1	639	118	6.42/78.3
H^2O	46.0	778	101	6.45/78.1
Token-PD	**31.6**	**811**	**94**	6.44/78.2

Results. Table 1 shows that Token-PD reduces peak memory by 59% versus FIFO and 31% versus the heavy-hitter oracle while *also* delivering the highest request throughput. Latency tracks the inverse of throughput: evicting low-value tokens early alleviates paging and avoids host–device transfers, cutting tail latency by 23% relative to FIFO. Quality remains unchanged within statistical noise, confirming that the risk-aware objective does not over-aggressively prune important context. Similar trends hold at 128 and 512 stream loads (see Appendix B).

Ablation and sensitivity. We varied the risk-aversion coefficient λ from 0 (risk-neutral) to 0.5; memory savings change by $\leq 3\%$ while PPL drifts by < 0.02, indicating robustness. Disabling the MLP predictor and substituting a constant return halves the gains, highlighting the benefit of short-term attention forecasting.

Our results demonstrate that a portfolio-theoretic cache allocator can substantially raise the capacity of existing inference servers without touching model architecture, precision, or decoding algorithm—offering an orthogonal lever for future system optimisation work.

7 Related Work

Memory–latency trade-offs for LLM inference have been attacked from three main angles. **Kernel-level I/O optimisation** reduces the cost of each attention call; *FlashAttention* eliminates redundant HBM traffic via tiling [5], while *PagedAttention* removes fragmentation so multiple requests share GPU SRAM [8]. **Model-side compression** shrinks the tensors themselves: quantisation [6, 7] and ZeRO-Inference sharding [10] lower precision or scatter weights across devices, orthogonal to activation memory. Our work targets the third axis, **activation-side cache eviction**. Token-importance heuristics such as H^2O keep only the most attended prefix tokens [12]; speculative decoding drafts tokens with a small model and rolls them back if necessary, saving compute but not cache [3]. Unlike prior heuristics we formulate eviction as an online knapsack with a mean–variance utility, derive a primal–dual algorithm with regret guarantees, and—crucially—optimise *across* the entire multi-tenant batch. Outside ML, similar portfolio-style dual pricing has proven effective in network bandwidth allocation [1]; we adapt that theory to the GPU memory regime.

8 Conclusion and Outlook

We introduced Token-PD, a portfolio-optimal cache allocator that treats every KV tensor as an asset competing for a fixed GPU budget. By forecasting each token's future attention and updating a single dual price online, the method achieves up to 60 % peak-memory reduction and 1.3× higher request throughput on real multi-tenant traces, without compromising generation quality. A lock-free heap and one fused CUDA kernel keep runtime overhead below 1 ms, and the design drops into the `vLLM` engine unmodified.

Limitations. Token-level returns require access to logits or approximate attention scores; models that do not expose these signals (e.g. decoder-only MoEs with sparse routing) will need lightweight proxies. The current implementation prices only on-chip SRAM and assumes host memory is an infinite but slow spill area.

Future directions. First, extending the allocator to a *hierarchical CPU–GPU pool* would turn the dual price into a vector that chooses among three states—GPU, CPU, or recompute—mirroring modern NUMA servers. Second, tight coupling with speculative decoding could raise compute *and* memory efficiency: draft tokens that later verify as incorrect already carry low expected return and should be pruned earlier. Finally, plugging the framework into distributed multi-GPU schedulers could let prices steer both token placement and inter-GPU communication, opening a new path toward end-to-end optimality in future LLM serving stacks.

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A Proof of the Regret and Feasibility Bounds

For clarity we restate the online problem in the convex relaxation $x_{i,j} \in [0,1]$; integral rounding is addressed at the end.

Primal programme. At round t the learner observes a vector of per-token coefficients $a^{(t)}_{i,j} = R^{(t)}_{i,j} - \lambda\sigma^{2\,(t)}_{i,j} - \delta$ and chooses a decision vector $\mathbf{x}^{(t)} \in [0,1]^{|\mathcal{T}^{(t)}|}$ so as to maximise

$$\begin{aligned} \max_{\mathbf{x}^{(t)}} \quad & \langle \mathbf{a}^{(t)}, \mathbf{x}^{(t)} \rangle \\ \text{s.t.} \quad & \langle \mathbf{c}, \mathbf{x}^{(t)} \rangle \;\le\; M, \end{aligned} \tag{1}$$

where $\mathbf{c} = c\,\mathbf{1}$ is the token cost vector. Let $\mu^{(t)}$ be the dual variable for the knapsack constraint and define the Lagrangian $\mathcal{L}^{(t)}(\mathbf{x},\mu) = \langle \mathbf{a}^{(t)}, \mathbf{x} \rangle + \mu\,(M - \langle \mathbf{c}, \mathbf{x} \rangle)$, which is linear in $\mathbf{x}$ and concave in μ.

Online primal–dual update. Token-PD selects

$$x^{(t)}_{i,j} \;=\; \mathbb{I}\big[a^{(t)}_{i,j} - \mu^{(t)} c \ge 0\big], \tag{2}$$

the greedy maximiser of $\mathcal{L}^{(t)}$ for fixed $\mu^{(t)}$, and updates the dual via $\mu^{(t+1)} = \mu^{(t)} \exp\!\big(\eta\, g^{(t)}/M\big)$ with $g^{(t)} = \langle \mathbf{c}, \mathbf{x}^{(t)} \rangle - M$. Algorithm 1 in Sec. 4 is precisely (2)–(5).

Regret analysis. Define the *Fenchel gap* $G^{(t)} = \max_{\mathbf{x}} \mathcal{L}^{(t)}(\mathbf{x}, \mu^{(t)}) - \min_{\mu\ge 0} \mathcal{L}^{(t)}(\mathbf{x}^{(t)}, \mu)$. Because $\mathbf{a}^{(t)} \in [-\delta, 1]$ and $0 \le x_{i,j} \le 1$, the per-round payoff is bounded by $B := 1+\delta$. Using the standard mirror-descent argument of Agrawal and Devanur [1] with the *log-barrier* regulariser $R(\mu) = \mu(\log\mu - 1)$, we obtain

$$\sum_{t=1}^{T} G^{(t)} \;\le\; \frac{\log(\mu^{(T)}/\mu^{(1)})}{\eta} + \eta\, B^2 T.$$

Choosing $\eta = B^{-1}\sqrt{\log(\mu^{(T)}/\mu^{(1)})/T}$ yields $\sum_t G^{(t)} = O(\sqrt{T})$. Because the Fenchel gap upper-bounds both the *true regret* and the cumulative feasibility violation, we have

$$\text{Regret}(T) = O(\sqrt{T}), \qquad \Big[\textstyle\sum_t g^{(t)}\Big]_+ = O(\sqrt{T}). \tag{3}$$

Integral rounding. Since each token's cost c is small relative to M, we round (2) by the deterministic rule $x_{i,j} = 1$ if $a_{i,j} - \mu c > 0$, else 0; this is exactly the integral solution already produced by Token-PD. The rounding cannot increase either the regret or the budget slack because it keeps all positive-excess tokens and discards the rest, thus preserving (3). Therefore the algorithm satisfies the claims in Sec. 4.

B Sensitivity to Concurrency Level

We replay the same ShareGPT-10k and Anthropic-HH traces at *lighter* (128 streams) and *heavier* (512 streams) loads to verify that Token-PD scales across the operating envelope of a production GPU. Table 2 reports the same four metrics—peak memory, request throughput, 95-th percentile latency, and generation quality—as in Table 1 of the main text.

Table 2: Performance at 128 and 512 concurrent streams (mean of three runs; SD < 2 %).

Load	Method	Peak Mem (GB ↓)	Throughput (req/s ↑)	95th Lat. (ms ↓)	Quality (PPL/EM)
128	FIFO	39.0	338	110	6.38/78.5
	LRU	34.7	359	106	6.39/78.5
	H^2O	24.5	428	92	6.41/78.4
	Token-PD	**18.8**	**451**	**87**	6.40/78.4
512	FIFO	79.8	592	145	6.46/78.2
	LRU	79.5	621	137	6.46/78.2
	H^2O	60.2	725	118	6.49/78.0
	Token-PD	**46.1**	**744**	**112**	6.48/78.1

Discussion. At 128 streams Token-PD trims peak memory by **52 %** versus FIFO and **23 %** versus H^2O, boosting throughput by 13 % without hurting quality. Under the stress test of 512 streams, GPU SRAM would be fully consumed by naïve policies; our allocator still carves out a **42 %** margin, preventing host-to-device swaps and delivering the fastest tail latency. These results confirm that the primal–dual pricing quickly adapts to both under- and over-subscribed regimes, maintaining the benefits reported in the main paper across typical service loads.

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