MAKE YOUR LVLM KV CACHE MORE LIGHTWEIGHT

Anonymous authors
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ABSTRACT

Key-Value (**KV**) cache has become a *de facto* component of modern Large Vision-Language Models (**LVLM**s) for inference. While it enhances decoding efficiency in Large Language Models (**LLMs**), its direct adoption in LVLMs introduces substantial GPU memory overhead due to the large number of vision tokens processed during the prefill stage. To tackle this problem, we propose LightKV, a novel approach that reduces KV cache size by exploiting the redundancy among vision-token embeddings. Guided by text prompts, LightKV employs cross-modality message passing to aggregate informative messages across vision tokens and progressively compress them during prefill. This prompt-aware guidance distinguishes our method from prior vision-only compression strategies. We evaluate LightKV on eight open-source LVLMs across eight public benchmarks, such as MME and SeedBench. Experimental results demonstrate that with only 50% of the original vision tokens, LightKV (i) halves KV cache size, (ii) reduces computation by up to 40%, and (iii) preserves general-purpose performance while significantly outperforming existing baselines.

1 INTRODUCTION

Benefiting from the rapid advancements in Large Language Models (LLMs) (Vicuna Team, 2023; OpenAI, 2024; Meta, 2024), Large Vision-Language Models (LVLMs) (Alayrac et al., 2022; Li et al., 2023b; Dai et al., 2023; Bai et al., 2023; Liu et al., 2023a; 2024b;c; Lu et al., 2024; Chen et al., 2024d;c; Wang et al., 2025; Chen et al., 2025) have recently garnered extensive attention. For example, LLaVA (Liu et al., 2023a) and DeepSeek-VL (Lu et al., 2024) have achieved impressive performance on a multitude of general-purpose multi-modal benchmarks (Fu et al., 2024; Yu et al., 2024; Li et al., 2023c). Despite their potential, the efficiency of LVLMs remains a significant bottleneck for researchers and practitioners in resource-constrained environments.

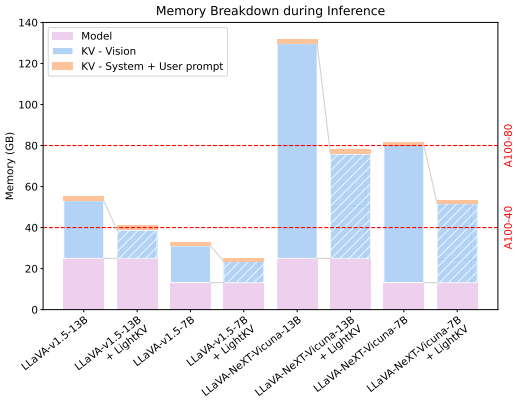

Figure 1: Breakdown of memory consumption in LLaVA models during the prefill stage shows the substantial reduction in KV cache usage with LightKV. Note that LLaVA-NeXT uses $4\times$ the *vision tokens* as LLaVA-v1.5, resulting in a sharp increase in the memory consumption.

Key-Value (**KV**) cache (Pope et al., 2023; Kwon et al., 2023) serves as a fundamental technique in optimizing the inference efficiency of mainstream LLMs and LVLMs. However, though the inference speed is improved without compromising model performance, the GPU memory consumed becomes more substantial. This limitation is especially severe with longer sequences generated (Yang et al., 2024; Liu et al., 2024a; Li et al., 2024d). To alleviate this issue, some training-based methods, such as MQA (Hu et al., 2025) and GQA (Ainslie et al., 2023), introduce the sharing of keys and values across attention heads. The overall KV cache size is accordingly reduced. These approaches, however, suffer from the requirement of heavy model retraining. In contrast, methods such as H2O (Zhang et al., 2023b), MiniCache (Liu et al., 2024a), and ElasticCache (Liu et al., 2024d) focus on pruning tokens within the KV cache *during inference* after the prefill stage. These methods offer greater flexibility and can be seamlessly applied to existing decoder-only models with minimal degradation in performance. *Given this, we primarily focus on token reduction during inference time.*

Unlike LLMs, reducing the cost of memory-bound KV cache is challenging in LVLMs due to the following two factors: (i) Tokens in LVLMs are heterogeneous, representing both image patches and text. Determining which tokens should be pruned thus becomes more difficult; (ii) The number of tokens computed during the *prefill stage* is significantly larger than that in LLMs. Each image or video frame in LVLMs is embedded into hundreds to thousands of tokens upfront (e.g. 576 in LLaVA-1.5 (Liu et al., 2023a) and 7,290 in LLaVA-OneVision (Li et al., 2024a)), a considerable amount compared to the context lengths of LLMs (see Fig. 1) (Meta, 2024; Jiang et al., 2023; Vicuna Team, 2023). As a result, current LVLMs are limited by significantly heavier GPU memory usage than their LLM counterparts during the prefill stage. A few recent studies have proposed addressing the first challenge on token heterogeneity (Chen et al., 2024a; Li et al., 2024c). However, existing research on solving the second remains largely sparse.

In this paper, we propose LightKV, a novel method for optimizing KV cache storage in LVLMs during the prefill stage **without retraining**. To this end, we leverage cross-modal prompt guidance for the compression of vision tokens. Our method follows a three-step design. *First*, we conceptually map each vision token to a graph node, constructing a bipartite graph with edges representing a feature divergence (FD) metric between the connected nodes. Nonetheless, computing FD in a pairwise manner is still expensive, especially with a large number of vision tokens. To alleviate this problem, *second*, we split the vision tokens into subwindows based on their original spatial locations. This allows us to reduce the complexity of computing FD and aggregating information across tokens, thus improving efficiency. *Third*, our method does not follow existing studies (Chen et al., 2024b) to perform vision token reduction independently, as the text prompts offer more informative signals for vision token importance. Consequently, we propose to leverage on-the-fly attention scores from text prompts for informed token updates. As found in our experiments, though this approach has been largely ignored by the existing literature, it delivers superior results than state-of-the-art baselines.

We apply LightKV to eight state-of-the-art LVLM models: LLaVA-v1.5-13B, LLaVA-v1.5-7B (Liu et al., 2023a), LLaVA-NeXT-13B, LLaVA-NeXT-7B (Liu et al., 2024b), InternVL2-8B (Chen et al., 2024c), EVE-7B-v1, EVE-7B-v1-HD (Diao et al., 2025), Qwen2.5-VL (Bai et al., 2025) and conduct extensive experiments across eight benchmarks: COCO Caption (Lin et al., 2014), GQA (Hudson & Manning, 2019), MME (Fu et al., 2024), NoCaps (Agrawal et al., 2019), POPE (Li et al., 2023c), SeedBench (Li et al., 2024b), ScienceQA (Lu et al., 2022), and VizWiz (Gurari et al., 2018). Our results demonstrate that LightKV can reduce the KV memory of vision tokens by 50% while maintaining, sometimes even surpassing, the vanilla LVLM performance. Furthermore, when constrained with the same token length generation budget, the inference overhead (in FLOPs) is significantly improved by 40%.

In summary, LightKV reduces the KV cache footprint in LVLMs by compressing vision tokens during the *prefill* stage under the guidance of text prompts. This prompt-aware design distinguishes it from existing SOTA vision-only methods, delivering (i) greater efficiency and (2) superior benchmark performance. Importantly, LightKV is entirely *training-free* and can be seamlessly applied to a wide range of LVLMs, including both vision encoder–based and encoder-free models.

2 Related Work

Large vision-language models Following the success of large language models (LLMs) in the language domain (Vicuna Team, 2023; OpenAI, 2024; Meta, 2024), large vision-language models (LVLMs) have showcased pervasive progress on various multimodal tasks (Team, 2024b;a; Driess et al., 2023). Current LVLMs primarily fall into the following three directions: (i) Fusion-based methods directly include vision information into the LLM decoders using cross-attention (Alayrac et al., 2022; Awadalla et al., 2023; Li et al., 2023a; Gong et al., 2023). (ii) Query-based LVLMs extract vision information with learnable query tokens, which are then concatenated with text tokens (Li et al., 2023b; Dai et al., 2023; Zhu et al., 2024; Li et al., 2024c; Zhang et al., 2023a). (iii) Projection-based methods, instead, directly map the encoded tokens from a vision encoder into the text space (Liu et al., 2023a; 2024b;c; Li et al., 2024a; Bai et al., 2023; Huang et al., 2023; Diao et al., 2025). However, despite their simplicity and effectiveness, the projection of vision tokens leads to a substantial increase in memory footprint.

KV cache optimization KV cache has been widely used in LLMs and LVLMs to improve their inference efficiency (Dao et al., 2022; Pope et al., 2023; Kwon et al., 2023; Lee et al., 2024). The core idea is to store the key and value tokens to reduce future redundant computations. However, in situations with long contexts, keeping the KV cache imposes an increased burden on GPU memory. Existing approaches addressing this can be roughly categorized into two groups: (i) KV-sharing-based and (ii) token-reduction-based. Specifically, methods from the (i) improve the multi-headed attention mechanism to achieve efficiency. For instance, MQA (Hu et al., 2025) and GQA (Ainslie et al., 2023) propose the sharing of keys and values across attention heads (Vaswani et al., 2017), reducing the amount of KV needed to be cached. In contrast, methods from the (ii) reduce KV cache size by pruning or merging tokens based either on minimal importance (Zhang et al., 2023b; Li et al., 2024d; Cai et al., 2024) or attention consistency across layers (Liu et al., 2023b; 2024d; Yang et al., 2024). Beyond LLMs, some initial efforts have been devoted to optimizing the KV cache for LVLMs. In particular, LLaVolta (Chen et al., 2024a), IVTP (Huang et al., 2024) and FastV (Chen et al., 2024b) propose pruning vision tokens at the decoder layers of the LLM backbone. The first two require model retraining; FastV, though training-free, prunes vision tokens without cross-modality guidance, yielding inconsistent results across models and benchmarks. In contrast, LightKV leverages guidance from text tokens to deliver more consistent and superior performance.

Vision token compression Tokens in vision transformers (ViTs) (Dosovitskiy et al., 2021) often exhibit high redundancy (Bolya et al., 2023; Pan et al., 2022; Chen et al., 2024b). To address this, some approaches train modules to identify and discard less important tokens (Rao et al., 2021; Bonnaerens & Dambre, 2023; Yin et al., 2022; Fayyaz et al., 2022; Wei et al., 2023; Chen et al., 2023; Zhang et al., 2024; Mao et al., 2025). Some other typical methods first group tokens based on similarity or distance (Bolya et al., 2023; Tran et al., 2024; Kim et al., 2024; Alvar et al., 2025) or image segmentation (Xu et al., 2022; Lu et al., 2023) and then prune or merge the tokens with the maximum similarity. These methods either (i) require the training of additional module(s), or (ii) do not support the vision-language joint reasoning as in LVLMs.

3 METHOD

3.1 PRELIMINARIES

Recent LLMs often operate in an autoregressive fashion: given a sequence of p text prompt tokens $[x_1, \ldots, x_p]$ (including both system prompt and user prompt), and $t-p$ previously generated tokens $[x_{p+1}, \ldots, x_t]$, an LLM with parameters Θ predicts the next token x_{t+1} with:

$$x_{t+1} \sim \mathbb{P}_\Theta\big(x_{t+1} \mid \underbrace{x_1, \ldots, x_p}_{\text{Prompt tokens}}, \underbrace{x_{p+1}, \ldots, x_t}_{\text{Generated tokens}}\big). \tag{1}$$

The above process is often implemented in two stages: prefill and generation (Golden et al., 2024). During *prefill*, the model tokenizes all p prompt tokens and computes the queries $Q_p = [\mathbf{q}_1, \mathbf{q}_2, \ldots, \mathbf{q}_p]$, similarly for keys K_p and values V_p (Vaswani et al., 2017). In contrast, during *generation*, when a new token arrives, the model first obtains the query $\mathbf{q}_{t+1}$, key $\mathbf{k}_{t+1}$, and value $\mathbf{v}_{t+1}$ vectors. It then computes the attention matrix by applying $\mathbf{q}_{t+1}$ to the full set of keys K_{t+1}:

$$\mathbf{A} = \mathrm{softmax}\left(\mathbf{q}_{t+1}\, K_{t+1}^\top / \sqrt{d_k}\right), \tag{2}$$

where d_k represents the embedding dimension. In practice, the attention output would be a concatenation of matrices $\mathbf{A} = [\mathbf{A}_1, \ldots, \mathbf{A}_H]$ from H independent attention heads.

KV cache From the above, we observe that the autoregressive nature of LLMs allows for the previously computed *keys* K_t and *values* V_t to be reused in future time steps during generation. This operation reduces the computational overhead by preventing the recomputation of key and value tokens (Xu et al., 2025). However, an increased consumption of GPU memory is usually induced by the growing size of the KV cache. This is often manifested as: (i) generating lengthy sequences and (ii) caching many contexts during prefill. In this work, we primarily focus on improving the second.

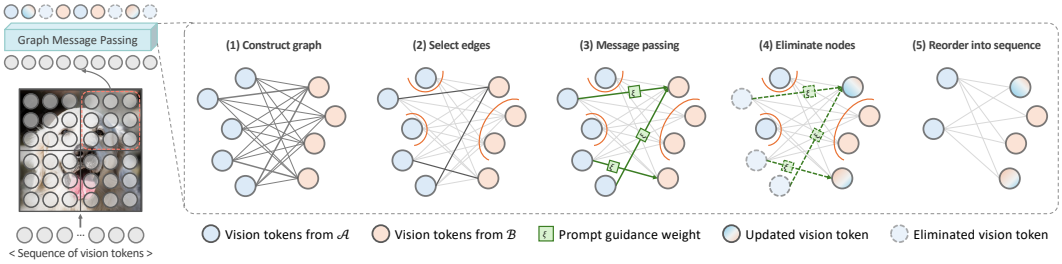

Figure 2: Method overview of intra-window token compression. **Step 1**: Construct a bipartite graph by splitting the vision tokens into sets $\mathcal{A}$ (blue) and $\mathcal{B}$ (orange), weigh each edge by an FD metric, as defined in Eq. 5. **Step 2**: Select edges with the smallest $\lfloor \rho v/2 \rfloor$ FD values and delete the rest. Unconnected nodes are left unchanged. **Step 3**: Pass messages from nodes in $\mathcal{A}$ to nodes in $\mathcal{B}$ weighted by its attention ξ, as defined in Eq. 7. Aggregate messages and update nodes in $\mathcal{B}$. **Step 4**: Eliminate now-redundant nodes from $\mathcal{A}$. **Step 5**: Reorder the remaining nodes into a sequence of vision tokens, serving as input to the next decoder layer.

LVLMs LVLMs build on LLMs by extending their architecture to process visual information. A common paradigm in LVLMs is to first map the split image patches into tokens using ViT-based encoders (Dosovitskiy et al., 2021; Radford et al., 2021; Bao et al., 2022), which are then concatenated with the prompt tokens to form the input sequence. In general, LVLMs generate tokens by conditioning on both text prompt tokens and vision tokens:

$$x_{t+1} \sim \mathbb{P}_\Theta\big(x_{t+1} \mid \underbrace{x_1, \ldots, x_p}_{\text{Prompt tokens}}, \underbrace{x_{p+1}, \ldots, x_{p+v}}_{\text{Vision tokens}}, \underbrace{x_{p+v+1}, \ldots, x_t}_{\text{Generated tokens}}\big). \tag{3}$$

We denote X_v as the sequence of v vision tokens in Eq. 3. Similar to LLMs, KV cache is a key component in speeding up inference in LVLMs. In this paper, we focus primarily on compressing vision tokens for two reasons: (i) as shown in Fig. 1, vision tokens greatly outnumber text prompt tokens; (ii) preliminary studies showed that reducing text tokens causes harsh performance degradation.

3.2 LightKV

As illustrated in Fig. 2, the pipeline of LightKV functions as follows: At each specified decoder layer during the prefill stage, given a sequence of vision tokens, we first reconstruct their grid structure as in the original image. These tokens are then partitioned into $w \times w$ small, non-overlapping windows, each containing an equal number of tokens. Within each window, we perform graph message passing to compress vision tokens, simultaneously reducing both KV size and the length of the vision input to the next decoder layer (as detailed in Sec. 3.2.1). A similar operation is repeated in later decoder layers with larger window sizes to achieve inter-window compression (further elaborated in Sec. 3.2.2).

3.2.1 Intra-window token compression

To address redundancy in vision tokens, we utilize graph message passing to aggregate information with low FD (defined below in Eq. 5), and then eliminate redundant nodes in *each* window ω. Note that the message passing and update procedure is performed independently for each window.

Graph construction We limit and refer the vision tokens in a window to a bipartite graph. For notational simplicity, we slightly abuse $\mathbf{x}$ as the embedding of a vision node. **Step 1**: In each window, we first map each token $\mathbf{x}$ to a graph node, with $\mathcal{X} = \{\mathbf{x} | \mathbf{x} \in X_\mathrm{v}\}$. Next, we split the set of nodes into two subsets $\mathcal{X}_\mathcal{A}$ and $\mathcal{X}_\mathcal{B}$ (colored blue and orange respectively in Fig. 2) of near-equal cardinality, and construct a bipartite graph from the two sets with edges $\mathcal{E}$:

$$\mathcal{E} = \mathcal{X}_\mathcal{A} \times \mathcal{X}_\mathcal{B} = \big\{(\mathbf{x}_\alpha, \mathbf{x}_\beta) \mid \forall\, \mathbf{x}_\alpha \in \mathcal{X}_\mathcal{A},\ \forall\, \mathbf{x}_\beta \in \mathcal{X}_\mathcal{B}\big\}, \tag{4}$$

where $\times$ denotes set cross product. We modify the feature divergence (FD) in (Tran et al., 2024; Wang et al., 2024) to weigh each edge in the graph:

$$\mathrm{FD}(\alpha, \beta) = 1 - \frac{\langle \mathbf{x}_\alpha, \mathbf{x}_\beta \rangle}{||\mathbf{x}_\alpha||\ ||\mathbf{x}_\beta||}, \tag{5}$$

where $\langle \cdot, \cdot \rangle$ denotes the inner product and $|| \cdot ||$ is the L^2-norm. **Step 2**: We define the adjacency matrix $M \in \{0,1\}^{|\mathcal{X}_\mathcal{A}| \times |\mathcal{X}_\mathcal{B}|}$ where:

$$M_{\alpha,\beta} = \begin{cases} 1, & \text{if } (\alpha, \beta) \in \mathcal{T}\rho, \\ 0, & \text{otherwise,} \end{cases} \tag{6}$$

to select $\lfloor \rho v/2 \rfloor$ pairs of (α, β) with the smallest values of $\mathrm{FD}(\alpha, \beta)$ as $\mathcal{T}_\rho$, where ρ is the chosen compression ratio. Edges not in $\mathcal{T}_\rho$ are temporarily removed and the remaining unconnected nodes $\mathcal{X}_\mathcal{R} = \{\mathbf{x}_r | \nexists\, \beta \text{ s.t.} (r, \beta) \in \mathcal{T}_\rho\}$ are left unchanged.

Token message passing In LVLMs, the heterogeneity of tokens introduces a challenge in evaluating the importance of each vision token, and prior works often disregard this by compressing tokens uniformly without accounting for their relative significance. Instead, LightKV reuses the attention weights from the LLM decoder to estimate token importance, which are *readily available during the prefill stage without additional computation*, as computed in Eq. 2. This serves as a signal to preserve the visual features that are most important to the prompt, and is used as guidance in the message-aggregation process. **Step 3**: Given $\mathbf{A} \in \mathbb{R}^{H \times (p+v) \times (p+v)}$ is the H-headed attention matrix *before the attention mask*, for a vision token with index i, we accumulate its attention from prompts:

$$\xi_i = \sum_{h=1}^{H} \sum_{j \in \mathcal{J}} \mathbf{A}[h, i, j], \tag{7}$$

where $\mathcal{J}$ is the set of indices for the p prompt tokens. Next, we gather the attention for each window ω into vectors $\boldsymbol{\xi}_\mathcal{A} \in \mathbb{R}^{|\mathcal{X}_\mathcal{A}|}$ and $\boldsymbol{\xi}_\mathcal{B} \in \mathbb{R}^{|\mathcal{X}_\mathcal{B}|}$ with the same partitions as $\mathcal{X}_\mathcal{A}$ and $\mathcal{X}_\mathcal{B}$. We update $X_\mathcal{B}$ by accumulating messages from its adjacent tokens:

$$X_\mathcal{B} = \underbrace{\left(\boldsymbol{\xi}_\mathcal{B} + M^\top \boldsymbol{\xi}_\mathcal{A}\right)^{-1}}_{\text{(iii) Normalize by sum of attentions}} \Bigg(\underbrace{X_\mathcal{B} \odot \boldsymbol{\xi}_\mathcal{B}}_{\text{(i) Prompt-guidance for } \mathcal{B}} + \underbrace{M^\top \underbrace{\left(X_\mathcal{A} \odot \boldsymbol{\xi}_\mathcal{A} \right)}_{\text{(i) Prompt-guidance for } \mathcal{A}}}_{\text{(ii) Message passing as defined by edges } M} \Bigg), \tag{8}$$

where $\odot$ is the Hadamard product. This can be broken down into three parts: **(i)** Messages from each token $\mathbf{x}_i$ are first weighed by its attention ξ_i. **(ii)** Next, sessages from the tokens in $\mathcal{X}_\mathcal{A}$ are passed to those in $\mathcal{X}_\mathcal{B}$ through the edges defined in M, updating tokens in $\mathcal{X}_\mathcal{B}$. The chosen direction is arbitrary but symmetrical. **(iii)** Finally, tokens in $\mathcal{X}_\mathcal{B}$ are normalized to remain scale-invariant.

Importantly, our aggregation operation utilizes the attention ξ as guidance, ensuring the preservation of visual information that is most relevant to the prompt and the generation of the final response. **Step 4**: After the update, the now-redundant nodes in $\mathcal{X}_\mathcal{A} \setminus \mathcal{X}_\mathcal{R}$ are deleted. **Step 5**: Finally, the unchanged tokens $\mathcal{X}_\mathcal{R}$ and the updated $\mathcal{X}_\mathcal{B}$ are concatenated to form the final sequence of tokens for window ω.

Complexity In contrast to computing fully pairwise FD among $v_\omega = v/(w \times w)$ vision tokens– which requires $\frac{1}{2} v_\omega (v_\omega - 1)$ time complexity, the bipartite matching strategy improves computational efficiency by reducing this number by half to $\sim \frac{1}{4}(v_\omega)^2$.

Difference from ToMe LightKV adopts a bipartite matching approach, similar to ToMe (Bolya et al., 2023), to reduce the cost of pairwise calculations. However, ToMe and subsequent methods assume all tokens are equally important, merging them without differentiation. In contrast, LightKV uses cross-modality attention to guide message passing and aggregation, preserving the most relevant information during compression, yielding superior results (see Sec. 4).

3.2.2 Inter-window token compression

Window partitioning As discussed above, we split the entire set of vision tokens into window partitions in a non-overlapping manner. Specifically, each window ω contains $v_\omega = v/(w \times w)$ vision tokens. This reduces the total number of operations involved in computing FD measures from the original $\frac{1}{2} v(v-1)$ to $\frac{1}{2} \frac{v}{w^2} (\frac{v}{w^2} - 1) \times w^2 \rightarrow \frac{1}{2} v (\frac{v}{w^2} - 1)$. Moreover, since spatially adjacent patches typically share semantic similarities, our window-based method confines message aggregation to within a small locality, preserving the positional information of tokens in the original image (Song et al., 2024; Norouzi et al., 2024). A global message passing strategy might inadvertently aggregate information from tokens representing unrelated entities, compromising locality and semantic coherence (Xu et al., 2022; Pan et al., 2022).

Hierarchical structure We adopt a *hierarchical* compression strategy to improve efficiency, as inspired by Swin-Transformer (Liu et al., 2021). In an LVLM with L layers, we perform $s < L$ compression iterations. Let $\Lambda = [\lambda_1, \ldots, \lambda_s]$, $\mathcal{W} = [w_1^2, \ldots, w_s^2]$, $\mathcal{P} = [\rho_1, \ldots, \rho_s]$, where λ_i is the index of the decoder layer where vision tokens are compressed, w_i^2 is the number of window partitions used at iteration i with $w_i > w_{i+1}$, and ρ_i is the compression ratio. After each decoder layer λ_i, the tokens are divided into w_i^2 windows. Within each window, vision-token messages are aggregated and compressed with ratio ρ_i, and only a fraction $(1 - \rho_i)$ of the vision tokens remains in subsequent layers. After each compression iteration, the number of windows is decreased (smaller w) to allow for message passing across greater spatial distances, as depicted in Fig. 3.

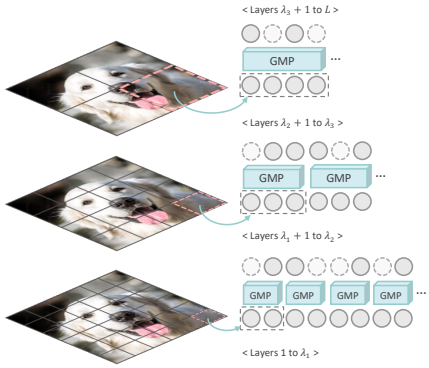

Figure 3: After each compression step, w is reduced to allow message passing across greater spatial distances.

3.3 Complexity analysis

Without any compression, the prefill stage processes in total $v \times L$ vision tokens[1]. With compression, the number of vision tokens processed during pre-fill now reduces to:

$$v \times \left\{ \lambda_1 + \sum_{i=2}^{s} \Big((\lambda_i - \lambda_{i-1}) \prod_{j=1}^{i-1} (1 - \rho_j) \Big) + (L - \lambda_s) \prod_{j=1}^{s} (1 - \rho_j) \right\} < v \times L. \tag{9}$$

For an LVLM with $L = 40$ decoder layers, choosing $\Lambda = [10, 20, 30]$ and $\mathcal{P} = [0.5, 0.5, 0.5]$ reduces the vision token count to 46.9% of the baseline. This is further elaborated in Sec. D.3.

4 Experiments

4.1 Experimental settings

LVLM base models We evaluated the efficiency and performance of LightKV by applying it to eight open-source LVLMs: LLaVA-v1.5-13B, LLaVA-v1.5-7B, LLaVA-NeXT-13B, LLaVA-NeXT-7B, InternVL2-8B, EVE-7B-v1, EVE-7B-v1-HD, and Qwen2.5-VL-7B-Instruct. LLaVA-v1.5 encodes 576 vision tokens per image, while LLaVA-NeXT uses 2,144. In contrast, InternVL2 and Qwen2.5-VL adopt dynamic vision encoding, with token counts determined by image resolution. It is worth noting that, unlike other models, which employ a dedicated image encoder, EVE is vision encoder-free. These methods are labeled as *Vanilla* in our results.

Datasets We utilized eight publicly available large-scale benchmarks for evaluation: COCO Caption (Lin et al., 2014), GQA (Hudson & Manning, 2019), MME (Fu et al., 2024), NoCaps (Agrawal et al., 2019), POPE (Li et al., 2023c), SeedBench (Li et al., 2024b), ScienceQA (Lu et al., 2022), and VizWiz (Gurari et al., 2018). These benchmarks cover a wide range of tasks, from general, everyday image understanding to fine-grained image reasoning. MME, POPE, SeedBench Lite, and ScienceQA are limited to single-choice answers, while COCO Caption, GQA, NoCaps, and VizWiz involve open-ended responses comprising long sentences.

Compared baselines We adapted two existing techniques from other related domains: ToMe (Bolya et al., 2023) (labeled *ToMe (C)*) and *ElasticCache* (Liu et al., 2024d). For comparison, we implemented two random-eviction baselines: *Rand* and *ImgRand*. *Rand* and *ElasticCache* prune both text and vision tokens, whereas *ImgRand* and ToMe reduce vision tokens only. It is important to note that the previously mentioned methods perform token reduction *after* the prefill stage. Additionally, for token reduction *during* prefill, we implemented ToMe (labeled *ToMe (P)*) and four recent SOTA strategies: *FastV* (Chen et al., 2024b), *PiToMe* (Tran et al., 2024), *ToFu* (Kim et al., 2024) and *HiRED*[2] (Arif et al., 2025).

[1]We omit the double estimation of key and value cache for simplicity.

[2]Uses the same model but with HuggingFace optimizations; efficiency metrics are omitted for fairness.

Table 1: Results of LightKV on LLaVA models at 55% compression of vision tokens in the KV cache. **Avg %** denotes the average of all performance metrics normalized against the vanilla model. Methods in each category are then sorted from lowest to highest Avg score.

	Method	FLOPS ↓ (Tera)	Mem ↓ (GB)	TTFT ↓ (sec)	COCO	MME C	MME P	NoCaps	POPE Acc	POPE F1	SEED	VizWiz	**Avg %**
LLaVA-v1.5-13B	Vanilla	19.4	0.55	0.111	1.16	295.4	1532.0	1.09	0.87	0.86	0.69	0.57	100.00
	Post prefill												
	Elastic	19.3	0.31	0.568	0.96	295.4	1534.5	0.87	0.43	0.96	OOM	0.14	68.54
	Rand	19.0	0.31	0.118	0.48	295.4	1532.9	0.46	0.46	0.89	0.70	0.13	70.53
	ImgRand	19.0	0.31	0.117	0.95	295.4	1532.9	0.86	0.69	0.91	0.70	0.19	85.09
	ToMe (C)	19.0	0.33	0.123	1.00	295.4	1532.9	0.92	0.79	0.88	0.70	0.18	87.10
	During prefill												
	ToFu	12.6	0.37	0.081	1.14	292.1	1535.7	1.08	0.86	0.86	0.38	0.55	93.36
	PiToMe	12.6	0.37	0.082	1.14	297.5	1529.0	1.07	0.87	0.85	0.38	0.55	93.42
	ToMe (P)	12.6	0.37	0.081	1.16	297.5	1529.9	1.07	0.87	0.86	0.39	0.55	93.96
	LightKV	12.6	0.37	0.084	1.15	302.1	1543.8	1.08	0.87	0.86	0.69	0.56	99.94
	FastV	12.4	0.36	0.077	1.16	308.9	1546.6	1.09	0.86	0.85	0.68	0.57	**100.22**
LLaVA-v1.5-7B	Vanilla	10.2	0.35	0.064	1.10	355.7	1509.6	1.05	0.87	0.86	0.66	0.54	100.00
	Post prefill												
	Elastic	10.2	0.20	0.428	0.41	350.4	1508.9	0.30	0.30	0.93	OOM	0.09	52.95
	Rand	9.9	0.21	0.070	0.13	350.4	1508.9	0.10	0.74	0.87	0.66	0.11	65.80
	ToMe (C)	10.0	0.20	0.075	0.13	350.4	1508.9	0.09	0.87	0.86	0.66	0.18	69.02
	ImgRand	9.9	0.20	0.070	0.22	350.4	1508.9	0.16	0.86	0.86	0.66	0.16	70.27
	During prefill												
	HiRED	-	-	-	1.03	335.0	1452.0	1.00	0.85	0.83	0.66	0.53	96.45
	ToFu	6.6	0.23	0.051	1.09	340.0	1482.3	1.02	0.86	0.85	0.66	0.52	97.98
	ToMe (P)	6.6	0.23	0.054	1.09	319.6	1490.5	1.01	0.87	0.86	0.66	0.52	97.52
	PiToMe	6.6	0.23	0.053	1.08	341.0	1498.5	1.02	0.86	0.85	0.65	0.51	97.63
	FastV	5.3	0.22	0.047	1.10	351.1	1513.7	1.04	0.85	0.83	0.66	0.54	99.03
	LightKV	6.6	0.23	0.051	1.11	357.5	1519.8	1.03	0.87	0.86	0.66	0.53	**99.79**
LLaVA-NeXT-13B	Vanilla	65.0	1.75	0.386	1.02	318.9	1575.1	0.88	0.88	0.86	0.69	0.64	100.00
	Post prefill												
	Elastic	-	-	-	OOM	OOM	OOM	OOM	OOM	OOM	OOM	OOM	0.00
	Rand	60.8	0.91	0.396	0.06	318.9	1575.1	0.04	0.82	0.86	0.69	0.08	64.51
	ToMe (C)	61.3	0.93	0.418	0.07	318.9	1575.1	0.05	0.87	0.86	0.69	0.08	65.48
	ImgRand	60.8	0.91	0.392	0.07	318.9	1575.1	0.05	0.87	0.86	0.69	0.08	65.50
	During prefill												
	ToMe (P)	37.3	1.05	0.268	0.97	308.5	1551.0	0.84	0.87	0.86	0.34	0.60	90.96
	ToFu	37.3	1.05	0.268	0.97	305.0	1539.5	0.83	0.88	0.87	0.36	0.60	91.31
	PiToMe	37.3	1.05	0.270	0.98	311.9	1558.2	0.86	0.87	0.86	0.34	0.60	91.56
	FastV	36.1	1.04	0.259	0.91	311.1	1477.5	0.81	0.82	0.78	0.68	0.61	93.80
	LightKV	37.3	1.05	0.271	0.96	326.1	1576.5	0.83	0.87	0.86	0.69	0.61	**98.12**
LLaVA-NeXT-7B	Vanilla	34.8	1.12	0.225	1.00	330.0	1528.2	0.88	0.88	0.86	0.68	0.61	100.00
	Post prefill												
	Elastic	34.7	0.58	1.675	0.02	332.1	1519.3	0.01	0.18	0.90	OOM	0.08	42.67
	Rand	32.2	0.58	0.234	0.02	322.5	1523.2	0.01	0.65	0.87	0.68	0.08	61.08
	ImgRand	32.2	0.58	0.234	0.02	322.5	1523.2	0.02	0.85	0.87	0.68	0.08	64.06
	ToMe (C)	32.5	0.60	0.251	0.03	322.5	1523.2	0.02	0.87	0.86	0.68	0.08	64.33
	During prefill												
	FastV	18.5	0.65	0.148	0.88	265.4	1341.3	0.78	0.81	0.77	0.69	0.58	90.37
	HiRED	-	-	-	0.73	297.9	1398.9	0.67	0.88	0.87	0.66	0.58	90.68
	ToMe (P)	21.1	0.67	0.155	0.93	292.9	1419.0	0.78	0.88	0.87	0.65	0.57	94.18
	ToFu	20.0	0.67	0.155	0.93	295.4	1427.2	0.78	0.88	0.87	0.66	0.57	94.52
	PiToMe	20.0	0.67	0.157	0.94	292.1	1415.5	0.79	0.88	0.87	0.65	0.58	94.58
	LightKV	22.3	0.67	0.159	0.98	338.6	1517.3	0.83	0.88	0.86	0.69	0.58	**98.85**

Implementation details In our experiments, we retain the default parameters of the LVLM backbones and use greedy decoding for reproducibility. For FastV, we adopt the reported optimal setting of $K = 2$ and vary only R to control the KV cache pruning ratio. For other methods, we adapted them to work with the LVLM backbones to the best of our abilities. To ensure consistency, we fix the configuration of LightKV's compression layers Λ, compression ratios $\mathcal{P}$, and window sizes $\mathcal{W}$ across all benchmarks for each LVLM model. We utilized *lmms-eval* (Zhang et al., 2025) for all benchmark evaluations. We profiled the time-to-first-token (TTFT) and the generation latency for 100 tokens by averaging results over 10 runs on an NVIDIA A100 GPU.

4.2 Main Results

We compare the performance of LightKV with other SOTA methods on LLaVA models (Table 1), InternVL (Table 2), EVE (Table 3) and Qwen2.5-VL (Fig. 4 and Table 7 in the appendix). For each LVLM model, we selected the optimal configurations of Λ and $\mathcal{W}$ based on performance on COCO and MME, and applied these hyperparameters to the remaining benchmarks. We also profiled efficiency metrics, including FLOPS, KV cache memory (from prompt, vision, and generated tokens),

Table 2: Results of LightKV on InternVL2-8B at two compression rates of vision tokens in KV cache. "**Avg %**" denotes the average of all metrics normalized against the vanilla model. Methods in each category are then sorted from lowest to highest Avg score.

Method	FLOPS ↓ (Tera)	Mem ↓ (GB)	TTFT ↓ (sec)	COCO	GQA	MME C	MME P	POPE Acc	POPE F1	SQA	VizWiz	**Avg %**
Vanilla	35.7	0.24	0.470	0.90	0.63	587.5	1623.8	0.88	0.87	0.97	0.61	100.00
During prefill, 60% vision compression												
FastV	24.8	0.15	0.520	0.80	0.50	569.6	1610.9	0.47	0.87	0.49	0.53	81.90
ToFu	24.0	0.15	0.520	0.81	0.62	502.1	1575.5	0.87	0.86	0.94	0.60	95.49
PiToMe	24.0	0.15	0.519	0.99	0.60	461.8	1545.3	0.87	0.86	0.90	0.60	95.99
ToMe (P)	24.0	0.15	0.523	0.87	0.62	551.4	1621.8	0.87	0.86	0.95	0.60	97.86
LightKV	24.0	0.15	0.519	0.91	0.63	590.0	1623.8	0.88	0.87	0.97	0.61	**100.19**
During prefill, 55% vision compression												
FastV	22.9	0.14	0.517	0.68	0.47	582.1	1611.1	0.56	0.85	0.46	0.48	79.49
PiToMe	22.9	0.14	0.518	1.00	0.61	442.9	1575.5	0.87	0.86	0.90	0.57	95.54
ToMe (P)	22.9	0.14	0.519	0.81	0.62	503.9	1570.0	0.87	0.86	0.95	0.60	95.62
ToFu	22.9	0.14	0.519	0.75	0.62	541.8	1619.1	0.87	0.85	0.95	0.60	95.82
LightKV	22.9	0.14	0.515	0.88	0.62	590.0	1623.8	0.88	0.87	0.97	0.61	**99.58**

and time to first token (TTFT) when generating 100 tokens (standard deviation reported in the appendix). Our key findings are summarized as follows:

- Tables 1, 2, 3 and 7 show that LightKV consistently preserves the performance of the base LVLMs across most benchmarks. In some cases, our method even surpasses the performance of vanilla LVLMs without compression.
- Compared to methods applied *during the prefill stage*, LightKV either outperforms or achieves highly competitive results. Specifically, it ranks first in 3 out of 4 LLaVA models and second in the remaining one, while other baselines exhibit inconsistent rankings with major degradations in performance. When efficiency is considered alongside performance, baseline methods are largely inferior—showing poorer memory usage and less effective FLOP reduction.
- At even more aggressive compression ratios (e.g. 20% and 30%), LightKV is capable of retaining 99% average performance across multiple benchmarks on Qwen2.5-VL (Fig. 4 and Table 7). This further highlights the robustness of our method.
- LightKV is compatible with not only vision encoder-based LVLMs, but also with encoder-free models such as EVE, which seek to reduce the strong inductive bias in the vision encoders. As shown in Table 3, our approach substantially outperforms FastV at the same compression rate, better preserving the LVLM's original capabilities.
- Post-prefill approaches substantially degrade performance on open-ended tasks e.g. COCO and NoCaps. Additionally, they yield minimal improvements in computational efficiency, since the prefill stage remains the dominant bottleneck in LVLMs. In contrast, LightKV operates on the prefill stage within the decoder layers. This results in significantly lower computational cost and memory footprint, while achieving stronger performance across a series of benchmarks.

Table 3: Results of LightKV on EVE-7B-v1 models at 55% compression of vision tokens in the KV cache.

Method	COCO	MME C	MME P	NoCaps	POPE Acc	POPE F1	VizWiz	**Avg %**
EVE-7B-v1								
Vanilla	0.96	269.2	1230.8	0.94	0.84	0.83	0.46	100.00
FastV	0.85	259.3	1144.5	0.78	0.80	0.77	0.44	92.07
LightKV	1.00	269.3	1203.1	0.93	0.84	0.83	0.43	**99.20**
EVE-7B-v1-HD								
Vanilla	1.05	304.6	1314.1	1.02	0.86	0.85	0.56	100.00
FastV	0.97	290.3	1238.6	0.93	0.83	0.82	0.55	94.90
LightKV	0.97	291.4	1308.9	0.94	0.86	0.85	0.54	**96.61**

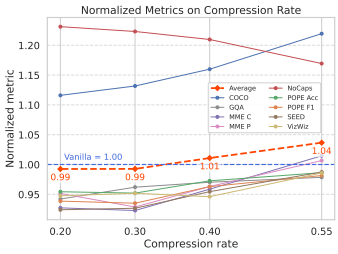

Figure 4: Effect of varying compression rates on Qwen2.5-VL.

4.3 Additional Experiments

Latency profiling Table 4 illustrates the reduction in time to first token latency achieved by LightKV. Since our approach requires explicit attention matrices for token reduction, it is incompatible with

I/O-optimized mechanisms like FlashAttention (Dao et al., 2022). To overcome this, we selectively switch to eager computation in the small subset ($s \ll L$) of layers where compression is applied, while retaining the optimized attention implementation for the majority. The marginal overhead introduced is effectively offset by the increased throughput gained from processing fewer vision tokens in the downstream layers. See Sec. E.3 for a more detailed analysis of both TTFT and the generation latency of 100 tokens with their corresponding standard deviations.

Table 4: Time to first token (ms) $\pm$ Std. Dev. on LLaVA 13B models.

Method	LLaVA-v1.5	LLaVA-NeXT
Vanilla	111 ± 0.91	386 ± 2.22
LightKV	84 ± 0.72	271 ± 0.79

Influence of hierarchical compression We conducted experiments with the same configuration of Λ while varying the window sizes, as presented in Table 5. Across different compression layers λ, the results show a similar general trend: there is more pronounced degradation with a global compression strategy $w = 1$, likely due to the inadvertent destruction of spatial locality (Xu et al., 2022; Pan et al., 2022; Song et al., 2024; Norouzi et al., 2024). However, with larger values of w, similar degradation occurs. This is attributed to the small number of tokens within each window, resulting in the compression of mismatched tokens with high FD scores. Furthermore, we summarize the FLOPs and KV cache memory usage for different inference configurations in Table 6. The results indicate that larger window sizes in the early layers lead to higher efficiency improvements.

Influence of compression layers We investigate the impact of varying layers for token compression, as illustrated in Fig. 6 in the appendix. Trends between the compression layer and model performance reveal that compressing in the shallow layers has a more substantial impact on performance. This effect is particularly pronounced in VizWiz, where LVLMs must refrain from answering (e.g., when the ground truth is "unanswerable"). Compression in the deeper layers yields performance nearly identical to the base LVLM models, but offers little reduction in memory usage.

Table 5: Effect of varying window sizes w at various compression layers on InternVL-8B.

Method	$\mathcal{W}$	COCO	GQA	MME		POPE		SQA	VizWiz
				C	P	Acc	F1		
Vanilla	-	0.90	0.63	587.5	1623.8	0.88	0.87	0.97	0.61
LightKV					$\boldsymbol{\lambda}$**= 3**				
	1	0.80	0.62	547.5	1602.5	0.87	0.86	0.95	0.60
	2	0.83	0.59	555.0	1621.1	0.87	0.86	0.96	0.60
	4	0.90	0.60	546.8	1594.8	0.87	0.85	0.95	0.60
					$\boldsymbol{\lambda}$**= 14**				
	1	0.89	0.62	577.1	1615.8	0.87	0.86	0.97	0.61
	2	0.90	0.62	577.1	1620.3	0.87	0.86	0.97	0.61
	4	0.92	0.62	577.9	1617.5	0.88	0.86	0.97	0.61

Table 6: Profiling results by varying compression layers Λ and window sizes $\mathcal{W}$ on LLaVA 13B models.

Method	Λ	$\mathcal{W}$	**LLaVA-v1.5-13B** FLOPS	**LLaVA-v1.5-13B** Mem	**LLaVA-NeXT-13B** FLOPS	**LLaVA-NeXT-13B** Mem
Vanilla	-	-	19.4	0.55	65.0	1.75
LightKV	15,23,31	4,2,1	12.6	0.37	37.3	1.05
		6,4,2	12.6	0.37	37.3	1.05
	17,24,31	4,2,1	13.1	0.38	39.0	1.09
		6,4,2	13.1	0.38	39.0	1.09

5 Conclusion

In this paper, we present LightKV, a novel *training-free* approach for optimizing KV cache storage in general LVLMs. It leverages *text-prompt–guided graph message passing and aggregation* to informatively compress vision tokens during the *prefill* stage of inference. Our method is designed to be: (i) memory-efficient: by progressively and dynamically compressing vision nodes through a hierarchical multi-stage process; and (ii) compute-efficient: by employing window-based graph partitioning and bipartite matching to accelerate message aggregation. The experimental results demonstrate that our approach: (a) largely preserves the general-purpose performance of the base LVLM across multiple benchmarks, and (b) outperforms existing baselines in KV cache efficiency.

Limitations We acknowledge two limitations of this work: (i) LightKV leverages a bipartite graph matching algorithm, which splits vision tokens into two disjoint sets, then finds optimal pairings between nodes across the sets. This limits the compression rate to a maximum of 50% per step, thus requiring multiple iterations to achieve higher overall reduction. (ii) Furthermore, our method requires explicitly computing attention matrices for cross-modality guidance during a few compression steps, similar to other efficient methods (Chen et al., 2024b; Liu et al., 2023a), which are less compatible with FlashAttention (Dao et al., 2022).

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APPENDIX

A DECLARATION OF THE USE OF LLMS

The use of LLMs was limited to language editing and formatting support; the intellectual contributions, analysis, results, and conclusions presented in this work remain entirely those of the authors.

B ETHICS STATEMENT

The authors have reviewed and conformed with ICLR Code of Ethics `https://iclr.cc/public/CodeOfEthics`.

C REPRODUCIBILITY STATEMENT

We introduced details of our method in Sec. 3. We are committed to releasing the code upon the acceptance of this paper, with sufficient details for reproducibility.

D METHOD

D.1 METHOD OVERVIEW

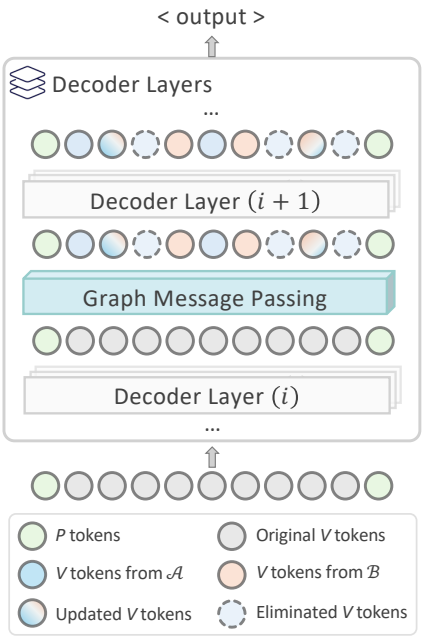

Figure 5: LightKV dynamically compresses vision tokens between two consecutive LVLM decoder layers. The key and value tokens are compressed simultaneously for latter layers, reducing the memory used by KV cache.

As illustrated in Fig. 5, we insert graph message passing-based compression between two selected decoder layers in the LVLM, simultaneously reducing the KV cache size and the number of vision tokens processed by downstream layers. Compression is performed 3 times in our experiments to achieve the overall compression ratio.

D.2 ADJACENCY MATRIX

In Section 3.2, we defined for our bipartite graph the adjacency matrix $M \in \{0,1\}^{|\mathcal{X}_\mathcal{A}| \times |\mathcal{X}_\mathcal{B}|}$, whose rows correspond to nodes in $\mathcal{X}_\mathcal{A}$ and columns to nodes in $\mathcal{X}_\mathcal{B}$. However, as the two subsets need not

contain the same number of nodes, M is generally rectangular. Conventionally, for a standard graph, the adjacency matrix is square with side length equal to the total number of nodes. The analogous square adjacency matrix for our bipartite graph is

$$\begin{pmatrix} 0 & M \\ M^\top & 0 \end{pmatrix}, \tag{10}$$

where the upper-left and lower-right blocks are zero by definition. Throughout our paper, we work directly with M, as this rectangular form is sufficient for message passing between the two partitions.

D.3 Complexity analysis

In section 3.3, we claimed that the total number of vision tokens processed during pre-fill reduces to:

$$N \times \left\{ \underbrace{\lambda_1}_{(1)} + \underbrace{\sum_{i=2}^{k} \left((\lambda_i - \lambda_{i-1}) \prod_{j=1}^{i-1} (1-\rho_j) \right)}_{(2)} + \underbrace{(L - \lambda_k) \prod_{j=1}^{k} (1-\rho_j)}_{(3)} \right\}. \tag{11}$$

We consider the number of vision tokens in each layer independently, then the total number of vision tokens processed in L decoder layers in a vanilla LVLM is simply $N \times L$. However, the number of vision tokens reduces at every accumulation layer λ_i (note that message passing and accumulation occur after each decoder layer λ_i). Let $N_i = N \times \prod_{j=1}^{i-1}(1-\rho_j)$ be the number of remaining vision tokens after $i-1$ accumulation steps. Between each pair of accumulation layers λ_{i-1} and λ_i, the number of vision tokens processed is $N_i \times (\lambda_i - \lambda_{i-1})$. Therefore, Eq. 11 can be broken down into:

1. Percentage of vision tokens processed before the first accumulation step,
2. Percentage of vision tokens processed between the first and the last accumulation step,
3. Percentage of vision tokens processed after the last accumulation step.

E Additional Results

E.1 Additional backbones

QwenVL We also evaluated LightKV on Qwen2.5-VL-7B-Instruct (Bai et al., 2025) across multiple compression ratios. The results in Table 7 demonstrate that LightKV yields substantial improvements compared to baseline approaches, preserving accuracy more effectively and delivering stronger overall performance under compression. Notably, as presented in Table 8, at more aggressive compression ratios, LightKV still delivers near-identical performance to the vanilla model.

Table 7: Results of LightKV on Qwen2.5-VL-7B-Instruct model at 55% compression of vision tokens in the KV cache. **Avg %** denotes the average of all performance metrics normalized against the vanilla model. Methods in each category are then sorted from lowest to highest Avg score.

Method	COCO	GQA	MME		NoCaps	POPE		SEED	VizWiz	**Avg %**
			C	P		Acc	F1			
Vanilla	0.319	0.604	638.21	1695.25	0.372	0.875	0.862	0.790	0.704	100.00
FastV	0.339	0.587	625.35	1687.78	0.386	0.869	0.853	0.744	0.698	98.77
ToMe	0.329	0.591	640.71	1687.75	0.425	0.862	0.782	0.782	0.683	100.04
PiToMe	0.389	0.584	624.64	1671.09	0.433	0.860	0.842	0.774	0.691	100.24
ToFu	0.383	0.587	657.86	1683.05	0.418	0.857	0.839	0.788	0.696	100.75
LightKV	0.389	0.591	647.50	1706.38	0.435	0.863	0.846	0.780	0.694	**101.37**

E.2 Additional ablation studies

Influence of window sizes The choice of W is closely related to the number of vision tokens used by the LVLM. A larger initial window size is appropriate when the model encodes images at high resolution, e.g., LLaVA-NeXT encodes an image into 2,144 tokens. In contrast, a smaller value

Table 8: Results of LightKV on Qwen2.5-VL-7B-Instruct model at various compression of vision tokens in the KV cache. **Avg %** denotes the average of all performance metrics normalized against the vanilla model.

Rate	COCO	GQA	MME		NoCaps	POPE		SEED	VizWiz	**Avg %**
			C	P		Acc	F1			
Vanilla	0.319	0.604	638.21	1695.25	0.372	0.875	0.862	0.790	0.704	100.00
55%	0.389	0.591	647.50	1706.38	0.435	0.863	0.846	0.780	0.694	101.37
40%	0.370	0.586	611.78	1632.64	0.450	0.851	0.830	0.754	0.666	101.01
30%	0.361	0.581	588.93	1574.34	0.455	0.833	0.806	0.732	0.670	98.89
20%	0.356	0.569	591.78	1612.83	0.458	0.835	0.809	0.730	0.667	99.24

of is more favorable when there are fewer vision tokens, e.g., LLaVA-v1.5, which uses 576 vision tokens per image. In our experiments, we used $W = [6, 4, 2]$ for LLaVA-NeXT and $W = [4, 2, 1]$ for LLaVA-v1.5. We found that using a large window size with fewer vision tokens overly restricts token matching, often resulting in mismatches. As shown in Table 9 below, larger windows yield better overall performance.

Table 9: Effect of W on LLaVA-13B models.

Method	COCO	DocVQA	GQA	MME		NoCaps	POPE		SQA	SEED	VizWiz	**Avg %**
				C	P		Acc	F1				
LLaVA-v1.5-13B												
Vanilla	1.16	0.23	0.63	295.36	1532.0	1.09	0.87	0.86	0.73	0.69	0.57	100.00
LightKV W=[4,2,1]	1.15	0.22	0.62	302.14	1543.8	1.08	0.87	0.86	0.72	0.69	0.56	99.18
LightKV W=[6,4,2]	1.16	0.22	0.63	301.79	1541.1	1.08	0.87	0.86	0.72	0.69	0.56	99.01
LLaVA-NeXT-13B												
Vanilla	1.02	0.71	0.65	318.93	1575.1	0.88	0.88	0.86	0.73	0.69	0.64	100.00
LightKV W=[4,2,1]	0.96	0.53	0.43	311.43	1576.3	0.83	0.87	0.86	0.59	0.69	0.61	101.39
LightKV W=[6,4,2]	0.96	0.51	0.43	326.07	1576.5	0.83	0.87	0.86	0.59	0.69	0.61	102.19

Influence of compression layers We investigate the impact of varying layers for token compression, as illustrated in Fig. 6. Trends between the compression layer and model performance reveal that compressing in the shallow layers has a more substantial impact on performance. This effect is particularly pronounced in VizWiz, where LVLMs must refrain from answering (e.g., when the ground truth is "unanswerable"). Compression in the deeper layers yields performance nearly identical to the base LVLM models, but offers little reduction in memory usage.

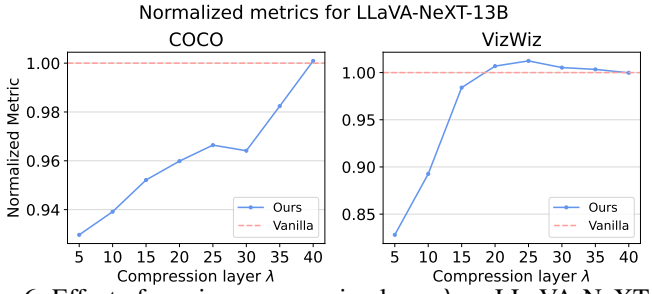

Figure 6: Effect of varying compression layer λ on LLaVA-NeXT-13B.

E.3 Additional Latency Profiles

We evaluate model responsiveness using two latency metrics: time-to-first-token (TTFT) and generation latency for 100 tokens. As shown in Table 10, TTFT highlights the overhead of the pre-filling stage and directly reflects user-perceived responsiveness, while generation latency characterizes decoding efficiency. Together, these results provide a comprehensive view of both initial response delay and sustained throughput.

Table 10: Latency comparison across LLaVA models. TTFT = Time to First Token. Gen latency = generation latency per output.

Method	TTFT (ms)	Gen latency (s)	TTFT (ms)	Gen latency (s)
	LLaVA-v1.5-13B		**LLaVA-v1.5-7B**	
Vanilla	111 ± 0.905	3.85 ± 0.017	64 ± 0.889	3.00 ± 0.012
FastV	77 ± 0.788	2.52 ± 0.001	47 ± 0.381	1.70 ± 0.013
PiToMe	82 ± 0.818	2.85 ± 0.002	53 ± 0.171	2.14 ± 0.022
ToFu	81 ± 0.622	2.86 ± 0.001	51 ± 0.677	2.13 ± 0.004
ToMe (P)	81 ± 0.889	2.86 ± 0.003	54 ± 0.641	2.10 ± 0.011
LightKV	84 ± 0.715	2.87 ± 0.005	51 ± 0.801	2.11 ± 0.009
	LLaVA-NeXT-13B		**LLaVA-NeXT-7B**	
Vanilla	386 ± 2.224	4.17 ± 0.027	225 ± 1.552	3.20 ± 0.026
FastV	259 ± 1.759	2.94 ± 0.006	148 ± 1.110	1.83 ± 0.021
PiToMe	270 ± 0.776	3.29 ± 0.003	157 ± 0.602	2.26 ± 0.025
ToFu	268 ± 1.317	3.28 ± 0.003	155 ± 0.607	2.24 ± 0.011
ToMe (P)	268 ± 2.023	3.28 ± 0.004	155 ± 0.820	2.23 ± 0.028
LightKV	271 ± 0.788	3.31 ± 0.003	159 ± 1.000	2.24 ± 0.006

E.4 VISUALIZATION

We provide visualization cases for vision token compression of COCO images in Fig. 7 for a 3-stage compression on LLaVA-v1.5-13B, reducing the number of tokens from $576 \rightarrow 288 \rightarrow 145 \rightarrow 77$. Unlike conventional vision encoders, vision tokens in LVLMs incorporate prompt information. As a result, visually similar patches may differ significantly in the embedding space, making it plausible to aggregate non-adjacent patches. To this end, our intra-window strategy imposes constraints on this aggregation process to maintain spatial coherence during compression.

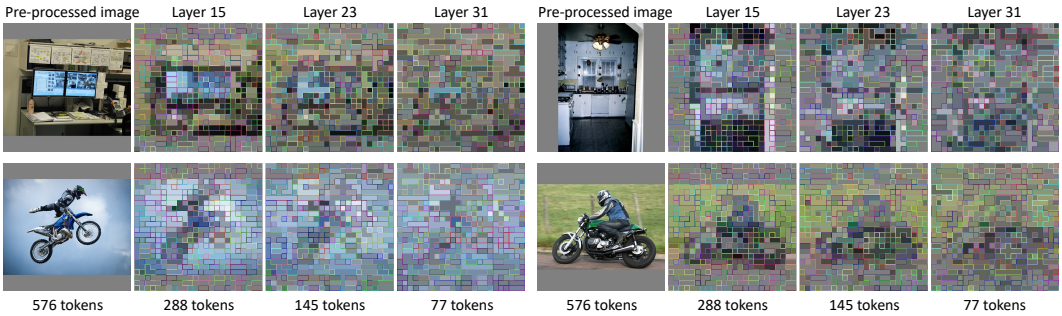

Figure 7: Visualization of a 3-stage vision token compression, halving tokens at each stage and achieving 55% KV cache reduction. Distant patches may be compressed into a single token.