

# Video Compression Commander: Plug-and-Play Inference Acceleration for Video Large Language Models















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**Paper:** <https://arxiv.org/pdf/2505.14454>

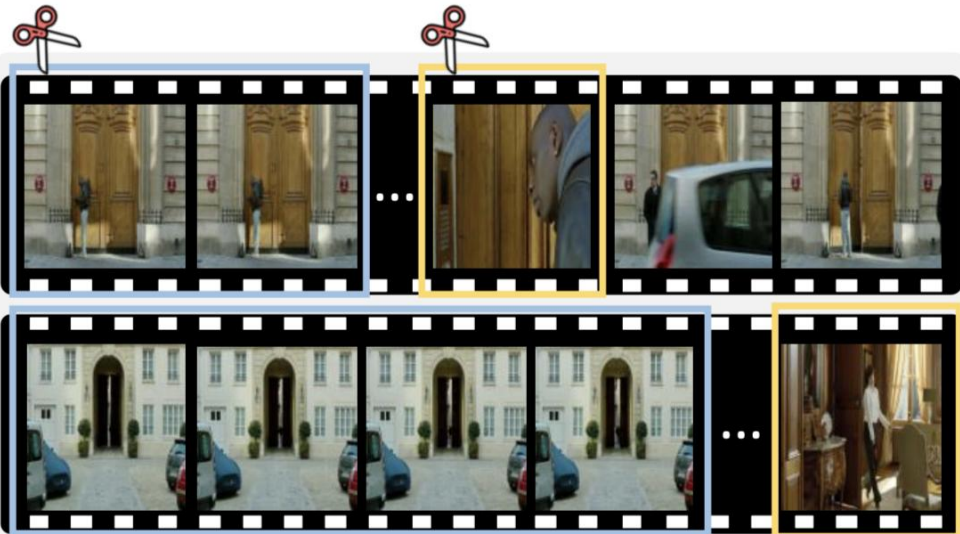
**Code:** <https://github.com/xuyang-liu16/VidCom2>

# Research Background: Token Overhead in Visual Understanding

 Single-Image	     ... N Crops	$(1 + 9) * 729 = 7290$ Tokens
$729 + N * 729$ Tokens		
 Multi-Image	  ... N Images	$12 * 729 = 8748$ Tokens
$N * 729$ Tokens		
 Video	    ... N Frames	$32 * 196 = 6272$ Tokens
$N * 196$ Tokens		
Example on Token Strategy		Max Tokens

As model capabilities improve, the demand for high-resolution image and long-video understanding is growing, making the **token overhead issue increasingly pronounced** in visual understanding.

# Relevant Works: Token Compression for VideoLLMs



The image shows two sequences of video frames. The top sequence shows a transition from an outdoor scene with a car to an indoor scene with a person. The bottom sequence shows a transition from an outdoor street scene to an indoor living room scene. In both sequences, the frames at the transition point are highlighted with a yellow border and a scissors icon, indicating a cut or a change in scene.

Question: "What scene changes occur in this video?"

Answer1: "It is from the doorbell to the indoors." ✓

Answer2: "It is from the street to the living room." ✗

Methods	Pre-LLM	Intra-LLM	[CLS] Dependency	Video-Specific	Frame Uniqueness	Efficient Attention
FastV		✓				
PDrop		✓				
SparseVLM		✓				
MUSTDrop	✓	✓	✓			
FiCoCo	✓	✓	✓			
FasterVLM	✓		✓			✓
DyCoke	✓			✓		✓
VidCom <sup>2</sup>	✓			✓	✓	✓

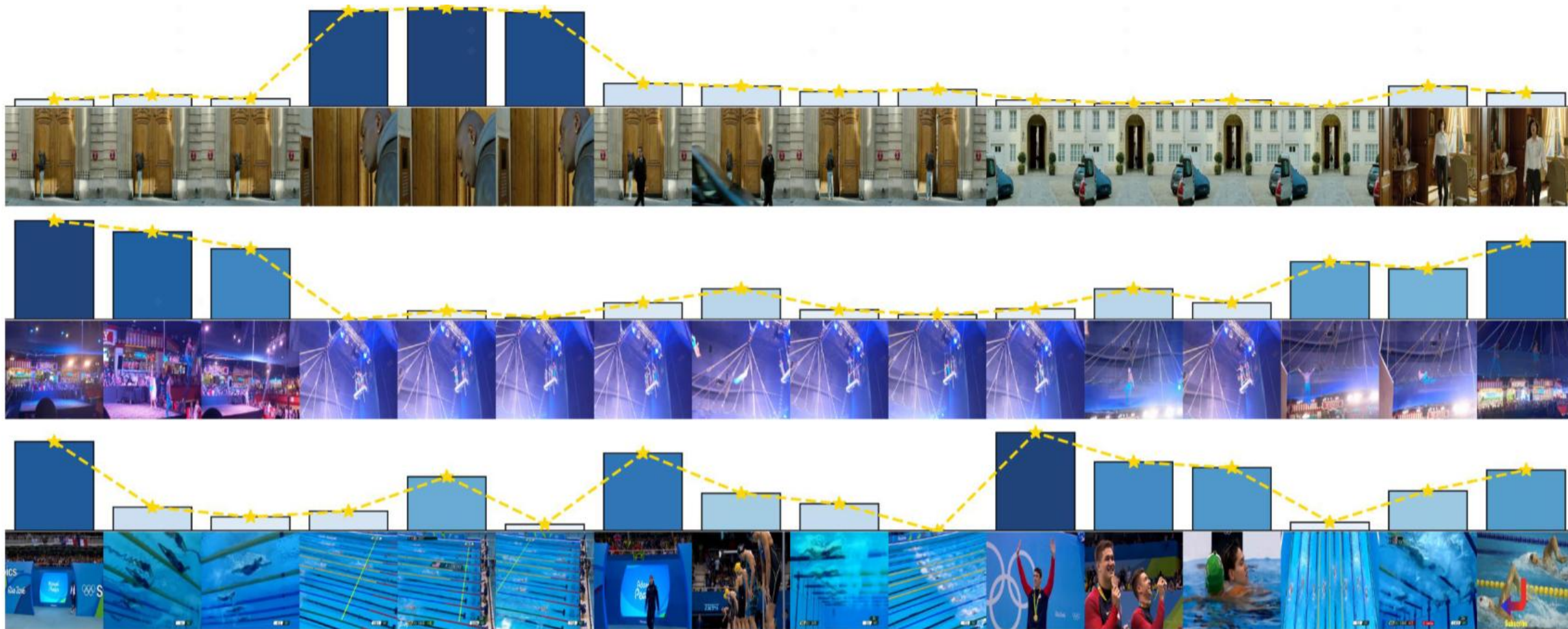
Current methods face **two critical issues** for VideoLLMs:

- **Design Myopia:** ignoring frame uniqueness, leading to over-compression of distinctive video information.
- **Implementation Constraints:** limited to the specific model architectures or incompatible with Flash Attention.

**Takeaway:** We derive **three key principles** for effective token compression of VideoLLMs: (i) model adaptability, (ii) frame uniqueness, and (iii) operator compatibility.



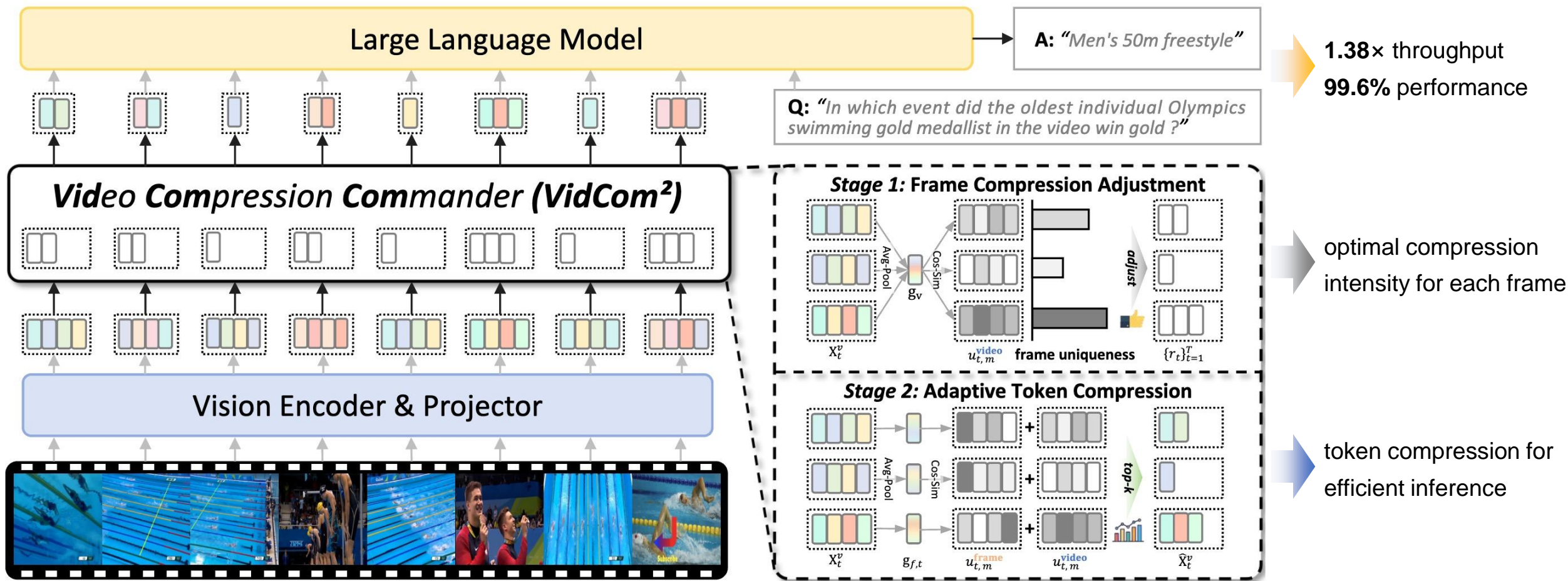
# Key Highlights: Adaptive Compression by Frame Uniqueness



**Core Argument:** We suggest that visually distinctive frames throughout the video should retain more visual information, i.e., be allocated a larger visual token budget.

Xuyang Liu, Yiyu Wang, Junpeng Ma, Linfeng Zhang, "Video Compression Commander: Plug-and-Play Inference Acceleration for Video Large Language Models". In *the 2025 Conference on Empirical Methods in Natural Language Processing (EMNLP 2025)*.

# Our Solution: Video Compression Commander (VidCom<sup>2</sup>)



We present VidCom<sup>2</sup>, a plug-and-play framework that dynamically compresses video tokens based on frame uniqueness, achieving state-of-the-art efficiency and performance across various VideoLLMs and benchmarks.

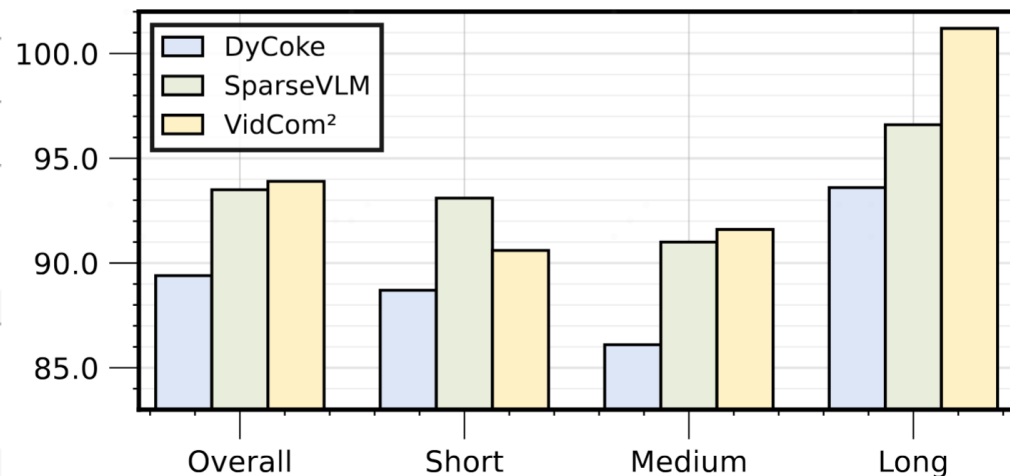
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# Experimental Results: State-of-The-Art Performance

Methods	MVBench	LongVideoBench	MLVU	Overall	VideoMME			Average (%)
					Short	Medium	Long	
<i>Upper Bound</i>								
LLaVA-OV-7B	56.9	56.4	63.0	58.6	70.3	56.6	48.8	100.0
<i>Retention Ratio=30%</i>								
DyCoke[CVPR'25]	56.6	54.7	60.3	56.1	67.1	54.6	46.6	96.5
<i>Retention Ratio=25%</i>								
Random	54.2	52.7	59.7	55.6	65.4	53.0	48.3	94.8
FastV[ECCV'24]	55.5	53.3	59.6	55.3	65.0	53.8	47.0	94.9
PDrop[CVPR'25]	55.3	51.3	57.1	55.5	64.7	53.1	48.7	94.1
SparseVLM[ICML'25]	56.4	53.9	60.7	57.3	68.4	55.2	48.1	97.5
DyCoke[CVPR'25]	49.5	48.1	55.8	51.0	61.1	48.6	43.2	87.0
<b>VidCom<sup>2</sup></b>	<b>57.2</b>	<b>54.9</b>	<b>62.5</b>	<b>58.6</b>	<b>69.8</b>	<b>56.4</b>	<b>49.4</b>	<b>99.6</b>
<i>Retention Ratio=15%</i>								
FastV[ECCV'24]	51.6	48.3	55.0	48.1	51.4	49.4	43.3	85.0
PDrop[CVPR'25]	53.2	47.6	54.7	50.1	58.7	48.7	45.0	87.4
SparseVLM[ICML'25]	52.9	49.7	57.4	53.4	61.0	52.1	47.0	91.2
<b>VidCom<sup>2</sup></b>	<b>54.3</b>	<b>52.0</b>	<b>58.9</b>	<b>56.2</b>	<b>65.8</b>	<b>54.8</b>	<b>48.1</b>	<b>95.1</b>
<i>Upper Bound</i>								
LLaVA-Video-7B	60.4	59.6	70.3	64.3	77.2	62.1	53.4	100.0
<i>Retention Ratio=30%</i>								
DyCoke[CVPR'25]	57.5	55.5	60.6	61.3	73.4	59.3	51.2	93.8
<i>Retention Ratio=25%</i>								
FastV[ECCV'24]	53.8	51.2	57.8	59.3	67.1	60.0	<b>50.8</b>	89.7
SparseVLM[ICML'25]	55.4	54.2	58.9	60.1	71.1	59.1	50.1	91.6
DyCoke[CVPR'25]	50.8	53.0	56.9	56.1	65.8	53.6	48.9	86.3
<b>VidCom<sup>2</sup></b>	<b>57.0</b>	<b>55.5</b>	<b>59.0</b>	<b>61.7</b>	<b>73.0</b>	<b>61.7</b>	50.0	<b>93.6</b>
<i>Retention Ratio=15%</i>								
FastV[ECCV'24]	44.0	44.6	53.8	51.3	56.4	51.1	46.2	78.0
SparseVLM[ICML'25]	53.1	<b>52.7</b>	56.2	55.7	65.0	53.9	48.3	86.3
<b>VidCom<sup>2</sup></b>	<b>53.3</b>	51.5	<b>56.8</b>	<b>58.3</b>	<b>68.0</b>	<b>57.3</b>	<b>49.7</b>	<b>88.5</b>

Performance on VideoMME with Qwen2-VL



Methods	EgoSchema	PerceptionTest
<i>Upper Bound</i>		
LLaVA-OV-7B	60.4 (100%)	57.1 (100%)
<i>Retention Ratio=25%</i>		
FastV[ECCV'24]	57.5 (95.2%)	55.4 (97.0%)
PDrop[CVPR'25]	58.0 (96.0%)	55.6 (97.4%)
DyCoke[CVPR'25]	59.5 (98.5%)	56.4 (98.8%)
<b>VidCom<sup>2</sup></b>	<b>59.7 (98.8%)</b>	<b>56.7 (99.3%)</b>

VidCom<sup>2</sup> achieves state-of-the-art performance across models and benchmarks.

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# Experimental Results: State-of-The-Art Efficiency

Methods	LLM Generation↓ Latency (s)	Model Generation↓ Latency (s)	Total↓ Latency (min:sec)	GPU Peak↓ Memory (GB)	Throughput↑ (samples/s)	Performance↑
LLaVA-OV-7B	618.0	1008.4	26:03	17.7	0.64	56.9
<i>Retention Ratio=25%</i>						
Random	178.2 (↓71.2%)	566.0 (↓43.9%)	18:44 (↓28.1%)	16.0 (↓9.6%)	0.89 (1.39×)	54.6 (↓2.3)
FastV [ECCV'24]	260.9 (↓57.8%)	648.6 (↓35.7%)	20:07 (↓22.8%)	24.7 (↑39.5%)	0.83 (1.30×)	55.5 (↓1.4)
PDrop [CVPR'25]	205.6 (↓66.7%)	592.6 (↓41.2%)	18:50 (↓27.7%)	24.5 (↑38.4%)	0.88 (1.38×)	55.3 (↓1.6)
SparseVLM [ICML'25]	410.6 (↓33.6%)	807.7 (↓19.9%)	25:03 (↓3.8%)	27.1 (↑53.1%)	0.67 (1.05×)	56.4 (↓0.5)
DyCoke [CVPR'25]	205.2 (↓66.8%)	598.0 (↓40.7%)	18:56 (↓27.4%)	16.1 (↓9.0%)	0.88 (1.38×)	49.5 (↓7.4)
<b>VidCom<sup>2</sup></b>	<b>180.7 (↓70.8%)</b>	<b>574.7 (↓43.0%)</b>	<b>18:46 (↓28.0%)</b>	<b>16.0 (↓9.6%)</b>	<b>0.88 (1.38×)</b>	<b>57.2 (↑0.3)</b>
<i>Retention Ratio=15%</i>						
Random	130.3 (↓78.9%)	532.5 (↓47.2%)	18:02 (↓30.8%)	15.8 (↓10.7%)	0.92 (1.44×)	53.1 (↓3.8)
FastV [ECCV'24]	172.4 (↓72.1%)	599.3 (↓40.6%)	18:19 (↓29.7%)	24.6 (↑39.0%)	0.91 (1.42×)	51.6 (↓5.3)
PDrop [CVPR'25]	165.3 (↓73.3%)	552.6 (↓45.2%)	18:32 (↓28.9%)	24.5 (↑38.4%)	0.90 (1.41×)	53.2 (↓3.7)
SparseVLM [ICML'25]	370.4 (↓40.1%)	764.8 (↓24.2%)	24:09 (↓7.3%)	27.1 (↑53.1%)	0.69 (1.08×)	52.9 (↓4.0)
<b>VidCom<sup>2</sup></b>	<b>129.2 (↓79.1%)</b>	<b>533.0 (↓47.1%)</b>	<b>18:11 (↓30.2%)</b>	<b>15.8 (↓10.7%)</b>	<b>0.92 (1.44×)</b>	<b>54.3 (↓2.6)</b>

VidCom<sup>2</sup> achieves outstanding efficiency with a 70.8% reduction in LLM generation latency and 1.38× higher throughput, while remaining compatible with efficient attention operators.

# Thanks!

## Q & A