

Global Compression Commander: Plug-and-Play Inference Acceleration for High-Resolution Large Vision-Language Models

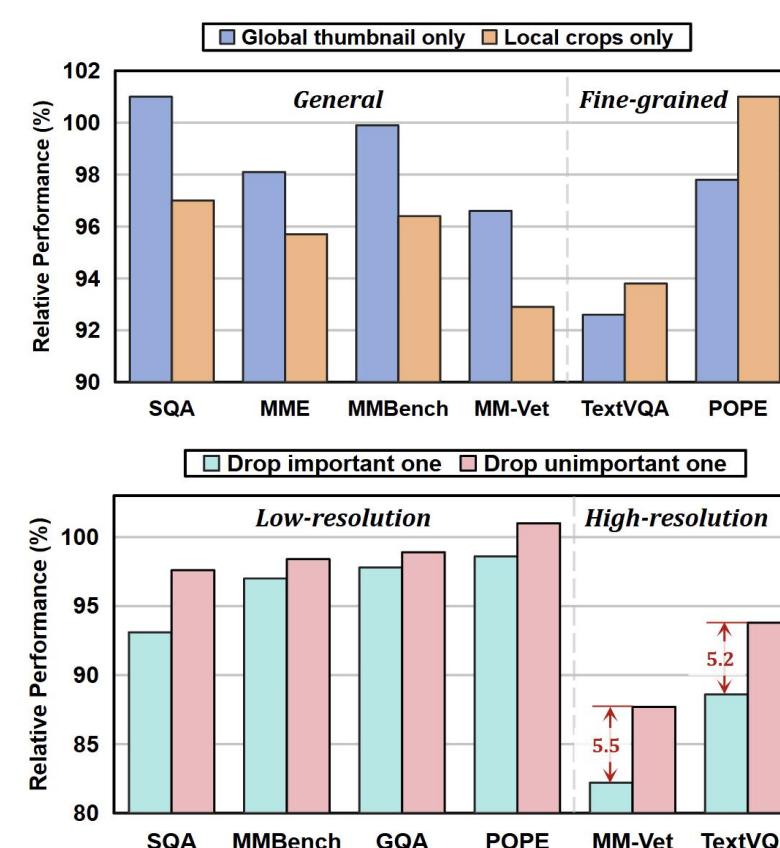
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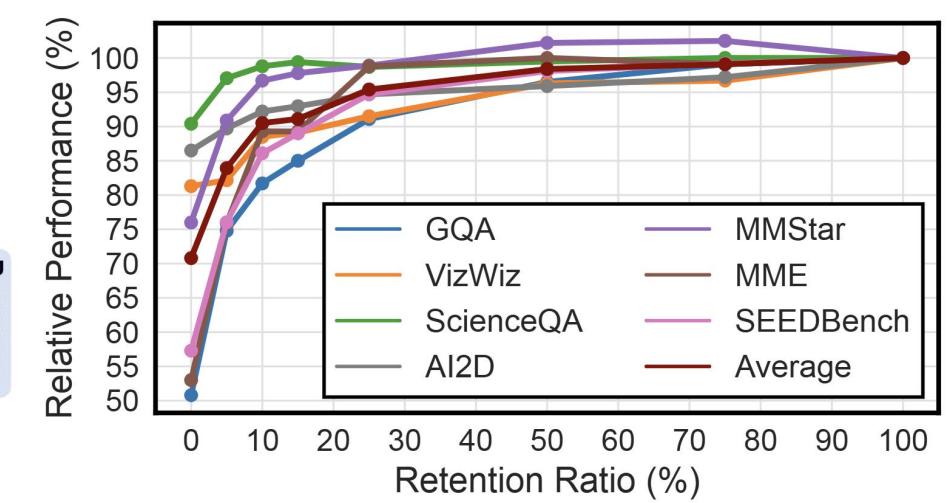
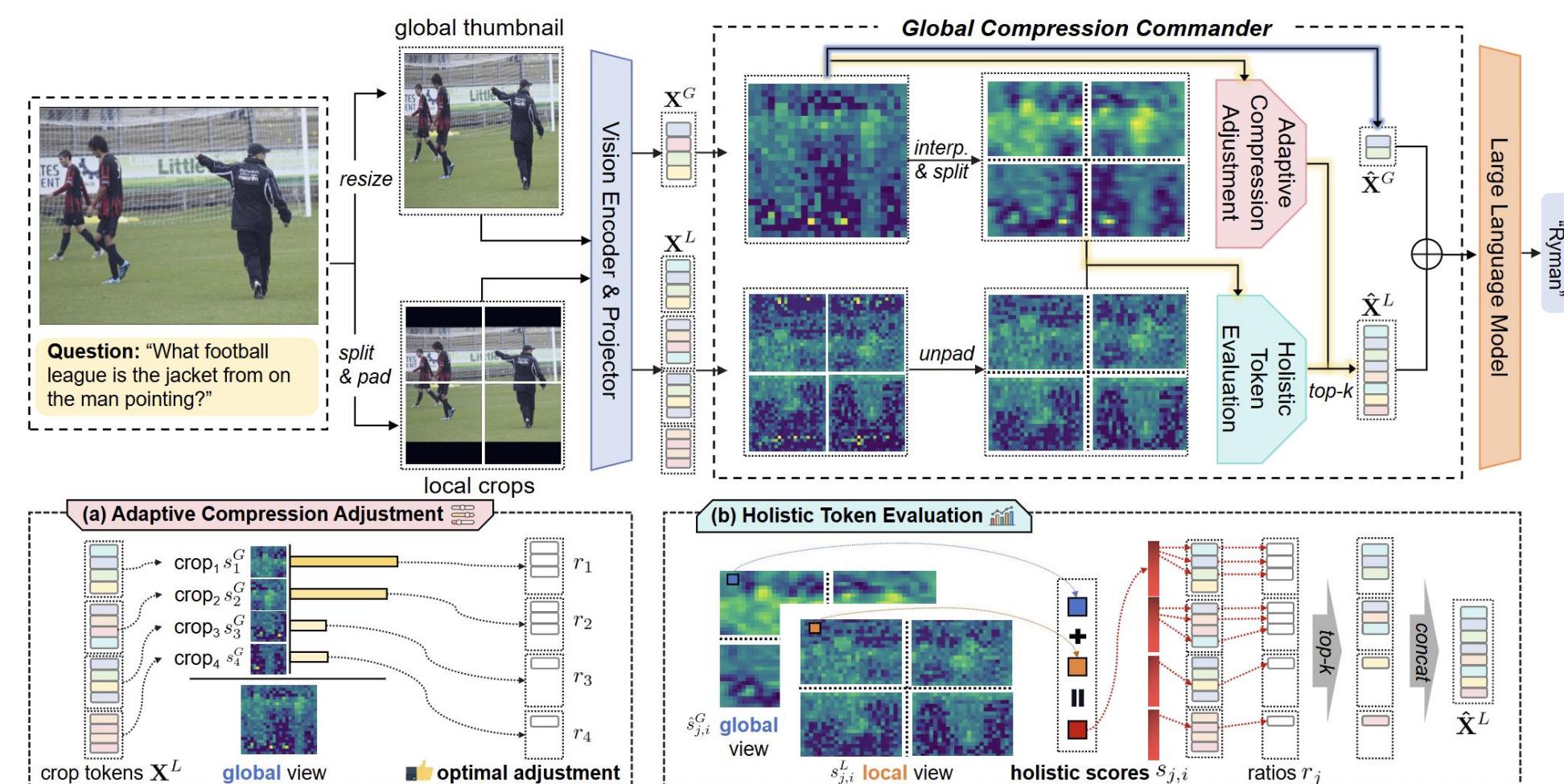
Motivation and Research Status: The Characteristics of HR-LVLMs and the Limitations of Existing Methods



Takeaways: We derive *two observations* for LVLMs with dynamic cropping: **(i)** Thumbnails and crops serve complementary roles in HR-LVLMs with dynamic cropping. **(ii)** Crops exhibit varying information richness, leading to different contributions.

Contributions: **(i)** analyze dynamic-cropping HR-LVLMs, revealing global-context neglect, crop informativeness disparity, and content-agnostic positional bias; **(ii)** propose GlobalCom², a training-free plug-and-play global-to-local compressor; **(iii)** retain >90% performance while pruning 90% visual tokens.

Our Solution: Global Compression Commander (GlobalCom²) - “Global-to-Local” Guided Compression Philosophy



Performance: GlobalCom² maintains over 90% performance while compressing 90% visual tokens across multiple vision-language understanding benchmarks.

Efficiency: GlobalCom² cuts FLOPs to 9.1% and peak GPU memory to 60%, delivering a 1.8x throughput gain.

Experimental Results: Optimal Performance-Efficiency Tradeoffs

Method	GQA	VizWiz	SQA	MMB	POPE	VQA ^T	MME	MM-Vet	Average
<i>Upper Bound, 2880 Tokens</i>									
LLaVA-NeXT-7B	64.2	57.6	70.1	67.4	86.5	64.9	1519.0	43.9	100.0%
<i>Ratio=50%, Retain up to 1440 Tokens</i>									
FastV (ECCV24)	61.8	54.9	69.0	67.4	85.5	59.6	1490.3	37.6	95.5%
PDrop (CVPR25)	63.7	57.9	69.2	67.7	87.9	61.6	1499.6	37.5	97.4%
SparseVLM (ICML25)	63.7	57.2	68.3	67.6	87.9	60.5	1507.2	36.8	96.8%
FasterVLM (2024.12)	63.4	56.4	69.1	67.4	87.7	58.9	1533.3	39.6	97.3%
GlobalCom²	63.9	56.5	68.5	67.6	88.1	62.3	1552.9	40.4	98.5%
<i>Ratio=25%, Retain up to 720 Tokens</i>									
FastV (ECCV24)	60.4	54.2	68.8	65.6	83.1	58.4	1477.3	35.4	93.4%
PDrop (CVPR25)	60.3	56.8	68.5	65.6	85.5	59.8	1473.7	31.1	93.3%
SparseVLM (ICML25)	59.9	56.0	67.5	65.6	85.0	58.3	1465.9	38.5	94.6%
FasterVLM (2024.12)	61.3	55.4	67.1	66.0	87.2	58.8	1454.6	37.8	94.8%
GlobalCom²	61.5	55.7	68.1	65.9	87.6	60.9	1493.5	40.7	96.7%
<i>Ratio=10%, Retain up to 288 Tokens</i>									
FastV (ECCV24)	55.9	53.1	68.1	61.6	71.7	55.7	1282.9	27.2	85.4%
PDrop (CVPR25)	54.5	54.4	67.7	59.0	77.6	54.4	1262.1	24.0	84.3%
SparseVLM (ICML25)	56.3	52.1	68.5	60.0	80.1	53.9	1334.2	26.5	86.1%
PruMerge (ICCV25)	53.6	54.0	66.4	61.3	60.8	50.6	1149.3	25.5	80.6%
FasterVLM (2024.12)	56.9	52.6	66.5	61.6	83.6	56.5	1359.2	35.0	89.9%
GlobalCom²	57.1	54.6	68.7	61.8	83.8	58.4	1365.5	36.4	91.6%

Ablation Studies

Method	GQA	POPE	VQA ^T	MME	MM-Vet	Avg.
<i>Upper Bound, 2880 Tokens</i>						
Vanilla	70.1	86.5	64.9	1519.0	43.9	100.0%
<i>Ratio=25%, Retain up to 720 Tokens</i>						
Uniform	67.1	87.2	60.1	1454.6	37.8	94.2%
n _{top-k}	67.4	87.3	59.8	1471.5	35.7	94.5%
Softmax (max)	67.3	87.2	60.3	1462.6	38.4	94.7%
Softmax (sum)	67.6	87.4	60.6	1473.3	39.6	95.6%
Method	GQA	POPE	VQA ^T	MME	MM-Vet	Avg.
<i>Upper Bound, 2880 Tokens</i>						
Vanilla	70.1	86.5	64.9	1519.0	43.9	100.0%
<i>Ratio=25%, Retain up to 720 Tokens</i>						
Local only	67.6	87.4	60.6	1473.3	39.6	95.6%
Global only	67.9	86.4	60.2	1488.5	37.8	94.7%
Global and Local	68.1	87.6	60.9	1493.5	40.7	96.7%

Method	TFLOPs↓	Memory↓	Throughput↑	Performance↑
<i>Upper Bound, 2880 Tokens</i>				