SPLIT-VLM: Salience-Guided Partitioning towards Local Coverage for Importance-Aware Token Dropping in Vision-Language Models

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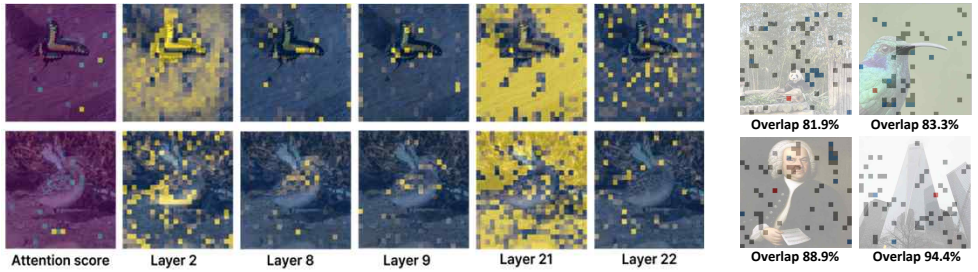
1. Motivation

- Vision tokens are the efficiency bottleneck in VLMs
  - High-res inputs (*e.g.,* LLaVA-Next) yield ≈2,880 vision tokens vs. <200 text tokens
  - 70–90% of the token is visual → attention cost $\mathcal{O}((N+M)^2)$, KV-cache explodes
- Prior token-dropping has complementary weaknesses
  - Salience-based (attention scores / hidden norms):
    → Needs dense attention (Lim. 1), Salience-only (Lim. 2) → weak speedup, position bias
  - Diversity-based (pivot selection):
    → Pivots cluster (Lim. 3), Hyperparam-sensitive (Lim. 4) → poor local coverage, unstable

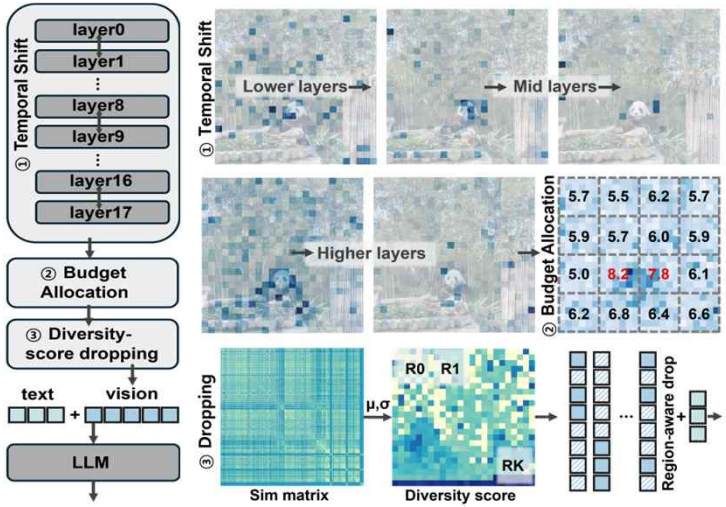
✓ Can we preserve both salience and diversity?
✓ Can we guarantee local coverage under tight budgets?

2. Key Idea



✓ Temporal shift highlights salient regions across layers, unlike attention
✓ High pivot overlap shows pivot selection keeps redundant tokens

3. Method — SPLIT



Overall Architecture

- **Temporal Shift** → Solution for Lim.1 & 2
  - Temporal shift: normalized hidden-state shift across model layers
  - *Attention-free salience* → *efficient and free of position bias*

$$\frac{\|\boldsymbol{h}_\ell(\boldsymbol{x}) - \boldsymbol{h}_{\ell-1}(\boldsymbol{x})\|_2}{\|\boldsymbol{h}_\ell(\boldsymbol{x})\|_2}$$

Eq. Temporal Shift

- **Local Budget Allocation** → Solution for Lim.3
  - *Each region gets its own budget* instead of one global budget
  - A uniform floor guarantees every region keeps minimum coverage
  - An importance-weighted term *gives salient regions more budgets*

$$\widetilde{\boldsymbol{B}}_k = \frac{\boldsymbol{B}}{\boldsymbol{K}} + \boldsymbol{B} \cdot \frac{\boldsymbol{I}(\boldsymbol{X}_k)}{\sum_j \boldsymbol{I}(\boldsymbol{X}_j)}$$

Eq. Local Budgeting

- **Diversity-Score Selection** → Solution for Lim.4
  - Rank tokens by *distinctiveness (σ) and redundancy (μ)*
  - Keep the most distinctive, non-redundant tokens per region
  - Robust without tuning pivot counts or distance thresholds

$$\boldsymbol{S_j} = \left\langle \frac{\boldsymbol{x_i}}{\|\boldsymbol{x_i}\|_2}, \frac{\boldsymbol{x_j}}{\|\boldsymbol{x_j}\|_2} \right\rangle, \boldsymbol{D(i)} = \boldsymbol{\lambda}\,\boldsymbol{\sigma_i} - \boldsymbol{\mu_i}$$

Eq. Diversity Score

- **Theoretical Guarantee** → Hausdorff coverage
  - A minimum budget makes *every region non-empty*
  - Adaptive budgets give tighter guarantees than uniform splits

$$\boldsymbol{d_H(X_k, R_k)} = \sup_{\boldsymbol{x \in X_k}} \inf_{\boldsymbol{r \in R_k}} \|x - r\|$$

Eq. Hausdorff distance

4. Experiments

Method	GQA	MMB	MME	POPE	SQA	VQAtxt	Avg.
Vanilla	61.2	63.1	1477.7	85.4	68.1	48.7	100%
HiRed	54.0	50.3	1297.5	78.0	66.3	39.2	86.8%
GreedyP	55.0	55.2	1365.1	82.6	64.6	40.3	91.0%
DivPrune	58.4	58.6	1362.1	83.7	67.3	40.8	91.7%
DART	55.1	59.7	1357.6	82.6	67.9	40.7	91.4%
Ours	59.0	60.1	1375.5	84.5	68.6	41.5	92.8%

Comparison on LLaVA-1.5-7B (88.9% token reduction)

Method	Token	Total Time	Prefill Time	FLOPs	POPE	Speedup	
						Total	Prefill
Vanilla	2880	46:34	28:59	100%	87.7	1.00×	1.00×
GreedyP	320	31:17	12:02	22.3%	85.4	1.49×	2.41×
DivPrune	320	26:34	10:57	19.8%	86.0	1.75×	2.65×
DART	320	27:28	11:19	24.8%	85.6	1.70×	2.56×
Ours	320	25:52	10:31	19.8%	86.2	1.80×	2.76×

Inference costs in LLaVA-Next-7B (POPE)

5. Conclusion

- **SPLIT preserves both salient and diverse visual tokens without missing regions uncovered**
- **Attention-score-free and threshold-free while ensuring *local coverage* under tight budgets**
- **SOTA *efficiency–accuracy trade-off* under extreme budgets on image & video VLMs**
- **No training required, *plug-and-play* into existing VLMs**