

ViPCap: Retrieval Text-based Visual Prompts for Lightweight Image Captioning

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Introduction

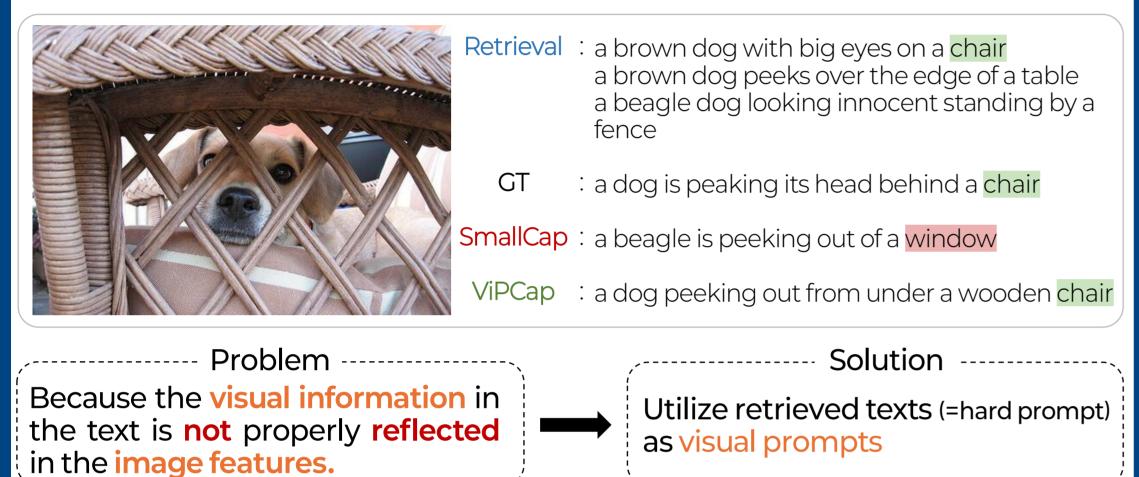
Lightweight image captioning



- < Using small mapping network [1] >
- < Using datastore [2] >

Problems in prior research

- ① Computational cost
 - Despite of mapping network, high computational costs are still required.
- ② Neglect of rich image descriptions
- Prior works only use retrieval data as a text prompt, not a visual prompt.
- 3 Rely on frozen CLIP image encoder
 - Prior works rely solely on the frozen CLIP encoder.

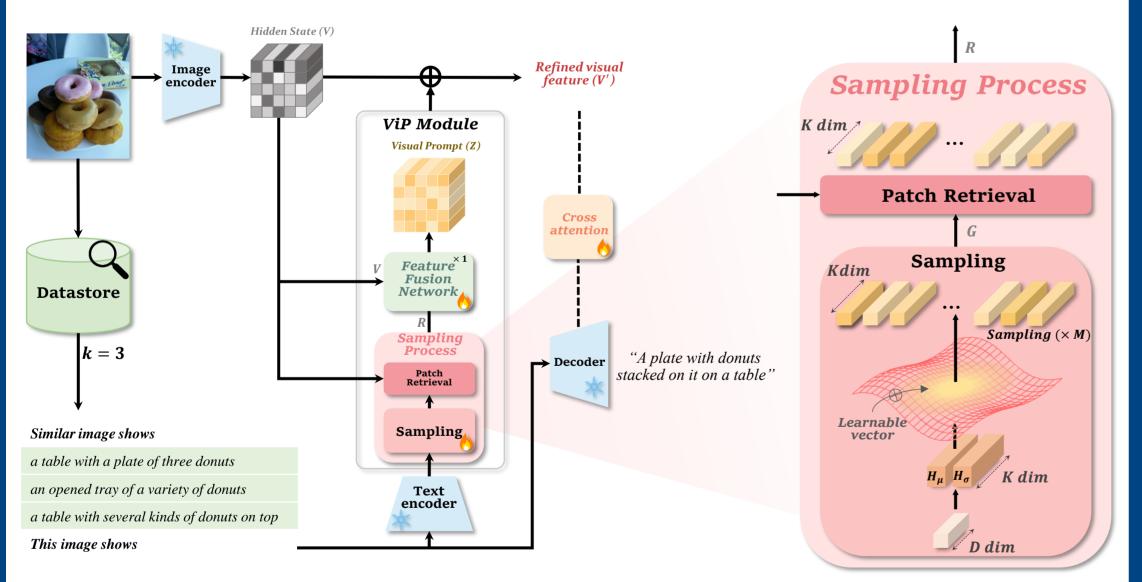


Proposed Framework

Contributions

- Generate visual prompts from text prompts.
- Align sampled semantic text features with visual representations.
- Flexible integration with various models and prompts (Plug-and-play).

Overall framework



Method

- Converts text prompts into semantic features using learnable distribution.
- Retrieves semantic features aligned with patch-level image features.
- Fuse these features with **FFN** to generate visual prompts.

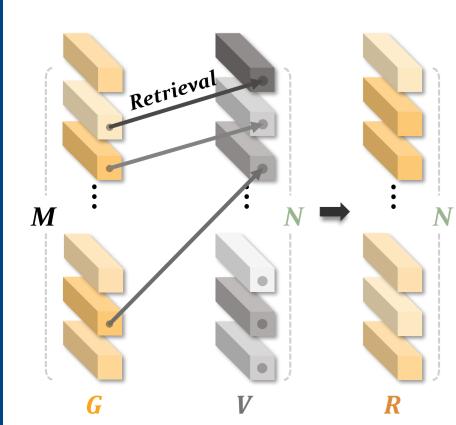
Sampling process

- Sampling from Gaussian distribution

 - Capture for fine-grained visual information $\times M \longrightarrow \mu = H_{\mu}(T) + \alpha \cdot \omega$, Add learnable vectors $\sigma = H_{\sigma}(T)$

Patch-retrieval module

Add learnable vectors



G: Semantic feature V: Image feature R: Retrieved semantic feature

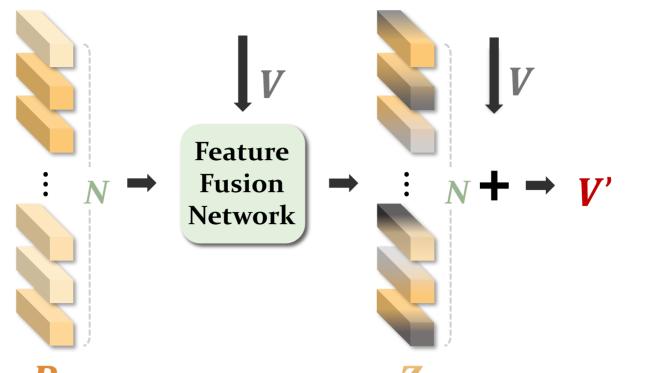
 Select Semantic features (G) to patchlevel using cosine similarity

$$\mathcal{L}(j) = argmax_{i \in [1:M]} sim(g_i, v_j)$$

 Provide the most relevant information for each patch (one to many)

$$\mathbf{R} = \left\{ g_{\mathcal{L}(j)} \right\}_{j=1}^{N} \in \mathbb{R}^{N \times K}$$

Feature Fusion Network (FFN)



Z: Visual prompt

V': Refined visual feature

- FFN (x 1 layer)
- Visual prompt
- Z = FFN(V, R)
- Refined visual feature
 - V' = V + Z

Experimental Results

Evaluation on COCO, Flickr30k, Nocaps.

Method	Training Param	COCO Test			kr30k est		NoCaps Val				
	θ	B@4	M	C	S	C	S	In	Near	Out	Entire
Large scale training models											
OSCAR _{Large} (2020)	338M	37.4	30.7	127.8	23.5	-	-	78.8	78.9	77.4	78.6
$LEMON_{Huge}$ (2022)	675M	41.5	30.8	139.1	24.1	-	-	118.0	116.3	120.2	117.3
SimVLM _{Huge} (2022a)	632M	40.6	33.7	143.3	25.4	-	-	113.7	110.9	115.2	112.2
BLIP2 _{ViT-g OPT_{2.7B}} (2023a)	1.1B	43.7	-	145.8	-	-	-	123.0	117.8	123.4	119.7
CogVLM (2024)	1.5B	-	-	148.7	-	94.9	-	-	-	132.6	128.3
$PaLI_{mT5-XXL}$ (2023)	1.6B	-	-	149.1	-	-	-	-	-	-	127.0
Lightweight models											
CaMEL (2022)	76M	39.1	29.4	125.7	22.2	-	-	-	-	-	-
I-Tuning _{Medium} (2023)	44M	35.5	<u>28.8</u>	120.0	<u>22.0</u>	72.3	19.0	<u>89.6</u>	77.4	58.8	75.4
ClipCap (2021)	43M	33.5	27.5	113.1	21.1	-	-	84.9	66.8	49.1	65.8
I-Tuning _{Base} (2023)	14M	34.8	28.3	116.7	21.8	61.5	16.9	83.9	70.3	48.1	67.8
SmallCap (2023)	7M	37.0	27.9	119.7	21.3	60.6	-	87.6	<u>78.6</u>	<u>68.9</u>	<u>77.9</u>
SmallCap _{d=16, Large} (2023)	47M	37.2	28.3	121.8	21.5	-	-	-	-	-	-
ViPCap (Ours)	14M	<u>37.7</u>	28.6	<u>122.9</u>	21.9	66.8	<u>17.2</u>	93.8	81.6	71.5	81.3

→ ViPCap demonstrates competitive performance

Evaluation on text-only captioning models.

In-Domain					Cross-Domain															
Method	СОСО					Flickr30k			$\overline{\text{COCO}} \Rightarrow \text{Flickr30k}$			Flickr30k ⇒ COCO			$COCO \Rightarrow NoCaps$					
Wicthou	B@4	M	C	S	B@4	M	C	S	B@4	M	C	S	B@4	M	C	S	In	Near	Out	Entire
CapDec (2022)	26.4	25.1	91.8	-	17.7	20.0	39.1	-	17.3	18.6	35.7	-	9.2	16.3	27.3	-	60.1	50.2	28.7	45.9
CapDec+ViP	27.0	25.6	94.2	18.8	18.6	20.1	44.4	14.4	15.7	18.0	35.8	11.8	9.5	16.3	30.7	9.2	60.2	50.9	33.7	47.8
Δ	0.6	0.5	2.4	-	0.9	0.1	5.3	-	-1.6	-0.6	0.1	-	0.3	-	3.4	-	0.1	0.7	5.0	1.9
ViECap (2023)	27.2	24.8	92.9	18.2	21.4	20.1	47.9	13.6	17.4	18.0	38.4	11.2	12.6	19.3	54.2	12.5	61.1	64.3	65.0	66.2
ViECap+ViP	27.3	25.1	93.6	18.4	21.2	20.2	48.8	13.9	17.4	18.1	40.2	11.1	13.6	19.3	55.2	12.7	62.2	64.9	67.1	67.2
Δ	0.1	0.3	0.7	0.2	-0.2	0.1	0.9	0.3	-	0.1	1.8	-0.1	1.0	-	1.0	0.2	1.1	0.6	2.1	1.0

→ Demonstrate its potential as image feature

Ablation Studies

Dromnt	ViP						
Prompt	×	✓					
"This image shows"	111.1	116.0 (4.9 ↑)					
Retrieval prompt	117.3	119.9 (2.6 ↑)					

→ Achieves notable performance without using retrieval prompts

Method	Enc.	Dec.	ViP	Ret	CIDEr
ViPCap	ViT	OPT -125M	\ \ \	× ✓	122.0 122.5 (0.5 ↑)
(Ours)	-B/32	XGLM		×	116.8 121.2 (4.4 ↑)
EVCap	EVA- CLIP-g	Vicuna -13B	× ✓	×	140.1 141.3 (1.2 ↑)

→ Outperformance based on various models

Qualitative Results



- a cow stands on the ground in front of a pink building a cow who is looking in the door of a house on a street a cow walking by a white building and a large decorated pole
- A white cow walking down the street next to some motorcycles
- a cow walking down a street next to a building
- V a cow walking down a street next to a pink building



- the charro or mexican cowboy is skilled in many techniques for control of animal behavior including using roping a man is riding a bucking brown horse
- a man in an arena rides a bucking horse **G** A man in a hat riding a horse
- **S** a man riding a horse in a dirt field
- V a man in cowboy hat riding a horse



- a cat sits in the middle of pavement as a bird swoops down a bull and flock of pigeons on a street an animal surrounded by a flock of birds
- **G** A cat looking at a large group of pigeons.
- a white and black cat sitting on top of pigeons an orange and white cat sitting on the ground near a bunch of pigeons

References

- [1] Junnan Li, Dongxu Li et al., "BLIP-2: Bootstrapping Language-Image Pre-training with F rozen Image Encoders and Large Language Models", ICML 2023
- [2] Ramos, Rita and Martins, Bruno and Elliott et al., "SmallCap: Lightweight Image Caption ing Prompted With Retrieval Augmentation", CVPR 2023
- [3] Li, Jiaxuan and Vo et al., "EVCap: Retrieval-Augmented Image Captioning with External Visual-Name Memory for Open-World Comprehension", CVPR 2024