

DICE: Disentangled Instance-Class knowlEdge prompt tuning via SAE for Vision-Language Models

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Paper



CV

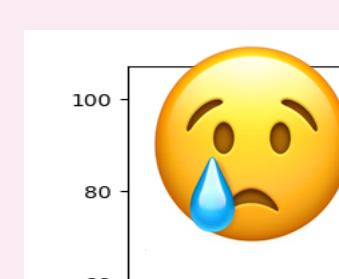
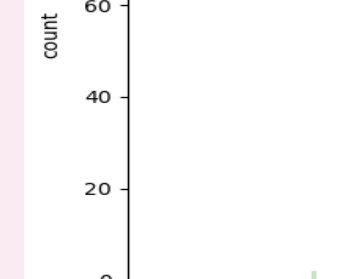
BACKGROUND Prompt tuning for VLMs

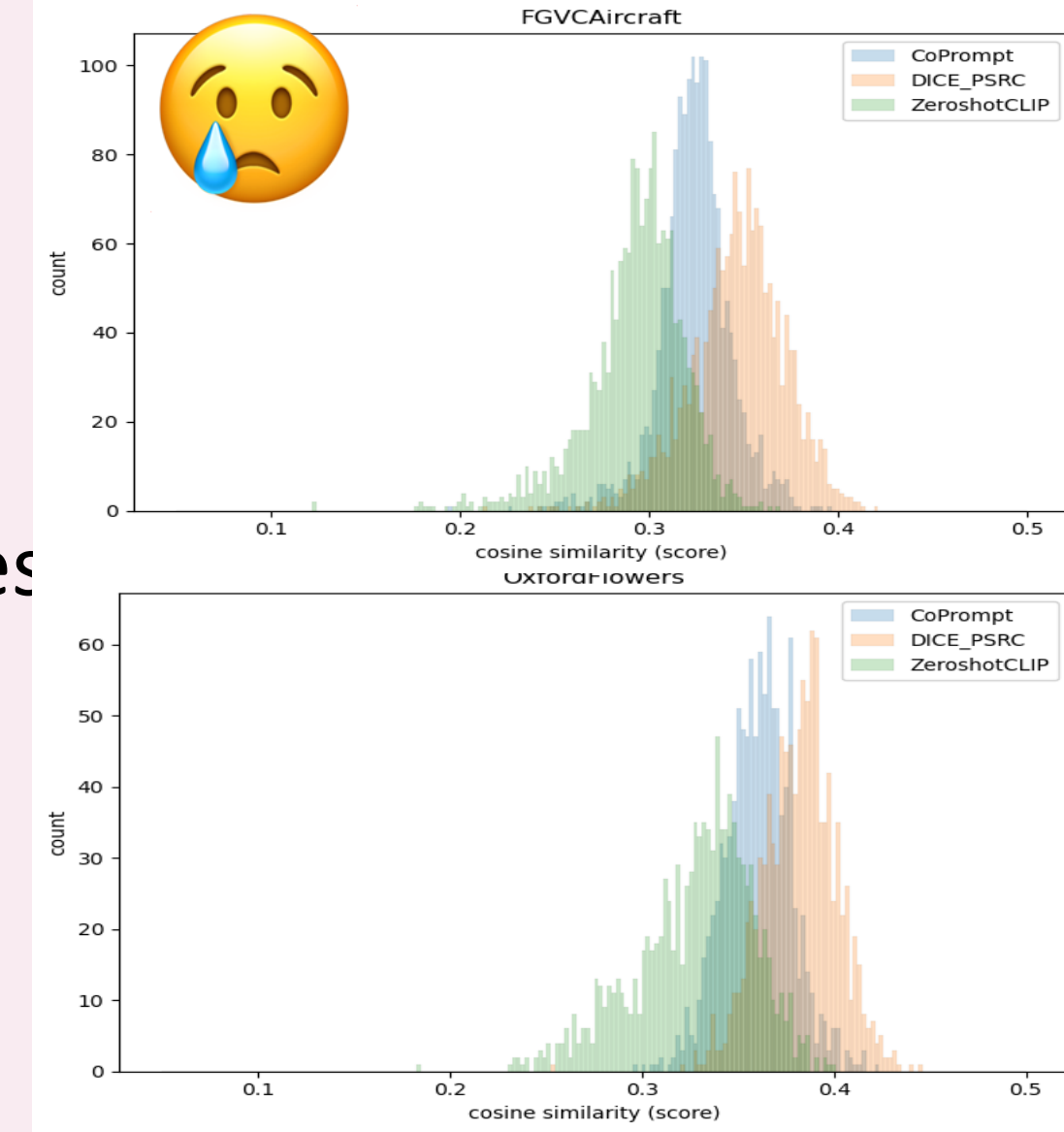
Among VLMs, CLIP is widely used in few-shot settings. In such settings, prompt tuning is commonly employed to adapt the models LLM-based prompt tuning aims to adapt CLIP with class-level priors to obtain discriminative semantics.

LIMITATIONS LLM-based Prompt Tuning

① Not grounded in vision

- Descriptions generated text-only, no image seen
- One description reused for every image in a class
→ captures class-average semantics only

FGVCAircraft	Descriptions	Score
	The de Havilland DH-82 Tiger Moth is a 1930s biplane designed by Geoffrey de Havilland and manufactured by the de Havilland Aircraft Company. It was operated as a primary trainer by the Royal Air Force (RAF).	0.34
	You can identify an aircraft DH-82 by its registration number.	0.31
	It looks like a small, single-engine airplane with two wings and a tail.	0.27
	A de Havilland Canada DHC-2 Beaver floatplane prepares to land in the waters of southeast Alaska.	0.19
	Cessna 182RG landing at McCarran International Airport	0.11



② Entangled & class-level only

- Rich LLM semantics remain entangled
- Exploited at class level, not instance level
→ instance-level visual variation unused

③ No joint class-instance structure

- Class-level alone → misses fine-grained differences
- Instance-level alone → poor generalization
→ no mechanism to combine both

HOW Integrate class + instance knowledge

Few-shot generalization needs **both class-level structure and instance-level detail**; disentangling LLM priors into instance concepts and fusing them with class embeddings should improve generalization to unseen classes.

CONTRIBUTION Three contributions

SAE as a learnable concept dictionary enabling explicit and interpretable concept selection.

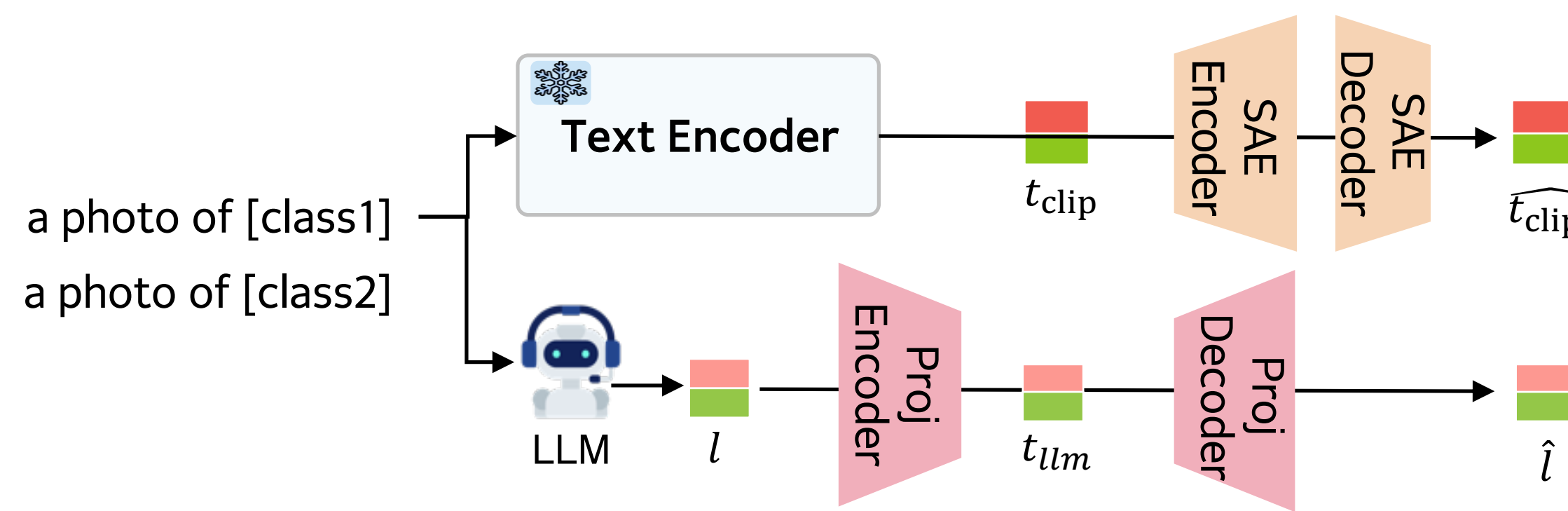
A **unified prompt** that integrates class-level priors with instance-specific visual concepts.

Concept-based prompts that adapt per instance, replacing predefined descriptions.

What SAE-based disentanglement & unified context

A Sparse Autoencoder decomposes LLM-derived priors into sparse concept units; the selected instance concepts are fused with class embeddings into a unified prompt.

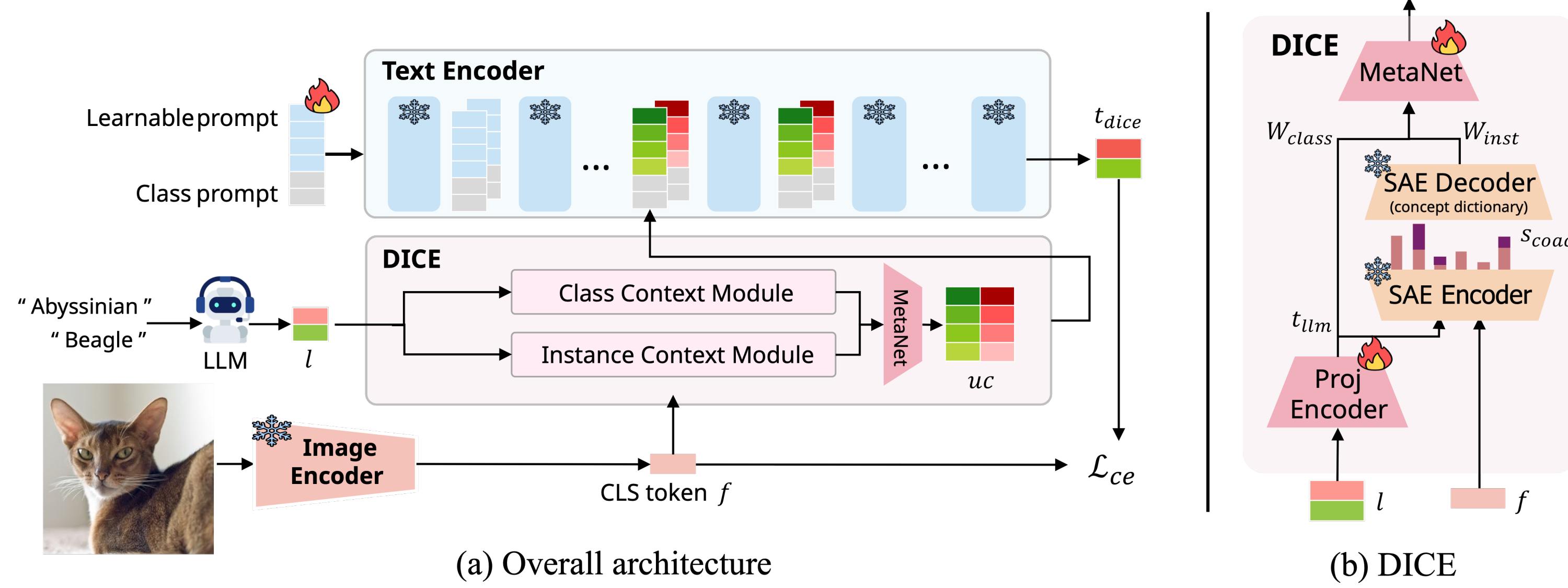
Pre-training stage



Training objectives

$$\mathcal{L}_{proj} = 1 - \cos(t_{llm}, t_{clip}), \quad \mathcal{L}_{llm_rec} = 1 - \cos(l, \hat{l}), \quad \mathcal{L}_{clip_rec} = \|t_{clip} - \hat{t}_{clip}\|^2$$

Prompt-tuning stage



1. Class context module

$$W_{class} = E_{proj}(l), \quad W_{class} \in \mathbb{R}^{C \times d}$$

2. Instance context module

- Concept selection from the SAE decoder

$$s_{class} = E_{sae}(t_{llm} - b_{pre}), \quad s_{inst} = E_{sae}(f - b_{pre})$$

$$s_{coact} = s_{class} \oplus s_{inst}$$

$$W_{inst} = \{D_{sae}[i] \mid i \in \text{Top-}k(s_{coact})\}, \quad W_{inst} \in \mathbb{R}^{C \times k \times d}$$

3. Unified context injection

$$UC = \text{MetaNet}(W_{class} + W_{inst})$$

RESULT 1

T1. Base-novel generalization

Method	Type	Average	ImageNet [11]	Caltech101 [14]	OxfordPets [34]
		Base Novel H	Base Novel H	Base Novel H	Base Novel H
CoOp [52]	tp	82.69	63.22	71.66	76.42
CoCoOp [51]	tp	80.47	71.69	75.83	75.08
KART [20]	tp	78.42	70.52	74.26	71.10
TCP [50]	tp	84.13	75.36	78.51	72.82
MaPLe [22]	mp	81.54	72.30	76.05	75.40
PSRC [23]	mp	84.26	76.10	79.97	77.60
HPT [46]	mp	84.32	76.86	80.23	77.95
CoPrompt [39]	mp	84.00	77.23	80.48	77.67
DICE	tp	84.45	76.77	80.43	76.87
CoOp w/DICE	tp	83.69	72.54	77.45	76.17
CoCoOp w/DICE	tp	82.70	73.19	77.65	76.30
PSRC w/DICE	mp	85.76	77.29	81.31	77.90

T2. Few-shot generalization

Method	Shots	1	2	4	8	16
CoOp		67.56	64.78	71.61	76.09	79.89
CoCoOp		66.79	67.65	71.21	72.96	74.90
PSRC		72.32	75.29	78.06	80.69	82.87
CoPrompt ¹		68.08	71.33	74.51	77.75	79.27
HPT ¹		69.72	72.49	76.19	78.53	81.15
CoOp w/DICE		68.93	72.33	75.18	77.70	80.96
CoCoOp w/DICE		66.92	70.52	72.68	75.25	77.97
PSRC w/DICE		72.94	75.90	79.01	81.19	83.21

T3. Cross generalization

Method	Type	ImageNet	Caltech	Pets	Cars	Flowers	Food	Aircraft	SUN397	DTD	EuroSAT	UCF	Avg
CoOp	tp	71.51	93.70	89.14	64.51	68.71	85.30	18.47	64.15	41.92	46.39	66.55	63.88
CoCoOp	tp	71.02	94.43	90.14	65.32	71.88	86.06	22.94	67.36	45.73	45.37	68.21	65.74
MaPLe	mp	70.72	93.53	90.49	65.57	72.23	86.20	24.74	67.01	46.49	48.06	68.69	66.30
PSRC	mp	71.27	93.60	90.25	65.70	70.25	86.15	23.90	67.10	46.87	45.50	68.75	65.81
TCP	tp	71.40	93.97	91.25	64.69	71.21	86.69	23.45	67.15	44.35	51.45	68.73	66.29
HPT	mp	71.72	94.20	92.63	66.33	74.84	86.21	25.68	68.75	50.87	47.36	70.50	67.73
CoPrompt	mp	70.80	94.50	90.73	65.67	72.30	86.43	24.00	67.57	47.07	51.90	69.73	67.00
CoOp w/DICE	tp	72.03	93.03	89.50	64.37	70.90	85.57	20.40	66.00	42.90	49.50	67.70	64.99
CoCoOp w/DICE	tp	71.76	96.13	90.23	59.57	70.73	88.93	25.83	71.25	50.93	57.60	70.20	68.14

RESULT 2

F1. Examples of disentangled latent interpretation

Concept	Latent	s_{coact}
facial	7878	0.20
freckle	9584	0.17
marbling	2862	0.17
patchiness	15844	0.15
four-wheeler	7830	0.20
truck bed	14	0.19
Truck	16148	0.18
hauling	1202	0.18
salad	8684	0.20
Ploughman's lunch	833	0.17
mozzarella	8015	0.17
tomato	2650	0.15
Italian bread	11935	0.16
Green salad	14713	0.16
mozzarella	8015	0.16
Salad plate	8712	0.15

T4. Class-wise latent activation analysis.

Dataset	Class	Latent	Act.	Ref.
StanfordCars	2007 Chevrolet Corvette	4910	0.1968	edge
	Ron Fellows Edition Z06	6382	0.1885	dashboard
		16351	0.1715	chair
		12769	0.1503	sports car
Caltech101	elephant	10579	0.1244	elephant
		4544	0.1187	tusker
		10851	0.1165	African elephant
		724	0.1052	big head
UCF101	Apply Eye Makeup	15299	0.1893	whiteface
		4	0.1869	eyelash
		4440	0.1848	front
		11337	0.1785	eyeliner

T5. Intra/inter-class similarity.

Dataset	s_{coact}	s_{inst}
	Intra ↑ Inter ↓	Intra ↑ Inter ↓
FGVCAircraft	0.14	0.18
Food101	0.12	0.09
OxfordPets	0.14	0.11

F2. Comparison of UMAP between LLM-based prompt tunings and ours.

