









VALSE 2024 重度

视觉与学习青年学者研讨会 VISION AND LEARNING SEMINAR

PromptKD: Unsupervised Prompt Distillation for Vision-Language Models

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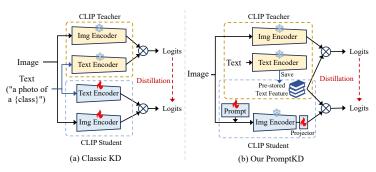
Background

Prompt learning is a technique that can efficiently adapt existing vision-language models to specific tasks through learnable textual or visual prompt.

Motivation

- ➤ Larger teacher models can provide better guidance for prompt learning.
- ➤ Leveraging decoupled-modality characteristics of CLIP can speed up training and inference.
- Training with extensive images leads to better prompt representations.

Overview



We propose to reuse the previously well-trained text features from the teacher pre-training stage and incorporate them into the student image encoder for both distillation and inference.

Method Save Fixed Pre-trained Teacher from (a) Distillati Labeled Text: (e.g. a photo of Project Lave Student Prompt Training Teacher Prompt Training (b) Student Prompt Distillation (a) Pre-train a large teacher model & Trainable Parameters 🔲 Visual Prompt Project Layer Test Images Student model Well-trained Student from (b) (c) Student Inference

- A novel two-stage unsupervised prompt distillation framework for VLMs.
- > Reuse high-quality teacher text features instead of training the student's own text encoder.
- > Distillation on extensive unlabeled domain images using soft labels provided by the teacher.
- PromptKD outperforms all existing methods on 11 diverse recognition datasets.

Impact of the components

Method	Base	Novel	HM
CLIP	72.43	68.14	70.22
Projector Only	78.48	72.79	75.53
Full Fine-tune	75.90	70.95	73.34
w/o Shared Text Feature	78.79	73.37	75.98
PromptKD	79.27	73.39	76.22

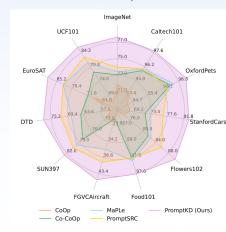
Different distillation ways.

Role (Method)	Img Backbone	Base	Novel	HM	
CLIP	ViT-B/16	72.43	68.14	70.22	
PromptSRC	ViT-B/16	77.60	70.73	74.01	
Teacher (CLIP)	ViT-L/14	79.18	74.03	76.52	
Student	ViT-B/16	76.53	72.58	74.50	
Teacher (MaPLe)	ViT-L/14	82.79	76.88	79.73	
Student	ViT-B/16	78.43	73.61	75.95	
Teacher (PromptSRC)	ViT-L/14	83.24	76.83	79.91	
Student	ViT-B/16	79.27	73.39	76.22	

Different pre-training methods.

Experiments

Setting: Teacher: ViT-L/14 CLIP, Student: ViT-B/16 CLIP

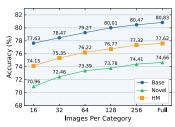


Base-to-novel experiments (HM) on 11 datasets.

Method	Domain Data	Base	Novel	HM
CLIP	Zero-shot	72.08	77.80	74.83
PromptSRC	Few-shot	98.07	76.50	85.95
CLIP-PR		65.05	71.13	67.96
UPL	Unlabeled	74.83	78.04	76.40
LaFTer		79.49	82.91	81.16
FPL		97.60	78.27	86.87
IFPL	Few-shot	97.73	80.27	88.14
GRIP	+	97.83	80.87	88.54
PromptKD	Unlabeled	99.42	82.62	90.24
Δ		+1.59	+1.75	+1.70

Comparison with existing works using unlabeled data.

KD Form	Loss	Base	Novel	HM
Feature	L1	73.09	65.98	69.35
	MSE	71.89	66.17	68.91
Logit	KL	79.27	73.39	76.22



Number of unlabeled images for distillation.

Different distillation forms and loss functions.