Understanding and Improving Visual Prompting: A Label-Mapping Perspective

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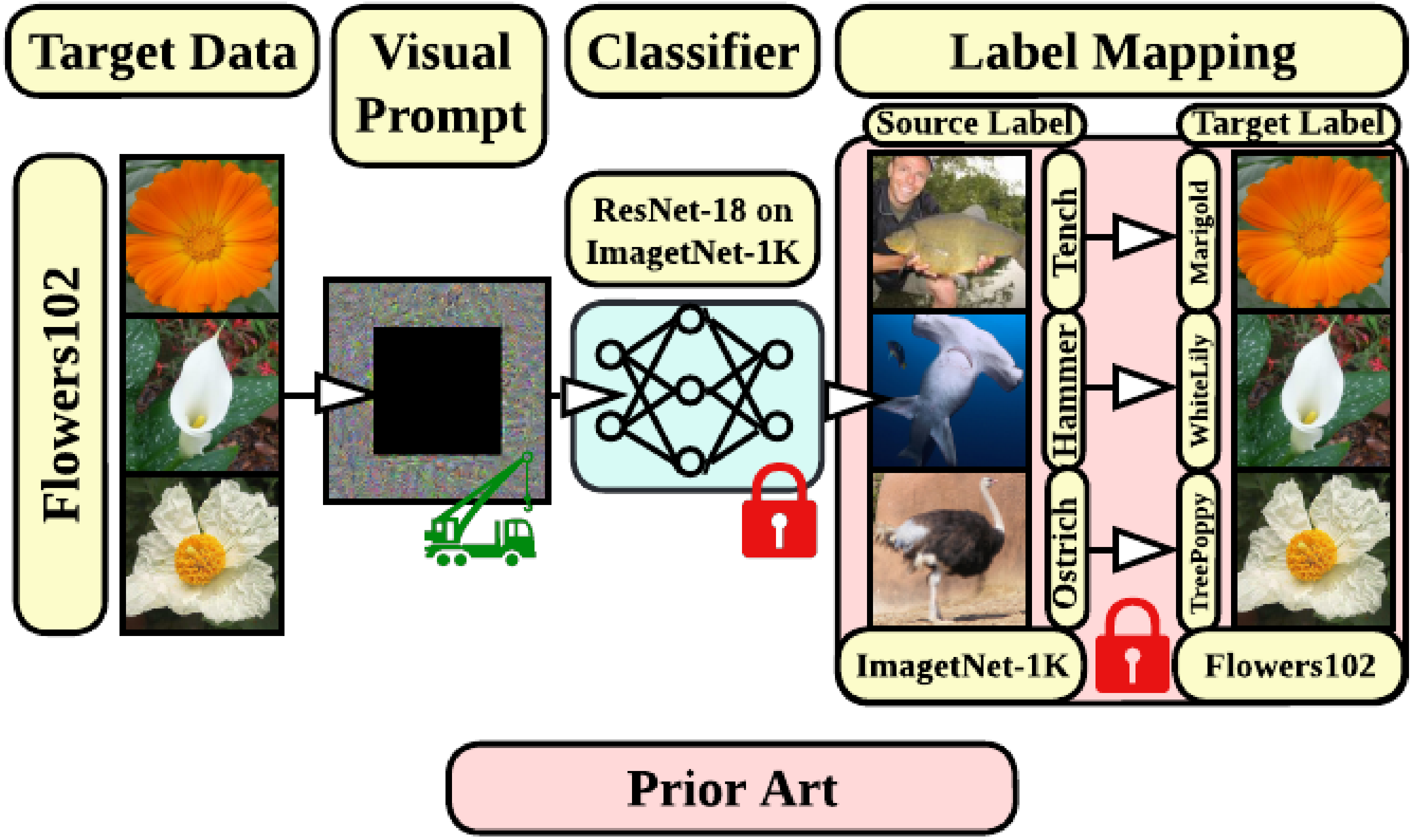
Visual Prompting for Transfer Learning



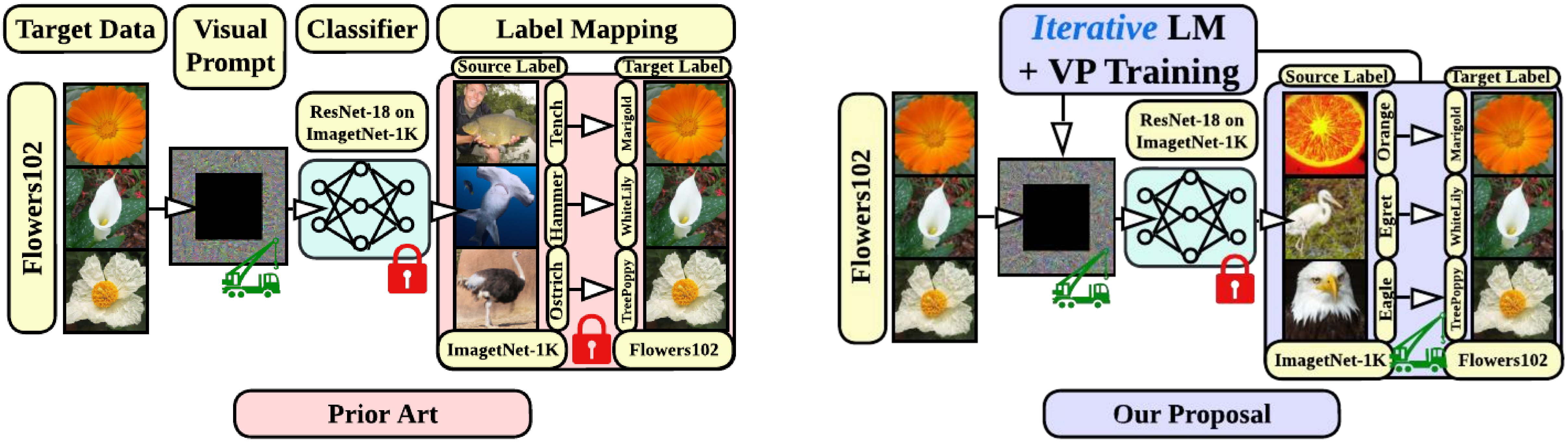
Label Mapping

- Mapping from source classes to downstream classes.
- Existing label mapping methods seem **ruleless**.
- A key building block for visual prompting.

Main Research Question

Given the source model, how to build a mapping from the source label space to the target label space so that the model's prediction directs to the correct target label?

Our Proposal: BLO based ILM-VP



Algorithm 2 Bi-level optimization based ILM-VP algorithm

1: **Initialize:** Given target training set $\mathcal{T}_{\mathrm{tr}}$, pre-trained model $f_{\boldsymbol{\theta}_{\mathrm{s}}}$, prompt pattern initialization $\boldsymbol{\delta}_0$, and upper-level learning rate λ for SGD
2: **for** Epoch $n = 0, 1, \ldots,$ **do**
3: **Lower-level label mapping**: Given $\boldsymbol{\delta}_{n-1}$, call LM for each target class y_{t} in $\mathcal{T}_{\mathrm{tr}}$
4: **Upper-level prompt learning**: Given LM, call SGD to update prompt $\boldsymbol{\delta}_n \leftarrow \boldsymbol{\delta}_{n-1}$
5: **end for**

Convergence of ILM-VP

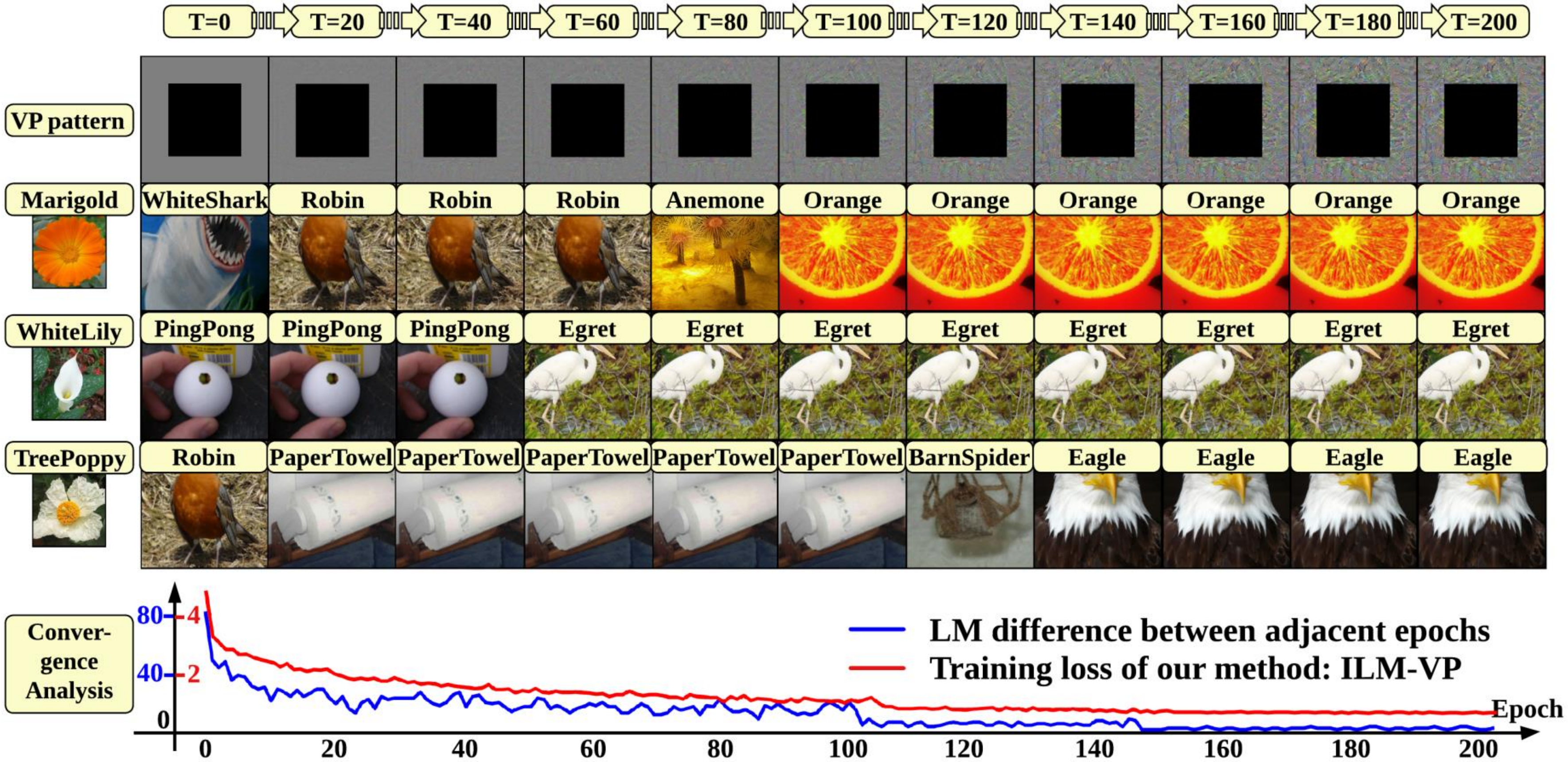


Figure 1. ILM-VP training dynamics from epoch 0 to 200. Rows show: (1) VP pattern vs. epoch number; (2-4) Learned source label mapping with respect to target label 'Marigold', 'White Lily', and 'Tree Poppy', together with explanation-by-example-identified source training examples to explain each re-purposed target label; (5) Convergence of training loss and LM difference between adjacent epochs measured by Hamming distance.

Accuracy Improvements

Source Model	ResNet-18 (ImageNet-1K)					ResNet-50 (ImageNet-1K)				ResNeXt-101-32x8d (Instagram)			
Method	Ours	Prompt baseline		Finetuning		Ours	Prompt base.	Finetuning		Ours	Prompt base.	Finetuning	
	ILM-VP	RLM-VP	FLM-VP	LP	FF	ILM-VP	FLM-VP	LP	FF	ILM-VP	FLM-VP	LP	FF
Parameter Size	0.05M	0.05M	0.05M	0.51M	11.7M	0.05M	0.05M	0.51M	25.6M	0.05M	0.05M	0.51M	88.8M
Flowers102	**27.9**±0.7	11.0±0.5	20.0±0.3	88.0±0.5	97.1±0.7	**24.6**±0.6	20.3±0.3	90.9±0.4	97.9±0.7	**27.9**±0.3	22.5±0.5	89.1±0.2	99.2±0.5
DTD	**35.3**±0.9	16.3±0.7	32.4±0.5	60.0±0.6	65.5±0.9	**40.5**±0.5	36.9±0.8	67.6±0.3	69.7±0.9	**41.4**±0.7	40.3±0.5	69.7±0.2	69.1±1.0
UCF101	**23.9**±0.5	6.6±0.4	18.9±0.5	63.2±0.8	73.0±0.6	**34.6**±0.2	33.9±0.4	70.8±0.3	78.0±0.8	**43.1**±0.8	41.9±0.6	76.9±0.5	79.1±0.7
Food101	**14.8**±0.2	3.8±0.3	12.8±0.1	50.6±0.3	75.4±0.8	**17.0**±0.3	15.3±0.2	57.6±0.5	80.3±0.9	**23.0**±0.4	20.5±0.5	76.0±0.4	82.5±0.3
GTSRB	**52.0**±1.2	46.1±1.3	45.5±1.0	77.4±1.2	98.0±0.3	**52.5**±1.4	47.6±1.1	77.8±0.7	97.6±1.0	**59.9**±1.0	56.2±0.6	73.5±0.7	97.6±0.9
EuroSAT	**85.2**±0.6	82.4±0.4	83.8±0.2	93.8±0.3	98.8±0.5	83.6±0.7	**84.8**±0.3	95.7±0.2	98.9±0.6	86.2±0.8	**87.8**±0.4	93.4±0.3	98.9±0.7
OxfordPets	**65.4**±0.7	9.3±0.4	62.9±0.1	87.2±0.6	87.8±0.5	76.2±0.6	**76.4**±0.2	90.4±0.3	91.9±0.4	**78.9**±0.8	76.8±0.6	93.6±0.4	90.1±0.9
StanfordCars	**4.5**±0.1	0.9±0.1	2.7±0.1	33.8±0.2	81.0±0.1	**4.7**±0.2	4.2±0.3	40.6±0.1	86.4±0.3	**7.0**±0.2	4.6±0.1	64.7±0.1	92.5±0.2
SUN397	**13.0**±0.2	1.0±0.1	10.4±0.1	46.1±0.2	53.2±0.2	**20.3**±0.2	19.8±0.1	53.5±0.1	59.0±0.1	**23.7**±0.2	21.6±0.3	62.3±0.1	61.0±0.2
CIFAR10	65.5±0.1	63.0±0.1	**65.7**±0.6	85.9±0.5	96.5±0.4	**76.6**±0.3	74.8±0.5	90.1±0.1	96.6±0.2	**81.7**±0.3	80.3±0.3	94.1±0.1	97.1±0.1
CIFAR100	**24.8**±0.1	12.9±0.1	18.1±0.2	63.3±0.8	82.5±1.2	**38.9**±0.3	32.0±0.4	70.7±0.7	83.4±0.9	**45.9**±0.2	39.7±0.2	76.2±0.9	84.6±1.2
SVHN	**75.2**±0.2	73.5±0.3	73.1±0.2	65.0±0.2	96.5±0.3	**75.8**±0.4	75.6±0.2	63.5±0.2	96.9±0.3	**81.4**±0.1	79.0±0.5	51.0±0.2	97.1±0.3
ABIDE	**76.9**±2.1	74.0±2.2	73.1±1.6	65.4±3.8	60.6±4.2	63.5±2.2	**64.4**±3.4	55.8±2.6	70.2±2.5	**67.3**±2.6	65.7±3.4	54.8±3.4	73.1±4.2

Table 1. (Main Results) Performance overview of ILM-VP, prompt baseline methods (RLM-VP and FLM-VP), and finetuning methods (LP and FF) over 13 target image classification datasets using 3 pretrained source models.

Target Dataset Analysis

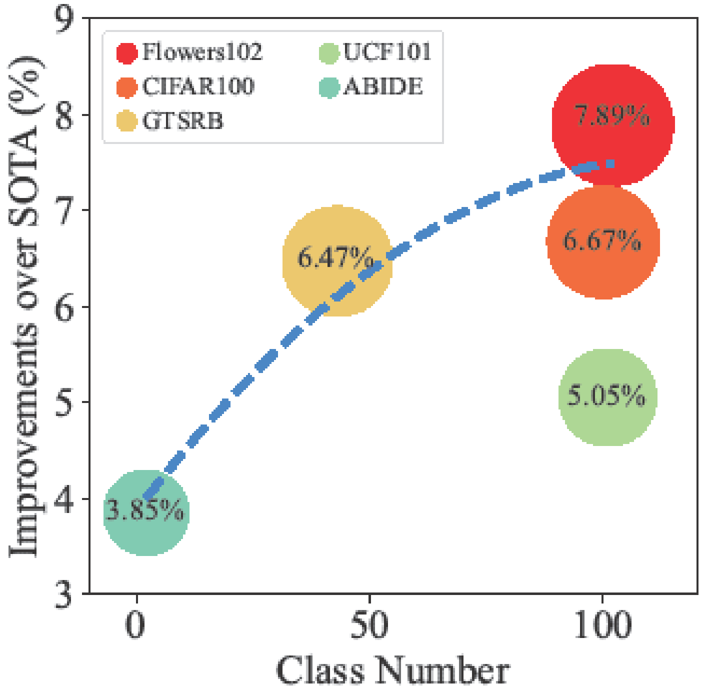


Figure 2. ILM-VP's improvements over FLM-VP on representative datasets (datasets with improvements over 3%) using ResNet-18.

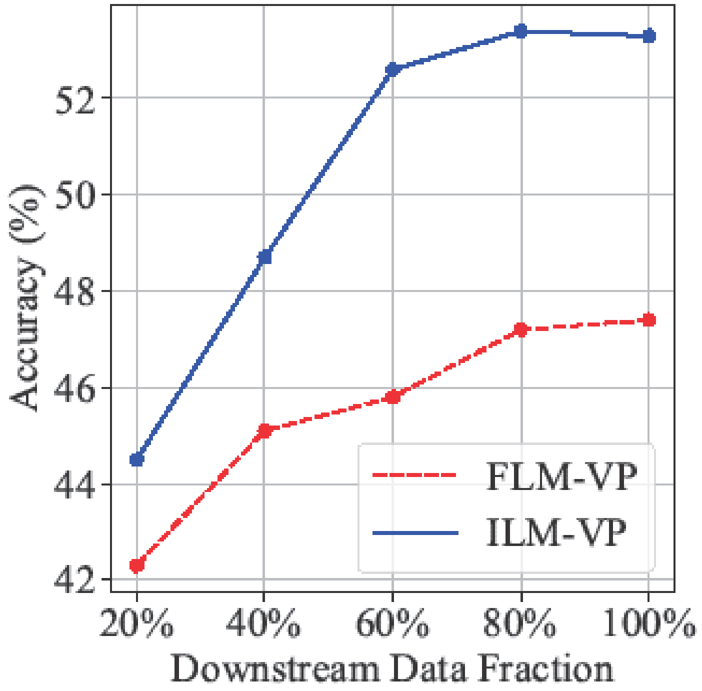
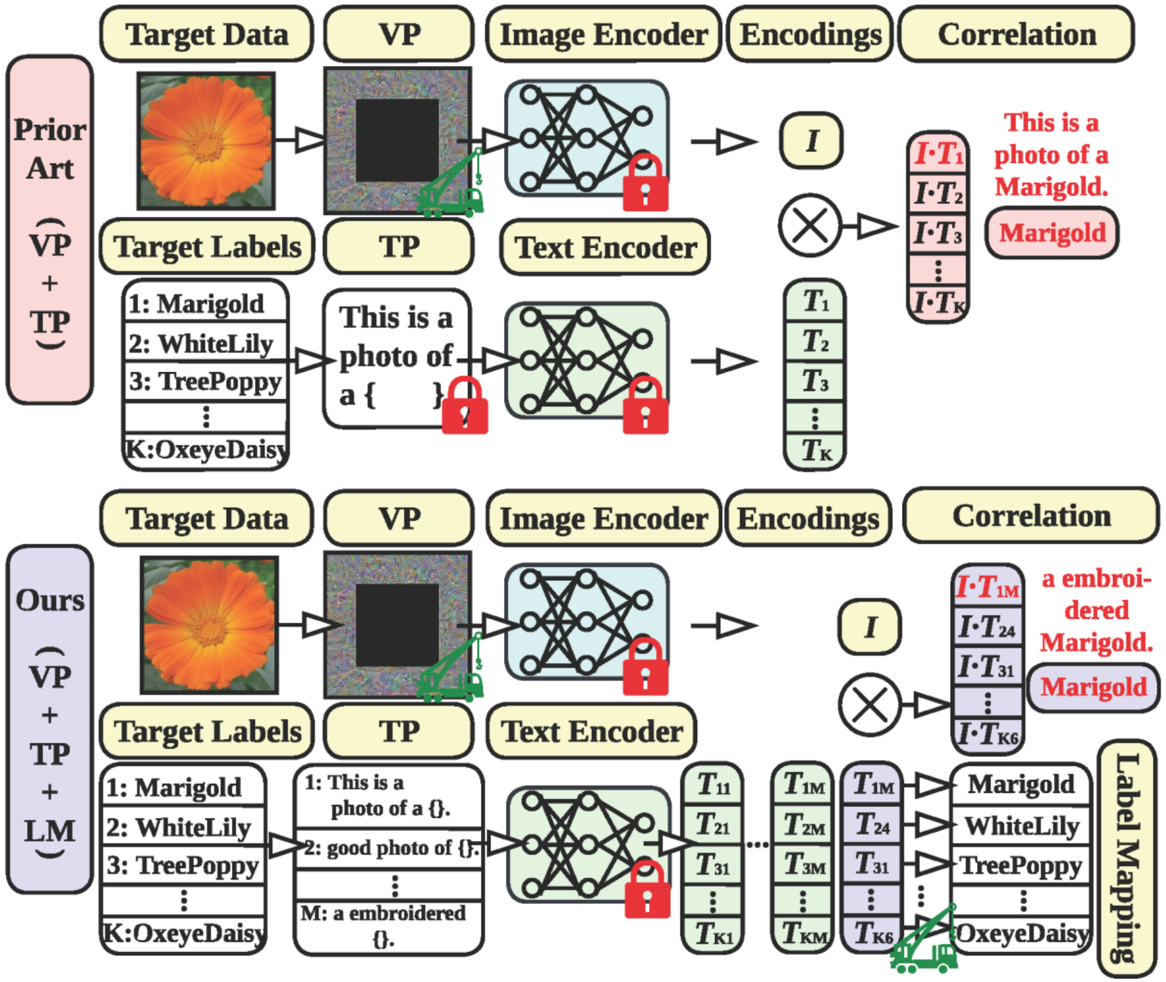


Figure 3. ILM-VP and FLM-VP performance on different fractions of GTSRB dataset (43 classes and more than 900 training samples per class) using ResNet-18.

Extension: LM in Text Domain for CLIP



Extension: LM in Text Domain for CLIP

Methods	VP+TP Acc(%)	Ours (VP+TP+LM) Acc(%)	Ours (VP+TP+LM) Examples of context prompt template → target label
Flowers102	70.0	**83.7**	a close-up photo of a {} → buttercup
DTD	56.8	**63.9**	graffiti of a {} → blotchy
UCF101	66.0	**70.6**	a {} in a video game → baseball pitch
Food101	78.9	**79.1**	a photo of the dirty {} → crab cake
SVHN	89.9	**91.2**	a photo of a {} → 7
EuroSAT	96.4	**96.9**	a pixelated photo of a {} → river
StanfordCars	57.2	**57.6**	the toy {} → 2011 audi s6 sedan
SUN397	60.5	**61.2**	a photo of a large {} → archive
CIFAR10	93.9	**94.4**	a pixelated photo of a {} → ship
ImageNet-R	67.5	**68.6**	a rendition of a {} → gold fish
ImageNet-Sketch	38.5	**39.7**	a sketch of a {} → eagle

Table 2. Results of CLIP-based prompt learning 'VP+TP+LM' and the baseline 'VP+TP' (restricted to using text prompt template "This is a photo of a {}") over 11 target datasets.

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More Explanation Examples

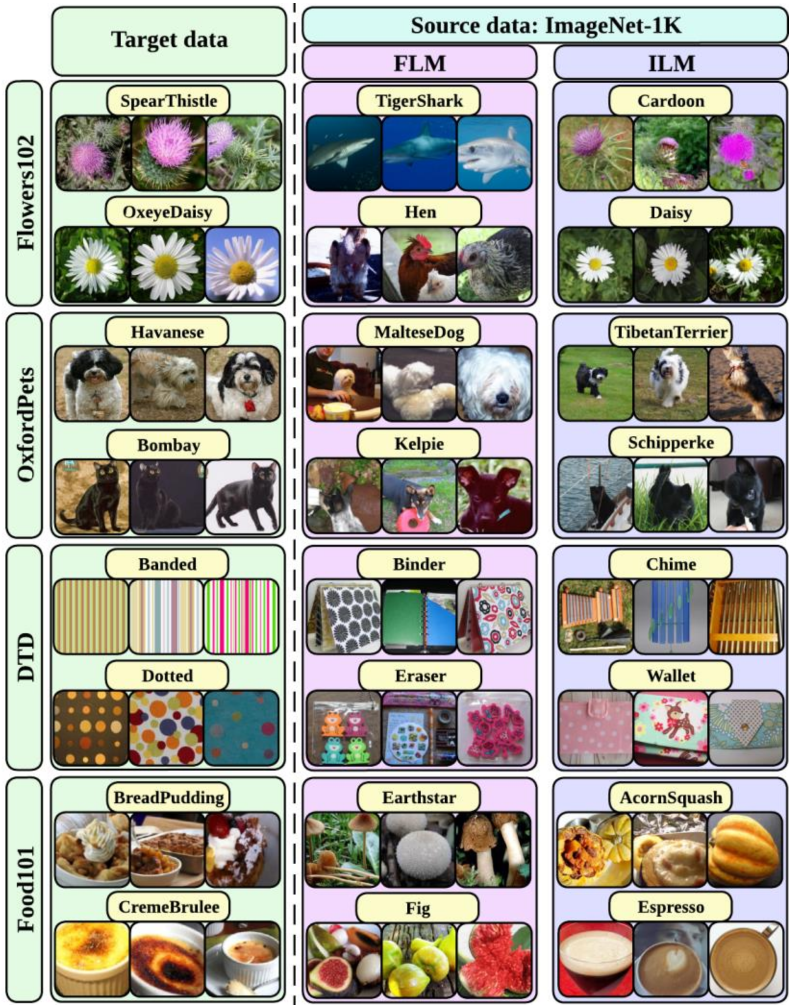

Figure 4. Interpretation merit of ILM vs. FLM, visualized by LM results in VP to re-purpose a ResNet-18 to conduct image classification tasks.

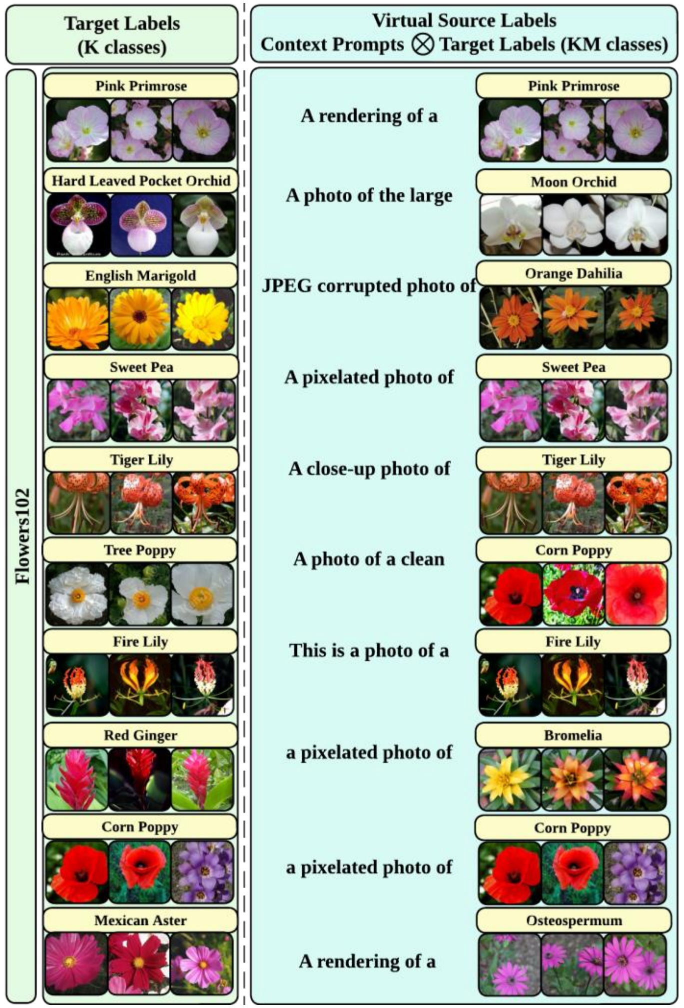

Figure 5. LM results of our proposed 'VP+TP+LM' method for CLIP, which shows significant interpretability.

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dank u