视觉提示学习研究进展
Vision Prompt Tuning Learning

分享人：高逸凡

2023.06.12

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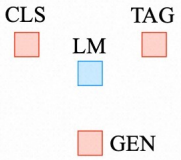
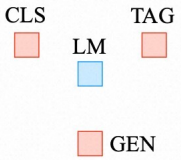
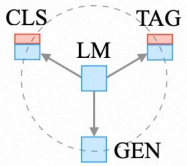
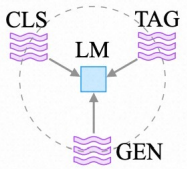
研究背景

- Prompt Learning
  - NLP中的四大范式

Paradigm	Engineering	Task Relation
a. Fully Supervised Learning (Non-Neural Network)	Features (e.g. word identity, part-of-speech, sentence length)	
b. Fully Supervised Learning (Neural Network)	Architecture (e.g. convolutional, recurrent, self-attentional)	
c. Pre-train, Fine-tune	Objective (e.g. masked language modeling, next sentence prediction)	
d. Pre-train, Prompt, Predict	Prompt (e.g. cloze, prefix)	

研究背景

- Prompt Learning
  - 什么是Prompt Learning?

Name	Notation	Example	Description
Input	$\boldsymbol{x}$	I love this movie.	One or multiple texts
Output	$\boldsymbol{y}$	++ (very positive)	Output label or text
Prompting Function	$f_{\text{prompt}}(\boldsymbol{x})$	`[X]` Overall, it was a `[Z]` movie.	A function that converts the input into a specific form by inserting the input $\boldsymbol{x}$ and adding a slot `[Z]` where answer $\boldsymbol{z}$ may be filled later.
Prompt	$\boldsymbol{x}'$	I love this movie. Overall, it was a `[Z]` movie.	A text where `[X]` is instantiated by input $\boldsymbol{x}$ but answer slot `[Z]` is not.
Filled Prompt	$f_{\text{fill}}(\boldsymbol{x}', \boldsymbol{z})$	I love this movie. Overall, it was a bad movie.	A prompt where slot `[Z]` is filled with any answer.
Answered Prompt	$f_{\text{fill}}(\boldsymbol{x}', \boldsymbol{z}^*)$	I love this movie. Overall, it was a good movie.	A prompt where slot `[Z]` is filled with a true answer.
Answer	$\boldsymbol{z}$	"good", "fantastic", "boring"	A token, phrase, or sentence that fills `[Z]`

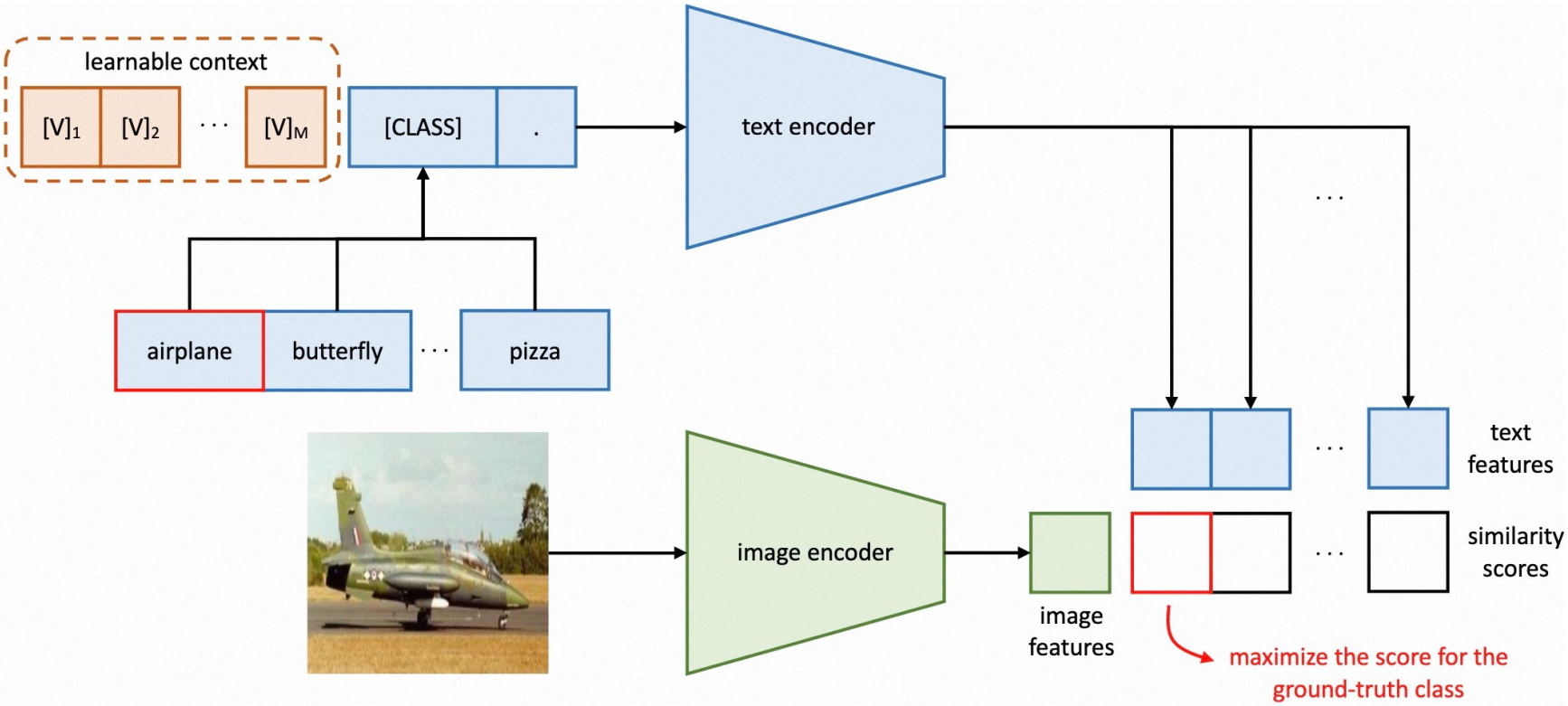
研究背景

- Prompt Learning
  - NLP中Prompt用于不同的下游任务

Type	Task	Input ([X])	Template	Answer ([Z])
Text CLS	Sentiment	I love this movie.	[X] The movie is [Z].	great fantastic ...
	Topics	He prompted the LM.	[X] The text is about [Z].	sports science ...
	Intention	What is taxi fare to Denver?	[X] The question is about [Z].	quantity city ...
Text-span CLS	Aspect Sentiment	Poor service but good food.	[X] What about service? [Z].	Bad Terrible ...
Text-pair CLS	NLI	[X1]: An old man with ... [X2]: A man walks ...	[X1]? [Z], [X2]	Yes No ...
Tagging	NER	[X1]: Mike went to Paris. [X2]: Paris	[X1][X2] is a [Z] entity.	organization location ...
Text Generation	Summarization	Las Vegas police ...	[X] TL;DR: [Z]	The victim ... A woman ... ...
	Translation	Je vous aime.	French: [X] English: [Z]	I love you. I fancy you. ...

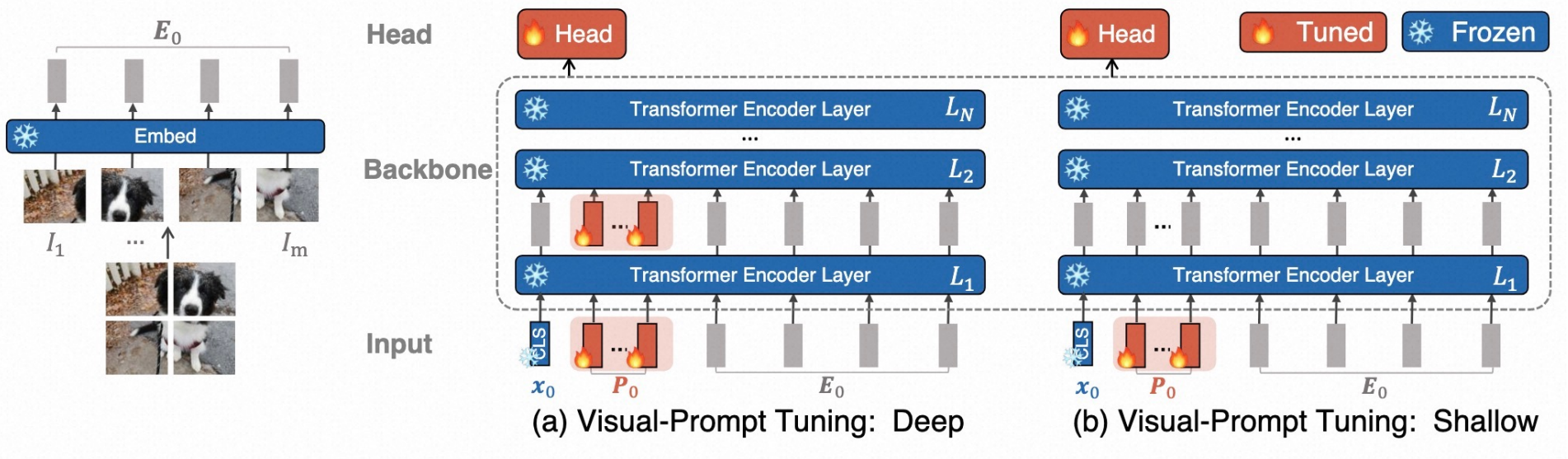
研究背景

- Prompt Learning in CV
  - VLM with PL
    - CoOp (IJCV 2022)、CoCoOp(CVPR 2022)



研究背景

- Prompt Learning in CV
  - VM with PL
    - VPT（ECCV 2022）



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- CLIP-ReID
- LPT
- 实验效果
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CLIP-ReID

CLIP-ReID: Exploiting Vision-Language Model for Image Re-Identification without Concrete Text Labels

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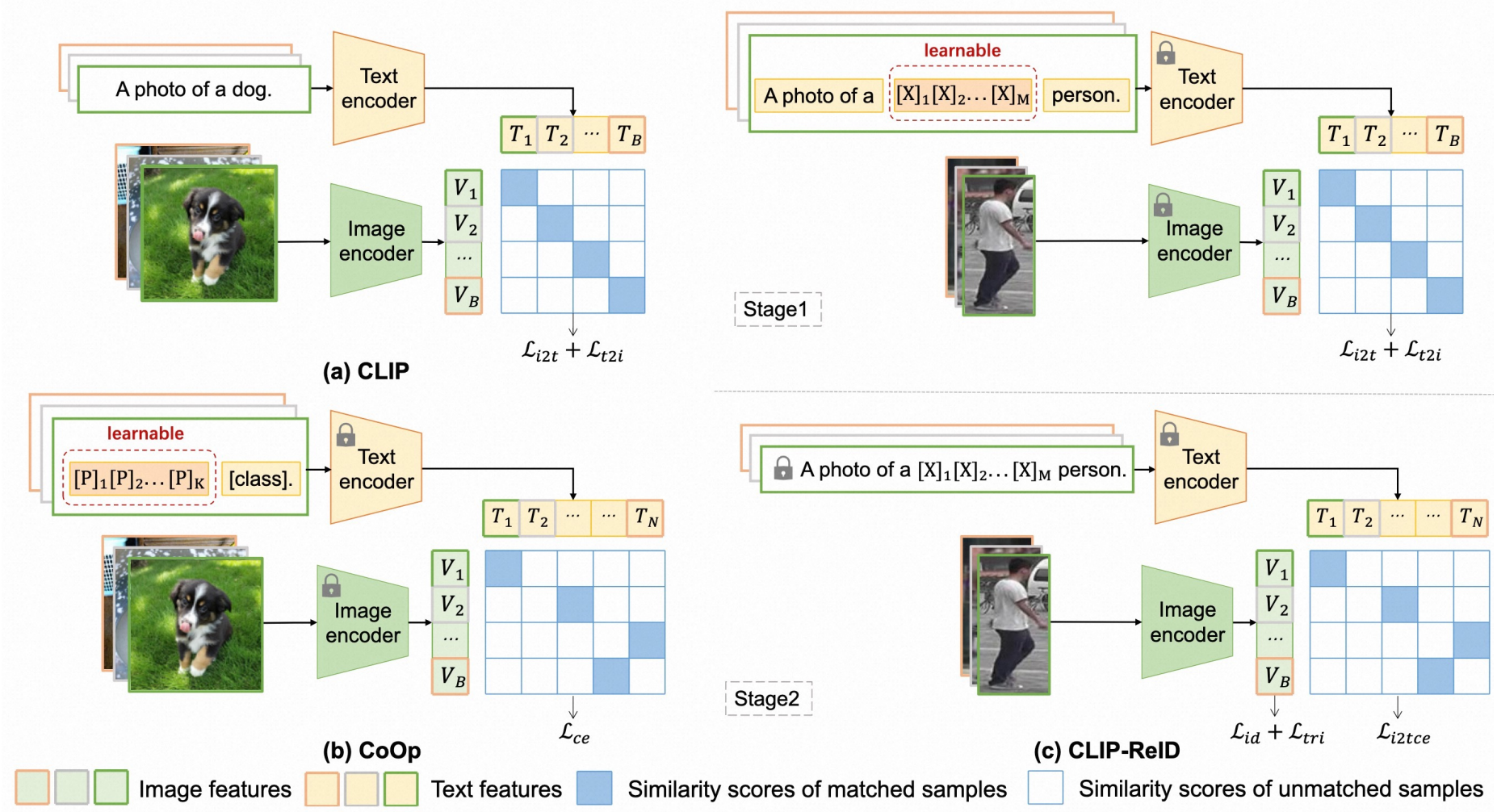
AAAI2023

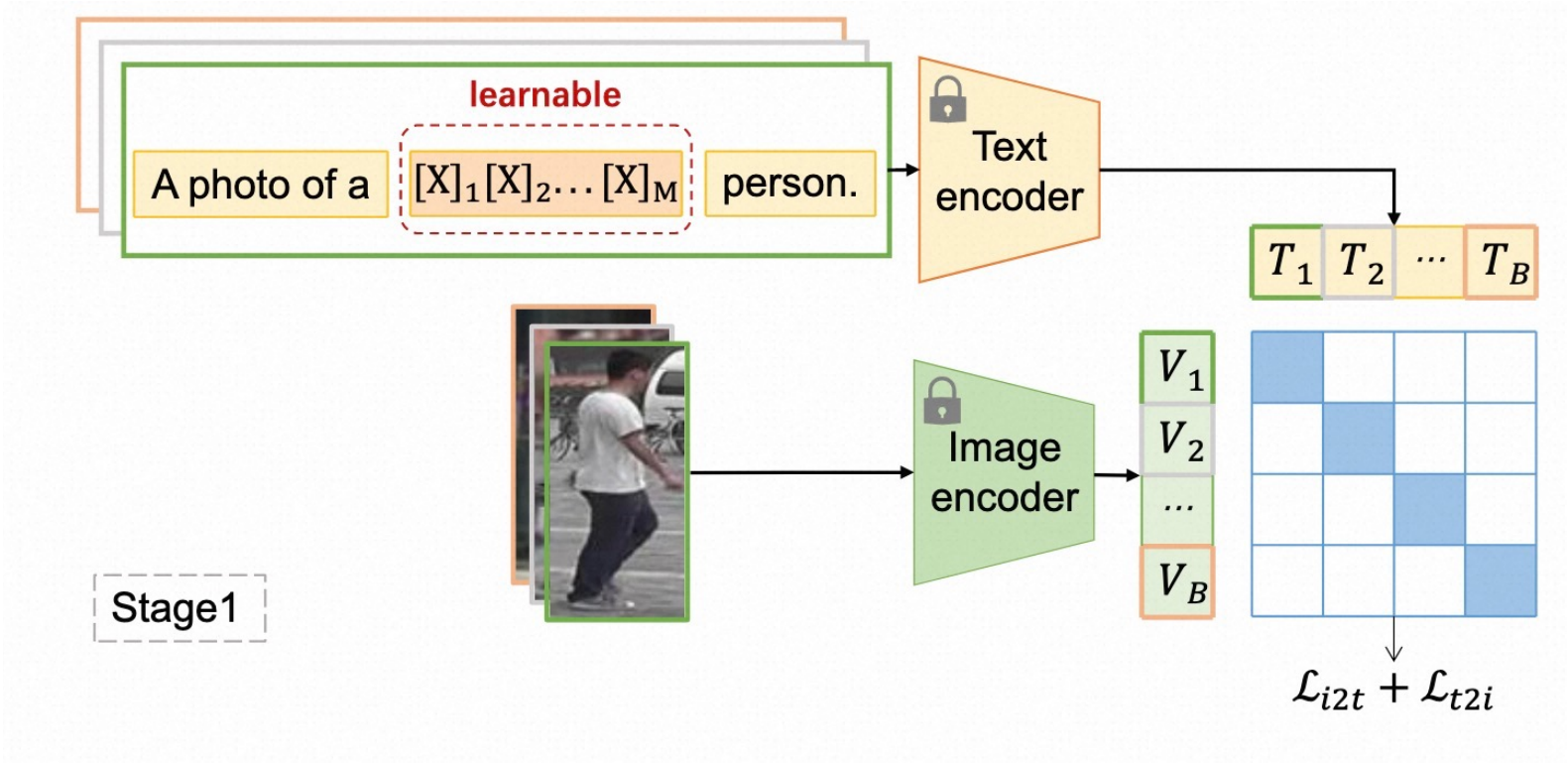
CLIP-ReID

- 方法


A photo of a dog.
Text encoder
Image encoder
T_1 T_2 ··· T_B
V_1 V_2 ... V_B
$\mathcal{L}_{i2t} + \mathcal{L}_{t2i}$
(a) CLIP
learnable
A photo of a $[X]_1[X]_2 \ldots [X]_M$ person.
Stage1
$\mathcal{L}_{i2t} + \mathcal{L}_{t2i}$
learnable
$[P]_1[P]_2 \ldots [P]_K$ [class].
T_1 T_2 ··· ··· T_N
$\mathcal{L}_{ce}$
(b) CoOp
A photo of a $[X]_1[X]_2 \ldots [X]_M$ person.
Stage2
$\mathcal{L}_{id} + \mathcal{L}_{tri}$
$\mathcal{L}_{i2tce}$
(c) CLIP-ReID
Image features
Text features
Similarity scores of matched samples
Similarity scores of unmatched samples

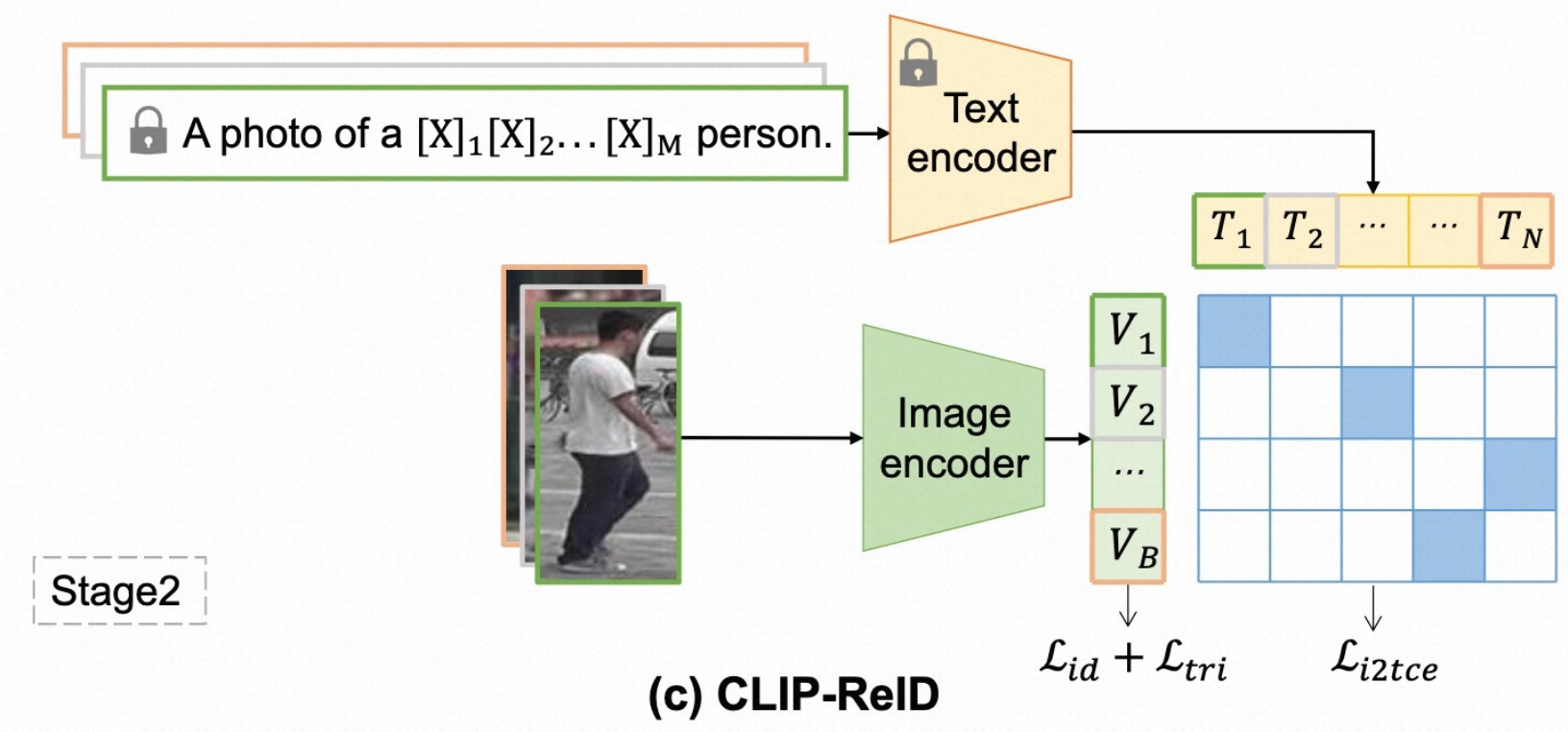
CLIP-ReID

- 第一阶段
  - Learn prompt



CLIP-ReID

- 第二阶段
  - Fine-tune Image Encoder



(c) CLIP-ReID

CLIP-ReID

- Person

Backbone	Methods	References	MSMT17		Market-1501		DukeMTMC		Occluded-Duke	
			mAP	R1	mAP	R1	mAP	R1	mAP	R1
CNN	PCB*	ECCV (2018)	-	-	81.6	93.8	69.2	83.3	-	-
	MGN*	MM (2018)	-	-	86.9	95.7	78.4	88.7	-	-
	OSNeT	ICCV (2019)	52.9	78.7	84.9	94.8	73.5	88.6	-	-
	ABD-Net*	ICCV (2019)	60.8	82.3	88.3	95.6	78.6	89.0	-	-
	Auto-ReID*	ICCV (2019)	52.5	78.2	85.1	94.5	-	-	-	-
	HOReID	CVPR (2020)	-	-	84.9	94.2	75.6	86.9	43.8	55.1
	ISP	ECCV (2020)	-	-	88.6	95.3	80.0	89.6	52.3	62.8
	SAN	AAAI (2020b)	55.7	79.2	88.0	**96.1**	75.5	87.9	-	-
	OfM	AAAI (2021a)	54.7	78.4	87.9	94.9	78.6	89.0	-	-
	CDNet	CVPR (2021)	54.7	78.9	86.0	95.1	76.8	88.6	-	-
	PAT	CVPR (2021b)	-	-	88.0	95.4	78.2	88.8	**53.6**	**64.5**
	CAL*	ICCV (2021)	56.2	79.5	87.0	94.5	76.4	87.2	-	-
	CBDB-Net*	TCSVT (2021)	-	-	85.0	94.4	74.3	87.7	38.9	50.9
	ALDER*	TIP (2021b)	59.1	82.5	88.9	95.6	78.9	89.9	-	-
	LTReID*	TMM (2022)	58.6	81.0	89.0	95.9	80.4	**90.5**	-	-
	DRL-Net	TMM (2022)	55.3	78.4	86.9	94.7	76.6	88.1	50.8	65.0
	baseline		60.7	82.1	88.1	94.7	79.3	88.6	47.4	54.2
	CLIP-ReID		**63.0**	**84.4**	**89.8**	95.7	**80.7**	90.0	53.5	61.0
ViT	AAformer*	arxiv (2021)	63.2	83.6	87.7	95.4	80.0	90.1	58.2	67.0
	TransReID+SIE+OLP	ICCV (2021)	67.4	85.3	88.9	95.2	82.0	90.7	59.2	66.4
	TransReID+SIE+OLP*		69.4	86.2	89.5	95.2	82.6	90.7	-	-
	DCAL	CVPR (2022)	64.0	83.1	87.5	94.7	80.1	89.0	-	-
	baseline		66.1	84.4	86.4	93.3	80.0	88.8	53.5	60.8
	CLIP-ReID		**73.4**	**88.7**	**89.6**	**95.5**	82.5	90.0	**59.5**	**67.1**
	CLIP-ReID+SIE+OLP		**75.8**	**89.7**	**90.5**	**95.4**	**83.1**	**90.8**	**60.3**	**67.2**

CLIP-ReID

- Car

Back-bone	Methods	VeRi-776		VehicleID	
		mAP	R1	R1	R5
CNN	PRN (2019)	74.3	94.3	78.4	92.3
	PGAN (2019)	79.3	96.5	77.8	92.1
	SAN (2020)	72.5	93.3	79.7	94.3
	UMTS (2020a)	75.9	95.8	80.9	-
	SPAN (2020)	68.9	94.0	-	-
	PVEN (2020)	79.5	95.6	84.7	97.0
	SAVER (2020)	79.6	96.4	79.9	95.2
	CFVMNet (2020)	77.1	95.3	81.4	94.1
	CAL (2021)	74.3	95.4	82.5	94.7
	EIA-Net (2018)	79.3	95.7	84.1	96.5
	FIDI (2021)	77.6	95.7	78.5	91.9
	baseline	79.3	95.7	84.4	96.6
	CLIP-ReID	**80.3**	**96.8**	**85.2**	**97.1**
ViT	TransReID (2021)	80.6	96.9	83.6	97.1
	TransReID!	82.0	97.1	85.2	97.5
	DCAL (2022)	80.2	96.9	-	-
	baseline	79.3	95.7	84.2	96.6
	CLIP-ReID	**83.3**	**97.4**	**85.3**	**97.6**
	CLIP-ReID!	**84.5**	**97.3**	**85.5**	97.2

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LPT

LPT: Long-tailed Prompt Tuning for Image Classification

Bowen Dong[1] **Pan Zhou**[2] **Shuicheng Yan**[2] **Wangmeng Zuo**[1,3]✉
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LPT

- 研究动机
  - 1）VPT帮助对齐数据分布 2）VPT提高模型判别性

Table 1: Prompt tuning results on Places-LT (Zhou et al., 2017a). Prompt tuning achieves better accuracy on all classes and tail classes (*i.e.* "Few" in the table) with different training settings.

Method	Balanced Sampling	Tuned Params (w/o classifier)	Overall	Many	Medium	Few
Linear	-	0	33.29%	46.48%	29.45%	18.77%
VPT	-	92K	**37.52%**	**50.42%**	**32.78%**	**23.29%**
Linear	✓	0	41.33%	**49.47%**	41.31%	27.51%
VPT	✓	92K	**44.17%**	45.79%	**46.73%**	**36.18%**

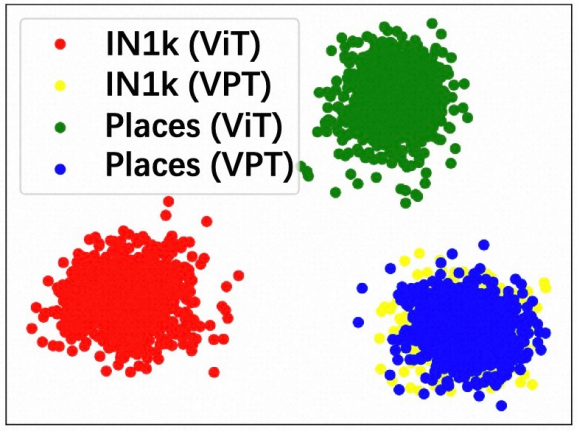


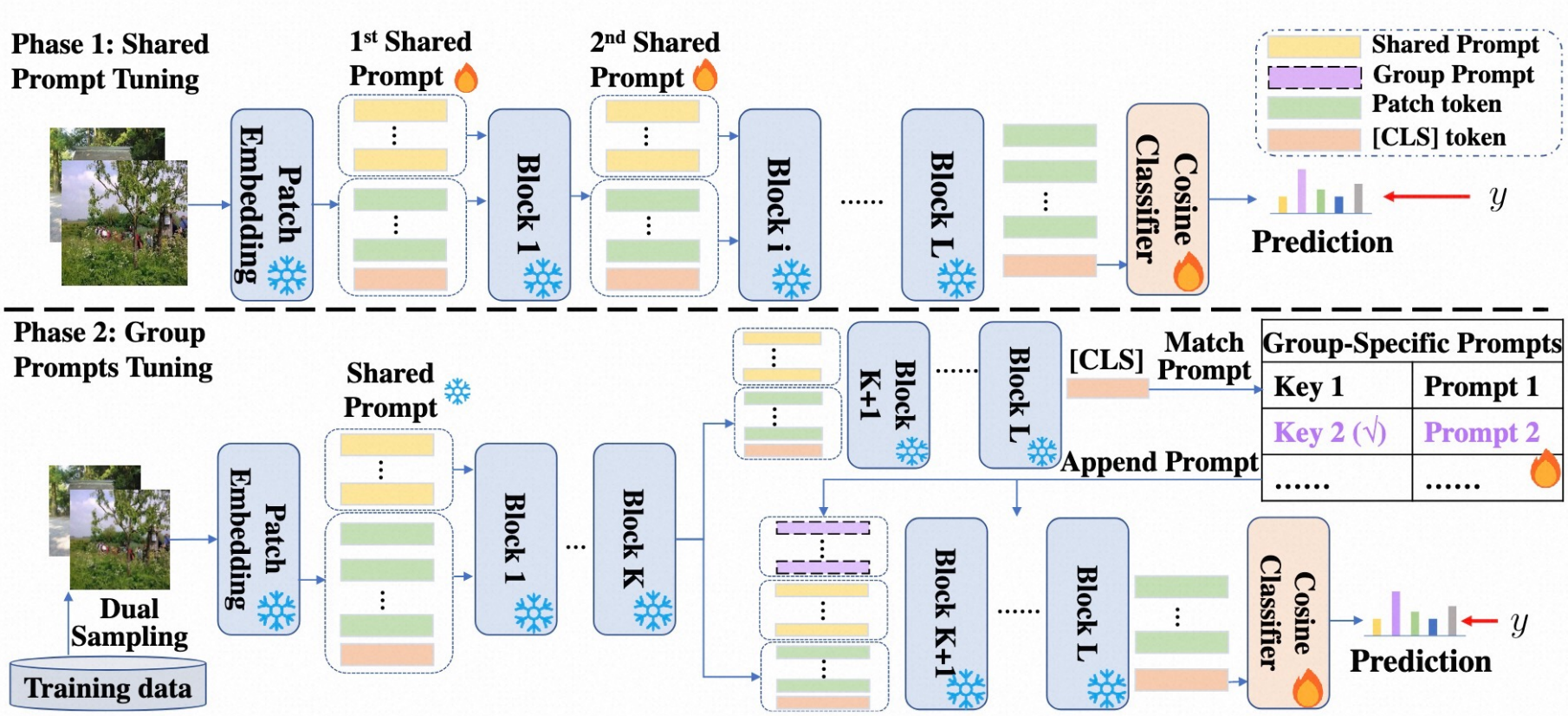
Figure 2: LDA visualization of VPT.

Table 2: Quantitative analysis of features learned by pretrained ViT-B and VPT. Features from VPT obtain better discriminative ability in terms of cluster compactness and also KNN accuracy.

Method	ViT-B	VPT
Pretrain Data	IN21k	IN21k
Fine-tuned	-	✓
Inner-class distance R_i	2.36±0.52	**1.82±0.43**
Inner-class / inter-class γ	0.171	**0.128**
K-NN Acc	30.80%	**31.90%**

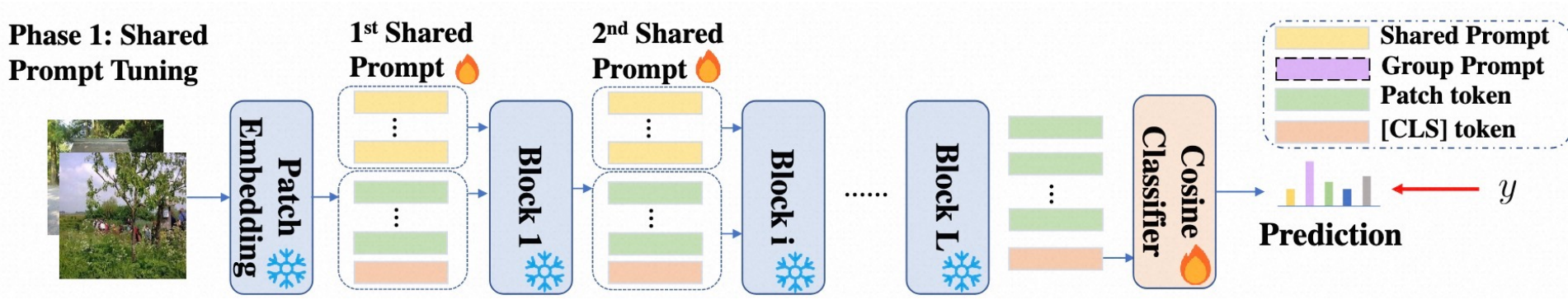
LPT

- 方法


Phase 1: Shared Prompt Tuning
1st Shared Prompt
2nd Shared Prompt
Patch Embedding
Block 1
Block i
Block L
Cosine Classifier
Shared Prompt
Group Prompt
Patch token
[CLS] token
Prediction
y
Phase 2: Group Prompts Tuning
Shared Prompt
Block K
Block K+1
[CLS]
Match Prompt
Append Prompt
Group-Specific Prompts
Key 1
Prompt 1
Key 2 (√)
Prompt 2
Dual Sampling
Training data

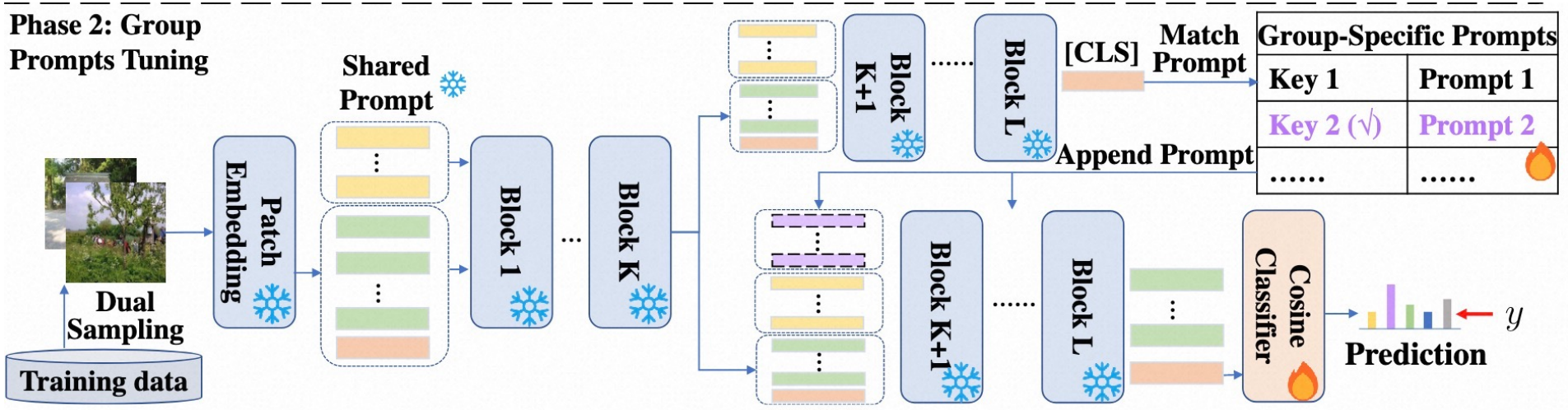
LPT

- 第一阶段


Phase 1: Shared Prompt Tuning
1st Shared Prompt
2nd Shared Prompt
Patch Embedding
Block 1
Block i
Block L
Cosine Classifier
Shared Prompt
Group Prompt
Patch token
[CLS] token
Prediction
y

LPT

- 第二阶段



$$\text{prompts } \mathcal{R} = \{(\mathbf{k}_1, \mathbf{r}^1), \ldots, (\mathbf{k}_m, \mathbf{r}^m)\}$$

$$[w_1, \ldots, w_k] = \text{top-k}(\langle \mathbf{q}, [\mathbf{k}_1, \ldots, \mathbf{k}_m] \rangle, k)$$

$$\mathbf{r} = \text{sum}([\mathbf{r}^{w_1}, \ldots, \mathbf{r}^{w_k}])/k,$$

$$\mathcal{L}_{P_2} = \beta \mathcal{L}_{\text{cls}}(\hat{\mathbf{s}}, \mathbf{y}) + (1 - \frac{1}{k} \sum_{i \in \mathbf{w}} \langle \mathbf{q}, \mathbf{k}_i \rangle),$$

LPT

- 对比实验 on Places-LT.

Table 3: Comparison with state-of-the-art long-tailed classification methods on Places-LT dataset (Zhou et al., 2017a). Our LPT achieves state-of-the-art performance among vision-only pretrained methods and achieves the same performance with state-of-the-art VL-based methods.

Method	Backbone	Tuned Params	Total Params	Extra Data (Inference)	Overall	Many	Medium	Few
Vision-only Pretrained								
OLTR (Liu et al., 2019)	Res152	60.34M	60.34M	-	35.9	44.7	37.0	25.3
TADE (Zhang et al., 2021a)	Res152	60.34M	60.34M	-	38.8	42.8	39.0	31.2
LWS (Kang et al., 2020)	Res152	60.34M	60.34M	-	37.6	40.6	39.1	28.6
MisLAS (Zhong et al., 2021)	Res152	60.34M	60.34M	-	40.4	39.6	43.3	36.1
ALA (Zhao et al., 2022)	Res152	60.34M	60.34M	-	40.1	43.9	40.1	32.9
PaCo (Cui et al., 2021)	Res152	60.34M	60.34M	-	41.2	36.1	47.9	35.3
VPT (Jia et al., 2022)	ViT-B	**0.09M**	86.66M	-	37.5	**50.4**	33.8	23.3
LPT (Ours)	ViT-B	**1.01M**	87.58M	-	**50.1**	49.3	**52.3**	**46.9**
Vision-Languge Pretrained with Extra Data								
RAC (Long et al., 2022)	ViT-B	86.57M	236.19M	IN21k Feat	47.2	48.7	48.3	41.8
BALLAD (Ma et al., 2021)	ViT-B	149.62M	149.62M	-	49.5	49.3	**50.2**	**48.4**
VL-LTR (Tian et al., 2022)	ViT-B	149.62M	149.62M	Wiki Text	**50.1**	**54.2**	48.5	42.0

LPT

- 对比实验 on CIFAR100-LT and iNaturalist 2018

Table 4: Comparison with state-of-the-art methods on CIFAR100-LT with various imbalanced ratio τ. LPT performs best among all methods.

Imb Ratio τ	200	100	50	10
Training from Scratch				
PaCo	-	52.0	56.0	64.2
Zhu et al. (2022)	-	51.9	56.6	64.9
Li et al. (2022)	44.9	48.7	53.6	-
Vision-only Pretrained				
VPT	72.8	81.0	84.8	89.6
LPT (Ours)	**87.9**	**89.1**	**90.0**	**91.0**
VL Pretrained with Extra Data				
Ma et al. (2021)	-	77.8	-	-

Table 5: Comparison with state-of-the-art methods on iNaturalist 2018. LPT performs best among vision-only pretrained methods.

Method	Overall	Few-shot
Vision-only Pretrained		
TADE	72.9	-
PaCo	75.2	74.7
ViT-B/16	73.2	-
Iscen et al. (2021)	75.3	73.2
ViT-L/16	75.9	-
LPT (Ours)	**76.1**	**79.3**
VL Pretrained with Extra Data		
VL-LTR	76.8	-
RAC	**80.2**	**81.0**

LPT

- 消融实验

Table 6: ImageNet-Sketch evaluation results from different fine-tuning methods.

Method	Backbone	Overall
Linear Probe	ViT-B	31.55%
Full fine-tune	ViT-B	32.25%
LPT (Ours)	ViT-B	**36.22%**

Table 8: Ablation study of each phase in LPT on Places-LT benchmark (Zhou et al., 2017a).

Method	Prompt	Phase 1	$\mathcal{L}_{\text{A-GCL}}$	Phase 2	Overall	Many	Medium	Few
Linear	-	-	-	-	33.29%	46.48%	29.45%	18.77%
VPT	✓	-	-	-	37.52%	**50.42%**	33.78%	23.29%
(a)	-	✓	-	-	41.33%	49.47%	41.31%	27.51%
(b)	✓	✓	-	-	49.10%	**49.62%**	51.53%	43.25%
(c)	✓	✓	✓	-	**49.41%**	46.89%	**52.54%**	**47.32%**
(d)	✓	✓	✓	✓	**50.07%**	49.27%	**52.31%**	**46.88%**

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总结反思

- PL在不同子任务上的应用有一定研究价值

Thank for your attention !