MMA : Multi-Modal Adapter for Vision-Language Models

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Paper Review

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>> Contents

>> Overview

- VLMs are powerful, but adapting them to downstream tasks is challenging
- This led to the emergence of PET (Parameter-Efficient Tuning), including prompt learning and adapter tuning (Representative methods include CoOp/CoCoOp/Clip-Adapter)

- However, prompt learning only modifies the text branch, and adapter methods mainly adjust the vision branch
- As a result, they lack effective cross-modal alignment
- **To address this, MMA (Multi-modal Adapter) is proposed**

>> Introduction

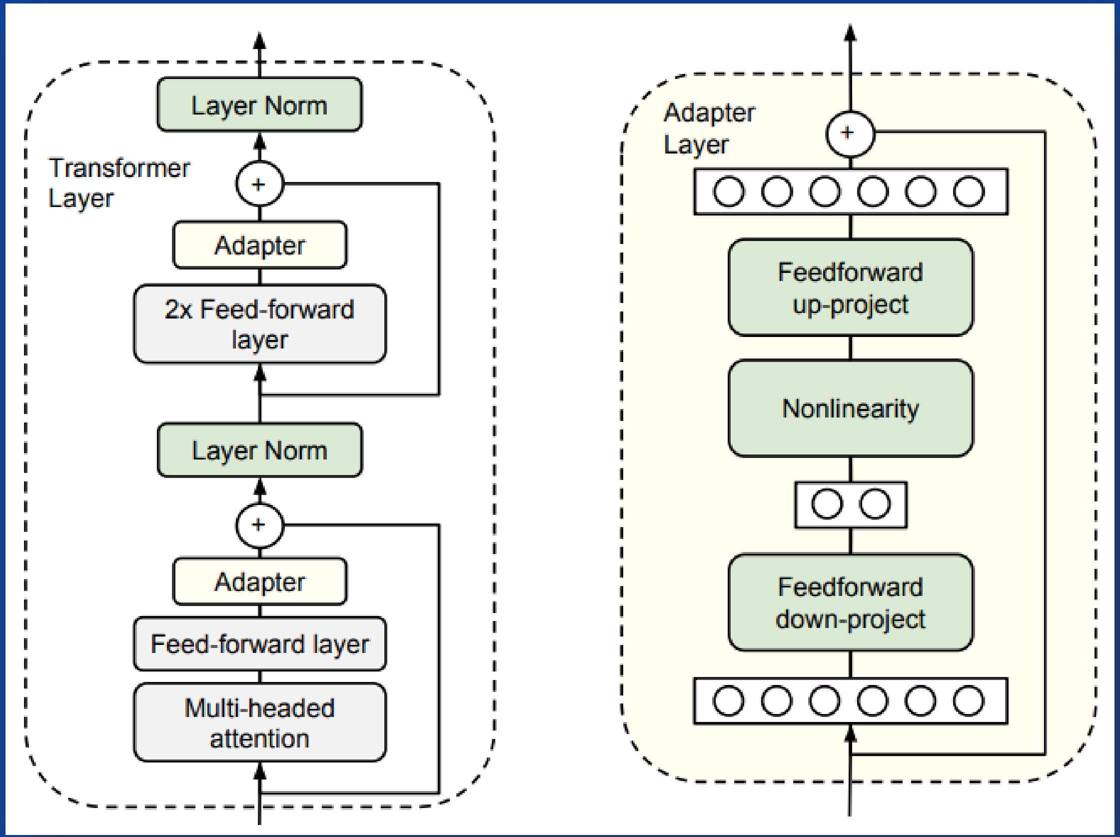
❑ Background

✓ Parameter-Efficient Tuning(PET)

- Large-scale VLMs (e.g., CLIP) are powerful but hard to adapt due to size
- Full fine-tuning is costly and prone to overfitting in few-shot setups
- PET = Adapting large models using few additional parameters

✓ Two main PET paradigms:

- Prompt Learning (e.g., CoOp, CoCoOp)
- Adapter Tuning (e.g., Clip-Adapter, Tip-Adapter)



[Parameter-Efficient Transfer Learning for NLP (Houlsby et al., 2019)]

>> Introduction

- ❑ **Background**
- ✓ **Prompt Learning**
- ✓ **CoOP**(Context Optimization)

Flowers102

Prompt	Accuracy
a photo of a [CLASS].	60.86
a flower photo of a [CLASS].	65.81
a photo of a [CLASS], a type of flower.	66.14
$[V]_1\ [V]_2 \ldots [V]_M$ [CLASS].	**94.51**

- ✓ **CoCoOP**(Conditional CoOP)

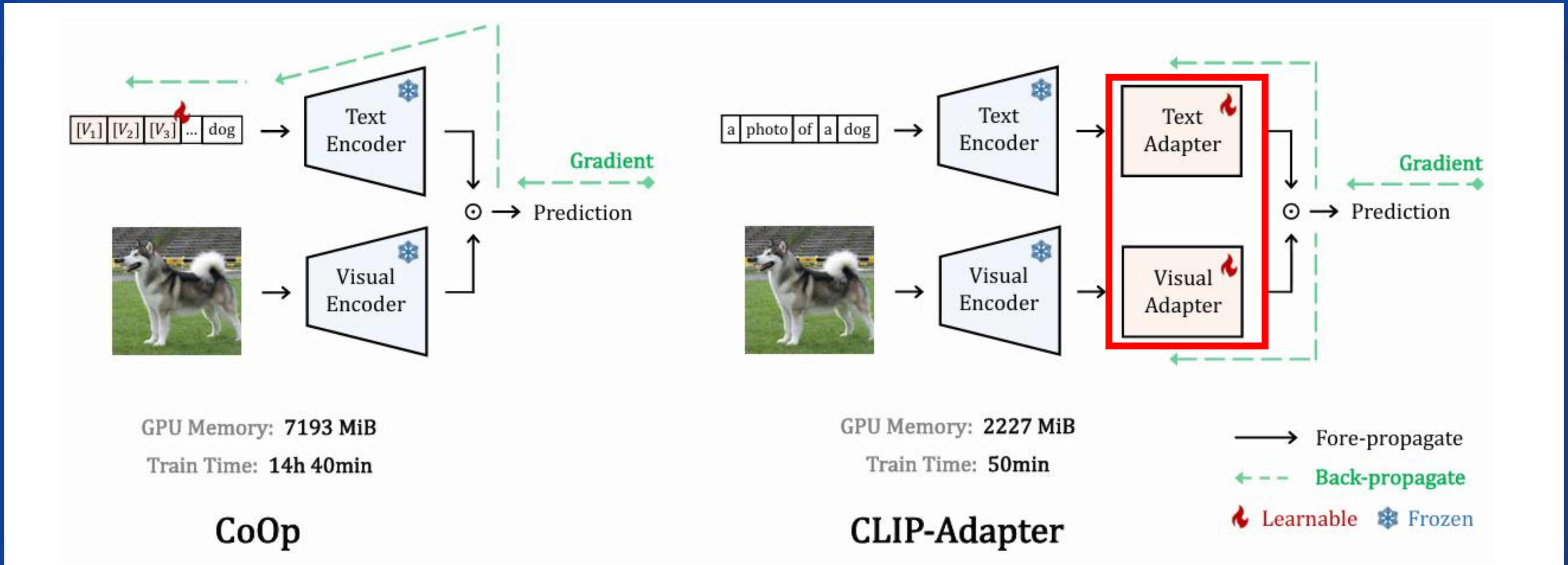
CoOp	CoCoOp
$[\boldsymbol{v}_1]\ [\boldsymbol{v}_2]\ \ldots\ [\boldsymbol{v}_M]$ [arrival gate].	$[\boldsymbol{v}_1(\boldsymbol{x})]\ [\boldsymbol{v}_2(\boldsymbol{x})]\ \ldots\ [\boldsymbol{v}_M(\boldsymbol{x})]$ [arrival gate].
$\vdots$	$\vdots$
$[\boldsymbol{v}_1]\ [\boldsymbol{v}_2]\ \ldots\ [\boldsymbol{v}_M]$ [cathedral].	$[\boldsymbol{v}_1(\boldsymbol{x})]\ [\boldsymbol{v}_2(\boldsymbol{x})]\ \ldots\ [\boldsymbol{v}_M(\boldsymbol{x})]$ [cathedral].

>> Introduction

❑ Background

✓ Adapter Tuning - CLIP Adapter

- CLIP-Adapter adds lightweight adapters after frozen CLIP encoders for both vision and text
- This method avoids backpropagation through the entire model, reducing memory and time costs
- Adapter tuning is efficient and maintains good performance with minimal training



GAO, Peng, et al. Clip-adapter: Better vision-language models with feature adapters. International Journal of Computer Vision, 2024, 132.2: 581-595.

>> Introduction

❑ Related Works

✓ Efficient Transfer Learning for VLMs

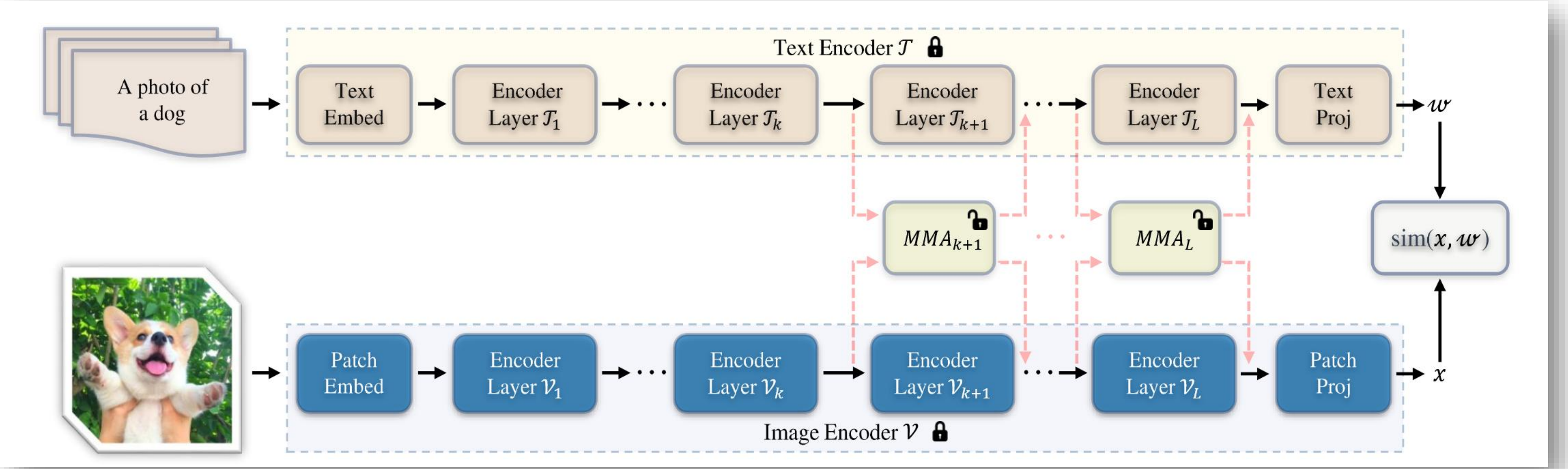
Full fine-tuning increases computational cost↑, risks overfitting

Parameter-efficient tuning

- Generalization ↓
  - uni-modal

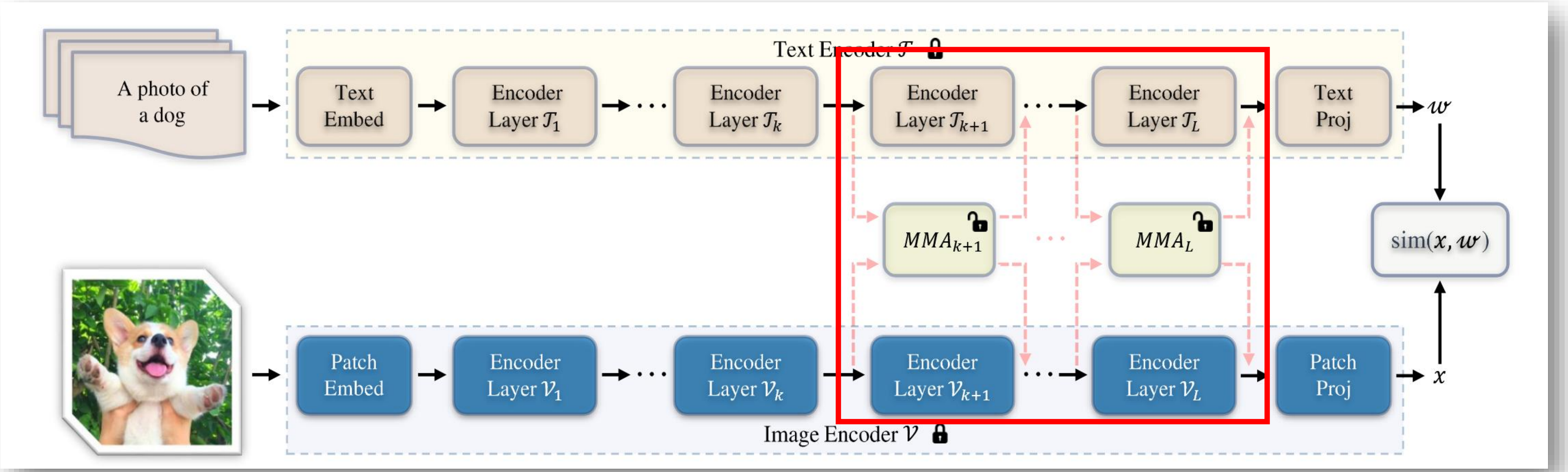
Multi-modal adapter

>> Proposed Method : MMA : Multi-modal adapter



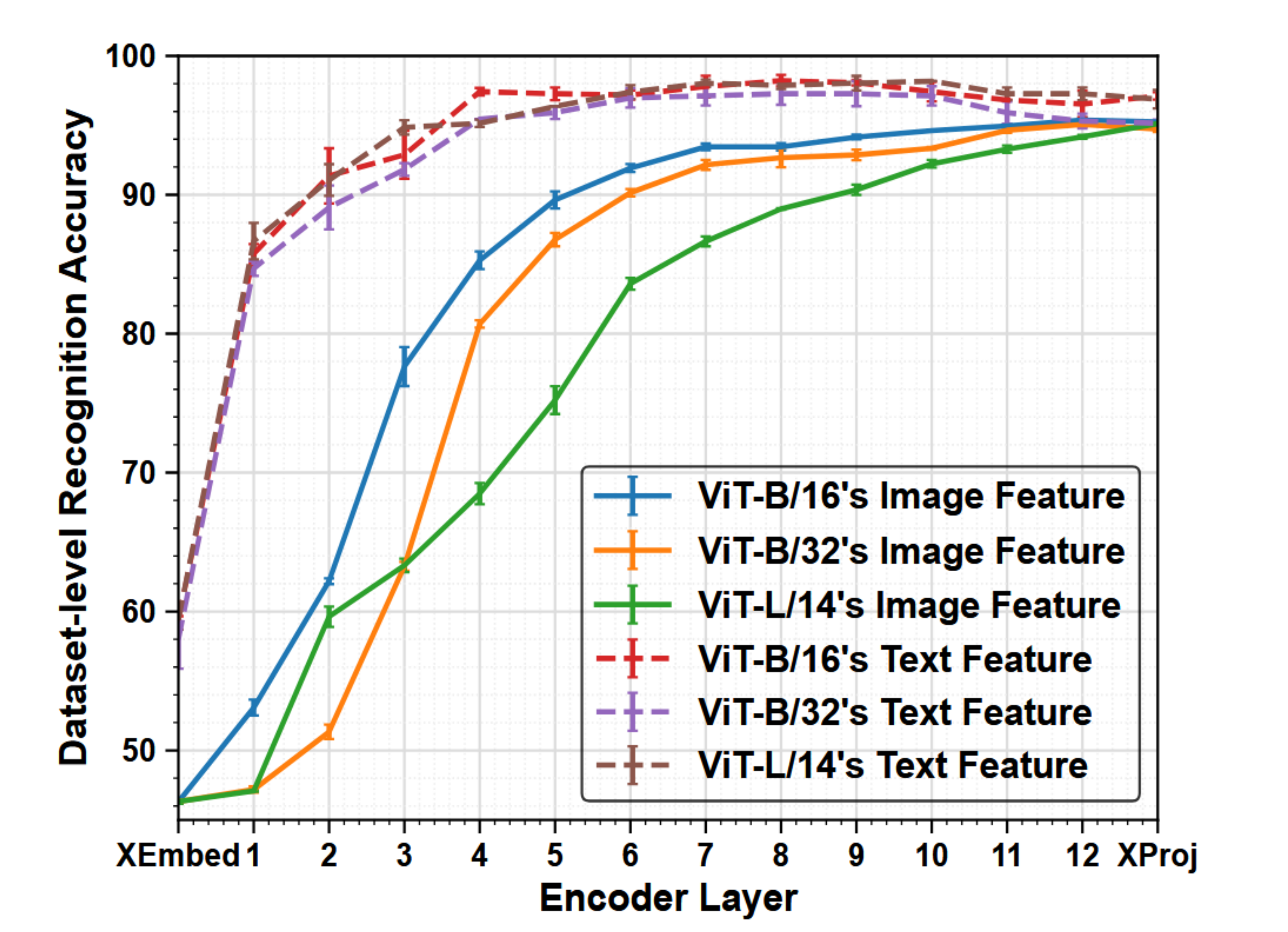
>> Proposed Method : MMA

- MMA builds on the CLIP architecture by inserting adapters only into the top k~L layers of the text and image encoders
- The encoders are frozen, only the adapters are trained, ensuring parameter efficiency
- This design allows for minimal modification while maximizing alignment performance

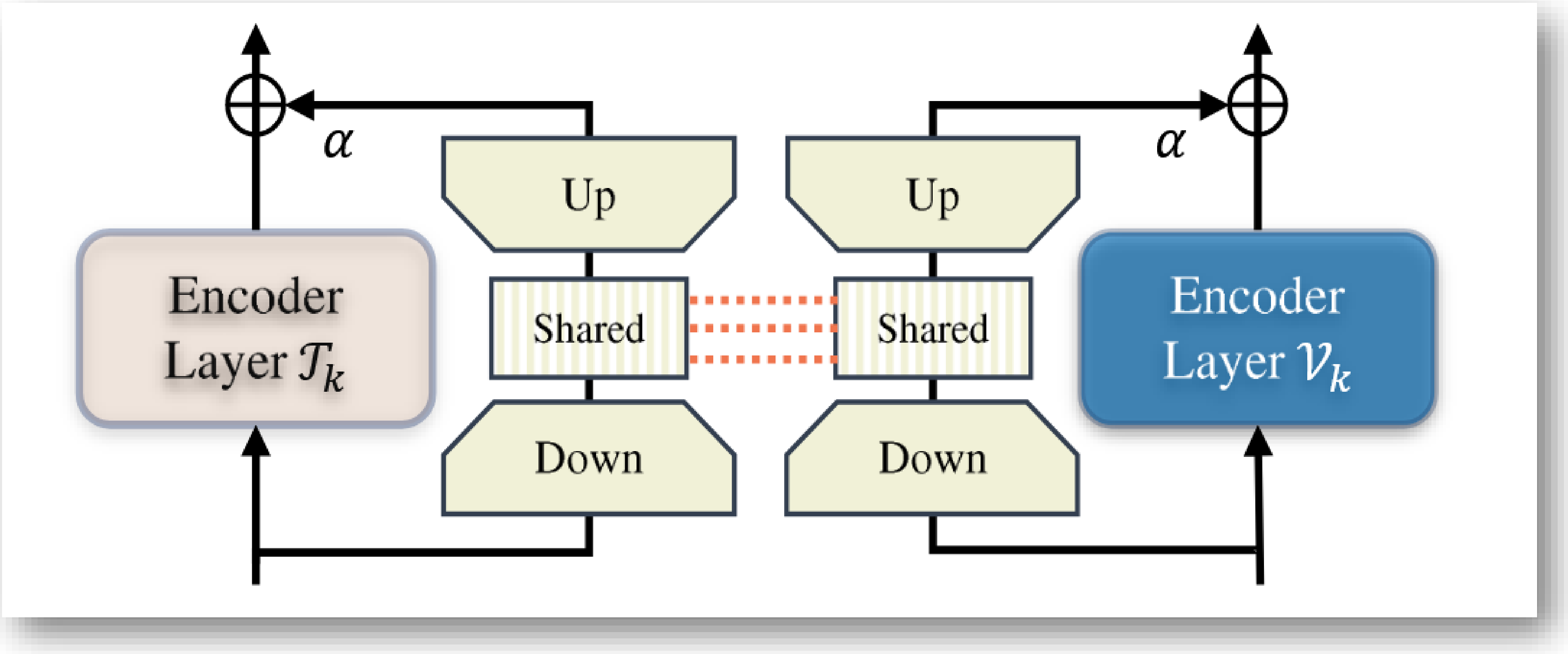


>> Proposed Method : MMA

✓ **Why High Layers Only?**



>> Proposed Method : MMA



>> Experiments

❑ Setting

✓ **Generalization from Base-to-Novel Classes**

- **Purpose : Evaluating whether a model trained on one dataset also performs well on datasets from other domains**
- **Dataset :**
  - **General Object Recognition**: ImageNet, Caltech101
  - **Fine-Grained Recognition**: *OxfordPets*, StanfordCars, Flowers102, Food101, FGVC Aircraft
  - **Other Domains**: SUN397 (scenes), DTD (textures), EuroSAT (satellite), UCF101 (action)

✓ **Cross-dataset Evaluation**

- **Purpose : Evaluating whether a model trained on one dataset also performs well on datasets from other domains**
- **Dataset : ImageNet**

✓ **Domain generalization**

- **Purpose : Measuring how robust the model is to domain shift (Out-of-distribution evaluation)**
- **Dataset : ImageNet**

>> Experiments

✓ Generalization from Base-to-Novel Classes

Methods	Average			ImageNet			Caltech101			OxfordPets		
	Base	Novel	HM	Base	Novel	HM	Base	Novel	HM	Base	Novel	HM
CLIP [ICML2021] [50]	69.34	74.22	71.70	72.43	68.14	70.22	96.84	94.00	95.40	91.17	97.26	94.12
CoOp [IJCV2022] [84]	82.69	63.22	71.66	76.47	67.88	71.92	98.00	89.81	93.73	93.67	95.29	94.47
CoOpOp [CVPR2022] [85]	80.47	71.69	75.83	75.98	70.43	73.10	97.96	93.81	95.84	95.20	97.69	96.43
ProDA [CVPR2022] [43]	81.56	72.30	76.65	75.40	70.23	72.72	98.27	93.23	95.68	95.43	97.83	96.62
KgCoOp [CVPR2023] [67]	80.73	73.60	77.00	75.83	69.96	72.78	97.72	**94.39**	96.03	94.65	97.76	96.18
MaPLe [CVPR2023] [33]	82.28	75.14	78.55	76.66	70.54	73.47	97.74	94.36	96.02	95.43	97.76	96.58
LASP [CVPR2023] [4]	82.70	74.90	78.61	76.20	70.95	73.48	98.10	94.24	96.16	**95.90**	97.93	**96.90**
LASP-V [CVPR2023] [4]	83.18	76.11	79.48	76.25	71.17	73.62	98.17	94.33	96.43	95.73	97.87	96.79
RPO [ICCV2023] [38]	81.13	75.00	77.78	76.60	**71.57**	74.00	97.97	94.37	96.03	94.63	97.50	96.05
MMA [this work]	**83.20**	**76.80**	**79.87**	**77.31**	71.00	**74.02**	**98.40**	94.00	**96.15**	95.40	**98.07**	96.72

Methods	StanfordCars			Flowers102			Food101			FGVCAircraft		
	Base	Novel	HM	Base	Novel	HM	Base	Novel	HM	Base	Novel	HM
CLIP [ICML2021] [50]	63.37	74.89	68.65	72.08	**77.80**	74.83	90.10	91.22	90.66	27.19	36.29	31.09
CoOp [IJCV2022] [84]	78.12	60.40	68.13	97.60	59.67	74.06	88.33	82.26	85.19	40.44	22.30	28.75
CoOpOp [CVPR2022] [85]	70.49	73.59	72.01	94.87	71.75	81.71	90.70	91.29	90.99	33.41	23.71	27.74
ProDA [CVPR2022] [43]	74.70	71.20	72.91	97.70	68.68	80.66	90.30	88.57	89.43	36.90	34.13	35.46
KgCoOp [CVPR2022] [67]	71.76	75.04	73.36	95.00	74.73	83.65	90.50	91.70	91.09	36.21	33.55	34.83
MaPLe [CVPR2022] [33]	72.94	74.00	73.47	95.92	72.46	82.56	90.71	**92.05**	91.38	37.44	35.61	36.50
LASP [CVPR2022] [4]	75.17	71.60	73.34	97.00	74.00	83.95	91.20	91.70	91.44	34.53	30.57	32.43
LASP-V [CVPR2022] [4]	75.23	71.77	73.46	97.17	73.53	83.71	**91.20**	91.90	**91.54**	38.05	33.20	35.46
RPO [ICCV2023] [38]	73.87	**75.53**	74.69	94.13	76.67	84.50	90.33	90.83	90.58	37.33	34.20	35.70
MMA [this work]	**78.50**	73.10	**75.70**	**97.77**	75.93	**85.48**	90.13	91.30	90.71	**40.57**	**36.33**	**38.33**

$$*HM = \frac{2 \cdot Base \cdot Novel}{Base + Novel}$$ (Ex. Base=90, Novel=50 → HM=64.3)

Methods	SUN397			DTD			EuroSAT			UCF101		
	Base	Novel	HM	Base	Novel	HM	Base	Novel	HM	Base	Novel	HM
CLIP [ICML2021] [50]	69.36	75.35	72.23	53.24	59.90	56.37	56.48	64.05	60.03	70.53	77.50	73.85
CoOp [IJCV2022] [84]	80.60	65.89	72.51	79.44	41.18	54.24	92.19	54.74	68.69	84.69	56.05	67.46
CoOpOp [CVPR2022] [85]	79.74	76.86	78.27	77.01	56.00	64.85	87.49	60.04	71.21	82.33	73.45	77.64
ProDA [CVPR2022] [43]	78.67	76.93	77.79	80.67	56.48	66.44	83.90	66.00	73.88	85.23	71.97	78.04
KgCoOp [CVPR2023] [67]	80.29	76.53	78.36	77.55	54.99	64.35	85.64	64.34	73.48	82.89	76.67	79.65
MaPLe [CVPR2023] [33]	80.82	78.70	79.75	80.36	59.18	68.16	94.07	73.23	82.35	83.00	78.66	80.77
LASP [CVPR2023] [4]	80.70	78.60	79.63	81.40	58.60	68.14	94.60	77.78	85.36	84.77	78.03	81.26
LASP-V [CVPR2023] [4]	80.70	**79.30**	80.00	81.10	62.57	70.64	**95.00**	**83.37**	**88.86**	85.53	78.20	81.70
RPO [ICCV2023] [38]	80.60	77.80	79.18	76.70	62.13	68.61	86.63	68.97	76.79	83.67	75.43	79.34
MMA [this work]	**82.27**	78.57	**80.38**	**83.20**	**65.63**	**73.38**	85.46	82.34	83.87	**86.23**	**80.03**	**82.20**

>> Experiments

✓ Cross-Dataset Evaluation setting

- MMA achieves the highest average accuracy (66.61) across 10 datasets in the cross-dataset generalization setting
- It consistently performs well across diverse domains, surpassing CoOp, CoCoOp, MaPLe, and PromptSRC

Methods	ImageNet	Caltech101	OxfordPets	StanfordCars	Flowers101	Food101	FGVCAircraft	SUN397	DTD	EuroSAT	UCF101	Average
CoOp [IJCV2022] [84]	**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 [CVPR2022] [85]	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 [CVPR2023] [33]	70.72	93.53	**90.49**	65.57	**72.23**	**86.20**	24.74	67.01	46.49	48.06	**68.69**	66.30
PromptSRC [ICCV2023] [34]	71.27	93.60	90.25	65.70	70.25	86.15	23.90	67.10	**46.87**	45.50	68.75	65.81
MMA [this work]	71.00	93.80	90.30	**66.13**	72.07	86.12	**25.33**	**68.17**	46.57	**49.24**	68.32	**66.61**

>> Experiments

✓ Domain Generalization setting

- MMA achieves the best performance on 3 out of 4 domain-shifted datasets, showing strong robustness to out-of-distribution data
- It outperforms CLIP, CoOp, CoCoOp, and MaPLe in most settings while maintaining high accuracy on ImageNet

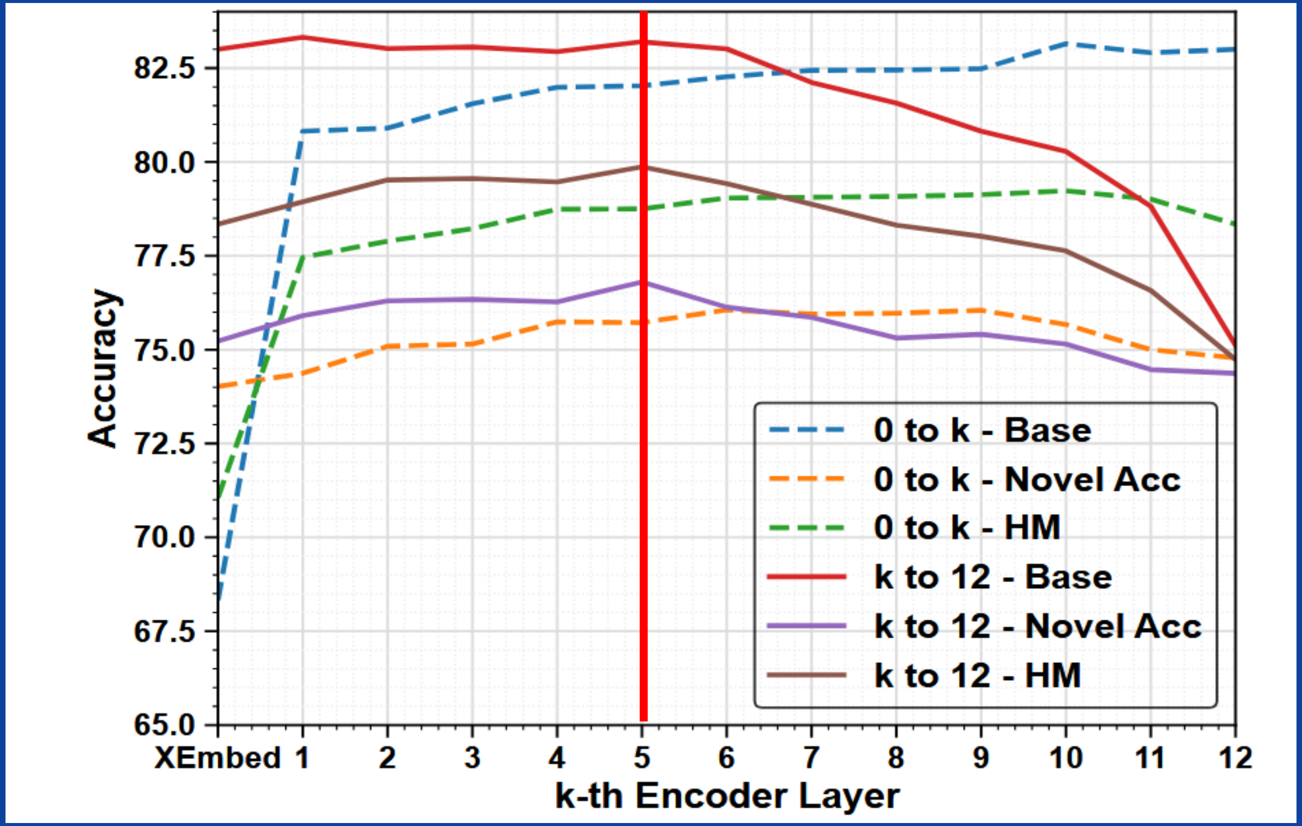
Methods	ImageNet	-V2	-S	-A	-R
CLIP [ICML2021] [50]	66.73	60.83	46.15	47.77	73.96
CoOp [IJCV2022] [84]	71.51	64.20	47.99	49.71	75.21
CoCoOp [CVPR2022] [85]	71.02	64.07	48.75	50.63	76.18
MaPLe [CVPR2023] [33]	70.72	64.07	**49.15**	50.90	76.98
MMA [this work]	71.00	**64.33**	49.13	**51.12**	**77.32**

Notaion	Name	Description
-V2	ImageNet-V2	ImageNet의 재구성 버전으로, 데이터 분포가 다름
-S	ImageNet-Sketch	스케치 스타일의 이미지, 시각적 형태만 유지
-A	ImageNet-A	ImageNet의 **어려운 예시들**로 구성된 벤치마크 (adversarial-like samples)
-R	ImageNet-Rendition	예술적 스타일/렌더링으로 변형된 이미지들 (e.g., cartoon, painting 등)

>> Ablation & Analysis

✓ Different choices of adding our proposed multi-modal units

- Lower layers → discrimination ↑, generalization ↓
- Higher layers → generalization ↑, but too high → base performance ↓
- Starting from layer **k = 5** provides the best trade-off, achieving the highest harmonic mean of 79.87



>> Ablation & Analysis

✓ Variants of Adding MMA

- Using adapters in both vision and language branches performs better than uni-modal setups
- Adding a shared projection layer further improves alignment and boosts HM score

(a) Performance with Different Model Variants

Model Variants	Base	Novel	HM
Only L-Adapter	80.36	75.81	78.02
Only V-Adapter	80.39	74.18	77.16
No SharedProj	82.43	76.21	79.20
FCAA [1]	79.11	75.64	77.34
MMA	**83.20**	**76.80**	**79.87**

(b) Dimensions of Shared Layers

Dims	Base	Novel	HM
8	82.66	76.17	79.28
16	82.80	76.48	79.52
32	**83.20**	**76.80**	**79.87**
64	83.41	76.17	79.63
128	82.98	76.54	79.58

(c) Scaling Factor α

α	Base	Novel	HM
0.0001	79.40	75.57	77.44
0.0005	81.81	76.08	78.84
0.001	83.20	**76.80**	**79.87**
0.005	83.80	75.37	79.36
0.01	**84.27**	74.32	78.98

>> Ablation & Analysis

✓ Variants of Adding MMA

- Mid-sized shared layers (dim ≈ 32) offer the best generalization
- Too large dimensions cause overfitting, hurting performance on novel classes

(a) Performance with Different Model Variants

Model Variants	Base	Novel	HM
Only L-Adapter	80.36	75.81	78.02
Only V-Adapter	80.39	74.18	77.16
No SharedProj	82.43	76.21	79.20
FCAA [1]	79.11	75.64	77.34
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0.005	83.80	75.37	79.36
0.01	**84.27**	74.32	78.98

>> Ablation & Analysis

✓ Variants of Adding MMA

- α = 0.001 yields the best trade-off between base and novel accuracy
- Too high or too low α values harm either generality or adaptability

(a) Performance with Different Model Variants

Model Variants	Base	Novel	HM
Only L-Adapter	80.36	75.81	78.02
Only V-Adapter	80.39	74.18	77.16
No SharedProj	82.43	76.21	79.20
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0.005	83.80	75.37	79.36
0.01	**84.27**	74.32	78.98

>> Ablation & Analysis

✓ Fine-tuning last few layers

- Tuning last CLIP layers boosts base but hurts novel accuracy
- More tuning leads to overfitting
- MMA offers a better balance with fewer updates

Layer	12	10→12	8→12	5→12	MMA
Base	80.77	83.02	**83.77**	83.21	83.20
Novel	74.08	74.55	73.77	70.95	**76.80**
HM	77.28	78.56	78.45	76.59	**79.87**

>> Conclusion

- Limitation
  - Although MMA achieves state-of-the-art performance on average, it underperforms comp eting methods on certain tasks or datasets
  - Moreover, the evaluation is limited to classification tasks, excluding more complex downs tream applications such as generation or multimodal reasoning

Conclusion

- Adapting large VLMs like CLIP to downstream tasks is challenging due to limited data and many trainable parameter
- The proposed MMA enhances cross-modal alignment by being inserted only into higher layers of the vision and language encoders
- MMA outperforms existing methods in generalization to novel classes, new datasets, and unseen domains

감사합니다