Visual Fourier Prompt Tuning

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Content

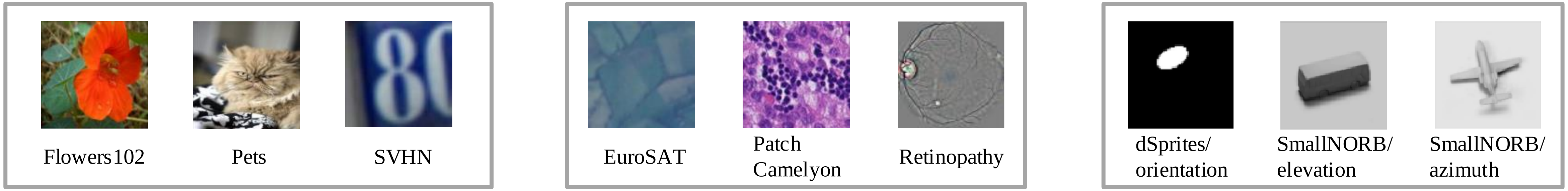
1. Introduction
2. Visual Fourier Prompt Tuning
3. Main Results
4. Study of Optimization
5. Study of Interpretability
6. Conclusion

Introduction

1. Introduction

- **Observation**

  A significant **performance degradation** occurs when there is a substantial **disparity** between the data used in pretraining and finetuning.



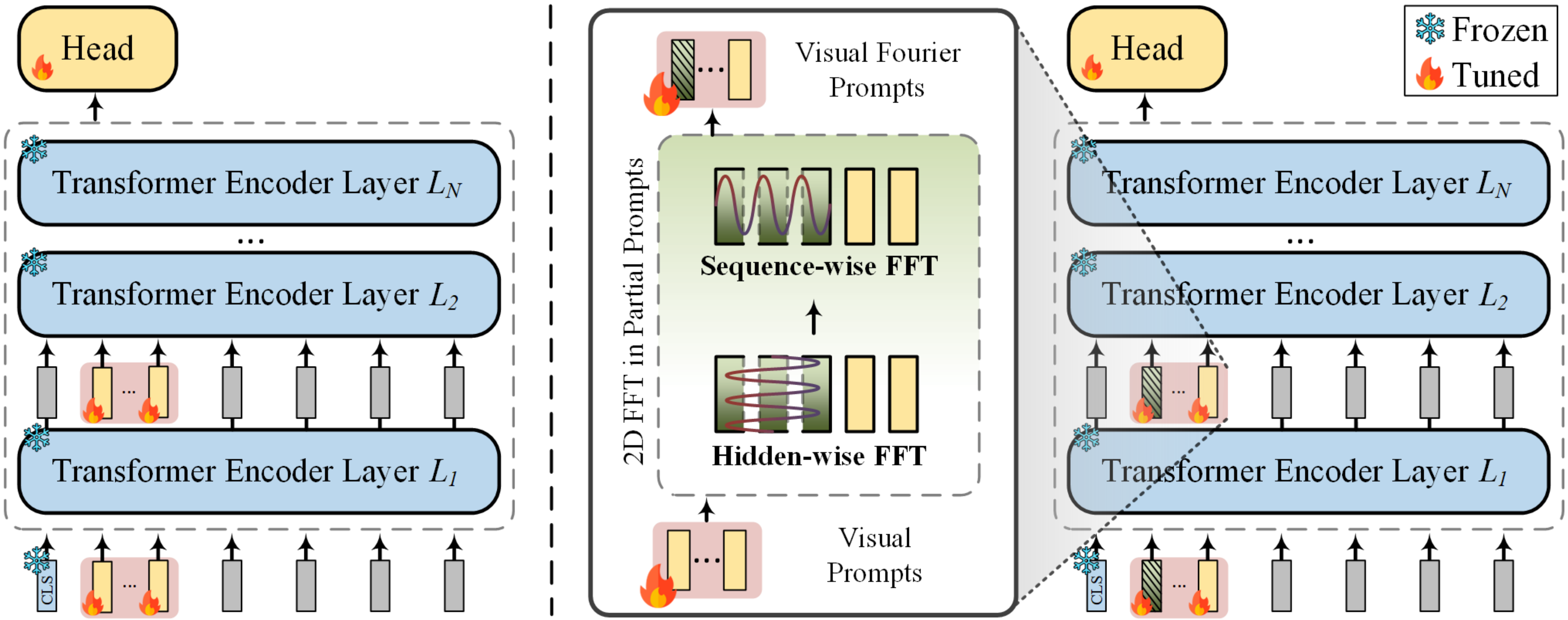
***Natural* <FID: 156.39>** ***Specialized* <FID: 245.69>** ***Structured* <FID: 234.96>**

- **Key Idea**

  Integrating **frequency domain** information into learnable prompt embeddings to elegantly assimilates data from both **spatial and frequency** domains.

Visual Fourier Prompt Tuning

2. Visual Fourier Prompt Tuning



(a) Visual Prompt Tuning (b) Fast Fourier Transform in Prompts (c) Visual Fourier Prompt Tuning

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Main Results

3. Main Results

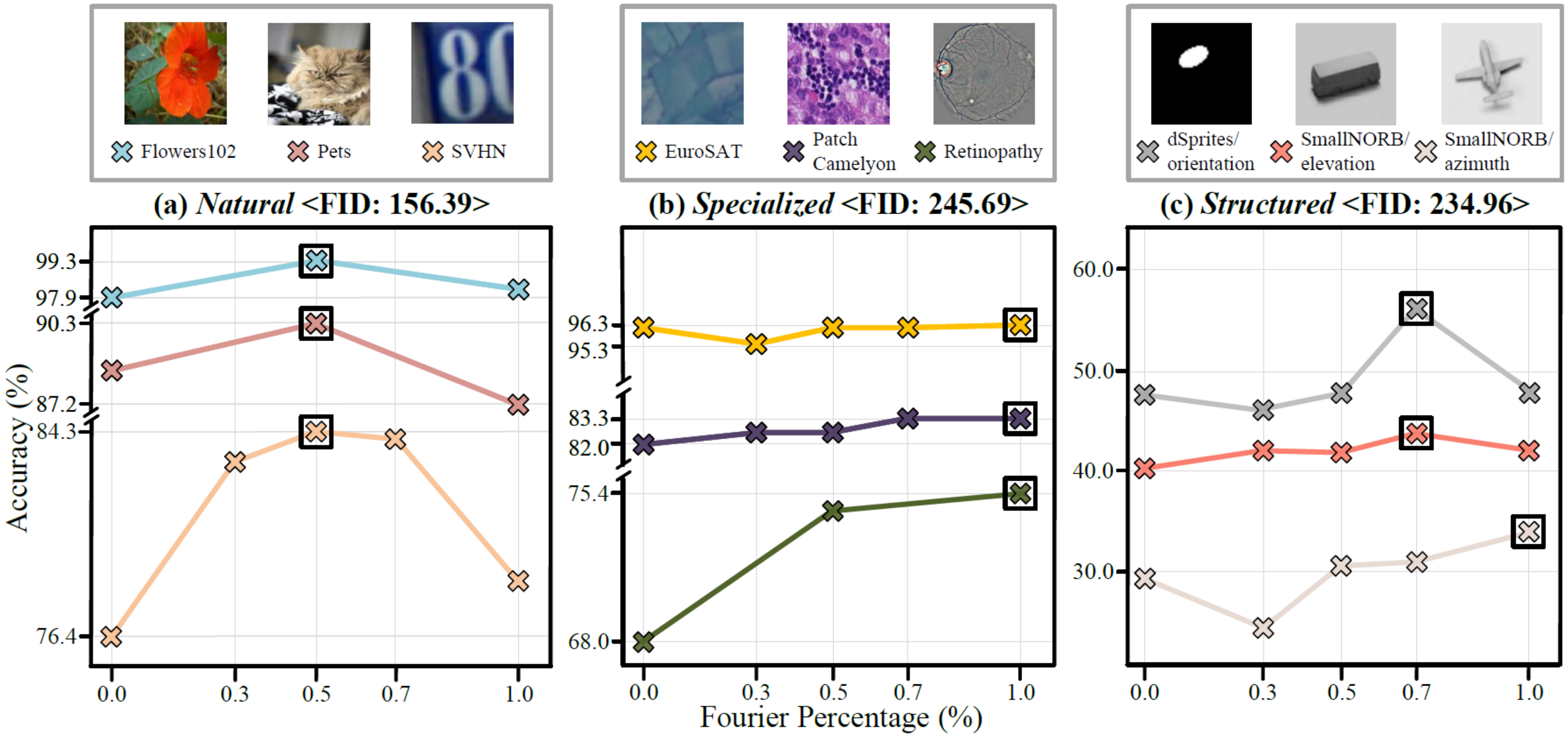
ViT-Base/16 [23] (85.8M)	Tuned/ Total	Scope Input	Scope Backbone	Extra params	FGVC [4] [5]	VTAB-1k [78] [19] *Natural* [7]	*Specialized* [4]	*Structured* [8]	Mean Total
Full [CVPR22][92]	100.00%		✓		88.54%	75.88%	83.36%	47.64%	65.57%
Linear [CVPR22][92]	0.08%				79.32% [0]	68.93% [1]	77.16% [1]	26.84% [0]	52.94%
Partial-1 [NeurIPS14][93]	8.34%				82.63% [0]	69.44% [2]	78.53% [0]	34.17% [0]	56.52%
MLP-3 [CVPR20][94]	1.44%			✓	79.80% [0]	67.80% [2]	72.83% [0]	30.62% [0]	53.21%
Sidetune [ECCV20][31]	10.08%		✓	✓	78.35% [0]	58.21% [0]	68.12% [0]	23.41% [0]	45.65%
Bias [NeurIPS17][30]	0.80%		✓		88.41% [3]	73.30% [3]	78.25% [0]	44.09% [2]	62.05%
Adapter [NeurIPS20][32]	1.02%		✓	✓	85.46% [1]	70.67% [4]	77.80% [0]	33.09% [0]	62.41%
LoRA [ICLR22][35]	—		✓	✓	89.46% [3]	78.26% [5]	83.78% [2]	56.20% [7]	72.25%
AdaptFormer [NeurIPS22][95]	—		✓	✓	—	<u>80.56%</u> [6]	84.88% [4]	<u>58.83%</u> [7]	<u>72.32%</u>
ARC_{att} [NeurIPS23][96]	—		✓	✓	89.12% [4]	80.41% [7]	**85.55%** [3]	58.38% [8]	72.32%
VPT-S [ECCV22][4]	0.16%	✓		✓	84.62% [1]	76.81% [4]	79.66% [0]	46.98% [4]	64.85%
VPT-D [ECCV22][4]	0.73%	✓		✓	89.11% [4]	78.48% [6]	82.43% [2]	54.98% [8]	69.43%
EXPRES [CVPR23][97]	—	✓		✓	—	79.69% [6]	84.03% [3]	54.99% [8]	70.20%
† E2VPT [ICCV23][5]	0.39%	✓	✓	✓	<u>89.22%</u> [4]	80.01% [6]	84.43% [3]	57.39% [8]	71.42%
▶ Ours	0.66%	✓		✓	**89.24%** [4] {4}	**81.35%** [6] {7}	<u>84.93%</u> [4] {4}	**60.19%** [8] {8}	**73.20%**

Swin-Base [24] (86.7M)	Tuned/ Total	VTAB-1k [78] [19] *Natural* [7]	*Specialized* [4]	*Structured* [8]
Full [ICLR23][98]	100.00%	79.10%	86.21%	59.65%
Linear [ICLR23][98]	0.06%	73.52% [5]	80.77% [0]	33.52% [0]
Partial-1 [NeurIPS14][93]	14.58%	73.11% [4]	81.70% [0]	34.96% [0]
MLP-3 [CVPR20][94]	2.42%	73.56% [5]	75.21% [0]	35.69% [0]
Bias [NeurIPS17][30]	0.29%	74.19% [2]	80.14% [0]	42.42% [0]
VPT [ECCV22][4]	0.25%	76.78% [6]	83.33% [0]	51.85% [0]
† E2VPT [ICCV23][5]	0.21%	<u>83.31%</u> [6]	<u>84.95%</u> [2]	<u>57.35%</u> [3]
▶ Ours	0.27%	**84.53%** [7] {5}	**86.15%** [2] {4}	**58.21%** [3] {6}

3. Main Results

Pretrained objectives / Methods	MAE [90] Tuned/ Total	MAE VTAB-1k [78] [19] *Natural* [7]	*Specialized* [4]	*Structured* [8]	MoCo v3 [26] Tuned/ Total	MoCo v3 VTAB-1k [78] [19] Natural [7]	Specialized [4]	Structured [8]
Full [CVPR22][92]	100.00%	59.31%	79.68%	53.82%	100.00%	71.95%	84.72%	51.98%
Linear [CVPR22][92]	0.04%	18.87% [0]	53.72% [0]	23.70% [0]	0.04%	67.46% [4]	81.08% [0]	30.33% [0]
Partial-1 [NeurIPS14][93]	8.30%	**58.44%** [5]	**78.28%** [1]	47.64%[1]	8.30%	72.31% [5]	84.58% [2]	47.89% [1]
Bias [NeurIPS17][30]	0.16%	54.55% [1]	75.68% [1]	**47.70%** [0]	0.16%	72.89% [3]	81.14% [0]	53.43% [4]
Adapter [NeurIPS20][32]	0.87%	54.90% [3]	75.19% [1]	38.98% [0]	1.12%	74.19% [4]	82.66% [1]	47.69% [2]
VPT-S [ECCV22][4]	0.05%	39.96% [1]	69.65% [0]	27.50% [0]	0.06%	67.34% [3]	82.26% [0]	37.55% [0]
VPT-D [ECCV22][4]	⋆ 0.31%	36.02% [0]	60.61% [1]	26.57% [0]	⋆ 0.22%	70.27% [4]	83.04% [0]	42.38% [0]
GPT [ICML23][101]	0.05%	47.61% [2]	76.86% [1]	36.80% [1]	0.06%	74.84% [4]	83.38% [1]	49.10% [3]
▶ Ours	0.38%	53.59% [6] {6}	77.75% [1] {3}	36.15% [1] {6}	0.22%	**77.47%** [5] {7}	**85.76%** [3] {4}	**58.74%** [6] {8}

3. Main Results



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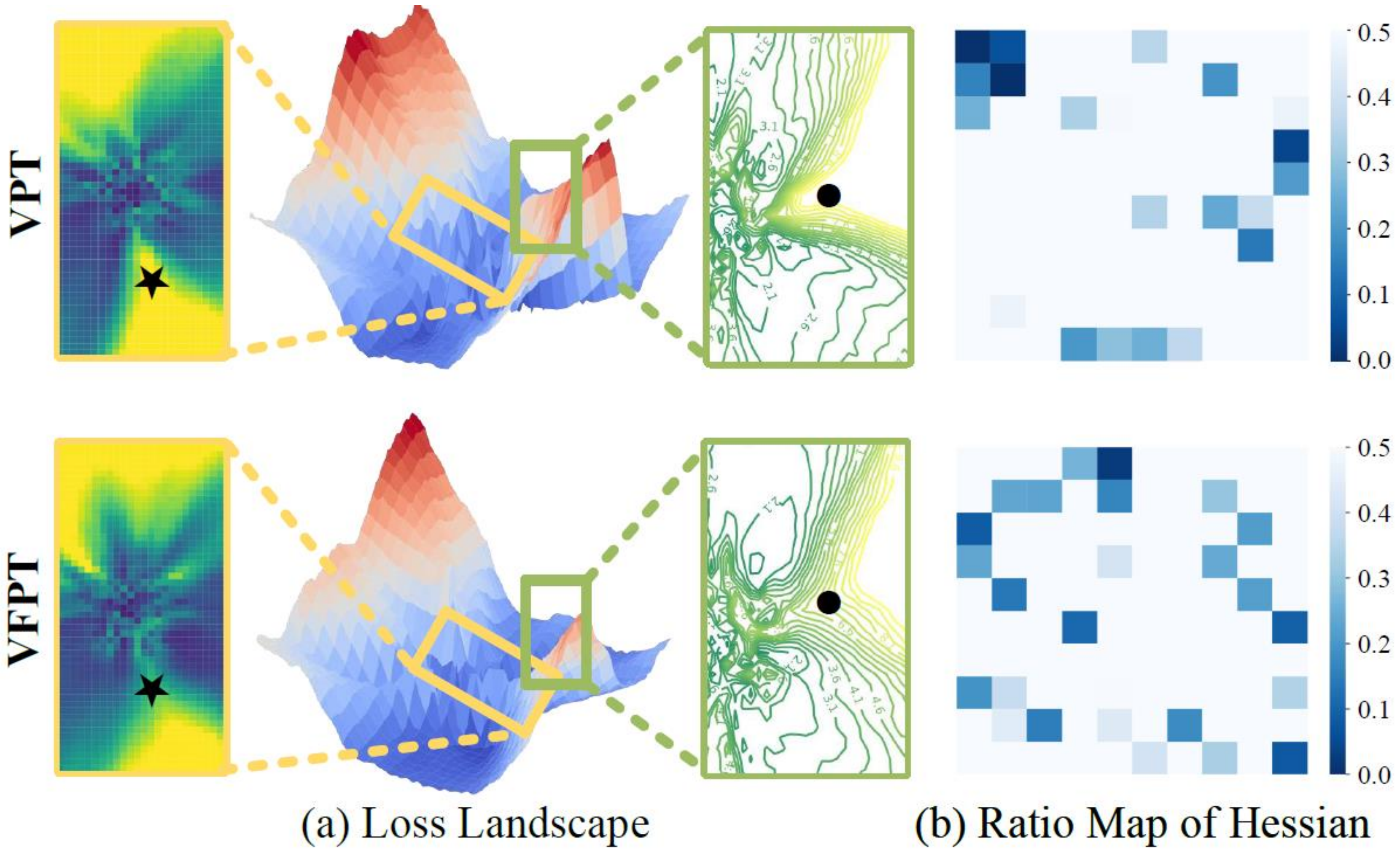
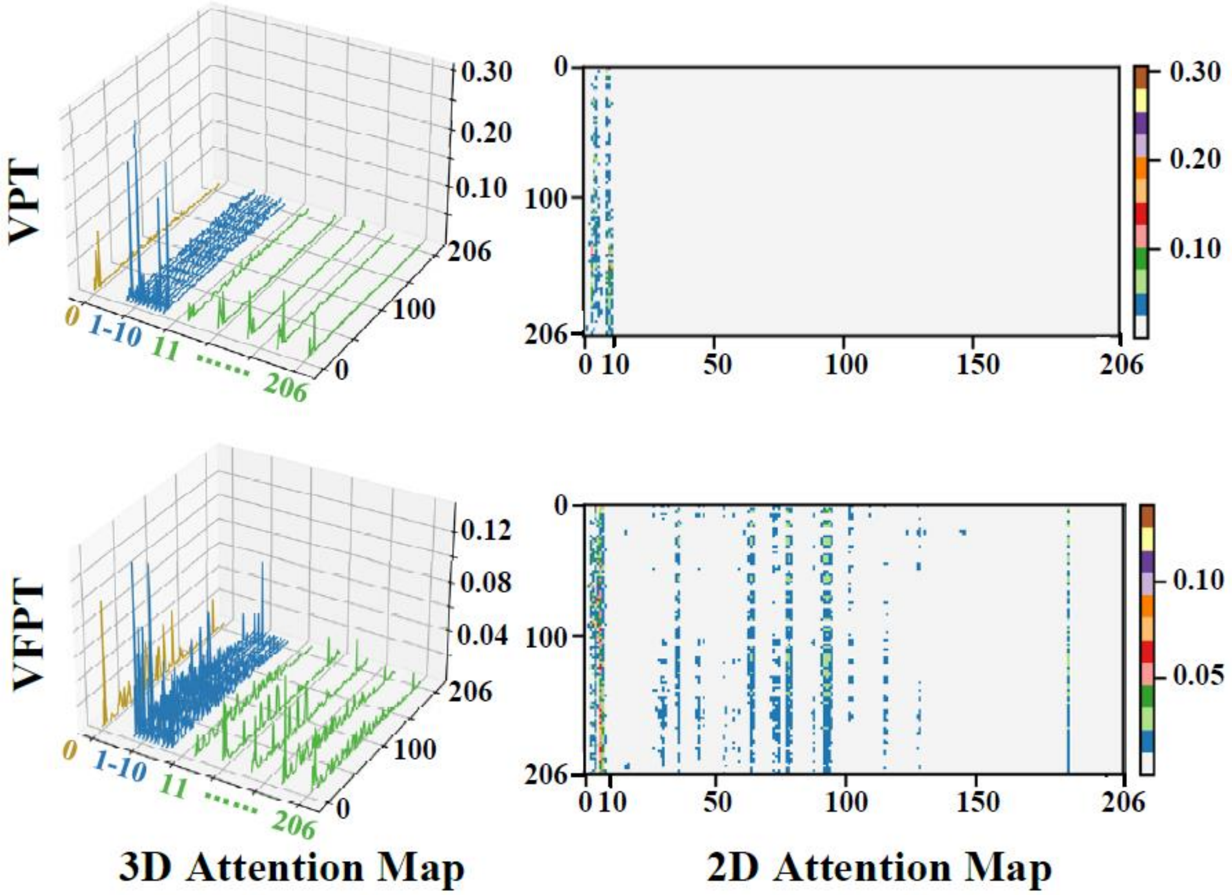
Study of Optimization

4. Study of Optimization

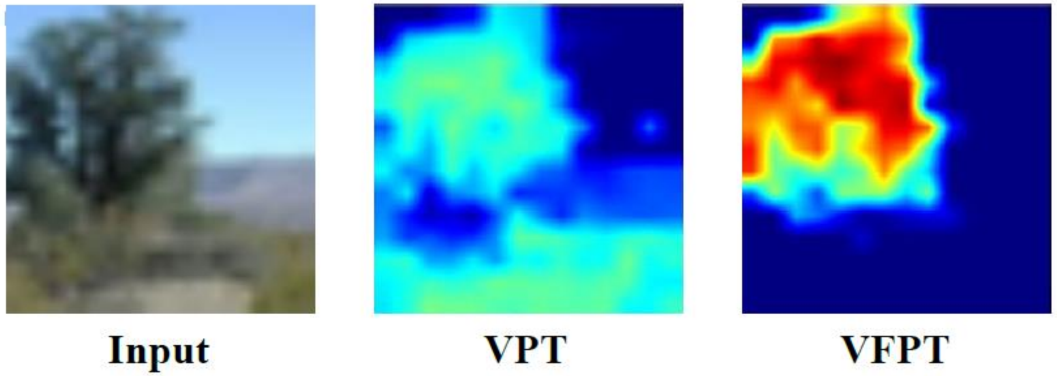


Study of Interpretability

5. Study of Interpretability



(a) Attention map



(b) GradCAM Heatmap

Conclusion

6. Conclusion

- **Simplicity**

  Integrating spatial and frequency domain information through an intuitive yet effective design.

- **Generality**

  Demonstrating generality across datasets with varying disparities while ensuring powerful performance.

- **Interpretability**

  Thoroughly investigating the associations between learnable prompts and frozen embeddings to elucidate our generality.

THANK YOU!