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TARP-VP: Towards Evaluation of Transferred Adversarial Robustness and Privacy on Label Mapping Visual Prompting Models

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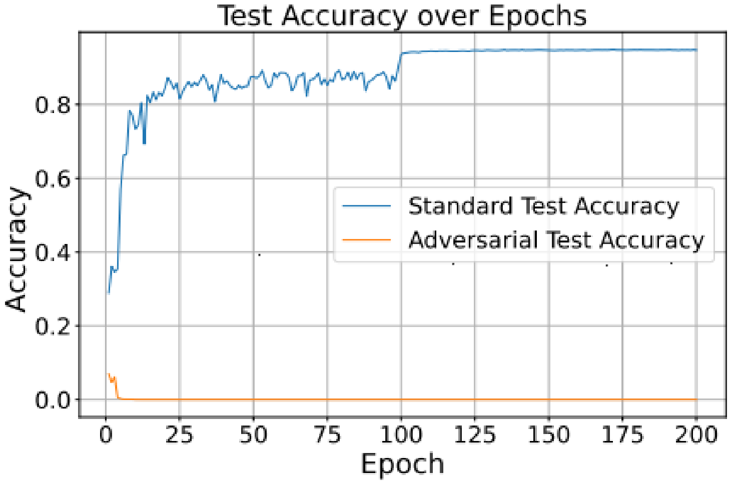
Outline

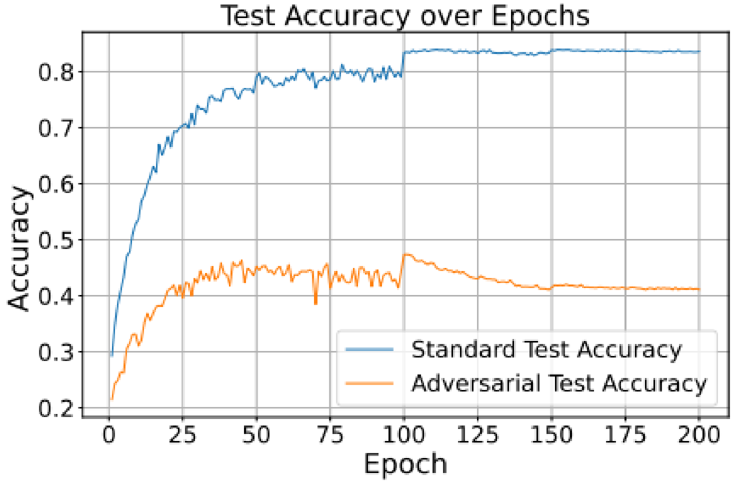
- Motivation
- White-box Adversarial Robustness of LM-VP
- Transferred Adversarial Robustness of LM-VP
- Privacy Evaluation of LM-VP

Motivation: Adversarial robustness and privacy trade-off

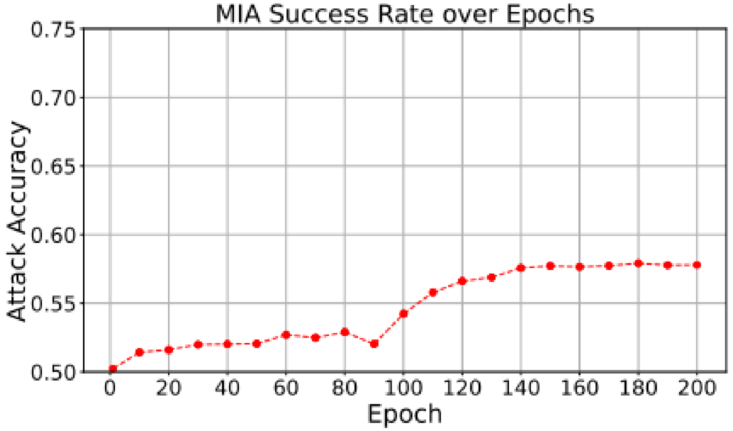
For a general deep learning model:



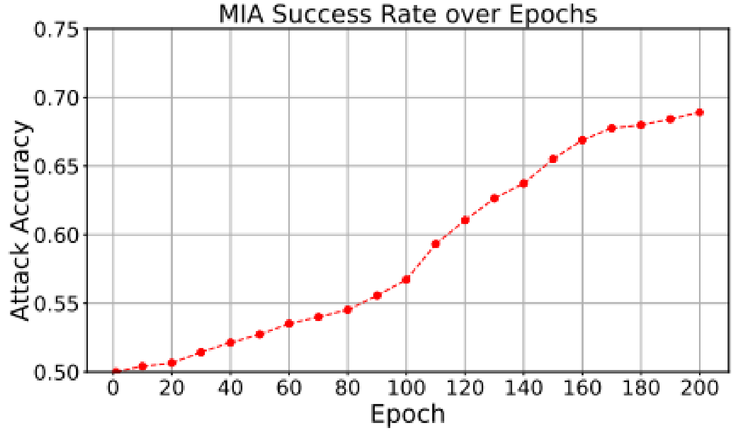
(a) Test Accuracy of Standard Training



(b) Test Accuracy of Adversarial Training



(c) MIA on Standard Training



(d) MIA on Adversarial Training

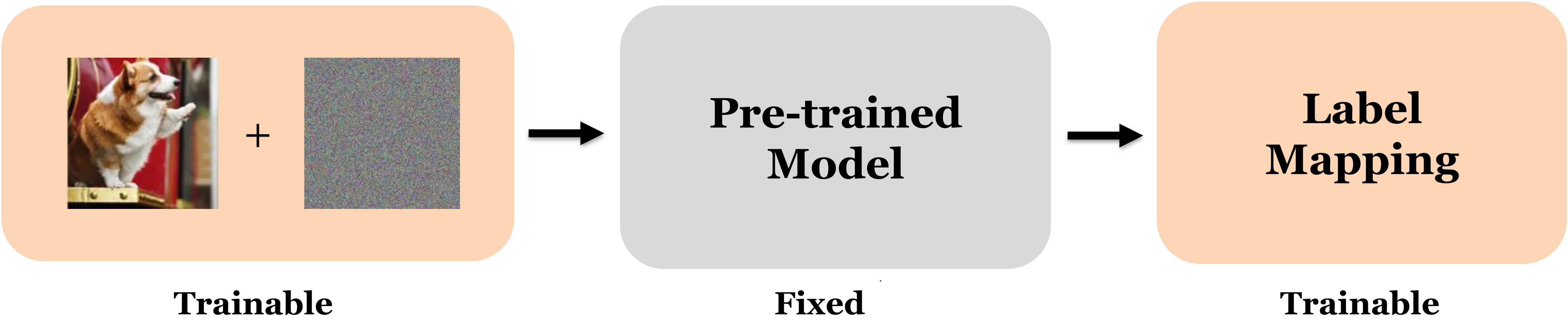
Figure 1: Trade-off between test accuracy and membership inference attacks of standard training and adversarial training along with training on CIFAR-10 with ℓ_∞ threat model using ResNet18.

More severe privacy risks on AT:

- Larger generalization error
- Higher sensitivity
- Robust overfitting

Label Mapping Visual Prompting Models

Design of Label Mapping Visual Prompting Models:



Design of Visual Prompting

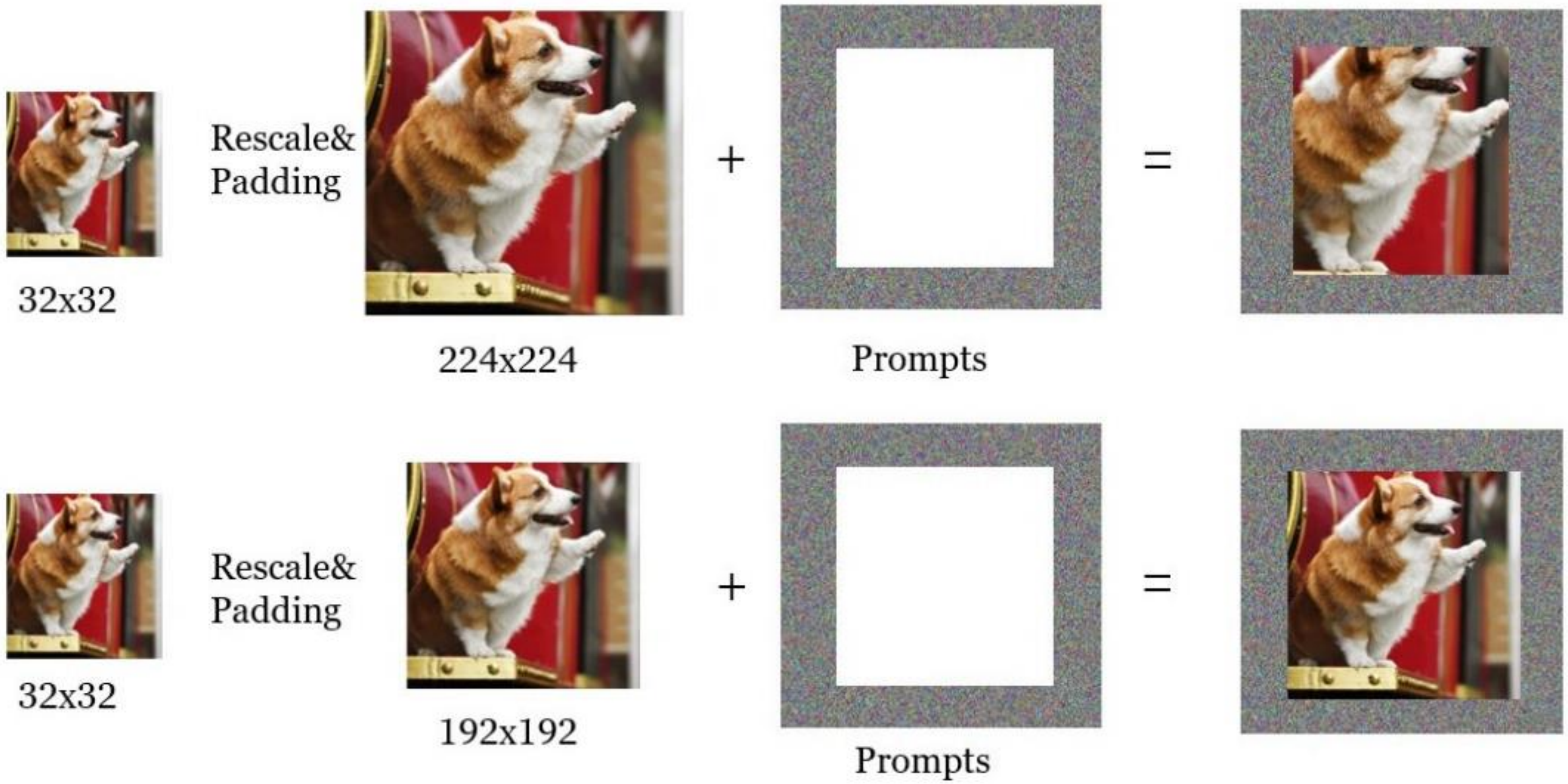
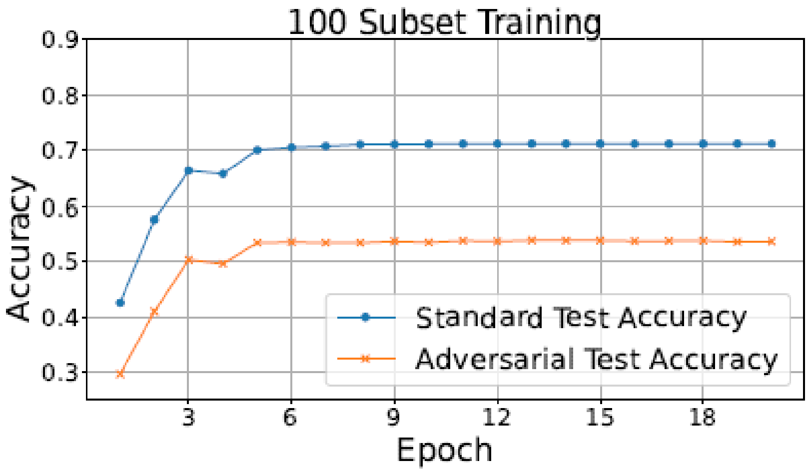


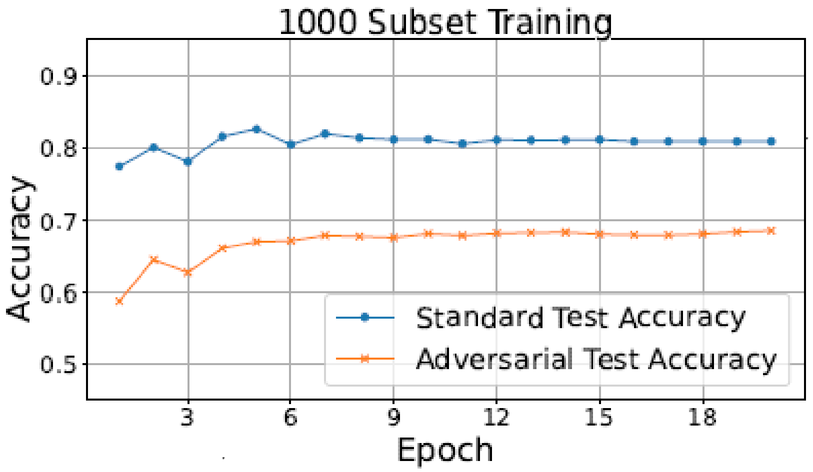
Figure 2: Two ways to add prompts: (1) Top: rescale a target image to the source domain size and replace the edge of the image with prompts; (2) Bottom: rescale a target image to a size smaller than the source domain and add prompts to make it the same size as source domain.

Characteristic of LM-VP

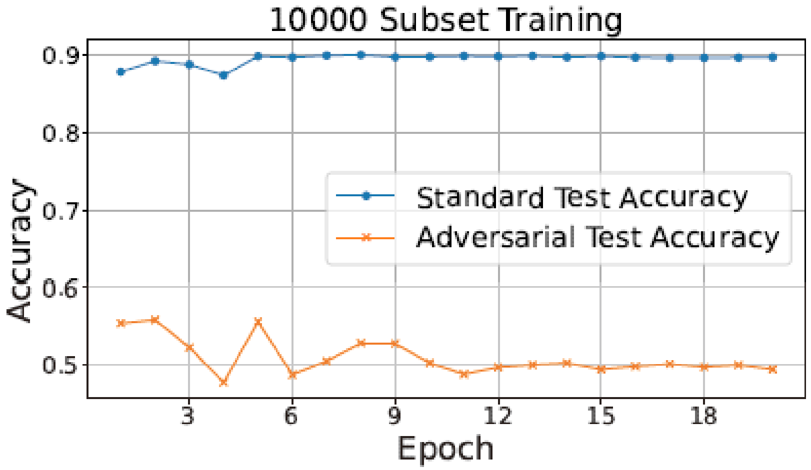
(1) Insufficient training data in LM-VP



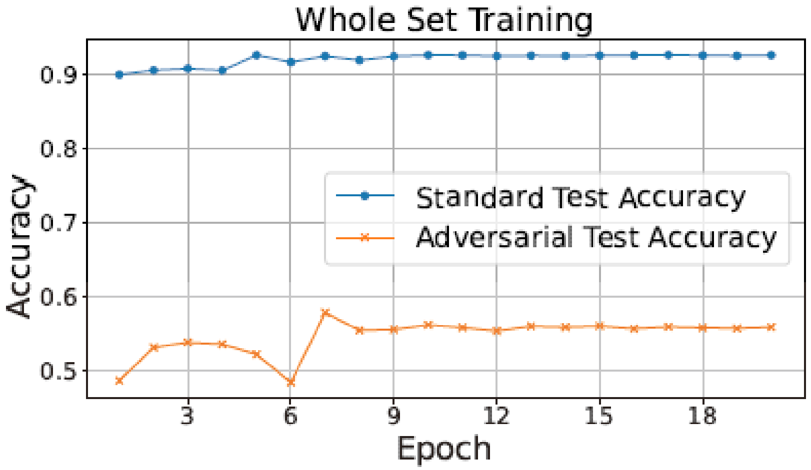
(a) Test Accuracy on Random 100 Subset Training



(b) Test Accuracy on Random 1000 Subset Training



(c) Test Accuracy on Random 10000 Subset Training



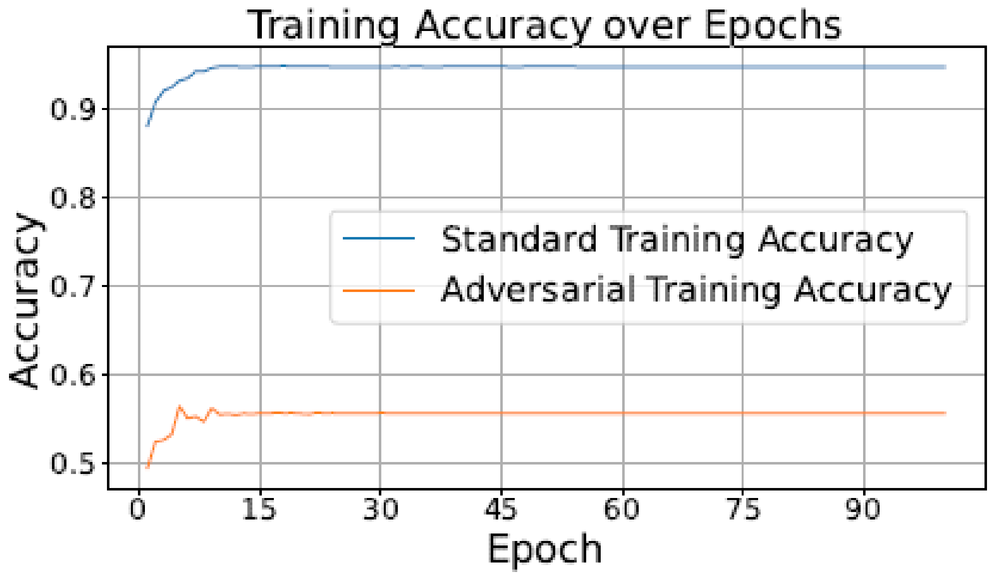
(d) Test Accuracy on Whole Training Set Training set

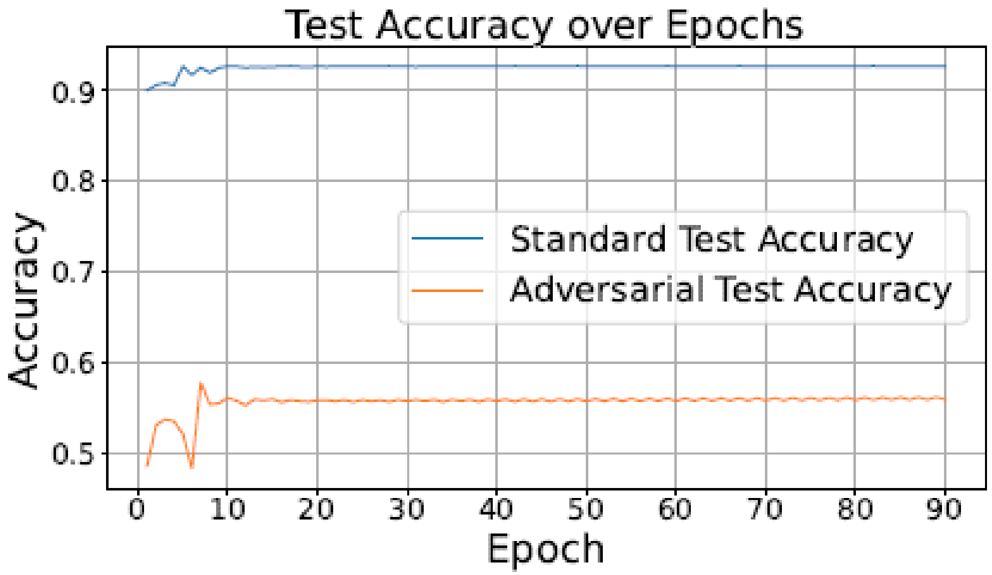
Lower sensitivity of LM-VP:

- Highest transferred adversarial robustness on 1000 subest training
- Similar standard accuracy on 10000 subst training

Characteristic of LM-VP

(2) Rapid convergence and minimal generalization error of LM-VP





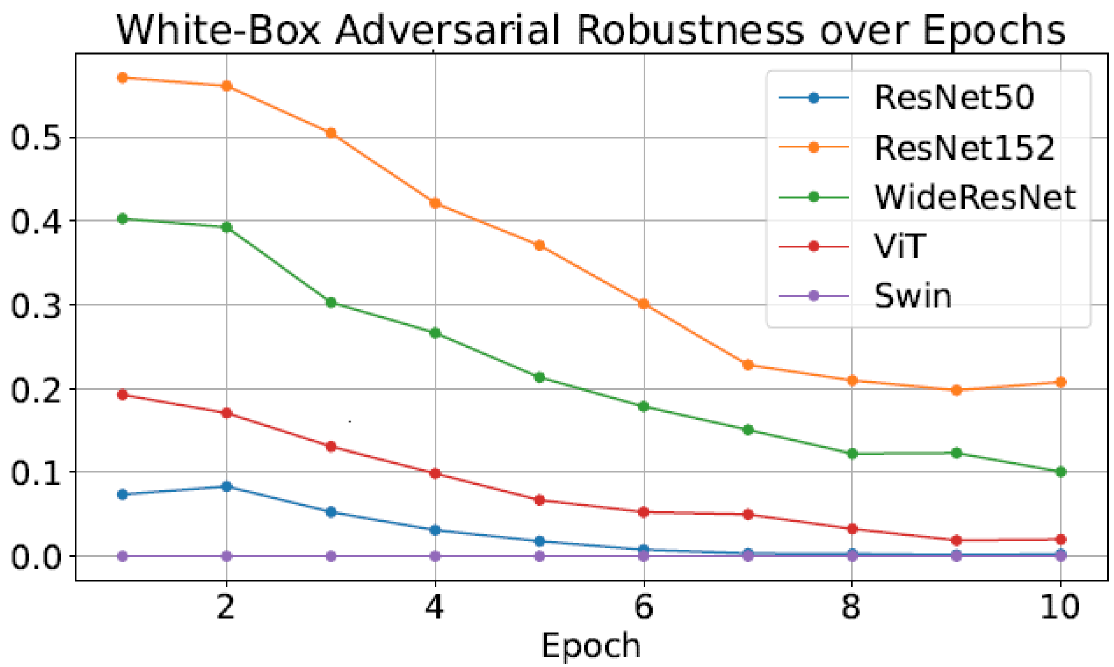
- Quickly achieve a near-optimal performance and then remain steady with continued training
- Minimal generalization error

White-box Adversarial Robustness of LM-VP

White-box adversarial robustness of LM-VP is largely influenced by the choice of pre-trained models and there is no clear pattern

Table 1: Best performance(%) on CIFAR-10 with different pre-trained models in Standard-Trained LM-VP models and Standard AT-Trained LM-VP models under white-box adversarial attacks.

Pre-trained models	Standard Training		Adversarial Training	
	Natural$_{te}$	PGD-20	Natural$_{te}$	PGD-20
ResNet50	80.52	8.33	23.10	0.8
ResNet152	84.76	57.09	14.24	0
Wideresnet	80.91	40.29	12.15	0
VIT	91.50	19.28	27.78	0
Swin	92.00	0	34.65	0
ConvNext	97.97	43.22	40.69	0



Transferred Adversarial Robustness

Transferred adversarial robustness of standard-trained LM-VP

Table 2: Best performance(%) on CIFAR-10 with different pre-trained models in Standard-Trained LM-VP models under Threat models ResNet18 or WRN-34-10.

Best Performance on natural examples and adversarial examples							
Pre-trained models	Threat models	Natural_{tr}	Natural_{te}	PGD-10_{tr}	PGD-20	CW-20	T/E
ResNet50	ResNet18	87.73	86.30	31.14	35.61	34.30	251s
ResNet152	ResNet18	90.39	89.51	36.76	35.99	35.67	440s
WRN-50-2	ResNet18	87.77	86.78	37.73	39.76	38.90	381s
VIT	ResNet18	94.91	92.67	51.25	51.95	50.70	589s
Swin	ResNet18	94.78	92.71	56.46	57.80	57.34	1025s
ConvNext	ResNet18	99.33	98.28	**88.70**	**89.11**	**89.37**	2116s
EVA	ResNet18	**99.66**	**98.54**	86.95	87.40	87.56	2674s
Best Performance on natural examples and adversarial examples							
Pre-trained models	Threat models	Natural_{tr}	Natural_{te}	PGD-10_{tr}	PGD-20	CW-20	T/E
ResNet50	WRN-34-10	87.18	85.87	30.33	32.32	30.98	-
ResNet152	WRN-34-10	89.95	89.42	37.24	37.26	37.08	-
WRN-50-2	WRN-34-10	87.97	87.01	38.25	41.36	39.90	-
VIT	WRN-34-10	94.78	92.77	51.41	52.23	52.12	-
Swin	WRN-34-10	95.08	92.8	55.23	59.20	57.54	-
ConvNext	WRN-34-10	99.19	98.03	**88.20**	**88.51**	**88.23**	-
EVA	WRN-34-10	**99.64**	**98.45**	86.21	86.98	87.24	-

Transferred Adversarial Robustness

Transferred adversarial robustness of transferred AT-trained LM-VP:

Table 3: Best performance(%) on CIFAR-10 with different pre-trained models in Transfered AT-Trained LM-VP models under Threat model ResNet18.

Best Performance on natural examples and adversarial examples							
Pre-trained models	Threat models	$Natural_{tr}$	$Natural_{te}$	$PGD\text{-}10_{tr}$	PGD-20	CW-20	T/E
ResNet50	ResNet18	68.84	70.37	64.10	63.01	61.78	671s
ResNet152		68.83	77.08	63.39	63.95	62.92	950s
WRN-50-2		69.68	70.42	62.07	62.86	60.89	875s
VIT		86.23	86.64	77.49	75.34	74.87	1380s
Swin		89.32	89.74	80.72	79.14	77.89	2205s
ConvNext		97.79	98.02	92.61	91.63	91.02	3446s
EVA		**98.64**	**98.32**	**93.19**	**92.43**	**91.50**	4136s

Transferred AT significantly enhances the transferred adversarial robustness at the cost of reduced natural accuracy

MIA-based Privacy Analysis

Privacy Analysis of LM-VP models:
(1) lower sensitivity of LM-VP models to training data
(2) minimal generalization error
(3) Prior knowledge embedded in different pre-trained models

$$MIA(\eta) = \frac{1}{2} \times \left(\frac{\sum_{(x,y)\in D_{\text{train}}} \mathbf{1}\left[f_\theta(x)_y \geq \eta\right]}{|D_{\text{train}}|} + \frac{\sum_{(x,y)\in D_{\text{test}}} \mathbf{1}\left[f_\theta(x)_y < \eta\right]}{|D_{\text{test}}|} \right)$$

$$\eta_{\text{optim}} = \arg\max_{\eta} MIA(\eta)$$

MIA Evaluation

Transfer AT improves both transferred adversarial robustness and MIA-based training data privacy

Table 4: MIA success rate(%) on CIFAR-10 with different pre-trained models in Standard and Transferred AT Trained LM-VP models under Threat model ResNet18.

Generation Gap and MIA Success Rate on Trained LM-VP Models				
Pre-trained models	Standard Training		Transfered AT	
	MIA Nat	MIA Adv	MIA Nat	MIA Adv
ResNet50	68.92	57.88	55.27	51.19
ResNet152	75.34	56.46	62.15	50.77
WRN-50-2	62.58	50.66	50.46	50.94
VIT	51.66	50.37	50.53	51.78
Swin	51.75	50.53	50.23	51.63
ConvNext	80.14	77.33	50.32	50.70
EVA	77.46	73.35	50.32	50.67

Conclusion

- Pre-trained models significantly influences the white-box adversarial robustness of LM-VP→hard to draw consistent conclusions
- Transfer AT achieve a good trade-off between transferred adversarial robustness and MIA-based privacy→consistent findings across various pretrained models