Enabling Heterogeneous Adversarial Transferability via Feature Permutation Attacks

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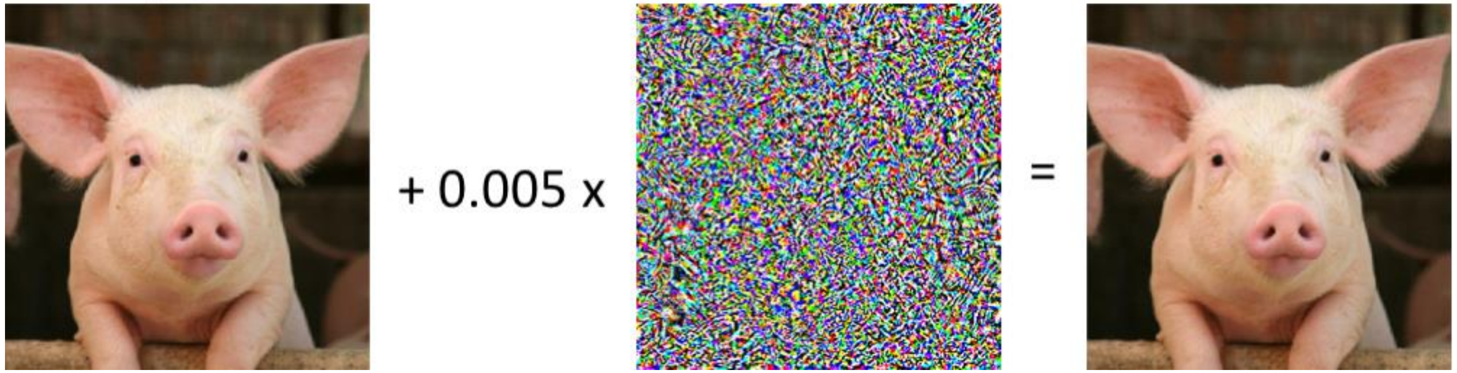
Background

Adversarial examples (AEs):

- Inputs to a deep learning model that have been intentionally modified in small, often imperceptible ways to cause the model to make wrong predictions.

"Making a pig fly" isn't that hard:



"pig"
91% confidence

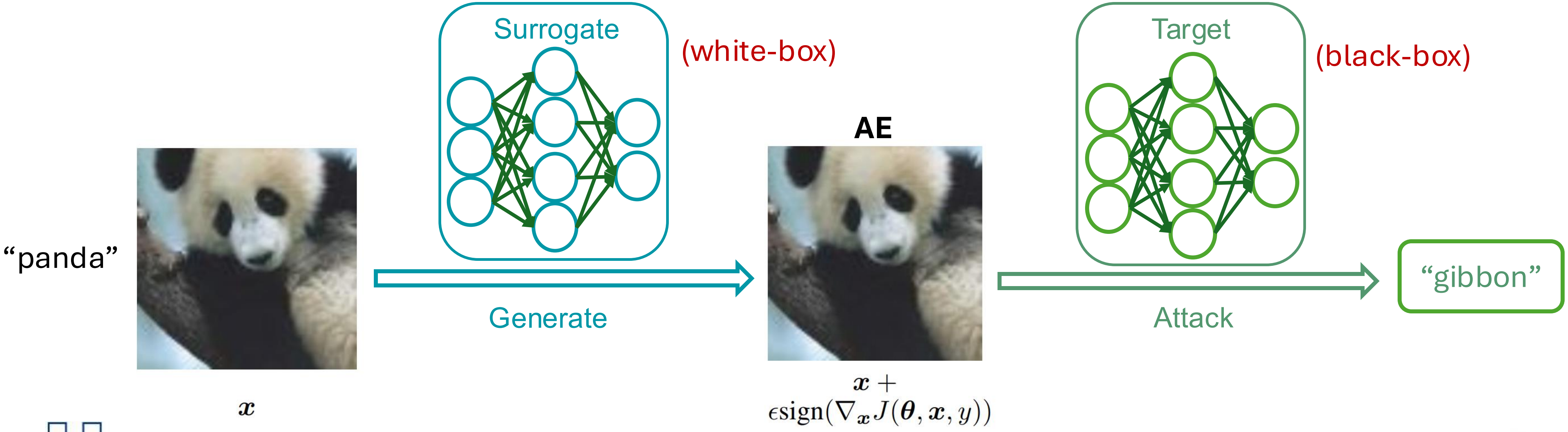
noise
non-random

"airliner"
99% confidence

Background

Transfer-based black-box attacks

- The most **realistic** attacks – requires little knowledge about target models
- The key is to generate “**transferable**” (**generalizable**) AEs

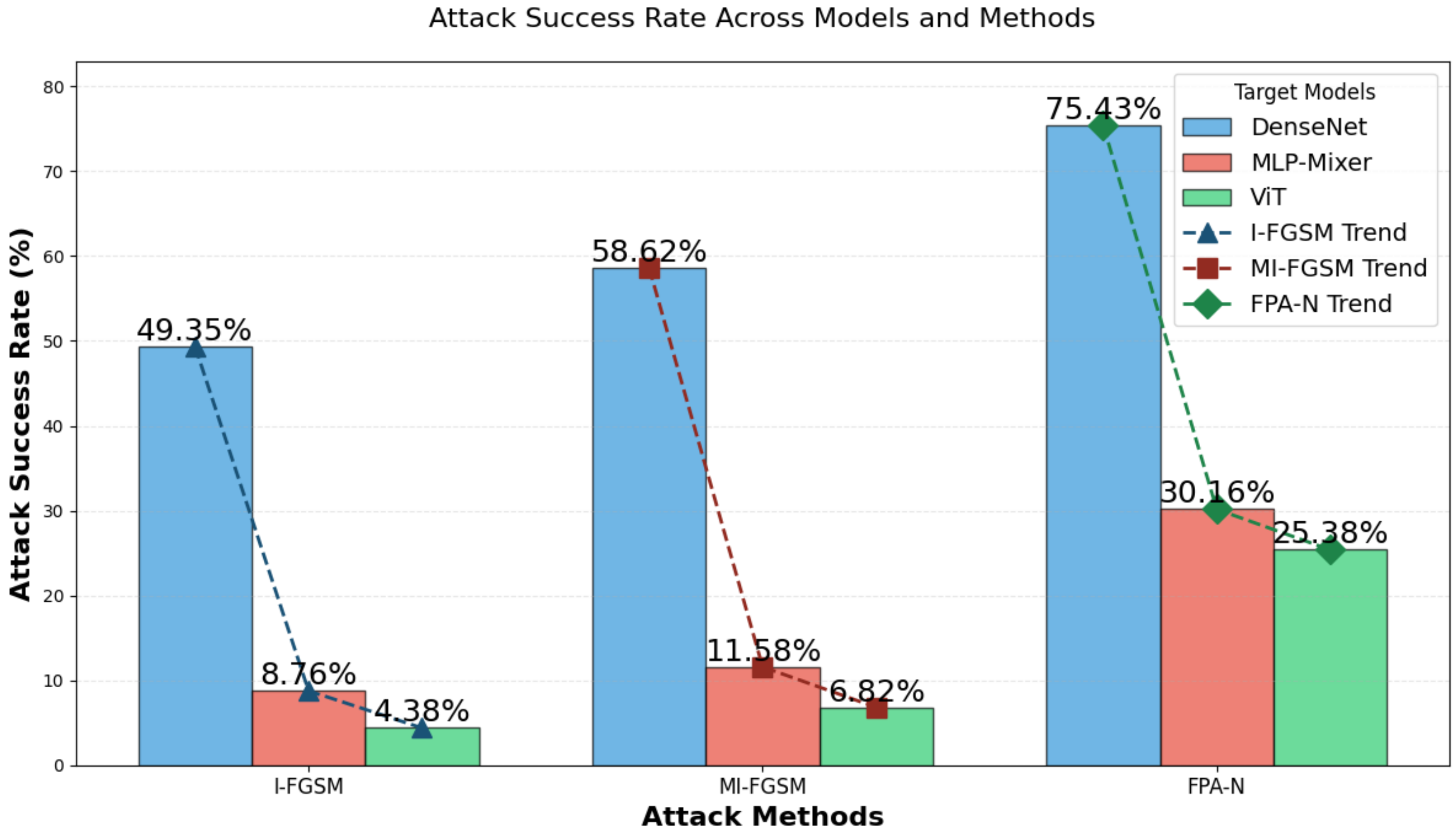


The gap

- Many such transferrable attacks have been proposed and shown to be successful (among CNNs)

- However, transferring across **heterogeneous architectures** (e.g., CNNs, ViTs, MLPs) has been rather **ineffective**

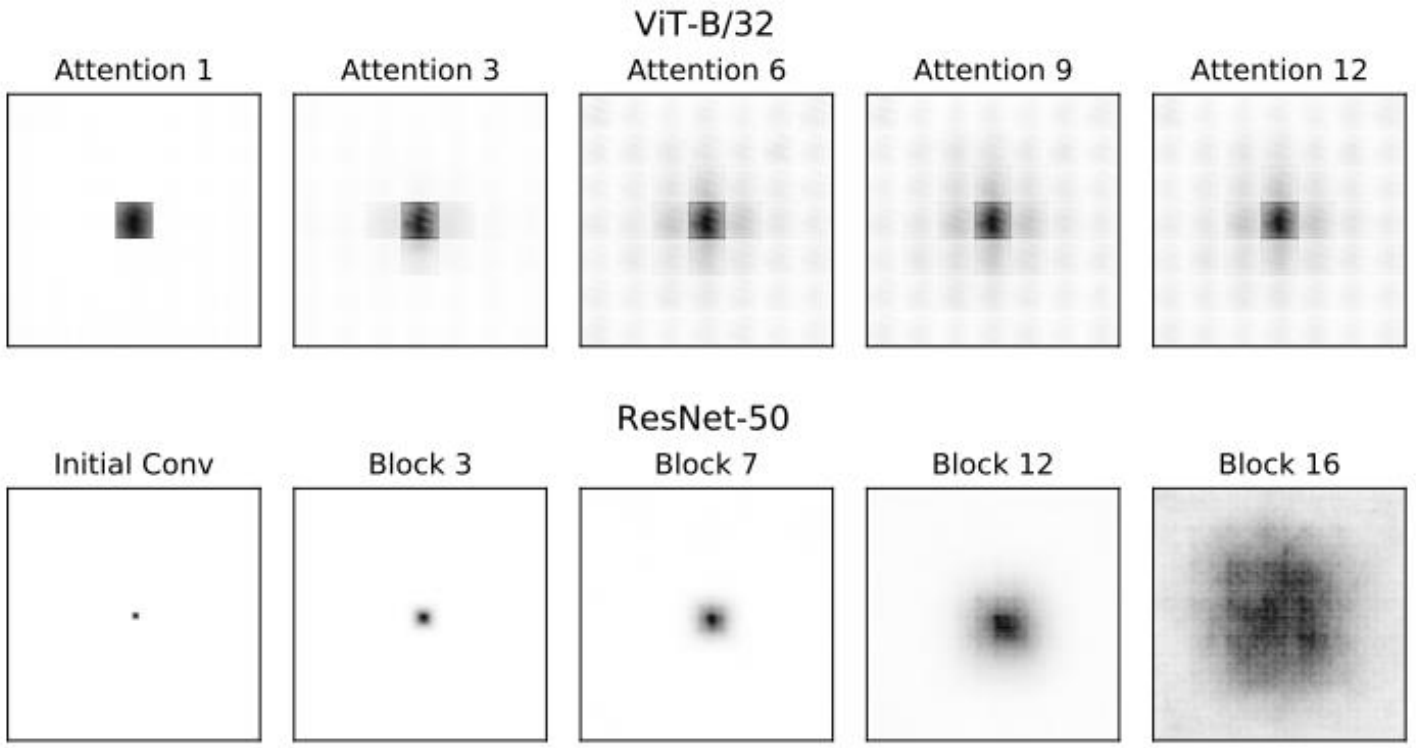
Our empirical finding:



Hypothesis

- Inspired by the observation of **receptive fields** of CNNs as compared to ViTs, we hypothesize that:
- The poor adversarial transferability is due to **CNNs' inadequacy** in attending to long-range dependencies and large contexts.

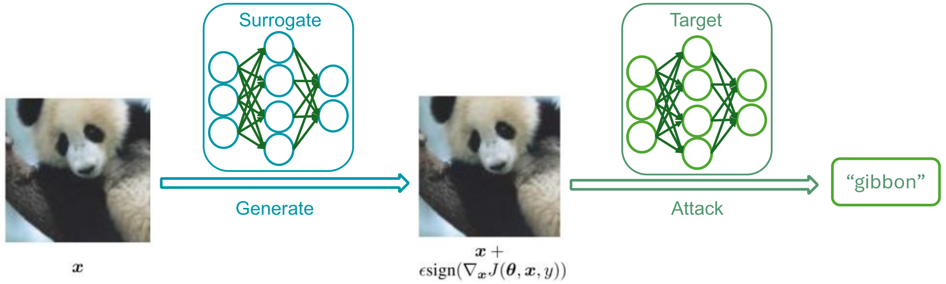
Inductive bias



Raghu, Maithra, et al. "Do vision transformers see like convolutional neural networks?" NeurIPS (2021).

Method

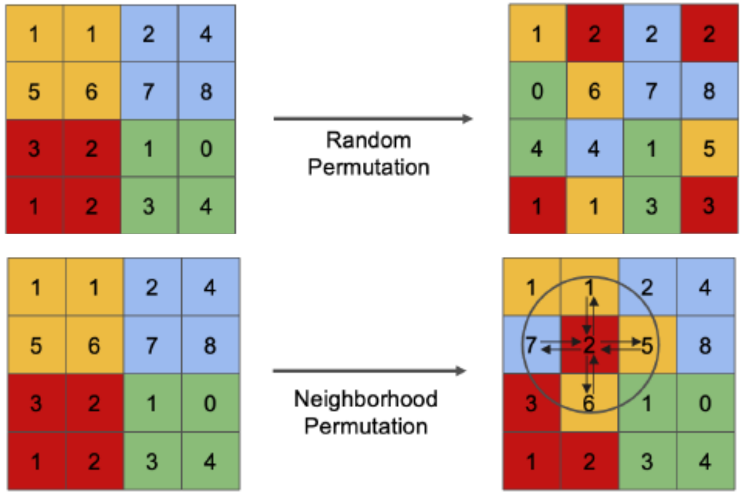
- Introduce long-range dependencies into CNNs
  - by proposing a Feature Permutation Attack (FPA)
- Permute feature maps inside the surrogate model during the process of generating AEs:
  - **FPA-R:** random
  - **FPA-N:** neighborhood



Rearrange pixels within a feature map randomly

Exchange each pixel with one of its four neighboring pixels (randomly chosen)

- **Difference?**
  - **FPA-R:** directly introduces global (long-range) dependency
  - **FPA-N:** much more indirect, preserves local spatial relationship more



- Since there are many feature maps in a CNN, which particular feature maps to permute? By how much?
  - l : Location (layer/block)
  - γ : ratio of channels
  - p : permutation probability per iteration

Experiments

- Target models under attack: 7 CNNs, 4 ViTs, 3 MLPs
  - **CNNs:** VGG-19 [22], ResNet-152 [10], Inception v3 [23], DenseNet121 [11], MobileNet v2 [21], WRN [37], PNASNet [15].
  - **ViTs:** ViT-B [7], DeiT-B [27], Swin-B [17], BEiT-B [1].
  - **MLPs:** Mixer-B [25], Res-MLP [26], gMLP [16].
- Surrogate model: ResNet-50
- 5,000 correctly classified test images from the ImageNet validation set (to generate AEs)

- **FPA-R:** l = 5, γ = 0.3, p= 0.2 (equiv: 6% of channels permuted)
- **FPA-N:** l = 2, γ = 0.6, p= 0.5 (equiv: 30% of channels permuted)

Results

- ASR: attack success rate
- FPA-N achieves the highest ASR in all 14 cases
  - **+14.57 points** on Swin-B (compared to the best non-FPA method)
  - **+14.48 points** on Res-MLP (compared to the best non-FPA method)
- FPA-R: the overall runner-up

I-FGSM served as the base attack for FPA

Method	VGG-19	ResNet-152	Inception-V3	DenseNet121	MobileNet-V2	WRN	PNASNet	ViT-B	DeiT-B	Swin-B	BEiT-B	Mixer-B	Res-MLP	gMLP	**Average**
I-FGSM	43.26%	23.65%	21.54%	49.35%	38.21%	45.32%	18.91%	4.38%	4.03%	4.96%	3.78%	8.76%	7.94%	7.12%	18.99%
MI-FGSM	52.89%	31.56%	32.16%	58.62%	50.35%	54.69%	29.32%	6.82%	5.86%	7.88%	6.76%	11.58%	10.92%	11.26%	27.83%
DIM	67.85%	41.25%	38.95%	70.26%	65.26%	68.42%	35.46%	10.49%	10.35%	11.06%	12.10%	15.68%	15.34%	14.82%	36.94%
TIM	46.78%	29.14%	27.83%	51.35%	48.31%	49.63%	25.34%	5.23%	5.65%	6.04%	4.97%	9.68%	10.03%	8.95%	26.08%
SIM	52.82%	35.68%	33.68%	58.96%	54.16%	58.47%	29.65%	9.35%	10.23%	10.56%	11.05%	11.65%	12.14%	10.98%	31.79%
Admix	66.95%	43.62%	39.46%	68.47%	59.21%	65.61%	30.49%	8.79%	9.62%	10.26%	11.67%	13.60%	13.43%	13.09%	34.63%
SGM	63.46%	46.52%	39.26%	71.26%	57.26%	64.18%	31.25%	11.24%	10.42%	10.96%	11.53%	14.82%	15.48%	15.67%	36.66%
LinBP	66.31%	50.18%	37.89%	69.43%	63.48%	68.14%	32.06%	12.06%	10.36%	11.23%	10.85%	14.62%	14.85%	15.21%	37.53%
FPA-R (ours)	56.83%	43.04%	35.62%	66.59%	58.72%	60.84%	28.89%	16.39%	14.85%	15.68%	17.32%	18.46%	19.15%	19.52%	37.70%
FPA-N (ours)	**70.25%**	**52.38%**	**42.85%**	**75.43%**	**69.48%**	**72.34%**	**39.74%**	**25.38%**	**24.64%**	**25.80%**	**26.19%**	**30.16%**	**31.43%**	**30.82%**	**45.59%**

FPA is very flexible

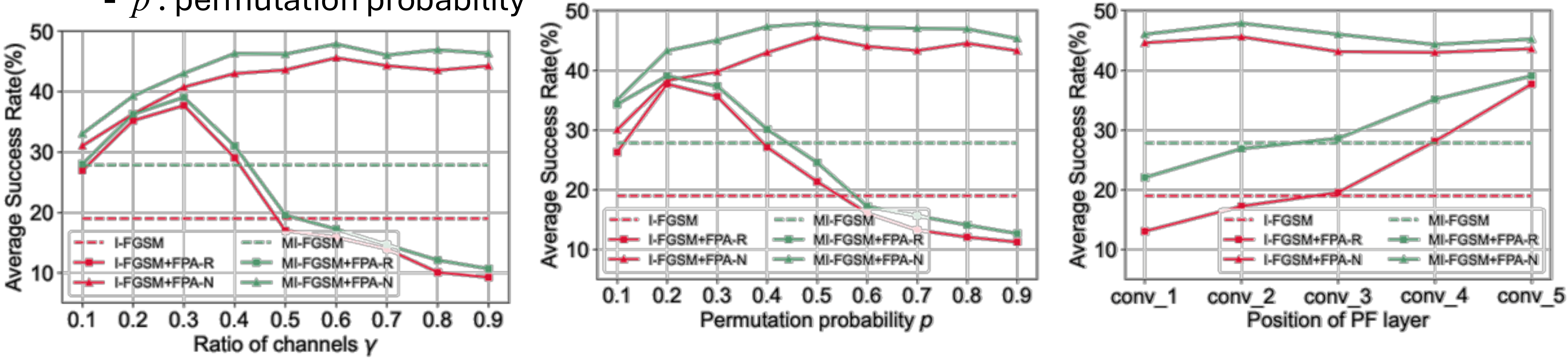
- Can be seamlessly integrated with **probably any attack**
  - Any attack could serve as the base and **gain significant attack strength**

Method	VGG-19	ResNet-152	Inception-V3	DenseNet121	MobileNet-V2	WRN	PNASNet	ViT-B	DeiT-B	Swin-B	BEiT-B	Mixer-B	Res-MLP	gMLP	**Average**
MI-FGSM	52.89%	31.56%	32.16%	58.62%	50.35%	54.69%	29.32%	6.82%	5.86%	7.88%	6.76%	11.58%	10.92%	11.26%	27.83%
MI-FGSM + FPA-R	66.32%	49.13%	45.12%	71.56%	65.14%	69.10%	42.95%	18.26%	18.03%	17.95%	17.52%	21.06%	22.16%	22.53%	39.06%
MI-FGSM + FPA-N	**75.46%**	**57.64%**	**38.95%**	**80.05%**	**73.94%**	**78.86%**	**49.14%**	**27.95%**	**28.49%**	**28.65%**	**29.33%**	**34.02%**	**34.57%**	**33.13%**	**47.87%**
DIM	67.85%	41.25%	38.95%	70.26%	65.26%	68.42%	35.46%	10.49%	10.35%	11.06%	12.10%	15.68%	15.34%	14.82%	36.94%
DIM + FPA-R	75.61%	49.12%	46.35%	76.12%	74.31%	77.03%	45.61%	21.30%	19.16%	18.94%	23.15%	24.96%	23.84%	25.61%	42.94%
DIM + FPA-N	**80.05%**	**54.10%**	**50.23%**	**79.96%**	**77.56%**	**82.04%**	**49.34%**	**29.65%**	**31.49%**	**33.16%**	**32.09%**	**36.16%**	**36.98%**	**35.88%**	**50.62%**
Admix	66.95%	43.62%	39.46%	68.47%	59.21%	65.61%	30.49%	8.79%	9.62%	10.26%	11.67%	13.60%	13.43%	13.09%	34.63%
Admix + FPA-R	74.35%	48.13%	45.19%	75.49%	68.95%	76.01%	38.49%	17.53%	19.23%	20.15%	22.36%	25.16%	25.01%	24.69%	41.48%
Admix + FPA-N	**79.64%**	**50.09%**	**51.29%**	**80.13%**	**76.95%**	**81.32%**	**44.68%**	**27.32%**	**28.96%**	**30.40%**	**33.46%**	**32.68%**	**32.92%**	**34.05%**	**53.24%**

- Performance increases **~20, 14, and 19 points** (see last column) by FPA-N
  - Even FPA-R achieves quite notable gains too

Ablation study

- l : Location (layer)
- γ : ration of channels
- p : permutation probability



- **FPA-N** (triangular marker) is **not sensitive** to hyperparameter variation
- Dash-lines (horizontal) are vanilla attacks without FPA
- FPA-N consistently outperforms FPA-R, as FPA-N better preserves local contextual information.

Efficiency

- Our proposed permutation operation is executed solely through memory operations without requiring matrix computations, additional parameters, or FLOPs.

Methods	I-FGSM	MI-FGSM	DIM	TIM	SIM	Admix	SGM	FPA-R	FPA-N
Time (mins)	4.2	4.9	5.9	6.7	21.6	15.3	4.5	4.2	4.3

Table 3: Comparing wall clock runtime for FPA and baseline attacks on ImageNet.

Conclusion

- We **hypothesize** that the failure of heterogeneous adversarial transfer is due to CNN's inadequacy of modeling **long-range dependencies**
- We propose **Feature Permutation Attack** to address this limitation

- **Flexible** plug-in: probably any attack can serve as the base
- FPA improves attack success rates significantly (by 8-26 percentage points) even in the heterogeneous setting (**from CNN to ViT and MLP**)

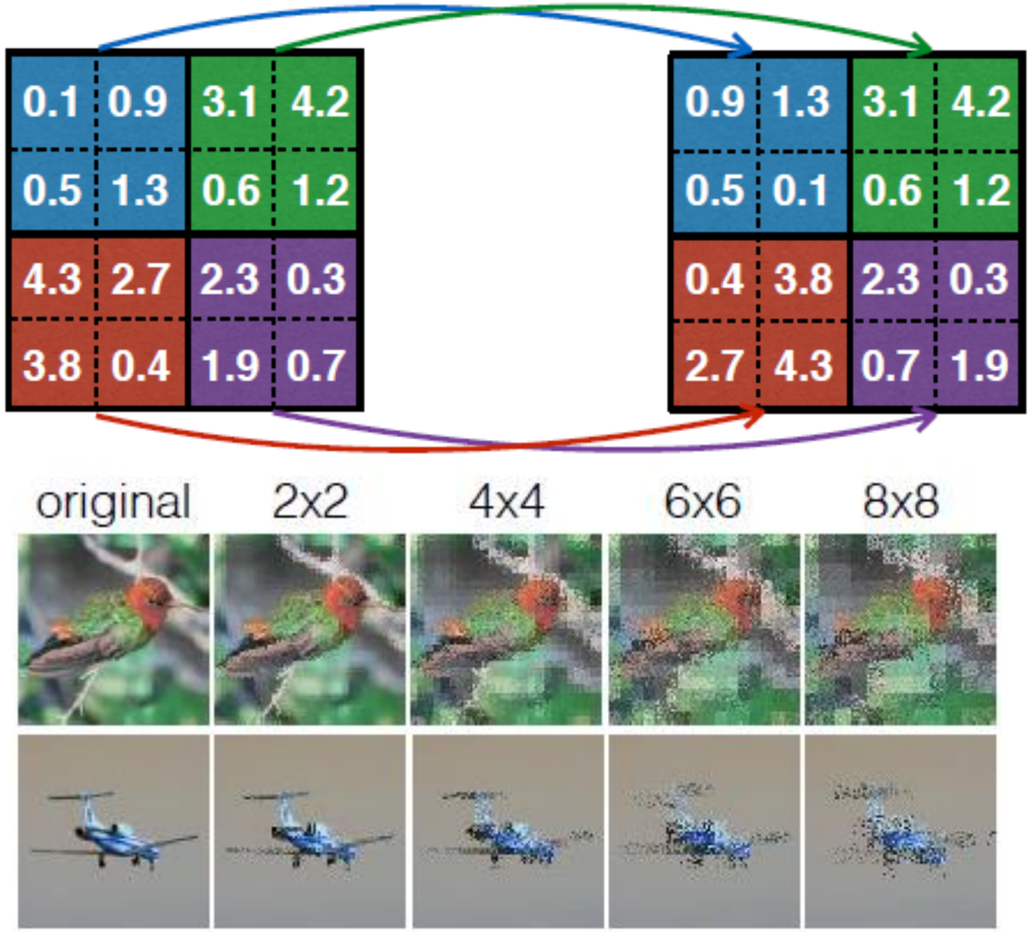
- FPA is **simple and efficient**: it introduces **zero FLOP** and **zero model parameters**.


תודה
Dankie
Gracias
Спасибо
شكراً
Merci
Takk
Köszönjük
Terima kasih
Grazie
Dziękujemy
Dėkojame
Ďakujeme
Vielen Dank
Paldies
Kiitos
Täname teid
谢谢
Thank You
Tak
感謝您
Obrigado
Teşekkür Ederiz
감사합니다
Σας Ευχαριστούμ
ขอบคุณ
Bedankt
Děkujeme vám
ありがとうございます
Tack

Comparison with related work

- Patchshuffle regularization
  - **Input space**
  - Patch-level permutation (shuffle within each patch; **local** scope)
  - A regularization technique (data augmentation)

- FPA (ours)
  - **Feature space**
  - Pixel-level permutation (**global** scope; **long-range**)
  - An adversarial attack



Kang, Guoliang, et al. "Patchshuffle regularization." arXiv preprint arXiv:1707.07103.