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Investigating Transferability of Adversarial Examples in Model Merging

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Part 1: Adversarial Examples

Adversarial examples



88% **tabby cat**

Adversarial examples



adversarial
perturbation →

88% **tabby cat**

Adversarial examples



adversarial
perturbation →



88% **tabby cat**

Adversarial examples



adversarial
perturbation →

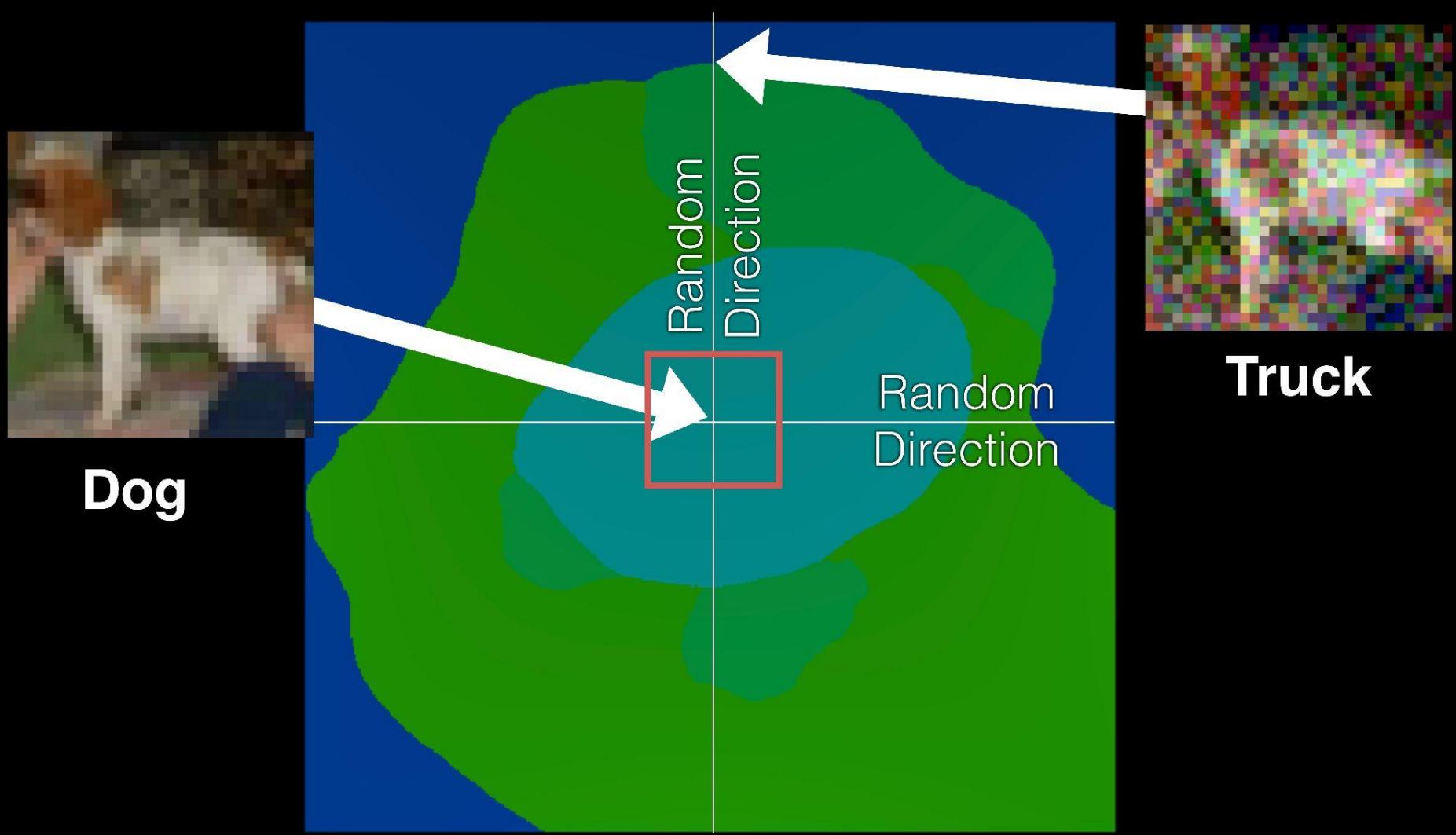


88% **tabby cat**

99% **guacamole**

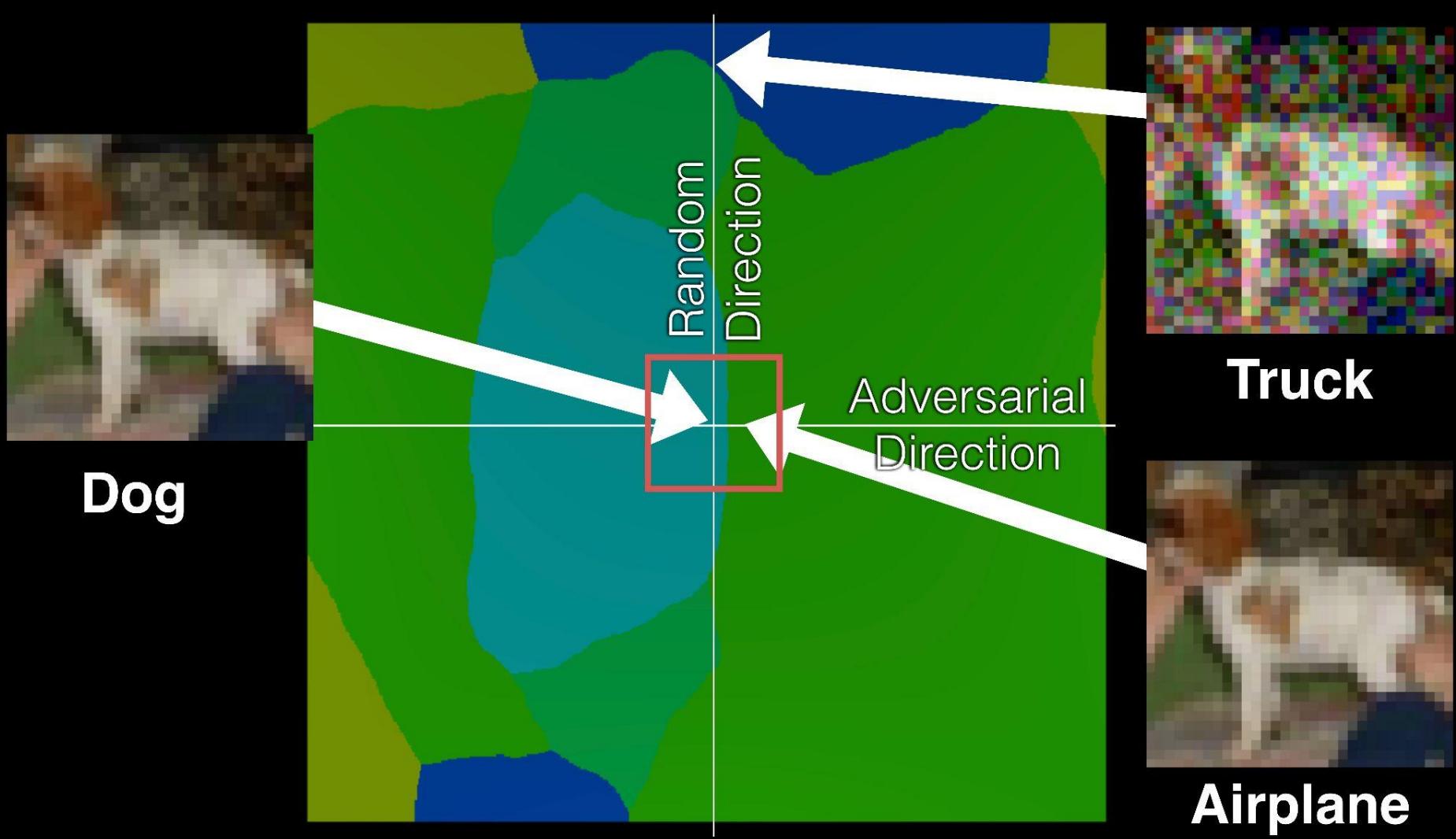
Adversarial examples

Generation



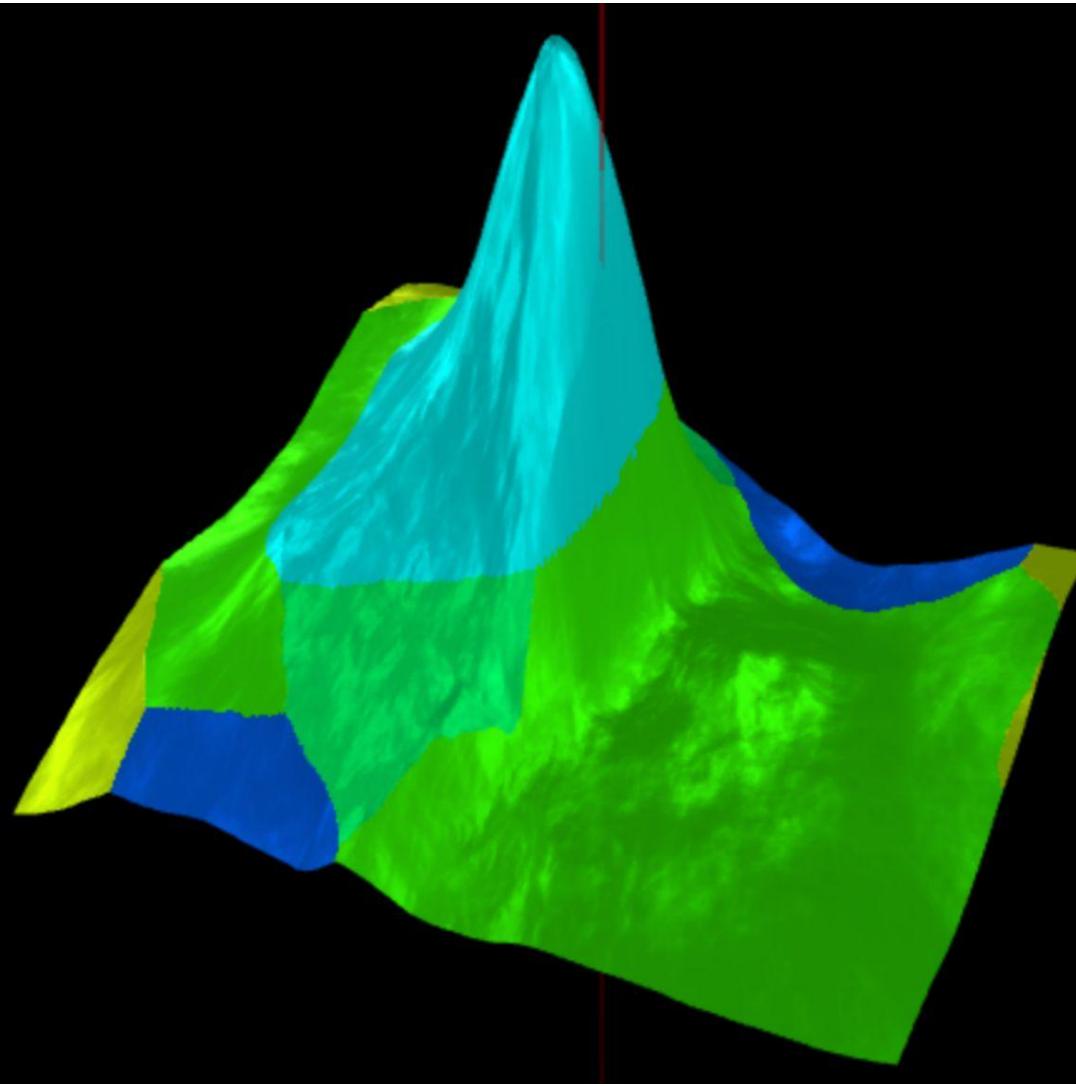
Adversarial examples

Generation



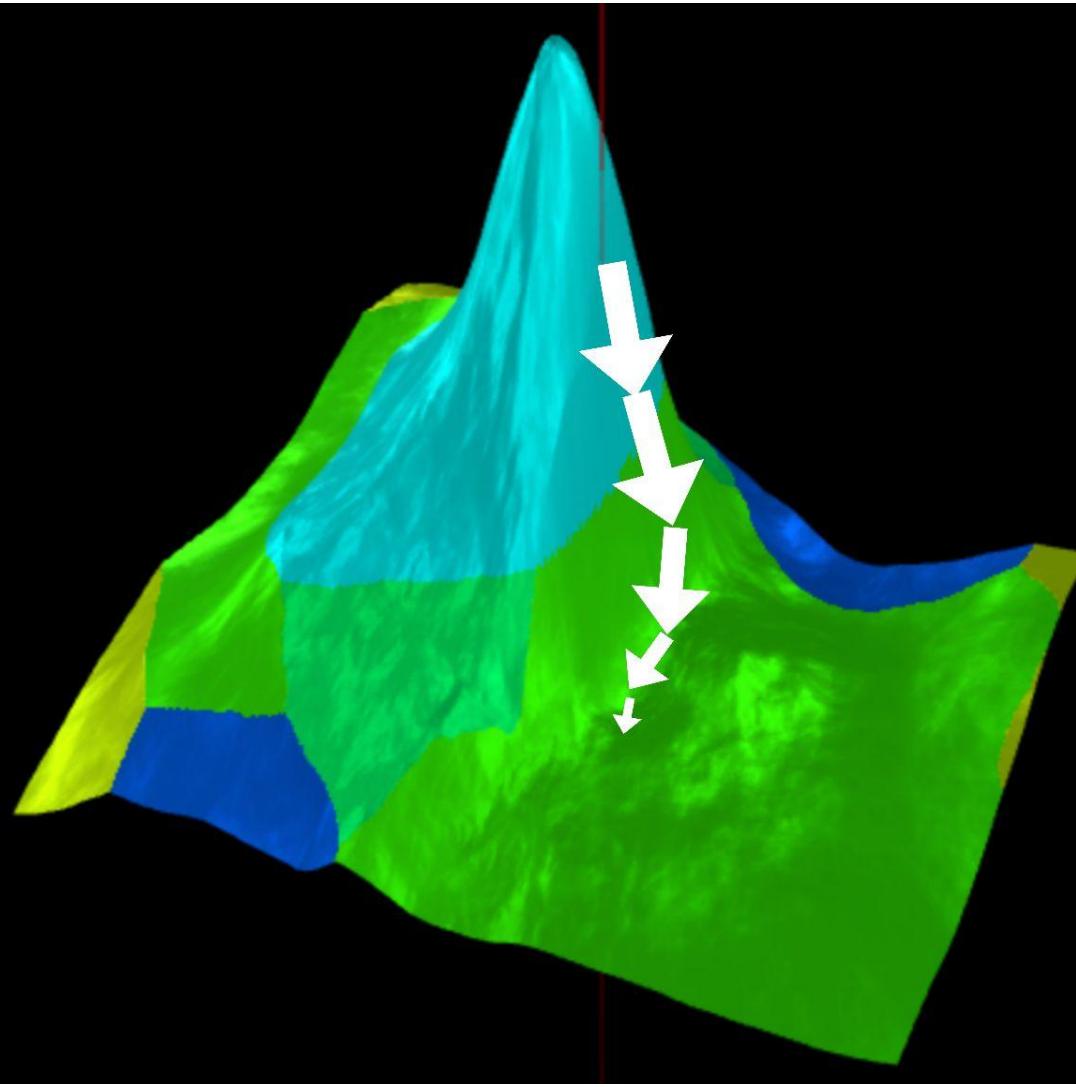
Adversarial examples

Generation



Adversarial examples

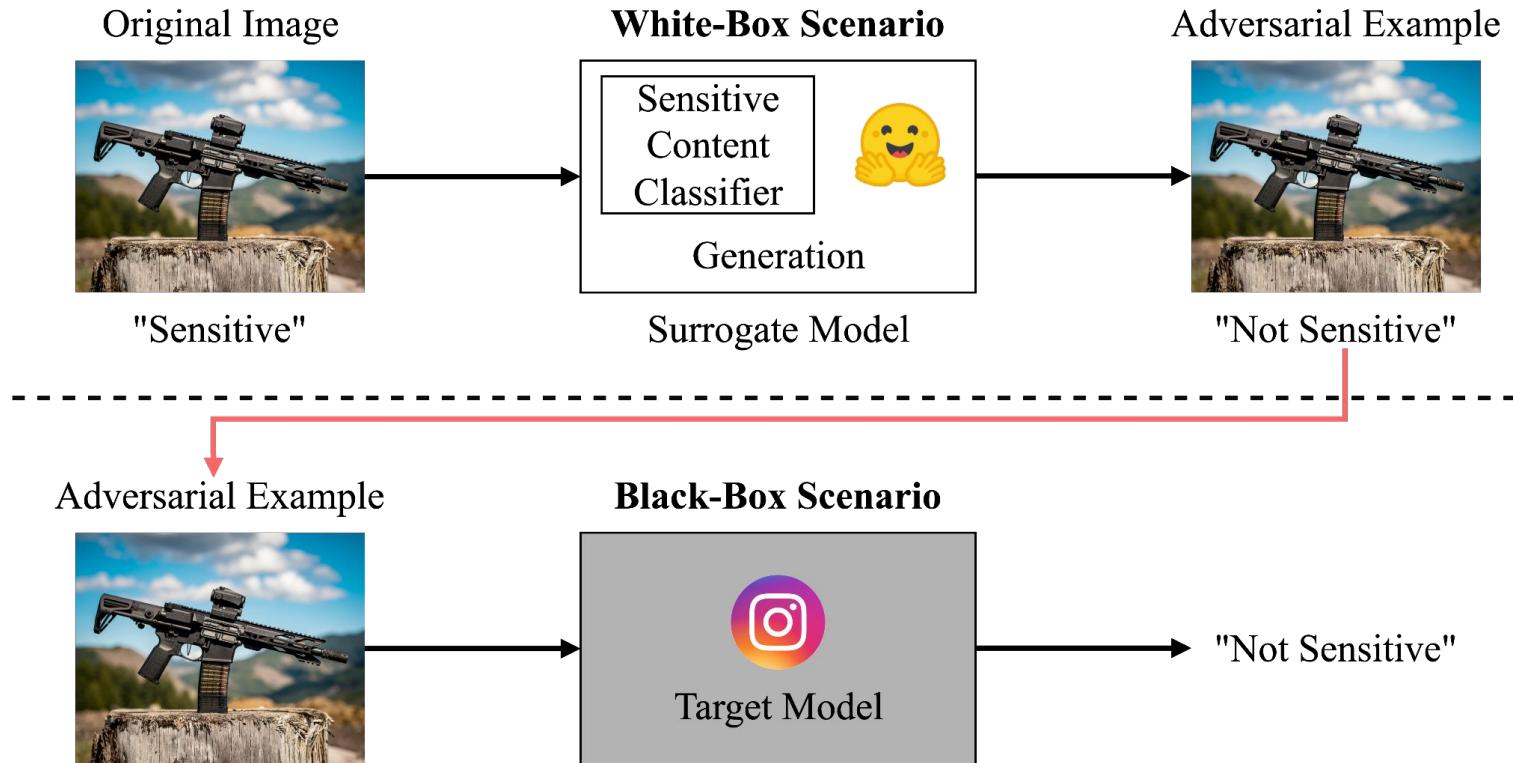
Generation



Adversarial examples

Transferability

Transferability Property of Adversarial Example



⚠️ **Launching an adversarial (evasion) attack does not require access to the target model** ⚠️

Adversarial examples

Transferability

- ❖ Higher transferability expected when:
 - Target model shares architecture with surrogate model.
 - Surrogate model's decision boundary is similar to target model (high test accuracy).

Adversarial examples

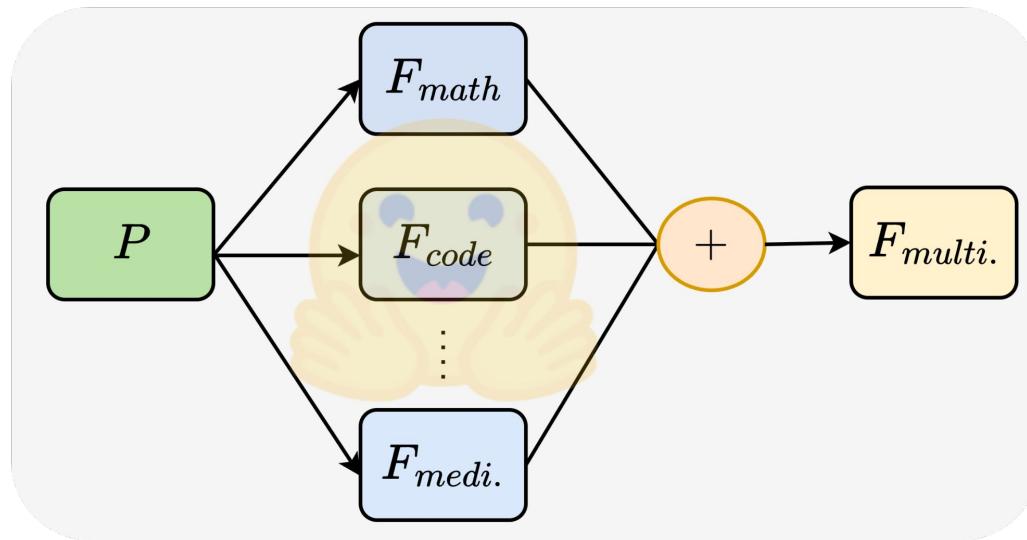
Takeaways

- ❖ Adversarial examples are a subclass of adversarial attacks called evasion attacks, which can cause **serious financial/societal harm**.
 - In 2022, a single case of unemployment fraud involving evasion attacks resulted in losses exceeding **\$2.5 million**.
- ❖ **Cheap to produce** - gradient descent/ascent on confidence/loss w.r.t. image works.
- ❖ Adversarial examples tend to **transfer** to other models performing similar tasks.

Part 2: Model Merging

Model Merging

- ❖ Model merging: (relatively) new and emerging framework to **combine multiple fine-tuned** models into single model.
 - **Alternative to multi-task learning:** no training data required to create multi-task models.

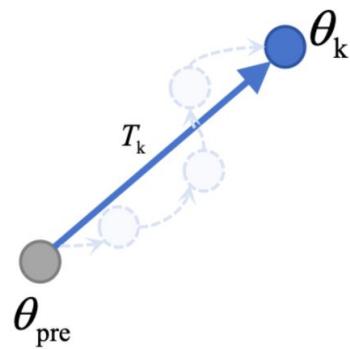


- ❖ **Over 30,000 merged models** available on Hugging Face.

Model Merging

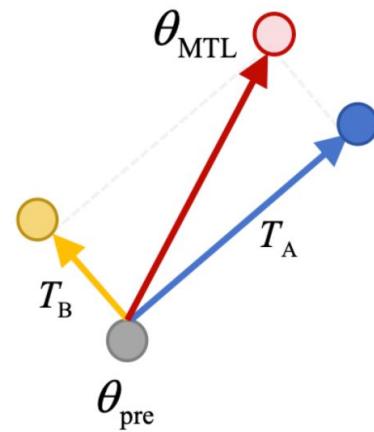
- ❖ Many methods: Weight Averaging, Task Arithmetic, AdaMerging, etc.

Task Vectors



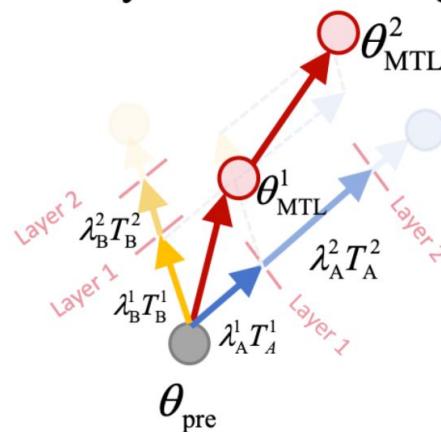
$$T_k = \theta_k - \theta_{pre}$$

Task Arithmetic



$$\theta_{MTL} = \theta_{pre} + \lambda(T_A + T_B)$$

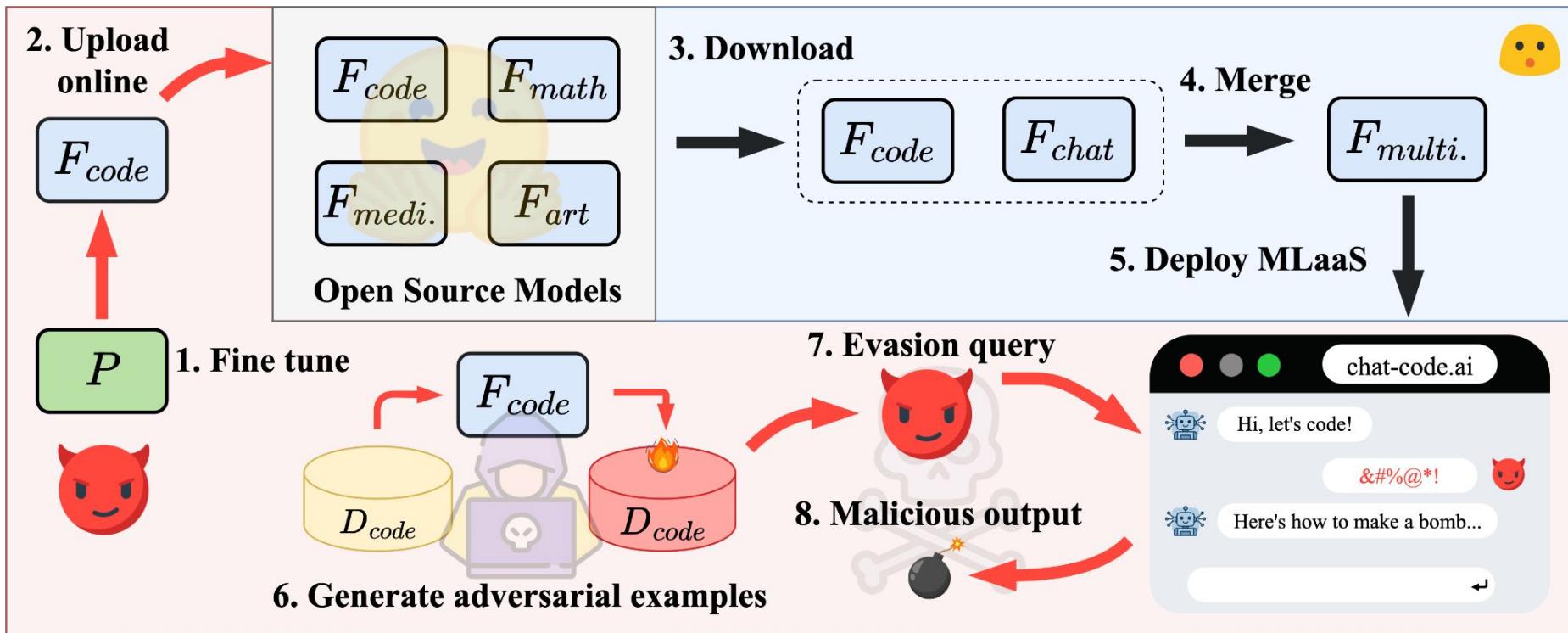
Layer-wise AdaMerging



$$\theta_{MTL} = \{\theta_{MTL}^l\}_{l=1}^2 = \{\theta_{pre}^l + (\lambda_A^l T_A^l + \lambda_B^l T_B^l)\}_{l=1}^2$$

Part 3: Adversarial Transferability in Model Merging

Transferability in Model Merging



Overview of Adversary's attack strategy

Part 4: Results

Results

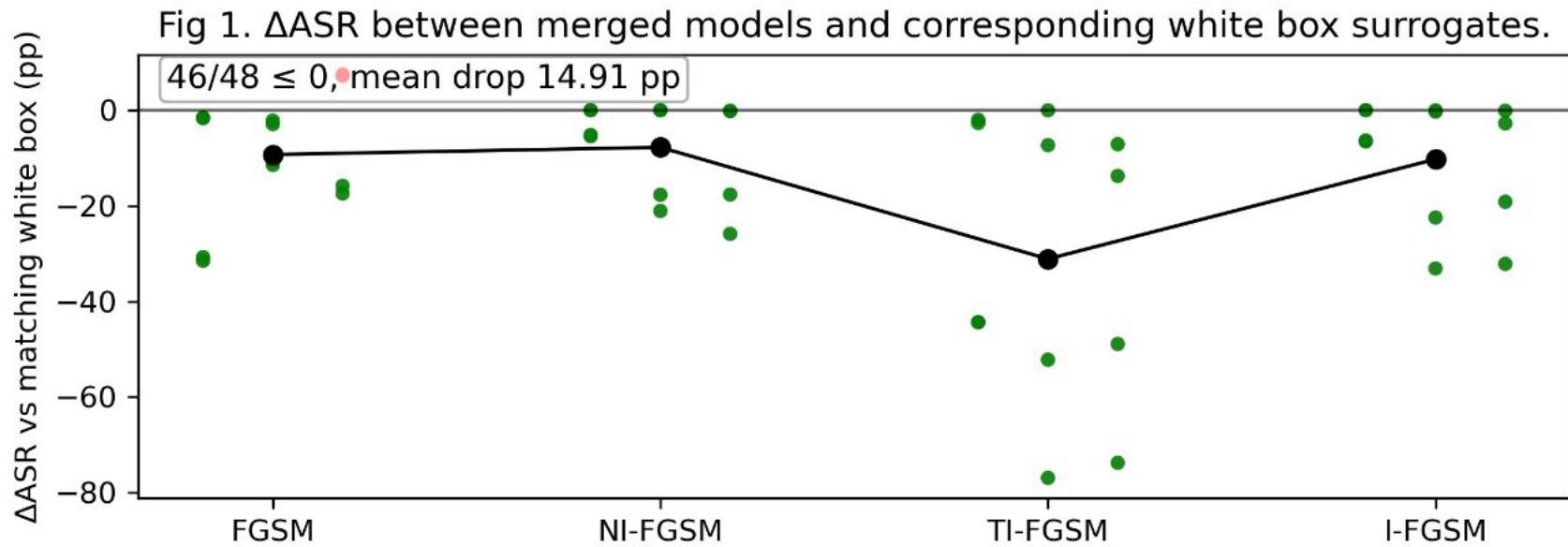
Table 1: ASRs (%) Across Datasets for Different Surrogate and Target Models. \mathcal{P} , \mathcal{F} denote pretrained and fine-tuned models, respectively, while \mathcal{M}_w and \mathcal{M}_s denote model merged via WA and Surgery+WA, respectively. Red and green denote the two cases where the ASR going from \mathcal{M}_w to \mathcal{M}_s (1) increases and (2) decreases or remains the same, respectively.

Attack	Surrogate ↓ / Target →	Cars				MNIST				EuroSAT			
		\mathcal{P}	\mathcal{F}	\mathcal{M}_w	\mathcal{M}_s	\mathcal{P}	\mathcal{F}	\mathcal{M}_w	\mathcal{M}_s	\mathcal{P}	\mathcal{F}	\mathcal{M}_w	\mathcal{M}_s
FGSM	\mathcal{P}	100.00	56.75	68.50	69.26	100.00	92.08	89.32	88.54	100.00	65.26	84.19	82.57
	\mathcal{F}	99.95	99.73	98.08	98.18	100.00	90.79	87.88	88.62	100.00	72.04	79.48	79.26
	\mathcal{M}_w	99.95	98.78	99.42	99.40	100.00	88.75	89.44	88.56	100.00	66.76	85.69	84.87
	\mathcal{M}_s	99.95	98.68	99.32	99.56	100.00	89.98	89.78	88.66	100.00	68.41	85.26	85.37
NI-FGSM	\mathcal{P}	100.00	88.09	94.55	94.83	100.00	21.97	78.92	82.31	100.00	69.41	82.35	74.13
	\mathcal{F}	99.93	100.00	100.00	100.00	99.97	100.00	100.00	100.00	100.00	100.00	99.81	99.89
	\mathcal{M}_w	99.61	100.00	100.00	100.00	99.80	98.77	100.00	100.00	100.00	87.96	100.00	100.00
	\mathcal{M}_s	99.69	100.00	100.00	100.00	100.00	97.76	100.00	100.00	100.00	93.89	100.00	100.00
TI-FGSM	\mathcal{P}	100.00	31.64	55.65	55.64	100.00	0.34	47.79	23.09	100.00	3.02	51.09	26.24
	\mathcal{F}	99.61	100.00	97.33	97.99	99.92	89.76	89.73	82.45	100.00	99.65	85.91	92.54
	\mathcal{M}_w	99.59	96.74	99.99	99.98	99.96	1.23	100.00	96.13	99.98	20.15	100.00	98.44
	\mathcal{M}_s	99.64	97.53	99.99	100.00	99.38	1.35	98.83	100.00	100.00	40.85	99.50	100.00
I-FGSM	\mathcal{P}	100.00	80.51	93.66	93.45	100.00	1.13	77.54	66.89	100.00	31.22	80.85	67.85
	\mathcal{F}	99.81	100.00	100.00	100.00	100.00	100.00	99.96	99.70	99.98	100.00	97.24	99.89
	\mathcal{M}_w	99.63	100.00	100.00	100.00	99.93	38.57	100.00	99.96	99.94	91.59	100.00	100.00
	\mathcal{M}_s	99.56	100.00	100.00	100.00	99.95	38.83	100.00	100.00	99.94	93.22	99.89	100.00

Results

Takeaway #1

- ❖ ASR on merged (target) models \leq ASR on surrogate models in 46/48 cases.
 - In most cases, model merging shown to reduce success of attack.

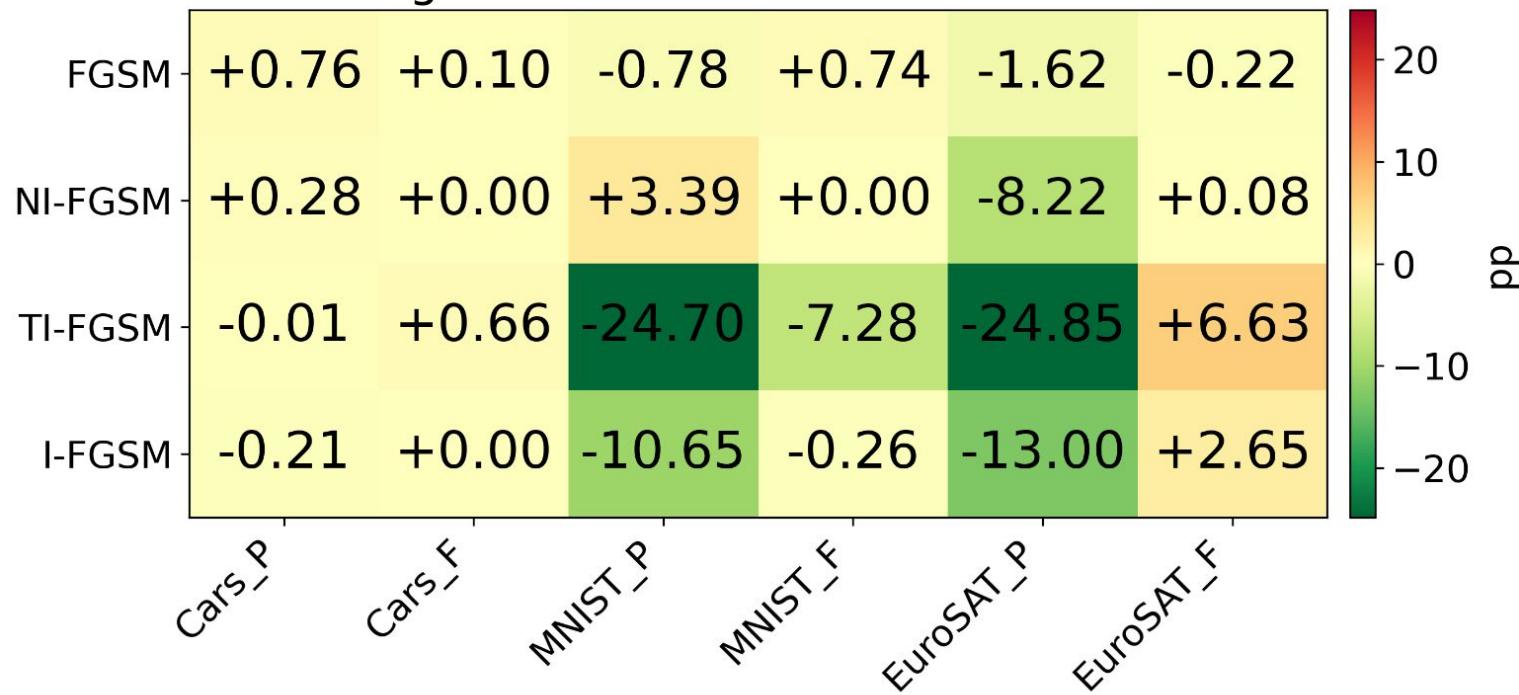


Results

Takeaway #2

- ❖ ASR decreases/remains same in 15/24 cases when a stronger merging method is used.
 - In more than half cases, stronger model merging doesn't increase success of attack.

Fig 2. ΔASR between Ms and Mw.

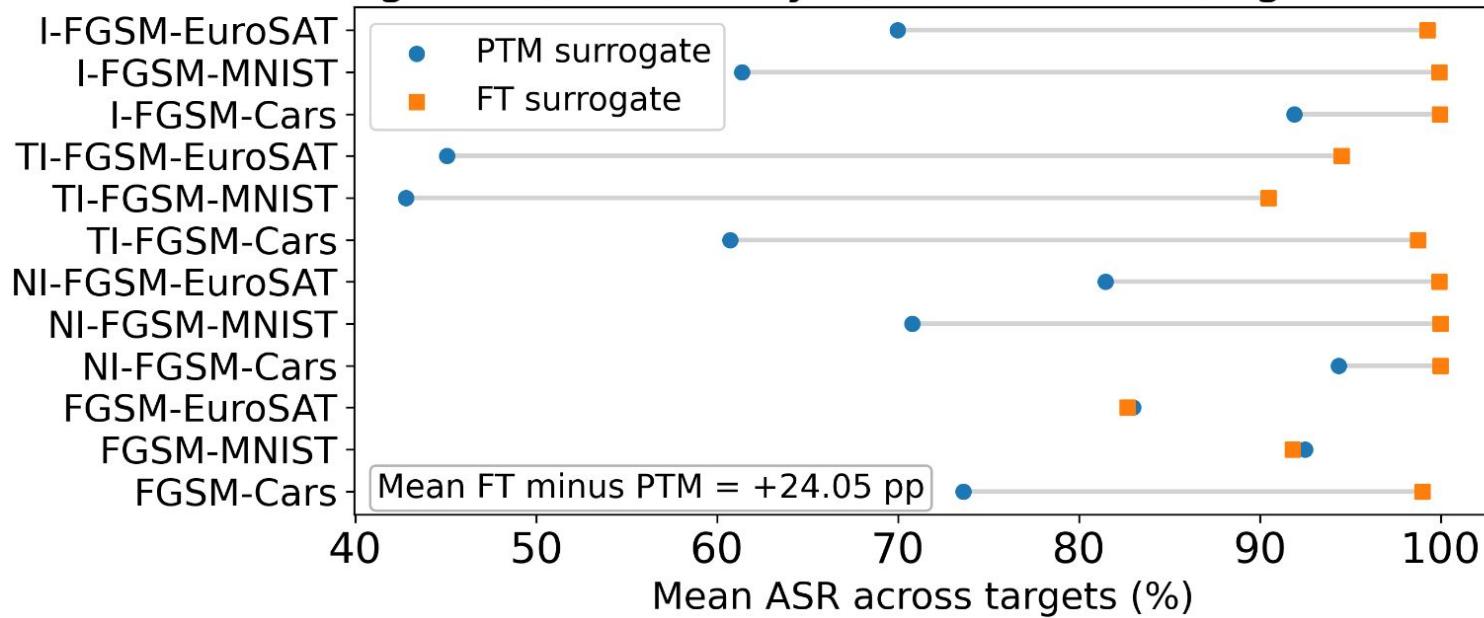


Results

Takeaway #3

- ❖ Pretrained model acts as a weaker surrogate relative to fine-tuned counterpart.
 - Merging an open-source fine-tuned model exposes you to threat of transfer attacks more.

Fig 3. Transferability when PTM is surrogate vs FT.



Conclusion and Future work

- ❖ The risk of transfer attack is real.
- ❖ Model merging could provide a “free lunch” of adversarial robustness.
- ❖ Theoretical analysis, statistical validation of the results.



Thank you!

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