



Morphence

Moving Target Defense Against
Adversarial Examples

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Adversarial Examples



Input

Picture of a Cat



Adv. crafting

Careful
perturbations of
the input



ML model

A highly
accurate Cats vs
Dogs classifier



Output

Wrong
prediction

Important Milestones

2014
**Gradient-based
Attacks**

FGSM[1], BIM[2]
and PGDM[3]

[1] <https://arxiv.org/abs/1412.6572>

[2] <https://arxiv.org/pdf/1611.01236.pdf>

[3] <https://arxiv.org/pdf/1706.06083.pdf>

2016
**Defences against
Gradient Attacks**

Defensive Distillation[4],
Gradient Masking, etc

[4] <https://arxiv.org/abs/1511.04508>

[5] <https://arxiv.org/abs/1608.04644>

[6] <https://arxiv.org/abs/1611.01236>

2017
**Carlini &
Wagner**

C&W[5]

2017
**Adversarial
training**

Adv
training[6]

2019
**Certified
Defenses**

Certified
Defenses[7],
PixelDP[8]

[7] <https://arxiv.org/abs/1705.07204>

[8] <https://arxiv.org/abs/1801.09344>

[9] <https://arxiv.org/abs/1802.03471>

2021
**Morphence
(this work)**

*Moving
Target
Defense*

Why Moving Target Defense?

Fixed Model

- Highly vulnerable to model approximation
- Given enough time, the adversary will eventually find a way to evade it
- Repeated Attack: Once successful, it is always successful

Moving Model

- Fitting the target model could be harder
- The defender is always one step ahead
- An attack can succeed only once

A Moving Model



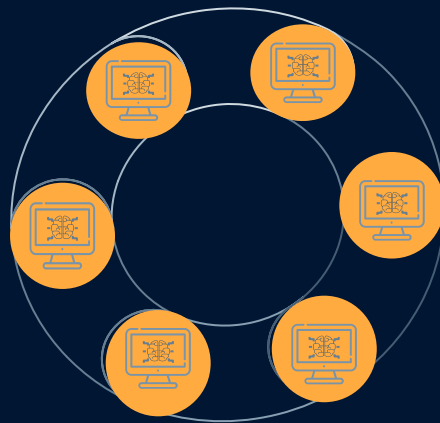
Input

Picture of a Cat



Adv. crafting

Careful perturbations of the input



Moving Model

A highly accurate Cats vs Dogs classifier



Output

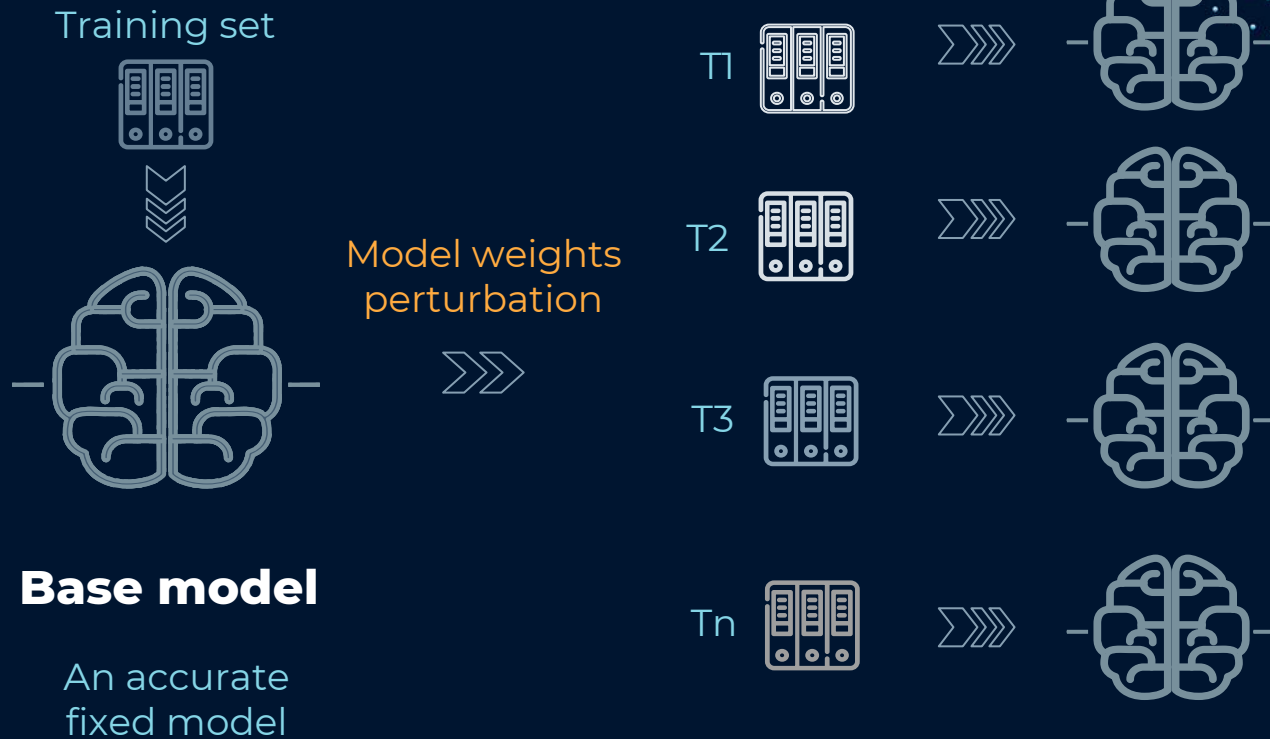
Correct prediction



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Towards Moving Target Defenses against
Adversarial Examples ...

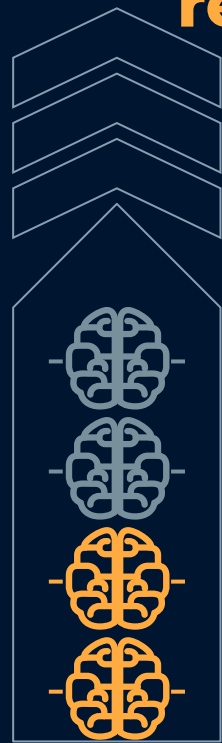
Model Pool Generation



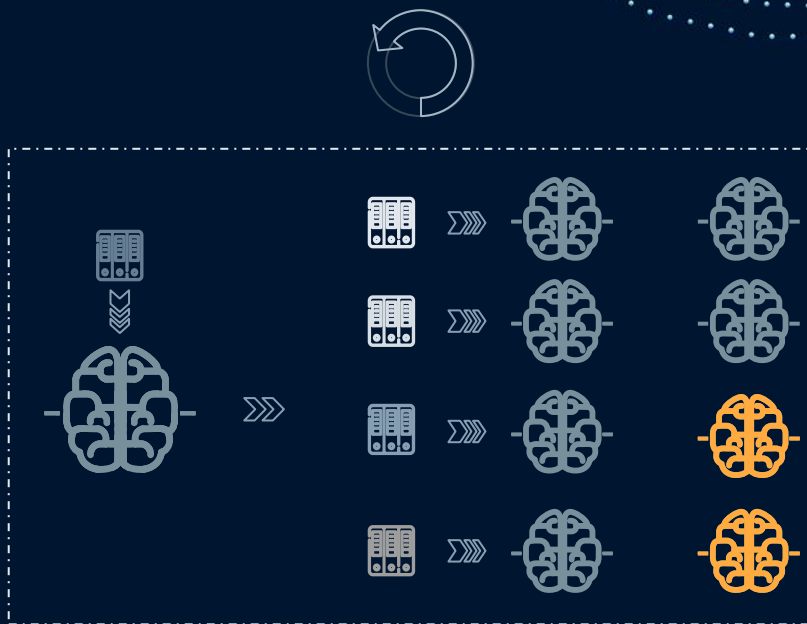
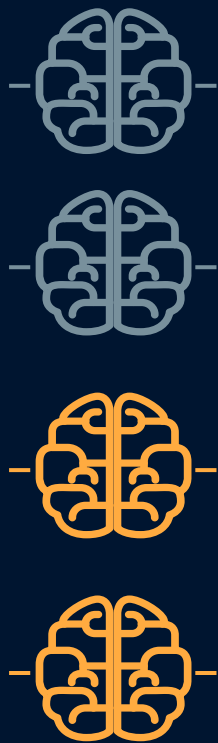
Another Layer of Robustness



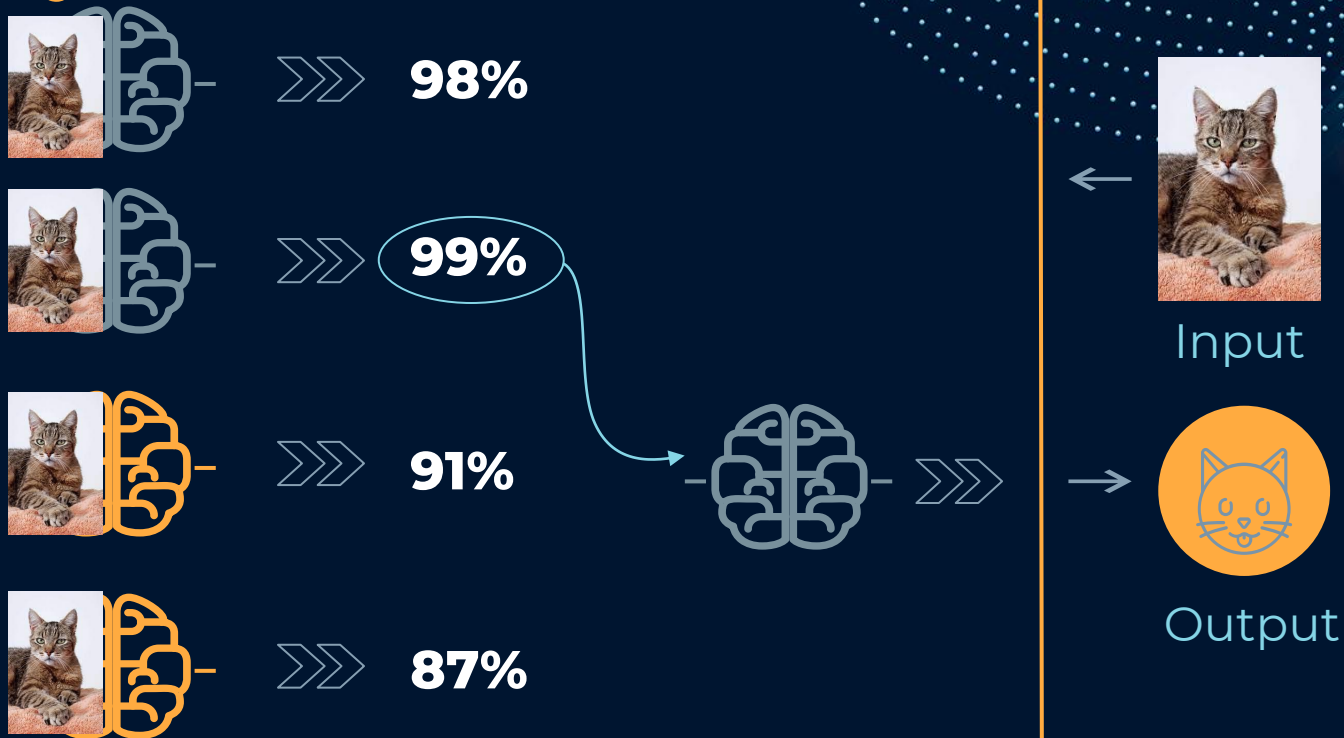
Local storage and repetitive generation



Stack



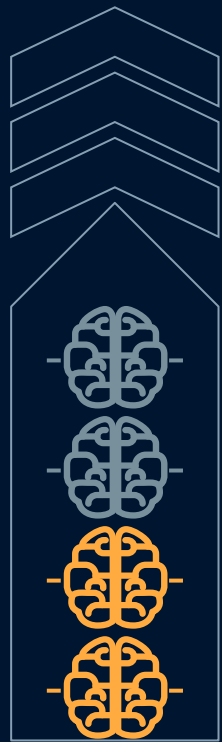
Deployment



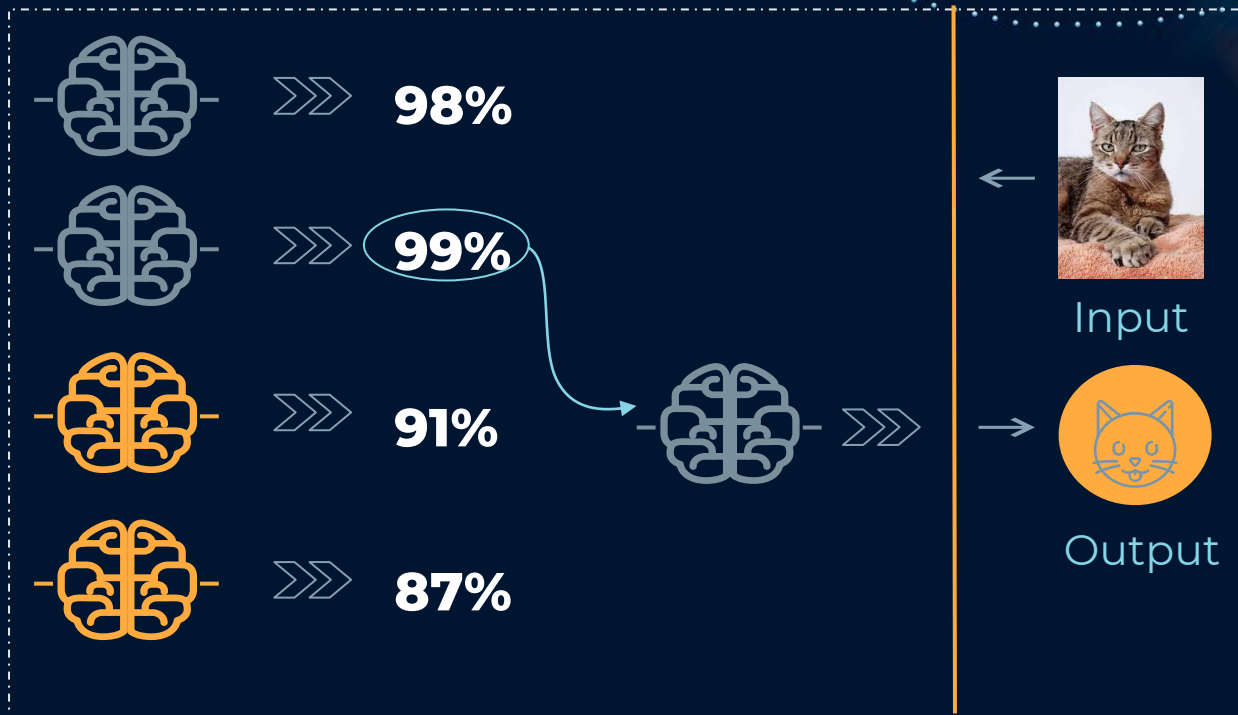
n models

Model Pool Renewal

queries = Q_{max}



Stack



Results on MNIST

	Undefended	Adversarially-trained	Morphence
No Attack	99.72%	97.17%	99.04%
FGSM	9.98%	42.38%	71.43%
C&W	0.0%	0.0%	97.75%
SPSA [10]	29.04%	59.43%	97.77%

Do not sacrifice accuracy on benign data

Significant increase compared to adv training

Overcomes C&W

Robust against iterative-query attacks

Results on CIFAR10

	Undefended	Adversarially-trained	Morphence
No Attack	83.63%	75.37%	84.64%
FGSM	9.98%	36.62%	38.78%
C&W	1.25%	1.34%	44.50%
SPSA	38.96%	59.43%	62.83%

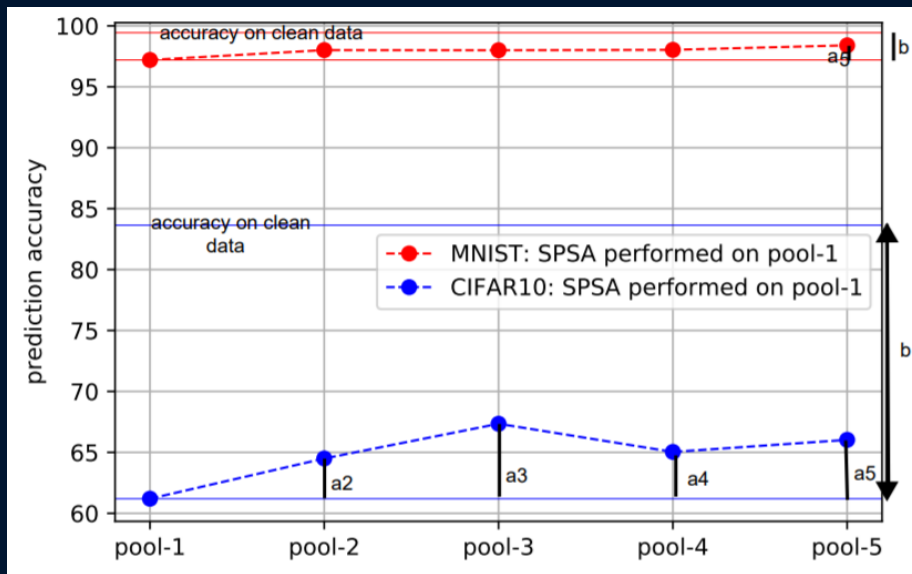
Can improve accuracy on benign data

Improvement compared to adv training

Significant improvement on C&W

Higher robustness against iterative-query attacks

Robustness Against Repeated Attacks



Does successful attacks on pool-1 remain evasive on different pool of models?

Detailed Results in the paper

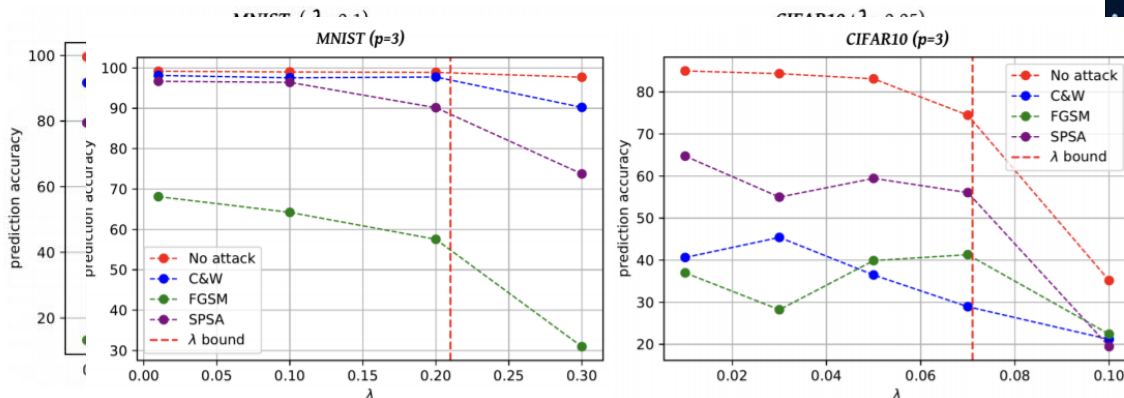


Fig. 5: Noise scale λ vs. accuracy.

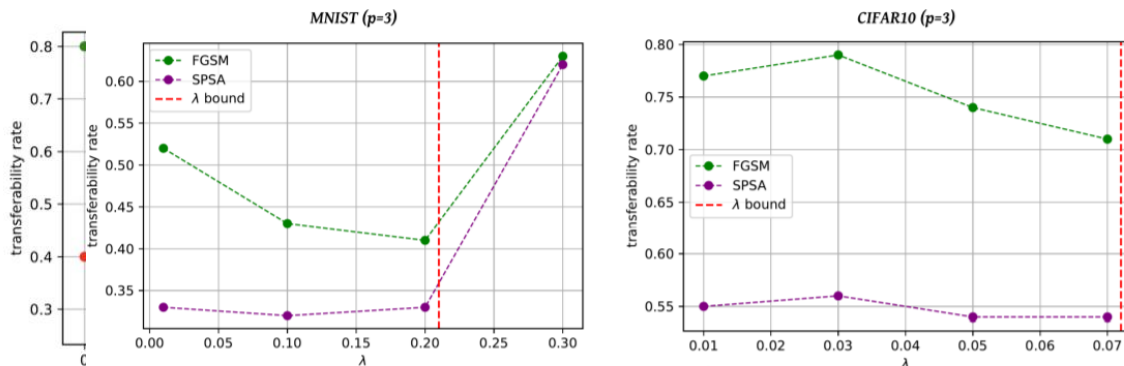
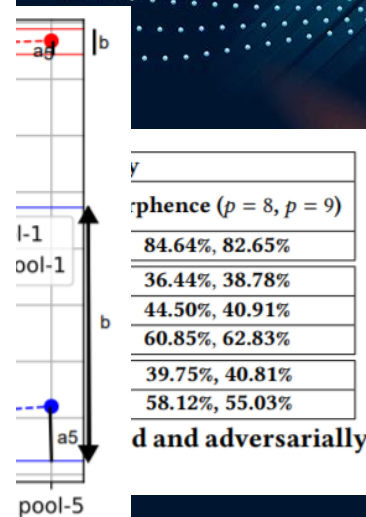


Fig. 6: Noise scale λ vs. average transferability rate.

Fig. 4: # adversarially trained models p vs. average transferability rate.



Conclusions

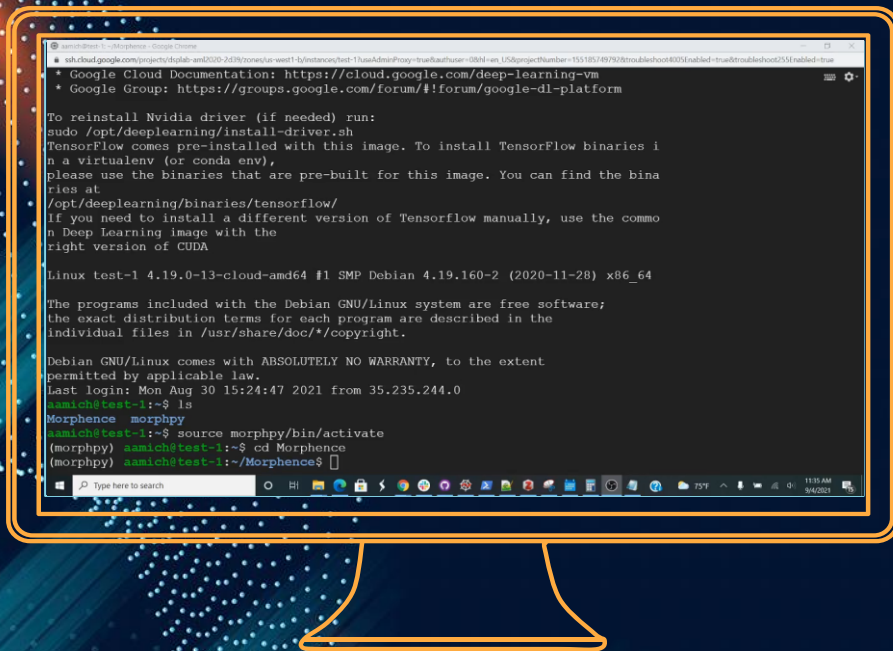
Morphence

Moving Target Defense
Against Adversarial
Examples

- A Moving target model is more robust than the best fixed model defense.
- A Moving target model can prevent falling to the same attack multiple times.
- Iteratively querying a moving target model is not effective to optimize adversarial perturbations.
- We hope that Morphence will be used as a new benchmark for robustness against evasion attacks

Available Artifact

<https://github.com/um-dsp/Morphence>



THANKS!

Do you have any questions?



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