

# Obfuscated Gradients Give a False Sense of Security: Circumventing Defenses to Adversarial Examples

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**How and Why**

Act I

**Background:**

Adversarial Examples  
for Neural Networks



88% **tabby cat**





adversarial  
perturbation



88% **tabby cat**





adversarial  
perturbation



88% **tabby cat**





adversarial  
perturbation



88% **tabby cat**

99% **guacamole**







Why should we care about  
adversarial examples?

*Make ML*  
***robust***

*Make ML*  
***better***





13 total defense papers at ICLR'18

9 are *white-box, non-certified*

6 of these are broken  
(~0% accuracy)

1 of these is partially broken





**How** did we evade them?

**Why** we able to evade them?





Act II

**HOW:**

**Our Attacks**

*How do we generate  
adversarial examples?*

**MAXIMIZE**

neural network loss  
on the given input

**SUCH THAT**

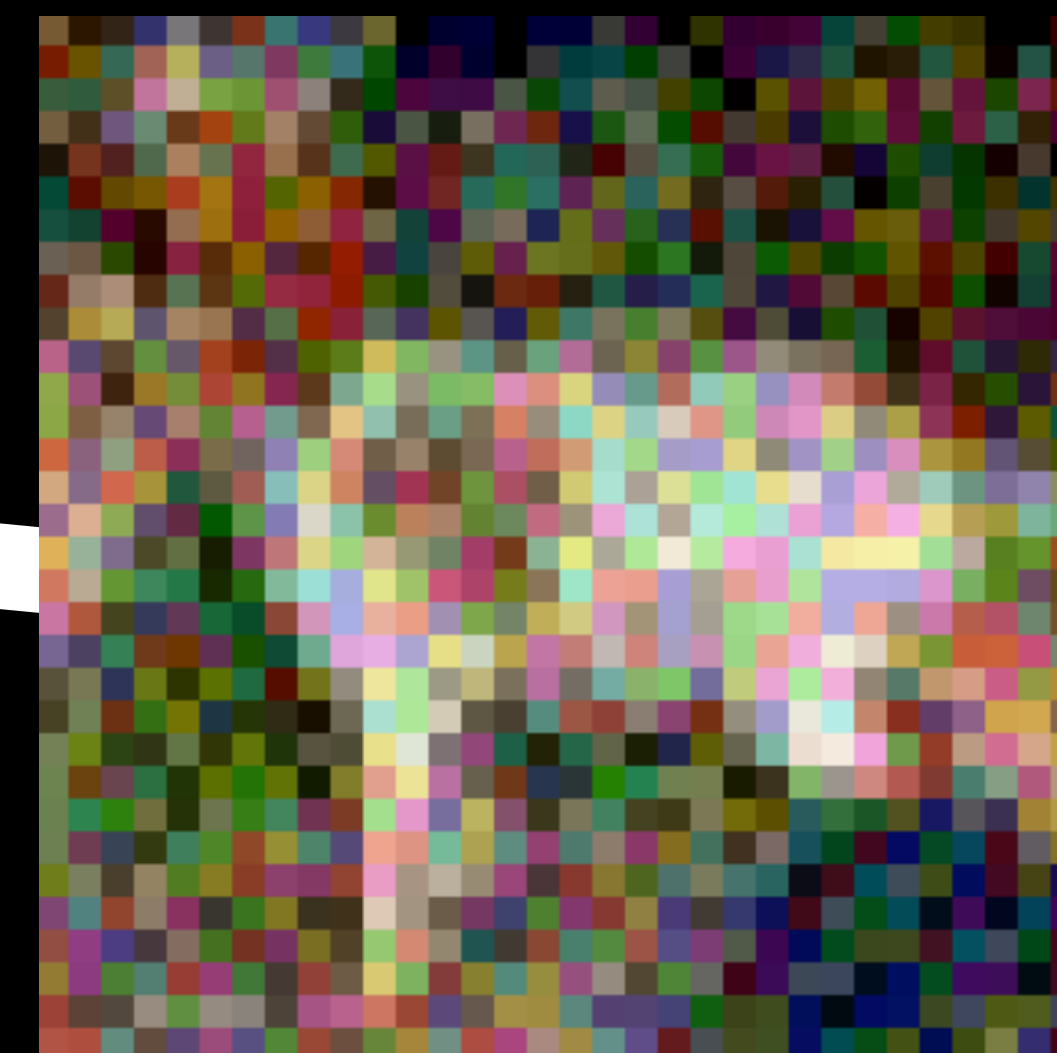
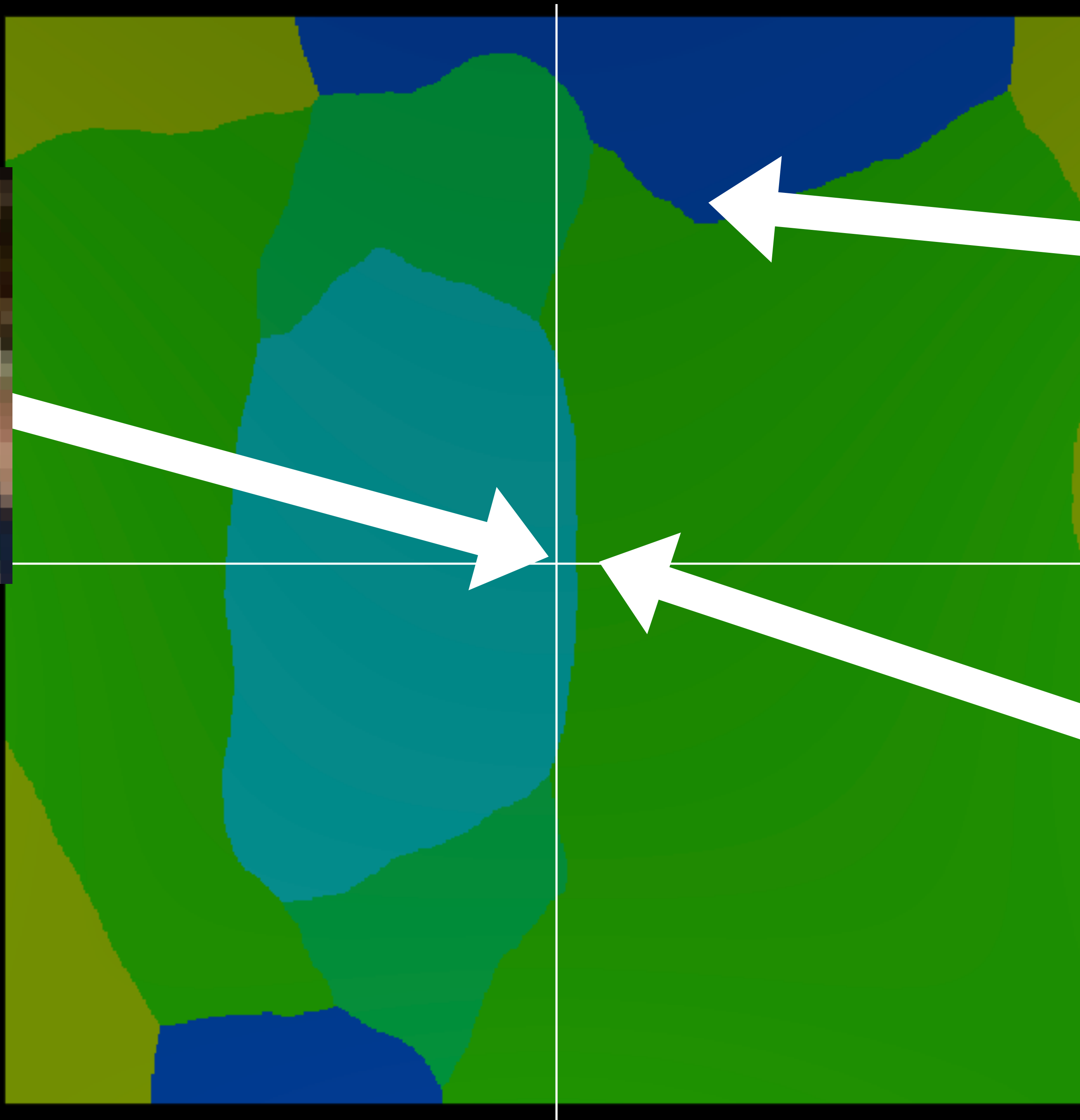
the perturbation is less  
than a given threshold



*Why* can we generate  
adversarial examples  
(with gradient descent)?



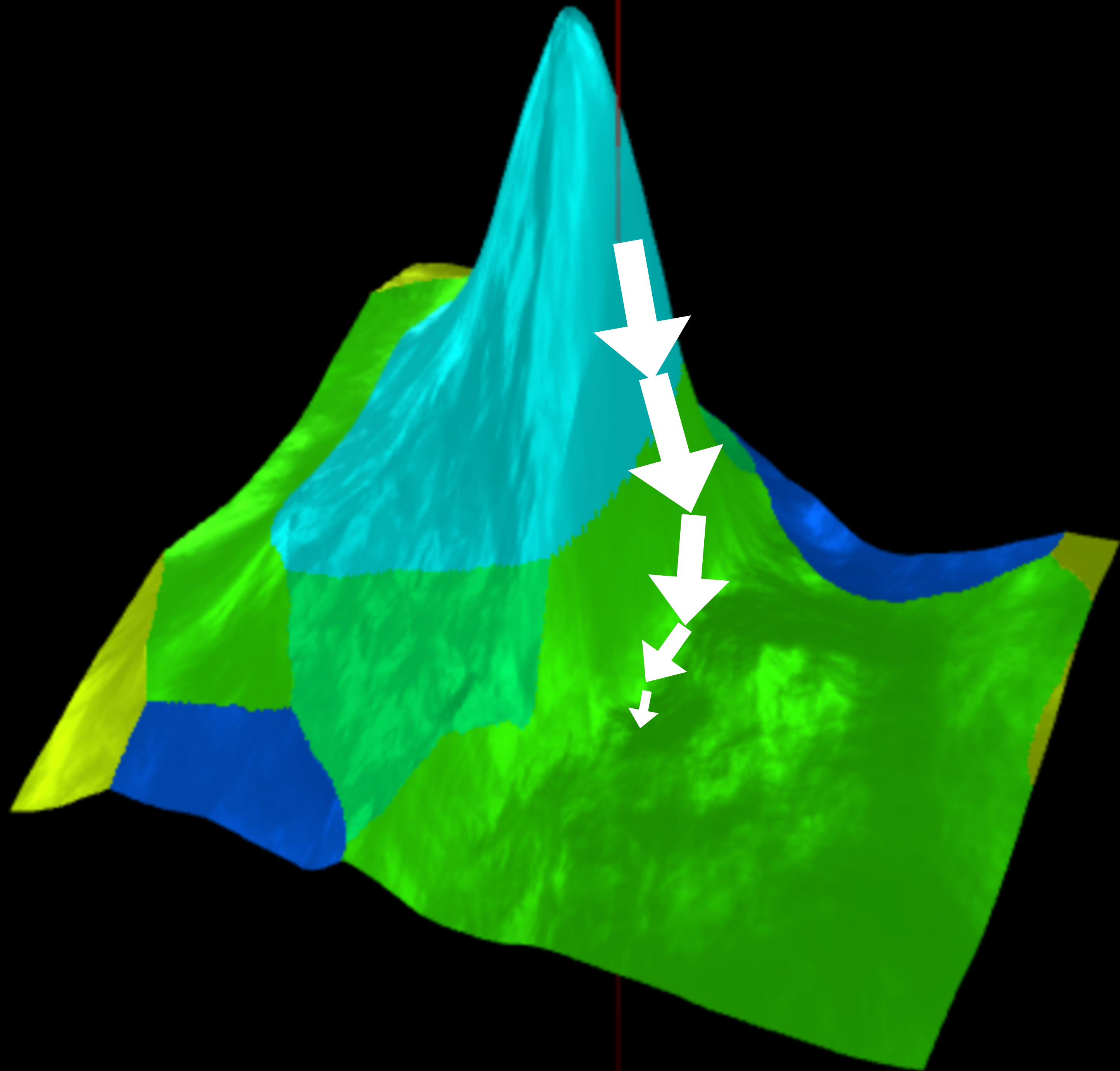
**Dog**



**Truck**



**Airplane**

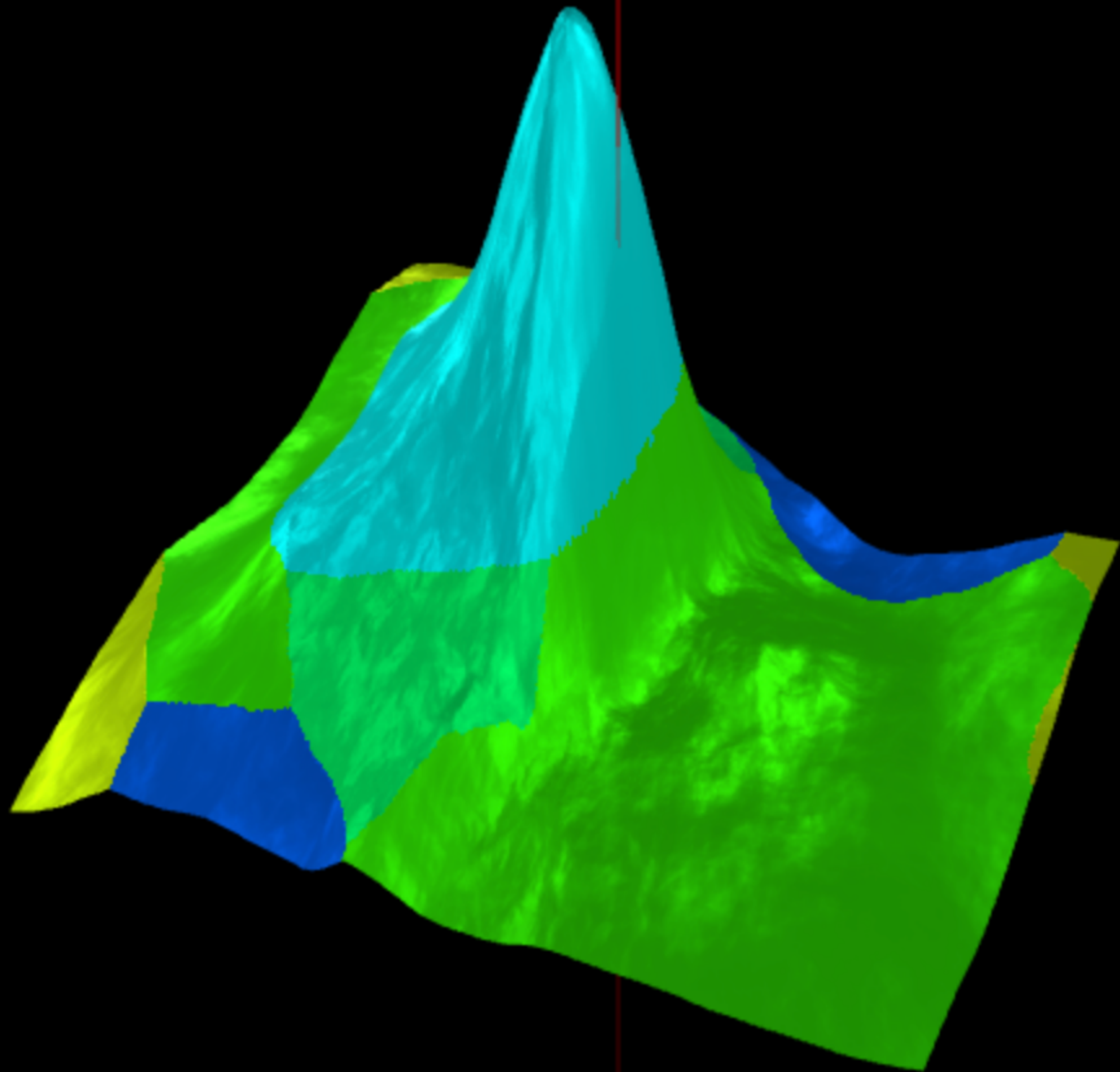




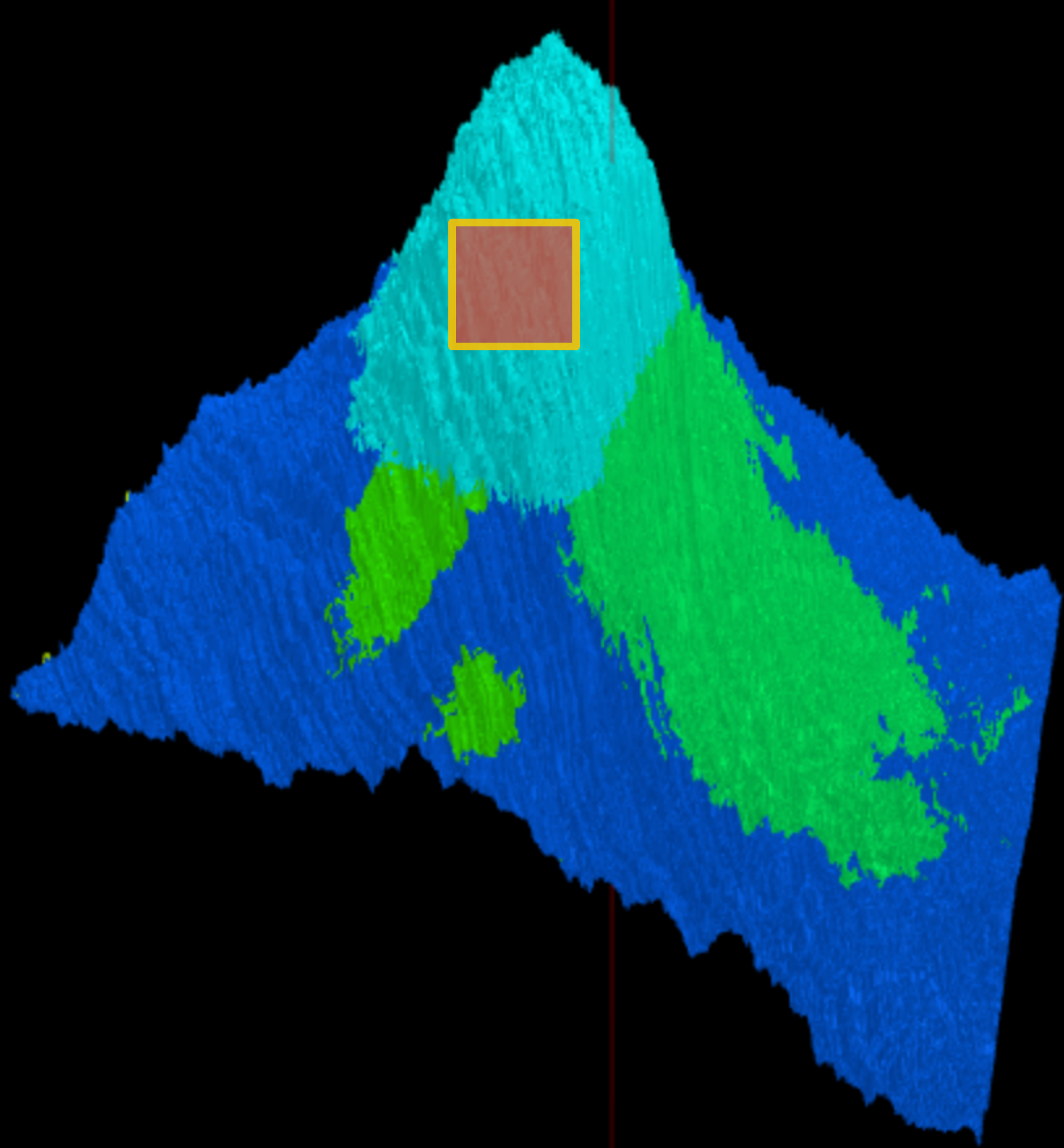


We find that 7 of 9 ICLR defenses  
rely on the same artifact:

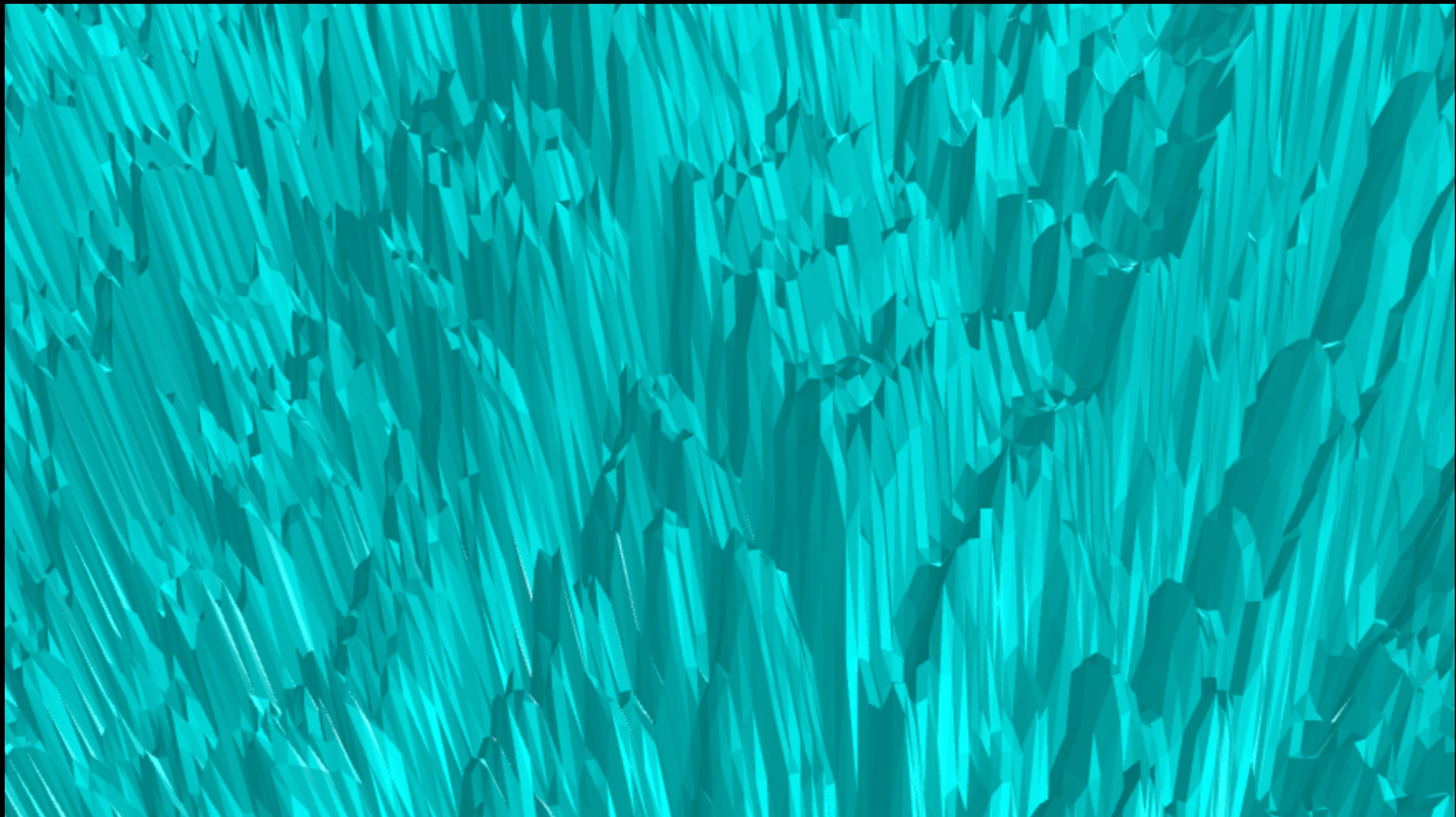
**obfuscated gradients**





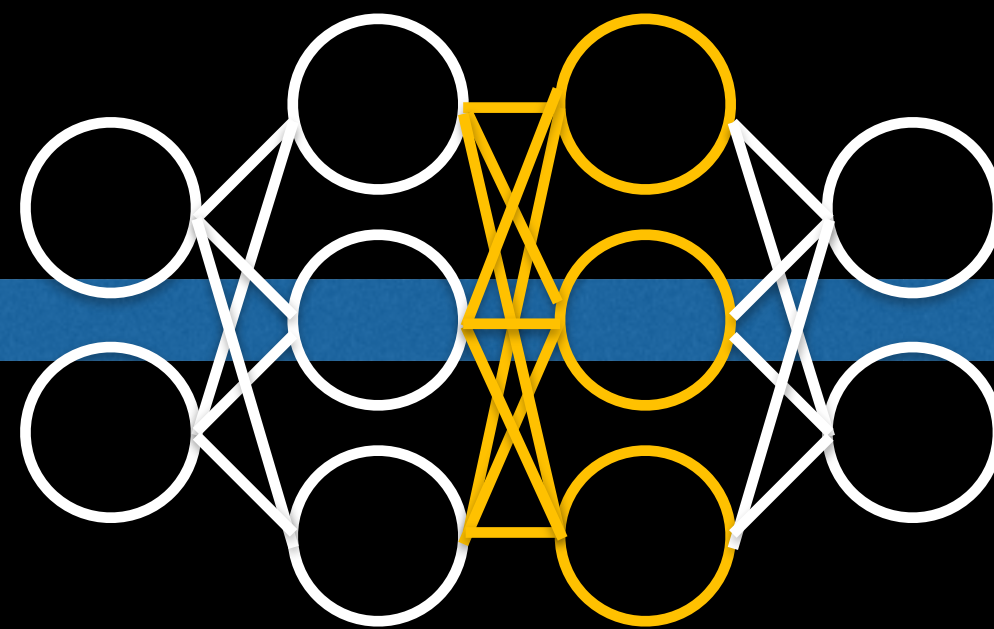
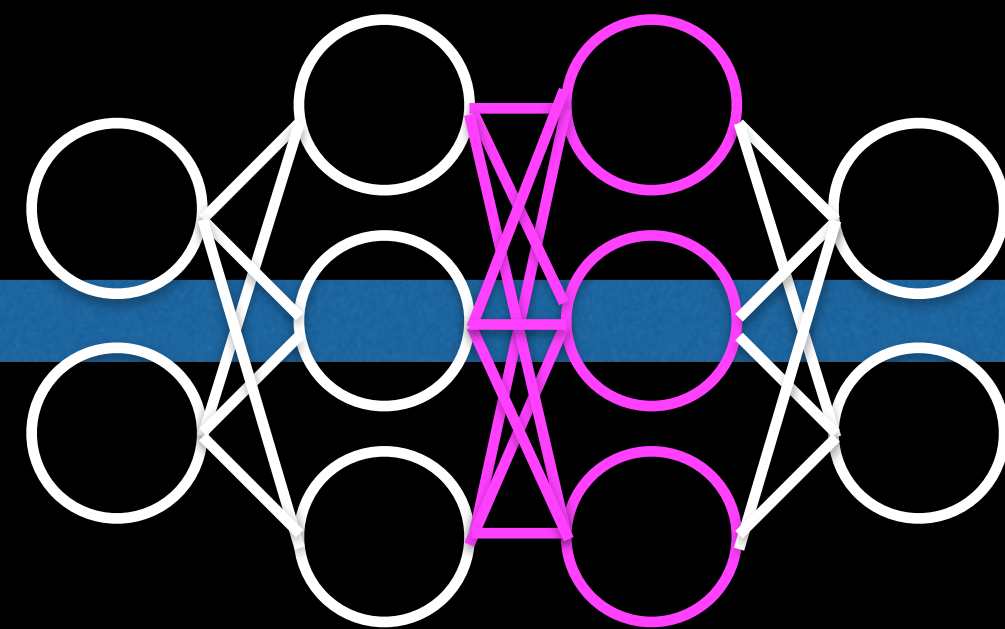




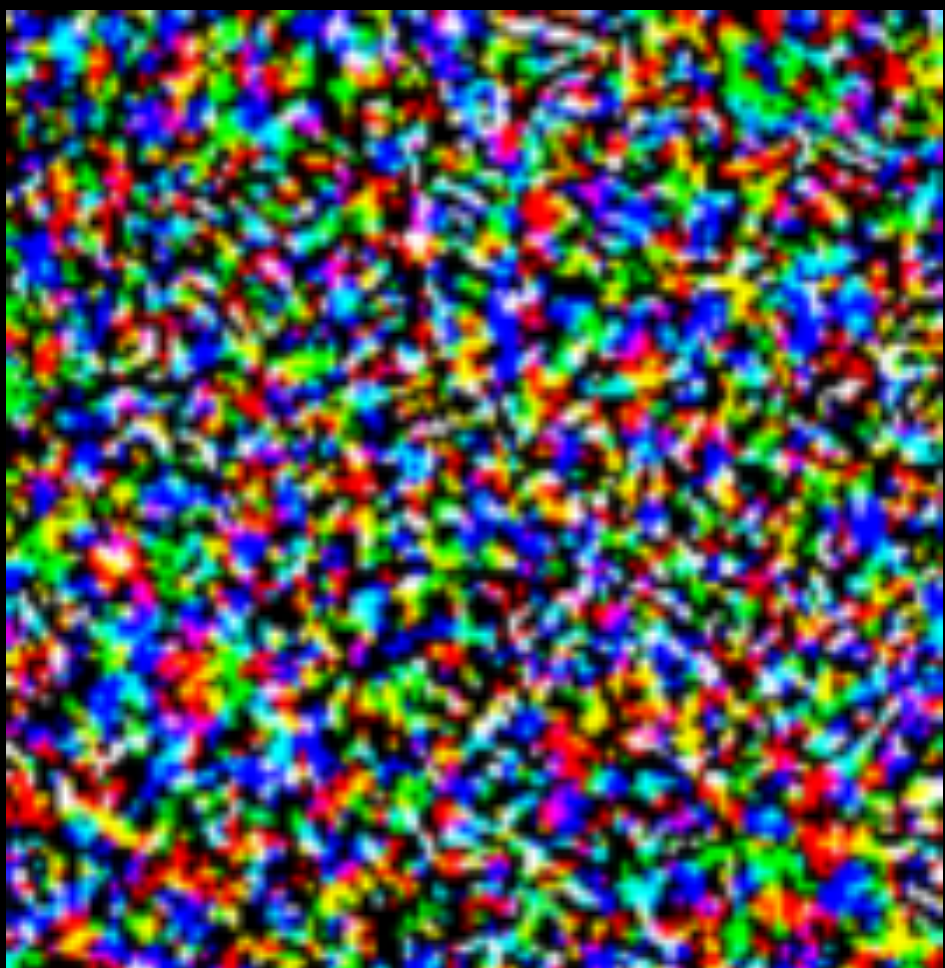




# "Fixing" Gradient Descent



**[0.1,  
0.3,  
0.0,  
0.2,  
0.4]**





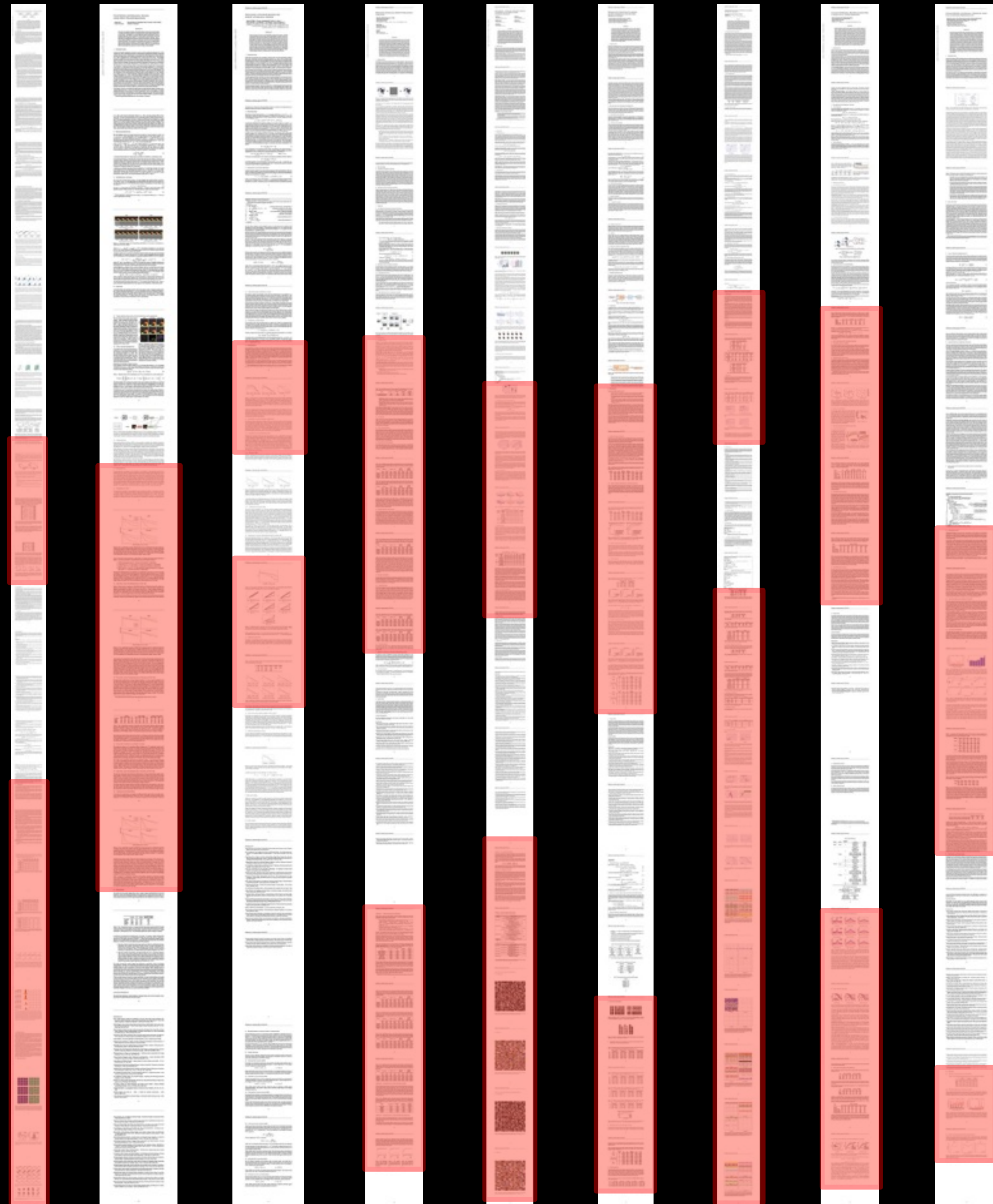


Act III

**WHY:**

**Evaluation**

**Methodology**



Serious effort  
to evaluate

By space, most  
papers are  $\frac{1}{2}$   
evaluation

What went wrong then?

```
acc, loss = model.evaluate(  
    x_test, y_test)
```

Is no longer sufficient.



There is no single  
test set for security

The only thing that  
matters is robustness  
against an adversary  
***targeting the defense***



The purpose of a  
defense evaluation is  
**NOT** to show  
the defense is **RIGHT**



The purpose of a  
defense evaluation is  
to **FAIL** to show  
the defense is **WRONG**





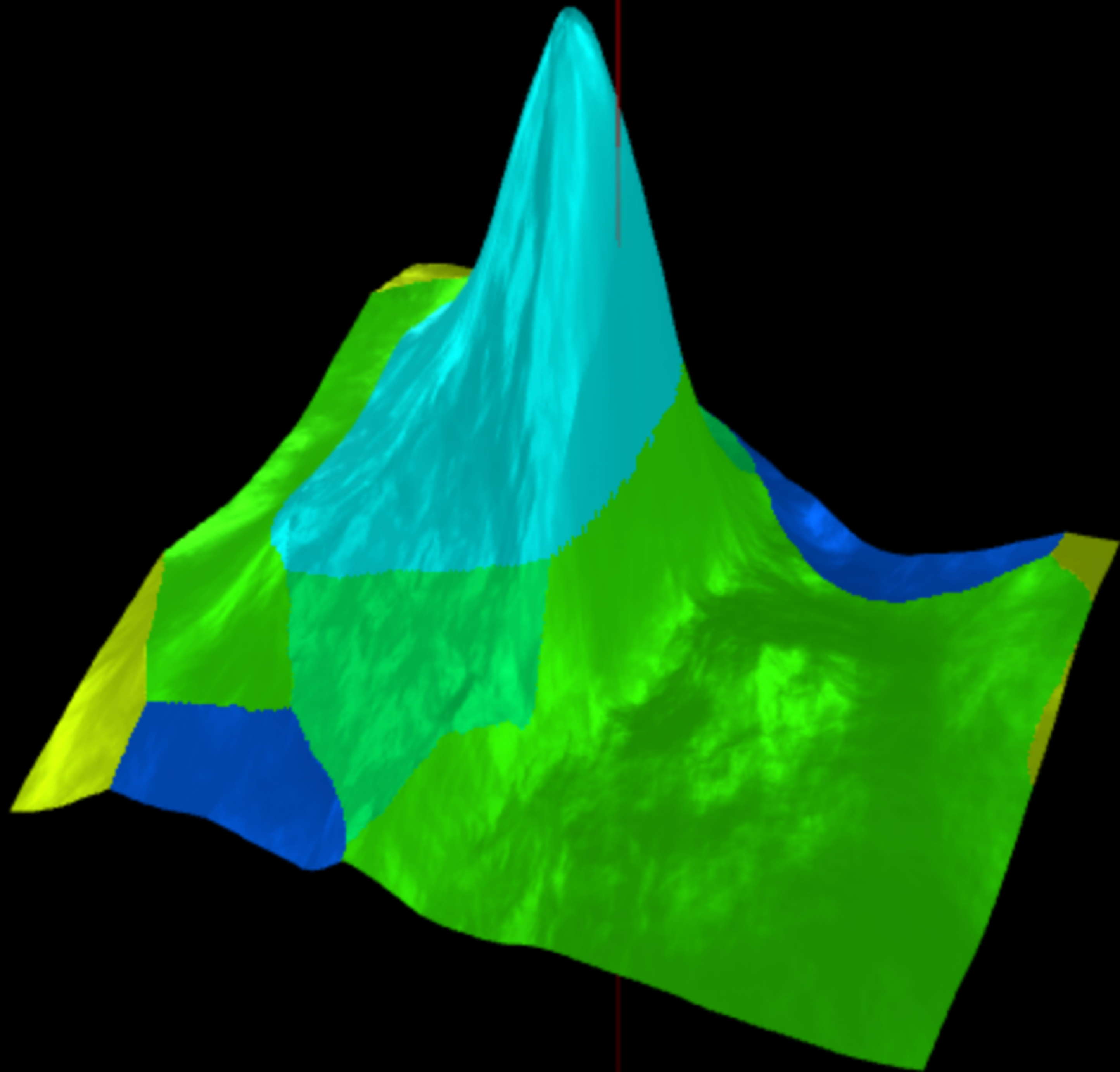
Act IV

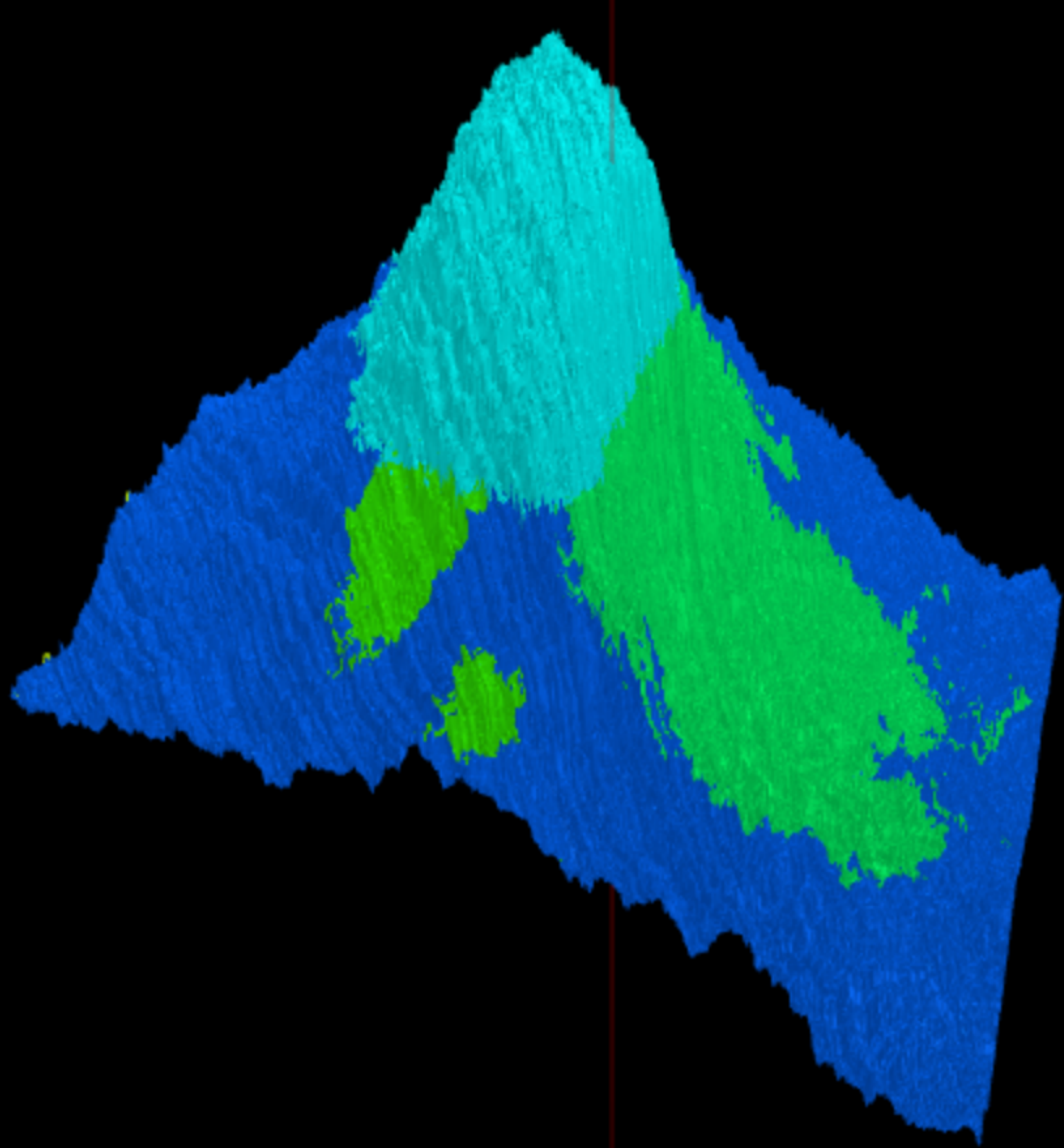
# **Making & Measuring Progress**

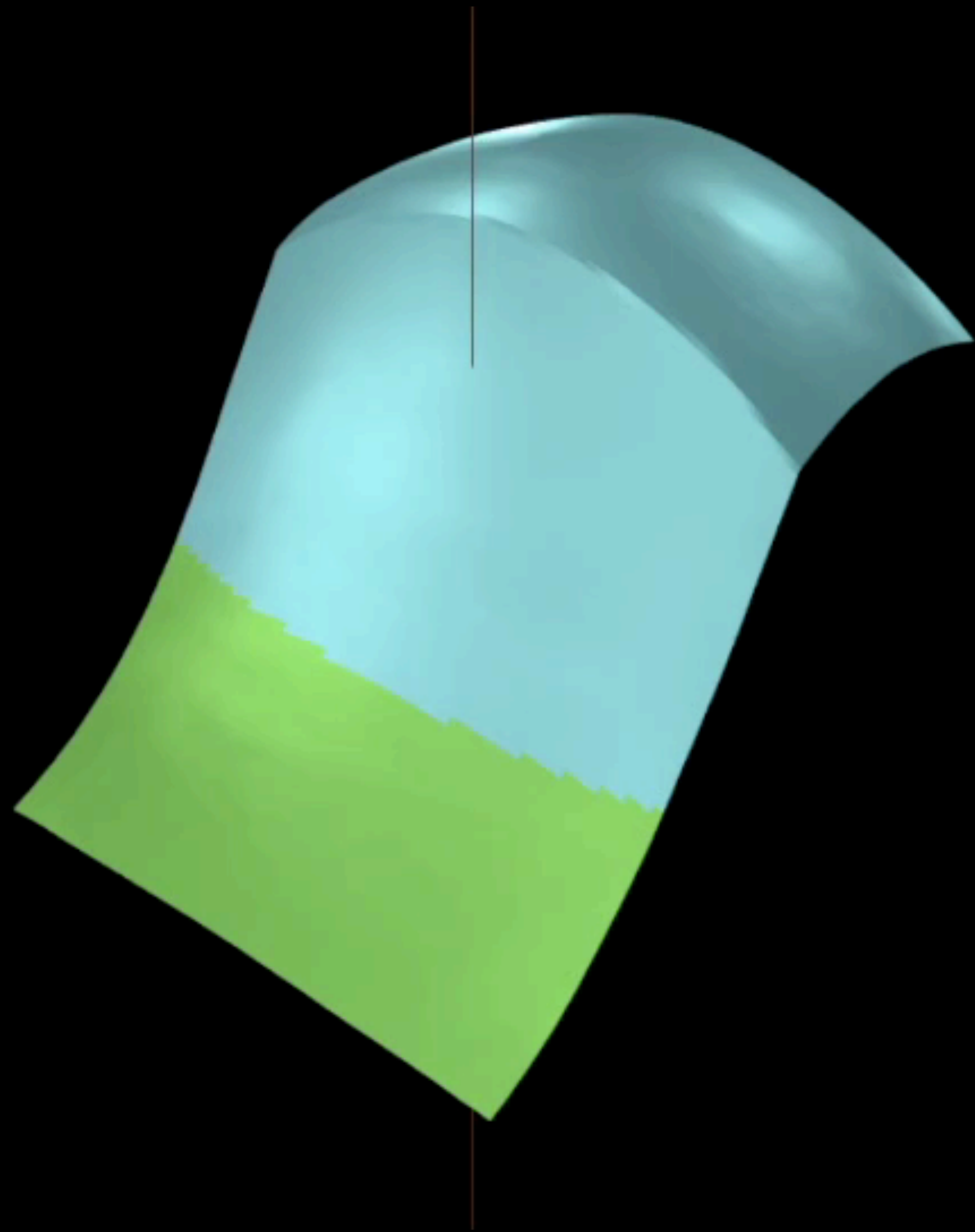


Strive for **simplicity**

over **complexity**











What metric should  
we optimize?

# Threat Model

The set of assumptions  
we place on the adversary

In the context of  
adversarial examples:

1. Perturbation Bounds & Measure
2. Model Access & Knowledge

The threat model **MUST**  
assume the attacker has read  
the paper and knows the  
defender is using those  
techniques to defend.

# Metrics for Success

Accuracy under  
existing  
threat models

More permissive  
threat models



"making the attacker think more"  
is **not** (usually) progress

The threat model doesn't limit  
the attacker's approach



Act V

# Conclusion

A paper can only do so  
much in an evaluation.

A paper can only do so much in an evaluation.

We need more re-evaluation papers.



# So you want to build a defense?

*"Anyone, from the most clueless amateur to the best cryptographer, can create an algorithm that he himself can't break."*

-- Bruce Schneier

# So you want to build a defense?

As a corollary: learn to break defenses  
**before** you try to build them

If you can't break the state-of-the-art,  
you are unlikely to be able to build on it

# Challenging Suggestions

## **Defense-GAN on MNIST**

We were able to break it only partially  
*Samangouei et al. 2018 ("Defense-GAN...")*

## **"Strong" Adversarial Training on CIFAR**

We were not able to break it at all  
*Madry et al. 2018 ("Towards Deep...")*

Visit our **poster** & originally scheduled **talk**  
(Today, #110) & (Tomorrow, A7 @ 2:50)

## **Email us**

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Me: [nicholas@carlini.com](mailto:nicholas@carlini.com)

**Track Progress**

[robust-ml.org](http://robust-ml.org)

**Source Code**

[git.io/obfuscated-gradients](https://git.io/obfuscated-gradients)







# Did we get it right?

1. We reproduced the original claims against the (weak) attacks initially attempted
2. We showed the papers authors' our results
3. It's possible we didn't. But our code is public:  
<https://github.com/anishathalye/obfuscated-gradients>

# Isn't this just gradient masking?

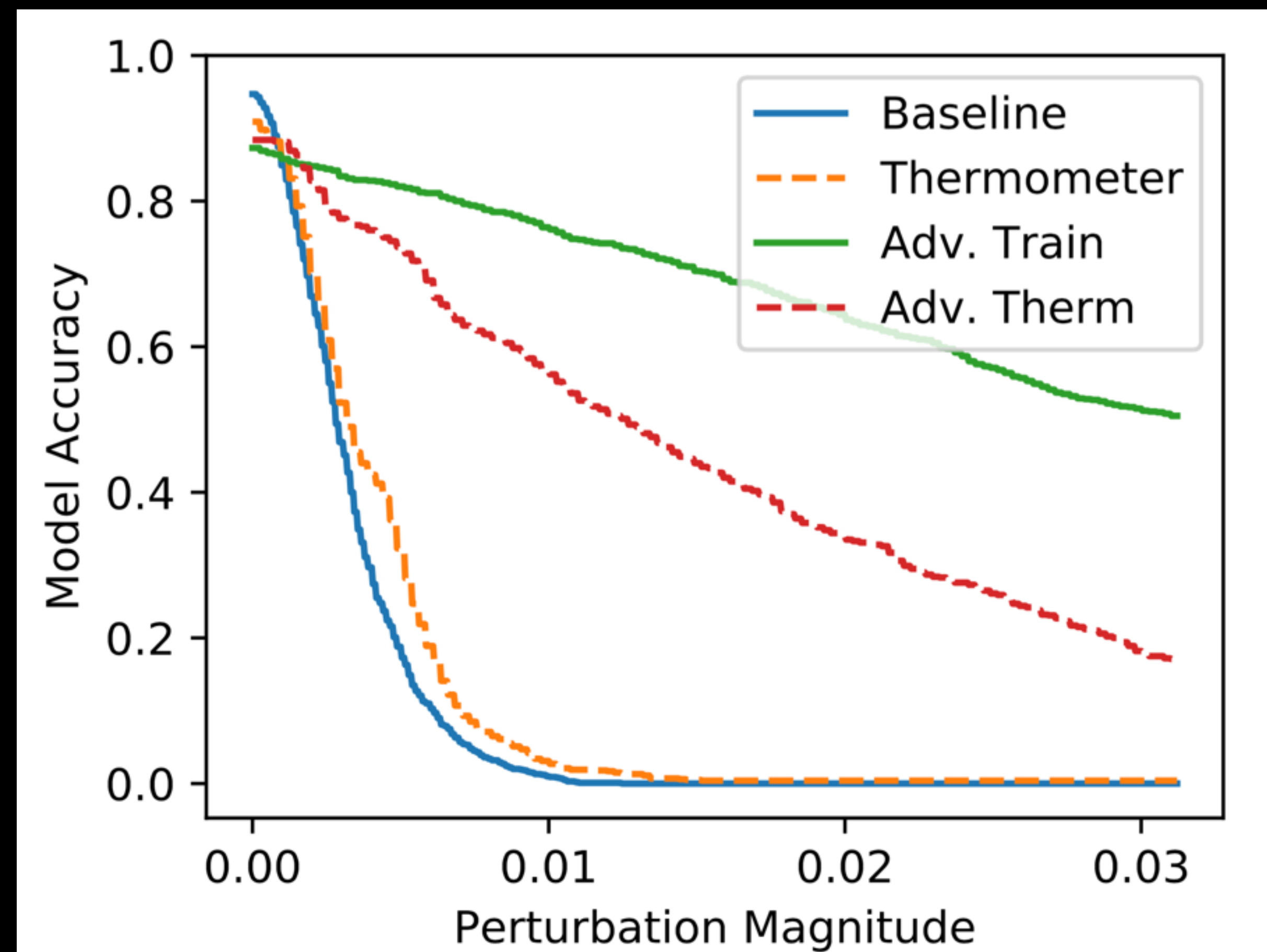
The short answer: **No**, if it were, we wouldn't have seen 7 of 9 ICLR defenses relying on it.

X defense has multiple parts, but you only broke each part separately.

True. Usually, an ensemble several weaker defenses is not an effective defense strategy, unless there is an argument they cover each other's weaknesses.

# Did you try X with adversarial training?

Not usually. In some cases the combination is *worse* than adversarial training alone



# Specific advice for performing evaluations

- Carlini *et al.* 2017 & S&P ("Towards Evaluating ...")
- Athalye *et al.* 2018 @ ICML ("Obfuscated ...")
- Madry *et al.* 2018 @ ICLR ("Towards Deep...")
- Uesato *et al.* 2018 @ ICML ("Adversarial Risk...")

Details in our originally-scheduled talk,  
Tomorrow @ 2:50 in A7

There is a true notion of  
robustness, for a computationally  
unbounded adversary.

We are forced to  
**approximate** this.

*Adversarial Risk and the Dangers of Evaluating Against Weak Attacks.*  
Jonathan Uesato, Brendan O'Donoghue, Aaron van den Oord, Pushmeet Kohli.  
ICML 2018.



