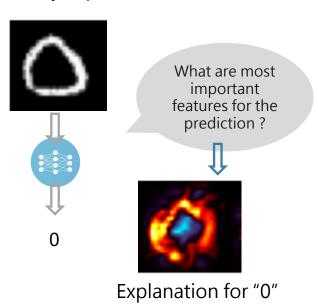
# Robust Models Are More Interpretable Because Attributions Look Normal

Zifan Wang, Matt Fredrikson, Anupam Datta Carnegie Mellon University

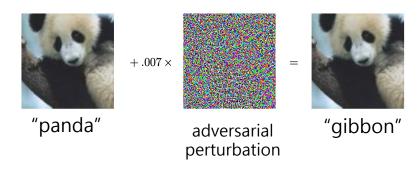
zifan@cmu.edu

# **Explanations and Robustness**

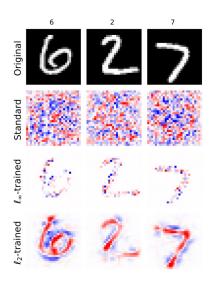
Gradient-based Explanations (Saliency Maps; Feature Attribution)

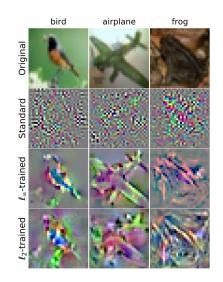


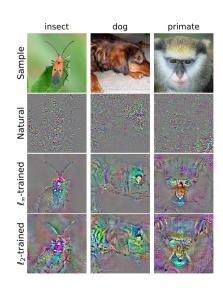
#### **Adversarial Robustness**



# **Robust Models Have Better Explanations**







Tsipras et al. 2019 Etmann et al. 2019

#### Goal

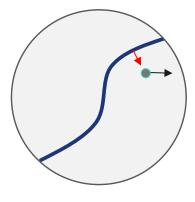
Main Question Why robust models have more interpretable explanations?

Main Methods Geometry-based Analysis Decision Boundary



#### Contribution 1

In robust models, explanations better align with normal vectors of decision boundaries



→ Explanation vector

Normal vector of decision boundary

How a model separates classes

CIFAR-10	standard	robust <sup>1</sup>
$\ell_2$ dist	59.96	1.23
cos dist	0.44	0.05

ImageNet	standard	robust <sup>1</sup>
$\ell_2$ dist	8.48	0.41
cos dist	0.28	0.13



#### Contribution 2

The better alignment can be proved for some robust one-layer network.

#### Corollary 3.4 (Informal)

In robust<sup>1</sup> models, explanations (Expl) are very close to normal vectors (n) of the decision boundaries

$$||Expl - n|| \le \lambda$$

And  $1/\lambda$  is proportional to the robustness.

# **Motivating Better Explanation Methods**

We study explanations form its geometric property and relate it with adversarial robustness.

#### Contribution 1 & 2

In robust models, explanations align better with normal vectors of the decision boundary.

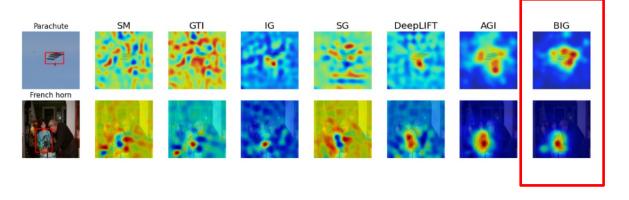


Searching for normal vectors of decision boundaries as explanations



#### Contribution 3

Incorporating boundaries to explain model's decision, we introduce **B**oundary-based Integrated **G**radient (BIG).



### Thank You

**Paper** 

Colab Demo

**Github** 

<u>Link</u> | QR Code

<u>Link</u> | QR Code

Link | QR Code





