





# BENCHMARKING ROBUSTNESS METRICS

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## WHAT IS IT ROBUSTNESS?

A model's ability to maintain accurate predictions under out-of-distribution inputs.

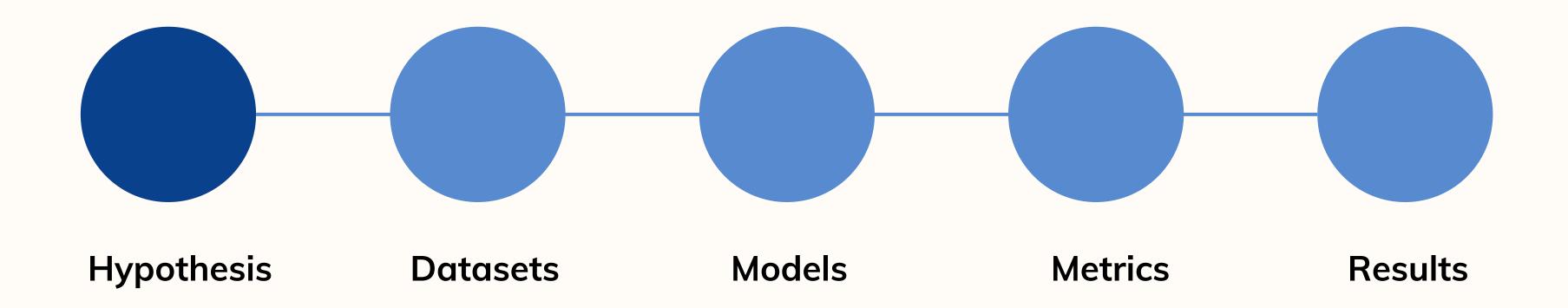
## WHY IS IT IMPORTANT?

- 1. Machine learning systems are deployed in high-stakes domains.
- 2. Criminals exploit small perturbations to mislead these systems.
- 3. Models must be robust to these attacks while guaranteeing performance over long-term changes in the data.

## OUR HYPOTHESIS

There is a single metric that could holistically measure robustness against these adversarial attacks and natural changes in the data

### THE ROAD TO ROBUSTNESS



### DATASET

#### **IMAGENET**

OR

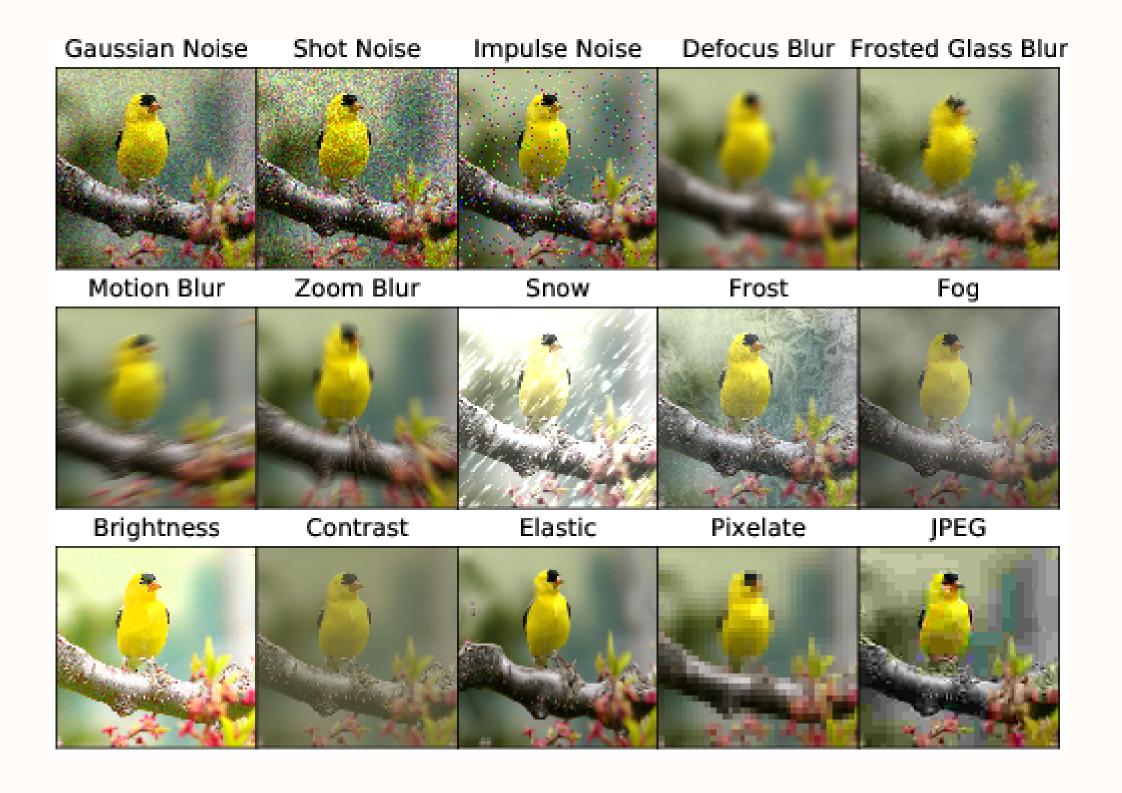
CIFAR-10

- 200 classes (62 used)
- 30000 images used
- Higher resolution (64)
- Higher computational cost

- 10 classes
- 30000 images used
- Lower resolution (32)
- Lower computational cost

# DATASET OOD TEST SETS

CIFAR-10.1 CIFAR-10C Attacked



# DATASET OOD TEST SETS

**CIFAR-10.1** 

CIFAR-10C

Attacked

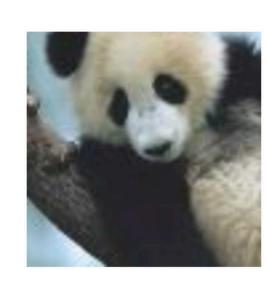
**FSGM** 

**PGD** 

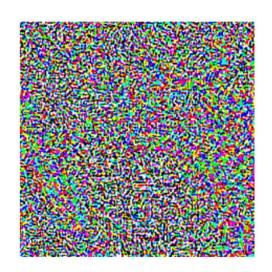
BIM

DeepFool

CW



x
"panda"
57.7% confidence



 $+.007 \times$ 

 $sign(\nabla_{\boldsymbol{x}}J(\boldsymbol{\theta},\boldsymbol{x},y))$  "nematode" 8.2% confidence



 $x + \epsilon \operatorname{sign}(\nabla_{x} J(\boldsymbol{\theta}, x, y))$ "gibbon"
99.3 % confidence

### MODELS

#### **Custom CNN**

**HYPERPARAMETERS** 

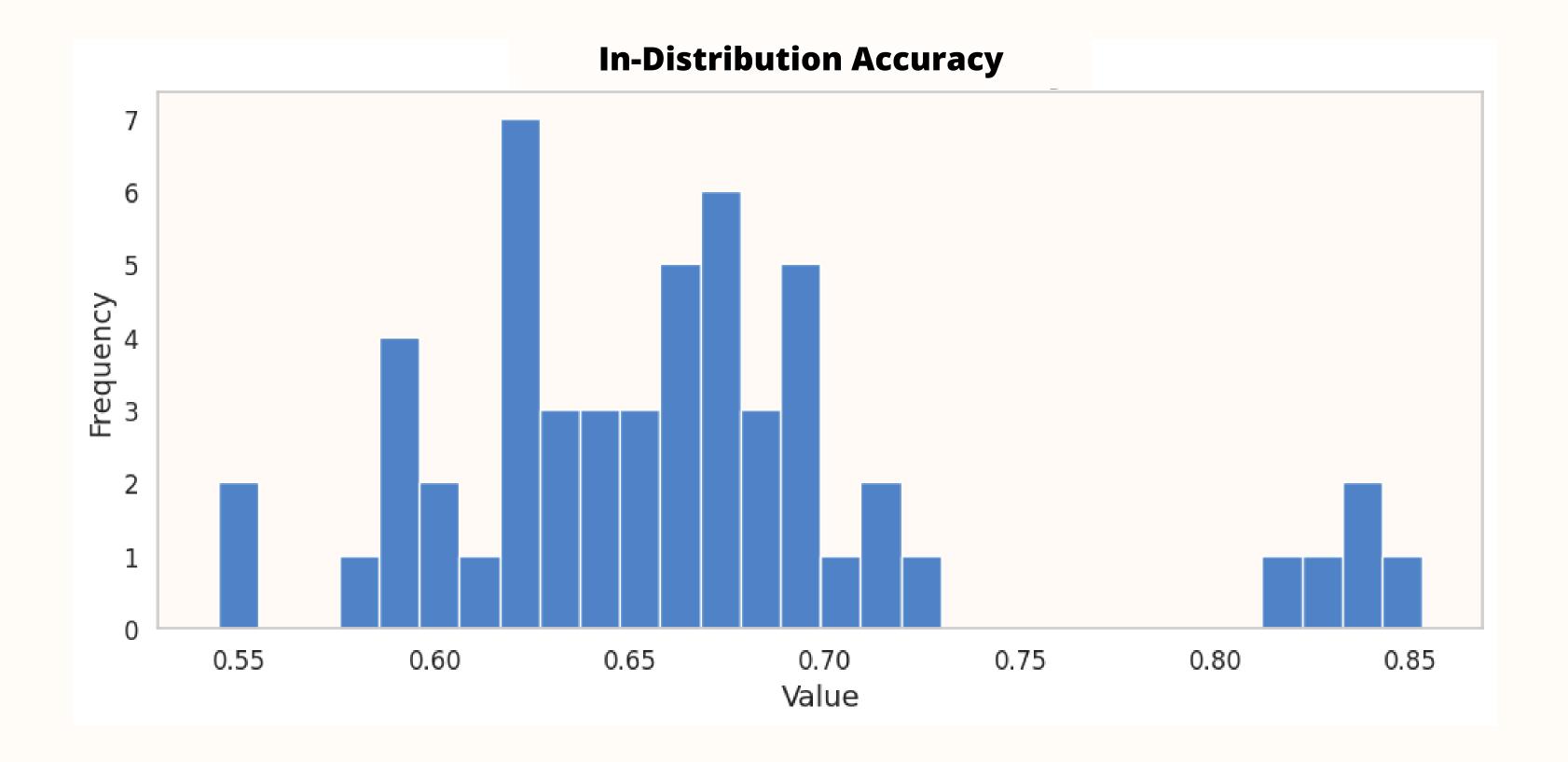
- 1. Optimizer
- 2. Learning Rate
- 3. Depth
- 4. Width
- 5. Dropout

#### VGG Inspired

**HYPERPARAMETERS** 

- 1. Optimizer
- 2. Learning Rate

Result: > 50 models



# METRICS

Performance

Sharpness

Norm-Based



# METRICS PERFORMANCE

Directly drawn from the network output

#### Classification:

- Accuracy
- Precision
- Recall
- F1-Score

Uncertainty?

### METRICS

#### IMPORTANCE OF UNCERTAINTY

"All models are wrong but some are useful."

George Box

### METRICS NORM-BASED

Weight norms reveal insights into model behavior

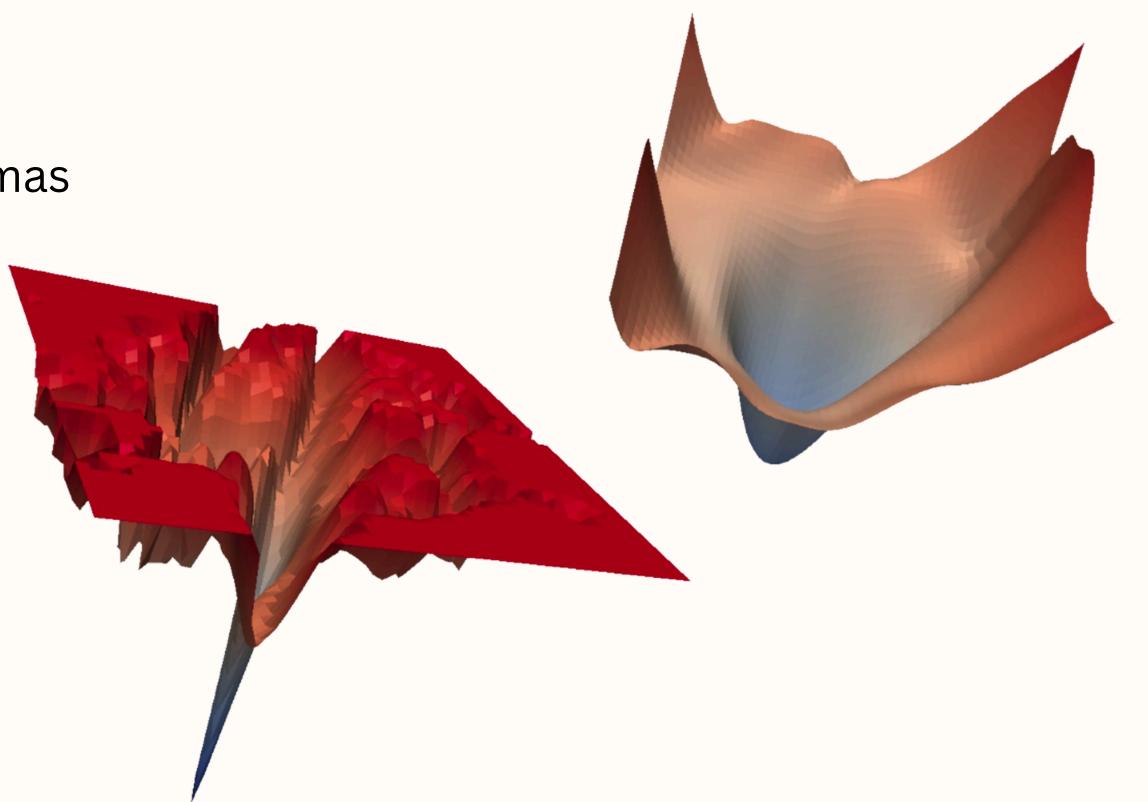
- Spectral Norm
- Frobeneous Norm
- Trace Norm
- Path Norm

Over the Margin....

### METRICS

#### **SHARPNESS**

Looking for the right sigmas



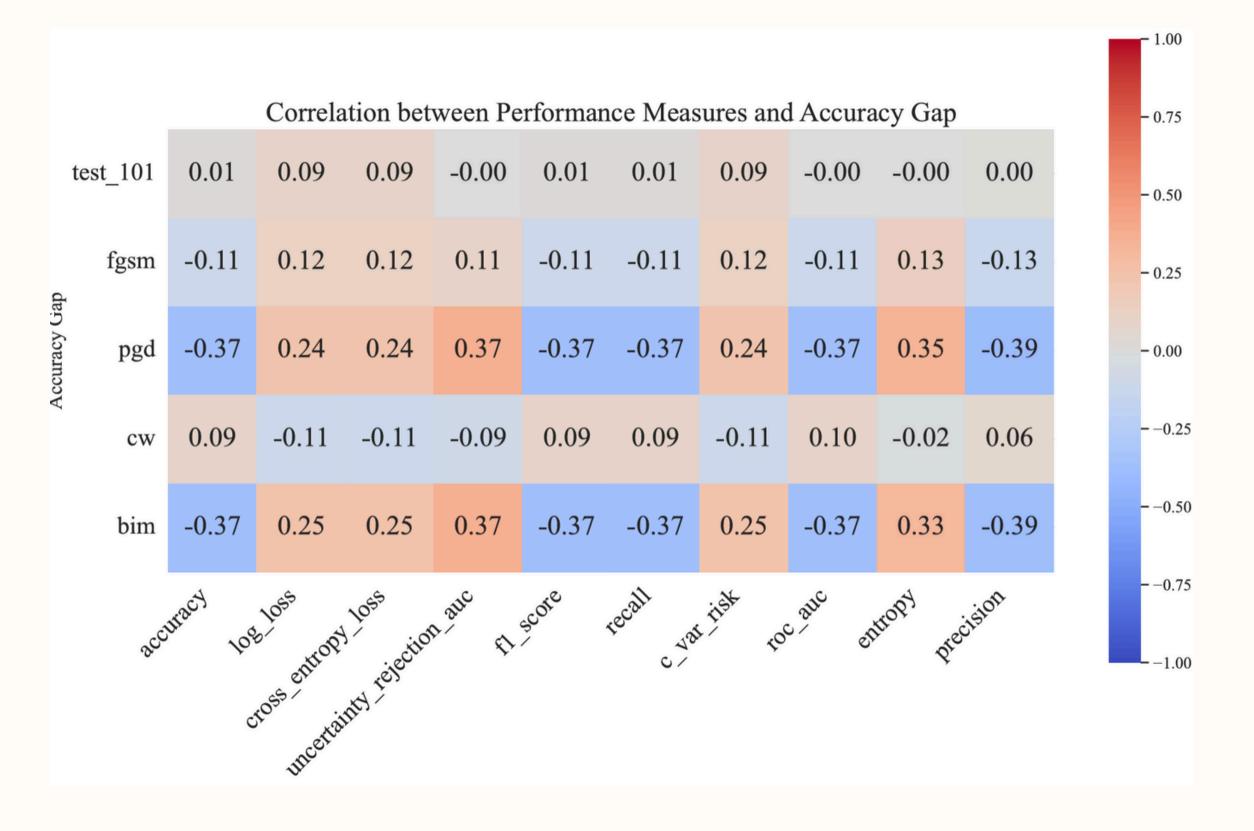
# METRICS SHARPNESS A CRITIQUE

- Requires arbitrary hyperparameters
- "Source" code and literature
   Pseudo-code don't match
- LONG computational times (~2h per model)

```
"""Algorithms for searching sigmas'"""
import numpy as np
import tensorflow as tf
def add noise to variables (variables):
  """Create tf ops for adding noise to a list of variables."""
  perturbation ph = {}
  add perturbation op = []
  subtract perturbation op = []
  for v in variables:
   perturbation ph[v] = tf.placeholder(
       tf.float32, shape=v.get shape().as list())
   add perturbation op.append(tf.assign add(v, perturbation ph[v]))
    subtract perturbation op.append(tf.assign add(v, -perturbation ph[v]))
  return perturbation ph, add perturbation op, subtract perturbation op
def get gaussian noise feed dict(ph_list, scale):
  """Get noise with standard deviation of scale."""
  feed dict = {}
  for ph in ph list:
    feed dict[ph] = np.random.normal(
       scale=scale, size=ph.get shape().as list())
  return feed dict
def flatten and concat(variable list):
 variable list = [tf.reshape(v, [-1]) for v in variable list]
  return tf.concat(variable list, axis=0)
def norm of weights (weights):
  flat weights = [np.reshape(w, -1)] for w in weights
  concat weight = np.concatenate(flat weights)
 weight norm = np.linalg.norm(concat weight)
  return weight norm
#################################PacBayes##################
```

# RESULTS HOW DID ROBUSTNESS PERFORM?

Not well....



### RESULTS

#### However!

The standard notion of robustness - Accuracy Gap - is limiting. We decided to assess robustness in **two** alternative ways

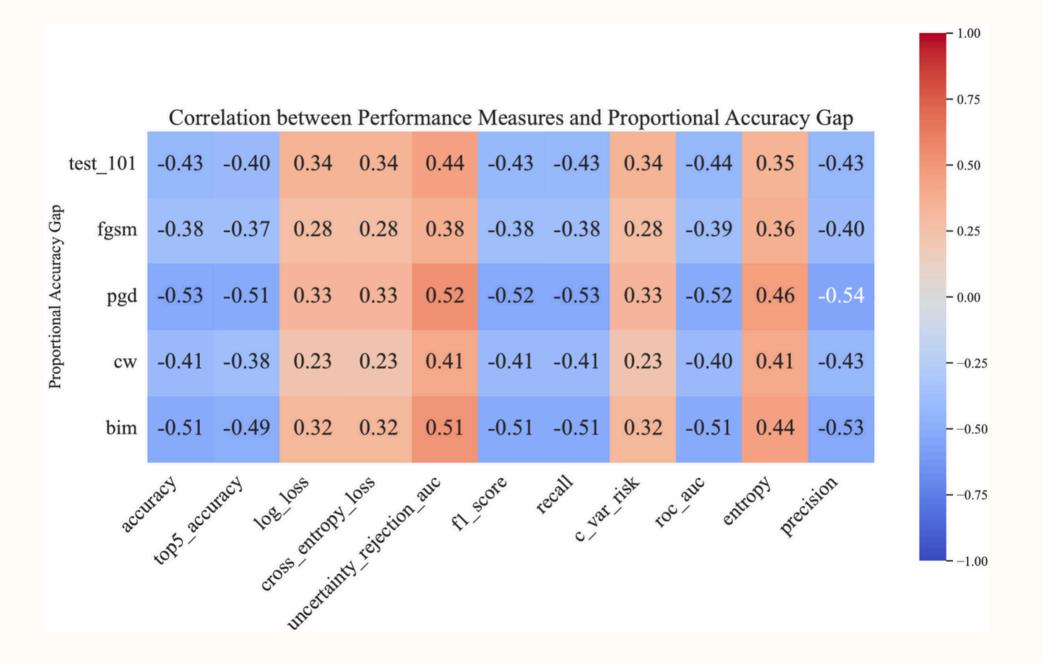
# RESULTS UPDATED DEFINITION

**Uncertainty Robustness:** How does the model certainty (Log-Loss) change in out-of-distribution scenarios?

**Relative Robustness:** What is the proportional drop in Accuracy/Certainty?

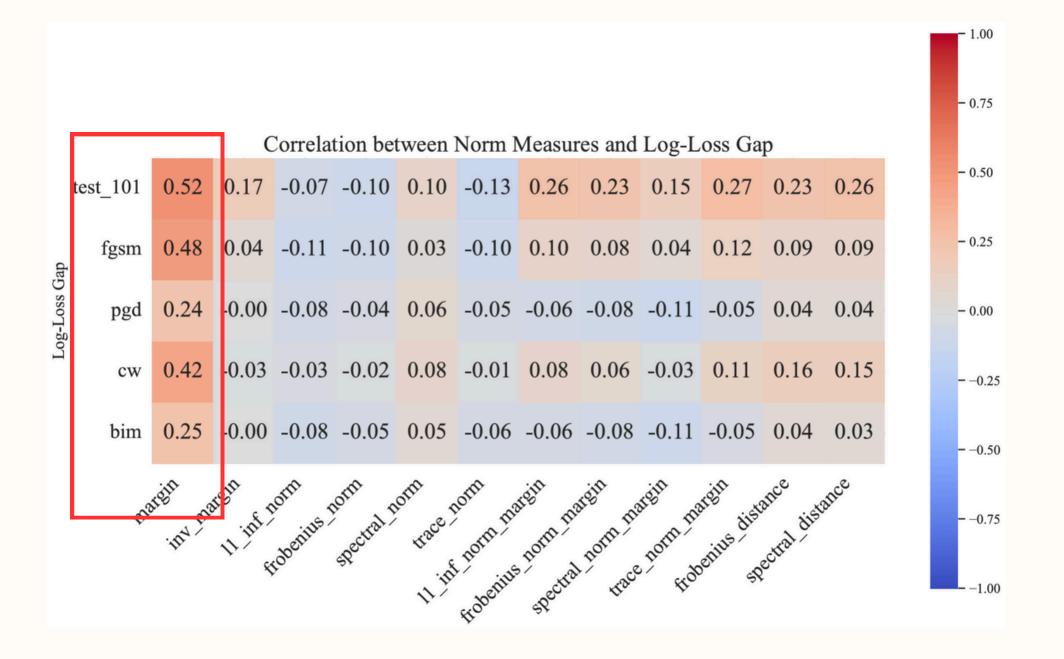
# RESULTS NEW INSIGHTS!

1. In-distribution
Performance and Model
Weight Norms over Margin
moderately predict relative
robustness.



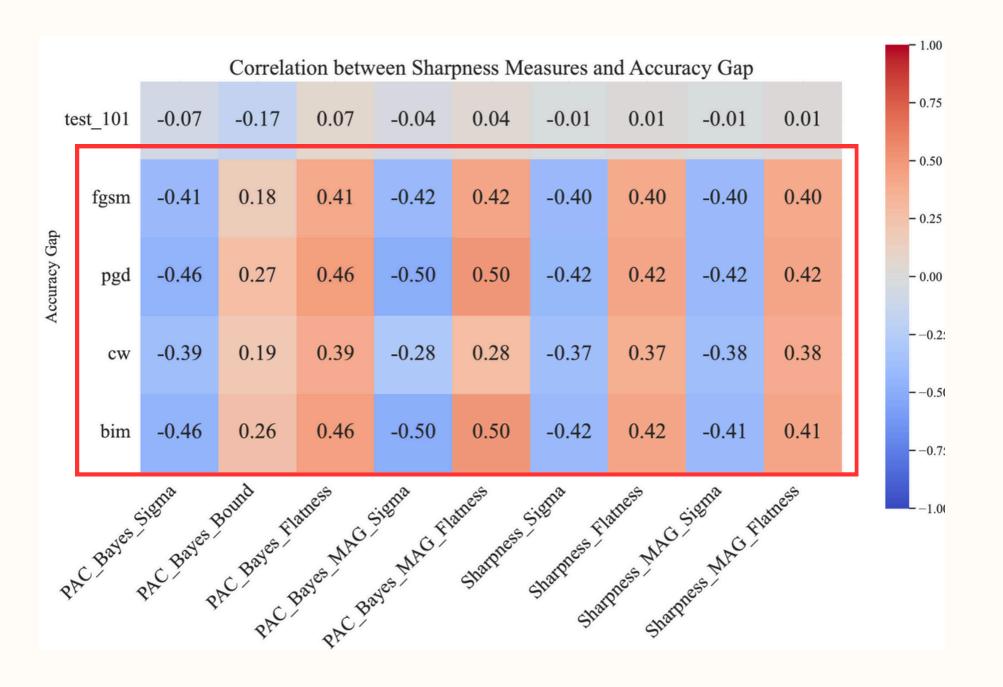
# RESULTS NEW INSIGHTS!

2. Margin and Entropy are moderately correlated with uncertainty robustness.



# RESULTS NEW INSIGHTS!

3. Sharpness moderately predicts relative robustness to adversarial attacks.



## NEXT STEPS?

New data

**More Models** 

**Different Metrics** 

Black-Box Attacks

# THANKYOU! QUESTIONS?