Pixel-Based Similarities as Alternative to Neural Data in CNN Regularization Against Adversarial Attacks

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Motivation

- Recent studies show that training CNNs with regularizers that promote brain-like representations, using neural recordings, improve model robustness.
- However, the requirement to use neural data severely restricts the utility of these methods.
- **Is it possible to develop regularizers that mimic the computational function of neural regularizers without the need for neural recordings?**

1. A neuroscience inspired objective to enhance robustness

We augment the CNNs objective function L_{task} with a term L_{sim} as in Li et al. [1]. Thus,

$$L = L_{task} + \alpha L_{sim}\,, \quad \text{where}$$

$$L_{sim} = \sum_{i \neq j} \left(\text{arctanh}(S_{ij}^{CNN}) - \text{arctanh}(S_{ij}^{target}) \right)^2 \quad \text{and} \quad S_{ij}^{CNN} = \sum_l \gamma_l S_{ij}^{CNN-l}\,.$$

S_{ij}^{CNN-l} is the mean-subtracted cosine feature similarity at layer l for image pairs (i,j); S_{ij}^{target} is the target similarity, and $\gamma_l \geq 0$ for all l, are trainable weights s.t. $\sum_l \gamma_l = 1$.

Li et al. [1] computed S_{ij}^{target} from a model trained to predict the neural recordings in mouse V1 for a given image. They showed that the regularized network is more robust.

2. Observation

We notice that similarities from the predictive model correlate with image pixel similarity.

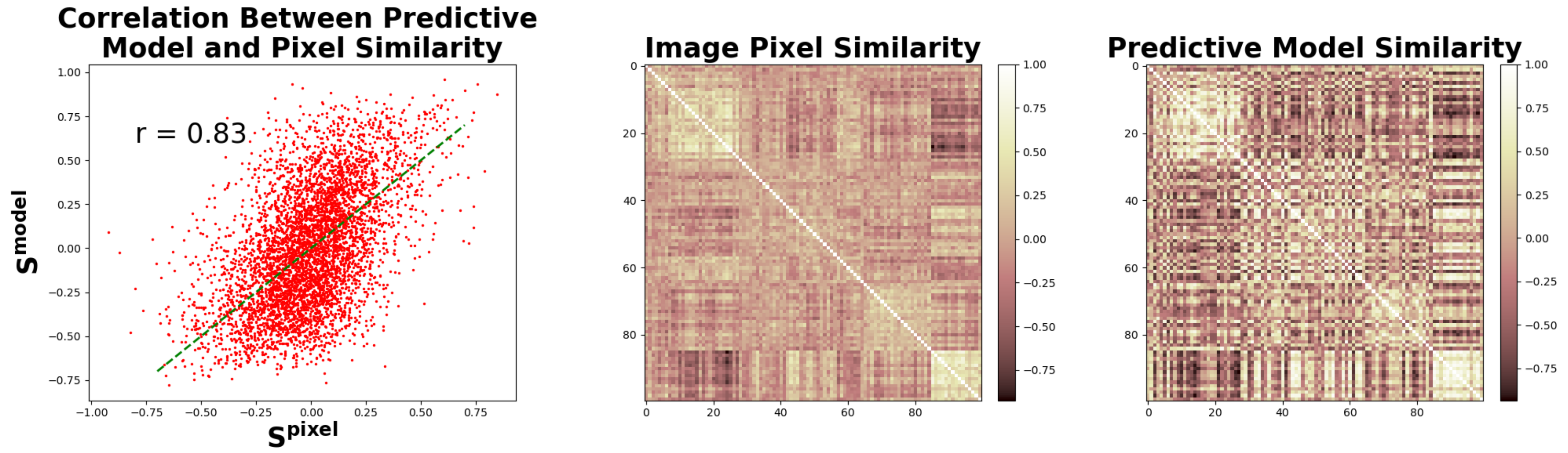

Correlation Between Predictive Model and Pixel Similarity

Image Pixel Similarity

Predictive Model Similarity

3. Introducing a pixel-based regularizer

We introduce a new S_{ij}^{target} based on the images pixel similarity S_{ij}^{pixel}, defined as :

$$S_{ij}^{target} = \begin{cases} 1 & \text{if } S_{ij}^{pixel} > Th \\ -1 & \text{if } S_{ij}^{pixel} < -Th\,, \text{ where } Th \in (0,1)\,. \\ 0 & \text{otherwise} \end{cases}$$

Th is a hyperparameter, chosen s.t. the task accuracy-robustness tradeoff is small.

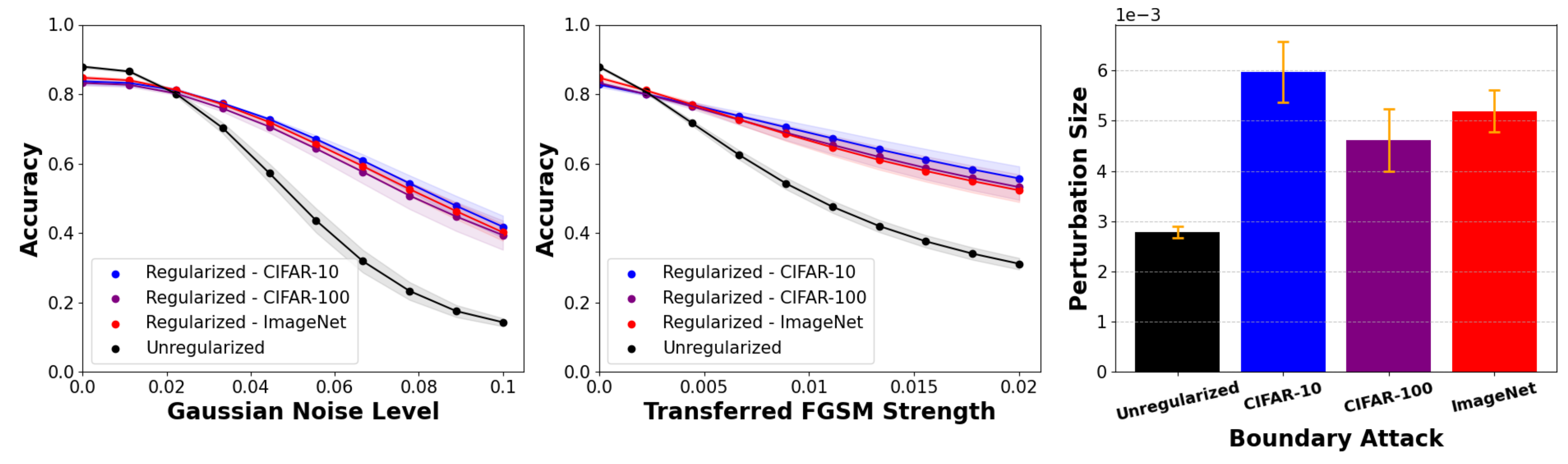
4. Main results

For consistency, we show results from ResNet18 trained to classify CIFAR-10. Datasets are grayscale. We also tested other classification datasets (CIFAR-100, MNIST, Fashion MNIST), as well as colored images, and observed an increase in robustness.

i. Increased robustness to a range of black-box adversarial attacks

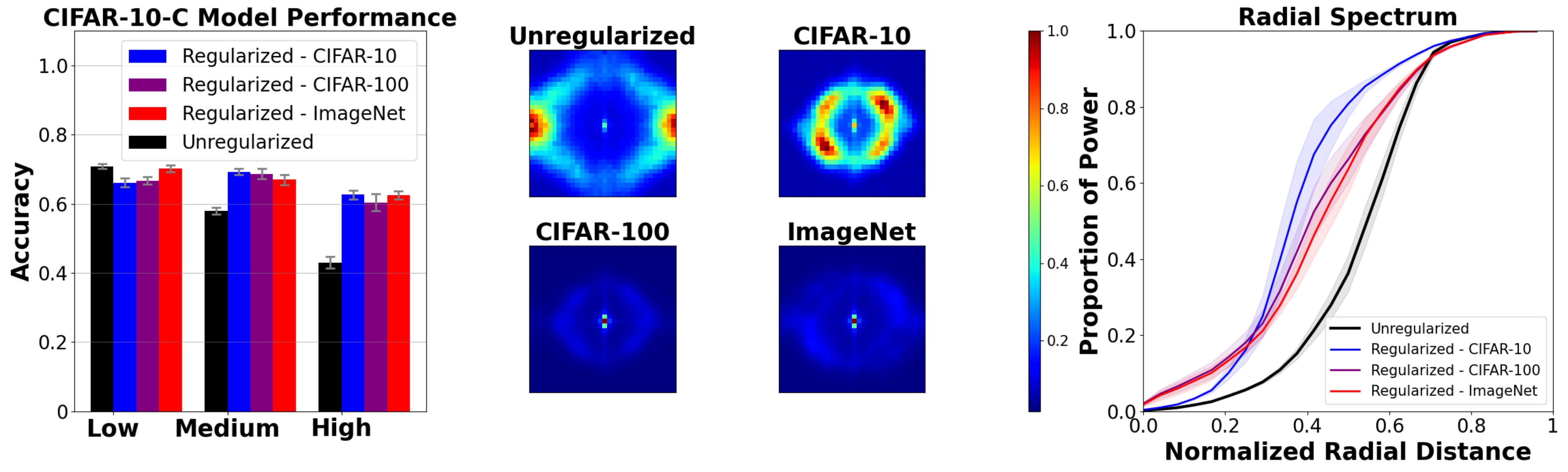
Different datasets can be successfully used for regularization as we see below.

ResNet18 Classifying CIFAR-10



ii. Sensitivity to low frequencies

Using a boundary attack, we find that minimal adversarial perturbations contain mostly low frequencies, and that regularized models are insensitive to high frequency perturbations.

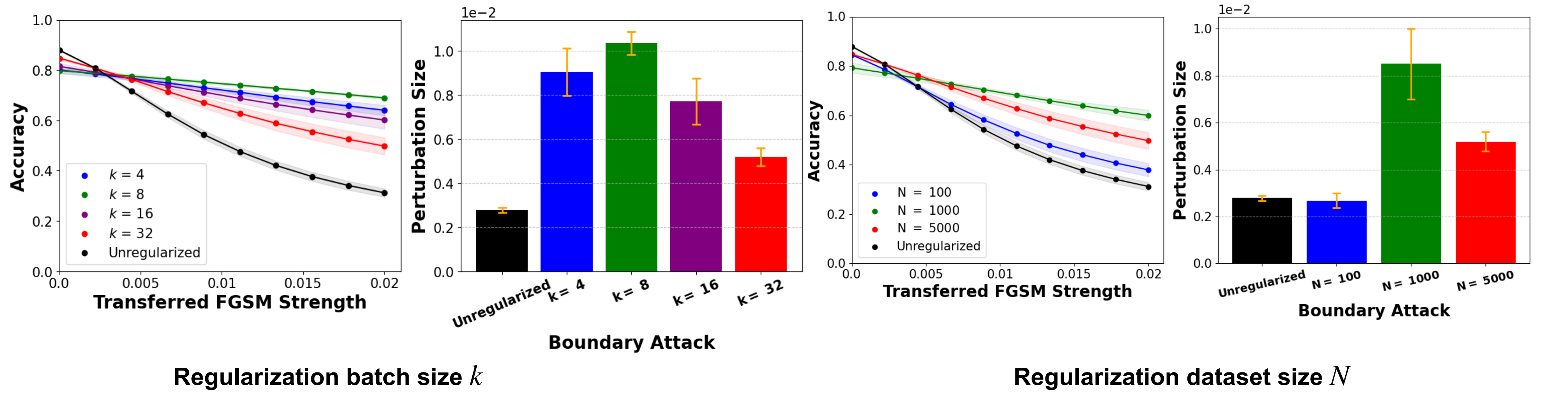

CIFAR-10-C Model Performance

Radial Spectrum

iii. Computational efficiency

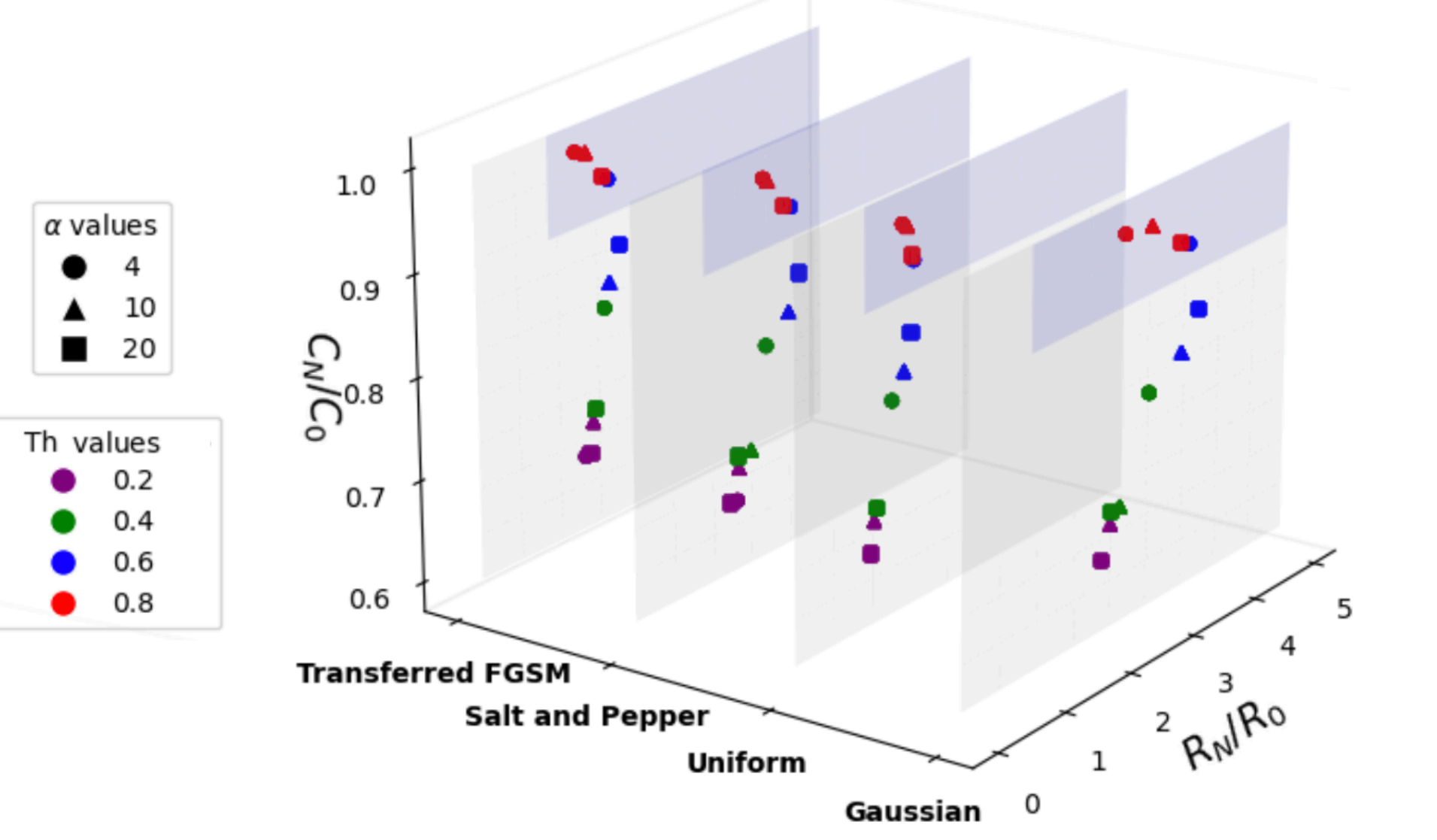
We find that a small regularization batch size and dataset are sufficient to significantly increase robustness.

ResNet18 Classifying CIFAR-10


Regularization batch size k

Regularization dataset size N

5. Accuracy-robustness tradeoff



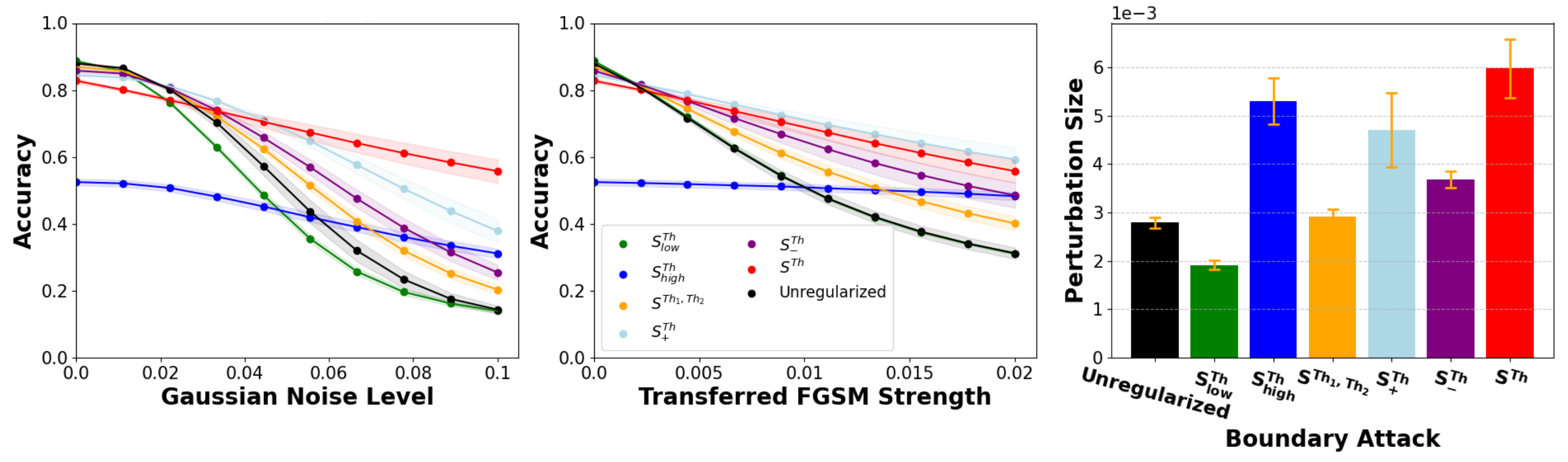
C_0, R_0 : the accuracy at zero-distortion, and distortion of $\epsilon = 0.1$(random attacks) and 0.02 (transferred FGSM) for the **Unregularized model.**

C_N, R_N : same as above but for a **Regularized model.**

ResNet18 Classifying CIFAR-10 Regularized with ImageNet

6. Investigating the different components of the regularizer

ResNet18 Classifying CIFAR-10



[1] Li et al., *Advances in neural information processing systems*, 32, 2019.