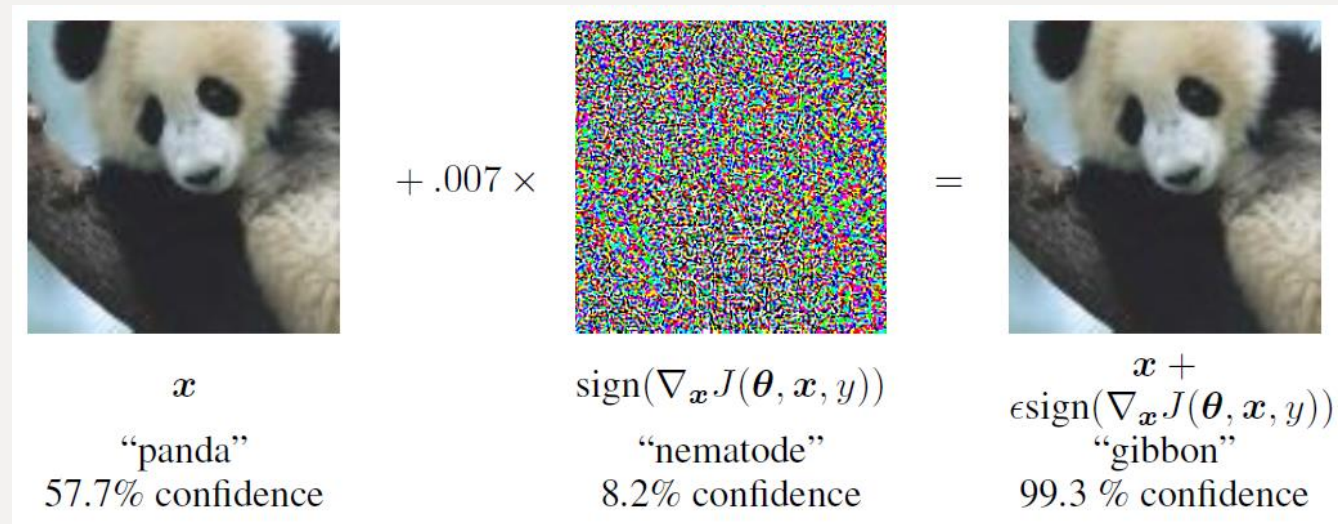


Improving Gradient Regularization using Complex- Valued Neural Networks

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Adversarial Examples



Goodfellow et al "Explaining and Harnessing Adversarial Examples", ICLR 2015

Gradient Regularization

Std. Loss Objective
(e.g., cross-entropy)

Gradient Regularization
Objective

The diagram illustrates the components of the Gradient Regularization Objective. Two blue arrows point downwards from the text labels above to the corresponding terms in the equation below. The first arrow points from 'Std. Loss Objective (e.g., cross-entropy)' to the loss function $\mathcal{L}(f, \underline{x}, \underline{y})$. The second arrow points from 'Gradient Regularization Objective' to the regularization term $\beta \left\| \nabla_{\underline{x}} \mathcal{L}(f, \underline{x}, \underline{y}) \right\|_p^2$.

$$\mathcal{L}(f, \underline{x}, \underline{y}) + \beta \left\| \nabla_{\underline{x}} \mathcal{L}(f, \underline{x}, \underline{y}) \right\|_p^2$$

Training with Gradient Regularization (Real)

$$\nabla_{W_i} \left[\mathcal{L}(f, \underline{x}, \underline{y}) + \beta \mathcal{R}(f, \underline{x}, \underline{y}) \right]$$

Gradient Regularization Term

$$\mathcal{R}(f, \underline{x}, \underline{y}) = \beta \left\| \frac{\partial L(f, \underline{x}, \underline{y})}{\partial \underline{x}} \right\|_p^2$$

$$= \underline{e}_{i\mathcal{L}} \underline{1}^T \cdot \frac{\partial(W_i \underline{x}_i)}{\partial W_i} + \beta \underline{e}_{i\mathcal{L}} \underline{e}_{i\mathcal{R}}^T \cdot \frac{\partial \frac{\partial(W_i \underline{x}_i)}{\partial \underline{x}_i}}{\partial W_i}$$

Std. Loss Gradient

$$= \underline{e}_{i\mathcal{L}} (\underline{x}_i + \beta \underline{e}_{i\mathcal{R}})^T$$

Input to layer i

G.R. Loss Gradient

Training with Gradient Regularization (Complex)

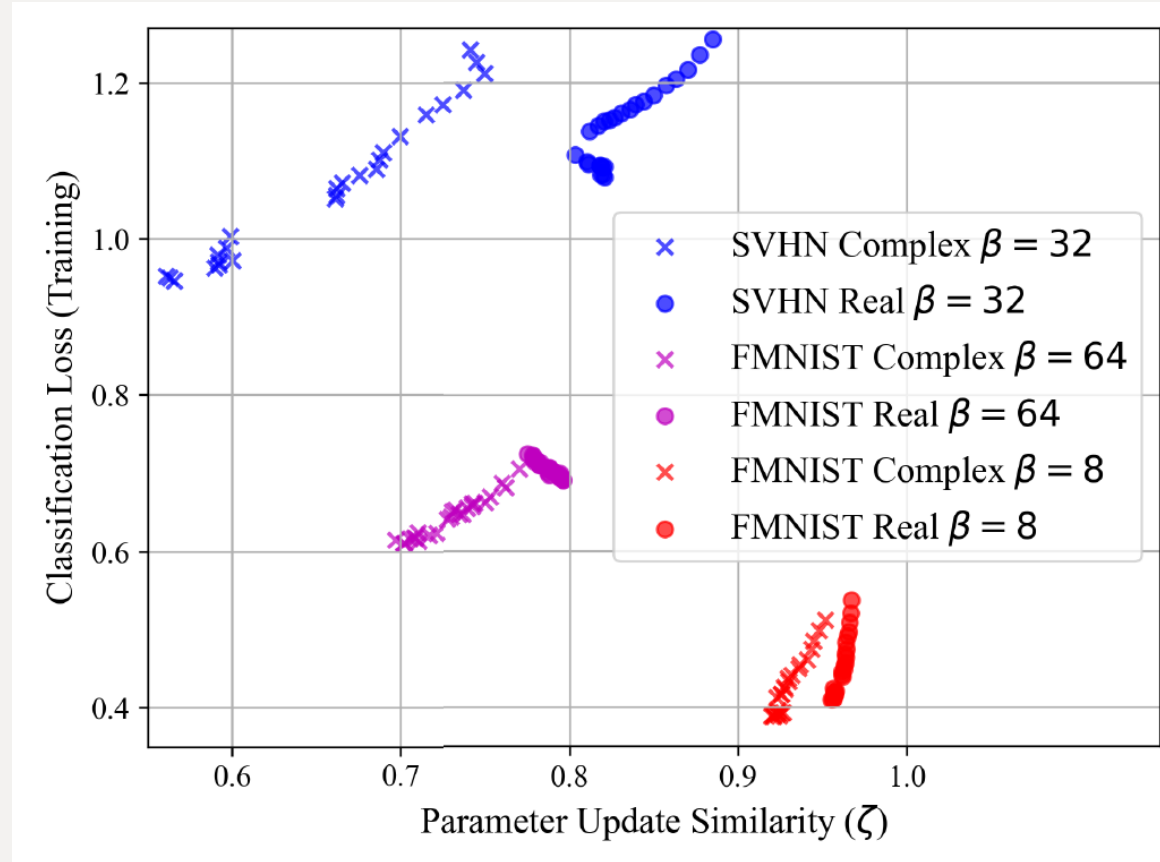
$$\nabla_{W_{iR}} \left[\mathcal{L}(f, \underline{x}, \underline{y}) + \beta \mathcal{R}(f, \underline{x}, \underline{y}) \right] =$$
$$\underbrace{\underline{e}_{i\mathcal{L}} \underline{1}^T \cdot \frac{\partial g_i(\underline{x}_i)}{\partial W_{iR}}}_{\text{Std. term}} + \underbrace{\beta \underline{e}_{i\mathcal{L}} \underline{e}_{i\mathcal{R}}^T \cdot \frac{\partial g_i(\underline{x}_i)}{\partial W_{iI}}}_{\text{G.R. term}}$$

$$\nabla_{W_{iI}} \left[\mathcal{L}(f, \underline{x}, \underline{y}) + \beta \mathcal{R}(f, \underline{x}, \underline{y}) \right] =$$
$$\underbrace{\underline{e}_{i\mathcal{L}} \underline{1}^T \cdot \frac{\partial g_i(\underline{x}_i)}{\partial W_{iI}}}_{\text{Std. term}} - \underbrace{\beta \underline{e}_{i\mathcal{L}} \underline{e}_{i\mathcal{R}}^T \cdot \frac{\partial g_i(\underline{x}_i)}{\partial W_{iR}}}_{\text{G.R. term}}$$

Derivative Constraint

$$\left(\frac{\partial g_i(\underline{x}_i)}{\partial W_{iR}} \right)^2 + \left(\frac{\partial g_i(\underline{x}_i)}{\partial W_{iI}} \right)^2 = 1$$

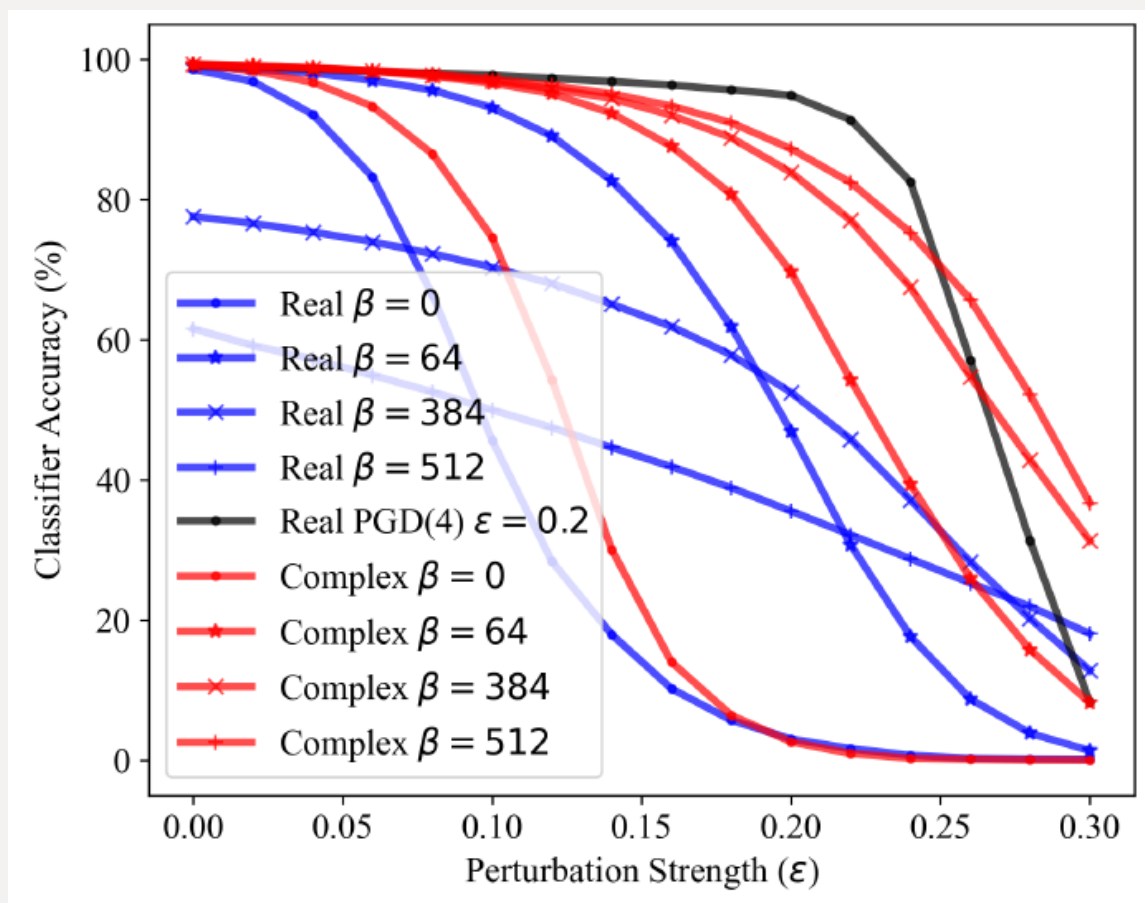
Training with Gradient Regularization



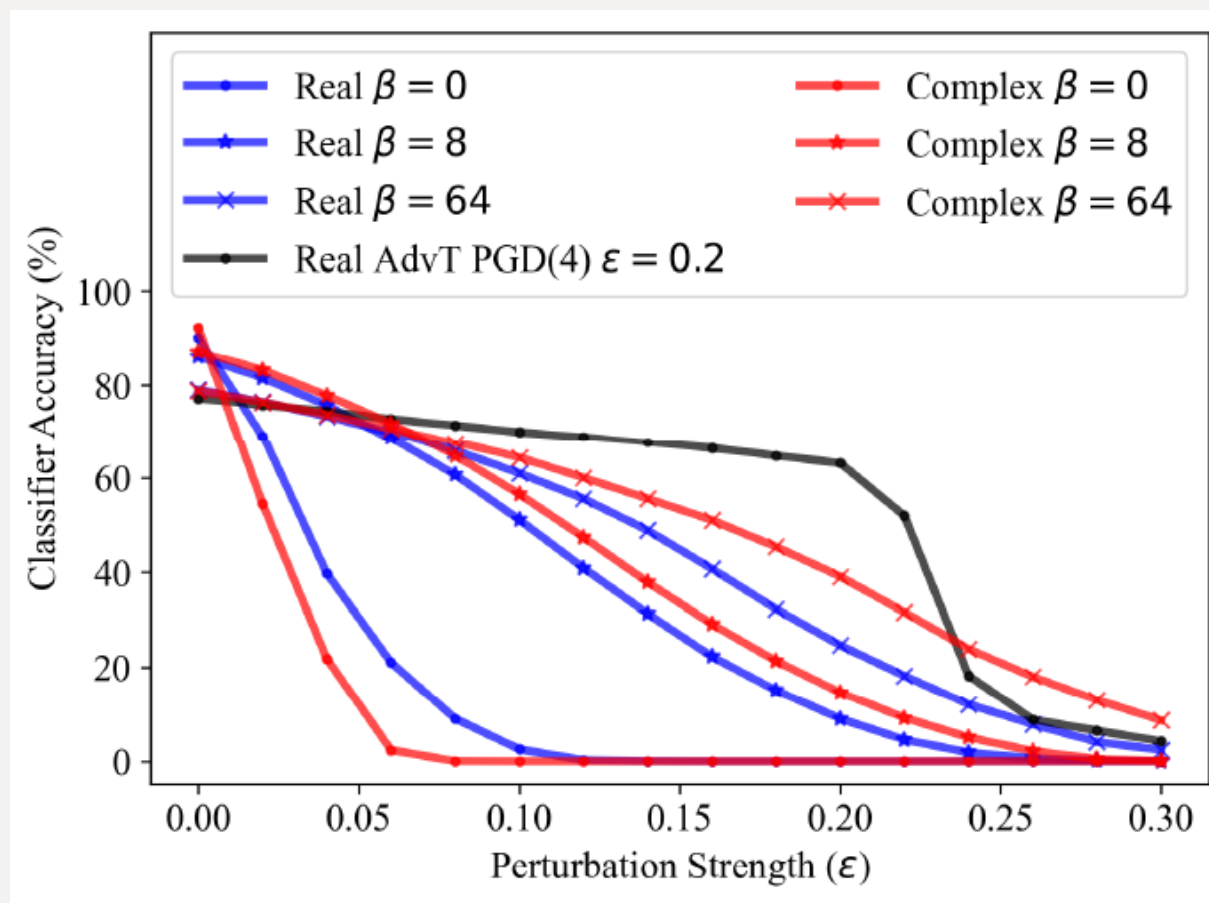
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$$\zeta = \frac{\nabla_f \mathcal{L}(f, \underline{x}, \underline{y}) \nabla_f [\mathcal{L}(f, \underline{x}, \underline{y}) + \beta \mathcal{R}(f, \underline{x}, \underline{y})]^T}{\|\nabla_f \mathcal{L}(f, \underline{x}, \underline{y})\|_2 \|\nabla_f [\mathcal{L}(f, \underline{x}, \underline{y}) + \beta \mathcal{R}(f, \underline{x}, \underline{y})]\|_2}$$

Attacks on MNIST and FashionMNIST

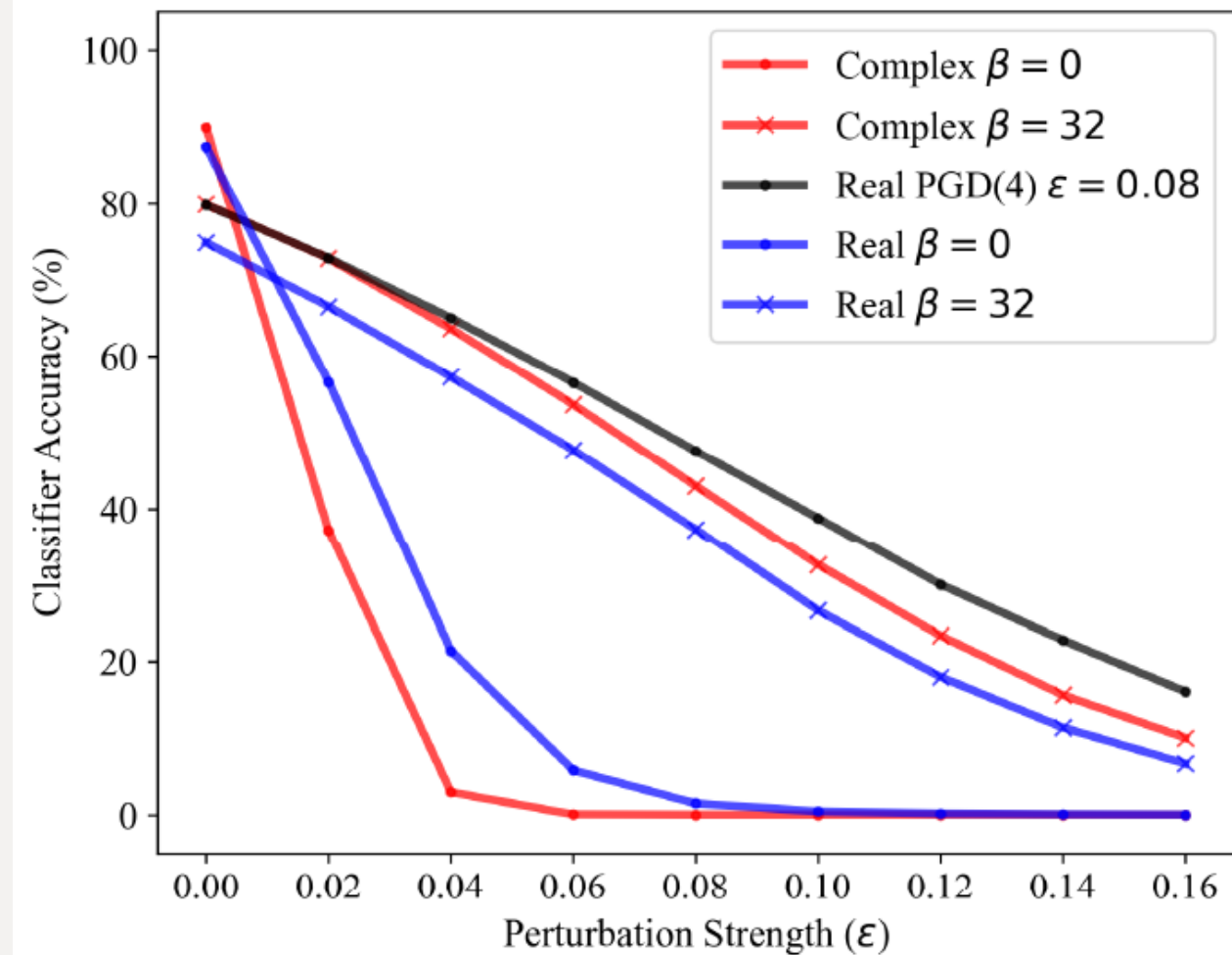


MNIST



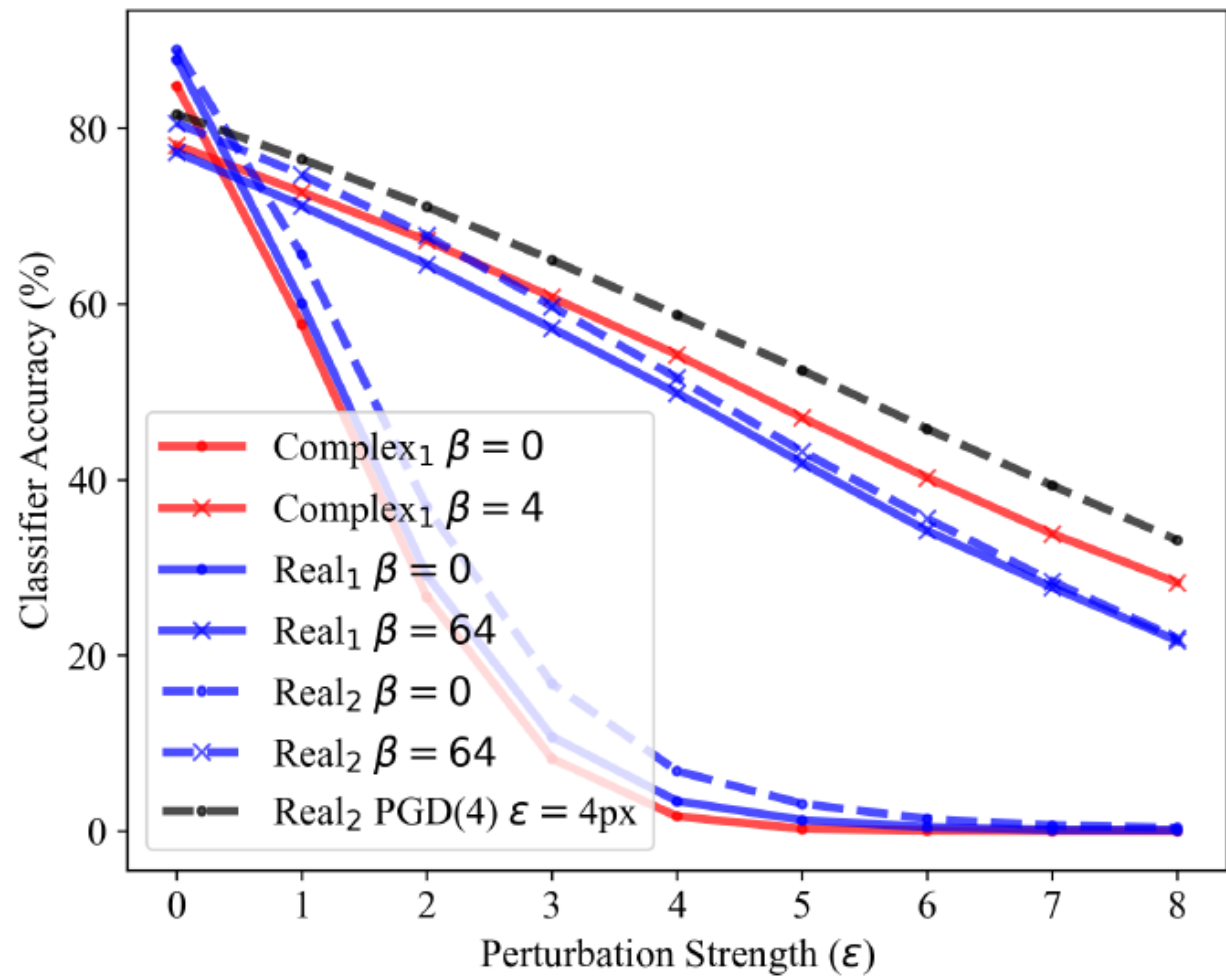
FashionMNIST

Attacks on SVHN and CIFAR-10



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SVHN



CIFAR-10

Resistance to Black-Box Transfer Attacks

TRANSFER TO NETWORK:	MNIST $\epsilon = 0.16$ $\beta = 0/64$	SVHN $\epsilon = 0.10$ $\beta = 0/32$	FMNIST $\epsilon = 0.16$ $\beta = 0/64$
FGSM FROM REAL-VALUED NETWORK (STD./G.R.)			
SELF	22.5 / 86.6	4.1 / 32.5	2.2 / 53.1
\mathbb{R} (STD.)	36.2 / 74.0	10.3 / 32.0	3.9 / 28.3
\mathbb{C} (STD.)	93.7 / 93.1	22.8 / 40.5	12.6 / 33.7
\mathbb{R} (G.R.)	93.0 / 91.5	52.9 / 34.9	63.9 / 53.8
\mathbb{C} (G.R.)	95.3 / 95.8	55.7 / 41.9	68.5 / 60.4
FGSM FROM COMPLEX-VALUED NETWORK (STD./G.R.)			
SELF	58.4 / 93.9	10.4 / 36.7	1.7 / 53.4
\mathbb{R} (STD.)	86.5 / 88.0	50.1 / 31.5	32.4 / 30.7
\mathbb{C} (STD.)	93.1 / 95.7	35.5 / 36.3	15.9 / 31.2
\mathbb{R} (G.R.)	97.1 / 95.8	63.0 / 37.8	70.2 / 57.6
\mathbb{C} (G.R.)	97.3 / 96.4	65.4 / 41.5	74.7 / 58.4

Resistance to Query-Based Attack

NES Attack on 1000 FashionMNIST Test Images
8-step PGD Attack $\epsilon = 0.16$
4000 Queries/image

Net Type	No Defense	$\beta=64$ G.R.	$\epsilon=0.2$ AdvTrain
Real-Valued	0%	62.3%	76.3%
Complex-Val.	0%	68.4%	

Ilyas et al. “Black-box Adversarial Attacks with Limited Queries and Information” ICML 2018

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Code Available: <https://github.com/ericyeats/cvnn-security>