#### REaaS: Enabling Adversarially Robust Downstream Classifiers via Robust Encoder as a Service

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#### Encoder as a Service

- Service provider
  - OpenAI, Clarifai
- Encoder
  - A general-purpose feature extractor
  - Supervised learning, self-supervised learning
- Client
  - Smartphone, IoT device, self-driving car, edge device

### Deployment of Encoder as a Service



**OpenAl's GPT-3** 

Clarifai's General Image Embedding

#### Standard Encoder as a Service



### Building a Downstream Classifier



### Adversarial Example



### Certified Defense

- A certified defense
  - Build a certifiably robust classifier
  - Derive the certified radius
- Certifiably robust classifier:

$$h(\mathbf{x} + \delta) = h(\mathbf{x}), \forall \|\delta\|_2 < R \quad \text{Certified radius}$$
Classifier Testing Perturbation input

### Certified Defense

- Base classifier (BC) based certification
  - CROWN, IBP
- Smoothed classifier (SC) based certification
  - Randomized smoothing

#### Base Classifier Based Certification

- Directly derive the certified radius of a given classifier (base classifier)
- White-box access to the base classifier



### Smoothed Classifier Based Certification

• Build a certifiably robust smoothed classifier upon a base classifier



• Requires the base classifier to predict the labels of multiple noisy versions of a testing input.



### Goal of A Client

- A client aims to
  - Build a certifiably robust classifier
  - Deriving its certified radius
- SEaaS
  - View composition of encoder and downstream classifier as a base classifier
  - BC or SC based certification



Base classifier

## Challenges of Existing SEaaS

- BC based certification
  - Not applicable
- SC based certification
  - Incur large communication cost



### Our Solution

- Robust Encoder as a Service (REaaS)
  - Feature-API
  - An extra API: F2IPerturb-API
    - Input: An image, a feature-space certified radius
    - Output: An image-space certified radius

### Feature-space Certified Radius

- View the downstream classifier as a base classifier
  - BC or SC based certification
    - Build a certifiably robust downstream classifier



Base classifier

Encoder Testing input  

$$h(f(\mathbf{x}) + \delta_F) = h(f(\mathbf{x})), \forall \|\delta_F\|_2 < R_F$$
Certifiably robust  
downstream classifier Feature-space  
perturbation Feature-space  
certified radius

### Image-space Certified Radius

Image-space  
certified radius 
$$\longrightarrow R = \max_{r} r$$
  
 $s.t. \max_{\|\delta\|_{2} < r} \|f(\mathbf{x} + \delta) - f(\mathbf{x})\|_{2} < R_{F}$ 

### Solving the Optimization Problem

- Binary search
  - We verify whether a given r satisfy the constraint

$$\max_{\|\delta\|_{2} < r} \|f(\mathbf{x} + \delta) - f(\mathbf{x})\|_{2} < R_{F}$$
  
Non-linear

- Key challenge
- Key idea

• Derive an upper bound of 
$$\max_{\|\delta\|_2 < r} \|f(\mathbf{x} + \delta) - f(\mathbf{x})\|_2$$

### Summary of REaaS



### Pre-training Robust Encoder

• Decomposition and spectral norm [1]

 $f(\cdot) = T^{n} \circ T^{n-1} \circ \cdots \circ T^{1}(\cdot) \qquad \left\| f(\mathbf{x}) - f(\mathbf{x} + \delta) \right\|_{2} \le \prod_{j=1}^{n} \left\| T^{j} \right\|_{s} \cdot \left\| \delta \right\|_{2}$ Spectral norm

• We use the following loss:

$$\frac{1}{m} \cdot \sum_{i=1}^{m} l(i) + \lambda \cdot \prod_{j=1}^{n} \left\| T^{j} \right\|_{s}$$

[1] Szegedy et al. "Intriguing properties of neural networks", in ICLR, 2014.

### Theoretical Comparison with SEaaS

• REaaS makes BC based certification applicable

• REaaS incurs a smaller communication cost for SC based certification

### Evaluation

- Pre-training dataset and algorithm:
  - Tiny-ImageNet
  - MoCo
- Downstream dataset and classifier:
  - CIFAR10, SVHN, STL10
  - A fully connected neural network

### **Evaluation Setting**

- BC based certification
  - CROWN
- SC based certification
  - Randomized smoothing

### **Evaluation Metrics**

- #Queries
  - #Queries per training input
  - #Queries per testing input
- Average certified radius (ACR)

### Comparing REaaS with SEaaS

Service	Downstream dataset	ACR	#Queries	
			Per training input	Per testing input
SEaaS	CIFAR10			
	SVHN	N/A		
	STL10			
REaaS	CIFAR10	0.138		
	SVHN	0.258	1	2
	STL10	0.090		

REaaS supports BC based certification while SEaaS does not.

### Comparing REaaS with SEaaS

Service	Downstream dataset	ACR	#Queries	
			Per training input	Per testing input
SEaaS	CIFAR10	0.157		
	SVHN	0.226	25	$1 \times 10^5$
	STL10	0.134		
REaaS	CIFAR10	0.171		
	SVHN	0.275	1	2
	STL10	0.143		

REaaS achieves larger ACR while incurring smaller communication cost for SC based certification

## Comparing Our Pre-training Method with Existing Ones

- Non-robust MoCo
- RoCL (generalize adversarial training)

### Comparing Our Pre-training Method with Existing Ones

Certification Method	Pre-training Method	ACR
	Non-robust MoCo	0.010
BC	RoCL	0.012
	Ours	0.139
	Non-robust MoCo	0.014
SC	RoCL	0.017
	Ours	0.173

Our pre-training method outperforms existing ones

### Extending REaaS to NLP Domain

ACR	#Queries		
	Per training input	Per testing input	
2.517	1	2	

### Conclusion

- We propose REaaS that enables a client to build a certifiably robust downstream classifier
- Our REaaS reduces the communication cost of SC based certification
- Our pre-training method improves the certified robustness of a downstream classifier

# Thank you!