

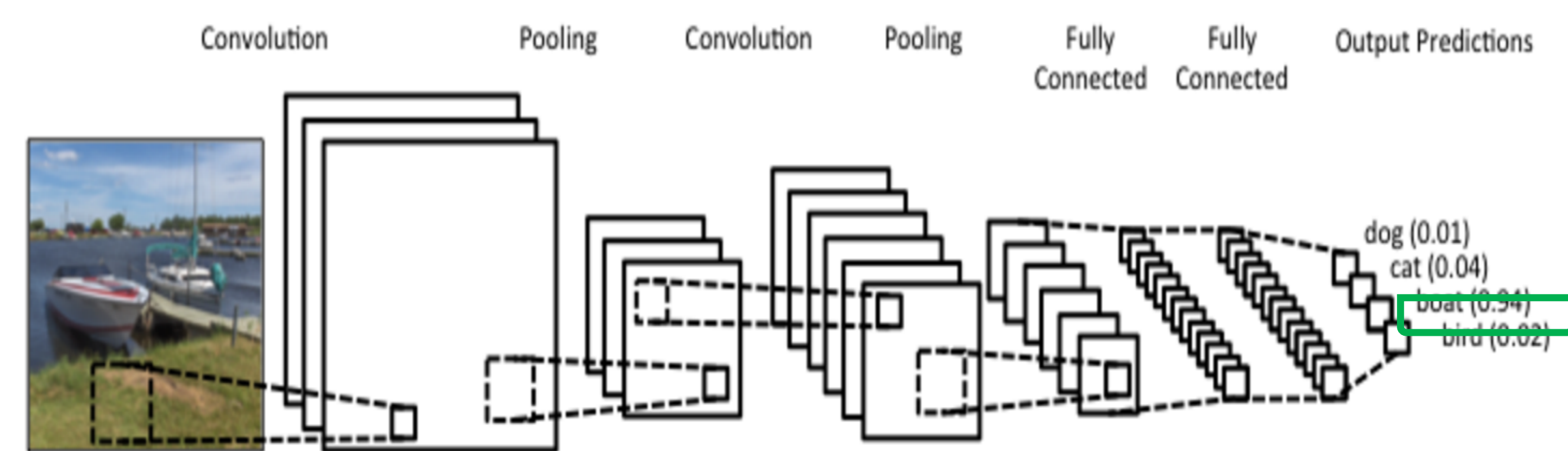
TOWARDS DEPENDABLE DEEP CNNs WITH OUT-DISTRIBUTION LEARNING

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INTRODUCTION

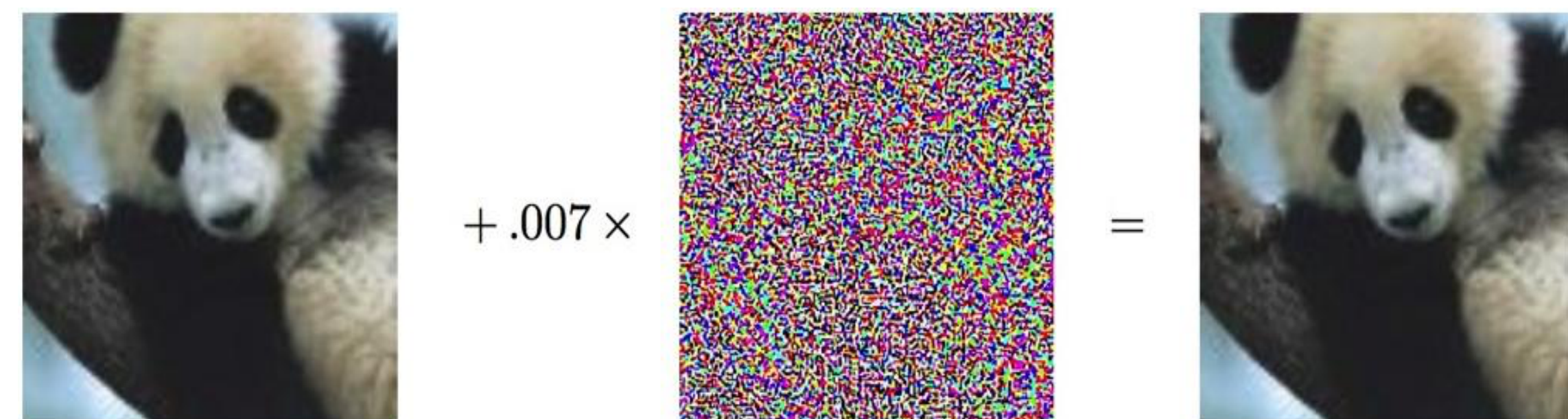
Convolutional Neural Networks (CNNs) have become popular for image classification and object recognition.



Despite of CNNs' high accuracy, they are vulnerable to:

1.1 Adversarial Example

Adding **small** but **smart** perturbations to an input image generates another image, called adversarial



Panda
57.7% confidence

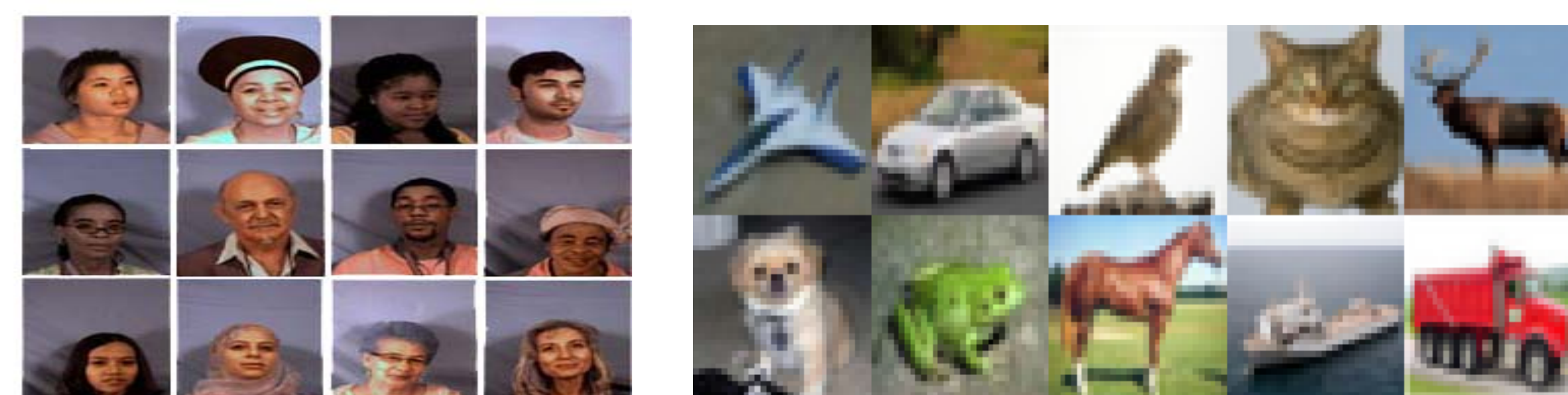
Gibbon
99.3% confidence

Adversarial Generation Models:

- FGS (Fast Gradient Sign)
- T-FGS (Targeted FGS)
- I-FGS (Iterative FGS)

1.2 Out-distribution samples

In-distribution samples are images from task-related dataset (e.g. Faces for Face Recognition Task). Images from other task-irrelevant dataset are called out-distribution samples (e.g. images of animals or objects for face recognition task)



Problem: CNNs classify confidently out-distribution samples into the task-related classes.

MOTIVATION

- Without adversarial training, adapting CNNs to allow error-less decisions in the presence of

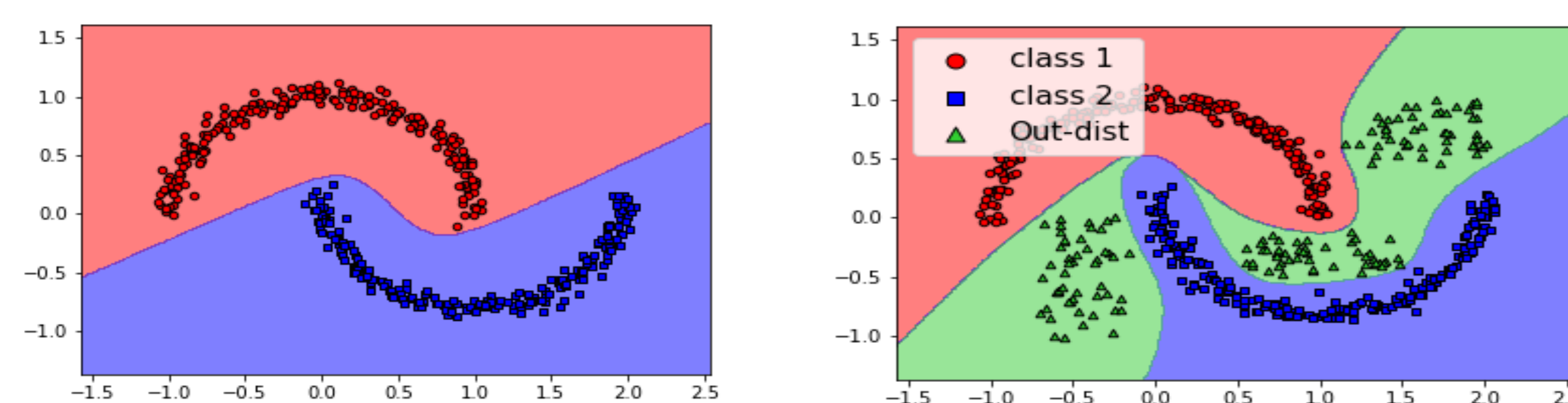
➤ **Adversarially perturbed albeit benign-looking data**

➤ **Out-distribution data**

OUT-DISTRIBUTION LEARNING

Augmented CNNs: Naïve CNNs with an extra class named "dustbin" which includes some out-distribution samples.

Augmented CNNs have more accurate boundries

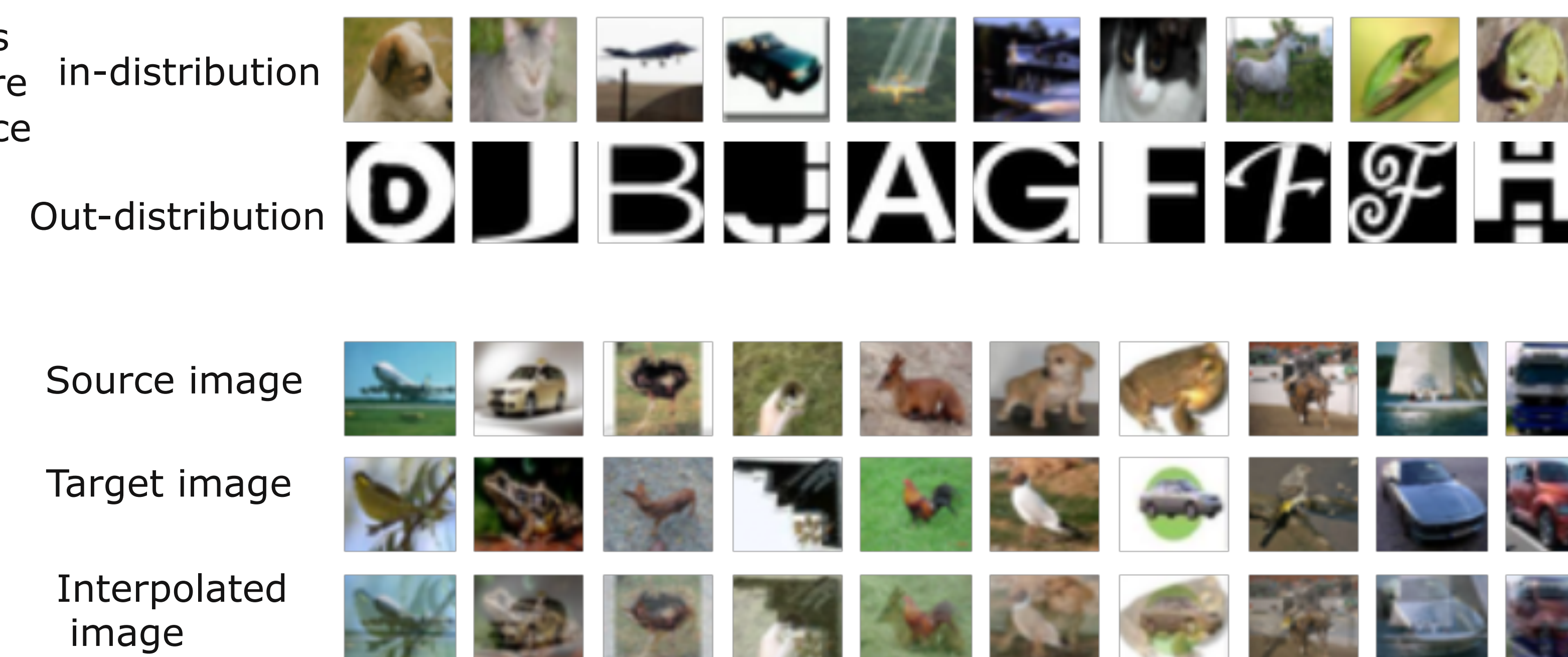


(a) a naive MLP

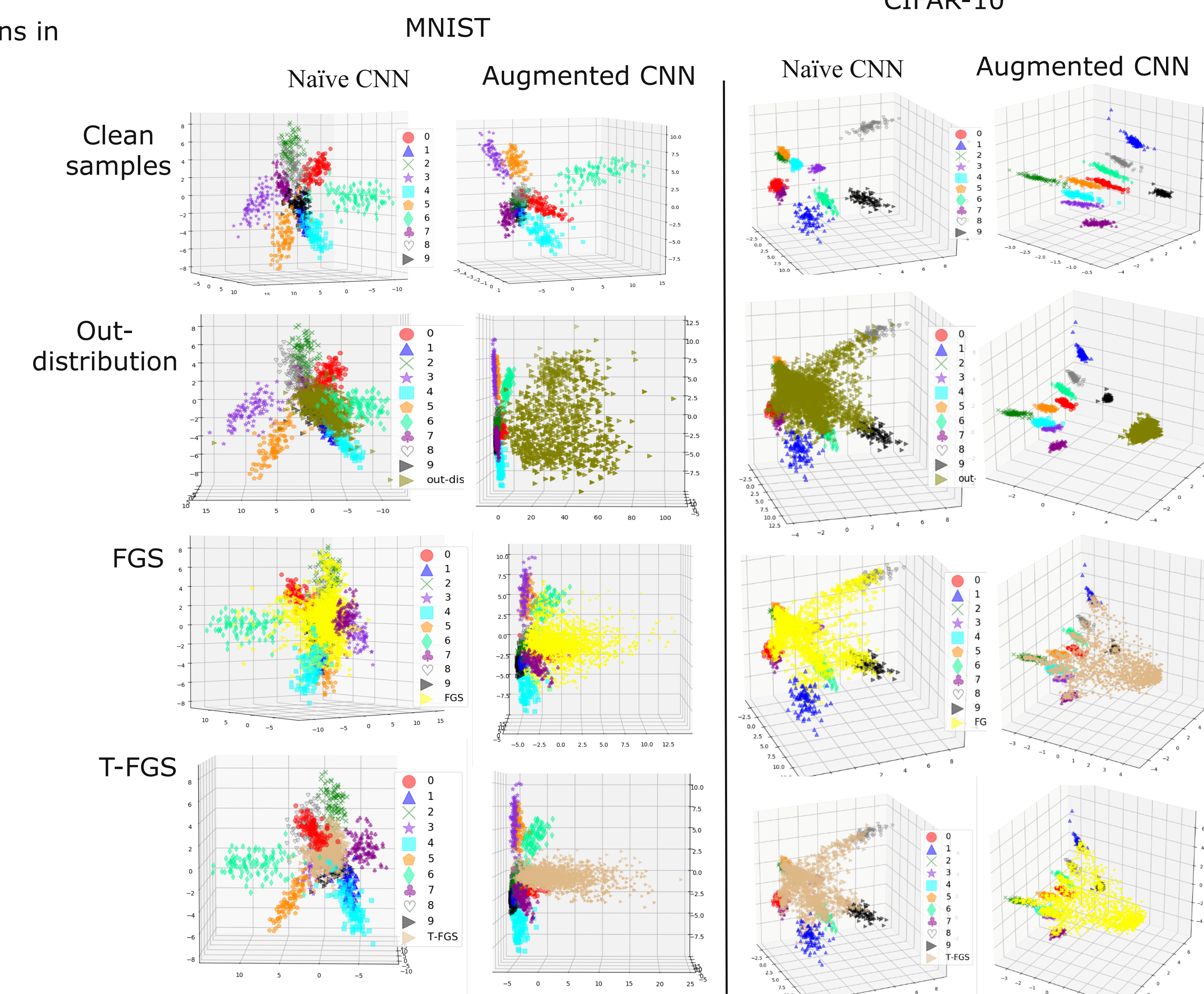
(b) The augmented MLP

Augmented CNNs are learned on:

- In-distribution samples:
 - Natural out-distribution samples from another dataset
 - Interpolated images created from in-distribution samples
- Out-distribution samples:



EVALUATION



MODELS		ATTACKS' SUCCESS RATE		
		FGS	T-FGS	I-FGS
MNIST	Naïve CNN	64.86	80.01	83.63
	Augmented CNN	0.06	0.0	0
CIFAR-10	Naïve CNN	63.84	63.76	49.66
	Augmented CNN	26.83	25.03	32.2