Training robust neural networks

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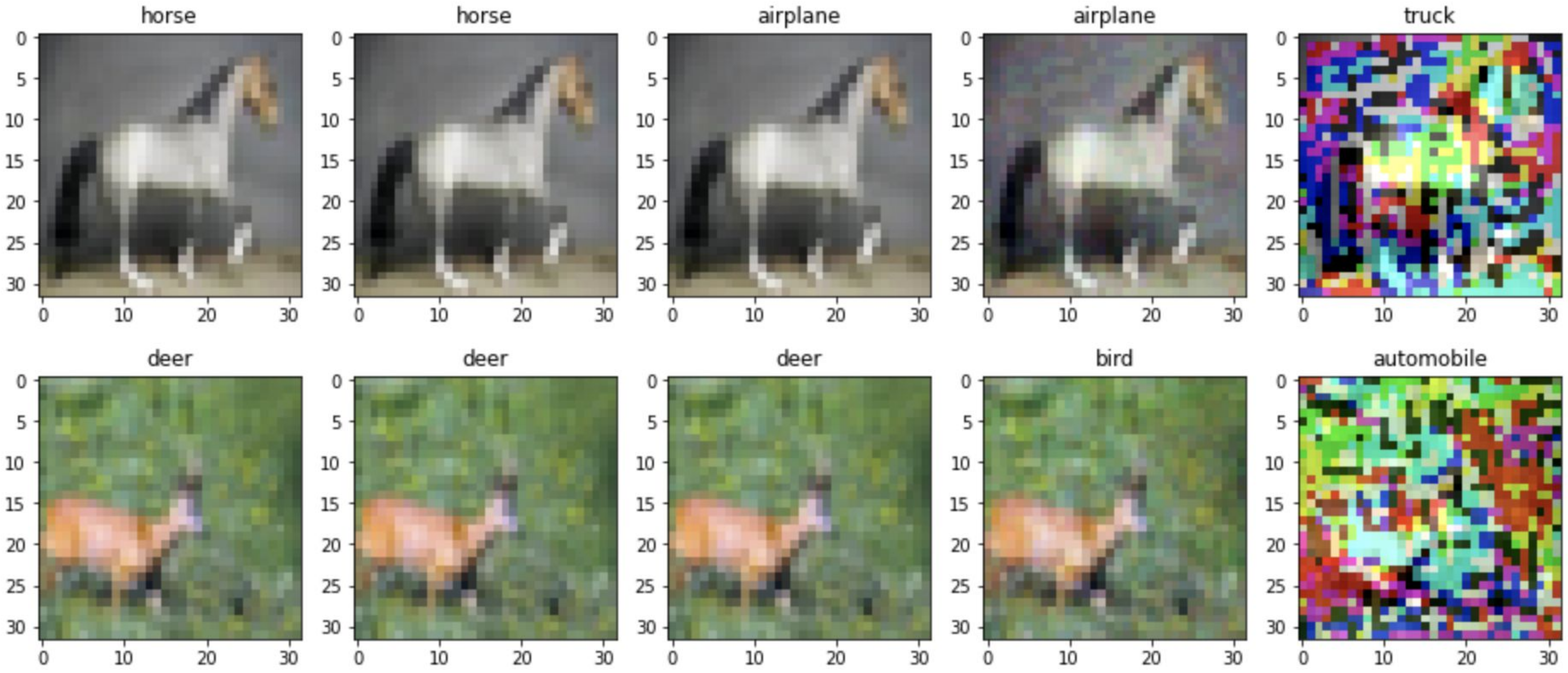
Plan

1. The problem
2. FGSM,PGD
3. Adversarial Training
4. Defensive Distillation
5. Defensive Randomized Networks
6. Other Attacks (C&W)

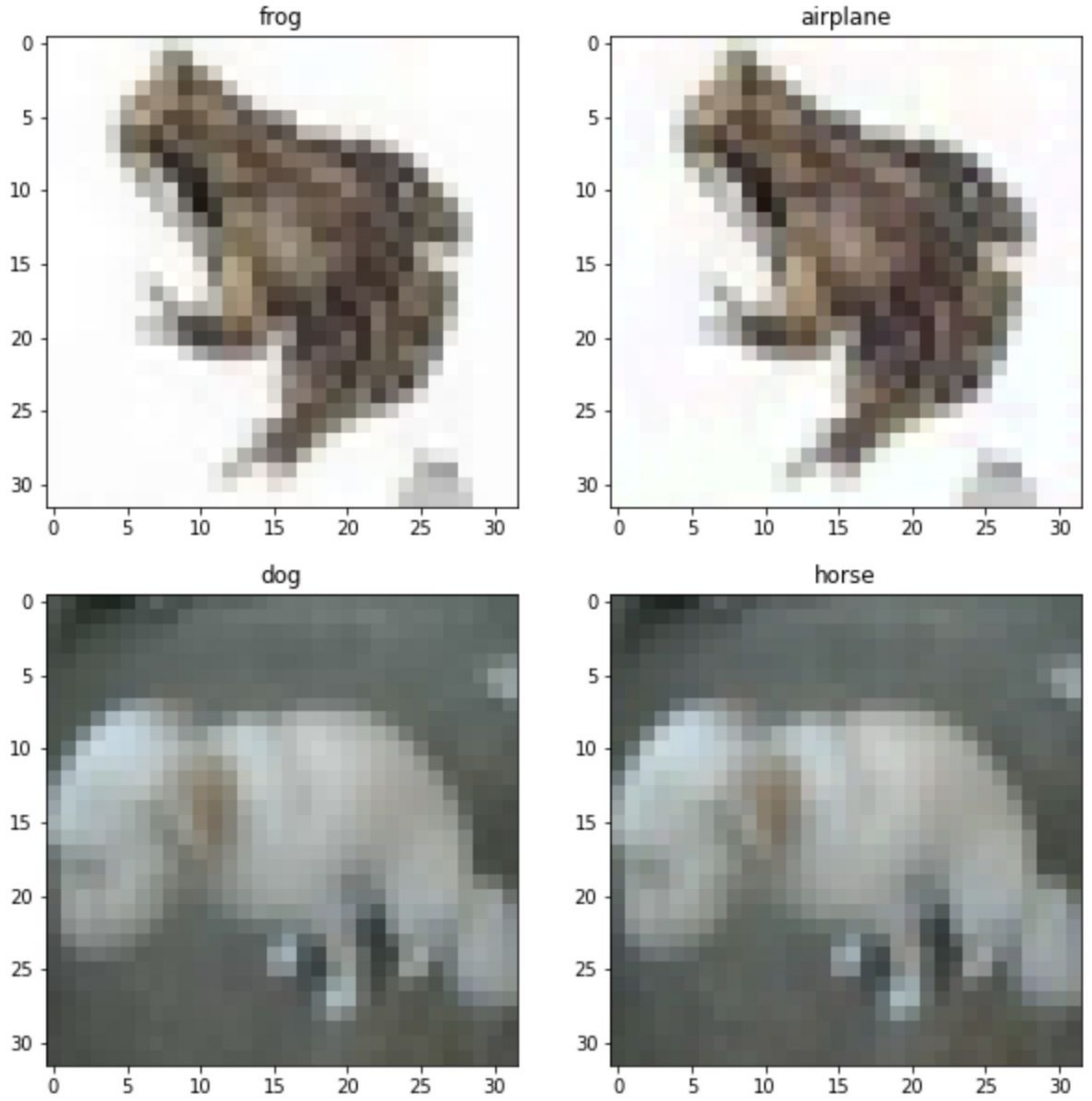
FGSM Attack [1]:

$$\text{perturbated\_image} = \text{image} + \text{epsilon} * \text{sign}(\text{data}_{\text{grad}}) = x + \epsilon * \text{sign}(\nabla_x J(\theta, \mathbf{x}, y))$$

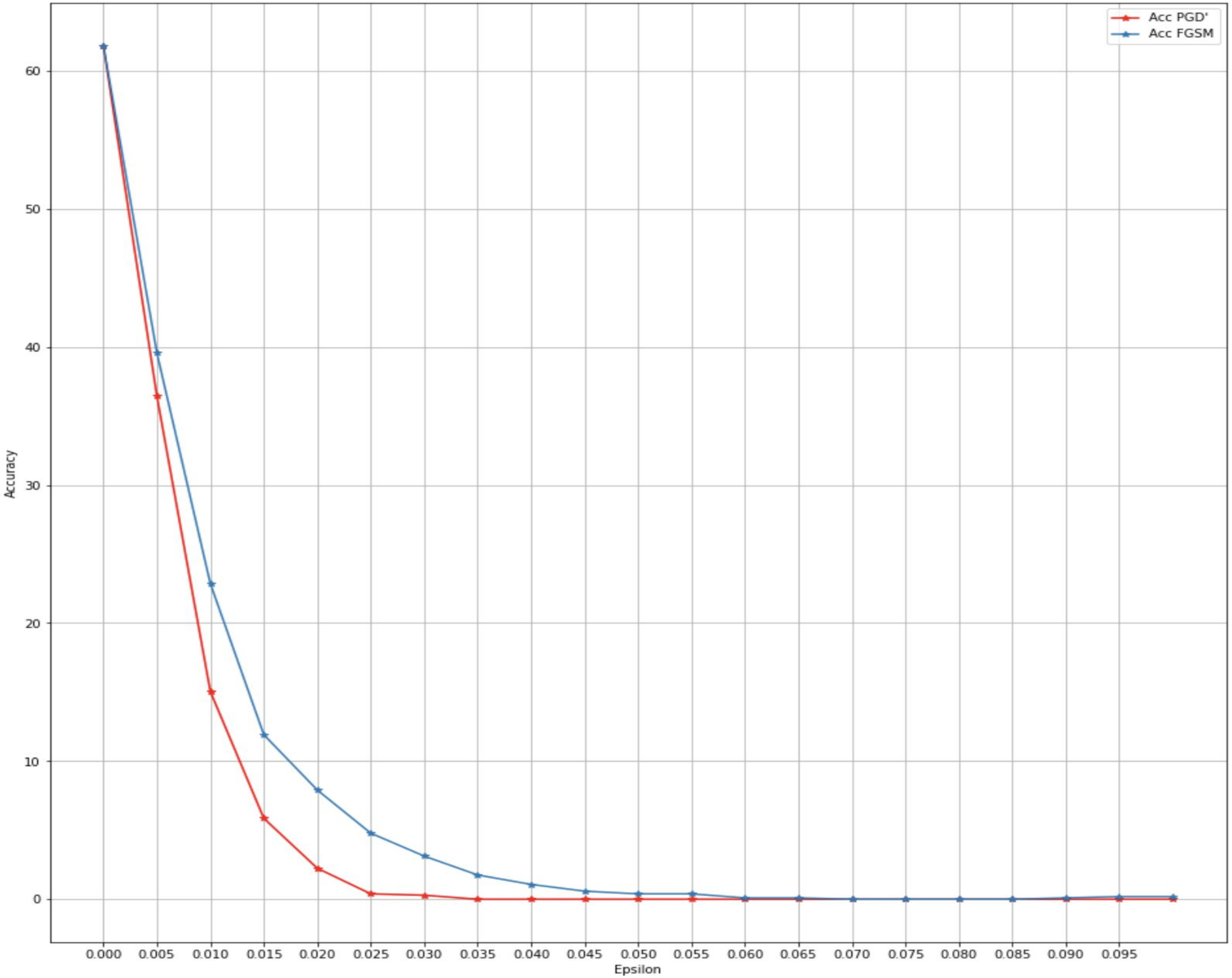
epsilon = [0, 0.0003, 0.003, 0.03, 0.3]



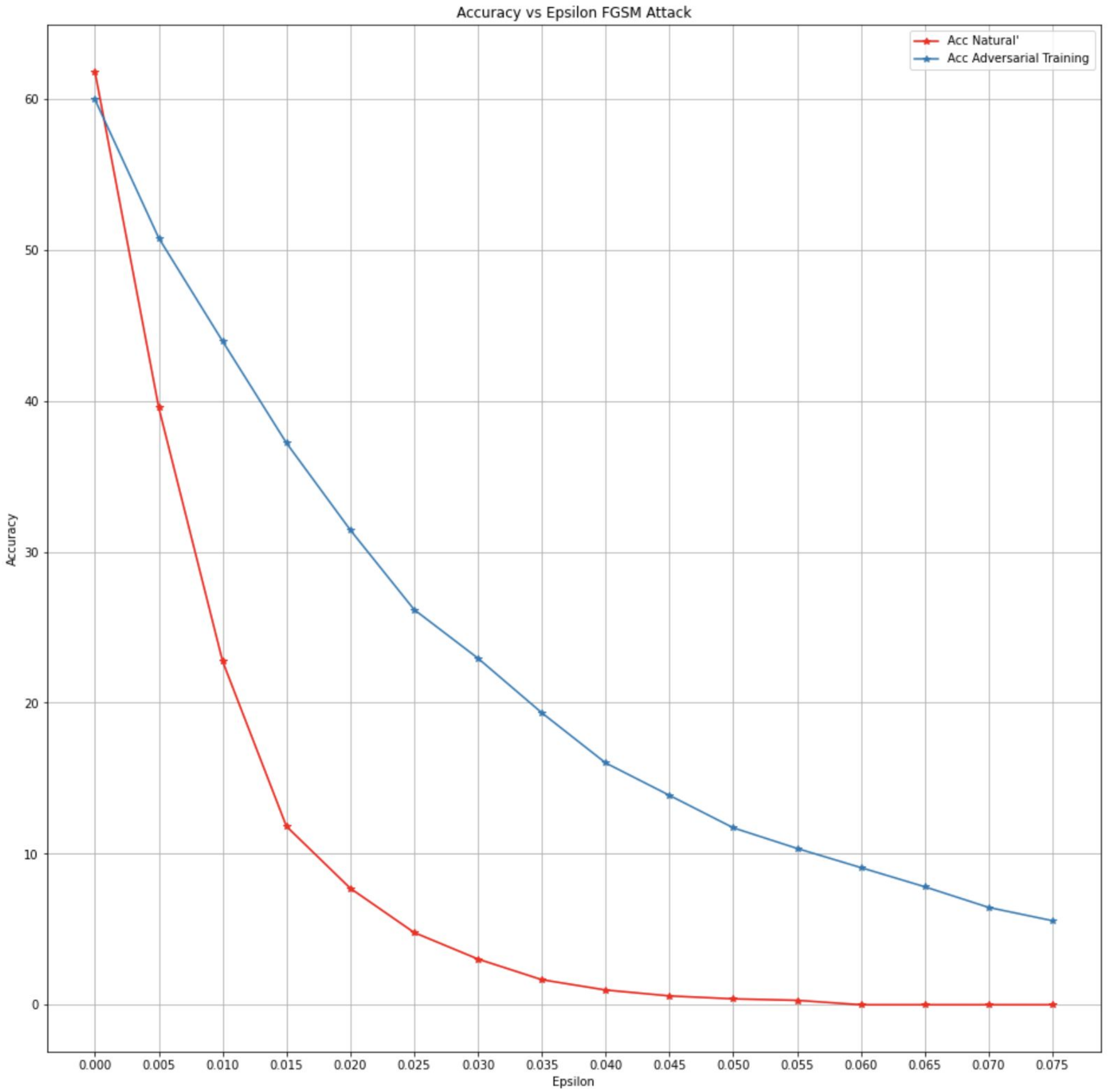
PGD Attack:

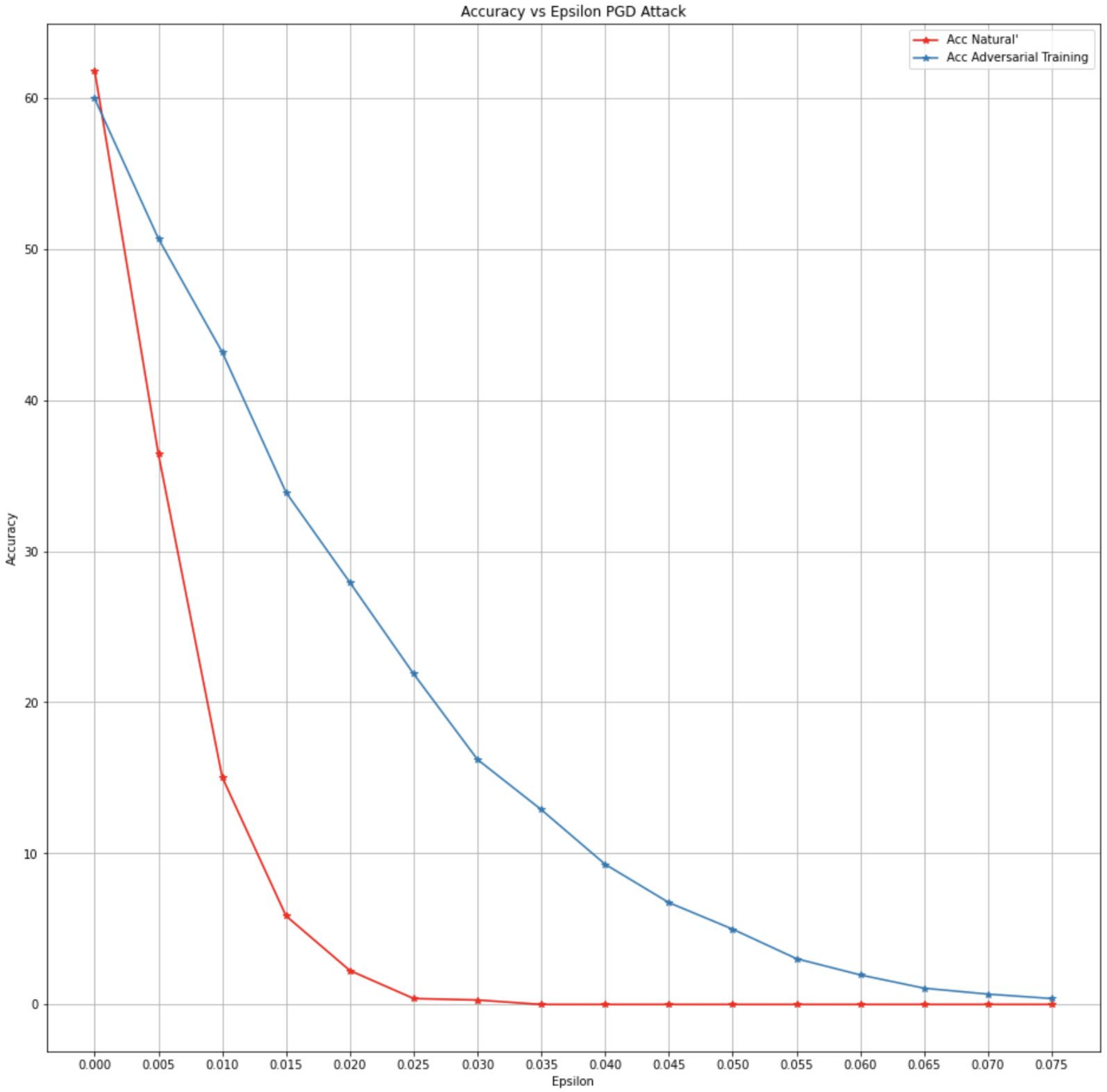


Accuracy results of FGSM and PGD attacks with epsilon from 0 to 0,095

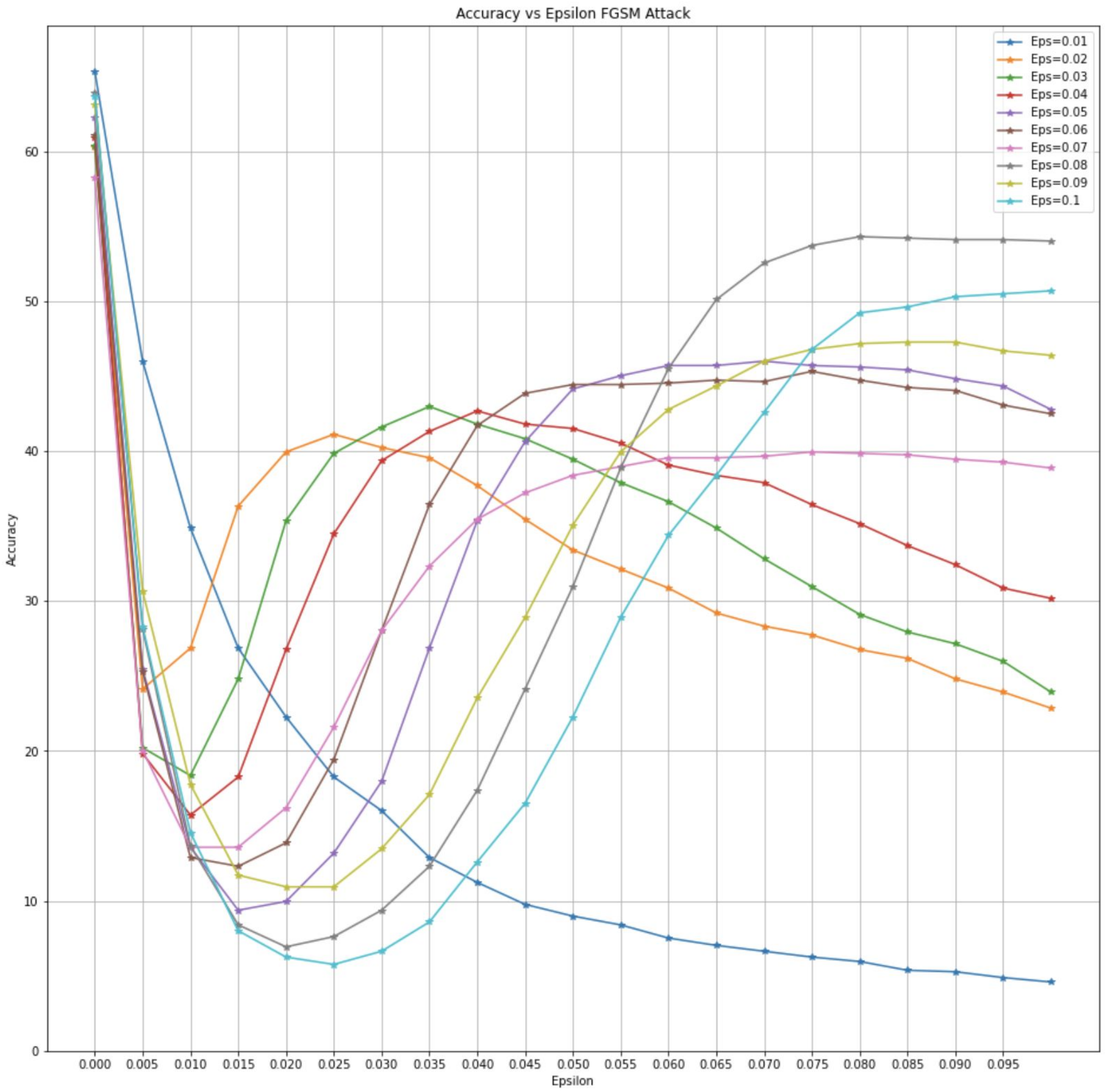


Adversarial Training[3] : Epsilon=0.01, 50% Natural Data, 50% Adversarial Data

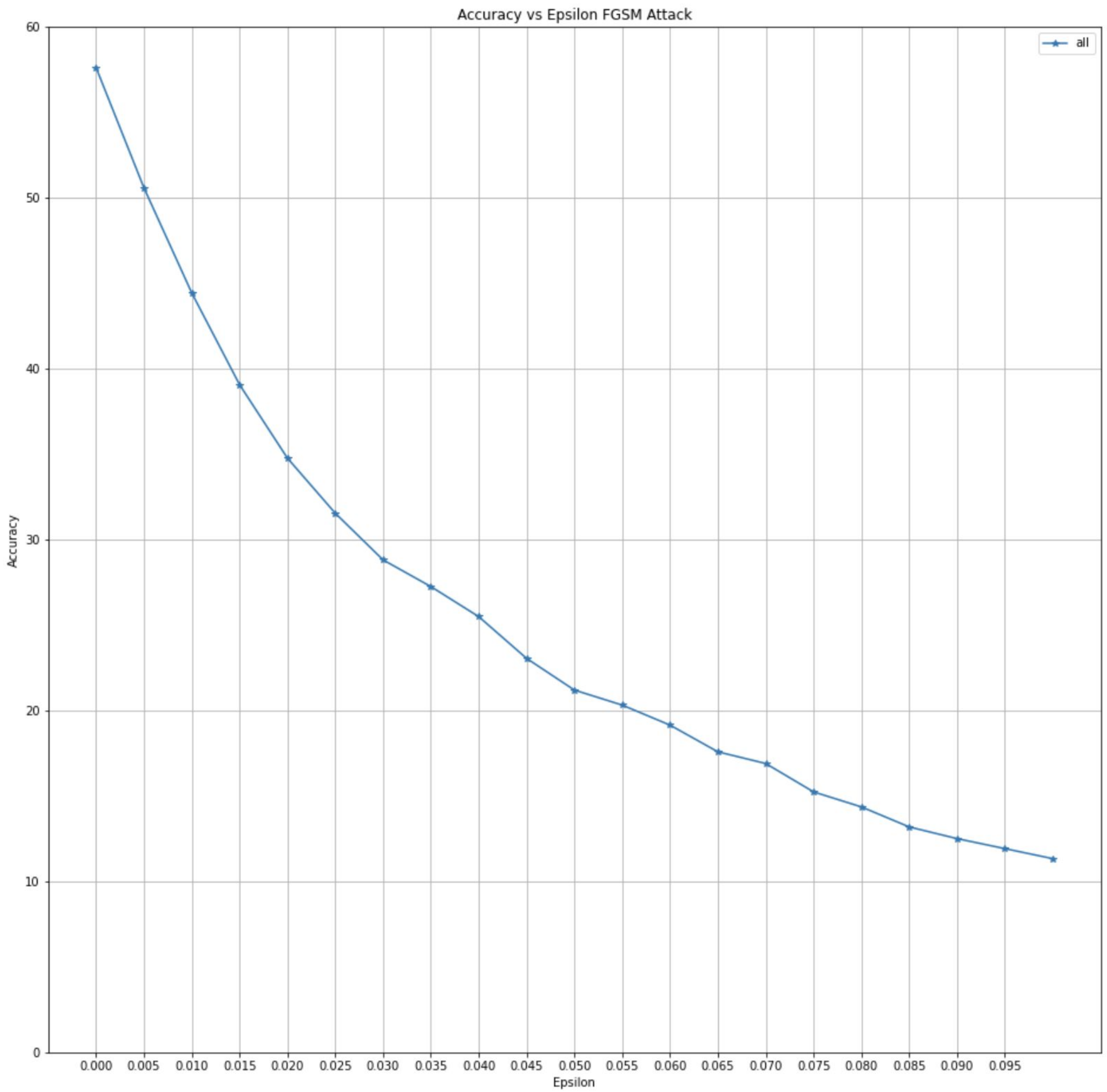




Results of Adversarial Training with FGSM

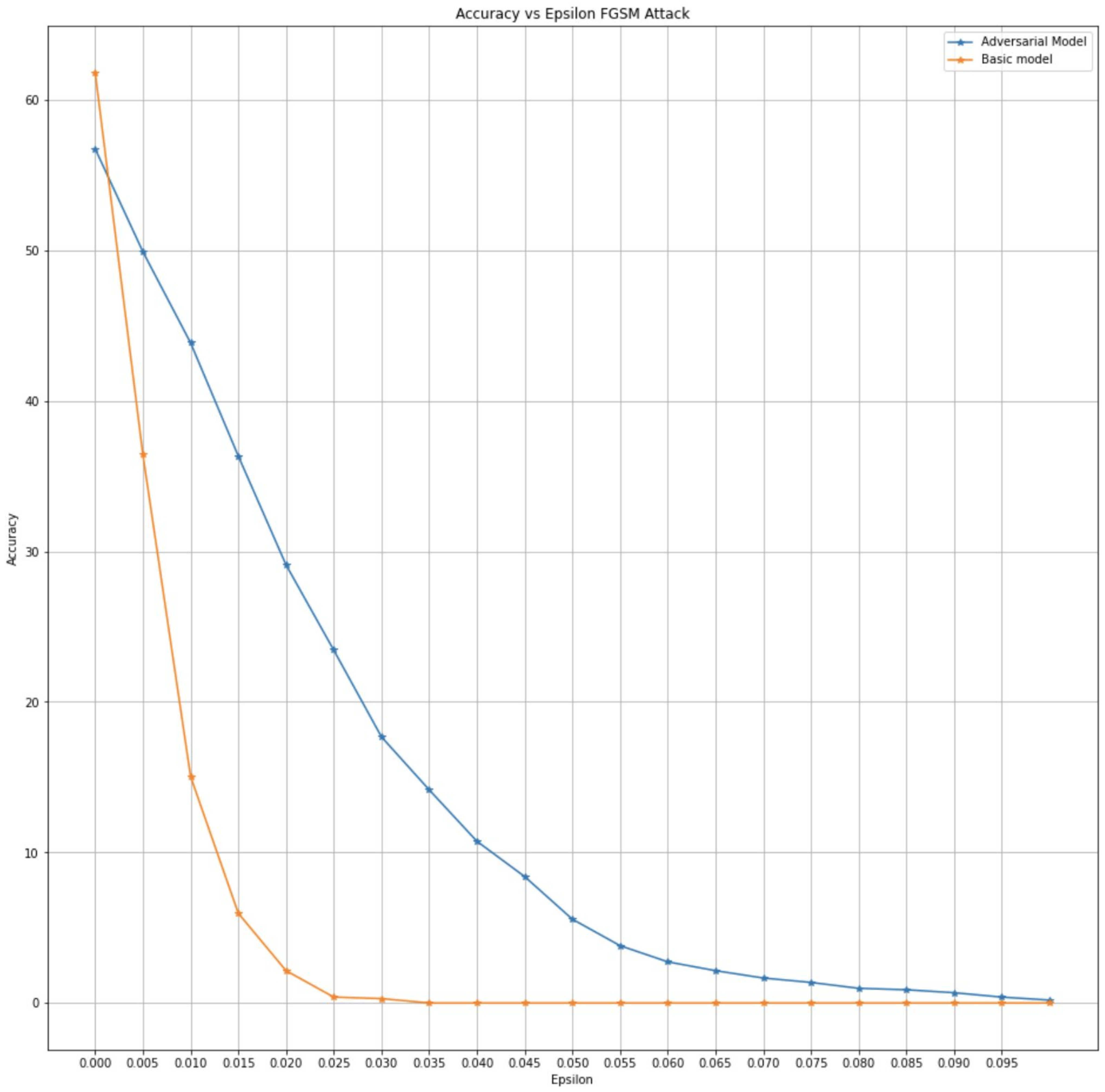


Accuracy vs Epsilon FGSM Attack
Eps=0.01
Eps=0.02
Eps=0.03
Eps=0.04
Eps=0.05
Eps=0.06
Eps=0.07
Eps=0.08
Eps=0.09
Eps=0.1
Accuracy
0
10
20
30
40
50
60
0.000
0.005
0.010
0.015
0.020
0.025
0.030
0.035
0.040
0.045
0.050
0.055
0.060
0.065
0.070
0.075
0.080
0.085
0.090
0.095
Epsilon


Accuracy vs Epsilon FGSM Attack
all
Accuracy
Epsilon
0
10
20
30
40
50
60
0.000
0.005
0.010
0.015
0.020
0.025
0.030
0.035
0.040
0.045
0.050
0.055
0.060
0.065
0.070
0.075
0.080
0.085
0.090
0.095

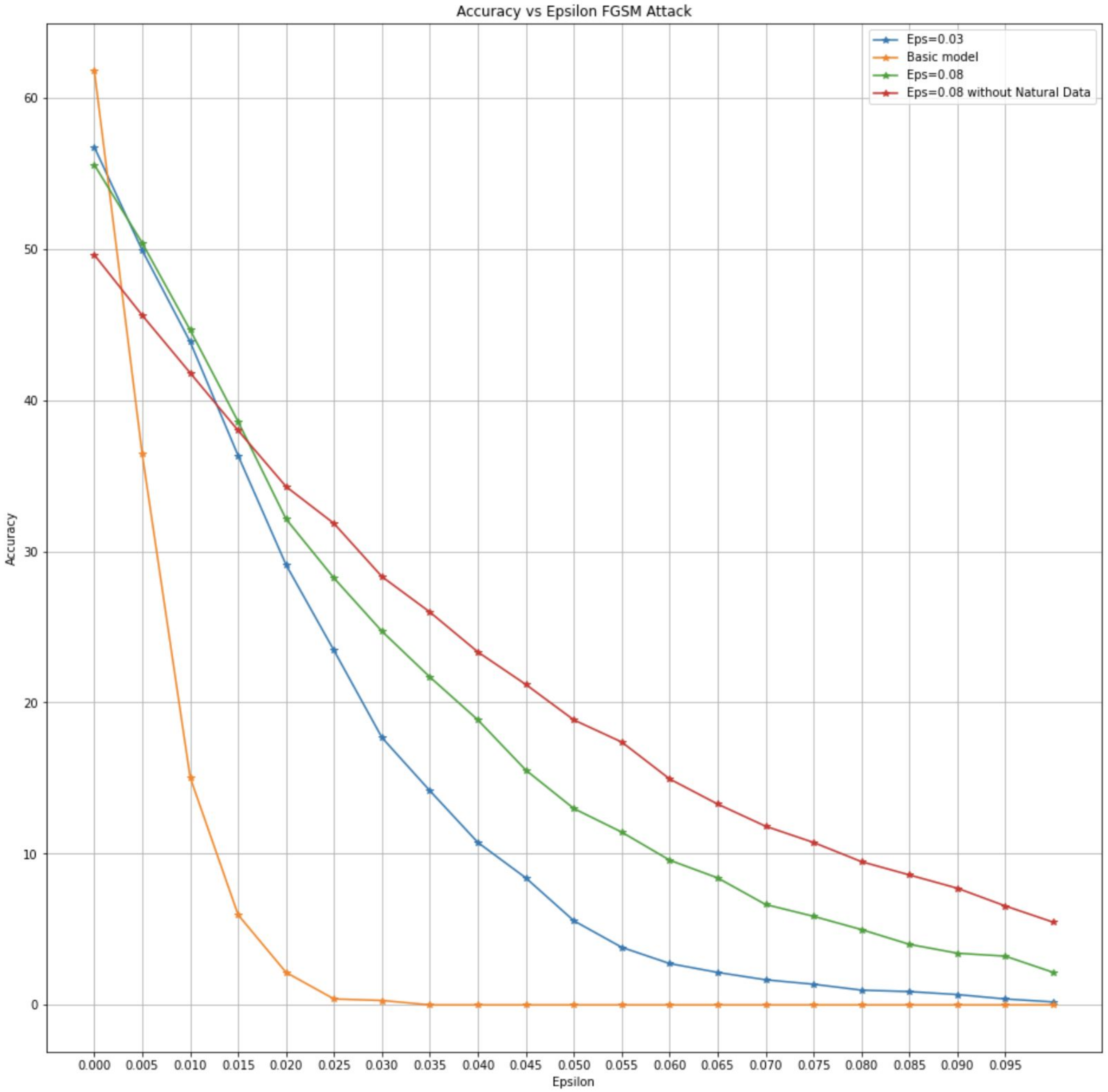
Adversarial Training[3]

Epsilon=0.03



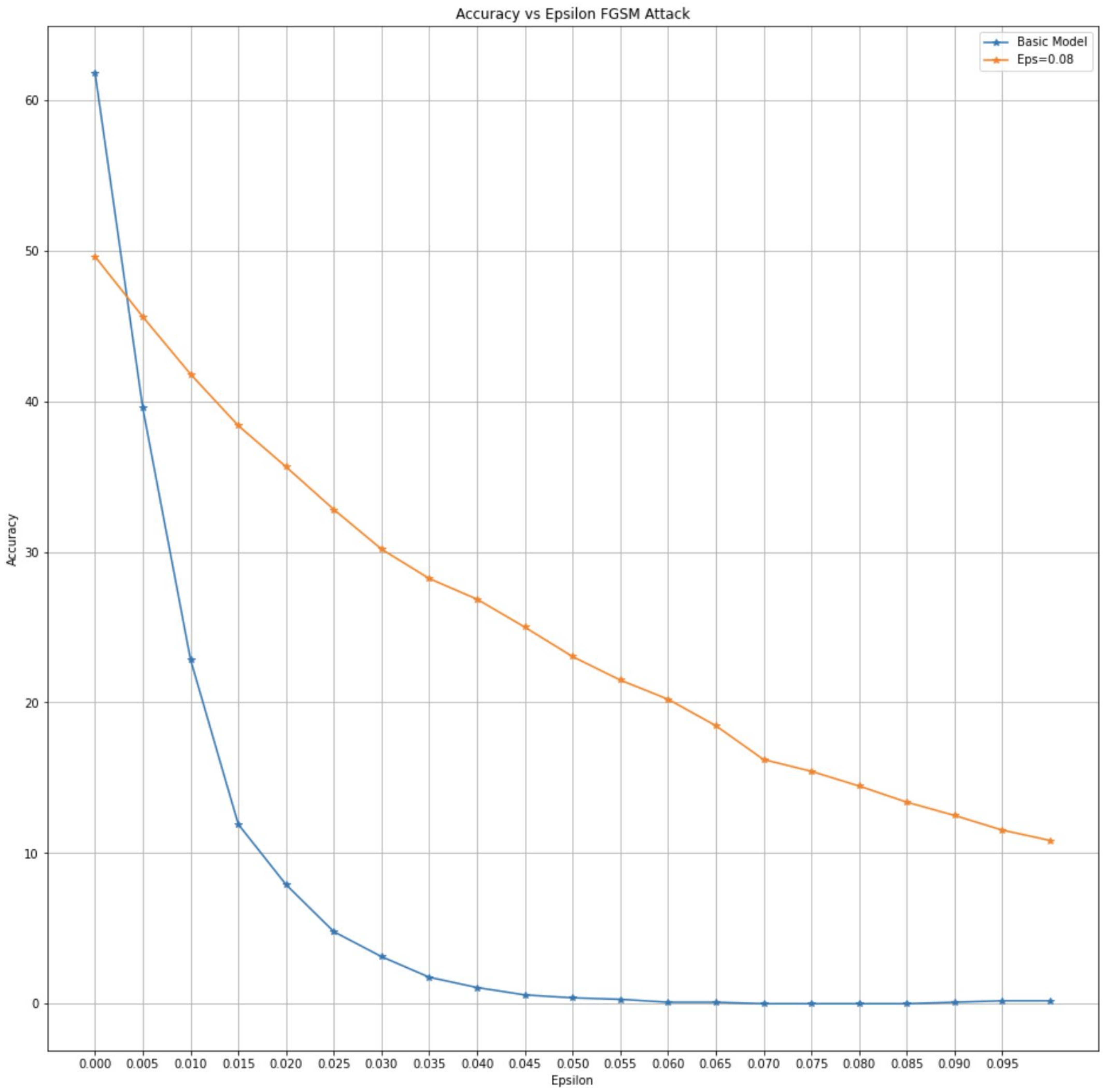
Results of Adversarial Training with PGD

Adversarial Training[3]



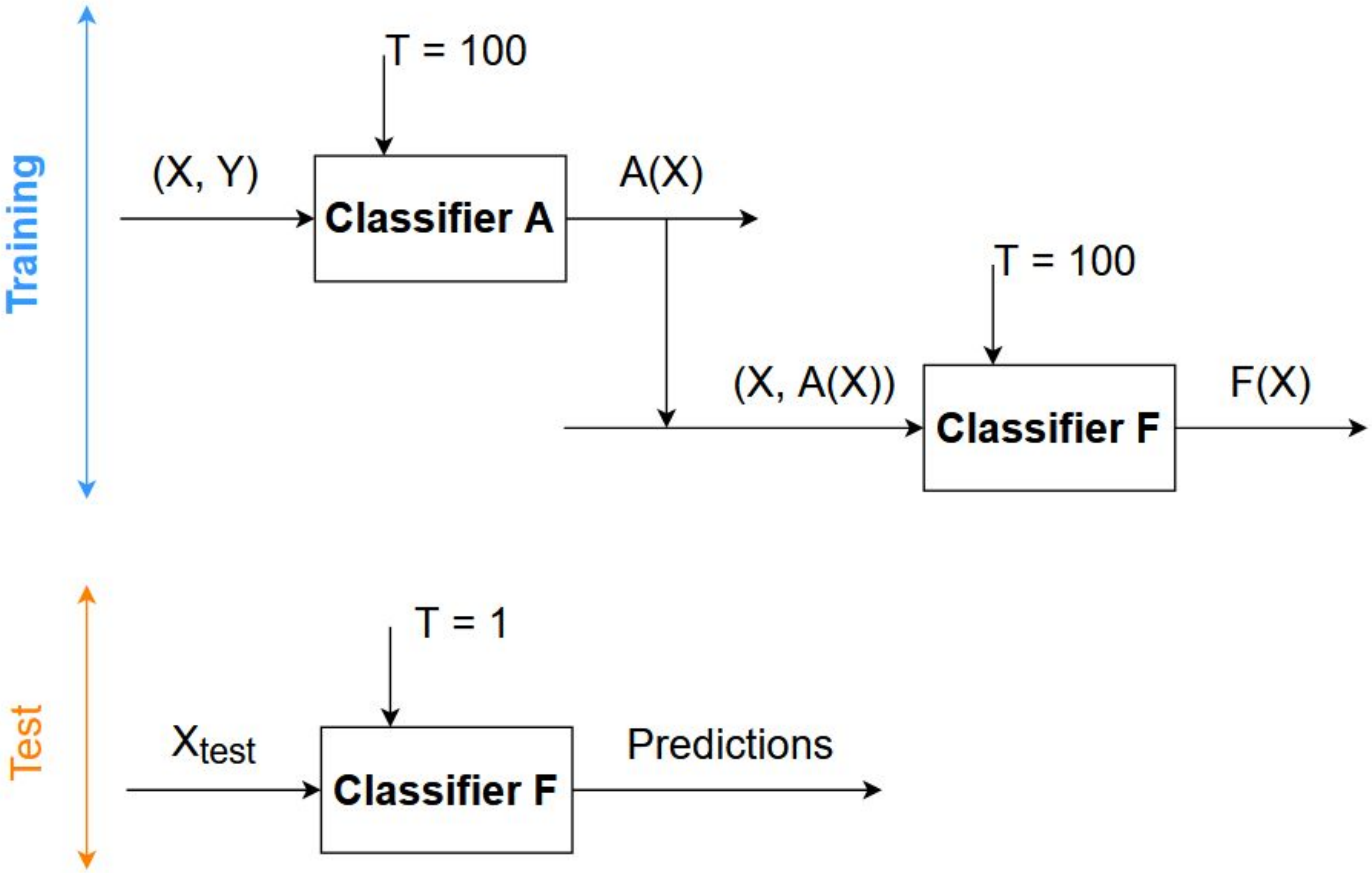
Results of Adversarial Training with PGD Vs PGD attack

Adversarial Training[3]

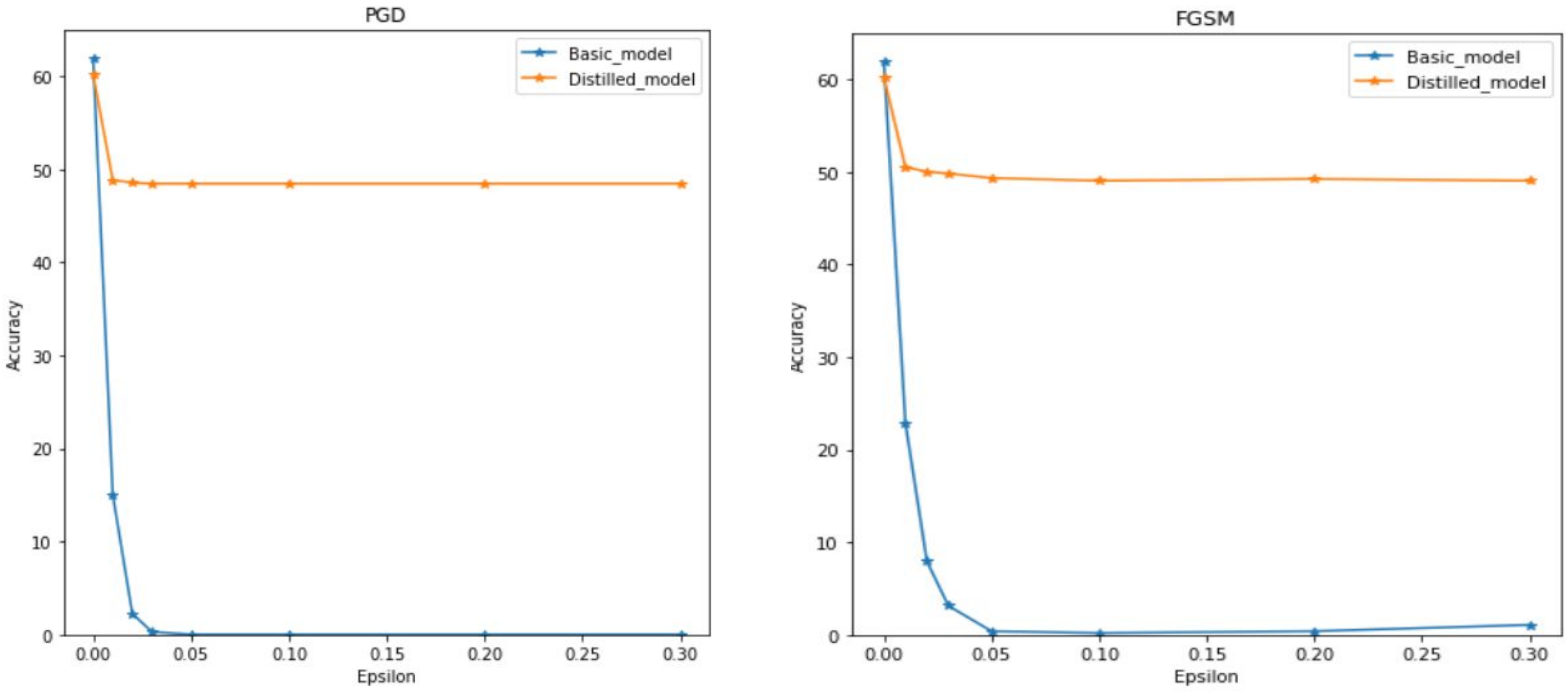


Results of Adversarial Training with PGD Vs FGSM attack

Defensive Distillation [4]:

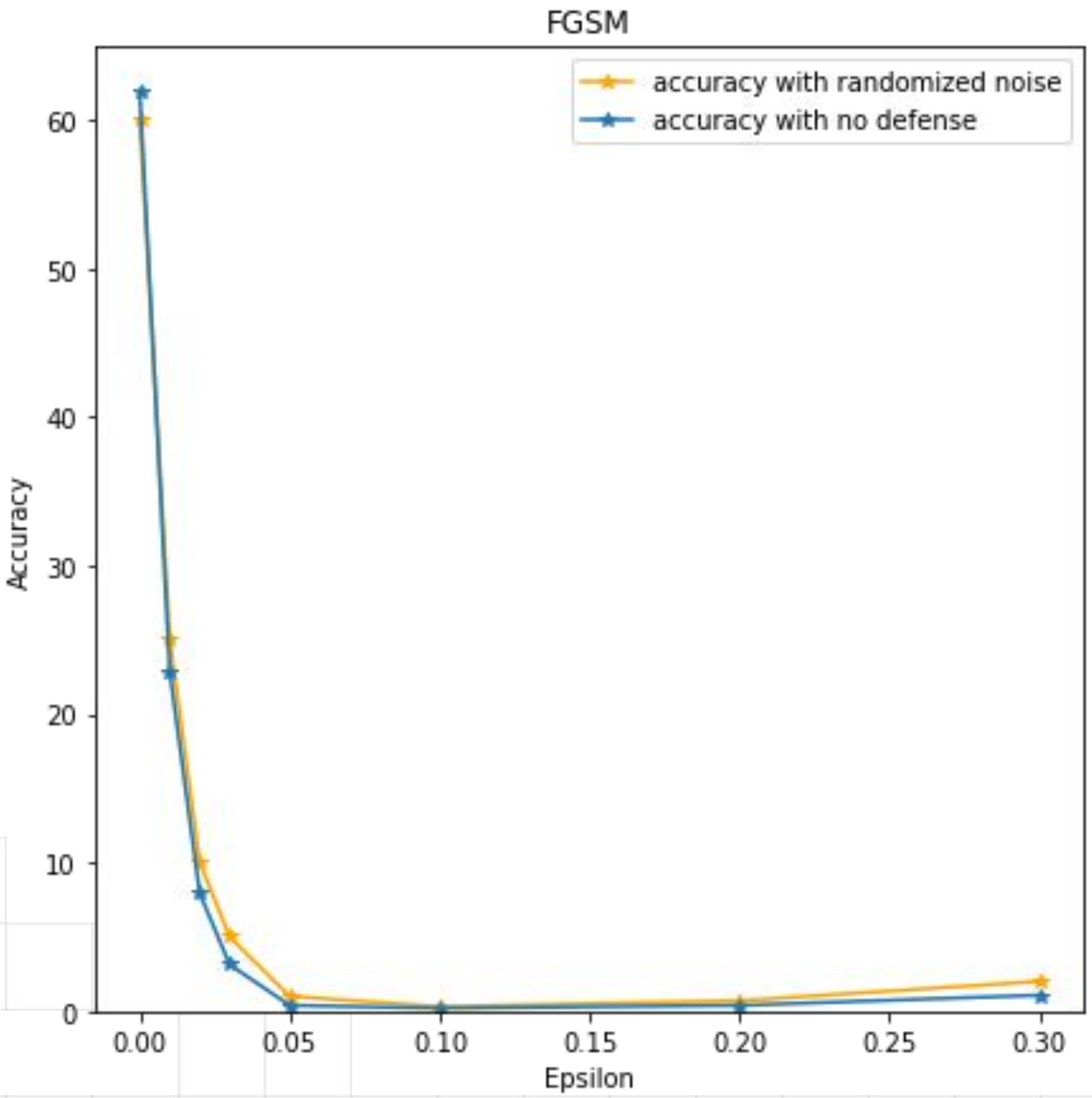


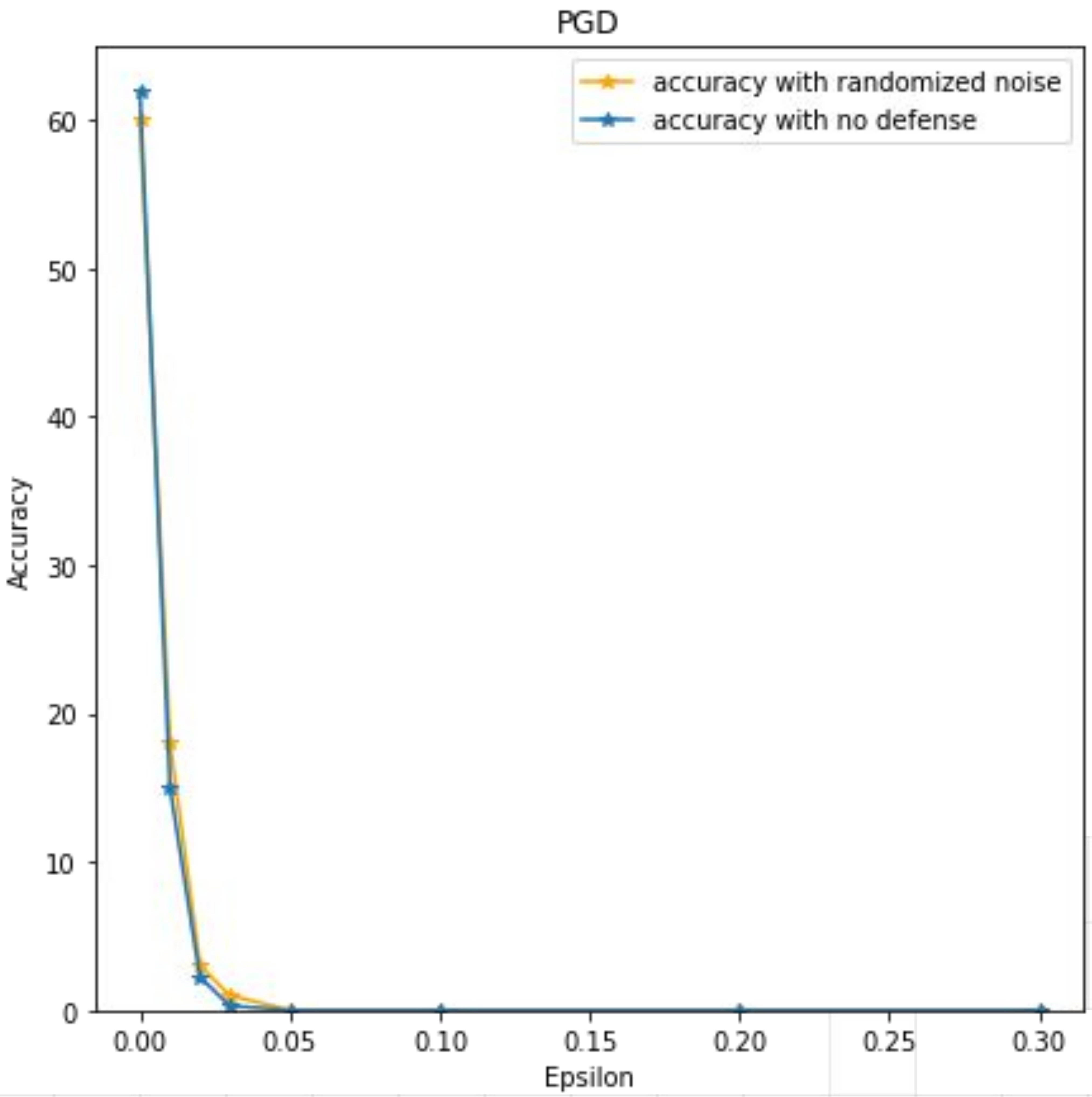
Basic and Distilled model against FGSM & PGD :



Randomized Networks [5]:

$$x_{test} = x_{test} + \textit{gaussian\_noise}(0, 0.01)$$





Ensemble of Networks

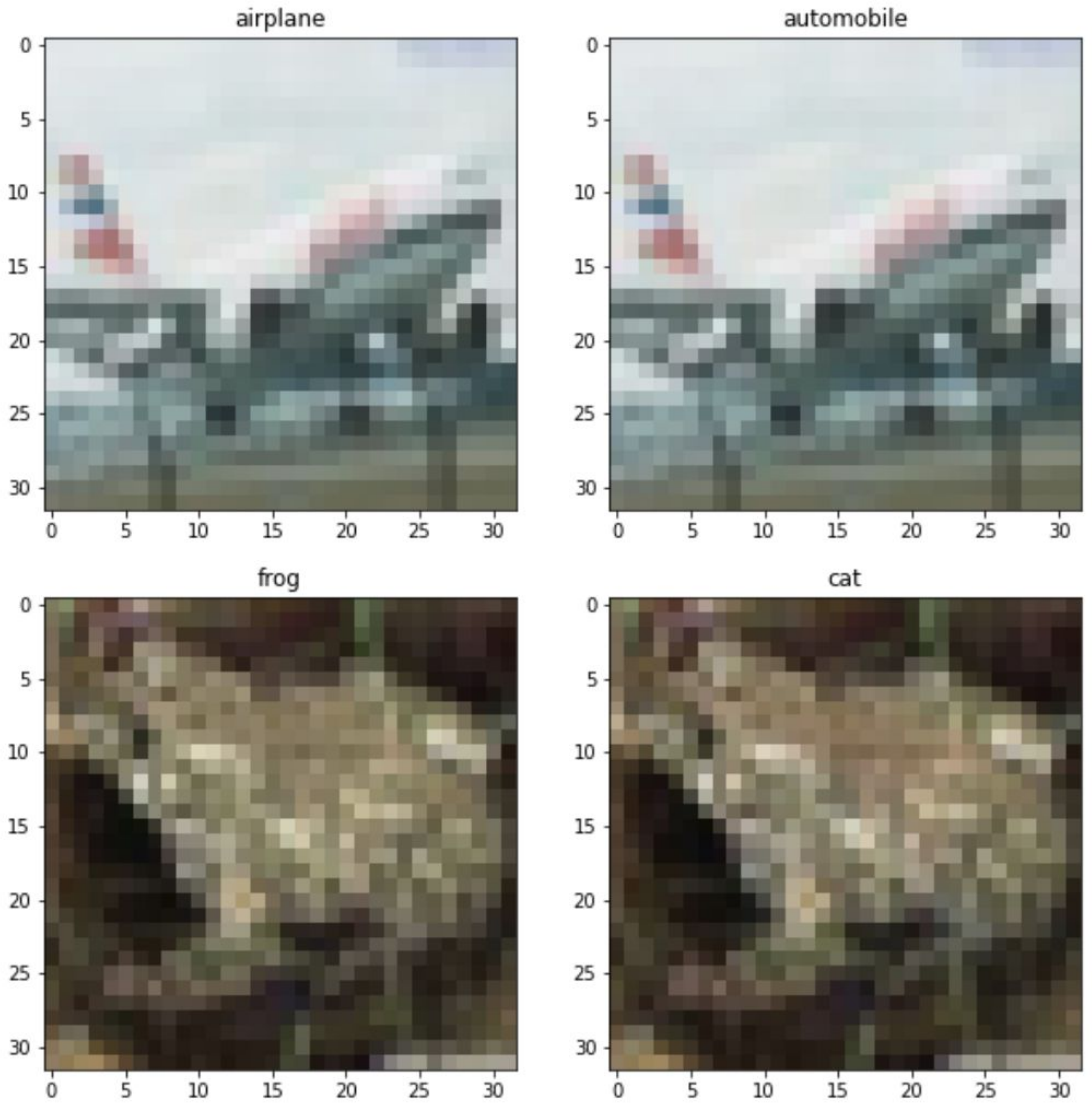
10 different networks with the same architecture and different ways of attacking and predicting

Carlini & Wagner [6] :

How it works?

$$
\begin{aligned}
\text{minimize} \quad & D(x, x+\delta) \\
\text{such that} \quad & C(x+\delta) = t \\
& x + \delta \in [0,1]^n
\end{aligned}
$$

$$f(x') = (\max_{i \neq t}(Z(x')_i) - Z(x')t)^+$$



Carlini & Wagner [6] :

Model	Accuracy	Accuracy after attack
Natural Model	61.81%	0%
Model trained with adversarial Data FGSM	59.96%	0%
Model trained with adversarial Data PGD	56.73%	0%
Distilled Model	60.15%	0%

Results of C&W attack on Basic model, Models with adversarial Training and Distilled Model

Conclusion and perspectives

Thank You!

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Bibliography:

[1] FGSM - Goodfellow, I. J., Shlens, J., & Szegedy, C. (2014). Explaining and harnessing adversarial examples. *arXiv preprint arXiv:1412.6572*.

[2] Defensive Distillation - Papernot, N., McDaniel, P., Wu, X., Jha, S., and Swami, A. Distillation as a defense to adversarial perturbations against deep neural networks. arXiv preprint arXiv:1511.04508, 2016b.

[3] Madry, Aleksander et al. "Towards Deep Learning Models Resistant to Adversarial Attacks." *ArXiv*abs/1706.06083 (2018): n. pag.

[4] Carlini, Nicholas and David A. Wagner. "Towards Evaluating the Robustness of Neural Networks." *2017 IEEE Symposium on Security and Privacy (SP)* (2017): 39-57.