

Adversarial attacks

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Project Data Science IASD
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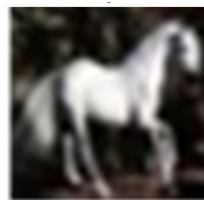
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Adversarial training

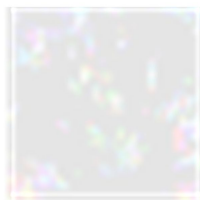
Principal and results

Adversarial machine learning



Clean Data

+



FGSM Perturbation

=

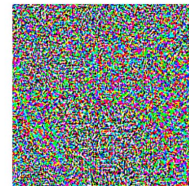


Perturbed Data



“panda”

+ .007 ×



noise

=



“gibbon”

White box Attacks

- Fast Gradient Sign Method
- Projected Gradient Descent (Linf, L2)
- Adversarial Model

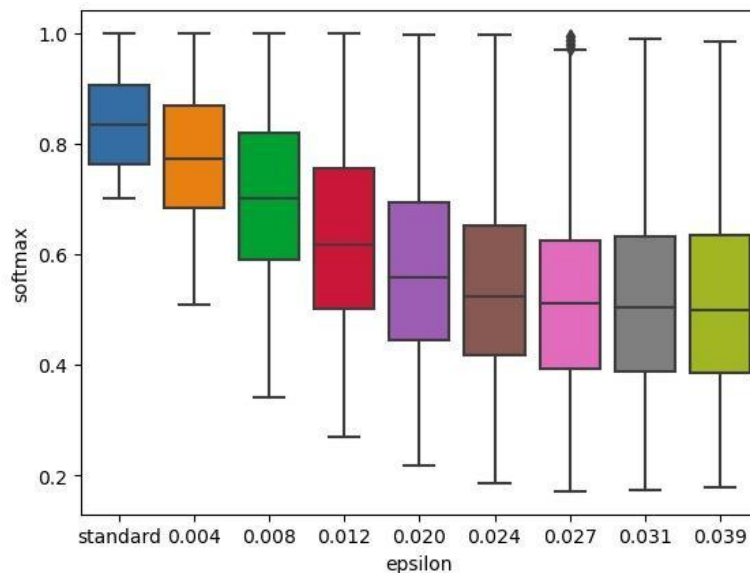
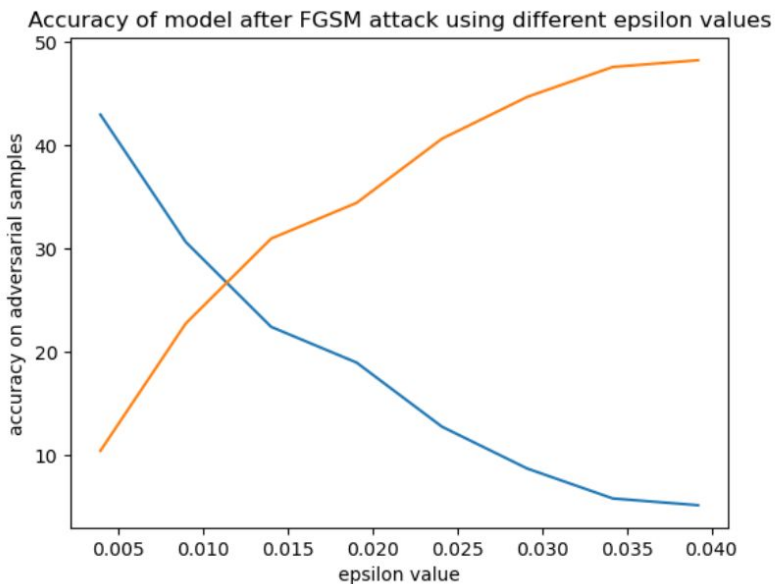


Fast Gradient Sign Method

(Goodfellow, 2015)

One-step gradient update is performed along the direction of gradient.

$$x^{adv} = x + \epsilon \operatorname{sign}(\nabla_x l(x, y))$$



Fast Gradient Sign Method

(Goodfellow, 2015)

One-step gradient update is performed along the direction of gradient.



Projected Gradient Descent



Iterative version of attack



Most complete



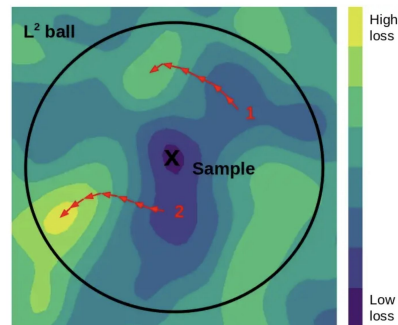
Constrained optimization

2 L^2 norm

L^∞ norm

Main Steps

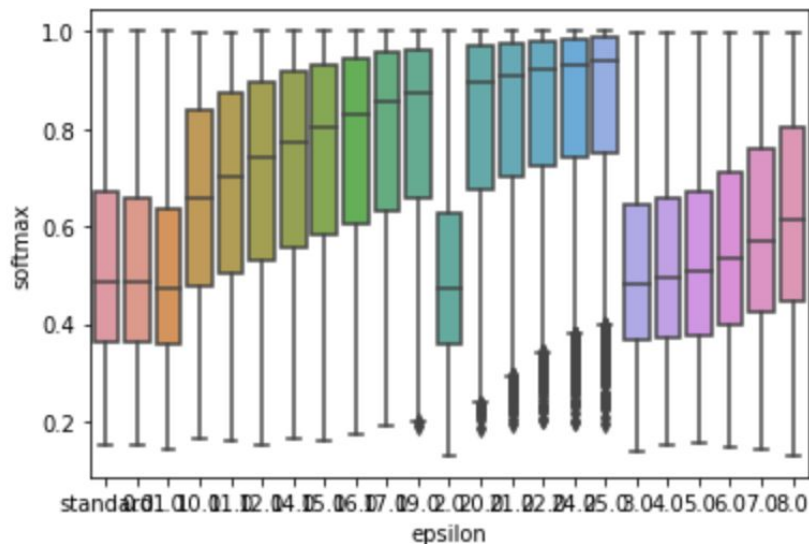
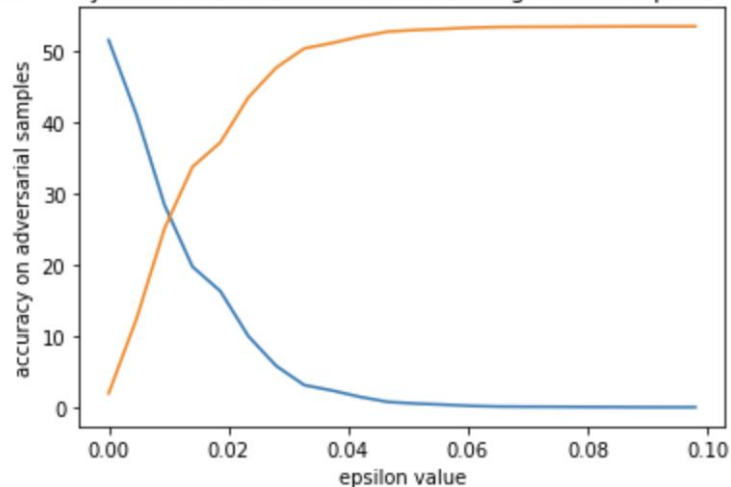
1. Start from a random perturbation in the ball around a sample.
2. Take a gradient step in the direction of greatest loss
3. Project perturbation back into the ball if necessary
4. Repeat until convergence



Projected Gradient Descent Linf

One-step gradient update is performed along the direction of gradient.

Accuracy of model after LinfPGD attack using different epsilon values



Projected Gradient Descent Linf

One-step gradient update is performed along the direction of gradient.

frog

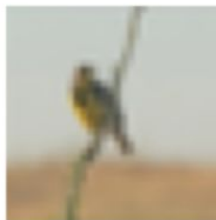


deer

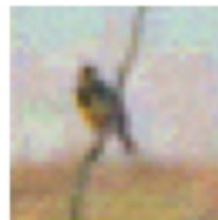


Epsilon: 0.01

bird



horse



Epsilon: 0.0314

truck

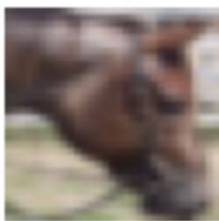


ship

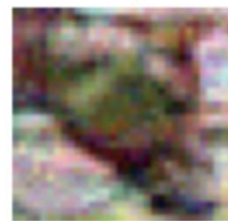


Epsilon: 0.06

dog



frog



Epsilon: 0.09

Adversarial Training

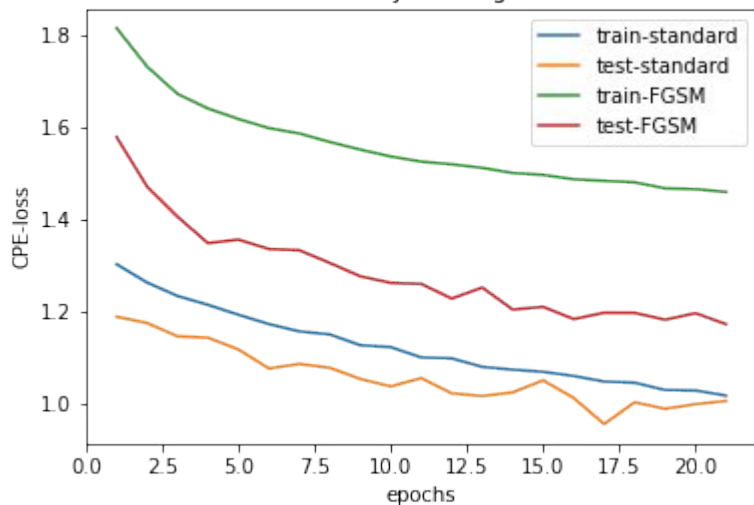
Adversarial training corresponds to the task of training a robust model to adversarial attacks; We want our model to perform well whatever the input received from an adversary agent. It can be modeled as a min-max optimization problem formulated as follows:

$$\min_{\theta} \frac{1}{|S_{train}|} \sum_{(x,y) \in S} \max_{\delta \leq \epsilon} l(h_{\theta}(x + \delta), y)$$

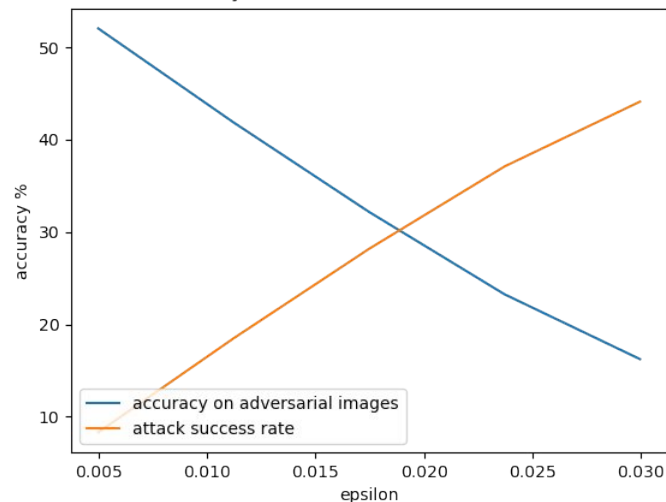
- A simple and intuitive strategy to solve this problem is to incorporate the process of generation of adversarial samples inside the training loop of the model.
- We'll try to use both attacks (FGSM and PGD) to train the classifier and compare losses curves and accuracies on test dataset

Adversarial Training using FGSM

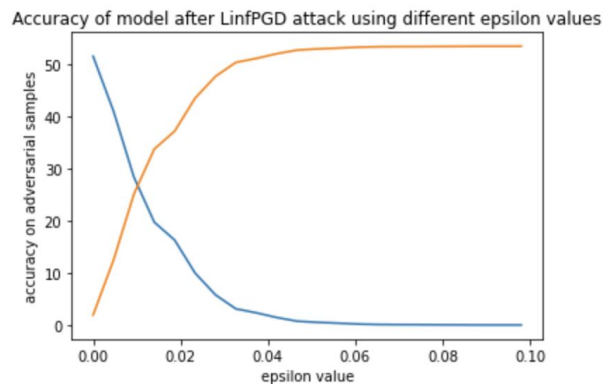
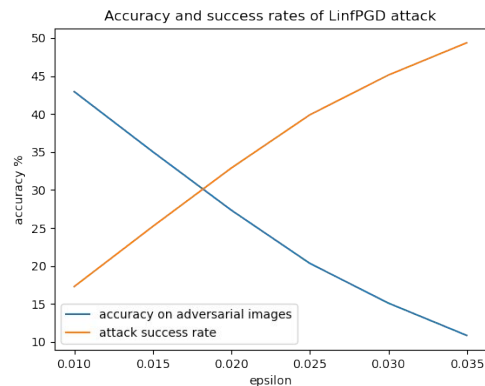
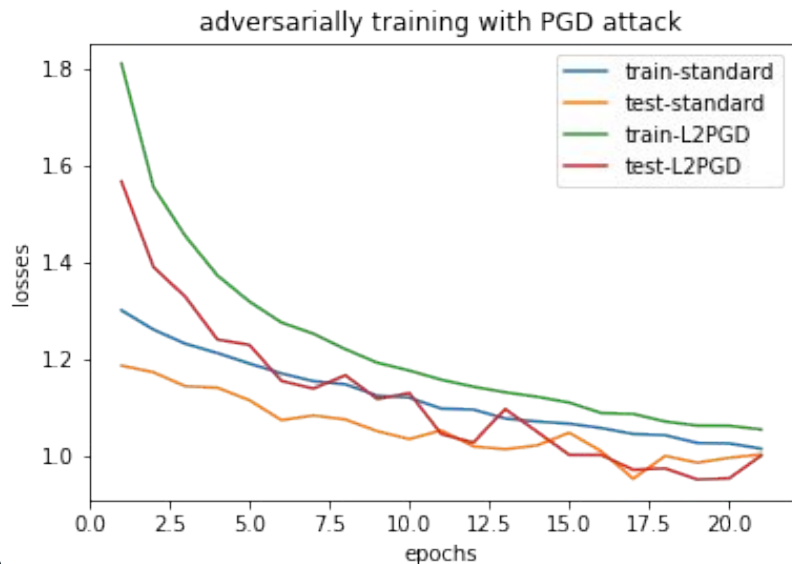
Losses curves for adversarially training with FGSM and standard



Accuracy and success rates of FGSM attack



Adversarial Training using PGD



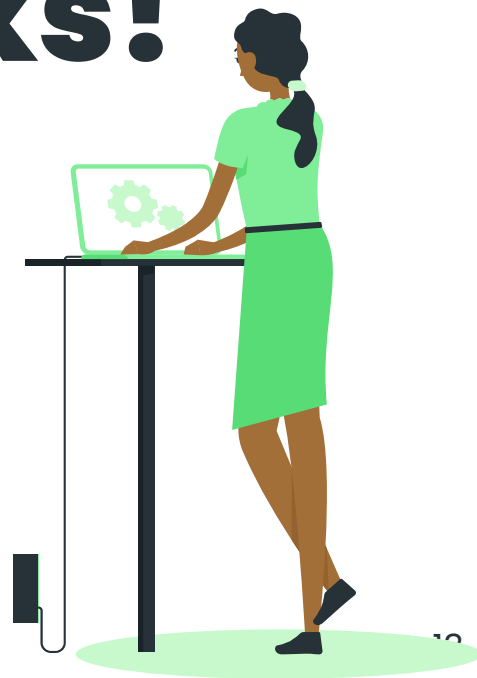
What is next?

In the 2nd stage of this project, we are looking to implement and try different defense mechanisms :

- Explore the utility of Bayesian neural networks to estimate uncertainty of models and to resist to white box adversary attacks.



Thanks!



References

- Goodfellow, I. J., Shlens, J., & Szegedy, C. (2014). Explaining and harnessing adversarial examples. arXiv preprint arXiv:1412.6572.
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- Gallicchio, Claudio, and Scardapane, Simone. "Deep Randomized Neural Networks." *arXiv*, 2020, <https://doi.org/10.48550/arXiv.2002.12287>. Accessed 9 Dec. 2022.
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