Adaptive Neighbourhoods for the Discovery of Adversarial Examples

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A thank you to my collaborators

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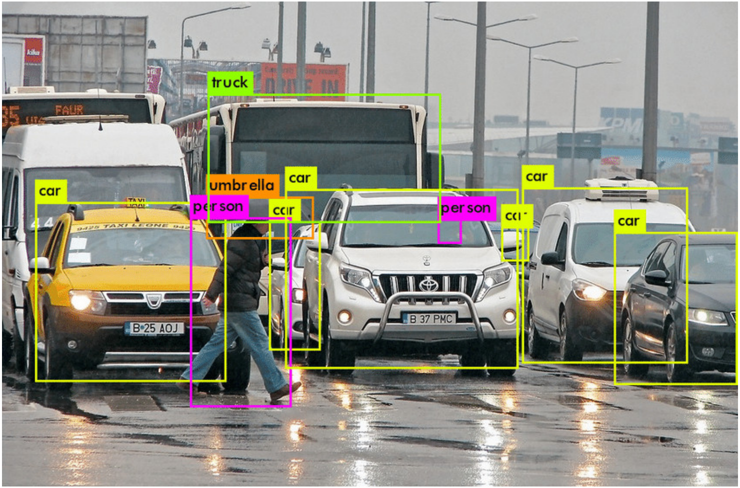
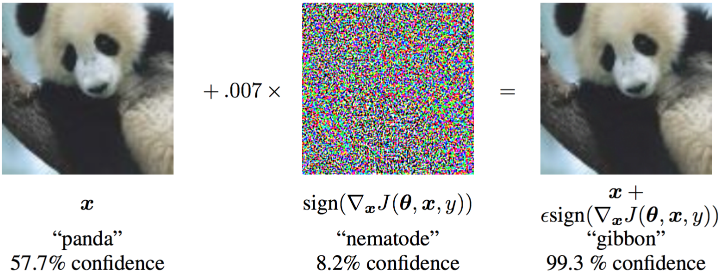
Swansea University

Deep Neural Networks



(Potdar, Kedar and Pai, Chinmay and Akolkar, Sukrut, 2018)

Adversarial Examples



(Goodfellow, Ian J and Shlens, Jonathon and Szegedy, Christian, 2014)

Motivating Principles

"stop"
to "30m speed limit"

"80m speed limit"
to "30m speed limit"

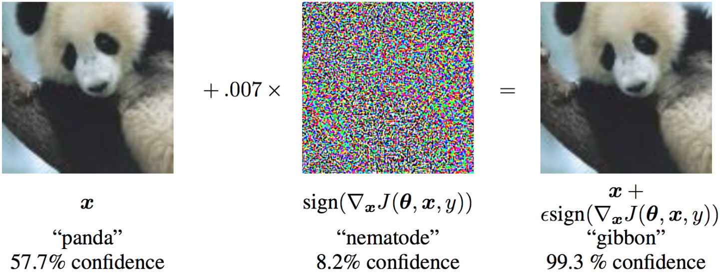
"go right"
to "go straight"

(Huang, Xiaowei and Kwiatkowska, Marta and Wang, Sen and Wu, Min, 2017)

Outline for this talk

1. Look at existing solutions
2. Our complimentary method
3. Some results on two tasks:
   - Iris Dataset
   - Solar Burst Detection
4. Some conclusions

Fast Gradient Sign Method (FGSM)



(Goodfellow, Ian J and Shlens, Jonathon and Szegedy, Christian, 2014)

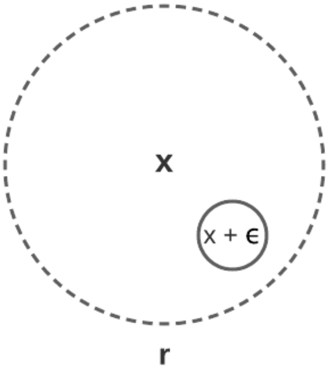
Projected Gradient Descent (PGD)

(Madry, Aleksander and Makelov, Aleksandar and Schmidt, Ludwig and Tsipras, Dimitris and Vladu, Adrian, 2017)

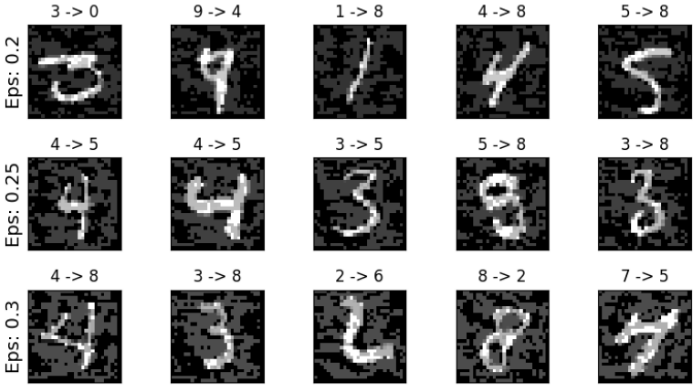
Carlini & Wagner (C&W)

(Carlini, Nicholas and Wagner, David, 2017)

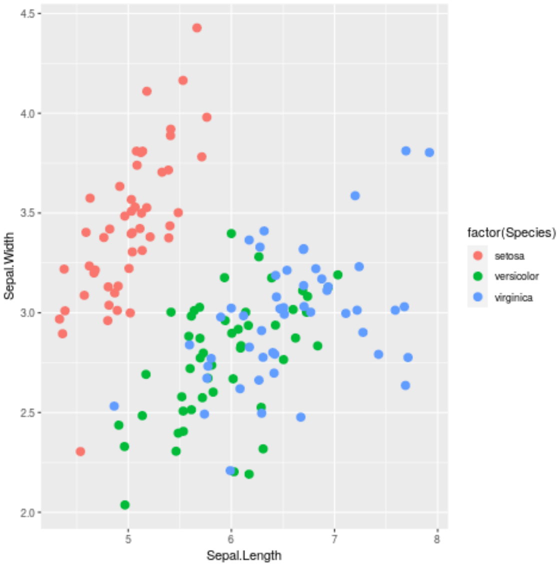
What do we learn from these methods?



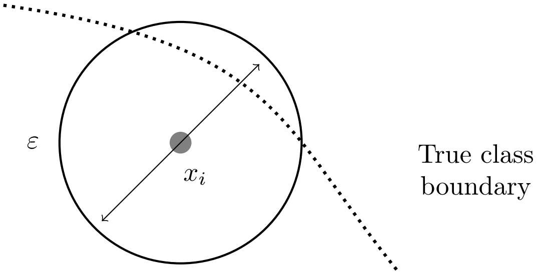
Amount of change is important



Non-image representations

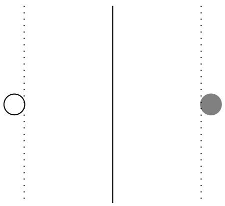


Perturbations shouldn't pass class boundaries

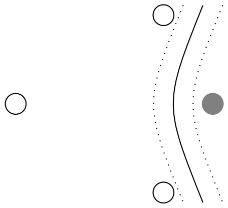


Example where a data point x_i lies close to the class decision boundary. In these situations, too large ε values, may push the synthetically generated point over true class boundaries.

Estimated boundaries can be deceiving



Sparse regions of the manifold may appear simple due to the lack of information.



More data points enable more precise estimation of the class boundary.

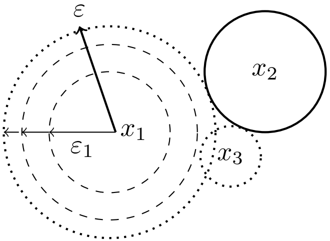
Estimating Sparsity/Density

$$\varphi(x;\overline{x}) = \frac{1}{\sqrt{1+(\varepsilon r)^2}}, \text{ where } r = \| \overline{x} - x \| \tag{1}$$

Providing the RBF's width parameter is suitably chosen, we achieve a good measure of the density through the sum of the RBFs centred on all data points X^c of class c (Eq.~2).

$$\rho_c(x) = \sum_{x_j \in X^c} \varphi(x; x_j) \tag{2}$$

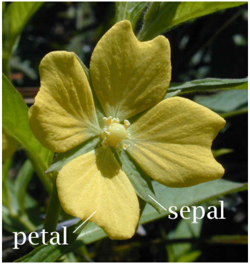
Expansion

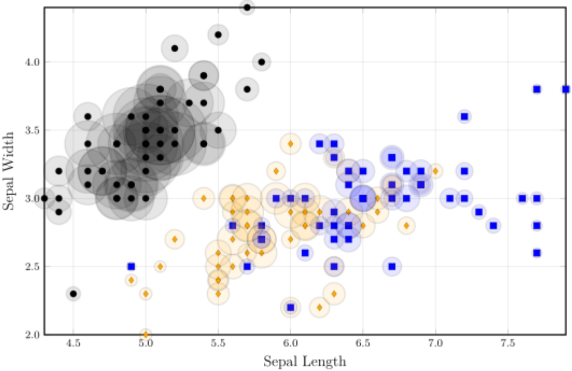


Iterative ε-expansion process in a binary class scenario. The two classes are distinguished by the dotted and solid circles.

$$\Delta\varepsilon_i^n = e^{-\rho_{c(i)}(x_i)\cdot n}$$

Iris Dataset





(Jay Morgan and Adeline Paiement and Arno Pauly and Monika Seisenberger, 2021)

Training

$$\mathcal{L}_{total} = (1-\alpha)\mathcal{L}_{cls} + \alpha\mathcal{L}_{adv}$$

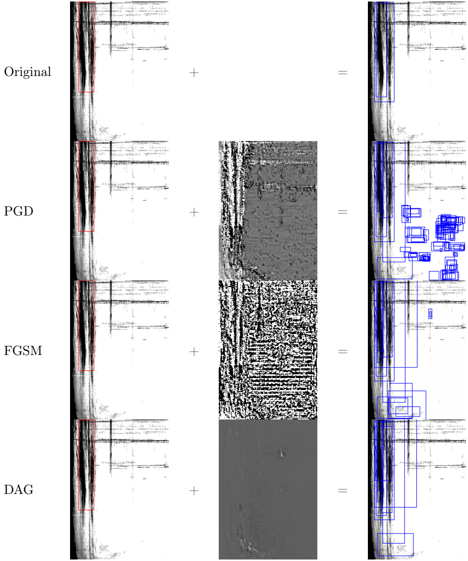
where $\mathcal{L}_{cls}$ and $\mathcal{L}_{adv}$ are the cross-entropy losses of the un-perturbed and perturbed data, respectively

Results

Table: F_1 score of DNN for the Iris dataset using various adversarial defence methods. Scores are in the format: mean (standard deviation) over 10 k-folds. Bold font face indicates the best form of attack for each type of defence method.

	Attack				
Defence	None	FGSM	PGD	FGSM+AN	PGD+AN
None	0.9745 (0.0413)	0.9278 (0.0618)	0.8572 (0.1036)	**0.7764 (0.0813)**	0.8461 (0.0968)
FGSM	0.9811 (0.0396)	0.9408 (0.0757)	0.8468 (0.1080)	**0.7873 (0.0785)**	0.8448 (0.0698)
PGD	0.9867 (0.0400)	0.9462 (0.0740)	0.8680 (0.0740)	**0.8508 (0.0746)**	0.8759 (0.0823)
Random+AN	0.9936 (0.0193)	0.9272 (0.0620)	0.8274 (0.0918)	**0.7935 (0.0822)**	0.8454 (0.0864)
FGSM+AN	0.9936 (0.0193)	0.9406 (0.0745)	0.8420 (0.0987)	**0.8140 (0.1085)**	0.8588 (0.1157)
PGD+AN	0.9936 (0.0193)	0.9472 (0.0642)	0.9472 (0.0642)	**0.8679 (0.0899)**	0.8753 (0.0864)

Adversarial Training for Solar Burst Detection



(Jay Morgan, 2022)

Results

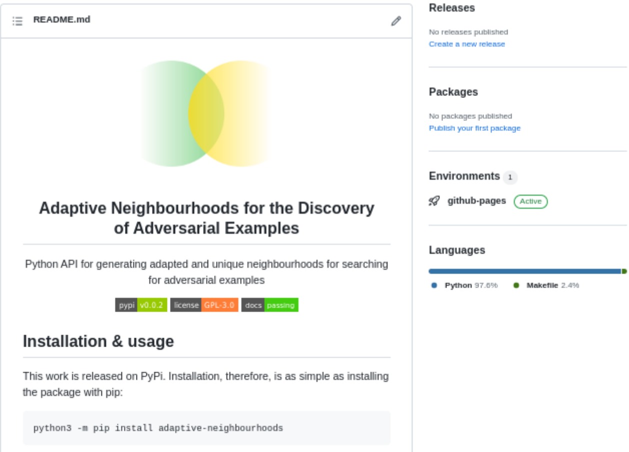
Table: F_1 score performance on the WAVES dataset using Faster R-CNN. Numbers highlighted in a bold font face indicate the best achieving adversarial attack for each form of defence.

		Attack					
Defence	None	FGSM	FGSM+AN	PGD	PGD+AN	DAG	DAG+AN
None	0.568	0.539	0.486	0.198	**0.105**	0.399	0.251
FGSM	0.463	0.458	0.178	0.013	**0.012**	0.055	0.028
FGSM+AN	0.480	0.465	0.462	**0.007**	**0.007**	0.043	0.023
PGD	0.421	0.425	0.379	0.391	0.359	0.378	**0.259**
PGD+AN	0.364	0.359	0.330	0.339	0.324	0.330	**0.212**

Summary of Results

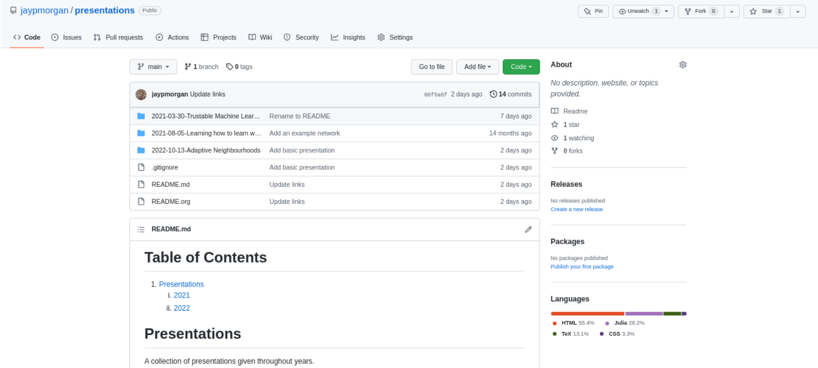
- Adaptive neighbourhoods is an effective method that compliments existing adversarial generation methods such as FGSM & PGD.
- Adaptive neighbourhoods performs better with optimisation-based procedures such as PGD.
- Through the use of adaptive neighbourhoods, one can meaningfully define searchable regions for datasets other than image-based data where adversarial examples can be visually inspected.

Source code



https://github.com/jaypmorgan/adaptive-neighbourhoods
https://gibtlab.com/jaymorgan/adaptive-neighbourhoods
https://git.sr.ht/~jaymorgan/adaptive-neighbourhoods

Link to the Slides



https://github.com/jaypmorgan/presentations

Thank you!

References

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