An Empirical Look at Gradient-based Black-box Adversarial Attacks on Deep Neural **Networks Using One-point Residual Estimates**

Author: Joost Jansen Supervisors: Stefanie Roos, Jihue Huang, Chi Hong

ŤUDelft

BACKGROUND

- Adversarial attacks on Deep Neural Networks (DNN): Adding imperceptible *perturbation* to an image results in DNN to *misclassify* the image
- Black-box: model not known to the attacker, only input-output correspondence (aueries).
- Gradient-based Attacks: use estimated gradient to minimise the class probability of the image.

Different gradient estimators		
Estimator	Number of queries per gradient estimation	Accuracy
Two-point central	2b	+++
Two-point Forward/Backward	b + 1	++
One-point residual	b	+ +

RESEARCH QUESTION

 Do one-point residual estimates improve untargeted gradient-based adversarial attacks in terms of reducing the number of queries while maintaining accuracy?

METHODOLOGY

- · Compare different gradient estimators to the one-point residual estimate:
 - Accuracy of attack
 - · Average number of gueries until a succesfull adversarial created
- · Using different PGD-attacks and datasets

A GRADIENT-BASED ADVERSARIAL ATTACK



white-box two-point-central two-point-forward - two-point-backwarr 1500 one-point-residual 0.0 0.4 0.6 0.8 epsilons Linf-PGD attack on f-mnist net3conv model white-box two-point-central two-point-forward 600 two-point-backward one-point-residual 400 % 200 100 0.0 0.2 0.4 0.6 0.8 1.0 epsilon

Linf-PGD attack on mnist net3cony model

0.8

0.6

0.4

0.2

0.0

0.8

10 0.6

0.2



- **MNIST:** One-point residual estimates have a lower accuracy compared to the twopoint estimates
- · One-point residual: Less gueries per iteration still leads to a higher average number of gueries until a succesfull adversarial is created.
- F-MNIST: One-point residual estimates have a corresponding accuracy compared to the two-point estimates

Hyperparameters



The one-point residual estimate is sensitive to some hyperparameters

 Determined optimal Hyperparameters for one-point residual estimates

EXAMPLES



DISCUSSION

- Limited to only PGD attacks
- · Bounded by computational power, estimates were only tested on low dimensional datasets

CONCLUSION

- · One-point residual estimates do not maintain accuracy for strong DNN's
- One-point residual estimates do maintain accuracy for weaker DNN's
- · Although it uses les queries per iteration, one-point residual estimates do not improve query efficiency

FUTURE WORK

- Test estimates on more complex datasets models and other attacks
- · Use grid search to find all optimal hyperparameters

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