

# **Exploring Ways To Counter Adversarial Attacks Against Image Classifiers**



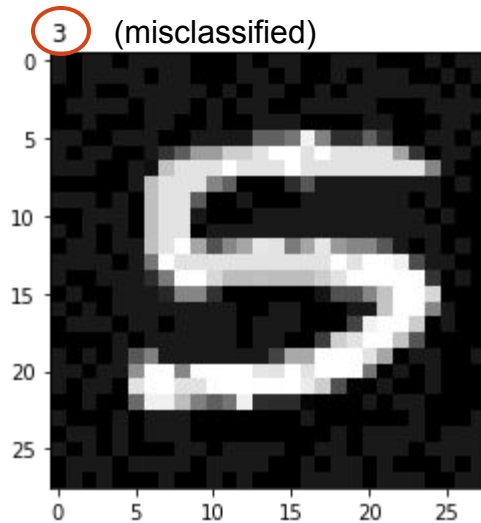
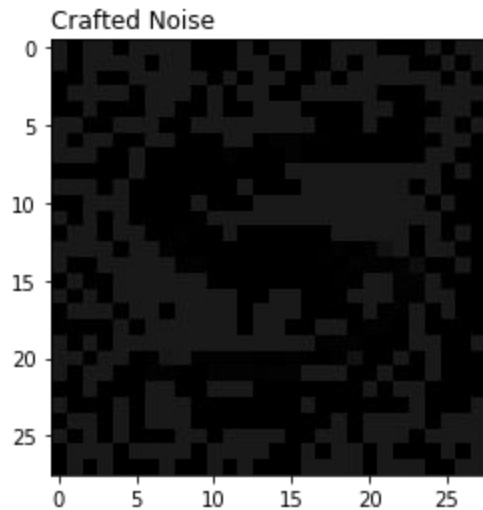
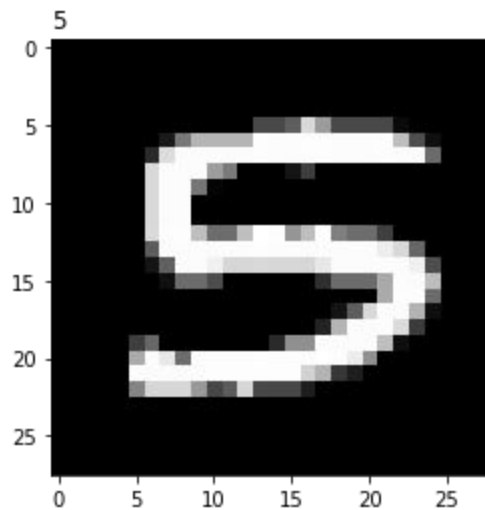
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# Description Of The Problem

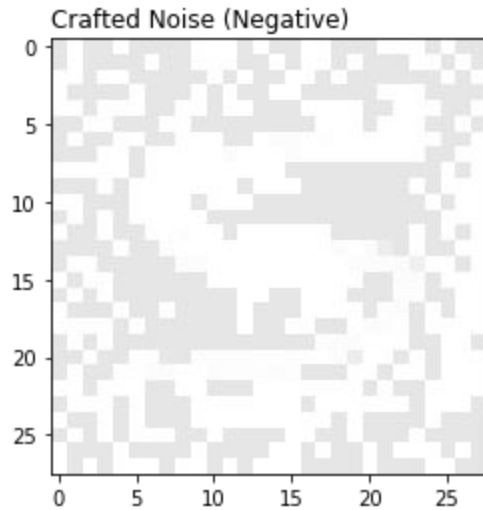
Adversarial attacks against image classifiers use small perturbations applied to input images to cause a misclassification.

The perturbations are hard to detect by the human eye because they are artificially constructed by adding the smallest amount of noise to the original input along an optimal path that would cross a decision boundary.

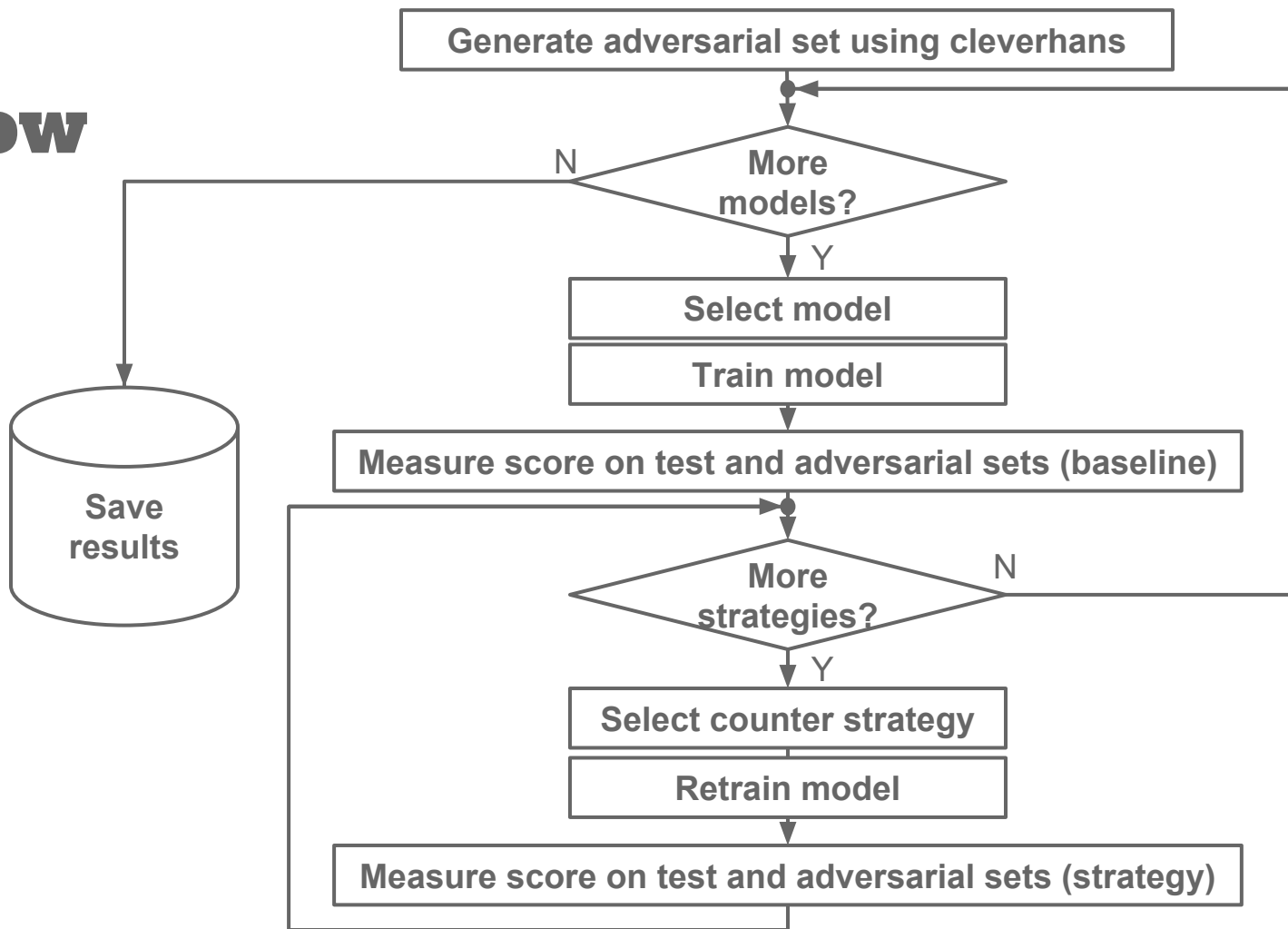
Robustness to malicious attacks or random variations in input for that matter is crucial for image classifiers deployed in mission critical systems (e.g. self-driving cars).



**Attack  
Example**



# Workflow



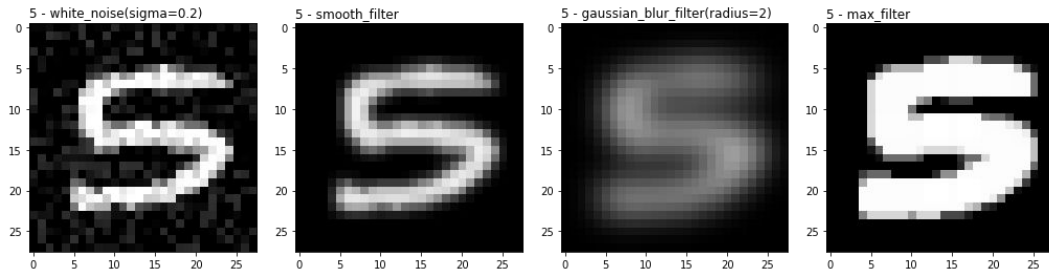
# Data Set And Classifiers

- Data set: MNIST 28x28 grayscale digits
- Classifiers:
  - KNN
  - SVM
  - Logistic Regression
  - CNN

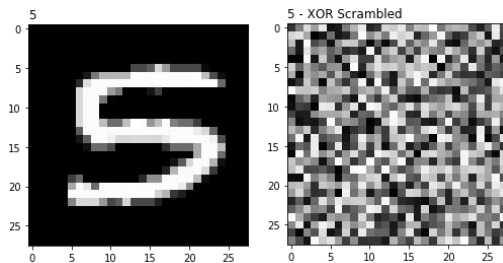


# Defense Strategies

- Noise/filter injection during the train and/or test phases

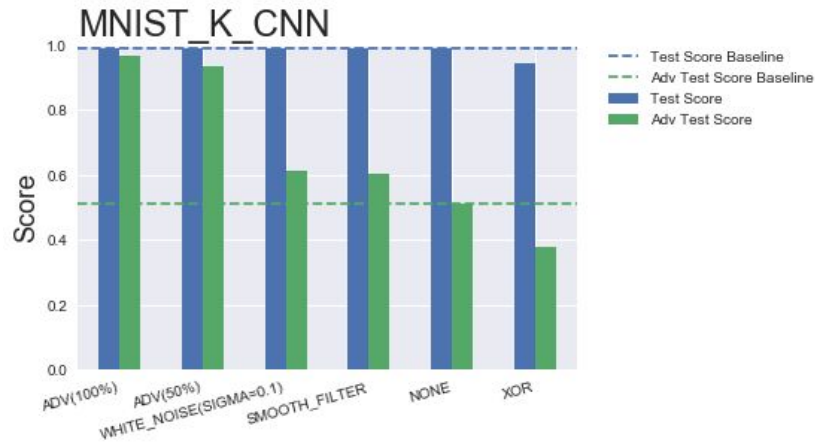
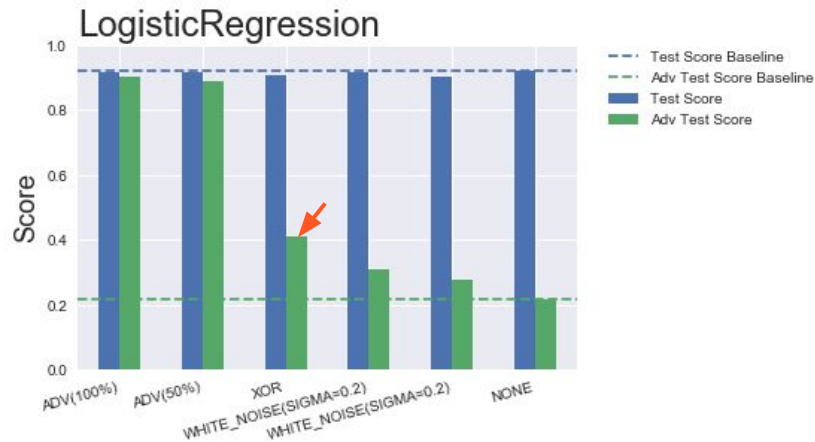
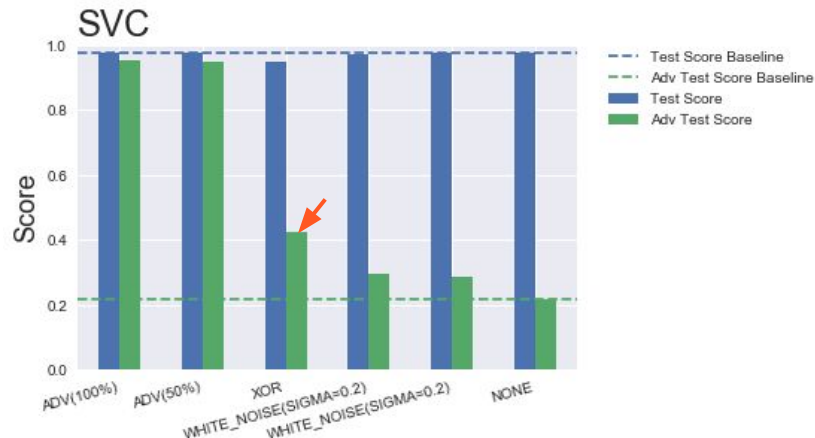
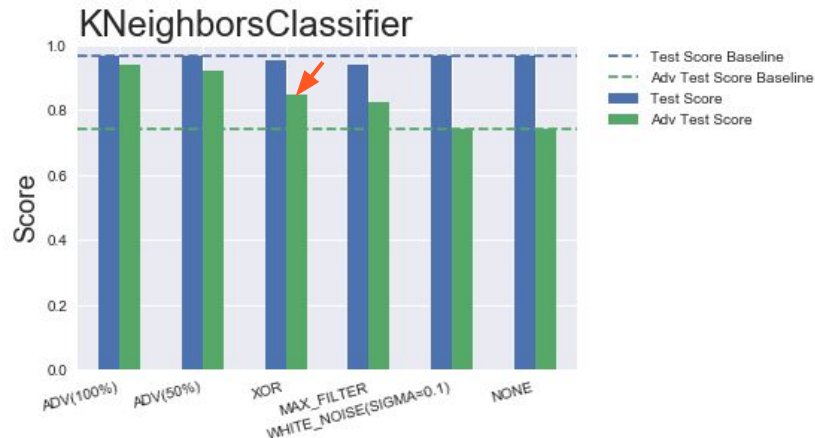


- Input scrambling using a XOR'ed pseudo-random sequence



- The addition of a percentage of adversarial generated data to the training set

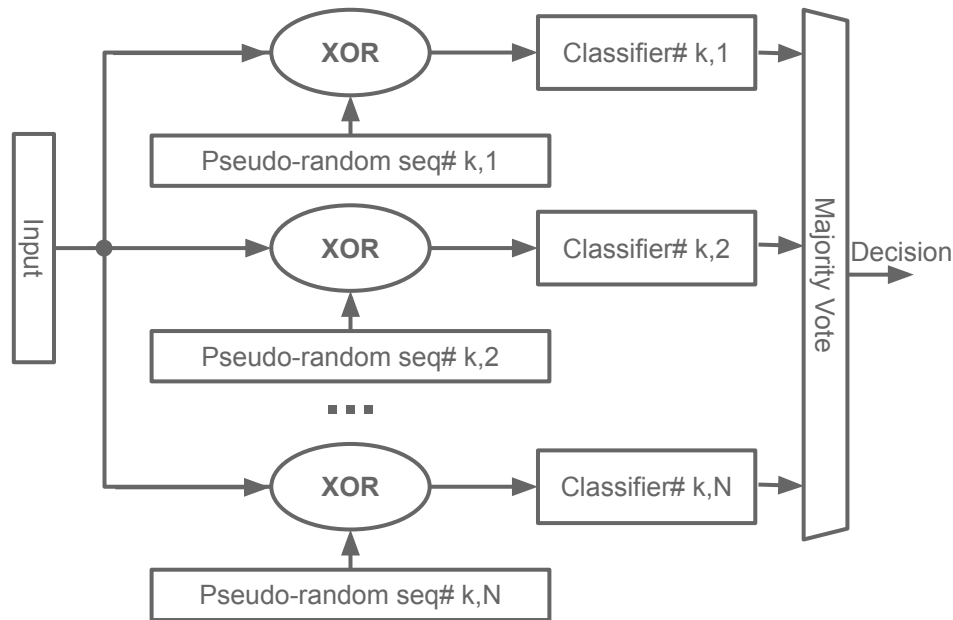
# Results



# Conclusions

- The noise strategy doesn't help
- The best results are achieved by adding the adversarial input to the training set. However this is attuned to a specific type of attack
- XOR scrambling shows some promise, especially for KNN. The intuition behind it is that it changes the decision boundaries in ways that the attack cannot anticipate

Suggested XOR based architecture using  $k$  sets of pseudo-random sequences and specifically trained classifiers,  $k = 1..M$





# References

- <http://www.cleverhans.io/>
- <https://github.com/tensorflow/cleverhans>
- <https://arxiv.org/abs/1602.02697>
- <https://blog.openai.com/adversarial-example-research/>
- <https://github.com/anishathalye/obfuscated-gradients>