Adversarial Machine Learning in Cybersecurity

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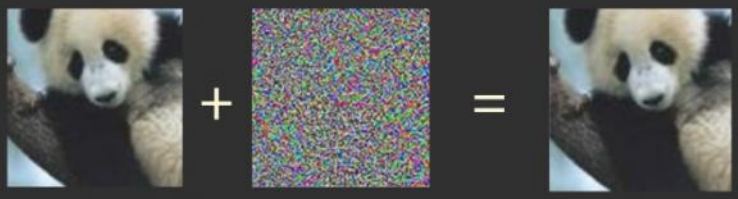
1. The Problem - Attacks to gain miss classification.



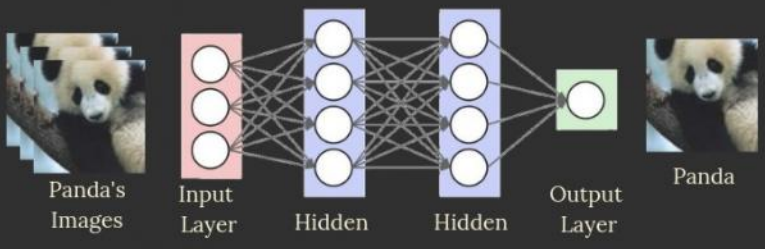
"Panda" 57.7% confidence

"nematode" 8.2% confidence

"Gibbon" 99.3 % confidence

2. How to It Works

Train a neural network with images and its associations (well known databases)



3. The Goal

Reduce missclassification

4. Possible Solutions:

Image Transformations

Rotation

Reflection

References

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- *Sinha, A., & Krishnamurthy, B. Understanding Adversarial Space through the lens of Attribution. http://www.research.ibm.com/labs/ireland/nemesis2018/pdf/paper4.pdf*
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