

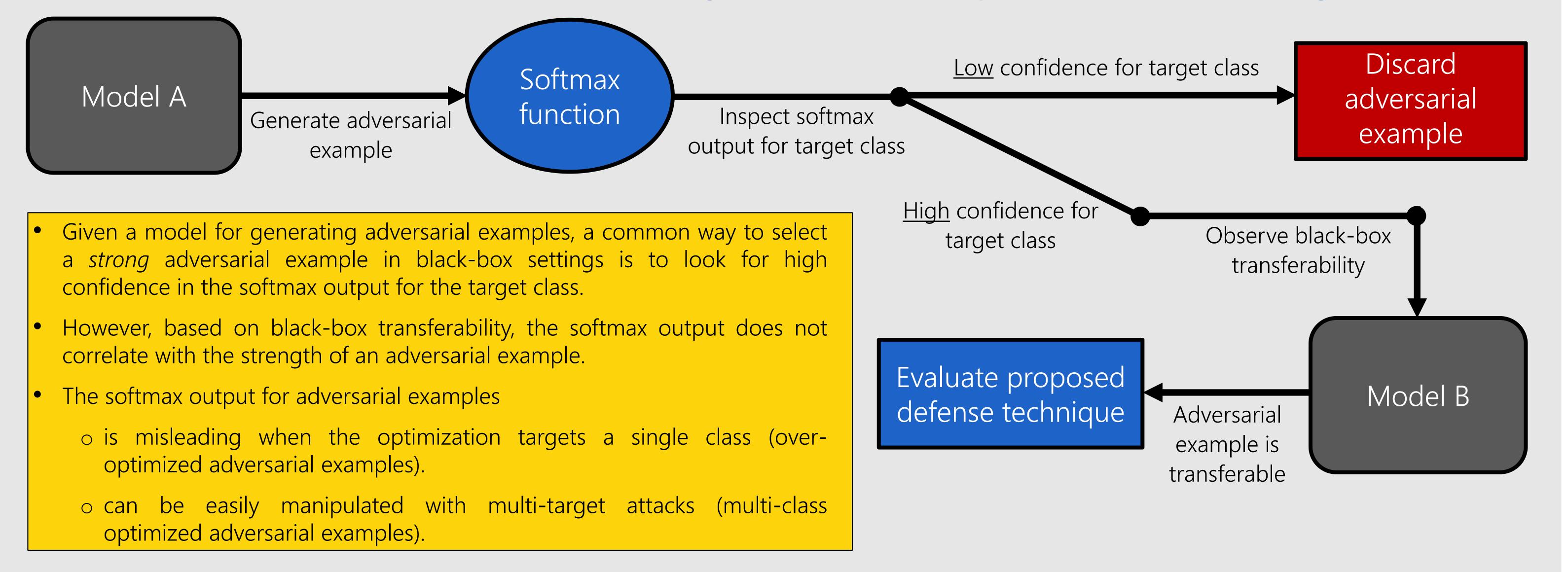


HOW THE SOFTMAX OUTPUT IS MISLEADING FOR EVALUATING THE STRENGTH OF ADVERSARIAL EXAMPLES

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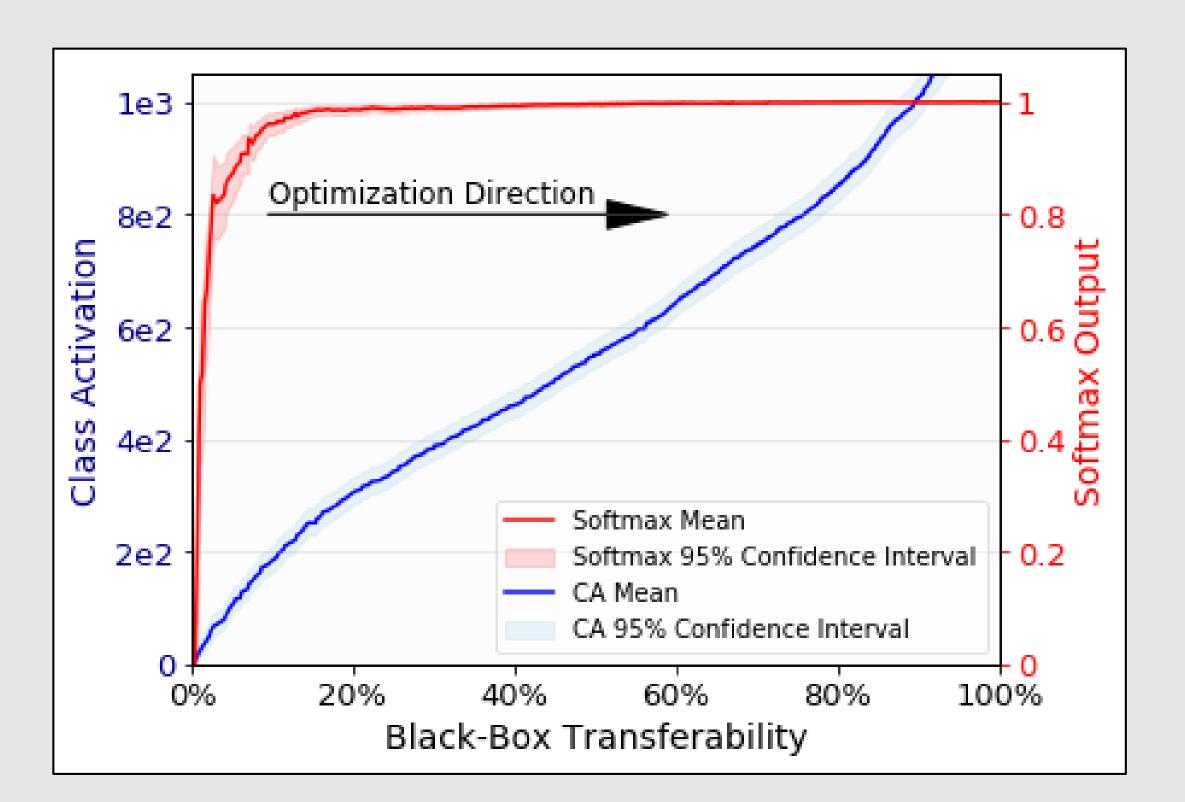
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A Common Method to Select Strong Adversarial Examples in Black-box Settings



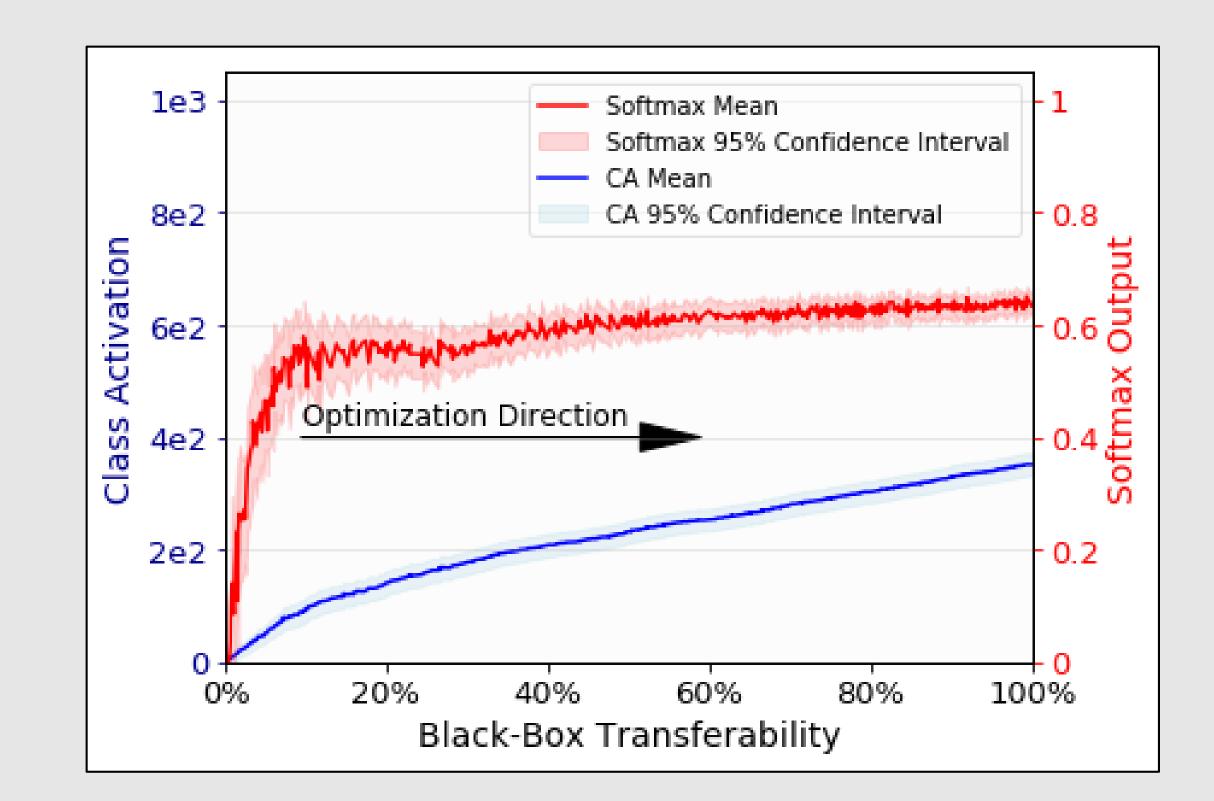
Over-optimized Adversarial Examples

- Generated by iteratively maximizing a single target class (similar to IFGS [1]): $X_{i+1} = X_i \alpha \nabla_x g(\theta, X_i)_c$.
- Forces the softmax output to shoot off to 100% immediately, making it impossible to detect whether the adversarial example is strong or not based on the softmax output.



Multi-class Optimized Adversarial Examples

- Generated by iteratively maximizing multiple classes (similar to CW [2]): $X_{i+1} = X_i \alpha \nabla_x g(\theta, X_i)_c \beta \nabla_x g(\theta, X_i)_d$.
- Forces the softmax output to stay idle with a value less than 100%, creating misleading results when the output of the softmax is observed.



The graphs above show the mean target class activations (logit values) and their corresponding softmax output as a function of black-box transferability from VGG-16 [3] to ResNet-50 [4], for a total of 2000 adversarial examples.

[1] A. Kurakin, I. J. Goodfellow, S. Bengio. Adversarial Examples in the Physical World
[2] N. Carlini, D. Wagner. Towards Evaluating the Robustness of Neural Networks
[3] K. Simonyan, A. Zisserman. Very Deep Convolutional Networks for Large-Scale Image Recognition
[4] K. He, X. Zhang, S. Ren, J. Sun. ImageNet Classification with Deep Convolutional Neural Networks



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