

SimBA: Black box attacks on Image classifiers

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Paper Link: [Simple Black-box Adversarial Attacks \(arxiv.org\)](#)

The problem

Paper

[Simple Black Box adversarial attacks](#)

Chuan Guo, Jacob R. Gardner, Yurong You, Andrew Gordon Wilson, Kilian Q. Weinberger. 2019.

Problem Statement

Try to make pretrained state of the art classifiers on Imagenet to misclassify data, using as less queries as possible in a black box fashion.

Experiment Setup

Experiments on a subset of Imagenet data ([Imagenette](#)) and Tiny Imagenet data with models available through the PyTorch [API](#).

Proposed Solution of the paper

Random Attack

In each attack random pixels are chosen and a channel(color) is chosen at random.

Orthonormal Basis

Now value of a chosen channel is changed in such a way so as to propagate the attack (cartesian basis).

Query Efficiency

Most of the images are misclassified successfully after only 5000 queries (70% success rate, as reported)

Attack Strategy

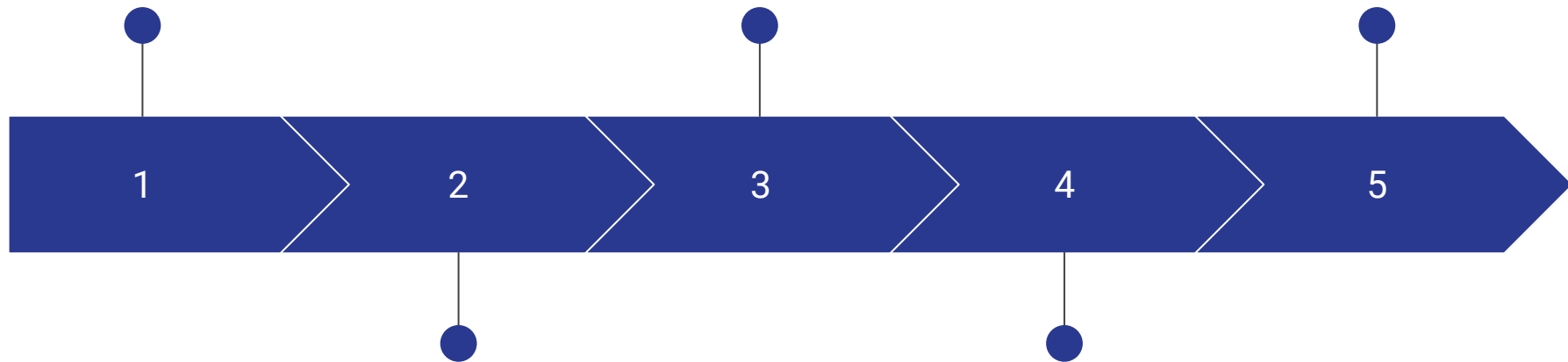
Cartesian Basis: a single independent feature of the sample

We perturb the individual channels of a pixel in each iteration by a small amount epsilon. At first we add the value to a random pixel, if the model probability decreases, we set that value else subtract from the value and try again. If the probability still doesn't change, we choose another random pixel in the next iteration.

Preliminary: FGSM
White Box attacks

TinyImageNet
experiments:
MobileNetV2

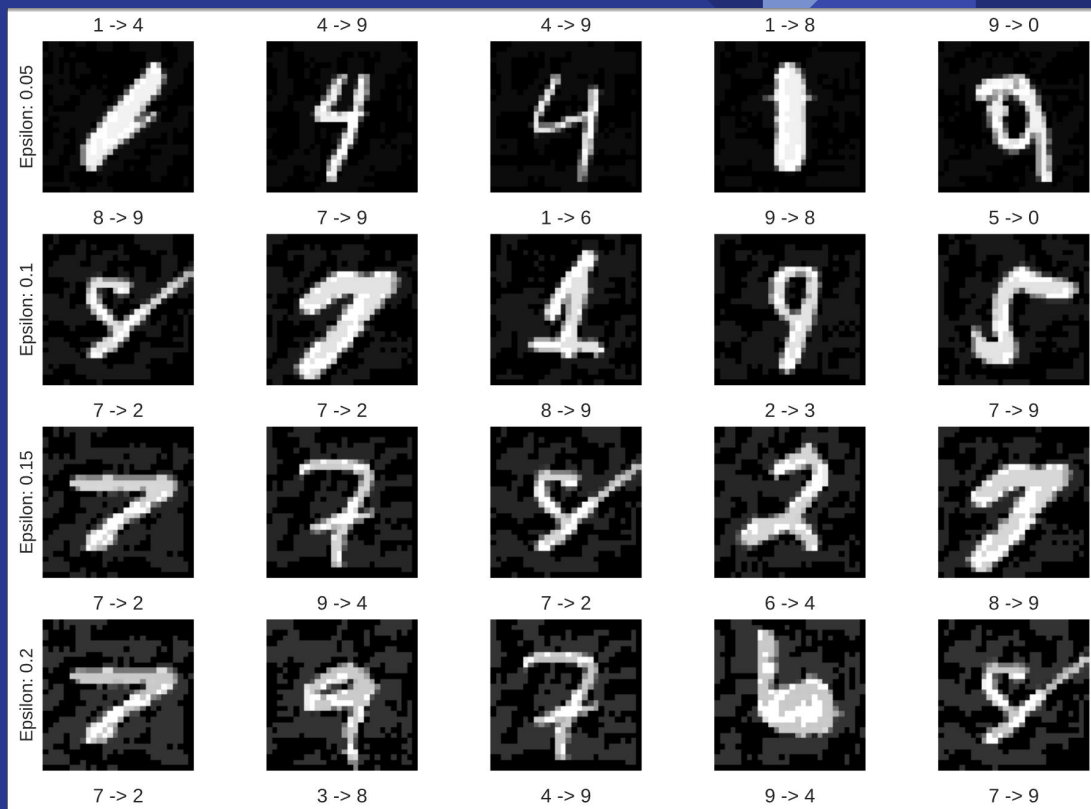
Targeted attack with
correct mappings, and
different strategies



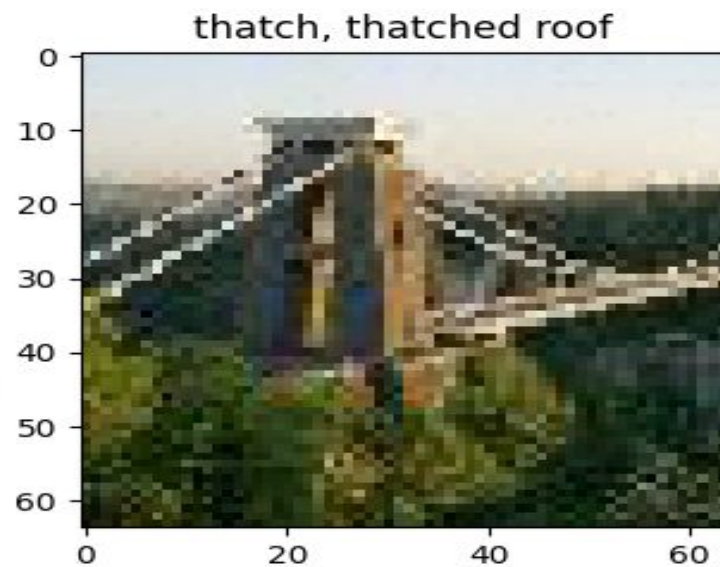
Replication of author's
code with ResNet50
with TinyImageNet

Targeted and
untargeted pixel attack
comparisons for
subset Data

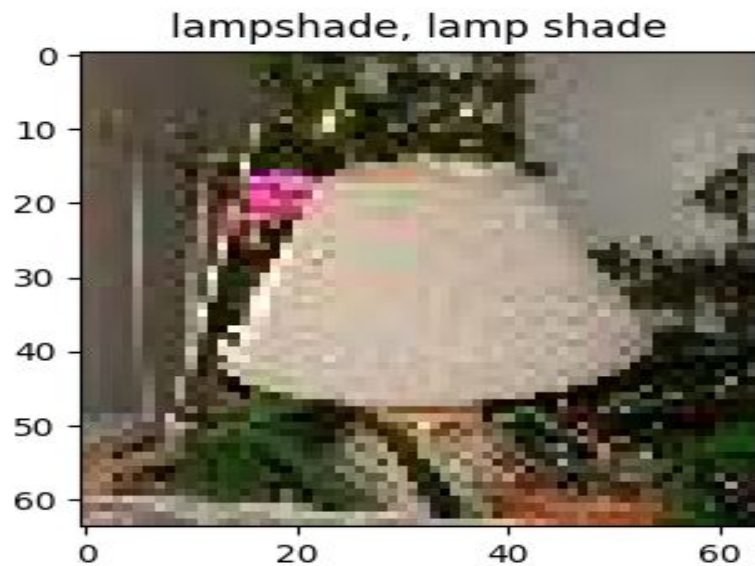
Results



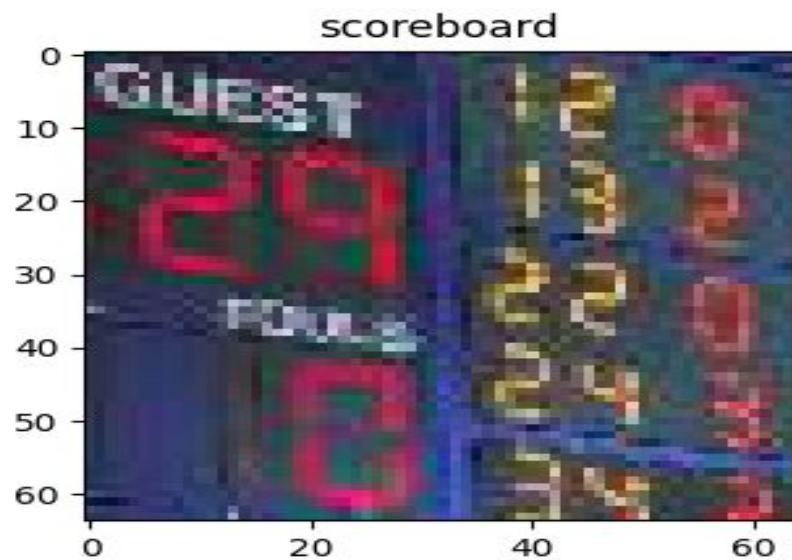
Untargeted attack on Tinyimagenet



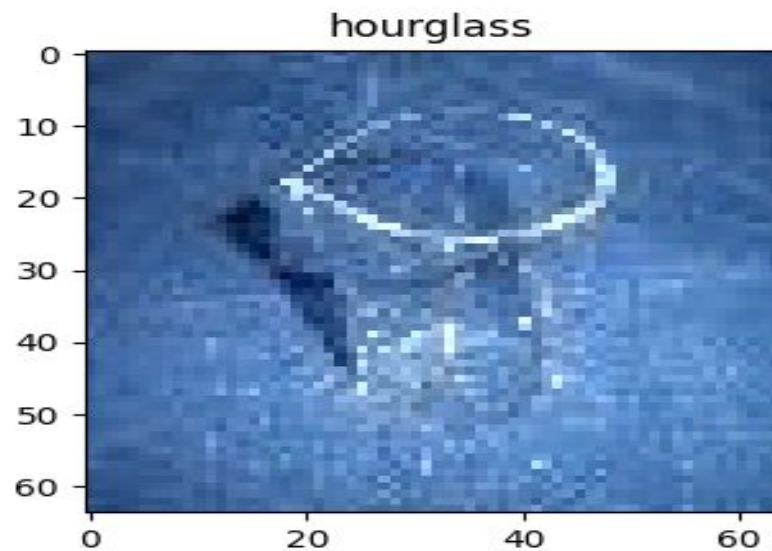
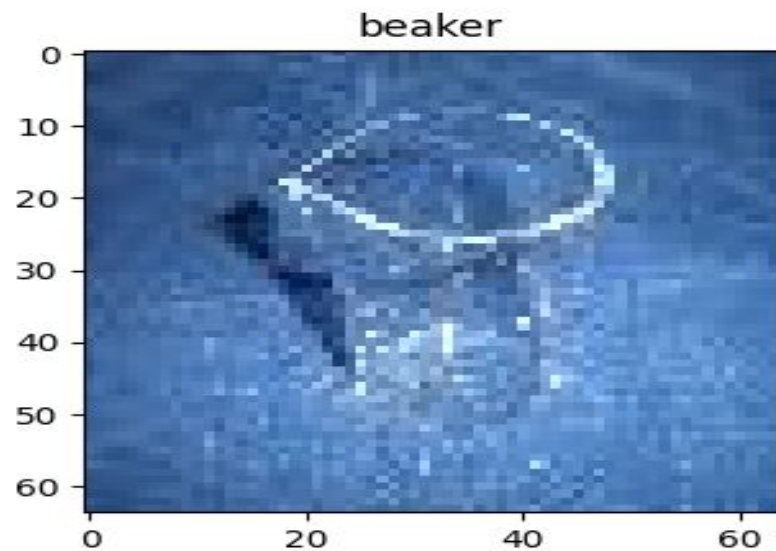
Untargeted attack on Tinyimagenet



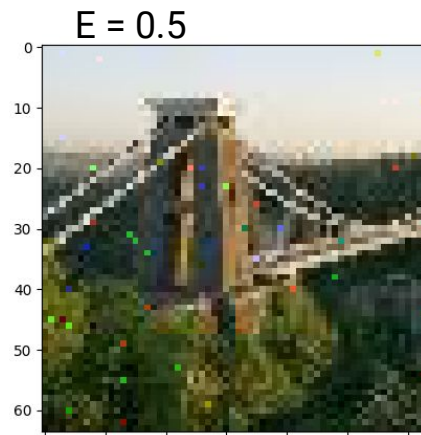
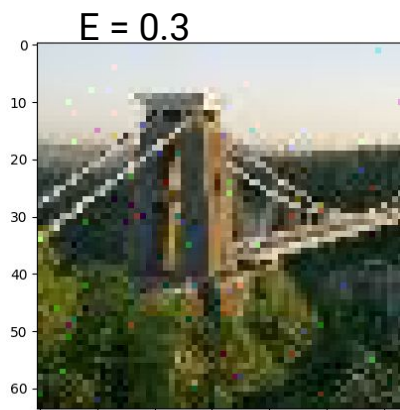
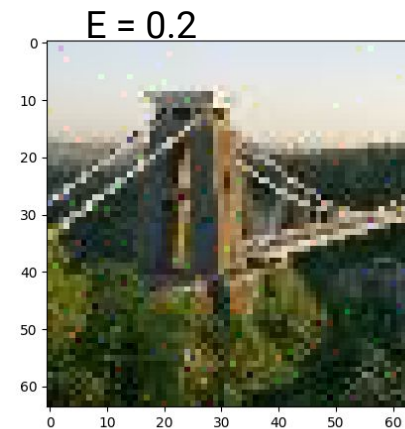
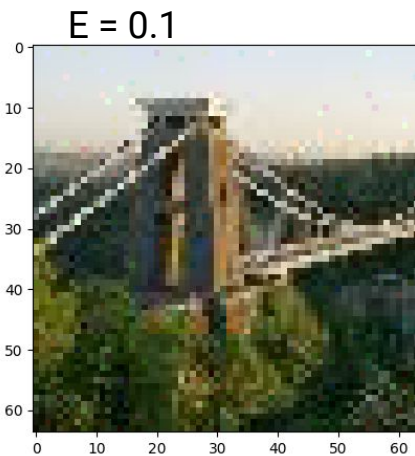
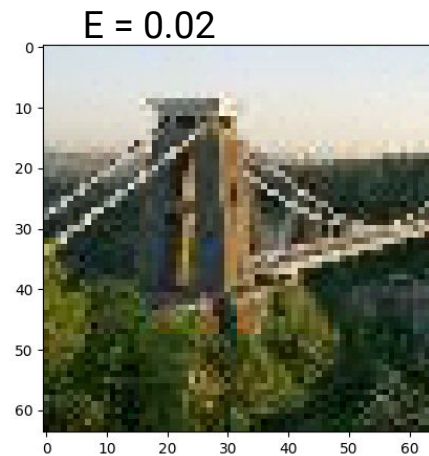
Targeted attack on Tinyimagenet: 5th likely class



Targeted attack on Tinyimagenet

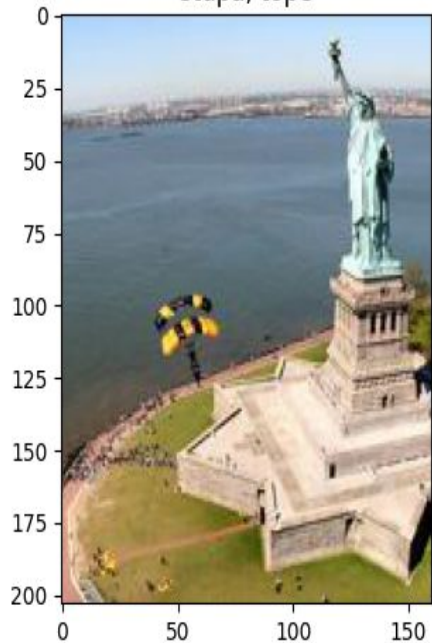


Visibility of attack with increasing Epsilon

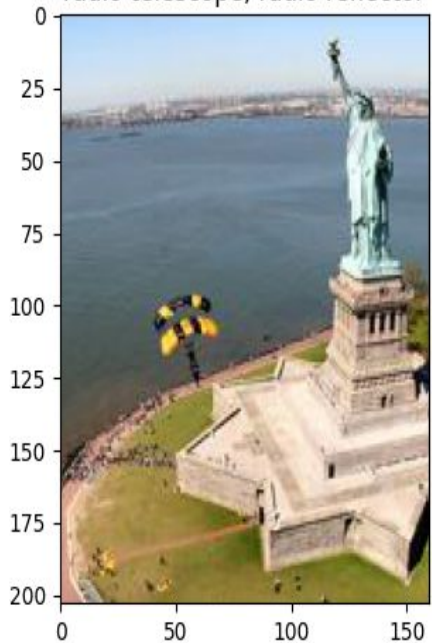


Untargeted attack on subset

stupa, tope



radio telescope, radio reflector



golf ball

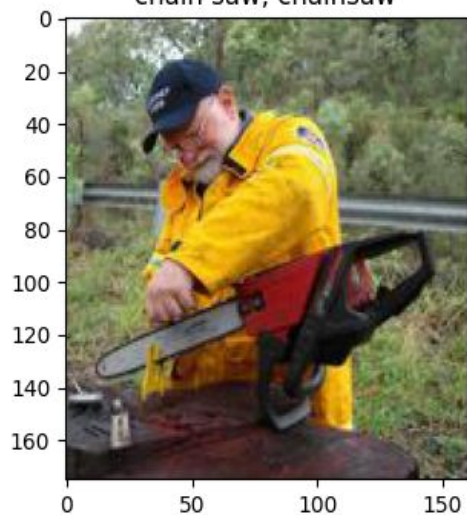


radio telescope, radio reflector

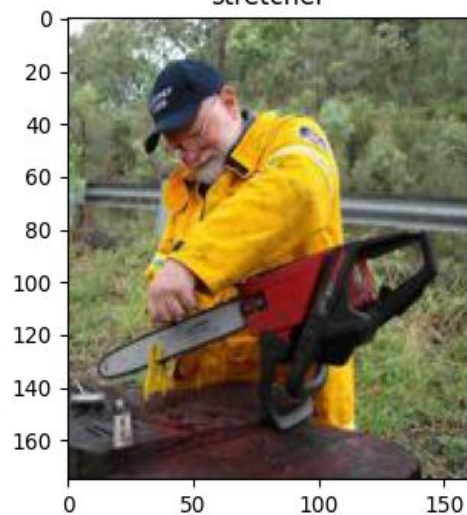


Untargeted attack on subset

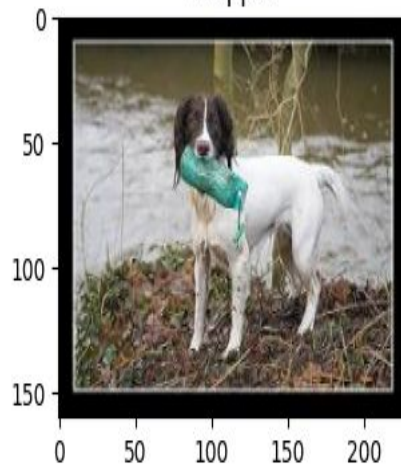
chain saw, chainsaw



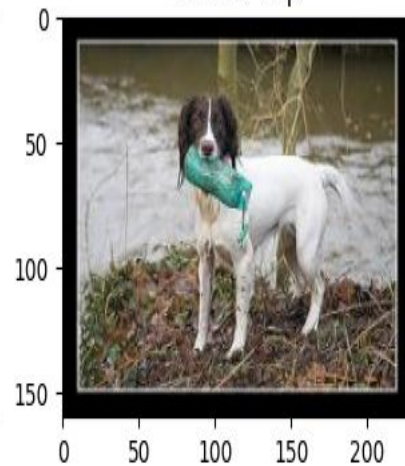
stretcher



whippet

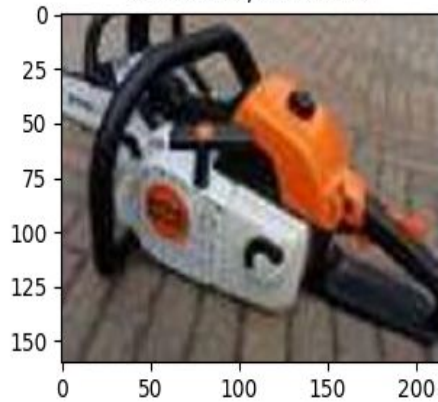


shower cap

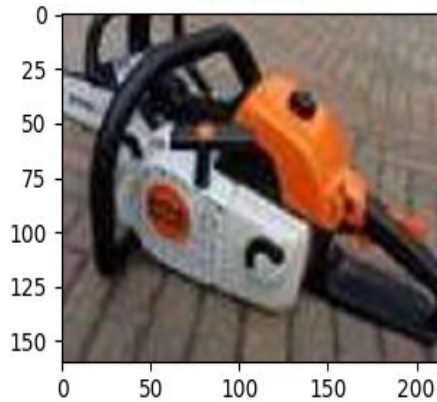


Target attack (epsilon=0.02) on subset

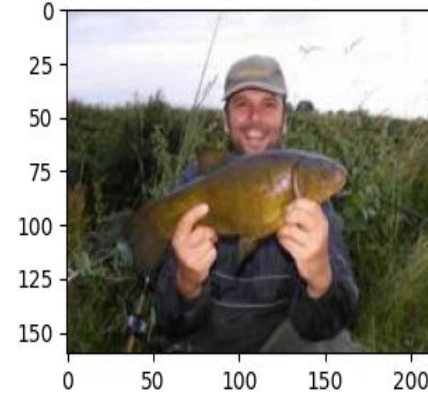
chain saw, chainsaw



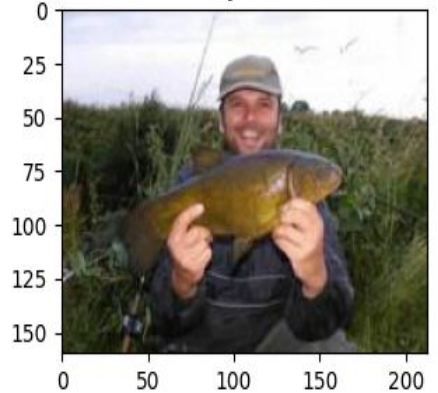
Band Aid



tench, Tinca tinca



military uniform



Target attack (epsilon=0.02) on subset

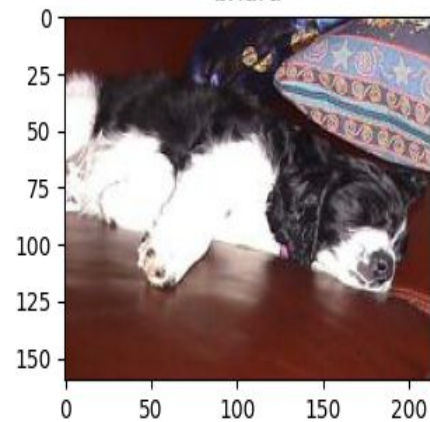
chain saw, chainsaw



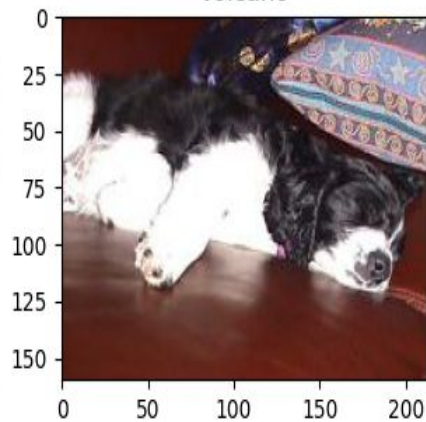
bow



briard

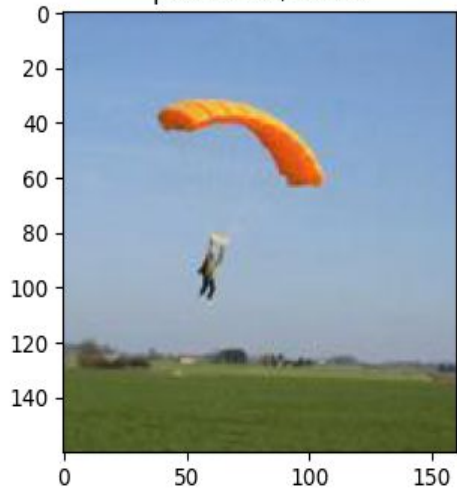


volcano

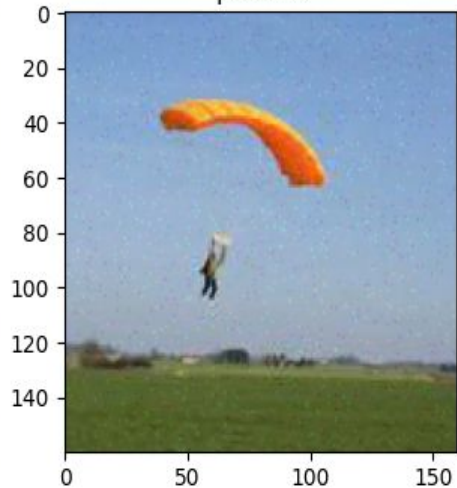


Target attack (epsilon=0.1) on subset

parachute, chute



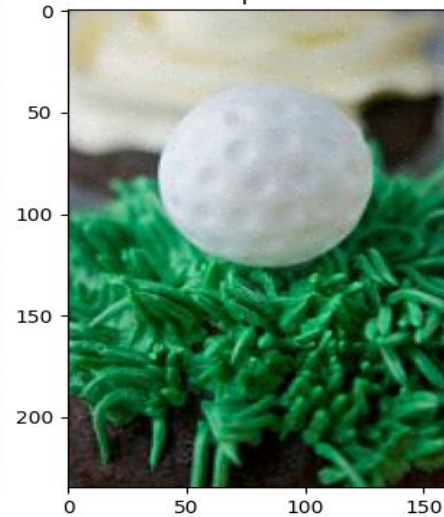
pelican



golf ball



face powder



Target attack (epsilon=0.1) on subset

mp, gasoline pump, petrol pump, island dispenser



Model T



garbage truck, dustcart



tractor



Target attack (epsilon=0.1) on subset

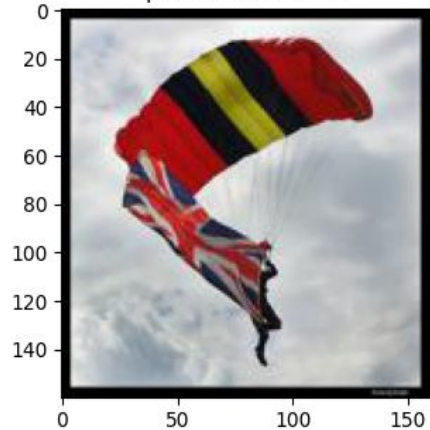
golf ball



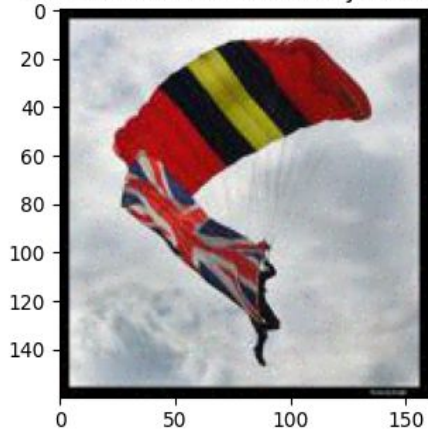
oil filter



parachute, chute

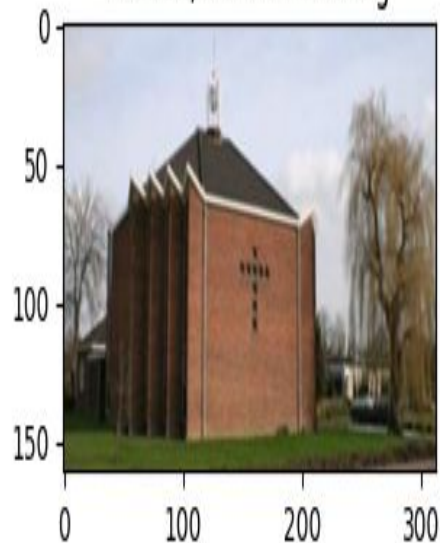


handkerchief, hankie, hanky, hanke!



Target attack (epsilon=0.2) on subset

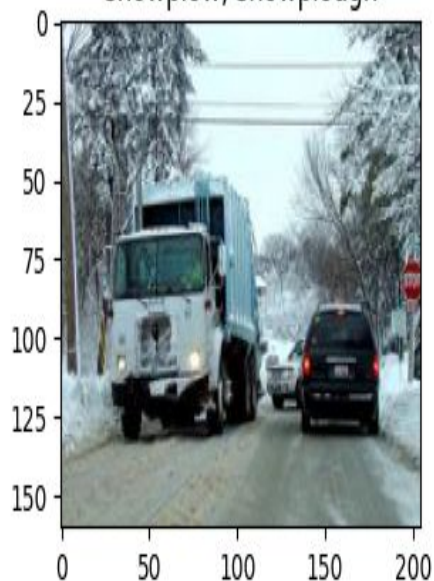
church, church building



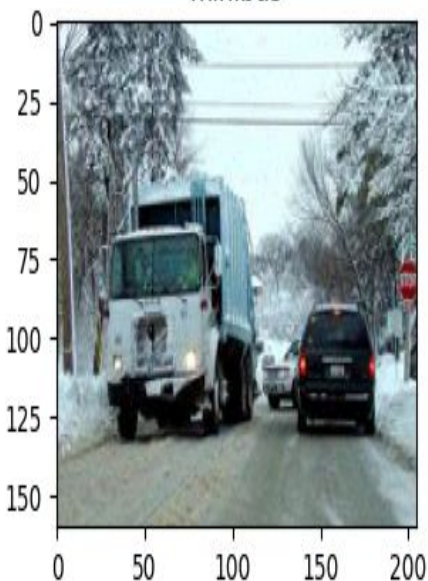
planetarium



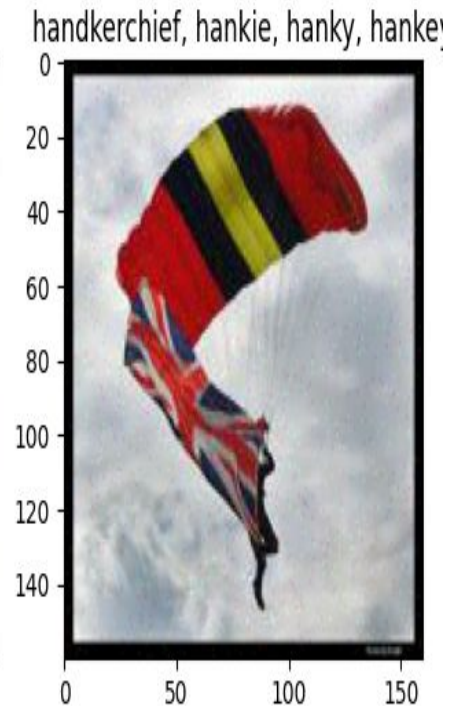
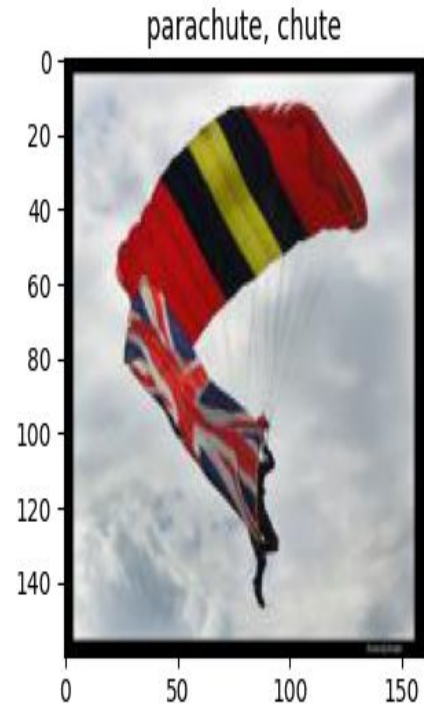
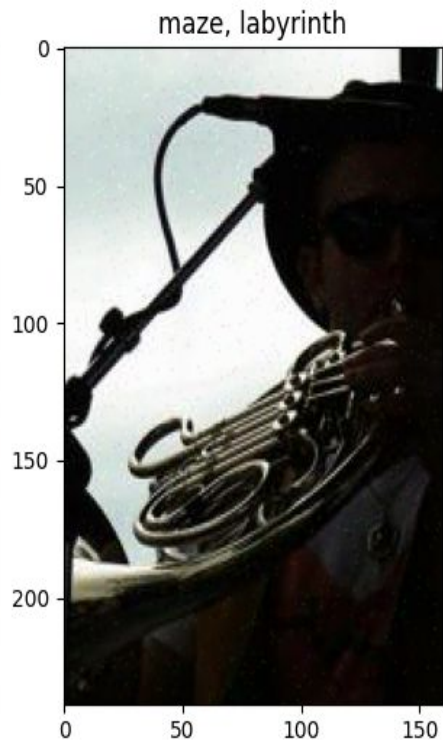
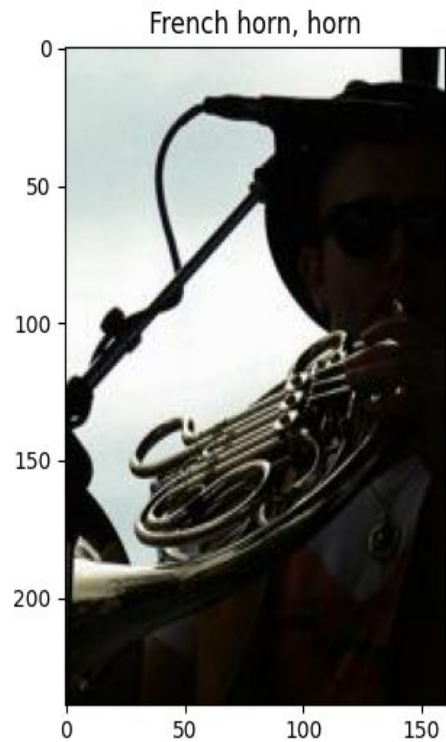
snowplow, snowplough



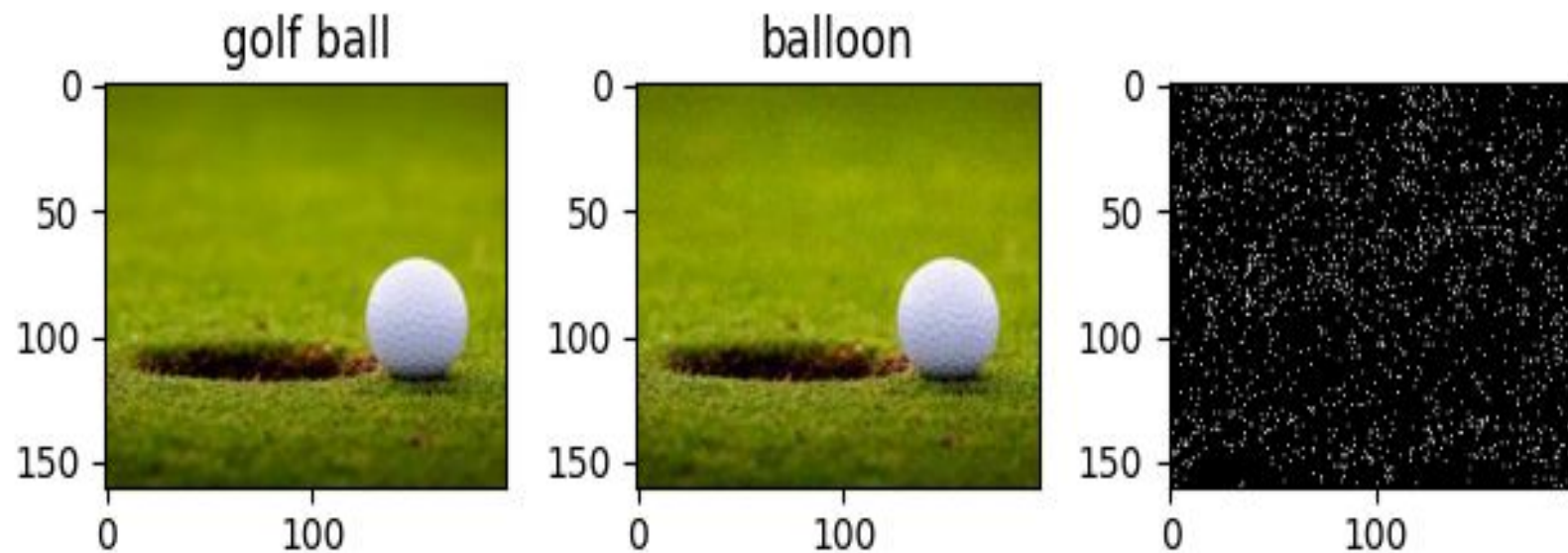
minibus



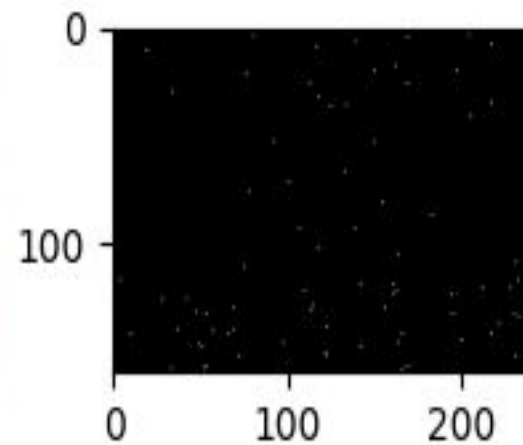
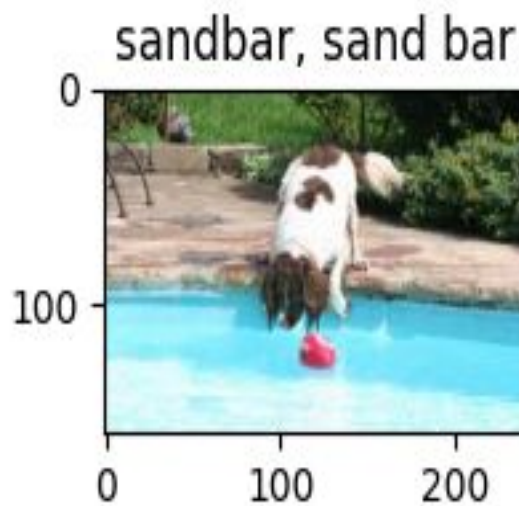
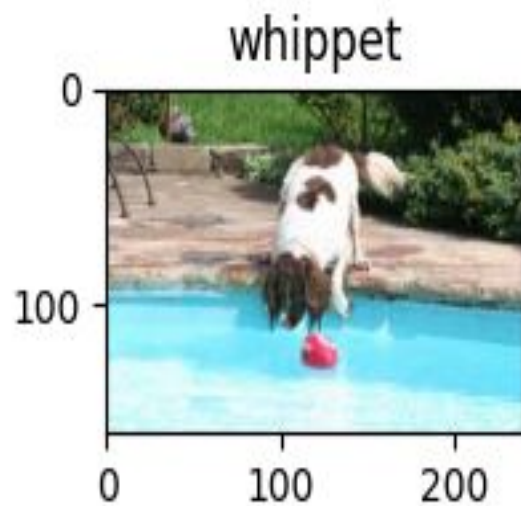
Target attack (epsilon=0.2) on subset



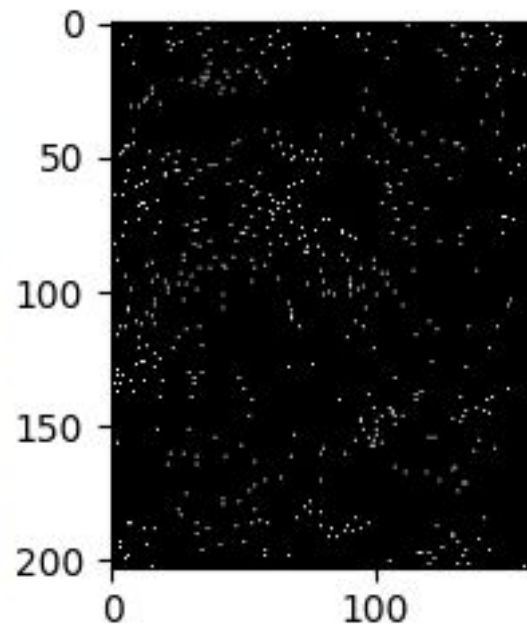
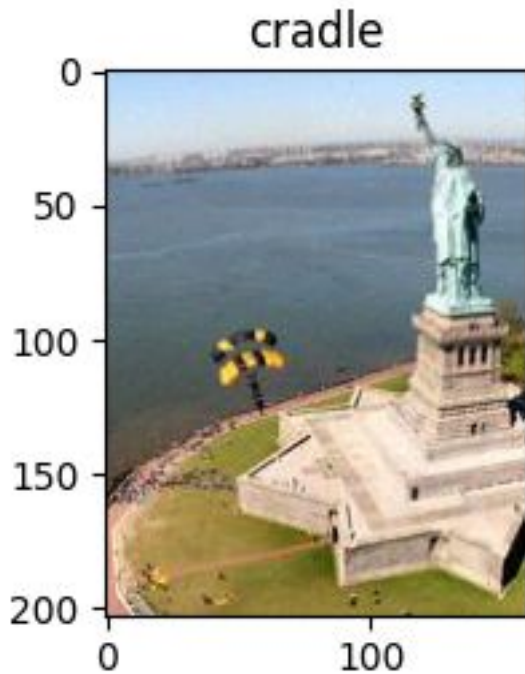
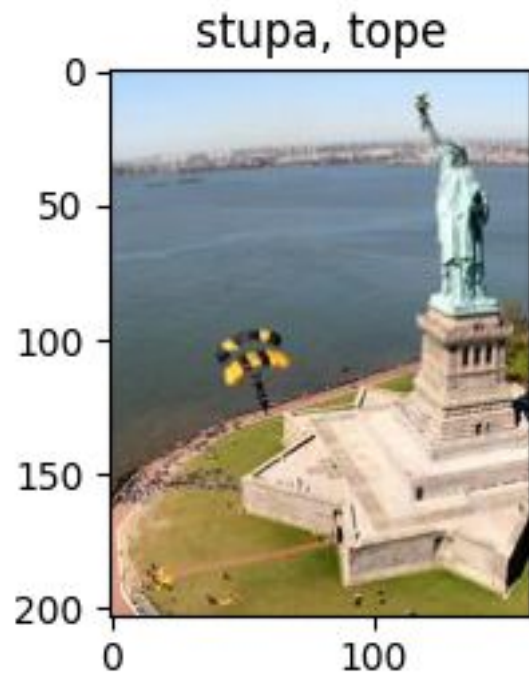
Visualization of pixel attack



Visualization of pixel attack



Visualization of pixel attack



Results on TinyImageNet (Untargeted Attack)

S.No	Epsilon	Attack Ratio	Avg. Iterations
1)	0.02	1.0	505
2)	0.1	1.0	126
3)	0.2	1.0	58
4)	0.3	1.0	39
5)	0.5	1.0	24

Results on TinyImageNet (Targeted Attack)

S.No	Epsilon	Attack Ratio	Avg. Iterations
1)	0.02	1.0	1331
2)	0.1	1.0	294
3)	0.2	1.0	162
4)	0.3	1.0	120
5)	0.5	1.0	79

Results on ImageNet Subset (Untargeted Attack)

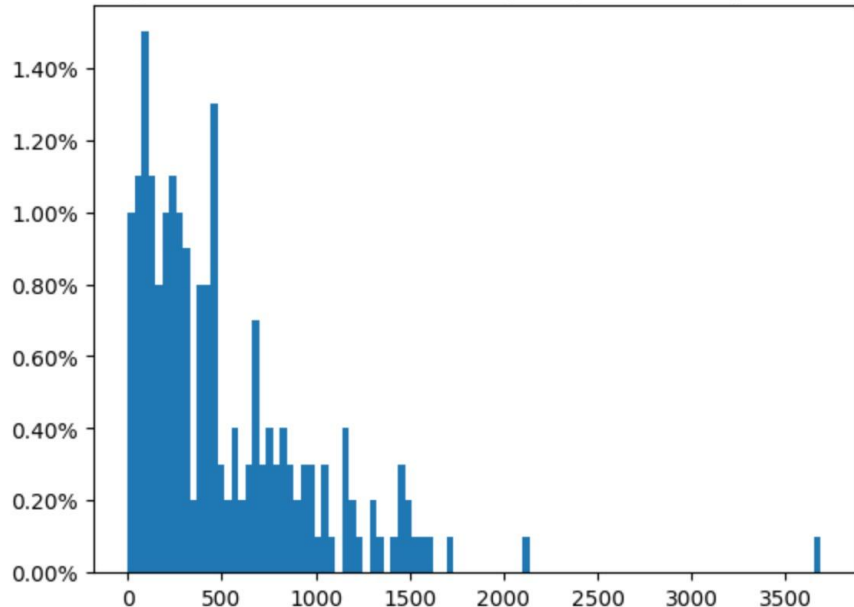
S.No	Epsilon	Attack Ratio	Avg. Iterations
1)	0.02	0.80	3126
2)	0.1	0.97	1648
3)	0.2	1.0	1240
4)	0.3	1.0	945
5)	0.5	1.0	658

Results on ImageNet Subset (Targeted Attack)

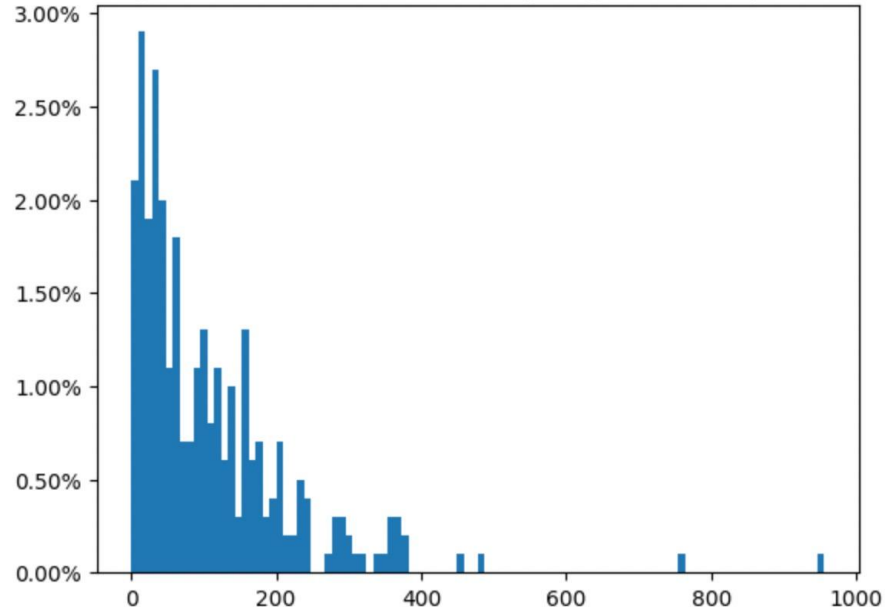
S.No	Epsilon	Attack Ratio	Avg. Iterations
1)	0.02	0.53	5383
2)	0.1	0.90	3383
3)	0.2	0.96	2824
4)	0.3	0.98	2636
5)	0.5	1.0	2410

Distribution of untargeted attack iterations over images

untargeted attack iterations on TinyImageNet with epsilon=0.02

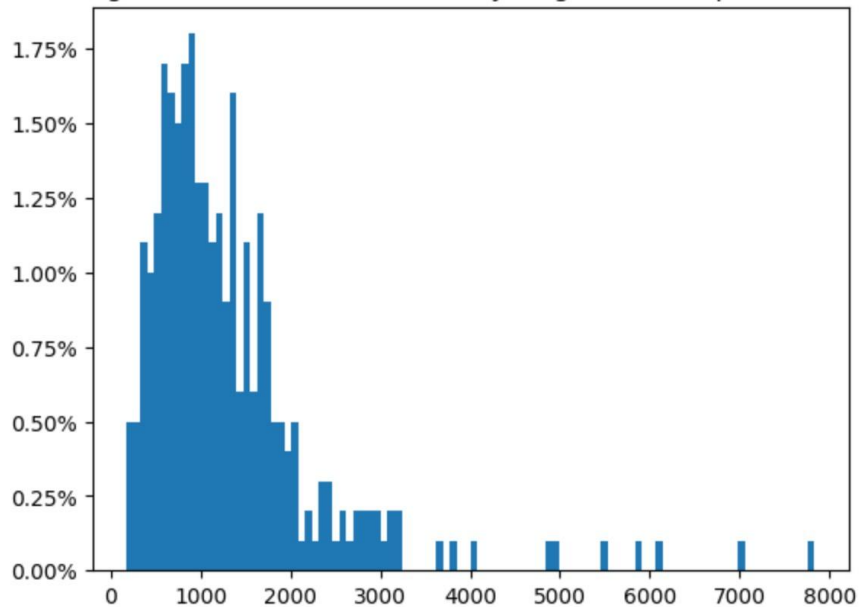


untargeted attack iterations on TinyImageNet with epsilon=0.1

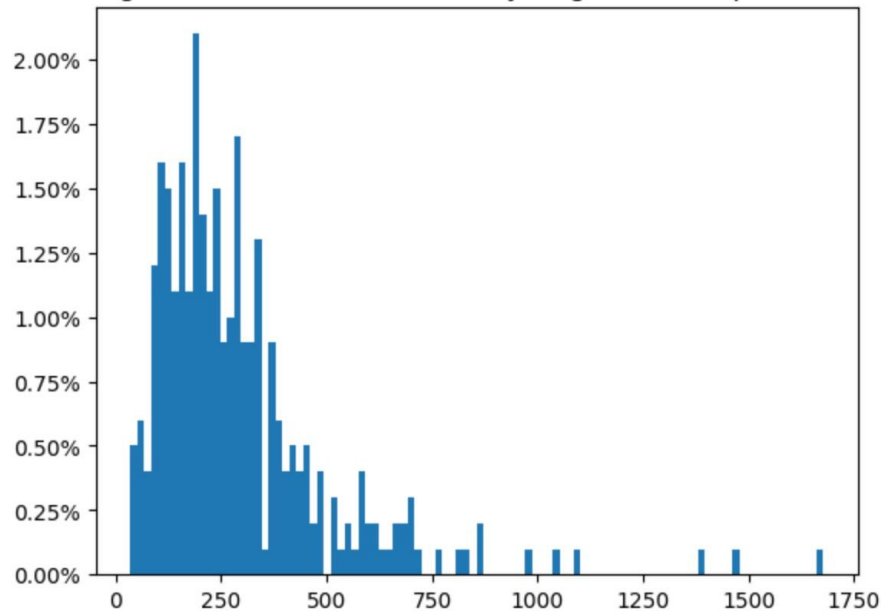


Distribution of targeted attack iterations over images

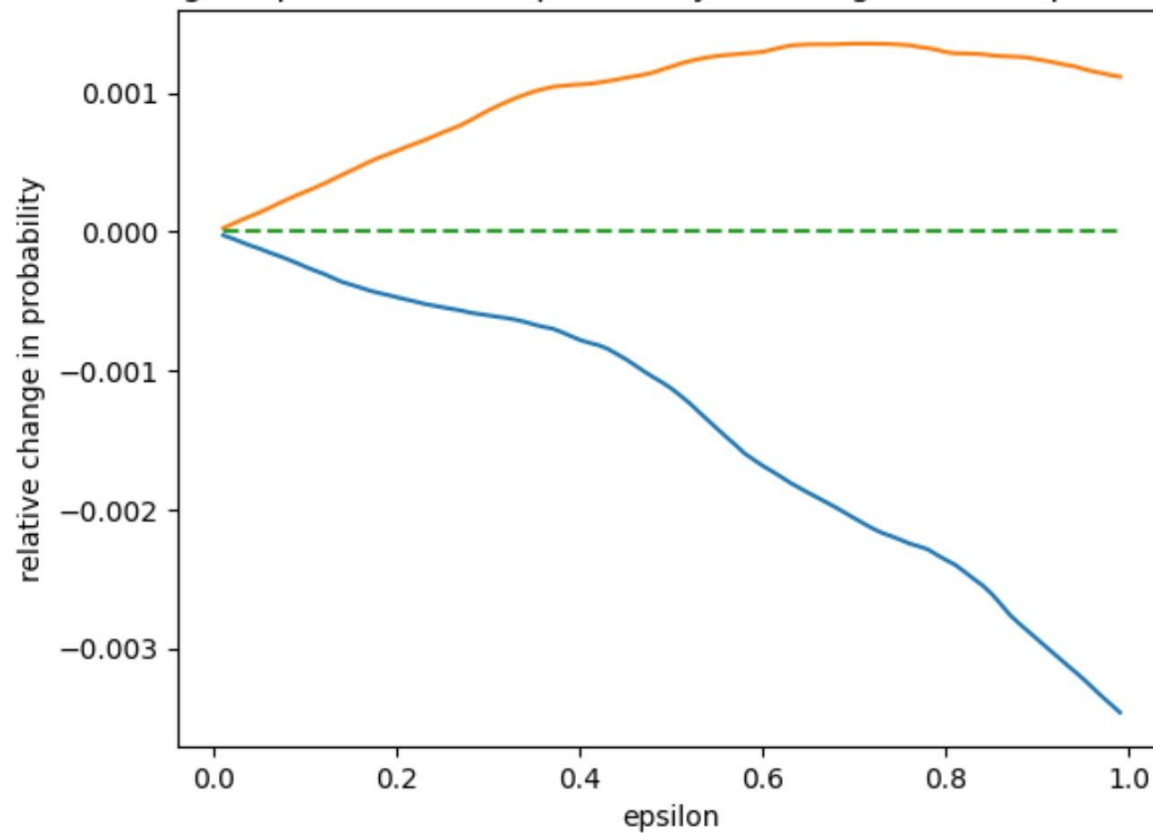
targetted attack iterations on TinyImageNet with epsilon=0.02



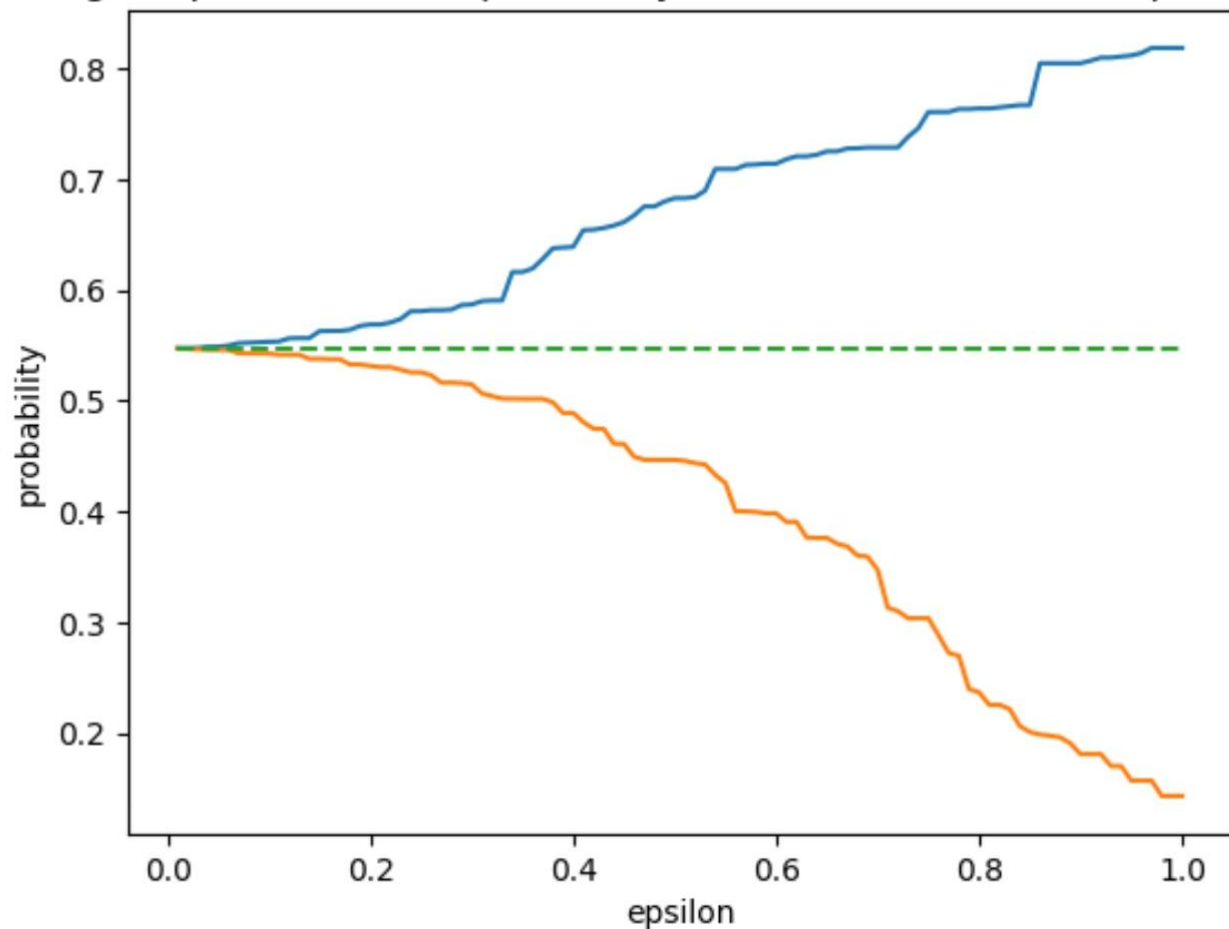
targetted attack iterations on TinyImageNet with epsilon=0.1

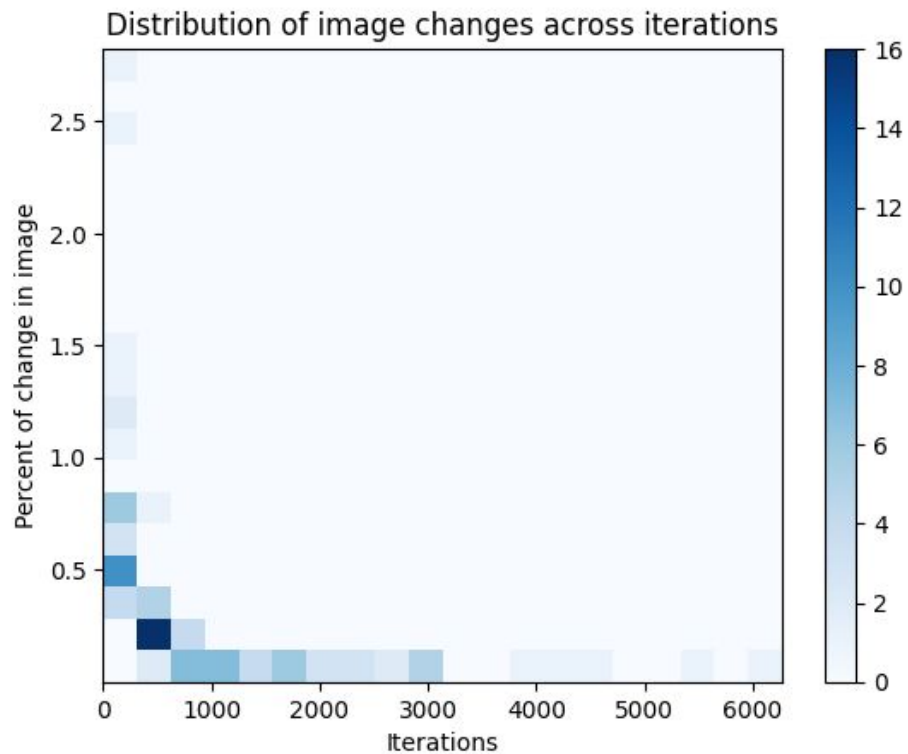


change of predicted class probability with single random pixel attack

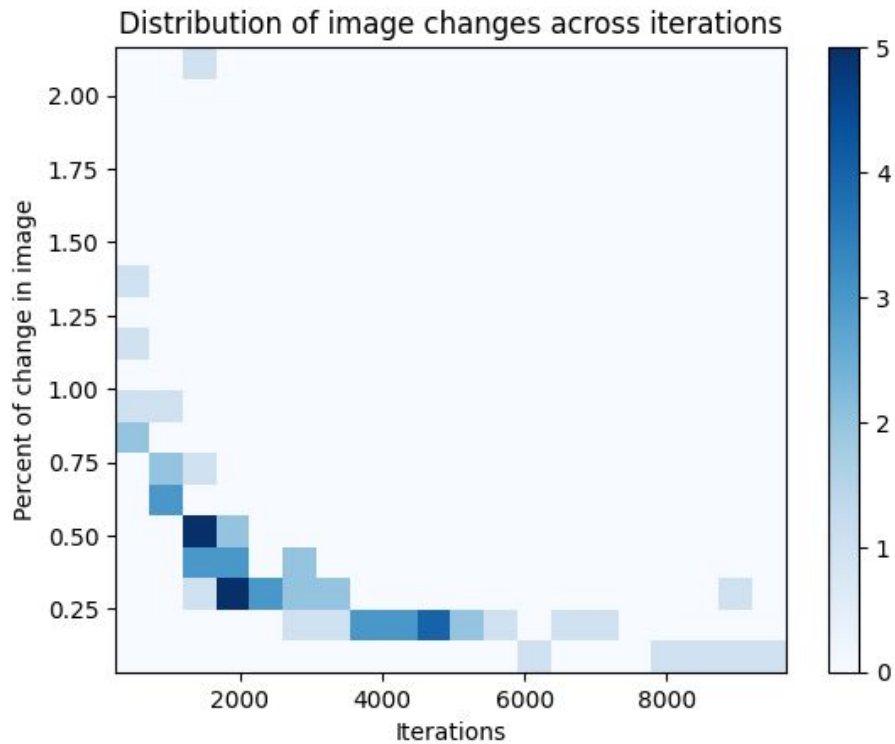


change of predicted class probability with continuous random pixel attack





Untargeted attack, 100 images, $\epsilon=0.2$



Targeted attack, 61 images, $\epsilon=0.2$

Improvements in strategy $\sim <1000$ iterations

Before gas pump, gasoline pump, petrol pump, island dispenser



Attack



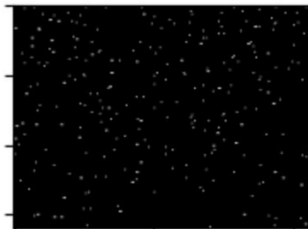
New label church, church building



Before garbage truck, dustcart



Attack



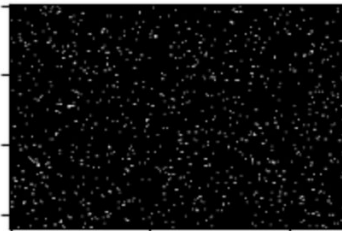
New label church, church building



Before golf ball



Attack



New label church, church building



Contribution:

Ardhendu Banerjee: Prepared the code for Black box pixel attack, extracted data subsets and label mappings for experimentation; conducted initial tests on multiple pretrained models for evaluating attack resistance v/s query time tradeoffs

Animesh Das: Compared various strategies for attack (localization) and conducted targeted attack visualization and performance tests; result compilation

Ritvik Gupta: Prepared code for attack on TinyImageNet and automated efficient runs for random image indices for tabulation and computation of success rate

Thank You