Testing Robustness of Commercial Online Image Recognition Systems

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Overview

Three Classifiers

- Google Cloud Vision
- Amazon Rekognition
- Salesforce MetaMind Einstein Vision

Purpose: Generate variety of adversarial images, interact with classifiers' APIs, record results

Google Cloud Vision - Generating Attacks

Dataset

- 20 predetermined images from imagenet
- Example labels: dog, strawberry, shoe, car

Pretrained Models for generation

- Resnet34
- GoogLeNet

Attacks - Foolbox

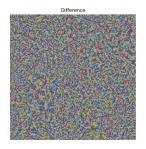
- L-infinity Projected Gradient Descent Attack (PGD)
- Fast Gradient Sign Method (FGSM)
- L-infinity Basic Iterative Method (BIA)

Perturbed Images

Images below: GoogLeNet, PGD attack, Epsilon 0.001

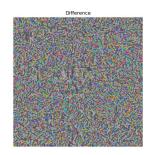






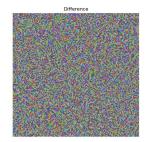












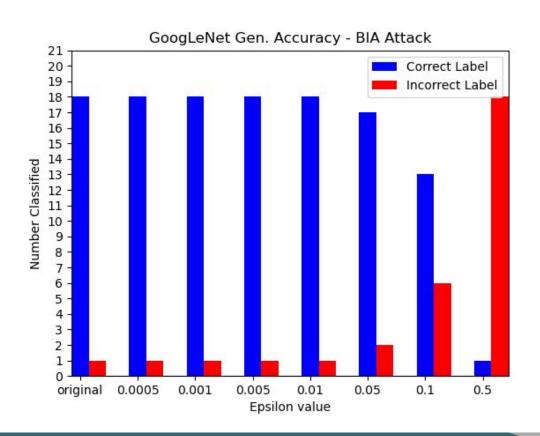




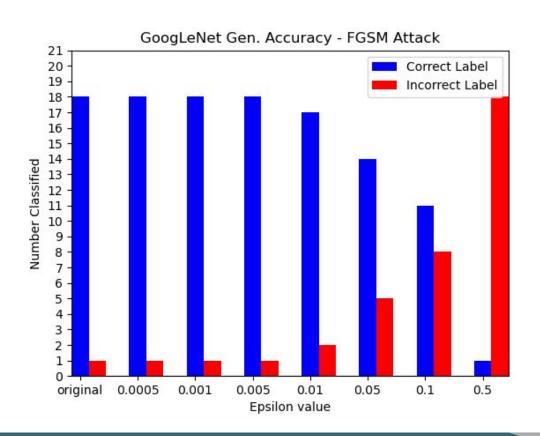


840 total -> 2 pretrained models, 20 base images, 3 generative attacks, 7 perturbation levels -- all generated images result in ~0% accuracy when tested on pretrained model with which they were generated

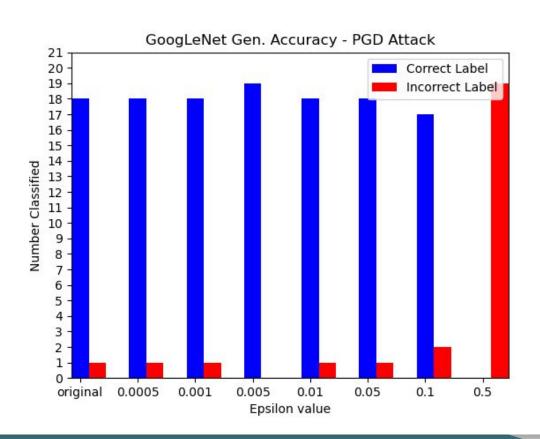
Results - GoogLeNet



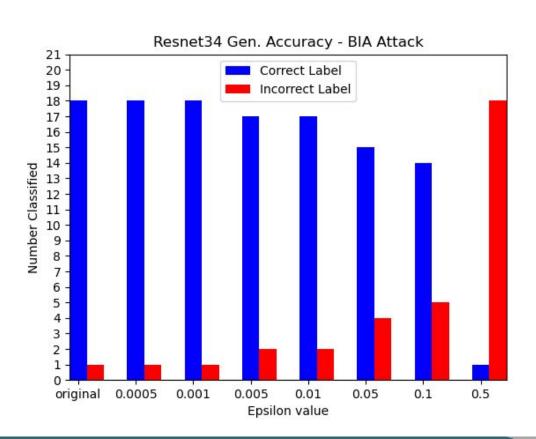
Results - GoogLeNet



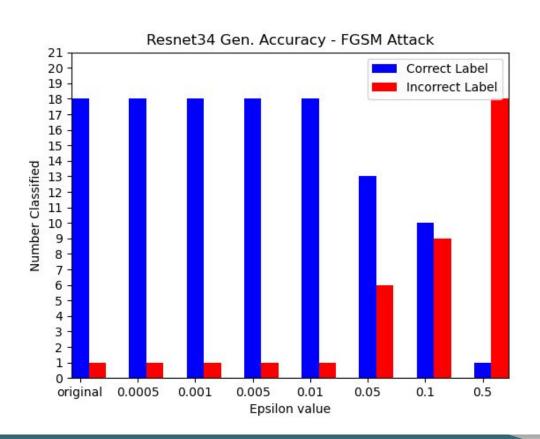
Results - GoogLeNet



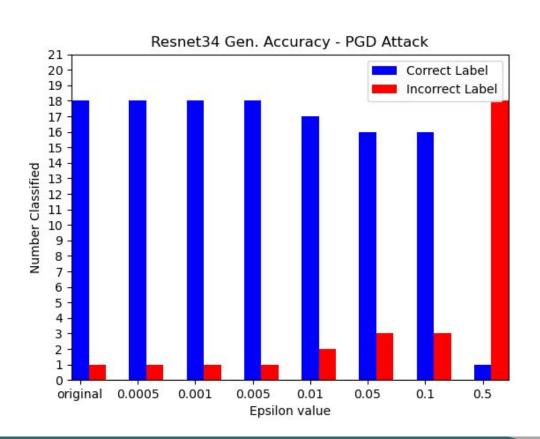
Results - Resnet34



Results - Resnet34



Results - Resnet34



Analysis of Results & Code Review

Best attack - FGSM

Effective epsilon range 0.005 to 0.1

Missed: TRUE: dalmatian, coach dog, carriage dog, dog breed, dog // GIVEN: carnivore or cat or felidae EPSVAL: 0.05



Missed: TRUE: Loafer, shoe // GIVEN: footwear or product or synthetic rubber EPSVAL: 0.05



Analysis of Results & Code Review

Missed: TRUE: bottlecap, bottle cap // GIVEN: font or art or

circle EPSVAL: original



Missed: TRUE: cannon // GIVEN: wheel or bicycle tire or

bicycle wheel EPSVAL: 0.1



Conclusions - Google Cloud Vision

Effectively robust

Errs on the side of overly general labels if low confidence - imagenet label specificity largely incompatible with Google labels (manual re-labeling required)

Loss of accuracy/misclassification rate correlated with high amount of visible, human-perceptible perturbation

For chosen attacks/models, epsilon 0.005 to 0.01 seems to be sweet spot for trade off of imperceptibility and misclassification

Black-box attacks largely ineffective

Amazon Rekognition

Major Works:

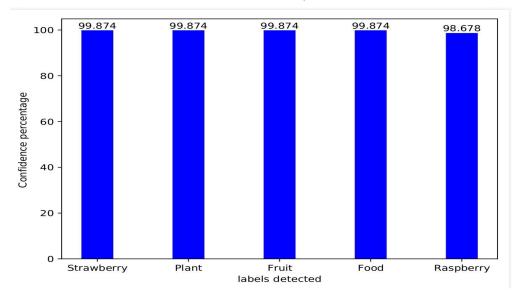
- Implemented API test using both S3 bucket and from the local directory.
- Taken Images (both original and with attacks) with different levels of perturbation ranging from 0.01 to 0.5.
- Checked if the API detected object labels present in the image correctly.
- Displayed the robustness of API using a bar graph showing labels and corresponding confidence percentage.

Experimental Results:

FGSM attack results:

1. Original Image:

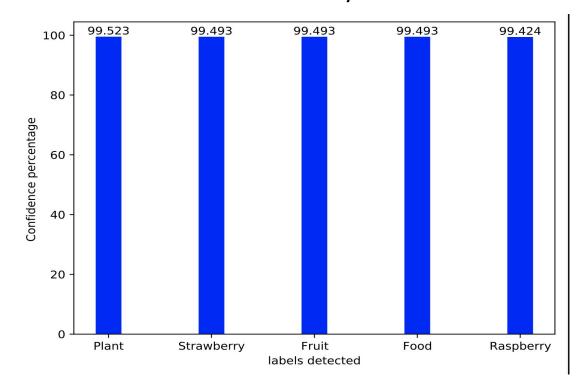




FGSM Continued...

Epsilon = 0.01

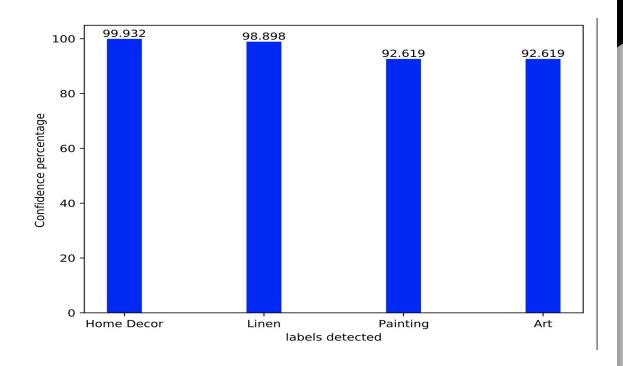




FGSM Continued...

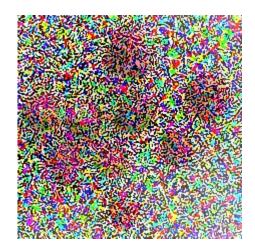
Epsilon = 0.1

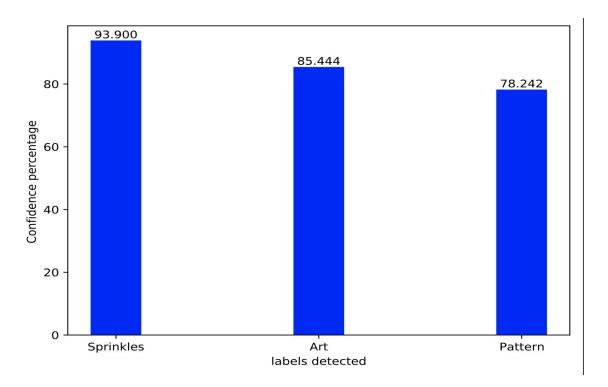




FGSM Continued...

Epsilon = 0.5

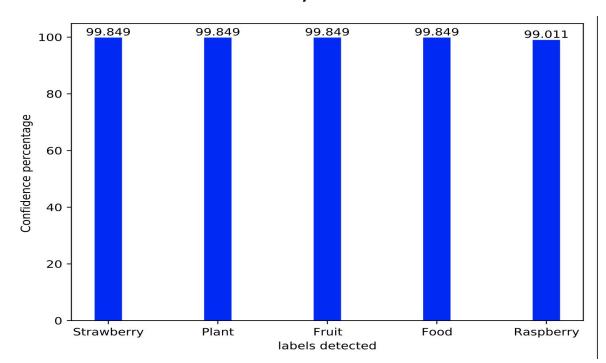




PGD attack Results:

Epsilon = 0.01

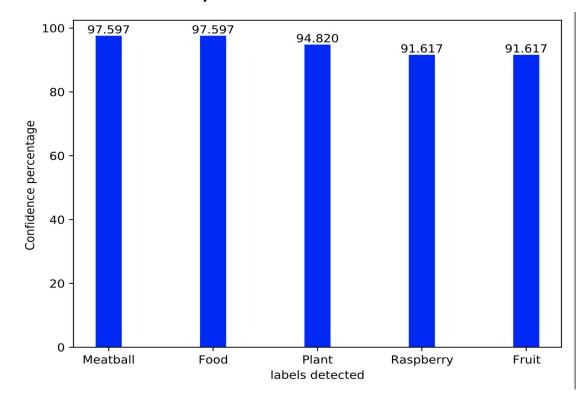




PGD Continued...

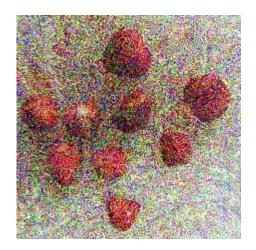
Epsilon = 0.1

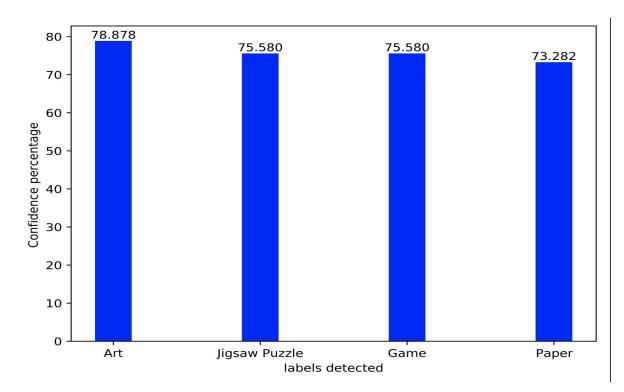




PGD Continued...

Epsilon = 0.5





Conclusion

Successfully tested Amazon Rekognition API using both original image and images with attacks.

To test the API Adversarial attacks like FGSM and PGD were used.

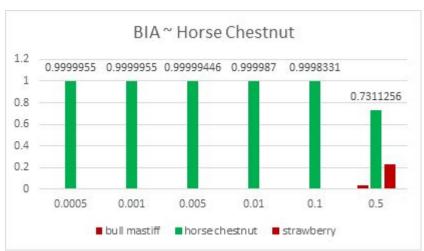
For FGSM attack the API failed to detect once the value of epsilon reached 0.1 as shown in the earlier confidence bar graph.

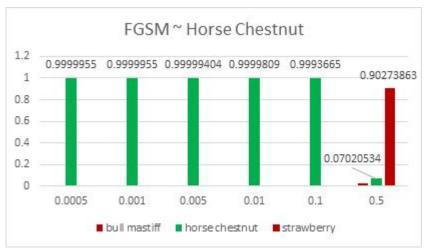
- For PGD model the API again failed once epsilon was 0.1 but API performed slightly better than with FGSM.

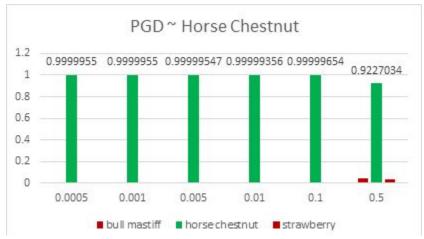
Salesforce MetaMind Einstein Vision

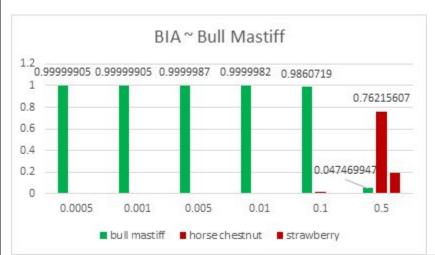
- Documentation: https://metamind.readme.io/docs
- Using the Einstein API, an image custom classifier was created
- API uses cUrl and an access token that is granted to a user with a .pem file
- Image classifier and model fairly restrictive in comparison to previous API's
- Used images pre-trained by Resnet34 perturbed using BIA, FGSM, and PGD

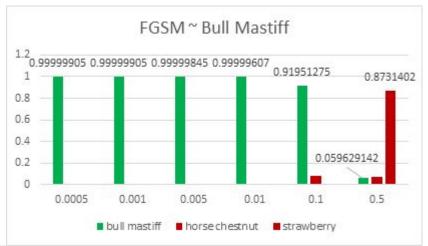


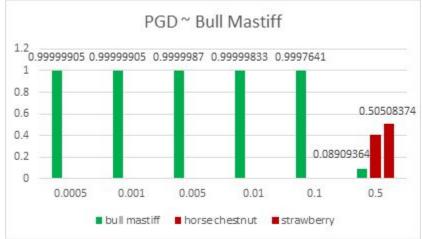


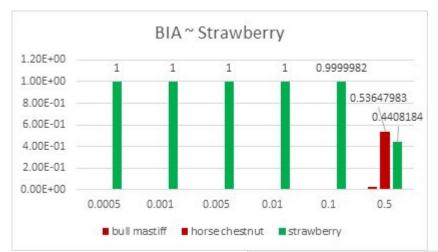


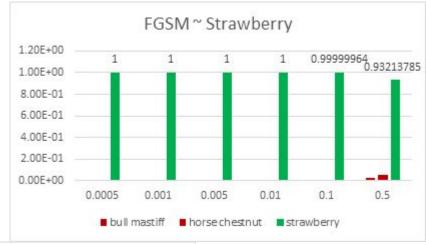


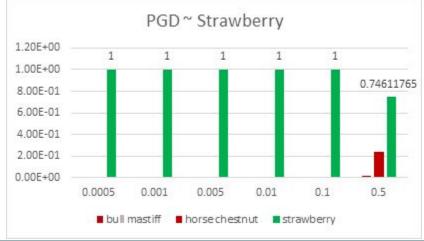








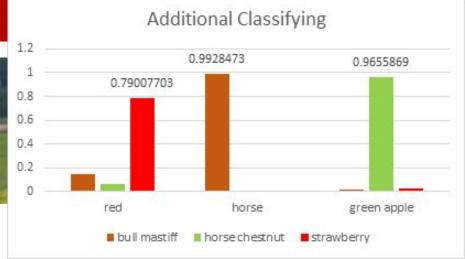


















Conclusion

- Robust but restrictive
- Black-box untargeted attacks ineffective; targeted attacks possibly effective
- Unconventional ways to attack model
- Future Work modify dataset and continue to experiment

Questions