Proudly supported by

Lab Manual

Using Foolbox for Adversarial Attack

Lab 33: Using Foolbox for Adversarial Attack

Steps to implement Foolbox Library

1. Visit the link: https://colab.google/
2. Click on 'New Notebook'
3. Start typing the code given below

   a. ***Installing the library***

```
pip install Foolbox
```

   b. ***Implementing the code for attack and visualization***

```
# Required installations (run in terminal or notebook if not already done):
# pip install foolbox torch torchvision matplotlib numpy pillow

import torch
import torchvision.models as models
import torchvision.transforms as transforms
from PIL import Image
import foolbox as fb
import numpy as np
import matplotlib.pyplot as plt

# Load pretrained ResNet18 model
model = models.resnet18(pretrained=True).eval()
fmodel = fb.PyTorchModel(model, bounds=(0, 1))

# Load and preprocess image
img_path = "cat.jpg"  # Make sure this image is in the same folder
img = Image.open(img_path).resize((224, 224))
transform = transforms.Compose([
    transforms.ToTensor()
])
image = transform(img).unsqueeze(0).clamp(0, 1)

# Predict original label
logits = model(image)
label = torch.argmax(logits, dim=1).item()

# Run FGSM attack
attack = fb.attacks.FGSM()
```

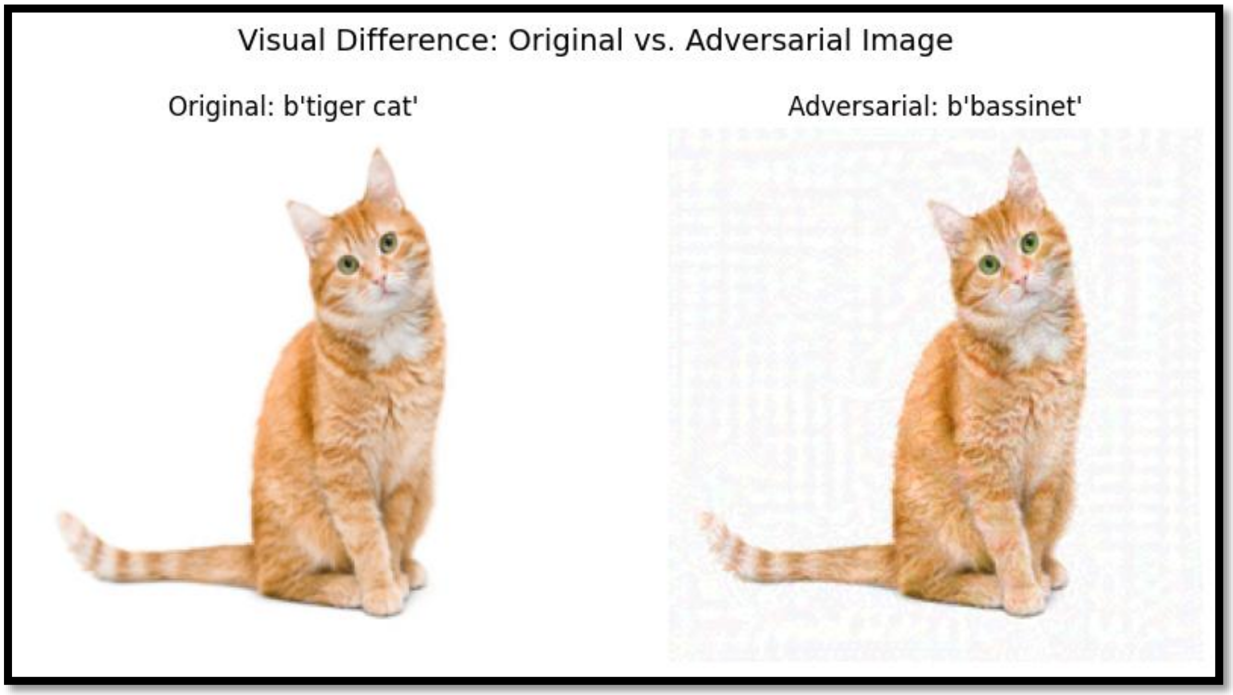
```
_, adv_image, success = attack(fmodel, image, torch.tensor([label]), epsilons=0.03)

# Predict adversarial label
adv_logits = model(adv_image)
adv_label = torch.argmax(adv_logits, dim=1).item()

# Load human-readable labels for visualization
import json
import urllib.request

url = "https://raw.githubusercontent.com/pytorch/hub/master/imagenet_classes.txt"
response = urllib.request.urlopen(url)
categories = [line.strip() for line in response.readlines()]
original_class = categories[label]
adversarial_class = categories[adv_label]

# Convert tensors to numpy for plotting
image_np = image.squeeze().permute(1, 2, 0).detach().numpy()
adv_image_np = adv_image.squeeze().permute(1, 2, 0).detach().numpy()

# Plot the original and adversarial images side by side
plt.figure(figsize=(10, 5))

plt.subplot(1, 2, 1)
plt.imshow(image_np)
plt.title(f"Original: {original_class}")
plt.axis('off')

plt.subplot(1, 2, 2)
plt.imshow(adv_image_np)
plt.title(f"Adversarial: {adversarial_class}")
plt.axis('off')

plt.suptitle("Visual Difference: Original vs. Adversarial Image", fontsize=14)
plt.show()

# Print success status
print("Was the attack successful?", success.item())
```

4. Click on the ***folder icon*** (shown on the left side) and then click on the ***upload icon***.

5. Upload the image of the cat from your device.

6. Now click on ***Run All*** or ***Ctrl + F9*** to run all the cells

Output:



Explanation

What you see

- **Left (Original):** This is your real image of a tiger cat. The model correctly predicts the label as tiger cat.
- **Right (Adversarial)**: This image looks the same to a human, but it has tiny invisible changes (perturbations). These are specially crafted to confuse the model. The model now thinks this is a bassinet!
- **Text Below**: Was the attack successful? ***True*** means that the adversarial image successfully fooled the AI into making the wrong prediction.

What are the changes

We used the ***FGSM attack (Fast Gradient Sign Method)***.

This method:

- Computes the gradient of the model's prediction with respect to the input image.
- Adds a small tweak (epsilon=0.03) to the image to change the prediction.

Try on your own:

If you want to try, when will the model fail - Make epsilon extremely small so that attack is weak.

Change the epsilon from ***0.03*** to ***1e - 6***

Concept	Explanation
Adversarial Example	An image that looks normal but is subtly changed to confuse AI.
Model Vulnerability	AI models can be easily tricked—even when humans see no difference.
Importance of AI Security	This is why security and robustness are **critical in real-world AI systems** (e.g., self-driving cars, healthcare).
Epsilon Value	Controls how strong the attack is. Higher epsilon means more visible change, but easier to fool the model.