Adversarial Attacks - Adversarial Patches Only

This tutorial was originally created by Phillip Lippe and modified by Dr. Brinnae Bent for use in "Emerging Trends in Explainable AI" at Duke University.

Click on the button below to open in Google Colab. You will need access to a GPU to run this code.

Open in Colab

```
## Standard libraries
import os
import json
import math
import time
import numpy as np
import scipy.linalg

## Imports for plotting
import matplotlib.pyplot as plt
%matplotlib inline
from IPython.display import set_matplotlib_formats
set_matplotlib_formats('svg', 'pdf') # For export
from matplotlib.colors import to_rgb
import matplotlib
matplotlib.rcParams['lines.linewidth'] = 2.0
import seaborn as sns
sns.set()

## Progress bar
from tqdm.notebook import tqdm

## PyTorch
import torch
import torch.nn as nn
import torch.nn.functional as F
import torch.utils.data as data
import torch.optim as optim
# Torchvision
import torchvision
from torchvision.datasets import CIFAR10
from torchvision import transforms
# PyTorch Lightning
try:
    import pytorch_lightning as pl
except ModuleNotFoundError: # Google Colab does not have PyTorch Lightning installed by default. Hence, we do it her
    !pip install --quiet pytorch-lightning>=1.4
    import pytorch_lightning as pl
from pytorch_lightning.callbacks import LearningRateMonitor, ModelCheckpoint

# Path to the folder where the datasets are/should be downloaded (e.g. MNIST)
DATASET_PATH = "../data"
# Path to the folder where the pretrained models are saved
CHECKPOINT_PATH = "../saved_models/tutorial10"

# Setting the seed
pl.seed_everything(42)

# Ensure that all operations are deterministic on GPU (if used) for reproducibility
torch.backends.cudnn.deterministic = True
torch.backends.cudnn.benchmark = False

# Fetching the device that will be used throughout this notebook
device = torch.device("cpu") if not torch.cuda.is_available() else torch.device("cuda:0")
print("Using device", device)
```

```
/tmp/ipython-input-1779675758.py:13: DeprecationWarning: `set_matplotlib_formats` is deprecated since IPython 7.23, d
  set_matplotlib_formats('svg', 'pdf') # For export
INFO:lightning_fabric.utilities.seed:Seed set to 42
Using device cuda:0
```

We have again a few download statements. This includes both a dataset, and a few pretrained patches we will use later.

```
import urllib.request
from urllib.error import HTTPError
import zipfile
# Github URL where the dataset is stored for this tutorial
base_url = "https://raw.githubusercontent.com/phlippe/saved_models/main/tutorial10/"
# Files to download
pretrained_files = [(DATASET_PATH, "TinyImageNet.zip"), (CHECKPOINT_PATH, "patches.zip")]
# Create checkpoint path if it doesn't exist yet
os.makedirs(DATASET_PATH, exist_ok=True)
os.makedirs(CHECKPOINT_PATH, exist_ok=True)

# For each file, check whether it already exists. If not, try downloading it.
for dir_name, file_name in pretrained_files:
    file_path = os.path.join(dir_name, file_name)
    if not os.path.isfile(file_path):
        file_url = base_url + file_name
        print(f"Downloading {file_url}...")
        try:
            urllib.request.urlretrieve(file_url, file_path)
        except HTTPError as e:
            print("Something went wrong. Please try to download the file from the GDrive folder, or contact the auth
        if file_name.endswith(".zip"):
            print("Unzipping file...")
            with zipfile.ZipFile(file_path, 'r') as zip_ref:
                zip_ref.extractall(file_path.rsplit("/",1)[0])
```

```
Downloading https://raw.githubusercontent.com/phlippe/saved_models/main/tutorial10/TinyImageNet.zip...
Unzipping file...
Downloading https://raw.githubusercontent.com/phlippe/saved_models/main/tutorial10/patches.zip...
Unzipping file...
```

Setup

For our experiments in this notebook, we will use common CNN architectures trained on the ImageNet dataset. Such models are luckily provided by PyTorch's torchvision package, and hence we just need to load the model of our preference. For the results on the website and default on Google Colab, we use a ResNet34. Feel free to experiment with other architectures as well, the code is mainly independent of the specific architecture we choose.

```
# Load CNN architecture pretrained on ImageNet
os.environ["TORCH_HOME"] = CHECKPOINT_PATH
pretrained_model = torchvision.models.resnet34(weights='IMAGENET1K_V1')
pretrained_model = pretrained_model.to(device)

# No gradients needed for the network
pretrained_model.eval()
for p in pretrained_model.parameters():
    p.requires_grad = False
```

```
Downloading: "https://download.pytorch.org/models/resnet34-b627a593.pth" to ../saved_models/tutorial10/hub/checkpoint
100%|██████████| 83.3M/83.3M [00:06<00:00, 13.9MB/s]
```

To perform adversarial attacks, we also need a dataset to work on. Given that the CNN model has been trained on ImageNet, it is only fair to perform the attacks on data from ImageNet. For this, we provide a small set of pre-processed images from the original ImageNet dataset (note that this dataset is shared under the same license as the original ImageNet dataset). Specifically, we have 5 images for each of the 1000 labels of the dataset. We can load the data below, and create a corresponding data loader.

```
# Mean and Std from ImageNet
NORM_MEAN = np.array([0.485, 0.456, 0.406])
NORM_STD = np.array([0.229, 0.224, 0.225])
# No resizing and center crop necessary as images are already preprocessed.
plain_transforms = transforms.Compose([
    transforms.ToTensor(),
    transforms.Normalize(mean=NORM_MEAN,
                         std=NORM_STD)
])

# Load dataset and create data loader
imagenet_path = os.path.join(DATASET_PATH, "TinyImageNet/")
assert os.path.isdir(imagenet_path), f"Could not find the ImageNet dataset at expected path \"{imagenet_path}\". " +
                                     f"Please make sure to have downloaded the ImageNet dataset here, or change the
```

```
dataset = torchvision.datasets.ImageFolder(root=imagenet_path, transform=plain_transforms)
data_loader = data.DataLoader(dataset, batch_size=32, shuffle=False, drop_last=False, num_workers=8)

# Load label names to interpret the label numbers 0 to 999
with open(os.path.join(imagenet_path, "label_list.json"), "r") as f:
    label_names = json.load(f)

def get_label_index(lab_str):
    assert lab_str in label_names, f"Label \"{lab_str}\" not found. Check the spelling of the class."
    return label_names.index(lab_str)
```

```
/usr/local/lib/python3.12/dist-packages/torch/utils/data/dataloader.py:627: UserWarning: This DataLoader will create
  warnings.warn(
```

Before we start with our attacks, we should verify the performance of our model. As ImageNet has 1000 classes, simply looking at the accuracy is not sufficient to tell the performance of a model. Imagine a model that always predicts the true label as the second-highest class in its softmax output. Although we would say it recognizes the object in the image, it achieves an accuracy of 0. In ImageNet with 1000 classes, there is not always one clear label we can assign an image to. This is why for image classifications over so many classes, a common alternative metric is "Top-5 accuracy", which tells us how many times the true label has been within the 5 most-likely predictions of the model. As models usually perform quite well on those, we report the error (1 - accuracy) instead of the accuracy:

```
def eval_model(dataset_loader, img_func=None):
    tp, tp_5, counter = 0., 0., 0.
    for imgs, labels in tqdm(dataset_loader, desc="Validating..."):
        imgs = imgs.to(device)
        labels = labels.to(device)
        if img_func is not None:
            imgs = img_func(imgs, labels)
        with torch.no_grad():
            preds = pretrained_model(imgs)
        tp += (preds.argmax(dim=-1) == labels).sum()
        tp_5 += (preds.topk(5, dim=-1)[1] == labels[...,None]).any(dim=-1).sum()
        counter += preds.shape[0]
    acc = tp.float().item()/counter
    top5 = tp_5.float().item()/counter
    print(f"Top-1 error: {(100.0 * (1 - acc)):4.2f}%")
    print(f"Top-5 error: {(100.0 * (1 - top5)):4.2f}%")
    return acc, top5
```

```
_ = eval_model(data_loader)
```

```
Validating...: 100%                                                 157/157 [00:12<00:00, 20.77it/s]
Top-1 error: 19.38%
Top-5 error: 4.38%
```

The ResNet34 achives a decent error rate of 4.3% for the top-5 predictions. Next, we can look at some predictions of the model to get more familiar with the dataset. The function below plots an image along with a bar diagram of its predictions. We also prepare it to show adversarial examples for later applications.

```
def show_prediction(img, label, pred, K=5, adv_img=None, noise=None):

    if isinstance(img, torch.Tensor):
        # Tensor image to numpy
        img = img.cpu().permute(1, 2, 0).numpy()
        img = (img * NORM_STD[None,None]) + NORM_MEAN[None,None]
        img = np.clip(img, a_min=0.0, a_max=1.0)
        label = label.item()

    # Plot on the left the image with the true label as title.
    # On the right, have a horizontal bar plot with the top k predictions including probabilities
    if noise is None or adv_img is None:
        fig, ax = plt.subplots(1, 2, figsize=(10,2), gridspec_kw={'width_ratios': [1, 1]})
    else:
        fig, ax = plt.subplots(1, 5, figsize=(12,2), gridspec_kw={'width_ratios': [1, 1, 1, 1, 2]})

    ax[0].imshow(img)
    ax[0].set_title(label_names[label])
    ax[0].axis('off')

    if adv_img is not None and noise is not None:
```

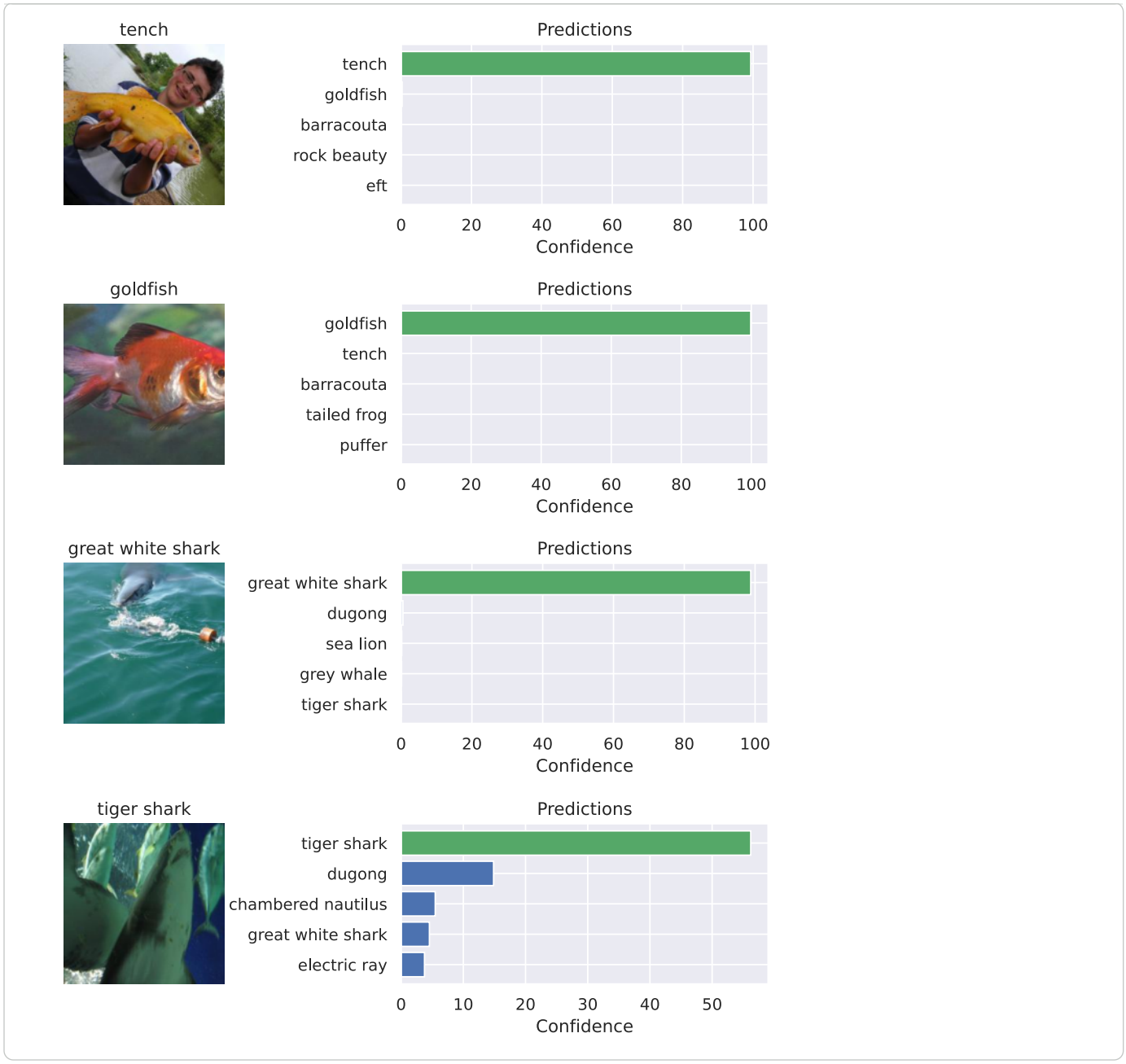
```
            # Visualize adversarial images
            adv_img = adv_img.cpu().permute(1, 2, 0).numpy()
            adv_img = (adv_img * NORM_STD[None,None]) + NORM_MEAN[None,None]
            adv_img = np.clip(adv_img, a_min=0.0, a_max=1.0)
            ax[1].imshow(adv_img)
            ax[1].set_title('Adversarial')
            ax[1].axis('off')
            # Visualize noise
            noise = noise.cpu().permute(1, 2, 0).numpy()
            noise = noise * 0.5 + 0.5 # Scale between 0 to 1
            ax[2].imshow(noise)
            ax[2].set_title('Noise')
            ax[2].axis('off')
            # buffer
            ax[3].axis('off')

        if abs(pred.sum().item() - 1.0) > 1e-4:
            pred = torch.softmax(pred, dim=-1)
        topk_vals, topk_idx = pred.topk(K, dim=-1)
        topk_vals, topk_idx = topk_vals.cpu().numpy(), topk_idx.cpu().numpy()
        ax[-1].barh(np.arange(K), topk_vals*100.0, align='center', color=["C0" if topk_idx[i]!=label else "C2" for i in
        ax[-1].set_yticks(np.arange(K))
        ax[-1].set_yticklabels([label_names[c] for c in topk_idx])
        ax[-1].invert_yaxis()
        ax[-1].set_xlabel('Confidence')
        ax[-1].set_title('Predictions')

        plt.show()
        plt.close()
```

Let's visualize a few images below:

```
exmp_batch, label_batch = next(iter(data_loader))
with torch.no_grad():
    preds = pretrained_model(exmp_batch.to(device))
for i in range(1,17,5):
    show_prediction(exmp_batch[i], label_batch[i], preds[i])
```



The bar plot on the right shows the top-5 predictions of the model with their class probabilities. We denote the class probabilities with "confidence" as it somewhat resembles how confident the network is that the image is of one specific class. Some of the images have a highly peaked probability distribution, and we would expect the model to be rather robust against noise for those. However, we will see below that this is not always the case. Note that all of the images are of fish because the data loader doesn't shuffle the dataset. Otherwise, we would get different images every time we run the notebook, which would make it hard to discuss the results on the static version.

Adversarial Patches

Instead of changing every pixel by a little bit, we can also try to change a small part of the image into whatever values we would like. In other words, we will create a small image patch that covers a minor part of the original image but causes the model to confidentially predict a specific class we choose. This form of attack is an even bigger threat in real-world applications than FSGM. Imagine a network in an autonomous car that receives a live image from a camera. Another driver could print out a specific pattern and put it on the back of his/her vehicle to make the autonomous car believe that the car is actually a pedestrian. Meanwhile, humans would not notice it. Tom Brown et al. proposed a way of learning such adversarial image patches robustly in 2017 and provided a short demonstration on YouTube. Interestingly, if you add a small picture of the target class (here *toaster*) to the original image, the model does not pick it up at all. A specifically designed patch, however, which only roughly looks like a toaster, can change the network's prediction instantaneously.

Let's take a closer look at how we can actually train such patches. We calculate gradients for the input, and update our adversarial input correspondingly. We do not calculate a gradient for every pixel. Instead, we replace parts of the input image with our patch and then calculate the gradients just for our patch. Secondly, we don't just do it for one image, but we want the patch to work with any possible image. Hence, we have a whole training loop where we train the patch using SGD. Lastly, image patches are usually designed to make the model predict a specific class, not just any other arbitrary class except the true label. For instance, we can try to create a patch for the class "toaster" and train the patch so that our pretrained model predicts the class "toaster" for any image with the patch in it.

Brown et al. randomly rotated and scaled the patch during training before placing it at a random position in an input image. This makes the patch more robust to small changes and is necessary if we want to fool a neural network in a real-world application.

This tutorial only shows how to make the patch robust to the location in the image.

Here is where you could:

- Randomly rotate patch
- Randomly scale the patch
- Improve random location of patch in the image

Note -- Instead of trying to make the patch more robust to it's location in an image, I tried to constrict the patch outputs to be close to black / white. So, my changes are not in the place_patch function, but in the patch_forward and training loop functions below.

My reason for constraining the patch as much as possible is so that I can hopefully recreat the patch by hand using embroidery thread. Since it would be basically impossible to match all of the colors generated in a non-constrained patch, black & white / greyscale would make the task more do-able.

Additionally I tried to generate patches of size 16 x 16, however they never reached any meaningful accuracy.

```
def place_patch(img, patch):
    for i in range(img.shape[0]):
        h_offset = np.random.randint(0,img.shape[2]-patch.shape[1]-1)
        w_offset = np.random.randint(0,img.shape[3]-patch.shape[2]-1)
        img[i,:,h_offset:h_offset+patch.shape[1],w_offset:w_offset+patch.shape[2]] = patch_forward(patch)
    return img
```

The patch itself will be an `nn.Parameter` whose values are in the range between $-\infty$ and ∞. Images are, however, naturally limited in their range, and thus we write a small function that maps the parameter into the image value range of ImageNet:

Comments Initially I tried to constrain the patch to be exactly black & white by rounding pixel values to either 0 or 1. This proved to be a problem, I believe due to the fact that the optimizer uses gradient descent, which requires smooth values to differentiate.

```
TENSOR_MEANS, TENSOR_STD = torch.FloatTensor(NORM_MEAN)[:,None,None], torch.FloatTensor(NORM_STD)[:,None,None]
def patch_forward(patch):
    # Map patch values from [-infty,infty] to ImageNet min and max
    patch = (torch.tanh(patch) + 1 - 2 * TENSOR_MEANS) / (2 * TENSOR_STD)

    #map patch values to 0 or 1
    #patch = (patch > 0.5).float()

    return patch
```

Before looking at the actual training code, we can write a small evaluation function. We evaluate the success of a patch by how many times we were able to fool the network into predicting our target class. A simple function for this is implemented below.

```
def eval_patch(model, patch, val_loader, target_class):
    model.eval()
    tp, tp_5, counter = 0., 0., 0.
    with torch.no_grad():
        for img, img_labels in tqdm(val_loader, desc="Validating...", leave=False):
            # For stability, place the patch at 4 random locations per image, and average the performance
            for _ in range(4):
                patch_img = place_patch(img, patch)
                patch_img = patch_img.to(device)
                img_labels = img_labels.to(device)
                pred = model(patch_img)
                # In the accuracy calculation, we need to exclude the images that are of our target class
                # as we would not "fool" the model into predicting those
                tp += torch.logical_and(pred.argmax(dim=-1) == target_class, img_labels != target_class).sum()
                tp_5 += torch.logical_and((pred.topk(5, dim=-1)[1] == target_class).any(dim=-1), img_labels != targe
                counter += (img_labels != target_class).sum()
    acc = tp/counter
    top5 = tp_5/counter
    return acc, top5
```

Finally, we can look at the training loop. Given a model to fool, a target class to design the patch for, and a size k of the patch in the number of pixels, we first start by creating a parameter of size $3 \times k \times k$. These are the only parameters we will train, and the network itself remains untouched. We use a simple SGD optimizer with momentum to minimize the classification loss of the model given the patch in the image. While we first start with a very high loss due to the good initial performance of the network, the loss quickly decreases once we start changing the patch. In the end, the patch will represent patterns that are characteristic of the class. For instance, if we would want the model to predict a "goldfish" in every image, we would expect the pattern to look somewhat like a goldfish. Over the iterations, the model finetunes the pattern and, hopefully, achieves a high fooling accuracy.

Note: I ended up making my final changes in just the training loop of the patch_attack() function. I changed the number of color channels in the patch parameter to 1 (from 3), which in theory only constrains the patches to greyscale, rather than purely black & white pixels.

I was not confident that this would be good enough for my purposes, but after generating a couple of test patches it appears that they still receive decent top 5 accuracy (up to 99% for 64 x 64). Strangely, after inspecting the pixels it appears that the 16 x 16 and 32 x 32 size patches ended up using only 2 colors. The 64 x 64 patch had some level of 'shading' between the two colors, but I was never going to be able to hand-stich a 64 x 64 patch in a reasonable amount of time so this was fine with me.

```
def patch_attack(model, target_class, patch_size=64, num_epochs=5):
    # Leave a small set of images out to check generalization
    # In most of our experiments, the performance on the hold-out data points
    # was as good as on the training set. Overfitting was little possible due
    # to the small size of the patches.
    train_set, val_set = torch.utils.data.random_split(dataset, [4500, 500])
    train_loader = data.DataLoader(train_set, batch_size=32, shuffle=True, drop_last=True, num_workers=8)
    val_loader = data.DataLoader(val_set, batch_size=32, shuffle=False, drop_last=False, num_workers=4)

    # Create parameter and optimizer
    if not isinstance(patch_size, tuple):
        patch_size = (patch_size, patch_size)

    #change channel number to 1 for greyscale
    patch = nn.Parameter(torch.zeros(1, patch_size[0], patch_size[1]), requires_grad=True)
    optimizer = torch.optim.SGD([patch], lr=1e-1, momentum=0.8)
    loss_module = nn.CrossEntropyLoss()

    # Training loop
    for epoch in range(num_epochs):
        t = tqdm(train_loader, leave=False)
        for img, _ in t:
            img = place_patch(img, patch)
            img = img.to(device)
            pred = model(img)
            labels = torch.zeros(img.shape[0], device=pred.device, dtype=torch.long).fill_(target_class)
            loss = loss_module(pred, labels)
            optimizer.zero_grad()
            loss.mean().backward()
            optimizer.step()
            t.set_description(f"Epoch {epoch}, Loss: {loss.item():4.2f}")
```

```
    # Final validation
    acc, top5 = eval_patch(model, patch, val_loader, target_class)

    return patch.data, {"acc": acc.item(), "top5": top5.item()}
```

To get some experience with what to expect from an adversarial patch attack, we want to train multiple patches for different classes. As the training of a patch can take one or two minutes on a GPU, we have provided a couple of pre-trained patches including their results on the full dataset. The results are saved in a JSON file, which is loaded below.

```
# Load evaluation results of the pretrained patches
json_results_file = os.path.join(CHECKPOINT_PATH, "patch_results.json")
json_results = {}
if os.path.isfile(json_results_file):
    with open(json_results_file, "r") as f:
        json_results = json.load(f)

# If you train new patches, you can save the results via calling this function
def save_results(patch_dict):
    result_dict = {cname: {psize: [t.item() if isinstance(t, torch.Tensor) else t
                                   for t in patch_dict[cname][psize]["results"]]
                           for psize in patch_dict[cname]}
                   for cname in patch_dict}
    with open(os.path.join(CHECKPOINT_PATH, "patch_results.json"), "w") as f:
        json.dump(result_dict, f, indent=4)
```

Additionally, we implement a function to train and evaluate patches for a list of classes and patch sizes. The pretrained patches include the classes *toaster*, *goldfish*, *school bus*, *lipstick*, and *pineapple*. We chose the classes arbitrarily to cover multiple domains (animals, vehicles, fruits, devices, etc.). We trained each class for three different patch sizes: 32×32 pixels, 48×48 pixels, and 64×64 pixels. We can load them in the two cells below.

```
def get_patches(class_names, patch_sizes):
    result_dict = dict()

    # Loop over all classes and patch sizes
    for name in class_names:
        result_dict[name] = dict()
        for patch_size in patch_sizes:
            c = label_names.index(name)
            file_name = os.path.join(CHECKPOINT_PATH, f"{name}_{patch_size}_patch.pt")
            # Load patch if pretrained file exists, otherwise start training
            if not os.path.isfile(file_name):
                patch, val_results = patch_attack(pretrained_model, target_class=c, patch_size=patch_size, num_epoch
                print(f"Validation results for {name} and {patch_size}:", val_results)
                torch.save(patch, file_name)
            else:
                patch = torch.load(file_name)
            # Load evaluation results if exist, otherwise manually evaluate the patch
            if name in json_results:
                results = json_results[name][str(patch_size)]
            else:
                results = eval_patch(pretrained_model, patch, data_loader, target_class=c)

            patch = (patch > 0.5).float()

            results = eval_patch(pretrained_model, patch, data_loader, target_class=c)

            # Store results and the patches in a dict for better access
            result_dict[name][patch_size] = {
                "results": results,
                "patch": patch
            }

    return result_dict
```

Feel free to add any additional classes and/or patch sizes.

Double-click (or enter) to edit

```
#reduce number of classes for speed
class_names = ['goldfish', 'school bus', 'bow tie', 'coffee mug', 'safe']
```

```
class_names = ['goldfish', 'school bus', 'bow tie', 'coffee mug', 'safe']


# class_names = ['toaster', 'goldfish', 'school bus', 'lipstick', 'pineapple', 'digital clock', 'hen', 'bowtie']

#reduce to just 32 x 32 for speed
patch_sizes = [16, 32, 64]
# patch_sizes = [32, 48, 64]

patch_dict = get_patches(class_names, patch_sizes)
save_results(patch_dict) # Uncomment if you add new class names and want to save the new results
```

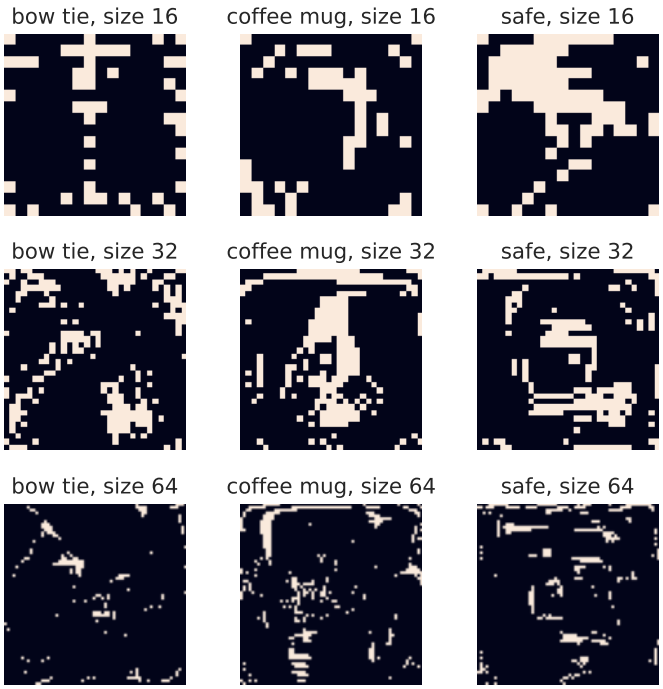
```
/usr/local/lib/python3.12/dist-packages/torch/utils/data/dataloader.py:627: UserWarning: This DataLoader will create
  warnings.warn(
/usr/local/lib/python3.12/dist-packages/torch/utils/data/dataloader.py:627: UserWarning: This DataLoader will create
  warnings.warn(
Validation results for bow tie and 16: {'acc': 0.0, 'top5': 0.006000000052154064}
Validation results for bow tie and 32: {'acc': 0.13527053594589233, 'top5': 0.3336673378944397}
Validation results for bow tie and 64: {'acc': 0.9884999990463257, 'top5': 0.9994999766349792}
Validation results for coffee mug and 16: {'acc': 0.0, 'top5': 0.0030060119461268187}
Validation results for coffee mug and 32: {'acc': 0.30611222982406616, 'top5': 0.6307615041732788}
Validation results for coffee mug and 64: {'acc': 0.8855000138282776, 'top5': 0.9934999942779541}
Validation results for safe and 16: {'acc': 0.0075150299817323685, 'top5': 0.044088177382946014}
Validation results for safe and 32: {'acc': 0.018537074327468872, 'top5': 0.2394789606332779}
Validation results for safe and 64: {'acc': 0.8289999961853027, 'top5': 0.9585000276565552}
```

Before looking at the quantitative results, we can actually visualize the patches.

```
def show_patches():
    fig, ax = plt.subplots(len(patch_sizes), len(class_names), figsize=(len(class_names)*2.2, len(patch_sizes)*2.2))
    for c_idx, cname in enumerate(class_names):
        for p_idx, psize in enumerate(patch_sizes):
            patch = patch_dict[cname][psize]["patch"]
            patch = (torch.tanh(patch) + 1) / 2 # Parameter to pixel values
            patch = patch.cpu().permute(1, 2, 0).numpy()
            patch = np.clip(patch, a_min=0.0, a_max=1.0)


            #Added some logic for adjusting sizing with Gemini oct 31. (Through else statement)
            # Adjust indexing based on the shape of ax
            if len(patch_sizes) == 1 and len(class_names) == 1:
                current_ax = ax
            elif len(patch_sizes) == 1:
                current_ax = ax[c_idx]
            elif len(class_names) == 1:
                current_ax = ax[p_idx]
            else:
                current_ax = ax[p_idx][c_idx]

            current_ax.imshow(patch)
            current_ax.set_title(f"{cname}, size {psize}")
            current_ax.axis('off')
    fig.subplots_adjust(hspace=0.3, wspace=0.3)
    plt.show()
show_patches()
```



We can see a clear difference between patches of different classes and sizes. In the smallest size, 32×32 pixels, some of the patches clearly resemble their class. For instance, the goldfish patch clearly shows a goldfish. The eye and the color are very characteristic of the class. Overall, the patches with 32 pixels have very strong colors that are typical for their class (yellow school bus, pink lipstick, greenish pineapple). The larger the patch becomes, the more stretched the pattern becomes. For the goldfish, we can still spot regions that might represent eyes and the characteristic orange color, but it is not clearly a single fish anymore. For the pineapple, we might interpret the top part of the image as the leaves of pineapple fruit, but it is more abstract than our small patches. Nevertheless, we can easily spot the alignment of the patch to class, even on the largest scale.

Let's now look at the quantitative results.

```
%%html
<!-- Some HTML code to increase font size in the following table -->
<style>
th {font-size: 120%;}
td {font-size: 120%;}
</style>
```

```
import tabulate
from IPython.display import display, HTML

def show_table(top_1=True):
    i = 0 if top_1 else 1
    table = [[name] + [f"{(100.0 * patch_dict[name][psize]['results'][i]):4.2f}%" for psize in patch_sizes]
             for name in class_names]
    display(HTML(tabulate.tabulate(table, tablefmt='html', headers=["Class name"] + [f"Patch size {psize}x{psize}" f
```

First, we will create a table of top-1 accuracy, meaning that how many images have been classified with the target class as highest prediction?

```
show_table(top_1=True)
```

Class name	Patch size 16x16	Patch size 32x32	Patch size 64x64
bow tie	0.03%	0.12%	0.02%
coffee mug	0.02%	0.02%	0.36%
safe	0.06%	0.11%	0.10%

The clear trend, that we would also have expected, is that the larger the patch, the easier it is to fool the model. For the largest patch size of 64×64, we are able to fool the model on almost all images, despite the patch covering only 8% of the image. The smallest patch

actually covers 2% of the image, which is almost neglectable. Still, the fooling accuracy is quite remarkable. A large variation can be however seen across classes. While *school bus* and *pineapple* seem to be classes that were easily predicted, *toaster* and *lipstick* seem to be much harder for creating a patch. It is hard to intuitively explain why our patches underperform on those classes. Nonetheless, a fooling accuracy of >40% is still very good for such a tiny patch.

Let's also take a look at the top-5 accuracy:

```
show_table(top_1=False)
```

Class name	Patch size 16x16	Patch size 32x32	Patch size 64x64
bow tie	0.37%	0.83%	0.40%
coffee mug	0.34%	0.47%	2.00%
safe	0.75%	1.05%	0.93%

We see a very similar pattern across classes and patch sizes. The patch size 64 obtains >99.7% top-5 accuracy for any class, showing that we can almost fool the network on any image. A top-5 accuracy of >70% for the hard classes and small patches is still impressive and shows how vulnerable deep CNNs are to such attacks.

Finally, let's create some example visualizations of the patch attack in action.

```
def perform_patch_attack(patch):
    patch_batch = exmp_batch.clone()
    patch_batch = place_patch(patch_batch, patch)
    with torch.no_grad():
        patch_preds = pretrained_model(patch_batch.to(device))
    for i in range(1,17,5):
        show_prediction(patch_batch[i], label_batch[i], patch_preds[i])
```