In [ ]:
```
#COMMENT IF NOT USING COLAB VM

# This mounts your Google Drive to the Colab VM.
from google.colab import drive
drive.mount('/content/drive')

# TODO: Enter the foldername in your Drive where you have saved the unzipped
# assignment folder, e.g. 'DeepLearning/assignments/assignment5/'
FOLDERNAME = "CS6353/Assignments/assignment5/assignment5/"
assert FOLDERNAME is not None, "[!] Enter the foldername."

# Now that we've mounted your Drive, this ensures that
# the Python interpreter of the Colab VM can load
# python files from within it.
import sys
sys.path.append('/content/drive/My Drive/{}'.format(FOLDERNAME))

# This downloads the CIFAR-10 dataset to your Drive
# if it doesn't already exist.
%cd /content/drive/My\ Drive/$FOLDERNAME/cs6353/datasets/
!bash get_datasets.sh
%cd /content/drive/My\ Drive/$FOLDERNAME
```

```
Mounted at /content/drive
/content/drive/My Drive/CS6353/Assignments/assignment5/assignment5/cs6353/datasets
--2024-11-27 09:53:35--  http://supermoe.cs.umass.edu/682/asgns/coco_captioning.zip
Resolving supermoe.cs.umass.edu (supermoe.cs.umass.edu)... 128.119.244.95
Connecting to supermoe.cs.umass.edu (supermoe.cs.umass.edu)|128.119.244.95|:80... co
nnected.
HTTP request sent, awaiting response... 200 OK
Length: 1035210391 (987M) [application/zip]
Saving to: ‘coco_captioning.zip’

coco_captioning.zip 100%[===================>] 987.25M  3.66MB/s    in 4m 50s

2024-11-27 09:58:25 (3.40 MB/s) - ‘coco_captioning.zip’ saved [1035210391/103521039
1]

Archive:  coco_captioning.zip
replace coco_captioning/coco2014_captions.h5? [y]es, [n]o, [A]ll, [N]one, [r]ename:
y
  inflating: coco_captioning/coco2014_captions.h5
replace coco_captioning/coco2014_vocab.json? [y]es, [n]o, [A]ll, [N]one, [r]ename: y
  inflating: coco_captioning/coco2014_vocab.json
replace coco_captioning/train2014_images.txt? [y]es, [n]o, [A]ll, [N]one, [r]ename:
y
  inflating: coco_captioning/train2014_images.txt
replace coco_captioning/train2014_urls.txt? [y]es, [n]o, [A]ll, [N]one, [r]ename: y
  inflating: coco_captioning/train2014_urls.txt
replace coco_captioning/train2014_vgg16_fc7.h5? [y]es, [n]o, [A]ll, [N]one, [r]enam
e: y
  inflating: coco_captioning/train2014_vgg16_fc7.h5  y

replace coco_captioning/train2014_vgg16_fc7_pca.h5? [y]es, [n]o, [A]ll, [N]one, [r]e
name:   inflating: coco_captioning/train2014_vgg16_fc7_pca.h5
replace coco_captioning/val2014_images.txt? [y]es, [n]o, [A]ll, [N]one, [r]ename: A
  inflating: coco_captioning/val2014_images.txt
  inflating: coco_captioning/val2014_urls.txt
  inflating: coco_captioning/val2014_vgg16_fc7.h5
  inflating: coco_captioning/val2014_vgg16_fc7_pca.h5
--2024-11-27 10:03:51--  http://supermoe.cs.umass.edu/682/asgns/squeezenet_tf.zip
Resolving supermoe.cs.umass.edu (supermoe.cs.umass.edu)... 128.119.244.95
Connecting to supermoe.cs.umass.edu (supermoe.cs.umass.edu)|128.119.244.95|:80... co
nnected.
HTTP request sent, awaiting response... 200 OK
Length: 9202140 (8.8M) [application/zip]
Saving to: ‘squeezenet_tf.zip’

squeezenet_tf.zip   100%[===================>]   8.78M  3.57MB/s    in 2.5s

2024-11-27 10:03:53 (3.57 MB/s) - ‘squeezenet_tf.zip’ saved [9202140/9202140]

Archive:  squeezenet_tf.zip
replace squeezenet.ckpt.data-00000-of-00001? [y]es, [n]o, [A]ll, [N]one, [r]ename: y
  inflating: squeezenet.ckpt.data-00000-of-00001
replace squeezenet.ckpt.index? [y]es, [n]o, [A]ll, [N]one, [r]ename: A
  inflating: squeezenet.ckpt.index
  inflating: squeezenet.ckpt.meta
--2024-11-27 10:04:40--  http://supermoe.cs.umass.edu/682/asgns/imagenet_val_25.npz
```

```
Resolving supermoe.cs.umass.edu (supermoe.cs.umass.edu)... 128.119.244.95
Connecting to supermoe.cs.umass.edu (supermoe.cs.umass.edu)|128.119.244.95|:80... co
nnected.
HTTP request sent, awaiting response... 200 OK
Length: 3940548 (3.8M)
Saving to: 'imagenet_val_25.npz.2'

imagenet_val_25.npz 100%[===================>]   3.76M  4.07MB/s    in 0.9s

2024-11-27 10:04:42 (4.07 MB/s) - 'imagenet_val_25.npz.2' saved [3940548/3940548]

/content/drive/My Drive/CS6353/Assignments/assignment5/assignment5
```

In [ ]:

```
# #UNCOMMENT IF USING CADE
# import os
# ##### Request a GPU #####
# ## This function locates an available gpu for usage. In addition, this function r
# ## memory space exclusively for your account. The memory reservation prevents the
# ## speed when other users try to allocate memory on the same gpu in the shared sy
# ## Note: If you use your own system which has a GPU with less than 4GB of memory,
# ## specified mimimum memory.
# def define_gpu_to_use(minimum_memory_mb = 3500):
#     thres_memory = 600 #
#     gpu_to_use = None
#     try:
#         os.environ['CUDA_VISIBLE_DEVICES']
#         print('GPU already assigned before: ' + str(os.environ['CUDA_VISIBLE_DEVI
#         return
#     except:
#         pass

#     for i in range(16):
#         free_memory = !nvidia-smi --query-gpu=memory.free -i $i --format=csv,noun
#         if free_memory[0] == 'No devices were found':
#             break
#         free_memory = int(free_memory[0])

#         if free_memory>minimum_memory_mb-thres_memory:
#             gpu_to_use = i
#             break

#     if gpu_to_use is None:
#         print('Could not find any GPU available with the required free memory of
#               + 'MB. Please use a different system for this assignment.')
#     else:
#         os.environ['CUDA_VISIBLE_DEVICES'] = str(gpu_to_use)
#         print('Chosen GPU: ' + str(gpu_to_use))

# ## Request a gpu and reserve the memory space
# define_gpu_to_use(4000)
```

Network Visualization (PyTorch)

In this notebook we will explore the use of *image gradients* for generating new images.

When training a model, we define a loss function which measures our current unhappiness with the model's performance; we then use backpropagation to compute the gradient of the loss with respect to the model parameters, and perform gradient descent on the model parameters to minimize the loss.

Here we will do something slightly different. We will start from a convolutional neural network model which has been pretrained to perform image classification on the ImageNet dataset. We will use this model to define a loss function which quantifies our current unhappiness with our image, then use backpropagation to compute the gradient of this loss with respect to the pixels of the image. We will then keep the model fixed, and perform gradient descent *on the image* to synthesize a new image which minimizes the loss.

In this notebook we will explore three techniques for image generation:

1. **Saliency Maps**: Saliency maps are a quick way to tell which part of the image influenced the classification decision made by the network.
2. **Fooling Images**: We can perturb an input image so that it appears the same to humans, but will be misclassified by the pretrained network.
3. **Class Visualization**: We can synthesize an image to maximize the classification score of a particular class; this can give us some sense of what the network is looking for when it classifies images of that class.

This notebook uses **PyTorch**;

In [ ]:
```
import torch
import torchvision
import torchvision.transforms as T
import random
import numpy as np
from scipy.ndimage import gaussian_filter1d
import matplotlib.pyplot as plt
from cs6353.image_utils import SQUEEZENET_MEAN, SQUEEZENET_STD
from PIL import Image

%matplotlib inline
plt.rcParams['figure.figsize'] = (10.0, 8.0) # set default size of plots
plt.rcParams['image.interpolation'] = 'nearest'
plt.rcParams['image.cmap'] = 'gray'
```

Helper Functions

Our pretrained model was trained on images that had been preprocessed by subtracting the per-color mean and dividing by the per-color standard deviation. We define a few helper functions for performing and undoing this preprocessing. You don't need to do anything in this cell.

In [ ]:
```
def preprocess(img, size=224):
    transform = T.Compose([
        T.Resize(size),
        T.ToTensor(),
        T.Normalize(mean=SQUEEZENET_MEAN.tolist(),
                    std=SQUEEZENET_STD.tolist()),
        T.Lambda(lambda x: x[None]),
    ])
    return transform(img)

def deprocess(img, should_rescale=True):
    transform = T.Compose([
        T.Lambda(lambda x: x[0]),
        T.Normalize(mean=[0, 0, 0], std=(1.0 / SQUEEZENET_STD).tolist()),
        T.Normalize(mean=(-SQUEEZENET_MEAN).tolist(), std=[1, 1, 1]),
        T.Lambda(rescale) if should_rescale else T.Lambda(lambda x: x),
        T.ToPILImage(),
    ])
    return transform(img)

def rescale(x):
    low, high = x.min(), x.max()
    x_rescaled = (x - low) / (high - low)
    return x_rescaled

def blur_image(X, sigma=1):
    X_np = X.cpu().clone().numpy()
    X_np = gaussian_filter1d(X_np, sigma, axis=2)
    X_np = gaussian_filter1d(X_np, sigma, axis=3)
    X.copy_(torch.Tensor(X_np).type_as(X))
    return X
```

Pretrained Model

For all of our image generation experiments, we will start with a convolutional neural network which was pretrained to perform image classification on ImageNet. We can use any model here, but for the purposes of this assignment we will use SqueezeNet [1], which achieves accuracies comparable to AlexNet but with a significantly reduced parameter count and computational complexity.

Using SqueezeNet rather than AlexNet or VGG or ResNet means that we can easily perform all image generation experiments on CPU.

[1] Iandola et al, "SqueezeNet: AlexNet-level accuracy with 50x fewer parameters and < 0.5MB model size", arXiv 2016

In [ ]:
```
# Download and load the pretrained SqueezeNet model.
model = torchvision.models.squeezenet1_1(pretrained=True)

# We don't want to train the model, so tell PyTorch not to compute gradients
```

```
# with respect to model parameters.
for param in model.parameters():
    param.requires_grad = False

# you may see warning regarding initialization deprecated, that's fine, please cont
```

```
/usr/local/lib/python3.10/dist-packages/torchvision/models/_utils.py:208: UserWarnin
g: The parameter 'pretrained' is deprecated since 0.13 and may be removed in the fut
ure, please use 'weights' instead.
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/torchvision/models/_utils.py:223: UserWarnin
g: Arguments other than a weight enum or `None` for 'weights' are deprecated since
0.13 and may be removed in the future. The current behavior is equivalent to passing
`weights=SqueezeNet1_1_Weights.IMAGENET1K_V1`. You can also use `weights=SqueezeNet1
_1_Weights.DEFAULT` to get the most up-to-date weights.
  warnings.warn(msg)
Downloading: "https://download.pytorch.org/models/squeezenet1_1-b8a52dc0.pth" to /ro
ot/.cache/torch/hub/checkpoints/squeezenet1_1-b8a52dc0.pth
100%|██████████| 4.73M/4.73M [00:00<00:00, 26.5MB/s]
```

Load some ImageNet images

We have provided a few example images from the validation set of the ImageNet ILSVRC 2012 Classification dataset. To download these images, descend into `cs6353/datasets/` and run `get_imagenet_val.sh`.

Since they come from the validation set, our pretrained model did not see these images during training.

Run the following cell to visualize some of these images, along with their ground-truth labels.

In [ ]:
```
from cs6353.data_utils import load_imagenet_val
X, y, class_names = load_imagenet_val(num=5)

plt.figure(figsize=(12, 6))
for i in range(5):
    plt.subplot(1, 5, i + 1)
    plt.imshow(X[i])
    plt.title(class_names[y[i]])
    plt.axis('off')
plt.gcf().tight_layout()
```

Saliency Maps

Using this pretrained model, we will compute class saliency maps as described in Section 3.1 of [2].

A **saliency map** tells us the degree to which each pixel in the image affects the classification score for that image. To compute it, we compute the gradient of the unnormalized score corresponding to the correct class (which is a scalar) with respect to the pixels of the image. If the image has shape `(3, H, W)` then this gradient will also have shape `(3, H, W)`; for each pixel in the image, this gradient tells us the amount by which the classification score will change if the pixel changes by a small amount. To compute the saliency map, we take the absolute value of this gradient, then take the maximum value over the 3 input channels; the final saliency map thus has shape `(H, W)` and all entries are nonnegative.

[2] Karen Simonyan, Andrea Vedaldi, and Andrew Zisserman. "Deep Inside Convolutional Networks: Visualising Image Classification Models and Saliency Maps", ICLR Workshop 2014.

Hint: PyTorch `gather` method

Recall in Assignment 1 you needed to select one element from each row of a matrix; if `s` is an numpy array of shape `(N, C)` and `y` is a numpy array of shape `(N, )` containing integers `0 <= y[i] < C`, then `s[np.arange(N), y]` is a numpy array of shape `(N,)` which selects one element from each element in `s` using the indices in `y`.

In PyTorch you can perform the same operation using the `gather()` method. If `s` is a PyTorch Tensor of shape `(N, C)` and `y` is a PyTorch Tensor of shape `(N,)` containing longs in the range `0 <= y[i] < C`, then

`s.gather(1, y.view(-1, 1)).squeeze()`

will be a PyTorch Tensor of shape `(N,)` containing one entry from each row of `s`, selected according to the indices in `y`.

run the following cell to see an example.

You can also read the documentation for the gather method and the squeeze method.

In [ ]:
```
# Example of using gather to select one entry from each row in PyTorch
def gather_example():
    N, C = 4, 5
    s = torch.randn(N, C)
    y = torch.LongTensor([1, 2, 1, 3])
    print(s)
    print(y)
```

```
    print(s.gather(1, y.view(-1, 1)).squeeze())
gather_example()
```

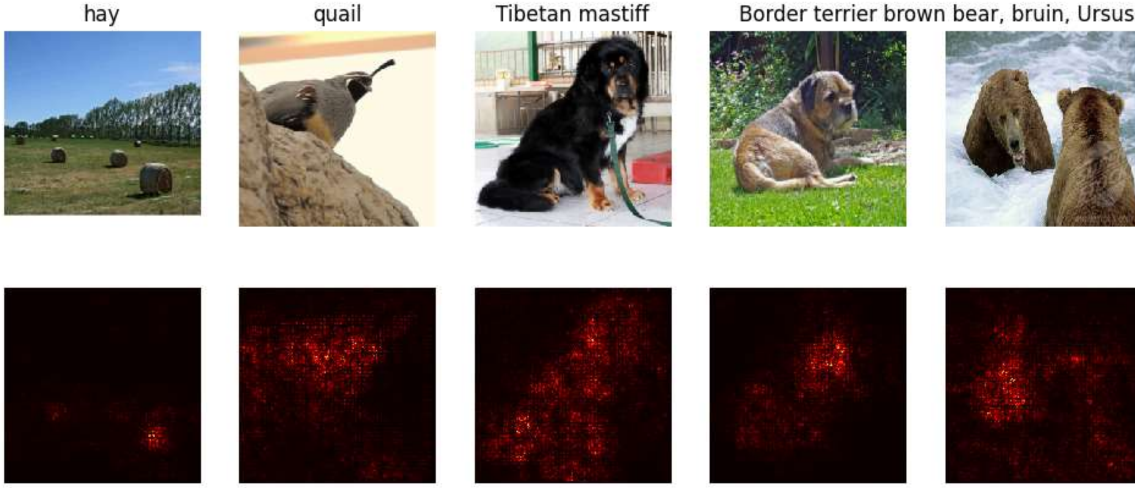
```
tensor([[-0.3255, -0.4475,  1.6392,  1.8355,  0.1879],
        [-1.6643, -1.8245, -1.1639,  0.3177,  0.1512],
        [-1.0997, -1.6267,  0.1507, -0.1027,  0.3247],
        [-0.6965,  1.6366,  0.0670,  1.6660,  0.1202]])
tensor([1, 2, 1, 3])
tensor([-0.4475, -1.1639, -1.6267,  1.6660])
```

In [ ]:

```
def compute_saliency_maps(X, y, model):
    """
    Compute a class saliency map using the model for images X and labels y.

    Input:
    - X: Input images; Tensor of shape (N, 3, H, W)
    - y: Labels for X; LongTensor of shape (N,)
    - model: A pretrained CNN that will be used to compute the saliency map.

    Returns:
    - saliency: A Tensor of shape (N, H, W) giving the saliency maps for the input
    images.
    """
    # Make sure the model is in "test" mode
    model.eval()

    # Make input tensor require gradient
    X.requires_grad_()

    saliency = None
    ##############################################################################
    # TODO: Implement this function. Perform a forward and backward pass through #
    # the model to compute the gradient of the correct class score with respect  #
    # to each input image. You first want to compute the loss over the correct   #
    # scores (we'll combine losses across a batch by summing), and then compute  #
    # the gradients with a backward pass.                                        #
    ##############################################################################
    # Forward pass
    scores = model(X)
    target_scores = scores.gather(dim=1, index=y.view(-1, 1)).squeeze()

    # Backward pass
    gradient_weights = torch.ones_like(target_scores)
    target_scores.backward(gradient_weights)

    gradients = X.grad.data
    absolute_gradients = gradients.abs()
    saliency, _ = absolute_gradients.max(dim=1)
    ##############################################################################
    #                             END OF YOUR CODE                               #
    ##############################################################################
    return saliency
```

Once you have completed the implementation in the cell above, run the following to visualize some class saliency maps on our example images from the ImageNet validation set:

In [ ]:
```
def show_saliency_maps(X, y):
    # Convert X and y from numpy arrays to Torch Tensors
    X_tensor = torch.cat([preprocess(Image.fromarray(x)) for x in X], dim=0)
    y_tensor = torch.LongTensor(y)

    # Compute saliency maps for images in X
    saliency = compute_saliency_maps(X_tensor, y_tensor, model)

    # Convert the saliency map from Torch Tensor to numpy array and show images
    # and saliency maps together.
    saliency = saliency.numpy()
    N = X.shape[0]
    for i in range(N):
        plt.subplot(2, N, i + 1)
        plt.imshow(X[i])
        plt.axis('off')
        plt.title(class_names[y[i]])
        plt.subplot(2, N, N + i + 1)
        plt.imshow(saliency[i], cmap=plt.cm.hot)
        plt.axis('off')
        plt.gcf().set_size_inches(12, 5)
    plt.show()

show_saliency_maps(X, y)
```



INLINE QUESTION

A friend of yours suggests that in order to find an image that maximizes the correct score, we can perform gradient ascent on the input image, but instead of the gradient we can actually use the saliency map in each step to update the image. Is this assertion true? Why or why not?

Answer:

No, using the saliency map for gradient ascent instead of the raw gradient won't work because the saliency map loses important information needed for optimization. The raw gradient tells us the exact direction (positive or negative) to change each pixel in every channel (red, green, blue) to maximize the score for a specific class. On the other hand, the saliency map collapses this information into a single channel by taking the absolute value and the maximum across the RGB channels, which means it doesn't know which way (positive or negative) to update each pixel. If we used the saliency map, the updates would all be positive and biased toward just one channel per pixel, which would lead to unbalanced changes and likely cause pixel values to blow up without achieving the desired outcome. To properly generate images, we must use the raw gradient, which has the full directional information for all three channels.

Fooling Images

We can also use image gradients to generate "fooling images" as discussed in [3]. Given an image and a target class, we can perform gradient **ascent** over the image to maximize the target class, stopping when the network classifies the image as the target class. Implement the following function to generate fooling images.

[3] Szegedy et al, "Intriguing properties of neural networks", ICLR 2014

In [ ]:
```
def make_fooling_image(X, target_y, model):
    """
    Generate a fooling image that is close to X, but that the model classifies
    as target_y.

    Inputs:
    - X: Input image; Tensor of shape (1, 3, 224, 224)
    - target_y: An integer in the range [0, 1000)
    - model: A pretrained CNN

    Returns:
    - X_fooling: An image that is close to X, but that is classifed as target_y
    by the model.
    """
    # Initialize our fooling image to the input image, and make it require gradient
    X_fooling = X.clone()
    X_fooling = X_fooling.requires_grad_()

    learning_rate = 1
    ##############################################################################
    # TODO: Generate a fooling image X_fooling that the model will classify as   #
    # the class target_y. You should perform gradient ascent on the score of the #
    # target class, stopping when the model is fooled.                           #
    # When computing an update step, first normalize the gradient:               #
    #   dX = learning_rate * g / ||g||_2                                         #
    #                                                                            #
    # You should write a training loop.                                          #
    #                                                                            #
    # HINT: For most examples, you should be able to generate a fooling image    #
    # in fewer than 100 iterations of gradient ascent.                           #
```

```
    # You can print your progress over iterations to check your algorithm.       #
    ##############################################################################
    for iteration in range(100):
        scores = model(X_fooling)
        predicted_class = torch.argmax(scores, dim=1)

        if predicted_class == target_y:
            print(f"Model fooled at iteration {iteration}: Predicted {predicted_cla
            break
        else:
            scores[:, target_y].backward()
            gradient_norm = torch.norm(X_fooling.grad.data)
            normalized_gradient = X_fooling.grad.data / gradient_norm
            update_step = learning_rate * normalized_gradient
            X_fooling.data += update_step
            X_fooling.grad.data.zero_()
    ##############################################################################
    #                             END OF YOUR CODE                               #
    ##############################################################################
    return X_fooling
```

Run the following cell to generate a fooling image. You should ideally see at first glance no major difference between the original and fooling images, and the network should now make an incorrect prediction on the fooling one. However you should see a bit of random noise if you look at the 10x magnified difference between the original and fooling images. Feel free to change the `idx` variable to explore other images.

In [ ]:
```
idx = 0
target_y = 6

X_tensor = torch.cat([preprocess(Image.fromarray(x)) for x in X], dim=0)
X_fooling = make_fooling_image(X_tensor[idx:idx+1], target_y, model)

scores = model(X_fooling)
assert target_y == scores.data.max(1)[1][0].item(), 'The model is not fooled!'
```

```
Model fooled at iteration 9: Predicted 6, Target 6
```

After generating a fooling image, run the following cell to visualize the original image, the fooling image, as well as the difference between them.

In [ ]:
```
X_fooling_np = deprocess(X_fooling.clone())
X_fooling_np = np.asarray(X_fooling_np).astype(np.uint8)

plt.subplot(1, 4, 1)
plt.imshow(X[idx])
plt.title(class_names[y[idx]])
plt.axis('off')

plt.subplot(1, 4, 2)
plt.imshow(X_fooling_np)
plt.title(class_names[target_y])
plt.axis('off')
```

```
plt.subplot(1, 4, 3)
X_pre = preprocess(Image.fromarray(X[idx]))
diff = np.asarray(deprocess(X_fooling - X_pre, should_rescale=False))
plt.imshow(diff)
plt.title('Difference')
plt.axis('off')

plt.subplot(1, 4, 4)
diff = np.asarray(deprocess(10 * (X_fooling - X_pre), should_rescale=False))
plt.imshow(diff)
plt.title('Magnified difference (10x)')
plt.axis('off')

plt.gcf().set_size_inches(12, 5)
plt.show()
```

Class visualization

By starting with a random noise image and performing gradient ascent on a target class, we can generate an image that the network will recognize as the target class. This idea was first presented in [2]; [3] extended this idea by suggesting several regularization techniques that can improve the quality of the generated image.

Concretely, let I be an image and let y be a target class. Let $s_y(I)$ be the score that a convolutional network assigns to the image I for class y; note that these are raw unnormalized scores, not class probabilities. We wish to generate an image I^* that achieves a high score for the class y by solving the problem

$$I^* = \arg\max_I (s_y(I) - R(I))$$

where R is a (possibly implicit) regularizer (note the sign of $R(I)$ in the argmax: we want to minimize this regularization term). We can solve this optimization problem using gradient ascent, computing gradients with respect to the generated image. We will use (explicit) L2 regularization of the form

$$R(I) = \lambda \|I\|_2^2$$

and implicit regularization as suggested by [3] by periodically blurring the generated image. We can solve this problem using gradient ascent on the generated image.

In the cell below, complete the implementation of the `create_class_visualization` function.

[2] Karen Simonyan, Andrea Vedaldi, and Andrew Zisserman. "Deep Inside Convolutional Networks: Visualising Image Classification Models and Saliency Maps", ICLR Workshop 2014.

[3] Yosinski et al, "Understanding Neural Networks Through Deep Visualization", ICML 2015 Deep Learning Workshop

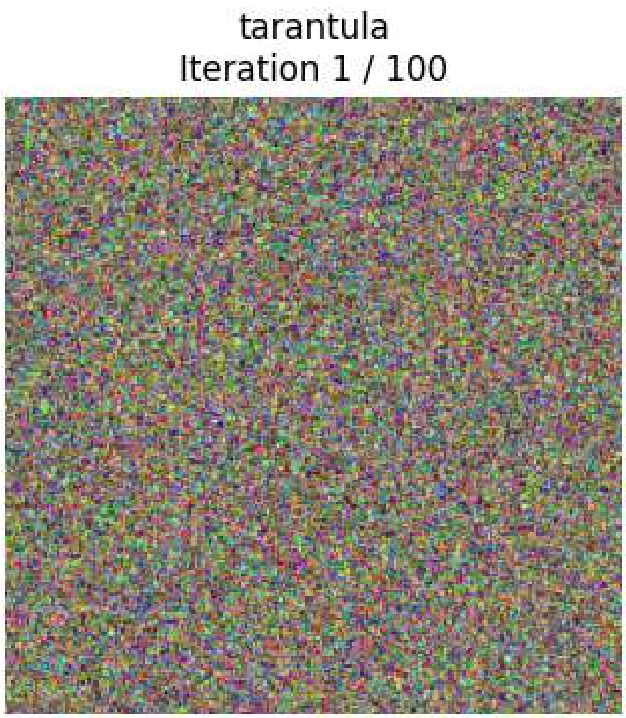
In [ ]:
```
def jitter(X, ox, oy):
    """
    Helper function to randomly jitter an image.

    Inputs
    - X: PyTorch Tensor of shape (N, C, H, W)
    - ox, oy: Integers giving number of pixels to jitter along W and H axes

    Returns: A new PyTorch Tensor of shape (N, C, H, W)
    """
    if ox != 0:
        left = X[:, :, :, :-ox]
        right = X[:, :, :, -ox:]
        X = torch.cat([right, left], dim=3)
    if oy != 0:
        top = X[:, :, :-oy]
        bottom = X[:, :, -oy:]
        X = torch.cat([bottom, top], dim=2)
    return X
```

In [ ]:
```
def create_class_visualization(target_y, model, dtype, **kwargs):
    """
    Generate an image to maximize the score of target_y under a pretrained model.

    Inputs:
    - target_y: Integer in the range [0, 1000) giving the index of the class
    - model: A pretrained CNN that will be used to generate the image
    - dtype: Torch datatype to use for computations

    Keyword arguments:
    - l2_reg: Strength of L2 regularization on the image
    - learning_rate: How big of a step to take
    - num_iterations: How many iterations to use
    - blur_every: How often to blur the image as an implicit regularizer
    - max_jitter: How much to gjitter the image as an implicit regularizer
    - show_every: How often to show the intermediate result
    """
    model.type(dtype)
    l2_reg = kwargs.pop('l2_reg', 1e-3)
    learning_rate = kwargs.pop('learning_rate', 25)
    num_iterations = kwargs.pop('num_iterations', 100)
    blur_every = kwargs.pop('blur_every', 10)
    max_jitter = kwargs.pop('max_jitter', 16)
    show_every = kwargs.pop('show_every', 25)
```

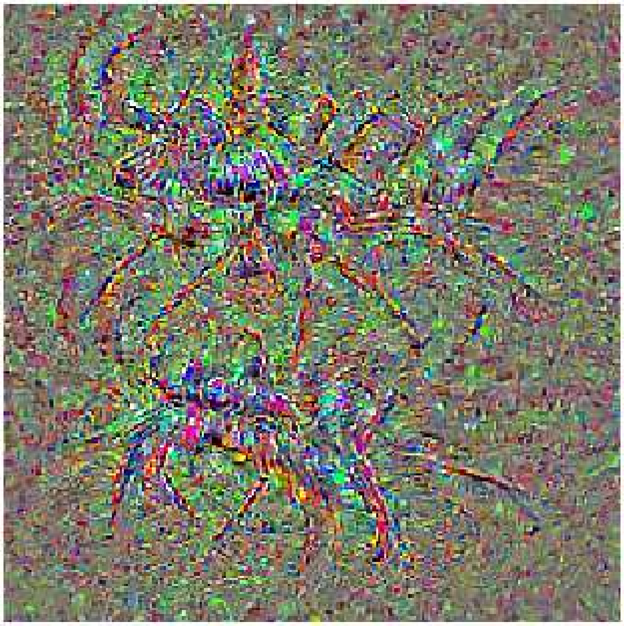
```
    # Randomly initialize the image as a PyTorch Tensor, and make it requires gradi
    img = torch.randn(1, 3, 224, 224).mul_(1.0).type(dtype).requires_grad_()

    for t in range(num_iterations):
        # Randomly jitter the image a bit; this gives slightly nicer results
        ox, oy = random.randint(0, max_jitter), random.randint(0, max_jitter)
        img.data.copy_(jitter(img.data, ox, oy))

        ########################################################################
        # TODO: Use the model to compute the gradient of the score for the     #
        # class target_y with respect to the pixels of the image, and make a   #
        # gradient step on the image using the learning rate. Don't forget the #
        # L2 regularization term!                                              #
        # Be very careful about the signs of elements in your code.            #
        ########################################################################
        scores = model(img)

        img_norm = torch.norm(img)
        img_norm_squared = torch.square(img_norm)
        l2_penalty = l2_reg * img_norm_squared

        target_score = scores[:, target_y] - l2_penalty

        target_score.backward()

        img.data += learning_rate * img.grad.data

        img.grad.data.zero_()
        ########################################################################
        #                             END OF YOUR CODE                         #
        ########################################################################

        # Undo the random jitter
        img.data.copy_(jitter(img.data, -ox, -oy))

        # As regularizer, clamp and periodically blur the image
        for c in range(3):
            lo = float(-SQUEEZENET_MEAN[c] / SQUEEZENET_STD[c])
            hi = float((1.0 - SQUEEZENET_MEAN[c]) / SQUEEZENET_STD[c])
            img.data[:, c].clamp_(min=lo, max=hi)
        if t % blur_every == 0:
            blur_image(img.data, sigma=0.5)

        # Periodically show the image
        if t == 0 or (t + 1) % show_every == 0 or t == num_iterations - 1:
            plt.imshow(deprocess(img.data.clone().cpu()))
            class_name = class_names[target_y]
            plt.title('%s\nIteration %d / %d' % (class_name, t + 1, num_iterations)
            plt.gcf().set_size_inches(4, 4)
            plt.axis('off')
            plt.show()

    return deprocess(img.data.cpu())
```

Once you have completed the implementation in the cell above, run the following cell to generate an image of a Tarantula:

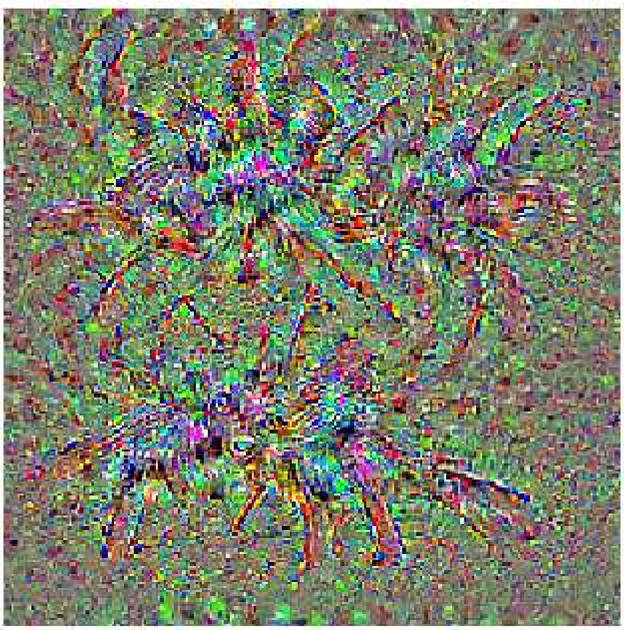
In [ ]:
```
dtype = torch.FloatTensor
# dtype = torch.cuda.FloatTensor # Uncomment this to use GPU
model.type(dtype)

target_y = 76 # Tarantula
# target_y = 78 # Tick
# target_y = 187 # Yorkshire Terrier
# target_y = 683 # Oboe
# target_y = 366 # Gorilla
# target_y = 604 # Hourglass
out = create_class_visualization(target_y, model, dtype)
```

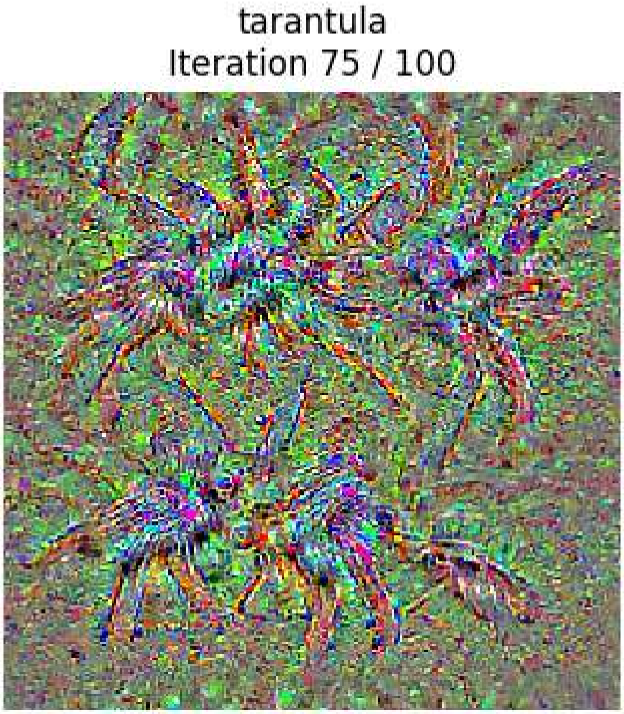


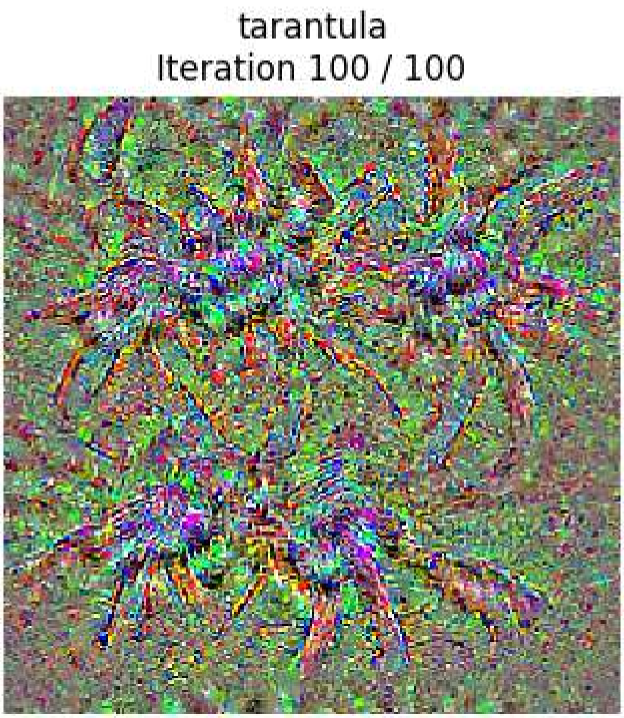
tarantula
Iteration 25 / 100



tarantula
Iteration 50 / 100







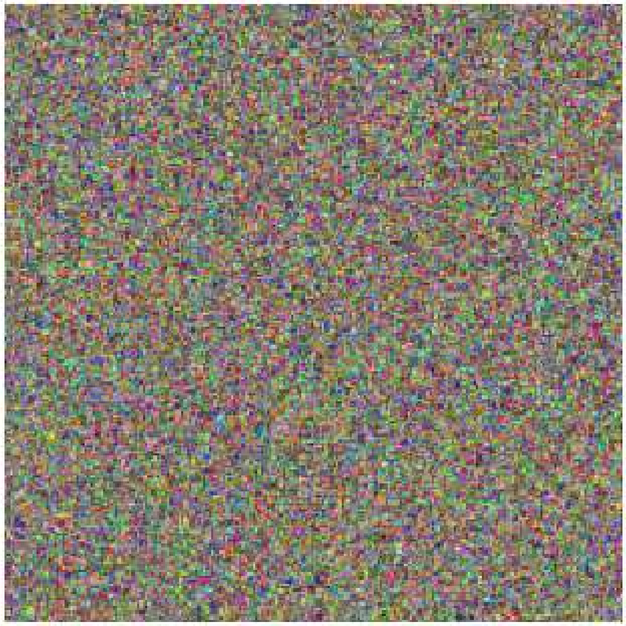
Try out your class visualization on other classes! You should also feel free to play with various hyperparameters to try and improve the quality of the generated image, but this is not required.

In [ ]:
```
# target_y = 78 # Tick
# target_y = 187 # Yorkshire Terrier
# target_y = 683 # Oboe
# target_y = 366 # Gorilla
target_y = 604 # Hourglass
target_y = np.random.randint(1000)
```

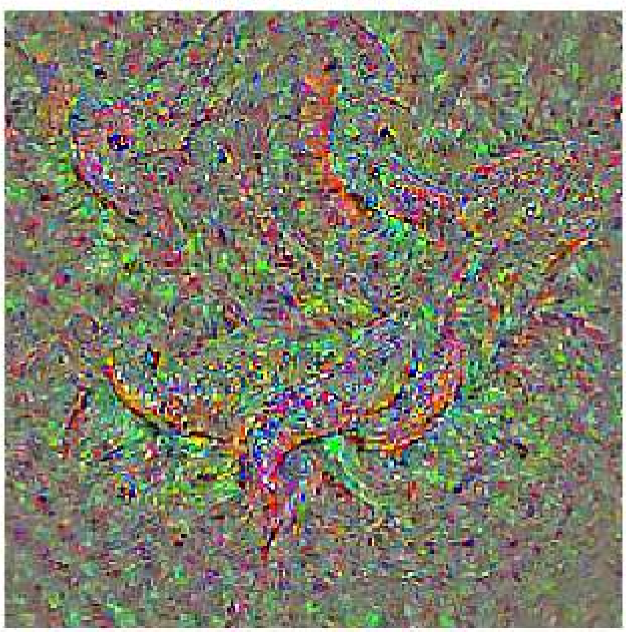
```
print(class_names[target_y])
X = create_class_visualization(target_y, model, dtype)
```

```
eft
```

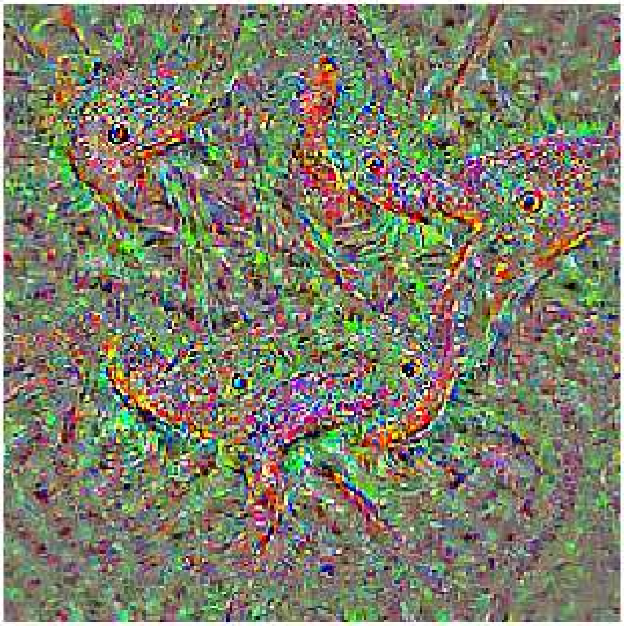
eft
Iteration 1 / 100



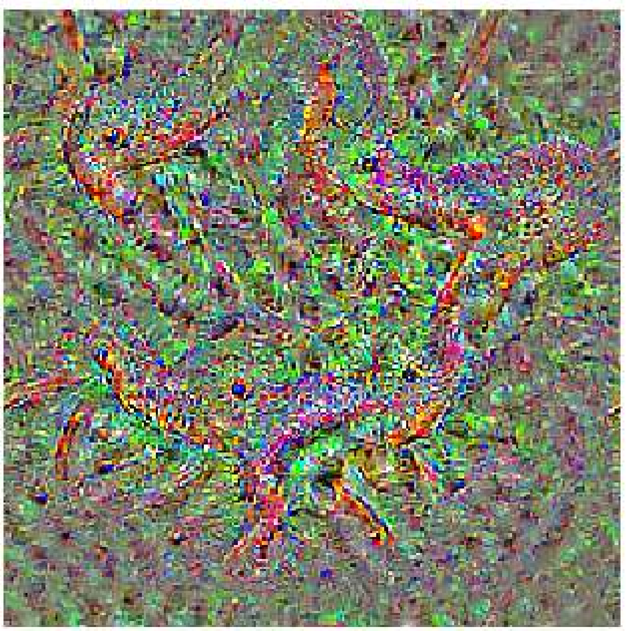
eft
Iteration 25 / 100



eft
Iteration 50 / 100



eft
Iteration 75 / 100



eft
Iteration 100 / 100