NetworkVisualization-PyTorch

October 10, 2019

1 Network Visualization (30 Points)

In this notebook we will explore the use of *image gradients* for generating new images, by studying and implementing key components in three papers:

- Karen Simonyan, Andrea Vedaldi, and Andrew Zisserman. "Deep Inside Convolutional Networks: Visualising Image Classification Models and Saliency Maps", ICLR Workshop 2014.
- Szegedy et al, "Intriguing properties of neural networks", ICLR 2014
- Yosinski et al, "Understanding Neural Networks Through Deep Visualization", ICML 2015 Deep Learning Workshop

You will need to first read the paper, and then we will guide you to understand them deeper with some problems.

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.

In this homework, 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.

This notebook is the first part of homwwork 2. 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.

We will use **PyTorch 1.1** to finish the problems in this notebook, which has been tested with Python3.6 on Linux and Mac.

Suppose you have already installed the dependencies in the last homework. **Before you start this one, here are some preparation work you need to do**:

- Download the imagenet_val_25 dataset

```
cd cs7643/datasets
bash get_imagenet_val.sh
```

** Note for grading**:

- The total credits for this notebook are 30 points, which are equally distributed in the three problems.
- Although we will run your notebook in grading, but you still need to **submit the notebook with all the outputs you generated**. Sometimes it will inform us if we get any inconsitent results with respect to yours.

```
In [1]: import torch
        from torch.autograd import Variable
        import torchvision
        import torchvision.transforms as T
        import random

        import numpy as np
        from scipy.ndimage.filters import gaussian_filter1d
        import matplotlib.pyplot as plt
        from cs7643.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'
```

1.0.1 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. Just run it.

```
In [2]: 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
```

2 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, 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 the experiments in this notebook on a CPU machine. You are encouraged to use a larger model to finish the rest of the experiments if GPU resouces are not a problem for you, but please highlight the backbone network you use in your implementation if you do it.

Switching a backbone network is quite easy in pytorch. You can refer to torchvision model zoos for more information.

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

In [3]:
```
# 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
```

```
c:\users\kingsman142\appdata\local\programs\python\python36\lib\site-packages\torchvision\model
  init.kaiming_uniform(m.weight.data)
c:\users\kingsman142\appdata\local\programs\python\python36\lib\site-packages\torchvision\model
```

```
  init.normal(m.weight.data, mean=0.0, std=0.01)
Downloading: "https://download.pytorch.org/models/squeezenet1_1-f364aa15.pth" to C:\Users\kings
100%|| 4966400/4966400 [00:00<00:00, 22074909.91it/s]
```

2.1 Load some ImageNet images

If you have not execute the downloading script. Here is a reminder that you have to do it now. We have provided a few example images from the validation set of the ImageNet ILSVRC 2012 Classification dataset.

To download these images and run

```
cd cs7643/datasets/
bash 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 [4]: from cs7643.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()
```

3 Saliency Maps (10 pts)

Using this pretrained model, we will compute class saliency maps as described in the paper:

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

We will also review this paper in the paper presentation.

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.

3.0.1 Hint: PyTorch `gather` method

Recall when you need 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 or Variable of shape `(N, C)` and `y` is a PyTorch Tensor or Variable 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 (or Variable) 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 [5]: # 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([[-0.8648,  0.2919,  0.5500, -0.1981,  0.7828],
        [-1.2895,  0.7038,  0.4059, -0.5389, -0.5836],
        [-1.6635,  0.5452,  0.6508, -1.2030,  1.1306],
        [-1.7789, -0.4799, -2.1077,  1.1106,  1.6560]])
tensor([1, 2, 1, 3])
tensor([0.2919, 0.4059, 0.5452, 1.1106])
```

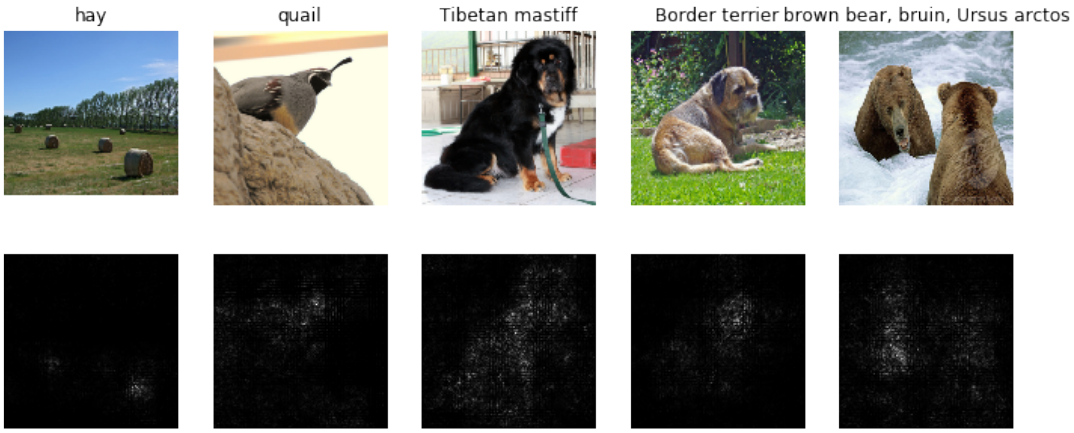
```
In [46]: def compute_saliency_maps(X, y, model):
             """
             Compute a class saliency map using the model for images X and labels y.

             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()

    # Wrap the input tensors in Variables
    X_var = Variable(X, requires_grad=True)
    y_var = Variable(y, requires_grad=False)
    saliency = None

    lam = 1e3 # This is the regularization parameter when you need it

    ##############################################################################
    # 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, and then compute the gradients with a backward pass.               #
    ##############################################################################
    N, C, H, W = X.shape
    criterion = torch.nn.CrossEntropyLoss()

    # feed images into network to get predictions
    pred = model(X_var)
    loss = criterion(pred, y_var)

    # backprop loss to get gradients
    loss.backward(retain_graph = True)

    # compute saliency max
    saliency = torch.abs(X_var.grad) # absolute value of all gradients
    saliency = torch.max(saliency, dim = 1)[0] # max along the channel dimension (R,
    ##############################################################################
    #                               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. You can compare to the figure 2 in the refered paper as a comparison for your results.

```
In [47]: 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.gray)
        plt.axis('off')
        plt.gcf().set_size_inches(12, 5)
    plt.show()

show_saliency_maps(X, y)
```



4 Fooling Images (10 pts)

We can also use the similar concept of image gradients to study the stability of the network. Consider a state-of-the-art deep neural network that generalizes well on an object recognition task. We expect such network to be robust to small perturbations of its input, because small perturbation cannot change the object category of an image. However, [2] find that applying an imperceptible non-random perturbation to a test image, it is possible to arbitrarily change the network's prediction.

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

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. We term the so perturbed examples "adversarial examples".

Read the paper, and then implement the following function to generate fooling images.

```
In [50]: 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.
             """

             model.eval()

             # Initialize our fooling image to the input image, and wrap it in a Variable.
             X_fooling = X.clone()
             X_fooling_var = Variable(X_fooling, requires_grad=True)

             # We will fix these parameters for everyone so that there will be
             # comparable outputs

             learning_rate = 10 # learning rate is 1
             max_iter = 100 # maximum number of iterations

             for it in range(max_iter):

             ##############################################################################
             # 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                                         #
             #                                                                            #
             # Inside of this loop, write the update rule.                                #
             #                                                                            #
             # HINT:                                                                      #
             # You can print your progress (current prediction and its confidence score)  #
             # over iterations to check your gradient ascent progress.                    #
             ##############################################################################
                 pred = model(X_fooling_var) # make predictions
                 pred_class = torch.argmax(pred) # find the predicted class
                 pred_conf = pred[0, pred_class] # score of the predicted class
                 true_conf = pred[0, target_y] # score of the desired class

                 # we are done with the task -- this image is now misclassified
```

```
            if pred_class == target_y:
                break

            # backprop loss to get gradients
            true_conf.backward()

            # calculate gradient with respect to input
            g = X_fooling_var.grad
            dX = X_fooling_var + learning_rate * g / g.norm()

            # reset variables for next iteration
            X_fooling = dX.clone()
            X_fooling_var = Variable(X_fooling, requires_grad=True)
        ##############################################################################
        #                               END OF YOUR CODE                             #
        ##############################################################################

        X_fooling = X_fooling_var.data

        return X_fooling
```

Now you can run the following cell to **generate a fooling image**. You will see the message 'Fooled the model' when you succeed.

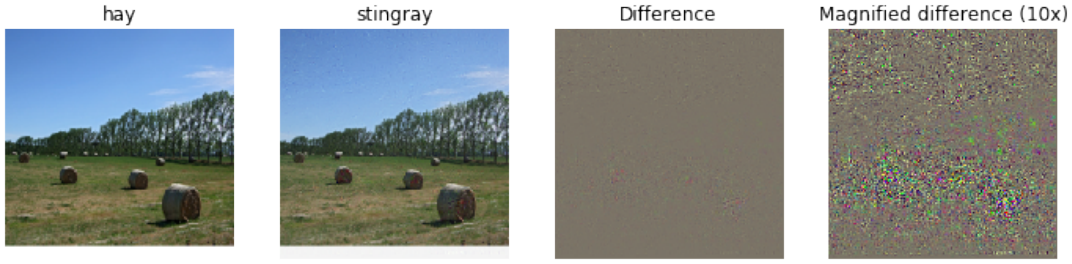
```
In [51]: idx = 0
         target_y = 6 # target label. Change to a different label to see the difference.

         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(Variable(X_fooling))

         if target_y == scores.data.max(1)[1][0]:
             print('Fooled the model!')
         else:
             print('The model is not fooled!')
```

```
Fooled the model!
```

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 [52]: 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()
```



5 Class visualization (10 pts)

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 [1]; [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.

[1] 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 the cell below, complete the implementation of the `create_class_visualization` function.

In [53]:
```
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 [56]:
```
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
```

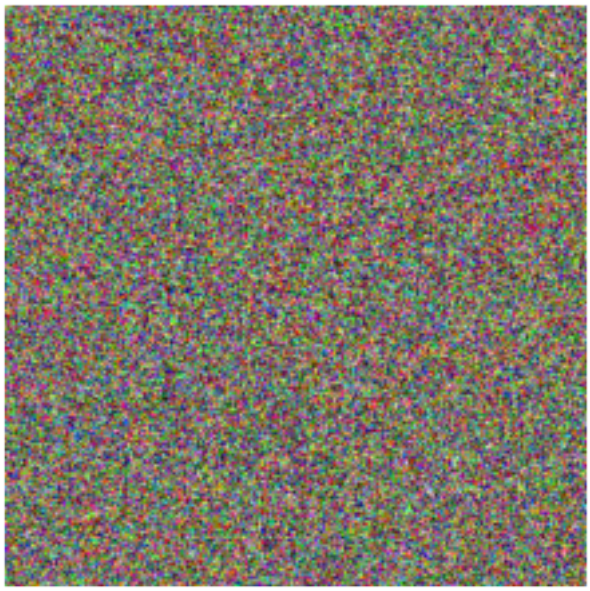
```
    - blur_every: How often to blur the image as an implicit regularizer
    - max_jitter: How much to gjitter the image as an implicit regularizer
    - show_every: How often to show the intermediate result
    """

    model.eval()

    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 also wrap it in
    # a PyTorch Variable.
    img = torch.randn(1, 3, 224, 224).mul_(1.0).type(dtype)
    img_var = Variable(img, requires_grad=True)

    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.copy_(jitter(img, 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.            #
        ########################################################################
        pred = model(img_var) # get the predictions
        loss = pred[0, target_y] # get the confidence/loss of the target class

        # backpropogate the loss to get the gradients
        loss.backward()

        # calculate gradient with respect to input
        g = img_var.grad
        dX = img_var + learning_rate * g / g.norm()

        # reset variables for next iteration
        img = dX.clone()
        img_var = Variable(img, requires_grad=True)
        img = img_var.data

        ########################################################################
```

```
            #                                 END OF YOUR CODE                             #
            ########################################################################

            # Undo the random jitter
            img.copy_(jitter(img, -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[:, c].clamp_(min=lo, max=hi)
            if t % blur_every == 0:
                blur_image(img, 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.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.cpu())
```

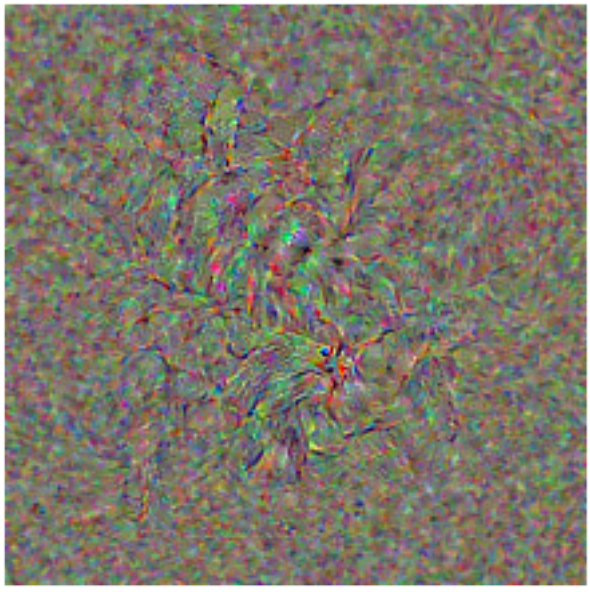
Once you have completed the implementation in the cell above, run the following cell to generate images of several classes. Show the generated images when you submitted your notebook.

```
In [57]: dtype = torch.FloatTensor
         # dtype = torch.cuda.FloatTensor # Uncomment this to use GPU
         model.type(dtype)

         # You can use a single class during your debugging session,
         # but please show all the generated outputs in your submitted notebook

         # 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

         targets = [76, 78, 187, 683, 366, 604]

         for target in targets:
             out = create_class_visualization(target, model, dtype)
```

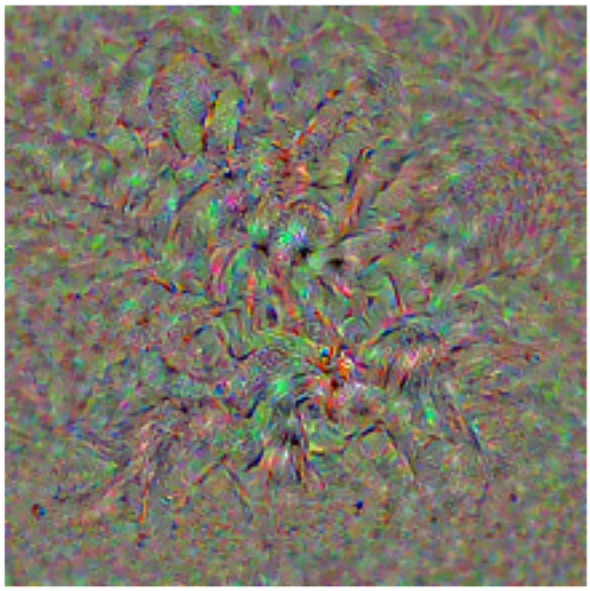
tarantula
Iteration 1 / 100



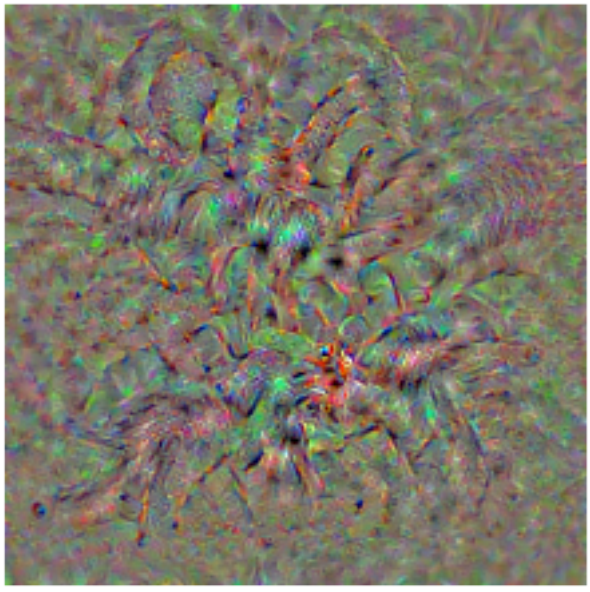
tarantula
Iteration 25 / 100



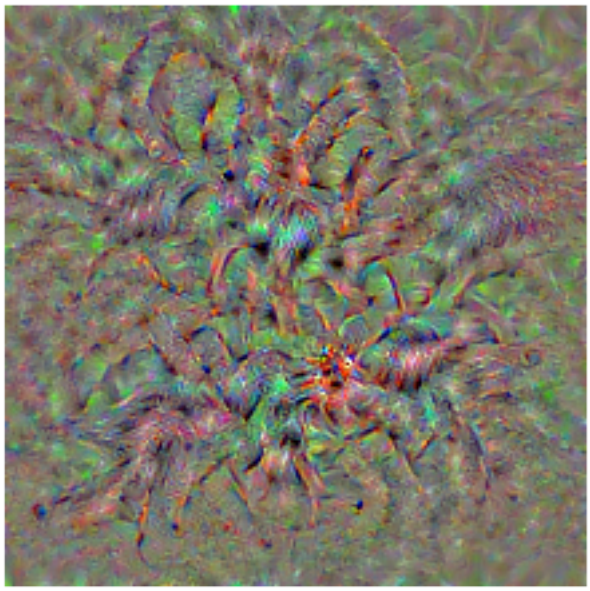
tarantula
Iteration 50 / 100



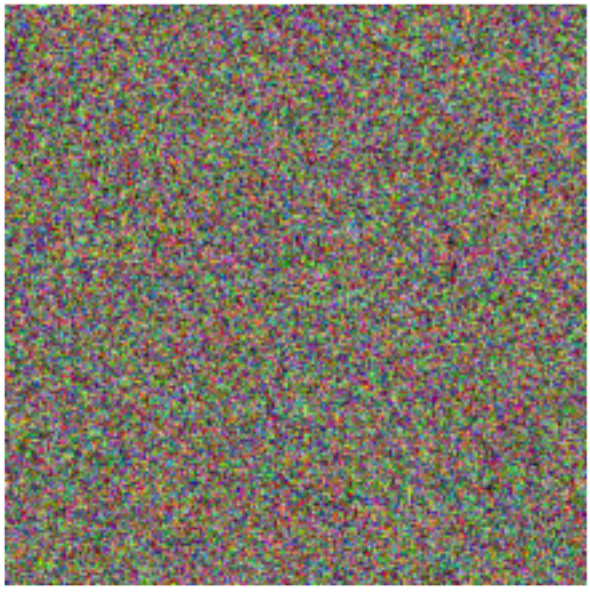
tarantula
Iteration 75 / 100



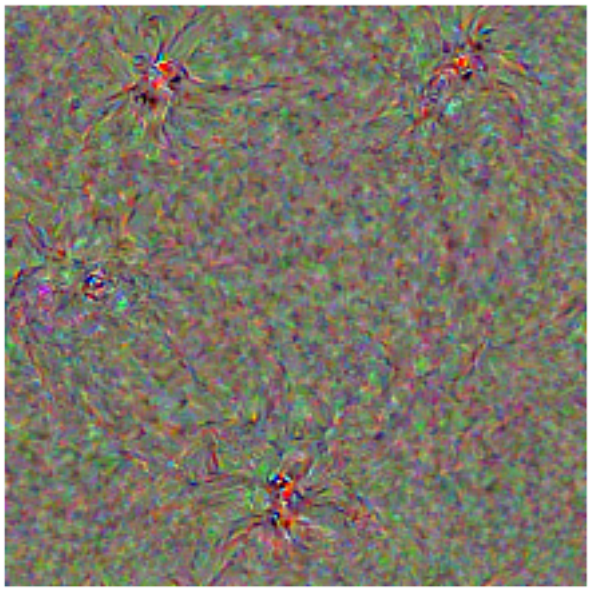
tarantula
Iteration 100 / 100



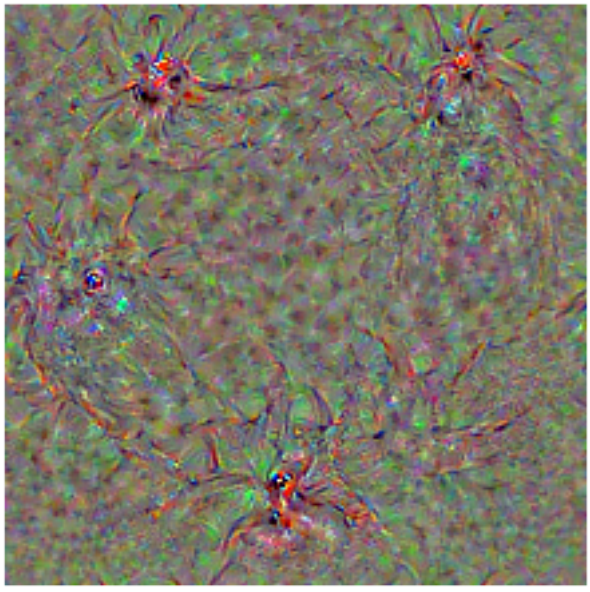
tick
Iteration 1 / 100



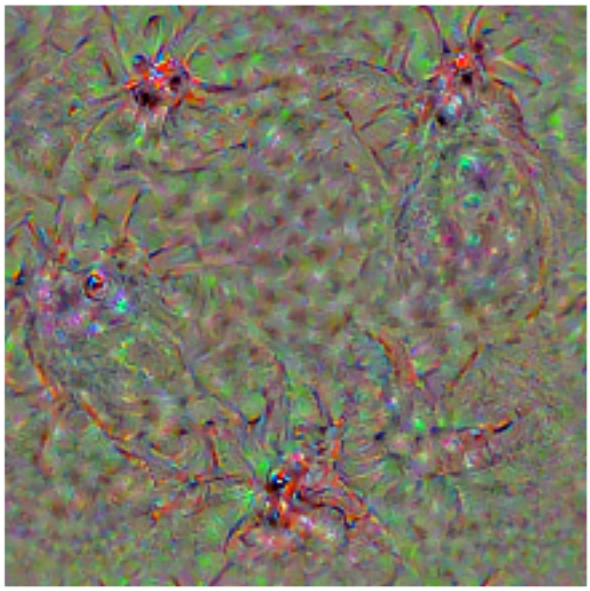
tick
Iteration 25 / 100



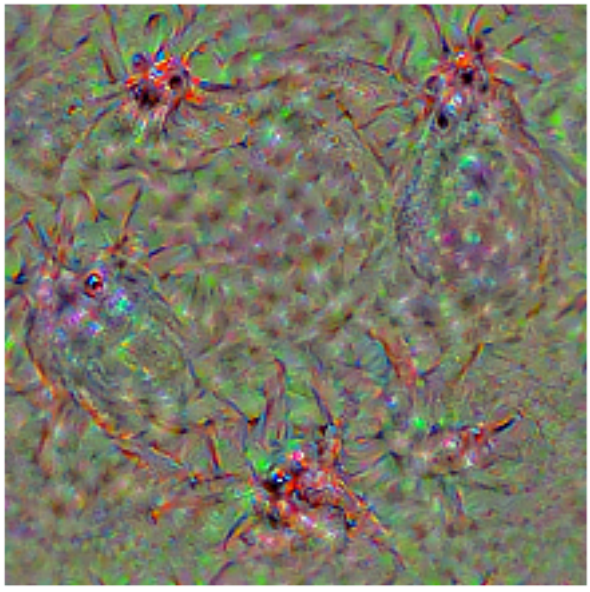
tick
Iteration 50 / 100



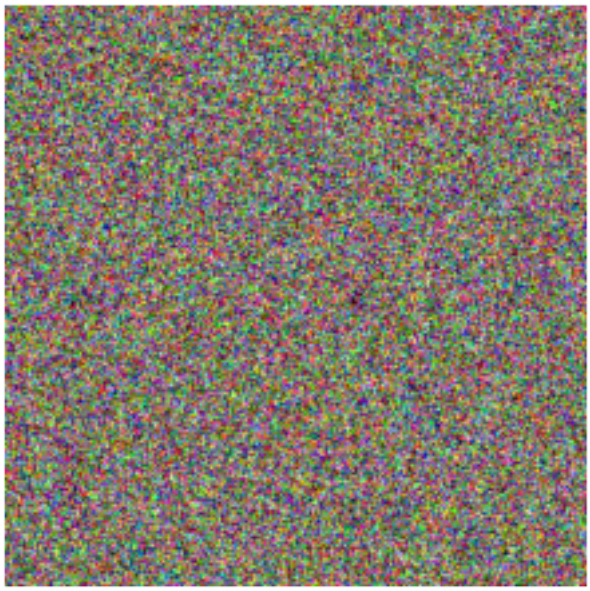
tick
Iteration 75 / 100



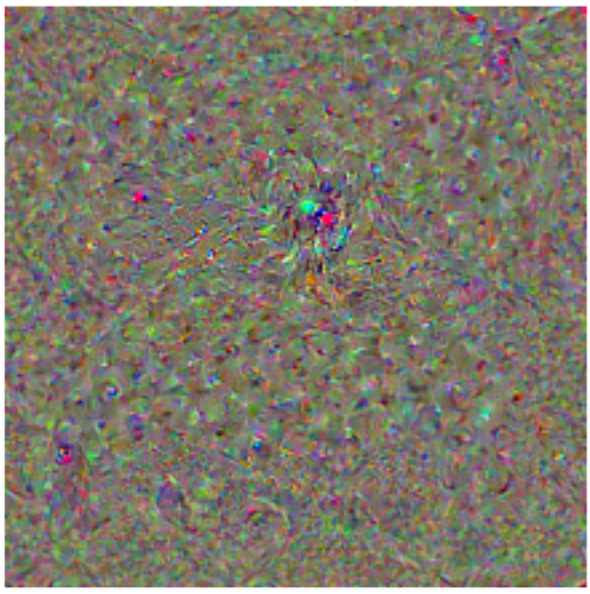
tick
Iteration 100 / 100



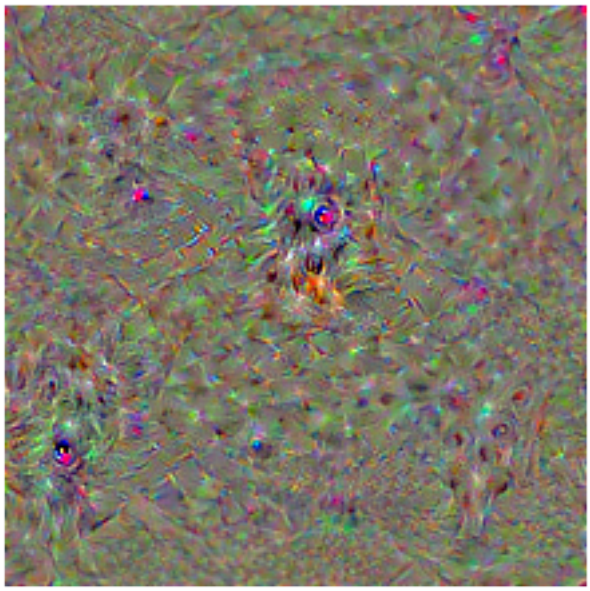
Yorkshire terrier
Iteration 1 / 100



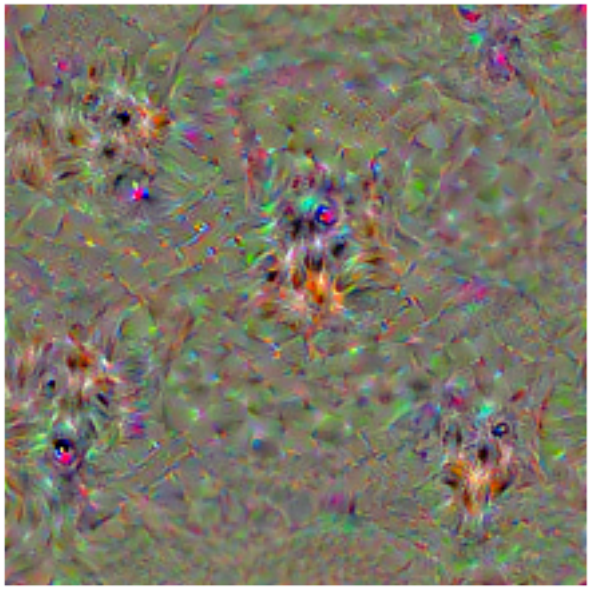
Yorkshire terrier
Iteration 25 / 100



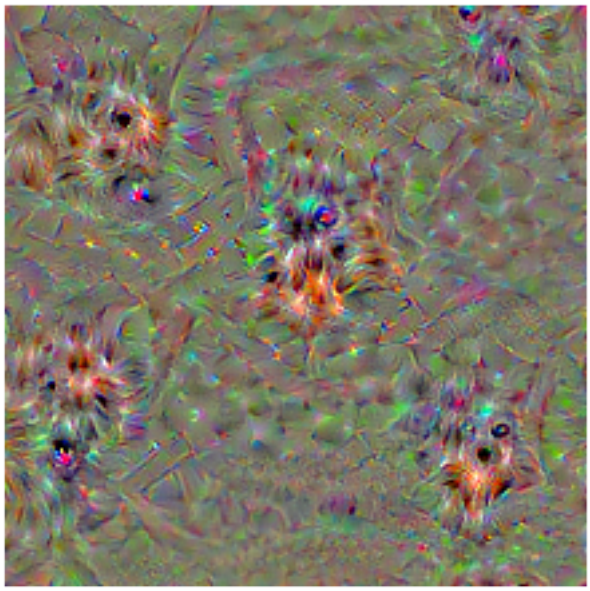
Yorkshire terrier
Iteration 50 / 100



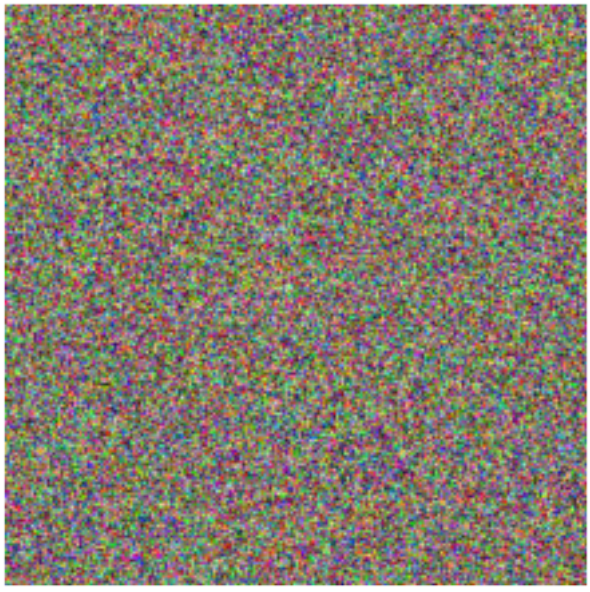
Yorkshire terrier
Iteration 75 / 100



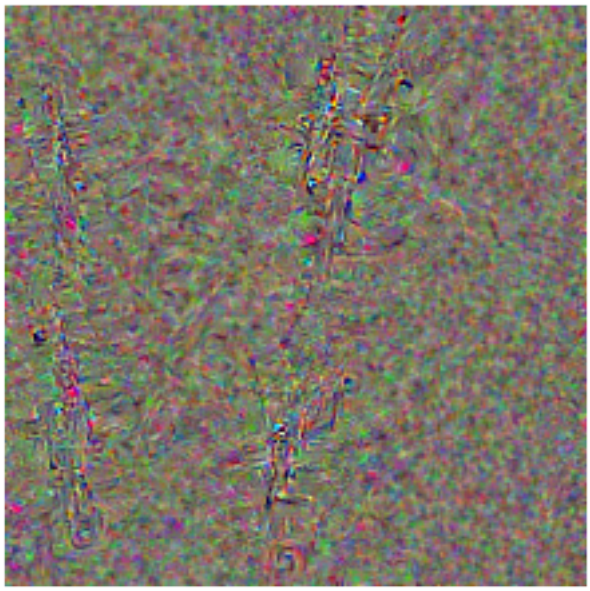
Yorkshire terrier
Iteration 100 / 100



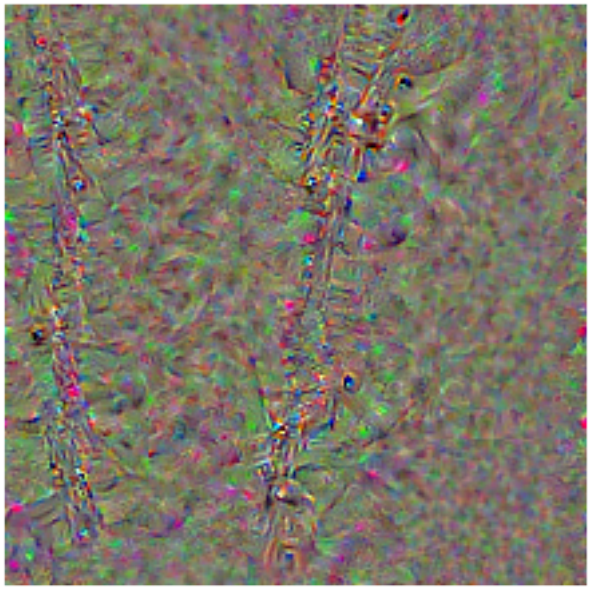
oboe, hautboy, hautbois
Iteration 1 / 100



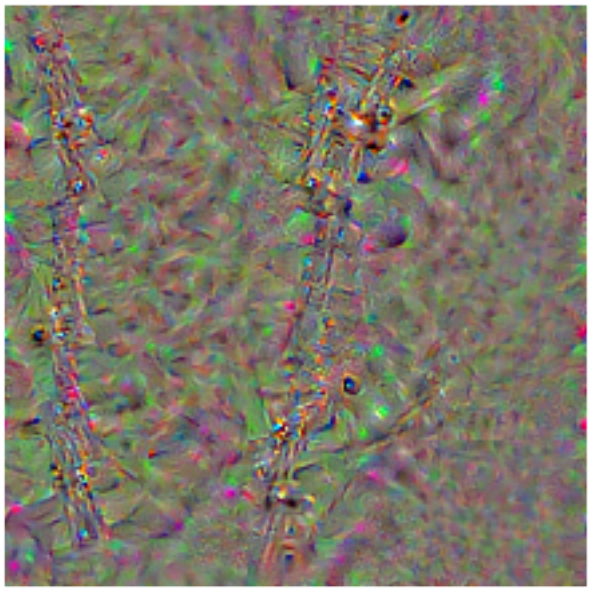
oboe, hautboy, hautbois
Iteration 25 / 100



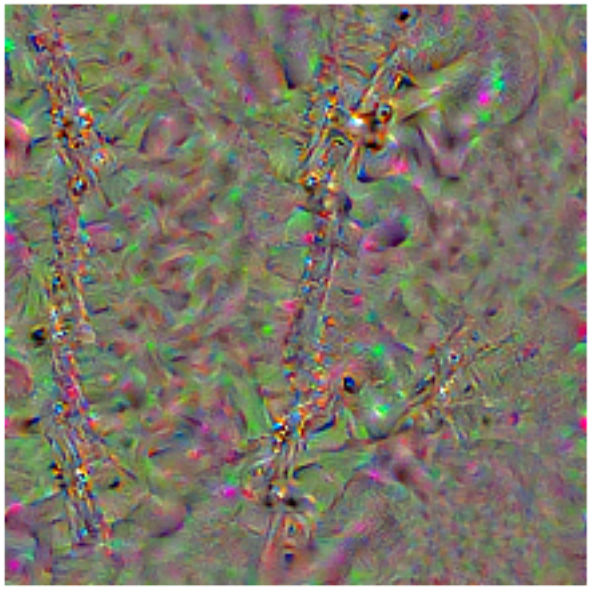
oboe, hautboy, hautbois
Iteration 50 / 100



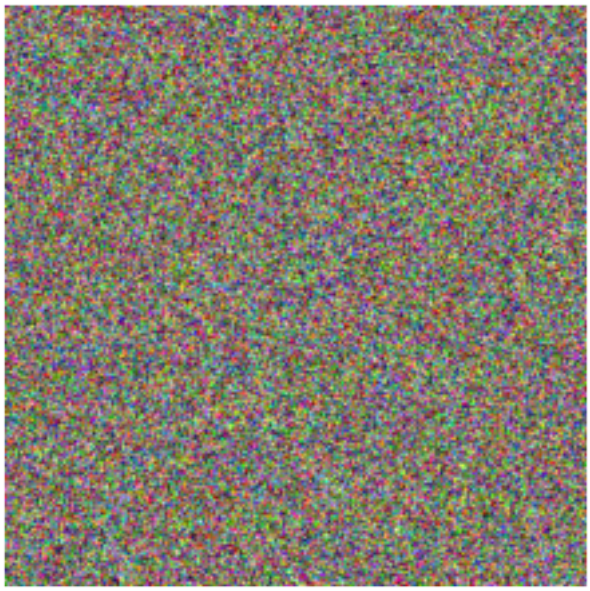
oboe, hautboy, hautbois
Iteration 75 / 100



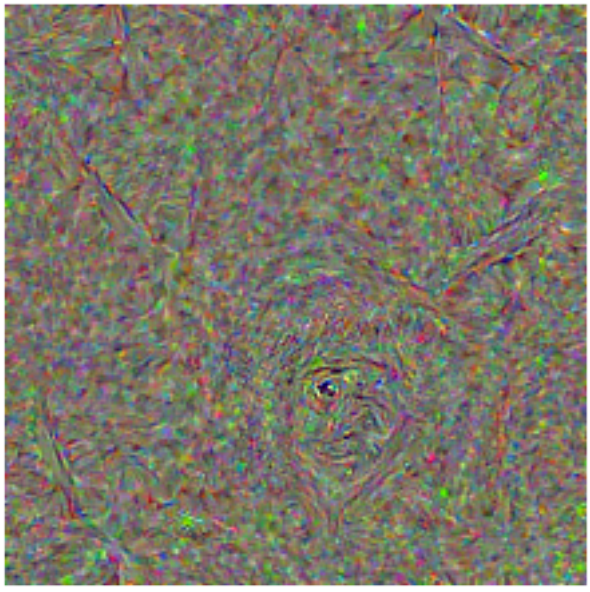
oboe, hautboy, hautbois
Iteration 100 / 100



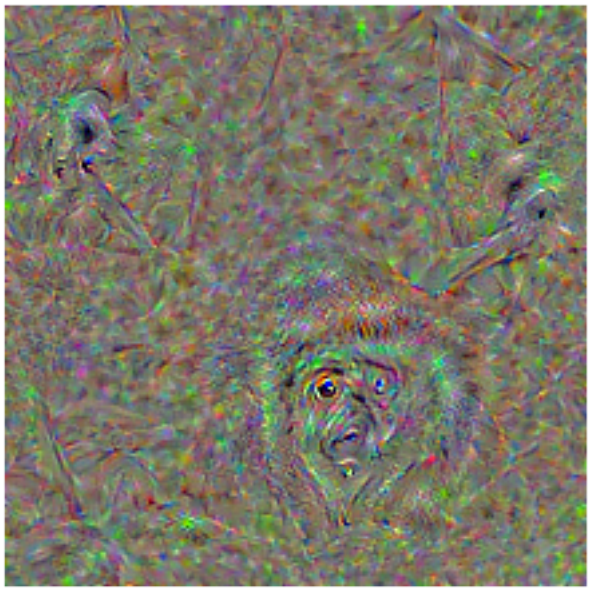
gorilla, Gorilla gorilla
Iteration 1 / 100



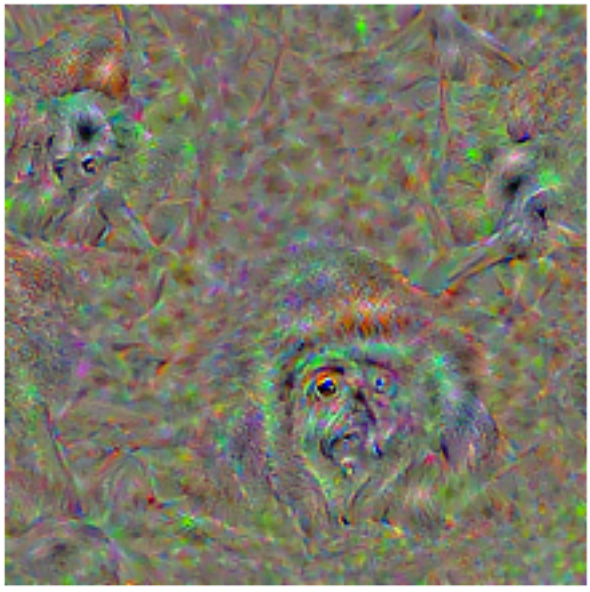
gorilla, Gorilla gorilla
Iteration 25 / 100



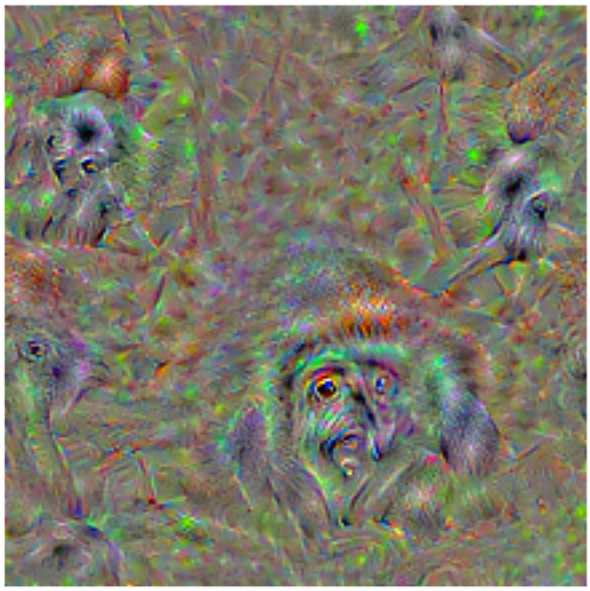
gorilla, Gorilla gorilla
Iteration 50 / 100



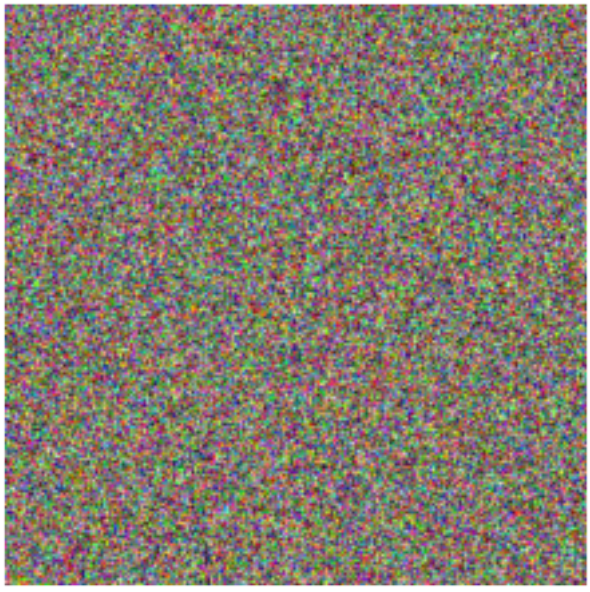
gorilla, Gorilla gorilla
Iteration 75 / 100



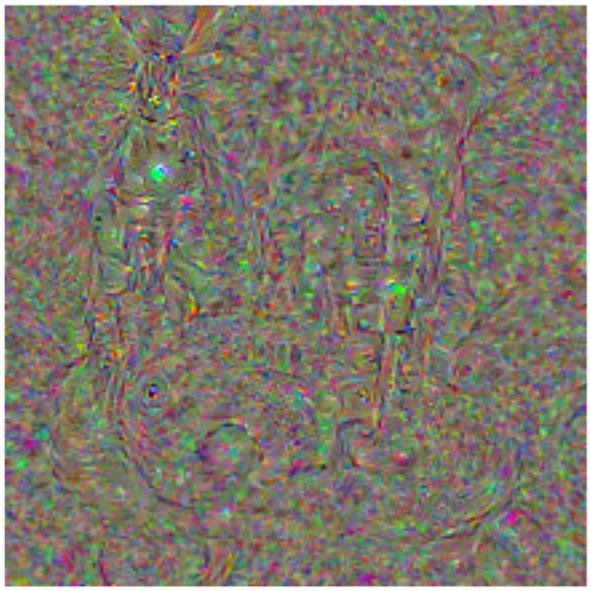
gorilla, Gorilla gorilla
Iteration 100 / 100



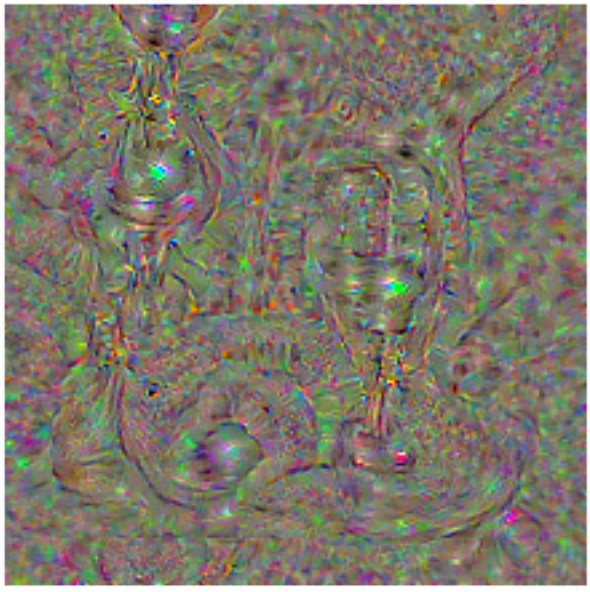
hourglass
Iteration 1 / 100



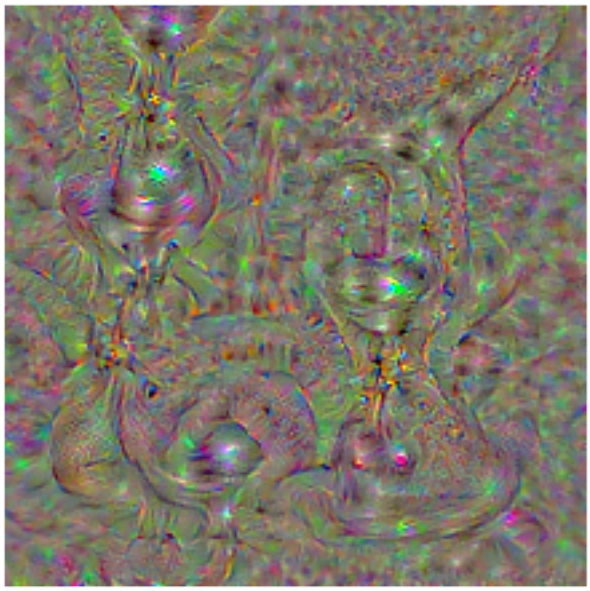
hourglass
Iteration 25 / 100



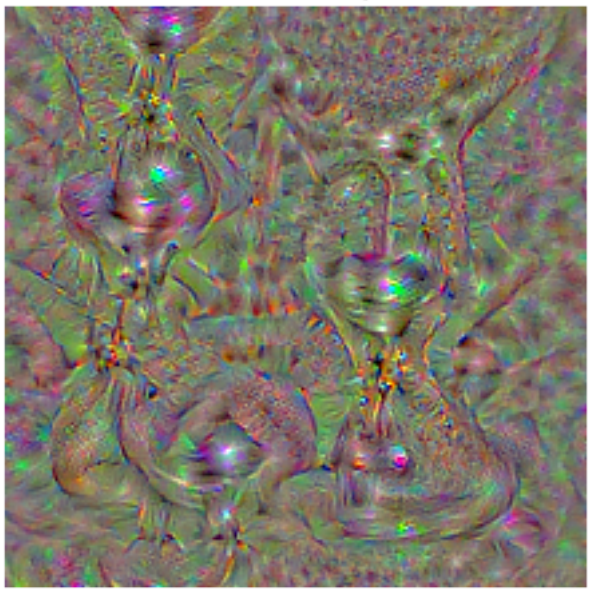
hourglass
Iteration 50 / 100



hourglass
Iteration 75 / 100



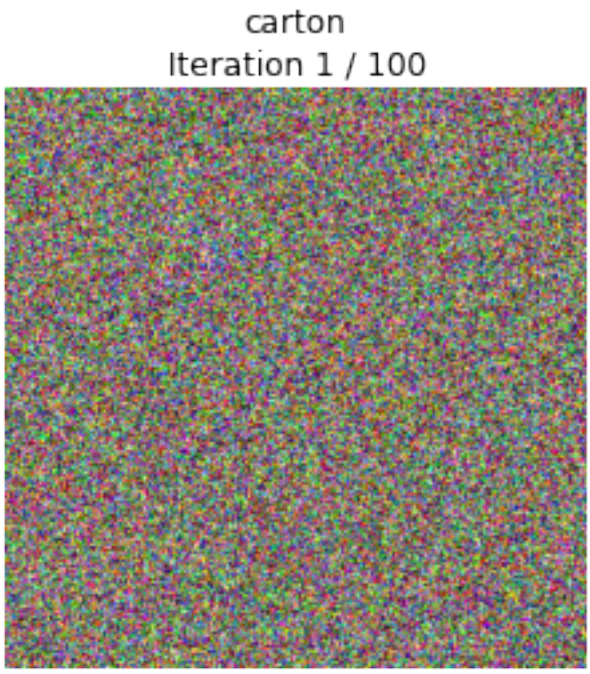
hourglass
Iteration 100 / 100



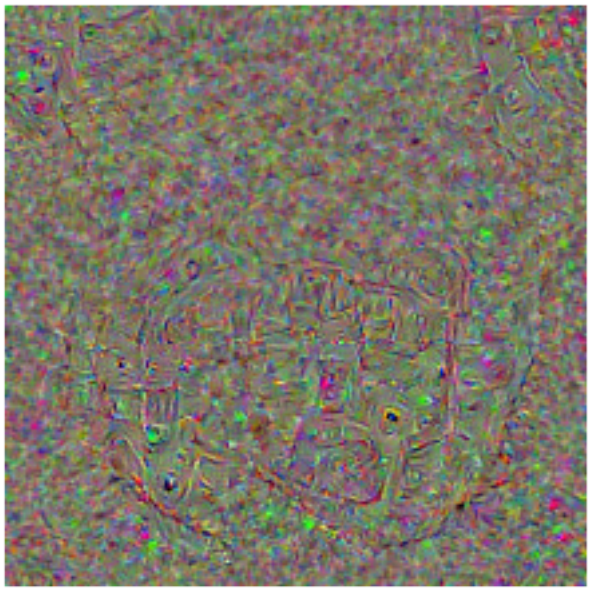
Try out your class visualization on other classes! You should also feel free to play with various hyperparameters to try and improve the quality of the generated image, but this is not required.

In [58]:
```
# 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)
```

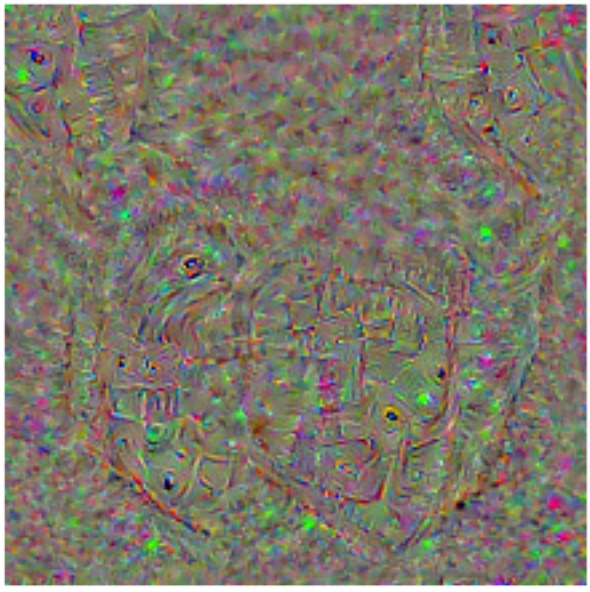
```
carton
```



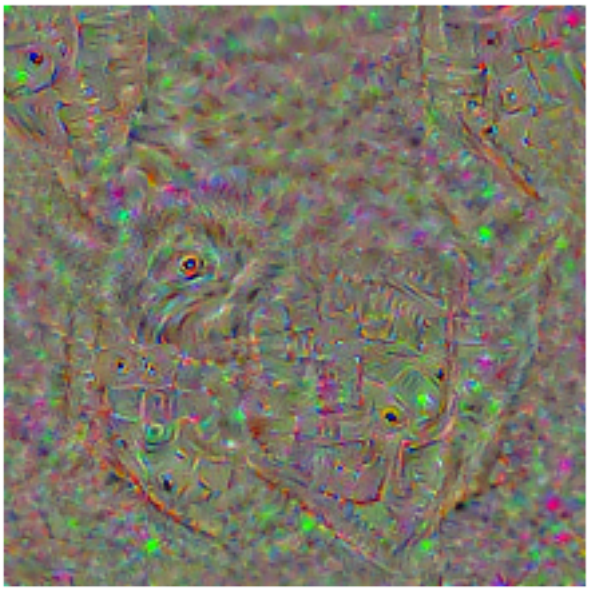
carton
Iteration 25 / 100



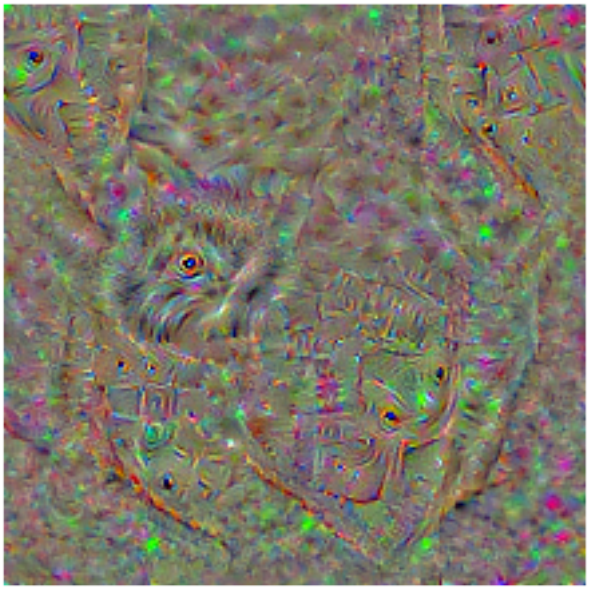
carton
Iteration 50 / 100



carton
Iteration 75 / 100



carton
Iteration 100 / 100



In [ ]: