"Neural Algorithm of Style" Notebook

April 25, 2016

1 Implementation of "A Neural Algorithm of Style"

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Spring 2016, CS6475 (Computational Photography)

This is an implementation in Python and Caffe of a recent paper, *A Neural Algorithm of Artistic Style* by Leon A. Gatys, Alexander S. Ecker, and Matthias Bethge, that became very well-known and has some online implementations such as https://deepart.io/. The paper is available at http://arxiv.org/abs/1508.06576 and I refer to many of its equations in this Python notebook. This took inspiration and methods from some of the numerous implementations already available of this:

- https://github.com/jcjohnson/neural-style
- https://github.com/kaishengtai/neuralart
- https://github.com/andersbll/neural_artistic_style
- https://github.com/fzliu/style-transfer
- https://github.com/woodrush/neural-art-tf

This is meant to be a comprehensible example, not an optimized, production-ready implementation. While this uses Caffe for a lot of the math, it does a lot else that could, and probably should, be offloaded to the GPU. The other implementations that I linked do this to some extent, and libraries like Caffe and TensorFlow are meant to work this way.

1.1 Setup

Most of the dependencies are just the imports below. `cv2` is needed only for image resizing and saving, and other Python libraries can do that (just make sure that floating-point images stay floating-point when resizing; SciPy `imresize` doesn't do this on its own.)

The most difficult one to install is probably `caffe`, via http://caffe.berkeleyvision.org/. As far as I know, it has bindings only for Python 2.x.

```
In [1]: import caffe, numpy, cv2, scipy.optimize
```

The below is only for the sake of displaying images in this notebook. If running this code standalone, it can be omitted (and calls inside of it). To actually run this notebook properly in Jupyter/IPython requires a whole zoo of other dependencies.

```
In [2]: import IPython.display
```

Now, set up Caffe to make use of GPU 0.

```
In [3]: caffe.set_device(0)
        caffe.set_mode_gpu()
```

If you have no GPU, your GPU isn't supported well in Caffe, or perhaps you're just trying to load a much larger model than will fit in GPU memory, then comment the above and uncomment the below. Things will just take a bit longer.

```
In [4]: # caffe.set_mode_cpu()
```

1.2 Loading Pre-trained Neural Network

We require a pre-trained neural network for this. Many will work here, but here I am using the Caffenet model from http://dl.caffe.berkeleyvision.org/bvlc_reference_caffenet.caffemodel and the network description from https://github.com/fzliu/style-transfer/blob/master/models/caffenet/deploy.prototxt. It is a small enough model that it fits on some more modest GPUs. The below loads this model into Caffe:

```
In [5]: net = caffe.Net("caffenet/deploy.prototxt",
                        "caffenet/bvlc_reference_caffenet.caffemodel",
                        caffe.TEST)
```

Check stdout/stderr if this call has problems. Errant `caffe` calls might also crash the whole Python instance.

See https://github.com/fzliu/style-transfer/tree/master/models for some models that are already in the correct format. Another interesting one, already in Caffe's format, is at http://illustration2vec.net/.

We can inspect the neural network's structure too. http://caffe.berkeleyvision.org/tutorial/net_layer_blob.html contains a good explanation of what Net, Layer, and Blob mean, to give this some context. http://caffe.berkeleyvision.org/tutorial/layers.html explains the different layer types shown below (and others). However, understanding this is not crucial to what else we do.

```
In [6]: for i,layer in enumerate(net.layers):
            print("%d: %s, %d blobs" % (i, layer.type, len(layer.blobs)))
            for j,blob in enumerate(layer.blobs):
                print("\tBlob %d: %d x %d channels of %dx%d" %
                      (j, blob.num, blob.channels, blob.width, blob.height))
```

```
0: Input, 0 blobs
1: Convolution, 2 blobs
        Blob 0: 96 x 3 channels of 11x11
        Blob 1: 96 x 1 channels of 1x1
2: ReLU, 0 blobs
3: Pooling, 0 blobs
4: LRN, 0 blobs
5: Convolution, 2 blobs
        Blob 0: 256 x 48 channels of 5x5
```

```
        Blob 1: 256 x 1 channels of 1x1
6: ReLU, 0 blobs
7: Pooling, 0 blobs
8: LRN, 0 blobs
9: Convolution, 2 blobs
        Blob 0: 384 x 256 channels of 3x3
        Blob 1: 384 x 1 channels of 1x1
10: ReLU, 0 blobs
11: Convolution, 2 blobs
        Blob 0: 384 x 192 channels of 3x3
        Blob 1: 384 x 1 channels of 1x1
12: ReLU, 0 blobs
13: Convolution, 2 blobs
        Blob 0: 256 x 192 channels of 3x3
        Blob 1: 256 x 1 channels of 1x1
14: ReLU, 0 blobs
15: Pooling, 0 blobs
```

The Blobs are the actual part we're interested in, particularly, those corresponding to convolution layers, and we can inspect some of them below:

```
In [7]: for name in net.blobs.keys():
            blob = net.blobs[name]
            print("Blob '%s': %d x %d channels of %dx%d" %
                  (name, blob.num, blob.channels, blob.width, blob.height))
```

```
Blob 'data': 10 x 3 channels of 227x227
Blob 'conv1': 10 x 96 channels of 55x55
Blob 'pool1': 10 x 96 channels of 27x27
Blob 'norm1': 10 x 96 channels of 27x27
Blob 'conv2': 10 x 256 channels of 27x27
Blob 'pool2': 10 x 256 channels of 13x13
Blob 'norm2': 10 x 256 channels of 13x13
Blob 'conv3': 10 x 384 channels of 13x13
Blob 'conv4': 10 x 384 channels of 13x13
Blob 'conv5': 10 x 256 channels of 13x13
Blob 'pool5': 10 x 256 channels of 6x6
```

We need to pick certain layers that represent "content", and certain layers that represent "style". The paper gives some more information on this, but these layers are also specific to the model and involve some level of trial-and-error. Lower layers capture more detailed pixel information, while higher layers capture a higher-level representation.

Experiment with these and see how they change the results. Also, all style layers have the same weight, and all content layers have the same weight (both multiplied by α and β) - but these weights can be independent too.

```
In [8]: style_layers = ["conv1", "conv2", "conv3", "conv4", "conv5"]
        content_layers = ["conv4"]
```

```
        layers = [l for l in net.blobs
                  if l in content_layers or l in style_layers]
```

1.3 Input Images

Next, we need a content image and a style image - an image which contributes content we're trying to match, and an image which contributes style we're trying to match. (Actually, there can be multiple content images and multiple style images, but that's another matter.)

Let's try this commonly-known artwork as a style image:

```
In [9]: style_image_filename = "./1280px-Great_Wave_off_Kanagawa2b.jpg"
        IPython.display.Image(filename = style_image_filename)
```

Out[9]:

and this photograph (shot on my phone here for another assignment, if anyone's curious) as a content image:

```
In [10]: content_image_filename = "french_park.jpg"
         IPython.display.Image(filename = content_image_filename)
```

Out[10]:

And actually load these images:

```
In [11]: style   = caffe.io.load_image(style_image_filename)
         content = caffe.io.load_image(content_image_filename)
```

1.4 Preprocessing

We need to condition our input images to be in the same format and range as the images on which the neural network was trained. Luckily, most of these networks were trained on ImageNet data and this information is available via `https://github.com/BVLC/caffe/blob/master/python/caffe/imagenet/ilsvrc_2012_mean.npy`.

We can load this and produce a `caffe.io.Transformer` from it. Note carefully that anytime we have outside image data going into the network's inputs, we must pass it through its `process` method, and anytime we want to produce sane image data from its inputs, we must use its `deprocess` call!

```
In [12]: mean_data = numpy.load("caffenet/ilsvrc_2012_mean.npy")
         xform = caffe.io.Transformer({"data": net.blobs["data"].data.shape})
         xform.set_mean("data", mean_data.mean(1).mean(1))
         xform.set_channel_swap("data", (2,1,0))
         xform.set_transpose("data", (2,0,1))
         xform.set_raw_scale("data", 255)
```

We also need to scale the images to a certain size, and in some cases scale the style image up a little if the aspect ratios are too far off. The below does this, using the familiar `cv2.resize` to scale each image's longest edge to `size` (but basically any image resizing routine will work).

```
In [13]: size = 1024
         style_scale = 1.2

         f = float(size) / max(content.shape[:2])
         content_scaled = cv2.resize(content, (0, 0), fx=f, fy=f,
                                     interpolation=cv2.INTER_LANCZOS4)
         f = style_scale * float(size) / max(style.shape[:2])
         style_scaled = cv2.resize(style, (0, 0), fx=f, fy=f,
                                   interpolation=cv2.INTER_LANCZOS4)
```

`size` can be made much larger for higher-resolution results, just be aware that it will raise computation time and memory requirements sharply. Also, note that a lot of the parameters in this are not particularly resolution-independent.

1.5 Feature Responses in Neural Network

Finally, at this point we can get into the actual method of the paper (around page 9 now). Below we are computing the *feature responses* of the content image on the layers of the neural network that we selected as content layers. The first part is adapting the neural network's shape to this particular image size, and then running a forward pass of the neural network using this (conditioned) input.

We make this part a function, since it comes up in many other places:

```
In [14]: def net_forward(img):
             ch, w, h = img.shape[2], img.shape[0], img.shape[1]
             net.blobs["data"].reshape(1, ch, w, h)
             xform.inputs["data"] = (1, ch, w, h)

             net.blobs["data"].data[0] = xform.preprocess("data", img)
             net.forward()
```

After the `net_forward` call, we need to collect the data from the layers we're concerned with. For the content representation, this is just the activations at those layers, flattened out a bit. We reuse this later, so it also is made a function:

```
In [15]: def get_content_repr(img):
             resp = {}
             for layer in layers:
                 act = net.blobs[layer].data[0].copy()
```

```
            act.shape = (act.shape[0], -1)
            resp[layer] = act
        return(resp)
```

We do nearly the same thing to compute the style representation on the style image. Where it differs from the content image is that here we're building a feature correlation, for which we use the Gram matrix (see page 10 of the paper). `numpy.dot(act, act.T)` is one easy way to compute this; `sgemm` from BLAS is another.

```
In [16]: def get_style_repr(img):
             resp = {}
             for layer in style_layers:
                 act = net.blobs[layer].data[0].copy()
                 act.shape = (act.shape[0], -1)
                 resp[layer] = numpy.dot(act, act.T)
             return(resp)

         net_forward(style_scaled)
         style_repr = get_style_repr(style_scaled)

         net_forward(content_scaled)
         content_repr = get_content_repr(content_scaled)
```

`content_repr` and `style_repr` then are dictionaries whose keys are the layer name, and whose values are the image representation at that layer (of the content features of our content image, and style features of our style image, respectively.)

Now, all we need to do is find an image that, when run through this same neural network, produces approximately the same content representation and the same style representation as what we just computed, and looks okay - for whatever vague definition of "approximately" and "looks okay" we choose to apply. That might be tricky, since this minimization problem has roughly this many dimensions:

```
In [17]: content_scaled.size

Out[17]: 3145728
```

1.6 Generating a New Image

The method of this that the paper suggests (around page 11) is to start from a white noise image, and use gradient-descent on that image to jointly minimize the difference between its content representation and style representation, and the content and style representation we computed above.

Some implementations instead started from a pink noise image or from the content image, rather than a white noise image. This is worth experimenting with.

Below, we just use white noise from `randn`, setting the random seed so that we get consistent results between runs:

```
In [18]: numpy.random.seed(12345)
         img_init = xform.preprocess(
             "data", numpy.random.randn(*(net.blobs["data"].data.shape[1:])))
```

1.6.1 Loss function

We can optimize this image with standard optimization routines, provided that we treat it as some giant-dimensional value, define some sort of overall loss function on it, and we have its gradient with respect to that generated image. Happily, since we are using neural networks that allow backpropagation, we have most of the tools needed for this.

The paper defines different loss function for content and for style. These equations are copied more or less verbatim in the loss function that is below, leaving the explanation to the paper and noting the relevant equations in comments. To avoid too many other parameters and functions, it appears below as one monolithic function.

Note the three parameters right at the top:

- `alpha` and α in equation 7 in the paper, and gives the weighting of content in the loss function.
- `beta` is β from the same equation, and gives the weighting of style.
- `tv_weight` is the weighting for *total variation gradient*, which contributes to smoothness. (This was was not defined in the paper, nor anywhere else I looked, but was used in various implementations, possibly first in kaishengtai/neuralart).

```
In [19]: alpha = 1
         beta = 1e3
         tv_strength = 1e-2

         def loss_function(x):
             # Reshape the (flattened) input and feed it into the network:
             net_in = x.reshape(net.blobs["data"].data.shape[1:])
             net.blobs["data"].data[0] = net_in
             net.forward()

             # Get content & style representation of net_in:
             content_repr_tmp = get_content_repr(net_in)
             style_repr_tmp = get_style_repr(net_in)

             # Starting at last layer (see self.layers), propagate error back.
             loss = 0
             net.blobs[layers[-1]].diff[:] = 0
             for i, layer in enumerate(reversed(layers)):
                 next_layer = None if i == len(layers)-1 else layers[-i-2]
                 grad = net.blobs[layer].diff[0]

                 # Matching paper notation for equations 1 to 7:
                 Pl = content_repr[layer]
                 Fl = content_repr_tmp[layer]
                 Nl = content_repr_tmp[layer].shape[0]
                 Ml = content_repr_tmp[layer].shape[1]
                 Gl = style_repr_tmp[layer]
                 Al = style_repr[layer]

                 # Content loss:
```

```
            w = 1.0 / len(content_layers)
            if layer in content_layers:
                d = Fl - Pl
                # Equations 1 & 2:
                loss += w * alpha * (d**2).sum() / 2
                grad += w * alpha * (d * (Fl > 0)).reshape(grad.shape)

            # Style loss:
            w = 1.0 / len(style_layers)
            if layer in style_layers:
                q = (Nl * Ml)**-2
                d = Gl - Al
                # Equation 4:
                El = q/4 * (d**2).sum()
                # Equation 6:
                dEl = q * numpy.dot(d, Fl) * (Fl > 0)
                # Equation 5:
                loss += w * beta * El
                # Equation 7 (ish):
                grad += w * beta * dEl.reshape(grad.shape)

            # Finally, propagate this error back into the network
            net.backward(start=layer, end=next_layer)
            if next_layer is None:
                grad = net.blobs["data"].diff[0]
            else:
                grad = net.blobs[next_layer].diff[0]

        # Total Variation Gradient:
        x_diff = net_in[:, :-1, :-1] - net_in[:, :-1, 1:]
        y_diff = net_in[:, :-1, :-1] - net_in[:, 1:, :-1]
        tv = numpy.zeros(grad.shape)
        tv[:, :-1, :-1] += x_diff + y_diff
        tv[:, :-1, 1:]  -= x_diff
        tv[:, 1:,  :-1] -= y_diff
        grad += tv_strength * tv

        # Flatten gradient (as minimize() wants to handle it):
        grad = grad.flatten().astype(numpy.float64)

        return loss, grad
```

1.6.2 Minimization

With this (large, kind of complicated-looking) loss function designed, what remains is to pass this function to some standard optimization routine. SciPy has several; we'll use L-BFGS-B, as many implementations do (some also use Adam).

Before that, we need to compute some bounds for the optimization. Regrettably, I have lit-

tle information on this step; it's more or less just copied from https://github.com/fzliu/style-transfer.

```
In [20]: data_min = -xform.mean["data"][:,0,0]
         data_max = data_min + xform.raw_scale["data"]
         data_bounds = [(data_min[0], data_max[0])]*(img_init.size/3) + \
                       [(data_min[1], data_max[1])]*(img_init.size/3) + \
                       [(data_min[2], data_max[2])]*(img_init.size/3)
```

Finally, the actual call to optimize `loss_function`. Note a few things:

- We've just made a simple wrapper. Parameter `iters` is the number of iterations (we can and should tune this to trade off quality and speed), and `start` is the starting image to optimize.
- As the gradient we're supplying is basically an analytical Jacobian of the loss function (see equations 2 and 6 of the paper), we've set `jac` to `True`.
- We tell it with `disp` to output detailed information - however, none of this is visible here in the Python notebook (it goes to stdout/stderr). We could also set a callback function via the `callback` argument if we wanted to be notified per-iteration - for instance, to print a time estimate of the remaining iterations, or to save the results incrementally, or to visualize the results in real-time.

```
In [21]: def iterate(iters, start):
             return scipy.optimize.minimize(loss_function,
                                            start.flatten(),
                                            args = (),
                                            options = {"maxiter": iters,
                                                       "maxcor": 8,
                                                       "disp": True},
                                            method = "L-BFGS-B",
                                            jac = True,
                                            bounds = data_bounds)
```

1.6.3 Collecting results

Whenever that call happens to return, we need to collect its results. We can do this via field `x` in `res`, the OptimizeResult that `scipy.optimize.minimize` returns, or we can get it directly from the neural network's inputs (in which case the data already is in the correct shape).

```
In [22]: def save_result(opt_res, filename):
             data = res.x.reshape(net.blobs["data"].data.shape)
             # Also acceptable:
             # data = net.blobs["data"].data
             image = (255 * xform.deprocess("data", data)).astype(numpy.uint8)
             # Note traversing backwards to put colors in right order for OpenCV
             cv2.imwrite(filename, image[:,:,::-1])
```

1.6.4 Iteration & Results

We could simply tell `iterate` to iterate for a large number of iterations, give it `img_init` as the starting point, and let it run however long it takes, but below we'll visualize its results incrementally to give some idea what it's starting from and what refinement is doing.

First, we let it iterate for 10 iterations on our starting image `img_init`...

```
In [23]: res = iterate(10, img_init)
         print(res)
```

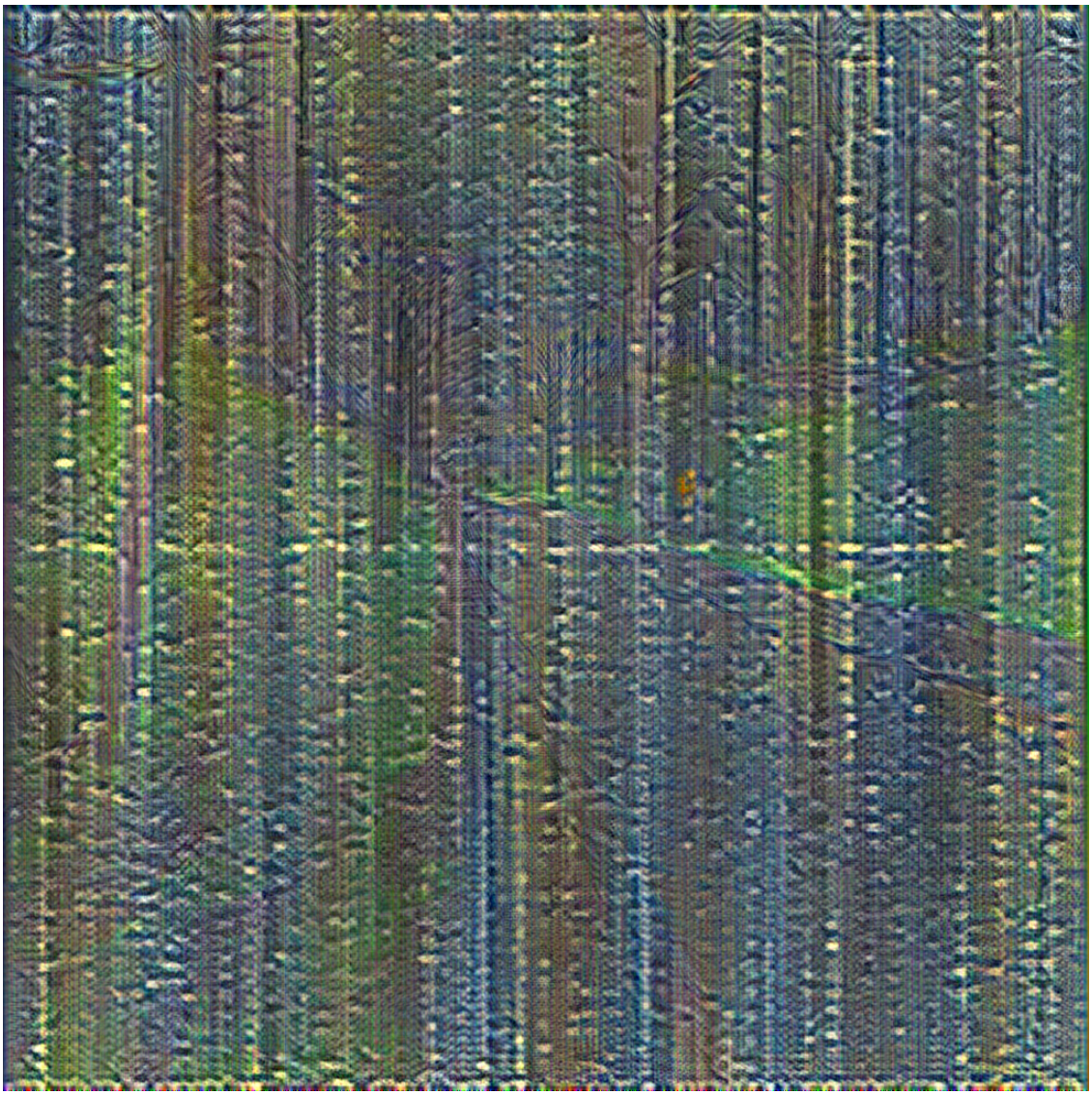
```
      fun: 14632715.968474206
 hess_inv: <3145728x3145728 LbfgsInvHessProduct with dtype=float64>
      jac: array([ 0.00297849, -0.06569262,  0.69664794, ..., -0.00944448,
       -0.48784581,  0.        ])
  message: 'STOP: TOTAL NO. of ITERATIONS EXCEEDS LIMIT'
     nfev: 14
      nit: 11
   status: 1
  success: False
        x: array([ -34.88158765,  -27.60735043,   -3.75908449, ...,  -69.31972038,
        -81.75000326,  132.32108566])
```

Note the results in `res`. `fun` gives us some idea of the loss function, though it's not especially useful on its own except relative to other iterations. `message` gives the reason why optimization stopped, and some settings will simply cause optimization to fail. If you look at what it's echoing to stdout, most of this some information will be there too. `x` gives the actual solution it found - and it's what we use in `save_result` up above.

Apply this to save the results and then visualize them:

```
In [24]: output_filename = "out_temp.png"
         save_result(res, output_filename)
         IPython.display.Image(filename = output_filename)
```

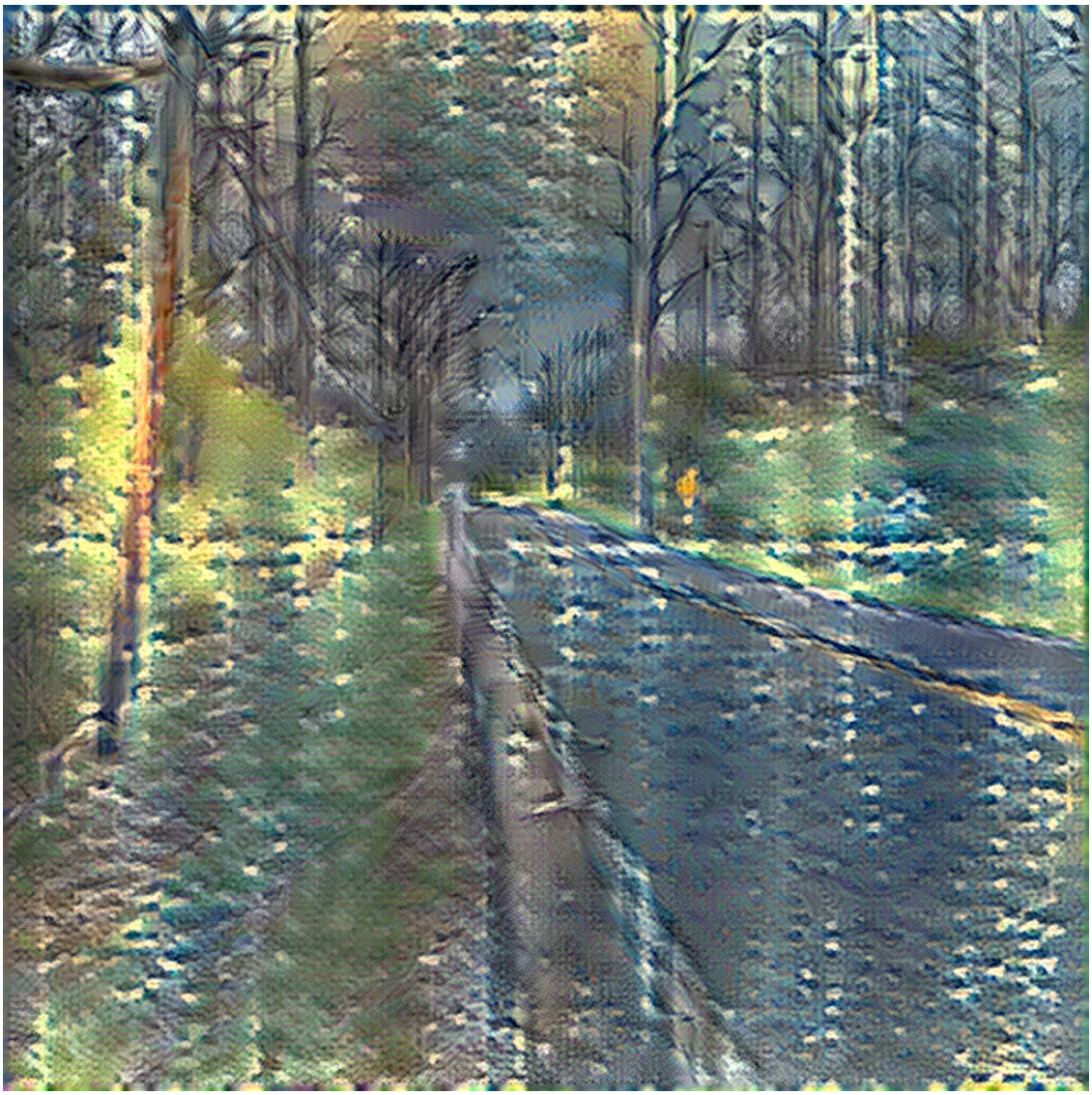
```
Out[24]:
```



Unsurprisingly, after 10 iterations it mostly looks like noise (though some edges are just barely visible behind this). We can easily iterate further starting from where we left off - the optimization routine provides us `res.x` in exactly the same format as our input data.

```
In [25]: res = iterate(40, res.x)
         save_result(res, output_filename)
         IPython.display.Image(filename = output_filename)
```

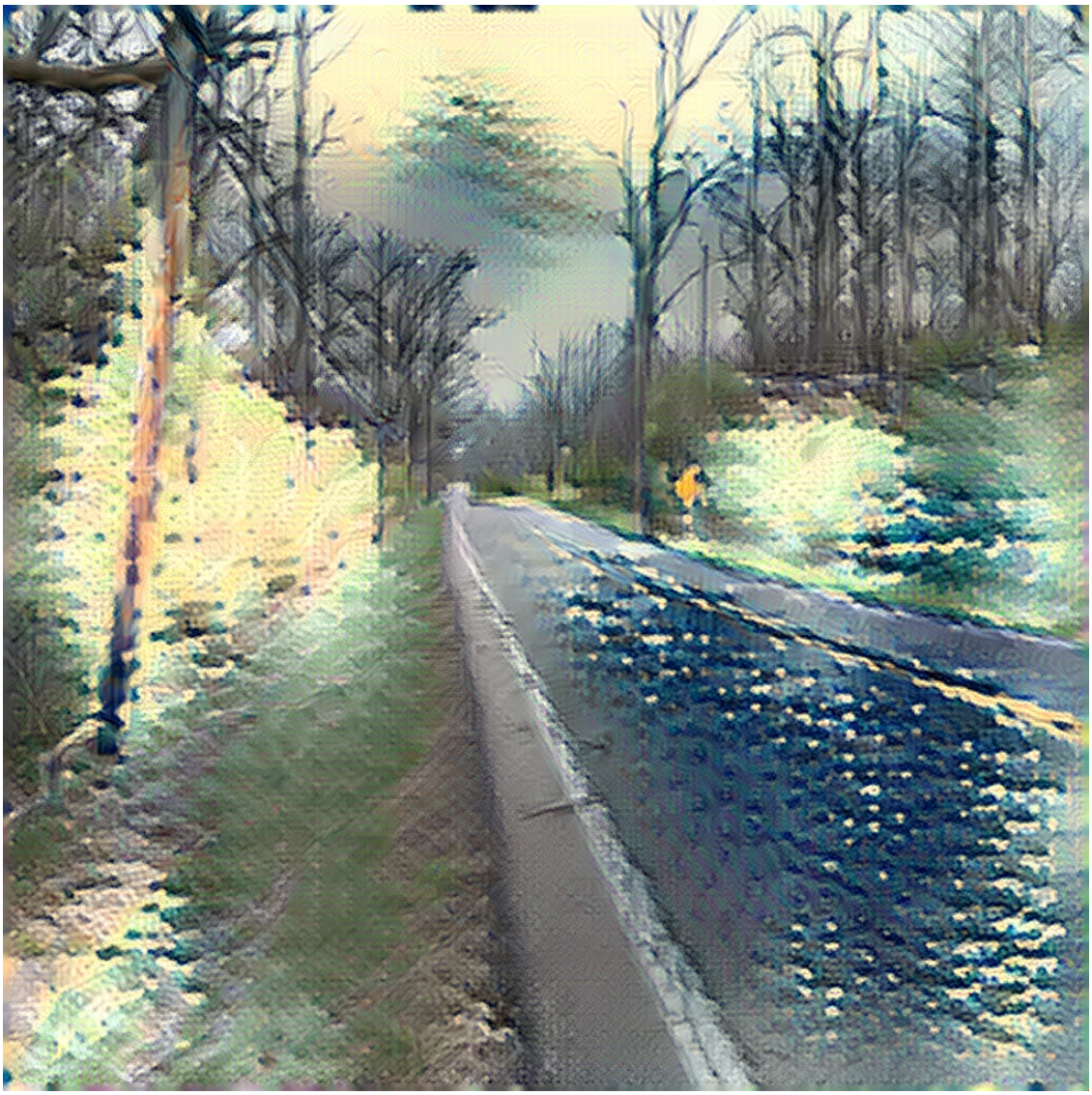
```
Out[25]:
```



This is forming a clear preview, but is still quite noisy. Run another 400 iterations:

```
In [26]: res = iterate(400, res.x)
         save_result(res, output_filename)
         IPython.display.Image(filename = output_filename)
```

Out[26]:



We could iterate further, but that's probably sufficient for a finished image.

In [ ]: