

Presentation on “Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks,” by Alec Radford, Luke Metz, and Soumith Chintala

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Introduction

- ▶ In the field of deep learning, we have crossed into an era where we are experimenting with designs that involve more than one neural network.
- ▶ Generative adversarial networks are a design pattern to employ two neural networks.
- ▶ “Unsupervised representational learning with deep convolutional generative adversarial networks” [1], is a milestone in the development of Generative Adversarial Networks where the authors report a reliable architecture that incorporates convolutional neural networks into the generative adversarial network design.
- ▶ The authors tout several applications of their design to prove its utility.
- ▶ For the remainder of this presentation, we will refer to the paper entitled , “Unsupervised representational learning with deep convolutional generative adversarial networks,” as, “the DCGAN’s paper,” or by its reference number [1].

Introduction

A note about the DCGAN's paper: we find the authors of [1] rely very little on mathematics to prove anything about their work. Instead, they make the software they report on in the paper publicly available [2]. One must study and execute this publicly available code in order to fully appreciate their work.

Background

A generative adversarial network (GAN) is a neural network with two components. Goodfellow *et. al* invent GAN's in [5]. To a first approximation, GAN's work as follows:

- ▶ The first component is a *generator* that learns to transform vectors of random numbers into output values that resemble instances from some dataset.
- ▶ The second component is a *discriminator* that classifies things into two categories:
 - ▶ the class of instances of the dataset, and
 - ▶ the class of generator outputs.
- ▶ “At convergence, the generators samples are indistinguishable from real data, and the discriminator outputs $\frac{1}{2}$ everywhere. The discriminator may then be discarded” [11]. from Deep learning , Goodfellow *et al.*

Background

- ▶ ... or not. The authors of the DCGAN paper find a use for the discriminator.
- ▶ In the context of this paper, the outputs are images. However, researchers use GAN's where the generators create other artifacts. We find an extensive list on Github [12] of over 500 research projects. Some examples from this list are:
 - ▶ imputing missing values in datasets,
 - ▶ generating music,
 - ▶ fraud detection, and
 - ▶ playing chess.

The authors of the paper make several contributions they...

- ▶ invent an architecture for DCGAN's,
- ▶ use the convolutional layer filters of trained DCGAN's discriminators as feature extractors for doing classifications,
- ▶ demonstrate that after training the DCGAN, its filters learn how to represent images, and
- ▶ present a method of doing vector arithmetic using DCGAN inputs to do inferences *à la* Word2Vec [6].

Architecture

A high-level overview of the architecture:

- ▶ Here is an example of code the authors write to link the generator and discriminator.

```
gX = gen(Z, *gen_params)

p_real = discrim(X, *discrim_params)
p_gen = discrim(gX, *discrim_params)

d_cost_real = bce(p_real, T.ones(p_real.shape)).mean()
d_cost_gen = bce(p_gen, T.zeros(p_gen.shape)).mean()
g_cost_d = bce(p_gen, T.ones(p_gen.shape)).mean()

d_cost = d_cost_real + d_cost_gen
g_cost = g_cost_d
```

- ▶ Keep in mind: the discriminator's output layer uses a softmax activation. we interpret the output layer values as probabilities.
- ▶ We associate a high cost with the discriminator giving an output with a high probability for any output for generated inputs because that means the generator fooled the discriminator. This is what `d_cost_gen` does.
- ▶ We associate a low cost for the discriminator's doing the same thing for "real," inputs. This is what `d_cost_real` does.
- ▶ We associate a low cost with the generator's producing an output that the discriminator gives a high probability output for.

- ▶ The **discriminator**:
 - ▶ is a convolutional neural network.
- ▶ Here is the code from [2] that defines it:

```
def discrim(X, w, w2, g2, b2, w3, g3, b3, w4, g4, b4, wy):  
    h = lrelu(dnn_conv(X, w, subsample=(2, 2),  
        border_mode=(2, 2)))  
    h2 = lrelu(batchnorm(dnn_conv(h, w2, subsample=(2, 2),  
        border_mode=(2, 2)), g=g2, b=b2))  
    h3 = lrelu(batchnorm(dnn_conv(h2, w3, subsample=(2, 2),  
        border_mode=(2, 2)), g=g3, b=b3))  
    h4 = lrelu(batchnorm(dnn_conv(h3, w4, subsample=(2, 2),  
        border_mode=(2, 2)), g=g4, b=b4))  
    h4 = T.flatten(h4, 2)  
    y = sigmoid(T.dot(h4, wy))  
    return y
```

- ▶ The important thing to notice in the code above is that the authors implement the discriminator as a six layer neural network with four convolutional layers, a flattening layer, and an output layer that uses the sigmoid activation but leaky rectified linear units (ReLU's) elsewhere.

Architecture

- ▶ The generator uses fractionally-strided layers.
- ▶ The authors of the paper prefer the term, “fractionally-strided.” However in the course of research one might encounter layers implemented with the same functionality referred to as deconvolutional layers.
- ▶ Here is the code for the discriminator implementation:

```
def gen(Z, w, g, b, w2, g2, b2, w3, g3, b3, w4, g4, b4, wx):  
    h = relu(batchnorm(T.dot(Z, w), g=g, b=b))  
    h = h.reshape((h.shape[0], ngf*8, 4, 4))  
    h2 = relu(batchnorm(deconv(h, w2, subsample=(2, 2),  
        border_mode=(2, 2)), g=g2, b=b2))  
    h3 = relu(batchnorm(deconv(h2, w3, subsample=(2, 2),  
        border_mode=(2, 2)), g=g3, b=b3))  
    h4 = relu(batchnorm(deconv(h3, w4, subsample=(2, 2),  
        border_mode=(2, 2)), g=g4, b=b4))  
    x = tanh(deconv(h4, wx, subsample=(2, 2), border_mode=(2, 2)))  
    return x
```

- ▶ The important thing to notice about the generator is that the input layer transforms a vector of random values into a $1024 \times 4 \times 4$ tensor. The authors then add 5 fractionally-strided convolutional layers, and use a tanh activation for the output layer. The authors write that using tanh gives better output as images, and speeds up training [1].

subsectionDeconvolution visualization The term deconvolution seems to have stuck because we see library functions in

▶ .

- ▶ The authors use three datasets for training:
 - ▶ Large Scale Scene Understanding (LSUN),
 - ▶ Imagenet 1-K, and
 - ▶ Faces.
- ▶ The authors two datasets for evaluating unsupervised learning:
 - ▶ Canadian Institute for Advanced Research (CIFAR) 10
 - ▶ StreetView House Numbers (SVHN)
- ▶ Note: the authors mention that they heuristically removed duplicate images from LSUN to prevent the DCGAN from memorizing images.

- ▶ The authors used images of bedrooms from the LSUN dataset [3] as input to their model.

Implementation Details

The code for this paper, as well as many others in the references and that one may find in the course of research, is on Github in the `dcgan_code` project [2].

This code is a bit outdated, however the `dcgan_code` Github project has a link to the DCGAN-tensorflow [4] project that we find more accessible.

Fractionally-strided convolutions

A deep convolutional generative adversarial network (DCGAN) is a GAN that uses convolutional neural networks for the generator and discriminator.

The discriminator uses convolutional layers in the sense we are familiar with, such as the convolutional layers LeCun describes in LeNet-5 [13].

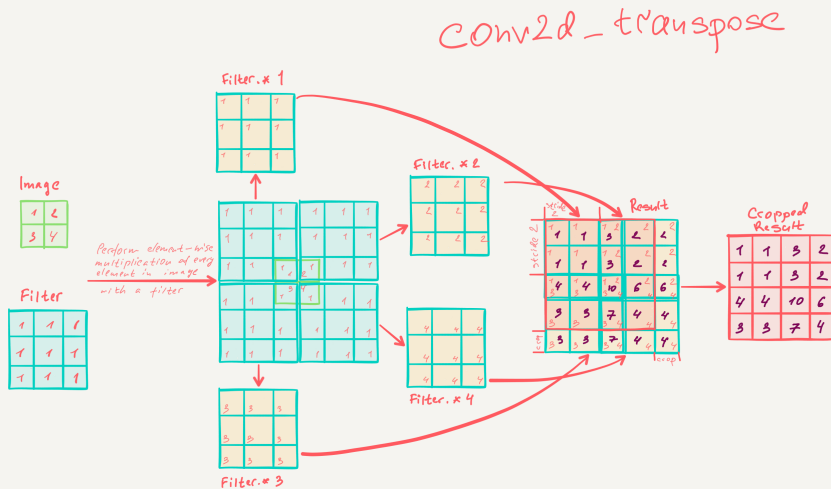
However, the generator uses convolutional layers that we find called deconvolutional layers in the source code that accompanies this paper [2], and elsewhere, but that in the paper the authors write that we should prefer the term “*fractionally-strided*.” The computations that comprise fractionally-strided convolutions are not clear to us from the paper or the source code that accompanies it. We find the source code unclear because the authors implement fractionally-strided convolutions using library functions, the source code of which we run out of time to peruse. The paper lacks detail on how to compute a fractionally-strided convolutions.

Fractionally-strided convolutions

On the other hand, the github project [2] that accompanies the paper [1] links to a Tensorflow implementation of the same code: [4] where the author of this code implements fractionally-strided convolutions using Tensorflow's `conv2d_transpose`. We did some internet searching and found [14]. This reference plus using `conv2d_transpose` in a small example helps us understand precisely how the fractionally-strided convolution operation works. We feel confident to rely on `conv2d_transpose` because the authors of the paper [1] we review here provide a link to the code in [4] in their own code. We feel the authors of the DCGAN's paper's endorsement of the Tensorflow code means `conv2d_transpose` is a valid method for doing what the authors of [1] refer to as fractionally-strided convolutions, and that a good understanding of `conv2d_transpose` is a good understanding of fractionally-strided convolutions.

Fractionally-strided convolutions

We found some example code, and a great diagram from a StackExchange.com discussion [15]. That explains in detail how conv2d_transpose works. This is the diagram we found:



Fractionally-strided convolutions

- ▶ Since anyone might write anything in online discussion forums, we decided to confirm that Tensorflow's `conv2d_transpose` operation works as the digram implies. `conv2d_transpose` has three important parameters: input tensor, filter, and stride.
- ▶ One should be careful not to confuse the term filter we have for `conv2d_transpose` and the filters that the authors of the DCGAN's paper show on page 9.
- ▶ In the context of the DCGAN paper it is better to think of the filter parameter of `conv2d_transpose` as a kernel for the `conv2d_transpose` operation, and the filter is the result of applying `conv2d_transpose` to the input tensor.

Fractionally-strided convolutions

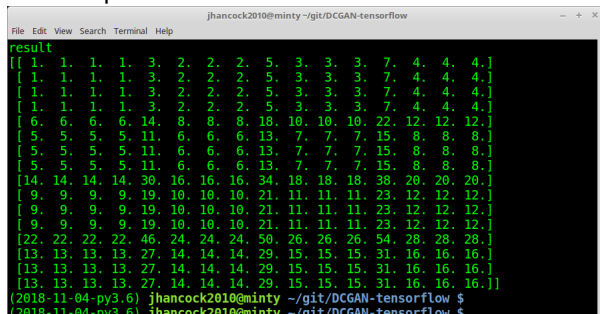
- ▶ The next slide shows a 4x4 input tensor, and the result of applying `conv2d_transpose` to that tensor, with stride of 1,4,4,1.
- ▶ `Conv2d_transpose` operates on 4 dimensional tensors, so we must embed the 4x4 matrix in a 4-dimensional tensor, and stride through it accordingly. Note on the next slide how most entries in the output tensor are copies of entries in the input tensor, except where the 5x5 kernels must overlap in order to achieve the 16x16 output.

Fractionally-strided convolutions

The input tensor:

$$\begin{bmatrix} 1 & 2 & 3 & 4 \\ 5 & 6 & 7 & 8 \\ 9 & 10 & 11 & 12 \\ 13 & 14 & 15 & 16 \end{bmatrix}$$

The output we can see the entries in the input matrix copied into 5x5 intermediate tensors and then added according to the stride of 4, and values are added when we have overlap. We show a screen shot to prove the code runs.



```
jhancock2010@minty ~/git/DCGAN-tensorflow
File Edit View Search Terminal Help
result
[[ 1.  1.  1.  1.  3.  2.  2.  2.  5.  3.  3.  3.  7.  4.  4.  4.]
 [ 1.  1.  1.  1.  3.  2.  2.  2.  5.  3.  3.  3.  7.  4.  4.  4.]
 [ 1.  1.  1.  1.  3.  2.  2.  2.  5.  3.  3.  3.  7.  4.  4.  4.]
 [ 1.  1.  1.  1.  3.  2.  2.  2.  5.  3.  3.  3.  7.  4.  4.  4.]
 [ 6.  6.  6.  6. 14.  8.  8.  8. 18. 10. 10. 10. 22. 12. 12. 12.]
 [ 5.  5.  5.  5. 11.  6.  6.  6. 13.  7.  7.  7. 15.  8.  8.  8.]
 [ 5.  5.  5.  5. 11.  6.  6.  6. 13.  7.  7.  7. 15.  8.  8.  8.]
 [ 5.  5.  5.  5. 11.  6.  6.  6. 13.  7.  7.  7. 15.  8.  8.  8.]
 [14. 14. 14. 14. 30. 16. 16. 16. 34. 18. 18. 18. 38. 20. 20. 20.]
 [ 9.  9.  9.  9. 19. 10. 10. 10. 21. 11. 11. 11. 23. 12. 12. 12.]
 [ 9.  9.  9.  9. 19. 10. 10. 10. 21. 11. 11. 11. 23. 12. 12. 12.]
 [ 9.  9.  9.  9. 19. 10. 10. 10. 21. 11. 11. 11. 23. 12. 12. 12.]
 [22. 22. 22. 22. 46. 24. 24. 24. 50. 26. 26. 26. 54. 28. 28. 28.]
 [13. 13. 13. 13. 27. 14. 14. 14. 29. 15. 15. 15. 31. 16. 16. 16.]
 [13. 13. 13. 13. 27. 14. 14. 14. 29. 15. 15. 15. 31. 16. 16. 16.]
 [13. 13. 13. 13. 27. 14. 14. 14. 29. 15. 15. 15. 31. 16. 16. 16.]
(2018-11-04-py3.6) jhancock2010@minty ~/git/DCGAN-tensorflow $
(2018-11-04-py3.6) jhancock2010@minty ~/git/DCGAN-tensorflow $
```

Fractionally-strided convolutions

The authors of the paper make several contributions: Here reference github code implementation How to run their mnist example:

- ▶ Use AWS Ubuntu Deep Learning Instance
 - ▶ Expensive \approx \$0.65 per hour!
 - ▶ Configure an alarm to shut the instance down after 3 hours!
- ▶ Create virtual environment
 - ▶ Use pip to install libraries
 - ▶ force install of Theano 0.9.0 (`pip install -I Theano 0.9.0`)
- ▶ Paper dcgan_code repository does not have MNIST data,
 - ▶ Download MNIST data from <https://github.com/Manuel4131/GoMNIST/tree/master/data>, and change location in `lib/config.py`

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