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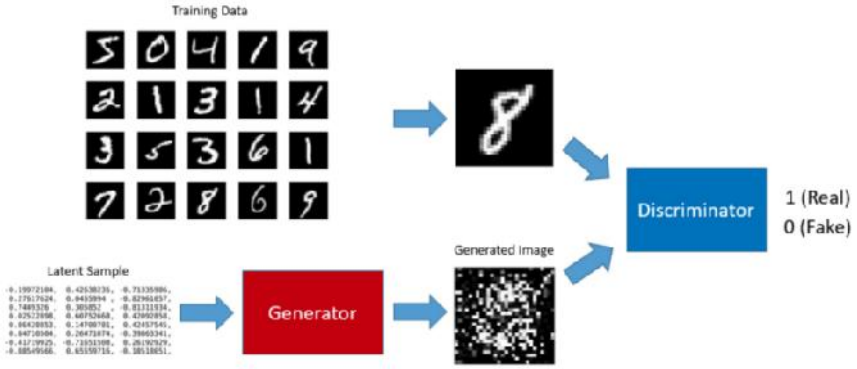
Understanding Generative Adversarial Networks



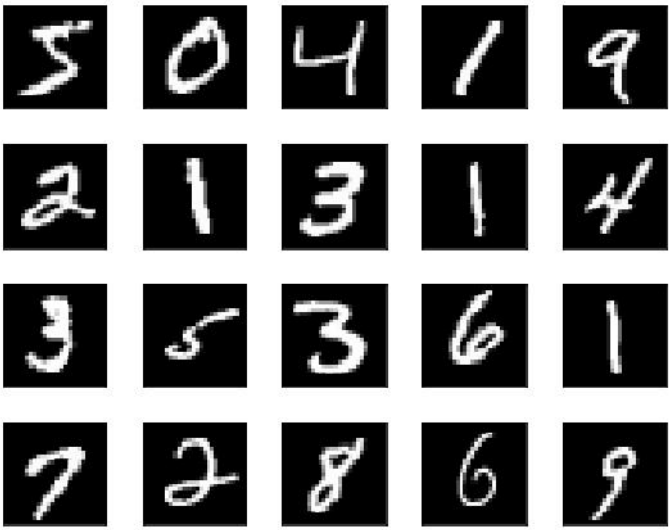
If you see the above image and it does not make much sense, this article is written for you. I explain how GAN works using a simple project that generates hand-written digit images.

I use Keras on TensorFlow and the notebook code is available in **my Github**.

Background

GAN (Generative Adversarial Network) is a framework proposed by Ian Goodfellow, Yoshua Bengio and others in 2014.

A GAN can be trained to generate images from random noises. For example, we can train a GAN to generate digit images that look like hand-written digit images from **MNIST** database.

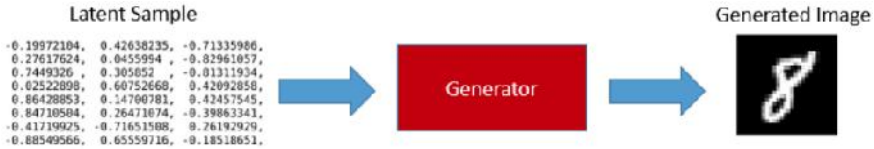


MNIST hand-written digit images

A GAN has two parts in it: the generator that generates images and the discriminator that classifies real and fake images.

The Generator

The input to the generator is a series of randomly generated numbers called **latent sample**. Once trained, the generator can produce digit images from latent samples.



Our generator is a simple fully connected network that takes a latent sample (100 randomly generated numbers) and produces 784 data points which can be reshaped into a 28 x 28 digit image which is the size used by all MNIST digit images.

```
generator = Sequential([
    Dense(128, input_shape=(100,)),
    LeakyReLU(alpha=0.01),
    Dense(784),
    Activation('tanh')
], name='generator')
```

The summary output is as follows:

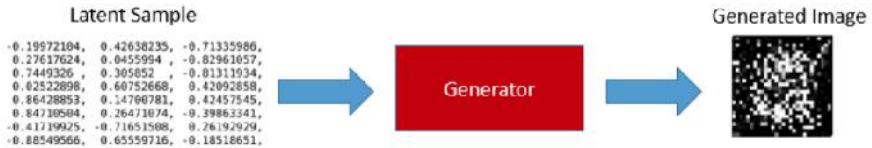
```
_________________________________________________________________
Layer (type)                 Output Shape              Param
#
=================================================================
```

```
=====
dense_1 (Dense)              (None, 128)               12928
_________________________________________________________________
_____
leaky_re_lu_1 (LeakyReLU)    (None, 128)               0
_________________________________________________________________
_____
dense_2 (Dense)              (None, 784)
101136
_________________________________________________________________
_____
activation_1 (Activation)    (None, 784)               0
=================================================================
=====
Total params: 114,064
Trainable params: 114,064
Non-trainable params: 0
_________________________________________________________________
_____
```

We use the **tanh** activation which is recommended in **How to Train a GAN? Tips and tricks to make GANs work**. It also means that we need to rescale the MNIST images to be between -1 and 1. More details are in **my Github**.

How to Train the Generator?

Without training, the generator produces garbage images only.



To train the generator, we need to train a GAN. Before talking about GAN, we shall discuss the discriminator.

The Discriminator

The discriminator is a classifier trained using the supervised learning. It classifies whether an image is real (1) or not (0).

We train the discriminator using both the MNIST images and the images generated by the generator.

If the input image is from the MNIST database, the discriminator should classify it as real.

If the input image is from the generator, the discriminator should classify it as fake.

The discriminator is also a simple fully connected neural network.

```
discriminator = Sequential([
    Dense(128, input_shape=(784,)),
    LeakyReLU(alpha=0.01),
    Dense(1),
    Activation('sigmoid')
], name='discriminator')
```

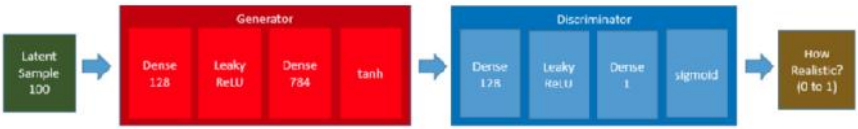
The summary output is as follows:

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_3 (Dense)              (None, 128)               100480
_________________________________________________________________
leaky_re_lu_2 (LeakyReLU)    (None, 128)               0
_________________________________________________________________
dense_4 (Dense)              (None, 1)                 129
_________________________________________________________________
activation_2 (Activation)    (None, 1)                 0
=================================================================
Total params: 100,609
Trainable params: 100,609
Non-trainable params: 0
_________________________________________________________________
```

The last activation is **sigmoid** to tell us the probability of whether the input image is real or not. So, the output can be any value between 0 and 1.

The GAN

We connect the generator and the discriminator to produce a GAN.



Keras has an easy way to connect two models as follows:

```
gan = Sequential([
    generator,
    discriminator
])
```

The structure of the network is shown below:

```
> gan.summary()

Layer (type)                 Output Shape              Param
#
=================================================================
```

```
=====
generator (Sequential)       (None, 784)
114064
_________________________________________________________________
_____
discriminator (Sequential)   (None, 1)
100609
=================================================================
=====
Total params: 214,673
Trainable params: 214,673
Non-trainable params: 0
_________________________________________________________________
_____
```

Now that we know the generator, the discriminator and the GAN, we shall discuss how to train the generator.

Training the GAN means Training the Generator

When we feed a latent sample to the GAN, the generator internally produces a digit image which is then passed to the discriminator for classification. If the generator does a good job, the discriminator returns a value close to 1 (high probability of the image being real).

We feed latent samples to the GAN while setting the expected outcome (label) to 1 (real) as we expect the generator to produce realistic image, and we expect the discriminator to say it is real or close to real.

However, the generator initially produces garbage images, and the loss value is high. So, the back-propagation updates the generator's weights

to produce more realistic images as the training continues. This is how we train the generator via training the GAN.

There is one catch in this process of training the generator via the GAN. We do not want the discriminator's weights to be affected because we are using the discriminator as merely a classifier.

For this reason, we set the discriminator non-trainable during the generator training.

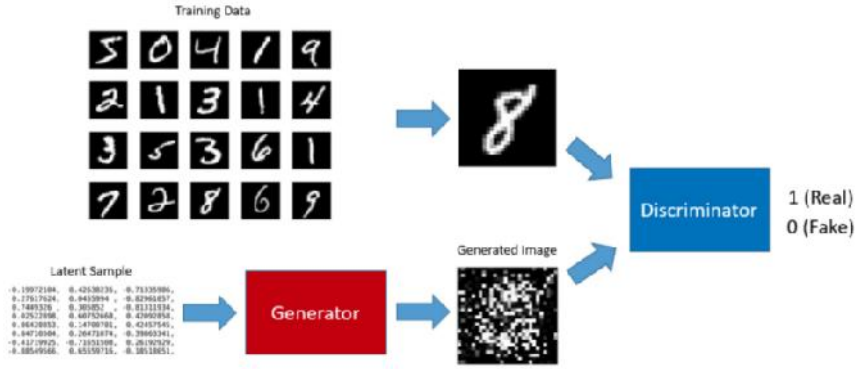
The Train Loop

Let's not forget that we also need to train the discriminator as well so that it can do a good job as a classifier of real and fake images.

We train the discriminator and the generator in turn in a loop as follows:

Step 1) Set the discriminator trainable

Step 2) Train the discriminator with the real MNIST digit images and the images generated by the generator to classify the real and fake images.



The Discriminator Training

Step 3) Set the discriminator non-trainable

Step 4) Train the generator as part of the GAN. We feed latent samples into the GAN and let the generator to produce digit images and use the discriminator to classify the image.

The Generator Training (via GAN)

The loop should ideally continue until they are both trained well and can not be improved any further.

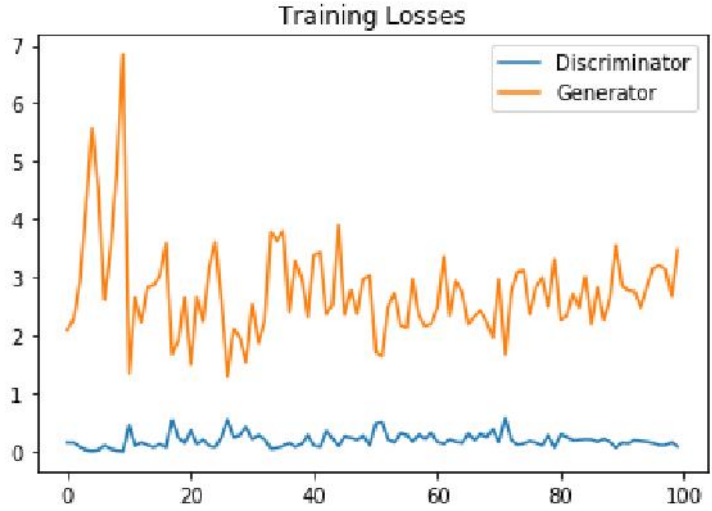
But does it actually work?

The result of the simple GAN is not outstanding. Some of them look pretty good but others are not.

As it turns out, training a GAN requires lots of hacks as per **How to Train a GAN? Tips and tricks to make GANs work** such as label smoothing and other techniques.

There are all sorts of empirical quirks. If I train the discriminator much faster than the generator, the generator gives up learning. In some case, the generator learns to deceive the discriminator and makes the discriminator unable to learn to classify properly.

I tried different hacks and the below plot of the loss values is what I could achieve after about one day experiments (full details in **my Github**).



The generator should have lower loss values than the above. I believe we can improve the performance if we use more complex networks like **DCGAN** (Deep Convolutional GAN).

The point of this article is to show how GAN works in principle using the simple GAN example. Once you know how, it should be easier to understand other GAN articles and implementations.

Moreover, there are many kinds of GANs (the whole list) and new types of GANs are invented as we speak. So, GANs do work and many people are researching GANs.

References

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[3] MNIST dataset

Yann LeCun

http://yann.lecun.com/exdb/mnist/

[4] How to Train a GAN? Tips and tricks to make GANs work

Facebook AI Research: Soumith Chintala, Emily Denton, Martin Arjovsky, Michael Mathieu

https://github.com/soumith/ganhacks

[5] Generative Models

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