

"(GANs), and the variations that are now being proposed is the most interesting idea in the last 10 years in ML, in my opinion." by Yann LeCun



#### Playing chess:

Compete with an opponent better than you beat him / her in the next game repeat this step defeat the opponent





#### Forger and an investigator:

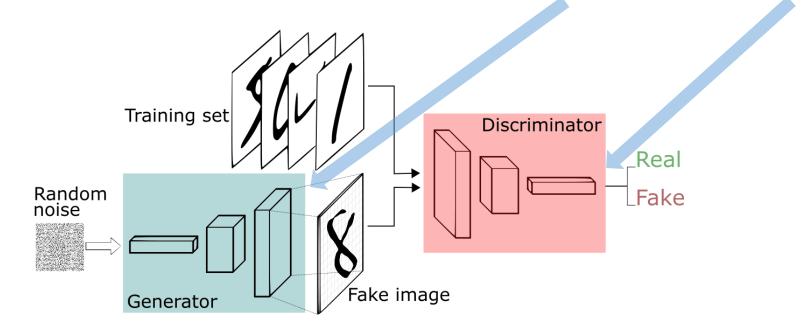
Forger: create fraudulent imitations Investigator: catch these forgers who create the fraudulent contest of forger vs investigator goes on world class investigators (and unfortunately world class forger)







### Two main components





#### **Define GAN**

Pdata(x) -> The distribution of real data

X -> Sample from pdata(x)

P(z) -> Distribution of generator

Z -> Sample from p(z)

G(z) -> Generator Network

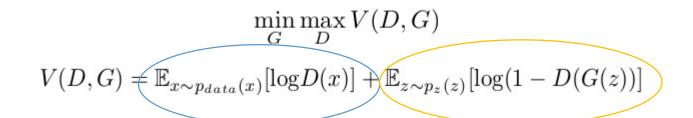
D(x) -> Discriminator Network

$$\min_{G} \max_{D} V(D, G)$$

$$V(D,G) = \mathbb{E}_{x \sim p_{data}(x)}[\log D(x)] + \mathbb{E}_{z \sim p_z(z)}[\log(1 - D(G(z)))]$$



### **Define GANs**

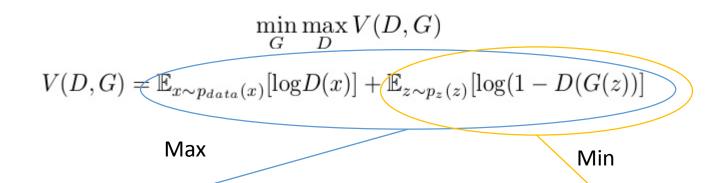


Entropy of (pdata(x)) data from real distribution

Entropy of (p(z)) data from random input



### **Define GANs**



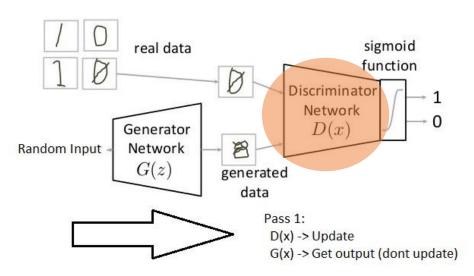
Discriminator is trying to maximize our function V

Generator is trying to minimize the function V



## Training GAN

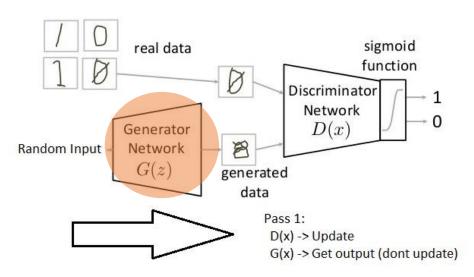
#### Pass 1: Freeze generator, Training discriminator





## Training GAN

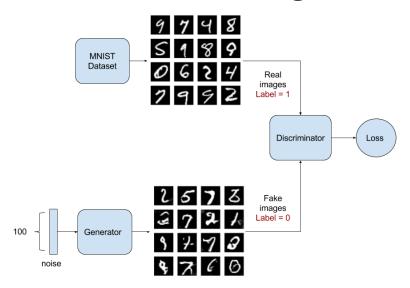
### Pass 2: freeze discriminator, Train generator





## GANs project: Define problem

#### Generate fake images



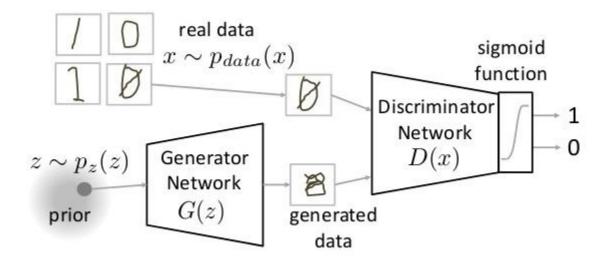
#### **MNIST Dataset Overview**

60,000 examples for training 10,000 examples for testing. 28x28 pixels with values from 0 to 1. Flattened 1-D array of 784 features (28\*28)



## GANs project: Define architecture

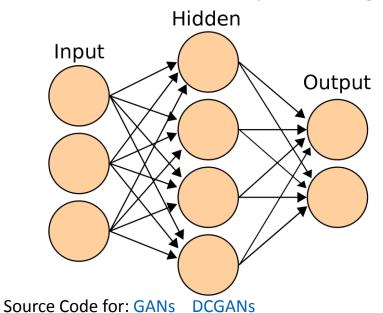
- One hidden layer for discriminator
- One hidden layer for generator





## GANs project: Define architecture

- One hidden layer for discriminator
- One hidden layer for generator



```
# Generator
def generator(x):
    hidden layer = tf.matmul(x, weights['gen hidden1'])
    hidden layer = tf.add(hidden layer, biases['gen hidden1'])
    hidden layer = tf.nn.relu(hidden layer)
    out layer = tf.matmul(hidden layer, weights['gen out'])
    out layer = tf.add(out layer, biases['gen out'])
    out layer = tf.nn.sigmoid(out layer)
    return out layer
# Discriminator
def discriminator(x):
    hidden layer = tf.matmul(x, weights['disc hidden1'])
    hidden_layer = tf.add(hidden_layer, biases['disc_hidden1'])
    hidden layer = tf.nn.relu(hidden layer)
    out layer = tf.matmul(hidden layer, weights['disc out'])
    out layer = tf.add(out layer, biases['disc out'])
    out layer = tf.nn.sigmoid(out layer)
    return out layer
```



## **GANs** project: Training

- 1. Train Discriminator on real data for n epochs
- 2. Generate fake inputs for generator
- 3. Train discriminator on fake data
- 4. Train generator with the output of discriminator
- 5. Repeat 1-4 steps
- 6. Check fake data result

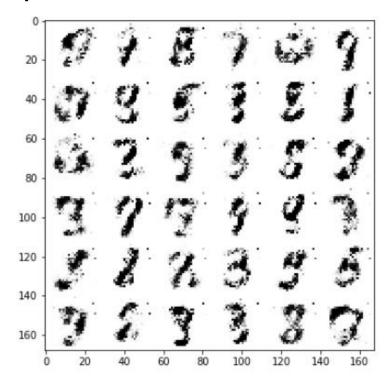


#### Training 10,000 steps

```
Step 1: Generator Loss: 1.057984, Discriminator Loss: 1.227529
Step 2000: Generator Loss: 4.775870, Discriminator Loss: 0.042116
Step 4000: Generator Loss: 3.751669, Discriminator Loss: 0.136570
Step 6000: Generator Loss: 3.318022, Discriminator Loss: 0.189792
Step 8000: Generator Loss: 4.373503, Discriminator Loss: 0.162921
Step 10000: Generator Loss: 3.622272, Discriminator Loss: 0.264043
```



#### Training 10,000 steps



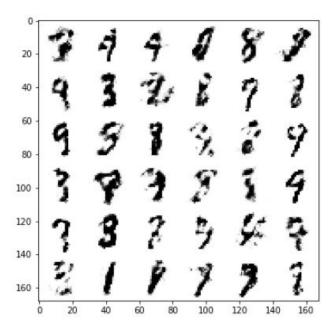


#### Training 40,000 steps

```
Step 1: Generator Loss: 1.022040. Discriminator Loss: 1.238947
Step 2000: Generator Loss: 4.983431, Discriminator Loss: 0.019256
Step 4000: Generator Loss: 4.562924, Discriminator Loss: 0.040434
Step 6000: Generator Loss: 4.215461. Discriminator Loss: 0.150144
Step 8000: Generator Loss: 4.020543, Discriminator Loss: 0.155626
Step 10000: Generator Loss: 3.525209, Discriminator Loss: 0.205117
Step 12000: Generator Loss: 3.320497, Discriminator Loss: 0.336670
Step 14000: Generator Loss: 2.778084, Discriminator Loss: 0.518560
Step 16000: Generator Loss: 3.285352, Discriminator Loss: 0.277530
Step 18000: Generator Loss: 3.258935, Discriminator Loss: 0.351666
Step 20000: Generator Loss: 3.346839, Discriminator Loss: 0.306597
Step 22000: Generator Loss: 4.782597, Discriminator Loss: 0.111715
Step 24000: Generator Loss: 3.731757, Discriminator Loss: 0.283805
Step 26000: Generator Loss: 3.880025, Discriminator Loss: 0.294006
Step 28000: Generator Loss: 3.450228, Discriminator Loss: 0.309087
Step 30000: Generator Loss: 3.259465, Discriminator Loss: 0.457083
Step 32000: Generator Loss: 3.081173, Discriminator Loss: 0.393552
Step 34000: Generator Loss: 2.973398, Discriminator Loss: 0.378245
Step 36000: Generator Loss: 3.155655, Discriminator Loss: 0.401714
Step 38000: Generator Loss: 3.191599, Discriminator Loss: 0.432039
Step 40000: Generator Loss: 3.334904, Discriminator Loss: 0.439917
```



#### Training 40,000 steps





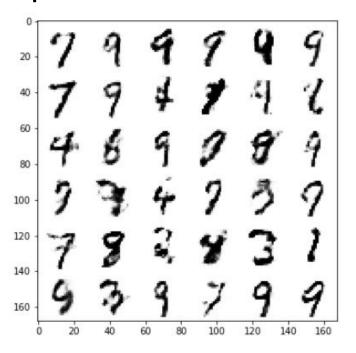
#### Training 80,000 steps

```
Step 1: Generator Loss: 0.482775, Discriminator Loss: 1.683681
Step 2000: Generator Loss: 4.478746, Discriminator Loss: 0.041249
Step 4000: Generator Loss: 4.232111. Discriminator Loss: 0.064319
Step 6000: Generator Loss: 4.142162, Discriminator Loss: 0.117743
Step 8000: Generator Loss: 4.063119, Discriminator Loss: 0.105196
Step 10000: Generator Loss: 4.291493, Discriminator Loss: 0.145389
Step 12000: Generator Loss: 4.307825, Discriminator Loss: 0.237374
Step 14000: Generator Loss: 3.159351, Discriminator Loss: 0.436120
Step 16000: Generator Loss: 4.056623, Discriminator Loss: 0.170912
Step 18000: Generator Loss: 3.793717, Discriminator Loss: 0.299633
Step 20000: Generator Loss: 3.716439, Discriminator Loss: 0.176631
Step 22000: Generator Loss: 4.162383, Discriminator Loss: 0.212528
Step 24000: Generator Loss: 3.983365, Discriminator Loss: 0.253197
Step 26000: Generator Loss: 3.086970, Discriminator Loss: 0.269977
Step 28000: Generator Loss: 3.215426, Discriminator Loss: 0.350482
Step 30000: Generator Loss: 3.515172, Discriminator Loss: 0.298617
Step 32000: Generator Loss: 3.115796, Discriminator Loss: 0.333084
Step 34000: Generator Loss: 3.320462, Discriminator Loss: 0.446589
Step 36000: Generator Loss: 2.987168, Discriminator Loss: 0.417386
Step 38000: Generator Loss: 2.822043, Discriminator Loss: 0.371045
Step 40000: Generator Loss: 2.740946. Discriminator Loss: 0.464534
```

```
Step 42000: Generator Loss: 3.136816, Discriminator Loss: 0.411526
Step 44000: Generator Loss: 2.939960, Discriminator Loss: 0.385261
Step 46000: Generator Loss: 2.284759, Discriminator Loss: 0.399092
Step 48000: Generator Loss: 3.116132. Discriminator Loss: 0.401034
Step 50000: Generator Loss: 2.924815, Discriminator Loss: 0.386848
Step 52000: Generator Loss: 2.809042, Discriminator Loss: 0.365831
Step 54000: Generator Loss: 2.610398, Discriminator Loss: 0.380060
Step 56000: Generator Loss: 2.778062, Discriminator Loss: 0.498709
Step 58000: Generator Loss: 2.868812, Discriminator Loss: 0.523331
Step 60000: Generator Loss: 2.862835, Discriminator Loss: 0.422131
Step 62000: Generator Loss: 3.039068, Discriminator Loss: 0.503733
Step 64000: Generator Loss: 2.840444, Discriminator Loss: 0.496952
Step 66000: Generator Loss: 3.080117, Discriminator Loss: 0.484358
Step 68000: Generator Loss: 2.903224, Discriminator Loss: 0.442403
Step 70000: Generator Loss: 2.672405, Discriminator Loss: 0.555055
Step 72000: Generator Loss: 3.142435, Discriminator Loss: 0.424716
Step 74000: Generator Loss: 2.633177, Discriminator Loss: 0.415394
Step 76000: Generator Loss: 2.820936, Discriminator Loss: 0.546896
Step 78000: Generator Loss: 2.968935, Discriminator Loss: 0.391308
Step 80000: Generator Loss: 2.738734, Discriminator Loss: 0.404072
```



#### Training 80,000 steps:



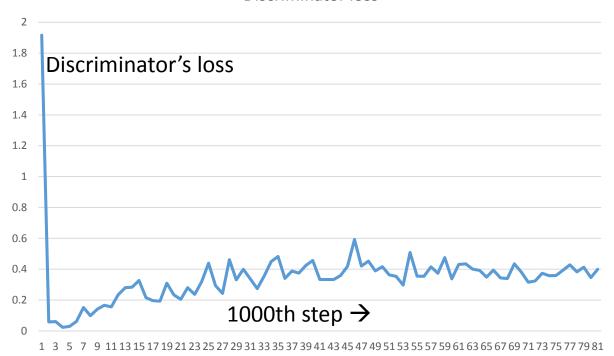


#### Gegerator loss



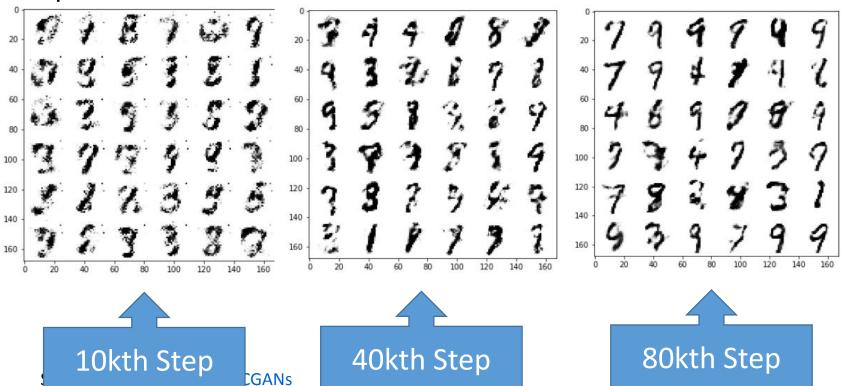


Discriminator loss



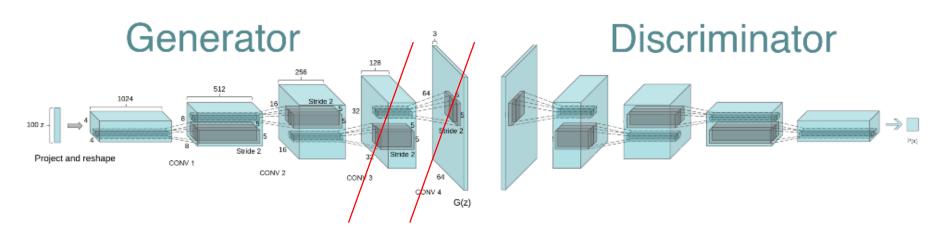


#### Step based evaluation:



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Source Code for: GANs

**DCGANs** 



#### References:

- •<u>Unsupervised representation learning with deep convolutional generative adversarial networks</u>. A Radford, L Metz, S Chintala, 2016.
- •<u>Understanding the difficulty of training deep feedforward neural networks</u>. X Glorot, Y Bengio. Aistats 9, 249-256
- •<u>Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift</u>. Sergey Ioffe, Christian Szegedy. 2015.

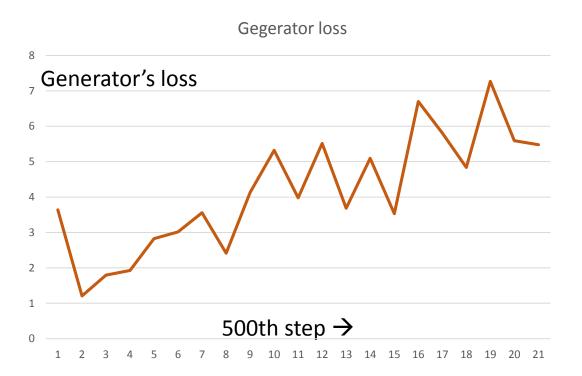


```
def generator(x, reuse=False):
   with tf.variable_scope('Generator', reuse=reuse):
       # TensorFlow Layers automatically create variables and calculate their
       # shape, based on the input.
       x = tf.layers.dense(x, units=7 * 7 * 128)
       x = tf.layers.batch normalization(x, training=is training)
       x = tf.nn.relu(x)
       # Reshape to a 4-D array of images: (batch, height, width, channels)
       # New shape: (batch, 7, 7, 128)
       x = tf.reshape(x, shape=[-1, 7, 7, 128])
       # Deconvolution, image shape: (batch, 14, 14, 64)
       x = tf.layers.conv2d transpose(x, 64, 5, strides=2, padding='same')
       x = tf.layers.batch normalization(x, training=is training)
       x = tf.nn.relu(x)
       # Deconvolution, image shape: (batch, 28, 28, 1)
       x = tf.layers.conv2d transpose(x, 1, 5, strides=2, padding='same')
       # Apply tanh for better stability - clip values to [-1, 1].
       x = tf.nn.tanh(x)
        return x
```

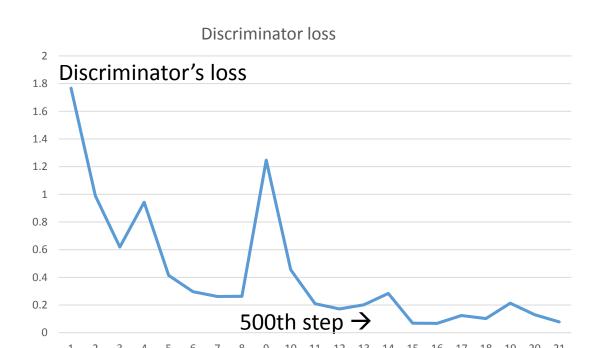


```
def discriminator(x, reuse=False):
    with tf.variable_scope('Discriminator', reuse=reuse):
        # Typical convolutional neural network to classify images.
        x = tf.layers.conv2d(x, 64, 5, strides=2, padding='same')
        x = tf.layers.batch normalization(x, training=is training)
        x = leakyrelu(x)
        x = tf.layers.conv2d(x, 128, 5, strides=2, padding='same')
        x = tf.layers.batch normalization(x, training=is training)
        x = leakyrelu(x)
       # Flatten
        x = tf.reshape(x, shape=[-1, 7*7*128])
        x = tf.layers.dense(x, 1024)
        x = tf.layers.batch normalization(x, training=is training)
        x = leakvrelu(x)
        # Output 2 classes: Real and Fake images
        x = tf.layers.dense(x, 2)
    return x
```











#### Step based evaluation:

