What is GANs

"(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

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What is GANs

Playing chess:

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

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What is GANs

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)

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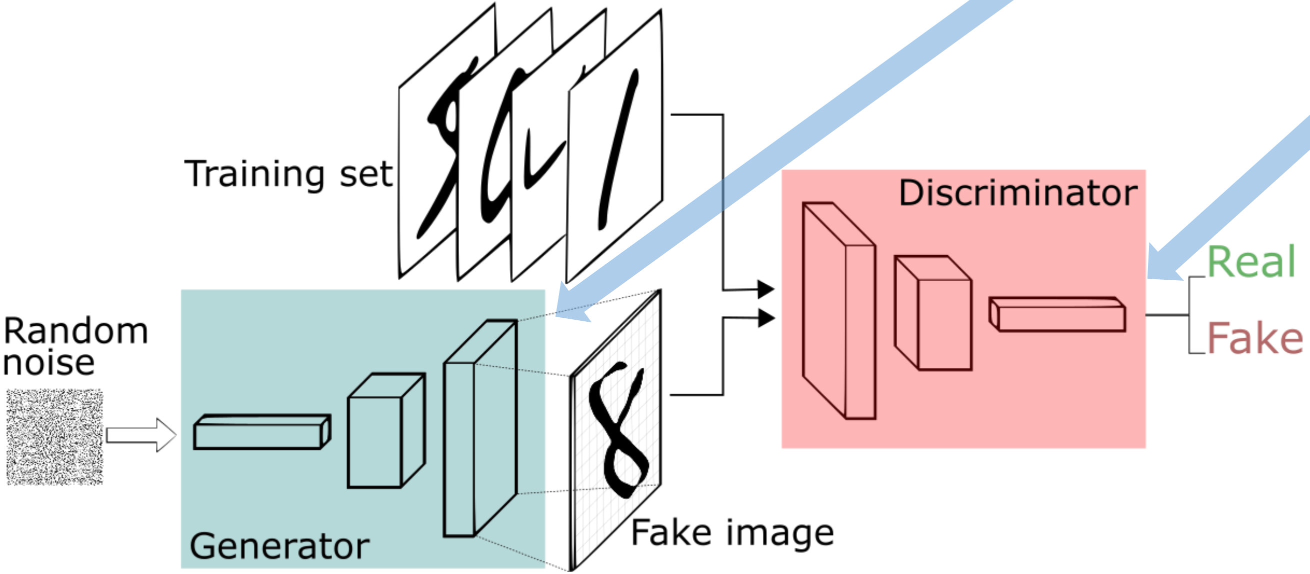
What is GANs

Two main components



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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

$$\min_G \max_D V(D, G)$$

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

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Define GANs

$$\min_G \max_D V(D, G)$$

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

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

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

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Define GANs

$$\min_G \max_D V(D, G)$$

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

Max

Min

Discriminator is trying to maximize our function V

Generator is trying to minimize the function V

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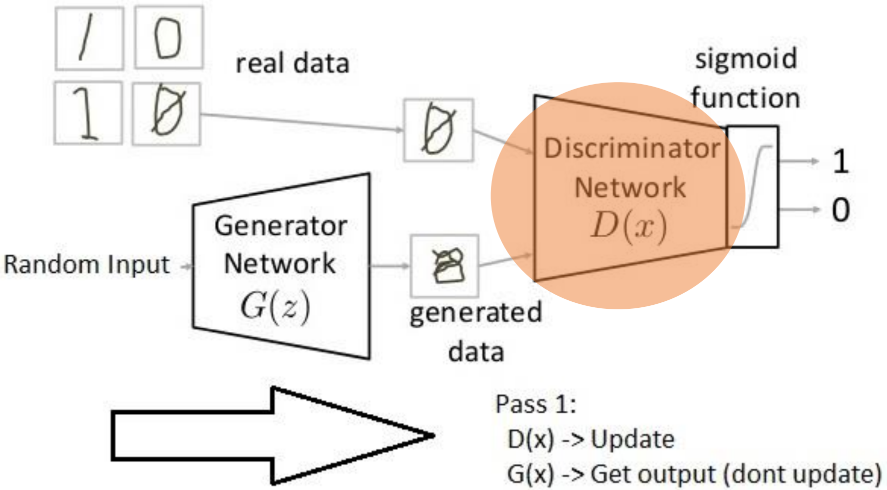
Training GAN

Pass 1: Freeze generator, Training discriminator



Pass 1:
D(x) -> Update
G(x) -> Get output (dont update)

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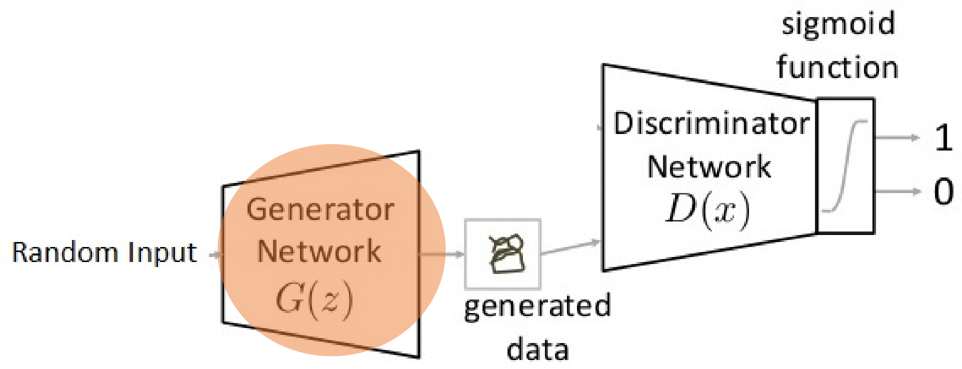
Training GAN

Pass 2: freeze discriminator, Train generator



Pass 2:
D(x) -> Get output (dont update)
G(x) -> Update

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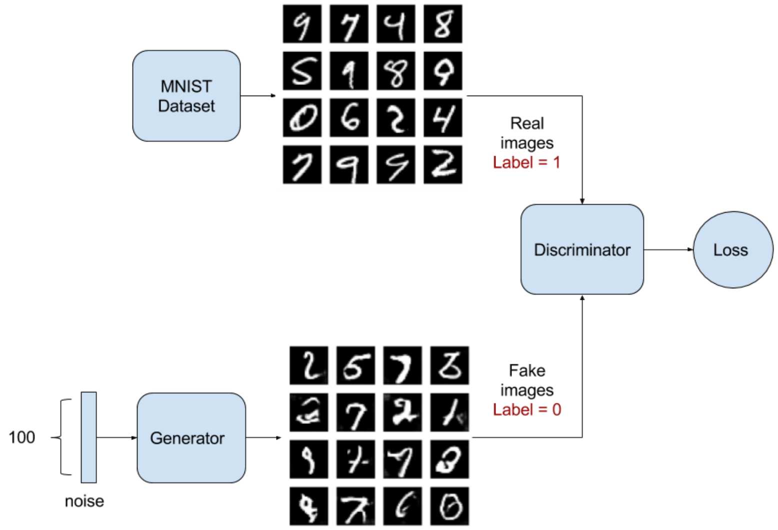
GANs project: Define problem

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)

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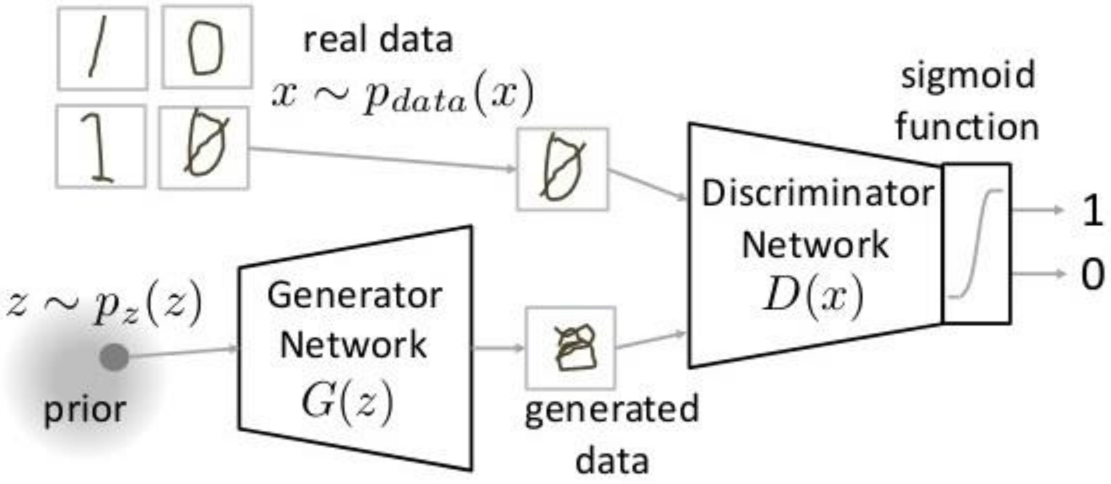
GANs project: Define architecture

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



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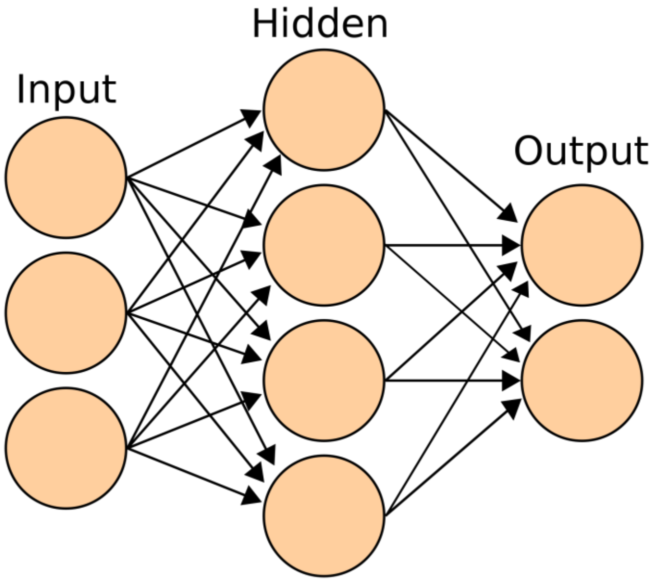
GANs project: Define architecture

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




```python
# 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
```

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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

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GANs project: Results

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
```

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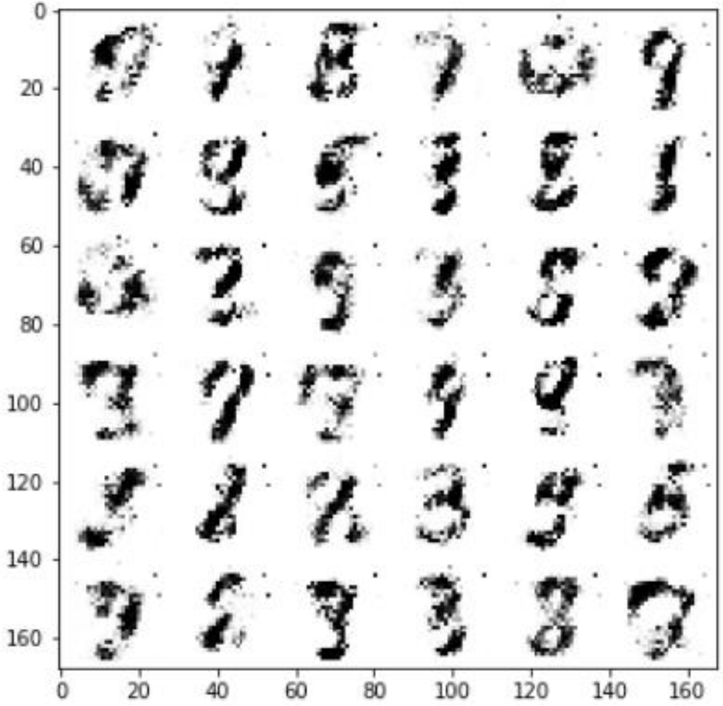
GANs project: Results

Training 10,000 steps



[Source code for GAN](#) [D](#)

GANs project: Results

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
```

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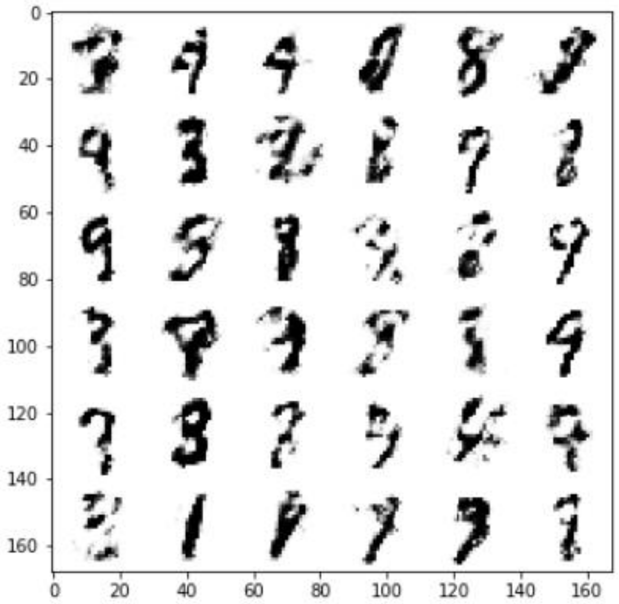
GANs project: Results

Training 40,000 steps



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GANs project: Results

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
```

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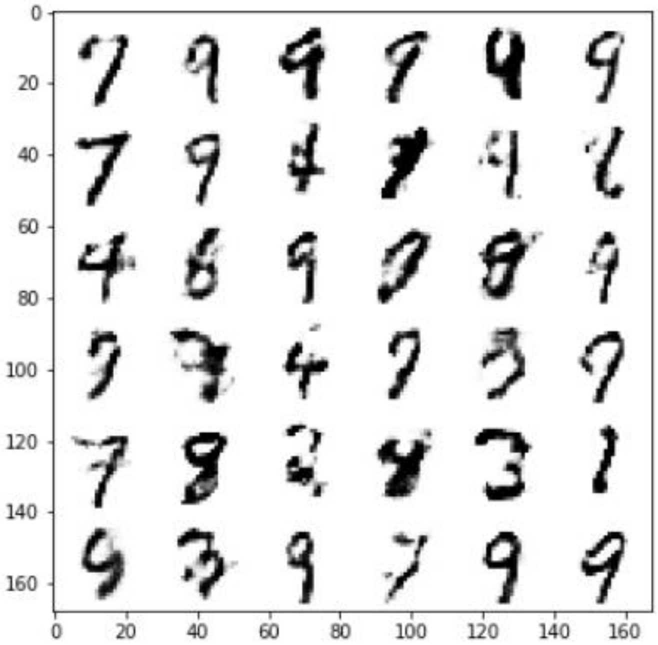
GANs project: Results

Training 80,000 steps:



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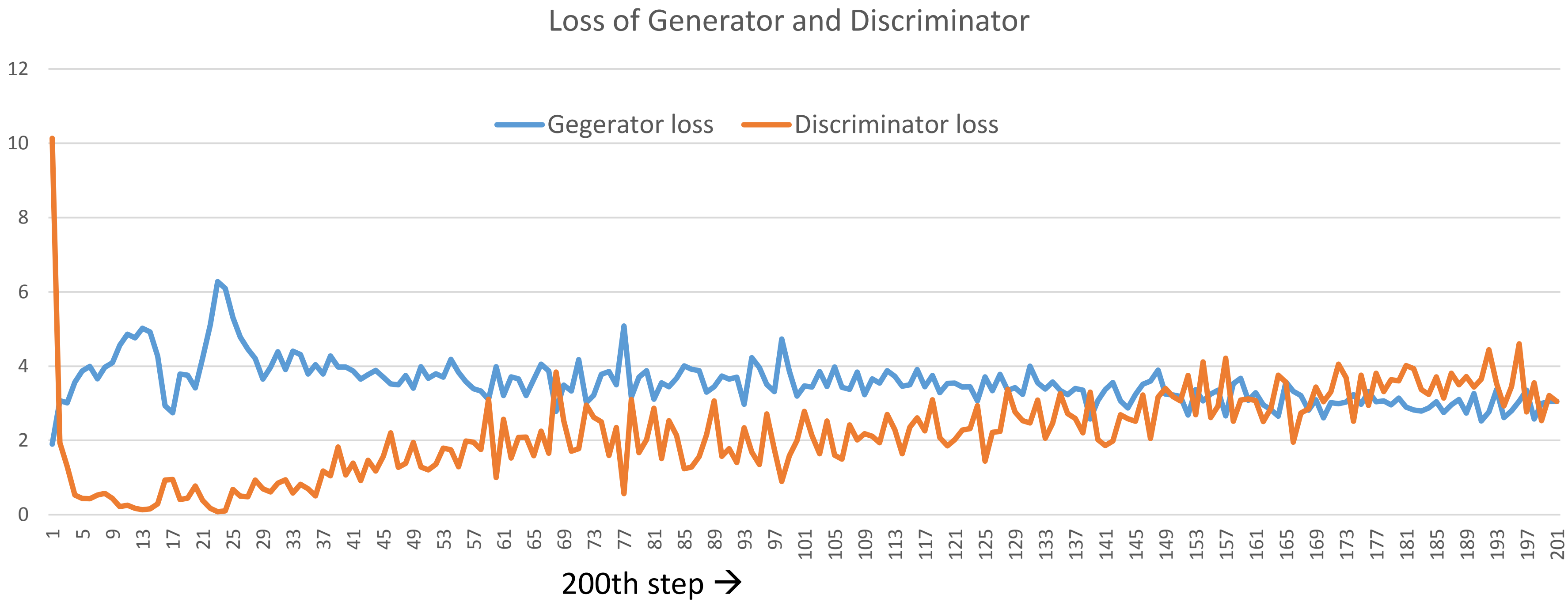
GANs project: Analysis



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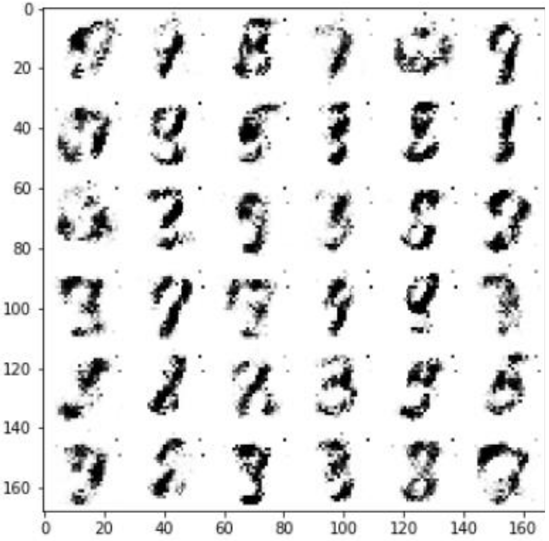
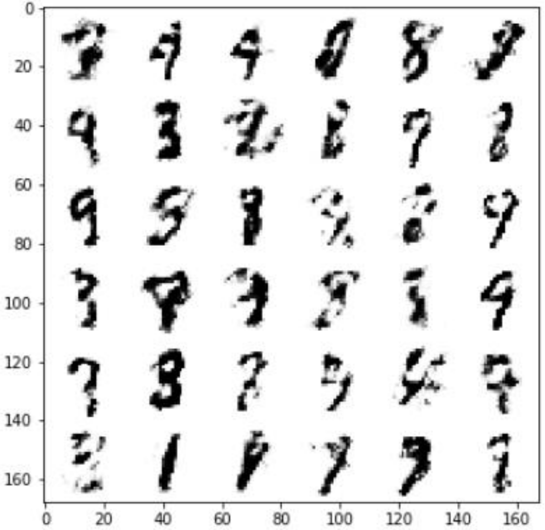
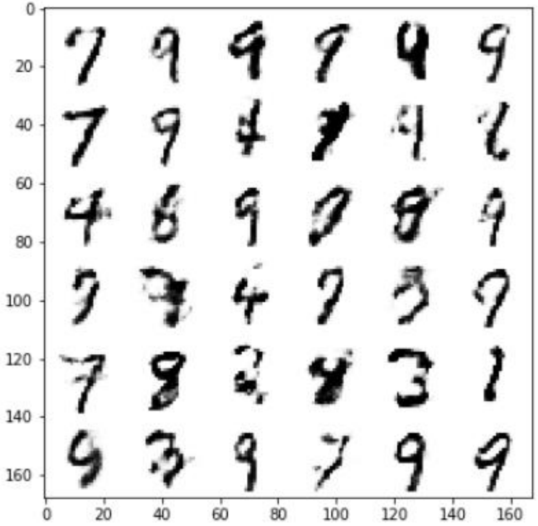
GANs project: Analysis

Step based evaluation:





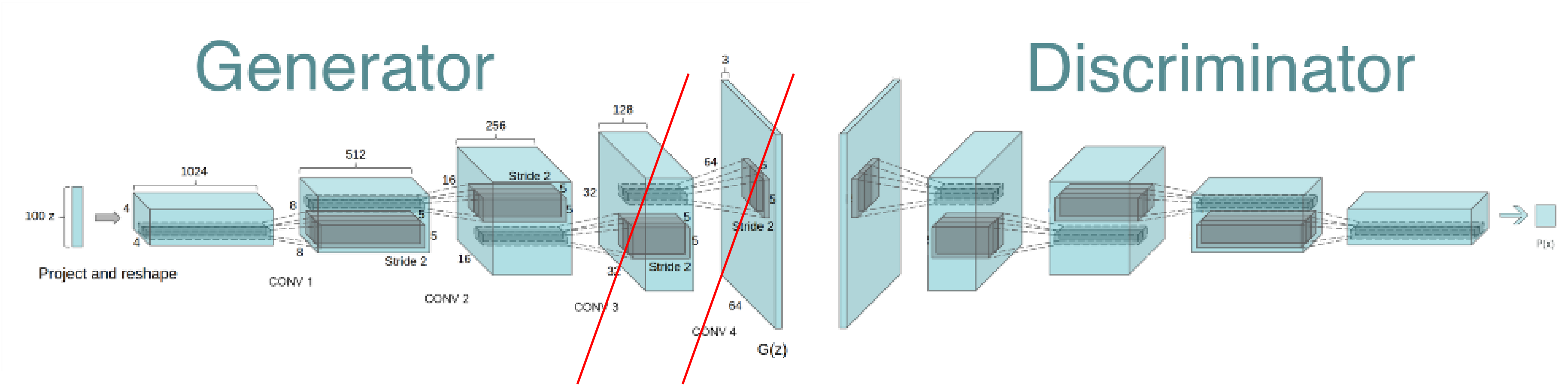


10kth Step

40kth Step

80kth Step

GANs project: DCGAN
Deep Convolutional Generative Adversarial Network



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GANs project: DCGAN
Deep Convolutional Generative Adversarial Network

References:

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

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GANs project: DCGAN
Deep Convolutional Generative Adversarial Network

```
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
```

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GANs project: DCGAN
Deep Convolutional Generative Adversarial Network

```python
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 = leakyrelu(x)
        # Output 2 classes: Real and Fake images
        x = tf.layers.dense(x, 2)
    return x
```

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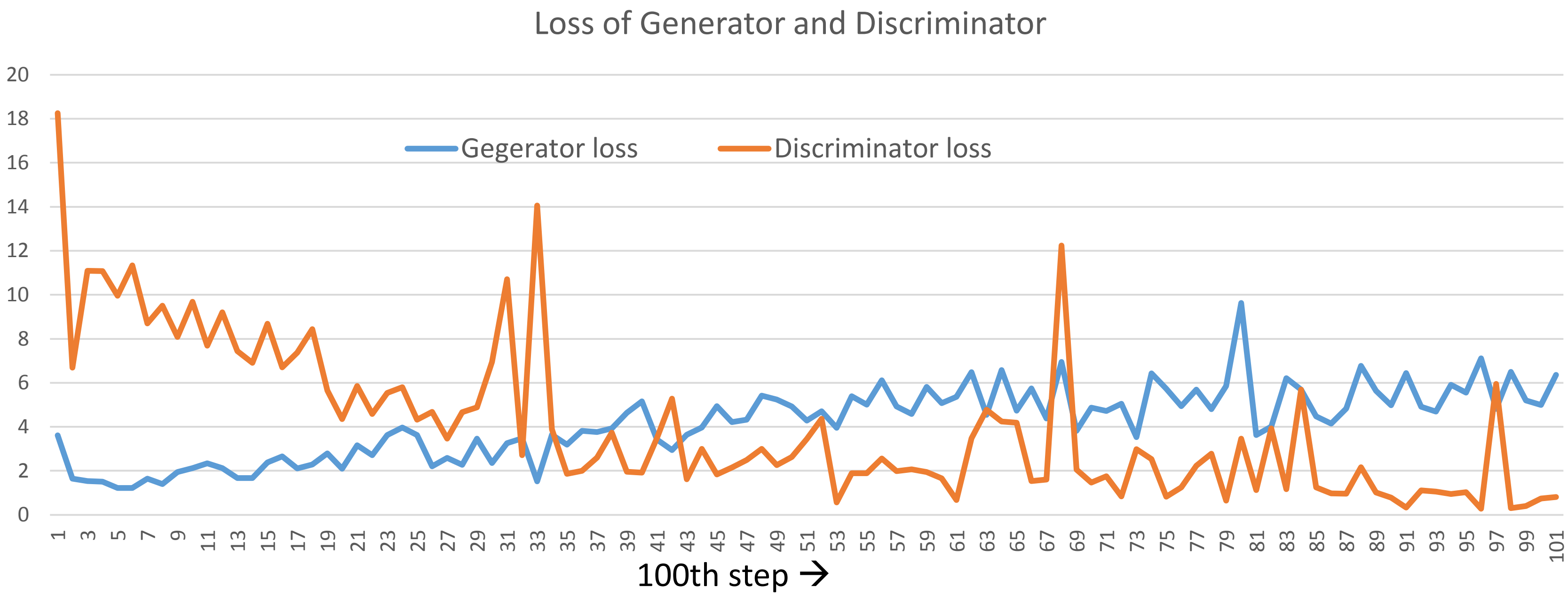
GANs project: Analysis



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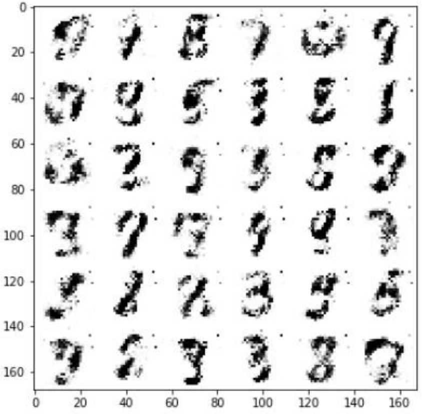
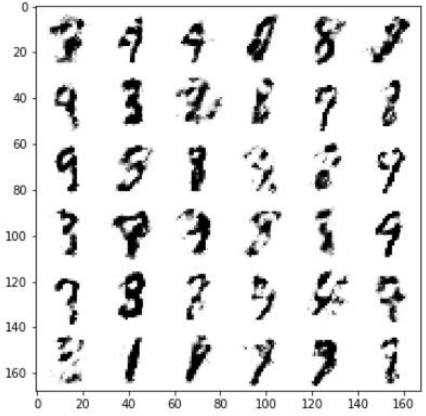
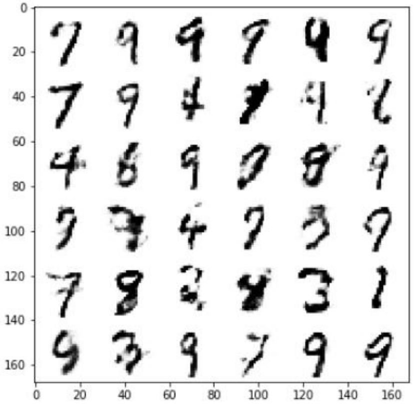
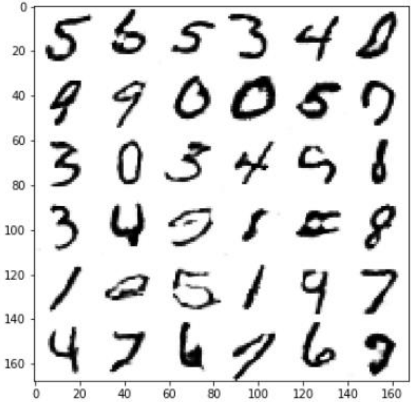
GANs project: Analysis

Step based evaluation:









GAN 10k

GAN 40k

GAN80k

DCGAN 10k

[Source code for GAN] [DCGAN]

GANs project: Analysis

This is the end

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