Generative Adversarial Networks (GANs)

From **Ian Goodfellow at al.**

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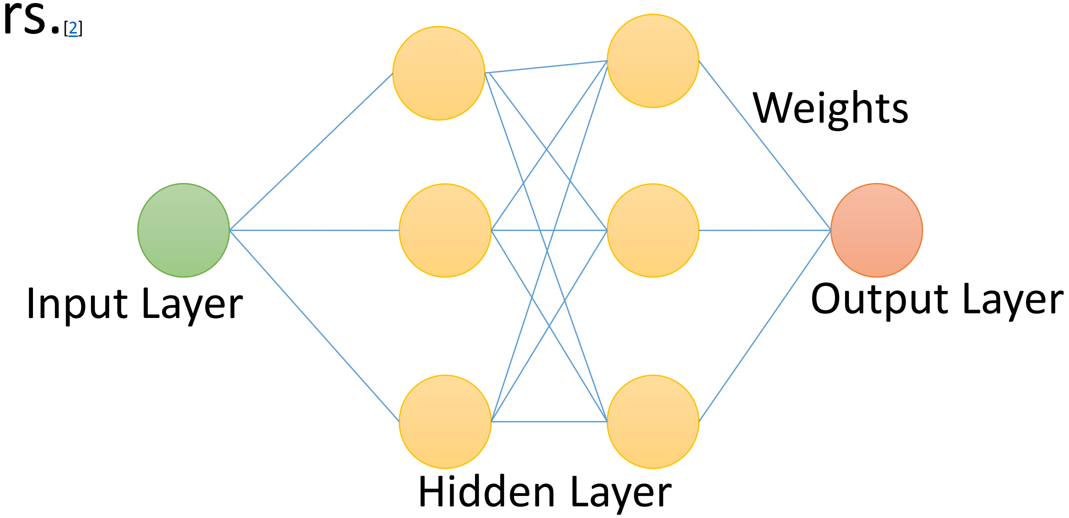
Contents

Introduction

- **Neural networks:**
  - These are computing system
  - Consist of many elements and layers.[2]



- **Deep Neural Network:**
  - Network with more than one or two hidden layers.
  - This is inspired by the structure and functions of brain called artificial neural networks.[1]

Introduction

- Networks learn from an examples.
- Networks use learning rules to learn and extract things from examples.
- **Learning rule** is a logic which improves the performance and results of network.
- Types of learning rules:
  - Supervised learning
  - Unsupervised learning
  - Reinforcement learning
- These rules are apply all over the network and updates the weights of the network.[3]

Introduction

- There are two types of models in Deep learning which are[4]:
  - **Generative models** (model distribution of each class).
  - **Discriminative models** (learn boundary between classes).
- Generative model are difficult to approximate and estimate.
- (Ian J. Goodfellow at all., 2014) propose new generative model estimation procedure which sidesteps these difficulties.
- The model is Generative Adversarial Network (GAN).

What is GAN?

- GAN (Generative Adversarial Network) is the most interesting idea in the last 10 years in Machine Learning.[5]
- GAN can learn to mimic any distribution of data.
- GAN consist of two deep learning neural networks generative and discriminative.

Working of GAN[5][6][7][8] [9][10]

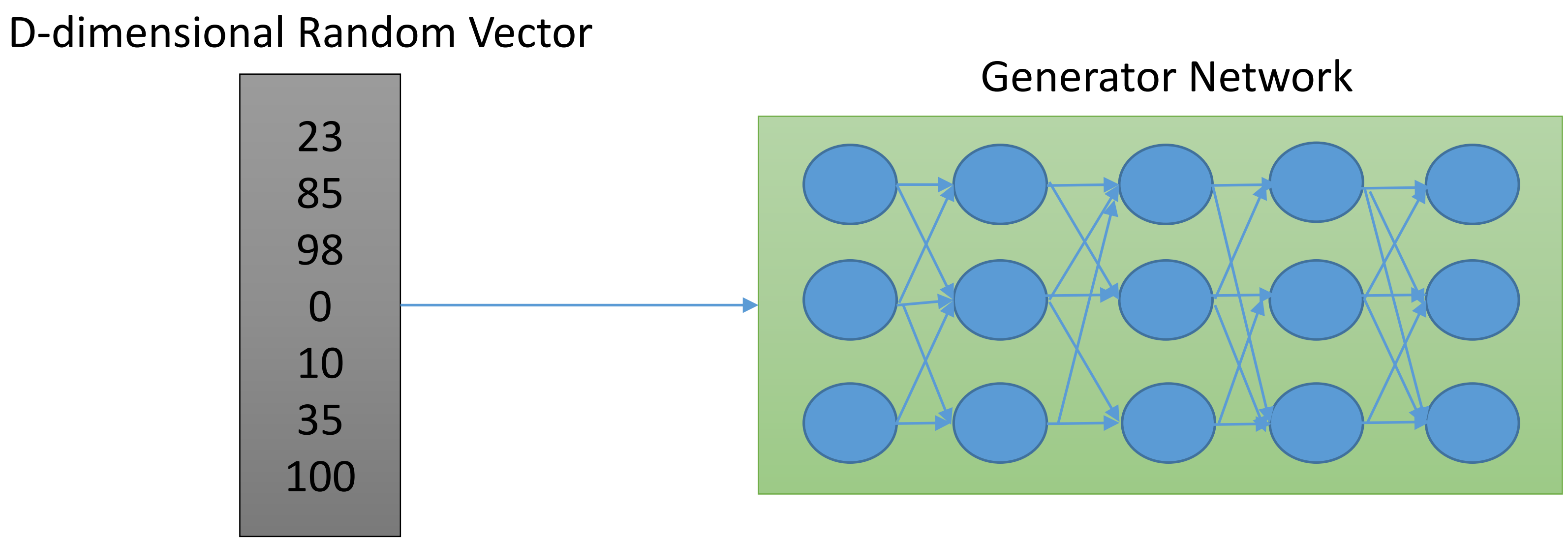
- In GAN two deep neural networks are in competition with each other.
- One network which is called a generator it generates forgeries.
- Other network is called discriminator which receive both forgeries and real images and its aim to differentiate them.
- The discriminator network is a standard convolutional network.[16]
- The generator network is an inverse convolutional network.[17]

Working of GAN

- Both networks are trying to optimize itself.
- If any one network changes its behavior its effect on other and vice versa.
- Both networks consist of multi and fully connected multilayers perceptron.
- Training of these networks are done one by one.
- Both networks are playing minimax game.

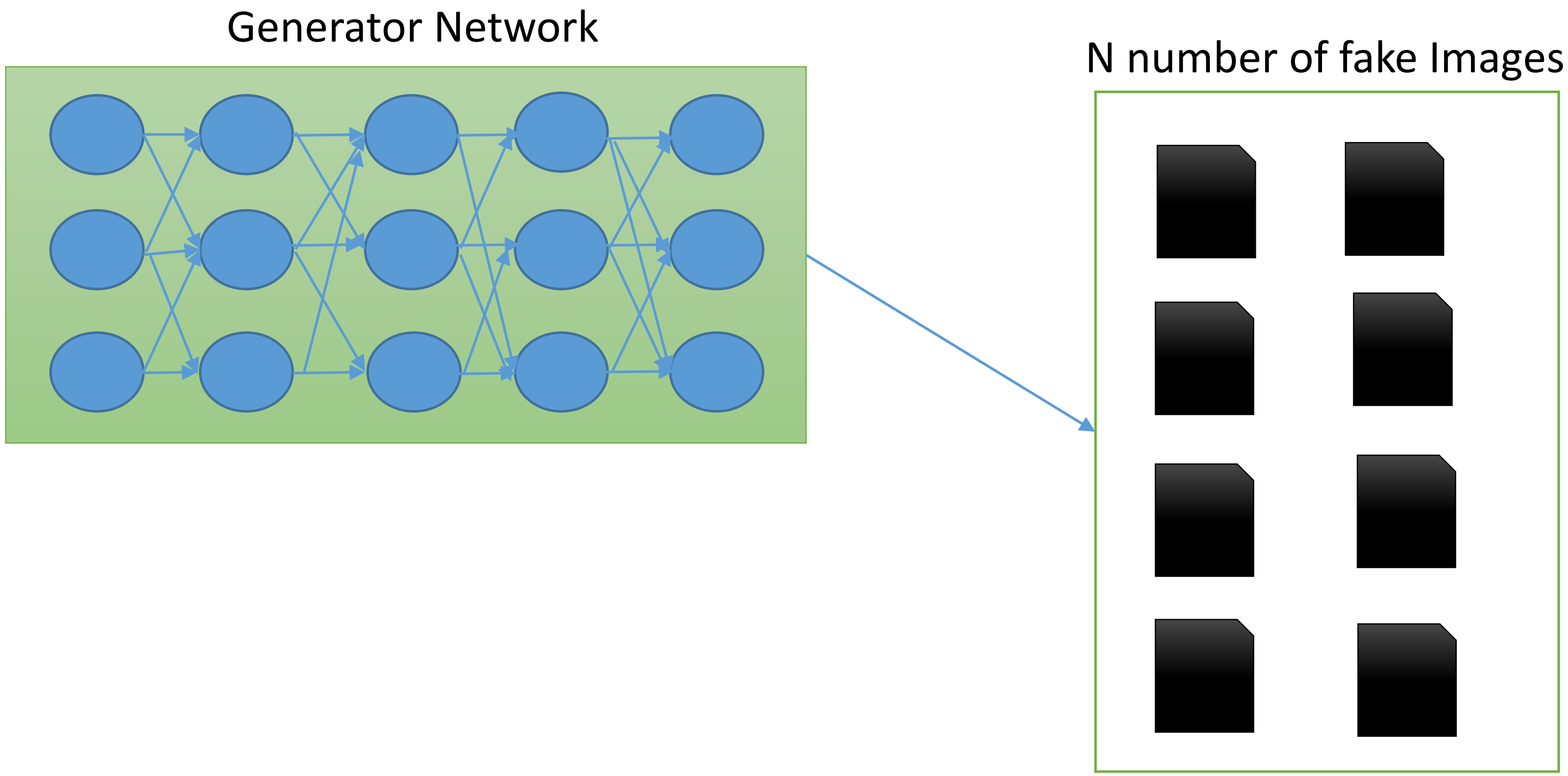
Working of GAN

- Steps[11]
  1. Define the problem
  2. Define architecture of GAN: There are many architectures of GAN. Each architecture has his own features and best fit according to the nature of problem.
  3. Random number of vector feed to generator network to generate fake images.



Working of GAN

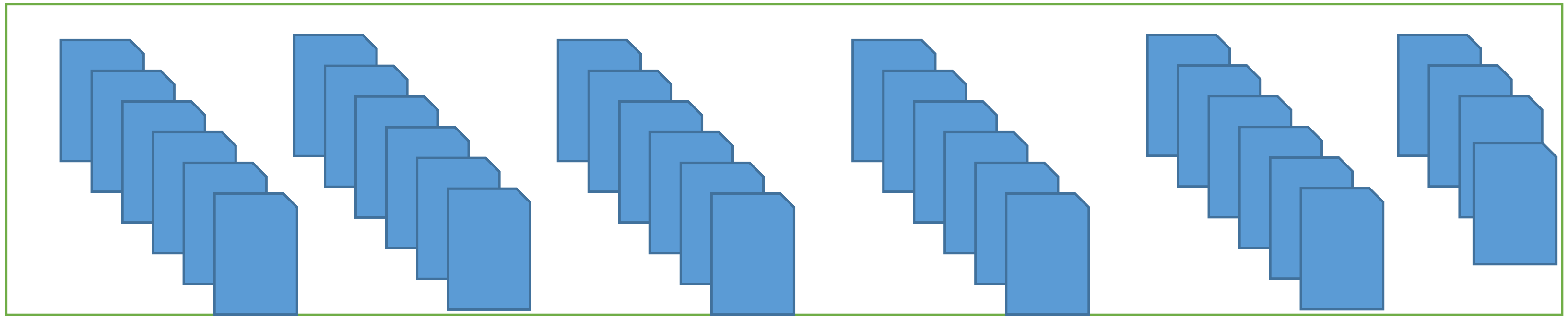
4. Generator network generate fake images.



Working of GAN

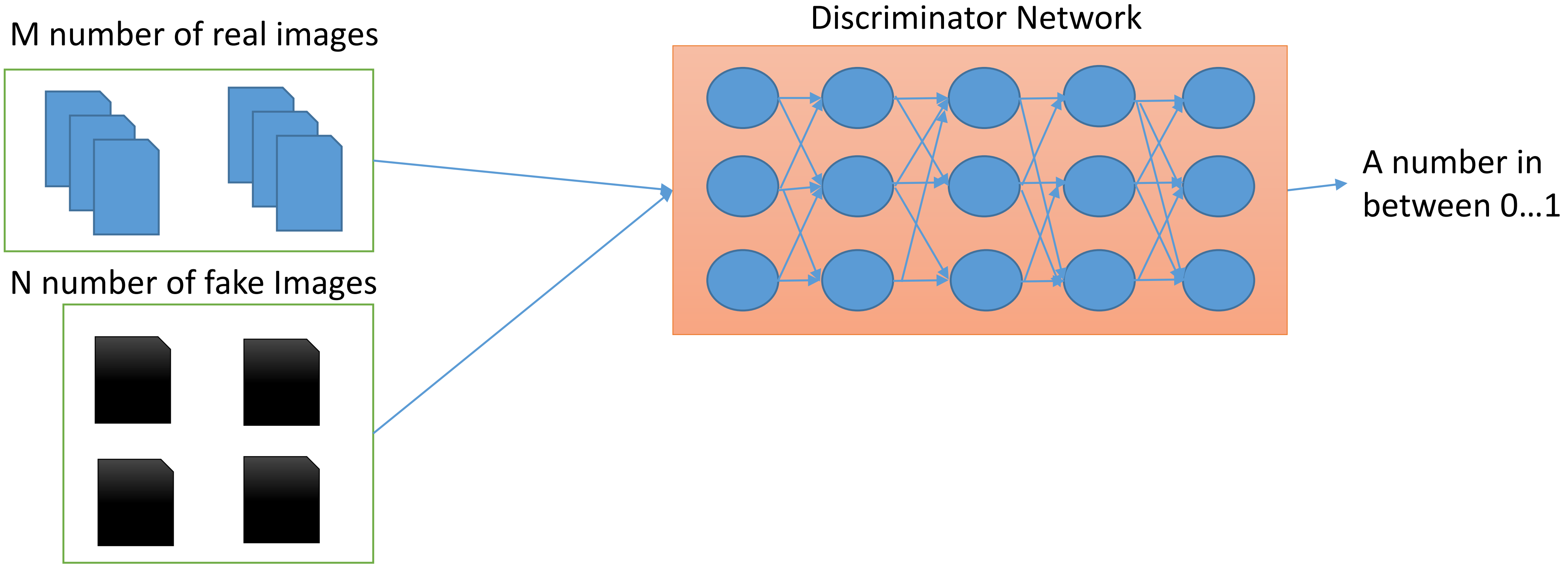
5. Now take a large sample of real images which are related to the problem.

M number of real images



Working of GAN

6. First train discriminator on real and fake generated images. Discriminator label images as fake or real based on their probabilities which varies in between 0 and 1. 0 means fake and 1 means real. The input of this network is either real or fake image in the form of vector and output is the number.



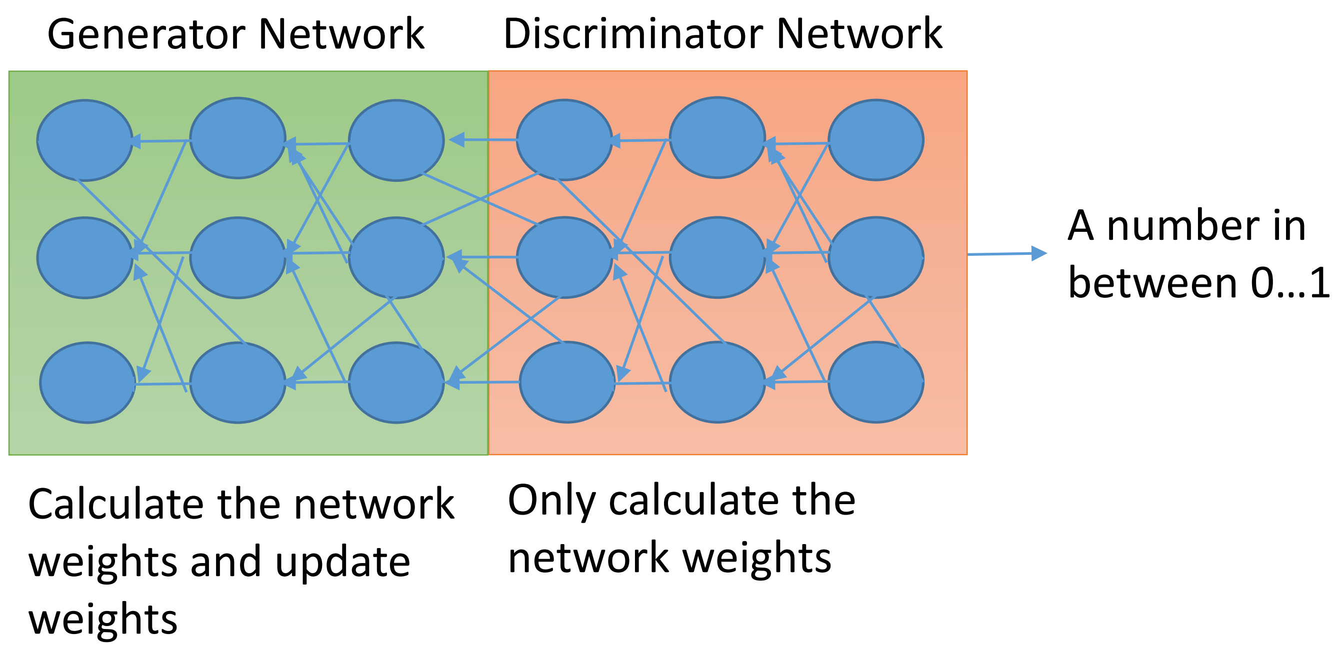
Working of GAN

7. Train until discriminator network become optimal.

8. Now stop training discriminator and backpropogate the output of the discriminator to update the parameters of generator to generate images which are near to real images.
    - Discriminator output → dis(x) → x=gen(random vector) → Random vector

9. Lets assume both networks as a single network and backpropogate the discriminator output by only calculating not updating the weights of discriminator network and calculating and updating the weights of generator network.[12]

Working of GAN



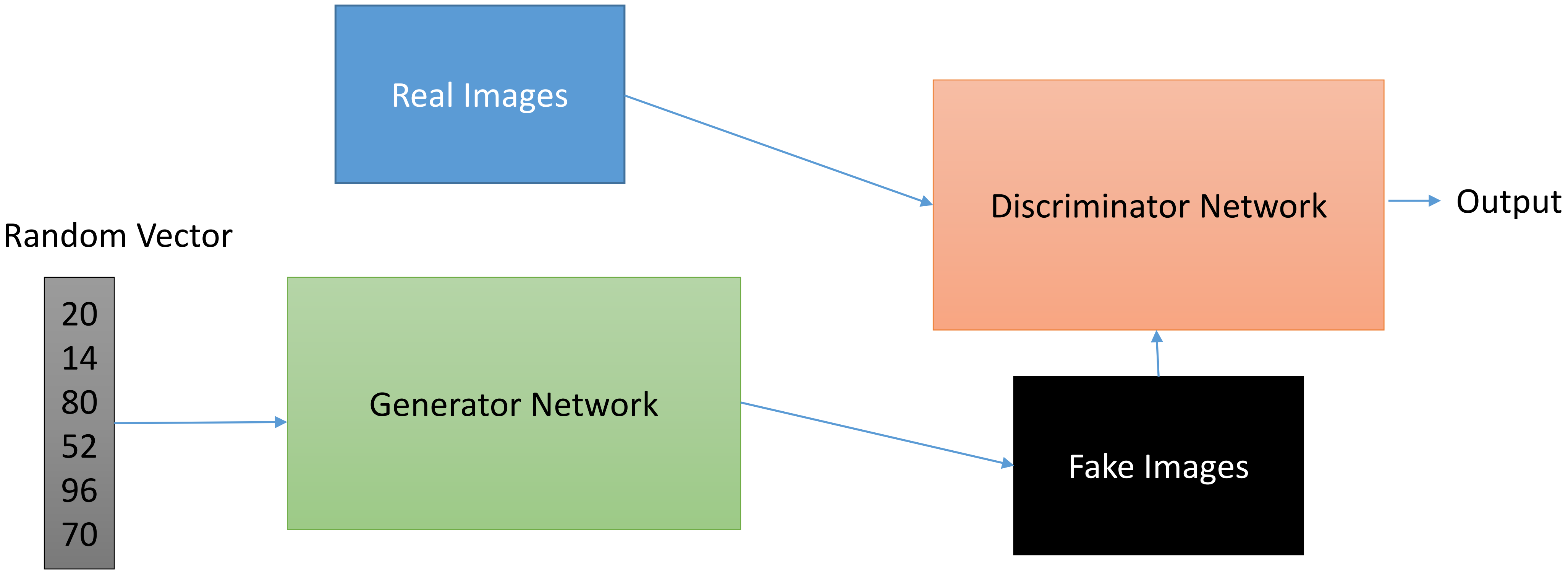
10. For new parameters of generator generate new images.

Working of GAN

11. Train generator and discriminator in this feed back loop for n epochs.
    i. Random vector → x=gen(random vector) → dis(x) → Discriminator output
    ii. Discriminator output → dis(x) → x=gen(random vector) → Random vector

12. Check fake data manually if it seems legit/real then stop training otherwise train both networks until they are optimal or reach the probability of 0.5

Working of GAN



GAN Functions[12]

- Functions which are used in real paper for training of both networks are:
  - Train discriminator to maximize the probability of real images, when generator is fixed
    - $\max_D V(D,G*)=E_{x\sim pdata}[\log D(x)]+E_{z\sim pz(z)}[\log(1-D(G*(z)))]$
  - Train generator to minimize the probability of real images, when discriminator is fixed
    - $\min_G V(D*,G)=E_{x\sim pdata}[\log D*(x)]+E_{z\sim pz(z)}[\log(1-D*(G(z)))]$

GAN Architectures[13]

- There are many architectures of GAN:
  - Fully Connected GAN
  - Convolutional GAN
    - Laplacian pyramid of GAN
    - Deep convolutional GAN
  - Conditional GAN
    - Info GAN
  - Adversarial Autoencoders
  - GAN with Inference model
    - Bidirectional GAN

GAN Applications

- GAN’s is a very vast field and has a lot of application to detect create and analyze things in different fields.
  - Image retrieval from historical archives
  - Text translation into images
  - Drug Discovery
  - Shadow detection
  - Draw Human Faces
  - Realistic Paintings
  - Designing

GAN Example

- Gaussian Data generation implementation using GAN’s:
  - Discriminator input Gaussian data and generator generated data.
  - Generator input random data.
  - Find the optimal Weight values for both networks to generate Gaussian data
  - Sigmoid Activation function for discriminator.
  - Tanh activation function for generator.
  - Binary cross entropy function for loss.
  - Torch library for network implementation.

Python code:

```
train() # Run the train function to start the program
def train():
    # Model parameters
    g_input_size = 1      # Random noise dimension coming into generator, per output vector
    g_hidden_size = 5     # Hidden layers of generator
    g_output_size = 1     # Size of generated output vector
    d_input_size = 500    # Mini batch size
    d_hidden_size = 10    # Hidden layers of discriminator
    d_output_size = 1     # Single dimension for 'real' vs. 'fake' classification
    minibatch_size = d_input_size # Size of the mini batch

    d_learning_rate = 1e-3 # Discriminator learning rate
    g_learning_rate = 1e-3 # Generator learning rate
    sgd_momentum = 0.9 # Momentum

    num_epochs = 5000 # Number of epochs
    print_interval = 1000 # Print interval for output
    d_steps = 20 # Training of discriminator for one epoch
```

Cont.

```
dfe, dre, ge = 0, 0, 0 # Variables to store errors

d_real_data, d_fake_data, g_fake_data = None, None, None # Variables to store data


discriminator_activation_function = torch.sigmoid # Activation function for discriminator

generator_activation_function = torch.tanh # Activation function for generator


d_sampler = get_distribution_sampler(data_mean, data_stddev) # Generate data for discriminator
```

```
def get_moments(d):
    # Return the first 4 moments of the data provided
    mean = torch.mean(d)
    diffs = d - mean
    var = torch.mean(torch.pow(diffs, 2.0))
    std = torch.pow(var, 0.5)
    zscores = diffs / std
    skews = torch.mean(torch.pow(zscores, 3.0))
    kurtoses = torch.mean(torch.pow(zscores, 4.0)) - 3.0  # excess kurtosis, should be 0 for Gaussian
    final = torch.cat((mean.reshape(1,), std.reshape(1,), skews.reshape(1,), kurtoses.reshape(1,)))
    return final
```

```
# parameters for Discriminator data
data_mean = 4
data_stddev = 1.25

# Data for discriminator
# Uncomment only one of these to define what data is actually sent to the Discriminator
(name, preprocess, d_input_func) = ("Only 4 moments", lambda data: get_moments(data), lambda x: 4)
#(name, preprocess, d_input_func) = ("Raw data", lambda data: data, lambda x: x)
#(name, preprocess, d_input_func) = ("Data and variances", lambda data: decorate_with_diffs(data, 2.0), lambda x: x * 2)
#(name, preprocess, d_input_func) = ("Data and diffs", lambda data: decorate_with_diffs(data, 1.0), lambda x: x * 2)

# Discriminator data generator for input

def get_distribution_sampler(mu, sigma):
    return lambda n: torch.Tensor(np.random.normal(mu, sigma, (1, n)))  # Gaussian
```

```
def decorate_with_diffs(data, exponent, remove_raw_data=False):
    mean = torch.mean(data.data, 1, keepdim=True)
    mean_broadcast = torch.mul(torch.ones(data.size()), mean.tolist()[0][0])
    diffs = torch.pow(data - Variable(mean_broadcast), exponent)
    if remove_raw_data:
        return torch.cat([diffs], 1)
    else:
        return torch.cat([data, diffs], 1)
```

Cont.

```
gi_sampler = get_generator_input_sampler() # Generate data for generator
```

```
def get_generator_input_sampler():
    return lambda m, n: torch.rand(m, n)  # Uniform-dist data into generator, _NOT_ Gaussian
```

```
# Generator model define
G = Generator(input_size=g_input_size,
        hidden_size=g_hidden_size,
        output_size=g_output_size,
        f=generator_activation_function)
```

```
# Generator model

class Generator(nn.Module):
  # Constructor of the generator class
  def __init__(self, input_size, hidden_size, output_size, f):
    super(Generator, self).__init__()
    self.map1 = nn.Linear(input_size, hidden_size)
    self.map2 = nn.Linear(hidden_size, hidden_size)
    self.map3 = nn.Linear(hidden_size, output_size)
    self.f = f

  # define the sequence of the layers with activation functions
  def forward(self, x):
    x = self.map1(x)
    x = self.f(x)
    x = self.map2(x)
    x = self.f(x)
    x = self.map3(x)
    return x
```

Cont.

```
# Discriminator model define
D = Discriminator(input_size=d_input_func(d_input_size),
          hidden_size=d_hidden_size,
          output_size=d_output_size,
          f=discriminator_activation_function)
```

```
# Discriminator model
class Discriminator(nn.Module):
  # Constructor of the discriminator class
  def __init__(self, input_size, hidden_size, output_size, f):
    super(Discriminator, self).__init__()
    self.map1 = nn.Linear(input_size, hidden_size)
    self.map2 = nn.Linear(hidden_size, hidden_size)
    self.map3 = nn.Linear(hidden_size, output_size)
    self.f = f

  # define the sequence of the layers with activation functions
  def forward(self, x):
    x = self.f(self.map1(x))
    x = self.f(self.map2(x))
    return self.f(self.map3(x))
```

```
criterion = nn.BCELoss()  # Loss function to calculate loss
d_optimizer = optim.SGD(D.parameters(), lr=d_learning_rate, momentum=sgd_momentum) # Discriminator parameters optimization
g_optimizer = optim.SGD(G.parameters(), lr=g_learning_rate, momentum=sgd_momentum) # Generator parameters optimization
```

Cont.

```
# Start of training
for epoch in range(num_epochs):
    for d_index in range(d_steps):
        # 1. Train D on real + fake
        D.zero_grad() # Define weights of discriminator network with zero

        #  1A: Train D on real
        d_real_data = Variable(d_sampler(d_input_size)) # Put real data into discriminator
        d_real_decision = D(preprocess(d_real_data)) # Put real data decisions one = true and zero = false
        d_real_error = criterion(d_real_decision, Variable(torch.ones([1,1]))) # Run the network and calculate the error
        d_real_error.backward() # Compute and store gradients, but don't change params why?????
        #  1B: Train D on fake
        d_gen_input = Variable(gi_sampler(minibatch_size, g_input_size)) # Divide data into mini batch size
        d_fake_data = G(d_gen_input).detach() # Put fake data into generator. Detach to avoid training G on these labels
        d_fake_decision = D(preprocess(d_fake_data.t())) # Put fake data decisions one = true and zero = false
        d_fake_error = criterion(d_fake_decision, Variable(torch.zeros([1,1]))) # Run the network and calculate the error
        d_fake_error.backward() # Compute and store gradients
        d_optimizer.step() # Only optimizes D's parameters; changes based on stored gradients from backward()
```

Cont.

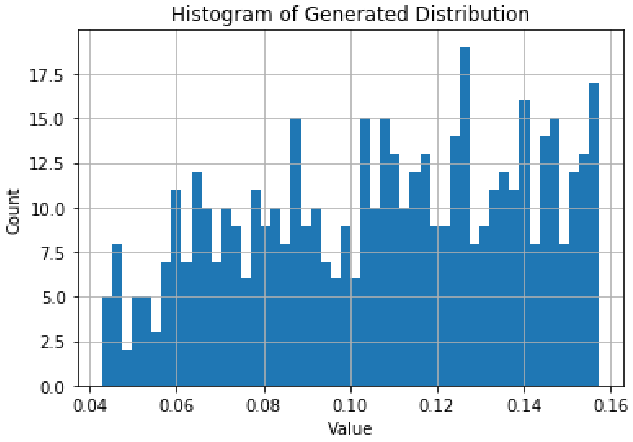
```
for g_index in range(g_steps):
    # 2. Train G on D's response (but DO NOT train D on these labels)
    G.zero_grad() # Define weights of generator network with zero

    gen_input = Variable(gi_sampler(minibatch_size, g_input_size)) # Divide data into mini batch size
    g_fake_data = G(gen_input) # Put fake data into generator.
    dg_fake_decision = D(preprocess(g_fake_data.t())) # Put fake data decisions from discriminator
    g_error = criterion(dg_fake_decision, Variable(torch.ones([1,1])))  # Run the network and calculate the error

    #Train G to pretend it's genuine
    g_error.backward() # Compute and store gradients
    g_optimizer.step()  # Only optimizes G's parameters
    ge = extract(g_error)[0] # Store generator data errors.
```

Cont.

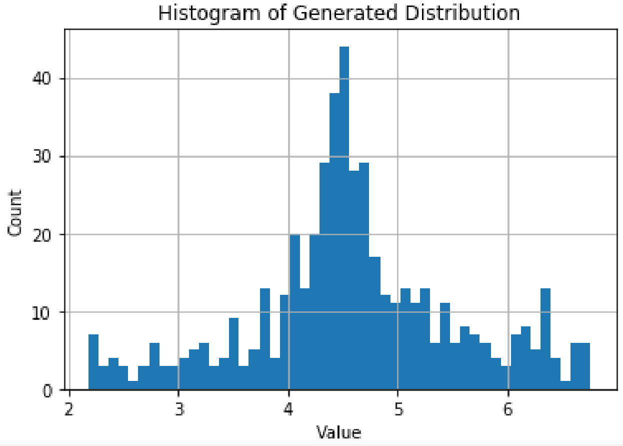
```
# Print the output after specified interval
if epoch % print_interval == 0:
    # Print epoch, all errors, and data
    print("Epoch %s: D (%s real_err, %s fake_err) G (%s err); Real Dist (%s),  Fake Dist (%s) " %
          (epoch, dre, dfe, ge, stats(extract(d_real_data)), stats(extract(d_fake_data))))

    # Print data on graph
    print("Plotting the generated distribution...")
    values = extract(g_fake_data)
    print(" Values: %s" % (str(values)))
    plt.hist(values, bins=50)
    plt.xlabel('Value')
    plt.ylabel('Count')
    plt.title('Histogram of Generated Distribution')
    plt.grid(True)
    plt.show()
```

Results:

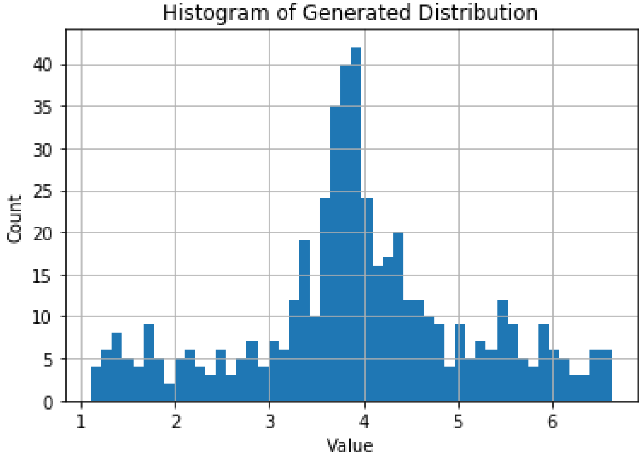
1000 Iterations:



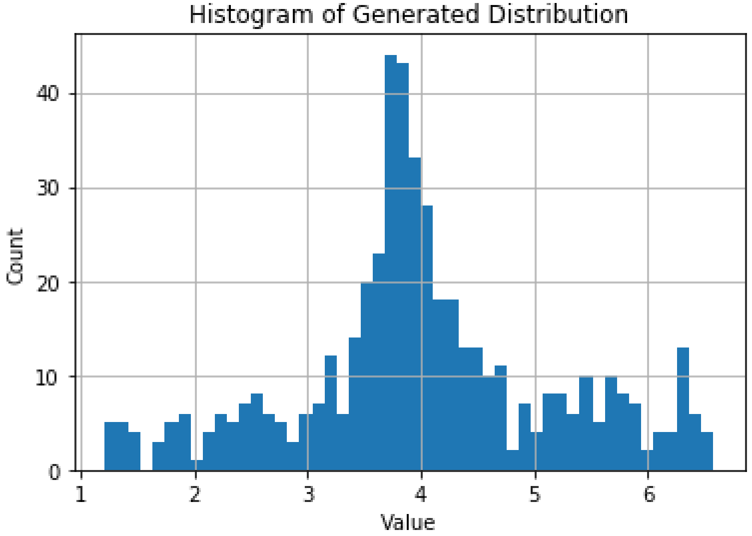
2000 Iterations:



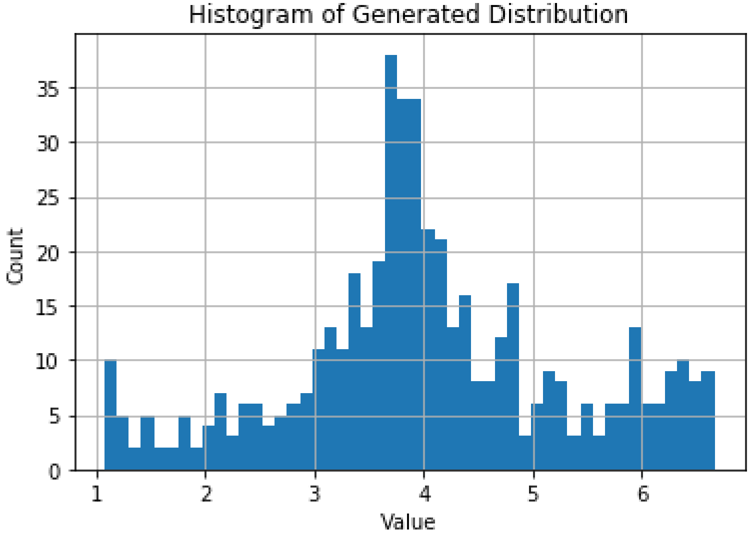
3000 Iterations:



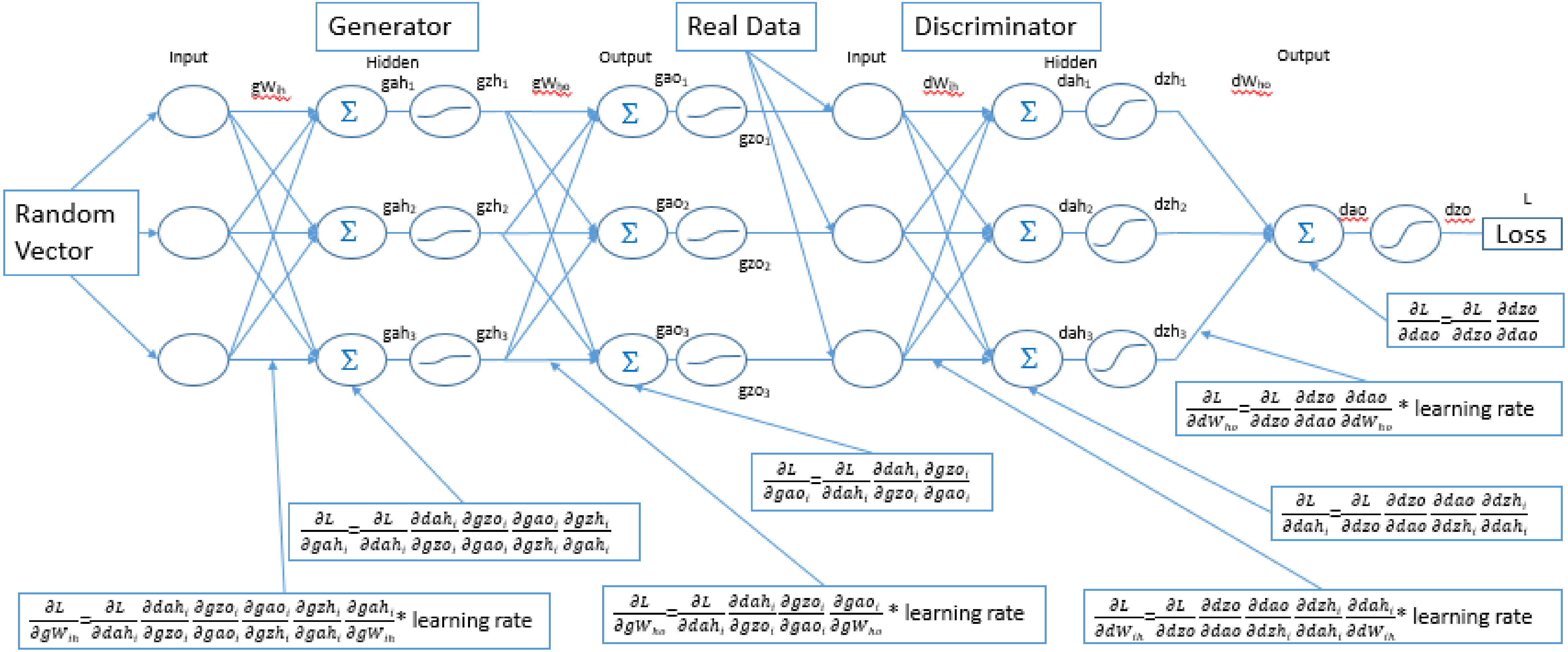
4000 Iterations:



5000 Iterations:



Structure of GAN:



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