# Lab 7: Style Transfer & Generative Adversarial Network

University of Washington

EE 596/AMATH 563

Spring 2021

# Outline

- **Part 1: Neural Style Transfer**
- What is style transfer?
- Style transfer implementation
- Example: Generating images using style transfer

- **Part 2: Generative Adversarial Network (GAN)**
- What is GAN?
- GAN implementation
- Training a GAN

- **Lab Assignment**

# **Part 1:** Neural Style Transfer

# Style Transfer

Style Source

Content Source

Output Image

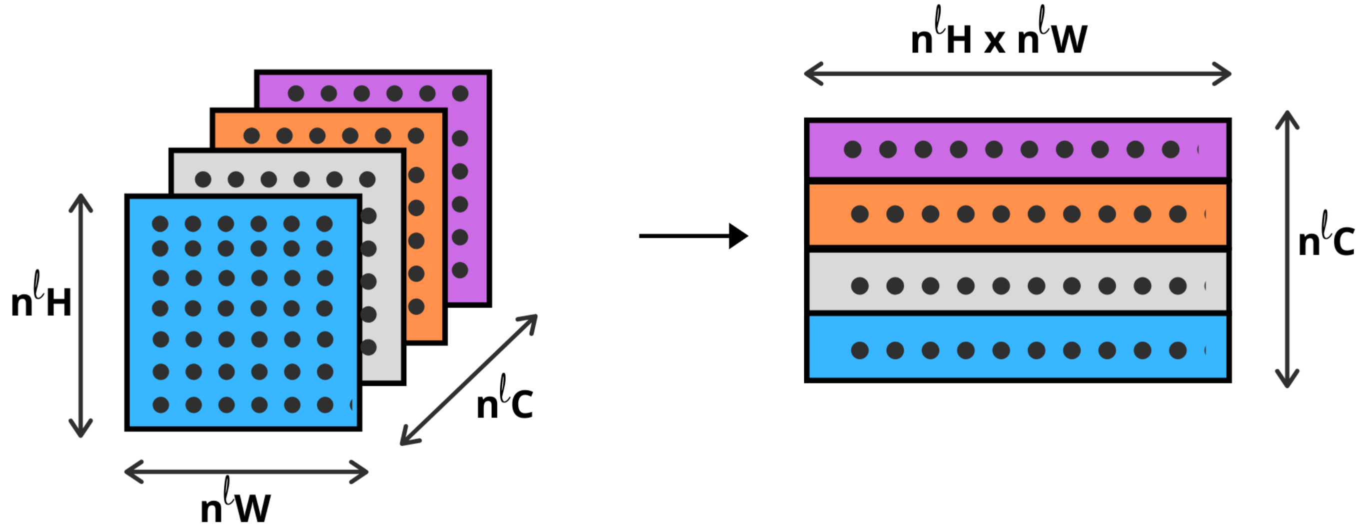
# Style Transfer Implementation

- Computing Loss
  - Content loss
  - Style loss
  - Total-variation regularization

- Put everything together: Style Transfer

# Content Loss

- Content loss measures how much the feature map of the **generated image** differs from the feature map of the **source image**.
- We only care about the **content representation** of one layer of the network
- We will work with **reshaped versions** of these feature maps.



# Content Loss

- $F^\ell \in \mathbb{R}^{C_\ell \times M_\ell}$: the feature map for the **current image**
- $P^\ell \in \mathbb{R}^{C_\ell \times M_\ell}$: the feature map for the **content source image**
- $M_\ell = H_\ell \times W_\ell$ = # of elements in each feature map
- $w_c$ = weight of the content loss term in the loss function

```python
def content_loss(content_weight, content_current, content_original):
    """
    Compute the content loss for style transfer.

    Inputs:
    - content_weight: Scalar giving the weighting for the content loss.
    - content_current: features of the current image; this is a PyTorch Tensor of shape
      (1, C_l, H_l, W_l).
    - content_target: features of the content image, Tensor with shape (1, C_l, H_l, W_l).

    Returns:
    - scalar content loss
    """
    loss = torch.sum( content_weight * (content_current - content_original)**2 )
    return loss
```

The **content loss** is given by:

$$L_c = w_c \times \sum_{i,j} (F_{ij}^\ell - P_{ij}^\ell)^2$$

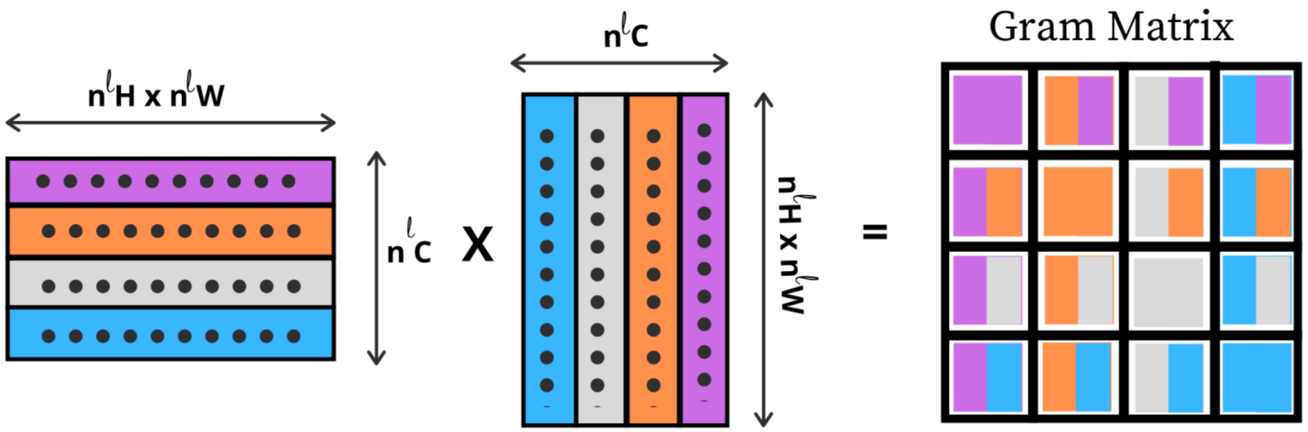
# Style Transfer Implementation

- Computing Loss
  - Content loss
  - Style loss
  - Total-variation regularization
- Put everything together: Style Transfer

# Style Loss

- For a given layer $\ell$, the style loss is defined as follows:
  - First, compute the **Gram matrix G** which represents the correlations between the values in each channel of the feature map.
  - The **Gram matrix** is an approximation of the covariance matrix.
  - We want the **activation statistics** of our **generated image** to match the **activation statistics** of our **style image.**

# Style Loss




The **feature map** is given by: $F^\ell \in \mathbb{R}^{C_\ell \times M_\ell}$

The **Gram matrix** is computed by: $G^\ell_{ij} = \sum_k F^\ell_{ik} F^\ell_{jk}$

The **Gram matrix** has shape: $(C_\ell, C_\ell)$

The **Gram matrix** from the feature map of the **current image**: $G^\ell$

The **Gram matrix** from the feature map of the **source style image**: $A^\ell$

# Style Loss

The **style loss** for the layer ℓ is simply the weighted Euclidean distance between the two Gram matrices:

$$L_s^\ell = w_\ell \sum_{i,j} \left(G_{ij}^\ell - A_{ij}^\ell\right)^2$$

In practice we usually compute the style loss at a set of layers L rather just a single layer ℓ; then the **total style loss** is the sum of style losses at each layer:

$$L_s = \sum_{\ell \in \mathcal{L}} L_s^\ell$$

```python
def gram_matrix(features, normalize=True):
    """
    Compute the Gram matrix from features.

    Inputs:
    - features: PyTorch Tensor of shape (N, C, H, W) giving features for
      a batch of N images.
    - normalize: optional, whether to normalize the Gram matrix
        If True, divide the Gram matrix by the number of neurons (H * W * C)

    Returns:
    - gram: PyTorch Tensor of shape (N, C, C) giving the
      (optionally normalized) Gram matrices for the N input images.
    """
    N, C, H, W = features.size()
    features = features.view(N*C,H*W) #reshape it
    gram_matrix = torch.mm(features, features.t())
    if (normalize):
        gram_matrix /= float(H*W*C)
    return gram_matrix
```

```python
def style_loss(feats, style_layers, style_targets, style_weights):
    """
    Computes the style loss at a set of layers.
    Inputs:
    - feats: list of the features at every layer of the current image, as produced by
      the extract_features function.
    - style_layers: List of layer indices into feats giving the layers to include in the
      style loss.
    - style_targets: List of the same length as style_layers, where style_targets[i] is
      a PyTorch Tensor giving the Gram matrix of the source style image computed at
      layer style_layers[i].
    - style_weights: List of the same length as style_layers, where style_weights[i]
      is a scalar giving the weight for the style loss at layer style_layers[i].
    Returns:
    - style_loss: A PyTorch Tensor holding a scalar giving the style loss.
    """
    loss = 0
    for i,layer in enumerate(style_layers):
        current = gram_matrix(feats[layer])
        loss += (style_weights[i] * torch.sum((current-style_targets[i])**2))
    return loss
```

# Style Transfer Implementation

- Computing Loss
  - Content loss
  - Style loss
  - Total-variation regularization
- Put everything together: Style Transfer

# Total-variation regularization

- Encourage **smoothness** in the image by adding "**total variation**"
- Computed as the sum of the squares of differences in the pixel values for all pairs of pixels that are next to each other (**horizontally or vertically**)

```python
def tv_loss(img, tv_weight):
    """
    Compute total variation loss.
    Inputs:
    - img: PyTorch Variable of shape (1, 3, H, W) holding an input image.
    - tv_weight: Scalar giving the weight w_t to use for the TV loss.
    Returns:
    - loss: PyTorch Variable holding a scalar giving the total variation loss
      for img weighted by tv_weight.
    """
    loss = 0
    #do the row one
    loss += torch.sum( ( img[:,:,1:,:] - img[:,:,:-1,:] )**2 )
    #on paper do for 2X2 and 3X3 then easy to see
    #do the column one
    loss += torch.sum( ( img[:,:,:,1:] - img[:,:,:,:-1] )**2 )
    #weighting
    loss *= tv_weight
    return loss
```

$$L_{tv} = w_t \times \left( \sum_{c=1}^{3} \sum_{i=1}^{H-1} \sum_{j=1}^{W} (x_{i+1,j,c} - x_{i,j,c})^2 + \sum_{c=1}^{3} \sum_{i=1}^{H} \sum_{j=1}^{W-1} (x_{i,j+1,c} - x_{i,j,c})^2 \right)$$

# Style Transfer Implementation

- Computing Loss
  - Content loss
  - Style loss
  - Total-variation regularization
- Put everything together: Style Transfer

# Put everything together

- Extract features for the content and style images separately
- Initialize output image to content or random noise
- Optimization setup
  - Hyperparameters
  - Optimizer choice
- Update loop
  - Compute losses
  - Update generated image

# **Example**: Generating images with style transfer

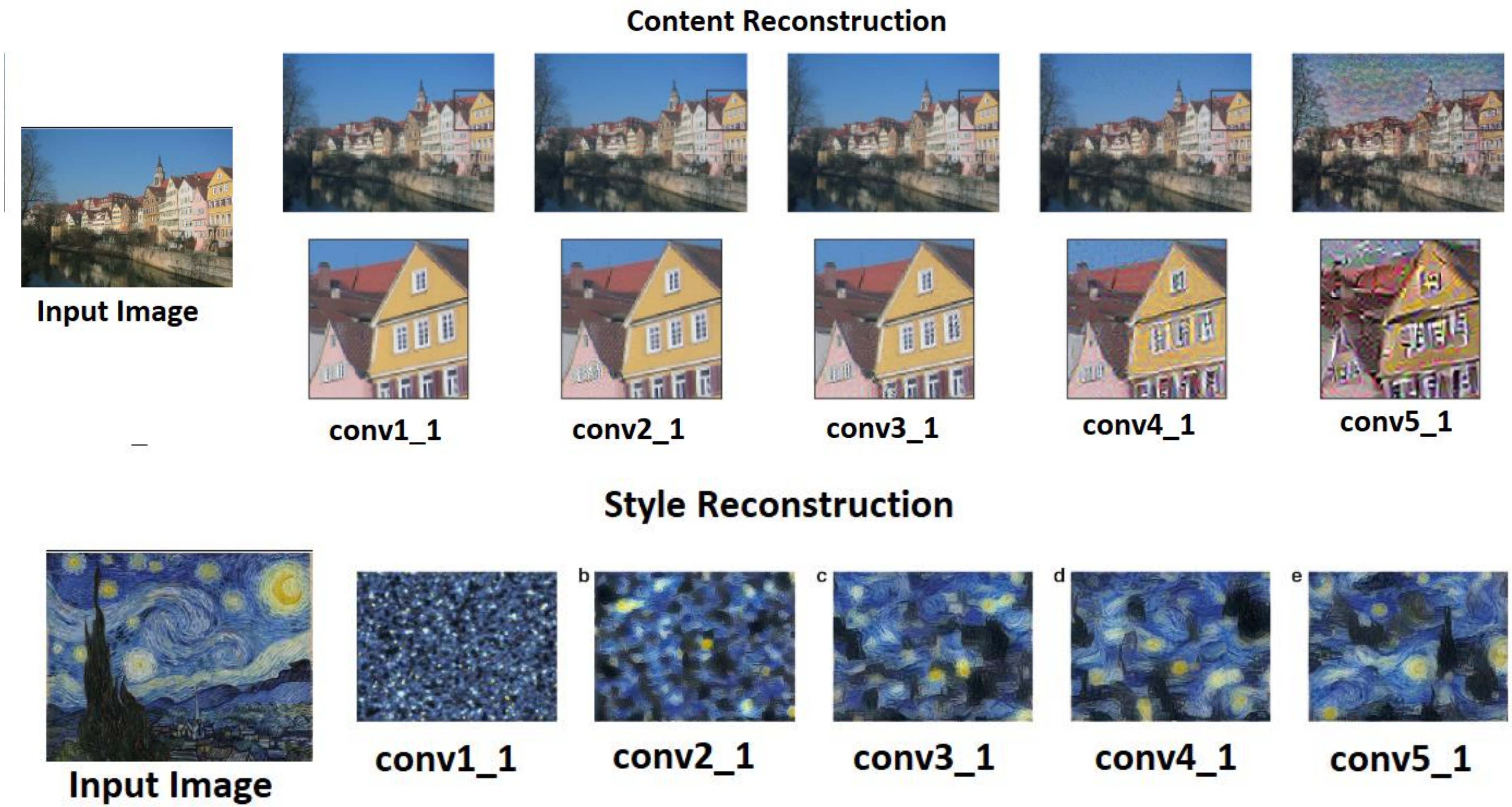
# Generating images with style transfer

- Use content image and style image to generate a new image
- Hyperparameters include:
  - The weights of content loss and style loss
  - The layer representations of content and style
  - Size of images

```
# Composition VII + Tubingen
params1 = {
    'content_image' : 'tubingen.jpg',
    'style_image' : 'composition_vii.jpg',
    'image_size' : 192,
    'style_size' : 512,
    'content_layer' : 'conv_2',
    'content_weight' : 5e-2,
    'style_layers' : ['conv_1', 'conv_3', 'conv_5', 'conv_7'],
    'style_weights' : (20000, 500, 1200, 1000),
    'tv_weight' : 5e-2
}

style_transfer(**params1)
```

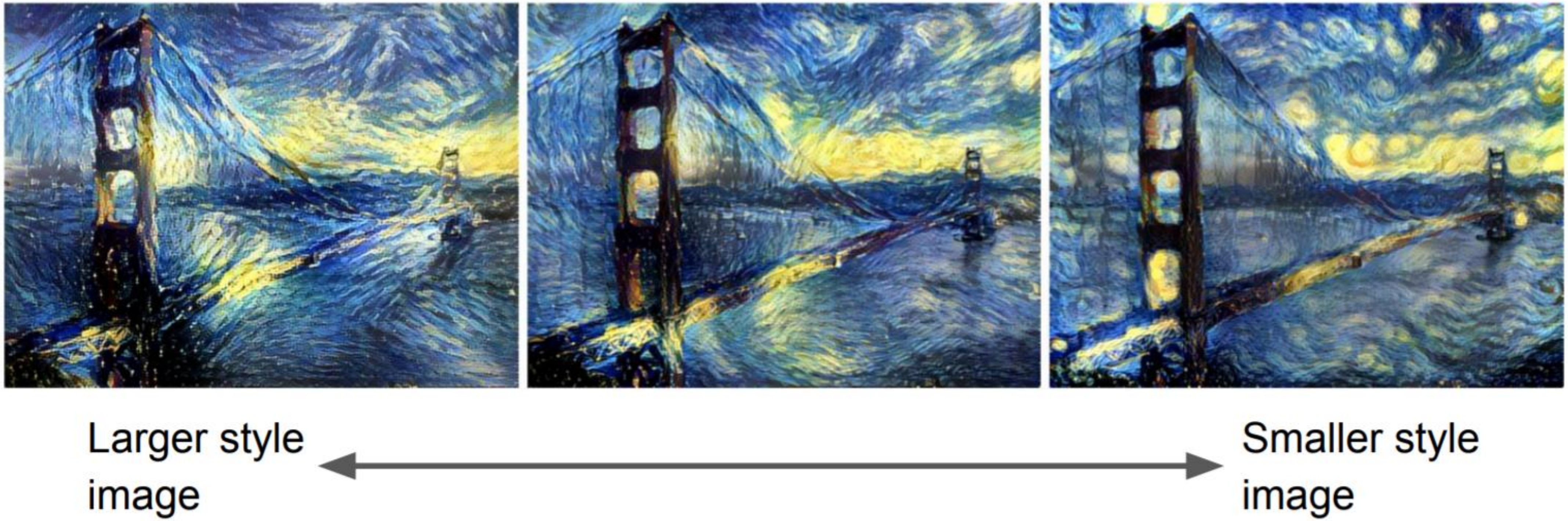
# Generating images with style transfer

# Generating images with style transfer



# Generating images with style transfer

Resizing style image before running style transfer algorithm can transfer different types of features



# **Part 2**: Generative Adversarial Networks (GANs)

# What is a GAN?

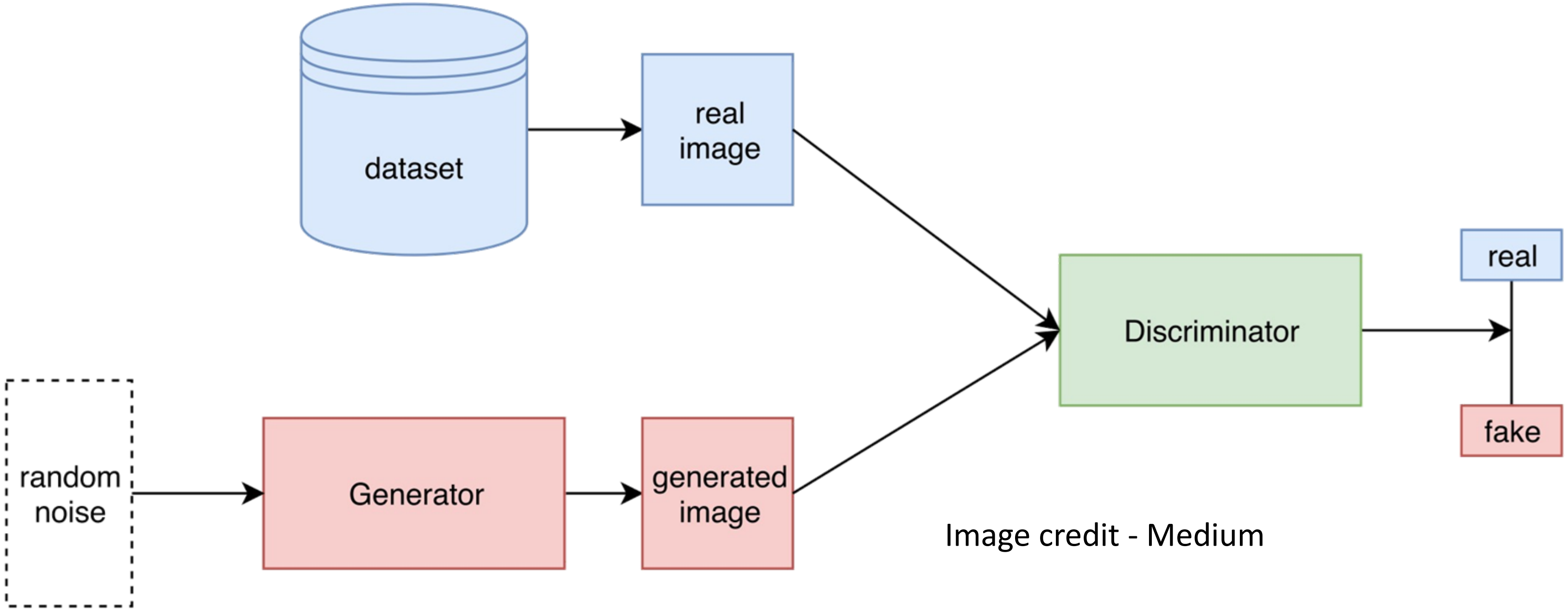



Image credit - Medium

# What is a GAN?

- Cost Function

$$\underset{G}{\text{minimize}}\ \underset{D}{\text{maximize}}\ \mathbb{E}_{x\sim p_{\text{data}}}\left[\log D(x)\right] + \mathbb{E}_{z\sim p(z)}\left[\log(1 - D(G(z)))\right]$$

- In practice, we alternate the following updates:
  - Update the **generator** (G) to maximize the probability of the discriminator making the incorrect choice on generated data:

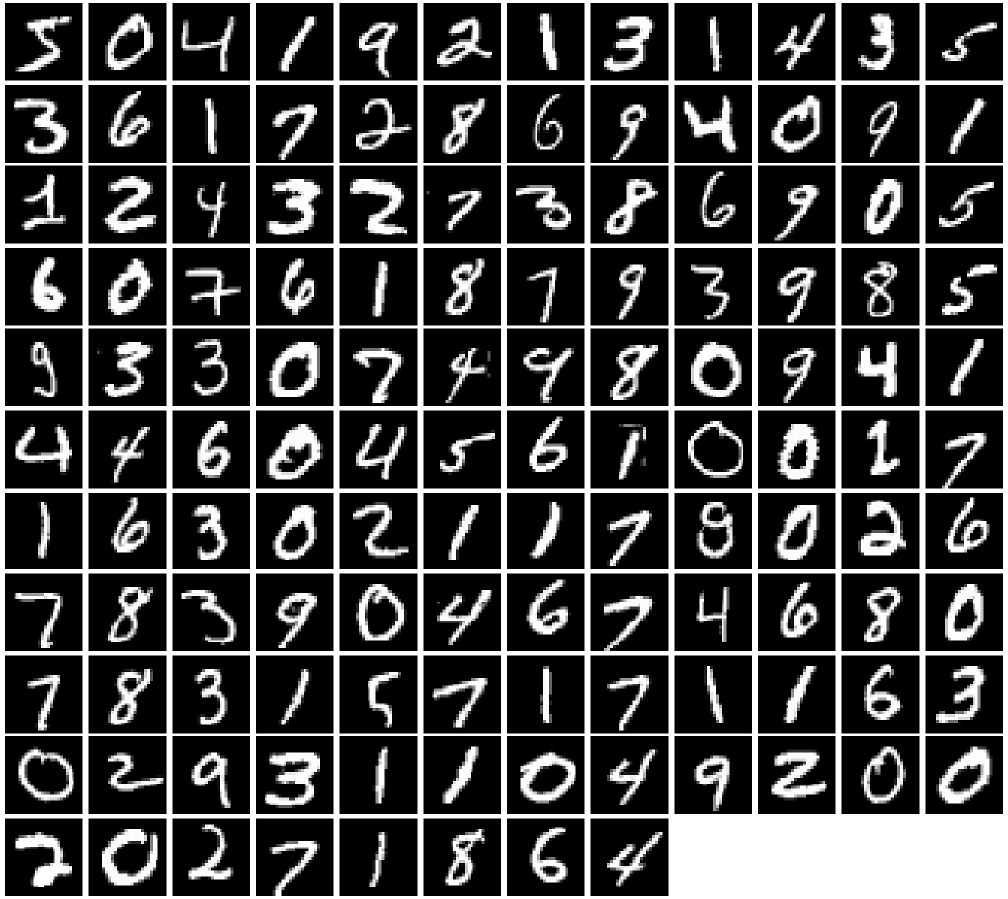
$$\underset{G}{\text{maximize}}\ \mathbb{E}_{z\sim p(z)}\left[\log D(G(z))\right]$$

  - Update the **discriminator** (D), to maximize the probability of the discriminator making the correct choice on real and generated data:

$$\underset{D}{\text{maximize}}\ \mathbb{E}_{x\sim p_{\text{data}}}\left[\log D(x)\right] + \mathbb{E}_{z\sim p(z)}\left[\log(1 - D(G(z)))\right]$$

# GAN Implementation

- Dataset: MNIST
- Random Noise
- Discriminator
- Generator
- GAN Loss
- Training a GAN



# GAN Implementation

- Dataset: MNIST
- Random Noise
  - Generate uniform noise from -1 to 1 with shape [batch_size, dim].
  - You can also use torch.rand
- Discriminator
- Generator
- GAN Loss
- Training a GAN

```python
def sample_noise(batch_size, dim):
    """
    Generate a PyTorch Tensor of uniform random noise.

    Input:
    - batch_size: Integer giving the batch size of noise to generate.
    - dim: Integer giving the dimension of noise to generate.

    Output:
    - A PyTorch Tensor of shape (batch_size, dim) containing uniform
      random noise in the range (-1, 1).
    """
    return torch.FloatTensor(batch_size, dim).uniform_(-1, 1)
```

# GAN Implementation

- Dataset: MNIST
- Random Noise
- Discriminator
  - FC layer (784 -> 256)
  - LeakyRelu with alpha 0.01
  - FC layer (256 -> 256)
  - LeakyRelu with alpha 0.01
  - FC layer (256 -> 1)
- Generator
- GAN Loss
- Training a GAN

```python
def discriminator():
    """
    Build and return a PyTorch model implementing the architecture above.
    """
    model = nn.Sequential( Flatten(),
                           nn.Linear(784, 256),
                           nn.LeakyReLU(inplace=True),
                           nn.Linear(256,256),
                           nn.LeakyReLU(inplace=True),
                           nn.Linear(256,1)
                         )
    return model
```

# GAN Implementation

- Dataset: MNIST
- Random Noise
- Discriminator
- Generator
  - FC layer (noise_dim -> 1024)
  - Relu
  - FC layer(1024 -> 1024)
  - Relu
  - FC layer (1024 -> 784)
  - Tanh (to clip the image to be in the range [-1, 1]
- GAN Loss
- Training a GAN

```python
def generator(noise_dim=NOISE_DIM):
    """
    Build and return a PyTorch model implementing the architecture above.
    """
    model = nn.Sequential( nn.Linear(noise_dim,1024),
                           nn.ReLU(inplace=True),
                           nn.Linear(1024,1024),
                           nn.ReLU(inplace=True),
                           nn.Linear(1024,784),
                           nn.Tanh()
                         )
    return model
```

# GAN Implementation

- Dataset: MNIST
- Random Noise
- Discriminator
- Generator
- GAN Loss
- Training a GAN

# GAN Loss

- The generator loss:

$$\ell_G = -\mathbb{E}_{z \sim p(z)} \left[\log D(G(z))\right]$$

- The discriminator loss:

$$\ell_D = -\mathbb{E}_{x \sim p_{\text{data}}} \left[\log D(x)\right] - \mathbb{E}_{z \sim p(z)} \left[\log(1 - D(G(z)))\right]$$

- We will use the binary cross entropy loss - Given a score ***s*** and a label ***y***, the binary cross entropy loss is:

$$bce(s, y) = -y * \log(s) - (1 - y) * \log(1 - s)$$

# GAN loss

- A naïve implementation of the binary cross entropy loss formula can be numerically unstable.

$$bce(s, y) = -y * \log(s) - (1 - y) * \log(1 - s)$$

```python
def bce_loss(input, target):
    """
    Numerically stable version of the binary cross-entropy loss function.

    As per https://github.com/pytorch/pytorch/issues/751
    See the TensorFlow docs for a derivation of this formula:
    https://www.tensorflow.org/api_docs/python/tf/nn/sigmoid_cross_entropy_with_logits

    Inputs:
    - input: PyTorch Tensor of shape (N, ) giving scores.
    - target: PyTorch Tensor of shape (N,) containing 0 and 1 giving targets.

    Returns:
    - A PyTorch Tensor containing the mean BCE loss over the minibatch of input data.
    """
    neg_abs = - input.abs()
    loss = input.clamp(min=0) - input * target + (1 + neg_abs.exp()).log()
    return loss.mean()
```

# GAN Loss

- Discriminator loss implementation

```
def discriminator_loss(logits_real, logits_fake):
    """
    Computes the discriminator loss described above.
    Inputs:
    - logits_real: PyTorch Tensor of shape (N,) giving scores for the real data.
    - logits_fake: PyTorch Tensor of shape (N,) giving scores for the fake data.
    Returns:
    - loss: PyTorch Tensor containing (scalar) the loss for the discriminator.
    """
    N, _ = logits_real.size()
    loss = (bce_loss(logits_real, torch.ones(N).type(dtype)))+(bce_loss(logits_fake, torch.zeros(N).type(dtype)))
    return loss
```

- Generator loss implementation

```
def generator_loss(logits_fake):
    """
    Computes the generator loss described above.
    Inputs:
    - logits_fake: PyTorch Tensor of shape (N,) giving scores for the fake data.
    Returns:
    - loss: PyTorch Tensor containing the (scalar) loss for the generator.
    """
    N, _ = logits_fake.size()
    loss = (bce_loss(logits_fake, torch.ones(N).type(dtype)))
    return loss
```

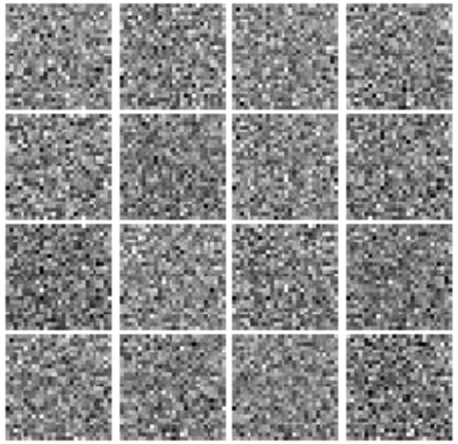
# Training a GAN

- **Training Discriminator**
  - Pass the **sample noise** to generator and get the fake images
  - Use **.detach()** to break gradient connection
  - Pass the fake images to discriminator, compute loss, and update discriminator
- **Training Generator**
  - Pass the sample noise to generator and get the fake images
  - Pass the fake images to discriminator
  - Compute generator loss and update generator

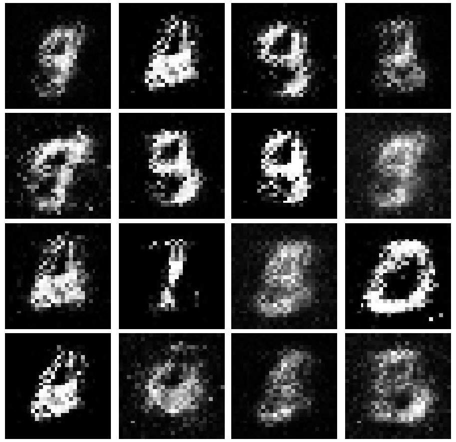
```python
def run_a_gan(D, G, D_solver, G_solver, discriminator_loss, generator_loss, show_every=250,
              batch_size=128, noise_size=96, num_epochs=10):
    """
    Train a GAN!

    Inputs:
    - D, G: PyTorch models for the discriminator and generator
    - D_solver, G_solver: torch.optim Optimizers to use for training the
      discriminator and generator.
    - discriminator_loss, generator_loss: Functions to use for computing the generator and
      discriminator loss, respectively.
    - show_every: Show samples after every show_every iterations.
    - batch_size: Batch size to use for training.
    - noise_size: Dimension of the noise to use as input to the generator.
    - num_epochs: Number of epochs over the training dataset to use for training.
    """
    iter_count = 0
    for epoch in range(num_epochs):
        for x, _ in loader_train:
            if len(x) != batch_size:
                continue
            D_solver.zero_grad()
            real_data = x.type(dtype)
            logits_real = D(2* (real_data - 0.5)).type(dtype)

            g_fake_seed = sample_noise(batch_size, noise_size).type(dtype)
            fake_images = G(g_fake_seed).detach()
            logits_fake = D(fake_images.view(batch_size, 1, 28, 28))

            d_total_error = discriminator_loss(logits_real, logits_fake)
            d_total_error.backward()
            D_solver.step()

            G_solver.zero_grad()
            g_fake_seed = sample_noise(batch_size, noise_size).type(dtype)
            fake_images = G(g_fake_seed)

            gen_logits_fake = D(fake_images.view(batch_size, 1, 28, 28))
            g_error = generator_loss(gen_logits_fake)
            g_error.backward()
            G_solver.step()
```

# Training a GAN

```
# Make the discriminator
D = discriminator().type(dtype)

# Make the generator
G = generator().type(dtype)

# Use the function you wrote earlier to get optimizers for the Discriminator and the Generator
D_solver = get_optimizer(D)
G_solver = get_optimizer(G)
# Run it!
run_a_gan(D, G, D_solver, G_solver, discriminator_loss, generator_loss)
```



Iteration 0



Iteration 1000

Iteration 2000

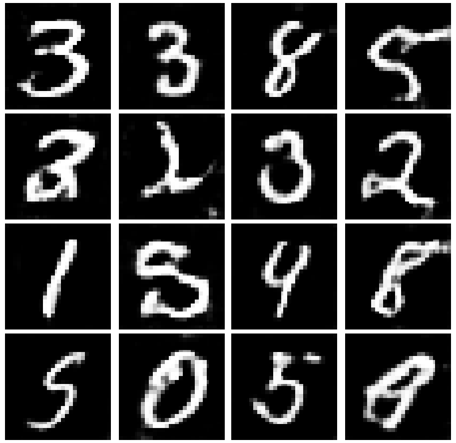
Iteration 3000

# **Lab Assignment**: Deep Convolutional GANs

# Assignment Details

- Implement a deep convolutional GAN (DCGAN) to generate much better fake images
- Implement the **discriminator** with:
    - Conv2D: 32 filters, 5x5, Stride 1
    - Leaky Relu (alpha = 0.01)
    - Max Pool 2x2, Stride 2
    - Conv2D: 64 filters, 5x5, Stride 1
    - Leaky ReLu (alpha = 0.01)
    - Max Pool 2x2 Stride 2
    - Flatten
    - Fully Connected with output size 4x4x64
    - Leaky Relu (alpha = 0.01)
    - Fully Connected with output size 1

Results of GAN

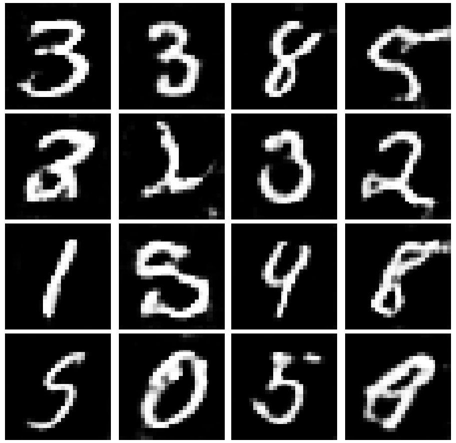


Results of DCGAN

# Assignment Details

- Implement the **generator** with:
  - Fully connected with output size 1024
  - Relu
  - BatchNorm
  - Fully connected with output size 7x7x128
  - ReLu
  - BatchNorm
  - Reshape into image Tensor of shape 7,7,128
  - Conv2D Transpose: 64 filters of 4x4, stride 2, ‘same’ padding (use padding = 1)
  - BatchNorm
  - Conv2D Transpose: 1 filter of 4x4, stride 2, ‘same’ padding (use padding = 1)
  - Tanh
  - Should have a 28x28x1 image, reshape back into 784 vector

Results of GAN



Results of DCGAN

Evaluation:

Train DCGAN on MNIST dataset and plot out the generated images every 150 training iterations for 5 epochs