Trustworthy AI Systems

-- Generative Modeling (Part I)

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Group Member Checkpoint

- For the course projects, two to three students will form a group, choose an AI application topic/task, and complete both midterm and final projects.

- The deadline is Jan. 27th, 11:59 pm

- If you cannot find your teammates, we will help randomly assign a group, but you will get 0 grade for this checkpoint.

Project Examples from Last Semester

- Research-oriented
  - Voice conversion and reversing the converted voice
  - Machine unlearning
  - Enhancing low-light image processing with Retinex-based algorithm
- Engineering-oriented
  - Attendance Record Based on Face Identification
  - LLM Agent for Food Classification
  - AI-assisted symptom analysis for healthcare diagnostics
  - Signature forgery detection using deep learning models

Last Lecture

- Semantic Segmentation

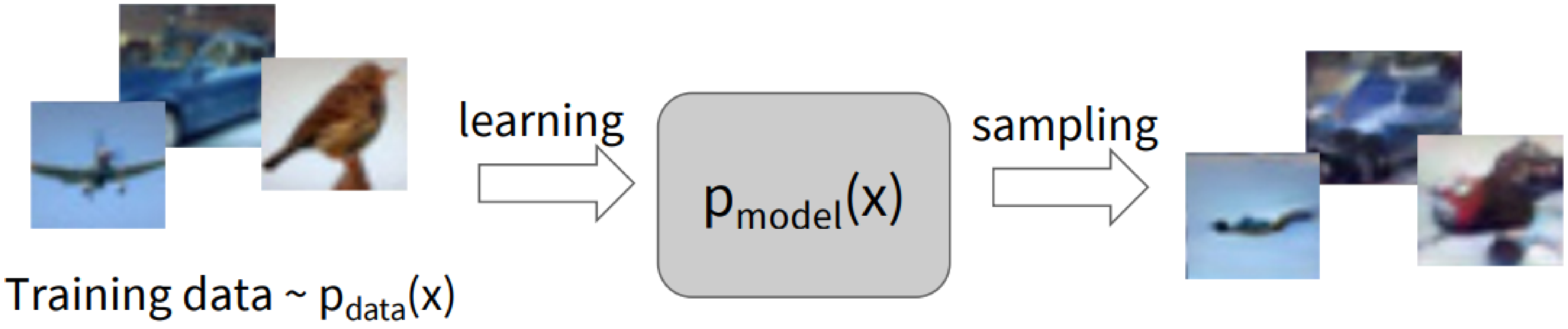
- Object Detection
  - R-CNN series
  - YOLO series

This Lecture

- Generative Modeling
- Generative Adversarial Network (GAN)
  - DCGAN
  - Conditional GAN
  - CycleGAN
- Neural Style Transfer

Generative Modeling

Given training data, generate new samples from same distribution



Objectives:

1. Learn $p_{model}(x)$ that approximates $p_{data}(x)$
2. Sampling new x from $p_{model}(x)$

Learn Data Distributions

- Minimizing certain divergence metrics between **the training data distribution**, and **the distribution that the model learns**.

- Training models that maximize the expected log likelihood of $p_\theta(x)$

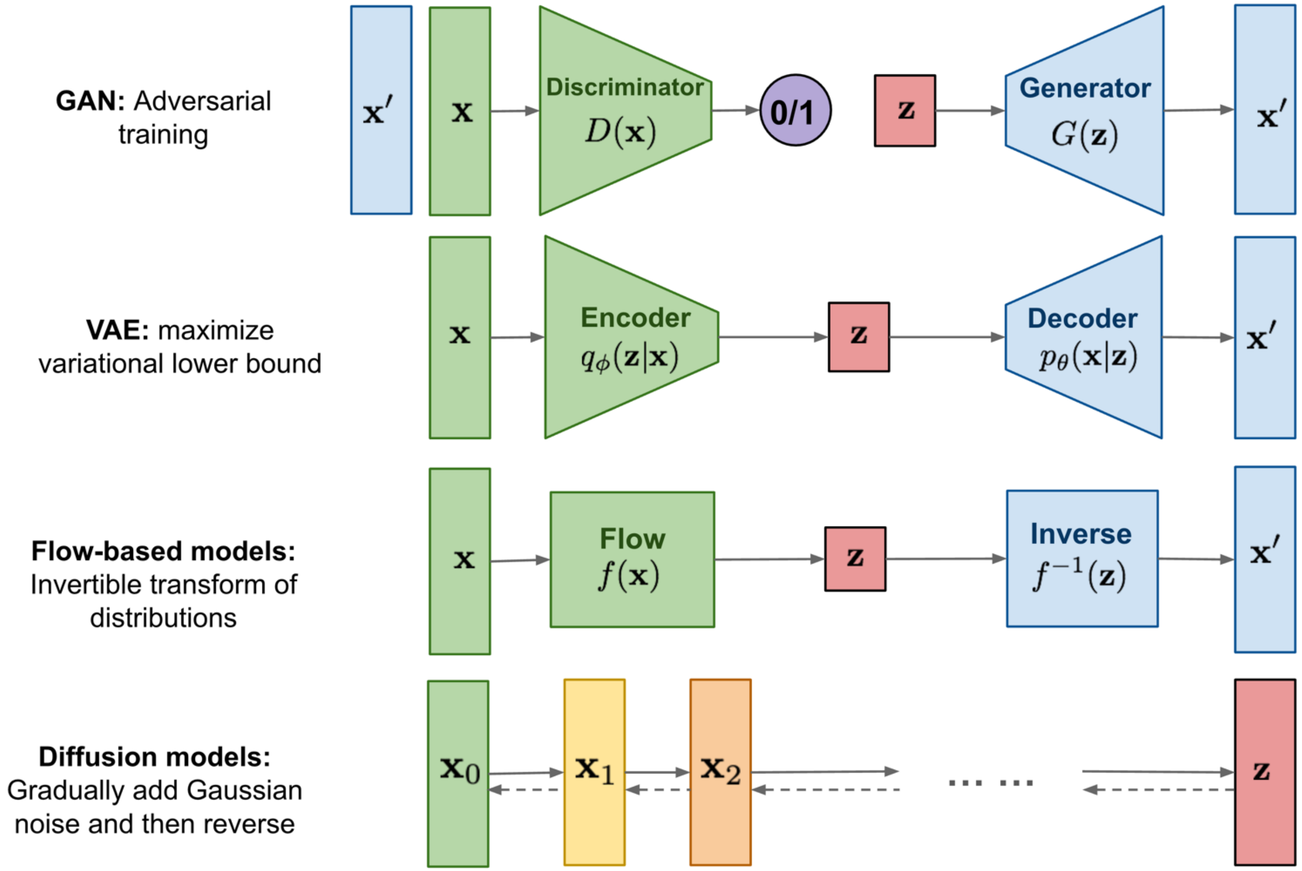
  If I sample from the distribution and get a

  - high likelihood ➔ likely the sample came from the training distribution
  - low likelihood ➔ the sample probably did not come from the training distribution

Why Generative Modeling?

- Realistic samples for artwork, super-resolution, colorization, etc.
- Learn useful features for downstream tasks such as classification.
- Getting insights from high-dimensional data (physics, medical imaging, etc.)
- Modeling physical world for simulation and planning (robotics and reinforcement learning applications)
- Many more …

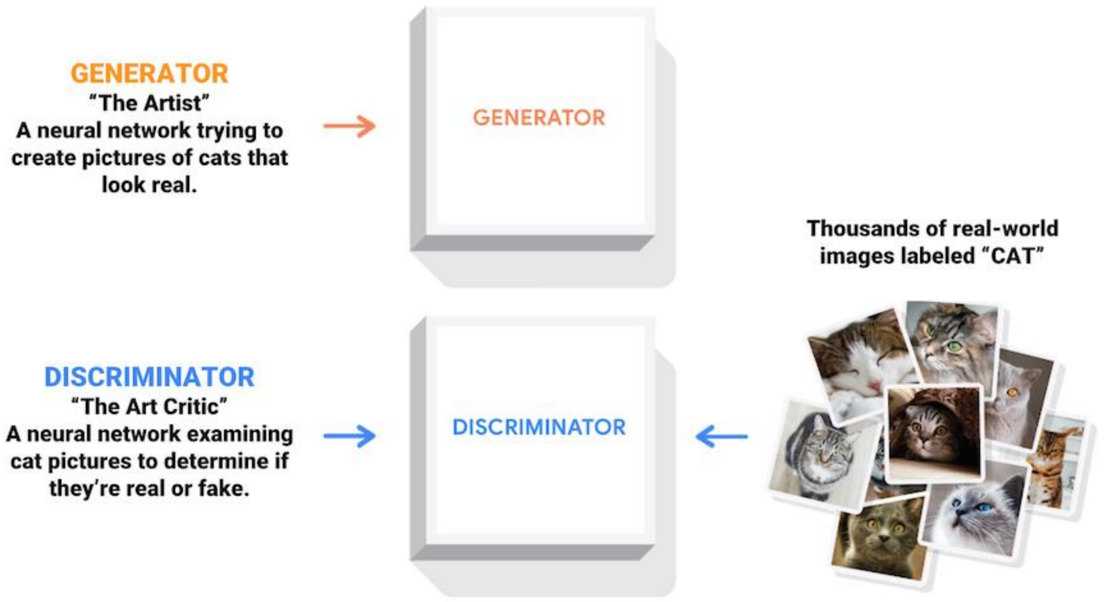
Overview of different types of generative models



Source: https://lilianweng.github.io/posts/2021-07-11-diffusion-models/

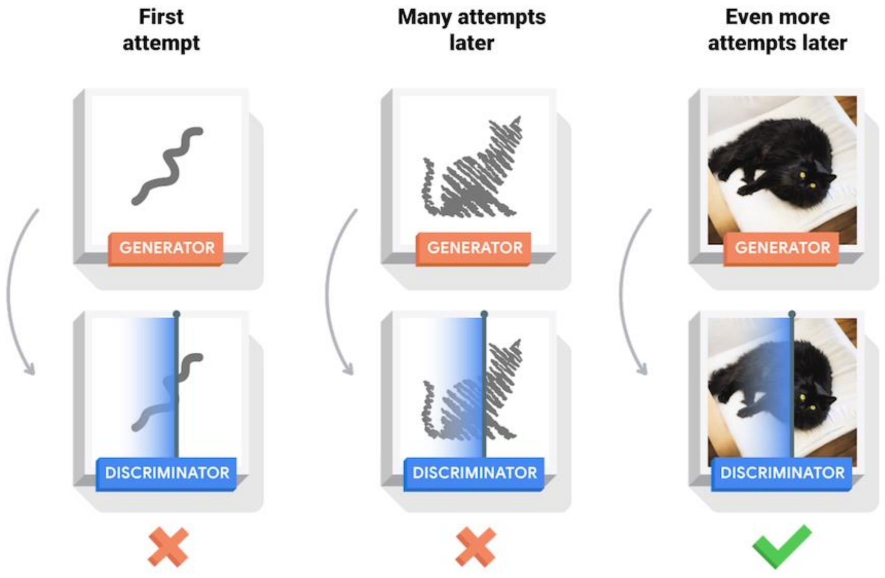
Generative Adversarial Network (GAN)

- Two models are trained simultaneously by an adversarial process.
  - A generator ("the artist") learns to create images that look real
  - A discriminator ("the art critic") learns to tell real images apart from fakes.



The idea of GAN

- During training, the generator progressively becomes better at creating images that look real, while the discriminator becomes better at telling them apart.
- The process reaches equilibrium when the *discriminator* can no longer distinguish real images from fakes.



Deep Convolutional GAN (DCGAN)

- Generator: **Upsampling layers** to produce an image from a seed (**random noise**)

```
def make_generator_model():
    model = tf.keras.Sequential()
    model.add(layers.Dense(7*7*256, use_bias=False, input_shape=(100,)))
    model.add(layers.BatchNormalization())
    model.add(layers.LeakyReLU())

    model.add(layers.Reshape((7, 7, 256)))
    assert model.output_shape == (None, 7, 7, 256)  # Note: None is the batch size

    model.add(layers.Conv2DTranspose(128, (5, 5), strides=(1, 1), padding='same', use_bias=False))
    assert model.output_shape == (None, 7, 7, 128)
    model.add(layers.BatchNormalization())
    model.add(layers.LeakyReLU())

    model.add(layers.Conv2DTranspose(64, (5, 5), strides=(2, 2), padding='same', use_bias=False))
    assert model.output_shape == (None, 14, 14, 64)
    model.add(layers.BatchNormalization())
    model.add(layers.LeakyReLU())

    model.add(layers.Conv2DTranspose(1, (5, 5), strides=(2, 2), padding='same', use_bias=False, activation=
    assert model.output_shape == (None, 28, 28, 1)

    return model
```

Deep Convolutional GAN (DCGAN)

- Discriminator: a classifier

```
def make_discriminator_model():
    model = tf.keras.Sequential()
    model.add(layers.Conv2D(64, (5, 5), strides=(2, 2), padding='same',
                                     input_shape=[28, 28, 1]))
    model.add(layers.LeakyReLU())
    model.add(layers.Dropout(0.3))

    model.add(layers.Conv2D(128, (5, 5), strides=(2, 2), padding='same'))
    model.add(layers.LeakyReLU())
    model.add(layers.Dropout(0.3))

    model.add(layers.Flatten())
    model.add(layers.Dense(1))

    return model
```

Deep Convolutional GAN (DCGAN)

- Loss function: optimization goal
  - Discriminator loss: how well the discriminator can distinguish real images from fakes
  - Generator loss: how well it was able to trick the discriminator

```
def discriminator_loss(real_output, fake_output):
    real_loss = cross_entropy(tf.ones_like(real_output), real_output)
    fake_loss = cross_entropy(tf.zeros_like(fake_output), fake_output)
    total_loss = real_loss + fake_loss
    return total_loss

def generator_loss(fake_output):
    return cross_entropy(tf.ones_like(fake_output), fake_output)
```

Deep Convolutional GAN (DCGAN)

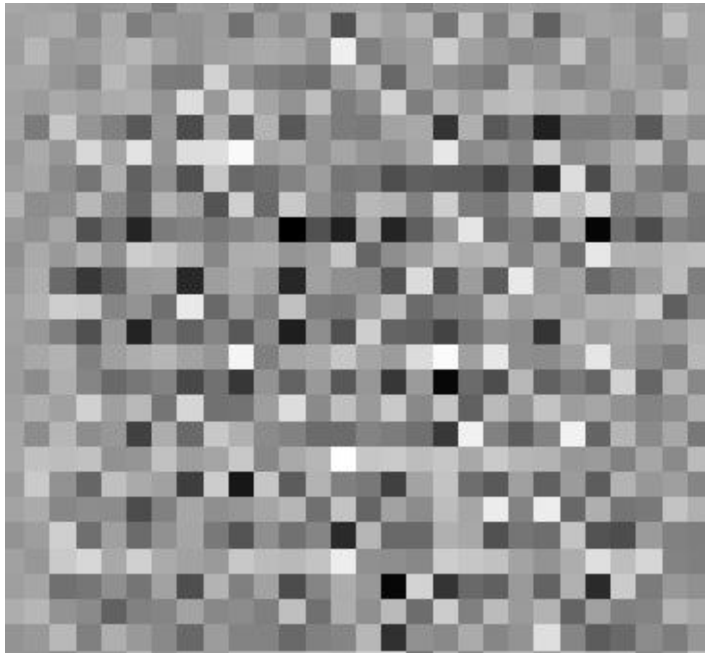
Architecture guidelines for stable Deep Convolutional GANs

- Replace any pooling layers with strided convolutions (discriminator) and fractional-strided convolutions (generator).
- Use batchnorm in both the generator and the discriminator.
- Remove fully connected hidden layers for deeper architectures.
- Use ReLU activation in generator for all layers except for the output, which uses Tanh.
- Use LeakyReLU activation in the discriminator for all layers.

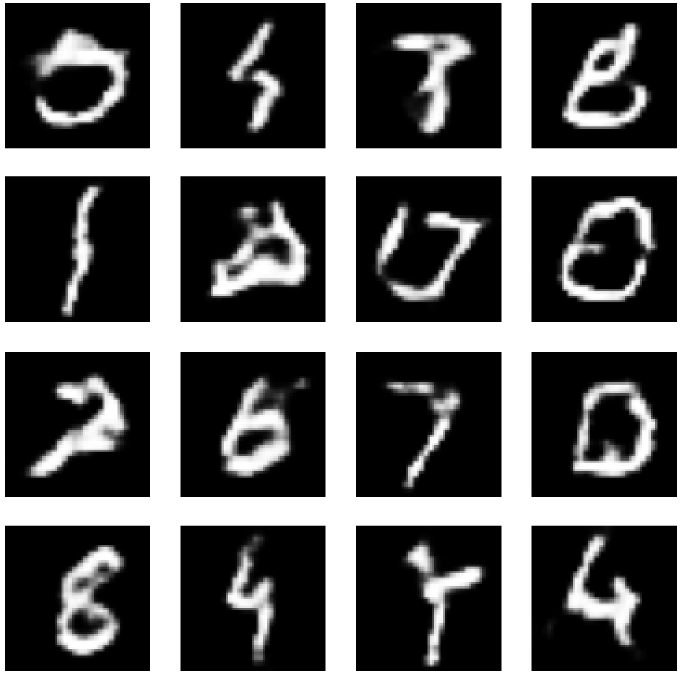
The GAN Zoo: https://github.com/hindupuravinash/the-gan-zoo
Tricks to make GAN better: https://github.com/soumith/ganhacks

Radford et al, "Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks", ICLR 2016

Effect of DCGAN



Start from: Random Noise



Synthesized Image

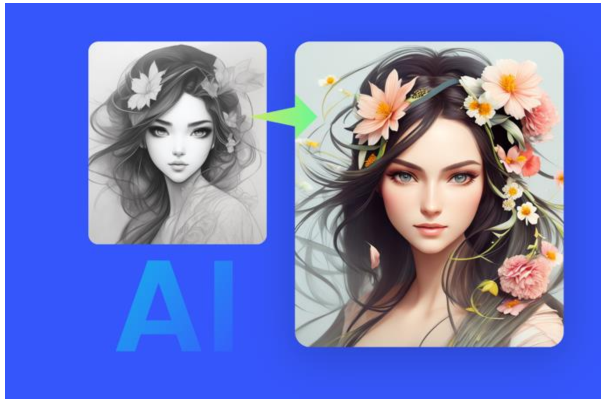
Conditional GAN (cGAN)

- Learns a mapping from input images to output images
- cGAN: **Condition on input images** and generate corresponding output images

Image-to-Image Translation with Conditional Adversarial Networks (CVPR 2017)

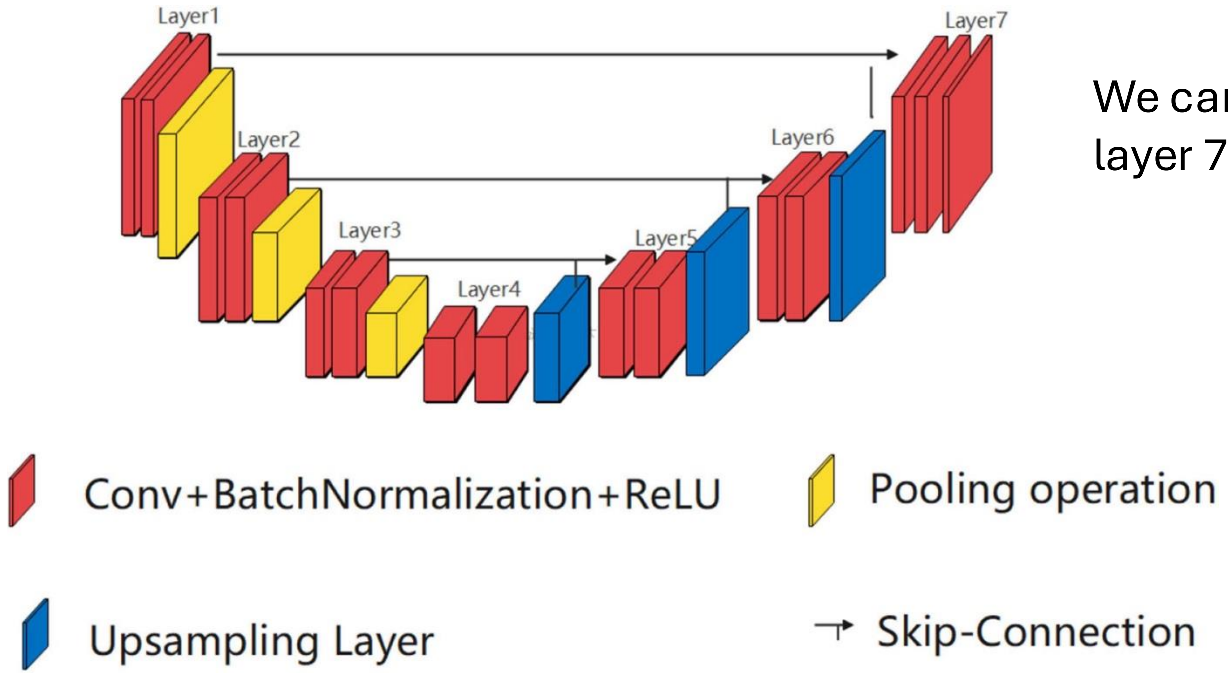
Applications of cGAN

- Synthesizing photos from label maps
- Generating colorized photos from black and white images
- Turning Google Maps photos into aerial images
- Transforming sketches into photos…



Conditional GAN (cGAN)

- Generator (UNet): an encoder (downsampler) and decoder (upsampler)



We can set the size of layer 7 the same as input

https://www.frontiersin.org/journals/aging-neuroscience/articles/10.3389/fnagi.2022.841297/full

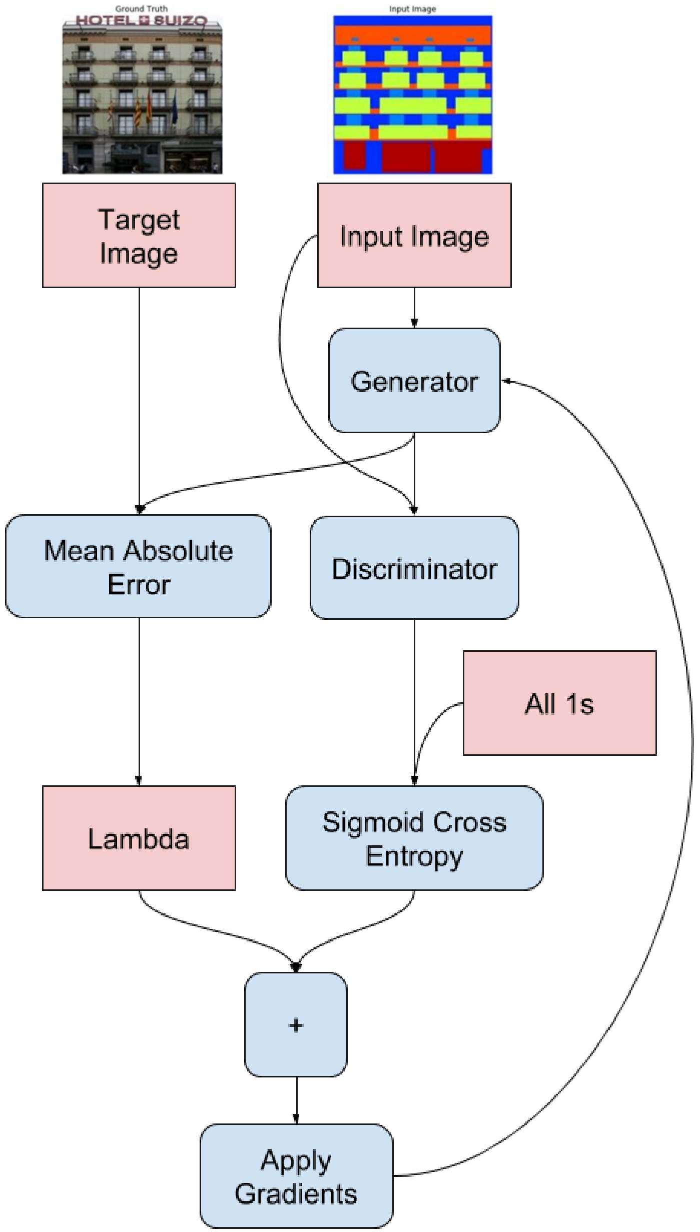
Training of Generator

```
def generator_loss(disc_generated_output, gen_output, target):
  gan_loss = loss_object(tf.ones_like(disc_generated_output), disc_generated_output)

  # Mean absolute error
  l1_loss = tf.reduce_mean(tf.abs(target - gen_output))

  total_gen_loss = gan_loss + (LAMBDA * l1_loss)

  return total_gen_loss, gan_loss, l1_loss
```



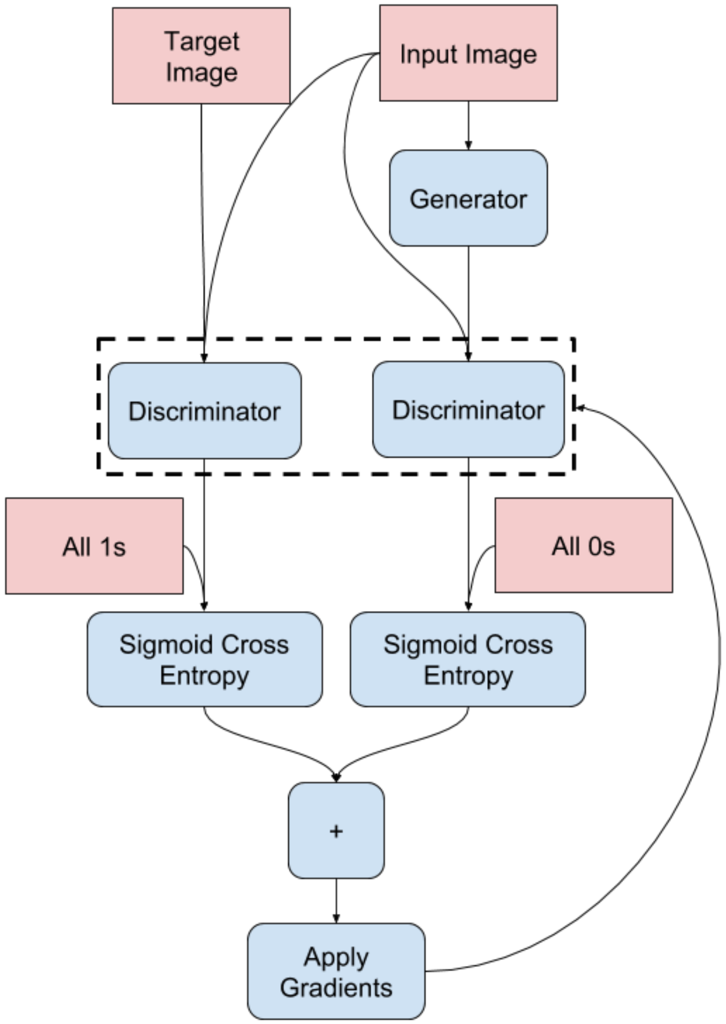
Train of Discriminator

```
def discriminator_loss(disc_real_output, disc_generated_output):
  real_loss = loss_object(tf.ones_like(disc_real_output), disc_real_output)

  generated_loss = loss_object(tf.zeros_like(disc_generated_output), disc_generated_output)

  total_disc_loss = real_loss + generated_loss

  return total_disc_loss
```



Discriminator in cGAN

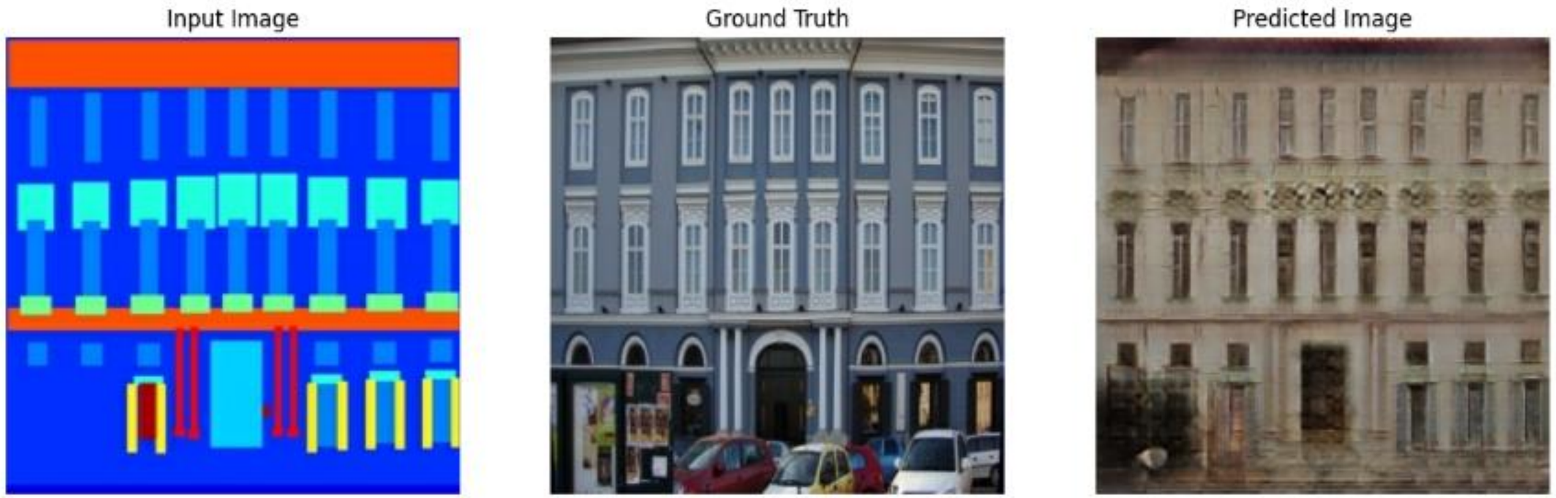
- Discriminator: a **convolutional PatchGAN** classifier—it tries to classify if each **image *patch*** is real or fake.

- The input image and the target image, which it should classify as real.

- The input image and the generated image (the output of the generator), which it should classify as fake.

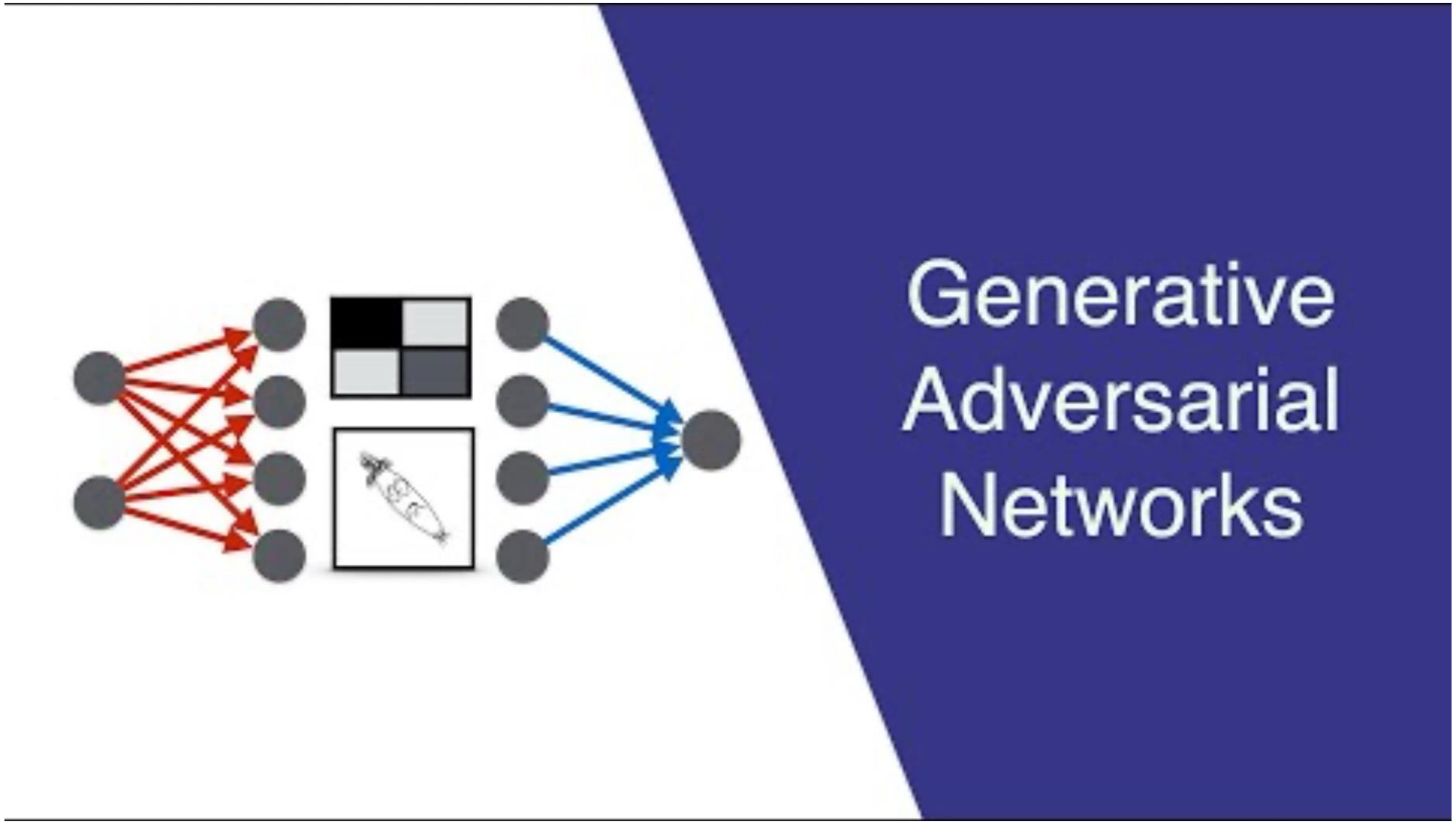
Effect of cGAN (Pixel2Pixel)

- Pass images from the test set to the generator.
- The generator will then translate the input image into the output.



https://www.tensorflow.org/tutorials/generative/pix2pix

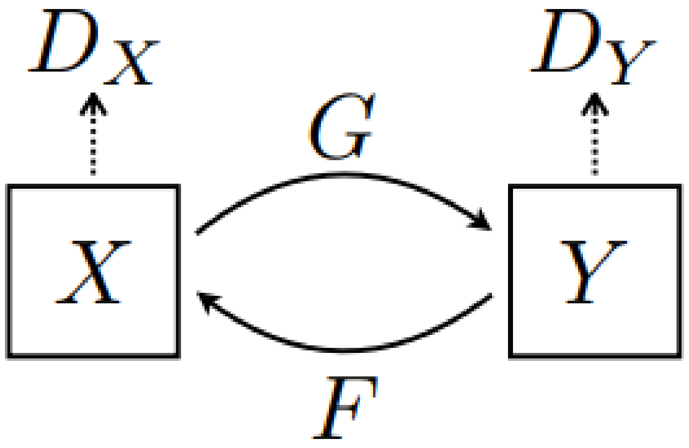
Take a Break



https://www.youtube.com/watch?v=8L11aMN5KY8

CycleGAN

There are 2 generators (G and F) and 2 discriminators (X and Y) being trained here.



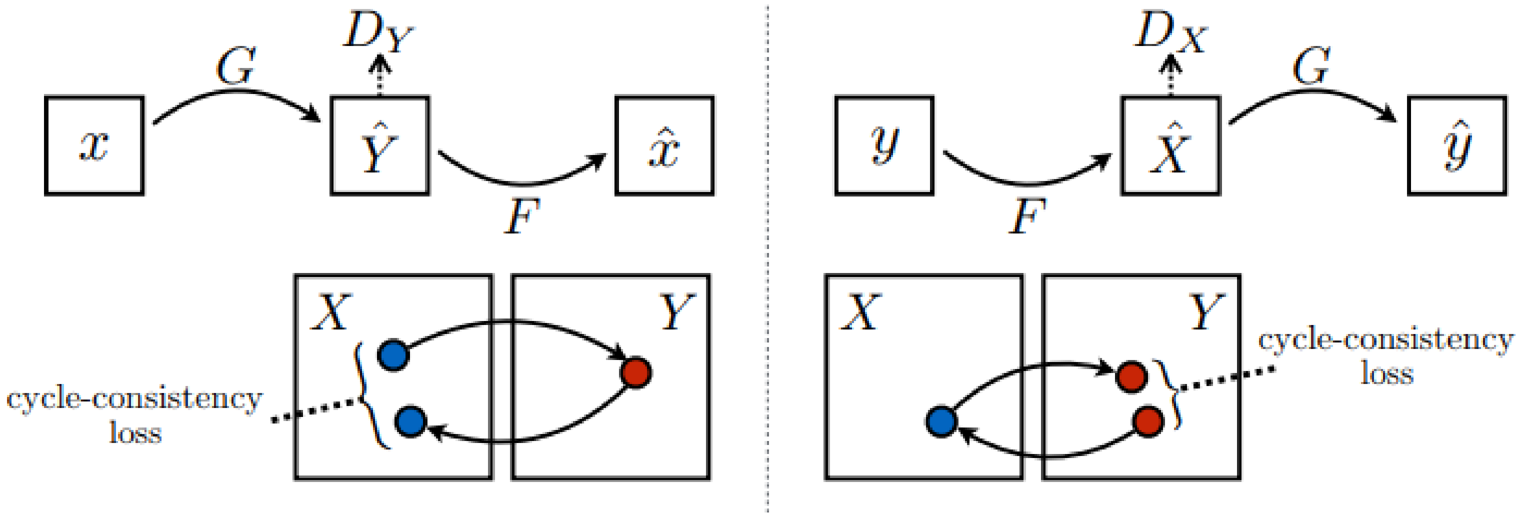
CycleGAN

- Pixel2Pixel needs paired training data.
- CycleGAN: unpaired training data.

- CycleGAN uses instance normalization instead of batch normalization.
- The CycleGAN paper uses a modified Resnet based Generator

Loss Function in CycleGAN

- There is no pair data to train on, so cycle consistency loss is designed to enforce the network to learn meaningful mapping.
- Cycle consistency means the result should be close to the original input.

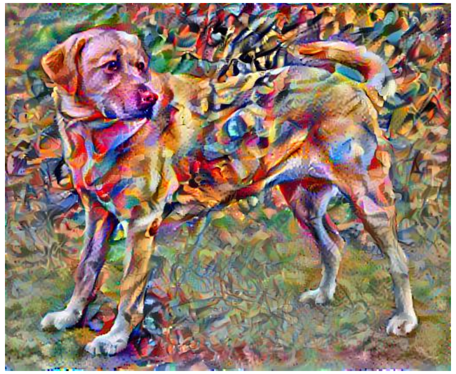


Neural Style Transfer

- A *content image* and a *style reference image* (such as an artwork by a famous painter)
- Blend them together so the output image looks like the content image, but "painted" in the style of the style reference image.

Content Image

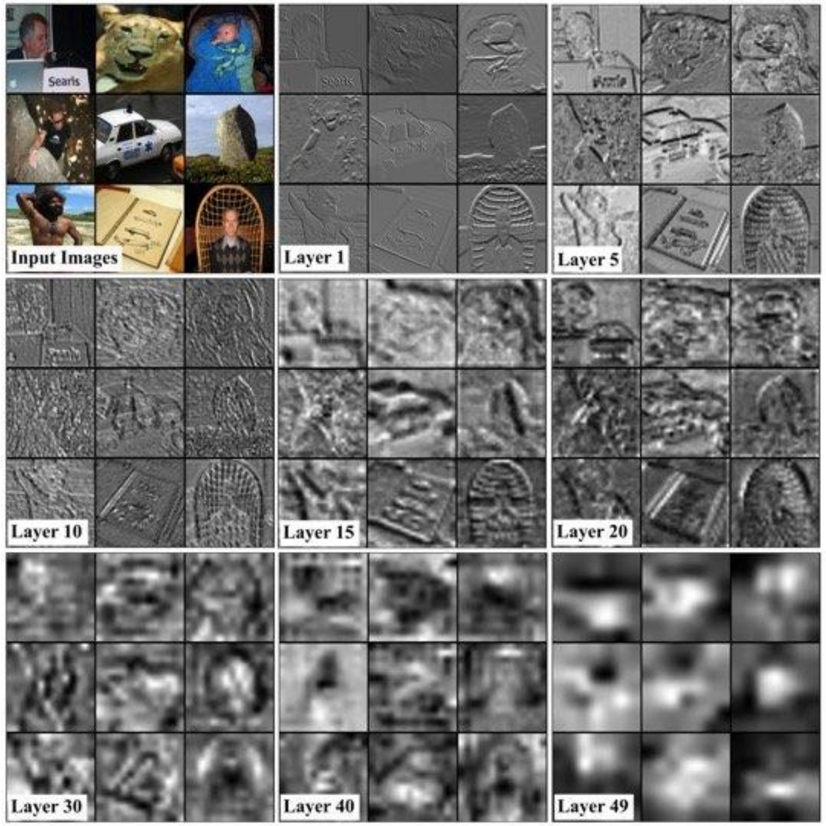
Style Image



Synthesized Image

Content and Style Representations

- Use the intermediate layers of the model to get the *content* and *style* repr esentations of the image.
- From edges, corners, textures to high-level concepts.



https://www.researchgate.net/figure/Visualization-of-example-features-of-layers-1-10-20-30-40-and-49-of-a-deep_fig1_319622441

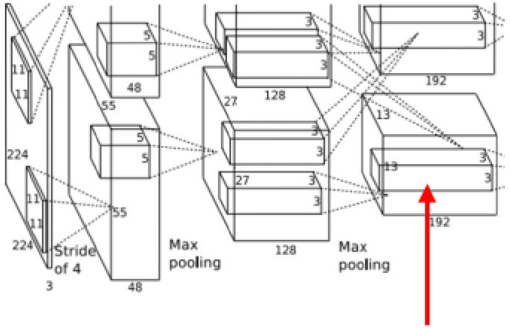
Content and Style Representations

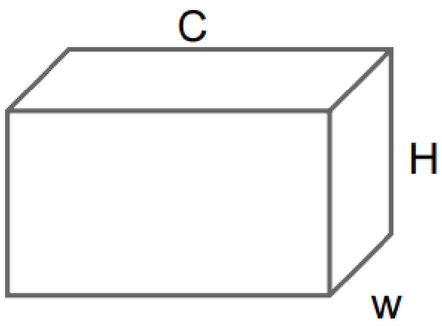
- The content of an image is represented by the values of the intermediate feature maps.

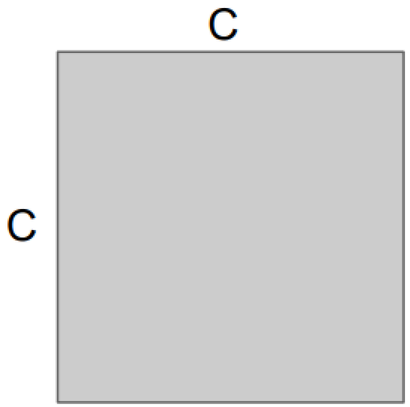
- The style of an image can be described by the means and correlations across the different feature maps.

Style Representation: Gram Matrix

This image is in the public domain.







Each layer of CNN gives C x H x W tensor of features; H x W grid of C-dimensional vectors

Outer product of two C-dimensional vectors gives C x C matrix measuring co-occurrence

Average over all HW pairs of vectors, giving **Gram matrix** of shape C x C

Efficient to compute; reshape features from

C x H x W to =C x HW

then compute $G = FF^T$

Gram matrix: Ignore the positions of features and get correlations among features.

Style Representation: Gram Matrix

The Gram matrix takes the outer product of the feature vector with itself at each location and averaging that outer product over all locations.

$$G^l_{cd} = \frac{\sum_{ij} F^l_{ijc}(x) F^l_{ijd}(x)}{IJ}$$

```python
def gram_matrix(input_tensor):
  result = tf.linalg.einsum('bijc,bijd->bcd', input_tensor, input_tensor)
  input_shape = tf.shape(input_tensor)
  num_locations = tf.cast(input_shape[1]*input_shape[2], tf.float32)
  return result/(num_locations)
```

Tensorflow Implementation

```python
def gram_matrix(input):
    a, b, c, d = input.size()  # a=batch size(=1)
    # b=number of feature maps
    # (c,d)=dimensions of a f. map (N=c*d)

    features = input.view(a * b, c * d)  # resize F_XL into \hat F_XL

    G = torch.mm(features, features.t())  # compute the gram product

    # we 'normalize' the values of the gram matrix
    # by dividing by the number of element in each feature maps.
    return G.div(a * b * c * d)
```

Pytorch Implementation

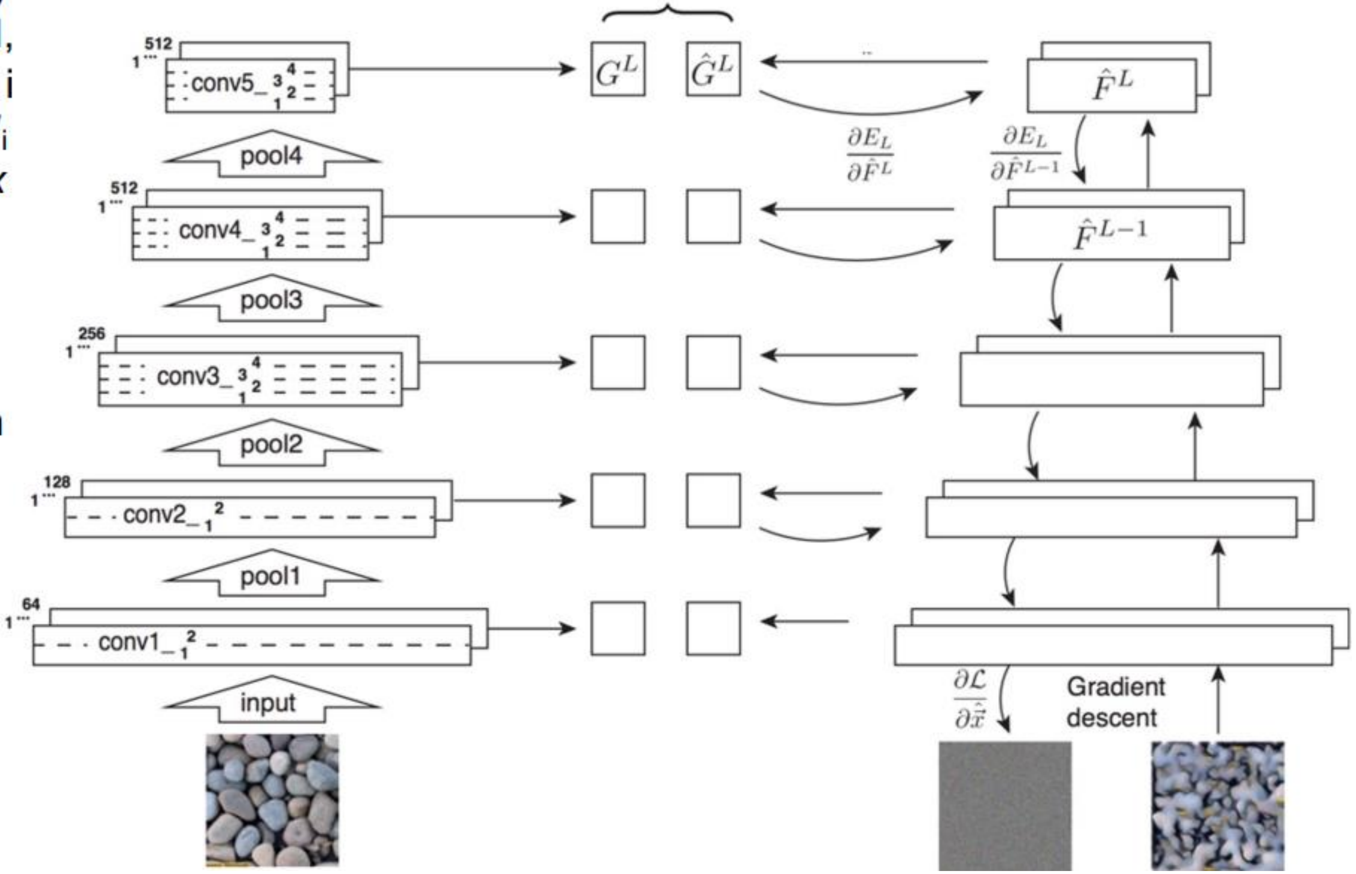
Neural Style Transfer

$$E_l = \frac{1}{4N_l^2 M_l^2} \sum_{i,j} \left(G_{ij}^l - \hat{G}_{ij}^l \right)^2 \qquad \mathcal{L}(\vec{x}, \hat{\vec{x}}) = \sum_{l=0}^{L} w_l E_l$$

1. Pretrain a CNN on ImageNet (VGG-19)
2. Run input texture forward through CNN, record activations on every layer; layer i gives feature map of shape $C_i \times H_i \times W_i$
3. At each layer compute the *Gram matrix* giving outer product of features:

$$G_{ij}^l = \sum_k F_{ik}^l F_{jk}^l \text{ (shape } C_i \times C_i\text{)}$$

4. Initialize generated image from random noise
5. Pass generated image through CNN, compute Gram matrix on each layer
6. Compute loss: weighted sum of L2 distance between Gram matrices
7. Backprop to get gradient on image
8. Make gradient step on image
9. GOTO 5



Learning Objective: MSE loss

```python
def style_content_loss(outputs):
    style_outputs = outputs['style']
    content_outputs = outputs['content']
    style_loss = tf.add_n([tf.reduce_mean((style_outputs[name]-style_targets[name])**2)
                           for name in style_outputs.keys()])
    style_loss *= style_weight / num_style_layers

    content_loss = tf.add_n([tf.reduce_mean((content_outputs[name]-content_targets[name])**2)
                             for name in content_outputs.keys()])
    content_loss *= content_weight / num_content_layers
    loss = style_loss + content_loss
    return loss
```

```python
@tf.function()
def train_step(image):
  with tf.GradientTape() as tape:
    outputs = extractor(image)
    loss = style_content_loss(outputs)

  grad = tape.gradient(loss, image)
  opt.apply_gradients([(grad, image)])
  image.assign(clip_0_1(image))
```

Gradient computation in TensorFlow

```python
# We want to optimize the input and not the model parameters so we
# update all the requires_grad fields accordingly
input_img.requires_grad_(True)
# We also put the model in evaluation mode, so that specific layers
# such as dropout or batch normalization layers behave correctly.
model.eval()
model.requires_grad_(False)

optimizer = get_input_optimizer(input_img)
```

Gradient computation in PyTorch

Neural Style Transfer

References

- https://cs231n.stanford.edu/slides/2024/lecture_11.pdf
- https://www.tensorflow.org/tutorials/generative/style_transfer
- https://pytorch.org/tutorials/advanced/neural_style_tutorial.html
- https://www.tensorflow.org/tutorials/generative/dcgan
- https://www.tensorflow.org/tutorials/generative/pix2pix
- https://www.tensorflow.org/tutorials/generative/cyclegan