Generative Adversarial Networks

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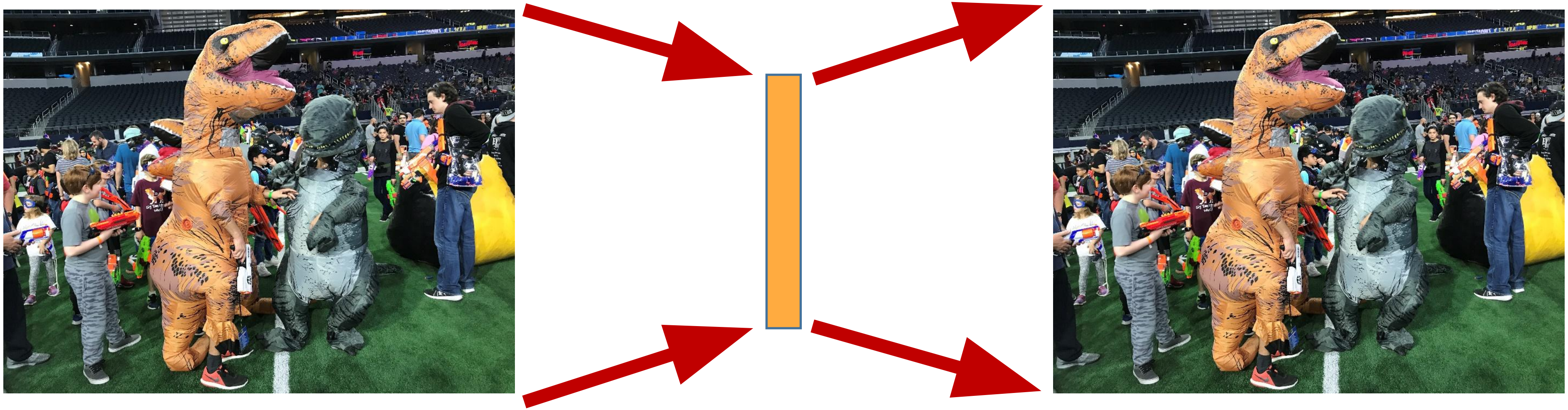
Compressing Images



Original Image

Compressed Representation

Decompress for Rendering

Compressing Images

$f(X)$

Z

$g(Z)$

Original Image

X

Compressed Representation

Decompress for Rendering

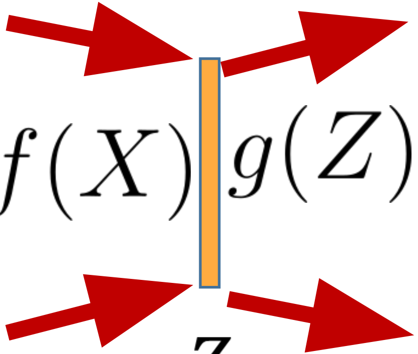
Y

Compressing Images

- We know what X and Y should be
- But, the compressed representation (Z) does not contain any specific semantic information

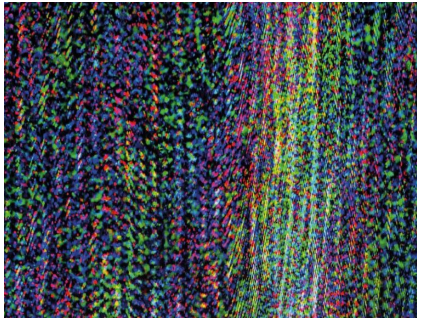
Autoencoder idea: we can use our gradient descent method to learn these representations ….

Training Autoencoders for Compressing Images



$f(X)$ $g(Z)$

Z



$?=$

X Y X

$$E = X - Y$$

Original Image **Compressed Representation** **Decompress for Rendering** **Desired Output**

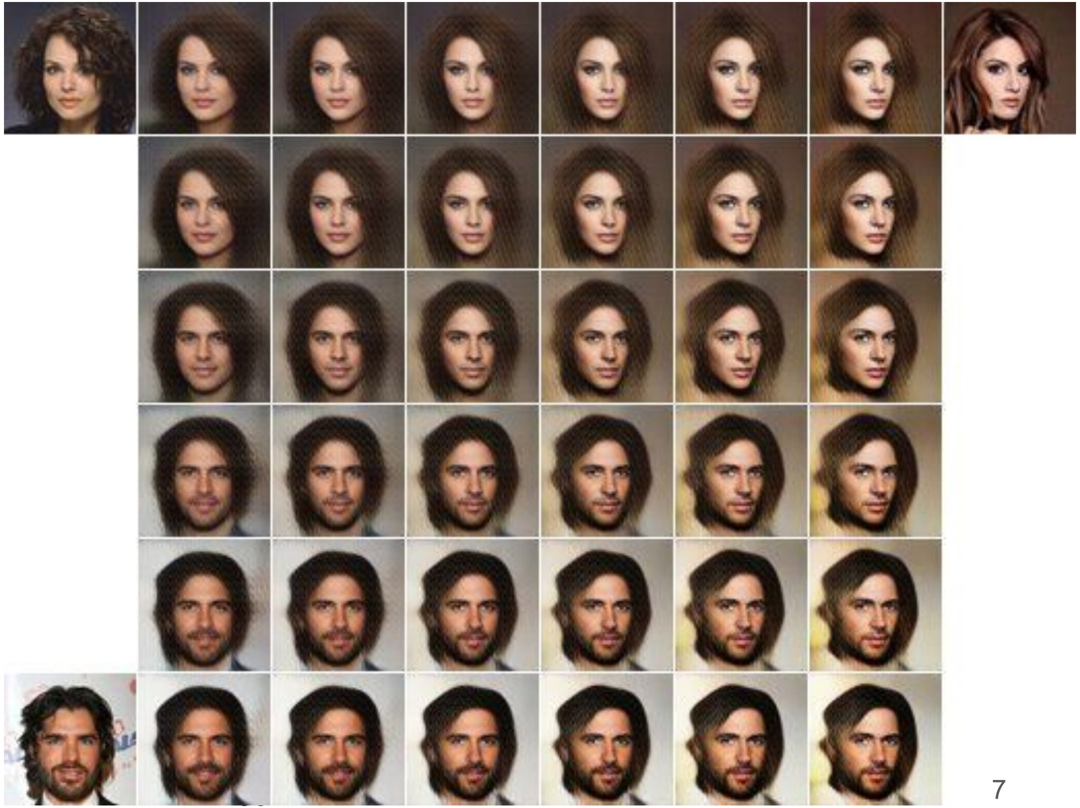
Training Autoencoders for Compressing Images

- Input and desired output are the same thing
  - This is a form of ***unsupervised learning***
  - Nobody determines explicitly what the compressed representation is (the algorithm does this!)
- With a large number of example images and sufficient compression:
  - Compressed representation (called ***latent*** representation) begins to have some semantic meaning

Interpolation in Latent Space

Latent dimensions include:

- Head orientation
- Hair color
- Sex



Interpolation in Latent Space

- A weighted average of two valid latent representations must also be a valid latent vector
  - I.E., the entire set of valid latent vectors must form a **compact set**
- When constructing autoencoders, we typically add regularization terms that require the latent representations fall within a Gaussian distribution

Thinking Bigger

- With autoencoders, our representation is limited to the set of examples that we used for training
- Yes, we can interpolate between these examples, but we want to be able to extrapolate, too

Goal: generate images that are realistic examples of scenes

Generating Images from Noise

Random Noise

$g(Z)$

Z

Compressed Representation

Decompress for Rendering

Y

Generator Evaluation

How might we evaluate the generated images?

Generator Evaluation

One idea:

- Learn another model that discriminates between real example images and the fake generated images
- This is a lot like our earlier image classifier

Discriminator

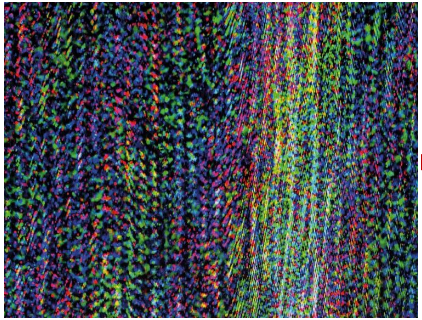
$$h(Y)$$

Probability of being real

Input Image

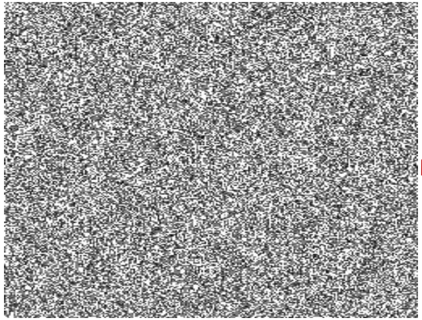
Discriminator

$h(Y)$ → **0.97**



$h(Y)$ → **0.03**

$h(Y)$ → **0.89**



$h(Y)$ → **0.01**

Full Architecture

What does it look like?

Full Architecture

What does it look like?

- Discriminator receives input from one of two sources:
  - Example real images
  - Images produced by the generator
- Learning:
  - Adjust discriminator parameters to better tell real from fake
  - Adjust generator parameters to better fool the discriminator with fakes
  - This sounds like a minimax problem!

Generative Adversarial Network

Discriminator desired output

Random Noise

$g(Z)$

Z

Y

$h(Y)$

0.0

OR

Probability of being real

1.0

Real Image

$$L_h = \text{crossentropy}(h(Y), D)$$

https://phillipi.github.io/pix2pix/

Generative Adversarial Network

Generator desired output

1.0

Random Noise

$g(Z)$

Z

Y

$h(Y)$

OR

Probability of being real

X

Real Image

$$L_g = \text{crossentropy}(h(Y), D)$$

https://phillipi.github.io/pix2pix/

Implementation Outline

```
// Create models
h = create_discriminator()

// Compile model with adjustable
//   parameters
h.compile(loss='binary_crossentropy', …)
```

Implementation Outline

```
// Create generator model
g = build_generator()

// Future uses of h will not be trainable
h.trainable = False
```

Implementation Outline

```
// Create the Meta-Model
Z = Input(shape=latent_shape)

// Create fake images
Y= g(Z)

// Apply discriminator to both image sets
p_fake = h(Y)


// Create the meta Model
model = Model(inputs=Z, outputs=p_fake, …)

// Compile it
model.compile(loss='binary_cross_entropy', …)
```

Implementation Outline

```
Loop
   z ~ sample_latent()
   x ~ sample_real()

   x_fake = g.predict(z)

   model.fit(x=z, y=ones(), epochs=1)

   d.fit(x=np.concat([x, x_fake]),
         y=np.concat([ones(), zeros()], epochs=1)
```

Adversarial Learning

The discriminator and generator are in an “arms race”:

- Early on, the generator does not produce interesting images.
- It is easy for the discriminator to do its job
- This gives the generator useful training information so it can produce better images
- In turn, the discriminator must catch up with the new generator
- Repeat

GAN Challenges

- Can take a long time to learn to generate even nominally interesting images
  - Especially when the generated images are large
- **Mode collapse**: no matter the randomly selected latent vector, the generator learns to ignore it and produce a single, realistic image
  - Can be a serious problem, especially if noise is injected only at the latent layer
  - Often introduce other regularization terms to force interesting variance

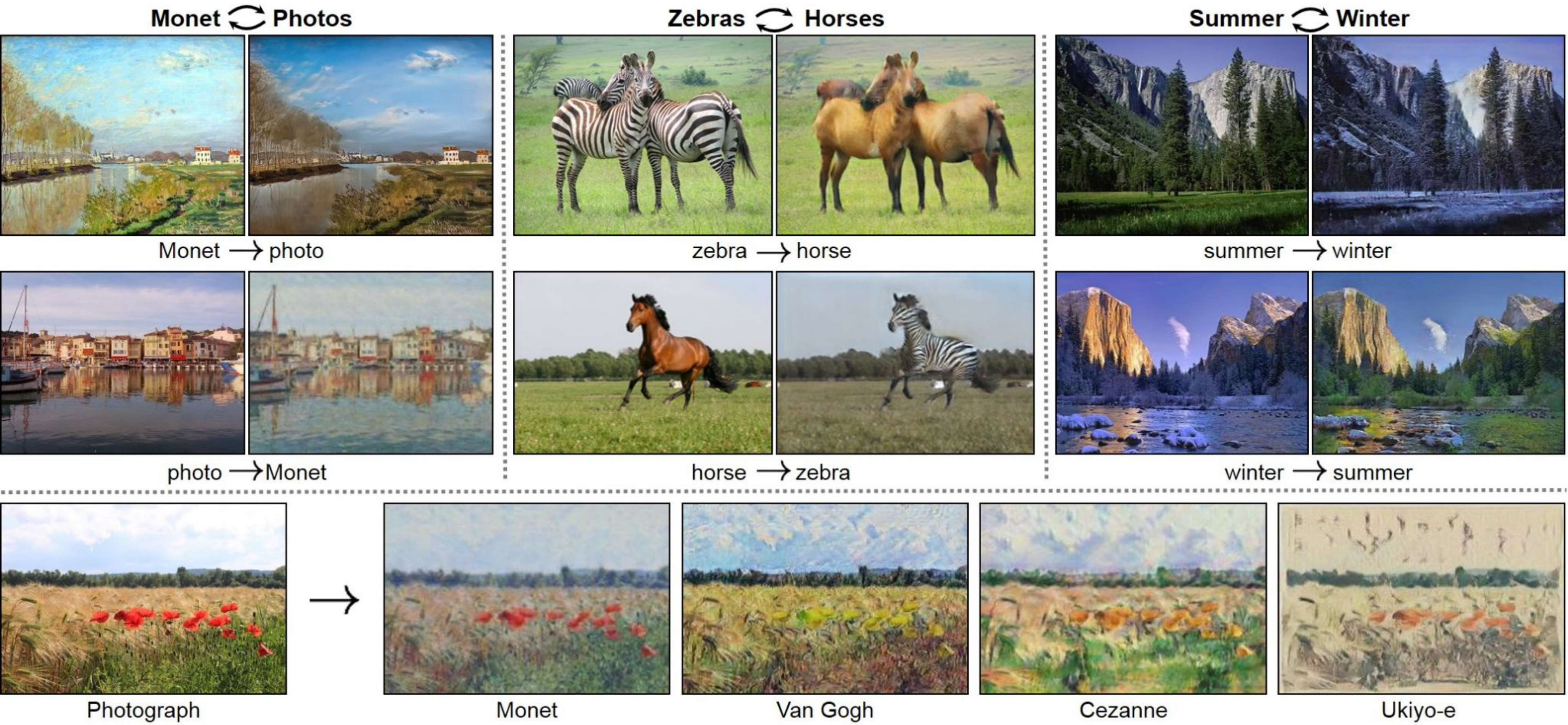
GAN Variations

- Wasserstein GANs: improved GAN training process
- Cycle GANs
- Style GANs
- Conditional GANS

Cycle GAN

Zhu et a., 2017

- Image to image translation
  - Translate an image in one domain into another domain
- We never have example image pairs (one for each domain)
  - Only singleton examples from each domain
- Approach:
  - Use discriminator for each domain to tell whether the translation was right
  - Use a U-Net to translate between domains



Monet ⇄ Photos
Zebras ⇄ Horses
Summer ⇄ Winter
Monet → photo
zebra → horse
summer → winter
photo → Monet
horse → zebra
winter → summer
Photograph
Monet
Van Gogh
Cezanne
Ukiyo-e

Cycle GAN Implementation

- Must train the image translators and the discriminators at the same time
- Convenient to use Model nesting to make this work

- One tool:
    - model.trainable property (a Boolean) controls whether the parameters in the model can be adjusted
    - Catch: this property is *only* read by model.compile()

Cycle GAN Implementation

```
// Create new models
dA = create_discriminator()
dB = create_discriminator()

// Compile these models with adjustable
//   parameters
dA.compile(loss='mse', …)
dB.compile(loss='mse', …)
```

Ref: David Foster (2019), “Generative Deep Learning”

Cycle GAN Implementation

```
// Create individual generator models
gAB = build_generator()
gBA = build_generator()

// Future uses of dA/dB will not be trainable
dA.trainable = False
dB.trainable = False
```

Cycle GAN Implementation

```
// Create the Meta-Model
inA = Input(shape=img_shape)
inB = Input(shape=img_shape)

// Create fake images
fakeA = gBA(inB)
fakeB = gAB(inA)

// Create duplicate images from the fakes
reconA = gBA(fakeB)
reconB = gAB(fakeA)

// Create image identities: don’t change an image if it is
// already the right type
idA = gBA(inA)
idB = gAB(inB)
```

Cycle GAN Implementation

```
// Evaluate the fake images
validA = dA(fakeA)
validB = dB(fakeB)

// Create the meta Model
model = Model(inputs=[inA, inB]
                   outputs=[validA, validB,
                            idA, idB,
                            reconA, reconB], …)

// Compile it
model.compile(loss=[‘mse’, ‘mse’,
                         ‘mae’, ‘mae’,
                         ‘mae’,‘mae’], …)
```

Cycle GAN Implementation

```
// Train one batch
imgsA, imgsB are the batch

fakeA = gBA(imgsB)
fakeB = gAB(imgsA)

dA.fit(epochs=1, inputs=np.concatenate([imgsA,fakeA]),
                  outputs=np.concatenate([1s,0s]))

dB.fit(epochs=1, inputs=np.concatenate([imgsB,fakeB]),
                  outputs=np.concatenate([1s,0s]))

model.fit(epochs=1, inputs=[imgsA, imgsB]
                     outputs=[1s, 1s,
                              imgsA, imgsB,
                              imgsA, imgsB], …)
```

Style GAN

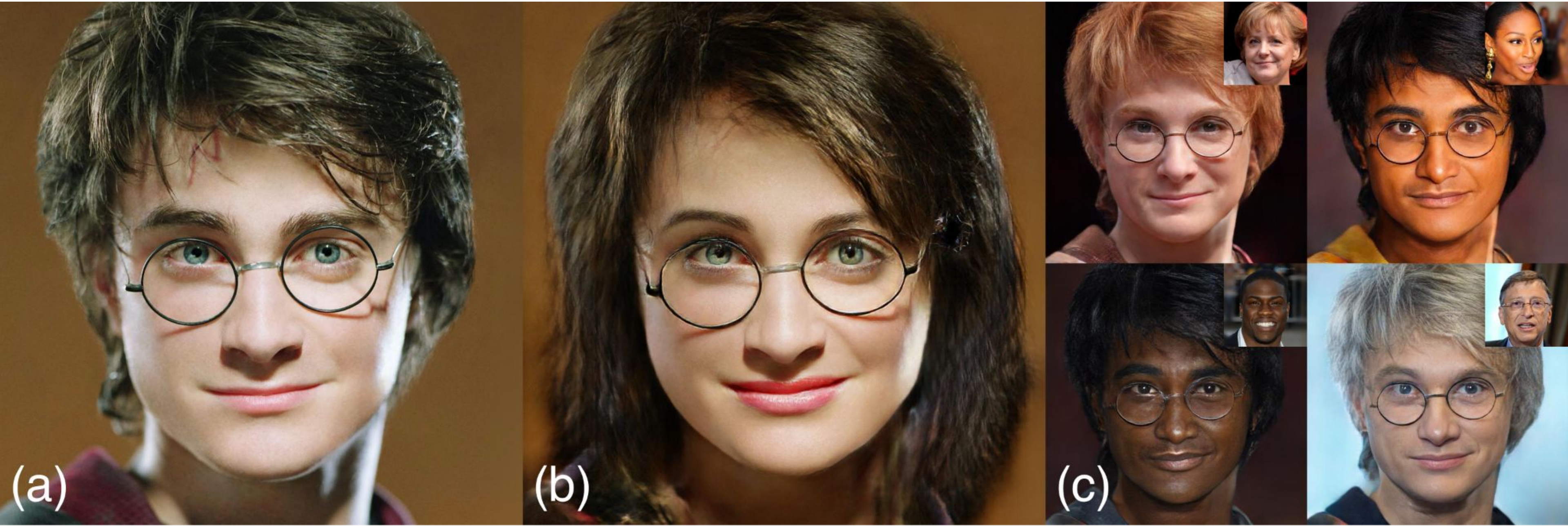
Two source images:

- Content: Goal is to create an image that maintains the detailed structure of the input image (e.g., where are the edges and other texture? What shapes are there?)
- Style: Goal is to create an image that tries to capture “style” elements in the image (higher-level features)
    - Color
    - Larger shapes and their spatial relationships

Style GAN

Adds to GANs:

- I_fake = generator(noise, latent_style)
- L = perceptual_loss(I, I_fake): compares the “style” of two images
- During generation:
    - Guess at latent_style
    - Generate fake image
    - Compute the gradient of L with respect to the latent_style
    - Update the style and repeat


(a)
(b)
(c)