Generative Adversarial Networks

ACTL3143 & ACTL5111 Deep Learning for Actuaries

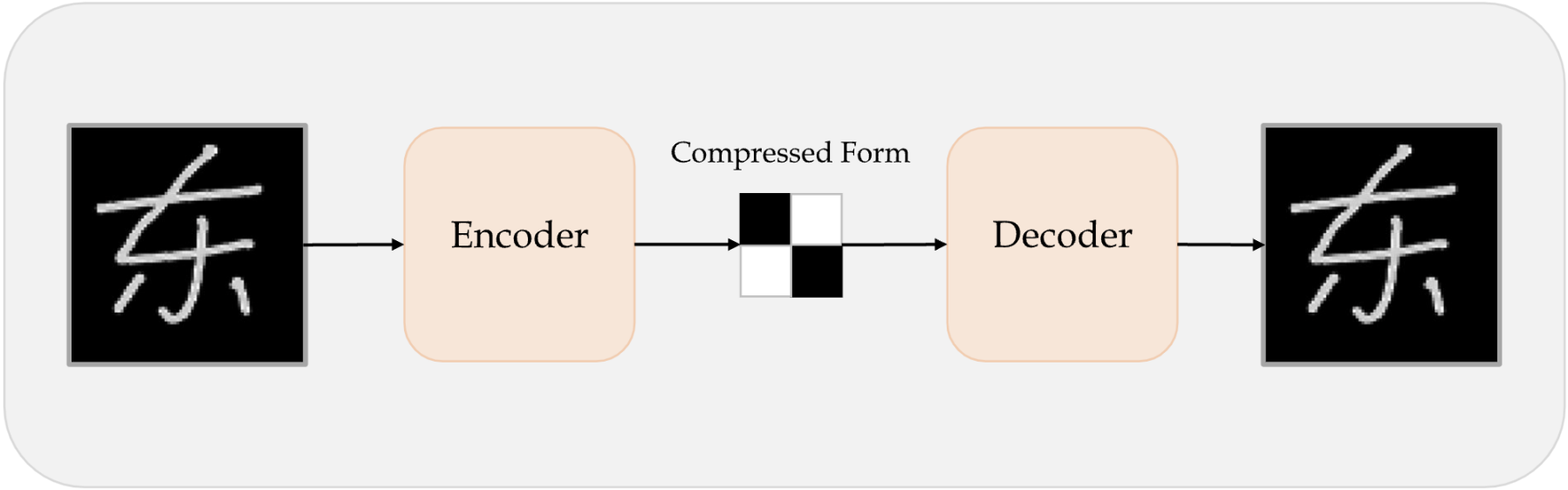
Patrick Laub

Lecture Outline

- **Traditional GANs**
- Training GANs
- Conditional GANs
- Image-to-image translation
- Problems with GANs
- Wasserstein GAN

Before GANs we had autoencoders

An autoencoder takes a data/image, maps it to a latent space via en encoder module, then decodes it back to an output with the same dimensions via a decoder module.



Schematic of an autoencoder.

Source: Marcus Lautier (2022).

GAN faces

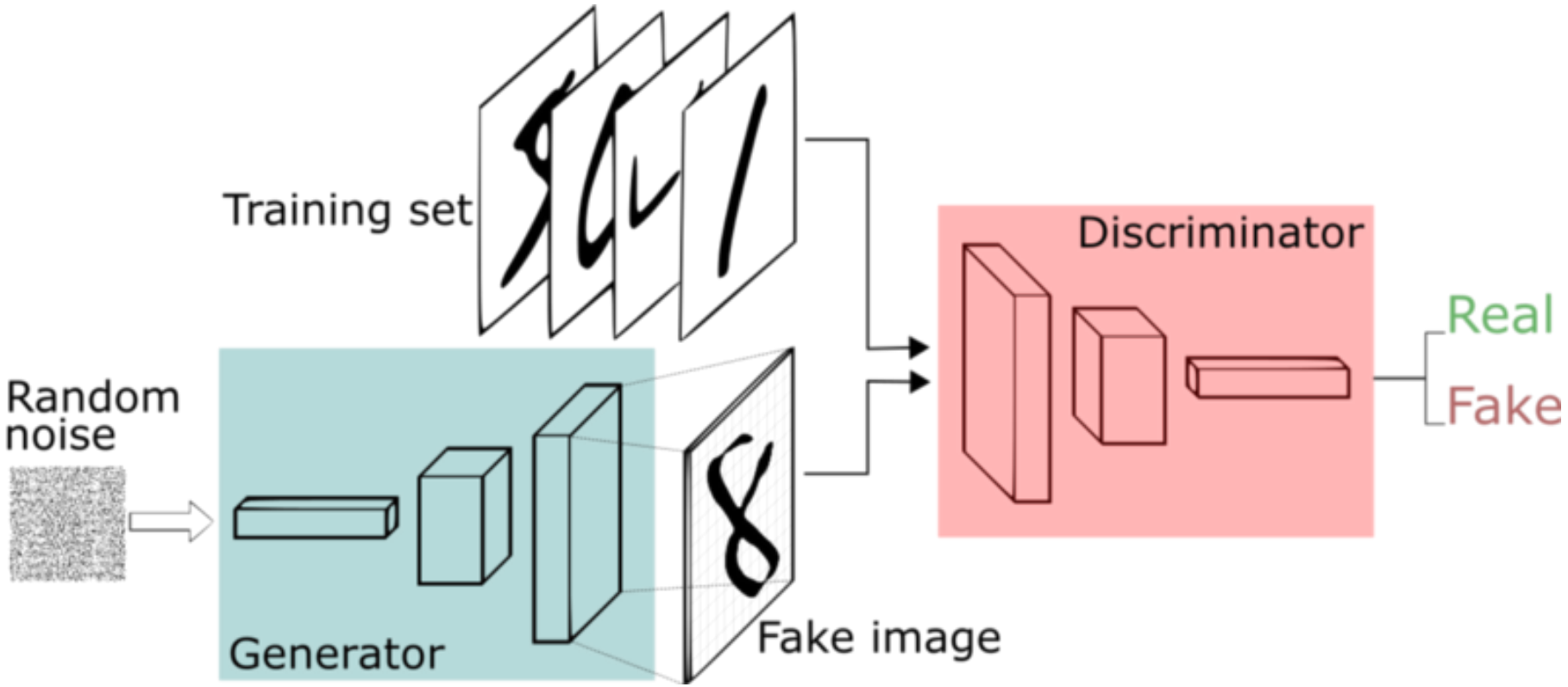
Try out https://www.whichfaceisreal.com.

Source: https://thispersondoesnotexist.com.

Example StyleGAN2-ADA outputs

Source: Jeff Heaton (2021), Training a GAN from your Own Images: StyleGAN2.

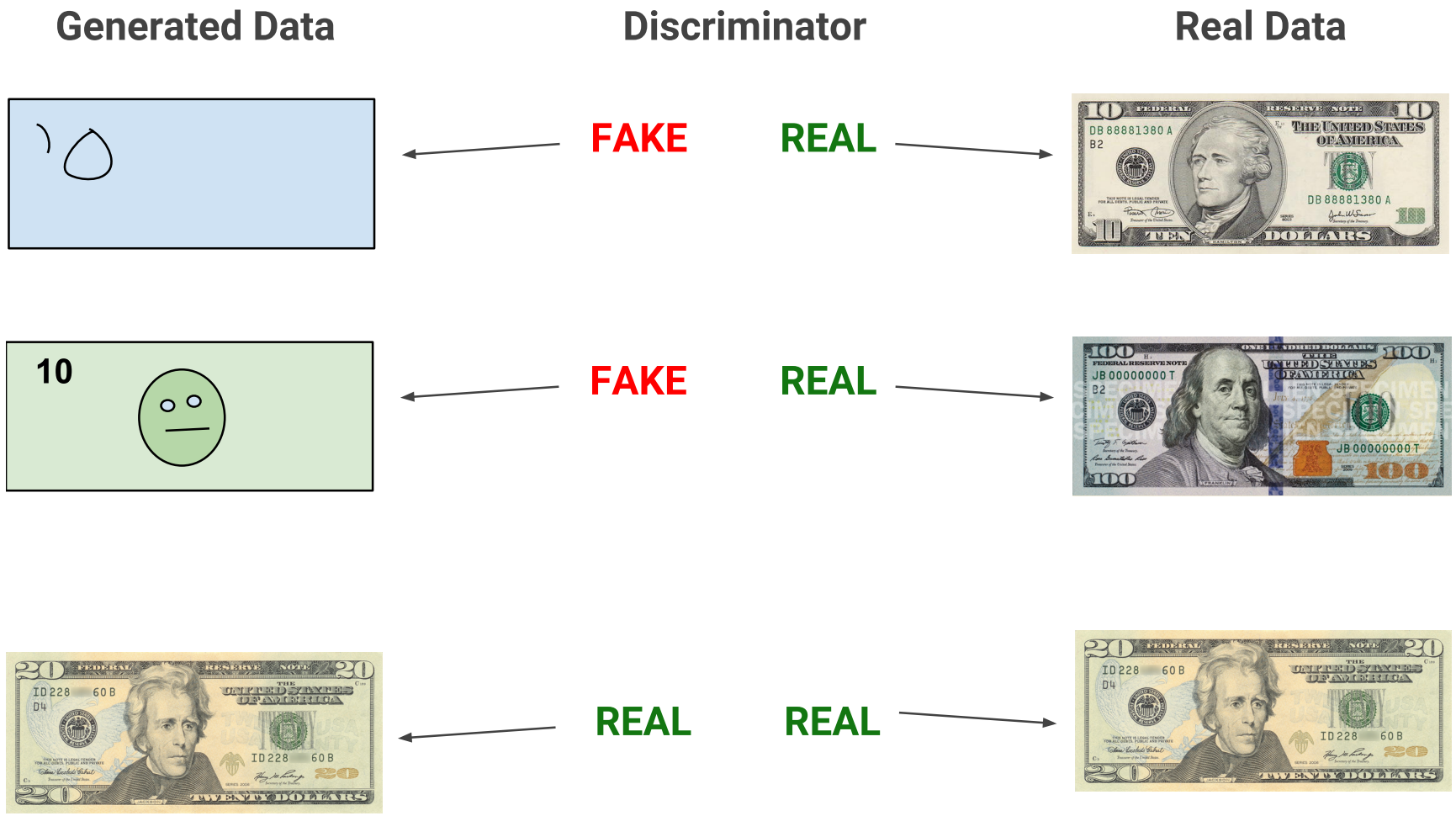
GAN structure



A schematic of a generative adversarial network.

Source: Thales Silva (2018), An intuitive introduction to Generative Adversarial Networks (GANs), freeCodeCamp.

GAN intuition



Source: Google Developers, Overview of GAN Structure, Google Machine Learning Education.

Intuition about GANs

- A forger creates a fake Picasso painting to sell to an art dealer.
- The art dealer assesses the painting.

How they best each other:

- The art dealer is given both authentic paintings and fake paintings to look at. Later on, the validity his assessment is evaluated and he trains to become better at detecting fakes. Over time, he becomes increasingly expert at authenticating Picasso's artwork.
- The forger receives an assessment from the art dealer everytime he gives him a fake. He knows he has to perfect his craft if the art dealer can detect his fake. He becomes increasingly adept at imitating Picasso's style.

Generative adversarial networks

- A GAN is made up of two parts:
  - Generator network: the forger. Takes a random point in the latent space, and decodes it into a synthetic data/image.
  - Discriminator network (or adversary): the expert. Takes a data/image and decide whether it exists in the original data set (the training set) or was created by the generator network.

Discriminator

```
lrelu = layers.LeakyReLU(alpha=0.2)

discriminator = keras.Sequential([
    keras.Input(shape=(28, 28, 1)),
    layers.Conv2D(64, 3, strides=2, padding="same", activation=lrelu),
    layers.Conv2D(128, 3, strides=2, padding="same", activation=lrelu),
    layers.GlobalMaxPooling2D(),
    layers.Dense(1)])

discriminator.summary()
```

Generator

```
latent_dim = 128
generator = keras.Sequential([
    layers.Dense(7 * 7 * 128, input_dim=latent_dim, activation=lrelu),
    layers.Reshape((7, 7, 128)),
    layers.Conv2DTranspose(128, 4, strides=2, padding="same", activation=lrelu),
    layers.Conv2DTranspose(128, 4, strides=2, padding="same", activation=lrelu),
    layers.Conv2D(1, 7, padding="same", activation="sigmoid")])
generator.summary()
```

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GAN cost functions

The loss function à la 3Blue1Brown.

GAN - Schematic process

First step: Training *discriminator*:

- Draw random points in the latent space (random noise).
- Use *generator* to generate data from this random noise.
- Mix generated data with real data and input them into the *discriminator*. The training targets are the correct labels of *real data* or *fake data*. Use *discriminator* to give feedback on the mixed data whether they are real or synthetic. Train *discriminator* to minimize the loss function which is the difference between the *discriminator*'s feedback and the correct labels.

GAN - Schematic process II

Second step: Training *generator*:

- Draw random points in the latent space and generate data with *generator*.
- Use *discriminator* to give feedback on the generated data. What the generator tries to achieve is to fool the *discriminator* into thinking all generated data are real data. Train *generator* to minimize the loss function which is the difference between the discriminator's feedback and the desired feedback: "All data are real data" (which is not true).

GAN - Schematic process III

- When training, the discriminator may end up dominating the generator because the loss function for training the discriminator tends to zero faster. In that case, try reducing the learning rate and increase the dropout rate of the discriminator.
- There are a few tricks for implementing GANS such as introducing stochasticity by adding random noise to the labels for the discriminator, using stride instead of pooling in the discriminator, using kernel size that is divisible by stride size, etc.

Train step

```python
# Separate optimisers for discriminator and generator.
d_optimizer = keras.optimizers.Adam(learning_rate=0.0003)
g_optimizer = keras.optimizers.Adam(learning_rate=0.0004)

# Instantiate a loss function.
loss_fn = keras.losses.BinaryCrossentropy(from_logits=True)

@tf.function
def train_step(real_images):
  # Sample random points in the latent space
  random_latent_vectors = tf.random.normal(shape=(batch_size, latent_dim))
  # Decode them to fake images
  generated_images = generator(random_latent_vectors)
  # Combine them with real images
  combined_images = tf.concat([generated_images, real_images], axis=0)

  # Assemble labels discriminating real from fake images
  labels = tf.concat([
    tf.zeros((batch_size, 1)),
    tf.ones((real_images.shape[0], 1))], axis=0)

  # Add random noise to the labels - important trick!
  labels += 0.05 * tf.random.uniform(labels.shape)

  # Train the discriminator
  with tf.GradientTape() as tape:
    predictions = discriminator(combined_images)
```

Grab the data

```
# Prepare the dataset.
# We use both the training & test MNIST digits.
batch_size = 64
(x_train, _), (x_test, _) = keras.datasets.mnist.load_data()
all_digits = np.concatenate([x_train, x_test])
all_digits = all_digits.astype("float32") / 255.0
all_digits = np.reshape(all_digits, (-1, 28, 28, 1))
dataset = tf.data.Dataset.from_tensor_slices(all_digits)
dataset = dataset.shuffle(buffer_size=1024).batch(batch_size)

# In practice you need at least 20 epochs to generate nice digits.
epochs = 1
save_dir = "./"
```

Train the GAN

```
%%time
for epoch in range(epochs):
  for step, real_images in enumerate(dataset):
    # Train the discriminator & generator on one batch of real images.
    d_loss, g_loss, generated_images = train_step(real_images)

    # Logging.
    if step % 200 == 0:
      # Print metrics
      print(f"Discriminator loss at step {step}: {d_loss:.2f}")
      print(f"Adversarial loss at step {step}: {g_loss:.2f}")
      break # Remove this if really training the GAN
```

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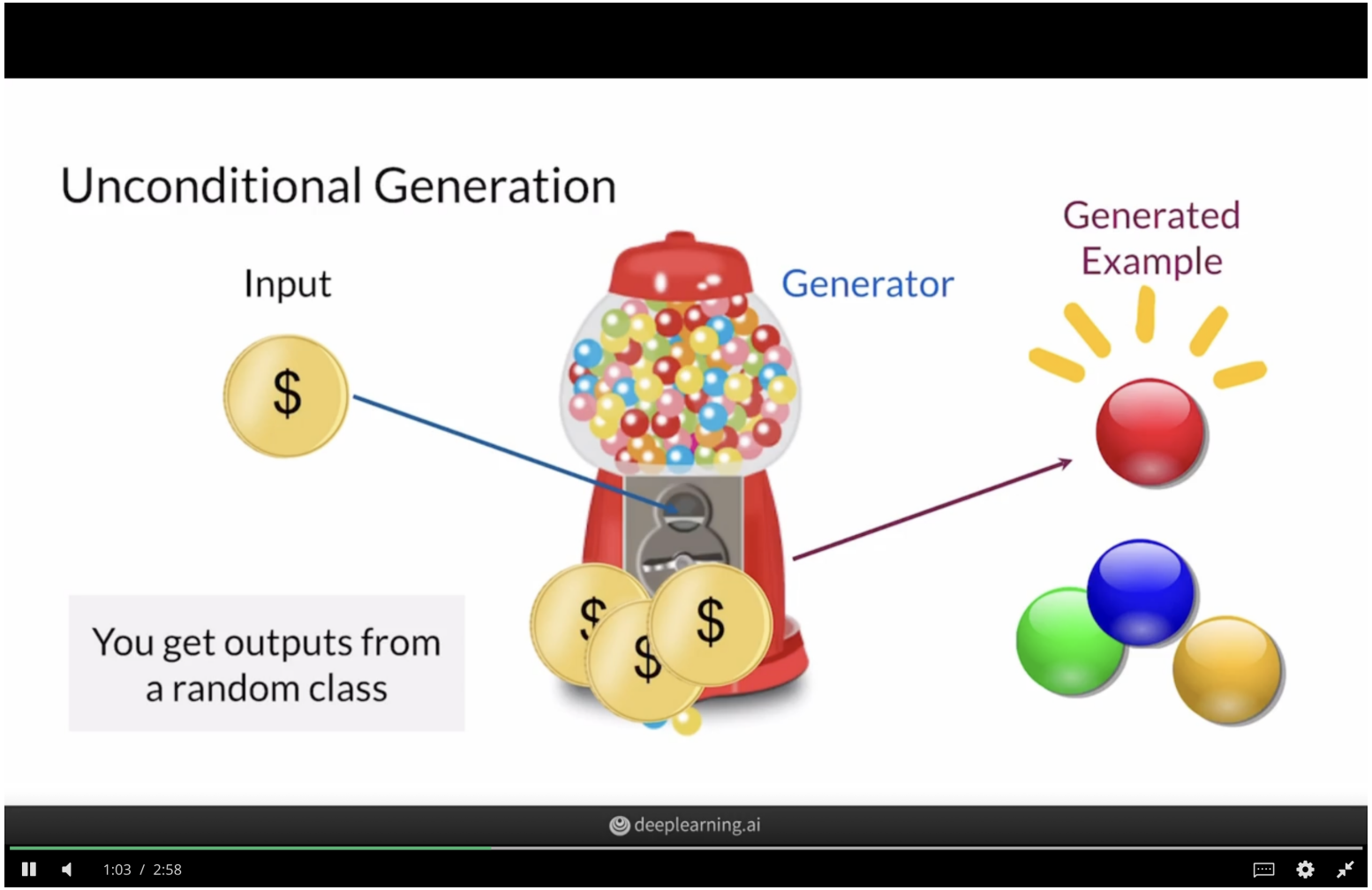
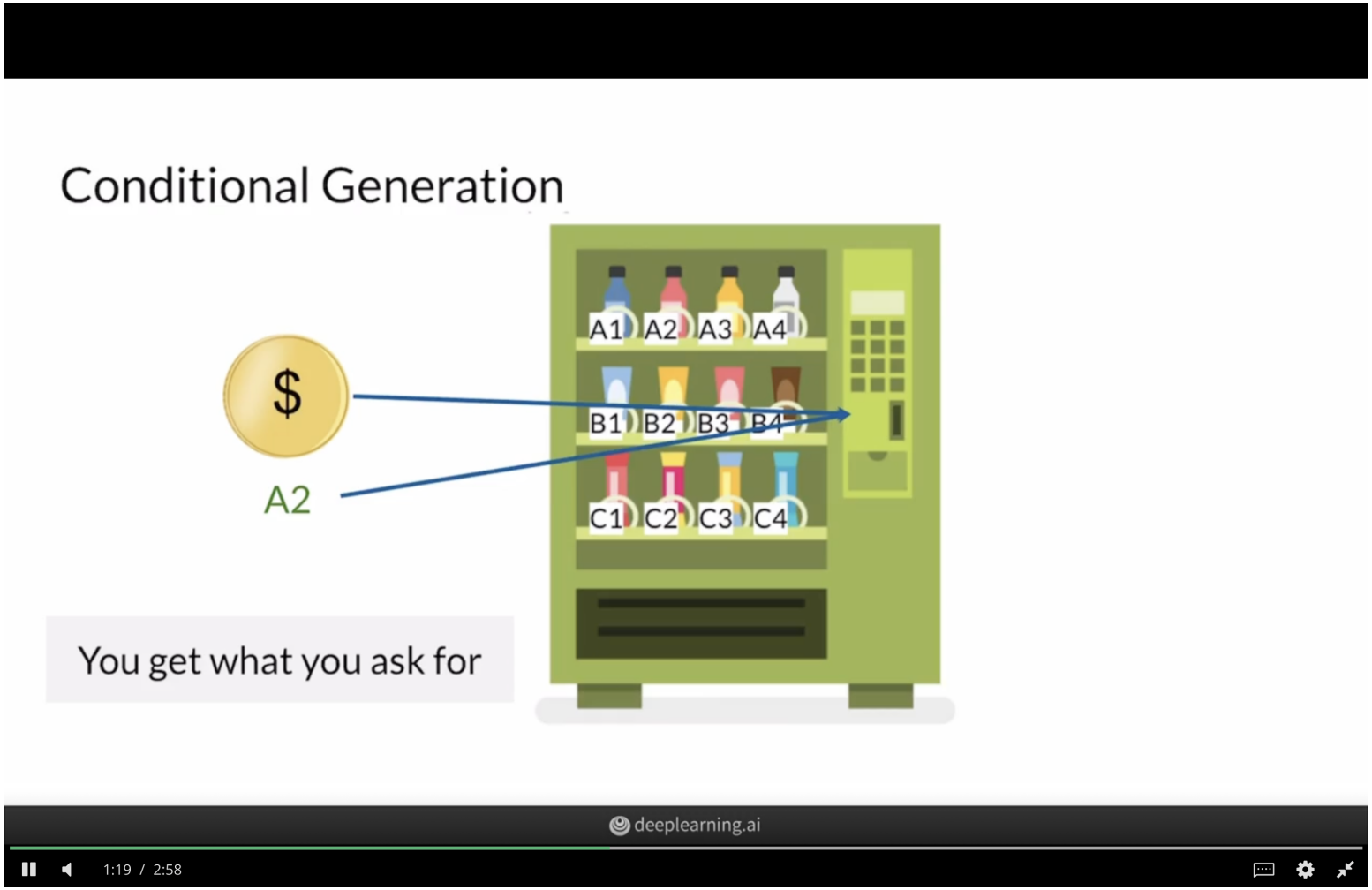
Unconditional GANs



Analogy for an unconditional GAN

Source: Sharon Zhou, *Conditional Generation: Intuition* Build Basic Generative Adversarial Networks (Week 4), DeepLearning.AI on Coursera.

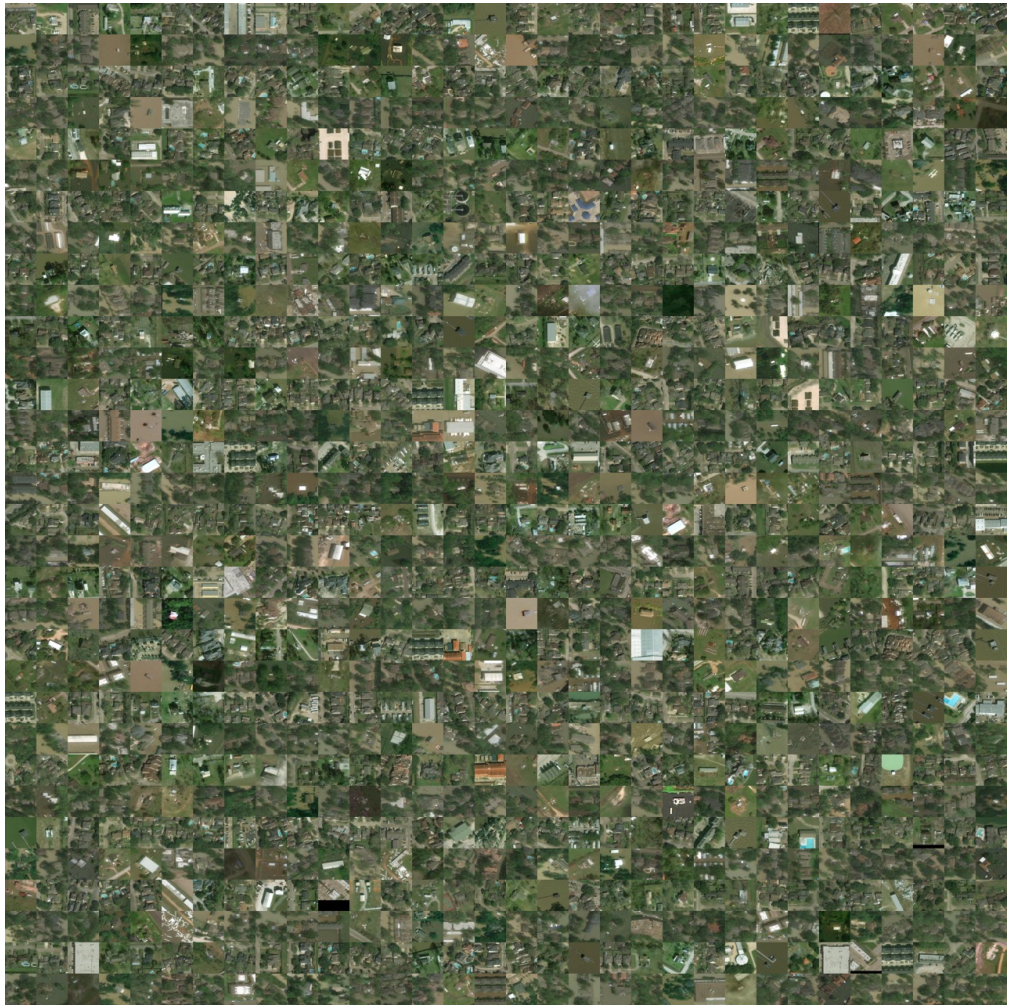
Conditional GANs



Analogy for a conditional GAN

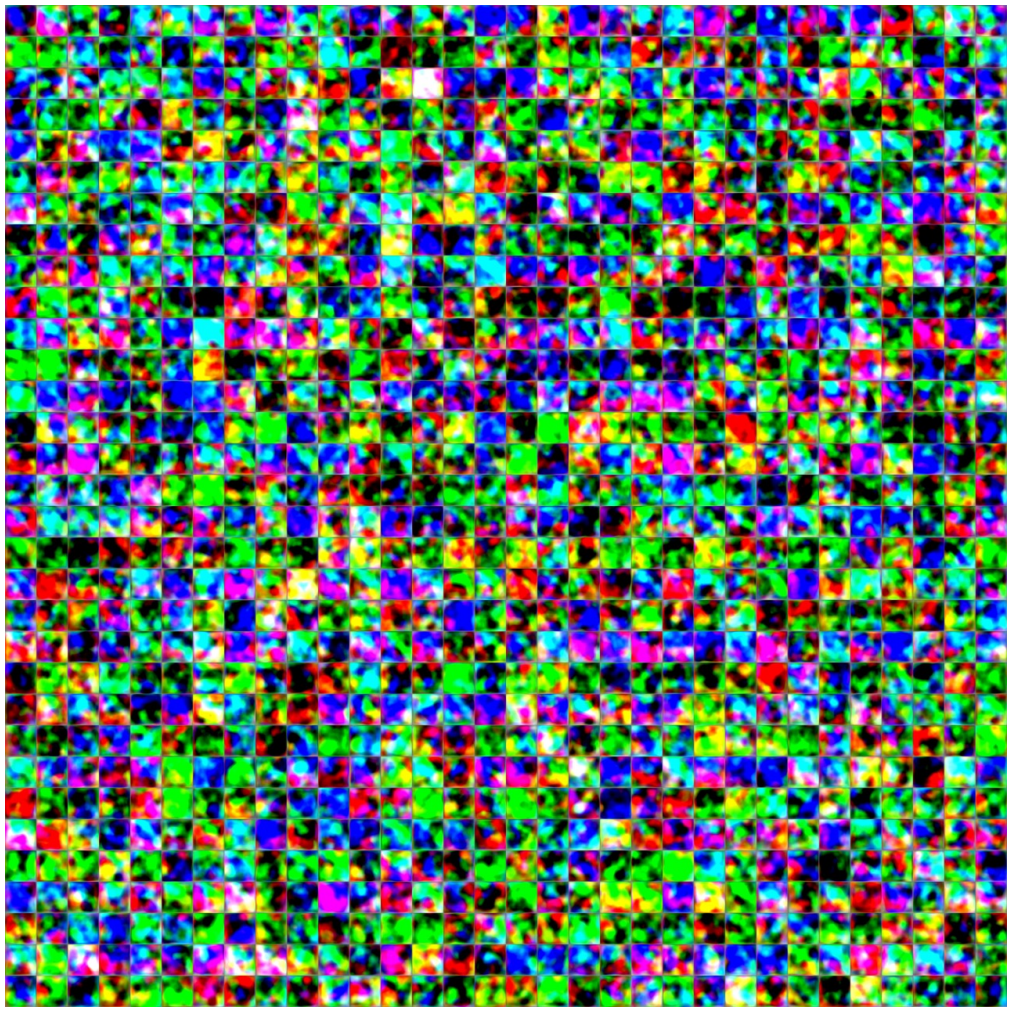
Source: Sharon Zhou, *Conditional Generation: Intuition* Build Basic Generative Adversarial Networks (Week 4), DeepLearning.AI on Coursera.

Hurricane example data



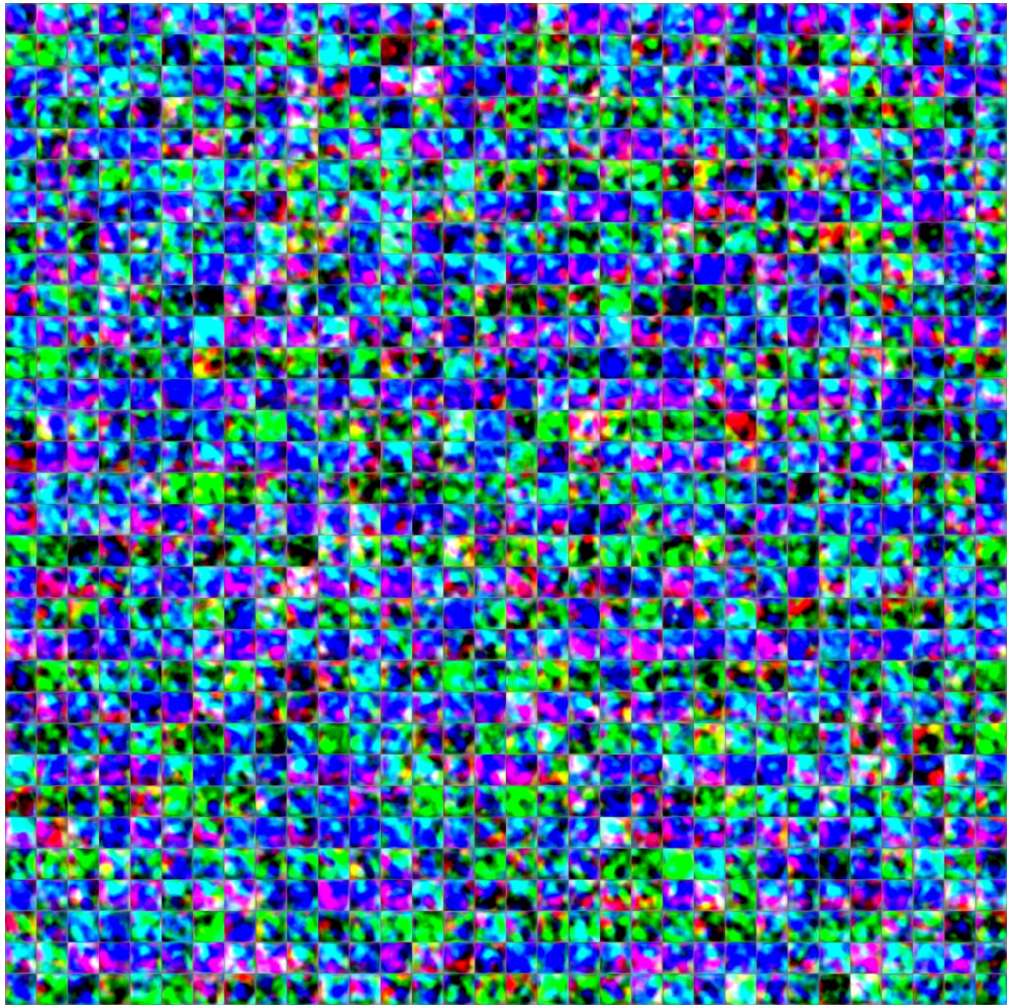
Original data

Hurricane example



Initial fakes

Hurricane example (after 54s)



Fakes after 1 iteration

Hurricane example (after 21m)

Fakes after 100 kimg

Hurricane example (after 47m)

Fakes after 200 kimg

Hurricane example (after 4h10m)

Fakes after 1000 kimg

Hurricane example (after 14h41m)

Fakes after 3700 kimg

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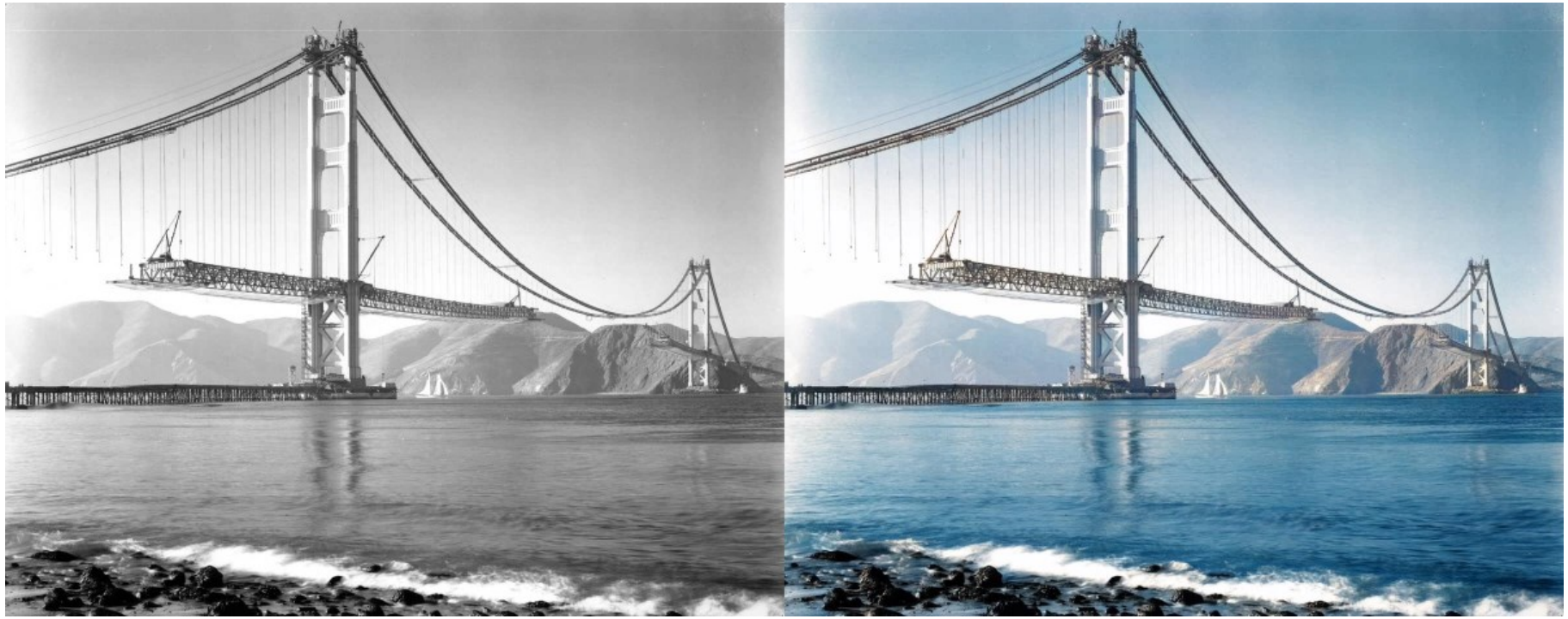
Example: Deoldify images #1

A deoldified version of the famous “Migrant Mother” photograph.

Source: Deoldify package.

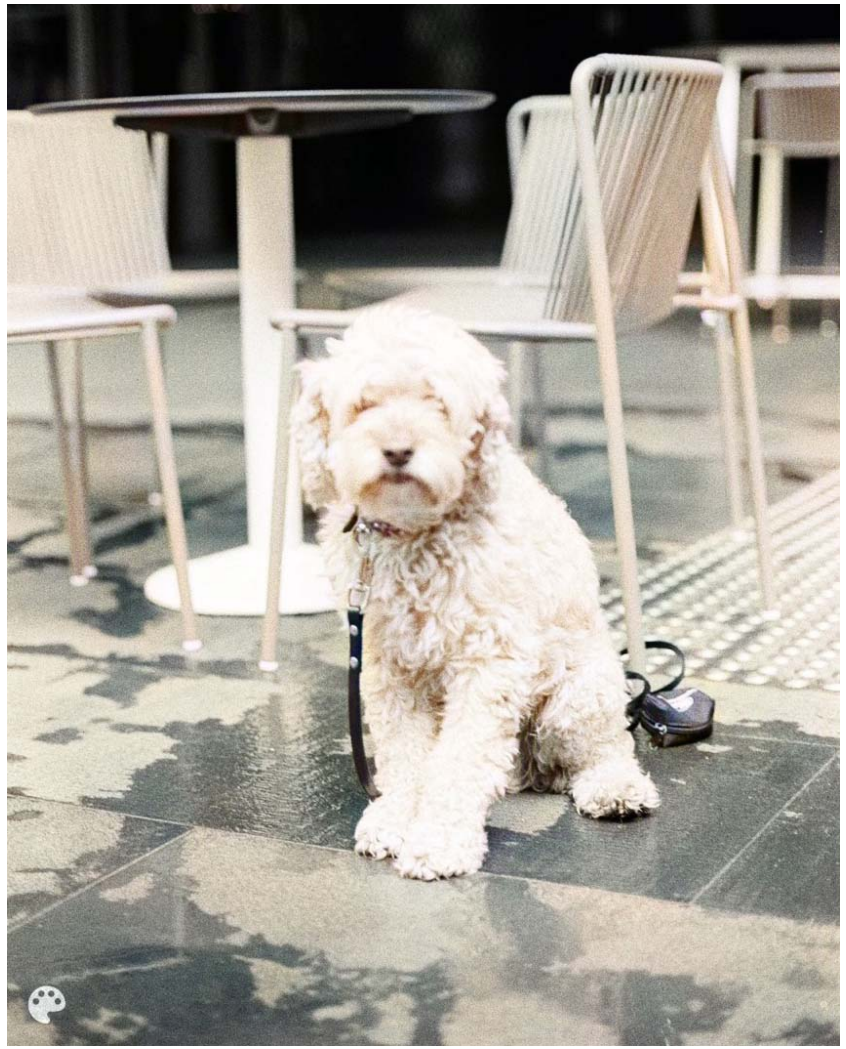
Example: Deoldify images #2



A deoldified Golden Gate Bridge under construction.

Source: Deoldify package.

Example: Deoldify images #3



Explore the latent space

Finding Myself in a trained StyleGAN2 ADA

Generator can’t generate everything

Target

Projection

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They are slow to train

StyleGAN2-ADA training times on V100s (1024x1024):

GPUs	1000 kimg	25000 kimg	sec / kimg	GPU mem	CPU mem
1	1d 20h	46d 03h	158	8.1 GB	5.3 GB
2	23h 09m	24d 02h	83	8.6 GB	11.9 GB
4	11h 36m	12d 02h	40	8.4 GB	21.9 GB
8	5h 54m	6d 03h	20	8.3 GB	44.7 GB

Source: NVIDIA's Github, StyleGAN2-ADA — Official PyTorch implementation.

Uncertain convergence

Converges to a Nash equilibrium.. if at all.

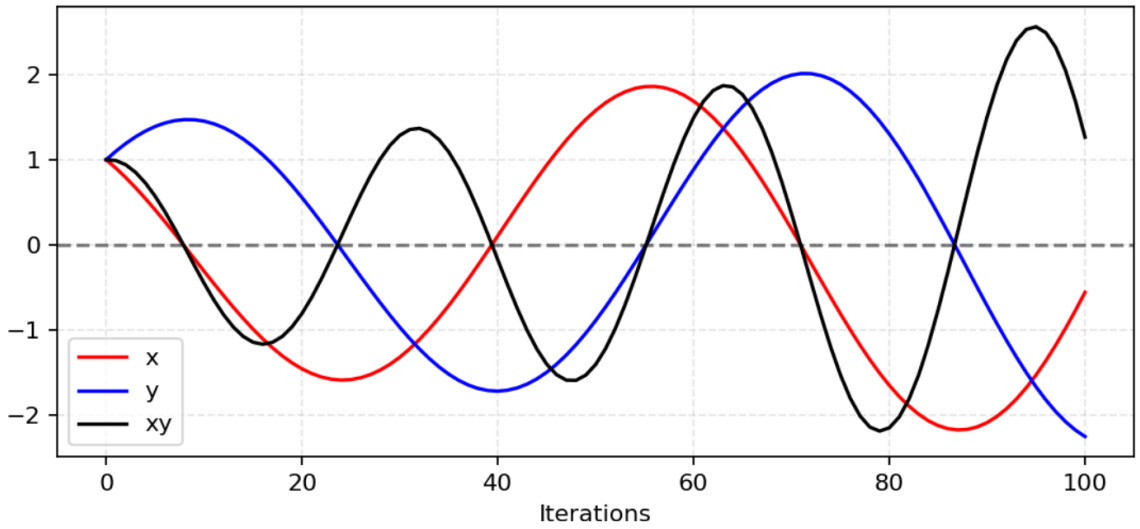
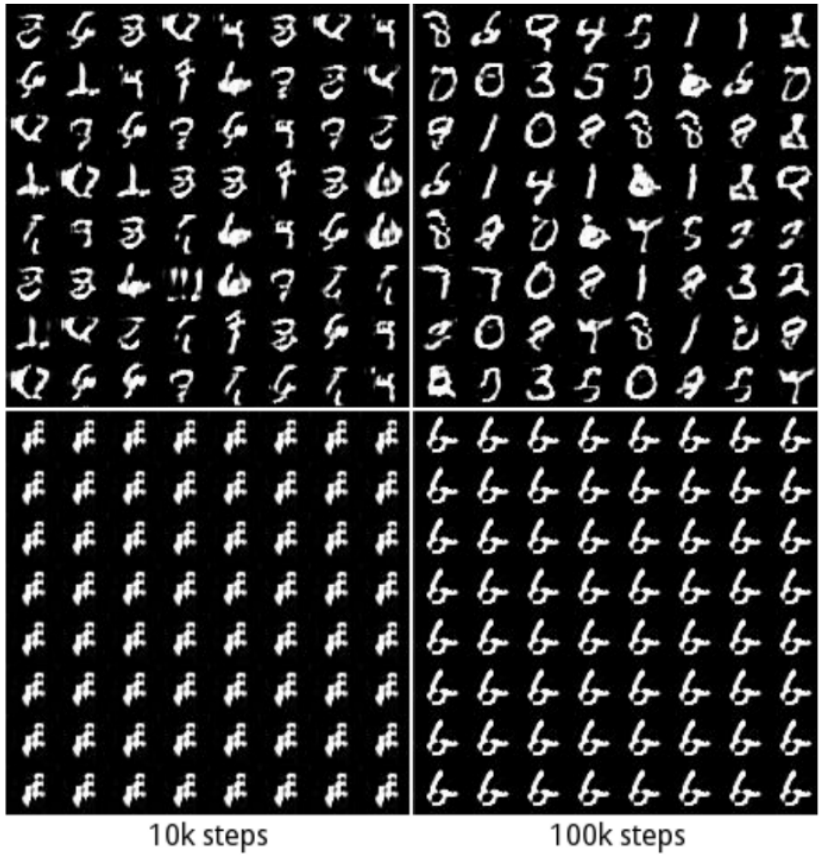


Figure 3: A simulation of our example for updating x to minimize xy and updating y to minimize $-xy$. The learning rate $\eta = 0.1$. With more iterations, the oscillation grows more and more unstable.

Analogy of minimax update failure.

Source: Lilian Weng (2019), *From GAN to WGAN*, ArXiV.

Mode collapse

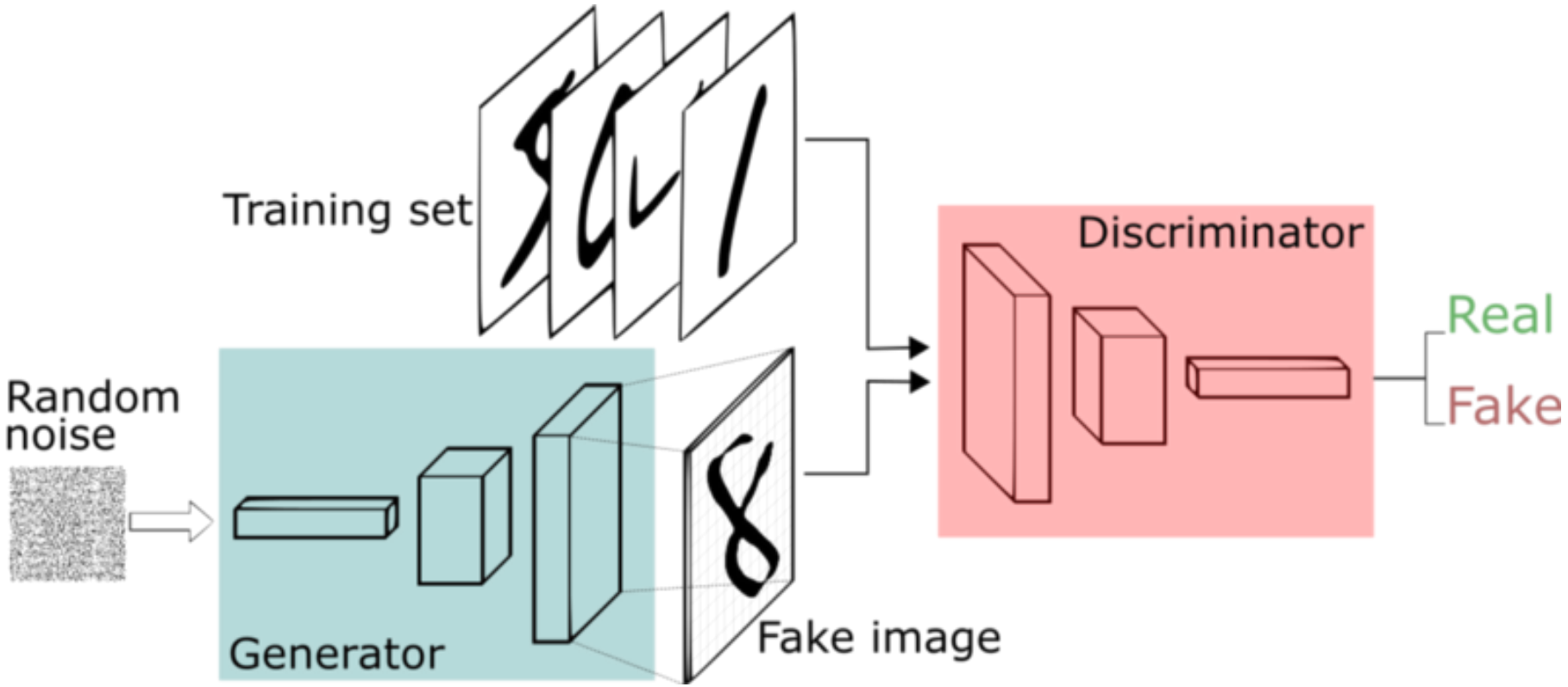



```
int getRandomNumber()
{
    return 4;  // chosen by fair dice roll.
               // guaranteed to be random.
}
```

Example of mode collapse

Source: Metz et al. (2017), Unrolled Generative Adversarial Networks and Randall Munroe (2007), xkcd #221: Random Number.

Generation is harder



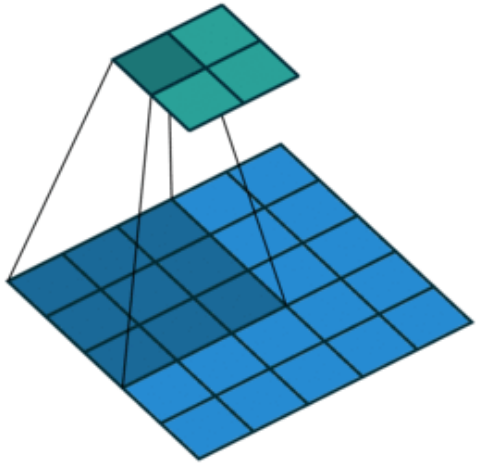
A schematic of a generative adversarial network.

```
# Separate optimisers for discriminator and generator.
d_optimizer = keras.optimizers.Adam(learning_rate=0.0003)
g_optimizer = keras.optimizers.Adam(learning_rate=0.0004)
```

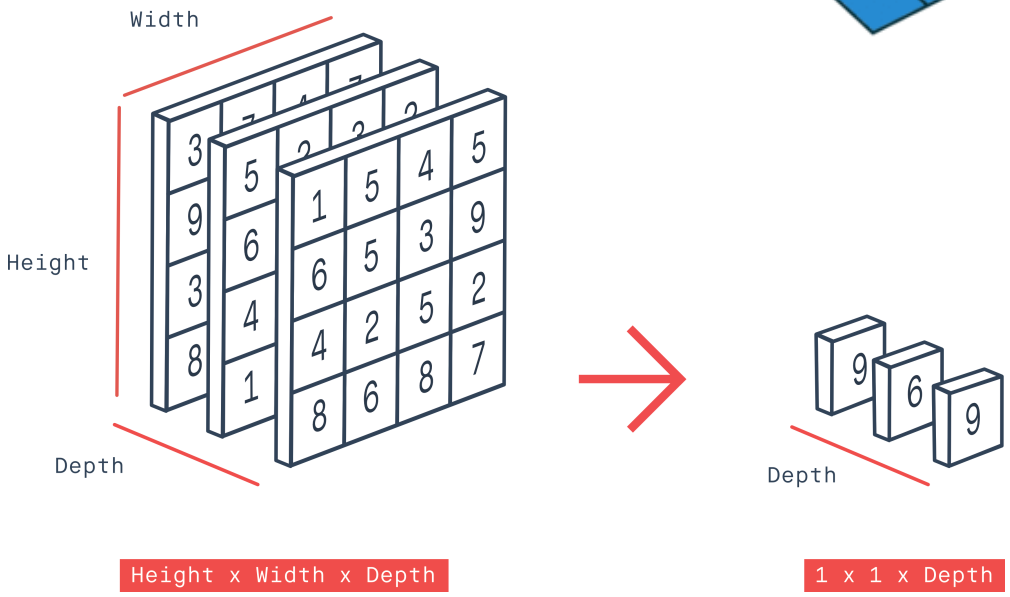
Source: Thales Silva (2018), An intuitive introduction to Generative Adversarial Networks (GANs), freeCodeCamp.

Advanced image layers

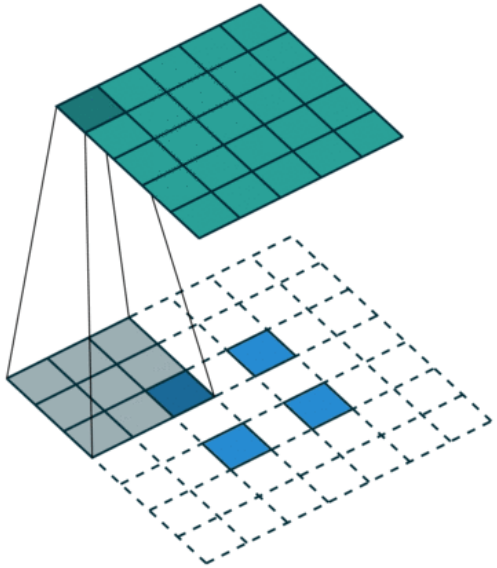
Conv2D



GlobalMaxPool2D

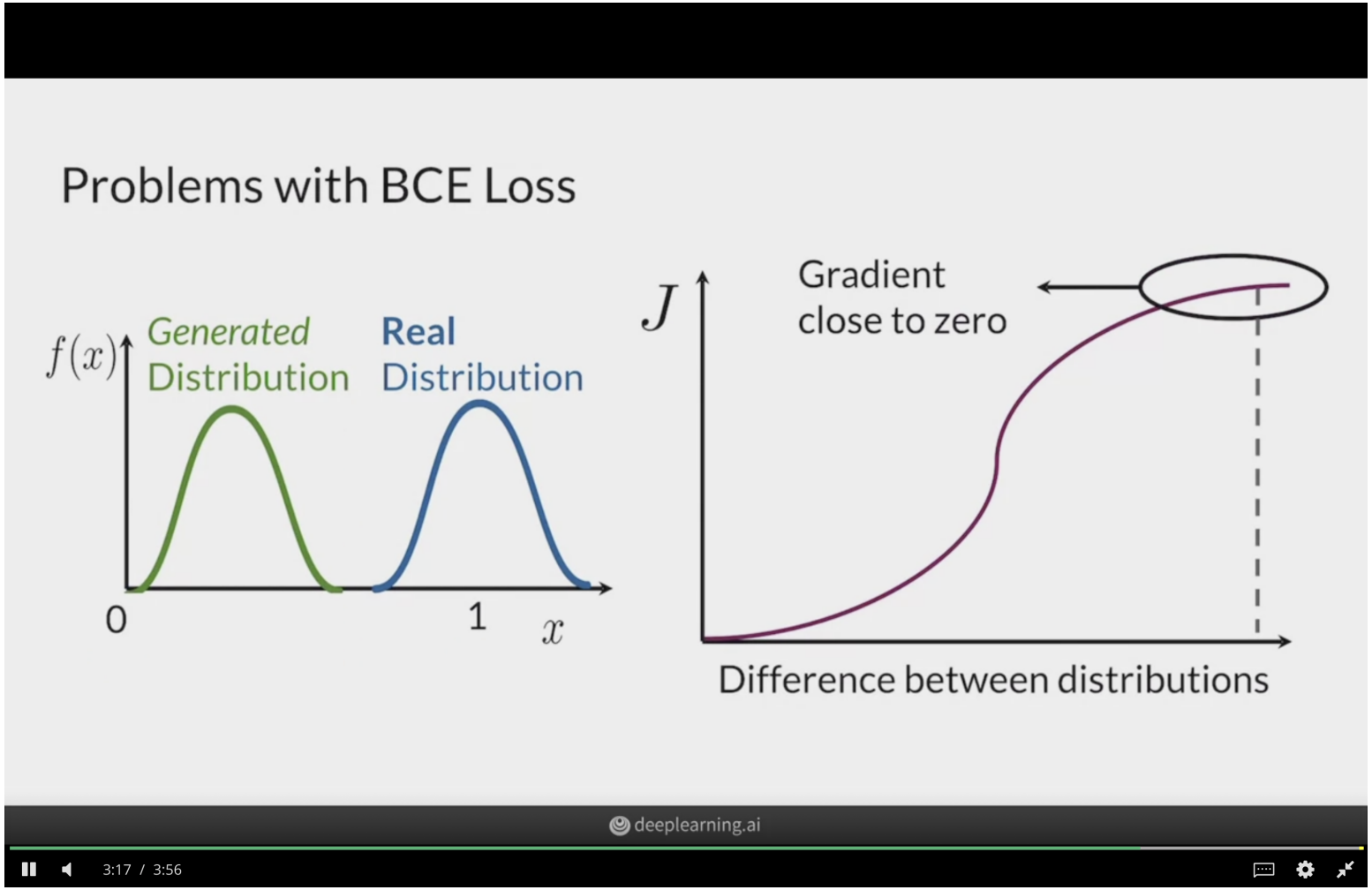


Conv2DTranspose



Sources: Pröve (2017), An Introduction to different Types of Convolutions in Deep Learning, and Peltarion Knowledge Center, Global max pooling 2D.

Vanishing gradients (I)



When the discriminator is too good, vanishing gradients

Source: Sharon Zhou, *Problem with BCE Loss*, Build Basic Generative Adversarial Networks (Week 3), DeepLearning.AI on Coursera.

Vanishing gradients (II)

4.3 Vanishing Gradient

When the discriminator is perfect, we are guaranteed with $D(x) = 1, \forall x \in p_r$ and $D(x) = 0, \forall x \in p_g$. Therefore the loss function L falls to zero and we end up with no gradient to update the loss during learning iterations. Fig. 5 demonstrates an experiment when the discriminator gets better, the gradient vanishes fast.

As a result, training a GAN faces an dilemma:

- If the discriminator behaves badly, the generator does not have accurate feedback and the loss function cannot represent the reality.
- If the discriminator does a great job, the gradient of the loss function drops down to close to zero and the learning becomes super slow or even jammed.

This dilemma clearly is capable to make the GAN training very tough.

5

Vanishing gradients

Source: Lilian Weng (2019), *From GAN to WGAN*, ArXiV.

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We're comparing distributions

Trying to minimise the distance between the *distribution of generated samples* and the *distribution of real data*.

Vanilla GAN is equivalent to minimising the Jensen–Shannon Divergence between the two.

An alternative distance between distributions is the *Wasserstein distance*.

~~Discriminator~~ Critic

Critic $D : \text{Input} \to \mathbb{R}$ how "authentic" the input looks. It can't discriminate real from fake exactly.

Critic's goal is

$$\max_{D \in \mathscr{D}} \mathbb{E}[D(X)] - \mathbb{E}[D(G(Z))]$$

where we $\mathscr{D}$ is space of 1-Lipschitz functions. Either use *gradient clipping* or penalise gradients far from 1:

$$\max_{D} \mathbb{E}[D(X)] - \mathbb{E}[D(G(Z))] + \lambda \mathbb{E}\left[(||\nabla D|| - 1)^2\right].$$

Schematic

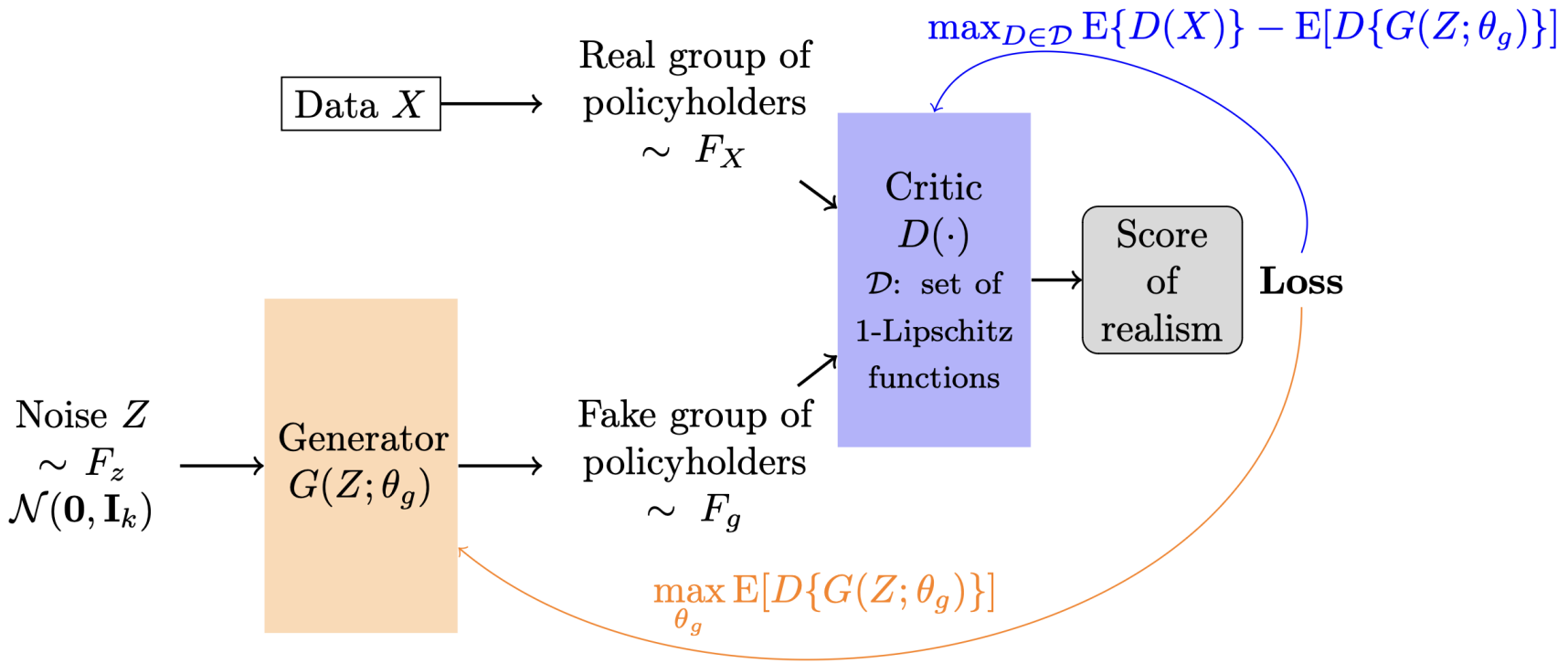

Figure 1: WGAN Schema. The arrows represent the flow of the training process.

Wasserstein

Source: Côté et al. (2020), *Synthesizing Property & Casualty Ratemaking Datasets using Generative Adversarial Networks*, Working Paper?.

Links

- Dongyu Liu (2021), TadGAN: Time Series Anomaly Detection Using Generative Adversarial Networks
- Jeff Heaton (2022), GANs for Tabular Synthetic Data Generation (7.5)
- Jeff Heaton (2022), GANs to Enhance Old Photographs Deoldify (7.4)