Lecture 12

Tian Han

Outline

- **Variational autoencoder**

- **Generative Adversarial Net**

Variational Autoencoder for Image Generation

Preliminary: Distance between Two Probability Distributions

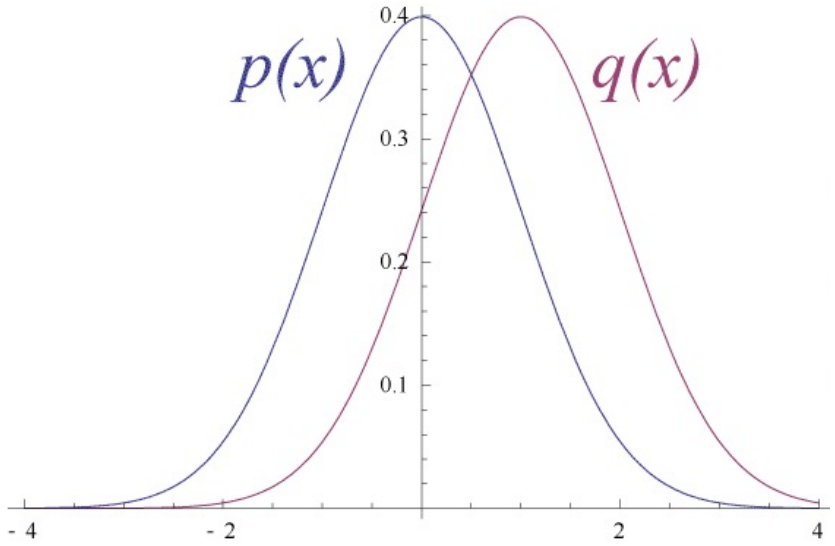
Distance between Two Vectors

- Distance between two vectors is measured by vector norms.
- Examples:
  - ℓ_1 distance: $\left|\left|\mathbf{a}-\mathbf{b}\right|\right|_1 = \sum_j \left|a_j - b_j\right|$.
  - ℓ_2 distance: $\left|\left|\mathbf{a}-\mathbf{b}\right|\right|_2 = \sqrt{\sum_j \left(a_j - b_j\right)^2}$.
  - ℓ_∞ distance: $\left|\left|\mathbf{a}-\mathbf{b}\right|\right|_\infty = \max_j \left|a_j - b_j\right|$.
  - ℓ_p distance: $\left|\left|\mathbf{a}-\mathbf{b}\right|\right|_p = \left[\sum_j \left(a_j - b_j\right)^p\right]^{1/p}$.

Distance between Two Probability Distributions

Question: What is the distance between $p(x)$ and $q(x)$?

- Let $p(x)$ and $q(x)$ be two Probability Density Functions (PDFs).
- E.g., the PDF of a Gaussian distribution is $p(x|\mu,\sigma) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right)$.



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Definition: The Kullback–Leibler (KL) divergence $D_{\mathrm{KL}}(p||q)$.

- For discrete probability distributions, the KL divergence is

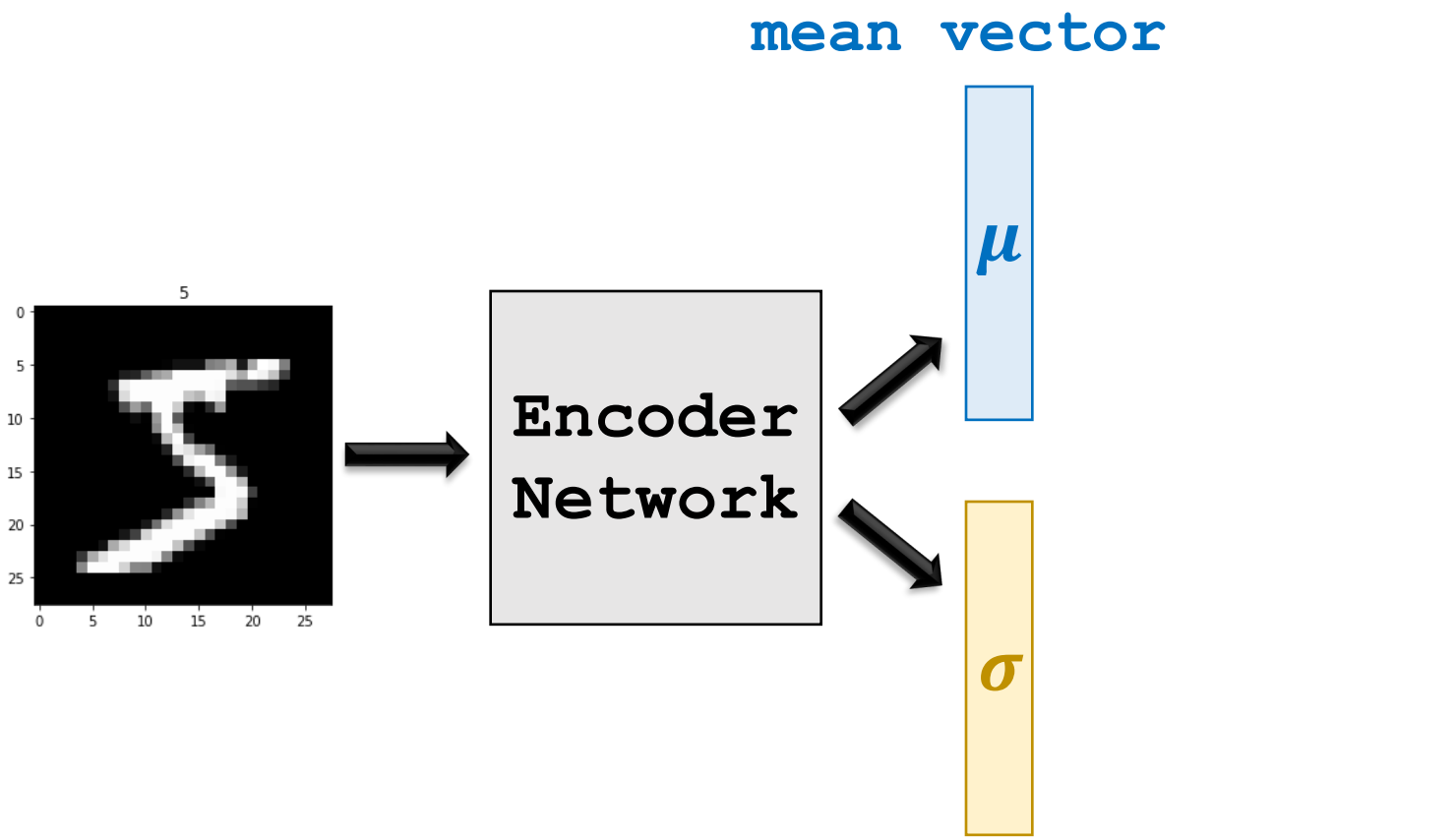
$$D_{\mathrm{KL}}(p||q) = -\sum_i p(i) \log \frac{q(i)}{p(i)}.$$

- For continuous probability distributions, the KL divergence is

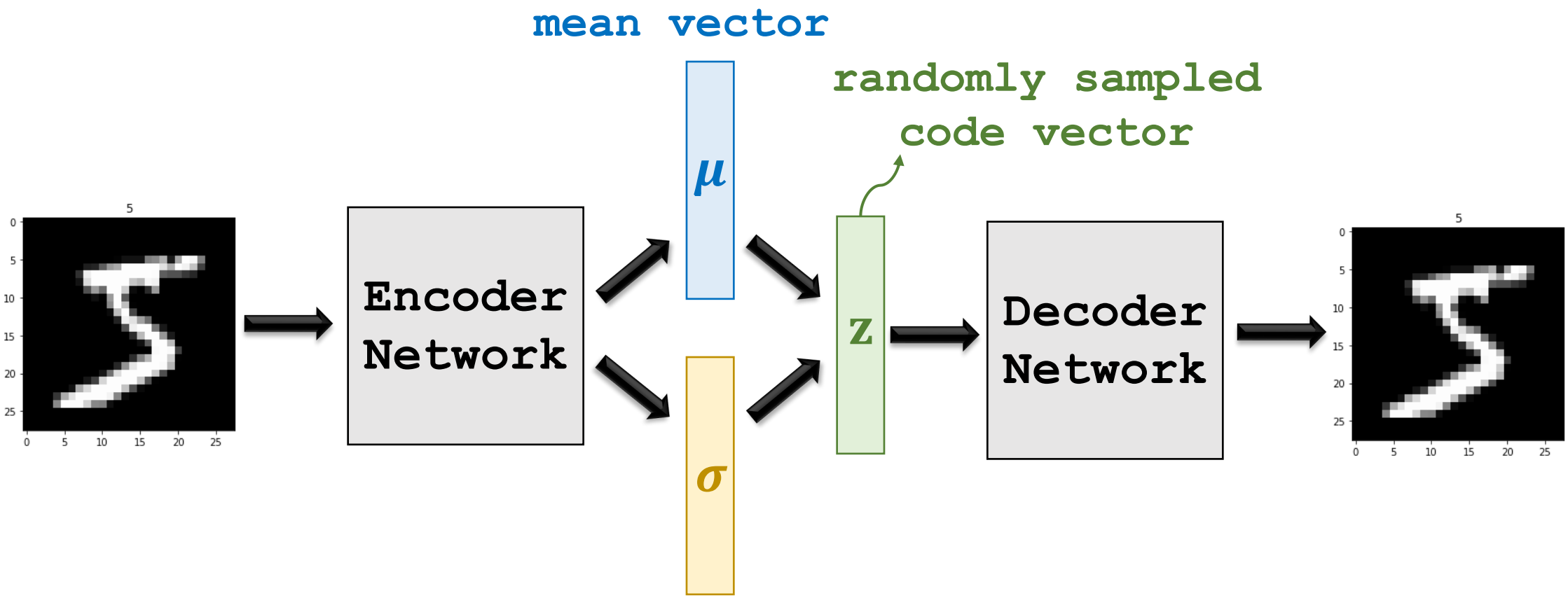
$$D_{\mathrm{KL}}(p||q) = -\int_{-\infty}^{+\infty} p(x) \log \frac{q(x)}{p(x)}\, dx.$$

Variational Autoencoder

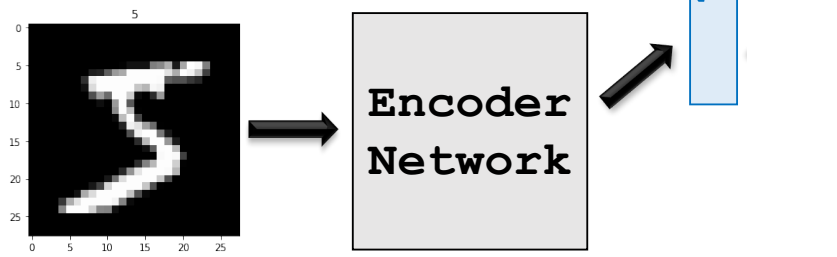
Variational Autoencoder (VAE)



Variational Autoencoder (VAE)



VAE Sampling

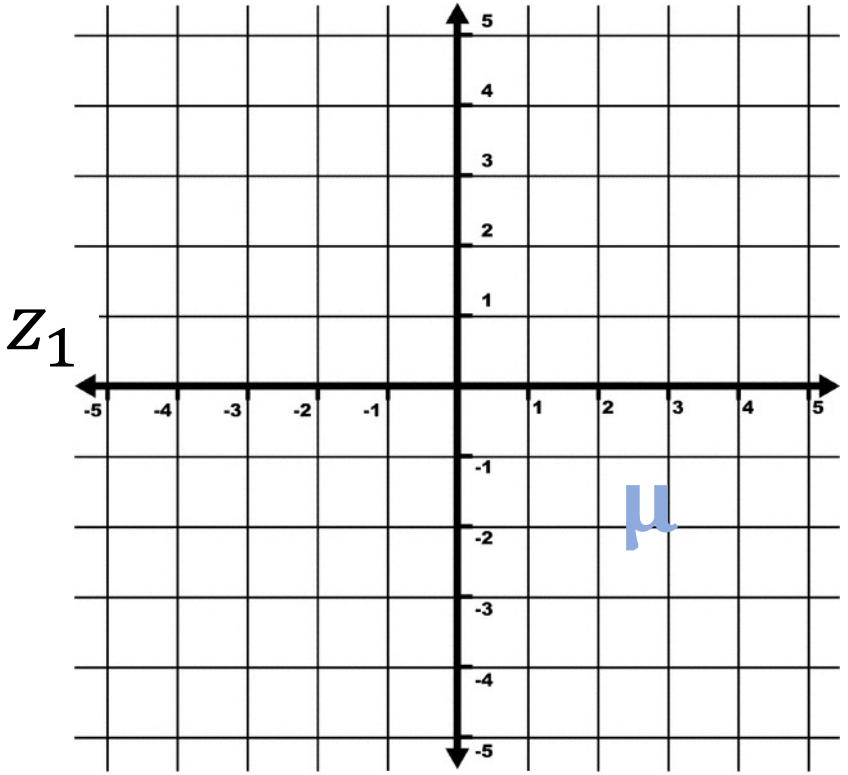


Encoder Network

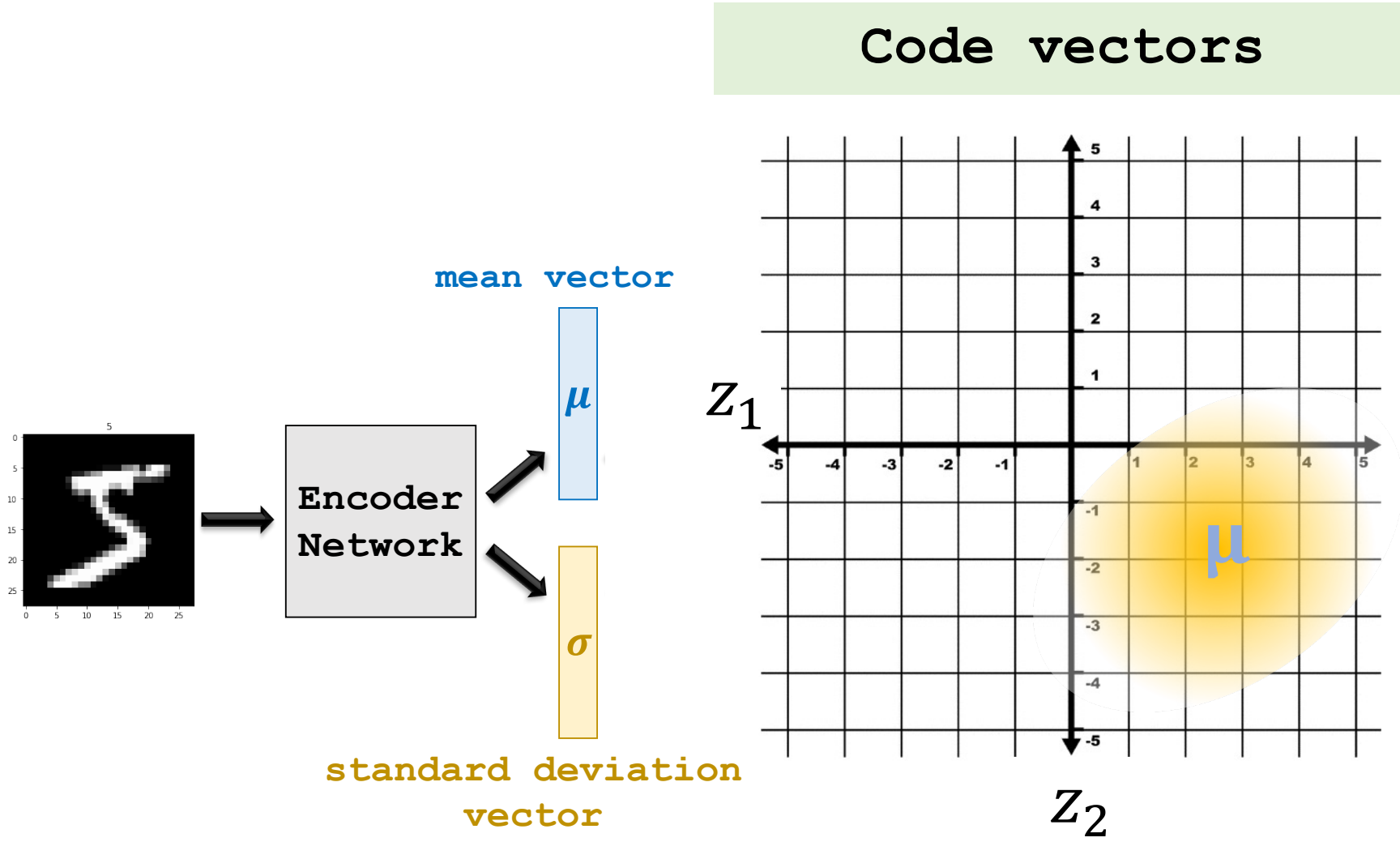
mean vector

μ

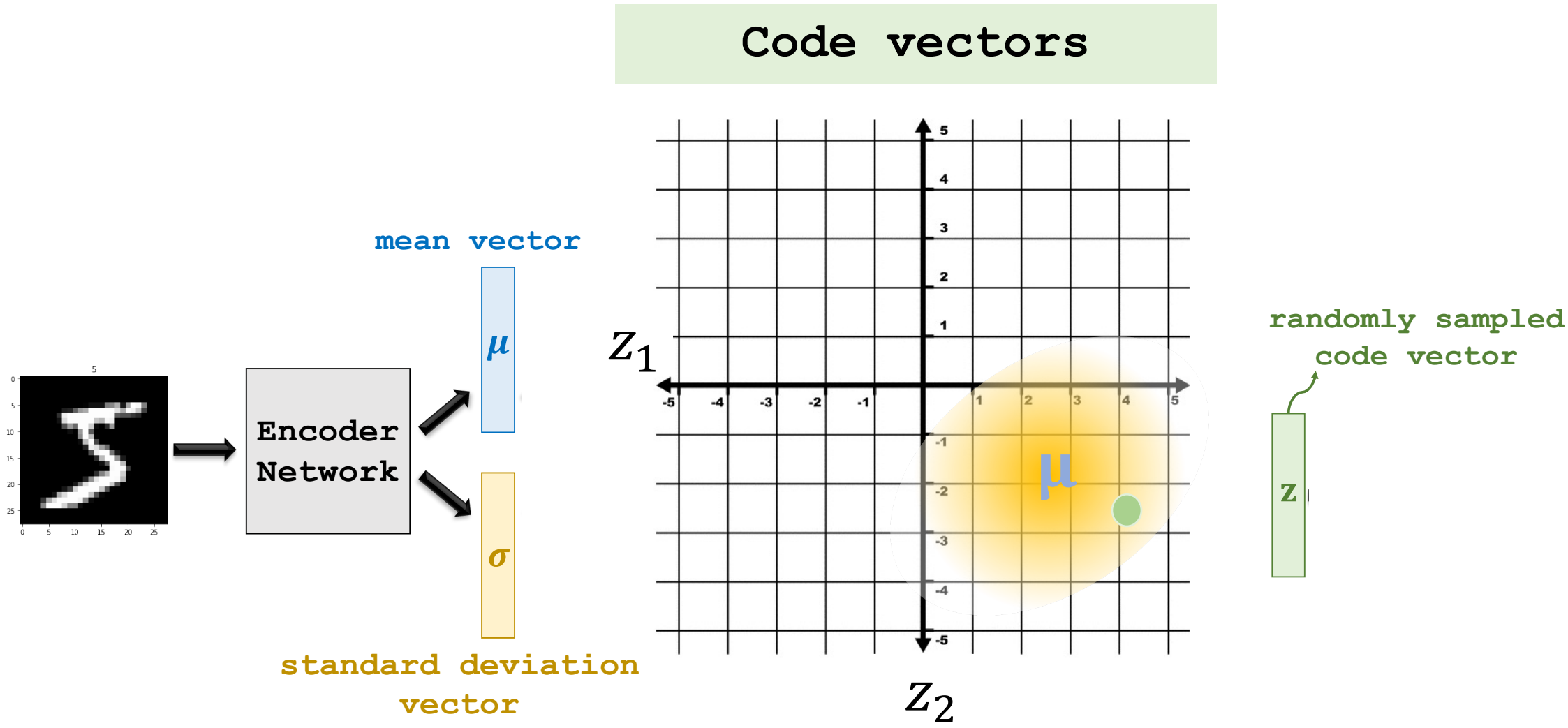
Code vectors



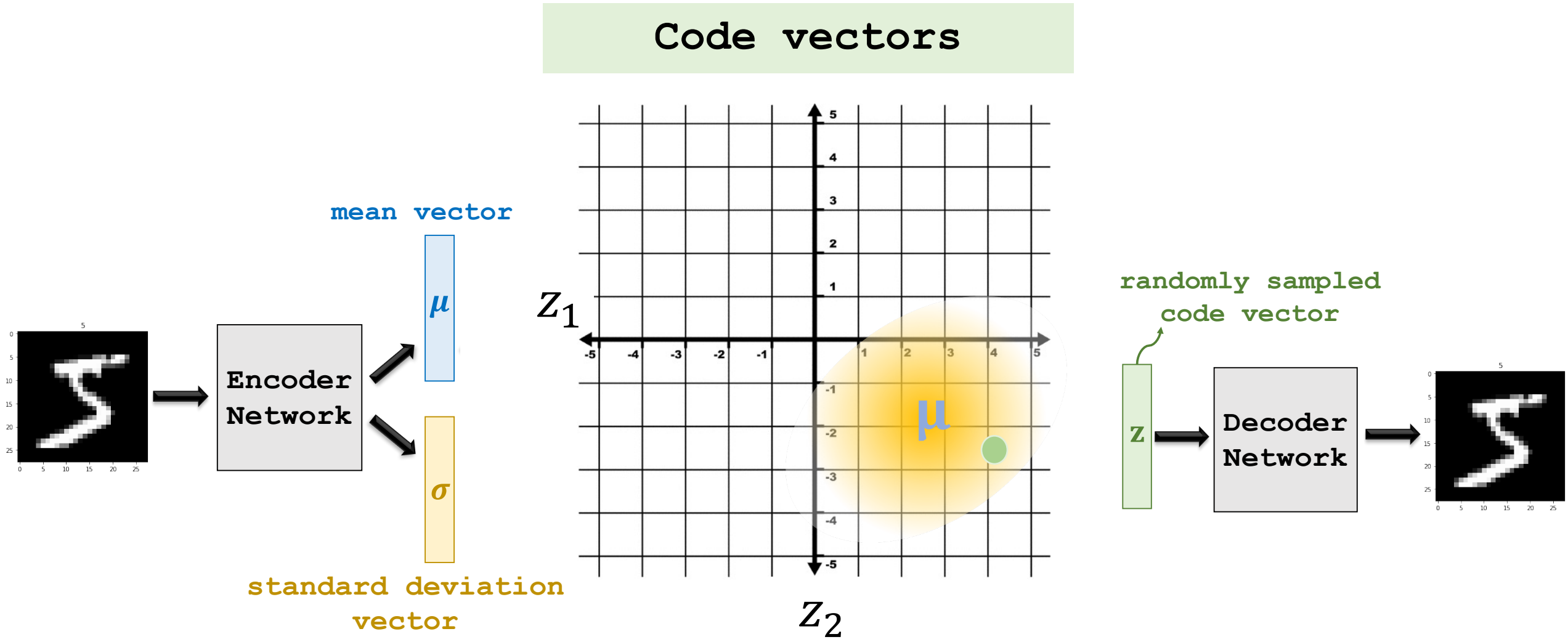
VAE Sampling



VAE Sampling



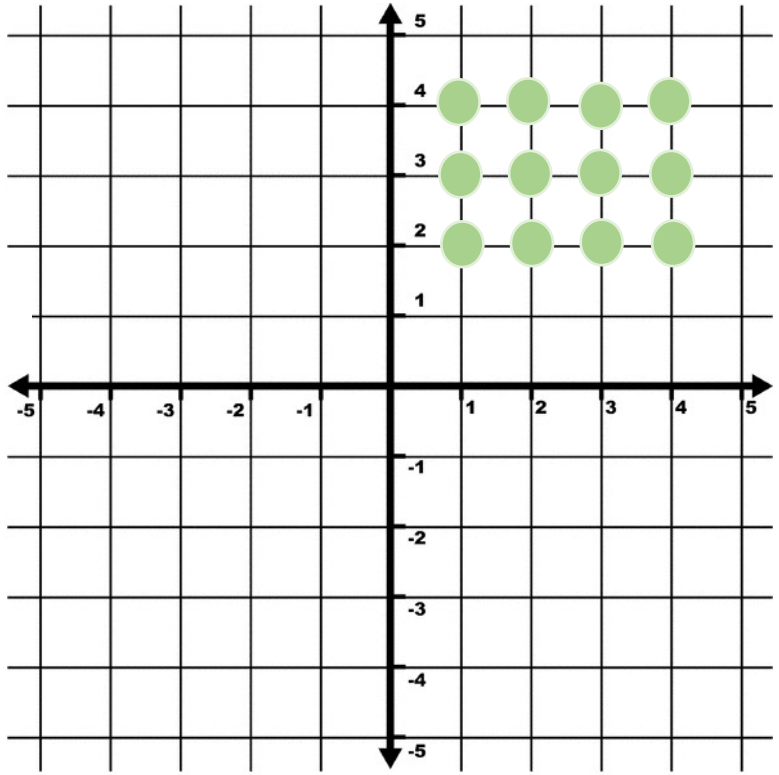
VAE Sampling



Visualize Code Vectors

Visualize code vectors.

Code vectors

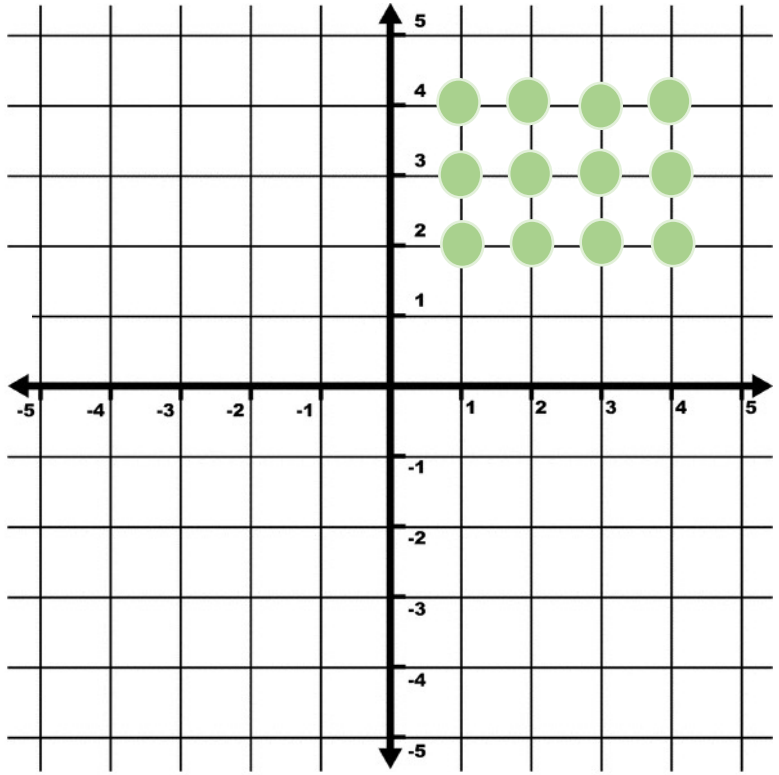


- Get a set of code vectors from the grid:

$$\mathbf{z}_1, \mathbf{z}_2, \mathbf{z}_3, \mathbf{z}_4, \mathbf{z}_5, \cdots$$

Visualize code vectors.

Code vectors



- Get a set of code vectors from the grid:

$$\mathbf{z}_1, \mathbf{z}_2, \mathbf{z}_3, \mathbf{z}_4, \mathbf{z}_5, \cdots$$

- For every code vector $\mathbf{z}_i$, map it to an image using the decoder:

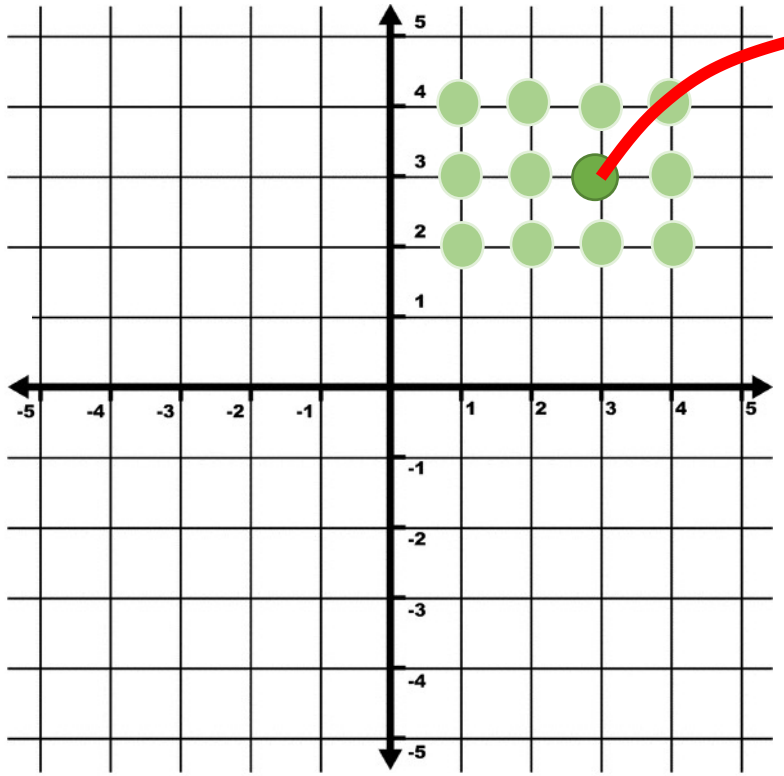
$$\text{image}_i = \text{Decoder}(\mathbf{z}_i).$$

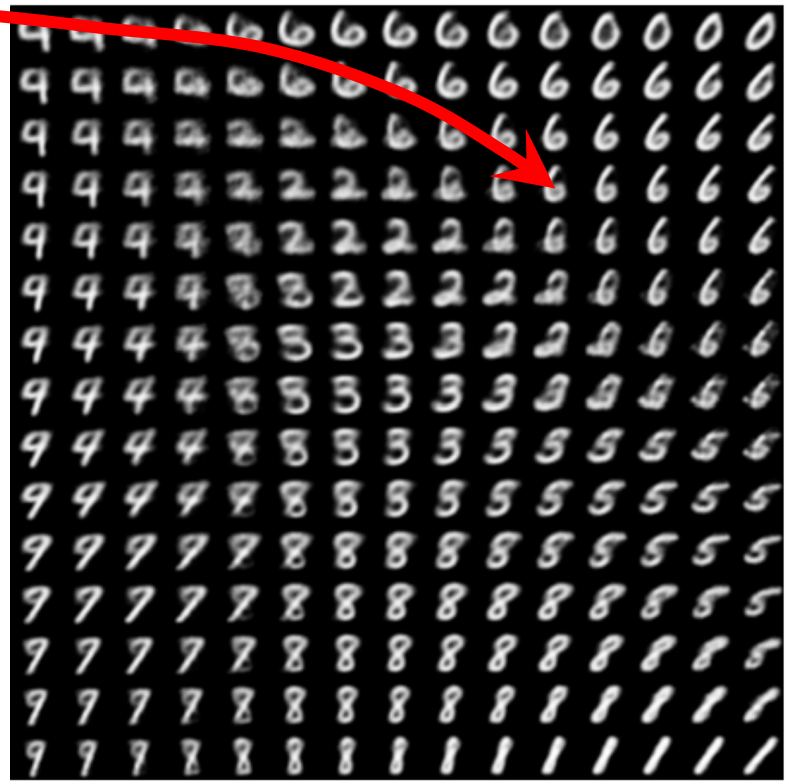
Visualize code vectors.

Code vectors

Images

Decoder





The decoder behaves like a continuous function.

- Function f is continuous if a small change in z (input) results in a small change in $f(z)$ (function value).

- The decoder network is trained to be (almost) continuous.
- If the code vectors $\mathbf{z}$ and $\mathbf{z}'$ are similar, then the images

$$\text{Decoder}(\mathbf{z}) \quad \text{and} \quad \text{Decoder}(\mathbf{z}')$$

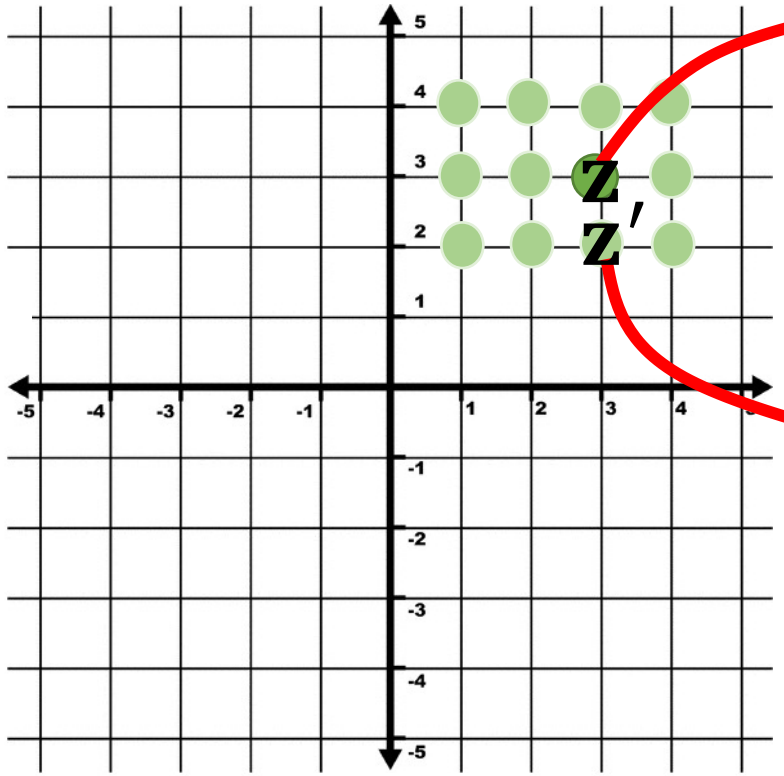
are similar as well.

The decoder behaves like a continuous function.

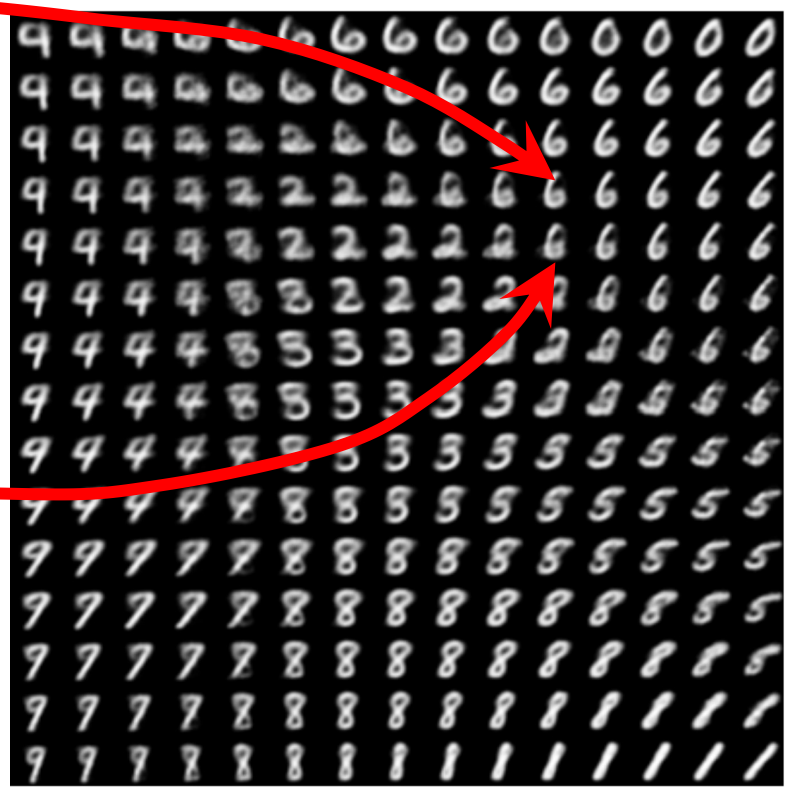
Code vectors

Images

Decoder



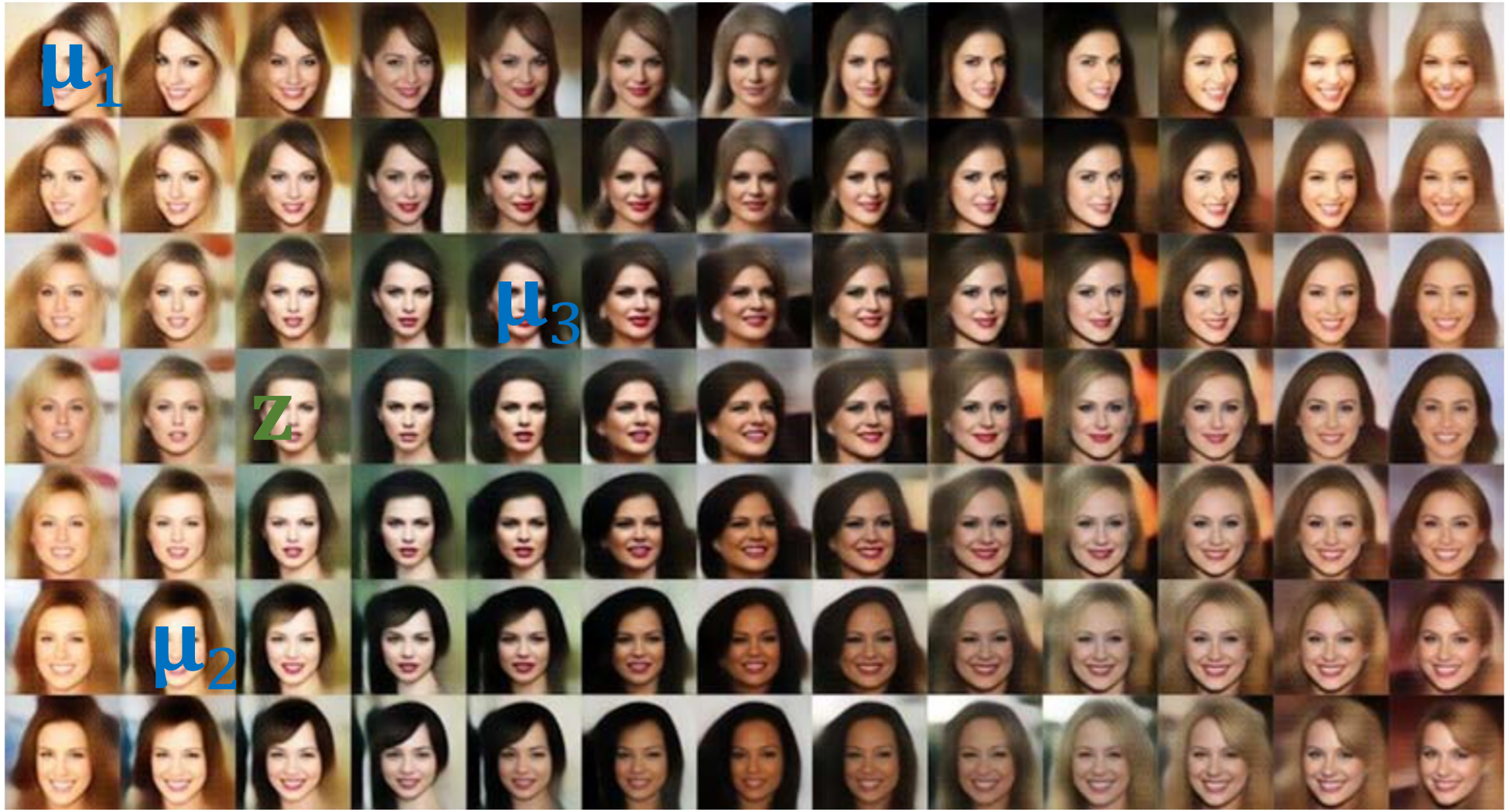
Decoder



The decoder behaves like a continuous function.

Visualization of the generated faces (by Tom White)

Averaging images via averaging code vectors



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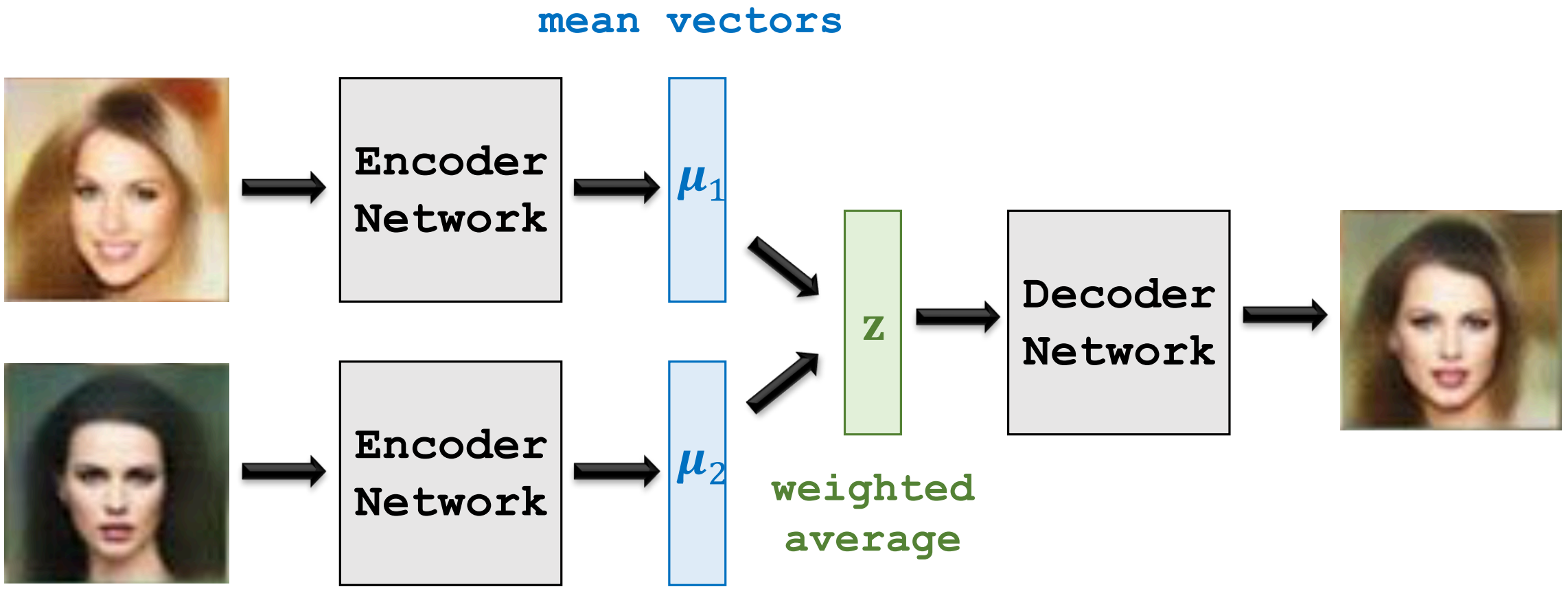
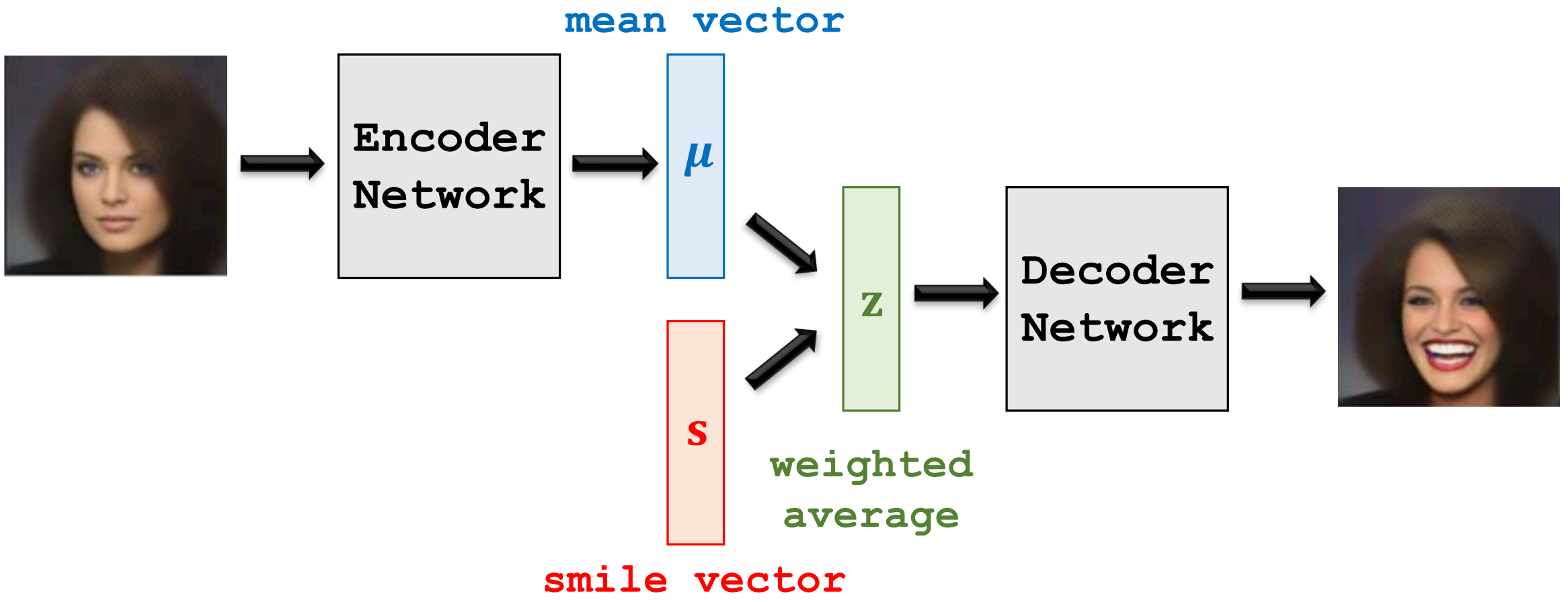
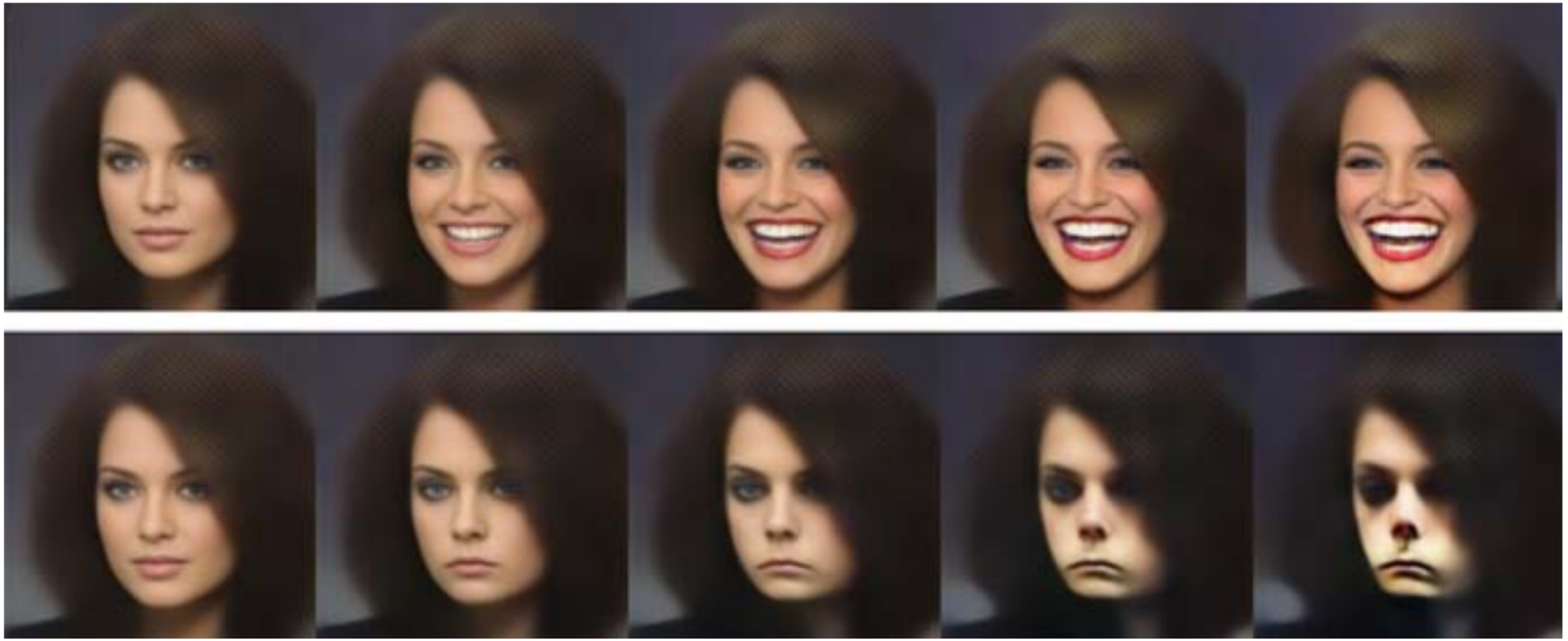


Editing images via editing code vectors



Editing images via editing code vectors

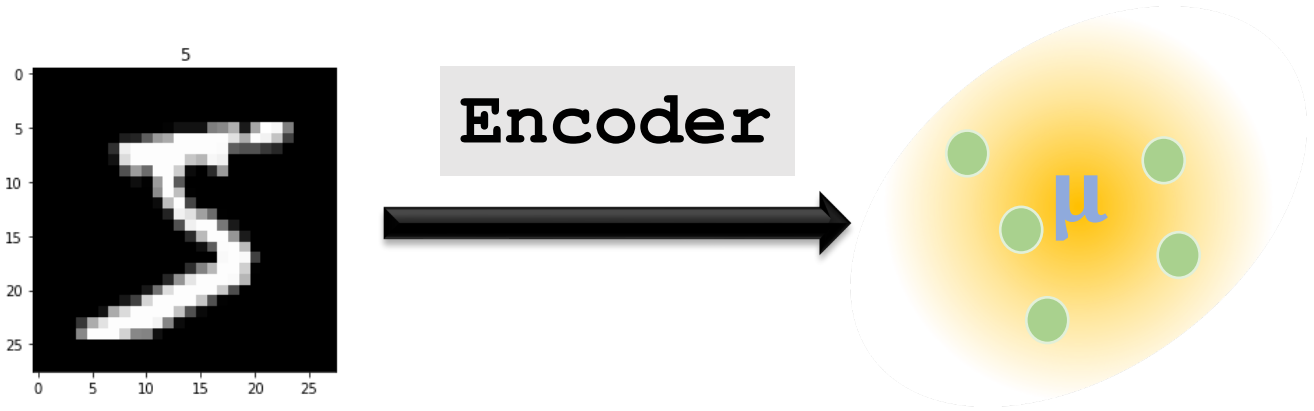
μ $\mu + s$ $\mu + 2s$ $\mu + 3s$ $\mu + 4s$



μ $\mu - s$ $\mu - 2s$ $\mu - 3s$ $\mu - 4s$

What makes the decoder continuous?

- Given $\boldsymbol{\mu}$ and $\boldsymbol{\sigma}$, sample $\mathbf{z}_i \sim \mathcal{N}\left(\boldsymbol{\mu}, \mathrm{diag}\left(\boldsymbol{\sigma}^2\right)\right)$, for $i = 1, 2, 3, \cdots$.



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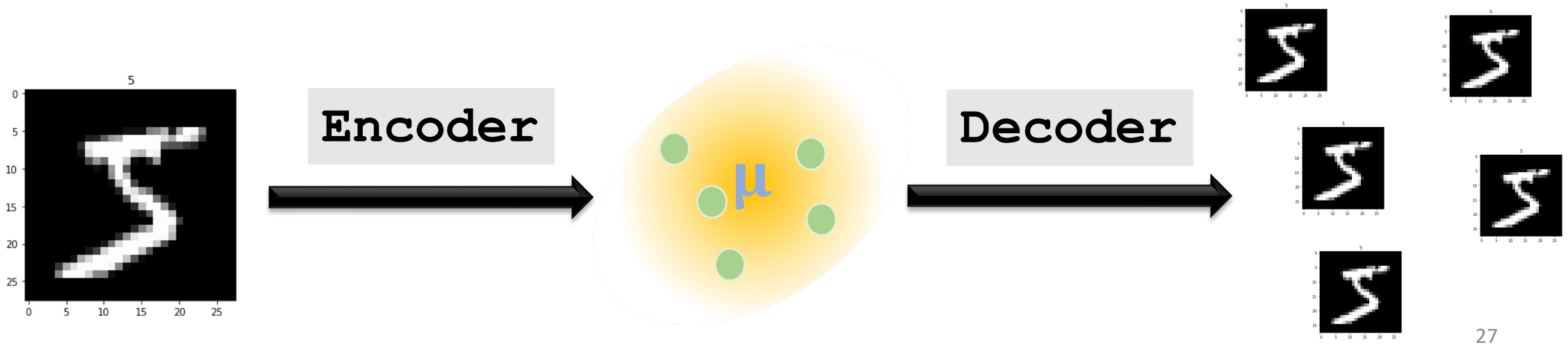
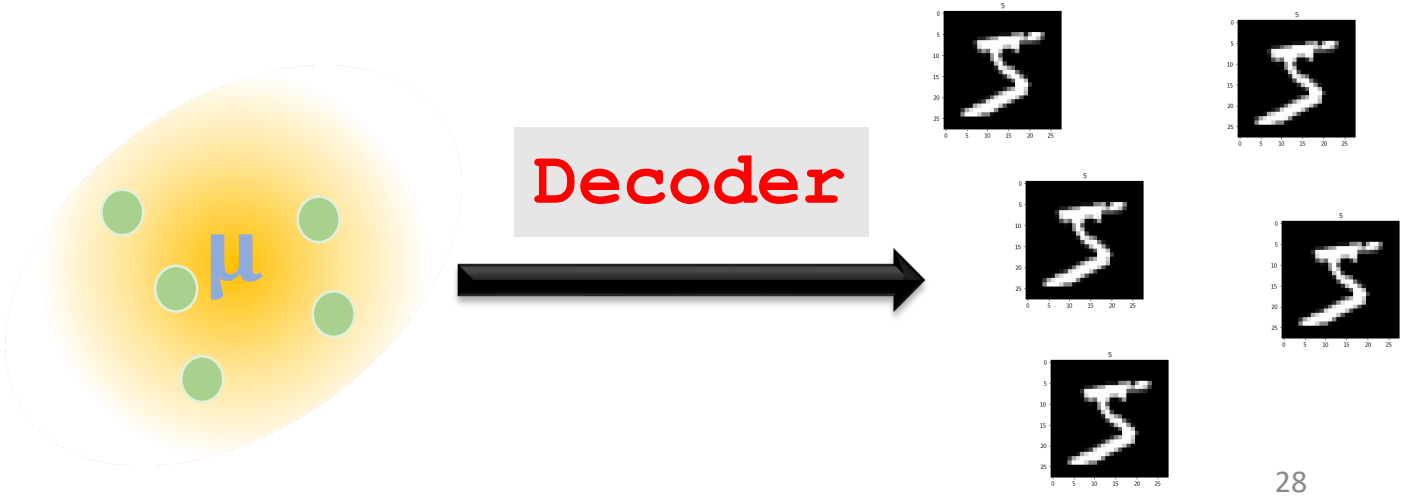
- Given $\boldsymbol{\mu}$ and $\boldsymbol{\sigma}$, sample $\mathbf{z}_i \sim \mathcal{N}\left(\boldsymbol{\mu}, \mathrm{diag}\left(\boldsymbol{\sigma}^2\right)\right)$, for $i = 1, 2, 3, \cdots$.
- Generate images, $\mathrm{Decoder}(\mathbf{z}_1), \mathrm{Decoder}(\mathbf{z}_2), \mathrm{Decoder}(\mathbf{z}_3), \cdots$, have the same target (which is the original image).



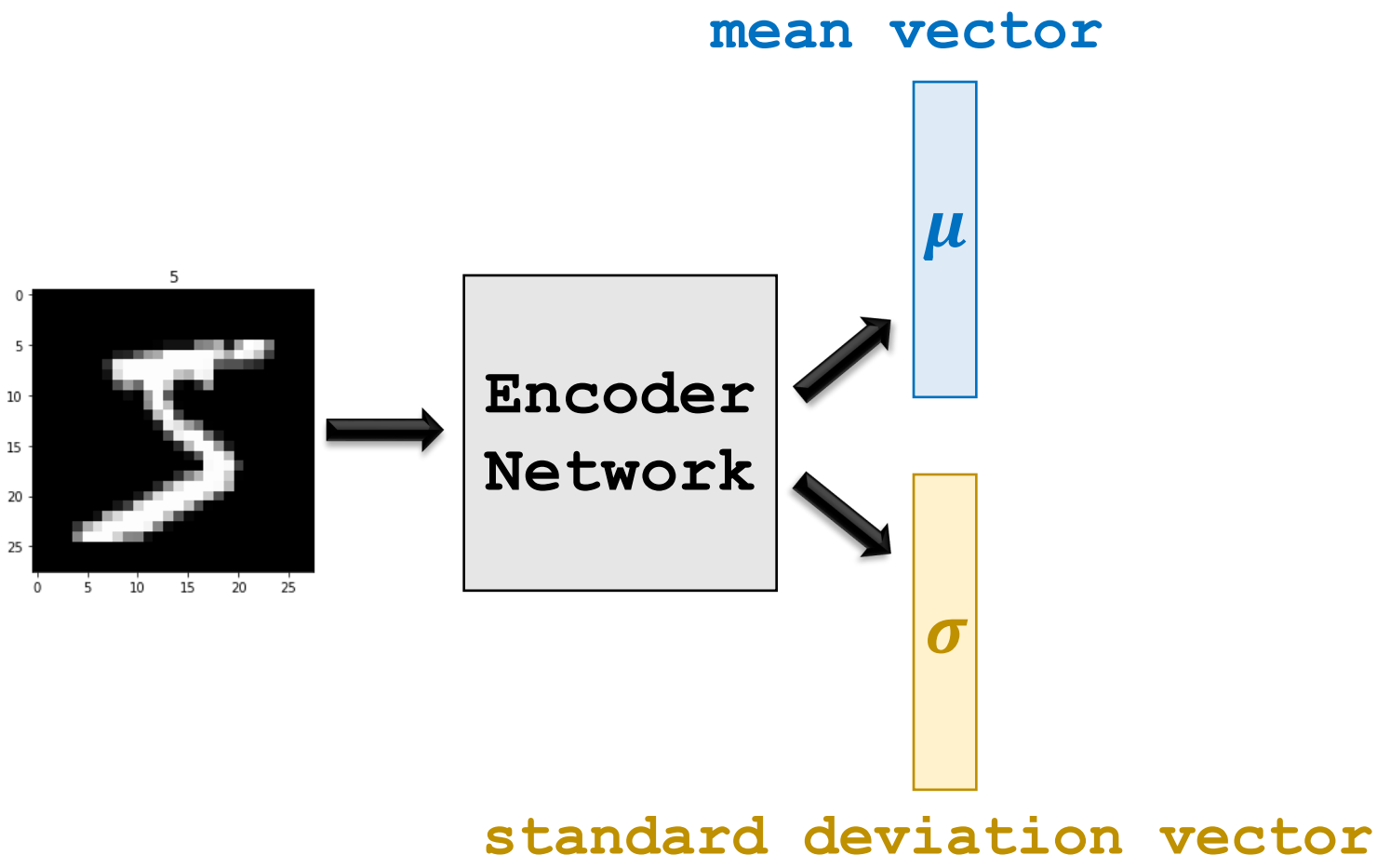
What makes the decoder continuous?

- Inputs (code vectors) are similar. (Because they are in a small neighborhood around μ.)
- Outputs (generated images) are encouraged to be similar. (Because they have the same target.)
- ➔ The decoder is trained to behave like a continuous function.



Build the Networks

1. The Encoder Network



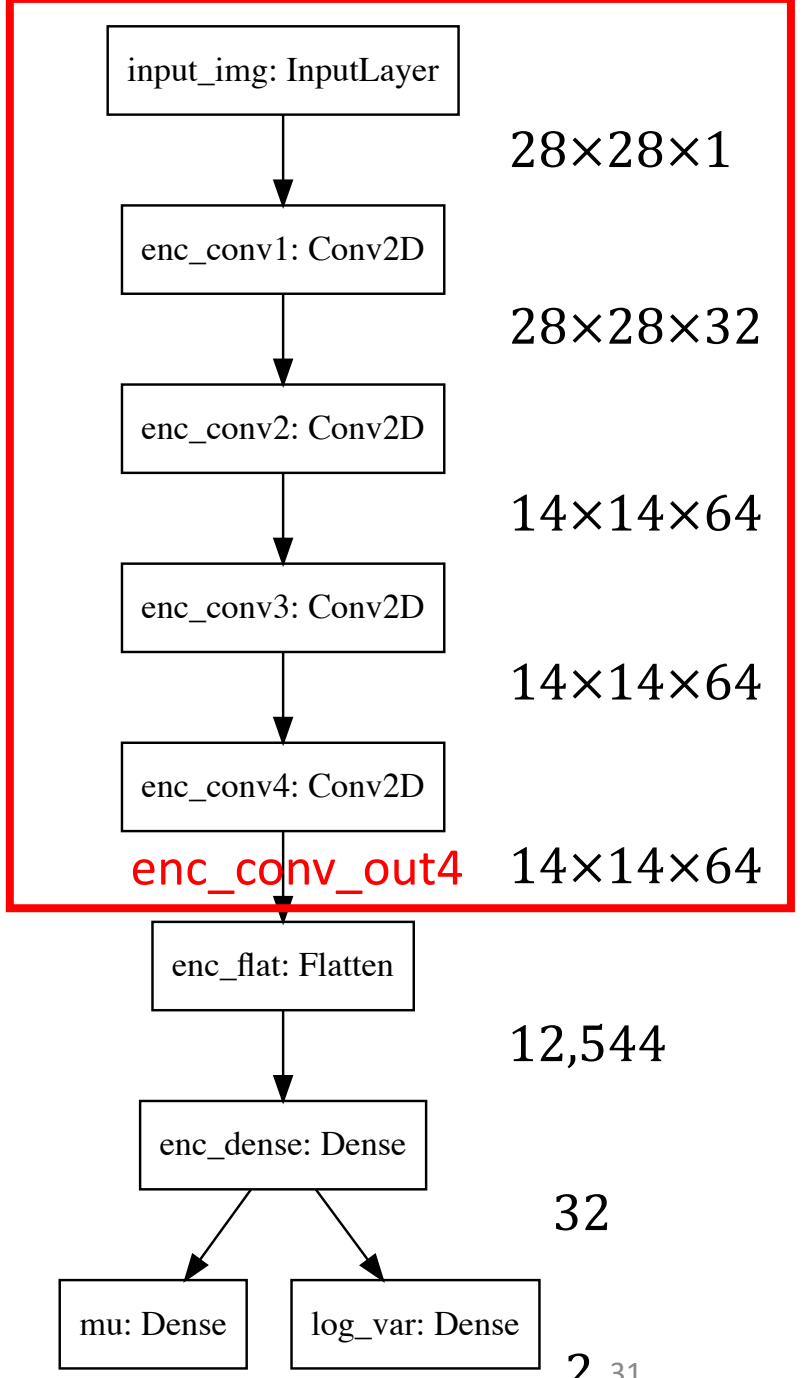
1. The Encoder Network

```
from keras.layers import Input, Conv2D, Flatten, Dense
from keras import models

shape_z = 2

# define convolutional layers
enc_conv1 = Conv2D(32, 3, padding='same',
                   activation='relu', name='enc_conv1')
enc_conv2 = Conv2D(64, 3, padding='same', activation='relu',
                      strides=(2, 2), name='enc_conv2')
enc_conv3 = Conv2D(64, 3, padding='same',
                   activation='relu', name='enc_conv3')
enc_conv4 = Conv2D(64, 3, padding='same',
                   activation='relu', name='enc_conv4')

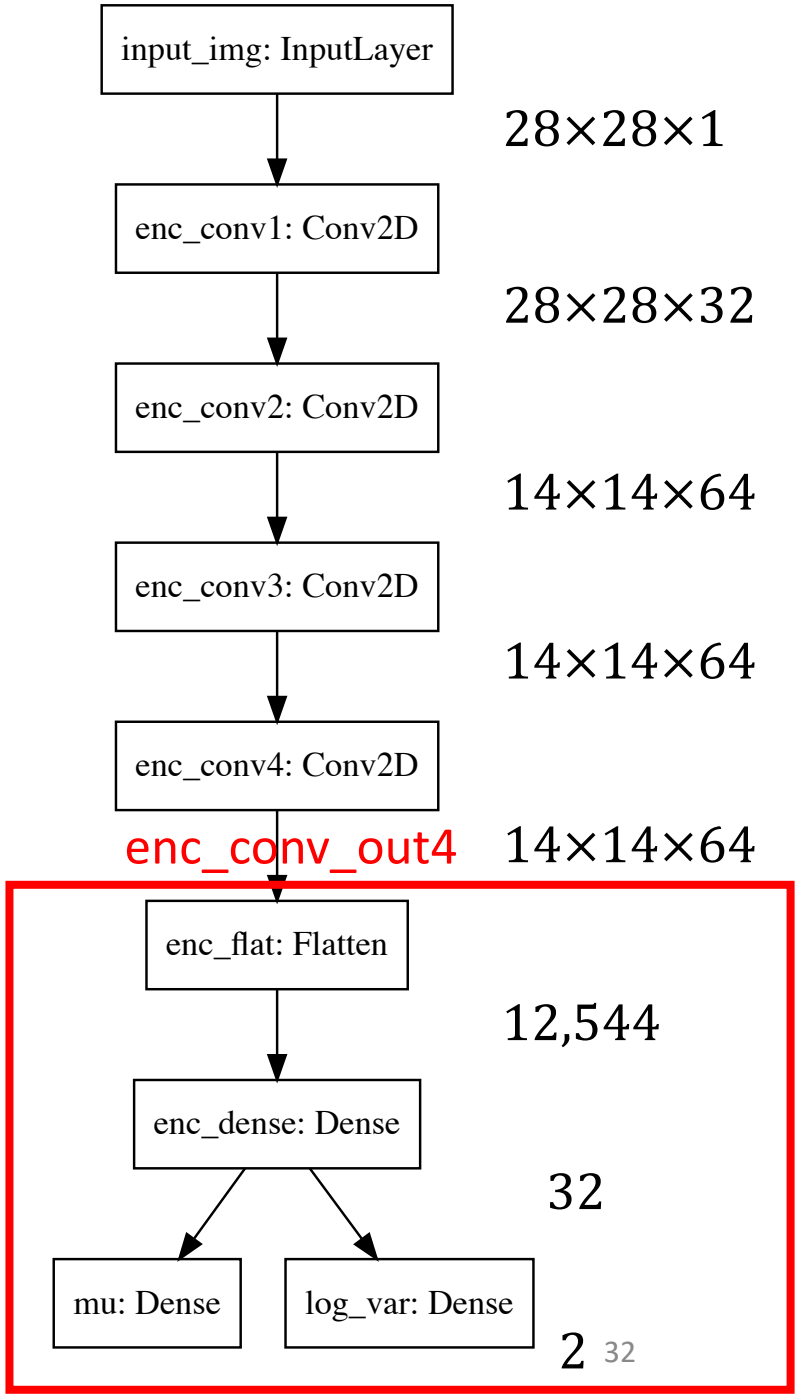
input_img = Input(shape=(28, 28, 1), name='input_img')
enc_conv_out1 = enc_conv1(input_img)
enc_conv_out2 = enc_conv2(enc_conv_out1)
enc_conv_out3 = enc_conv3(enc_conv_out2)
enc_conv_out4 = enc_conv4(enc_conv_out2)
```



1. The Encoder Network

```
# define flatten and dense layers
enc_flat = Flatten(name='enc_flat')
enc_dense = Dense(32, activation='relu',
                  name='enc_dense')
enc_mu = Dense(shape_z, name='mu')
enc_log_var = Dense(shape_z, name='log_var')

enc_flat_out = enc_flat(enc_conv_out4)
enc_dense_out = enc_dense(enc_flat_out)
mu = enc_mu(enc_dense_out)
log_var = enc_log_var(enc_dense_out)
```



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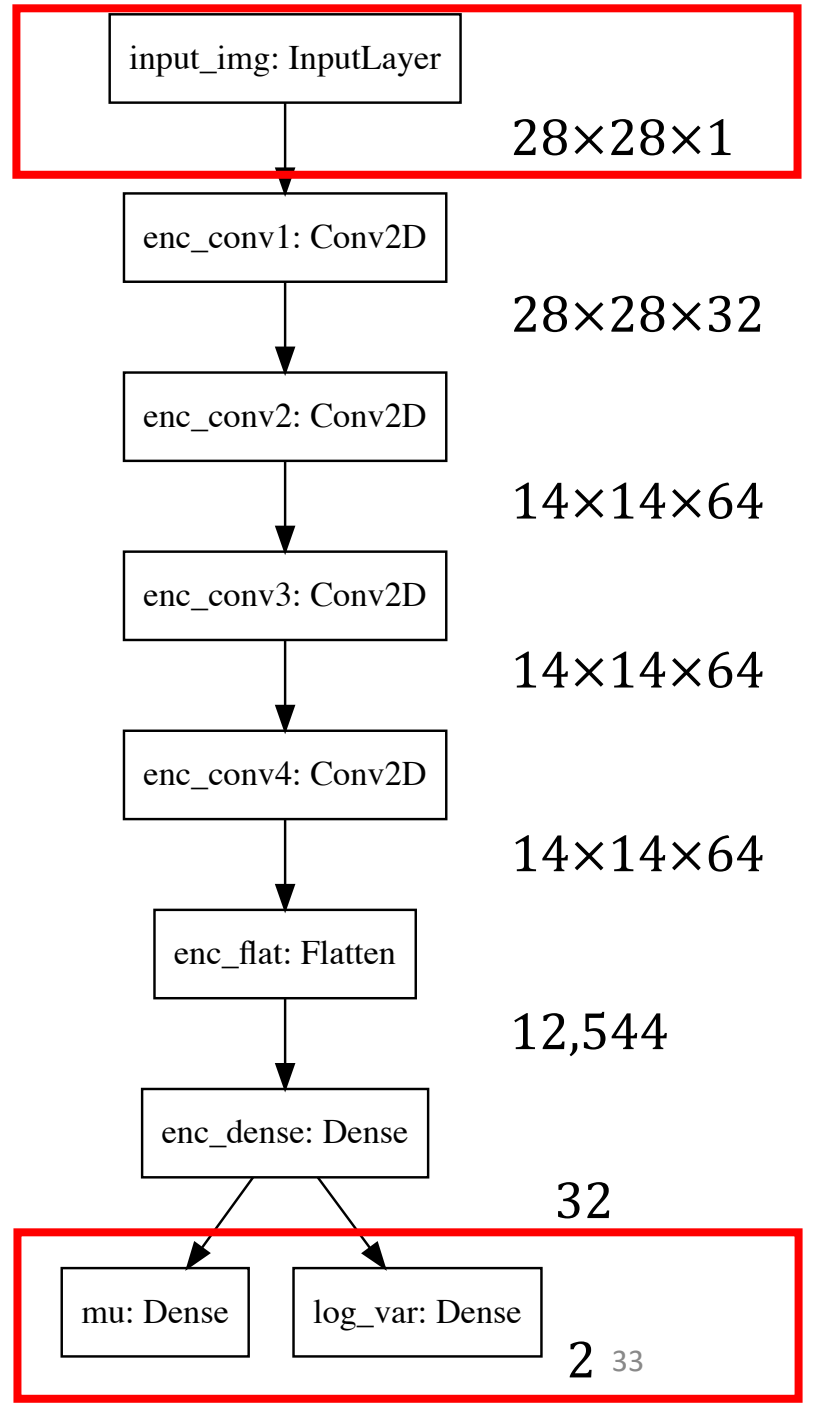
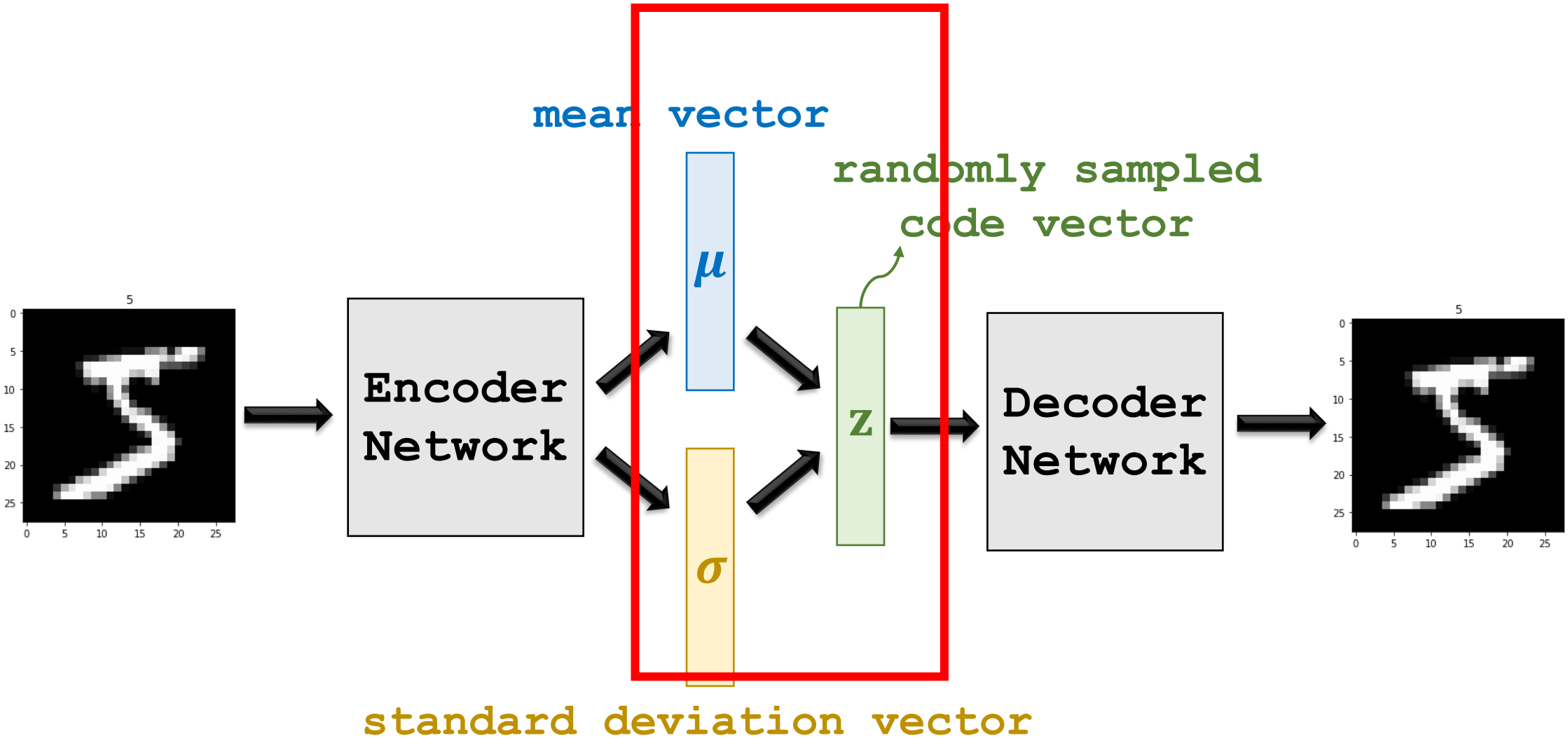
enc_flat_out = enc_flat(enc_conv_out4)
enc_dense_out = enc_dense(enc_flat_out)
mu = enc_mu(enc_dense_out)
log_var = enc_log_var(enc_dense_out)

# model
encoder = models.Model(inputs=input_img,
                       outputs=[mu, log_var],
                       name='encoder')
```



2. The Sampling Network

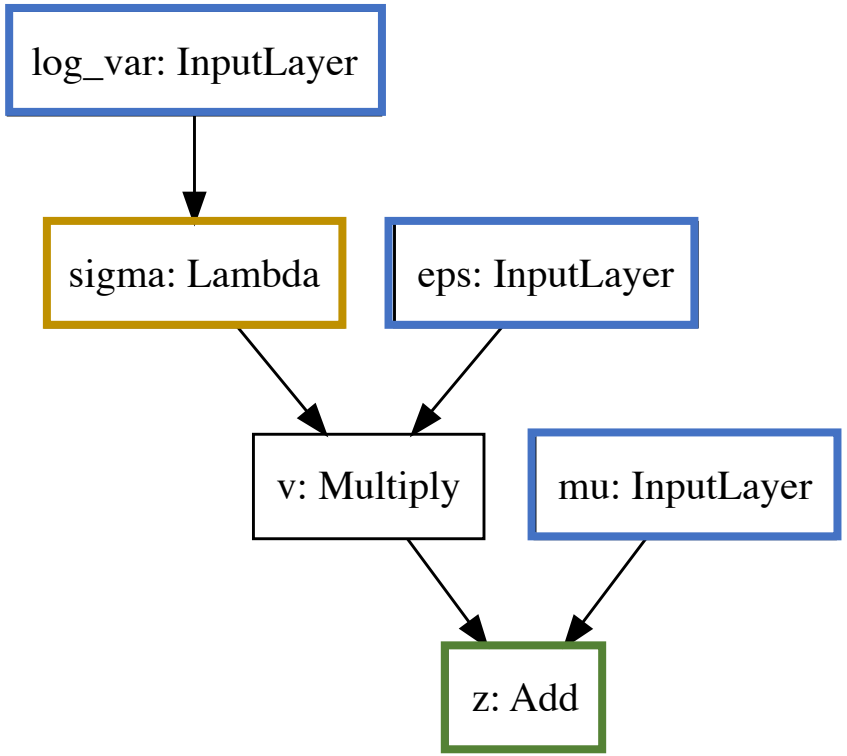


2. The Sampling Network

- The i-th element of $\mathbf{z}$ (denote z_i) is randomly sampled from $\mathcal{N}\left(\mu_i, \sigma_i^2\right)$.
- Equivalently,
  - Randomly sample scalar variable ϵ_i from $\mathcal{N}(0,1)$.
  - Let $v_i = \sigma_i \cdot \epsilon_i$. (Equivalently, v_i is sampled from $\mathcal{N}\left(0, \sigma_i^2\right)$.)
  - $z_i = \mu_i + v_i$.

2. The Sampling Network

- Shape of $\mathbf{z}$: k ($= 2$ in our implementation).
- Input of the sampling network.
  - Log variance: $\boldsymbol{\eta}$ (k-dim vector).
  - Mean: $\boldsymbol{\mu}$ (k-dim vector).
  - $\boldsymbol{\epsilon}$: randomly sampled from $\mathcal{N}(\mathbf{0}, \mathbf{I}_k)$.
- The sampling network:
  - $\boldsymbol{\sigma} = e^{0.5\boldsymbol{\eta}}$ (k-dim vector).
  - $\mathbf{v} = \boldsymbol{\sigma} \circ \boldsymbol{\epsilon}$ (k-dim vector).
  - $\mathbf{z} = \boldsymbol{\mu} + \mathbf{v}$ (k-dim vector).
  - Output $\mathbf{z}$.



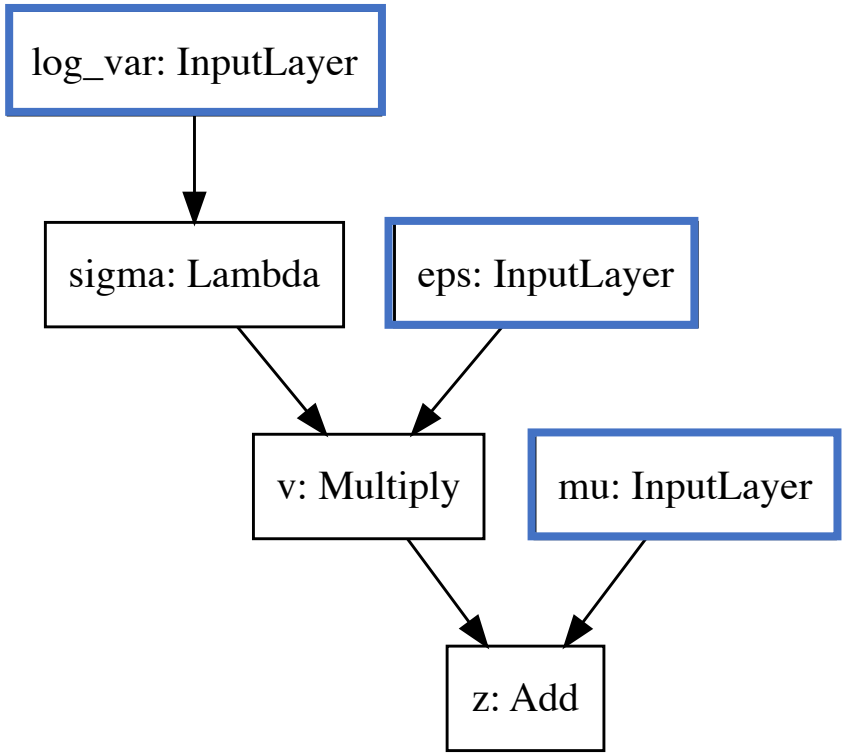
2. The Sampling Network

```
from keras.layers import Lambda, Multiply, Add
from keras import backend as K

# inputs
mu = Input(shape=(shape_z,), name='mu')
log_var = Input(shape=(shape_z,), name='log_var')
eps = Input(shape=(shape_z,), name='eps')

# layers
sigma = Lambda(lambda t: K.exp(.5*t), name='sigma')(log_var)
v = Multiply(name='v')([sigma, eps])
z = Add(name='z')([mu, v])

# model
sampling = models.Model(inputs=[mu, log_var, eps],
                        outputs=z,
                        name='sampling')
```



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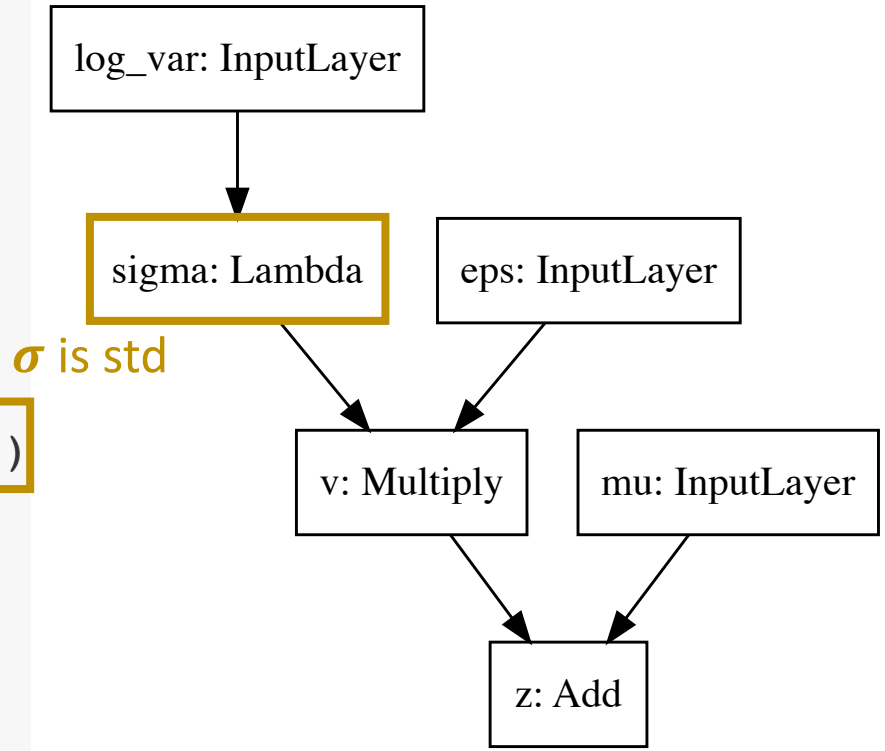

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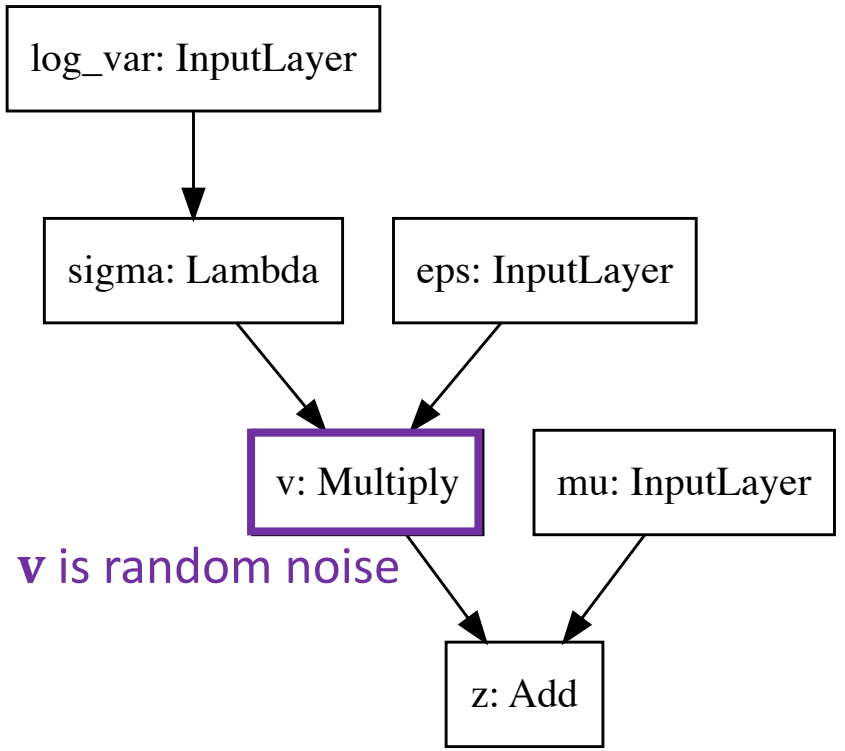

v is random noise

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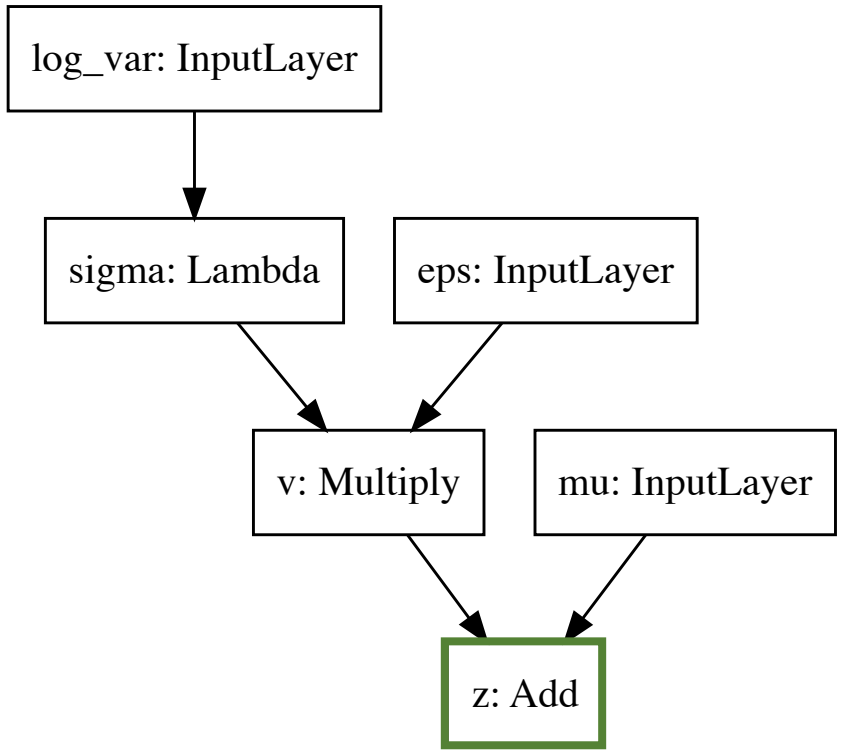
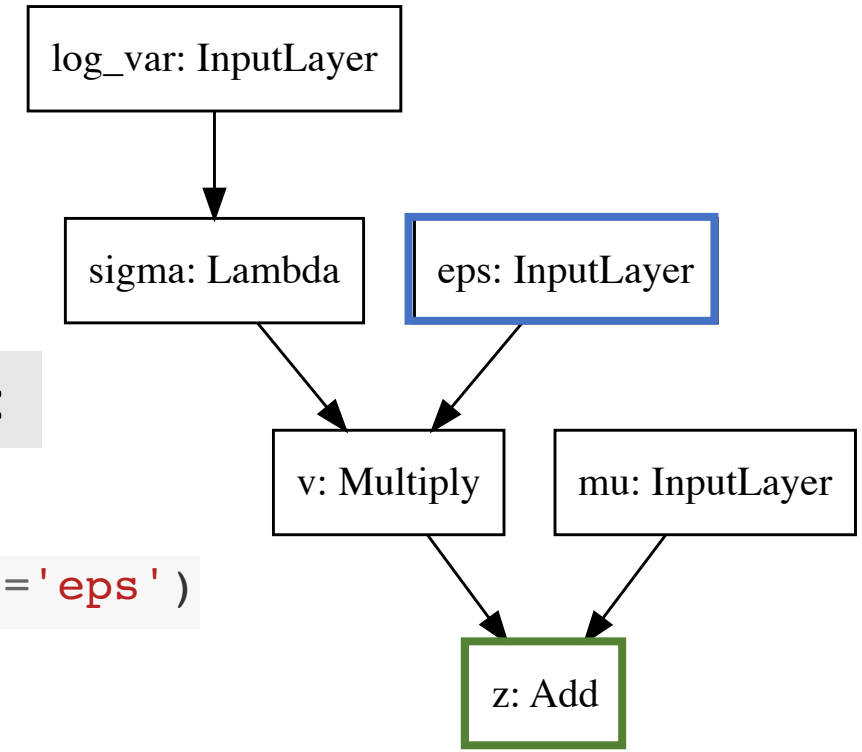
```



z is the sampled latent vector

2. The Sampling Network

Question: Where is the random sampling $\epsilon \sim \mathcal{N}(\mathbf{0}, \mathbf{I}_k)$?

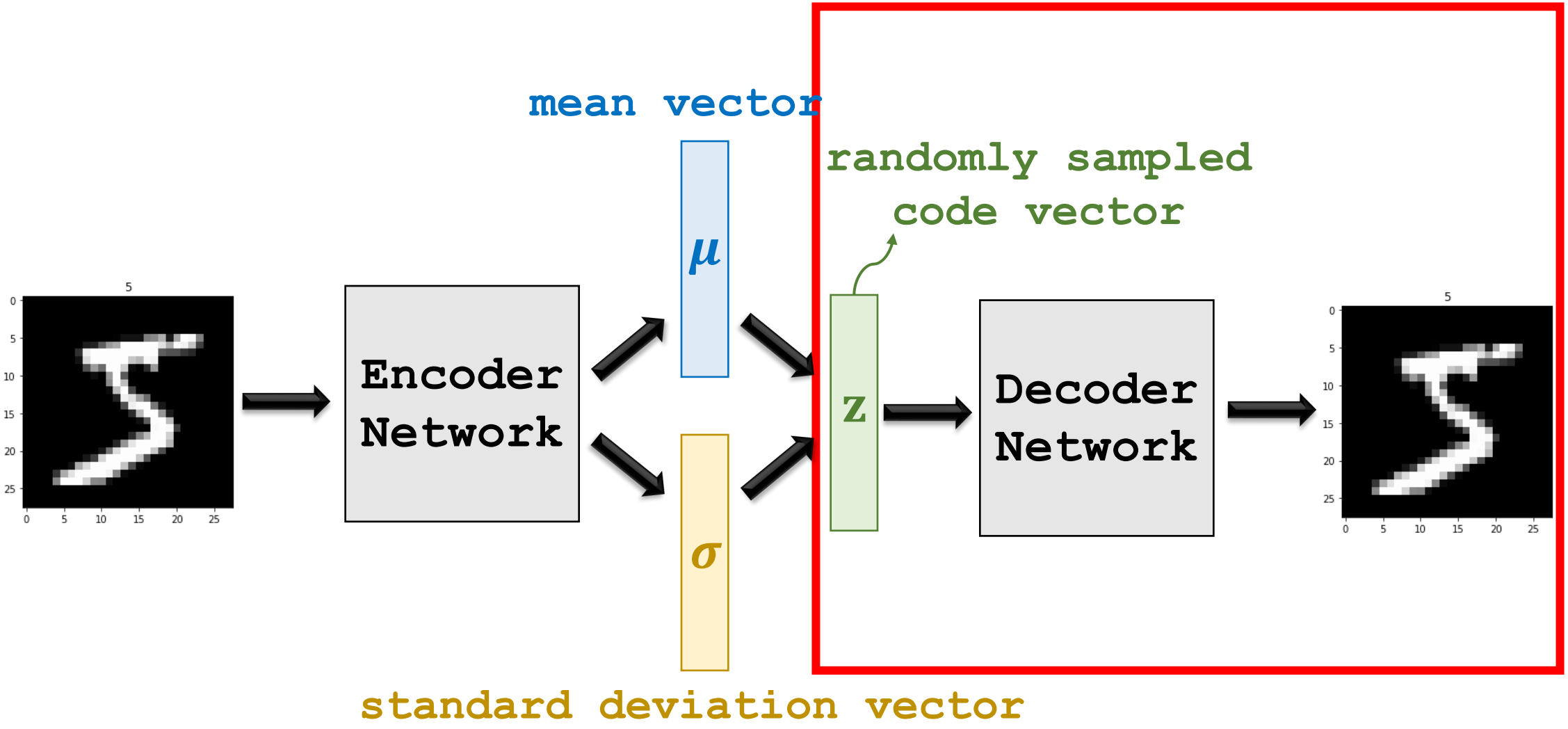


During training, set the input layer "eps" to the following code:

```
eps = Input(tensor=K.random_normal(shape=(n, shape_z)), name='eps')
```

z is the sampled latent vector

3. The Decoder Network



3. The Decoder Network

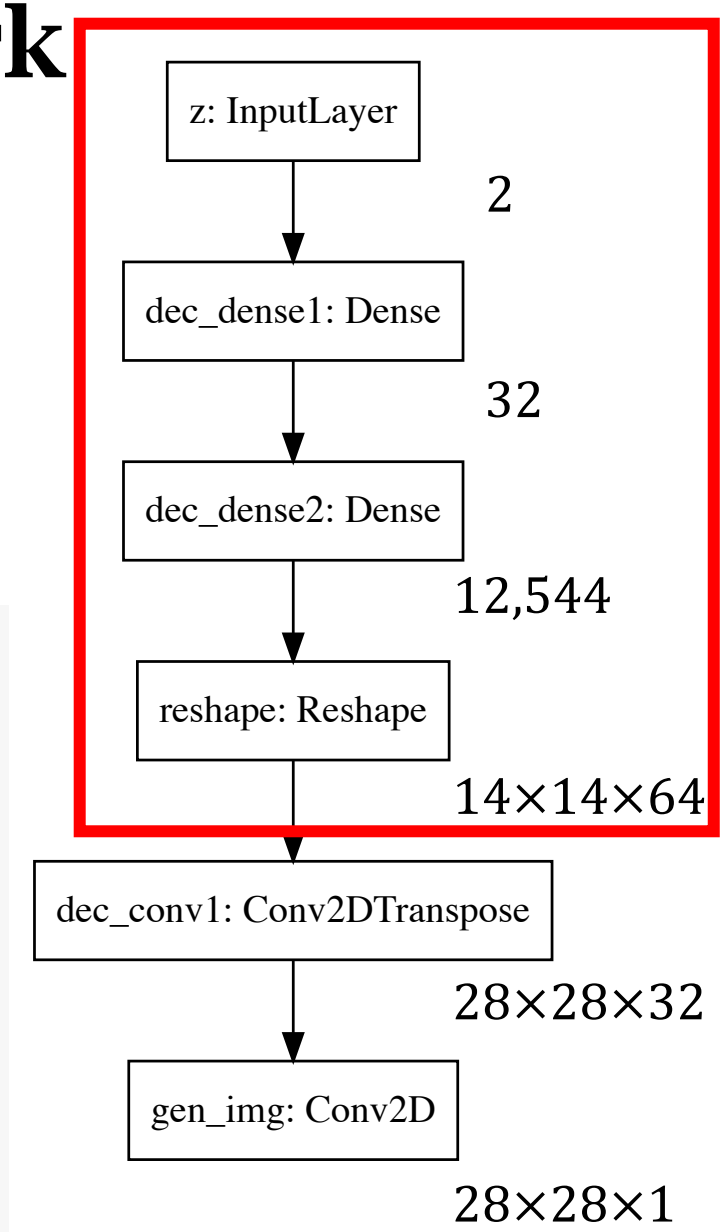
```
from keras import backend as K
import numpy

shape_before_flattening = K.int_shape(enc_conv_out4)[1:]
shape_after_flattening = numpy.prod(shape_before_flattening)
```

```
from keras.layers import Dense, Reshape, Conv2D, Conv2DTranspose

dec_dense1 = Dense(32, activation='relu', name='dec_dense1')
dec_dense2 = Dense(shape_after_flattening,
                   activation='relu', name='dec_dense2')
dec_reshape = Reshape(shape_before_flattening, name='reshape')

z = Input(shape=(shape_z,), name='z')
dec_dense_out1 = dec_dense1(z)
dec_dense_out2 = dec_dense2(dec_dense_out1)
dec_reshape_out = dec_reshape(dec_dense_out2)
```

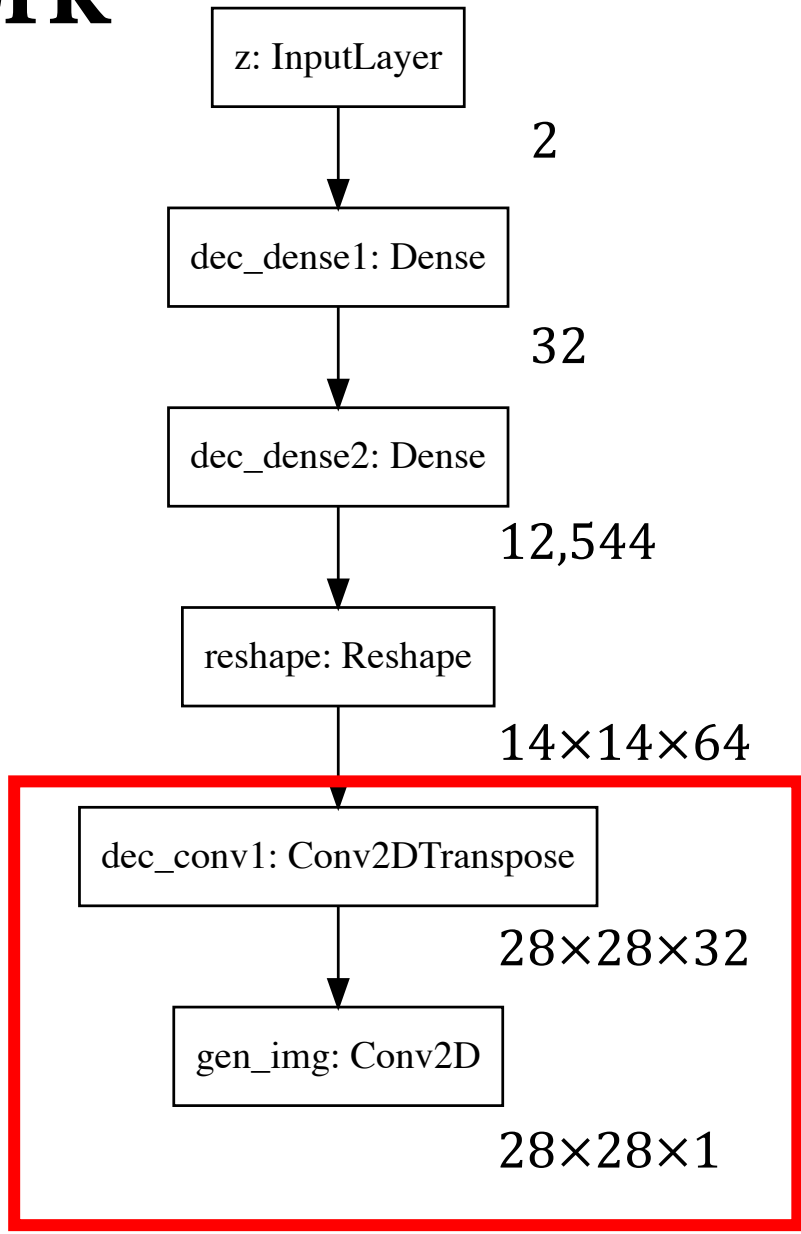


3. The Decoder Network

```
dec_conv1 = Conv2DTranspose(32, 3, padding='same',
                            activation='relu',
                            strides=(2, 2),
                            name='dec_conv1')
dec_conv2 = Conv2D(1, 3, padding='same',
                   activation='relu',
                   name='gen_img')

dec_conv_out1 = dec_conv1(dec_reshape_out)
gen_img = dec_conv2(dec_conv_out1)
```

```
decoder = models.Model(inputs=z,
                       outputs=gen_img,
                       name='decoder')
```



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```
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```

```
decoder = models.Model(inputs=z,
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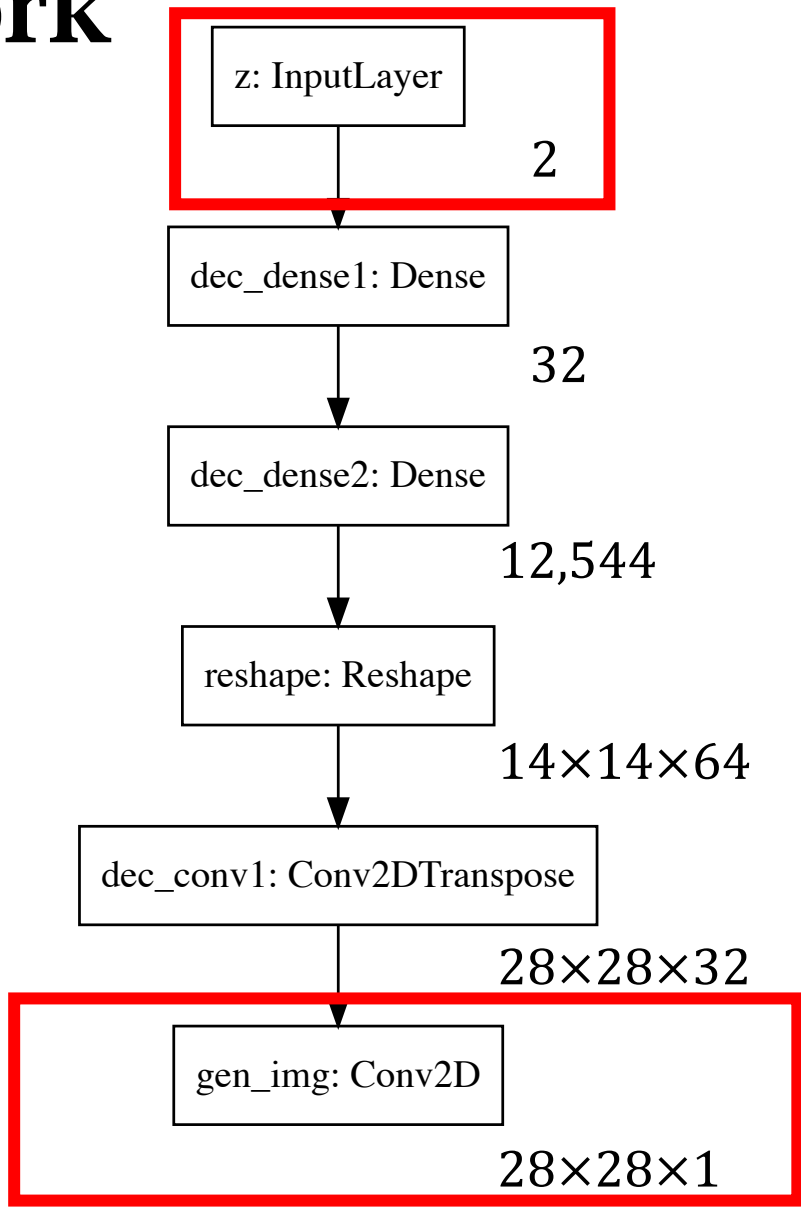
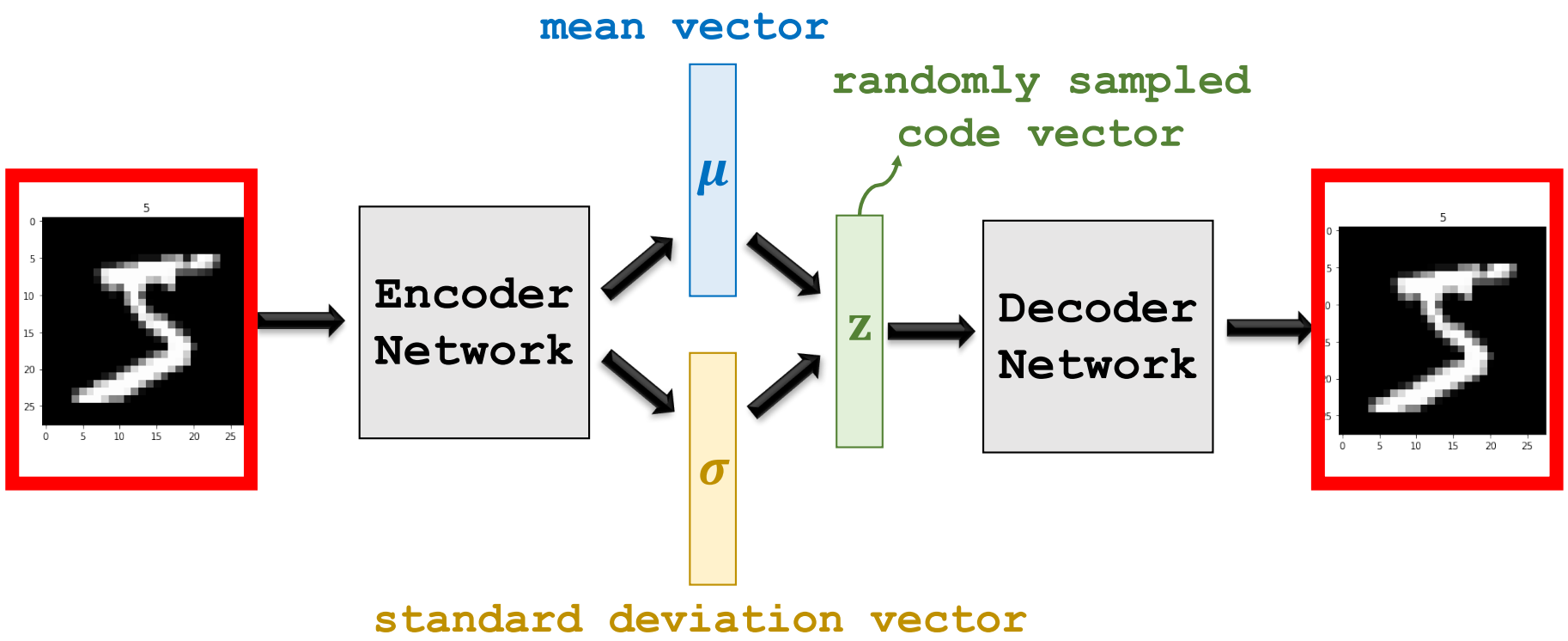


Loss Functions

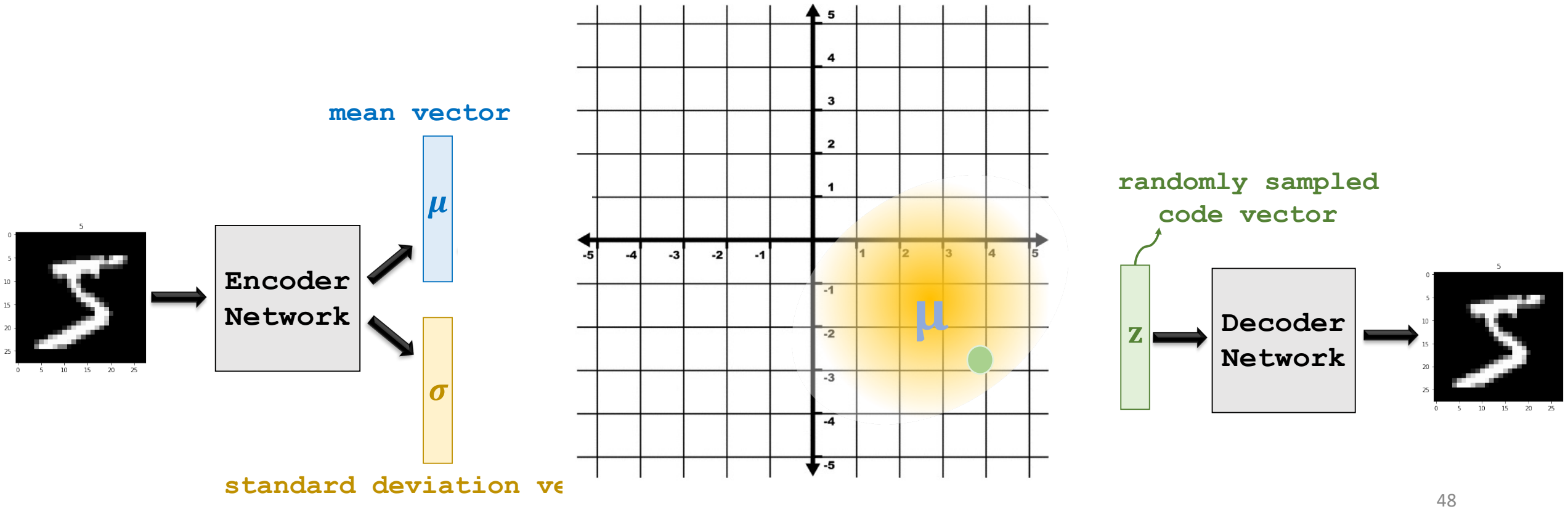
Generation Loss

- `GenLoss = dist(input_img, generated_img)`.
- E.g., the ℓ_2 distance, the cross-entropy, etc.



A problem with generation loss

Difficulty: The encoder network will learn an std vector $\sigma \to 0$.



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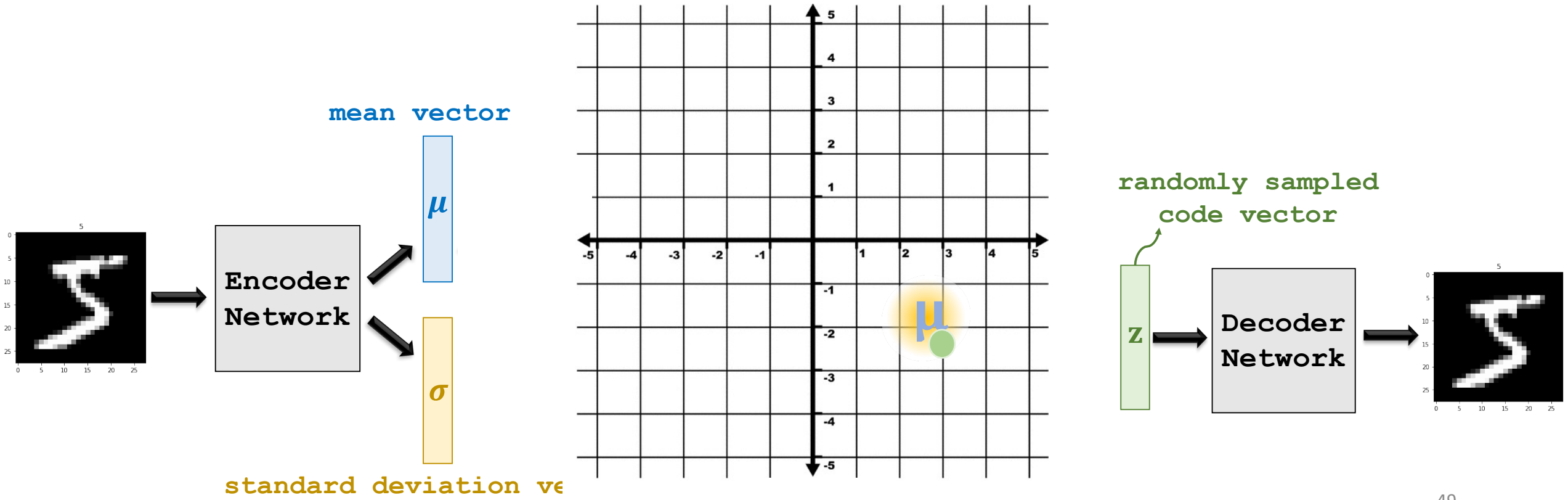
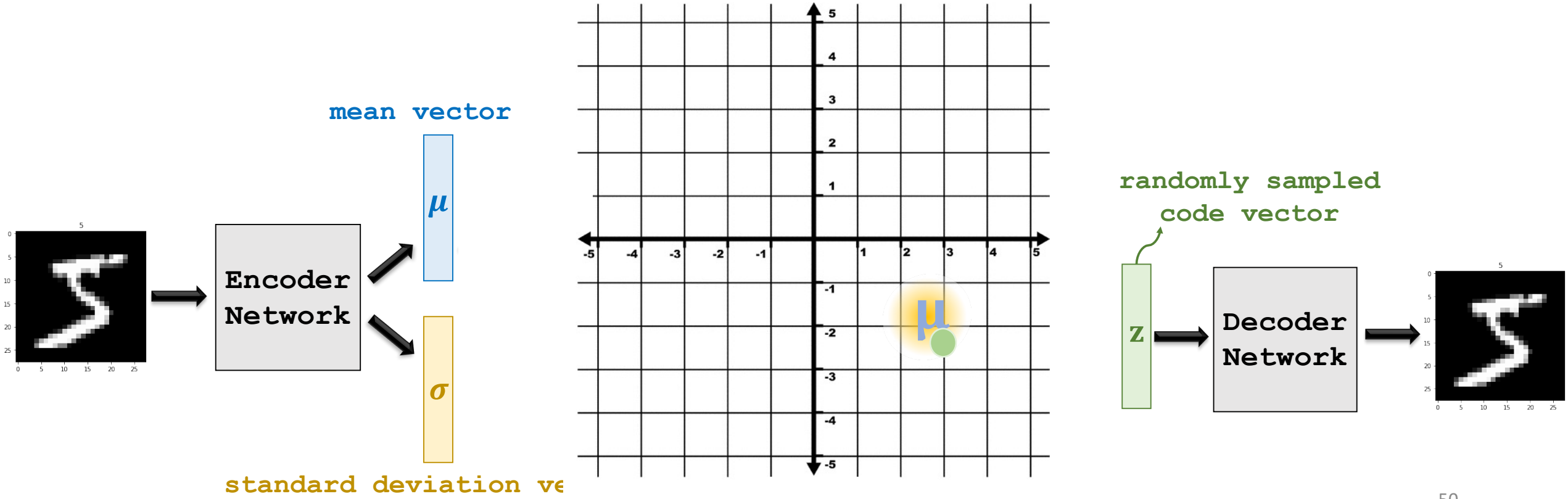


A problem with generation loss

Difficulty: The encoder network will learn an std vector $\sigma \to 0$. (Why?)

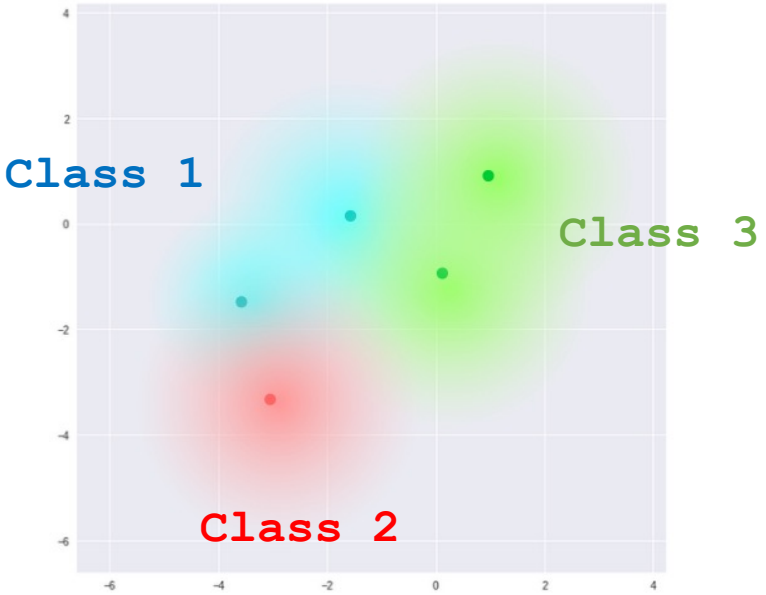
- Minimize `GenLoss` ➔ encourage z close to μ ➔ encourage small σ.
- VAE degrades to the standard AE (VAE with $\sigma = 0$ is exactly AE).



A problem with generation loss

Difficulty: By minimizing generation loss, VAE becomes standard AE.

Dots are code vectors ($\boldsymbol{\mu}$); shadows illustrate std ($\boldsymbol{\sigma}$).



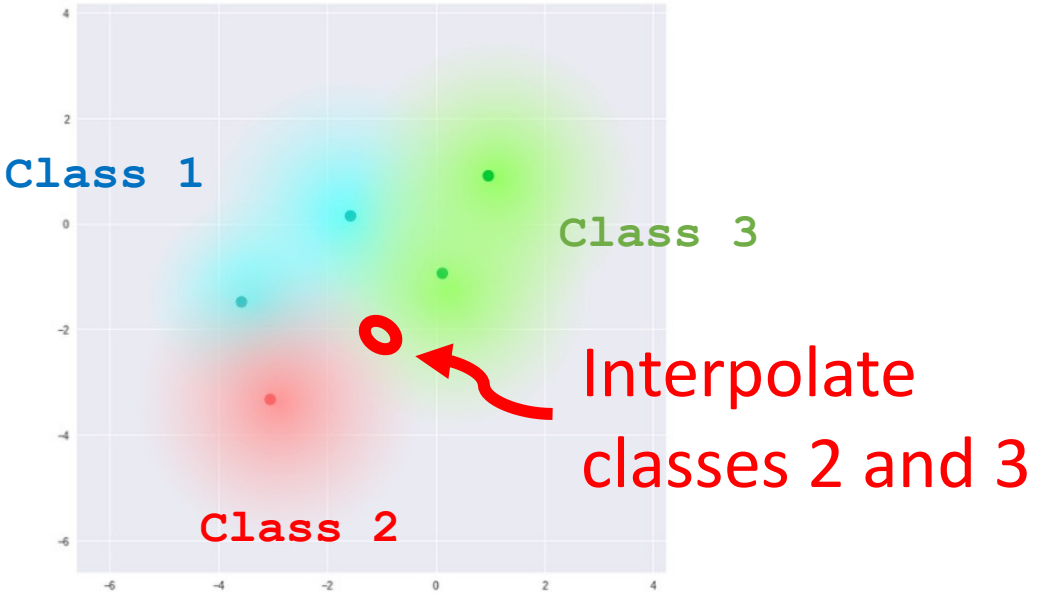
What we hope to learn.

What we actually learn by minimizing `GenLoss`.

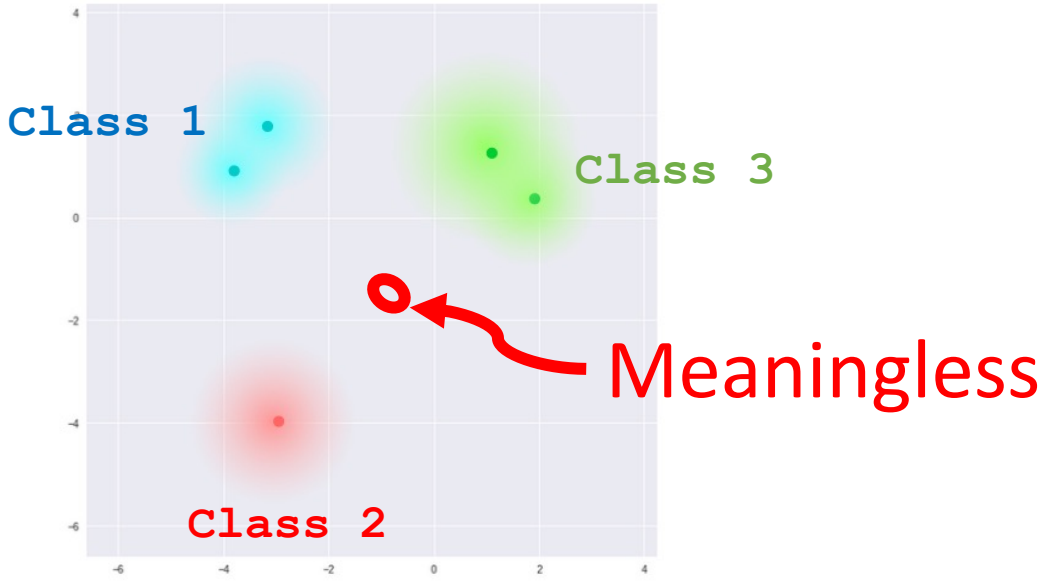
A problem with generation loss

Difficulty: By minimizing generation loss, VAE becomes standard AE.

Dots are code vectors ($\boldsymbol{\mu}$); shadows illustrate std ($\boldsymbol{\sigma}$).



What we hope to learn.



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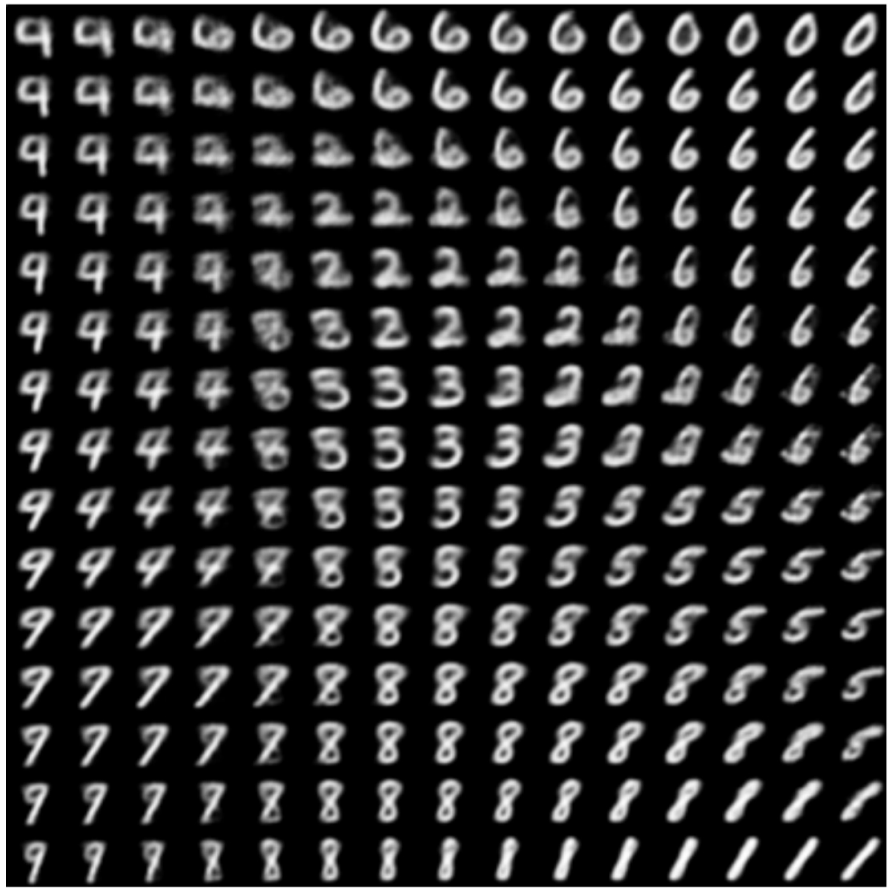
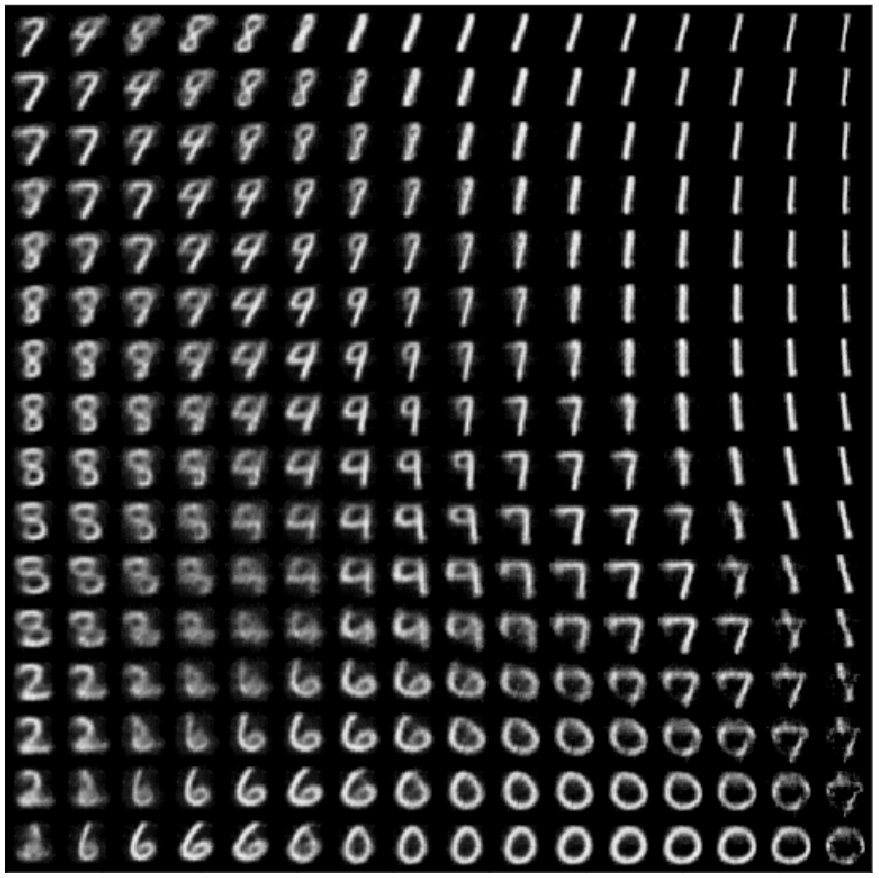


What we hope to learn.



What we actually learn by minimizing `GenLoss`.

A problem with generation loss

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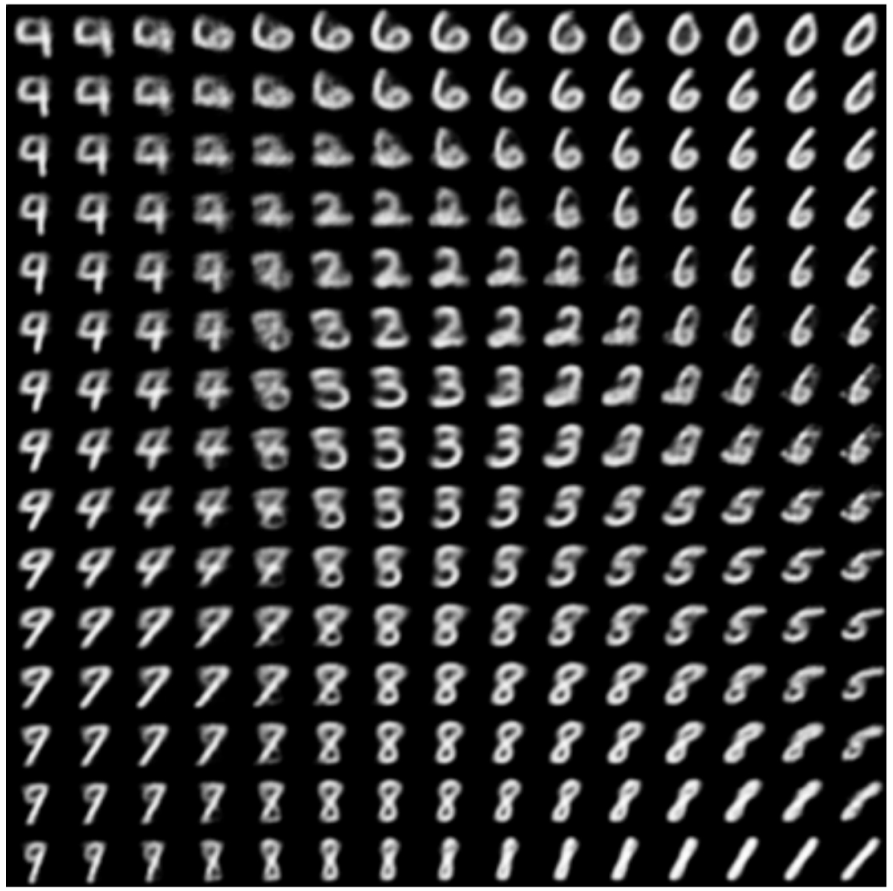
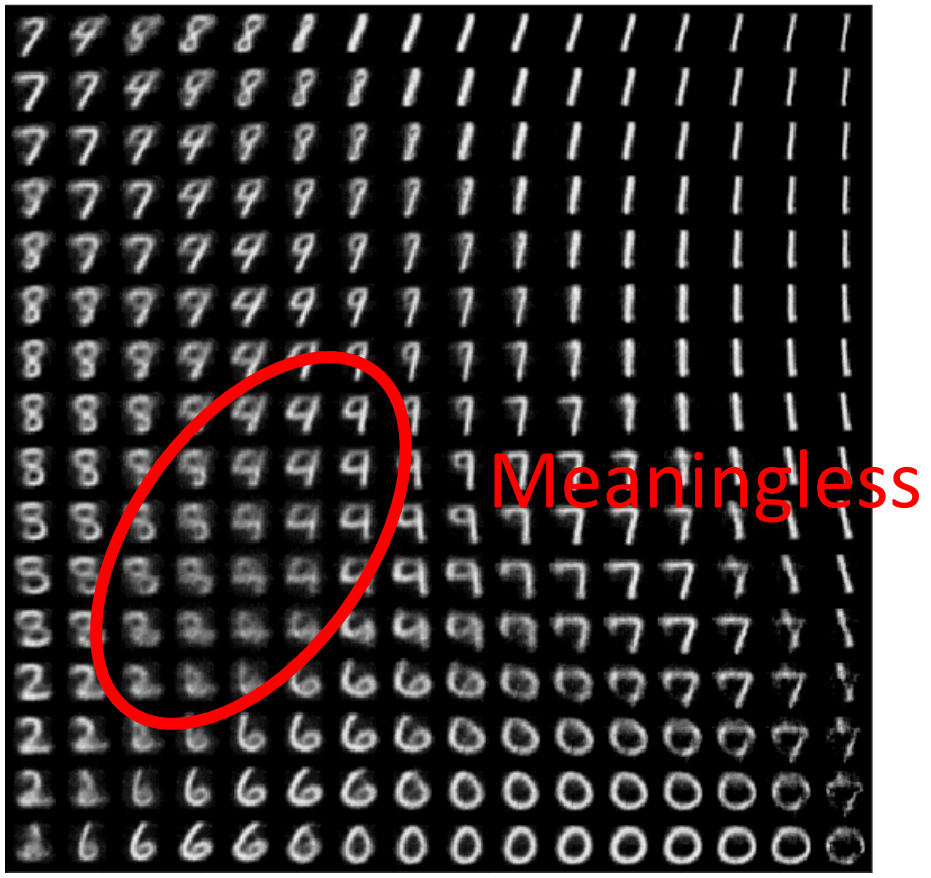


What we hope to learn.

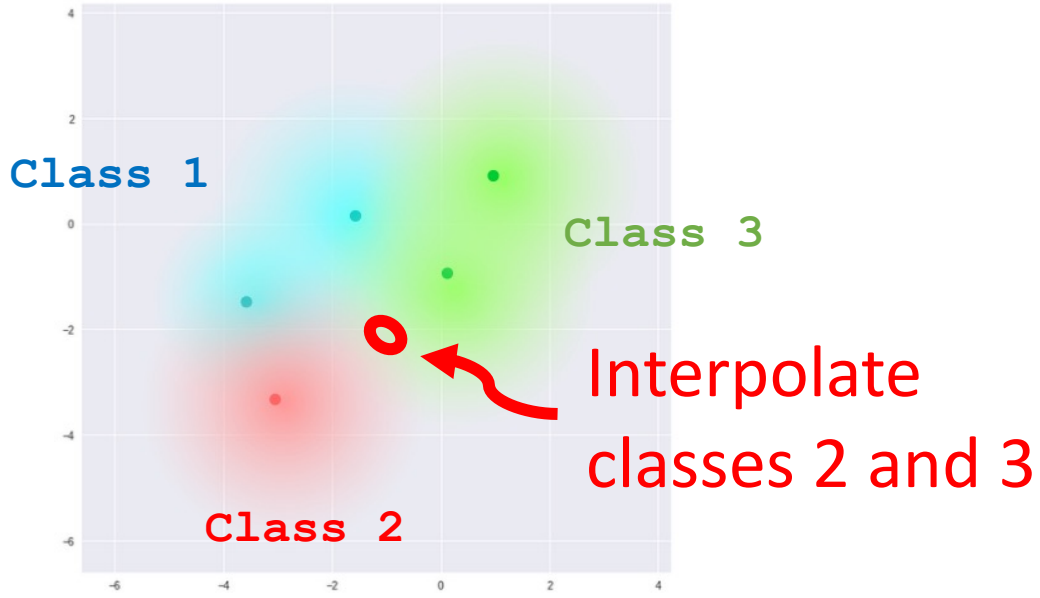


What we actually learn by minimizing `GenLoss`.

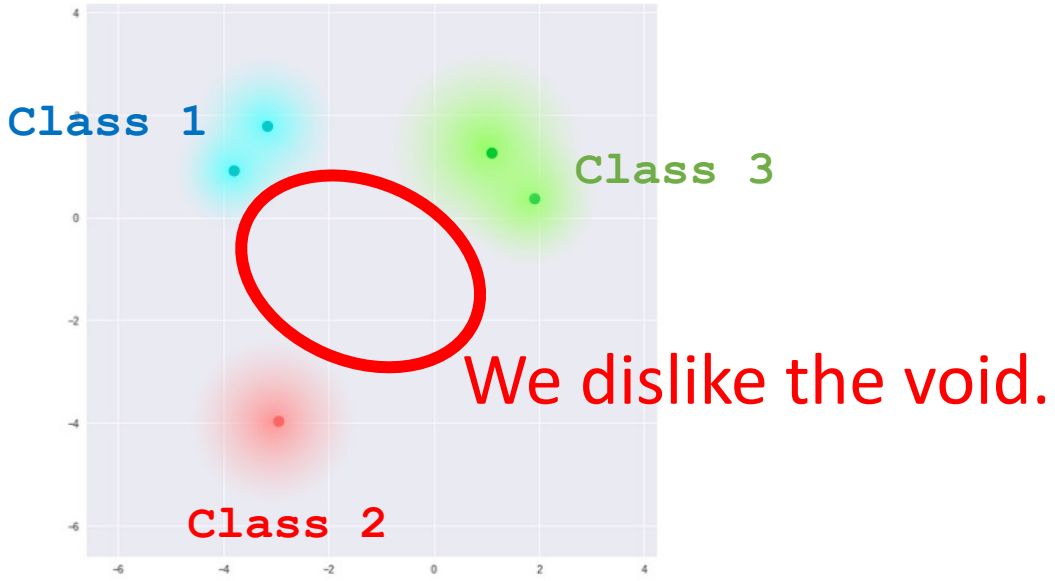
KL Loss

Idea: Encourage the distribution of $\mathbf{z}$ to be unit Gaussian.

- There will be a probability density everywhere around the origin.
- ➔ No more void.



What we hope to learn.

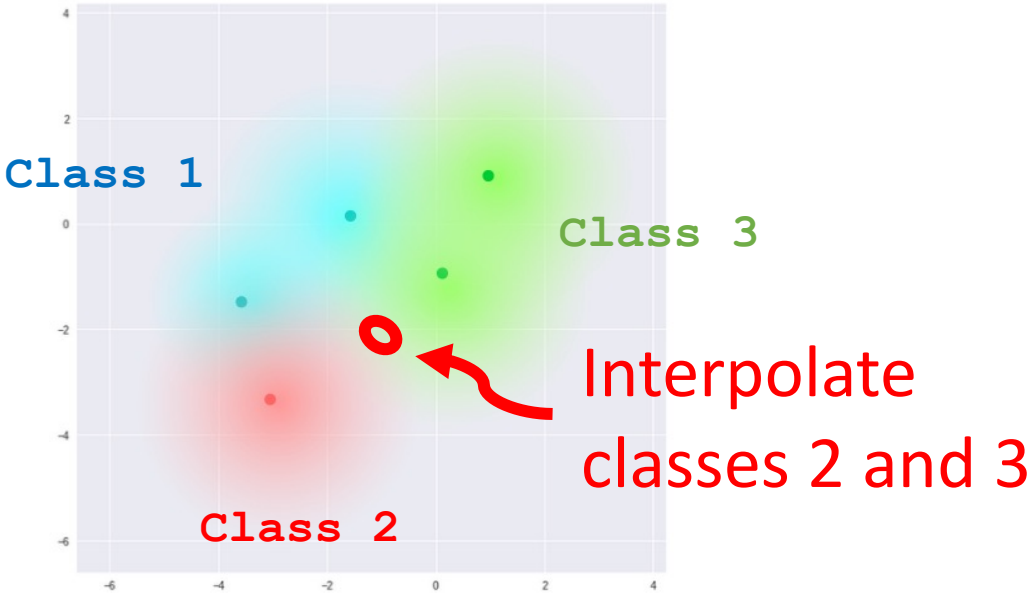


What we actually learn by minimizing `GenLoss`.

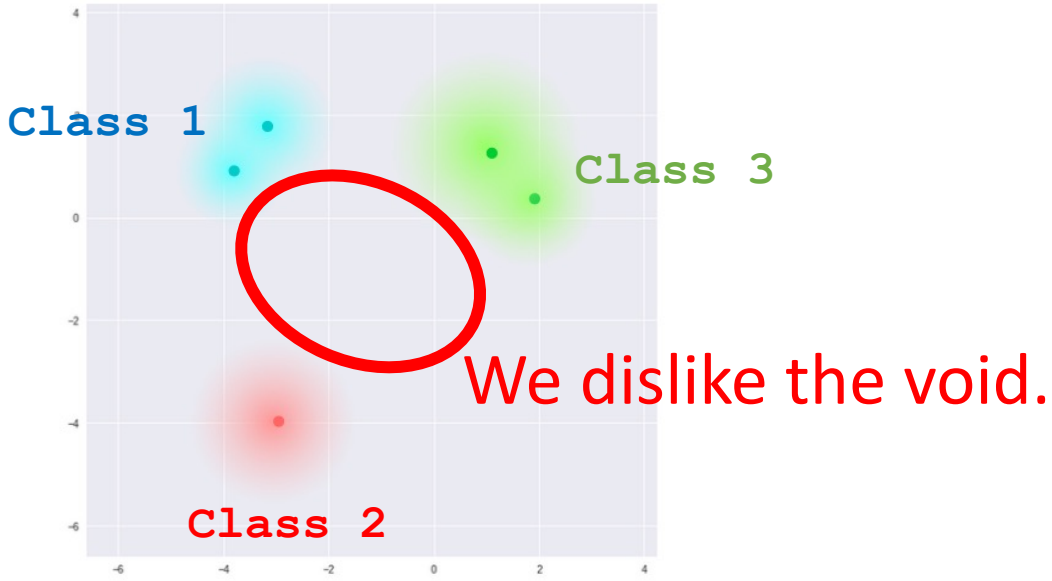
KL Loss

Idea: Encourage the distribution of $\mathbf{z}$ to be unit Gaussian.

- $\text{KLLoss} = D_{\text{KL}}\left(p(\mathbf{z}) \;||\; \mathcal{N}(0, \mathbf{I})\right)$



What we hope to learn.



What we actually learn by minimizing `GenLoss`.

KL Loss

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- $\text{KLLoss} = D_{\text{KL}}\left(p(\mathbf{z}) \;||\; \mathcal{N}(0, \mathbf{I})\right)$

- $\text{Loss} = \text{GenLoss} + \lambda \cdot \text{KLLoss}$

Generation Loss + KL Loss

- Generation loss:

$$\text{GenLoss} = \text{dist}(\text{input\_img}, \text{output\_img}).$$

```
l = keras.metrics.binary_crossentropy(input_img, output_img)
```

Generation Loss + KL Loss

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$$\text{GenLoss} = \text{dist}(\text{input\_img}, \text{output\_img}).$$

```
l = keras.metrics.binary_crossentropy(input_img, output_img)
```

- KL loss:

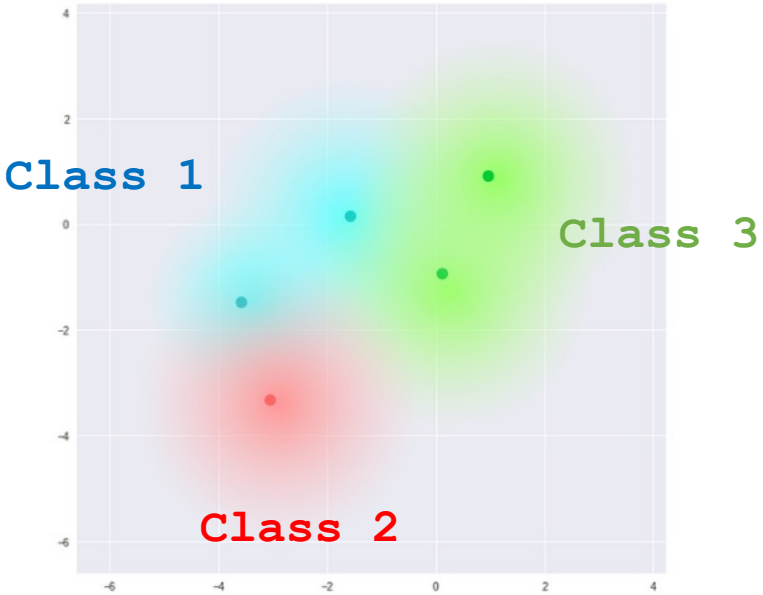
$$\text{KLLoss} = D_{\text{KL}}\big(p(\mathbf{z}) \;||\; \mathcal{N}(0, \mathbf{I})\big)$$

```
l = -0.5 * K.mean(1 + log_var - K.square(mu) - K.exp(log_var), axis=-1)
```

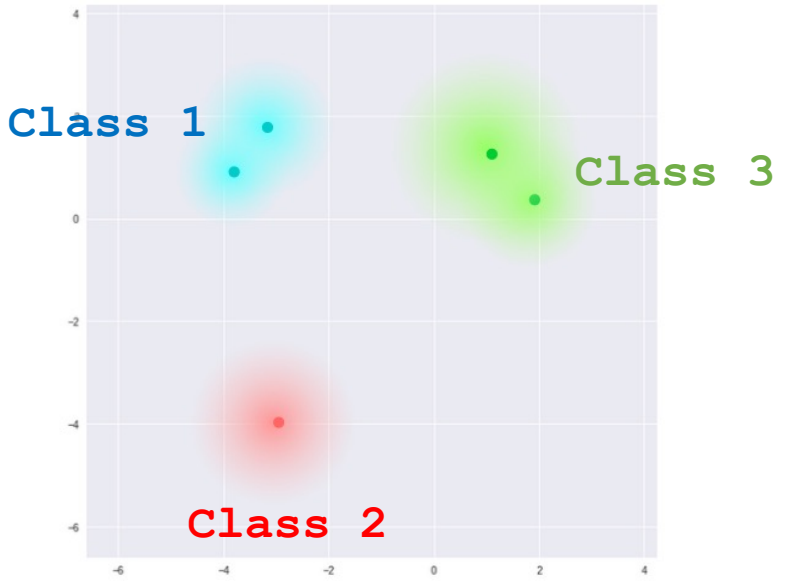
Another interpretation:

- Encourage the variance σ^2 to be big. (Avoid vanishing variance.)
- Pull the mean $\boldsymbol{\mu}$ towards the origin. (Avoid isolated clusters.)

Generation Loss + KL Loss



What we hope to learn.



What we actually learn by minimizing `GenLoss`.

Another interpretation:

- Encourage the variance σ^2 to be big. (Avoid vanishing variance.)
- Pull the mean $\boldsymbol{\mu}$ towards the origin. (Avoid isolated clusters.)

Generation Loss + KL Loss

- Generation loss:

$$\text{GenLoss} = \text{dist}(\text{input\_img}, \text{output\_img}).$$

```
l = keras.metrics.binary_crossentropy(input_img, output_img)
```

- KL loss:

$$\text{KLLoss} = D_{\text{KL}}\left(p(\mathbf{z}) \;||\; \mathcal{N}(0, \mathbf{I})\right)$$

```
l = -0.5 * K.mean(1 + log_var - K.square(mu) - K.exp(log_var), axis=-1)
```

- $\text{Loss} = \text{GenLoss} + 10^{-3} \cdot \text{KLLoss}$

Take `input_img` and `output_img` as inputs

tuning hyper-parameter

Take `log_var` and `mu` as inputs

Implement loss function

```
import keras
from keras import backend as K

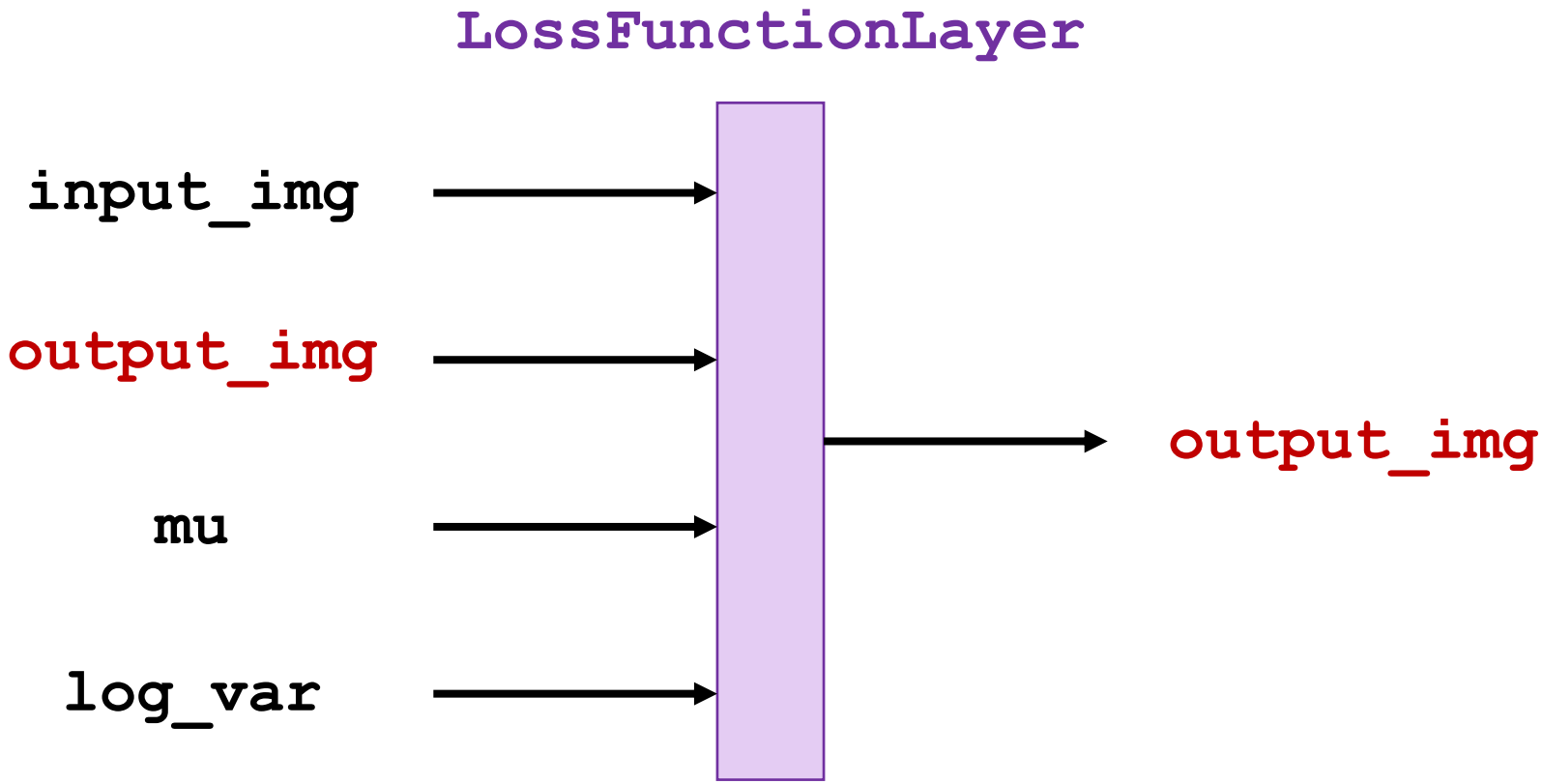
class LossFunctionLayer(keras.layers.Layer):
    param = 1E-3

    def kl_loss(self, mu, log_var):
        l = -0.5 * K.mean(1 + log_var - K.square(mu) - K.exp(log_var), axis=-1)
        return self.param * K.mean(l)

    def gen_loss(self, input_img, output_img):
        l = keras.metrics.binary_crossentropy(input_img, output_img)
        return K.mean(l)

    def call(self, inputs):
        input_img, output_img, mu, log_var = inputs
        loss1 = self.gen_loss(input_img, output_img)
        loss2 = self.kl_loss(mu, log_var)
        self.add_loss(loss1+loss2, inputs=inputs)
        return output_img
```

Implement loss function



Also compute the loss function.

- **input_img** and **output_img** for **GenerationLoss**.
- **mu** and **log_var** for **KLtLoss**.

Training

Connect the modules

We have defined 4 modules:

- **Encoder:** `[input_img]` → `[mu, log_var]`
- **Sampling:** `[mu, log_var, eps]` → `[z]`
- **Decoder:** `[z]` → `[output_img]`
- **LossFunctionLayer:** `[input_img, output_img, mu, log_var]` → `[output_img]`

```
input_img = Input(shape=(28,28,1), name='input_img')
n = K.shape(input_img)[0]
eps = Input(tensor=K.random_normal(shape=(n, shape_z)), name='eps')
```

Connect the modules

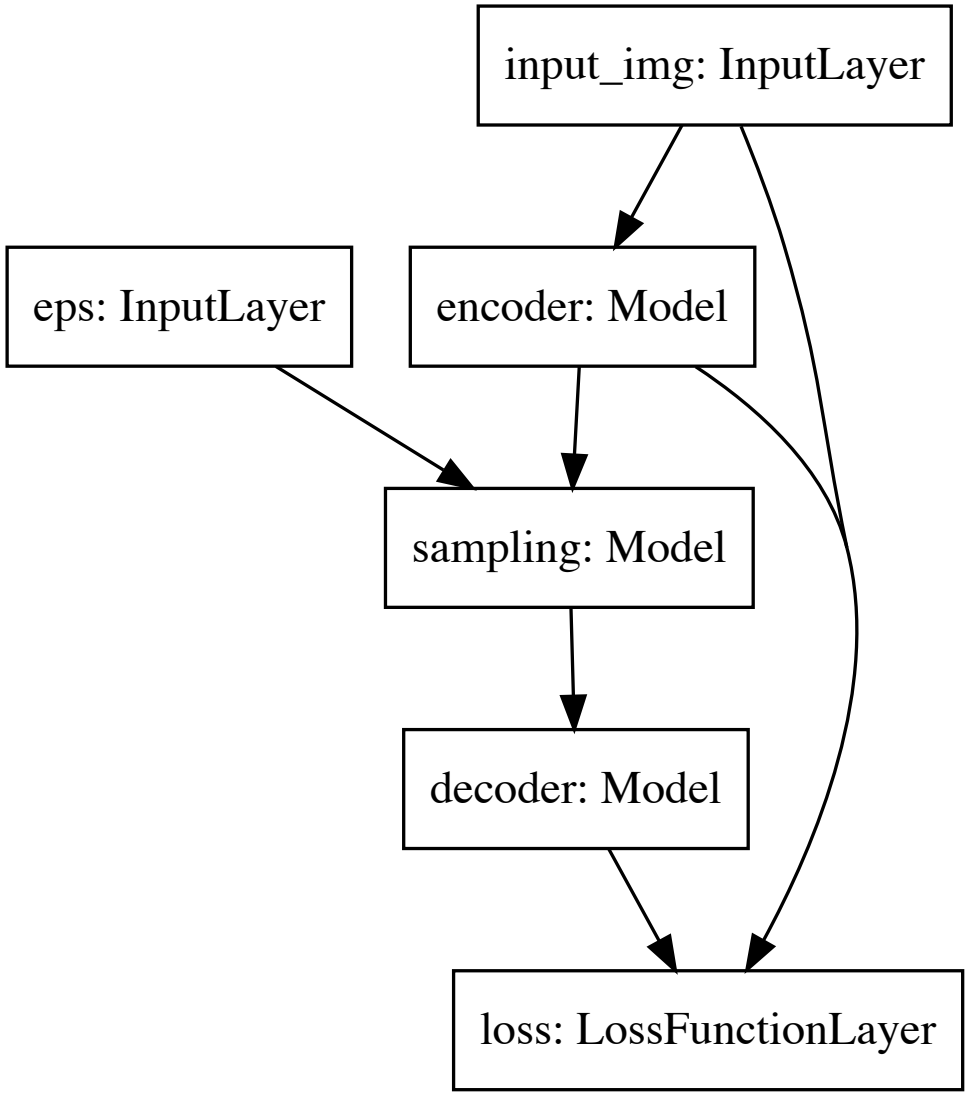
We have defined 4 modules:

- **Encoder:** `[input_img]` → `[mu, log_var]`
- **Sampling:** `[mu, log_var, eps]` → `[z]`
- **Decoder:** `[z]` → `[output_img]`
- **LossFunctionLayer:** `[input_img, output_img, mu, log_var]` → `[output_img]`

```
input_img = Input(shape=(28,28,1), name='input_img')
n = K.shape(input_img)[0]
eps = Input(tensor=K.random_normal(shape=(n, shape_z)), name='eps')

mu, log_var = encoder(input_img)
z = sampling([mu, log_var, eps])
output_img = decoder(z)
output_img = LossFunctionLayer(name='loss')([input_img, output_img, mu, log_var])
model = models.Model(inputs=[input_img, eps], outputs=output_img)
```

Connect the modules



Train the model on MNIST dataset

```
history = model.fit(
    x_train,
    None,
    shuffle=True,
    epochs=50,
    batch_size=128,
    validation_data=(x_test, None)
)
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/50
60000/60000 [==============================] - 231s 4ms/step - loss: 0.6717 - val_loss: 0.2194
Epoch 2/50
60000/60000 [==============================] - 251s 4ms/step - loss: 0.2139 - val_loss: 0.2083
Epoch 3/50
60000/60000 [==============================] - 299s 5ms/step - loss: 0.2066 - val_loss: 0.2096
    ⋮
Epoch 49/50
60000/60000 [==============================] - 240s 4ms/step - loss: 0.1839 - val_loss: 0.1859
Epoch 50/50
60000/60000 [==============================] - 233s 4ms/step - loss: 0.1837 - val_loss: 0.1858
```

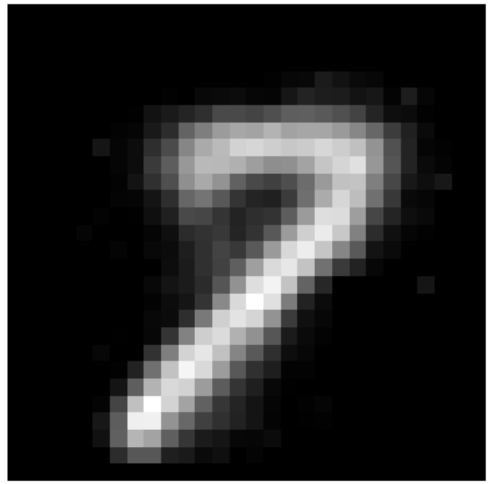
Visualize code vectors

arbitrary 2-dim vector

map the 2-dim vector to a 28×28 image

```
z_sample = np.array([0.1, 0.2]).reshape((1, 2))
x_decoded = decoder.predict(z_sample)[0].reshape((28, 28))

fig = plt.figure(figsize=(6, 6))
plt.imshow(x_decoded, cmap='gray')
plt.axis('off')
plt.show()
```

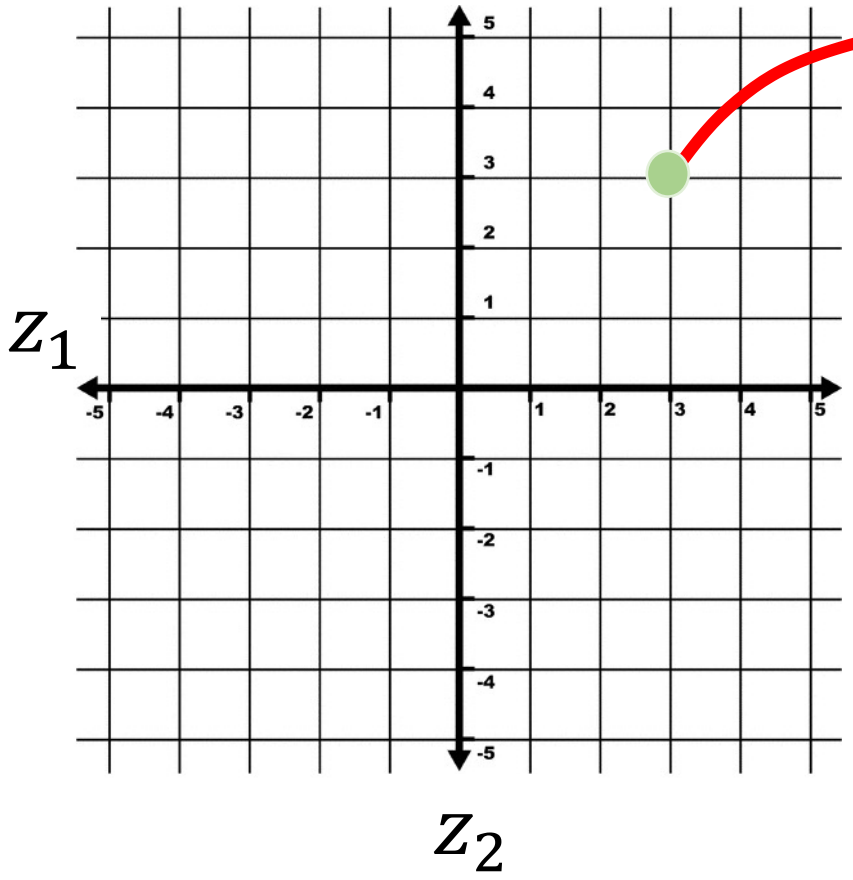


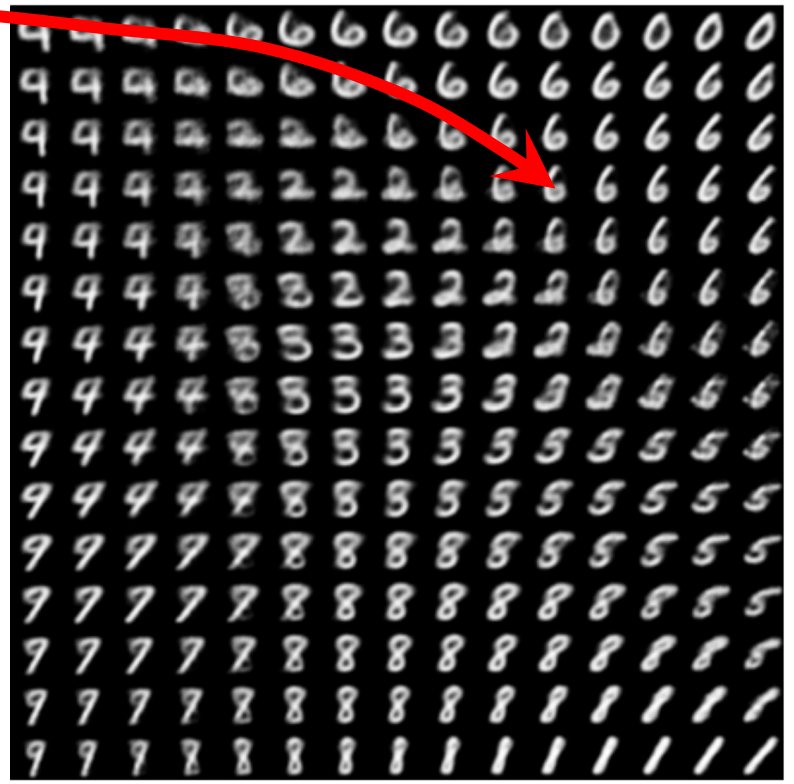
Visualize code vectors

Code vectors

Images

Decoder





Summary

Variational Autoencoder (VAE)

- VAE = AE + probability tricks.
- The decoder network behaves like a continuous function.

Variational Autoencoder (VAE)

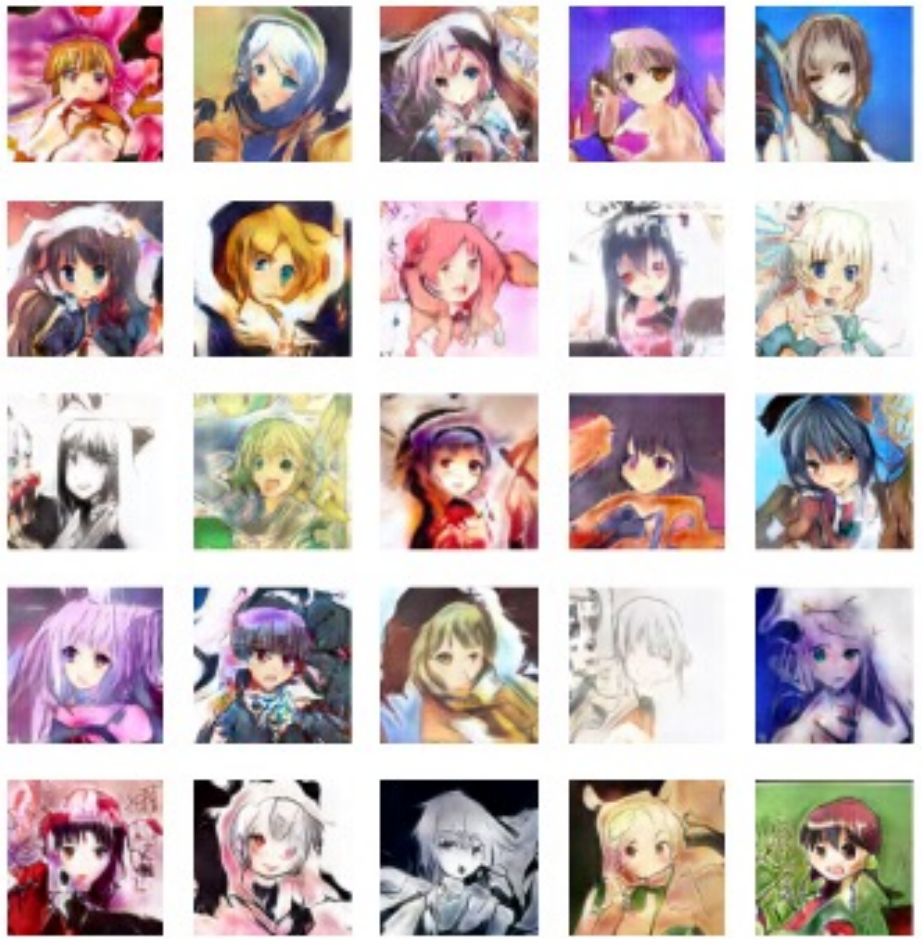
- VAE = AE + probability tricks.
- The decoder network behaves like a continuous function.
- Loss = Generation Loss + $\lambda \cdot$ KL Loss.
- Application: edit images via editing code vectors.
  - Average faces.
  - Add smile.

Generative Adversarial Networks (GANs)

Image Generation

real images for training

generated images



Reference: https://qiita.com/mattya/items/e5bfe5e04b9d2f0bbd47

GAN: Main Idea

- **Generator**: generates fake images to *fool* the discriminator.
- **Discriminator**: tries to *distinguish* between real and fake images.

- Train them against each other.
- Finally, the discriminator cannot distinguish between real and fake.
- It means the fake images look like real.

GAN: Main Idea

- **Generator**: a forger who wants to create a fake Picasso painting.
- **Discriminator**: an art dealer.

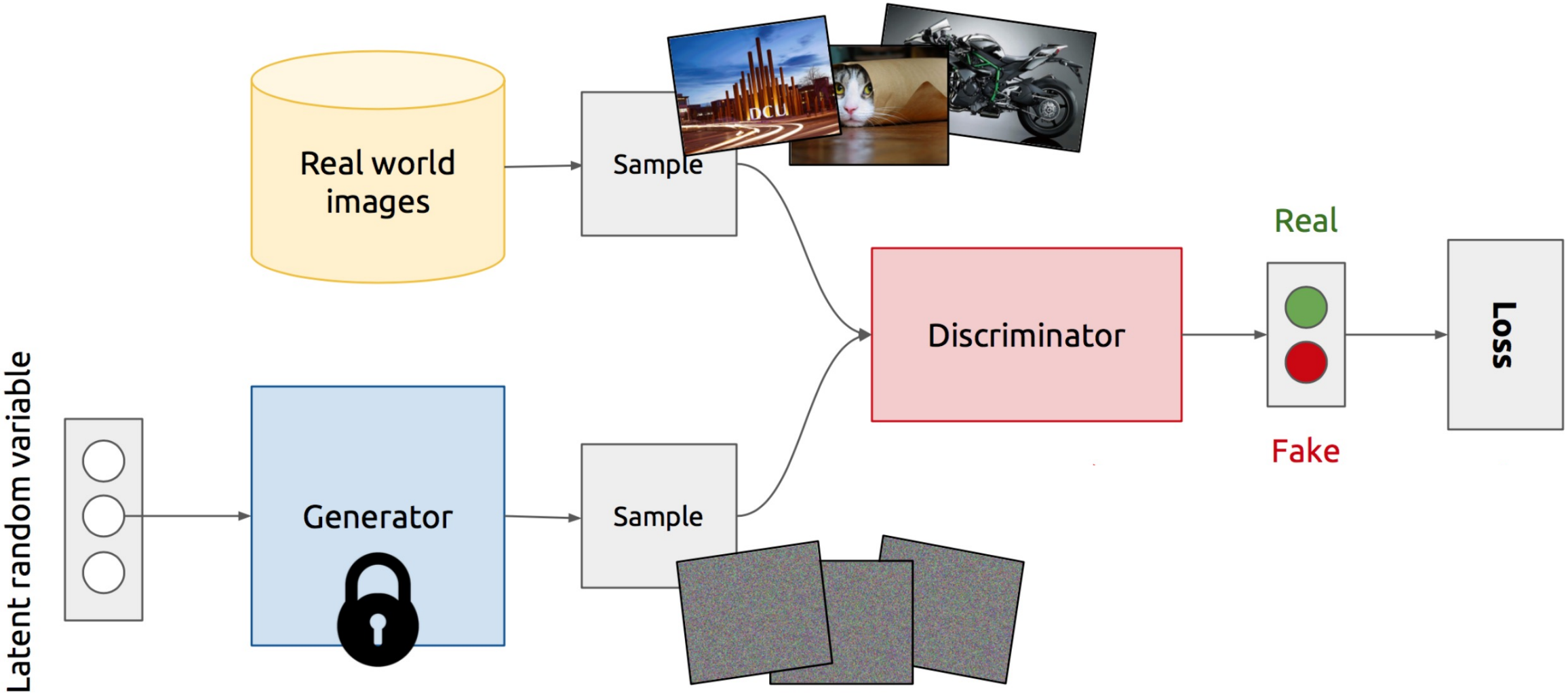
Which is real?

GAN: Main Idea

- **Generator**: a forger who wants to create a fake Picasso painting.
- **Discriminator**: an art dealer.

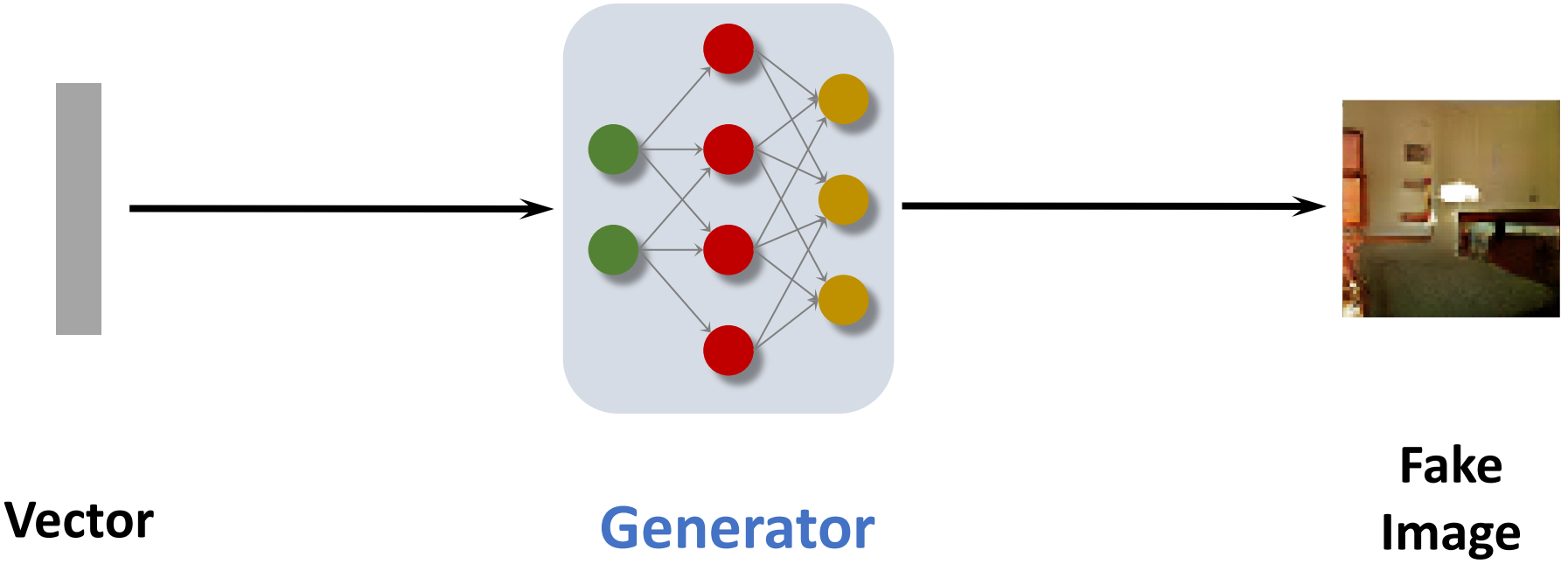
- Train them against each other.
  - Forger mixes his fake with authentic paintings and ask art dealer to assess them.
  - Art dealer gives feedback about what makes a Picasso look like a Picasso.
  - Forger improves his competence at imitating the style of Picasso.
  - Art dealer improves his competence at distinguishing real and fake Picasso.
- Finally, the art dealer cannot distinguish between real and fake.

GAN: Model Overview



Build Generator and Discriminator Networks

Generator: From Vector to Image



Generator: From Vector to Image

```
from keras.layers import Input, Activation, BatchNormalization, Dropout
from keras.layers import Dense, Reshape, UpSampling2D, Conv2DTranspose

depth = 256
dim = 7

input_vec = Input(shape=(100,), name='input_vec')

dense1 = Dense(dim*dim*depth, name='dense1')(input_vec)
bn1 = BatchNormalization(momentum=0.9, name='bn1')(dense1)
act1 = Activation('relu', name='act1')(bn1)
dropout1 = Dropout(rate=0.4, name='dropout1')(act1)
reshape1 = Reshape((dim, dim, depth), name='reshape1')(dropout1)

us2 = UpSampling2D(name='upsampling2')(reshape1)
convt2 = Conv2DTranspose(int(depth/2), 5, padding='same', name='convt2')(us2)
bn2 = BatchNormalization(momentum=0.9, name='bn2')(convt2)
act2 = Activation('relu', name='act2')(bn2)

us3 = UpSampling2D(name='upsampling3')(act2)
convt3 = Conv2DTranspose(int(depth/4), 5, padding='same', name='convt3')(us3)
bn3 = BatchNormalization(momentum=0.9, name='bn3')(convt3)
act3 = Activation('relu', name='act3')(bn3)

convt4 = Conv2DTranspose(int(depth/8), 5, padding='same', name='convt4')(act3)
bn4 = BatchNormalization(momentum=0.9, name='bn4')(convt4)
act4 = Activation('relu', name='act4')(bn4)

convt5 = Conv2DTranspose(1, 5, padding='same', activation='sigmoid', name='convt5')(act4)
```

Block 1:
from 100-dim to 7×7×256

Block 2:
from 7×7×256 to 14×14×128

Block 3:
From 14×14×128 to 28×28×64

Block 4:
From 28×28×64 to 28×28×32

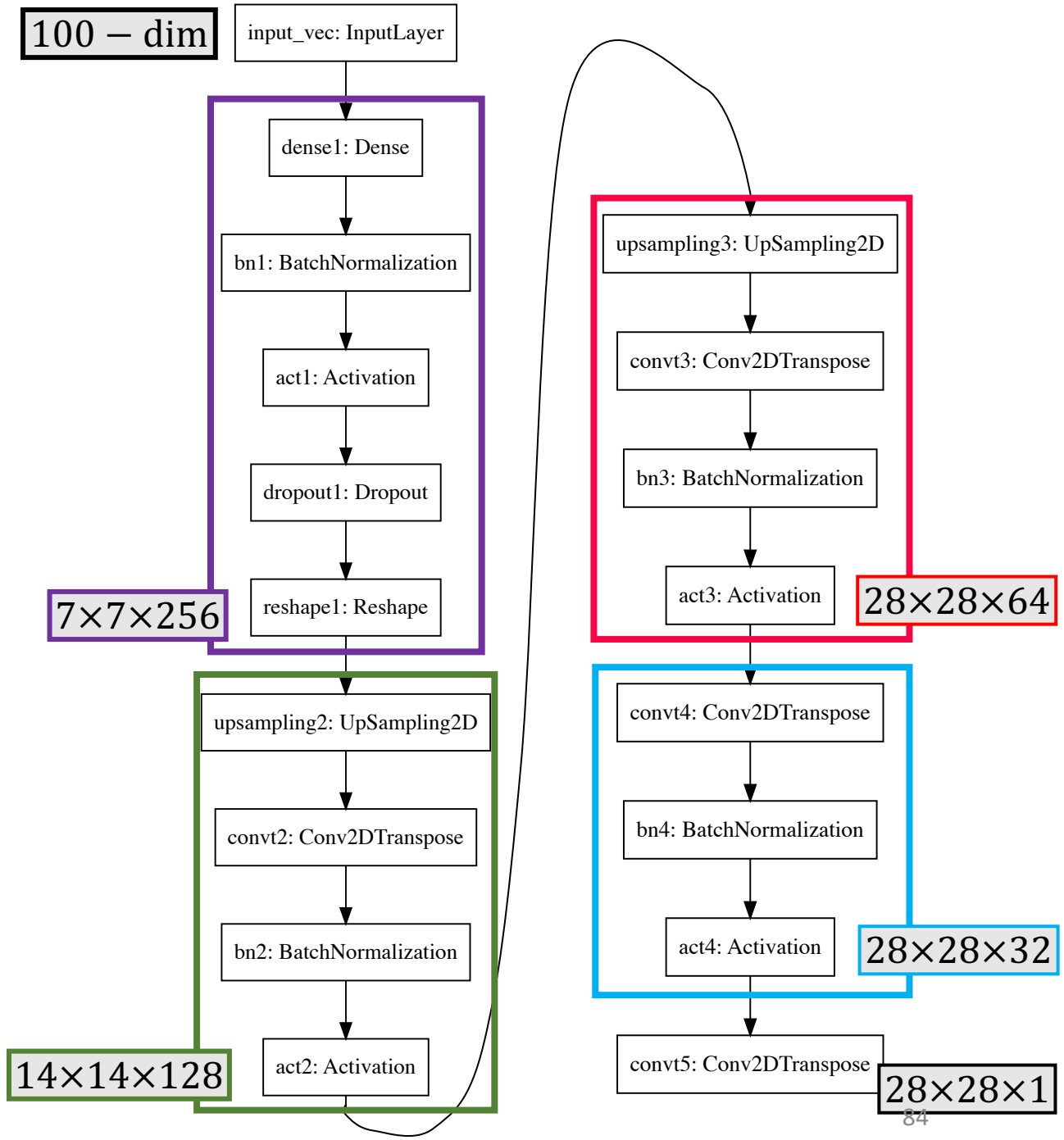
Generator: From Vector to Image

```
from keras.models import Model

generator = Model(inputs=input_vec, outputs=convt5, name='generator')
```

Layer (type)	Output Shape	Param #
input_vec (InputLayer)	(None, 100)	0
dense1 (Dense)	(None, 12544)	1266944
bn1 (BatchNormalization)	(None, 12544)	50176
act1 (Activation)	(None, 12544)	0
dropout1 (Dropout)	(None, 12544)	0
reshape1 (Reshape)	(None, 7, 7, 256)	0
upsampling2 (UpSampling2D)	(None, 14, 14, 256)	0
convt2 (Conv2DTranspose)	(None, 14, 14, 128)	819328
bn2 (BatchNormalization)	(None, 14, 14, 128)	512
act2 (Activation)	(None, 14, 14, 128)	0
upsampling3 (UpSampling2D)	(None, 28, 28, 128)	0
convt3 (Conv2DTranspose)	(None, 28, 28, 64)	204864
bn3 (BatchNormalization)	(None, 28, 28, 64)	256
act3 (Activation)	(None, 28, 28, 64)	0
convt4 (Conv2DTranspose)	(None, 28, 28, 32)	51232
bn4 (BatchNormalization)	(None, 28, 28, 32)	128
act4 (Activation)	(None, 28, 28, 32)	0
convt5 (Conv2DTranspose)	(None, 28, 28, 1)	801

Total params: 2,394,241
Trainable params: 2,368,705
Non-trainable params: 25,536



Discriminator: From Image to Binary

```
from keras.layers import Input, LeakyReLU, Dropout
from keras.layers import Dense, Flatten, Conv2D

depth = 64

input_img = Input(shape=(28, 28, 1), name='input_img')

conv1 = Conv2D(depth, 5, strides=2, padding='same', name='conv1')(input_img)
act1 = LeakyReLU(alpha=0.2, name='act1')(conv1)
dropout1 = Dropout(0.4, name='dropout1')(act1)

conv2 = Conv2D(depth*2, 5, strides=2, padding='same', name='conv2')(dropout1)
act2 = LeakyReLU(alpha=0.2, name='act2')(conv2)
dropout2 = Dropout(0.4, name='dropout2')(act2)

conv3 = Conv2D(depth*4, 5, strides=2, padding='same', name='conv3')(dropout2)
act3 = LeakyReLU(alpha=0.2, name='act3')(conv3)
dropout3 = Dropout(0.4, name='dropout3')(act3)

conv4 = Conv2D(depth*8, 5, strides=1, padding='same', name='conv4')(dropout3)
act4 = LeakyReLU(alpha=0.2, name='act4')(conv4)
dropout4 = Dropout(0.4, name='dropout4')(act4)

flat5 = Flatten(name='flat5')(dropout4)
dense5 = Dense(1, activation='sigmoid', name='dense5')(flat5)
```

Block 1:
from $28\times28\times1$ to $14\times14\times64$

Block 2:
from $14\times14\times64$ to $7\times7\times128$

Block 3:
From $7\times7\times128$ to $4\times4\times256$

Block 4:
From $4\times4\times256$ to $4\times4\times512$

Discriminator: From Image to Binary

```
from keras.models import Model

discriminator = Model(inputs=input_img, outputs=dense5, name='discriminator')
```

Training

Training of GAN

Alternating minimization

Repeat the 2 steps:

1. Update the discriminator network;
2. Update the generator network.

Update the Discriminator

Train a classifier

1. Generate a batch of fake images by the generator;
2. Randomly sample a batch of real images;
3. Inputs: $\mathbf{X} = [\text{real\_images}, \text{fake\_images}]$;
4. Targets: $\mathbf{y} = [\text{True}, \cdots, \text{True}, \text{False}, \cdots, \text{False}]$;
5. Update the discriminator network using $\mathbf{X}$ and $\mathbf{y}$.

Update the Discriminator

```
from keras.optimizers import RMSprop

optimizer = RMSprop(lr=0.0002, decay=6e-8)
discriminator.compile(loss='binary_crossentropy',
                      optimizer=optimizer,
                      metrics=['accuracy'])
```

Update the Discriminator

Uniformly sample a batch of real images

```
# train the discriminator
discriminator.trainable = True
rand_idx = np.random.randint(0, n, size=batch_size)
images_real = x_train[rand_idx]
latent_vecs = np.random.uniform(-1.0, 1.0, size=[batch_size, 100])
images_fake = generator.predict(latent_vecs)
x = np.concatenate((images_real, images_fake), axis=0)
y = np.concatenate([np.ones((batch_size, 1)),
                    np.zeros((batch_size, 1))])
d_loss = discriminator.train_on_batch(x, y)
```

Update the Discriminator

```
# train the discriminator
discriminator.trainable = True
rand_idx = np.random.randint(0, n, size=batch_size)
images_real = x_train[rand_idx]
latent_vecs = np.random.uniform(-1.0, 1.0, size=[batch_size, 100])
images_fake = generator.predict(latent_vecs)
x = np.concatenate((images_real, images_fake), axis=0)
y = np.concatenate([np.ones((batch_size, 1)),
                    np.zeros((batch_size, 1))])
d_loss = discriminator.train_on_batch(x, y)
```

Generate fake images

Update the Discriminator

```
# train the discriminator
discriminator.trainable = True
rand_idx = np.random.randint(0, n, size=batch_size)
images_real = x_train[rand_idx]
latent_vecs = np.random.uniform(-1.0, 1.0, size=[batch_size, 100])
images_fake = generator.predict(latent_vecs)
x = np.concatenate((images_real, images_fake), axis=0)
y = np.concatenate([np.ones((batch_size, 1)),
                    np.zeros((batch_size, 1))])
d_loss = discriminator.train_on_batch(x, y)
```

Set input and targets

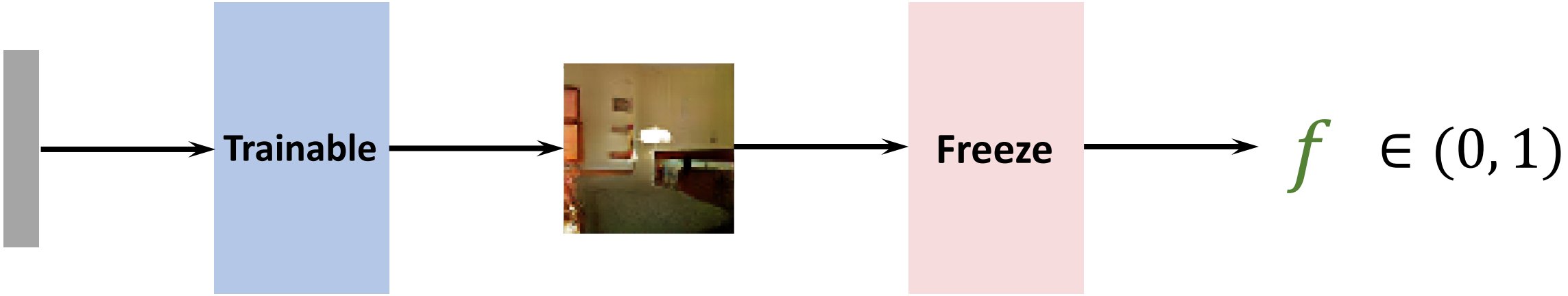
Update the Discriminator

```
# train the discriminator
discriminator.trainable = True
rand_idx = np.random.randint(0, n, size=batch_size)
images_real = x_train[rand_idx]
latent_vecs = np.random.uniform(-1.0, 1.0, size=[batch_size, 100])
images_fake = generator.predict(latent_vecs)
x = np.concatenate((images_real, images_fake), axis=0)
y = np.concatenate([np.ones((batch_size, 1)),
                    np.zeros((batch_size, 1))])
d_loss = discriminator.train_on_batch(x, y)
```

One update of the discriminator's parameters

Update the Generator

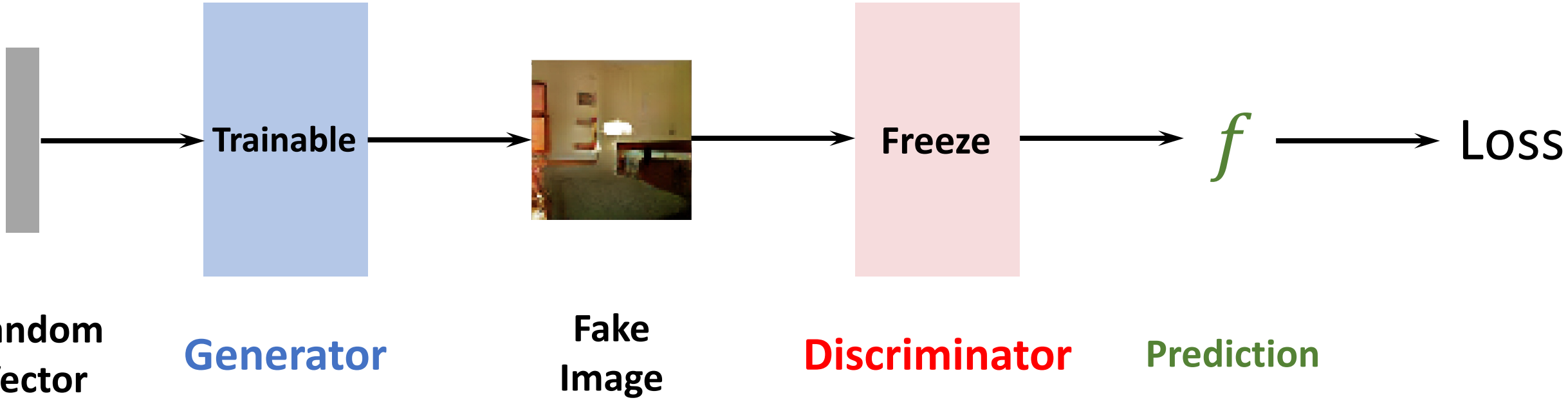
Connect the generator and discriminator (freeze discriminator's parameters).



Update the Generator

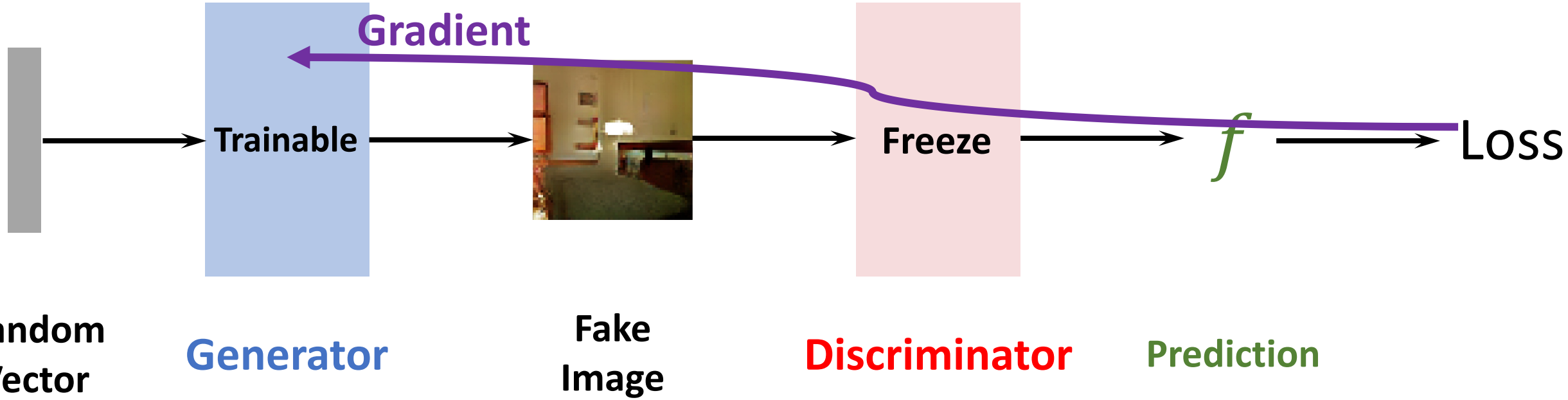
Connect the generator and discriminator (freeze discriminator's parameters).

Minimize $\text{Loss} = \text{Dist}(\text{True}, f)$ w.r.t. generator. (Encourage f be **True.**)



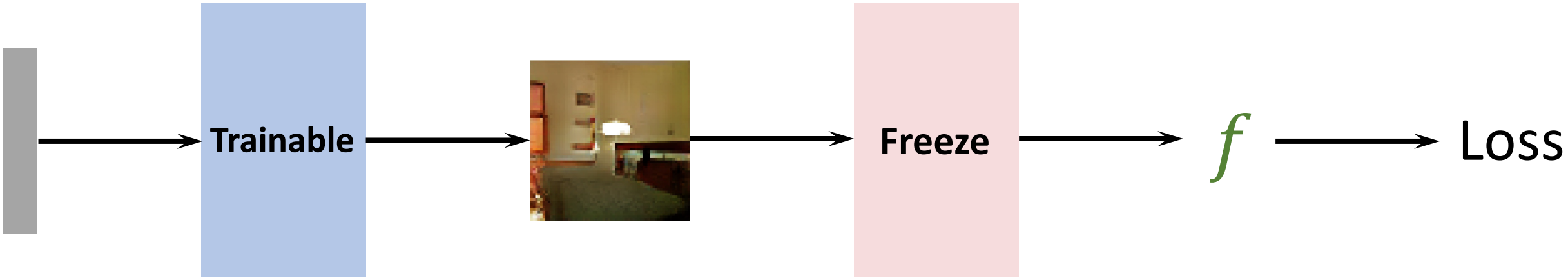
Update the Generator

- $\mathbf{W_G}$: parameters in the generator.
- Gradient: $\text{Grad} = \frac{\partial\ \text{Loss}}{\partial\ \mathbf{W_G}}$.



Update the Generator

- $\mathbf{W}_{\mathrm{G}}$: parameters in the generator.
- Gradient: $\mathrm{Grad} = \frac{\partial\ \mathrm{Loss}}{\partial\ \mathbf{W}_{\mathrm{G}}}$.
- Gradient descent: $\mathbf{W}_{\mathrm{G}} \leftarrow \mathbf{W}_{\mathrm{G}} - \alpha \cdot \mathrm{Grad}$.



Update the Generator

Question: What will happen if we do the followings? (We don't actually do.)

- Use the same **vector**.
- Generate a fake image using the updated generator.

Random Vector

Generator (updated)

Fake Image (new)

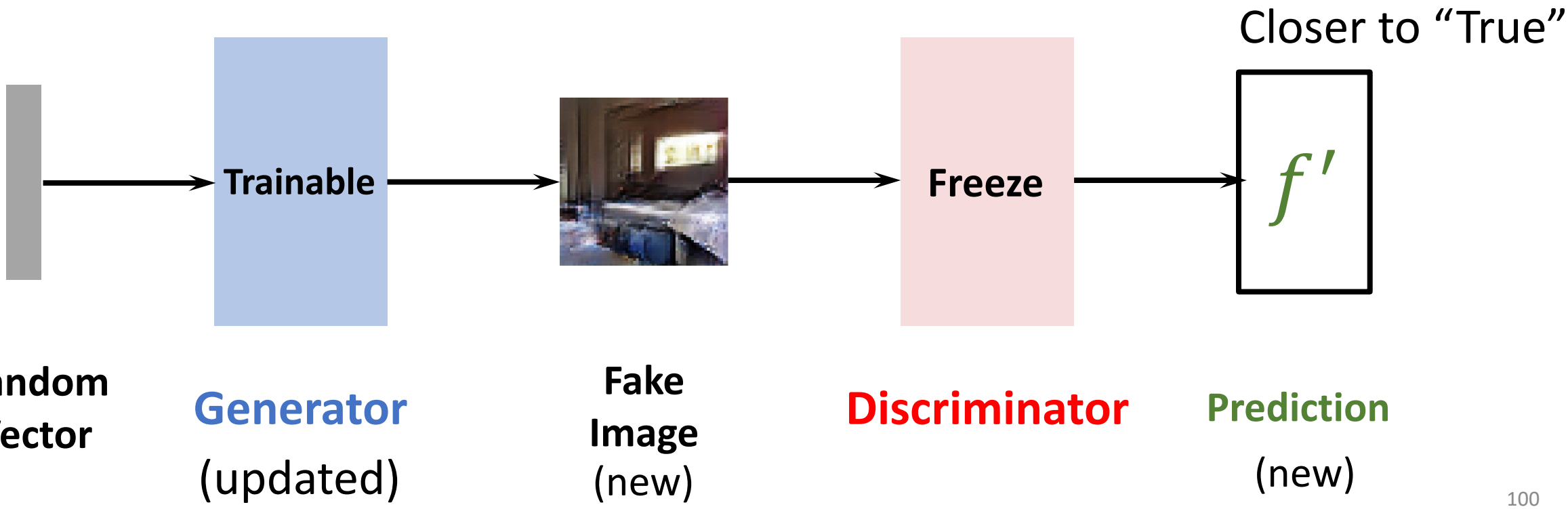
Discriminator

Prediction (new)

Update the Generator

Question: What will happen if we do the followings? (We don't actually do.)

- Use the same **vector**.
- Generate a fake image using the updated generator.
- The discriminator thinks the new fake image more "real" than before.



Update the Generator

Connect the generator and discriminator (freeze discriminator's parameters).

```
from keras.layers import Input
from keras.models import Model

discriminator.trainable = False
gan_input = Input(shape=(100,), name='gan_input')
fake_img = generator(gan_input)
f = discriminator(fake_img)
gan = Model(inputs=gan_input, outputs=f, name='gan')
```

Update the Generator

Connect the generator and discriminator (freeze discriminator's parameters).

Minimize $\text{Loss} = \text{Dist}(\text{True}, f)$ w.r.t. generator. (Encourage f be **True.**)

```
from keras.optimizers import RMSprop

gan_optimizer = RMSprop(lr=0.0001, decay=3e-8)
gan.compile(optimizer=gan_optimizer,
            loss='binary_crossentropy',
            metrics=['accuracy'])
```

Update the Generator

Connect the generator and discriminator (freeze discriminator's parameters).

Minimize $\text{Loss} = \text{Dist}(\text{True}, f)$ w.r.t. generator. (Encourage f be **True.**)

```
# train the generator
discriminator.trainable = False
fake_targets = np.ones([batch_size, 1]) # pretend the images are real
latent_vecs = np.random.uniform(-1.0, 1.0, size=[batch_size, 100])
a_loss = gan.train_on_batch(latent_vecs, fake_targets)
```

$\text{Loss} = \text{Dist}(\text{True}, f)$

Random vectors

All true

Summary of Training

```
for t in range(train_steps):
    # train the discriminator
    discriminator.trainable = True
    rand_idx = np.random.randint(0, n, size=batch_size)
    images_real = x_train[rand_idx]
    latent_vecs = np.random.uniform(-1.0, 1.0, size=[batch_size, 100])
    images_fake = generator.predict(latent_vecs)
    x = np.concatenate((images_real, images_fake), axis=0)
    y = np.concatenate([np.ones((batch_size, 1)),
                        np.zeros((batch_size, 1))])
    d_loss = discriminator.train_on_batch(x, y)

    # train the generator
    discriminator.trainable = False
    fake_targets = np.ones([batch_size, 1]) # pretend the images are real
    latent_vecs = np.random.uniform(-1.0, 1.0, size=[batch_size, 100])
    a_loss = gan.train_on_batch(latent_vecs, fake_targets)
```

Difficulties in Training GAN

Discriminator Shouldn't Be Too Good

- **Generator**: a forger who wants to create a fake Picasso painting.
- **Discriminator**: an art dealer providing feedbacks.

What if the art dealer is 100% correct at judging Picasso painting?

Discriminator Shouldn't Be Too Good

- **Generator**: a forger who wants to create a fake Picasso painting.
- **Discriminator**: an art dealer providing feedbacks.

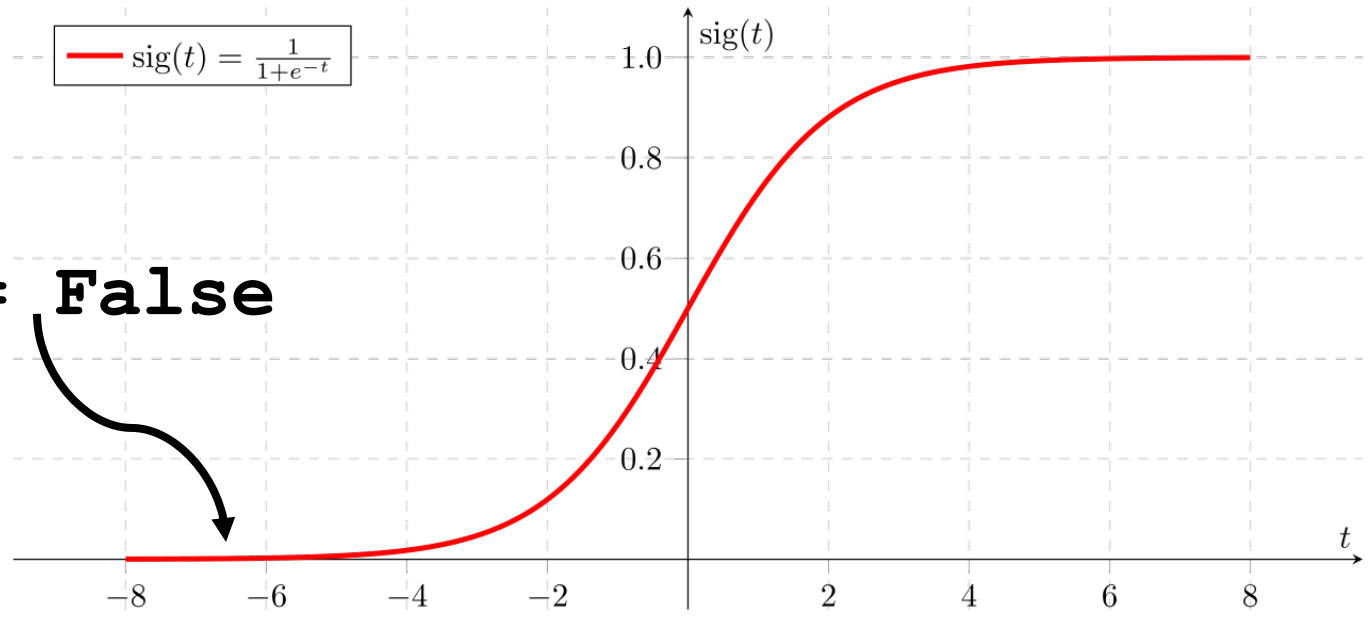
What if the art dealer is 100% correct at judging Picasso painting?

- Whatever forged painting sent to the art dealer is recognized as fake.
- The forger cannot learn anything from the *feedback*.
  - No positive case to follow.
- The forger need some success.
  - So he will know what kind of fake painting can fool the dealer.

Discriminator Shouldn't Be Too Good

Explanation: vanishing gradient

- Suppose the discriminator is perfect.
- Whatever the generators forged is recognized fake by the discriminator.
- ➔ The gradient is near zero.




```
Prediction = False
```

Discriminator Shouldn't Be Too Bad

- **Generator**: a forger who wants to create a fake Picasso painting.
- **Discriminator**: an art dealer providing feedbacks.

What if the art dealer cannot distinguish between real and fake paintings?

- The art dealer's judgement is almost *random guess*.
- The forger cannot learn anything from the *feedback*.
- ➔ When the forger's skill is good, getting amateurish art dealer's feedback is a not helpful.

Useful Tricks

1. Carefully tune the learning rates.

- If the discriminator improves too fast,
  - ➔ classification accuracy can be 100%,
  - ➔ vanishing gradient,
  - ➔ the generator is dead.

- If the discriminator improves too slowly,
  - ➔ the discriminator cannot provide useful feedback,
  - ➔ the generator has to wait for the discriminator,
  - ➔ slow convergence.

Useful Tricks

2. Add noise to the real and fake images; decay the noise over time.

- When training the discriminator, perturb the inputs (both real and fake images).

Useful Tricks

2. Add noise to the real and fake images; decay the noise over time.

- When training the discriminator, perturb the inputs (both real and fake images).

3. Add noise to the labels.

- When training the discriminator, perturb the labels (both real and fake images).
- `Real = 1` → `Real ~ Uniform(0.7, 1.2).`
- `Fake = 0` → `Fake ~ Uniform(0.0, 0.3).`

Useful Tricks

Many other tricks…

- Further reading:
- https://github.com/soumith/ganhacks

Thank you!