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Regione Emilia-Romagna



ER
Educazione
Ricerca
Emilia-Romagna

DATA LAB

GUARDA AVANTI

Big Data, nuove competenze
per nuove professioni.



UNIMORE
UNIVERSITÀ DEGLI STUDI DI
MODENA E REGGIO EMILIA



ALMA MATER STUDIORUM
UNIVERSITÀ DI BOLOGNA



Università
degli Studi
di Ferrara



UNIVERSITÀ
DI PARMA



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MILANO 1863
POLIGLIU TERRITORIALE DI
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UNIVERSITÀ
CATTOLICA
del Sacro Cuore

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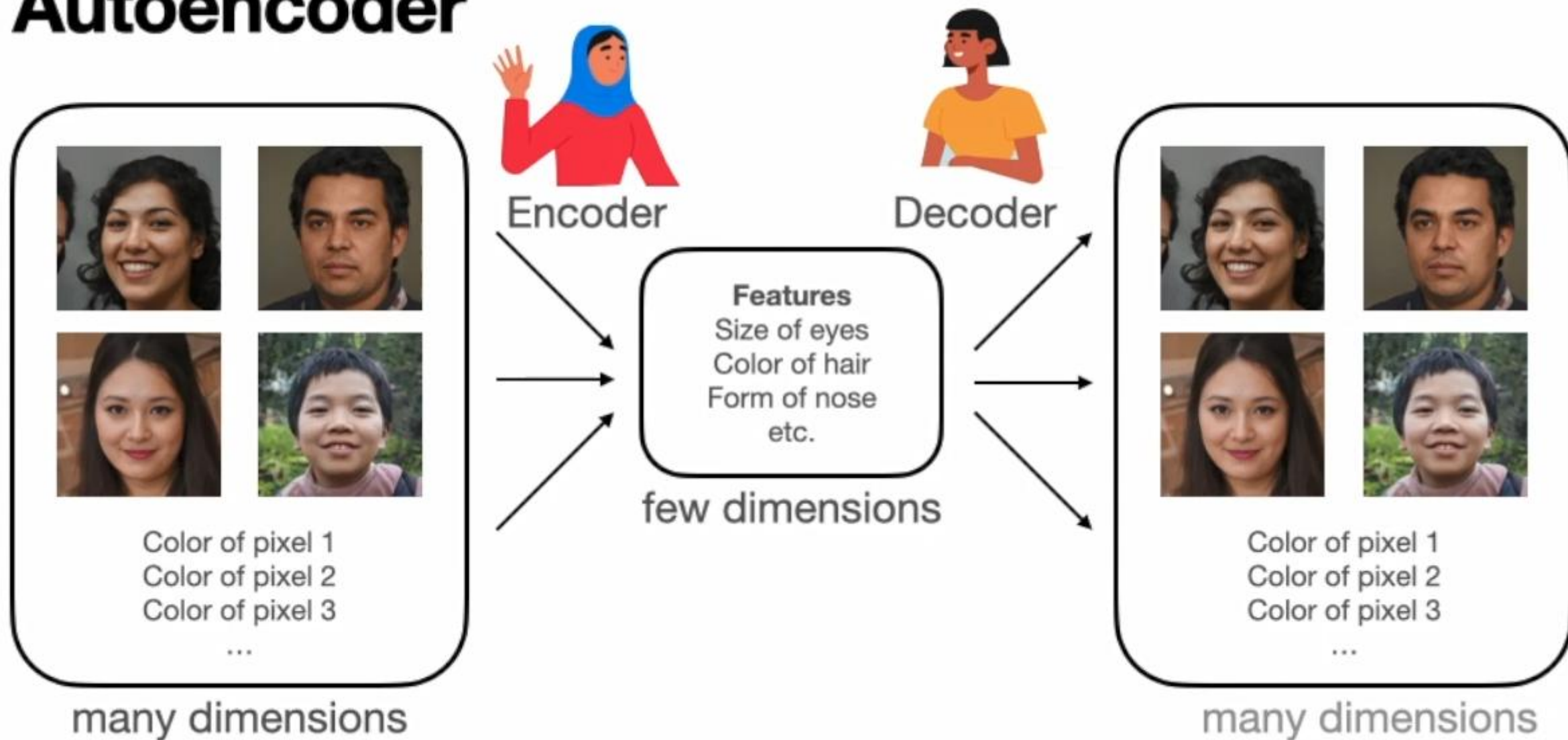
Deep Learning



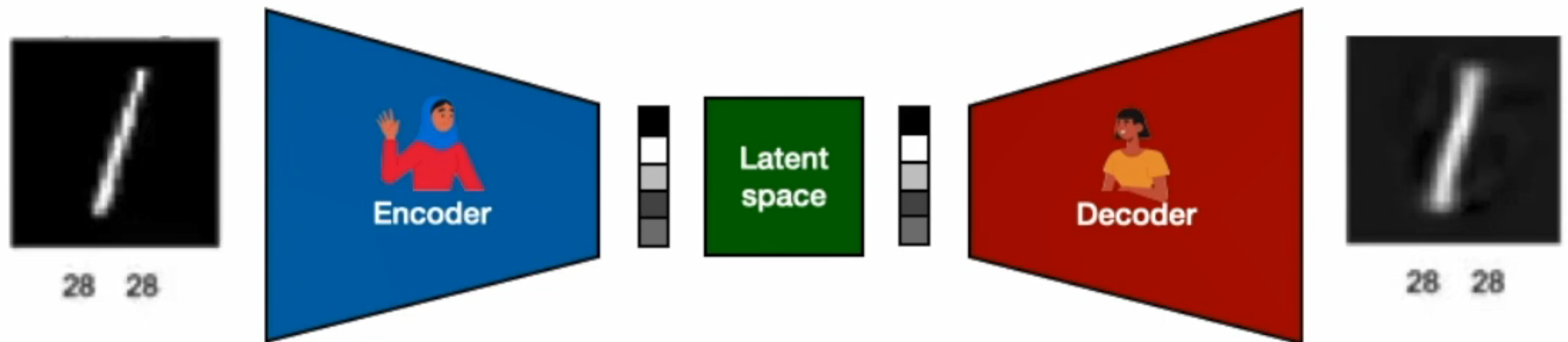
AUTOENCODER

VARIATIONAL AUTO ENCODER

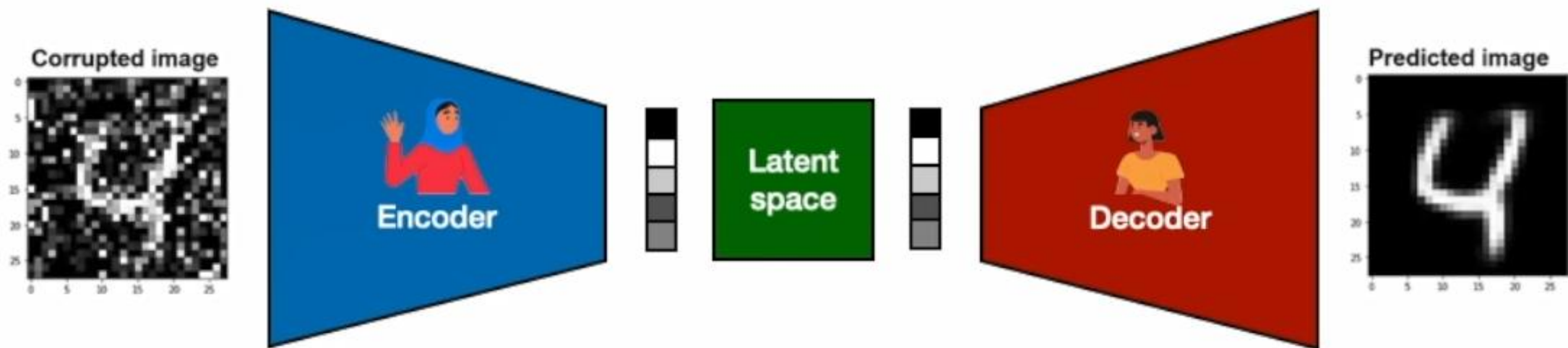
Autoencoder



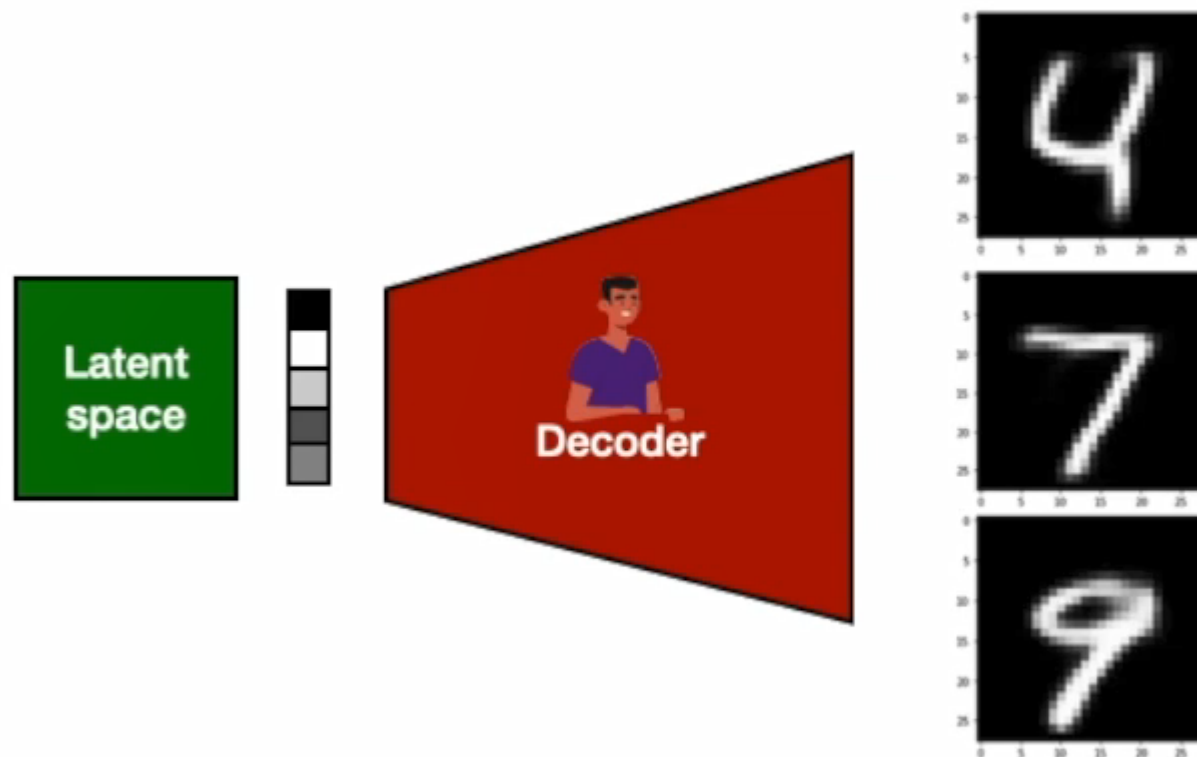
Autoencoders



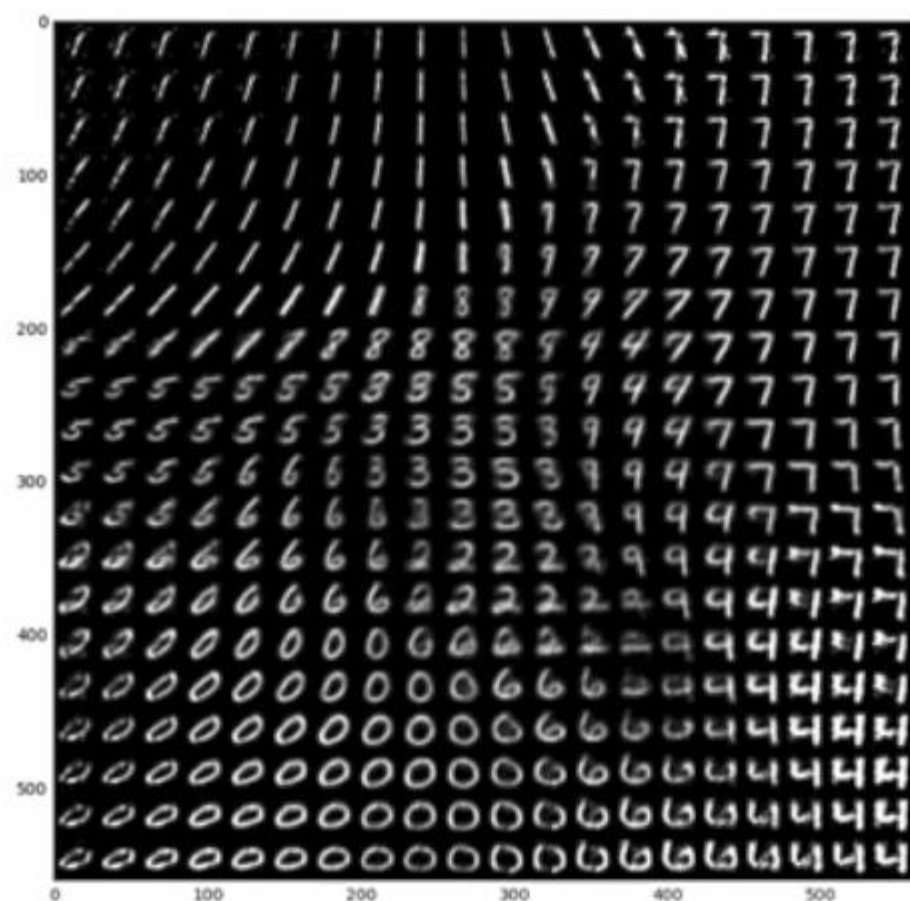
Denoising autoencoders



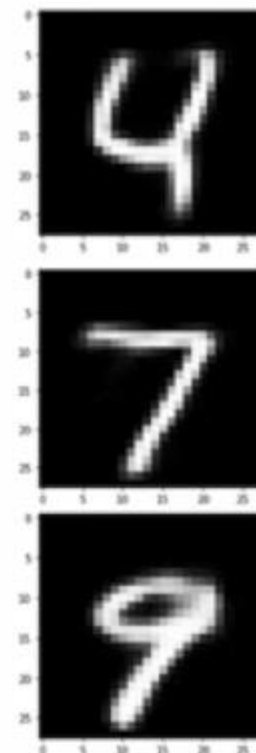
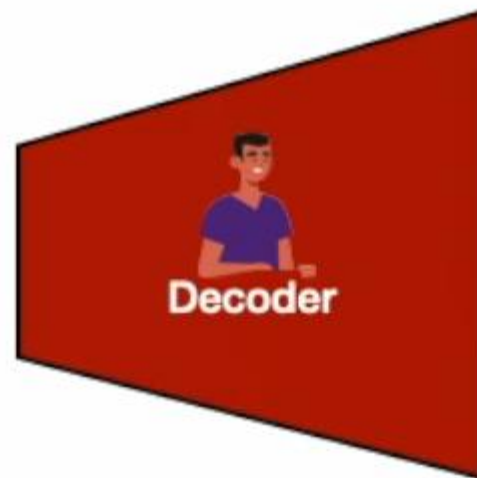
Variational autoencoders



Latent space



Latent
space

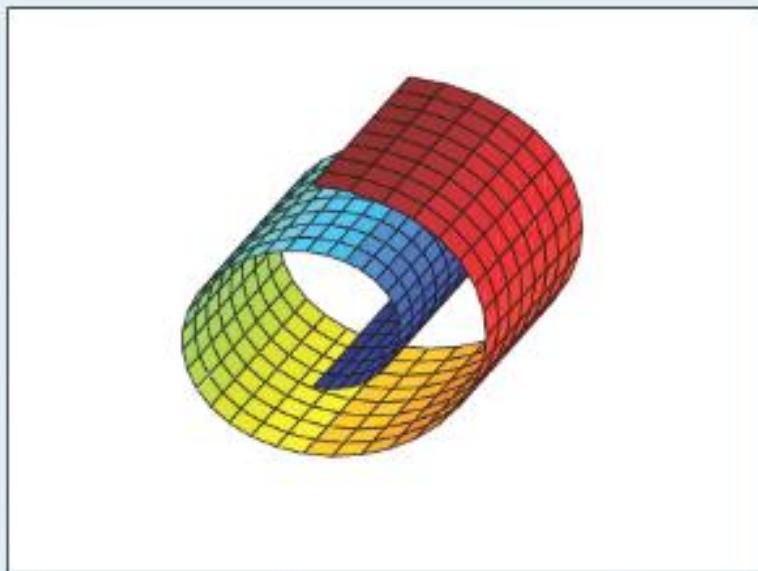


Images generated by a VAE

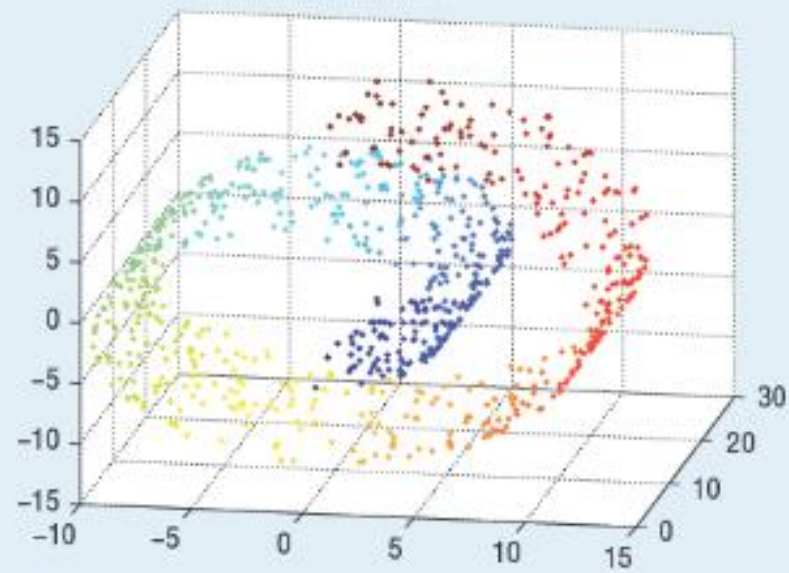


Source: Tom White

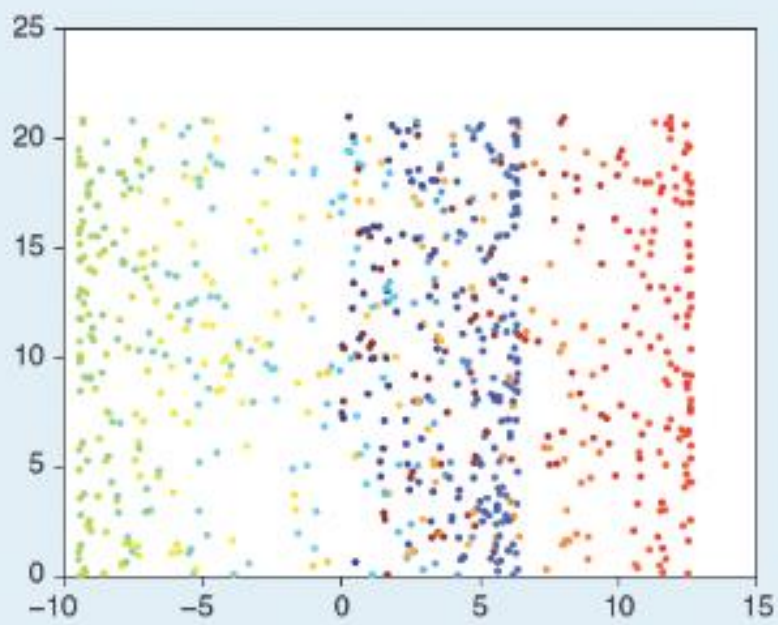
Dimensionality reduction



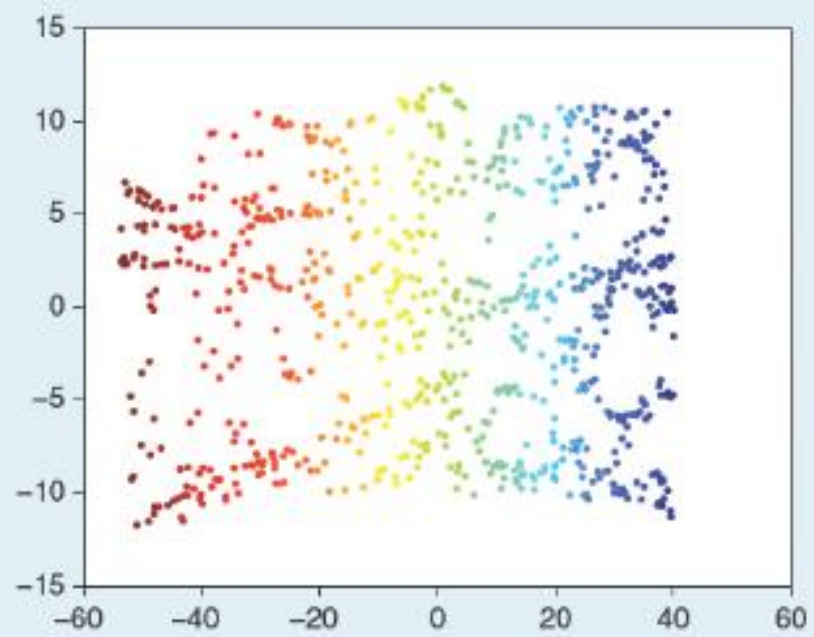
(a)



(b)



(c)



(d)

Dataset of images

4-dimensional



0.5	0.7
0.35	0.65



Dataset of images

0.8	0.45
0.45	0.8

0.1	0.7
0.7	0.1

0.3	0.9
0.9	0.3

0.5	0.5
0.5	0.5

0.48	0.97
0.97	0.48

0.95	0.04
0.04	0.95

2-dimensional

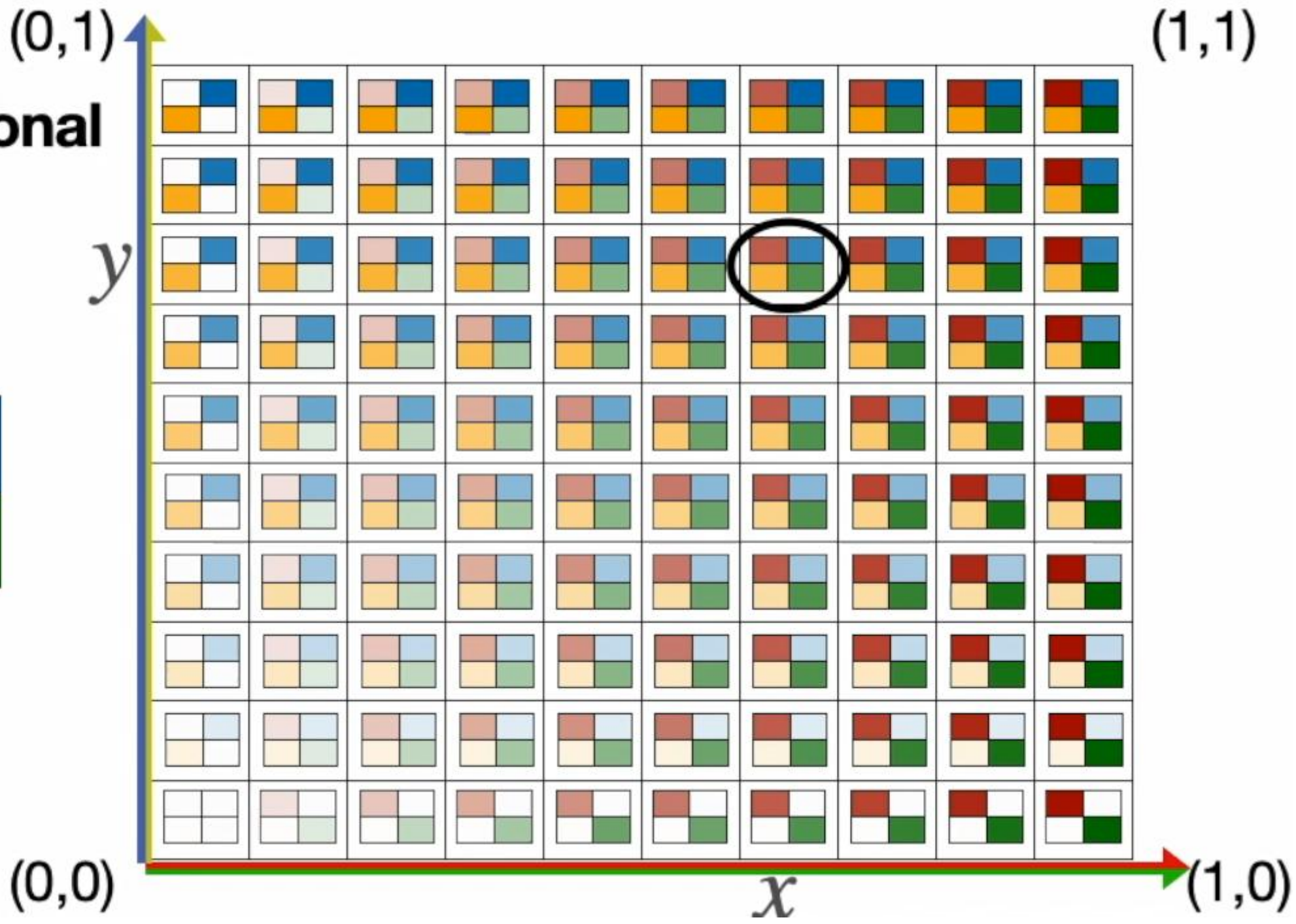
0.8



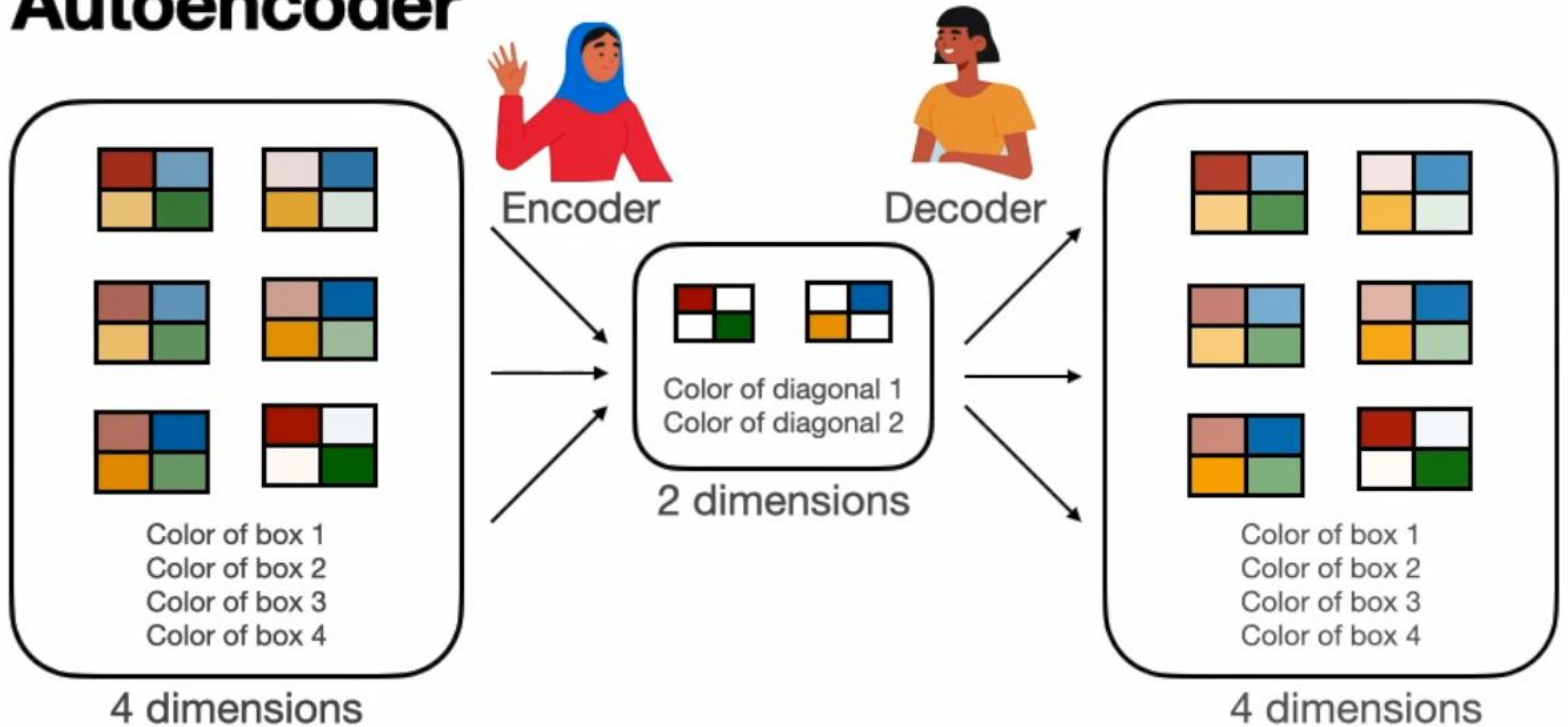
0.65



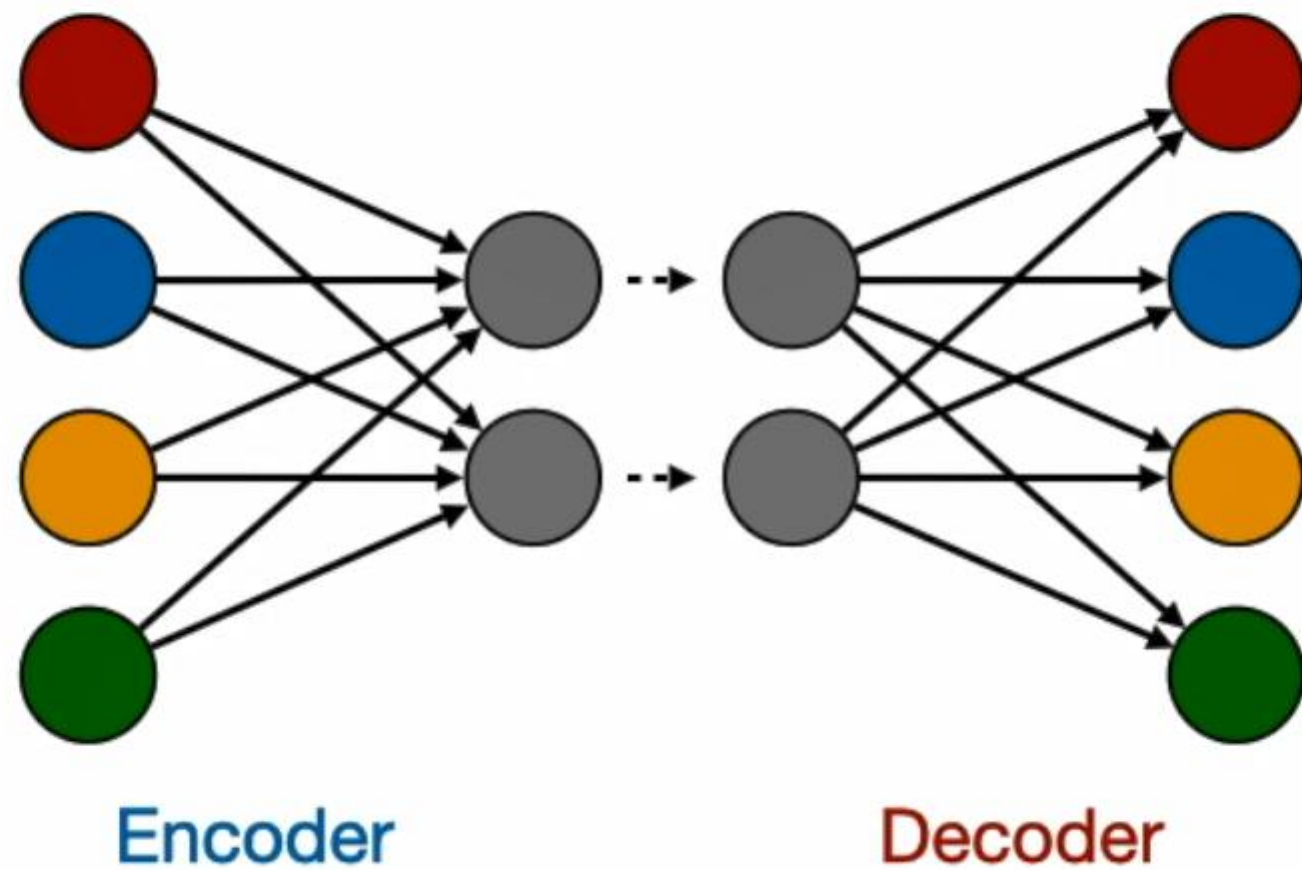
**2-dimensional
dataset**



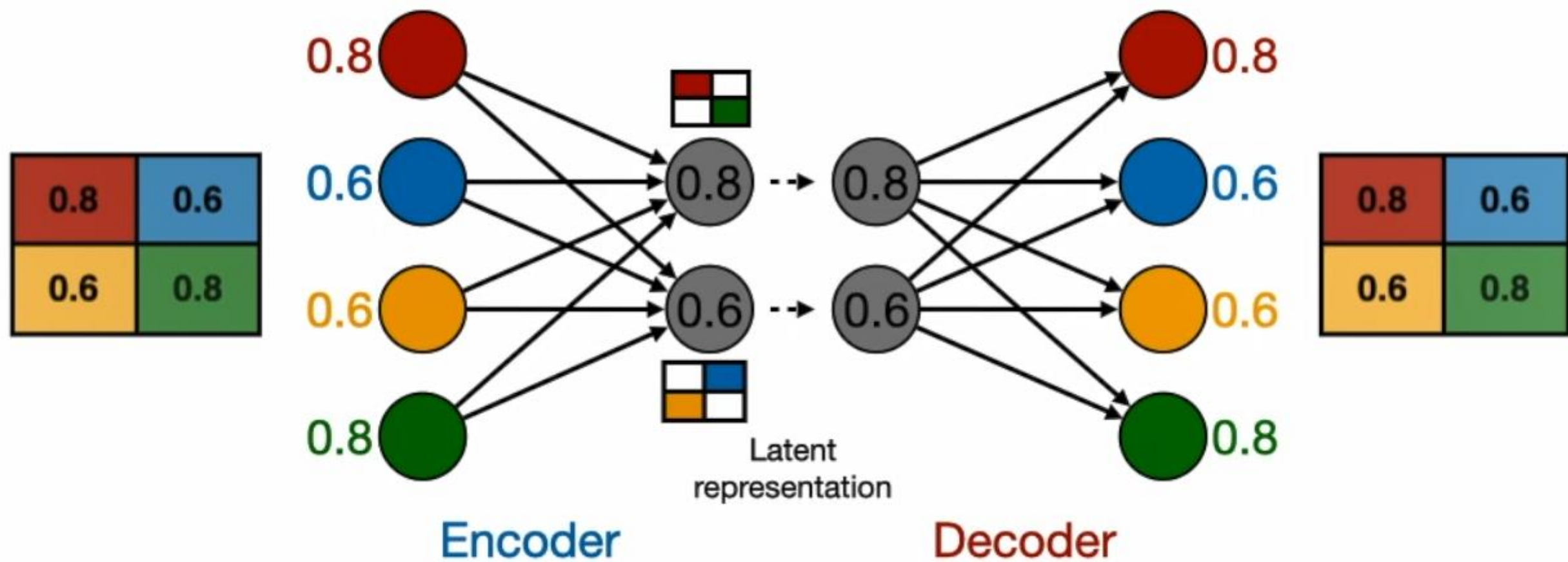
Autoencoder



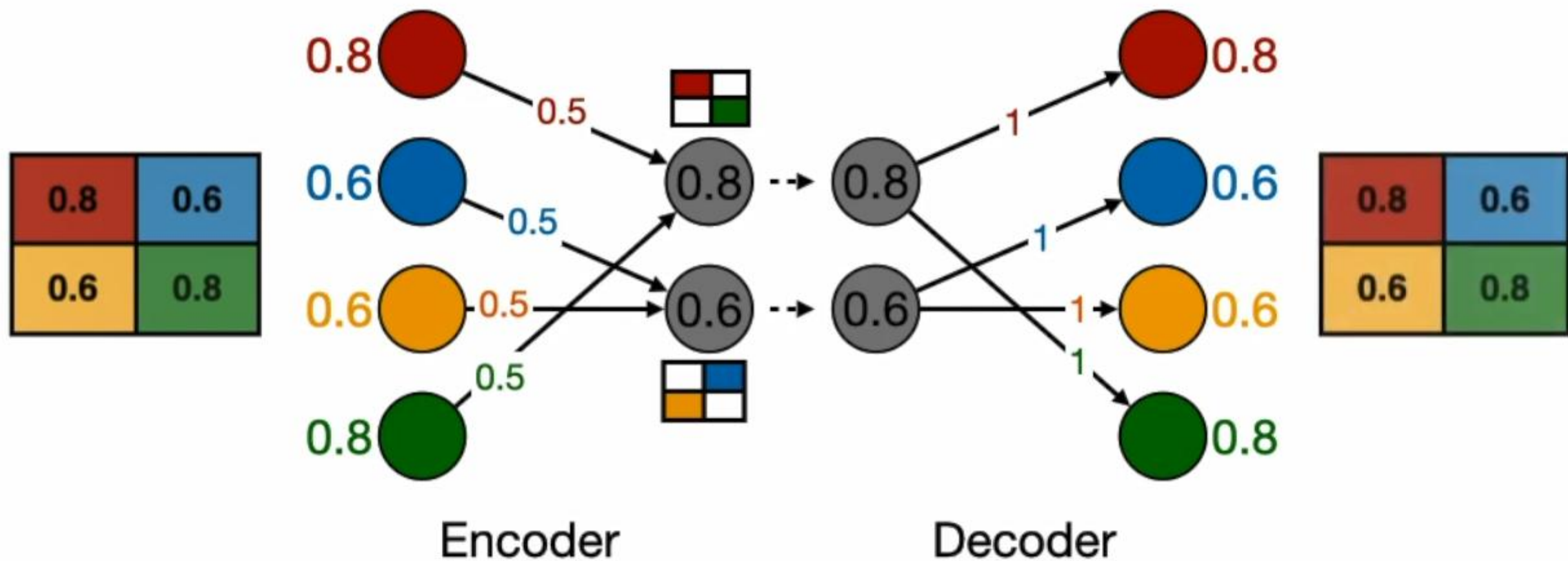
Autoencoder



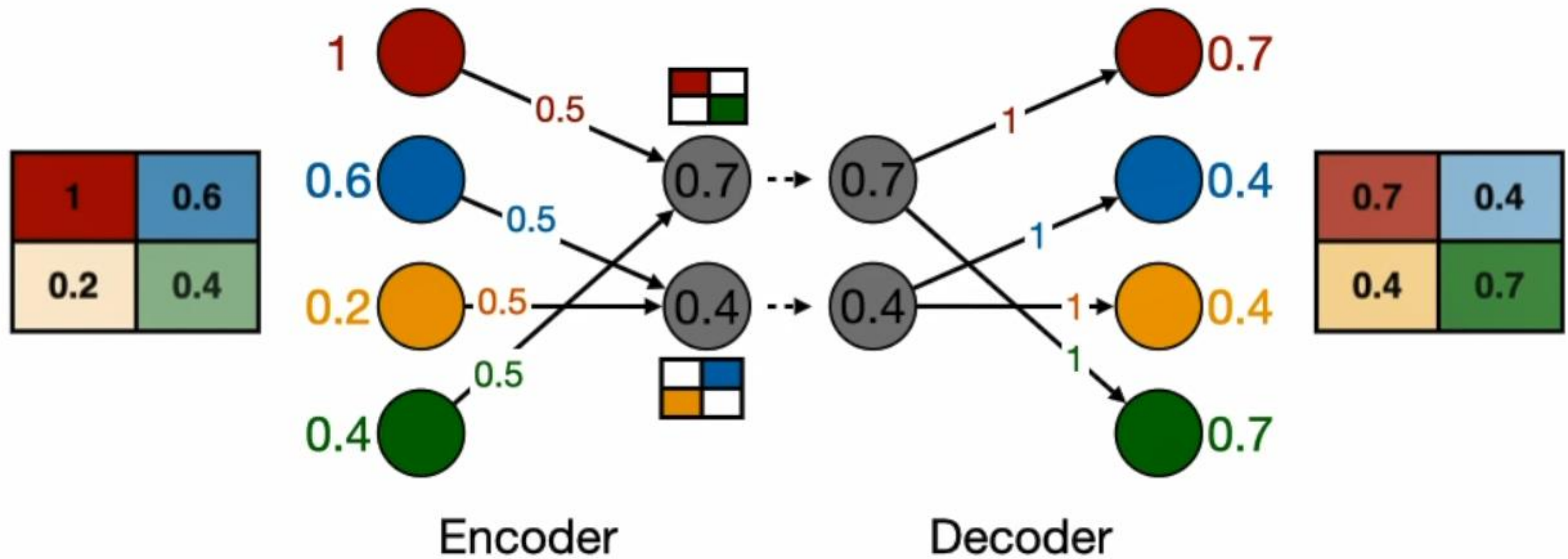
Autoencoder



Autoencoder



Denoising autoencoder



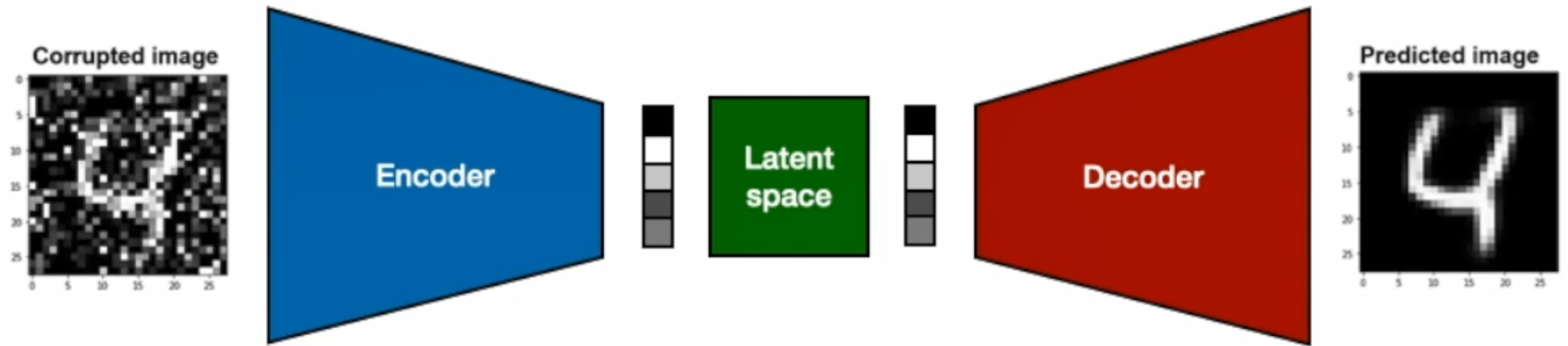
Correct noise

1	0.6
0.2	0.4

Denoise
----->

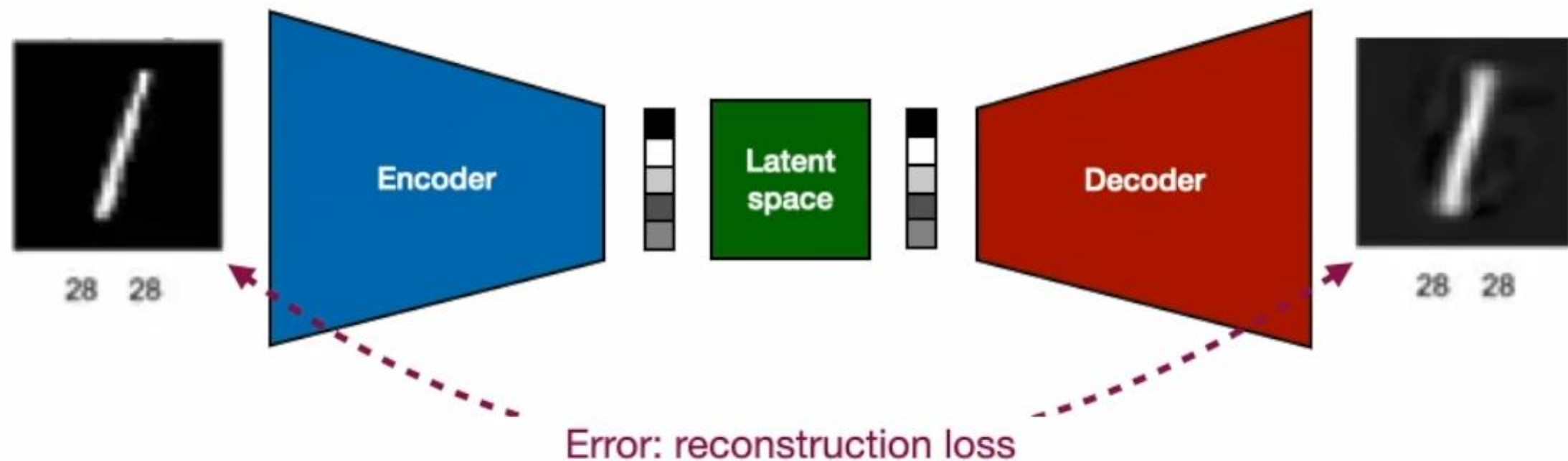
0.7	0.4
0.4	0.7

Denoising autoencoders



Training autoencoders

Initialize encoder and decoder
with random weights



Do backpropagation
and update weights

Reconstruction loss (Mean squared error)

x

0.6	0.4
0.4	0.6

y

0.65	0.42
0.36	0.59

$$MSE(x, y) = \sum_i (x_i - y_i)^2$$

$$(0.6 - 0.65)^2 + (0.4 - 0.42)^2 + (0.4 - 0.36)^2 + (0.6 - 0.59)^2 \\ = 0.0046$$

x

0.6	0.4
0.4	0.6

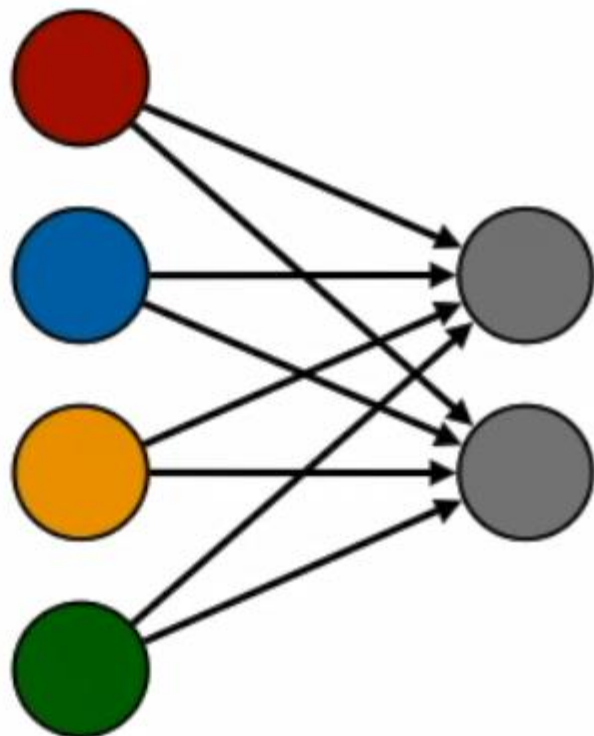
y

0.1	0.9
0.85	0.2

$$(0.6 - 0.1)^2 + (0.4 - 0.9)^2 + (0.4 - 0.85)^2 + (0.6 - 0.2)^2 \\ = 0.8625$$

Training an variational autoencoder

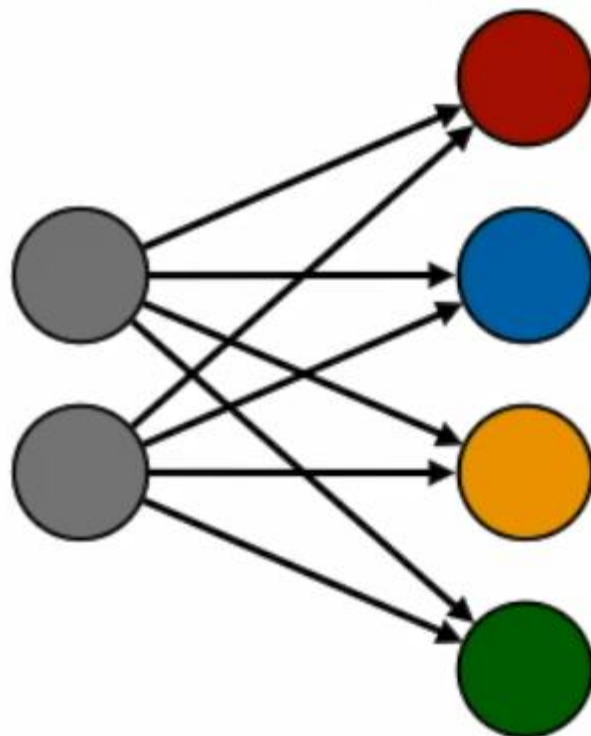
Encoder



0.8	0.4
0.4	0.8

σ
 σ

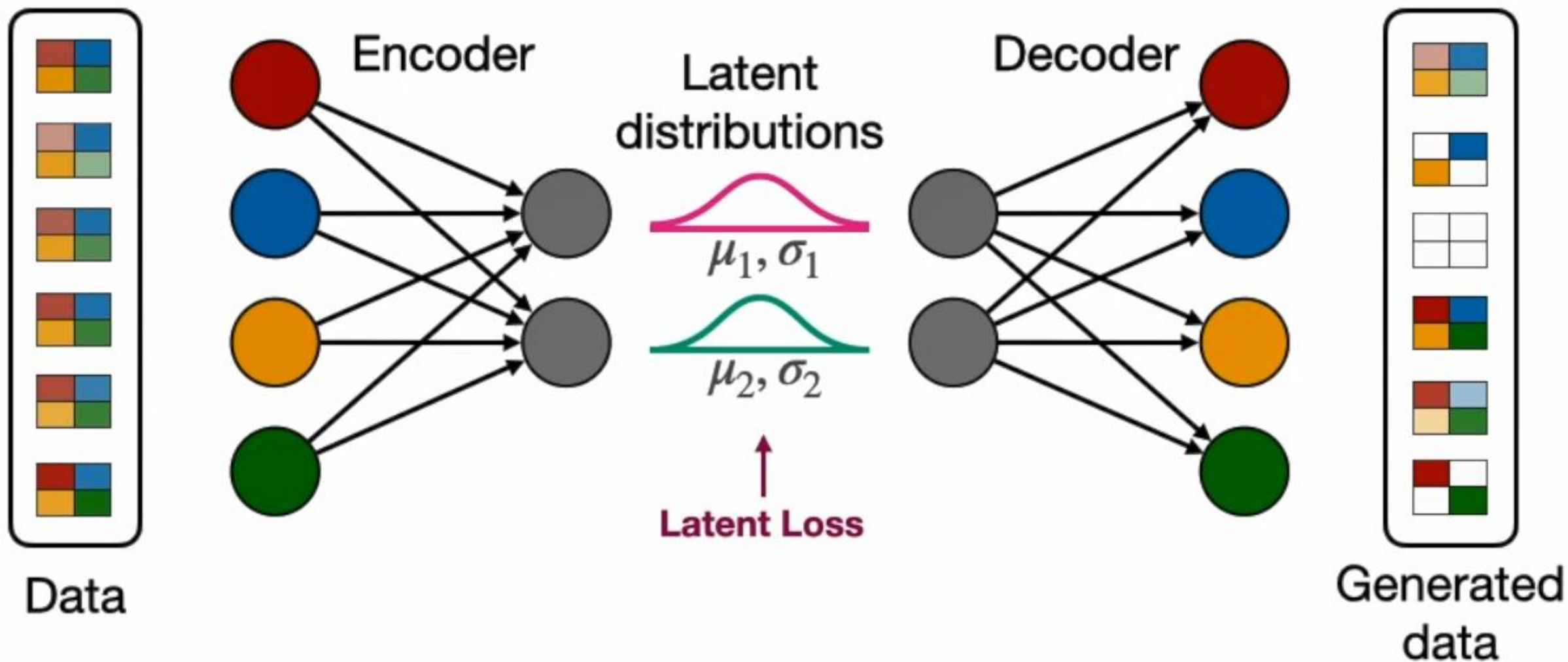
Decoder



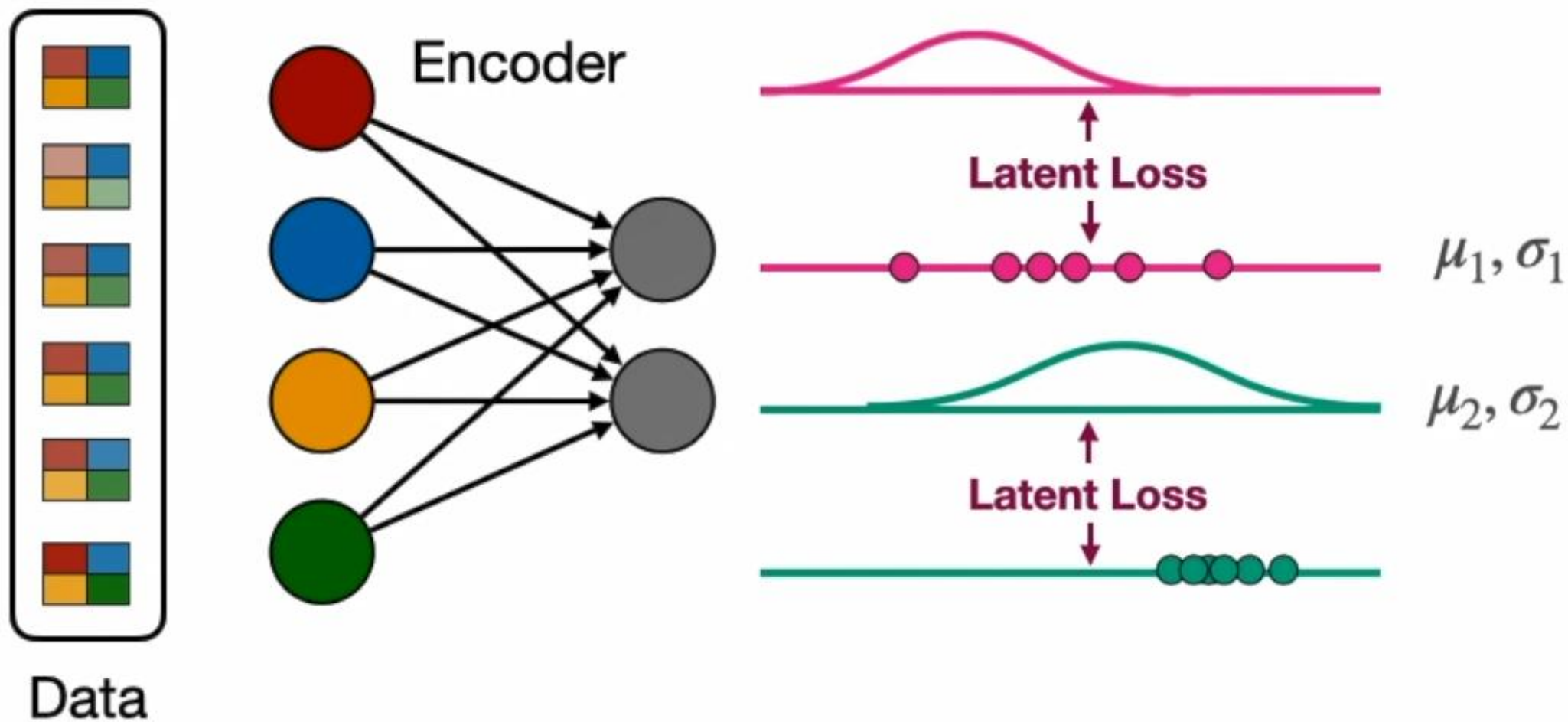
0.4	0.9
0.7	0.2

Reconstruction loss

Training a variational auto encoder

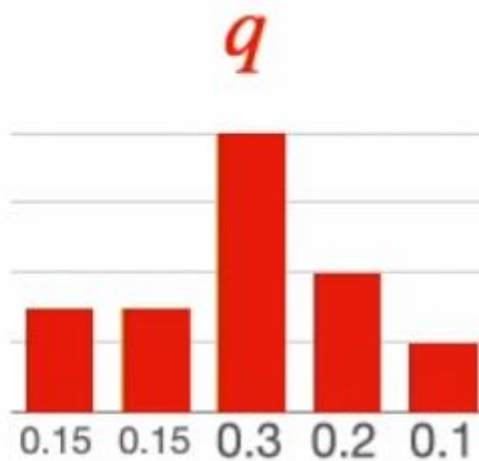
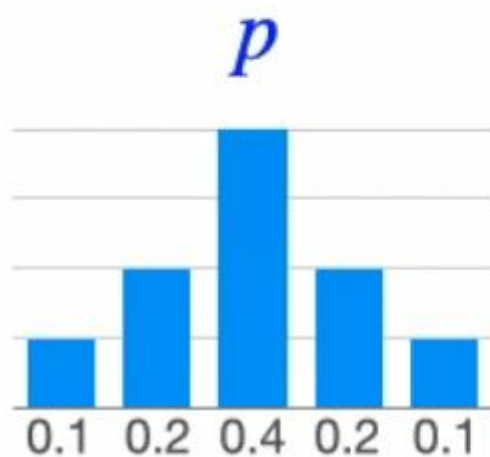


Training a variational auto encoder

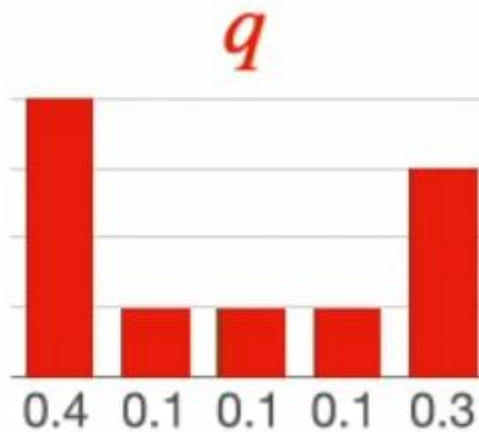
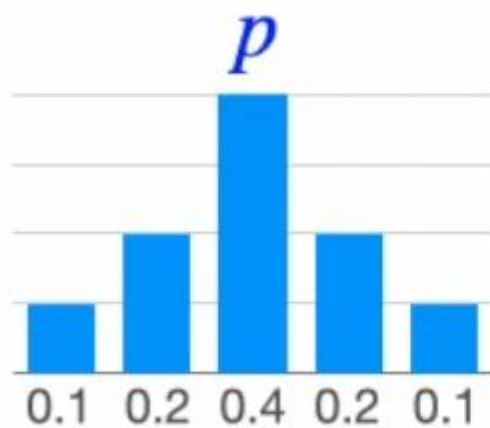


Latent loss (KL-divergence)

$$KL(p, q) = \sum_i p_i \ln \left(\frac{p_i}{q_i} \right)$$



$$0.1 \ln \frac{0.1}{0.15} + 0.2 \ln \frac{0.2}{0.15} + 0.4 \ln \frac{0.4}{0.4} + 0.2 \ln \frac{0.2}{0.2} + 0.1 \ln \frac{0.1}{0.1} = 0.132$$



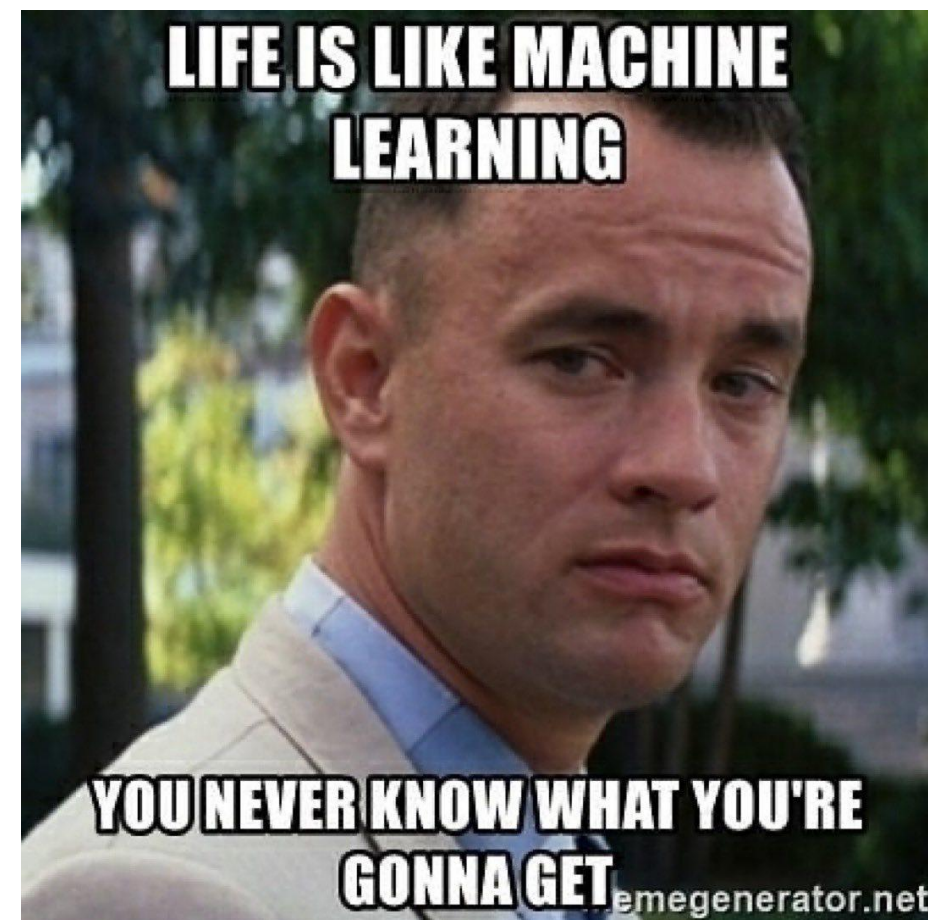
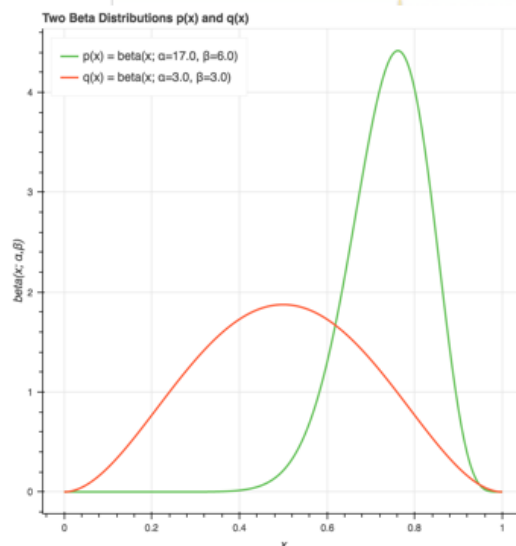
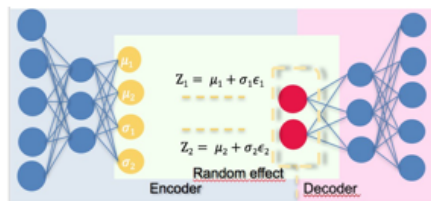
$$0.1 \ln \frac{0.1}{0.4} + 0.2 \ln \frac{0.2}{0.1} + 0.4 \ln \frac{0.4}{0.1} + 0.2 \ln \frac{0.2}{0.1} + 0.1 \ln \frac{0.1}{0.3} = 0.583$$

- ▶ Force ordering in latent space
- ▶ During training, you are minimising some loss function

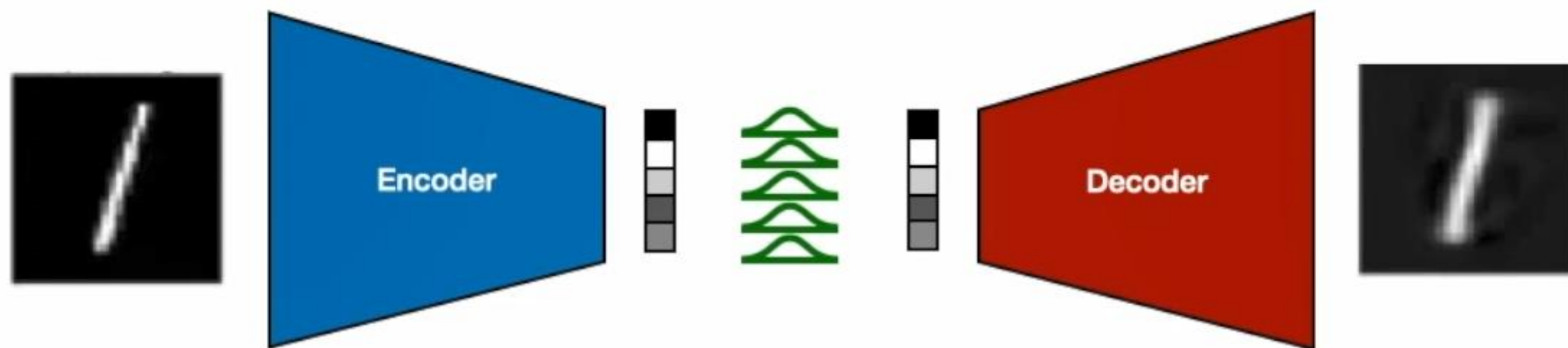
- ▶ For regression (normal AE):
 $\text{MSE}(\text{output} - \text{input})$

- ▶ Add KL-divergence term:
 $\sum_i \text{KL}(\mathcal{N}(\mu_i, \sigma_i), \mathcal{N}(0, 1)) := \text{KL}(\mu, \sigma)$

- ▶ So $\mathcal{L} = \text{MSE}(\text{output} - \text{input}) + \text{KL}(\mu, \sigma)$
- ▶ The KL divergence punishes latent space values far away from the center
- ▶ Also, every point has a variance that is pushed to 1
- ▶ Balance MSE and KL \rightarrow group similar structures around the center



Training a variational auto encoder



Gli autoencoder e i variational autoencoder (VAE) sono entrambi modelli di AI generativa per la compressione e la decompressione delle informazioni. Tuttavia, la principale differenza tra loro riguarda la modalità in cui trattano lo spazio latente, ovvero lo spazio di rappresentazione compresso delle informazioni.

Gli autoencoder tradizionali cercano di apprendere una rappresentazione compatta dei dati di input riducendoli in uno spazio latente tramite una funzione di codifica. Questo spazio latente viene poi utilizzato per decodificare una rappresentazione approssimata dei dati originali. Tuttavia, questo spazio latente non ha alcuna struttura specifica e le nuove rappresentazioni generate potrebbero non avere un significato coerente.

I VAE, d'altra parte, introducono una differenza chiave aggiungendo una componente di stocasticità allo spazio latente. Questo significa che invece di produrre un punto fisso nello spazio latente, il VAE produce una distribuzione di probabilità nello spazio latente. Questo permette al VAE di generare nuove immagini campionando casualmente punti nello spazio latente e decodificandoli, producendo così una varietà di immagini realistiche.

In sostanza, l'introduzione della componente stocastica nel VAE permette al modello di generare nuove immagini campionando da una distribuzione nello spazio latente, mentre negli autoencoder tradizionali non c'è questa possibilità poiché non c'è una struttura stocastica nello spazio latente.



That's all Folks!