Generative Models I

Dr. Parlett-Pelleriti

Outline

- Generative Model Examples
- Types of Generative Models
- Simple Generative Models
- Autoencoders Review
- Variational Autoencoders

Generative Models Examples

Generating New Faces

Image from: https://github.com/tdrussell/IllustrationGAN

Image from: https://arxiv.org/pdf/1710.10196v3.pdf

Generating Faces

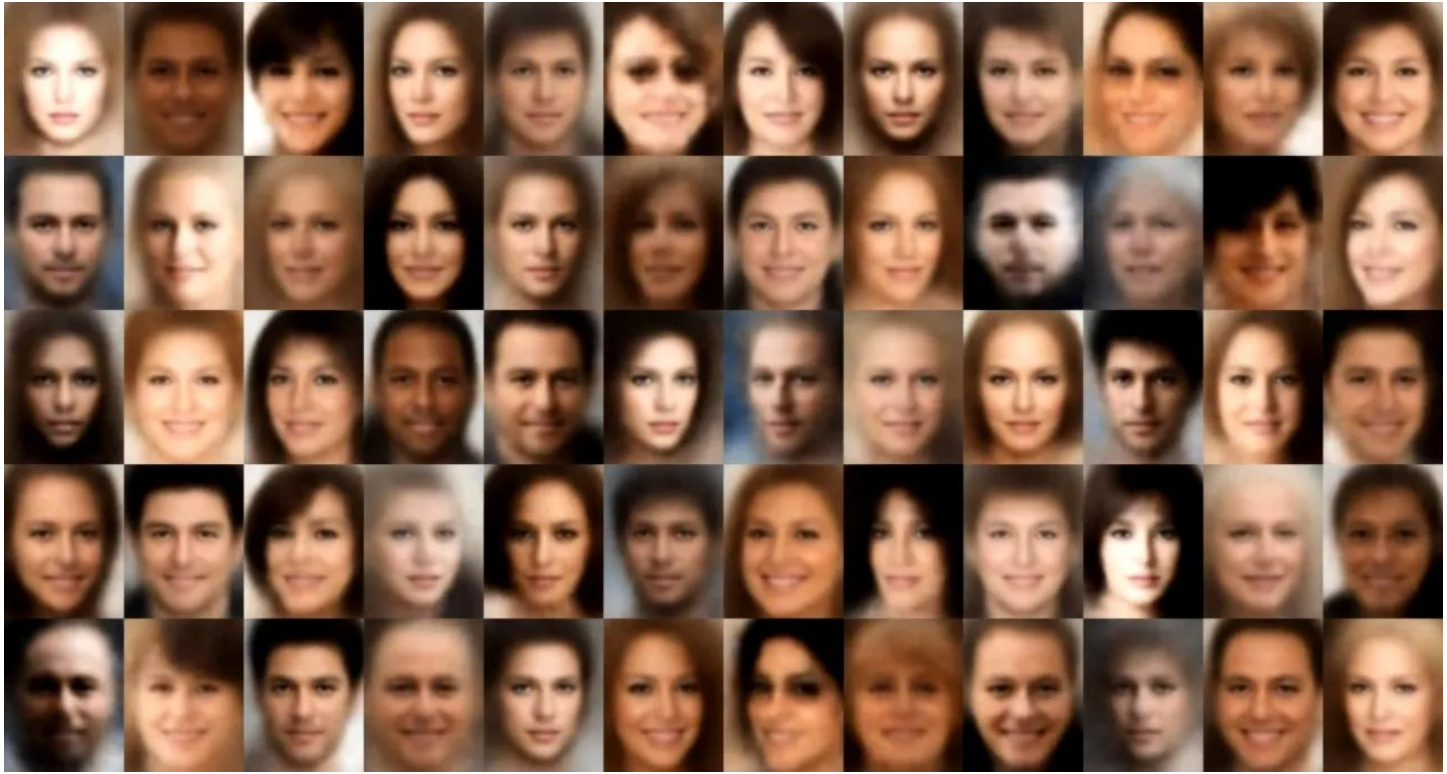
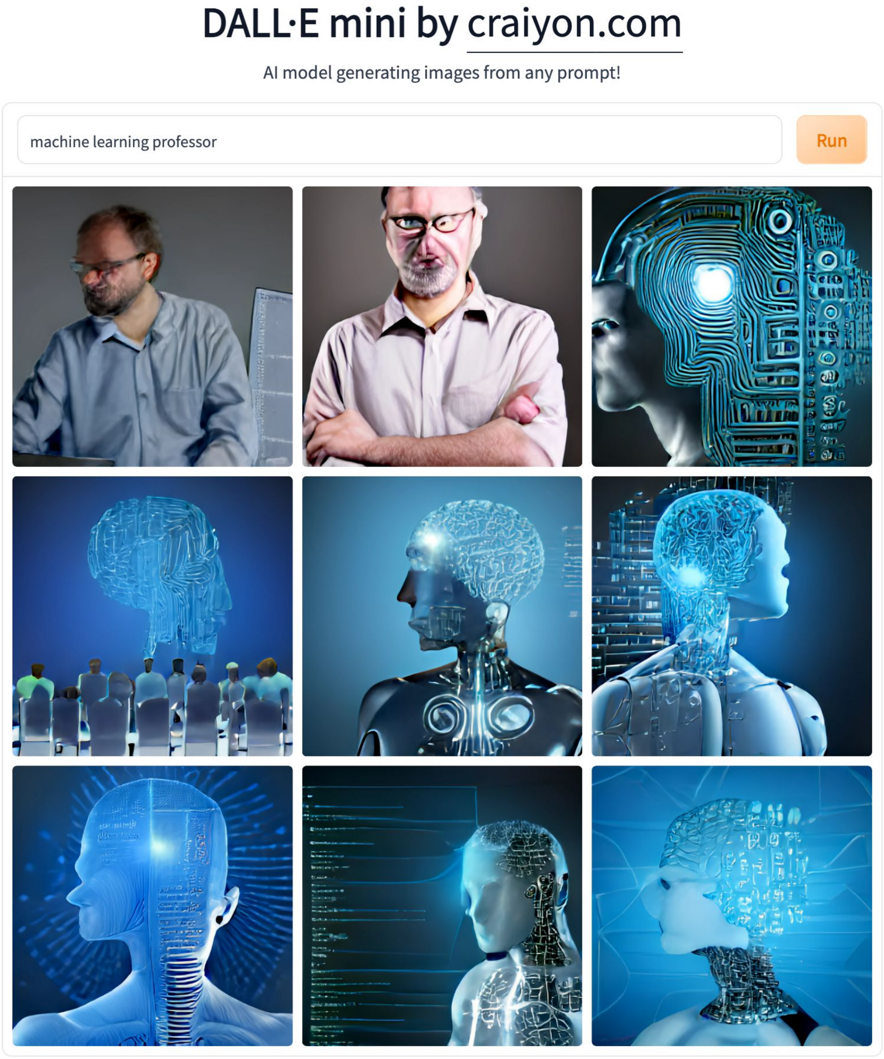


Image from: https://github.com/wojciechmo/vae

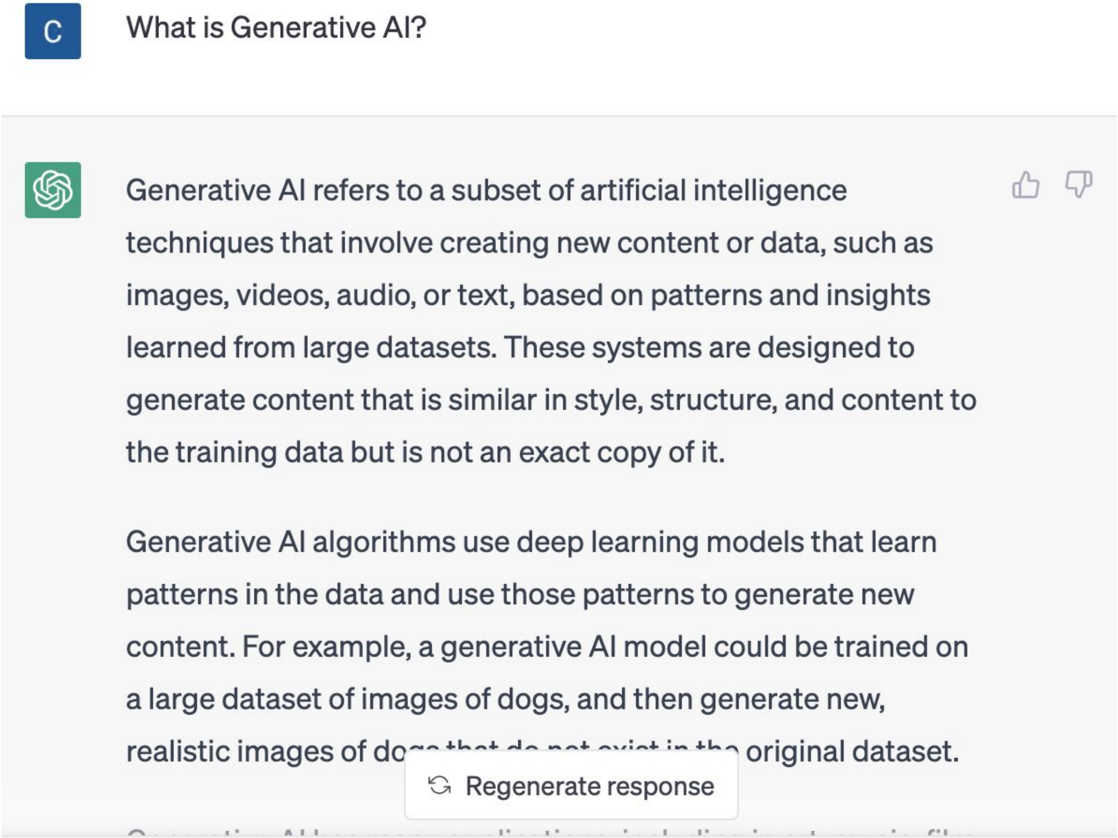
Generating Photos/Art



Neural Inpainting GANs

Image from: https://github.com/pathak22/context-encoder

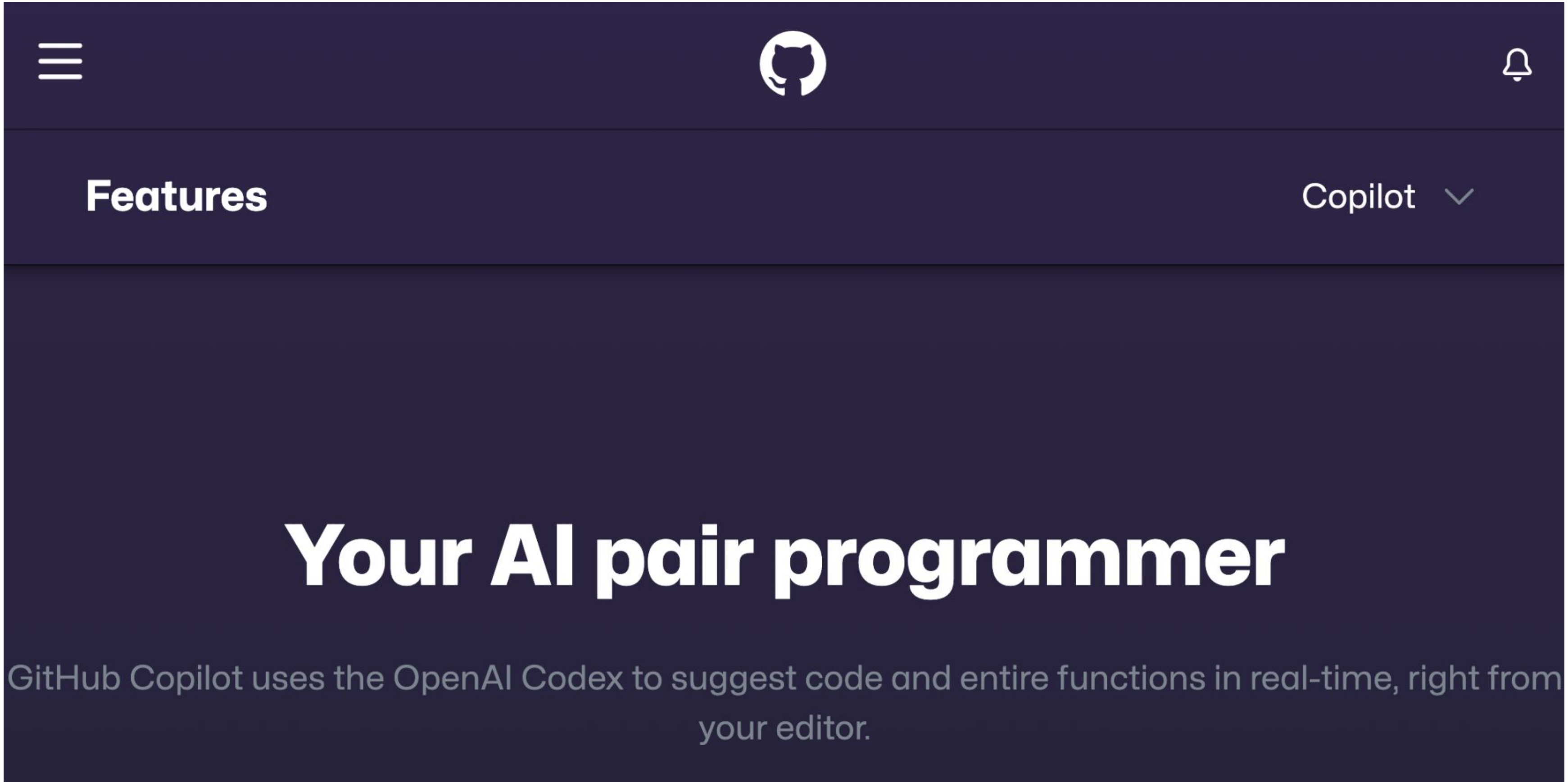
Generating Text



Generating Text

Image from: https://www.twitch.tv/watchmeforever via
https://techcrunch.com/2023/02/03/nothing-forever-ai-generated-seinfeld-twitch/

Generating Code



Generating Music

Generating Video Game Levels

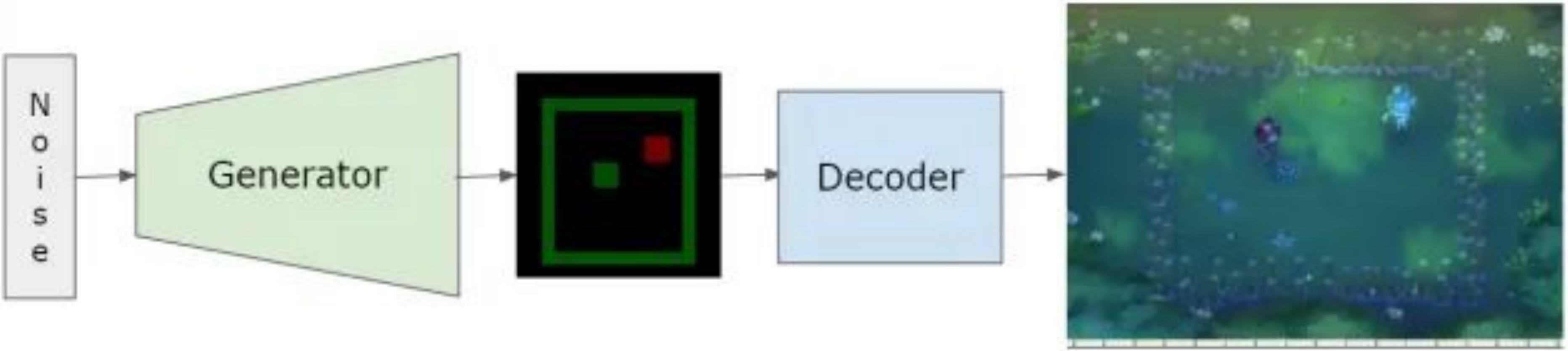


Image from: https://www.gamedeveloper.com/programming/game-level-generation-using-neural-networks

Style Transfer

Image from: https://arxiv.org/abs/1812.04948

Image from: https://www.reddit.com/r/Breath_of_the_Wild/comments/eio394/botw_x_starry_night_neural_style_transfer/

Face Aging GAN

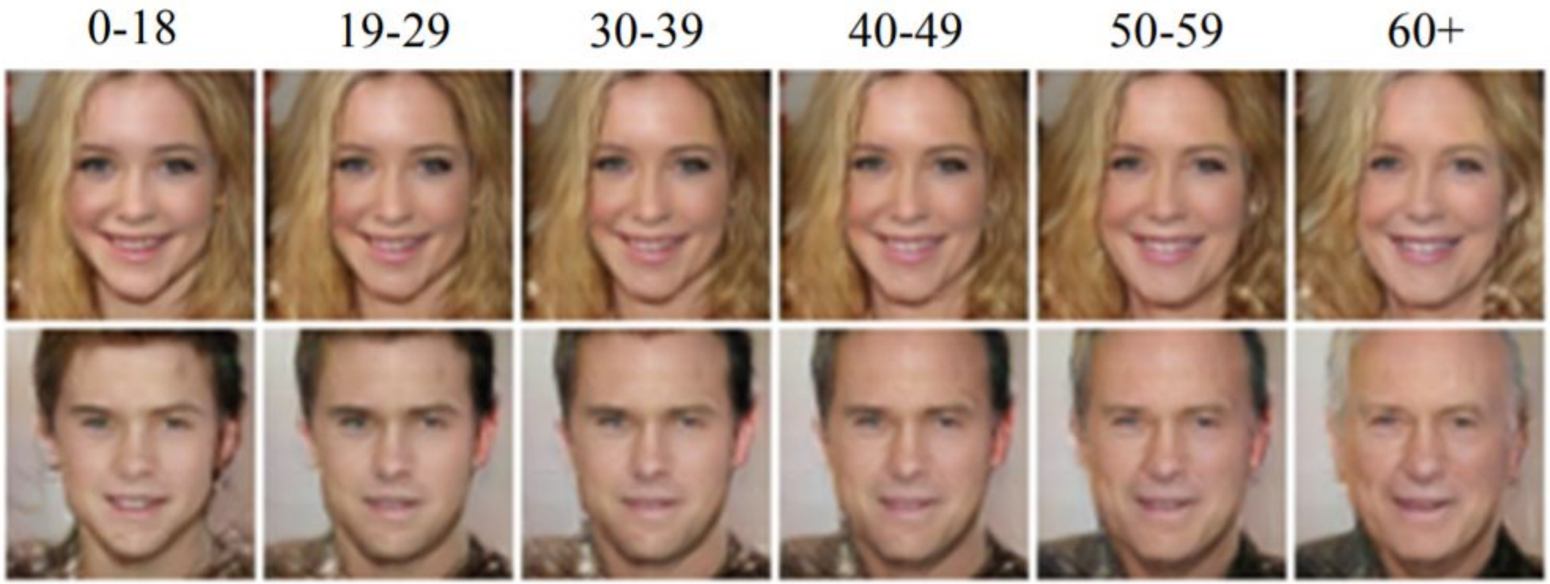


Image from: https://arxiv.org/pdf/1702.01983.pdf

Image Upscaling GANs

Image from: https://github.com/david-gpu/srez

Image Quality Improvement

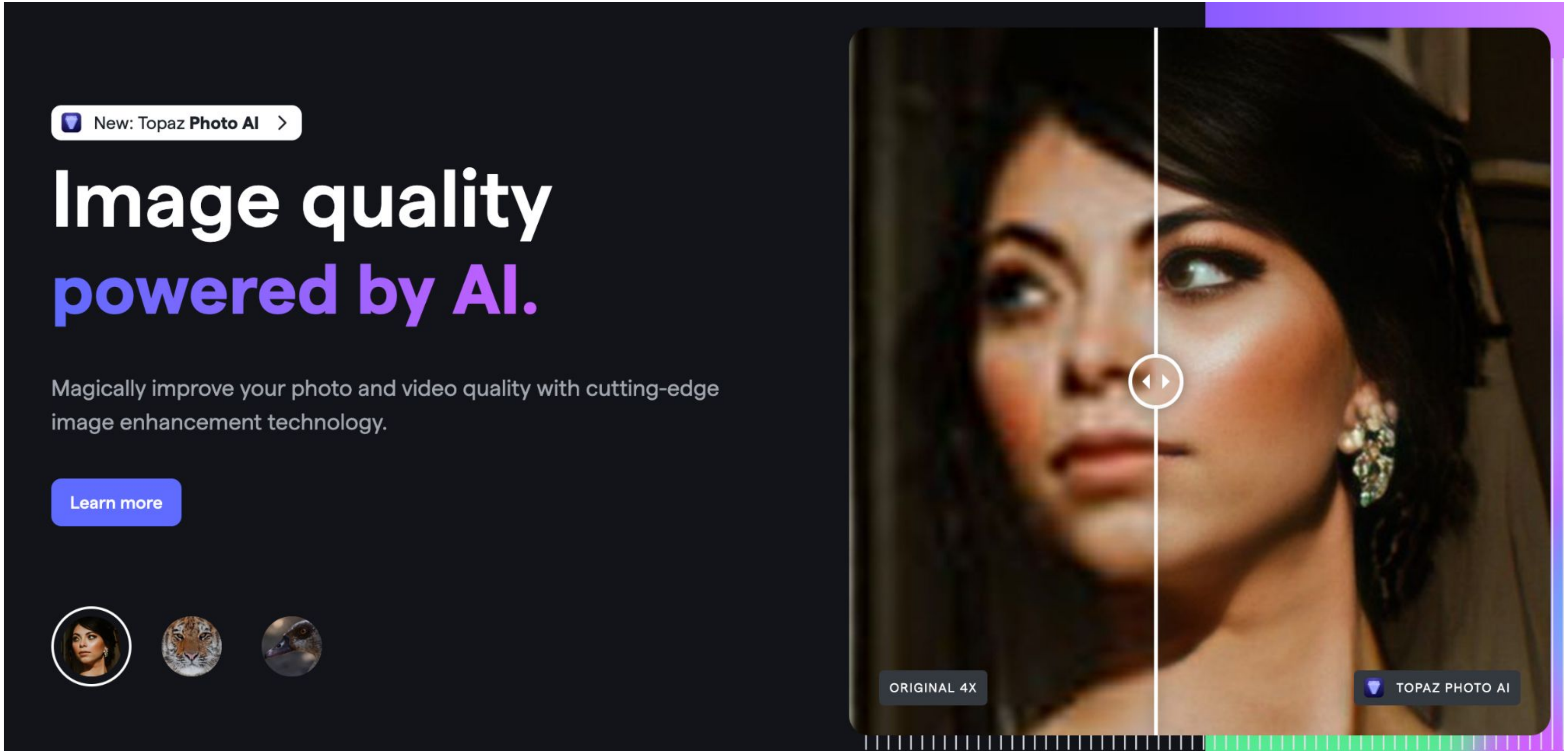
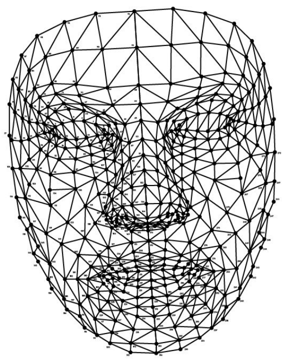


Image from: https://www.topazlabs.com/

Deep Fakes

Image from: https://thedirect.com/article/star-wars-luke-skywalker-deepfakes-cgi

TikTok Generative Filters



468 points

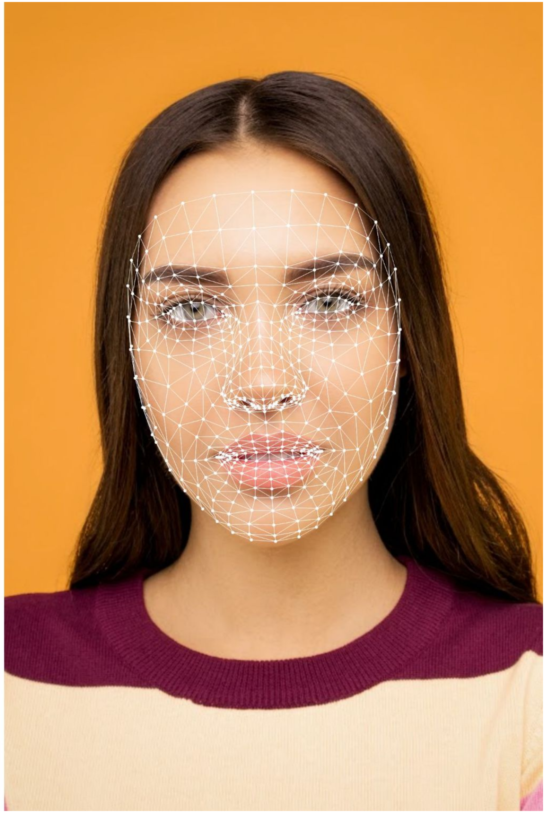


Image from: https://www.theverge.com/2023/3/2/23621751/bold-glamour-tiktok-face-filter-beauty-ai-ar-body-dismorphia

Image from: https://developers.google.com/ml-kit/vision/face-mesh-detection

Scam Robo-Calls

Scammers are using AI to impersonate your loved ones. Here's what to watch out for

The next time you get a call from a family member or friend in need, you might want to make sure it's not a robot first.

Written by **Sabrina Ortiz,** Associate Editor on March 9, 2023

Kilito Chan/Getty Images

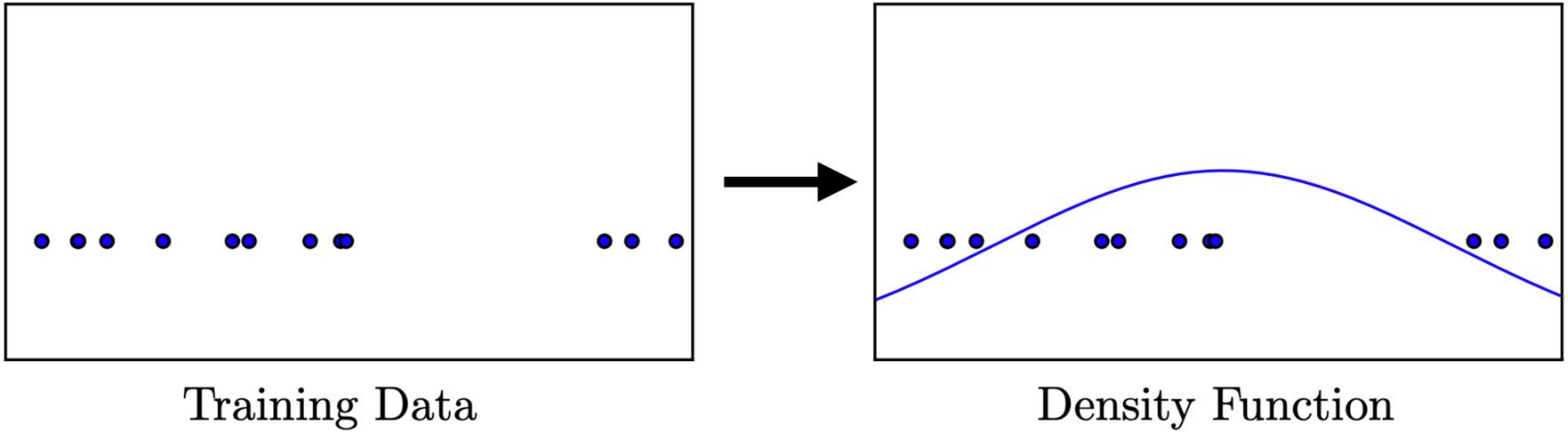
/ related

OpenAI will pay you to hunt for ChatGPT bugs

Image from: Kilito Chan/Getty Images via https://www.zdnet.com/article/scammers-are-using-ai-to-impersonate-your-loved-ones-heres-what-to-watch-for/

Types of Generative Models

Generative Modeling: Density Estimation



(Goodfellow 2018)

Generative Modeling: Sample Generation

Training Data
(CelebA)

Sample Generator
(Karras et al, 2017)

(Goodfellow 2018)

Generative Models You Know

- Naive Bayes
- Gaussian Mixture Models

Naive Bayes Exan

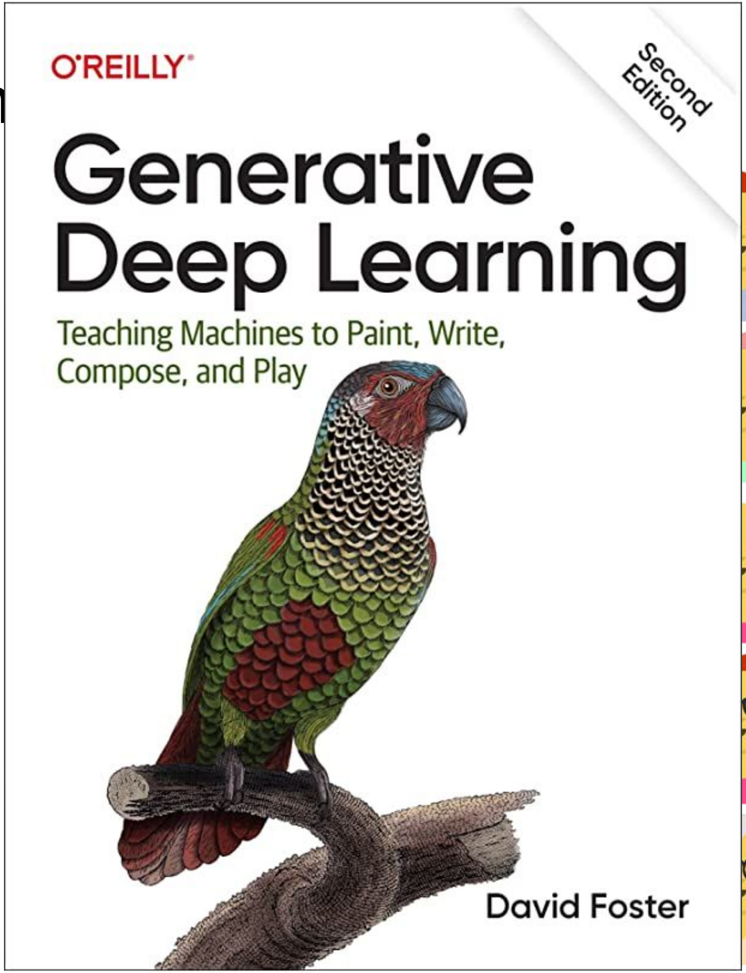


Image from: Generative Deep Learning: Teaching Machines to P

Naive Bayes Example

Image from: Generative Deep Learning: Teaching Machines to Paint, Write, Compose and Play by David Foster

Naive Bayes

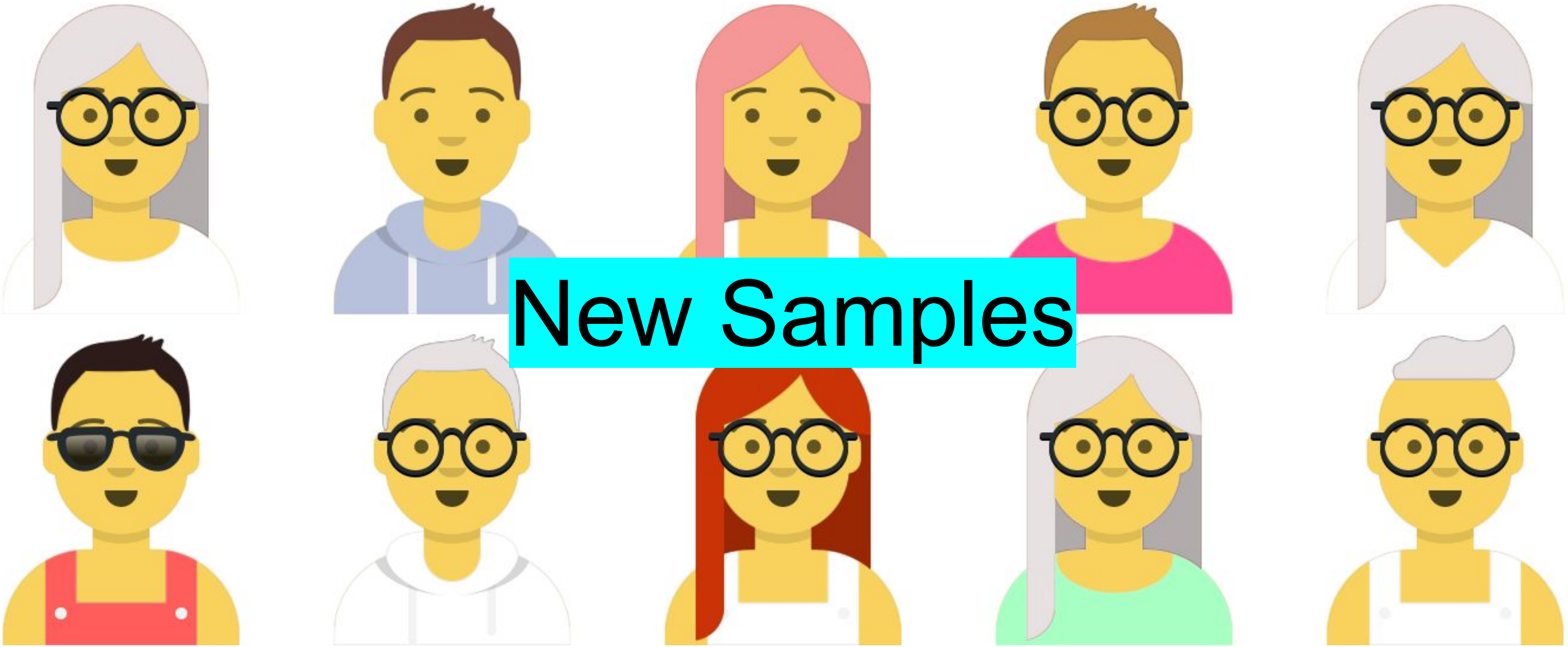


Image from: Generative Deep Learning: Teaching Machines to Paint, Write, Compose and Play by David Foster

Naive Bayes (Unlabeled)

Image from: Generative Deep Learning: Teaching Machines to Paint, Write, Compose and Play by David Foster

Naive Bayes (Unlabeled)

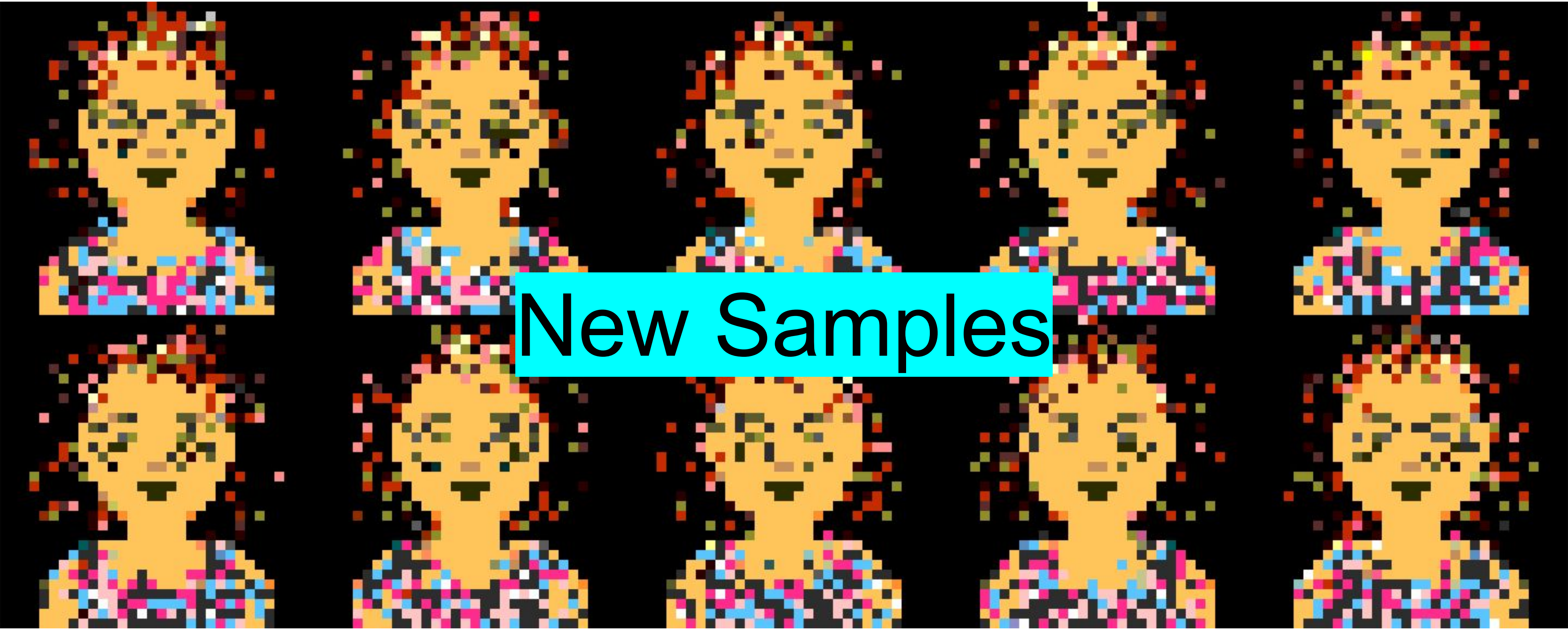
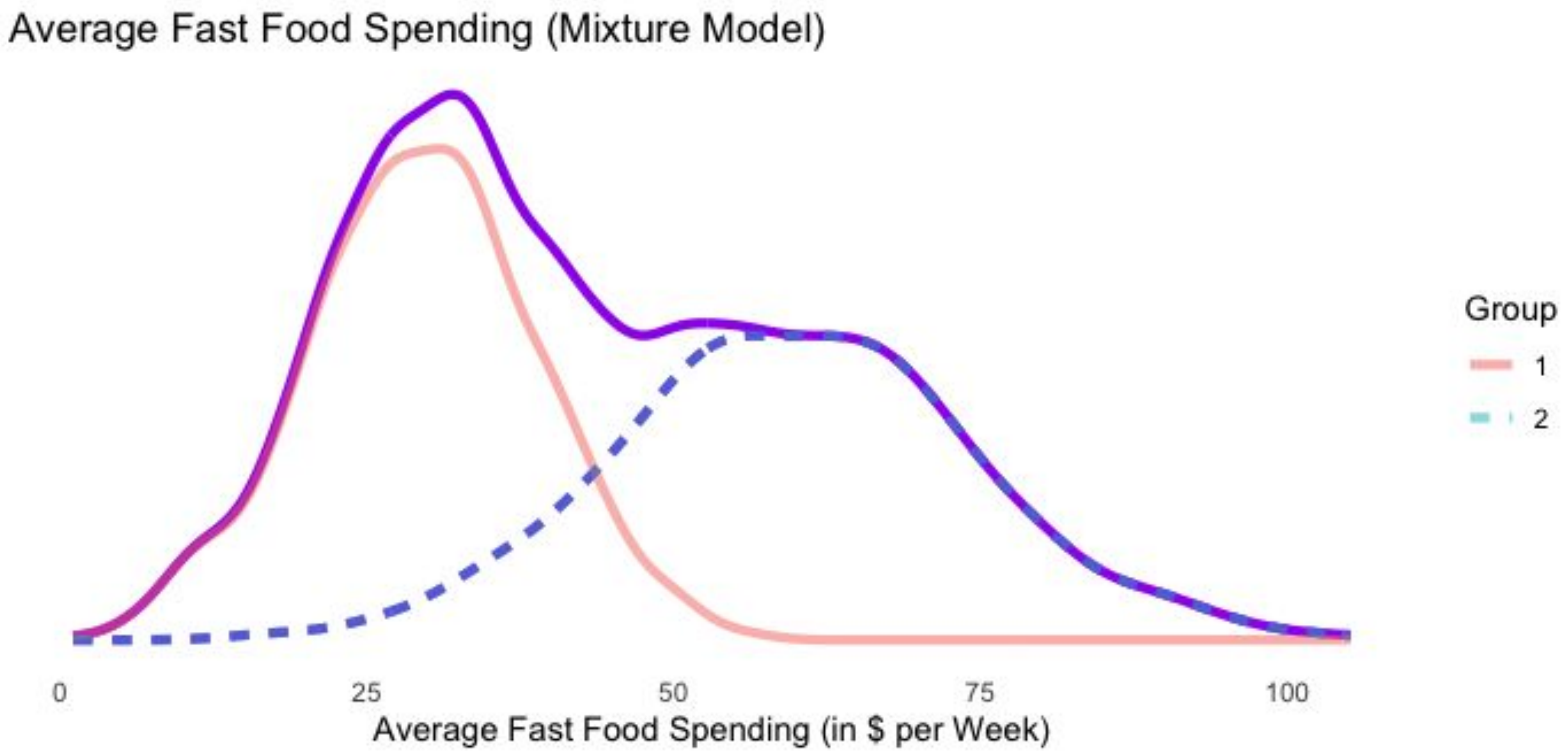
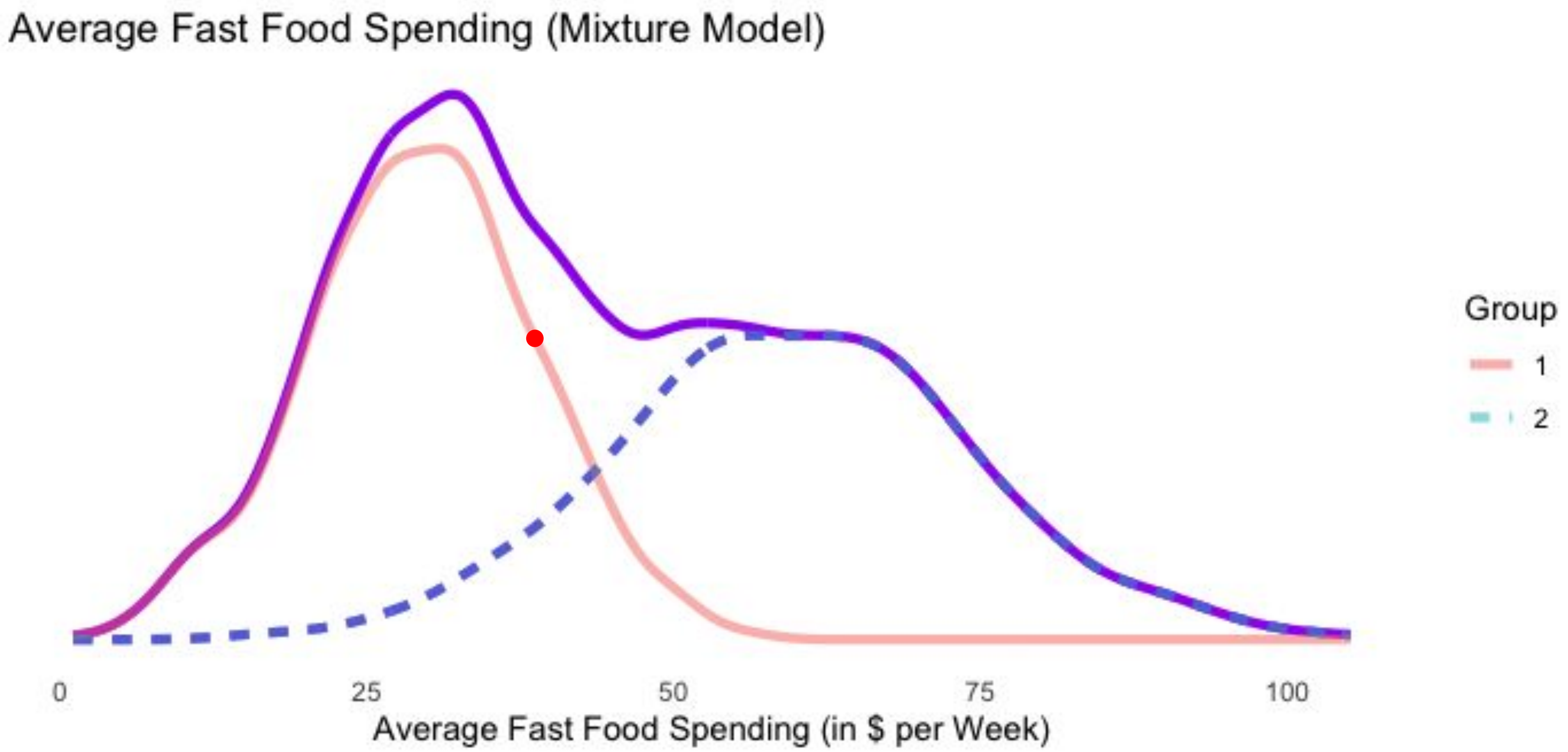


Image from: Generative Deep Learning: Teaching Machines to Paint, Write, Compose and Play by David Foster

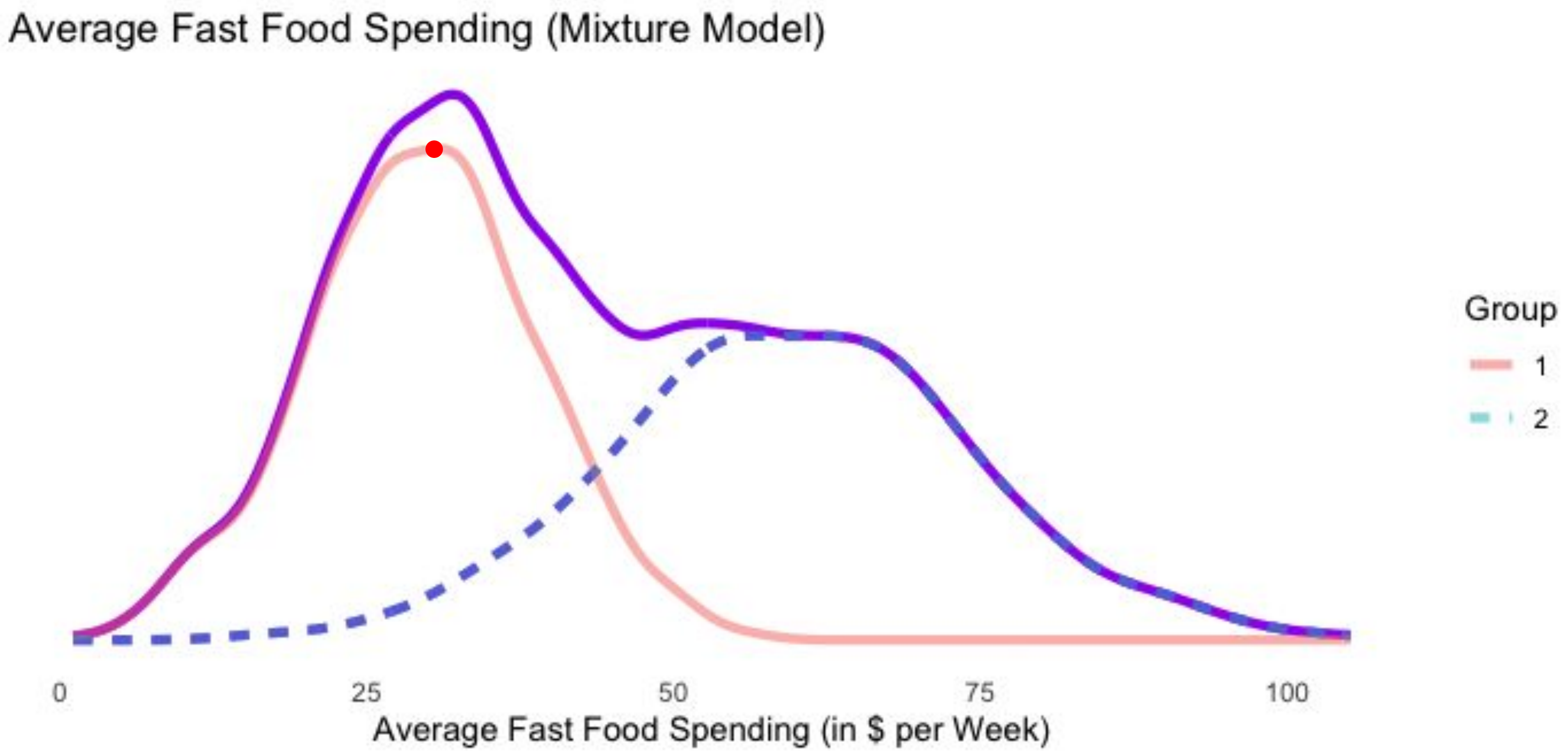
Gaussian Mixture Models



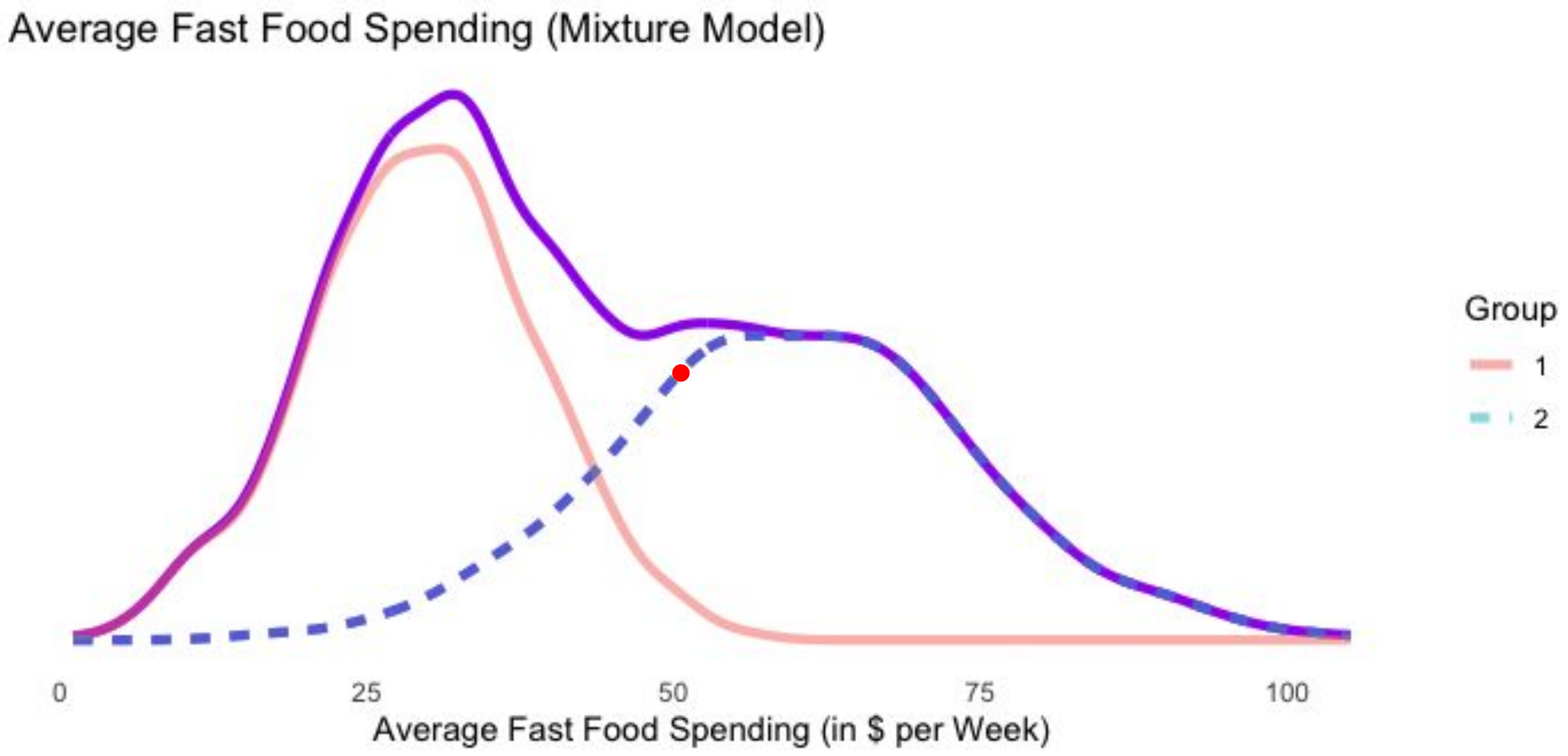
Gaussian Mixture Models



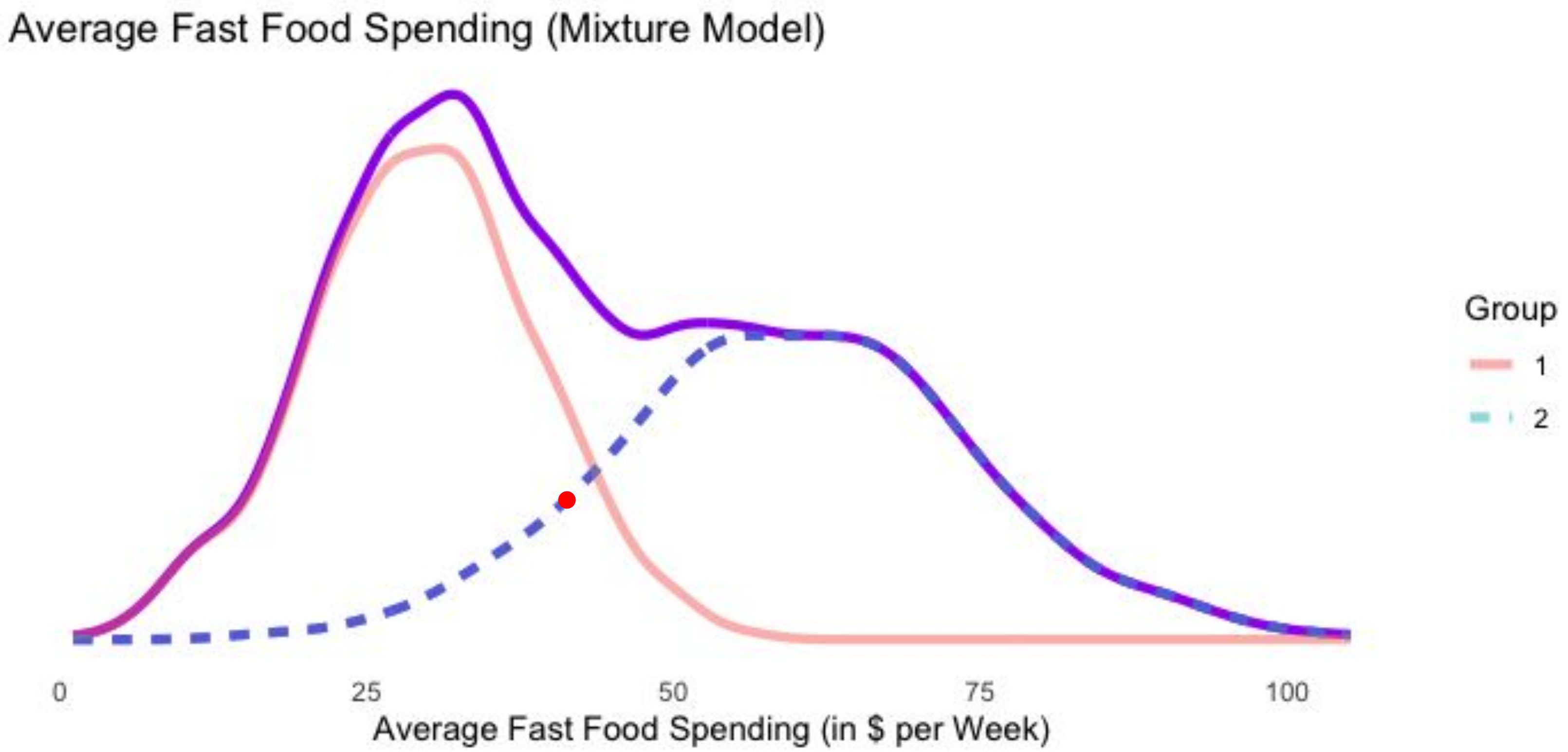
Gaussian Mixture Models



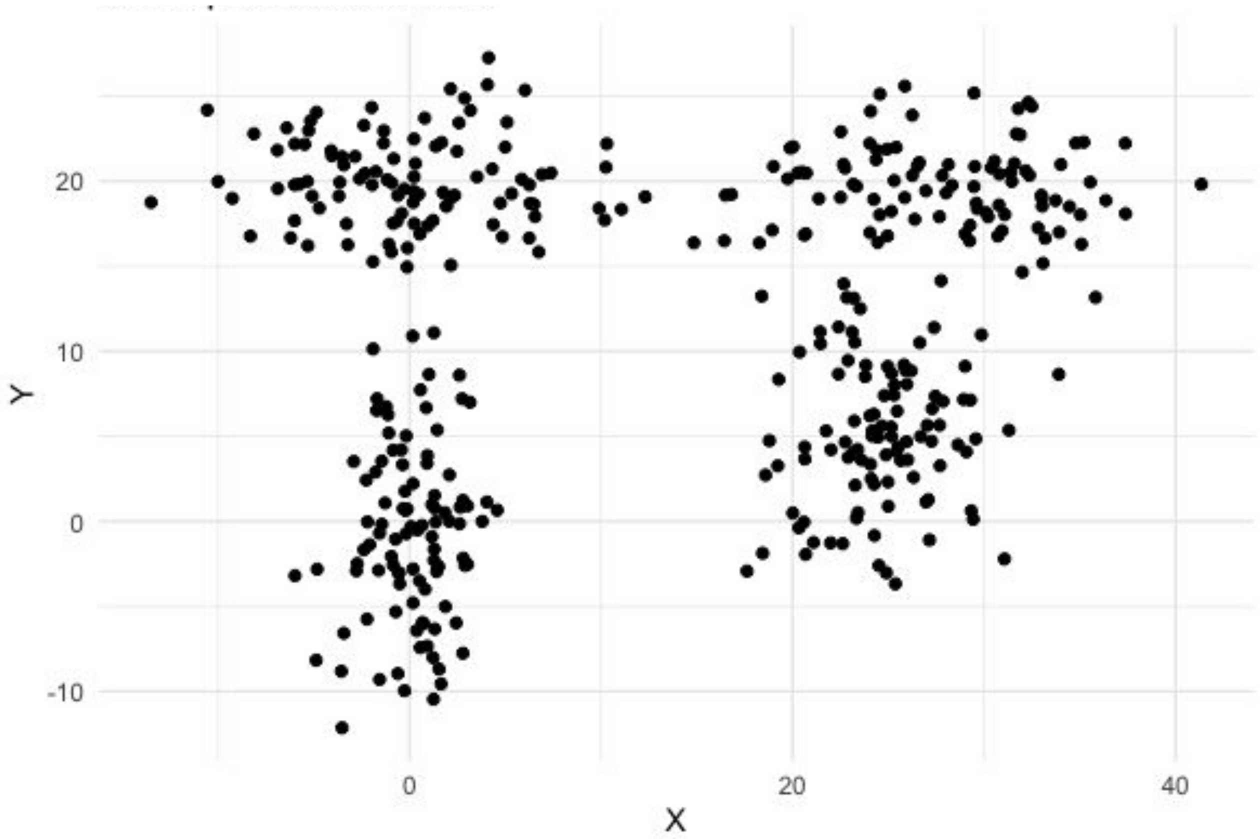
Gaussian Mixture Models



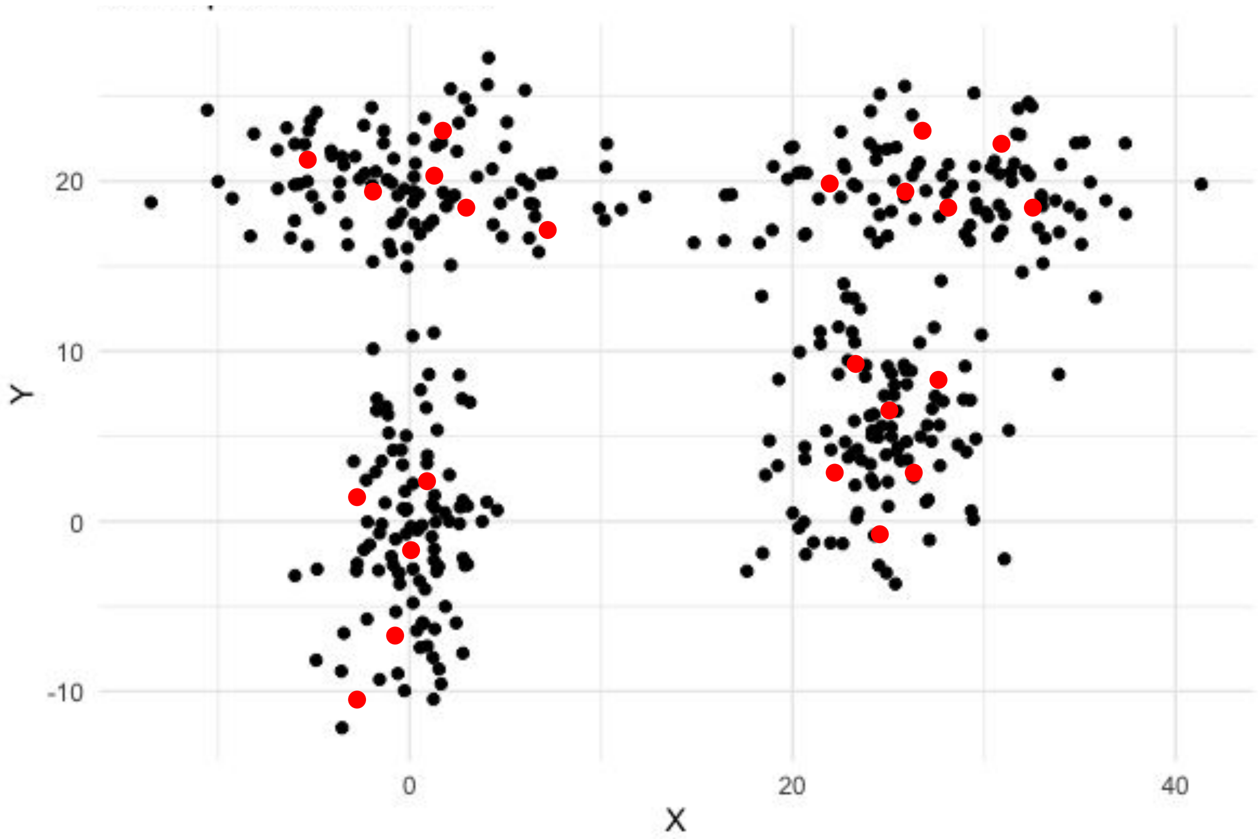
Gaussian Mixture Models



Gaussian Mixture Models



Gaussian Mixture Models



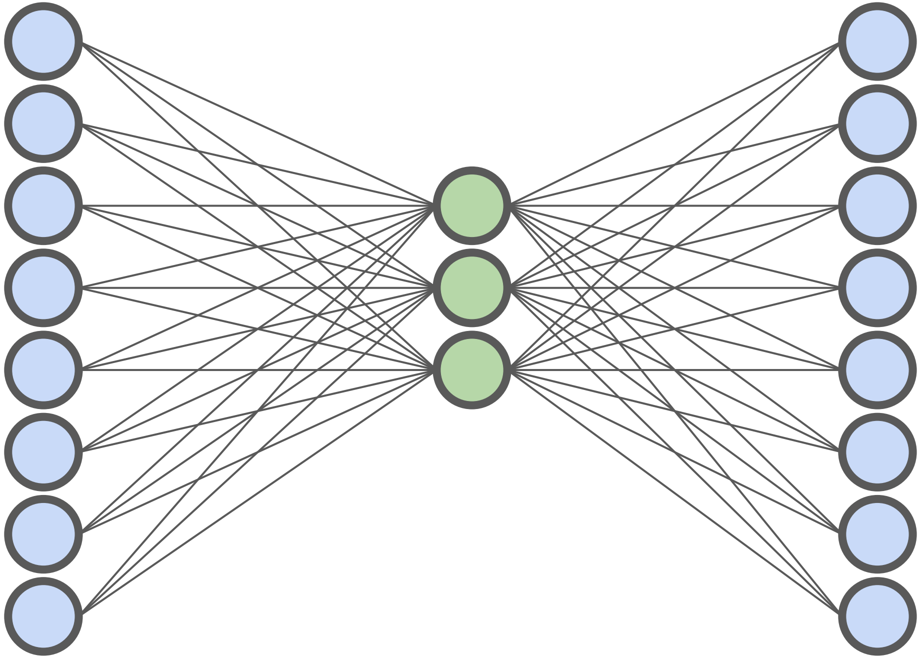
Density Estimation

Both **GMM** and **NB** do explicit density estimation, however they’re limited

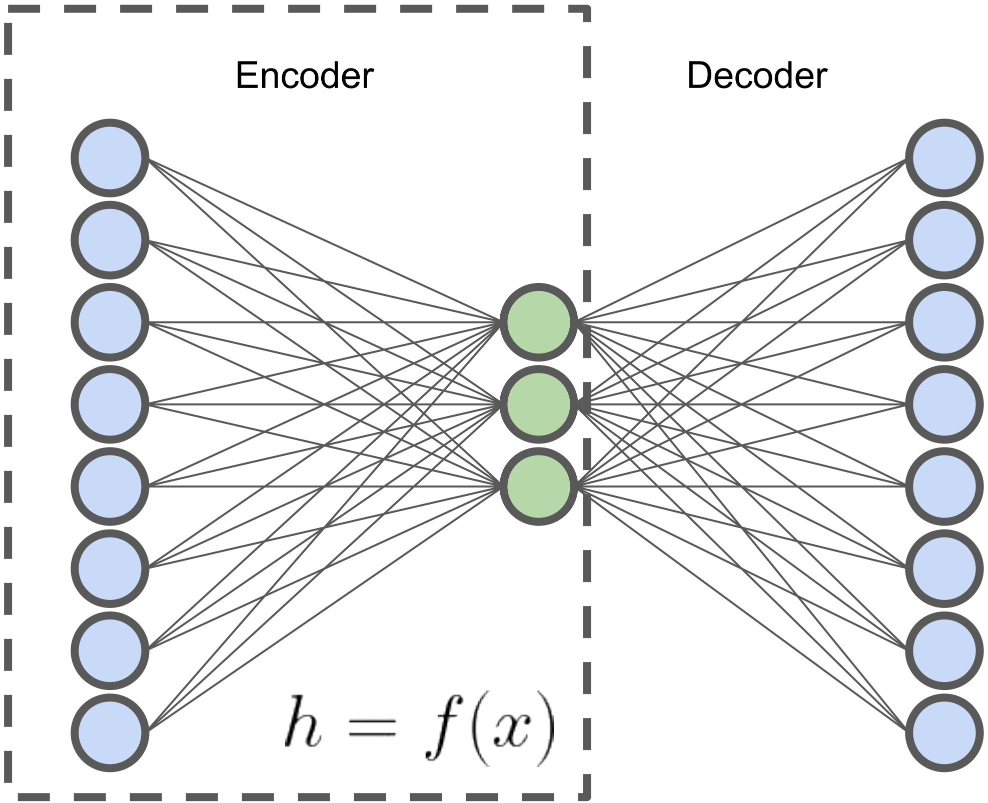
Enter: **Variational Autoencoders**

Autoencoders Review

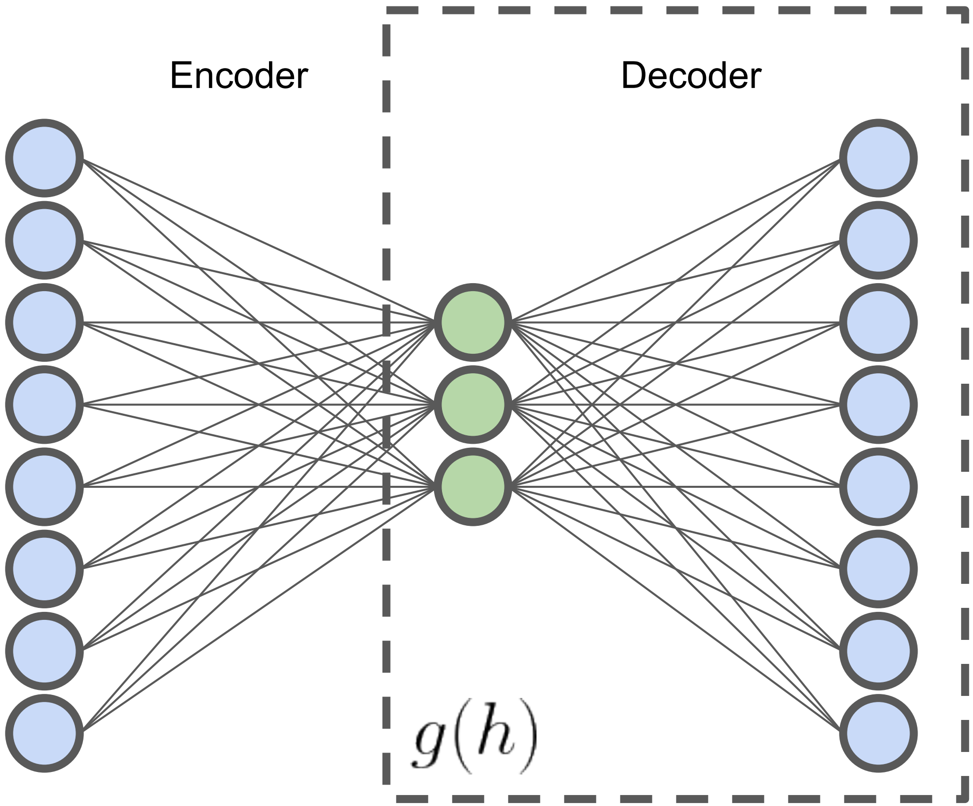
Autoencoder Architecture



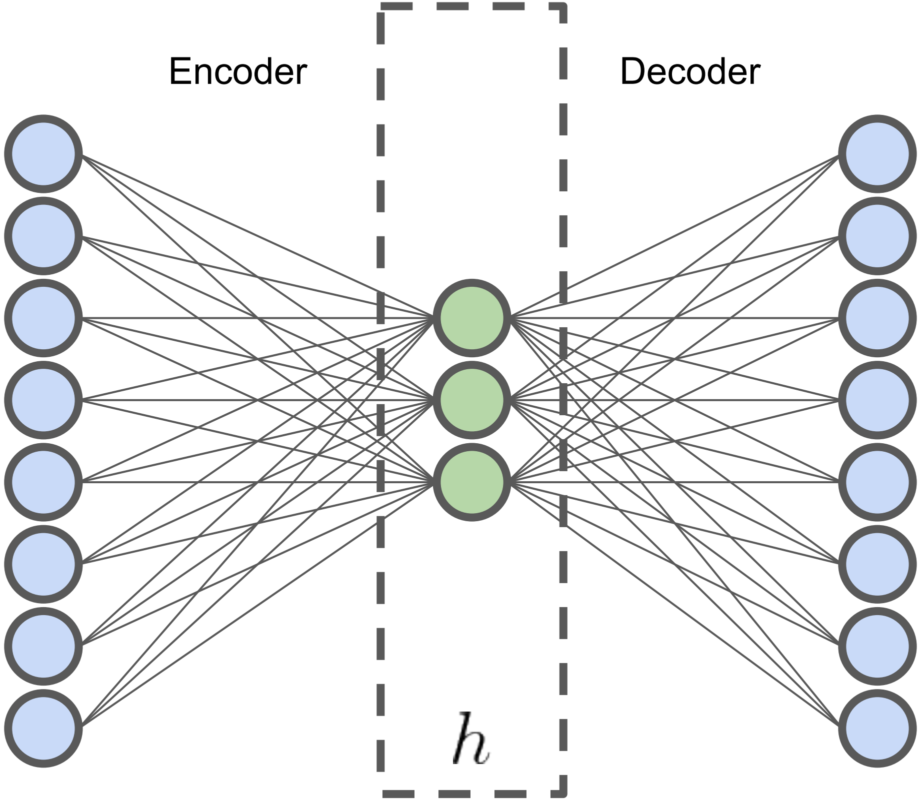
Autoencoder Architecture



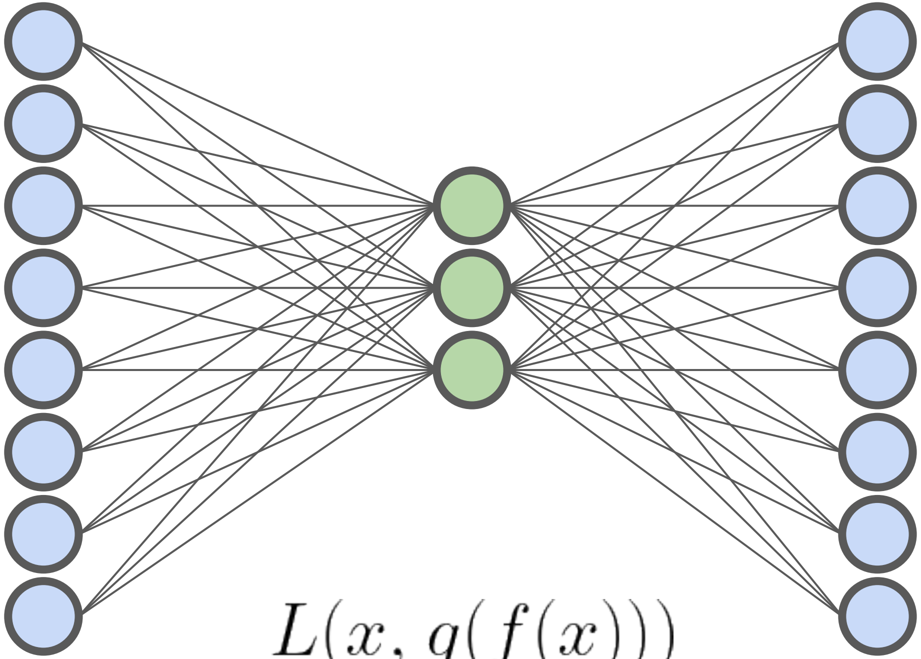
Autoencoder Architecture



Autoencoder Architecture



Autoencoder Architecture



$$L(x, g(f(x)))$$

Penalizing Derivatives

$$L(x, g(f(x))) + \boxed{\Omega(h, x)}$$

$$\boxed{\Omega(h, x)} = \lambda \sum_i \|\nabla_x h_i\|^2$$

Variational Autoencoders

Concept Vectors

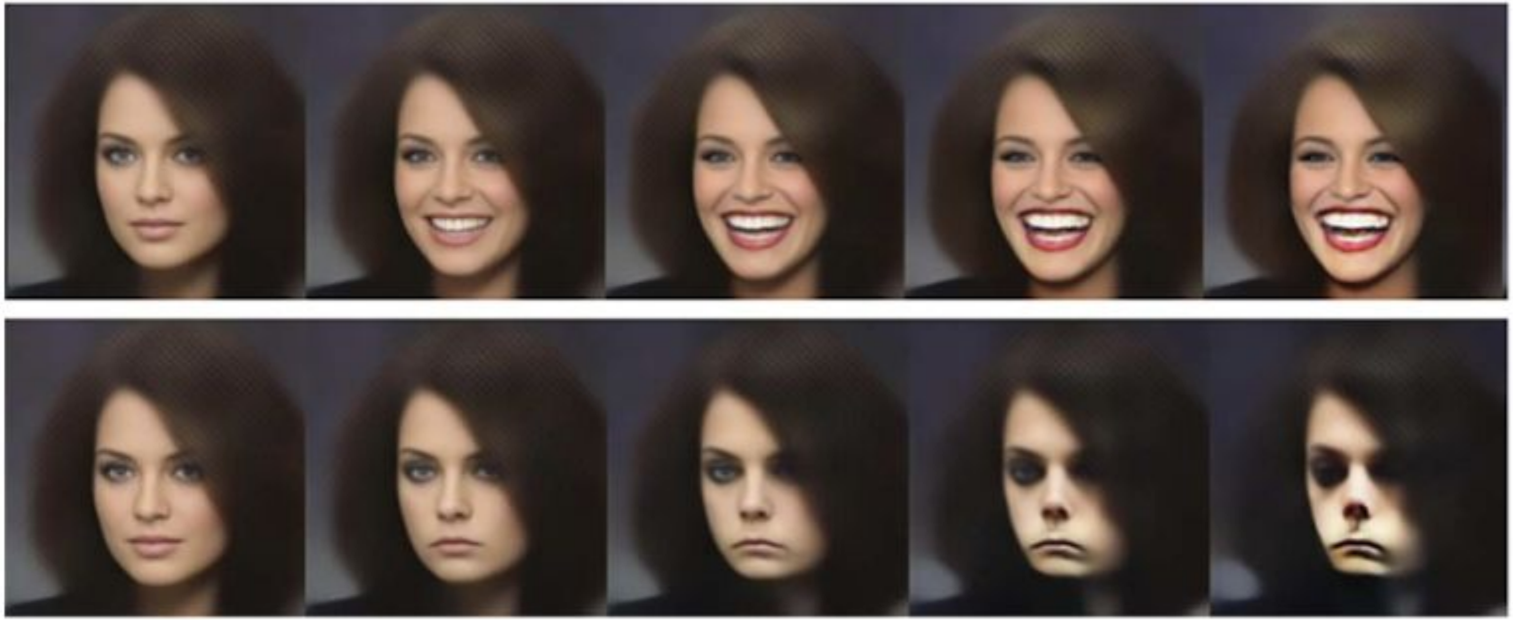
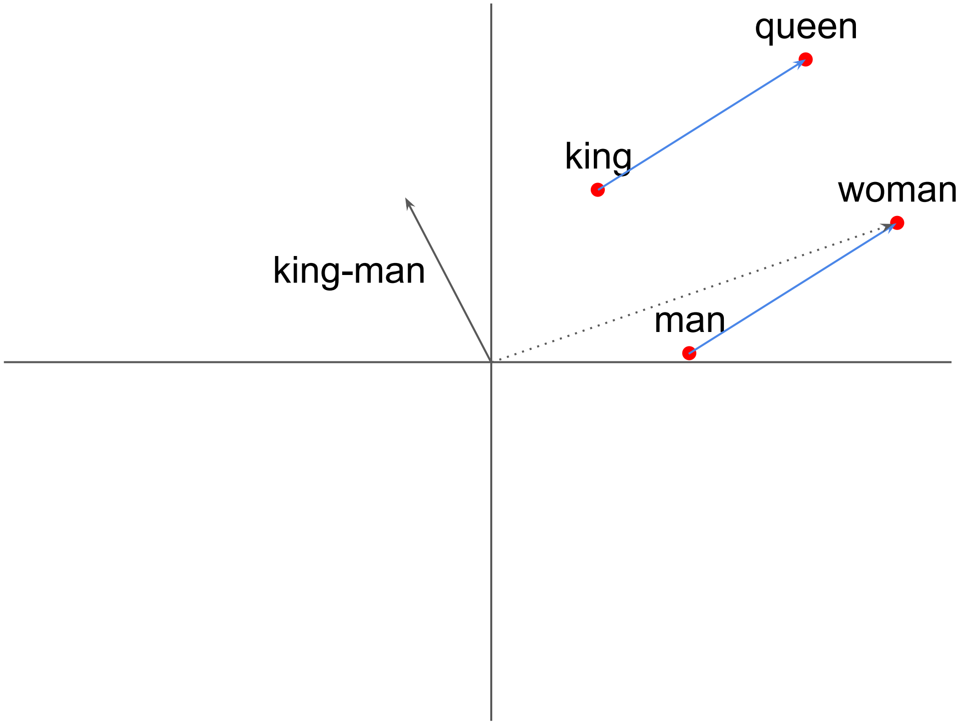
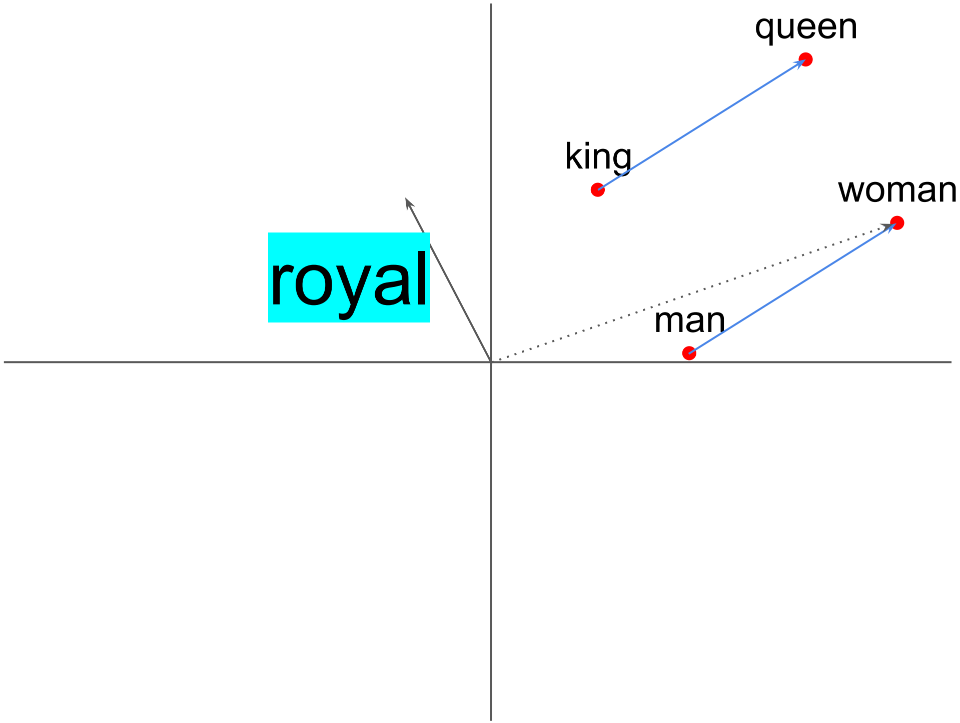


Figure 12.15 The smile vector

Word Concept Vectors



Word Concept Vectors



VAE Intuition

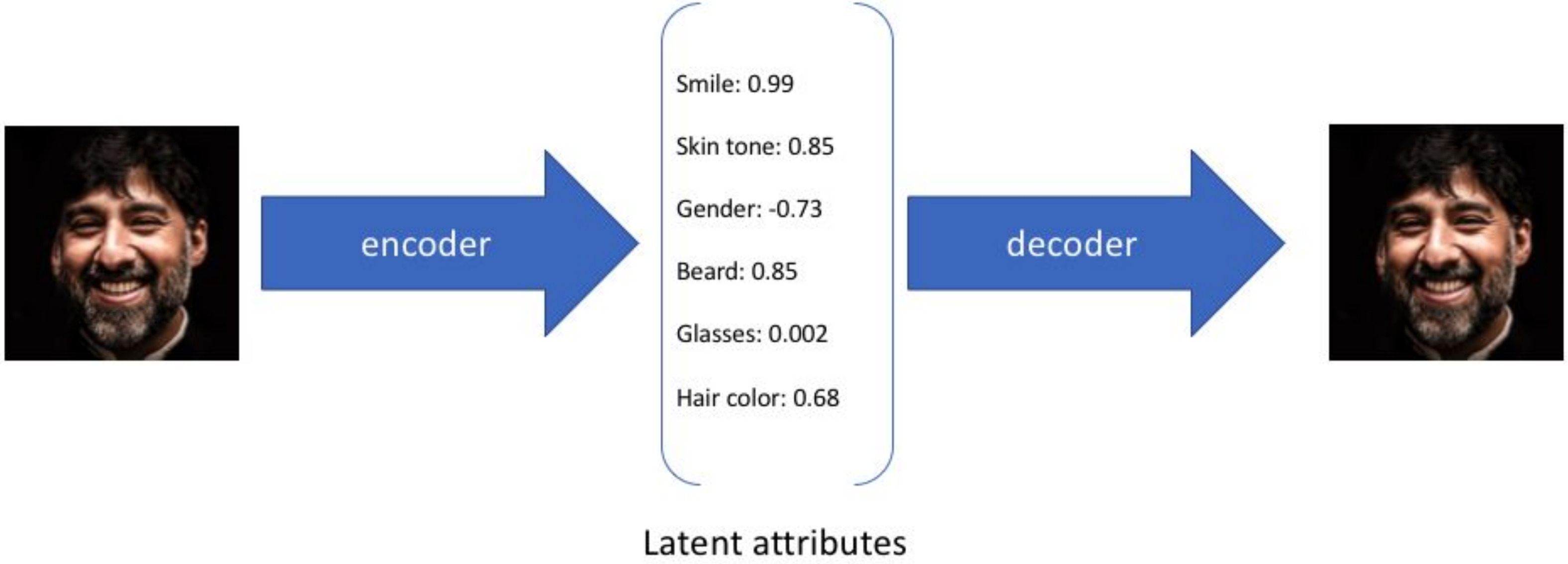


Image from: https://www.jeremyjordan.me/variational-autoencoders/

VAE Intuition

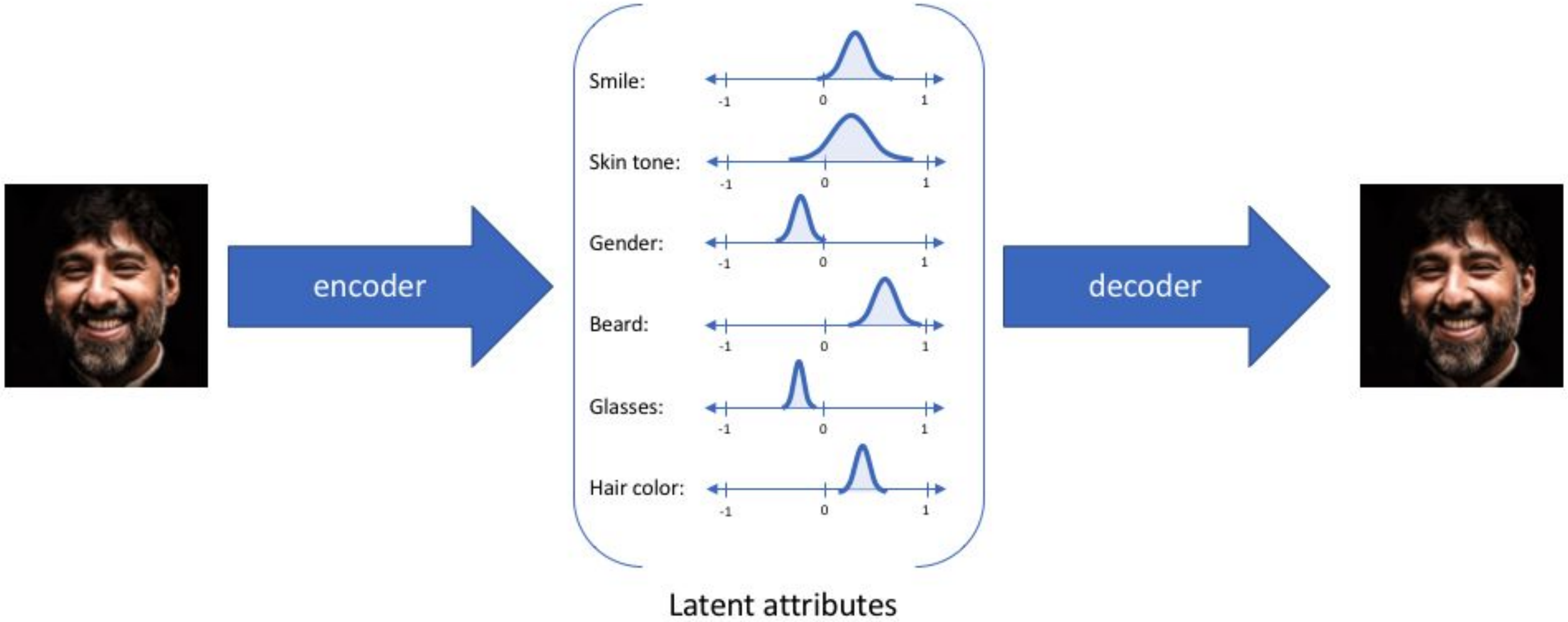


Image from: https://www.jeremyjordan.me/variational-autoencoders/

VAE Intuition

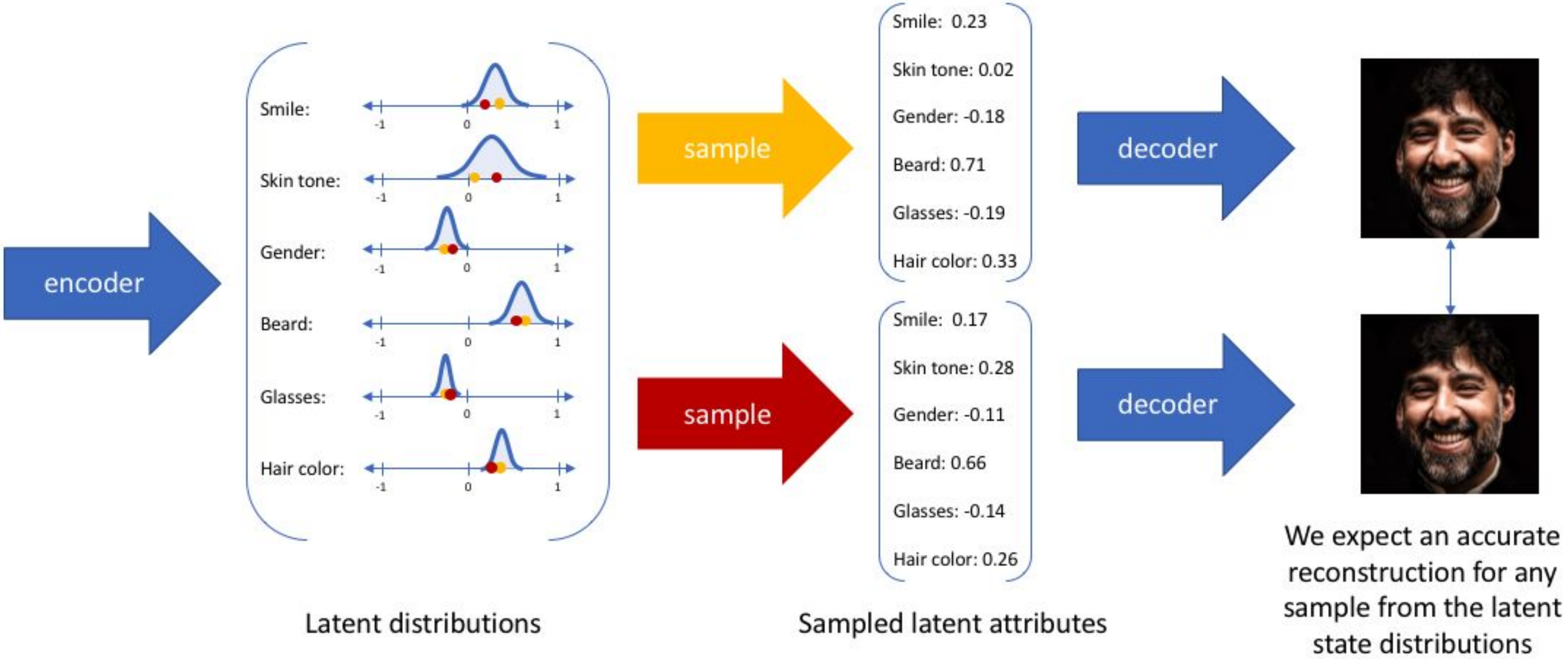
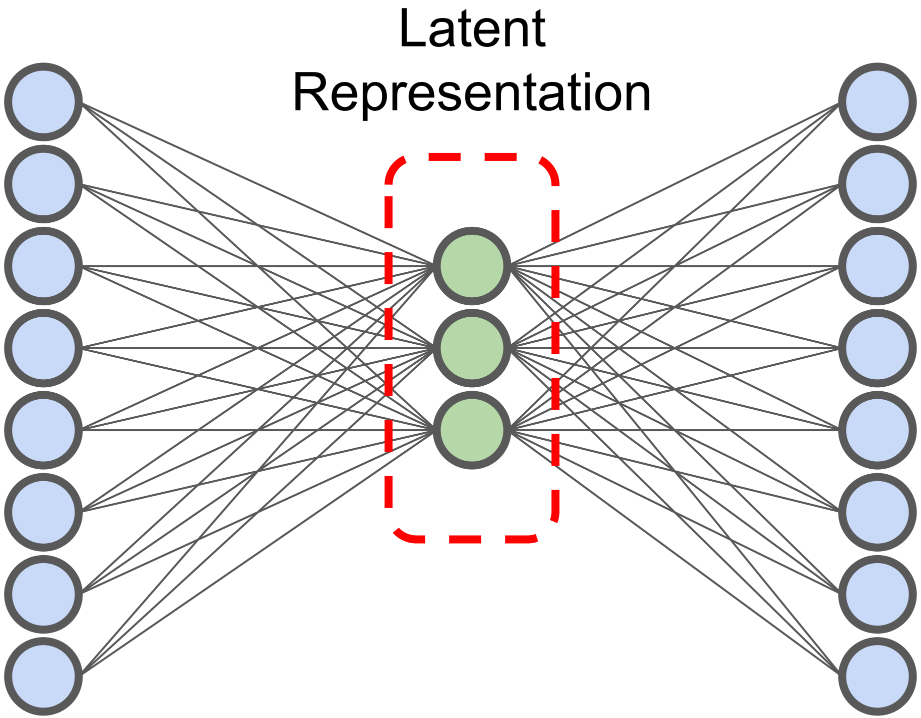
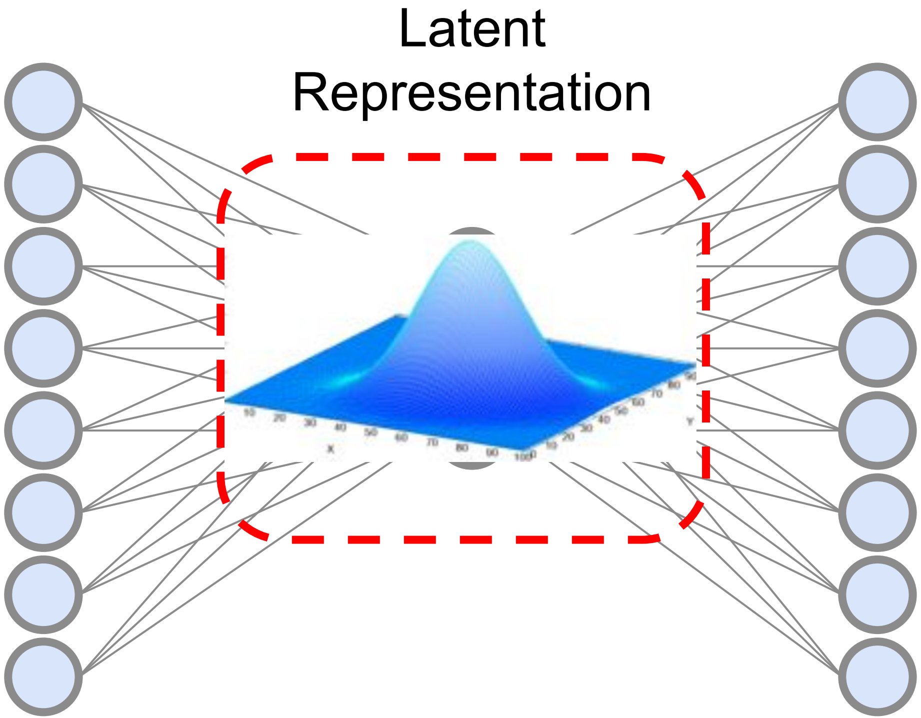


Image from: https://www.jeremyjordan.me/variational-autoencoders/

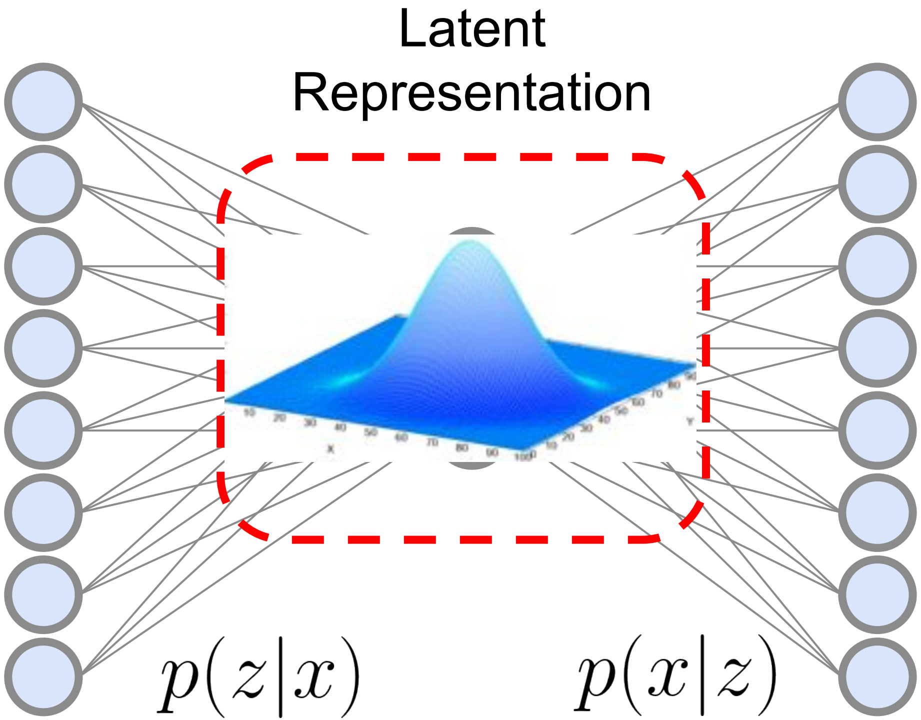
Autoencoder Architecture



Variational Autoencoder Architecture



Variational Autoencoder Architecture



Variational Autoencoder Architecture

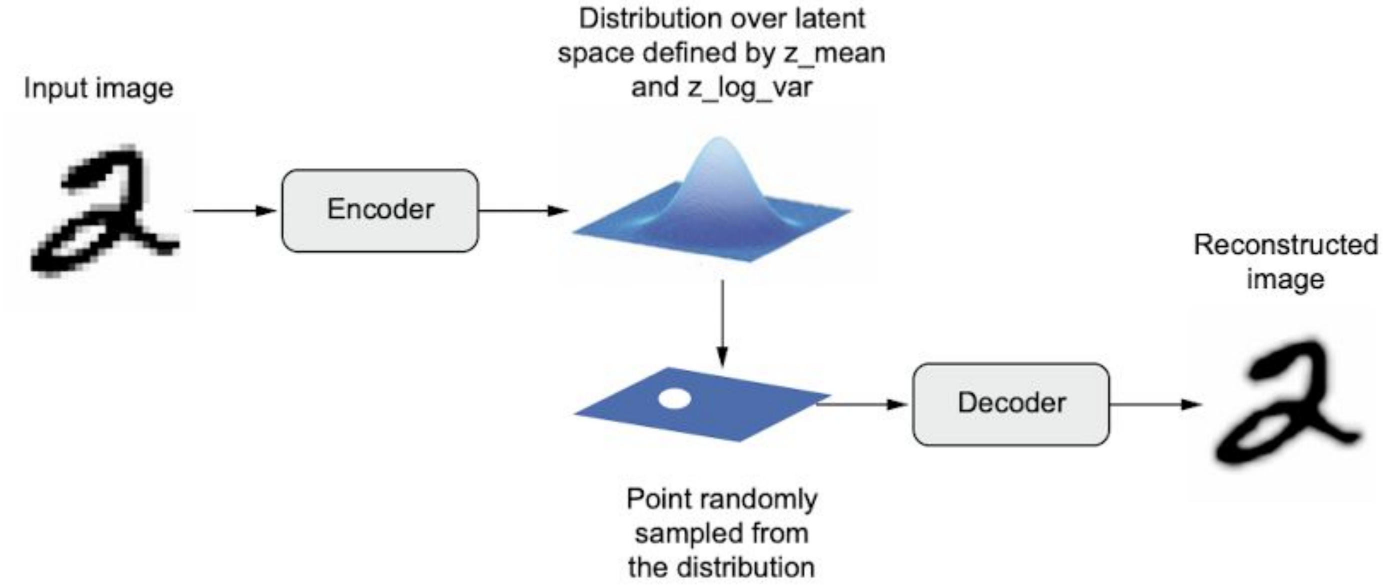
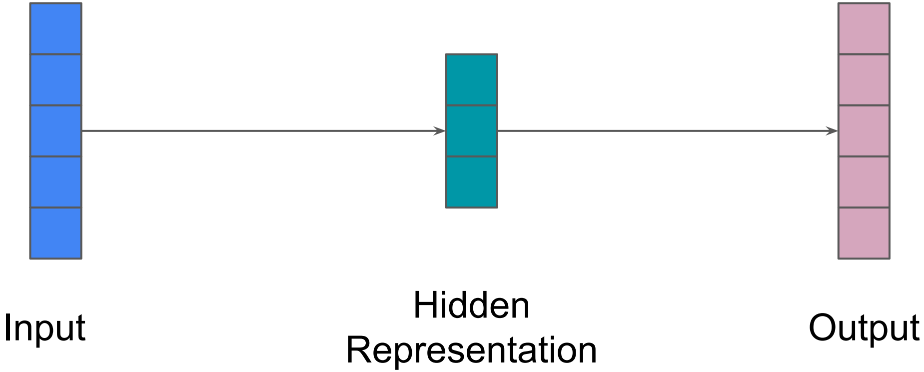


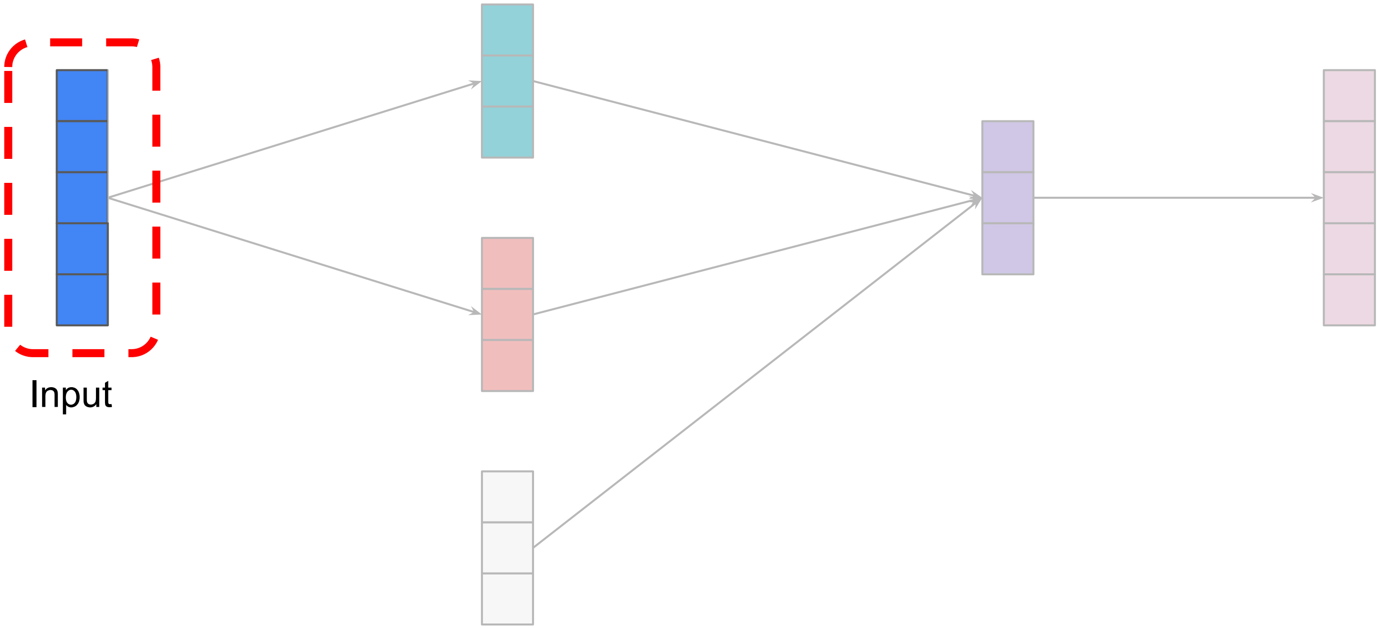
Figure 12.17 A VAE maps an image to two vectors, `z_mean` and `z_log_sigma`, which define a probability distribution over the latent space, used to sample a latent point to decode.

Image from: Deep Learning with Python 2nd Edition (Chollet)

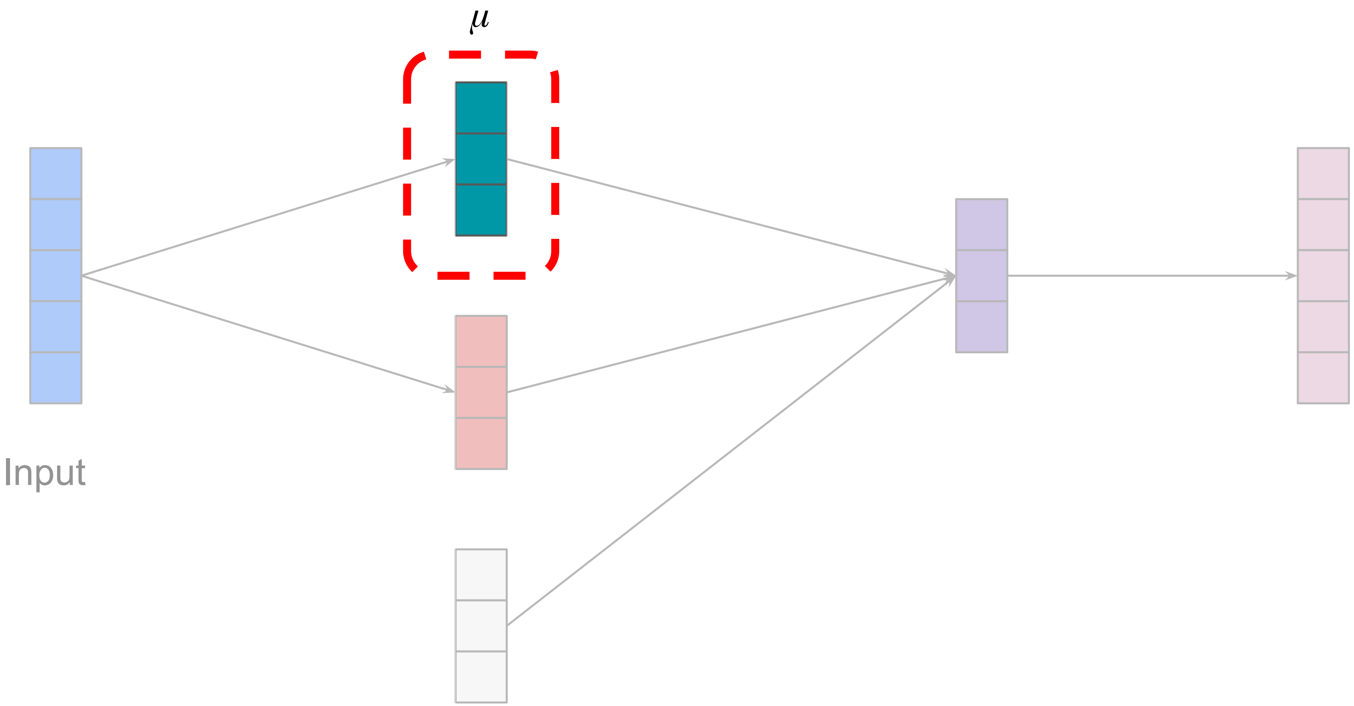
AE



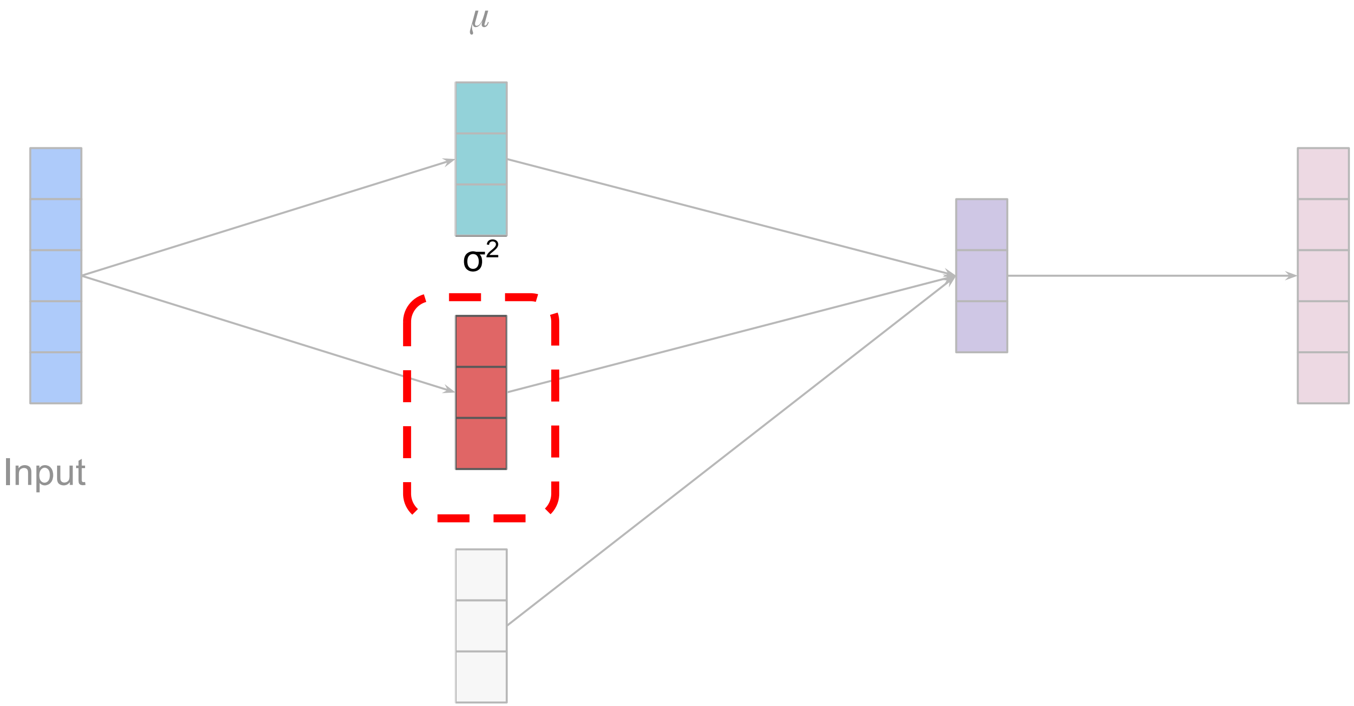
VAE



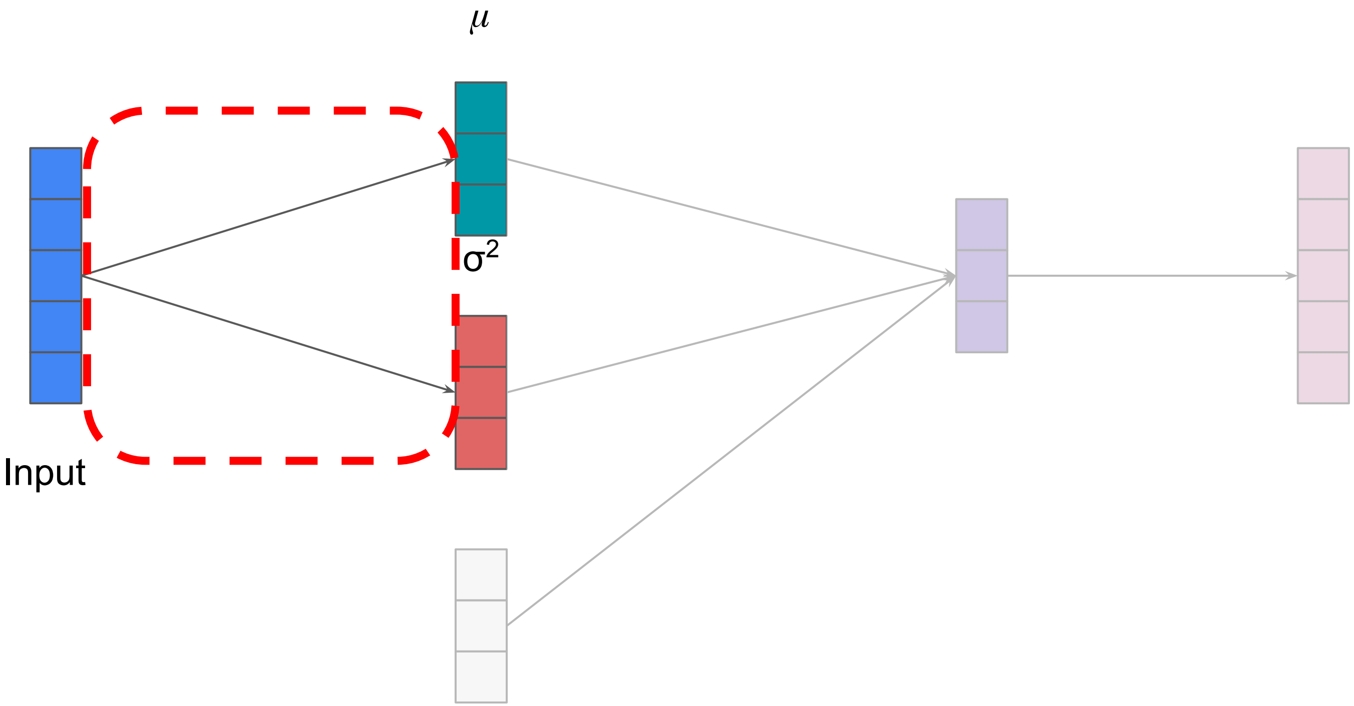
VAE



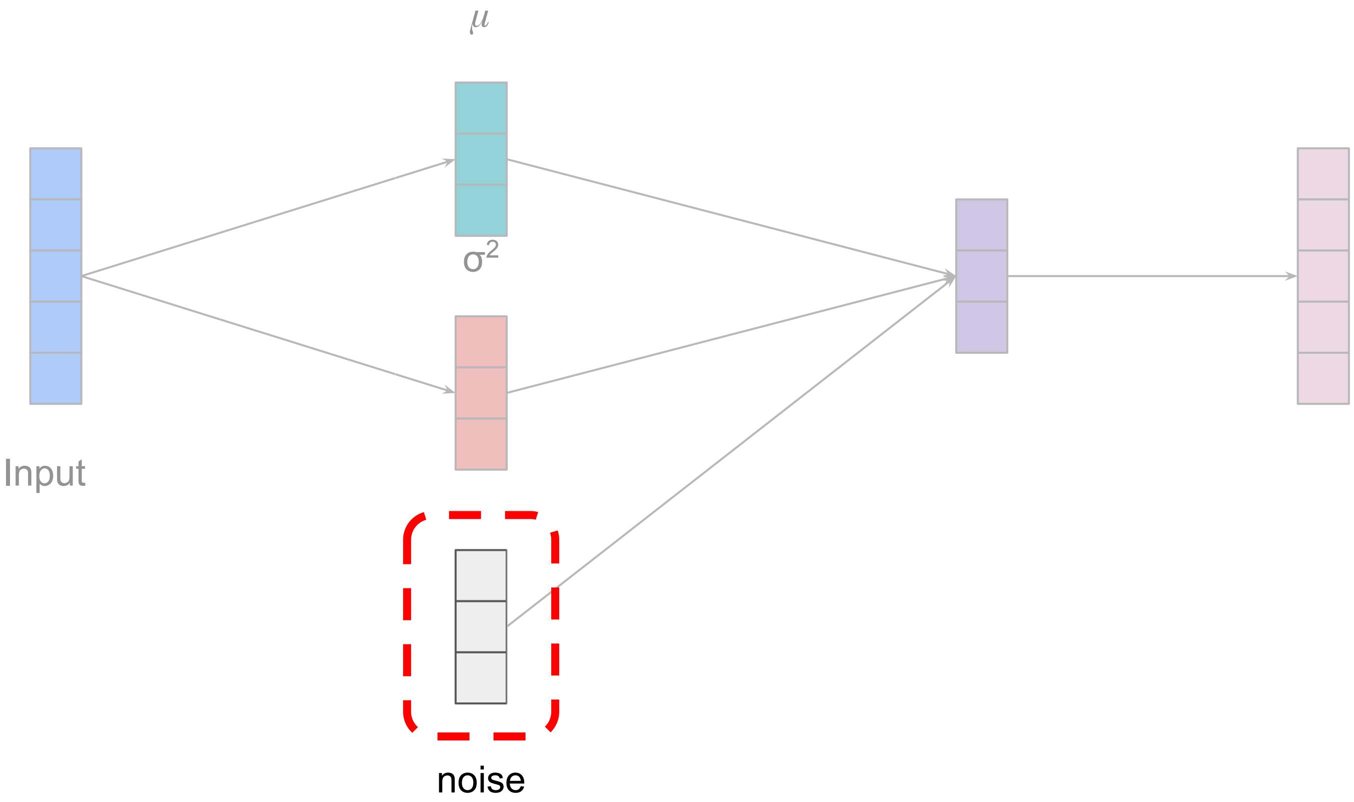
VAE



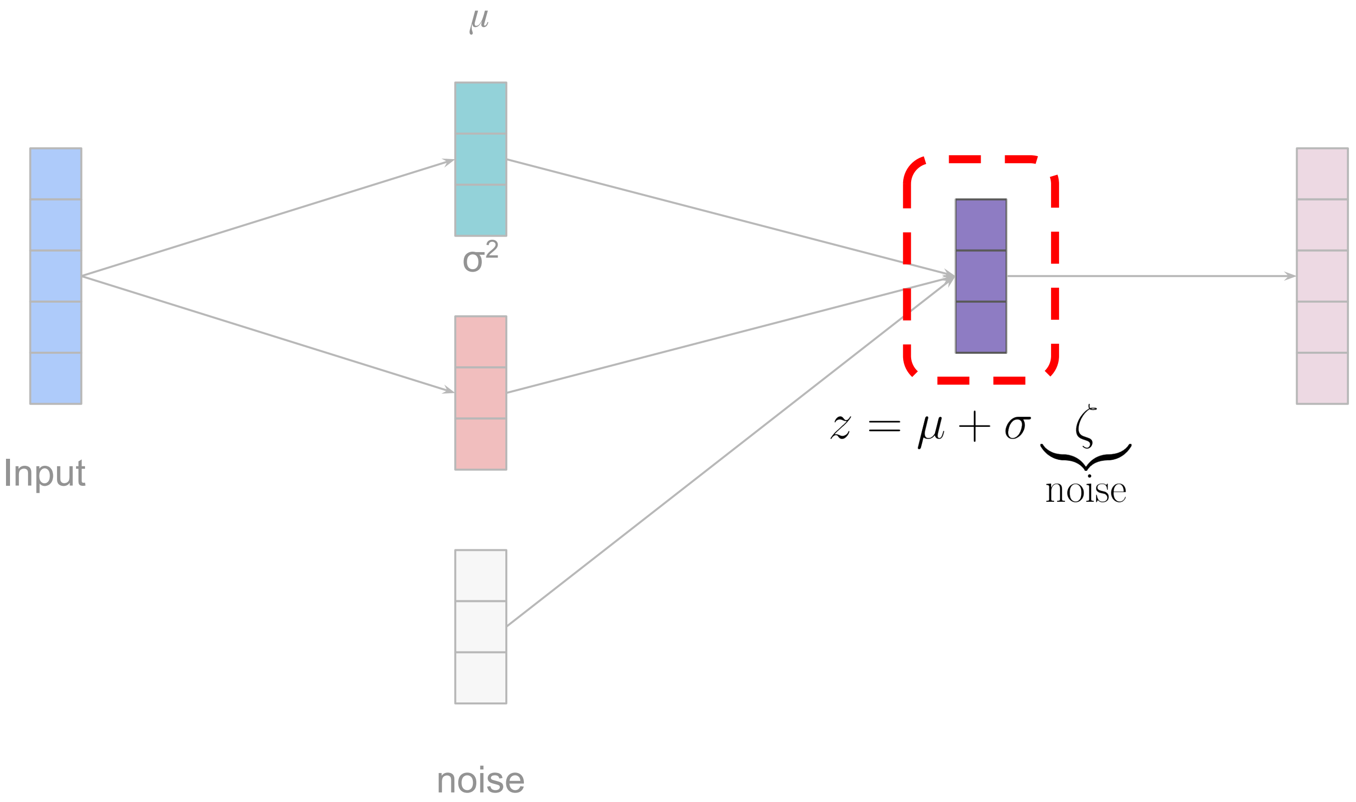
VAE



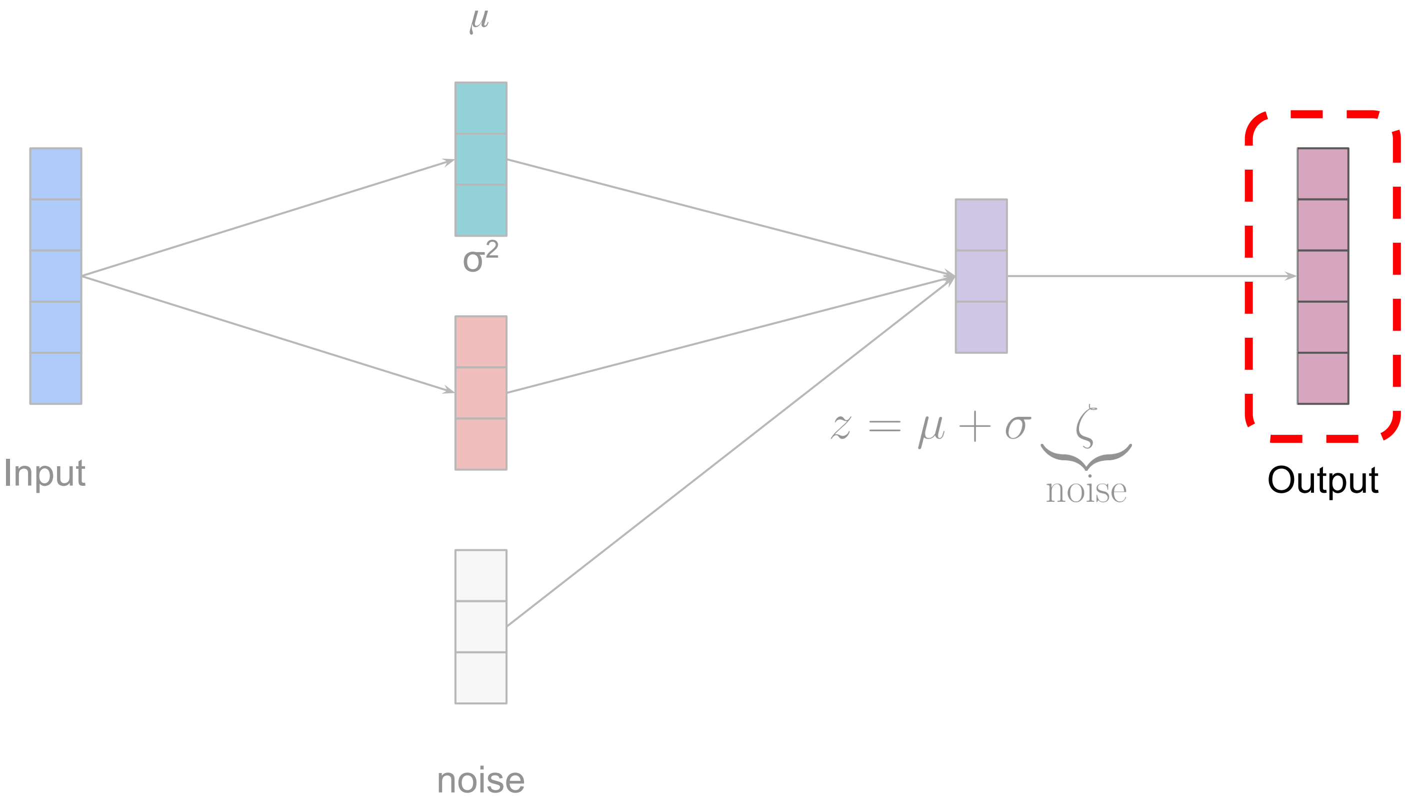
VAE



VAE

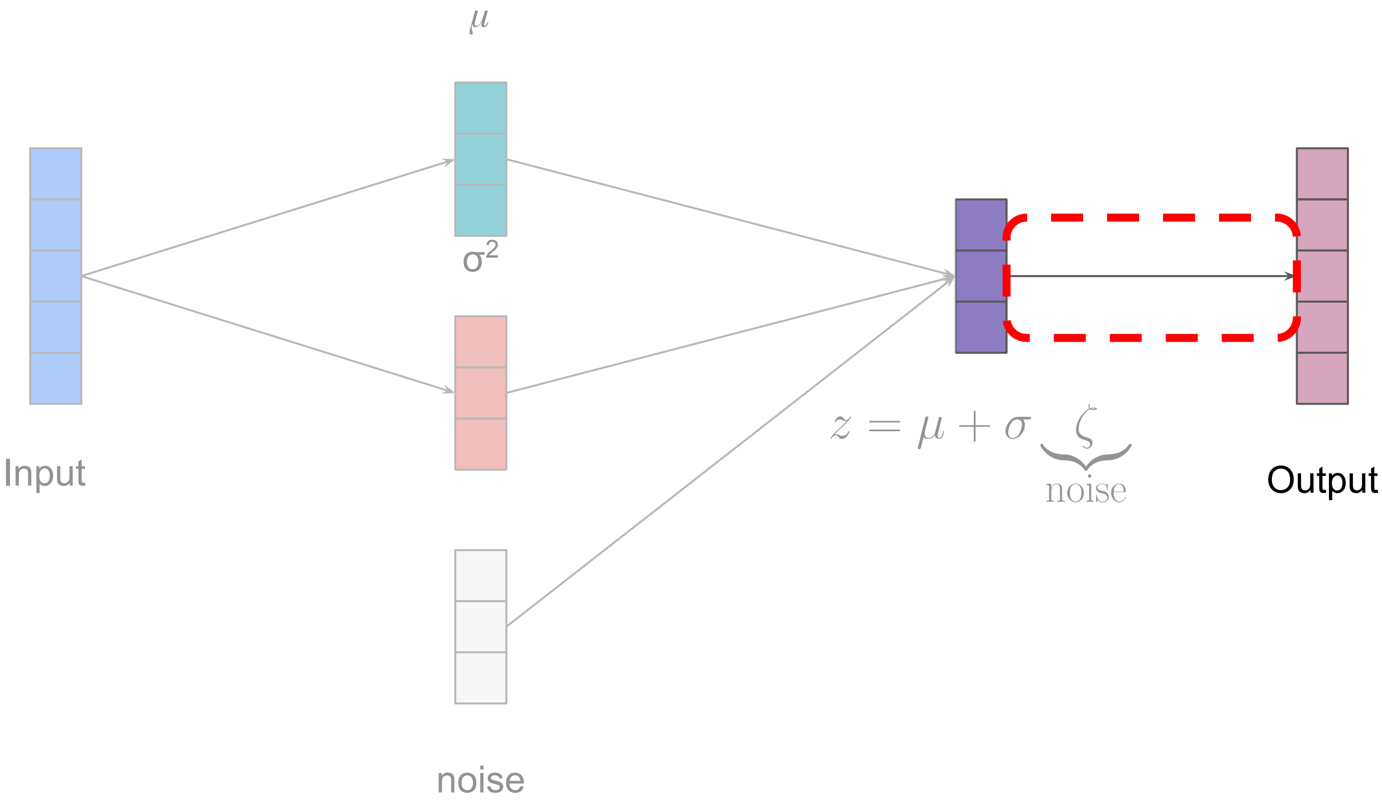


VAE



μ
σ^2
Input
noise
$z = \mu + \sigma \underbrace{\zeta}_{\text{noise}}$
Output

VAE


μ
σ^2
Input
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$z = \mu + \sigma \underbrace{\zeta}_{\text{noise}}$
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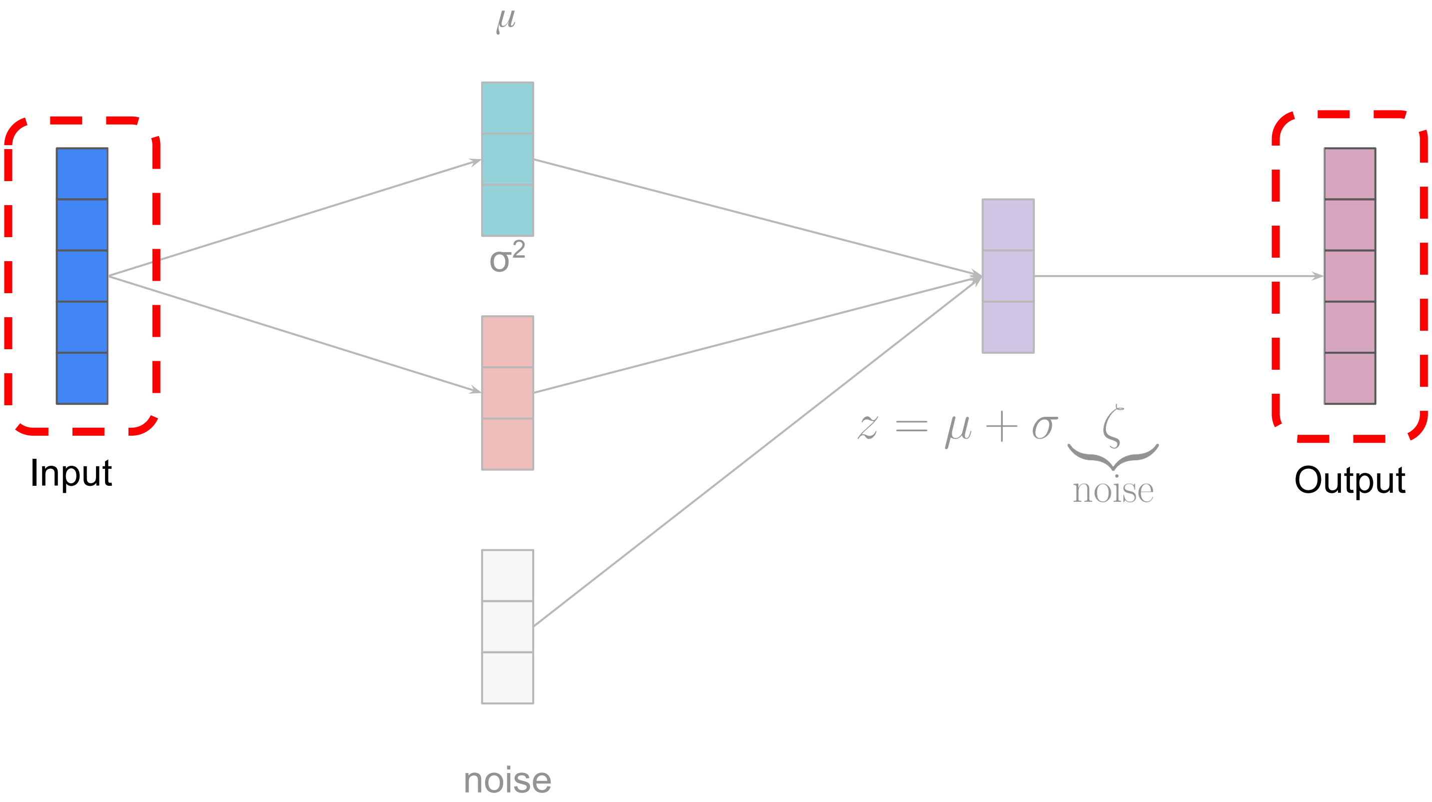
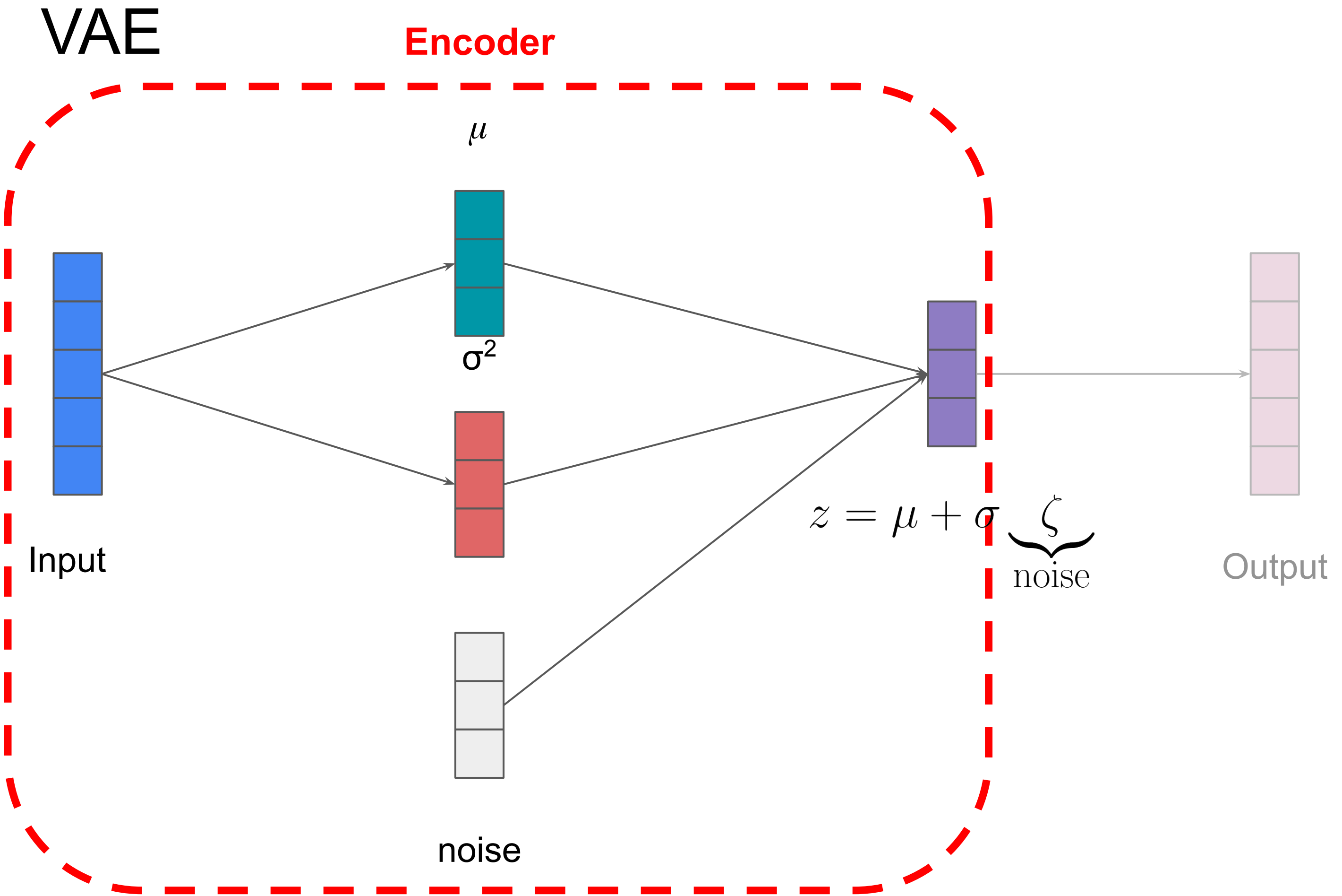
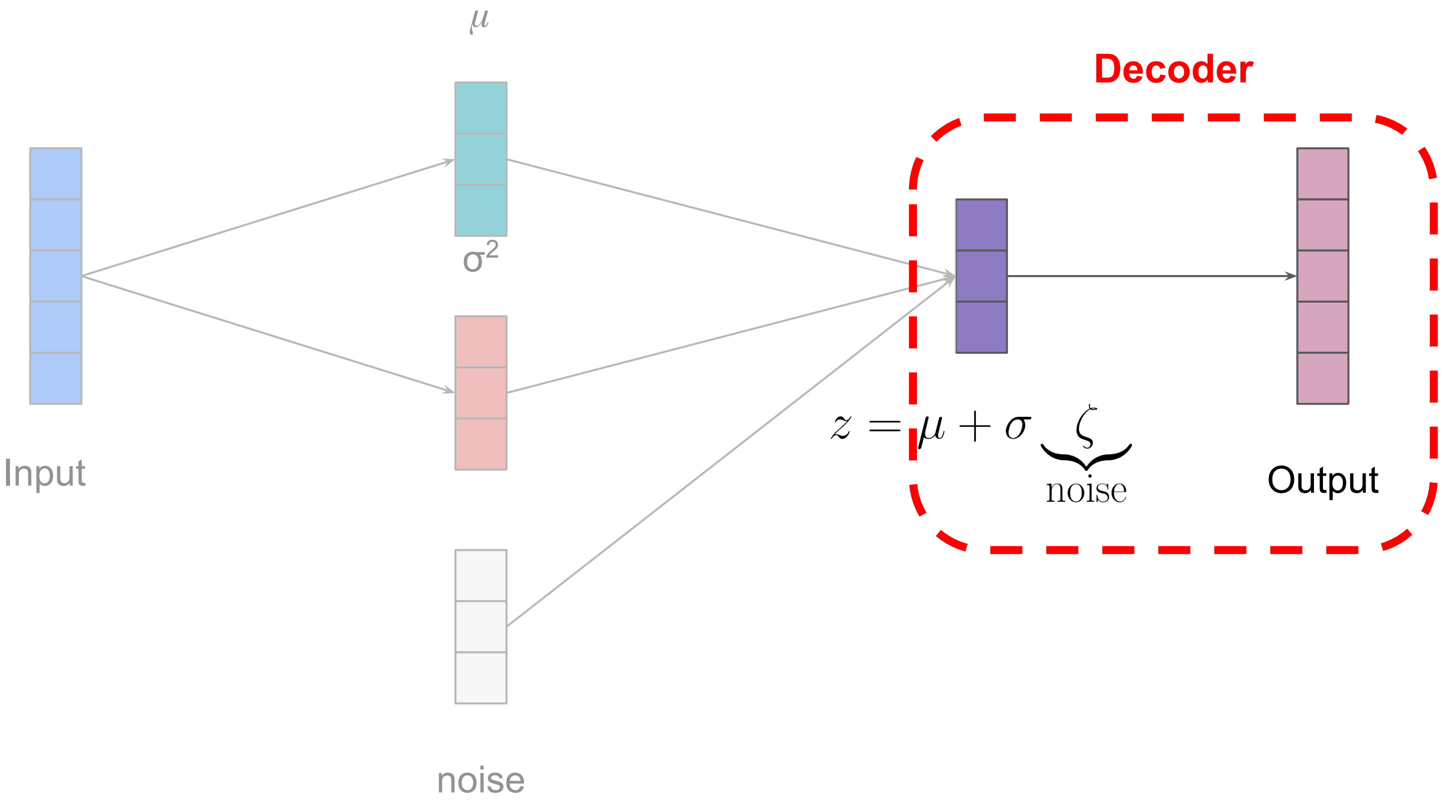
VAE



μ
σ^2
Input
$z = \mu + \sigma \underbrace{\zeta}_{\text{noise}}$
Output
noise


VAE
Encoder
μ
σ^2
Input
noise
$z = \mu + \sigma \underbrace{\zeta}_{\text{noise}}$
Output

VAE



μ
σ^2
Decoder
Input
$z = \mu + \sigma \underbrace{\zeta}_{\text{noise}}$
Output
noise

VAE Pseudocode

Variational Autoencoder Pseudocode

```
z_mean, z_log_variance = encoder(input_img)

z = z_mean + exp(z_log_variance) * epsilon

reconstructed_img = decoder(z)

model = Model(input_img, reconstructed_img)
```

Variational Autoencoder Pseudocode

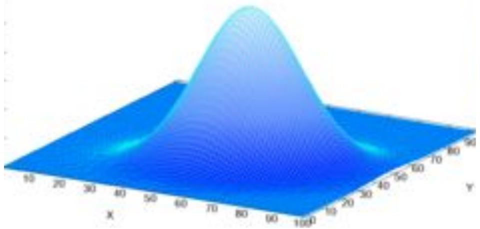
```
z_mean, z_log_variance = encoder(input_img)

z = z_mean + exp(z_log_variance) * epsilon

reconstructed_img = decoder(z)

model = Model(input_img, reconstructed_img)
```

The encoder generates a hidden representation for the input using a multivariate normal *distribution* with two parameters, μ and σ^2



Variational Autoencoder Pseudocode

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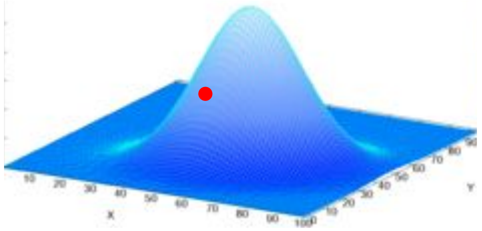
z = z_mean + exp(z_log_variance) * epsilon
reconstructed_img = decoder(z)
model = Model(input_img, reconstructed_img)
```

Sample from a normal distribution with mean (`z_mean`) and variance (`exp(z_log_variance)`)



Variational Autoencoder Pseudocode

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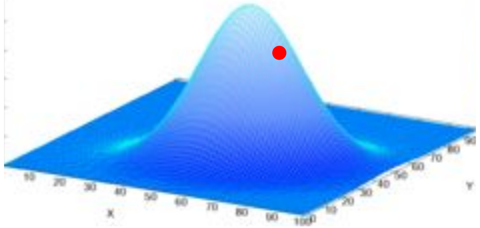


Variational Autoencoder Pseudocode

```
z_mean, z_log_variance = encoder(input_img)

z = z_mean + exp(z_log_variance) * epsilon

reconstructed_img = decoder(z)

model = Model(input_img, reconstructed_img)
```

Decoder takes random sample and tries to re-generate input

Variational Autoencoder Pseudocode

```
z_mean, z_log_variance = encoder(input_img)

z = z_mean + exp(z_log_variance) * epsilon

reconstructed_img = decoder(z)

model = Model(input_img, reconstructed_img)
```

Decoder takes random sample and tries to re-generate input

we expect different samples to create similar images

VAE Loss Function

VAE Loss (Reconstruction)

$$\text{AE loss} = \boxed{\|x - \hat{x}\|^2}$$

$$\text{VAE loss} = \boxed{\|x - \hat{x}\|^2} + KL(N(\mu, \sigma^2), N(0, 1))$$

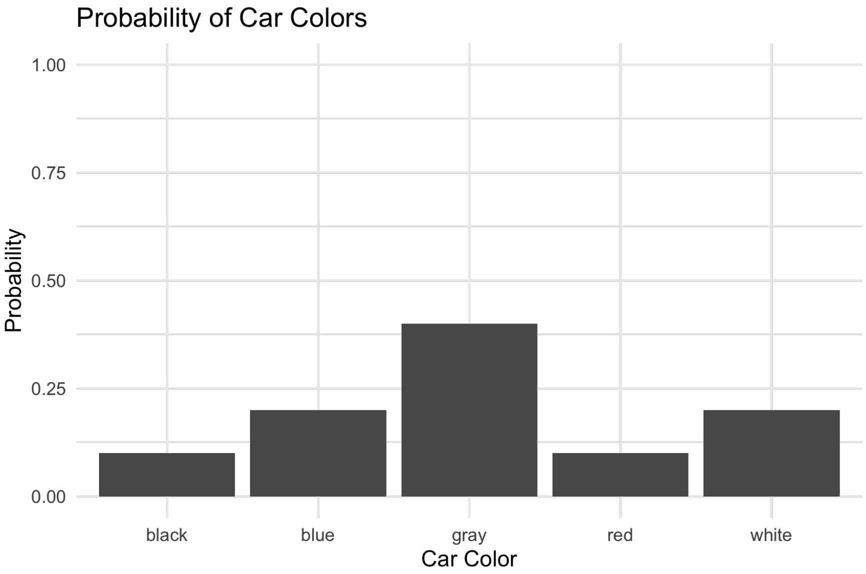
VAE Loss (Regularization)

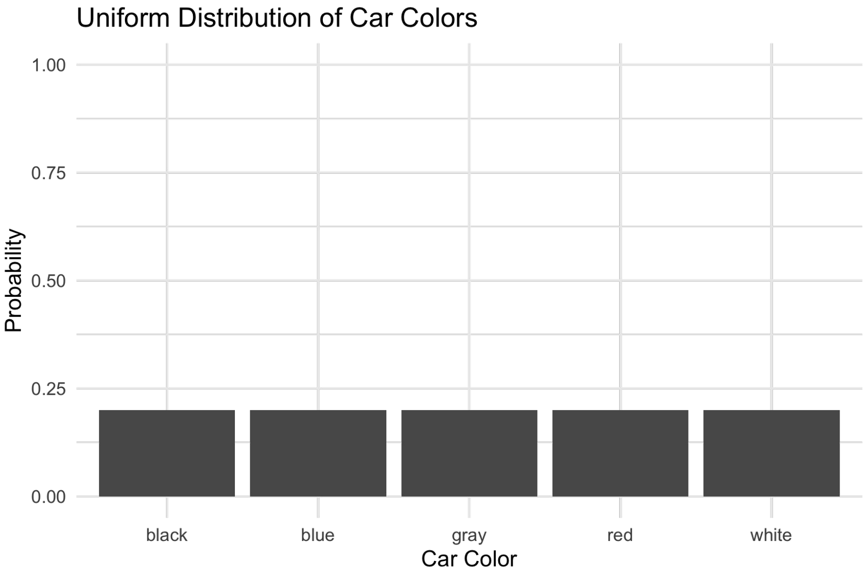
$$\text{AE loss} = \|x - \hat{x}\|^2$$

$$\text{VAE loss} = \|x - \hat{x}\|^2 + \boxed{KL(N(\mu, \sigma^2), N(0,1))}$$

KL Divergence

$$D_{KL}(p||q) = \sum_{i=1}^{N} p(x_i) \cdot (log\ p(x_i) - log\ q(x_i))$$



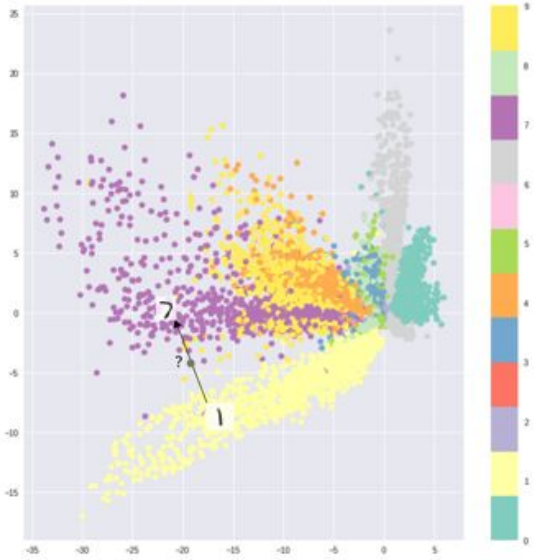


VAE Loss (Regularization)

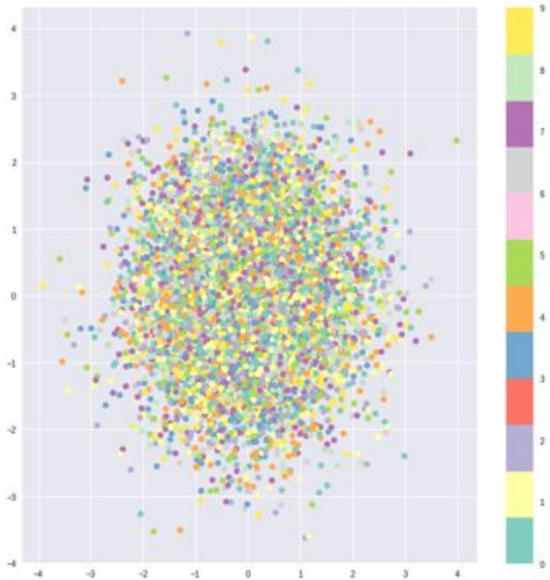
$$\text{AE loss} = \|x - \hat{x}\|^2$$

$$\text{VAE loss} = \|x - \hat{x}\|^2 + \boxed{KL(N(\mu, \sigma^2), N(0,1))}$$

Only reconstruction loss



Only KL divergence



Combination

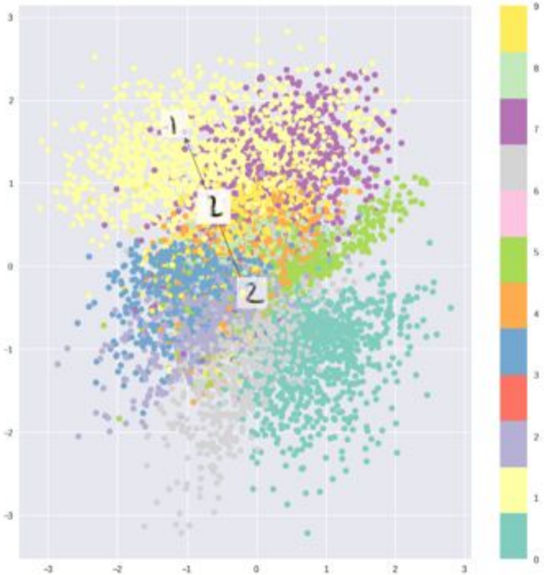


Image from: https://www.jeremyjordan.me/variational-autoencoders/

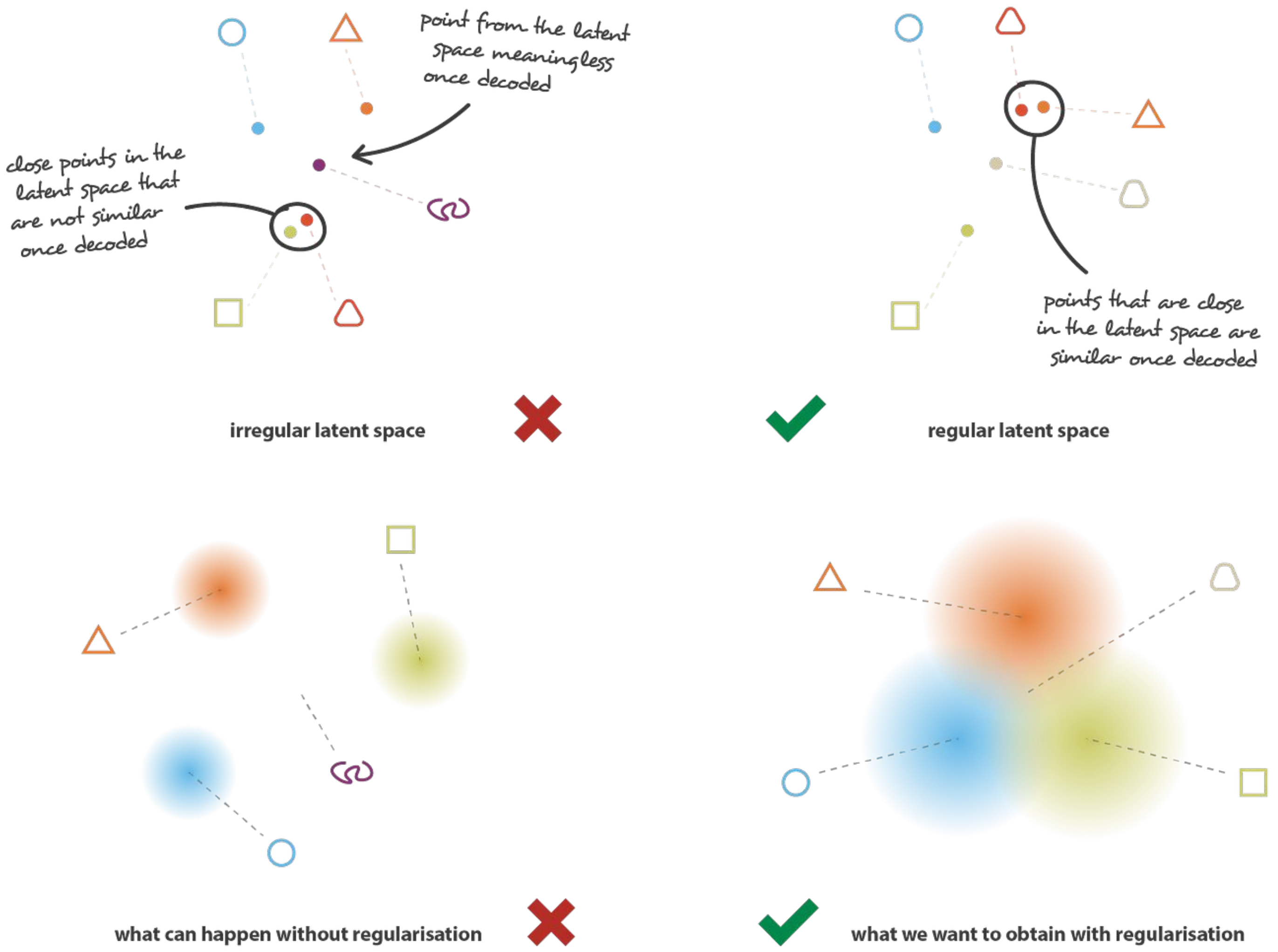


Image from: https://towardsdatascience.com/understanding-variational-autoencoders-vaes-f70510919f73

VAE Output

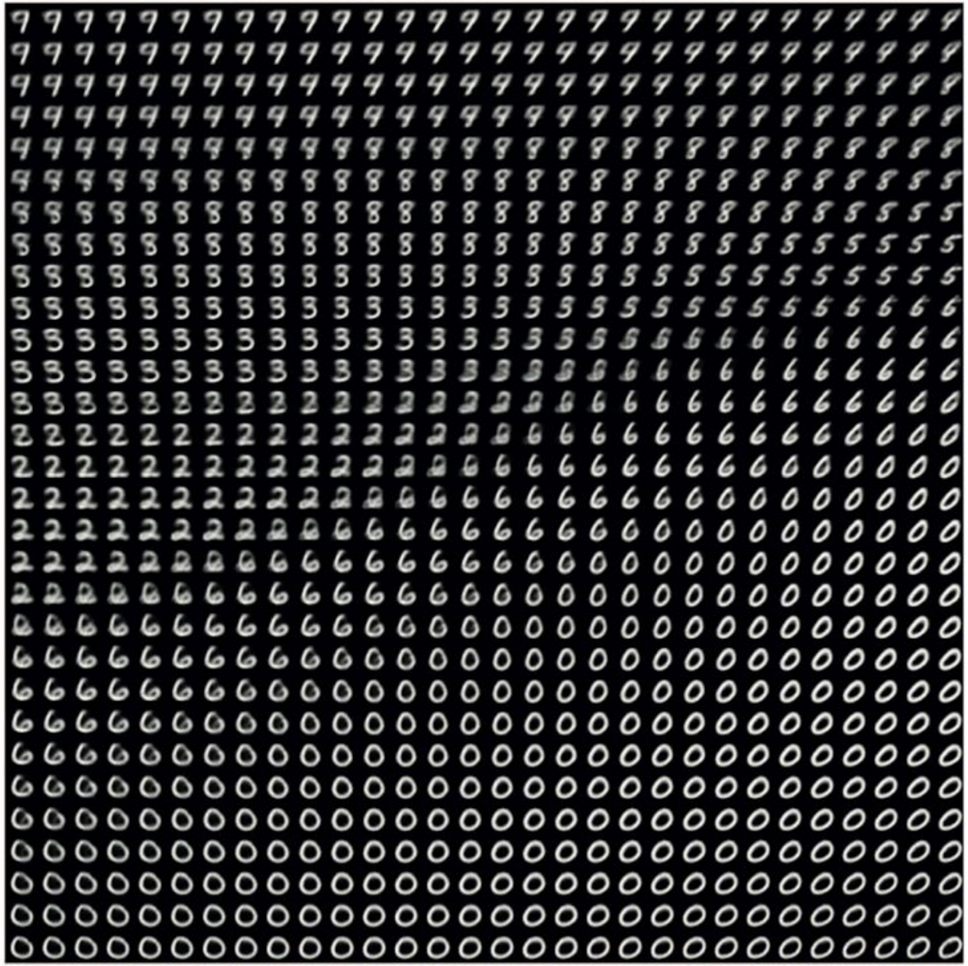


Figure 12.18 Grid of digits decoded from the latent space

Image from: Deep Learning with Python 2nd Edition (Chollet)

Ideal Latent Spaces

- Representation
- Realism
- Smoothness

Idea from: https://magenta.tensorflow.org/music-vae

Ideal Latent Spaces

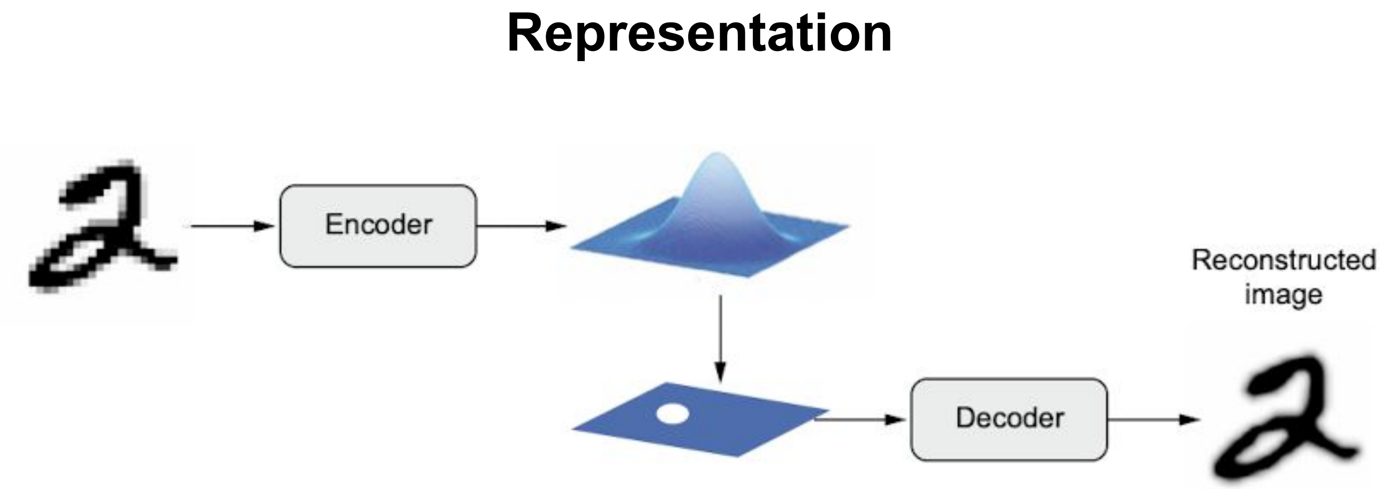


Image from: Deep Learning with Python 2nd Edition (Chollet)

Ideal Latent Spaces

Realism

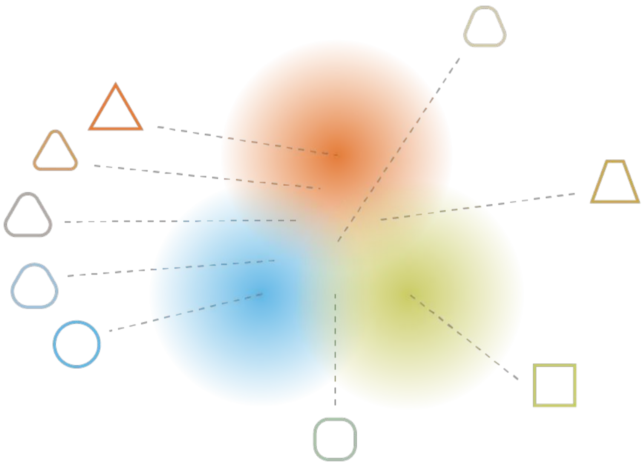


Image from: https://towardsdatascience.com/understanding-variational-autoencoders-vaes-f70510919f73

Ideal Latent Spaces

Smoothness

Image from: https://magenta.tensorflow.org/music-vae

NOTE

- Convolutional Neural Networks for learning features preferred **max pooling** to strides
- However, max pooling does not preserve location
- In C-VAEs **strides** are used to preserve information location

Strides	**Max Pooling**
Where are things in an image	What's in an image

Music VAE

Interpolation: a mathematical technique to estimate the values of unknown data points that fall in between existing, known data points.

From: https://www.investopedia.com/terms/i/interpolation.asp