UCL ARTIFICIAL
INTELLIGENCE SOCIETY

TUTORIAL #9

Session 9

Generative Models

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LECTURE OVERVIEW

01 Introduction to Generative AI

What is it? Why do we care?

02 Types of Generative Models

GANs, VAEs, ...

03 Variational Autoencoders

The theory and how to train VAE models

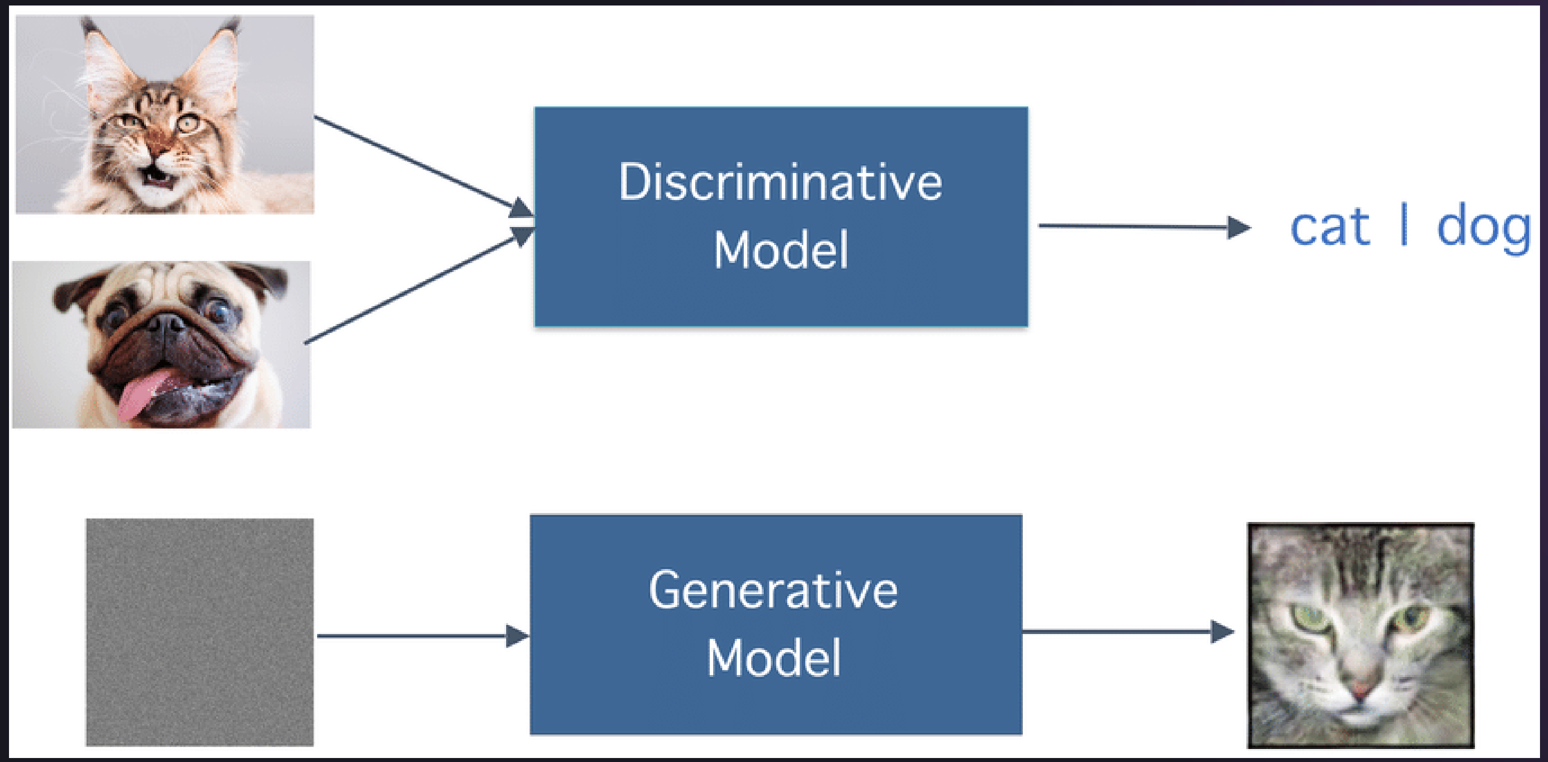
Theory

INTRODUCTION TO GENERATIVE AI

Discriminative v. Generative

– **Discriminative models** – discriminate between different kinds of data instances

– **Generative models** – can generate new data instances



Theory

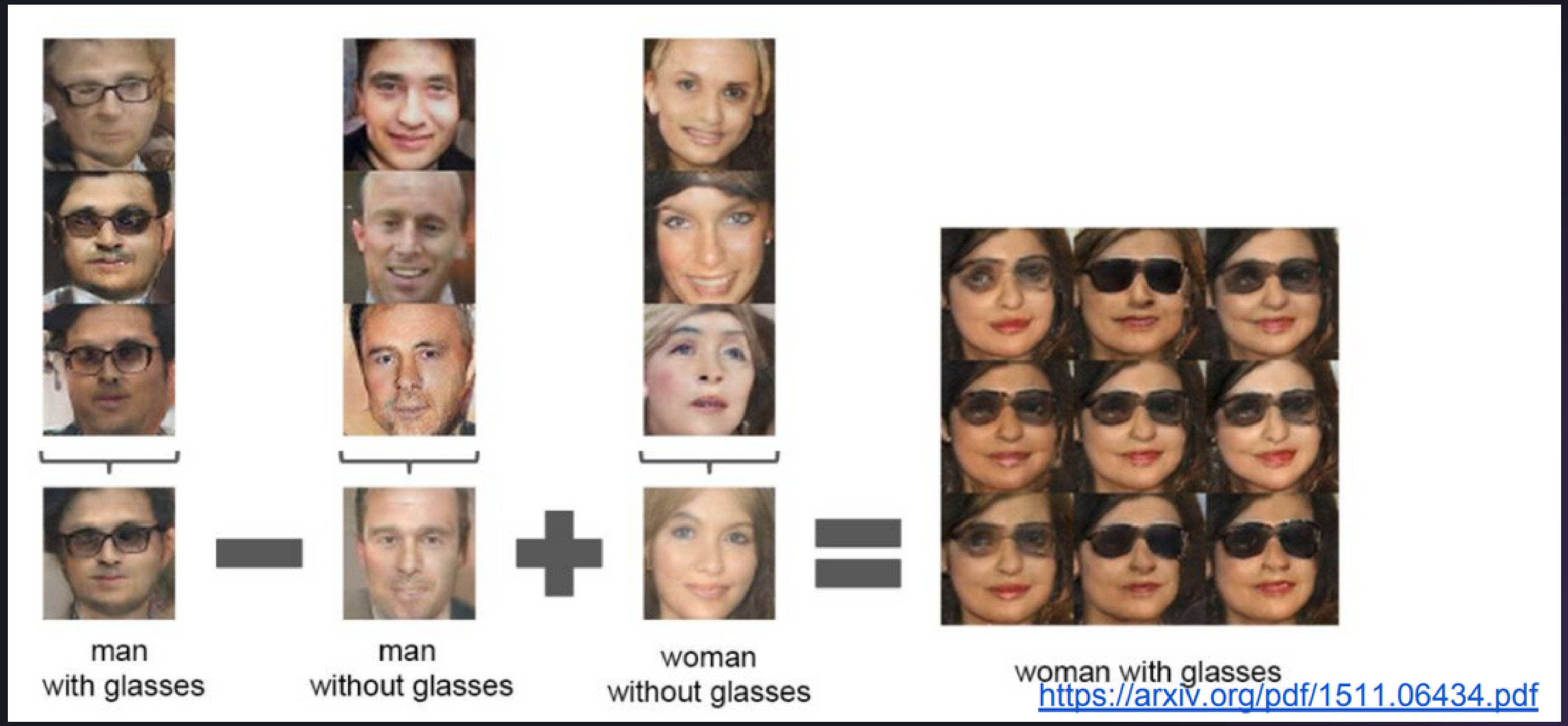
INTRODUCTION TO GENERATIVE AI

Why are generative models important?

- Generative models can generate new unseen data
- They can be used to create synthetic data
- Help in uncovering hidden relationships in the data
- Their ability to generate new data has wide-ranging applications in fields such as drug discovery, creative writing, and environment simulation

Theory

INTRODUCTION TO GENERATIVE AI



Theory

INTRODUCTION TO GENERATIVE AI

> *“What I cannot create, I do not understand.”*
>
> *—Richard Feynman*

Theory

TYPES OF GENERATIVE MODELS

- **Variational Autoencoder (VAE)** - Learns compact data representation and generates new samples.

- **Generative Adversarial Networks (GANs)** - A deep learning model for generative process using two competing neural networks.

- **Autoregressive Models**
- **Transformer Models**
- **Flow-based Models**
- **Generative Pre-trained Transformer (GPT)**

Theory

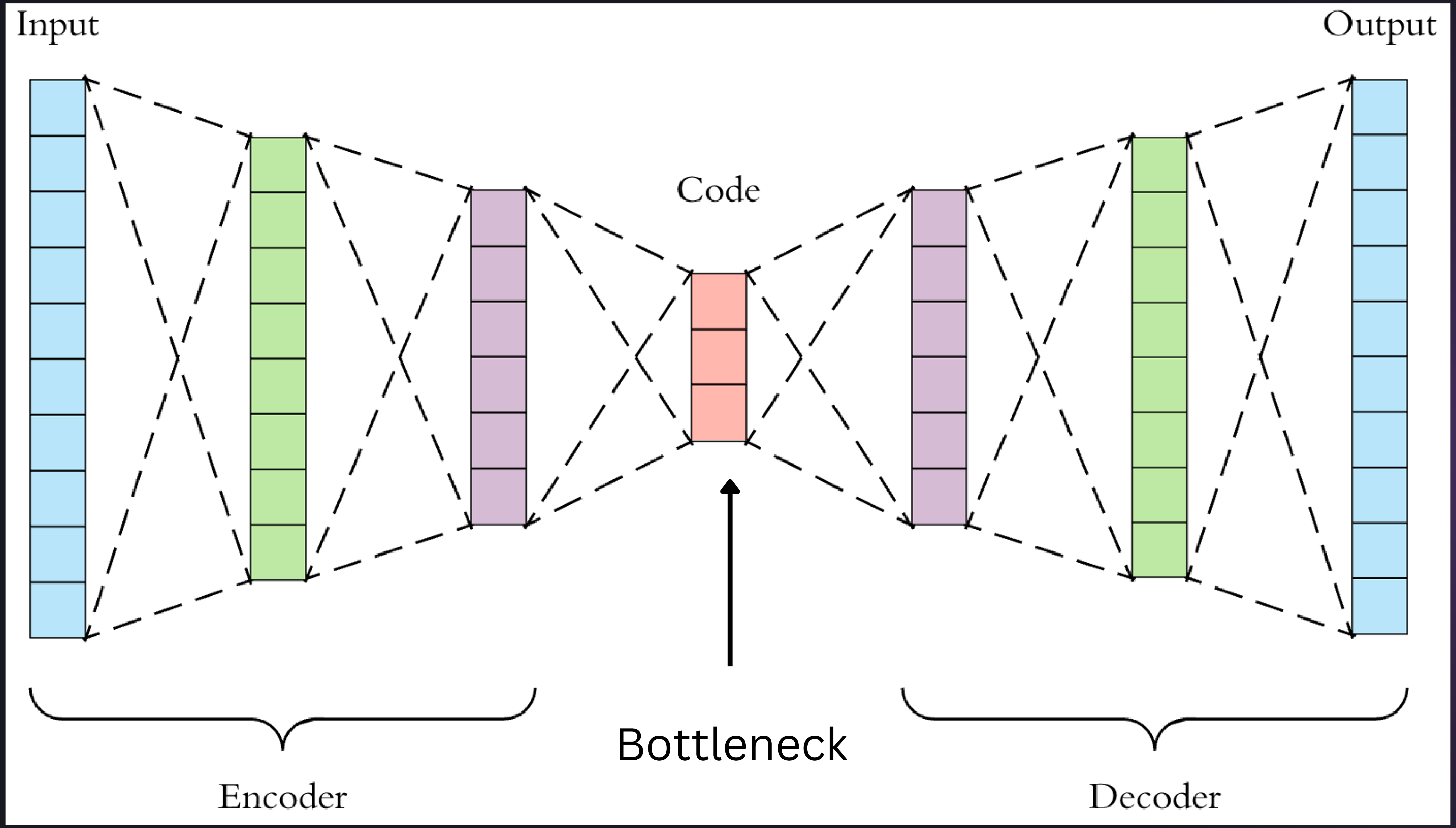
AUTOENCODERS

INPUT DIMENSIONS: 28X28

FIRST, REDUCE DIMENSIONS AND THEN INCREASE DIMENSIONS.

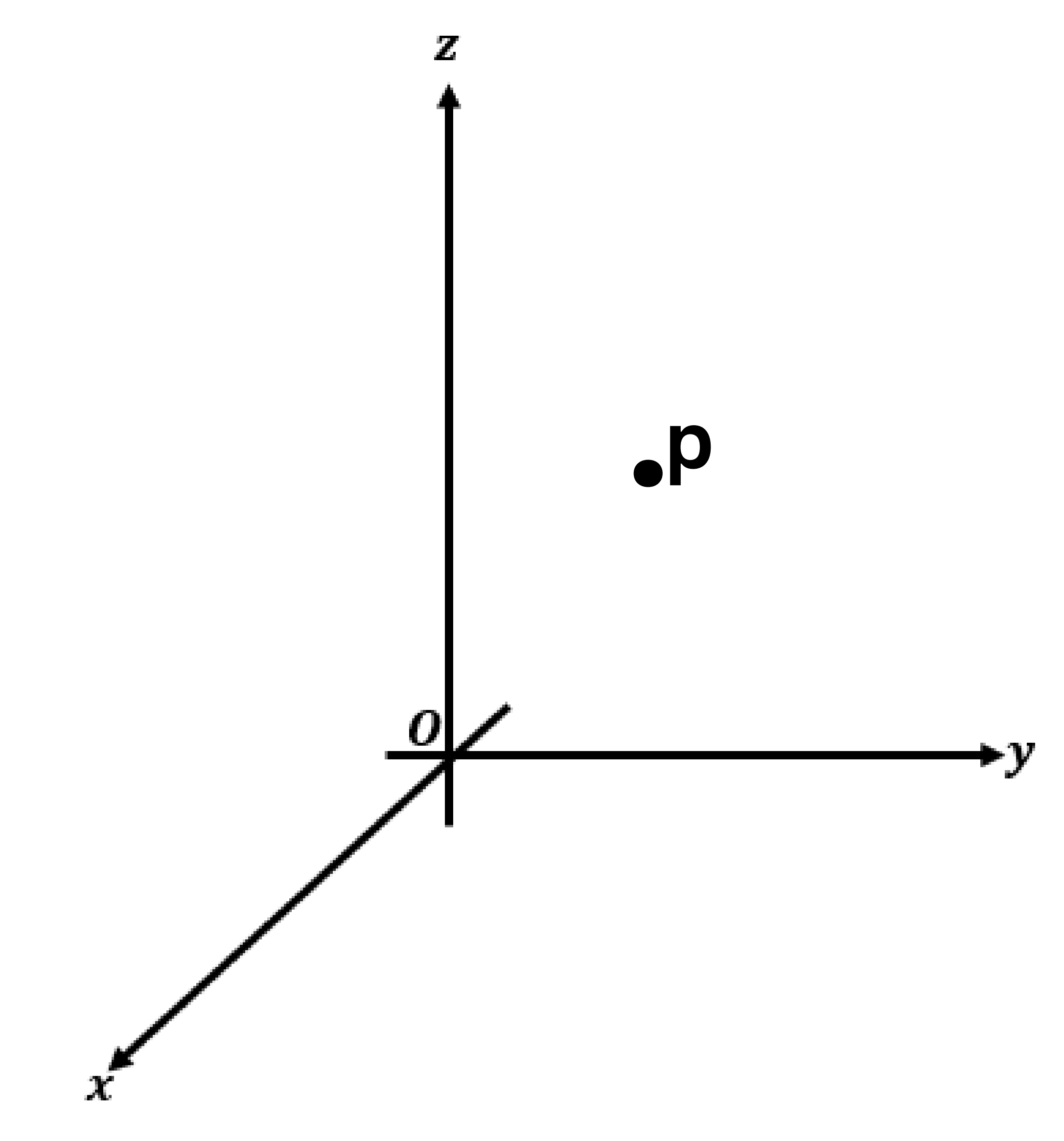
OUTPUT DIMENSIONS: 28X28

THE BOTTLENECK MUST BE BIG ENOUGH TO REPRESENT THE INPUT, BUT SMALL ENOUGH THAT THE WHOLE OPERATION IS NOT TRIVIAL



Theory

AUTOENCODERS



Let p be a point in n dimensional space.

For a n dimensional space $p = [p_1, p_2, p_3 ... p_n]$

Say $f(p)$ is a function that maps the point p from an n dimensional space to a m dimensional space.

For example.

let point $p = [5, 3, 7]$ and,

$q = f(p) = (x_1 + x_2,\ x_3)$ where $f : R^3 \rightarrow R^2$

therefore, $q = [8, 7]$

Theory

AUTOENCODERS

Uses

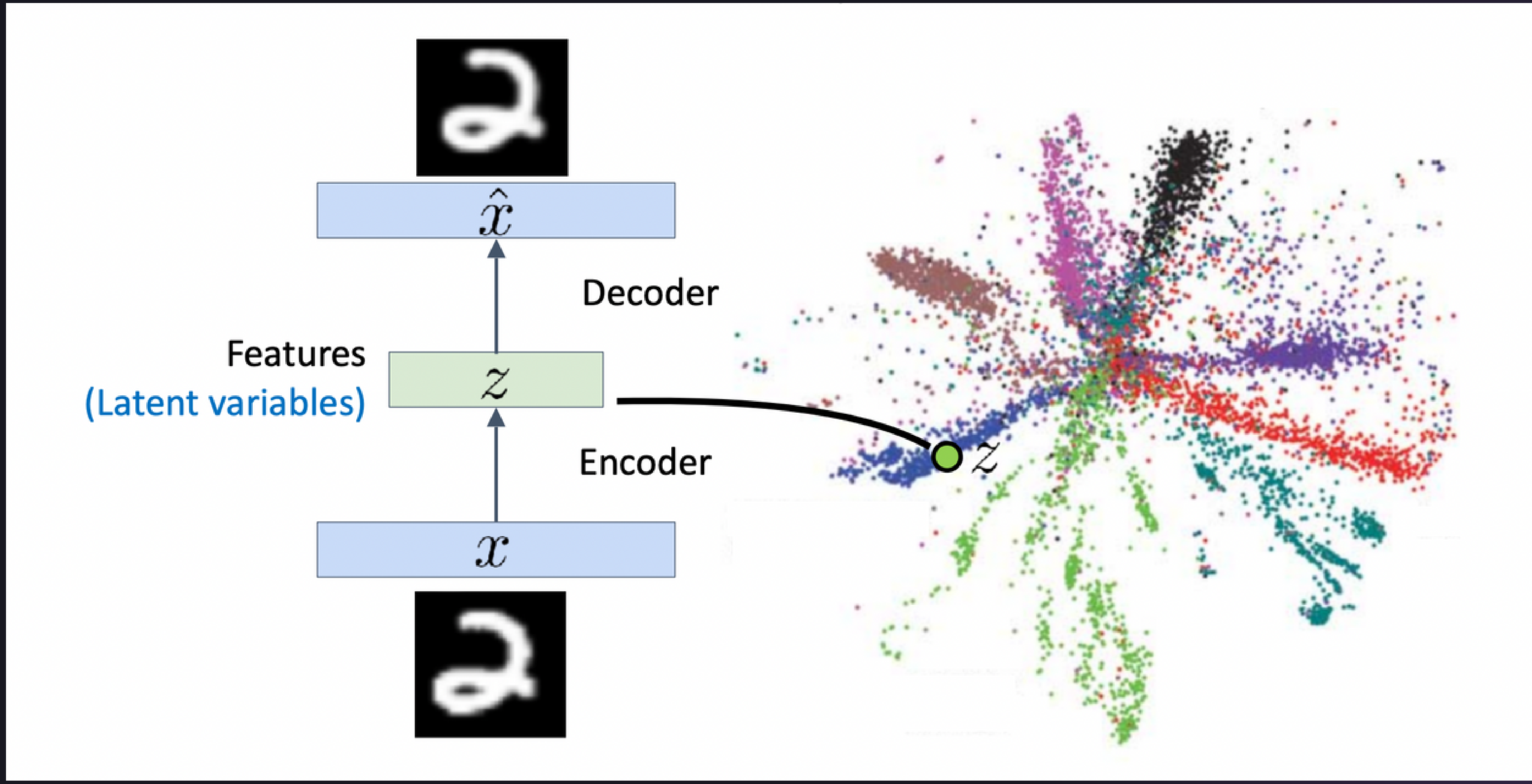
- Denoising
- Image compression (is comparable/better than JPEG)
- Supersampling in images
- Dimensionality reduction (example, non-images)
- Anomaly detection
- Generating data points in latent space (drug molecule generation etc.)

Theory

AUTOENCODERS

Latent space is a compressed feature space (usually of lower dimension), where similar points are placed closer together.

Essentially, an autoencoder learns how to remap data points such that similar data points are closer together



Theory

AUTOENCODERS

Theory

VARIATIONAL AUTOENCODERS

Training a good latent space

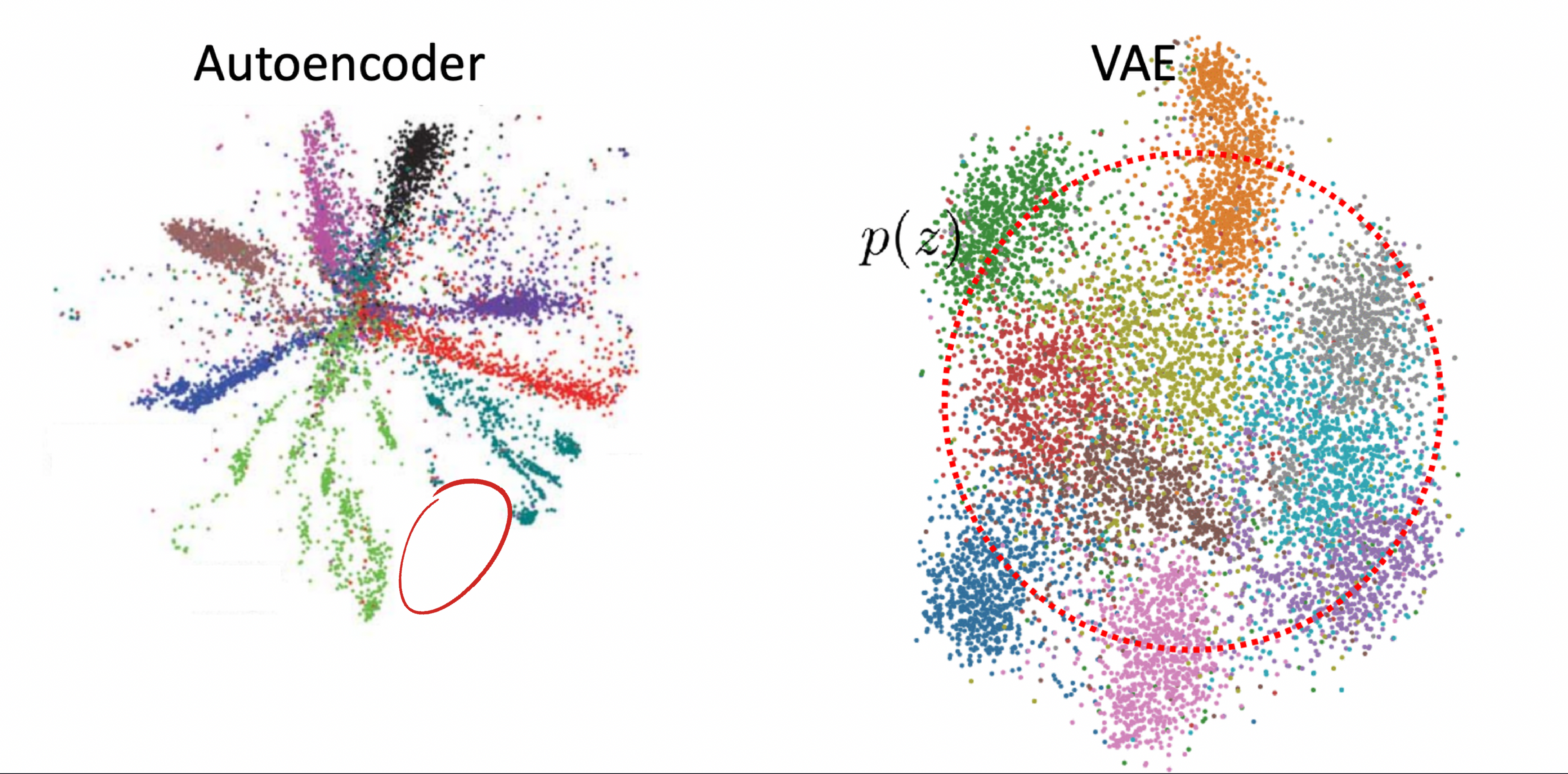
The beauty of autoencoders is in their ability to represent a data point in a lower dimensional space.

NOTE: This latent space is not interpretable.

The latent space is sparse (not enough data points for the model to learn what to do). We can bypass this by adding a constraint to the latent space.

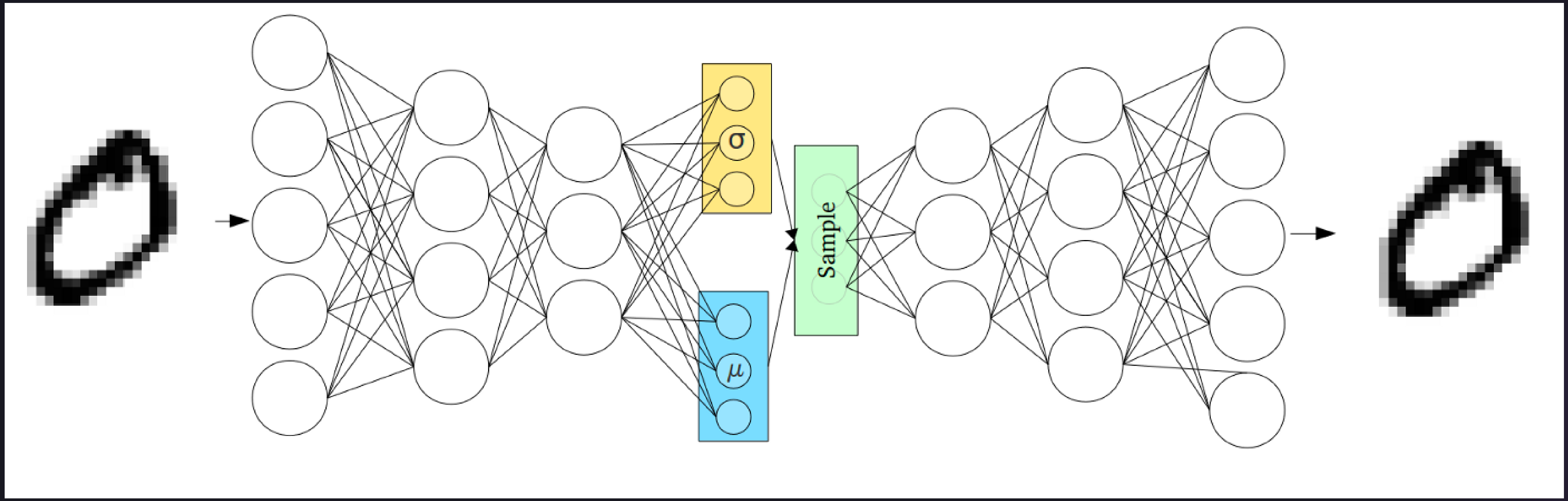
Theory

RESAMPLING



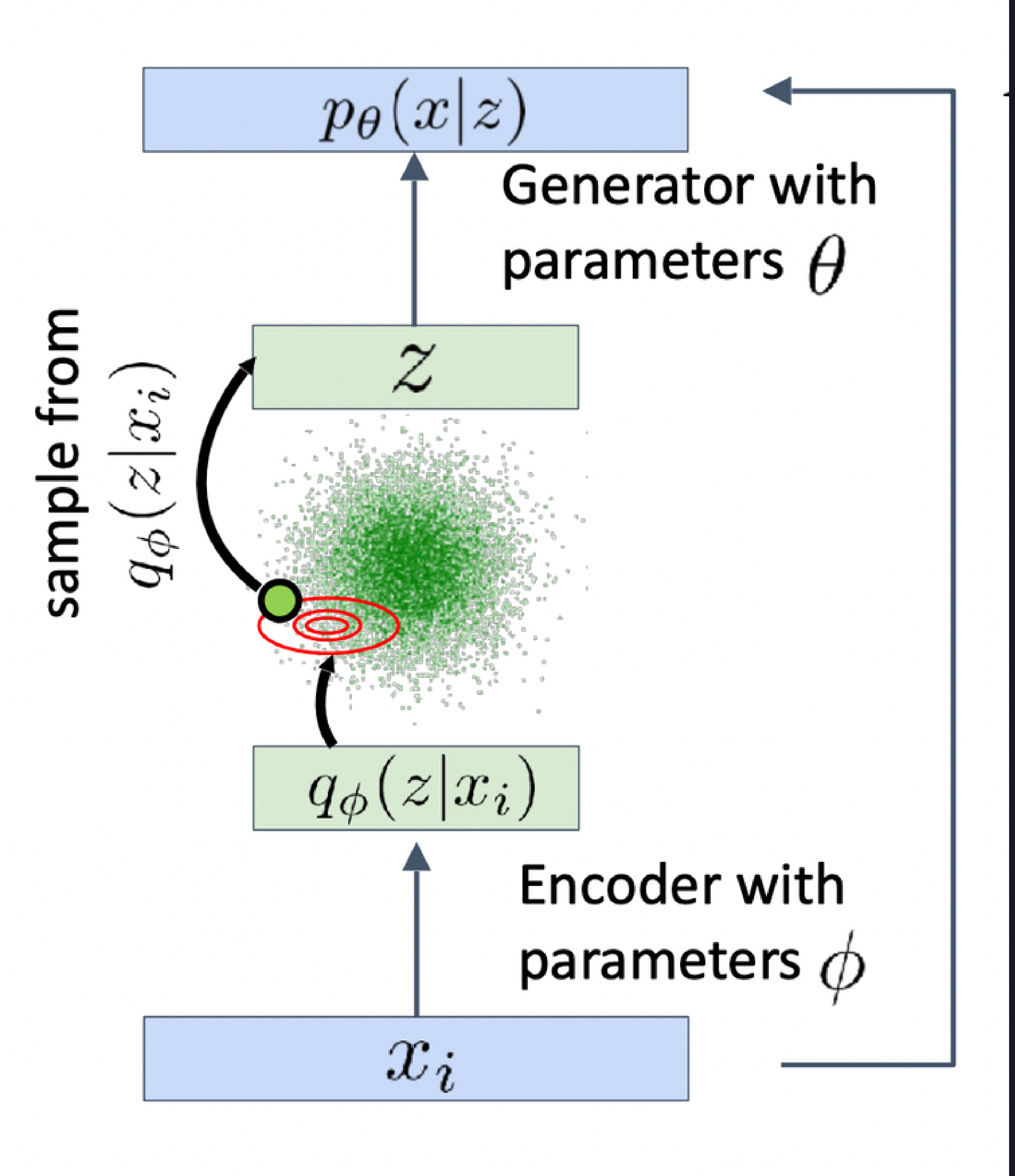
Theory

VARIATIONAL AUTOENCODERS



Theory

VARIATIONAL AUTOENCODERS



Objective:

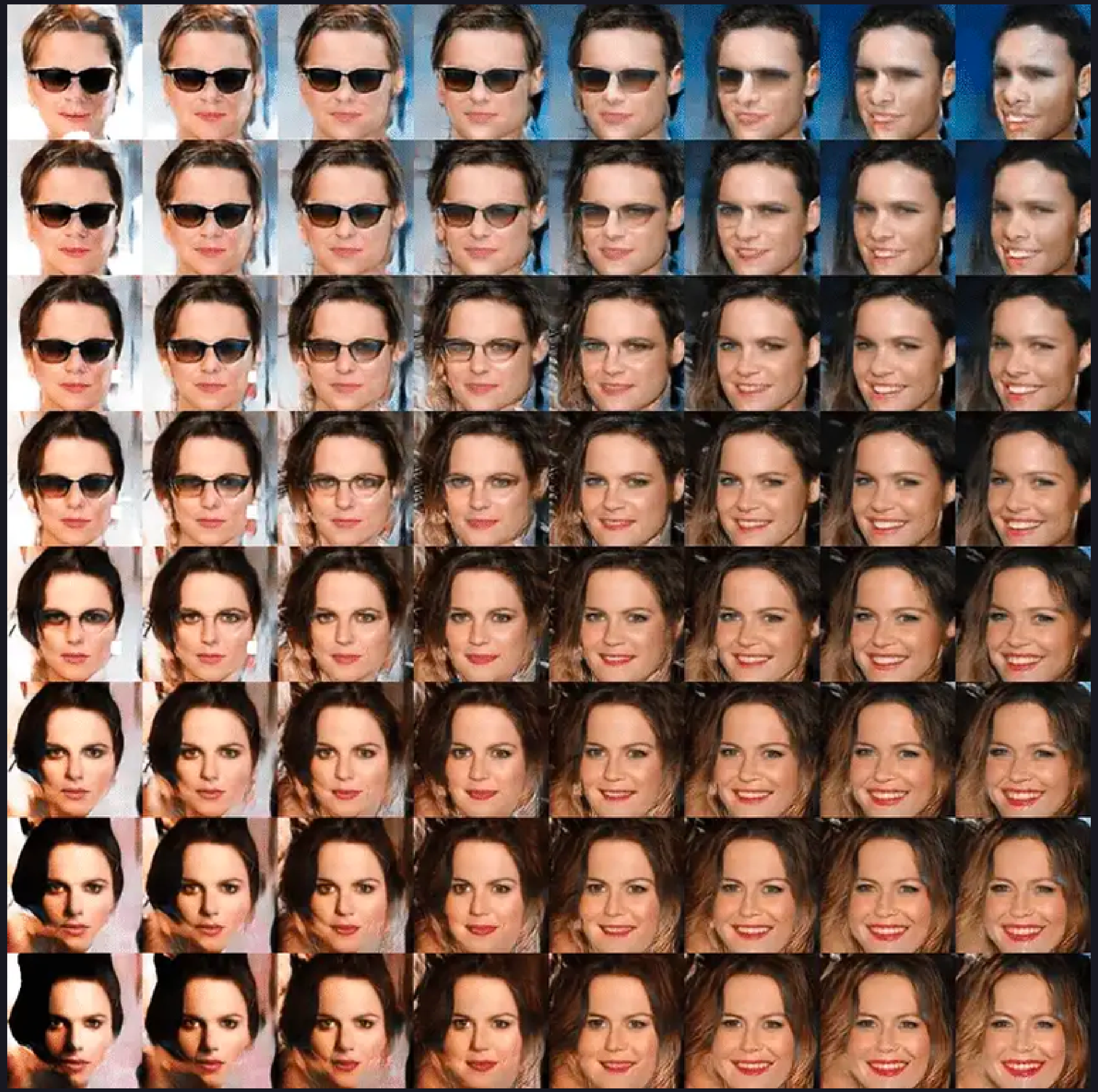
1. Ensure that the output is a close reconstruction of the input*
2. Find a latent space that closely resembles a gaussian distribution**

*use a mean squared error or similar loss function

**use a loss function called KL Divergence

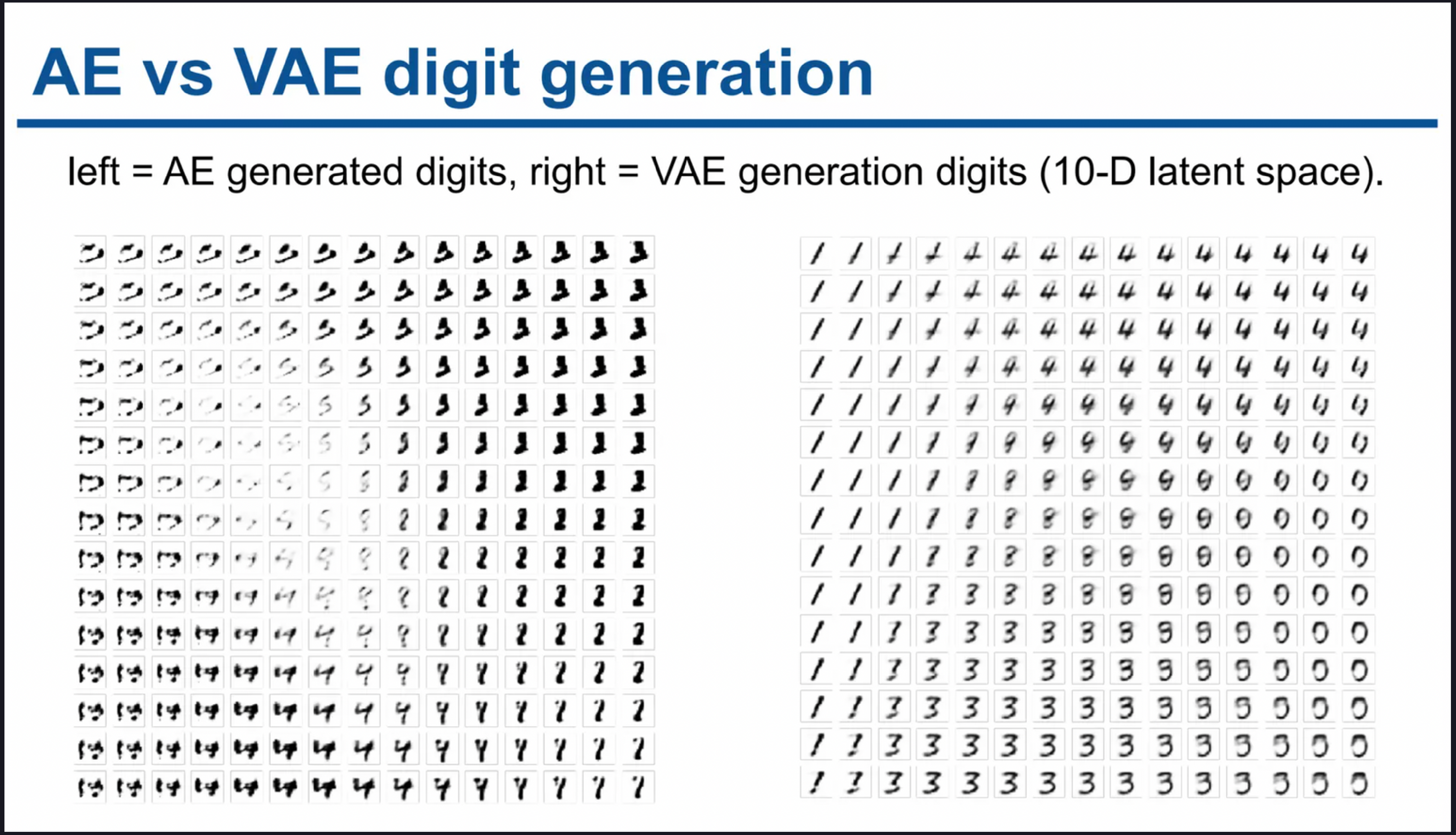
Theory

EXAMPLES



Theory

EXAMPLES



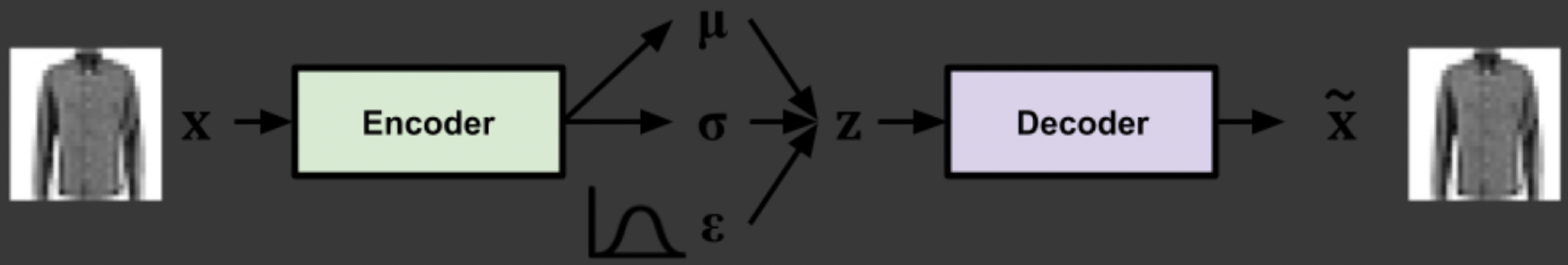
Theory

CODE

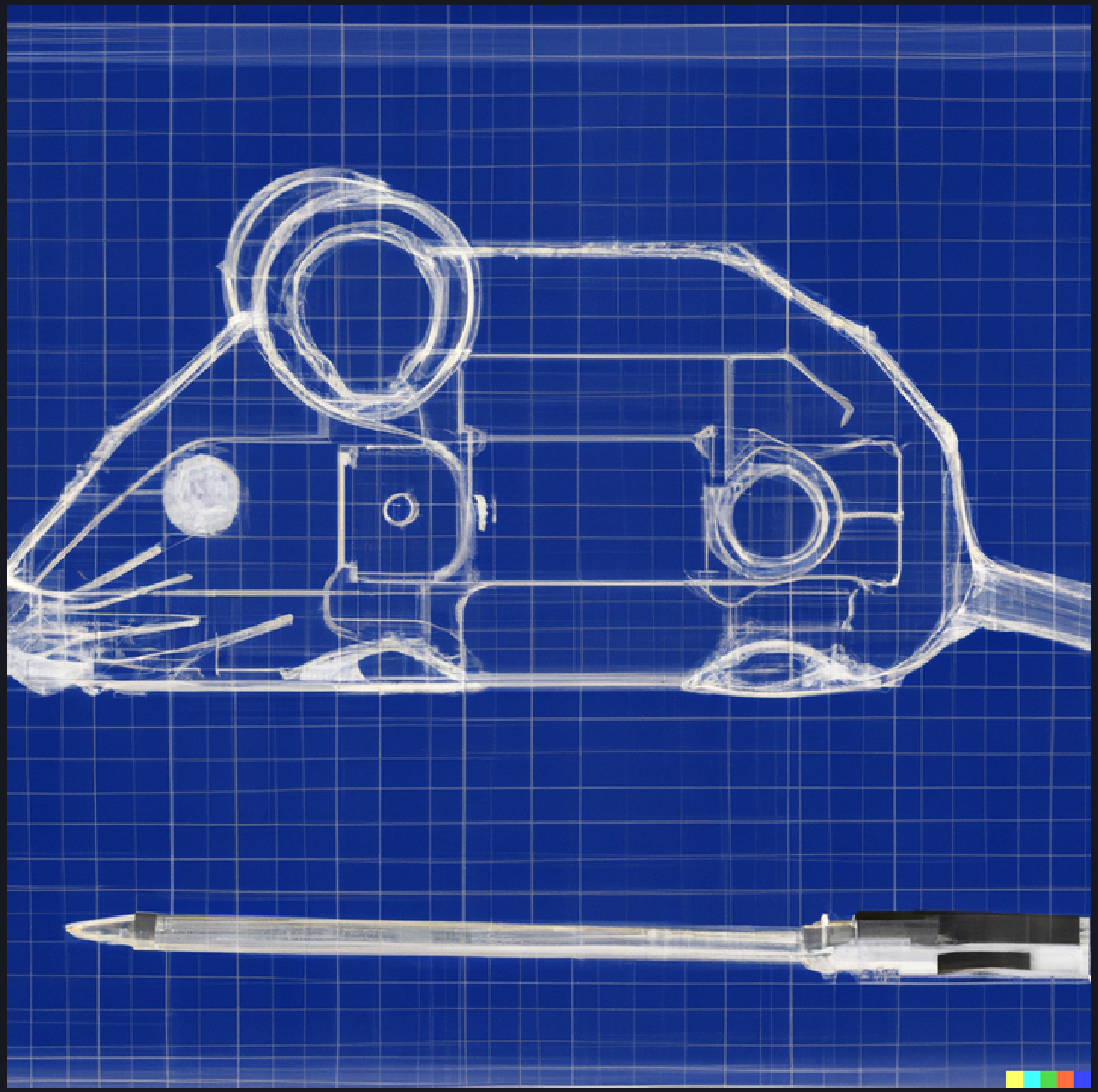
Open in Colab

Variational Autoencoder (VAE) (article)

The original variational autoencoder network, using tensorflow_probability



QUESTIONS?



SEE YOU NEXT TIME