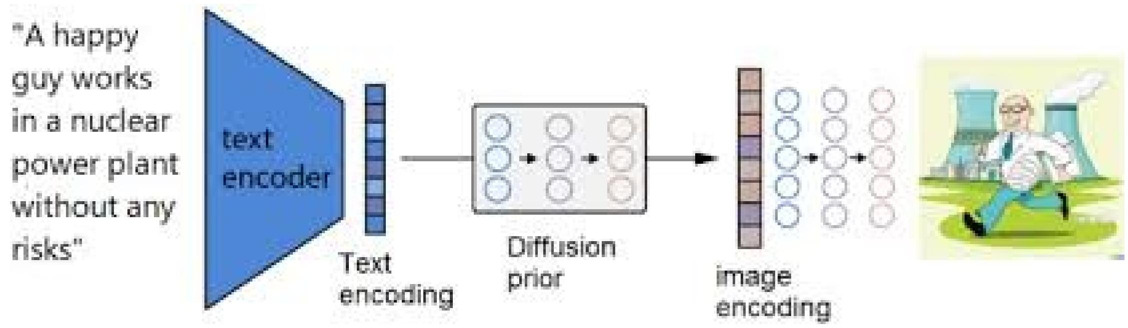
Generative AI

Definition and Overview

Definition

Generative AI refers to artificial intelligence systems that can create new content, such as text, images, audio, video, or other data, by learning patterns from existing data. These systems use machine learning models, often based on neural networks, to generate outputs that mimic or creatively extend the characteristics of their training data.

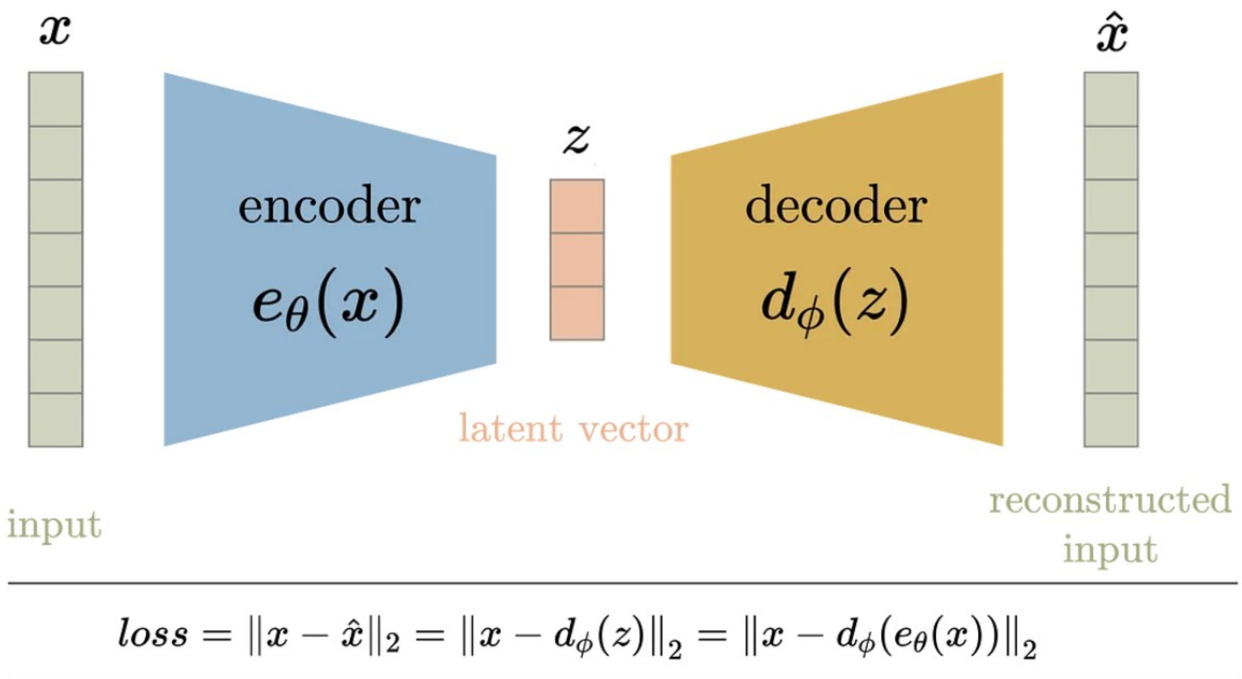


Model	What It Generates	Core Idea
VAEs	Images, audio	Encode + decode, probabilistic latent space
GANs	High-res images, videos	Competing networks (Generator vs Discriminator)
Diffusion Models	Ultra-realistic images	Iterative denoising from pure noise
Autoregressive Models	Text, music, code	Predict next token step by step
Transformers (LLMs)	Text, code, reasoning	Attention-based sequence modeling
Flow Models	Invertible data generation	Learn exact likelihood and sampling

AEs and VAEs

AutoEnconders

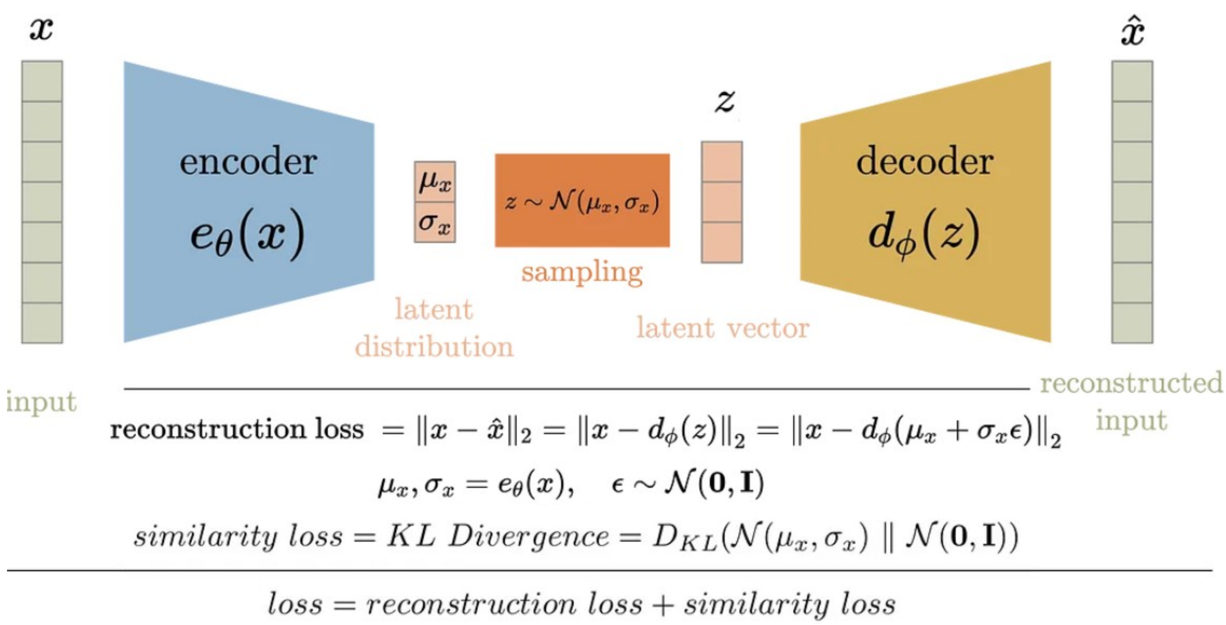
An Autoencoder (AE) is an unsupervised neural network architecture used for learning efficient data encodings. It aims to compress input data into a latent-space representation and then reconstruct the output from this compressed form.



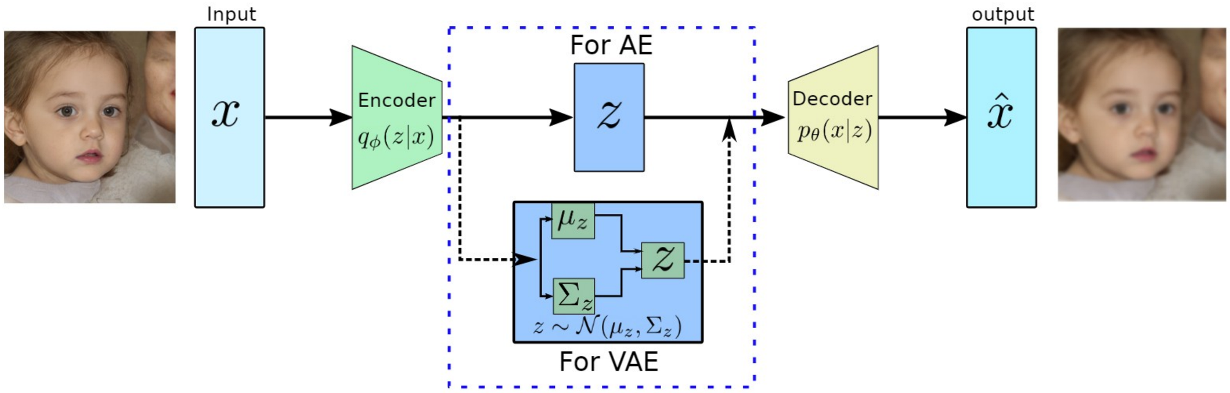
[medium.com]

Variational AutoEncoders

A Variational Autoencoder (VAE) is a generative model that extends the AE by learning the underlying distribution of the data. Instead of learning a deterministic latent code, VAE learns a probabilistic latent space, allowing for the generation of new data.



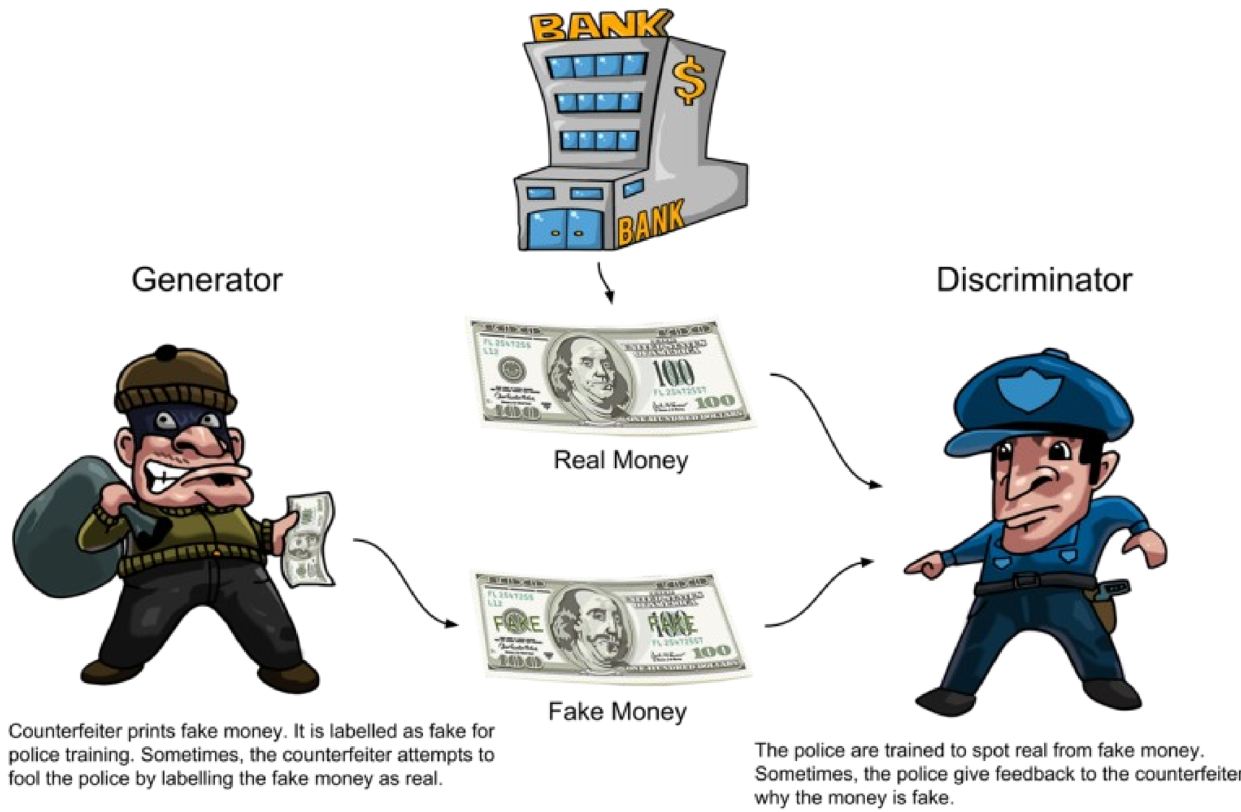
[medium.com]

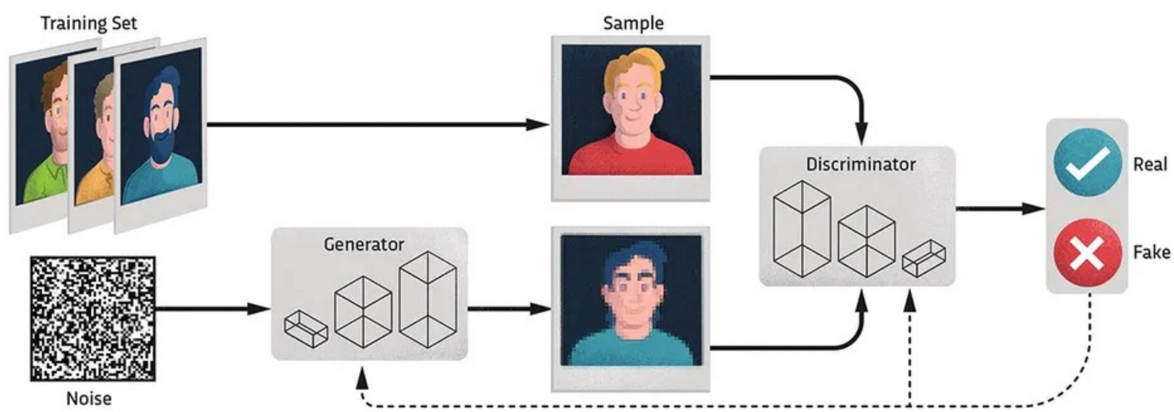


Model	Strength in GenAI	Key Use Cases
AE	Efficient latent representation	Denoising, anomaly detection, style transfer
VAE	Generative modeling with latent sampling	Image/text/audio generation, interpolation, conditional generation

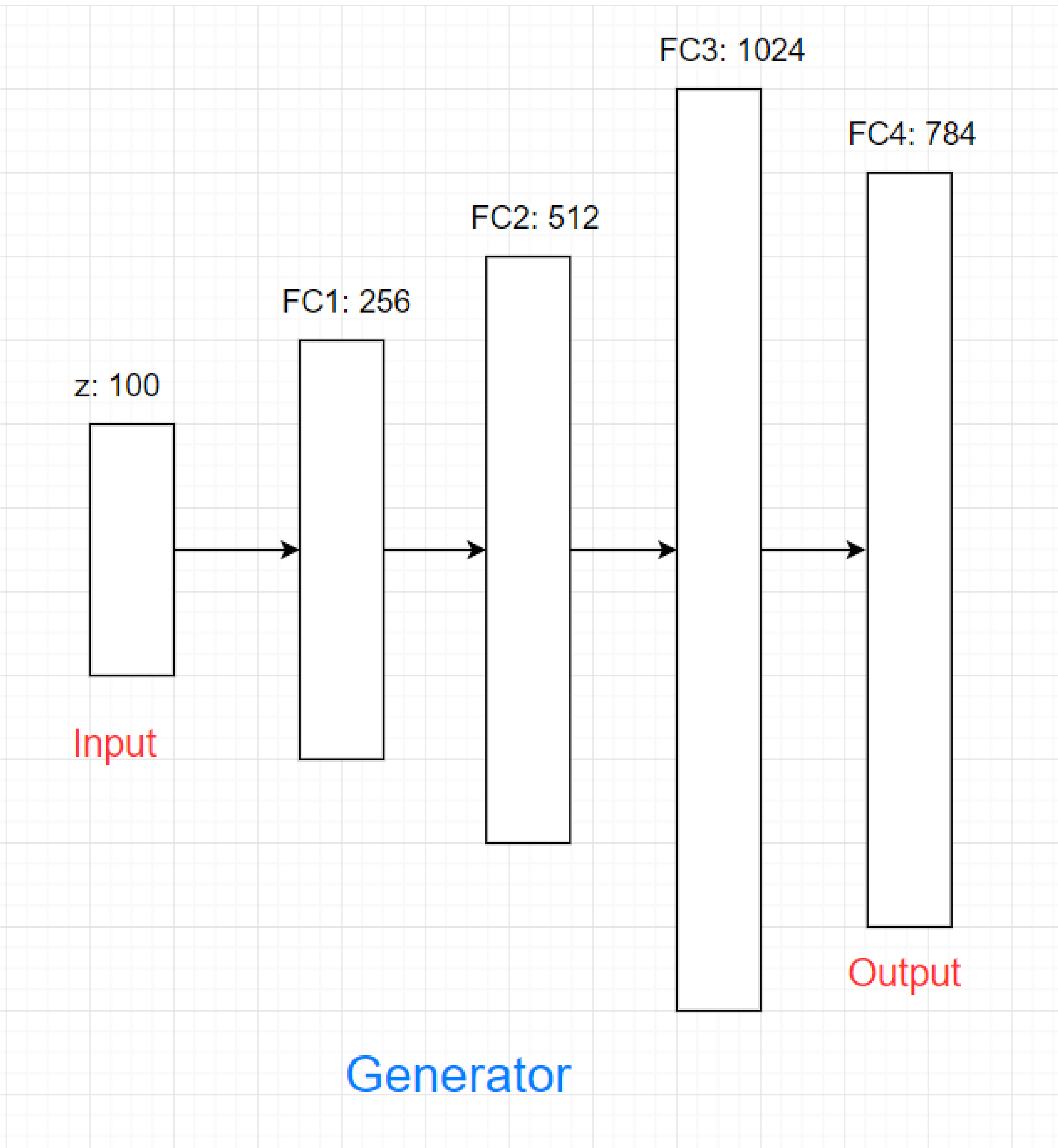
Generative Adversarial Networks (GANs)

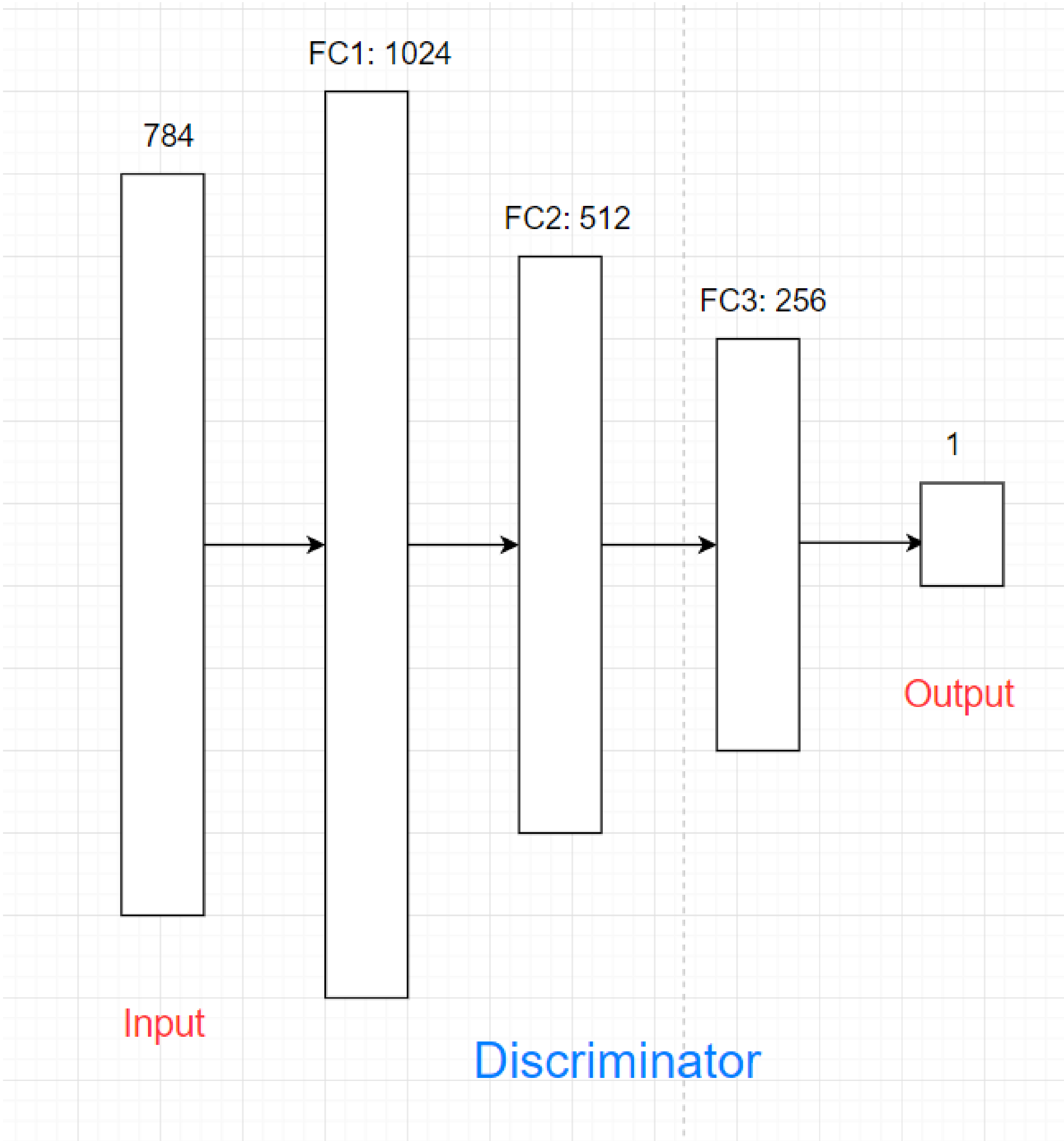
GANs (generative adversarial networks) are clever machine learning (ML) algorithms that use neural networks (simplified computer models of the brain) in a specific way.





[sciencefocus.com]


FC3: 1024
FC4: 784
FC2: 512
FC1: 256
z: 100
Input
Output
Generator


FC1: 1024
784
FC2: 512
FC3: 256
1
Output
Input
Discriminator

GANs consist of two neural networks that play a **minimax game**:

- **Generator (G):**
  Learns to generate fake data $G(z)$ from a random noise vector $z \sim \mathcal{N}(0, I)$.
- **Discriminator (D):**
  Learns to distinguish between real data x and generated data $G(z)$.

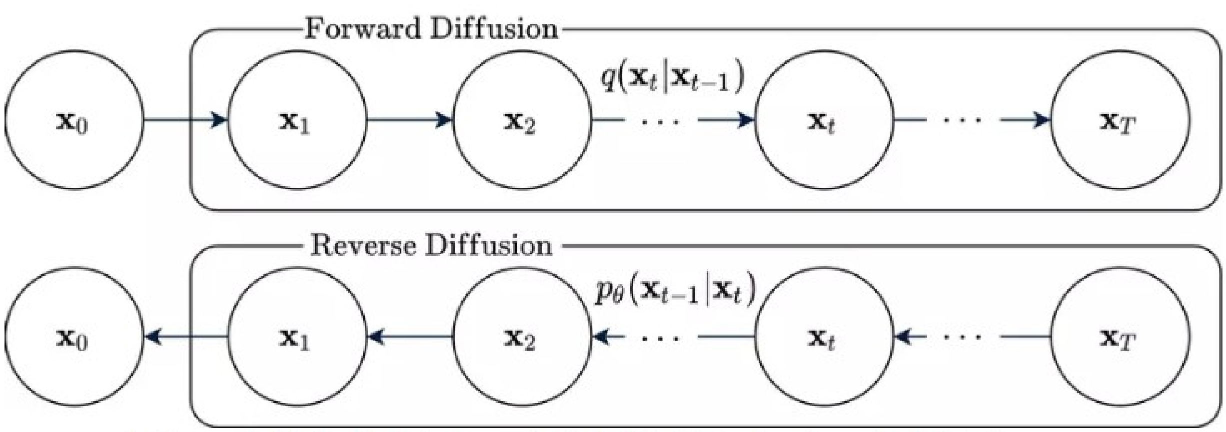
The objective is:

$$\min_G \max_D \mathbb{E}_{x \sim p_{\text{data}}(x)}[\log D(x)] + \mathbb{E}_{z \sim p(z)}[\log(1 - D(G(z)))]$$

- The **Generator** improves to produce more realistic data to fool the Discriminator.
- The **Discriminator** improves to better detect fake data.

Diffusion

Diffusion models are generative models used primarily for image generation and other computer vision tasks. Diffusion-based neural networks are trained through deep learning to progressively “diffuse” samples with random noise, then reverse that diffusion process to generate high-quality images.



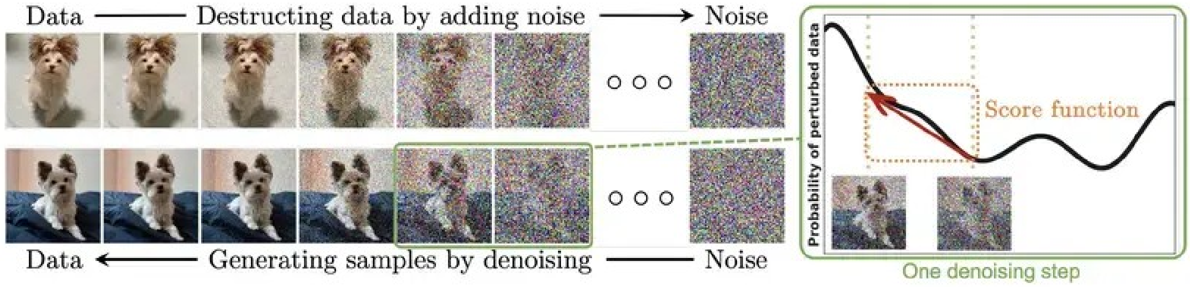


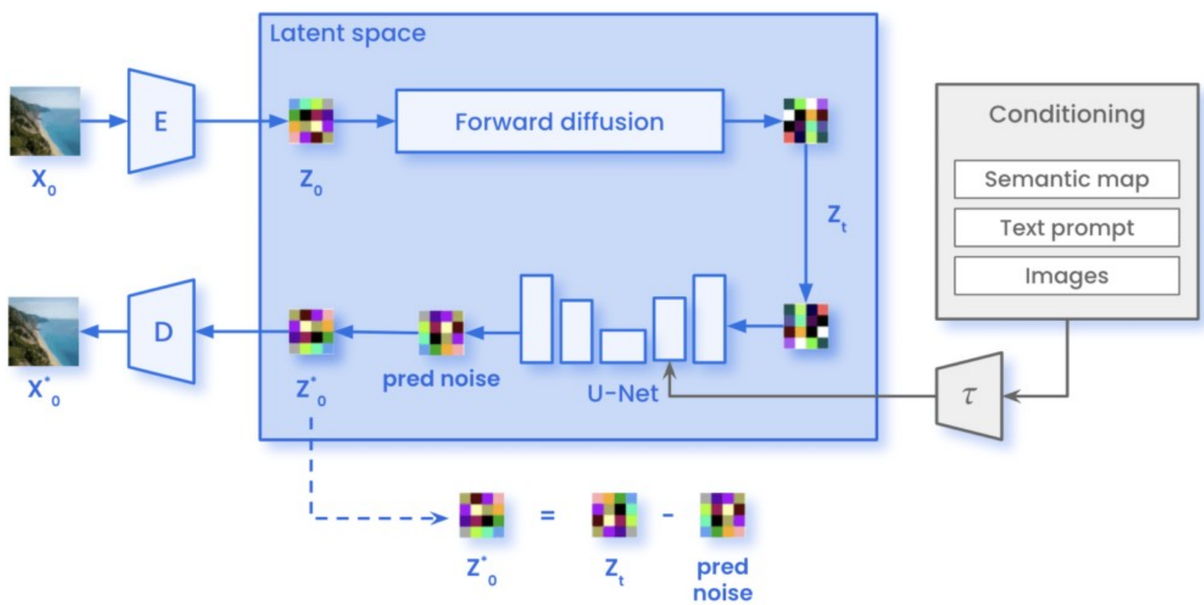
Fig. 2. Diffusion models smoothly perturb data by adding noise, then reverse this process to generate new data from noise. Each denoising step in the reverse process typically requires estimating the score function (see the illustrative figure on the right), which is a gradient pointing to the directions of data with higher likelihood and less noise.

[https://www.superannotate.com/]

Stable Diffusion

Stable Diffusion is a text-to-image latent diffusion model (LDM) introduced by the CompVis group in 2022. Unlike standard diffusion models that operate in pixel space, Stable Diffusion applies the denoising process in a compressed latent space, allowing high-quality image generation with much lower computational cost.

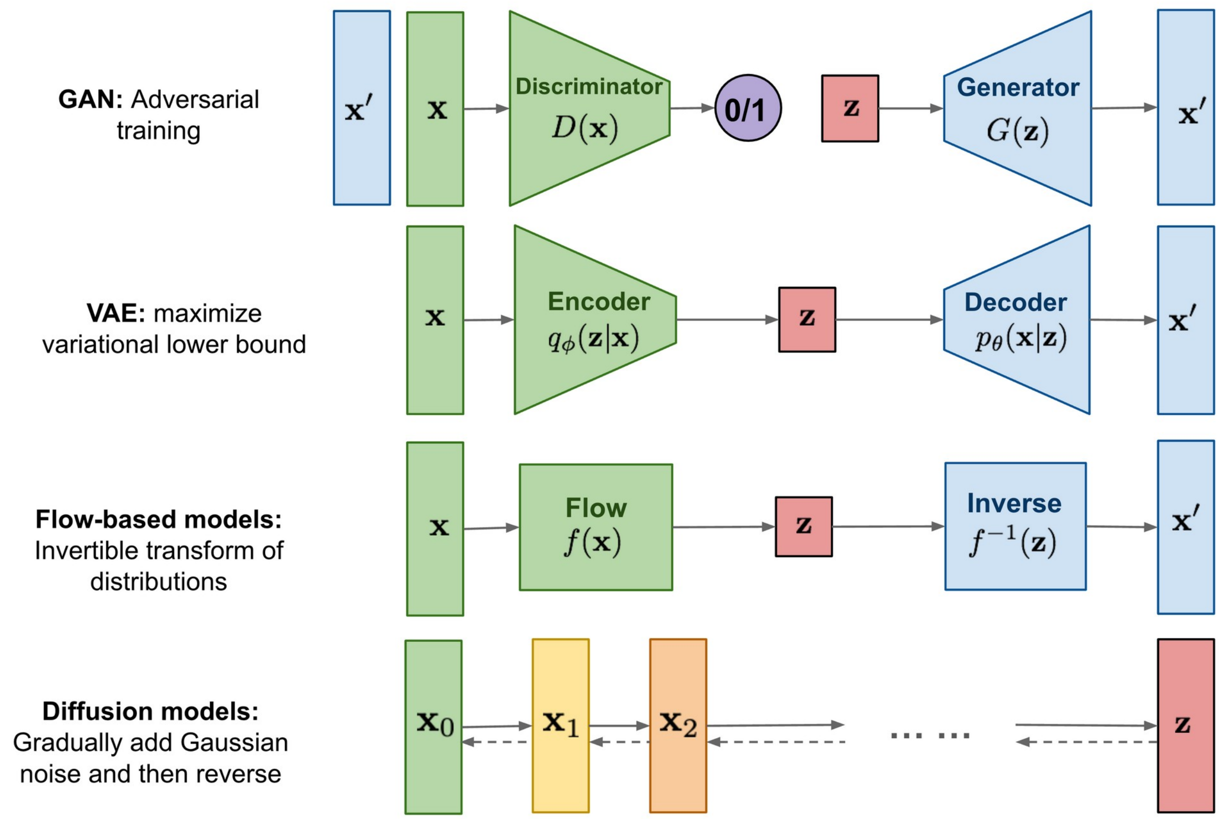
So what happens since we add a prompt ??



CLIP with the relationship visualization:

Projector TensorFlow

Comparison - OPTIONAL



Aspect	**Variational Autoencoder (VAE)**	**Generative Adversarial Network (GAN)**	**Diffusion Model**
Core Idea	Encode data into latent space and decode with reconstruction + KL loss	Train a generator to fool a discriminator in an adversarial setup	Model data generation as a reverse denoising process from noise
Training Objective	Maximize Evidence Lower Bound (ELBO) = Reconstruction Loss + KL Divergence	Minimax Game: Generator vs. Discriminator	Learn reverse diffusion process by minimizing denoising error
Architecture	Encoder + Decoder	Generator + Discriminator	Denoising U-Net or Transformer (often unpaired)
Sampling Process	Fast (1-step decode from latent z)	Fast (1 forward pass through generator)	Slow (many denoising steps, e.g., 50–1000 steps)
Training Stability	Stable and easy to train	Often unstable (mode collapse, non-convergence)	Stable but computationally expensive

Aspect	**Variational Autoencoder (VAE)**	**Generative Adversarial Network (GAN)**	**Diffusion Model**
Output Quality	Decent, often blurry due to Gaussian assumptions	Sharp, high-fidelity images	Extremely realistic and high-quality images
Latent Space	Explicit, structured latent space (e.g., Gaussian)	Implicit, not always meaningful	Usually implicit, but newer methods add latent control (e.g., Latent Diffusion)
Controllability	Good for interpolation and latent editing	Difficult without extra mechanisms (e.g., Conditional GANs)	Emerging; latent diffusion allows control; prompt-based conditioning is strong
Use Cases	Representation learning, anomaly detection, image interpolation	Image generation, style transfer, deepfakes	Text-to-image generation (e.g., Stable Diffusion), inpainting, super-resolution
Advantages	Interpretable latent space, stable training	High visual fidelity, fast inference	Best quality outputs, flexible conditioning
Disadvantages	Blurry outputs, limited expressiveness	Mode collapse, hard to train	Slow inference, high compute requirement

#Practice

VAEs

```
# □ 1. Install and Import Libraries
import torch
import torch.nn as nn
import torch.optim as optim
from torchvision import datasets, transforms
from torch.utils.data import DataLoader, Subset
import matplotlib.pyplot as plt


#device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
device = torch.device("cpu")
print("Step 1: finished") #just for debugging if needed

# □ 2. Load the MNIST Dataset
transform = transforms.ToTensor()

# Download full MNIST dataset
full_train = datasets.MNIST(root='./data', train=True,
transform=transform, download=True)

# Filter only digit '5'
indices = [i for i, target in enumerate(full_train.targets) if target
== 5]
```

```
subset = Subset(full_train, indices)

# DataLoader
train_loader = DataLoader(subset, batch_size=64, shuffle=True)
print(f"Number of digit-4 samples: {len(subset)}")
print("Step 2: finished")
```

```
Step 1: finished
Number of digit-4 samples: 5421
Step 2: finished
```

```
# □ 3. Define the VAE Model

class VAE(nn.Module):
    def __init__(self, latent_dim=20):
        super(VAE, self).__init__()

        # Encoder: Fully connected layer to reduce input dimension
        self.fc1 = nn.Linear(28*28, 400)  # Input layer: 784 → 400

        # Latent space mappings
        self.fc_mu = nn.Linear(400, latent_dim)      # Mean vector
(μ): 400 → latent_dim
        self.fc_logvar = nn.Linear(400, latent_dim)  # Log-variance
(logσ²): 400 → latent_dim

        # Decoder: reconstruct from latent space
        self.fc_decode = nn.Linear(latent_dim, 400)  # Latent vector z
→ 400
        self.fc_out = nn.Linear(400, 28*28)          # Output layer:
400 → 784 (28×28 image)

        # Activation functions
        self.relu = nn.ReLU()         # Used in hidden layers
        self.sigmoid = nn.Sigmoid()  # Used in output layer to squash
values to [0,1]


    def encode(self, x):
        h1 = self.relu(self.fc1(x))
        mu = self.fc_mu(h1)
        logvar = self.fc_logvar(h1)
        return mu, logvar

    def reparameterize(self, mu, logvar):
        std = torch.exp(0.5*logvar)
        eps = torch.randn_like(std)
        return mu + eps * std

    def decode(self, z):
        h2 = self.relu(self.fc_decode(z))
```

```
        return self.sigmoid(self.fc_out(h2))

    def forward(self, x):
        x = x.view(-1, 28*28)
        mu, logvar = self.encode(x)
        z = self.reparameterize(mu, logvar)
        recon = self.decode(z)
        return recon, mu, logvar


# □ 4. Loss Function and Optimizer

def vae_loss(recon_x, x, mu, logvar):
    BCE = nn.functional.binary_cross_entropy(recon_x, x.view(-1,
28*28), reduction='sum')
    KLD = -0.5 * torch.sum(1 + logvar - mu.pow(2) - logvar.exp())
    return BCE + KLD

model = VAE().to(device)
optimizer = optim.Adam(model.parameters(), lr=1e-3)
print("Step 3,4: finished")
```

```
Step 3,4: finished
```

```
# □ 5. Training Loop

epochs = 10
model.train()
for epoch in range(epochs):
    total_loss = 0
    for x, _ in train_loader:
        x = x.to(device)
        optimizer.zero_grad()
        recon, mu, logvar = model(x)
        loss = vae_loss(recon, x, mu, logvar)
        loss.backward()
        optimizer.step()
        total_loss += loss.item()
    print(f"Epoch [{epoch+1}/{epochs}] Loss: {total_loss /
len(train_loader.dataset):.2f}")
print("Step 5: finished")
```

```
Epoch [1/10] Loss: 226.94
Epoch [2/10] Loss: 160.03
Epoch [3/10] Loss: 145.98
Epoch [4/10] Loss: 136.39
Epoch [5/10] Loss: 129.67
Epoch [6/10] Loss: 125.32
Epoch [7/10] Loss: 122.14
Epoch [8/10] Loss: 119.53
Epoch [9/10] Loss: 117.40
```

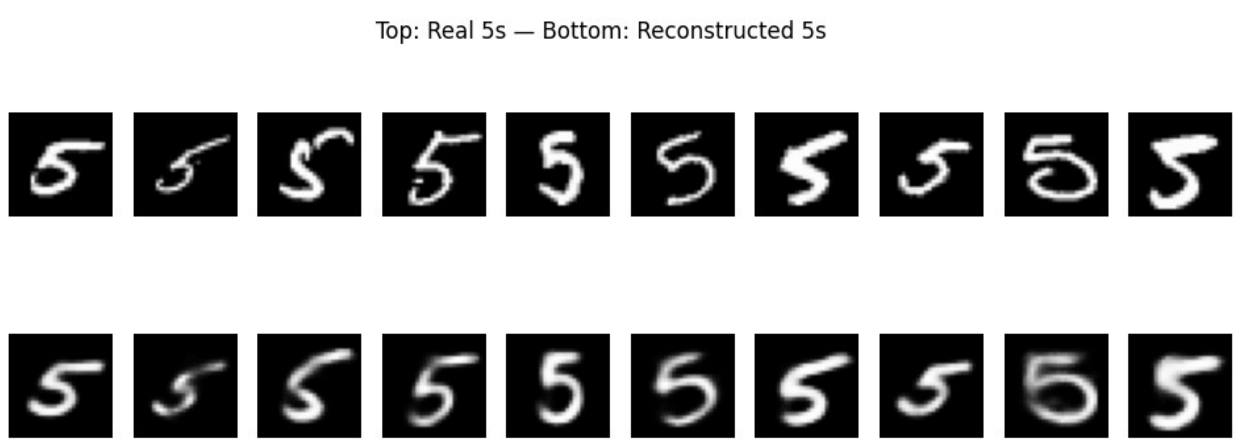
```
Epoch [10/10] Loss: 115.87
Step 5: finished

# □ 6. Visualize Reconstruction

model.eval()
with torch.no_grad():
    for x, _ in train_loader:
        x = x.to(device)
        recon, _, _ = model(x)
        break

    x = x.view(-1, 1, 28, 28).cpu()
    recon = recon.view(-1, 1, 28, 28).cpu()

    plt.figure(figsize=(12, 4))
    for i in range(10):
        plt.subplot(2, 10, i+1)
        plt.imshow(x[i].squeeze(), cmap='gray')
        plt.axis('off')
        plt.subplot(2, 10, i+11)
        plt.imshow(recon[i].squeeze(), cmap='gray')
        plt.axis('off')
    plt.suptitle("Top: Real 5s — Bottom: Reconstructed 5s")
    plt.show()
```

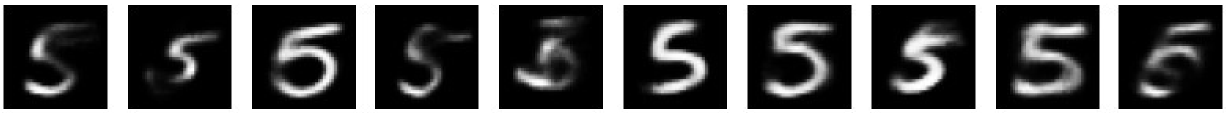



```
with torch.no_grad():
    z = torch.randn(10, 20).to(device)
    samples = model.decode(z).cpu().view(-1, 1, 28, 28)

    plt.figure(figsize=(10, 2))
    for i in range(10):
        plt.subplot(1, 10, i+1)
        plt.imshow(samples[i].squeeze(), cmap='gray')
        plt.axis('off')
```

```
    plt.suptitle("Generated samples (digit 5 style)")
    plt.show()
```

Generated samples (digit 5 style)



GANs

```
# 1. Set up
import torch
import torch.nn as nn
import torch.optim as optim
from torchvision import datasets, transforms
from torch.utils.data import DataLoader, Subset
import matplotlib.pyplot as plt

device = torch.device("cpu")

# 2. Load digit "4"
transform = transforms.ToTensor()
mnist = datasets.MNIST(root='./data', train=True, download=True,
transform=transform)
digit4_indices = [i for i, label in enumerate(mnist.targets) if label
== 4]
digit4_subset = Subset(mnist, digit4_indices)
train_loader = DataLoader(digit4_subset, batch_size=64, shuffle=True)
print(f"Training only on digit '4': {len(digit4_subset)} samples")
```

```
Training only on digit '4': 5842 samples
```

```
latent_dim = 100  # Dimension of the input noise vector (z)
# 3. Define generator and discriminator

# Generator
class Generator(nn.Module):
    def __init__(self):
        super().__init__()
        self.net = nn.Sequential(
            # Input: latent vector z of size 100
            nn.Linear(latent_dim, 256),  # → hidden layer
            nn.ReLU(),                   # → activation

            nn.Linear(256, 512),         # increase complexity
            nn.ReLU(),
```

```
            nn.Linear(512, 784),         # Output: 28×28 image flattened
            nn.Tanh()                    # Output pixel range: [-1, 1]
        )

    def forward(self, z):
        # Forward pass through generator
        return self.net(z).view(-1, 1, 28, 28)  # Reshape to image format


# Discriminator
class Discriminator(nn.Module):
    def __init__(self):
        super().__init__()
        self.net = nn.Sequential(
            nn.Flatten(),               # Flatten 28×28 image → 784
            nn.Linear(784, 512),        # → hidden layer
            nn.LeakyReLU(0.2),          # LeakyReLU helps gradient flow

            nn.Linear(512, 256),
            nn.LeakyReLU(0.2),

            nn.Linear(256, 1),          # Output: single scalar (real/fake)
            nn.Sigmoid()                # Output range: [0, 1] (probability)
        )

    def forward(self, x):
        return self.net(x)


# 4. Initialize Models and Optimizers
# Instantiate Generator and Discriminator
G = Generator().to(device)
D = Discriminator().to(device)

# Binary cross-entropy loss for GAN
loss_fn = nn.BCELoss()

# Adam optimizers (standard for GAN training)
opt_G = optim.Adam(G.parameters(), lr=2e-4)
opt_D = optim.Adam(D.parameters(), lr=2e-4)

# 5. Traning
epochs = 20
for epoch in range(epochs):
    for real_imgs, _ in train_loader:
        real_imgs = real_imgs.to(device) * 2 - 1  # Normalize to [-1,
```

```
1]

        # === Train Discriminator ===
        # Step 1: Train D to classify real and fake images correctly
        z = torch.randn(real_imgs.size(0), latent_dim).to(device)
        fake_imgs = G(z).detach()  # No grad update to G

        real_labels = torch.ones(real_imgs.size(0), 1).to(device)
        fake_labels = torch.zeros(real_imgs.size(0), 1).to(device)

        D_real = D(real_imgs)
        D_fake = D(fake_imgs)
        D_loss = loss_fn(D_real, real_labels) + loss_fn(D_fake,
fake_labels)

        opt_D.zero_grad()
        D_loss.backward()
        opt_D.step()

        # === Train Generator ===
        # Step 2: Train G to fool D (want D(G(z)) = 1)
        z = torch.randn(real_imgs.size(0), latent_dim).to(device)
        fake_imgs = G(z)
        G_loss = loss_fn(D(fake_imgs), real_labels)

        opt_G.zero_grad()
        G_loss.backward()
        opt_G.step()

    print(f"Epoch {epoch+1}/{epochs}, D_loss: {D_loss.item():.4f},
G_loss: {G_loss.item():.4f}")
```

```
Epoch 1/20, D_loss: 0.1418, G_loss: 3.6224
Epoch 2/20, D_loss: 0.0289, G_loss: 4.8440
Epoch 3/20, D_loss: 0.0653, G_loss: 4.3888
Epoch 4/20, D_loss: 0.0590, G_loss: 7.0805
Epoch 5/20, D_loss: 0.0475, G_loss: 6.3536
Epoch 6/20, D_loss: 0.0401, G_loss: 6.4371
Epoch 7/20, D_loss: 0.0847, G_loss: 6.8830
Epoch 8/20, D_loss: 0.1186, G_loss: 5.6227
Epoch 9/20, D_loss: 0.0563, G_loss: 5.9713
Epoch 10/20, D_loss: 0.0517, G_loss: 5.2613
Epoch 11/20, D_loss: 0.0961, G_loss: 2.7510
Epoch 12/20, D_loss: 0.5434, G_loss: 4.1278
Epoch 13/20, D_loss: 0.3551, G_loss: 6.4273
Epoch 14/20, D_loss: 0.3271, G_loss: 4.3460
Epoch 15/20, D_loss: 0.1777, G_loss: 5.5540
Epoch 16/20, D_loss: 0.3255, G_loss: 5.4922
Epoch 17/20, D_loss: 1.1382, G_loss: 4.8886
Epoch 18/20, D_loss: 0.5802, G_loss: 4.2210
```

```
Epoch 19/20, D_loss: 0.2759, G_loss: 7.3800
Epoch 20/20, D_loss: 0.2904, G_loss: 3.7544

# 6. Generate and Display Samples
G.eval()
with torch.no_grad():
    z = torch.randn(10, latent_dim).to(device)
    samples = G(z).cpu() * 0.5 + 0.5  # Rescale from [-1, 1] to [0, 1]

    plt.figure(figsize=(10, 2))
    for i in range(10):
        plt.subplot(1, 10, i + 1)
        plt.imshow(samples[i][0], cmap='gray')
        plt.axis('off')
    plt.suptitle("Generated '4'-like Digits")
    plt.show()
```

Stable Diffusion

Traning

```
# 1. Pre-process: resize all images to a consistent size
import os
from PIL import Image

# Input and output folders
input_folder = '/content/drive/MyDrive/DatasetSD'
output_folder = '/content/drive/MyDrive/DatasetSD/resized'
os.makedirs(output_folder, exist_ok=True)

# Target image size (standard for Stable Diffusion)
target_size = (512, 512)

# List image files only (skip prompt.json)
image_files = [f for f in os.listdir(input_folder) if
f.endswith(('.jpg', '.png'))]

for filename in image_files:
    input_path = os.path.join(input_folder, filename)
    output_path = os.path.join(output_folder, filename)

    # Open and resize
```

```
    img = Image.open(input_path).convert("RGB")
    img_resized = img.resize(target_size, Image.LANCZOS)  # High-
quality downsampling
    img_resized.save(output_path)

print(f"✅ Resized {len(image_files)} images to 512×512 and saved to
'resized' folder.")
```

```
✅ Resized 6 images to 512×512 and saved to 'resized' folder.
```

```
# 2. Load resized images, load the corresponding text prompt, apply
transforms for Stable Diffusion
import json
from torch.utils.data import Dataset
from torchvision import transforms
from PIL import Image

class TextImageDataset(Dataset):
    def __init__(self, image_dir, json_path, size=512):
        self.image_dir = image_dir
        self.size = size

        # Load image → prompt mapping
        with open(json_path, 'r') as f:
            self.prompt_dict = json.load(f)

        # Sort keys to ensure consistent order
        self.image_filenames = sorted(self.prompt_dict.keys())

        # Image transform
        self.transform = transforms.Compose([
            transforms.Resize((size, size),
interpolation=Image.BICUBIC),
            transforms.ToTensor(),  # [0,1]
            transforms.Normalize([0.5], [0.5])  # Normalize to [-1,1]
        ])

    def __len__(self):
        return len(self.image_filenames)

    def __getitem__(self, idx):
        filename = self.image_filenames[idx]
        prompt = self.prompt_dict[filename]

        img_path = os.path.join(self.image_dir, filename)
        image = Image.open(img_path).convert("RGB")
        image = self.transform(image)

        return {
            "image": image,
            "text": prompt,
```

```python
            "filename": filename
        }


# Path to resized images and prompt.json
image_dir = "/content/drive/MyDrive/DatasetSD/resized"
json_path = "/content/drive/MyDrive/DatasetSD/prompt.json"

# Create the dataset
dataset = TextImageDataset(image_dir, json_path)

# Optional: wrap in DataLoader
from torch.utils.data import DataLoader
loader = DataLoader(dataset, batch_size=2, shuffle=True)

# Test one sample
sample = next(iter(loader))
print("Text prompt:", sample['text'][0])
print("Image shape:", sample['image'][0].shape)
```

```
Text prompt: a dog holding a green ball is running on the grass
Image shape: torch.Size([3, 512, 512])
```

```python
# 3. Tokenize Prompts using CLIP
!pip install transformers diffusers accelerate
# At this step, we use Hugging Face Transformers library to load the
tokenizer and model.
```

```
Requirement already satisfied: transformers in
/usr/local/lib/python3.11/dist-packages (4.53.0)
Requirement already satisfied: diffusers in
/usr/local/lib/python3.11/dist-packages (0.34.0)
Requirement already satisfied: accelerate in
/usr/local/lib/python3.11/dist-packages (1.8.1)
Requirement already satisfied: filelock in
/usr/local/lib/python3.11/dist-packages (from transformers) (3.18.0)
Requirement already satisfied: huggingface-hub<1.0,>=0.30.0 in
/usr/local/lib/python3.11/dist-packages (from transformers) (0.33.1)
Requirement already satisfied: numpy>=1.17 in
/usr/local/lib/python3.11/dist-packages (from transformers) (2.0.2)
Requirement already satisfied: packaging>=20.0 in
/usr/local/lib/python3.11/dist-packages (from transformers) (24.2)
Requirement already satisfied: pyyaml>=5.1 in
/usr/local/lib/python3.11/dist-packages (from transformers) (6.0.2)
Requirement already satisfied: regex!=2019.12.17 in
/usr/local/lib/python3.11/dist-packages (from transformers)
(2024.11.6)
Requirement already satisfied: requests in
/usr/local/lib/python3.11/dist-packages (from transformers) (2.32.3)
Requirement already satisfied: tokenizers<0.22,>=0.21 in
```

```
/usr/local/lib/python3.11/dist-packages (from transformers) (0.21.2)
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/usr/local/lib/python3.11/dist-packages (from diffusers) (11.2.1)
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/usr/local/lib/python3.11/dist-packages (from accelerate) (5.9.5)
Requirement already satisfied: torch>=2.0.0 in
/usr/local/lib/python3.11/dist-packages (from accelerate)
(2.6.0+cu124)
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hub<1.0,>=0.30.0->transformers) (2025.3.2)
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hub<1.0,>=0.30.0->transformers) (4.14.0)
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in /usr/local/lib/python3.11/dist-packages (from torch>=2.0.0-
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```

```
>accelerate) (10.3.5.147)
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Requirement already satisfied: charset-normalizer<4,>=2 in
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(3.4.2)
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(3.10)
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(2.4.0)
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/usr/local/lib/python3.11/dist-packages (from requests->transformers)
(2025.6.15)
Requirement already satisfied: MarkupSafe>=2.0 in
/usr/local/lib/python3.11/dist-packages (from jinja2->torch>=2.0.0-
>accelerate) (3.0.2)
```

```python
from transformers import CLIPTokenizer, CLIPTextModel
import torch
```

```
# Load pretrained CLIP (text part only)
tokenizer = CLIPTokenizer.from_pretrained("openai/clip-vit-large-
patch14")
text_encoder = CLIPTextModel.from_pretrained("openai/clip-vit-large-
patch14").to(device)
# Example batch from your dataset
batch = next(iter(loader))
prompts = batch["text"]

# Tokenize prompts
inputs = tokenizer(prompts, padding="max_length", truncation=True,
max_length=77, return_tensors="pt").to(device)

# Encode with CLIP
with torch.no_grad():
    embeddings = text_encoder(**inputs).last_hidden_state  # Shape:
[batch_size, 77, 768]

# 4. Encode Images with VAE
# Stable Diffusion uses a pretrained Variational Autoencoder (VAE) to
# compress 512×512 images into a latent space (usually 64×64×4). This
makes diffusion faster and more efficient.

######################################################

# Load the VAE Encoder
from diffusers import AutoencoderKL

# Load pretrained VAE (used in Stable Diffusion v1.4/1.5)
vae = AutoencoderKL.from_pretrained("CompVis/stable-diffusion-v1-4",
subfolder="vae").to(device)
vae.eval()

# Get image batch from dataset
images = batch["image"].to(device)  # shape: [B, 3, 512, 512]

# Encode image to latent space using VAE
with torch.no_grad():
    latents = vae.encode(images).latent_dist.sample()  # Sample from
latent distribution
    latents = latents * 0.18215  # 0.18215 - Stability AI to match
latent statistics with pixel-space outputs during training and
sampling
```

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ion_minor":0}

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ion_minor":0}

```python
# 5. Add Noise and Train U-Net (Core of Diffusion)
'''
1./ We have a latent image z from VAE: z ∈ [B, 4, 64, 64] (batch size,
channels, height, width)

2./ Sample a timestep t from 1 to T (usually 1000 steps)

3./ Add Gaussian noise to z → get z_noised

4./ Pass z_noised and text_embedding into U-Net

5./ U-Net tries to predict the noise that was added

6./ Compute loss between predicted noise and actual noise
'''
from diffusers import UNet2DConditionModel, DDPMScheduler
# Load Stable Diffusion's U-Net
unet = UNet2DConditionModel.from_pretrained("CompVis/stable-diffusion-
v1-4", subfolder="unet").to(device)
# Scheduler defines how noise is added at each timestep
noise_scheduler = DDPMScheduler(num_train_timesteps=1000)



# Forward
# Step 1: Get latent and text embeddings
latents = latents.to(device)
text_embeddings = embeddings.to(device)  # shape: [B, 77, 768]

# Step 2: Sample a timestep for each image in the batch
batch_size = latents.shape[0]
timesteps = torch.randint(0, 1000, (batch_size,),
device=device).long()

# Step 3: Add noise
noise = torch.randn_like(latents)  # random Gaussian noise
noisy_latents = noise_scheduler.add_noise(latents, noise, timesteps)

# Step 4: Predict noise with U-Net (conditioned on text)
with torch.no_grad():
    predicted_noise = unet(noisy_latents, timesteps,
encoder_hidden_states=text_embeddings).sample

# Step 5: Compute MSE loss between predicted and actual noise
loss_fn = torch.nn.MSELoss()
loss = loss_fn(predicted_noise, noise)

print("Loss:", loss.item())
```

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ion_minor":0}

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```
Loss: 0.013185910880565643
```

```
# Trainnnnn
from tqdm import tqdm
import torch.nn.functional as F

# Set to training mode
unet.train()
text_encoder.eval()
vae.eval()

# Optimizer for U-Net only
optimizer = torch.optim.AdamW(unet.parameters(), lr=1e-5)

# Epochs
num_epochs = 1

for epoch in range(num_epochs):
    loop = tqdm(loader, desc=f"Epoch {epoch+1}/{num_epochs}",
leave=False)
    total_loss = 0

    for batch in loop:
        # === Prepare text ===
        prompts = batch["text"]
        inputs = tokenizer(prompts, padding="max_length",
truncation=True, max_length=77, return_tensors="pt").to(device)
        with torch.no_grad():
            text_embeddings = text_encoder(**inputs).last_hidden_state

        # === Prepare image ===
        images = batch["image"].to(device)
        with torch.no_grad():
            latents = vae.encode(images).latent_dist.sample() *
0.18215

        # === Sample timestep & noise ===
        bsz = latents.shape[0]
        noise = torch.randn_like(latents)
        timesteps = torch.randint(0, 1000, (bsz,),
device=device).long()
        noisy_latents = noise_scheduler.add_noise(latents, noise,
timesteps)

        # === Predict noise using U-Net ===
        noise_pred = unet(noisy_latents, timesteps,
encoder_hidden_states=text_embeddings).sample
```

```
        # === Compute loss ===
        loss = F.mse_loss(noise_pred, noise)

        # === Backprop ===
        optimizer.zero_grad()
        loss.backward()
        optimizer.step()

        total_loss += loss.item()
        loop.set_postfix(loss=loss.item())

    print(f"□ Epoch {epoch+1}: Avg Loss = {total_loss /
len(loader):.4f}")

save_path = "/content/drive/MyDrive/DatasetSD/trained_unet"
unet.save_pretrained(save_path)
print("□ U-Net saved to:", save_path)
```

```
 Epoch 1/1:   0%|          | 0/3 [00:00<?, ?it/s]
```

```
# 6. Load Trained U-Net

# Load from saved path
unet = UNet2DConditionModel.from_pretrained(save_path).to(device)
from diffusers import StableDiffusionPipeline
import torch

# Load full pipeline and replace U-Net
pipe = StableDiffusionPipeline.from_pretrained(
    "CompVis/stable-diffusion-v1-4",
    torch_dtype=torch.float16 if torch.cuda.is_available() else
torch.float32,
    revision="fp16" if torch.cuda.is_available() else None,
).to(device)

pipe.unet = unet  # Replace U-Net with fine-tuned version
pipe.enable_attention_slicing()

# Set prompt
prompt = "a yellow dog with a blue ball"

# Generate
with torch.autocast("cuda" if torch.cuda.is_available() else "cpu"):
    image = pipe(prompt, guidance_scale=7.5).images[0]

# Show
image.show()
```

Testing

Online testing at: Hugging Face - Stable Diffusion

```
!pip install -U diffusers
```

```
Requirement already satisfied: diffusers in
/usr/local/lib/python3.11/dist-packages (0.34.0)
Requirement already satisfied: importlib_metadata in
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/usr/local/lib/python3.11/dist-packages (from diffusers) (0.5.3)
Requirement already satisfied: Pillow in
/usr/local/lib/python3.11/dist-packages (from diffusers) (11.2.1)
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/usr/local/lib/python3.11/dist-packages (from huggingface-hub>=0.27.0-
>diffusers) (2025.3.2)
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(3.10)
Requirement already satisfied: urllib3<3,>=1.21.1 in
/usr/local/lib/python3.11/dist-packages (from requests->diffusers)
(2.4.0)
```

```
Requirement already satisfied: certifi>=2017.4.17 in
/usr/local/lib/python3.11/dist-packages (from requests->diffusers)
(2025.6.15)
```

```python
# Test with a pretrained model
from diffusers import DiffusionPipeline
from IPython.display import display

# Load the pipeline
pipe = DiffusionPipeline.from_pretrained("CompVis/stable-diffusion-v1-
4")
pipe = pipe.to("cuda")  # Use GPU if available for faster generation

# Define prompt and generate image
prompt = "A high tech solarpunk utopia in the Amazon rainforest"
image = pipe(prompt).images[0]

# Display the image in Colab
display(image)
```

```
/usr/local/lib/python3.11/dist-packages/huggingface_hub/utils/
_auth.py:94: UserWarning:
The secret `HF_TOKEN` does not exist in your Colab secrets.
To authenticate with the Hugging Face Hub, create a token in your
settings tab (https://huggingface.co/settings/tokens), set it as
secret in your Google Colab and restart your session.
You will be able to reuse this secret in all of your notebooks.
Please note that authentication is recommended but still optional to
access public models or datasets.
  warnings.warn(
```


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