Week 0e: Generative AI

The Creation Challenge

Machine Learning for Smarter Innovation

BSc-Level Course

October 6, 2025

Outline

Traditional ML:
"What is this?"

- Email: spam or not?
- Image: cat or dog?
- Text: positive sentiment?
- Patient: high risk?

Limitation: Analysis only

Generative AI:
"Create something new"

- Generate: realistic images
- Write: coherent articles
- Compose: original music
- Design: novel molecules

Power: Creation & innovation

The fundamental shift: from understanding existing data to creating new possibilities

Discriminative Models

Learn: $P(y|x)$
"Given input x, what's the label y?"

Examples:

- Logistic regression
- Random Forest
- Neural networks (classification)
- SVM

Goal: Decision boundaries

Generative Models

Learn: $P(x)$ or $P(x, y)$
"What does the data distribution look like?"

Examples:

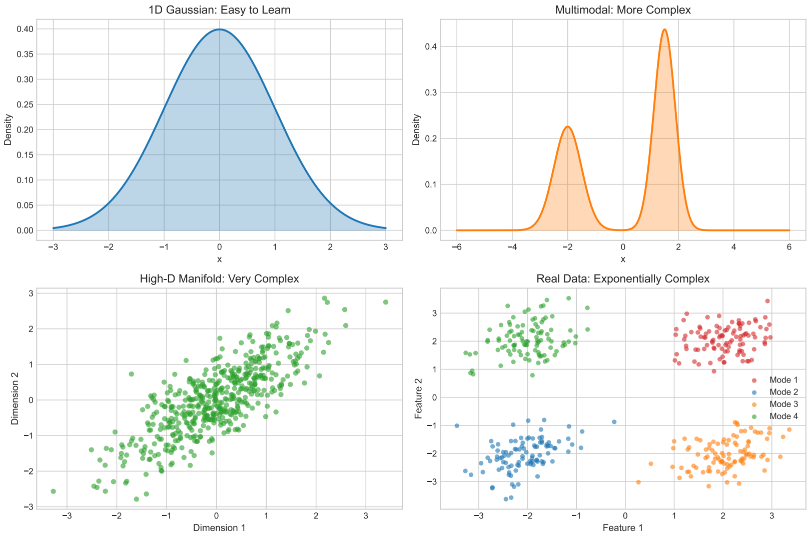
- Gaussian Mixture Models
- Variational Autoencoders
- GANs
- Diffusion models

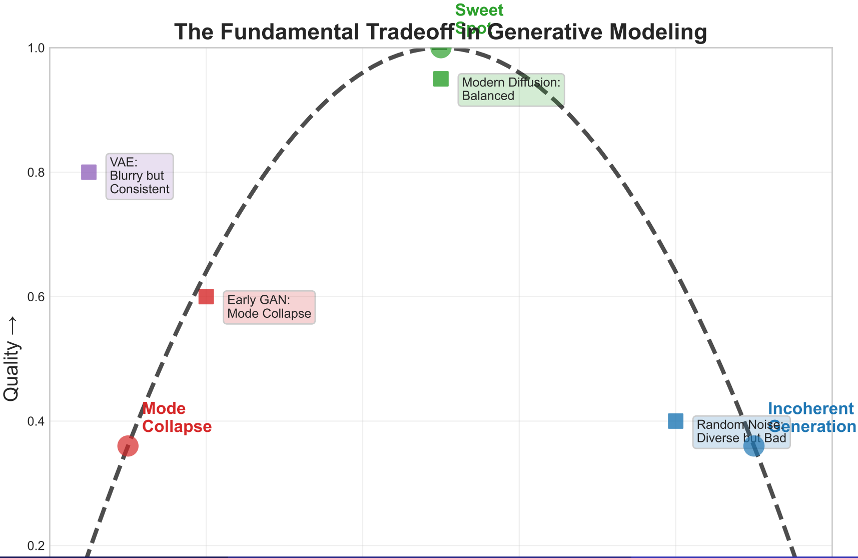
Goal: Data generation

Discriminative: "Is this a cat?" — Generative: "Draw me a cat"

The Hard Problem

Why Generation is Fundamentally Difficult

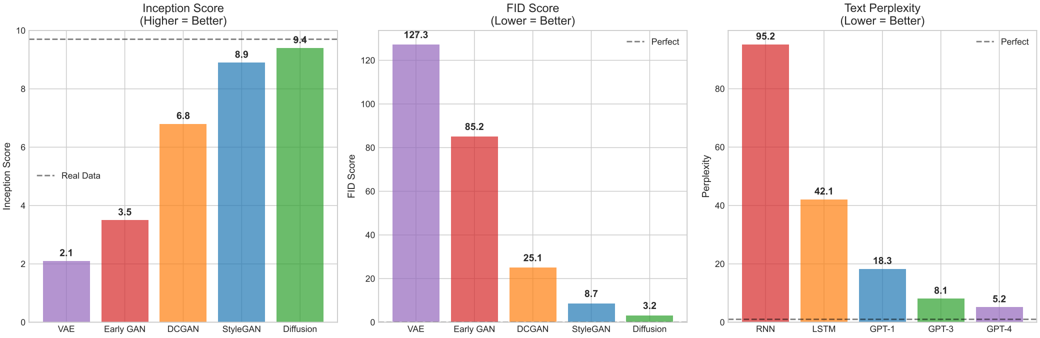




Sweet Spot
The Fundamental Tradeoff in Generative Modeling
1.0
0.8
0.6
0.4
0.2
Quality →
Modern Diffusion: Balanced
VAE: Blurry but Consistent
Early GAN: Mode Collapse
Mode Collapse
Random Noise: Diverse but Bad
Incoherent Generation

Measuring Generation Quality

Metrics for Evaluating Generative Models



Inception Score (IS)

- Range: 1-1000+
- Higher = better
- Quality & diversity
- $IS = \exp(E[KL(p(y|x)||p(y))])$

FID Score

- Range: 0-500+
- Lower = better
- Feature distance
- Real vs generated

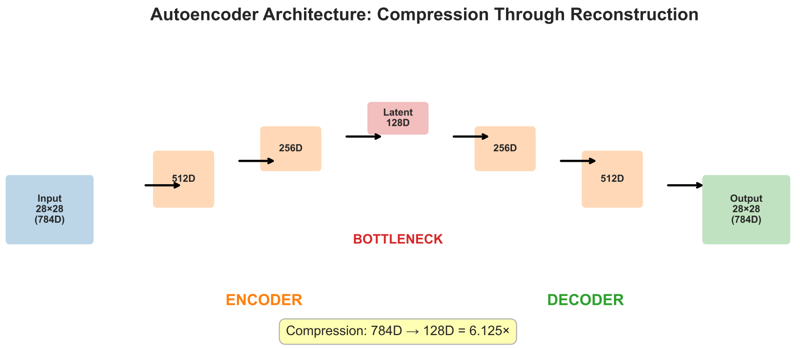
Perplexity (Text)

- Range: 1-10,000+
- Lower = better
- Predictability
- Language fluency

Quantitative evaluation: IS=300+ (excellent), FID¡10 (photorealistic), Perplexity¡20 (human-like text)

Autoencoders: The Foundation

Learning Compressed Representations



Encoder

- 784D -¿ 128D
- $z = f_{enc}(x)$

Latent Space

- Bottleneck: 128D
- Key features

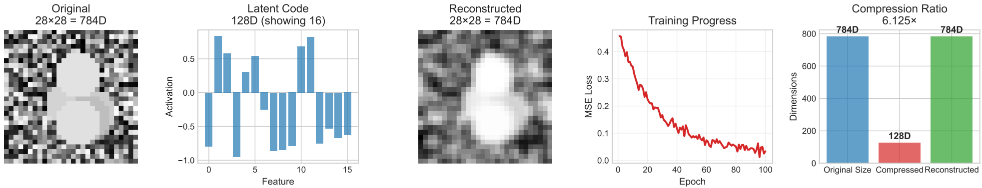
Decoder

- 128D -¿ 784D
- $\hat{x} = f_{dec}(z)$

Force information through bottleneck, learn to reconstruct

Worked Example: MNIST Compression

From 784 Pixels to 128 Features



Architecture Details:

- Input: 28x28 = 784 pixels
- Encoder: 784 -¿ 512 -¿ 256 -¿ 128
- Decoder: 128 -¿ 256 -¿ 512 -¿ 784
- Activation: ReLU (hidden), Sigmoid (output)

Training Process:

- Loss: $L = ||x - \hat{x}||^2$
- Optimizer: Adam, lr=0.001
- Epochs: 100
- Compression ratio: 784/128 = 6.125x

Reconstruction loss: MSE drops from 0.45 to 0.03 over 100 epochs

Autoencoder Successes

What Works Well

Autoencoder Successes

Visualization Placeholder

(Chart 12)

[+] SUCCESSES:

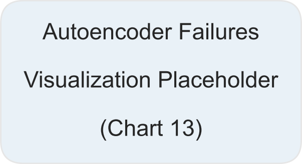
- Dimensionality reduction: 784D -¿ 128D

Quantitative Results:

- MSE: 0.031, Compression: 6.125x

Autoencoder Limitations

The Generation Problem



[-] FAILURES:

- Blurry outputs (averaging)

Generation Metrics:

Metric	Score
IS	2.1

Root Cause Analysis

Why Autoencoders Generate Poorly

Averaging Problem

Visualization Placeholder

(Chart 14)

The Averaging Problem:

- Loss: $L = ||x - \hat{x}||^2$

Mathematical Insight:

- $\hat{x} = \arg\min E[||x - \hat{x}||^2]$

Variational Autoencoders (VAEs)

The Probabilistic Solution

Vae Framework

Visualization Placeholder

(Chart 15)

Key Innovation:

- Encode to distribution, not point

VAE Loss:

$$\mathcal{L} = -E[\log p_\theta(x|z)] + KL(q||p)$$

Human Learning Analogy

How Artists Develop Mastery

Artist Learning Process

Visualization Placeholder

(Chart 16)

Traditional Art Education:

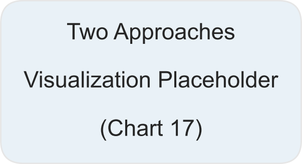
- Student creates artwork

Key Insights:

- Adversarial feedback drives improvement

Two Revolutionary Approaches

Beyond VAEs to Better Generation



Approach 1: Adversarial

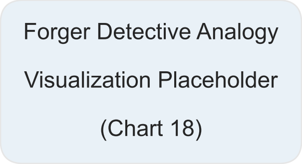
- Two networks compete

Approach 2: Diffusion

- Iterative denoising

GANs: The Forger vs Detective Game

Adversarial Training in Plain English



Forger (Generator):

- Creates fakes from noise

Detective (Discriminator):

- Examines: real or fake?

Reverse Corruption Analogy

Visualization Placeholder

(Chart 19)

Forward (Corruption):

- Clean image -¿ pure noise

Reverse (Generation):

- Pure noise -¿ clean image

GAN Dynamics: Geometric View

Understanding the Adversarial Process

Gan Geometric Dynamics

Visualization Placeholder

(Chart 20)

Generator:

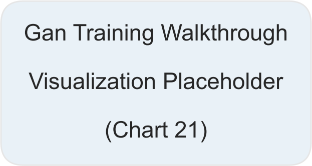
- Maps noise z to data x

Discriminator:

- Separates real from fake

GAN Training: Step-by-Step Example

Real Loss Values from MNIST Training



Epoch 1:

- D_loss: 1.386

Epoch 100:

- D_loss: 0.695

Diffusion Mathematics

Visualization Placeholder

(Chart 22)

Forward (Fixed):

$$q(x_t|x_{t-1}) = \mathcal{N}(\sqrt{1-\beta_t}x_{t-1}, \beta_t I)$$

Noise schedule: β_t (0.0001 ... 0.02)

Reverse (Learned):

$$p_\theta(x_{t-1}|x_t) = \mathcal{N}(\mu_\theta, \Sigma_\theta)$$

Network ϵ_θ predicts noise

Latent Space Interpolation

Smooth Transitions in Generated Content

Latent Interpolation

Visualization Placeholder

(Chart 23)

GAN Interpolation:

- Sample $z_1, z_2 \sim \mathcal{N}(0, I)$

Applications:

- Style transfer, face morphing

Diffusion Denoising Visualization

From Noise to Image in 1000 Steps

Denoising Steps

Visualization Placeholder

(Chart 24)

Key Time Steps:

- T=1000: Pure noise

Process Control:

- Guidance scale

Why Adversarial Training Works

The Mathematical Guarantee

Adversarial Theory

Visualization Placeholder

(Chart 25)

Theory:

- Minimax convergence

Benefits:

- Sharp, realistic images

Experimental Validation

Quality Metrics Throughout Training

Quality Metrics Over Time

Visualization Placeholder

(Chart 26)

GAN Progress:

- Start: IS=1.2, FID=450

Diffusion Progress:

- 100k: FID=200

Implementation: Stable Diffusion API

Production-Ready Generative AI

Stable Diffusion Api

Visualization Placeholder

(Chart 27)

Basic Usage:

```
import requests

response = requests.post(
    api_url,
    headers={"Authorization": key},
```

Parameters:

- cfg_scale: Adherence (1-20)
- steps: Quality (10-150)
- seed: Reproducible

Cost: $0.004 per image

The Generative AI Landscape

Four Fundamental Approaches

Generative Landscape

Visualization Placeholder

(Chart 28)

VAEs: Probabilistic, smooth latent, blurry
GANs: Adversarial, sharp outputs, unstable
Diffusion: Iterative denoising, high quality, slow
Transformers: Sequential, excellent text, scalable

Each approach has unique strengths - modern systems combine techniques

Fundamental Trade-offs

No Free Lunch in Generative Modeling

Generative Tradeoffs

Visualization Placeholder

(Chart 29)

Training Stability:

- VAEs, Diffusion: Stable
- GANs: Unstable

Quality:

- Diffusion, GANs: Excellent
- VAEs: Blurry

State-of-the-Art Applications

Production Generative AI Systems

Modern Applications

Visualization Placeholder

(Chart 30)

Image Generation:

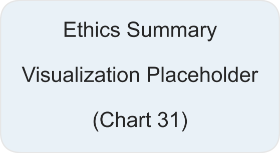
- DALL-E 3, Midjourney
- Stable Diffusion, Firefly

Text Generation:

- GPT-4, Claude, Gemini
- Llama 2 (open)

Summary & Ethical Considerations

Power and Responsibility in Generative AI



Capabilities:

- Realistic images from text
- Human-like writing

Challenges:

- Deepfakes, misinformation
- Copyright issues