Week 0e: Generative AI

The Creation Challenge

Machine Learning for Smarter Innovation

BSc-Level Course

October 6, 2025

Outline

The Creation Challenge

Moving Beyond Classification

Traditional ML: "What is this?"

- Email spam detector: Classify existing emails
- Medical diagnosis: Analyze X-ray images
- Sentiment analysis: Judge customer reviews

Limitation: Only analyzes, never creates

Generative AI: "Create something new"

- Generate phishing emails for security training
- Synthesize medical images for rare diseases
- Write product descriptions automatically
- Compose music for video backgrounds

Power: Creation enables innovation

Fundamental shift: from pattern recognition to content generation

Discriminative Models
Learn: $P(y|x)$ - Conditional probability
What it does:

- Given x, predict label y
- Learns decision boundaries
- Divides input space

Examples: Logistic, RF, SVM
Can sample new x? NO - only classifies existing data

Generative Models
Learn: $P(x)$ - Joint or marginal distribution
What it does:

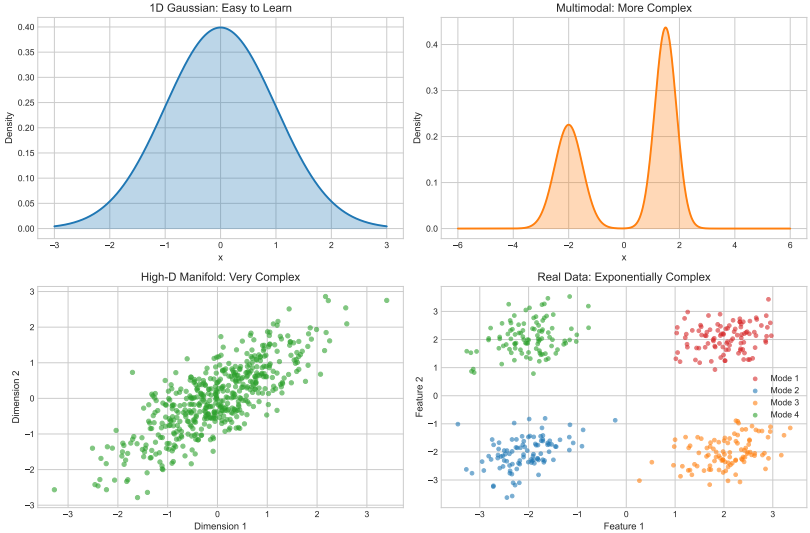
- Models entire data distribution
- Samples new $x \sim P(x)$
- Creates novel instances

Examples: VAEs, GANs, Diffusion
Can sample new x? YES - generates from distribution

Key distinction: Discriminative draws boundaries, Generative learns distributions enabling sampling

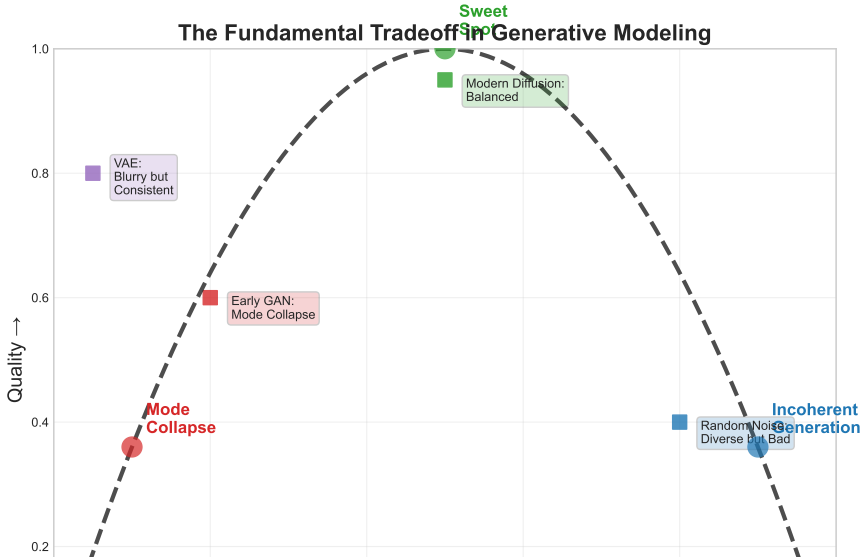
The Hard Problem

Why Generation is Fundamentally Difficult



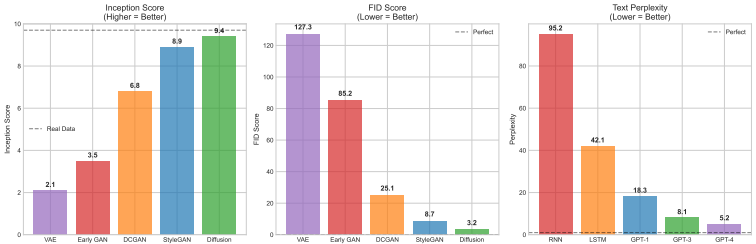
The Fundamental Tradeoff

Quality vs Diversity Dilemma



Measuring Generation Quality

Metrics for Evaluating Generative Models



Inception Score (IS)

- Range: 1-1000
- Higher = better
- Quality & diversity

Interpretation:

- >300: Excellent
- 100-300: Good
- <100: Poor

FID Score

- Range: 0-500
- Lower = better
- Feature distance

Interpretation:

- <10: Photorealistic
- 10-50: Good quality
- >50: Noticeable artifacts

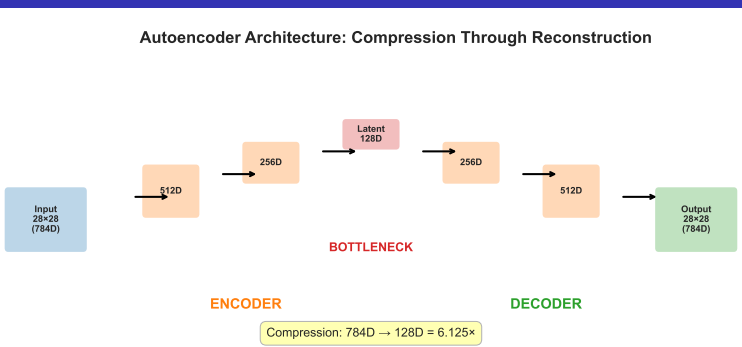
Perplexity (Text)

- Range: 1-10,000
- Lower = better
- Predictability

Interpretation:

- <20: Human-like
- 20-100: Coherent
- >100: Gibberish

Quantitative metrics enable objective quality assessment and model comparison



Encoder

- 784D -¿ 128D
- $z = f_{enc}(x)$

Why compress?

- Forces selective encoding
- Filters noise

Latent (Bottleneck)

- 128D representation
- Key features only
- Compressed 6.1x

Bottleneck forces:

- Information prioritization

Decoder

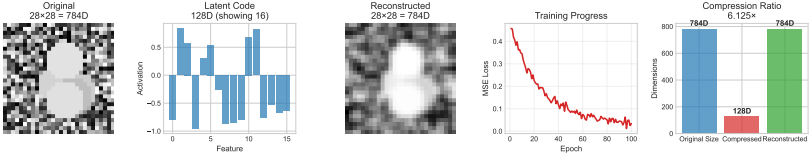
- 128D -¿ 784D
- $\hat{x} = f_{dec}(z)$

Reconstruction:

- Lossy process
- Preserves essentials

Worked Example: MNIST Compression

From 784 Pixels to 128 Features



Architecture:

- Input: 784 pixels
- Encoder: 784 -¿ 128
- Decoder: 128 -¿ 784

Training:

- Loss: $L = ||x - \hat{x}||^2$
- Optimizer: Adam
- Compression: 6.125x

MSE drops 0.45 -¿ 0.03 over 100 epochs

Autoencoder Successes

Visualization Placeholder

(Chart 12)

[+] SUCCESSES:

- Dimensionality reduction: 784D -¿ 128D

Quantitative Results:

- MSE: 0.031, Compression: 6.125x

Autoencoder Failures

Visualization Placeholder

(Chart 13)

[-] FAILURES:

- Blurry outputs (averaging)

Generation Metrics:

Metric	Score
IS	2.1

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
- $q_\phi(z|x) = \mathcal{N}(\mu(x), \sigma^2(x))$

VAE Loss (ELBO):

$$\mathcal{L} = \underbrace{-E[\log p_\theta(x|z)]}_{\text{Reconstruction}} + \underbrace{KL(q_\phi(z|x)||p(z))}_{\text{Regularization}}$$

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

Two Approaches

Visualization Placeholder

(Chart 17)

Approach 1: Adversarial

- Two networks compete

Approach 2: Diffusion

- Iterative denoising

Forger Detective Analogy

Visualization Placeholder

(Chart 18)

Forger (Generator):

- Creates fakes from noise

Detective (Discriminator):

- Examines: real or fake?

Diffusion: The Reverse Corruption Process

Denoising in Plain English

Reverse Corruption Analogy

Visualization Placeholder

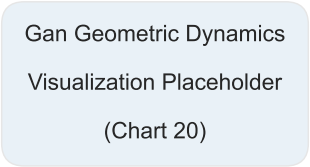
(Chart 19)

Forward (Corruption):

- Clean image -¿ pure noise

Reverse (Generation):

- Pure noise -¿ clean image



Generator:

- Maps noise z to data x

Discriminator:

- Separates real from fake

GAN Training: Step-by-Step Example

Real Loss Values from MNIST Training

Gan Training Walkthrough

Visualization Placeholder

(Chart 21)

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:

- Linear: 0.0001 -¿ 0.02

Reverse (Learned):

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

Network ϵ_θ predicts added noise

Training objective:

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

Adversarial Theory

Visualization Placeholder

(Chart 25)

Theory:

- Minimax convergence

Benefits:

- Sharp, realistic images

Experimental Validation

Quality Metrics vs Training Progress

Quality Metrics Over Time

Visualization Placeholder

(Chart 26)

Generative Model Results (MNIST):

Method	IS	FID	Time
Baseline (random)	1.0	500	-

Key Observations:

- Diffusion: Best quality, longest training
- GAN: Near-diffusion quality, 4x faster

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

Generative Landscape

Visualization Placeholder

(Chart 28)

VAEs: Probabilistic, smooth latent, blurry
GANs: Adversarial, sharp outputs, unstable
Each approach has unique strengths - modern systems combine techniques

Diffusion: Iterative denoising, high quality, slow
Transformers: Sequential, excellent text, scalable

Choosing Your Generative Model

Decision Framework for Practitioners

Decision Criteria:

1. **What are you generating?**
   - Images: Diffusion or GAN
   - Text: Transformer (GPT family)
   - Structured data: VAE
   - Multimodal: Diffusion + Transformer
2. **Data size?**
   - $<$ 10k samples: VAE (stable)
   - 10k-100k: GAN or VAE
   - $>$ 100k: Diffusion or Transformer
3. **Priority?**
   - Quality: Diffusion (FID ¡ 5)
   - Speed: GAN (single pass)
   - Stability: VAE (always converges)
   - Control: Diffusion (guidance)

Recommendation Table:

Use Case	Best	Why
Photorealistic	Diffusion	Quality
Fast prototype	GAN	Speed
Data augment	VAE	Stable
Text gen	Transformer	Sequential
Style transfer	VAE	Interpolate
Research	VAE	Interpret

When NOT to Use:

- VAE: Need sharp images
- GAN: Limited data, need stability
- Diffusion: Real-time inference required
- All: Insufficient compute resources

Model selection requires balancing quality, speed, stability against problem constraints

Common Pitfalls: What Can Go Wrong

Failure Modes and Solutions

VAE Pitfalls

1. **Posterior Collapse**
   - Symptom: KL term -¿ 0
   - Decoder ignores latent
   - Fix: -VAE, KL warm-up
2. **Blurry Outputs**
   - Inherent to MSE loss
   - Reconstruction averages
   - Fix: Perceptual loss, adversarial

GAN Pitfalls

1. **Mode Collapse**
   - Generator ignores diversity
   - Produces limited variety
   - Fix: Minibatch discrimination, unrolled GAN
2. **Training Instability**
   - Loss oscillates wildly
   - No convergence
   - Fix: Wasserstein loss, spectral norm, TTUR

Diffusion Pitfalls

1. **Slow Sampling**
   - 1000 steps = slow
   - Latency bottleneck
   - Fix: DDIM, distillation, 50 steps
2. **Memory Intensive**
   - High-res = huge memory
   - Training cost
   - Fix: Latent diffusion, gradient checkpointing

Each approach has characteristic failure modes requiring specific mitigation strategies

Generative AI Best Practices

From Research to Production

Training Best Practices:

1. **Start Simple**
   - Low resolution first (64x64 before 1024x1024)
   - Small models before large
   - Validate on toy datasets
2. **Monitor Obsessively**
   - Log every 100 steps
   - Visual inspection of samples
   - Track FID/IS throughout
   - Watch for collapse/divergence
3. **Use Pretrained Models**
   - Transfer learning saves weeks
   - Fine-tune from Stable Diffusion
   - Leverage foundation models
4. **Ablation Studies**
   - Test each component independently
   - Measure contribution to performance
   - Simplify when possible

Deployment Best Practices:

1. **Quality Control**
   - Human-in-the-loop review
   - NSFW content filtering
   - Bias detection systems
   - Watermarking for traceability
2. **Performance Optimization**
   - Model quantization (FP16, INT8)
   - Distillation for speed
   - Caching common generations
   - Batch processing
3. **Safety Measures**
   - Rate limiting to prevent abuse
   - Content moderation
   - Prompt injection defenses
   - User consent and attribution
4. **Continuous Improvement**
   - Collect user feedback
   - Retrain on curated data

Generative Tradeoffs

Visualization Placeholder

(Chart 29)

Training Stability:

- VAEs, Diffusion: Stable
- GANs: Unstable

Quality:

- Diffusion, GANs: Excellent
- VAEs: Blurry

Modern Applications

Visualization Placeholder

(Chart 30)

Image Generation:

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

Text Generation:

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

Ethics Summary

Visualization Placeholder

(Chart 31)

Capabilities:

- Realistic images from text
- Human-like writing

Challenges:

- Deepfakes, misinformation
- Copyright issues