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:

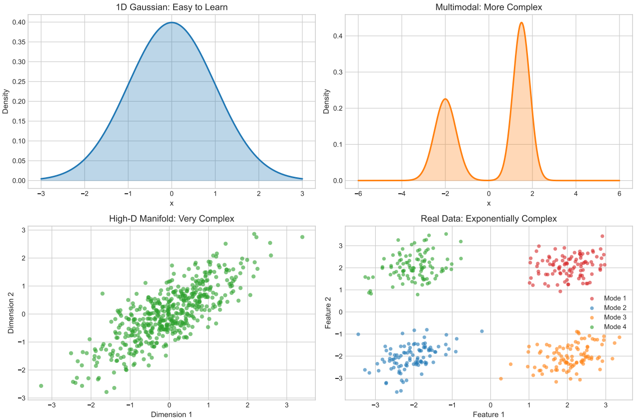
- Models entire data distribution
- Samples new $x \sim P(x)$
- Creates novel instances

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



Challenges:

- High-dimensional spaces
- Multimodal distributions

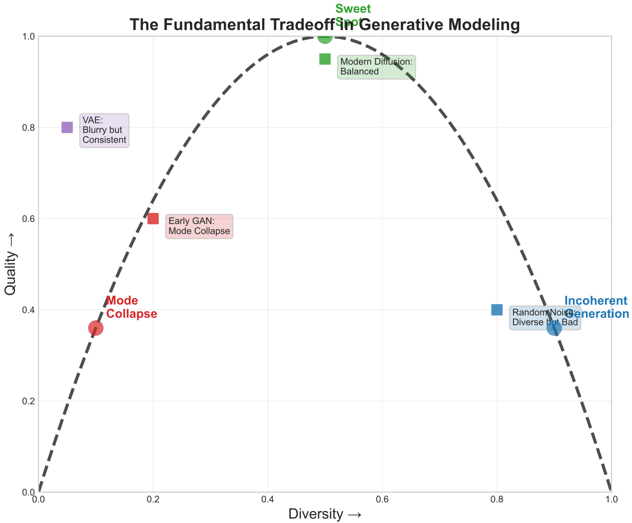
Requirements:

- Capture all patterns
- Maintain realism

Real data lives on complex manifolds - learning full distribution is exponentially hard

The Fundamental Tradeoff

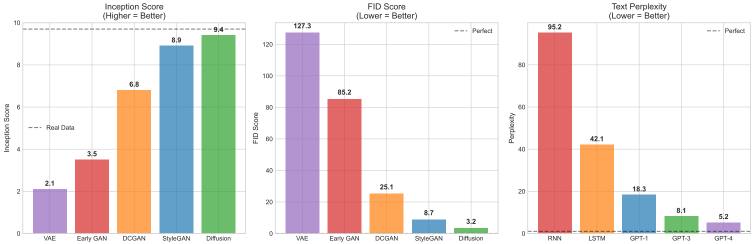
Quality vs Diversity Dilemma



High Quality **Balanced** **High Diversity**

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

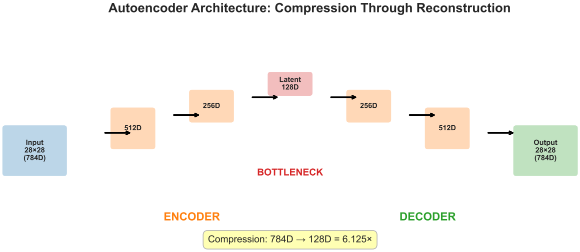
Interpretation:

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

Quantitative metrics enable objective quality assessment and model comparison

Autoencoders: The Foundation

Learning Compressed Representations



Encoder

- 784D -¿ 128D
- Forces selective encoding
- Filters noise

Latent

- 128D bottleneck
- Key features only
- 6.1x compressed

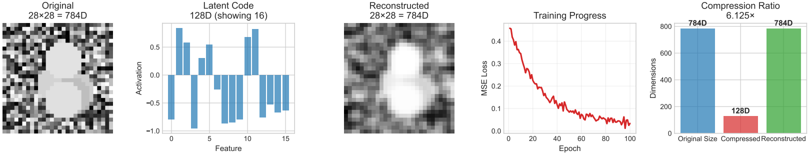
Decoder

- 128D -¿ 784D
- Lossy reconstruction
- Preserves essentials

Bottleneck forces meaningful compression

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

What Works Well

Autoencoder Successes

Visualization Placeholder

(Chart 12)

[+] SUCCESSES:

- Dimensionality reduction: 784D -¿ 128D
- Feature learning, denoising
- Anomaly detection

Results:

- MSE: 0.031
- Compression: 6.1x
- Training: 2.3 min

Autoencoders excel at representation and compression

Autoencoder Limitations

The Generation Problem

Autoencoder Failures

Visualization Placeholder

(Chart 13)

[-] FAILURES:

- Blurry outputs
- Poor generation
- Holes in latent space

Autoencoders reconstruct, NOT generate

Metrics:

IS	2.1
FID	127

Real: IS=9.7, FID=3.2

Root Cause Analysis

Why Autoencoders Generate Poorly

Averaging Problem

Visualization Placeholder

(Chart 14)

Problem:

- Loss: $L = ||x - \hat{x}||^2$
- Multiple inputs -¿ same code
- Decoder outputs average

Math:

- $\hat{x} = \text{arg min } E[||x - \hat{x}||^2]$
- Solution: $\hat{x} = E[x]$
- Need probabilistic approach

MSE loss forces averaging

Variational Autoencoders (VAEs)

The Probabilistic Solution

Vae Framework

Visualization Placeholder

(Chart 15)

Key Innovation:

- Encode to distribution: $q_\phi(z|x) = \mathcal{N}(\mu, \sigma^2)$
- Sample: $z = \mu + \sigma \odot \epsilon$

Reparameterization Trick:

- Can't backprop through sampling
- Make z deterministic function
- Gradient flows through μ, σ

VAE Loss (ELBO):

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

Two terms:

- Reconstruction: Decode accurately
- KL: Keep z smooth, continuous
- β-VAE: $\beta \times KL$ for balance

Reparameterization enables gradient optimization of probabilistic encoder

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

GANs: The Forger vs Detective Game

Adversarial Training in Plain English

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

GAN Dynamics: Geometric View

Understanding the Adversarial Process

Gan Geometric Dynamics

Visualization Placeholder

(Chart 20)

Generator:

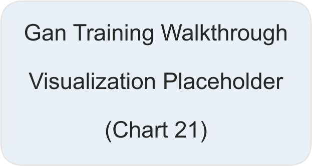
- Maps noise z to data x

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 Mathematical Framework

Forward and Reverse Processes

Diffusion Mathematics

Visualization Placeholder

(Chart 22)

Forward:

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

Noise Schedule:

- Linear: 0.0001 -¿ 0.02
- Cosine: Variable rate
- Matters: Smooth degradation

Reverse:

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

Training:

$$L = E[||\epsilon - \epsilon_\theta(x_t, t)||^2]$$

Intuition: Predict noise, subtract it

Linear noise schedule works for most cases

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:

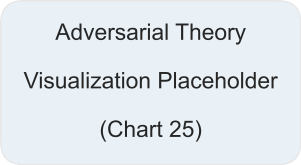
- T=1000: Pure noise

Process Control:

- Guidance scale

Why Adversarial Training Works

The Mathematical Guarantee



Theory:

- Minimax convergence

Benefits:

- Sharp, realistic images

Experimental Validation

Quality Metrics vs Training Progress

Quality Metrics Over Time

Visualization Placeholder

(Chart 26)

Results (MNIST):

Method	IS	FID	Time
Random	1.0	500	-
VAE	5.2	48	30min
GAN	9.1	9	2hr
Diffusion	9.3	3	8hr
Real	9.7	0	-

Observations:

- Diffusion: Best quality
- GAN: 4x faster, nearly as good
- VAE: Fast but blurry

Patterns:

- VAE: Monotonic
- GAN: Oscillates

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

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**
   - KL -¿ 0
   - Fix: β-VAE, warm-up
2. **Blurry**
   - MSE averages
   - Fix: Perceptual loss

GAN Pitfalls

1. **Mode Collapse**
   - Limited variety
   - Fix: Minibatch disc
2. **Unstable**
   - Oscillates
   - Fix: Wasserstein, spectral norm

Diffusion Pitfalls

1. **Slow (1000 steps)**
   - Latency issue
   - Fix: DDIM (50 steps)
2. **Memory**
   - High-res costly
   - Fix: Latent diffusion

Each approach has characteristic failure modes with specific solutions

Generative AI Best Practices

From Research to Production

Training:

1. **Start Simple**
   - Low res first (64x64 before 1024x1024)
   - Validate on toy datasets
2. **Monitor Obsessively**
   - Log every 100 steps
   - Visual sample inspection
   - Track FID/IS
3. **Use Pretrained**
   - Transfer learning saves weeks
   - Fine-tune Stable Diffusion
4. **Ablation Studies**
   - Test components independently

Deployment:

1. **Quality Control**
   - Human-in-the-loop review
   - Content filtering
   - Watermarking
2. **Performance**
   - Quantization (FP16, INT8)
   - Distillation for speed
   - Caching
3. **Safety**
   - Rate limiting
   - Content moderation
   - Prompt injection defenses
4. **Continuous Improvement**
   - User feedback
   - A/B testing

Production requires systematic validation and continuous monitoring

Comprehensive Trade-offs

No Free Lunch in Generative Modeling

Generative Tradeoffs

Visualization Placeholder

(Chart 29)

Stability:

- VAEs, Diffusion: Stable
- GANs: Unstable

Speed:

- VAEs, GANs: Fast
- Diffusion: Slow

Quality:

- Diffusion, GANs: Excellent
- VAEs: Blurry

Control:

- Diffusion, Transformers: High
- GANs: Limited

Choose based on requirements

State-of-the-Art Applications

Production Generative AI Systems

Modern Applications

Visualization Placeholder

(Chart 30)

Image:

- DALL-E 3, Midjourney
- Stable Diffusion, Firefly
- 1024x1024, 10-30 sec

Text:

- GPT-4, Claude, Gemini
- Llama 2 (open)
- 32k-200k tokens, 100+ languages

Production systems achieve human-level performance

Summary & Future of Generative AI

What We Learned and What's Next

Ethics Summary

Visualization Placeholder

(Chart 31)

What We Learned:

- Autoencoders: Compress but blurry
- VAEs: Probabilistic latent space
- GANs: Adversarial for realism
- Diffusion: Best quality, slow
- When to use each approach
- Common pitfalls and solutions

Ethical Challenges:

- Deepfakes, misinformation
- Copyright, attribution
- Bias amplification
- Worker displacement

Solutions:

- Watermarking, detection