

Week 0e: Generative AI

The Creation Challenge

Machine Learning for Smarter Innovation

BSc-Level Course

October 6, 2025

1 Act 1: The Challenge

2 Act 2: Variational Autoencoders

3 Act 3: Adversarial & Diffusion

4 Act 4: Synthesis

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

Fundamental shift: from pattern recognition to content generation

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

Mathematical Foundation

Two Approaches to Learning

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

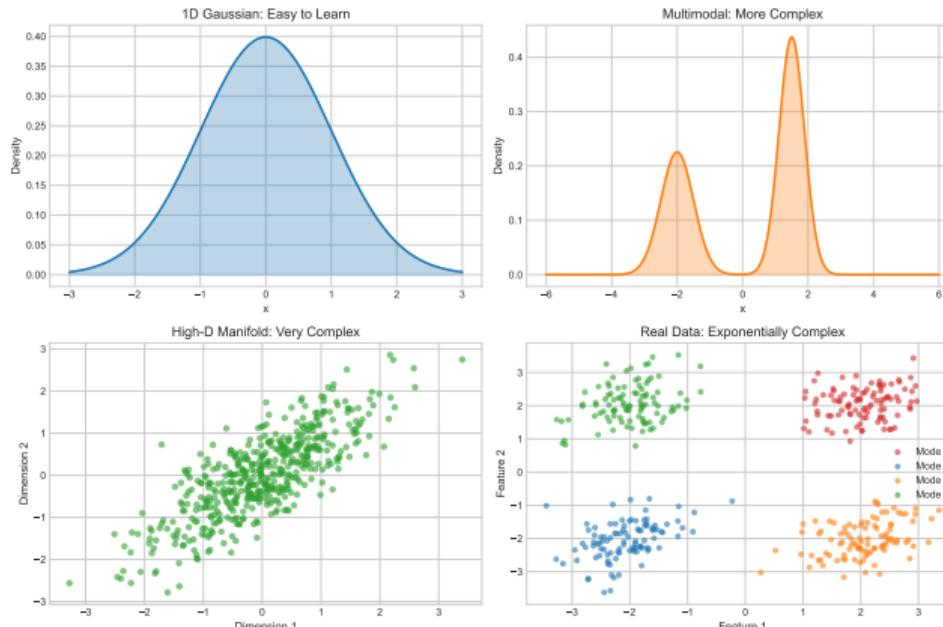
Examples: VAEs, GANs, Diffusion

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

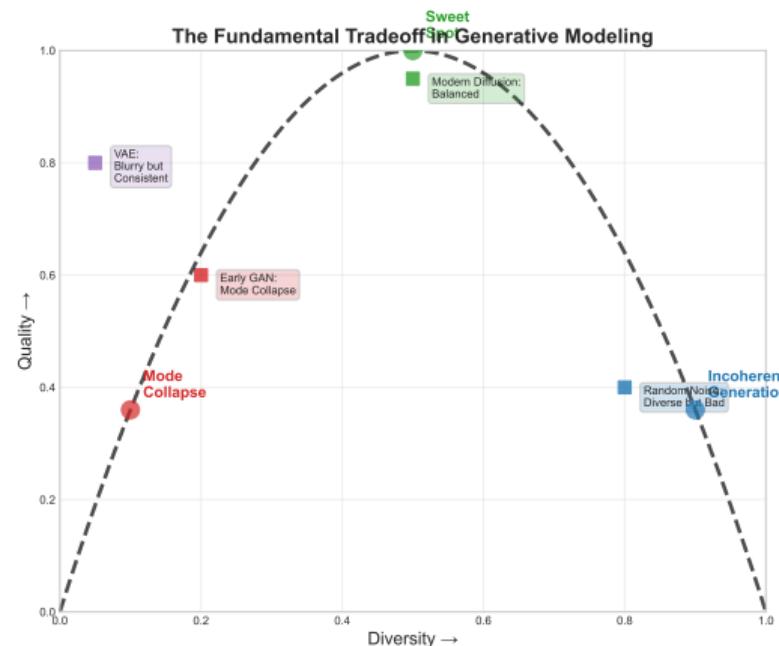
Real data lives on complex manifolds - learning full distribution is exponentially hard

Requirements:

- Capture all patterns
- Maintain realism

The Fundamental Tradeoff

Quality vs Diversity Dilemma



High Quality: Mode collapse, repetitive

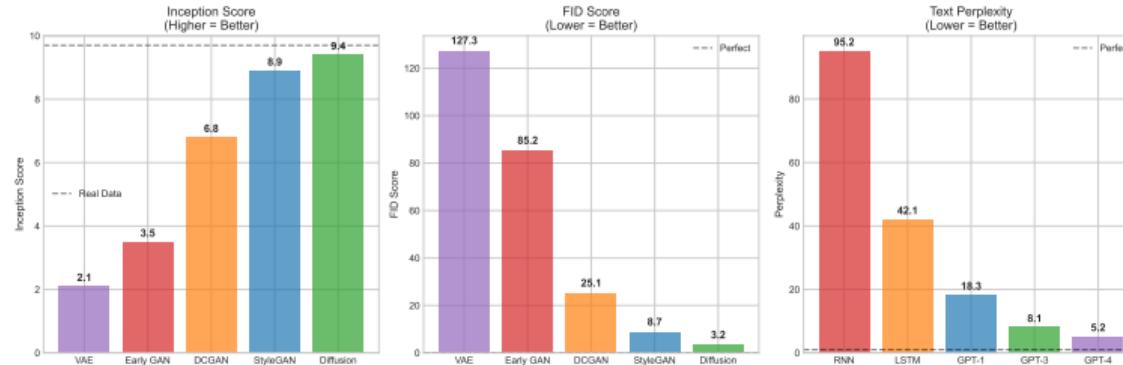
Balanced: Realistic variety

High Diversity: Unrealistic

Realistic AND diverse remains the central challenge

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:

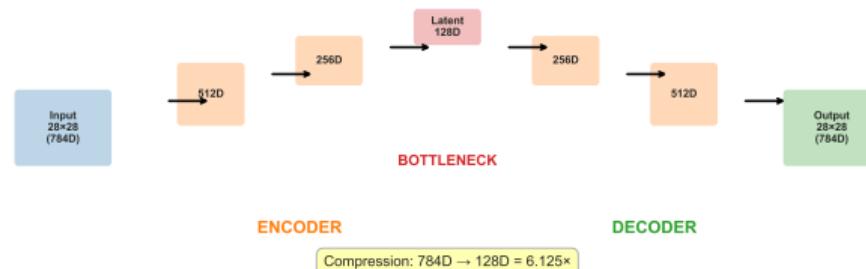
- <20: Human-like
- 20-100: Coherent
- >100: Gibberish

Quantitative metrics enable objective quality assessment and model comparison

Autoencoders: The Foundation

Learning Compressed Representations

Autoencoder Architecture: Compression Through Reconstruction



Encoder

- 784D \rightarrow 128D
- Forces selective encoding
- Filters noise

Latent

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

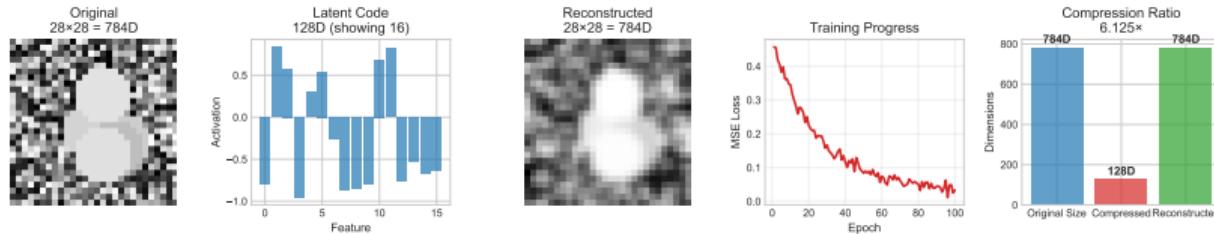
Decoder

- 128D \rightarrow 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 \rightarrow 128
- Decoder: 128 \rightarrow 784

Training:

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

MSE drops 0.45 \rightarrow 0.03 over 100 epochs

Autoencoder Successes

What Works Well

Autoencoder Successes

Visualization Placeholder

(Chart 12)

[+] SUCCESSES:

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

Autoencoders excel at representation and compression

Results:

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

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 - \downarrow same code
- Decoder outputs average

MSE loss forces averaging

Math:

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

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

Human Learning Analogy

How Artists Develop Mastery

Artist Learning Process

Visualization Placeholder

(Chart 16)

Art Education:

- Student creates
- Teacher critiques
- Student improves

Adversarial learning inspired GANs

Insights:

- Adversarial feedback drives improvement
- Both improve together

Two Revolutionary Approaches

Beyond VAEs to Better Generation

Two Approaches

Visualization Placeholder

(Chart 17)

Adversarial

- Two networks compete
- Sharp, realistic

Both address VAE limitations

Diffusion

- Iterative denoising
- Stable, controllable

GANs: The Forger vs Detective Game

Adversarial Training in Plain English

Forger Detective Analogy

Visualization Placeholder

(Chart 18)

Forger:

- Creates fakes
- Fools detective

Result: Detective can't tell fake from real!

Competition drives both to excellence

Detective:

- Examines: real/fake?
- Gets better at detection

Diffusion: The Reverse Corruption Process

Denoising in Plain English

Reverse Corruption Analogy

Visualization Placeholder

(Chart 19)

Forward:

- Clean \rightarrow noise
- 1000 steps

Reverse:

- Noise \rightarrow clean
- 1000 steps

Key: Learn to undo corruption

Like sculptor revealing statue

GAN Dynamics: Geometric View

Understanding the Adversarial Process

Gan Geometric Dynamics
Visualization Placeholder
(Chart 20)

Generator:

- Maps z to x
- Loss: $-\log D(G(z))$

Discriminator:

- Separates real/fake
- Loss: $-\log D(x) - \log(1 - D(G))$

Equilibrium: Generator = Real, D accuracy = 50%

GAN Training: Step-by-Step Example

Real Loss Values from MNIST Training

Gan Training Walkthrough

Visualization Placeholder

(Chart 21)

Epoch 1:

- D: 1.386, G: 0.693
- Images: noise

Healthy: Total \approx 1.4

Both networks balanced at equilibrium

Epoch 100:

- D: 0.695, G: 0.698
- Images: realistic

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

Linear noise schedule works for most cases

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

Latent Space Interpolation

Smooth Transitions in Generated Content

Latent Interpolation

Visualization Placeholder

(Chart 23)

Method:

- Sample z_1, z_2
- Interpolate: $z_t = (1 - t)z_1 + tz_2$
- Generate: $x_t = G(z_t)$

Meaningful latent spaces enable smooth interpolation

Applications:

- Style transfer
- Face morphing
- Drug discovery

Diffusion Denoising Visualization

From Noise to Image in 1000 Steps

Denoising Steps

Visualization Placeholder

(Chart 24)

Steps:

- $T=1000$: Noise
- $T=500$: Structure
- $T=0$: High quality

Gradual refinement

Control:

- Guidance scale
- Step count

Why Adversarial Training Works

The Mathematical Guarantee

Adversarial Theory

Visualization Placeholder

(Chart 25)

Theory:

- Minimax convergence
- Equilibrium: $p_g = p_{data}$

Benefits:

- Sharp, realistic
- Fine details
- No averaging

Adversarial pressure prevents averaging

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)

Usage:

```
response = requests.post(  
    api_url,  
    headers={"Auth": key},  
    json={  
        "text_prompts": [{"text": "city"}],  
        "cfg_scale": 7,  
        "steps": 30  
    })
```

APIs: DALL-E 3, Midjourney, Stable Diffusion

Parameters:

- cfg_scale: 1-20
- steps: 10-150

Cost: \$0.004/image

The Generative AI Landscape

Four Fundamental Approaches

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 \downarrow 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 $\rightarrow 0$
- 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

Choose based on requirements

Quality:

- Diffusion, GANs: Excellent
- VAEs: Blurry

Control:

- Diffusion, Transformers: High
- GANs: Limited

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

Production systems achieve human-level performance

Text:

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

Summary & Future of Generative AI

What We Learned and What's Next

Ethics Summary

Visualization Placeholder

(Chart 31)

Learned:

- VAEs: Probabilistic, blurry
- GANs: Adversarial, realistic
- Diffusion: Best quality
- Decision framework, pitfalls

Future:

- Faster, multimodal, edge

Balance capability with responsibility

Ethics:

- Deepfakes, copyright
- Bias, displacement

Solutions:

- Watermarking, auditing
- Governance

Next: Apply to innovation