

# Week 0e: Generative AI

## The Creation Challenge

Machine Learning for Smarter Innovation

BSc-Level Course

October 6, 2025



# 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

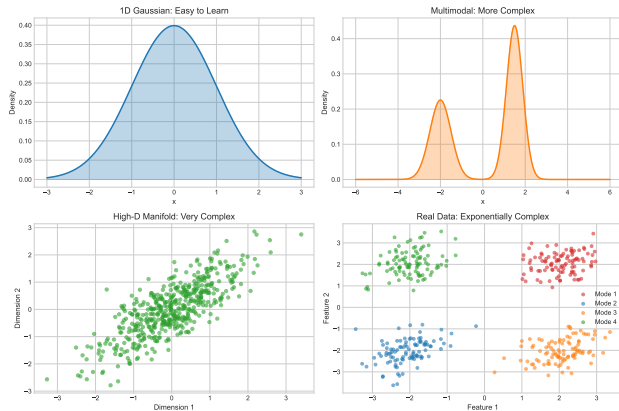
**Examples:** VAEs, GANs, Diffusion

**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

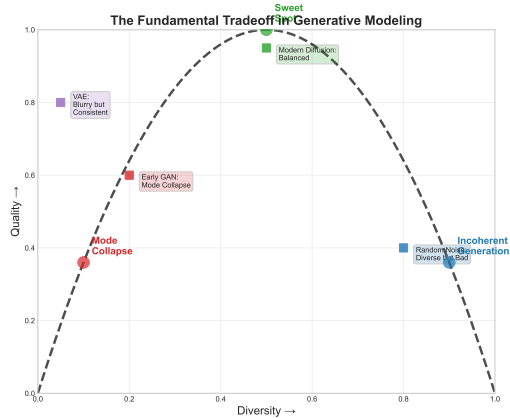
Real data lives on complex manifolds - learning full distribution is exponentially hard

## Requirements:

- Capture all patterns
- Maintain realism

# The Fundamental Tradeoff

## Quality vs Diversity Dilemma



**High Quality:** Mode collapse, repetitive

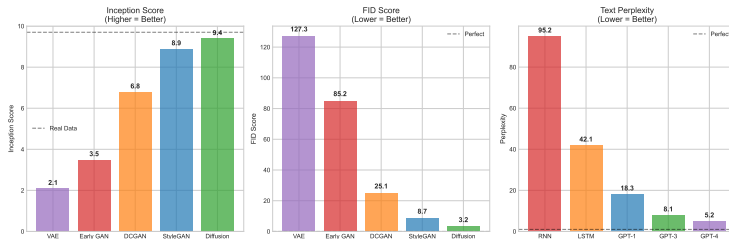
**Balanced:** Realistic variety

**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:

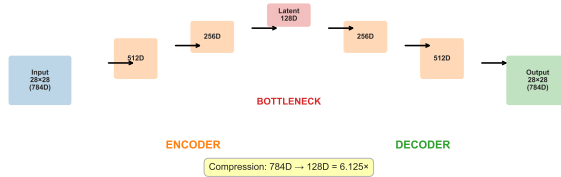
- <20: Human-like
- 20-100: Coherent
- >100: Gibberish

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

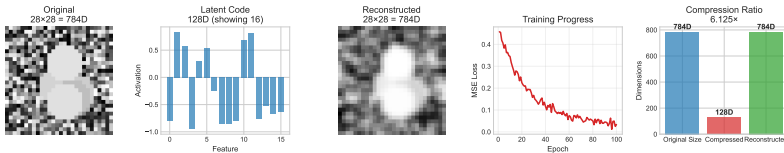
- 128D  $\rightarrow$  784D
- Lossy reconstruction
- Preserves essentials

Bottleneck forces meaningful compression



# Worked Example: MNIST Compression

From 784 Pixels to 128 Features



## Architecture:

- Input: 784 pixels
- Encoder: 784 → 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  $\rightarrow$  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 -> 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:

- Make  $z$  deterministic
- Gradient flows

Reparameterization enables gradient optimization

## VAE Loss:

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

## Two terms:

- Reconstruction
- KL regularization
- $\beta$ -VAE balances

# 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

**Key:** Learn to undo corruption

Like sculptor revealing statue

## Reverse:

- Noise  $\rightarrow$  clean
- 1000 steps

# 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:  $x_t = G(z_t)$

## Applications:

- Style transfer
- Face morphing
- Drug discovery

Meaningful latent spaces enable smooth interpolation

# 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:  $p_g = p_{data}$

Adversarial pressure prevents averaging

## Benefits:

- Sharp, realistic
- Fine details
- No 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
- GAN: 4x faster
- VAE: Fast, blurry

Patterns:

- VAE: Monotonic
- GAN: Oscillates

Quality-speed tradeoff guides selection



# 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 ↓)
- Speed: GAN (single pass)
- Stability: VAE (always converges)
- Control: Diffusion (guidance)

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

## 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

# Common Pitfalls: What Can Go Wrong

## Failure Modes and Solutions

### VAE Pitfalls

#### 1. Posterior Collapse

- $KL - \log 0$
- Fix:  $\beta$ -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

### 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)

## 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