Week 0e: Generative AI

The Creation Challenge

Machine Learning for Smarter Innovation

BSc-Level Course

October 7, 2025

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3. Part 3: Adversarial & Diffusion
4. Part 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

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

Generative models learn full data distributions enabling sampling - classification learns boundaries, generation learns manifolds

Mathematical Foundation

Two Approaches to Learning

Discriminative Models
Learn: $P(y|x)$ - Conditional probability
(Ng & Jordan 2002: Defined distinction)
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:

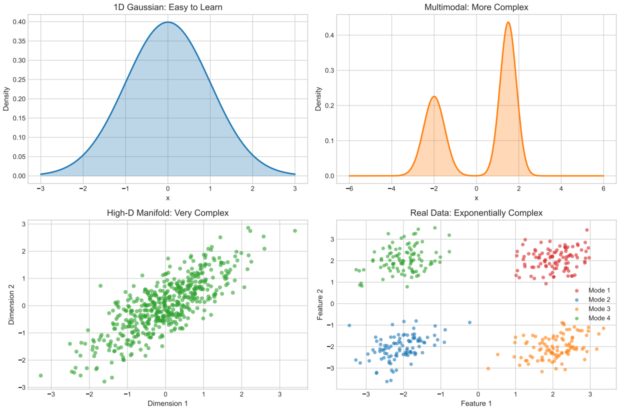
- Models entire data distribution
- Sample via ancestral sampling or MCMC
- Samples new $x \sim P(x)$
- Creates novel instances

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

Discriminative models $P(y|x)$ learn boundaries while generative models $P(x)$ or $P(x, y)$ learn distributions - fundamental distinction enables creation

The Hard Problem

Why Generation is Fundamentally Difficult



1D Gaussian: Easy to Learn

Multimodal: More Complex

High-D Manifold: Very Complex

Real Data: Exponentially Complex

Challenges:

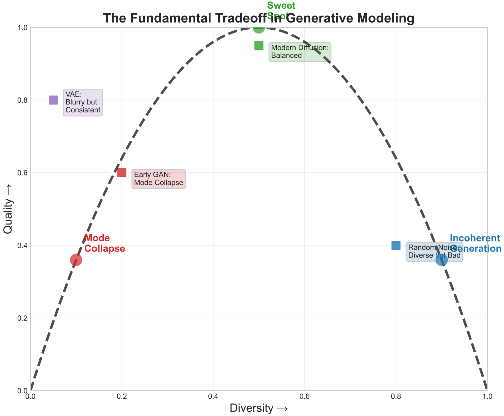
- High-dimensional spaces
- Multimodal distributions
- Curse of dimensionality (data lies on low-dimensional manifolds)
- Sample complexity grows exponentially

Requirements:

- Capture all patterns
- Maintain realism
- Computational tractability (exact inference intractable)

The Fundamental Tradeoff

Quality vs Diversity Dilemma

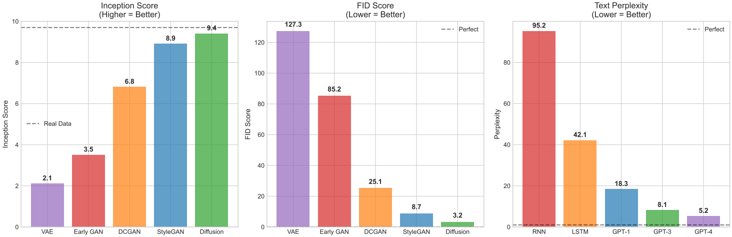


High Quality: Mode collapse, repetitive
Balanced: Realistic variety
High Diversity: Unrealistic
Explanations:

- Mode Collapse: Generator produces limited variety (high quality, low diversity)
- Coverage Issue: Generator spreads thin (high diversity, low quality)

Measuring Generation Quality

Metrics for Evaluating Generative Models



Inception Score (IS)
(Salimans et al. 2016)

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

Interpretation:

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

FID Score
(Heusel et al. 2017: Fréchet Inception Distance)

- 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

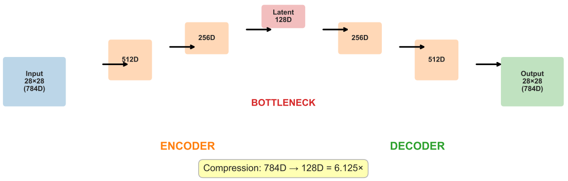
Note: Human evaluation remains gold standard

Quantitative metrics approximate perceptual quality - IS measures label confidence and diversity, FID measures feature distribution distance, perplexity measures predictability

Autoencoders: The Foundation

Learning Compressed Representations

Autoencoder Architecture: Compression Through Reconstruction



Encoder

- 784D -¿ 128D
- Learns $q(z|x)$ mapping
- Forces selective encoding
- Filters noise

Latent

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

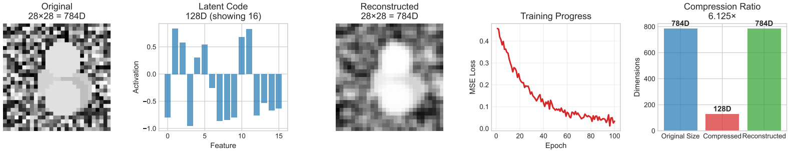
Decoder

- 128D -¿ 784D
- Learns $p(x|z)$ mapping
- Lossy reconstruction
- Preserves essentials

Bottleneck architecture forces dimensionality reduction - information bottleneck principle requires encoding only essential features for reconstruction

Worked Example: MNIST Compression

From 784 Pixels to 128 Features



Architecture:

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

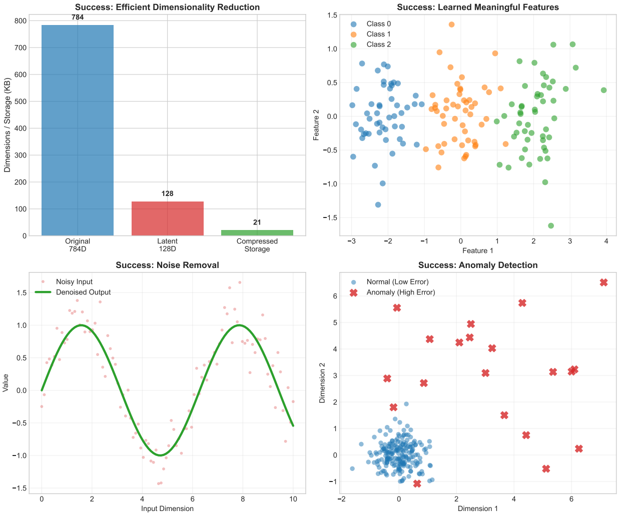
Training:

- Loss: $L = ||x - \hat{x}||^2$
- Optimizer: Adam
- Epoch 1: MSE=0.45
- Epoch 100: MSE=0.03
- Compression: 6.125x

Reconstruction loss decreases monotonically with training - 6x compression ratio demonstrates learned features capture digit essence while discarding pixel-level noise

Autoencoder Successes

What Works Well

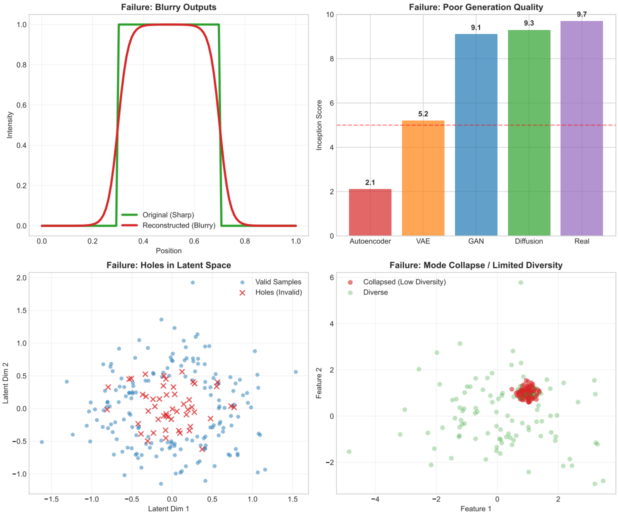


[+] SUCCESSES:

Results:

Autoencoder Limitations

The Generation Problem



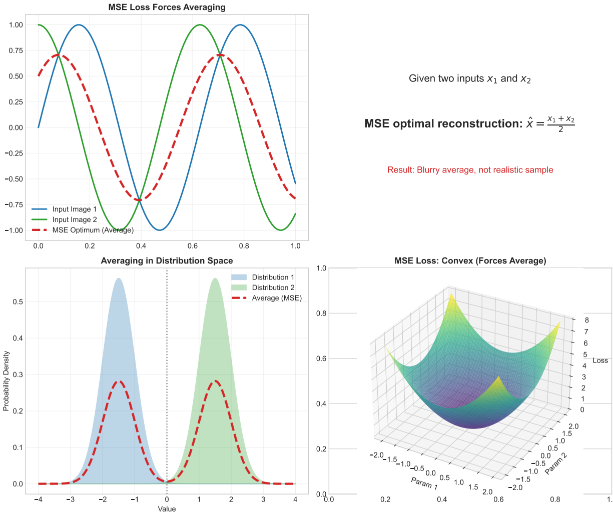
[-] FAILURES:

Metrics:

IS	2.1

Root Cause Analysis

Why Autoencoders Generate Poorly



Given two inputs x_1 and x_2

MSE optimal reconstruction: $\hat{x} = \frac{x_1 + x_2}{2}$

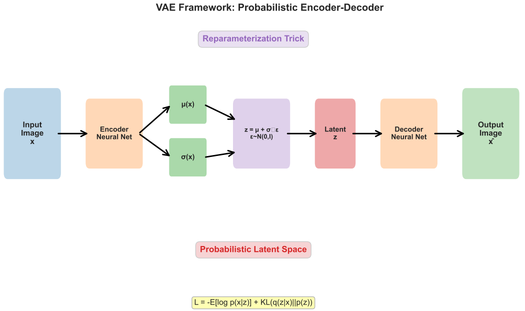
Result: Blurry average, not realistic sample

Problem:

Math:

Variational Autoencoders (VAEs)

The Probabilistic Solution (Kingma & Welling 2013, Rezende et al. 2014)



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

VAE Loss (ELBO):

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

Two terms:

- Reconstruction quality
- KL forces $q(z|x)$ close to prior $p(z) = \mathcal{N}(0, I)$
- β-VAE balances

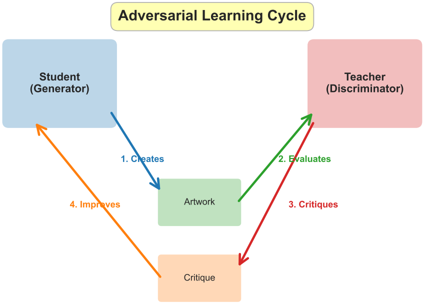
ELBO = Evidence Lower Bound: Tractable objective

Reparameterization trick $z = \mu + \sigma \odot \epsilon$ separates stochasticity enabling backpropagation through sampling - VAEs optimize variational lower bound on log-likelihood

Human Learning Analogy

How Artists Develop Mastery

How Artists Improve Through Critique → GANs



Both Student and Teacher Improve Through Competition

Art Education:

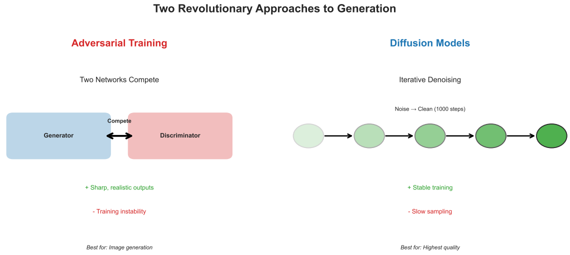
- Student creates
- Teacher critiques
- Student improves

Insights:

- Adversarial feedback drives improvement
- Both improve together

Two Revolutionary Approaches

Beyond VAEs to Better Generation



Adversarial

- Two networks compete
- Sharp, realistic
- No explicit likelihood

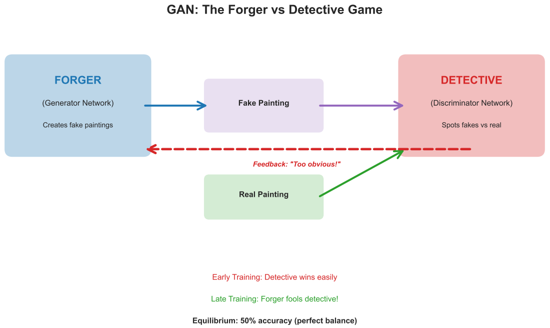
Diffusion

- Iterative denoising
- Stable, controllable
- Likelihood-based, traceable gradients

Adversarial and diffusion approaches overcome VAE's MSE averaging problem through different mechanisms - competition vs iterative refinement both avoid explicit averaging

GANs: The Forger vs Detective Game

Adversarial Training in Plain English


GAN: The Forger vs Detective Game
FORGER
(Generator Network)
Creates fake paintings
Fake Painting
DETECTIVE
(Discriminator Network)
Spots fakes vs real
Feedback: "Too obvious!"
Real Painting
Early Training: Detective wins easily
Late Training: Forger fools detective!
Equilibrium: 50% accuracy (perfect balance)

Forger:

- Creates fakes
- Fools detective

Result: Detective can't tell fake from real!

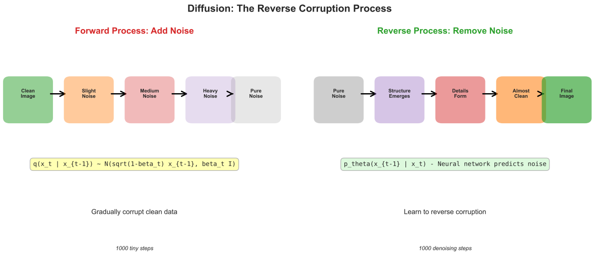
Competition drives both to excellence

Detective:

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

Diffusion: The Reverse Corruption Process

Denoising in Plain English


Diffusion: The Reverse Corruption Process
Forward Process: Add Noise
Reverse Process: Remove Noise
Clean Image
Slight Noise
Medium Noise
Heavy Noise
Pure Noise
Pure Noise
Structure Emerges
Details Form
Almost Clean
Final Image
q(x_t | x_{t-1}) ~ N(sqrt(1-beta_t) x_{t-1}, beta_t I)
p_theta(x_{t-1} | x_t) - Neural network predicts noise
Gradually corrupt clean data
Learn to reverse corruption
1000 tiny steps
1000 denoising steps

Forward:

- Clean -¿ noise
- 1000 steps

Reverse:

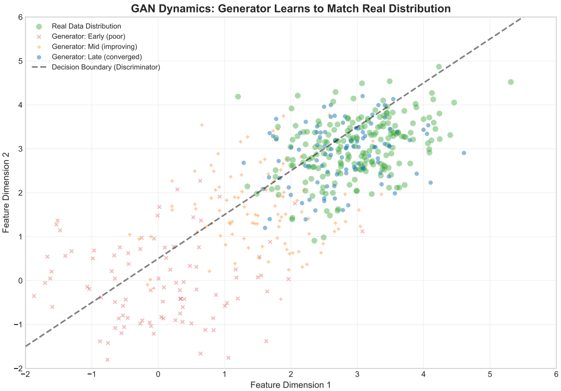
- Noise -¿ clean
- 1000 steps
- Training: Learn to predict noise at each step
- Inference: Start from pure noise, denoise 1000 times

Key: Learn to undo corruption

Diffusion inverts gradual noise corruption process - learning reverse process enables sampling by denoising pure noise, avoiding VAE averaging through iterative refinement

GAN Dynamics: Geometric View

Understanding the Adversarial Process (Goodfellow et al. 2014)



Generator:

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

Discriminator:

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

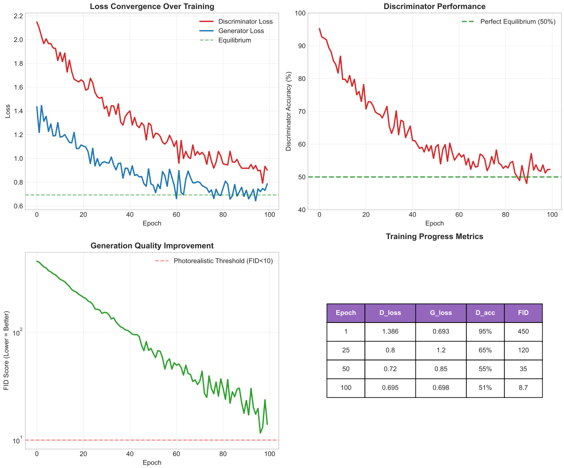
Minimax objective:

$$\min_G \max_D V(D, G)$$

Nash equilibrium occurs when $p_g = p_{data}$ and discriminator accuracy equals 50% - adversarial objective mathematically guarantees convergence under ideal

GAN Training: Step-by-Step Example

Real Loss Values from MNIST Training



Epoch	D_loss	G_loss	D_acc	FID
1	1.386	0.693	95%	450
25	0.8	1.2	65%	120
50	0.72	0.85	55%	35
100	0.695	0.698	51%	8.7

Epoch 1:

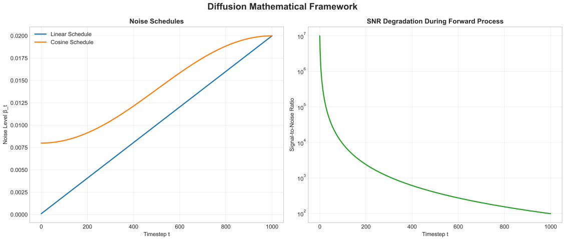
- D: 1.386, G: 0.693
- Images: noise

Epoch 100:

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

Diffusion Mathematical Framework

Forward and Reverse Processes (Ho et al. 2020 - DDPM)



Forward:

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

Noise Schedule:

- β_t controls 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:

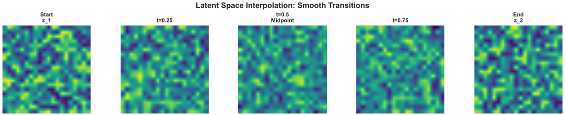
$$L = E[||\epsilon - \epsilon_\theta(x_t, t)||^2]$$

Denoising objective: Predict noise ϵ, not image x_0
Intuition: Predict noise, subtract it

Noise prediction objective enables stable training - predicting $\epsilon_\theta(x_t, t)$ instead of x_0 reduces variance, noise schedule controls diffusion speed (linear $\beta_t : 10^{-4} \rightarrow 2 \times 10^{-2}$ standard)

Latent Space Interpolation

Smooth Transitions in Generated Content



Method:

- Sample z_1, z_2
- Interpolate: $z_t = (1 - t)z_1 + tz_2$
- Generate: $x_t = G(z_t)$
- Spherical interpolation: Better than linear for normalized spaces

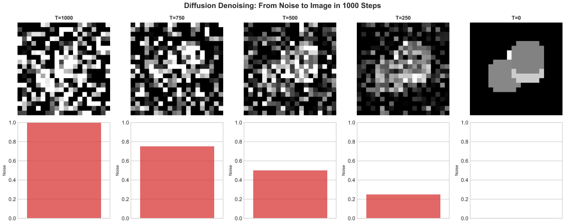
Applications:

- Style transfer
- Face morphing
- Molecule generation (drug discovery latent optimization)
- Drug discovery

Continuous latent spaces enable semantic interpolation - walking along manifold generates smooth transitions revealing learned structure organization and enabling controlled generation

Diffusion Denoising Visualization

From Noise to Image in 1000 Steps



Steps:

- T=1000: Noise
- T=500: Structure
- T=0: High quality
- Controllable: Stop early for variations
- DDIM (Song et al. 2020): 50 steps, 20x speedup

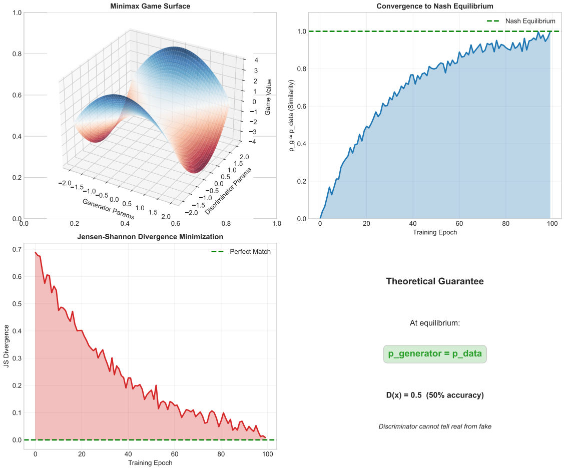
Control:

- Guidance scale
- Step count

Progressive denoising reveals hierarchical generation - coarse structure emerges early (T=1000-¿500), fine details refine late (T=500-¿0), enabling quality-speed trade-offs

Why Adversarial Training Works

The Mathematical Guarantee



Theoretical Guarantee

At equilibrium:

p_generator = p_data

D(x) = 0.5 (50% accuracy)

Discriminator cannot tell real from fake

Theory:

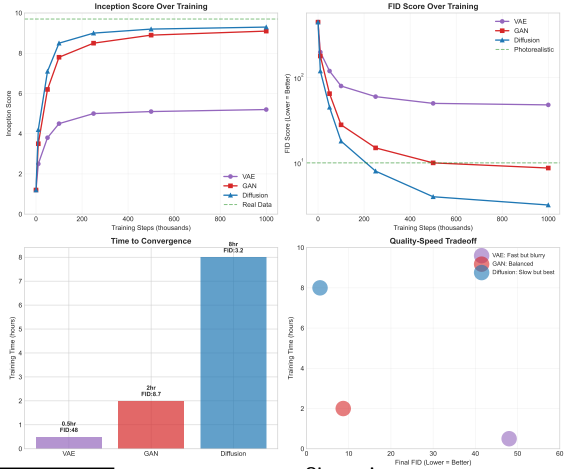
- Minimax convergence
- Equilibrium: $p_g = p_{data}$

Benefits:

- Sharp, realistic
- Fine details

Experimental Validation

Quality Metrics vs Training Progress



Results (MNIST):

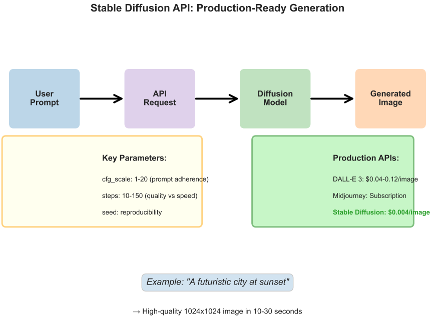
Method	IS	FID	Time
Random	1.0	500	-
VAE	5.2	48	30min
GAN	9.1	9	2hr
Diffusion	9.3	3	8hr

Observations:

- Diffusion: Best
- GAN: 4x faster
- VAE: Fast, blurry

Implementation: Stable Diffusion API

Production-Ready Generative AI


Stable Diffusion API: Production-Ready Generation
User Prompt
API Request
Diffusion Model
Generated Image
Key Parameters:
cfg_scale: 1-20 (prompt adherence)
steps: 10-150 (quality vs speed)
seed: reproducibility
Production APIs:
DALL-E 3: $0.04-0.12/image
Midjourney: Subscription
Stable Diffusion: $0.004/image
Example: "A futuristic city at sunset"
→ High-quality 1024x1024 image in 10-30 seconds

Usage:

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

Parameters:

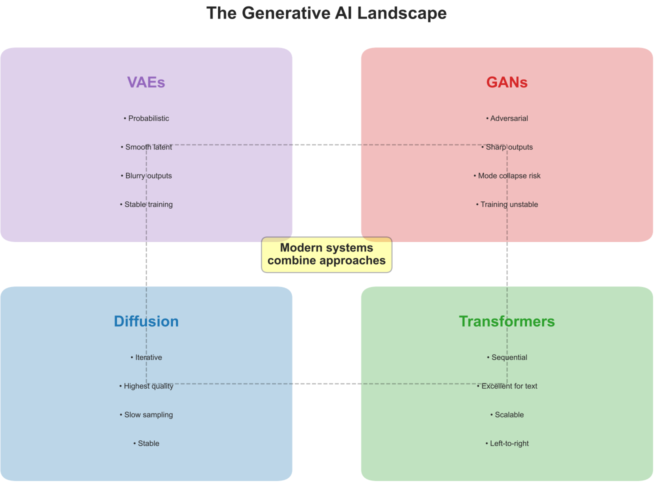
- cfg scale: 1-20 (balance prompt adherence vs diversity)
- steps: 10-150 (quality-speed trade-off: 10=fast/rough, 150=slow/perfect)

Cost: $0.004/image

Production APIs abstract complexity - configuration parameters control guidance strength and quality-speed tradeoffs, enabling accessible deployment without

The Generative AI Landscape

Four Fundamental Approaches



VAEs (2013): Probabilistic, smooth latent, blurry - First scalable
GANs (2014): Adversarial, sharp outputs, unstable - Realism breakthrough

Diffusion (2020): Iterative denoising, high quality, slow - SOTA quality
Transformers (2017): Sequential, excellent text, scalable - Attention

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
- All: Need deterministic outputs (use retrieval instead)

Model selection requires systematic decision framework - prioritize constraints (data size, latency, quality requirements) then match to architectural strengths balancing engineering and scientific considerations

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
3. **KL Annealing**
   - Warm-up schedule prevents collapse

GAN Pitfalls

1. **Mode Collapse**
   - Limited variety
   - Fix: Minibatch disc
2. **Unstable**
   - Oscillates
   - Fix: Wasserstein, spectral norm
3. **Label Smoothing**
   - Prevents D overconfidence

Diffusion Pitfalls

1. **Slow (1000 steps)**
   - Latency issue
   - Fix: DDIM (50 steps)
2. **Memory**
   - High-res costly
   - Fix: Latent diffusion
3. **Classifier-Free Guidance**
   - Better control

Understanding failure modes enables proactive mitigation - posterior collapse, mode collapse, and inference speed have well-established solutions requiring architecture-specific debugging strategies

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
5. **Reproducibility**
   - Fix seeds, log hyperparameters, version data

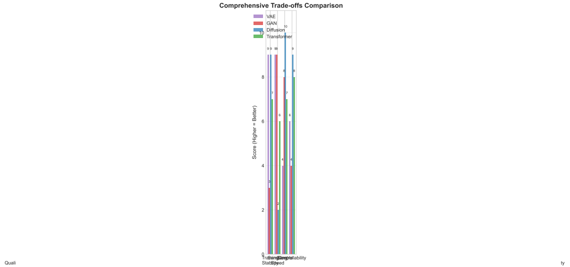
Deployment:

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
5. **Versioning**
   - Model registry, A/B testing, rollback capability

Production deployment requires systematic engineering - start simple for validation, monitor obsessively for failure detection, use transfer learning for efficiency, implement safety guardrails for responsible deployment

Comprehensive Trade-offs

No Free Lunch in Generative Modeling



Stability:

- VAEs, Diffusion: Stable
- GANs: Unstable

Speed:

- VAEs, GANs: Fast
- Diffusion: Slow

Data Efficiency:

- VAE > Diffusion > GAN (sample requirements)

Quality:

- Diffusion, GANs: Excellent
- VAEs: Blurry

Control:

- Diffusion, Transformers: High
- GANs: Limited

Interpretability:

- VAE > Diffusion > GAN (latent structure)

Training Stability:

- Diffusion > VAE > GAN (convergence reliability)

No free lunch theorem applies - stability vs quality vs speed form fundamental trade-off triangle, optimal choice depends on problem constraints and deployment

State-of-the-Art Applications

Production Generative AI Systems

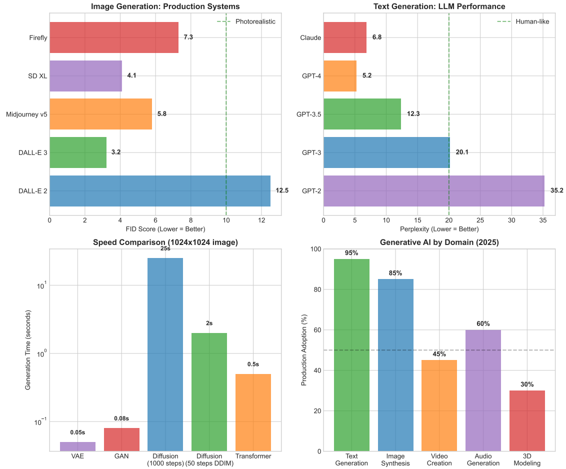


Image Generation: Production Systems

Text Generation: LLM Performance

Speed Comparison (1024x1024 image)

Generative AI by Domain (2025)

Image:

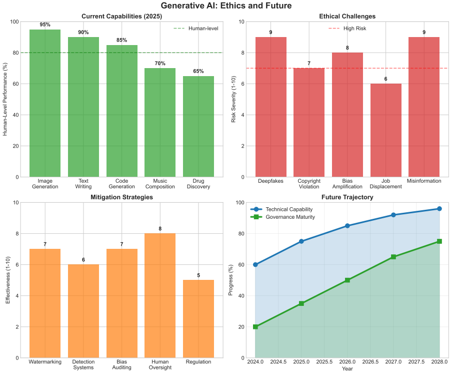
- DALL-E 3, Midjourney
- Stable Diffusion, Firefly

Text:

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

Summary & Future of Generative AI

What We Learned and What's Next



Learned:

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

Future:

Ethics:

- Deepfakes, copyright
- Bias, displacement
- Attribution: Training data transparency

Solutions:

- Watermarking, auditing