Lecture 15:

Generative Models - GAN

Deep Learning

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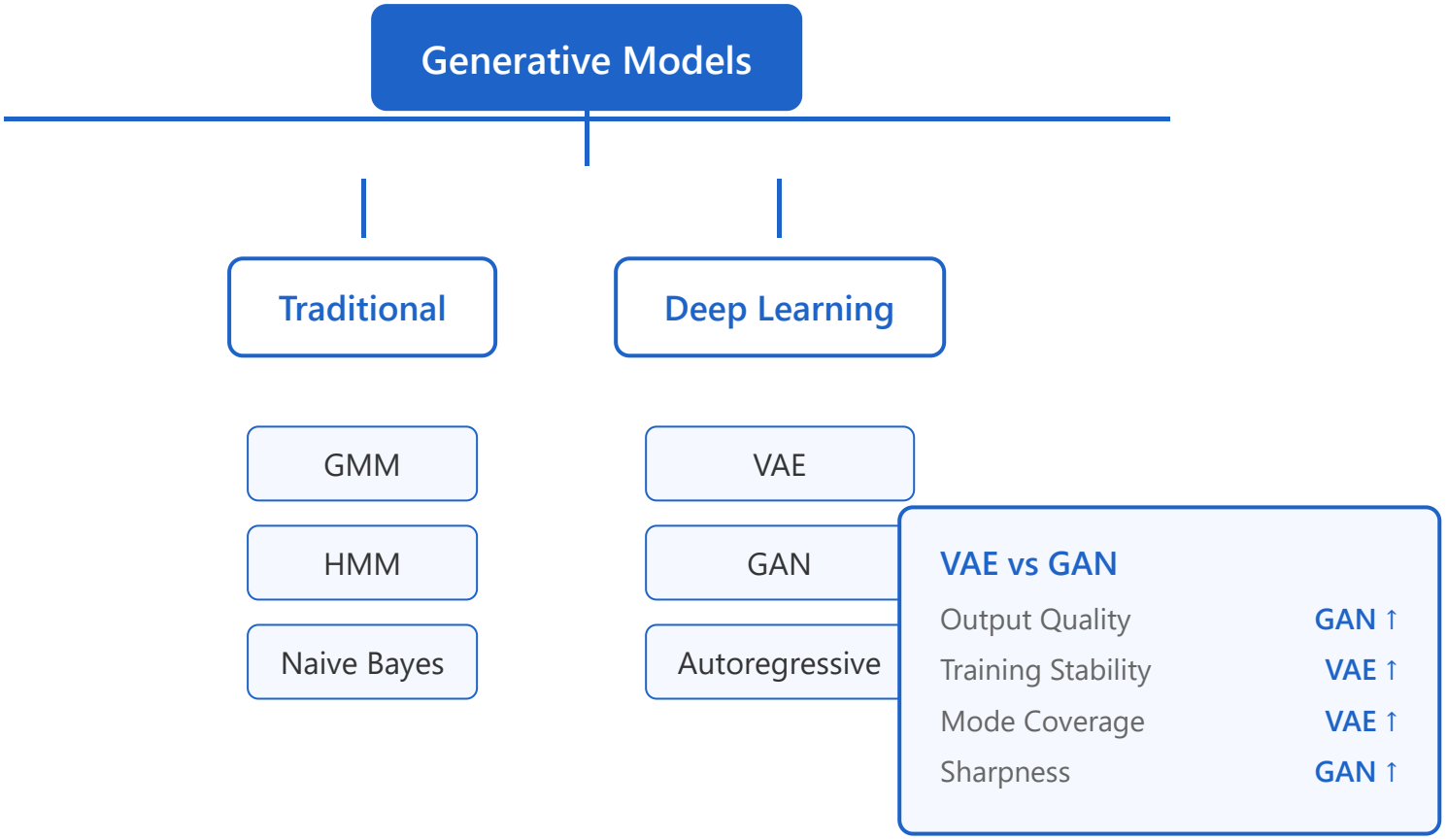
Lecture Contents

Part 1/6:

Introduction & Motivation

1. What are Generative Models?
2. Why GANs?
3. GAN Architecture Overview

Generative Models Taxonomy



1. GMM (Gaussian Mixture Model)

📌 **Basic Principle**

GMM is a probabilistic model that assumes data is generated from a **mixture of multiple Gaussian distributions (normal distributions)**. Each Gaussian component represents a specific cluster in the data, and the model calculates the probability that each data point was generated from which component.

$$p(x) = \Sigma \pi_k \cdot N(x \mid \mu_k, \Sigma_k)$$

Here, π_k is the mixing coefficient of the k-th component, μ_k is the mean, and Σ_k is the covariance matrix. Parameters are learned using the EM (Expectation-Maximization) algorithm.

🎯 Main Applications

- **Clustering:** Modeling more flexible cluster shapes than K-means
- **Image Segmentation:** Segmenting images into multiple regions
- **Anomaly Detection:** Detecting data that deviates from normal data distribution
- **Speech Recognition:** Phoneme modeling
- **Density Estimation:** Approximating complex data distributions

💡 **Advantages:** Soft clustering (probabilistic assignment), capable of modeling elliptical clusters
⚠️ **Disadvantages:** Number of components must be specified in advance, performance degrades in high-dimensional data

2. HMM (Hidden Markov Model)

📌 Basic Principle

HMM is a probabilistic model for **time series data**, assuming that observable events are generated by hidden states. The system transitions between invisible states and generates observations from each state.

Core Components:

- **Transition Probability (A):** Probability of moving from one state to another
- **Emission Probability (B):** Probability of an observation occurring in a specific state
- **Initial State Probability (π):** Probability of each state at the start

$$P(O|\lambda) = \Sigma\ P(O|Q,\ \lambda)\ \cdot\ P(Q|\lambda)$$

Uses **Forward-Backward algorithm** (inference), **Viterbi algorithm** (optimal path search), and **Baum-Welch algorithm** (learning).

🎯 Main Applications

- **Speech Recognition:** Recognizing words from phoneme sequences
- **Natural Language Processing:** Part-of-speech (POS) tagging
- **Bioinformatics:** Gene sequence analysis, DNA pattern recognition
- **Gesture Recognition:** Recognizing motion patterns in video
- **Financial Time Series:** Stock pattern and market state analysis

💡 **Advantages:** Models temporal dependencies, can handle incomplete observation data

⚠️ **Disadvantages:** Markov assumption (present depends only on previous state), difficulty in choosing number of states

3. Naive Bayes

📌 Basic Principle

Based on Bayes' theorem, it makes the "naive" assumption that all features are **conditionally independent**. While this assumption is unrealistic, it works surprisingly well in practice.

$$P(y|x_1,...,x_n) = P(y) \cdot \prod P(x_i|y) / P(x_1,...,x_n)$$

Given class y, it assumes each feature x_i is independent. This allows decomposing high-dimensional joint probabilities into simple products of conditional probabilities, making computation very efficient.

Main Variants:

- **Gaussian NB:** For continuous data, features follow normal distribution
- **Multinomial NB:** For text classification, based on word frequency
- **Bernoulli NB:** For binary features, word presence/absence

🎯 Main Applications

- **Text Classification:** Spam filtering, sentiment analysis, news categorization
- **Document Classification:** Email classification, document categorization

- **Recommendation Systems:** Predicting user preferences
- **Medical Diagnosis:** Calculating disease probability based on symptoms
- **Real-time Prediction:** Classification tasks requiring fast speed

💡 **Advantages:** Very fast and efficient, can learn with small data, easy to interpret
⚠️ **Disadvantages:** Feature independence assumption is unrealistic, ignores correlations between features

4. VAE (Variational Autoencoder)

📌 Basic Principle

VAE is a deep learning generative model that combines an **autoencoder architecture** with **variational inference**. It encodes data into a low-dimensional latent space and reconstructs data from this latent representation.

Core Architecture:

- **Encoder ($q_\phi(z|x)$):** Maps input data x to probability distribution of latent variable z (mean μ, variance σ^2)
- **Reparameterization Trick:** Samples $z = \mu + \sigma \odot \varepsilon$ ($\varepsilon \sim N(0,1)$) to enable backpropagation
- **Decoder ($p_\theta(x|z)$):** Reconstructs original data from latent variable z

📊 Loss Function (ELBO)

VAE is trained by maximizing the Evidence Lower Bound (ELBO), which balances two terms:

$$L = E[\log p_\theta(x|z)] - KL(q_\phi(z|x) \,||\, p(z))$$

First term (Reconstruction Loss): How well the decoder reconstructs the original data

Second term (KL Divergence): Difference between the learned distribution and prior distribution (usually N(0,1))

> 🔑 **Key Insight:** The KL term regularizes the latent space to make it smooth and continuous, enabling meaningful interpolation when generating new samples.

🎨 Properties of Latent Space

VAE's latent space has the following important properties:

- **Continuity:** Similar data points are located close in latent space
- **Interpolability:** Smooth movement between two points generates meaningful intermediate samples
- **Structured:** Specific dimensions control specific attributes (e.g., facial expression, angle)
- **Regularity:** Regularization to prior distribution reduces empty spaces

🎯 Main Applications

- **Image Generation:** Generating new faces, landscapes, artworks
- **Data Augmentation:** Generating transformed images to expand training data
- **Anomaly Detection:** Identifying samples with high reconstruction error as anomalies
- **Dimensionality Reduction:** Capturing non-linear relationships better than t-SNE, PCA
- **Image Editing:** Changing specific attributes by manipulating latent vectors
- **Semi-supervised Learning:** Learning representations with limited labels
- **Drug Design:** Exploring latent space of molecular structures

⚖️ Detailed VAE vs GAN Comparison

VAE Strengths:

- **Stable Training:** Single objective function, no mode collapse
- **Complete Probabilistic Model:** Explicit probability density estimation
- **Interpretable Latent Space:** Learning structured and meaningful representations
- **Mode Coverage:** Better capturing diverse data distributions

VAE Weaknesses:

- **Blurry Output:** Reconstruction loss (MSE) generates averaged images
- **Lower Sample Quality:** Generated images are less sharp than GAN's
- **Prior Distribution Assumption:** Usually assumes Gaussian, which may differ from actual distribution

💡 **Practical Tip:** Use β-VAE (weight β on KL term) to adjust balance between reconstruction and regularization. β > 1 learns more disentangled representations but may reduce reconstruction quality.

🔬 Main Variants

- **β-VAE:** KL weight adjustment for disentangled representation learning
- **Conditional VAE (CVAE):** Adding label information for conditional generation
- **VQ-VAE:** Using discrete latent space, high-quality image/audio generation
- **Hierarchical VAE:** Modeling complex structures with multi-level latent variables

📐 Input/Output Calculation Example

Let's examine a VAE that encodes MNIST handwritten digit images (28×28) into a 2-dimensional latent space.

Network Structure:

- **Input:** 28×28 = 784-dimensional image vector
- **Encoder:** 784 → 400 → (μ: 2-dim, log σ^2: 2-dim)
- **Latent space:** 2-dimensional (good for visualization)
- **Decoder:** 2 → 400 → 784
- **Output:** 28×28 reconstructed image

🔄 Forward Pass Calculation Process

Step 1: Input Image

$$x \in \mathbb{R}^{784} = [0.1, 0.9, 0.8, ..., 0.0] \text{ (normalized pixel values)}$$

Step 2: Encoder - Hidden Layer

$$h = \text{ReLU}(W_1 \cdot x + b_1) \in \mathbb{R}^{400}$$

Example: Using $W_1 \in \mathbb{R}^{(400\times784)}$, $b_1 \in \mathbb{R}^{400}$ to compress 784 dimensions to 400 dimensions

Step 3: Encoder - Computing Mean and Variance

$$\mu = W_\mu \cdot h + b_\mu \in \mathbb{R}^2 = [1.2, -0.8]$$
$$\log \sigma^2 = W_\sigma \cdot h + b_\sigma \in \mathbb{R}^2 = [-0.5, -1.2]$$

We predict $\log \sigma^2$ for numerical stability.

Actual standard deviation: $\sigma = \exp(0.5 \cdot \log \sigma^2) = [0.78, 0.55]$

Step 4: Reparameterization Trick

$$\varepsilon \sim N(0, I) \in \mathbb{R}^2 = [0.3, -0.7] \text{ (random sampling)}$$
$$z = \mu + \sigma \odot \varepsilon = [1.2, -0.8] + [0.78, 0.55] \odot [0.3, -0.7]$$
$$z = [1.2 + 0.234, -0.8 - 0.385] = [1.434, -1.185]$$

> 💡 **Key Point:** By sampling ε, backpropagation becomes possible. We can calculate gradients with respect to μ and σ.

Step 5: Decoder - Hidden Layer

$$h' = \text{ReLU}(W_2 \cdot z + b_2) \in \mathbb{R}^{400}$$

Example: Using $W_2 \in \mathbb{R}^{400\times2}$, $b_2 \in \mathbb{R}^{400}$ to expand 2 dimensions to 400 dimensions

Step 6: Decoder - Output (Reconstruction)

$$\hat{x} = \sigma(W_3 \cdot h' + b_3) \in \mathbb{R}^{784}$$

σ is the sigmoid function that constrains output to [0, 1] range.

$\hat{x}$ = [0.09, 0.88, 0.82, ..., 0.01] (reconstructed image)

📊 Loss Calculation

Reconstruction Loss:

$$L_{recon} = -\Sigma_i [x_i \cdot \log(\hat{x_i}) + (1-x_i) \cdot \log(1-\hat{x_i})] \text{ (Binary Cross-Entropy)}$$

Or MSE can be used:

$$L_{recon} = \Sigma_i (x_i - \hat{x_i})^2 / 784$$

Example: L_recon = 0.025 (average error per pixel)

KL Divergence:

$$KL = -0.5 \cdot \Sigma_j [1 + \log \sigma_j^2 - \mu_j^2 - \sigma_j^2]$$

Calculating per dimension:

$$j=1: -0.5 \cdot [1 + (-0.5) - 1.2^2 - e^{(-0.5)}] = -0.5 \cdot [0.5 - 1.44 - 0.61] = 0.775$$
$$j=2: -0.5 \cdot [1 + (-1.2) - 0.8^2 - e^{(-1.2)}] = -0.5 \cdot [-0.2 - 0.64 - 0.30] = 0.570$$
$$KL\_total = 0.775 + 0.570 = 1.345$$

Total Loss:

$$L\_total = L\_recon + KL = 0.025 + 1.345 = 1.370$$

> 🎯 **Interpretation:**
>
> - Low reconstruction loss (0.025) → Good reconstruction of image
> - High KL (1.345) → Learned distribution deviates significantly from standard normal
> - As training progresses, both losses will balance out

🎨 Generating New Images

After training is complete, to generate new images:

```
1. Sample from standard normal: z_new ~ N(0, I) = [-0.5, 1.2]
2. Use decoder only: x_new = Decoder(z_new)
3. Generate new handwritten digit image!
```

Interpolation in latent space is also possible:

$$z\_interpolate = \alpha \cdot z_1 + (1-\alpha) \cdot z_2, \quad \alpha \in [0, 1]$$
$$\text{Example: When } \alpha=0.5,\ z = 0.5 \cdot [1.4, -1.2] + 0.5 \cdot [-0.8, 0.9] = [0.3, -0.15]$$

Practical Examples:

- Generate from z = [2.0, 0.0] → Image of '1' with thick lines
- Generate from z = [0.0, 2.0] → Round '0' image
- Generate from z = [1.0, 1.0] → Intermediate form mixing both styles

💡 **Parameter Count Calculation:**

• Encoder: 784×400 + 400 + 400×2 + 2 + 400×2 + 2 = 315,604

• Decoder: 2×400 + 400 + 400×784 + 784 = 315,184

• Total parameters: ~630K (relatively small model)

Birth of GANs

2013
VAE Era

2014
GAN Born

2015+
Rapid Growth

Original Paper

"Generative Adversarial Networks"

Authors: Ian Goodfellow et al.

Published: NIPS 2014

Institution: Université de Montréal

Citations: 50,000+ (Most cited AI paper)

Key Innovation

First framework to train generative models through **adversarial process** - two neural networks competing in a game-theoretic scenario. No need for explicit density estimation or Markov chains.

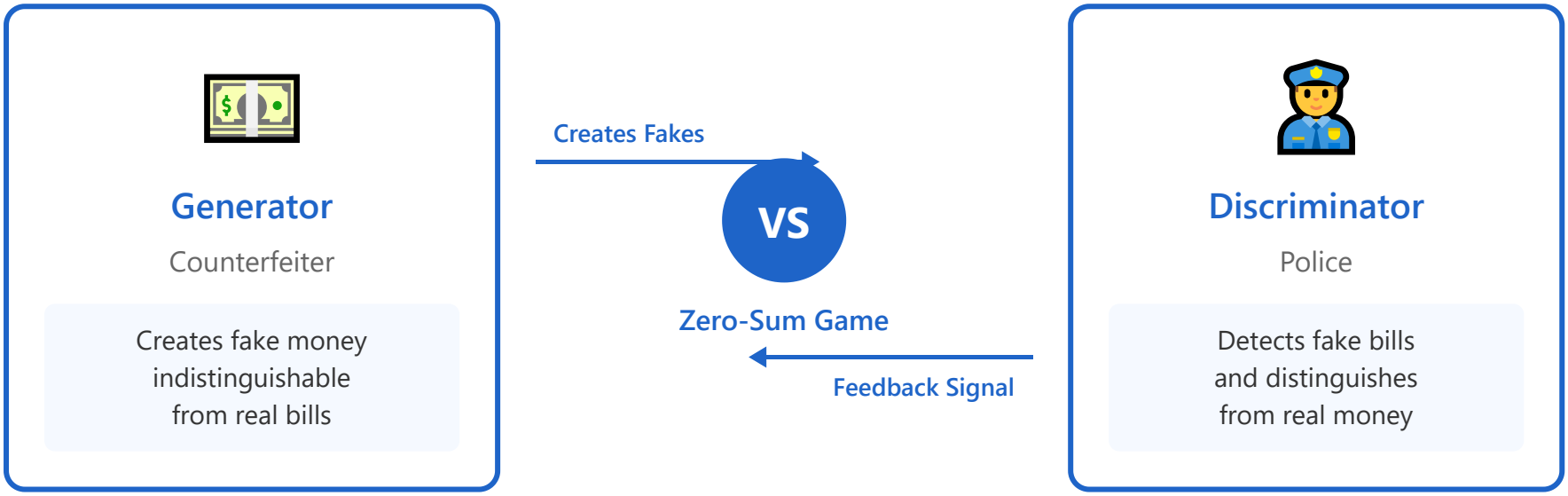
Revolutionary Impact on AI

10+
Years of Innovation

1000+
GAN Variants

∞
Applications

GAN: The Counterfeiter Analogy



Iterative Improvement Process

1. Generator creates fake samples
2. Discriminator learns to detect fakes
3. Generator improves based on feedback
4. Both improve through competition

🎯 Equilibrium

Perfect fakes become indistinguishable from real data

Part 2/6:

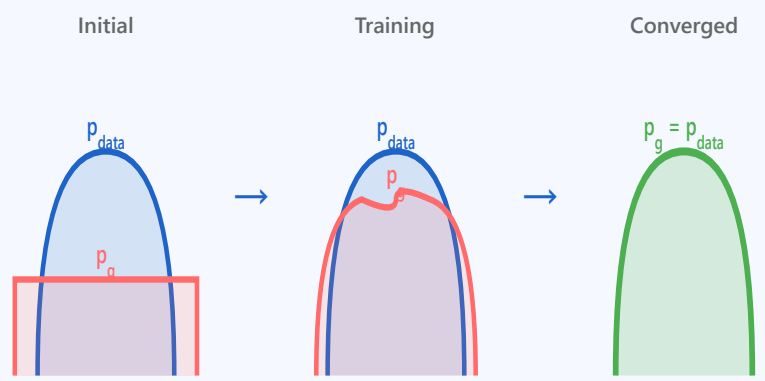
Mathematical Foundations

4. Probability Distribution Perspective
5. Mathematical Definition of GAN
6. Value Function Analysis
7. Deriving Optimal Discriminator
8. Global Optimum

Part 2/6: Mathematical Foundations

Probability Distribution Perspective

Distribution Convergence Process



Real Data Distribution

$p_{data}(x)$ - True distribution of training data

Generator Distribution

$p_g(x)$ - Distribution learned by generator

Objective

Minimize distance between distributions

$$D(p_{data} \,||\, p_g) \rightarrow 0$$

Sampling Process

- **z** Sample from latent space: $z \sim p_z(z)$
- **G** Neural network transformation: $G(z)$
- **x** Generate sample: $x \sim p_g(x)$

Key Advantages

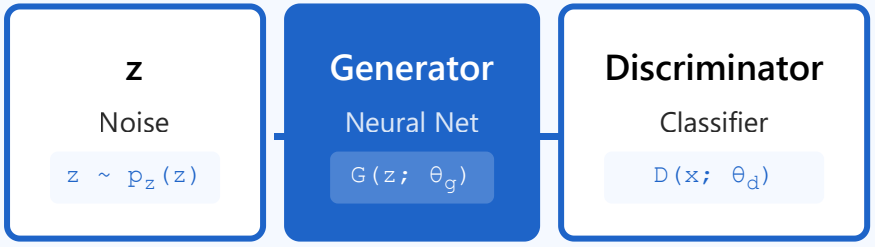
- ✓ Implicit density modeling
- ✓ No explicit likelihood computation
- ✓ Direct sampling capability

Mathematical Definition of GAN

Minimax Objective

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

Two-Player Game Architecture



Generator G

Maps noise to data space

Discriminator D

Outputs probability [0,1]

Training

Alternating optimization

Solution

Nash equilibrium

Value Function V(D, G)

$$V(D,G) = \mathbb{E}_{x \sim p_{data}}[\log D(x)] + \mathbb{E}_{z \sim p_z}[\log(1 - D(G(z)))]$$

Real Data Term

D classifies real as real

Fake Data Term

D classifies fake as fake

Value Function Analysis

Discriminator Maximizes

Correctly classify real and fake samples

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

Generator Minimizes

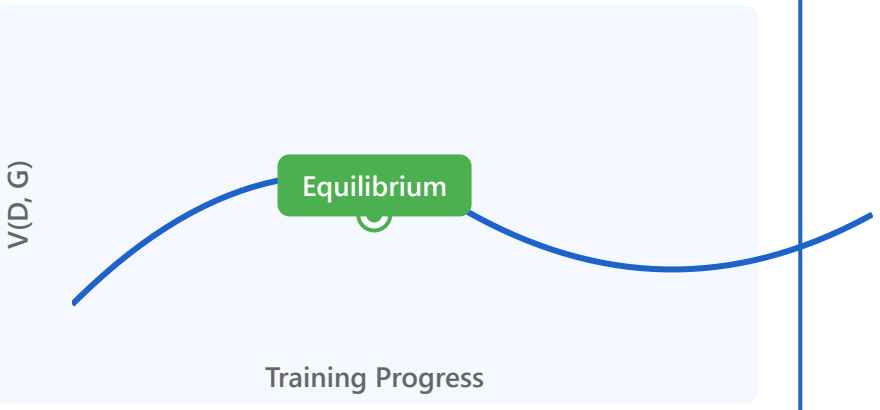
Fool the discriminator effectively

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

Theoretical Insights

- Cross-entropy loss interpretation
- Jensen-Shannon divergence connection
- Global optimality guarantees

Value Function Landscape



Optimal Discriminator

$$D^*(x) = p_{data}(x) / (p_{data}(x) + p_g(x))$$

Global Optimality Conditions

Theoretical Optimum	Discriminator at Equilibrium	Value Function
$p_g = p_{data}$	$D^*(x) = 1/2$	$V(D^*, G^*) = -\log(4)$

Deriving Optimal Discriminator

Derivation Steps

1 Fix generator G, optimize D

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

↓

2 Calculus of variations

$$\partial V/\partial D(x) = 0$$

↓

3 Solve for optimal D

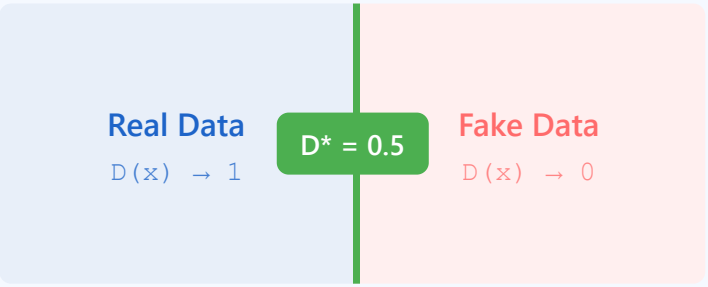
$$p_{data}(x)/D(x) = p_g(x)/(1-D(x))$$

✓ Optimal Discriminator

Key Insights

- Sigmoid activation natural choice
- Binary cross-entropy loss
- Depends on density ratio
- Neural network approximation

Decision Boundary



At equilibrium: $p_g = p_{data}$

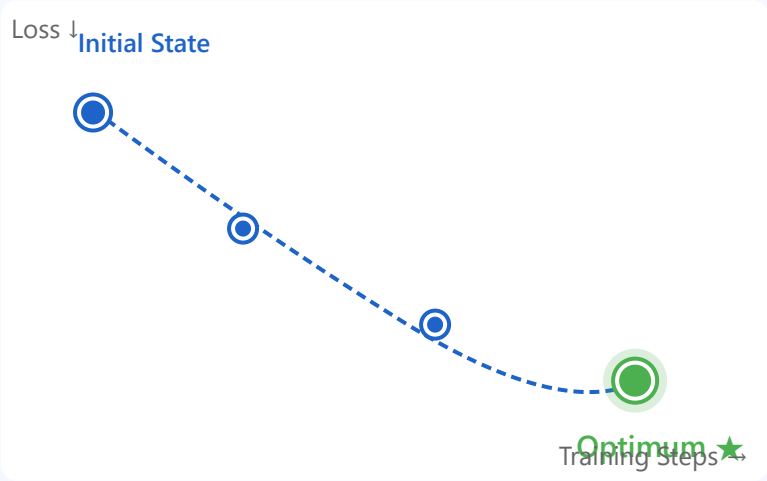
$$D^*(x) = p_{data}(x) / (p_{data}(x) + p_g(x))$$

Global Optimum

🎯 Theorem

Global minimum achieved if and only if $p_g = p_{data}$

Convergence Trajectory



At Global Optimum

Discriminator	$D^*(x) = 1/2$
Value Function	$V = -\log(4)$
Distributions	$p_g = p_{data}$

JS Divergence Connection

Minimizing GAN objective equals minimizing Jensen-Shannon divergence

$$JS(p_{data} \,||\, p_g) = 0 \Leftrightarrow p_g = p_{data}$$

✓ Convergence Properties

- Uniqueness of global optimum
- Proof under ideal conditions
- Theoretical guarantees

⚠ Practical Challenges

- Mode collapse issues
- Training instability
- Non-convex optimization

Part 3/6:

Training Algorithm

9. Training Process Overview
10. Detailed Algorithm
11. Gradient Flow
12. Non-Saturating Loss
13. Practical Tips

Training Process Overview

Alternating Optimization Loop

1 Update Discriminator *k steps*

Train D to distinguish real from fake samples

↓

2 Update Generator *1 step*

Train G to generate realistic samples

↓

Repeat until convergence

Strategy Details

- k = 1 typically in practice
- Mini-batch SGD
- Separate optimizers for G and D

Optimization Setup

Learning Rate
Scheduling required

Batch Size
Mini-batch based

Optimizers
Adam (typical)

📊 Stability Monitoring

Track loss curves, gradient norms, and output quality metrics

Detailed Algorithm

Training Procedure

1 Sample minibatch of m noise samples $\{z^{(1)}...z^{(m)}\}$

2 Sample minibatch of m real samples $\{x^{(1)}...x^{(m)}\}$

3 Update Discriminator by ascending gradient:

$$\nabla_{\theta_d} \left[1/m \sum \left(\log D(x^{(i)}) + \log(1-D(G(z^{(i)})))\right)\right]$$

Switch to Generator

4 Sample new minibatch of noise samples

5 Update Generator by descending gradient:

$$\nabla_{\theta_g} \left[1/m \sum \log(1-D(G(z^{(i)})))\right]$$

Update Strategy

D Ascending gradient (maximize)

G Descending gradient (minimize)

Notation

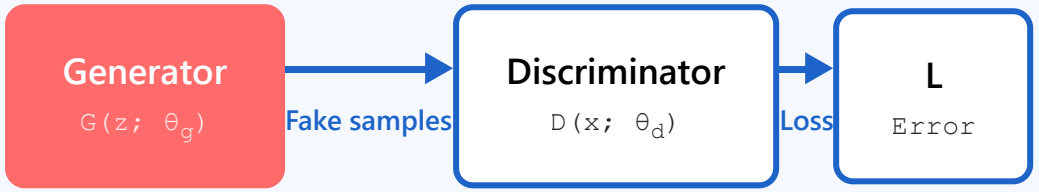
m	Minibatch size
z	Noise vector
x	Real sample
θ_d	D parameters
θ_g	G parameters

6 Repeat until convergence

Iterate Until Equilibrium

Gradient Flow

Backpropagation Through Networks



Gradient Backpropagation

Chain Rule

$$\partial L/\partial G = \partial L/\partial D \times \partial D/\partial G$$

Gradient Signals

- Real vs fake classification error
- Chain rule application

Key Challenge

- Gradient magnitude balance
- Stable signal propagation

⚠ Vanishing Gradients

When D is too strong, gradients become too small for G to learn

⚡ Exploding Gradients

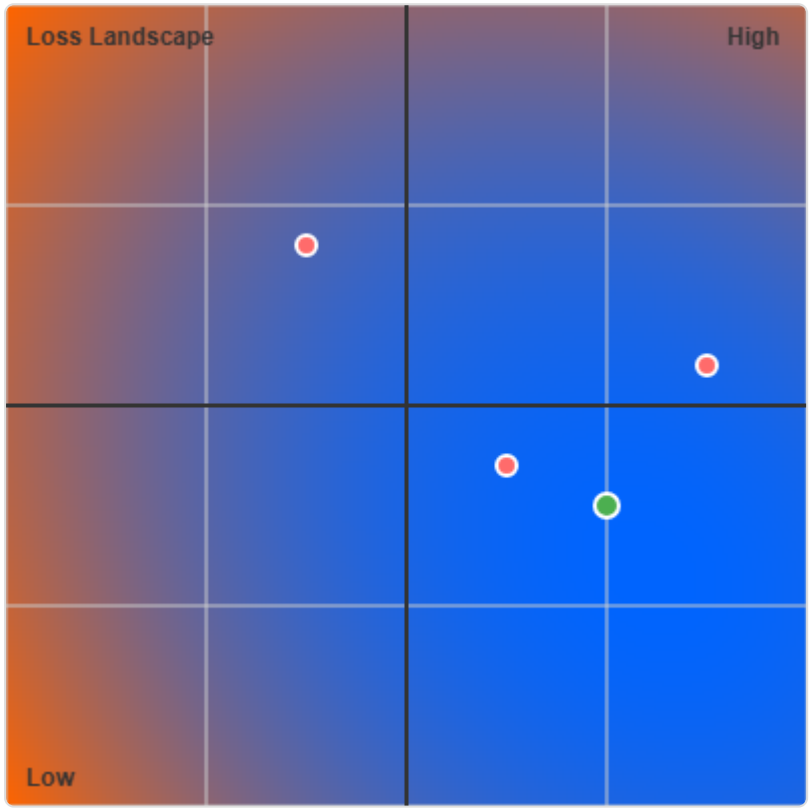
In early training, gradients can become unstable and too large

✓ Solutions

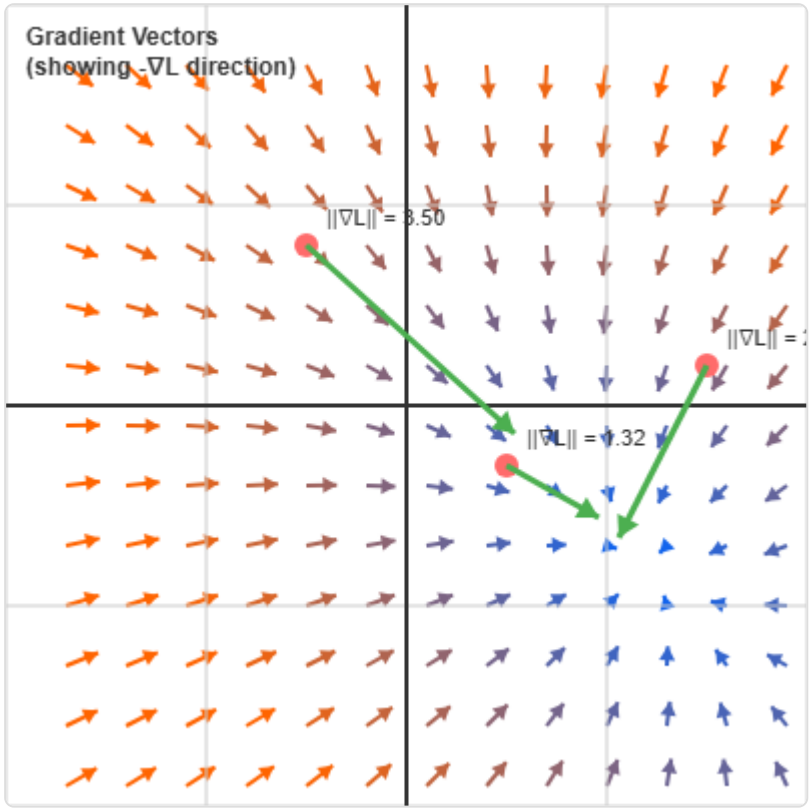
Gradient penalty techniques (e.g., WGAN-GP) help stabilize training

Interactive Gradient Flow Visualization

Loss Landscape



Gradient Field



Reset | Add Sample Point | Clear Points | Gradient Scale: Normal

Numerical Example: 2D Gradient Computation

Step 1: Define Loss Function

```
L(x, y) = (x - 1)² + (y + 0.5)² + 0.5·x·y
```

This represents a simplified discriminator loss in 2D parameter space

Step 2: Compute Partial Derivatives

```
∂L/∂x = 2(x - 1) + 0.5·y
∂L/∂y = 2(y + 0.5) + 0.5·x
```

Step 3: Example at Point (0.5, -0.3)

```
x = 0.5, y = -0.3

∂L/∂x = 2(0.5 - 1) + 0.5·(-0.3) = -1.0 - 0.15 = -1.15
∂L/∂y = 2(-0.3 + 0.5) + 0.5·(0.5) = 0.4 + 0.25 = 0.65
```

Gradient Vector: $\nabla L = (-1.15, 0.65)$
Magnitude: $||\nabla L|| = \sqrt{(1.15^2 + 0.65^2)} \approx 1.32$

Step 4: Parameter Update (Gradient Descent)

```
Learning rate: α = 0.1

x_new = x - α·(∂L/∂x) = 0.5 - 0.1·(-1.15) = 0.615
y_new = y - α·(∂L/∂y) = -0.3 - 0.1·(0.65) = -0.365
```

Updated Position: (0.615, -0.365)
Movement towards minimum: Point moves closer to (1, -0.5)

Gradient Magnitude Impact

- $||\nabla L|| < 0.01$: Vanishing
- $0.01 \leq ||\nabla L|| \leq 10$: Normal

Backprop Through Generator

$\partial L/\partial \theta_g = \partial L/\partial x \cdot \partial x/\partial \theta_g$

Chain rule multiplies gradients

- $||\nabla L|| > 10$: Exploding
- Affects learning speed

Deep networks: many multiplications

Can cause vanishing/exploding

Critical Insights

- Gradient direction: steepest ascent
- Negative gradient: descent
- Zero gradient: local min/max
- Balance is crucial for GANs

Real GAN Scenario

If D too good: $\partial L/\partial D \to 0$

Then: $\partial L/\partial G \to 0$ (vanishing)

G cannot learn effectively

Needs balanced training

Practical Tips

1 Data & Activation

- ✓ Normalize inputs to `[-1, 1]`
- ✓ Use `tanh` activation for generator output
- ✓ `LeakyReLU` in D, `ReLU` in G

2 Normalization & Regularization

- ✓ Batch normalization (except last G, first D layer)
- ✓ Label smoothing: `real=0.9, fake=0.1`
- ✓ Add noise to discriminator inputs

3 Optimization

- ✓ Use Adam optimizer with $\beta_1 = 0.5$

Architecture Guide

Generator	Discriminator
Dense/Conv Layers	No BN (First Layer)
ReLU	LeakyReLU
Batch Norm	Batch Norm
...	...
No BN (Last Layer)	LeakyReLU
tanh Output	Sigmoid Output

⚠ Monitoring

Watch D loss carefully - if it drops to 0, G won't learn properly

✓ Monitor D loss - shouldn't go to 0

✓ Recommended Optimizer

Adam with $\beta_1 = 0.5$, $\beta_2 = 0.999$

Practical Tips

1 Data & Activation

- ✓ Normalize inputs to `[-1, 1]`
- ✓ Use `tanh` activation for generator output
- ✓ `LeakyReLU` in D, `ReLU` in G

2 Normalization & Regularization

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Architecture Guide

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✓ Recommended Optimizer

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Adam with $\beta_1 = 0.5$, $\beta_2 = 0.999$

Interactive Practice

Try GAN Lab →

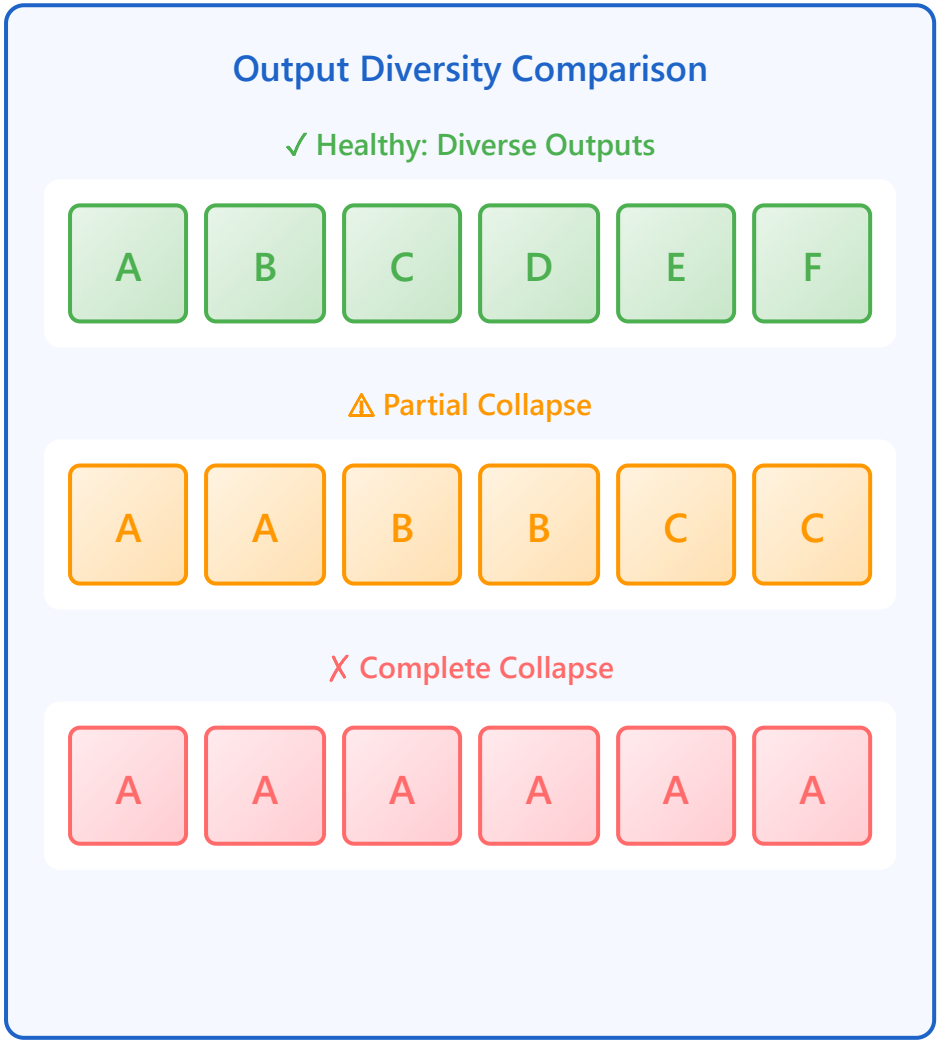
Part 4/6:

Key Challenges

14. Mode Collapse
15. Training Instability
16. Evaluation Difficulties
17. Vanishing Gradient Details
18. Common Failure Patterns

Part 4/6: Key Challenges

Mode Collapse



Problem Description

- Limited variety of samples
- Entire noise → few modes
- Poor gradient signals

Types of Collapse

Partial Collapse
Missing some data modes

Complete Collapse
Single output regardless of input

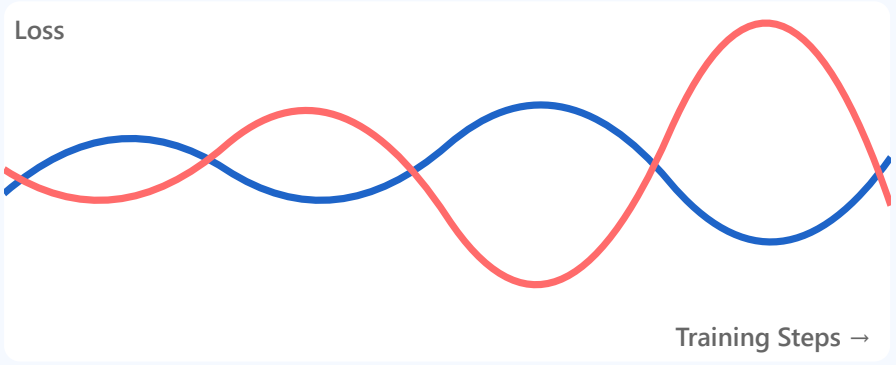
Solutions

- Minibatch Discrimination
- Unrolled GANs
- Feature Matching
- Diversity Penalties

Part 4/6: Key Challenges

Training Instability

Oscillating Loss Patterns



Key Issues

- ⚠ No convergence
- ⚠ G/D imbalance
- ⚠ No stopping criterion
- ⚠ Loss ≠ Quality

Characteristics

- Oscillating losses
- Hyperparameter sensitive
- Loss-quality disconnect

Core Problems

- ✗ Generator/Discriminator imbalance
- ✗ No clear stopping criterion
- ✗ Loss doesn't correlate with quality

✓ Stabilization Techniques

- Spectral Normalization
- Self-Attention
- Progressive Growing
- LR Scheduling

Part 4/6: Key Challenges

Evaluation Difficulties

⚠ **No single metric captures generation quality completely**

Metric	What It Measures	Quality	Diversity
Inception Score (IS)	Quality and diversity via classifier confidence	High	High
Fréchet Inception Distance (FID)	Distribution similarity between real and generated	High	High
Precision	Quality of generated samples (realism)	High	Low
Recall	Coverage of real data modes	Low	High
Human Evaluation	Subjective assessment by human raters	High	High

🏆 Gold Standard

Human evaluation remains the most reliable method despite being time-

⚠ Key Challenge

Mode coverage assessment is difficult - metrics may miss partial collapse

💻 Computational Cost

Most metrics require running large pre-trained models, making evaluation

consuming and subjective

expensive

Vanishing Gradient Details

Problem Cascade

1. Discriminator becomes too successful

↓

2. D correctly classifies fake samples with high confidence

$$D(G(z)) \rightarrow 0$$

↓

3. Original loss function saturates

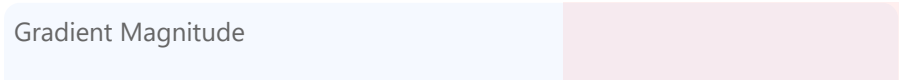
$$\log(1 - D(G(z))) \rightarrow \log(1) = 0$$

↓

4. Gradients vanish - Generator receives no learning signal

$$\nabla_G \rightarrow 0$$

Gradient Magnitude Over Training



When It Occurs

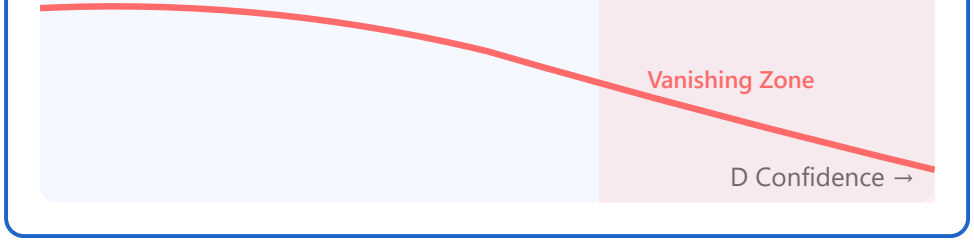
- ⚠ D is too successful
- ⚠ D(G(z)) approaches 0
- ⚠ No learning signal for G

⚖ Key Insight

Careful capacity balance between G and D is crucial to prevent one from dominating

✓ Solutions

- Non-saturating loss
- WGAN (Wasserstein GAN)
- Gradient penalty methods
- Balance G and D capacity


Vanishing Zone
D Confidence →

Common Failure Patterns

VISUAL

Checkerboard Artifacts

Grid-like patterns appear in generated images due to deconvolution operations

Image Quality

COLOR

Unrealistic Colors

Color distributions don't match real data, often oversaturated or unnatural

Distribution

TEXTURE

Inconsistent Transitions

Mix of blurry and sharp regions without logical consistency

Coherence

ANATOMY

Anatomical Errors

Incorrect features in faces, hands, or body proportions

Realism

CRITICAL

Training Collapse After Initial Success

Model performance degrades suddenly after showing good results, often unrecoverable without restart

Training Dynamics

Visual Artifacts

- Checkerboard patterns
- Color inconsistencies

Video Issues

Temporal inconsistency between frames in video generation tasks

Resolution Limits

Quality degrades without progressive growing techniques

- Blurry/sharp mixing

Part 5/6:

Improvement Techniques

19. DCGAN Architecture
20. Wasserstein GAN
21. Conditional GAN
22. Other Variants

DCGAN (2015)

Deep Convolutional GAN

Architecture Overview

Generator

- z (Noise)
- ↓
- Project & Reshape
- ↓
- Fractional-Strided Conv
- Batch Norm + ReLU
- ↓
- Fractional-Strided Conv
- Batch Norm + ReLU
- ↓
- Fractional-Strided Conv
- Batch Norm + ReLU

Discriminator

- Image
- ↓
- Strided Conv
- LeakyReLU
- ↓
- Strided Conv
- Batch Norm + LeakyReLU
- ↓
- Strided Conv
- Batch Norm + LeakyReLU
- ↓
- Strided Conv

Architecture Guidelines

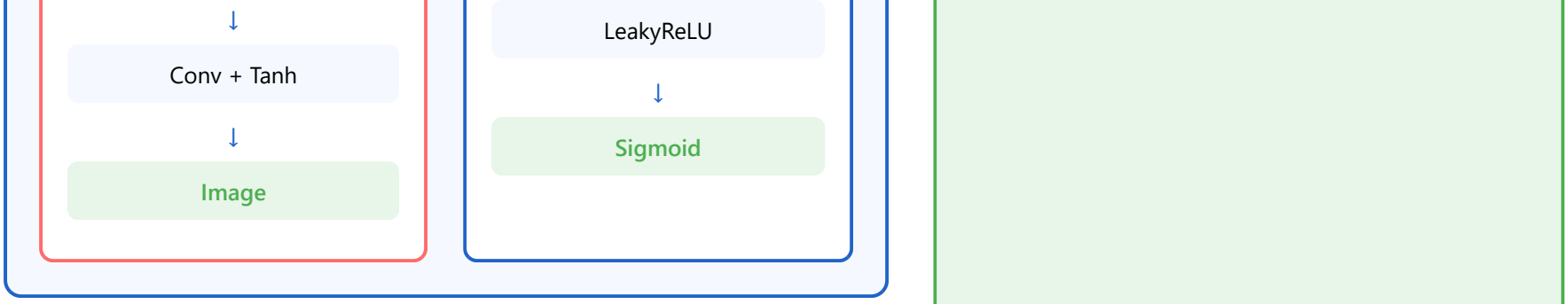
Generator
Fractional-strided conv + ReLU (tanh output)

Discriminator
Strided conv + LeakyReLU

Normalization
Batch norm (except G output, D input)

✓ Benefits

- ★ Stable training
- ★ Higher resolutions
- ★ Better image quality
- ★ Foundation for future GANs



Key Features

- ✓ Replace fully connected layers with convolutions
- ✓ No pooling layers - use strided convolutions
- ✓ Batch normalization in both G and D

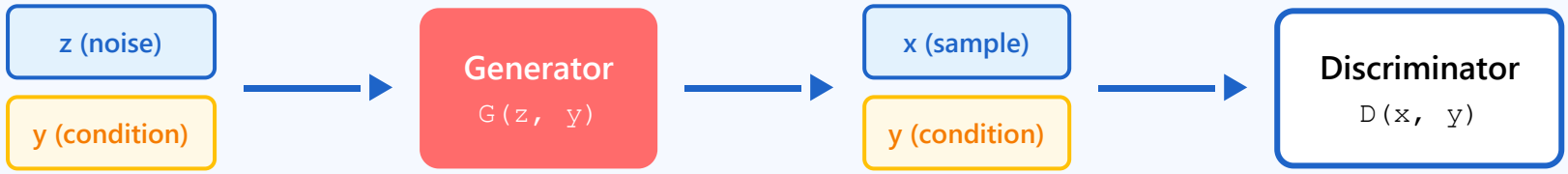
Original Paper

Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks

Radford et al., 2015

Conditional GAN (cGAN)

Conditional Architecture



Key Idea: **Both G and D are conditioned on additional information y**

Conditioning Types

y can be: class labels, text descriptions, images, or any structured information

Core Concept

Condition generation on additional information to enable controllable and targeted output

Applications

- Class-conditional generation
- Image-to-image (Pix2Pix)
- Text-to-image synthesis
- Super-resolution

✓ Key Benefit

Controllable generation capabilities - direct control over output characteristics

- Style transfer

Original Paper

Conditional Generative Adversarial Nets

Mehdi Mirza, Simon Osindero (2014)

View on arXiv

Part 5/6: Improvement Techniques

Wasserstein GAN (WGAN)

ORIGINAL **Standard GAN**

Distance Metric

Jensen-Shannon divergence

$$JS(p_{data} \,||\, p_g)$$

Output Layer

Sigmoid (Discriminator)

Constraint

No explicit constraint

Training

Unstable, oscillating losses

VS

WGAN **Wasserstein GAN**

Distance Metric

Wasserstein distance (Earth Mover)

$$W(p_{data}, p_g)$$

Output Layer

Linear (Critic, no sigmoid)

Constraint

Lipschitz constraint (weight clipping)

Training

Stable, meaningful loss

Stable Training

More consistent convergence dynamics

Meaningful Loss

Loss correlates with quality

Mode Coverage

Better distribution coverage

WGAN-GP Enhancement

Gradient penalty replaces weight clipping for better Lipschitz constraint enforcement

Original Papers

WGAN

Wasserstein GAN

Arjovsky et al., 2017

WGAN-GP

Improved Training of Wasserstein GANs

Gulrajani et al., 2017

Other Improvements

ProGAN

2017

Progressive growing of resolution for high-quality image generation

Resolution Scaling

SAGAN

2018

Self-attention mechanisms for long-range dependencies

Attention

CycleGAN

2017

Unpaired image-to-image translation with cycle consistency

Unpaired Translation

StyleGAN

2018

Style-based generator architecture with unprecedented control

Style Control

BigGAN

2018

Large-scale training with architectural tricks and optimization

Scale

GauGAN

2019

NVIDIA's semantic image synthesis from layout sketches

Semantic Control

Continuous Evolution

Alternative Approach

Each variant addresses specific limitations and pushes boundaries in different directions: resolution, quality, control, and applicability

Diffusion models emerged as a powerful alternative, offering stable training and high-quality generation

Part 6/6:

Hands-on & Applications

Lecture15_31 Placeholder

콘텐츠 준비 중입니다.

Lecture15_32 Placeholder

콘텐츠 준비 중입니다.

Thank you

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