Lecture 9:

Initialization and Normalization

Ho-min Park

homin.park@ghent.ac.kr

powersimmani@gmail.com

Lecture Contents

Part 1: Initialization Strategies

Strategies for setting **weights and biases** before training begins. Proper initialization prevents gradient vanishing/exploding problems, accelerates training speed, and ensures better convergence. (e.g., Xavier, He initialization)

Part 2: Normalization Techniques

Techniques for normalizing the **input distribution** to each layer during training. Reduces Internal Covariate Shift, stabilizes training, and enables the use of higher learning rates. (e.g., Batch Norm, Layer Norm, Group Norm)

Part 3: Normalization and Generalization

Explores how normalization techniques affect model **generalization performance**. Covers theoretical and empirical analysis of how normalization prevents overfitting, improves test performance, and enhances model robustness.

Part 1/3:

Initialization Strategies

1. Why is Initialization Important?
2. Problems with Zero Initialization
3. Random Initialization and Breaking Symmetry
4. Gradient Vanishing/Exploding
5. Xavier/Glorot Initialization
6. He Initialization (for ReLU)
7. LSUV Initialization
8. Leveraging Pre-trained Weights
9. Comparison of Initialization Strategies

Why is Initialization Important?

Sets starting point for **gradient descent**

Affects **convergence speed** & performance

Prevents **vanishing/exploding** gradients

Initialization Strategy

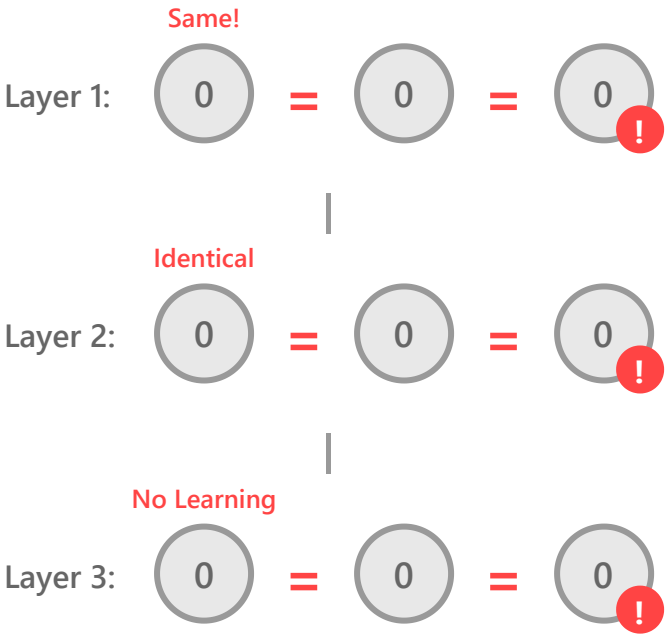
Determines learning **effectiveness**

Ensures **training stability**

Critical for **deep networks**

Influences **final accuracy**

Problems with Zero Initialization



1. **Symmetry problem:** All neurons compute identical outputs
2. Gradients are **identical** for all neurons in same layer
3. Network fails to **break symmetry** during backpropagation
4. Results in **redundant neurons** learning same features
5. **No learning** occurs - weights remain constant
6. Effectively reduces network to **single neuron** per layer

Random Initialization and Breaking Symmetry

✗ Zero Initialization

All neurons identical
Symmetry problem

↓

✓ Random Initialization

Each neuron unique
Symmetry broken!

Common Distributions

`N(0, 0.01) or U(-0.01, 0.01)`

Key Benefits

- **Breaks symmetry** between neurons with small random values
- Each neuron learns **different features** independently
- Enables **diverse representation** learning across layers
- **Scale matters:** Too large → saturation, Too small → vanishing gradients
- Foundation for **all modern methods**

Practical Example: Why Zero Initialization Fails

❌ Zero Initialization

$$W_{1\,1} = W_{1\,2} = W_{2\,1} = W_{2\,2} = 0$$

$$h_1 = W_{1\,1} \cdot x_1 + W_{1\,2} \cdot x_2$$
$$= 0 \cdot 1 + 0 \cdot 2 = \mathbf{0}$$

$$h_2 = W_{2\,1} \cdot x_1 + W_{2\,2} \cdot x_2$$
$$= 0 \cdot 1 + 0 \cdot 2 = \mathbf{0}$$

$h_1 = h_2 = 0$ (Identical!)

Gradient Update:

$$\partial L/\partial W_{1\,1} = \partial L/\partial W_{1\,2} \quad \text{(same)}$$
$$\partial L/\partial W_{2\,1} = \partial L/\partial W_{2\,2} \quad \text{(same)}$$

$W_{1\,1}$ and $W_{1\,2}$ stay identical

$W_{2\,1}$ and $W_{2\,2}$ stay identical

⚠ Symmetry Never Broken

✅ Random Initialization

$$W_{1\,1} = 0.5,\ W_{1\,2} = -0.3$$

$$W_{2\,1} = 0.2,\ W_{2\,2} = 0.4$$

$$h_1 = W_{1\,1} \cdot x_1 + W_{1\,2} \cdot x_2$$
$$= 0.5 \cdot 1 + (-0.3) \cdot 2$$
$$= 0.5 - 0.6 = \mathbf{-0.1}$$

$$h_2 = W_{2\,1} \cdot x_1 + W_{2\,2} \cdot x_2$$
$$= 0.2 \cdot 1 + 0.4 \cdot 2$$
$$= 0.2 + 0.8 = \mathbf{1.0}$$

$h_1 = -0.1 \neq h_2 = 1.0$ (Different!)

Gradient Update:

$$\partial L/\partial W_{1\,1} \neq \partial L/\partial W_{1\,2} \quad \text{(different)}$$
$$\partial L/\partial W_{2\,1} \neq \partial L/\partial W_{2\,2} \quad \text{(different)}$$

Each weight learns
unique features independently

✓ Symmetry Broken Successfully

Gradient Vanishing/Exploding Problems

↓ Vanishing Gradients

Gradients become **extremely small** in early layers, preventing effective learning in deep networks.

↑ Exploding Gradients

Gradients grow **exponentially large** during backpropagation, causing training instability.

Key Causes & Effects

Cause: Repeated multiplication of small/large values during backpropagation

Susceptible activations: Sigmoid/tanh particularly vulnerable

Impact: Prevents effective learning in deep networks

Consequence: Slow convergence or complete training failure

✓ **Solution**

Proper initialization helps maintain gradient magnitude throughout the network

Xavier/Glorot Initialization

Designed for Activations

sigmoid tanh

Variance maintained ≈ 1.0

Uniform Distribution

$$W \sim U(-\sqrt{(6/(n_{in} + n_{out}))}, \sqrt{(6/(n_{in} + n_{out}))})$$

Gaussian Distribution

$$W \sim N(0, 2/(n_{in} + n_{out}))$$

Key Properties

- **Variance maintained** across layers during forward/backward pass
- Keeps activation variance approximately **1.0**
- **Prevents saturation** in early training stages
- Standard for **fully connected networks**
- Optimal for **tanh/sigmoid** activation functions

Calculation Examples

Example 1: Uniform Distribution

Input neurons (n_{in}):	784
Output neurons (n_{out}):	128
Weight matrix size:	784 × 128

1 Calculate sum

$$n_{in} + n_{out} = 784 + 128 = 912$$

2 Calculate fraction

$$6 / (n_{in} + n_{out}) = 6 / 912 = 0.006579$$

3 Calculate square root

$$\sqrt{(0.006579)} = 0.0811$$

Example 2: Gaussian Distribution

Input neurons (n_{in}):	256
Output neurons (n_{out}):	64
Weight matrix size:	256 × 64

1 Calculate sum

$$n_{in} + n_{out} = 256 + 64 = 320$$

2 Calculate variance

$$\sigma^2 = 2 / (n_{in} + n_{out}) = 2 / 320 = 0.00625$$

3 Standard deviation (σ)

$$\sigma = \sqrt{(0.00625)} = 0.0791$$

W ~ U(-0.0811, +0.0811)

Weight samples (partial)

```
[-0.0523  0.0701 -0.0198  0.0445]
[ 0.0312 -0.0789  0.0621 -0.0356]
[-0.0678  0.0234  0.0789 -0.0512]
[ 0.0456 -0.0123  0.0654  0.0289]
```

W ~ N(0, σ=0.0791)

Weight samples (partial)

```
[-0.0423  0.0612 -0.0891  0.0234]
[ 0.0756 -0.0189  0.0523 -0.0678]
[-0.0345  0.0801 -0.0267  0.0445]
[ 0.0589 -0.0734  0.0123  0.0690]
```

Example 3: Small Network

Input neurons (n_{in}):	10
Output neurons (n_{out}):	5
Weight matrix size:	10 × 5

1 Uniform Distribution calculation

$$n_{in} + n_{out} = 10 + 5 = 15$$

$$\sqrt{(6/15)} = \sqrt{(0.4)} = 0.6325$$

W ~ U(-0.6325, +0.6325)

Full weight matrix (10×5)

Example 4: Large Network Comparison

Input neurons (n_{in}):	2048
Output neurons (n_{out}):	1024
Weight matrix size:	2048 × 1024

1 Uniform Distribution

$$\sqrt{(6/(2048+1024))} = \sqrt{(6/3072)}$$

$$= \sqrt{(0.001953)} = 0.0442$$

2 Gaussian Distribution

```
[-0.3421  0.5234 -0.1823  0.4512 -0.2901]
[ 0.2134 -0.4823  0.3912  0.1567 -0.5123]
[-0.4567  0.2901  0.5421 -0.3234  0.1789]
[ 0.3789 -0.2156  0.4234 -0.5678  0.2912]
[-0.1234  0.4567 -0.3812  0.2345  0.5234]
[ 0.4912 -0.3567  0.1234 -0.4321  0.3678]
[-0.2678  0.5012 -0.4156  0.1923  0.3456]
[ 0.3234 -0.1789  0.4678 -0.2567  0.5123]
[-0.4123  0.2678  0.3567 -0.5234  0.1456]
[ 0.5678 -0.3012  0.2134  0.4789 -0.3901]
```

$$\sigma = \sqrt{(2/3072)} = \sqrt{(0.000651)} = 0.0255$$

Uniform: W ~ U(-0.0442, +0.0442)
Gaussian: W ~ N(0, σ=0.0255)

💡 **Observation:** As the network grows larger, the initialization range becomes smaller. This prevents the sum of many inputs from becoming too large.

He Initialization (for ReLU)

ReLU Effect: Half Neurons Output 0

Approximately **50% neurons killed** by ReLU

He Initialization Formula

$$W \sim N(0, 2/n_{in})$$

Variance factor of **2** compensates for ReLU's effect

Key Features

- Specifically designed for **ReLU activation** functions
- Accounts for ReLU **killing half** the neurons (output 0)
- **Maintains signal strength** in deep ReLU networks
- Significantly improves training of **very deep networks**

✓ Default Choice

Standard initialization for modern **CNN architectures** and deep learning models with ReLU

📊 Practical Calculation Example

Example 1: Layer with 4 inputs → 3 outputs

Step 1: Calculate Standard Deviation

Example 2: Layer with 128 inputs → 64 outputs

Step 1: Calculate Standard Deviation

$n_{in} = 4$

$\sigma = \sqrt{(2/n_{in})} = \sqrt{(2/4)} = \sqrt{0.5}$

$\sigma \approx 0.707$

Step 2: Generate Weight Matrix (3×4)

Sample from $N(0, 0.707^2)$

```
W = [[ 0.423, -0.891, 0.156, 0.734]
[-0.612, 0.289, -0.445, 0.821]
[ 0.534, -0.178, 0.693, -0.356]]
```

Verification

Variance ≈ 0.5 ✓

Compensates for ReLU killing ~50% neurons

$n_{in} = 128$

$\sigma = \sqrt{(2/n_{in})} = \sqrt{(2/128)}$

$\sigma = \sqrt{0.015625}$

$\sigma \approx 0.125$

Step 2: Generate Weight Matrix (64×128)

Sample from $N(0, 0.125^2)$

```
W[0,:5] = [ 0.089, -0.134, 0.112, -0.078,
0.156]
W[1,:5] = [-0.091, 0.145, -0.123, 0.067,
-0.089]
W[2,:5] = [ 0.134, -0.056, 0.178, -0.145,
0.103]
...
(Much smaller values due to larger n_in)
```

Key Insight

Larger n_{in} → Smaller weights

Prevents activation explosion 🚀

🔍 Comparison: Xavier vs He Initialization

Layer Size (n_{in})	Xavier: $\sigma = \sqrt{(1/n_{in})}$	He: $\sigma = \sqrt{(2/n_{in})}$	Ratio (He/Xavier)
4	0.500	0.707	√2 ≈ 1.41×

16	0.250	0.354	√2 ≈ 1.41×
64	0.125	0.177	√2 ≈ 1.41×
256	0.0625	0.088	√2 ≈ 1.41×

Key Takeaway

He initialization uses **√2 times larger** weights than Xavier
This compensates for ReLU zeroing out half the neurons
Result: **Stable gradient flow** in deep ReLU networks

LSUV Initialization

Layer-Sequential Unit-Variance Initialization

Two-Step Process

1. Initialize with **orthogonal matrices**

↓

2. Normalize to **unit variance** layer by layer

Key Characteristics

Sequential process: Initializes and normalizes one layer at a time

Orthogonal initialization: Provides better starting point than random

Data-driven: Uses actual data to estimate variance

More sophisticated: Advanced compared to Xavier/He methods

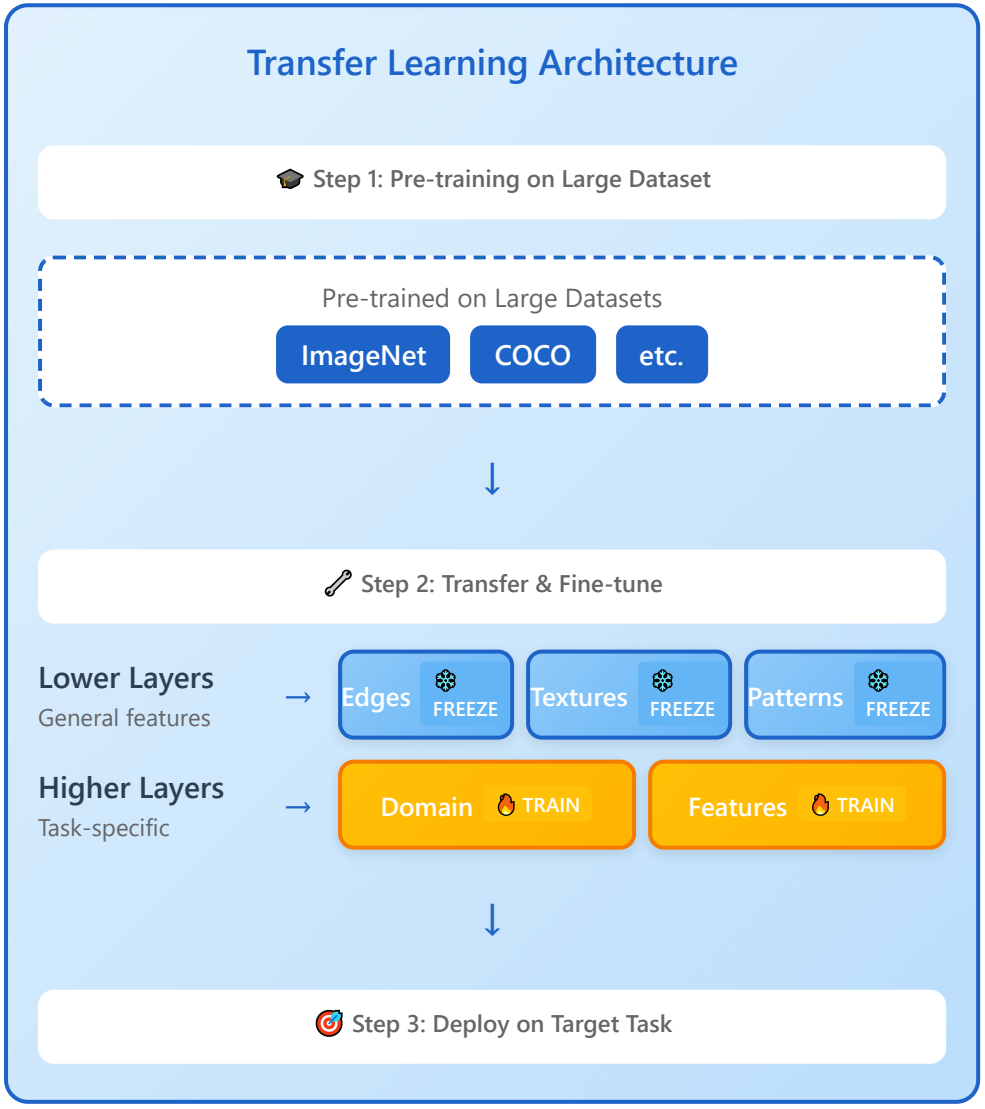
✓ Particularly Effective

Excels in **very deep networks** with **100+ layers**

Uses small batch of data for variance estimation

📚 Additional Resource: DeepLearning.AI - Weight Initialization Guide

Leveraging Pre-trained Weights



Key Benefits

- **Reuse learned features** from large-scale datasets
- **Dramatically reduces** training time and data requirements
- **Fine-tune** pre-trained weights for specific tasks
- Lower layers: **general features** (edges, textures)
- Higher layers: **domain-specific** features

✓ Standard Practice

Widely adopted in **Computer Vision** and **NLP**

Comparison of Initialization Strategies

Method	Best Use Case	Recommendation
Zero Init	**Never use** - causes symmetry problem	✗ Avoid
Random Small Values	Basic approach, often **insufficient** for deep networks	⚠ Basic
Xavier/Glorot	Best for **tanh/sigmoid** activations	✓ Recommended
He Initialization	Best for **ReLU** and variants (LeakyReLU, PReLU)	✓ Recommended
LSUV	Best for **extremely deep networks** (100+ layers)	✓✓ Advanced
Pre-trained Weights	Best when **transfer learning** is applicable	✓✓ Preferred

Key Takeaway: Choice depends on network architecture and activation functions. Modern practice favors He

initialization for ReLU networks and pre-trained weights when available.

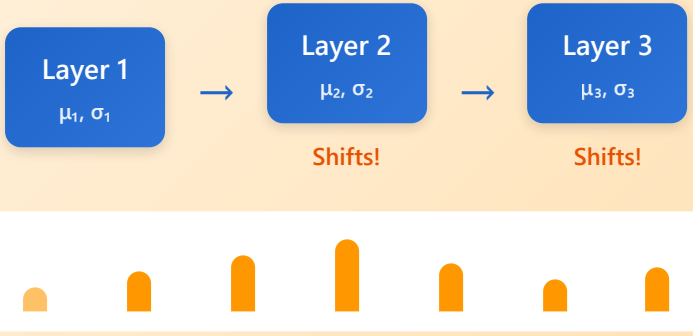
Part 2/3:

Normalization Techniques

10. Internal Covariate Shift
11. Batch Normalization (Batch Norm)
12. Layer Normalization (Layer Norm)
13. Instance Normalization
14. Group Normalization
15. Weight Normalization
16. Spectral Normalization
17. Comparison of Normalization Techniques
18. When to Use Which Normalization?

Internal Covariate Shift

Distribution Shifts During Training



⚠ Training Impact

Requires lower learning rates for stable training

Key Problems

Distribution changes as previous layers update during training

Forces layers to **continuously adapt** to new distributions

Slows down training and reduces stability

More **pronounced in deeper** networks

✓ Solution

Normalization techniques address this problem directly by stabilizing distributions

Mathematical Explanation

Input Distribution Changes per Layer

$$x^{(l)} = f(x^{(l-1)}; \theta^{(l-1)})$$

Batch Normalization Formula

$$\mu_B = (1/m) \Sigma x_i$$

Input of layer l depends on parameters $\theta^{(l-1)}$ of previous layer

$$\theta^{(l-1)} \rightarrow \theta^{(l-1)} + \Delta\theta$$

When parameters update, input distribution $P(x^{(l)})$ changes

Quantifying Covariate Shift

$$D_{KL}(P_{old}(x) \;||\; P_{new}(x))$$

Measure shift magnitude using **KL-Divergence** between old and new distributions

Calculate batch mean

$$\sigma^2_B = (1/m) \sum (x_i - \mu_B)^2$$

Calculate batch variance

$$\hat{x_i} = (x_i - \mu_B) / \sqrt{(\sigma^2_B + \varepsilon)}$$

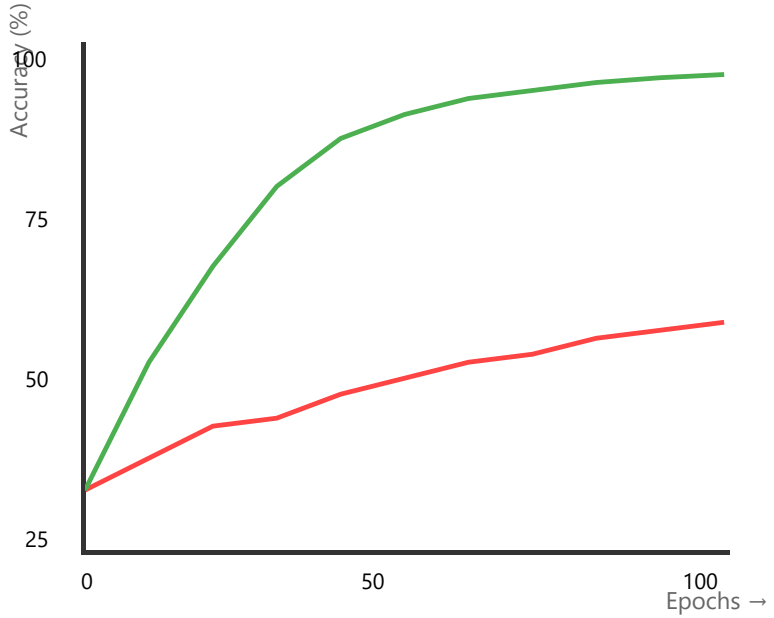
Normalized value (mean 0, variance 1)

$$y_i = \gamma \hat{x_i} + \beta$$

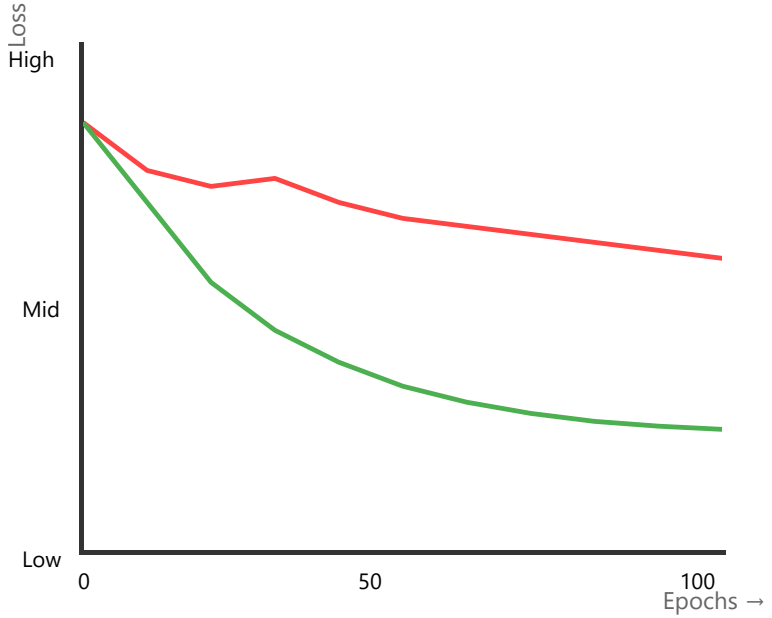
Scale and shift with learnable γ, β parameters

Experimental Results

Training Accuracy Over Epochs



Loss Over Epochs



Before vs After Comparison

✗ Without Normalization

Learning Rate	0.001 (Very Low)
Convergence Time	~200 epochs
Training Stability	Unstable
Gradient Flow	Poor

Distribution Behavior

✓ With Batch Normalization

Learning Rate	0.01-0.1 (Higher)
Convergence Time	~50 epochs
Training Stability	Stable
Gradient Flow	Excellent

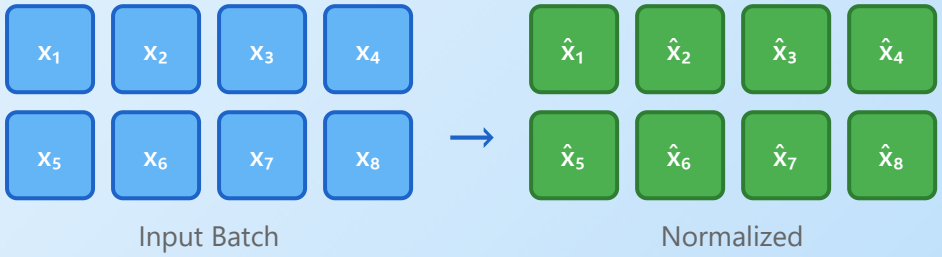
Distribution Behavior

Key Insight

Batch Normalization allows **10-100x higher learning rates** and reduces training time by **~75%**

Batch Normalization (Batch Norm)

Normalizes Across Batch Dimension



Batch Norm Formula

$$\hat{x} = (x - \mu_{batch}) / \sqrt{(\sigma^2_{batch} + \varepsilon)}$$

$$y = \gamma \cdot \hat{x} + \beta$$

Learnable: **γ** (scale) & **β** (shift)

Key Benefits

- **Reduces** internal covariate shift significantly
- Enables **higher learning rates** and faster convergence
- Acts as **regularizer**, reduces need for dropout
- Normalizes inputs across the **batch dimension**
- **Learnable parameters** (γ, β) maintain expressiveness

✓ Most Widely Used

Standard normalization technique in **Convolutional Neural Networks (CNNs)**

How Batch Normalization Works

⚠ Internal Covariate Shift Problem

As neural networks get deeper, the **data distribution changes** progressively through each layer, causing problems.

Sigmoid Activation Function

Steepest Region:
-2 to 2

Early Layers ✅	Deep Layers ❌
Data in -2~2 range	Data drifts away
Fast Learning	Slow Learning (Vanishing Gradient)

✨ Batch Normalization Solution

Re-normalize data at each layer to maintain optimal distribution throughout the network.

Applied at Every Layer:

1. Calculate batch mean and variance
2. Normalize data to -2~2 range
3. Scale with γ and shift with β
4. Pass to next layer

Without Normalization	With Normalization
🐌 Slow Convergence	🚀 Fast Convergence

💡 Key Insight 1: Alleviates Vanishing Gradient

Keeps data in the steepest region of sigmoid (-2~2), significantly reducing the vanishing gradient problem.

💡 Key Insight 2: Faster Training

Transforms the loss function from a valley shape to a bowl shape, finding the optimum much faster.

💡 Key Insight 3: Regularization Effect

Normalizing with slightly different mean/variance per batch naturally adds noise, providing regularization similar to Dropout.

📊 Numerical Calculation Example

1 Input Batch Data

Batch Size: **4 samples**

Input values: x = [1, 3, 5, 7]

2 Calculate Mean

$$\mu = (1 + 3 + 5 + 7) / 4$$

$\mu_{batch} = 4.0$

3 Calculate Variance

$$\sigma^2 = [(1-4)^2 + (3-4)^2 + (5-4)^2 + (7-4)^2] / 4$$

$$\sigma^2 = [9 + 1 + 1 + 9] / 4$$

$\sigma^2_{batch} = 5.0$

4 Normalize

$$\hat{x} = (x - \mu) / \sqrt{(\sigma^2 + \varepsilon)}$$

$\varepsilon = 0.001$ (for stability)

$\hat{x}_1 = (1 - 4) / \sqrt{5.001} = -1.34$

$\hat{x}_2 = (3 - 4) / \sqrt{5.001} = -0.45$

$\hat{x}_3 = (5 - 4) / \sqrt{5.001} = 0.45$

$\hat{x}_4 = (7 - 4) / \sqrt{5.001} = 1.34$

5 Apply Scale & Shift

Learnable Parameters:

γ (scale) = 2.0

β (shift) = 0.0

Final Formula:

$$y = \gamma \cdot \hat{x} + \beta$$

β (shift) = 1.0

y = 2.0 · x^ + 1.0

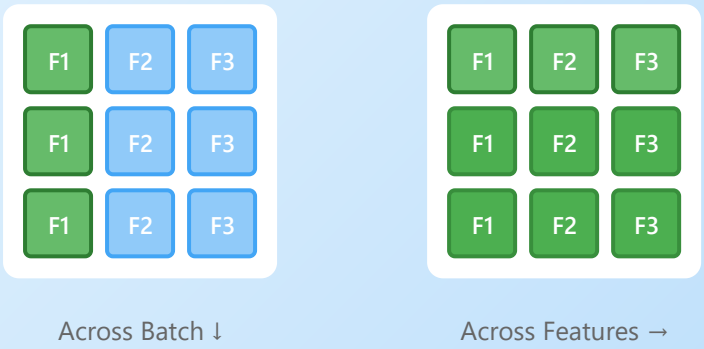
✨ Final Output Values

y_1	y_2	y_3	y_4
-1.68	0.10	1.90	3.68

Original: [1, 3, 5, 7] → After Normalization: [-1.68, 0.10, 1.90, 3.68]

Layer Normalization (Layer Norm)

Batch Norm vs Layer Norm



Normalizes across **feature dimension** per sample

✓ Independent of Batch Size

Works with batch size = 1
Each sample normalized independently

Key Features

- **Independent** of batch size during training/inference
- Each sample normalized **independently**
- No dependence on **batch statistics**
- Essential for **RNNs and Transformers** (sequential models)

✓ Standard in NLP

Used in modern NLP architectures:
BERT, GPT, and Transformers

📐 Layer Normalization Formula

$$\mu = (1/H) \sum x_i$$

Mean: Average value of all features in the layer

$$\sigma^2 = (1/H) \sum (x_i - \mu)^2$$

Variance: Average of squared deviations from the mean

$$\hat{x} = (x - \mu) / \sqrt{(\sigma^2 + \varepsilon)}$$

Normalization: Transform to mean 0 and variance 1

$$y = \gamma \odot \hat{x} + \beta$$

Scale & Shift: Adjust with learnable parameters

- γ **(gamma)**: Scale parameter (learnable)
- β **(beta)**: Shift parameter (learnable)
- ε **(epsilon)**: Small constant for numerical stability (e.g., 10^{-5})
- H: Number of hidden units in the layer

🔄 What is Internal Covariate Shift?

Internal Covariate Shift refers to the phenomenon where the distribution of inputs to each layer continuously changes during neural network training. As the parameters of previous layers are updated, the statistical characteristics of the inputs received by the current layer change with each iteration.

⚠️ Problems that Arise

- Training instability: Each layer must constantly adapt to changing input distributions
- Slow convergence: Requires smaller learning rates
- Gradient problems: Risk of vanishing/exploding gradients
- Worse in deep networks: Cumulative effect increases with depth

✅ Layer Normalization Solution

- Stabilizes input distribution: Normalizes each sample independently
- Faster training: Enables larger learning rates
- Improved gradient flow: Stabilizes gradients during backpropagation
- Consistent representations: Model can learn stable features

Why Layer Norm is Used in Transformers

1 Independent Sequence Processing

Transformers process each input sequence independently. Rather than sharing statistics across batches like Batch Normalization, normalization needs to be applied independently for each sample (sentence).

2 Variable-Length Sequence Handling

Sentences vary in length, and each token carries different meanings. Layer Norm normalizes across the feature dimension of each token, operating stably regardless of sequence length.

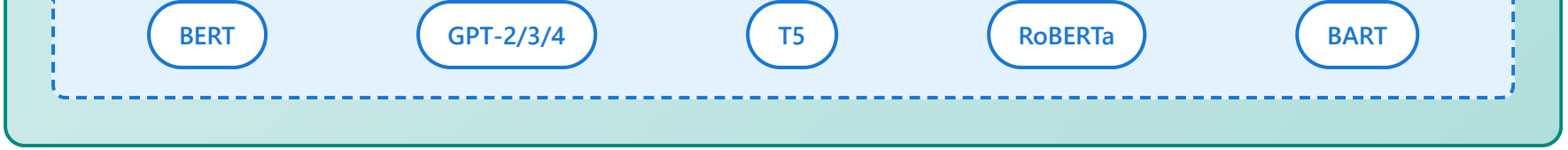
3 Self-Attention Stabilization

In the Self-Attention mechanism, each token references all tokens in the sequence. Layer Normalization is applied before and after these attention operations to maintain consistent representations and accelerate training convergence.

4 Batch Size Independence

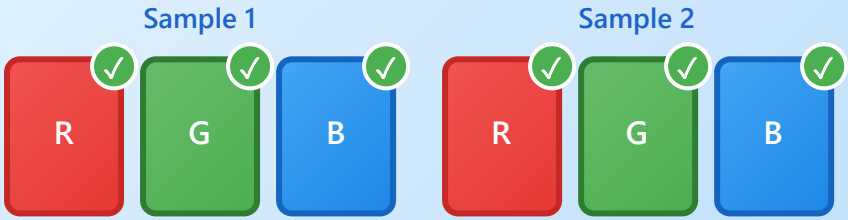
During inference, the batch size may be 1. Since Layer Norm does not depend on batch size, it behaves consistently during both training and inference, ensuring stability.

Layer Norm Application in Major NLP Models


BERT
GPT-2/3/4
T5
RoBERTa
BART

Instance Normalization

Normalizes Per Instance, Per Channel



Each **spatial map** normalized **separately**

Style vs Content

Normalizes Style

Preserves Content

Key Features

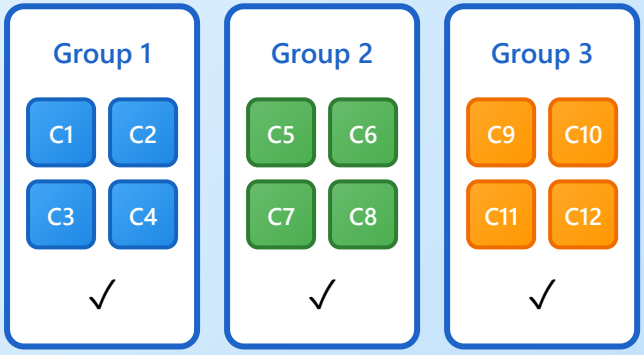
- Normalizes each sample and channel **independently**
- Removes **instance-specific contrast** information
- **Preserves content** while normalizing style
- Better than Batch Norm for **style-related tasks**

✓ Primary Applications

Used in **Style Transfer** and **GANs** for image generation tasks

Group Normalization

Divides Channels into Groups



Typical: 32 channels per group

Each group normalized independently

Compromise Between

Layer Norm (All channels) ↔ **Group Norm** (Channel groups) ↔ **Instance Norm** (Per channel)

Key Features

- **Independent of batch size** like Layer Norm
- Better than Layer Norm for **visual tasks (CNNs)**
- **Stable performance** across different batch sizes
- Compromise between **Layer Norm and Instance Norm**

✓ Ideal For

Small batch training in tasks like object detection and segmentation

Weight Normalization

Reparameterization

$$w = g \cdot (v / ||v||)$$

g
Magnitude
Scale

×

v/||v||
Direction
Normalized

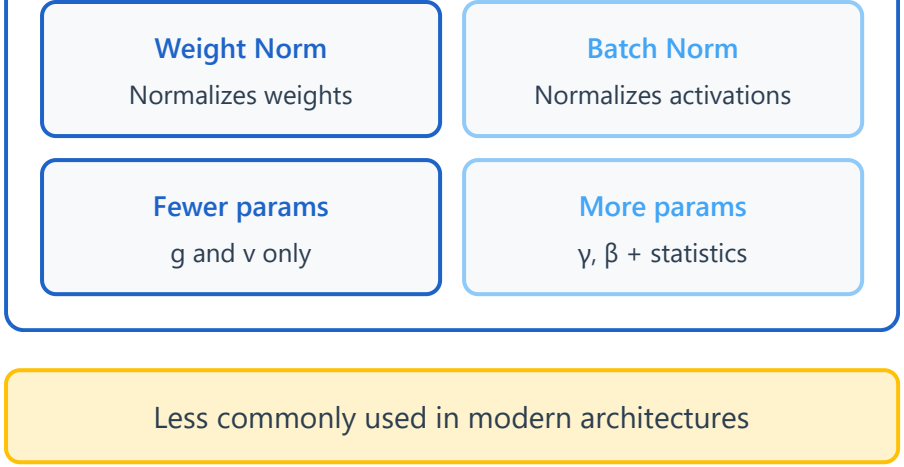
Weight Norm vs Batch Norm

Key Features

- **Decouples magnitude (g) and direction (v)** of weights
- Normalizes **weights** rather than activations
- **Reduces parameters** compared to Batch Norm
- **Faster training** than Batch Norm in some cases

✓ **Works Well With**

RNNs and **Reinforcement Learning** applications



Less commonly used in modern architectures

Spectral Normalization

Constrains Spectral Norm

$$W_{SN} = W / \sigma(W)$$

Divides weights by **largest singular value** (σ)

✓ Ensures Lipschitz Continuity

Controls gradient flow through network layers

Critical for GAN Training

Key Features

- Constrains **spectral norm** of weight matrices
- Ensures **Lipschitz continuity** of network layers
- **Prevents gradient explosion** in discriminator
- Improves training stability **without batch statistics**

✓ Standard in GANs

Used in modern GAN architectures: **BigGAN, StyleGAN**

Comparison of Normalization Techniques

Technique	Best Use Cases	Key Characteristics
Batch Norm	CNNs, Large batches	Normalizes across batch dimension
Layer Norm	RNNs, Transformers, Small batches	Independent of batch size
Instance Norm	Style Transfer, GANs	Per instance, per channel
Group Norm	Small batch vision, Detection, Segmentation	Groups channels, batch-independent
Weight Norm	RNNs, Reinforcement Learning	Normalizes weights, not activations
Spectral Norm	GAN discriminators, BigGAN, StyleGAN	Ensures Lipschitz continuity

Key Insight: Each normalization technique addresses different aspects of training stability. Choose based on your architecture, batch size constraints, and specific task requirements.

When to Use Which Normalization?

Large Batch CNNs

Training CNNs with large batch sizes

↓

Batch Normalization

Transformers / RNNs

Sequential models, language tasks

↓

Layer Normalization

Style Transfer

Artistic tasks, style manipulation

↓

Small Batch Detection

Object detection, segmentation

↓

Instance Normalization

Group Normalization

GANs

Discriminator stability in GANs

↓

Spectral Normalization

Online Learning

Single sample or streaming data

↓

Layer / Group Norm

⚠ Key Considerations

Batch Size Constraints

Computational Cost

Architecture Type

Task Requirements

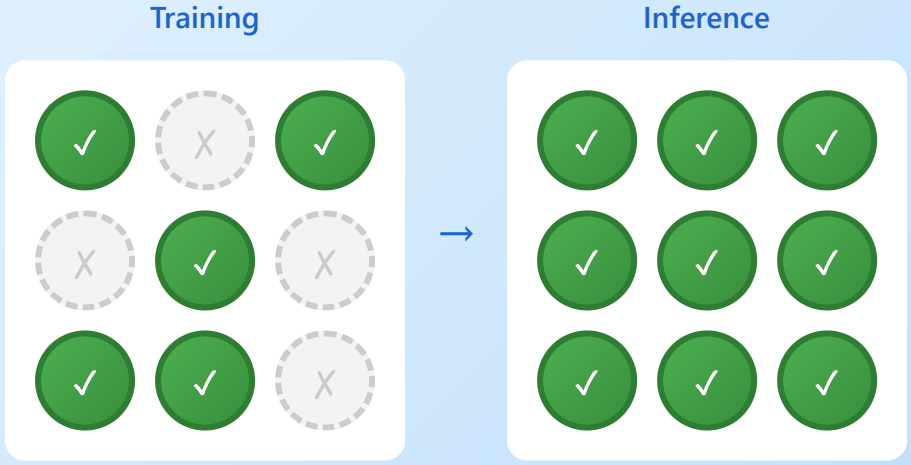
Part 3/3:

Normalization and Generalization

19. Principles of Dropout
20. Dropout Variants (DropConnect, DropBlock)
21. Stochastic Depth
22. Data Augmentation Strategies
23. Mixup and CutMix
24. Early Stopping
25. Ensemble Methods

Principles of Dropout

Training vs Inference



Typical Dropout Rate

0.2 - 0.5 (20% - 50%)

At Inference

```
activation × (1 - dropout_rate)
```

Key Principles

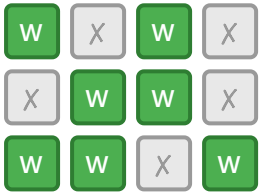
- **Randomly drops neurons** during training (output set to 0)
- Prevents **co-adaptation** of neurons
- Trains **ensemble of sub-networks** simultaneously
- **Powerful regularization** technique

✓ Main Benefit

Reduces **overfitting significantly** in large networks

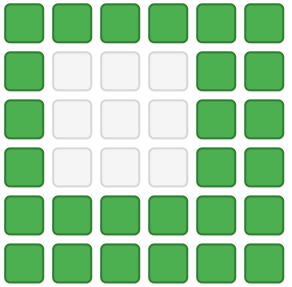
Dropout Variants (DropConnect, DropBlock)

DropConnect



Drops **weights** instead of activations

DropBlock



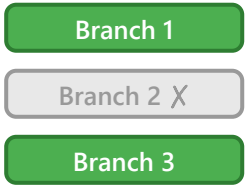
Drops **contiguous regions** in feature maps

✓ Better for CNNs
Prevents info leaking

Spatial Dropout

Drops entire **feature channels**

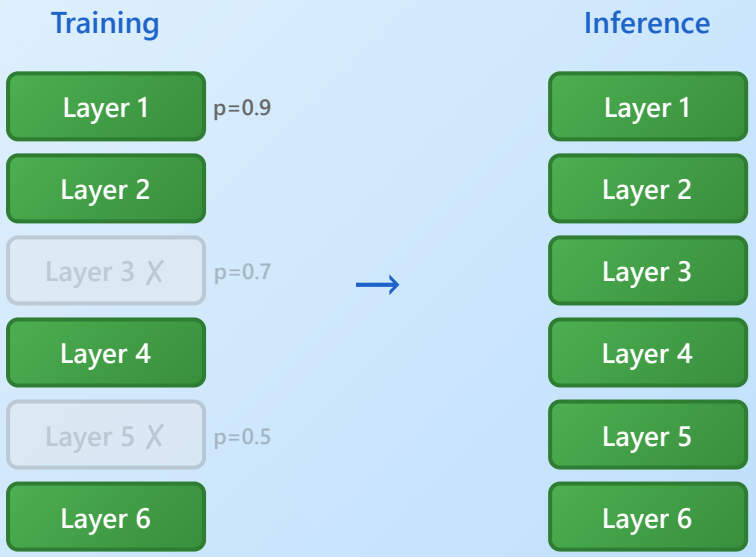
DropPath



Drops entire **paths** in multi-branch architectures

Stochastic Depth

Training vs Inference



Survival Probability

Decreases with layer depth

Early layers (High) — Deep layers (Low)

Key Benefits

- Randomly drops **entire layers** during training
- Creates **shorter networks** during training
- **Improves gradient flow** to early layers
- **Reduces training time** significantly

✓ Enables Extreme Depth

Training of **extremely deep networks** (1000+ layers)

Data Augmentation Strategies

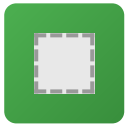
Geometric

Flips, rotations, crops

Color Jittering

Brightness, contrast, saturation

Cutout



Randomly mask patches

Rotation

Random angle rotations

Random Crop

Crop different regions

Random Erasing

Erase random regions

✓ Key Benefits

Increases training diversity

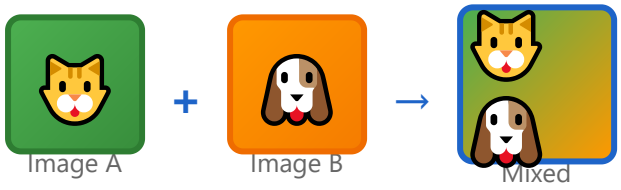
Improves generalization

No additional data needed

Mixup and CutMix

Mixup

Linear Interpolation



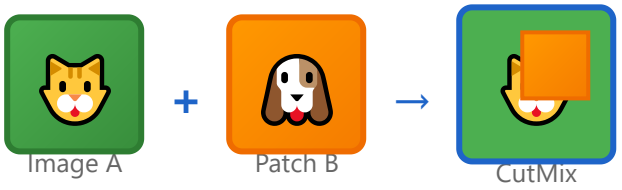
Formula

$$x_{mix} = \lambda \cdot x_i + (1-\lambda) \cdot x_j$$
$$y_{mix} = \lambda \cdot y_i + (1-\lambda) \cdot y_j$$

- ✓ Blends entire images
- ✓ Smooth interpolation

CutMix

Cut and Paste Regions



Mixing Ratio

$$\lambda \sim \text{Beta}(\alpha, \alpha)$$

Paste cut region to another

- ✓ Retains local features
- ✓ More natural appearance

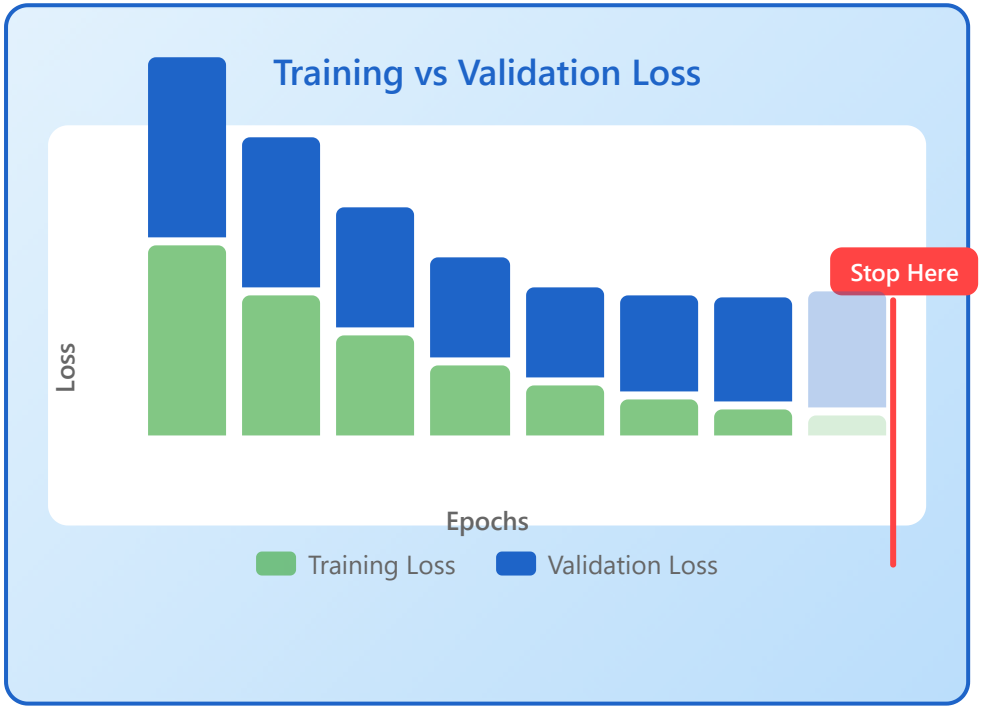
Shared Benefits

Smoother decision boundaries

Improved robustness

Better calibration

Early Stopping



Patience Parameter

Wait N epochs before stopping

Key Features

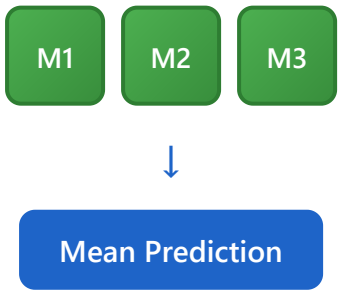
- **Monitors validation** performance during training
- Stops when validation loss **stops improving**
- **Prevents overfitting** to training data
- Saves **best model** based on validation metric

✓ Simple & Effective

Widely used regularization technique, often combined with learning rate scheduling

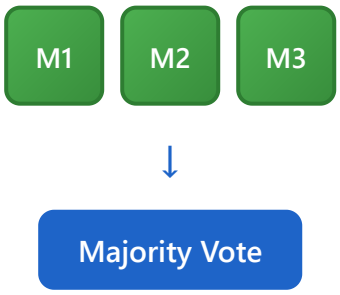
Ensemble Methods

Averaging



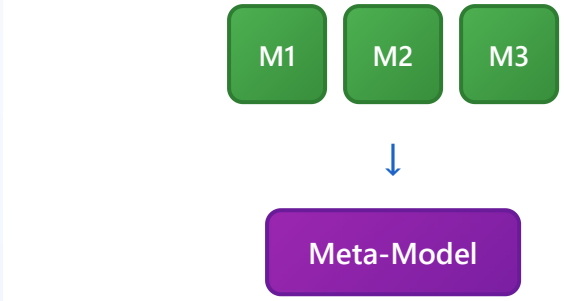
Averages predictions from multiple models

Voting



Takes majority vote for classification

Stacking



Trains meta-model on base predictions

Typical Size

3-10 models in ensemble

✓ Key Benefits

- **Reduces variance** across predictions
- **Improves robustness** of the model

⚖ Trades **computational cost** for **higher accuracy**

Thank you

Ho-min Park

homin.park@ghent.ac.kr

powersimmani@gmail.com