جامعة الملك عبدالله
للعلوم والتقنية
King Abdullah University of
Science and Technology

أكاديمية كاوست
KAUST ACADEMY

The Art of Training Deep Neural Networks

King Abdullah University of Science and Technology (KAUST)
KAUST Academy

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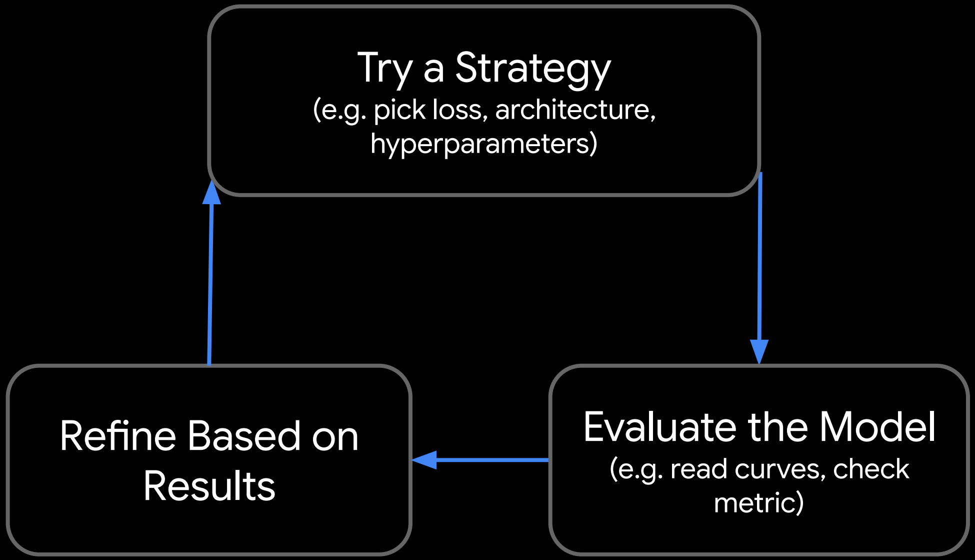
Table of Contents

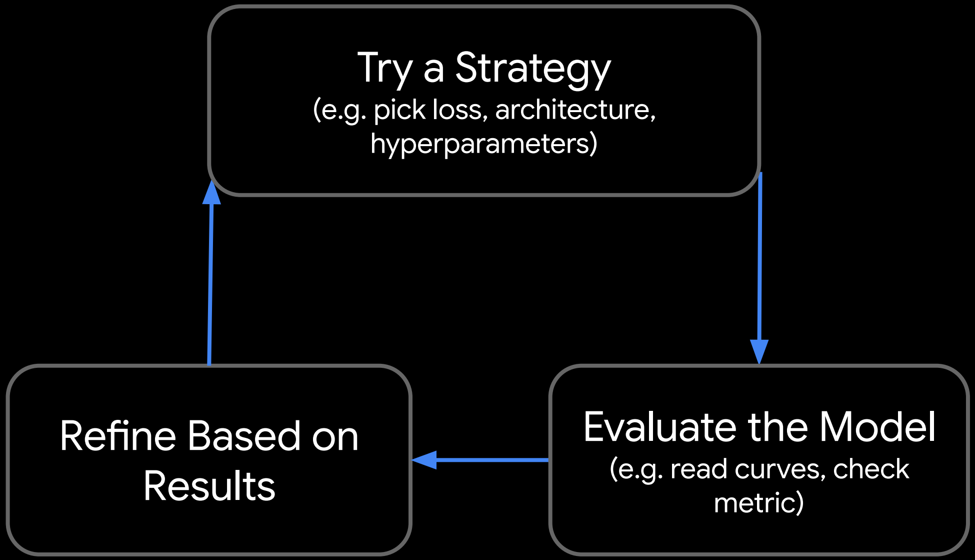
Introduction

- Training AI models is an iterative process of trying, failing, and refining.
- Success depends on empirical experimentation, not just theory.
- Practically, we can offer guidelines on what is likely to work, but there are no guarantees.



Introduction

- In this session, we'll explore the key components that influence deep learning training.
- What they are, why they matter, and how to optimize them.



Losses & Metrics

What You Optimize Is What You Get.

Loss vs Metric: spot the difference

Role	Used during	Differentiable?	Typical examples
Loss	?	?	Cross-Entropy, MSE, L1, Huber, Focal, Dice-Loss
Metric	?	?	Accuracy, F1, mAP, IoU, AUC-ROC, MAE

Loss vs Metric: spot the difference

Role	Used during	Differentiable?	Typical examples
Loss	Back-prop optimisation	Yes	Cross-Entropy, MSE, L1, Huber, Focal, Dice-Loss
Metric	Validation / reporting	No	Accuracy, F1, mAP, IoU, AUC-ROC, MAE

"Loss is for machines, metrics are for humans."

Some Popular Losses

Loss	Minimises …	Used for …
Mean Squared Error (MSE)	L^2 distance between points/pixels	Regression / autoencoders
Mean Absolute Error (MAE)	?	Regression / autoencoders
Huber (Smooth L1) Loss	?	Regression / autoencoders
Dice / IoU Loss	?	Segmentation / Detection
Cross-Entropy (CE) / KL divergence	?	Classification / language models (LLMs)

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Is MAE differentiable?👀

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Is MAE differentiable? No, but we can use a special type of gradient (subgradient) to minimize it.

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Cross-Entropy (CE) / KL divergence	Information (entropy) difference between probability distributions	Classification / language models (LLMs)

Some Popular Losses

Q: Can we optimize for multiple losses at the same time?👀

Some Popular Composite Losses

Scenario	Composite Loss	Purpose
Detection (Yolo)	`BCE_obj + BCE_cls + λ·IoU_reg`	Objectness + class + boxes
Segmentation (UNet)	`CE + λ·Dice`	Pixels + mask overlap
Generative (VAE)	`Reconstruction_obj + β·KL`	Rebuild + Gaussian latent
Generative (GAN)	`CE_adv + λ·Perceptual`	Realism + texture & color details

Hyperparameters Tuning

Loss tells us where to climb
Hyper-params decide how fast and which path.

Hyperparameters

What are Hyper-parameters?

⇒ values you set before training (not learned).

Role?

⇒ steer optimisation speed, capacity & generalisation.

How to set them?

⇒ pick sensible starters → train → inspect → iterate.

Hyperparameters Tuning

Hyperparameter	Quick rule-of-thumb
Optimiser	Usually Adam/AdamW works the best.
LR	*CNNs-based*: (1e-3–1e-4)-ish ↔ *Transformers-based*: (1e-5–1e-6)-ish. Usually used with a scheduler (learning rate decay).
Batch size	Vision: (4–32)-ish ↔ Text: (1–16)-ish keep fixed; scale only if needed.
Epochs	Vision ≈ 5–300; NLP ≈ 1-10; LLMs ≈ 1 (up to 3).
Img size / sequence length	prototype small (e.g. img_size ≈ 224*224, seq_len ≈ 256) → upscale when everything else is stable.
Backbone family & size	start tiny → scale up once pipeline is stable (e.g. EfficientNetV2-Small → EfficientNetV2-Large, BERT-base → BERT-large, etc.).

Hyperparameters Tuning

Tip: Scale batch size when adjusting learning rate.

But by how much?

Hyperparameters Tuning

Tip: Scale batch size when adjusting learning rate.

1. SGD: Use linear scaling rule*

$$\mathrm{LR}_{new} = \mathrm{LR}_{old} \times \frac{\text{Batch Size}_{new}}{\text{Batch Size}_{old}}$$

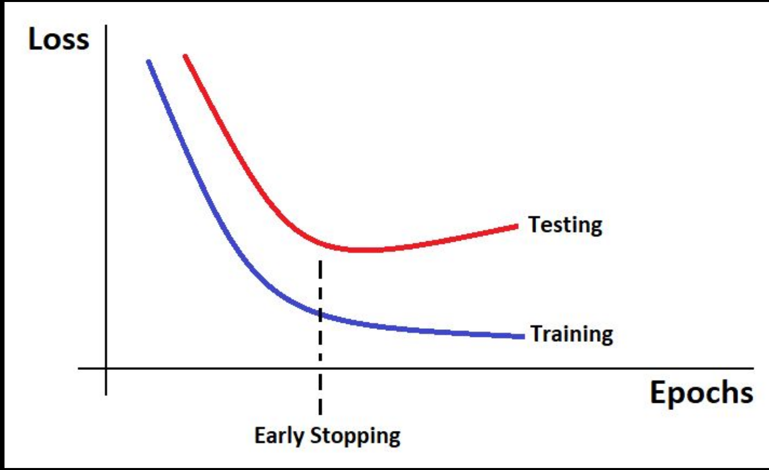
2. Adam/AdamW: Square-root scaling rule*

$$\mathrm{LR}_{new} = \mathrm{LR}_{old} \times \sqrt{\frac{\text{Batch Size}_{new}}{\text{Batch Size}_{old}}}$$

Granziol D., Zohren S., Roberts S., "Learning Rates as a Function of Batch Size: A Random Matrix Theory Approach to Neural Network Training," arXiv:2006.09092, 2020.

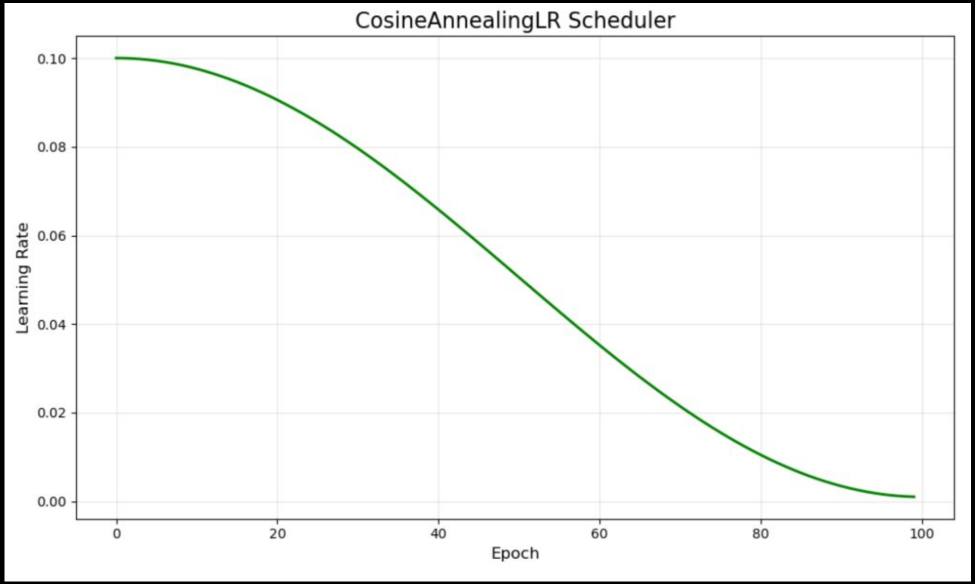
Early Stopping

- **Goal:** stop training just after validation metric flattens or degrades.
- **How:** monitor `val-loss / val-metric` → `patience=N` epochs.
- Helps auto-select optimal epochs value.



Schedulers

- **A scheduler** is the rule that automatically adjusts the learning rate during training.
- They help speed convergence, escape plateaus, and reach a better optimum.
- Most teams now default to cosine decay.



Schedulers Types

Scheduler Type	How It Triggers	Typical Use-case
Step-based	After every optimiser step	When low number of epochs used (e.g. NLP)
Epoch-based	After every epoch	When a high number of epochs used (e.g. Vision, Audio,...etc)

Warm-up

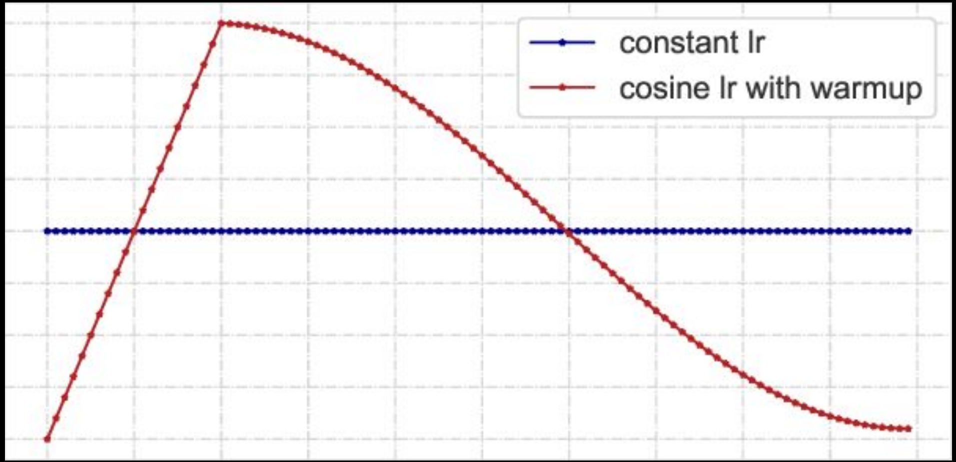
- **Problem:**
  - large initial LR + random weights

    ⇒ gradients explode.
  - large initial LR + Pretrained weights

    ⇒ Forget previous knowledge.

Warm-up

- **Solution:** gradually increase LR from 0 ⟶ base LR over some steps/epochs (or 3-5 % of total steps/epochs).
- Usually used with Transformers.



Early-Stopping vs Fixed Epochs

- **Which one is better:**
  - Many epochs + Early stopping.
  - Fixed epochs + Learning rate scheduler.

Early-Stopping vs Fixed Epochs

- **Which one is better:**
  - Many epochs + Early stopping.
  - Fixed epochs + Learning rate scheduler.

⇒ **Recommended:**

1. Use early stopping initially to discover optimal epoch range.
2. Then, set a fixed number of epochs and apply a scheduler to smoothly decay the learning rate within that range.

Augmentations

- **Data augmentation** is generating new training examples from existing ones through various transformations.
- **Types:**

Random Augmentations:
Flip, Crop, Noise,...

Mix Augmentations:
MixUp, CutMix,...

- **How to choose?** do error analysis
  → add augs that mimics real mistakes.
- **Note**: heavy augs ⇒ add more epochs.

Tuning Order (practical)

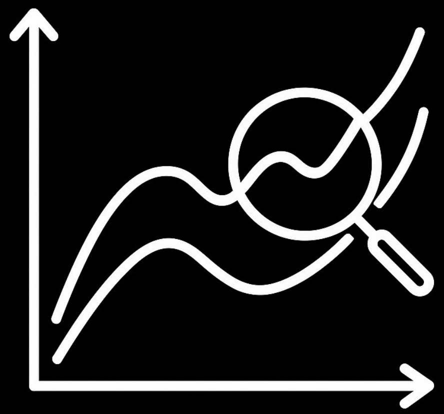
1. **LR & Epochs:** lock batch size unless GPU forces change.
2. **Scheduler:** cosine is usually the best.
3. **Augmentations:** add gradually, re-train.
4. **Model / Input complexity:** scale backbone, image size, sequence length.

Tuning Order (practical)

- **Tips:**
  - Make one change at a time.
  - Start with small experiments, then scale up.
  - Always ensure the loss behaves normally and check for common bugs (e.g., exploding loss, NaNs, unstable curves).

Reading & Debugging Loss Curves

See the Signal, Catch the Bug

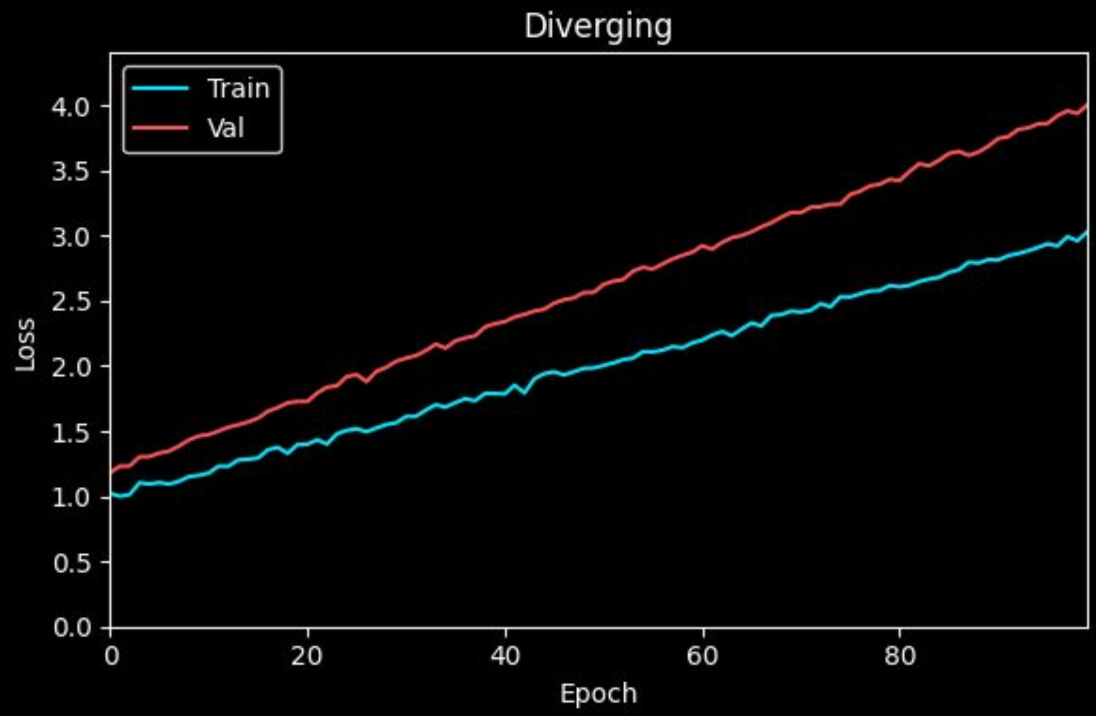


Debugging Loss Curves

- Let’s have a look at some plots…

Case 1: Diverging

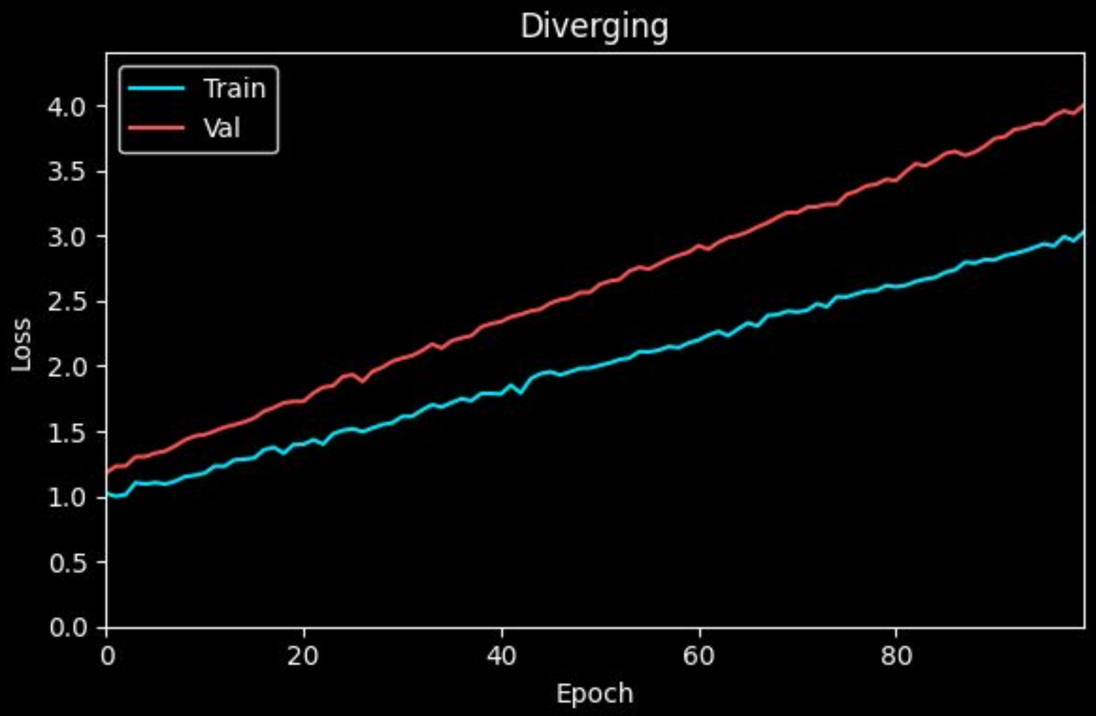
Why did this happen?



Case 1: Diverging

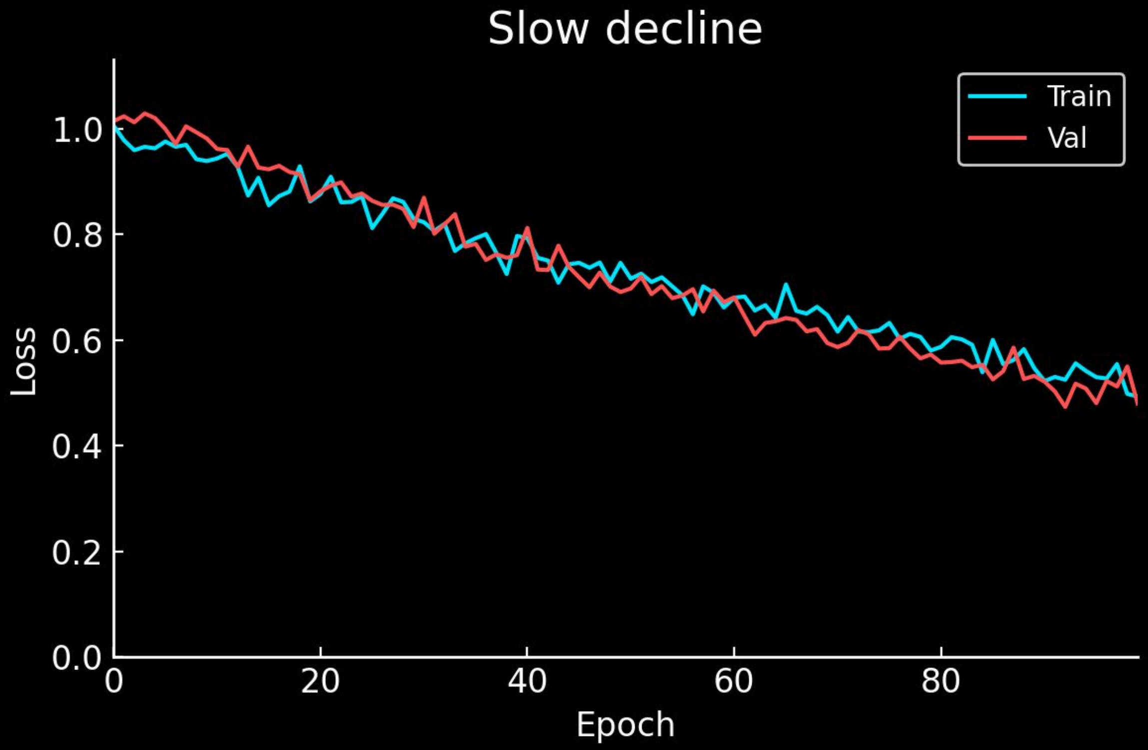
Why did this happen?

- High LR
- Exploding gradient
- Bad data
- No normalization



Case 2: Slow Decline

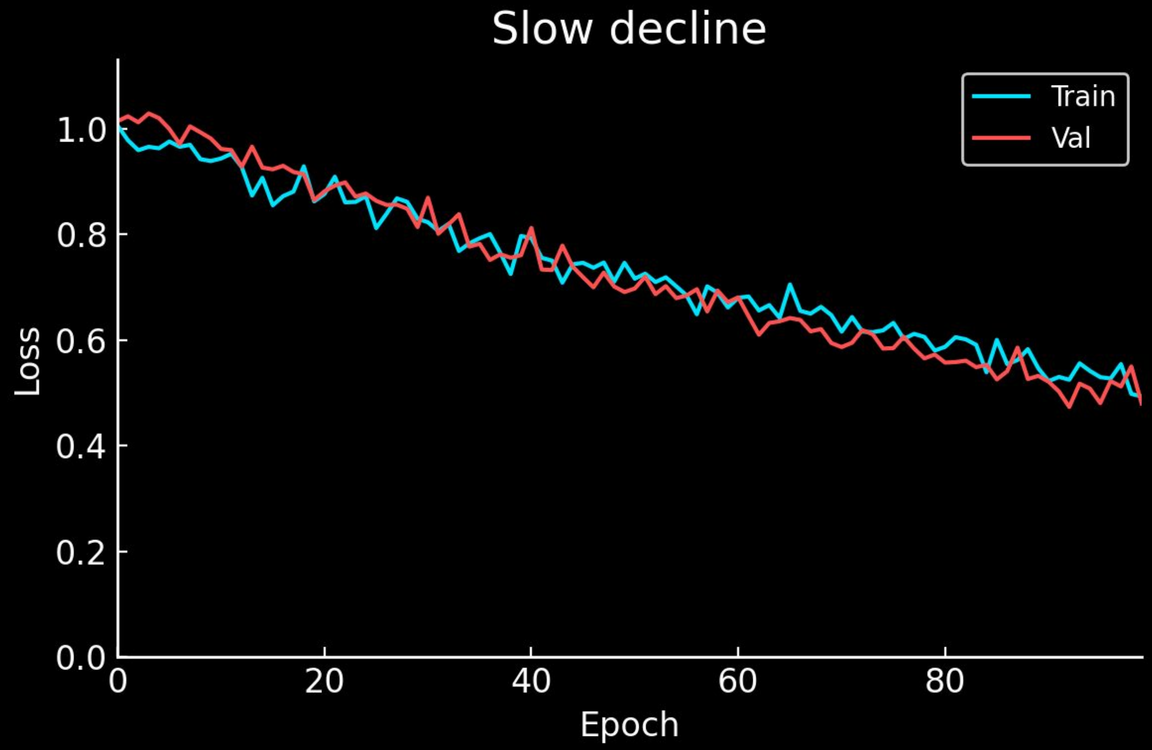
Why did this happen?



Case 2: Slow Decline

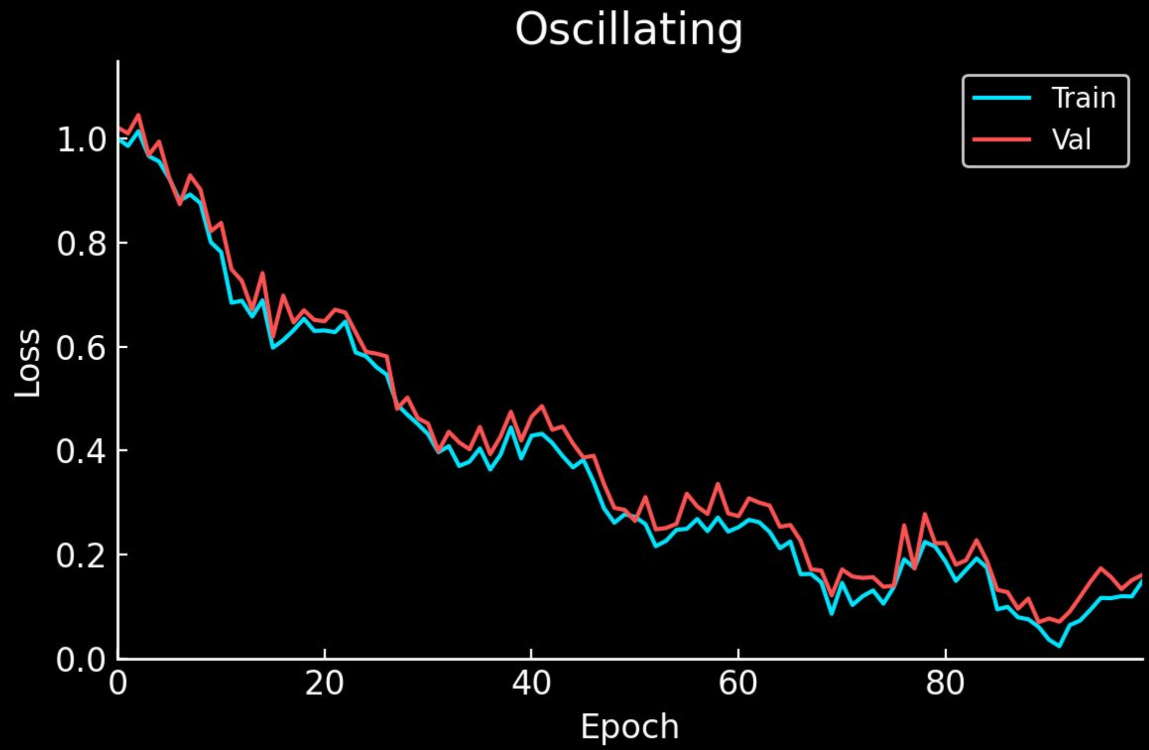
Why did this happen?

- Very small LR
- Vanishing gradients



Case 3: Oscillating

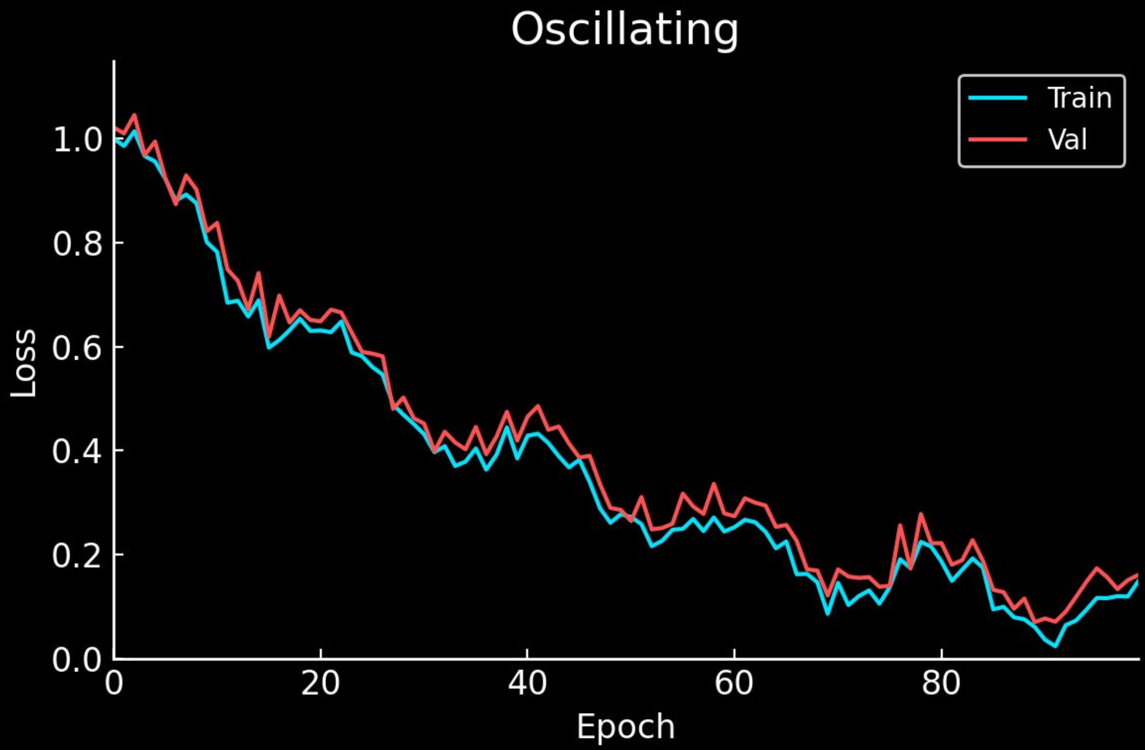
Why did this happen?



Case 3: Oscillating

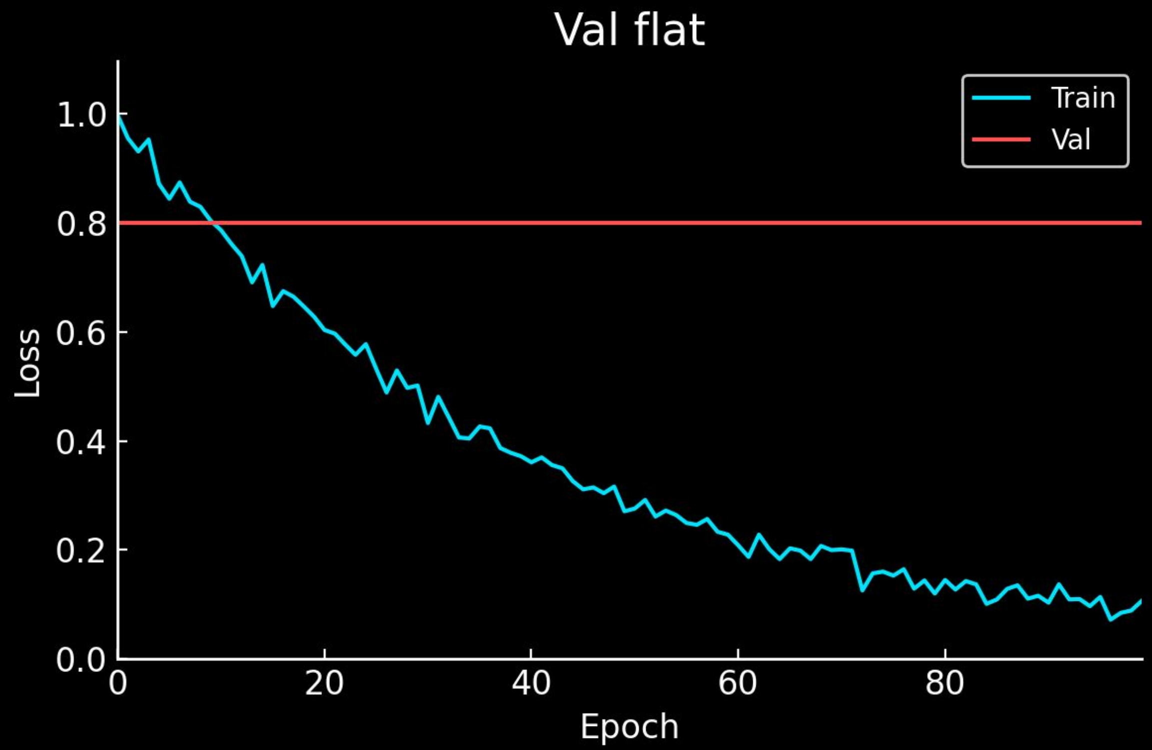
Why did this happen?

- High LR
- Small batch size
- Poor shuffle
- A lot of bad samples



Case 4: Val flat

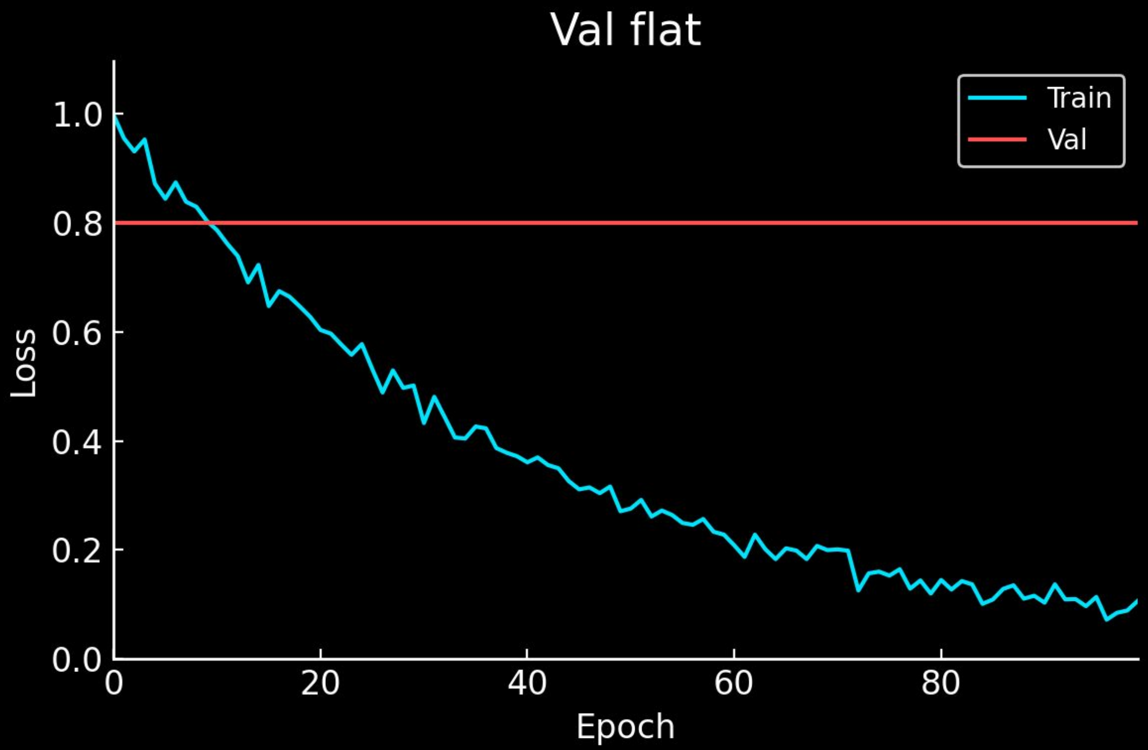
Why did this happen?



Case 4: Val flat

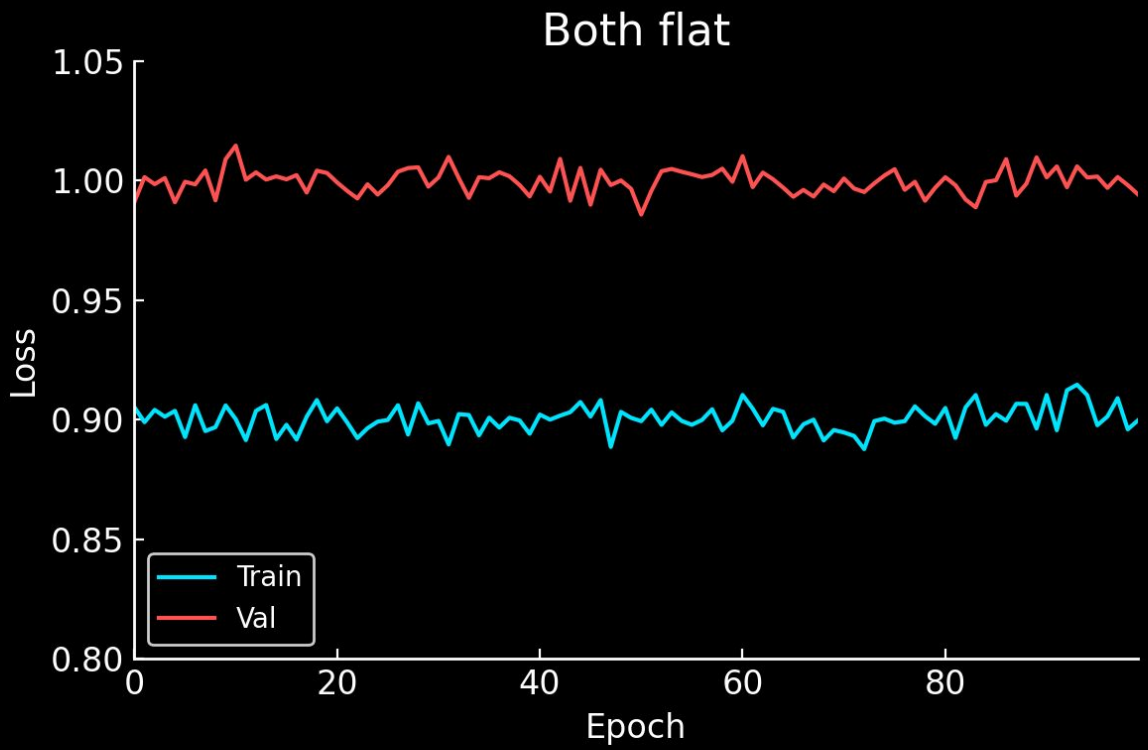
Why did this happen?

- Coding bug in data preparation (e.g. wrong labels)
- Very hard val (distribution shift)
- Significant imbalance



Case 5: Both flat

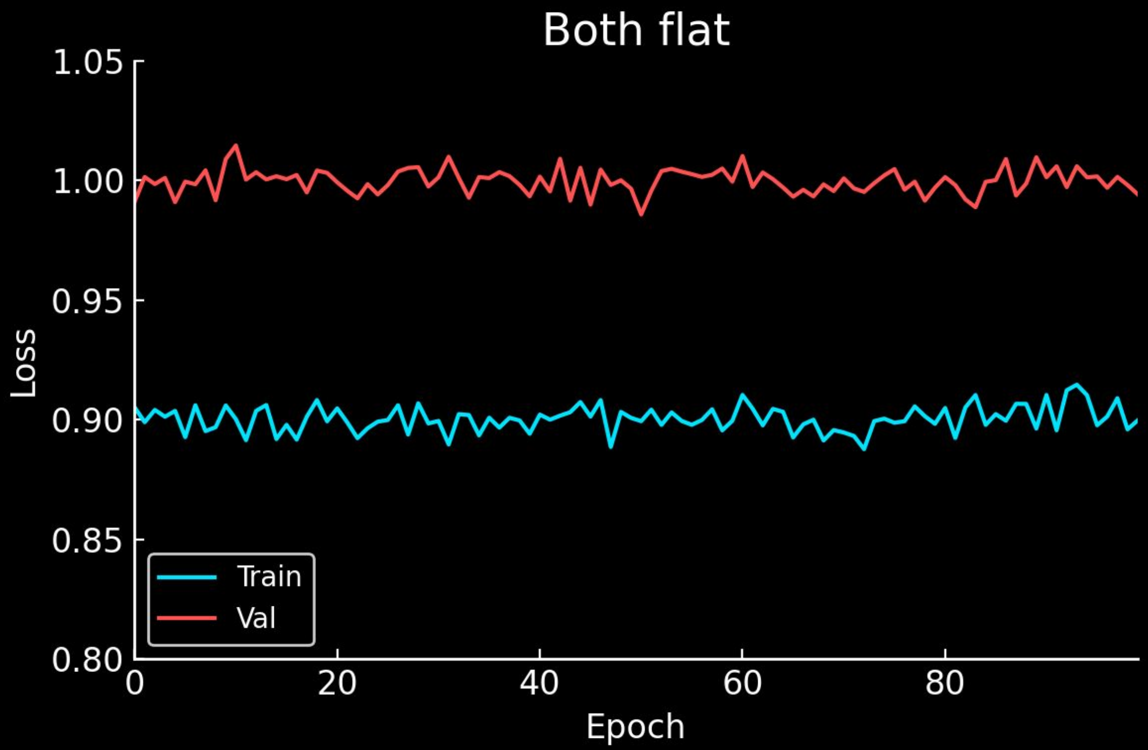
Why did this happen?



Case 5: Both flat

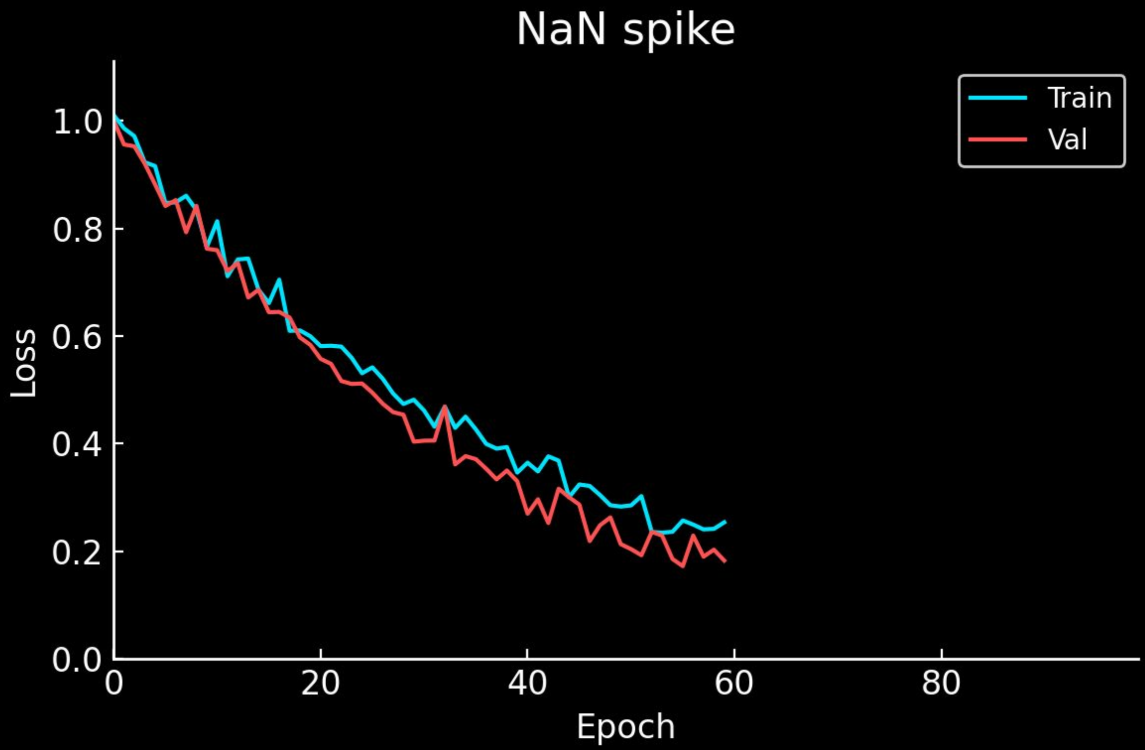
Why did this happen?

- Wrong loss
- Arch mismatch
- Bad labels
- Frozen grads
- Very small LR
- No normalization



Case 6: NaN Loss

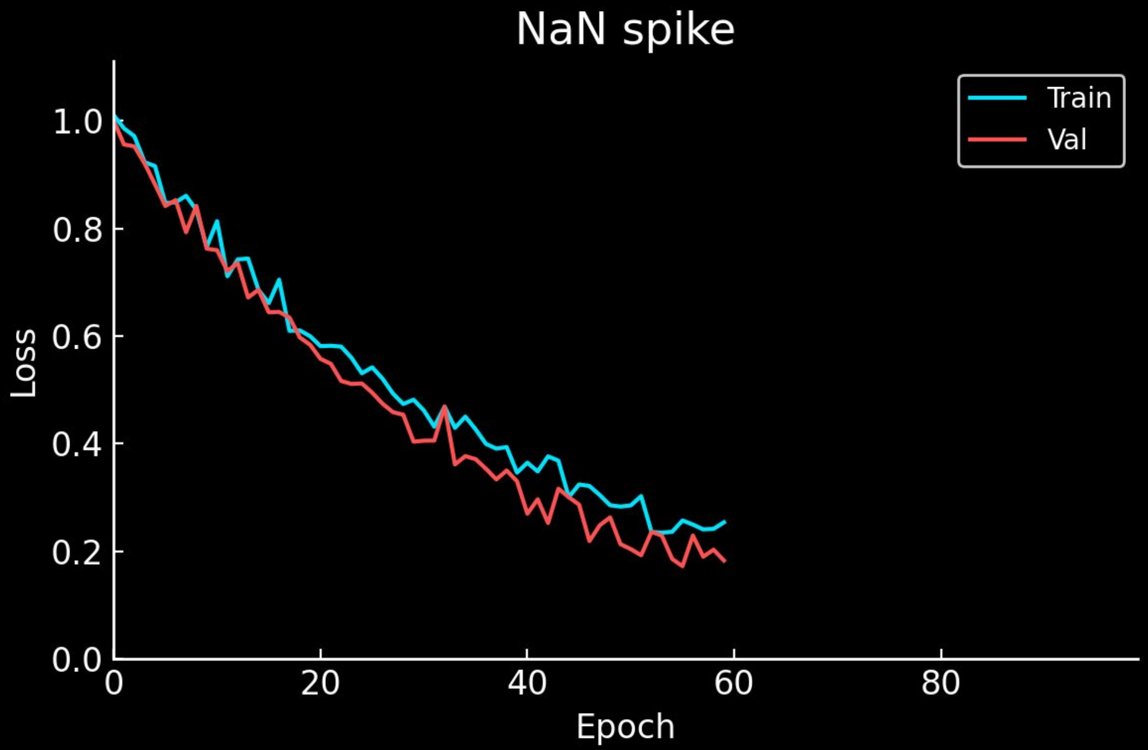
Why did this happen?



Case 6: NaN Loss

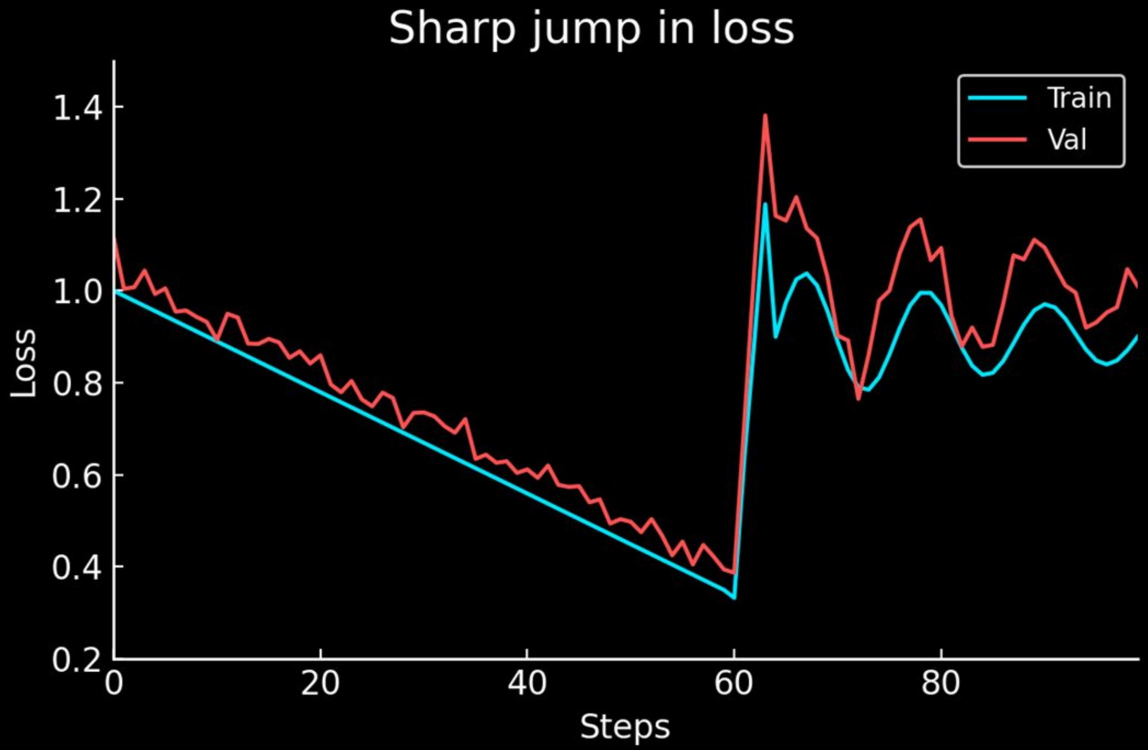
Why did this happen?

- Grad explode
- Log/Div 0



Case 7: Sharp jump

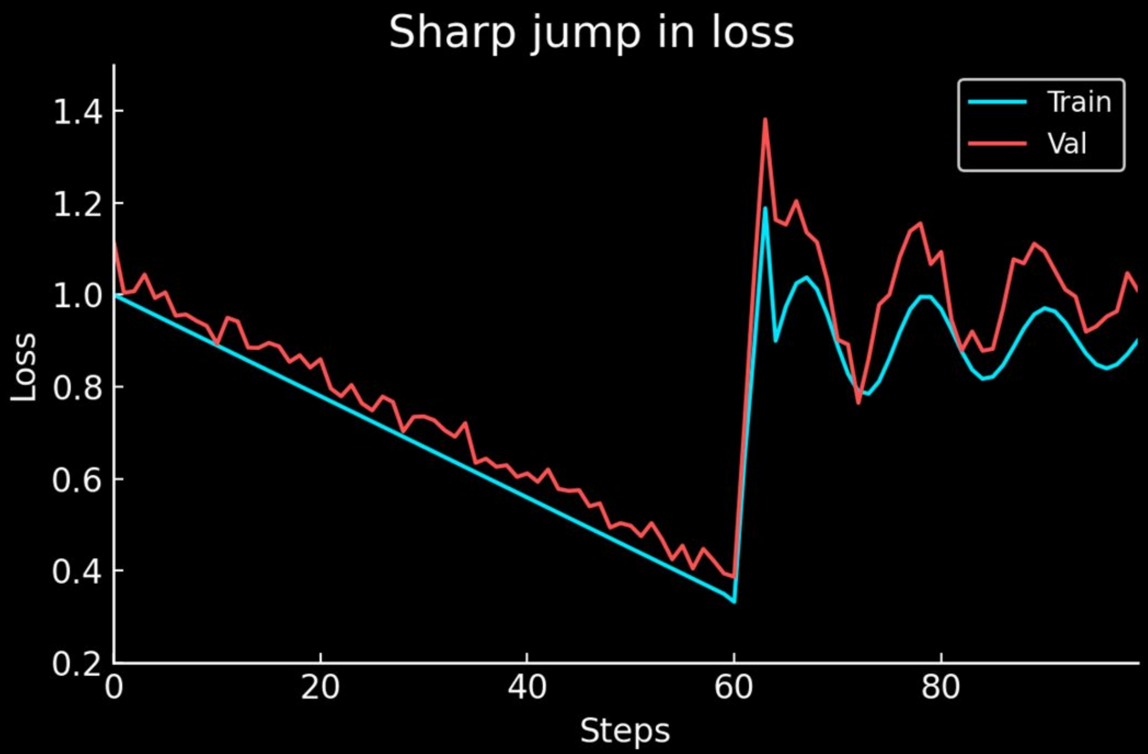
Why did this happen?



Case 7: Sharp jump

Why did this happen?

- NaNs/Inf
- Outliers
- Poor shuffling



Case 8: Val rises, train falls

Why did this happen?

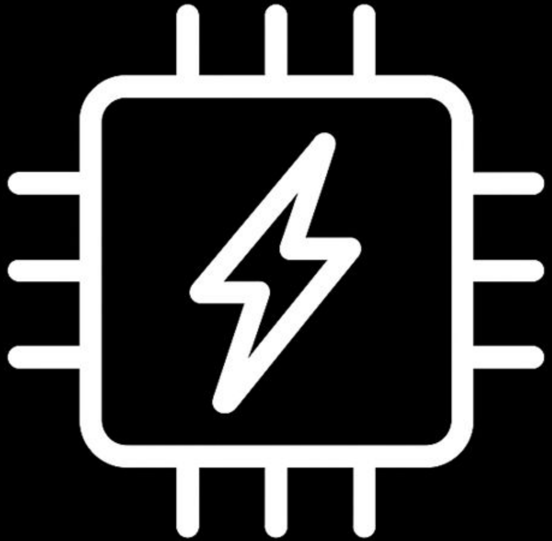
Case 8: Val rises, train falls

Why did this happen?

- Overfitting (Big Model, many epochs, few data, weak aug,...)

Memory & Speed Optimisation

Train Faster, Fit Bigger.

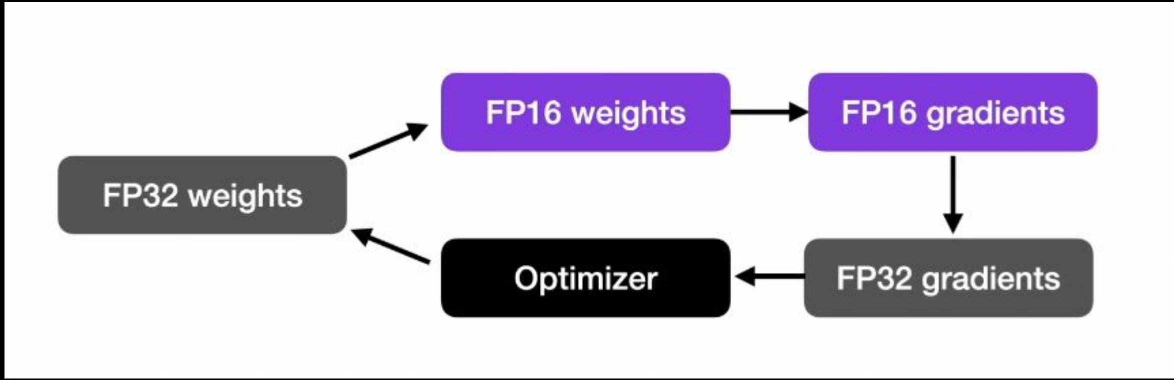


Mixed Precision

- **Mixed precision** combines the use of both FP32 and lower bit floating points (FP16) to reduce memory footprint during model training.
- It halves GPU memory use and often boosts training throughput by 1.5–2×.
- Implementation.

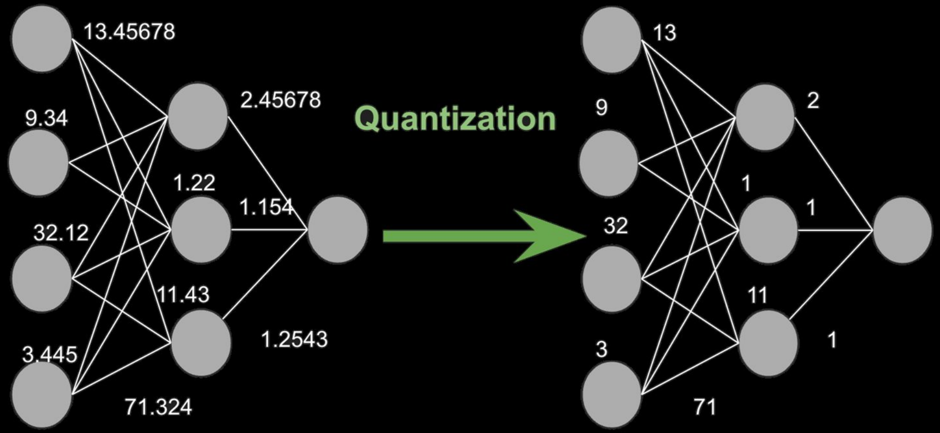
Mixed Precision

- **How it works?**
  1. FP32 original weights are kept for full-precision updates.
  2. Cast to FP16 for forward/backward.
  3. Compute FP16 gradients, then cast back to FP32.
  4. Optimizer updates the FP32 "original" copy.



Quantization

- Convert the weights of a trained model from FP32 ⟶ INT8/4.
- **Why?**
  - Model size ↓ 4–8×
  - Inference speed ↑ 2–4×
  - Minimal accuracy drop ↓



Mixed Precision vs Quantization

	Mixed Precision	Quantization
Data type	FP32 ↔ FP16 (floats)	FP32 → INT8/4 (integers)
When to use	Training	Inference
Benefit	½ memory & 1.5–2× training speed	4–8× smaller model & 2–4× faster inference
Drawback	Needs GPU support (AMP)	Possible small accuracy drop

Why not training on INT8/4 to make training even faster/lighter?👀

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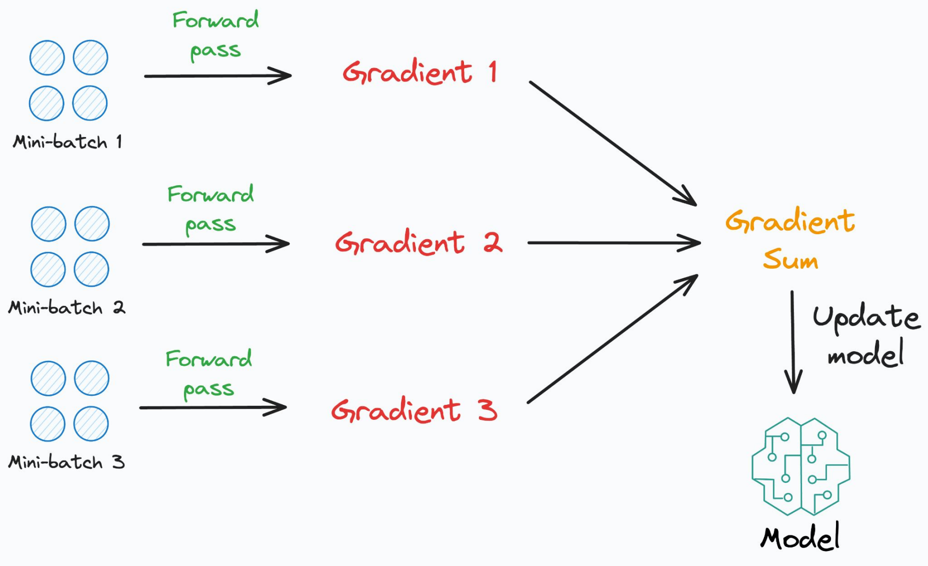
Why not training on INT8/4 to make training even faster/lighter? unstable or no learning.

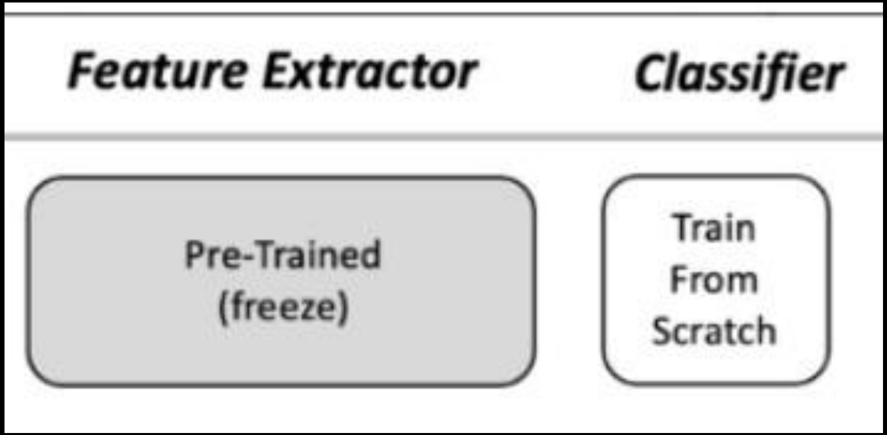
Gradient Accumulation

- Simulate large-batch training on limited GPU memory.
- How: accumulate gradients over k mini-batches before optimizer step.
- Result:
  - Stable updates
  - Bigger effective batch size without OOM.



Freezing Backbone

- Freeze pretrained backbone and train only head or adapter layers.
- Benefits:
  - Faster training
  - Lower memory
  - Less overfitting on small data



Knowledge Distillation (Teacher-Student Models)

- Knowledge distillation is a machine learning technique that aims to transfer the learnings of a large pre-trained model (teacher) to a smaller model (student).
- Why?
  - ≈ 95 % accuracy with < ½ parameters.
  - Memory & latency ↓ → deploy on edge/phone.
  - Decrease inference cost significantly.

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  - Decrease inference cost significantly.

Example: GPT-o3 → GPT-o3-mini

Knowledge Distillation (Teacher-Student Models)

There are many ways of doing distillation, but simplest way is:

1. Inference teacher on large unlabeled pool ⟶ soft logits.
2. Consider these logits as labels.
3. Train student on these labels with loss:

```
KLDiv(Student logits // Teacher logits)
```

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Thanks for Attending!

Prepared By: Mohamed Eltayeb