[0.3] Optimization, Hyperparameters, and Scale

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ARENA

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  2. Experiment tracking + hyperparameter sweeps with Weights & Biases.
  3. Distributed training — when one GPU isn't enough.

The training loop

- Same four steps every iteration: *forward*, *loss*, *backward*, *step*.

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for x, y in dataloader:
    y_hat = model(x)
    loss = loss_fn(y,y_hat)
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- `optimizer.step()` applies an update rule (e.g. Adam: momentum + per-parameter adaptive learning rate).
- `zero_grad()` before backward: gradients **accumulate** by default in PyTorch.

Loss landscapes & why this is hard

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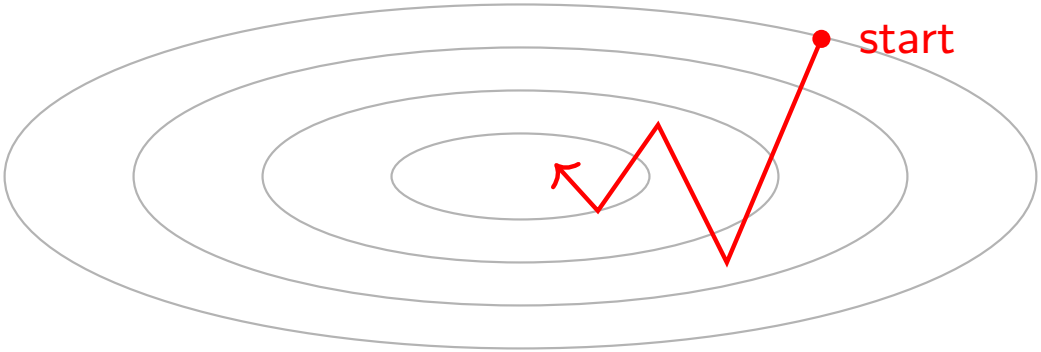
  - **Plateaus:** gradient is tiny; nothing moves.



ill-conditioned "ravine" — SGD zigzags

Gradient descent recap

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- **Batch size:**
  - Larger $\rightarrow$ (+) lower-variance gradient, better GPU utilization
  - Larger $\rightarrow$ (-) more memory, fewer optimizer steps per epoch, often worse generalization at scale

SGD

$$\theta_{t+1} = \theta_t - \alpha\, g_t$$

```
class SGD(Optimizer):
    def __init__(self, params, lr):
        self.params = list(params)
        self.lr = lr

    @torch.no_grad()
    def step(self):
        for p in self.params:
            p = p - self.lr * p.grad  # SGD update

    def zero_grad(self):
        for p in self.params:
            p.grad.zero_()
```

Momentum

SGD with momentum

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- Equivalent picture: a ball with mass rolling down the landscape. Reaches a *terminal velocity* along consistent directions.

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- distill.pub/2017/momentum has a beautiful interactive on this.

RMSprop

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$$s_{t+1} = \beta\, s_t + (1-\beta)\left(\nabla_\theta \mathcal{L}\right)^2$$

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- **Memory cost:** s_t is parameter-sized $\Rightarrow 2\times$ memory vs SGD.

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Adam vs AdamW: the weight-decay subtlety

- **Naive weight decay:** add $\frac{\lambda}{2}\|\theta\|^2$ to the loss. Looks innocent, but for adaptive methods, the L2 gradient $\lambda\theta$ gets divided by $\sqrt{\hat{v}_t}$ along with everything else — so parameters with large historical gradients are decayed less. Not what you want.

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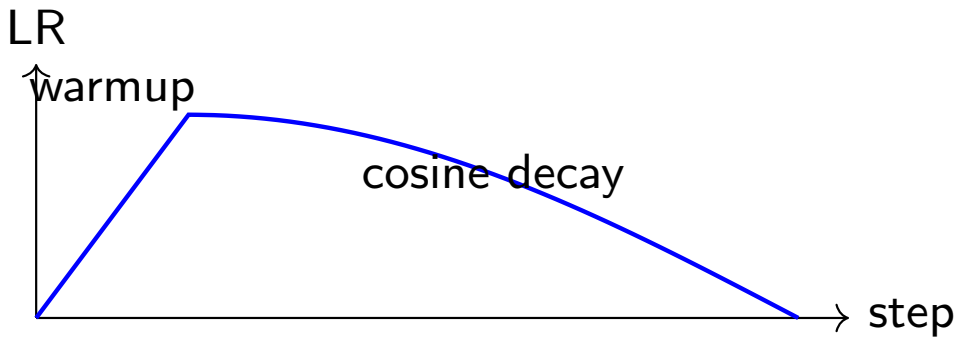
- In practice: just use `AdamW`.

Schedules & parameter groups

- Fixed LR is fine for toy problems. Real training uses a **schedule**: warmup (linear ramp from 0) + decay (cosine or linear).

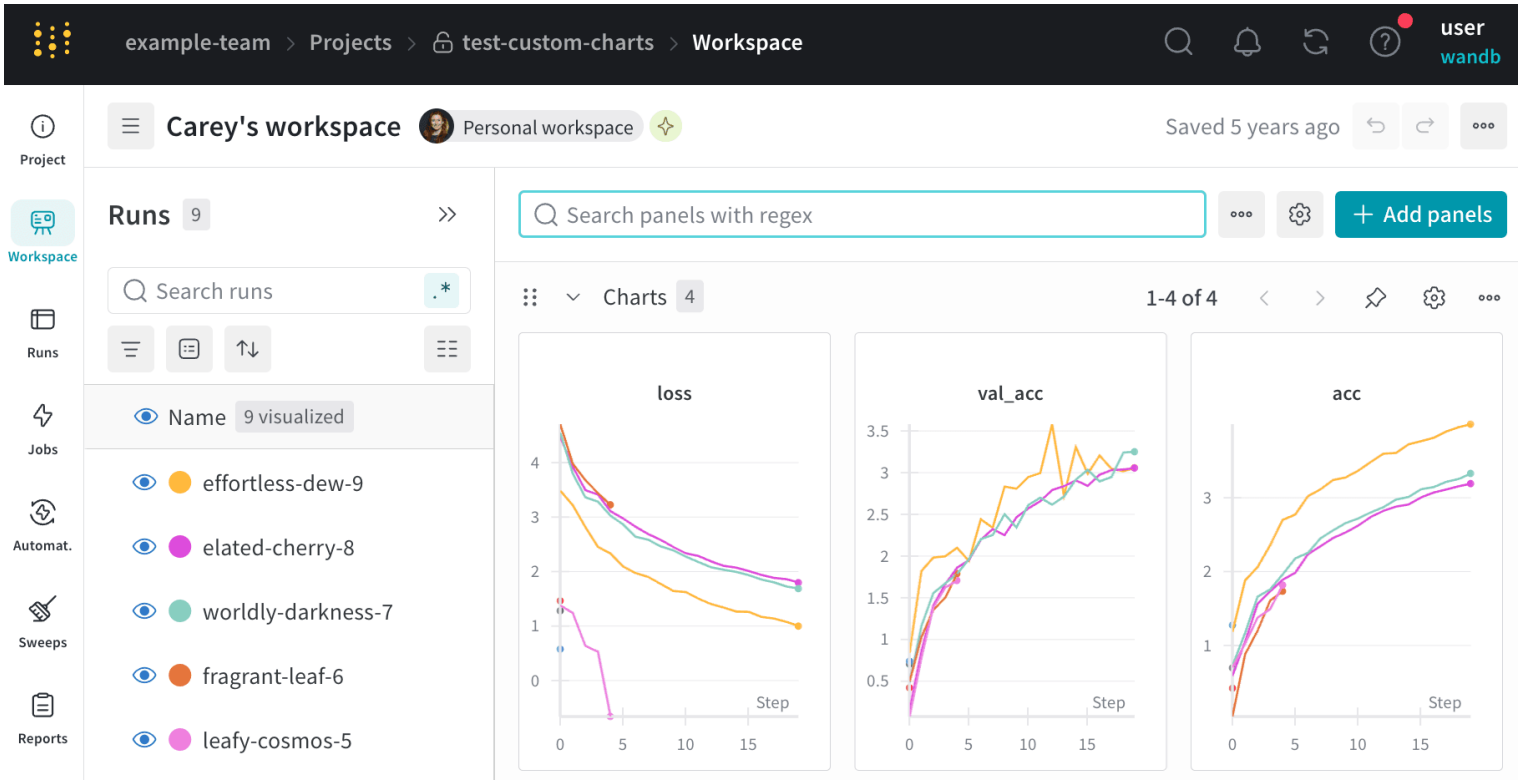


- **Parameter groups:** different learning rates for different parts of the model. Common in fine-tuning (slow backbone, fast head):

```
optimizer = torch.optim.AdamW([
    {"params": backbone.parameters(), "lr": 1e-5, "weight_decay": 0.01},
    {"params": head.parameters(),     "lr": 1e-3, "weight_decay": 0.0},
])
```

Why track experiments? Weights & Biases

- WandB is the de-facto tool: can easily track and log loss, accuracy etc. while the model is training

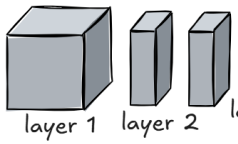


Parallel processes:

process 1
process 2
process 3
⋮

(each represents computations happening on a different GPU)

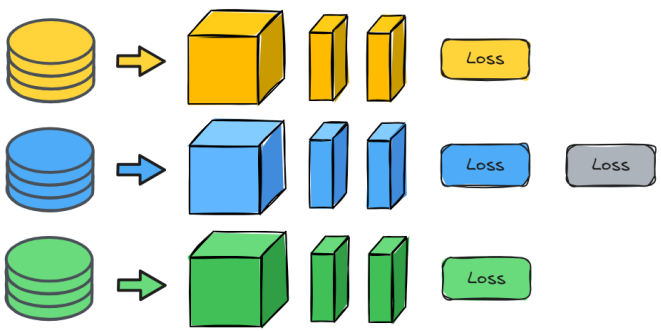
Model:



(each layer is a sequential step)

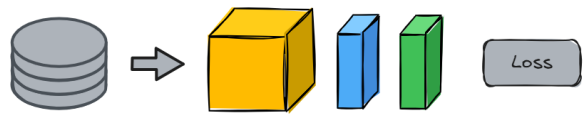
Data Parallelism

- Splitting batches of data across processes
- Easiest form to implement & manage; supported by PyTorch



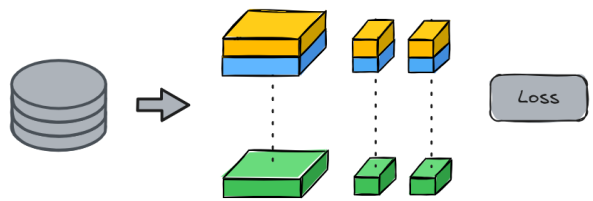
Pipeline Parallelism / Vertical Model Parallelism

- Splitting model into serialized stages, e.g. layers
- Requires careful management of inter-stage latency
- Natively supported by PyTorch: torch.distributed.pipelining



Tensor Parallelism / Horizontal Model Parallelism

- Splitting model into parallel stages (often splitting parameters into shards)
- Most complex to implement (requires fine-grained control over computations)
- Experimentally supported by PyTorch: torch.distributed.tensor.parallel



Glossary

- **Optimizer**: the rule for turning $\nabla \mathcal{L}$ into a parameter update.
- **Learning rate** α: step size. The most important dial.
- **Momentum** (μ): exponentially weighted average of past gradients.
- **Weight decay** (λ): shrink parameters toward zero each step.
- **Adam**: momentum + per-parameter adaptive LR + bias correction.
- **AdamW**: Adam with decoupled weight decay. Use by default.
- **LR schedule**: warmup then decay; pretty much always.
- **Parameter group**: subset of parameters with its own LR / weight decay.
- **WandB**: experiment-tracking dashboard
- **Sweep**: automated hyperparameter search