[0.2] CNNs and ResNets

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ARENA

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  5. Feature extraction: stand on the shoulders of pretrained giants.

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- Interpretability work later: knowing exactly what the model is made of is the prerequisite for taking it apart.

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```
class Linear(nn.Module):
    def __init__(self, d_in, d_out):
        super().__init__()
        # define parameters here
        self.W = nn.Parameter(torch.randn(d_out, d_in))
        self.b = nn.Parameter(torch.zeros(d_out))

    def forward(self, x):
        # defines what the module does
        y = einsum(x, self.W, "... d_in, d_out d_in -> ... d_out") + self.b
        # equiv. y = x @ self.W.T + self.b
        return y

>>> module = Linear(d_in=3, d_out=5)
>>> module(x) #equiv. to module.forward(x)
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- Modules can nest other modules; used often today

The training loop

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

```
for x, y in dataloader:                    # sample data in batches
    y_hat = model(x)                       # forward pass through model
    loss = my_loss_function(y,y_hat)       # how good was the model?
    loss.backward()                        # compute gradient of loss w.r.t parameters
    optimizer.step()                       # update parameters to decrease loss
    optimizer.zero_grad()                  # reset gradients before next batch
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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.

Cross-entropy loss

- Model outputs logits $z \in \mathbb{R}^K$; convert to probabilities with softmax:

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- PyTorch's `F.cross_entropy` takes *logits directly* and fuses softmax + log internally for numerical stability.

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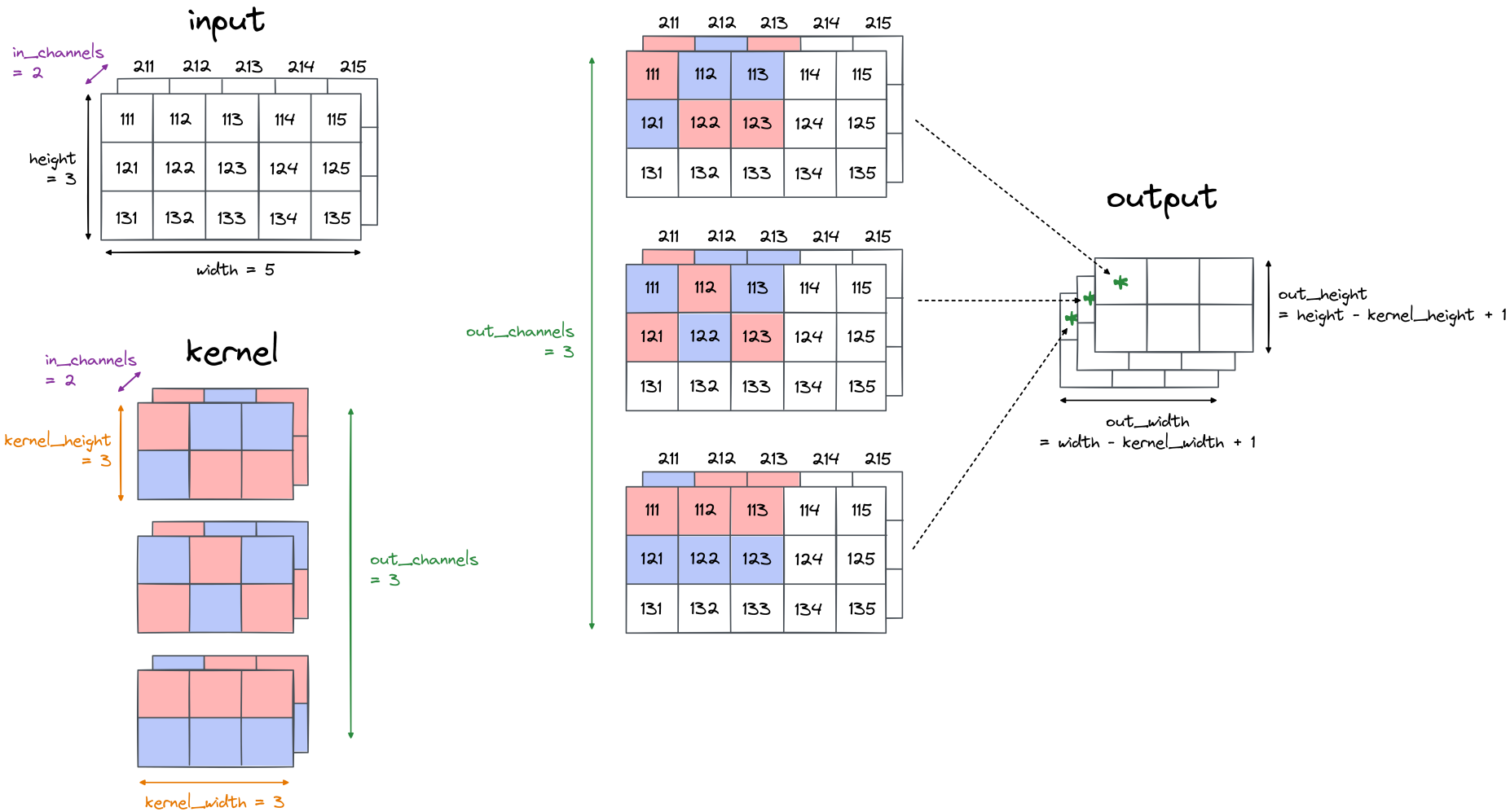
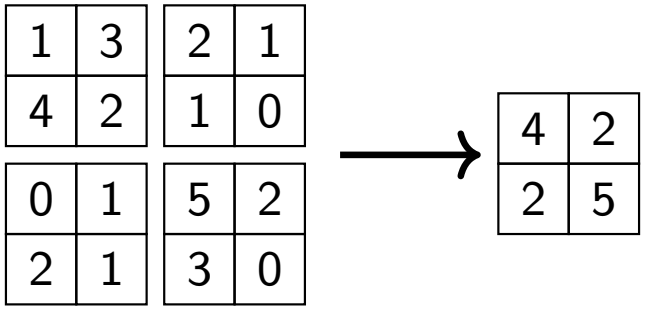
- Same idea, different domain: this is to images what attention is to sequences.


input
in_channels
= 2
211 212 213 214 215
111 112 113 114 115
121 122 123 124 125
131 132 133 134 135
height
= 3
width = 5
kernel
in_channels
= 2
kernel_height
= 3
kernel_width = 3
out_channels
= 3
out_channels
= 3
output
out_height
= height - kernel_height + 1
out_width
= width - kernel_width + 1

MaxPool

- **Pooling** downsamples a feature map; we replace each $k \times k$ window with its maximum:



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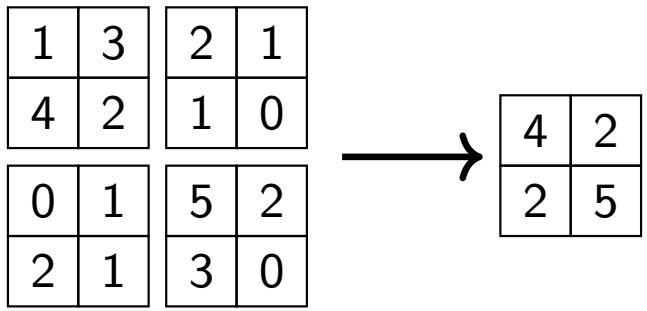

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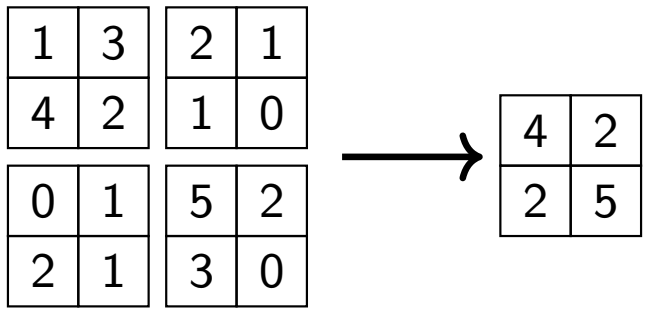

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- Used between conv stages to gradually trade spatial resolution for channel depth.

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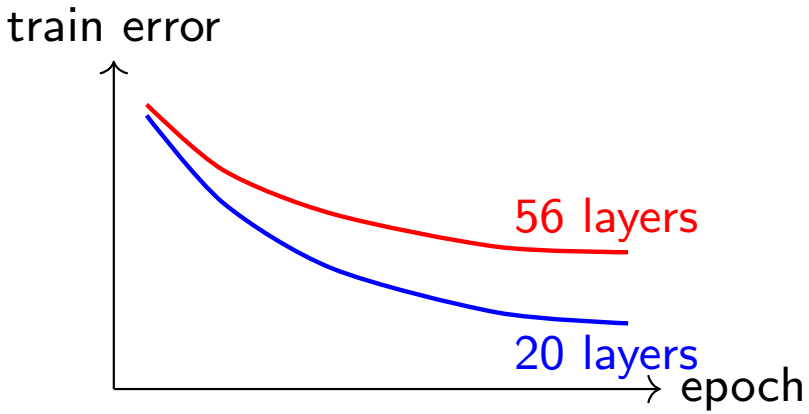

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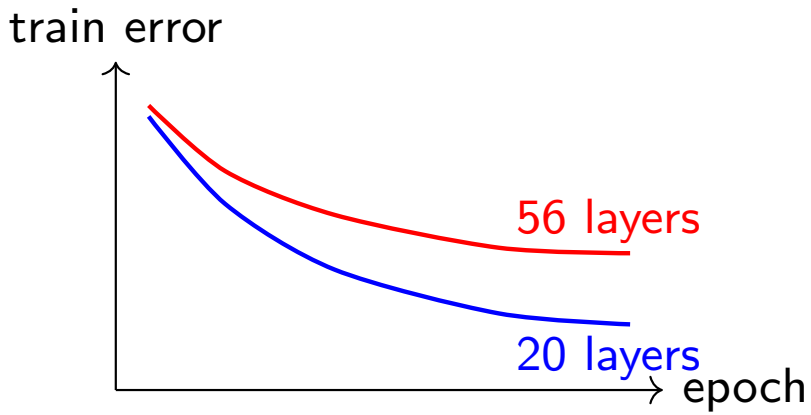

- Gradients struggle to propagate cleanly through many layers; identity is hard to *learn* from scratch.

Skip connections (residual learning)

- **Idea:** make identity the *default*. Each block learns a residual $F(x)$ added to its input.

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- Now training 100+ layer networks is routine.

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- Today: take your ResNet34, freeze it, retrain the head on CIFAR-10.

Glossary

- **Module** (`nn.Module`): bundle of parameters + a `forward`. Composable.
- **Parameter** vs **Buffer**: both stored in `state_dict`; only Parameters get gradients.
- **ReLU**: $\max(0, x)$. The default nonlinearity.
- **Linear**: $y = Wx + b$. Kaiming-init for ReLU nets.
- **Cross-entropy**: $\mathcal{L} = -\log \hat{p}_{y^*}$.
- **Conv2d**: kernel + stride + padding sliding over spatial dims.
- **MaxPool**: take the max over a $k \times k$ window; no params.
- **BatchNorm**: normalize per channel; learned γ, β; running stats in eval mode.
- **Residual block**: $y = F(x) + x$. Identity is the default.
- **Training step:** forward $\rightarrow$ loss $\rightarrow$ `backward` $\rightarrow$ `step` $\rightarrow$ `zero_grad`.
- **Feature extraction:** freeze backbone, train new head on a new task.

The whole point of today: build each row above yourself, so by the end none of it is a black box.