CS498: Algorithmic Engineering

Lecture 23: PyTorch in Practice, CNNs & Language Modeling

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Week 13

Outline

1. PyTorch in Practice
2. Convolutional Neural Networks
3. (Only if there is time) Beyond Images: Sequence Data

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2 Convolutional Neural Networks

3 (Only if there is time) Beyond Images: Sequence Data

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Today: practical APIs (`nn.Module`, `DataLoader`, training loop), then CNNs for images, then language modeling.

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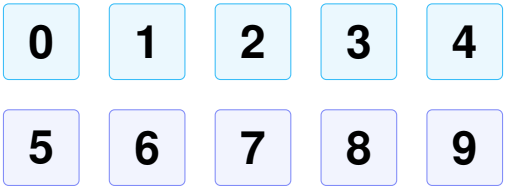

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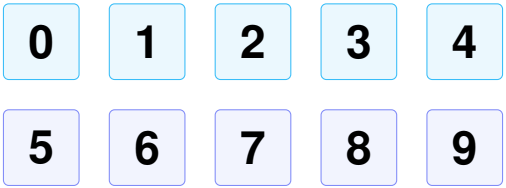

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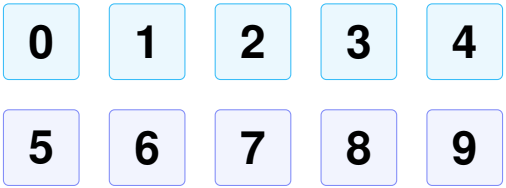

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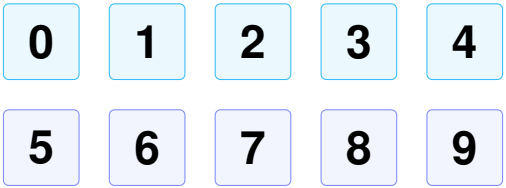

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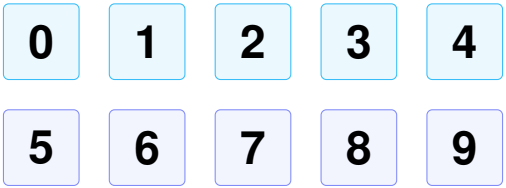

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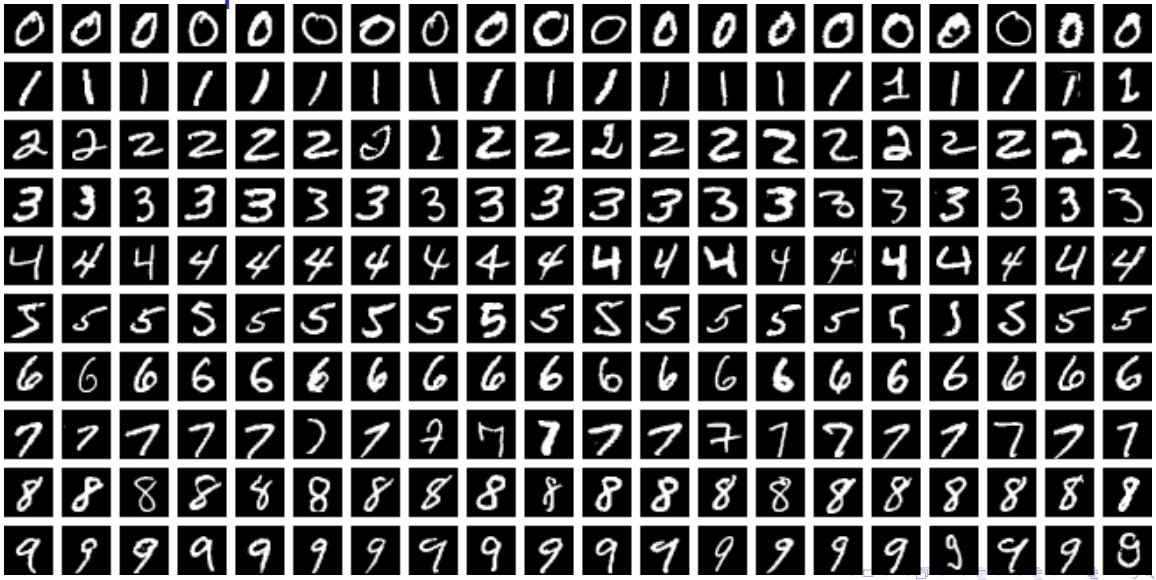
This is a **10-class classification** problem.

Some Samples



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This is the input vector to our MLP. Each of the 784 entries is one pixel.

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    nn.Flatten(), #(batch_size x 784)
    nn.Linear(784, 256), #(784 x 256)
    nn.ReLU(), #Relu activation
    nn.LayerNorm(256), #Add layer normalization, can also use nn.RMSNorm
    nn.Dropout(0.1), #Add dropout
    nn.Linear(256, 256), #(256, 256)
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Trade-off: simpler code, but no residual connections or branching. Use `nn.Sequential` for simple stacks.

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```python
import torch.nn as nn

class CustomSuperDuperMLP(nn.Module):
    def __init__(self):
        super().__init__()
        self.flatten = nn.Flatten()
        self.block1 = nn.Sequential(nn.Linear(784, 256), nn.ReLU(),nn.LayerNorm(256), nn.Dropout(0.1))
        self.block2 = nn.Sequential(nn.Linear(256, 256), nn.ReLU(),nn.LayerNorm(256), nn.Dropout(0.1))
        self.head = nn.Linear(256, 10)

    def forward(self, x):
        x = self.flatten(x)          # [B, 1, 28, 28] -> [B, 784]
        h = self.block1(x)           # [B, 784] -> [B, 256]
        h = self.block2(h) + h       # residual connection!
        return self.head(h)          # [B, 256] -> [B, 10]
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Notice: **LayerNorm**, **Dropout**, and a **residual connection**.

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Calling `model(x)` invokes `model.forward(x)` automatically.

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For reference: GPT-3 has 175B parameters. GPT-4 is estimated at $\sim$1.8 trillion.

DataLoader: Batching and Shuffling

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from torchvision import datasets, transforms
from torch.utils.data import DataLoader

transform = transforms.Compose([
    transforms.ToTensor(),             # PIL image -> tensor, scales to [0,1]
])

train_data = datasets.MNIST('data', train=True,  download=True, transform=transform)
test_data  = datasets.MNIST('data', train=False, download=True, transform=transform)

train_loader = DataLoader(train_data, batch_size=64, shuffle=True)
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`Normalize((mean,), (std,))`: centers and scales pixel values. `DataLoader` handles: batching (64 images per batch), shuffling (randomize each epoch), parallel loading (`num_workers`).

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optimizer = torch.optim.AdamW(model.parameters(), lr=1e-3)
loss_fn = nn.CrossEntropyLoss()

model.train()
for epoch in range(10):
    for images, labels in train_loader:
        images, labels = images.to(device), labels.to(device)  # data to GPU
        logits = model(images)             # 1. forward pass
        loss = loss_fn(logits, labels)     # 2. compute loss
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We use `AdamW` (from Lecture 21). `model.train()` enables Dropout and sets LayerNorm to training mode.

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`nn.CrossEntropyLoss` does softmax + log + negate in one **numerically stable** operation.

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with torch.no_grad():              # don't track gradients
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Result: $\sim$**98%** accuracy on MNIST with our simple MLP.

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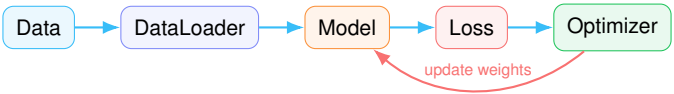

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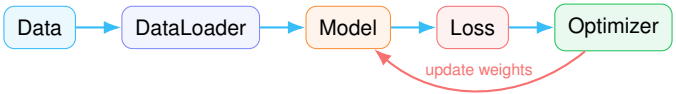

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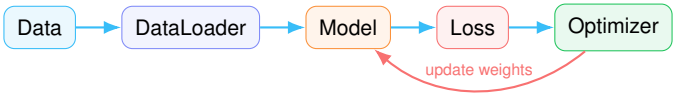

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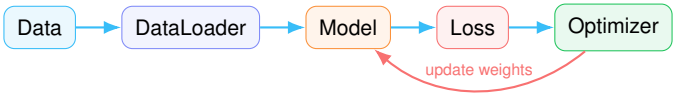

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Want to classify cats vs. dogs? Swap the dataset and adjust the model. Want to predict stock prices? Same thing.

1 PyTorch in Practice

2 Convolutional Neural Networks

3 (Only if there is time) Beyond Images: Sequence Data

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Idea: build these two properties *into the architecture itself*.

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This kernel computes: (left value) $-$ (right value). It is a **difference detector**. Negative output $\Rightarrow$ values increasing. Positive $\Rightarrow$ values decreasing.

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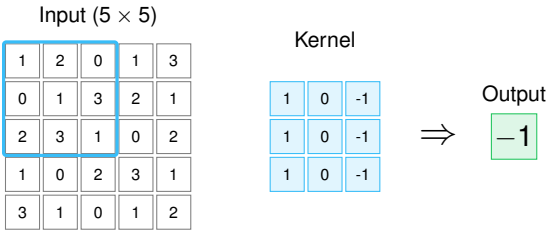

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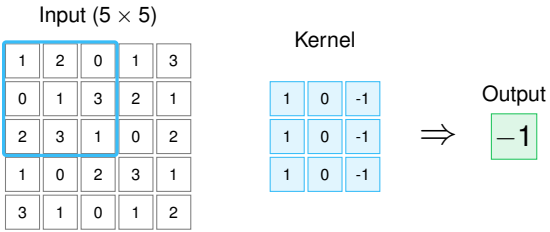

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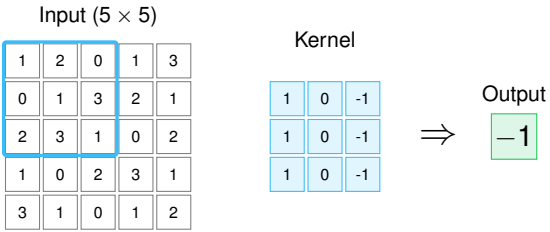

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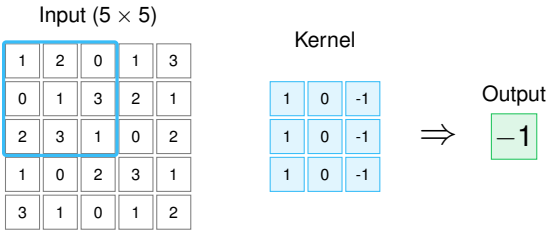

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A 5×5 input with a 3×3 kernel $\Rightarrow (5 - 3 + 1) \times (5 - 3 + 1) = 3 \times 3$ output.

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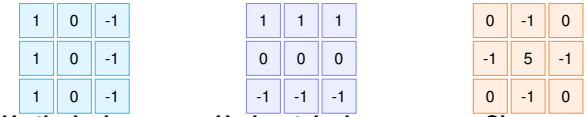

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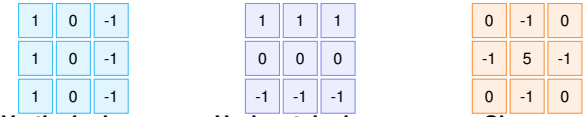

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The network discovers which patterns are useful for the task through gradient descent.

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The network does not need to re-learn the same pattern at every location.

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Each kernel learns to respond to a different kind of visual pattern (for example: an edge, a corner, or a texture).

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With 32 kernels of size 3×3: `[64, 3, 32, 32]` $\Rightarrow$ `[64, 32, 30, 30]`

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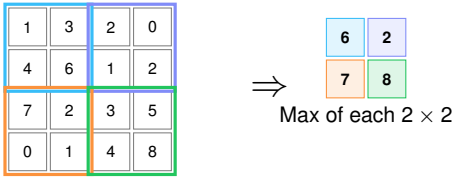

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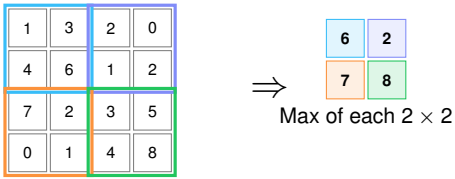

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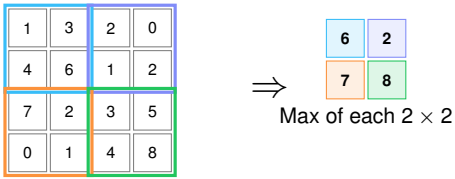

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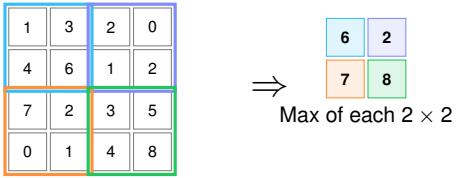

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Purpose: reduces computation, adds some translation tolerance. If a feature was detected *anywhere* in the 2×2 region, the max captures it.

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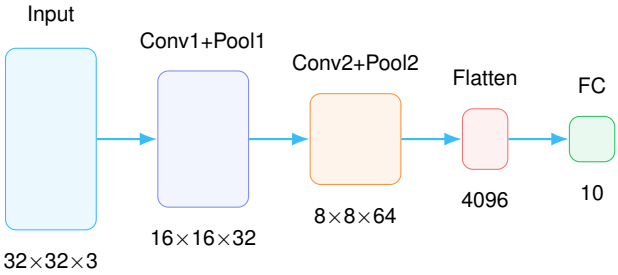
`padding=0`: output shrinks (default).
`padding=1` with a 3×3 kernel: output size = input size.

A CNN Architecture



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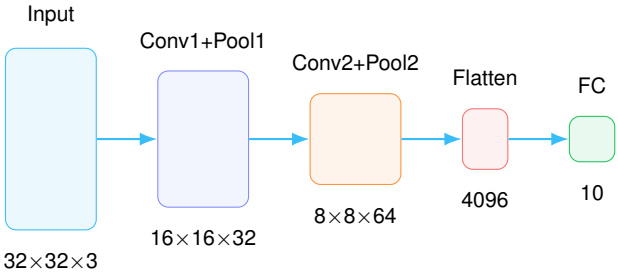

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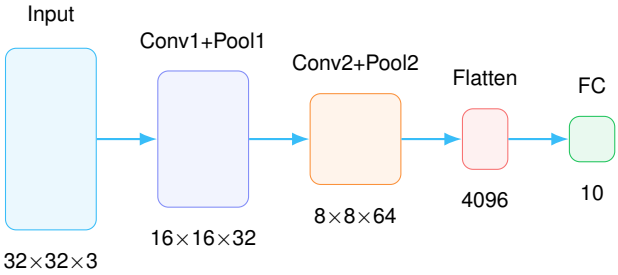

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- Conv1: 32 kernels, 3×3, stride 1, padding 1 $\Rightarrow 32 \times 32 \times 32$
- Pool1: 2×2, stride 2 $\Rightarrow 16 \times 16 \times 32$
- Conv2: 64 kernels, 3×3, stride 1, padding 1 $\Rightarrow 16 \times 16 \times 64$
- Pool2: 2×2, stride 2 $\Rightarrow 8 \times 8 \times 64$

CNN in PyTorch

```python
class CNN(nn.Module):
    def __init__(self):
        super().__init__()
        self.features = nn.Sequential(
            nn.Conv2d(3, 32, kernel_size=3, padding=1),  # [B,3,32,32] -> [B,32,32,32]
            nn.ReLU(),
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        )
        self.classifier = nn.Sequential(
            nn.Flatten(),                                # [B,64,8,8] -> [B,4096]
            nn.Linear(64 * 8 * 8, 256), nn.ReLU(), nn.Dropout(0.3),
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    def forward(self, x):
        x = self.features(x)
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`Conv2d(in_channels, out_channels, kernel_size, padding)`

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            nn.Conv2d(3, 32, kernel_size=3, padding=1),  # [B,3,32,32] -> [B,32,32,32]
            nn.ReLU(),
            nn.MaxPool2d(2),                             # [B,32,32,32] -> [B,32,16,16]
            nn.Conv2d(32, 64, kernel_size=3, padding=1), # [B,32,16,16] -> [B,64,16,16]
            nn.ReLU(),
            nn.MaxPool2d(2),                             # [B,64,16,16] -> [B,64,8,8]
        )
        self.classifier = nn.Sequential(
            nn.Flatten(),                                # [B,64,8,8] -> [B,4096]
            nn.Linear(64 * 8 * 8, 256), nn.ReLU(), nn.Dropout(0.3),
            nn.Linear(256, 10)
        )

    def forward(self, x):
        x = self.features(x)
        return self.classifier(x)
```

`Conv2d(in_channels, out_channels, kernel_size, padding)`

`MaxPool2d(2)` halves spatial dimensions. `Flatten()` collapses [C, H, W] into one dim.

CNN in PyTorch

```python
class CNN(nn.Module):
    def __init__(self):
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        self.features = nn.Sequential(
            nn.Conv2d(3, 32, kernel_size=3, padding=1),  # [B,3,32,32] -> [B,32,32,32]
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Shapes are tracked in comments. Always verify your shapes!

Conv2d Parameters Explained

```
nn.Conv2d(in_channels, out_channels, kernel_size, stride=1, padding=0)
```

Conv2d Parameters Explained

`nn.Conv2d(in_channels, out_channels, kernel_size, stride=1, padding=0)`

`in_channels`	Number of channels in the input (3 for RGB, 32 for a previous conv output)
`out_channels`	Number of kernels = number of output feature maps
`kernel_size`	Size of each kernel (3 means 3×3)
`stride`	Step size when sliding the kernel (default 1)
`padding`	Zeros added to each border (1 preserves spatial size for 3×3)

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Example: `Conv2d(3, 32, 3, padding=1)` has $32 \times 3 \times 3 \times 3 + 32 = 896$ parameters.

Residual Connections in CNNs: ResNets

Skip connections from Lecture 22, applied to conv blocks:

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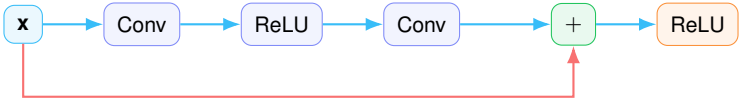

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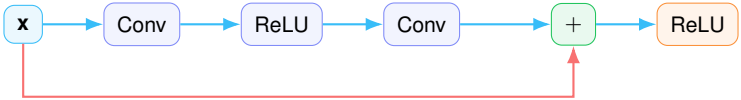

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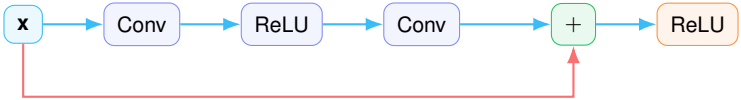

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ResNet (He et al., 2015): stack many residual blocks.

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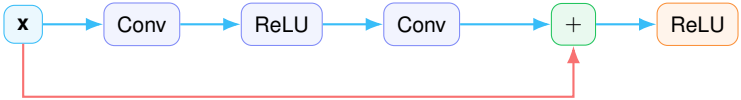

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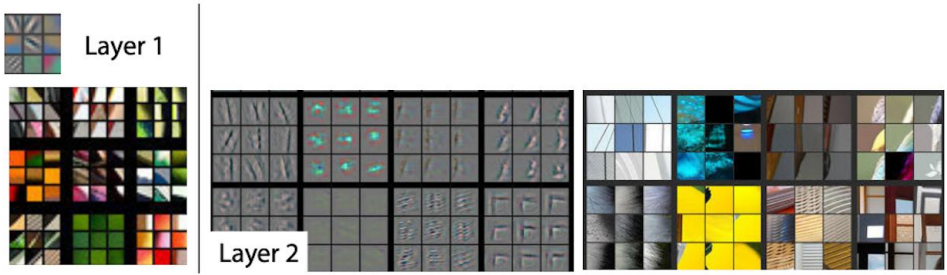
ResNet (He et al., 2015): stack many residual blocks.

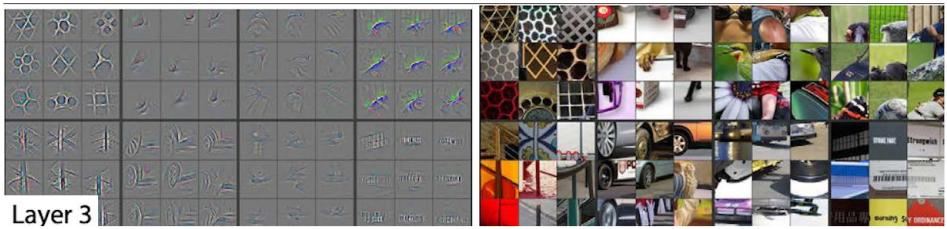
Model	Depth	ImageNet Top-5
ResNet-18	18 layers	10.9% error
ResNet-50	50 layers	7.1% error
ResNet-152	152 layers	5.7% error

What CNNs Learn: Early Layers



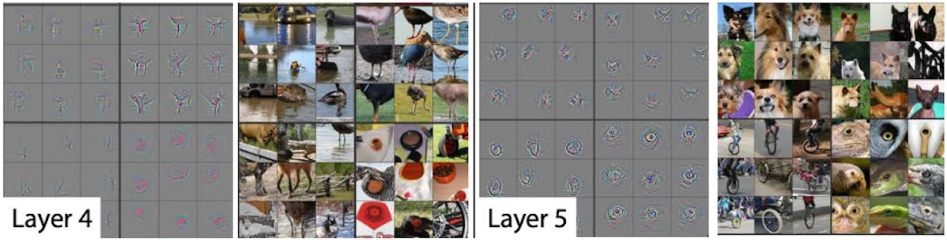
Early layers learn simple local detectors: **edges, color contrasts, and blobs.**

What CNNs Learn: Middle Layers



Middle layers combine simple detectors into **textures, corners, and repeated patterns.**

What CNNs Learn: Later Layers



Later layers respond to larger structures: **parts, motifs, and more semantic patterns.**

Takeaway

CNNs learn a **hierarchy of features**:

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Key point: we do not manually specify these detectors. We choose the architecture, and **training learns the useful features automatically**.

1. PyTorch in Practice
2. Convolutional Neural Networks
3. (Only if there is time) Beyond Images: Sequence Data

CNNs Are Great for Images. But...

Many important problems involve **sequences**, not grids:

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For language, we often need to connect words that are far apart: "The cat *that I saw yesterday at the park near the river* **was** orange."

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Language modeling: given previous words, predict the next one.

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Nearly all modern NLP is built on language modeling.

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Simple, fast, and they actually work reasonably well for short contexts.

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The question: can we learn a function that generalizes to contexts never seen in training?

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Next lectures:

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Next lectures:

Tokenization: how to represent text as numbers.

The attention mechanism: every token can look at every other token simultaneously.