Learning Deep Learning with PyTorch

(4) Convolutional Neural Networks

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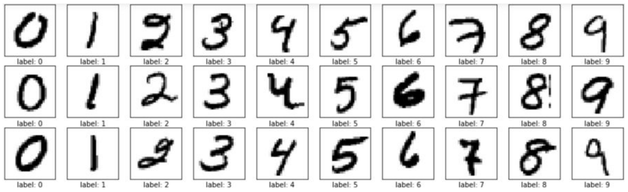
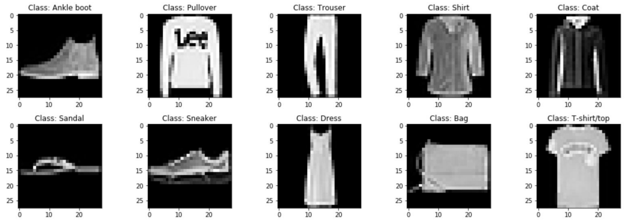
April 29, 2020

“Hello-World” Image Classification Problems

- MNIST dataset of handwritten digits
  - 28x28 pixel grey images
  - 10 classes
  - training set: 60,000, test set: 10,000



- Fashion MNIST dataset
  - 28x28 pixel grey images
  - 10 classes
  - training set: 60,000, test set: 10,000



- CIFAR-10
  - 32x32 pixel color images
  - 10 classes
  - training set: 50,000, test set: 10,000

Dogs vs. Cats Kaggle Challenge

- Redux: Kernels Edition
  - Submission scored by the probability of dogs using log loss

$$L = -\frac{1}{n}\sum_{i=1}^{n}\left[y_i \log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i)\right]$$

- Dataset
  - Training set: 25,000 dogs and cats images
  - Testing set: 12,500 images
  - Images with different sizes
    - Neural network needs fixed sized input.
    - We will resize images to 150x150 pixels
  - Images are colored
    - Represented by Red-Green-Blue channels
    - One image ⇒ 150x150x3 matrices

Digitalization for Color Images

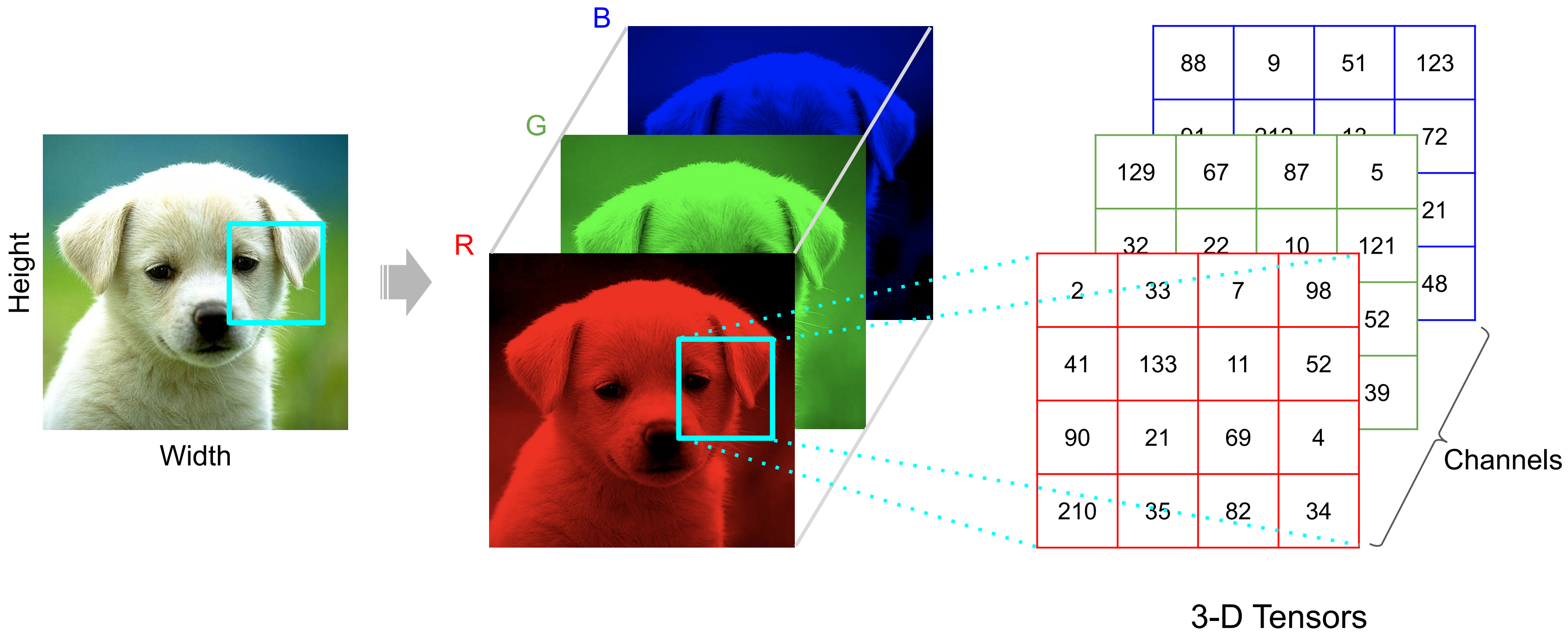


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Image data conversion in PyTorch

- PIL to convert JPG to PIL Image
  - pil.Image.open(path).convert('RGB')

- Resize to the uniform sizes for all images
  - torchvision.transforms.Resize((150, 150))

- Convert to tensors:
  - torchvision.transforms.ToTensor()
    - Indexes $(H \times W \times C) \Rightarrow (C \times H \times W)$
    - Range $[0, 255] \Rightarrow [0.0, 1.0]$

Python Image Library (PIL)

- Pillow as newer versions
- Various image processing
- Per-pixel manipulations

Torchvision is a package for computer vision, containing:

- Popular datasets
- Model architectures
- Image transformations

Datasets and Data loading

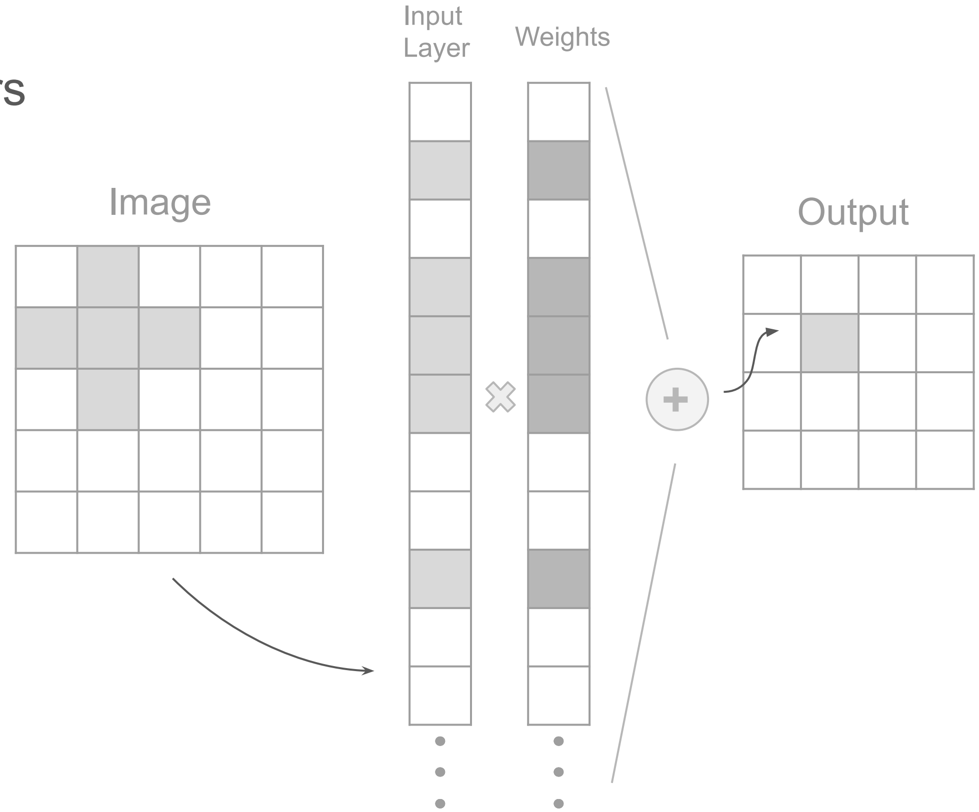
- Defining the dataset class
  - Subclassing torch.utils.data.Dataset
  - PyTorch dataset object requires 2 methods:
    - `__len__()`
    - `__getitem__()`
  - Wrapping conversions in `__getitem__()`

- Loading the dataset with `torch.utils.data.DataLoader`
  - Batching the data
  - Shuffling the data
  - Loading the data in parallel using multiprocessing workers

Limits of fully connected model

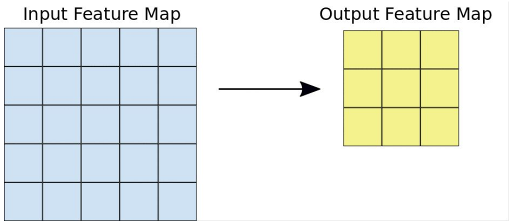
- Not scale well with pixel numbers
  - 1024x1024 RGB image
    One 1024-feature hidden layer
  - → 3 billion parameters
    → 12 GB ram for 32-bit floats
    → Hard to fit in a GPU

- Not translation-invariant
  - Shifting 1 pixel
    → Re-learn!

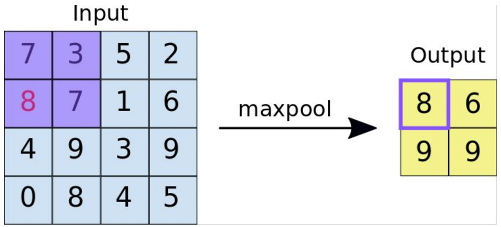


Convolutional Neural Networks (CNNs)

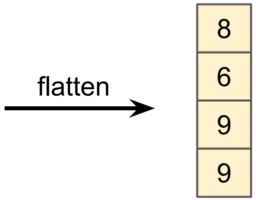
- A special network architecture
- 3 processes in CNNs:
    - Convolutions to extract as tiles



    - Poolings to downsample



    - Flattening



- Logic behind CNNs
    - Sparse connectivity (characteristic features in smaller local regions)
    - Parameter equivariance & sharing (features appear in different locations)
    - Translation invariance (some sampling will not lose main information)

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One Channel, One Filter

Kernel Matrix

0	-1	0
-1	5	-1
0	-1	0

0	0	0	0	0	0
0	105	102	100	97	96
0	103	99	103	101	102
0	101	98	104	102	100
0	99	101	106	104	99
0	104	104	104	100	98

Image Matrix

320				

Output Matrix

$$
\begin{aligned}
&0*0+0*-1+0*0\\
&+0*-1+105*5+102*-1\\
&+0*0+103*-1+99*0 \quad = 320
\end{aligned}
$$

Convolution with horizontal and vertical strides = 1

Multiple Channels

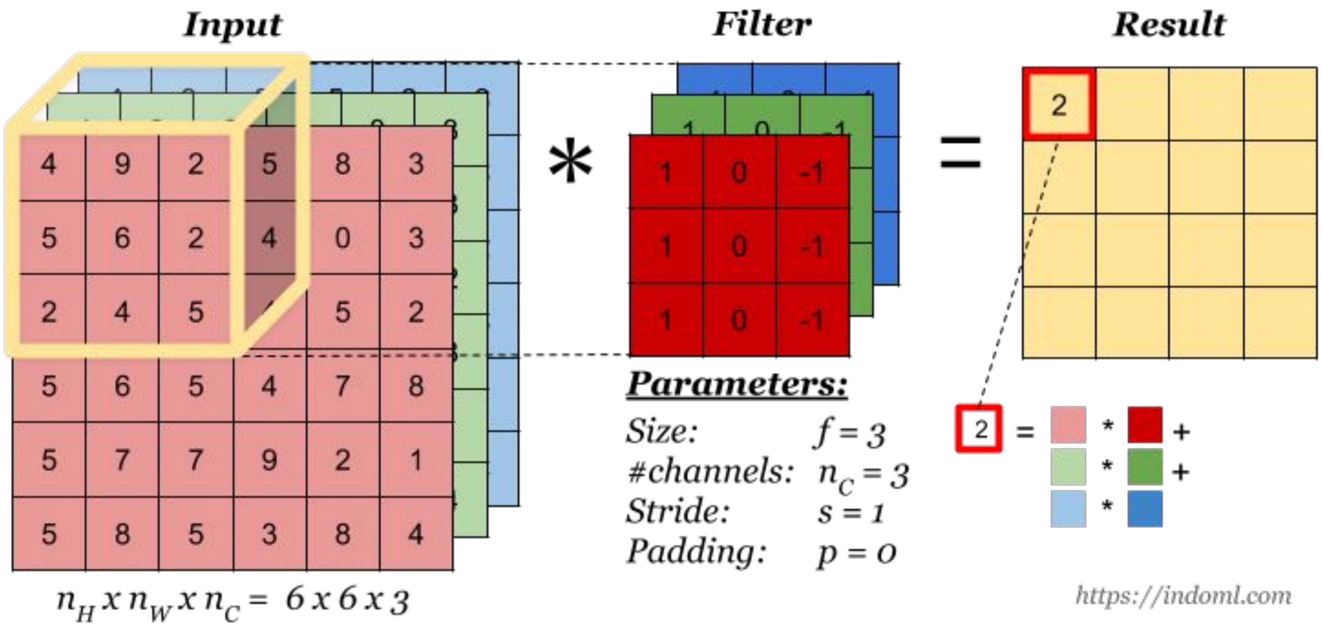
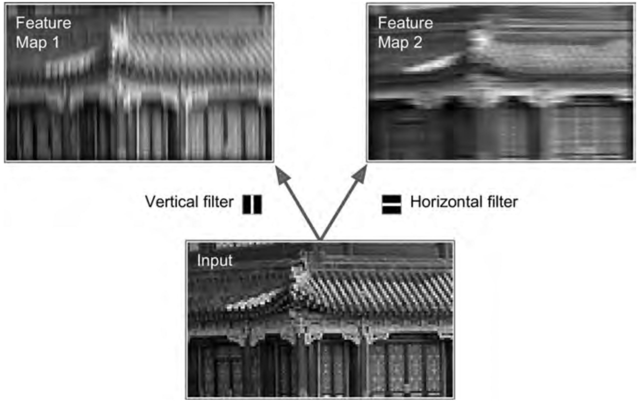
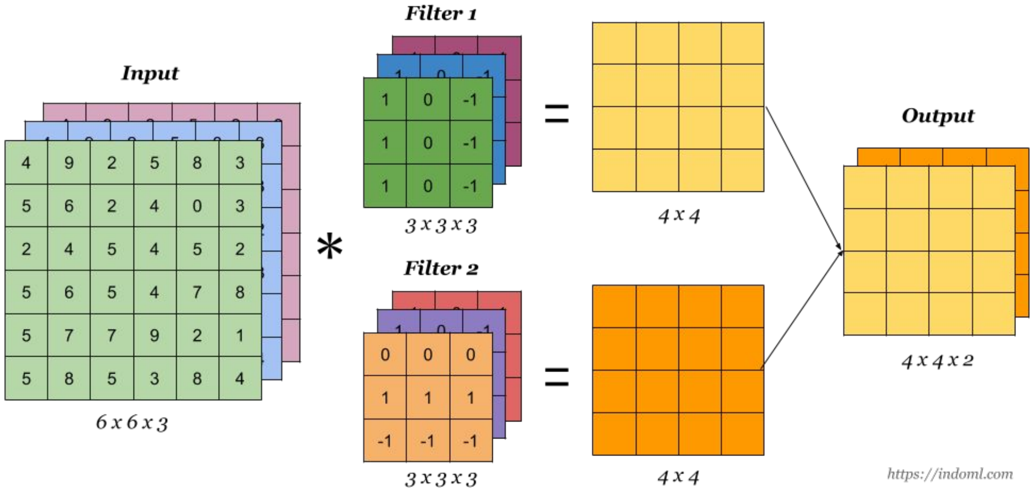


Figure Source

Multiple Filters





Figures from Aurélien Géron's [1st Ed. Book]

Figure [Source]

A Convolutional layer

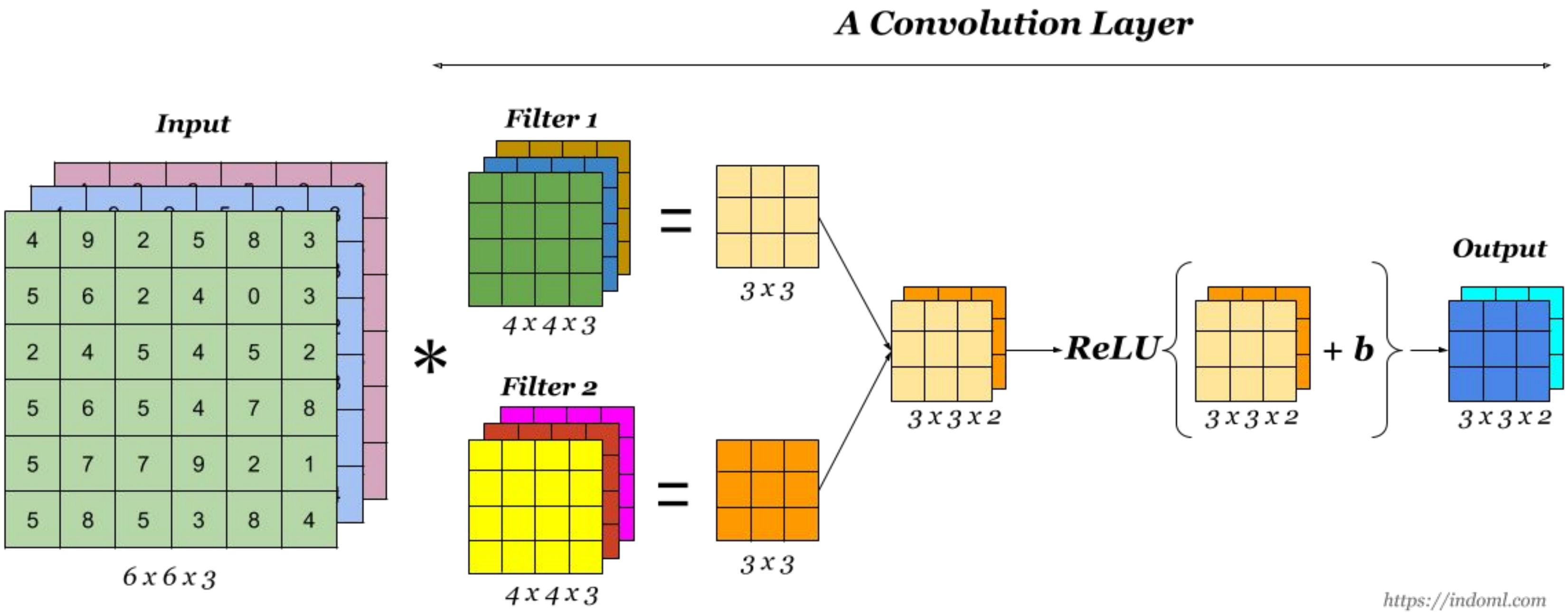


Figure Source

Pooling Layer

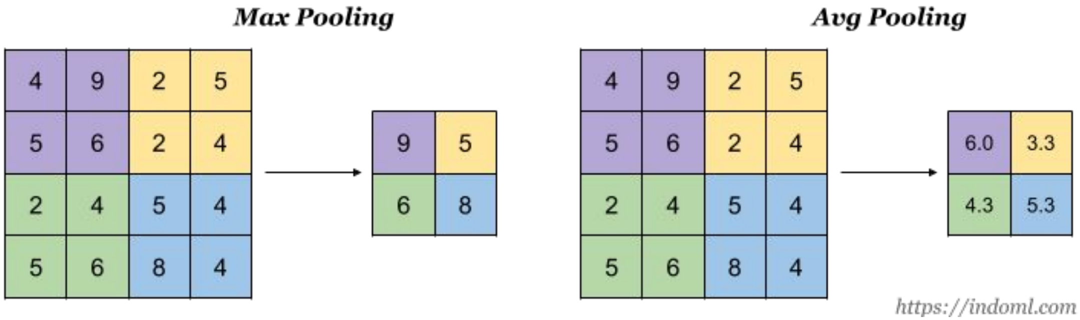
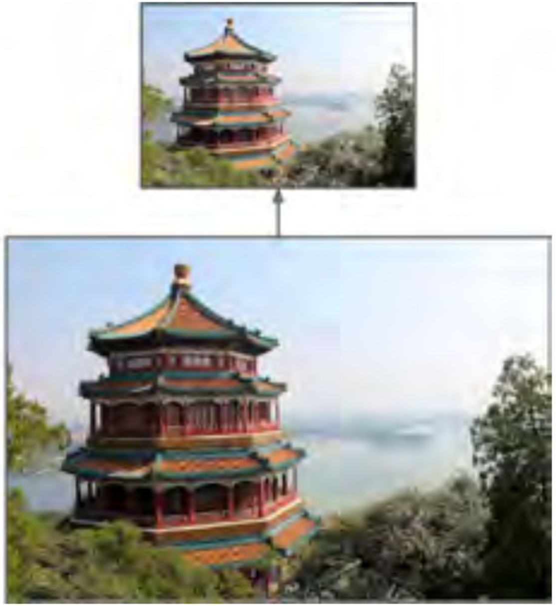


Figure Source



Figures from Aurélien Géron's 1st Ed. Book

- Assuming downsampling will not lose the major information.

Architecture of Convolutional Neural Networks

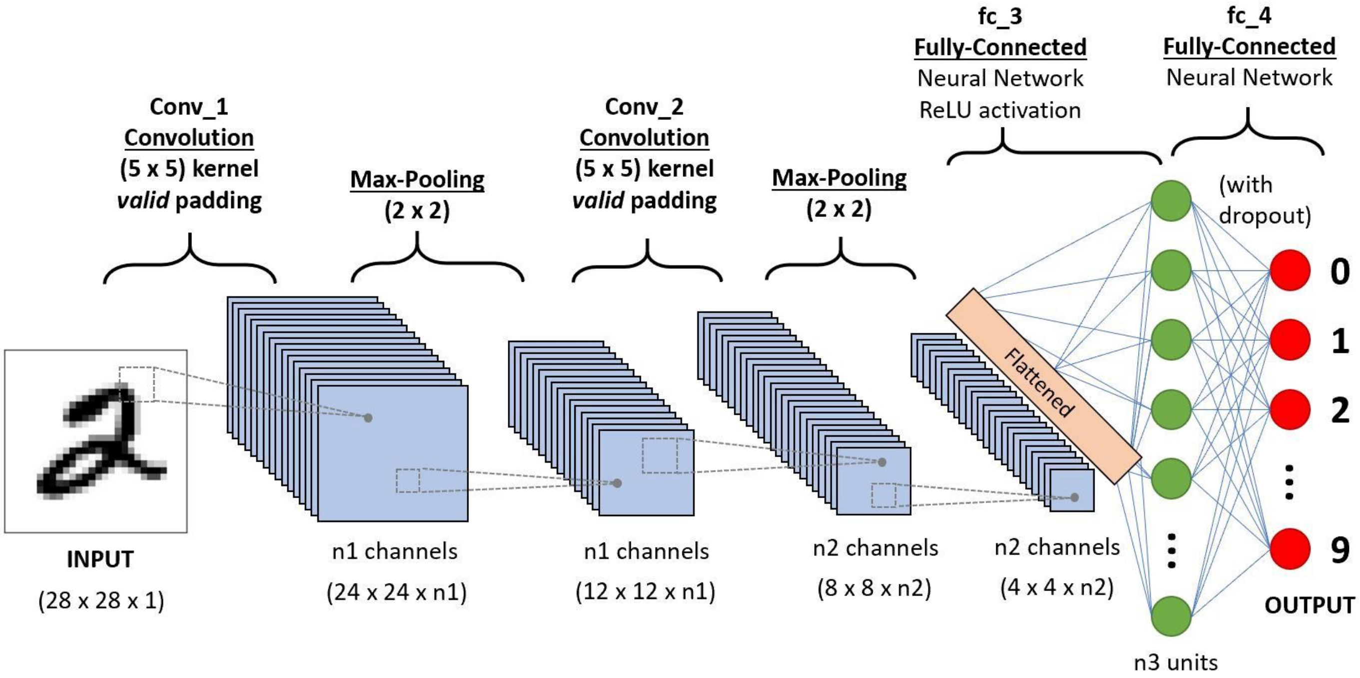
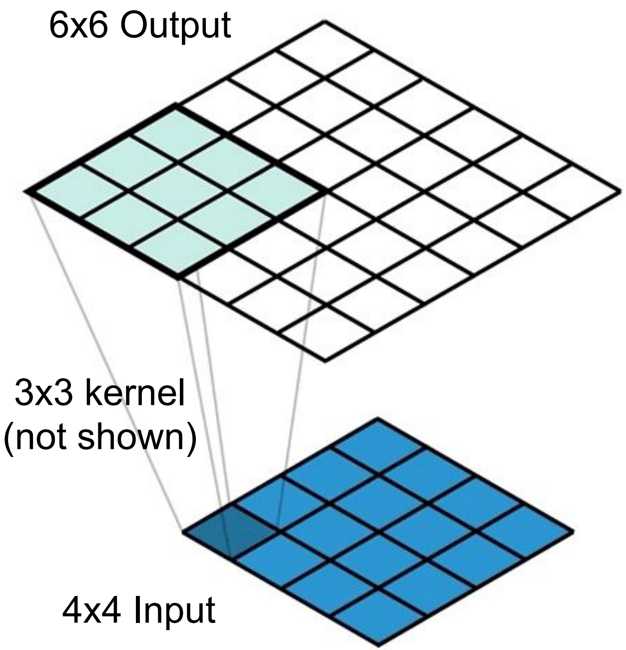
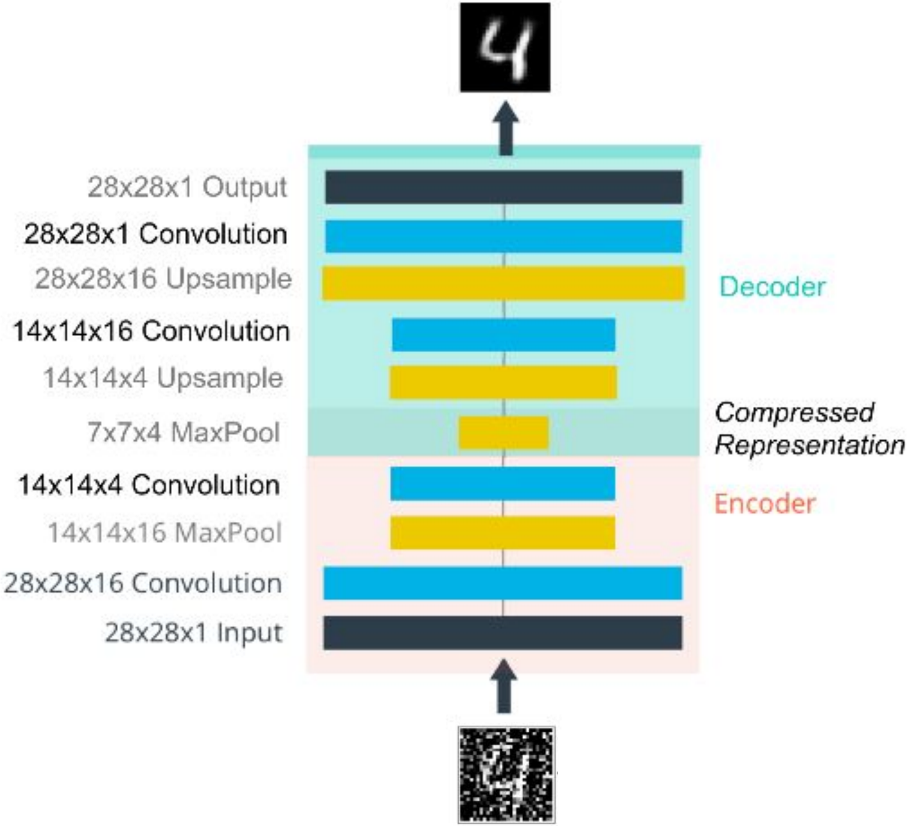


Figure Source

Convolution and "Deconvolution": Autoencoder





Construct CNN architecture for Dogs-vs.-Cats Problem

- 4 Convolution layers:

  [torch.nn.Conv2d(in_channels, out_channels, kernel_size, ...)]

  - Input size: (N, C_{in}, H, W)
  - Output size: $(N, C_{out}, H_{out}, W_{out})$
  - Activation function: torch.nn.functional.relu(...)

- MaxPooling layer:

  torch.nn.max_pool2d(...)

  - Kernel size: 2
  - Default: stride=None, padding=0, dilation=1

- Flattened layer
  - Manually flattening tensor by views

- Dense (linear) layer

  torch.nn.Linear(in_features, out_features)

  - Units: 512 and 2
  - Activation: ‘relu’ and ‘softmax’

```
class CatAndDogNet(nn.Module):
    def __init__(self):
        super().__init__()
        self.conv1 = nn.Conv2d(in_channels = 3, out_channels = 32, kernel_size=(3, 3))
        self.conv2 = nn.Conv2d(in_channels = 32, out_channels = 64, kernel_size=(3, 3))
        self.conv3 = nn.Conv2d(in_channels = 64, out_channels = 128, kernel_size=(3, 3))
        self.conv4 = nn.Conv2d(in_channels = 128, out_channels = 128, kernel_size=(3, 3))
        self.fc1 = nn.Linear(in_features= 128 * 7 * 7, out_features=512)
        self.fc2 = nn.Linear(in_features=512, out_features=2)

    def forward(self, X):
        X = F.relu(self.conv1(X))
        X = F.max_pool2d(X, 2)

        X = F.relu(self.conv2(X))
        X = F.max_pool2d(X, 2)

        X = F.relu(self.conv3(X))
        X = F.max_pool2d(X, 2)

        X = F.relu(self.conv4(X))
        X = F.max_pool2d(X, 2)

        X = X.view(-1, self.num_flat_features(X))
        X = F.relu(self.fc1(X))
        X = self.fc2(X)
        return X

    def num_flat_features(self, x):
        size = x.size()[1:]  # all dimensions except the batch dimension
        num_features = 1
        for s in size:       # Get the products
            num_features *= s
        return num_features
```

(148,148,32)

(74,74,32)

(72,72,64)

(7,7,128)

6272

Save and Load the model in PyTorch

- Need to save the trained model
  - Colab's active session time is limited.
  - Models can be re-used at user's end (e.g. browser with tf.js or phone with tf.lite)
- PyTorch's 3 core functions:
  - torch.save: saves a serialized object to disk
  - torch.load: deserializes pickled object files to memory
  - torch.nn.Module.load_state_dict: loads parameters using a deserialized state_dict
- Recommended usage (for inference):
  - torch.save(model.state_dict(), PATH)
  - model.load_state_dict(torch.load(PATH))
  - model.eval()
- Saving & loading a checkpoint for resuming training (link)

Before running the colab demo in this workshop

1. Register a Kaggle account
    - Kaggle.com → “Register”

2. Create Kaggle API token and download json file
    - Sign in → Your Profile → “Account” → “Create New API Token”

3. Join the competition → “Join Competition”
    - Dogs-vs-Cats Challenge

Colab Hands-on

[bit.ly/LDL_02](bit.ly/LDL_02)

Don’t forget to

- Github Repo:
  - https://github.com/huqy/idre-learning-deep-learning-pytorch
- Slack workspace:
  - bit.ly/join-LDL
- Contact me
  - huqy@idre.ucla.edu
  - Direct message in Slack
- IF you don’t have plan to attend the rest of workshops,:
  - Please fill out our series survey: bit.ly/2X2phyS