# Deep Learning

## 10 Building Blocks of CNNs

Dr. Konda Reddy Mopuri
Dept. of AI, IIT Hyderabad
Jan-May 2023

# CNNs



- The Convolutional Neural Networks

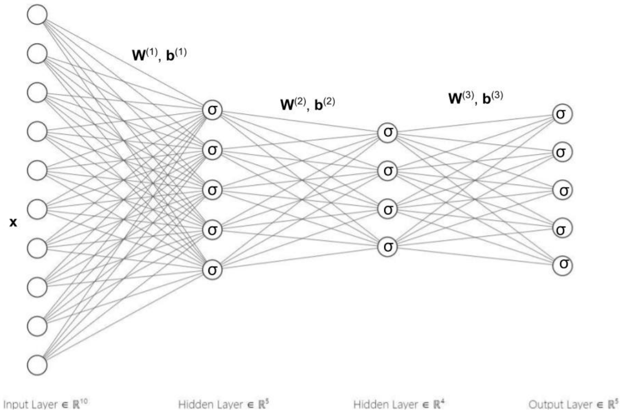
# CNNs



- The Convolutional Neural Networks
- Class of ANNs that are Shift/Space invariant
  - Makes CNNs very well suited for *Signal Processing* (Why?).

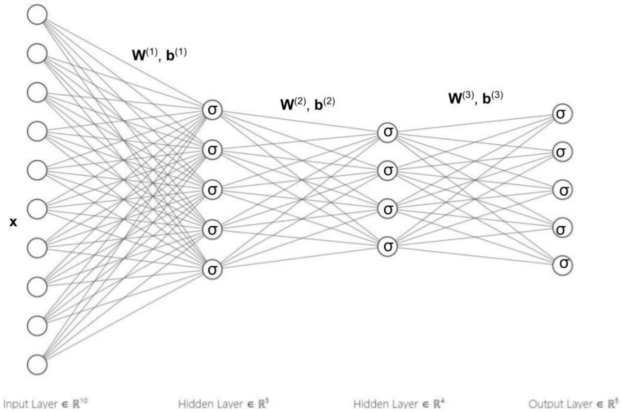
# An MLP

- Input is a vector



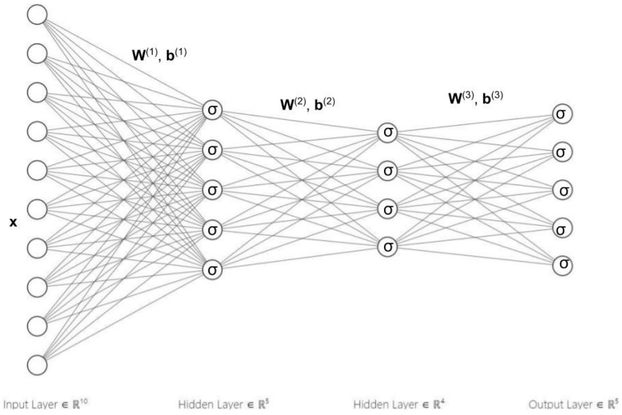
# An MLP

- Input is a vector
- Series of densely connected hidden layers



# An MLP

- Input is a vector
- Series of densely connected hidden layers
- Neurons in each layer are independent!



# An MLP for processing an image

- Say, we want to process a $200 \times 200$ RGB image

# An MLP for processing an image

- Say, we want to process a $200 \times 200$ RGB image
- Vectorizing leads to $200 \times 200 \times 3 \rightarrow 120K$ neurons in the input layer

# An MLP for processing an image

- Say, we want to process a $200 \times 200$ RGB image
- Vectorizing leads to $200 \times 200 \times 3 \rightarrow 120K$ neurons in the input layer
- A hidden layer of same size leads to $\approx 1.44e^{10}$ weights $\rightarrow \approx 58GB$ :-(

# An MLP for processing an image

- Full connectivity blows the number of weights $\rightarrow$ hardware limits, overfitting, etc.

# An MLP for processing an image

- Full connectivity blows the number of weights $\rightarrow$ hardware limits, overfitting, etc.
- Flattening removes the structure

# Large Signals



- Have invariance in translation

# Large Signals

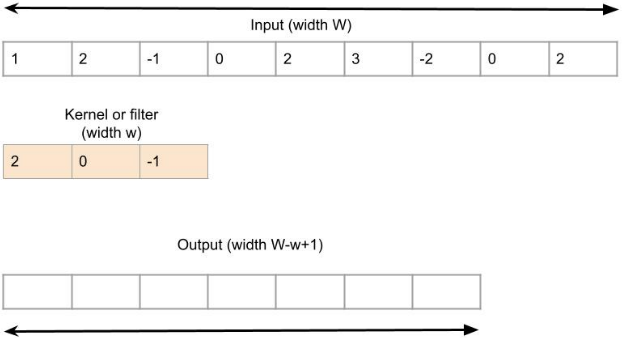
- Have invariance in translation
- Features may occur at different locations in the signal

# Large Signals

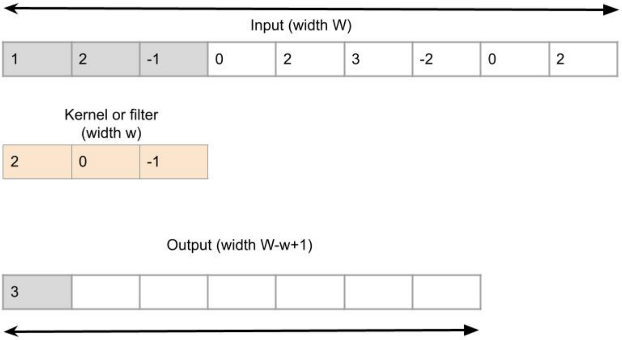
- Have invariance in translation
- Features may occur at different locations in the signal
- Convolution incorporates this idea: Applies same linear operation at all the locations and preserves the structure

# Convolution



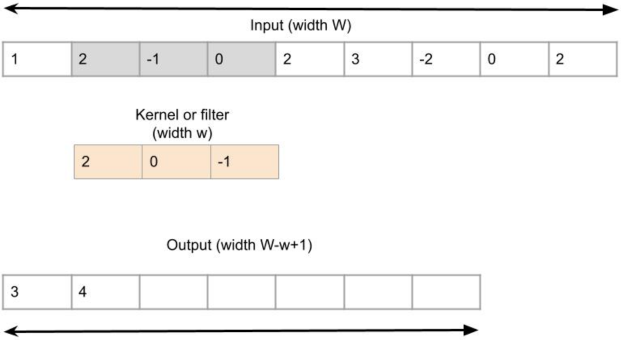


# Convolution

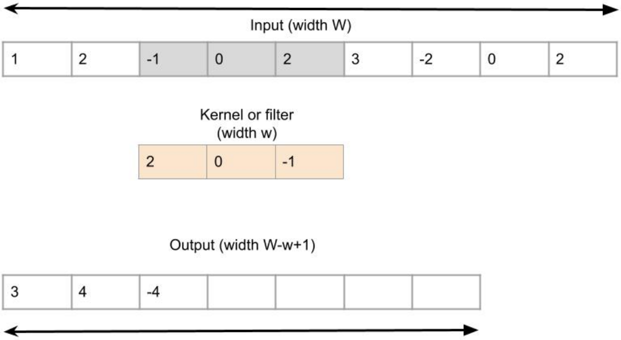


# Convolution

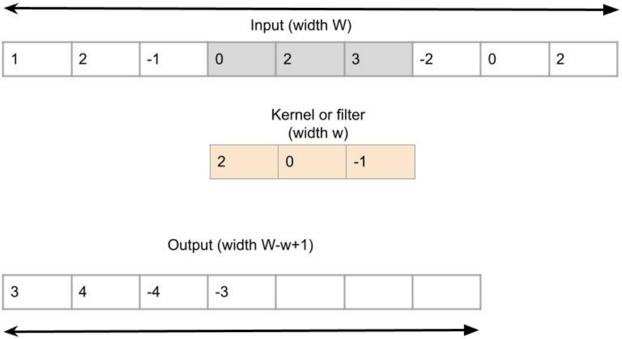




# Convolution

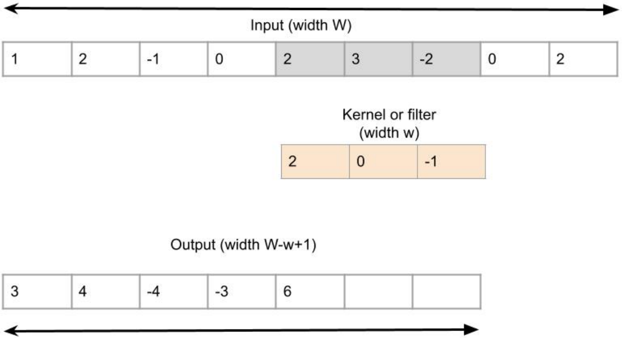


# Convolution

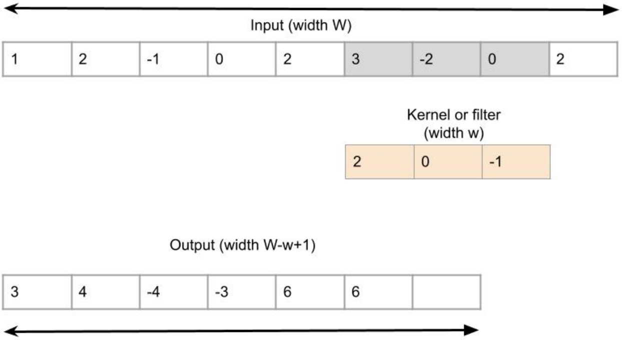


# Convolution

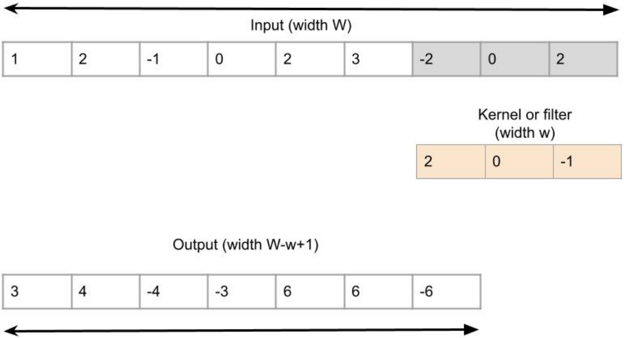




# Convolution



# Convolution



# Convolution

- Preserves the structure

# Convolution

- Preserves the structure
  - if the i/p is a 2D tensor $\rightarrow$ o/p is also a 2D tensor

# Convolution



- Preserves the structure
  - if the i/p is a 2D tensor $\rightarrow$ o/p is also a 2D tensor
  - There exist a relation between the locations of i/p and o/p values

# Convolution

- Let $\mathbf{x} = (x_1, x_2, \ldots x_W)$ is the input, $\mathbf{k} = (k_1, k_2, \ldots k_w)$ is the kernel

# Convolution

- Let $\mathbf{x} = (x_1, x_2, \ldots x_W)$ is the input, $\mathbf{k} = (k_1, k_2, \ldots k_w)$ is the kernel
- The result $(x \circledast k)$ of convolving $\mathbf{x}$ with $\mathbf{k}$ will be a 1D tensor of size $W - w + 1$

$$
\begin{aligned}
(x \circledast k)_i &= \sum_{j=1}^{w} x_{i-1+j} k_j \\
&= (x_i, \ldots x_{i+w-1}) \cdot \mathbf{k}
\end{aligned}
$$

# Convolution

- Powerful feature extractor

# Convolution

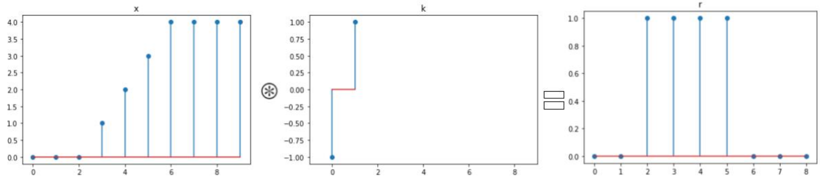
- Powerful feature extractor
- For instance, it can perform differential operation and look for interesting patterns in the input

# Convolution



- Powerful feature extractor
- For instance, it can perform differential operation and look for interesting patterns in the input
-

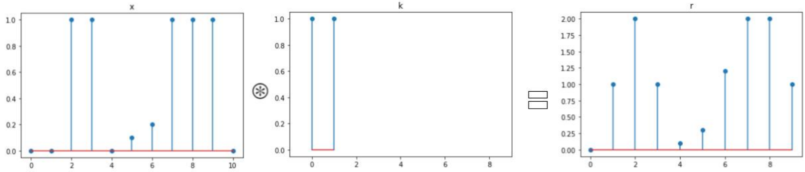
$$(0, 0, 0, 1, 2, 3, 4, 4, 4, 4) \circledast (-1, 1) = (0, 0, 1, 1, 1, 1, 0, 0, 0)$$



# Convolution

- Powerful feature extractor
- For instance, it can perform differential operation and look for interesting patterns in the input
-

$$(0, 0, 1, 1, 0, 0.1, 0.2, 1, 1, 1, 0) \circledast (1, 1) = (0, 1, 2, 1, 0.1, 0.3, 1.2, 2, 2, 1)$$



# Convolution

- Naturally generalizes to multiple dimensions

# Convolution

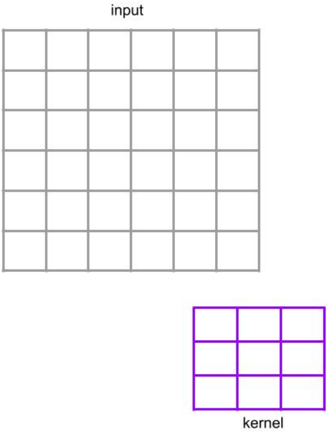
- Naturally generalizes to multiple dimensions
- CNNs process 3D tensors of size $C \times H \times W$ with kernels of size $C \times h \times w$ and result in 2D tensors of size $H - h + 1 \times W - w + 1$

# Convolution

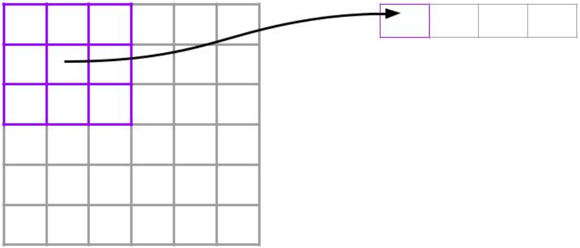


- Naturally generalizes to multiple dimensions
- CNNs process 3D tensors of size $C \times H \times W$ with kernels of size $C \times h \times w$ and result in 2D tensors of size $H - h + 1 \times W - w + 1$
- Note that we generally refer to these inputs as 2D signal (despite having C channels) (Why?)

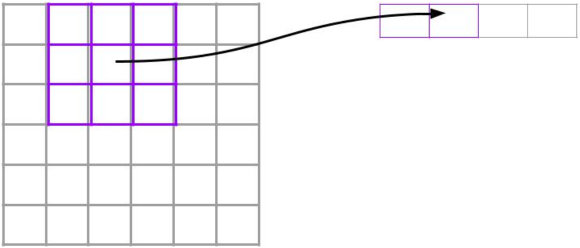
# 2D Convolution



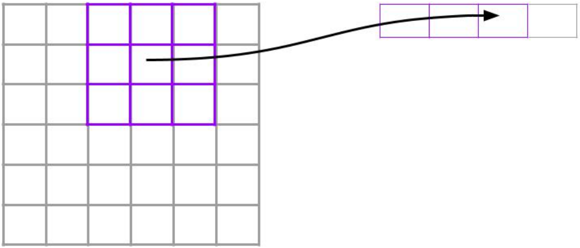
# 2D Convolution



# 2D Convolution

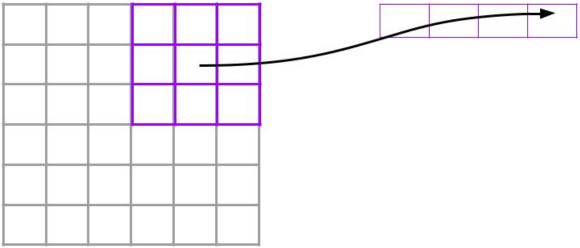


# 2D Convolution

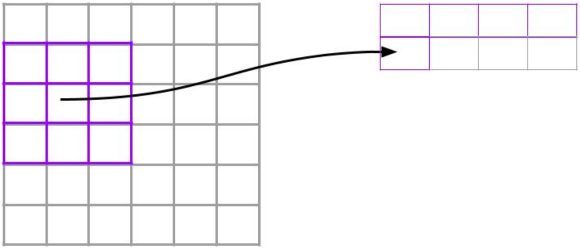


# 2D Convolution

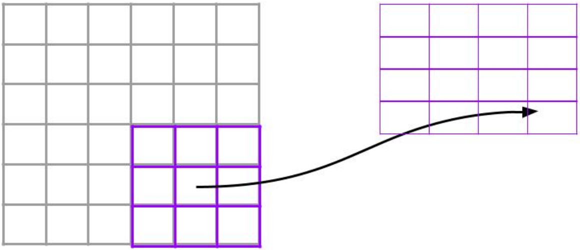




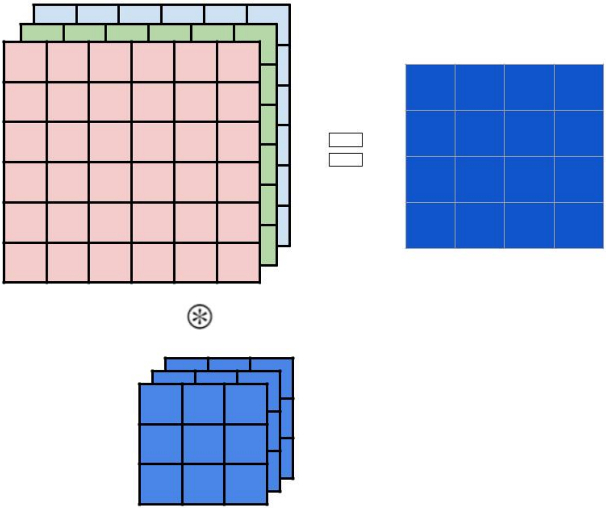
# 2D Convolution



# 2D Convolution

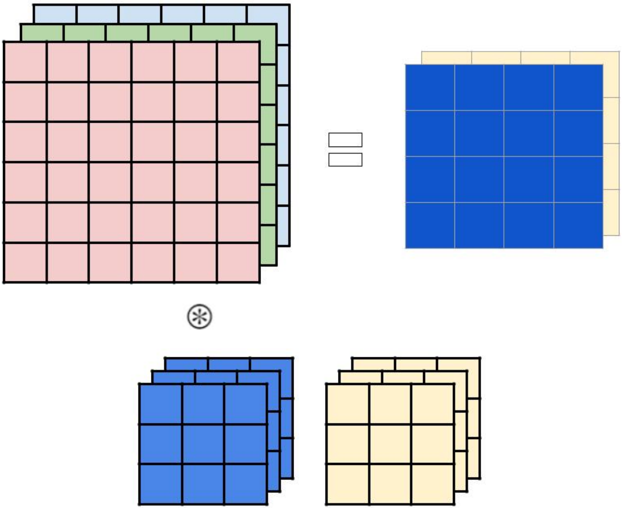


# 2D Convolution



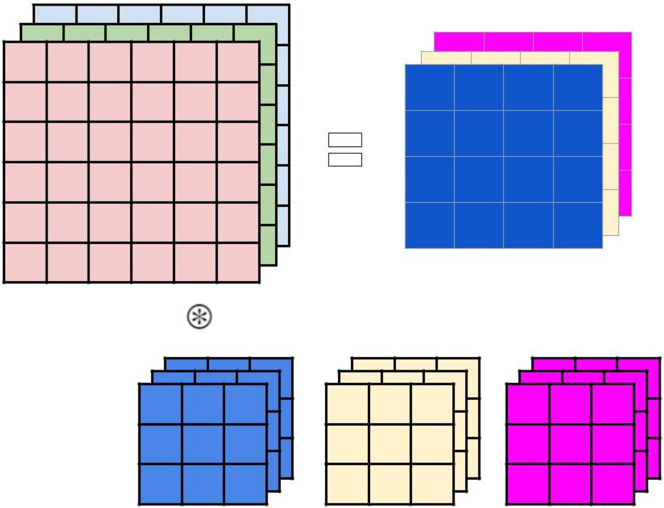
# 2D Convolution



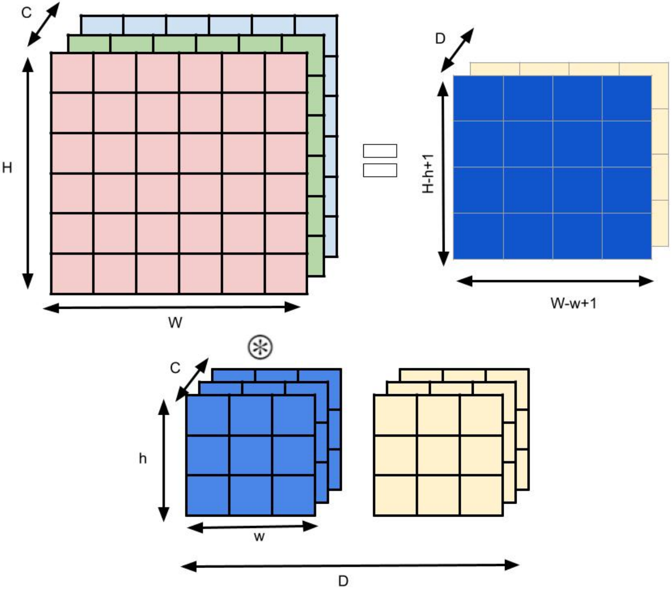


# 2D Convolution





# 2D Convolution

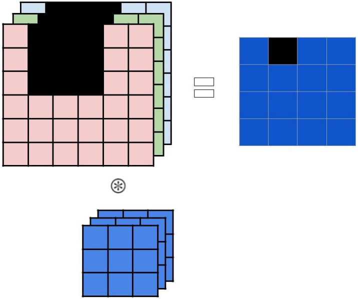


# 2D Convolution

- Kernel is not convolved in the channel dimension

# 2D Convolution

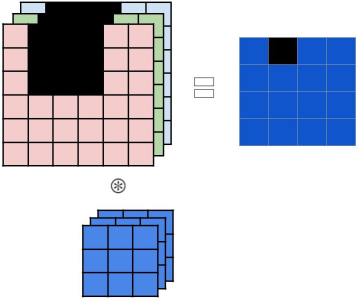
- Kernel is not convolved in the channel dimension
- Another way to interpret convolution is that an affine function is applied on an input block of size $C \times h \times w$



# 2D Convolution



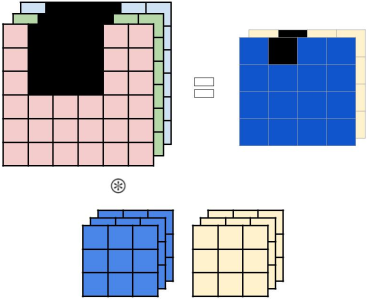
- Kernel is not convolved in the channel dimension
- Another way to interpret convolution is that an affine function is applied on an input block of size $C \times h \times w$



- Same affine function is applied on all such blocks in the input

# 2D Convolution

- Kernel is not convolved in the channel dimension
- Another way to interpret convolution is that an affine function is applied on an input block of size $C \times h \times w$



- Same affine function is applied on all such blocks in the input

# Convolution

- Preserves the input structure

# Convolution

- Preserves the input structure
  - 1D signal outputs 1D signal, 2D signal outputs 2D signal

# Convolution

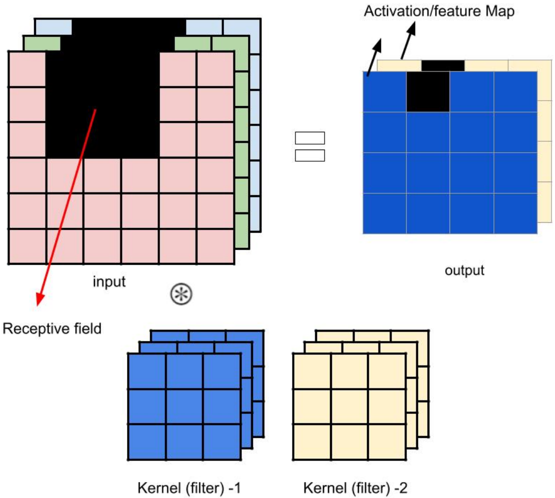
- Preserves the input structure
  - 1D signal outputs 1D signal, 2D signal outputs 2D signal
  - Adjacent components in o/p are influenced by adjacent parts in the i/p

# Convolution

- Preserves the input structure
  - 1D signal outputs 1D signal, 2D signal outputs 2D signal
  - Adjacent components in o/p are influenced by adjacent parts in the i/p
- If the channel dimension has a metric meaning (e.g. time) 3D convolution can be employed (e.g. frames in a video)

# Terminology in Convolution





# Convolution function in PyTorch

భారతీయ సాంకేతిక విజ్ఞాన సంస్థ హైదరాబాద్
भारतीय प्रौद्योगिकी संस्थान हैदराबाद
Indian Institute of Technology Hyderabad

- `F.conv2d(input, weight, bias=None, stride=1, padding=0, dilation=1, groups=1)`

# Convolution function in PyTorch

- `F.conv2d(input, weight, bias=None, stride=1, padding=0, dilation=1, groups=1)`
- `weight` is $D \times C \times h \times w$ dimensional kernels

# Convolution function in PyTorch

- `F.conv2d(input, weight, bias=None, stride=1, padding=0, dilation=1, groups=1)`
- `weight` is $D \times C \times h \times w$ dimensional kernels
- `bias` $D$ dimensional

# Convolution function in PyTorch

- `F.conv2d(input, weight, bias=None, stride=1, padding=0, dilation=1, groups=1)`
- `weight` is $D \times C \times h \times w$ dimensional kernels
- `bias` $D$ dimensional
- `input` is $N \times C \times H \times W$ dimensional signal

# Convolution function in PyTorch

- `F.conv2d(input, weight, bias=None, stride=1, padding=0, dilation=1, groups=1)`
- `weight` is $D \times C \times h \times w$ dimensional kernels
- `bias` $D$ dimensional
- `input` is $N \times C \times H \times W$ dimensional signal
- Output is $N \times D \times (H - h + 1) \times (W - w + 1)$ tensor

# Convolution function in PyTorch

- `F.conv2d(input, weight, bias=None, stride=1, padding=0, dilation=1, groups=1)`
- `weight` is $D \times C \times h \times w$ dimensional kernels
- `bias` $D$ dimensional
- `input` is $N \times C \times H \times W$ dimensional signal
- Output is $N \times D \times (H - h + 1) \times (W - w + 1)$ tensor
- Autograd compliant

# Convolution function in PyTorch

```
input = torch.empty(128, 3, 20, 20).normal_()
weight = torch.empty(5, 3, 5, 5).normal_()
bias = torch.empty(5).normal_()
output = F.conv2d(input, weight, bias)
output.size()
torch.Size([128, 5, 16, 16])
```

# Look/Access the filters

```
 weight[0,0]
tensor([[-0.6974, 0.1342, -0.2632, -0.4672, 0.1827],
[-0.1184, -0.2164, 0.2772, -0.1099, 0.0103],
[-0.8272, 0.3580, 0.2398, -0.5795,-0.9472],
[-1.1734, -0.1019, 0.7394, 0.3342, 0.1699],
[ 1.9271, 0.1250, 0.4222, 0.2014, 1.1100]])
```

# Conv layer in PyTorch

- `Class torch.nn.Conv2d(in_channels, out_channels, kernel_size, stride=1, padding=0, dilation=1, groups=1, bias=True)`

# Conv layer in PyTorch

- Class `torch.nn.Conv2d(in_channels, out_channels, kernel_size, stride=1, padding=0, dilation=1, groups=1, bias=True)`
- `kernel_size` can be either a pair `(h, w)` or a single value $k$ interpreted as `(k, k)`.

# Conv layer in PyTorch

- `Class torch.nn.Conv2d(in_channels, out_channels, kernel_size, stride=1, padding=0, dilation=1, groups=1, bias=True)`
- `kernel_size` can be either a pair `(h, w)` or a single value $k$ interpreted as `(k, k)`.
- Encloses the convolution as a module

# Conv layer in PyTorch

- `Class torch.nn.Conv2d(in_channels, out_channels, kernel_size, stride=1, padding=0, dilation=1, groups=1, bias=True)`
- `kernel_size` can be either a pair `(h, w)` or a single value $k$ interpreted as `(k, k)`.
- Encloses the convolution as a module
- Initializes the kernel parameters and biases as random

# Conv layer in PyTorch

```
f = nn.Conv2d(in_channels = 3, out_channels = 5,
kernel_size = (2, 3))
for n, p in f.named_parameters():
...print(n, p.size())

>>weight torch.Size([5, 3, 2, 3])
>>bias torch.Size([5])
```

# Conv layer in PyTorch



```
f = nn.Conv2d(in_channels = 3, out_channels = 5,
kernel_size = (2, 3))
for n, p in f.named_parameters():
...print(n, p.size())

>>weight torch.Size([5, 3, 2, 3])
>>bias torch.Size([5])

input = torch.empty(128, 3, 28, 28).normal_()
output = f(input)
output.size()
>>torch.Size([128, 5, 27, 26])
```

# Padding in Convolution

- Adds zeros around the input

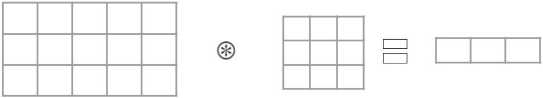
# Padding in Convolution

- Adds zeros around the input
- Takes cares of size reduction after convolution

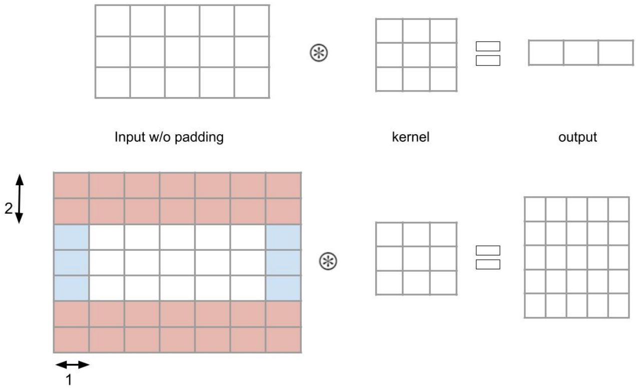
# Padding in Convolution

- Adds zeros around the input
- Takes cares of size reduction after convolution
- Instead of zeros, one may pad with signal values at the edges

# Padding in Convolution



# Padding in Convolution



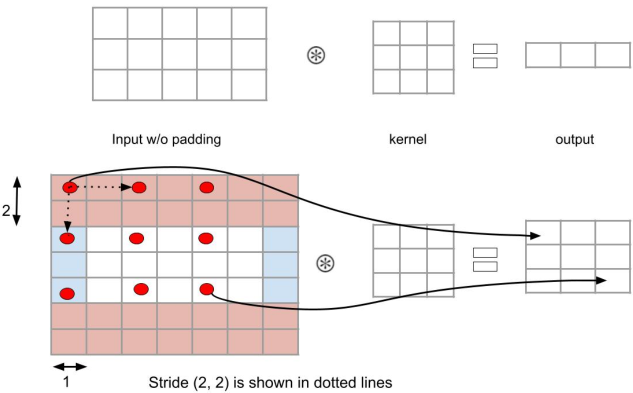
# Stride in Convolution

- Specifies the step size taken while performing convolution

# Stride in Convolution

- Specifies the step size taken while performing convolution
- Default value is 1, i.e., move the kernel across the signal densely (without skipping)

# Padding and Stride in Convolution



# Dilation in Convolution

- Manipulates the size of the kernel via expanding its size without adding weights.

# Dilation in Convolution

- Manipulates the size of the kernel via expanding its size without adding weights.
- In other words, it inserts 0s in between the kernel values

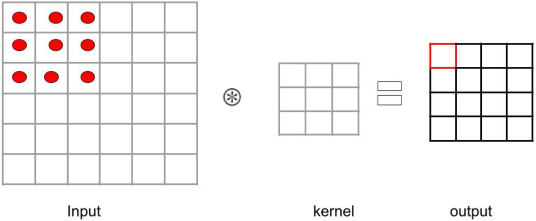
# Output size of the Convolution

- Input width - W, Kernel size - k, Padding - p, and stride - s

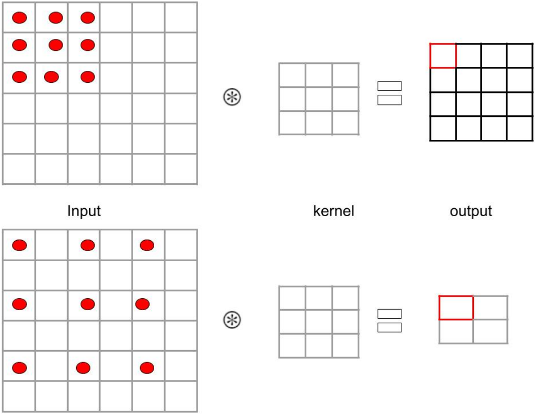
# Output size of the Convolution

- Input width - W, Kernel size - k, Padding - p, and stride - s
- Output width $= \frac{W-k+2p}{s} + 1$ (similarly for the height)

# Without Dilation



# Dilation (2, 2)



# Dilation

- Expands the kernel by adding rows and columns of zeros

# Dilation

- Expands the kernel by adding rows and columns of zeros
- Default value for dilation is 1, i.e., no zeros placed

# Dilation

- Expands the kernel by adding rows and columns of zeros
- Default value for dilation is 1, i.e., no zeros placed
- Any higher value of dilation makes the kernel sparse

# Dilation



- Expands the kernel by adding rows and columns of zeros
- Default value for dilation is 1, i.e., no zeros placed
- Any higher value of dilation makes the kernel sparse
- Dilation increases the receptive field

# Dilation

- Expands the kernel by adding rows and columns of zeros
- Default value for dilation is 1, i.e., no zeros placed
- Any higher value of dilation makes the kernel sparse
- Dilation increases the receptive field
- It is referred to as 'atrous' convolution

# Pooling

# Pooling

- Groups multiple activations and replaces by a representative one

# Pooling

- Groups multiple activations and replaces by a representative one
- Reduces the dimensionality of the signal progressively $\rightarrow$ considers non-overlapping stride

# Pooling

- Groups multiple activations and replaces by a representative one
- Reduces the dimensionality of the signal progressively $\rightarrow$ considers non-overlapping stride
- Also called sub-sampling layer

# Pooling

- Groups multiple activations and replaces by a representative one
- Reduces the dimensionality of the signal progressively $\rightarrow$ considers non-overlapping stride
- Also called sub-sampling layer
- Generally found between two convolution layers (and parameter free)

# Max Pooling

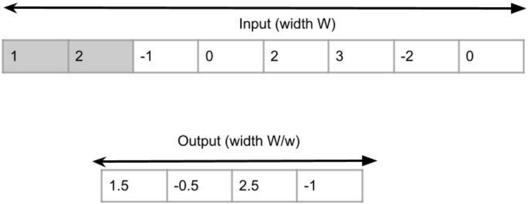
- Standard in CNNs

# Max Pooling

- Standard in CNNs
- Computes maximum value over a non-overlapping blocks in the input

# Average Pooling

- Computes the average of the receptive field



# Pooling in 2D

- Same as 1D, but the receptive field is 2D and non-overlapping

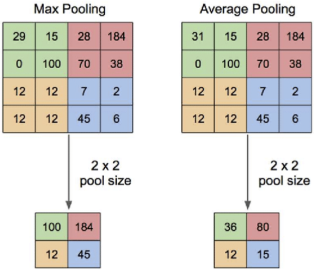


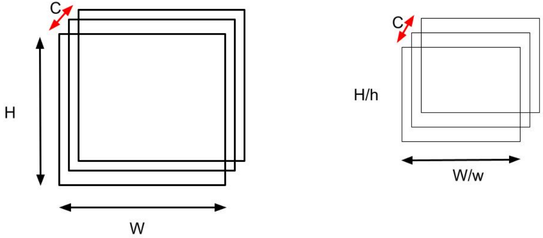

Figure credits: Preston Hoang and Quora

# Pooling in 2D

- Contrary to Convolution, Pooling applies channel wise

# Pooling in 2D

- Contrary to Convolution, Pooling applies channel wise
- No reduction in number of channels, only spatial size reduction



# Pooling provides weak invariance



- Operation is invariant to any permutation within the block

# Pooling provides weak invariance

- Operation is invariant to any permutation within the block
- Withstands deformations caused by local translations

# Max_Pooling PyTorch



```
F.max_pool2d(input, kernel_size, stride=None, padding=0,
dilation=1, ceil_mode=False, return_indices=False)
```

- Applies max pooling on each of the channels separately

# Max_Pooling PyTorch

```
F.max_pool2d(input, kernel_size, stride=None, padding=0,
dilation=1, ceil_mode=False, return_indices=False)
```

- Applies max pooling on each of the channels separately
- `input` is $N \times C \times H \times W$ tensor

# Max_Pooling PyTorch

```
F.max_pool2d(input, kernel_size, stride=None, padding=0,
dilation=1, ceil_mode=False, return_indices=False)
```

- Applies max pooling on each of the channels separately
- `input` is $N \times C \times H \times W$ tensor
- `kernel_size` is $(h, w)$ or $k$

# Max_Pooling PyTorch

```
F.max_pool2d(input, kernel_size, stride=None, padding=0,
dilation=1, ceil_mode=False, return_indices=False)
```

- Applies max pooling on each of the channels separately
- `input` is $N \times C \times H \times W$ tensor
- `kernel_size` is $(h, w)$ or $k$
- Result would be a tensor of size $N \times C \times \lfloor H/h \rfloor \times \lfloor W/w \rfloor$

# Pooling in PyTorch

- Default stride is the kernel size (for convolution, it is 1)

# Pooling in PyTorch



- Default stride is the kernel size (for convolution, it is 1)
- But, it can be modulated if required

# Pooling in PyTorch

- Default stride is the kernel size (for convolution, it is 1)
- But, it can be modulated if required
- Default padding is zero

# Pooling Layer in PyTorch

```
class torch.nn.MaxPool2d(kernel_size, stride=None,
padding=0, dilation=1, return_indices=False,
ceil_mode=False)
```

# Putting it all together

# Architecture of a simple CNN

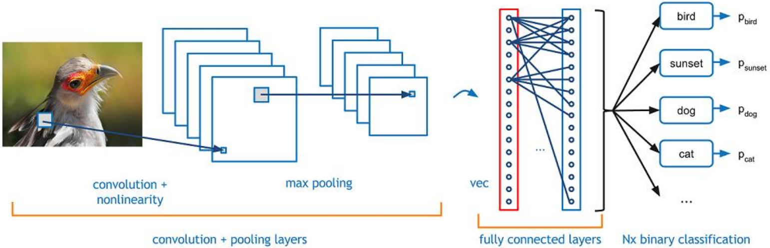
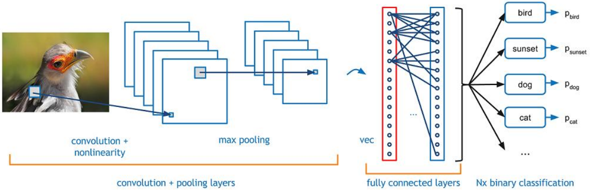



Figure credits: Adit Deshpande

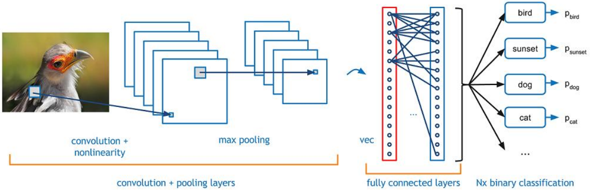
# Architecture of a simple CNN




- Initially Conv layer with nonlinearity

Figure credits: Adit Deshpande

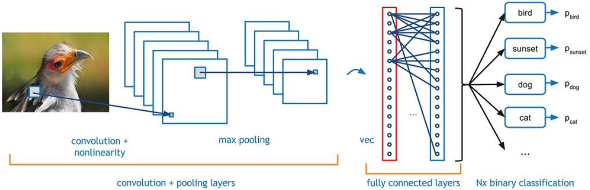
# Architecture of a simple CNN




- Initially Conv layer with nonlinearity
- Followed by a few Conv + Nonlinearity layers

Figure credits: Adit Deshpande

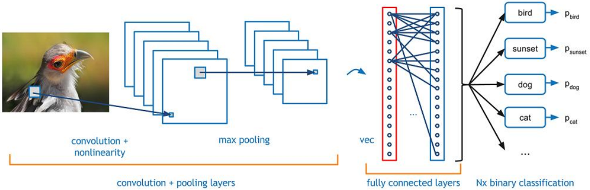
# Architecture of a simple CNN




- Initially Conv layer with nonlinearity
- Followed by a few Conv + Nonlinearity layers
- Have Pooling layers in between Conv layers → reduce the feature map size sufficiently

Figure credits: Adit Deshpande

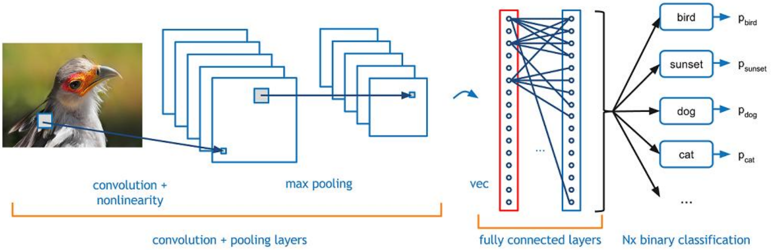
# Architecture of a simple CNN




- Initially Conv layer with nonlinearity
- Followed by a few Conv + Nonlinearity layers
- Have Pooling layers in between Conv layers → reduce the feature map size sufficiently
- Vectorize and and fully connected layers

Figure credits: Adit Deshpande

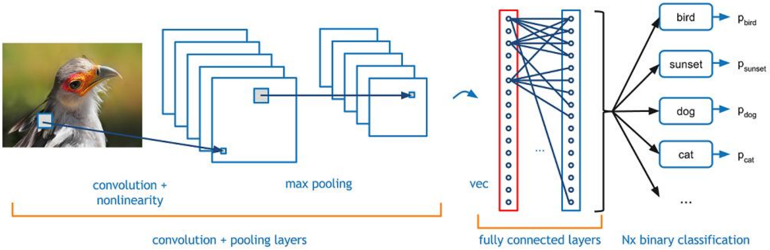
# Architecture of a simple CNN




INPUT -> [[CONV -> RELU] *N -> POOL]*M -> [FC->RELU]*K -> FC

Figure credits: Adit Deshpande

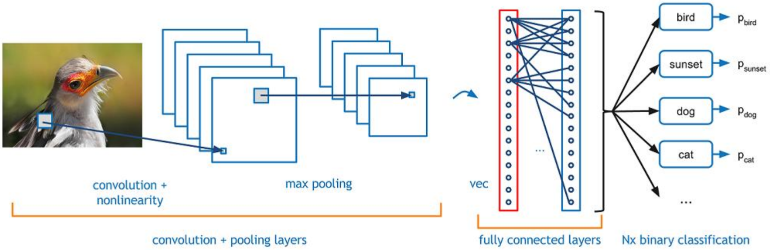
# Architecture of a simple CNN




INPUT -> [[CONV -> RELU] *N -> POOL]*M -> [FC->RELU]*K -> FC

Figure credits: Adit Deshpande

# Architecture of a simple CNN




INPUT -> [[CONV -> RELU] *N -> POOL]*M -> [FC->RELU]*K -> FC

---

Figure credits: Adit Deshpande

# Case study: LeNet-like architecture

| input size/ layer information | output size | # parameters | # products |
|---|---|---|---|
| $1 \times 28 \times 28$<br>`nn.Conv2d(1, 32, kernel_size=5)` | | | |

# Case study: LeNet-like architecture

| input size/ layer information | output size | # parameters | # products |
|---|---|---|---|
| $1 \times 28 \times 28$<br>`nn.Conv2d(1, 32, kernel_size=5)` | $32 \times 24 \times 24$ | | |

# Case study: LeNet-like architecture

| input size/ layer information | output size | # parameters | # products |
|---|---|---|---|
| $1 \times 28 \times 28$<br>`nn.Conv2d(1, 32, kernel_size=5)` | $32 \times 24 \times 24$ | $32.(5^2 + 1)$<br>$= 832$ | |

# Case study: LeNet-like architecture



| input size/ layer information | output size | # parameters | # products |
|---|---|---|---|
| $1 \times 28 \times 28$ `nn.Conv2d(1, 32, kernel_size=5)` | $32 \times 24 \times 24$ | $32.(5^2 + 1) = 832$ | $32.24^2.5^2 = 460800$ |
| $32 \times 24 \times 24$ `F.max_pool2d(., kernel_size=3)` | | | |

# Case study: LeNet-like architecture



| input size/ layer information | output size | # parameters | # products |
|---|---|---|---|
| $1 \times 28 \times 28$<br>`nn.Conv2d(1, 32, kernel_size=5)` | $32 \times 24 \times 24$ | $32.(5^2 + 1)$<br>$= 832$ | $32.24^2.5^2$<br>$= 460800$ |
| $32 \times 24 \times 24$<br>`F.max_pool2d(., kernel_size=3)` | $32 \times 8 \times 8$ | 0 | 0 |

# Case study: LeNet-like architecture



| input size/ layer information | output size | # parameters | # products |
|---|---|---|---|
| $1 \times 28 \times 28$ `nn.Conv2d(1, 32, kernel_size=5)` | $32 \times 24 \times 24$ | $32.(5^2 + 1)$ $= 832$ | $32.24^2.5^2$ $= 460800$ |
| $32 \times 24 \times 24$ `F.max_pool2d(., kernel_size=3)` | $32 \times 8 \times 8$ | 0 | 0 |
| $32 \times 8 \times 8$ / `F.relu(.)` | $32 \times 8 \times 8$ | 0 | 0 |

# Case study: LeNet-like architecture



| input size/ layer information | output size | # parameters | # products |
|---|---|---|---|
| $1 \times 28 \times 28$<br>`nn.Conv2d(1, 32, kernel_size=5)` | $32 \times 24 \times 24$ | $32.(5^2 + 1)$<br>$= 832$ | $32.24^2.5^2$<br>$= 460800$ |
| $32 \times 24 \times 24$<br>`F.max_pool2d(., kernel_size=3)` | $32 \times 8 \times 8$ | 0 | 0 |
| $32 \times 8 \times 8$ / `F.relu(.)` | $32 \times 8 \times 8$ | 0 | 0 |
| $32 \times 8 \times 8$<br>`nn.conv2d(32, 64, kernel_size=5)` | | | |

# Case study: LeNet-like architecture



| input size/ layer information | output size | # parameters | # products |
|---|---|---|---|
| $1 \times 28 \times 28$ `nn.Conv2d(1, 32, kernel_size=5)` | $32 \times 24 \times 24$ | $32.(5^2 + 1) = 832$ | $32.24^2.5^2 = 460800$ |
| $32 \times 24 \times 24$ `F.max_pool2d(., kernel_size=3)` | $32 \times 8 \times 8$ | 0 | 0 |
| $32 \times 8 \times 8$ / `F.relu(.)` | $32 \times 8 \times 8$ | 0 | 0 |
| $32 \times 8 \times 8$ `nn.conv2d(32, 64, kernel_size=5)` | $64 \times 4 \times 4$ | | |

# Case study: LeNet-like architecture

| input size/ layer information | output size | # parameters | # products |
| --- | --- | --- | --- |
| $1 \times 28 \times 28$<br>`nn.Conv2d(1, 32, kernel_size=5)` | $32 \times 24 \times 24$ | $32.(5^2+1)$<br>$= 832$ | $32.24^2.5^2$<br>$= 460800$ |
| $32 \times 24 \times 24$<br>`F.max_pool2d(., kernel_size=3)` | $32 \times 8 \times 8$ | 0 | 0 |
| $32 \times 8 \times 8$ / `F.relu(.)` | $32 \times 8 \times 8$ | 0 | 0 |
| $32 \times 8 \times 8$<br>`nn.conv2d(32, 64, kernel_size=5)` | $64 \times 4 \times 4$ | $64.(32.5^2+1)$<br>$= 51264$ | |

# Case study: LeNet-like architecture

| input size/ layer information | output size | # parameters | # products |
| --- | --- | --- | --- |
| $1 \times 28 \times 28$<br>`nn.Conv2d(1, 32, kernel_size=5)` | $32 \times 24 \times 24$ | $32.(5^2 + 1)$<br>$= 832$ | $32.24^2.5^2$<br>$= 460800$ |
| $32 \times 24 \times 24$<br>`F.max_pool2d(., kernel_size=3)` | $32 \times 8 \times 8$ | 0 | 0 |
| $32 \times 8 \times 8$ / `F.relu(.)` | $32 \times 8 \times 8$ | 0 | 0 |
| $32 \times 8 \times 8$<br>`nn.conv2d(32, 64, kernel_size=5)` | $64 \times 4 \times 4$ | $64.(32.5^2 + 1)$<br>$= 51264$ | $64.32.4^2.5^2$<br>$= 819200$ |

# Case study: LeNet-like architecture



| input size/ layer information | output size | # parameters | # products |
|---|---|---|---|
| $1 \times 28 \times 28$ `nn.Conv2d(1, 32, kernel_size=5)` | $32 \times 24 \times 24$ | $32.(5^2 + 1) = 832$ | $32.24^2.5^2 = 460800$ |
| $32 \times 24 \times 24$ `F.max_pool2d(., kernel_size=3)` | $32 \times 8 \times 8$ | 0 | 0 |
| $32 \times 8 \times 8$ / `F.relu(.)` | $32 \times 8 \times 8$ | 0 | 0 |
| $32 \times 8 \times 8$ `nn.conv2d(32, 64, kernel_size=5)` | $64 \times 4 \times 4$ | $64.(32.5^2 + 1) = 51264$ | $64.32.4^2.5^2 = 819200$ |
| $64 \times 4 \times 4$ `F.max_pool2d(., kernel_size=2)` | $64 \times 2 \times 2$ | 0 | 0 |

# Case study: LeNet-like architecture



| input size/ layer information | output size | # parameters | # products |
|---|---|---|---|
| $1 \times 28 \times 28$ `nn.Conv2d(1, 32, kernel_size=5)` | $32 \times 24 \times 24$ | $32.(5^2+1)$ $= 832$ | $32.24^2.5^2$ $= 460800$ |
| $32 \times 24 \times 24$ `F.max_pool2d(., kernel_size=3)` | $32 \times 8 \times 8$ | 0 | 0 |
| $32 \times 8 \times 8$ / `F.relu(.)` | $32 \times 8 \times 8$ | 0 | 0 |
| $32 \times 8 \times 8$ `nn.conv2d(32, 64, kernel_size=5)` | $64 \times 4 \times 4$ | $64.(32.5^2+1)$ $= 51264$ | $64.32.4^2.5^2$ $= 819200$ |
| $64 \times 4 \times 4$ `F.max_pool2d(., kernel_size=2)` | $64 \times 2 \times 2$ | 0 | 0 |
| $64 \times 2 \times 2$ / `F.relu(.)` | $64 \times 2 \times 2$ | 0 | 0 |

# Case study: LeNet-like architecture



| input size/ layer information | output size | # parameters | # products |
|---|---|---|---|
| $1 \times 28 \times 28$<br>`nn.Conv2d(1, 32, kernel_size=5)` | $32 \times 24 \times 24$ | $32.(5^2 + 1)$<br>$= 832$ | $32.24^2.5^2$<br>$= 460800$ |
| $32 \times 24 \times 24$<br>`F.max_pool2d(., kernel_size=3)` | $32 \times 8 \times 8$ | 0 | 0 |
| $32 \times 8 \times 8$ / `F.relu(.)` | $32 \times 8 \times 8$ | 0 | 0 |
| $32 \times 8 \times 8$<br>`nn.conv2d(32, 64, kernel_size=5)` | $64 \times 4 \times 4$ | $64.(32.5^2 + 1)$<br>$= 51264$ | $64.32.4^2.5^2$<br>$= 819200$ |
| $64 \times 4 \times 4$<br>`F.max_pool2d(., kernel_size=2)` | $64 \times 2 \times 2$ | 0 | 0 |
| $64 \times 2 \times 2$ / `F.relu(.)` | $64 \times 2 \times 2$ | 0 | 0 |
| $64 \times 2 \times 2$<br>`x.view(-1,256)` | 256 | 0 | 0 |
| 256<br>`nn.Linear(256,200)` | 200 | | |

# Case study: LeNet-like architecture

| input size/ layer information | output size | # parameters | # products |
|---|---|---|---|
| $1 \times 28 \times 28$ `nn.Conv2d(1, 32, kernel_size=5)` | $32 \times 24 \times 24$ | $32.(5^2+1)$ $= 832$ | $32.24^2.5^2$ $= 460800$ |
| $32 \times 24 \times 24$ `F.max_pool2d(., kernel_size=3)` | $32 \times 8 \times 8$ | 0 | 0 |
| $32 \times 8 \times 8$ / `F.relu(.)` | $32 \times 8 \times 8$ | 0 | 0 |
| $32 \times 8 \times 8$ `nn.conv2d(32, 64, kernel_size=5)` | $64 \times 4 \times 4$ | $64.(32.5^2+1)$ $= 51264$ | $64.32.4^2.5^2$ $= 819200$ |
| $64 \times 4 \times 4$ `F.max_pool2d(., kernel_size=2)` | $64 \times 2 \times 2$ | 0 | 0 |
| $64 \times 2 \times 2$ / `F.relu(.)` | $64 \times 2 \times 2$ | 0 | 0 |
| $64 \times 2 \times 2$ `x.view(-1,256)` | 256 | 0 | 0 |
| 256 `nn.Linear(256,200)` | 200 | 200(256+1)=51400 | 200.256=51200 |

# Case study: LeNet-like architecture



| input size/ layer information | output size | # parameters | # products |
|---|---|---|---|
| $1 \times 28 \times 28$<br>`nn.Conv2d(1, 32, kernel_size=5)` | $32 \times 24 \times 24$ | $32.(5^2 + 1)$<br>$= 832$ | $32.24^2.5^2$<br>$= 460800$ |
| `F.max_pool2d(., kernel_size=3)` | $32 \times 8 \times 8$ | 0 | 0 |
| $32 \times 8 \times 8$ / `F.relu(.)` | $32 \times 8 \times 8$ | 0 | 0 |
| $32 \times 8 \times 8$<br>`nn.conv2d(32, 64, kernel_size=5)` | $64 \times 4 \times 4$ | $64.(32.5^2 + 1)$<br>$= 51264$ | $64.32.4^2.5^2$<br>$= 819200$ |
| $64 \times 4 \times 4$<br>`F.max_pool2d(., kernel_size=2)` | $64 \times 2 \times 2$ | 0 | 0 |
| $64 \times 2 \times 2$ / `F.relu(.)` | $64 \times 2 \times 2$ | 0 | 0 |
| $64 \times 2 \times 2$<br>`x.view(-1,256)` | 256 | 0 | 0 |
| 256<br>`nn.Linear(256,200)` | 0<br>200 | 0<br>200(256+1)=51400 | 0<br>200.256=51200 |
| 200 / `F.relu(.)` | 200 | 0 | 0 |
| 200<br>`nn.Linear(200,10)` | 0<br>10 | 0<br>10(200+1)=2010 | 0<br>10.200=2000 |

# Recent architectures are far more sophisticated

- Note that LeNet is a classical architecture and does not reflect the recent CNNs in complexity

# Recent architectures are far more sophisticated

- Note that LeNet is a classical architecture and does not reflect the recent CNNs in complexity
- Recent CNN architectures are far more sophisticated [Contents of the next lecture(s)]
  - More depth
  - Machinery to handle the depth