भारतीय प्रौद्योगिकी संस्थान हैदराबाद
Indian Institute of Technology Hyderabad

Deep Learning

8 Building Blocks of CNNs

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CNNs

- Neurons are similar to that of MLP

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    - Perform a linear (dot product) operation and have a nonlinearity

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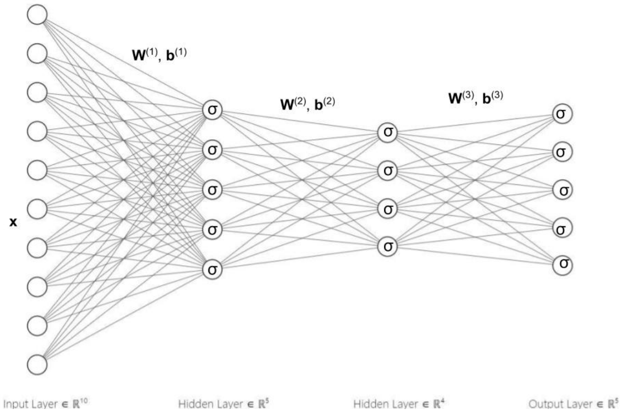
  - Perform a linear (dot product) operation and have a nonlinearity
- Architecture will have a differentiable loss function, backpropagation is used
- So, what changes?

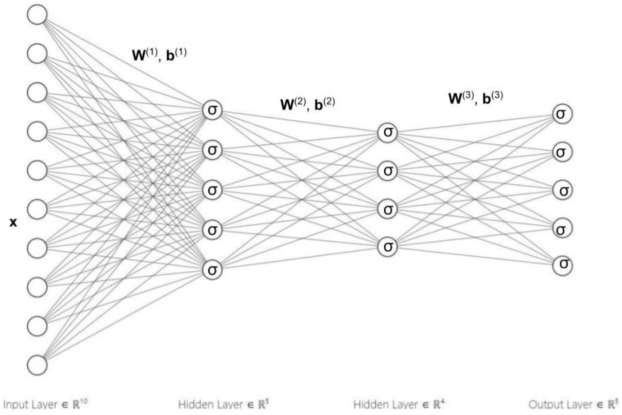
An MLP

- Input is a vector



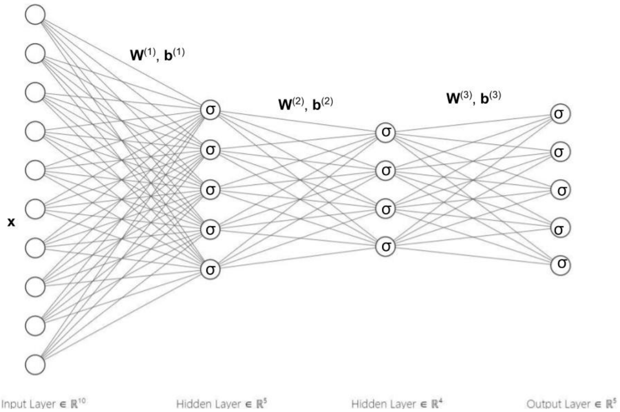
An MLP

- 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

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- 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

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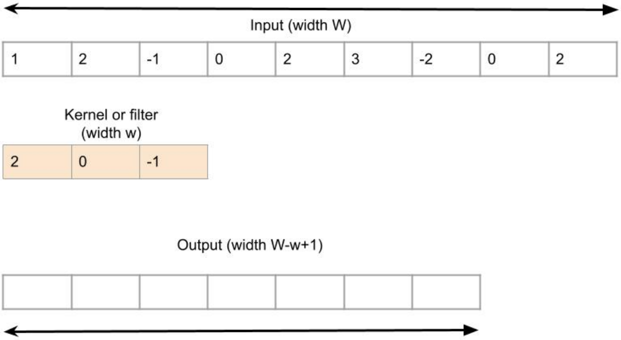
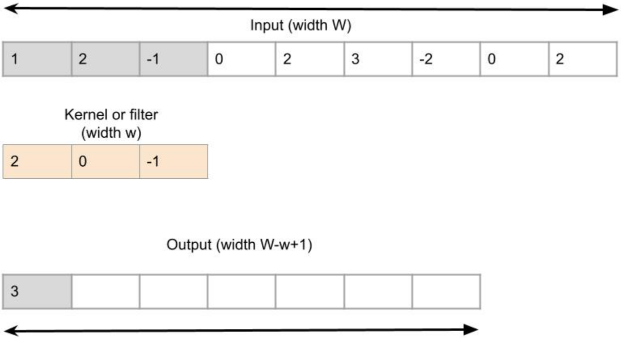
Large Signals

- 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



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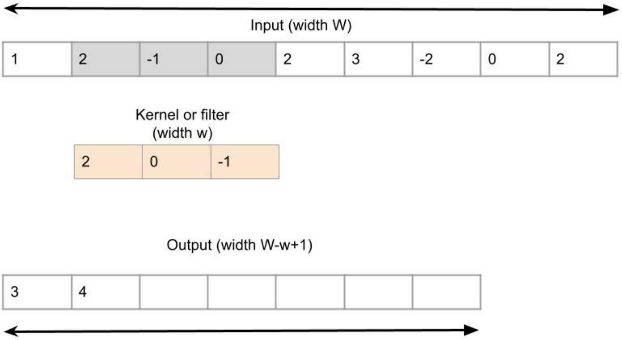
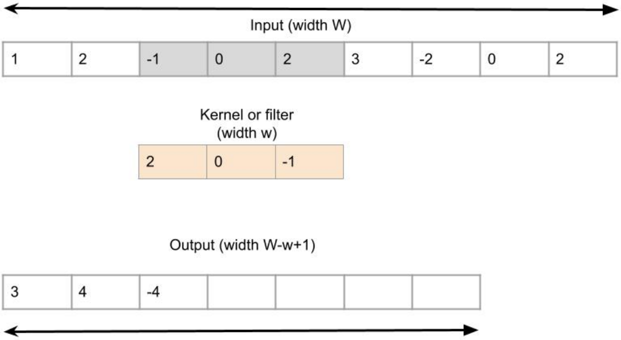


Convolution



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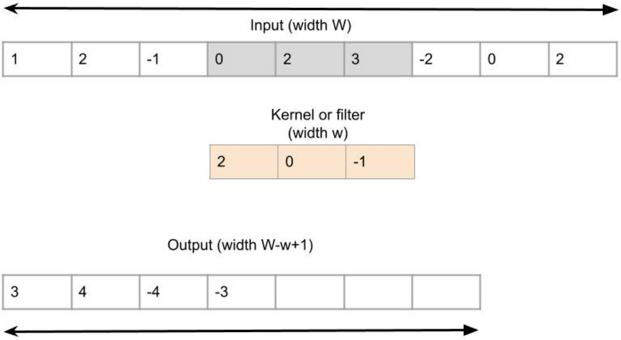

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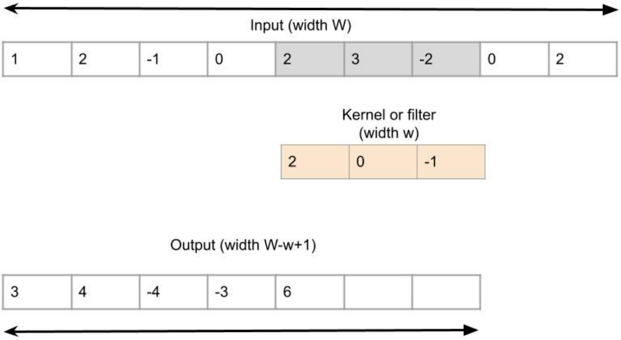

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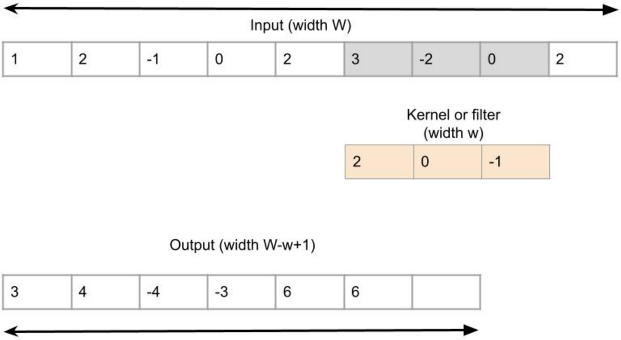

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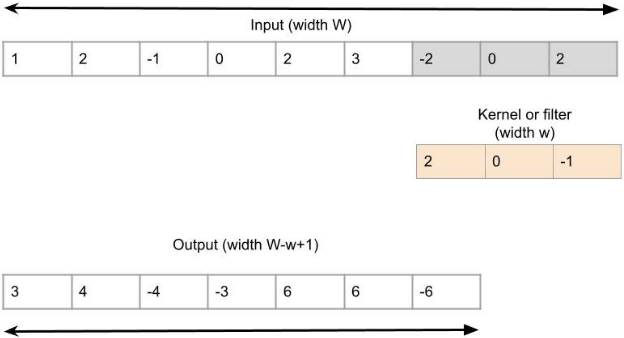

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  - if the i/p is a 2D tensor $\rightarrow$ o/p is also a 2D tensor

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  - 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

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- 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 $W - w + 1$

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

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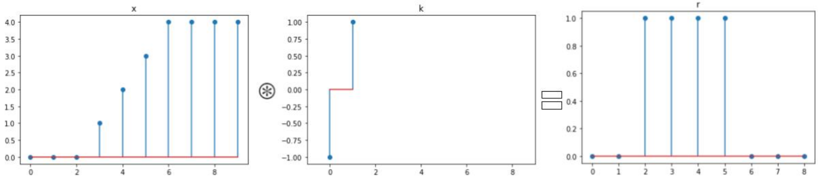
$$(0, 0, 0, 1, 2, 3, 4, 4, 4, 4) \circledast (-1, 1) = (0, 0, 1, 1, 1, 1, 0, 0, 0)$$



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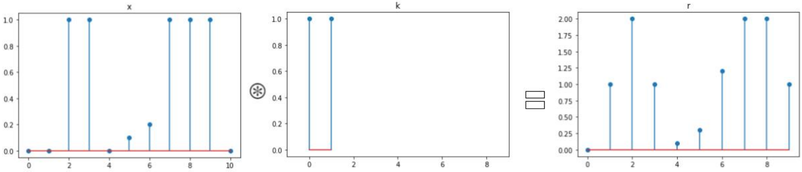
- For instance, it can perform differential operation and look for interesting patterns in the input
-

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



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- 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 $H - h + 1 \times W - w + 1$

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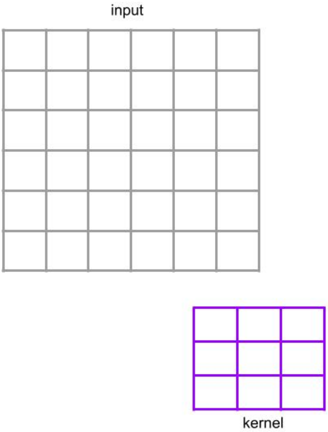
- Naturally generalizes to multiple dimensions
- CNNs process 3D tensors of size $C \times H \times W$ with kernels of size $C \times h \times w$ and result in 2D tensors of size $H - h + 1 \times W - w + 1$
- Note that we generally refer to these inputs as 2D signal (despite having C channels) (Why?)

2D Convolution



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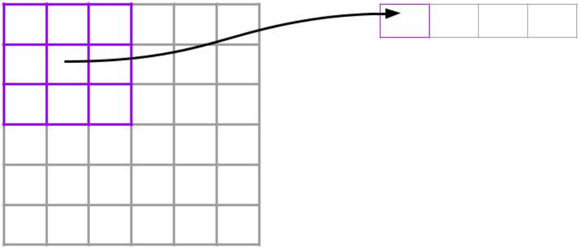

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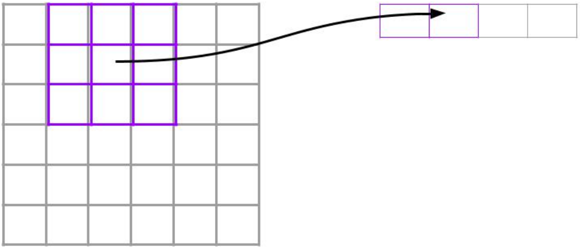

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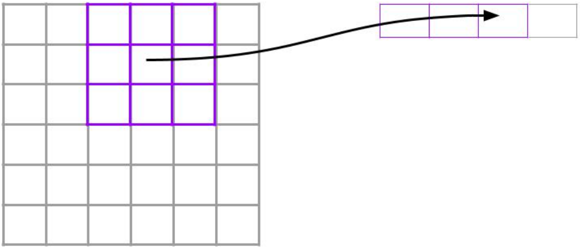

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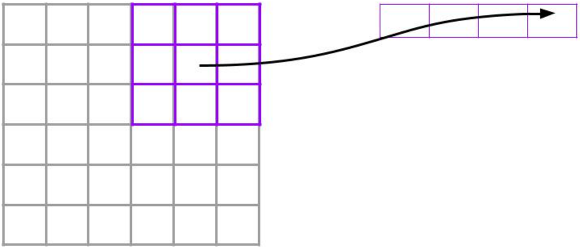

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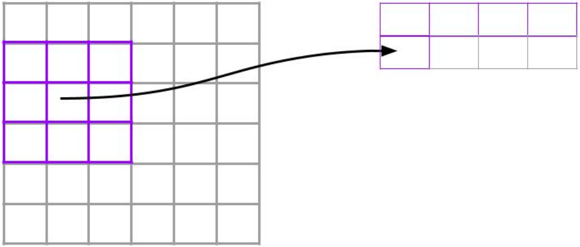

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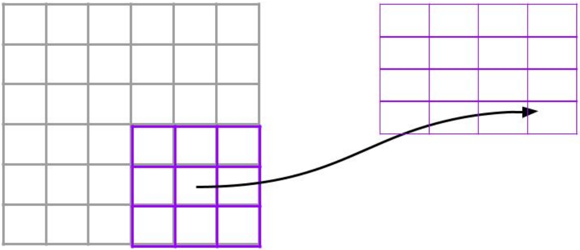

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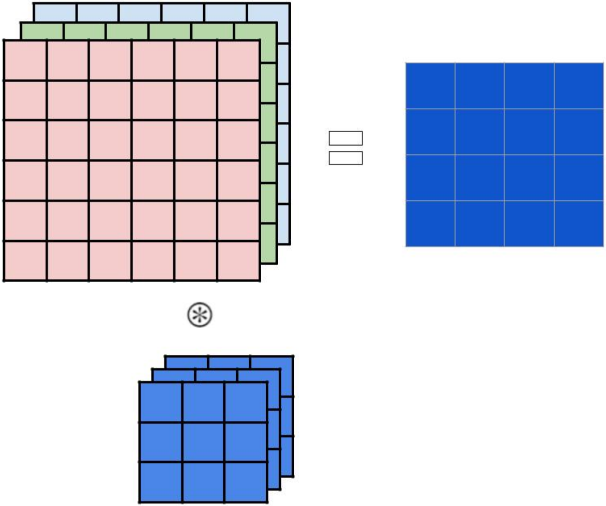

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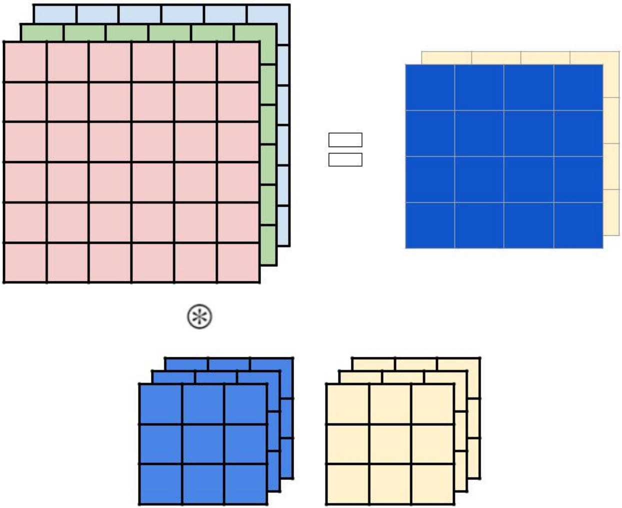

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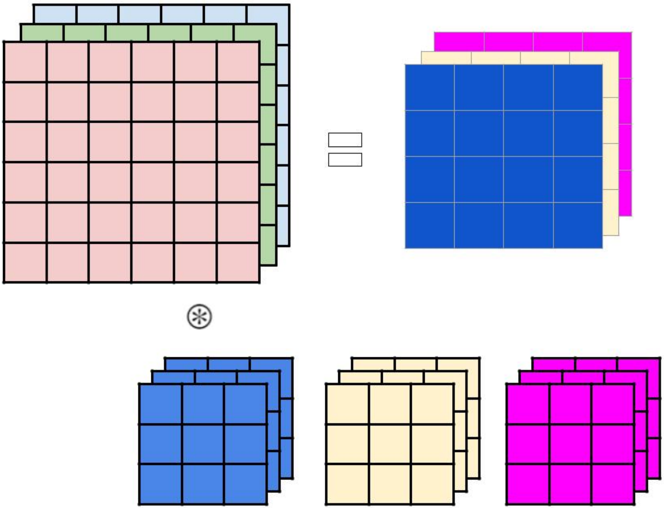

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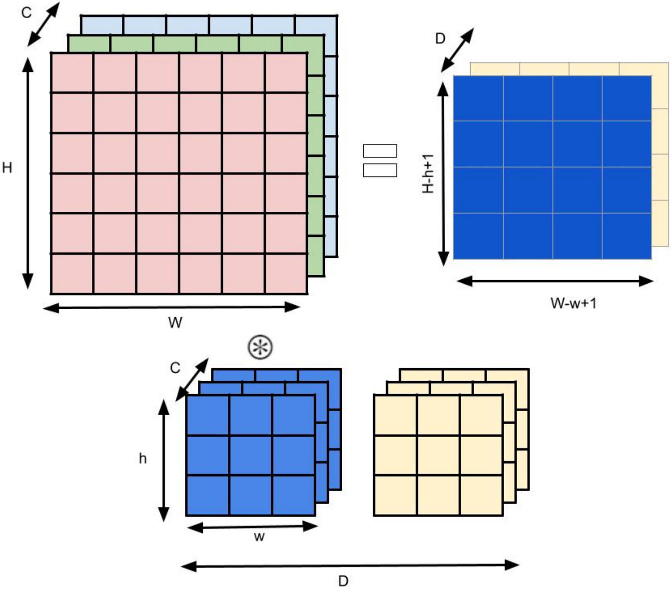

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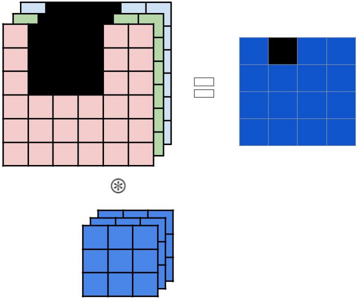

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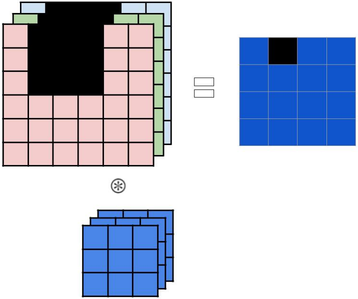

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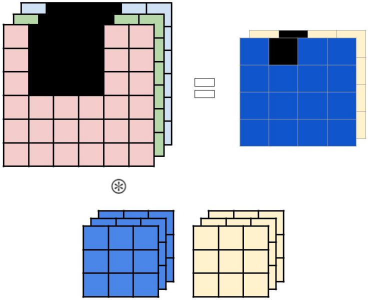

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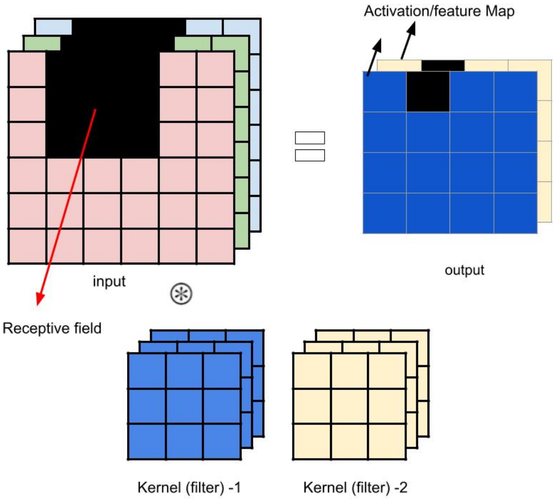
  - Adjacent components in o/p are influenced by adjacent parts in the i/p
- If the channel dimension has a metric meaning (e.g. time) 3D convolution can be employed (e.g. frames in a video)

Terminology in Convolution



Convolution function in PyTorch

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- `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

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- `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]])
```

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- `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

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>>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

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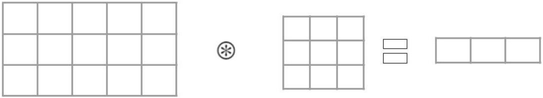
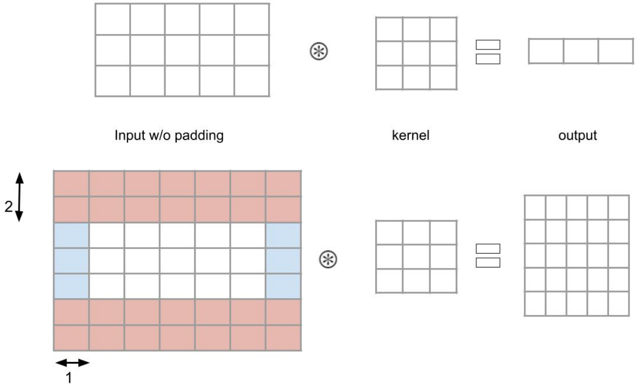
- Takes cares of size reduction after convolution
- Instead of zeros, one may pad with signal values at the edges

Padding in Convolution



Padding in Convolution



Stride in Convolution

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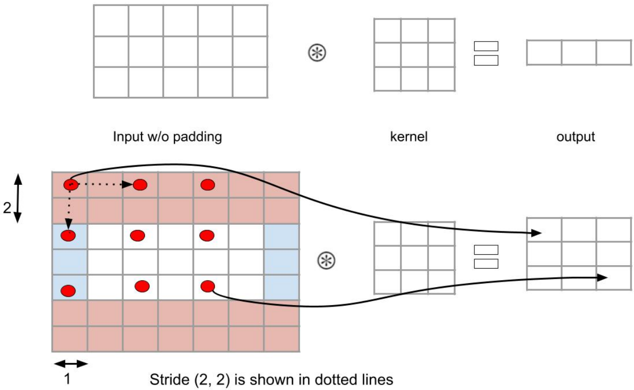
- Default value is 1, i.e., move the kernel across the signal densely (without skipping)

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

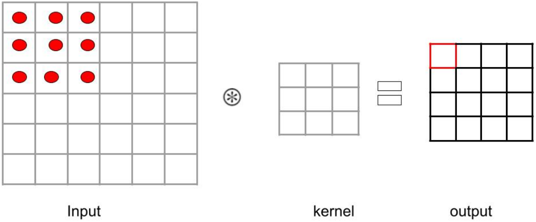
Output size of the Convolution

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

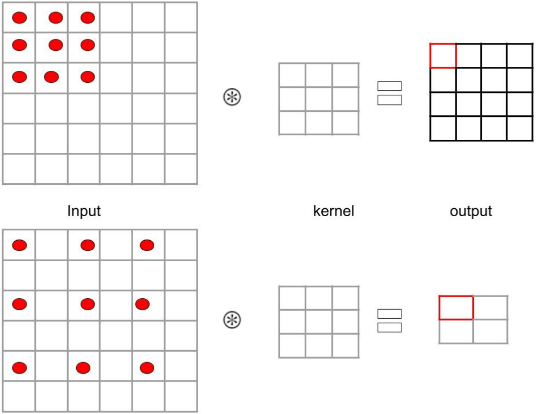
Output size of the Convolution

- 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

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Dilation

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- Any higher value of dilation makes the kernel sparse
- Dilation increases the receptive field
- It is referred to as 'atrous' convolution

Pooling

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- 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

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- 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

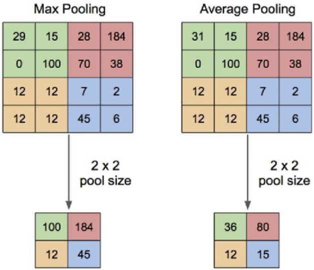


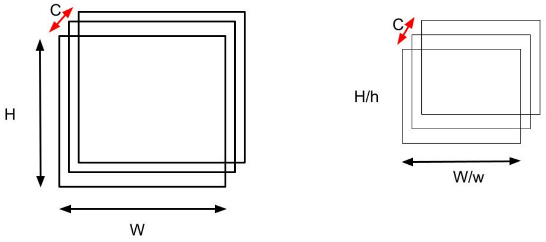
Figure credits: Preston Hoang and Quora

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

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- `input` is $N \times C \times H \times W$ tensor

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```

- 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)

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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

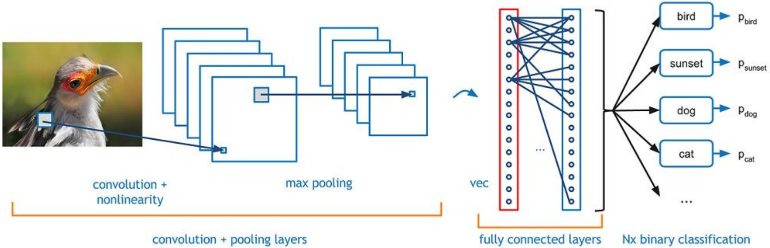
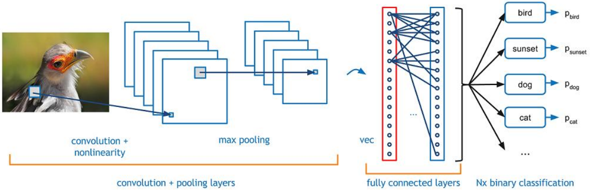


Figure credits: Adit Deshpande

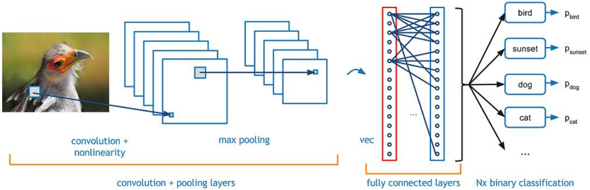
Architecture of a simple CNN



- Initially Conv layer with nonlinearity

Figure credits: Adit Deshpande

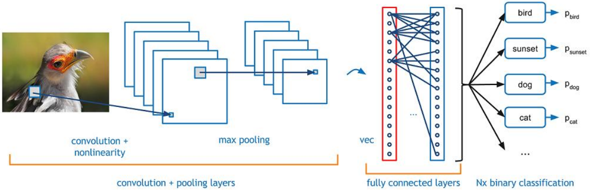
Architecture of a simple CNN



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

Figure credits: Adit Deshpande

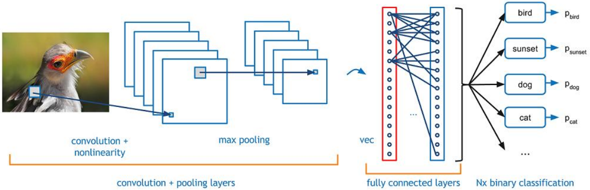
Architecture of a simple CNN



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

Figure credits: Adit Deshpande

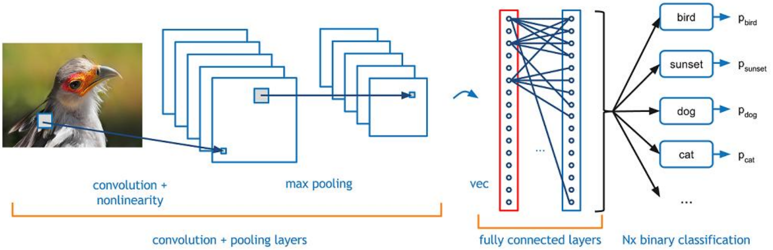
Architecture of a simple CNN



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

Figure credits: Adit Deshpande

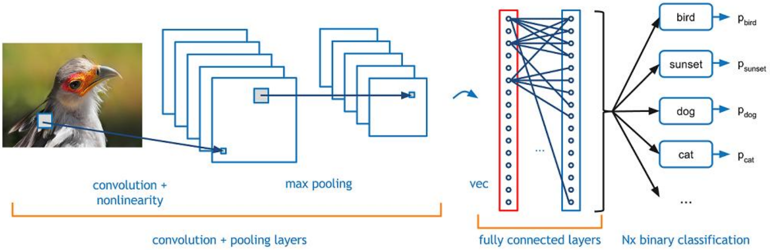
Architecture of a simple CNN



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

Figure credits: Adit Deshpande

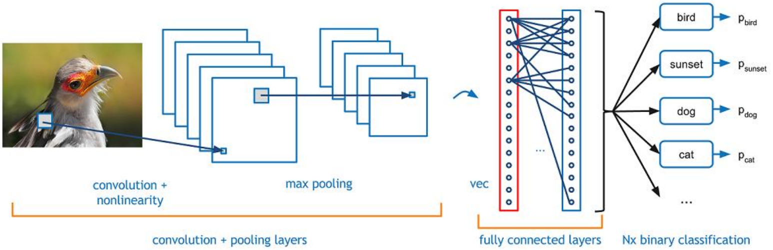
Architecture of a simple CNN



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
$1 \times 28 \times 28$ `nn.Conv2d(1, 32, kernel_size=5)`			

Case study: LeNet-like architecture

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$1 \times 28 \times 28$ `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
$1 \times 28 \times 28$ `nn.Conv2d(1, 32, kernel_size=5)`	$32 \times 24 \times 24$	$32.(5^2 + 1)$ $= 832$	

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
$1 \times 28 \times 28$ `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

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
$1 \times 28 \times 28$ `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)`			

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
$1 \times 28 \times 28$ `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)`	$64 \times 4 \times 4$	$64.(32.5^2 + 1)$ $= 51264$	

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)`	$64 \times 4 \times 4$	$64.(32.5^2+1)$ $= 51264$	$64.32.4^2.5^2$ $= 819200$

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

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$1 \times 28 \times 28$ `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		

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
$1 \times 28 \times 28$ `nn.Conv2d(1, 32, kernel_size=5)`	$32 \times 24 \times 24$	$32.(5^2+1)$ $= 832$	$32.24^2.5^2$ $= 460800$
`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
$32 \times 8 \times 8$ `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)`	0 200	0 200(256+1)=51400	0 200.256=51200
200 / `F.relu(.)`	200	0	0
200 `nn.Linear(200,10)`	0 10	0 10(200+1)=2010	0 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