

# **Single & Multi-Channel Convolution**

Instructor - Simon Lucey

**16-720B - Computer Vision**



**DON'T PANIC**

# Today

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- Why Convolution?
- Reminder: Single Channel Convolution
- 2D Convolution & Separable Filters
- Multi-Channel Convolution

# 3 Biggest Problems in Computer Vision?

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REGISTRATION

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(Prof. Takeo Kanade - Robotics Institute - CMU.)

# What is Registration?

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“Source Image”



“Template Image”

# What is Registration?

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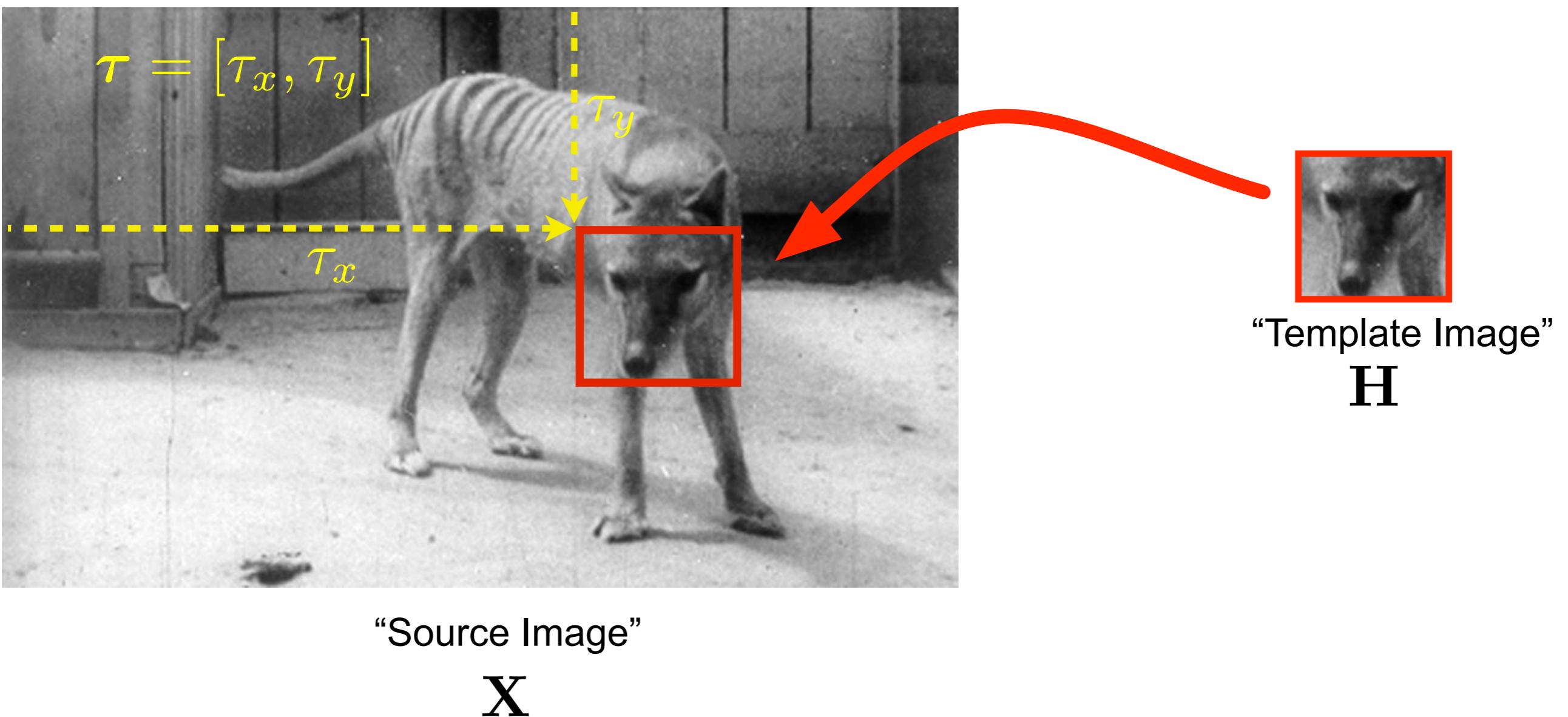
“Source Image”

**X**



“Template Image”  
**H**

# What is Registration?





$$\mathbf{Y} = \mathbf{X} * \mathbf{H}$$

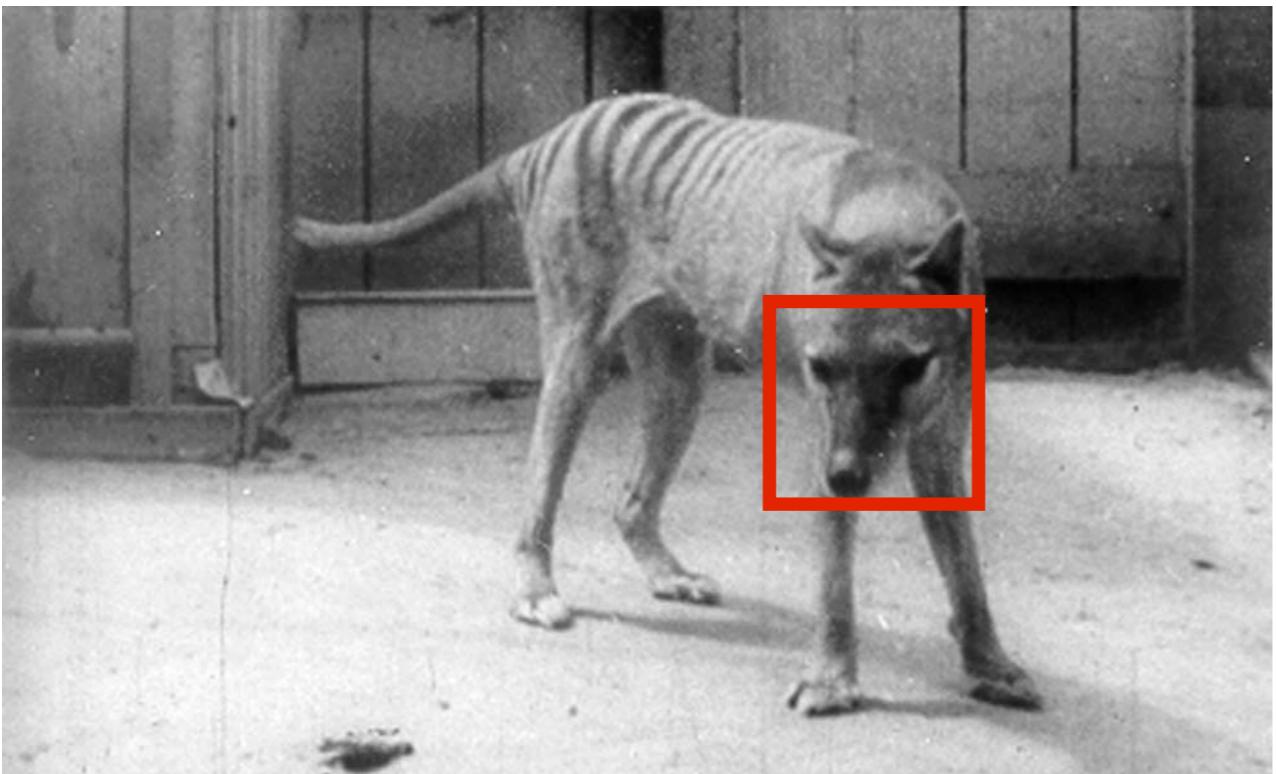


$$\mathbf{Y} = \mathbf{X} * \mathbf{H}$$



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```
>>> from scipy.ndimage import convolve as imconv  
>>> Y = imconv(X, H)
```

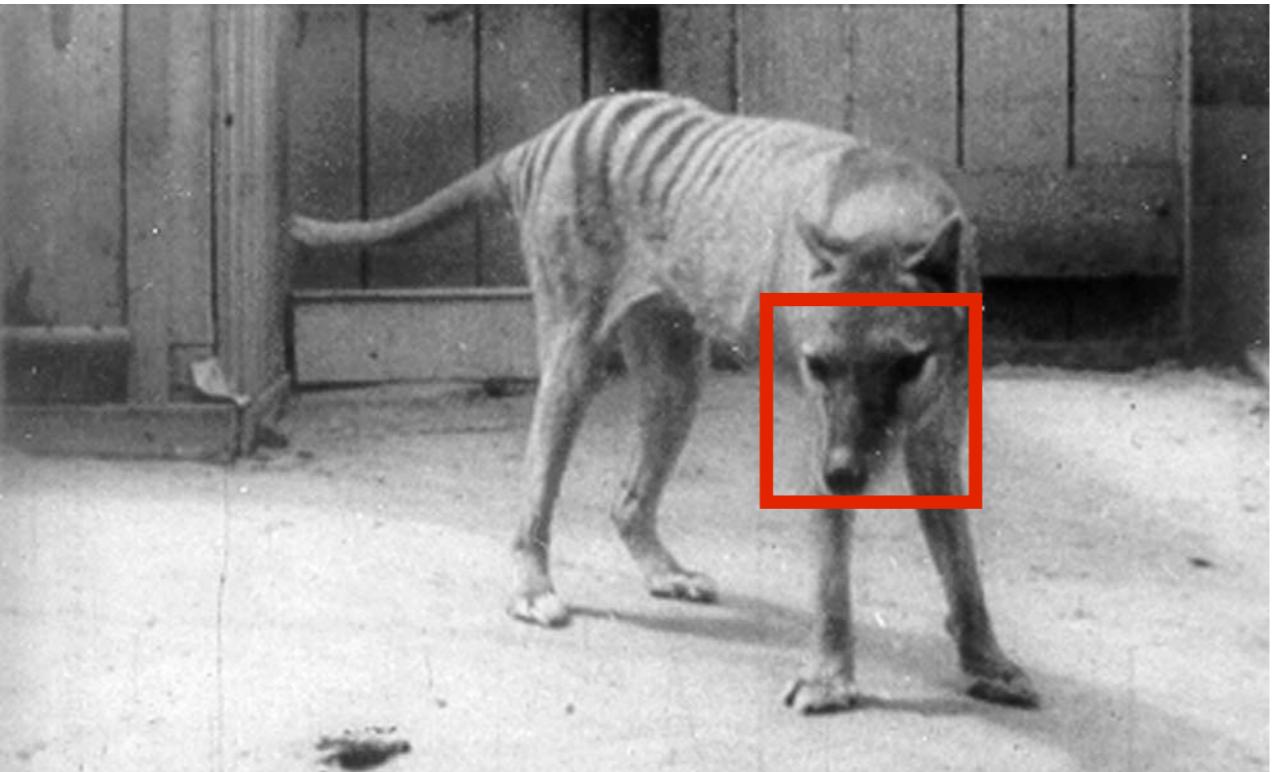


X

\*

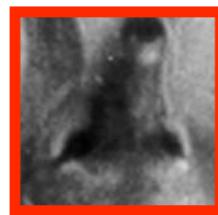


H

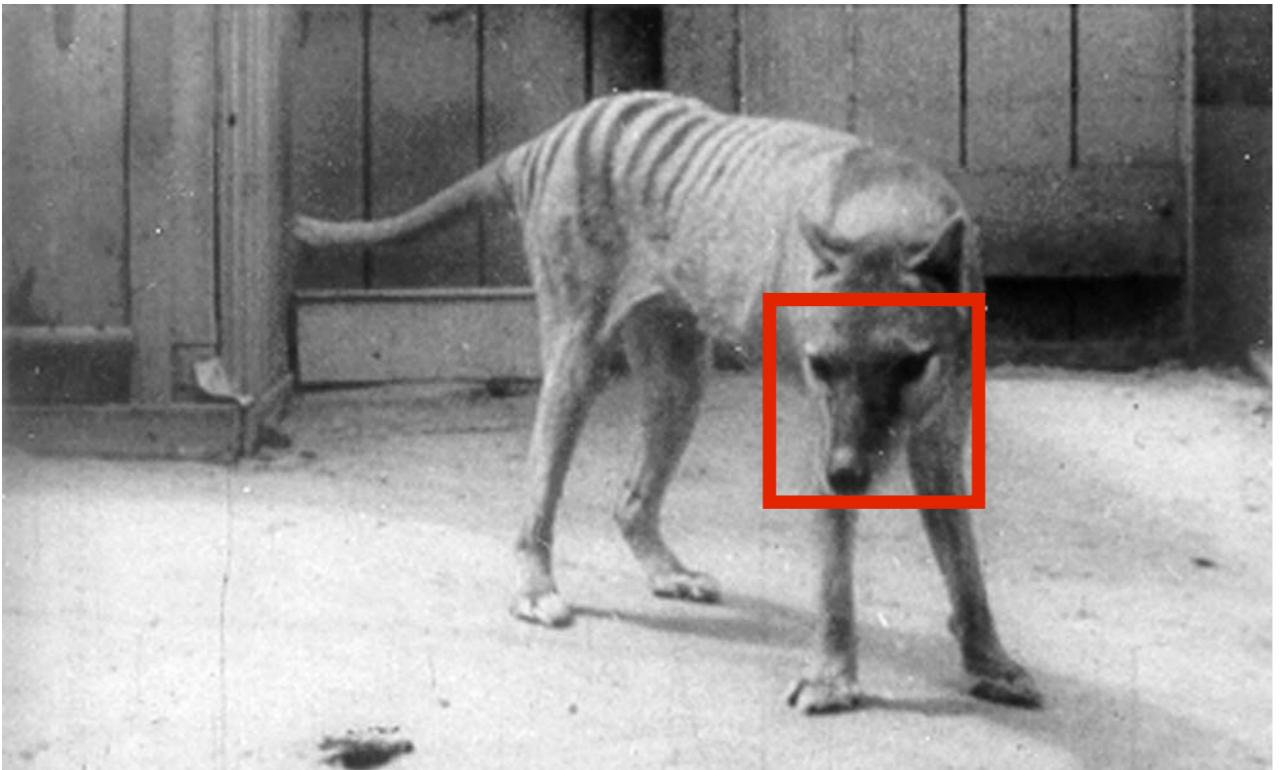


X

\*



H

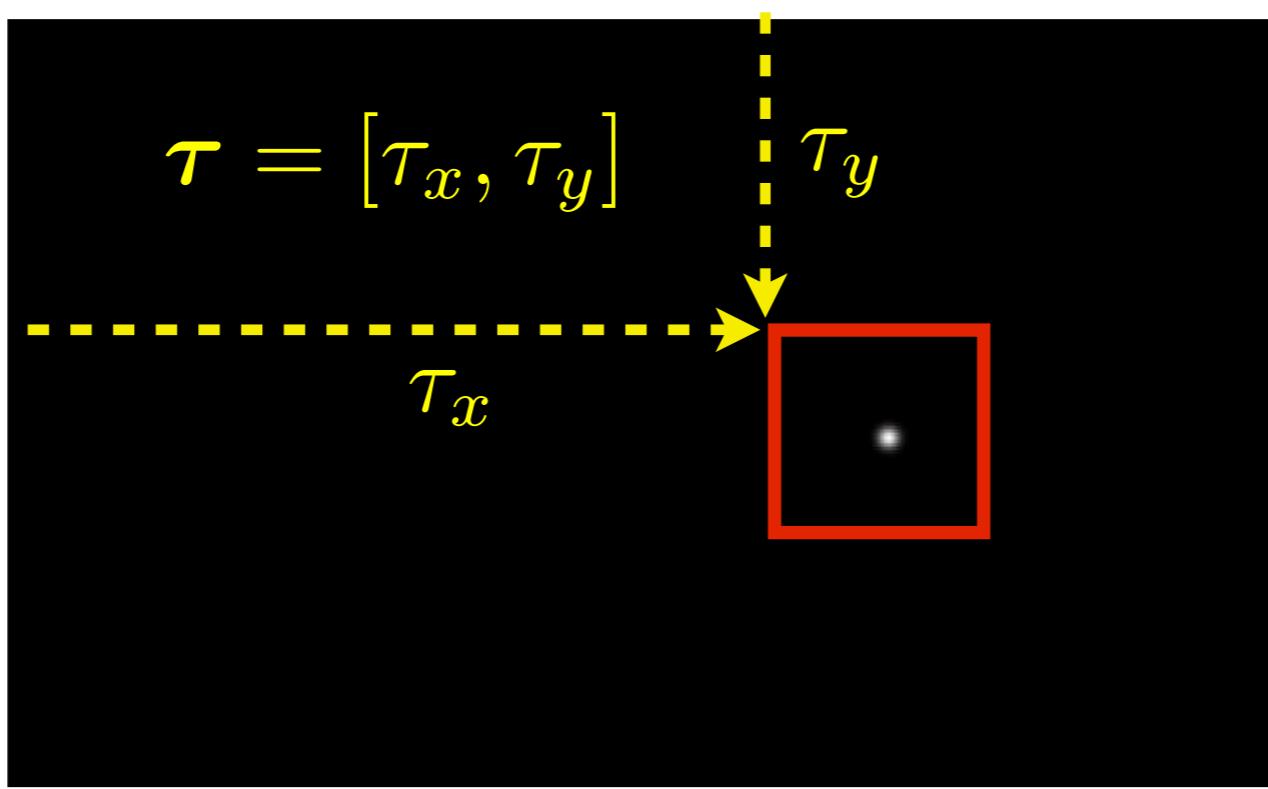


X

\*



H



Y

# Reminder

207	245	77	21	247	211	240	1
219	41	58	179	161	154	184	98
215	145	187	71	251	249	65	100
192	2	189	247	166	63	232	213
105	94	66	190	156	61	89	145
159	154	87	184	101	105	72	71
192	111	6	94	60	70	65	226
175	120	210	226	80	183	168	184
134	56	36	240	159	178	76	135
239	244	199	9	132	104	188	185
245	210	78	199	0	92	9	246
5	121	187	122	107	47	12	119
230	171	135	36	82	54	65	37
61	140	79	19	161	96	127	187
56	223	46	6	180	186	142	244
28	20	61	2	178	187	98	220

X

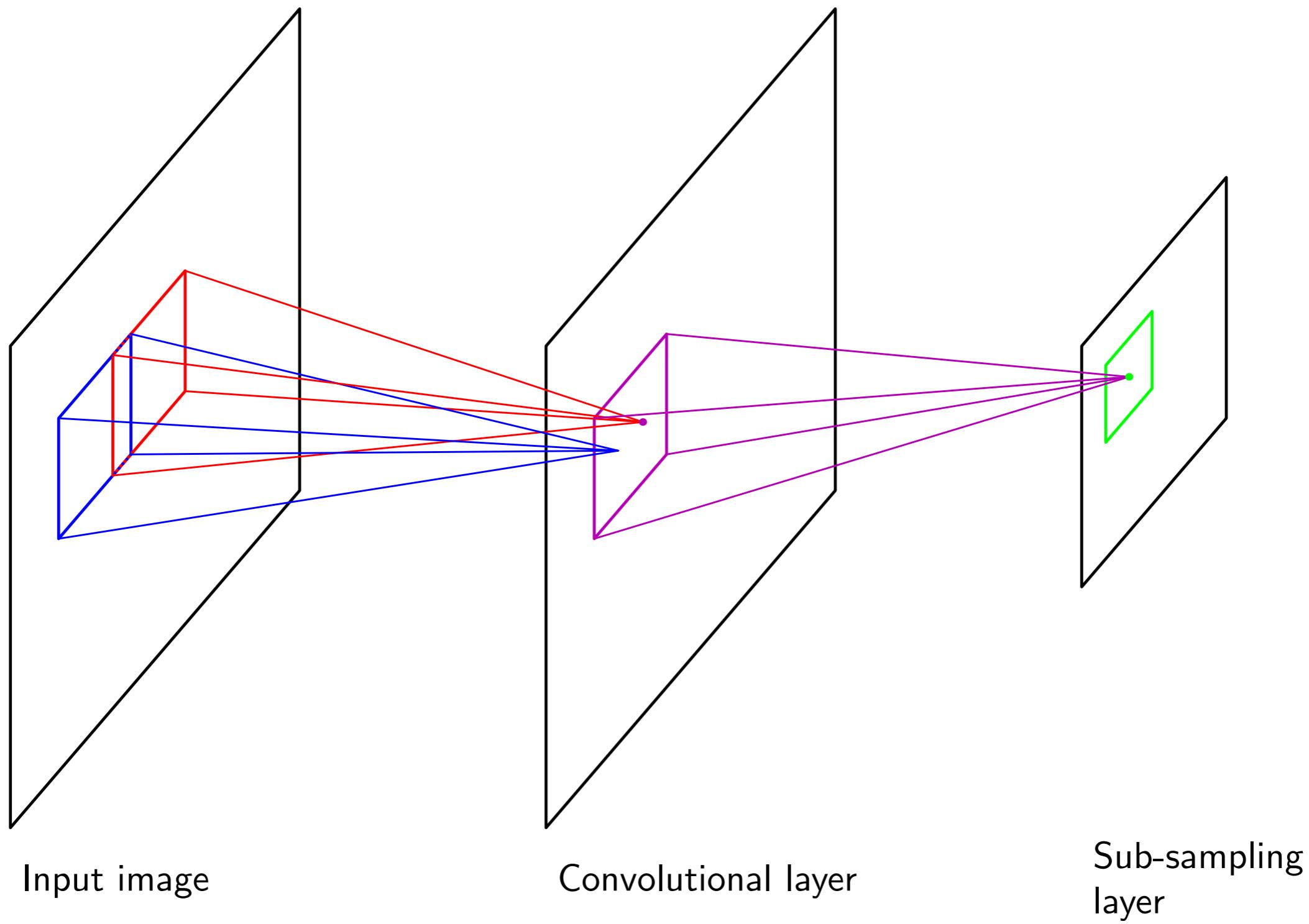
# Reminder

---



$\phi\{\mathbf{X}\}$

# Convolutional Neural Network



# Important: My Notation

$a \leftarrow$  scalar      “*lower case italic*”

$\mathbf{a} = \begin{bmatrix} a_1 \\ \vdots \\ a_M \end{bmatrix} \leftarrow$  vector      “**lower case bold**”

$\mathbf{A} = \begin{bmatrix} a_{1,1} & \dots & a_{1,N} \\ \vdots & \ddots & \vdots \\ a_{M,1} & \dots & a_{M,N} \end{bmatrix} \rightarrow$  matrix      “**Upper Case Bold**”

$\mathcal{A}(x) = \cos(x) \leftarrow$  function      “**Upper Case Mathcal**”

# Today

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- 2D Convolution & Separable Filters
- Multi-Channel Convolution

# Reminder: 1D Convolution

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$$y[i] = \sum_u x[u]h[i - u]$$

# Python PyLab Assumption

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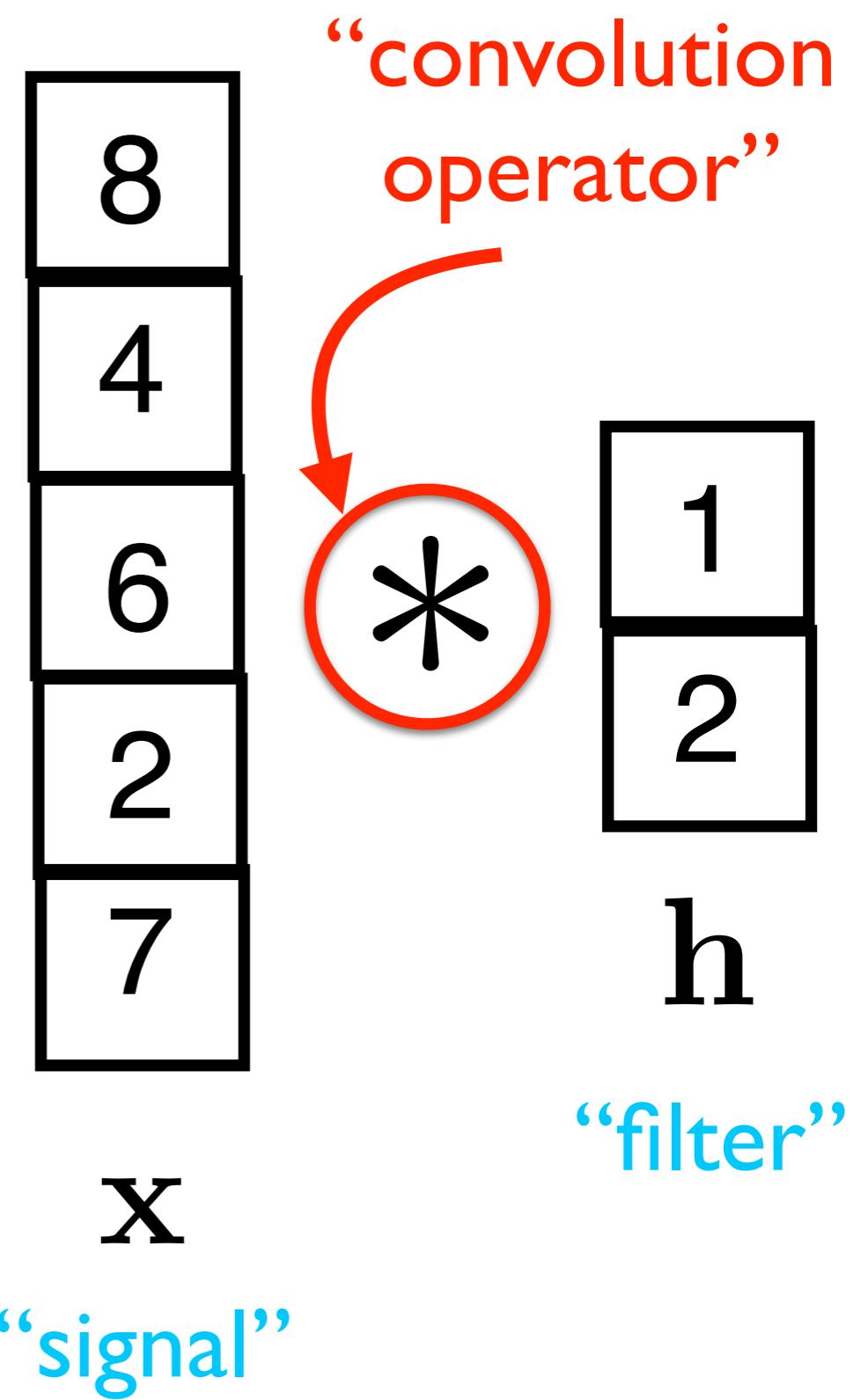
- We will be showing python code snippets in the lecture notes, these will make the assumption that you:-

```
>>> from pylab import *
```

- PyLab is a module that belongs to the Python mathematics library Matplotlib.
- PyLab combines the numerical module numpy with the graphical plotting module pyplot.
- PyLab was designed with the interactive Python interpreter in mind, and therefore many of its functions are short and require minimal typing.
- In scripts, however, you should name everything you import to avoid namespace conflicts.

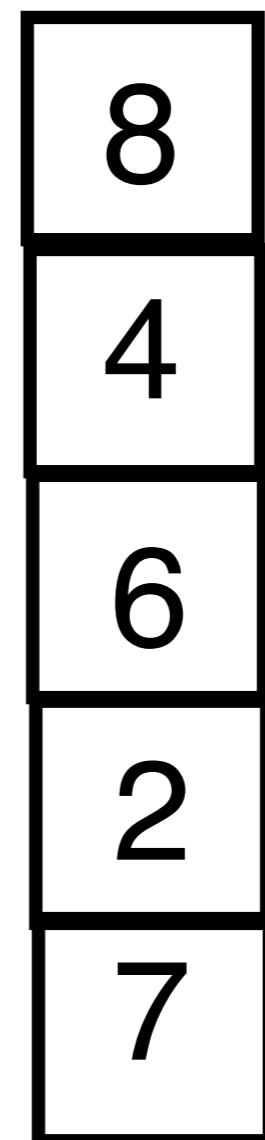
```
>>> import numpy as np
```

# Reminder: Convolution



# Reminder: Convolution

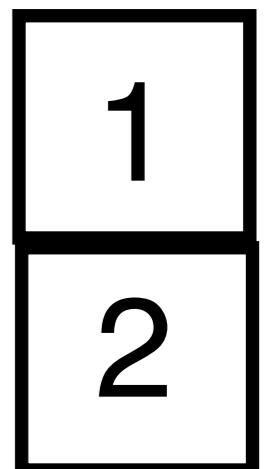
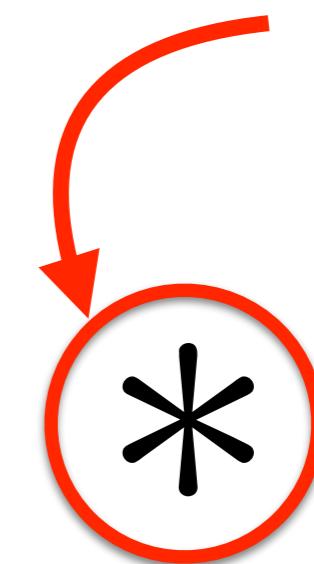
```
>>> from scipy.signal import \
    convolve as conv
>>> conv(x,h,'valid')
array([20, 14, 14, 11])
```



$x$

“signal”

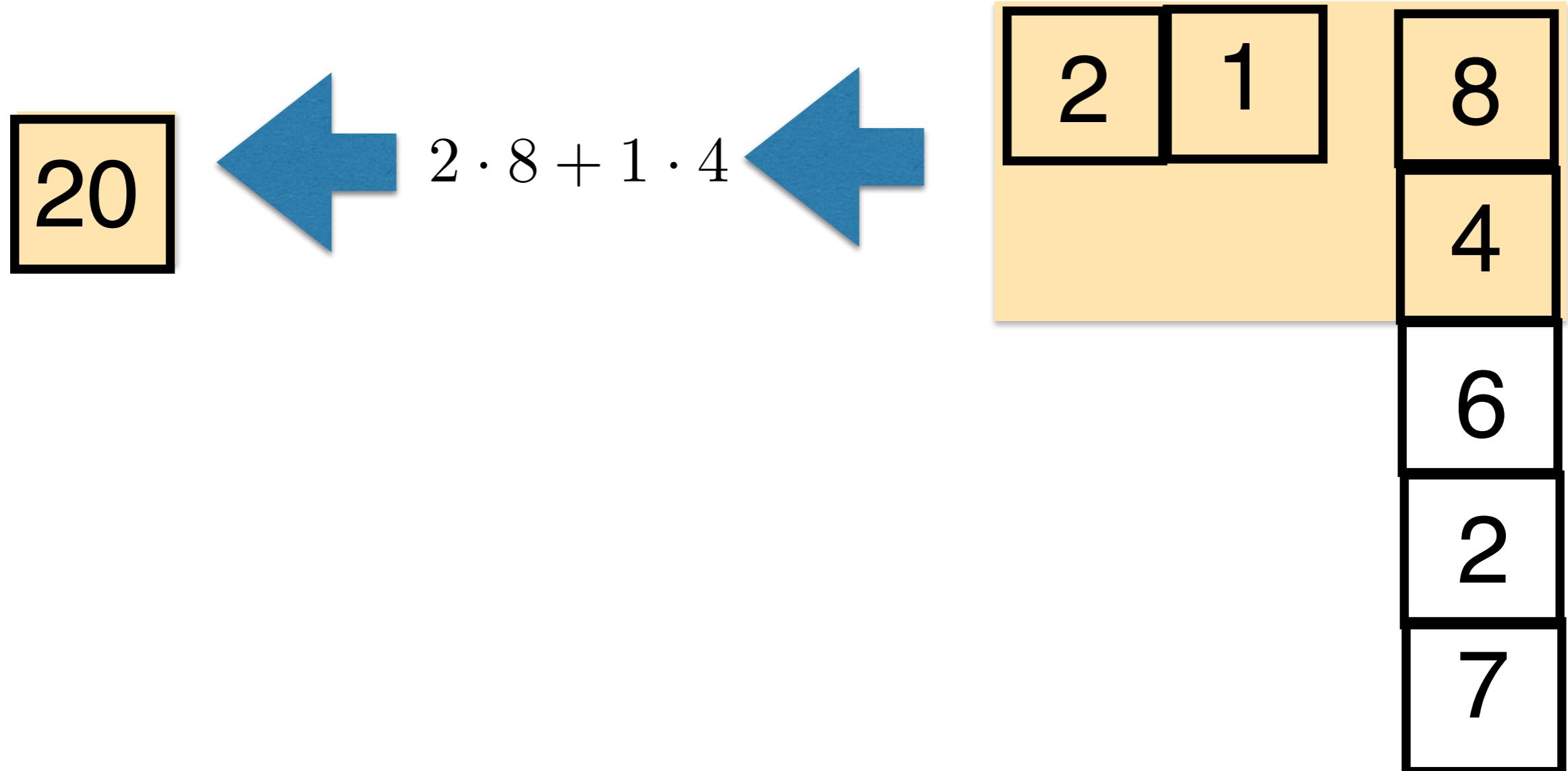
“convolution  
operator”



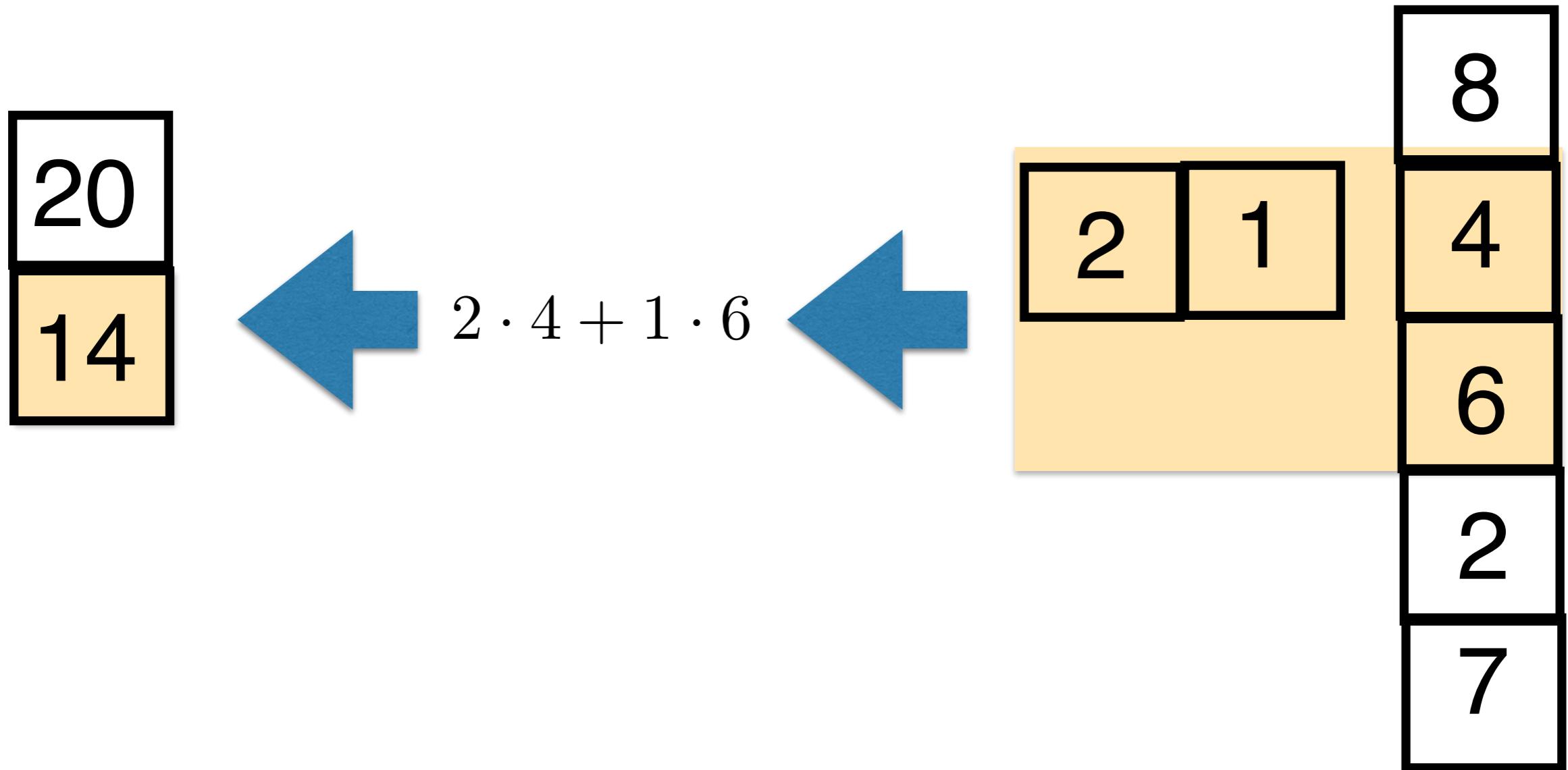
$h$

“filter”

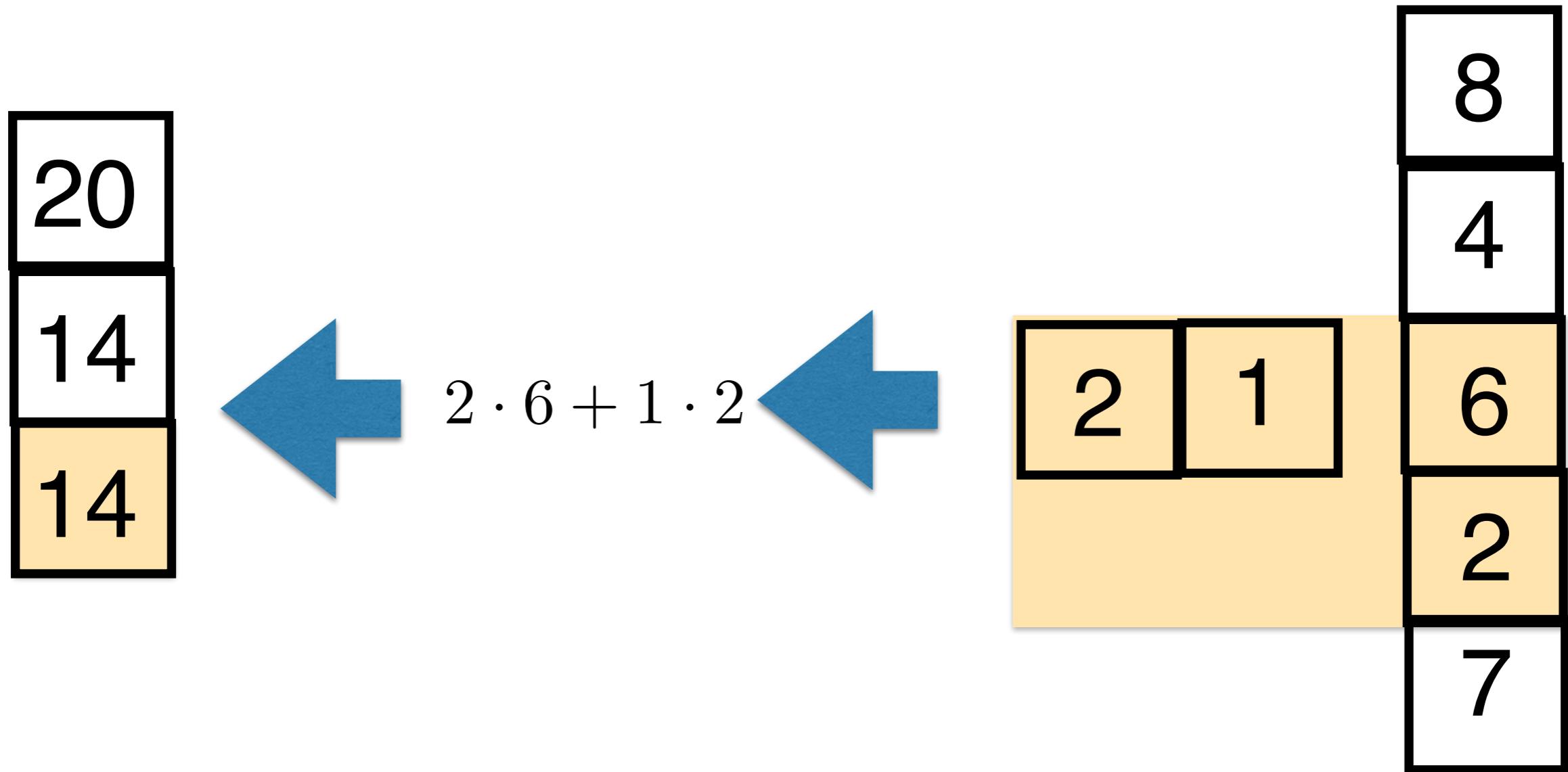
# Reminder: 1D Convolution



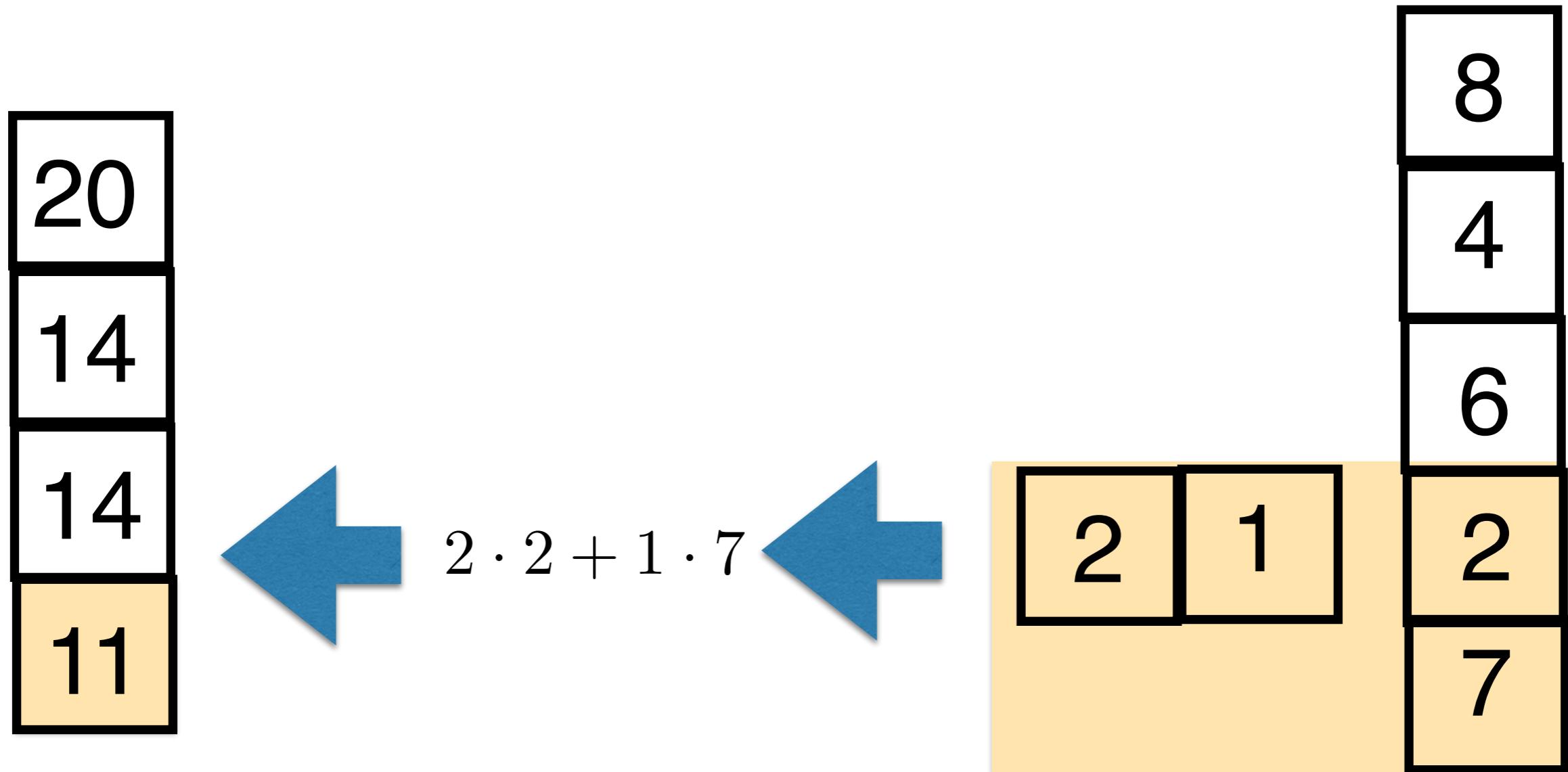
# Reminder: 1D Convolution



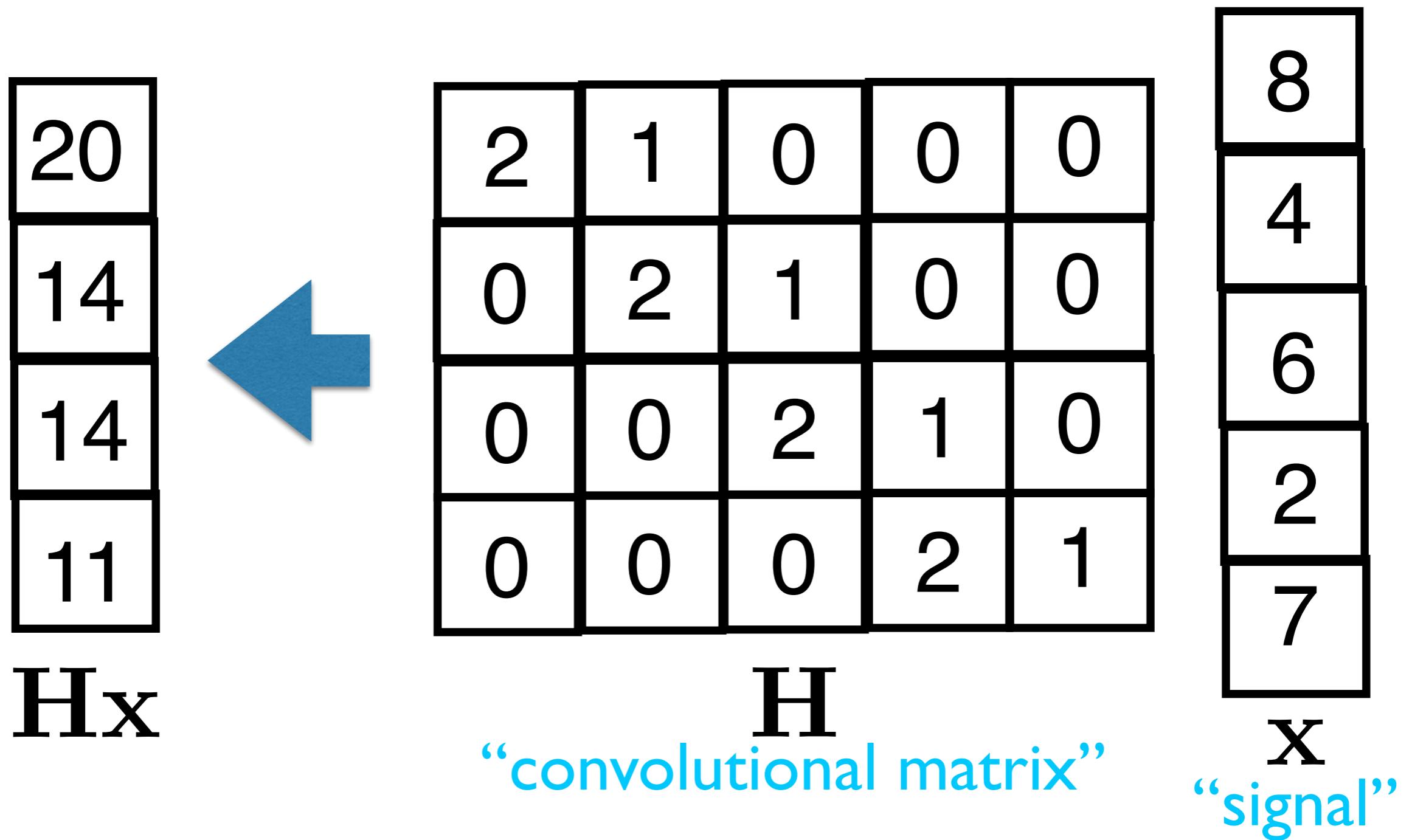
# Reminder: 1D Convolution



# Reminder: 1D Convolution



# Reminder: 1D Convolution



# Types of Convolution

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- More than just one type of convolutional operator:-

- “Valid” convolution

```
>>> conv(x,h,'valid')
```

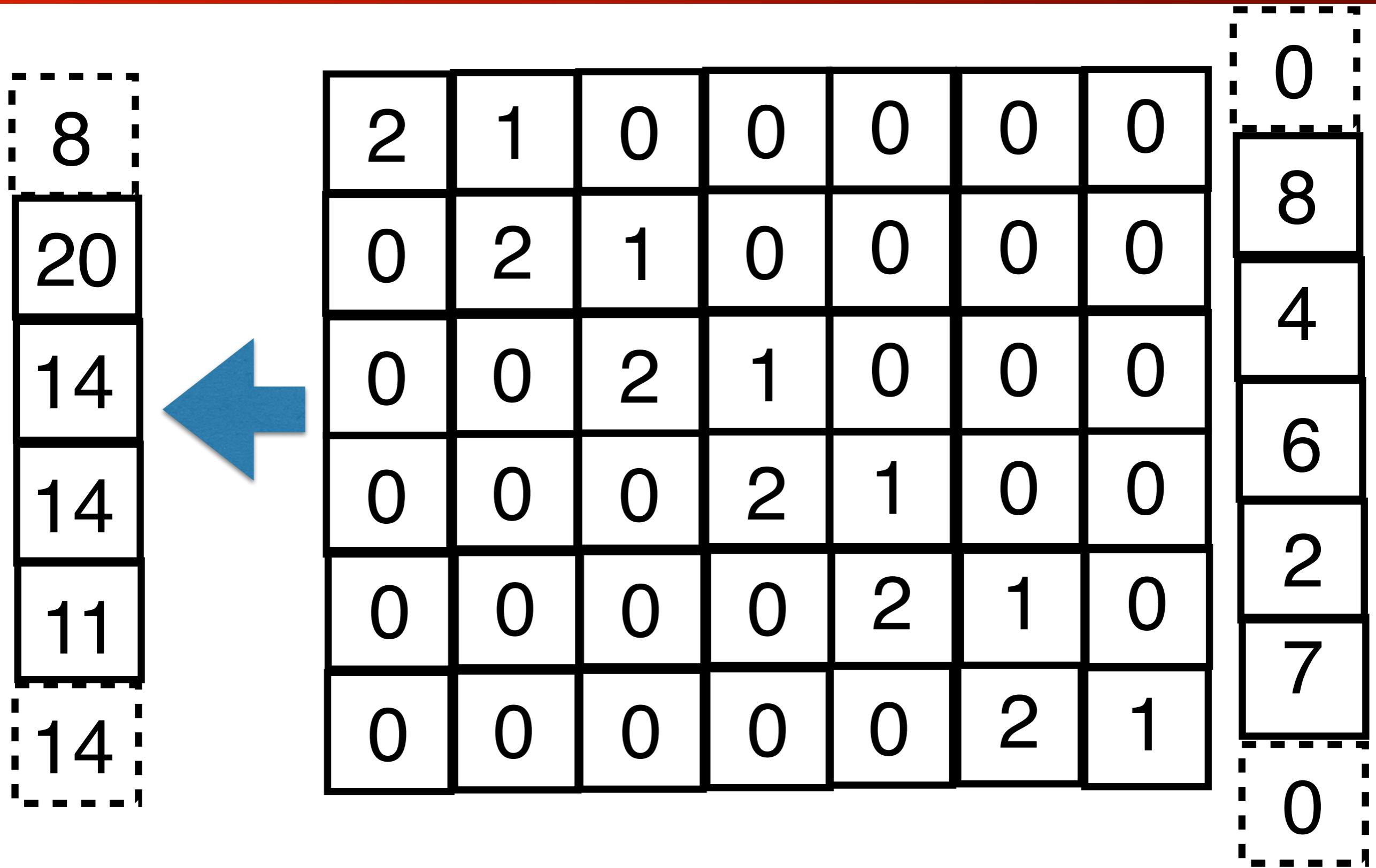
- “Same” convolution

```
>>> conv(x,h,'same')
```

- “Full” convolution

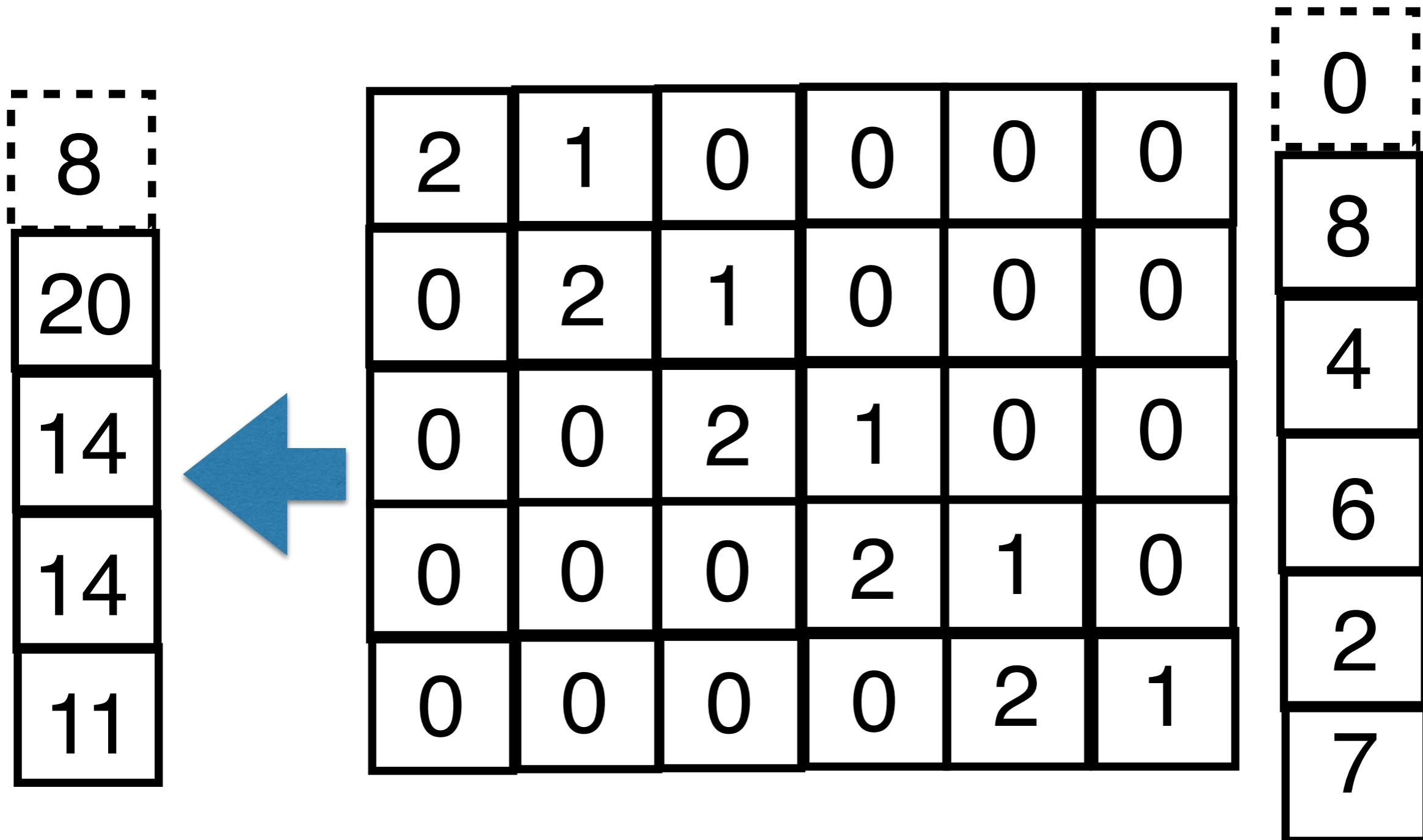
```
>>> conv(x,h,'full')
```

# Zero-Padded Convolution



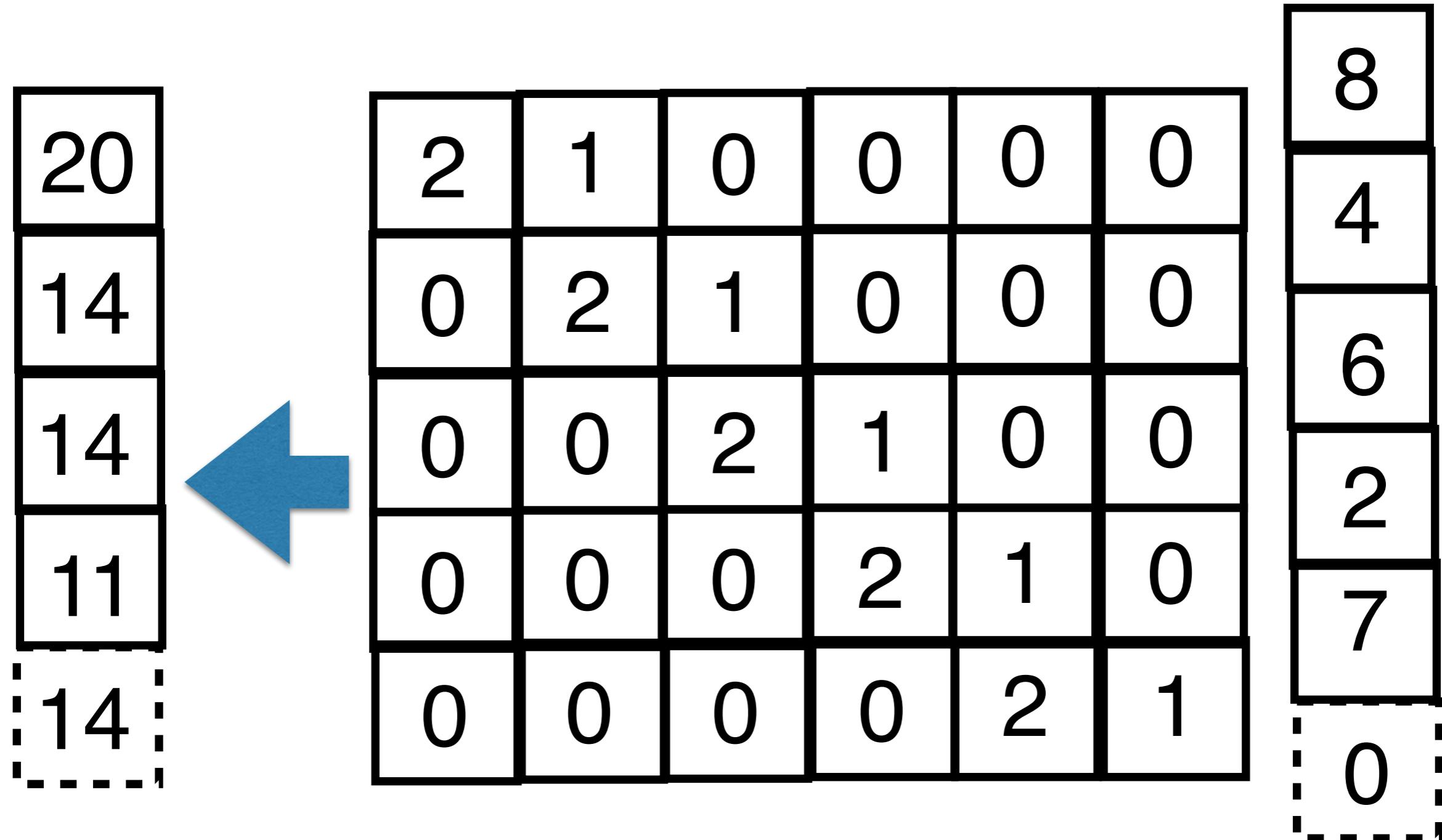
```
>>> conv(x, h, 'full')
```

# Zero-Padded Convolution



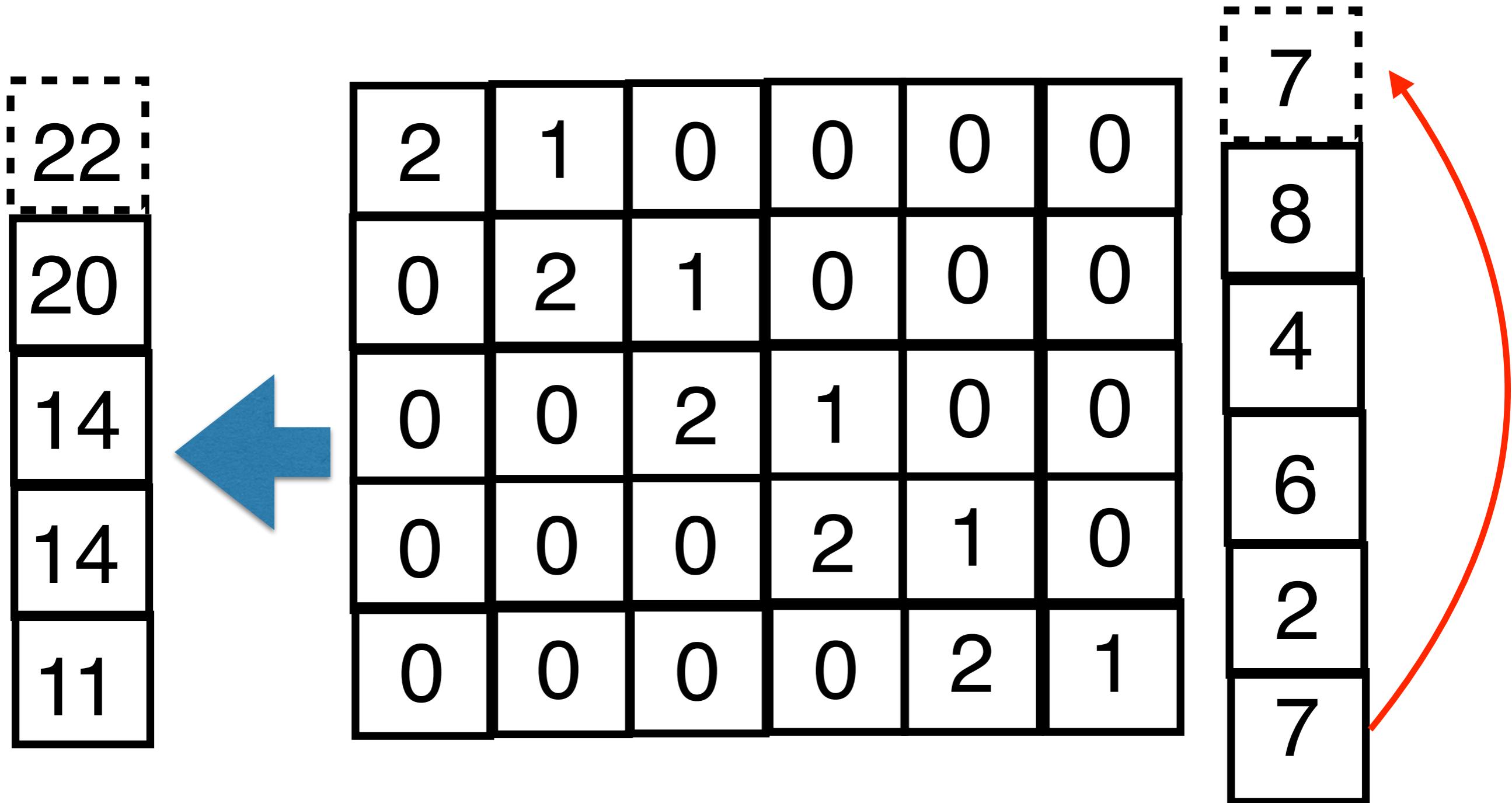
```
>>> conv(x, h, 'same')
```

# Zero-Padded Convolution



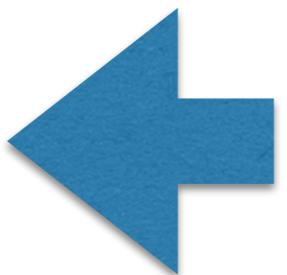
```
>>> imconv(x, h, 'same')
```

# Circular Convolution



H

22
20
14
14
11



1	0	0	0	2
2	1	0	0	0
0	2	1	0	0
0	0	2	1	0
0	0	0	2	1

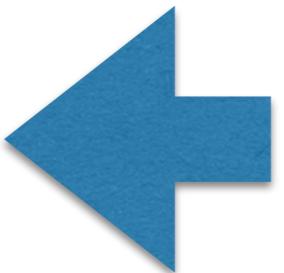
8
4
6
2
7

H

x

# Circular Convolution

22
20
14
14
11



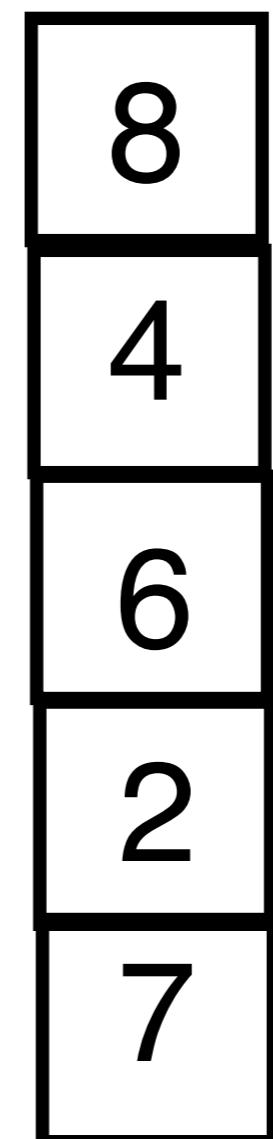
8	7	2	6	4
4	8	7	2	6
6	4	8	7	2
2	6	4	8	7
7	2	6	4	8

X

1
2
0
0
0

h

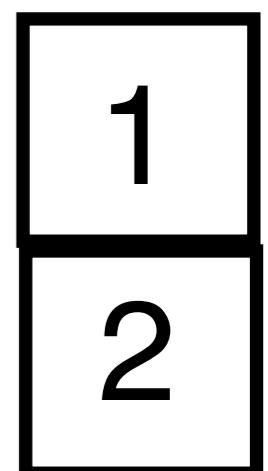
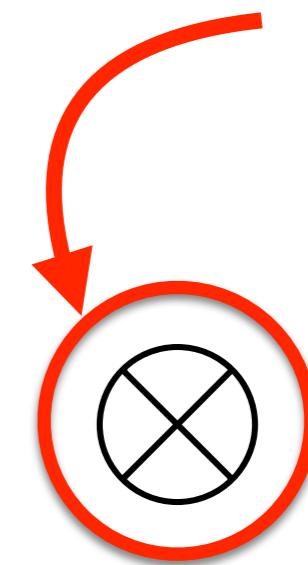
# Correlation



**x**

“signal”

“correlation  
operator”

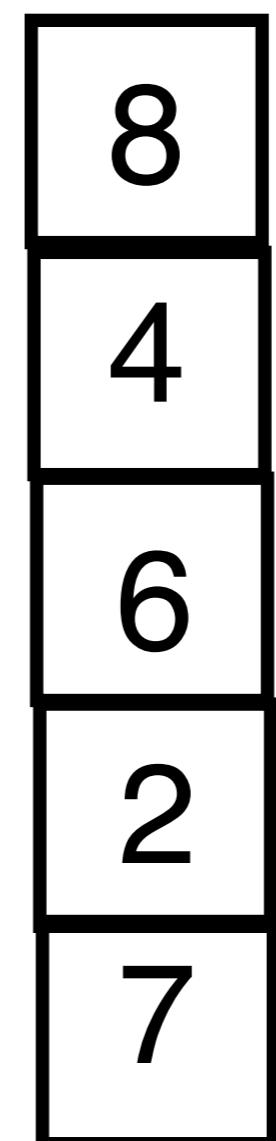


**h**

“filter”

# Correlation

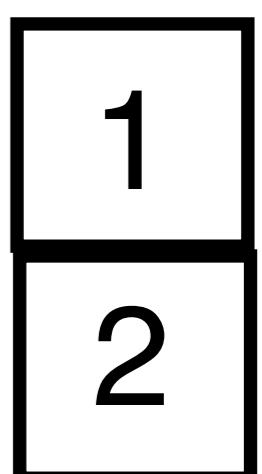
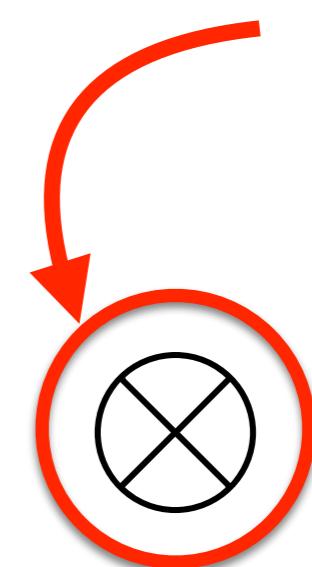
```
>>> from scipy.signal import \
correlate as corr
>>> corr(x,h,'same')
array([16,16,16,10,16])
```



**x**

“signal”

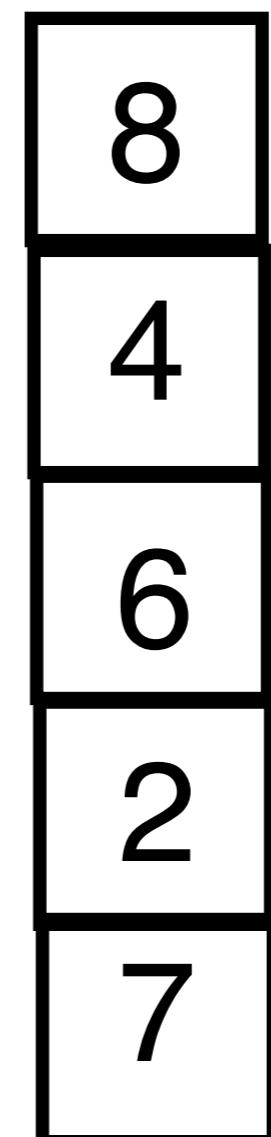
“correlation  
operator”



**h**

“filter”

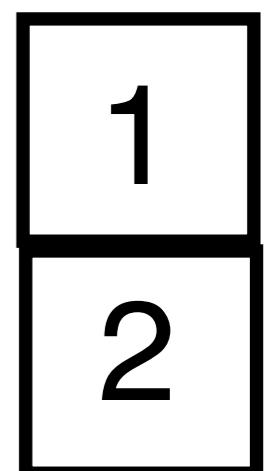
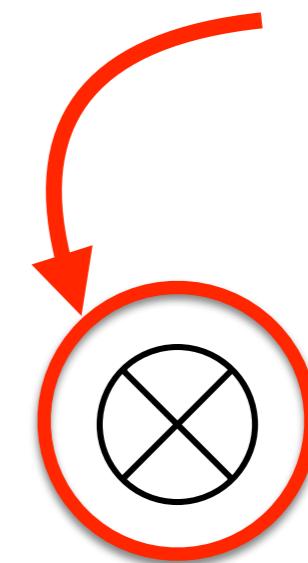
# Correlation



**x**

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“correlation  
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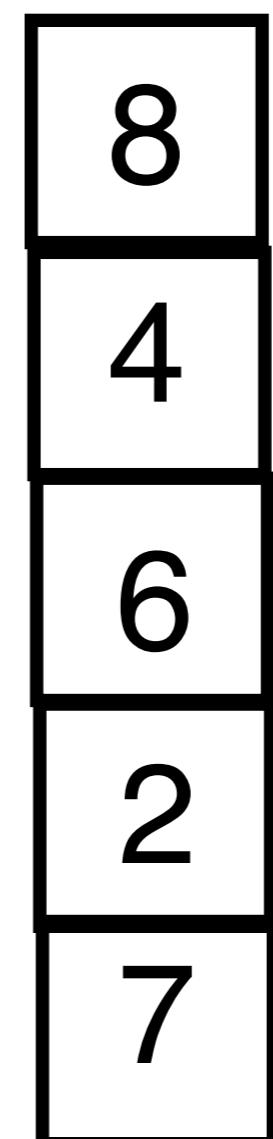


**h**

“filter”

# Correlation

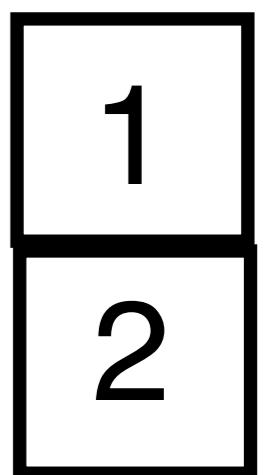
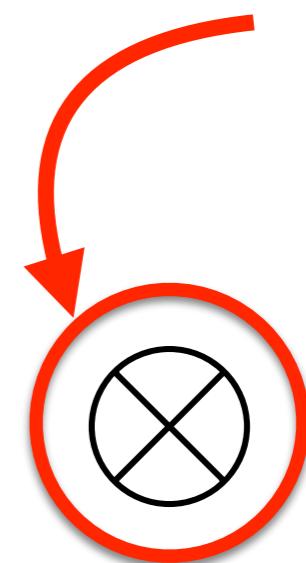
```
>>> conv(x, np.flipud(h), 'same')  
array([16, 16, 16, 10, 16])
```



**x**

“signal”

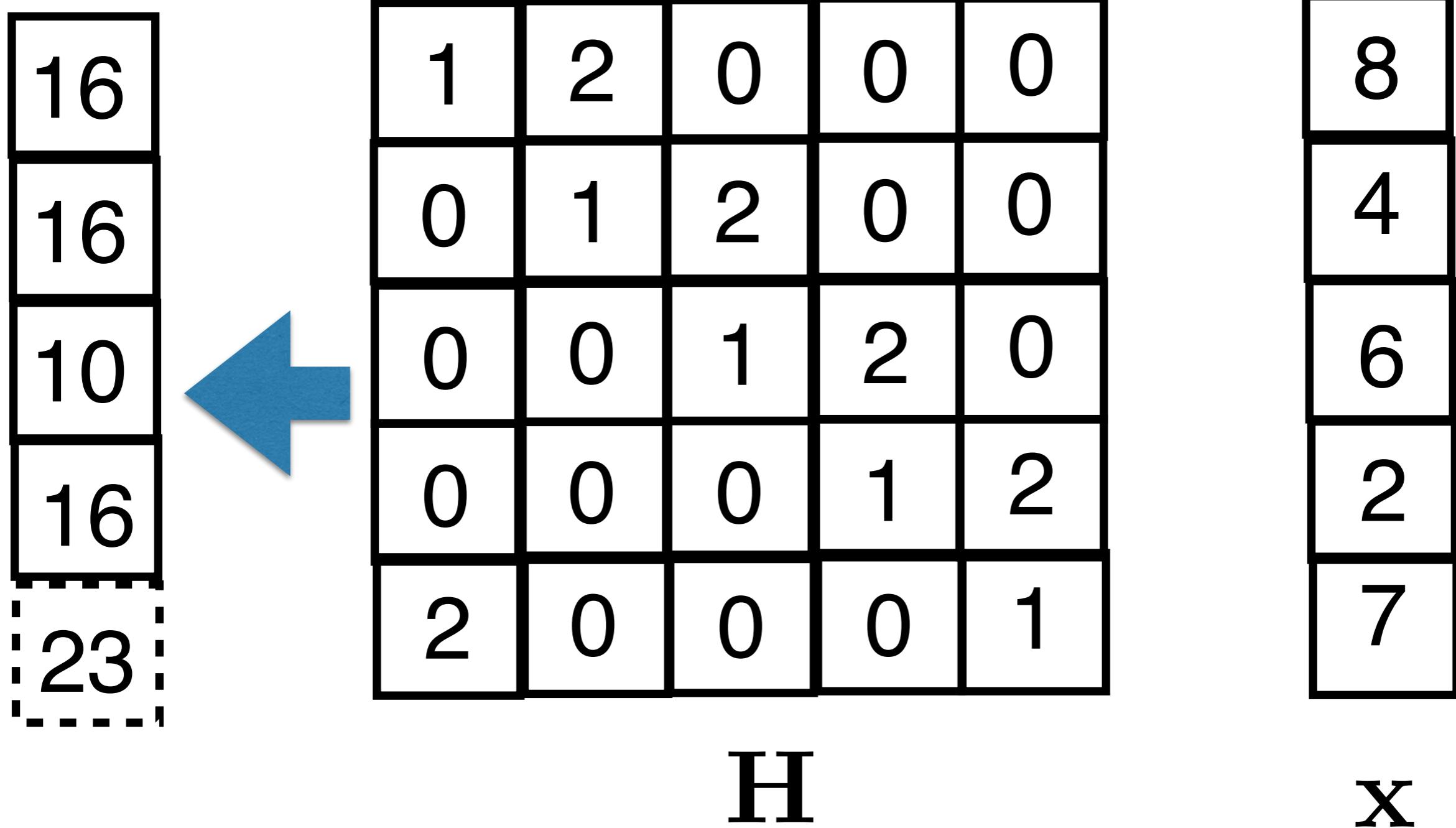
“correlation  
operator”



**h**

“filter”

# Circular Correlation



# Correlation vs. Convolution

---

- Convolution is preferred mathematically over correlation as it is,

$$g * (h * x) = (g * h) * x \text{ (associative)}$$

$$h * x = x * h \text{ (communicative)}$$

# Correlation vs. Convolution

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- Correlation is neither!!!

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$$g \otimes (h \otimes x) \neq (g \otimes h) \otimes x$$

$$h \otimes x \neq x \otimes h$$

# Correlation vs. Convolution

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- Convolution is preferred mathematically over correlation as it is,

$$g * (h * x) = (g * h) * x \text{ (associative)}$$

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- Correlation is neither!!!

$$g \otimes (h \otimes x) \neq (g \otimes h) \otimes x$$

$$h \otimes x \neq x \otimes h$$

- Correlation, however, preferred for signal matching/detection.

# Today

---

- Why Convolution?
- Reminder: Single Channel Convolution
- 2D Convolution & Separable Filters
- Multi-Channel Convolution

# Reminder: 2D Convolution

---

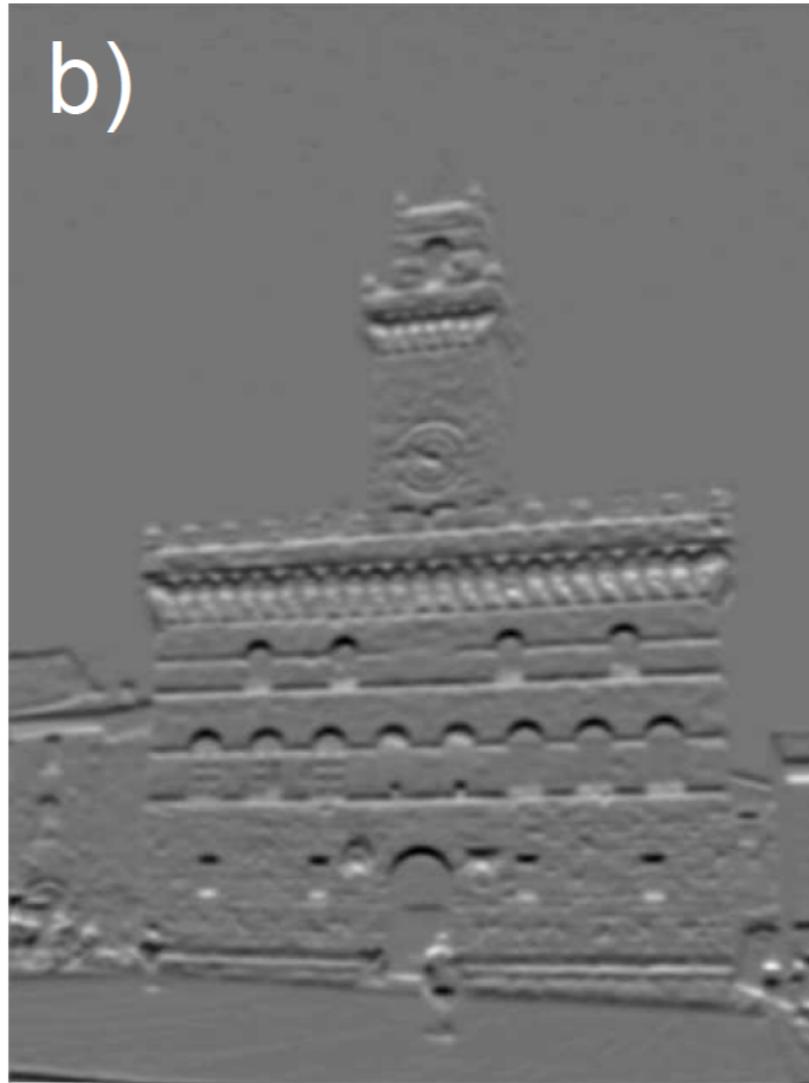
$$Y[j, i] = \sum_v \sum_u X[u, v] H[j - v, i - u]$$

# Reminder: 2D Convolution

---

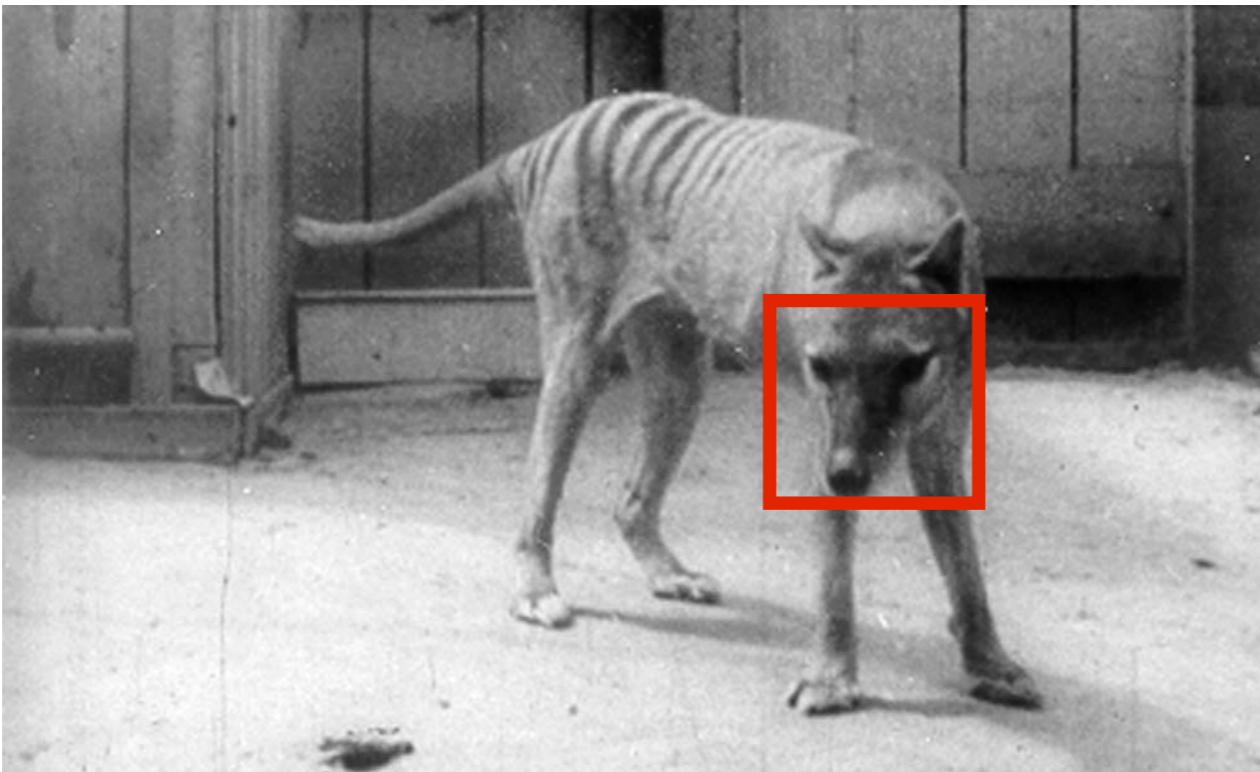
$$Y = X * H$$

# Estimating Image Gradients



Compute horizontal and vertical gradient images.

# 2D Convolution vs. Correlation



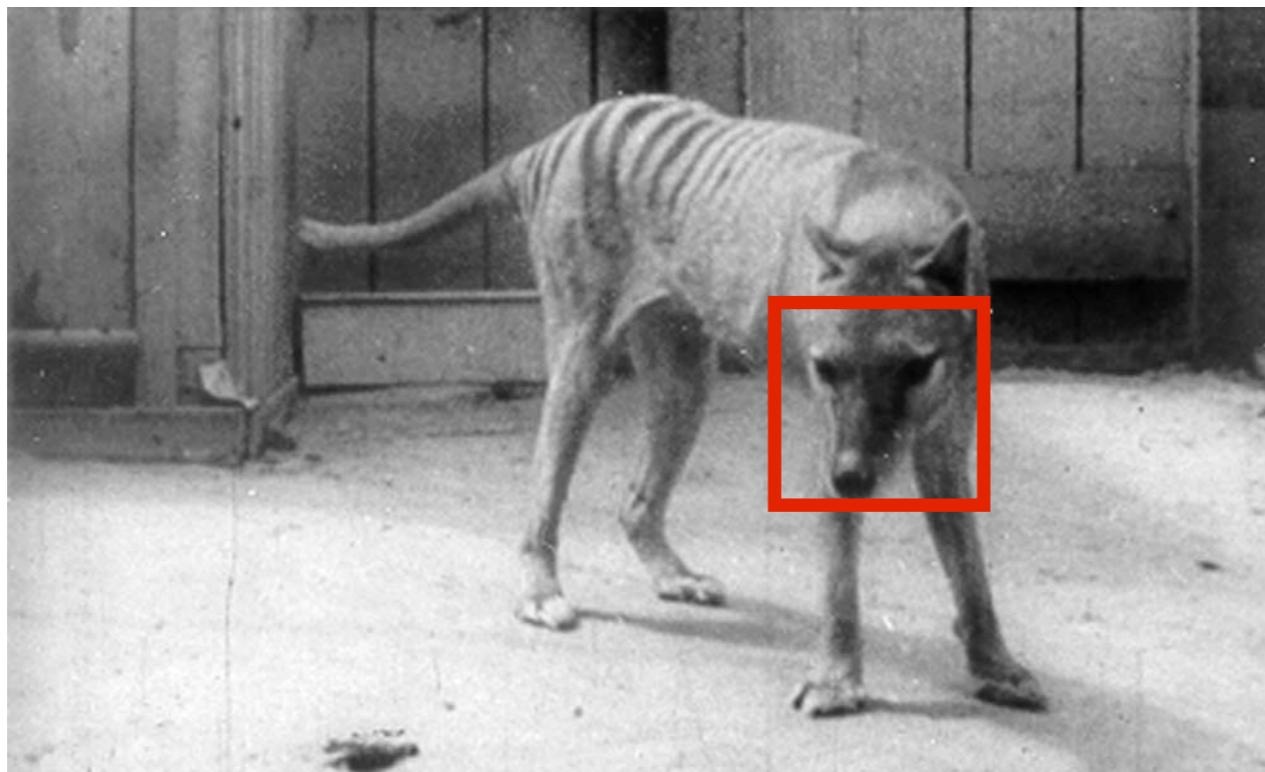
X



G

```
>>> from scipy.ndimage import \
correlation as imcorr
>>> Y = imcorr(X, G)
```

# 2D Convolution vs. Correlation



X

\*



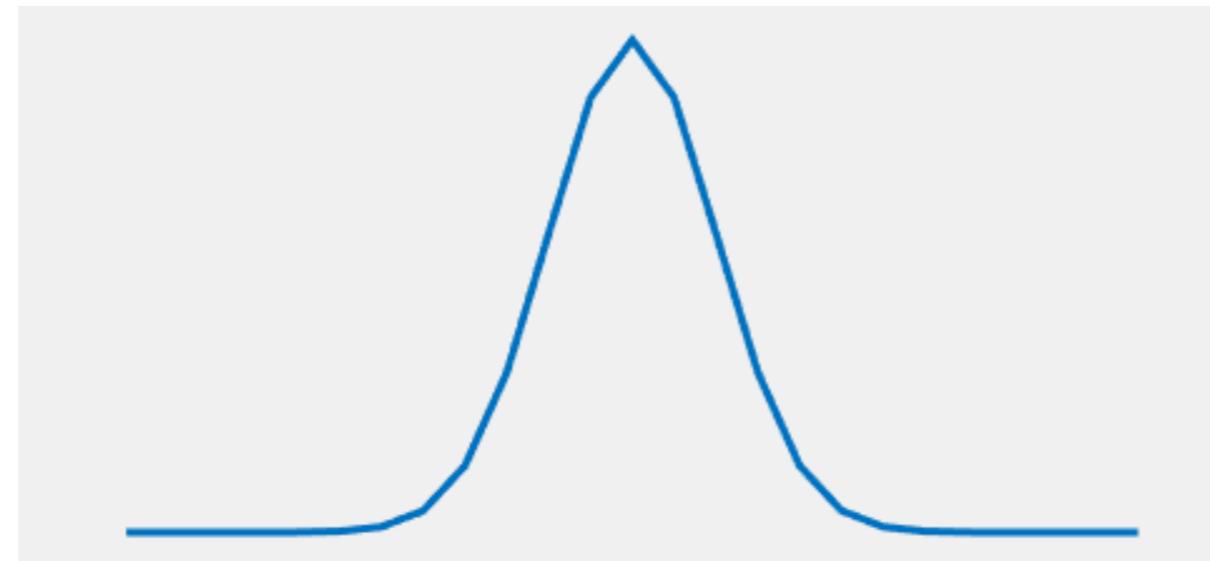
H

```
>>> H = flipud(fliplr(G))  
>>> Y = imconv(X, H)
```

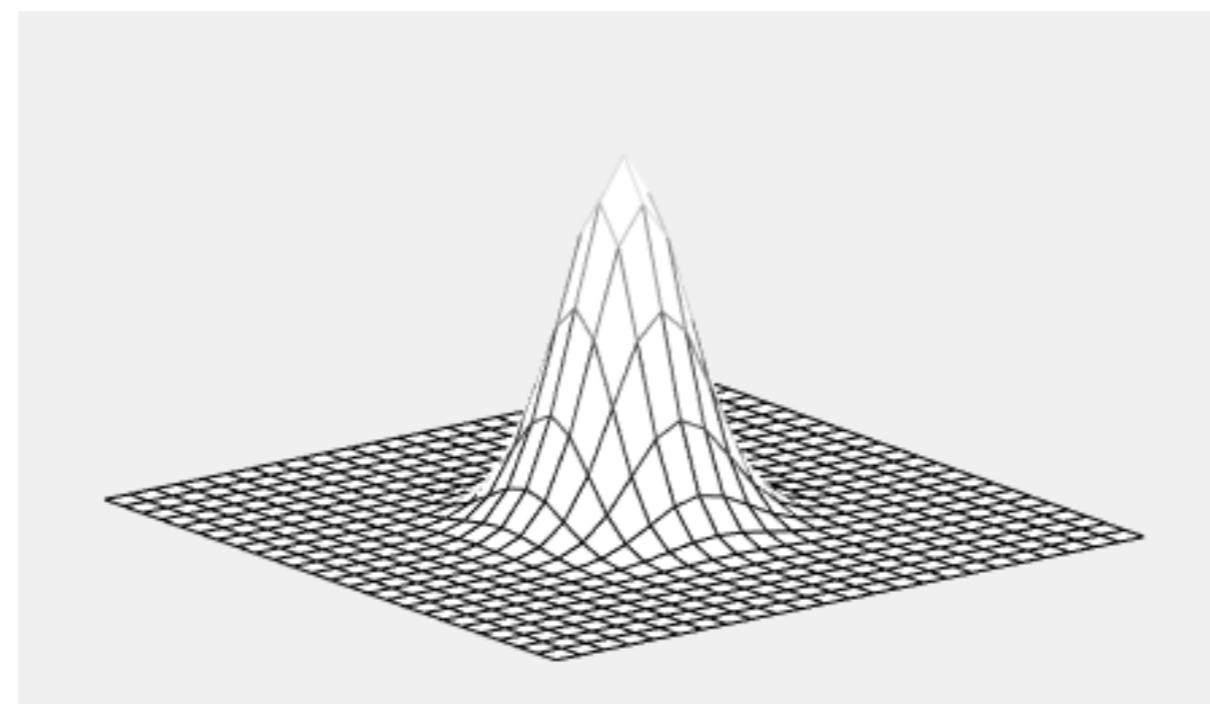
# Gaussian Filter is Separable

In Python,

```
>>> from scipy.signal.windows import gaussian  
>>> h = asmatrix(gaussian(25, 3))
```



```
>>> H = dot(h, h.T)
```



# Separable Filters

---

- In some circumstances the 2D filter will be of low rank such that,

$$\text{rank}(H) = 1$$

# Separable Filters

---

- In some circumstances the 2D filter will be of low rank such that,

$$\mathbf{H} = (\mathbf{h}\mathbf{g}^T)$$

# Separable Filters

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- Using the properties of associativity we can therefore show,

$$\mathbf{Y} = \mathbf{X} * \mathbf{H}$$

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$$\mathbf{H} = (\mathbf{h}\mathbf{g}^T)$$

- Using the properties of associativity we can therefore show,

$$\mathbf{Y} = (\mathbf{X} * \mathbf{h}) * \mathbf{g}^T$$

Can you show why?

# Vectorized Notation

$$\mathbf{A} = \begin{bmatrix} a_{1,1} & \dots & a_{1,N} \\ \vdots & \ddots & \vdots \\ a_{M,1} & \dots & a_{M,N} \end{bmatrix} \rightarrow \text{matrix}$$

$$\mathbf{a} = \text{vec}(\mathbf{A}) = \begin{bmatrix} a_{1,1} \\ \vdots \\ a_{M,N} \end{bmatrix}$$

# Vectorized Convolution Notation

---

$$Y = X * H$$

# Vectorized Convolution Notation

---

$$\text{vec}(\mathbf{Y}) = \text{vec}(\mathbf{X} * \mathbf{H})$$

# Vectorized Convolution Notation

---

$$\mathbf{y} = \mathbf{x} * \mathbf{h}$$

# Vectorized Convolution Notation

---

$$\mathbf{y} = \mathbf{x} \circledast \mathbf{h}$$

“Does not ALWAYS imply 1D convolution”

# Vectorized Convolution Notation

---

$$\mathbf{y} = \mathbf{H}\mathbf{x}$$

“2D convolutional matrix”

# Vectorized Convolution Notation

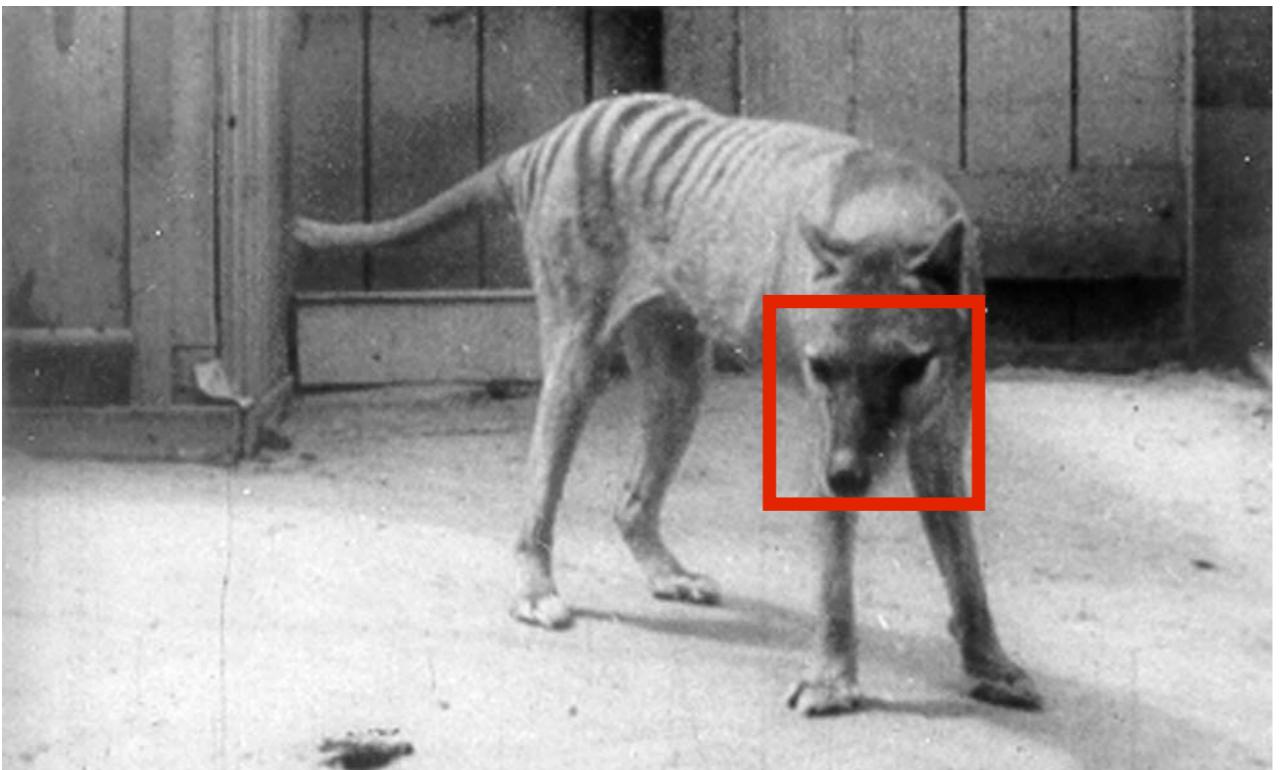
---

$$\mathbf{y} = \mathbf{X}\mathbf{h}$$

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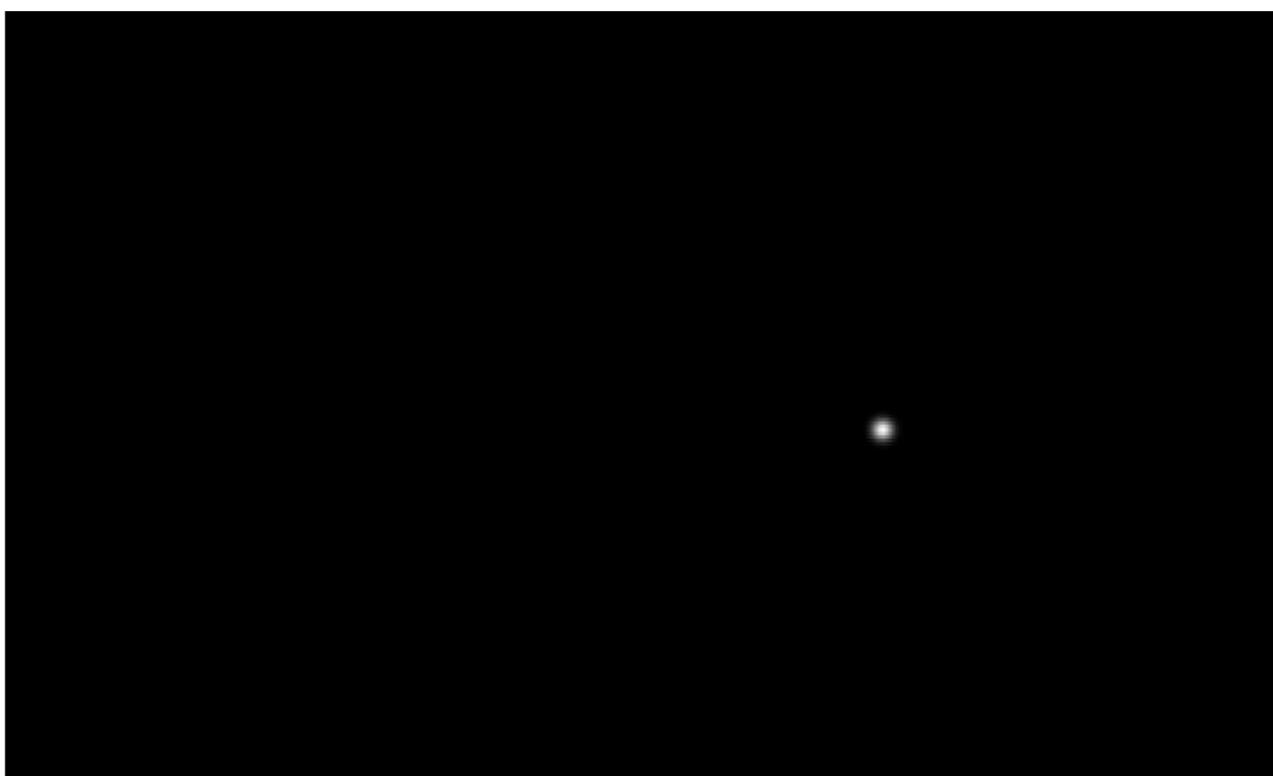


X

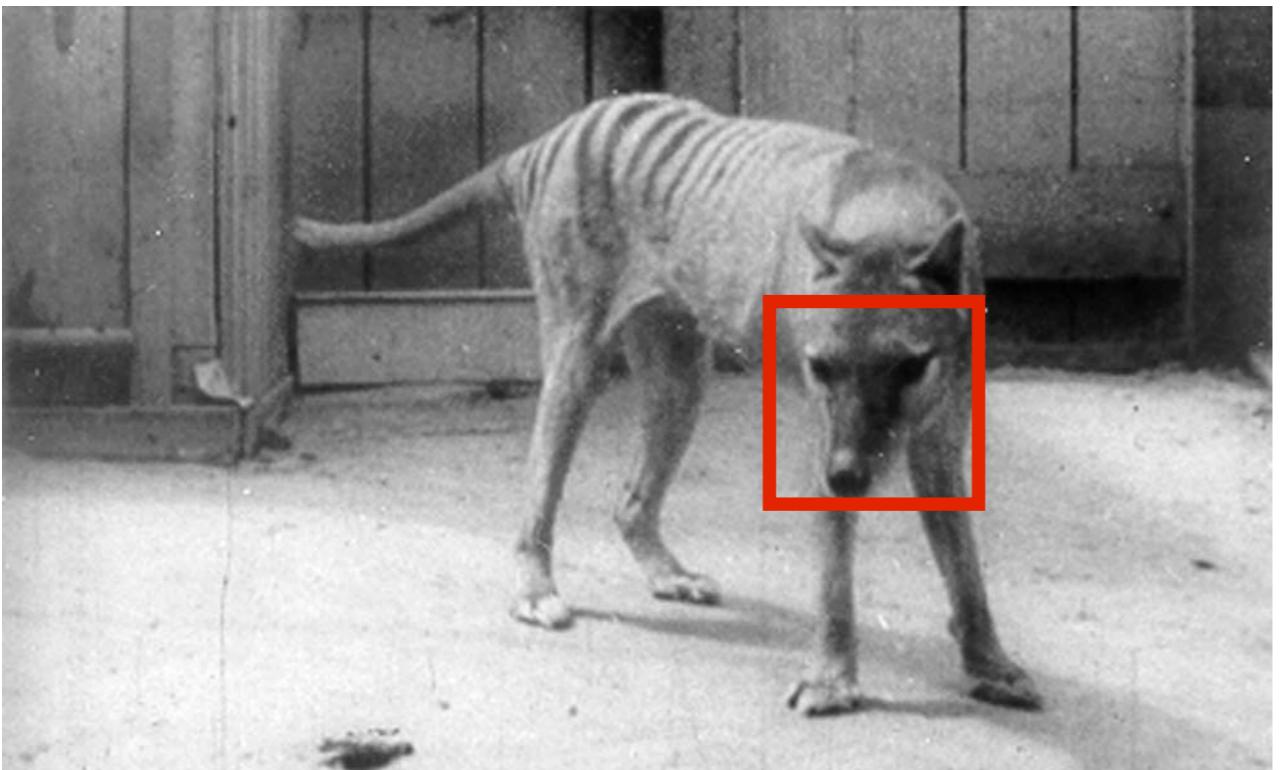
\*



H



Y

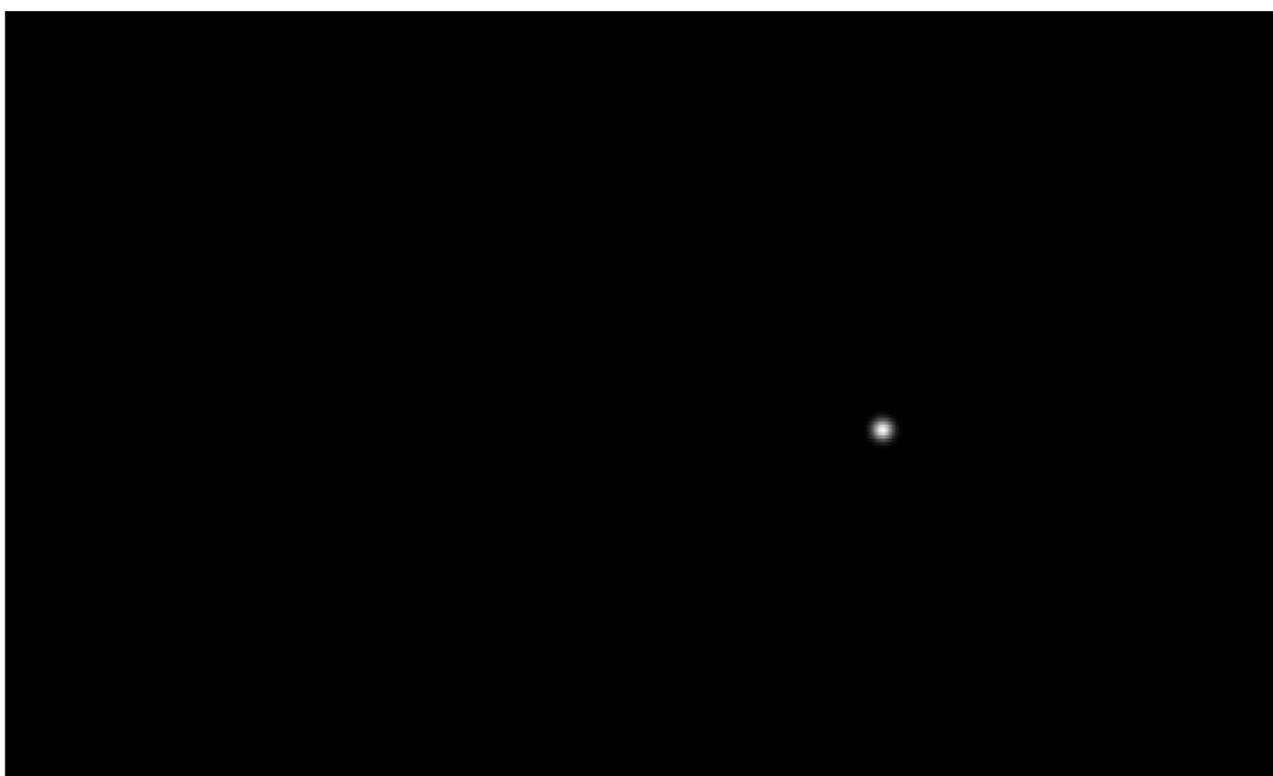


**x**

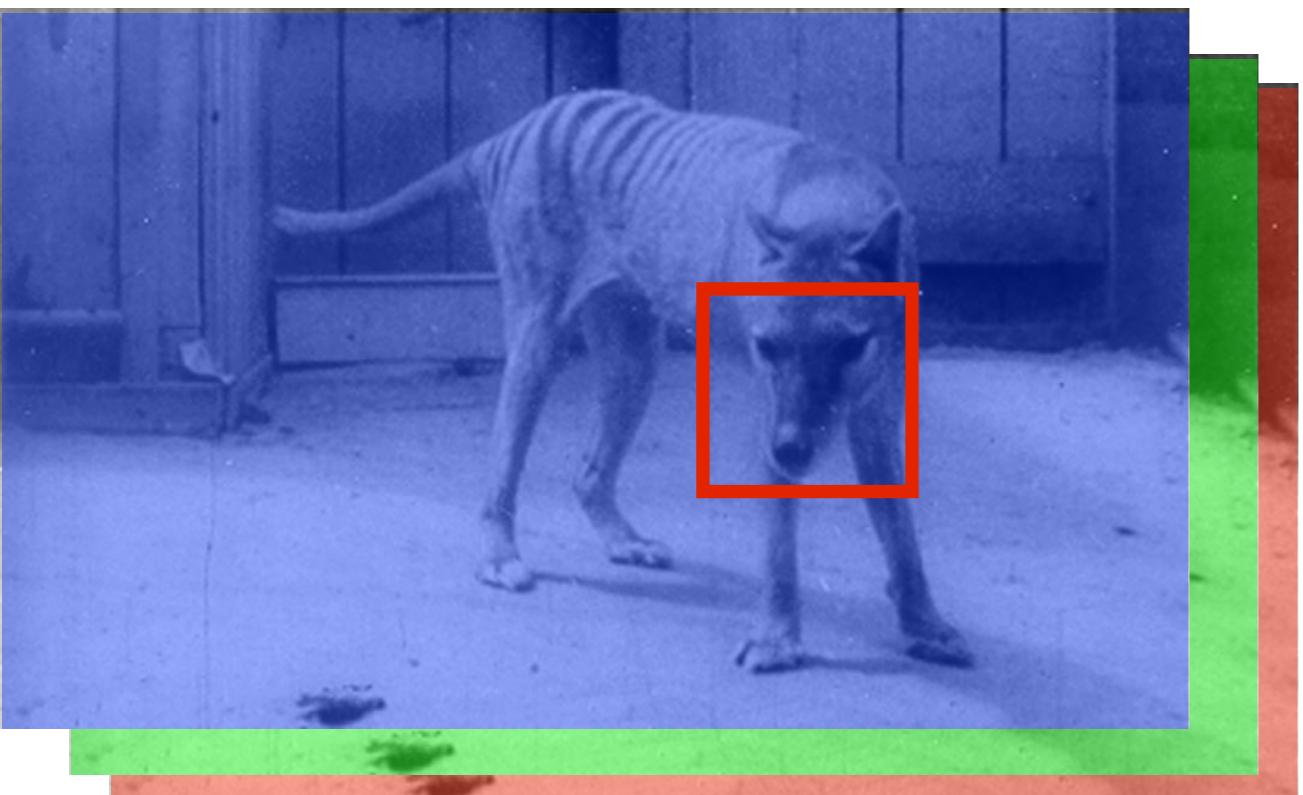
\*



**h**

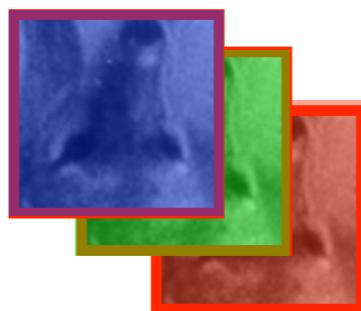


**y**

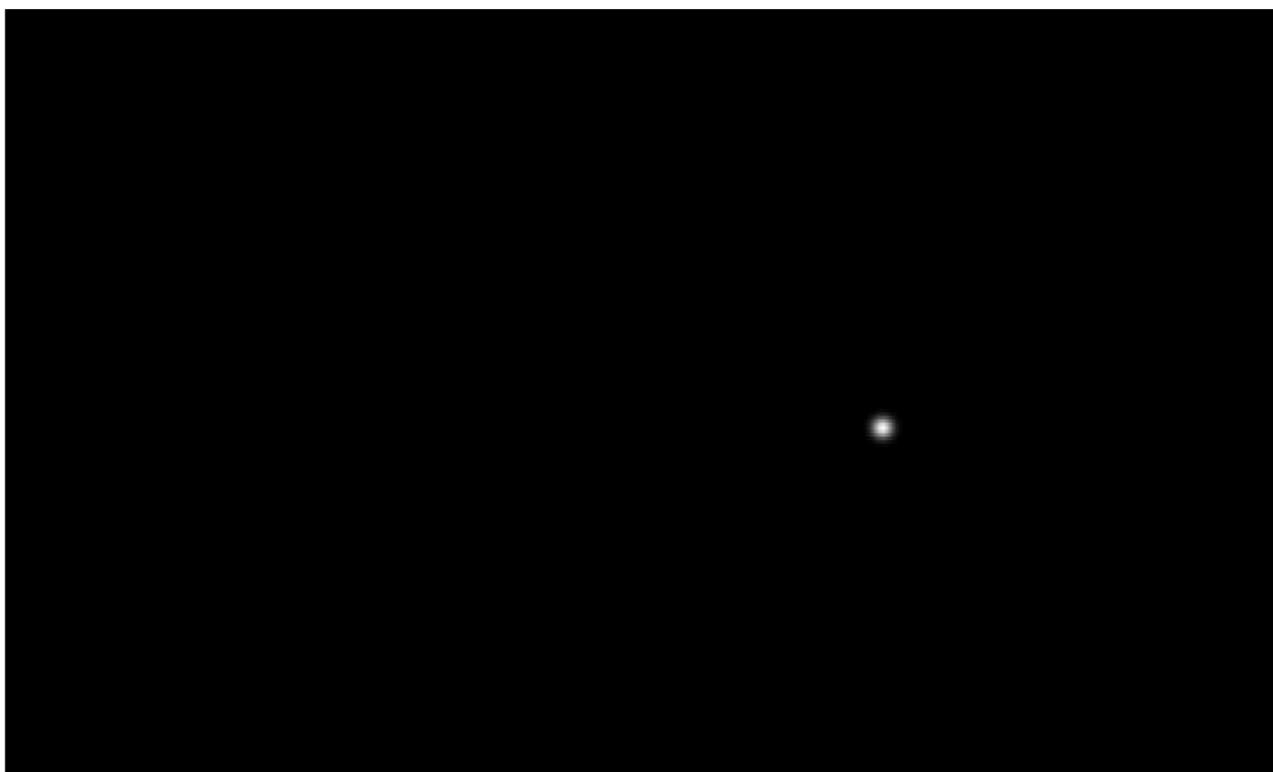


$$\{\mathbf{x}^{(k)}\}_{k=1}^K$$

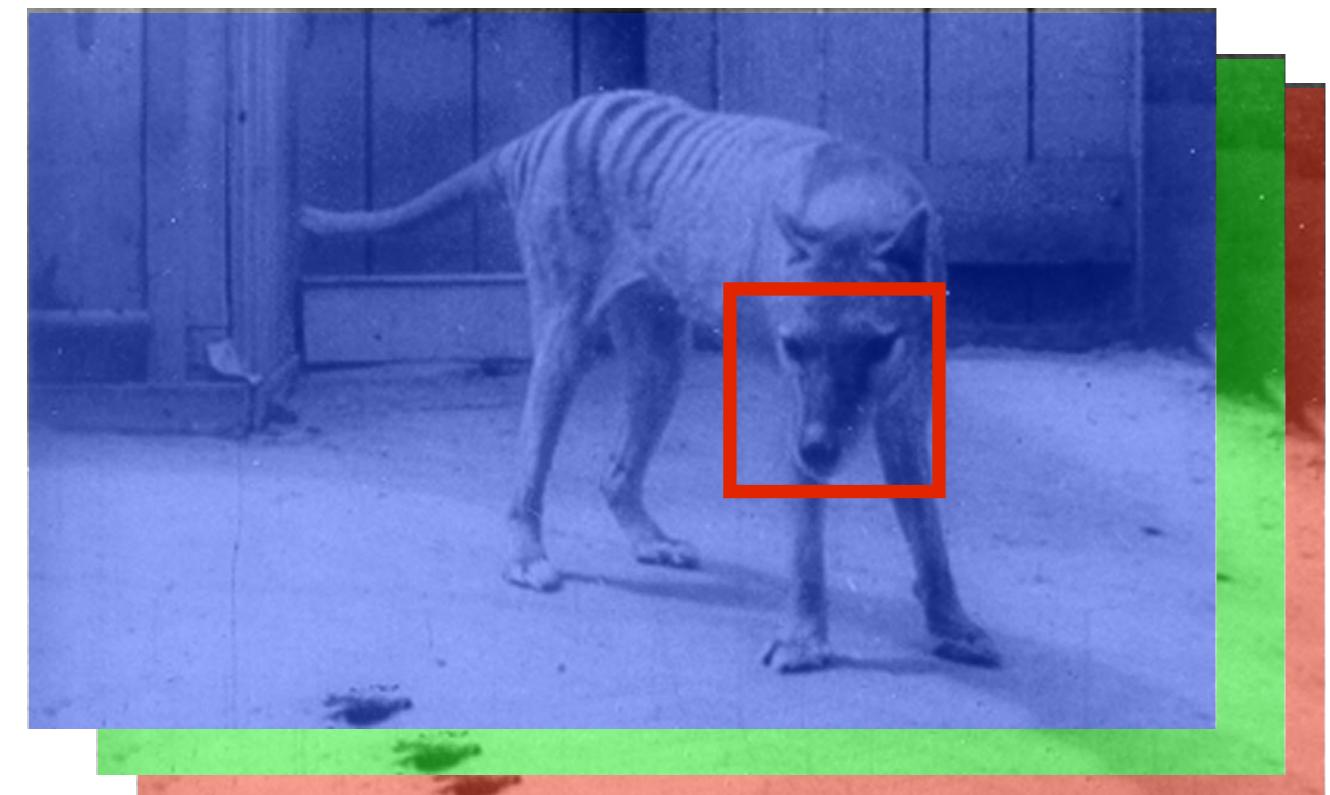
\*



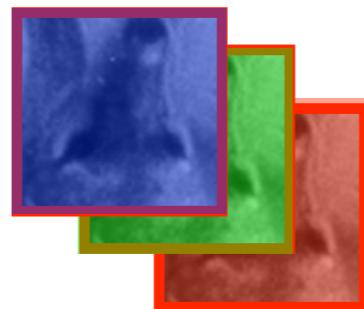
$$\{\mathbf{h}^{(k)}\}_{k=1}^K$$



$\mathbf{y}$



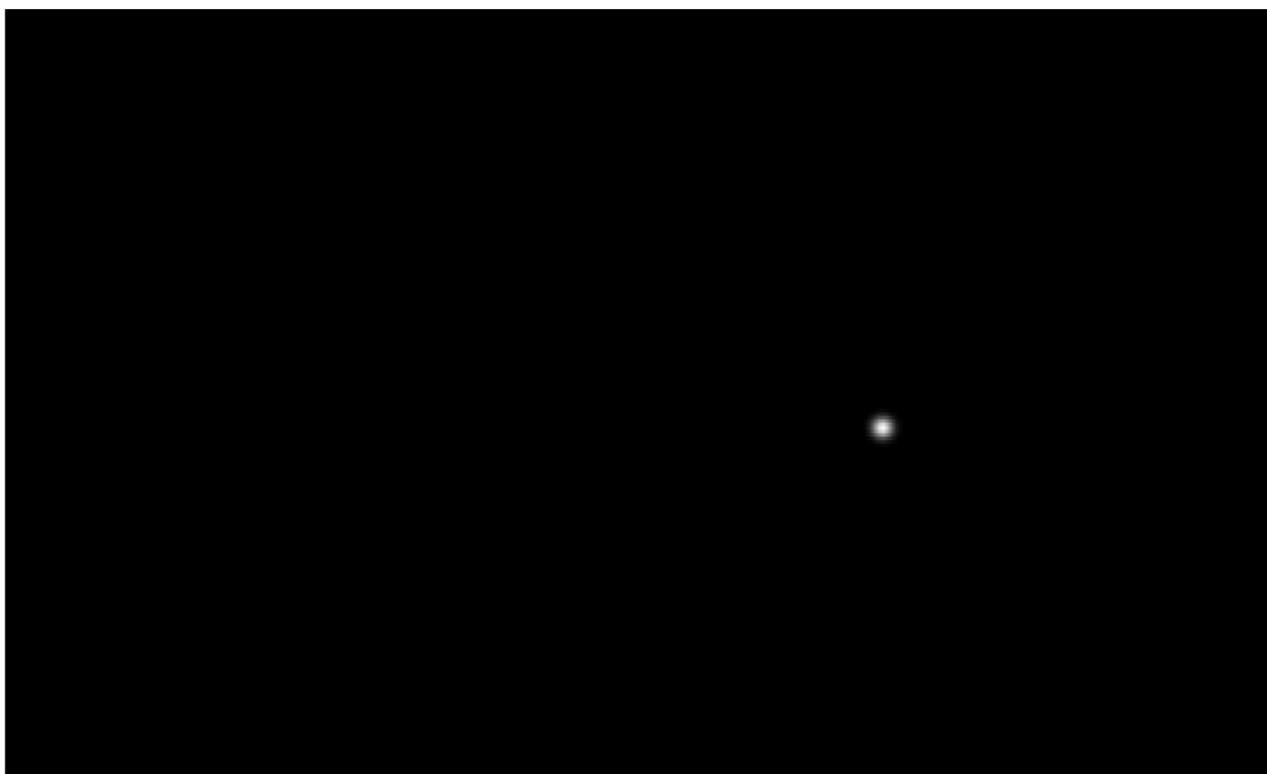
\*



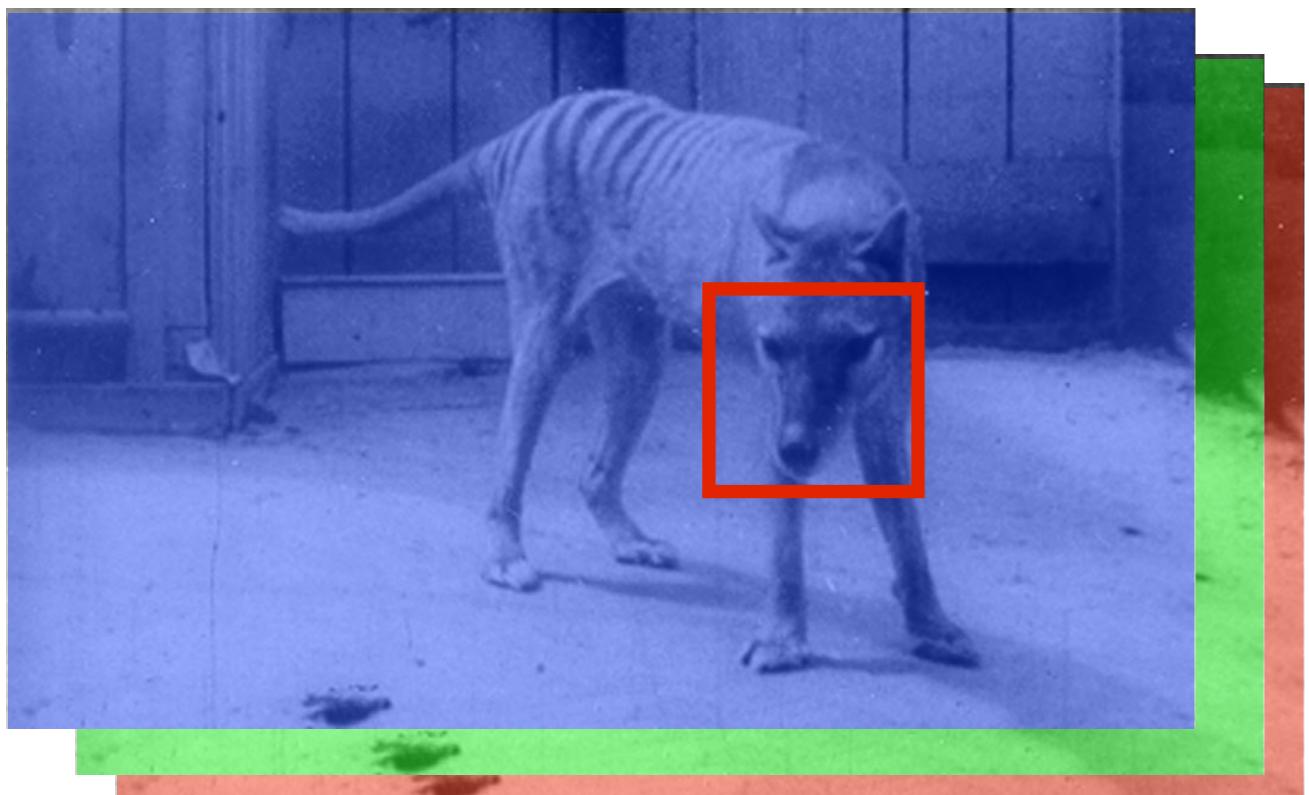
$$\{\mathbf{h}^{(k)}\}_{k=1}^K$$

$$\{\mathbf{x}^{(k)}\}_{k=1}^K$$

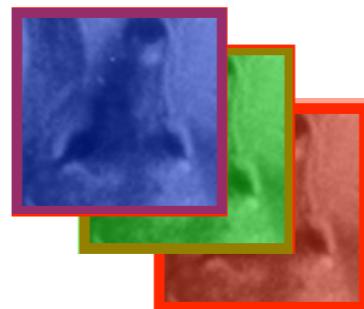
K = no. of input channels



y



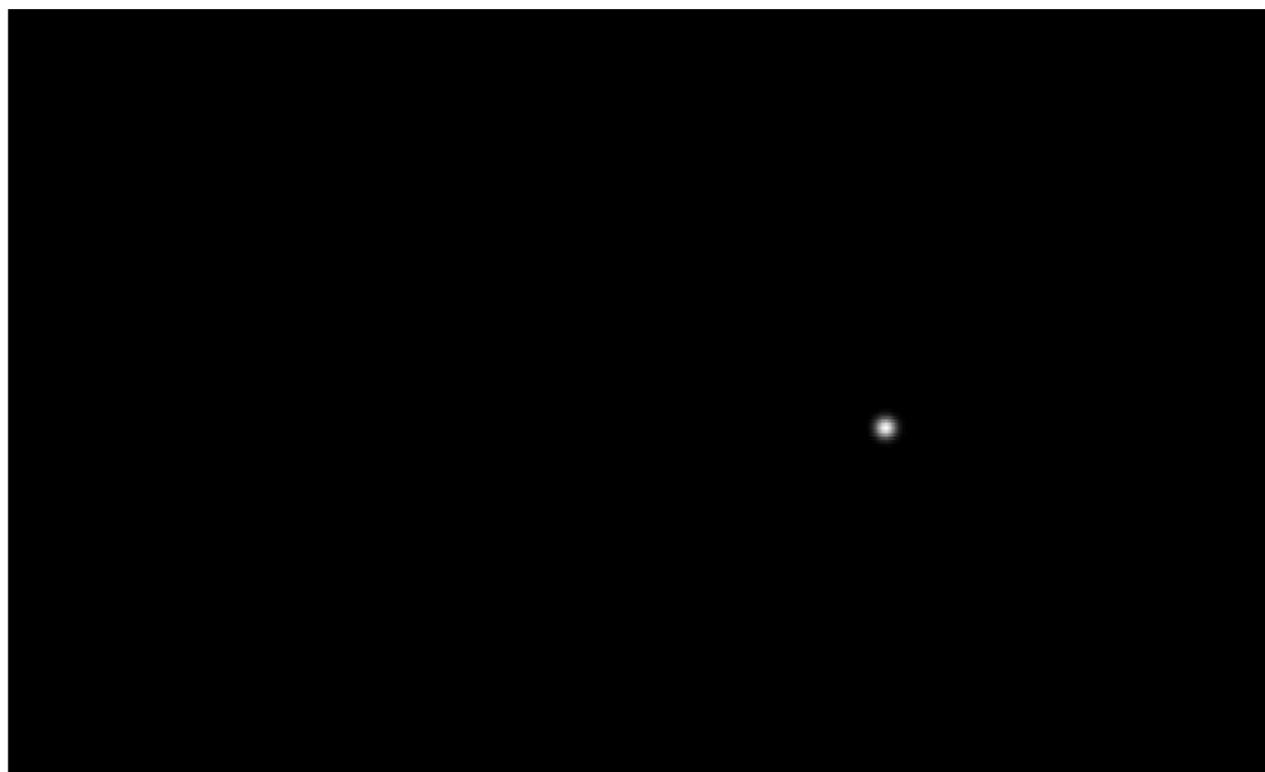
\*



$$\{\mathbf{h}^{(k)}\}_{k=1}^K$$

$$\{\mathbf{x}^{(k)}\}_{k=1}^K$$

K = no. of input channels



y

“output still single channel!!!”

# Multi-Channel 2D-Convolution

---

$$\mathbf{Y}[j, i] = \sum_k \sum_v \sum_u \mathbf{X}^{(k)}[u, v] \mathbf{H}^{(k)}[j - v, i - u]$$

# Multi-Channel 2D-Convolution

---

$$\mathbf{Y}[j, i] = \sum_k \sum_v \sum_u \mathbf{X}^{(k)}[u, v] \mathbf{H}^{(k)}[j - v, i - u]$$

# Multi-Channel 2D-Convolution

$$\mathbf{Y}[j, i] = \sum_k \sum_v \sum_u \mathbf{X}^{(k)}[u, v] \mathbf{H}^{(k)}[j - v, i - u]$$



“vectorized form”

$$\mathbf{y} = \sum_k \mathbf{x}^{(k)} * \mathbf{h}^{(k)}$$

# Multi-Channel 2D-Convolution

$$\mathbf{Y}[j, i] = \sum_k \sum_v \sum_u \mathbf{X}^{(k)}[u, v] \mathbf{H}^{(k)}[j - v, i - u]$$



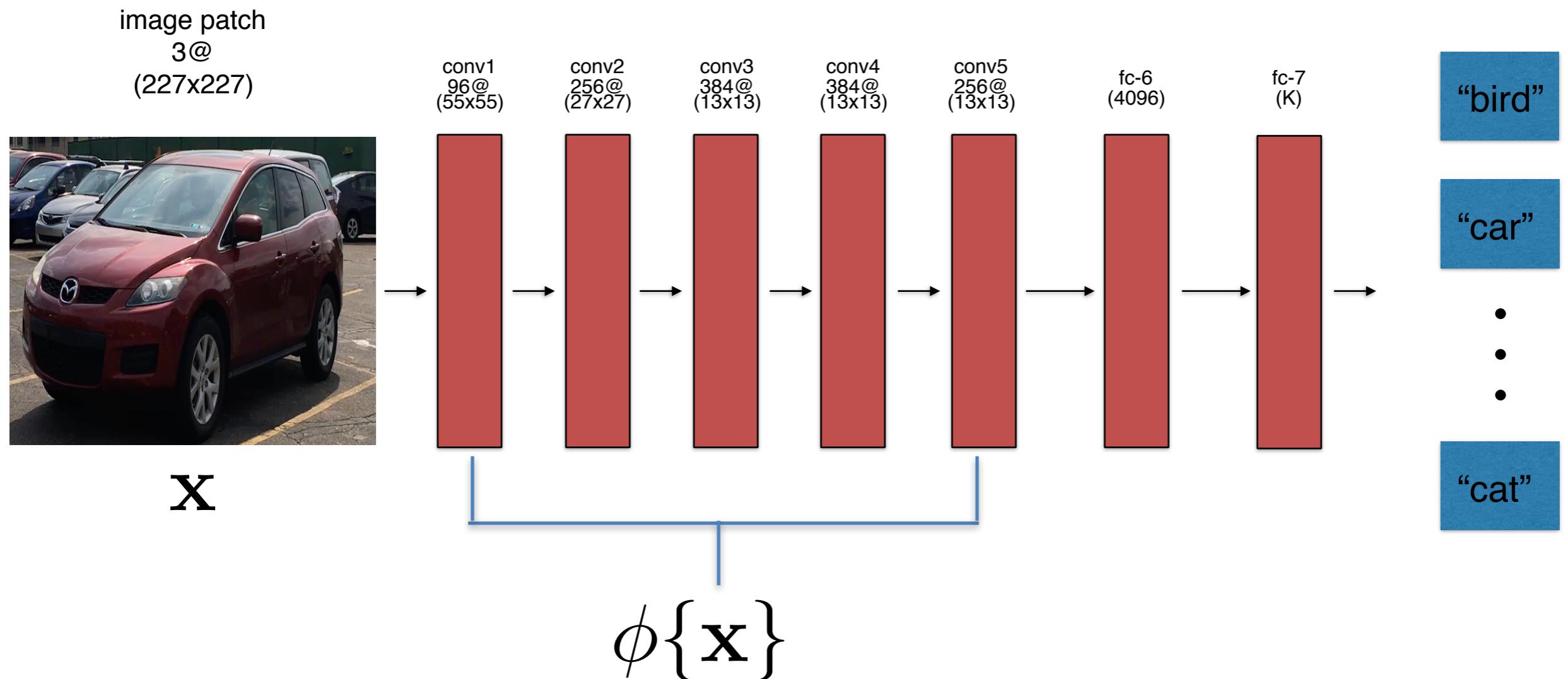
“vectorized form”

$$\mathbf{y} = \sum_k \mathbf{x}^{(k)} * \mathbf{h}^{(k)}$$

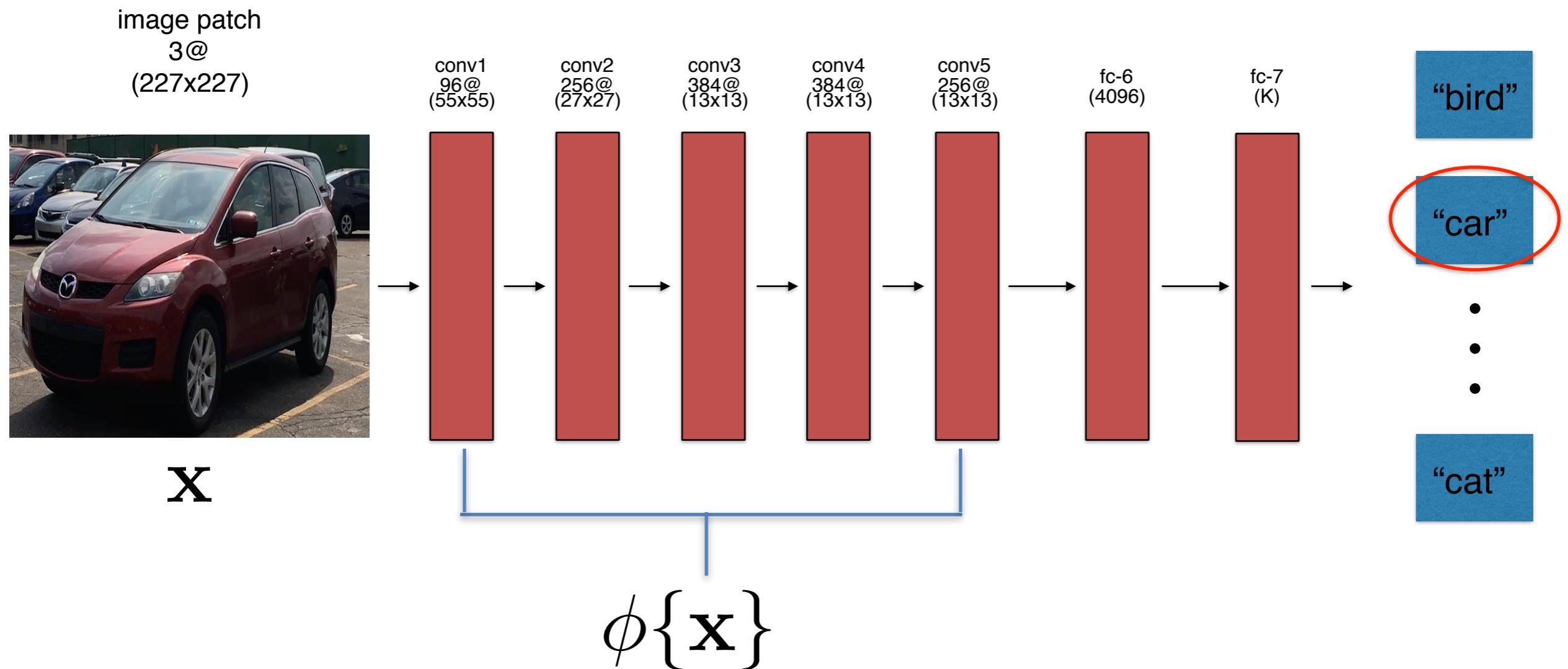
This is NOT 3D Convolution!!

Can you show why?

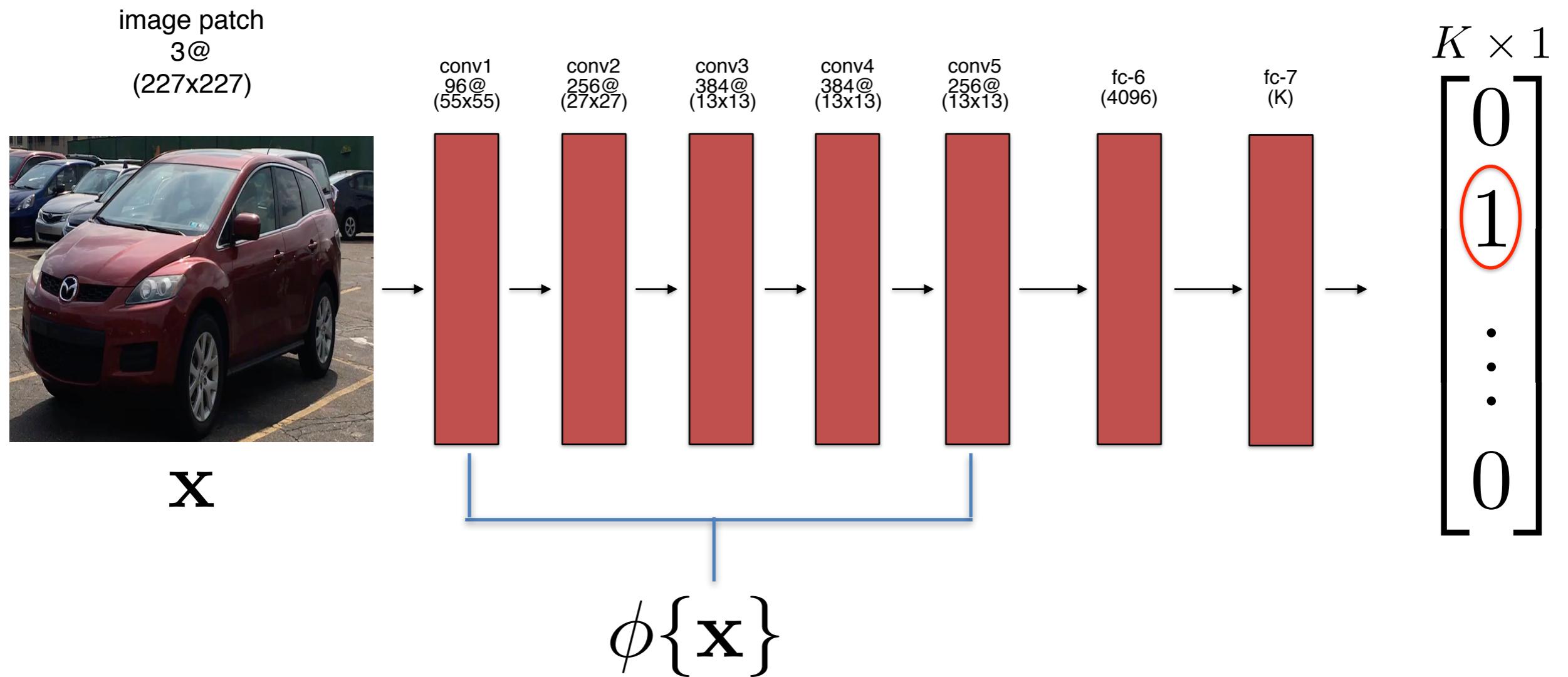
# Importance to Deep Learning



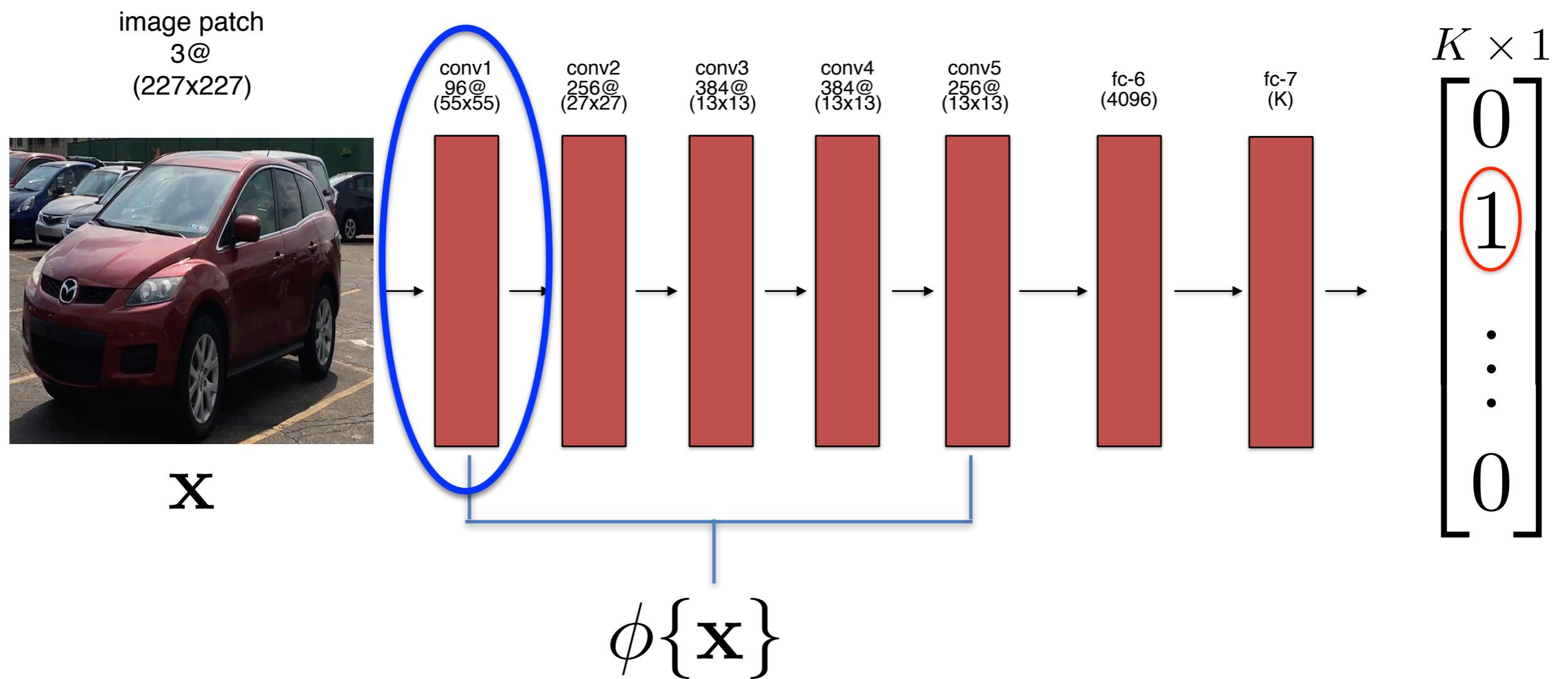
# Importance to Deep Learning



# Importance to Deep Learning



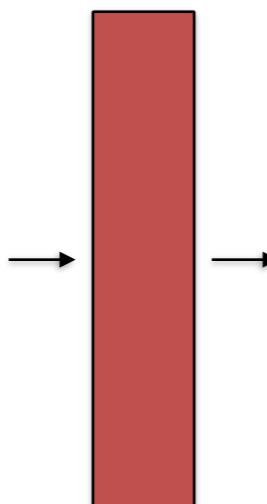
# Importance to Deep Learning



# Importance to Deep Learning

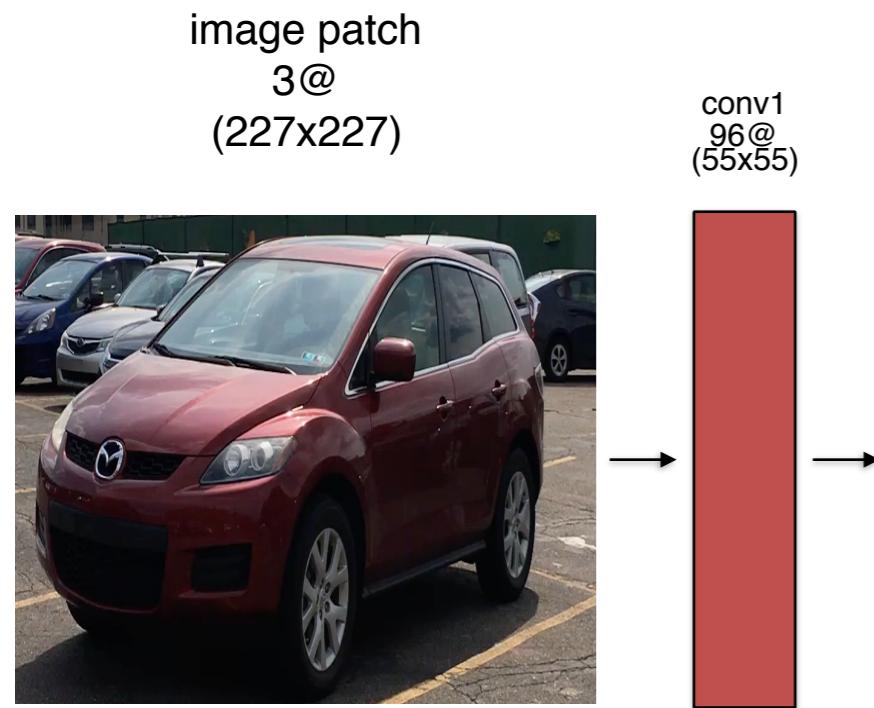
image patch  
3@  
(227x227)

conv1  
96@  
(55x55)



**X**

# Importance to Deep Learning

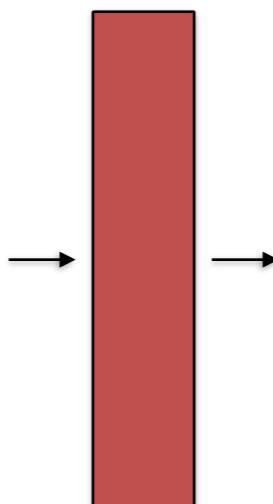


$$\{\mathbf{x}^{(k)}\}_{k=1}^K$$

# Importance to Deep Learning

image patch  
3@  
(227x227)

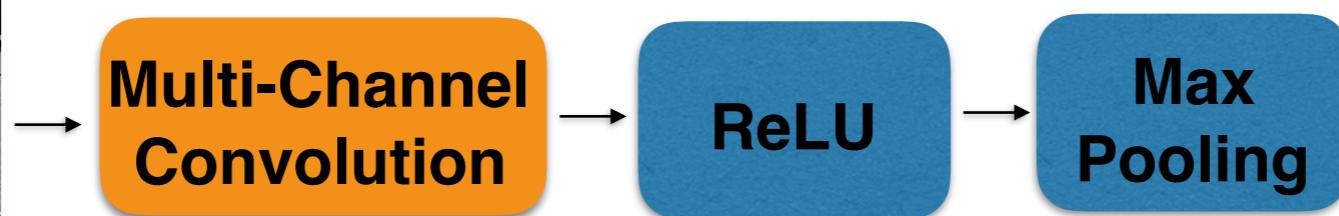
conv1  
96@  
(55x55)



$$\{\mathbf{x}^{(k)}\}_{k=1}^K$$

# Importance to Deep Learning

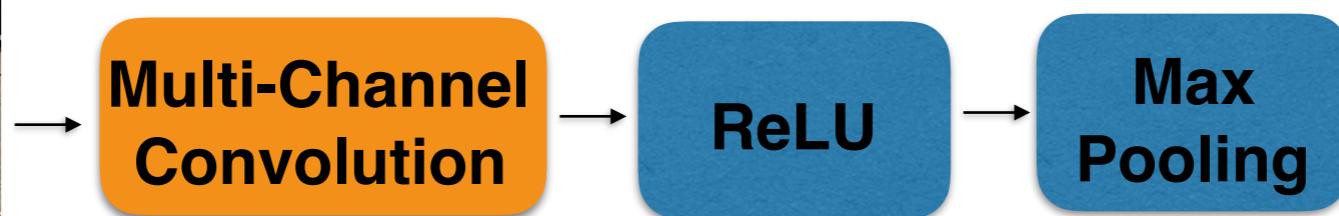
image patch  
3@  
(227x227)



$$\{\mathbf{x}^{(k)}\}_{k=1}^K \quad \mathbf{y}^{(j)} = \sum_{k=1}^K [\mathbf{x}^{(k)} * \mathbf{h}^{(j,k)}]$$

# Importance to Deep Learning

image patch  
3@  
(227x227)

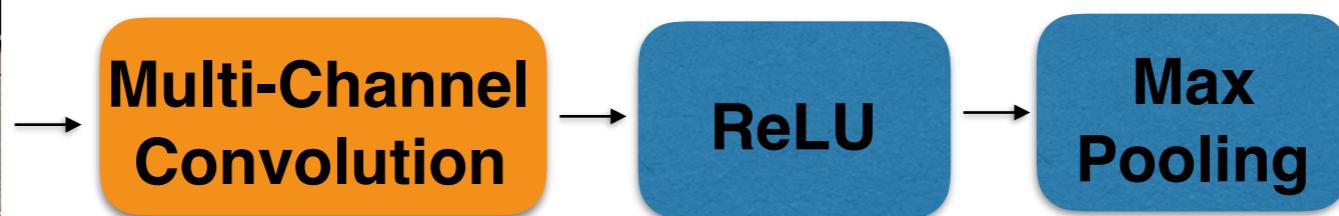


$$\{\mathbf{x}^{(k)}\}_{k=1}^K$$

$$\mathbf{y}^j = \sum_{k=1}^K [\mathbf{x}^{(k)} * \mathbf{h}^{j,k}]$$

# Importance to Deep Learning

image patch  
3@  
(227x227)



$$\{\mathbf{x}^{(k)}\}_{k=1}^K$$

$$\mathbf{y}^j = \sum_{k=1}^K [\mathbf{x}^{(k)} * \mathbf{h}^{j,k}] + b_j$$

# PyTorch Example

---

```
>>> x = array([8,4,6,2,7]).astype('float')
>>> h = array([1,2]).astype('float')
```

# PyTorch Example

---

```
>>> x = array([8,4,6,2,7]).astype('float')
>>> h = array([1,2]).astype('float')

>>> import torch
>>> xt = torch.from_numpy(reshape(x, (1,1,1,x.size)))
>>> ht = torch.from_numpy(reshape(h, (1,1,1,h.size)))
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# PyTorch Example

---

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>>> xt.shape
torch.Size([1, 1, 1, 5])
```

# PyTorch Example

---

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tensor([[[[16., 16., 10., 16.]]]], dtype=torch.fl
```

# PyTorch Example

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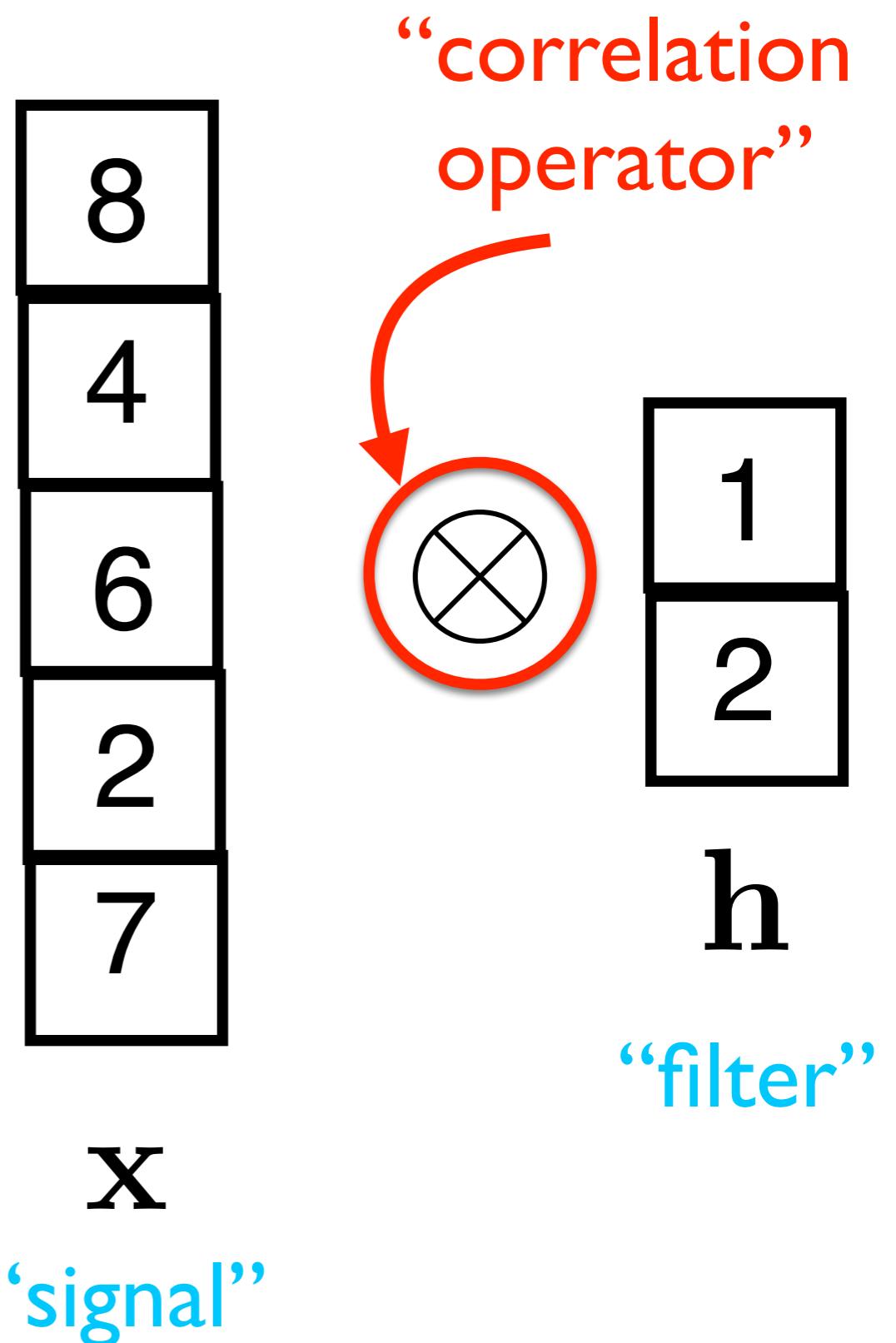
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>>> ht = torch.from_numpy(reshape(h, (1,1,1,h.size)))

>>> xt.shape
torch.Size([1, 1, 1, 5])

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tensor([[[[16., 16., 10., 16.]]]], dtype=torch.fl
```

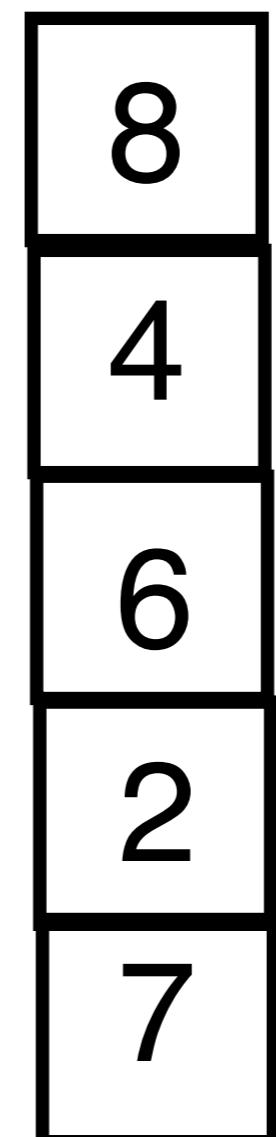
**Is this convolution or correlation?**

# Reminder: Correlation



# Reminder: Correlation

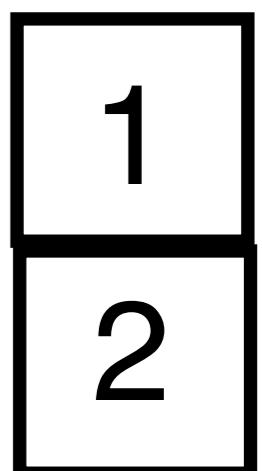
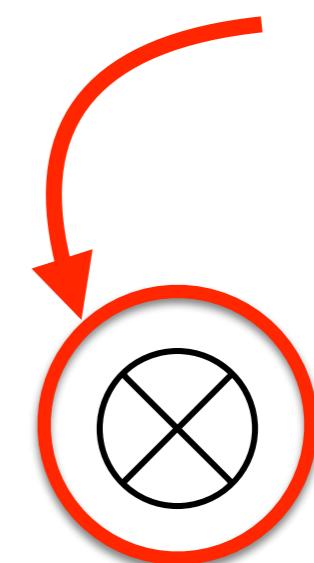
```
>>> from scipy.signal import \
correlate as corr
>>> corr(x,h,'same')
array([16,16,16,10,16])
```



**x**

“signal”

“correlation  
operator”

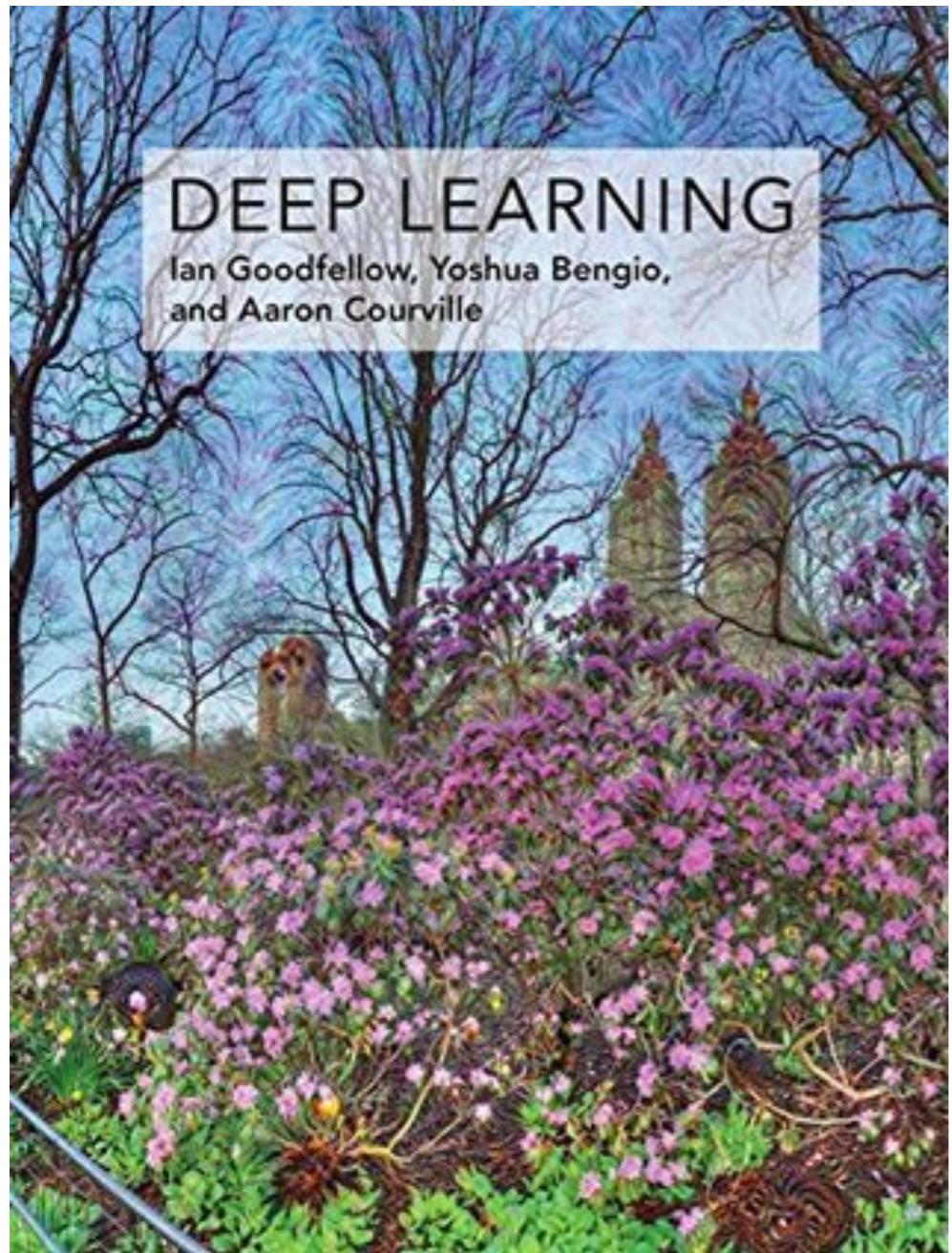


**h**

“filter”

# More to read...

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- Goodfellow et al.
  - Chapter 9, Section 1.