

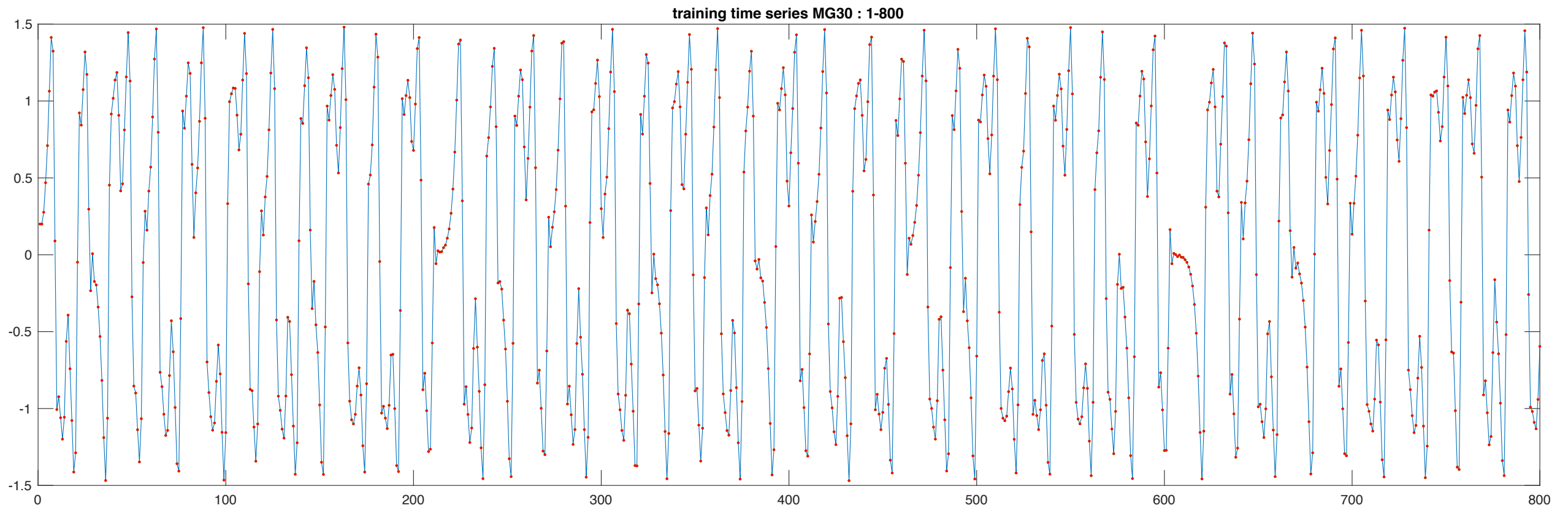
Neural Organization : Convolution

Mackey-Glass 30

$$\frac{\partial x}{\partial t} = \frac{ax(t - \tau)}{1 + x^c(t - \tau)} - bx(t),$$

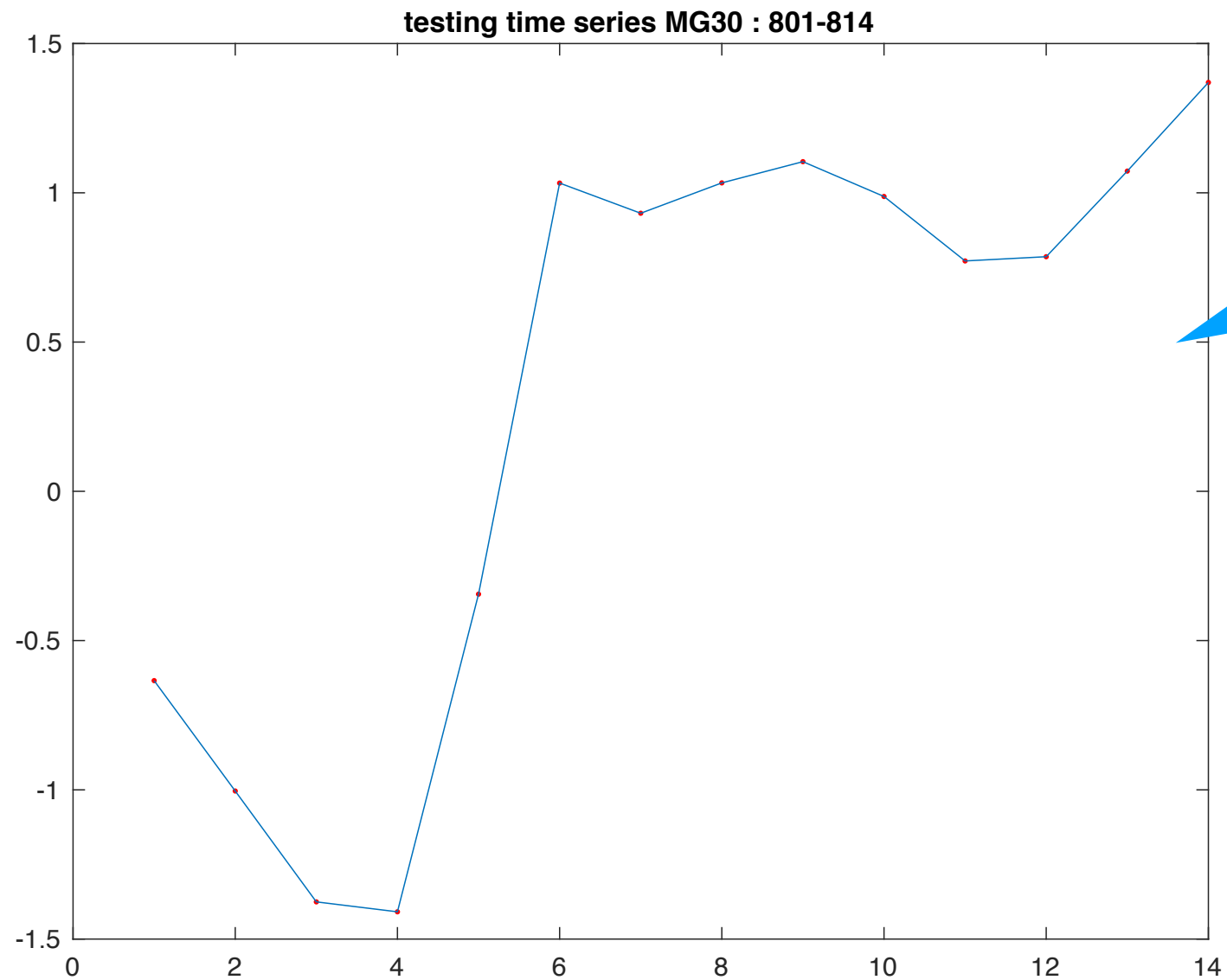
$\tau = 30$ $a = 0.2$, $c = 10$ and $b = 0.1$.

Training time series MG30 : 1-800



save MG30_time_series.mat x_training x_testing

Testing time series MG30 : 801-814

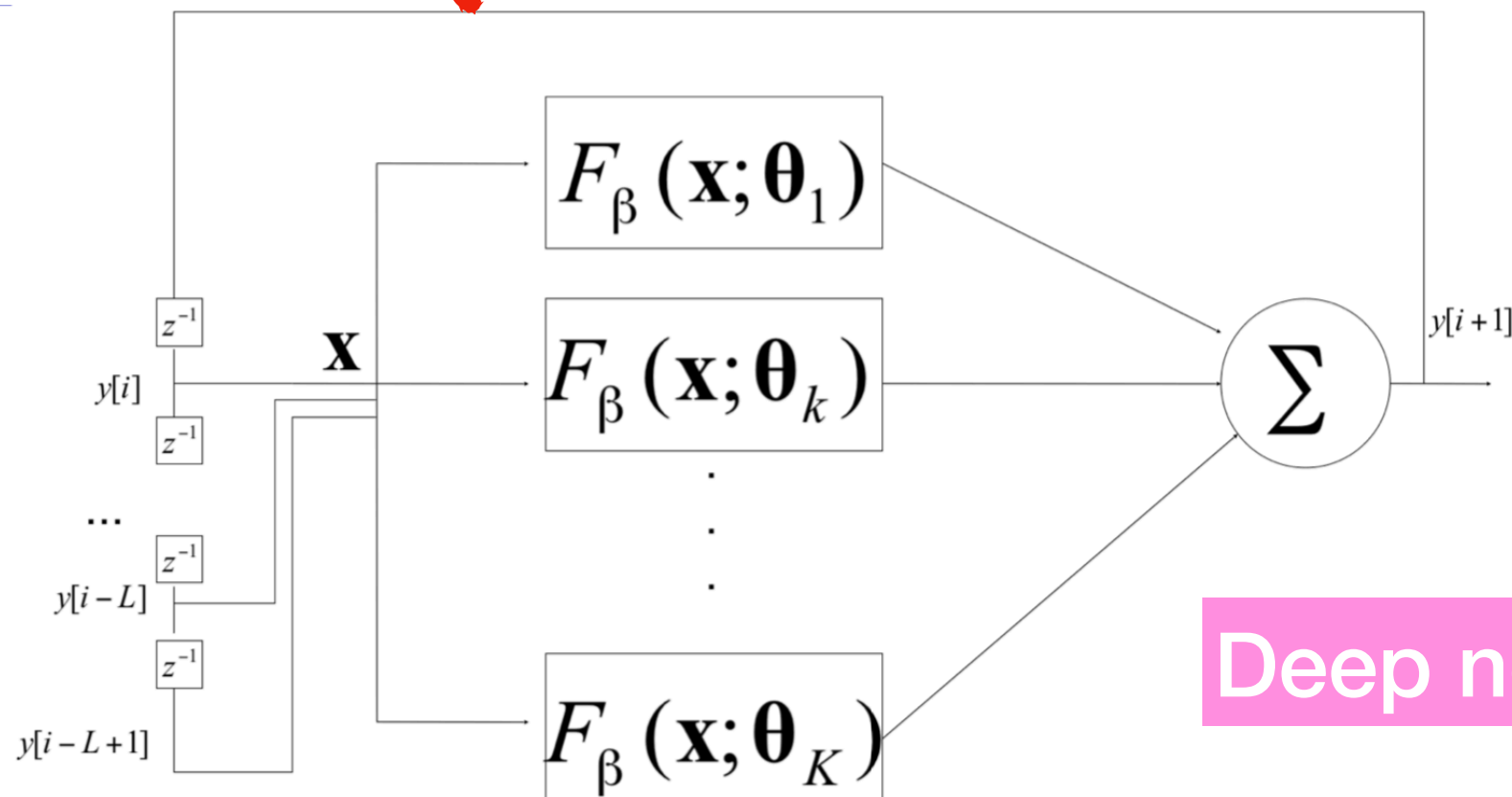


14-step
prediction
at a time

Training time series MG30 :

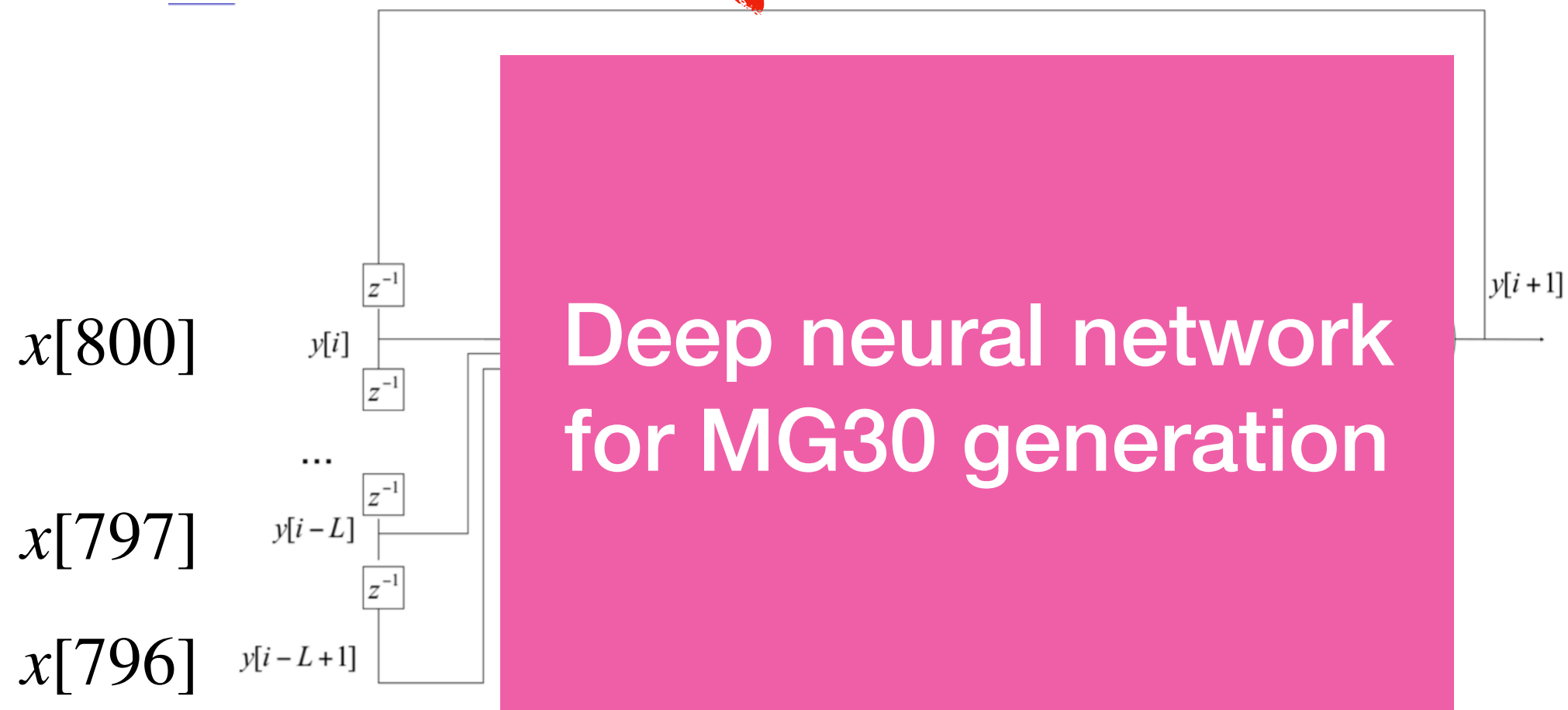
1-800

Deep Learning



$$o_t = f(\mathbf{x}_t = (o_{t-L}, o_{t-L+1}, \dots, o_{t-1})^T),$$

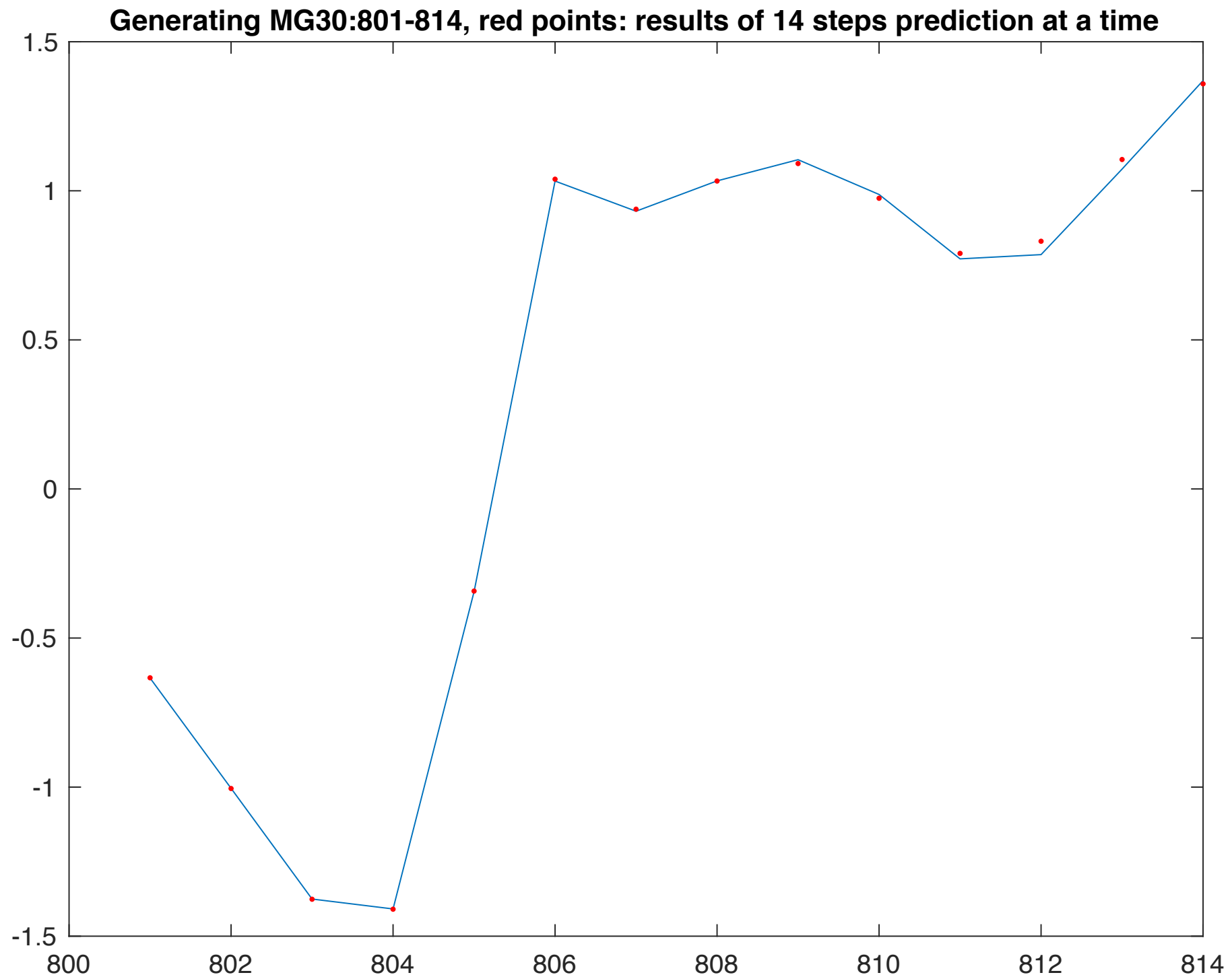
Initialization with $x[796] \dots x[800]$



$$o_t = f(\mathbf{x}_t = (o_{t-L}, o_{t-L+1}, \dots, o_{t-1})^T),$$

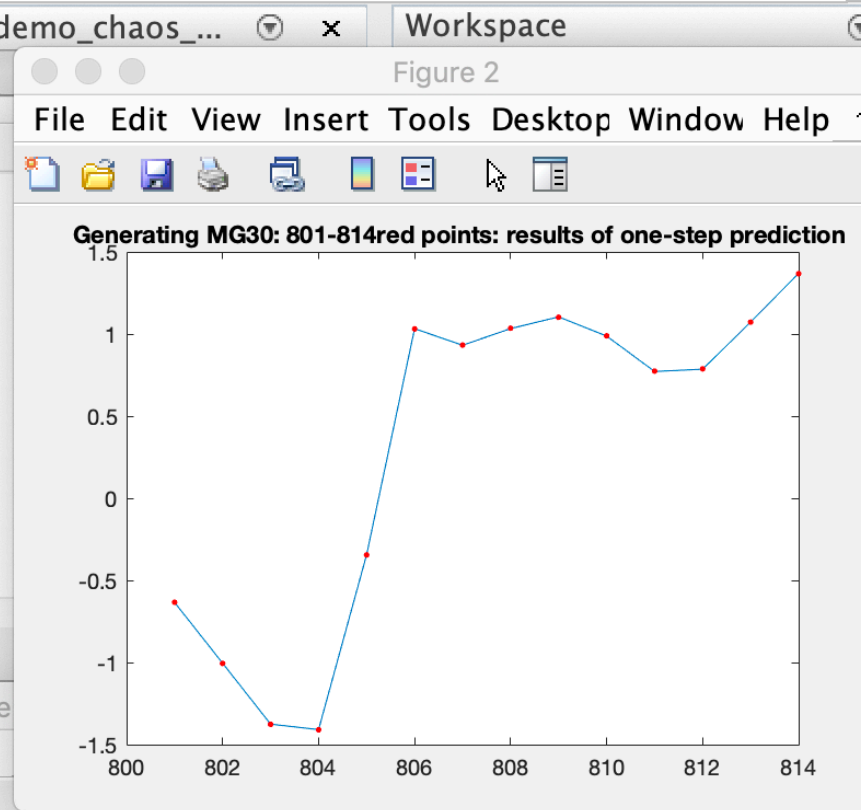
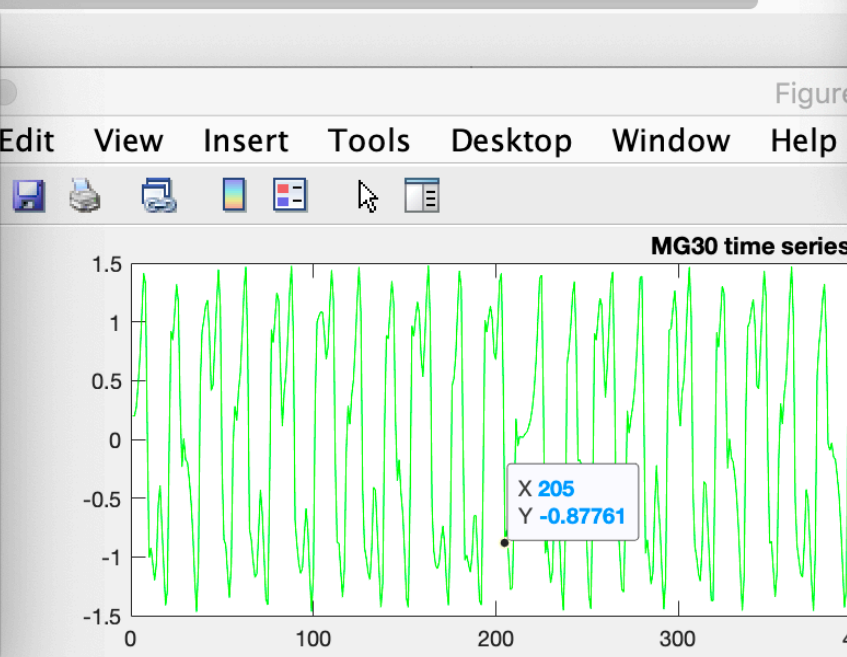
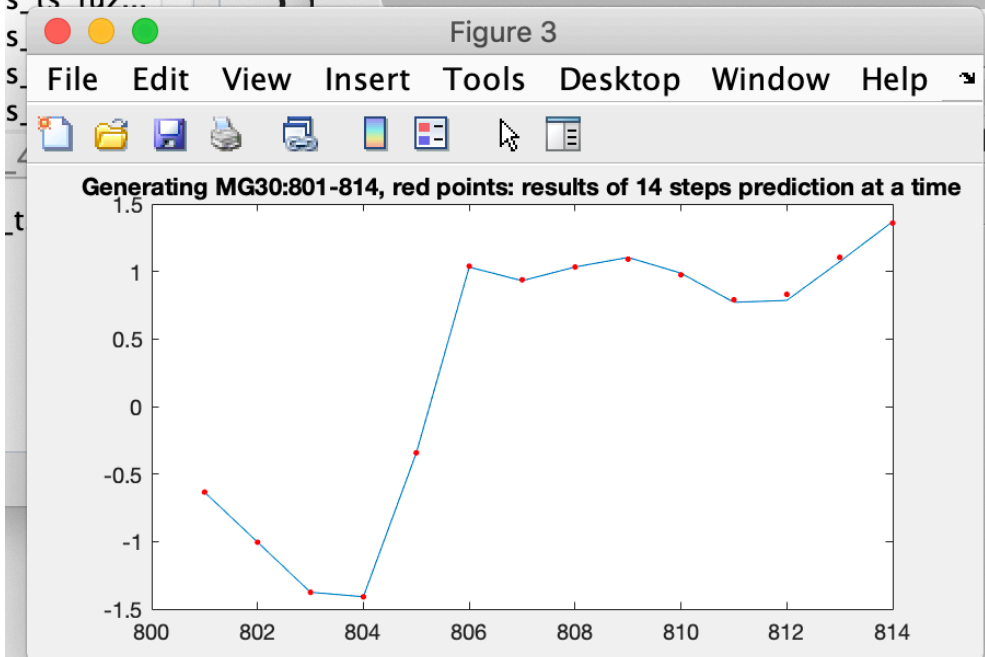
for generating testing time series MG30 : 801-814

Generated MG30: 801-814 for prediction

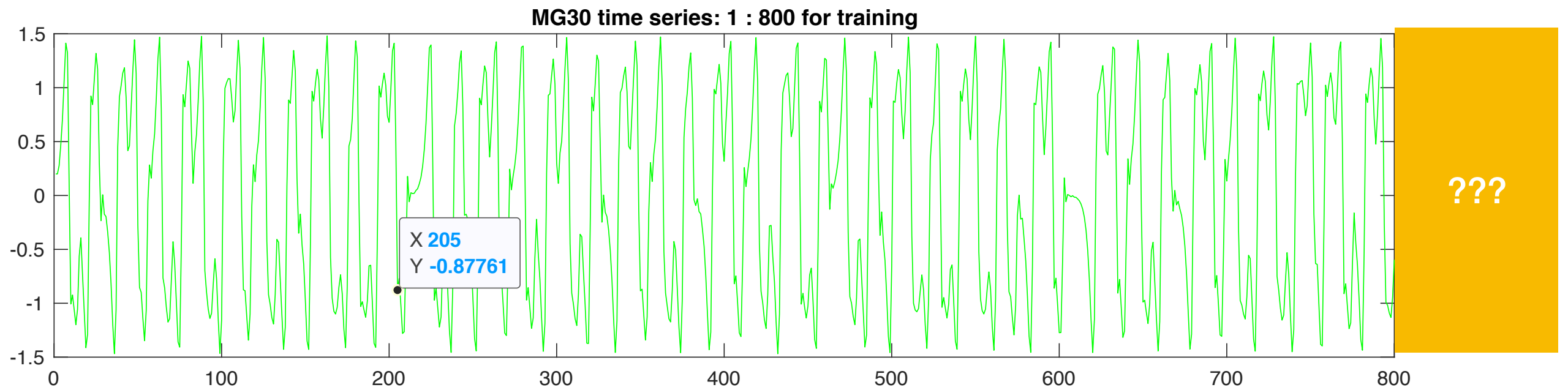


Users ▶ apple ▶ Desktop ▶ Jiann-Ming Wu ▶ code2019 ▶ code2006 ▶ Apps ▶ FunAppr ▶ chaosTimeSeries ▶

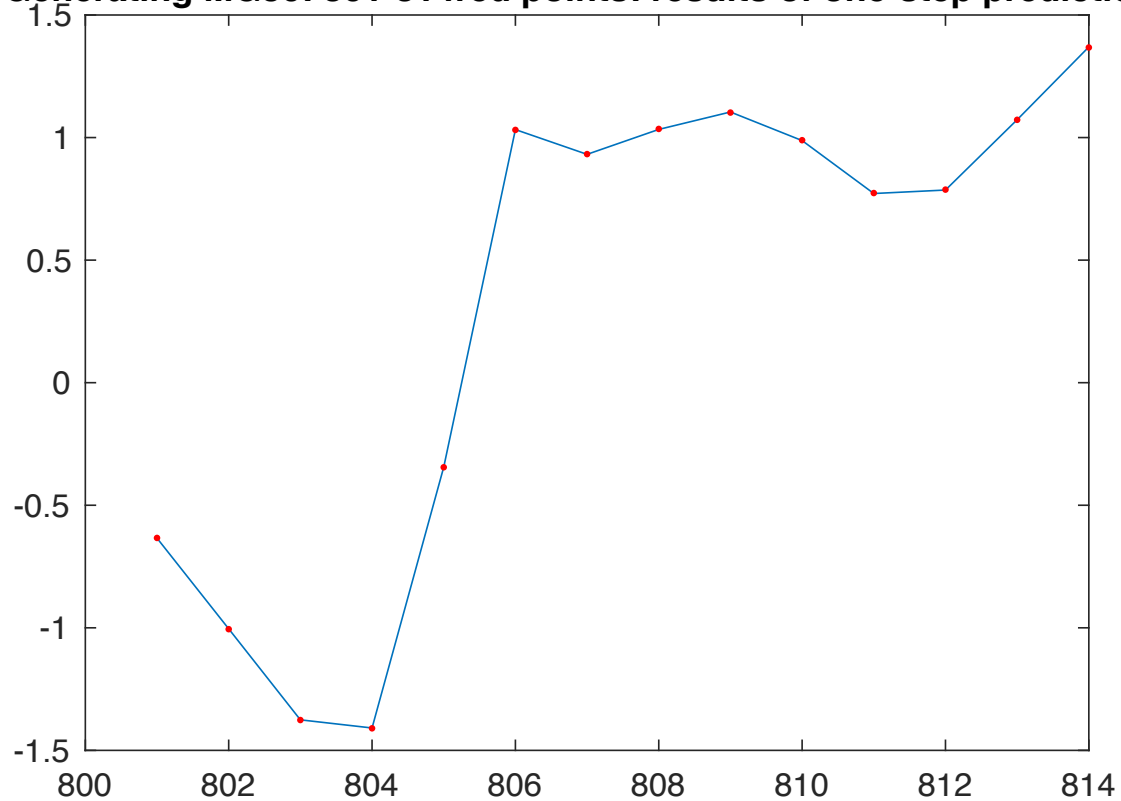
```
Editor - /Users/apple/Desktop/Jiann-Ming Wu/code2019/code2006/Apps/FunAppr/chaosTimeSeries/demo_chaos_...  
demo_dec2bin.m x demo_chaos_ts_4LNRBF_temp_Lterm.m x demo_chaos_ts_4LNRBF_temp.m x  
47  
48  
49 >> demo_chaos_ts_4LNRBF_temp_Lterm  
50 keyin new n2 for long term prediction:14  
51  
52 new_n2 =  
53  
54 14  
55
```



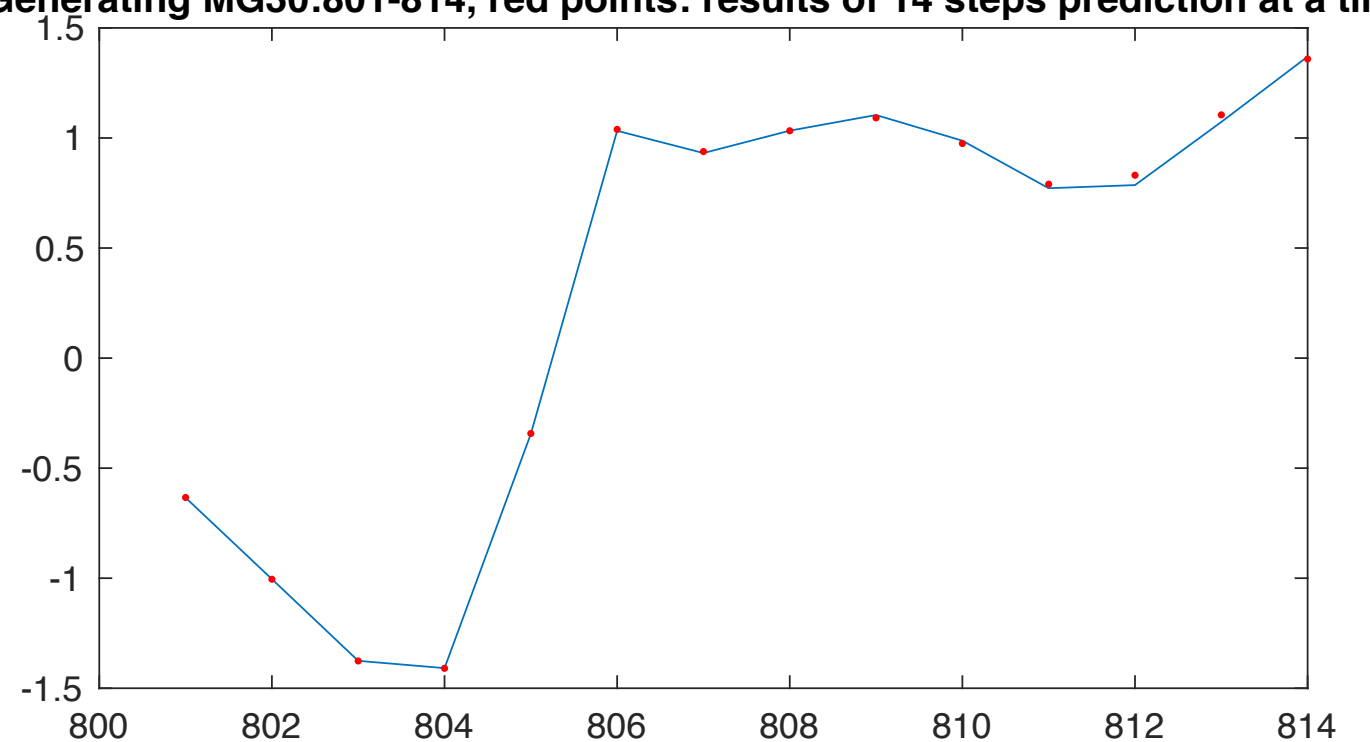
Generating MG30:801-814, red points: results of 14 steps prediction at a time



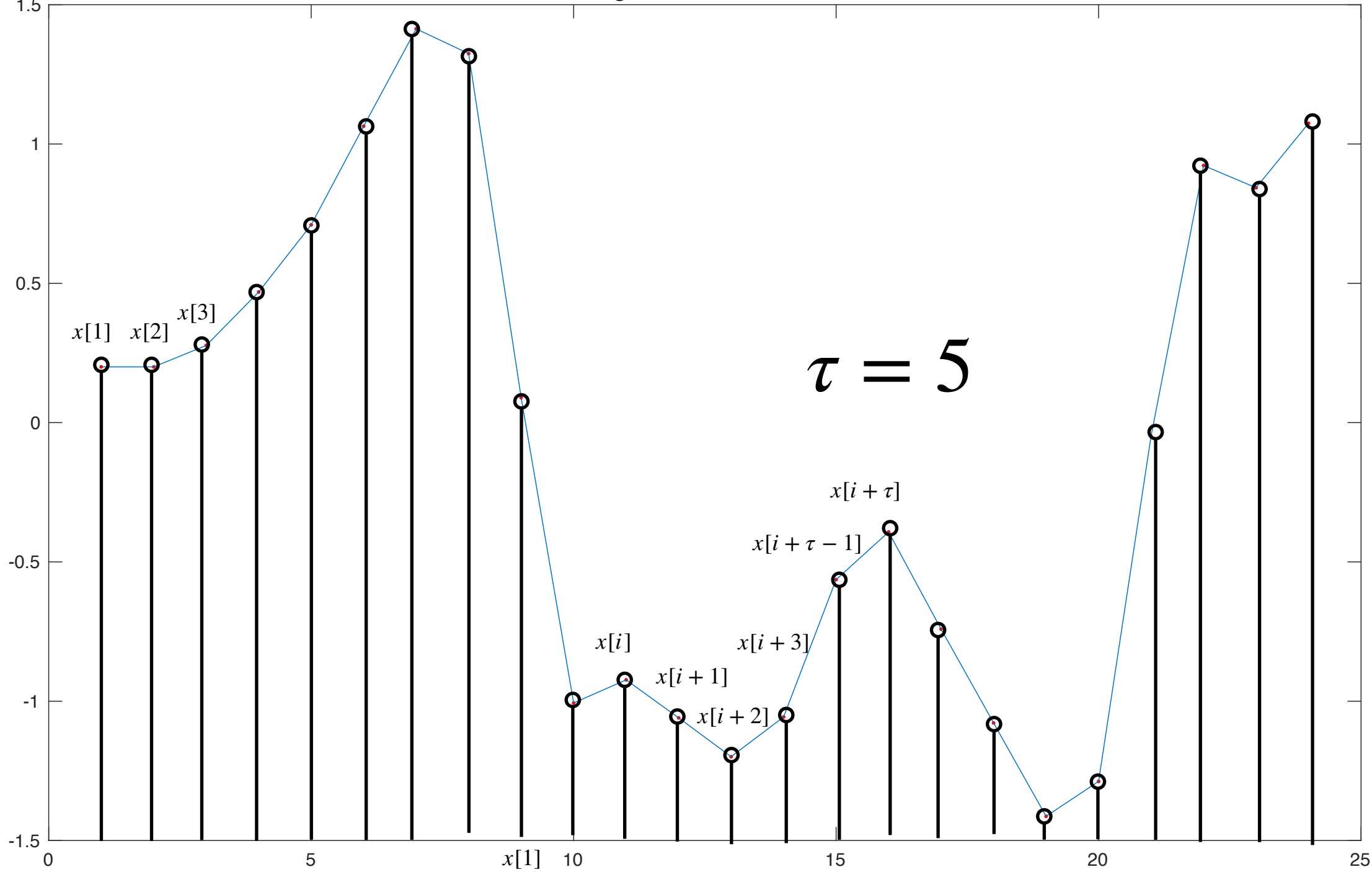
Generating MG30: 801-814 red points: results of one-step prediction

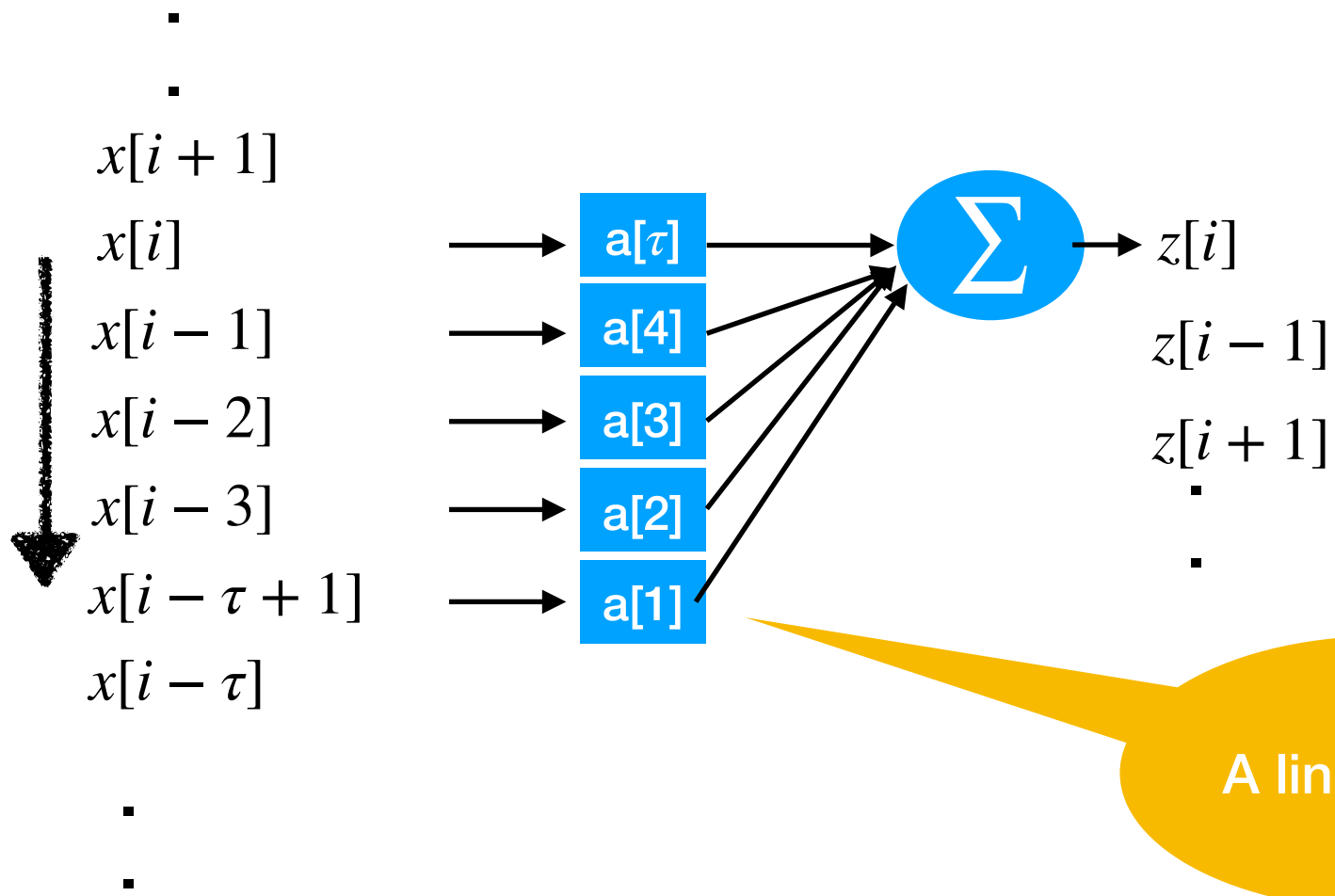
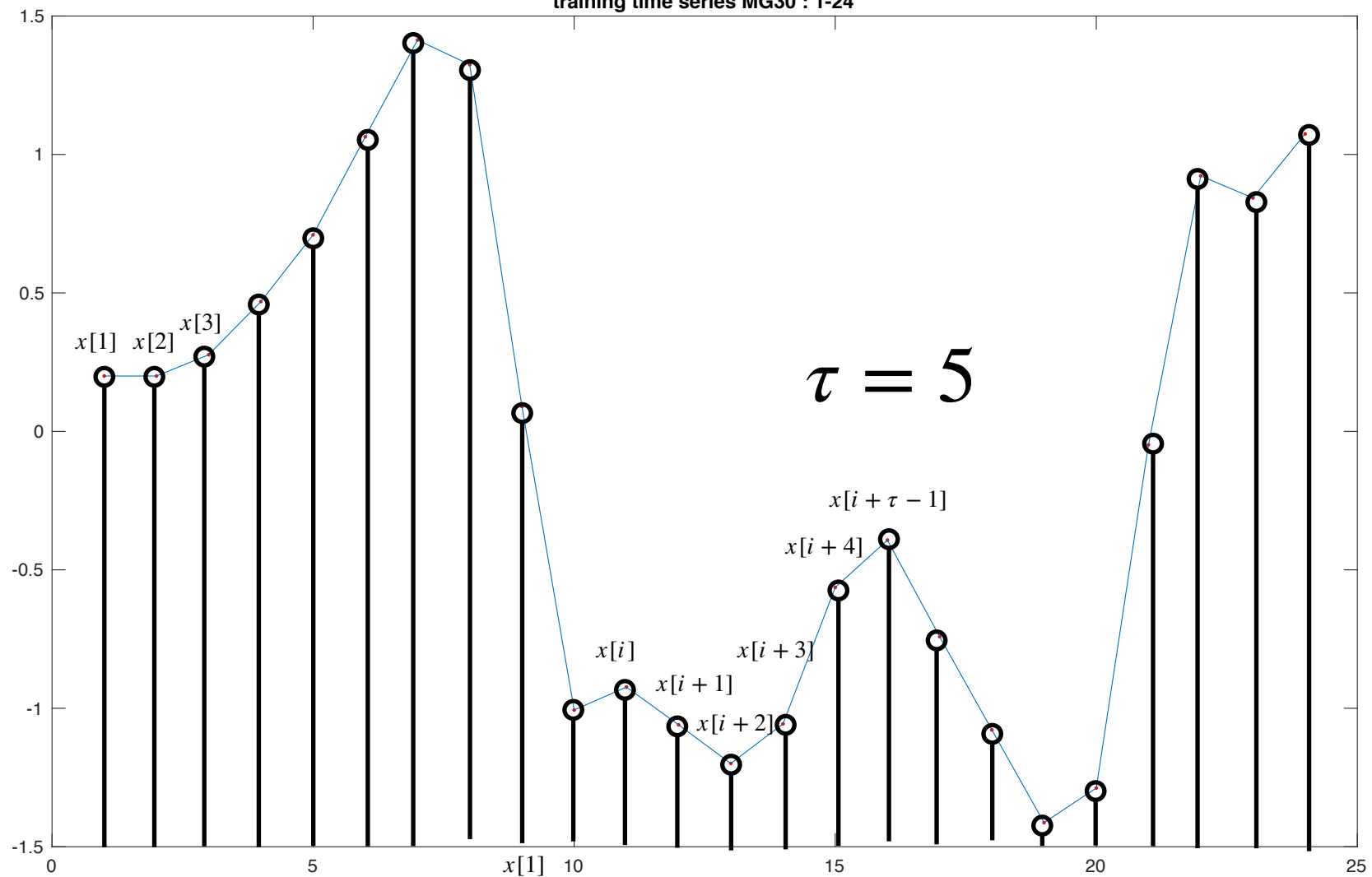


Generating MG30:801-814, red points: results of 14 steps prediction at a time

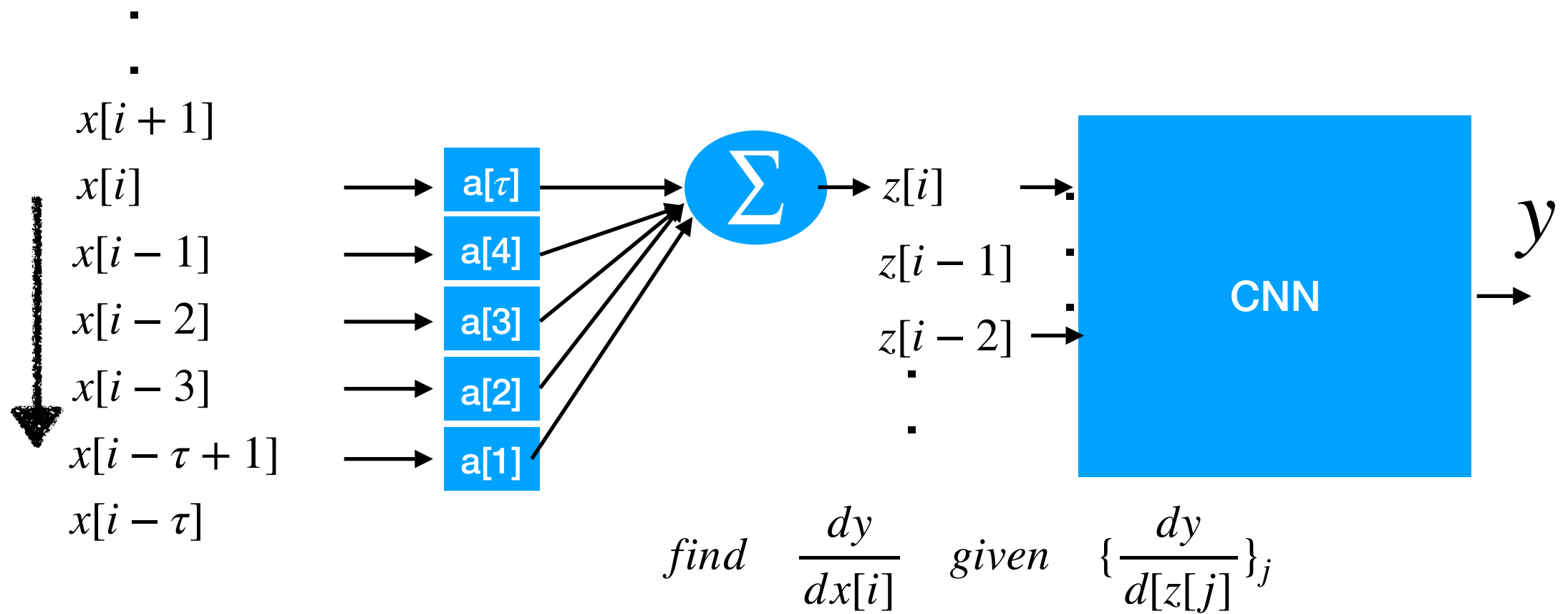


training time series MG30 : 1-24





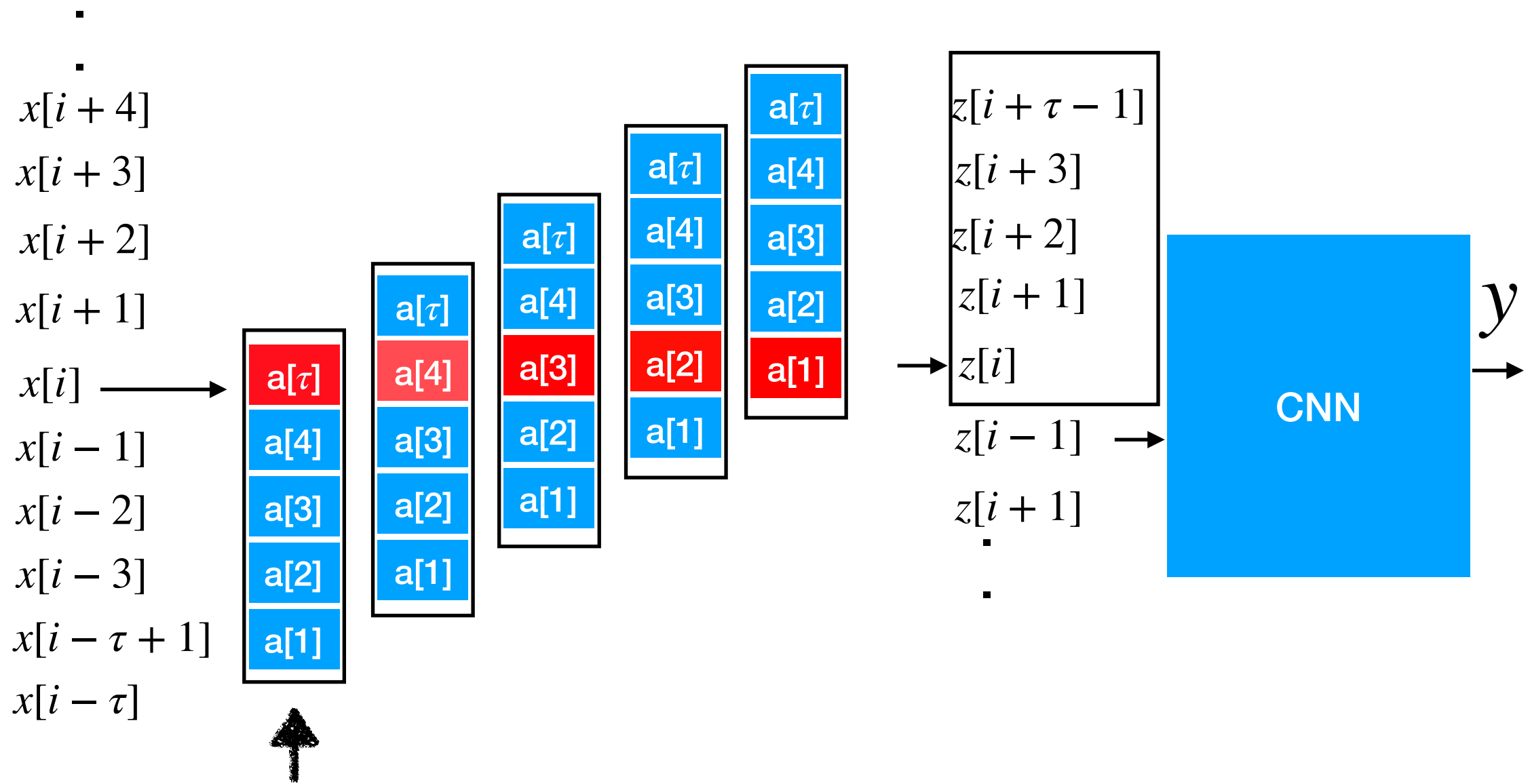
Feedforward calculation for 1D linear convolution



$$z[i] = \sum_{k=1}^{\tau} a[k]x[i - \tau + k]$$

$$= a[1]x[i - \tau + 1] + a[2]x[i - \tau + 2] + a[3]x[i - \tau + 3] + a[4]x[i - \tau + 4] + a[\tau]x[i - \tau + \tau]$$

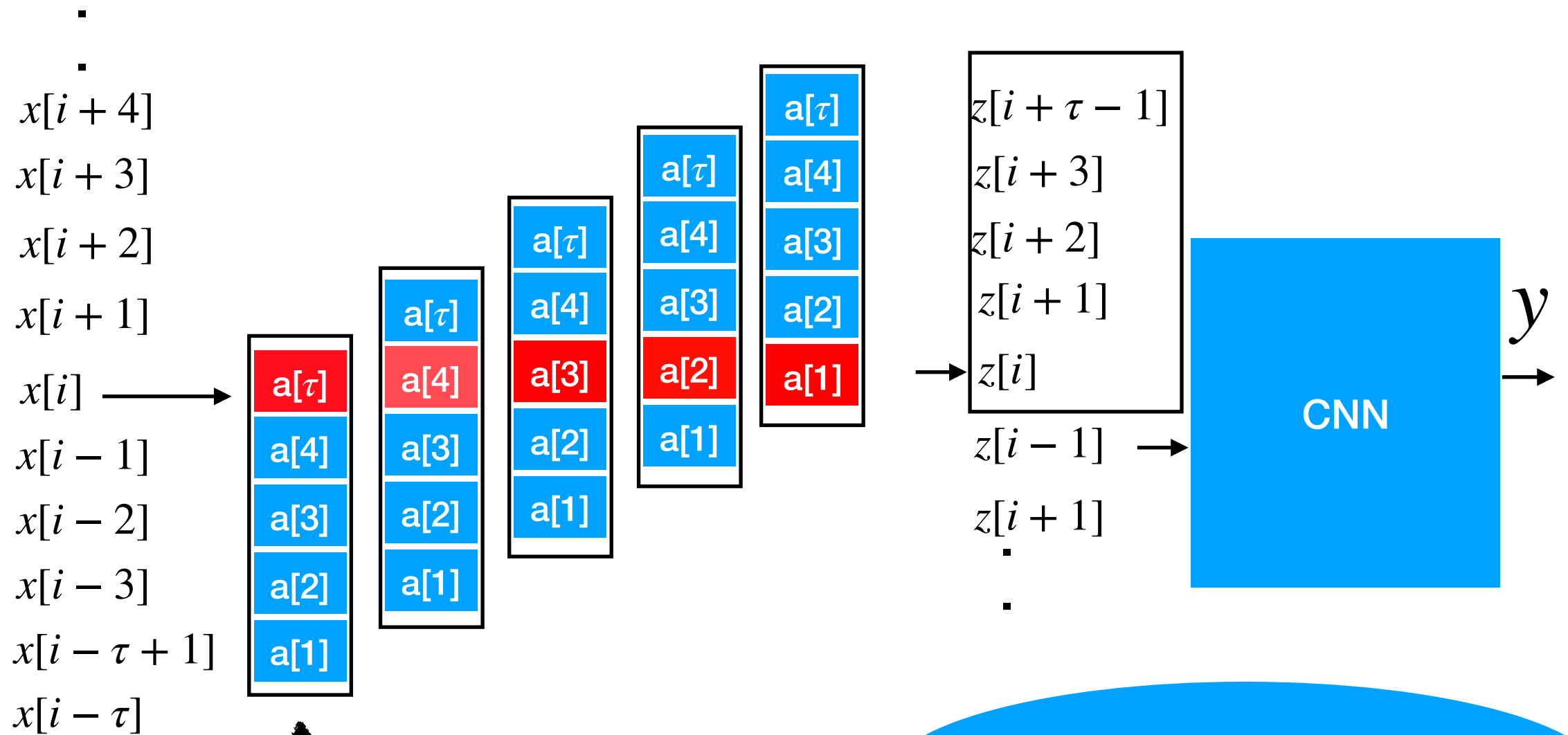
$x[i]$ contributes to $z[i], \dots, z[i + \tau - 1]$



respectively through $a[\tau], a[4], \dots, a[1]$

$$\frac{dz[i]}{dx[i]} = ? \quad \frac{dz[i+1]}{dx[i]} = ? \quad \frac{dz[i+2]}{dx[i]} = ? \quad \frac{dz[i+3]}{dx[i]} = ? \quad \frac{dz[i+\tau-1]}{dx[i]} = ?$$

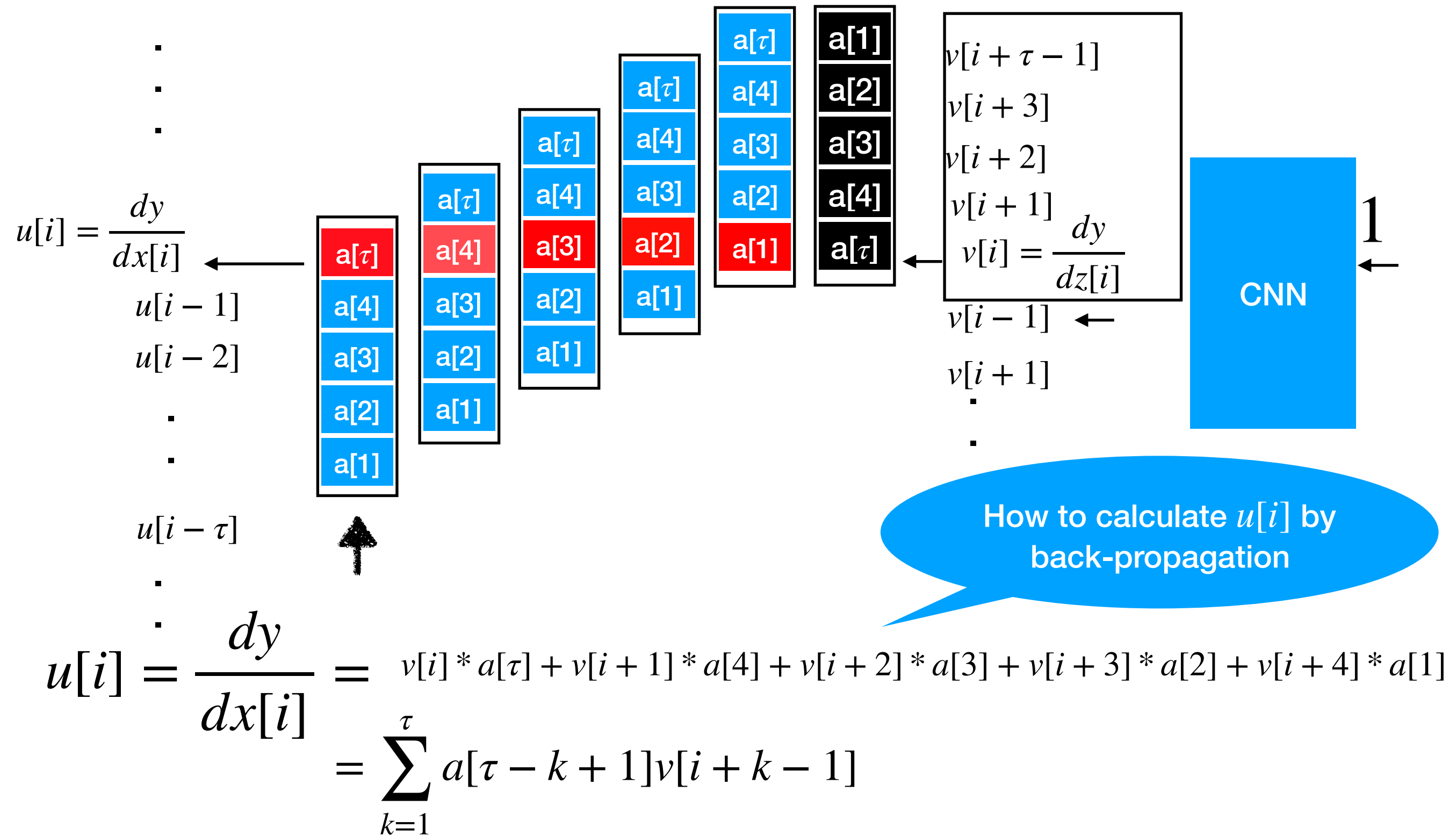
Gradient back-propagation



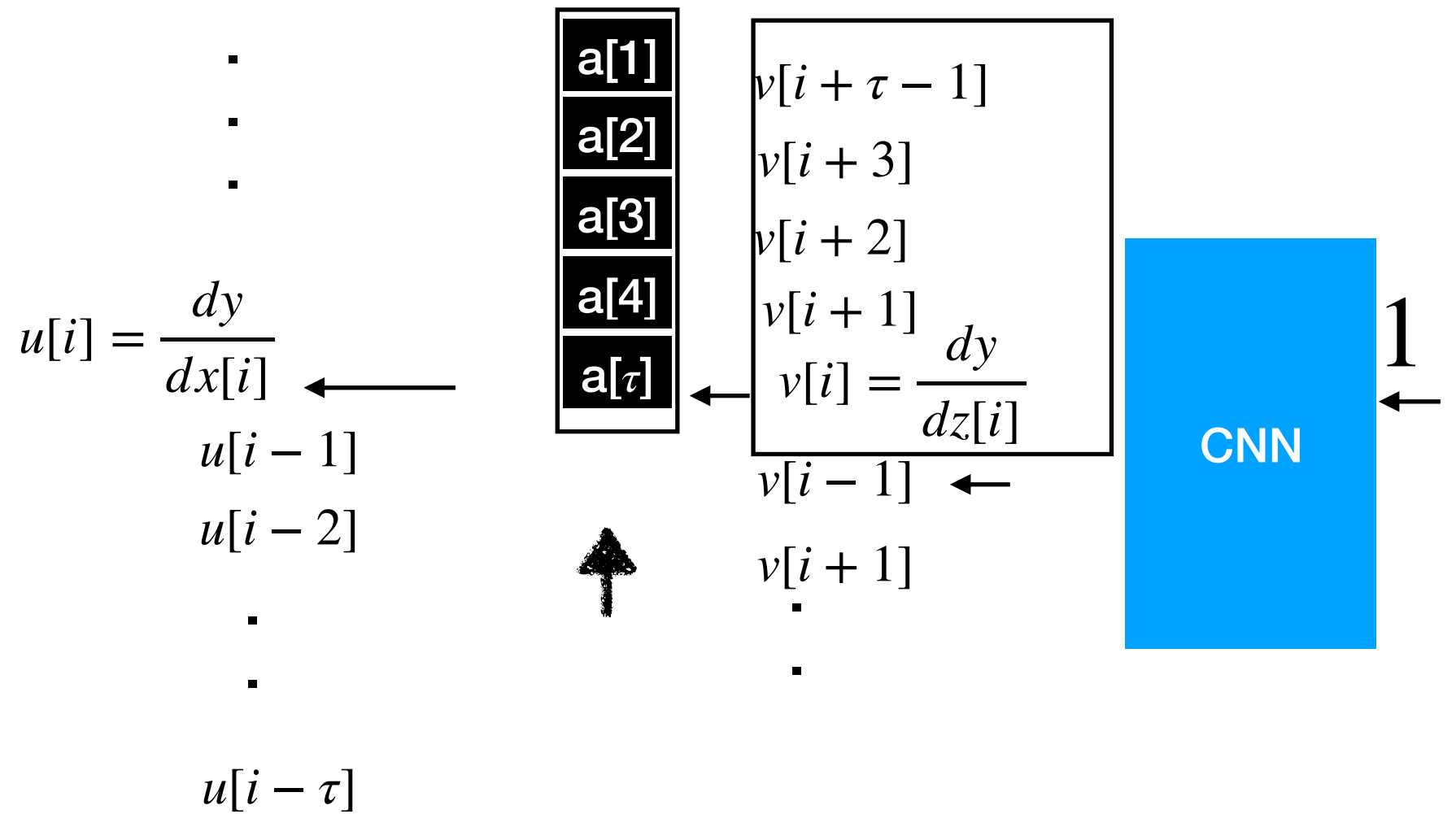
$$u[i] = \frac{dy}{dx[i]} = ?$$

How to calculate $u[i]$ by back-propagation

Back-propagation of Gradients

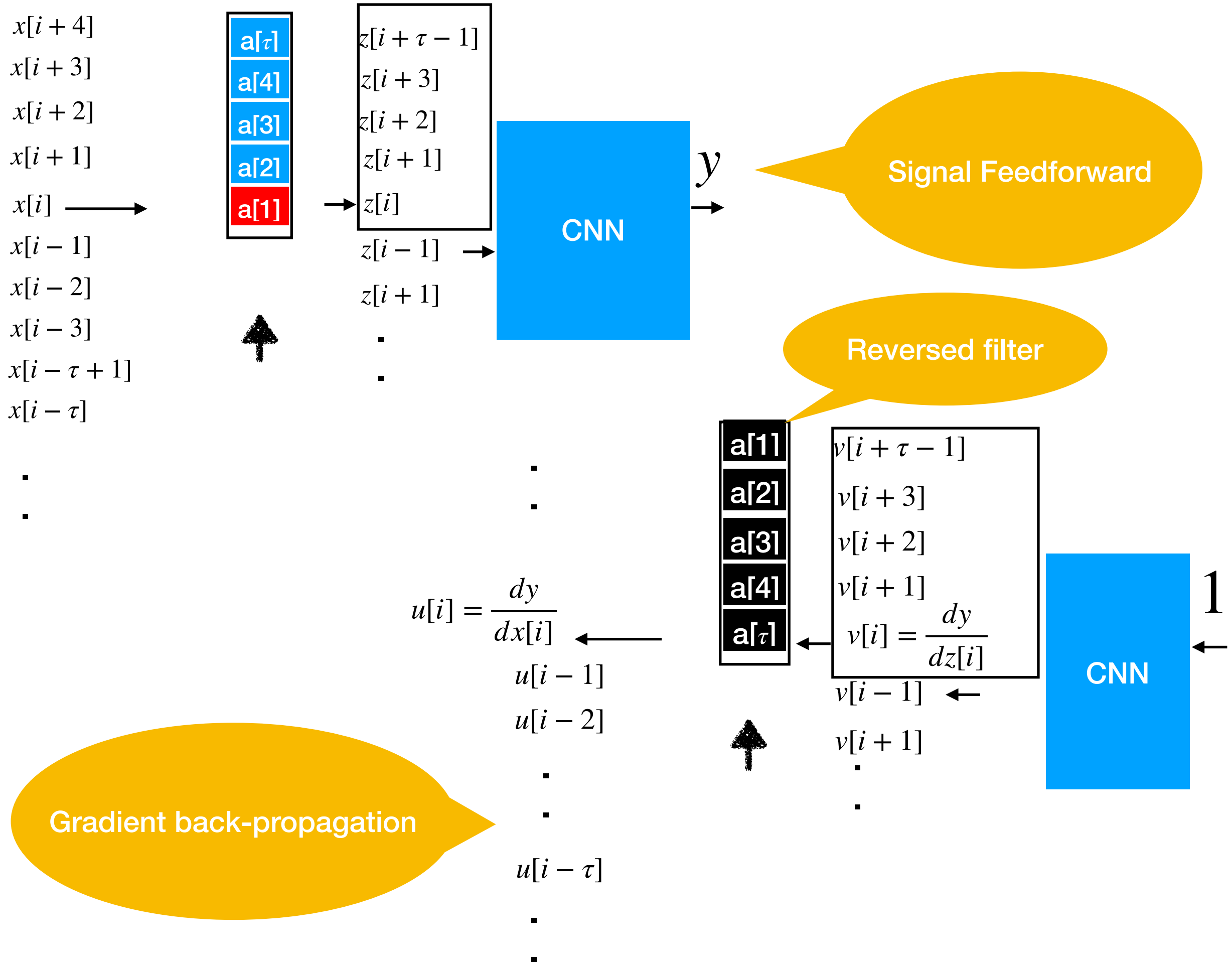


Gradient back-propagation



$$u[i] = \frac{dy}{dx[i]}$$

$$= \sum_{k=1}^{\tau} a[\tau - k + 1] v[i + k - 1]$$



2D convolution

Full Convolution

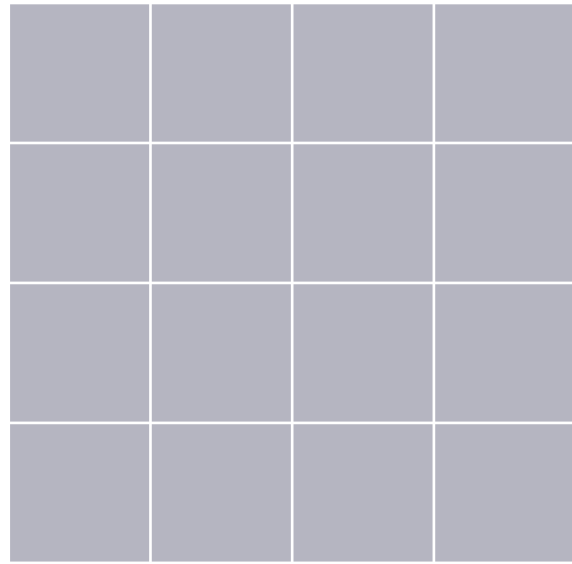
```
A = rand(3);  
B = rand(4);  
Cfull = conv2(A,B)
```

Cfull = 6×6

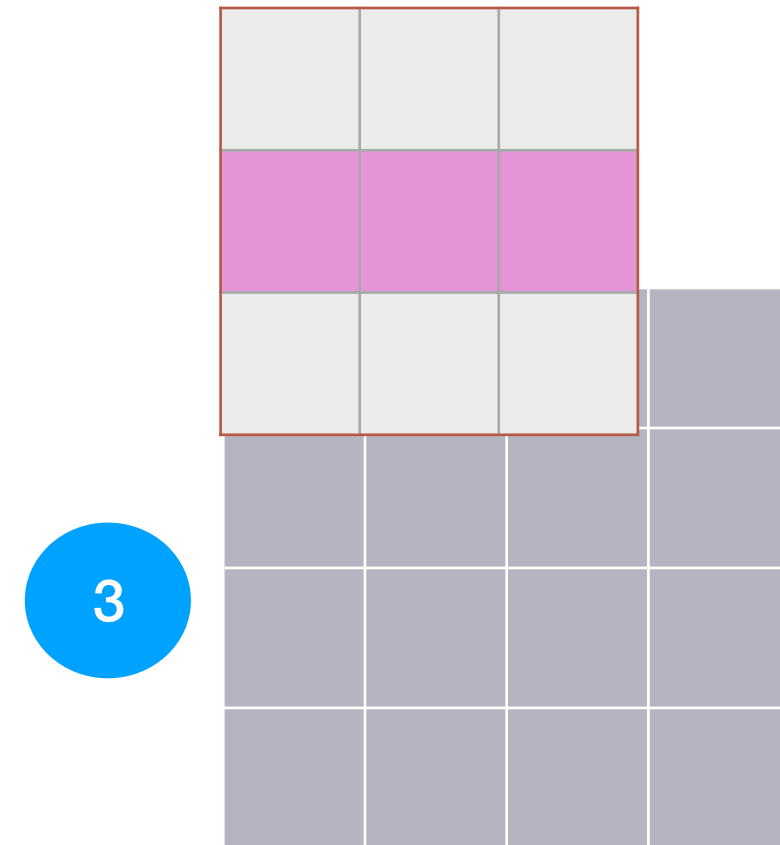
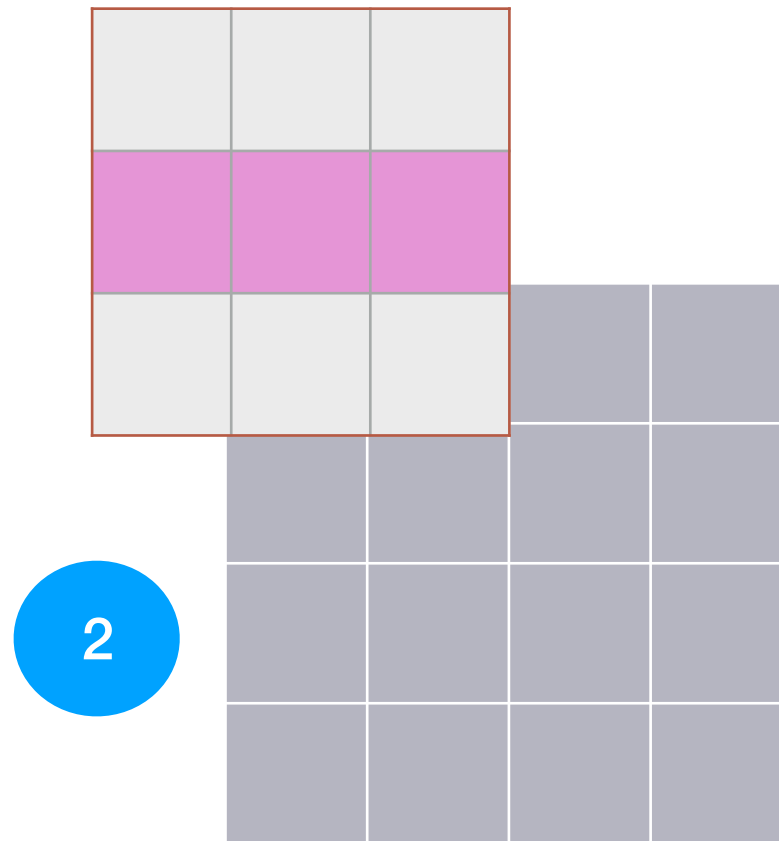
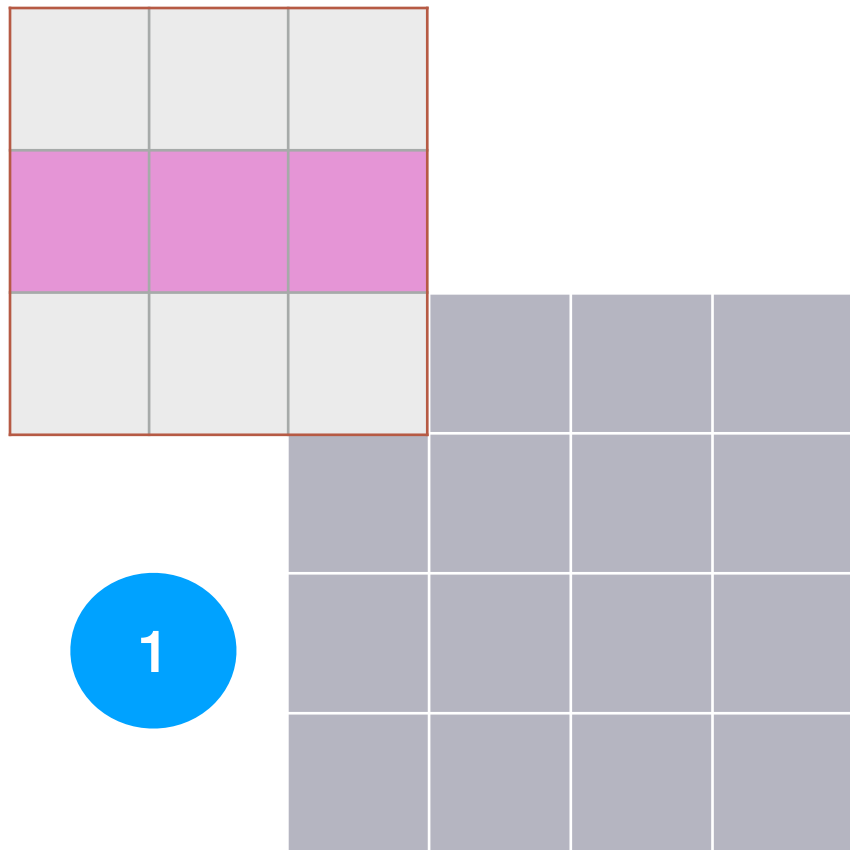
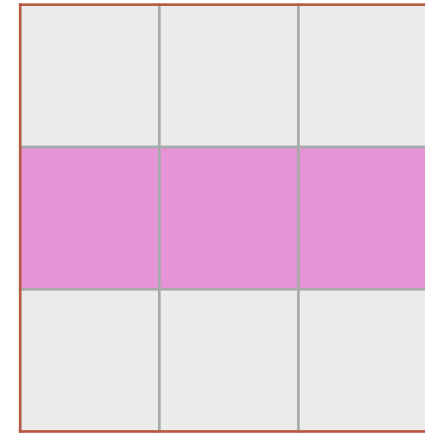
0.7861	1.2768	1.4581	1.0007	0.2876	0.0099
1.0024	1.8458	3.0844	2.5151	1.5196	0.2560
1.0561	1.9824	3.5790	3.9432	2.9708	0.7587
1.6790	2.0772	3.0052	3.7511	2.7593	1.5129
0.9902	1.1000	2.4492	1.6082	1.7976	1.2655
0.1215	0.1469	1.0409	0.5540	0.6941	0.6499

Full Convolution

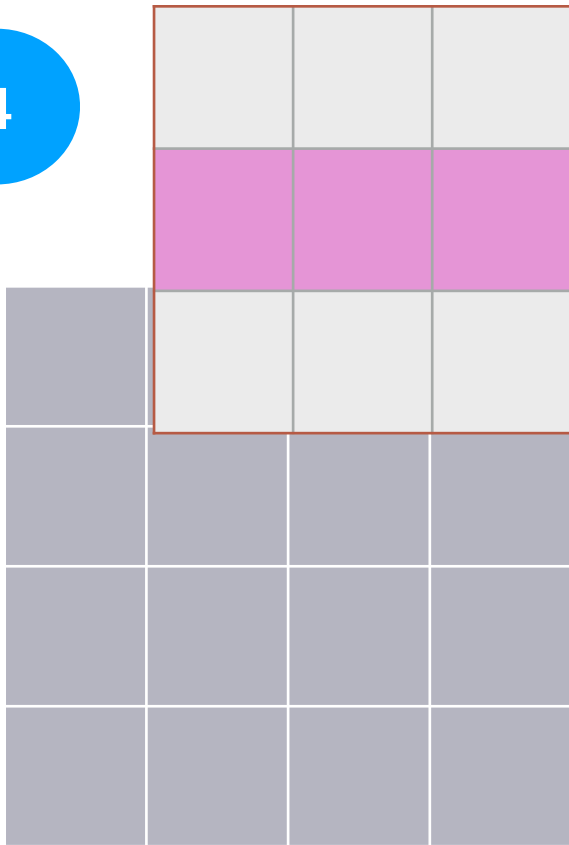
B



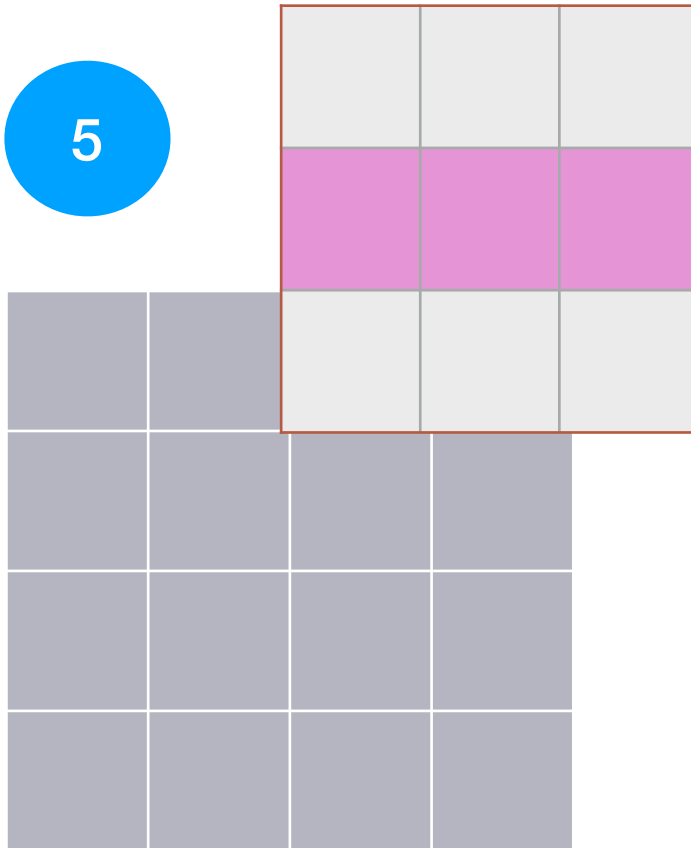
A



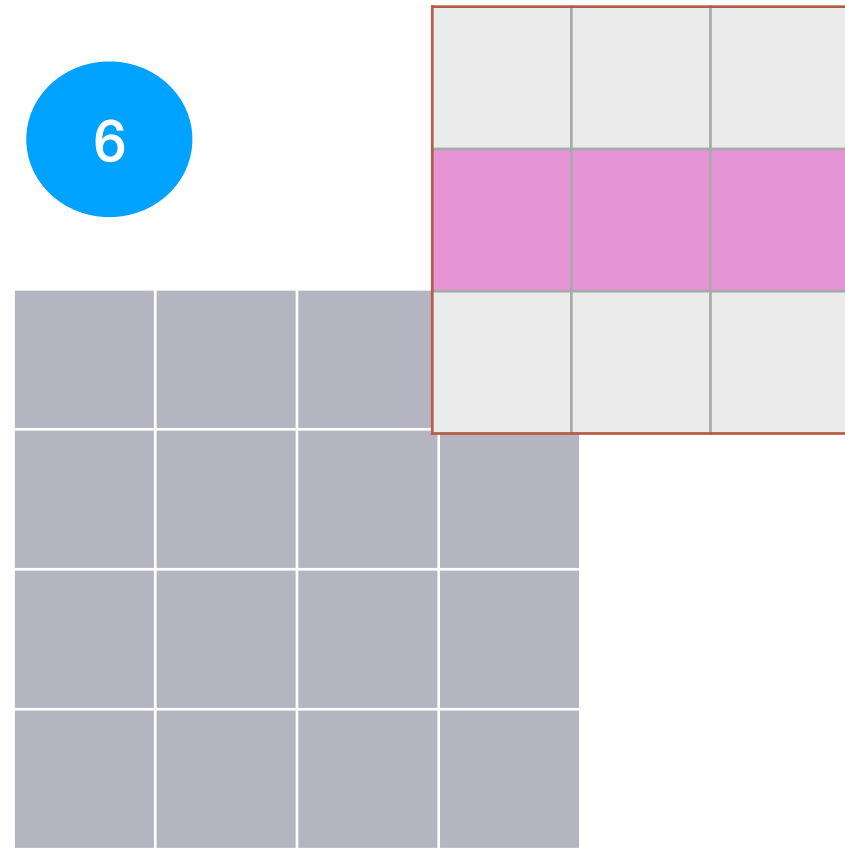
4



5

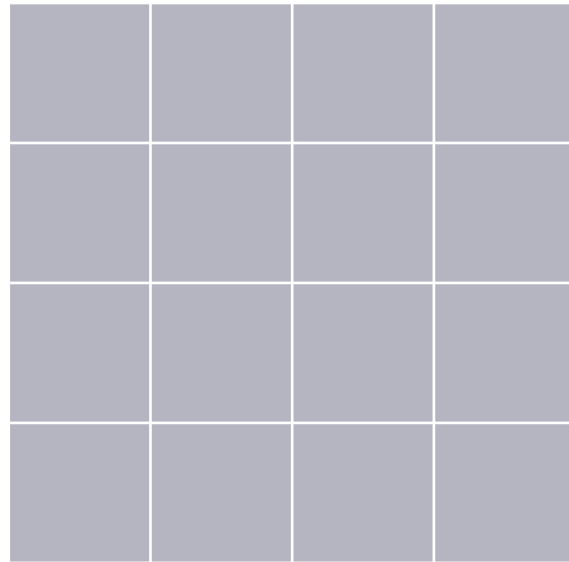


6

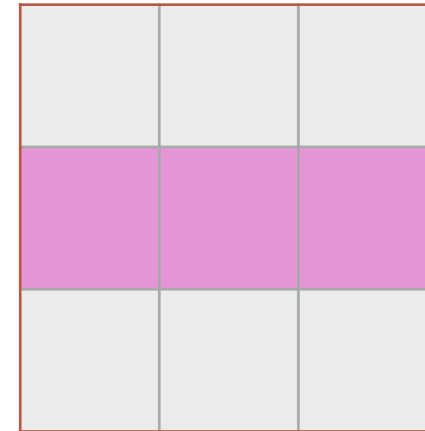


Full Convolution

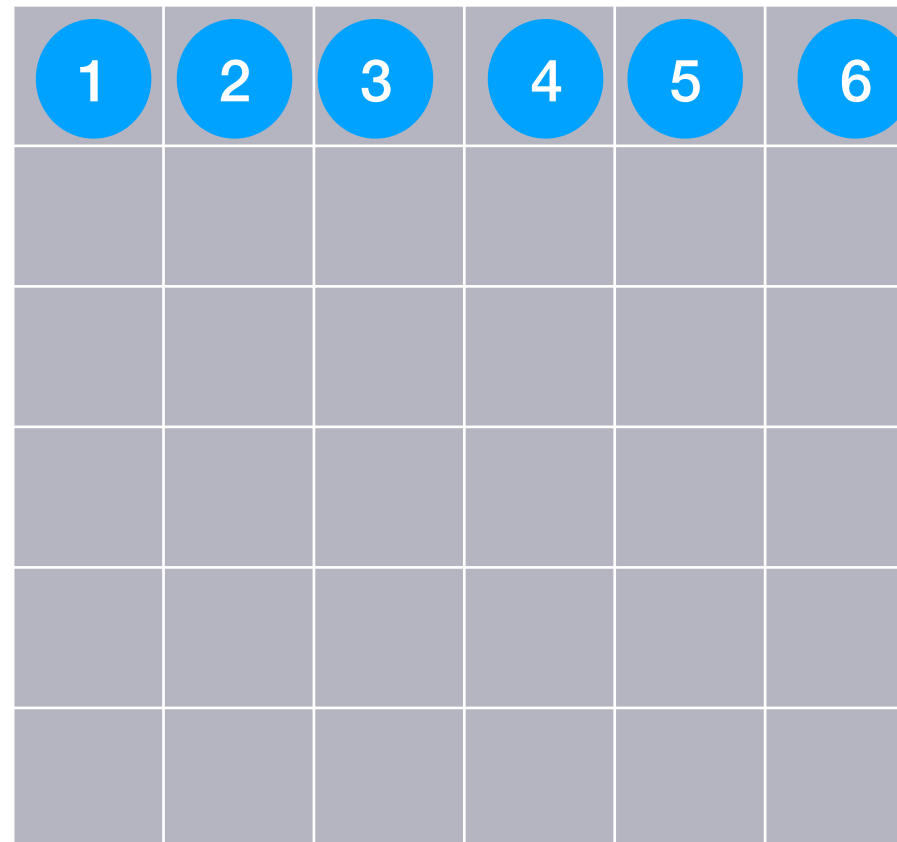
B



A

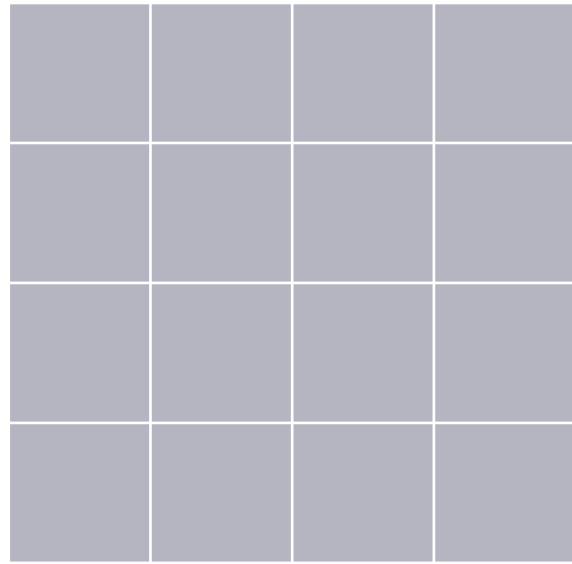


conv2(A,B)

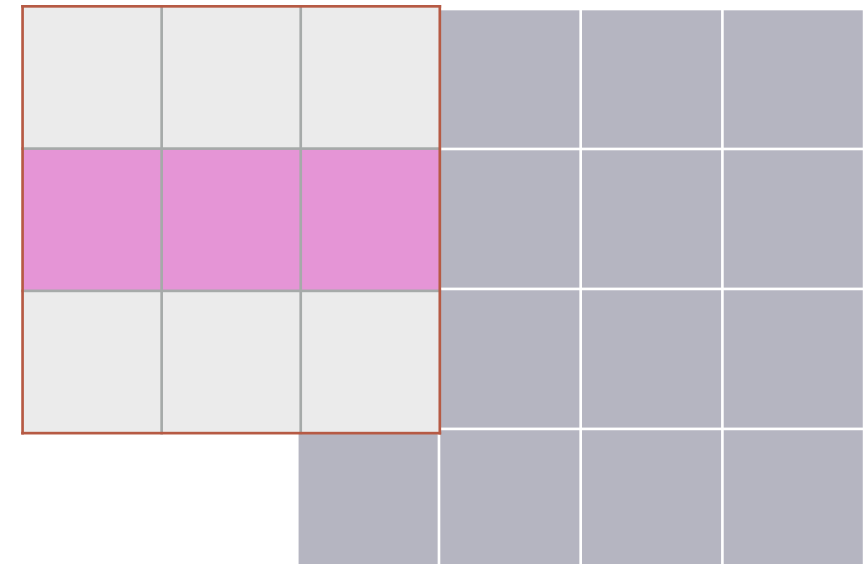
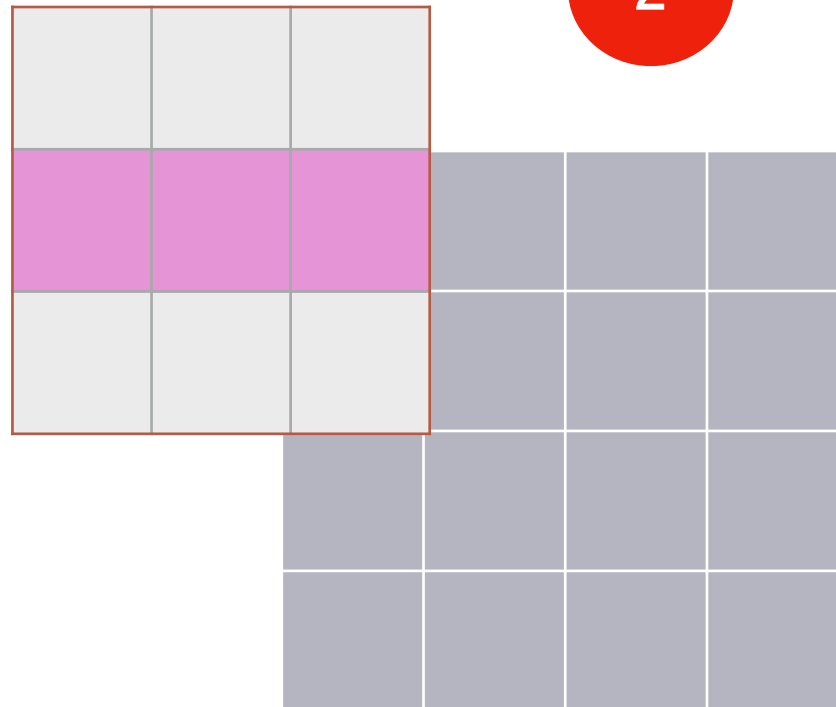
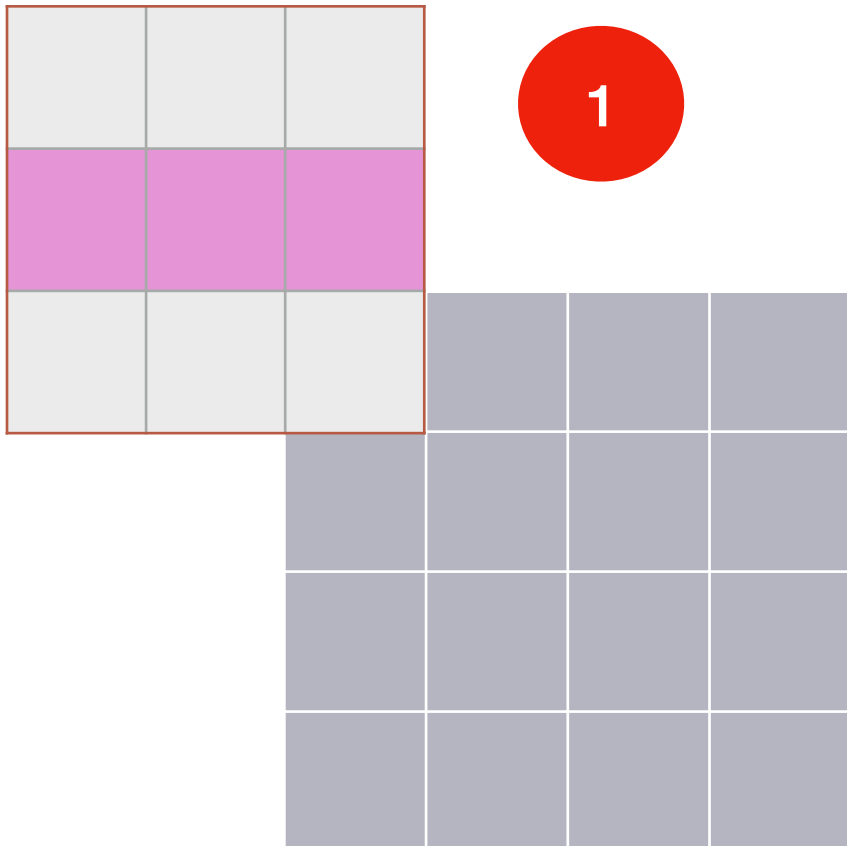
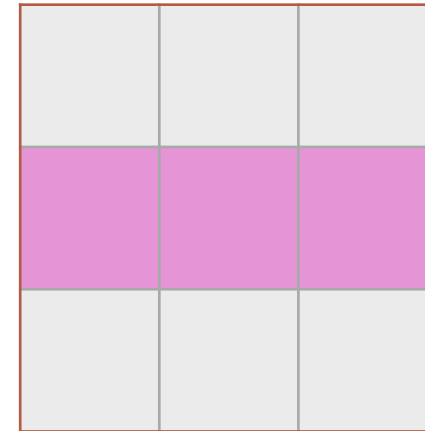


Full Convolution

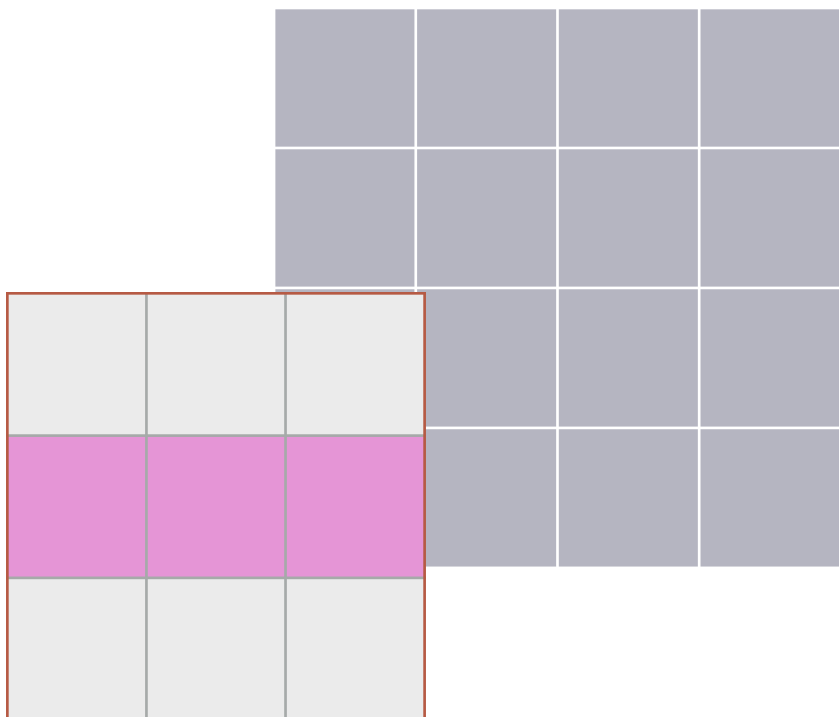
B



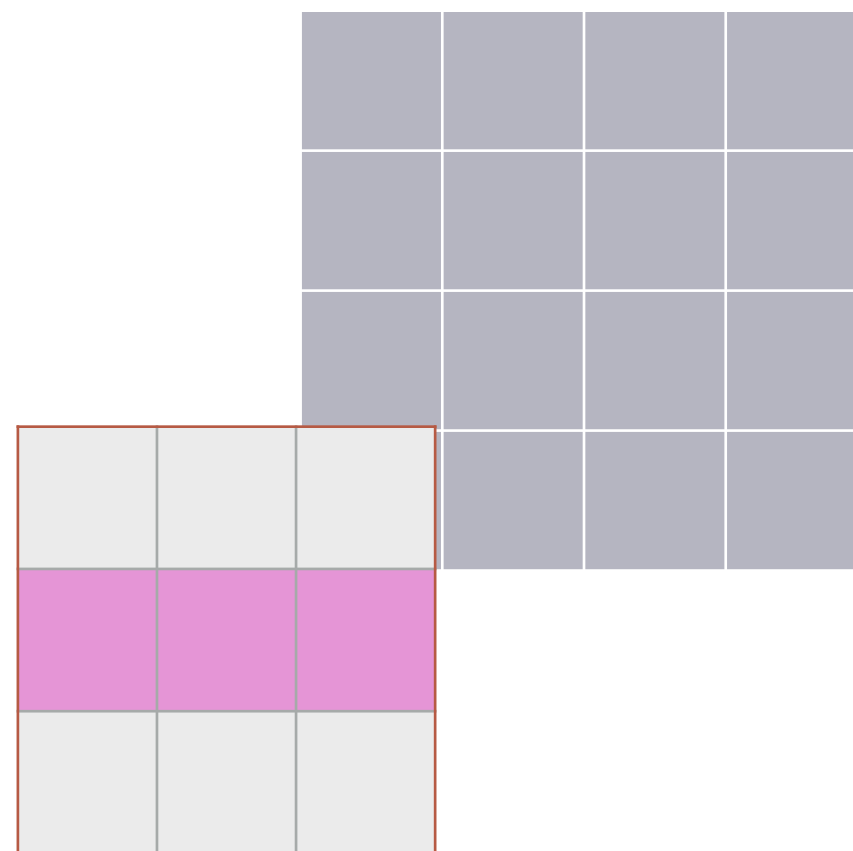
A



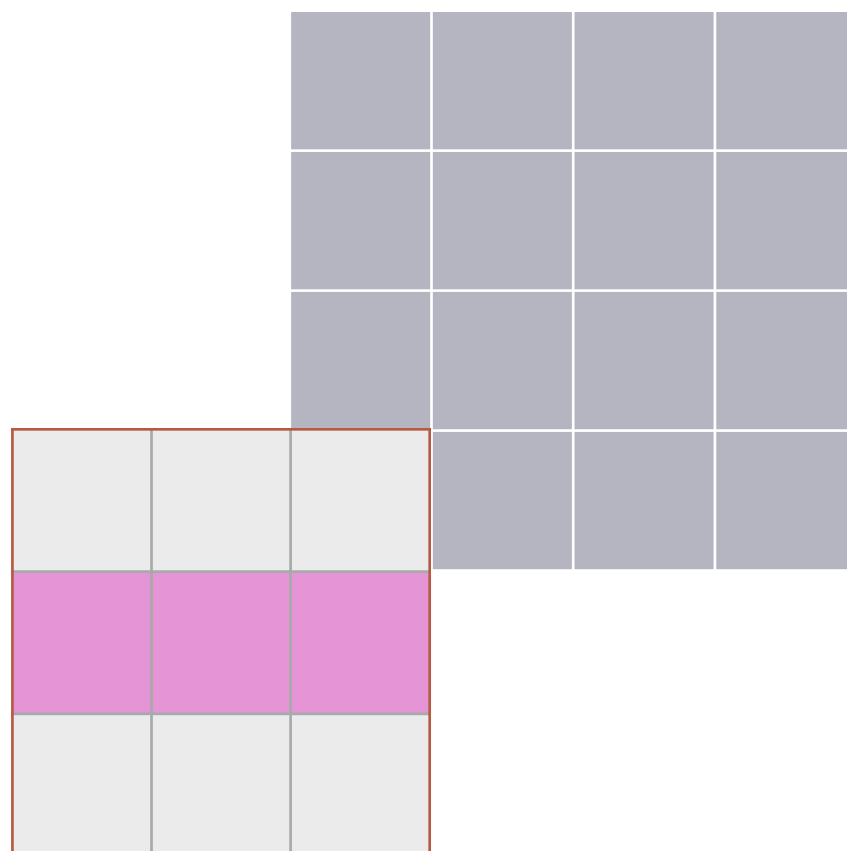
4



5

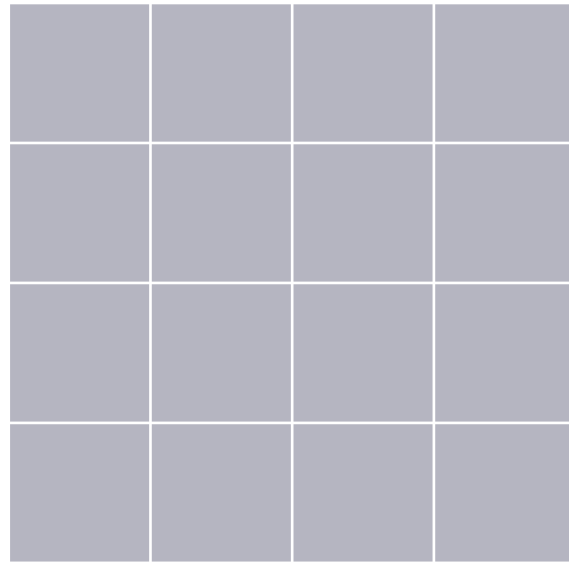


6

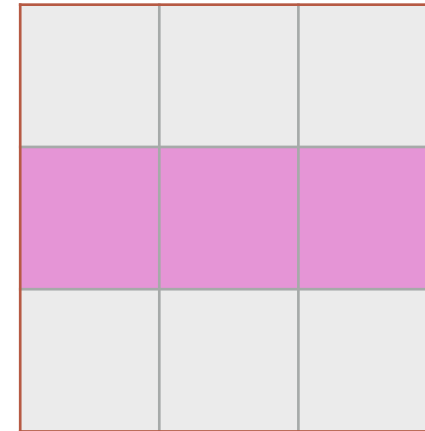


Full Convolution

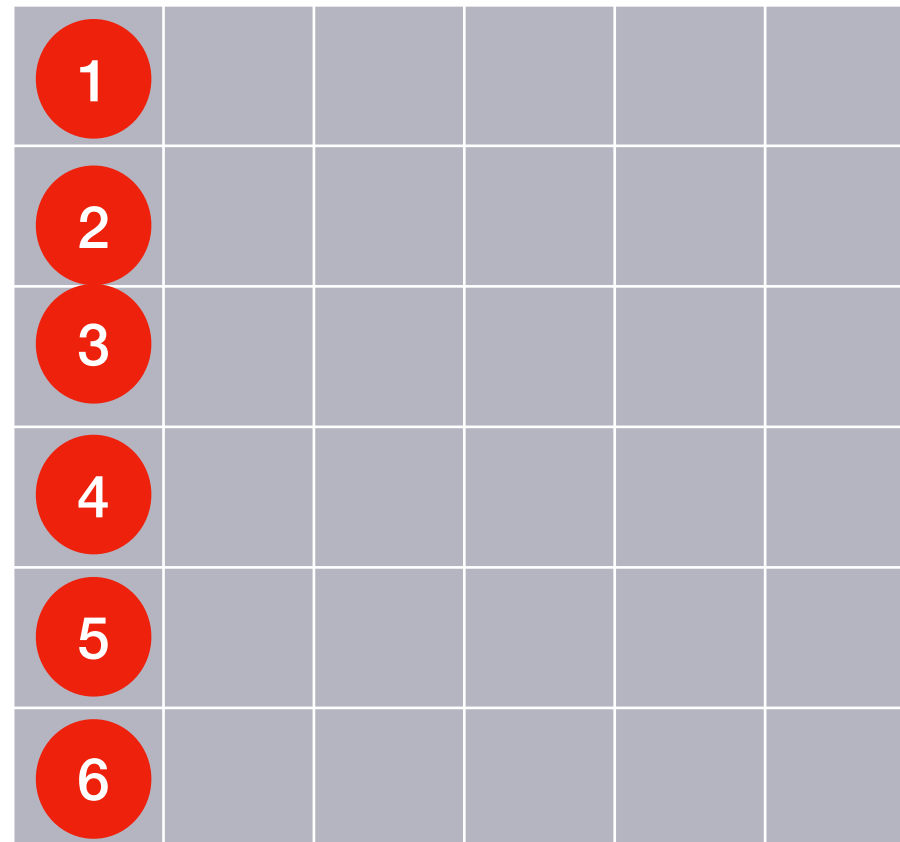
B



A

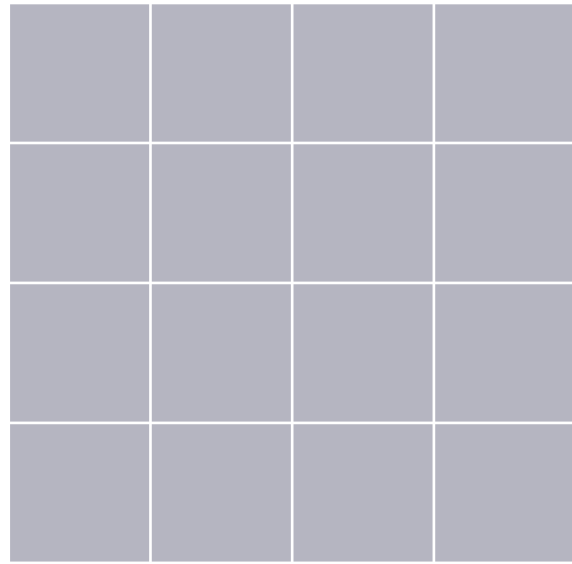


conv2(A,B)

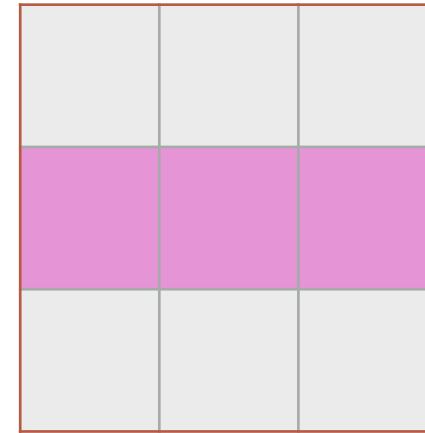


Valid Convolution

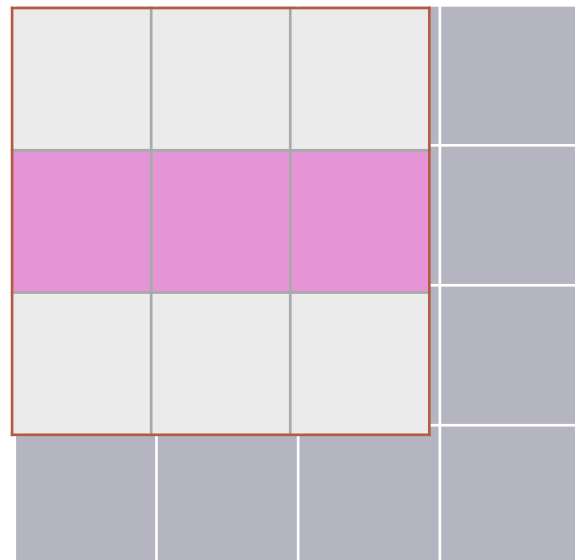
B



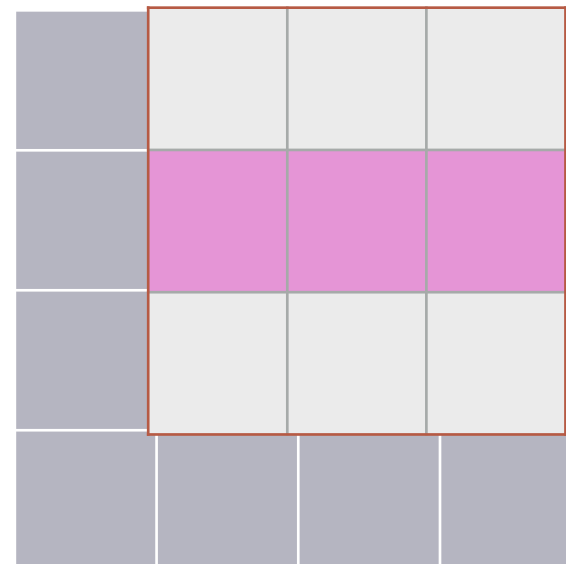
A



1

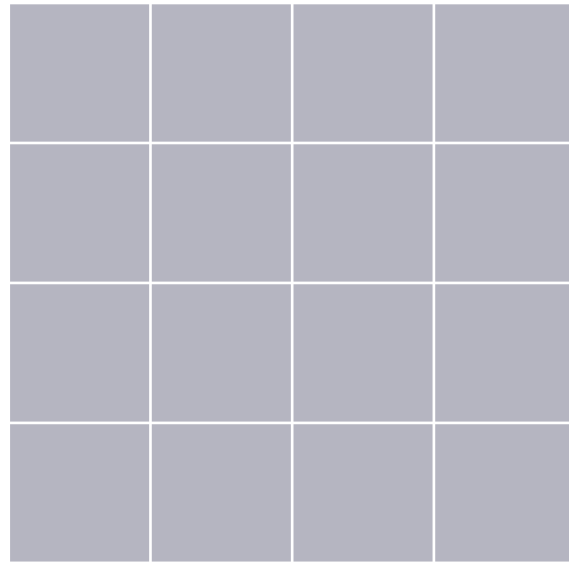


2

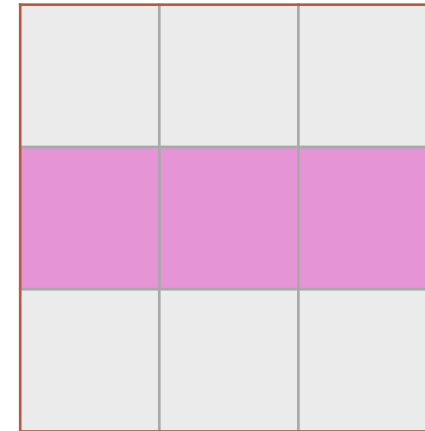


Valid Convolution

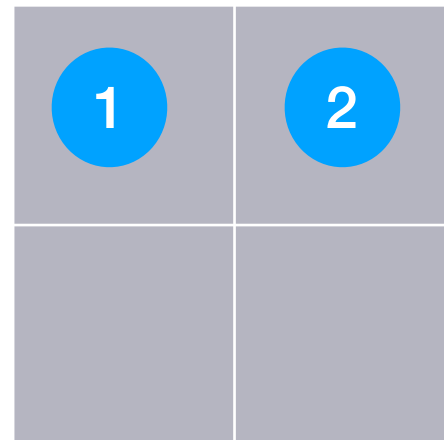
B



A

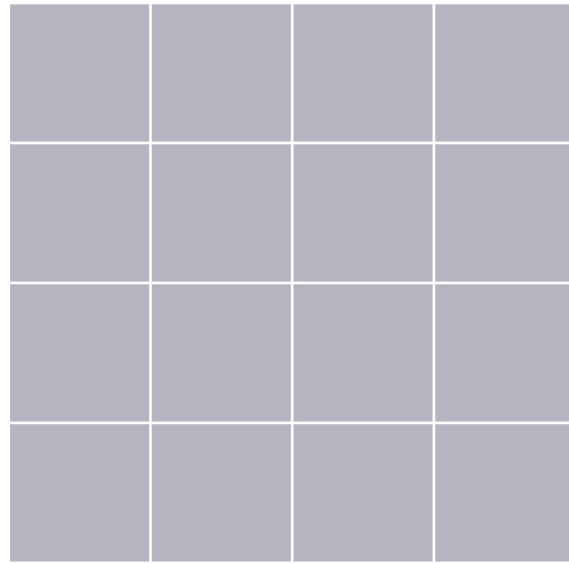


conv2(A,B,'valid')

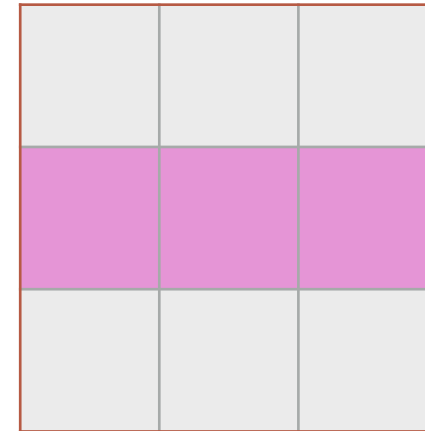


Valid Convolution

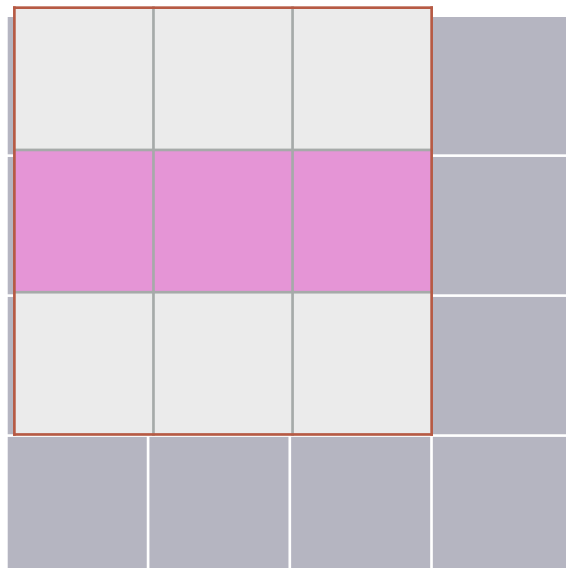
B



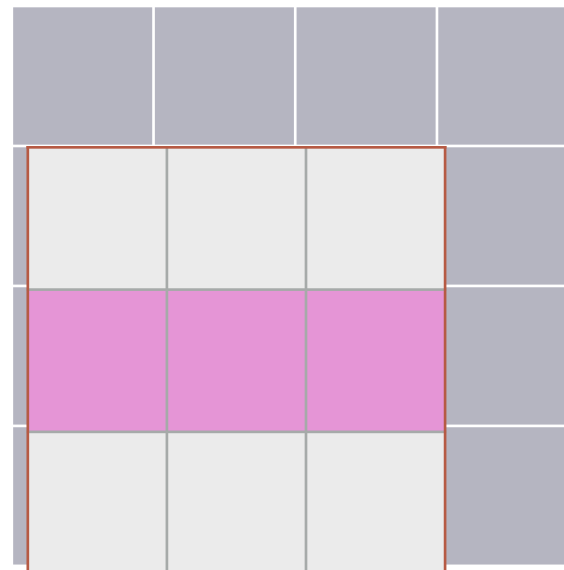
A



1

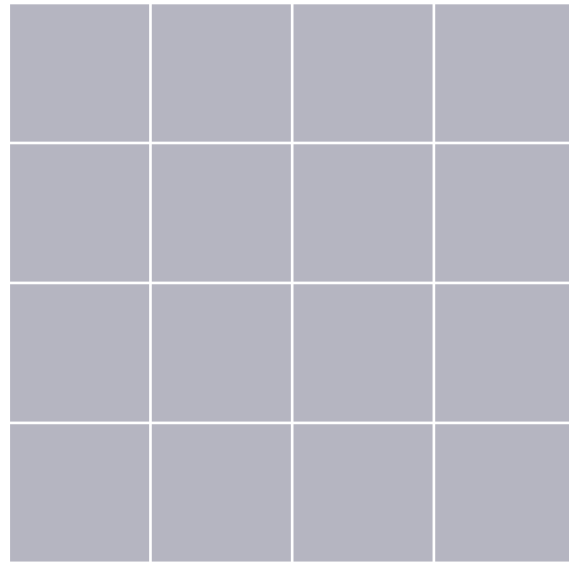


2

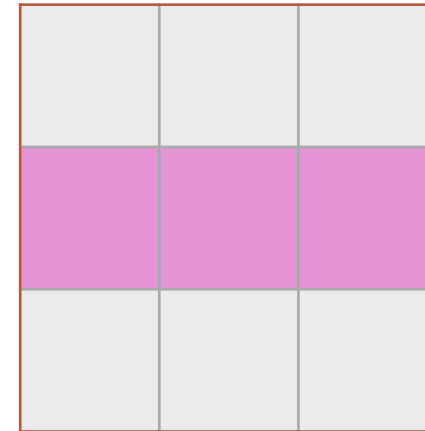


Valid Convolution

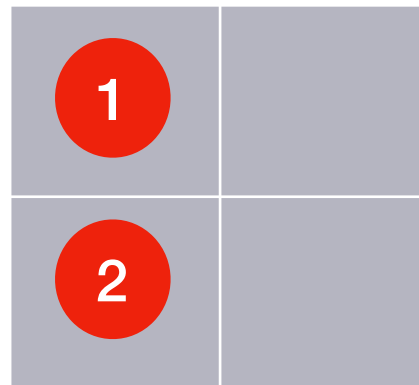
B



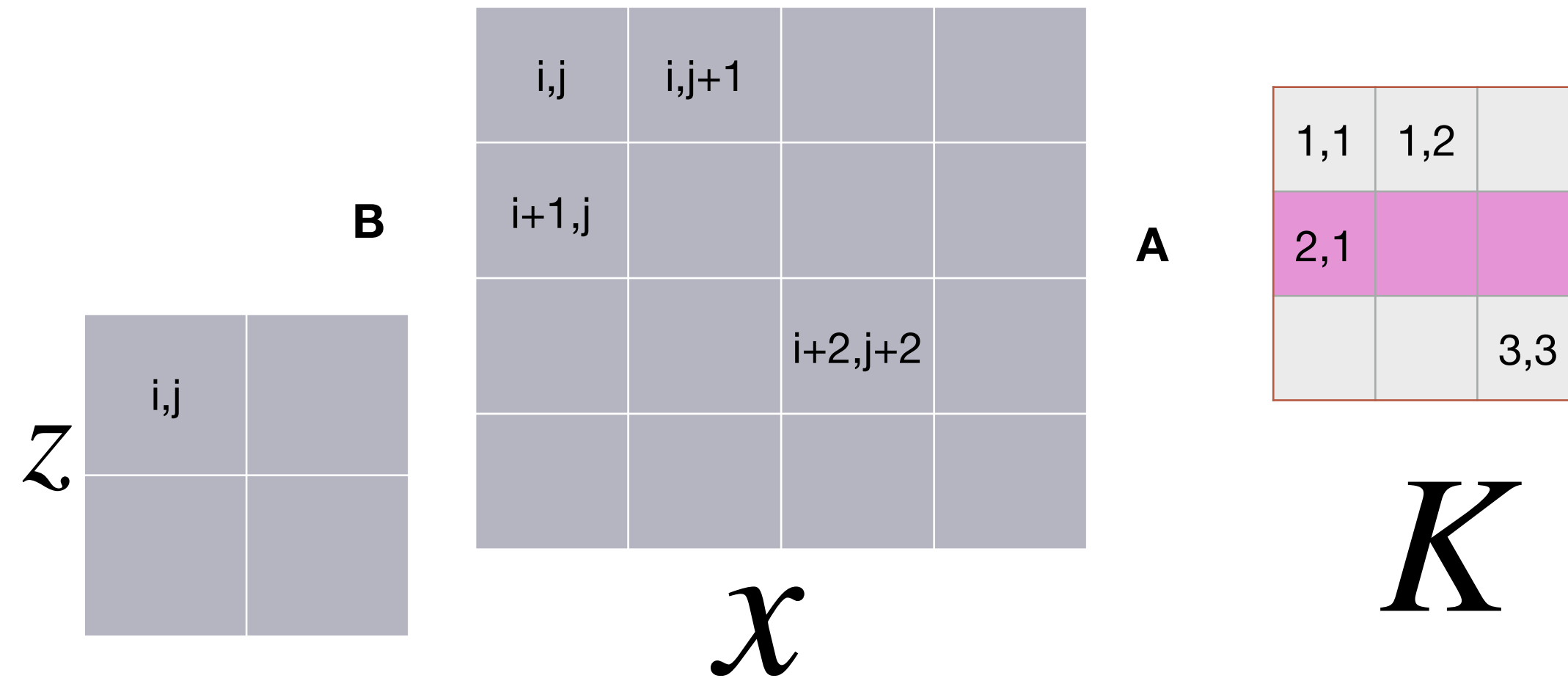
A



conv2(A,B,'valid')



Valid Convolution



`conv2(A,B,'valid')`

$$\text{size}(B,1) \geq \text{size}(A,1); \quad \text{size}(B,2) \geq \text{size}(A,2)$$

$$z[i,j] = \sum_m^{\tau} \sum_n^{\tau} K(m,n) * x[i+m-1,j+n-1]$$

where $i = 1 : \text{size}(B,1) - \text{size}(A,1) + 1$
 $j = 1 : \text{size}(B,2) - \text{size}(A,2) + 1$

Valid convolution

表格 1

B	=				
		1	1	1	1
		1	1	1	1
		1	1	1	1
		1	1	1	1

```
>> B=ones(4,4);A=ones(3,3)/9;  
>> z=conv2(B,A,'valid')
```

z =

```
1.0000 1.0000  
1.0000 1.0000
```

表格 1-1

A	=				
		0.1111	0.1111	0.1111	
		0.1111	0.1111	0.1111	
		0.1111	0.1111	0.1111	

```
function z=my_valid_conv2(x,K)
```

```
assert(size(x,1) >= size(K,1) & size(x,2) >= size(K,2),"invalid matrix size")
```

```
fo
```

```
er
```



```
>> B=ones(4,4);A=ones(3,3)/9;  
>> z=my_valid_conv2(B,A)
```

```
z =
```

```
 1  1  
 1  1
```

表格 1

A =			
	0.2348	0.0154	0.6491
	0.3532	0.0430	0.7317
	0.8212	0.1690	0.6477

表格 1-1

B =				
	0.4509	0.1890	0.6256	0.7757
	0.5470	0.6868	0.7802	0.4868
	0.2963	0.1835	0.0811	0.4359
	0.7447	0.3685	0.9294	0.4468

```
>> sum(sum(B(2:4,1:3).*A))
```

```
ans =
```

```
2.0932
```

```
>> z2=my_valid_conv2(B,A)
```

```
z2 =
```

```
1.6354 1.6366  
2.0932 1.6255
```

```
>> sum(sum(B(1:3,1:3).*A))
```

```
ans =
```

```
1.6354
```

```
>> sum(sum(B(1:3,2:4).*A))
```

```
ans =
```

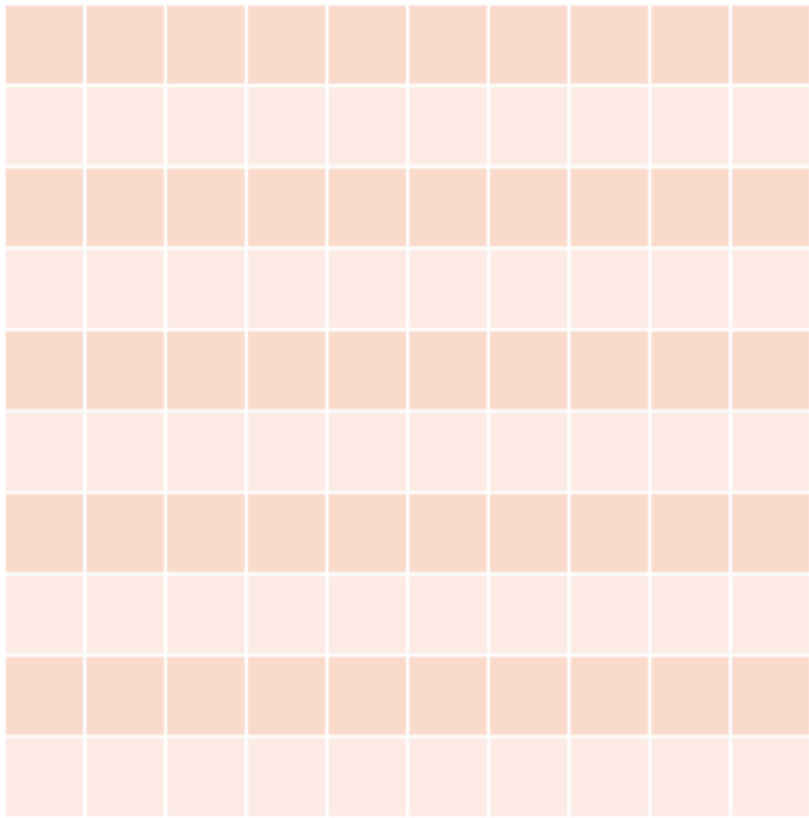
```
1.6366
```

```
>> sum(sum(B(2:4,2:4).*A))
```

```
ans =
```

```
1.6255
```

inputmap



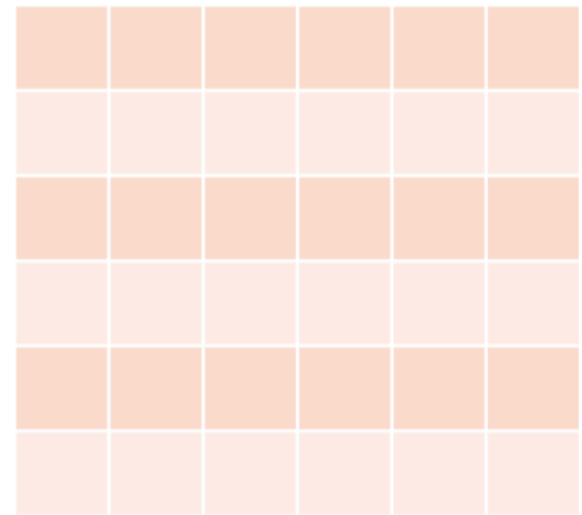
filters



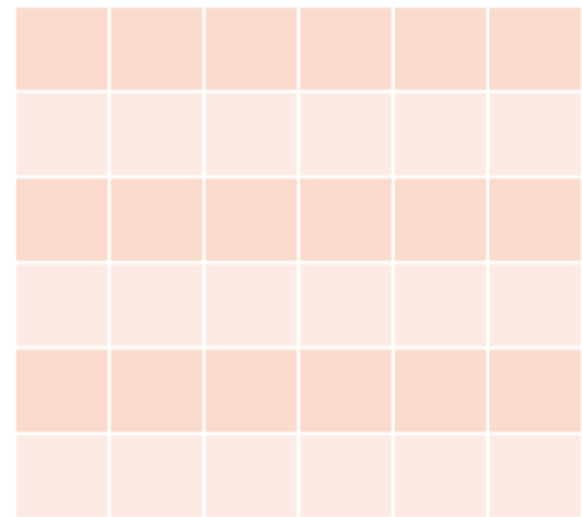
⋮



mapsize=10-5+1
outputmaps

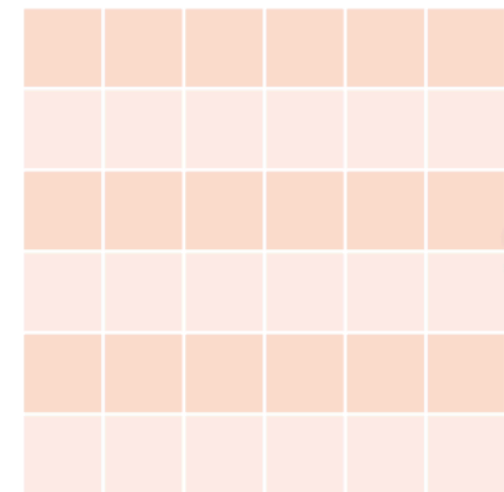
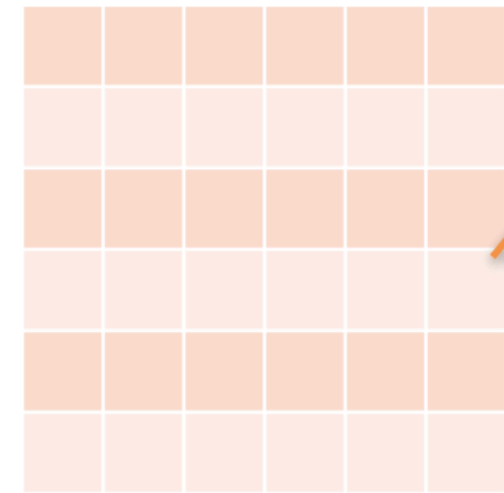
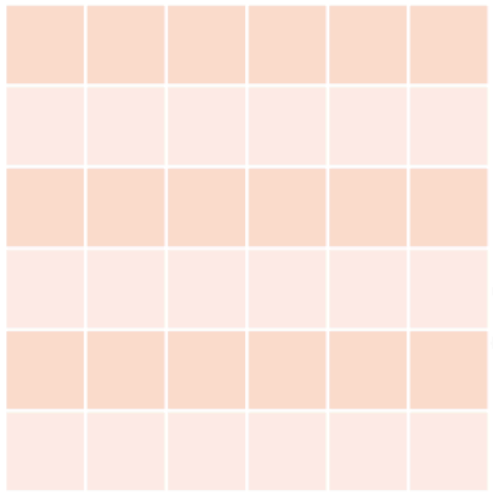


⋮

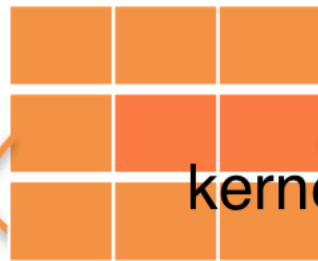


A stack of output maps

inputmap



filters



kernel(1,1)

kernel(2,1)

kernel(3,1)



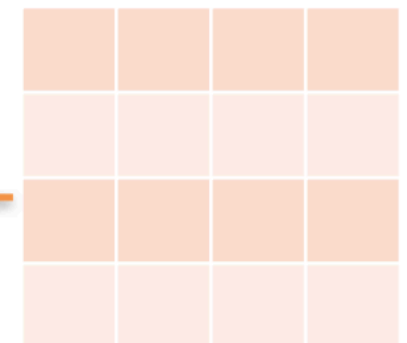
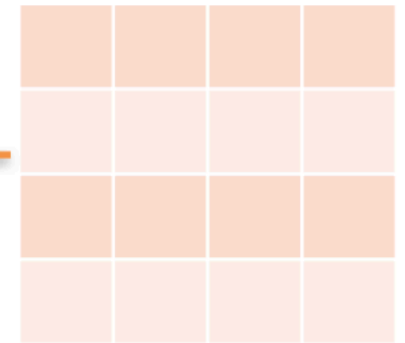
kernel(1,2)

kernel(2,2)

kernel(3,2)

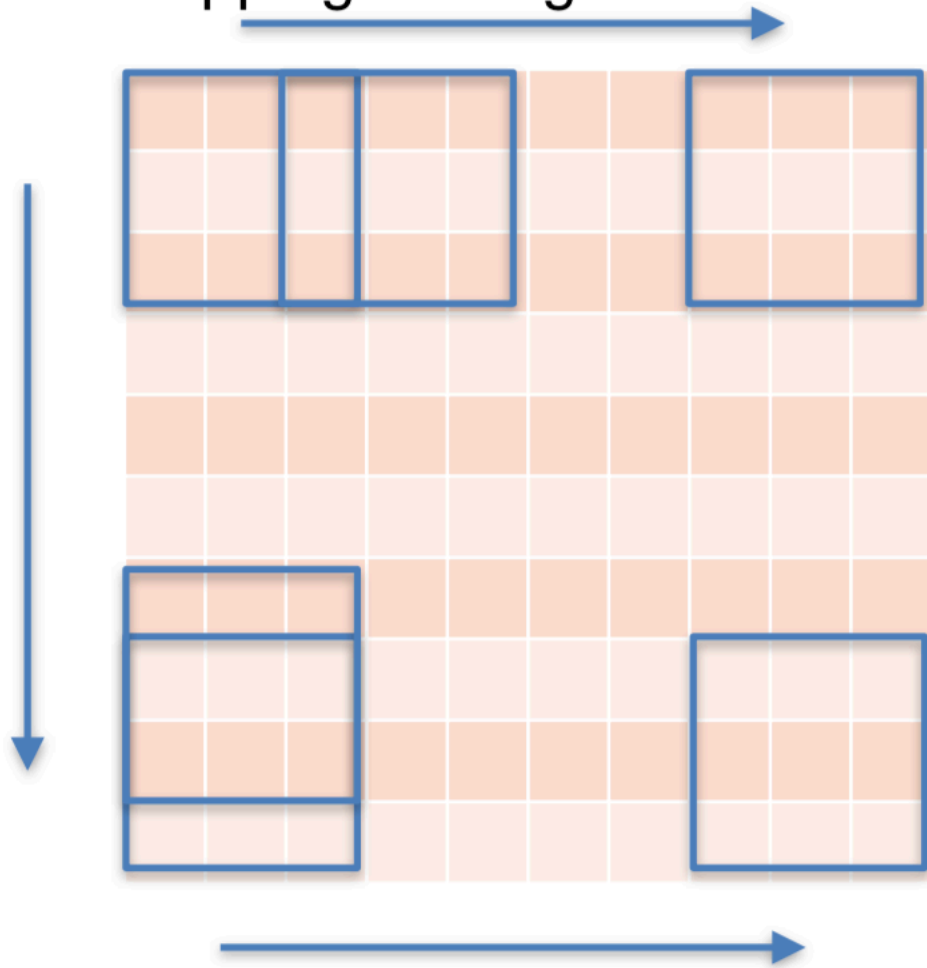
mapsize=6-3+1

outputmaps

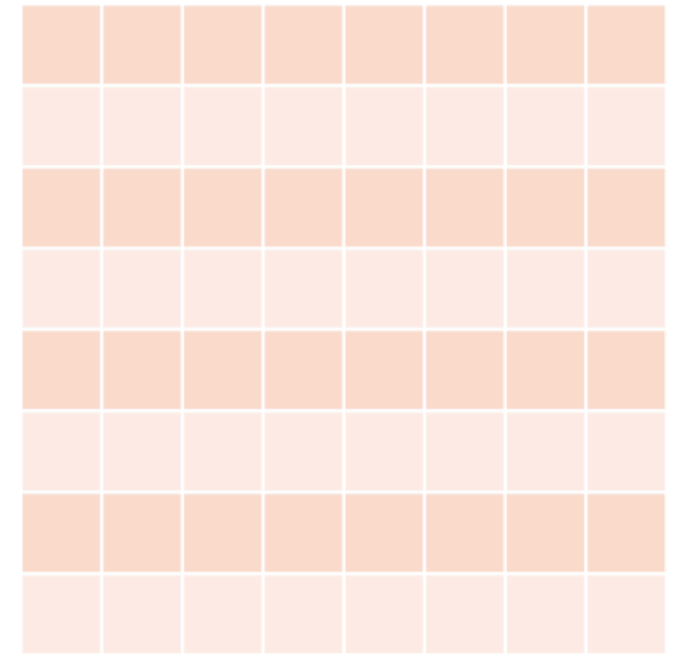


2D Convolution

overlapping moving of filters



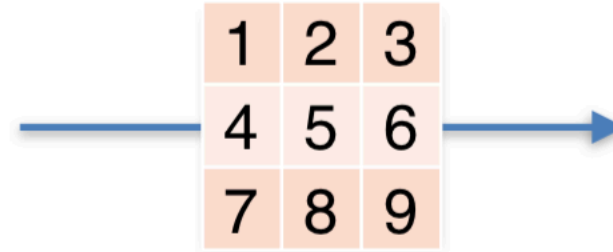
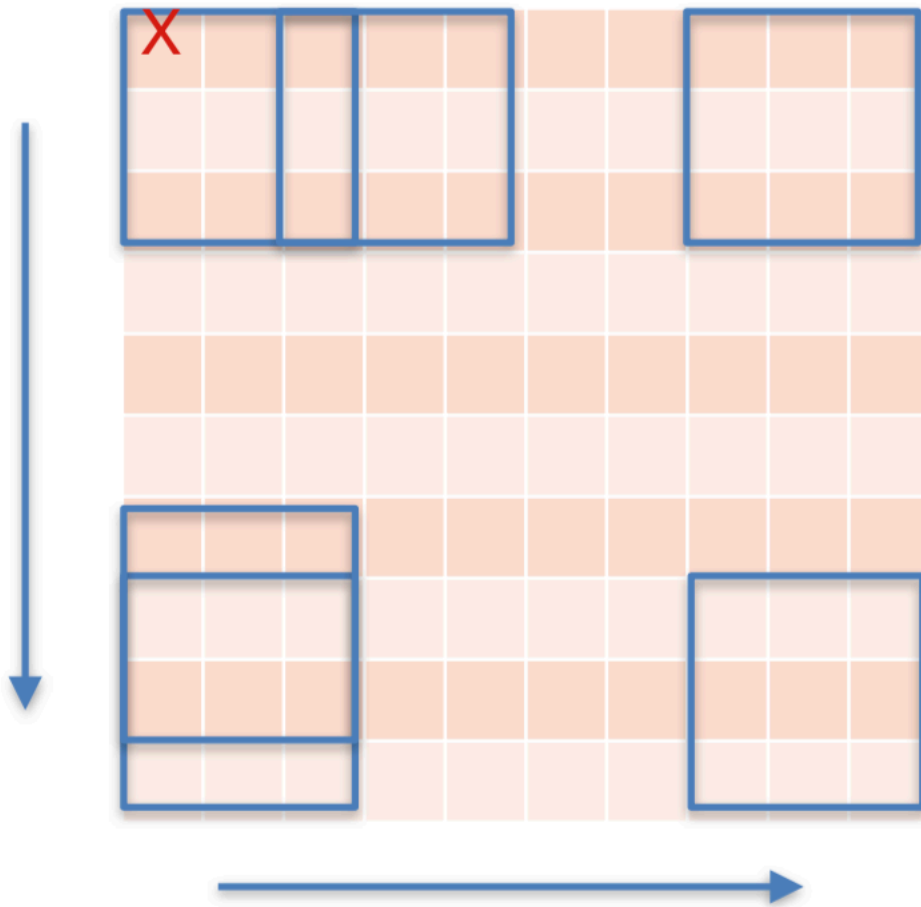
10-3+1



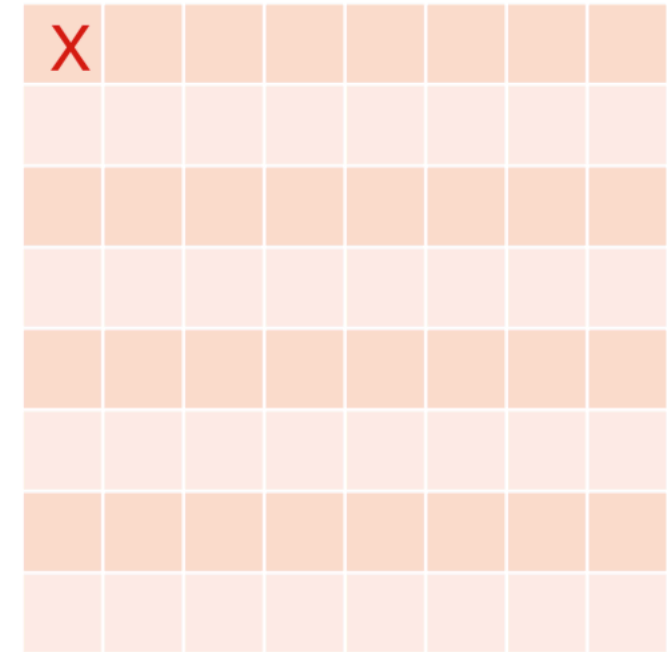
```
>> C=conv2(B,A,'valid')  
C =  
    1.0000    1.0000  
    1.0000    1.0000  
  
>> B  
B =  
    1    1    1    1  
    1    1    1    1  
    1    1    1    1  
    1    1    1    1  
  
>> A  
A =  
    0.1111    0.1111    0.1111  
    0.1111    0.1111    0.1111  
    0.1111    0.1111    0.1111  
  
>>
```

2D Convolution

overlapping moves of filters



10-3+1



Sampling by convolution

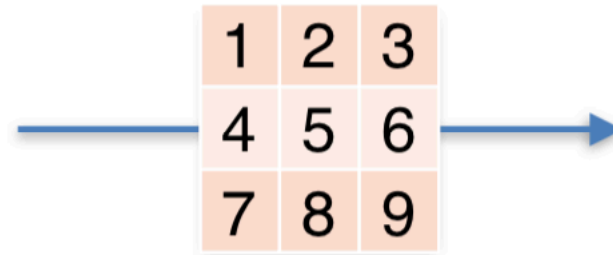
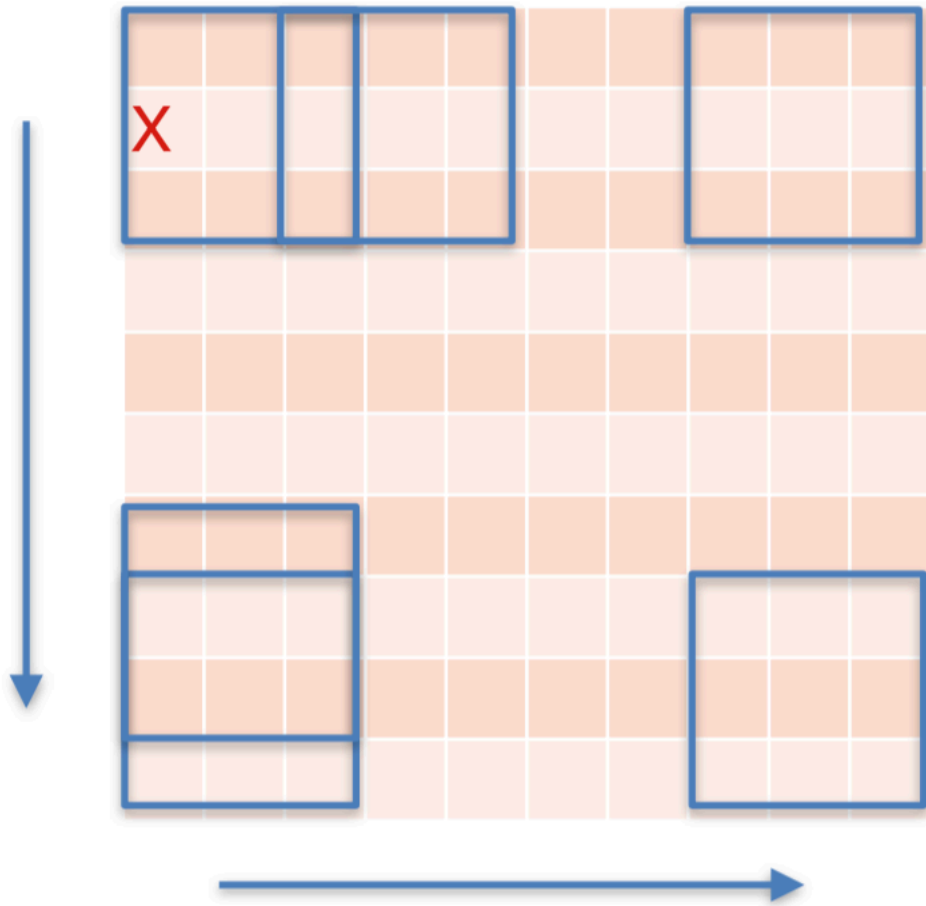


Position x on the activation map contributes to only position X of the resulting map through k(1)

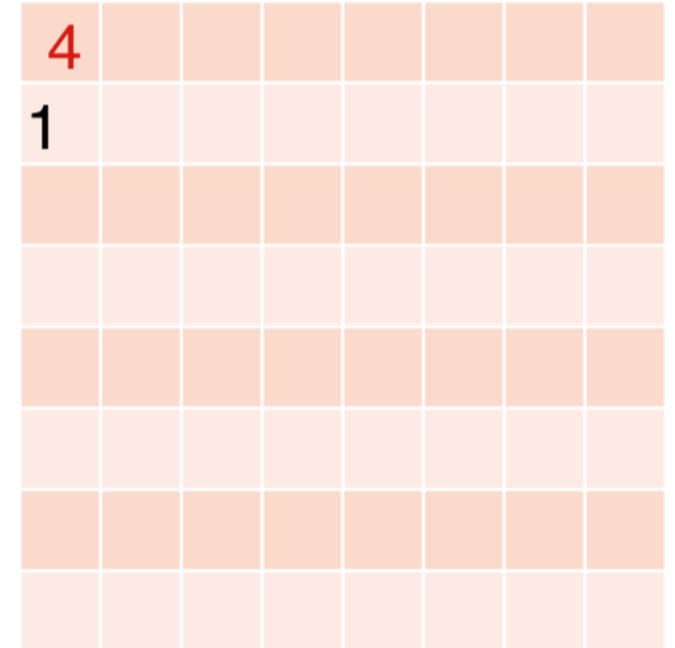
$$z[i, j] = \sum_m^{\tau} \sum_n^{\tau} K(m, n) * x[i + m - 1, j + n - 1]$$

2D Convolution

overlapping moves of filters



$10-3+1$



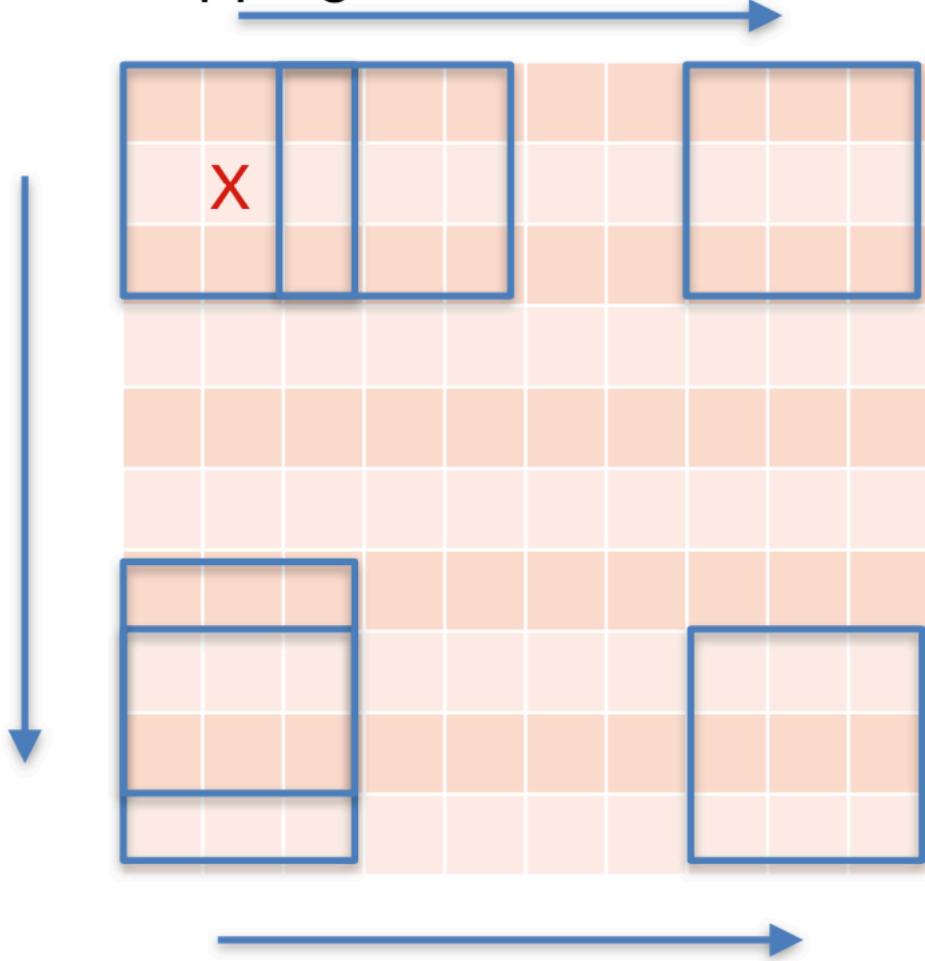
Sampling by convolution



Position x on the activation map contributes to only positions with label 4 and 1 through $k(4)$ and $k(1)$ respectively

2D Convolution

overlapping moves of filters

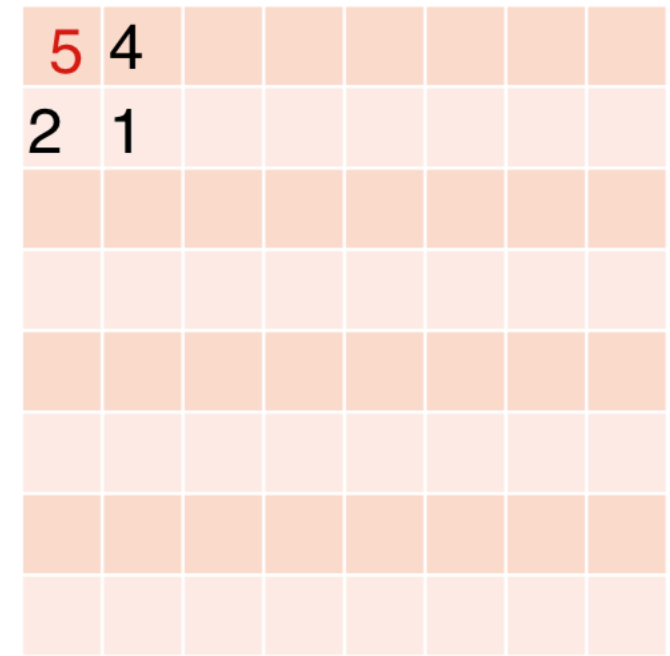


1	2	3
4	5	6
7	8	9

Sampling by convolution



$$10-3+1$$

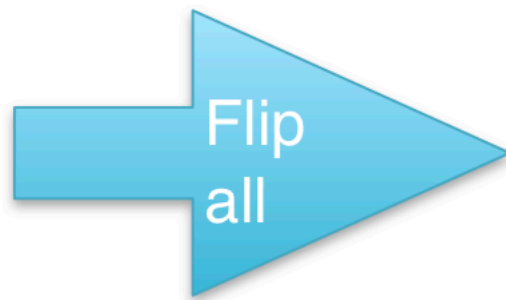


.There are four validly convoluted samples that contain position X

.Position x on the activation map contributes to only positions labeled 1,2,4 and 5 through k(

5	4
2	1

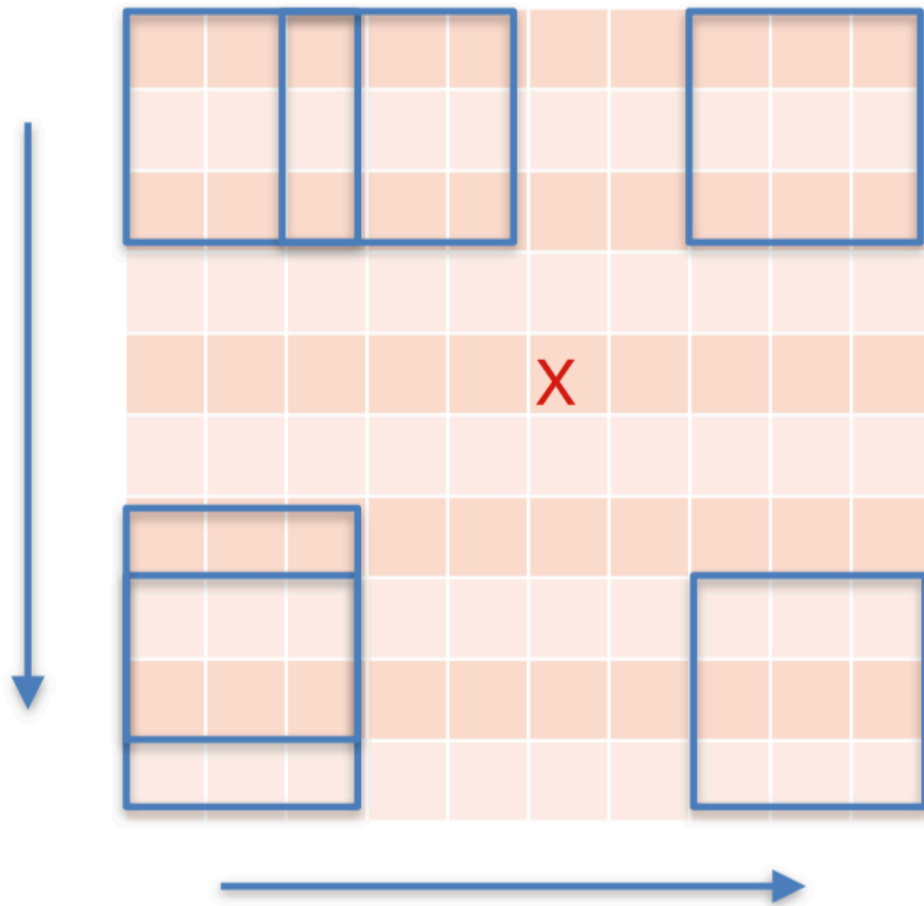
1	2	3
4	5	6
7	8	9



9	8	7
6	5	4
3	2	1

2D Convolution

overlapping moves of filters

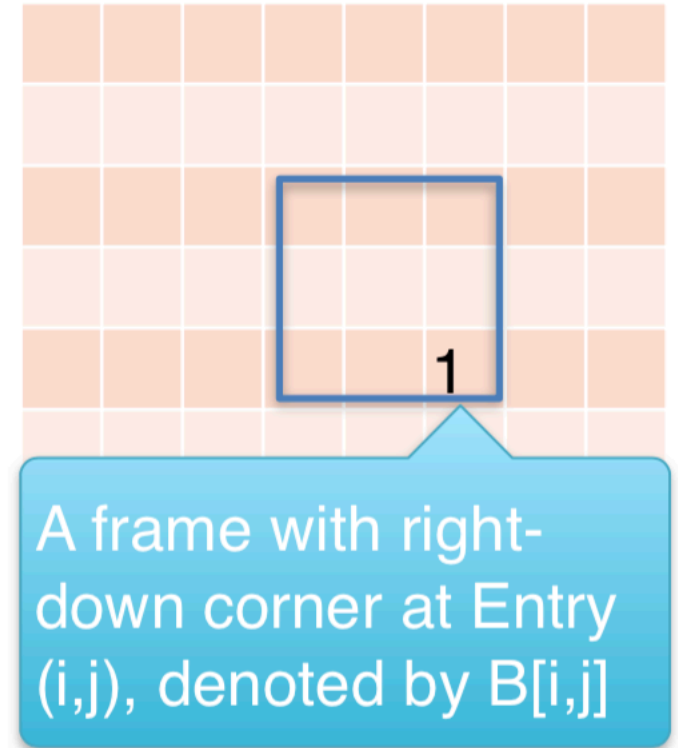


1	2	3
4	5	6
7	8	9

Sampling by convolution



10-3+1



.There are 9 validly convoluted samples that contain position X at entry (i,j)

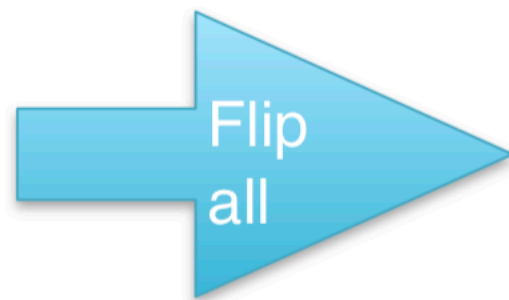
.Position x on the activation map contributes to positions labeled with 1-9 through k(

9	8	7
6	5	4
3	2	1

)

1	2	3
4	5	6
7	8	9

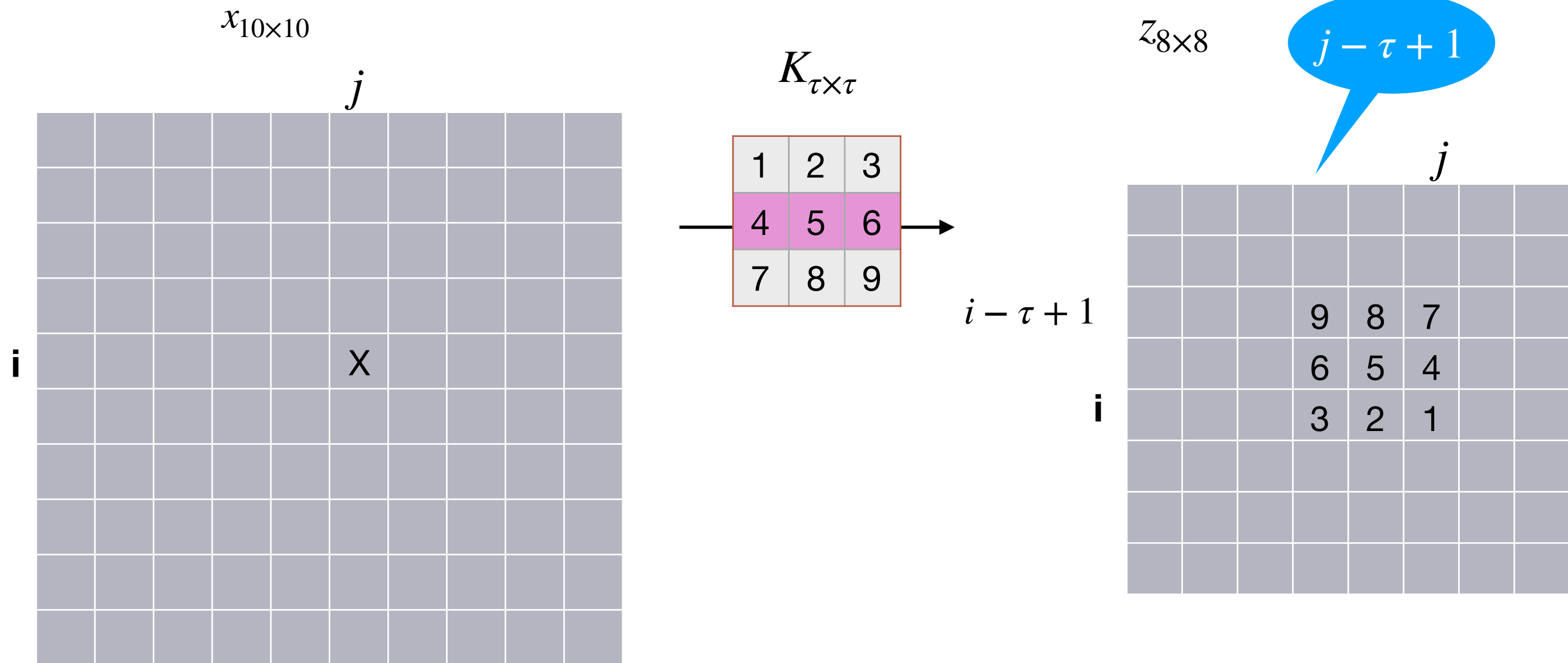
K



9	8	7
6	5	4
3	2	1

H

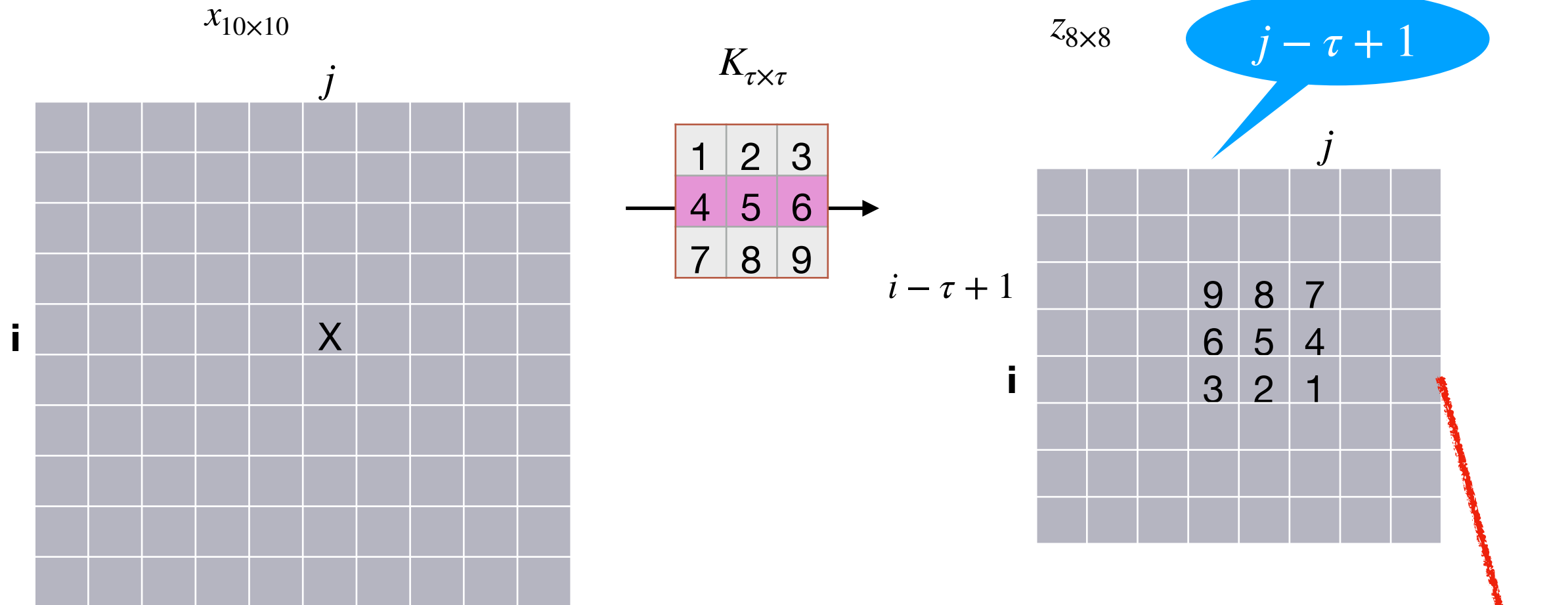
9	8	7
6	5	4
3	2	1



$x[i, j]$

contributes to

$$\begin{array}{ccc}
 z[i - \tau + 1, j - \tau + 1] & \cdots & z[i - \tau + 1, j] \\
 \vdots & & \vdots \\
 \vdots & & \vdots \\
 z[i, j - \tau + 1] & z[i, j - 1] & z[i, j]
 \end{array}$$



$x[i, j]$

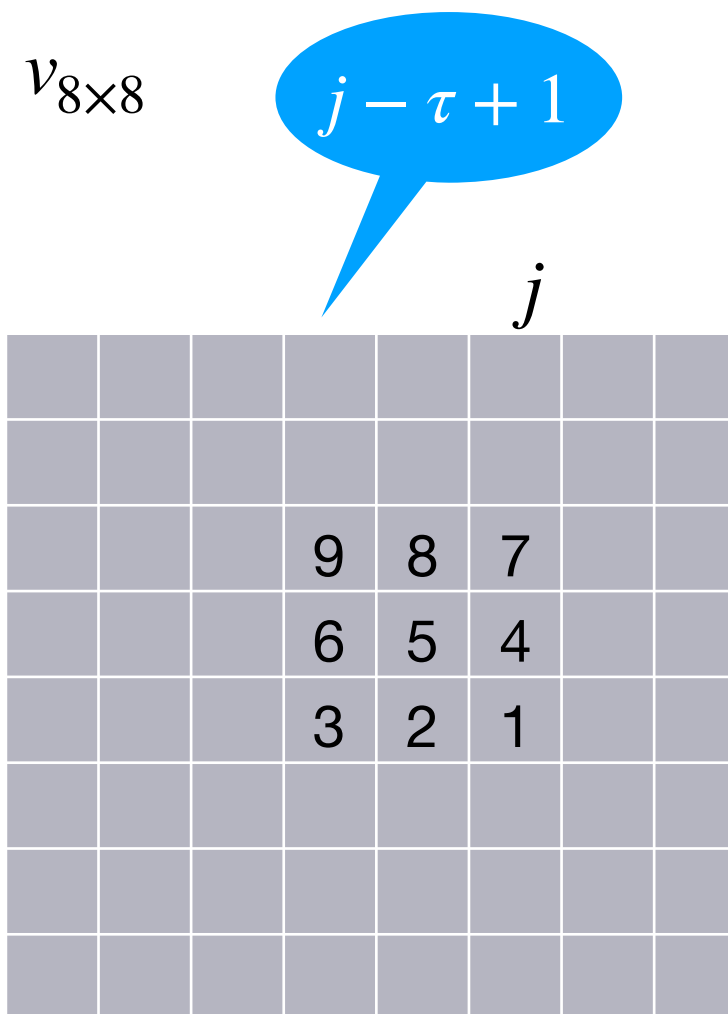
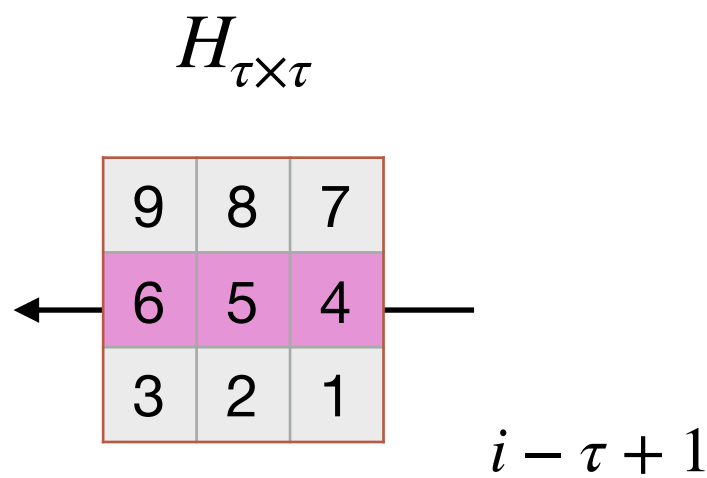
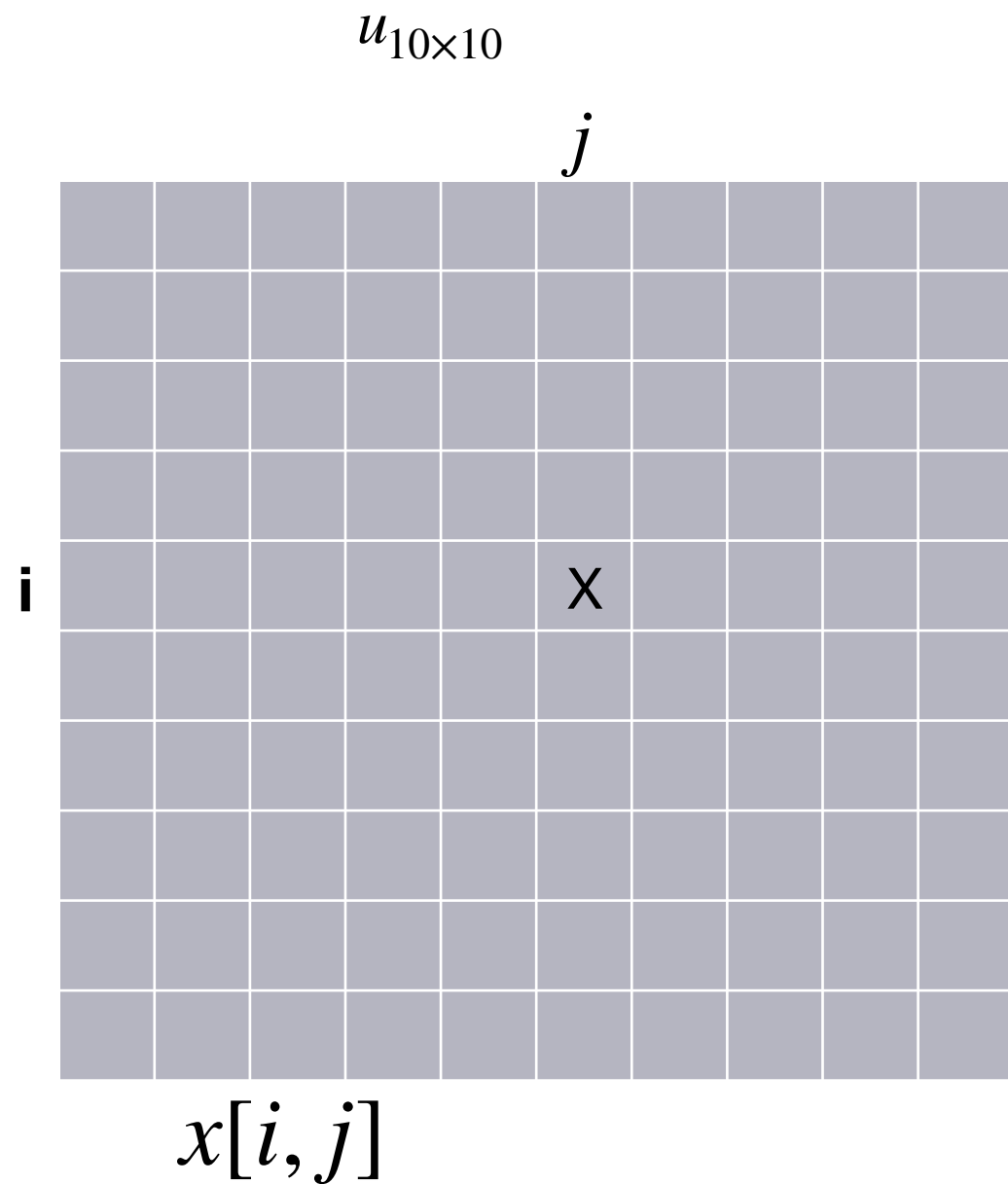
contributes to

$$\begin{array}{ccc}
 z[i - \tau + 1, j - \tau + 1] & \dots & z[i - \tau + 1, j] \\
 \vdots & & \vdots \\
 \vdots & & z[i - 1, j] \\
 \vdots & & \vdots \\
 z[i, j - \tau + 1] & z[i, j - 1] & z[i, j]
 \end{array}$$

CNN

y

Given $v[i, j] = \frac{dy}{dz[i, j]}$ $u[i, j] = \frac{dy}{dx[i, j]} = ?$

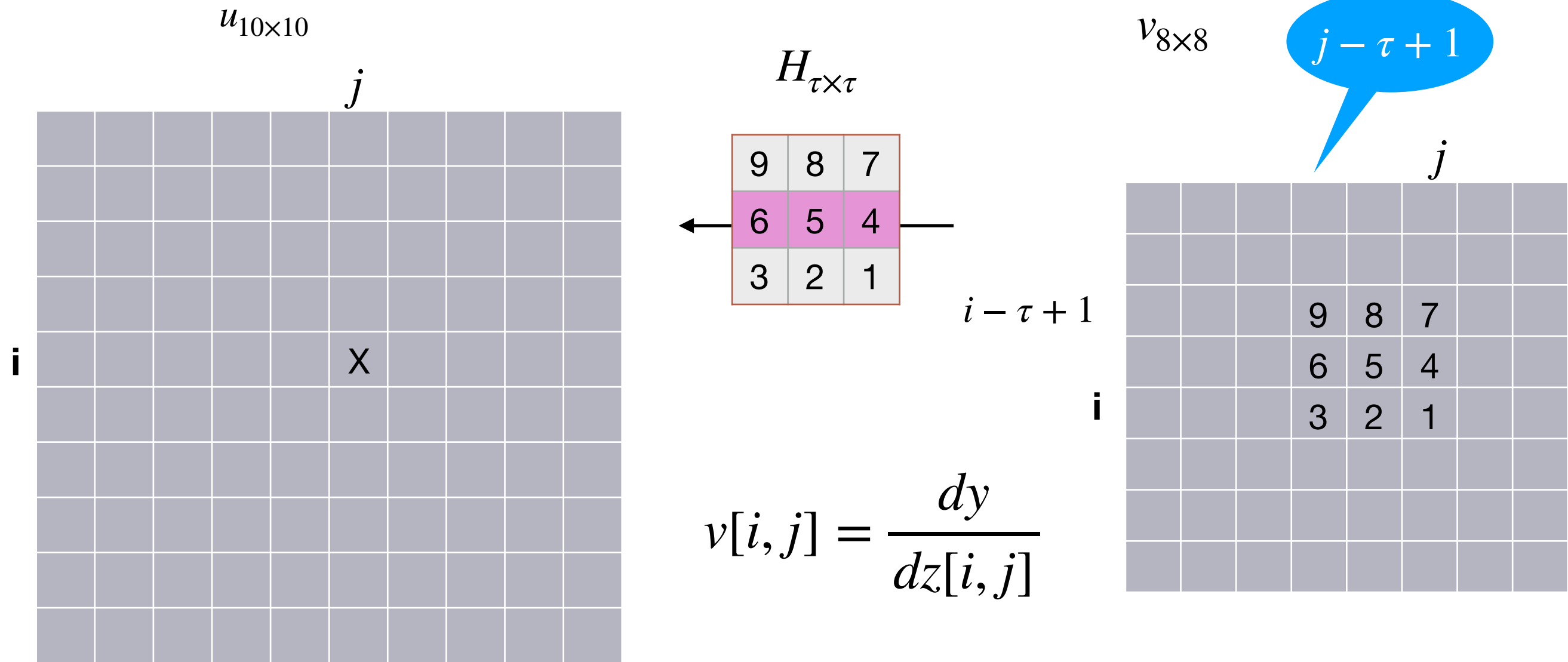


$$v[i, j] = \frac{dy}{dz[i, j]}$$

contributes to

$$\begin{array}{ccc}
 z[i - \tau + 1, j - \tau + 1] & \cdots & z[i - \tau + 1, j] \\
 \vdots & & \vdots \\
 \vdots & & \vdots \\
 z[i, j - \tau + 1] & z[i, j - 1] & z[i, j]
 \end{array}$$

$$u[i, j] = \frac{dy}{dx[i, j]} = \sum_m^{\tau} \sum_n^{\tau} H(m, n) * v[i - \tau + m, j - \tau + n]$$



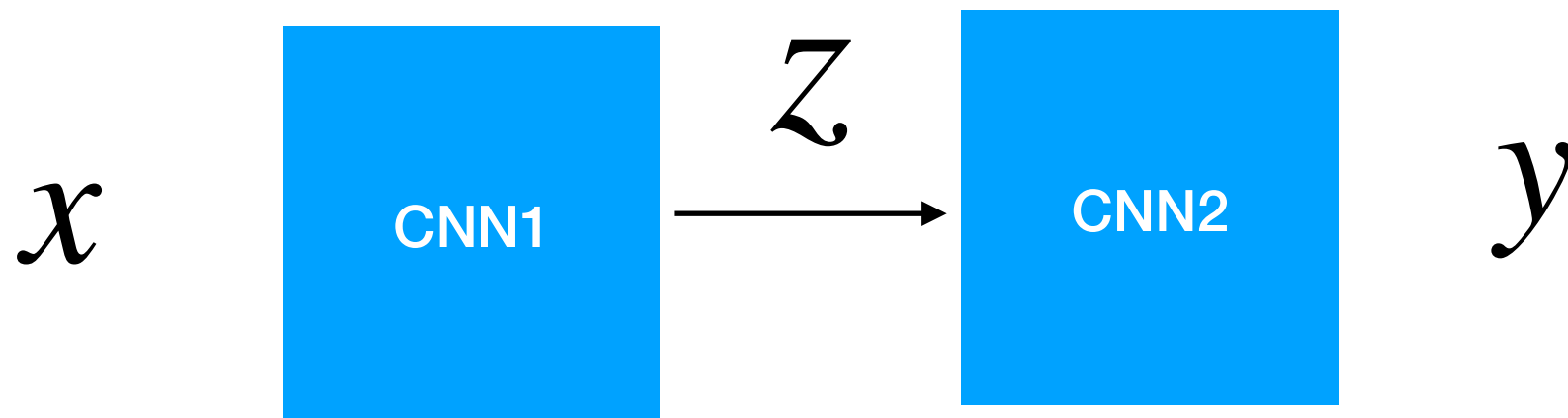
Signals translate forward

$$z[i, j] = \sum_m^{\tau} \sum_n^{\tau} K(m, n) * x[i + m - 1, j + n - 1]$$

Gradient back propagation

$$u[i, j] = \frac{dy}{dx[i, j]} = \sum_m^{\tau} \sum_n^{\tau} H(m, n) * v[i - \tau + m, j - \tau + n]$$

Our idea



Given $\frac{dy}{dz[i, j]}$ how to calculate $\frac{dy}{dx[i, j]}$ = ?