



Pattern Analysis

Convolution

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V1.0

“All mathematics is is a language that is well tuned, finely honed, to describe patterns; be it patterns in a star, which has five points that are regularly arranged, be it patterns in numbers like 2, 4, 6, 8, 10 that follow very regular progression.”

Brian Greene ([link](#))
(1963-)

Convolution

Given two continuous sequences in one dimension $f(t)$ and $g(t)$, the convolution $f * g$ is computed as

$$f(t) * g(t) \triangleq \underbrace{\int_{-\infty}^{\infty} f(\tau)g(t - \tau) d\tau}_{(f*g)(t)}$$

Given two discrete data or signal sequences in one dimension f and g , the discrete convolution $f * g$ is computed as

$$(f * g)[n] = \sum_{m=-\infty}^{\infty} f[n - m]g[m]$$

If we assume that the discrete sequences are periodic, the circular convolution can be computed as

$$(f * g_N)[n] = \sum_{m=0}^{N-1} f[m]g_N[n - m]$$

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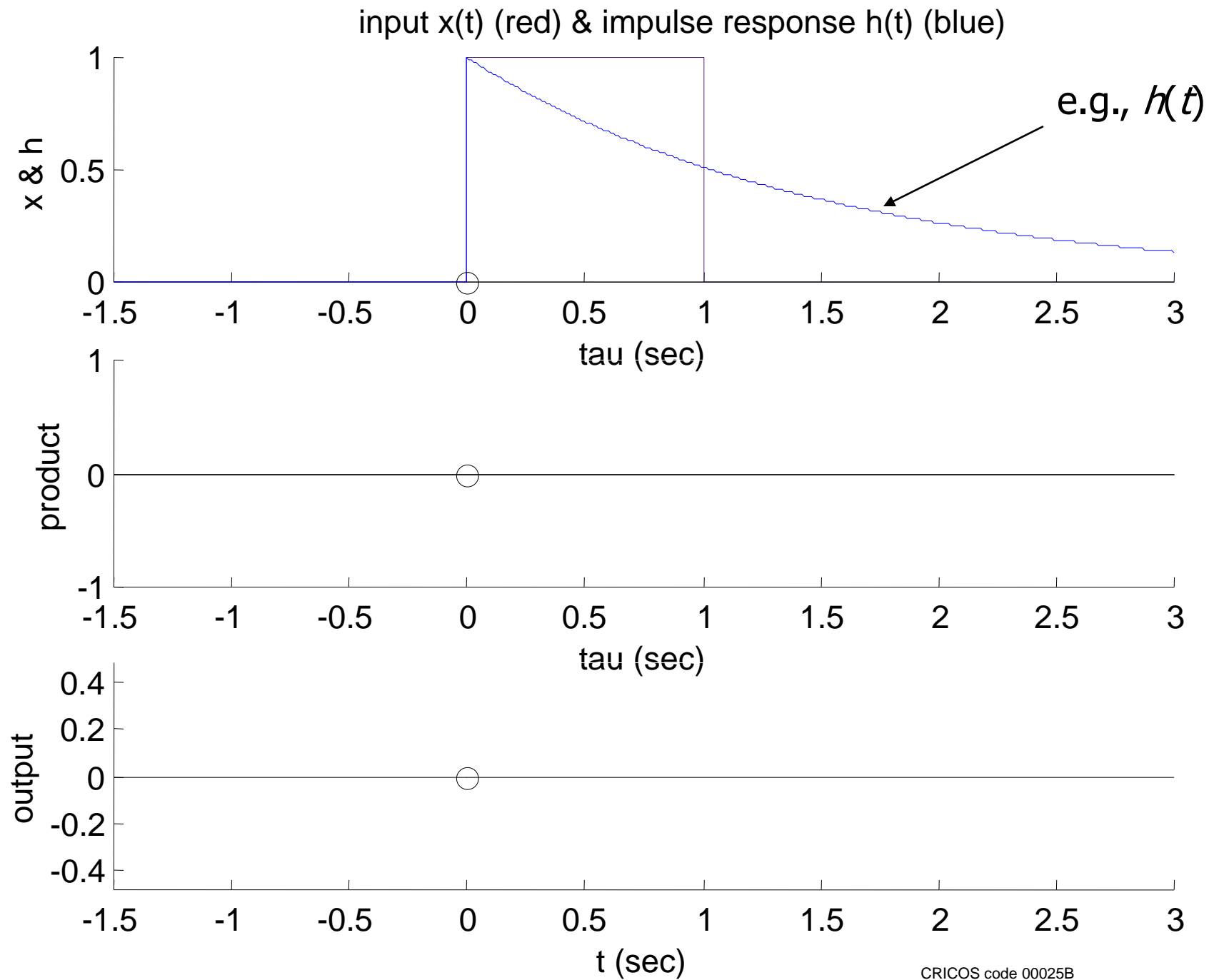
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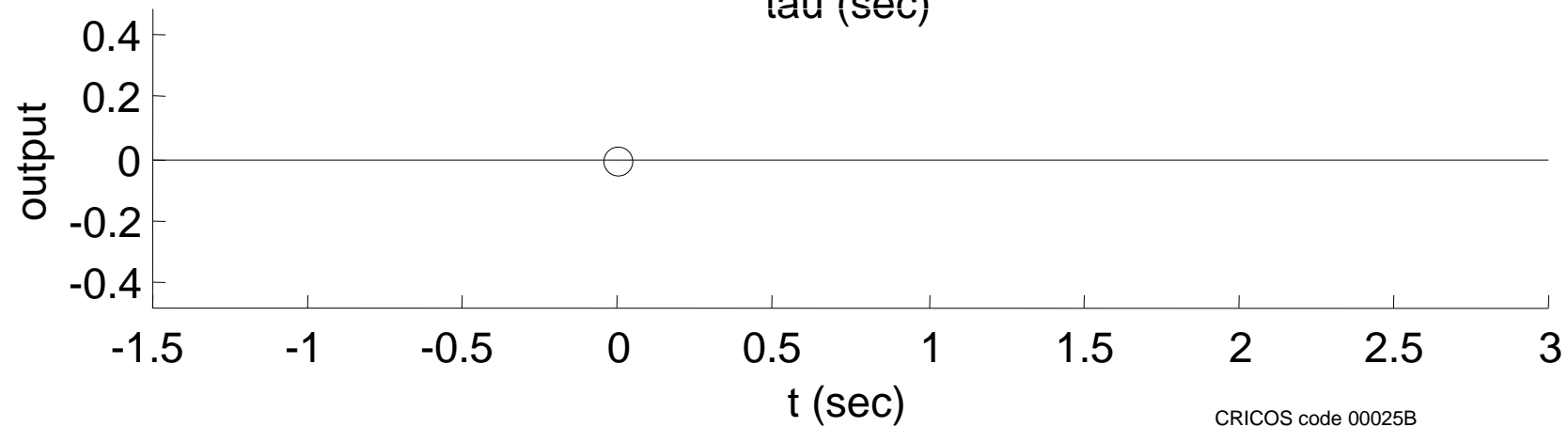
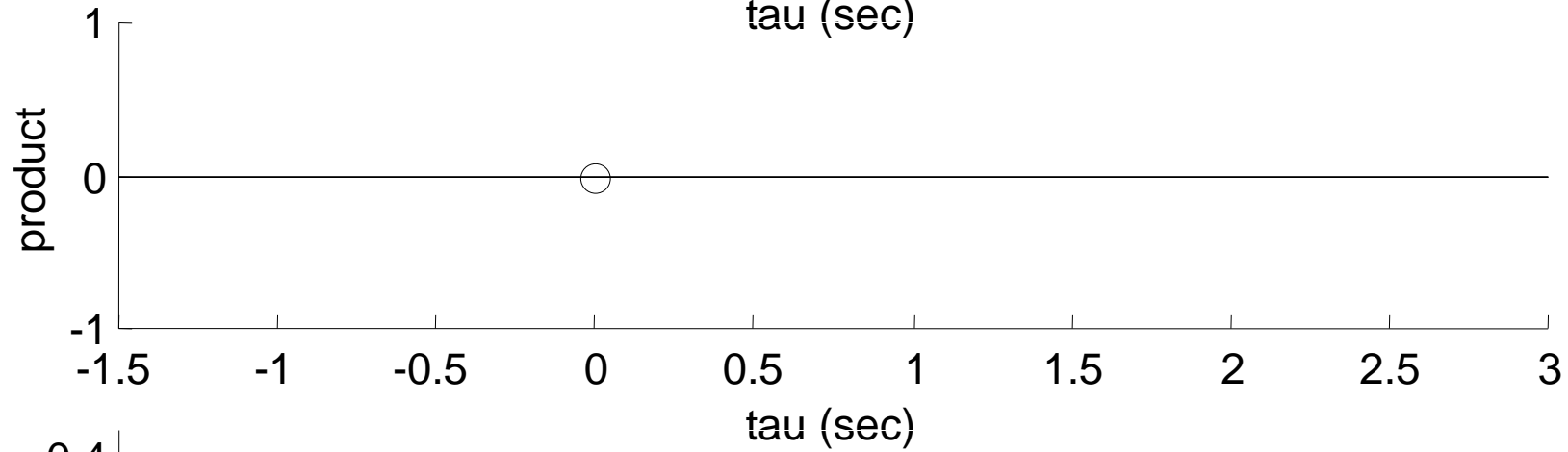
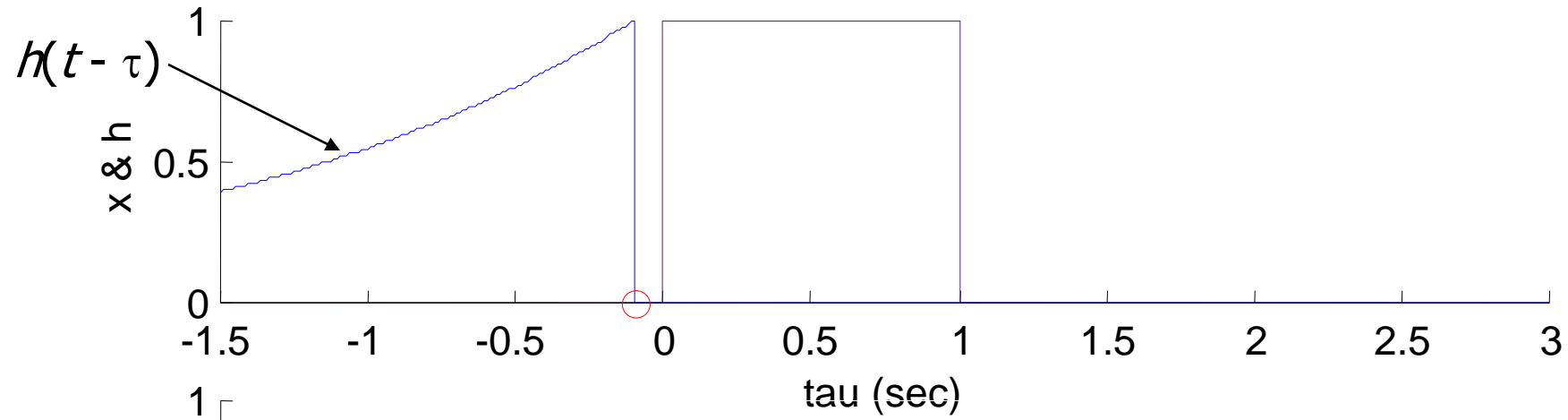
$$(f * g_N)[n] = \sum_{m=0}^{N-1} f[m]g_N[n - m]$$

It's Just A Sliding Window Dot Product!

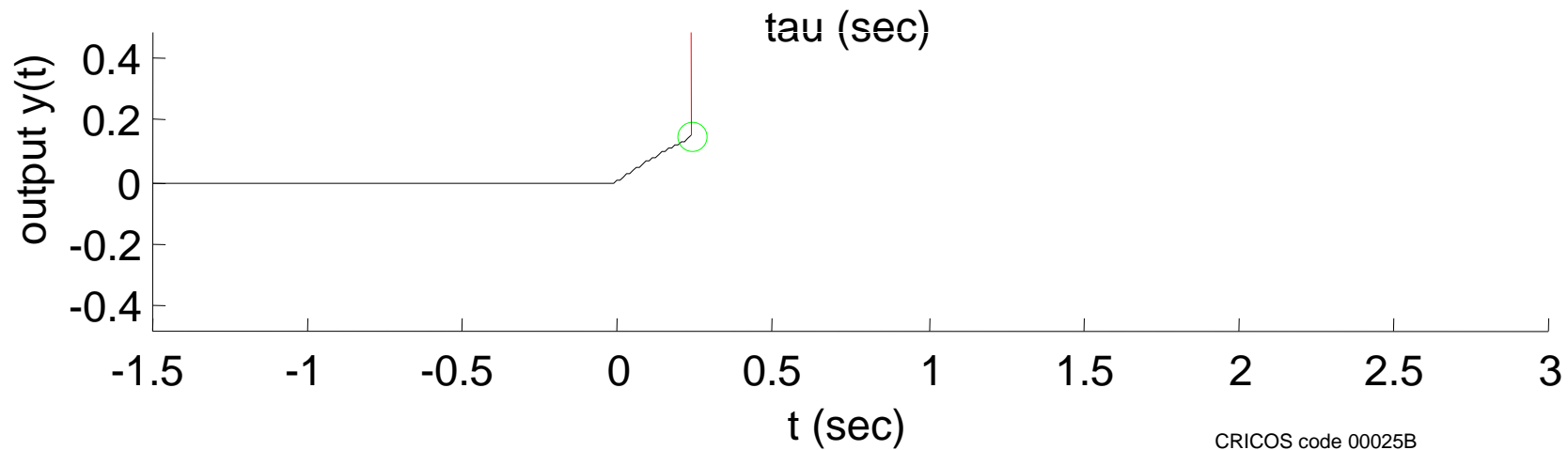
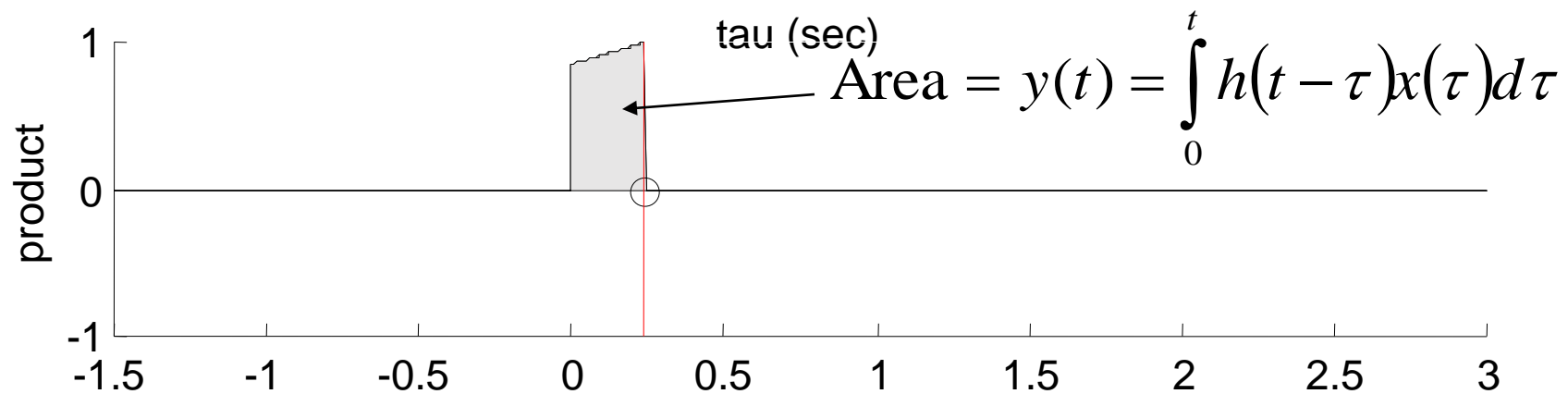
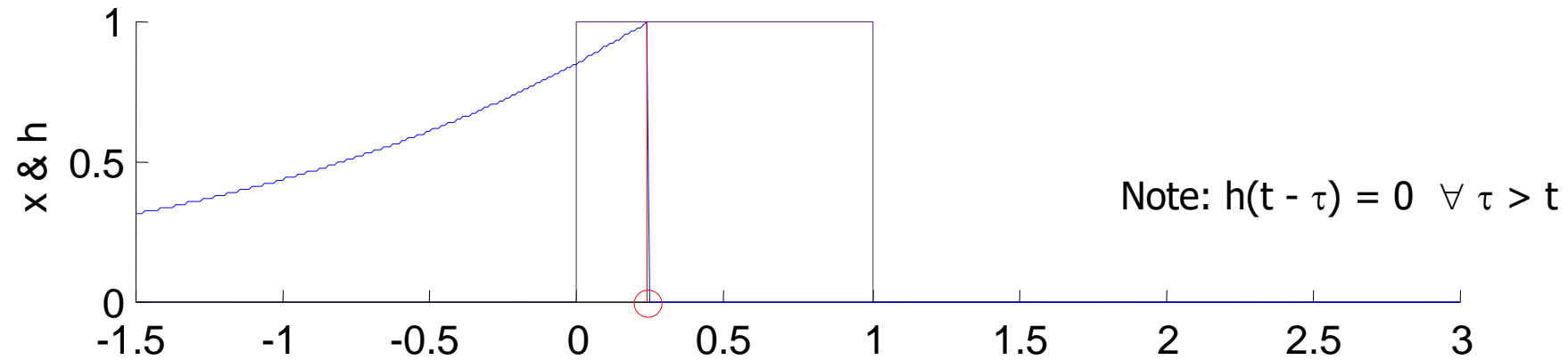


Region (i) $t < 0$

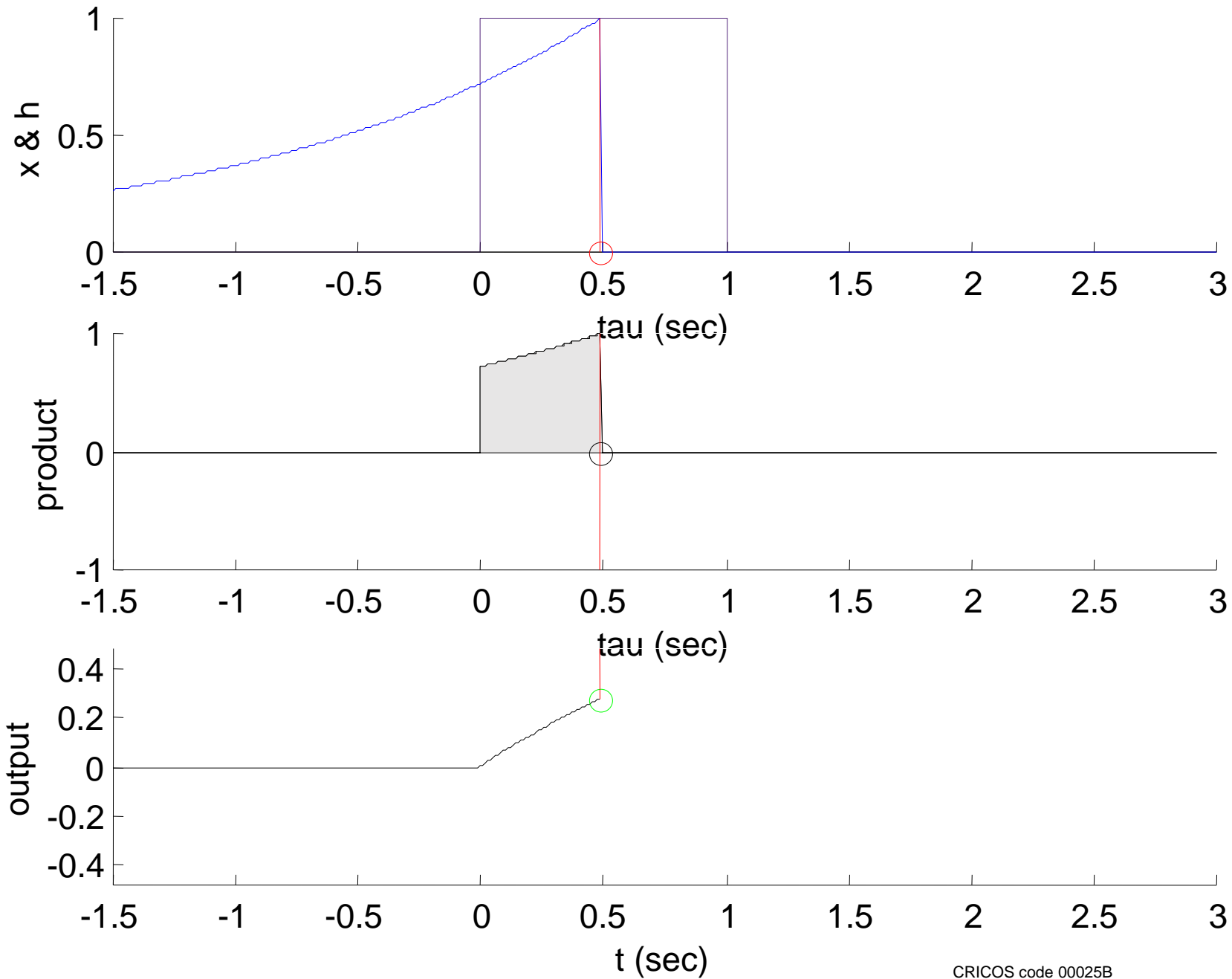
input (red) & time-reversed impulse response (blue), $t < 0$



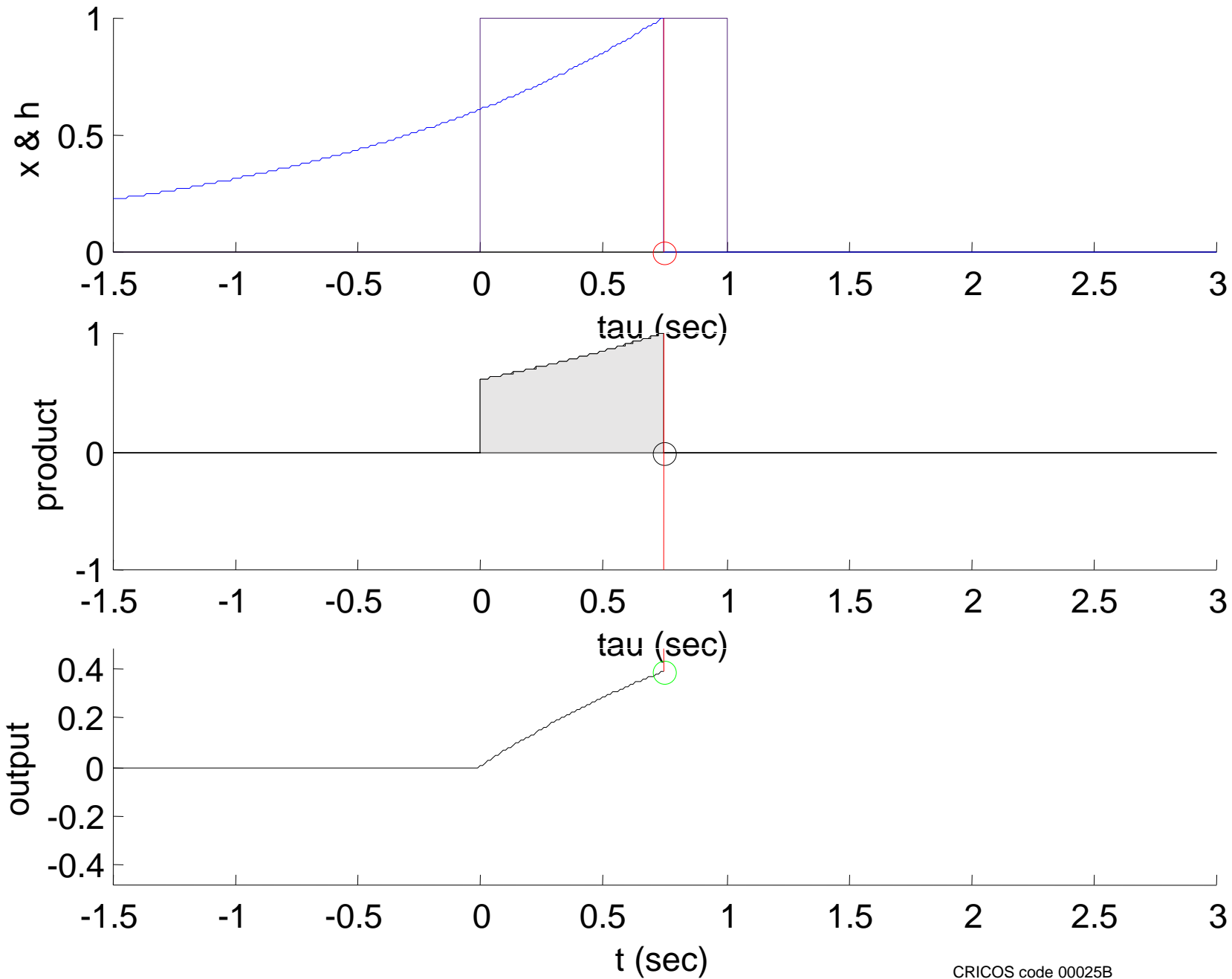
Region (ii) $0 \leq t < 1$ input (red) & time-reversed impulse response (blue) $t = 0.25$



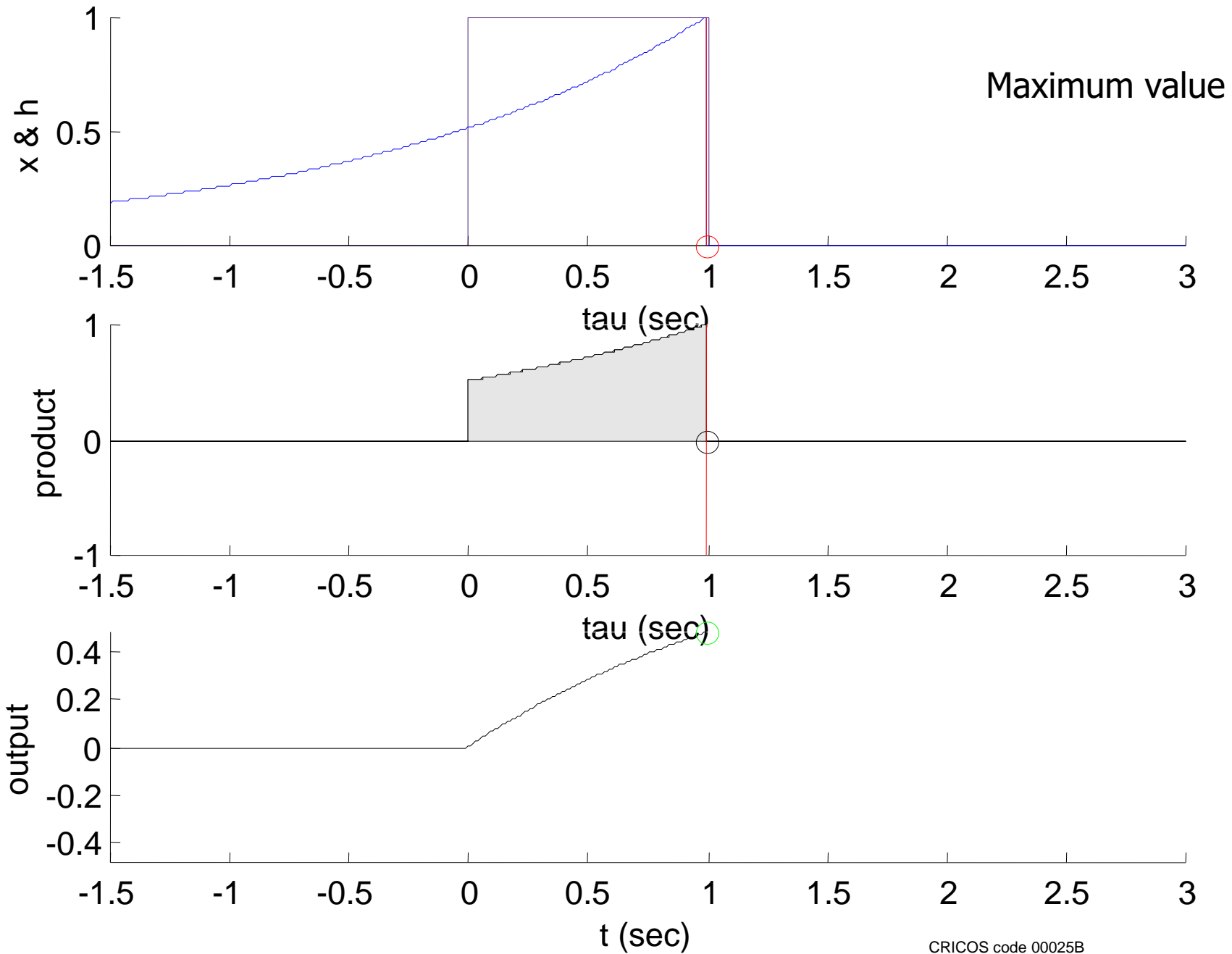
Region (ii) $0 \leq t < 1$ input (red) & time-reversed impulse response (blue) $t = 0.5$



Region (ii) $0 \leq t < 1$ input (red) & time-reversed impulse response (blue) $t = 0.75$

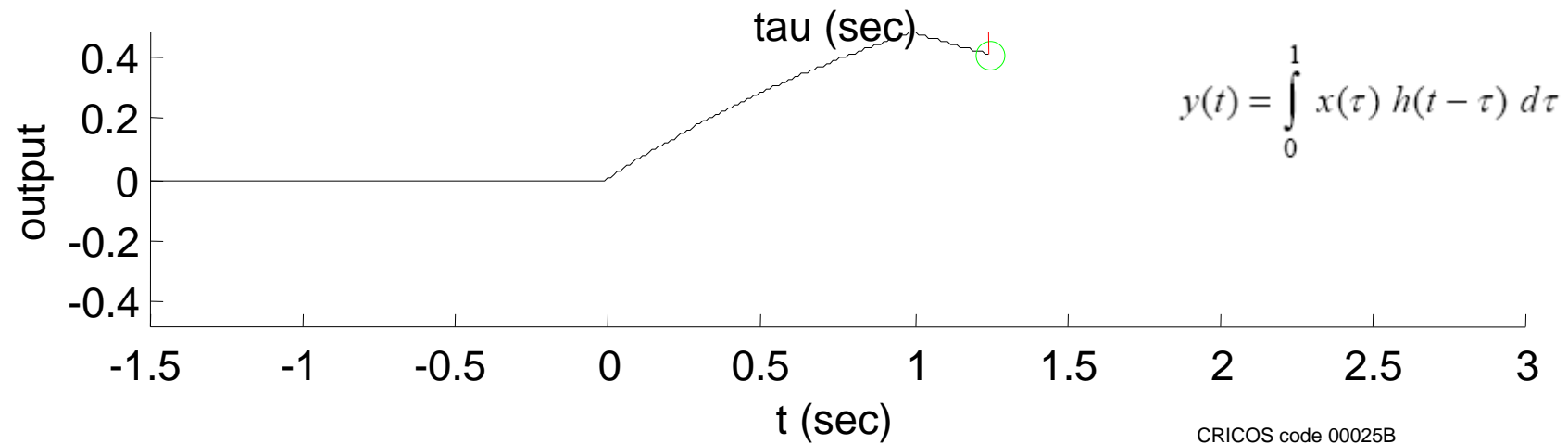
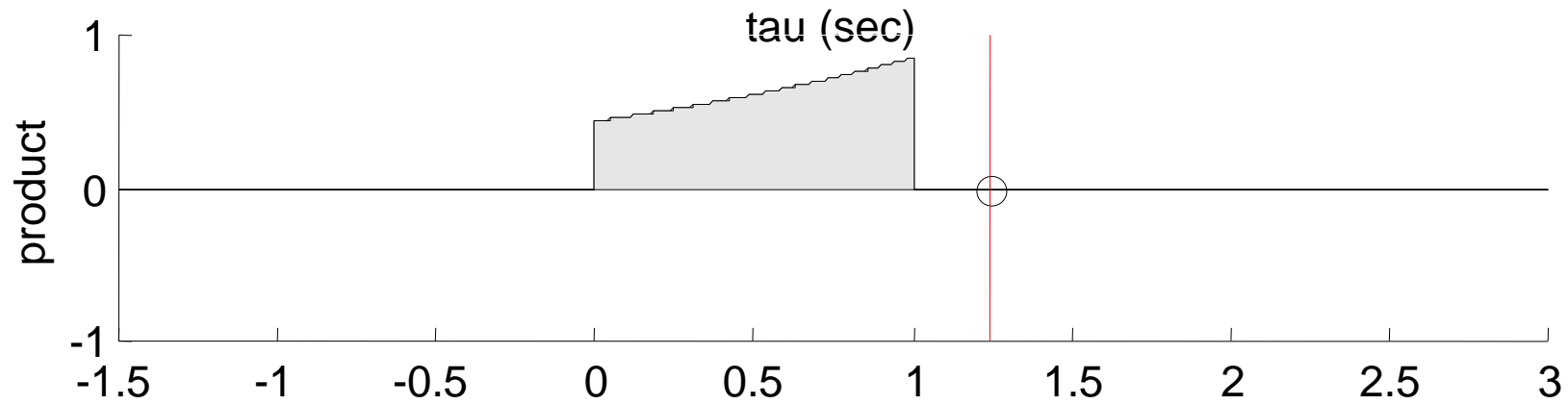
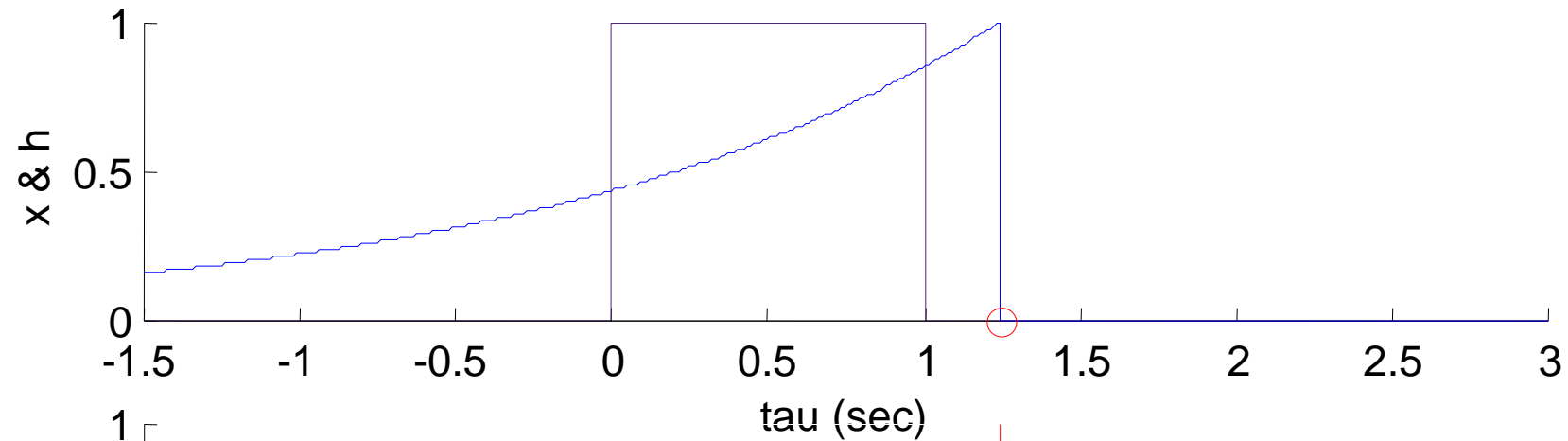


Region (ii) $0 \leq t < 1$ input (red) & time-reversed impulse response (blue) $t = 1$



Region (iii) $t \geq 1$

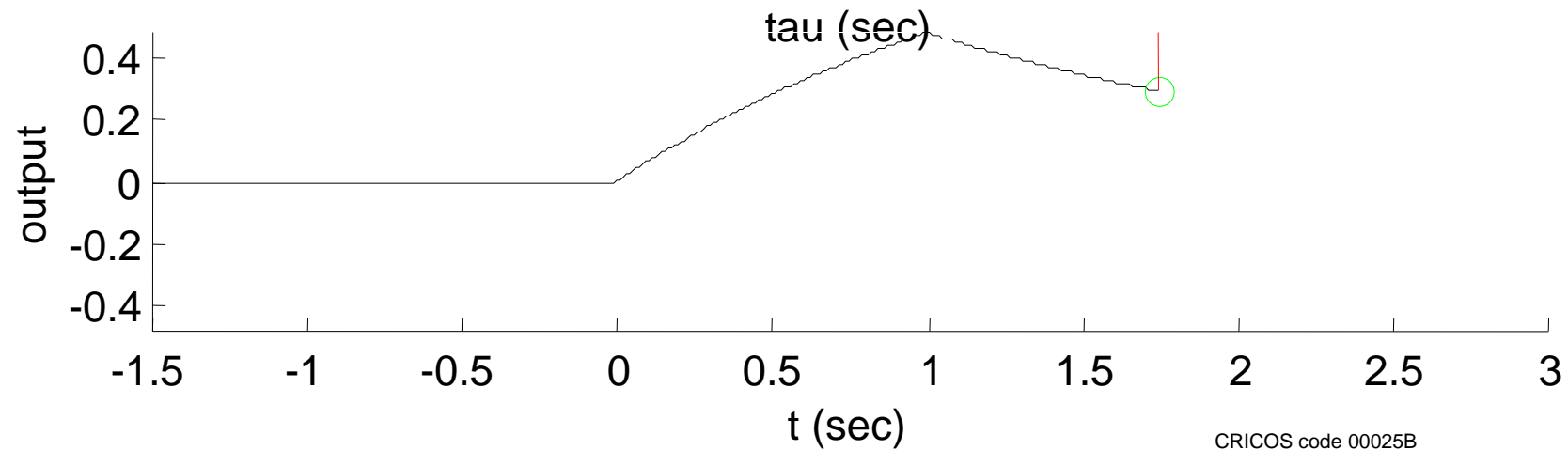
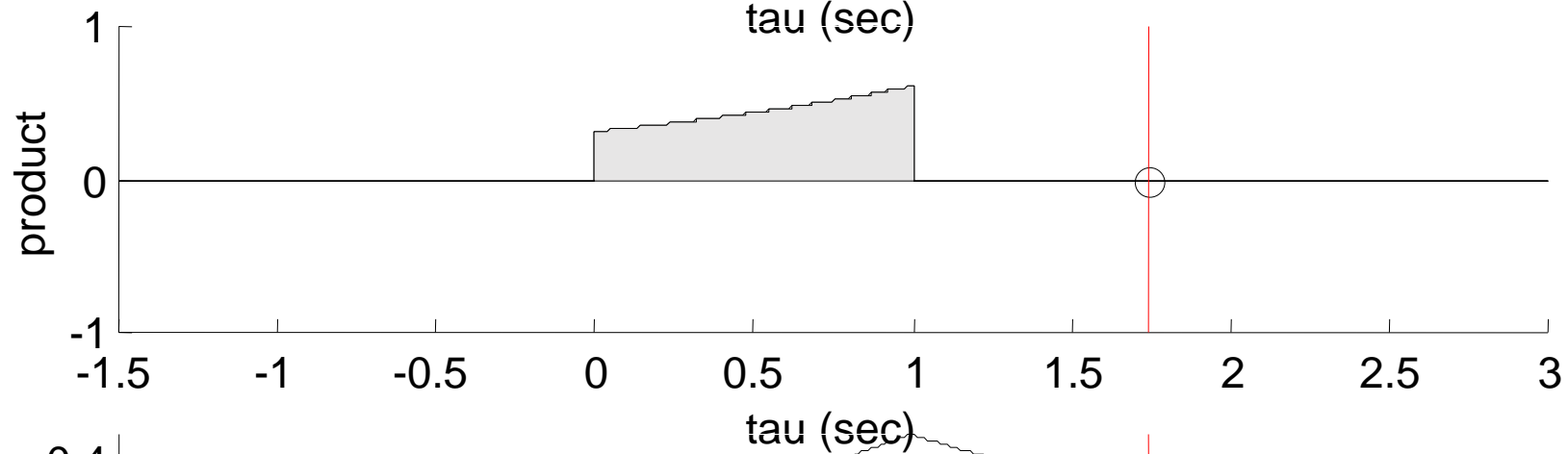
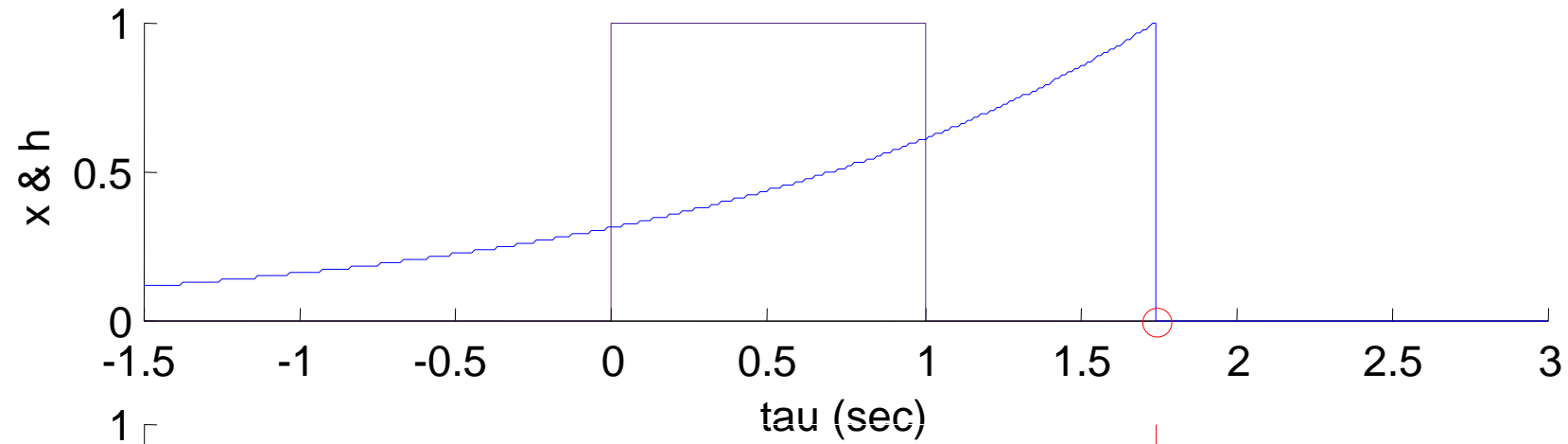
input (red) & time-reversed impulse response (blue) $t = 1.25$



$$y(t) = \int_0^1 x(\tau) h(t - \tau) d\tau$$

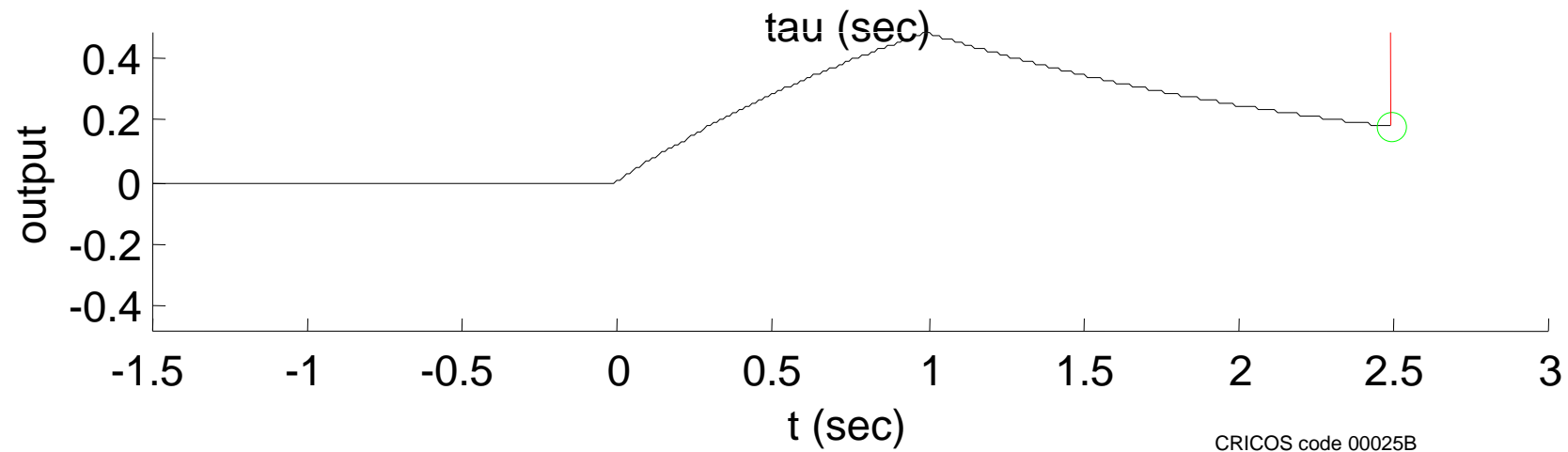
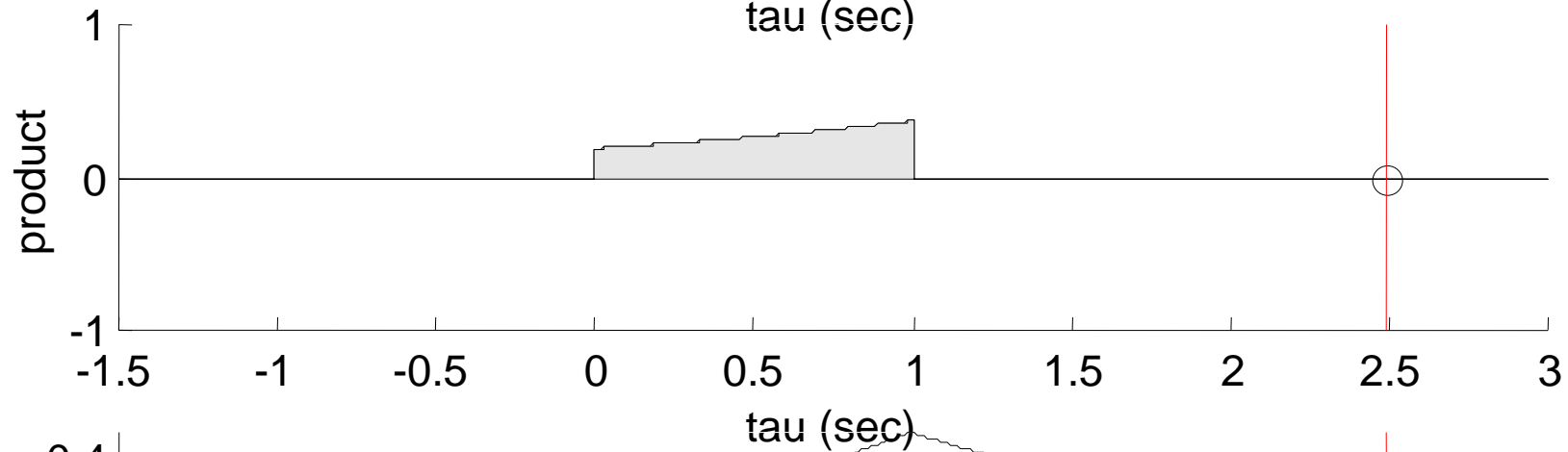
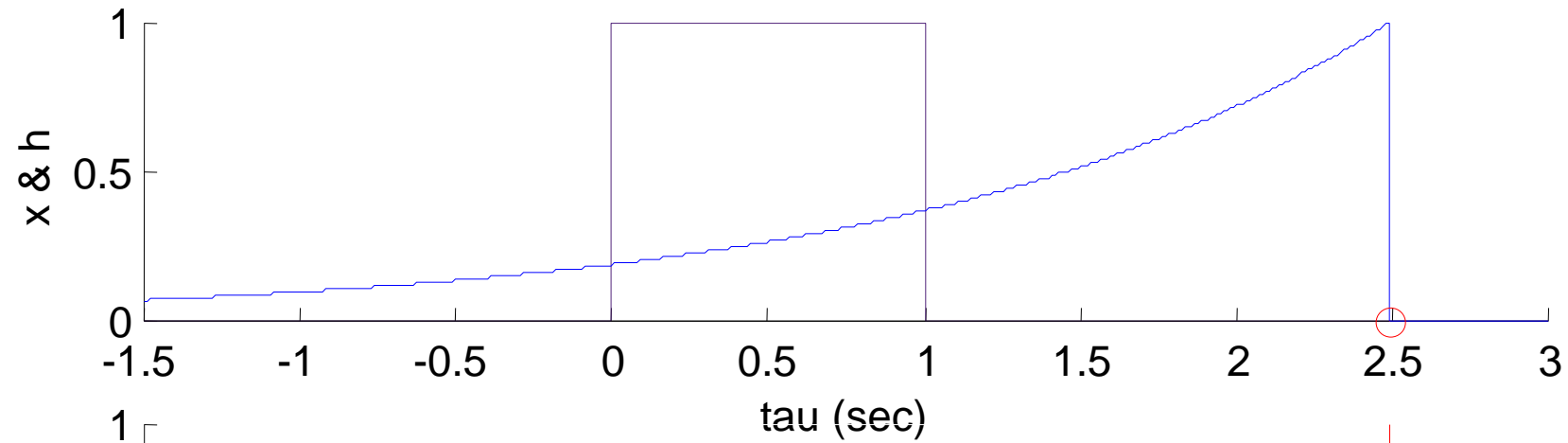
Region (iii) $t \geq 1$

input (red) & time-reversed impulse response (blue) $t = 1.75$



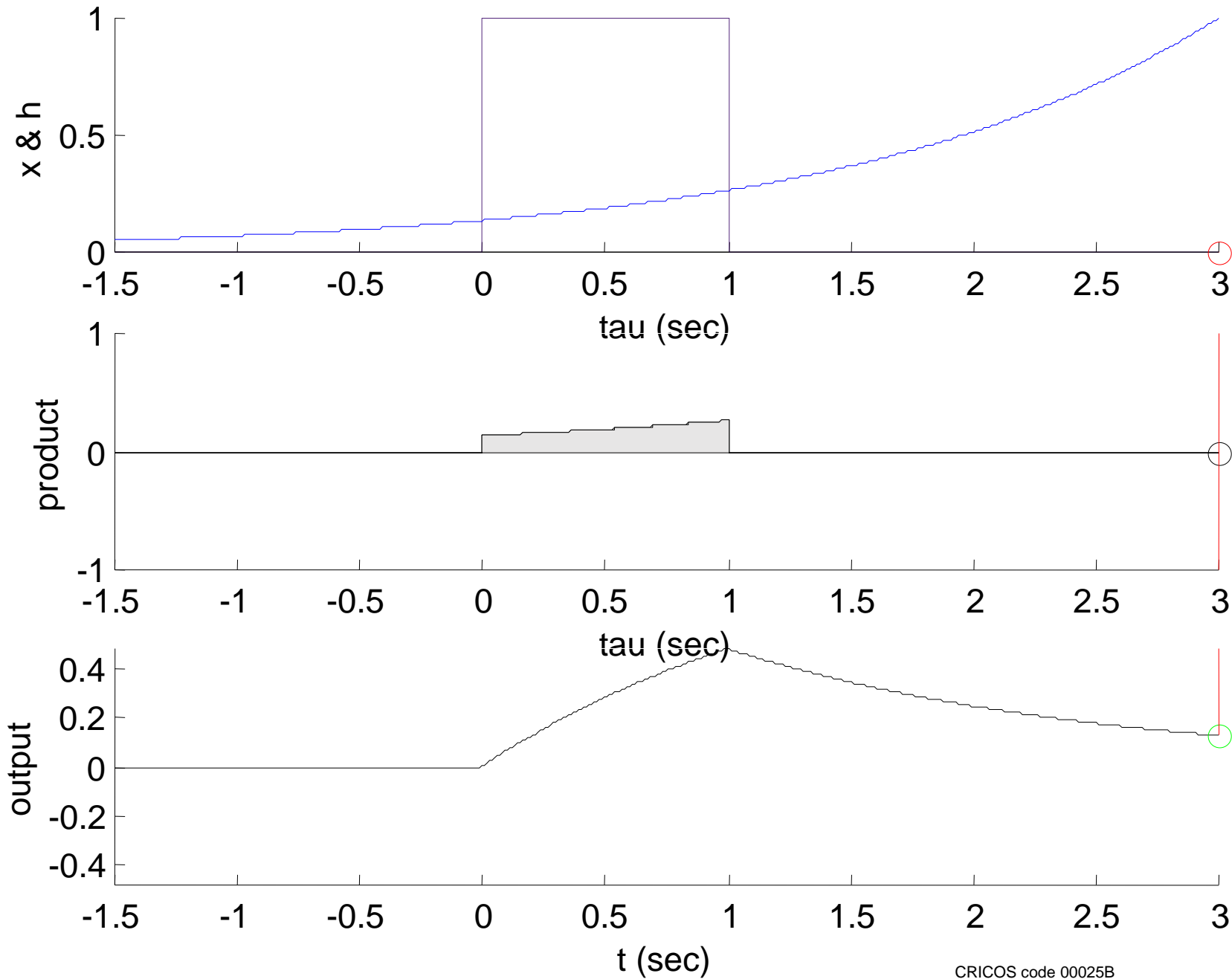
Region (iii) $t \geq 1$

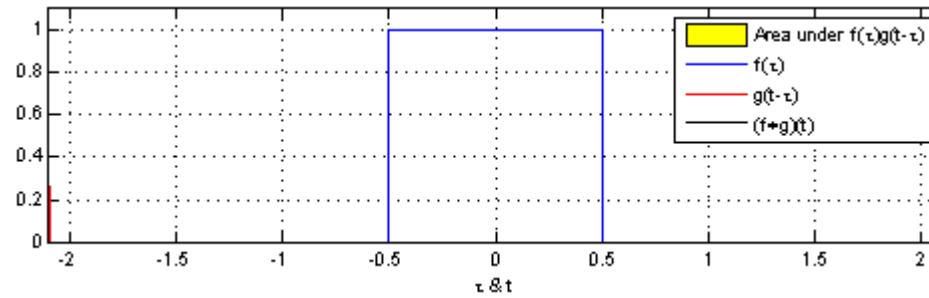
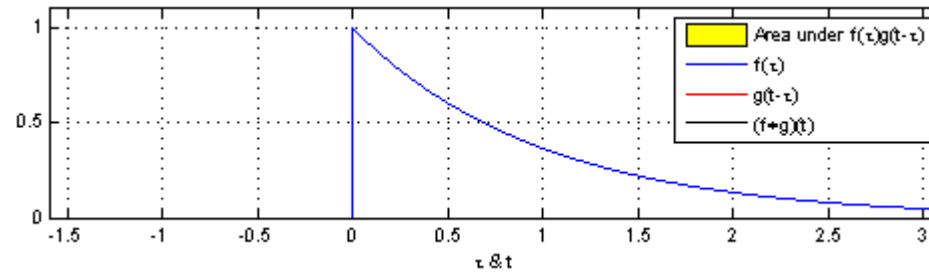
input (red) & time-reversed impulse response (blue) $t = 2.5$



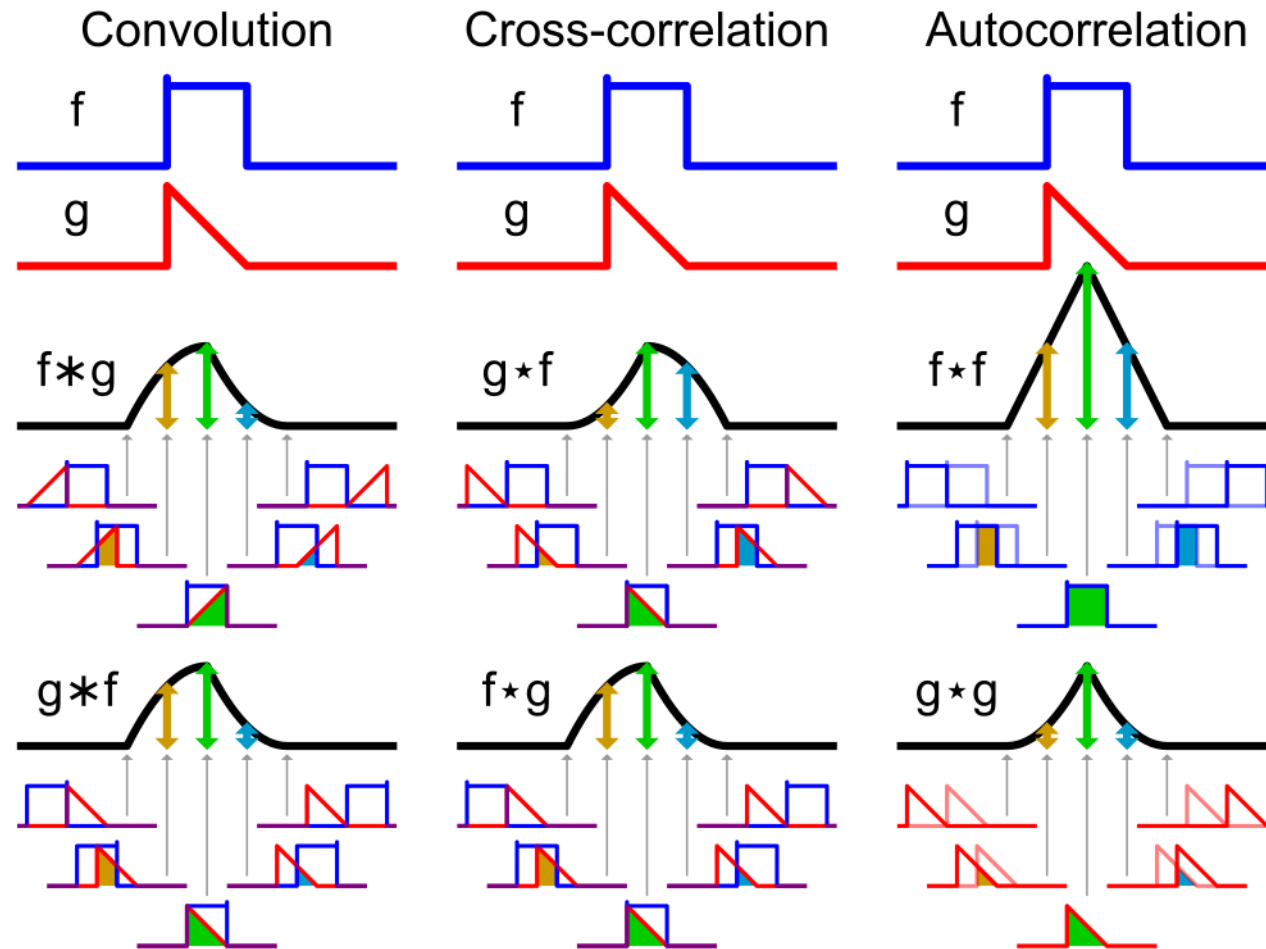
Region (iii) $t \geq 1$

input (red) & time-reversed impulse response (blue) $t = 3$





Brian Amberg derivative work: Tinos (talk), CC BY-SA 3.0,
<https://commons.wikimedia.org/w/index.php?curid=11003835>



Discrete-time Convolution

$$y[n] = \sum_{m=0}^{\infty} h[n-m]x[m] = h[n] * x[n]$$

Example, $x[n] = \{1, 2, 3\}$ and $h[n] = \{1, 0.5, 0.25\}$

1. Time reverse $h[n]$: $h[-m] = \{0.25, 0.5, 1\}$

2. Apply $h[n-m]$ to $x[m]$:

	1	2	3	
$h[-m] \ n = 0:$	0.25	0.5	1	$y[n] = [$
$h[1-m] \ n = 1:$	0.25	0.5	1	
$h[2-m] \ n = 2:$	0.25	0.5	1	
$h[3-m] \ n = 3:$		0.25	0.5	
$h[4-m] \ n = 4:$			0.25	
				1
				2.5
				4.25
				2
				0.75
				$]$

Discrete-time Convolution

What is the length of $y[n]$?

- If $x[n]$ is length N
 - And $h[n]$ is length M
- Then $y[n]$ will be length $N+M-1$

So, for the previous example

- $N = M = 3$ and so $y[n]$ is length $3+3-1 = \underline{5}$

In MATLAB:

```
x = [1 2 3];  
h = [1 0.5 0.25];  
y = conv(x,h) % Note: same as conv(h,x)  
y = 1.0000 2.5000 4.2500 2.0000 0.7500
```

Matrix Formulation of Convolution

$y = \mathbf{H}x$ Where \mathbf{H} is a Toeplitz Matrix

$$\begin{bmatrix} 0.75 \\ 2 \\ 4.25 \\ 2 \\ 0.75 \end{bmatrix} = \begin{bmatrix} 1 & 0.5 & 0.25 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0.5 & 0.25 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0.5 & 0.25 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0.5 & 0.25 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0.5 & 0.25 \end{bmatrix} \bullet \begin{bmatrix} 0 \\ 0 \\ 3 \\ 2 \\ 1 \\ 0 \\ 0 \end{bmatrix}$$

Concise maths, but not how you implement it!

Convolution Theorem

Convolution in the time-domain is equivalent to multiplication in the Fourier and Laplace domains

$$\begin{aligned}x_1(t) * x_2(t) &= L^{-1}\{X_1(s)X_2(s)\} \\ &= F^{-1}\{X_1(w)X_2(w)\}\end{aligned}$$

$$\begin{aligned}L\{x_1(t)x_2(t)\} &= \frac{1}{2\pi j} X_1(s) * X_2(s) \\ F\{x_1(t)x_2(t)\} &= \frac{1}{2\pi} X_1(w) * X_2(w)\end{aligned}$$

e.g., frequency modulation

Circular and Linear Convolution

Let's revisit our simple MATLAB example

Now let's do the convolution via multiplication in Frequency domain

Different answer!

- Wrong length ☹

```
x = [1 2 3];  
h = [1 0.5 0.25];  
y = conv(x,h)  
y = 1  2.5  4.25  2  0.75
```

```
X = fft(x); % go to Freq. domain!  
H = fft(h);  
% Do element-wise (dot) multiply  
Y = H.*X;  
y = ifft(Y);  
y = 3  3.25  4.25
```

This is 'circular' convolution

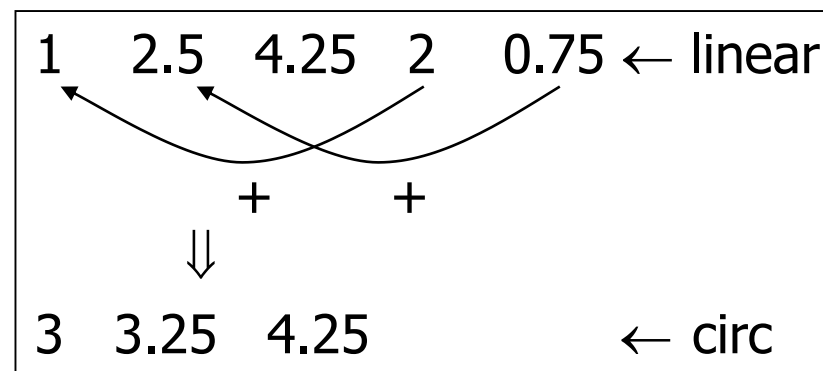
Circular and Linear Convolution

Problem:

- $x[n]$ is assumed periodic by the DFT
 - Period incorrect
 - Overlaps with $h[n]$
 - More on this later...

Solution:

- Zero pad to correct length $(M+N-1)$
- Period of $x[n]$ correct
 - No overlap 😊
 - Linear convolution



```
x = [1 2 3 0 0];
h = [1 0.5 0.25 0 0];
X = fft(x);
H = fft(h);
Y = H.*X;
y = ifft(Y)
y = 1   2.5   4.25   2   0.75
```

Image Convolution

0	0	0	0	0	0	...
0	156	155	156	158	158	...
0	153	154	157	159	159	...
0	149	151	155	158	159	...
0	146	146	149	153	158	...
0	145	143	143	148	158	...
...

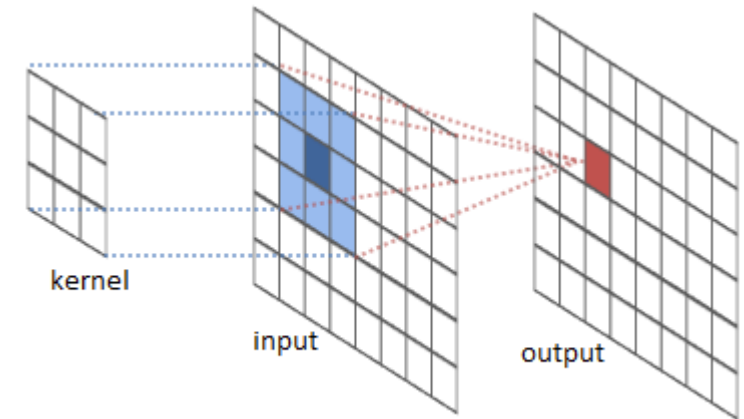
Input Channel #1 (Red)

0	0	0	0	0	0	...
0	167	166	167	169	169	...
0	164	165	168	170	170	...
0	160	162	166	169	170	...
0	156	156	159	163	168	...
0	155	153	153	158	168	...
...

Input Channel #2 (Green)

0	0	0	0	0	0	...
0	163	162	163	165	165	...
0	160	161	164	166	166	...
0	156	158	162	165	166	...
0	155	155	158	162	167	...
0	154	152	152	157	167	...
...

Input Channel #3 (Blue)



-1	-1	1
0	1	-1
0	1	1

Kernel Channel #1

1	0	0
1	-1	-1
1	0	-1

Kernel Channel #2

0	1	1
0	1	0
1	-1	1

Kernel Channel #3

308

+

-498

+

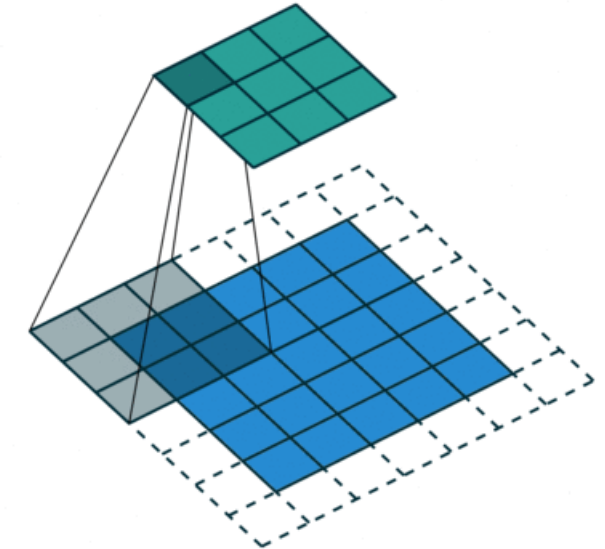
164

+ 1 = -25

Bias = 1

Output

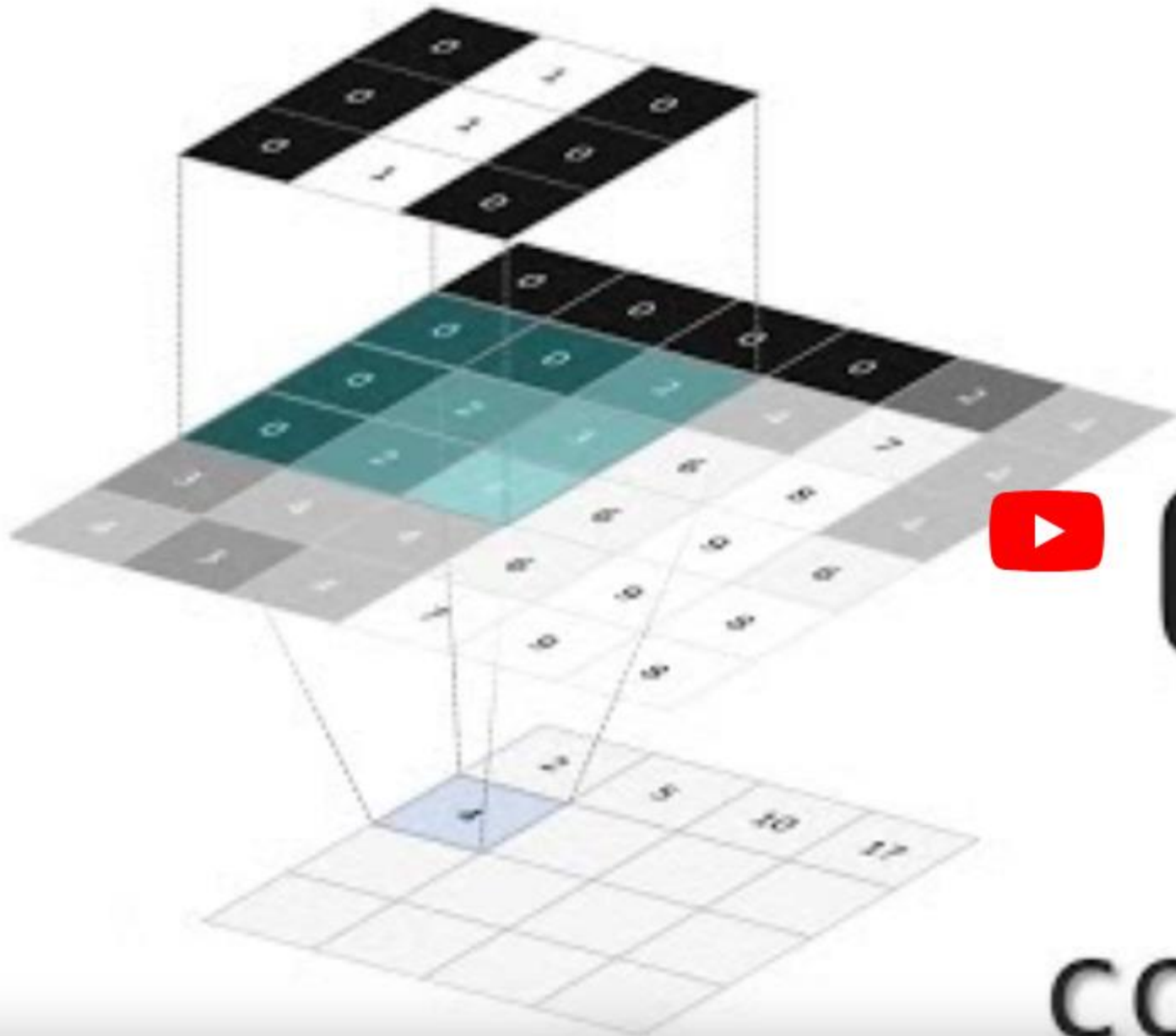
-25				...
				...
				...
				...
...



Links

<http://colah.github.io/posts/2014-07-Understanding-Convolutions/>

<https://towardsdatascience.com/a-comprehensive-guide-to-convolutional-neural-networks-the-eli5-way-3bd2b1164a53>



DEEP LEARNING CONCEPTS

pt.1

convolution

Conclusion

- Convolution is an important operation in many fields
- We can process a per pixel filtering operation across data very efficiently using convolutions
- Careful consideration have to be made between convolutions, correlations, circular convolutions and auto correlations
- Convolution theorem can be used to efficiently implement discrete convolutions

What's Next?

Convolutions form the key part in the success of deep learning in computer vision and image analysis. We will develop the concept of convolutional neural networks in the next lecture ...



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CREATE CHANGE

Thank you

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