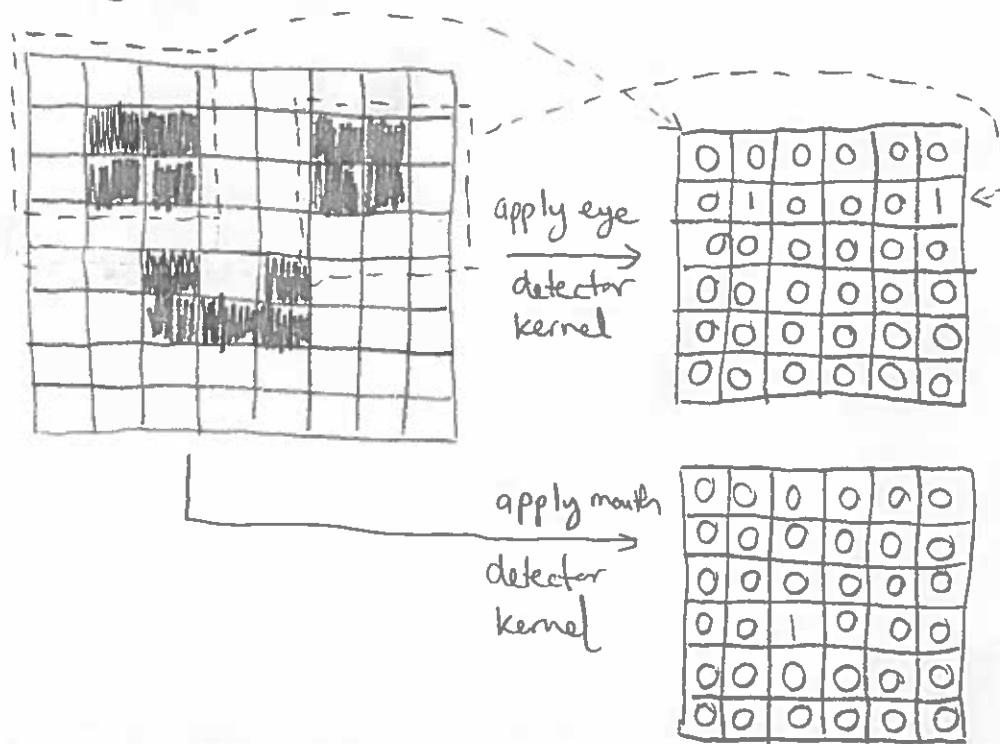


COMPUTING CONVOLUTIONS

① When we run the happy face detector, we need to apply each kernel to each 3×3 window of the image:



② By "apply a kernel to a window," we mean that we compute:

$$\text{Sum} \left(\underbrace{\begin{array}{|c|c|c|} \hline & & \\ \hline & & \\ \hline & & \\ \hline \end{array}}_{\text{image window}} + \underbrace{\begin{array}{|c|c|c|} \hline & & \\ \hline & & \\ \hline & & \\ \hline \end{array}}_{\text{convolution kernel}} \right)$$

Hadamard (elementwise) product

COMPUTING CONVOLUTIONS

- ③ How can we do this efficiently (i.e. leverage matrix multiplication libraries as much as possible)?

Let's consider a simpler example, in which we have a 3×3 "image":

| | | |
|---|---|---|
| 1 | 1 | 0 |
| 0 | 0 | 1 |
| 1 | 0 | 1 |

and a single 2×2 kernel:

| | |
|---|----|
| 1 | 2 |
| 0 | -1 |

- ④ To "convolve" the image with the kernel (with no padding and stride 1), we want to compute the matrix:

| | |
|---|---|
| $\text{sum} \left(\begin{bmatrix} 1 & 1 \\ 0 & 0 \end{bmatrix} \oplus \begin{bmatrix} 1 & 2 \\ 0 & -1 \end{bmatrix} \right)$ | $\text{sum} \left(\begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \oplus \begin{bmatrix} 1 & 2 \\ 0 & -1 \end{bmatrix} \right)$ |
| $\text{sum} \left(\begin{bmatrix} 0 & 0 \\ 1 & 0 \end{bmatrix} \oplus \begin{bmatrix} 1 & 2 \\ 0 & -1 \end{bmatrix} \right)$ | $\text{sum} \left(\begin{bmatrix} 0 & 1 \\ 0 & 1 \end{bmatrix} \oplus \begin{bmatrix} 1 & 2 \\ 0 & -1 \end{bmatrix} \right)$ |

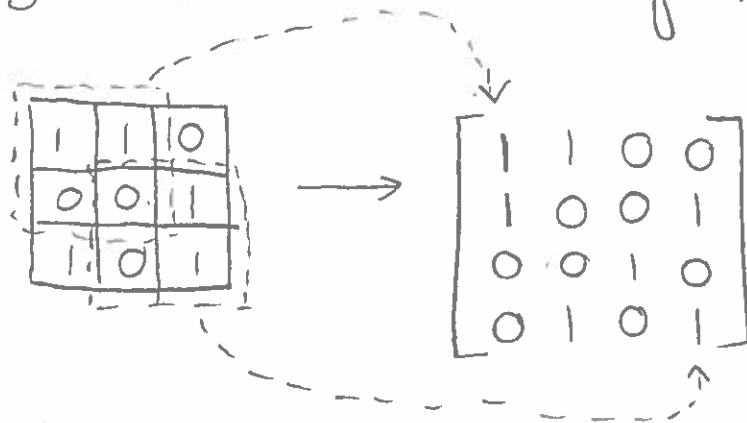
$$= \begin{bmatrix} 3 & 0 \\ 0 & 1 \end{bmatrix}$$

COMPUTING CONVOLUTIONS

- ⑤ We can express these computations as a matrix multiplication by expressing the kernel as a row vector:

$$\begin{bmatrix} 1 & 2 \\ 0 & -1 \end{bmatrix} \longrightarrow [1 \ 2 \ 0 \ -1]$$

and the image windows as columns of a matrix:



- ⑥ When we multiply the row vector by the column matrix, we get:

$$[1 \ 2 \ 0 \ -1] \begin{bmatrix} 1 & 1 & 0 & 0 \\ 1 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 \end{bmatrix} = [3 \ 0 \ 0 \ 1]$$

↑
sum $\left(\begin{bmatrix} 1 & 1 \\ 0 & 0 \end{bmatrix} \oplus \begin{bmatrix} 1 & 2 \\ 0 & -1 \end{bmatrix} \right)$

which we can reshape into a 2×2 matrix to get the desired result:

$$[3 \ 0 \ 0 \ 1] \longrightarrow \begin{bmatrix} 3 & 0 \\ 0 & 1 \end{bmatrix}$$

COMPUTING CONVOLUTIONS

- ⑦ It's not too hard to do this with multiple kernels at once (e.g. an eye detector and a mouth detector).

Let's add a kernel to our example, so we have now a 3x3 image:

| | | |
|---|---|---|
| 1 | 1 | 0 |
| 0 | 0 | 1 |
| 1 | 0 | 1 |

and two 2x2 kernels:

| | |
|---|----|
| 1 | 2 |
| 0 | -1 |

and

| | |
|----|---|
| 3 | 0 |
| -2 | 4 |

- ⑧ Convoluting the image with these kernels (with no padding and stride 1), we get:

$$\left[\begin{array}{cc} \text{Sum} \left(\begin{array}{|c|c|} \hline 1 & 1 \\ \hline 0 & 0 \\ \hline \end{array} + \begin{array}{|c|c|} \hline 1 & 2 \\ \hline 0 & -1 \\ \hline \end{array} \right) & \text{Sum} \left(\begin{array}{|c|c|} \hline 1 & 0 \\ \hline 0 & 1 \\ \hline \end{array} + \begin{array}{|c|c|} \hline 1 & 2 \\ \hline 0 & -1 \\ \hline \end{array} \right) \\ \text{Sum} \left(\begin{array}{|c|c|} \hline 0 & 0 \\ \hline 1 & 0 \\ \hline \end{array} + \begin{array}{|c|c|} \hline 1 & 2 \\ \hline 0 & -1 \\ \hline \end{array} \right) & \text{Sum} \left(\begin{array}{|c|c|} \hline 0 & 1 \\ \hline 0 & 1 \\ \hline \end{array} + \begin{array}{|c|c|} \hline 1 & 2 \\ \hline 0 & -1 \\ \hline \end{array} \right) \end{array} \right] , \left[\begin{array}{cc} \text{Sum} \left(\begin{array}{|c|c|} \hline 1 & 1 \\ \hline 0 & 0 \\ \hline \end{array} + \begin{array}{|c|c|} \hline 3 & 0 \\ \hline -2 & 4 \\ \hline \end{array} \right) & \text{Sum} \left(\begin{array}{|c|c|} \hline 1 & 0 \\ \hline 0 & 1 \\ \hline \end{array} + \begin{array}{|c|c|} \hline 3 & 0 \\ \hline -2 & 4 \\ \hline \end{array} \right) \\ \text{Sum} \left(\begin{array}{|c|c|} \hline 0 & 0 \\ \hline 1 & 0 \\ \hline \end{array} + \begin{array}{|c|c|} \hline 3 & 0 \\ \hline -2 & 4 \\ \hline \end{array} \right) & \text{Sum} \left(\begin{array}{|c|c|} \hline 0 & 1 \\ \hline 0 & 1 \\ \hline \end{array} + \begin{array}{|c|c|} \hline 3 & 0 \\ \hline -2 & 4 \\ \hline \end{array} \right) \end{array} \right]$$

$$= \left[\begin{array}{|c|c|} \hline 3 & 0 \\ \hline 0 & 1 \\ \hline \end{array} , \begin{array}{|c|c|} \hline 3 & 7 \\ \hline -2 & -2 \\ \hline \end{array} \right]$$

COMPUTING CONVOLUTIONS

⑨ We can perform the same trick, expressing each kernel as a row in a "kernel-row" matrix, and each image window as a column in a "window column" matrix. Then we multiply the matrices to obtain our desired quantities:

window-column matrix

kernel quantities:

kernel 1 \rightarrow $\underbrace{\begin{bmatrix} 1 & 2 & 0 & -1 \\ 3 & 0 & -2 & 4 \end{bmatrix}}_{\text{kernel-row matrix}}$

kernel 2 \rightarrow $\underbrace{\begin{bmatrix} 1 & 1 & 0 & 0 \\ 1 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 \end{bmatrix}}_{\text{window-column matrix}}$

$= \begin{bmatrix} 3 & 0 & 0 & 1 \\ 3 & 7 & -2 & -2 \end{bmatrix}$

image window 1 \uparrow

image window 4 \uparrow

which we can reshape into a $2 \times 2 \times 2$ tensor to get the desired result:

$$\begin{bmatrix} 3 & 0 & 0 & 1 \\ 3 & 7 & -2 & -2 \end{bmatrix} \rightarrow \left[\begin{array}{c|c} 3 & 0 \\ \hline 0 & 1 \end{array}, \begin{array}{c|c} 3 & 7 \\ \hline -2 & -2 \end{array} \right]$$

COMPUTING CONVOLUTIONS

- ⑩ There are a couple additional complications. While grayscale images are stored as matrices, color images are often represented by order-3 tensors — one matrix for each red, green, and blue "channel", e.g.

$$\left[\begin{array}{|c|c|c|} \hline 1 & 0 & 1 \\ \hline 0 & 1 & 0 \\ \hline 1 & 0 & 1 \\ \hline \end{array} \right], \begin{array}{|c|c|c|} \hline 1 & 1 & 0 \\ \hline 0 & 0 & 1 \\ \hline 1 & 0 & 1 \\ \hline \end{array}, \begin{array}{|c|c|c|} \hline 0 & 0 & 1 \\ \hline 0 & 1 & 0 \\ \hline 1 & 0 & 0 \\ \hline \end{array} \right]$$

red channel green channel blue channel

- ⑪ In this case, each kernel is also an order-3 tensor, one matrix for each channel, e.g:

$$\left[\begin{array}{|c|c|} \hline 1 & 0 \\ \hline 0 & 0 \\ \hline \end{array} \right], \begin{array}{|c|c|} \hline 0 & 0 \\ \hline 1 & 0 \\ \hline \end{array}, \begin{array}{|c|c|} \hline -1 & 0 \\ \hline 0 & 0 \\ \hline \end{array} \right]$$

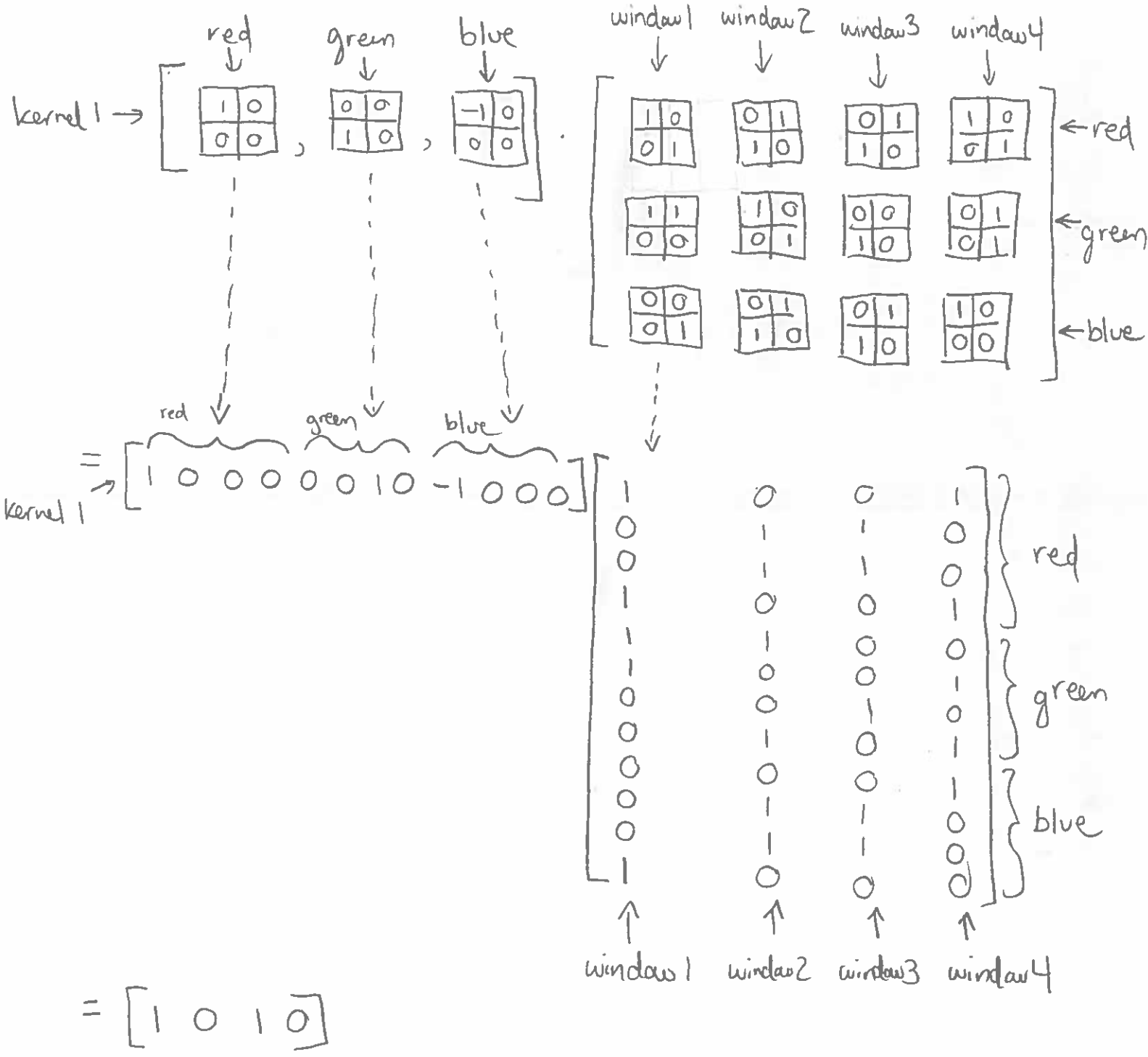
red kernel green kernel blue kernel

- ⑫ The convolution is:

$$\begin{array}{|c|c|} \hline \text{Sum} \left(\begin{array}{|c|c|} \hline 1 & 0 \\ \hline 0 & 1 \end{array} + \begin{array}{|c|c|} \hline 1 & 0 \\ \hline 0 & 0 \end{array} \right) + \text{Sum} \left(\begin{array}{|c|c|} \hline 1 & 1 \\ \hline 0 & 0 \end{array} + \begin{array}{|c|c|} \hline 0 & 0 \\ \hline 1 & 0 \end{array} \right) + \text{Sum} \left(\begin{array}{|c|c|} \hline 0 & 0 \\ \hline 0 & 1 \end{array} + \begin{array}{|c|c|} \hline -1 & 0 \\ \hline 0 & 0 \end{array} \right) & \text{Sum} \left(\begin{array}{|c|c|} \hline 0 & 1 \\ \hline 1 & 0 \end{array} + \begin{array}{|c|c|} \hline 1 & 0 \\ \hline 0 & 0 \end{array} \right) + \text{Sum} \left(\begin{array}{|c|c|} \hline 1 & 0 \\ \hline 0 & 1 \end{array} + \begin{array}{|c|c|} \hline 0 & 0 \\ \hline 1 & 0 \end{array} \right) \\ \hline & = \begin{array}{|c|c|} \hline 1 & 0 \\ \hline 1 & 0 \\ \hline \end{array} \end{array}$$

COMPUTING CONVOLUTIONS

⑬ Ok, no problem! We can still compute this as the multiplication of a kernel-row matrix with a window-column matrix: we just need to concatenate the channels.



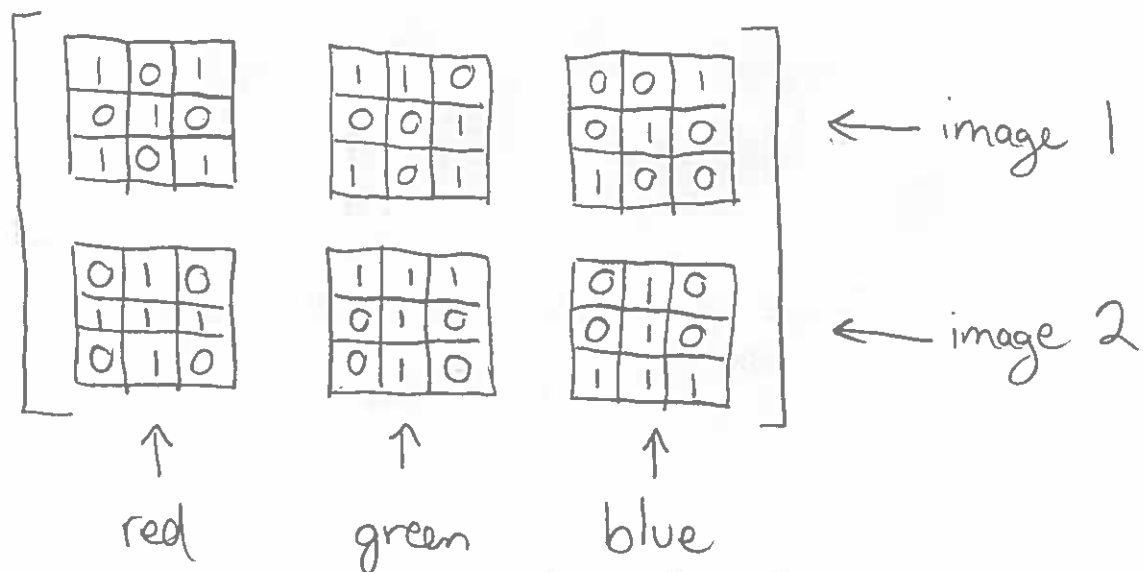
COMPUTING CONVOLUTIONS

- ⑭ The resulting matrix can then be reshaped into a $1 \times 2 \times 2$ tensor to get the result of convolution.
- ↑ num kernels ↑ resulting image size

$$[1 \ 0 \ 1 \ 0] \rightarrow \begin{bmatrix} 1 & 0 \\ 1 & 0 \end{bmatrix}$$

- ⑮ All right. That's almost, but not quite, everything. The last complication is, in minibatch training, we're usually not convolving one image at a time, but actually a batch of images.

So the input to our convolution might actually be an order-4 tensor like this:



This tensor has shape $2 \times 3 \times 3 \times 3$.

↑ num images ↑ image size
↑ RGB

COMPUTING CONVOLUTIONS

- ⑩ This is a straightforward (ish) extension. The kernels haven't changed, so the kernel-row matrix doesn't change. We just need to add the other image's windows as additional columns of the window-column matrix.

kernel \rightarrow $\begin{bmatrix} \text{red} & \text{green} & \text{blue} \\ \downarrow & \downarrow & \downarrow \\ \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} & \begin{bmatrix} 0 & 0 \\ 1 & 0 \end{bmatrix} & \begin{bmatrix} -1 & 0 \\ 0 & 0 \end{bmatrix} \end{bmatrix}$

image 1: win1 win2 win3 win4

image 2: win1 win2 win3 win4

← red

← green

← blue

$=$ $\begin{bmatrix} \text{red} & \text{green} & \text{blue} \\ \downarrow & \downarrow & \downarrow \\ 1 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & -1 & 0 & 0 & 0 \end{bmatrix}$

image 1: win1 win2 win3 win4

image 2: win1 win2 win3 win4

red

green

blue

$= [1 \ 0 \ 1 \ 0 \ 1 \ 2 \ 2 \ 1]$

num images
num kernels
image size

which can be reshaped into a $2 \times 1 \times 2 \times 2$ tensor to get the result of convolution:

$\begin{bmatrix} \begin{bmatrix} 1 & 0 \\ 1 & 0 \end{bmatrix} \\ \begin{bmatrix} 1 & 2 \\ 2 & 1 \end{bmatrix} \end{bmatrix}$