Convolutional Layer Backpropagation

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1 Single Kernel

$f_{0,0}$	$f_{0,1}$	$f_{0,2}$
$f_{1,0}$	$f_{1,1}$	$f_{1,2}$
$f_{2,0}$	$f_{2,1}$	$f_{2,2}$

Forward:

$$y_{i,j}^l = \sum_{i'=0}^{\text{kernel kernel height width}} \sum_{j'=0}^{l} w_{i',j'}^l \cdot f_{i+i',j+j'}^{l-1} + b^l$$

$$f_{i,j}^l = h(y_{i,j}^l)$$

Backward:

$$\delta_{i,j}^l = \frac{\partial h(y_{i,j}^l)}{\partial y_{i,j}^l} \cdot \sum_{i'=0}^{\substack{\text{kernel kernel} \\ \text{height width}}} w_{i',j'}^{l+1} \cdot \delta_{i-i',j-j'}^{l+1}$$

with zero padding:

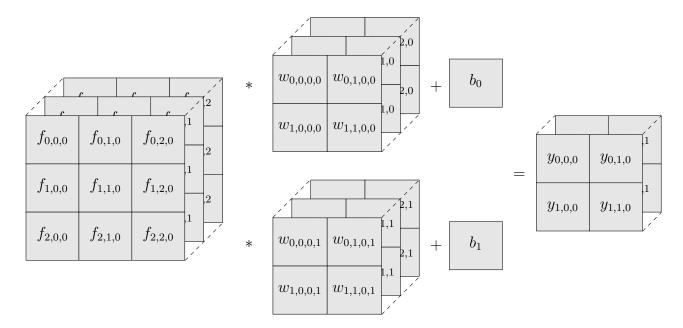
$$\delta_{x,y}^{l+1} := 0 \quad \text{if } x \notin [0, \text{output height}] \text{ or } y \notin [0, \text{output width}]$$

Gradient step:

$$w_{i,j}^l = w_{i,j}^l - \alpha \cdot \sum_{i'=0}^{\text{output output height width}} \sum_{j'=0}^{\text{output output height width}} \delta_{i',j'}^l \cdot f_{i+i',j+j'}^{l-1}$$

$$b^l = b^l - \alpha \cdot \sum_{i'=0}^{\text{output output height width}} \sum_{i'=0}^{-1} \delta^l_{i',j'}$$

2 Multiple Kernels



Forward:

$$y_{i,j,f}^l = \sum_{i'=0}^{\text{kernel kernel kernel height width depth height width depth}} \sum_{i'=0}^{-1} \sum_{j'=0}^{-1} \sum_{k'=0}^{-1} w_{i',j',k',f}^l \cdot f_{i+i',j+j',k'}^{l-1} + b_f^l$$

$$f_{i,j,f}^l = h(y_{i,j,f}^l)$$

Backward:

$$\delta_{i,j,f}^{l} = \frac{\partial h(y_{i,j,f}^{l})}{\partial y_{i,j,f}^{l}} \cdot \sum_{i'=0}^{\text{kernel kernel # of height width kernels}} \sum_{i'=0}^{-1} \sum_{j'=0}^{-1} w_{i',j',f,f'}^{l+1} \cdot \delta_{i-i',j-j',f'}^{l+1}$$

with zero padding:

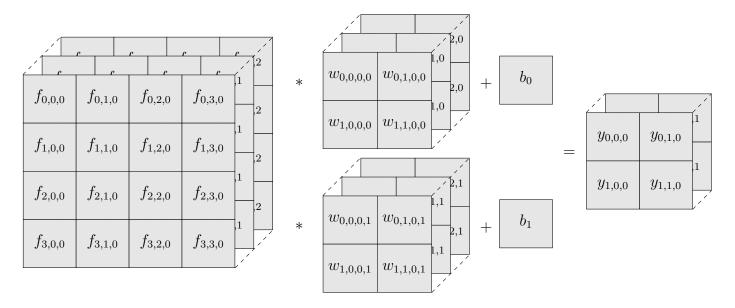
$$\delta_{x,y,z}^{l+1} := 0$$
 if $x \notin [0, \text{output height}]$ or $y \notin [0, \text{output width}]$

Gradient step:

$$w_{i,j,k,f}^{l} = w_{i,j,k,f}^{l} - \alpha \cdot \sum_{i'=0}^{\text{output output width}} \sum_{j'=0}^{\text{output output width}} \delta_{i',j',f}^{l} \cdot f_{i+i',j+j',k}^{l-1}$$

$$b_f^l = b_f^l - \alpha \cdot \sum_{i'=0}^{\text{output output height width}} \sum_{j'=0}^{l} \delta_{i',j',f}^l$$

3 Multiple Kernels with stride



Forward:

$$y_{i,j,f}^l = \sum_{i'=0}^{\text{kernel kernel kernel height width depth height width depth}} \sum_{i'=0}^{-1} \sum_{j'=0}^{-1} \sum_{k'=0}^{-1} w_{i',j',k',f}^l \cdot f_{i\cdot stride+i',j\cdot stride+j',k'}^{l-1} + b_f^l$$

$$f_{i,j,f}^l = h(y_{i,j,f}^l)$$

Backward:

$$\delta_{i,j,f}^{l} = \frac{\frac{\partial h(y_{i,j,f}^{l})}{\partial y_{i,j,f}^{l}} \cdot \sum_{i'=0}^{-1} \sum_{j'=0}^{-1} \sum_{f'=0}^{-1} w_{i\%stride+i'\cdot stride,j\%stride+j'\cdot stride,f,f'}^{l+1} \cdot \delta_{i/stride-i',j/stride-j',f'}^{l+1}$$

with zero padding:

$$\delta_{x,y,z}^{l+1} := 0 \quad \text{if } x \notin [0, \text{output height}] \text{ or } y \notin [0, \text{output width}]$$

Gradient step:

$$w_{i,j,k,f}^l = w_{i,j,k,f}^l - \alpha \cdot \sum_{i'=0}^{\text{output output}} \sum_{j'=0}^{\text{output output}} \delta_{i',j',f}^l \cdot f_{i+i'\cdot stride,j+j'\cdot stride,k}^{l-1}$$

$$b_f^l = b_f^l - \alpha \cdot \sum_{i'=0}^{\text{output output height width}} \sum_{i'=0}^{-1} \delta_{i',j',f}^l$$