# 6.819 PSET 4 10/05/2017

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#### Convolution 1

## a. Forward Propagation

$$x_{out}[i] = f_n(x_{in})$$

$$x_{out} = \sum_{i=0}^{k-1} x_{in} [i - \frac{k-1}{2} + j] W[j]$$

Where i is specific index of  $x_{in}$  where convolution is being done and j ranges from 0 to k-1

# b. Gradients of Input and Update Rules

 $W^{(i+1)=W^i+\eta \frac{\partial C}{\partial W}}$ 

$$\begin{split} W^{(i+1)=W^i+\eta \frac{\partial C}{\partial W}} \\ \frac{\partial C}{\partial X_{in1}} &= \frac{\partial C}{\partial X_{out1}} \frac{\partial X_{out1}}{\partial X_{in1}} + \dots + \frac{\partial C}{\partial X_{outN}} \frac{\partial X_{outN}}{\partial X_{in1}} \\ \frac{\partial X_{outi}}{\partial X_{inj}} &= \frac{\partial}{\partial x_{in}[i]} (x_{in}[i - \frac{k-1}{2} + 1]W[1] + x_{in}[i - \frac{k-1}{2} + 2]W[2] + \dots + x_{in}[i - \frac{k-1}{2} + g]W[g]), g = [0, k - 1] \\ &= \frac{\partial}{\partial x_{in}[i]} (x_{in}[i - \frac{k-1}{2} + g]W[\frac{k-1}{2}]), i = i + g - \frac{k-1}{2}, \text{ hence } g = \frac{k-1}{2} \\ &= \frac{\partial}{\partial x_{in}[i]} (x_{in}[i - \frac{k-1}{2} - (i - j)]W[\frac{k-1}{2}]) \\ &= \frac{\partial}{\partial x_{in}[i]} (x_{in}[i - \frac{k-1}{2} + j]W[\frac{k-1}{2}]) = W[\frac{k-1}{2}] \end{split}$$

$$\frac{\partial C}{\partial x_{in}[j]} = \sum_{i=0}^{N-1} \frac{\partial C}{\partial x_{out}[i]} \frac{\partial x_{out}[i]}{\partial x_{in}[j]} = \sum_{i=0}^{N-1} \frac{\partial C}{\partial x_{out}[i - \frac{k-1}{2} + j]} W[\frac{k-1}{2}]$$

Hence

$$\frac{\partial C}{\partial x_{in}[j]} = \sum_{i=0}^{N-1} \frac{\partial C}{\partial x_{out}[i - \frac{k-1}{2} + j]} W[\frac{k-1}{2}]$$

$$\frac{\partial C}{\partial W[j]} = \sum_{i=0}^{k-1} \frac{\partial C}{\partial x_{out}[i]} \frac{\partial X_{out}[i]}{\partial W[j]}, j$$

specific point where we compute gradient

$$= \frac{\partial}{\partial W[j]} (x_{in}[i - \frac{k-1}{2} + 1]W[1] + x_{in}[i - \frac{k-1}{2} + 2]W[2] + \dots + x_{in}[i - \frac{k-1}{2} + g]w[g], g = [0, k])$$

$$= \sum_{i=0}^{k-1} \frac{\partial}{\partial w[j]} (x_{in}[i - \frac{k-1}{2} + j]W[j]) = x_{in}[i - \frac{k-1}{2} + j]$$
$$\frac{\partial C}{\partial W[j]} = \sum_{i=0}^{k-1} \frac{\partial C}{\partial x_{out}[i]} x_{in}[i - \frac{k-1}{2} + j]$$

Hence

$$W^{(i+1)} = W^{(i)} + \eta \sum_{i=0}^{k-1} \frac{\partial C}{\partial x_{out}[i]} x_{in}[i - \frac{k-1}{2} + j]$$

### c. Handling Boundaries

Since the kernel is being slid across the image, it is likely to go out of bounds. Hence, zero pad the kernel when out of range to take care of out of bounds error for  $j \notin [1-\frac{k-1}{2},i+\frac{k-1}{2}]$