

## Lecture 6 - The Convolutional Layer in Convolutional Networks

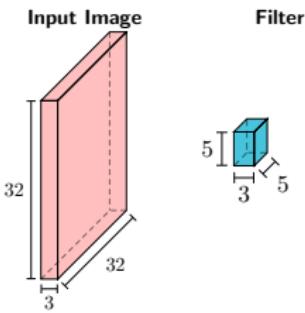
ConvNets for RGB Images: **The Convolution Layer**

DD2424

April 19, 2017

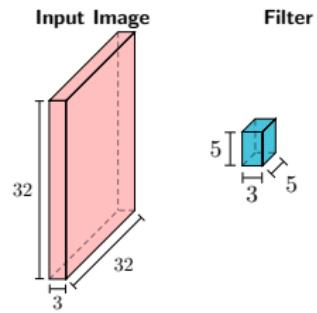
### Convolution Layer

### Convolution Layer



X is  $32 \times 32 \times 3$

F is  $5 \times 5 \times 3$

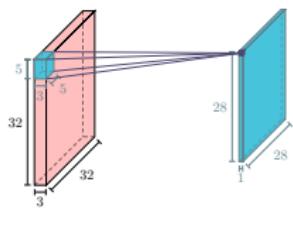


X is  $32 \times 32 \times 3$

F is  $5 \times 5 \times 3$

Note: Filter & input image always have the same depth.

## Convolution Layer

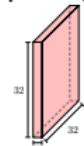


**Convolve** the image,  $X$ , with the filter  $F$ .

- Slide filter over all spatial locations in image.
- At each location output 1 number:

compute dot product between  $F$  and a  $5 \times 5 \times 3$  chunk of  $X$

**Input Image**



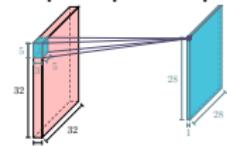
$X$   
Size:  $32 \times 32 \times 3$

**Filter**



$F$   
Size:  $5 \times 5 \times 3$

**Output response map**

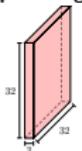


$S = X * F$   
Size:  $28 \times 28 \times 1$

## Convolution Layer

Can apply multiple filters.

**Input Image**



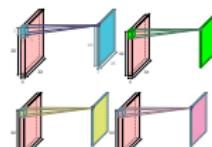
**Filters**



$F_1, F_2, F_3, F_4$

$X$   
Size:  $32 \times 32 \times 3$

**Output response maps**

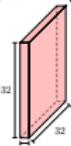


$S_i = X * F_i$

Size  $S_i$ :  $28 \times 28 \times 1$

Apply multiple filters and get multiple response maps

**Input Image**



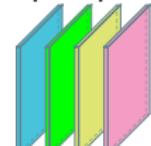
**Filters**



$F_1, F_2, F_3, F_4$

$X$

**Output response maps**



$S_1, S_2, S_3, S_4$

Each  $S_i = X * F_i$

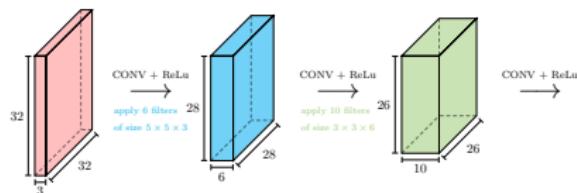
- Stack the multiple response maps to get a new image  $S$ .
  - In our example
    - $S = \{S_1, S_2, S_3, S_4\}$  and
    - $S$  has size  $28 \times 28 \times 4$
  - Apply the non-linear activation function to each element of  $S$ .
- $$H = \max(0, S)$$



## Most basic Convolutional Network layers

Basic ConvNet is a composition of

- Convolution Layer
- Activation function



## How do we produce final probs for $C$ class labels?

- Add **fully connected layer(s)** after the convolutional layers.
- Example network:  
1 convolutional layer + 1 fully connected layer

$$S_i = X * F_i + b_i \quad \text{for } i = 1, \dots, n_F \quad \leftarrow \text{apply convolution filters}$$

$$S = \{S_1, \dots, S_{n_F}\} \quad \leftarrow \text{stack response maps, get new 3D image}$$

$$H = \max(0, S) \quad \leftarrow \text{apply ReLu}$$

$$s = W \text{vec}(H) + \mathbf{b} \quad \leftarrow \text{fully-connected layer to get } C \text{ scores}$$

$$\mathbf{p} = \text{SOFTMAX}(\mathbf{s}) \quad \leftarrow \text{turn scores into probabilities}$$

- Dimensions of inputs, outputs and parameters:

- $X$  is  $w \times h \times 3$
- Each  $F_i$  is  $f \times f \times 3$  and  $b_i$  is a scalar
- Each  $S_i$  is  $(w - f + 1) \times (h - f + 1)$
- $S$  and  $H$  are  $(w - f + 1) \times (h - f + 1) \times n_F$
- $W$  is  $C \times (w - f + 1)(h - f + 1)n_F$
- $\mathbf{b}, \mathbf{s}$  and  $\mathbf{p}$  are  $C \times 1$

## How do we learn the parameters of the network?

- Add **fully connected layer(s)** after the convolutional layers.
- Example network:  
1 convolutional layer + 1 fully connected layer

$$\begin{aligned} S_i &= X * F_i + b_i \quad \text{for } i = 1, \dots, n_F \quad \leftarrow \text{apply convolution filters} \\ S &= \{S_1, \dots, S_{n_F}\} \quad \leftarrow \text{stack response maps, get new 3D image} \\ H &= \max(0, S) \quad \leftarrow \text{apply ReLu} \\ s &= W \text{vec}(H) + b \quad \leftarrow \text{fully-connected layer to get } C \text{ scores} \\ p &= \text{SOFTMAX}(s) \quad \leftarrow \text{turn scores into probabilities} \end{aligned}$$

- Dimensions of inputs, outputs and parameters:

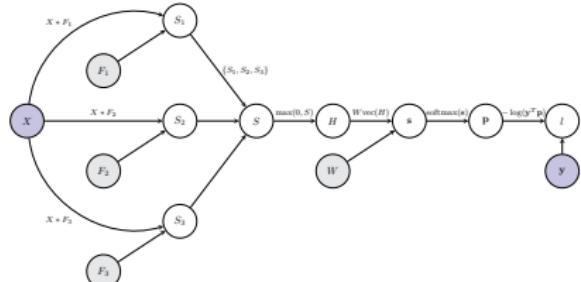
- $X$  is  $w \times h \times 3$
- Each  $F_i$  is  $f \times f \times 3$  and  $b_i$  is a scalar
- Each  $S_i$  is  $(w - f + 1) \times (h - f + 1)$
- $S$  and  $H$  are  $(w - f + 1) \times (h - f + 1) \times n_F$
- $W$  is  $C \times (w - f + 1)(h - f + 1)n_F$
- $b$ ,  $s$  and  $p$  are  $C \times 1$ .

## Gradient Computations for one Convolutional layer

## How do we learn the parameters of the network?

- Optimize the usual cross-entropy loss (+  $L_2$  regularization term) on the training data.
- Use mini-batch gradient descent to perform optimization.
- $\implies$  need to compute the gradient of the loss w.r.t. the convolutional parameters....

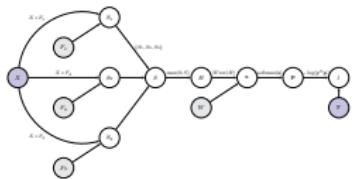
### Computational Graph for our simple network



#### Notes about the above figure

- Apply 3 filters in the convolutional layer ( $n_F = 3$ ).
- $X = \{X_1, X_2, X_3\}$  and each  $X_i$  has size  $w \times h$
- Each  $F_i = \{F_{i1}, F_{i2}, F_{i3}\}$  and has size  $f \times f \times 3$
- Have omitted the bias weights for clarity.

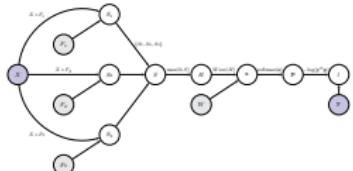
## Computational Graph for our simple network



From previous lectures know that

$$\begin{aligned}\frac{\partial l}{\partial s} &= -\frac{\mathbf{y}^T}{\mathbf{y}^T \mathbf{p}} (\text{diag}(\mathbf{p}) - \mathbf{p} \mathbf{p}^T) \\ \frac{\partial l}{\partial \text{vec}(H)} &= \frac{\partial l}{\partial s} W \\ \frac{\partial l}{\partial \text{vec}(S)} &= \frac{\partial l}{\partial \text{vec}(H)} \text{diag}(\text{Ind}(\text{vec}(S) > 0))\end{aligned}$$

## Computational Graph for our simple network



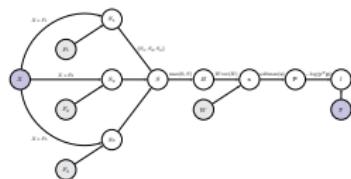
From reading the computational graph we can see that

$$\frac{\partial l}{\partial \text{vec}(F_i)} = \frac{\partial l}{\partial \text{vec}(S)} \frac{\partial \text{vec}(S)}{\partial \text{vec}(S_i)} \frac{\partial \text{vec}(S_i)}{\partial \text{vec}(F_i)}$$

↑ already known

for  $i = 1, 2, 3$ .

## Computational Graph for our simple network

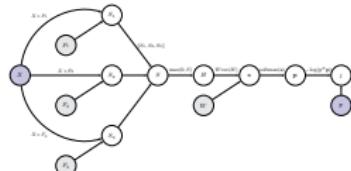


From reading the computational graph we can see that

$$\begin{aligned}\frac{\partial l}{\partial \text{vec}(F_i)} &= \frac{\partial l}{\partial \text{vec}(S_i)} \frac{\partial \text{vec}(S_i)}{\partial \text{vec}(F_i)} \\ &= \frac{\partial l}{\partial \text{vec}(S)} \frac{\partial \text{vec}(S)}{\partial \text{vec}(S_i)} \frac{\partial \text{vec}(S_i)}{\partial \text{vec}(F_i)}\end{aligned}$$

for  $i = 1, 2, 3$ .

## Computational Graph for our simple network



From reading the computational graph we can see that

$$\frac{\partial l}{\partial \text{vec}(F_i)} = \frac{\partial l}{\partial \text{vec}(S)} \frac{\partial \text{vec}(S)}{\partial \text{vec}(S_i)} \frac{\partial \text{vec}(S_i)}{\partial \text{vec}(F_i)}$$

↑ calculate now

for  $i = 1, 2, 3$ .

- Have  $S = \{S_1, S_2, S_3\} \implies$

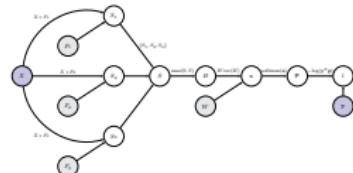
$$\text{vec}(S) = \begin{pmatrix} \text{vec}(S_1) \\ \text{vec}(S_2) \\ \text{vec}(S_3) \end{pmatrix}$$

- Then

$$\frac{\partial \text{vec}(S)}{\partial \text{vec}(S_1)} = \begin{pmatrix} I_t \\ 0 \\ 0 \end{pmatrix}, \quad \frac{\partial \text{vec}(S)}{\partial \text{vec}(S_2)} = \begin{pmatrix} 0 \\ I_t \\ 0 \end{pmatrix}, \quad \frac{\partial \text{vec}(S)}{\partial \text{vec}(S_3)} = \begin{pmatrix} 0 \\ 0 \\ I_t \end{pmatrix}$$

where  $t = (w - f + 1) \times (h - f + 1)$  and each 0 denotes a square matrix of zeros of size  $t \times t$ .

- Each  $\frac{\partial \text{vec}(S)}{\partial \text{vec}(S_i)}$  has size  $3t \times t$



From reading the computational graph we can see that

$$\frac{\partial l}{\partial \text{vec}(F_i)} = \frac{\partial l}{\partial \text{vec}(S)} \frac{\partial \text{vec}(S)}{\partial \text{vec}(S_i)} \frac{\partial \text{vec}(S_i)}{\partial \text{vec}(F_i)}$$

↑ calculate now

for  $i = 1, 2, 3$ .

### Simple Example

- Have for  $i = 1, 2, 3$ :

$$S_i = X * F_i$$

- Can write a convolution (not in a very memory efficient way) as a matrix multiplication

$$\text{vec}(S_i) = M_X^{\text{im}} \text{vec}(F_i)$$

- $M_X^{\text{im}}$  has size  $(w - f + 1)(h - f + 1) \times (3f^2)$
- What are the entries of  $M_X^{\text{im}}$ ?

- Have an input image  $X$  of size  $6 \times 6 \times 1$ .

- Have a filter  $F$  of size  $3 \times 3 \times 1$ .

- Convolve  $X$  by  $F$  gives a response map of size  $4 \times 4$

$$S = X * F$$

- Each entry of  $S$  can be written as

$$S_{lm} = \sum_{k=1}^1 \sum_{i=1}^3 \sum_{j=1}^3 X_{k,i+l-1,j+m-1} F_{kij}$$



## Writing a convolution as a matrix multiplication

### Simple Example

Want to write this convolution as a matrix multiplication:

$$S = \begin{pmatrix} X_{11} & X_{12} & X_{13} & X_{14} & X_{15} & X_{16} \\ X_{21} & X_{22} & X_{23} & X_{24} & X_{25} & X_{26} \\ X_{31} & X_{32} & X_{33} & X_{34} & X_{35} & X_{36} \\ X_{41} & X_{42} & X_{43} & X_{44} & X_{45} & X_{46} \\ X_{51} & X_{52} & X_{53} & X_{54} & X_{55} & X_{56} \\ X_{61} & X_{62} & X_{63} & X_{64} & X_{65} & X_{66} \end{pmatrix} + \begin{pmatrix} F_{11} & F_{12} & F_{13} \\ F_{21} & F_{22} & F_{23} \\ F_{31} & F_{32} & F_{33} \end{pmatrix}$$

### One Solution:

$$\begin{pmatrix} S_{11} \\ S_{12} \\ S_{13} \\ S_{14} \\ S_{15} \\ S_{16} \end{pmatrix} = \begin{pmatrix} X_{11} & X_{12} & X_{13} & X_{21} & X_{22} & X_{23} & X_{31} & X_{32} \\ X_{12} & X_{13} & X_{14} & X_{22} & X_{23} & X_{24} & X_{32} & X_{33} \\ X_{13} & X_{14} & X_{15} & X_{23} & X_{24} & X_{25} & X_{33} & X_{34} \\ X_{14} & X_{15} & X_{16} & X_{24} & X_{25} & X_{26} & X_{34} & X_{35} \\ X_{15} & X_{16} & X_{17} & X_{25} & X_{26} & X_{27} & X_{35} & X_{36} \\ X_{16} & X_{17} & X_{18} & X_{26} & X_{27} & X_{28} & X_{36} & X_{37} \end{pmatrix} \begin{pmatrix} F_{11} \\ F_{12} \\ F_{13} \\ F_{21} \\ F_{22} \\ F_{23} \\ F_{31} \\ F_{32} \\ F_{33} \end{pmatrix}$$

new row corresponds to

$$\begin{pmatrix} X_{11} & X_{12} & X_{13} & X_{14} & X_{15} & X_{16} \\ X_{21} & X_{22} & X_{23} & X_{24} & X_{25} & X_{26} \\ X_{31} & X_{32} & X_{33} & X_{34} & X_{35} & X_{36} \\ X_{41} & X_{42} & X_{43} & X_{44} & X_{45} & X_{46} \\ X_{51} & X_{52} & X_{53} & X_{54} & X_{55} & X_{56} \\ X_{61} & X_{62} & X_{63} & X_{64} & X_{65} & X_{66} \end{pmatrix}$$

## Writing a convolution as a matrix multiplication

### Simple Example

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### One Solution:

$$\begin{pmatrix} S_{11} \\ S_{12} \\ S_{13} \\ S_{14} \\ S_{15} \\ S_{16} \\ \vdots \\ S_{44} \end{pmatrix} = \begin{pmatrix} X_{11} & X_{12} & X_{13} & X_{14} & X_{15} & X_{16} \\ X_{12} & X_{13} & X_{14} & X_{15} & X_{16} & X_{17} \\ X_{13} & X_{14} & X_{15} & X_{16} & X_{17} & X_{18} \\ X_{14} & X_{15} & X_{16} & X_{17} & X_{18} & X_{19} \\ X_{15} & X_{16} & X_{17} & X_{18} & X_{19} & X_{20} \\ X_{16} & X_{17} & X_{18} & X_{19} & X_{20} & X_{21} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ X_{41} & X_{42} & X_{43} & X_{44} & X_{45} & X_{46} \end{pmatrix} \begin{pmatrix} F_{11} \\ F_{12} \\ F_{13} \\ F_{21} \\ F_{22} \\ F_{23} \\ \vdots \\ F_{31} \\ F_{32} \\ F_{33} \end{pmatrix}$$

new row corresponds to

$$\begin{pmatrix} X_{11} & X_{12} & X_{13} & X_{14} & X_{15} & X_{16} \\ X_{21} & X_{22} & X_{23} & X_{24} & X_{25} & X_{26} \\ X_{31} & X_{32} & X_{33} & X_{34} & X_{35} & X_{36} \\ X_{41} & X_{42} & X_{43} & X_{44} & X_{45} & X_{46} \\ X_{51} & X_{52} & X_{53} & X_{54} & X_{55} & X_{56} \\ X_{61} & X_{62} & X_{63} & X_{64} & X_{65} & X_{66} \end{pmatrix}$$

## Writing a convolution as a matrix multiplication

### Simple Example

Want to write this convolution as a matrix multiplication:

$$S = \begin{pmatrix} X_{11} & X_{12} & X_{13} & X_{14} & X_{15} & X_{16} \\ X_{21} & X_{22} & X_{23} & X_{24} & X_{25} & X_{26} \\ X_{31} & X_{32} & X_{33} & X_{34} & X_{35} & X_{36} \\ X_{41} & X_{42} & X_{43} & X_{44} & X_{45} & X_{46} \\ X_{51} & X_{52} & X_{53} & X_{54} & X_{55} & X_{56} \\ X_{61} & X_{62} & X_{63} & X_{64} & X_{65} & X_{66} \end{pmatrix} + \begin{pmatrix} F_{11} & F_{12} & F_{13} \\ F_{21} & F_{22} & F_{23} \\ F_{31} & F_{32} & F_{33} \end{pmatrix}$$

### One Solution:

$$\begin{pmatrix} S_{11} \\ S_{12} \\ S_{13} \\ S_{14} \\ S_{15} \\ S_{16} \\ \vdots \\ S_{44} \end{pmatrix} = \begin{pmatrix} X_{11} & X_{12} & X_{13} & X_{21} & X_{22} & X_{23} & X_{31} & X_{32} \\ X_{12} & X_{13} & X_{14} & X_{22} & X_{23} & X_{24} & X_{32} & X_{33} \\ X_{13} & X_{14} & X_{15} & X_{23} & X_{24} & X_{25} & X_{33} & X_{34} \\ X_{14} & X_{15} & X_{16} & X_{24} & X_{25} & X_{26} & X_{34} & X_{35} \\ X_{15} & X_{16} & X_{17} & X_{25} & X_{26} & X_{27} & X_{35} & X_{36} \\ X_{16} & X_{17} & X_{18} & X_{26} & X_{27} & X_{28} & X_{36} & X_{37} \\ \vdots & \vdots \\ X_{41} & X_{42} & X_{43} & X_{44} & X_{45} & X_{46} & X_{51} & X_{52} \end{pmatrix} \begin{pmatrix} F_{11} \\ F_{12} \\ F_{13} \\ F_{21} \\ F_{22} \\ F_{23} \\ F_{31} \\ F_{32} \\ F_{33} \end{pmatrix}$$

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$M_X^{\text{im}}$  size 16 × 9

$$\text{vec}(S) = M_X^{\text{im}} \text{vec}(F)$$

## Multiple planes: Convolution → Matrix multiplication

- What about when  $X$  and  $F_1$  have multiple planes?
- Say  $X = \{X_1, X_2, X_3, X_4\}$  has size  $6 \times 6 \times 4$ ,
- $F_1 = \{F_{11}, F_{12}, F_{13}, F_{14}\}$  has size  $3 \times 3 \times 4$ .
- Let

$$S_1 = X * F_1 \quad (S_1 \text{ has size } 4 \times 4)$$

- Then

$$\text{vec}(S_1) = M_X^{\text{im}} \text{vec}(F_1)$$

where

$$M_X^{\text{im}} = (M_{X_1}^{\text{im}} \quad M_{X_2}^{\text{im}} \quad M_{X_3}^{\text{im}} \quad M_{X_4}^{\text{im}})$$

and has size  $16 \times 36$ .

- Have for  $i = 1, 2, 3$ :

$$S_i = X * F_i$$

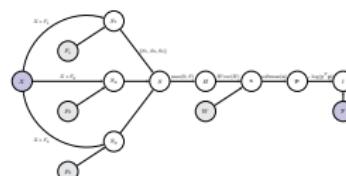
- Can write a convolution (not in a very memory efficient way) as a matrix multiplication

$$\text{vec}(S_i) = M_X^{\text{im}} \text{vec}(F_i)$$

- $M_X^{\text{im}}$  has size  $(w - f + 1)(h - f + 1) \times (3f^2)$

- Thus

$$\frac{\partial \text{vec}(S_i)}{\partial \text{vec}(F_i)} = M_X^{\text{im}}$$



Thus

$$\begin{aligned} \frac{\partial l}{\partial \text{vec}(F_i)} &= \frac{\partial l}{\partial \text{vec}(S)} \frac{\partial \text{vec}(S)}{\partial \text{vec}(S_1)} \frac{\partial \text{vec}(S_1)}{\partial \text{vec}(F_i)} = \frac{\partial l}{\partial \text{vec}(S)} \begin{pmatrix} I_t \\ 0 \\ 0 \end{pmatrix} M_X^{\text{im}} \\ &= \left( \frac{\partial l}{\partial \text{vec}(S_1)} \quad \frac{\partial l}{\partial \text{vec}(S_2)} \quad \frac{\partial l}{\partial \text{vec}(S_3)} \right) \begin{pmatrix} M_{X_1}^{\text{im}} & M_{X_2}^{\text{im}} & M_{X_3}^{\text{im}} \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix} \\ &= \sum_{i=1}^3 \frac{\partial l}{\partial \text{vec}(S_i)} M_{X_i}^{\text{im}} \end{aligned}$$

## Gradient of the loss w.r.t. $F_i$

- May want expression for  $\frac{\partial l}{\partial F_i}$  instead of  $\frac{\partial l}{\partial \text{vec}(F_i)}$ .

- **Option 1:**

Reshape  $\frac{\partial l}{\partial \text{vec}(F_i)}$  (size  $1 \times 3f^2$ ) to  $\frac{\partial l}{\partial F_i}$  (size  $f \times f \times 3$ ).

## Gradient of the loss w.r.t. $F_i$

- May want expression for  $\frac{\partial l}{\partial F_i}$  instead of  $\frac{\partial l}{\partial \text{vec}(F_i)}$ .

- **Option 2:**

Return to our simple example ...

Writing a certain matrix multiplication as a convolution

## **Return to Simple Example**

Consider the case

$$\begin{pmatrix} v_1 & v_2 & \dots & v_9 \end{pmatrix} = \begin{pmatrix} g_1 & g_2 & \dots & g_{16} \end{pmatrix}$$

$$\left( \begin{array}{ccccccccc} X_{11} & X_{12} & X_{13} & X_{21} & X_{22} & X_{23} & X_{31} & X_{32} & X_{33} \\ X_{12} & X_{13} & X_{14} & X_{22} & X_{23} & X_{24} & X_{32} & X_{33} & X_{34} \\ X_{13} & X_{14} & X_{15} & X_{23} & X_{24} & X_{25} & X_{33} & X_{34} & X_{35} \\ X_{14} & X_{15} & X_{16} & X_{24} & X_{25} & X_{26} & X_{34} & X_{35} & X_{36} \\ X_{21} & X_{22} & X_{23} & X_{31} & X_{32} & X_{33} & X_{41} & X_{42} & X_{43} \\ & & & & & & \vdots & & \\ & & & & & & \vdots & & \\ X_{44} & X_{45} & X_{46} & X_{54} & X_{55} & X_{56} & X_{64} & X_{65} & X_{66} \end{array} \right) M_{16 \times 9}^{\text{size}}$$

Writing a certain matrix multiplication as a convolution

## [Return to Simple Example](#)

Consider the case

$$\begin{pmatrix} e_1 & v_2 & \dots & v_9 \end{pmatrix} = \begin{pmatrix} g_1 & g_2 & \dots & g_{16} \end{pmatrix}$$

where red column in  $M_X^{\text{im}}$  corresponds to this red block in  $X$ .

Writing a certain matrix multiplication as a convolution

## [Return to Simple Example](#)

Consider the case

Consider the Case	$\begin{pmatrix} X_{11} & \textcolor{red}{X}_{12} & X_{13} & X_{21} & X_{22} & X_{23} & X_{31} & X_{32} & X_{33} \\ X_{12} & \textcolor{red}{X}_{13} & X_{14} & X_{22} & X_{23} & X_{24} & X_{32} & X_{33} & X_{34} \\ X_{13} & \textcolor{red}{X}_{14} & X_{15} & X_{23} & X_{24} & X_{25} & X_{33} & X_{34} & X_{35} \\ X_{14} & \textcolor{red}{X}_{15} & X_{16} & X_{24} & X_{25} & X_{26} & X_{34} & X_{35} & X_{36} \\ X_{21} & \textcolor{red}{X}_{22} & X_{23} & X_{31} & X_{32} & X_{33} & X_{41} & X_{42} & X_{43} \\ & & & & & & \vdots & & \\ & & & & & & \vdots & & \\ X_{44} & \textcolor{red}{X}_{45} & X_{46} & X_{54} & X_{55} & X_{56} & X_{64} & X_{65} & X_{66} \end{pmatrix}$
$(v_1 \quad v_2 \quad \dots \quad v_9) = (g_1 \quad g_2 \quad \dots \quad g_{16})$	$M_{16 \times 9}^{\text{size}}$

Writing a certain matrix multiplication as a convolution

## [Return to Simple Example](#)

Consider the case

Consider the Case	$\left( \begin{array}{cccccc} X_{11} & X_{12} & \textcolor{red}{X_{13}} & X_{21} & X_{22} & X_{23} & X_{31} & X_{32} \\ X_{12} & X_{13} & \textcolor{red}{X_{14}} & X_{22} & X_{23} & X_{24} & X_{32} & X_{33} \\ X_{13} & X_{14} & \textcolor{red}{X_{15}} & X_{23} & X_{24} & X_{25} & X_{33} & X_{34} \\ X_{14} & X_{15} & \textcolor{red}{X_{16}} & X_{24} & X_{25} & X_{26} & X_{34} & X_{35} \\ X_{21} & X_{22} & \textcolor{red}{X_{23}} & X_{31} & X_{32} & X_{33} & X_{41} & X_{42} \\ & & & & & & \vdots & \\ & & & & & & \vdots & \\ X_{44} & X_{45} & \textcolor{red}{X_{46}} & X_{54} & X_{55} & X_{56} & X_{64} & X_{65} \end{array} \right) M_{16}^{**} \text{ size } 16 \times 9$
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where red column in  $M_X^{\text{im}}$  corresponds to this red block in  $X$

$$\begin{pmatrix} X_{11} & X_{12} & X_{13} & X_{14} & X_{15} & X_{16} \\ X_{21} & X_{22} & X_{23} & X_{24} & X_{25} & X_{26} \\ X_{31} & X_{32} & X_{33} & X_{34} & X_{35} & X_{36} \\ X_{41} & X_{42} & X_{43} & X_{44} & X_{45} & X_{46} \\ X_{51} & X_{52} & X_{53} & X_{54} & X_{55} & X_{56} \\ X_{61} & X_{62} & X_{63} & X_{64} & X_{65} & X_{66} \end{pmatrix}$$

## Writing a certain matrix multiplication as a convolution

### Return to Simple Example

Consider the case

$$(v_1 \ v_2 \ v_3 \ \textcolor{red}{v}_4 \ \cdots \ v_9) - (g_1 \ g_2 \ \cdots \ g_{16}) = \begin{pmatrix} X_{11} & X_{12} & X_{13} & \textcolor{red}{X}_{14} & X_{22} & X_{23} & X_{31} & X_{32} & X_{33} \\ X_{12} & X_{13} & X_{14} & \textcolor{red}{X}_{15} & X_{23} & X_{24} & X_{32} & X_{33} & X_{34} \\ X_{13} & X_{14} & X_{15} & \textcolor{red}{X}_{16} & X_{24} & X_{25} & X_{33} & X_{34} & X_{35} \\ X_{14} & X_{15} & X_{16} & \textcolor{red}{X}_{23} & X_{24} & X_{26} & X_{34} & X_{35} & X_{36} \\ X_{21} & X_{22} & X_{23} & \textcolor{red}{X}_{31} & X_{32} & X_{33} & X_{41} & X_{42} & X_{43} \\ & & & \vdots & & & & & \\ X_{44} & X_{45} & X_{46} & \textcolor{red}{X}_{54} & X_{55} & X_{56} & X_{64} & X_{65} & X_{66} \end{pmatrix}$$

$M_X^{\text{im}}$  size 16 × 9

where **red column** in  $M_X^{\text{im}}$  corresponds to this **red block** in  $X$

$$\begin{pmatrix} X_{11} & X_{12} & X_{13} & X_{14} & X_{15} & X_{16} \\ X_{21} & \textcolor{red}{X}_{22} & X_{23} & \textcolor{red}{X}_{24} & X_{25} & X_{26} \\ X_{31} & X_{32} & X_{33} & \textcolor{red}{X}_{34} & X_{35} & X_{36} \\ X_{41} & X_{42} & X_{43} & \textcolor{red}{X}_{44} & X_{45} & X_{46} \\ X_{51} & X_{52} & X_{53} & \textcolor{red}{X}_{54} & X_{55} & X_{56} \\ X_{61} & X_{62} & X_{63} & X_{64} & X_{65} & X_{66} \end{pmatrix}$$

## Writing a certain matrix multiplication as a convolution

### Return to Simple Example

Consider the case

$$(v_1 \ v_2 \ v_3 \ \textcolor{red}{v}_4 \ \cdots \ v_9) - (g_1 \ g_2 \ \cdots \ g_{16}) = \begin{pmatrix} X_{11} & X_{12} & X_{13} & X_{21} & X_{22} & X_{23} & X_{31} & X_{32} & \textcolor{red}{X}_{33} \\ X_{12} & X_{13} & X_{14} & X_{21} & X_{23} & X_{24} & X_{32} & X_{33} & \textcolor{red}{X}_{34} \\ X_{13} & X_{14} & X_{15} & X_{21} & X_{24} & X_{25} & X_{33} & X_{34} & \textcolor{red}{X}_{35} \\ X_{14} & X_{15} & X_{16} & X_{21} & X_{25} & X_{26} & X_{34} & X_{35} & \textcolor{red}{X}_{36} \\ X_{21} & X_{22} & X_{23} & X_{31} & X_{32} & X_{33} & X_{41} & X_{42} & \textcolor{red}{X}_{43} \\ & & & \vdots & & & & & \\ X_{44} & X_{45} & X_{46} & X_{51} & X_{52} & X_{53} & X_{64} & X_{65} & \textcolor{red}{X}_{66} \end{pmatrix}$$

$M_X^{\text{im}}$  size 16 × 9

where **red column** in  $M_X^{\text{im}}$  corresponds to this **red block** in  $X$

$$\begin{pmatrix} X_{11} & X_{12} & X_{13} & X_{14} & X_{15} & X_{16} \\ X_{21} & X_{22} & X_{23} & \textcolor{red}{X}_{24} & X_{25} & X_{26} \\ X_{31} & X_{32} & \textcolor{red}{X}_{33} & X_{34} & X_{35} & X_{36} \\ X_{41} & X_{42} & X_{43} & \textcolor{red}{X}_{44} & X_{45} & X_{46} \\ X_{51} & X_{52} & X_{53} & \textcolor{red}{X}_{54} & X_{55} & X_{56} \\ X_{61} & X_{62} & X_{63} & \textcolor{red}{X}_{64} & X_{65} & X_{66} \end{pmatrix}$$

## Writing a certain matrix multiplication as a convolution

### Return to Simple Example

• • •

$$(v_1 \ v_2 \ v_3 \ \textcolor{red}{v}_4 \ \cdots \ v_9) - (g_1 \ g_2 \ \cdots \ g_{16}) = \begin{pmatrix} X_{11} & X_{12} & X_{13} & X_{21} & X_{22} & X_{23} & X_{31} & X_{32} & \textcolor{red}{X}_{33} \\ X_{12} & X_{13} & X_{14} & X_{21} & X_{23} & X_{24} & X_{32} & X_{33} & \textcolor{red}{X}_{34} \\ X_{13} & X_{14} & X_{15} & X_{21} & X_{23} & X_{25} & X_{33} & X_{34} & \textcolor{red}{X}_{35} \\ X_{14} & X_{15} & X_{16} & X_{21} & X_{24} & X_{26} & X_{34} & X_{35} & \textcolor{red}{X}_{36} \\ X_{21} & X_{22} & X_{23} & X_{31} & X_{32} & X_{33} & X_{41} & X_{42} & \textcolor{red}{X}_{43} \\ & & & \vdots & & & & & \\ X_{44} & X_{45} & X_{46} & X_{51} & X_{52} & X_{53} & X_{64} & X_{65} & \textcolor{red}{X}_{66} \end{pmatrix}$$

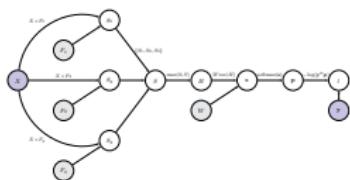
$M_X^{\text{im}}$  size 16 × 9

where **red column** in  $M_X^{\text{im}}$  corresponds to this **red block** in  $X$

$$\begin{pmatrix} X_{11} & X_{12} & X_{13} & X_{14} & X_{15} & X_{16} \\ X_{21} & X_{22} & X_{23} & \textcolor{red}{X}_{24} & X_{25} & X_{26} \\ X_{31} & X_{32} & \textcolor{red}{X}_{33} & X_{34} & X_{35} & X_{36} \\ X_{41} & X_{42} & \textcolor{red}{X}_{43} & X_{44} & X_{45} & X_{46} \\ X_{51} & X_{52} & X_{53} & \textcolor{red}{X}_{54} & X_{55} & X_{56} \\ X_{61} & X_{62} & X_{63} & \textcolor{red}{X}_{64} & X_{65} & X_{66} \end{pmatrix}$$

Thus

$$\begin{pmatrix} v_1 & v_2 & v_3 \\ v_4 & v_5 & v_6 \\ v_7 & v_8 & v_9 \end{pmatrix} = X * \begin{pmatrix} g_1 & g_2 & g_3 & g_4 \\ g_5 & g_6 & g_7 & g_8 \\ g_{10} & g_{11} & g_{12} & \\ g_{13} & g_{14} & g_{15} & g_{16} \end{pmatrix}$$



Gradient Computations for two Convolutional layers

Know

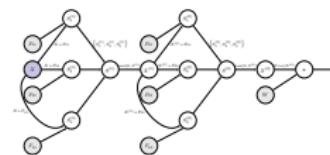
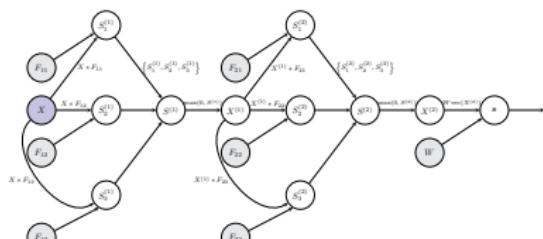
$$\frac{\partial l}{\partial \text{vec}(F_i)} = \sum_{j=1}^3 \frac{\partial l}{\partial \text{vec}(S_i)} M_{X_j}^{\text{im}}$$

but our simple example  $\implies$

$$\frac{\partial l}{\partial F_i} = \sum_{j=1}^3 X_j * \frac{\partial l}{\partial S_i}$$

## Computational Graph: two convolutional layers

How do we back-propagate the gradient to node  $X^{(1)}$ ?



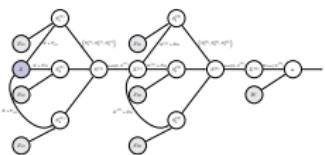
- Children of node  $X^{(1)}$  are  $S_1^{(2)}, S_2^{(2)}$  and  $S_3^{(2)}$
- Thus

$$\frac{\partial l}{\partial \text{vec}(X^{(1)})} = \sum_{i=1}^3 \frac{\partial l}{\partial \text{vec}(S_i^{(2)})} \frac{\partial \text{vec}(S_i^{(2)})}{\partial \text{vec}(X^{(1)})}$$

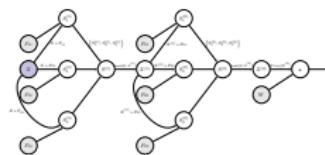
Notes about the figure

- Apply 3 filters at each convolutional layer.
- Have omitted the bias weights for clarity.

How do we back-propagate the gradient to node  $X^{(1)}$ ?



How do we back-propagate the gradient to node  $X^{(1)}$ ?



- Children of node  $X^{(1)}$  are  $S_1^{(2)}, S_2^{(2)}$  and  $S_3^{(2)}$
- Thus

$$\frac{\partial l}{\partial \text{vec}(X^{(1)})} = \sum_{i=1}^3 \frac{\partial l}{\partial \text{vec}(S_i^{(2)})} \frac{\partial \text{vec}(S_i^{(2)})}{\partial \text{vec}(X^{(1)})}$$

↑ already know

- Children of node  $X^{(1)}$  are  $S_1^{(2)}, S_2^{(2)}$  and  $S_3^{(2)}$
- Thus

$$\frac{\partial l}{\partial \text{vec}(X^{(1)})} = \sum_{i=1}^3 \frac{\partial l}{\partial \text{vec}(S_i^{(2)})} \frac{\partial \text{vec}(S_i^{(2)})}{\partial \text{vec}(X^{(1)})}$$

↑ calculate now

Jacobian of  $\text{vec}(S_i^{(2)})$  w.r.t.  $\text{vec}(X^{(1)})$

Writing convolution as a matrix multiplication

- Have for  $i = 1, 2, 3$ :

$$S_i^{(2)} = X^{(1)} * F_{2i}$$

- Can write a convolution (not in a very memory efficient way) as a matrix multiplication

$$\text{vec}(S_i^{(2)}) = M_{F_{2i}}^{\text{filter}} \text{vec}(X^{(1)})$$

- $M_{F_{2i}}$  has size  $(w - f + 1)(h - f + 1) \times 3wh$  (assuming  $X^{(1)}$  has size  $w \times h \times 3$  and  $F_{2i}$  has size  $f \times f \times 3$ )
- What are the entries of  $M_{F_{2i}}^{\text{filter}}$ ?

### Simple Example

- Have an input image  $X$  of size  $6 \times 6 \times 1$ .
- Have a filter  $F$  of size  $3 \times 3 \times 1$ .
- Convolve  $X$  by  $F$  gives a response map of size  $4 \times 4$

$$S = X * F$$

- Each entry of  $S$  can be written as

$$S_{lm} = \sum_{k=1}^1 \sum_{i=1}^3 \sum_{j=1}^3 X_{k,i+l-1,j+m-1} F_{kij}$$



## Writing convolution as a matrix multiplication

## Writing convolution as a matrix multiplication

## Simple Example

Write this convolution as a matrix multiplication involving  $\text{vec}(X)$

$$S = \begin{pmatrix} X_{11} & X_{12} & X_{13} & X_{14} & X_{15} & X_{16} \\ X_{21} & X_{22} & X_{23} & X_{24} & X_{25} & X_{26} \\ X_{31} & X_{32} & X_{33} & X_{34} & X_{35} & X_{36} \\ X_{41} & X_{42} & X_{43} & X_{44} & X_{45} & X_{46} \\ X_{51} & X_{52} & X_{53} & X_{54} & X_{55} & X_{56} \end{pmatrix} + \begin{pmatrix} F_{11} & F_{12} & F_{13} \\ F_{21} & F_{22} & F_{23} \\ F_{31} & F_{32} & F_{33} \end{pmatrix}$$

**Solution:**

$$\begin{pmatrix} S_{11} \\ S_{12} \\ S_{13} \\ S_{14} \\ S_{21} \end{pmatrix} = \underbrace{\begin{pmatrix} F_{11} & F_{12} & F_{13} & 0 & 0 \\ 0 & F_{11} & F_{12} & F_{13} & 0 \\ 0 & 0 & F_{11} & F_{12} & F_{13} \\ 0 & 0 & 0 & F_{11} & F_{12} \\ 0 & 0 & 0 & 0 & F_{11} \end{pmatrix}}_{\text{entries corresponding to row 1 of } X} \quad \underbrace{\begin{pmatrix} F_{21} & F_{22} & F_{23} & 0 & 0 \\ 0 & F_{21} & F_{22} & F_{23} & 0 \\ 0 & 0 & F_{21} & F_{22} & F_{23} \\ 0 & 0 & 0 & F_{21} & F_{22} \\ 0 & 0 & 0 & 0 & F_{21} \end{pmatrix}}_{\text{row 2 of } X} \quad \underbrace{\begin{pmatrix} F_{31} & F_{32} & F_{33} & 0 & 0 \\ 0 & F_{31} & F_{32} & F_{33} & 0 \\ 0 & 0 & F_{31} & F_{32} & F_{33} \\ 0 & 0 & 0 & F_{31} & F_{32} \\ 0 & 0 & 0 & 0 & F_{31} \end{pmatrix}}_{\text{row 3 of } X} \quad \cdots \quad \text{vec}(X)$$

$S_{21}$  is the dot product between  $F$  and red entries of  $X$ :

$X_{11}$	$X_{12}$	$X_{13}$	$X_{14}$	$X_{15}$	$X_{16}$
$X_{21}$	$X_{22}$	$X_{23}$	$X_{24}$	$X_{25}$	$X_{26}$
$X_{31}$	$X_{32}$	$X_{33}$	$X_{34}$	$X_{35}$	$X_{36}$
$X_{41}$	$X_{42}$	$X_{43}$	$X_{44}$	$X_{45}$	$X_{46}$
$X_{51}$	$X_{52}$	$X_{53}$	$X_{54}$	$X_{55}$	$X_{56}$
$X_{61}$	$X_{62}$	$X_{63}$	$X_{64}$	$X_{65}$	$X_{66}$

## Writing convolution as a matrix multiplication

## Simple Example

Write this convolution as a matrix multiplication involving  $\text{vec}(X)$

$$S = \begin{pmatrix} X_{11} & X_{12} & X_{13} & X_{14} & X_{15} & X_{16} \\ X_{21} & X_{22} & X_{23} & X_{24} & X_{25} & X_{26} \\ X_{31} & X_{32} & X_{33} & X_{34} & X_{35} & X_{36} \\ X_{41} & X_{42} & X_{43} & X_{44} & X_{45} & X_{46} \\ X_{51} & X_{52} & X_{53} & X_{54} & X_{55} & X_{56} \\ X_{61} & X_{62} & X_{63} & X_{64} & X_{65} & X_{66} \end{pmatrix} + \begin{pmatrix} F_{11} & F_{12} & F_{13} \\ F_{21} & F_{22} & F_{23} \\ F_{31} & F_{32} & F_{33} \end{pmatrix}$$

**Solution:**

Thus

$$\text{vec}(S) = M_E^{\text{filter}} \text{vec}(X)$$

## Simple Example

Write this convolution as a matrix multiplication involving  $\text{vec}(X)$

$$S = \begin{pmatrix} X_{11} & X_{12} & X_{13} & X_{14} & X_{15} & X_{16} \\ X_{21} & X_{22} & X_{23} & X_{24} & X_{25} & X_{26} \\ X_{31} & X_{32} & X_{33} & X_{34} & X_{35} & X_{36} \\ X_{41} & X_{42} & X_{43} & X_{44} & X_{45} & X_{46} \\ X_{51} & X_{52} & X_{53} & X_{54} & X_{55} & X_{56} \\ X_{61} & X_{62} & X_{63} & X_{64} & X_{65} & X_{66} \end{pmatrix} + \begin{pmatrix} F_{11} & F_{12} & F_{13} \\ F_{21} & F_{22} & F_{23} \\ F_{31} & F_{32} & F_{33} \end{pmatrix}$$

**Solution:**

$$\begin{matrix} & \text{entries corresponding to row 1 of } X & & \text{row 2 of } X & & \text{row 3 of } X & & \cdots \\ \left( \begin{matrix} S_{11} \\ S_{12} \\ S_{13} \\ S_{14} \\ S_{21} \end{matrix} \right) = & \left( \begin{matrix} F_{11} & F_{12} & F_{13} & 0 & 0 & F_{21} & F_{22} & F_{23} & 0 & 0 & F_{31} & F_{32} & F_{33} & 0 & 0 \\ 0 & F_{11} & F_{12} & F_{13} & 0 & 0 & F_{21} & F_{22} & F_{23} & 0 & 0 & F_{31} & F_{32} & F_{33} & 0 & 0 \\ 0 & 0 & F_{11} & F_{12} & F_{13} & 0 & 0 & F_{21} & F_{22} & F_{23} & 0 & 0 & F_{31} & F_{32} & F_{33} & 0 & 0 \\ 0 & 0 & 0 & F_{11} & F_{12} & F_{13} & 0 & 0 & F_{21} & F_{22} & F_{23} & 0 & 0 & F_{31} & F_{32} & F_{33} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & F_{11} & F_{12} & F_{13} & 0 & 0 & F_{21} & F_{22} & F_{23} & 0 & 0 \end{matrix} \right) & \text{vec}(X) \end{matrix}$$

Multiple planes: Convolution → Matrix multiplication

- What about when  $X$  and  $F_1$  have multiple planes?
  - $X = \{X_1, X_2, X_3, X_4\}$  has size  $6 \times 6 \times 4$
  - $F_1 = \{F_{11}, F_{12}, F_{13}, F_{14}\}$  has size  $3 \times 3 \times 4$
  - Let

$$S_1 = X * F_1$$

$$\text{vec}(S_1) = M_E^{\text{filter}} \text{vec}(X)$$

where

$$M_{F_1^*}^{\text{filter}} = (M_{F_1^{*,1}}^{\text{filter}} \quad M_{F_1^{*,2}}^{\text{filter}} \quad M_{F_1^{*,3}}^{\text{filter}} \quad M_{F_1^{*,4}}^{\text{filter}})$$

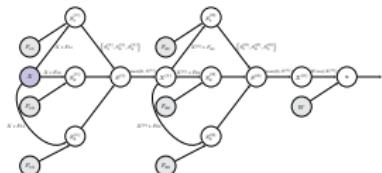
and has size  $16 \times 144$ .

- Have for  $i = 1, 2, 3$ :

$$S_i^{(2)} = X^{(1)} * F_{2i}$$

- Can write a convolution (not in a very memory efficient way) as a matrix multiplication

$$\text{vec}(S_i^{(2)}) = M_{F_{2i}}^{\text{filter}} \text{vec}(X^{(1)})$$



- Thus

- $M_{F_{2i}}^{\text{filter}}$  has size  $(w' - f + 1)(h' - f + 1) \times 3w'h'$  (where  $w' = w - f + 1$  and  $h' = h - f + 1$ ).

- Thus

$$\frac{\partial \text{vec}(S_i^{(2)})}{\partial \text{vec}(X^{(1)})} = M_{F_{2i}}^{\text{filter}}$$

Gradient of the loss w.r.t.  $X^{(1)}$ 

- May want expression for  $\frac{\partial l}{\partial X^{(1)}}$  instead of  $\frac{\partial l}{\partial \text{vec}(X^{(1)})}$ .

- **Option 1:**

Reshape  $\frac{\partial l}{\partial \text{vec}(X^{(1)})}$  (size  $1 \times 3w'h'$ ) to  $\frac{\partial l}{\partial X^{(1)}}$  (size  $w' \times h' \times 3$ ).

- May want expression for  $\frac{\partial l}{\partial X^{(1)}}$  instead of  $\frac{\partial l}{\partial \text{vec}(X^{(1)})}$ .

- **Option 2:**

Return to our simple example ...

Gradient of the loss w.r.t.  $X^{(1)}$

Turn our matrix multiplication to convolution

Consider the case

$$\begin{pmatrix} x_1 & x_2 & \dots & x_m \end{pmatrix} = \begin{pmatrix} g_1 & g_2 & \dots & g_m \end{pmatrix} \begin{pmatrix} 0 & 0 & \dots & 0 \\ 0 & 0 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & 0 \end{pmatrix}$$

$$v_1 = g_1 F_{11}$$

Turn matrix multiplication to convolution

Turn matrix multiplication to convolution

$$w_1 = g_1 F_{11}$$

$$v_2 = g_1 F_{12} + g_2 F_{11}$$

Turn matrix multiplication to convolution

$$v_1 = g_1 F_{11}$$

$$v_2 = g_1 F_{12} + g_2 F_{11}$$

$$v_3 = g_1 F_{13} + g_2 F_{12} + g_3 F_{11}$$



- $X = \{X_1, X_2, X_3, X_4\}$  has size  $6 \times 6 \times 4$
- $F = \{F_1, F_2, F_3, F_4\}$  has size  $3 \times 3 \times 4$
- Let

$$S = X * F \quad (S_1 \text{ has size } 4 \times 4)$$

- Then

$$\text{vec}(S) = M_F^{\text{filter}} \text{vec}(X)$$

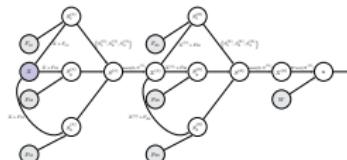
where  $M_F^{\text{filter}}$  has size  $16 \times 144$ .

- Let

$$\mathbf{v}^T = \mathbf{g}^T M_F^{\text{filter}}$$

- Let  $\text{vec}(V) = \mathbf{v}$  and  $\text{vec}(G) = \mathbf{g}$  then

$$V = \{G_{\text{zero-pad}} * F_1^{\text{rot180}}, G_{\text{zero-pad}} * F_2^{\text{rot180}}, G_{\text{zero-pad}} * F_3^{\text{rot180}}, G_{\text{zero-pad}} * F_4^{\text{rot180}}\}$$



Know

$$\frac{\partial l}{\partial \text{vec}(X^{(1)})} = \sum_{i=1}^3 \frac{\partial l}{\partial \text{vec}(S_i^{(2)})} M_{F_{2i}}^{\text{filter}}$$

then

$$\frac{\partial l}{\partial X^{(1)}} = \sum_{i=1}^3 \left\{ G_i^{\text{zero-pad}} * F_{2i,1}^{\text{rot180}}, G_i^{\text{zero-pad}} * F_{2i,2}^{\text{rot180}}, G_i^{\text{zero-pad}} * F_{2i,3}^{\text{rot180}} \right\}$$

where  $G_i = \frac{\partial l}{\partial S_i^{(2)}}$  and  $F_{2i} = \{F_{2i,1}, F_{2i,2}, F_{2i,3}\}$ .