

CNN

Arquiteturas e Backpropagation

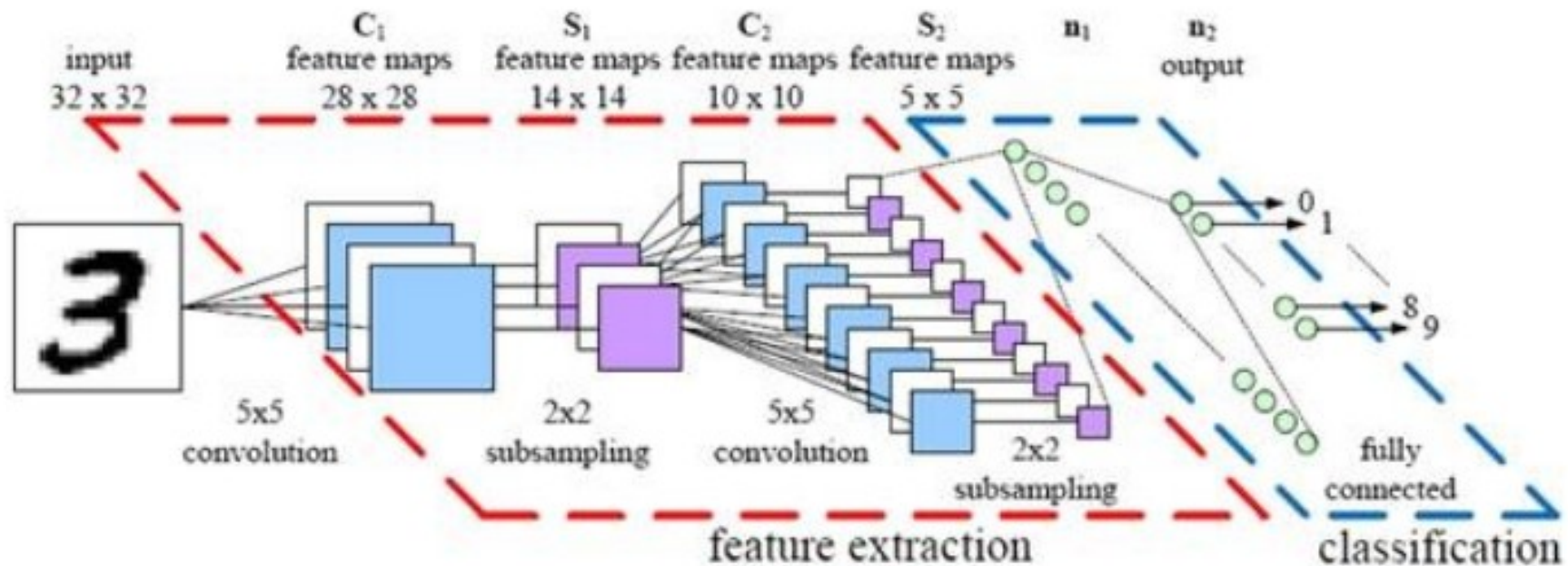
CNN - recapitulando

Tipos de camadas

- Convolutacional : Definem os filtros (Aprendizado / BackPropagation)
- Ativação: Neurônios (Relu / Sigmoid / TangH)
- Pooling : Reduzem as escalas (Max, Median, etc..)
- Fully-Connected (FC): Camada que determina as classes (Classificador)

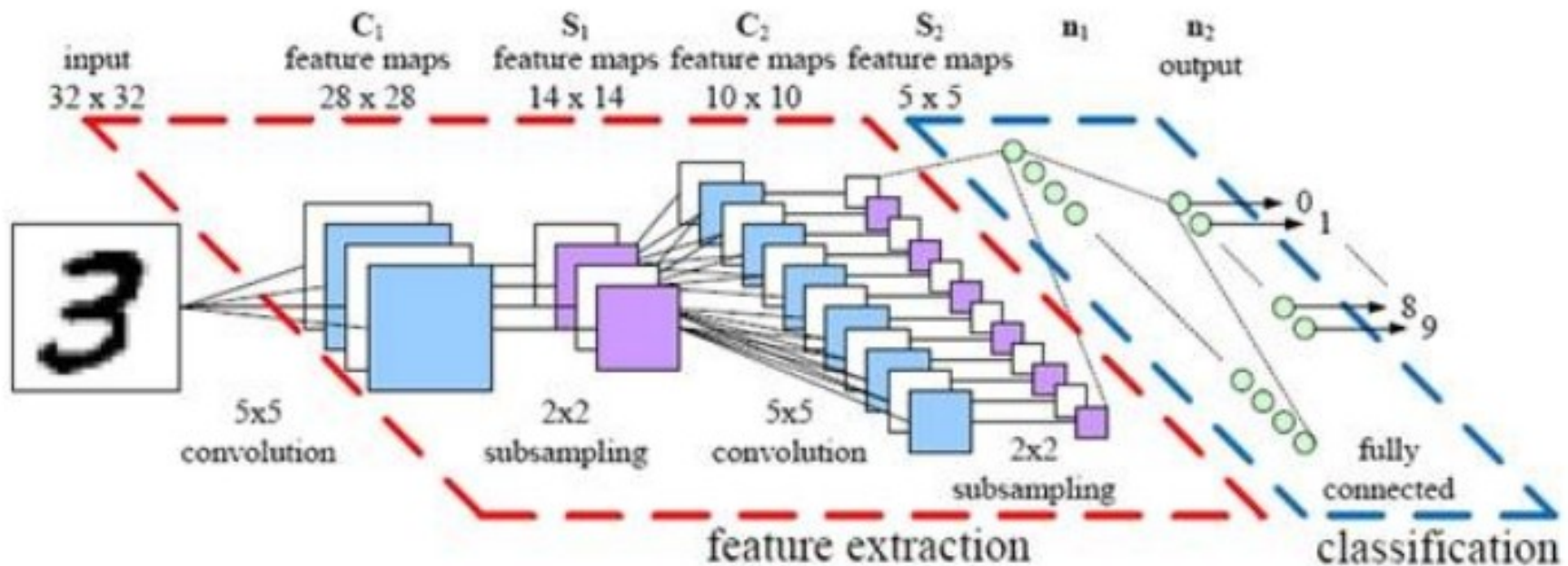
CNN - recapitulando

- Compostas de duas grandes etapas:
 - Extração de Características pelas Camadas Convolucionais
 - Classificação



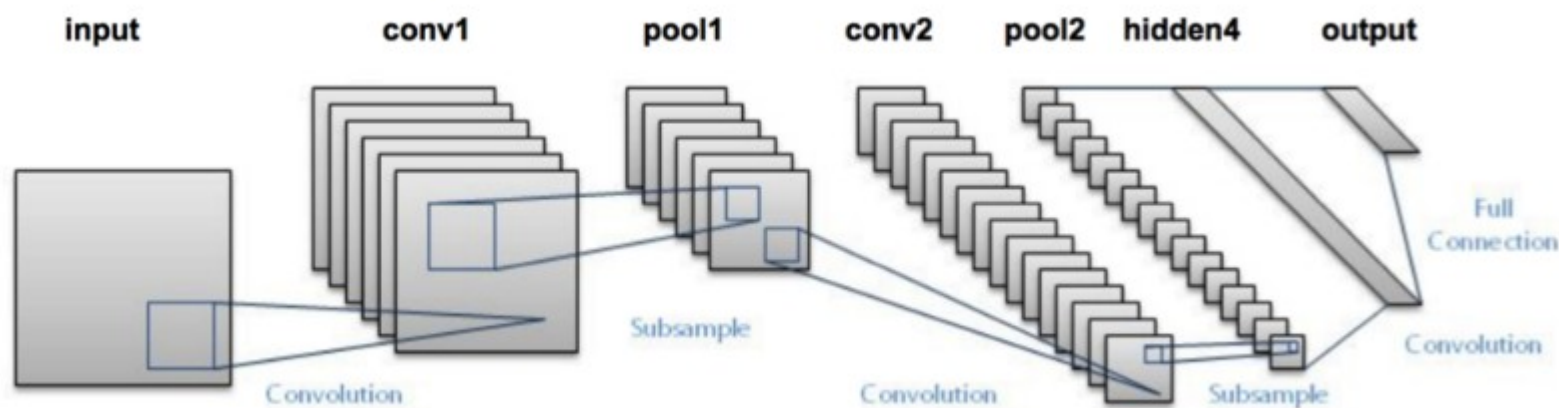
CNN - Arquiteturas

A maneira como estas camadas são conectadas definem as arquiteturas.



CNN - Arquiteturas

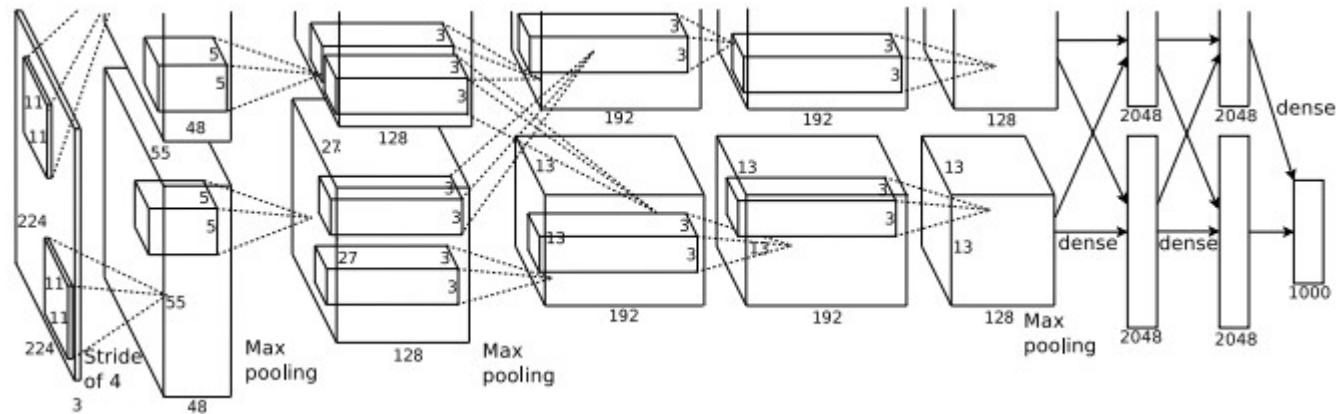
LeNet-5 (1998)



Pioneira – aplicada a bancos de dados de escrita manual para classificação de dígitos.

CNN - Arquiteturas

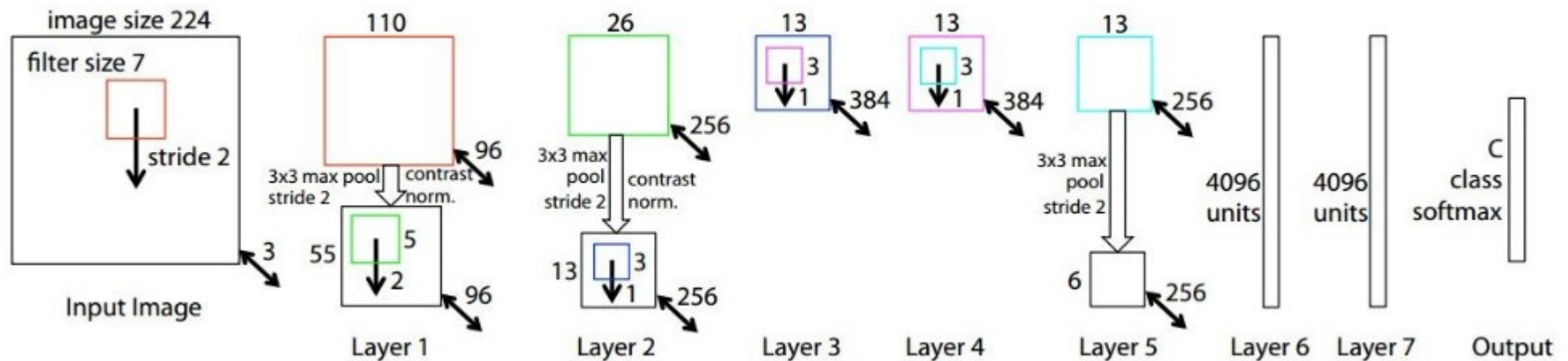
AlexNet (2012)



A rede tinha uma arquitetura muito semelhante à LeNet. Mas era mais profunda, com mais filtros por camada e com camadas convolucionais Empilhadas.

CNN - Arquiteturas

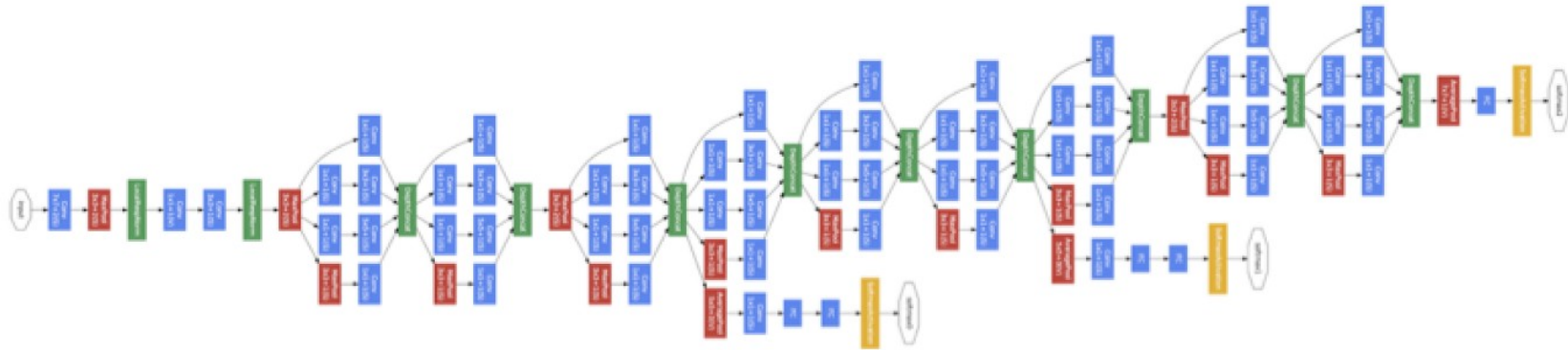
ZFNet (2013)



Foi uma melhoria obtida ajustando os hiperparâmetros do AlexNet, mantendo a mesma estrutura com elementos adicionais de Deep Learning.

CNN - Arquiteturas

GoogleNet/Inception (2014)

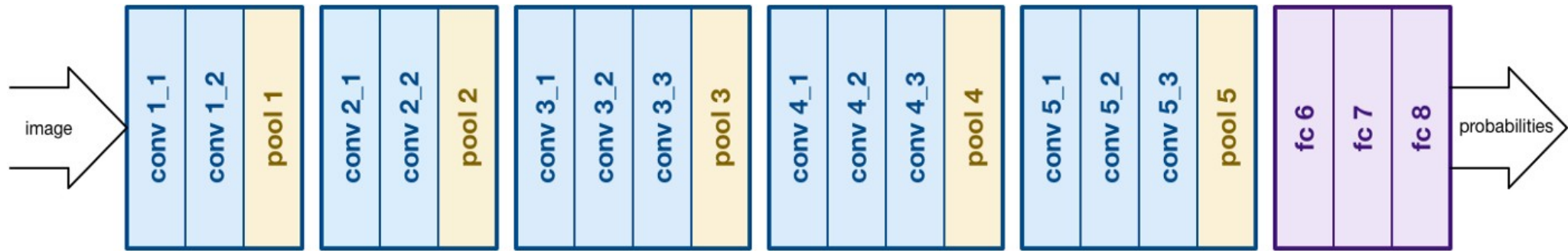


Sua arquitetura consistia em uma CNN com 22 camadas de profundidade, mas reduziu o número de parâmetros de 60 milhões (AlexNet) para 4 milhões.

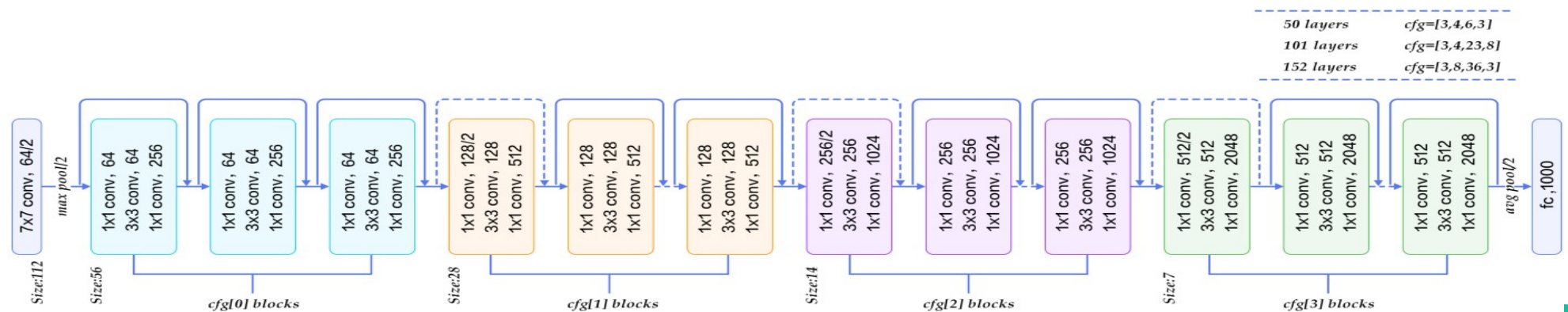


CNN - Arquiteturas

VGGNet (2014)



ResNet (2015)



CNN - Arquiteturas

ImageNet Large Scale Visual Recognition Challenge (ILSVRC)

Year	CNN	Developed by	Place	Top-5 error rate	No. of parameters
1998	LeNet(8)	Yann LeCun et al			60 thousand
2012	AlexNet(7)	Alex Krizhevsky, Geoffrey Hinton, Ilya Sutskever	1st	15.3%	60 million
2013	ZFNet()	Matthew Zeiler and Rob Fergus	1st	14.8%	
2014	GoogLeNet(19)	Google	1st	6.67%	4 million
2014	VGG Net(16)	Simonyan, Zisserman	2nd	7.3%	138 million
2015	<u>ResNet(152)</u>	Kaiming He	1st	3.6%	

CNN - Backpropagation

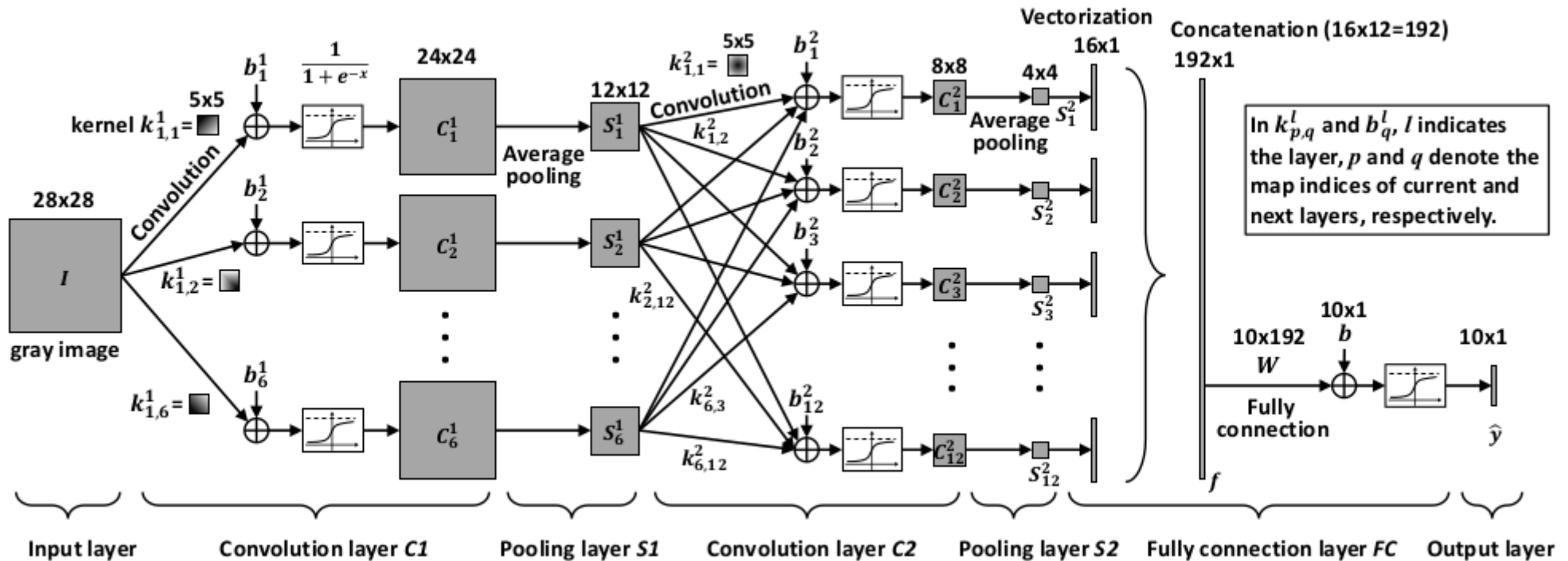
Artigo

Derivation of Backpropagation in Convolutional Neural Network (CNN)

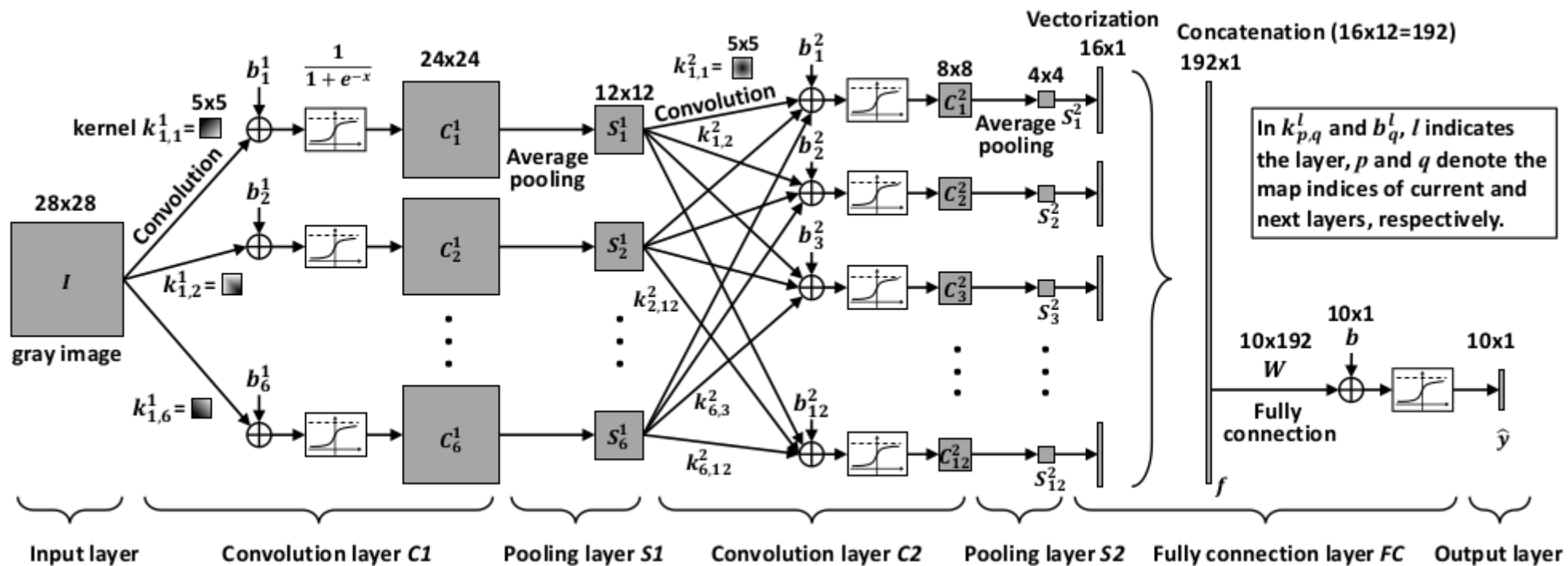
Zhifei Zhang

University of Tennessee, Knoxville, TN

CNN - Backpropagation



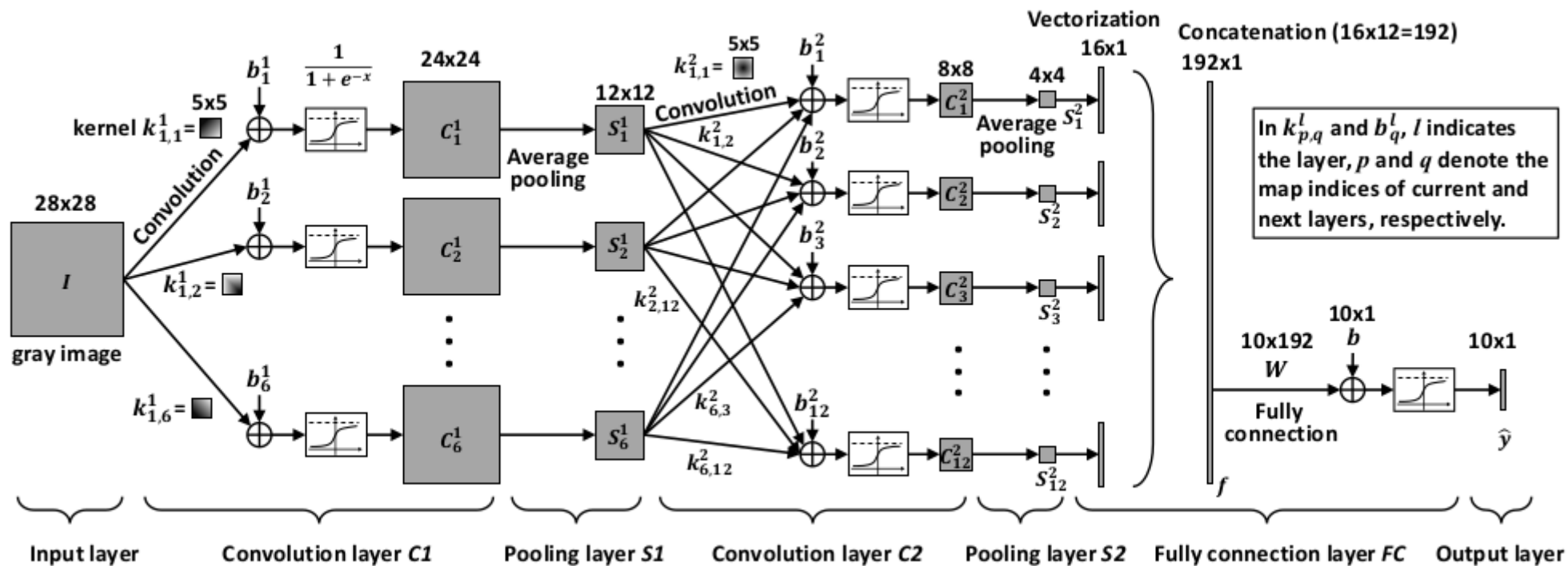
CNN - Backpropagation



Inicialização de parâmetros:

- C1 layer, $k_{1,p}^1$ (size 5×5) and b_p^1 (size 1×1), $p = 1, 2, \dots, 6$
- C2 layer, $k_{p,q}^2$ (size 5×5) and b_q^2 (size 1×1), $q = 1, 2, \dots, 12$
- FC layer, W (size 10×192) and b (size 10×1)

CNN - Backpropagation



Inicialização de parâmetros:

bias, b_p^1 , b_q^2 , and b , are initialize to zero

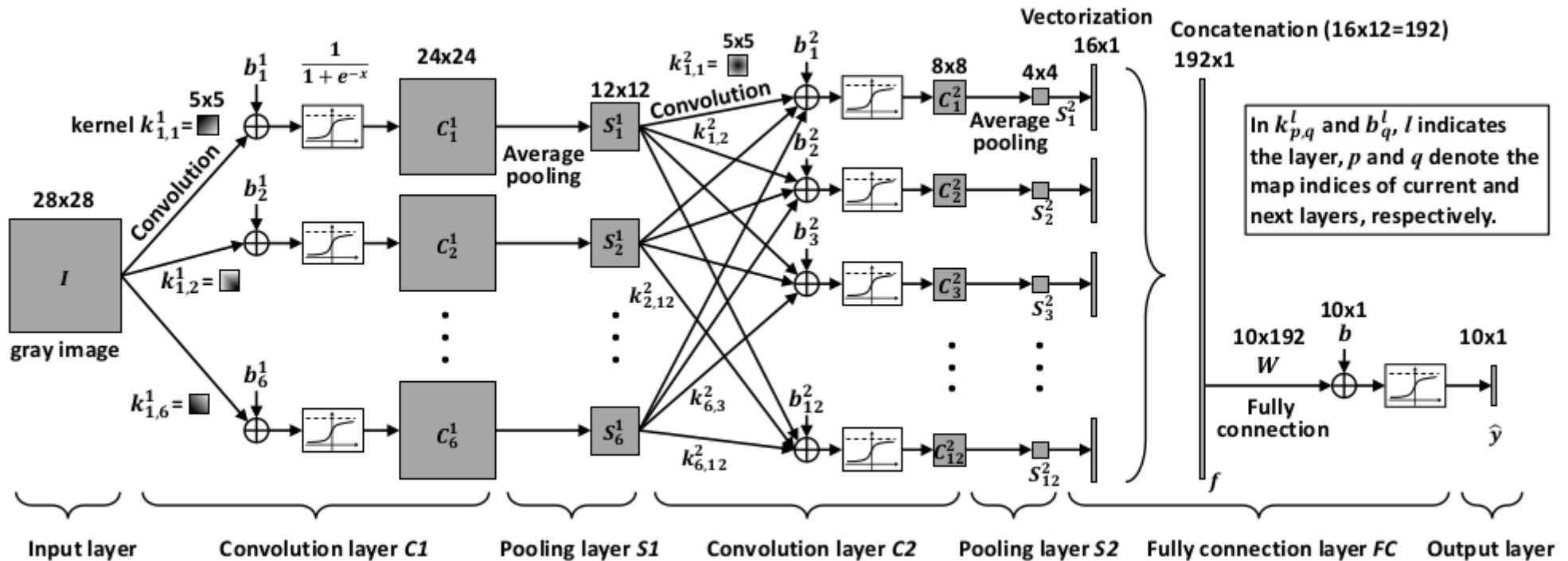
Aleatório
com
distribuição
uniforme

$$k_{1,p}^1 \sim U\left(\pm \sqrt{\frac{6}{(1+6) \times 5^2}}\right)$$

$$k_{p,q}^2 \sim U\left(\pm \sqrt{\frac{6}{(6+12) \times 5^2}}\right)$$

$$W \sim U\left(\pm \sqrt{\frac{6}{192+10}}\right)$$

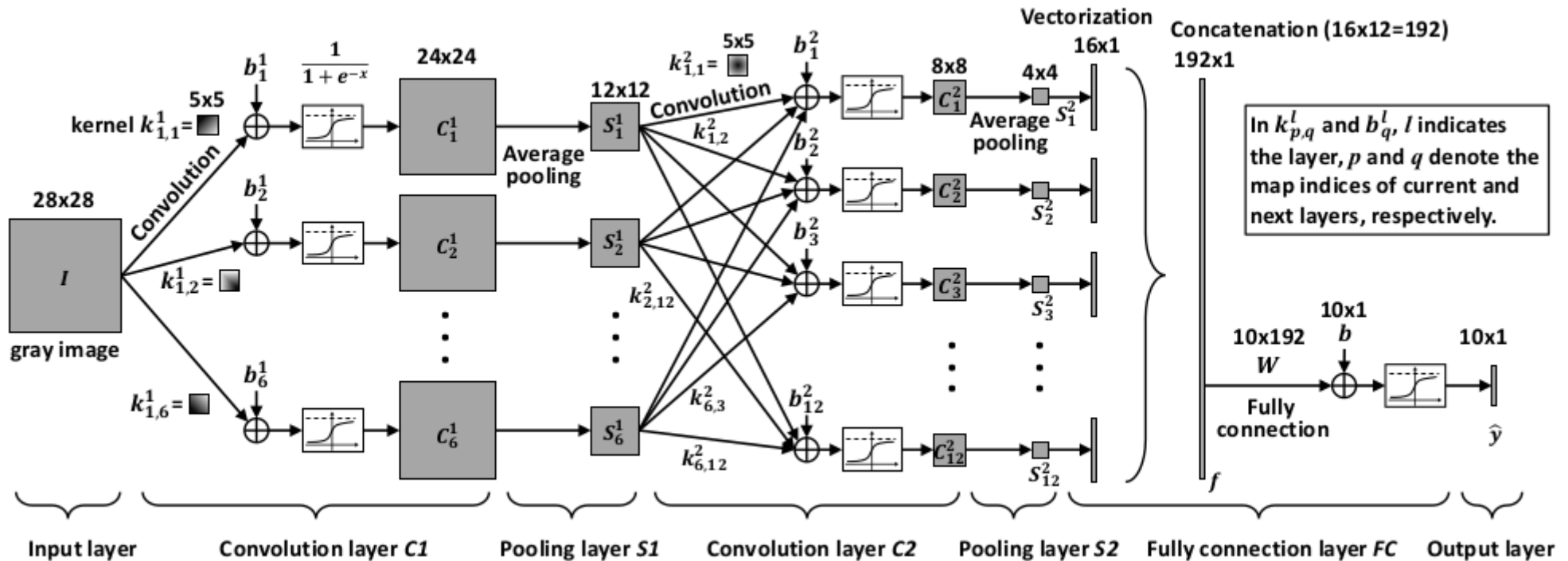
CNN - Backpropagation



$$C_p^1 = \sigma(I * k_{1,p}^1 + b_p^1), \text{ where } \sigma(x) = \frac{1}{1 + \exp^{-x}}$$

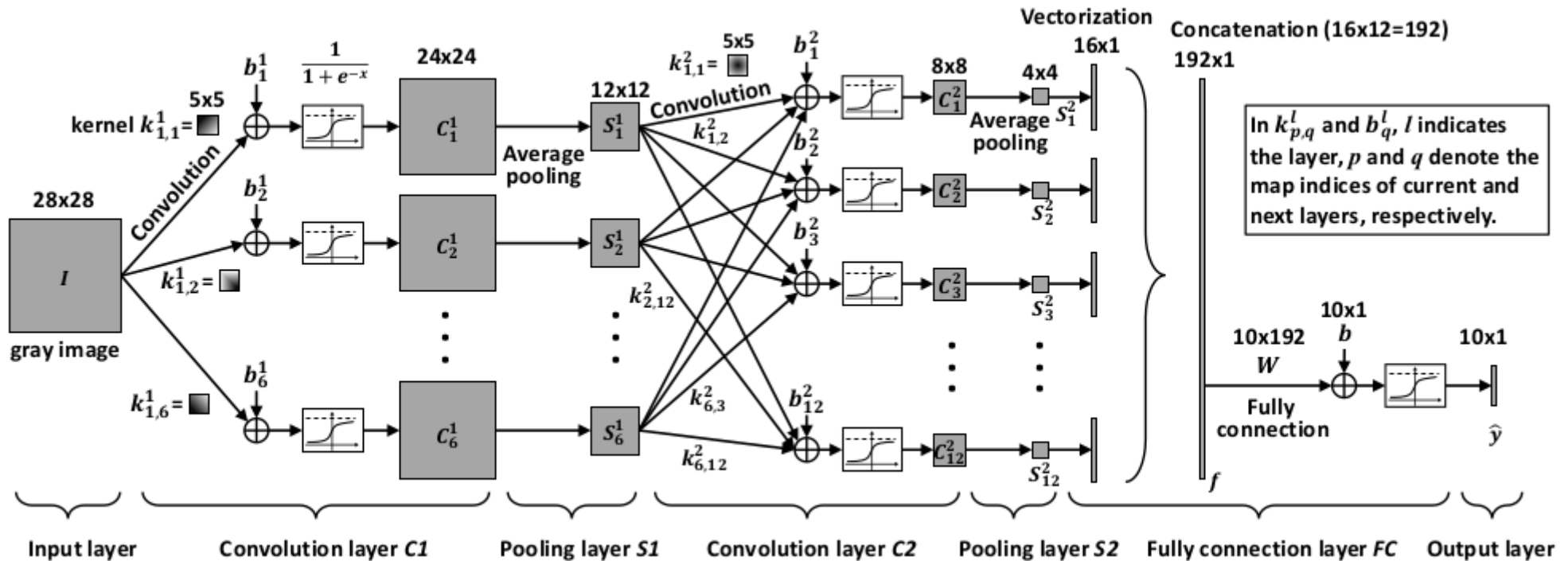
$$C_p^1(i, j) = \sigma \left(\sum_{u=-2}^2 \sum_{v=-2}^2 I(i-u, j-v) \cdot k_{1,p}^1(u, v) + b_p^1 \right)$$

CNN - Backpropagation



$$S_p^1(i, j) = \frac{1}{4} \sum_{u=0}^1 \sum_{v=0}^1 C_p^1(2i - u, 2j - v), \quad i, j = 1, 2, \dots, 12$$

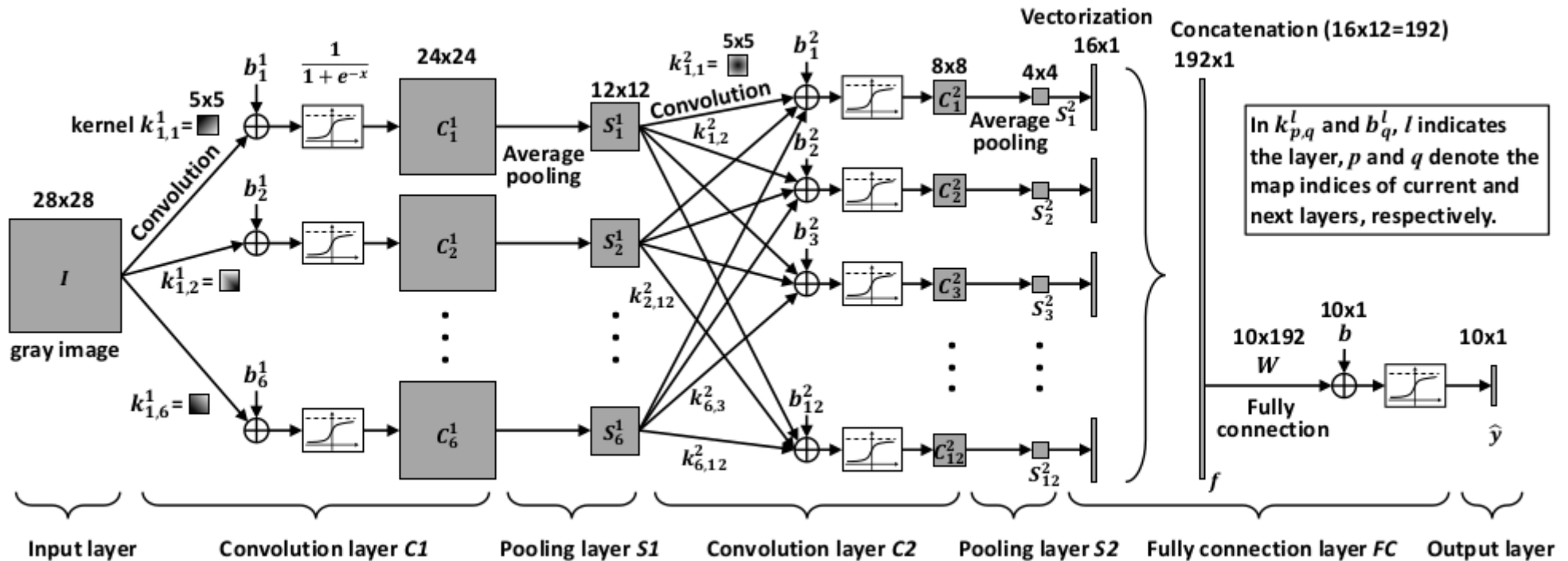
CNN - Backpropagation



$$C_q^2 = \sigma \left(\sum_{p=1}^6 S_p^1 * k_{p,q}^2 + b_q^2 \right)$$

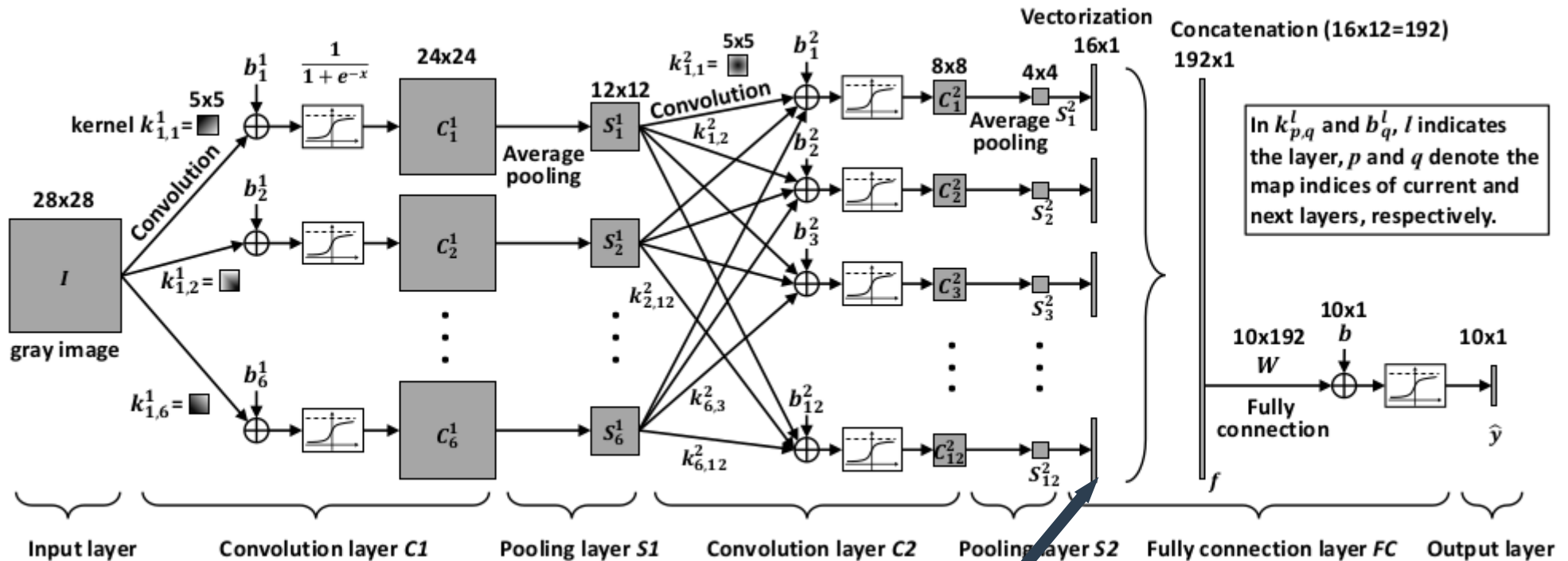
$$C_q^2(i, j) = \sigma \left(\sum_{p=1}^6 \sum_{u=-2}^2 \sum_{v=-2}^2 S_p^1(i-u, j-v) \cdot k_{p,q}^2(u, v) + b_q^2 \right)$$

CNN - Backpropagation



$$S_q^2(i, j) = \frac{1}{4} \sum_{u=0}^1 \sum_{v=0}^1 C_q^2(2i - u, 2j - v), \quad i, j = 1, 2, \dots, 4$$

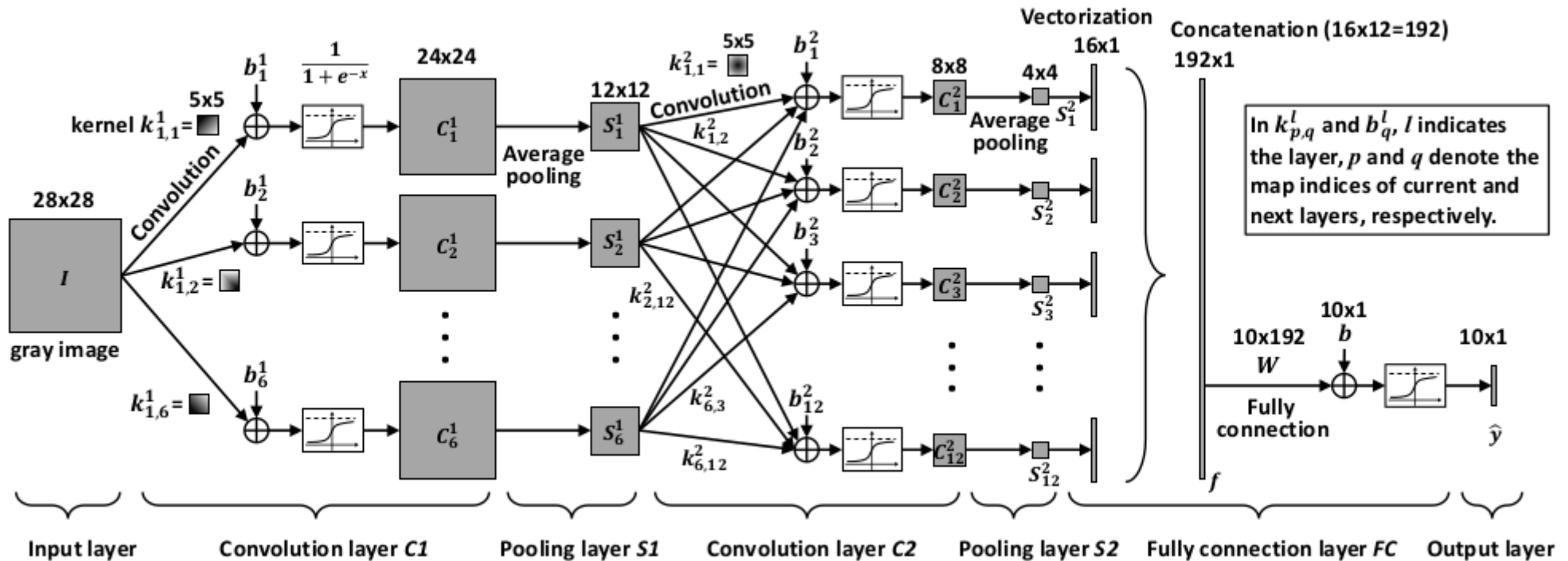
CNN - Backpropagation



Vetorização: $f = F(\{S_q^2\}_{q=1,2,\dots,12})$

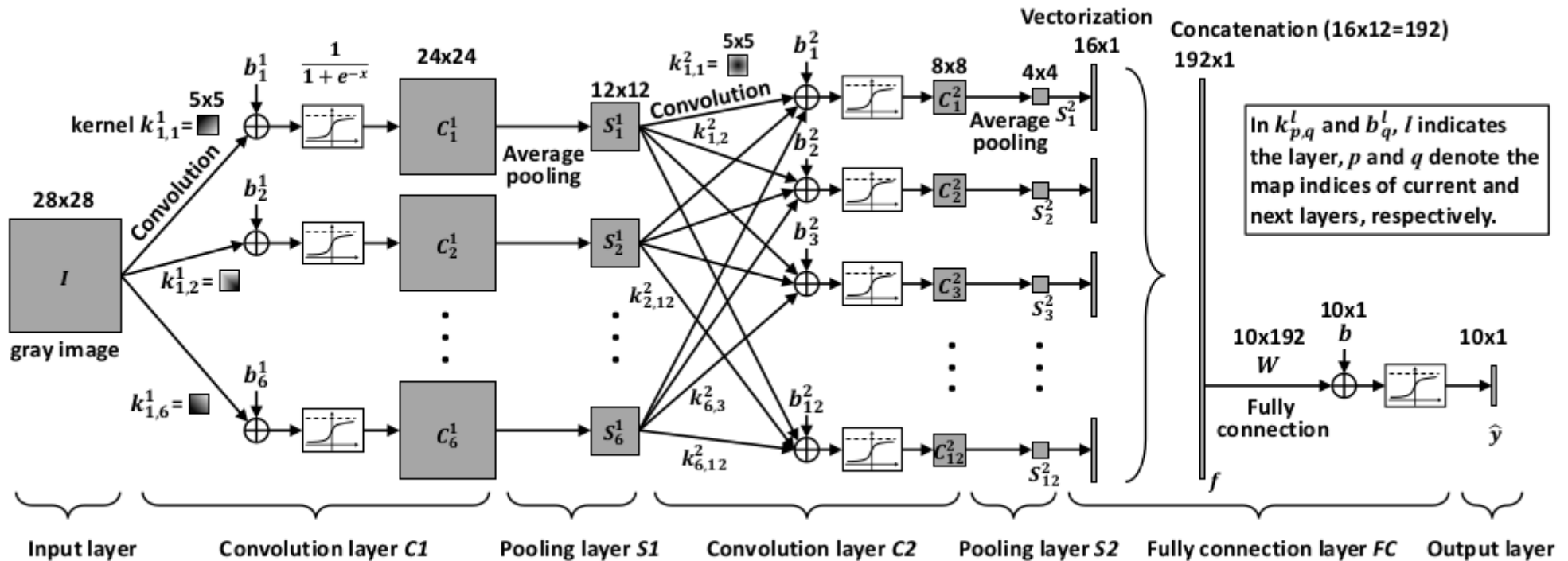
Operação Inversa: $\{S_q^2\}_{q=1,2,\dots,12} = F^{-1}(f)$

CNN - Backpropagation



$$\hat{y} = \sigma(W \times f + b)$$

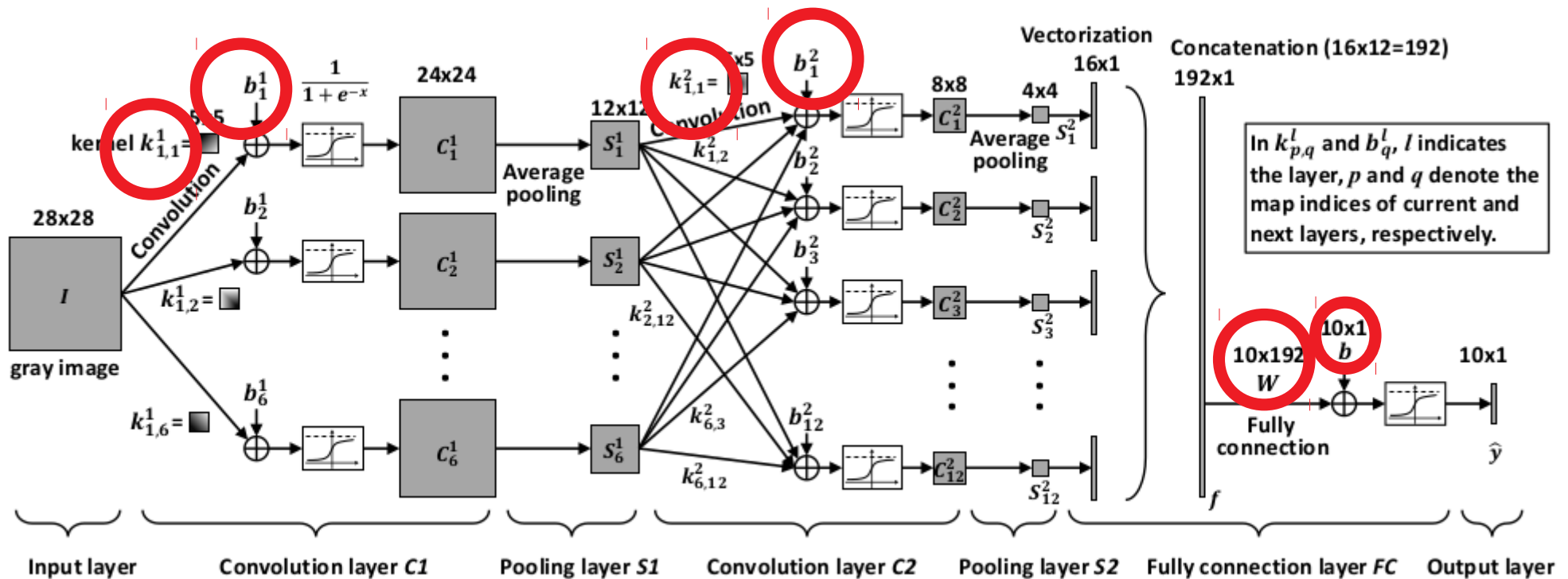
CNN - Backpropagation



Função de custo

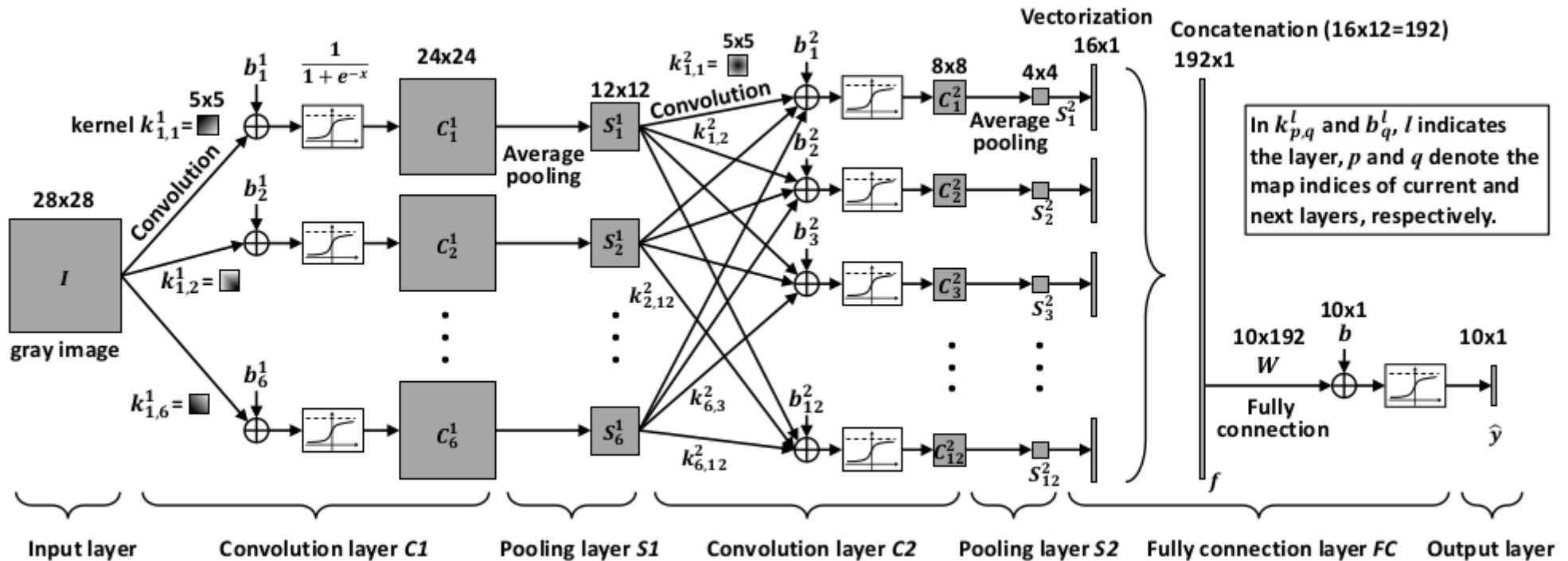
$$L = \frac{1}{2} \sum_{i=1}^{10} (\hat{y}(i) - y(i))^2$$

CNN - Backpropagation



Queremos ajustar estes parâmetros para minimizar a função de custo

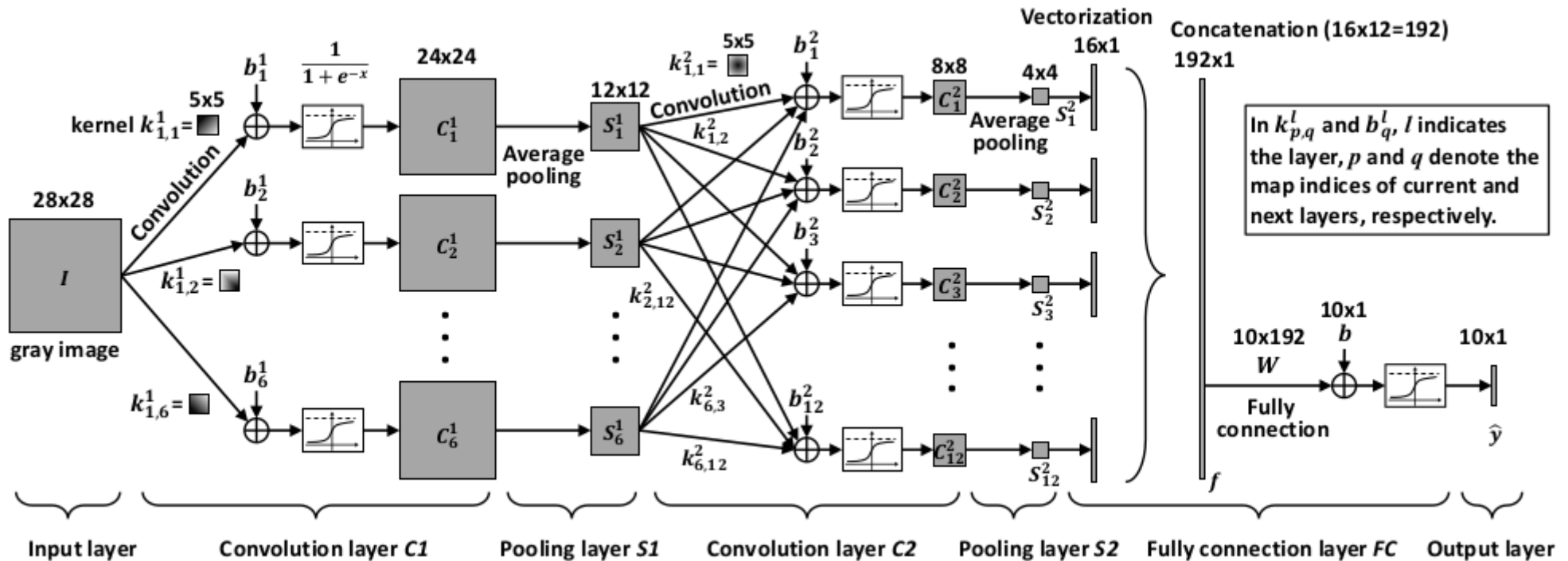
CNN - Backpropagation



$$\Delta W(i, j) = \frac{\partial L}{\partial W(i, j)}$$

$$\begin{aligned} \Delta W(i, j) &= \Delta \hat{y}(i) \cdot f(j) \\ \Rightarrow \Delta W &= \Delta \hat{y} \times f^T \end{aligned}$$

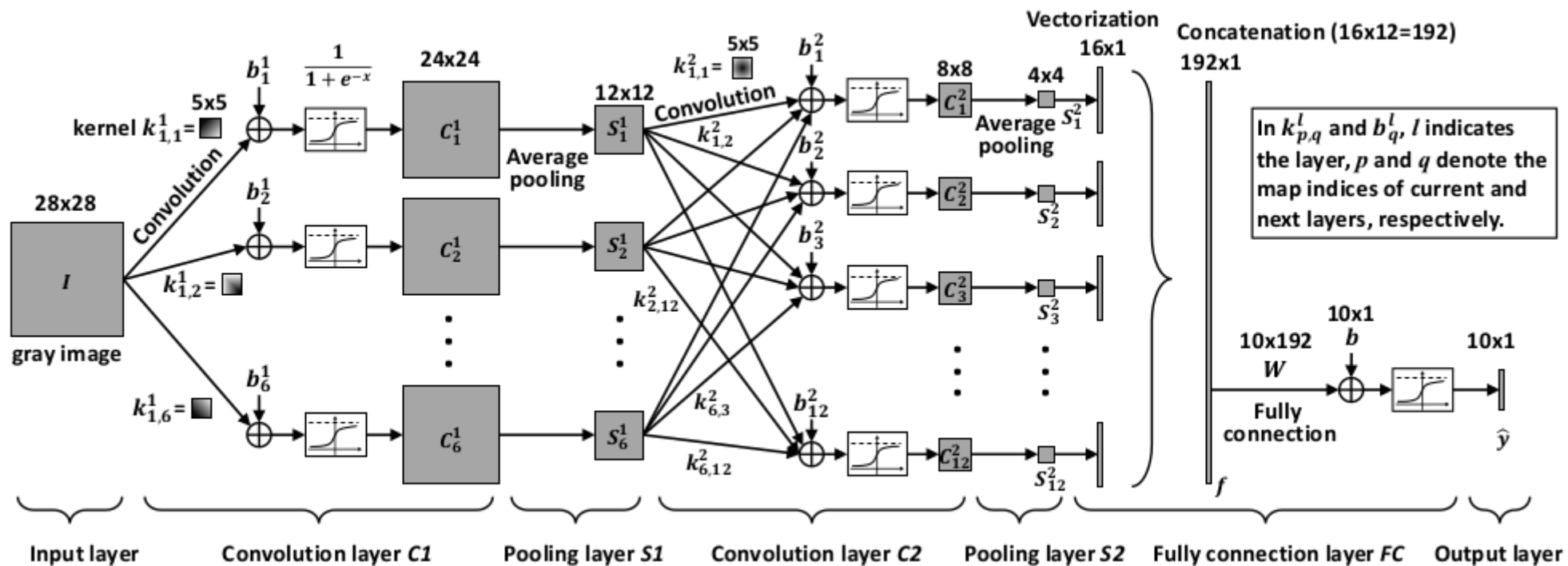
CNN - Backpropagation



$$\Delta b(i) = \frac{\partial L}{\partial b(i)}$$

$$\Delta b = \Delta \hat{y}$$

CNN - Backpropagation



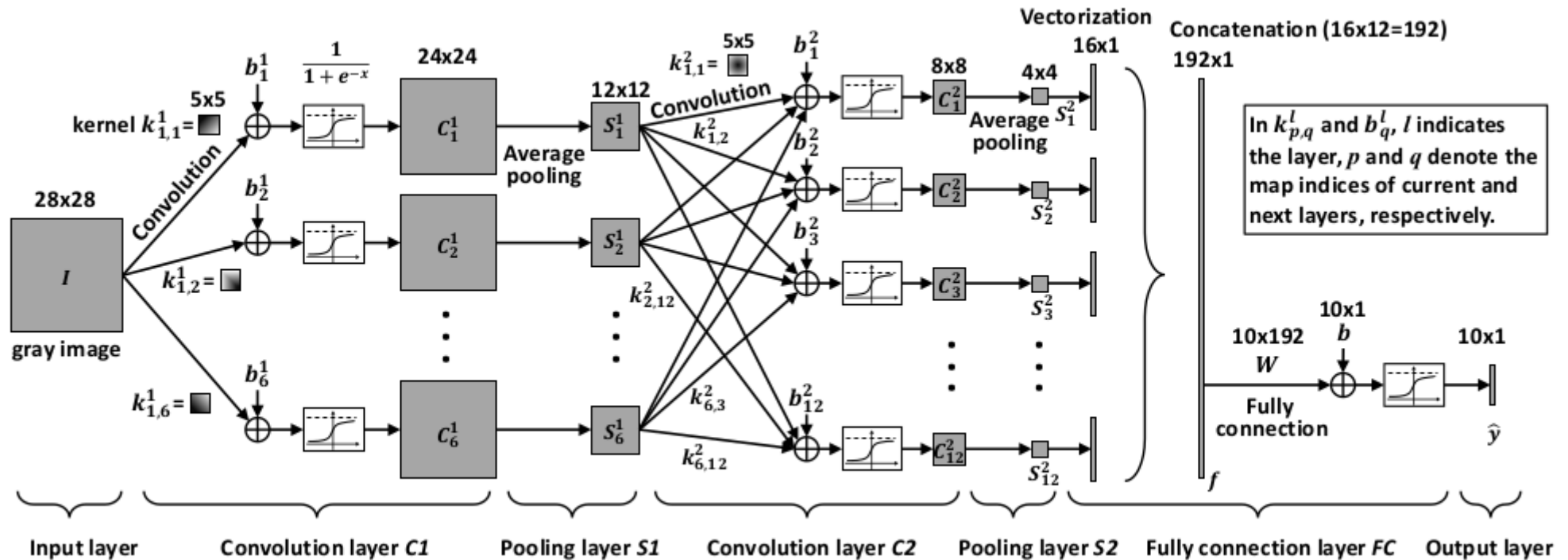
$\Delta k^2_{p,q}$ (size 5×5) Calculamos $\Delta f(j) = \frac{\partial L}{\partial f} \Rightarrow \Delta f = W^T \times \Delta \hat{y}$

Reformatamos o vetor $\{\Delta S^2_q\}_{q=1,2,\dots,12} = F^{-1}(\Delta f)$

Então calculamos $\Delta C^2_q(i, j) = \frac{1}{4} \Delta S^2_q(\lceil i/2 \rceil, \lceil j/2 \rceil)$, $i, j = 1, 2, \dots, 8$
(upsampling)

$\lceil \cdot \rceil$ denotes the ceiling function

CNN - Backpropagation

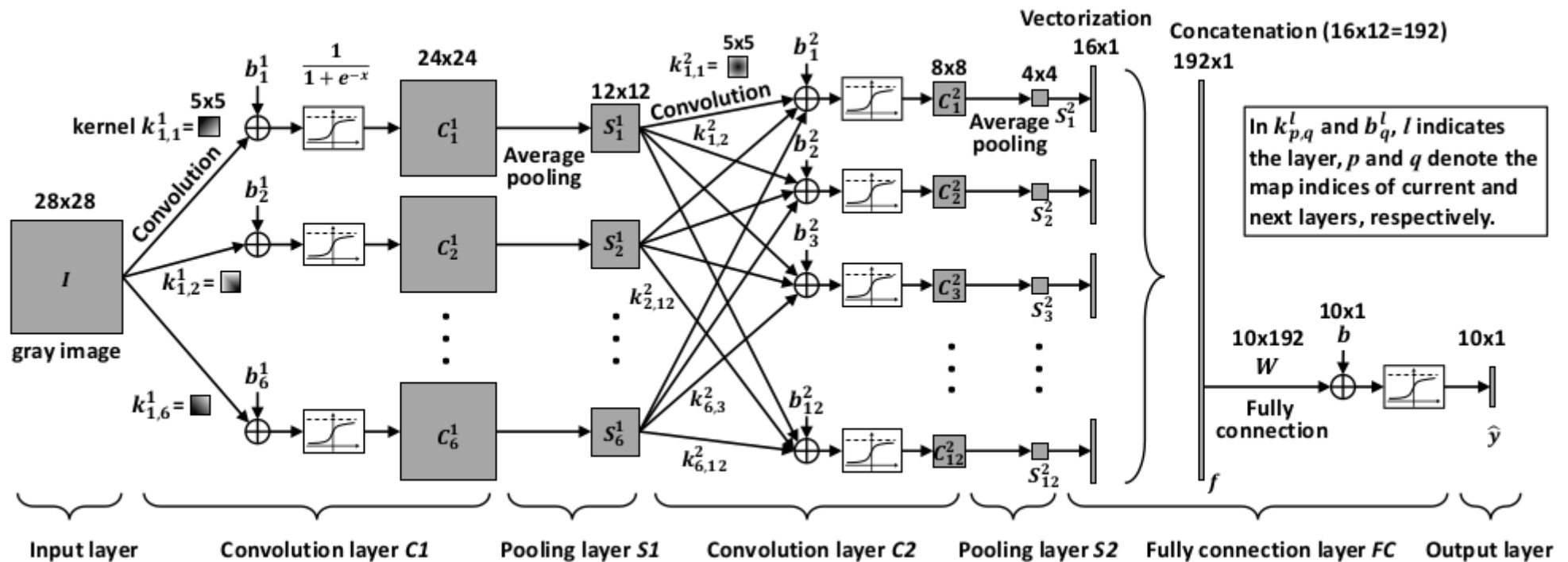


$$\Delta k_{p,q}^2 \text{ (size } 5 \times 5)$$

$$\Delta k_{p,q}^2(u, v) = \frac{\partial L}{\partial k_{p,q}^2(u, v)}$$

$$= \sum_{i=1}^8 \sum_{j=1}^8 \Delta C_q^2(i, j) \cdot C_q^2(i, j) (1 - C_q^2(i, j)) \cdot S_p^1(i - u, j - v)$$

CNN - Backpropagation

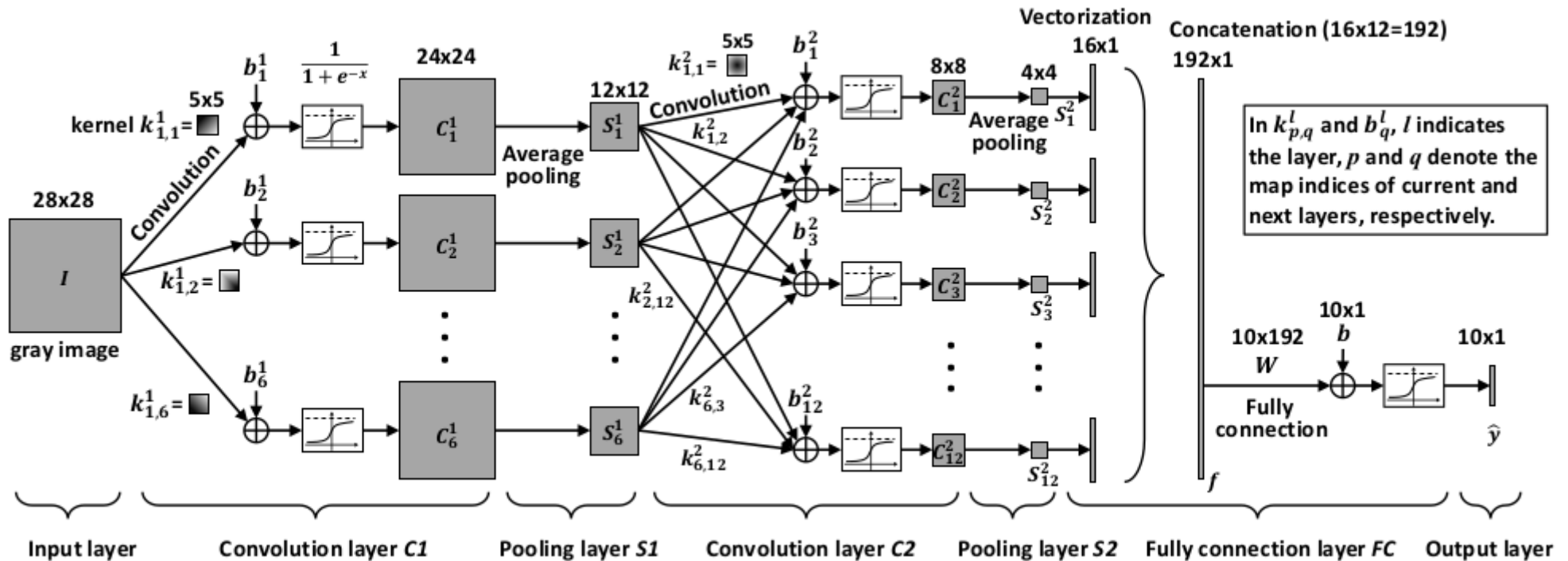


$$\Delta k_{p,q}^2 \text{ (size } 5 \times 5\text{)}$$

Rotating S_p^1 180 degrees, we get $S_{p,rot180}^1$

$$S_{p,rot180}^1(u-i, v-j) = S_p^1(i-u, j-v)$$

CNN - Backpropagation

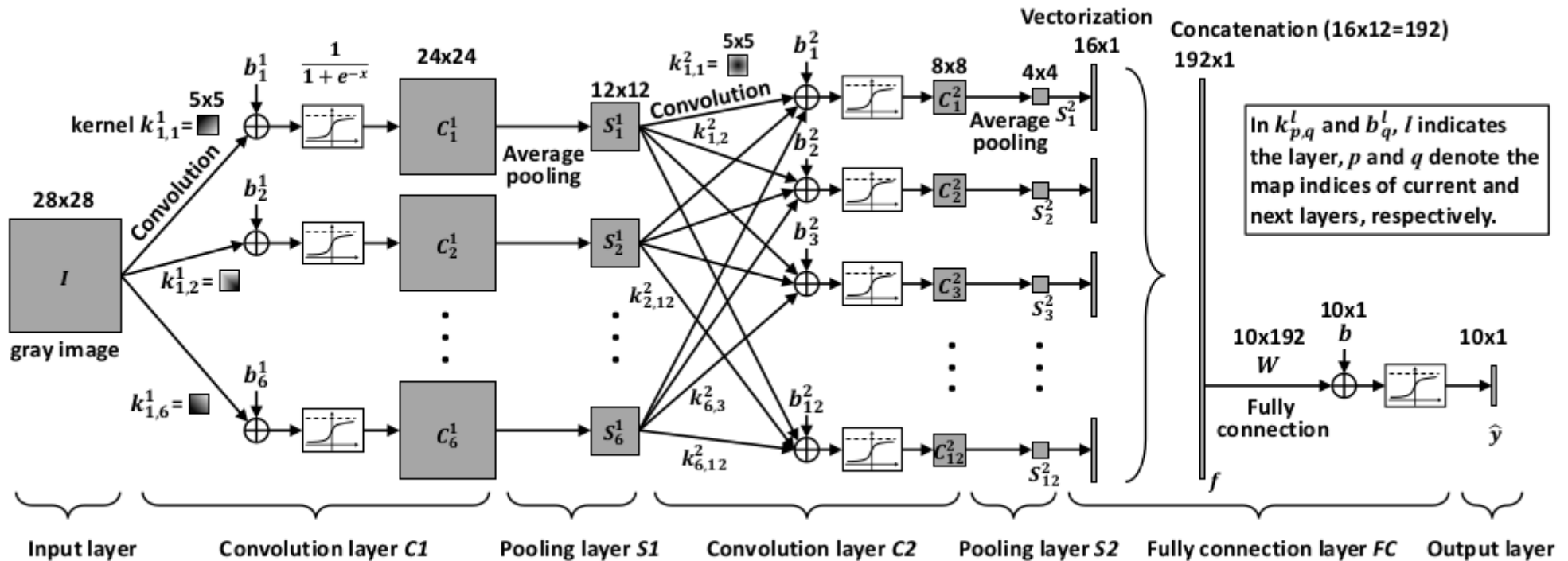


$$\Delta k_{p,q}^2 \text{ (size } 5 \times 5\text{)}$$

$$\Delta k_{p,q}^2(u, v) = \sum_{i=1}^8 \sum_{j=1}^8 S_{p,rot180}^1(u-i, v-j) \cdot \Delta C_{q,\sigma}^2(i, j)$$

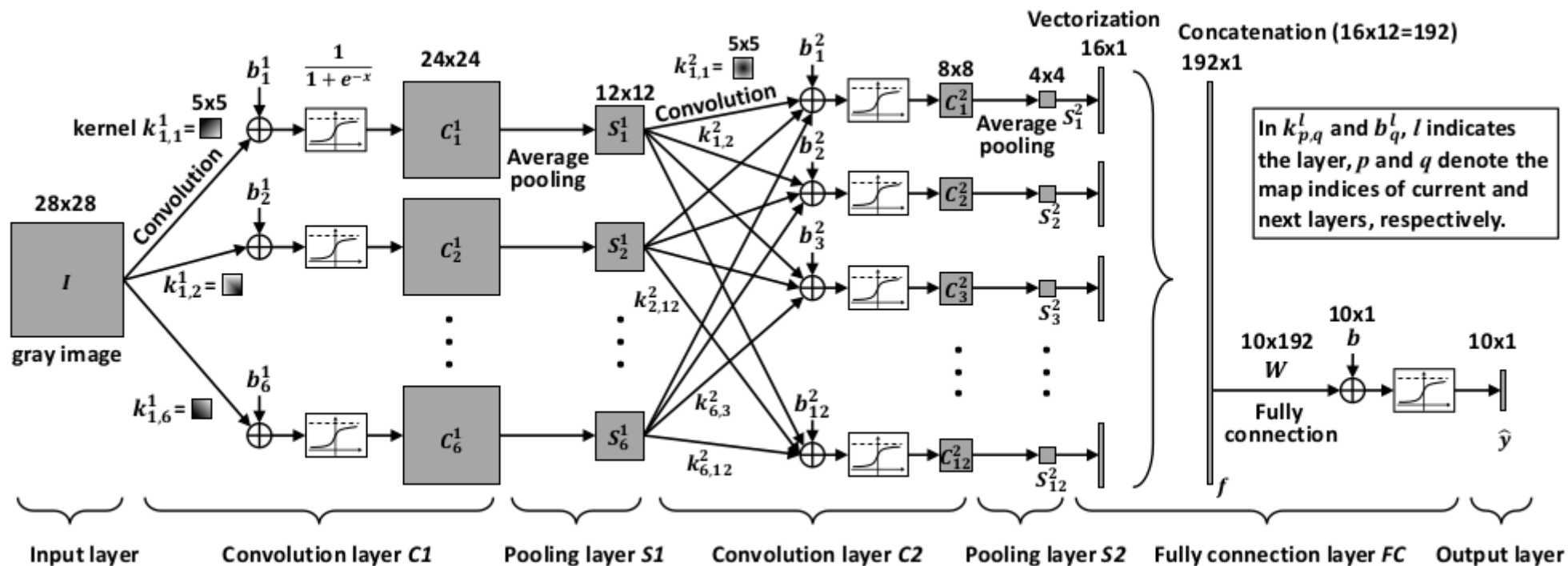
$$\Rightarrow \Delta k_{p,q}^2 = S_{p,rot180}^1 * \Delta C_{q,\sigma}^2$$

CNN - Backpropagation



$$\Delta b_q^2 = \frac{\partial L}{\partial b_q^2} = \sum_{i=1}^8 \sum_{j=1}^8 \Delta C_{q,\sigma}^2(i, j)$$

CNN - Backpropagation

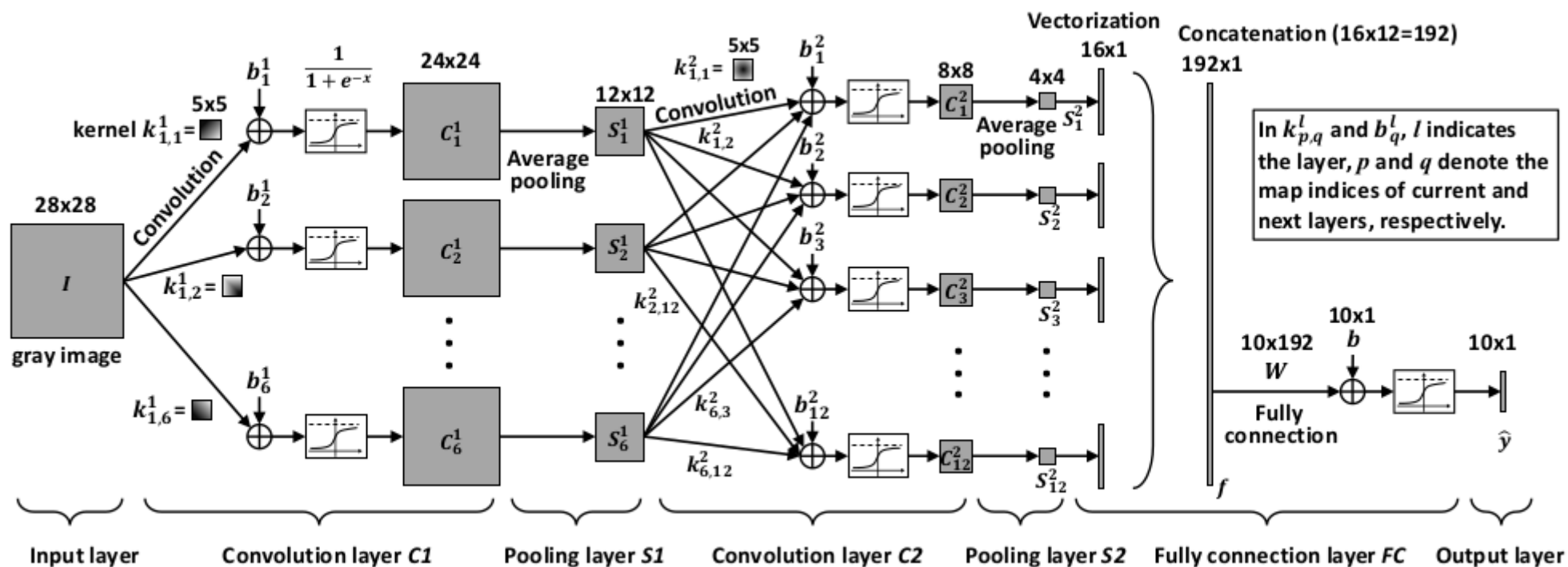


$\Delta k_{1,p}^1$ (size 5×5)

$$\Delta S_p^1(i, j) = \frac{\partial L}{\partial S_p^1(i, j)} = \sum_{q=1}^{12} \sum_{u=-2}^2 \sum_{v=-2}^2 \Delta C_{q,\sigma}^2(i+u, j+v) \cdot k_{p,q}^2(u, v)$$

Rotating $k_{p,q}^2$ 180 degrees, we get $k_{p,q,rot180}^2(-u, -v) = k_{p,q}^2(u, v)$

CNN - Backpropagation

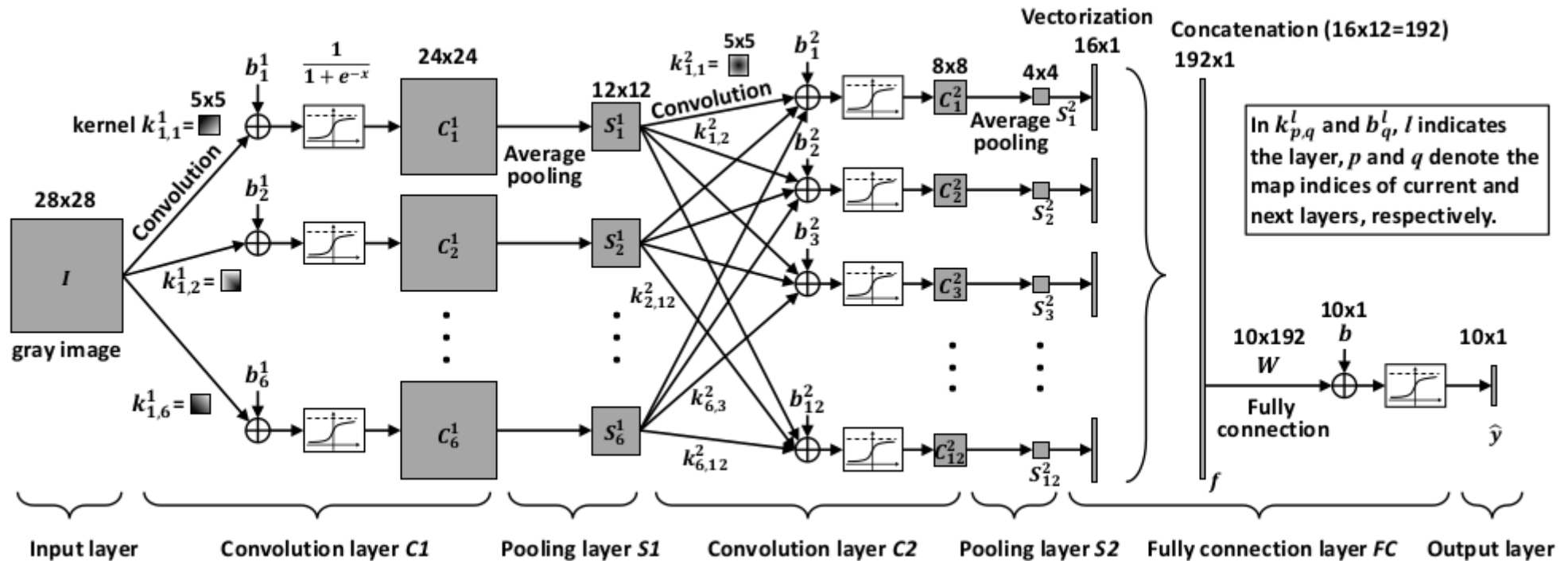


$$\Delta k_{1,p}^1 \text{ (size } 5 \times 5)$$

$$\Delta S_p^1(i, j) = \sum_{q=1}^{12} \sum_{u=-2}^2 \sum_{v=-2}^2 \Delta C_{q,\sigma}^2(i - (-u), j - (-v)) \cdot k_{p,q,rot180}^2(-u, -v)$$

$$\Rightarrow \Delta S_p^1 = \sum_{q=1}^{12} \Delta C_{q,\sigma}^2 * k_{p,q,rot180}^2$$

CNN - Backpropagation

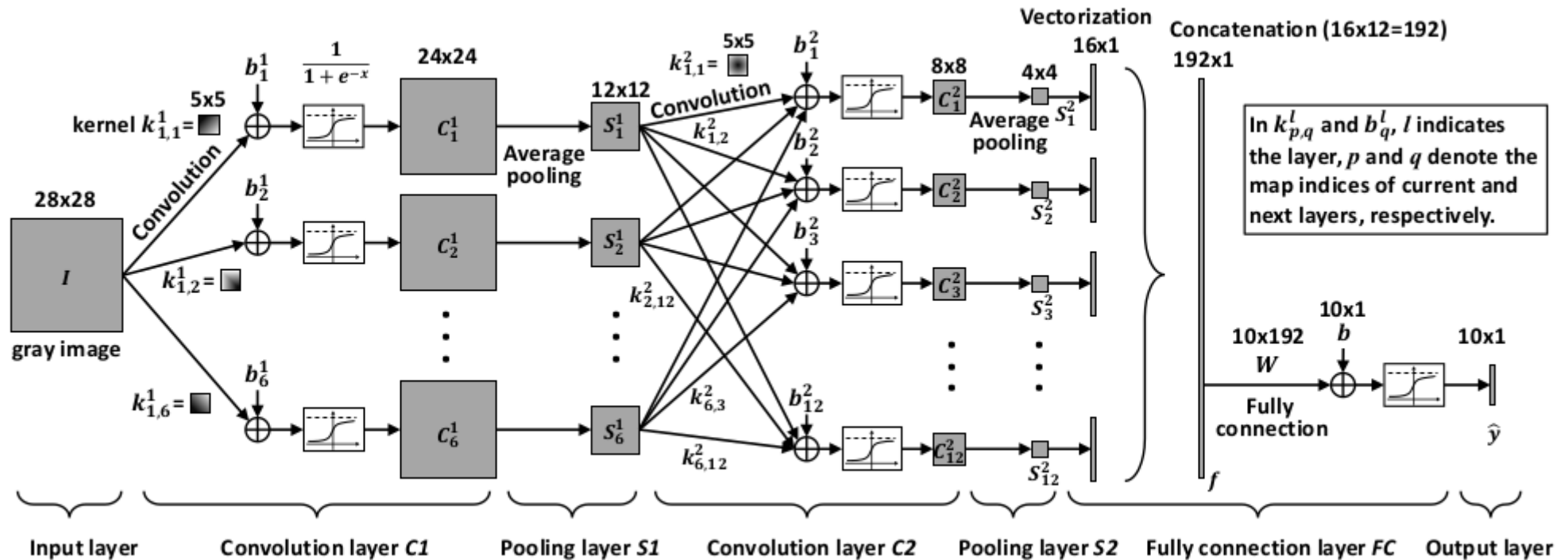


$$\Delta k_{1,p}^1 \text{ (size } 5 \times 5)$$

Upsampling

$$\Delta C_p^1(i, j) = \frac{1}{4} \Delta S_p^1(\lceil i/2 \rceil, \lceil j/2 \rceil), \quad i, j = 1, 2, \dots, 24$$

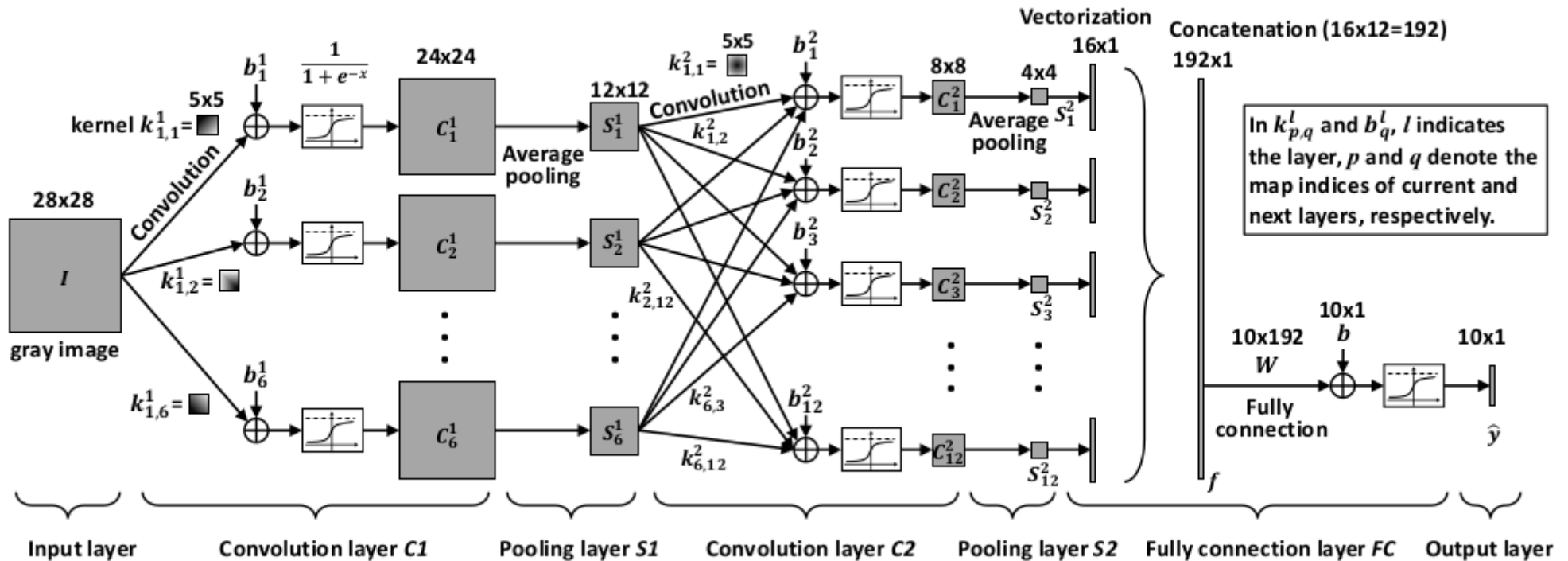
CNN - Backpropagation



$$\Delta k^1_{1,p} \text{ (size } 5 \times 5) \quad \Delta k^1_{1,p}(u, v) = \frac{\partial L}{\partial k^1_{1,p}(u, v)}$$

$$= \sum_{i=1}^{24} \sum_{j=1}^{24} \Delta C^1_p(i, j) \cdot C^1_p(i, j) (1 - C^1_p(i, j)) \cdot I(i - u, j - v)$$

CNN - Backpropagation



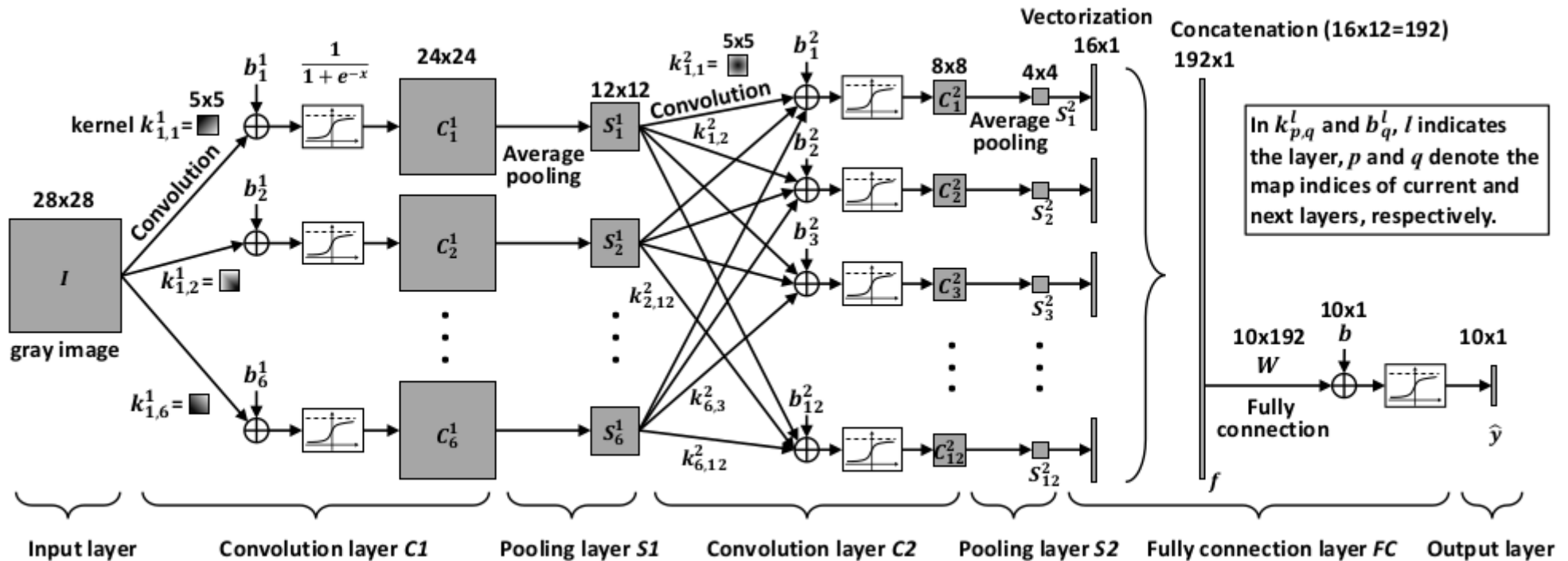
$\Delta k_{1,p}^1$ (size 5×5)

Rotacionando I de 180°

$$\Delta k_{1,p}^1(u, v) = \sum_{i=1}^{24} \sum_{j=1}^{24} I_{rot180}(u-i, v-j) \cdot \Delta C_{p,\sigma}^1(i, j)$$

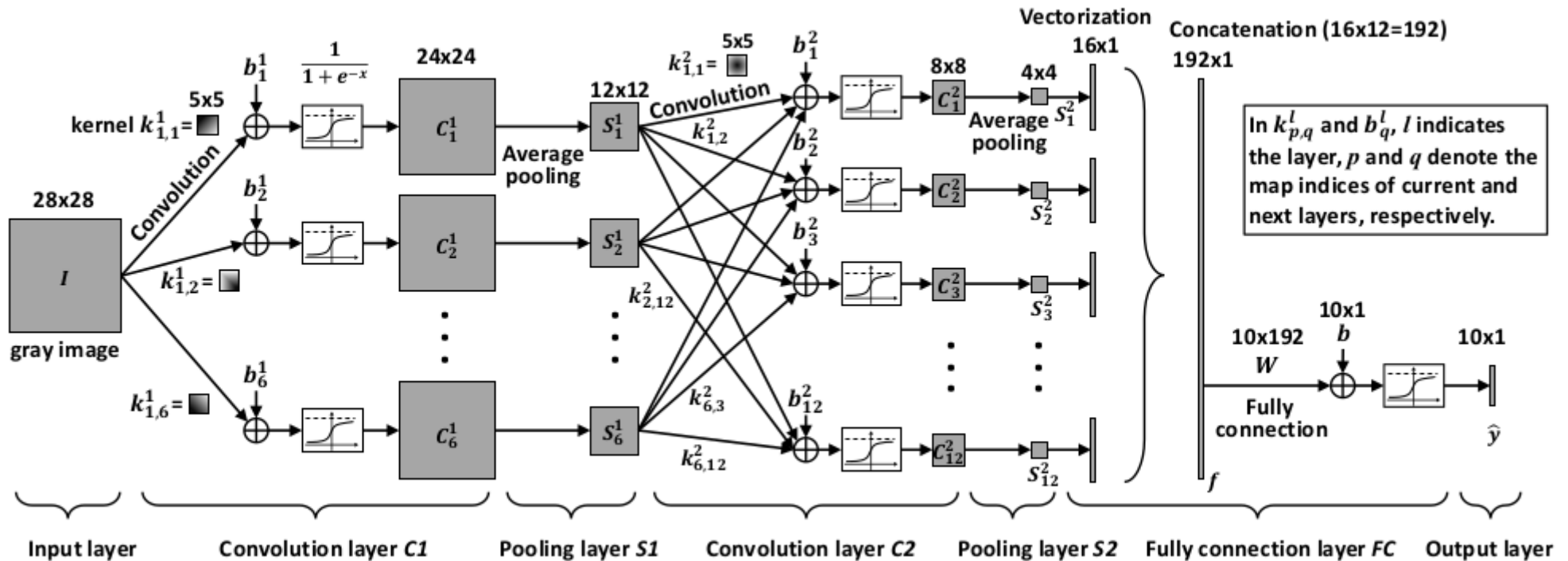
$$\Rightarrow \Delta k_{1,p}^1 = I_{rot180} * \Delta C_{p,\sigma}^1$$

CNN - Backpropagation



$$\Delta b_p^1 = \frac{\partial L}{\partial b_p^1} = \sum_{i=1}^{24} \sum_{j=1}^{24} \Delta C_{p,\sigma}^1(i, j)$$

CNN - Backpropagation



$$k_{1,p}^1 \leftarrow k_{1,p}^1 - \alpha \cdot \Delta k_{1,p}^1$$

$$b_p^1 \leftarrow b_p^1 - \alpha \cdot \Delta b_p^1$$

$$k_{p,q}^2 \leftarrow k_{p,q}^2 - \alpha \cdot \Delta k_{p,q}^2$$

$$b_q^2 \leftarrow b_q^2 - \alpha \cdot \Delta b_q^2$$

$$W \leftarrow W - \alpha \cdot \Delta W$$

$$b \leftarrow b - \alpha \cdot \Delta b$$

Referências

- <https://medium.com/analytics-vidhya/cnns-architectures-lenet-alexnet-vgg-googlenet-resnet-and-more-666091488df5>