

Intro to ML

HW8

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1.

1. Let X and W be arrays,

$$X = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 3 & 3 & 3 & 0 \\ 0 & 3 & 3 & 3 & 0 \\ 0 & 3 & 2 & 3 & 0 \\ 0 & 3 & 2 & 3 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}, \quad W = \begin{bmatrix} 1 & -1 \\ 1 & -1 \end{bmatrix}.$$

Let Z be the 2D convolution (without reversal):

$$Z[i, j] = \sum_{k_1, k_2} W[k_1, k_2] X[i + k_1, j + k_2]. \quad (1)$$

Assume that the arrays are indexed starting at $(0, 0)$.

- (a) What are the limits of the summations over k_1 and k_2 in (1)?
- (b) What is the size of the output $Z[i, j]$ if the convolution is computed only on the *valid* pixels (i.e. the pixel locations (i, j) where the summation in (1) does not exceed the boundaries of W or X).
- (c) What is the largest positive value of $Z[i, j]$ and state one pixel location (i, j) where that value occurs.
- (d) What is the largest negative value of $Z[i, j]$ and state one pixel location (i, j) where that value occurs.
- (e) Find one pixel location where $Z[i, j] = 0$.

- (a)
 $0 \leq (k_1 + k_2) \leq 2$
- (b)
If the convolution is computed only on the valid pixels, the size of $Z[i, j]$ will be (5,4)
- (c)
The largest positive value of $Z[i, j]$ is 6, you can find it at point (1,3), (2,3), or (3,3)
- (d)
The largest negative value of $Z[i, j]$ is -6, you can find it at point (1,0), (2,0), or (3,0)
- (e)
Location (0,1), (0,2), (1,1), (1,2)

2. Suppose that a convolutional layer of a neural network has an input tensor $X[i, j, k]$ and computes an output via a convolution and ReLU activation,

$$Z[i, j, m] = \sum_{k_1} \sum_{k_2} \sum_n W[k_1, k_2, n, m] X[i + k_1, j + k_2, n] + b[m],$$

$$U[i, j, m] = \max\{0, Z[i, j, m]\}.$$

for some weight kernel $W[k_1, k_2, n, m]$ and bias $b[m]$. Suppose that X has shape (48,64,10) and W has shape (3,3,10,20). Assume the convolution is computed on the *valid* pixels.

- What are the shapes of Z and U ?
- What are the number of input channels and output channels?
- How many multiplications must be performed to compute the convolution in that layer?
- If W and b are to be learned, what are the total number of trainable parameters in the layer?

- (a)
Size of Z and U : (46,62,20)
- (b)
input channel: 10, output channel: 20
- (c)
One pixel needs $3 * 3$ times.
Thus we need $3 * 3 * 46 * 62 * 20 * 10 = 5.13 * 10^6$ multiplications.
- (d)
The total number of trainable parameters is : $3 * 3 * 10 * 20 + 20 = 1820$

3. Suppose that a convolutional layer in some neural network is described as a linear convolution followed by a sigmoid activation,

$$Z[i, j, m] = \sum_{k_1} \sum_{k_2} \sum_n W[k_1, k_2, n, m] X[i + k_1, j + k_2, n] + b[m],$$

$$U[i, j, m] = 1/(1 + \exp(-Z[i, j, m])).$$

where $X[i, j, n]$ is the input of the layer and $U[i, j, m]$ is the output. Suppose that during back-propagation, we have computed the gradient $\partial J / \partial U$ for some loss function J . That is, we have computed the components $\partial J / \partial U[i, j, m]$. Show how to compute the following:

- The gradient components $\partial J / \partial Z[i, j, m]$.
- The gradient components $\partial J / \partial W[k_1, k_2, n, m]$.
- The gradient components $\partial J / \partial X[i, j, n]$.

- (a)
 $\frac{\partial U}{\partial Z} = \frac{1}{1+e^{-z}}' = \frac{e^{-z}}{(1+e^{-z})^2}$
According to the chain rule, $\frac{\partial J}{\partial Z} = \frac{\partial J}{\partial U} * \frac{\partial U}{\partial Z} = \frac{\partial J}{\partial U} * \frac{e^{-z}}{(1+e^{-z})^2}$
- (b)
 $\frac{\partial Z}{\partial W} = \sum_i \sum_j X[i + k_1, j + k_2, n]$
According to the chain rule,
 $\frac{\partial J}{\partial W} = \frac{\partial J}{\partial Z} * \frac{\partial Z}{\partial W} = \sum_i \sum_j X[i + k_1, j + k_2, n] * \frac{\partial J}{\partial U} * \frac{e^{-z}}{(1+e^{-z})^2}$

- (c)

$$\frac{\alpha J}{\alpha X} = \frac{\alpha J}{\alpha Z} * \frac{\alpha Z}{\alpha X}$$

Suppose we have two new variables l_1, l_2 , where $k_1 = l_1 - i, k_2 = l_2 - j$.

$$Z[i, j, m] = \sum_{l_1-i} \sum_{l_2-j} \sum_n W[l_1 - i, l_2 - j, n, m] X[l_1, l_2, n] + b[m]$$

$$\frac{\alpha Z}{\alpha X} = W[l_1 - i, l_2 - j, n, m]$$

$$\frac{\alpha J}{\alpha X} = \sum_i \sum_j \frac{\alpha J}{\alpha U} * \frac{e^{-z}}{(1+e^{-z})^2} * W[l_1 - i, l_2 - j, n, m]$$