Deep Learning DS-GA 1008 Assignment2

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1 Convolution

(a) What is the dimensionality of the output if we forward propagate the image over the given convolution kernel with no padding and stride of 1?

Answer: The dimension is 3x3

(b) Give a general formula of the output width O in terms of the input width I, kernel width K, stride S, and padding P (both in the beginning and in the end).

Answer:

$$O = \frac{I - K + 2P}{S} + 1$$

In the example of (a), I=5, K=3, P=0, S=1. We can get the same answer that the dimension O=3.

(c) Compute the output C of forward propagating the image over the given convolution kernel. Assume that the bias term of the convolution is zero.

Answer:

109	92	72
108	85	74
110	74	79

(d) Suppose the gradient backpropagated from the layers above this layer is a 3–3 matrix of all 1s. Write the value of the gradient (w.r.t. the input image) backpropagated out of this layer.

Answer

Assume $a_{ij} \in A$,and $i, j \in \{1, 2, \cdots, 5\}$

$$\frac{\partial E}{\partial A} = \frac{\partial E}{\partial C} \frac{\partial C}{\partial A}$$

Since for each scalar

$$\frac{\partial E}{\partial c_{ij}} = 1$$

So $\frac{\partial E}{\partial C}$ is a 3x3 matrix

1	1	1
1	1	1
1	1	1

For each

$$\frac{\partial E}{\partial a_{ij}} = 1 * \frac{\partial C}{\partial a_{ij}}$$

For each $\frac{\partial C}{\partial a_{ij}}$, is to figure out how many weights in the kernel apply on the a_{ij}

Since

$$\frac{\partial C}{\partial A} = \begin{bmatrix} \frac{\partial C}{\partial a_{11}} & \frac{\partial C}{\partial a_{12}} & \cdots & \frac{\partial C}{\partial a_{15}} \\ \frac{\partial C}{\partial a_{21}} & \frac{\partial C}{\partial a_{22}} & \cdots & \frac{\partial C}{\partial a_{25}} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial C}{\partial a_{51}} & \frac{\partial C}{\partial a_{52}} & \cdots & \frac{\partial C}{\partial a_{55}} \end{bmatrix} = \begin{bmatrix} 4 & 7 & 10 & 6 & 3 \\ 9 & 17 & 25 & 16 & 8 \\ 11 & 23 & 34 & 22 & 11 \\ 4 & 12 & 18 & 12 & 6 \\ 2 & 6 & 9 & 6 & 3 \end{bmatrix}$$

So, the backpropagation of this layer is

$$\begin{bmatrix} 4 & 7 & 10 & 6 & 3 \\ 9 & 17 & 25 & 16 & 8 \\ 11 & 23 & 34 & 22 & 11 \\ 4 & 12 & 18 & 12 & 6 \\ 2 & 6 & 9 & 6 & 3 \end{bmatrix}$$

2 Pooling

(a)

- 1. torch.nn.MaxPool2d— will pick the maximum value over each kernel size area from the input. In regular max pooling, you downsize an input set by taking the maximum value of smaller N x N subsections of the set (often 2x2), and try to reduce the set by a factor of N, where N is an integer.
- $2.\ torch.nn. AvgPool2d—will take the average of value over each kernel size area from the input$
- 3. torch.nn.LPPool2d—Learn-norm Pooling will apply a 2D power-average pooling over an input signal composed of several input planes.
- 4. torch.nn.AdaptiveAvgPool2d—Applies a adaptive average pooling over an input signal composed of several input planes.

5.torch.nn.FractionalMaxPool2d—Slightly differenct from maxpooling. The overall reduction ratio N does not have to be an integer. The sizes of the pooling regions are generated randomly but are fairly uniform.

(b)

1. Max Pooling 2d, when $S_{i,j}^k$ is the indices of X^k .

$$Y_{i,j}^{k} = \max(X_{i}^{k} n) = \max(X^{k} [S_{i,j}^{k}])$$
(1)

2. Average Pooling 2d

$$Y_{i,j}^k = average(X_i^k n) = average(X_i^k [S_{i,j}^k])$$
(2)

3. LP-Pooling 2d

$$Y_{i,j}^{k} = \sqrt[p]{\sum_{x \in X^{k}[S_{i,j}^{k}]k} x^{p}}$$
 (3)

- x is the elements in sub-region X^k
- At $p = \infty, f(X)$ gets Max Pooling
- At p = 1, one gets Sum Pooling (which is proportional to Average Pooling)

(c)Answer:

109	92
110	85

(d)

In LP pooling

When power p = 1, one gets Sum Pooling (which is proportional to Average Pooling)

$$Y_{i,j}^{k} = \sqrt[p]{\sum_{x \in X^{k}[S_{i,j}^{k}]} x^{p}} = \sqrt[1]{\sum_{x \in X^{k}[S_{i,j}^{k}]} x} = \sum_{x \in X^{k}[S_{i,j}^{k}]} x = S_{i,j}^{k} count \cdot average(X^{k}[S_{i,j}^{k}]) = count\{S_{i,j}^{k}\} \cdot Y_{avg,ij}^{k}$$

$$(4)$$

When $p = \infty$,

$$Y_{i,j}^{k} = \sqrt[p]{\sum_{x \in X^{k}[S_{i,j}^{k}]} x^{p}} \approx \sqrt[p]{\max_{x \in X^{k}[S_{i,j}^{k}]} (x^{p})} = \max(X^{k}[S_{i,j}^{k}])$$
 (5)