CS280 Spring 2023 Assignment 2 Part A

Convolutional Neural Network March 15, 2023

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1. Convolution Cost (10 points)

Assume an input of shape $c_i \times h \times w$ and a convolution kernel of shape $c_o \times c_i \times k_h \times k_w$, padding of (p_h, p_w) , and stride of (s_h, s_w) .

• What is the computational cost (multiplications and additions) for the forward propagation? **Solution:**

The output size has the formula as follows:

$$c_{out} = \#\{kernels\}$$

$$h_{out} = \left\lfloor \frac{h_{in} + 2 \times padding_size_h - (kernel_size_h - 1) - 1}{stride_size_h} + 1 \right\rfloor$$

$$w_{out} = \left\lfloor \frac{w_{in} + 2 \times padding_size_w - (kernel_size_w - 1) - 1}{stride_size_w} + 1 \right\rfloor$$

Substitute h_{in} , w_{in} , $padding_size_h$, $padding_size_w$, $stride_size_h$, $stride_size_w$, $kernel_size_h$ and $kernel_size_w$ with h, w, p_h , p_w , s_h , s_w , k_h and k_w respectively, the output size is

$$c_{out} = c_0$$

$$h_{out} = \left\lfloor \frac{h + 2p_h - k_h}{s_h} + 1 \right\rfloor$$

$$w_{out} = \left\lfloor \frac{w + 2p_w - k_w}{s_w} + 1 \right\rfloor$$

Then for each element in output, it is calculated by $c_i \times k_h \times k_w$ times multiplications and $c_i \times k_h \times k_w - 1$ times additions. Thus, the computational cost is

$$cost = c_0 \left[\frac{h + 2p_h - k_h}{s_h} + 1 \right] \left[\frac{w + 2p_w - k_w}{s_w} + 1 \right] (2c_i k_h k_w - 1)$$

• What is the memory footprint?

2. Convolution Kernel (10 points)

Assume there are two convolution kernels of size k_1 and k_2 respectively (with no nonlinear activation function in-between).

• Prove that the results of the two convolution operations can be expressed by a single convolution operation.

Proof:

Define the input as X and Y, Z are the output of the first and the second convolution layer, where

$$Y = conv_1(X)$$
$$Z = conv_2(Y)$$

Then define A(x, y) as the element at position (x, y) of A. By the definition of convolution operation, we have

$$Z(i,j) = \sum_{p=0}^{k_2-1} \sum_{q=0}^{k_2-1} kernel_2(p,q)Y(i+p,j+q)$$
$$Y(i+p,j+q) = \sum_{m=0}^{k_1-1} \sum_{n=0}^{k_1-1} kernel_1(m,n)X(i+p+m,j+q+n)$$

Substitute Y(i + p, j + q) into Z(i, j) and we get:

$$\begin{split} Z(i,j) &= \sum_{p=0}^{k_2-1} \sum_{q=0}^{k_2-1} kernel_2(p,q) \sum_{m=0}^{k_1-1} \sum_{n=0}^{k_1-1} kernel_1(m,n) X(i+p+m,j+q+n) \\ &= \sum_{p=0}^{k_2-1} \sum_{q=0}^{k_2-1} \sum_{m=0}^{k_1-1} \sum_{n=0}^{k_1-1} kernel_2(p,q) kernel_1(m,n) X(i+p+m,j+q+n) \\ &= \sum_{q=0}^{k_3-1} \sum_{k=0}^{k_3-1} kernel_3(a,b) X(i+a,j+b) \end{split}$$

where $k_3 = k_2 + k_1 - 1$ and

$$kernel_3(a,b) = \sum_{x=\max(0,a-k_1+1)}^{\min(a,k_2-1)} \sum_{x=\max(0,b-k_1+1)}^{\min(b,k_2-1)} kernel_2(x,y) \cdot kernel_1(a-x,b-y)$$

$$= kernel_2 * kernel_1$$

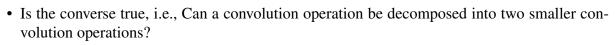
Remark: $kernel_3$ is the "real" convolution result between $kernel_1$ and $kernel_2$. It's different from the image convolution operation described in the question, which is actually correlation operation.

Since $Z(i,j) = \sum_{a=0}^{k_3-1} \sum_{b=0}^{k_3-1} kernel_3(a,b) X(i+a,j+b)$, Z(i,j) can be computed from single convolution.

• What is the dimensionality of the equivalent single convolution?

Solution:

Based on the previous proof, we know $Z(i,j) = \sum_{a=0}^{k_3-1} \sum_{b=0}^{k_3-1} kernel_3(a,b) X(i+a,j+b)$ where $k_3 = k_1 + k_2 - 1$, we know that the kernel size of equivalent single convolution is $(k_1 + k_2 - 1) \times (k_1 + k_2 - 1)$.



Solution:

The converse is false,