

Deep Learning Assignment

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Theory:

Raj Patil:

CS18BTECH11039

1. a) zero padding the signal such that the final activations ~~are of the~~ is of the same size

$$I' = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 2 & 0 & 1 \\ 0 & 1 & -1 & 2 \end{bmatrix}$$

$$F = \begin{bmatrix} 1 & -1 \\ 1 & -1 \end{bmatrix}, \text{ flipping } F \text{ by multiplying}$$

$$F * I' = \begin{bmatrix} 1 & -1 & 2 & -1 \\ -1 & 1 & -2 & 1 \end{bmatrix} \begin{bmatrix} 2 & -2 & 1 \\ 3 & -4 & 4 \end{bmatrix}$$

$$b) F = \begin{bmatrix} 1 & -1 \\ 1 & -1 \end{bmatrix} = \begin{bmatrix} a & b \\ c & d \end{bmatrix}$$

$$\therefore ac = 1$$

$$ad = -1$$

$$bc = 1$$

$$bd = -1$$

$$a = b$$

$$c = -d$$

$$\therefore a = b = c = 1$$

$$d = -1$$

$$\therefore F = \begin{bmatrix} 1 \\ 1 \end{bmatrix} \begin{bmatrix} 1 & -1 \end{bmatrix}$$

$\swarrow F_1 \qquad \searrow F_2$

$$\therefore (F_1 * I)' = \begin{bmatrix} 0 & 2 & 0 & 1 \\ 0 & 3 & -1 & 3 \end{bmatrix}$$

flipping F_1 $\odot \dots$ $\begin{bmatrix} 0 & 2 & 0 & 1 \\ 0 & 3 & -1 & 3 \end{bmatrix}$

$$\begin{bmatrix} 0 & 2 & 0 & 1 \\ 0 & 3 & -1 & 3 \end{bmatrix}$$

$$F_2 * (F_1 * I) = \begin{bmatrix} 2 & -2 & 1 \\ 3 & -4 & 4 \end{bmatrix}$$

flipping F_2 $\odot \dots$ $\begin{bmatrix} 2 & -2 & 1 \\ 3 & -4 & 4 \end{bmatrix}$ \therefore same as $F * I$.

c) P.T. $F * I' = F_2 * (F_1 * I)$

defining row & column convolutions for $F_1 \odot F_2$ mathematically \therefore

$$(F_1 * I)_{ij} = \sum_k I_{i-k, j} F_{1k}$$

$$(F_1 * I)_{ij} = \sum_k I_{i-k, j} F_{1k}$$

$$\odot (F_2 * I)_{ij} = \sum_l I_{i, j-l} F_{2l}$$

Using these in equation (1) \therefore

Using these to obtain equation (2)

$$(F_2 * (F_1 * I))_{ij} =$$

$$= \sum_l F_{2l} ((F_1 * I)_{i,j-l})$$

$$= \sum_l F_{2l} \left(\sum_k I_{i-k,j-l} F_{1k} \right)$$

$$= \sum_l \sum_k I_{i-k,j-l} F_{1k} F_{2l}$$

being ~~$F = F_1 * F_2 \iff F_{k,l} = F_{1k} * F_{2l}$~~

now, observe that --

$$F_{i,j} = F_{1i} \cdot F_{2j}$$

$$\therefore (F_2 * (F_1 * I))_{ij}$$

$$= \sum_l \sum_k I_{i-k,j-l} F_{k,l}$$

$$= (F * I)_{ij} \quad (\text{by equation (1) given in question statement})$$

$$\forall i,j \left((F_2 * (F_1 * I))_{ij} = (F * I)_{ij} \right)$$

$$\iff F_2 * (F_1 * I) = F * I \quad \text{q.e.d.}$$

d) part a) for each activation,
we needed 4 multiplications
& there are 6 activations

$$\therefore \text{total multiplications for part a} = 6 \times 4 = \boxed{24}$$

part b) for each intermediate activation,
we needed 2 multiplications
 $F_1 \times I_5$ $\rightarrow F_2 \times F_1 \times I$
there are 8 + 6 such
activations

\therefore total multiplications needed:

$$14 \times 2 = \boxed{28}$$

the first way requires lesser multiplications but that is only because the problem size is small yet & this will change for a larger computation.

e) for simple convolution:

final output size (no zero padding)
is

$$(M_1 - M_2 + 1) \times (N_1 - N_2 + 1)$$

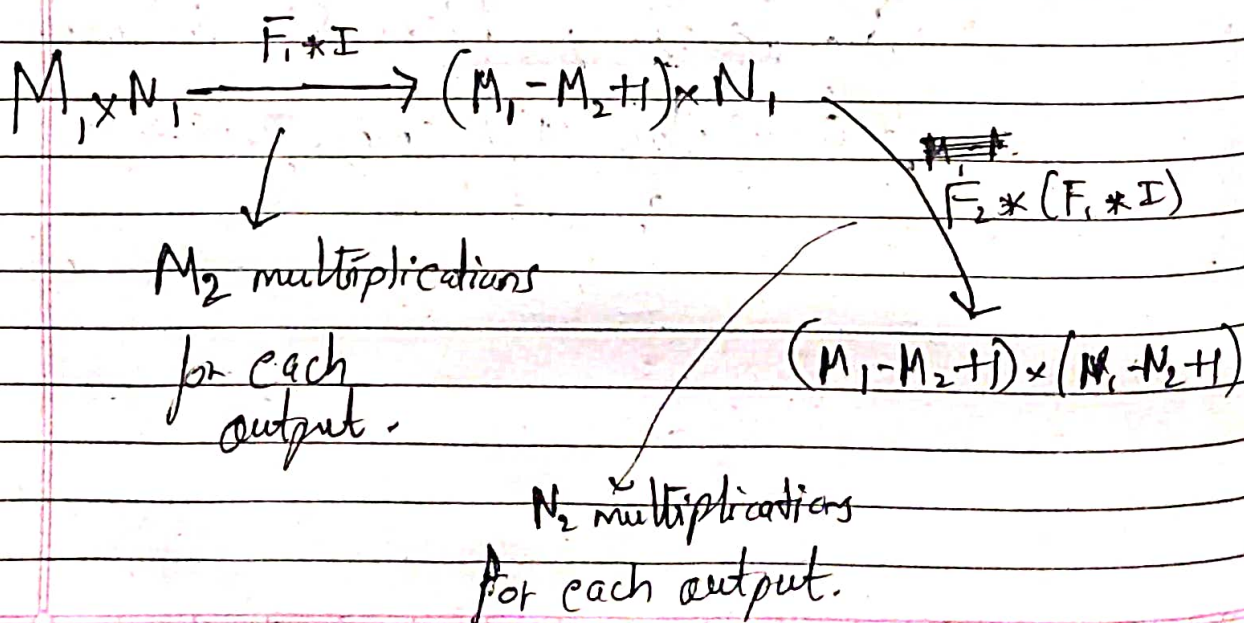
for each activation, we need $M_2 \times N_2$
multiplications

\therefore total multiplications =

$$M_2 \times N_2 \times (M_1 - M_2 + 1) \times (N_1 - N_2 + 1)$$

$$\in O(M_2 N_2 M_1 N_1)$$

for Correlative 2D convolutions, the
output size transitions as follows



\therefore total multiplications =

$$M_2 \times (M_1 - M_2 + 1) \times N_1 \\ + N_2 \times (M_1 - M_2 + 1) \times (N_1 - N_2 + 1)$$

$$\in O(M_1 N_1 (M_2 + N_2))$$

Answers Summarized.

i) $M_2 N_2 (M_1 - M_2 + 1) (N_1 - N_2 + 1)$

ii) $M_2 (M_1 - M_2 + 1) N_1 + N_2 (M_1 - M_2 + 1) (N_1 - N_2 + 1)$

iii) 2 successive 1-D convolutions are faster than a single 2-D convolution asymptotically - as

$$\boxed{O(M_1 N_1 (M_2 + N_2)) \subset O(M_1 N_1 M_2 N_2)}$$

2.7 a) for points on x axis, under the transformation application of

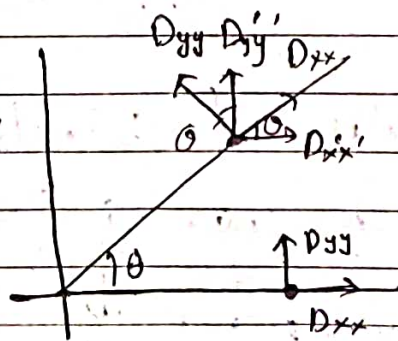
$$\begin{pmatrix} \cos \theta & 0 \\ \sin \theta & 0 \end{pmatrix} \begin{pmatrix} x \\ 0 \end{pmatrix} \rightarrow \begin{pmatrix} x \cos \theta \\ x \sin \theta \end{pmatrix}$$

Comparing Initial and final gradient magnitudes.

Initially, as the edge is horizontal

~~D_{xx} is less than D_{yy} so we only look at D_{yy} for the final gradient magnitude.~~

~~D_{yy}~~ new gradients can be found as



$$D_{yy'} = D_{yy} \cos \theta + D_{xx} \sin \theta$$

$$D_{xx'} = D_{xx} \cos \theta - D_{yy} \sin \theta$$

\therefore new gradient magnitude =

$$\begin{aligned} & \sqrt{(D_{yy}')^2 + (D_{xx}')^2} \\ &= \sqrt{(D_{yy} \cos^2 \theta + D_{xx} \sin^2 \theta + 2 D_{xx} D_{yy} \sin \theta \cos \theta + D_{yy} \sin^2 \theta + D_{xx} \cos^2 \theta - 2 D_{xx} D_{yy} \sin \theta \cos \theta)} \\ &= \sqrt{(D_{xx}^2 + D_{yy}^2)} = \text{old gradient magnitude.} \end{aligned}$$

\therefore The edge will still be detected by Canny edge detector.

b) Because the prominent edges are detected, the higher threshold (h) is low enough to deal with the disconnected long edges, one needs decrease the lower threshold (l) for more neighboring pixels of the long edges to occur in the middle band. For the numerous spurious edges, increase h slightly so as to not make the long edges disappear but only push the noisy gradient magnitudes into the middle band where they don't have neighboring strong edges.