PROBLEM 4 Yanis Tazi

Q1

In [1]: from PIL import Image, ImageDraw
Image.open('alexnet_PARAMS.png')

Out[1]:

| | Layers | Description | Size of Tensor | Number of weights | Number of blases | Number of Parameters |
|----------------------------|----------|---|--|---------------------------|------------------|----------------------------|
| Computations Yanis Tazi | Input | Image 227*227*3 | 227*227*3 | 0 | 0 | 0 |
| | Conv1 | 96 kernels of size 11*11,stride 4,0 padding | [(227-11+2*0)/4]+1 = 55 55*55*96 | 11*11*3*96=34848 | 96 | 34848+96= 34944 |
| | MaxPool1 | 3*3 stride 2 | (55-3)/2 +1=27 27*27*96 | 0 | 0 | |
| | Conv2 | 256 kernels of size 5*5,stride 1, padding 2 | [(27-5+2*2)/1]+1 =27 27*27*256 | 5*5*96*256 = 614400 | 256 | 614400+256= 614656 |
| | MaxPool2 | 3*3 stride 2 | (27-3)/2 +1=13 13*13*256 | 0 | 0 | |
| | Conv3 | 384 kernels of size 3*3,stride 1 ,padding 1 | [(13-3+2*1)/1]+1= 13 13*13*384 | 3*3*256*384= 884736 | 384 | 884736+384= 885120 |
| | Conv4 | 384 kernels of size 3*3,stride 1 ,padding 1 | [(13-3+2*1)/1]+1= 13 13*13*384 | 3*3*384*384= 1327104 | 384 | 1327104+384= 1327488 |
| | Conv5 | 256 kernels of size 3*3,stride 1 ,padding 1 | [(13-3+2*1)/1]+1= 13 13*13*256 | 3*3*384*256= 884736 | 256 | 884736+256= 884992 |
| | MaxPool3 | 3*3 stride 2 | (13-3)/2 +1 =6 6*6*256 | 0 | 0 | |
| | FC1 | 4096 neurons | 4096 | 6*6*256*4096= 37748736 | 4096 | 37748736+4096= 37752832 |
| | FC2 | 4096 neurons | 4096 | 4096*4096= 16777216 | 4096 | 16777216+4096= 16781312 |
| | FC3 | 1000 neurons | 1000 | 4096*1000= 4096000 | 1000 | 4096000+1000= 4097000 |
| | Total | | | | | 62378344 |

Q2

In [2]: Image.open('vgg_PARAMS.png')

Out[2]:

| Layer | Number of Activations (Memory) | Parameters (Compute) | | | |
|-----------|--------------------------------|---------------------------|--|--|--|
| Input | 224*224*3=150K | 0 | | | |
| CONV3-64 | 224*224*64=3.2M | (3*3*3)*64 = 1,728 | | | |
| CONV3-64 | 224*224*64=3.2M | (3*3*64)*64 = 36,864 | | | |
| POOL2 | 112*112*64=800K | 0 | | | |
| CONV3-128 | 112*112*128 = 1.6M | (3*3*64)*128=73728 | | | |
| CONV3-128 | 112*112*128 = 1.6M | (3*3*128)*128=147456 | | | |
| POOL2 | 56*56*128=400K | 0 | | | |
| CONV3-256 | 56*56*256= 800K | (3*3*128)*256=294912 | | | |
| CONV3-256 | 56*56*256=800K | (3*3*256)*256 = 589,824 | | | |
| CONV3-256 | 56*56*256= 800K | (3*3*256)*256=589824 | | | |
| CONV3-256 | 56*56*256= 800K | (3*3*256)*256=589824 | | | |
| POOL2 | 28*28*256= 200K | 0 | | | |
| CONV3-512 | 28*28*512=400K | (3*3*256)*512 = 1,179,648 | | | |
| CONV3-512 | 28*28*512=400K | (3*3*512)*512=2359296 | | | |
| CONV3-512 | 28*28*512=400K | (3*3*512)*512=2359296 | | | |
| CONV3-512 | 28*28*512=400K | (3*3*512)*512=2359296 | | | |
| POOL2 | 14*14*512=100K | 0 | | | |
| CONV3-512 | 14*14*512 = 100K | (3*3*512)*512=2359296 | | | |
| CONV3-512 | 14*14*512 = 100K | (3*3*512)*512=2359296 | | | |
| CONV3-512 | 14*14*512 = 100K | (3*3*512)*512=2359296 | | | |
| CONV3-512 | 14*14*512 = 100K | (3*3*512)*512=2359296 | | | |
| POOL2 | 7*7*512= 25K | 0 | | | |
| FC | 4096 | 25088*4096=102760448 | | | |
| FC | 4096 | 4096*4096 = 16,777,216 | | | |
| FC | 1000 | 4096*1000=4096000 | | | |
| TOTAL | ~16.3M | ~138M | | | |

Table 1: VGG19 memory and weights

Q3

Input size L ,Filter (F*F) , Pad = 0 (P), Stride = 1 (S)

For one filter of size F*F,Output activation map length is L-F+1

For two stacked filters of size F*F, Output activation map length is (L-F+1)-F+1 = L-2F+2.

Therefore, for N stacked filters of size F*F, Output activation map length is L - NF + N.

For one filter of size (NF – N + 1)*(NF – N + 1), Output activation map lenth is L-(NF-N+1)+1=L-NF+N-1+1=L-NF+N.

For 3 stacked filters of size 5x5, Output activation map length is L-3*5+3=L-12. Therefore, the receptive field is 13*13.

Q4

a)

The idea is to have efficient computation to be able to use very deep neural networks. For that, they have been using stacked 1*1 convolutions and this also reduce the problem of overfitting. This allows us to keep computational constraints while increasing depth of the network. We saw the benefits of using stacked of small filters in the previous question in terms of computational reduction.

In terms of intuition, we can say that usually we do not know the size of the filters that we want because detecting a specific characteristic of an image will vary from images to images so the idea is to have several different filter sizes on the same level.

Also, it preserves local and sparse correlations, parallel convolutional filters of different sizes

b)

For the naive one, it is

$$32 * 32 * (128 + 192 + 96 + 256) = 32 * 32 * 672$$

For the dimensionality reduction one, it is:

$$32 * 32 * (128 + 192 + 96 + 64) = 32 * 32 * 480$$

c)

For the naive version, we have:

$$(1*1*256*128+128) + (3*3*256*192+192) + (5*5*256*96+96)$$

For the dimensionality reduction version, we have:

$$(1*1*256*128+128) + (1*1*256*128+128) + (1*1*256*32+32) + (5*5*32*96+96) + (1*1*256*64) = 388672$$

d)

In the dimension reduction architecture, we have added an extra 11 convolution before adding the 33 and 55 filters. Doing so allowed us to reduce the number of input channel and it becomes much cheaper to compute the convolution filters now since the depth has decreased with the 11 convolutions.

Dimension reduction module has reduced computational complexity compared to naïve version by a factor of 2.8!

In []: