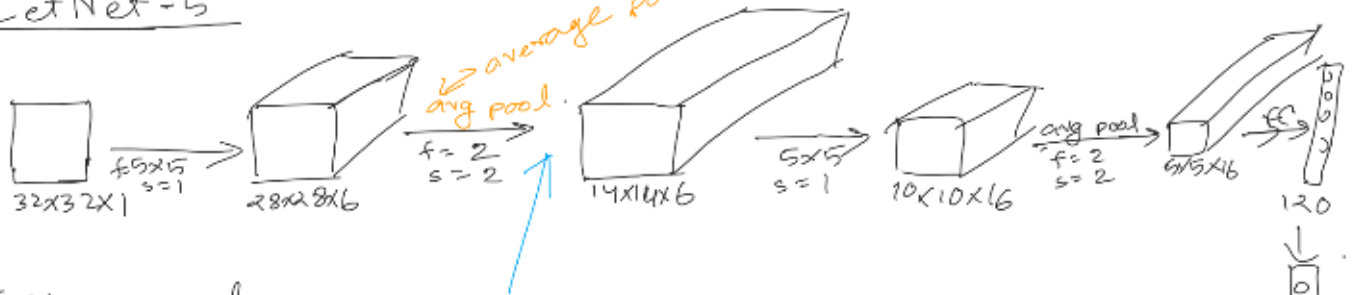


C4w2

Classic neural network architecture:-

- LeNet-5
- AlexNet
- VGGz
- ResNet (155 layers)

LetNet-5



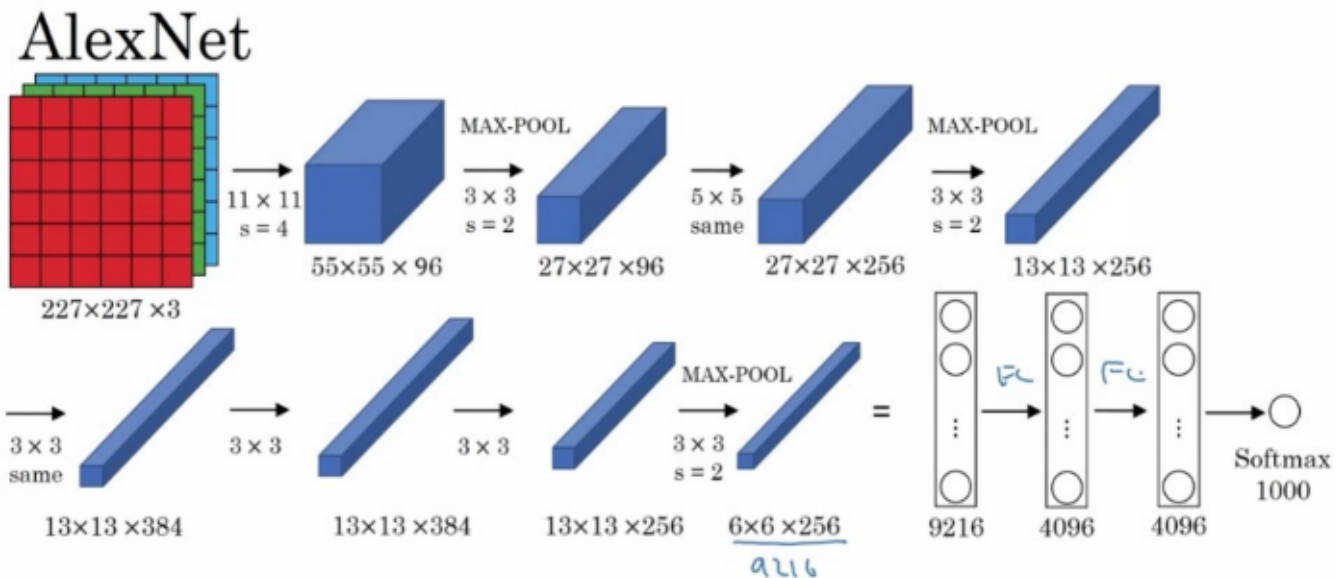
60k parameters

No padding was used.

non linearity was done after pooling.
sigmoid/tanh was used.

softmax not used.

AlexNet:-



[Krizhevsky et al., 2012. ImageNet classification with deep convolutional neural networks]

Andrew Ng

-60M parameters.

- ReLU

- Multiple GPU.

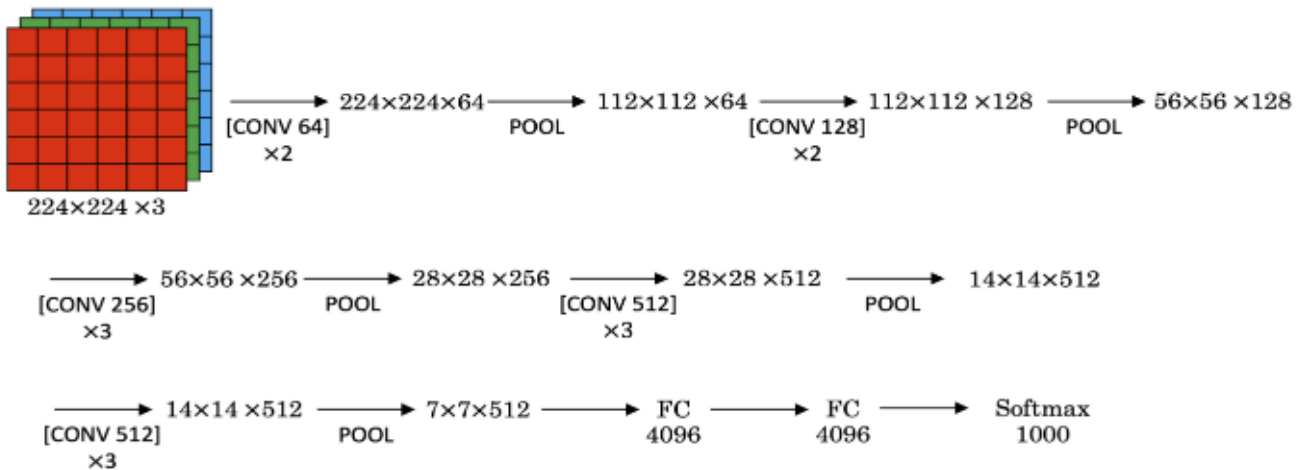
- Local response normalization (LRN) - it normalizes along the channel.

VGG-16

VGG - 16

CONV = 3×3 filter, $s = 1$, same

MAX-POOL = 2×2 , $s = 2$



[Simonyan & Zisserman 2015. Very deep convolutional networks for large-scale image recognition]

Andrew Ng

160M parameters.

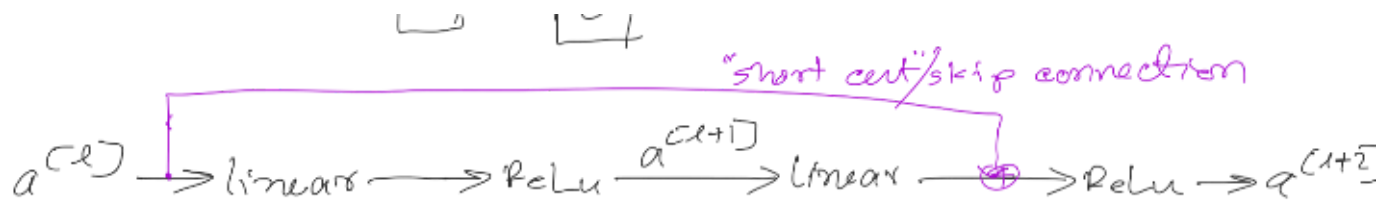
it's simplicity makes it popular (like same filter size)

Residual Network (ResNet): -

Very, very deep neural networks are harder to train because of vanishing & exploding gradient.

Residual block :-





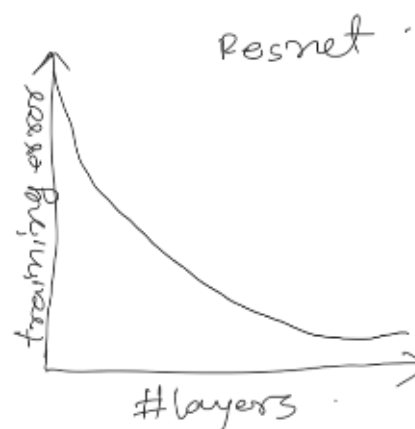
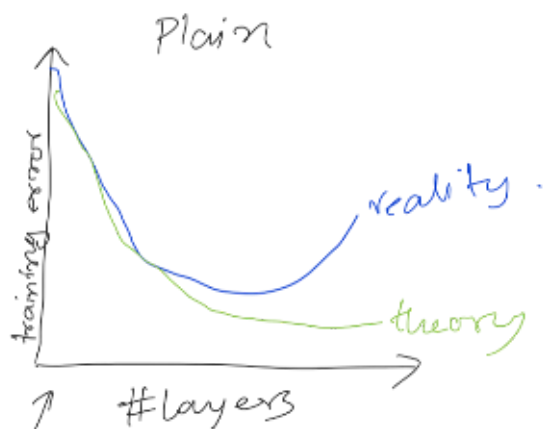
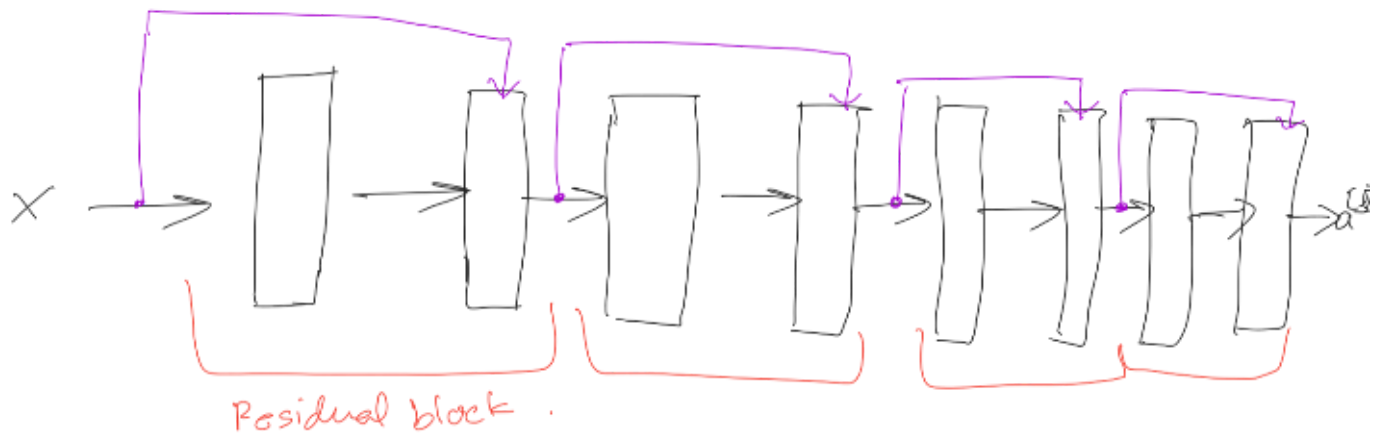
$$z^{[l+1]} = w^{[l+1]} a^{[l]} + b^{[l+1]}$$

$$z^{[l+2]} = w^{[l+2]} a^{[l+1]} + b^{[l+2]}$$

$$a^{[l+1]} = g(z^{[l+1]})$$
~~$$a^{[l+2]} = g(z^{[l+2]})$$~~

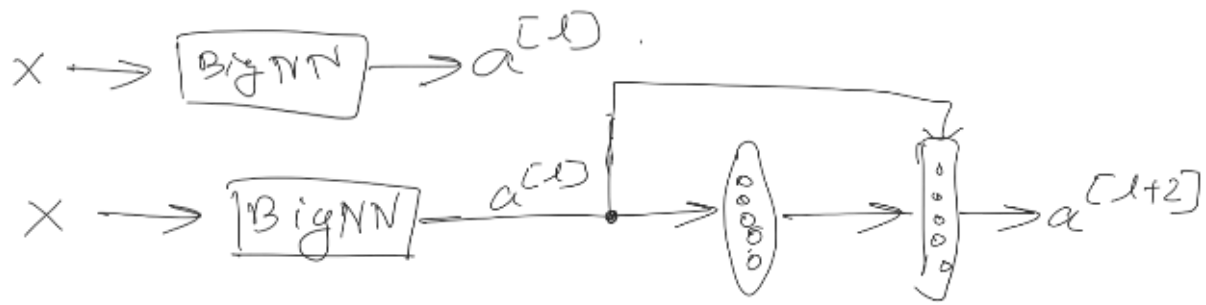
$$a^{[l+2]} = g(z^{[l+2]} + a^{[l]})$$

Residual network:-



↗ this might happen for vanishing
exploding gradients.

why resNet work:-



$$\begin{aligned}
 a^{[l+2]} &\rightarrow g(z^{[l+2]} + a^{[l]}) \\
 &\rightarrow g(w^{[l+2]} a^{[l+1]} + b^{[l+2]} + \underbrace{w_s}_{256 \times 128} \underbrace{a^{[l]}}_{128}) \\
 &\rightarrow g(a^{[l]})
 \end{aligned}$$

(vanishing gradient / regularizer)

Identity function is easy to learn for residual block.

if dimension of $a^{[l+2]}$ & $a^{[l]}$ is different then we have to multiply the term $a^{[l]}$ with w_s . w_s might be fixed value matrix. or it may 0 pads the $a^{[l]}$ to match the dimensions of $a^{[l+2]}$

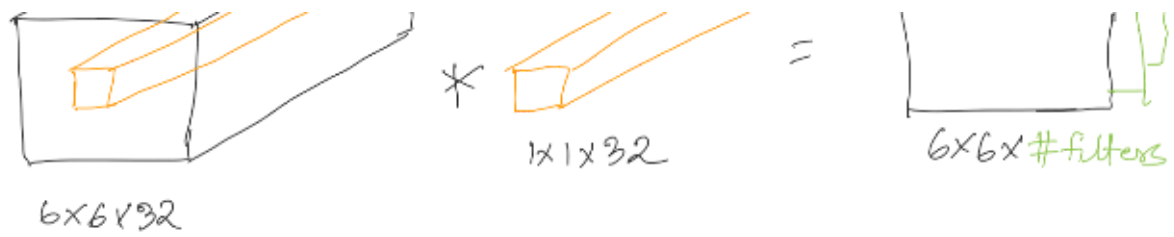
What does 1x1 filter do?

$$\begin{bmatrix} 1 & 3 & 4 & 5 & 6 & 7 \\ 2 & 3 & 6 & \dots & \dots & \dots \\ \dots & \dots & \dots & \dots & \dots & \dots \\ \dots & \dots & \dots & \dots & \dots & \dots \\ \dots & \dots & \dots & \dots & \dots & \dots \end{bmatrix} * \begin{bmatrix} 2 \end{bmatrix} = \begin{bmatrix} 2 & 6 & 8 & 10 & 12 & 14 \\ 4 & 6 & 12 & \dots & \dots & \dots \\ \dots & \dots & \dots & \dots & \dots & \dots \\ \dots & \dots & \dots & \dots & \dots & \dots \\ \dots & \dots & \dots & \dots & \dots & \dots \end{bmatrix}$$

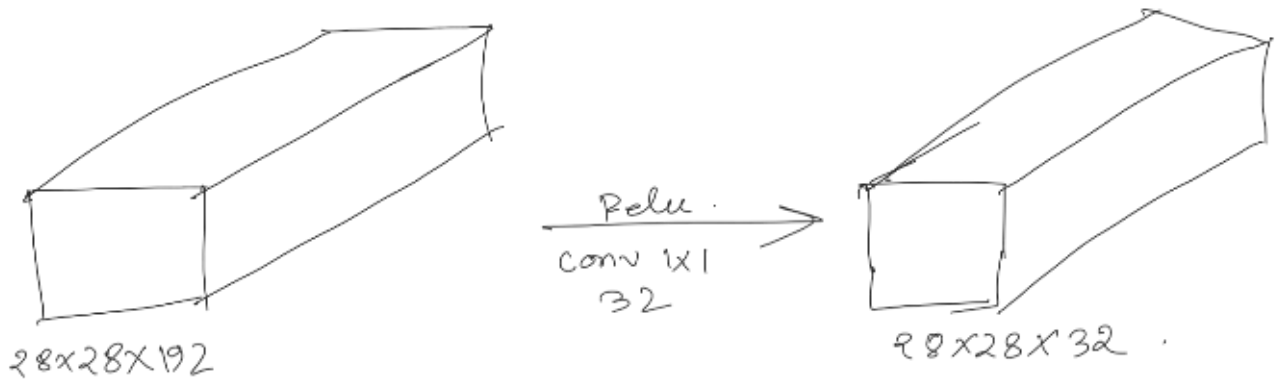
it seems 1x1 filter just multiply the original data. which is not useful. But it is useful in multidimensional image

Multidimension:-





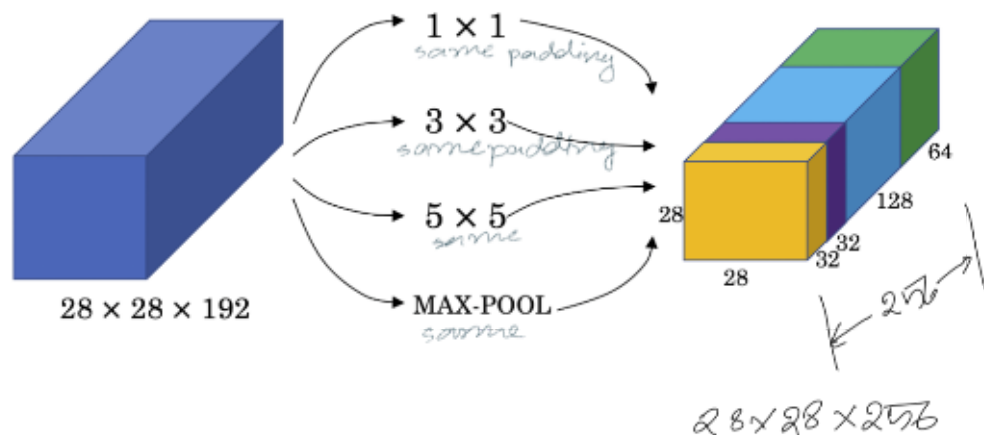
it is also called **network in network architecture**.



if we have a large channel and want to shrink the channel then we can use 1×1 filter to shrink the channel
pooling layer is used to shrink the height & width.

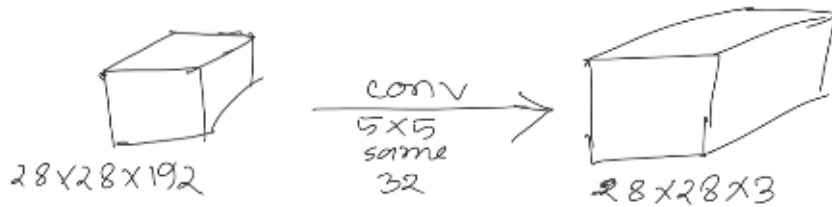
Inception network:- (GoogleNet)

Instead of choosing the filter size/max pooling/avg pooling. inception network does all of them at the same time. And it let the parameter learn whatever it wants to learn



Computational cost is higher for inception :-

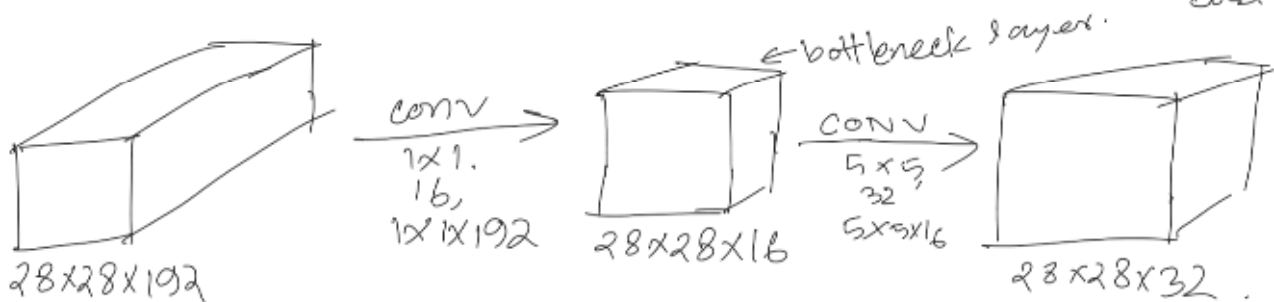
Let's focus on the computational cost of 5×5 filter



each of the 32 filters are $5 \times 5 \times 192$

so total computation, $28 \times 28 \times 32 \times 5 \times 5 \times 192 = 120 \text{ M}$.

We can use 1×1 convolution to reduce the computation cost :-



Cost :-

$$28 \times 28 \times 16 \times 1 \times 1 \times 192 = 2.4 \text{ M} \quad 28 \times 28 \times 32 \times 5 \times 5 \times 16 = 10 \text{ M}$$

