CNN

Week 2

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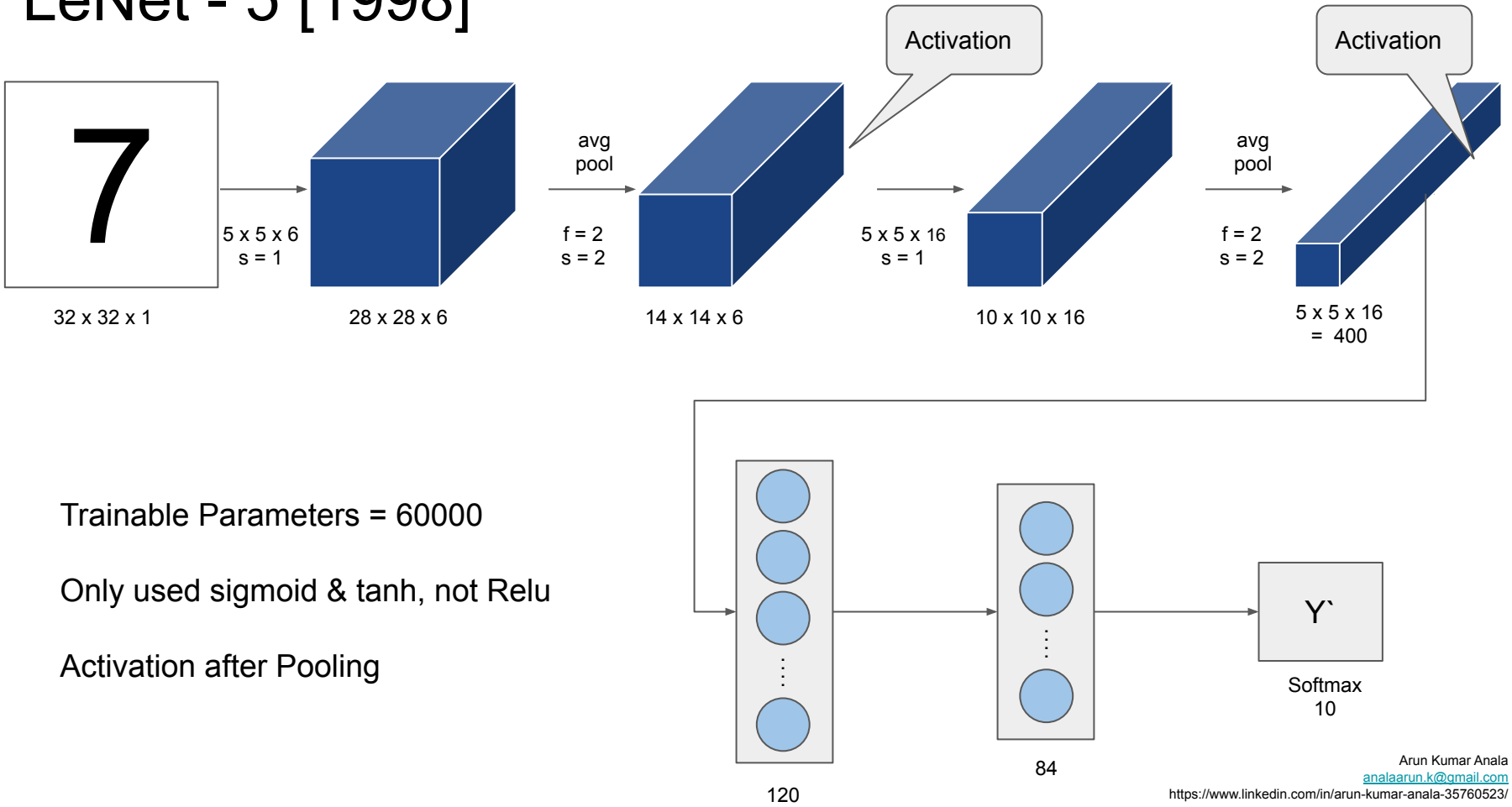
LeNet - 5 [1998]



Trainable Parameters = 60000

Only used sigmoid & tanh, not Relu

Activation after Pooling

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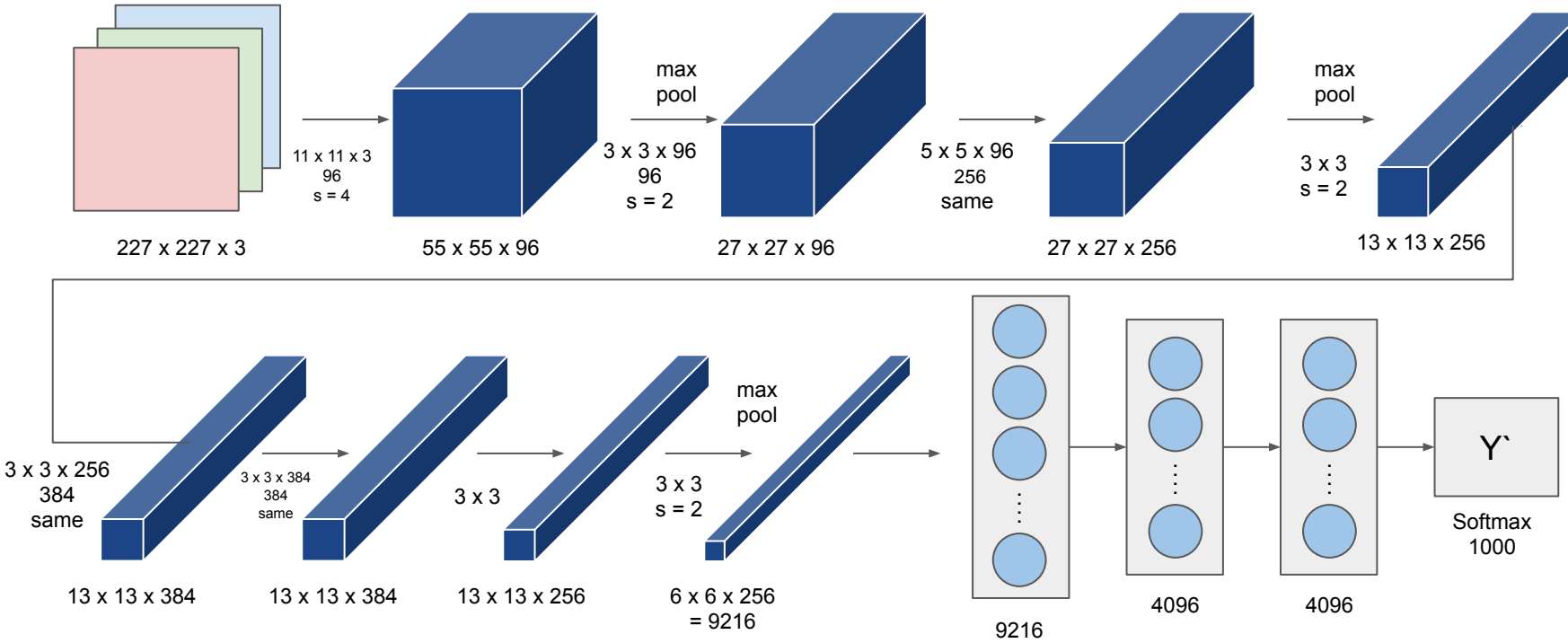
AlexNet [2012]



Trainable Parameters = 60 million

Used Relu

First Time Training on Multiple GPUs

Similar to LeNet but much bigger

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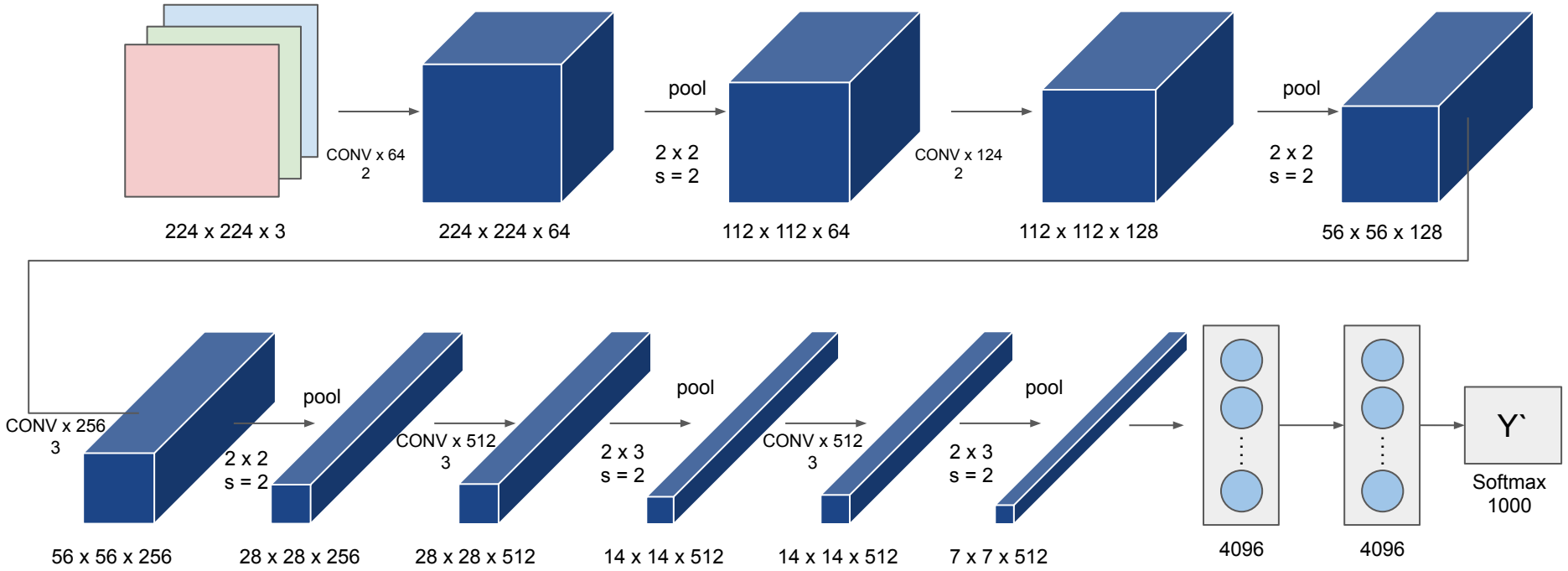
VGG 16 [2015]

CONV = 3 x 3 , s = 1 , SAME
MAX POOL = 2 x 2, s = 2



Trainable Parameters = 138 million
Pros - Uniformity
Goes Deeper by factor of 2
Multiple conv layers
3 x 3 filters across all layers

Cons - Bigger Network

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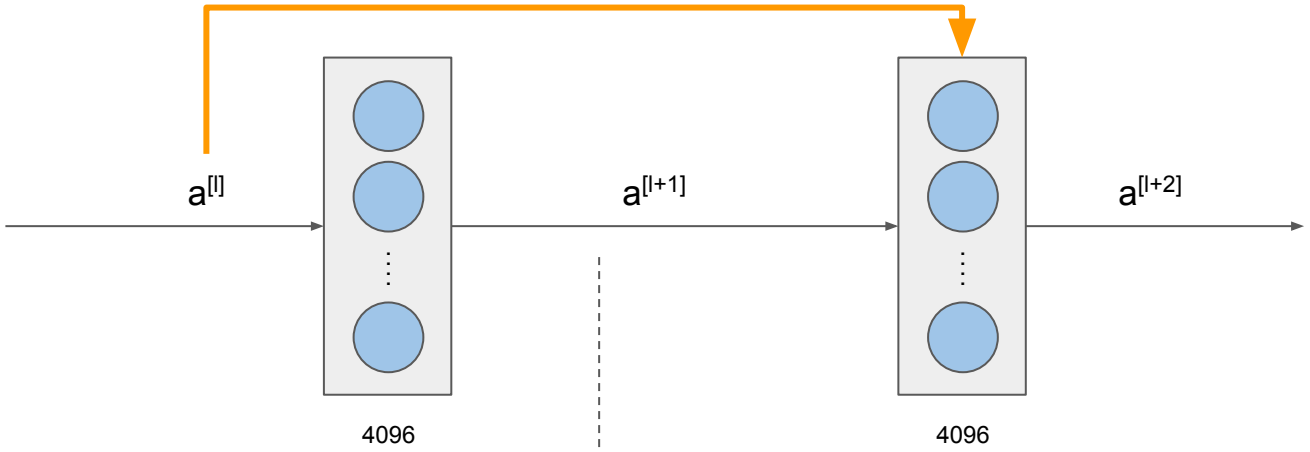
ResNets [2015]



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

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

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

Also called Residual blocks / Skip Connection / Shortcuts

Using Residual blocks we can pass information much deeper into network, here train much deep networks,

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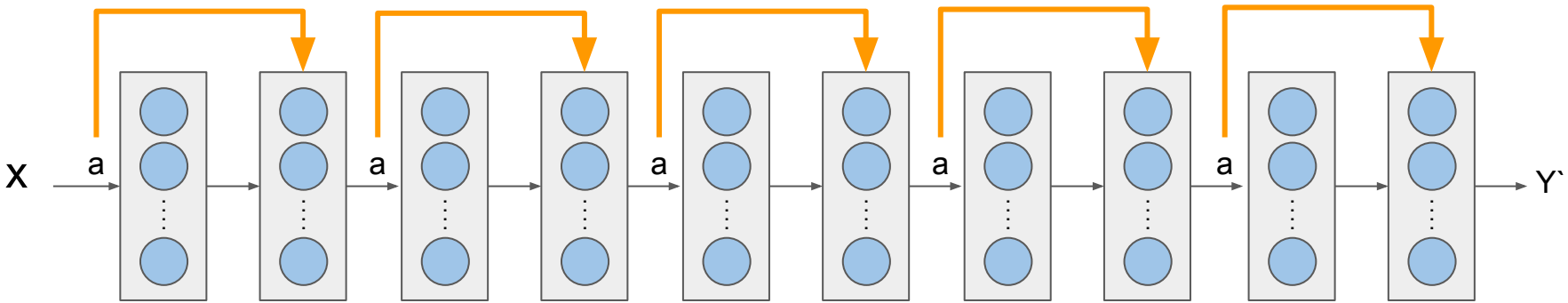
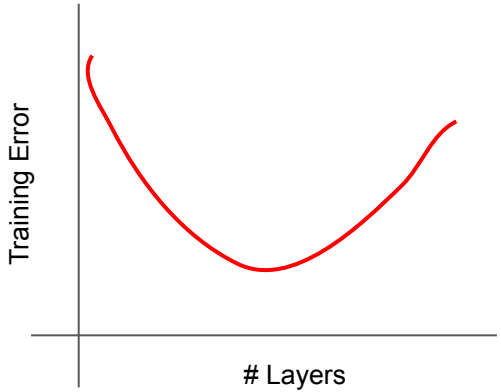
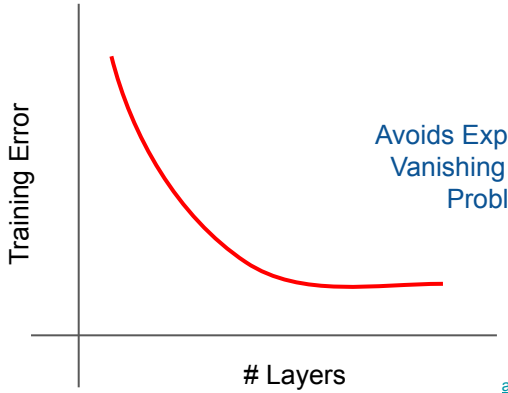
ResNets [2015]



Plain Network



ResNet



Avoids Exploding and Vanishing Gradient Problems

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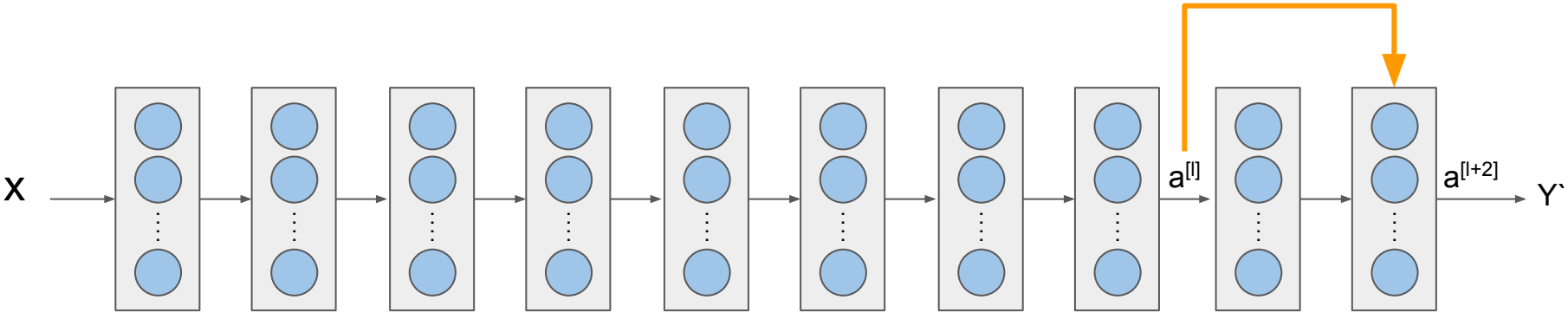
ResNets [2015]



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

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

$a^{[l+2]} = g(w^{[l+2]} a^{[l+1]} + b^{[l+2]} + a^{[l]})$ $w^{[l+2]} \sim 0,\ b^{[l+2]} \sim 0$

$a^{[l+2]} = g(a^{[l]}) = a^{[l]}$ Since Relu, $a^{[l]} > 0$

In case, dimension of $a^{[l+2]}$!= dimension of $a^{[l]}$
Ws can be used to match the dimension. Ws can be trainable parameters or fixed values like zero padding

$a^{[l+2]} = g(w^{[l+2]} a^{[l+1]} + b^{[l+2]} + W_s a^{[l]})$

Adding Residual Blocks does not hurts the performance of the plain network.

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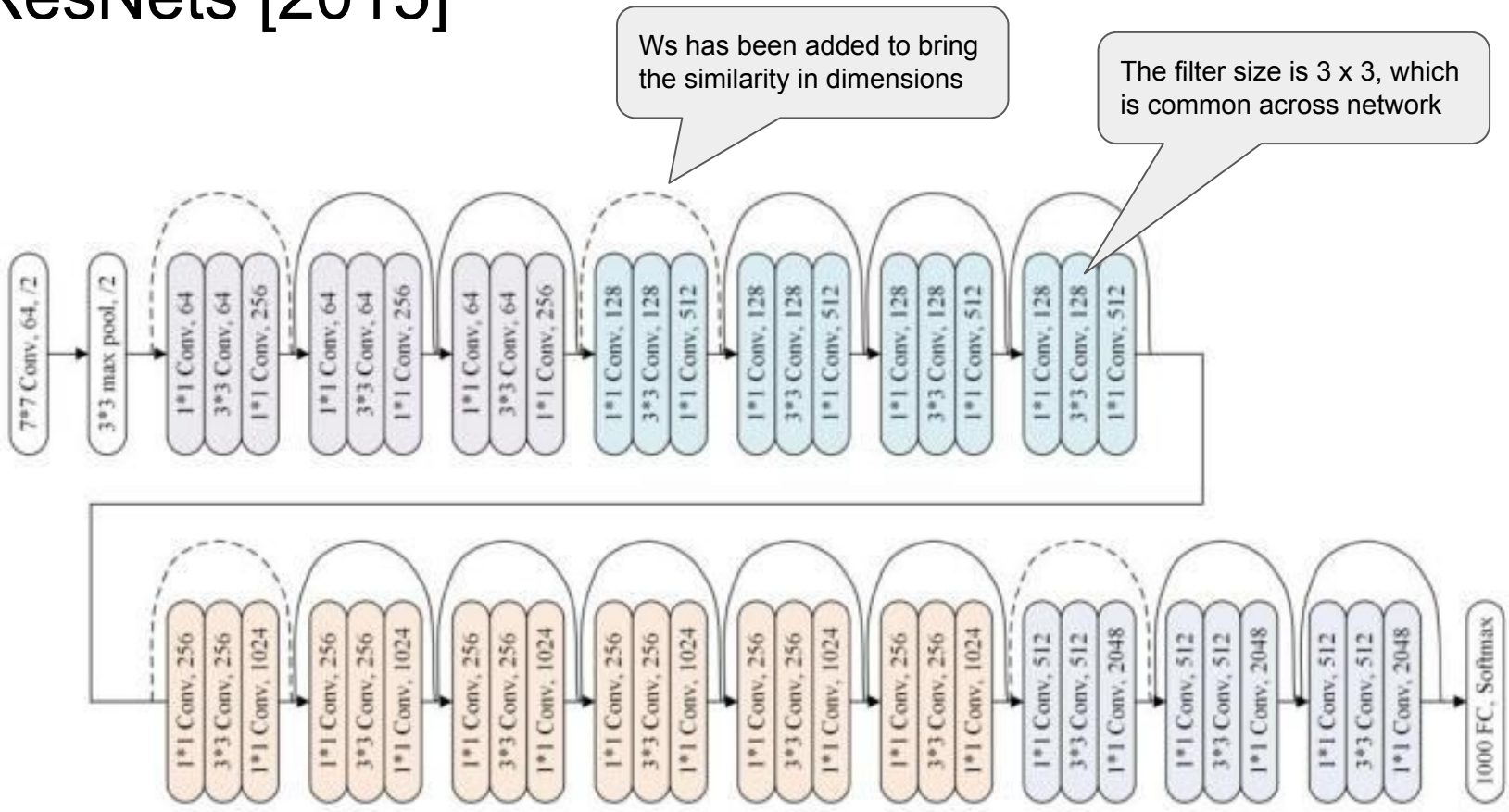
ResNets [2015]



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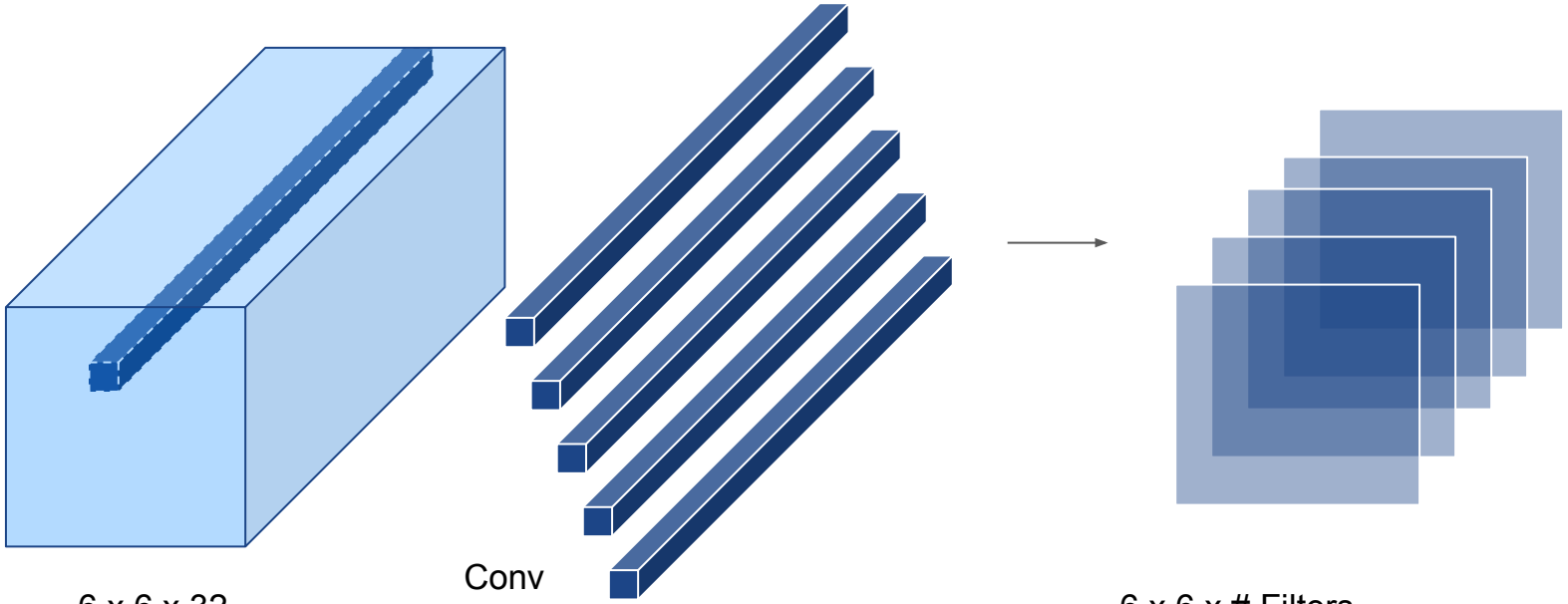
1 x 1 Convolution



1 x 1 Convolution does not affects the height and width, but it's very useful in decreasing or increasing the depth.

Or Just keep the output size same 6 x 6 x 32, so that we can bring in non-linearity.

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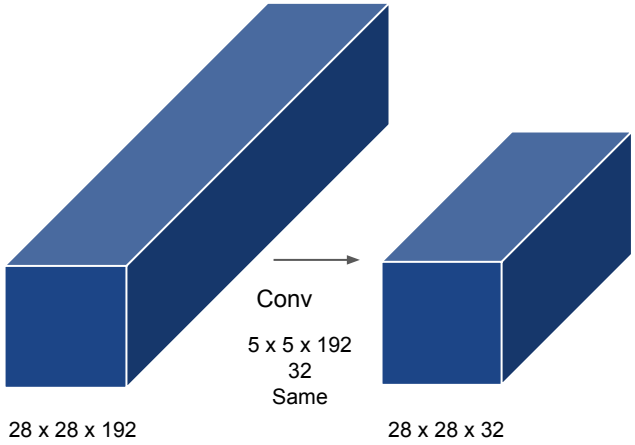
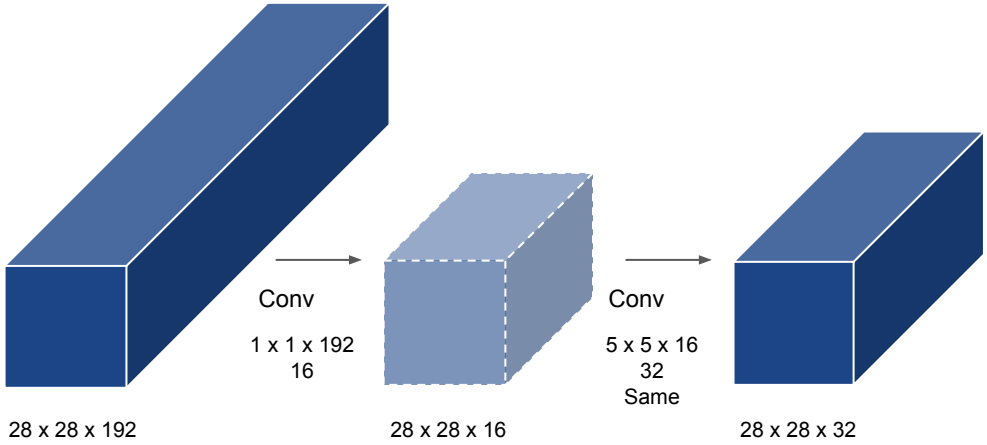
1 x 1 Convolution



Total Multiplications = (28 x 28 x 32) x (5 x 5 x 192)
= 120 million



Total Multiplications = [(28 x 28 x 16) x (1 x 1 x 192)] + [(28 x 28 x 32) x (5 x 5 x 16)]
= 2.4 million + 10 million
= 12.4 million

Using 1 x 1 convolution, the cost of multiplication operations can be brought to 1/10th and here boost to performance

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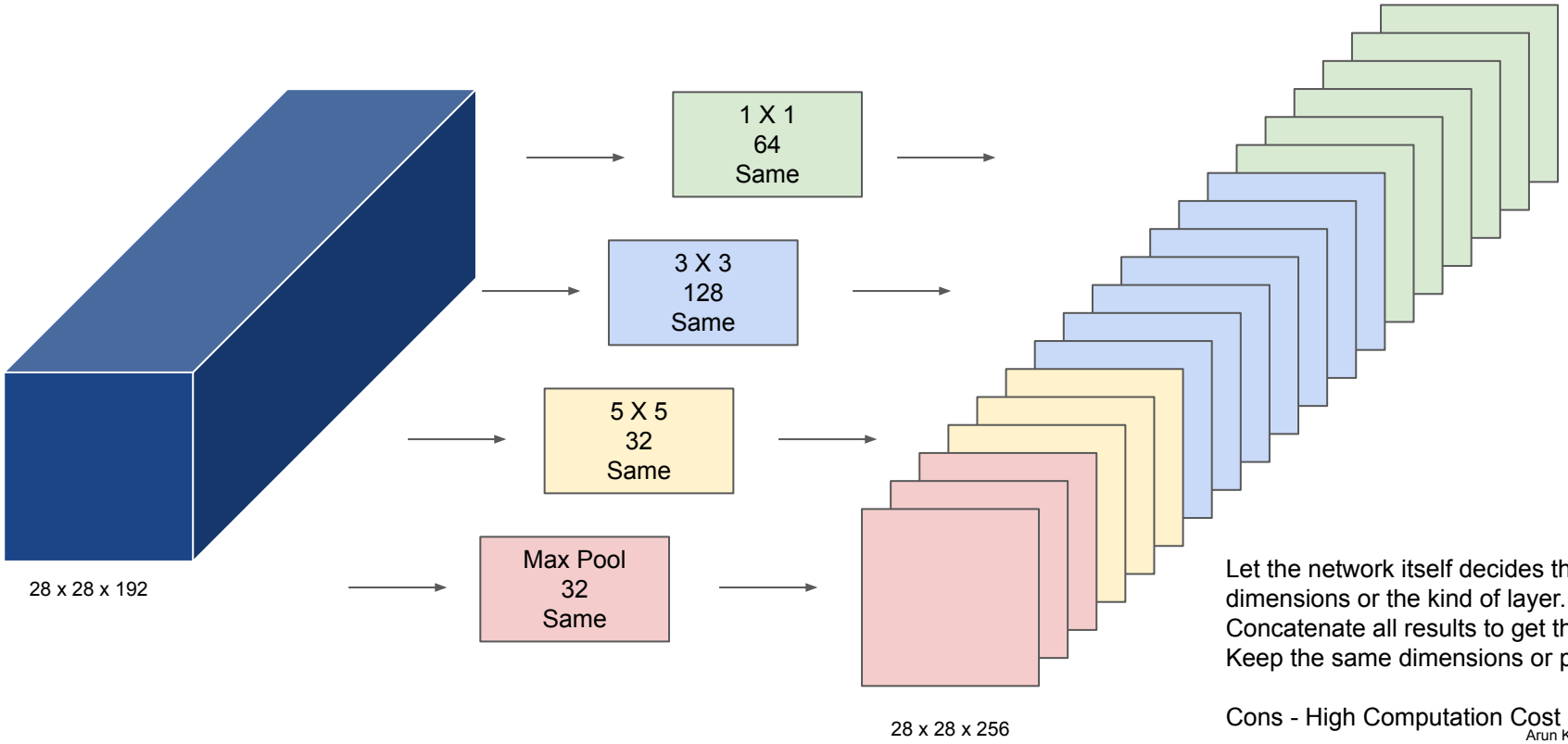
Inception [2014] , GoogleNet



Let the network itself decides the filter dimensions or the kind of layer.
Concatenate all results to get the output.
Keep the same dimensions or padding

Cons - High Computation Cost

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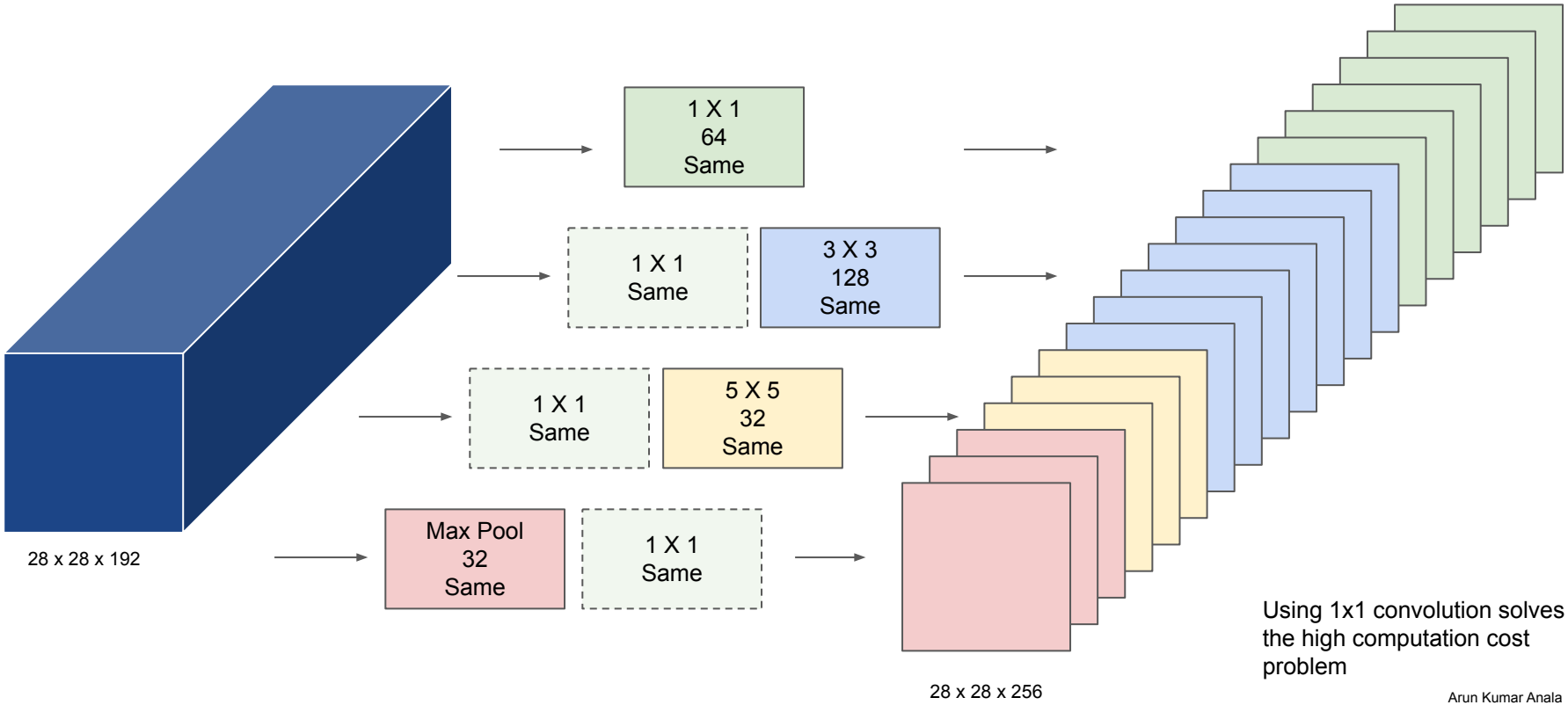

Using 1x1 convolution solves the high computation cost problem

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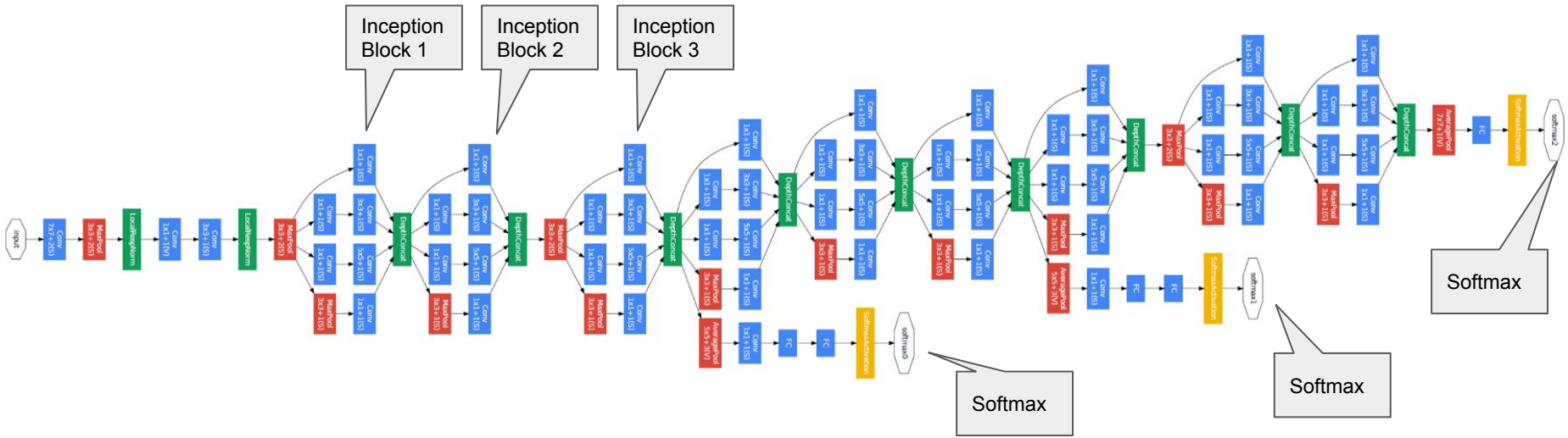

Having Softmax, at multiple layers of network gives the opportunity to intermediate layers to learn better from the losses. This also have regularizing effect on intermediate layers and prevents overfitting.

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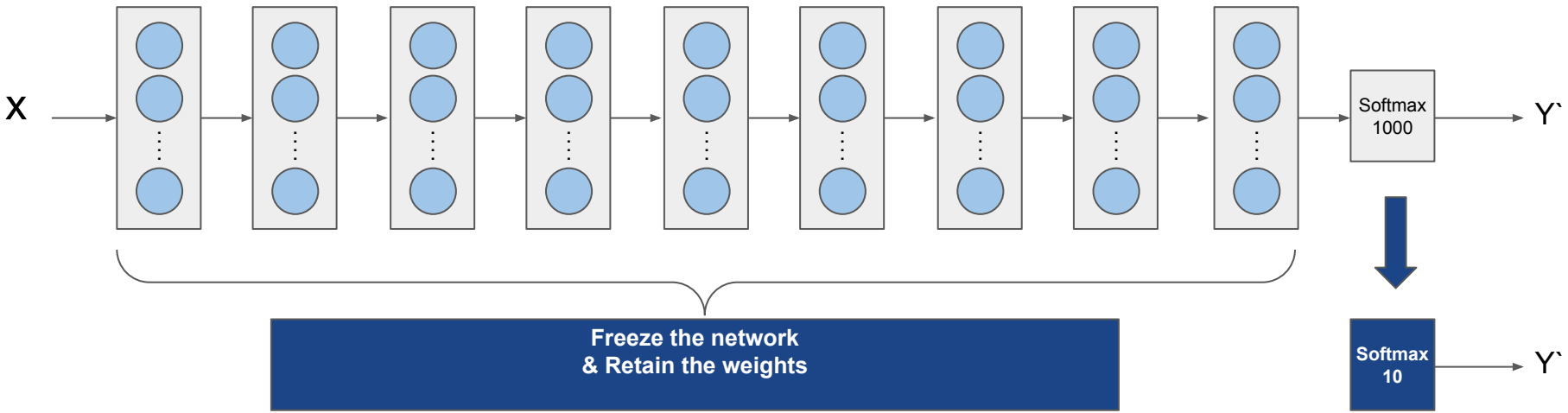
Transfer Learning



When data set is less

10 Classes to predict.

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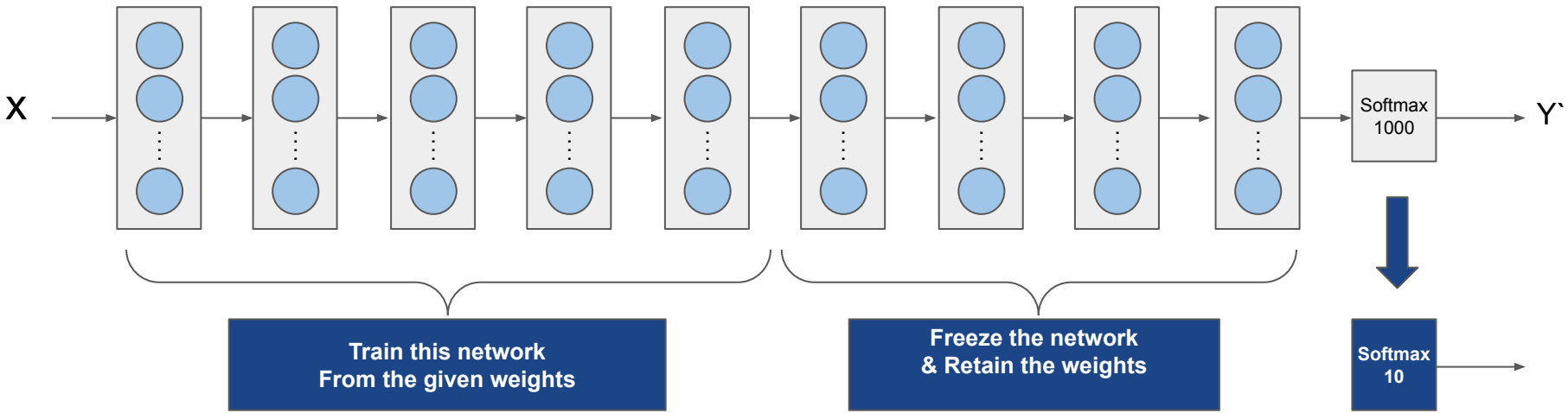
Transfer Learning



When data set is large

10 Classes to predict.

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Data vs Hand Engineering

Little Data

Lots of Data

Object Detection

Image Recognition

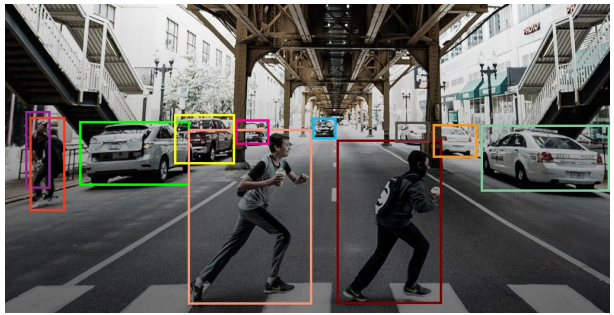
Speech Recognition

More Hand Engineering

Less Hand Engineering

Transfer Learning

Simpler Algorithms



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