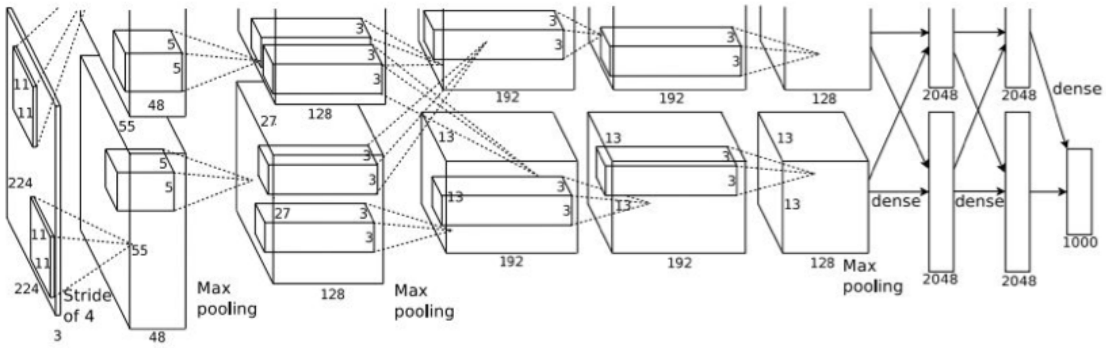
CNN Architectures

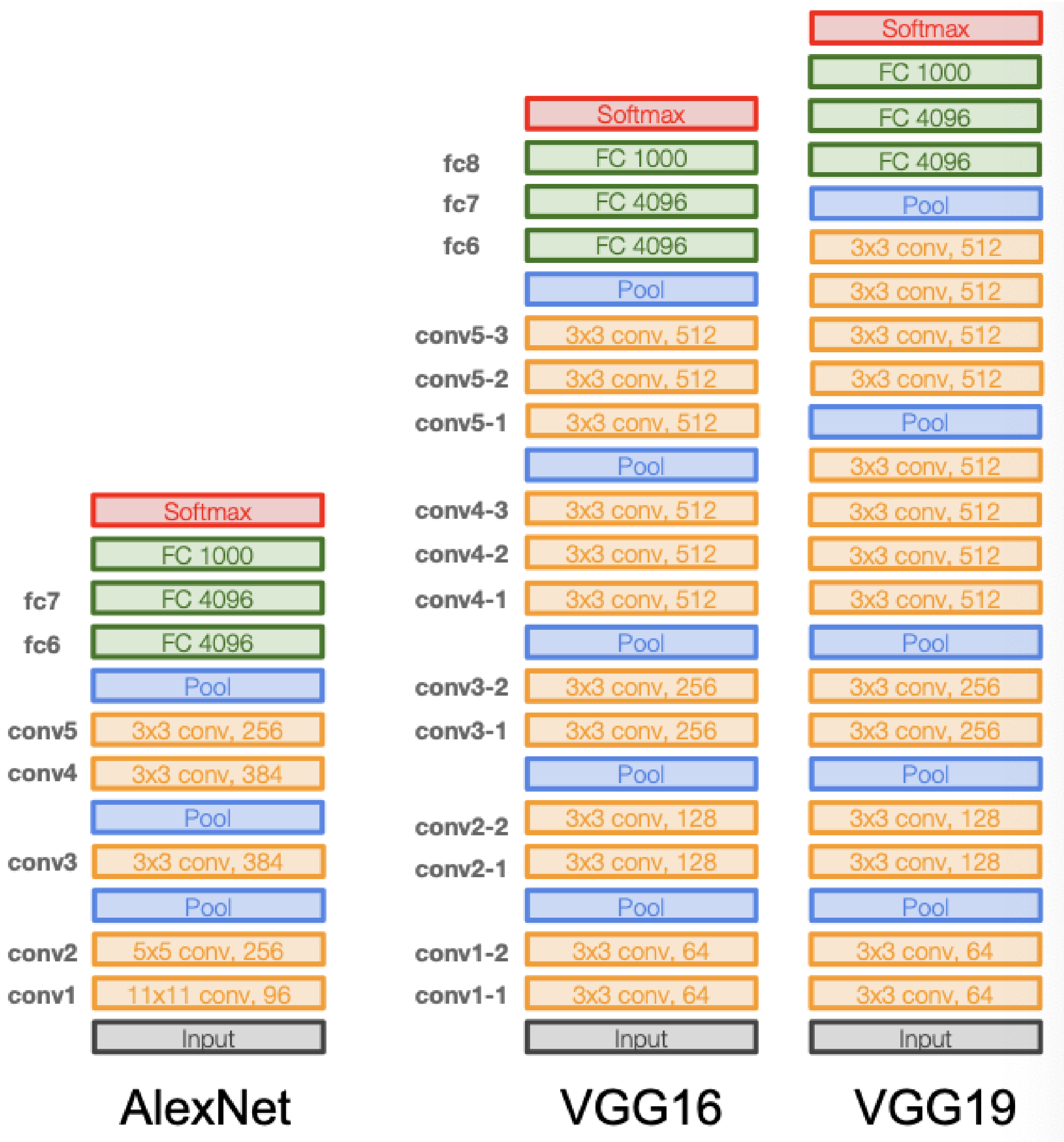
Major Architectures

1. AlexNet



   a. First deep learning based ConvNet (8 layers)
   b. At first layer (CONV1)
      i. input image size: 227 x 227 x 3
      ii. output volume size: 55 x 55 x 96
         - 96개의 11 x 11 filters with stride 4
      iii. total number of parameters: 11 * 11 * 3 * 96 = 35K
   c. At second layer (POOL1)
      i. output volume size: 27 x 27 x 96
         - 3 x 3 filters with stride 2
         - preserve the depth
      ii. total number of parameters: 0
         - parameters are the weights we try to learn
         - but pooling just take the max value in one region

2. VGGNet



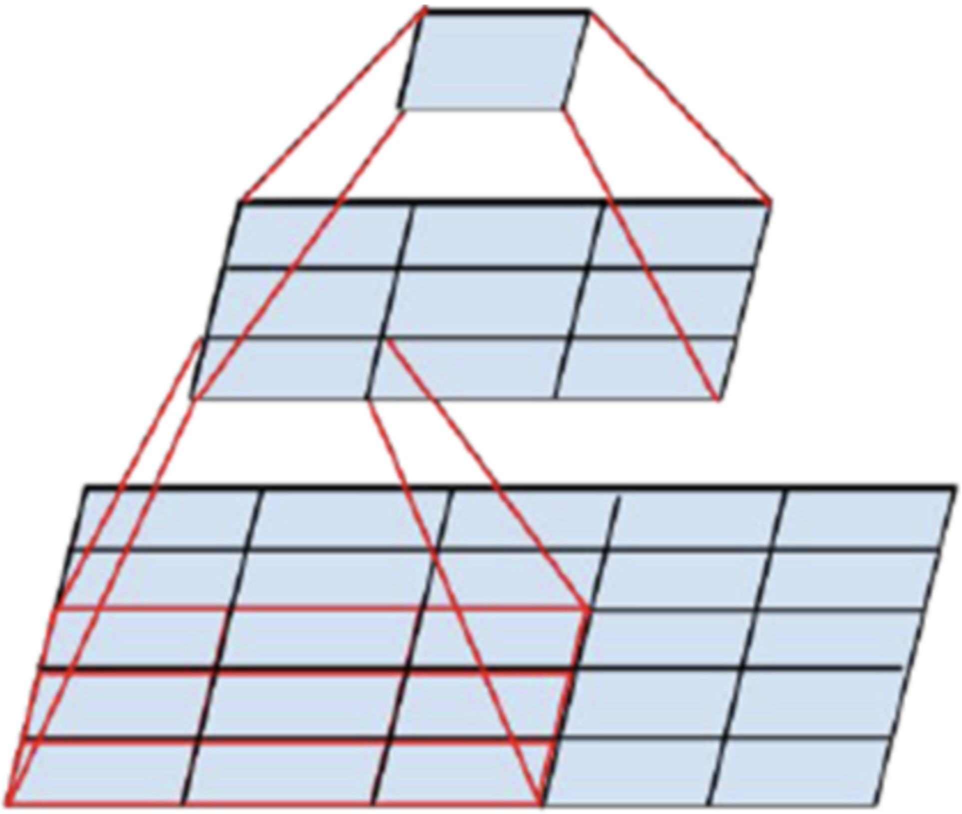
a. Deeper networks (16-19 layers) with small filters

   i. why use smaller filters? (3 x 3 conv)

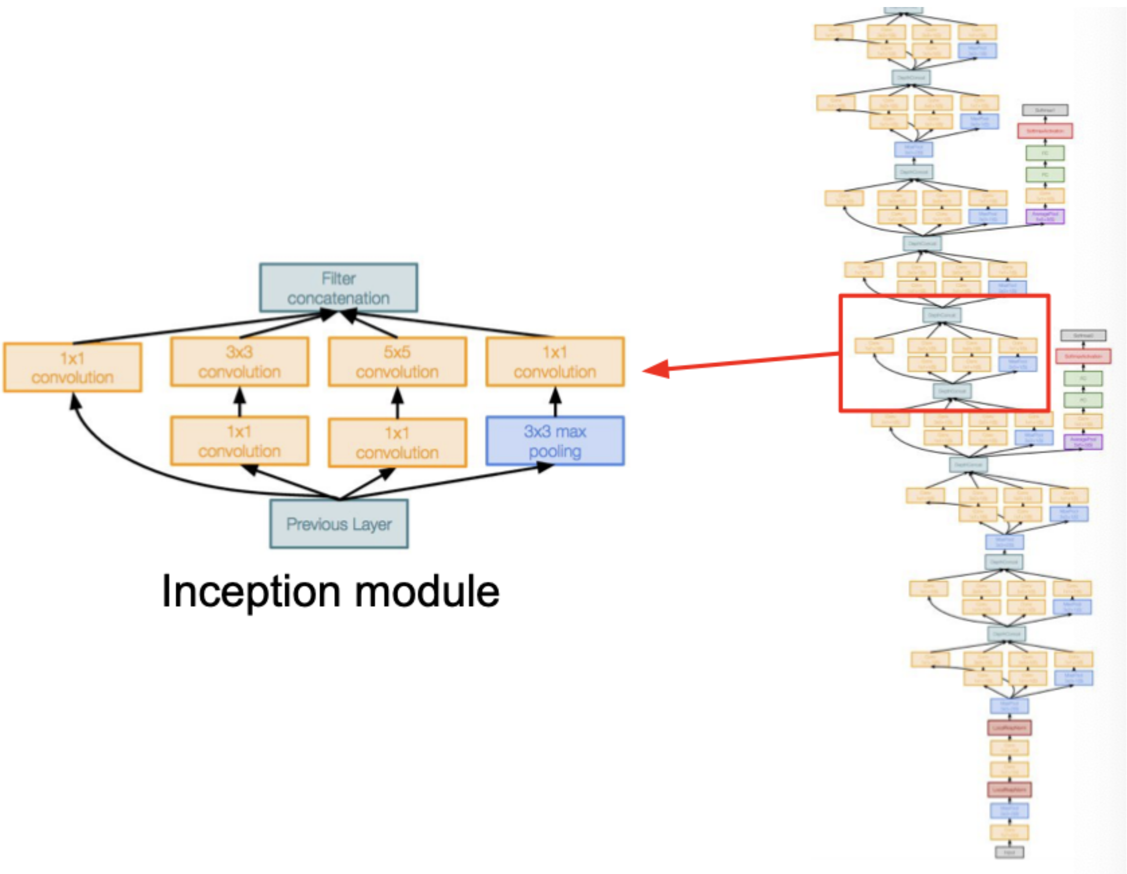
      - Stack of three 3 x 3 conv with stride 1 layers has same ***effective receptive field*** as one 7 x 7 conv layer
      - fewer parameters per layer

   ii. what is the ***effective receptive field*** of three 3 x 3 conv with stride 1 layers?

      - 크기가 큰 filter 를 작은 filter 로 factorize 하는 방식으로 3 layer 를 사용하면 3 x 3 → 5 x 5 → 7 x 7 크기의 filter 와 동일한 효과를 냄
      - e.g.,



3. GoogLeNet


Filter concatenation
1x1 convolution
3x3 convolution
5x5 convolution
1x1 convolution
1x1 convolution
1x1 convolution
3x3 max pooling
Previous Layer
Inception module

a. Deeper network (22 layers) with computational efficiency

b. Use ***inception module***

   i. design a good local network topology (network within a network) and then stack these modules on top of each other

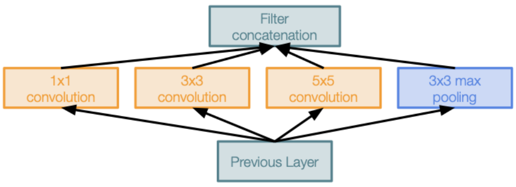
   ii. apply parallel filter operations on the input from previous layer

   iii. concatenate all filter outputs together depth-wise

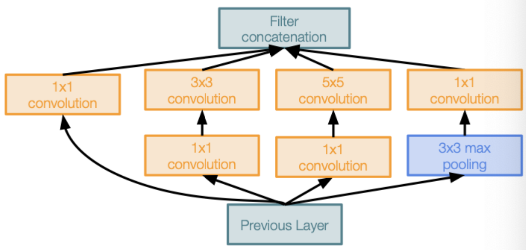
c. what is the problem with this?

   i. high computational complexity

d. Solution: use ***bottleneck layers*** (1 x 1 conv) to reduce feature depth



Naive Inception module

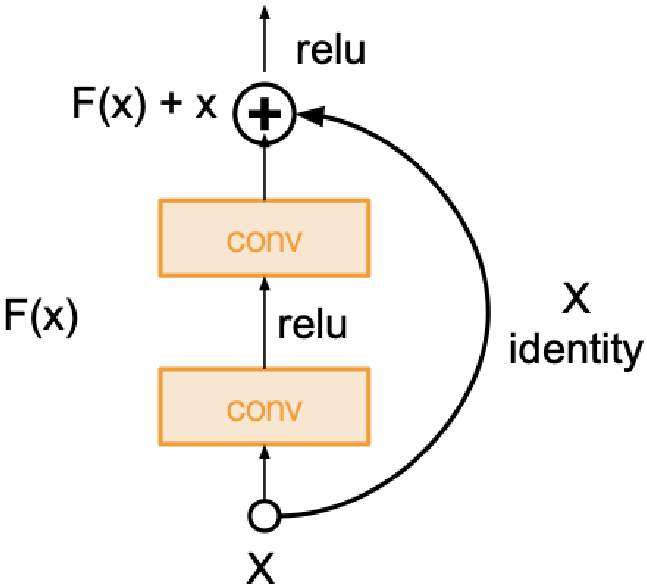


Inception module with dimension reduction

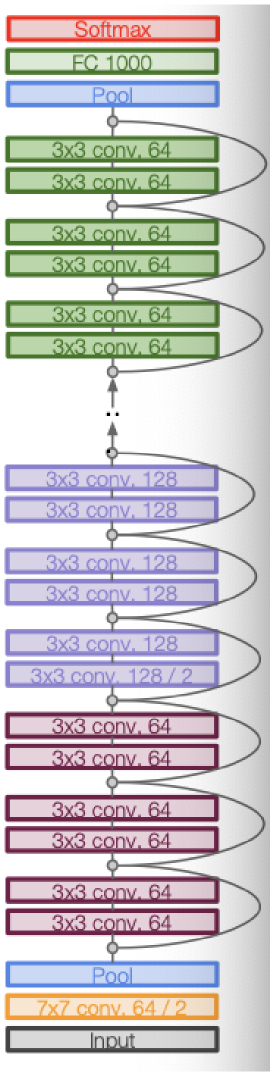
   i. preserve spatial dimension and only reduce depth

   ii. use zero-padding to preserve spatial dimension

4. ResNet



Residual block



a. Very deep networks using residual connections

   i. what happens when we continue stacking deeper layers on a plain convolutional neural network?

      - not able to do better than shallow model

b. Hypothesis: the problem is an optimization problem, deeper models are harder to optimize

c. Solution: use network layers to fit a residual mapping instead of directly trying to fit a desired underlying mapping

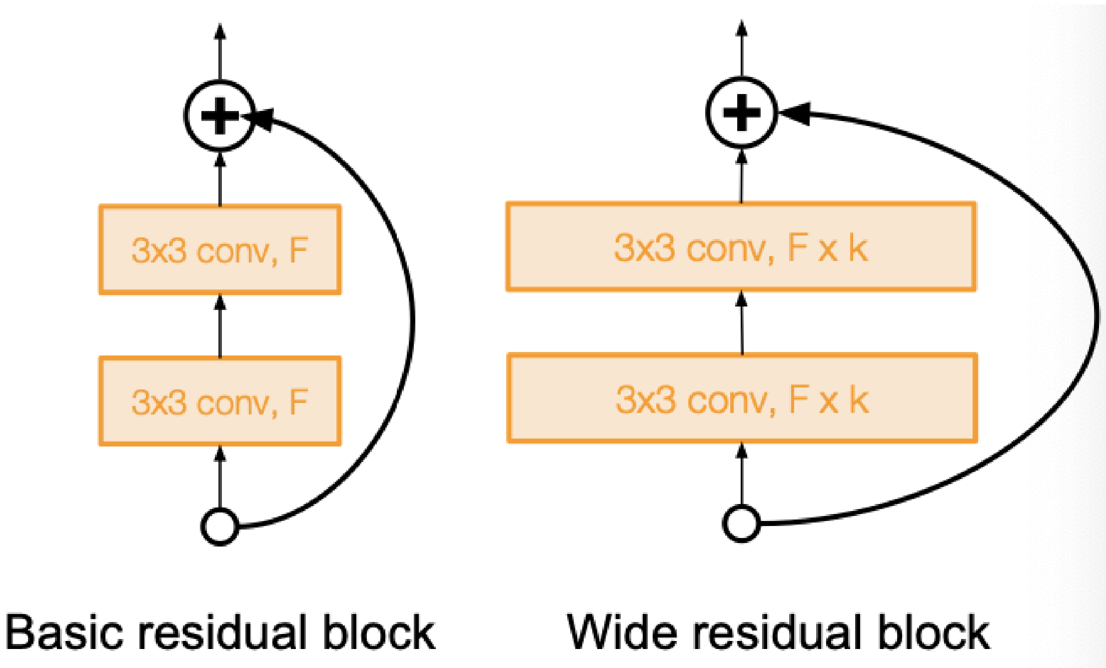
   i. plain layers: x → F(x) → H(x)

   ii. residual block: x → F(x) → F(x) + x (= H(x))

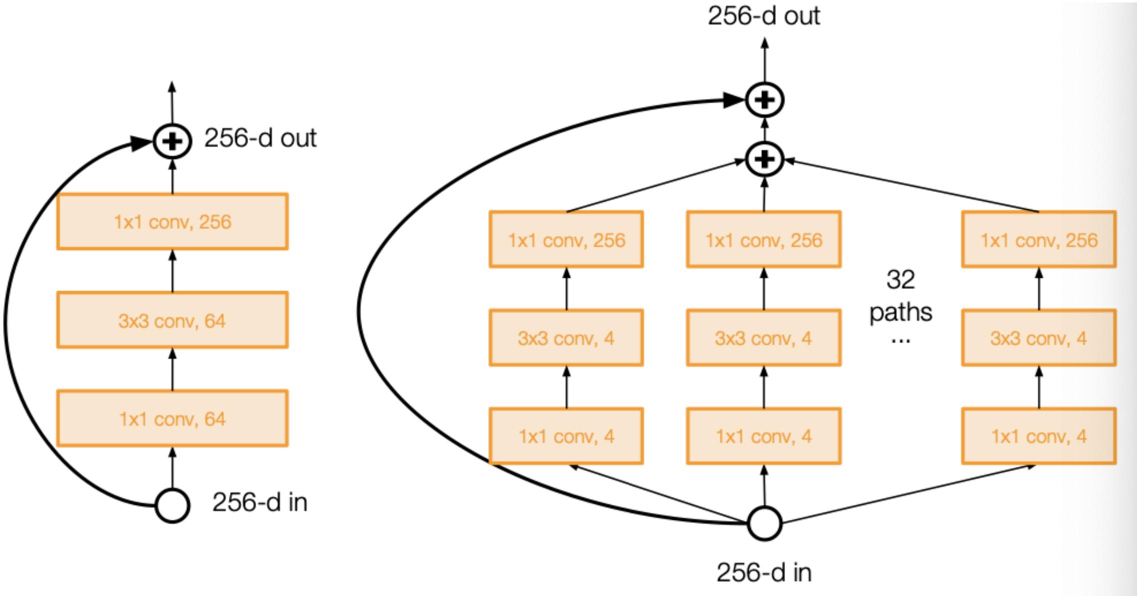
d. For deeper networks, use bottleneck layer to improve efficiency

Minor Architectures

1. NiN (Network in Network)
    a. Use micronetwork within each conv layer to compute more abstract features for local patches
        i. micronetwork uses multilayer perceptron
2. Wide ResNet

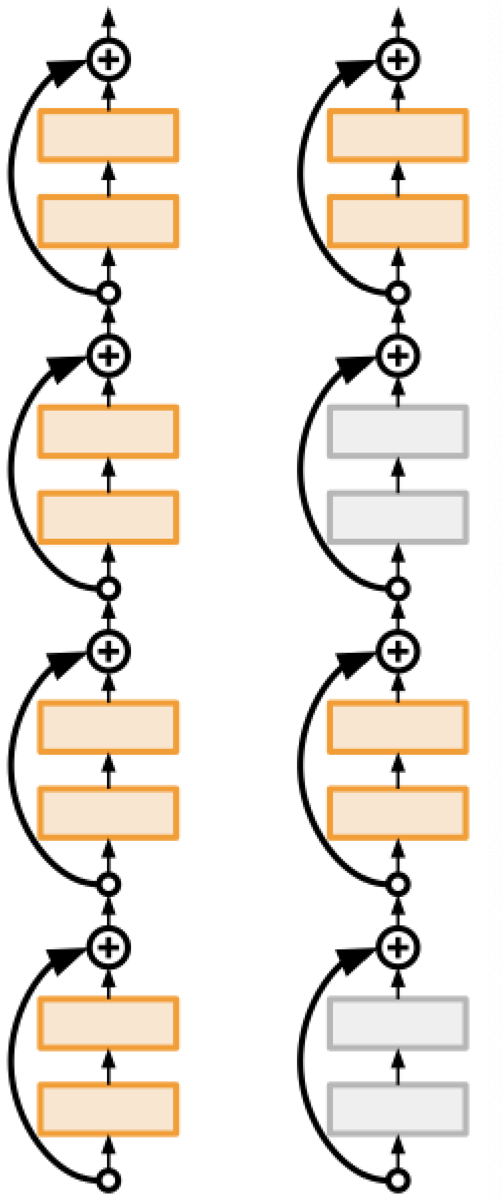


    a. Use wider residual blocks
        i. F x k filters instead of F filters in each layer
    b. Increase width instead of depth for computational efficiency
3. ResNeXt



a. Increase width of residual block through multiple parallel pathways

4. Stochastic Depth



a. Motivation: reduce vanishing gradients and training time through short networks during training

b. Randomly drop a subset of layers during each training pass

5. FractalNet

   a. Use both shallow and deep paths to output

   b. Train with dropping out subpaths

6. DenseNet

   a. Dense blocks of each layer are connected to every other layer in feedforward fashion

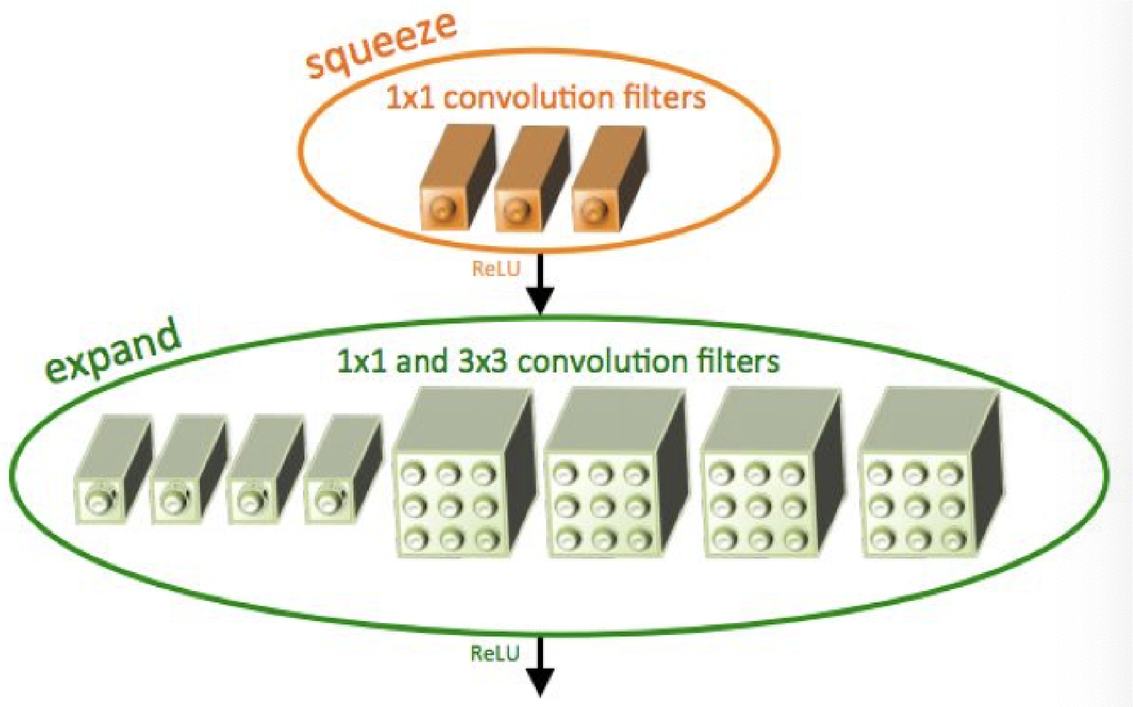
b. Advantages

    i. alleviate vanishing gradient

    ii. strengthen feature propagation

    iii. encourage feature reuse

7. SqueezeNet



    a. Consist of a squeeze layer with 1 x 1 filters feeding an expand layer with 1 x 1 and 3 x 3 filters