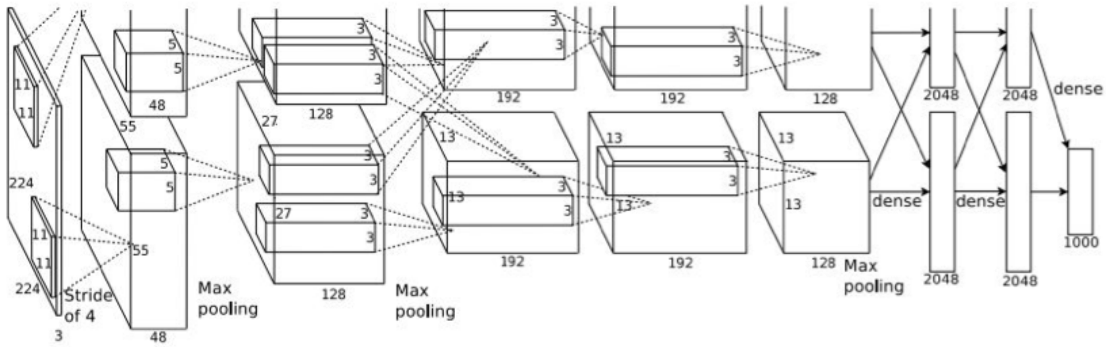
CNN Architectures

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)

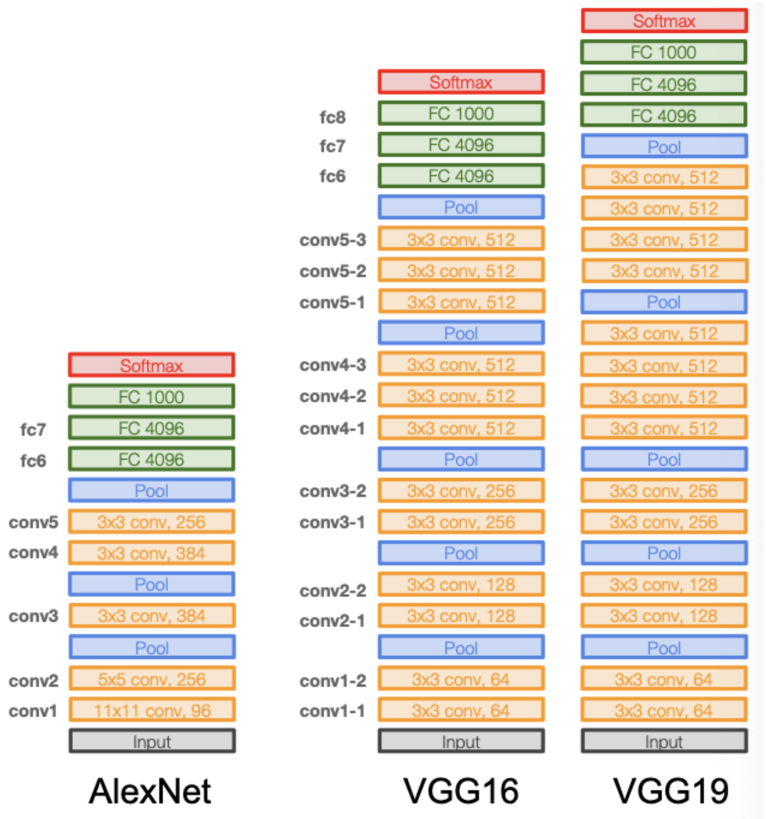
      i. output volume size: 27 x 27 x 96

         - 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



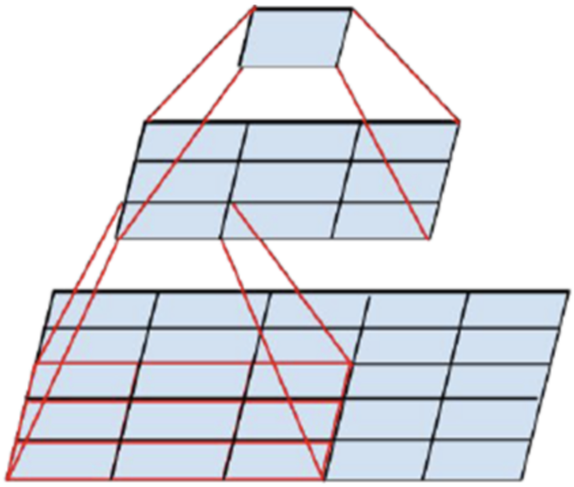
a. Deeper networks (16-19 layers) with small filters

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

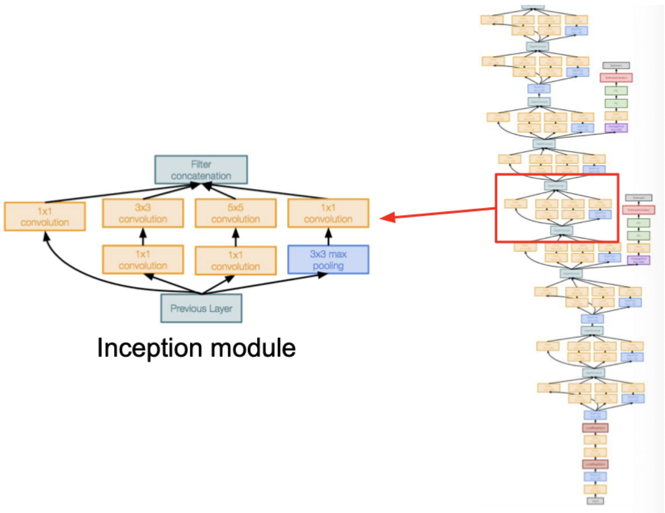
      - Stack of three 3 x 3 conv with stride 1 layers has same ***effective receptive field*** as one 7 x 7 conv layer
      - fewer parameters per layer

   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



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

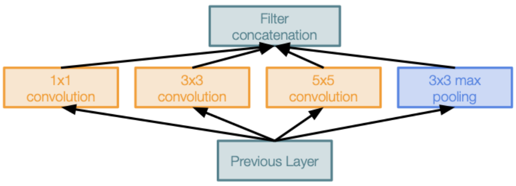
   ii. apply parallel filter operations on the input from previous layer

   iii. concatenate all filter outputs together depth-wise

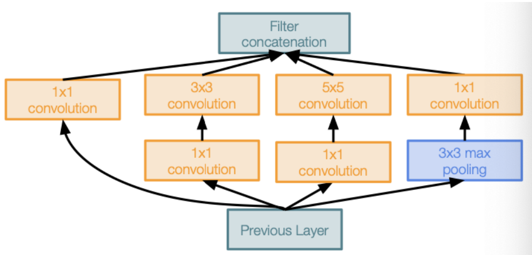
c. what is the problem with this?

   i. high computational complexity

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



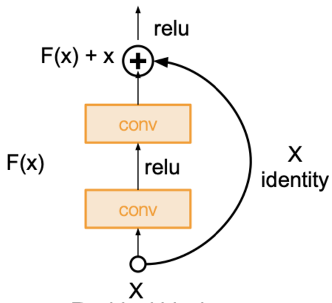
Naive Inception module



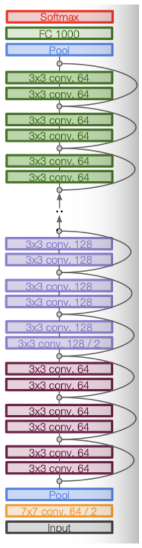
Inception module with dimension reduction

   i. preserve spatial dimension and only reduce depth
   ii. use zero-padding to preserve spatial dimension

4. ResNet



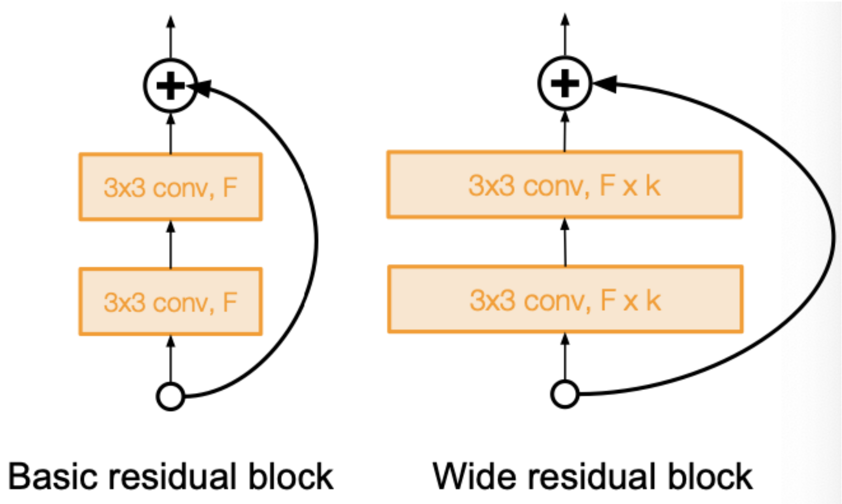
Residual block



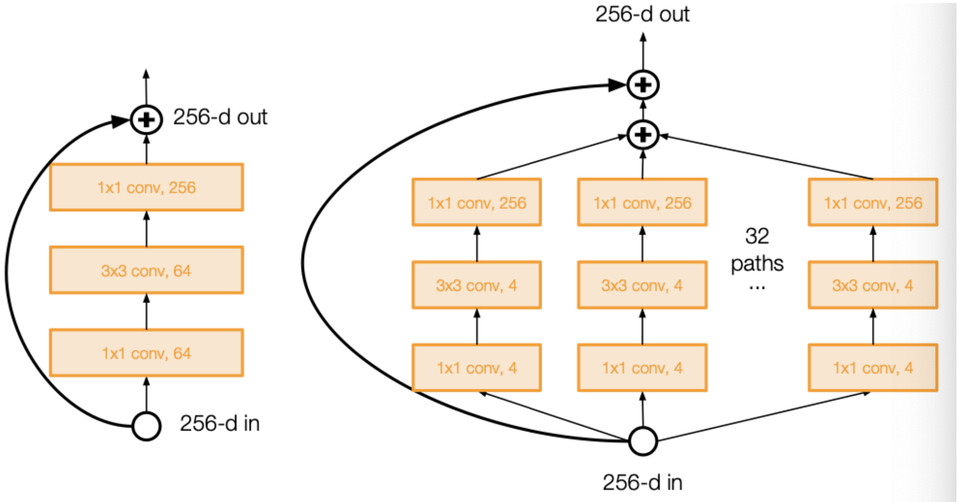
   a. Very deep networks using residual connections
      i. what happens when we continue stacking deeper layers on a plain convolutional neural network?
         - not able to do better than shallow model
   b. Hypothesis: the problem is an optimization problem, deeper models are harder to optimize
   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

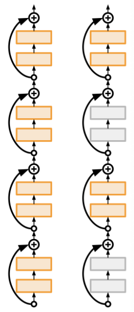


    a. Use wider residual blocks
        i. F x k filters instead of F filters in each layer
    b. Increase width instead of depth for computational efficiency
3. ResNeXt



    a. Increase width of residual block through multiple parallel pathways

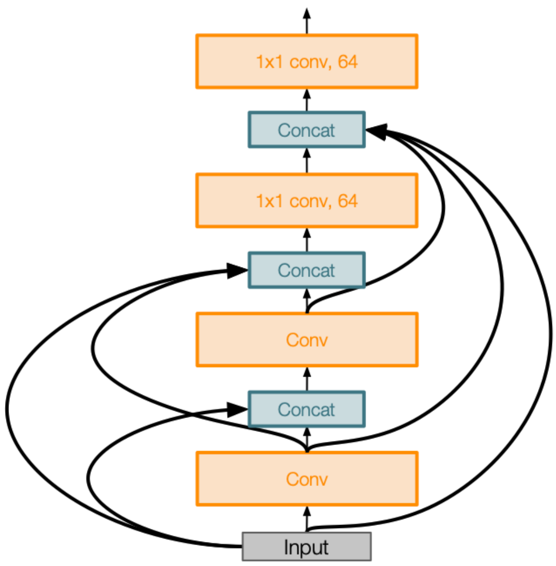
4. Stochastic Depth



    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



Dense Block

    a. Dense blocks of each layer are connected to every other layer in feedforward fashion
    b. Each layer obtain additional information from previous layers and feature maps are concatenated, not summed
        i. 극도로 deep 하거나 wide 한 구조로부터 representational power 를 끌어내는 대신 feature 의 재사용을 통해 네트워크의 잠재력을 활용함
        ii. 따라서 학습하기 쉽고 효율적인 parameter 를 가진 압축된 모델로 만들어졌고, 후속 layer의 input 에 variation 을 주면서 효율을 개선함

   iii. 위 부분들이 ResNet 과의 주요 차이점이며 inception module 보다 더 간단하고 효율적일 수 있는 이유라고 함

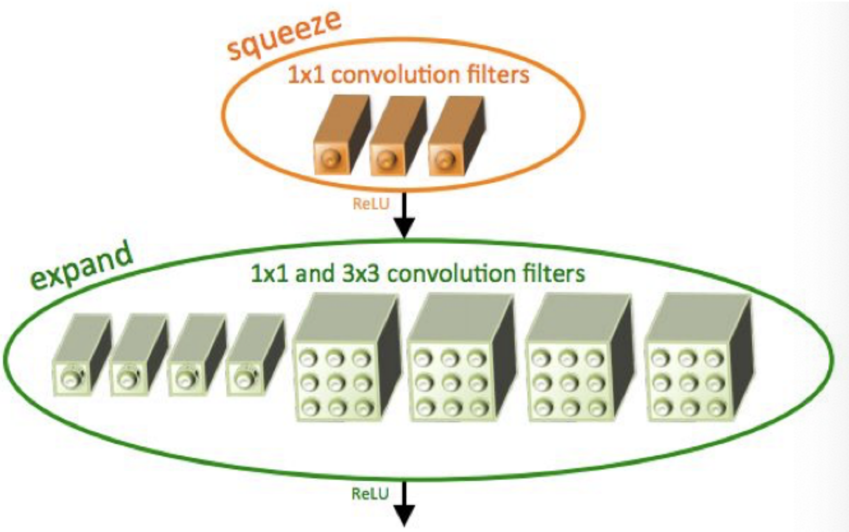
c. Advantages

   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