Deep Learning for Computer Vision

Evolution of CNN Architectures: InceptionNet, ResNet

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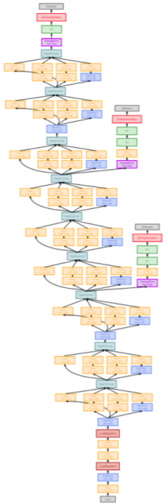
InceptionNet (GoogleNet)

- **Deeper networks with focus on efficiency**: reduce parameter count, memory usage, and computation



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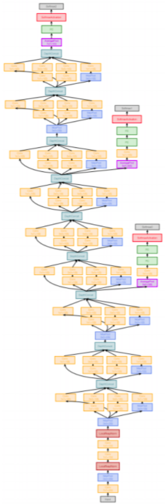

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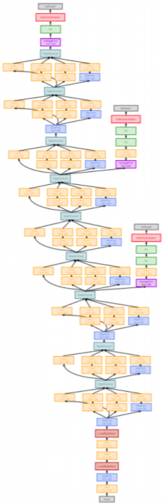

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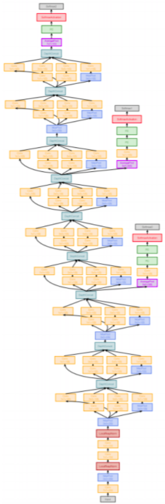

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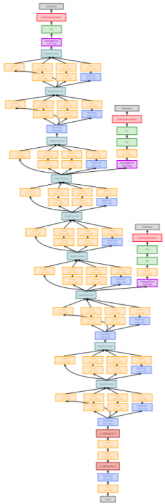

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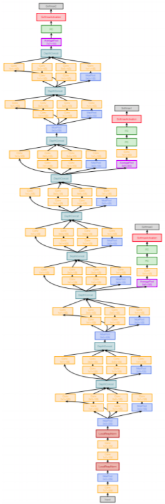
- **ILSVRC'14 classification winner** (6.7% top-5 error)



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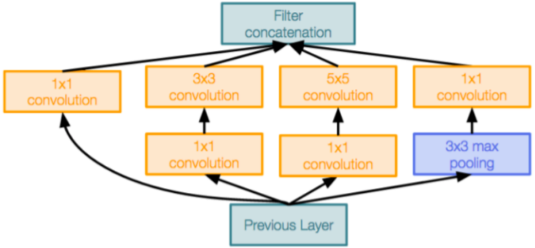
- **Inception module:** Local unit with parallel branches
- Local structure repeated many times throughout the network



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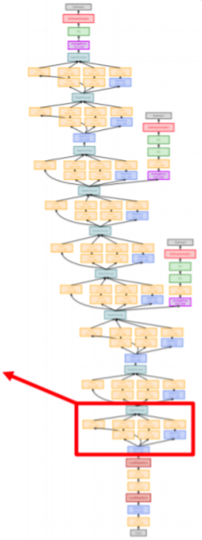

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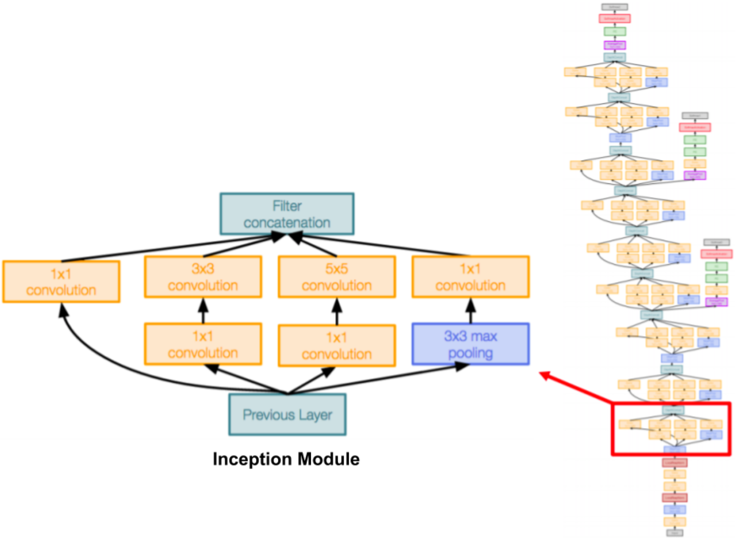

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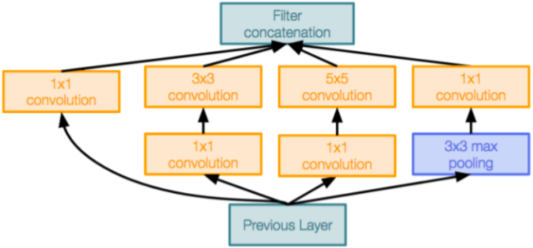

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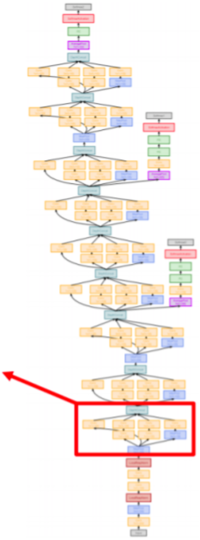

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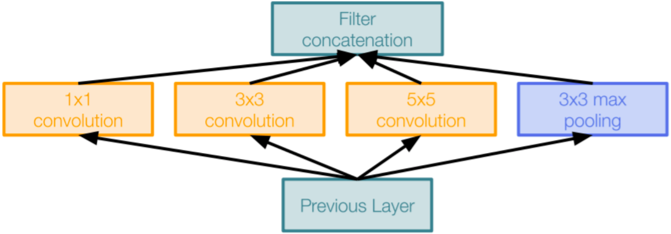

Naive Inception module

- Apply parallel filter operations on the input from previous layer:
  - Multiple receptive field sizes for convolution (1×1, 3×3, 5×5)
  - Pooling operation (3×3 max pooling)
- Concatenate all filter outputs together depth-wise

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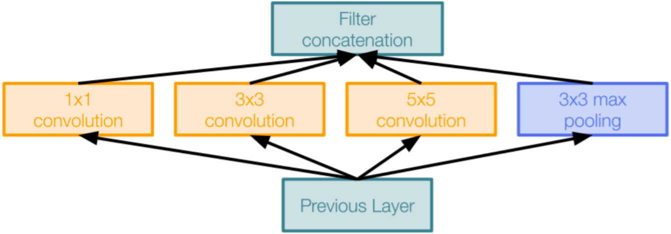

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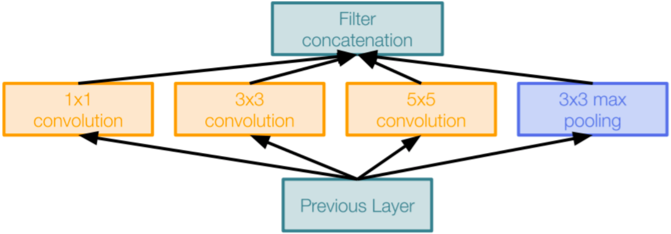

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- **What's the problem with this?** Computationally very expensive

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InceptionNet (GoogleNet)

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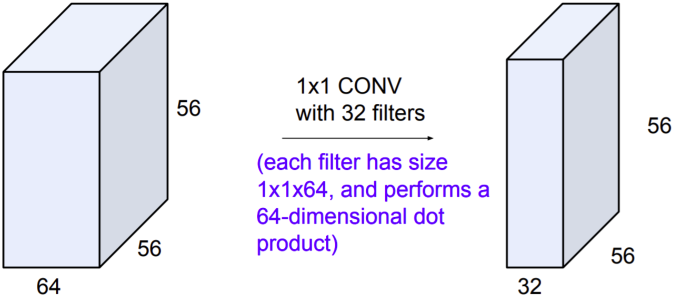

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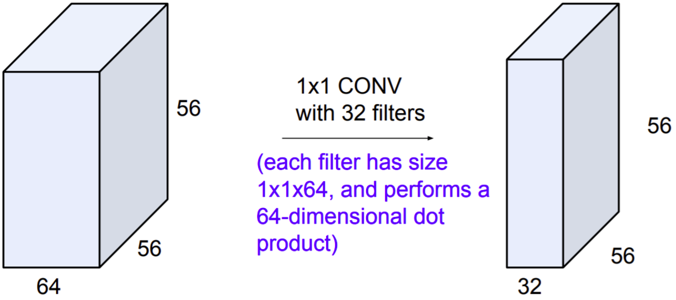

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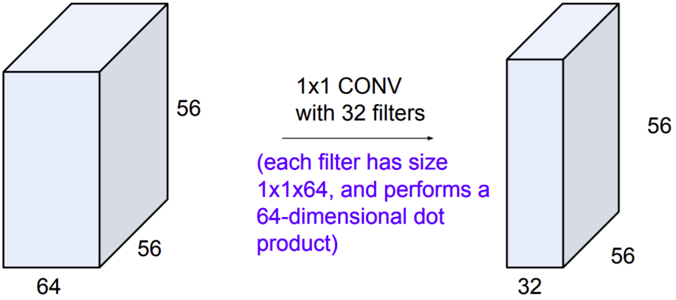

- Preserves spatial dimensions, reduces depth!
- Projects depth to lower dimension (combination of feature maps)

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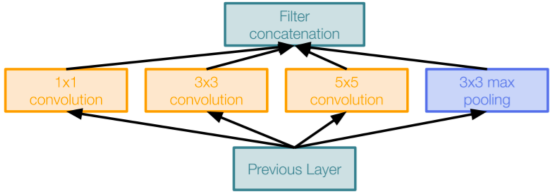
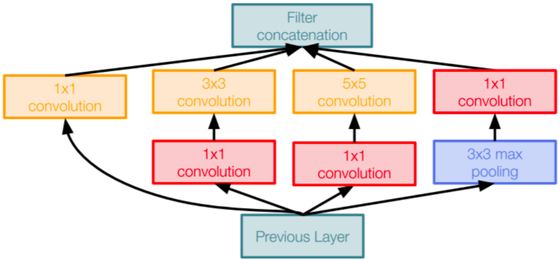


Naive Inception module

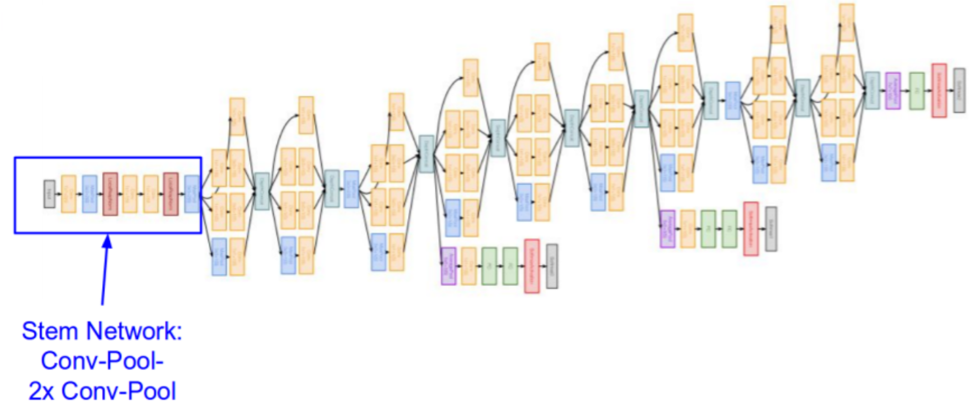
1x1 conv “bottleneck” layers



Inception module with dimension reduction

Credit: Fei-Fei Li, Justin Johnson and Serena Yeung, CS231n course, Stanford, Spring 2019

Full Architecture:



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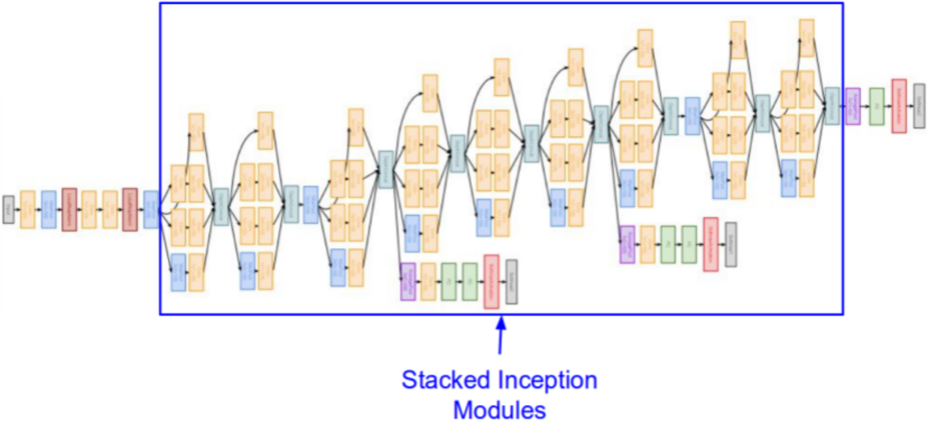

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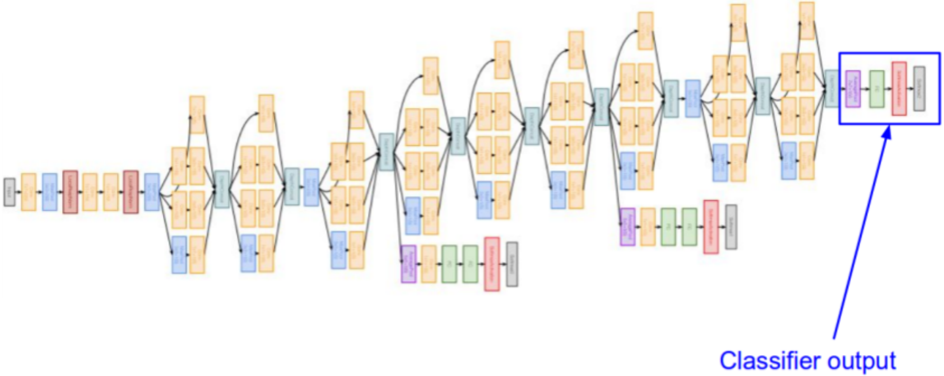

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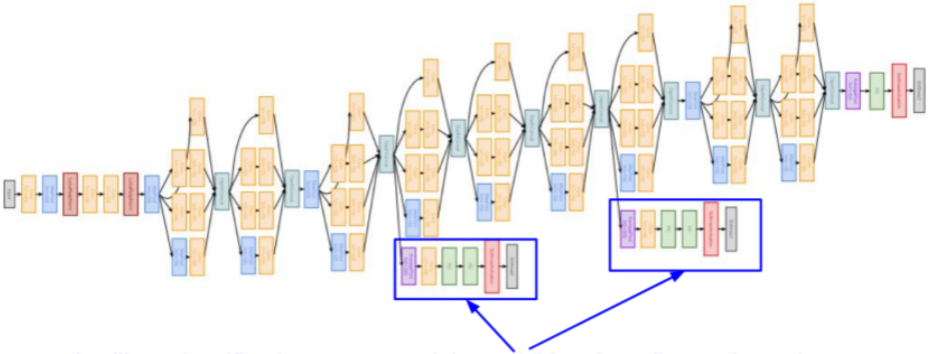

Auxiliary classification outputs to inject additional gradient at lower layers
(AvgPool-1x1Conv-FC-FC-Softmax)

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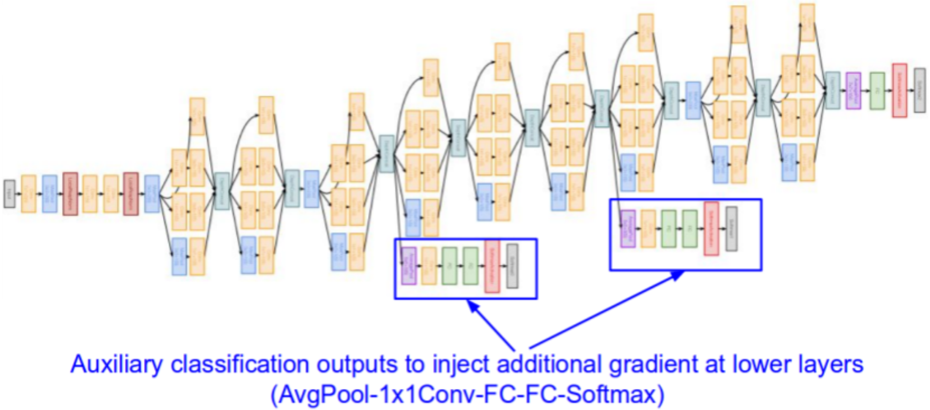

22 total layers (parallel layers count as 1 layer. Auxiliary output layers not counted)

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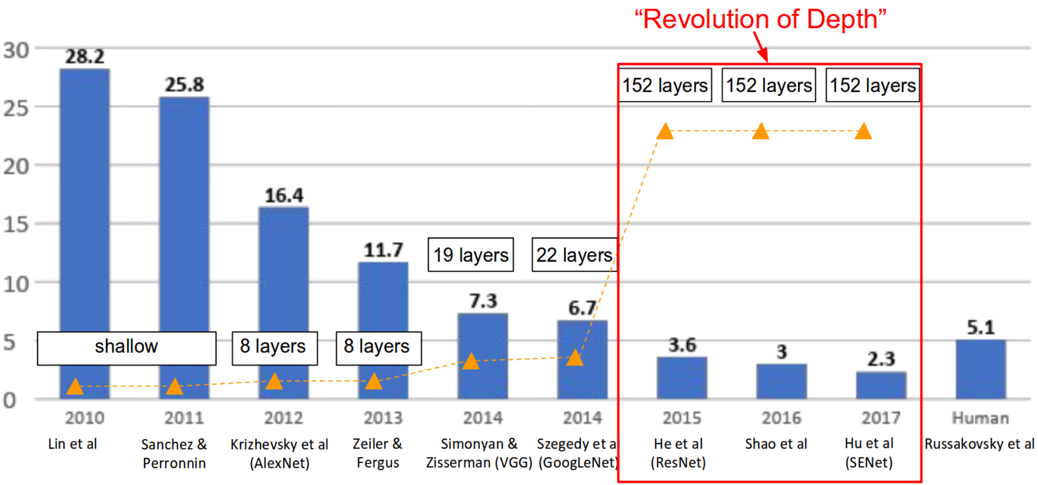
Deeper the Merrier



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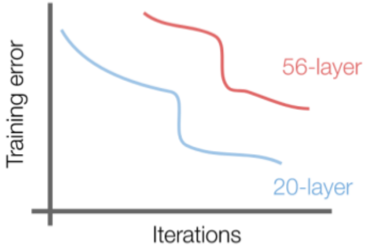

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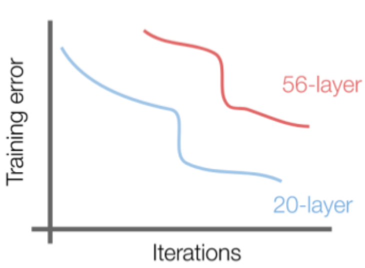

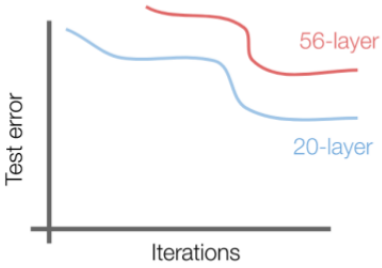

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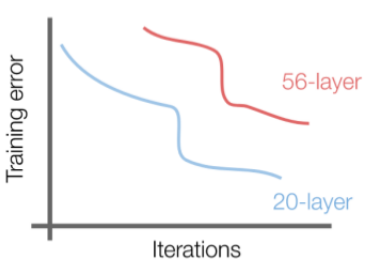

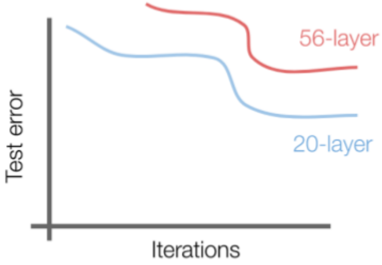

Deeper model does worse than shallow model!

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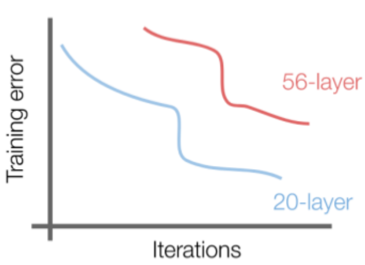

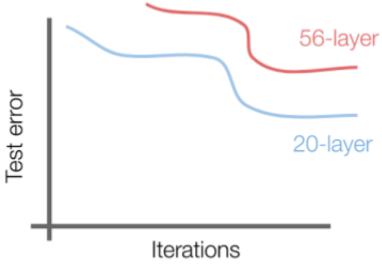

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Deeper model does worse than shallow model! **Why?**

The initial guess is that the deep model is **overfitting** since it is much bigger than the shallow model

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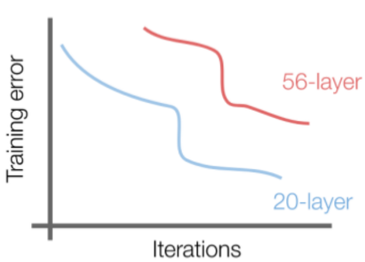

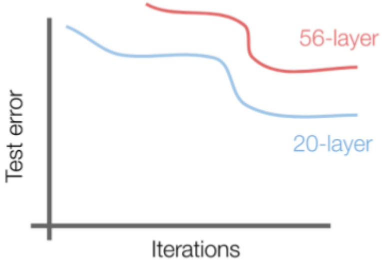

Deeper model does worse than shallow model! **Why?**

The deep model is actually **underfitting** since it also performs worse than the shallow model on the training set

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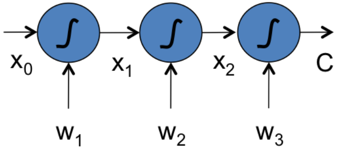
How deep can we go? Vanishing/Exploding Gradient

Consider a simple network:



$$\frac{\partial L}{\partial x_0} = \overset{<1/4}{\boxed{\sigma'(w_3^T x_2)}} \times w_3 \times \overset{<1/4}{\boxed{\sigma'(w_2^T x_1)}} \times w_2 \times \overset{<1/4}{\boxed{\sigma'(w_1^T x_0)}} \times w_1$$

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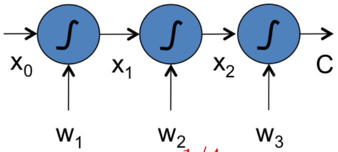

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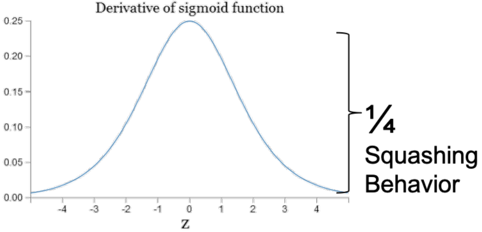

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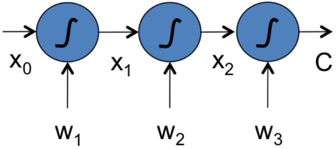

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- **Vanishing gradients:** Deeper the network, gradients vanish quickly, thereby slowing the rate of change in initial layers
- **Exploding gradients:** Happen when the individual layer gradients are much higher than 1, for instance - can be overcome by **gradient clipping**

ResNet

The deeper model should be able to perform at least as well as the shallower model;how?

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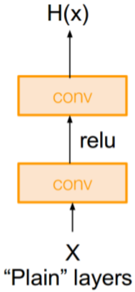

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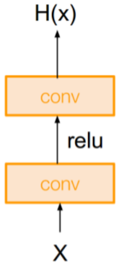
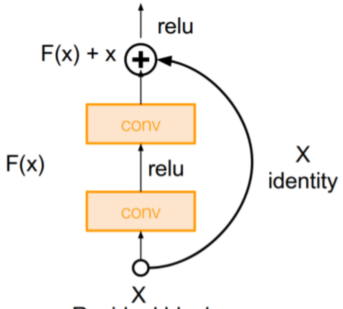


"Plain" layers



Residual block

Use network layers to fit residual F(x) = H(x) - x instead of H(x) directly

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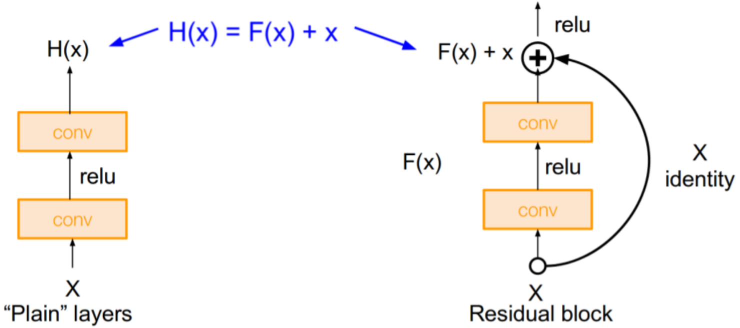

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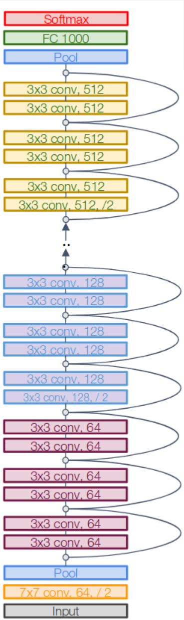
- Each residual block has two 3×3 conv layers



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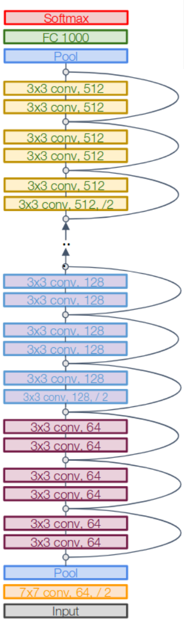

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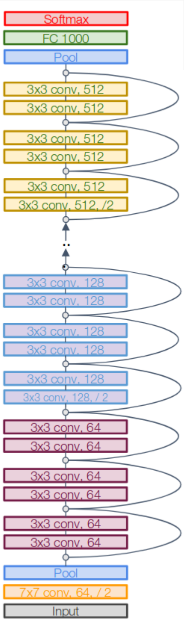

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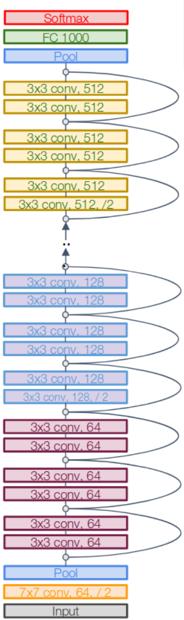

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- Each residual block has two 3×3 conv layers
- Periodically, double number of filters and downsample spatially using stride 2 ($/2$ in each dimension)
- Use **global average pooling** and a single linear layer at the end (FC 1000 to output classes)
- Total depths of 34, 50, 101, or 152 layers for ImageNet dataset

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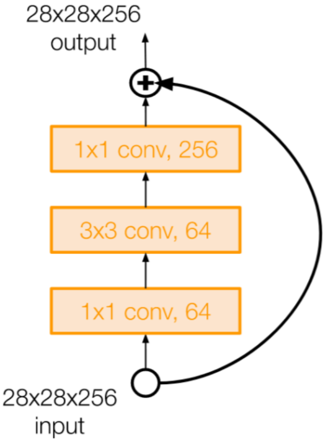
For deeper networks (ResNet-50+), use "bottleneck" layer to improve efficiency (similar to GoogLeNet)



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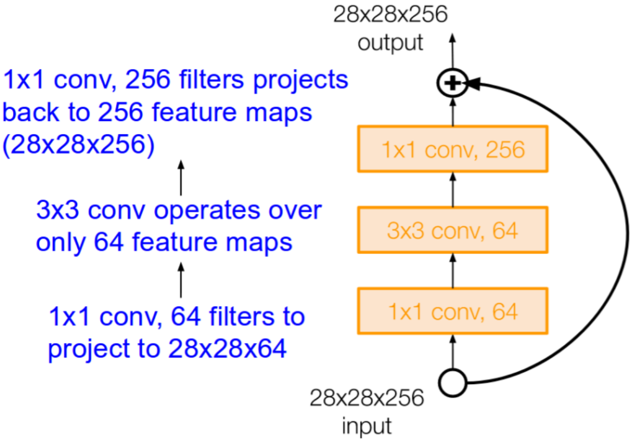

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ResNet

- Able to train very deep networks
- Deeper networks performs better than shallow networks now (as expected); residual blocks help avoid vanishing gradient
- 1st place in all ILSVRC and COCO 2015 competitions
- We will discuss detection, localization, segmentation and the COCO dataset a bit later

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ResNet

- Able to train very deep networks
- Deeper networks performs better than shallow networks now (as expected); residual blocks help avoid vanishing gradient
- 1st place in all ILSVRC and COCO 2015 competitions
- We will discuss detection, localization, segmentation and the COCO dataset a bit later

ResNet @ ILSVRC & COCO 2015 Competitions

1st place in all five major challenges

- ImageNet Classification: "Ultra-deep" 152-layer nets
- ImageNet Detection: 16% better than the 2nd best
- ImageNet Localization: 27% better than the 2nd best
- COCO Detection: 11% better than the 2nd best
- COCO Segmentation: 12% better than the 2nd best

Credit: Fei-Fei Li, Justin Johnson and Serena Yeung, CS231n course, Stanford, Spring 2019

Homework

Readings

- Tutorial: Illustrated: 10 CNN Architectures
  - Read 4-6: Inception-v1, Inception-v3, ResNet-50
- (Optional) For more details, skim through the following papers:
  - ImageNet Classification with Deep Convolutional Neural Networks
  - Very Deep Convolutional Networks for Large-Scale Image Recognition
  - Going Deeper with Convolutions
  - Deep Residual Learning for Image Recognition

Exercise

- Show that minimizing negative log likelihood in a neural network with a softmax activation function in the last layer is equivalent to minimizing cross-entropy error function (*Hint:* Read Chapter 3 of Nielsen's online book on basics of NNs)

References

[1] Yann LeCun et al. "Gradient-based learning applied to document recognition". In: 1998.

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[4] Christian Szegedy et al. "Going deeper with convolutions". In: *2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)* (2015), pp. 1–9.

[5] Kaiming He et al. "Deep Residual Learning for Image Recognition". In: *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)* (2016), pp. 770–778.

[6] *Johnson, Justin, EECS 498-007 / 598-005 - Deep Learning for Computer Vision (Fall 2019)*. URL: https://web.eecs.umich.edu/~justincj/teaching/eecs498/ (visited on 06/29/2020).

[7] *Li, Fei-Fei; Johnson, Justin; Serena, Yeung; CS 231n - Convolutional Neural Networks for Visual Recognition (Spring 2019)*. URL: http://cs231n.stanford.edu/2019/ (visited on 06/29/2020).