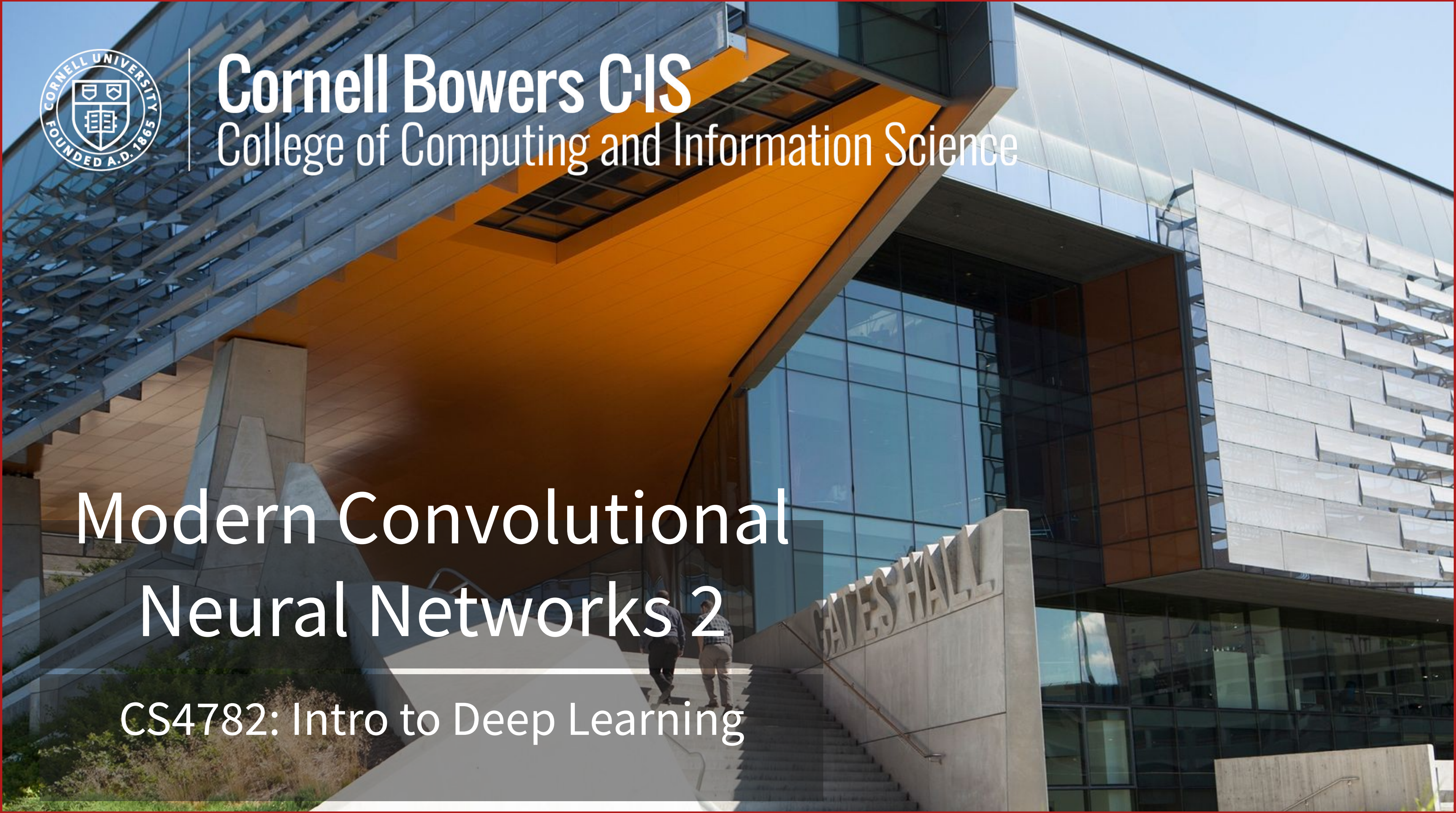


Cornell Bowers C·IS
College of Computing and Information Science

Modern Convolutional Neural Networks 2

CS4782: Intro to Deep Learning

Thanks to:

Varsha Kishore
Justin Lovelace
Anissa Dallmann
Stephanie Ginting

Logistics

- **HW1+P1** is due Thursday (February 13) 11:59 PM
- Late submissions accepted until Saturday (February 15) 11:59 PM

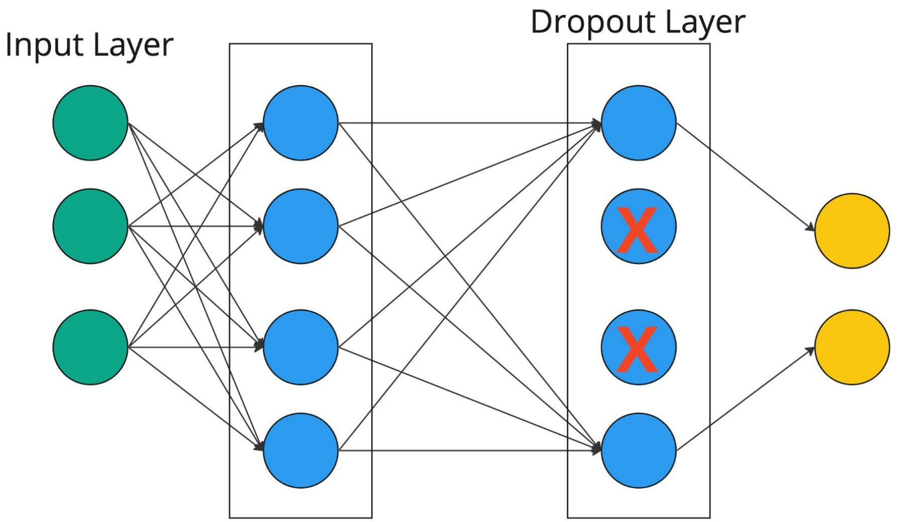
- **HW2** to be released this Thursday (February 13) - due Thursday (February 27)
- **P2** release timelines to be confirmed soon - due Thursday (February 27)

- Office hours are listed on the course website
- Homework clarifications are listed as pinned posts under HW1 on Ed
- Post questions on Ed

Clarification: Dropout

In each forward pass, randomly set some neurons to zero.

The probability of ~~keeping~~ zeroing a neuron is a hyperparameter; p=0.5 is common.

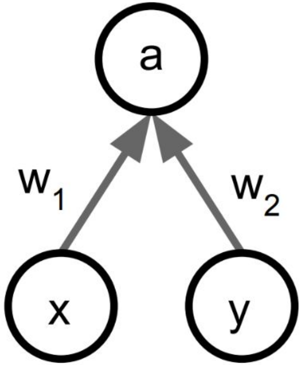


Deep Net with Dropout Layer

[Srivastava et al. 2014]

Clarification: Dropout During Test Time

Need to re-scale activations so they are the same (in expectation) during training and testing



Consider a single neuron.

At test time we have: $E[a] = w_1 x + w_2 y$

During training we have:

$$E[a] = \frac{1}{4}(w_1 x + w_2 y) + \frac{1}{4}(w_1 x + 0y) + \frac{1}{4}(0x + 0y) + \frac{1}{4}(0x + w_2 y) = \frac{1}{2}(w_1 x + w_2 y)$$

At test time, **multiply** by **(1 - p)**

http://cs231n.stanford.edu/slides/2018/cs231n_2018_lecture07.pdf

Review: Image Classification

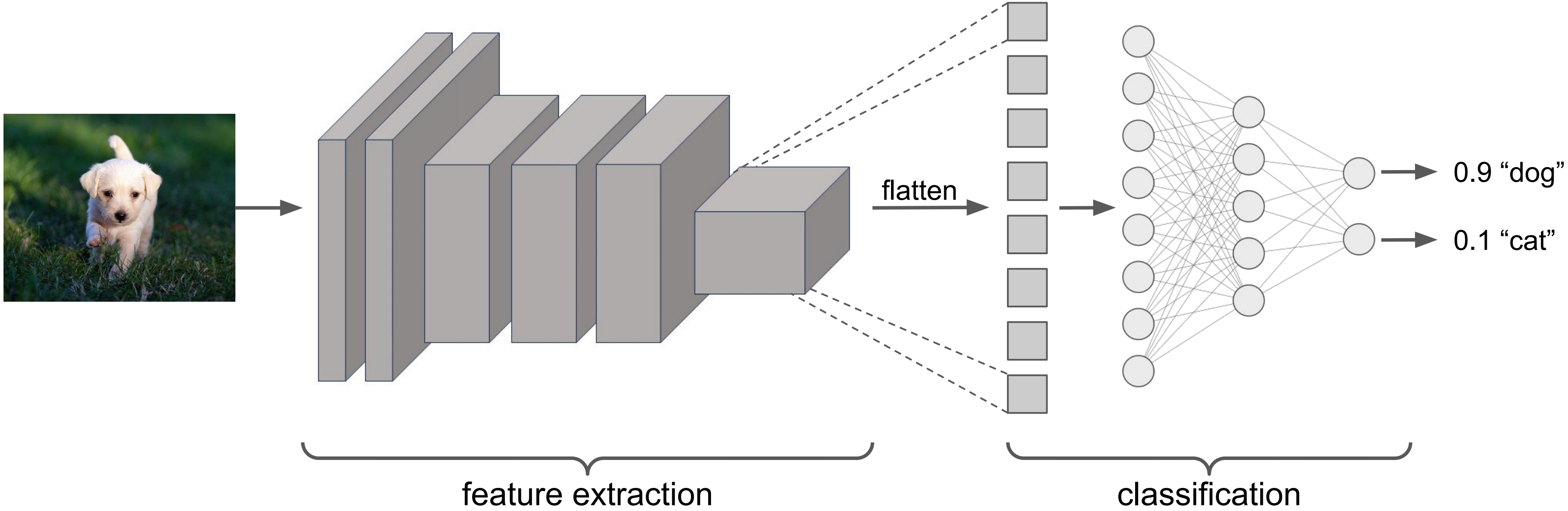
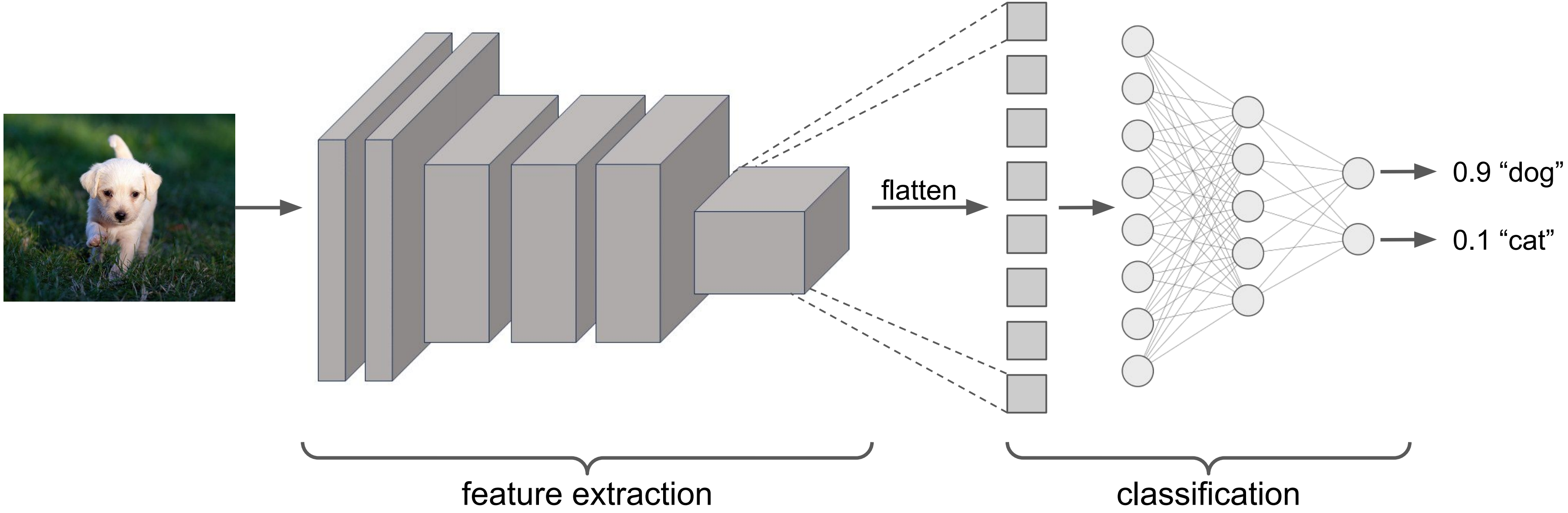


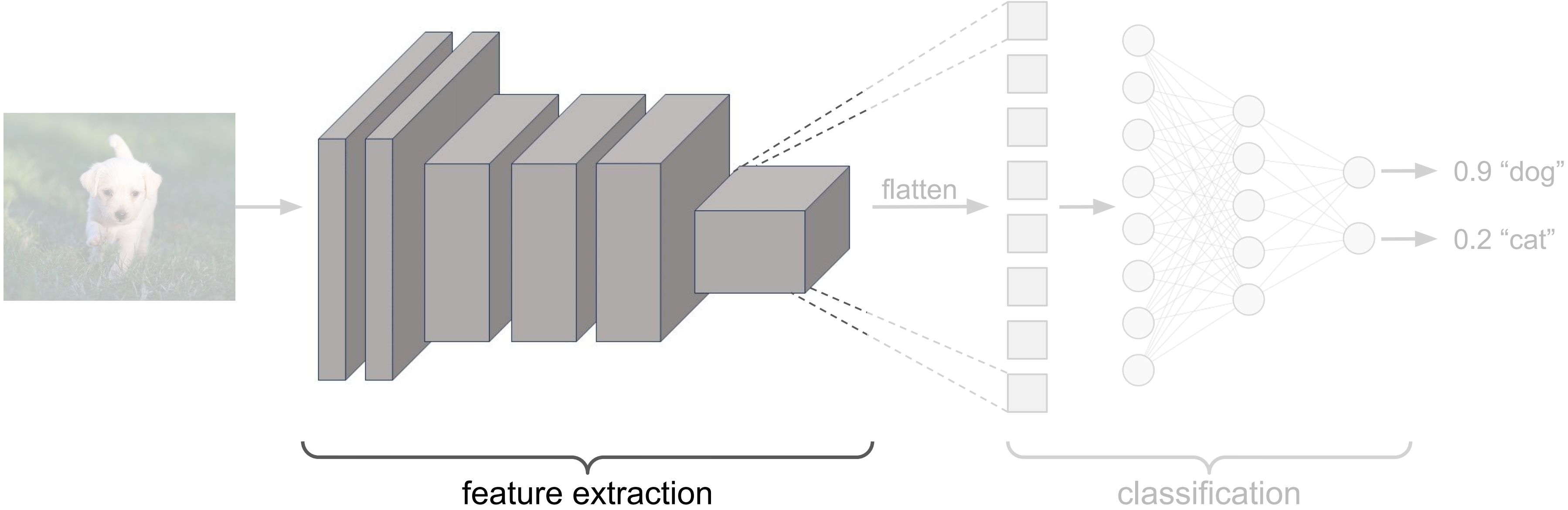
Image Classification

- Important: Everything is differentiable!
- Can calculate gradient of the loss with backpropagation
  - Train with SGD/Adam/etc.
  - Learn convolutional filters and classification head end-to-end!

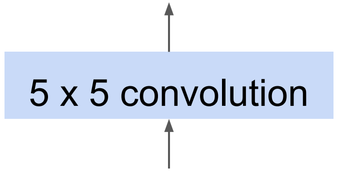


Cornell Bowers C·IS

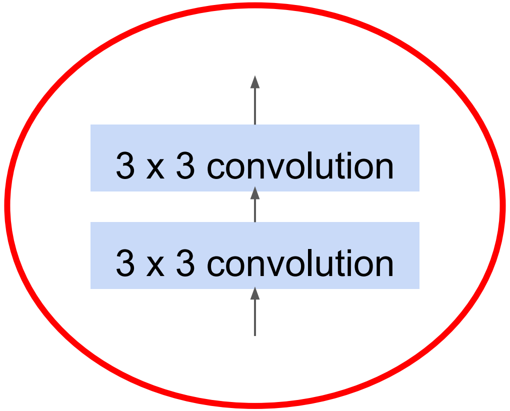
Deeper CNN Architectures



Deeper CNN Architectures

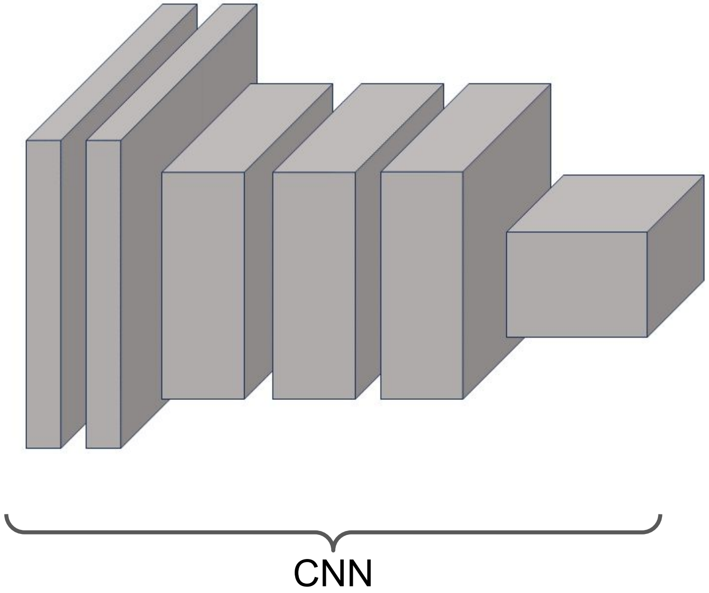


vs

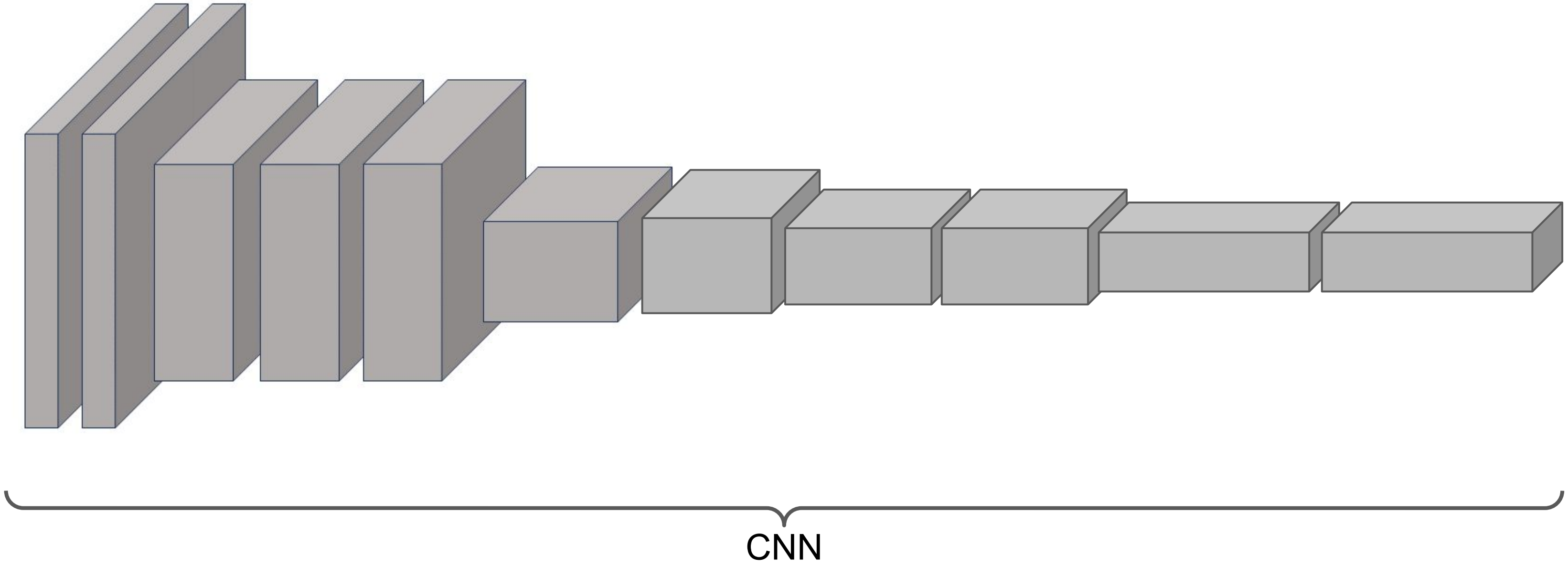


Performed better!

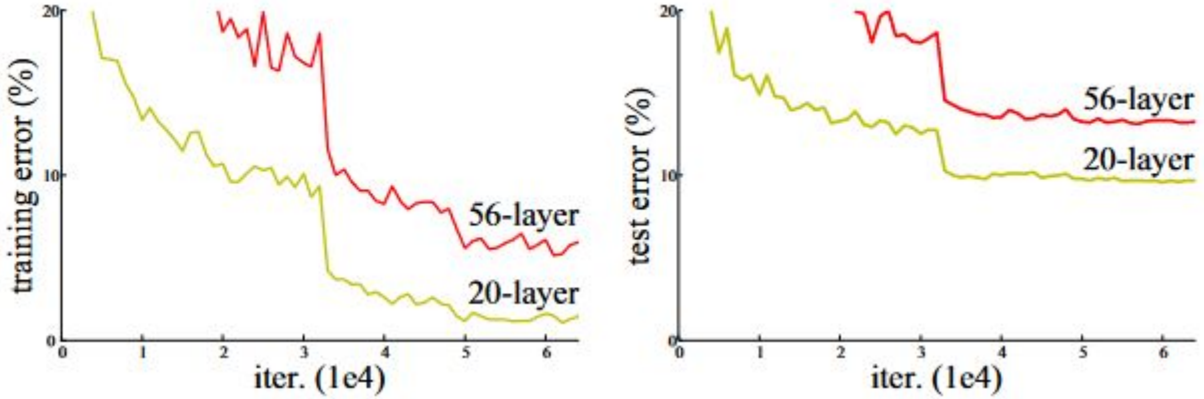
Deeper == better



Deeper == better

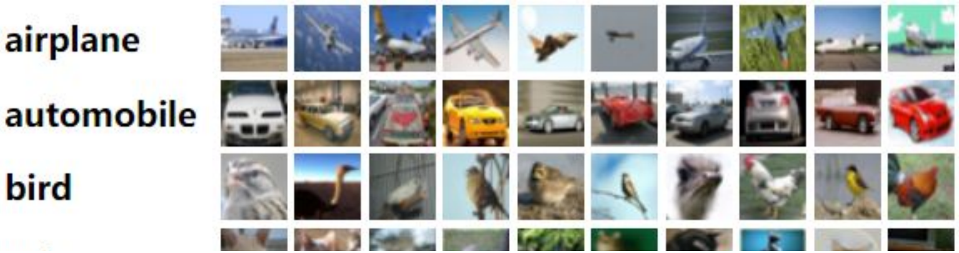


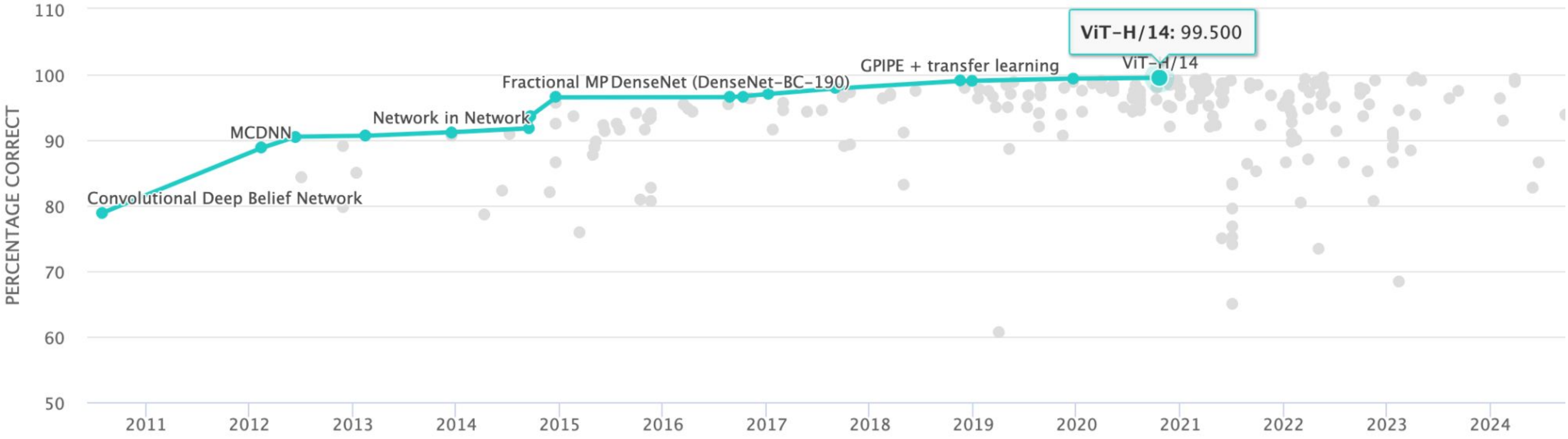
Deeper == better?



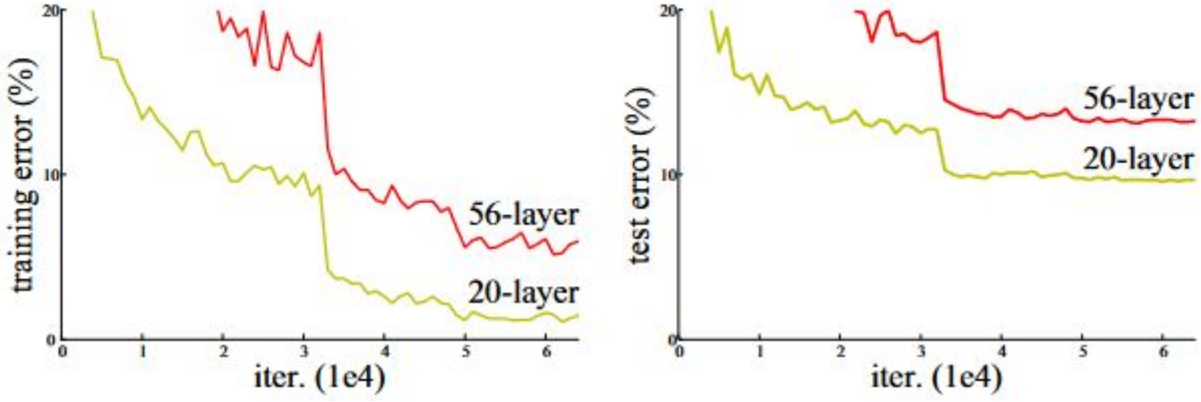
56 layer CNN has higher training and test error than 20 layer CNN on CIFAR-10 dataset for image classification

[He, Kaiming, et al. "Deep residual learning for image recognition." *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2016.]


airplane
automobile
bird


ViT-H/14: 99.500
PERCENTAGE CORRECT
110
100
90
80
70
60
50
2011
2012
2013
2014
2015
2016
2017
2018
2019
2020
2021
2022
2023
2024
Convolutional Deep Belief Network
MCDNN
Network in Network
Fractional MP
DenseNet (DenseNet-BC-190)
GPIPE + transfer learning
ViT-H/14

Discuss: How can a larger network achieve a higher training error?



56 layer CNN has higher training and test error than 20 layer CNN on CIFAR-10 dataset for image classification

Deeper != better

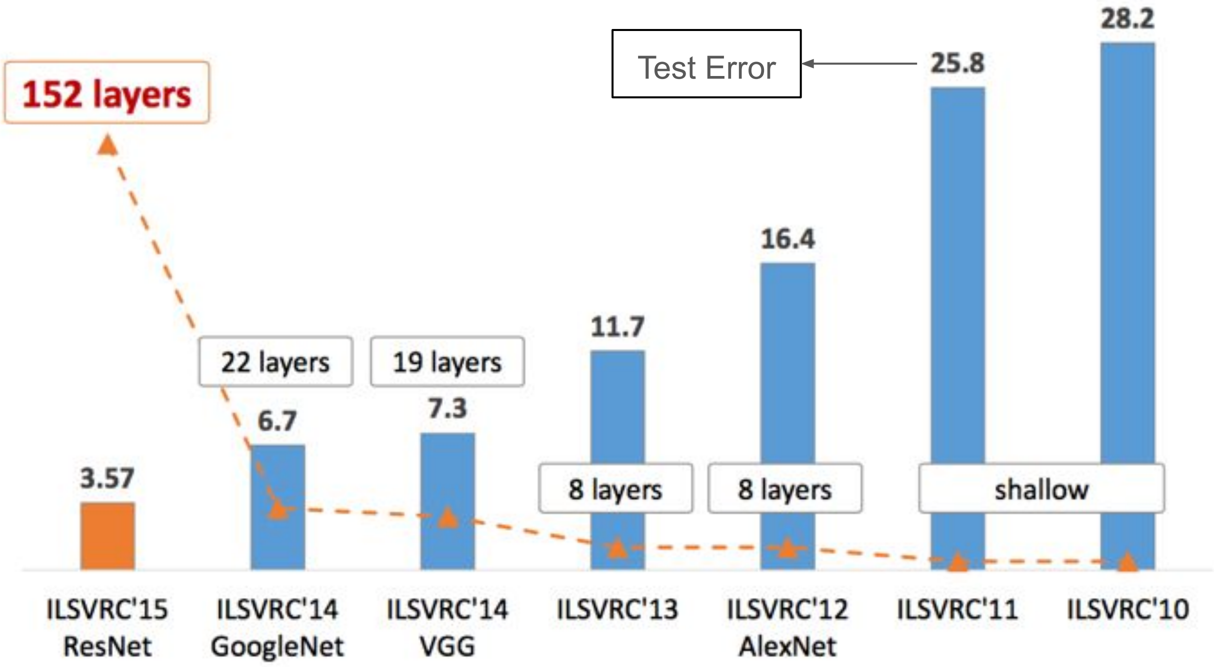
- Long training times

- Vanishing gradient problem
  - Recall backpropagation to update weights

$$\frac{\partial z}{\partial z_i} = \frac{\partial z}{\partial z_{n-1}} \frac{\partial z_{n-1}}{\partial z_{n-2}} \cdots \frac{\partial z_{i+1}}{\partial z_i}$$

  - If each term <<< 1, gradient “vanishes” as the entire multiplication goes towards 0
  - => Weights not updated properly

ImageNet Classification Challenge: Deeper == better

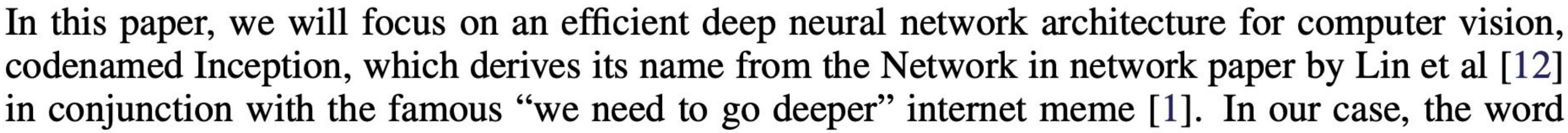


[Nguyen, Kien & Fookes, Clinton & Ross, Arun & Sridharan, Sridha. (2017). Iris Recognition with Off-the-Shelf CNN Features: A Deep Learning Perspective. IEEE Access. PP. 1-1. 10.1109/ACCESS.2017.2784352.]

GoogLeNet/Inception Net

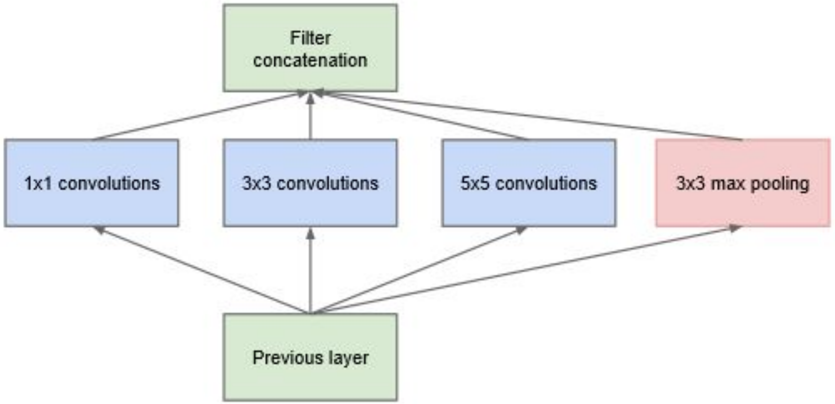
Goal: given a fixed computational budge
network

=> Deeper networks with computationa


In this paper, we will focus on an efficient deep neural network architecture for computer vision, codenamed Inception, which derives its name from the Network in network paper by Lin et al [12] in conjunction with the famous "we need to go deeper" internet meme [1]. In our case, the word

[Szegedy, Christian, et al. "Going deeper with convolutions." *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2015.]

Inception Module

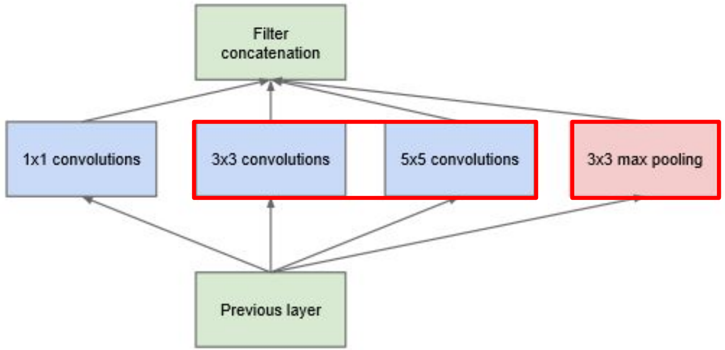


Inception module = main building blocks

[Szegedy, Christian, et al. "Going deeper with convolutions." *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2015.]

Inception Module

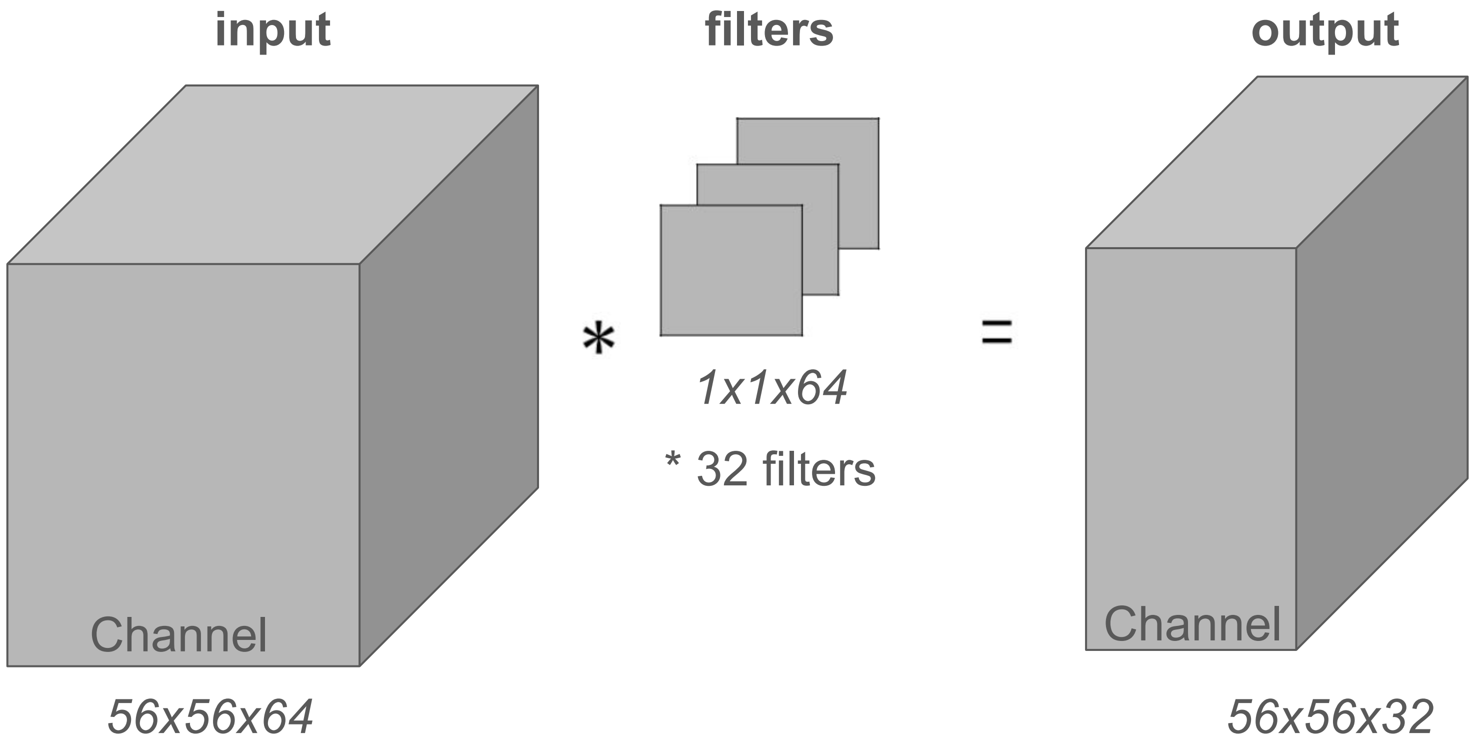
Still expensive!



- 3x3 and 5x5 convolutions have large number of operations
- Output of pooling layer increases the output channel dimension when concatenated

[Szegedy, Christian, et al. "Going deeper with convolutions." *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2015.]

Remember: 1x1 convolutions



Discuss: Impact of Dimension Reduction

Assume you have an input feature map with 256 channels/features.

Compare the parameter counts from:

1. 3x3 conv with 256 filters
2. 1x1 conv with 64 filters → 3x3 conv with 64 filters → 1x1 conv with 256 filters

Discuss: Impact of Dimension Reduction

Assume you have an input feature map with 256 channels/features.

Compare the parameter counts from:

1. 3x3 conv with 256 filters
   3*3*256*256 = ~590k parameters

2. 1x1 conv with 64 filters → 3x3 conv with 64 filters → 1x1 conv with 256 filters

Discuss: Impact of Dimension Reduction

Assume you have an input feature map with 256 channels/features.

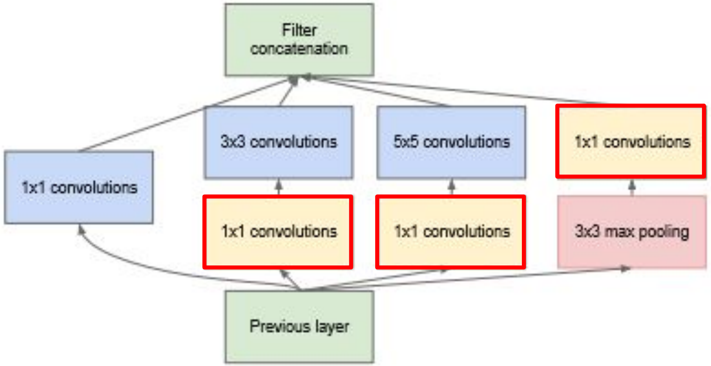
Compare the parameter counts from:

1. 3x3 conv with 256 filters
   3*3*256*256 = ~590k parameters

2. 1x1 conv with 64 filters → 3x3 conv with 64 filters → 1x1 conv with 256 filters
   1*1*256*64 + 3*3*64*64 + 1*1*64*256 = ~70k parameters

Inception Module

Solution: Inception module with dimension reduction

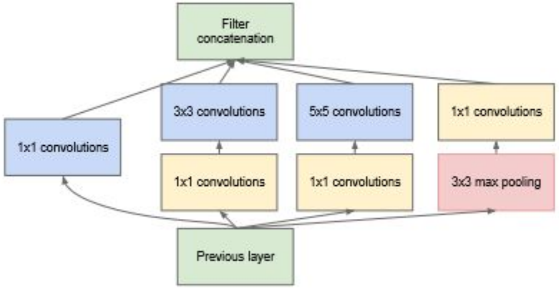


- “Bottleneck” with 1x1 convolutions to reduce dimensions

[Szegedy, Christian, et al. "Going deeper with convolutions." *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2015.]

GoogLeNet Architecture

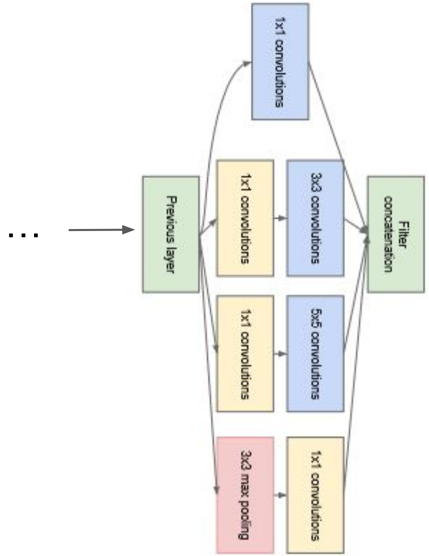
Key idea: stack inception modules together



[Szegedy, Christian, et al. "Going deeper with convolutions." *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2015.]

GoogLeNet Architecture

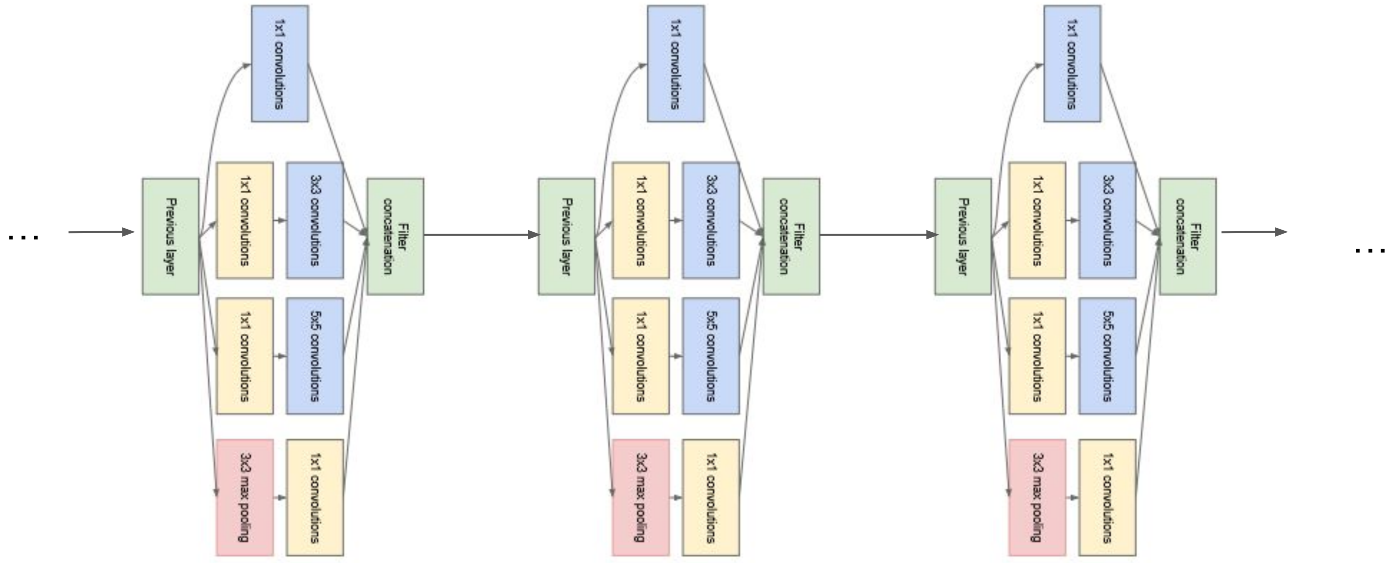
Key idea: stack inception modules together



[Szegedy, Christian, et al. "Going deeper with convolutions." *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2015.]

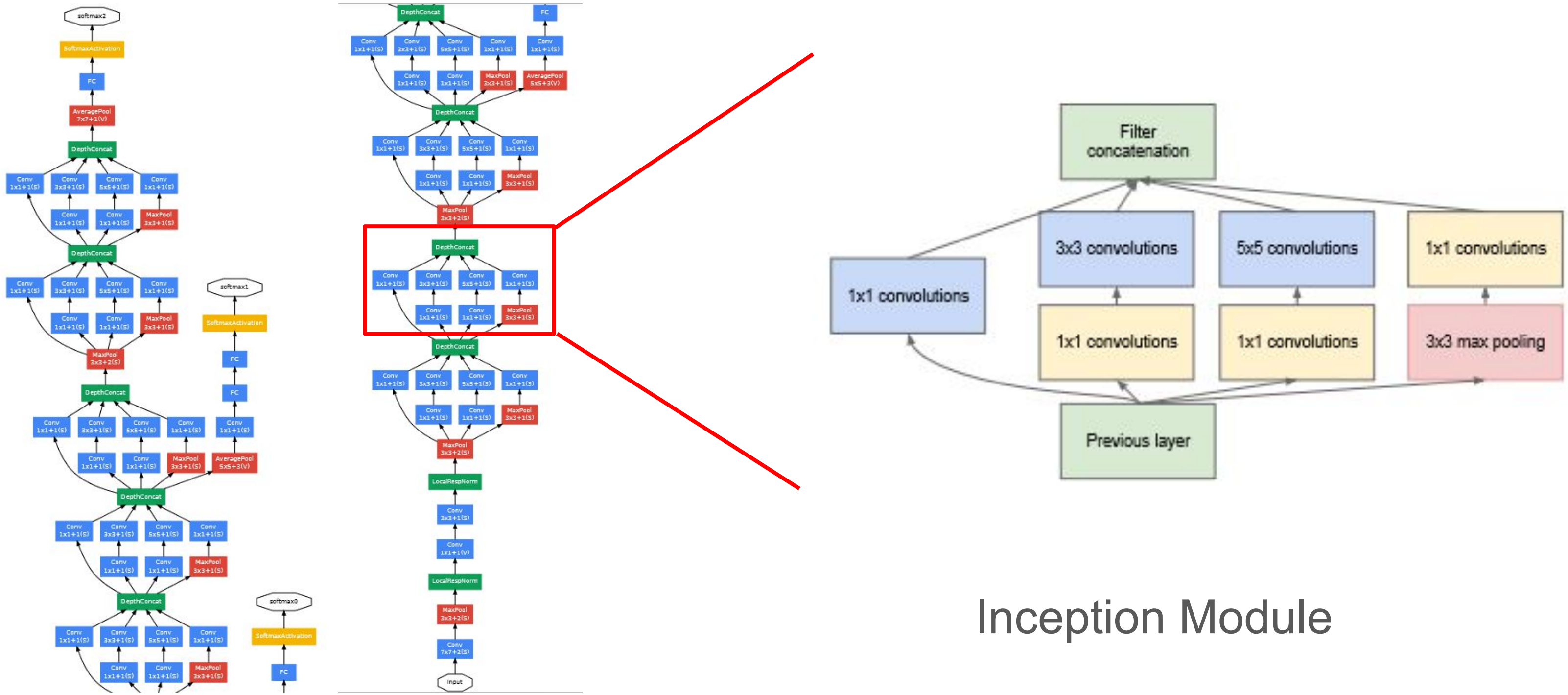
GoogLeNet Architecture

Key idea: stack inception modules together



[Szegedy, Christian, et al. "Going deeper with convolutions." *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2015.]

The Entire GoogLeNet Architecture



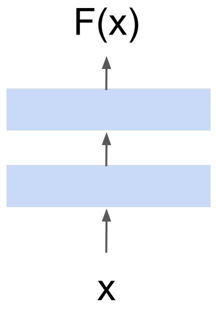
Inception Module

[Szegedy, Christian, et al. "Going deeper with convolutions." *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2015.]

CNN Architectures

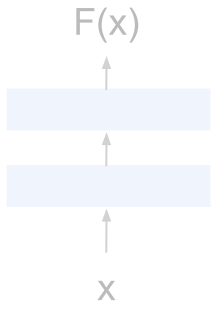
“Plain” CNN

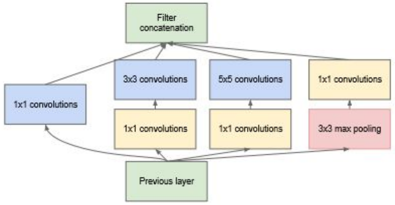
Simple connection from previous to next layer



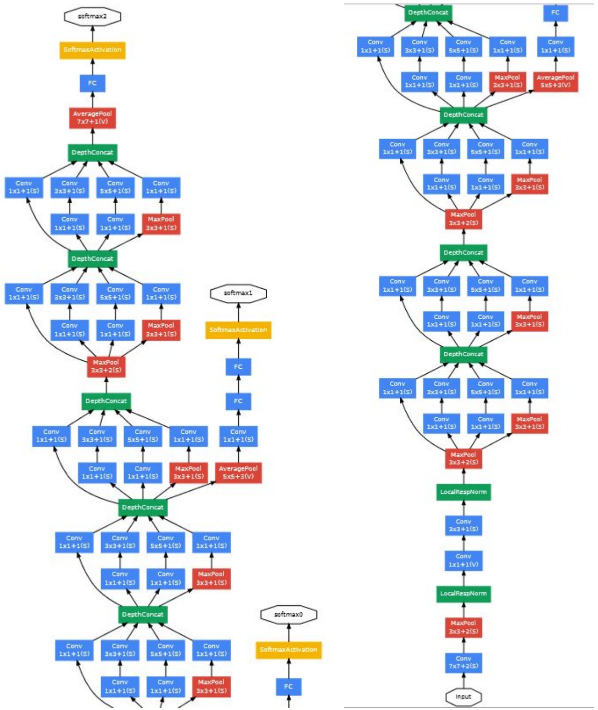
CNN Architectures

“Plain” CNN	GoogLeNet
Simple connection from previous to next layer	1x1, 3x3, 5x5 convolutions and pooling between each layer

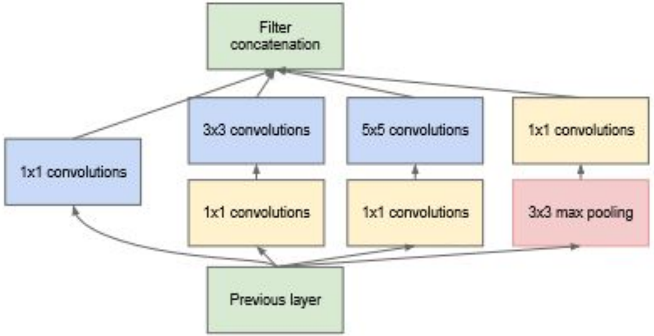




The Entire GoogleNet Architecture

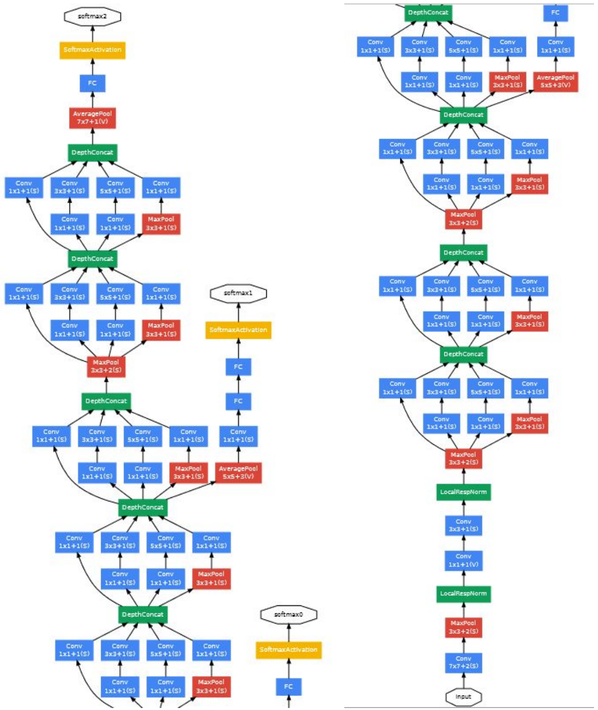


Very complicated - how exactly did this architecture solve the problem?

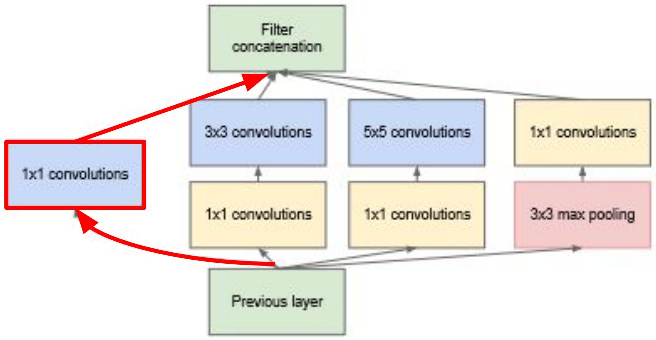


[Szegedy, Christian, et al. "Going deeper with convolutions." *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2015.]

The Entire GoogleNet Architecture



Very complicated - how exactly did this architecture solve the problem?

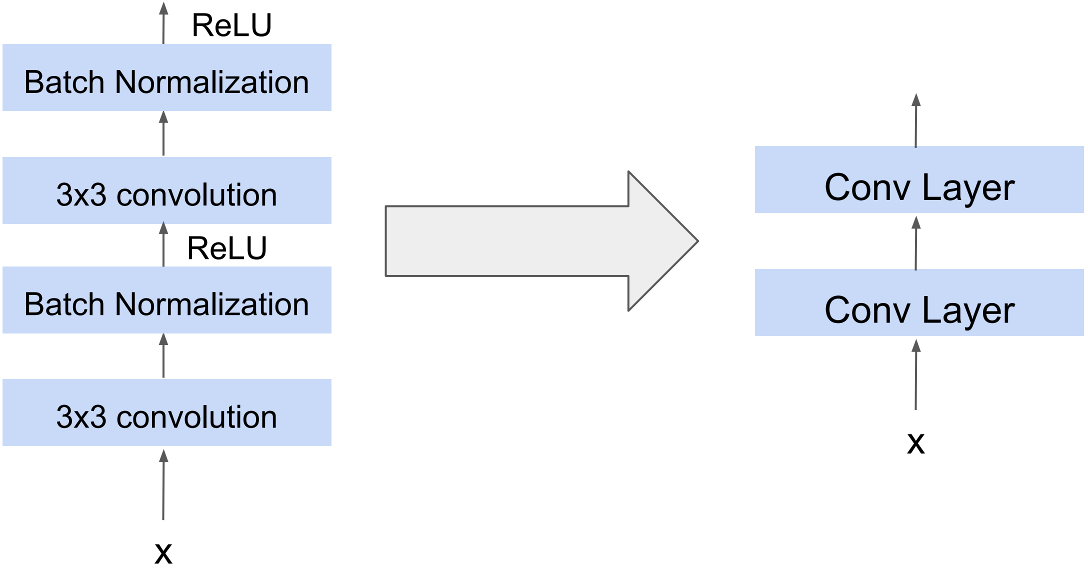


Residual connections

[Szegedy, Christian, et al. "Going deeper with convolutions." *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2015.]

Cornell Bowers CIS

Aside: Conv Layer Abstraction



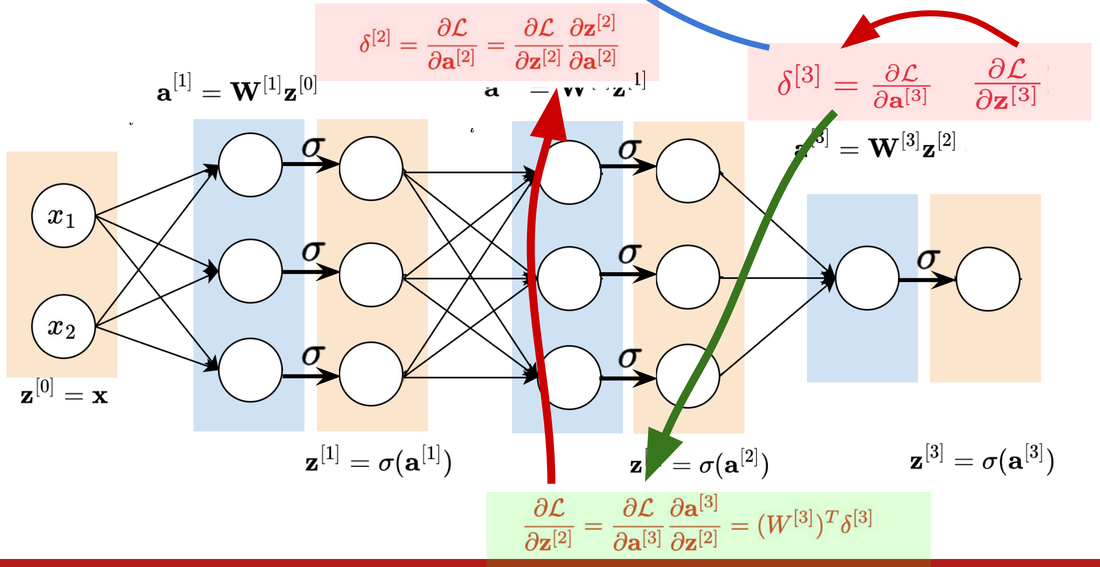
Backpropagation

$$\frac{\partial \mathcal{L}}{\partial \mathbf{W}^{[3]}} = \frac{\partial \mathcal{L}}{\partial \mathbf{a}^{[3]}} \frac{\partial \mathbf{a}^{[3]}}{\partial \mathbf{W}^{[3]}}$$

$$= \delta^{[3]} (\mathbf{z}^{[2]})^T$$

Algorithm Backward Pass through MLP (Detailed)

```
Input: ${\mathbf{z}^{[1]}, \dots, \mathbf{z}^{[L]}}, {\mathbf{a}^{[1]}, \dots, \mathbf{a}^{[L]}}$, loss gradient $\frac{\partial \mathcal{L}}{\partial \mathbf{z}^{[L]}}$
$\delta^{[L]} = \frac{\partial \mathcal{L}}{\partial \mathbf{a}^{[L]}} = \frac{\partial \mathcal{L}}{\partial \mathbf{z}^{[L]}} \frac{\partial \mathbf{z}^{[L]}}{\partial \mathbf{a}^{[L]}} = \frac{\partial \mathcal{L}}{\partial \mathbf{z}^{[L]}} \odot \sigma^{[L]\prime}(\mathbf{a}^{[L]})$    ▷ Error term
for $l = L$ to 1 do
    $\frac{\partial \mathcal{L}}{\partial \mathbf{W}^{[l]}} = \frac{\partial \mathcal{L}}{\partial \mathbf{a}^{[l]}} \frac{\partial \mathbf{a}^{[l]}}{\partial \mathbf{W}^{[l]}} = \delta^{[l]} (\mathbf{z}^{[l-1]})^T$    ▷ Gradient of weights
    $\frac{\partial \mathcal{L}}{\partial \mathbf{b}^{[l]}} = \frac{\partial \mathcal{L}}{\partial \mathbf{a}^{[l]}} \frac{\partial \mathbf{a}^{[l]}}{\partial \mathbf{b}^{[l]}} = \delta^{[l]}$    ▷ Gradient of biases
    $\frac{\partial \mathcal{L}}{\partial \mathbf{z}^{[l-1]}} = \frac{\partial \mathcal{L}}{\partial \mathbf{a}^{[l]}} \frac{\partial \mathbf{a}^{[l]}}{\partial \mathbf{z}^{[l-1]}} = (\mathbf{W}^{[l]})^T \delta^{[l]}$
    $\delta^{[l-1]} = \frac{\partial \mathcal{L}}{\partial \mathbf{a}^{[l-1]}} = \frac{\partial \mathcal{L}}{\partial \mathbf{z}^{[l-1]}} \frac{\partial \mathbf{z}^{[l-1]}}{\partial \mathbf{a}^{[l-1]}} = ((\mathbf{W}^{[l]})^T \delta^{[l]}) \odot \sigma^{[l-1]\prime}(\mathbf{a}^{[l-1]})$
end for
Output: $\frac{\partial \mathcal{L}}{\partial \mathbf{W}^{[1:L]}}, \frac{\partial \mathcal{L}}{\partial \mathbf{b}^{[1:L]}}$
```



$$\delta^{[2]} = \frac{\partial \mathcal{L}}{\partial \mathbf{a}^{[2]}} = \frac{\partial \mathcal{L}}{\partial \mathbf{z}^{[2]}} \frac{\partial \mathbf{z}^{[2]}}{\partial \mathbf{a}^{[2]}}$$

$$\delta^{[3]} = \frac{\partial \mathcal{L}}{\partial \mathbf{a}^{[3]}} \quad \frac{\partial \mathcal{L}}{\partial \mathbf{z}^{[3]}}$$

$$\frac{\partial \mathcal{L}}{\partial \mathbf{z}^{[2]}} = \frac{\partial \mathcal{L}}{\partial \mathbf{a}^{[3]}} \frac{\partial \mathbf{a}^{[3]}}{\partial \mathbf{z}^{[2]}} = (W^{[3]})^T \delta^{[3]}$$

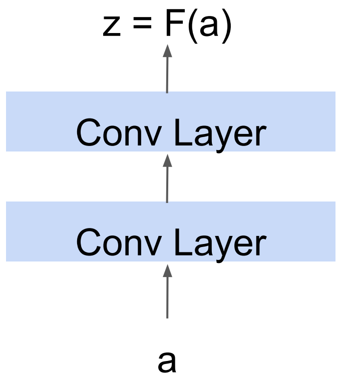
$\mathbf{a}^{[1]} = \mathbf{W}^{[1]}\mathbf{z}^{[0]}$
$\mathbf{a}^{[2]} = \mathbf{W}^{[2]}\mathbf{z}^{[1]}$
$\mathbf{a}^{[3]} = \mathbf{W}^{[3]}\mathbf{z}^{[2]}$
x_1
x_2
σ
$\mathbf{z}^{[0]} = \mathbf{x}$
$\mathbf{z}^{[1]} = \sigma(\mathbf{a}^{[1]})$
$\mathbf{z}^{[2]} = \sigma(\mathbf{a}^{[2]})$
$\mathbf{z}^{[3]} = \sigma(\mathbf{a}^{[3]})$

$$\mathcal{L}(\mathbf{z}^{[3]}, \mathbf{y})$$

We can directly compute $\frac{\partial \mathcal{L}}{\partial \mathbf{z}^{[3]}}$!

Backpropagation through "plain" conv layers

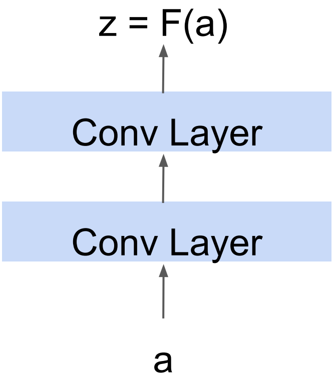
"Plain" layers



$$\frac{\partial L}{\partial a} = \frac{\partial L}{\partial z}\frac{\partial z}{\partial a} = \frac{\partial L}{\partial z}\boxed{(F'(a))}$$

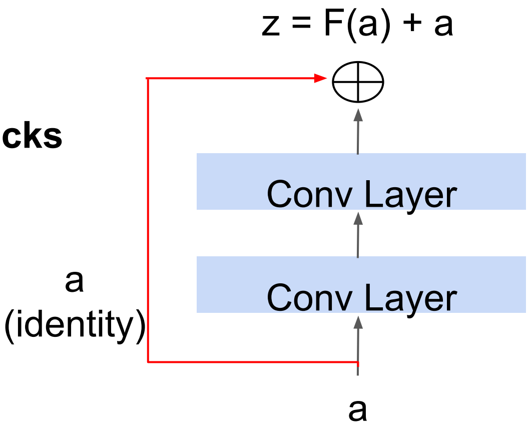
Discussion: Backpropagation through Residual blocks

"Plain" layers



$$\frac{\partial L}{\partial a} = \frac{\partial L}{\partial z}\frac{\partial z}{\partial a} = \frac{\partial L}{\partial z}\boxed{(F'(a))}$$

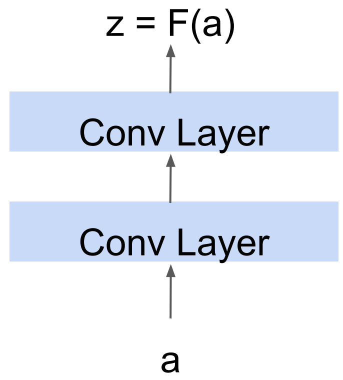
Residual Blocks



$$\frac{\partial L}{\partial a} = \boxed{}$$

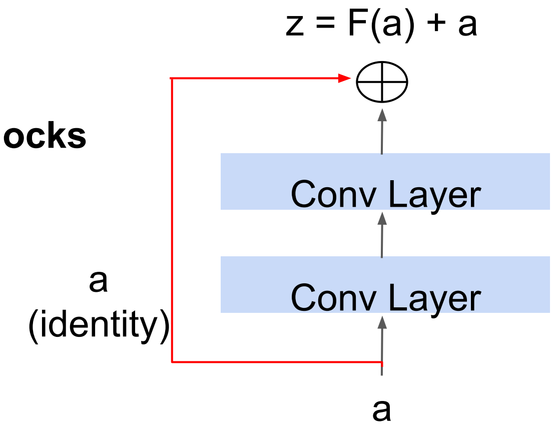
Backpropagation through Residual blocks

“Plain” layers



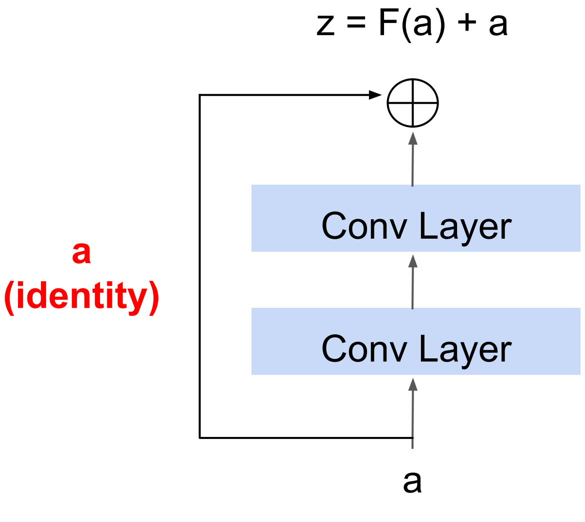
$$\frac{\partial L}{\partial a} = \frac{\partial L}{\partial z}\frac{\partial z}{\partial a} = \frac{\partial L}{\partial z}\boxed{(F'(a))}$$

Residual Blocks



$$\frac{\partial L}{\partial a} = \frac{\partial L}{\partial z}\frac{\partial z}{\partial a} = \frac{\partial L}{\partial z}\boxed{(1 + F'(a))}$$

Residual Connections



Residual Blocks

Identity mapping

- can propagate features forward
- only learn *difference* of feature maps

Additive component of identity

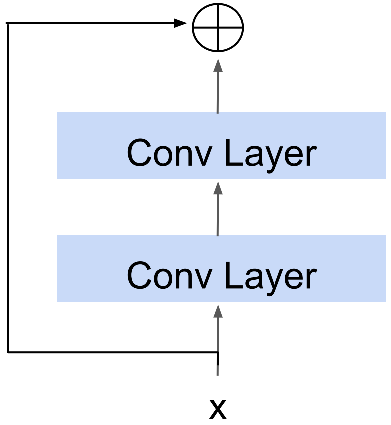
- alleviates vanishing gradients

$$\frac{\partial L}{\partial a} = \frac{\partial L}{\partial z}\frac{\partial z}{\partial a} = \frac{\partial L}{\partial z}\boxed{(1 + F'(a))}$$

[He, Kaiming, et al. "Deep residual learning for image recognition." *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2016.]

ResNet

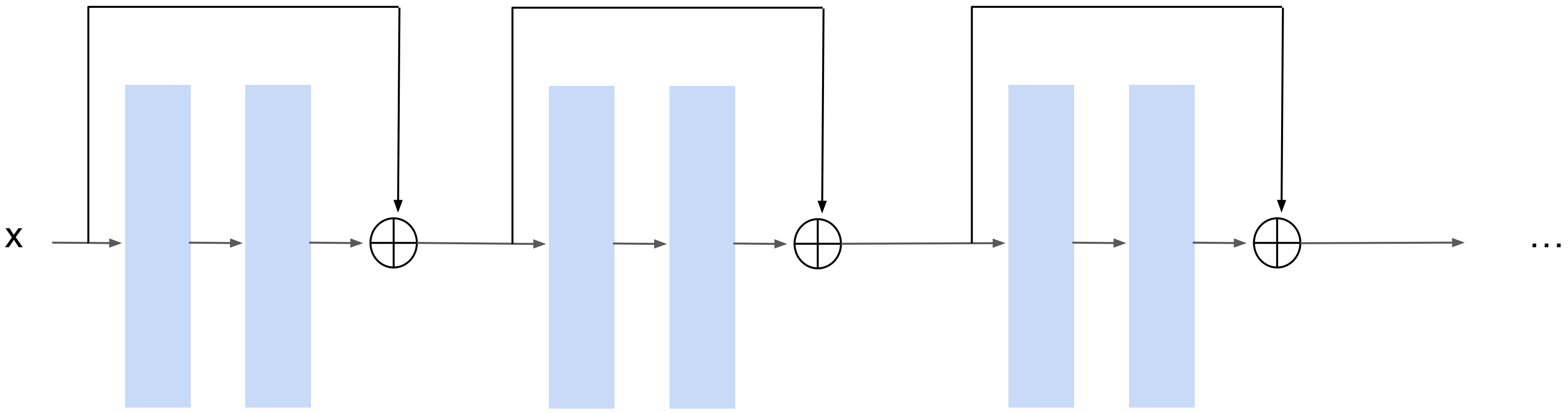
Stack residual blocks together!



[He, Kaiming, et al. "Deep residual learning for image recognition." *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2016.]

ResNet

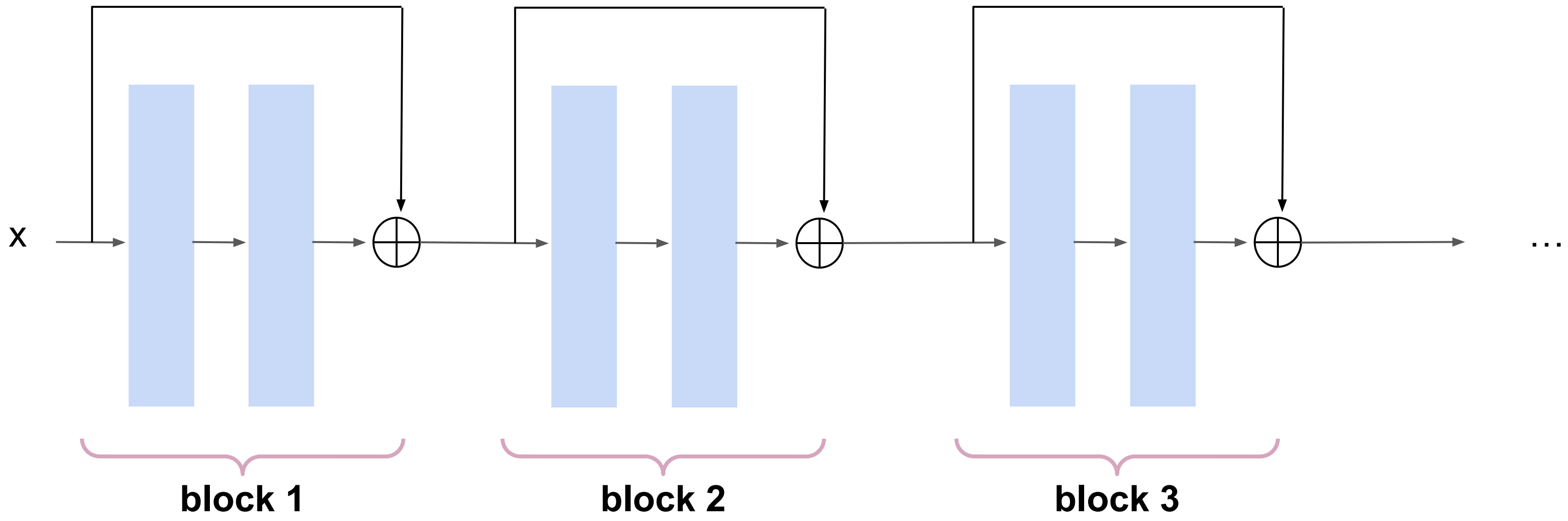
Stack residual blocks together!



[He, Kaiming, et al. "Deep residual learning for image recognition." *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2016.]

ResNet

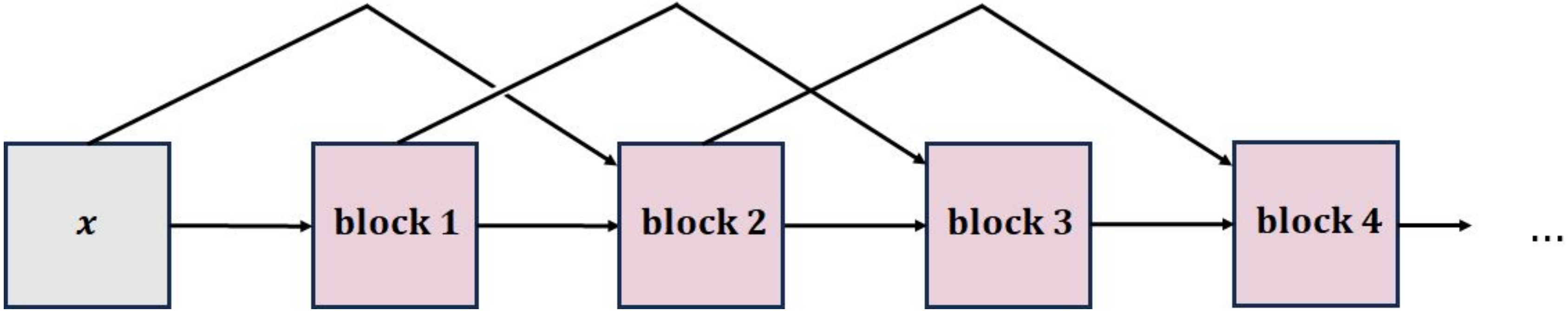
Stack residual blocks together!



[He, Kaiming, et al. "Deep residual learning for image recognition." *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2016.]

ResNet

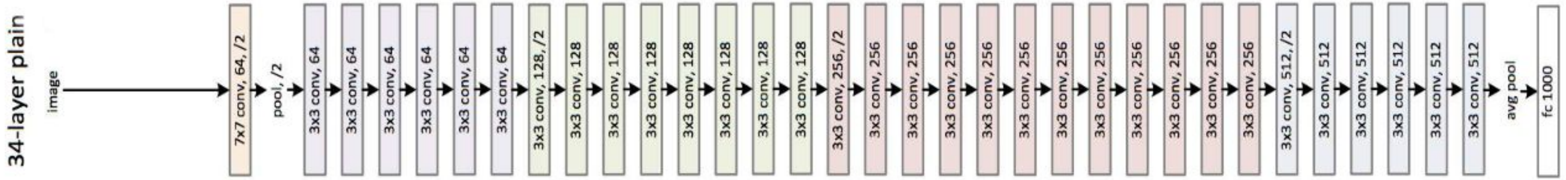
Stack residual blocks together!



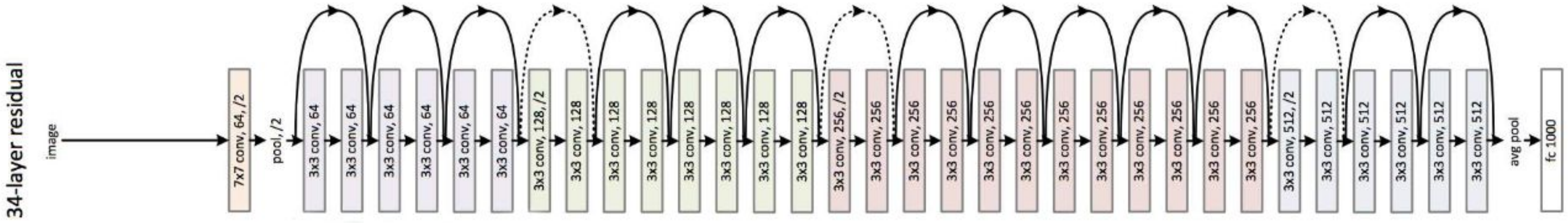
[He, Kaiming, et al. "Deep residual learning for image recognition." *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2016.]

Full ResNet Architecture

“Plain” Network

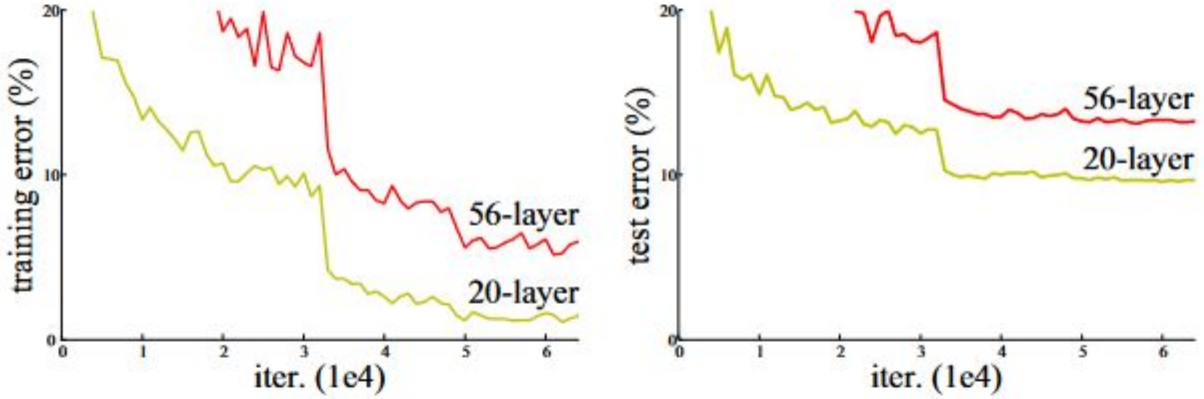


ResNet



[He, Kaiming, et al. "Deep residual learning for image recognition." *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2016.]

Recall: How can a larger network achieve a higher training error?



56 layer CNN has higher training and test error than 20 layer CNN on CIFAR-10 dataset for image classification

Deeper == better

Can train deeper models!

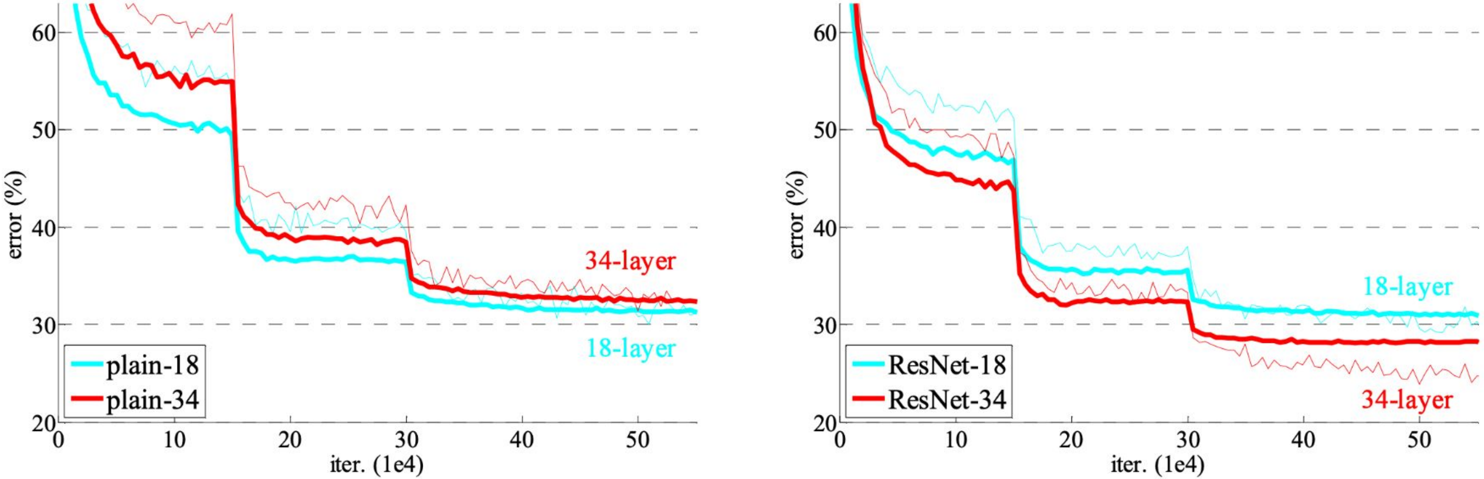
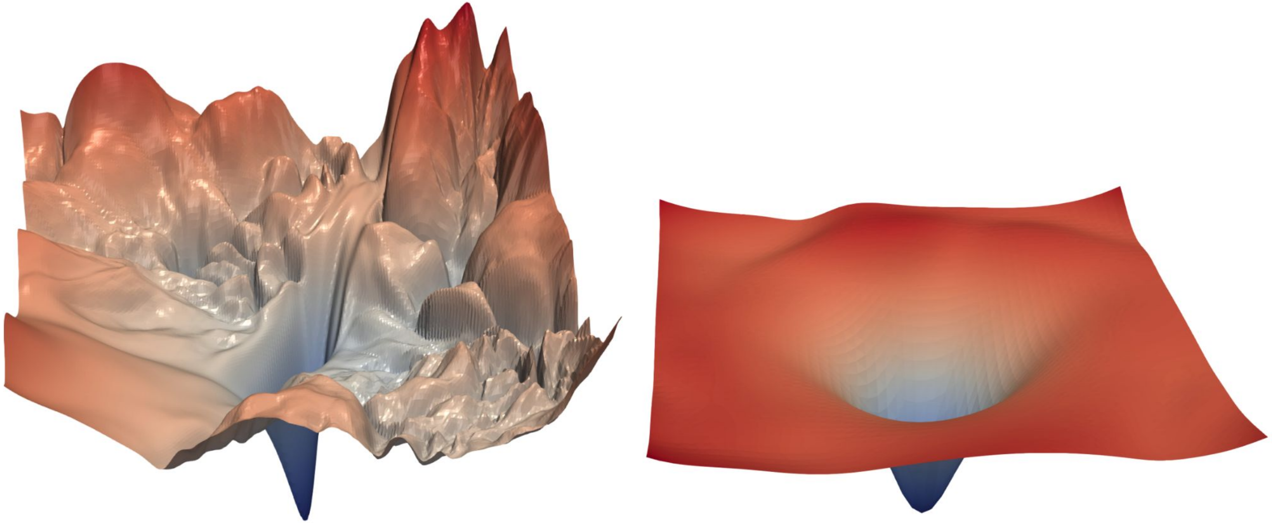


Figure 4. Training on **ImageNet**. Thin curves denote training error, and bold curves denote validation error of the center crops. Left: plain networks of 18 and 34 layers. Right: ResNets of 18 and 34 layers. In this plot, the residual networks have no extra parameter compared to their plain counterparts.

Visualizing the Effect of Skip Connections

Makes optimization easier!



(a) without skip connections

(b) with skip connections

Figure 1: The loss surfaces of ResNet-56 with/without skip connections. The proposed filter normalization scheme is used to enable comparisons of sharpness/flatness between the two figures.

[Li, Hao, et al. "Visualizing the loss landscape of neural nets." Advances in neural information processing systems 31 (2018).]

Stochastic Depth

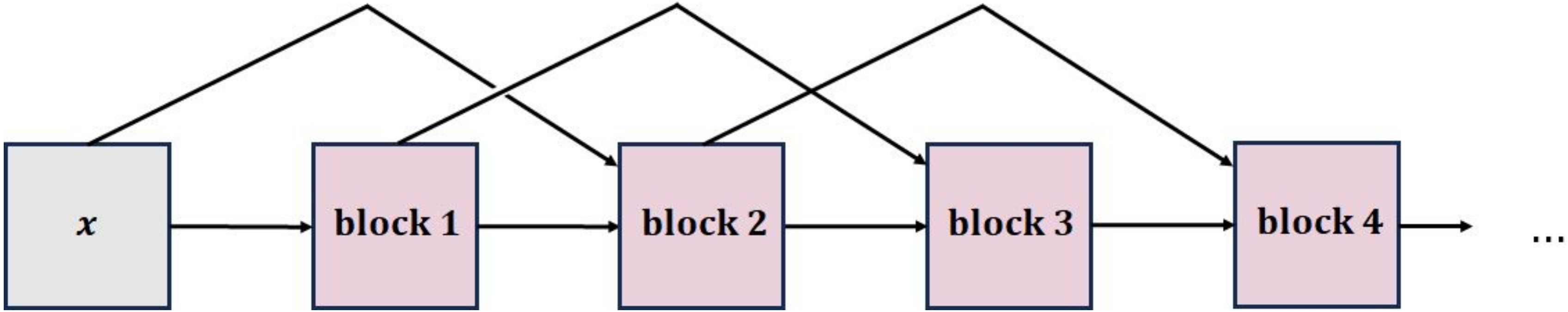
Still have long training times! Solution: stochastic depth

[Huang, Gao, et al. "Deep networks with stochastic depth." *Computer Vision–ECCV 2016: 14th European Conference, Amsterdam, The Netherlands, October 11–14, 2016, Proceedings, Part IV 14.* Springer International Publishing, 2016.]

Stochastic Depth

During training, randomly drop Residual Blocks using skip connections

Like dropout but with residual blocks instead of individual neurons

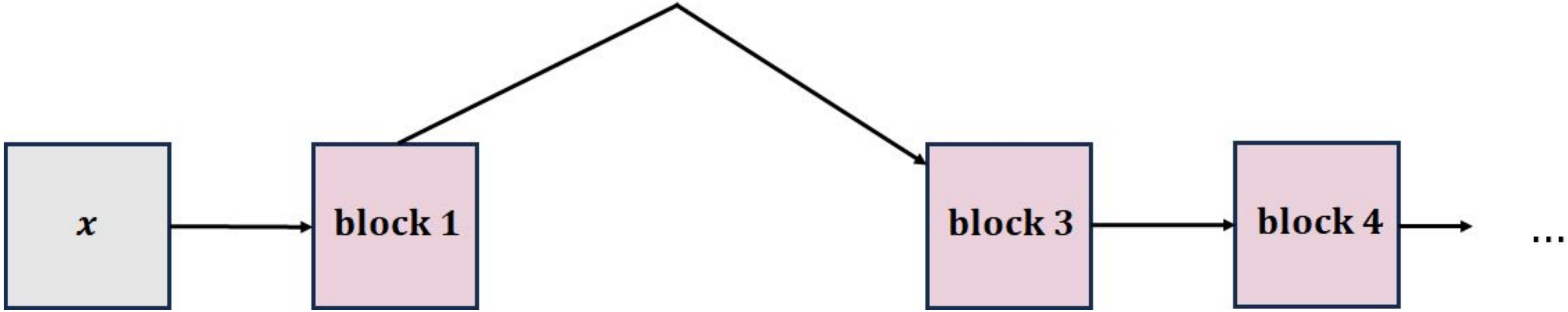


[Huang, Gao, et al. "Deep networks with stochastic depth." *Computer Vision–ECCV 2016: 14th European Conference, Amsterdam, The Netherlands, October 11–14, 2016, Proceedings, Part IV 14.* Springer International Publishing, 2016.]

Stochastic Depth

During training, randomly drop Residual Blocks using skip connections

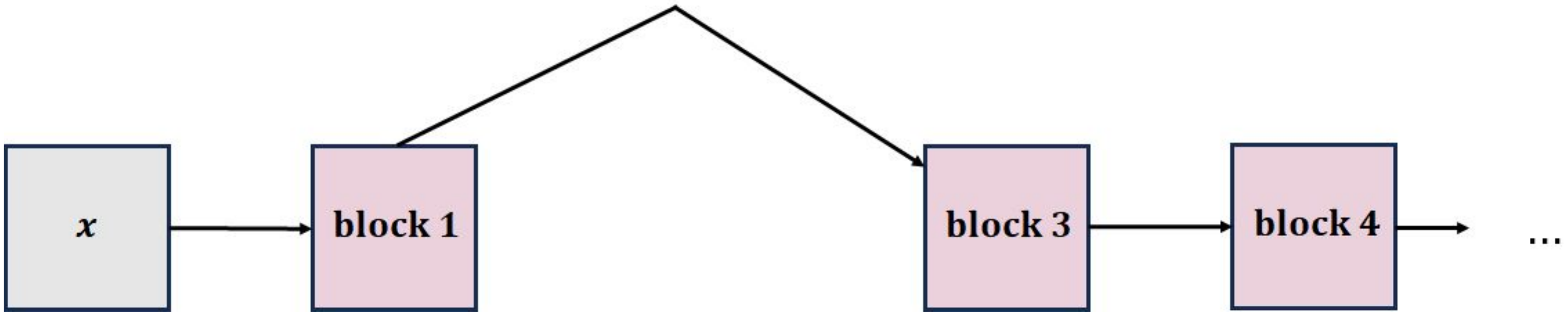
Like dropout but with residual blocks instead of individual neurons



[Huang, Gao, et al. "Deep networks with stochastic depth." *Computer Vision–ECCV 2016: 14th European Conference, Amsterdam, The Netherlands, October 11–14, 2016, Proceedings, Part IV 14.* Springer International Publishing, 2016.]

Stochastic Depth

Another benefit: robustness/mitigating overfitting



[Huang, Gao, et al. "Deep networks with stochastic depth." *Computer Vision–ECCV 2016: 14th European Conference, Amsterdam, The Netherlands, October 11–14, 2016, Proceedings, Part IV 14.* Springer International Publishing, 2016.]

Cornell Bowers C·IS

Stochastic Depth

Increases training loss, but… decreases te

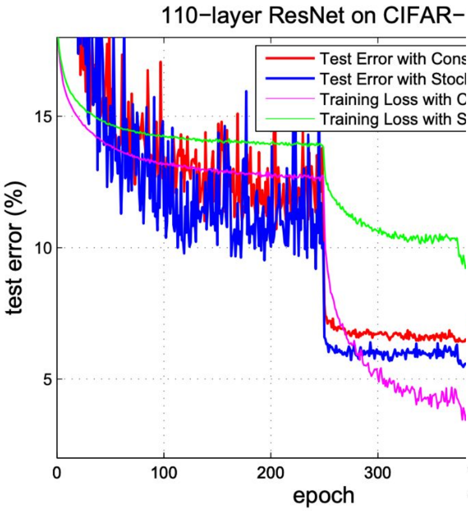


Fig. 3. Test error on CIFAR-1
data augmentation, correspond

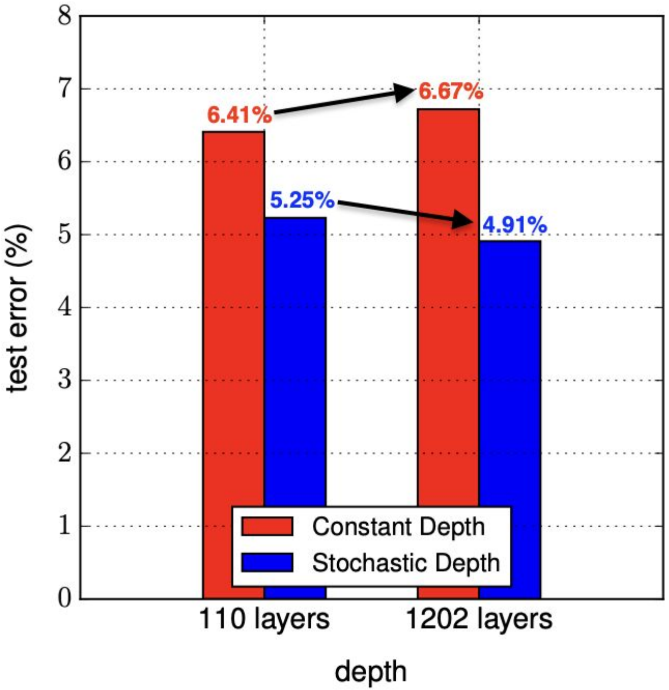
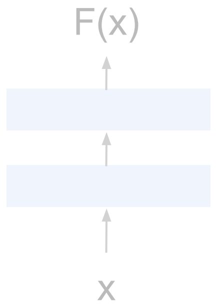


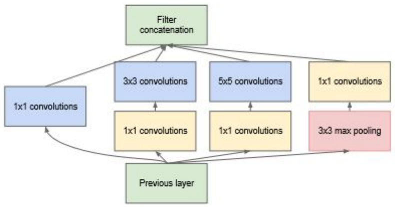
Fig. 5. With stochastic depth, the 1202-layer ResNet still significantly improves over the 110-layer one.

[Huang, Gao, et al. "Deep networks with stochastic depth." *Computer Vision–ECCV 2016: 14th European Conference, Amsterdam, The Netherlands, October 11–14, 2016, Proceedings, Part IV 14.* Springer International Publishing, 2016.]

CNN Architectures

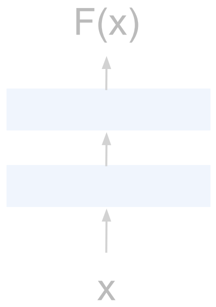
“Plain” CNN	**GoogLeNet**
Simple connection from previous to next layer	1x1, 3x3, 5x5 convolutions and pooling between each layer

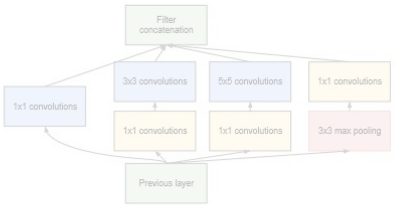


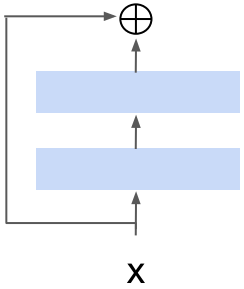


CNN Architectures

“Plain” CNN	GoogLeNet	ResNet
Simple connection from previous to next layer	1x1, 3x3, 5x5 convolutions and pooling between each layer	Skip connections Add output of previous layer to next layer

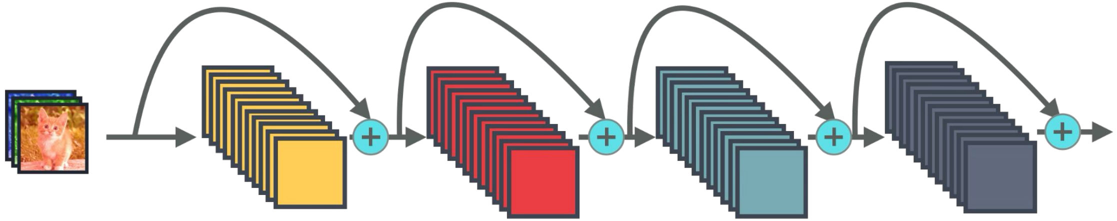






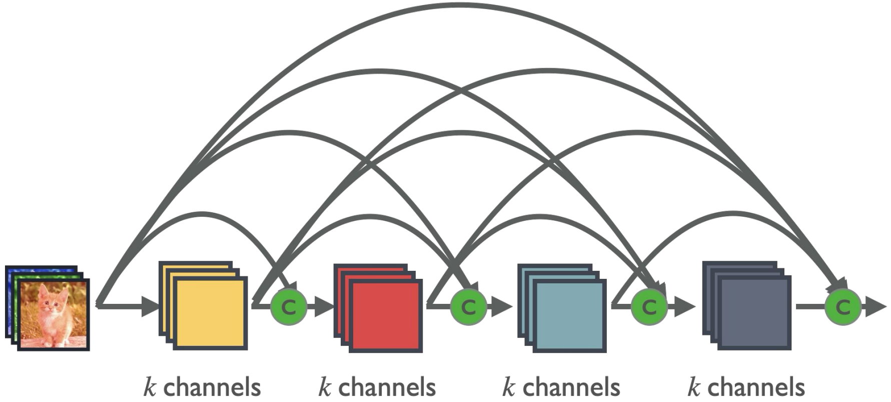
From ResNets to DenseNets

ResNet



⊕ : Element-wise addition

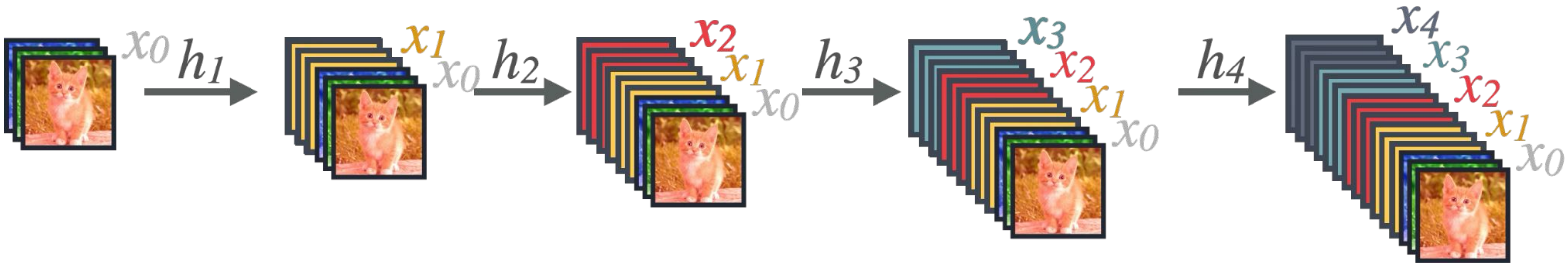
DenseNet



[Huang, Gao, et al. "Densely connected convolutional networks." *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2017.]

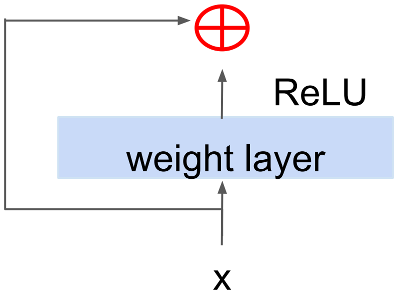
DenseNets

Feature concatenation

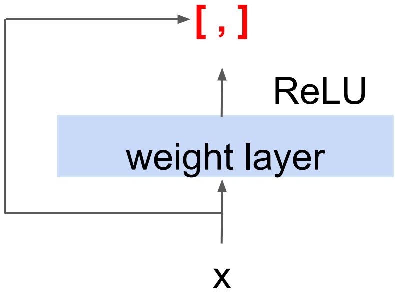


Dense Blocks

To create dense connections, dense blocks use the same structure as residual blocks, but concatenate (denoted by [,]) inputs instead of simply adding them



Residual Blocks



Dense Blocks

[Huang, Gao, et al. "Densely connected convolutional networks." *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2017.]

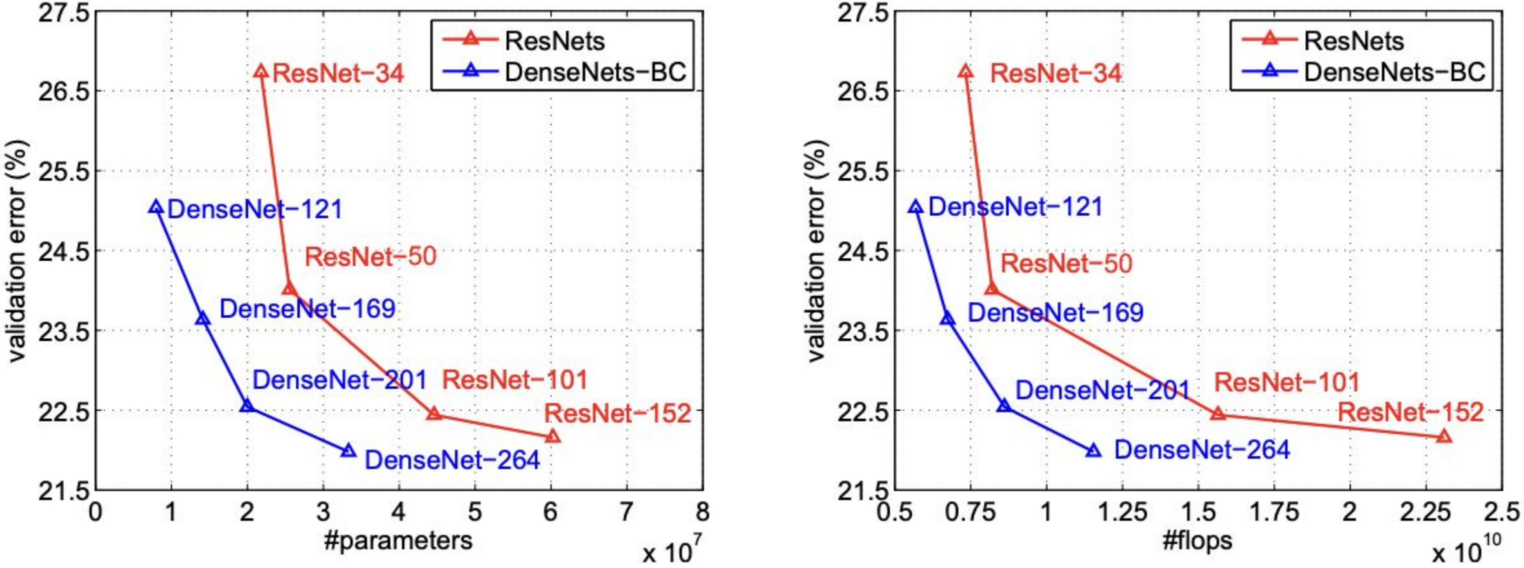
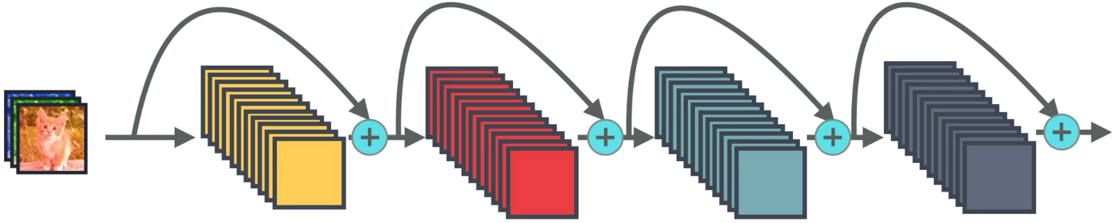


Figure 3: Comparison of the DenseNets and ResNets top-1 error rates (single-crop testing) on the ImageNet validation dataset as a function of learned parameters (*left*) and FLOPs during test-time (*right*).

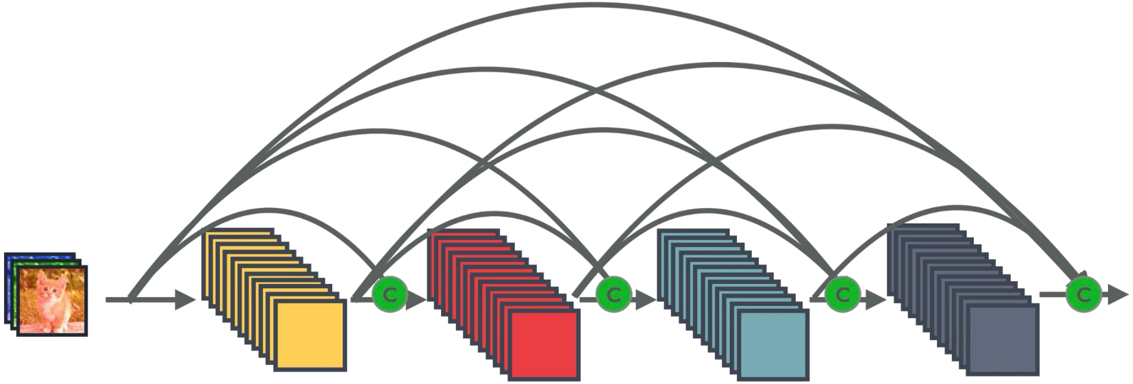
Discussion: What design choices might allow a ~100-layer DenseNet to have fewer parameters than a ~100-layer ResNet?

ResNet



⊕ : Element-wise addition

DenseNet

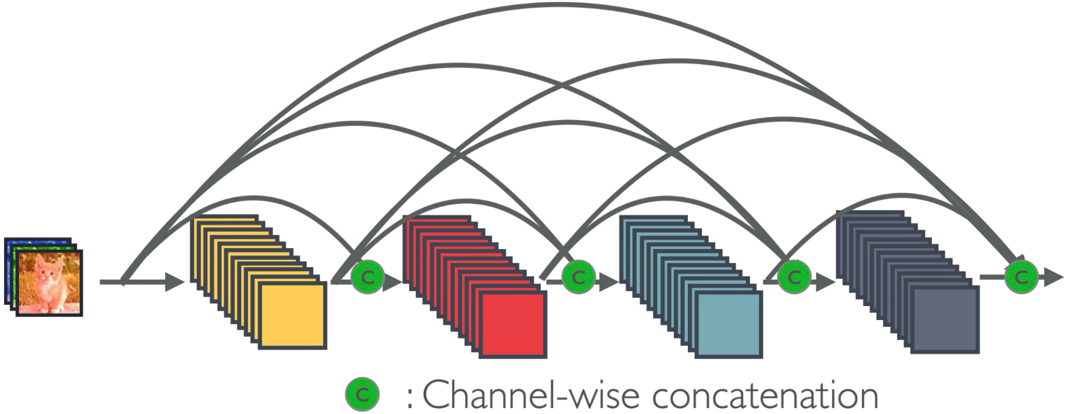


Ⓒ : Channel-wise concatenation

Dense Connections

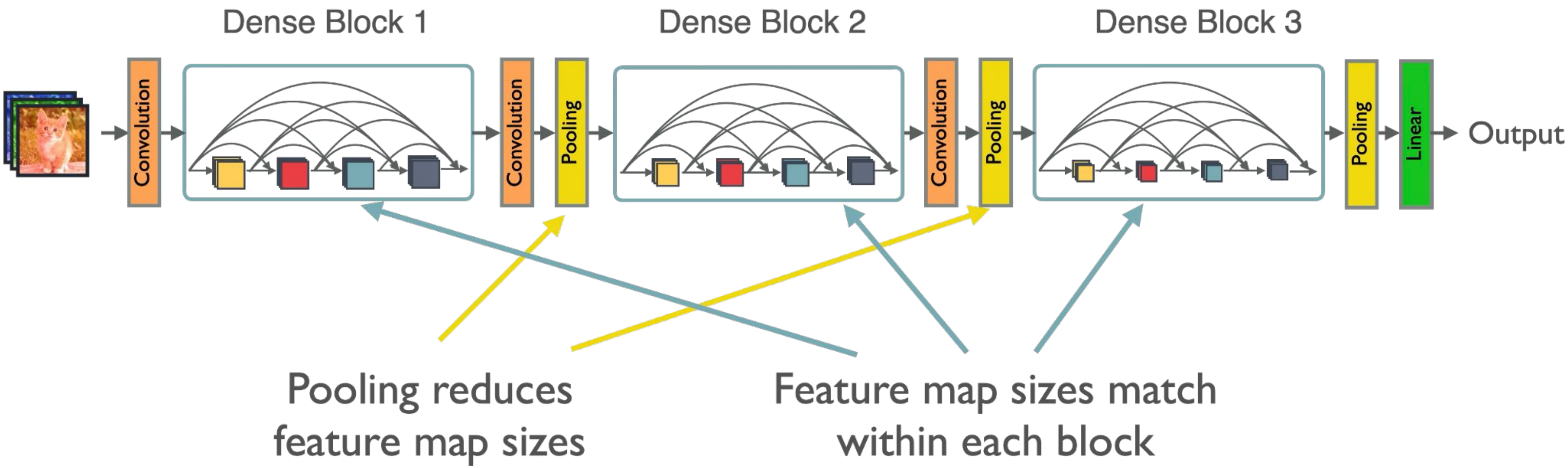
Each layer has access to every other layer before it, which:

- maximizes information flow
- allows for feature-map reuse
- less parameters to learn
- alleviates vanishing gradient



[Huang, Gao, et al. "Densely connected convolutional networks." *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2017.]

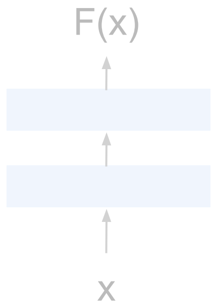
DenseNets

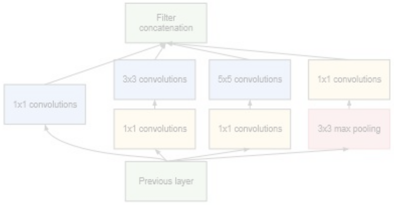


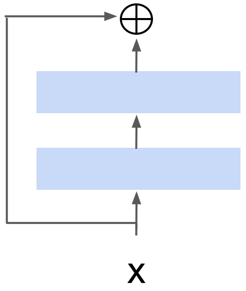
[Huang, Gao, et al. "Densely connected convolutional networks." *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2017.]

CNN Architectures

"Plain" CNN	GoogLeNet	ResNet
Simple connection from previous to next layer	1x1, 3x3, 5x5 convolutions and pooling between each layer	Skip connections Add output of previous layer to next layer

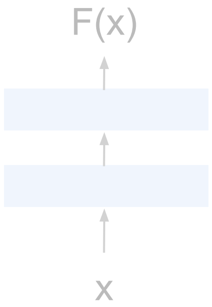


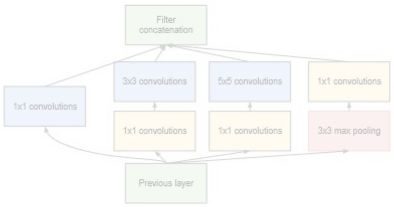


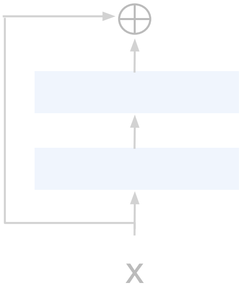


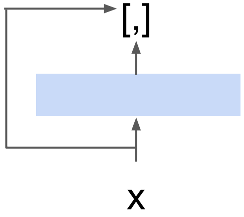
CNN Architectures

“Plain” CNN	GoogLeNet	ResNet	DenseNet
Simple connection from previous to next layer	1x1, 3x3, 5x5 convolutions and pooling between each layer	Skip connections Add output of previous layer to next layer	Dense connections Concatenate output of previous layer to next layer



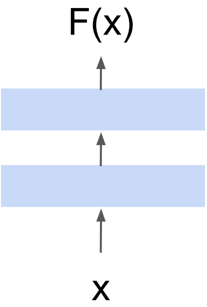


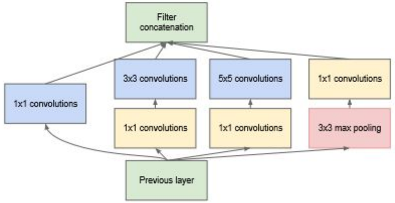


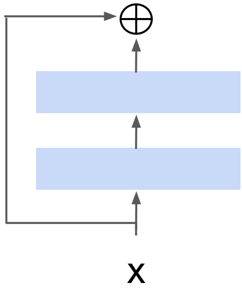


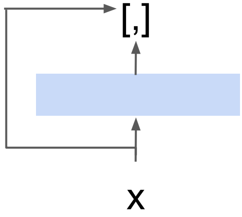
Summary of Models

"Plain" CNN	Google Net	ResNet	DenseNet
Simple connection from previous to next layer	1x1, 3x3, 5x5 convolutions and pooling between each layer	Skip connections Add output of previous layer to next layer	Dense connections Concatenate output of previous layer to next layer









Summary

- Deep CNNs outperform shallow CNNs
- But…
  - Harder optimization problem!
- Residual (and dense) connections make training easier!
  - Can train networks with 100s of layers!
- Stochastic depth let’s you train deeper networks faster
  - 1000+ layers!
- In general…
  - Build large networks as stacks of (many!) simple building blocks