Architectures

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April 24, 2023

Outline

Early Architectures

Deeper Models

Learning Architectures

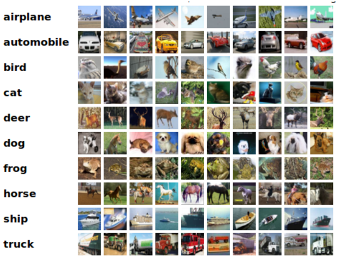
Datasets for Object Detection / Image Classification

ImageNet Dataset [11]

- 1000 classes
- $>$ 14 Mio. images
- Subsets used for ImageNet Large Scale Visual Recognition Challenges (ILSVRC)
- Natural images of varying size

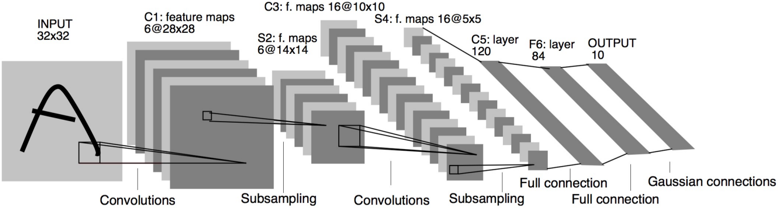
CIFAR 10 / 100

- 10 / 100 classes
- 50 k training / 10 k testing
- 32 $\times$ 32 images



Early Architectures

LeNet-5 (1998) [9]



Key features

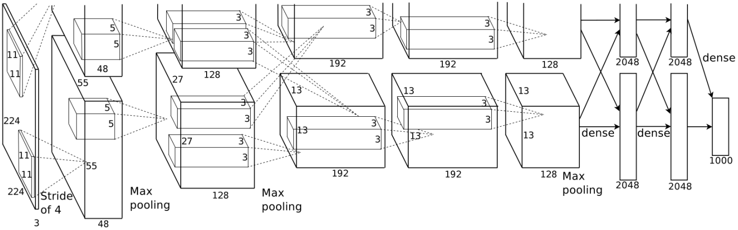
- Convolution for spatial features
- Subsampling using average pooling
- Non-linearity: `tanh`
- Sparse connectivity between S2 and C3 (efficiency, robustness)
- MLP as final classifier
- Sequence: Convolution, pooling, non-linearity

→ Foundation for many other architectures

('•' Technique still used in recent architectures)

Source: [9]

AlexNet (2012) [7]



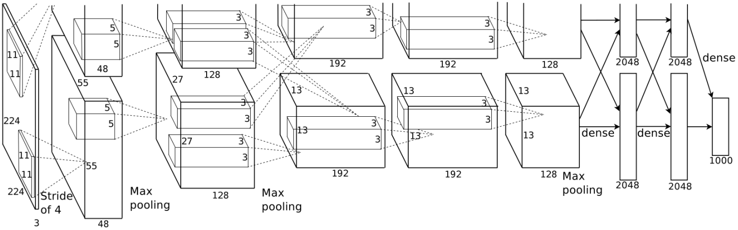
Winner of the ImageNet 2012 challenge ⇒ Breakthrough of CNNs

Key features I

- 8 Layers
- Use of GPU(s) to reduce training time
- Overlapping max pooling (stride: 2, size: 3)
- Non-linearity: ReLU

Source: [7]

AlexNet (2012) [7]



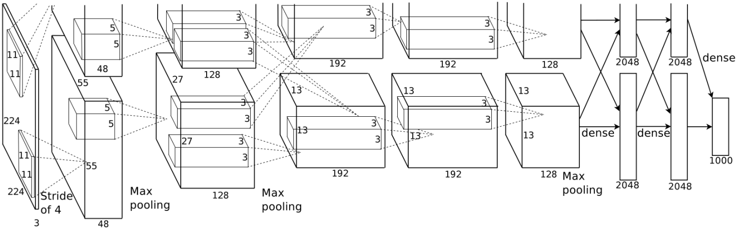
Winner of the ImageNet 2012 challenge ⇒ Breakthrough of CNNs

Key features II

- Combat overfitting:
  - Dropout w. $p = 0.5$ in the first two FC layers
  - Data augmentation (random transformations, random intensity variation)

Source: [7]

AlexNet (2012) [7]



Winner of the ImageNet 2012 challenge ⇒ Breakthrough of CNNs

Key features III

- Learning: mini-batch SGD w. momentum (0.9) + (L_2) weight decay $(5 \cdot 10^{-5})$
- Weight initialization: $\mathcal{N}(0, 0.01)$

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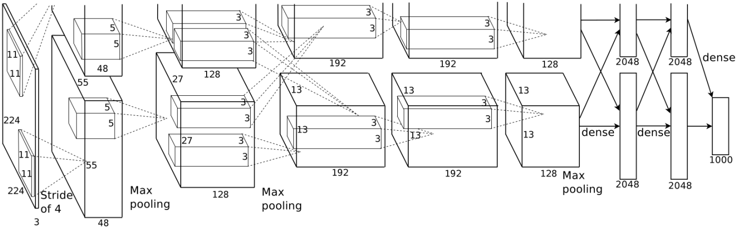


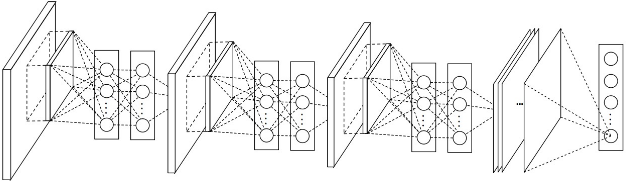
Winner of the ImageNet 2012 challenge ⇒ Breakthrough of CNNs

Key features III

- Learning: mini-batch SGD w. momentum (0.9) + (L_2) weight decay $(5 \cdot 10^{-5})$
- Weight initialization: $\mathcal{N}(0, 0.01)$
- Historical note: Small GPUs ➔network split across two GPUs

Source: [7]

Network In Network [10]

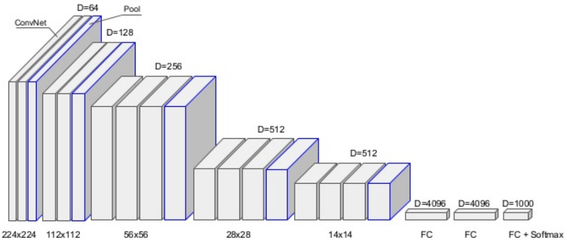


Key features

- 1×1 filters
  - Conventional conv layers only learn linear functions of input
  - ➔ Connect conv layers by FC layers that can learn non-linear functions
  - ➔ Equivalent to FC layer: conv layer with 1×1 filters
  - ➔ Very few parameters, shared across all activations
- Global (spatial) average pooling as last layer
  - ➔ Less prone to overfitting than final FC layers

Source: [10]

VGG Network (Visual Geometry Group – University of Oxford) [12]



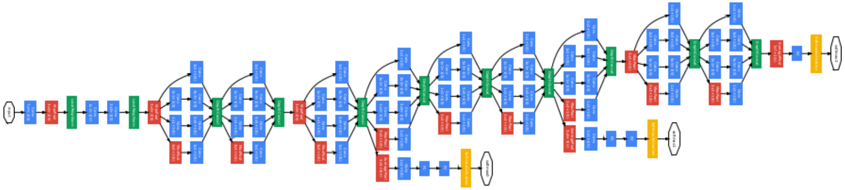
Key features

- Small kernel sizes in each convolution (3×3)
  - ➔ Combination of multiple smaller kernels emulate larger receptive fields
- 16 / 19 layers, max pooling between some layers (stride: 2, size: 2)
- Learning procedure similar to AlexNet

— hard to train (in practice: pre-training with shallower networks)

Source: https://www.slideshare.net/holbertonschool/deep-learning-class-2-by-louis-monier

GoogleNet (Inception-v1) [14]



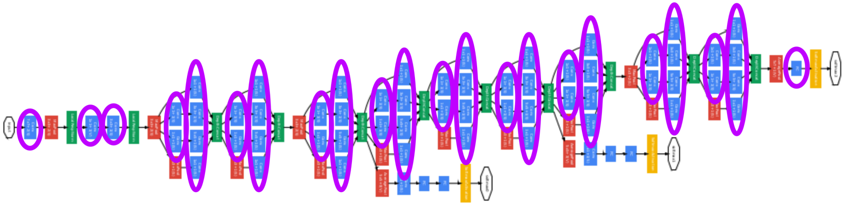
Goal

- Network design with embedded hardware in mind

➔ maximum 1.5 billion MAD (multiply-add) operations at inference time

Source: [14]

GoogleNet (Inception-v1) [14]

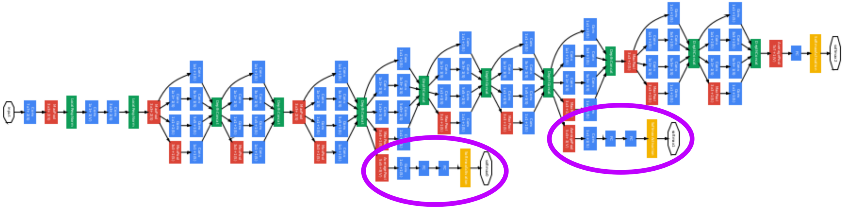


Key features

- 22 layers + global average pooling as final layer

Source: [14]

GoogleNet (Inception-v1) [14]



Key features

- 22 layers + global average pooling as final layer
- Auxiliary classifiers (only at training): error weighted by 0.3 added to global error ➔ additional regularization
- No fully connected layers (except for linear layer and auxiliary networks)

Source: [14]

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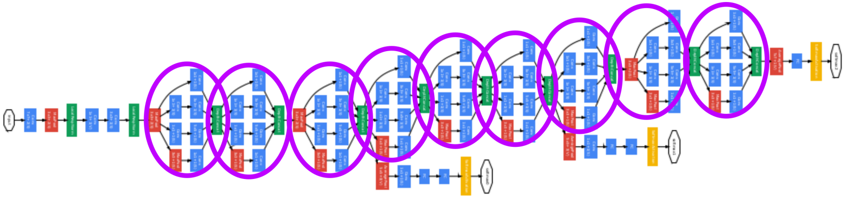

Key features

- 22 layers + global average pooling as final layer
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- Inception modules

Source: [14]

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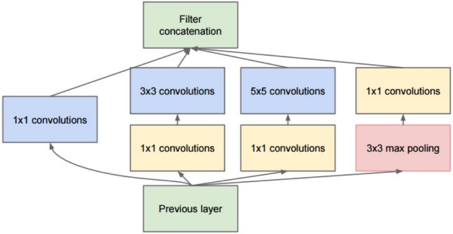

Inception Module

- Derived from NiN concept
- Parallel filter combinations (split-transform-merge strategy)
  - ➔ Network decides filter size by itself
- 1×1 filters serve as “bottleneck layer”

➔ Representational power of large and dense layers but with much lower computational complexity

Source: [14]

Bottleneck Layer

Features are correlated, redundancy can be removed by 1×1 filters

Example:

- Before: 256 input feature maps, 256 output feature maps, 3×3 convolution

➔ $256 \times 3 \times 3 \times 256 \approx 600\text{k MAD}$

- Instead: Reduce number of feature maps that have to be convolved, e.g. 64

$$
\begin{aligned}
256 \times 1 \times 1 \times 64 &\approx 16,000 \\
64 \times 3 \times 3 \times 64 &\approx 36,000 \\
64 \times 1 \times 1 \times 256 &\approx 16,000
\end{aligned}
$$

➔ $\approx 70\text{k MAD}$

NEXT TIME
ON DEEP LEARNING

FRIEDRICH-ALEXANDER-UNIVERSITÄT ERLANGEN-NÜRNBERG
SCHOOL OF ENGINEERING

Architectures - Part 2

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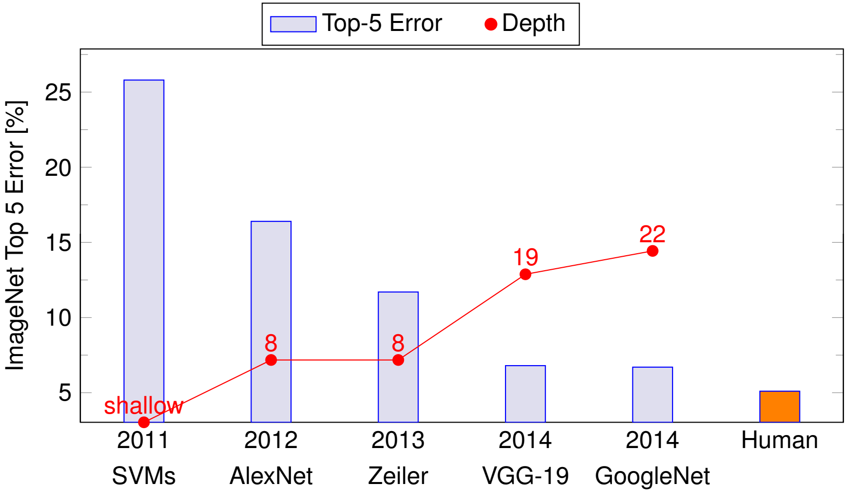
Deeper Models

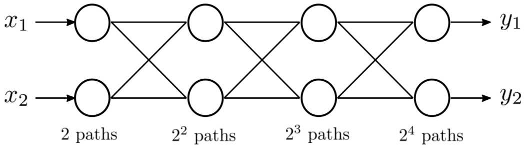
Evolution of Depth



Source: image-net.org, Russakovsky et al. 2015

Advantages of Deeper Networks

- Exponential feature reuse



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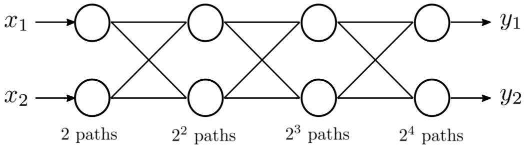
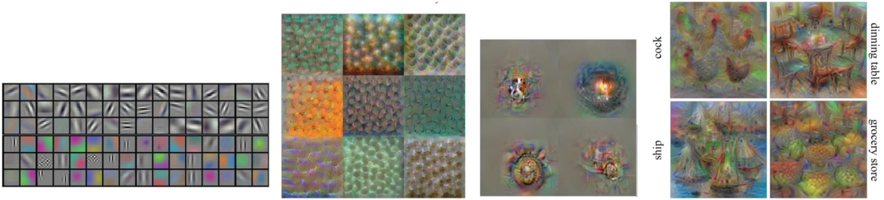


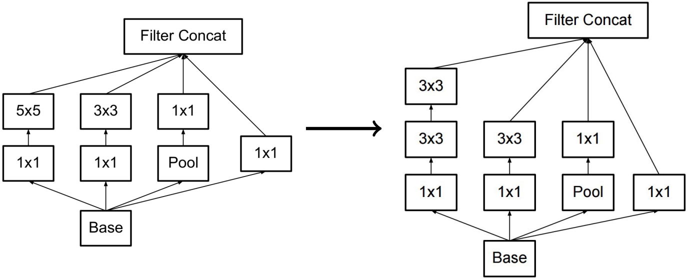
- Increasingly abstract features



Conv 1: Edge+Blob **Conv 3: Texture** **Conv 5: Object Parts** **Fc8: Object Classes**

Source: `http://vision03.csail.mit.edu/cnn_art/index.html`

Inception-v2 [15]



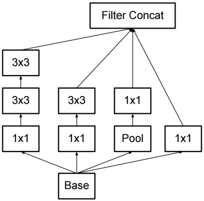
Key features

- Change basic inception layer: Replace 7×7 and 5×5 filters by multiple 3×3 convolutions.

Source: [15]

Inception-v2 [15]

$\rightarrow 3\times$

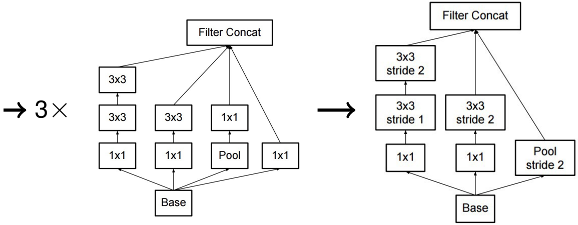


Key features II

- 42 layers – start with several 3×3 convolutions and 3 modified inception modules

Source: [15]

Inception-v2 [15]

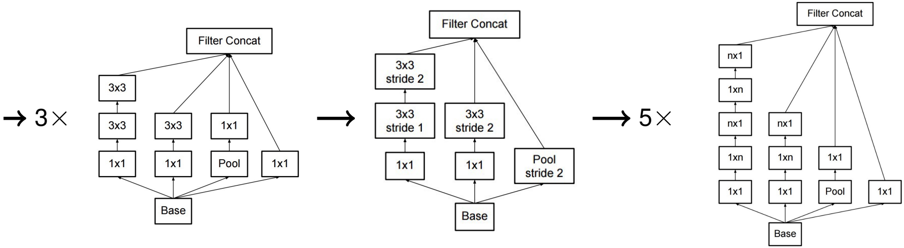


Key features II

- 42 layers – start with several 3×3 convolutions and 3 modified inception modules
- Efficient grid size reduction

Source: [15]

Inception-v2 [15]



Key features II

- 42 layers – start with several 3×3 convolutions and 3 modified inception modules
- Efficient grid size reduction
- 5 modules of flattened convolutions ($n = 7$)
- Efficient grid size reduction + average pooling + softmax

Source: [15]

Inception-v3 [15]

Inception-v2 +

- RMSProp
- Bach-normalization also in the FC layers of auxiliary classifiers
- Label-smoothing regularization

Label-smoothing regularization

Standard label distribution:

$$q(k|x) = \delta_{k,y}$$

x: training sample, $k \in \{1, \dots, K\}$: specific label, y: ground truth label

- For Softmax to predict exactly 0 / 1, $|\textbf{activations}| \mapsto \infty$

➔ Continue to learn larger and larger weights, making more extreme predictions

➔ Use weight decay and/or label-smoothing

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Label-smoothing [8]

Exchange label distribution with

$$q'(k|x) = (1 - \epsilon)\delta_{k,y} + \epsilon u(k)$$

where authors chose: $u(k) = 1/K$, $\epsilon = 0.1$

+ Prevent hard probabilities without discouraging correct classification.

NEXT TIME

ON DEEP LEARNING

Problems with going deeper

... why not just stack more layers?

Architectures - Part 3

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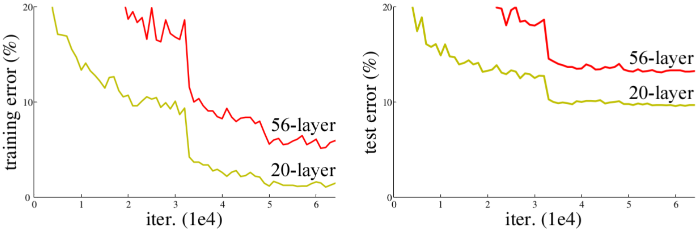
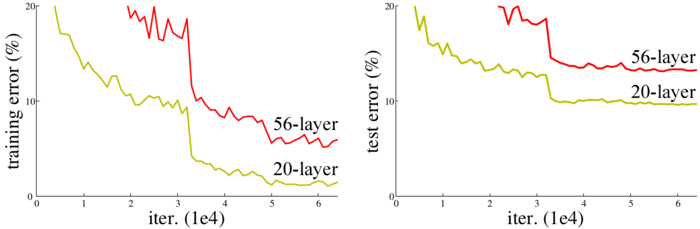
Degradation of Training Error



Deeper models tend to have higher **training & test error** than shallower models

➔ Not just caused by overfitting!

Degradation of Training Error



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Possible Reasons

- Vanishing gradient problem
  - ➔ ReLU (or successors)
  - ➔ Proper initialization

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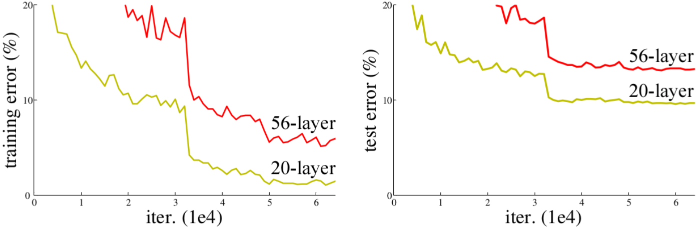

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- Internal co-variate shift
  - ➔ Batch normalization
  - ➔ ELU / SELU

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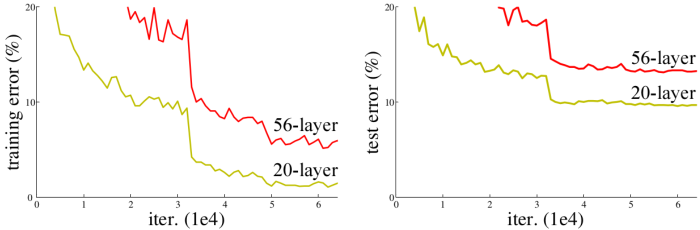

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Possible Reasons

- Vanishing gradient problem
  - ➔ ReLU (or successors)
  - ➔ Proper initialization
- Internal co-variate shift
  - ➔ Batch normalization
  - ➔ ELU / SELU
- Degradation problem: poor propagation of activations and gradients

Source: [2]

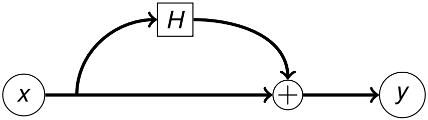
(One) Solution: Residual Units

Residual Units [2], [3]

Idea: Simplify "identity solution"

- Non-residual nets: learn mapping $F(x)$
- Instead: learn residual mapping:

$$H(x) = F(x) - x \Leftrightarrow F(x) = H(x) + x$$



Residual Block [2], [3]

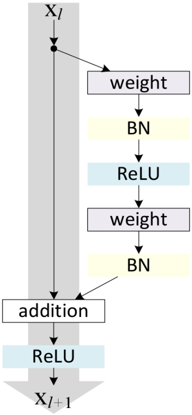
- General form of the l-th residual unit over K layers:

$$\mathbf{x}_{l+1} = h\Big(g(\mathbf{x}_l) + H_{l+1}\big(\mathbf{x}_l, \{\mathbf{W}_{l+1,K}\}\big)\Big)$$

$\mathbf{x}_l,\ \mathbf{x}_{l+1}$: input, output activations

$\{\mathbf{W}_{l+1,K}\} = \{\mathbf{W}_{l+1,k} | 1 \leq k \leq K\}$

g, h : activation functions



- BN: Batch normalization
- Typically $K = 2$ or $K = 3$
- Original: g: identity, h: ReLU

Source: [3]

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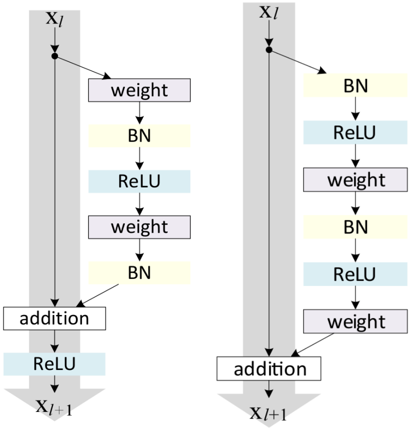
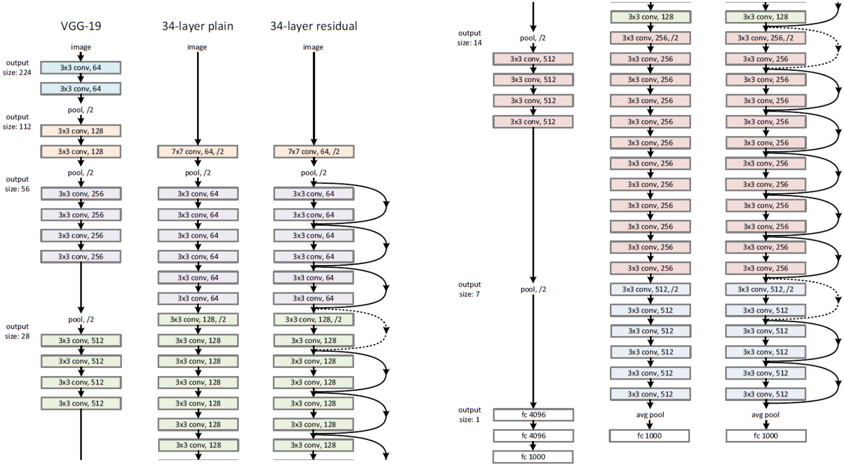


- BN: Batch normalization
- Typically $K = 2$ or $K = 3$
- Original: g: identity, h: ReLU
- Better: g and h: identity $\Rightarrow$ pre-activation

Source: [3]

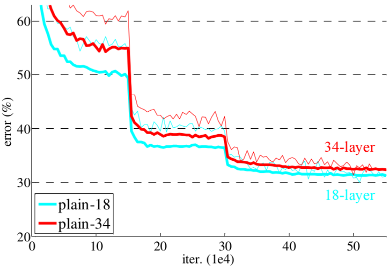
Residual Networks [2], [3]



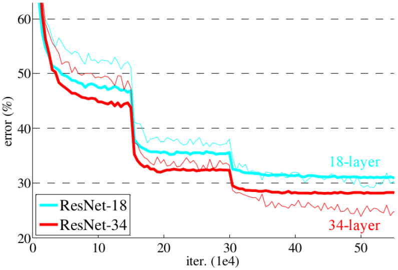
VGG: 19.6 billion FLOPs, Plain / ResNet: 3.6 billion FLOPs

Source: [2]

Residual Networks [2], [3]



Plain networks

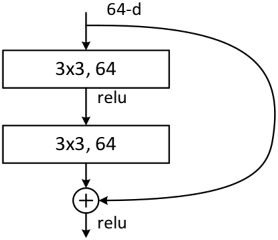


Residual networks

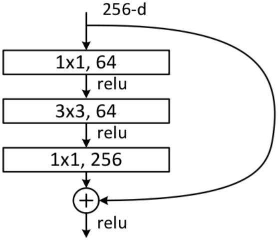
➔ Training / validation error of deeper nets is now lower!

Source: [2]

Bottleneck Residual Block



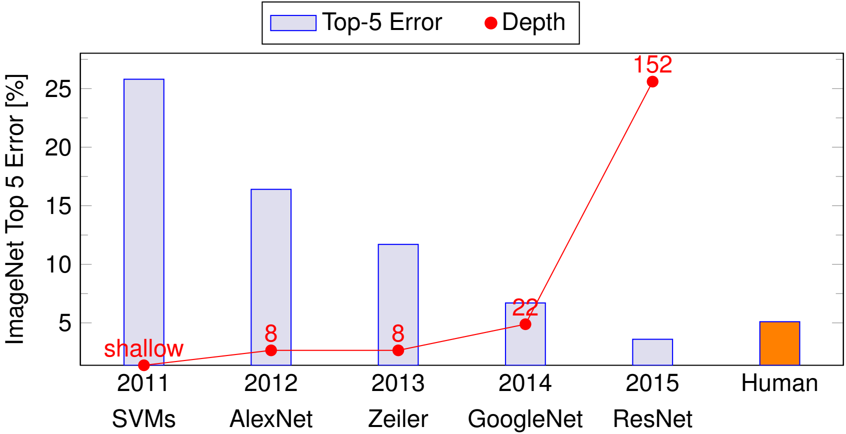
Example standard building block



Example bottleneck building block

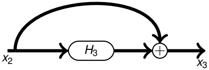
- Standard building block:
  For networks up to 34 layers or small input image sizes
- Bottleneck building block:
  For deeper networks and larger input image sizes

Evolution of Depth



Source: image-net.org, Russakovsky et al. 2015

The Ensemble View [17]

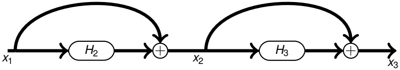


$$\mathbf{x}_{l+1} = \mathbf{x}_l + H_{l+1}(\mathbf{x}_l)$$

Consider 3 layer ResNet:

$$\mathbf{x}_3 = \mathbf{x}_2 + H_3(\mathbf{x}_2)$$

The Ensemble View [17]



$$\mathbf{x}_{l+1} = \mathbf{x}_l + H_{l+1}(\mathbf{x}_l)$$

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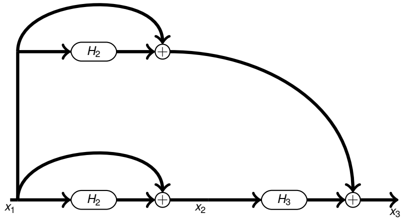
$$\begin{aligned}\mathbf{x}_3 &= \mathbf{x}_2 + H_3(\mathbf{x}_2) \\ &= [\mathbf{x}_1 + H_2(\mathbf{x}_1)] + H_3(\mathbf{x}_1 + H_2(\mathbf{x}_1))\end{aligned}$$

The Ensemble View [17]



Unroll

$$\mathbf{x}_{l+1} = \mathbf{x}_l + H_{l+1}(\mathbf{x}_l)$$

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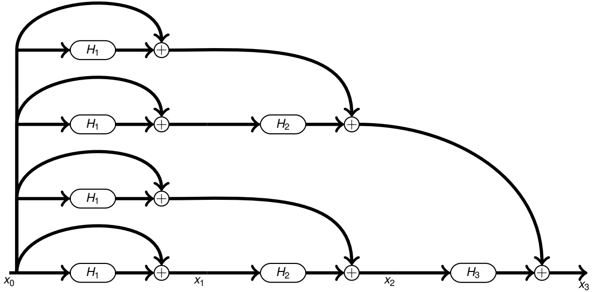

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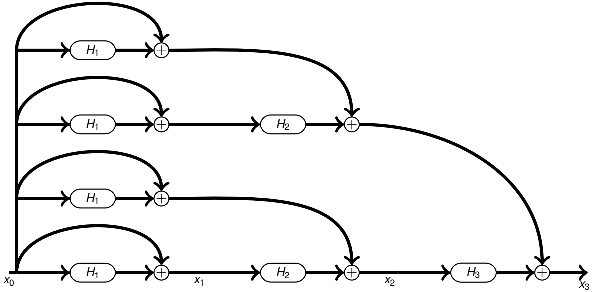


ResNets behave like ensemble of shallow networks

➔ Implicitly average exponentially many networks

Classical Feed-forward Network vs. Residual Networks

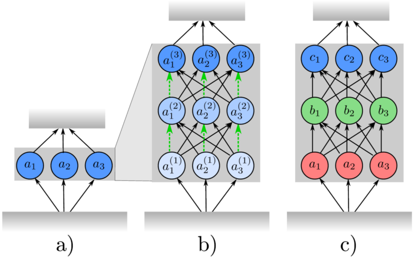
Classical feed-forward network:

- At layer level: one single path
- At neuron level: many different paths of **same** length (= exponential in #layers)

Residual networks:

- At layer level: 2^n paths
- At neuron layer: many different paths of **varying** length going through different subsets of layers.

The Representation View [1]



(a) Single layer: direct computation

(b) Residual Network: unrolled iterative estimation

(c) Classic network: produces new representation at each layer

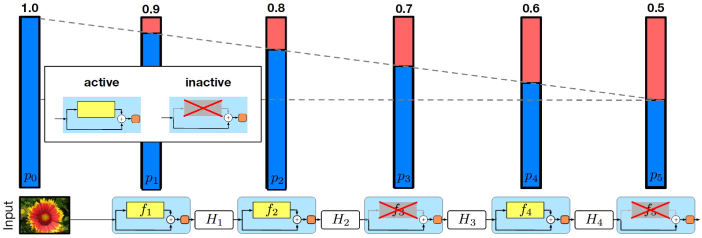
- Residual blocks do not compute entirely new representations
- They instead iteratively refine their input representations

→ Residual networks allow removal of connections without significant drop in perfomance

→ This can even be exploited: stochastic depth

Source: [1]

Deep Networks with Stochastic Depth [5]



- Stochastic depth: layer-wise dropout, i.e., drop random layers and bypass with identity

$\rightarrow$ Ensemble of exponentially many small networks

- Network are short during training $\rightarrow$ decreased training time
- 1200 layers trainable (CIFAR-10 Error: 4.91%)

Source: [5]

NEXT TIME

ON DEEP LEARNING

The rise of residual connections

Architectures - Part 4

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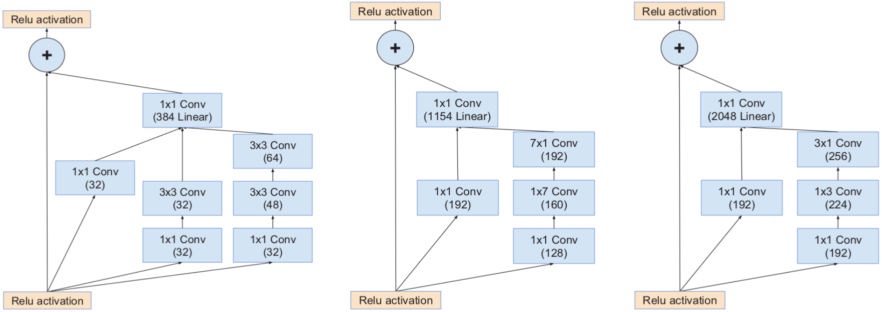
April 24, 2023

Inception-ResNet [16]

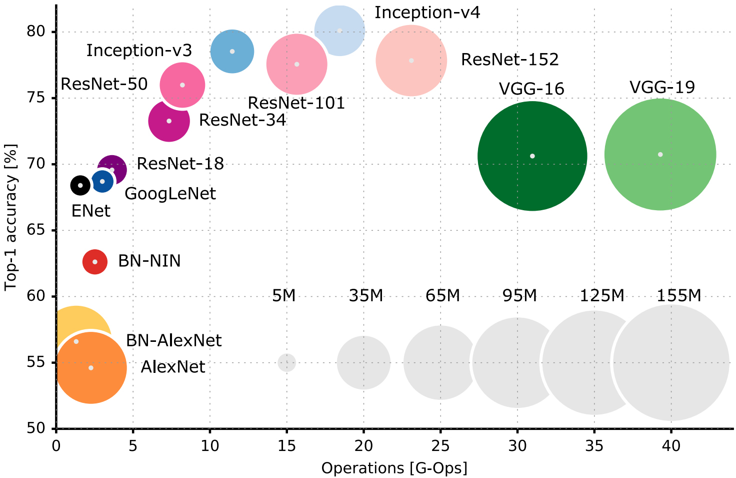


- Combination of inception architecture and residual connections

➔ Faster convergence and better performance than without residual connections

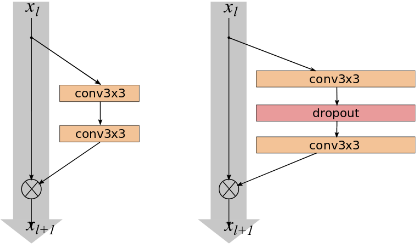
Source: [16]

Top1 vs. Operations



Source: https://towardsdatascience.com/neural-network-architectures-156e5bad51ba (visited 2017/12/01), s. also Canziani et al., 2016

Wide Residual Networks [20]



Key features

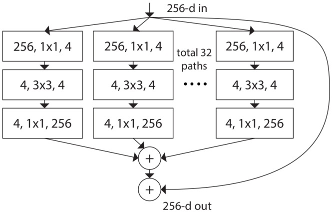
- Decrease depth, increase width of ResNet blocks
- Use dropout in residual block

➔ 16 layer deep network w. similar #params outperforms 1000 layer deep network

➔ Power not from depth but from residual connections

Source: [20]

ResNeXt [18]

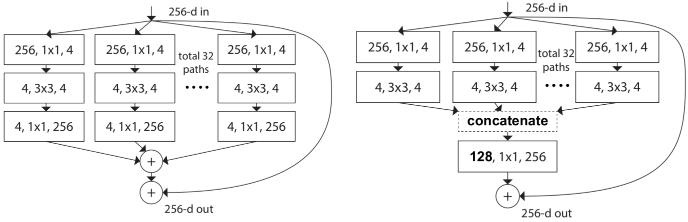


Key features

- Aggregated residual transformations (inception layer w. same trafo)

Source: [18]

ResNeXt [18]



Key features

- Aggregated residual transformations (inception layer w. same trafo)
- Equivalent: early concatenation

Source: [18]

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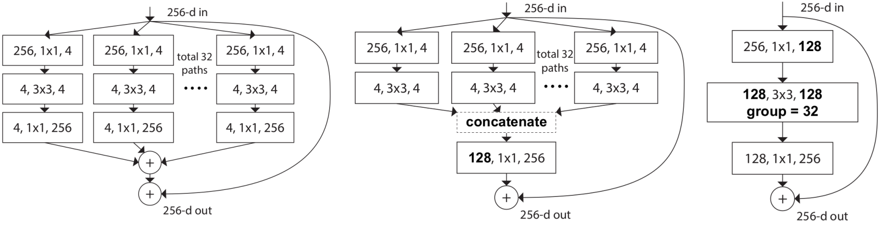

Key features

- Aggregated residual transformations (inception layer w. same trafo)
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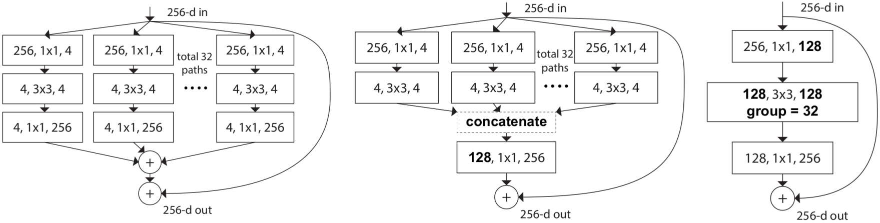
- Equivalent: grouped convolution (input/output chans are divided into groups, convolutions separately performed within each group)

Source: [18]

ResNeXt [18]

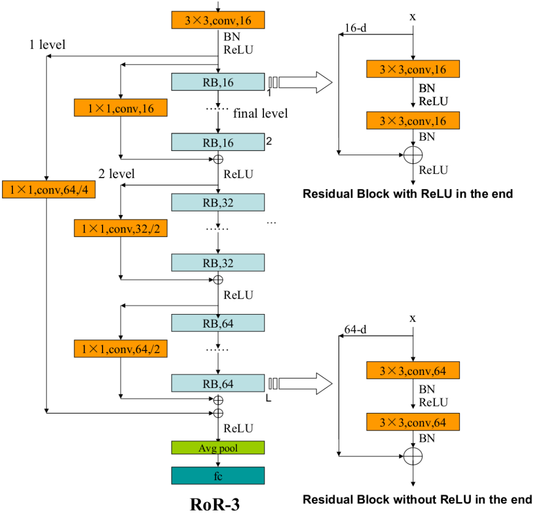


Key features

- Aggregated residual transformations (inception layer w. same trafo)
- Equivalent: early concatenation
- Equivalent: grouped convolution (input/output chans are divided into groups, convolutions separately performed within each group)
- Similar FLOPS and #params than ResNet bottleneck block
  But: wider, sparsely connected module!

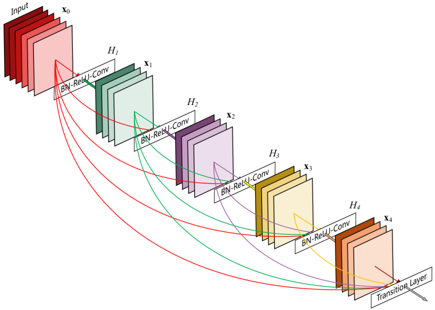
Source: [18]

ResNet-of-ResNets [21]



Source: [21]

DenseNets: Densely Connected Convolutional Networks [6]



- Layer input: feature-maps of all preceding layers

➔ Feature propagation, feature reuse

➔ Alleviates the vanishing-gradient problem

- Up to 264 Layers – needs actually $\approx 1/3$ less params for same performance than ResNet due to transition layers using 1×1 convolutions

Source: [6]

Squeeze-and-Excitation Networks (SENet) [4]

- ImageNet Challenge winner (classification) 2017: 2.3 % top-5 error
- **Motivation**: Explicitly model channel interdependencies : channels have different relevance depending on content
- Example: “Dog features” not important when differentiating cars

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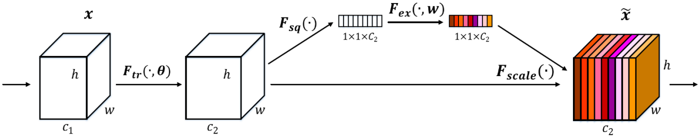
- ImageNet Challenge winner (classification) 2017: 2.3 % top-5 error
- **Motivation**: Explicitly model channel interdependencies : channels have different relevance depending on content
- Example: “Dog features” not important when differentiating cars
- **Idea**: Add trainable module that allows **rescaling of channels** depending on input

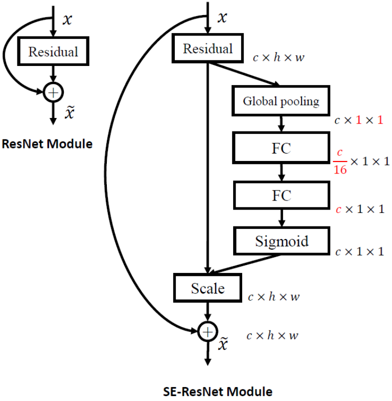


SENet module with scaled channels

Source: [4]

Squeeze-and-Excitation Networks (SENet) [4] (cont.)

- **Squeeze**: Compress each channel into one value (global avg. pooling)
  ➔ Vector of size c, $c = \#$ channels



SEN extension for ResNet module

Source: [4]

Squeeze-and-Excitation Networks (SENet) [4] (cont.)

- **Squeeze**: Compress each channel into one value (global avg. pooling)
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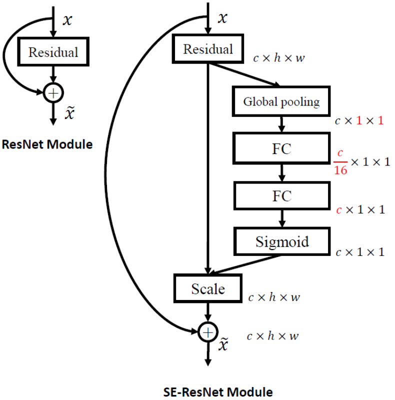

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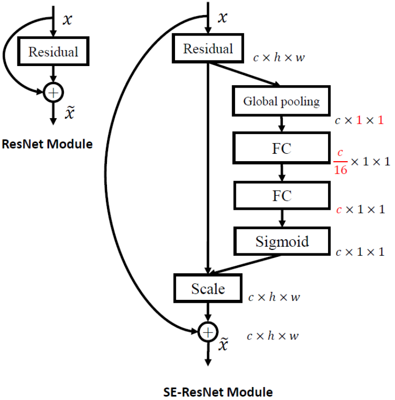

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Squeeze-and-Excitation Networks (SENet) [4] (cont.)

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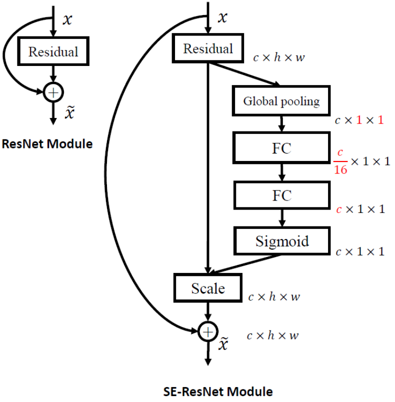
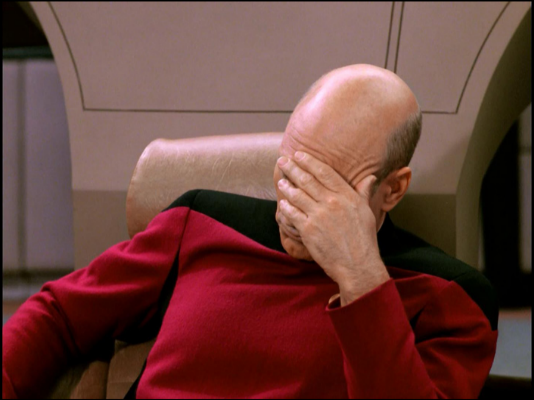
- **Excitation**: FC layers & sigmoid to achieve scaling vector ➔ compare to gating in LSTMs (next week)
- **Scale**: Scale input feature maps
- Can be combined with most architectures, e.g., Inception, ResNet, ResNeXt, ...



SEN extension for ResNet module

Source: [4]



NOT ANOTHER ARCHITECTURE

NEXT TIME

ON DEEP LEARNING

Architectures - Part 5

A. Maier, V. Christlein, K. Breininger, Z. Yang, L. Rist, M. Nau, S. Jaganathan, C. Liu, N. Maul, L. Folle, K. Packhäuser, M. Zinnen
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April 24, 2023

Learning Architectures

Learning Architectures

Goal: Self-developing network structures

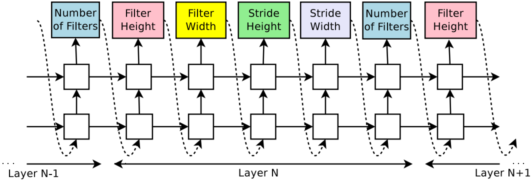
Optimized with respect to

- Accuracy
- FLOPs

Possible option: Grid-search typically too time-consuming

Learning Architectures

With reinforcement learning [22]



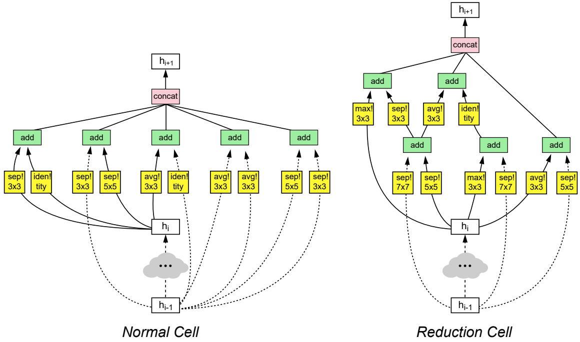
- Recurrent neural network (RNN) to generate model descriptions of networks
- Train RNN with reinforcement learning to maximize expected accuracy

Other options

- Reinforcement learning for small building blocks transferred to large CNNs
- Genetic algorithms
- Energy-based
- ...

Source: [22]

What do the learned architectures look like?



NASNet-A

- Performance for ImageNet on par with SENets, with lower computational costs
- Optimization of networks of different size, e.g., for mobile platforms

Source: [22]

ImageNet Challenge - Where are we?

- ImageNet results for classification typically <5 % in most submissions
- Substantial and significant improvements more and more difficult to show
- Last “official” challenge (with CVPR workshop) in 2017, now on Kaggle

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- ImageNet results for classification typically <5 % in most submissions
- Substantial and significant improvements more and more difficult to show
- Last "official" challenge (with CVPR workshop) in 2017, now on Kaggle
- New data sets are generated/needed, e.g., 3D scenes and human-level understanding
- **Examples**: MS COCO (http://cocodataset.org), Visual Genome Dataset (https://visualgenome.org/)
- Additional research directions: Speed and size of networks on mobile platforms

Conclusion

Summary

- 1×1 filters to reduce parameters and add regularization
- Inception layers
- Residual connections
- New architectures can be learned

Rise of deeper models (from 5 layers to more than 1000)

However

- Often a smaller net is sufficient
- Dependent on amount of training data
- Deep vs. wide layers

NEXT TIME

ON DEEP LEARNING

Coming Up

- Recurrent neural networks
- (Truncated) Backpropagation through time
- Long short-term memory
- Gated recurrent unit

Comprehensive Questions

- What are the advantages of deeper models in comparison to shallow networks?
- Why can we say that residual networks learn an ensemble of shallow networks?
- How does a bottleneck layer work?
- What is the standard inception module and how can it be improved?

Further Reading

- Current state of the art networks:
  - Dual Path Networks
    http://papers.nips.cc/paper/7033-dual-path-networks,
  - Squeeze-and-Excitation Networks https://arxiv.org/abs/1709.01507
- Some interesting state-of-the-art works can be found here:
  https://medium.com/@karpathy/iclr-2017-vs-arxiv-sanity-d1488ac5c131
  (visited: 03-12-2017)
- MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications https://arxiv.org/abs/1704.04861
- Deep networks without residual connections:
  - https://arxiv.org/abs/1706.00388,
  - https://arxiv.org/abs/1703.01827

References

References I

[1] Klaus Greff, Rupesh K. Srivastava, and Jürgen Schmidhuber. “Highway and Residual Networks learn Unrolled Iterative Estimation”. In: International Conference on Learning Representations (ICLR). Toulon, Apr. 2017. arXiv: 1612.07771.

[2] Kaiming He, Xiangyu Zhang, Shaoqing Ren, et al. “Deep Residual Learning for Image Recognition”. In: 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR). Las Vegas, June 2016, pp. 770–778. arXiv: 1512.03385.

[3] Kaiming He, Xiangyu Zhang, Shaoqing Ren, et al. “Identity mappings in deep residual networks”. In: Computer Vision – ECCV 2016: 14th European Conference, Amsterdam, The N 2016, pp. 630–645. arXiv: 1603.05027.

References II

[4] J. Hu, L. Shen, and G. Sun. "Squeeze-and-Excitation Networks". In: ArXiv e-prints (Sept. 2017). arXiv: 1709.01507 [cs.CV].

[5] Gao Huang, Yu Sun, Zhuang Liu, et al. "Deep Networks with Stochastic Depth". In: Computer Vision – ECCV 2016, Proceedings, Part IV. Cham: Springer International Publishing, 2016, pp. 646–661.

[6] Gao Huang, Zhuang Liu, and Kilian Q. Weinberger. "Densely Connected Convolutional Networks". In: 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR). Honolulu, July 2017. arXiv: 1608.06993.

[7] Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton. "ImageNet Classification with Deep Convolutional Neural Networks". In: Advances In Neural Information Processing Systems 25. Curran Associates, Inc., 2012, pp. 1097–1105. arXiv: 1102.0183.

References III

[8] Yann A LeCun, Léon Bottou, Genevieve B Orr, et al. “Efficient BackProp”. In: Neural Networks: Tricks of the Trade: Second Edition. Vol. 75. Berlin, Heidelberg: Springer Berlin Heidelberg, 2012, pp. 9–48.

[9] Y LeCun, L Bottou, Y Bengio, et al. “Gradient-based Learning Applied to Document Recognition”. In: Proceedings of the IEEE 86.11 (Nov. 1998), pp. 2278–2324. arXiv: 1102.0183.

[10] Min Lin, Qiang Chen, and Shuicheng Yan. “Network in network”. In: International Conference on Learning Representations. Banff, Canada, Apr. 2014. arXiv: 1102.0183.

[11] Olga Russakovsky, Jia Deng, Hao Su, et al. “ImageNet Large Scale Visual Recognition Challenge”. In: International Journal of Computer Vision 115.3 (Dec. 2015), pp. 211–252.

References IV

[12] Karen Simonyan and Andrew Zisserman. “Very Deep Convolutional Networks for Large-Scale Image Recognition”. In: International Conference on Learning Representations (ICLR). San Diego, May 2015. arXiv: 1409.1556.

[13] Rupesh Kumar Srivastava, Klaus Greff, Urgen Schmidhuber, et al. “Training Very Deep Networks”. In: Advances in Neural Information Processing Systems 28. Curran Associates, Inc., 2015, pp. 2377–2385. arXiv: 1507.06228.

[14] C. Szegedy, Wei Liu, Yangqing Jia, et al. “Going deeper with convolutions”. In: 2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR). June 2015, pp. 1–9.

References V

[15] C. Szegedy, V. Vanhoucke, S. Ioffe, et al. "Rethinking the Inception Architecture for Computer Vision". In: 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR). June 2016, pp. 2818–2826.

[16] Christian Szegedy, Sergey Ioffe, and Vincent Vanhoucke. "Inception-v4, Inception-ResNet and the Impact of Residual Connections on Learning". In: Thirty-First AAAI Conference on Artificial Intelligence (AAAI-17) Inception-v4, San Francisco, Feb. 2017. arXiv: 1602.07261.

[17] Andreas Veit, Michael J Wilber, and Serge Belongie. "Residual Networks Behave Like Ensembles of Relatively Shallow Networks". In: Advances in Neural Information Processing Systems 29. Curran Associates, Inc., 2016, pp. 550–558.

References VI

[18] Di Xie, Jiang Xiong, and Shiliang Pu. "All You Need is Beyond a Good Init: Exploring Better Solution for Training Extremely Deep Convolutional Neural Networks with Orthonormality and Modulation". In: 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR). Honolulu, July 2017. arXiv: 1703.01827.

[19] Lingxi Xie and Alan Yuille. Genetic CNN. Tech. rep. 2017. arXiv: 1703.01513.

[20] Sergey Zagoruyko and Nikos Komodakis. "Wide Residual Networks". In: Proceedings of the British Machine Vision Conference (BMVC). BMVA Press, Sept. 2016, pp. 87.1–87.12.

References VII

[21] K Zhang, M Sun, X Han, et al. "Residual Networks of Residual Networks: Multilevel Residual Networks". In: IEEE Transactions on Circuits and Systems for Video Technology PP.99 (2017), p. 1.

[22] Barret Zoph, Vijay Vasudevan, Jonathon Shlens, et al. Learning Transferable Architectures for Scalable Image Recognition. Tech. rep. 2017. arXiv: 1707.07012.