Modern CNNs

Industrial AI Lab.

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CNNs for Computer Vision

[Krizhevsky 2012]

[Ciresan et al. 2013]

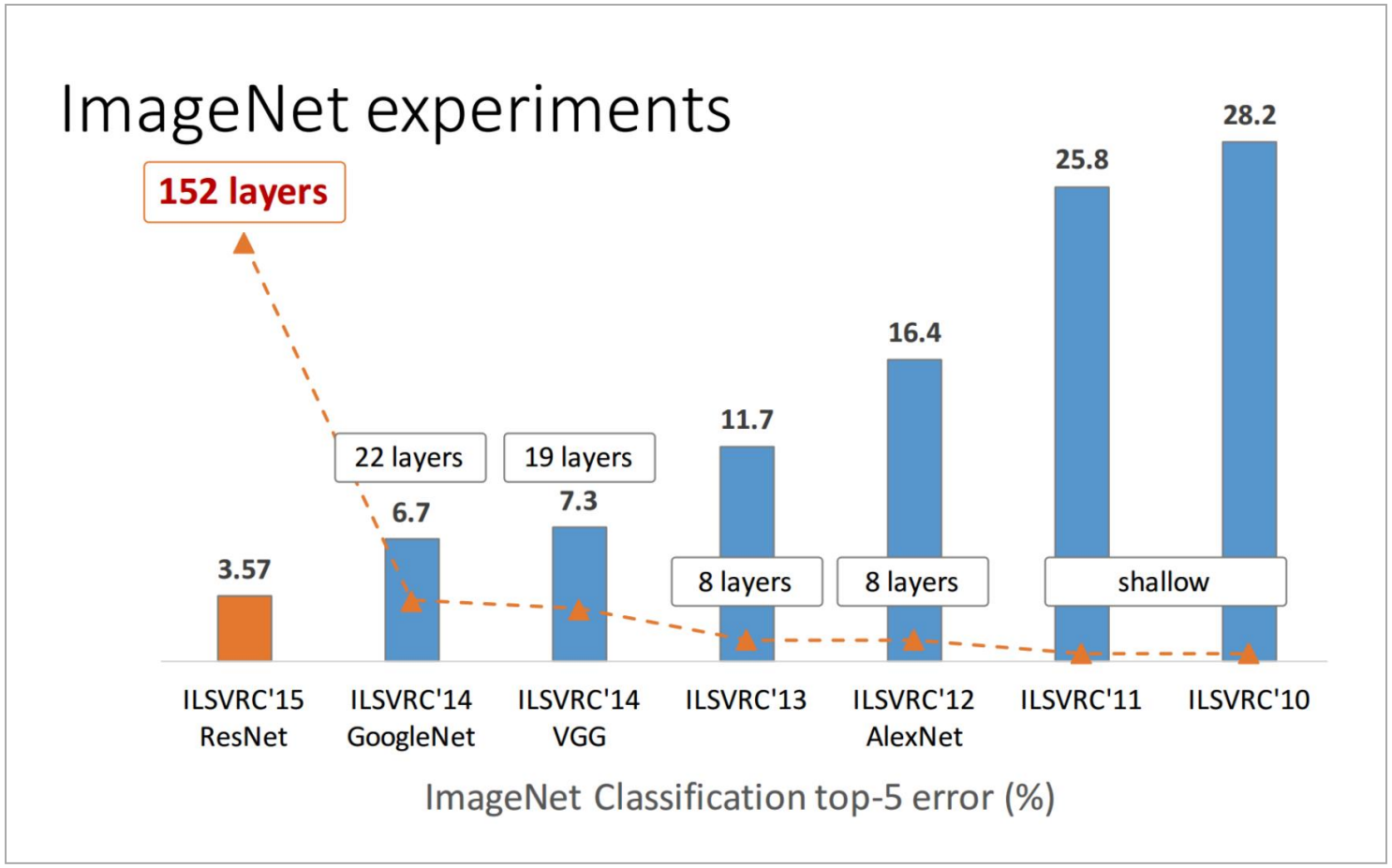
[Faster R-CNN - Ren 2015]

[NVIDIA dev blog]

Modern CNN

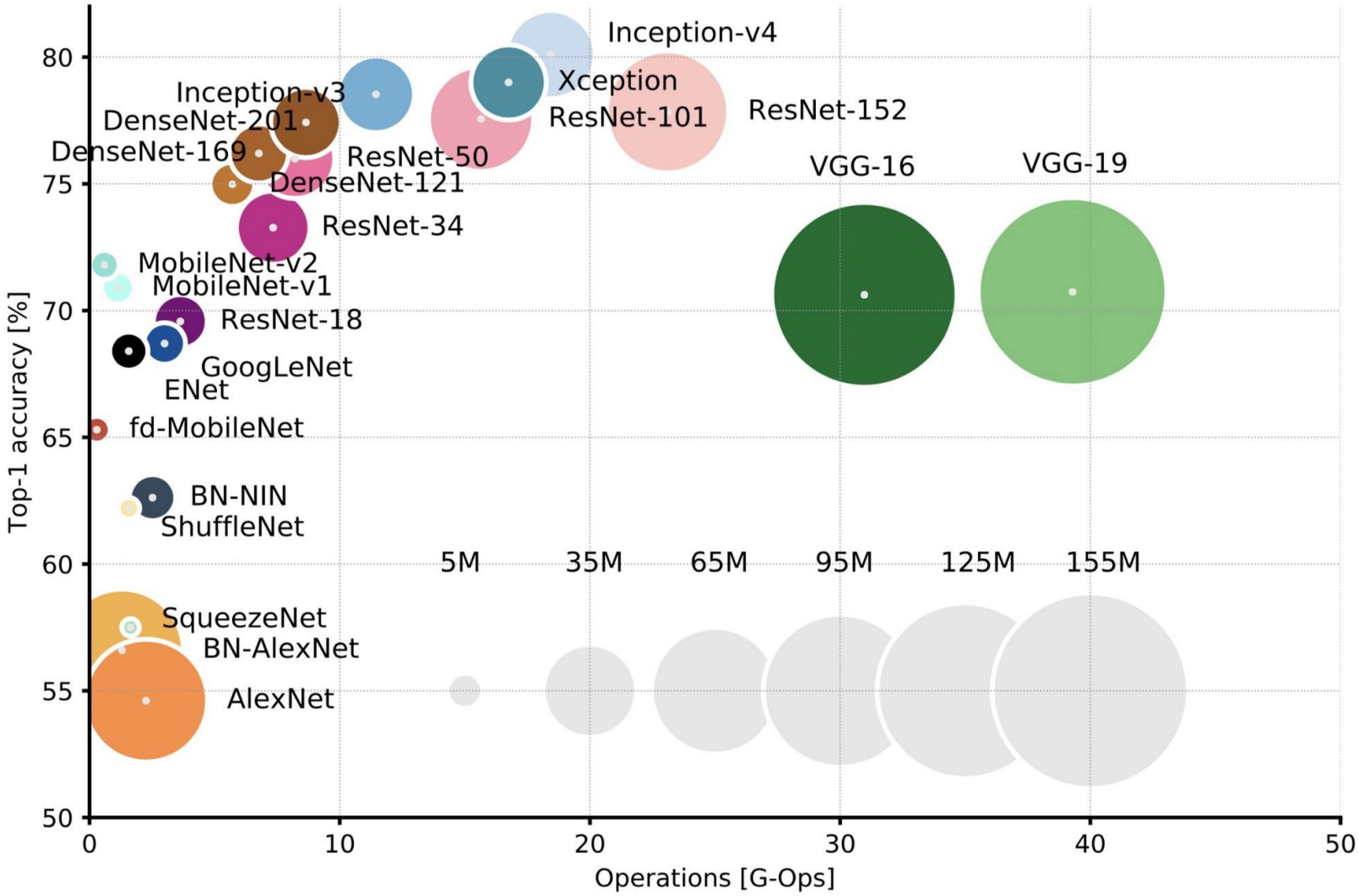
ImageNet

- Human performance = 5.1 %



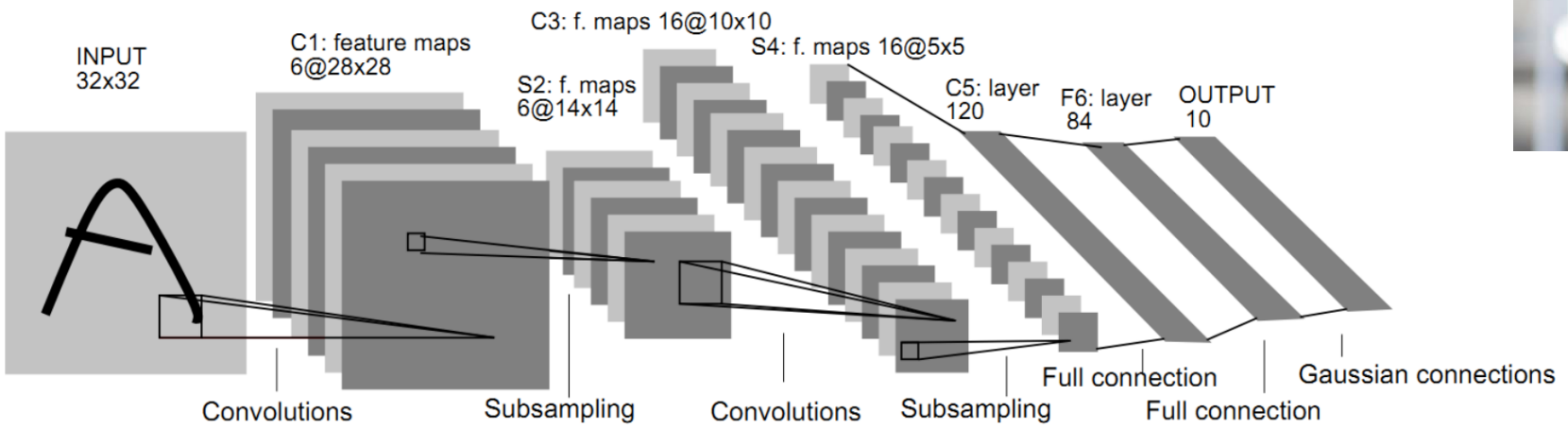
from Kaiming He slides "Deep residual learning for image recognition." ICML. 2016.

ImageNet


Inception-v4
Xception
Inception-v3
ResNet-101
ResNet-152
DenseNet-201
DenseNet-169
ResNet-50
VGG-16
VGG-19
DenseNet-121
ResNet-34
MobileNet-v2
MobileNet-v1
ResNet-18
GoogLeNet
ENet
fd-MobileNet
BN-NIN
ShuffleNet
5M
35M
65M
95M
125M
155M
SqueezeNet
BN-AlexNet
AlexNet
Top-1 accuracy [%]
Operations [G-Ops]
80
75
70
65
60
55
50
0
10
20
30
40
50

LeNet

- CNN = Convolutional Neural Networks = ConvNet
- LeCun, Y., Bottou, L., Bengio, Y., and Haffner, P. (1998). Gradient-based learning applied to document recognition.
- All are still the basic components of modern ConvNets!

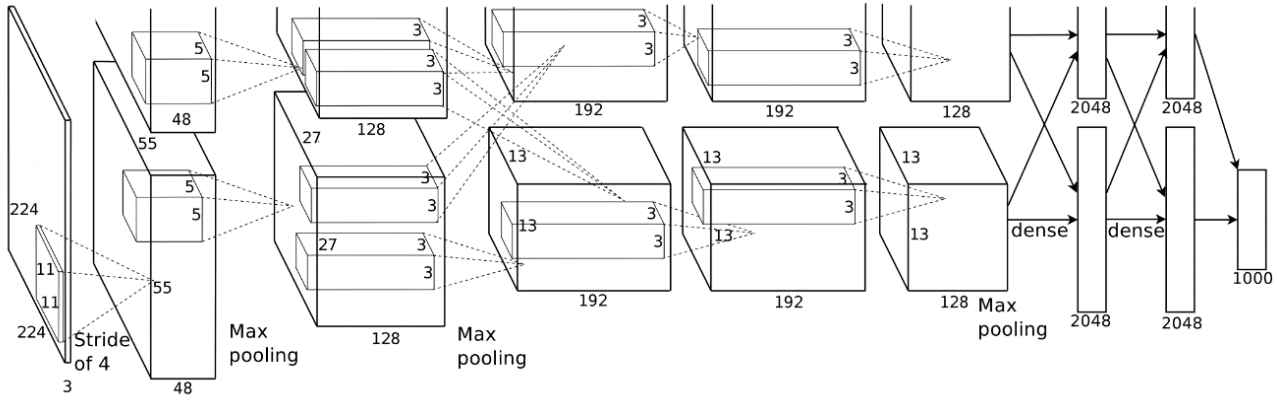


Yann LeCun

AlexNet

- Simplified version of Krizhevsky, Alex, Sutskever, and Hinton. "Imagenet classification with deep convolutional neural networks." NIPS 2012

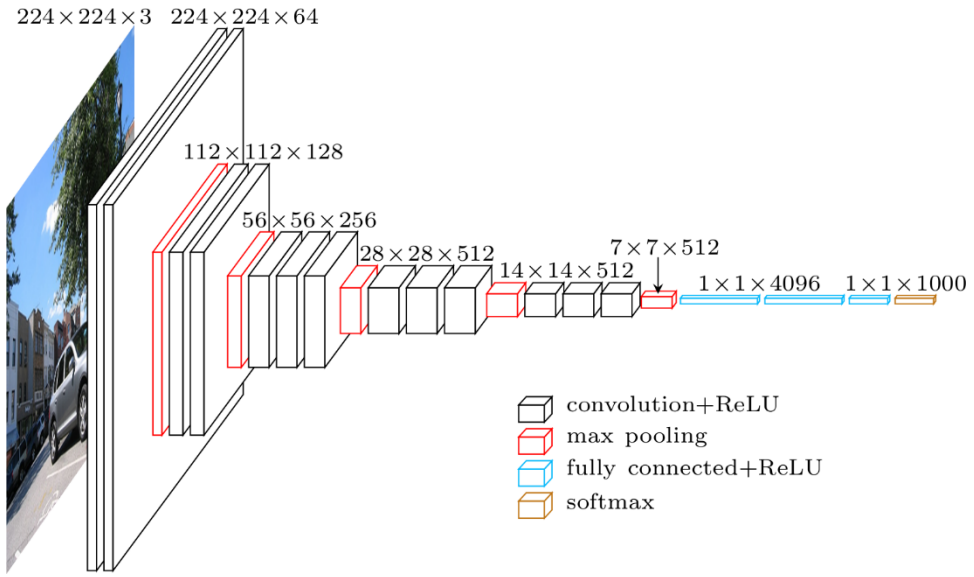
- LeNet-style backbone, plus:
  - ReLU [Nair & Hinton 2010]
    - "RevoLUtion of deep learning"*
    - Accelerate training; better grad prop (vs. tanh)
  - Dropout [Hinton et al 2012]
    - In-network ensembling
    - Reduce overfitting
  - Data augmentation
    - Label-preserving transformation
    - Reduce overfitting

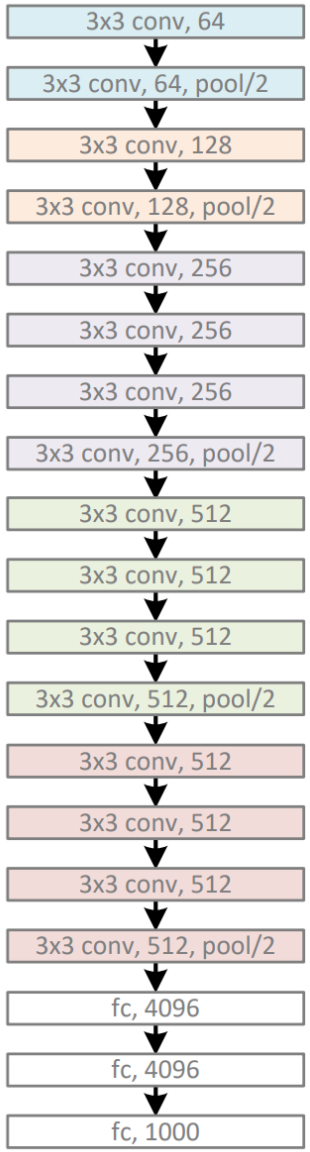


VGG-16/19

- Simonyan, Karen, and Zisserman. "Very deep convolutional networks for large-scale image recognition." (2014)

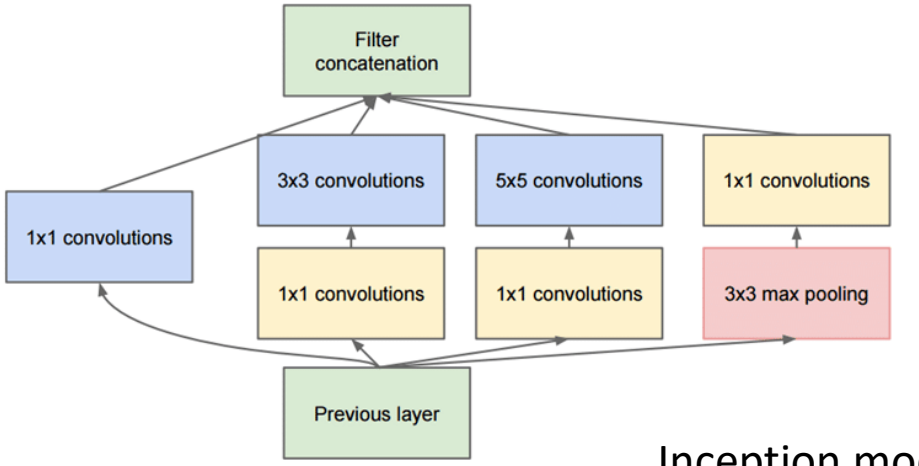
- Simply “Very Deep”!
  - Modularized design
    - 3x3 Conv as the module
    - Stack the same module
    - Same computation for each module
  - Stage-wise training
    - VGG-11 → VGG-13 → VGG-16
    - We need a better initialization…



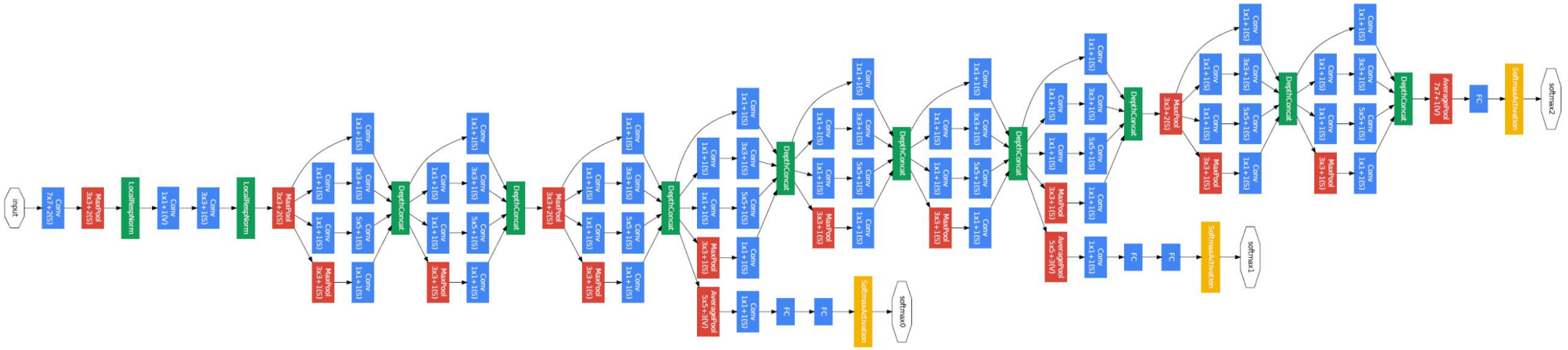


GoogleNet/Inception

- Multiple branches
  - e.g., 1x1, 3x3, 5x5, pool
- Shortcuts
  - stand-alone 1x1, merged by concat.
- Bottleneck
  - Reduce dim by 1x1 before expensive 3x3/5x5 conv



Inception module

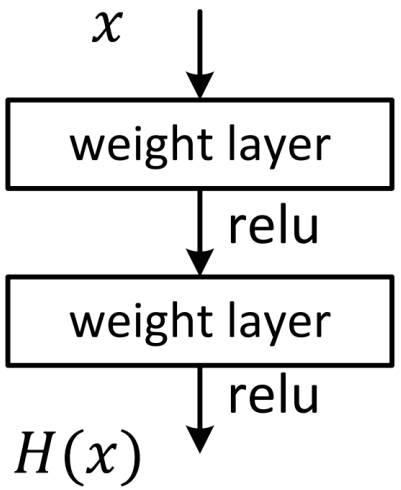


ResNet (Deep Residual Learning)

- He, Kaiming, et al. "Deep residual learning for image recognition." CVPR. 2016.
- Plane net

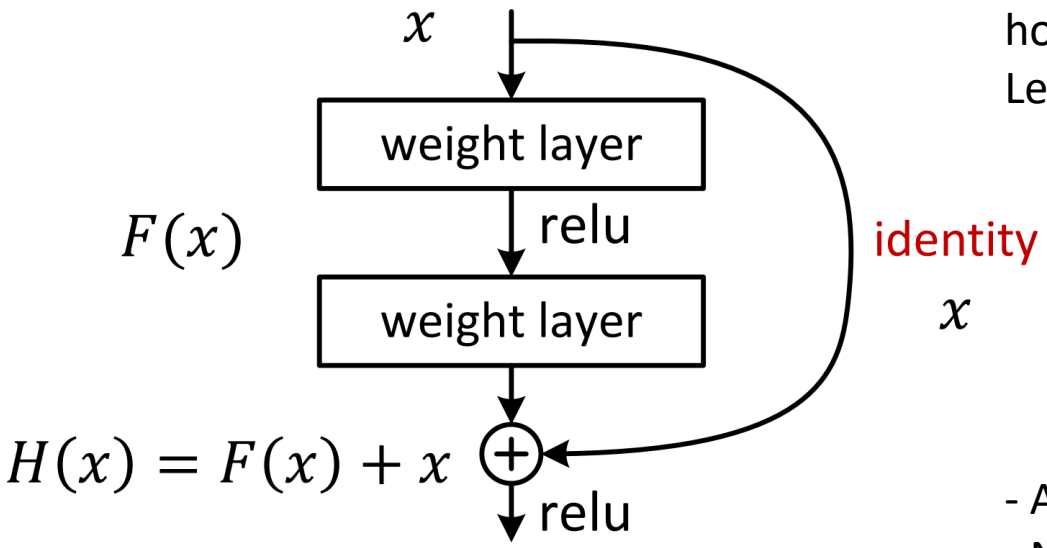
$H(x)$ is any desired mapping,
hope the small subnet fit $H(x)$

any small subnet



ResNet (Deep Residual Learning)

- He, Kaiming, et al. "Deep residual learning for image recognition." CVPR. 2016.
- Residual net
- Skip connection

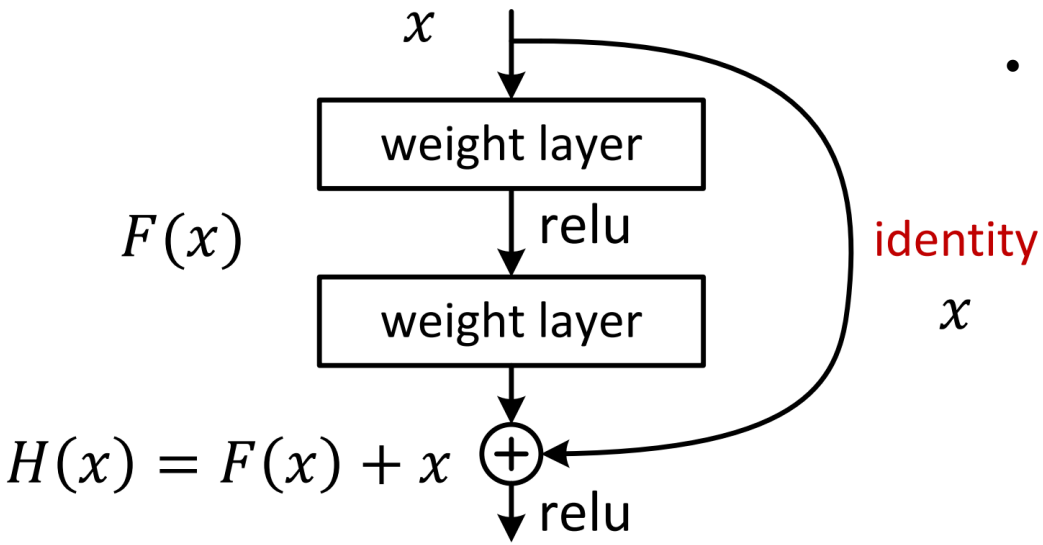


$H(x)$ is any desired mapping,
~~hope the small subnet fit $H(x)$~~
hope the small subnet fit $F(x)$
Let $H(x) = F(x) + x$

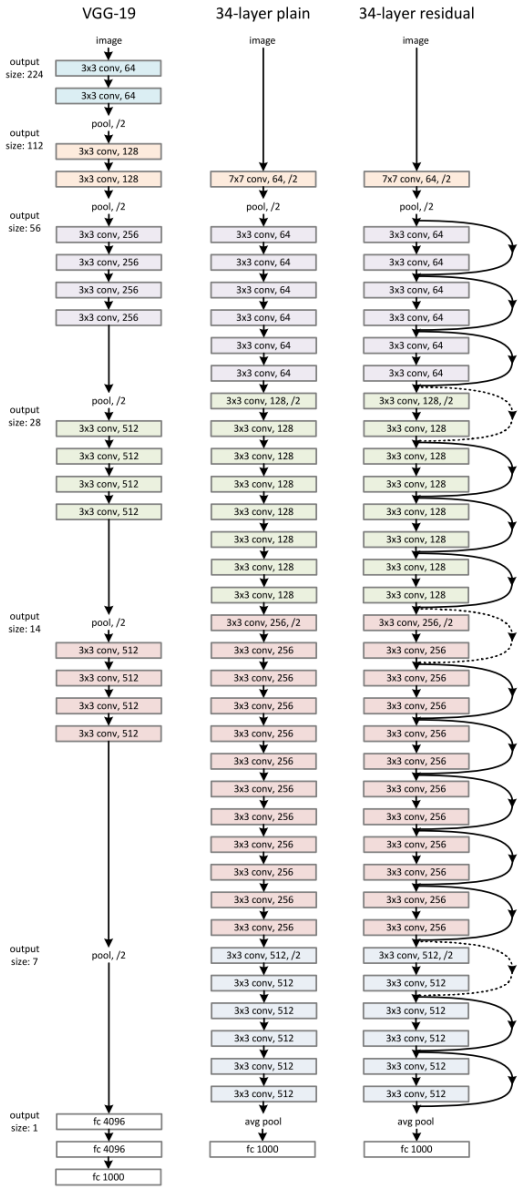
- A direct connection between 2 non-consecutive layers
- No vanishing gradient

ResNet (Deep Residual Learning)

- Parameters are optimized to learn a residual, that is the difference between the value before the block and the one needed after.
- $F(x)$ is a residual mapping w.r.t. identity

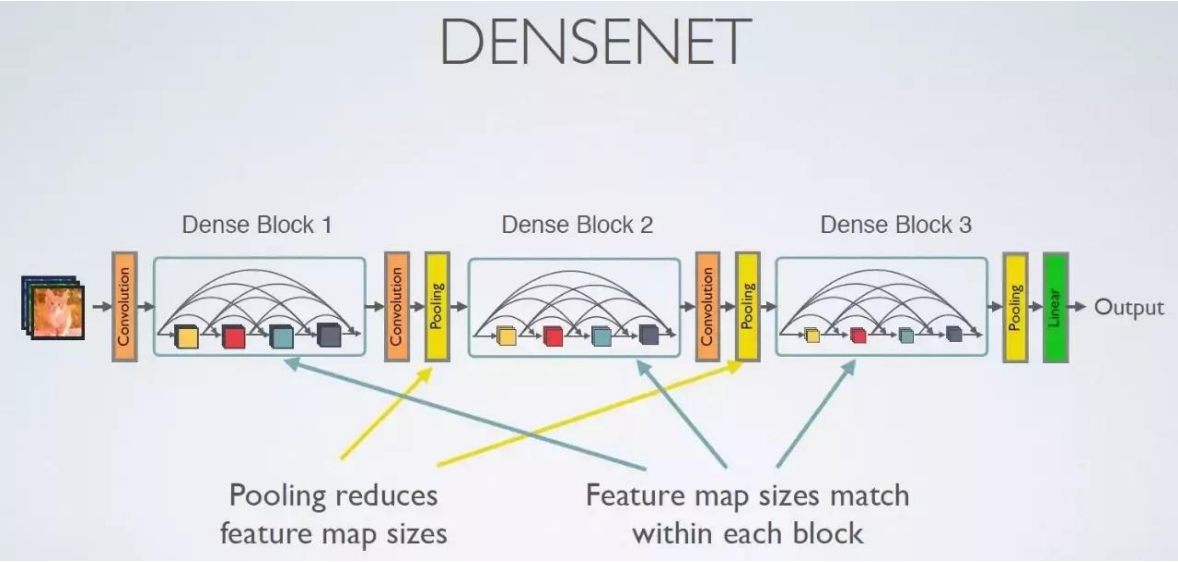


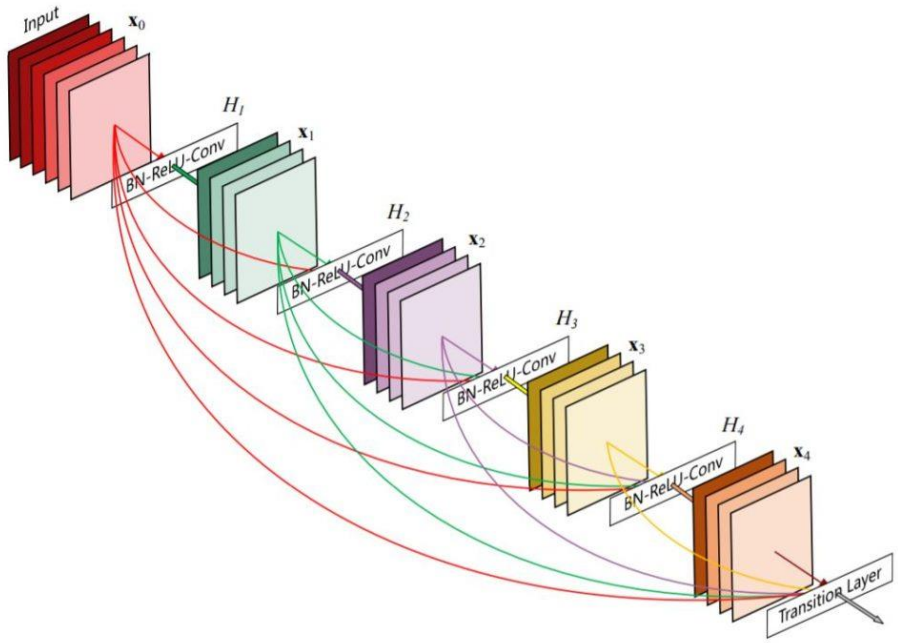
- If identity were optimal, easy to set weights as 0
- If optimal mapping is closer to identity, easier to find small fluctuations



DensNets

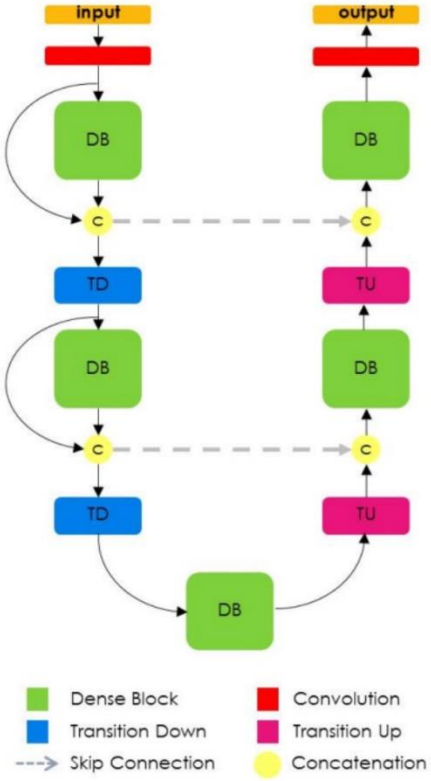
- Densely Connected Convolutional Networks

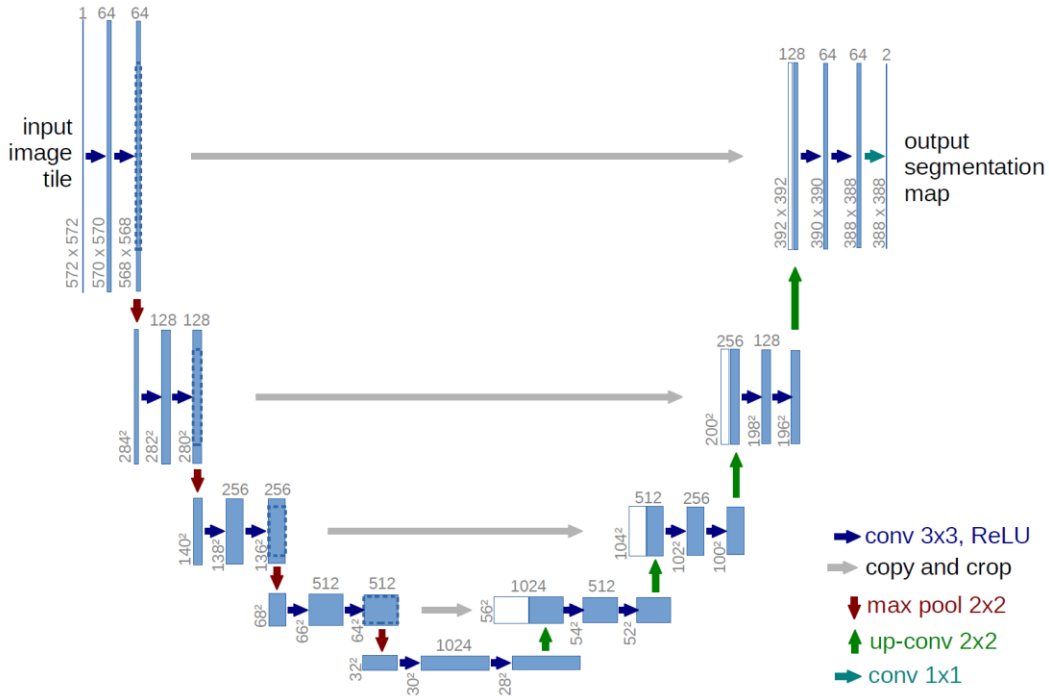




Huang, Gao, et al., “Densely connected convolutional networks”
Proceedings of the IEEE conference on computer vision and pattern recognition. Vol. 1. No. 2. 2017.

U-Net





Ronneberger, Olaf; Fischer, Philipp; Brox, Thomas (2015),
"U-Net: Convolutional Networks for Biomedical Image Segmentation." arXiv:1505.04597

U-Net

- The U-Net owes its name to its symmetric shape
- The U-Net architecture is built upon the Fully Convolutional Network and modified in a way that it yields better segmentation in medical imaging.
- Compared to FCN-8, the two main differences are
  - U-net is symmetric and
  - the skip connections between the downsampling path and the upsampling path apply a concatenation operator instead of a sum.
- These skip connections intend to provide local information to the global information while upsampling. Because of its symmetry, the network has a large number of feature maps in the upsampling path, which allows to transfer information.

Pre-trained Models

- Training a model on ImageNet from scratch takes days or weeks.
- Many models trained on ImageNet and their weights are publicly available!
- Transfer learning
  - Use pre-trained weights, remove last layers to compute representations of images
  - Train a classification model from these features on a new classification task
  - The network is used as a generic feature extractor
  - Better than handcrafted feature extraction on natural images

Pre-trained Models

- Training a model on ImageNet from scratch takes days or weeks.
- Many models trained on ImageNet and their weights are publicly available!
- Fine-tuning
  - Retraining the (some) parameters of the network (given enough data)
  - Truncate the last layer(s) of the pre-trained network
  - Freeze the remaining layers weights
  - Add a (linear) classifier on top and train it for a few epochs
  - Then fine-tune the whole network or the few deepest layers
  - Use a smaller learning rate when fine tuning