CARTE ML Workshop

Convolutional Neural Networks

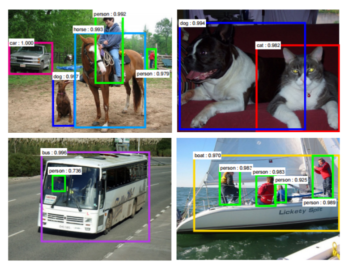
Introduction: Why ConvNets?

- **Fully Connected Networks Challenges:**
  - High dimensionality of inputs
  - Loss of spatial structure when flattening inputs
- **Convolutional Neural Networks (CNNs):**
  - Address high-dimensional input challenges
  - Preserve spatial structure through local receptive fields and parameter sharing
  - Efficient for pattern recognition due to reduced parameter count and computational efficiency

Used everywhere for Vision

[Krizhevsky 2012]

[Ciresan et al. 2013]



[Faster R-CNN - Ren 2015]

[NVIDIA dev blog]

Many other applications

Speech recognition & speech synthesis

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Natural Language Processing

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Speech recognition & speech synthesis

Natural Language Processing

Protein/DNA binding prediction

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Any problem with a spatial (or sequential) structure

ConvNets for image classification

CNN = Convolutional Neural Networks = ConvNet

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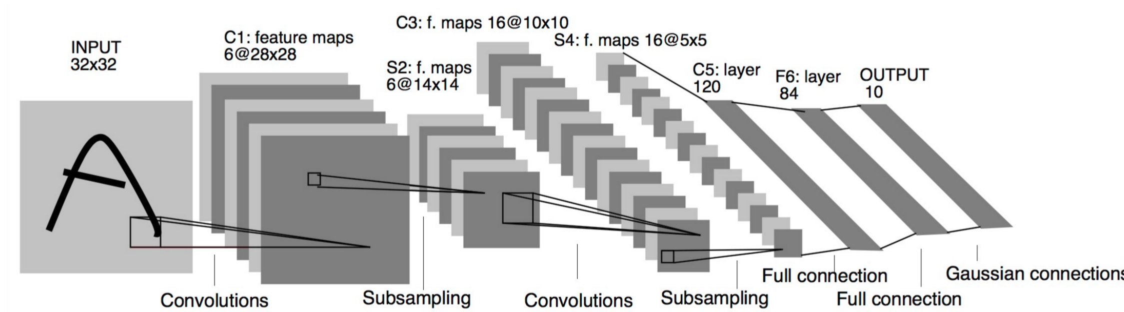

LeCun, Y., Bottou, L., Bengio, Y., and Haffner, P. (1998). Gradient-based learning applied to document recognition.

Outline

Convolutions

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Convolutions

CNNs for Image Classification

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CNNs for Image Classification

CNN Architectures

Convolutions

Motivations

Standard Dense Layer for an image input:

```
x = Input((640, 480, 3), dtype='float32')
# shape of x is: (None, 640, 480, 3)
x = Flatten()(x)
# shape of x is: (None, 640 x 480 x 3)
z = Dense(1000)(x)
```

How many parameters in the Dense layer?

Motivations

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$640 \times 480 \times 3 \times 1000 + 1000 = 922M!$

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Spatial organization of the input is destroyed by Flatten

Fully Connected Network: MLP

```
input_image = Input(shape=(28, 28, 1))
x = Flatten()(input_image)
x = Dense(256, activation='relu')(x)
x = Dense(10, activation='softmax')(x)
mlp = Model(inputs=input_image, outputs=x)
```

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Convolutional Network

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input_image = Input(shape=(28, 28, 1))
x = Conv2D(32, 5, activation='relu')(input_image)
x = MaxPool2D(2, strides=2)(x)
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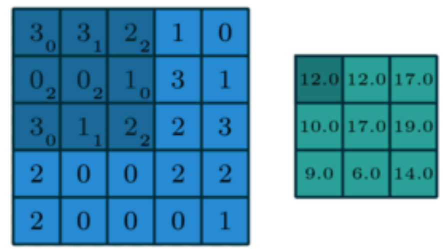
2D spatial organization of features preserved untill Flatten.

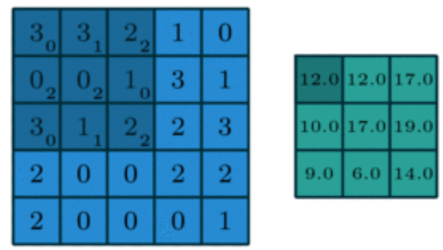
Convolution in a neural network



- x is a 3×3 chunk (dark area) of the image *(blue array)*
- Each output neuron is parametrized with the 3×3 weight matrix $\mathbf{w}$ *(small numbers)*

These slides extensively use convolution visualisation by V. Dumoulin available at https://github.com/vdumoulin/conv_arithmetic

Convolution in a neural network



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The activation obtained by sliding the 3×3 window and computing:

$$z(x) = relu(\mathbf{w}^T x + b)$$

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Local connectivity

- A neuron depends only on a few local input neurons
- Translation invariance

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Comparison to Fully connected

- Parameter sharing: reduce overfitting
- Make use of spatial structure: **strong prior** for vision!

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Animal Vision Analogy

Hubel & Wiesel, RECEPTIVE FIELDS OF SINGLE NEURONES IN THE CAT'S STRIATE CORTEX (1959)

Channels

Colored image = tensor of shape $(\text{height}, \text{width}, \text{channels})$

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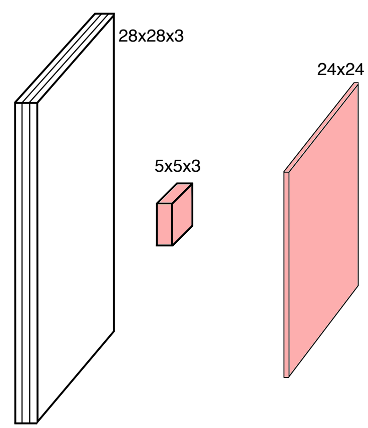
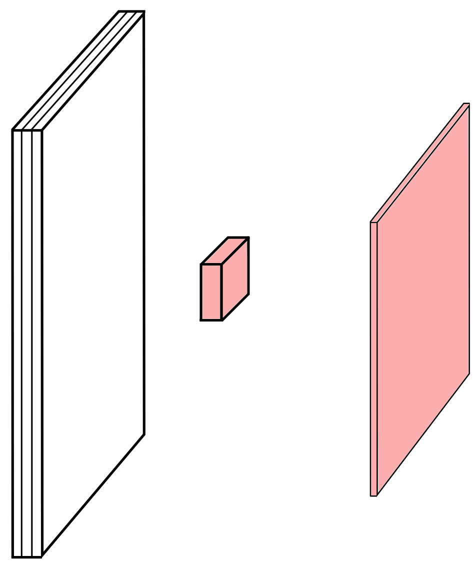
Convolutions are usually computed for each channel and summed:



Multiple convolutions



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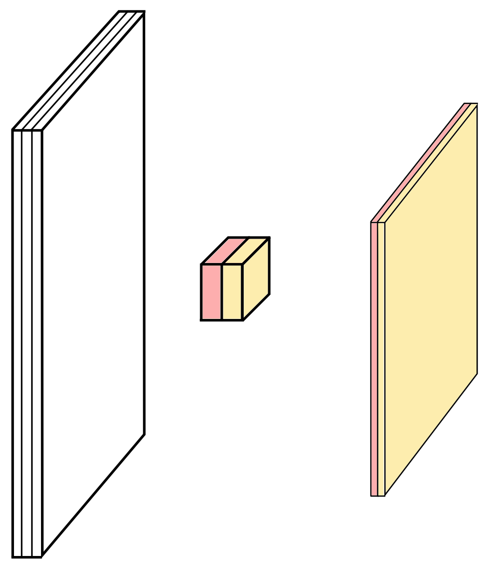

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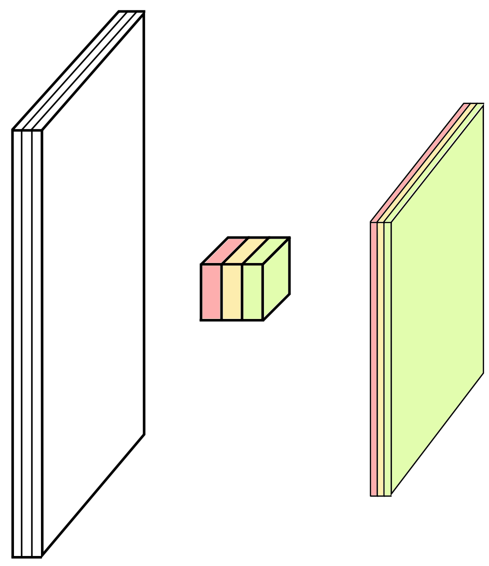

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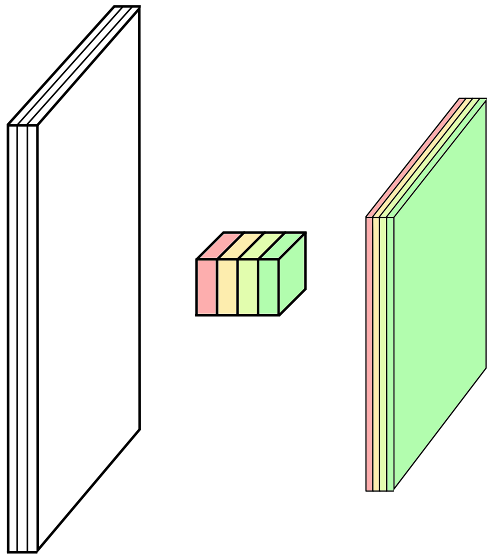

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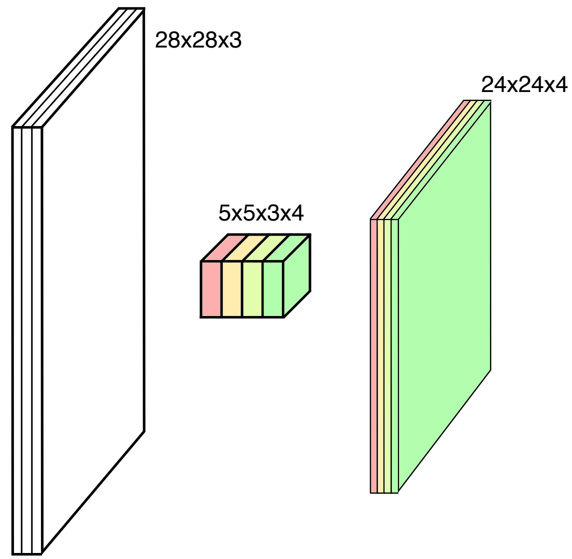

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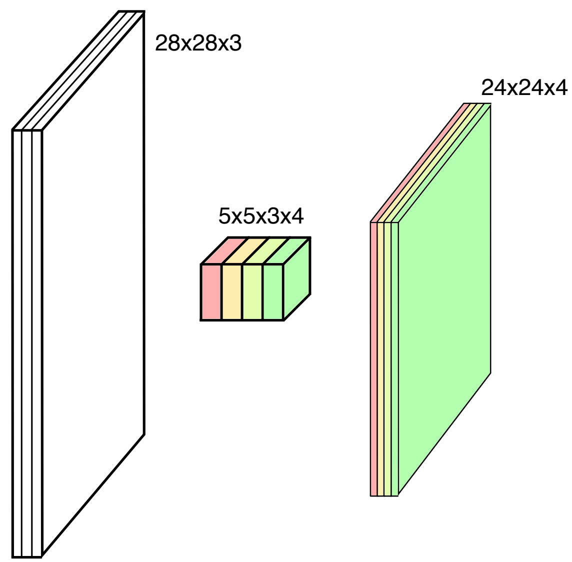
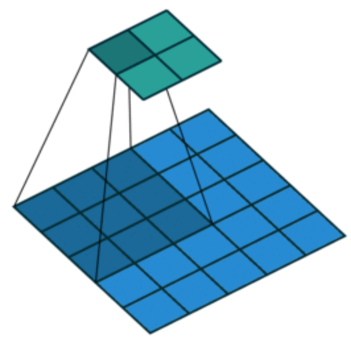


- Kernel size aka receptive field (usually 1, 3, 5, 7, 11)
- Output dimension: length - kernel_size + 1

Strides

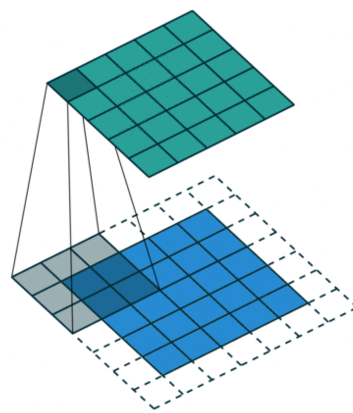
- Strides: increment step size for the convolution operator
- Reduces the size of the output map



Example with kernel size 3×3 and a stride of 2 (image in blue)

Padding

- Padding: artificially fill borders of image
- Useful to keep spatial dimension constant across filters
- Useful with strides and large receptive fields
- Usually: fill with 0s



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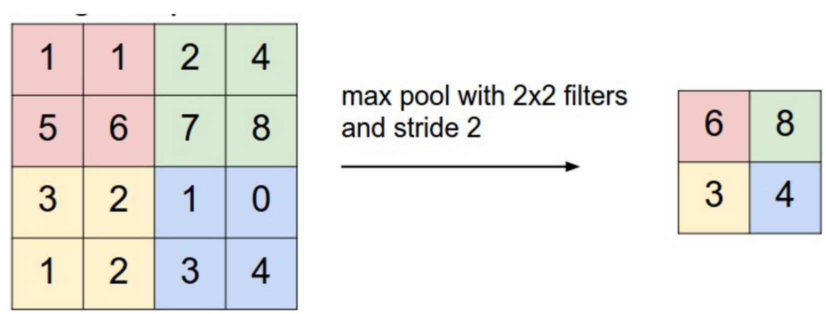

Schematic from Stanford http://cs231n.github.io/convolutional-networks

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- Local invariance
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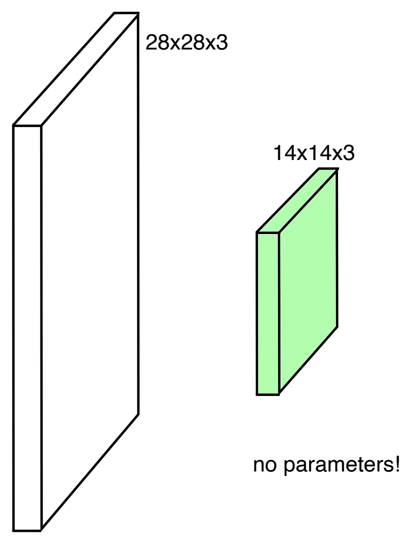

Architectures

Classic ConvNet Architecture

Input

Classic ConvNet Architecture

Input

Conv blocks

- Convolution + activation (relu)
- Convolution + activation (relu)
- ...
- Maxpooling 2x2

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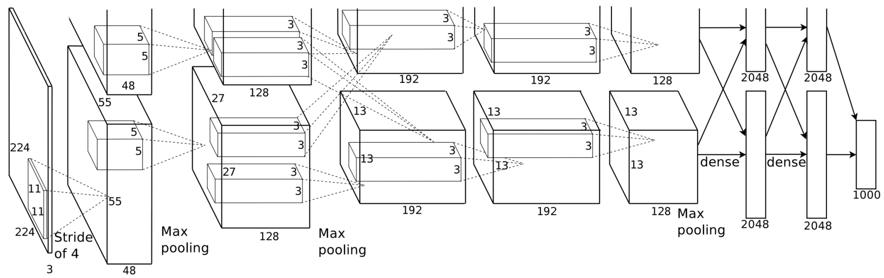
Output

- Fully connected layers
- Softmax

AlexNet



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

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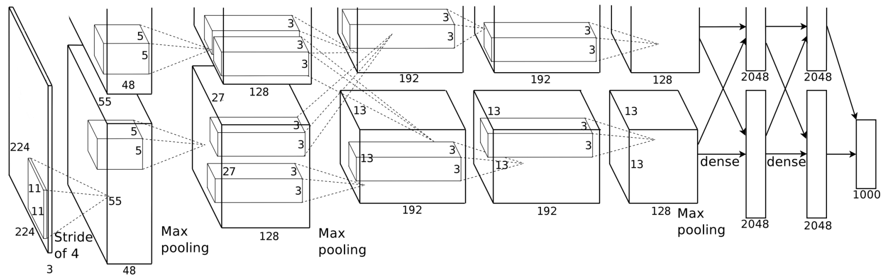

First conv layer: kernel 11x11x3x96 stride 4

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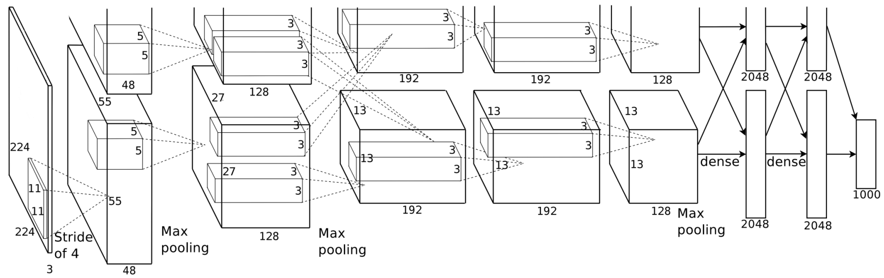
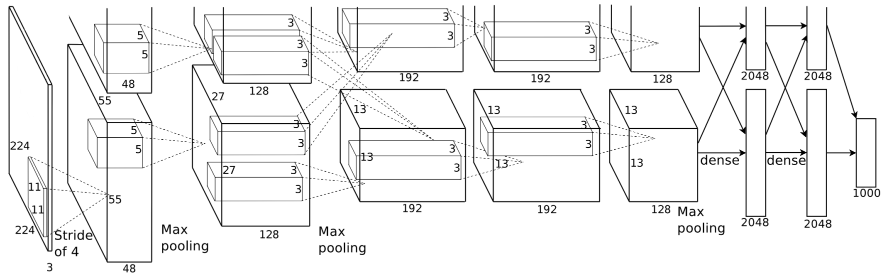


First conv layer: kernel 11x11x3x96 stride 4

- Kernel shape: (11,11,3,96)
- Output shape: (55,55,96)
- Number of parameters: 34,944
- Equivalent MLP parameters: 43.7 x 1e9

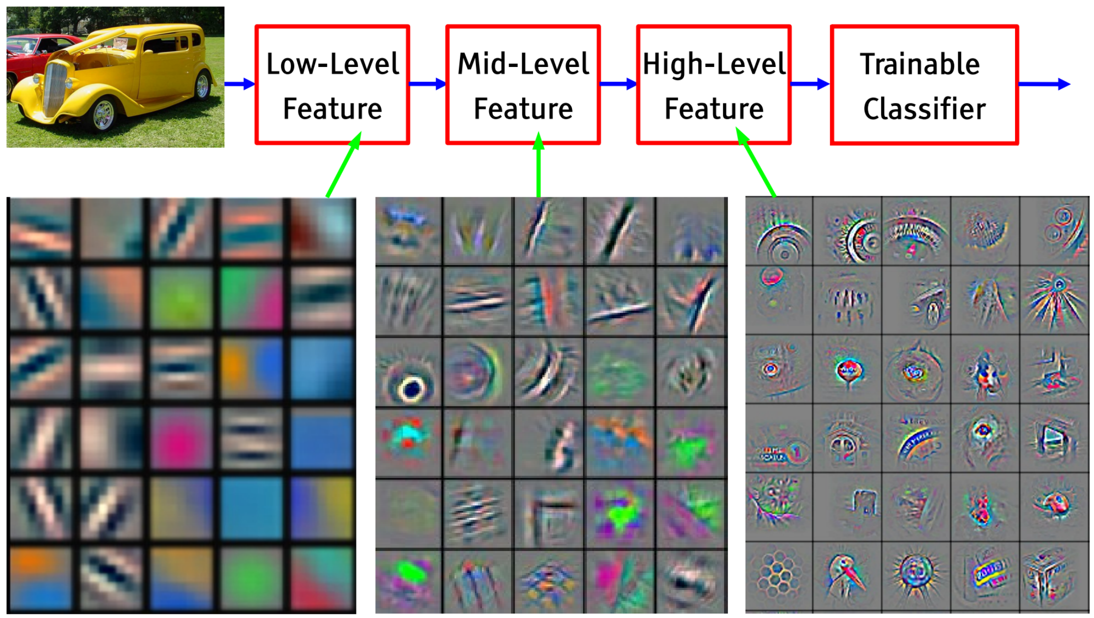
Simplified version of Krizhevsky, Alex, Sutskever, and Hinton. "Imagenet classification with deep convolutional neural networks." NIPS 2012

AlexNet



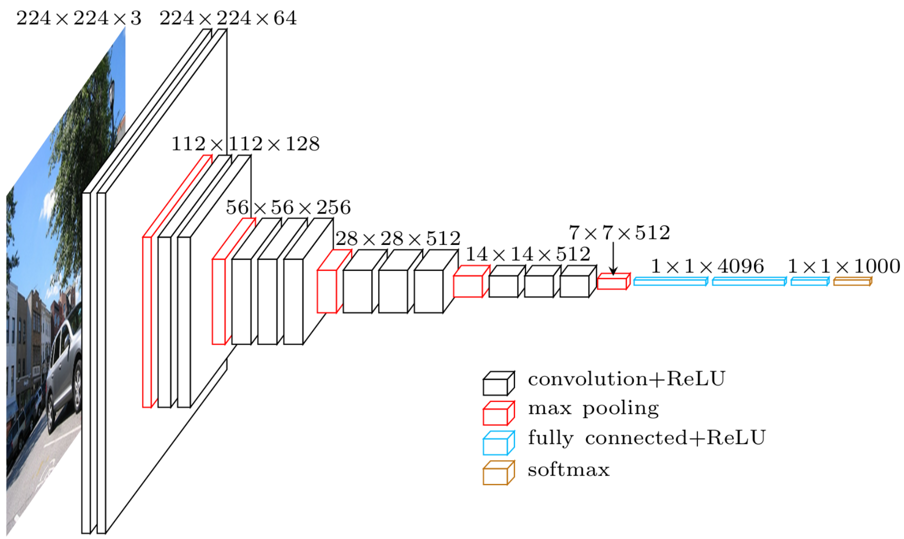
INPUT: [227x227x3]
CONV1: [55x55x96] 96 11x11 filters at stride 4, pad 0
MAX POOL1: [27x27x96] 3x3 filters at stride 2
CONV2: [27x27x256] 256 5x5 filters at stride 1, pad 2
MAX POOL2: [13x13x256] 3x3 filters at stride 2
CONV3: [13x13x384] 384 3x3 filters at stride 1, pad 1
CONV4: [13x13x384] 384 3x3 filters at stride 1, pad 1
CONV5: [13x13x256] 256 3x3 filters at stride 1, pad 1
MAX POOL3: [6x6x256] 3x3 filters at stride 2
FC6: [4096] 4096 neurons
FC7: [4096] 4096 neurons
FC8: [1000] 1000 neurons (softmax logits)

Hierarchical representation



Feature visualization of convolutional net trained on ImageNet from [Zeiler & Fergus 2013]

VGG-16



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

VGG in Keras

```
model.add(Convolution2D(64, 3, 3, activation='relu',input_shape=(3,224,224)))
model.add(Convolution2D(64, 3, 3, activation='relu'))
model.add(MaxPooling2D((2,2), strides=(2,2)))

model.add(Convolution2D(128, 3, 3, activation='relu'))
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model.add(MaxPooling2D((2,2), strides=(2,2)))

model.add(Convolution2D(256, 3, 3, activation='relu'))
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model.add(Convolution2D(256, 3, 3, activation='relu'))
model.add(MaxPooling2D((2,2), strides=(2,2)))

model.add(Convolution2D(512, 3, 3, activation='relu'))
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model.add(MaxPooling2D((2,2), strides=(2,2)))

model.add(Flatten())
model.add(Dense(4096, activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(4096, activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(1000, activation='softmax'))
```

Memory and Parameters

	Activation maps		Parameters	
INPUT:	[224x224x3]	= 150K	0	
CONV3-64:	[224x224x64]	= 3.2M	(3x3x3)x64 =	1,728
CONV3-64:	[224x224x64]	= 3.2M	(3x3x64)x64 =	36,864
POOL2:	[112x112x64]	= 800K	0	
CONV3-128:	[112x112x128]	= 1.6M	(3x3x64)x128 =	73,728
CONV3-128:	[112x112x128]	= 1.6M	(3x3x128)x128 =	147,456
POOL2:	[56x56x128]	= 400K	0	
CONV3-256:	[56x56x256]	= 800K	(3x3x128)x256 =	294,912
CONV3-256:	[56x56x256]	= 800K	(3x3x256)x256 =	589,824
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POOL2:	[28x28x256]	= 200K	0	
CONV3-512:	[28x28x512]	= 400K	(3x3x256)x512 =	1,179,648
CONV3-512:	[28x28x512]	= 400K	(3x3x512)x512 =	2,359,296
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POOL2:	[7x7x512]	= 25K	0	
FC:	[1x1x4096]	= 4096	7x7x512x4096 =	102,760,448
FC:	[1x1x4096]	= 4096	4096x4096 =	16,777,216
FC:	[1x1x1000]	= 1000	4096x1000 =	4,096,000

TOTAL activations: 24M x 4 bytes ~= 93MB / image (x2 for backward)
TOTAL parameters: 138M x 4 bytes ~= 552MB (x2 for plain SGD, x4 for Adam)

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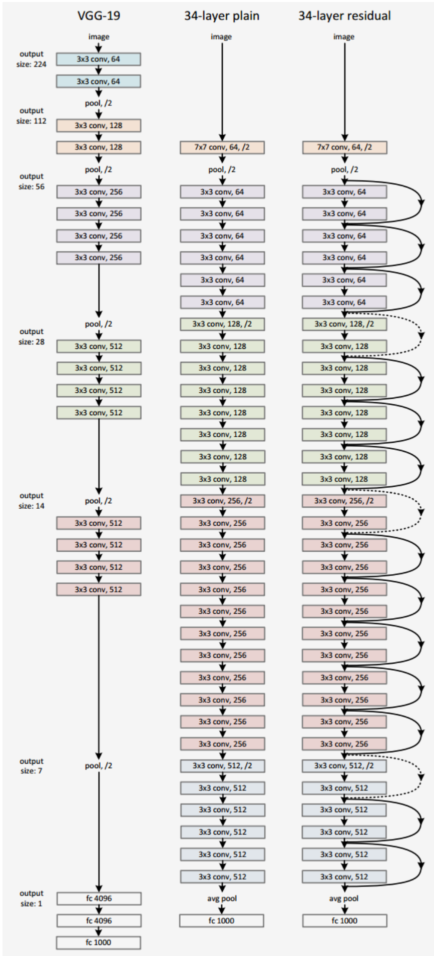
ResNet

Even deeper models:

34, 50, 101, 152 layers



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

ResNet

A block learns the residual w.r.t. identity

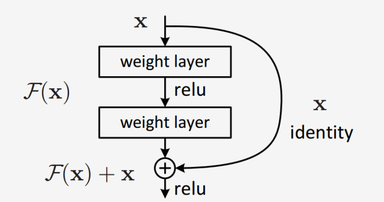


Figure 2. Residual learning: a building block.

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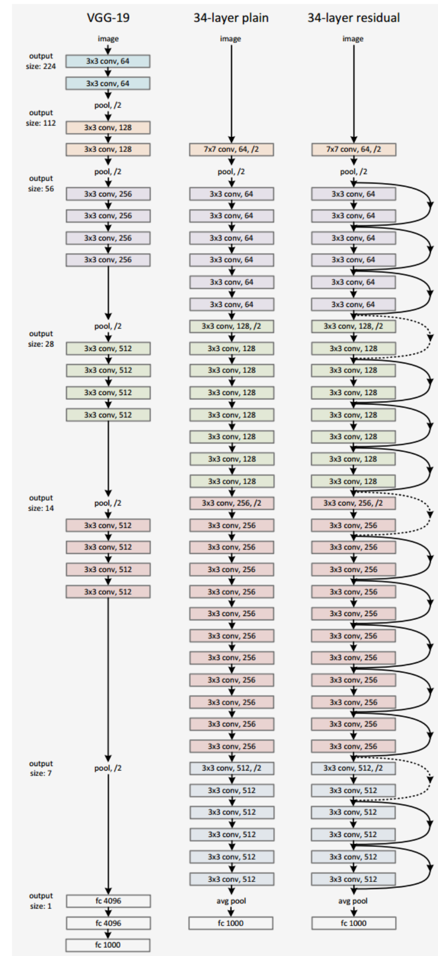

ResNet

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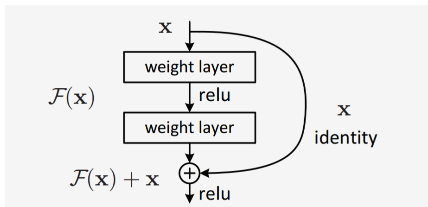

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- Good optimization properties

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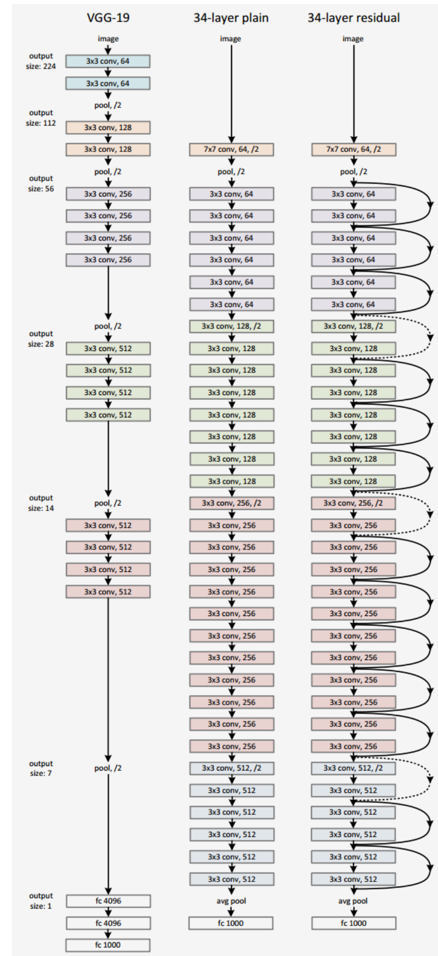

ResNet

ResNet50 Compared to VGG:

Superior accuracy in all vision tasks
5.25% top-5 error vs 7.1%

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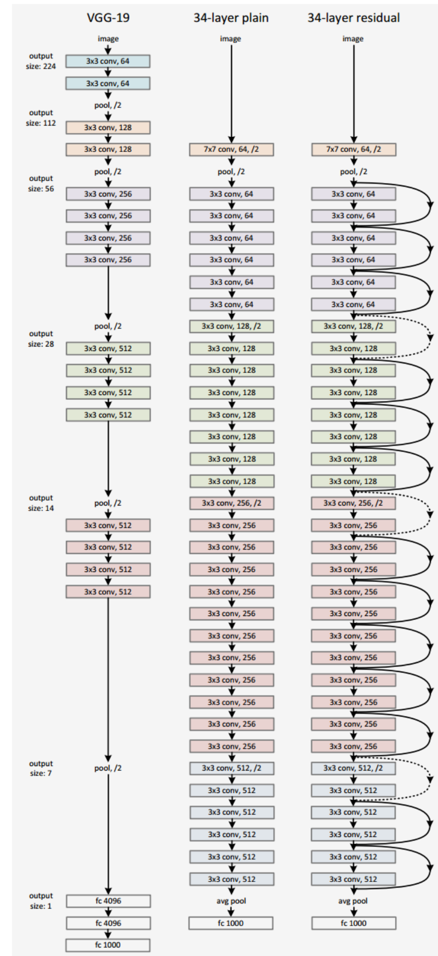

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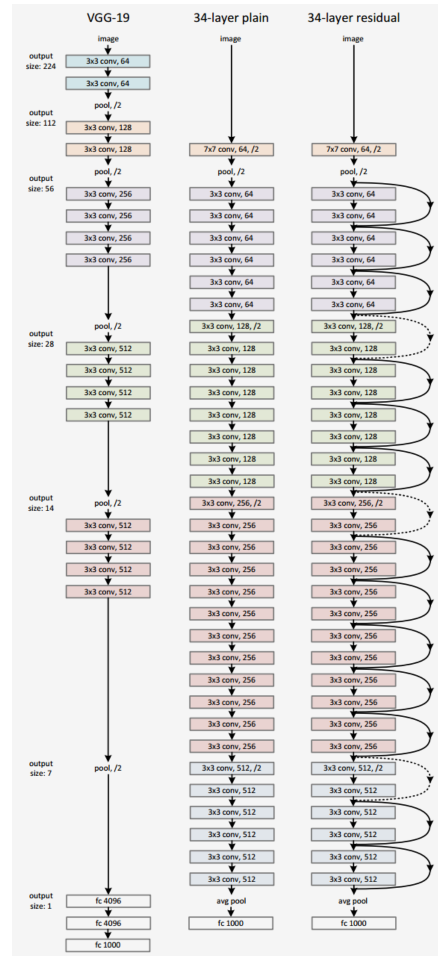

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Computational complexity
3.8B Flops vs 15.3B Flops

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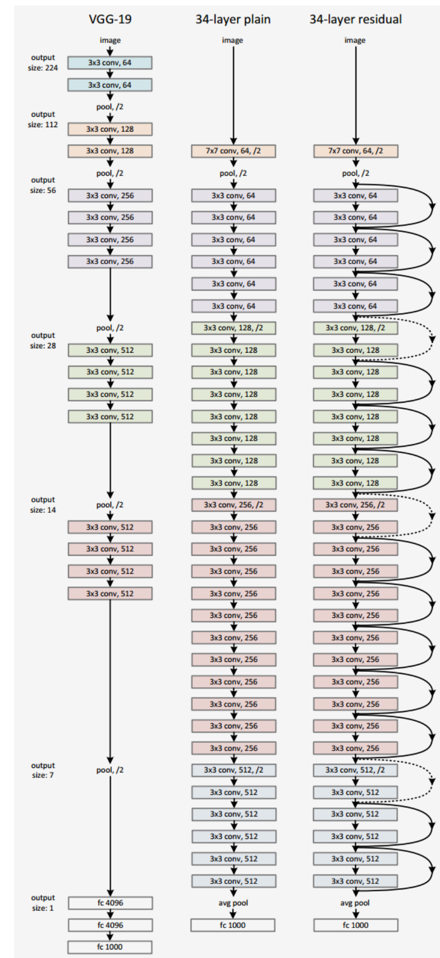

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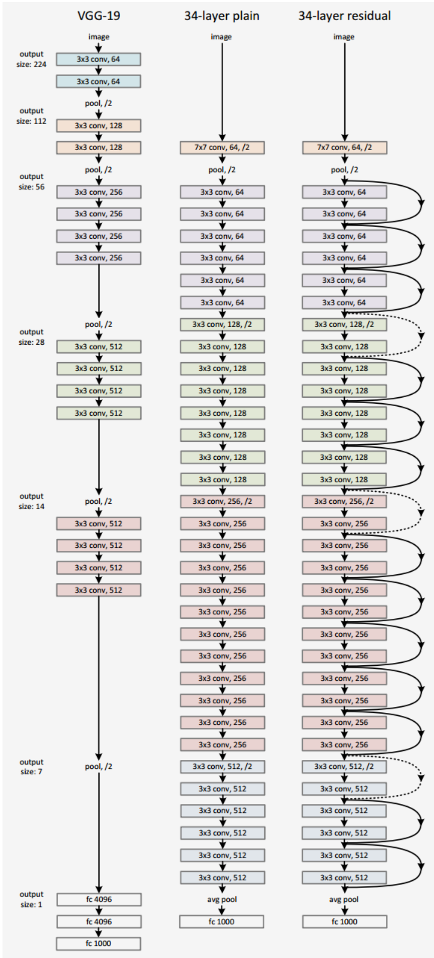
25M vs 138M

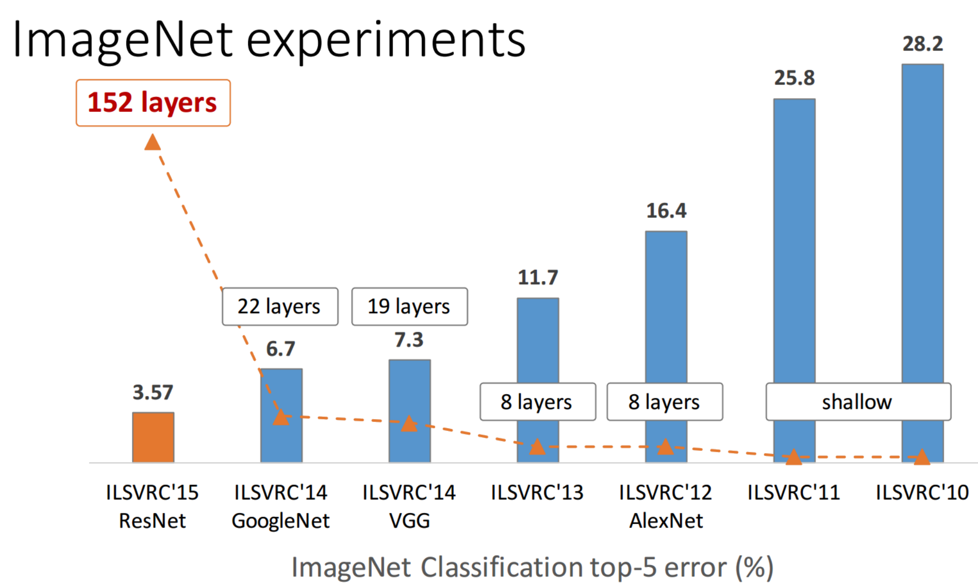
Computational complexity
3.8B Flops vs 15.3B Flops

Fully Convolutional until the last layer



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

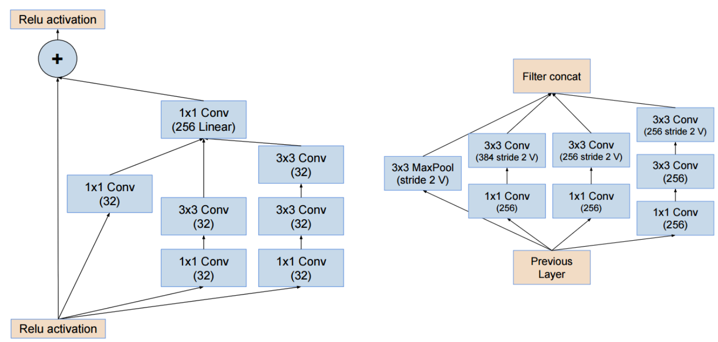
Deeper is better



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

State of the art

- Finding right architectures: Active area of research

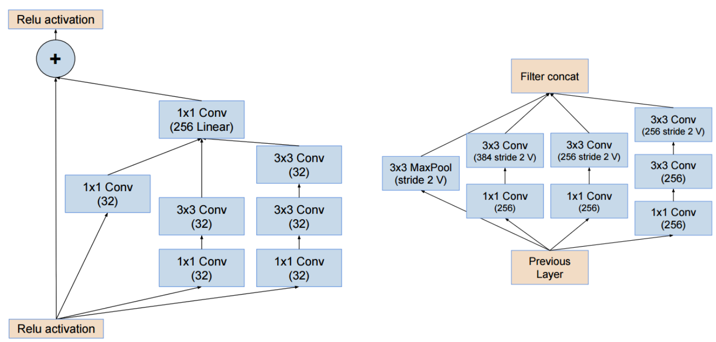


Modular building blocks engineering

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

State of the art

- Finding right architectures: Active area of research



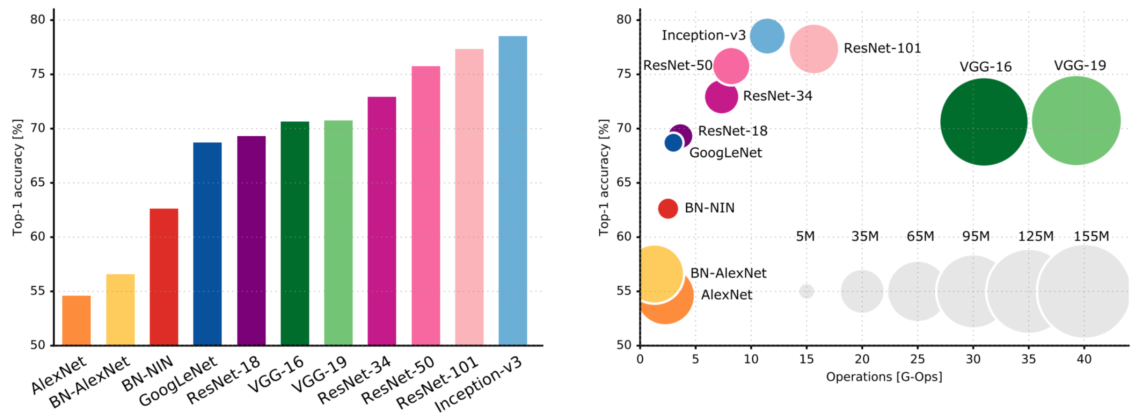
Modular building blocks engineering

see also DenseNets, Wide ResNets, Fractal ResNets, ResNeXts, Pyramidal ResNets

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

State of the art

Top 1-accuracy, performance and size on ImageNet



See also: https://paperswithcode.com/sota/image-classification-on-imagenet

Canziani, Paszke, and Culurciello. "An Analysis of Deep Neural Network Models for Practical Applications." (May 2016).

More ImageNet SOTA

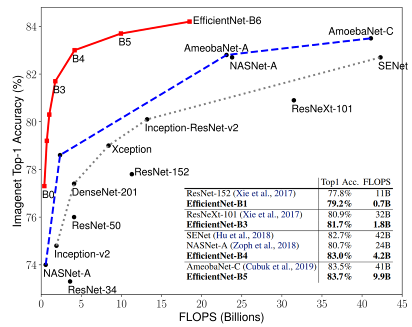
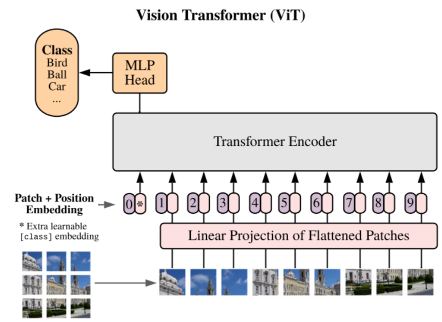


Figure 5. **FLOPS vs. ImageNet Accuracy –** Similar to Figure 1 except it compares FLOPS rather than model size.



- Mingxing Tan, Quoc V. Le, [EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks](), ICML 2019.
- Irwan Bello, [LambdaNetworks: Modeling long-range Interactions without Attention](), ICLR 2021
- Dosovitskiy A. et al, [An Image is worth 16X16 Words: Transformers for Image Recognition at Scale](), ICLR 2021

State of the art

Method	# Params	Extra Data	ImageNet Top-1	ImageNet Top-5	ImageNet-ReaL [6] Precision@1
ResNet-50 [24]	26M	–	76.0	93.0	82.94
ResNet-152 [24]	60M	–	77.8	93.8	84.79
DenseNet-264 [28]	34M	–	77.9	93.9	–
Inception-v3 [62]	24M	–	78.8	94.4	83.58
Xception [11]	23M	–	79.0	94.5	–
Inception-v4 [61]	48M	–	80.0	95.0	–
Inception-resnet-v2 [61]	56M	–	80.1	95.1	–
ResNeXt-101 [78]	84M	–	80.9	95.6	85.18
PolyNet [87]	92M	–	81.3	95.8	–
SENet [27]	146M	–	82.7	96.2	–
NASNet-A [90]	89M	–	82.7	96.2	82.56
AmoebaNet-A [52]	87M	–	82.8	96.1	–
PNASNet [39]	86M	–	82.9	96.2	–
AmoebaNet-C + AutoAugment [12]	155M	–	83.5	96.5	–
GPipe [29]	557M	–	84.3	97.0	–
EfficientNet-B7 [63]	66M	–	85.0	97.2	–
EfficientNet-B7 + FixRes [70]	66M	–	85.3	97.4	–
EfficientNet-L2 [63]	480M	–	85.5	97.5	–
ResNet-50 Billion-scale SSL [79]	26M	3.5B labeled Instagram	81.2	96.0	–
ResNeXt-101 Billion-scale SSL [79]	193M	3.5B labeled Instagram	84.8	–	–
ResNeXt-101 WSL [42]	829M	3.5B labeled Instagram	85.4	97.6	88.19
FixRes ResNeXt-101 WSL [69]	829M	3.5B labeled Instagram	86.4	98.0	89.73
Big Transfer (BiT-L) [33]	928M	300M labeled JFT	87.5	98.5	90.54
Noisy Student (EfficientNet-L2) [77]	480M	300M unlabeled JFT	88.4	98.7	90.55
Noisy Student + FixRes [70]	480M	300M unlabeled JFT	88.5	98.7	–
Vision Transformer (ViT-H) [14]	632M	300M labeled JFT	88.55	–	90.72
EfficientNet-L2-NoisyStudent + SAM [16]	480M	300M unlabeled JFT	88.6	98.6	–
Meta Pseudo Labels (EfficientNet-B6-Wide)	390M	300M unlabeled JFT	90.0	98.7	**91.12**
Meta Pseudo Labels (EfficientNet-L2)	480M	300M unlabeled JFT	**90.2**	**98.8**	91.02

Meta Pseudo Labels, Hieu Pham et al. (Jan 2021)

Pre-trained models

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Training a model on ImageNet from scratch takes **days or weeks**.

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Many models trained on ImageNet and their weights are publicly available!

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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

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Fine-tuning

Retraining the (some) parameters of the network (given enough data)

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- 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

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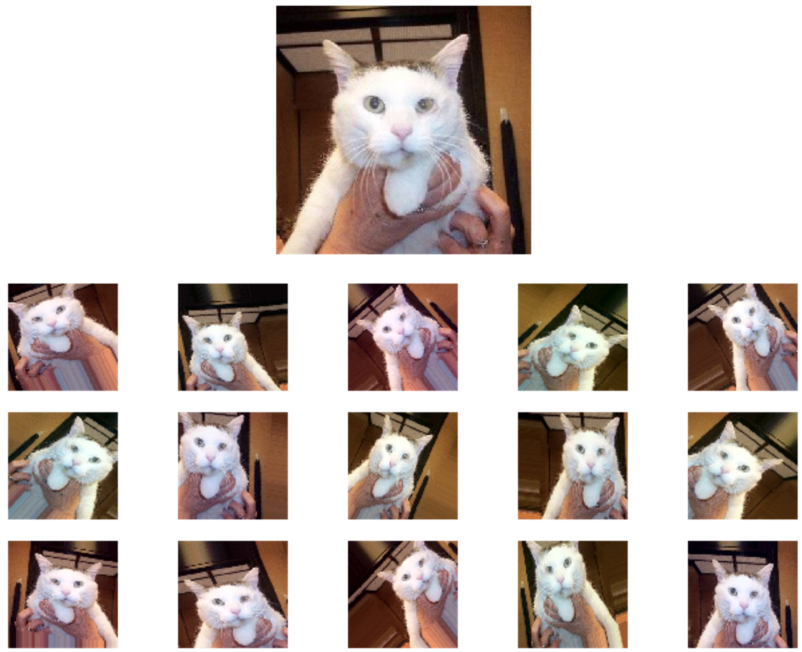
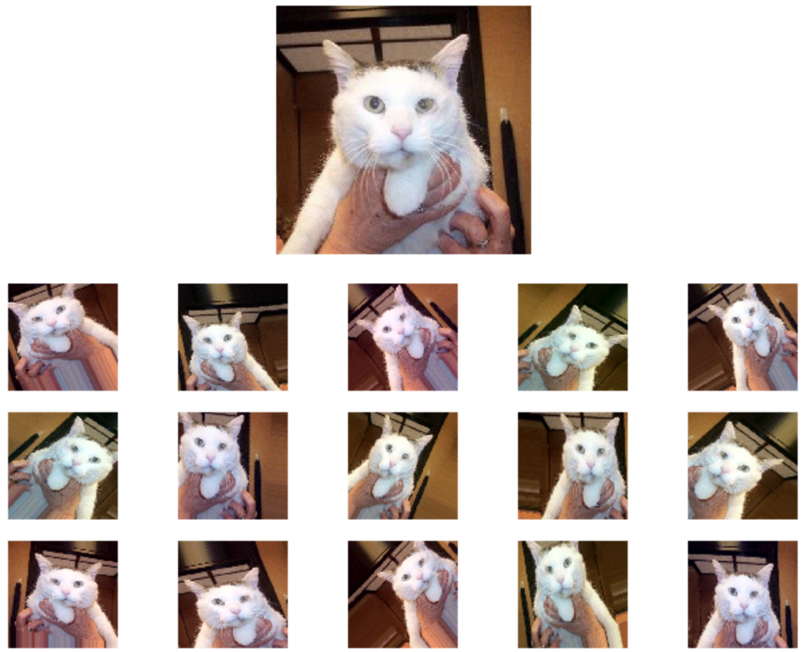
- Truncate the last layer(s) of the pre-trained network
- Freeze the remaining layers weights
- Add a (linear) classifier on top and train it for a few epochs
- Then fine-tune the whole network or the few deepest layers
- Use a smaller learning rate when fine tuning

Data Augmentation

Data Augmentation



Data Augmentation



See also: [RandAugment] and [Unsupervised Data Augmentation for Consistency Training].

Data Augmentation

With Keras:

```
from keras.preprocessing.image import ImageDataGenerator

image_gen = ImageDataGenerator(
    rescale=1. / 255,
    rotation_range=40,
    width_shift_range=0.2,
    height_shift_range=0.2,
    shear_range=0.2,
    zoom_range=0.2,
    horizontal_flip=True,
    channel_shift_range=9,
    fill_mode='nearest'
)

train_flow = image_gen.flow_from_directory(train_folder)
model.fit_generator(train_flow, train_flow.n)
```

Next: Lab