Going deeper

For a fixed parameter budget deeper is better

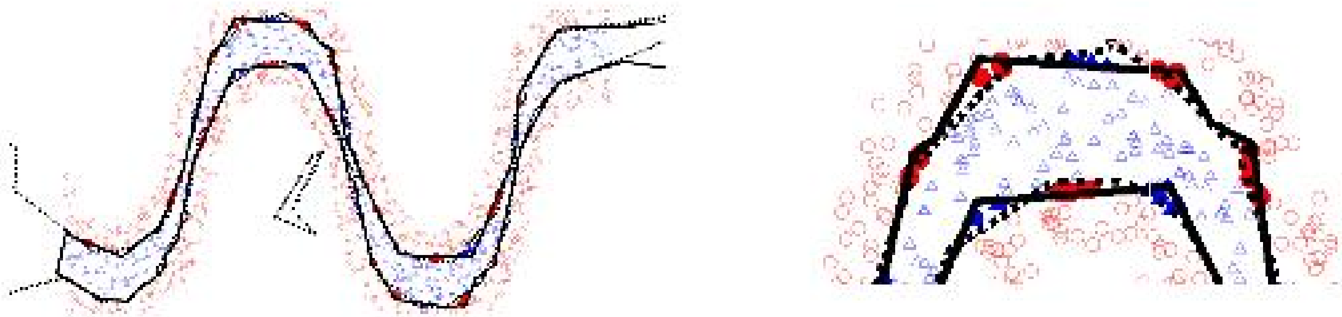
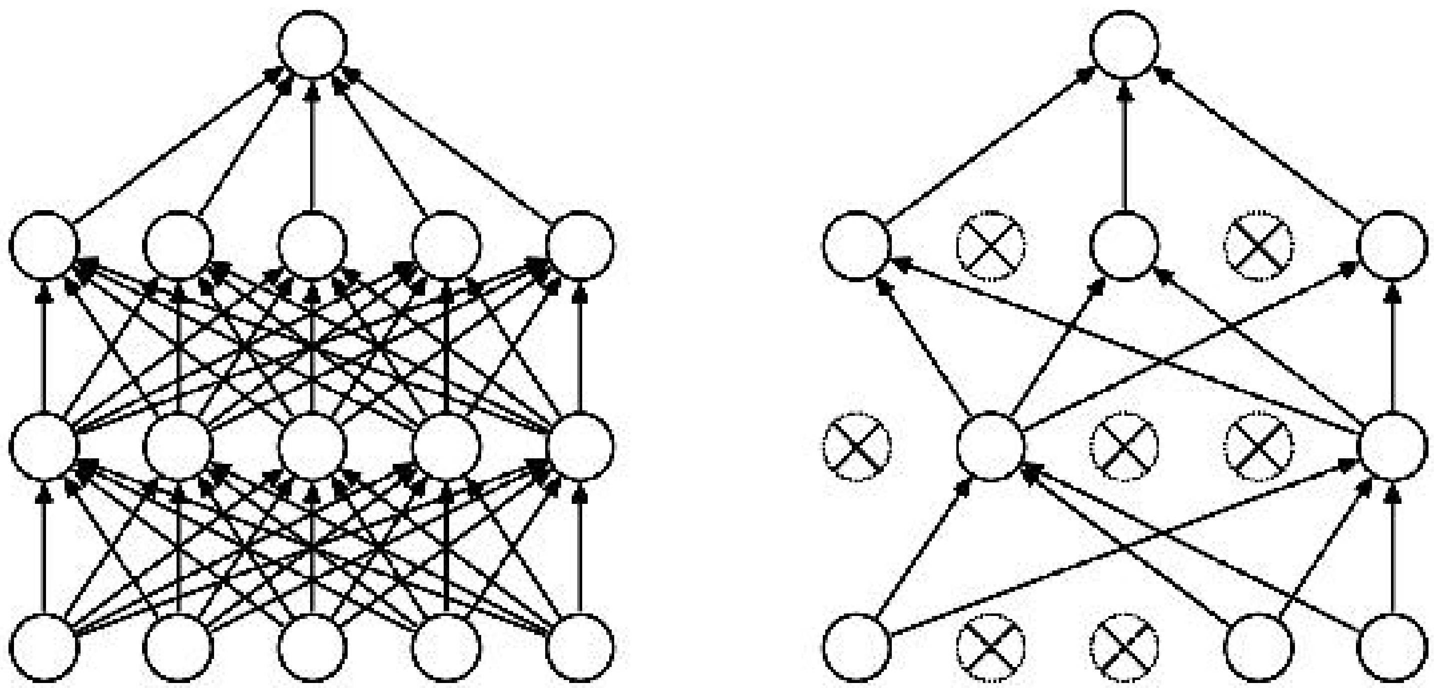


Figure 1: Binary classification using a shallow model with 20 hidden units (solid line) and a deep model with two layers of 10 units each (dashed line). The right panel shows a close-up of the left panel. Filled markers indicate errors made by the shallow model.

On the number of linear regions of deep neural networks; Montufar et al., 2014

Dropout

- First "deep" regularization technique
- Remove units at random during the forward pass on each sample
- Put them all back during test



(a) Standard Neural Net (b) After applying dropout.

Dropout: A Simple Way to Prevent Neural Networks from Overfitting, Srivastava et al., JMLR 2014

Dropout

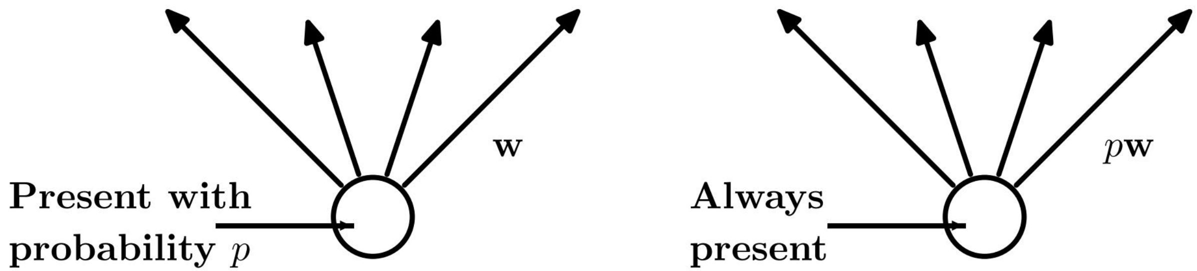
Interpretation

- Reduces the network dependency to individual neurons and distributes representation
- More redundant representation of data

Ensemble interpretation

- Equivalent to training a large ensemble of shared-parameters, binary-masked models
- Each model is only trained on a single data point
- A network with dropout can be interpreted as an ensemble of 2^N models with heavy weight sharing (Goodfellow et al., 2013)

Dropout

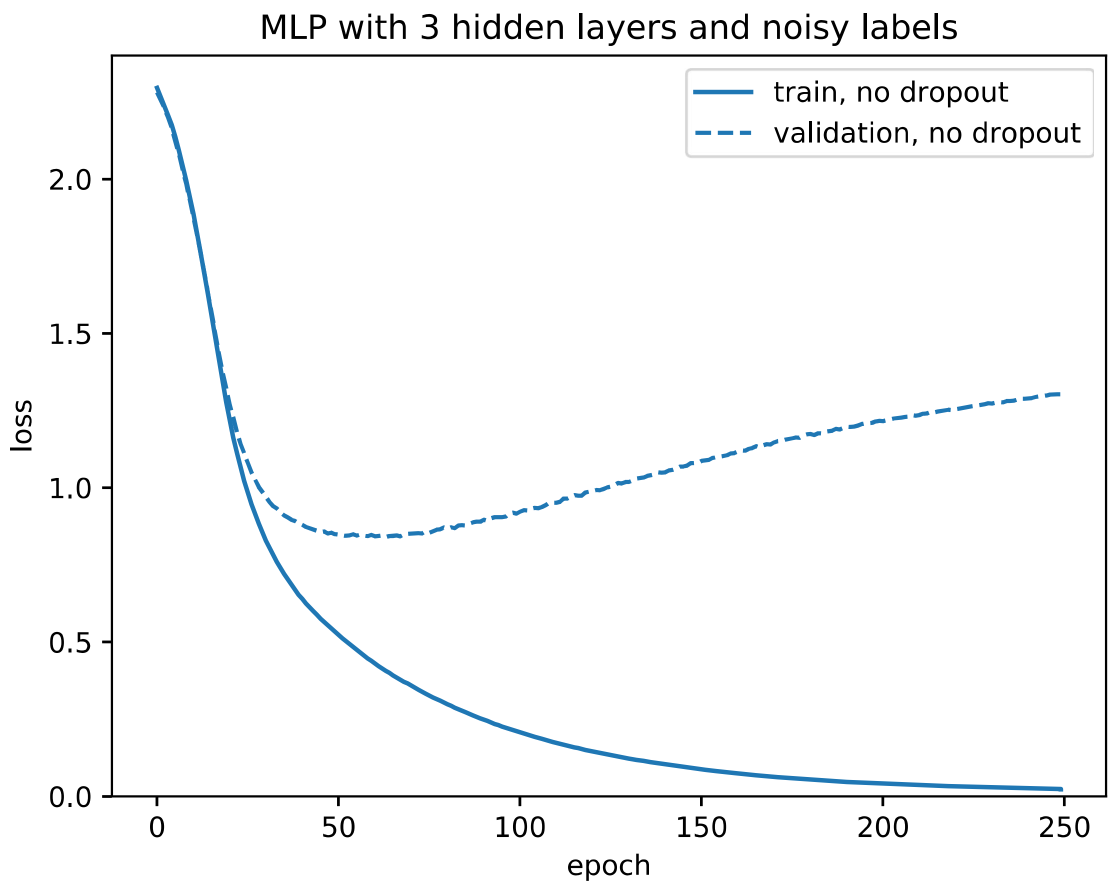


(a) At training time (b) At test time

- One has to decide on which units/layers to use dropout, and with what probability p units are dropped.
- During training, for each sample, as many Bernoulli variables as units are sampled independently to select units to remove.
- To keep the means of the inputs to layers unchanged, the initial version of dropout was multiplying activations by p during test.
- The standard variant is the "inverted dropout": multiply activations by $\frac{1}{1-p}$ during training and keep the network untouched during test.

Dropout

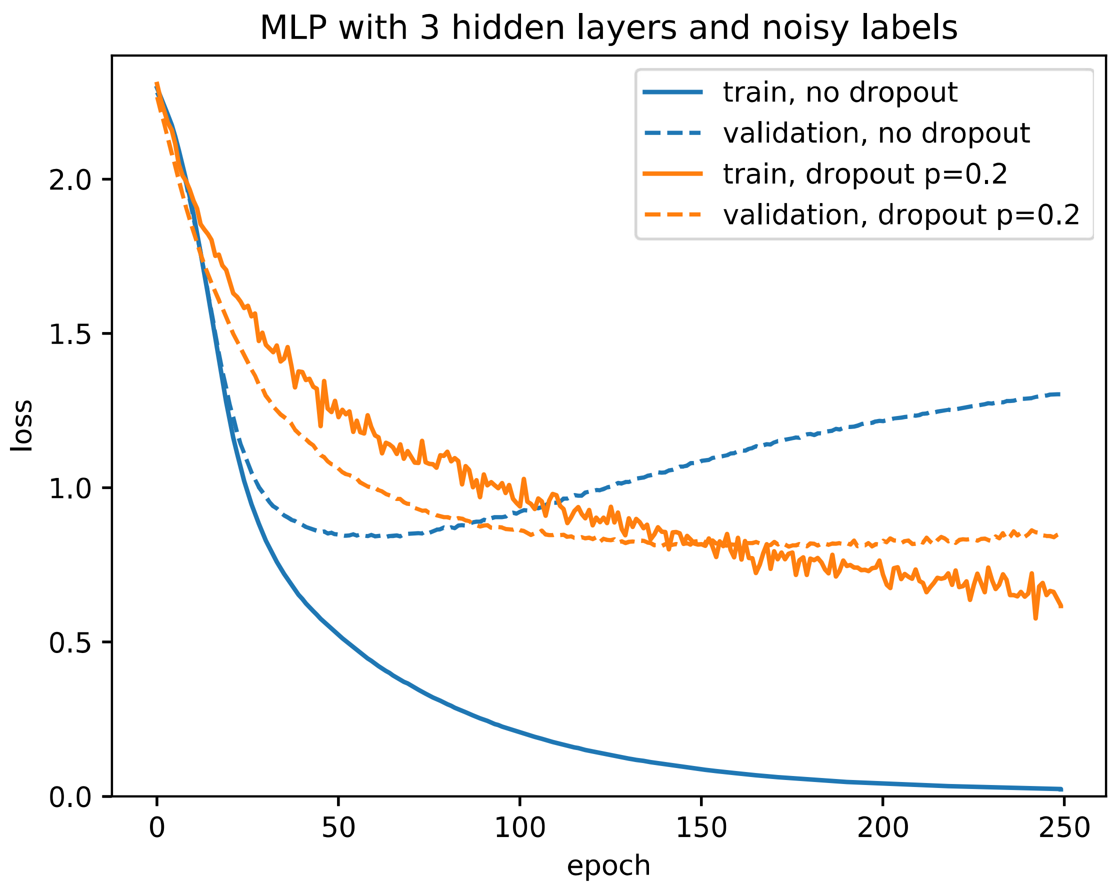
Overfitting noise



Slide credit: C. Ollion & O. Grisel, M2DS Deep Learning

Dropout

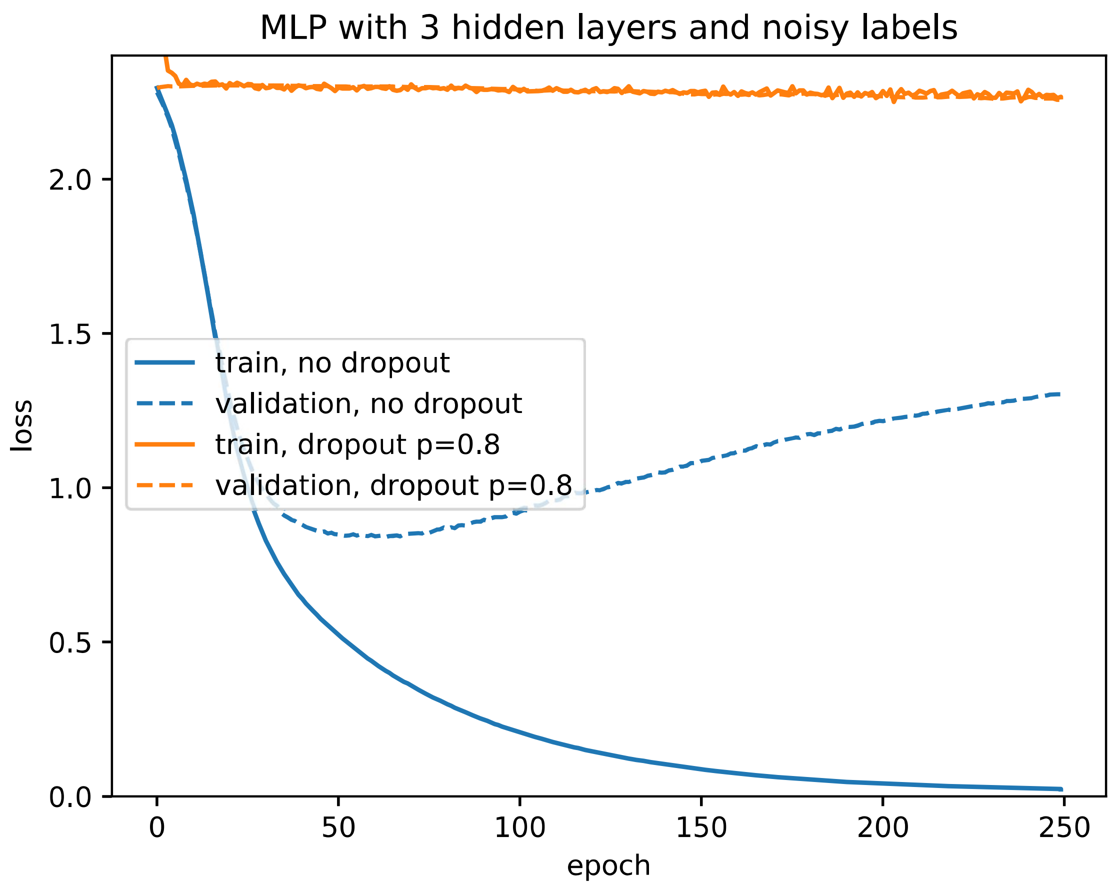
A bit of Dropout



Slide credit: C. Ollion & O. Grisel, M2DS Deep Learning

Dropout

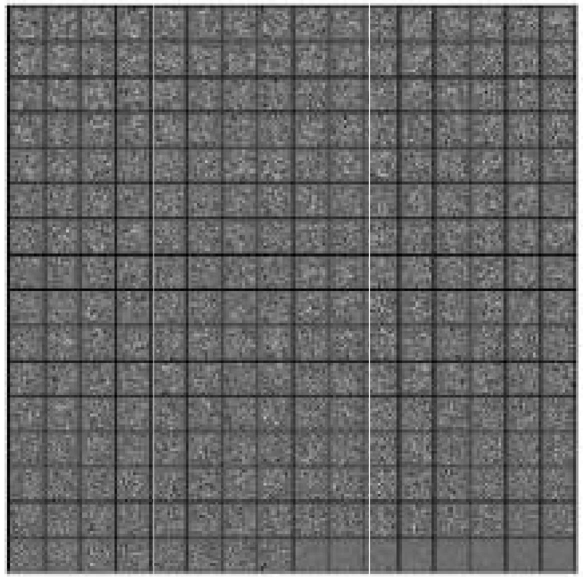
Too much: underfitting

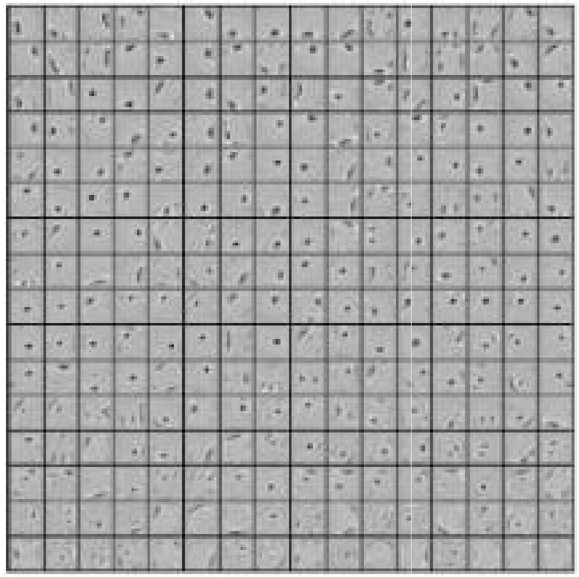


Slide credit: C. Ollion & O. Grisel, M2DS Deep Learning

Dropout

Features learned on MNIST with one hidded layer autoencoders having 256 rectified linear units


(a) Without dropout


(b) Dropout with $p = 0.5$.

Dropout: A Simple Way to Prevent Neural Networks from Overfitting, Srivastava et al., JMLR 2014

Dropout

```
>>> x = Variable(torch.Tensor(3, 9).fill_ (1.0), requires_grad = True)
>>> x.data
1 1 1 1 1 1 1 1 1
1 1 1 1 1 1 1 1 1
1 1 1 1 1 1 1 1 1
[torch.FloatTensor of size 3x9]

>>> dropout = nn.Dropout(p = 0.75)
>>> y = dropout(x)
>>> y.data
4 0 4 4 4 0 4 0 0
4 0 0 0 0 0 0 0 0
0 0 0 0 4 0 4 0 4
[torch.FloatTensor of size 3x9]

>>> l = y.norm(2, 1).sum()
>>> l.backward()
>>> x.grad.data
1.7889 0.0000 1.7889 1.7889 0.0000 0.0000 1.7889 0.0000 0.0000
4.0000 0.0000 0.0000 1.7889 0.0000 0.0000 0.0000 2.3094 0.0000
0.0000 0.0000 0.0000 0.0000 2.3094 0.0000 0.0000 0.0000 2.3094
[torch.FloatTensor of size 3x9]
```

Dropout

For a given network

```
model = nn.Sequential(nn.Linear(10, 100), nn.ReLU(),
                      nn.Linear(100, 50), nn.ReLU(),
                      nn.Linear(50, 2));
```

Dropout

For a given network

```
model = nn.Sequential(nn.Linear(10, 100), nn.ReLU(),
                      nn.Linear(100, 50), nn.ReLU(),
                      nn.Linear(50, 2));
```

we can simply add dropout layers

```
model = nn.Sequential(nn.Linear(10, 100), nn.ReLU(),
                      nn.Dropout(),
                      nn.Linear(100, 50), nn.ReLU(),
                      nn.Dropout(),
                      nn.Linear(50, 2));
```

Dropout

A model using dropout has to be set in "train" or "test" mode

Dropout

A model using dropout has to be set in "train" or "test" mode

The method nn.Module.train(mode) recursively sets the flag training to all sub-modules.

```
>>> dropout = nn.Dropout()
>>> model = nn.Sequential(nn.Linear(3, 10), dropout, nn.Linear(10, 3))
>>> dropout.training
True
>>> model.train(False)
Sequential (
(0): Linear (3 -> 10) (1): Dropout (p = 0.5) (2): Linear (10 -> 3)
)
>>> dropout.training
False
```

Spatial Dropout

As pointed out by Tompson et al. (2015), units in a 2d activation map are generally locally correlated, and dropout has virtually no effect.

They proposed SpatialDropout, which drops channels instead of individual units.

Spatial Dropout

```
>>> dropout2d = nn.Dropout2d()
>>> x = Variable(Tensor(2, 3, 2, 2).fill_(1.0))
>>> dropout2d(x)
Variable containing:
(0 ,0 ,.,.) =
0 0
0 0

(0 ,1 ,.,.) =
0 0
0 0

(0 ,2 ,.,.) =
2 2
2 2

(1 ,0 ,.,.) =
2 2
2 2

(1 ,1 ,.,.) =
0 0
0 0

(1 ,2 ,.,.) =
```

Batch normalization

We saw that maintaining proper statistics of the activations and derivatives was a critical issue to allow the training of deep architectures.

It is the main motivation behind weight initialization rules (we'll cover them later).

Batch normalization

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It is the main motivation behind weight initialization rules (we'll cover them later).

A different approach consists of explicitly forcing the activation statistics during the forward pass by re-normalizing them.

Batch normalization proposed by Ioffe and Szegedy (2015) was the first method introducing this idea.

Batch normalization

Normalize activations in each mini-batch before activation function: speeds up and stabilizes training (less dependent on init)

Batch normalization forces the activation first and second order moments, so that the following layers do not need to adapt to their drift.

Batch normalization

Normalize activations in each mini-batch before activation function: speeds up and stabilizes training (less dependent on init)

Input: Values of x over a mini-batch: $\mathcal{B} = \{x_{1\ldots m}\}$;
Parameters to be learned: γ, β
Output: $\{y_i = \mathrm{BN}_{\gamma,\beta}(x_i)\}$

$$\mu_{\mathcal{B}} \leftarrow \frac{1}{m}\sum_{i=1}^{m} x_i \qquad \text{// mini-batch mean}$$

$$\sigma_{\mathcal{B}}^2 \leftarrow \frac{1}{m}\sum_{i=1}^{m} (x_i - \mu_{\mathcal{B}})^2 \qquad \text{// mini-batch variance}$$

$$\widehat{x}_i \leftarrow \frac{x_i - \mu_{\mathcal{B}}}{\sqrt{\sigma_{\mathcal{B}}^2 + \epsilon}} \qquad \text{// normalize}$$

$$y_i \leftarrow \gamma \widehat{x}_i + \beta \equiv \mathrm{BN}_{\gamma,\beta}(x_i) \qquad \text{// scale and shift}$$

Batch normalization: Accelerating deep network training by reducing internal covariate shift, Ioffe and Szegedy, ICML 2015

Batch normalization

During training batch normalization shifts and rescales according to the mean and variance estimated on the batch.

Input: Values of x over a mini-batch: $\mathcal{B} = \{x_{1\ldots m}\}$;
Parameters to be learned: γ, β

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As for dropout, the model behaves differently during train and test.

Batch normalization

At inference time, use average and standard deviation computed on the whole dataset instead of batch

Widely used in ConvNets, but requires the mini-batch to be large enough to compute statistics in the minibatch.

Batch normalization

As dropout, batch normalization is implemented as a separate module torch.BatchNorm1d that processes the input components separately.

```
>>> x = torch.Tensor(10000, 3).normal_()
>>> x = x * torch.Tensor([2, 5, 10]) + torch.Tensor([-10, 25, 3])
>>> x = Variable(x)
>>> x.data.mean(0)
-9.9898
24.9165
2.8945
[torch.FloatTensor of size 3]

>>> x.data.std(0)
2.0006
5.0146
9.9501
[torch.FloatTensor of size 3]
```

Batch normalization

Since the module has internal variables to keep statistics, it must be provided with the sample dimension at creation.

```
>>> bn = nn.BatchNorm1d(3)
>>> bn.bias.data = torch.Tensor([2, 4, 8])
>>> bn.weight.data = torch.Tensor([1, 2, 3])
>>> y = bn(x)
>>> y.data.mean(0)

 2.0000
 4.0000
 8.0000
[torch.FloatTensor of size 3]
>>> y.data.std(0)

 1.0000
 2.0001
 3.0001
[torch.FloatTensor of size 3]
```

Batch normalization

BatchNorm2d example

```
>>> x = Variable(torch.randn(20, 100, 35, 45))
>>> bn2d = nn.BatchNorm2d(100)
>>> y = bn2d(x)
>>> x.size()

torch.Size([20, 100, 35, 45])
>>> bn2d.weight.data.size()

torch.Size([100])
>>> bn2d.bias.data.size()

torch.Size([100])
```

Batch normalization

Results on ImageNet LSVRC 2012:

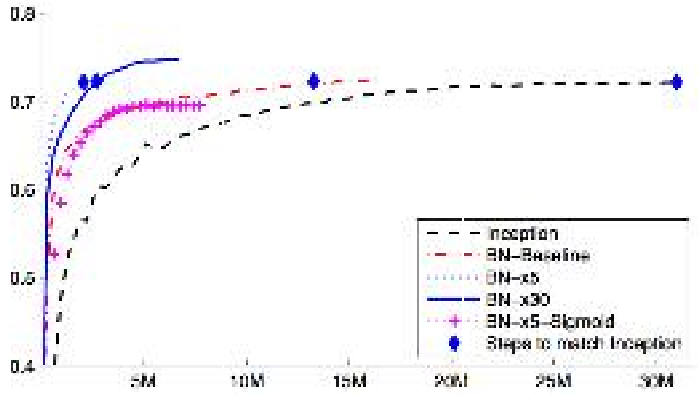

Figure 2: *Single crop validation accuracy of Inception and its batch-normalized variants, vs. the number of training steps.*

Model	Steps to 72.2%	Max accuracy
Inception	$31.0 \cdot 10^6$	72.2%
BN-Baseline	$13.3 \cdot 10^6$	72.7%
BN-x5	$2.1 \cdot 10^6$	73.0%
BN-x30	$2.7 \cdot 10^6$	74.8%
BN-x5-Sigmoid		69.8%

Figure 3: *For Inception and the batch-normalized variants, the number of training steps required to reach the maximum accuracy of Inception (72.2%), and the maximum accuracy achieved by the network.*

Batch normalization: Accelerating deep network training by reducing internal covariate shift, Ioffe and Szegedy, ICML 2015

Batch normalization

Results on ImageNet LSVRC 2012:

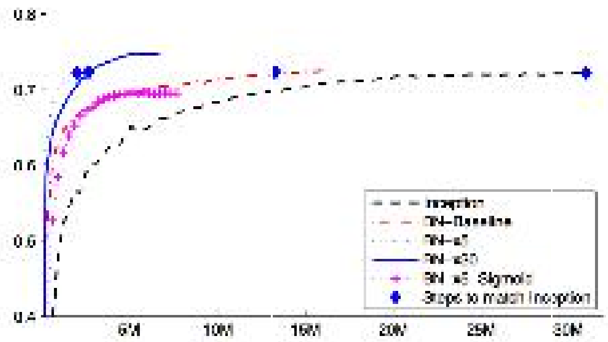

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Figure 3: *For Inception and the batch-normalized variants, the number of training steps required to reach the maximum accuracy of Inception (72.2%), and the maximum accuracy achieved by the network.*

- learning rate can be greater
- dropout and local normalization are not necessary
- L^2 regularization influence should be reduced

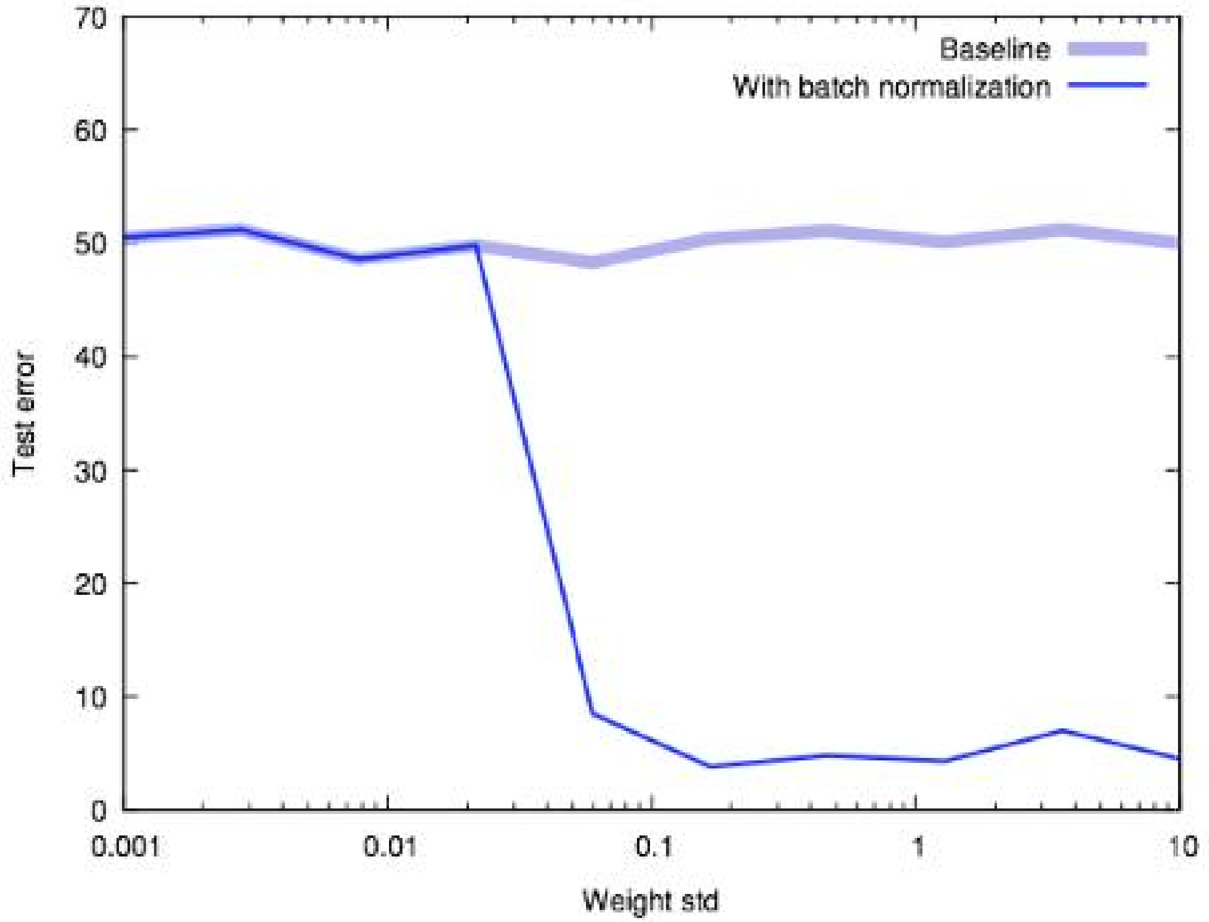
Batch normalization: Accelerating deep network training by reducing internal covariate shift, Ioffe and Szegedy, ICML 2015

Batch normalization

Deep MLP on a 2d "disc" toy example, with naive Gaussian weight initialization, cross-entropy, standard SGD, $\eta = 0.1$.

```
def create_model(with_batchnorm, nc = 32, depth = 16):
    modules = []

    modules.append(nn.Linear(2, nc))
    if with_batchnorm: modules.append(nn.BatchNorm1d(nc))
    modules.append(nn.ReLU())

    for d in range(depth):
        modules.append(nn.Linear(nc, nc))
        if with_batchnorm: modules.append(nn.BatchNorm1d(nc))
        modules.append(nn.ReLU())

    modules.append(nn.Linear(nc, 2))

    return nn.Sequential(*modules)
```

Batch normalization



Slide credit: F. Fleuret, EE-559 Deep learning

Layer Normalizations

Normalize on the statistics of the layer activations instead of mini-batch.

$$\mu^l = \frac{1}{H}\sum_{i=1}^{H} a_i^l \qquad \sigma^l = \sqrt{\frac{1}{H}\sum_{i=1}^{H}\left(a_i^l - \mu^l\right)^2}$$

Layer Normalization, Ba et al., 2016

Layer Normalizations

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Layer Normalization, Ba et al., 2016

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The algorithm is then similar as Batch Normalization

Suited for RNNs, degrades performance of CNNs

Layer Normalization, Ba et al., 2016

Weight Normalization

Reparametrize weights of neurons, to decouple direction and norm of the weight:

$$\mathbf{w} = \frac{g}{||\mathbf{v}||}\mathbf{v}$$

Weight normalization: A simple reparameterization to accelerate training of deep neural networks, Salimans, NIPS 2016.

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Reparametrize weights of neurons, to decouple direction and norm of the weight:

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One new parameter g to learn per neuron

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Weight Normalization

Reparametrize weights of neurons, to decouple direction and norm of the weight:

$$\mathbf{w} = \frac{g}{||\mathbf{v}||}\mathbf{v}$$

One new parameter g to learn per neuron

Careful data-based initialization of g and neuron bias b is better (not applicable to RNNs)

Weight normalization: A simple reparameterization to accelerate training of deep neural networks, Salimans, NIPS 2016.

Multiple variants

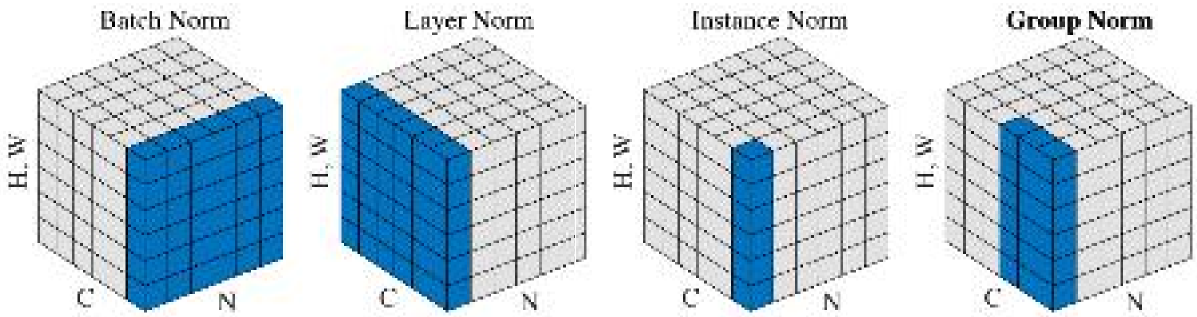


Figure 2. **Normalization methods**. Each subplot shows a feature map tensor, with N as the batch axis, C as the channel axis, and (H, W) as the spatial axes. The pixels in blue are normalized by the same mean and variance, computed by aggregating the values of these pixels.

Architectures

Architectures

torchvision.models provides a collection of reference networks for computer vision, e.g.:

```
import torchvision
alexnet = torchvision.models.alexnet()
```

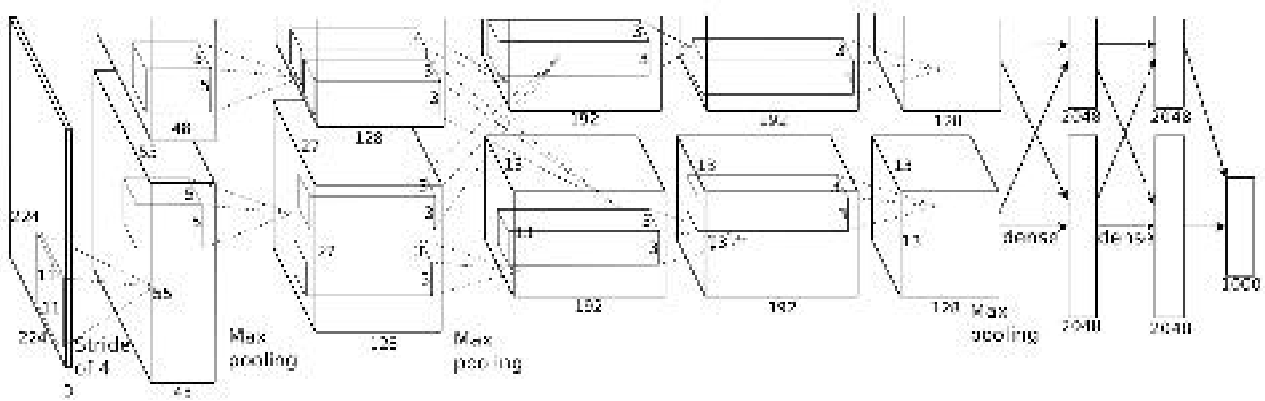
The trained models can be obtained by passing pretrained = True to the constructor(s). This may involve an heavy download given there size.

LeNet5

10 classes, input 1 x 28 x 28

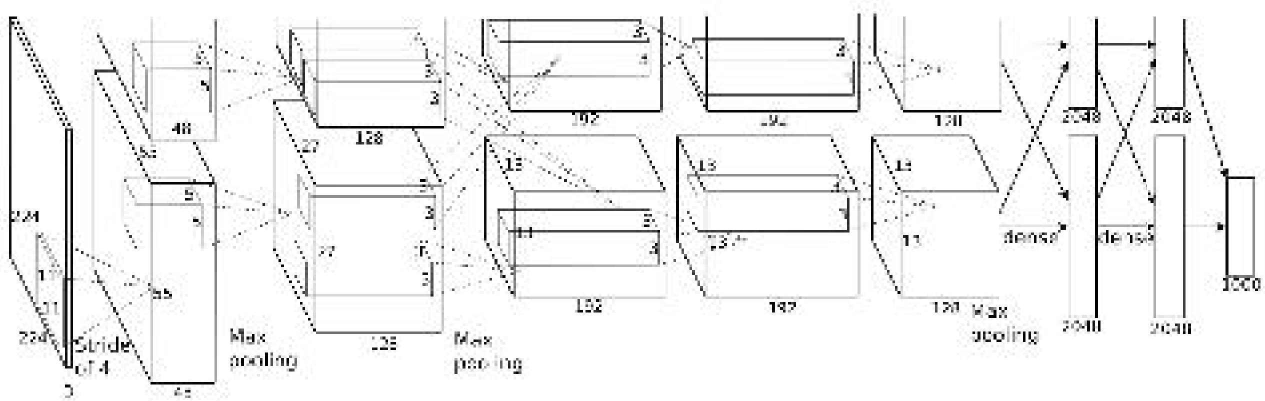
```
(features): Sequential (
(0): Conv2d(1, 6, kernel_size=(5, 5), stride=(1, 1))
(1): ReLU (inplace)
(2): MaxPool2d (size=(2, 2), stride=(2, 2), dilation=(1, 1))
(3): Conv2d(6, 16, kernel_size=(5, 5), stride=(1, 1))
(4): ReLU (inplace)
(5): MaxPool2d (size=(2, 2), stride=(2, 2), dilation=(1, 1))
)
(classifier): Sequential (
(0): Linear (400 -> 120)
(1): ReLU (inplace)
(2): Linear (120 -> 84)
(3): ReLU (inplace)
(4): Linear (84 -> 10) )
```

AlexNet



Imagenet classification with deep convolutional neural networks, Krizhevsky et al., NIPS 2012

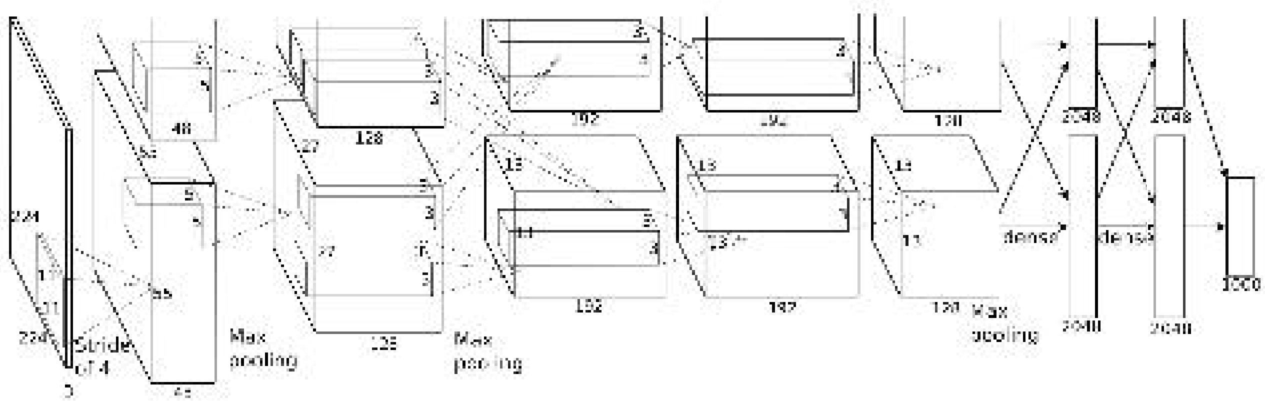
AlexNet



First conv layer: kernel 11x11x3x96 stride 4

Imagenet classification with deep convolutional neural networks, *Krizhevsky et al., NIPS 2012*

AlexNet



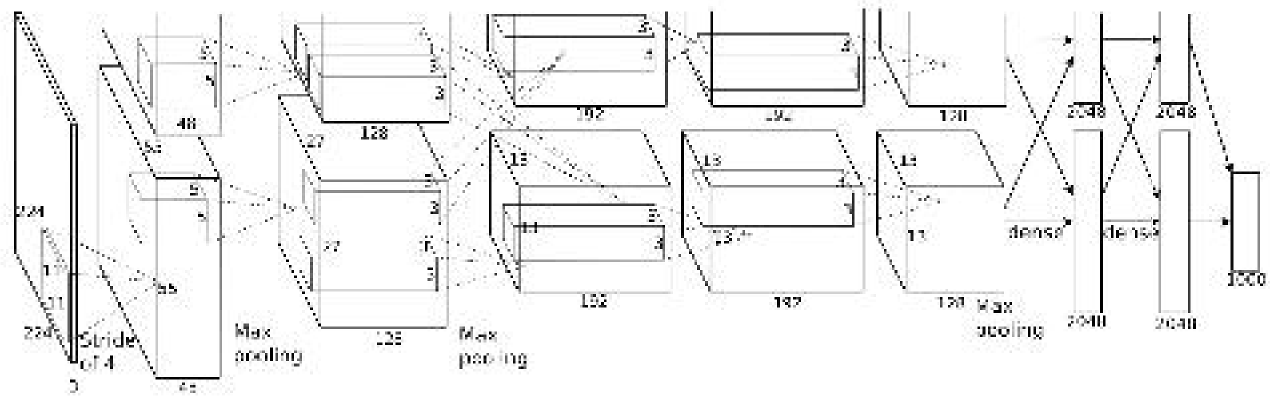
First conv layer: kernel 11x11x3x96 stride 4

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

Imagenet classification with deep convolutional neural networks, Krizhevsky et al., NIPS 2012

Slide credit: C. Ollion & O. Grisel, M2DS Deep Learning

AlexNet



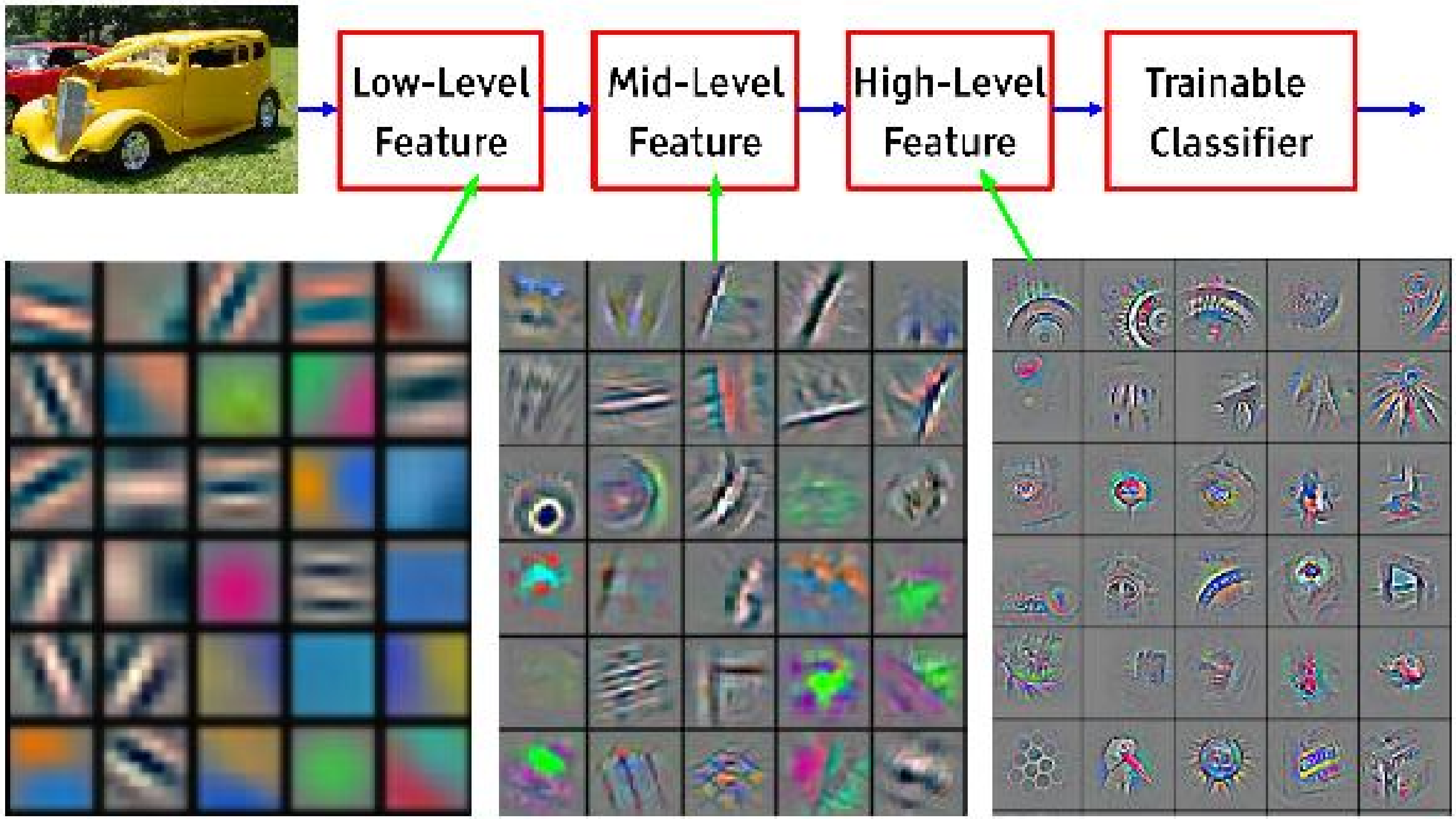
INPUT:	[227x227x3]		
CONV1:	[55x55x96]	96 11x11	filters at stride 4, pad 0
MAX POOL1:	[27x27x96]	3x3	filters at stride 2
CONV2:	[27x27x256]	256 5x5	filters at stride 1, pad 2
MAX POOL2:	[13x13x256]	3x3	filters at stride 2
CONV3:	[13x13x384]	384 3x3	filters at stride 1, pad 1
CONV4:	[13x13x384]	384 3x3	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)	

Slide credit: C. Ollion & O. Grisel, M2DS Deep Learning

AlexNet

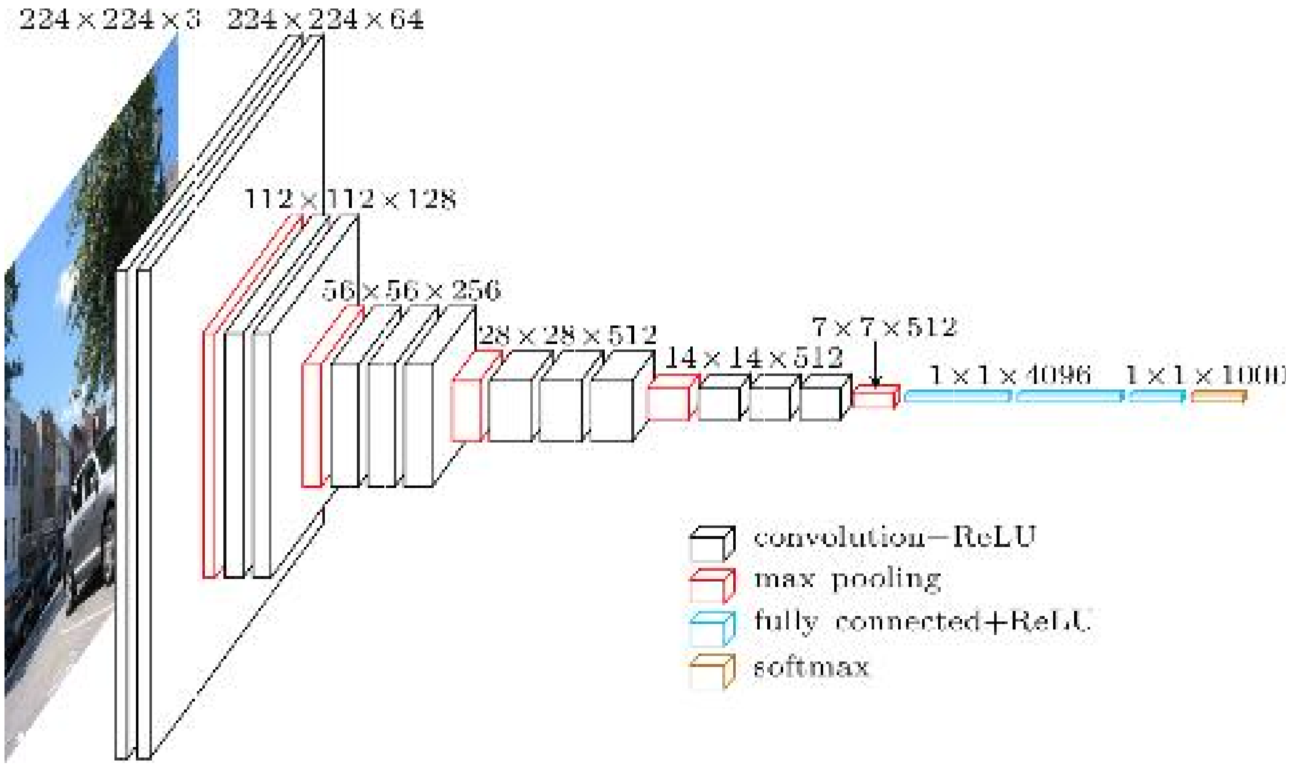
```
(features): Sequential (
(0): Conv2d(3, 64, kernel_size=(11, 11), stride=(4, 4), padding=(2, 2))
(1): ReLU (inplace)
(2): MaxPool2d (size=(3, 3), stride=(2, 2), dilation=(1, 1))
(3): Conv2d(64, 192, kernel_size=(5, 5), stride=(1, 1), padding=(2, 2))
(4): ReLU (inplace)
(5): MaxPool2d (size=(3, 3), stride=(2, 2), dilation=(1, 1))
(6): Conv2d(192, 384, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
(7): ReLU (inplace)
(8): Conv2d(384, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
(9): ReLU (inplace)
(10): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
(11): ReLU (inplace)
(12): MaxPool2d (size=(3, 3), stride=(2, 2), dilation=(1, 1))
)

(classifier): Sequential (
(0): Dropout (p = 0.5)
(1): Linear (9216 -> 4096)
(2): ReLU (inplace)
(3): Dropout (p = 0.5)
(4): Linear (4096 -> 4096)
(5): ReLU (inplace)
(6): Linear (4096 -> 1000)
)
```

Hierarchical representation



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

VGG-16



Very deep convolutional networks for large-scale image recognition, Simonyan and Zisserman, NIPS 2014

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
CONV3-256:	[56x56x256]	= 800K	(3x3x256)x256 =	589,824
POOL2:	[28x28x256]	= 200K	0	
CONV3-512:	[28x28x512]	= 400K	(3x3x256)x512 =	1,179,648
CONV3-512:	[28x28x512]	= 400K	(3x3x512)x512 =	2,359,296
CONV3-512:	[28x28x512]	= 400K	(3x3x512)x512 =	2,359,296
POOL2:	[14x14x512]	= 100K	0	
CONV3-512:	[14x14x512]	= 100K	(3x3x512)x512 =	2,359,296
CONV3-512:	[14x14x512]	= 100K	(3x3x512)x512 =	2,359,296
CONV3-512:	[14x14x512]	= 100K	(3x3x512)x512 =	2,359,296
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)

Slide credit: C. Ollion & O. Grisel, M2DS Deep Learning

Memory and Parameters

Layer	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
CONV3-256:	[56x56x256]	= 800K	(3x3x256)x256 =	589,824
POOL2:	[28x28x256]	= 200K	0	
CONV3-512:	[28x28x512]	= 400K	(3x3x256)x512 =	1,179,648
CONV3-512:	[28x28x512]	= 400K	(3x3x512)x512 =	2,359,296
CONV3-512:	[28x28x512]	= 400K	(3x3x512)x512 =	2,359,296
POOL2:	[14x14x512]	= 100K	0	
CONV3-512:	[14x14x512]	= 100K	(3x3x512)x512 =	2,359,296
CONV3-512:	[14x14x512]	= 100K	(3x3x512)x512 =	2,359,296
CONV3-512:	[14x14x512]	= 100K	(3x3x512)x512 =	2,359,296
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)

VGG-19

```
(0): Conv2d(3, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
(1): ReLU (inplace)
(2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
(3): ReLU (inplace)
(4): MaxPool2d (size=(2, 2), stride=(2, 2), dilation=(1, 1))
(5): Conv2d(64, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
(6): ReLU (inplace)
(7): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
(8): ReLU (inplace)
(9): MaxPool2d (size=(2, 2), stride=(2, 2), dilation=(1, 1))
(10): Conv2d(128, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
(11): ReLU (inplace)
(12): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
(13): ReLU (inplace)
(14): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
(15): ReLU (inplace)
(16): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
(17): ReLU (inplace)
(18): MaxPool2d (size=(2, 2), stride=(2, 2), dilation=(1, 1))
(19): Conv2d(256, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
(20): ReLU (inplace)
(21): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
(22): ReLU (inplace)
(23): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
```

VGG-19

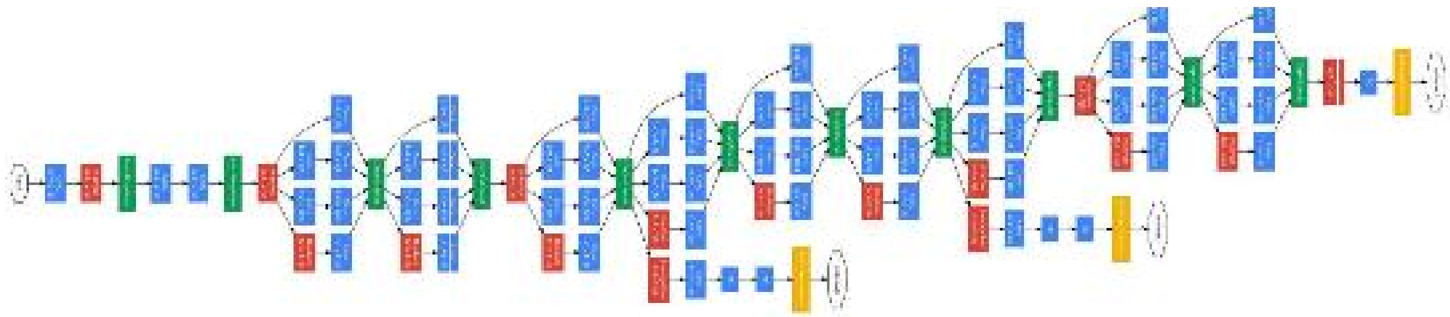
...

```
(30): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
(31): ReLU (inplace)
(32): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
(33): ReLU (inplace)
(34): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
(35): ReLU (inplace)
(36): MaxPool2d (size=(2, 2), stride=(2, 2), dilation=(1, 1))

(classifier): Sequential ( (0): Linear (25088 -> 4096)
(1): ReLU (inplace)
(2): Dropout (p = 0.5)
(3): Linear (4096 -> 4096)
(4): ReLU (inplace)
(5): Dropout (p = 0.5) (6): Linear (4096 -> 1000)
)
```

GoogLeNet / Inception

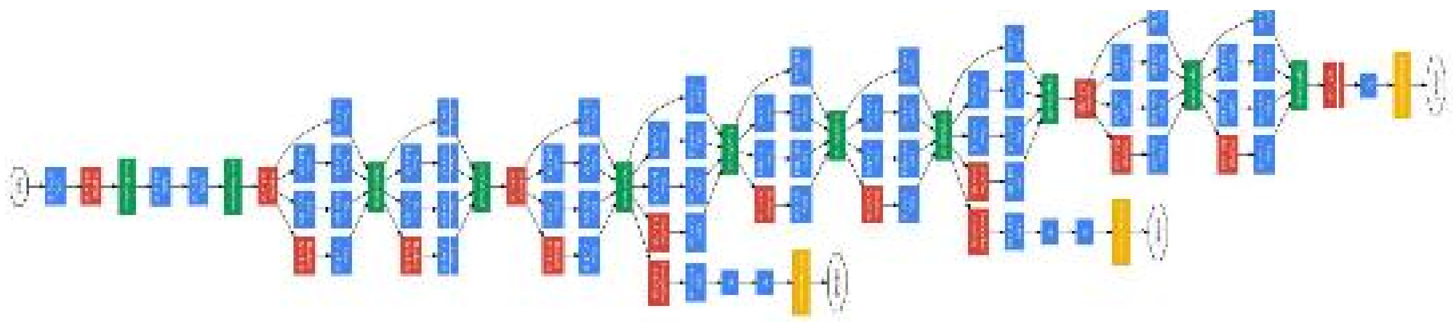
Szegedy et al. (2015) also introduce the idea of "auxiliary classifiers" to help the propagation of the gradient in the early layers.

This is motivated by the reasonable performance of shallow networks that indicates early layers already encode informative and invariant features.



GoogLeNet / Inception

The resulting GoogLeNet has 12 times less parameters than AlexNet and is more accurate on ILSVRC14 (Szegedy et al., 2015).



It was later extended with batch-normalization (Ioffe and Szegedy, 2015) and pass-through a la resnet (Szegedy et al., 2016)

GoogLeNet / Inception

type	patch size/ stride	output size	depth	#1×1	#3×3 reduce	#3×3	#5×5 reduce	#5×5	pool proj	params	ops
convolution	7×7/2	112×112×64	1							2.7K	34M
max pool	3×3/2	56×56×64	0								
convolution	3×3/1	56×56×192	2		64	192				112K	360M
max pool	3×3/2	28×28×192	0								
inception (3a)		28×28×256	2	64	96	128	16	32	32	159K	128M
inception (3b)		28×28×480	2	128	128	192	32	96	64	380K	304M
max pool	3×3/2	14×14×480	0								
inception (4a)		14×14×512	2	192	96	208	16	48	64	364K	73M
inception (4b)		14×14×512	2	160	112	224	24	64	64	437K	88M
inception (4c)		14×14×512	2	128	128	256	24	64	64	463K	100M
inception (4d)		14×14×528	2	112	144	288	32	64	64	580K	119M
inception (4e)		14×14×832	2	256	160	320	32	128	128	840K	170M
max pool	3×3/2	7×7×832	0								
inception (5a)		7×7×832	2	256	160	320	32	128	128	1072K	54M
inception (5b)		7×7×1024	2	384	192	384	48	128	128	1388K	71M
avg pool	7×7/1	1×1×1024	0								
dropout (40%)		1×1×1024	0								
linear		1×1×1000	1							1000K	1M
softmax		1×1×1000	0								

Fun features:

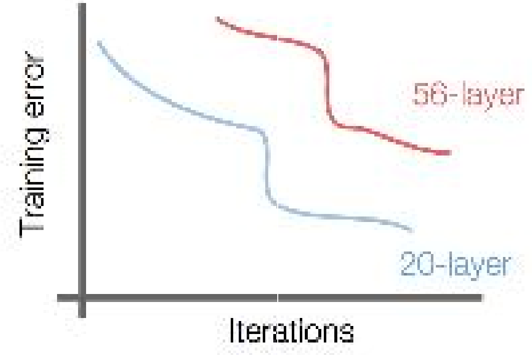
- Only 5 million params! (Removes FC layers completely)

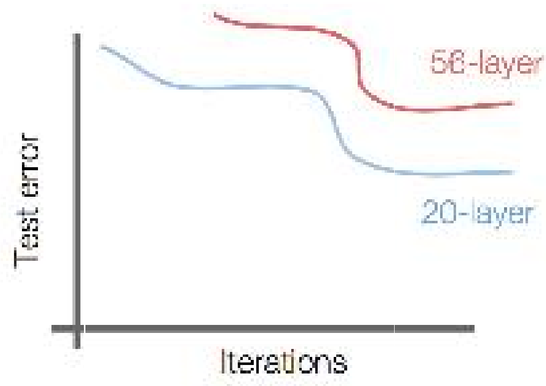
Compared to AlexNet:
- 12X less params
- 2x more compute
- 6.67% (vs. 16.4%)

Slide credit: A. Karpathy

A saturation point

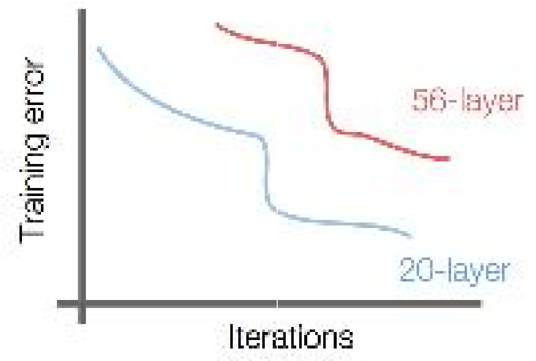
If we continue stacking more layers on a CNN:

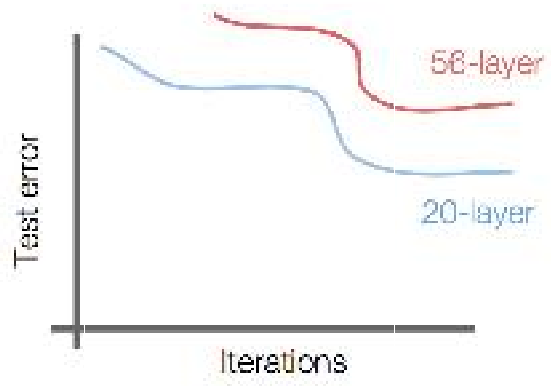




A saturation point

If we continue stacking more layers on a CNN:





Deeper models are harder to optimize

Slide credit: J. Johnson, CS231n Convolutional Neural Networks for Visual Recognition

ResNet

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

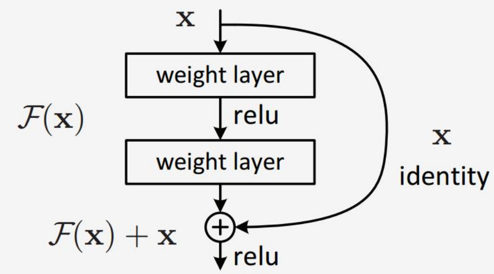


Figure 2. Residual learning: a building block.

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

ResNet

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

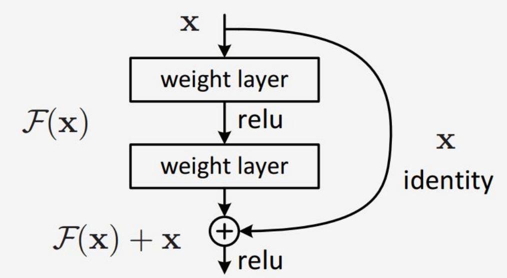


Figure 2. Residual learning: a building block.

- Good optimization properties

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

ResNet

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

Even deeper models:

34, 50, 101, 152 layers

ResNet

5.25% top-5 error vs 7.1%

ResNet50 Compared to VGG:

Superior accuracy in all vision tasks

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

ResNet

5.25% top-5 error vs 7.1%

Less parameters
25M vs 138M

ResNet50 Compared to VGG:

Superior accuracy in all vision tasks

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

ResNet

ResNet50 Compared to VGG:

Superior accuracy in all vision tasks

5.25% top-5 error vs 7.1%

Less parameters
25M vs 138M

Computational complexity
3.8B Flops vs 15.3B Flops

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

ResNet

5.25% top-5 error vs 7.1%

Less parameters
25M vs 138M

Computational complexity
3.8B Flops vs 15.3B Flops

Fully Convolutional until the last layer

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

ResNet50 Compared to VGG:

Superior accuracy in all vision tasks

ResNet

Performance on ImageNet

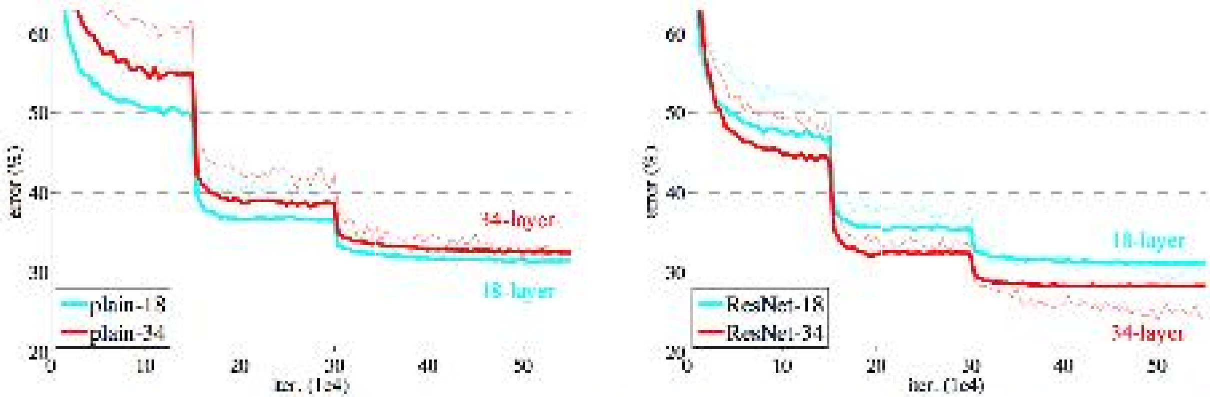
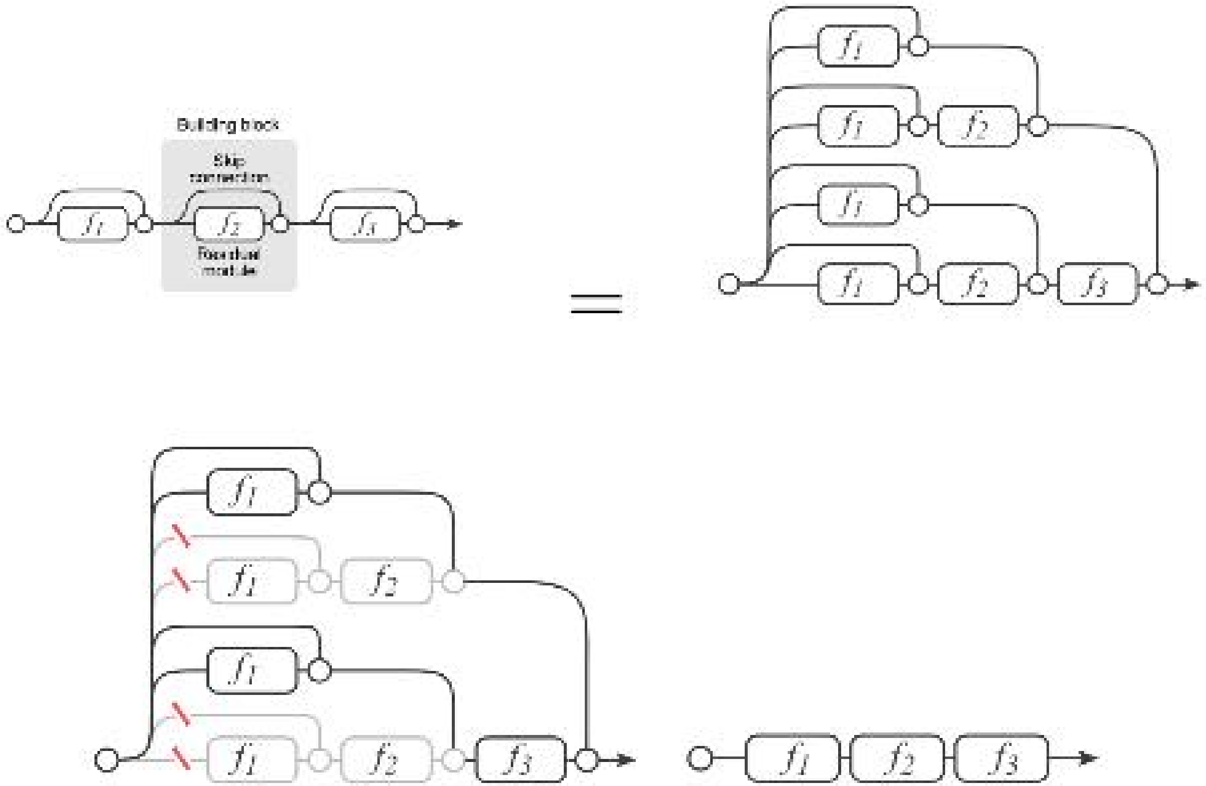


Figure 4. Training on **ImageNet**. Thin curves denote training error, and bold curves denote validation error of the center crops. Left: plain networks of 18 and 34 layers. Right: ResNets of 18 and 34 layers. In this plot, the residual networks have no extra parameter compared to their plain counterparts.

ResNet

The output of a residual network can be understood as an ensemble, which explains in part its stability



Residual Networks Behave Like Ensembles of Relatively Shallow Networks, A. Veit et al., NIPS 2016

ResNet

Results

layer name	output size	18-layer	34-layer	50-layer	101-layer	152-layer
conv1	112×112	7×7, 64, stride 2				
		3×3 max pool, stride 2				
conv2_x	56×56	$\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$
conv3_x	28×28	$\begin{bmatrix} 3\times3, 128 \\ 3\times3, 128 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 128 \\ 3\times3, 128 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times8$
conv4_x	14×14	$\begin{bmatrix} 3\times3, 256 \\ 3\times3, 256 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 256 \\ 3\times3, 256 \end{bmatrix}\times6$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times6$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times23$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times36$
conv5_x	7×7	$\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$
	1×1	average pool, 1000-d fc, softmax				
FLOPs		1.8×10^9	3.6×10^9	3.8×10^9	7.6×10^9	11.3×10^9

Table 1. Architectures for ImageNet. Building blocks are shown in brackets (see also Fig. 5), with the numbers of blocks stacked. Down-sampling is performed by conv3_1, conv4_1, and conv5_1 with a stride of 2.

ResNet

Results

method	top-5 err. (**test**)
VGG [41] (ILSVRC'14)	7.32
GoogLeNet [44] (ILSVRC'14)	6.66
VGG [41] (v5)	6.8
PReLU-net [13]	4.94
BN-inception [16]	4.82
ResNet (ILSVRC'15)	**3.57**

Table 5. Error rates (%) of **ensembles**. The top-5 error is on the test set of ImageNet and reported by the test server.

ResNet

In PyTorch:

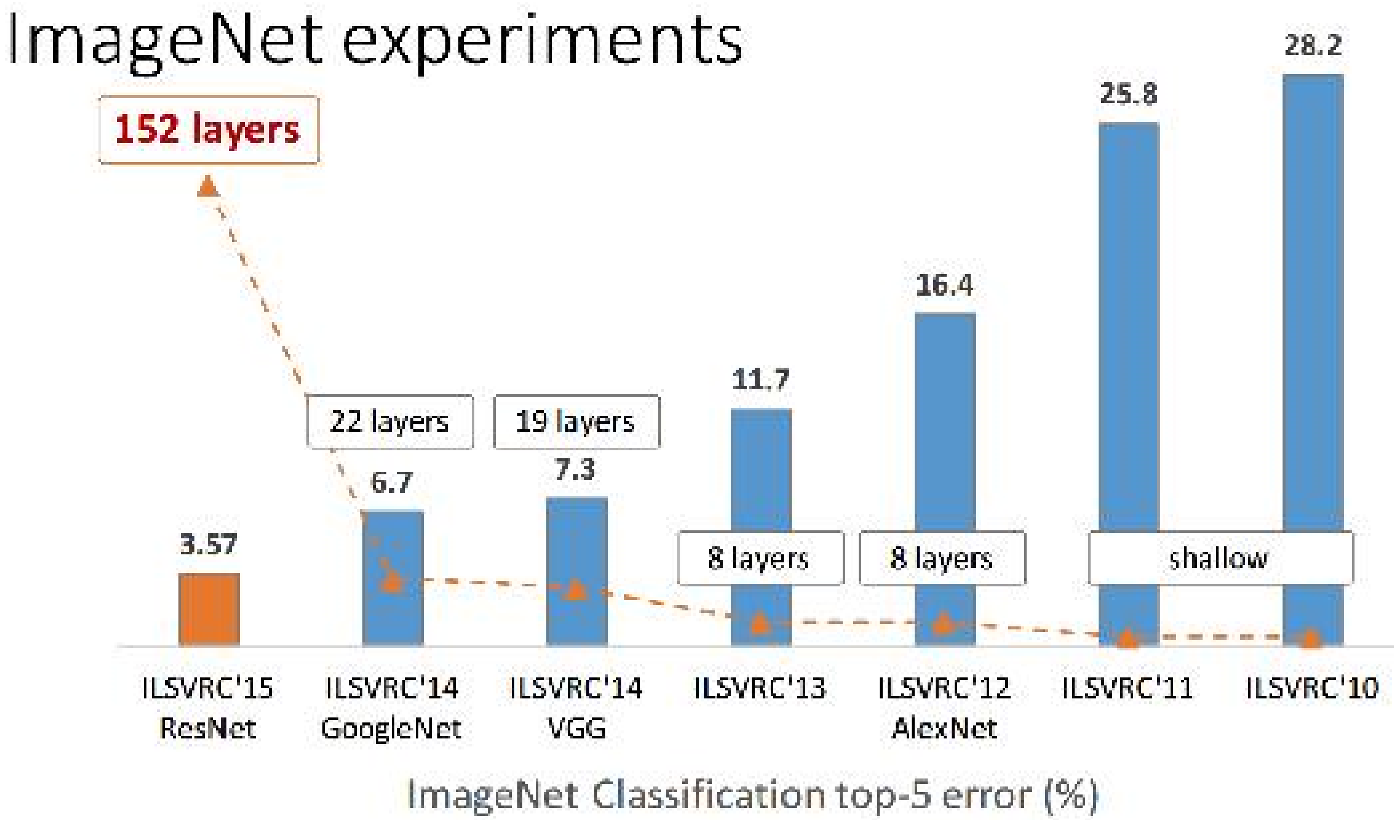
```
def make_resnet_block(num_feature_maps , kernel_size = 3):

    return nn.Sequential(

        nn.Conv2d(num_feature_maps , num_feature_maps ,
                  kernel_size = kernel_size ,
                  padding = (kernel_size - 1) // 2),

        nn.BatchNorm2d(num_feature_maps),

        nn.ReLU(inplace = True),
        nn.Conv2d(num_feature_maps , num_feature_maps ,
                   kernel_size = kernel_size ,
                    padding = (kernel_size - 1) // 2),

        nn.BatchNorm2d(num_feature_maps),
)
```

ResNet

In PyTorch:

```
def __init__(self, num_residual_blocks, num_feature_maps)
...
    self.resnet_blocks = nn.ModuleList()
    for k in range(nb_residual_blocks):
        self.resnet_blocks.append(make_resnet_block(num_feature_maps , 3))
...


def forward(self,x):
...
    for b in self.resnet_blocks:
        x = x + b(x)
...
    return x
```

Deeper is better

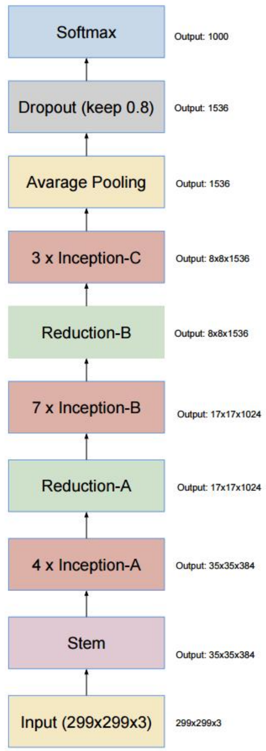


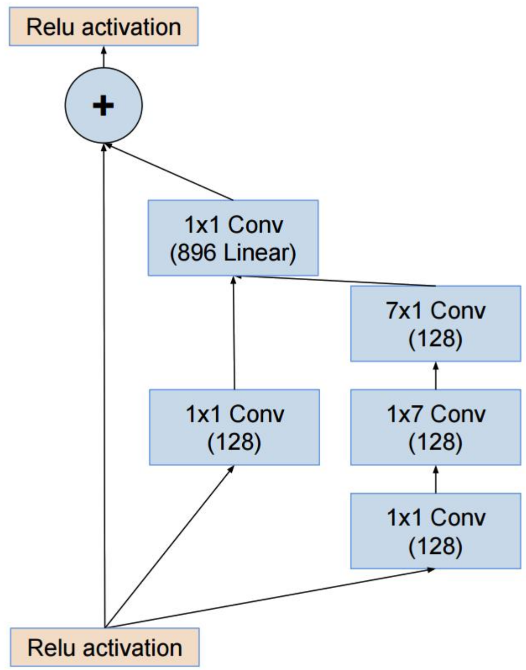
from Kaiming He slides "Deep residual learning for image recognition." ICML. 2016.

Inception-V4 / -ResNet-V2

Deep, modular and state-of-the-art

Achieves 3.1% top-5 classification error on imagenet





Inception-v4, inception-resnet and the impact of residual connections on learning, C. Szegedy et al., 2016

Slide credit: C. Ollion & O. Grisel, M2DS Deep Learning

Resnet variants: Stochastic Depth Networks

- DropOut at layer level
- Allows training up to 1K layers

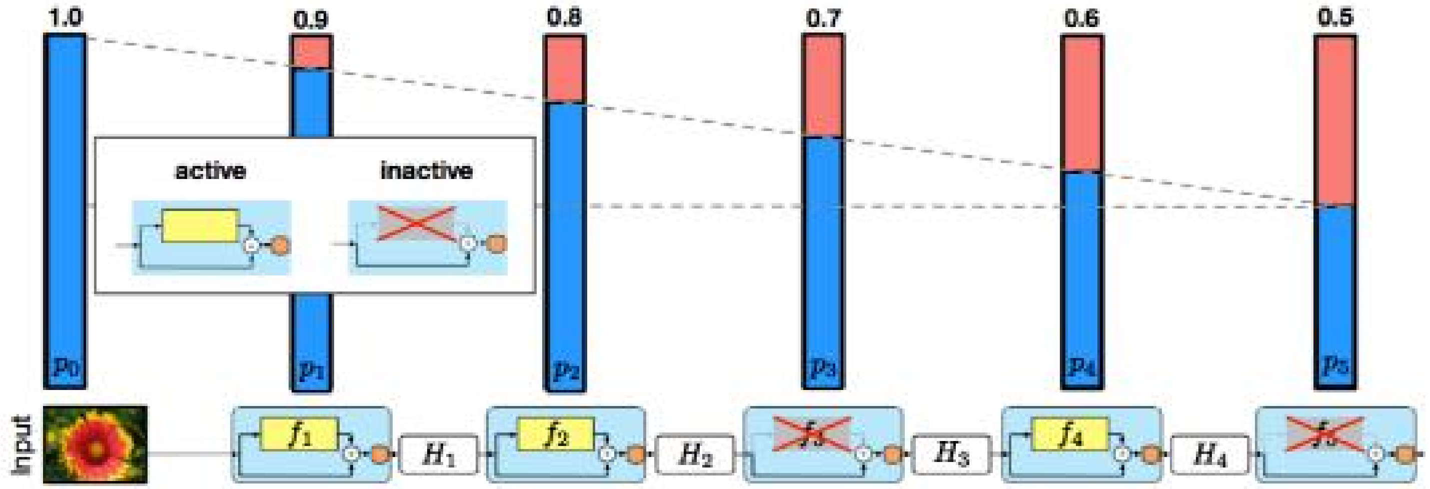
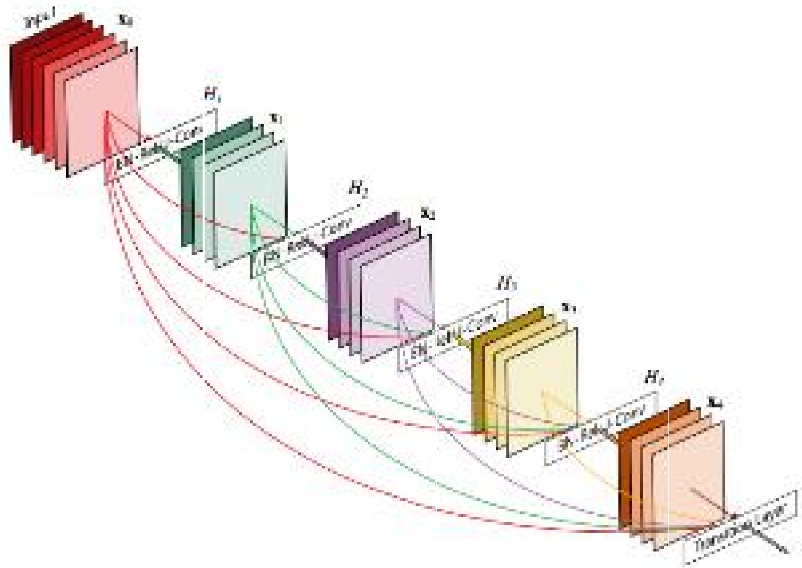


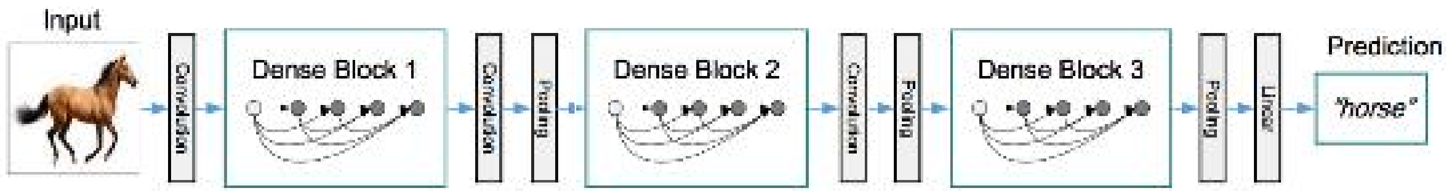
Fig. 2. The linear decay of p_ℓ illustrated on a ResNet with stochastic depth for $p_0 = 1$ and $p_L = 0.5$. Conceptually, we treat the input to the first ResBlock as H_0, which is always active.

Deep Networks with Stochastic Depth, Huang et al., ECCV 2016

Resnet variants: DenseNet

- Copying feature maps to upper layers via skip-connections
- Better reuse of parameters and redundancy avoidance

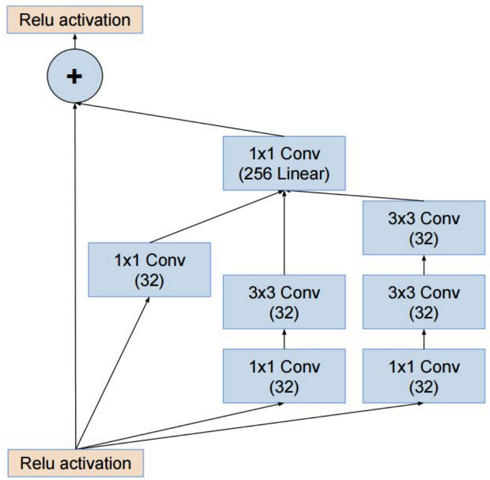


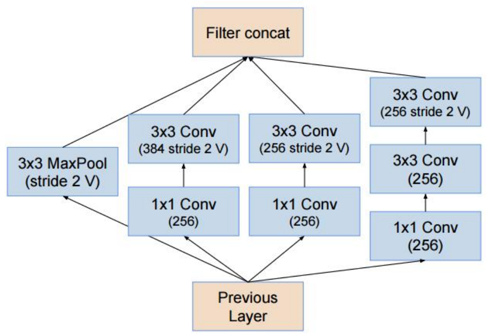


Densely Connected Convolutional Networks, Huang et al., CVPR 2017

Inception-V4 / -ResNet-V2

More building blocks engineering...

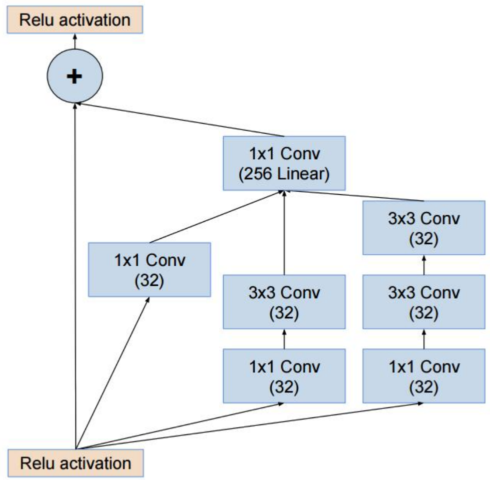


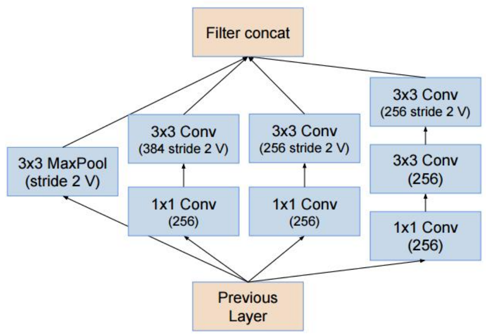


Inception-v4, inception-resnet and the impact of residual connections on learning, C. Szegedy et al., 2016

Inception-V4 / -ResNet-V2

More building blocks engineering...



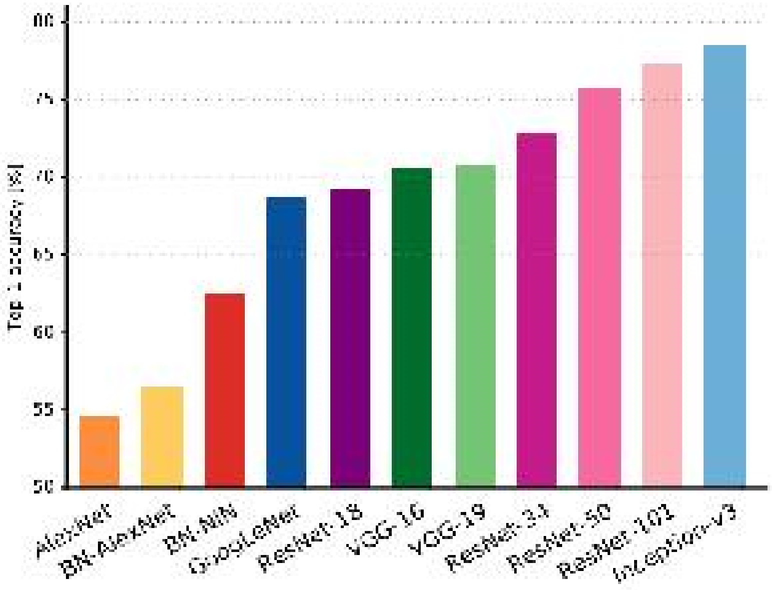


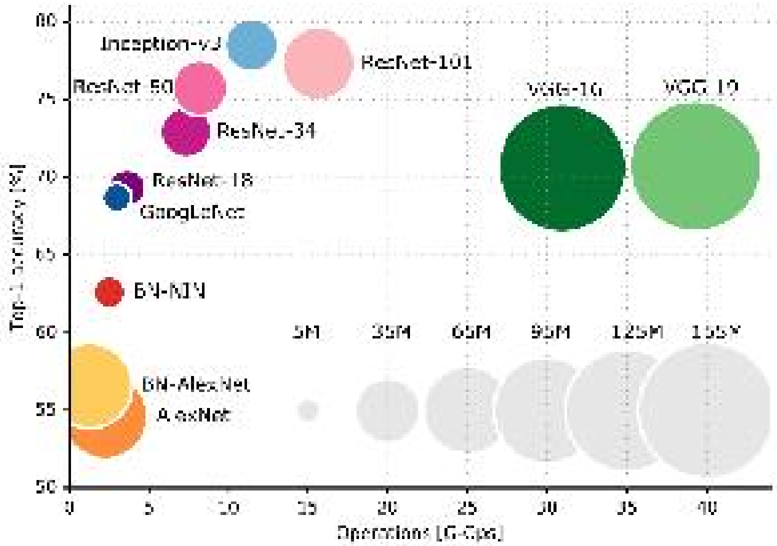
- Active area or research
- See also DenseNets, Wide ResNets, Fractal ResNets, ResNeXts, Pyramidal ResNets...

Inception-v4, inception-resnet and the impact of residual connections on learning, C. Szegedy et al., 2016

Comparison of models

Top 1-accuracy, performance and size on ImageNet

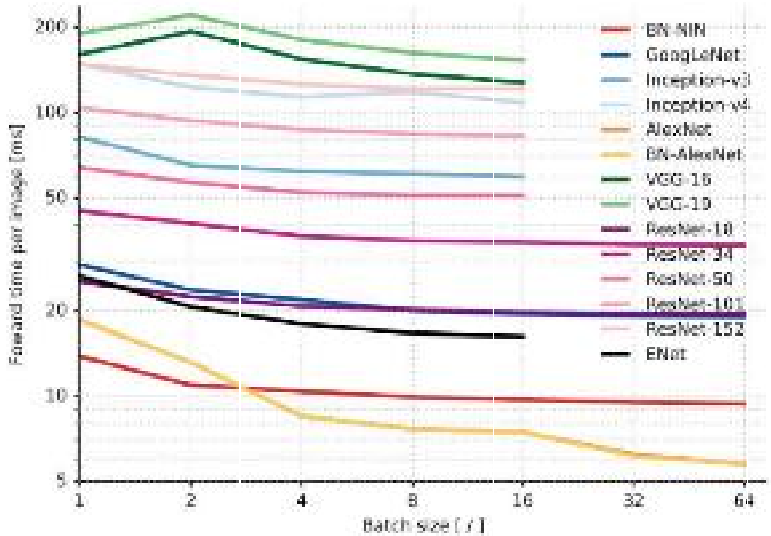


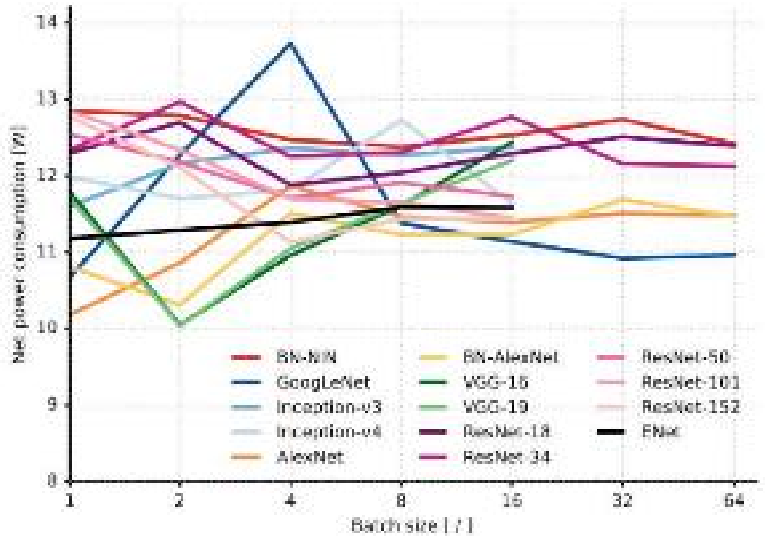


An Analysis of Deep Neural Network Models for Practical Applications, Canziani et al., 2016

Comparison of models

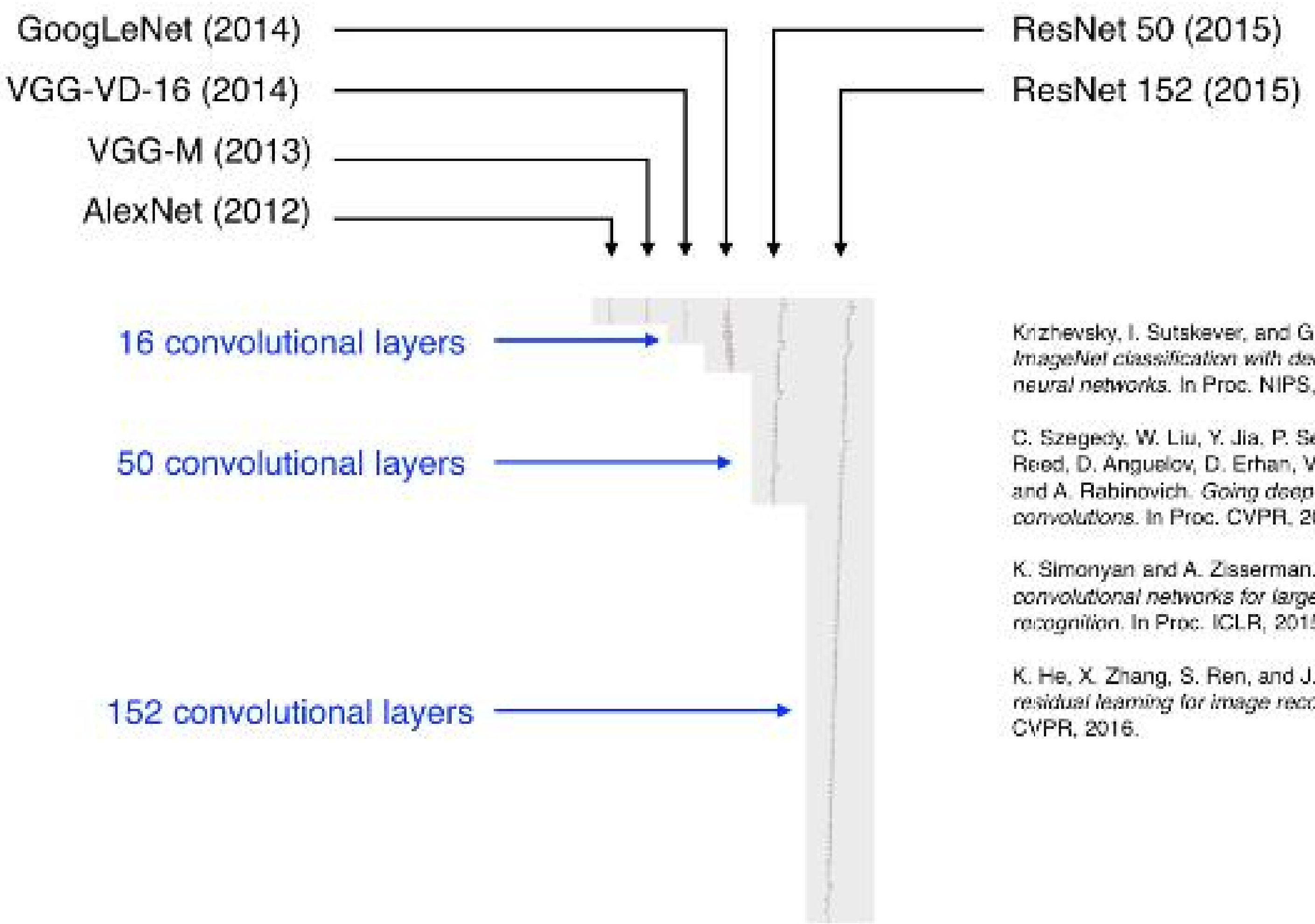
Forward pass time and power consumption





An Analysis of Deep Neural Network Models for Practical Applications, Canziani et al., 2016

Comparison of models



Krizhevsky, I. Sutskever, and G. E. Hinton. *ImageNet classification with deep convolutional neural networks*. In Proc. NIPS, 2012.

C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. Reed, D. Anguelov, D. Erhan, V. Vanhoucke, and A. Rabinovich. *Going deeper with convolutions*. In Proc. CVPR, 2015.

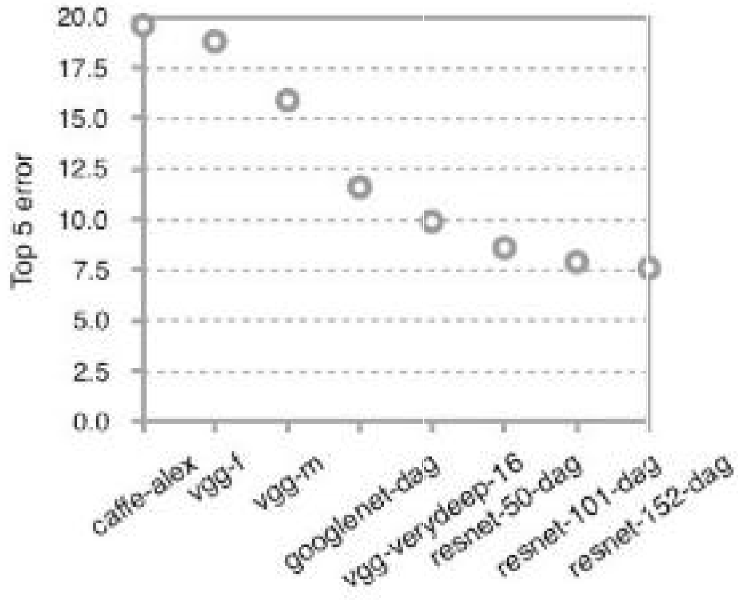
K. Simonyan and A. Zisserman. *Very deep convolutional networks for large-scale image recognition*. In Proc. ICLR, 2015.

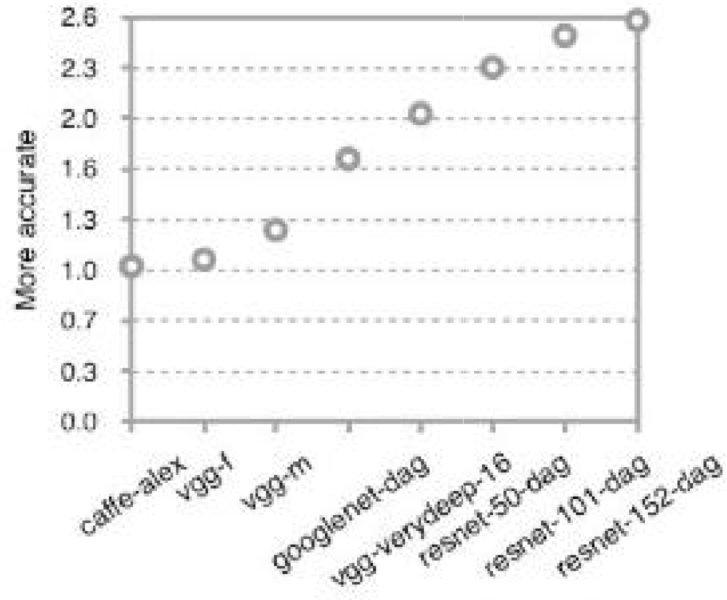
K. He, X. Zhang, S. Ren, and J. Sun. *Deep residual learning for image recognition*. In Proc. CVPR, 2016.

Slide credit: A. Vedaldi

Comparison of models

3 x more accurate in 3 years



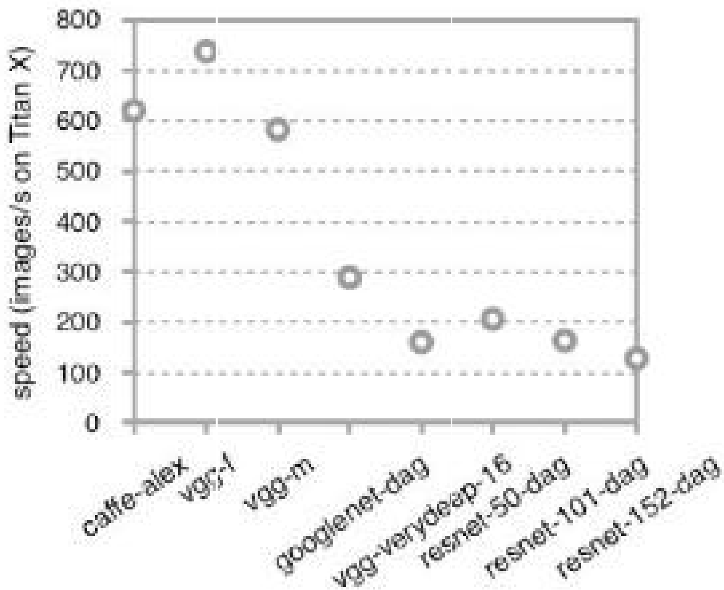


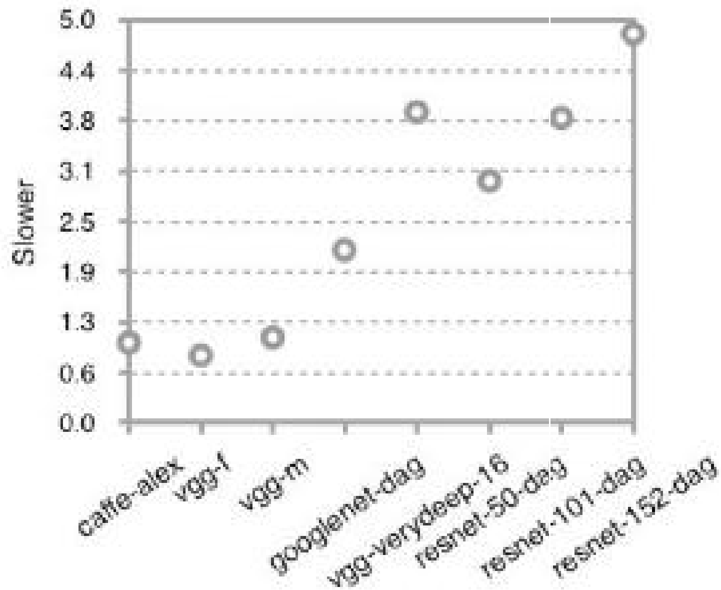
101 ResNet Layers same size/speed as 16 VGG-VD layers

Slide credit: A. Vedaldi

Comparison of models

Number of parameters is about the same

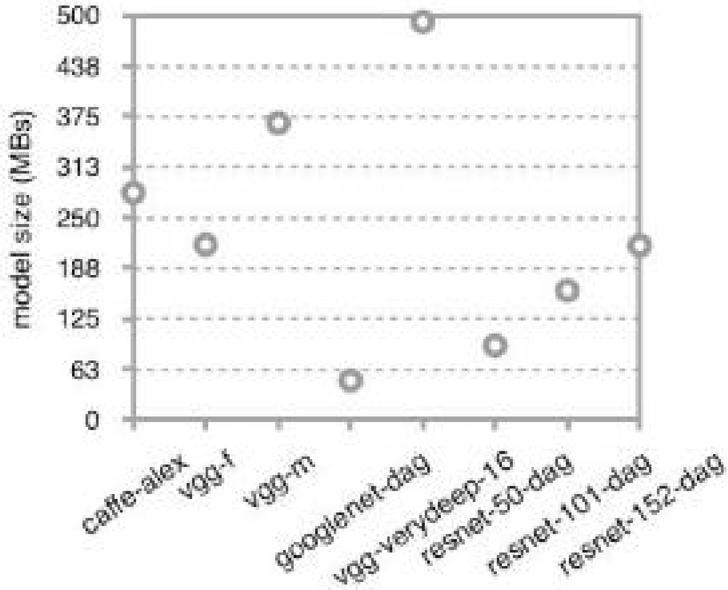


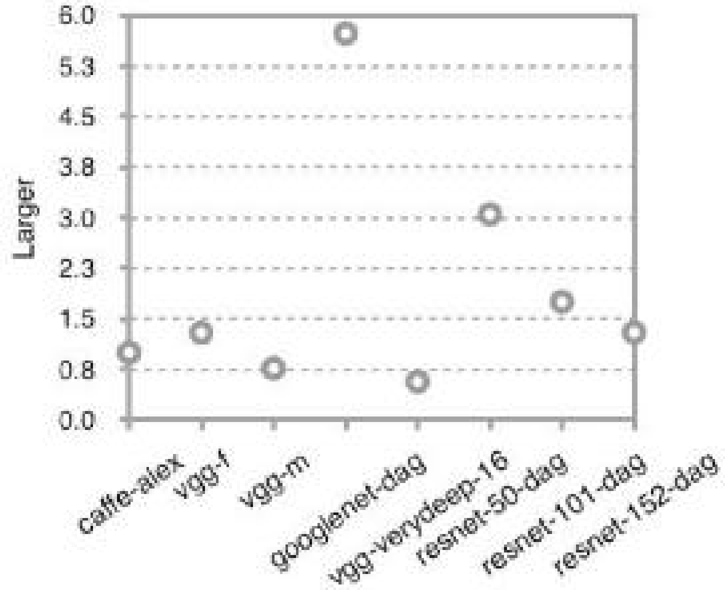


Slide credit: A. Vedaldi

Comparison of models

5 x slower





Slide credit: A. Vedaldi

Recap

- Convolutions and convolutional layers
  - activation functions
  - pooling
  - dilated convolutions
- Regularization for deep neural networks:
  - DropOut
  - Batch Normalization
- Popular neural network architectures:
  - LeNet5, AlexNet, VGG, Inception/GoogLeNet, ResNet, DenseNet

Up next:

Under the hood of neural networks