Deep learning

8.2. Networks for image classification

François Fleuret

https://fleuret.org/dlc/

UNIVERSITÉ DE GENÈVE

Standard convnets

The standard model for image classification are the LeNet family (LeCun et al., 1989, 1998), and its modern variants such as AlexNet (Krizhevsky et al., 2012) and VGGNet (Simonyan and Zisserman, 2014).

They share a common structure of several convolutional layers seen as a feature extractor, followed by fully connected layers seen as a classifier.

The performance of AlexNet was a wake-up call for the computer vision community, as it vastly out-performed other methods in spite of its simplicity.

Recent advances rely on moving from standard convolutional layers to more complex local architectures to reduce the model size.

`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 here `weights = 'IMAGENET1K_V1'` to the constructor(s). This may involve an heavy download given there size.

The networks from PyTorch listed in the coming slides may differ slightly from the reference papers which introduced them historically.

LeNet5 (LeCun et al., 1989). 10 classes, input $1 \times 28 \times 28$.

```
(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 (256 -> 120)
  (1): ReLU (inplace)
  (2): Linear (120 -> 84)
  (3): ReLU (inplace)
  (4): Linear (84 -> 10)
)
```


Notes

Although debatable, a LeNet5 can be seen as a "feature extractor" consisting of several convolution layers, and a classifier made of fully connected layers, that is formally a standard multilayer perceptron.

Alexnet (Krizhevsky et al., 2012). $1,000$ classes, input $3 \times 224 \times 224$.

```
(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)
)
```


Notes

AlexNet is very similar to LeNet5 with a few differences: the input image is of size 224×224, and the initial filters are big (11×11) which is rather usual nowadays.
The classifier part contains 60 million parameters in the three linear layers. This AlexNet here outputs 1,000 values because it was trained on ImageNet.

Krizhevsky et al. used **data augmentation** during training to reduce over-fitting.

They generated $2,048$ samples from every original training example through two classes of transformations:

- crop a 224×224 image at a random position in the original 256×256, and randomly reflect it horizontally,
- apply a color transformation using a PCA model of the color distribution.

During test the prediction is averaged over five random crops and their horizontal reflections.

VGGNet19 (Simonyan and Zisserman, 2014). $1,000$ classes, input $3 \times 224 \times 224$. 16 convolutional layers + 3 fully connected layers.

```
  (features): Sequential (
    (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))
    (24): ReLU (inplace)
    (25): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (26): ReLU (inplace)
    (27): MaxPool2d (size=(2, 2), stride=(2, 2), dilation=(1, 1))
/.../
```


Notes

The VGG family of networks are bigger than LeNet and AlexNet. The main pattern is a series of several (between two and four) convolutional and ReLU layers, followed by a MaxPool to reduce the size of the signal.
The filters are all 3×3, which is way smaller than in AlexNet.

VGGNet19 (cont.)

```
(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)
)
```


Notes

The classifier of VGG is bigger than the one of AlexNet, with 120 million parameters.

We can illustrate the convenience of these pre-trained models on a simple image-classification problem.

To be sure this picture did not appear in the training data, it was not taken from the web.

```python
import PIL, torch, torchvision

# Load and normalize the image
to_tensor = torchvision.transforms.ToTensor()
img = to_tensor(PIL.Image.open('../example_images/blacklab.jpg'))
img = img.unsqueeze(0)
img = 0.5 + 0.5 * (img - img.mean()) / img.std()

# Load and evaluate the network
alexnet = torchvision.models.alexnet(weights = 'IMAGENET1K_V1')
alexnet.eval()

output = alexnet(img)

# Prints the classes
scores, indexes = output.view(-1).sort(descending = True)

class_names = eval(open('imagenet1000_clsid_to_human.txt', 'r').read())

for k in range(12):
    print(f'#{k+1} {scores[k].item():.02f} {class_names[indexes[k].item()]}')
```


Notes

Remember that PyTorch models expect as input a batch of samples. To apply a model on a single RGB image, the input should be of size $1 \times 3 \times H \times W$, hence the `img.unsqueeze(0)` that adds a new dimension to the tensor.
The model is put in "eval" mode because of the dropout layers.
The `output` is of shape 1×1000, corresponding to one score for each class of ImageNet.
The remaining of the code ranks the output by descending order, and prints the top fifteen values and corresponding class names.

```
12.26 Weimaraner
10.95 Chesapeake Bay retriever
10.87 Labrador retriever
10.10 Staffordshire bullterrier, Staffordshire bull terrier
9.55 flat-coated retriever
9.40 Italian greyhound
9.31 American Staffordshire terrier, Staffordshire terrier, American pit bull terrier, pit bull terrier
9.12 Great Dane
8.94 German short-haired pointer
8.53 Doberman, Doberman pinscher
8.35 Rottweiler
8.25 kelpie
8.24 barrow, garden cart, lawn cart, wheelbarrow
8.12 bucket, pail
8.07 soccer ball
```

Weimaraner

Chesapeake Bay retriever

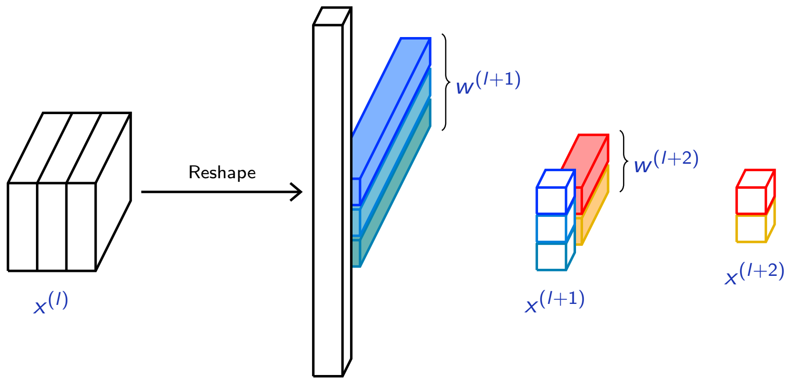
Notes

The top three results correspond to dog breeds very similar to the one on the original image. Despite some bizarre results with quite high scores down the rankings, these results show how convenient it has become to be able to download and use with few lines of code a large-scale deep model.

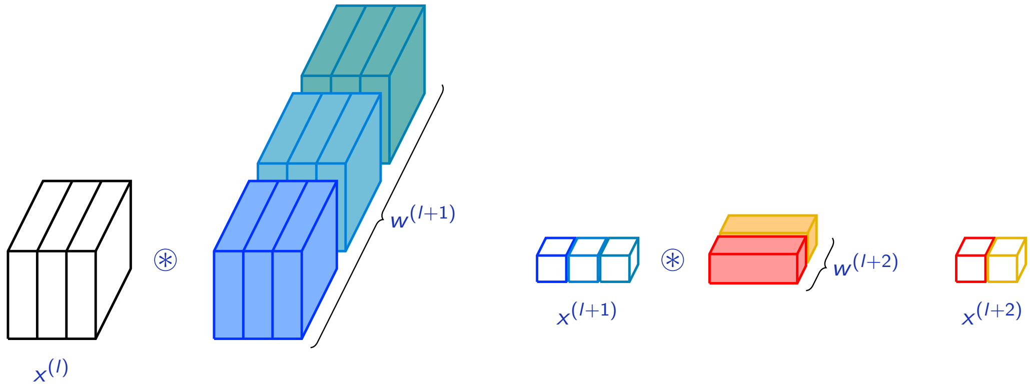
Fully convolutional networks

Standard convolutional networks reshape the tensor $x^{(l)}$ produced by the "feature extractor" composed of convolutional layers into a 1d tensor, before feeding it to the series of fully connected layers that compose the "classifier" part of the model.

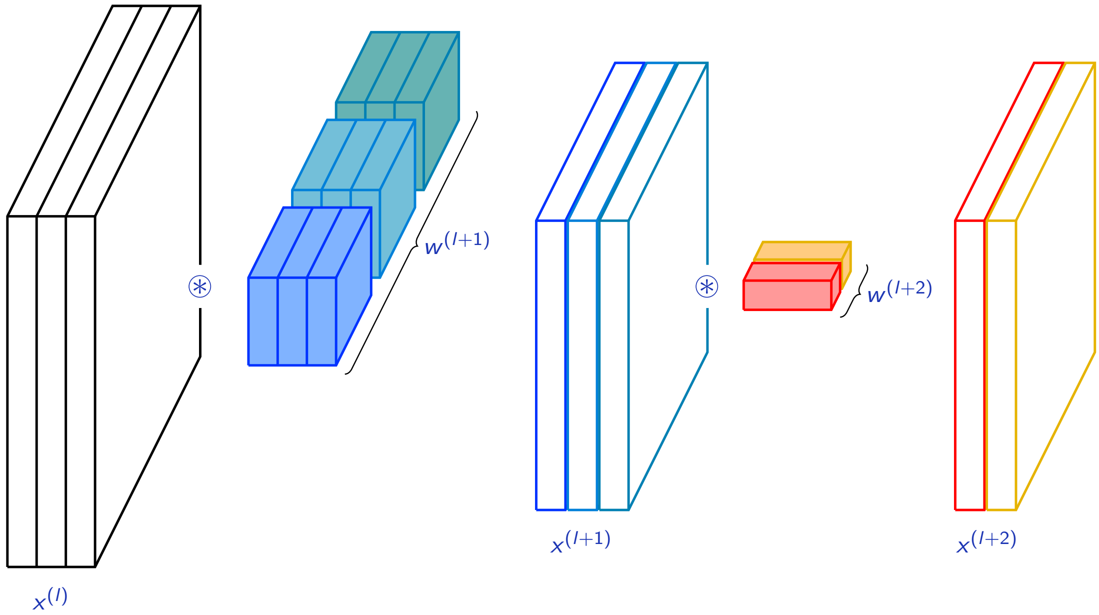
The output of every fully connected layer from there is a 1d tensor, and it is computed by taking the dot product between the 2d input tensor to the layer and the 1d weight vectors corresponding to the weight matrix rows.



Instead of reshaping the input tensor we can instead replace the fully connected layers by convolution layers whose filters are **as big as the input tensor**, hence computing a single activation per filter.



This “convolutionization” does not change anything if the input size is such that the output has a single spatial cell, however when the input is larger, **it fully re-uses computation to get a prediction at multiple locations**.



Notes

The convolutionized version of a fully connected network re-uses computation of early layers to do the computation of the classifier:
With the standard version of the AlexNet, if one wants to apply the network at multiple locations of a large image, it should be done in a sliding window fashion: Each position would be processed separately, and no computation would be shared. With the fully convolutional version, the computation of the early layers is performed only once at each location, and the classifier part receives an activation map which can be used by the convolutional filters.

We can write a routine that transforms a series of layers from a standard convnets to make it fully convolutional:

```
def convolutionize(layers, input_size):
    result_layers = []
    x = torch.zeros((1, ) + input_size)

    for m in layers:
        if isinstance(m, torch.nn.Linear):
            n = torch.nn.Conv2d(in_channels = x.size(1),
                                out_channels = m.weight.size(0),
                                kernel_size = (x.size(2), x.size(3)))
            with torch.no_grad():
                n.weight.view(-1).copy_(m.weight.view(-1))
                n.bias.view(-1).copy_(m.bias.view(-1))
            m = n

        result_layers.append(m)
        x = m(x)

    return result_layers
```

This function makes the [strong and disputable] assumption that only `nn.Linear` has to be converted.

Notes

In this `convolutionize` function, we forward a dummy tensor into the network to compute the shape of the tensors after each linear layer, and reshape their weights accordingly. When the layer is not `nn.Linear`, it is copied as is.

To apply this to AlexNet

```
model = torchvision.models.alexnet(weights = 'IMAGENET1K_V1')
print(model)

layers = list(model.features) + list(model.classifier)

model = nn.Sequential(*convolutionize(layers, (3, 224, 224)))
print(model)
```

```
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)
  )
)
```


Notes

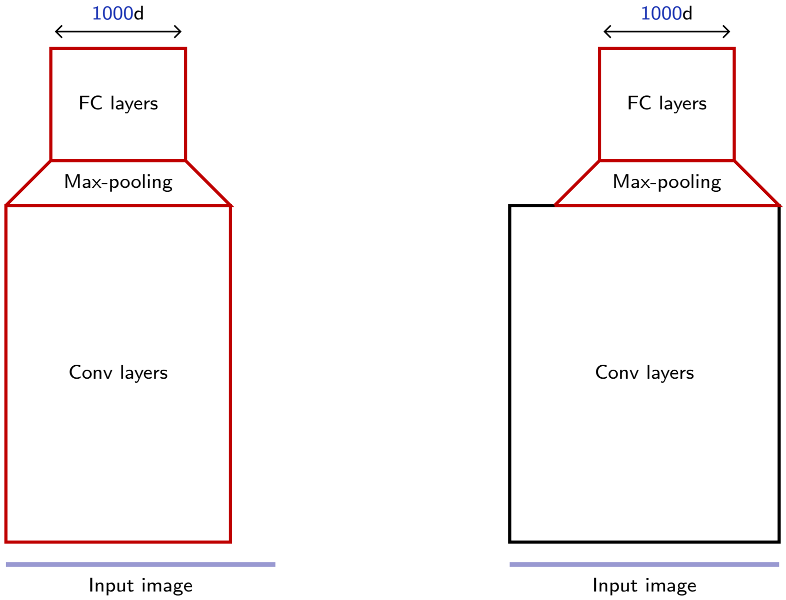
This is the structure of the standard AlexNet with fully connected layers in the classifier part, the `Linear` layers.

```
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))
  (13): Dropout (p = 0.5)
  (14): Conv2d(256, 4096, kernel_size=(6, 6), stride=(1, 1))
  (15): ReLU (inplace)
  (16): Dropout (p = 0.5)
  (17): Conv2d(4096, 4096, kernel_size=(1, 1), stride=(1, 1))
  (18): ReLU (inplace)
  (19): Conv2d(4096, 1000, kernel_size=(1, 1), stride=(1, 1))
)
```


Notes

This is the convolutionized version of AlexNet where the linear layers of the classifier have been replaced by convolution layers.

In their "overfeat" approach, Sermanet et al. (2013) combined this with a stride 1 final max-pooling to get multiple predictions.



AlexNet random cropping | Overfeat dense max-pooling

Doing so, they could afford parsing the scene at 6 scales to improve invariance.

Notes

On the left is the procedure used to run AlexNet at multiple locations on the 256×256 input: the full network is applied at several locations.
On the right is the "overfeat" version of AlexNet which computes the convolution on the full image, and only "move" the fully connected layers on the output of the feature extractor.
The part of the network shown in red is the part which needs to be computed when we want a prediction at a given location. The black part "conv layers" on the right is computed once for all.

This “convolutionization” has a practical consequence, as we can now re-use classification networks for **dense prediction** without re-training.

Also, and maybe more importantly, it blurs the conceptual boundary between “features” and “classifier” and leads to an intuitive understanding of convnet activations as gradually transitioning from appearance to semantic.

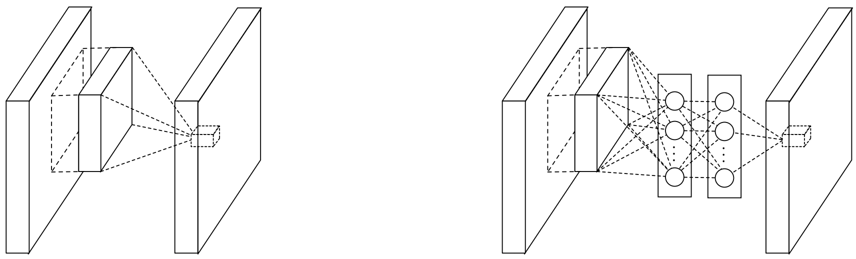
We will come back to this in lecture 9.2. “Looking at activations”.

In the case of a large output prediction map, a final prediction can be obtained by averaging the final output map channel-wise.

If the last layer is linear, the averaging can be done first, as in the residual networks (He et al., 2015).

Network in network

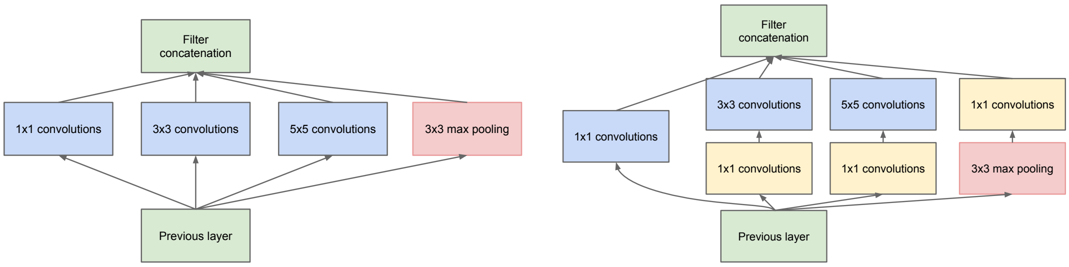
Lin et al. (2013) re-interpreted a convolution filter as a one-layer perceptron, and extended it with an "MLP convolution" (aka "network in network") to improve the capacity vs. parameter ratio.



(Lin et al., 2013)

As for the fully convolutional networks, such local MLPs can be implemented with 1×1 convolutions.

The same notion was generalized by Szegedy et al. (2015) for their GoogLeNet, through the use of module combining convolutions at multiple scales to let the optimal ones be picked during training.



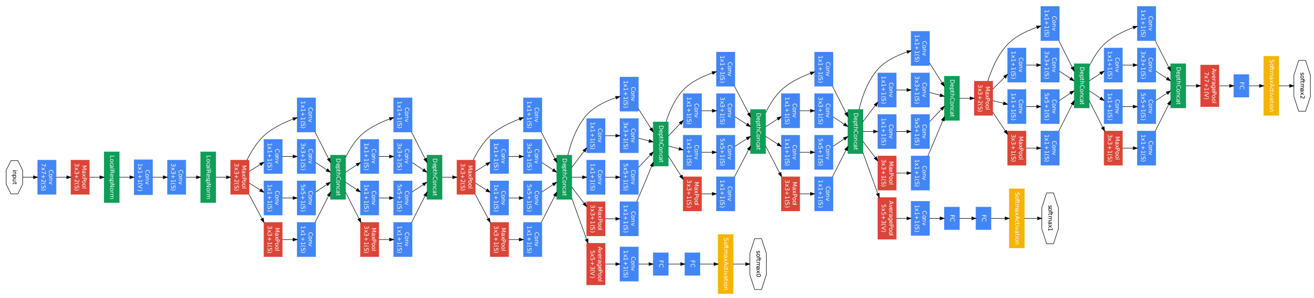
(a) Inception module, naïve version (b) Inception module with dimension reductions

(Szegedy et al., 2015)

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.

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



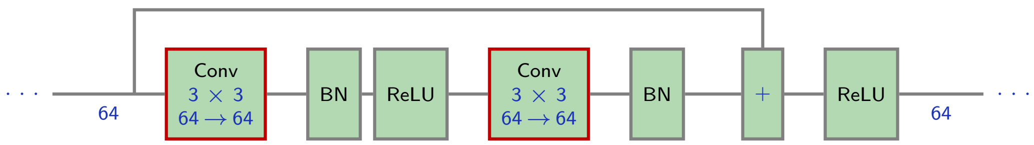
(Szegedy et al., 2015)

It was later extended with techniques we are going to see in the next slides: batch-normalization (Ioffe and Szegedy, 2015) and pass-through à la resnet (Szegedy et al., 2016).

Residual networks

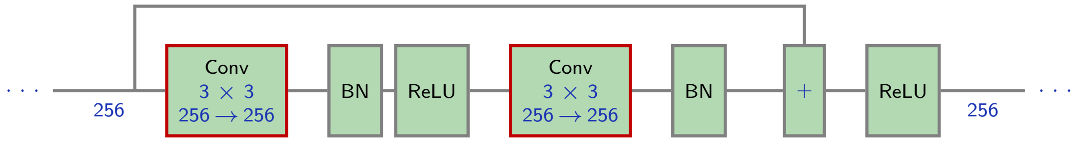
We already saw the structure of the residual networks and how well they perform on CIFAR10 (He et al., 2015).

The default residual block proposed by He et al. is of the form



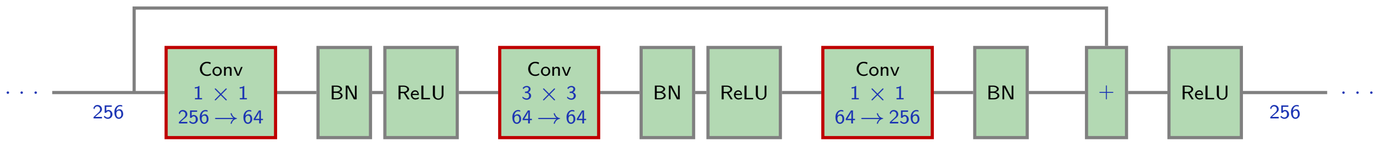
and as such requires $2 \times (3 \times 3 \times 64 + 1) \times 64 \simeq 73k$ parameters.

To apply the same architecture to ImageNet, more channels are required, e.g.



However, such a block requires $2 \times (3 \times 3 \times 256 + 1) \times 256 \simeq 1.2m$ parameters.

They mitigated that requirement with what they call a **bottleneck** block:



$$256 \times 64 + (3 \times 3 \times 64 + 1) \times 64 + 64 \times 256 \simeq 70k \text{ parameters.}$$

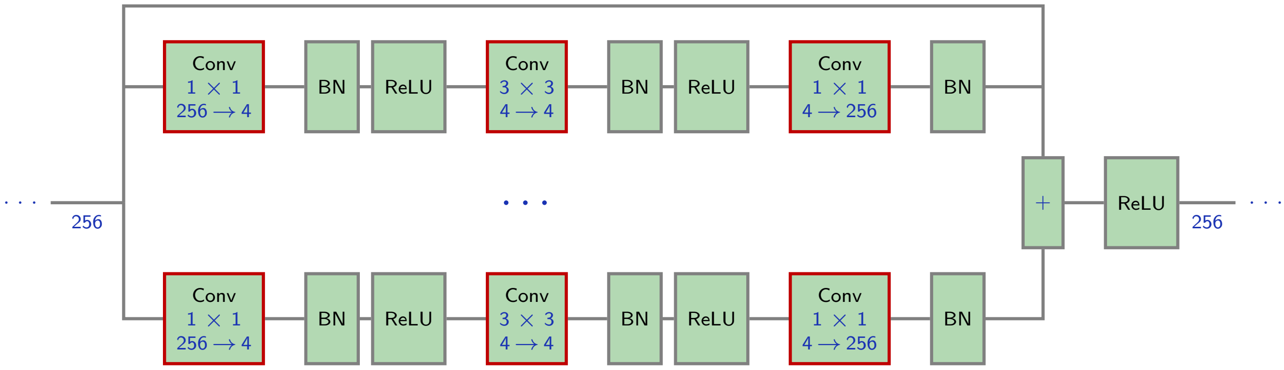
The encoding pushed between blocks is high-dimensional, but the "contextual reasoning" in convolutional layers is done on a simpler feature representation.

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.

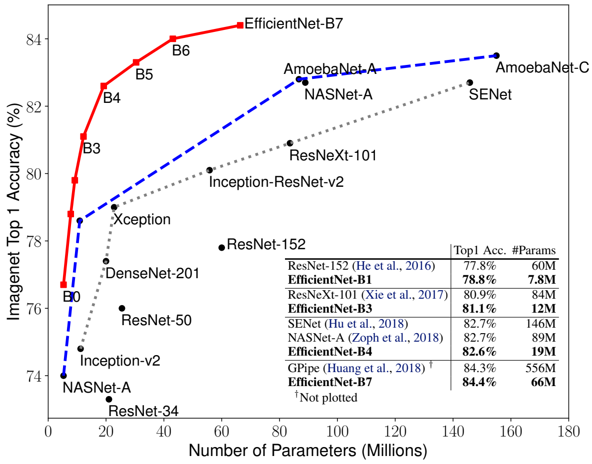
(He et al., 2015)

This was extended to the ResNeXt architecture by Xie et al. (2016), with blocks with similar number of parameters, but split into 32 "aggregated" pathways.



When equalizing the number of parameters, this architecture performs better than a standard resnet.

Tan and Le (2019) proposed to scale depth, width, and resolutions uniformly when increasing the size of a network.



	Top1 Acc.	#Params
ResNet-152 (He et al., 2016)	77.8%	60M
EfficientNet-B1	**78.8%**	**7.8M**
ResNeXt-101 (Xie et al., 2017)	80.9%	84M
EfficientNet-B3	**81.1%**	**12M**
SENet (Hu et al., 2018)	82.7%	146M
NASNet-A (Zoph et al., 2018)	82.7%	89M
EfficientNet-B4	**82.6%**	**19M**
GPipe (Huang et al., 2018) †	84.3%	556M
EfficientNet-B7	**84.4%**	**66M**

†Not plotted

Figure 1. **Model Size vs. ImageNet Accuracy.** All numbers are for single-crop, single-model. Our EfficientNets significantly outperform other ConvNets. In particular, EfficientNet-B7 achieves new state-of-the-art 84.4% top-1 accuracy but being 8.4x smaller and 6.1x faster than GPipe. EfficientNet-B1 is 7.6x smaller and 5.7x faster than ResNet-152. Details are in Table 2 and 4.

(Tan and Le, 2019)

Notes

To go from a given network to another one on a more challenging data set, the main question is how to increase this model?

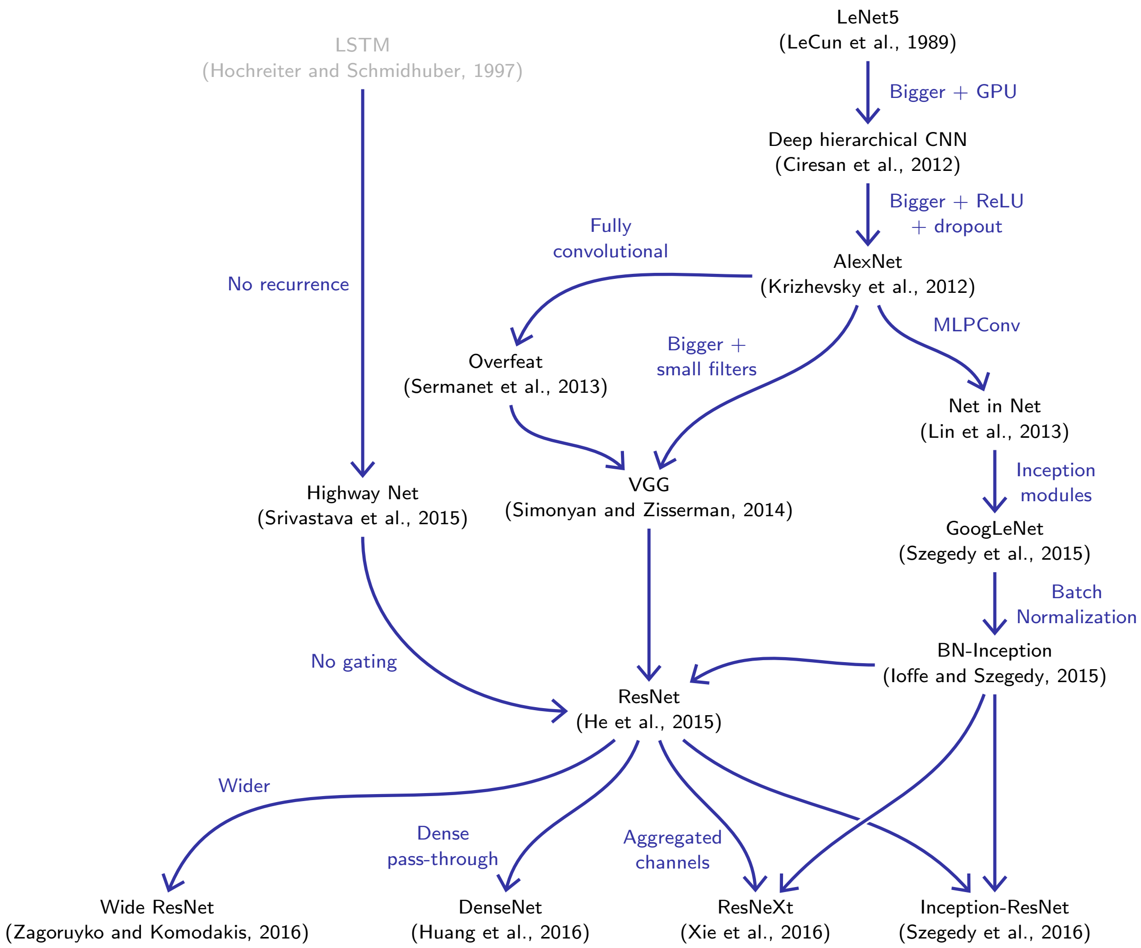
- should we increase the number of layers?
- should we increase the number of channels?
- should the resolution be increased?
- should the stride be increased?

Summary

To summarize roughly the evolution of convnets for image classification:

- standard ones are extensions of LeNet5,
- everybody loves ReLU,
- state-of-the-art networks have 100s of channels and 10s of layers,
- they can (should?) be fully convolutional,
- pass-through connections allow deeper “residual” nets,
- bottleneck local structures reduce the number of parameters,
- aggregated pathways reduce the number of parameters.

Image classification networks



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