

EE-559 – Deep learning

7.1. Computer vision tasks

François Fleuret

<https://fleuret.org/ee559/>

Mon Feb 18 13:35:37 UTC 2019

Computer vision tasks and data-sets

Computer vision tasks:

- classification,
- object detection,
- semantic or instance segmentation,

Computer vision tasks:

- classification,
- object detection,
- semantic or instance segmentation,
- other (tracking in videos, camera pose estimation, body pose estimation, 3d reconstruction, denoising, super-resolution, auto-captioning, synthesis, etc.)

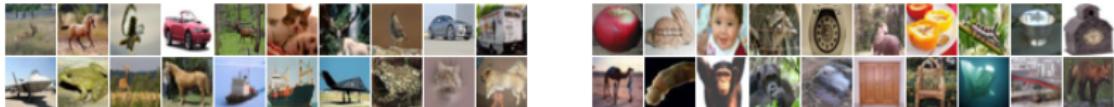
“Small scale” classification data-sets.

MNIST and Fashion-MNIST: 10 classes (digits or pieces of clothing) 50,000 train images, 10,000 test images, 28 × 28 grayscale.



(LeCun et al., 1998; Xiao et al., 2017)

CIFAR10 and CIFAR100 (10 classes and 5×20 “super classes”), 50,000 train images, 10,000 test images, 32×32 RGB



(Krizhevsky, 2009, chap. 3)

ImageNet

<http://www.image-net.org/>

This data-set is build by filling the leaves of the “Wordnet” hierarchy, called “synsets” for “sets of synonyms”.

- 21,841 non-empty synsets,
- 14,197,122 images,
- 1,034,908 images with bounding box annotations.

ImageNet

<http://www.image-net.org/>

This data-set is build by filling the leaves of the “Wordnet” hierarchy, called “synsets” for “sets of synonyms”.

- 21,841 non-empty synsets,
- 14,197,122 images,
- 1,034,908 images with bounding box annotations.

ImageNet Large Scale Visual Recognition Challenge 2012

- 1,000 classes taken among all synsets,
- 1,200,000 training, and 50,000 validation images.

Persian cat

A long-haired breed of cat

- > fungus (308)
- > person, individual, someone, :
 - > animal, animate being, beast, invertebrate (766)
 - > homeotherm, homoiotherm
 - > work animal (4)
 - > darter (0)
 - > survivor (0)
 - > range animal (0)
 - > creepy-crawly (0)
 - > domestic animal, domesticata
 - > domestic cat, house cat,
 - > Egyptian cat (0)
 - > Persian cat (0)
 - > kitty, kitty-cat, puss, p
 - > tiger cat (0)
 - > Angora, Angora cat (1)
 - > tom, tomcat (1)
 - > Siamese cat, Siamese
 - > Marx, Marx cat (0)
 - > Maltese, Maltese cat
 - > tabby, queen (0)
 - > Burmese cat (0)
 - > alley cat (0)
 - > Abyssinian, Abyssinia
 - > tabby, tabby cat (0)
 - > tortoiseshell, tortoise
 - > mouser (0)

Treemap Visualization



1662 pictures

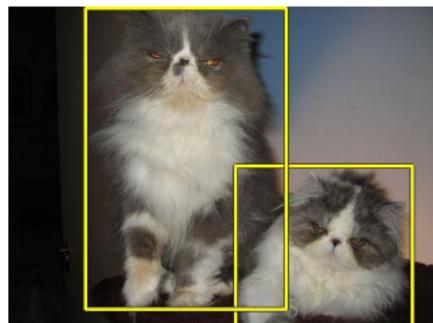
59.56% Popularity Percentile

Wordnet IDs

n02123394_2084.xml

```
<annotation>
  <folder>n02123394</folder>
  <filename>n02123394_2084</filename>
  <source>
    <database>ImageNet database</database>
  </source>
  <size>
    <width>500</width>
    <height>375</height>
    <depth>3</depth>
  </size>
  <segmented>0</segmented>
  <object>
    <name>n02123394</name>
    <pose>Unspecified</pose>
    <truncated>0</truncated>
    <difficult>0</difficult>
    <bndbox>
      <xmin>265</xmin>
      <ymin>185</ymin>
      <xmax>470</xmax>
      <ymax>374</ymax>
    </bndbox>
  </object>
  <object>
    <name>n02123394</name>
    <pose>Unspecified</pose>
    <truncated>0</truncated>
    <difficult>0</difficult>
    <bndbox>
      <xmin>90</xmin>
      <ymin>1</ymin>
      <xmax>323</xmax>
      <ymax>353</ymax>
    </bndbox>
  </object>
</annotation>
```

n02123394_2084.JPG



Cityscapes data-set

<https://www.cityscapes-dataset.com/>

Images from 50 cities over several months, each is the 20th image from a 30 frame video snippets (1.8s). Meta-data about vehicle position + depth.

- 30 classes
 - flat: road, sidewalk, parking, rail track
 - human: person, rider
 - vehicle: car, truck, bus, on rails, motorcycle, bicycle, caravan, trailer
 - construction: building, wall, fence, guard rail, bridge, tunnel
 - object: pole, pole group, traffic sign, traffic light
 - nature: vegetation, terrain
 - sky: sky
 - void: ground, dynamic, static
- 5,000 images with fine annotations
- 20,000 images with coarse annotations.

Cityscapes fine annotations (5,000 images)



Cityscapes coarse annotations (20,000 images)



Tasks and performance measures

Image classification consists of predicting its class, which is often the class of the “main object” visible in it.

The standard performance measures are:

- The **error rate** $\hat{P}(f(X) \neq Y)$ or conversely the **accuracy** $\hat{P}(f(X) = y)$,
- the **balanced error rate** (BER) $\frac{1}{C} \sum_{y=1}^C \hat{P}(f(X) \neq y \mid Y = y)$.

In the two-class case, we can define the True Positive (TP) rate as $\hat{P}(f(X) = 1 \mid Y = 1)$ and the False Positive (FP) rate as $\hat{P}(f(X) = 1 \mid Y = 0)$.

The ideal algorithm would have $TP \simeq 1$ and $FP \simeq 0$.

In the two-class case, we can define the True Positive (TP) rate as $\hat{P}(f(X) = 1 \mid Y = 1)$ and the False Positive (FP) rate as $\hat{P}(f(X) = 1 \mid Y = 0)$.

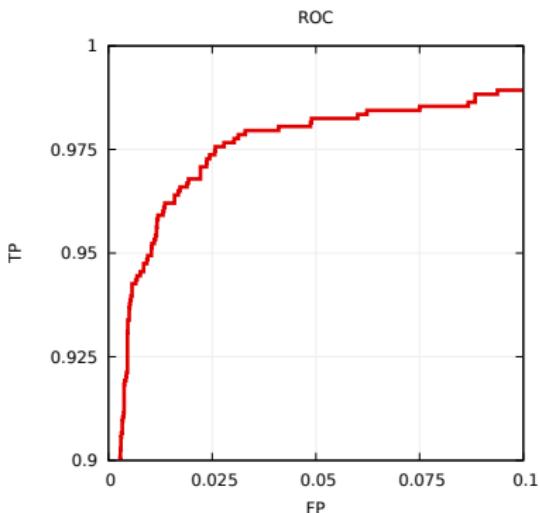
The ideal algorithm would have $TP \simeq 1$ and $FP \simeq 0$.

Most of the algorithms produce a score, and the decision threshold is application-dependent:

- Cancer detection: Low threshold to get a high TP rate (you do not want to miss a cancer), at the cost of a high FP rate (it will be double-checked by a oncologist anyway),
- Image retrieval: High threshold to get a low FP rate (you do not want to bring an image that does not match the request), at the cost of a low TP rate (you have so many images that missing a lot is not an issue).

In that case, a standard performance representation is the **Receiver operating characteristic** (ROC) that shows performance at multiple thresholds.

It is the minimum increasing function above the True Positive (TP) rate $\hat{P}(f(X) = 1 | Y = 1)$ vs. the False Positive (FP) rate $\hat{P}(f(X) = 1 | Y = 0)$.



A standard measure is the **area under the curve** (AUC).

Object detection aims at predicting **classes and locations** of targets in an image. The notion of “location” is ill-defined. In the standard setup, the output of the predictor is a series of bounding boxes, each with a class label.

A standard performance assessment considers that a predicted bounding box \hat{B} is correct if there is an annotated bounding box B for that class, such that the **Intersection over Union** (IoU) is large enough

$$\frac{\text{area}(B \cap \hat{B})}{\text{area}(B \cup \hat{B})} \geq \frac{1}{2}.$$

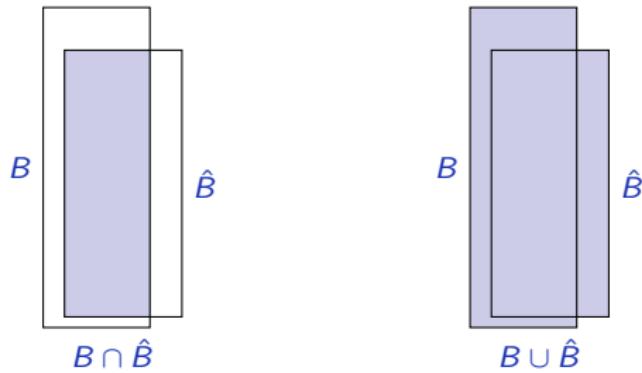


Image segmentation consists of labeling individual pixels with the class of the object it belongs to, and may also involve predicting the instance it belongs to.

The standard performance measure frames the task as a classification one. For VOC2012, the **segmentation accuracy** (SA) for a class is defined as

$$SA = \frac{n}{n + e}$$

- n number of pixels of the right class, predicted as such,
- e number of pixels erroneously labeled.

All these performance measures are debatable, and in practice they are highly application-dependent.

In spite of their weaknesses, the ones adopted as standards by the community enable an assessment of the field's "long-term progress".

The end

References

- A. Krizhevsky. Learning multiple layers of features from tiny images. Master's thesis, Department of Computer Science, University of Toronto, 2009.
- Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner. Gradient-based learning applied to document recognition. *Proceedings of the IEEE*, 86(11):2278–2324, 1998.
- H. Xiao, K. Rasul, and R. Vollgraf. Fashion-MNIST: a novel image dataset for benchmarking machine learning algorithms. *CoRR*, abs/1708.07747, 2017.

EE-559 – Deep learning

7.2. Networks for image classification

François Fleuret

<https://fleuret.org/ee559/>

Mon Feb 18 13:35:44 UTC 2019

Image classification, standard convnets

The most standard networks for image classification are the LeNet family (LeCun et al., 1998), and its modern extensions, among which 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 most standard networks for image classification are the LeNet family (LeCun et al., 1998), and its modern extensions, among which 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.

The most standard networks for image classification are the LeNet family (LeCun et al., 1998), and its modern extensions, among which 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 local complex 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()
```

`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.

`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.



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)
)
```

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)
)
```

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.

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))
  /.../
```

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)
)
```

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.

```
import PIL, torch, torchvision

# Imagenet class names
class_names = eval(open('imagenet1000_clsid_to_human.txt', 'r').read())

# Load and normalize the image
to_tensor = torchvision.transforms.ToTensor()
img = to_tensor(PIL.Image.open('example_images/blacklab.jpg'))
img = img.view(1, img.size(0), img.size(1), img.size(2))
img = 0.5 + 0.5 * (img - img.mean()) / img.std()
```

```
import PIL, torch, torchvision

# Imagenet class names
class_names = eval(open('imagenet1000_clsid_to_human.txt', 'r').read())

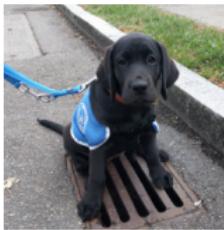
# Load and normalize the image
to_tensor = torchvision.transforms.ToTensor()
img = to_tensor(PIL.Image.open('example_images/blacklab.jpg'))
img = img.view(1, img.size(0), img.size(1), img.size(2))
img = 0.5 + 0.5 * (img - img.mean()) / img.std()

# Load and evaluate the network
alexnet = torchvision.models.alexnet(pretrained = True)
alexnet.eval()

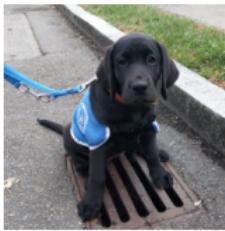
output = alexnet(img)

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

for k in range(15):
    print('%.02f' % scores[k].item(), class_names[indexes[k].item()])
```



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



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



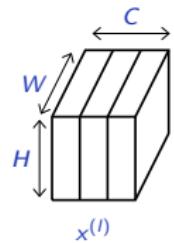
Weimaraner



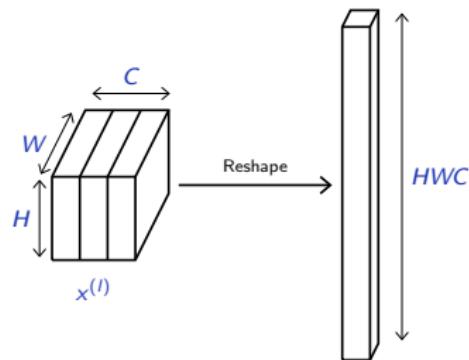
Chesapeake Bay retriever

Fully convolutional networks

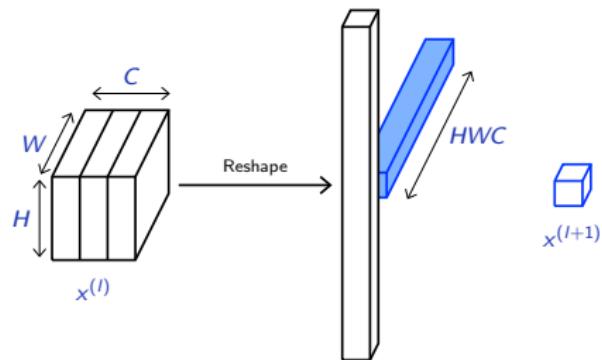
In many applications, standard convolutional networks are made **fully convolutional** by converting their fully connected layers to convolutional ones.



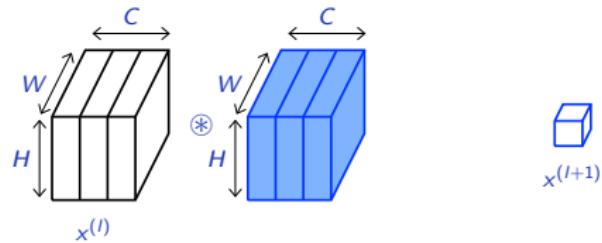
In many applications, standard convolutional networks are made **fully convolutional** by converting their fully connected layers to convolutional ones.



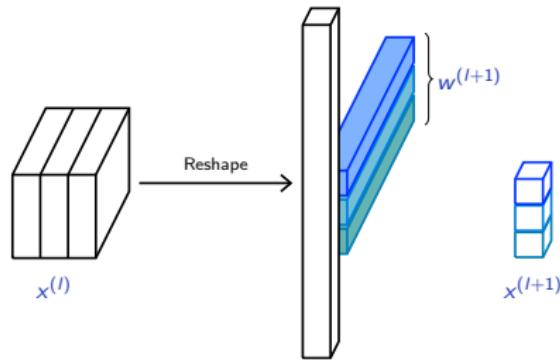
In many applications, standard convolutional networks are made **fully convolutional** by converting their fully connected layers to convolutional ones.



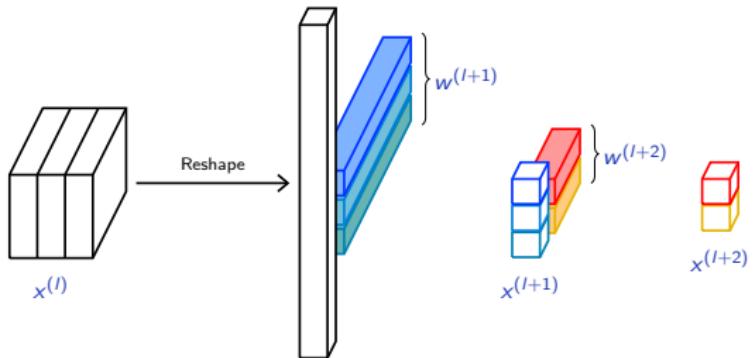
In many applications, standard convolutional networks are made **fully convolutional** by converting their fully connected layers to convolutional ones.



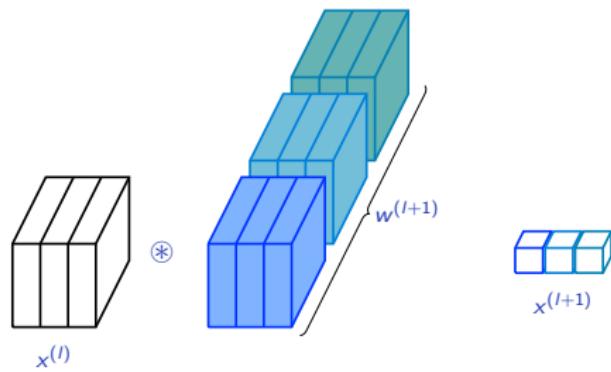
In particular multiple 1×1 convolutions can be interpreted as computing a fully-connected layer at every location of an activation map.



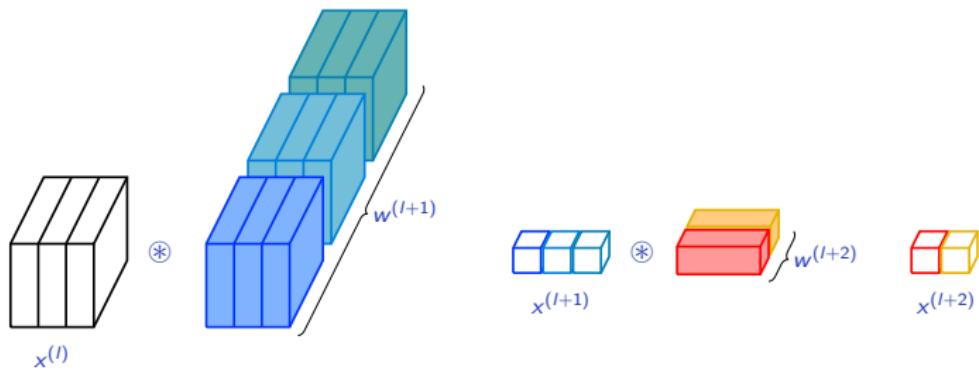
In particular multiple 1×1 convolutions can be interpreted as computing a fully-connected layer at every location of an activation map.



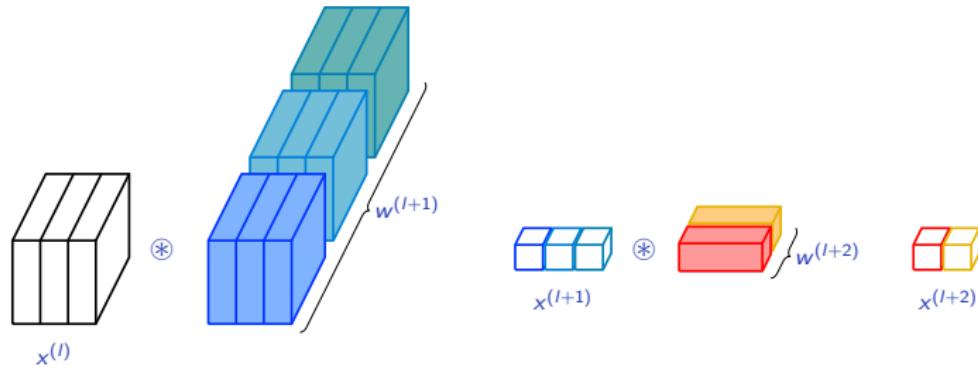
In particular multiple 1×1 convolutions can be interpreted as computing a fully-connected layer at every location of an activation map.



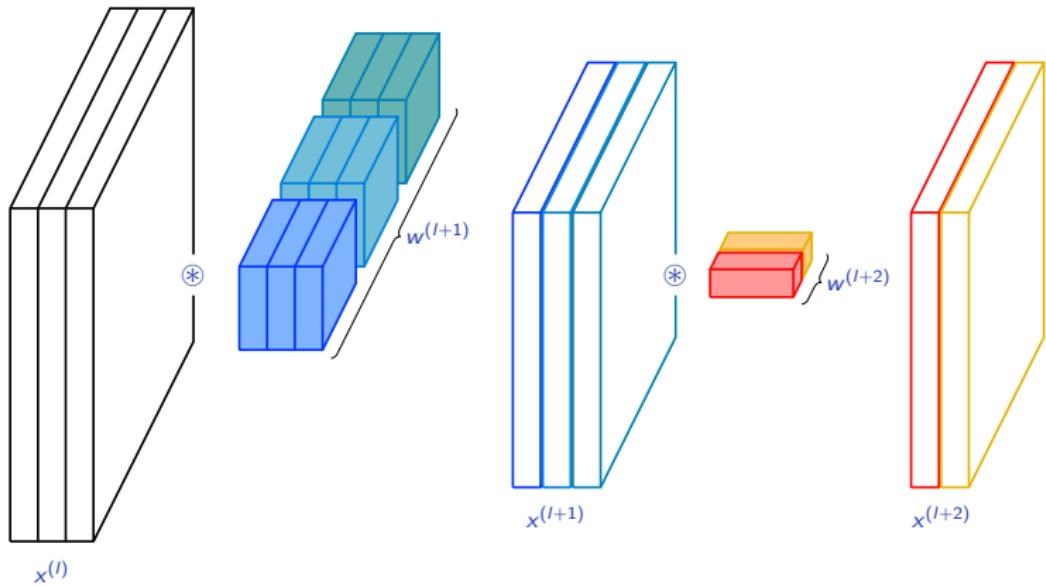
In particular multiple 1×1 convolutions can be interpreted as computing a fully-connected layer at every location of an activation map.



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



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



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.

To apply this to AlexNet

```
model = torchvision.models.alexnet(pretrained = True)
print(model)

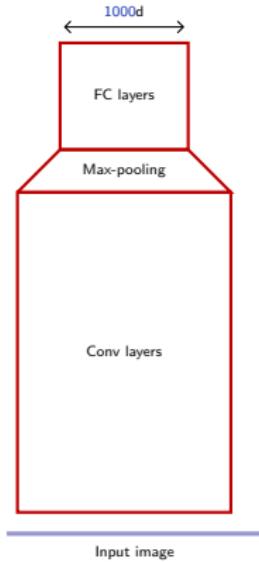
layers = list(model.features) + list(model.classifier)

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)
    )
)
```

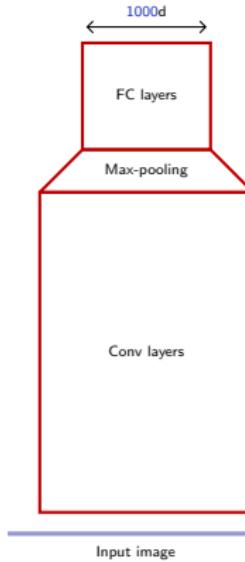
```
Sequential (
  (0): Conv2d(3, 64, kernel_size=(11, 11), stride=(4, 4), padding=(2, 2))
  (1): ReLU (inplace)
  (2): MaxPool2d (size=(3, 3), stride=(2, 2), dilation=(1, 1))
  (3): Conv2d(64, 192, kernel_size=(5, 5), stride=(1, 1), padding=(2, 2))
  (4): ReLU (inplace)
  (5): MaxPool2d (size=(3, 3), 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))
)
```

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



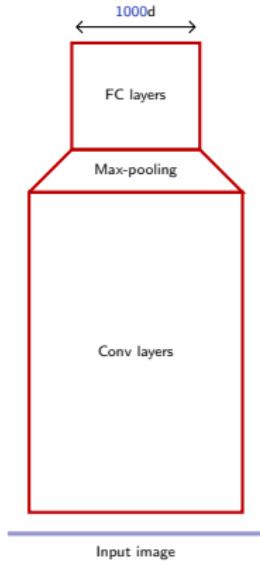
AlexNet random cropping

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



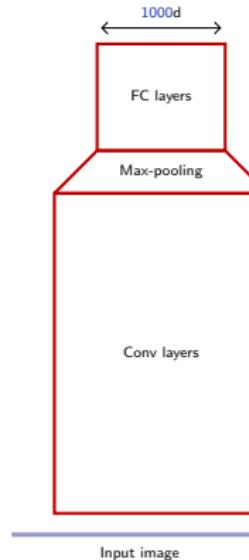
AlexNet random cropping

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



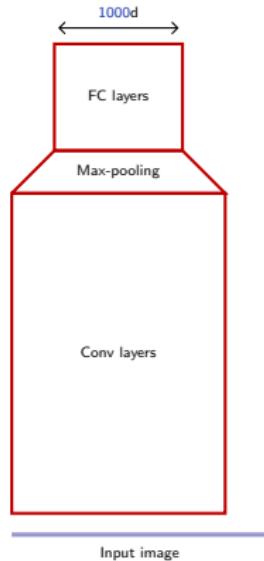
AlexNet random cropping

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



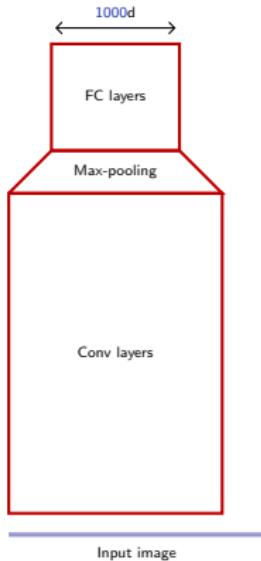
AlexNet random cropping

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

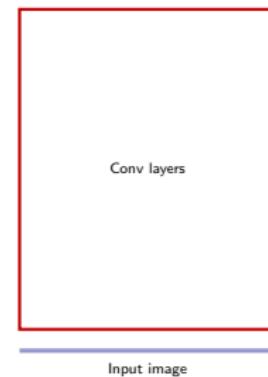


AlexNet random cropping

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

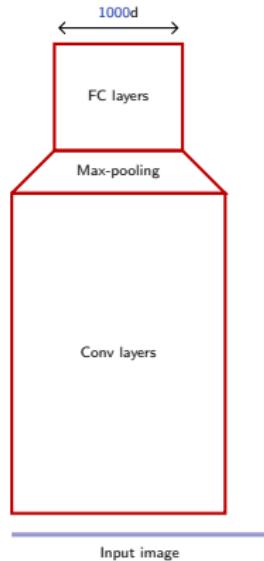


AlexNet random cropping

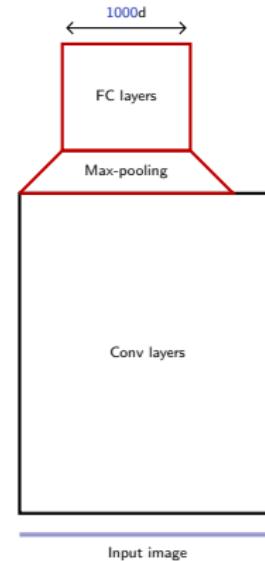


Overfeat dense max-pooling

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

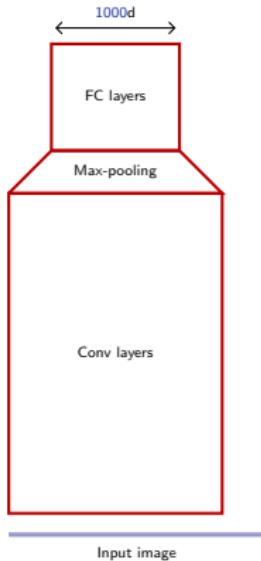


AlexNet random cropping

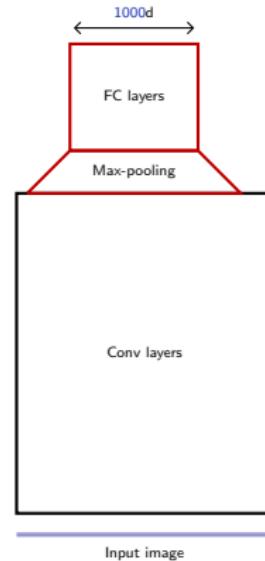


Overfeat dense max-pooling

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

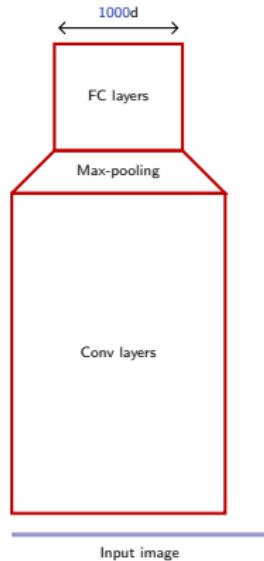


AlexNet random cropping

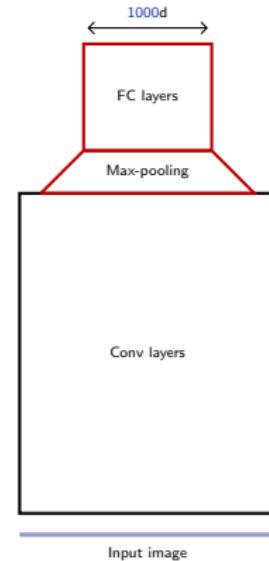


Overfeat dense max-pooling

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

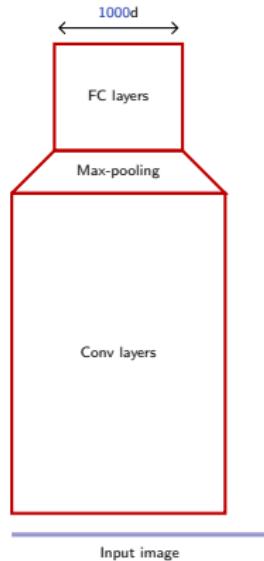


AlexNet random cropping

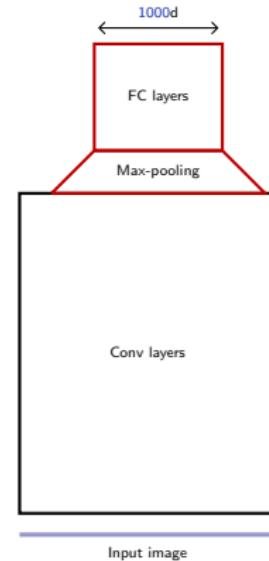


Overfeat dense max-pooling

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

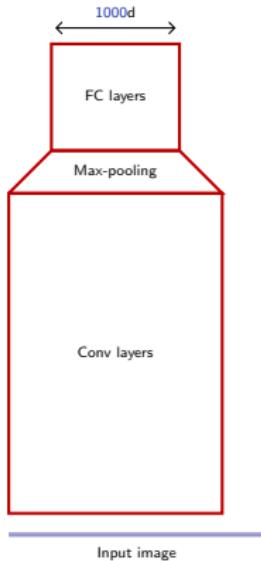


AlexNet random cropping

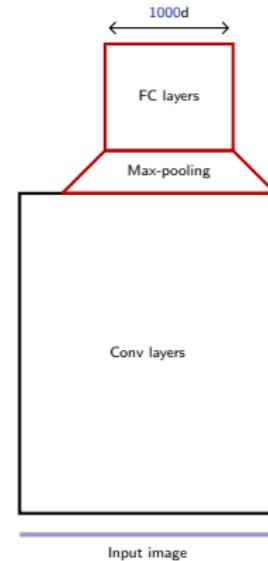


Overfeat dense max-pooling

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

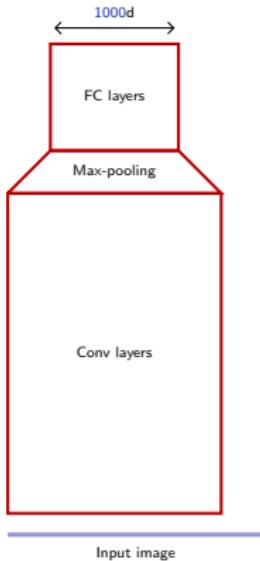


AlexNet random cropping

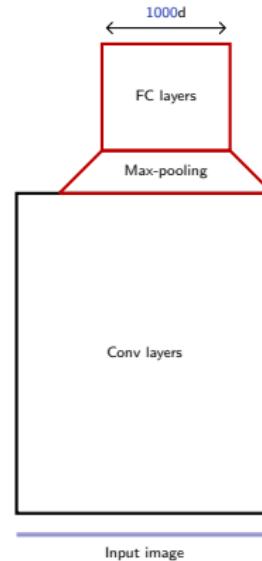


Overfeat dense max-pooling

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.

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

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

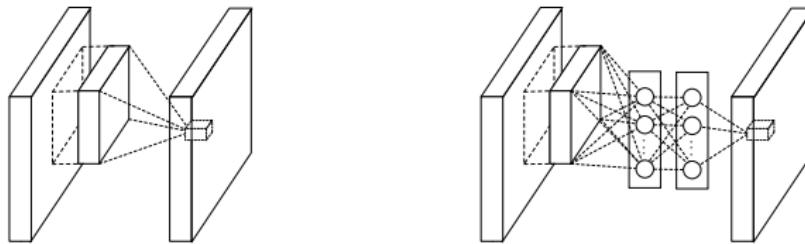
Also, and maybe more importantly, it blurs the conceptual boundary between “features” and “classifier” and leads to an intuitive understanding of convnet activations as gradually transitioning from appearance to semantic.

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).

Image classification, network in network

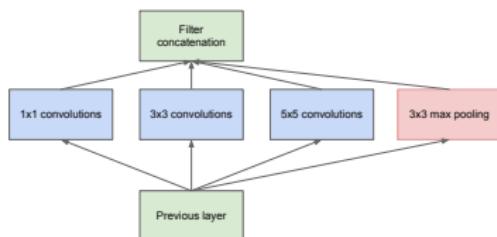
Lin et al. (2013) re-interpreted a convolution filter as a one-layer perceptron, and extended it with an “MLP convolution” (aka “network in network”) to improve the capacity vs. parameter ratio.



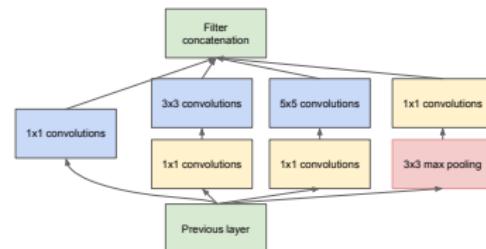
(Lin et al., 2013)

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



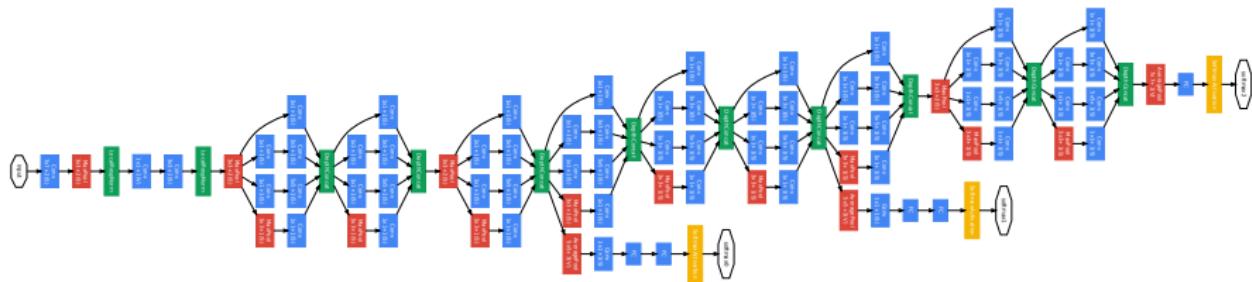
(b) Inception module with dimension reductions

(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).



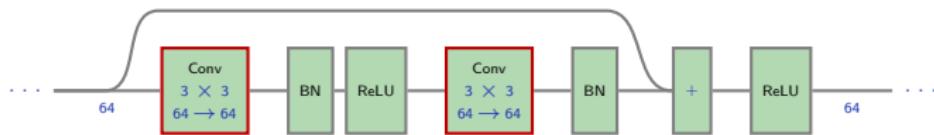
(Szegedy et al., 2015)

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).

Image classification, residual networks

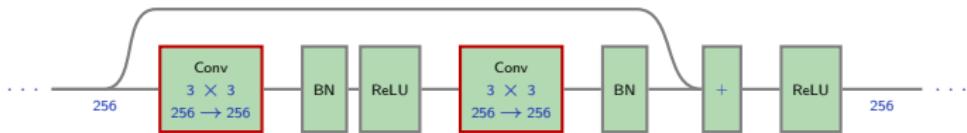
We already saw the structure of the residual networks and how well they perform on CIFAR10 (He et al., 2015).

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



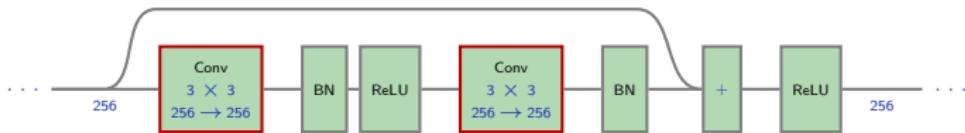
and as such requires $2 \times (3 \times 3 \times 64 + 1) \times 64 \simeq 73k$ parameters.

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



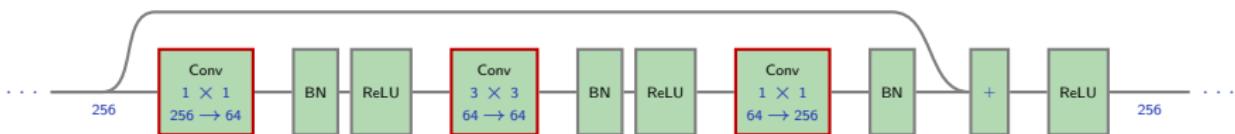
However, such a block requires $2 \times (3 \times 3 \times 256 + 1) \times 256 \simeq 1.2m$ parameters.

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



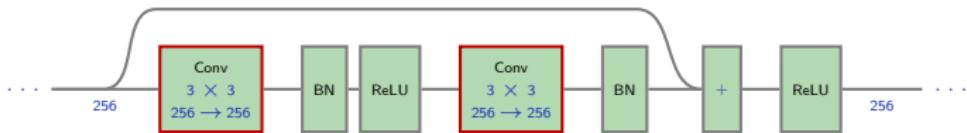
However, such a block requires $2 \times (3 \times 3 \times 256 + 1) \times 256 \simeq 1.2m$ parameters.

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



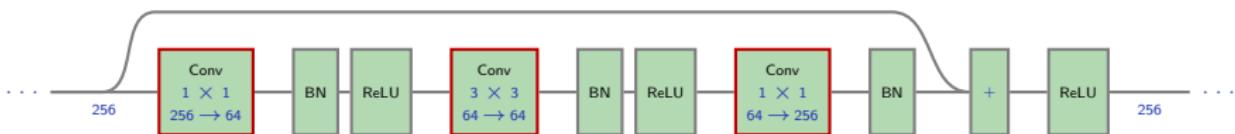
$256 \times 64 + (3 \times 3 \times 64 + 1) \times 64 + 64 \times 256 \simeq 70k$ parameters.

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:



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

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

layer name	output size	18-layer	34-layer	50-layer	101-layer	152-layer
conv1	112×112			$7 \times 7, 64, \text{stride } 2$		
conv2_x	56×56	$\left[\begin{array}{l} 3 \times 3, 64 \\ 3 \times 3, 64 \end{array} \right] \times 2$	$\left[\begin{array}{l} 3 \times 3, 64 \\ 3 \times 3, 64 \end{array} \right] \times 3$	$\left[\begin{array}{l} 1 \times 1, 64 \\ 3 \times 3, 64 \\ 1 \times 1, 256 \end{array} \right] \times 3$	$\left[\begin{array}{l} 1 \times 1, 64 \\ 3 \times 3, 64 \\ 1 \times 1, 256 \end{array} \right] \times 3$	$\left[\begin{array}{l} 1 \times 1, 64 \\ 3 \times 3, 64 \\ 1 \times 1, 256 \end{array} \right] \times 3$
conv3_x	28×28	$\left[\begin{array}{l} 3 \times 3, 128 \\ 3 \times 3, 128 \end{array} \right] \times 2$	$\left[\begin{array}{l} 3 \times 3, 128 \\ 3 \times 3, 128 \end{array} \right] \times 4$	$\left[\begin{array}{l} 1 \times 1, 128 \\ 3 \times 3, 128 \\ 1 \times 1, 512 \end{array} \right] \times 4$	$\left[\begin{array}{l} 1 \times 1, 128 \\ 3 \times 3, 128 \\ 1 \times 1, 512 \end{array} \right] \times 4$	$\left[\begin{array}{l} 1 \times 1, 128 \\ 3 \times 3, 128 \\ 1 \times 1, 512 \end{array} \right] \times 8$
conv4_x	14×14	$\left[\begin{array}{l} 3 \times 3, 256 \\ 3 \times 3, 256 \end{array} \right] \times 2$	$\left[\begin{array}{l} 3 \times 3, 256 \\ 3 \times 3, 256 \end{array} \right] \times 6$	$\left[\begin{array}{l} 1 \times 1, 256 \\ 3 \times 3, 256 \\ 1 \times 1, 1024 \end{array} \right] \times 6$	$\left[\begin{array}{l} 1 \times 1, 256 \\ 3 \times 3, 256 \\ 1 \times 1, 1024 \end{array} \right] \times 23$	$\left[\begin{array}{l} 1 \times 1, 256 \\ 3 \times 3, 256 \\ 1 \times 1, 1024 \end{array} \right] \times 36$
conv5_x	7×7	$\left[\begin{array}{l} 3 \times 3, 512 \\ 3 \times 3, 512 \end{array} \right] \times 2$	$\left[\begin{array}{l} 3 \times 3, 512 \\ 3 \times 3, 512 \end{array} \right] \times 3$	$\left[\begin{array}{l} 1 \times 1, 512 \\ 3 \times 3, 512 \\ 1 \times 1, 2048 \end{array} \right] \times 3$	$\left[\begin{array}{l} 1 \times 1, 512 \\ 3 \times 3, 512 \\ 1 \times 1, 2048 \end{array} \right] \times 3$	$\left[\begin{array}{l} 1 \times 1, 512 \\ 3 \times 3, 512 \\ 1 \times 1, 2048 \end{array} \right] \times 3$
	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.

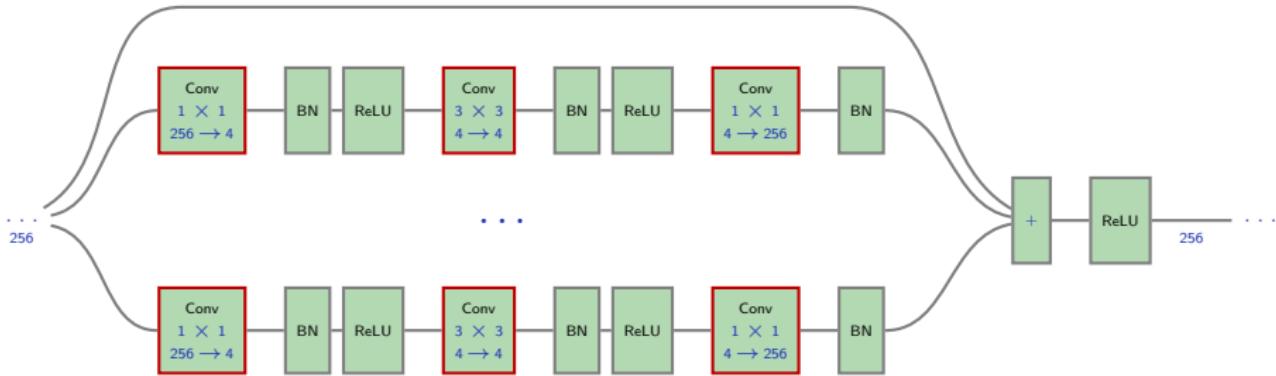
(He et al., 2015)

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

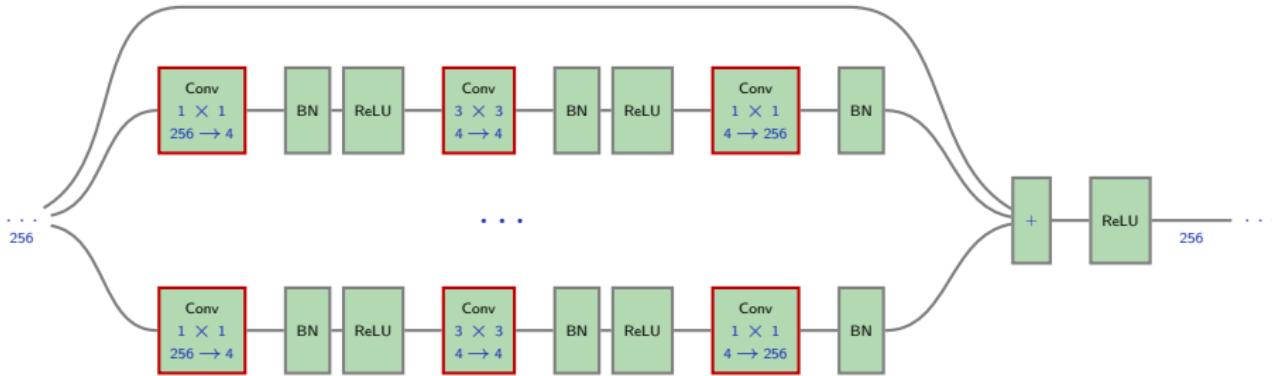
Table 5. Error rates (%) of **ensembles**. The top-5 error is on the test set of ImageNet and reported by the test server.

(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.



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.

Image classification, 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,

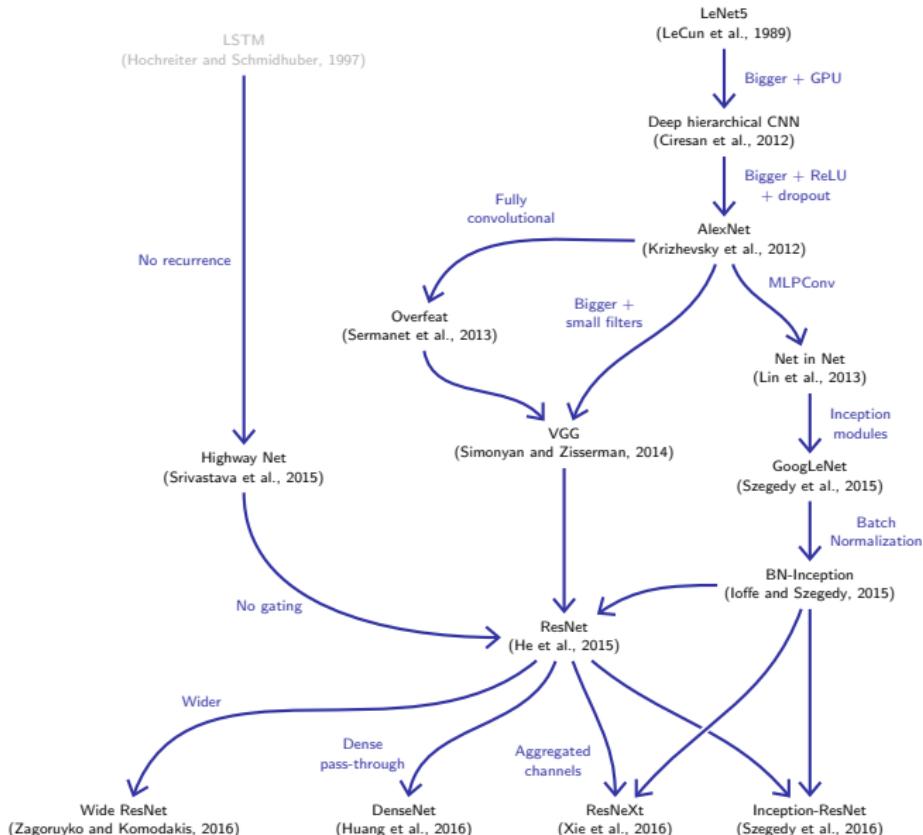
To summarize roughly the evolution of convnets for image classification:

- 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,

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



The end

References

- D. Ciresan, U. Meier, and J. Schmidhuber. Multi-column deep neural networks for image classification. *CoRR*, abs/1202.2745, 2012.
- K. He, X. Zhang, S. Ren, and J. Sun. Deep residual learning for image recognition. *CoRR*, abs/1512.03385, 2015.
- S. Hochreiter and J. Schmidhuber. Long short-term memory. *Neural Computation*, 9(8):1735–1780, 1997.
- G. Huang, Z. Liu, K. Weinberger, and L. van der Maaten. Densely connected convolutional networks. *CoRR*, abs/1608.06993, 2016.
- S. Ioffe and C. Szegedy. Batch normalization: Accelerating deep network training by reducing internal covariate shift. In *International Conference on Machine Learning (ICML)*, 2015.
- A. Krizhevsky, I. Sutskever, and G. Hinton. Imagenet classification with deep convolutional neural networks. In *Neural Information Processing Systems (NIPS)*, 2012.
- Y. LeCun, B. Boser, J. S. Denker, D. Henderson, R. E. Howard, W. Hubbard, and L. D. Jackel. Backpropagation applied to handwritten zip code recognition. *Neural Computation*, 1(4):541–551, 1989.
- Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner. Gradient-based learning applied to document recognition. *Proceedings of the IEEE*, 86(11):2278–2324, 1998.
- M. Lin, Q. Chen, and S. Yan. Network in network. *CoRR*, abs/1312.4400, 2013.

- P. Sermanet, D. Eigen, X. Zhang, M. Mathieu, R. Fergus, and Y. LeCun. Overfeat: Integrated recognition, localization and detection using convolutional networks. *CoRR*, abs/1312.6229, 2013.
- K. Simonyan and A. Zisserman. Very deep convolutional networks for large-scale image recognition. *CoRR*, abs/1409.1556, 2014.
- R. Srivastava, K. Greff, and J. Schmidhuber. Highway networks. *CoRR*, abs/1505.00387, 2015.
- C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. Reed, D. Anguelov, D. Erhan, V. Vanhoucke, and A. Rabinovich. Going deeper with convolutions. In *Conference on Computer Vision and Pattern Recognition (CVPR)*, 2015.
- C. Szegedy, S. Ioffe, and V. Vanhoucke. Inception-v4, inception-resnet and the impact of residual connections on learning. *CoRR*, abs/1602.07261, 2016.
- S. Xie, R. Girshick, P. Dollár, Z. Tu, and K. He. Aggregated residual transformations for deep neural networks. *CoRR*, abs/1611.05431.pdf, 2016.
- S. Zagoruyko and N. Komodakis. Wide residual networks. *CoRR*, abs/1605.07146, 2016.

EE-559 – Deep learning

7.3. Networks for object detection

François Fleuret

<https://fleuret.org/ee559/>

Mon Feb 18 13:35:48 UTC 2019

The simplest strategy to move from image classification to object detection is to classify local regions, at multiple scales and locations.



Parsing at fixed scale



Final list of detections

The simplest strategy to move from image classification to object detection is to classify local regions, at multiple scales and locations.



Parsing at fixed scale



Final list of detections

The simplest strategy to move from image classification to object detection is to classify local regions, at multiple scales and locations.



Parsing at fixed scale



Final list of detections

The simplest strategy to move from image classification to object detection is to classify local regions, at multiple scales and locations.



Parsing at fixed scale



Final list of detections

The simplest strategy to move from image classification to object detection is to classify local regions, at multiple scales and locations.



Parsing at fixed scale



Final list of detections

The simplest strategy to move from image classification to object detection is to classify local regions, at multiple scales and locations.



Parsing at fixed scale



Final list of detections

The simplest strategy to move from image classification to object detection is to classify local regions, at multiple scales and locations.



Parsing at fixed scale



Final list of detections

The simplest strategy to move from image classification to object detection is to classify local regions, at multiple scales and locations.



Parsing at fixed scale



Final list of detections

The simplest strategy to move from image classification to object detection is to classify local regions, at multiple scales and locations.



Parsing at fixed scale



Final list of detections

The simplest strategy to move from image classification to object detection is to classify local regions, at multiple scales and locations.

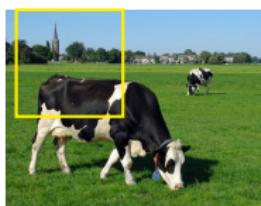


Parsing at fixed scale



Final list of detections

The simplest strategy to move from image classification to object detection is to classify local regions, at multiple scales and locations.



Parsing at fixed scale



Final list of detections

The simplest strategy to move from image classification to object detection is to classify local regions, at multiple scales and locations.



Parsing at fixed scale



Final list of detections

The simplest strategy to move from image classification to object detection is to classify local regions, at multiple scales and locations.



Parsing at fixed scale



Final list of detections

The simplest strategy to move from image classification to object detection is to classify local regions, at multiple scales and locations.

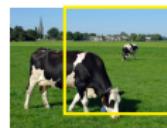


Parsing at fixed scale



Final list of detections

The simplest strategy to move from image classification to object detection is to classify local regions, at multiple scales and locations.



Parsing at fixed scale



Final list of detections

The simplest strategy to move from image classification to object detection is to classify local regions, at multiple scales and locations.



Parsing at fixed scale

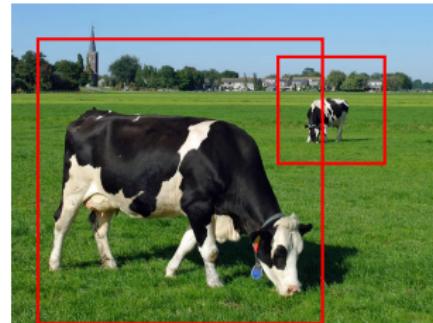


Final list of detections

The simplest strategy to move from image classification to object detection is to classify local regions, at multiple scales and locations.



Parsing at fixed scale

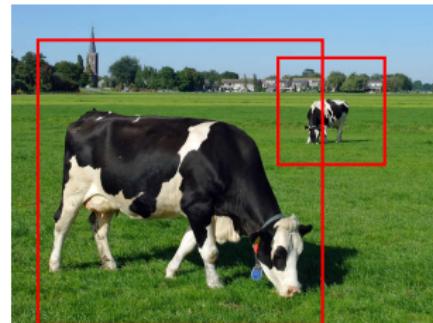


Final list of detections

The simplest strategy to move from image classification to object detection is to classify local regions, at multiple scales and locations.



Parsing at fixed scale

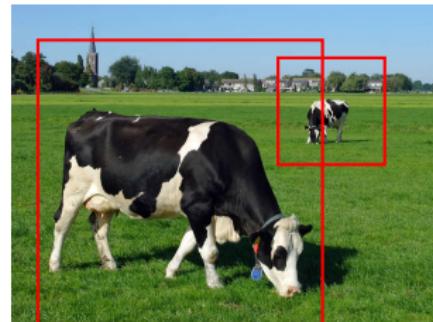


Final list of detections

The simplest strategy to move from image classification to object detection is to classify local regions, at multiple scales and locations.

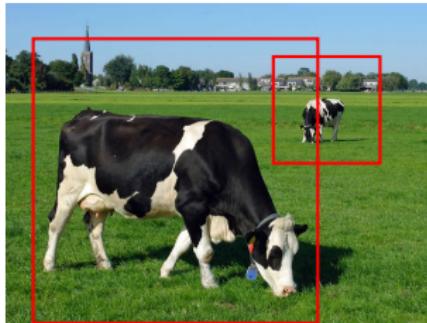


Parsing at fixed scale



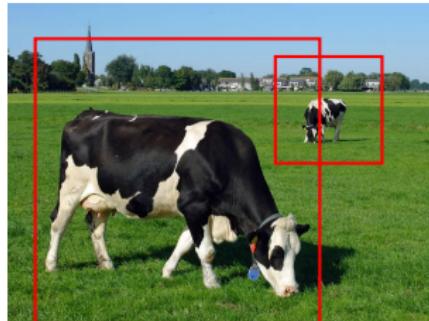
Final list of detections

The simplest strategy to move from image classification to object detection is to classify local regions, at multiple scales and locations.



Final list of detections

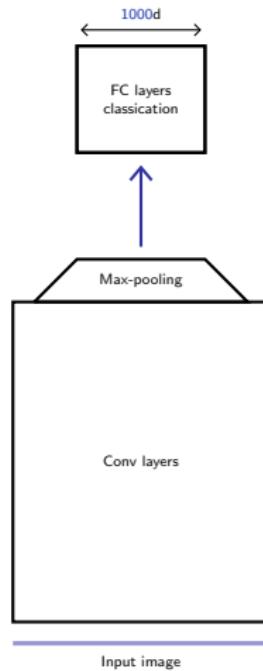
The simplest strategy to move from image classification to object detection is to classify local regions, at multiple scales and locations.



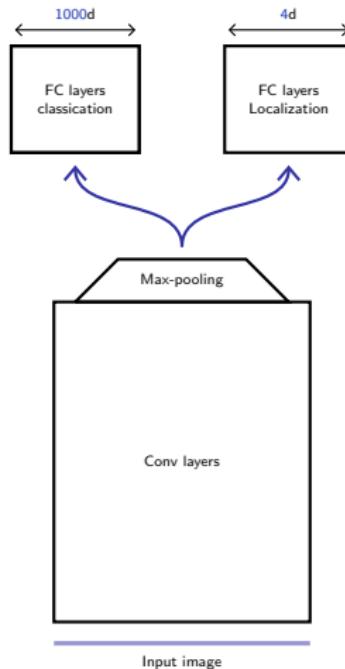
Final list of detections

This “sliding window” approach evaluates a classifier multiple times, and its computational cost increases with the prediction accuracy.

This was mitigated in overfeat (Sermanet et al., 2013) by adding a regression part to predict the object's bounding box.



This was mitigated in overfeat (Sermanet et al., 2013) by adding a regression part to predict the object's bounding box.



In the single-object case, the convolutional layers are frozen, and the localization layers are trained with a ℓ_2 loss.

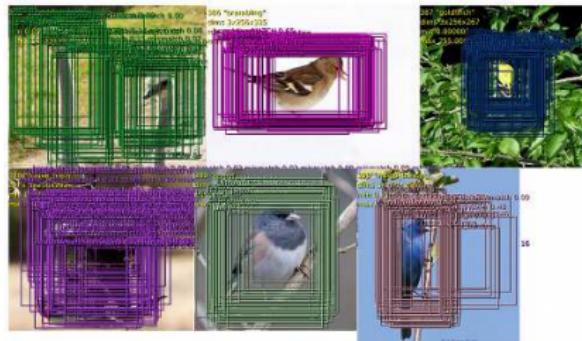


Figure 7: **Examples of bounding boxes produced by the regression network**, before being combined into final predictions. The examples shown here are at a single scale. Predictions may be more optimal at other scales depending on the objects. Here, most of the bounding boxes which are initially organized as a grid, converge to a single location and scale. This indicates that the network is very confident in the location of the object, as opposed to being spread out randomly. The top left image shows that it can also correctly identify multiple location if several objects are present. The various aspect ratios of the predicted bounding boxes shows that the network is able to cope with various object poses.

(Sermanet et al., 2013)

Combining the multiple boxes is done with an *ad hoc* greedy algorithm.

This architecture can be applied directly to detection by adding a class “Background” to the object classes.

Negative samples are taken in each scene either at random or by selecting the ones with the worst miss-classification.

This architecture can be applied directly to detection by adding a class “Background” to the object classes.

Negative samples are taken in each scene either at random or by selecting the ones with the worst miss-classification.

Surprisingly, using class-specific localization layers did not provide better results than having a single one shared across classes (Sermanet et al., 2013).

Other approaches evolved from AlexNet, relying on **region proposals**:

- Generate thousands of proposal bounding boxes with a non-CNN “objectness” approach such as Selective search (Uijlings et al., 2013),
- feed to an AlexNet-like network sub-images cropped and warped from the input image (“R-CNN”, Girshick et al., 2013), or from the convolutional feature maps to share computation (“Fast R-CNN”, Girshick, 2015).

Other approaches evolved from AlexNet, relying on **region proposals**:

- Generate thousands of proposal bounding boxes with a non-CNN “objectness” approach such as Selective search (Uijlings et al., 2013),
- feed to an AlexNet-like network sub-images cropped and warped from the input image (“R-CNN”, Girshick et al., 2013), or from the convolutional feature maps to share computation (“Fast R-CNN”, Girshick, 2015).

These methods suffer from the cost of the region proposal computation, which is non-convolutional and non-GPUified.

They were improved by Ren et al. (2015) in “Faster R-CNN” by replacing the region proposal algorithm with a convolutional processing similar to Overfeat.

The most famous algorithm from this lineage is “You Only Look Once” (YOLO, Redmon et al. 2015).

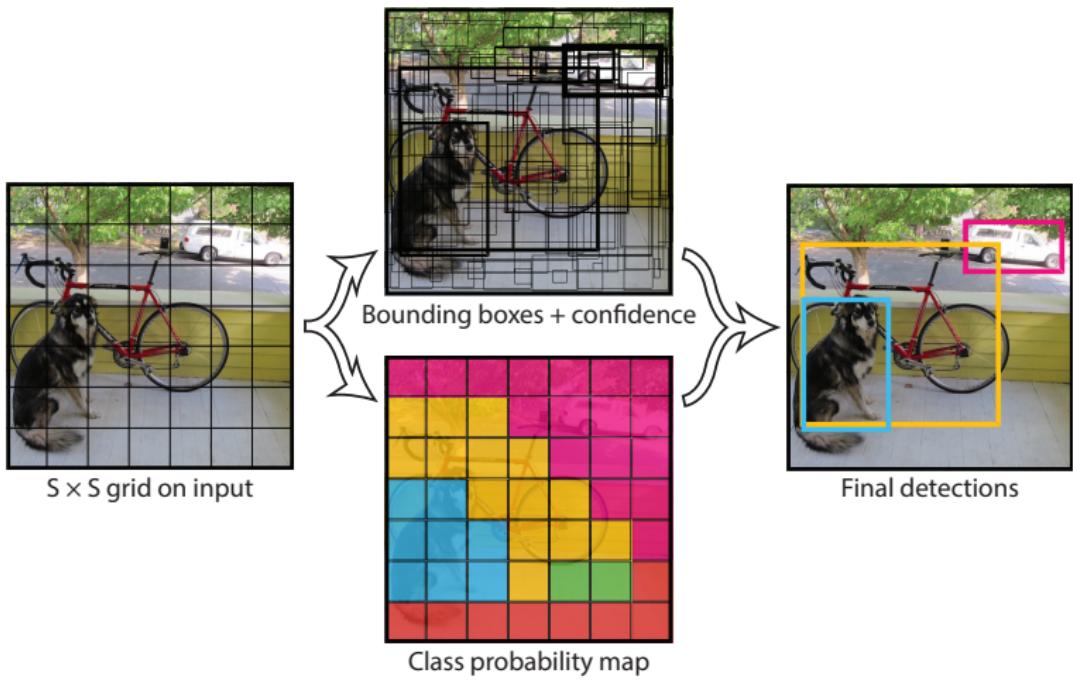
The most famous algorithm from this lineage is “You Only Look Once” (YOLO, Redmon et al. 2015).

It comes back to a classical architecture with a series of convolutional layers followed by a few fully connected layers. It is sometime described as “one shot” since a single information pathway suffices.

The most famous algorithm from this lineage is “You Only Look Once” (YOLO, Redmon et al. 2015).

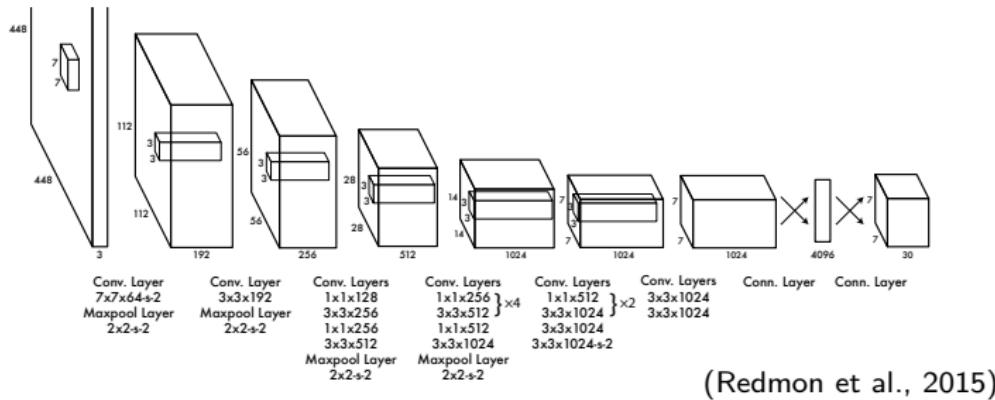
It comes back to a classical architecture with a series of convolutional layers followed by a few fully connected layers. It is sometime described as “one shot” since a single information pathway suffices.

YOLO’s network is not a pre-existing one. It uses leaky ReLU, and its convolutional layers make use of the 1×1 bottleneck filters (Lin et al., 2013) to control the memory footprint and computational cost.

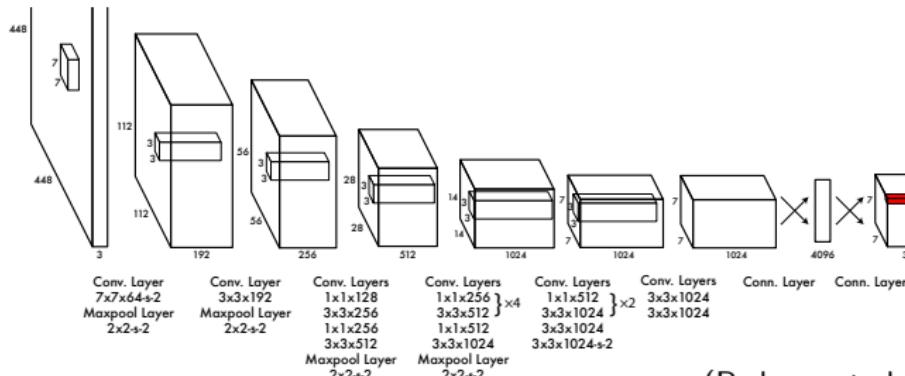


(Redmon et al., 2015)

The output corresponds to splitting the image into a regular $S \times S$ grid, with $S = 7$

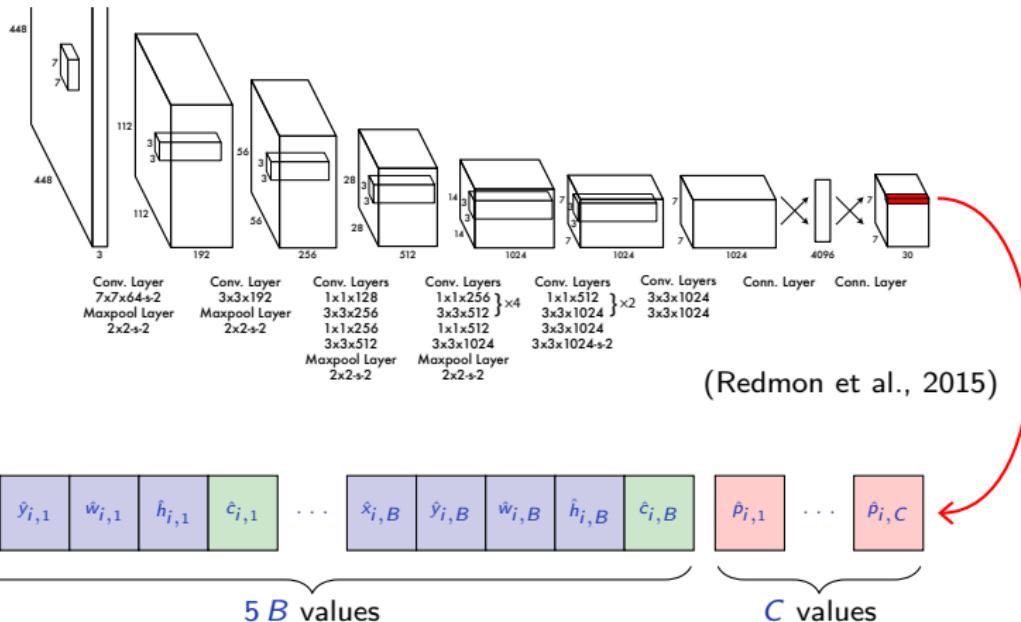


The output corresponds to splitting the image into a regular $S \times S$ grid, with $S = 7$, and for each cell, to predict a 30d vector



The output corresponds to splitting the image into a regular $S \times S$ grid, with $S = 7$, and for each cell, to predict a 30d vector:

- $B = 2$ bounding boxes coordinates and confidence,
- $C = 20$ class probabilities, corresponding to the classes of Pascal VOC.



So the network predicts class scores and bounding-box regressions, and **although the output comes from fully connected layers, it has a 2D structure.**

So the network predicts class scores and bounding-box regressions, and **although the output comes from fully connected layers, it has a 2D structure.**

It allows in particular YOLO to leverage the absolute location in the image to improve performance (e.g. vehicles tend to be at the bottom, umbrella at the top), which may or may not be desirable.

During training, YOLO makes the assumption that any of the S^2 cells contains at most [the center of] a single object. We define for every image, cell index $i = 1, \dots, S^2$, predicted box index $j = 1, \dots, B$ and class index $c = 1, \dots, C$

- $\mathbf{1}_i^{obj}$ is 1 if there is an object in cell i and 0 otherwise,
- $\mathbf{1}_{i,j}^{obj}$ is 1 if there is an object in cell i and predicted box j is the most fitting one, 0 otherwise.
- $p_{i,c}$ is 1 if there is an object of class c in cell i , and 0 otherwise,
- x_i, y_i, w_i, h_i the annotated object bounding box (defined only if $\mathbf{1}_i^{obj} = 1$, and relative in location and scale to the cell),
- $c_{i,j}$ IOU between the predicted box and the ground truth target.

The training procedure first computes on each image the value of the $\mathbf{1}_{i,j}^{obj}$ s and $c_{i,j}$, and then does one step to minimize

$$\begin{aligned}
 & \lambda_{coord} \sum_{i=1}^{S^2} \sum_{j=1}^B \mathbf{1}_{i,j}^{obj} \left((x_i - \hat{x}_{i,j})^2 + (y_i - \hat{y}_{i,j})^2 + \left(\sqrt{w_i} - \sqrt{\hat{w}_{i,j}} \right)^2 + \left(\sqrt{h_i} - \sqrt{\hat{h}_{i,j}} \right)^2 \right) \\
 & + \lambda_{obj} \sum_{i=1}^{S^2} \sum_{j=1}^B \mathbf{1}_{i,j}^{obj} (c_{i,j} - \hat{c}_{i,j})^2 + \lambda_{noobj} \sum_{i=1}^{S^2} \sum_{j=1}^B \left(1 - \mathbf{1}_{i,j}^{obj} \right) \hat{c}_{i,j}^2 \\
 & + \lambda_{classes} \sum_{i=1}^{S^2} \mathbf{1}_i^{obj} \sum_{c=1}^C \left(p_{i,c} - \hat{p}_{i,c} \right)^2.
 \end{aligned}$$

where $\hat{p}_{i,c}, \hat{x}_{i,j}, \hat{y}_{i,j}, \hat{w}_{i,j}, \hat{h}_{i,j}, \hat{c}_{i,j}$ are the network's outputs.

(slightly re-written from Redmon et al. 2015)

Training YOLO relies on many engineering choices that illustrate well how involved is deep-learning “in practice” :

- Pre-train the 20 first convolutional layers on ImageNet classification,
- use 448×448 input for detection, instead of 224×224 ,
- use Leaky ReLU for all layers,
- dropout after the first fully connected layer,

Training YOLO relies on many engineering choices that illustrate well how involved is deep-learning "in practice":

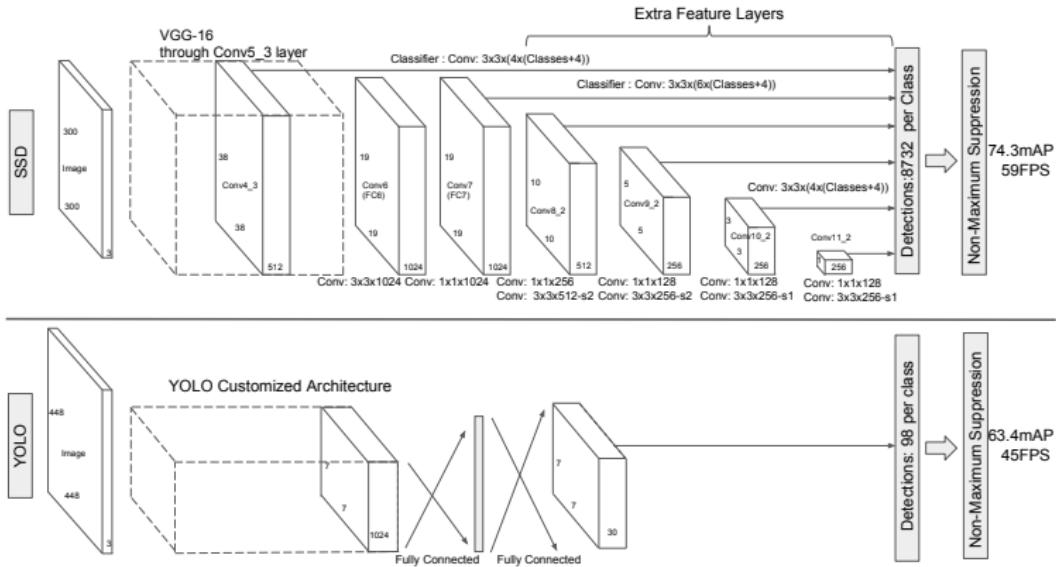
- Pre-train the 20 first convolutional layers on ImageNet classification,
- use 448×448 input for detection, instead of 224×224 ,
- use Leaky ReLU for all layers,
- dropout after the first fully connected layer,
- normalize bounding boxes parameters in $[0, 1]$,
- use a quadratic loss not only for the bounding box coordinates, but also for the confidence and the class scores,
- reduce the weight of large bounding boxes by using the square roots of the size in the loss,
- reduce the importance of empty cells by weighting less the confidence-related loss on them,

Training YOLO relies on many engineering choices that illustrate well how involved is deep-learning “in practice” :

- Pre-train the 20 first convolutional layers on ImageNet classification,
- use 448×448 input for detection, instead of 224×224 ,
- use Leaky ReLU for all layers,
- dropout after the first fully connected layer,
- normalize bounding boxes parameters in $[0, 1]$,
- use a quadratic loss not only for the bounding box coordinates, but also for the confidence and the class scores,
- reduce the weight of large bounding boxes by using the square roots of the size in the loss,
- reduce the importance of empty cells by weighting less the confidence-related loss on them,
- use momentum 0.9, decay $5e - 4$,
- data augmentation with scaling, translation, and HSV transformation.

A critical technical point is the design of the loss function that articulates both a classification and a regression objectives.

The Single Shot Multi-box Detector (SSD, Liu et al., 2015) improves upon YOLO with a fully-convolutional architectures and multi-scale maps.

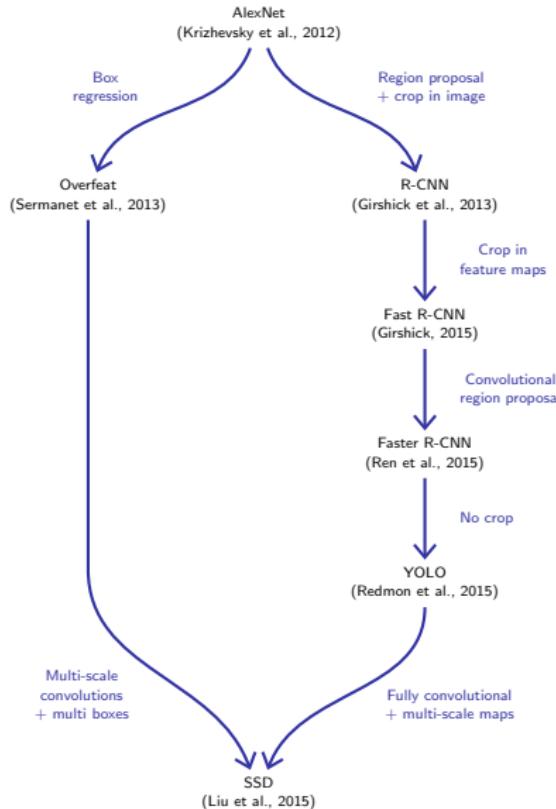


(Liu et al., 2015)

To summarize roughly how “one shot” deep detection can be achieved:

- networks trained on image classification capture localization information,
- regression layers can be attached to classification-trained networks,
- object localization does not have to be class-specific,
- multiple detections are estimated at each location to account for different aspect ratios and scales.

Object detection networks



The end

References

- R. Girshick. Fast R-CNN. *CoRR*, abs/1504.08083, 2015.
- R. Girshick, J. Donahue, T. Darrell, and J. Malik. Rich feature hierarchies for accurate object detection and semantic segmentation. *CoRR*, abs/1311.2524, 2013.
- A. Krizhevsky, I. Sutskever, and G. Hinton. Imagenet classification with deep convolutional neural networks. In *Neural Information Processing Systems (NIPS)*, 2012.
- M. Lin, Q. Chen, and S. Yan. Network in network. *CoRR*, abs/1312.4400, 2013.
- W. Liu, D. Anguelov, D. Erhan, C. Szegedy, S. E. Reed, C. Fu, and A. C. Berg. SSD: single shot multibox detector. *CoRR*, abs/1512.02325, 2015.
- J. Redmon, S. K. Divvala, R. B. Girshick, and A. Farhadi. You only look once: Unified, real-time object detection. *CoRR*, abs/1506.02640, 2015.
- S. Ren, K. He, R. B. Girshick, and J. Sun. Faster R-CNN: towards real-time object detection with region proposal networks. *CoRR*, abs/1506.01497, 2015.
- P. Sermanet, D. Eigen, X. Zhang, M. Mathieu, R. Fergus, and Y. LeCun. Overfeat: Integrated recognition, localization and detection using convolutional networks. *CoRR*, abs/1312.6229, 2013.
- J. Uijlings, K. van de Sande, T. Gevers, and A. Smeulders. Selective search for object recognition. *International Journal of Computer Vision*, 104(2):154–171, 2013.

EE-559 – Deep learning

7.4. Networks for semantic segmentation

François Fleuret

<https://fleuret.org/ee559/>

Mon Feb 18 13:35:51 UTC 2019

The historical approach to image segmentation was to define a measure of similarity between pixels, and to cluster groups of similar pixels.

The historical approach to image segmentation was to define a measure of similarity between pixels, and to cluster groups of similar pixels. Such approaches account poorly for semantic content.

The historical approach to image segmentation was to define a measure of similarity between pixels, and to cluster groups of similar pixels. Such approaches account poorly for semantic content.

The deep-learning approach re-casts semantic segmentation as pixel classification, and re-uses networks trained for image classification by making them fully convolutional.

Shelhamer et al. (2016) use a pre-trained classification network (e.g. VGG 16 layers) from which the final fully connected layer is removed, and the other ones are converted to 1×1 convolutional filters.

They add a final 1×1 convolutional layers with 21 output channels (VOC 20 classes + “background”).

Since VGG16 has 5 max-pooling with 2×2 kernels, with proper padding, the output is $1/2^5 = 1/32$ the size of the input.

Shelhamer et al. (2016) use a pre-trained classification network (e.g. VGG 16 layers) from which the final fully connected layer is removed, and the other ones are converted to 1×1 convolutional filters.

They add a final 1×1 convolutional layers with 21 output channels (VOC 20 classes + “background”).

Since VGG16 has 5 max-pooling with 2×2 kernels, with proper padding, the output is $1/2^5 = 1/32$ the size of the input.

This map is then up-scaled with a de-convolution layer with kernel 64×64 and stride 32×32 to get a final map of same size as the input image.

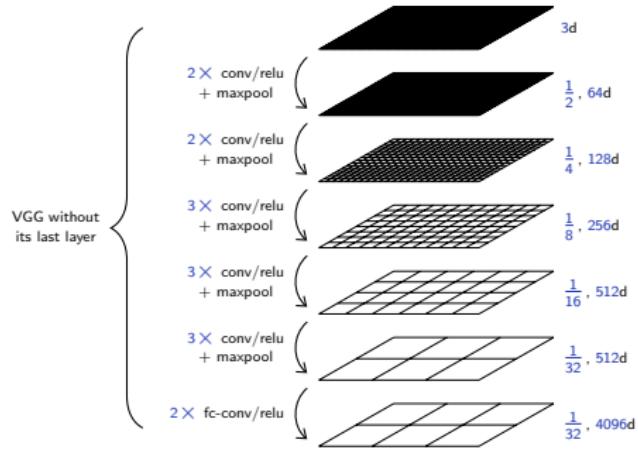
Shelhamer et al. (2016) use a pre-trained classification network (e.g. VGG 16 layers) from which the final fully connected layer is removed, and the other ones are converted to 1×1 convolutional filters.

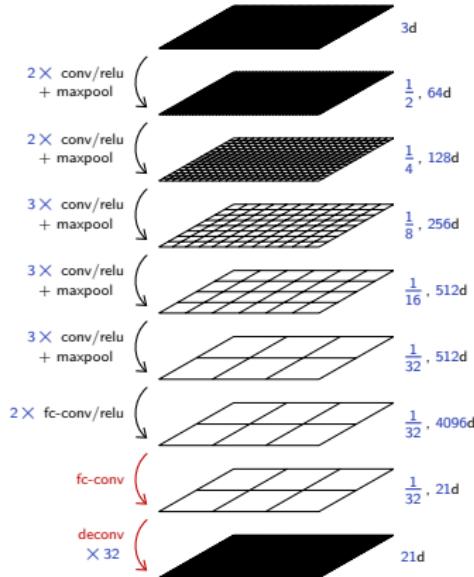
They add a final 1×1 convolutional layers with 21 output channels (VOC 20 classes + “background”).

Since VGG16 has 5 max-pooling with 2×2 kernels, with proper padding, the output is $1/2^5 = 1/32$ the size of the input.

This map is then up-scaled with a de-convolution layer with kernel 64×64 and stride 32×32 to get a final map of same size as the input image.

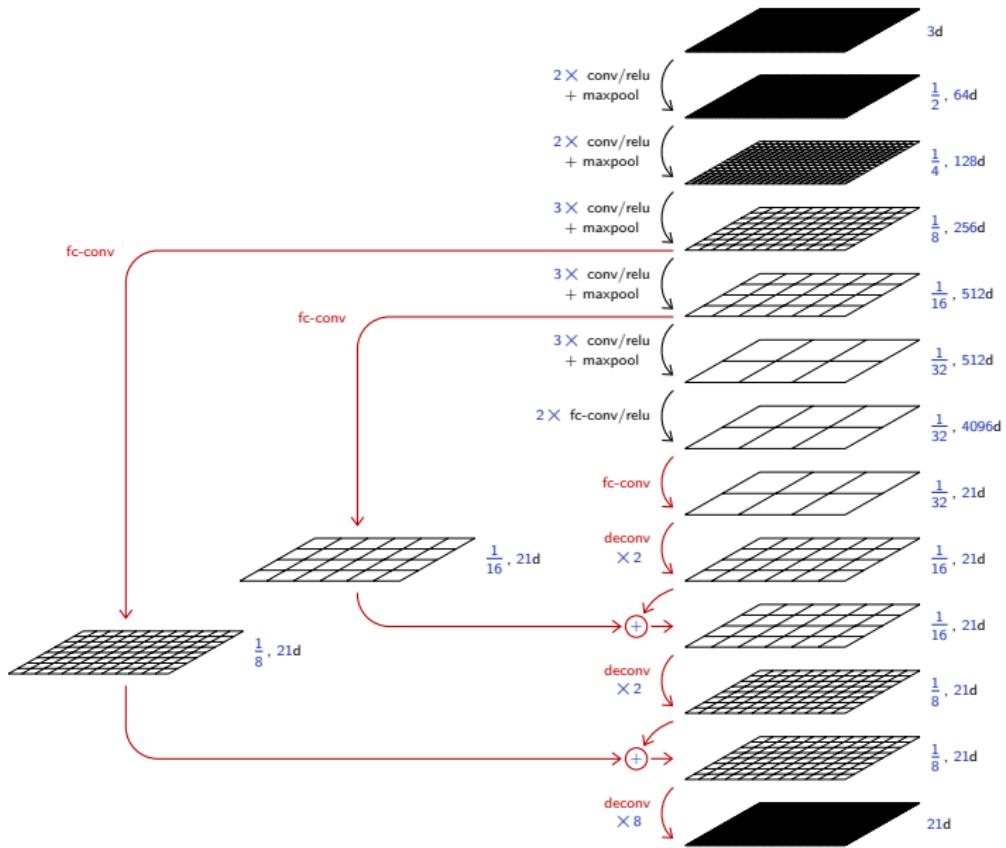
Training is achieved with full images and pixel-wise cross-entropy, starting with a pre-trained VGG16. All layers are fine-tuned, although fixing the up-scaling de-convolution to bilinear does as well.

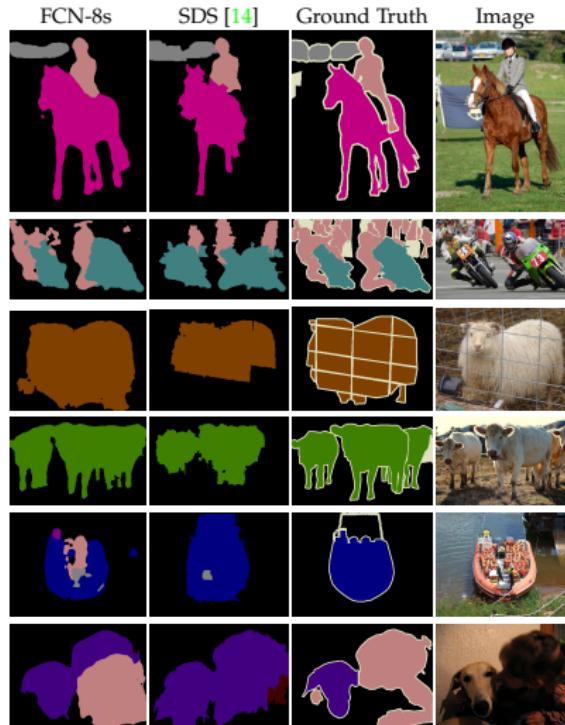




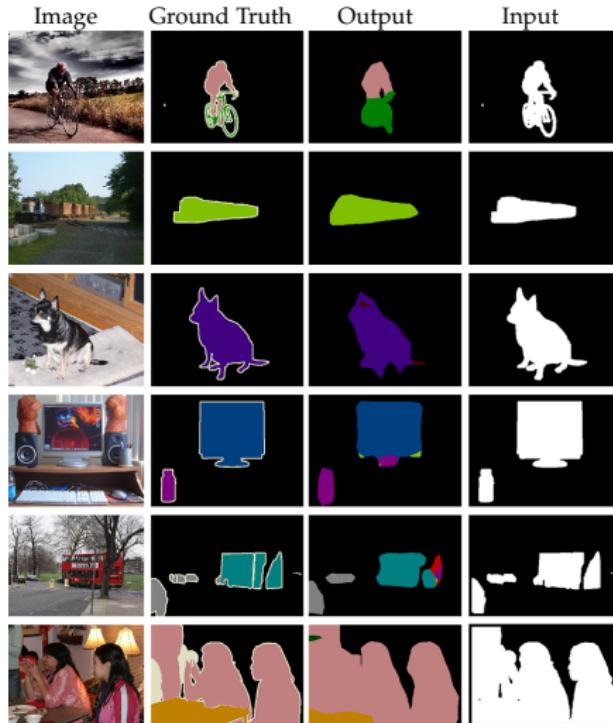
Although this Fully Connected Network (FCN) achieved almost state-of-the-art results when published, its main weakness is the coarseness of the signal from which the final output is produced ([1/32](#) of the original resolution).

Shelhamer et al. proposed an additional element, that consists of using the same prediction/up-scaling from intermediate layers of the VGG network.





Left column is the best network from Shelhamer et al. (2016).



Results with a network trained from mask only (Shelhamer et al., 2016).

It is noteworthy that for detection and semantic segmentation, there is an heavy re-use of large networks trained for classification.

The models themselves, as much as the source code of the algorithm that produced them, or the training data, are generic and re-usable assets.

The end

References

- E. Shelhamer, J. Long, and T. Darrell. Fully convolutional networks for semantic segmentation. *CoRR*, abs/1605.06211, 2016.

EE-559 – Deep learning

7.5. DataLoader and neuro-surgery

François Fleuret

<https://fleuret.org/ee559/>

Mon Feb 18 13:35:55 UTC 2019



```
torch.utils.data.DataLoader
```

Until now, we have dealt with image sets that could fit in memory, and we manipulated them as regular tensors, e.g.

```
train_set = torchvision.datasets.MNIST('./data/mnist/',
                                         train = True, download = True)
train_input = train_set.train_data.view(-1, 1, 28, 28).float()
train_target = train_set.train_labels
```

Until now, we have dealt with image sets that could fit in memory, and we manipulated them as regular tensors, e.g.

```
train_set = torchvision.datasets.MNIST('./data/mnist/',
                                         train = True, download = True)
train_input = train_set.train_data.view(-1, 1, 28, 28).float()
train_target = train_set.train_labels
```

However, large sets do not fit in memory, and samples have to be constantly loaded during training.

This require a [sophisticated] machinery to parallelize the loading itself, but also the normalization, and data-augmentation operations.

PyTorch offers the `torch.utils.data.DataLoader` object which combines a data-set and a sampling policy to create an iterator over mini-batches.

Standard data-sets are available in `torchvision.datasets`, and they allow to apply transformations over the images or the labels transparently.

```
from torch.utils.data import DataLoader
from torchvision import datasets, transforms

train_transforms = transforms.Compose(
    [
        transforms.ToTensor(),
        transforms.Normalize(mean = (0.1302,), std = (0.3069, ))
    ]
)

train_loader = DataLoader(
    datasets.MNIST(root = './data/mnist', train = True, download = True,
                   transform = train_transforms),
    batch_size = 100,
    num_workers = 4,
    shuffle = True,
    pin_memory = torch.cuda.is_available()
)
```

Given this `train_loader`, we can now re-write our training procedure with a loop over the mini-batches

```
for e in range(nb_epochs):
    for input, target in iter(train_loader):

        input, target = input.to(device), target.to(device)

        output = model(input)
        loss = criterion(output, target)

        model.zero_grad()
        loss.backward()
        optimizer.step()
```

Note that for data-sets that can fit in memory this is quite inefficient, as they are constantly moved from the CPU to the GPU memory.

Example of neuro-surgery and fine-tuning in PyTorch

As an example of re-using a network and fine-tuning it, we will construct a network for CIFAR10 composed of:

- the first layer of an [already trained] AlexNet,

As an example of re-using a network and fine-tuning it, we will construct a network for CIFAR10 composed of:

- the first layer of an [already trained] AlexNet,
- several resnet blocks,

As an example of re-using a network and fine-tuning it, we will construct a network for CIFAR10 composed of:

- the first layer of an [already trained] AlexNet,
- several resnet blocks,
- a final channel-wise averaging, using `nn.AvgPool2d`, and

As an example of re-using a network and fine-tuning it, we will construct a network for CIFAR10 composed of:

- the first layer of an [already trained] AlexNet,
- several resnet blocks,
- a final channel-wise averaging, using `nn.AvgPool2d`, and
- a final fully connected linear layer `nn.Linear`.

As an example of re-using a network and fine-tuning it, we will construct a network for CIFAR10 composed of:

- the first layer of an [already trained] AlexNet,
- several resnet blocks,
- a final channel-wise averaging, using `nn.AvgPool2d`, and
- a final fully connected linear layer `nn.Linear`.

During training, we keep the AlexNet features frozen for a few epochs. This is done by setting `requires_grad` of the related `Parameters` to `False`.

```
data_dir = os.environ.get('PYTORCH_DATA_DIR') or './data/cifar10/'

num_workers = 4
batch_size = 64

transform = torchvision.transforms.ToTensor()

train_set = datasets.CIFAR10(root = data_dir, train = True,
                           download = True, transform = transform)

train_loader = utils.data.DataLoader(train_set, batch_size = batch_size,
                                      shuffle = True, num_workers = num_workers)

test_set = datasets.CIFAR10(root = data_dir, train = False,
                           download = True, transform = transform)

test_loader = utils.data.DataLoader(test_set, batch_size = batch_size,
                                    shuffle = False, num_workers = num_workers)
```

```
class ResBlock(nn.Module):
    def __init__(self, nb_channels, kernel_size):
        super(ResBlock, self).__init__()

        self.conv1 = nn.Conv2d(nb_channels, nb_channels, kernel_size,
                           padding = (kernel_size-1)//2)
        self.bn1 = nn.BatchNorm2d(nb_channels)

        self.conv2 = nn.Conv2d(nb_channels, nb_channels, kernel_size,
                           padding = (kernel_size-1)//2)
        self.bn2 = nn.BatchNorm2d(nb_channels)

    def forward(self, x):
        y = self.bn1(self.conv1(x))
        y = F.relu(y)
        y = self.bn2(self.conv2(y))
        y += x
        y = F.relu(y)
        return y
```

```
class Monster(nn.Module):
    def __init__(self, nb_blocks, nb_channels):
        super(Monster, self).__init__()

        nb_alexnet_channels = 64
        alexnet_feature_map_size = 7 # For 32x32 (e.g. CIFAR)

        alexnet = torchvision.models.alexnet(pretrained = True)

        self.features = nn.Sequential(
            alexnet.features[0],
            nn.ReLU(inplace = True)
        )

        self.conv0 = nn.Conv2d(nb_alexnet_channels, nb_channels, kernel_size = 1)

        self.resblocks = nn.Sequential(
            # A bit of fancy Python
            *(ResBlock(nb_channels, kernel_size = 3) for _ in range(nb_blocks))
        )

        self.avg = nn.AvgPool2d(kernel_size = alexnet_feature_map_size)
        self.fc = nn.Linear(nb_channels, 10)
```

```
def freeze_features(self, q):
    for p in self.features.parameters():
        # q = True means that it is frozen and we do NOT need the gradient
        p.requires_grad = not q

def forward(self, x):
    x = self.features(x)
    x = F.relu(self.conv0(x))
    x = self.resblocks(x)
    x = F.relu(self.avg(x))
    x = x.view(x.size(0), -1)
    x = self.fc(x)
    return x
```

```
nb_epochs = 50
nb_blocks, nb_channels = 8, 64

model, criterion = Monster(nb_blocks, nb_channels), nn.CrossEntropyLoss()

model.to(device)
criterion.to(device)

optimizer = torch.optim.Adam(model.parameters(), lr = 1e-2)

for e in range(nb_epochs):
    model.freeze_features(e < nb_epochs // 2)
    acc_loss = 0.0

    for input, target in iter(train_loader):
        input, target = input.to(device), target.to(device)

        output = model(input)
        loss = criterion(output, target)
        acc_loss += loss.item()

        optimizer.zero_grad()
        loss.backward()
        optimizer.step()

    print(e, acc_loss)
```

```
nb_test_errors, nb_test_samples = 0, 0

model.train(False)

for input, target in iter(test_loader):
    input, target = input.to(device), target.to(device)

    output = model(input)
    wta = torch.max(output.data, 1)[1].view(-1)

    for i in range(0, target.size(0)):
        nb_test_samples += 1
        if wta[i] != target[i]: nb_test_errors += 1

print('test_error {:.02f}% ({:d}/{:d})'.format(
    100 * nb_test_errors / nb_test_samples,
    nb_test_errors,
    nb_test_samples)
)
```

The end

References