Lecture 5:
Image Classification with CNNs

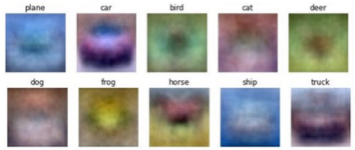
Image Classification: A core task in Computer Vision

(assume given a set of labels)
{dog, cat, truck, plane, ...}

→ cat
dog
bird
deer
truck

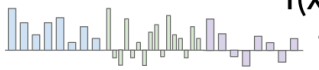
Pixel space

$f(x) = Wx$



Class scores

Image features



Feature Representation

$f(x) = Wx$

Class scores

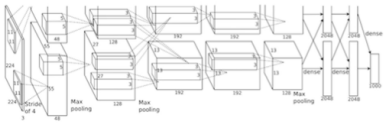
Image features vs. ConvNets

Feature Extraction

f

10 numbers giving scores for classes

training



10 numbers giving scores for classes

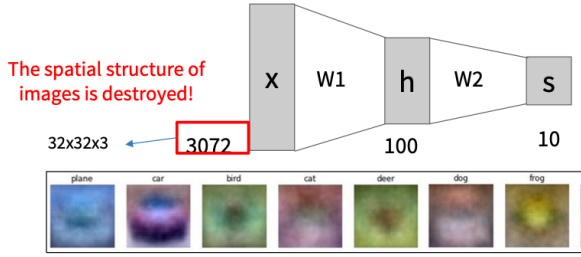
training

Last Time: Neural Networks

Linear score function: $f = Wx$

2-layer Neural Network $f = W_2 \max(0, W_1 x)$

The spatial structure of images is destroyed!



Next: Convolutional Neural Networks

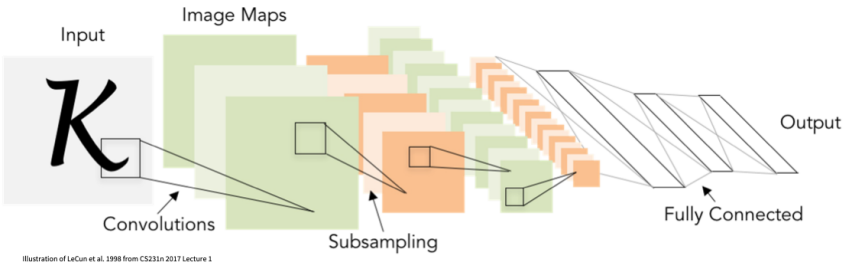
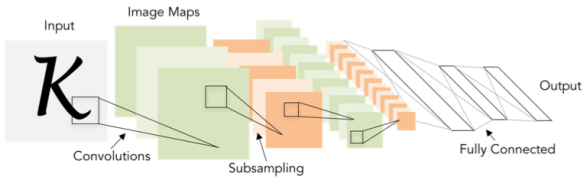


Illustration of LeCun et al. 1998 from CS231n 2017 Lecture 1

A bit of history:

Gradient-based learning applied to document recognition
[LeCun, Bottou, Bengio, Haffner 1998]



LeNet-5

A bit of history:

ImageNet Classification with Deep Convolutional Neural Networks [Krizhevsky, Sutskever, Hinton, 2012]

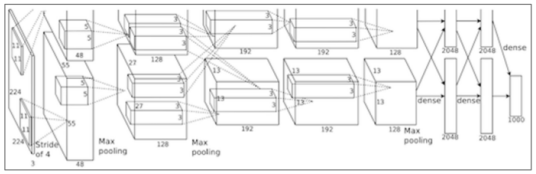
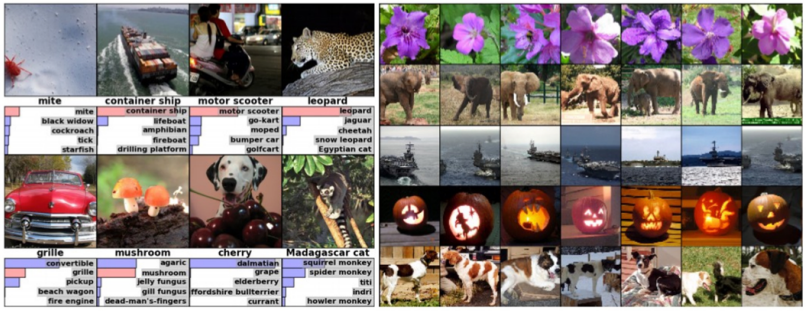


Figure copyright Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton, 2012. Reproduced with permission.

"AlexNet"

Fast-forward: ConvNets are everywhere

Classification Retrieval



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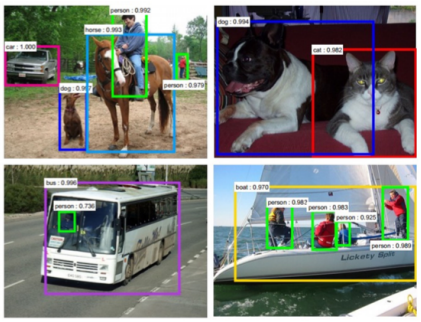
Fast-forward: ConvNets are everywhere

Detection Segmentation



Figures copyright Shaoqing Ren, Kaiming He, Ross Girschick, Jian Sun, 2015. Reproduced with permission.

[Faster R-CNN: Ren, He, Girshick, Sun 2015]

Figures copyright Clement Farabet, 2012. Reproduced with permission.

[Farabet et al., 2012]

No errors Minor errors Somewhat related

A white teddy bear sitting in the grass

A man in a baseball uniform throwing a ball

A woman is holding a cat in her hand

A man riding a wave on top of a surfboard

A cat sitting on a suitcase on the floor

A woman standing on a beach holding a surfboard

Image Captioning

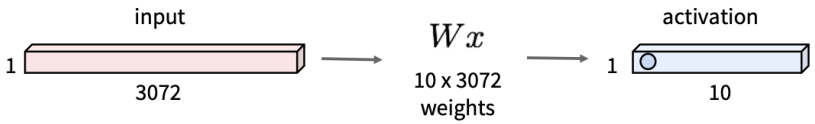
[Vinyals et al., 2015]
[Karpathy and Fei-Fei, 2015]

Captions generated by Justin Johnson using Neuraltalk2

Convolutional Neural Networks

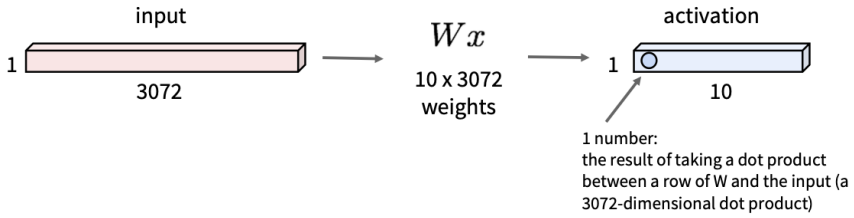
Recap: Fully Connected Layer

32x32x3 image -> stretch to 3072 x 1



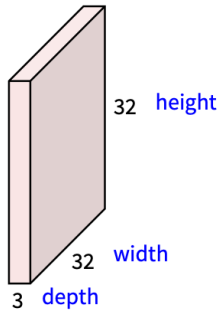
Fully Connected Layer

32x32x3 image -> stretch to 3072 x 1



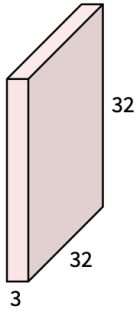
Convolution Layer

32x32x3 image -> preserve spatial structure



Convolution Layer

32x32x3 image



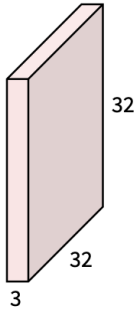
5x5x3 filter

Convolve the filter with the image
i.e. “slide over the image spatially,
computing dot products”

Convolution Layer

Filters always extend the full depth of the input volume

32x32x3 image

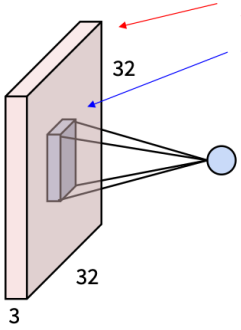


5x5x3 filter

Convolve the filter with the image
i.e. “slide over the image spatially,
computing dot products”

Convolution Layer

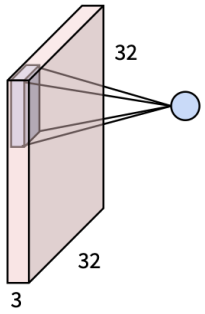
32x32x3 image
5x5x3 filter w



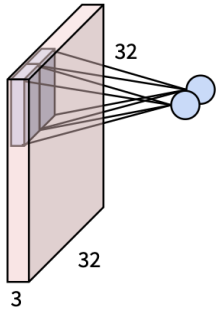
1 number:
the result of taking a dot product between the filter and a small 5x5x3 chunk of the image
(i.e. 5*5*3 = 75-dimensional dot product + bias)

$$w^T x + b$$

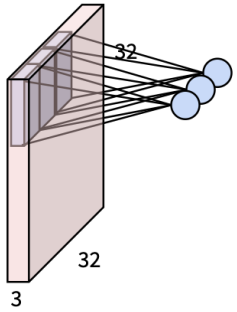
Convolution Layer



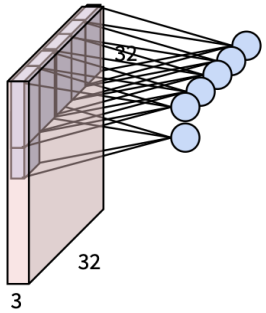
Convolution Layer



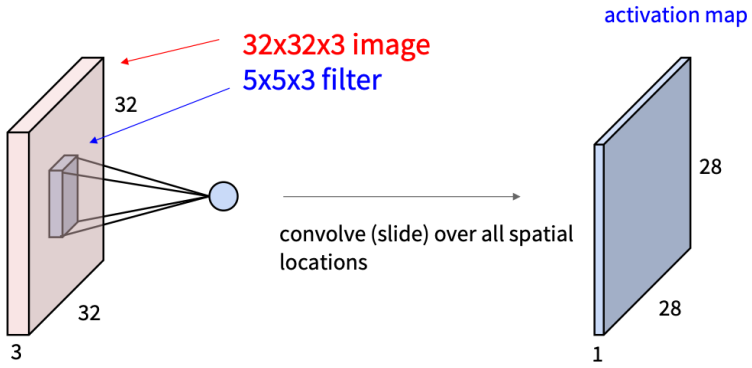
Convolution Layer



Convolution Layer

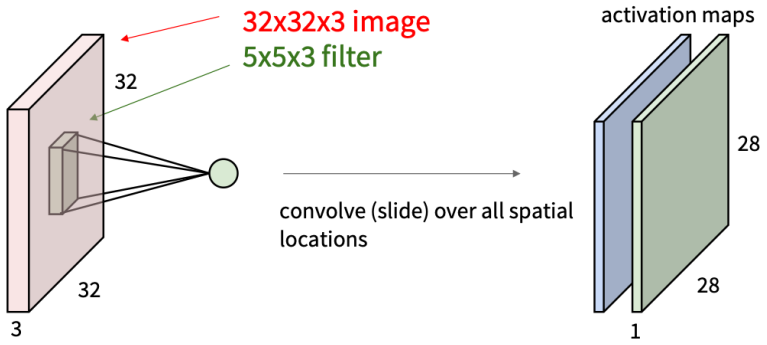


Convolution Layer

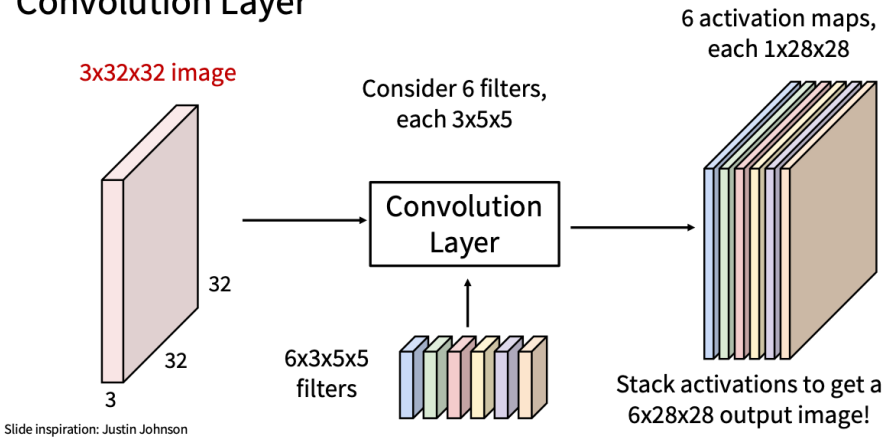


Convolution Layer

consider a second, green filter

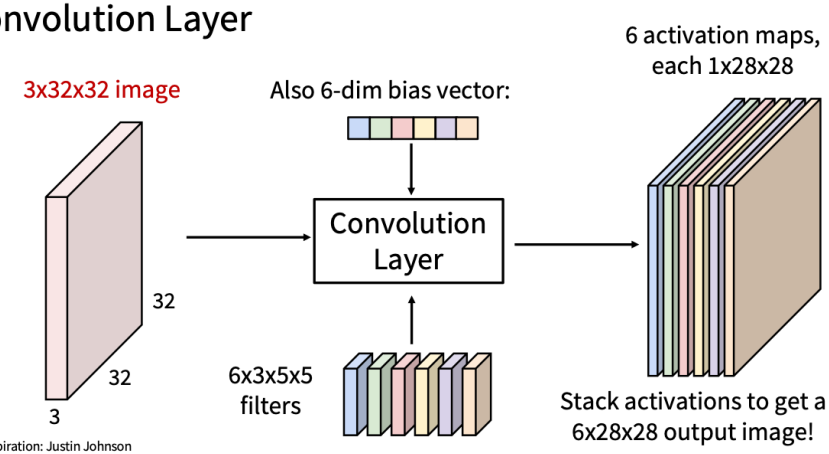


Convolution Layer



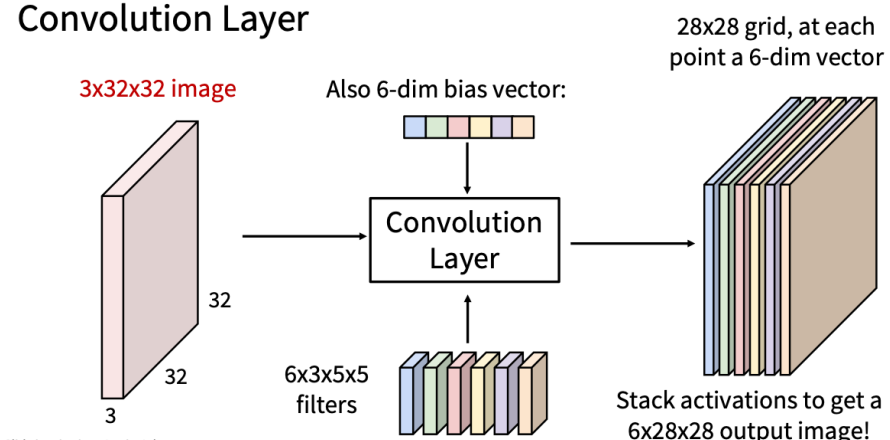
Slide inspiration: Justin Johnson

Convolution Layer



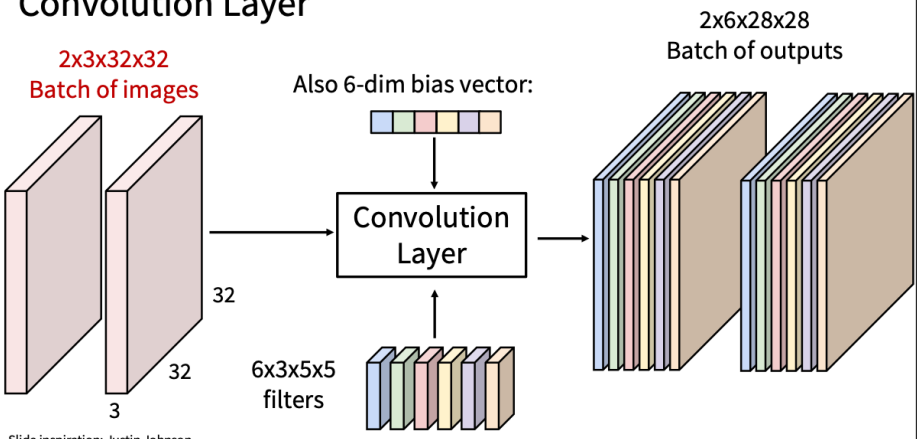
Slide inspiration: Justin Johnson

Convolution Layer



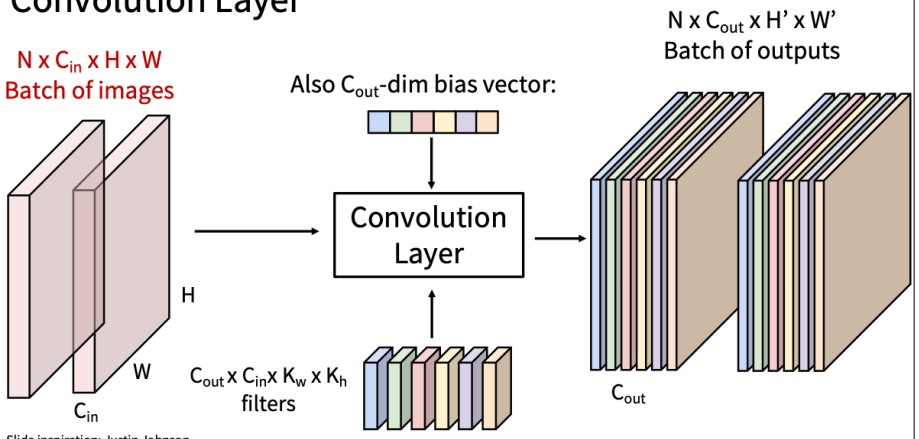
Slide inspiration: Justin Johnson

Convolution Layer



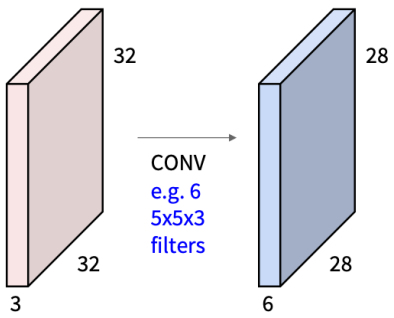
Slide inspiration: Justin Johnson

Convolution Layer

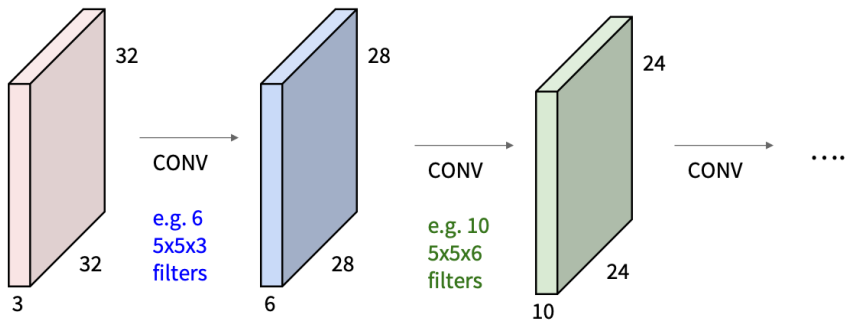


Slide inspiration: Justin Johnson

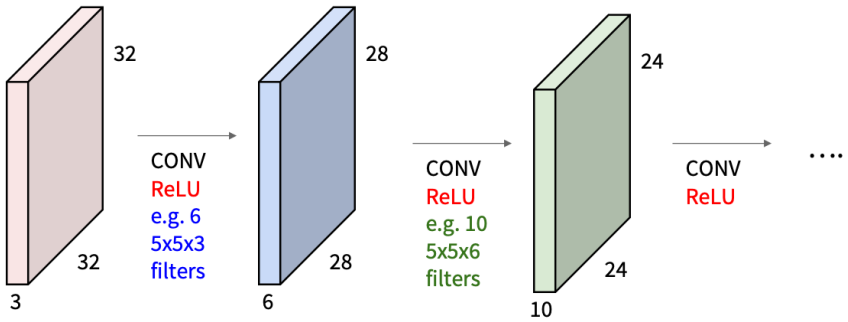
Preview: ConvNet is a sequence of Convolution Layers



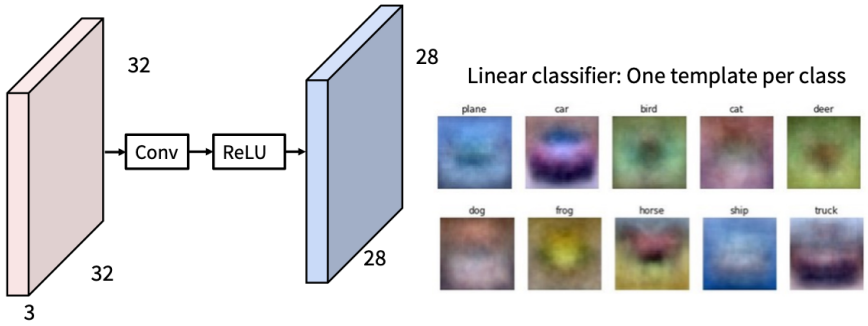
Preview: ConvNet is a sequence of Convolution Layers



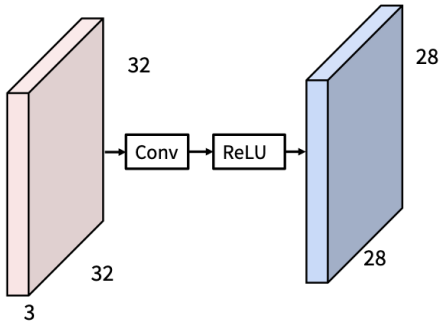
Preview: ConvNet is a sequence of Convolution Layers, interspersed with activation functions



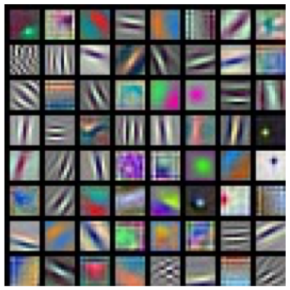
Preview: What do convolutional filters learn?



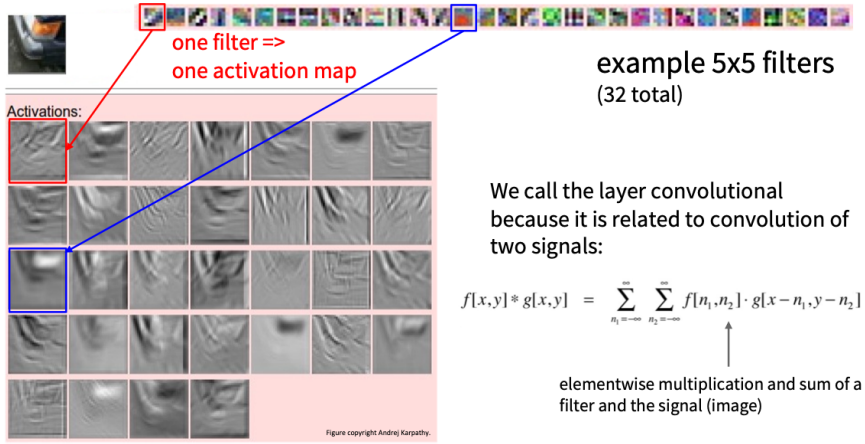
Preview: What do convolutional filters learn?



First-layer conv filters: local image templates
(Often learns oriented edges, opposing colors)



AlexNet: 64 filters, each 3x11x11



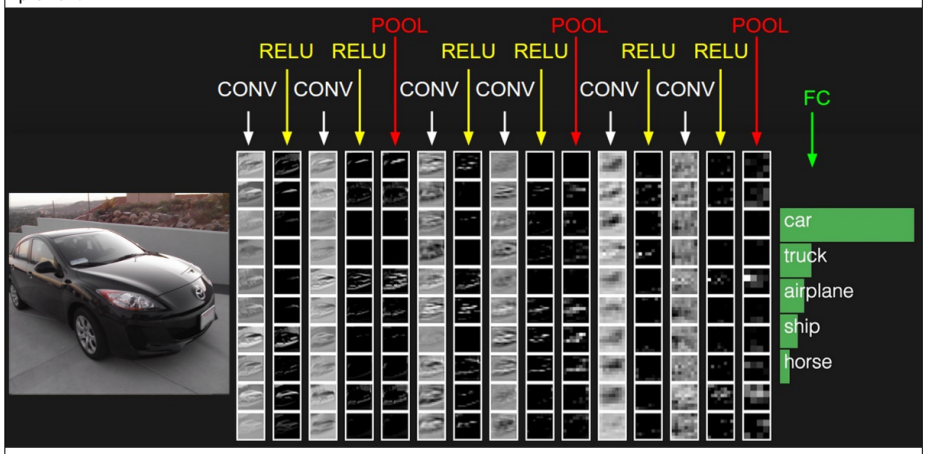
example 5x5 filters
(32 total)

We call the layer convolutional because it is related to convolution of two signals:

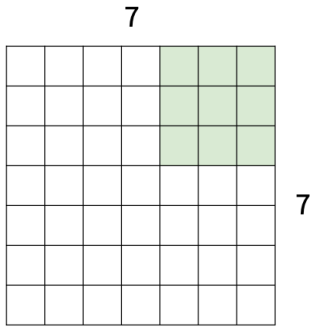
$$f[x,y] * g[x,y] = \sum_{n_1=-\infty}^{\infty} \sum_{n_2=-\infty}^{\infty} f[n_1,n_2] \cdot g[x-n_1, y-n_2]$$

elementwise multiplication and sum of a filter and the signal (image)

preview:



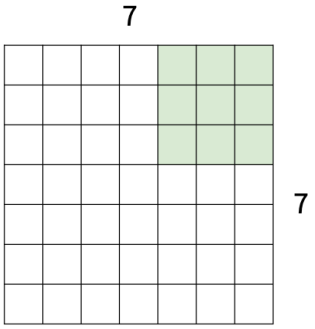
A closer look at spatial dimensions:



7x7 input (spatially)
assume 3x3 filter

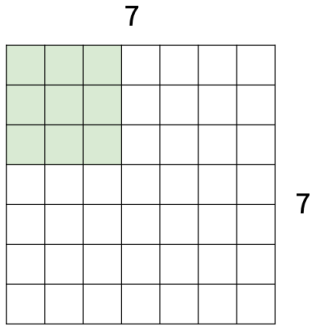
=> 5x5 output

A closer look at spatial dimensions:



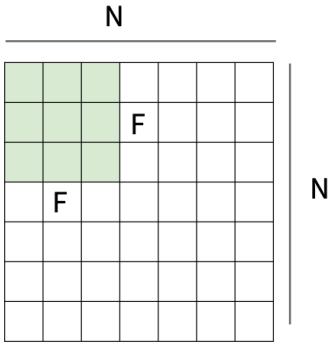
7x7 input (spatially)
assume 3x3 filter
applied with stride 2
=> 3x3 output!

A closer look at spatial dimensions:



7x7 input (spatially)
assume 3x3 filter
applied with stride 3?

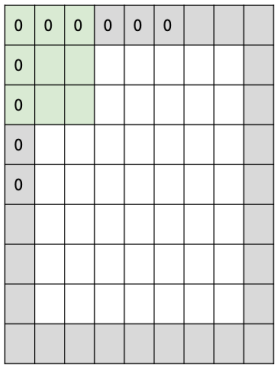
doesn't fit!
cannot apply 3x3 filter on 7x7
input with stride 3.



Output size:
(N - F) / stride + 1

e.g. N = 7, F = 3:
stride 1 => (7 - 3)/1 + 1 = 5
stride 2 => (7 - 3)/2 + 1 = 3
stride 3 => (7 - 3)/3 + 1 = 2.33 :\

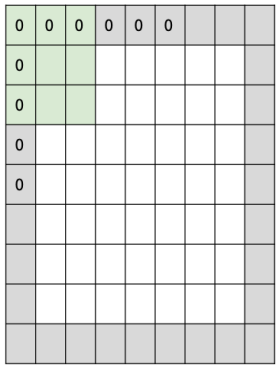
In practice: Common to zero pad the border



e.g. input 7x7
3x3 filter, applied with stride 1
pad with 1 pixel border => what is the output?

(recall:)
(N - F) / stride + 1

In practice: Common to zero pad the border

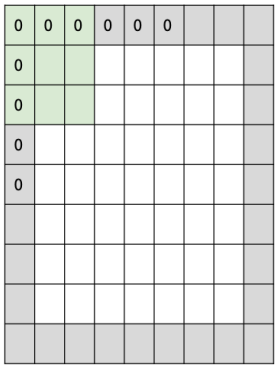


e.g. input 7x7
3x3 filter, applied with stride 1
pad with 1 pixel border => what is the output?

7x7 output!

(recall:)
(N + 2P - F) / stride + 1

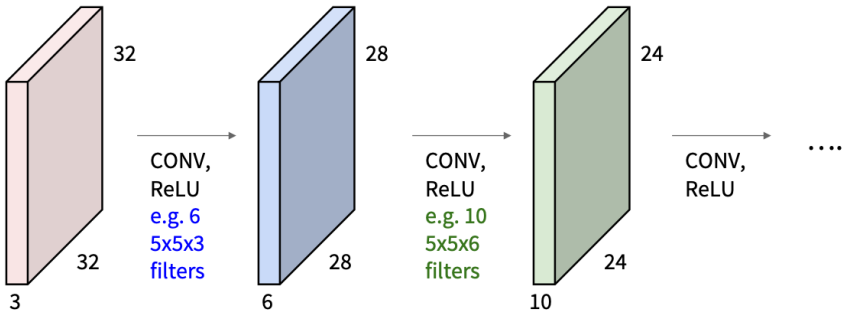
In practice: Common to zero pad the border



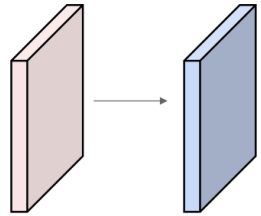
e.g. input 7x7
3x3 filter, applied with stride 1
pad with 1 pixel border => what is the output?

7x7 output!
in general, common to see CONV layers with stride 1, filters of size FxF, and zero-padding with (F-1)/2. (will preserve size spatially)
e.g. F = 3 => zero pad with 1
F = 5 => zero pad with 2
F = 7 => zero pad with 3

Remember back to…
E.g. 32x32 input convolved repeatedly with 5x5 filters shrinks volumes spatially!
(32 -> 28 -> 24 ...). Shrinking too fast is not good, doesn't work well.



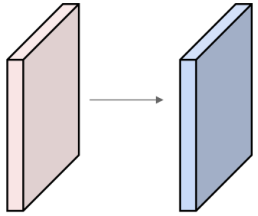
Examples time:



Input volume: 32x32x3
10 5x5 filters with stride 1, pad 2

Output volume size: ?

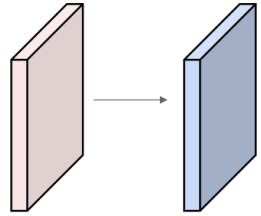
Examples time:



Input volume: 32x32x3
10 5x5 filters with stride 1, pad 2

Output volume size:
(32+2*2-5)/1+1 = 32 spatially, so
32x32x10

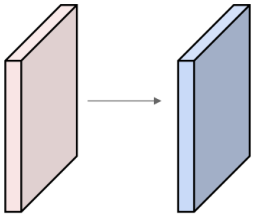
Examples time:



Input volume: 32x32x3
10 5x5 filters with stride 1, pad 2

Number of parameters in this layer?

Examples time:

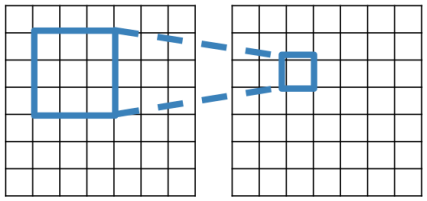


Input volume: 32x32x3
10 5x5 filters with stride 1, pad 2

Number of parameters in this layer?
each filter has 5*5*3 + 1 = 76 params (+1 for bias)
=> 76*10 = 760

Receptive Fields

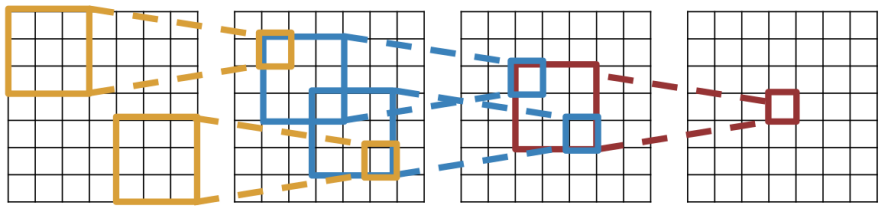
For convolution with **kernel size K**, each element in the output depends on a K x K receptive field in the input



Slide inspiration: Justin Johnson

Receptive Fields

Each successive convolution adds K – 1 to the receptive field size
With L layers the receptive field size is 1 + L * (K – 1)

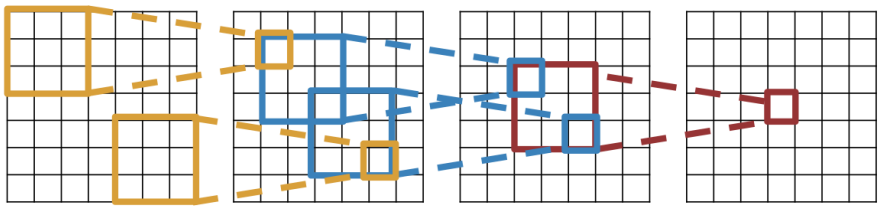


Be careful – "receptive field in the input" vs. "receptive field in the previous layer"

Slide inspiration: Justin Johnson

Receptive Fields

Each successive convolution adds K – 1 to the receptive field size
With L layers the receptive field size is 1 + L * (K – 1)



Problem: For large images we need many layers for each output to "see" the whole image image

Solution: Downsample inside the network

Slide inspiration: Justin Johnson

Convolution layer: summary

Common settings:

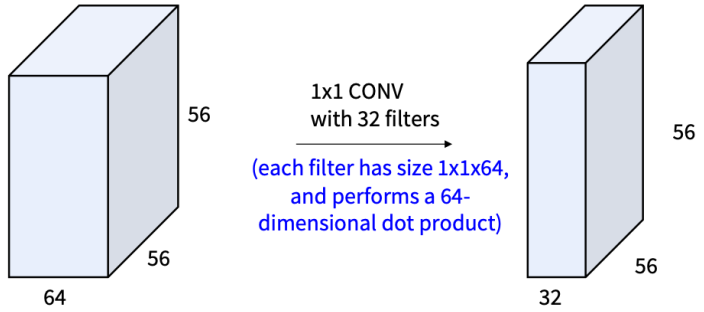
K = (powers of 2, e.g. 32, 64, 128, 512)
- F = 3, S = 1, P = 1
- F = 5, S = 1, P = 2
- F = 5, S = 2, P = ? (whatever fits)
- F = 1, S = 1, P = 0

Let's assume input is W_1 x H_1 x C
Conv layer needs 4 hyperparameters:
- Number of filters K
- The filter size F
- The stride S
- The zero padding P

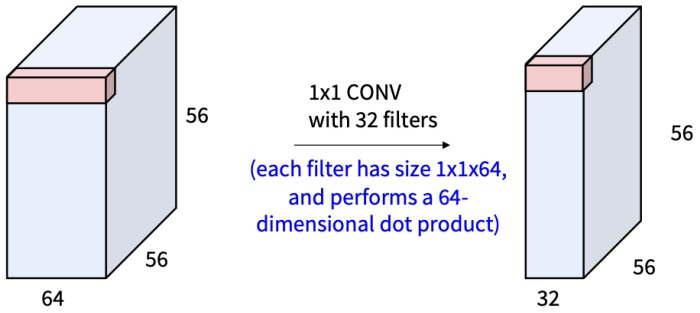
This will produce an output of W_2 x H_2 x K
where:
- $W_2 = (W_1 - F + 2P)/S + 1$
- $H_2 = (H_1 - F + 2P)/S + 1$

Number of parameters: F^2CK and K biases

(btw, 1x1 convolution layers make perfect sense)

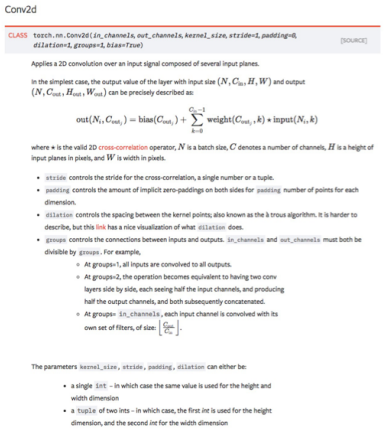


(btw, 1x1 convolution layers make perfect sense)



Example: CONV layer in PyTorch

Conv layer needs 4 hyperparameters:
- Number of filters K
- The filter size F
- The stride S
- The zero padding P


Conv2d

CLASS torch.nn.Conv2d(in_channels, out_channels, kernel_size, stride=1, padding=0, dilation=1, groups=1, bias=True) [SOURCE]

Applies a 2D convolution over an input signal composed of several input planes.

In the simplest case, the output value of the layer with input size (N, C_{in}, H, W) and output $(N, C_{out}, H_{out}, W_{out})$ can be precisely described as:

$$\text{out}(N_i, C_{out_j}) = \text{bias}(C_{out_j}) + \sum_{k=0}^{C_{in}-1} \text{weight}(C_{out_j}, k) \star \text{input}(N_i, k)$$

where $\star$ is the valid 2D cross-correlation operator, N is a batch size, C denotes a number of channels, H is a height of input planes in pixels, and W is width in pixels.

- stride controls the stride for the cross-correlation, a single number or a tuple.
- padding controls the amount of implicit zero-paddings on both sides for padding number of points for each dimension.
- dilation controls the spacing between the kernel points; also known as the à trous algorithm. It is harder to describe, but this link has a nice visualization of what dilation does.
- groups controls the connections between inputs and outputs. in_channels and out_channels must both be divisible by groups. For example,
  - At groups=1, all inputs are convolved to all outputs.
  - At groups=2, the operation becomes equivalent to having two conv layers side by side, each seeing half the input channels, and producing half the output channels, and both subsequently concatenated.
  - At groups= in_channels, each input channel is convolved with its own set of filters, of size: $\left\lfloor \frac{C_{out}}{C_{in}} \right\rfloor$.

The parameters kernel_size, stride, padding, dilation can either be:

- a single int – in which case the same value is used for the height and width dimension
- a tuple of two ints – in which case, the first *int* is used for the height dimension, and the second *int* for the width dimension

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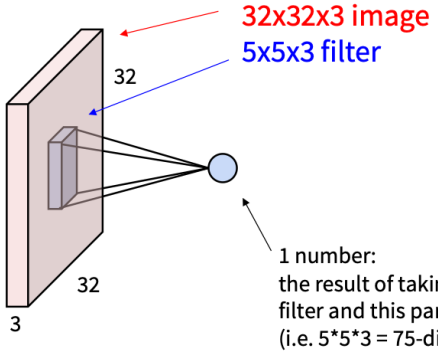
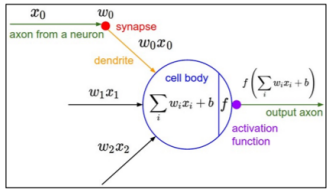
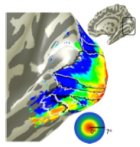
The brain/neuron view of CONV Layer



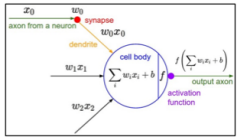


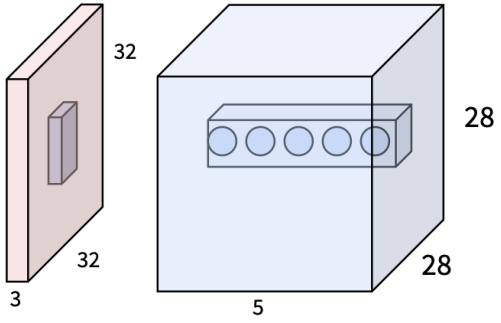
It's just a neuron with local connectivity...

1 number:
the result of taking a dot product between the filter and this part of the image
(i.e. 5*5*3 = 75-dimensional dot product)



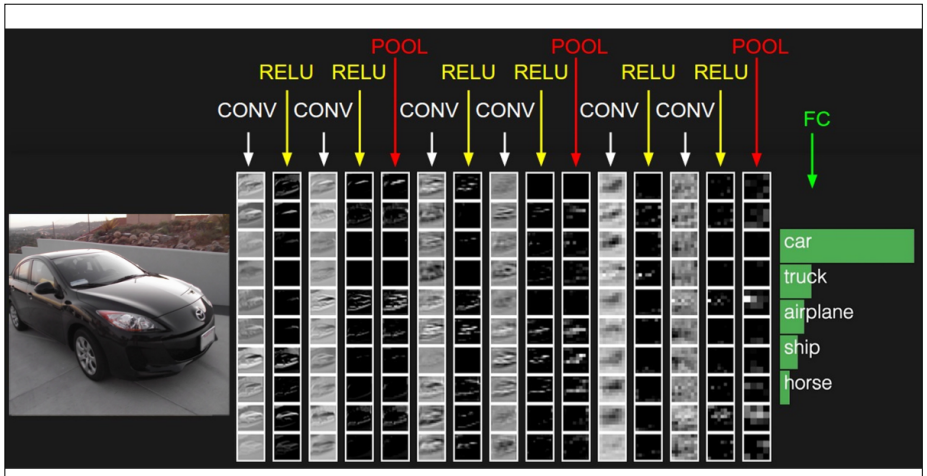
The brain/neuron view of CONV Layer





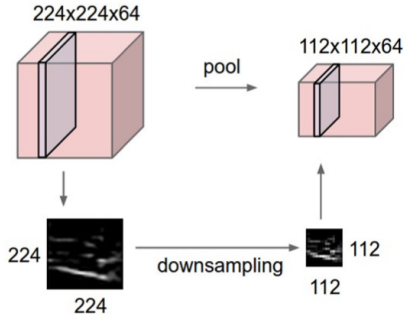
E.g. with 5 filters,
CONV layer consists of neurons arranged in a 3D grid (28x28x5)

There will be 5 different neurons all looking at the same region in the input volume

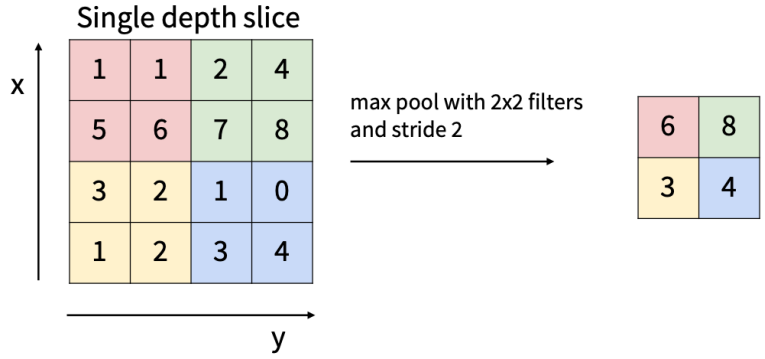


Pooling layer

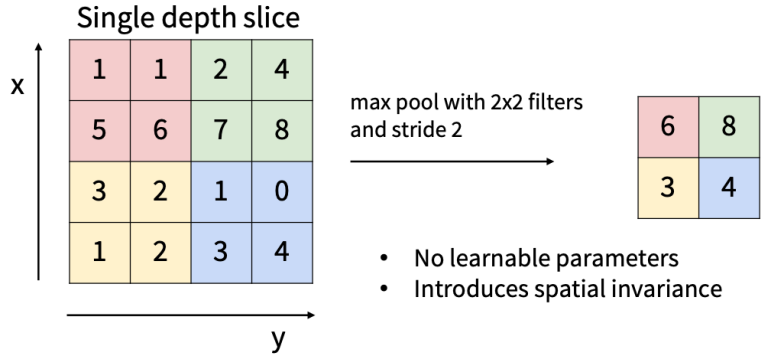
- makes the representations smaller and more manageable
- operates over each activation map independently



MAX POOLING



MAX POOLING



- No learnable parameters
- Introduces spatial invariance

Pooling layer: summary

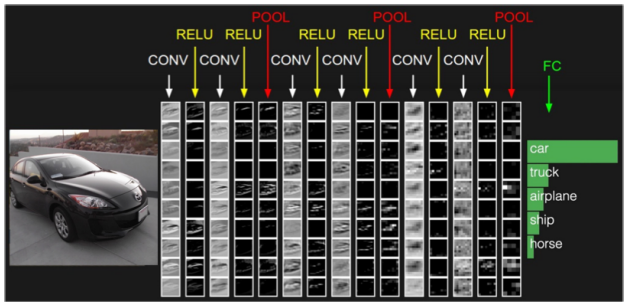
Let's assume input is W_1 x H_1 x C
Conv layer needs 2 hyperparameters:
- The spatial extent F
- The stride S

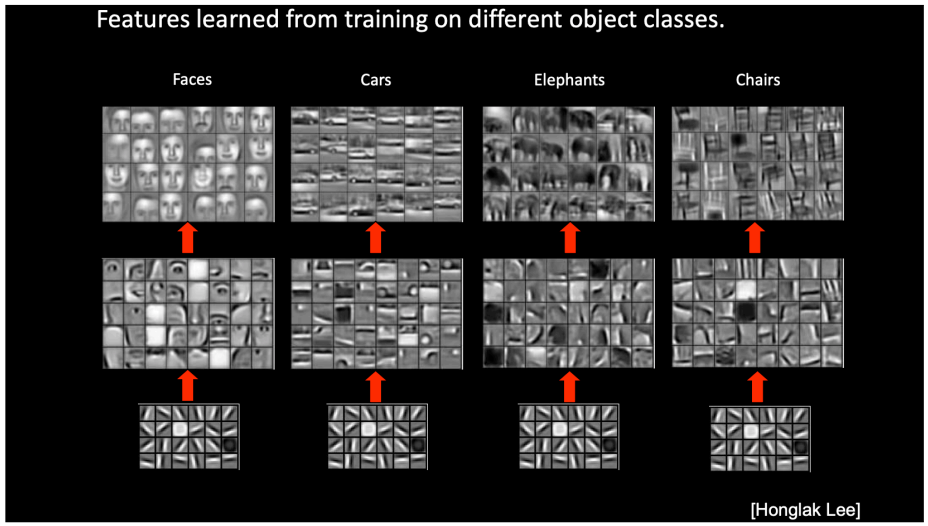
This will produce an output of W_2 x H_2 x C where:
- $W_2 = (W_1 - F)/S + 1$
- $H_2 = (H_1 - F)/S + 1$

Number of parameters: 0

Fully Connected Layer (FC layer)

- Contains neurons that connect to the entire input volume, as in ordinary Neural Networks





Alexnet

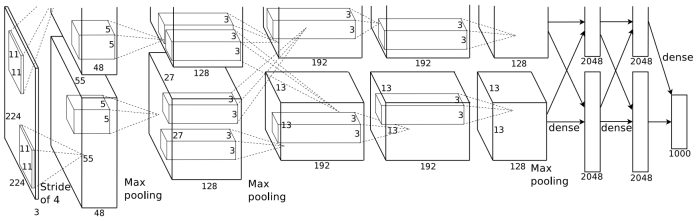


Figure 2: An illustration of the architecture of our CNN, explicitly showing the delineation of responsibilities between the two GPUs. One GPU runs the layer-parts at the top of the figure while the other runs the layer-parts at the bottom. The GPUs communicate only at certain layers. The network's input is 150,528-dimensional, and the number of neurons in the network's remaining layers is given by 253,440–186,624–64,896–64,896–43,264–4096–4096–1000.

"ImageNet Classification with Deep Convolutional Neural Networks", NIPS, 2012

Pytorch

```python
class AlexNet(nn.Module):
    def __init__(self, num_classes: int = 1000, dropout: float = 0.5) -> None:
        super().__init__()
        self.features = nn.Sequential(
            nn.Conv2d(3, 64, kernel_size=11, stride=4, padding=2),
            nn.ReLU(inplace=True),
            nn.MaxPool2d(kernel_size=3, stride=2),
            nn.Conv2d(64, 192, kernel_size=5, padding=2),
            nn.ReLU(inplace=True),
            nn.MaxPool2d(kernel_size=3, stride=2),
            nn.Conv2d(192, 384, kernel_size=3, padding=1),
            nn.ReLU(inplace=True),
            nn.Conv2d(384, 256, kernel_size=3, padding=1),
            nn.ReLU(inplace=True),
            nn.Conv2d(256, 256, kernel_size=3, padding=1),
            nn.ReLU(inplace=True),
            nn.MaxPool2d(kernel_size=3, stride=2),
        )
        self.avgpool = nn.AdaptiveAvgPool2d((6, 6))
        self.classifier = nn.Sequential(
            nn.Dropout(p=dropout),
            nn.Linear(256 * 6 * 6, 4096),
            nn.ReLU(inplace=True),
            nn.Dropout(p=dropout),
            nn.Linear(4096, 4096),
            nn.ReLU(inplace=True),
            nn.Linear(4096, num_classes),
        )

    def forward(self, x: torch.Tensor) -> torch.Tensor:
        x = self.features(x)
        x = self.avgpool(x)
        x = torch.flatten(x, 1)
        x = self.classifier(x)
        return x
```

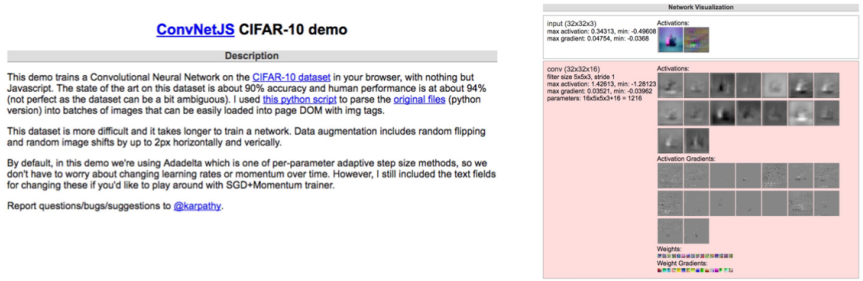
AlexNet was originally introduced in "ImageNet Classification with Deep Convolutional Neural Networks". This implementation is based instead on the "One Weird Trick for Parallelizing Convolutional Neural Networks" paper.

single-column model with 64, 192, 384, 384, 256 filters in the five convolutional layers, respectively

Pytorch

```python
import torch
from PIL import Image
from torchvision import transforms

model = torch.hub.load('pytorch/vision:v0.10.0', 'alexnet', pretrained=True)
model.eval()

input_image = Image.open(filename)
preprocess = transforms.Compose([
    transforms.Resize(256),
    transforms.CenterCrop(224),
    transforms.ToTensor(),
    transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225]),
])
input_tensor = preprocess(input_image)
# create a mini-batch as expected by the model
input_batch = input_tensor.unsqueeze(0)

if torch.cuda.is_available():
    input_batch = input_batch.to('cuda')
    model.to('cuda')

with torch.no_grad():
    output = model(input_batch)
    probabilities = torch.nn.functional.softmax(output[0], dim=0)

print(torch.topk(probabilities, 5))
# https://raw.githubusercontent.com/pytorch/hub/master/imagenet_classes.txt
```

[ConvNetJS demo: training on CIFAR-10]



http://cs.stanford.edu/people/karpathy/convnetjs/demo/cifar10.html

Summary

- ConvNets stack CONV,POOL,FC layers
- Trend towards smaller filters and deeper architectures
- Trend towards getting rid of POOL/FC layers (just CONV)
- Historically architectures looked like
  [(CONV-RELU)*N-POOL?]*M-(FC-RELU)*K,SOFTMAX
  where N is usually up to ~5, M is large, 0 <= K <= 2.
- But recent advances such as ResNet/GoogLeNet have challenged this paradigm

Transfer learning

You need a lot of a data if you want to train/use CNNs?

Transfer Learning with CNNs

Donahue et al, "DeCAF: A Deep Convolutional Activation Feature for Generic Visual Recognition", ICML 2014
Razavian et al, "CNN Features Off-the-Shelf: An Astounding Baseline for Recognition", CVPR Workshops 2014

1. Train on Imagenet

Transfer Learning with CNNs

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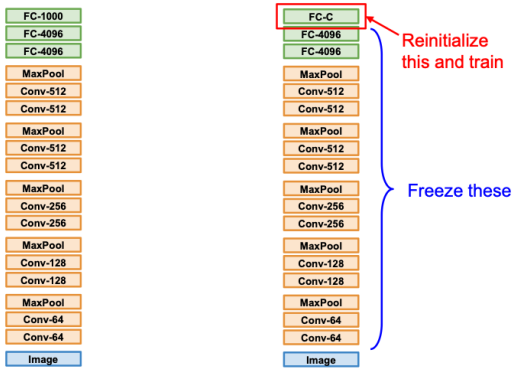
Razavian et al, "CNN Features Off-the-Shelf: An Astounding Baseline for Recognition", CVPR Workshops 2014

1. Train on Imagenet
2. Small Dataset (C classes)



Transfer Learning with CNNs

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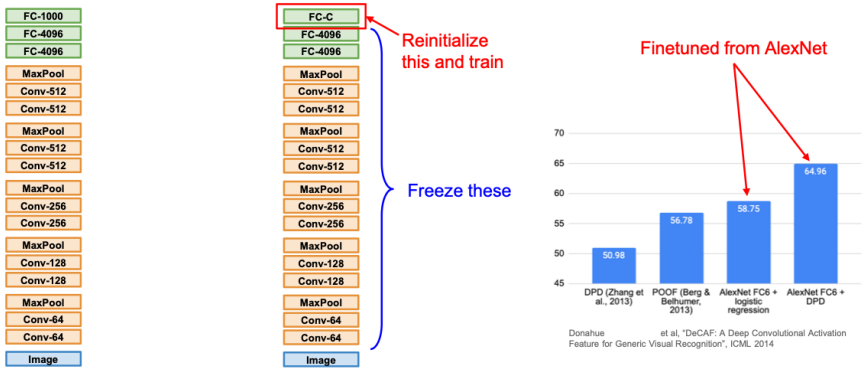
1. Train on Imagenet
2. Small Dataset (C classes)



Transfer Learning with CNNs

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Razavian et al, "CNN Features Off-the-Shelf: An Astounding Baseline for Recognition", CVPR Workshops 2014

1. Train on Imagenet
2. Small Dataset (C classes)
3. Bigger dataset