Deep Learning

Convolutional Neural Networks

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Deep learning

- Deep learning transformed the area of computer vision (CV) because now the creators of AI systems do not need to tailor algorithms for specific tasks
- Instead, they can provide lots of data to the algorithm and later retrain the model to be able to execute another type of task
- For example, we can train a model to be able to execute face detection and later retrain the model to be able to detect diseases on medical images

Image classification

- Image classification is the task of taking an input image and outputting a class (a cat, dog, etc.), or a probability of classes that best describes the image

- For us, humans, this is a very natural task
- This is not the case with computers…

3

There are other tasks other than classification, as for example, regression, but we will concentrate on classification

For humans, this task of recognition is one of the first skills we learn from the moment we are born and is one that comes naturally and effortlessly as adults. Without even thinking twice, we're able to quickly and seamlessly identify the environment we are in as well as the objects that surround us. When we see an image or just when we look at the world around us, most of the time we are able to immediately characterize the scene and give each object a label, all without even consciously noticing. These skills of being able to quickly recognize patterns, generalize from prior knowledge, and adapt to different image environments are ones that we do not share with our fellow machines.

Vision is one of the most important senses that humans possess. We rely on vision every day for things like navigation, manipulation of objects, how can we pick objects, object recognition, recognize complex human emotions and behaviors.

In this chapter, we are going to be learning how deep learning can build powerful computer visions systems capable of solving extraordinary complex tasks that would not be possible to solve 15 years ago.

Inputs

What we see

08	02	22	97	38	15	00	40	00	75	04	05	07	78	52	12	50	77	91	08
49	49	99	40	17	81	18	57	60	87	17	40	98	43	69	48	04	56	62	00
81	49	31	73	55	79	14	29	93	71	40	67	53	88	30	03	49	13	36	65
52	70	95	23	04	60	11	42	69	24	68	56	01	32	56	71	37	02	36	91
22	31	16	71	51	67	63	89	41	92	36	54	22	40	40	28	66	33	13	80
24	47	32	60	99	03	45	02	44	75	33	53	78	36	84	20	35	17	12	50
32	98	81	28	64	23	67	10	26	38	40	67	59	54	70	66	18	38	64	70
67	26	20	68	02	62	12	20	95	63	94	39	63	08	40	91	66	49	94	21
24	55	58	05	66	73	99	26	97	17	78	78	96	83	14	88	34	89	63	72
21	36	23	09	75	00	76	44	20	45	35	14	00	61	33	97	34	31	33	95
78	17	53	28	22	75	31	67	15	94	03	80	04	62	16	14	09	53	56	92
16	39	05	42	96	35	31	47	55	58	88	24	00	17	54	24	36	29	85	57
86	56	00	48	35	71	89	07	05	44	44	37	44	60	21	58	51	54	17	58
19	80	81	68	05	94	47	69	28	73	92	13	86	52	17	77	04	89	55	40
04	52	08	83	97	35	99	16	07	97	57	32	16	26	26	79	33	27	98	66
88	36	68	87	57	62	20	72	03	46	33	67	46	55	12	32	63	93	53	69
04	42	16	73	38	25	39	11	24	94	72	18	08	46	29	32	40	62	76	36
20	69	36	41	72	30	23	88	34	62	99	69	82	67	59	85	74	04	36	16
20	73	35	29	78	31	90	01	74	31	49	71	48	86	81	16	23	57	05	54
01	70	54	71	83	51	54	69	16	92	33	48	61	43	52	01	89	19	67	48

What computers see

Inputs

- When a computer takes an image as input, it will see an array of pixel values
- Let's say we have a color image in JPG form and its size is 480 x 480
- The representative array of numbers will have dimensions 480 x 480 x 3 (3 refers to RGB values)
- Each of these numbers is given a value from 0 to 255, describing the pixel intensity at that point
- These numbers are the only inputs available to the computer

Outputs

- The idea is that we give the computer this array of numbers and it will output numbers that describe the probability of the image belonging to a certain class (.80 for cat, .15 for dog, .05 for bird, etc.)

Feature detection

- In order to correctly classify an image, the system must be able to identify the features that are specific to each class

Eyes,
Nose,
Mouth,
...

Doors,
Windows
Roof,
...

Wheels,
Licence plate,
Headlights,
...

7

If the system is able to identify the features of some class it can tell with pretty high confidence that the image corresponds to that class.

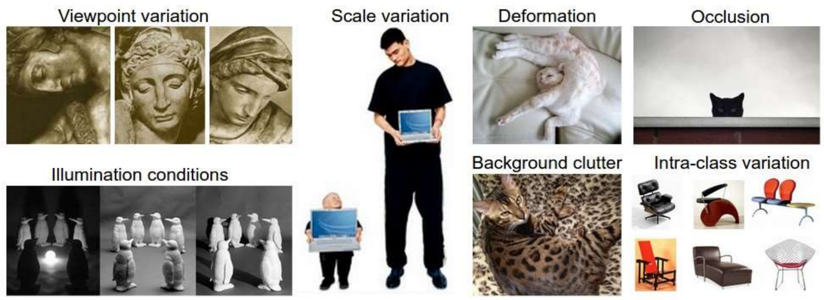
Manual feature detection

- In order to be able to classify images in some domain, we can use our knowledge about the domain to define the features that are needed and then build a system that is able to detect those features

Manual feature detection

- Challenge: How do we detect the features?

A good image classification model must be invariant to all these variations, while simultaneously retaining sensitivity to the inter-class variations



- Manual extraction of features (that is, developing algorithms able to extract features) is a very difficult task

9

However, the detection of features is a bottleneck in this task.

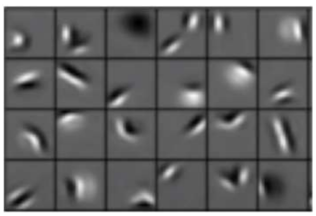
There can be lots of variations in the images (viewpoint, scale, deformation, backround clutter, illumination conditions, occlusions, intra class variation, etc.).

And when we build a classification system it must be invariant to these variations. That is, it should be sensitive to variations between classes but invariant to variations within the same class.

Feature detection

- Can we automatically learn a hierarchy of features directly from the data instead of manual engineering them?

Low level features



Edges, dark spots,…

Mid level features

Eyes, ears, noses,…

High level features

Faces

10

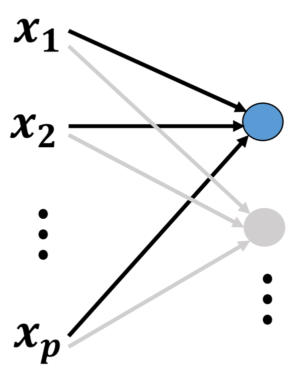
That is, can we build a system that is able to first identify low level features as, for example, edges, dark or light spots, then use these to identify mid level features likes, for example, eyes, ears and noses and, finally, be able to identify faces?

Convolutional neural networks

- This can be done with convolutional neural networks
- These networks are able to learn the visual features directly from data, as well as a hierarchy of these features and build a representation of what makes up our final classes labels
- The patterns they learn are translation invariant -> after learning a certain pattern, a convnet can recognize it anywhere
- Let us first see why don’t we do it with MLPs

Image classification using MLPs

Input: we would need to collapse our 2D image into a 1D vector of pixel values



Problems

- Spatial information lost
- Many parameters (weights)

Every pixel would feed each unit of the 1st hidden layer

12

Spatial structure information

Image classification with NNs

How can we use spatial structure in the input to design the architecture of the network?

13

Feature Extraction

Feature extraction

X

-1	-1	-1	-1	-1	-1	-1	-1	-1
-1	1	-1	-1	-1	-1	-1	1	-1
-1	-1	1	-1	-1	-1	1	-1	-1
-1	-1	-1	1	-1	1	-1	-1	-1
-1	-1	-1	-1	1	-1	-1	-1	-1
-1	-1	-1	1	-1	1	-1	-1	-1
-1	-1	1	-1	-1	-1	1	-1	-1
-1	1	-1	-1	-1	-1	-1	1	-1
-1	-1	-1	-1	-1	-1	-1	-1	-1

X?

-1	-1	-1	-1	-1	-1	-1	-1	-1
-1	-1	-1	-1	-1	-1	1	-1	-1
-1	1	1	-1	-1	1	-1	-1	-1
-1	-1	-1	1	-1	1	-1	-1	-1
-1	-1	-1	-1	1	-1	-1	-1	-1
-1	-1	-1	1	-1	1	1	-1	-1
-1	-1	-1	1	-1	-1	-1	1	-1
-1	-1	1	-1	-1	-1	-1	-1	-1
-1	-1	-1	-1	-1	-1	-1	-1	-1

We want to be able to classify an X as an X even if it is shifted, shrunk, rotated or deformed

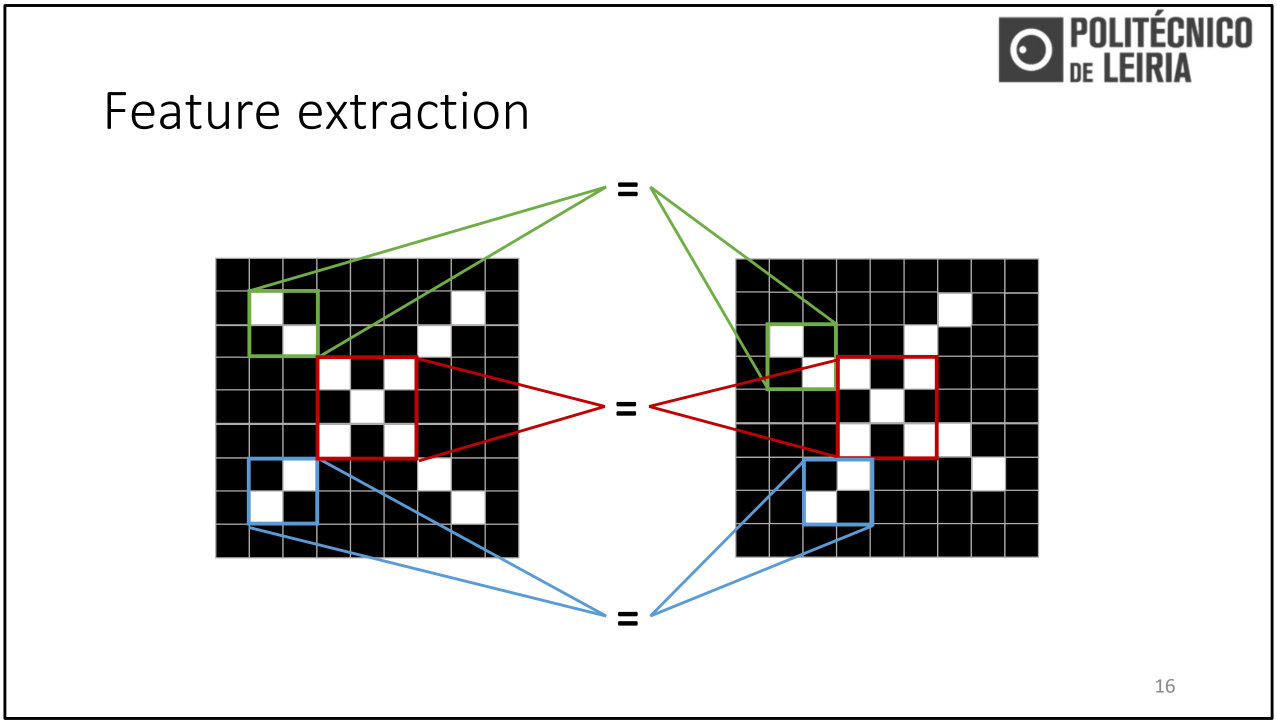
15

Suppose that we want to be able to classify Xs on black and white images.

So, inputs will be images represented as matrices of pixel values, where black is represented as -1 and white by 1.

Well, we could just try to compare the input matrices with a perfect X image. And if an image is close enough, we would classify it as an X.

However, we can’t do this because there is too much variation on images and we want to be able to classify an X image as an X even if it is shifted, shrunk, rotated or deformed.



So, instead of just comparing our input image with a perfect X, we will try to identify the important pieces or patches that characterize an X.

That is, during the training phase of the model/network we will try to identify the features that characterize an X image.

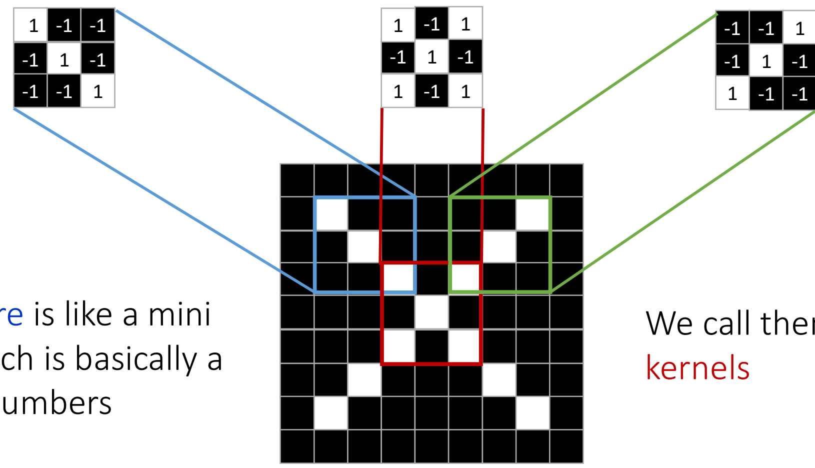
Later, once trained, the model will look for those features in the input image.

If our model is able to find rough X features matches, then it can classify our input image with pretty high confidence as an X.

We can also say that if two images share the same features, then we can say that they belong to the same class or that they represent the same object.

Feature extraction

Filters



Each feature is like a mini image, which is basically a matrix of numbers

We call them filters or kernels

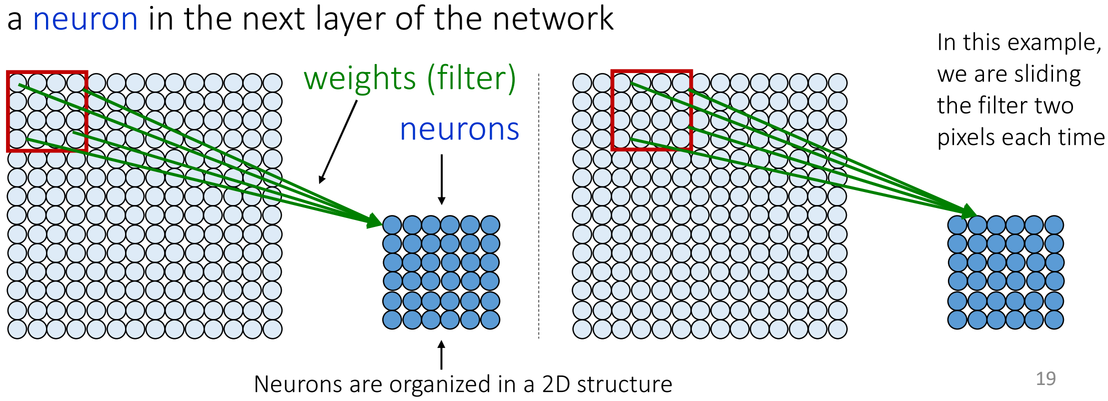
Feature extraction

- We want to have a way of computing if a feature occurs in the image and where does it occur (because it may occur more than once in different places)
- We may train different feature detectors (each one detects one feature) and each detetor moves around the image looking for that feature in different windows of the image
- We need also to somehow save information about the occurrence of each feature in each window

Feature extraction

1	-1	-1	1
-1	1	1	-1
-1	1	1	-1
1	-1	-1	1

- We may slide each filter across the image. For each image window (called receptive field) *versus* filter, a value is computed and “saved” in a neuron in the next layer of the network



19

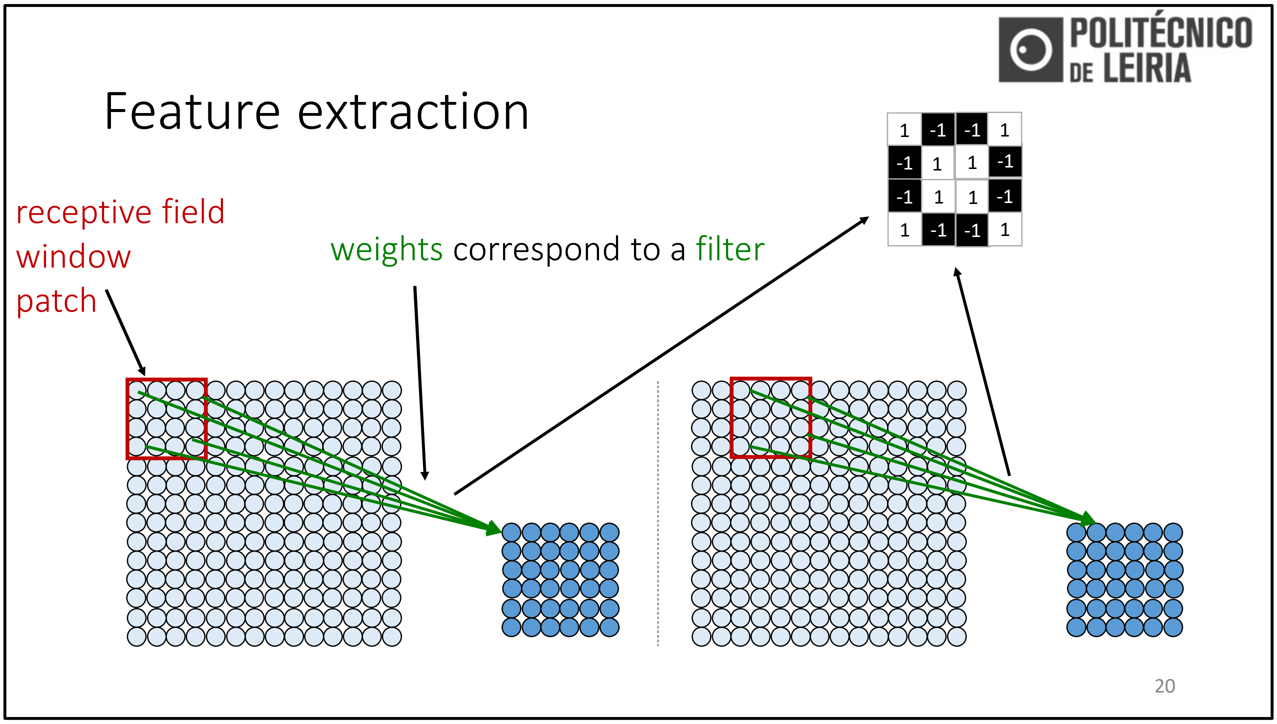
In order to do that, we may slide each filter across the image and connect each window in the image to a neuron in the next layer of the network.

And for each image window *versus* filter, a value is computed and “saved” in a neuron in the next layer of the network.

So, each neuron is influenced only by a small region of the image.

Please, notice also that the neurons are also organized in a 2D structure.

All this allows us to keep spatial information of the input image.



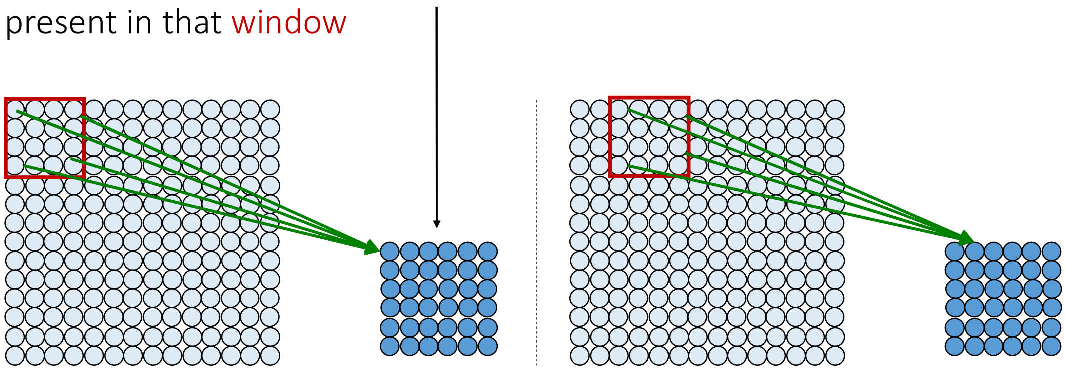
In the image, the filter values correspond to the weights of the links.

So, going first by column then by line, the 1st weight will have value 1, the 2nd will have value -1, the 3rd value -1 and so on…

Feature extraction

1	-1	-1	1
-1	1	1	-1
-1	1	1	-1
1	-1	-1	1

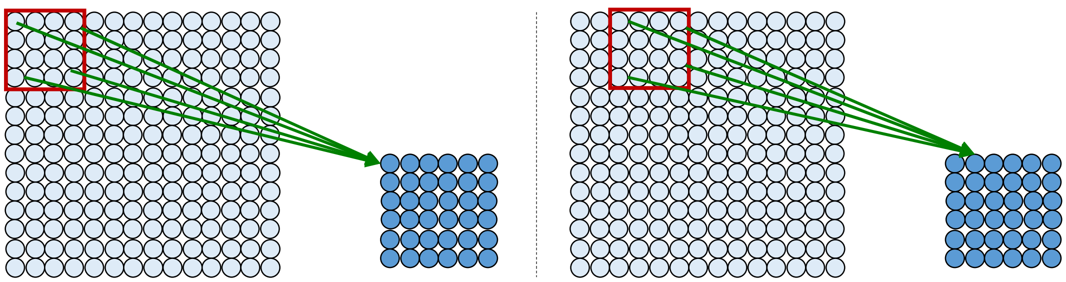
Each neuron is connected to just one window and it computes a value that somehow reflects "how much" is the feature present in that window



Feature extraction

1	-1	-1	1
-1	1	1	-1
-1	1	1	-1
1	-1	-1	1

The state/value of each neuron is computed as a weighted sum of the pixel values using the weights of the filter values and it is this operation that is used to extract features in the image



22

Later we will see how this operation allows to extract features.

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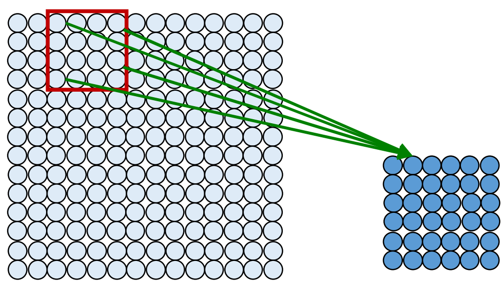
Feature extraction with convolution



- Filter of size 4x4: 16 weights (in this case)
- Apply this same filter to 4x4 windows (compute weighted sum)
- Shift the filter across all the image (by 2 pixels, in this example)

This operation is called Convolution

23

So, in the example that we have been seeing so far we are using a 4x4 filter, which means that we have 16 different weights.

We apply this same filter to 4x4 windows across the entire input image and we'll use the result of that operation to define the state of the neurons in the next hidden layer of the network.

The convolution operation

The power of convolutional neural networks comes from the convolution operation

This operation is a way of extracting features from a signal

- For example, if we have a 2D signal (an image) a feature can be a small part of what we want to find

- If we are analysing images of cats, a feature can be an eye, a ear or a tale

The convolution operation

1	1	1	0	0
0	1	1	1	0
0	0	1	1	1
0	0	1	1	0
0	1	1	0	0

Input

1	0	1
0	1	0
1	0	1

Filter / Kernel

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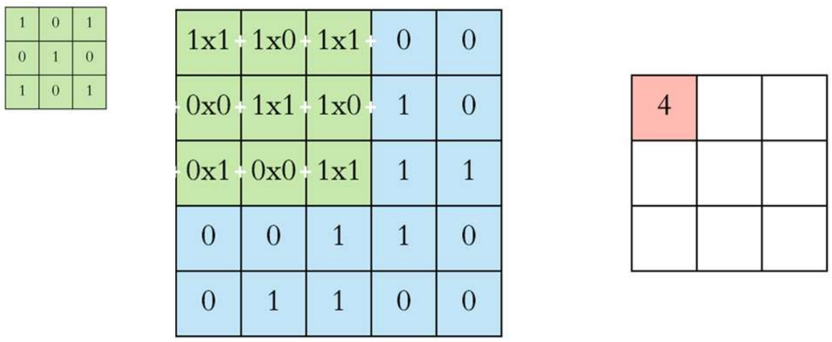
The convolution operation



The application of a filter to a window consists in performing an element-wise multiplication and then sum all the results

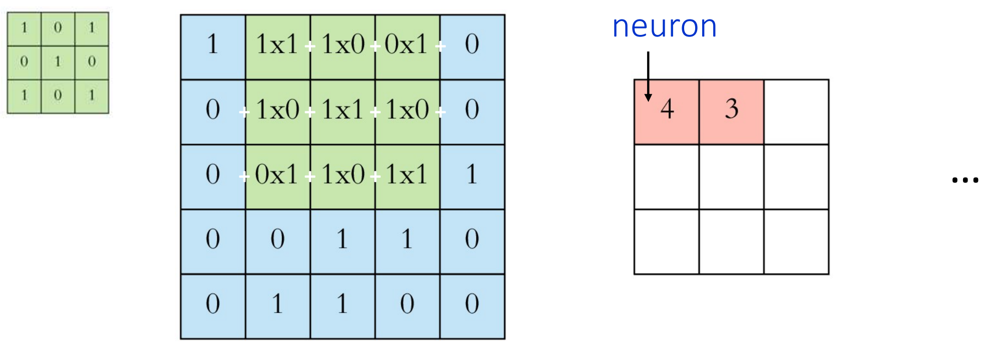
We can also think about this operation as a weigthed sum since the values of the "pixels" of each filter correspond to the weights of that filter

26

Remember that the green area where the convolution operation takes place is called the *receptive field. (that we also call window…)*

Element-wise operations: operations that are applied independently to each entry in the tensors being considered.

The convolution operation



The filter shifts accross the image and the weigthed sum is applied to different windows;
The output of each of each these operations becomes the state of a neuron

The convolution operation

1	0	1
0	1	0
1	0	1

…

1	1	1	0	0
0	1	1	1	0
0	0	1x1	1x0	1x1
0	0	1x0	1x1	0x0
0	1	1x1	0x0	0x1

4	3	4
2	4	3
2	3	4

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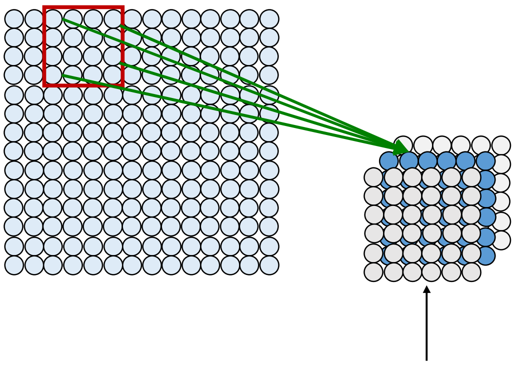
Feature maps



3 feature maps resulting from the application of 3 different filters

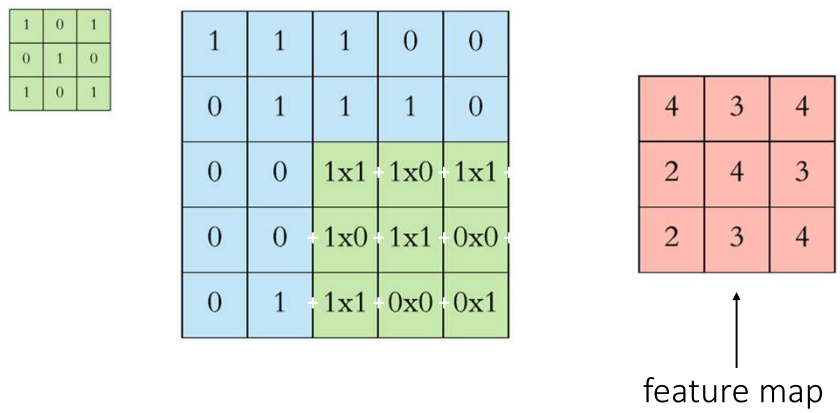
- So far, we have seen the application of just one filter
- However, each filter allows the extraction of just one feature across the image
- And we want our network to be able to extract many features
- So multiple filters are used to extract different features
- A set of neurons whose state is computed using the same filter is called a feature map

29

We perform multiple convolutions on an input, each using a different filter and resulting in a distinct feature map.

So, after the convolution step we end up with a stack of feature maps.

Convolution



30

This is just another way of looking at it…

How does the convolution operation support the extraction of features?

31

Until now we have seen that the convolution operator allows for feature extraction.

However, we haven't seen so far how or why does the convolution operator allows the extraction of features from images.

Feature extraction and convolution

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input image

-1	-1	-1	-1	-1	-1	-1	-1	-1
-1	1	-1	-1	-1	-1	-1	1	-1
-1	-1	1	-1	-1	-1	1	-1	-1
-1	-1	-1	1	-1	1	-1	-1	-1
-1	-1	-1	-1	1	-1	-1	-1	-1
-1	-1	-1	1	-1	1	-1	-1	-1
-1	-1	1	-1	-1	-1	1	-1	-1
-1	1	-1	-1	-1	-1	-1	1	-1
-1	-1	-1	-1	-1	-1	-1	-1	-1

conv

filter

1	-1	-1
-1	1	-1
-1	-1	1

=

feature map

7	-1	1	3	5	-1	3
-1	9	-1	3	-1	1	-1
1	-1	9	-3	1	-1	5
3	3	-3	5	-3	3	3
5	-1	1	-3	9	-1	1
-1	1	-1	3	-1	9	-1
3	-1	5	3	1	-1	7

The larger values in the feature map correspond to windows that better resemble the filter/feature

The feature map reflects where in the image there is activation by this particular filter

Exercise

input image

-1	-1	-1	-1	-1	-1	-1	-1	-1
-1	1	-1	-1	-1	-1	-1	1	-1
-1	-1	1	-1	-1	-1	1	-1	-1
-1	-1	-1	1	-1	1	-1	-1	-1
-1	-1	-1	-1	1	-1	-1	-1	-1
-1	-1	-1	1	-1	1	-1	-1	-1
-1	-1	1	-1	-1	-1	1	-1	-1
-1	1	-1	-1	-1	-1	-1	1	-1
-1	-1	-1	-1	-1	-1	-1	-1	-1

conv

filter

1	-1	1
-1	1	-1
1	-1	1

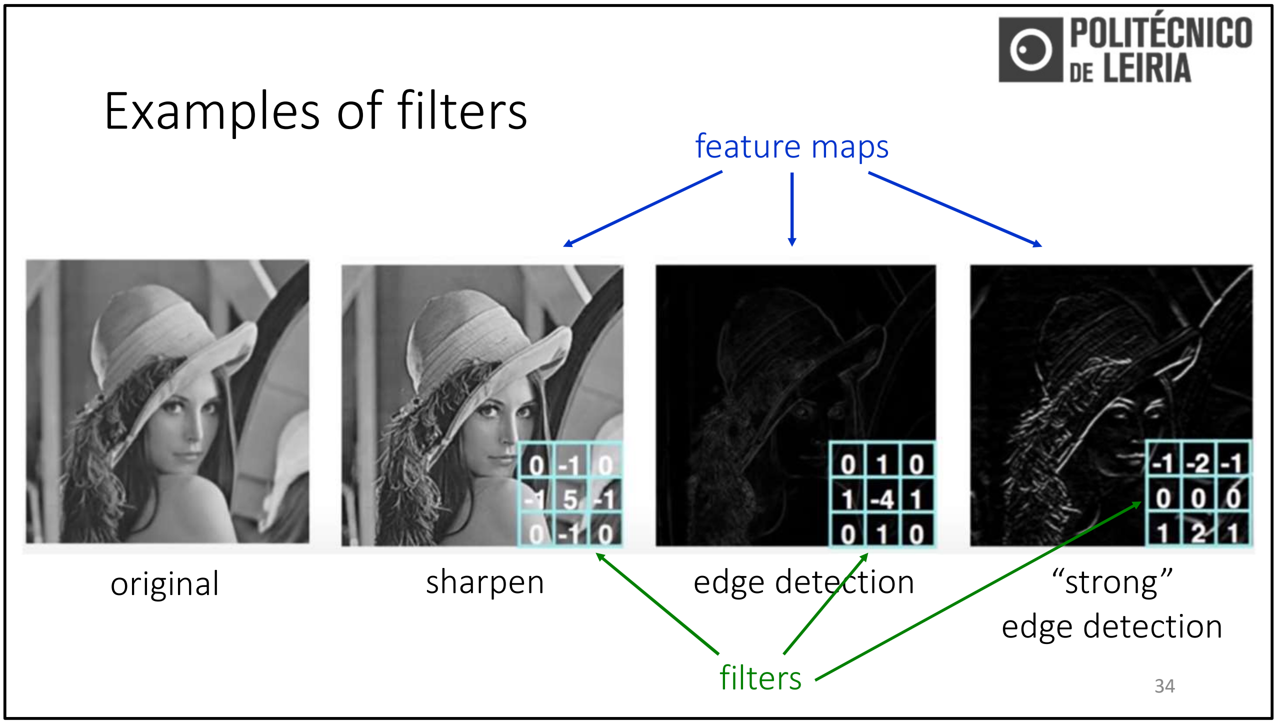
=

feature map

?

Note: Shift the filter one pixel to the right/down each time

33

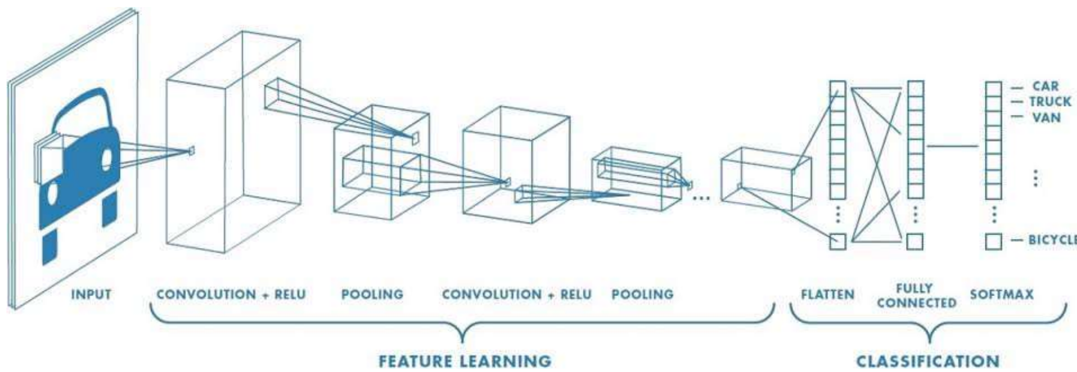


Simply by changing the weights of a filter, we can change what the filter is looking for in the image.

Convolutional Neural Networks

(CNNs)

CNNs general architecture



36

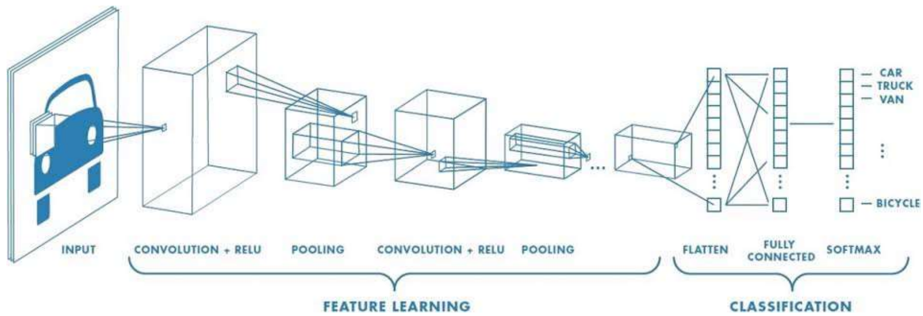
A CNN model can be thought as a combination of two parts/sections: the feature extraction part and the classification part.

The convolution + pooling layers perform feature extraction.

For example given an image, the convolution layer detects features such as eyes, ears, legs, tail and so on.

The fully connected layers then act as a classifier on top of these features and assign a probability for the input image being, for example, some animal.

CNNs main components



1. Convolutional layers: apply filters to generate feature maps
2. Non-linearity (ReLU): non-linear function applied to the feature map values
3. Pooling layers: used to down sample feature maps
4. Fully connected layers: the layers responsible for the classification task

37

Non-linearity allows us to deal with nonlinear data and to introduce complexity into the learning pipeline so that more complex tasks can be solved (this way we can build more complex and powerful models.

Pooling layers: By downsampling we become also able to deal with multiple scales of the image (we abstract data).

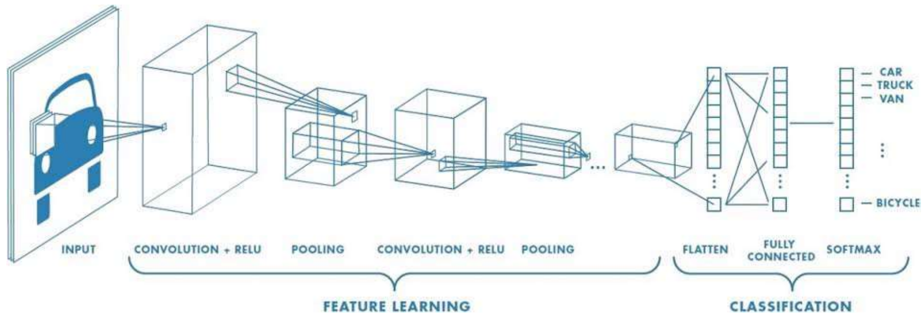
Usually, the fully connected or dense layers output values that represent the probabiliies that the image belongs to each one of the classes the network has been trained to identify.

When we use a CCN for image classification, the ideia is to:

- Train the network with image data
- Learn the weights of the filters in the convolutional and dense (fully connected) layers

In a moment we'll go through each one of these operations and break these ideas down a little bit further.

CNNs general architecture

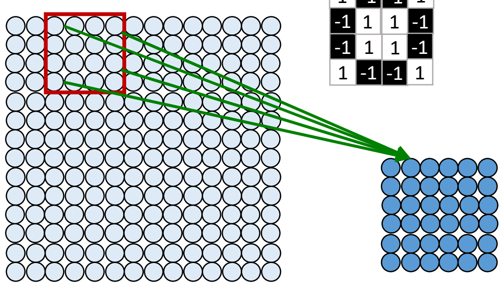


There can be several Conv + Pool blocks

That's why these networks are called deep neural networks

38

Convolutional layers



1	-1	-1	1
-1	1	1	-1
-1	1	1	-1
1	-1	-1	1

In this example, each filter would be a 4x4 matrix of weights

For each neuron in the hidden layer:

1. Take inputs from window
2. Compute weighted sum
3. Apply bias

filter weight

pixel value

$$\sum_{i=1}^{4}\sum_{j=1}^{4} w_{ij}x_{p+i,q+j} + b$$

For neuron (p, q) in hidden layer

39

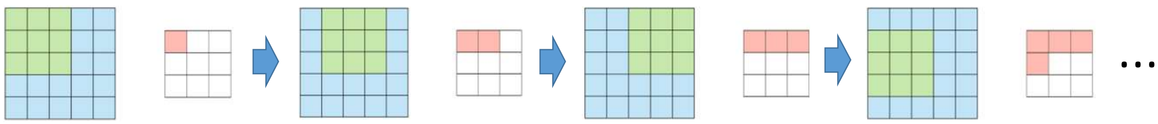
This slide basically explains again the convolutional operator but with more detail.

The only thing new here is the addition of the bias

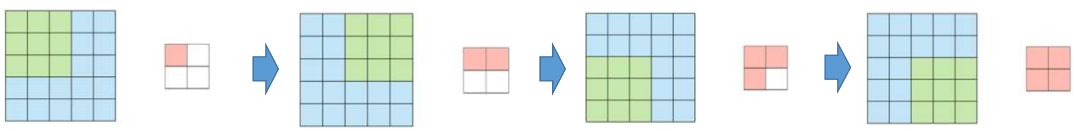
Stride

Specifies how much we move the convolution filter at each step

Stride 1



Stride 2

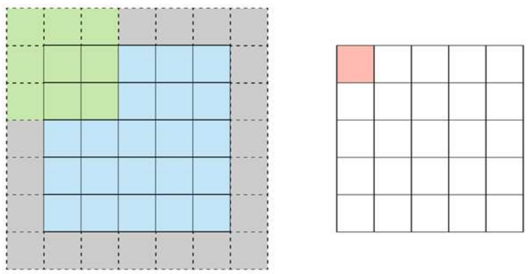


Usually, stride 1 is used

40

Padding

It is used to preserve the size of the feature map equal to the size of the input



Usually, 0s are used in the padding area (grey area) -> this is called zero-padding

Note: in this example, stride = 1

41

In the previous slides, we see that the size of the feature map is smaller than the input, because the convolution filter needs to be contained in the input.

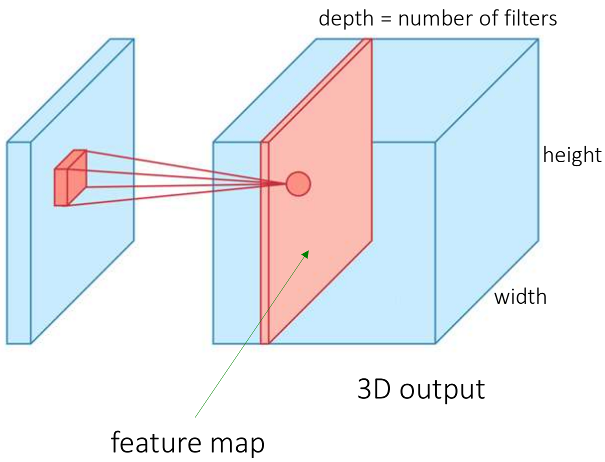
If we want to maintain the same dimensionality, we can use *padding* to surround the input with zeros.

The grey area around the input is the padding.

We either pad with zeros or the values on the edge of the image.

Now the dimensionality of the feature map matches the input. Padding is commonly used in CNN to preserve the size of the feature maps

Convolutional layers – multiple filters



As we have seen before, we will have multiple filters, that allow us to extract multiple features

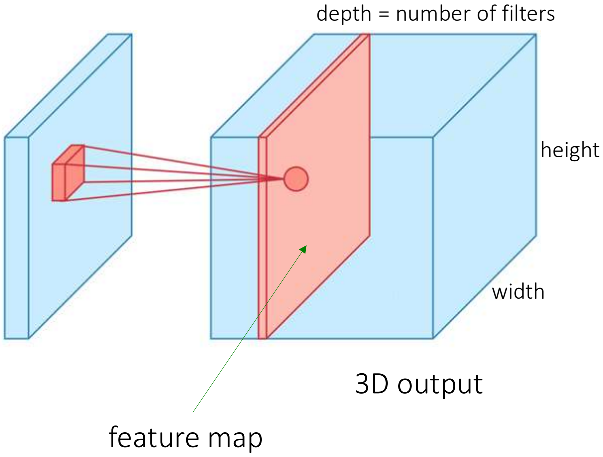
Therefore, the output of a convolutional layer is composed of a volume of feature maps (we may think on these feature maps as images)

The height and width of the feature maps depend on the filter size, on the stride value and if padding is used

42

It is our responsibility to define the number and size of the filters, the stride value and if padding is used or not.

Convolutional layers



Common configurations:

- 3 x 3 filters
- Stride 1
- With padding

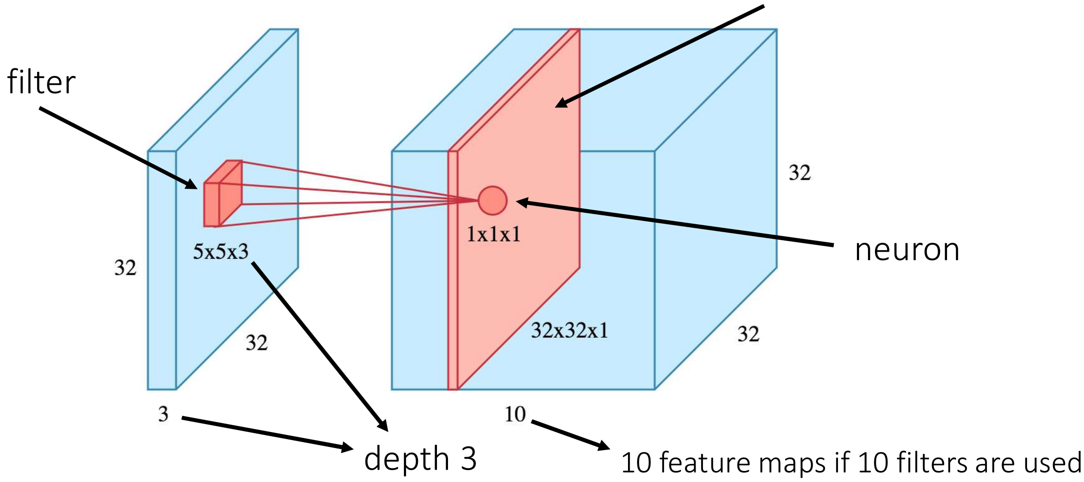
3D output

It is our responsibility to define the number and size of the filters and the stride value.

RGB images

- Until now, we have considered black and white or grey scale images
- What about RGB images (the majority)?
- RGB images are represented as a 3D matrix where the depth corresponds to color channels
- So, in these cases, the filters are also 3D, with depth 3
- But the result of the application of the filter to a receptive field is still a scalar

RGB images



feature map
filter
32
5x5x3
1x1x1
neuron
32
32x32x1
32
32
3
10
depth 3
10 feature maps if 10 filters are used

Feature map size

- Given
  - W: size of the input volume (for example, 28 for an image of 28 x 28 pixels)
  - F: size of the receptive field/filters (for example, 3 for 3 x 3 filters)
  - S: stride value
  - P: amount of zero padding

the size of the feature map is given by

$$\frac{W - F + 2P}{S} + 1$$

Exercise: confirm this with examples given in previous slides

Number of weights of a conv layer

- Given
  - *FM*: number of feature maps of the layer
  - *F*: size of the receptive field/filters (for example, 3 for 3 x 3 filters)
  - *FMP*: number of feature maps of the previous layer

the number of weights of a conv layer is given by

$$FM \times (F \times F \times FMP + \underbrace{1}_{\text{One bias per feature map}})$$

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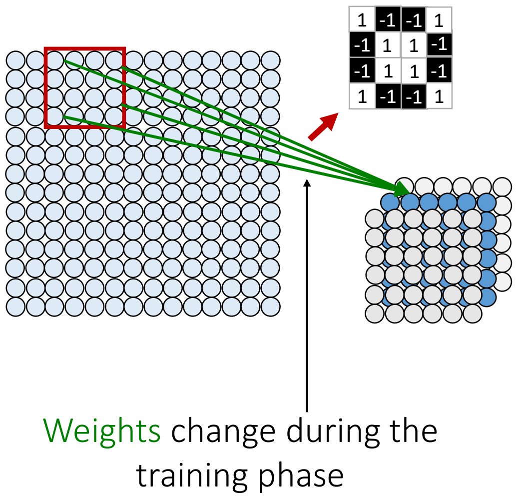
How are filters generated?



- The features are not engineered “manually”
- Instead, they are learnt during the training phase
- In fact, the training phase consists in changing progressively the weights of the network until it works as desired
- Remember that each filter/feature is defined by the weights associated with each feature map
- So, we can say that the features are discovered and tuned during the training phase

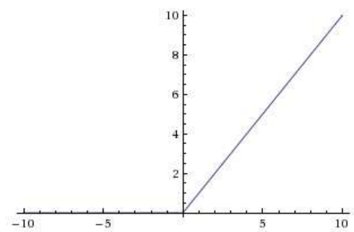
Applying non-linearity

Non-linearity is applied to all neurons/pixels of all feature maps after the convolution operation

This allows a model to respond in a non-linear way to the inputs

The most commonly used activation function after the convolutional layer is the ReLU function

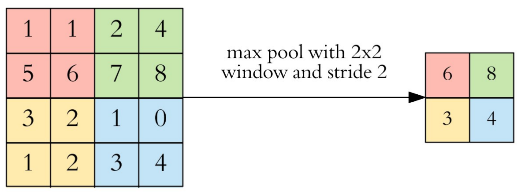
Rectified linear unit (ReLU)



$$g(z) = \max(0, z)$$

Pooling layers

feature map



Goal of pooling layers: down sampling feature maps while keeping the important information

Most common technique: **max pooling**

Max pooling: slide a window over the feature map and simply take the max value in the (pooling) window

Contrary to the convolution operation, pooling has no parameters (weights)

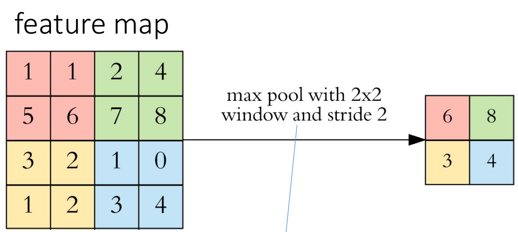
As for convolution, we need to specify the window size and stride

50

This layer usually comes right after every convolutional layers.

We shrink the spatial dimension while maintaining the spatial structure.

Pooling layers



The most common configuration

Pooling layers down sample each feature map independently

They reduce the height and width, keeping the depth intact

Thus, pooling layers reduce the number of parameters

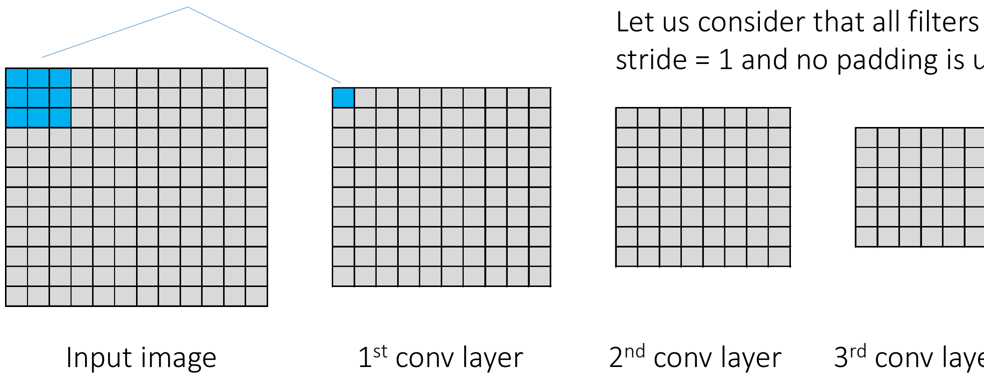
This both shortens the training time and combats overfitting

Why not average pooling?

- Well, we can use it…
- However, usually, max pooling achieves better results
- This is because the idea it to register/assess if some feature is present in some region of the image
- Computing the max value in that region allows us to do that
- Computing the average may cause us to miss or dilute feature-presence information

If we don't use pooling

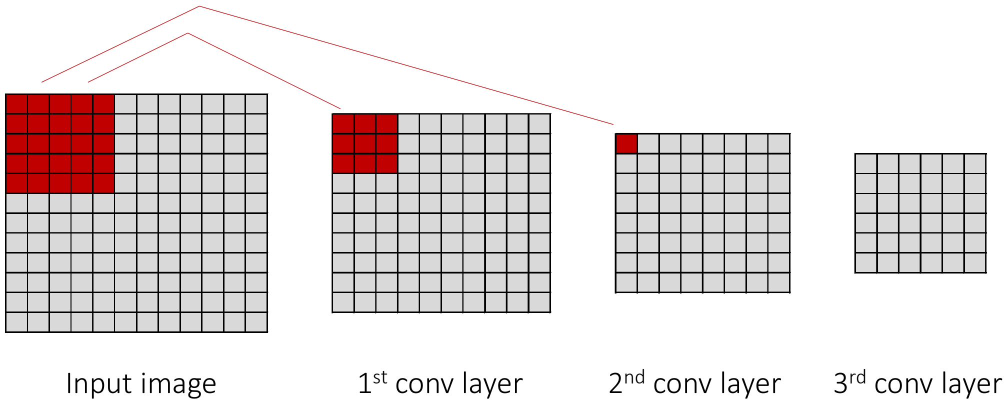
Let us consider that all filters are 3 x 3, stride = 1 and no padding is used



Each neuron in the 1st conv layer contains information coming from a 3x3 window in the input image

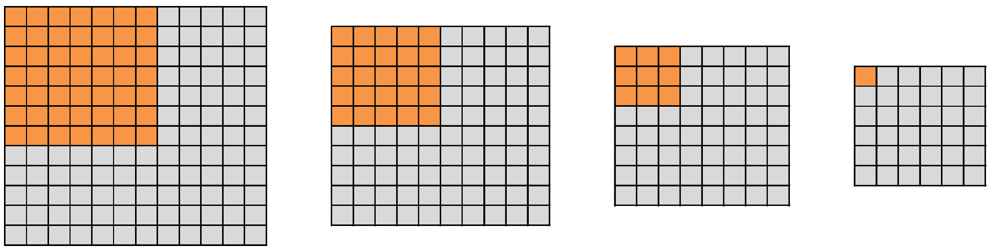
53

If we don't use pooling



Each neuron in the 2nd conv layer contains information coming from a 5x5 window in the input image

If we don't use pooling



Input image

1st conv layer

2nd conv layer

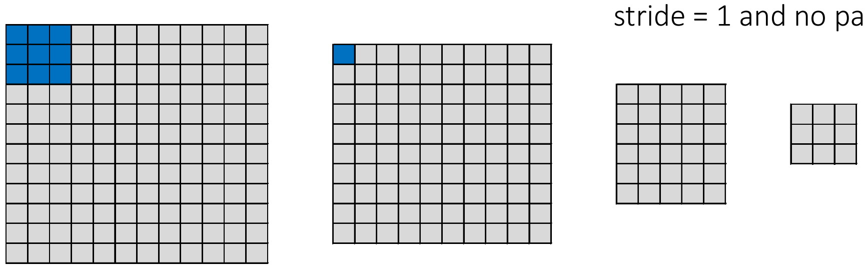
3rd conv layer

Each neuron in the 3rd conv layer contains information coming from a 7x7 window in the input image

55

If we use pooling

Let us consider that all filters are 3 x 3, stride = 1 and no padding is used

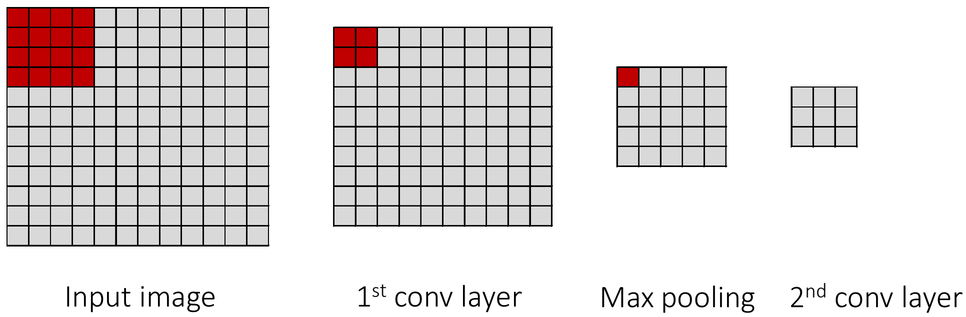


max pooling of 2 x 2 and stride 2

Input image | 1st conv layer | Max pooling | 2nd conv layer

Each neuron in the 1st conv layer contains information coming from a 3x3 window in the input image

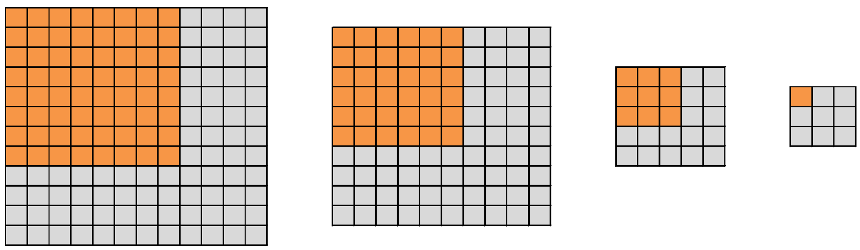
If we use pooling



Each neuron in the max pooling layer contains information coming from a 4x4 window in the input image

57

If we use pooling



Each neuron in the 2nd conv layer contains information coming from an 8x8 window in the input image

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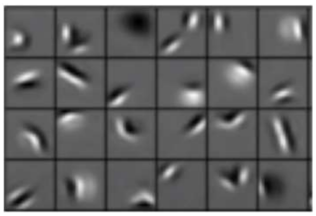
Feature detection

Remember this slide?

- Can we automatically learn a hierarchy of features directly from the data instead of manual engineering them?

Low level features



Edges, dark spots,…

Mid level features

Eyes, ears, noses,…

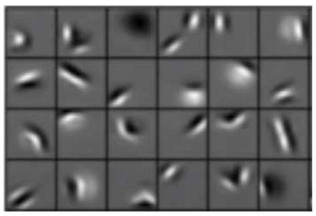
High level features

Faces

59

That is, can we build a system that is able to first identify low level features as, for example, edges, dark or light spots, then use these to identify mid level features likes eyes, ears and noses and, finally, be able to identify faces, just to give an example?

Learning (a hierarchy of) features with CNNs

Low level features	Mid level features	High level features
		
Edges, dark spots,…	Eyes, ears, noses,…	Faces
1st Conv layer	Some conv layers ahead	Last conv layer

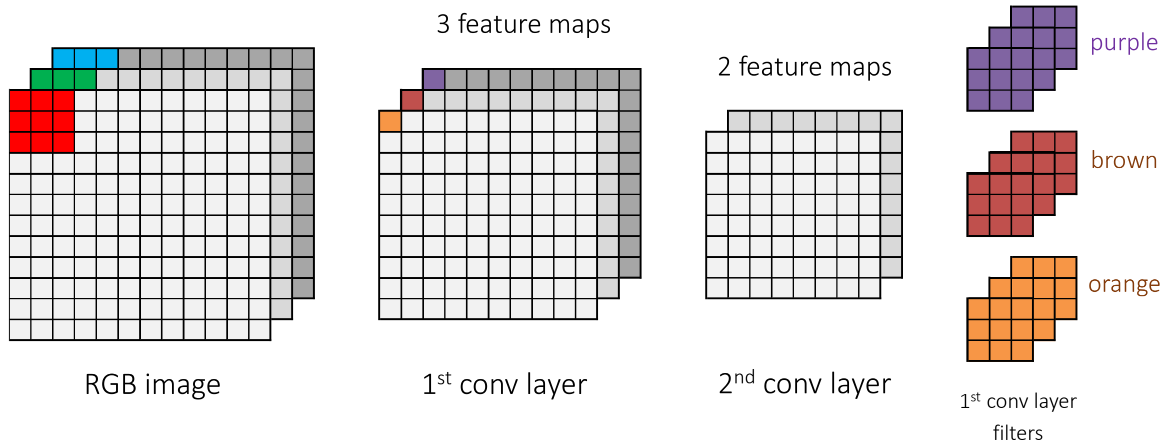
60

The convolution layers are the main powerhouse of a CNN model.

The convolution layers learn to detect meaningful and complex features by building on top of each other.

The first layers detect edges, the next layers combine them to detect shapes, the following layers merge this information to infer that this is a nose, etc.

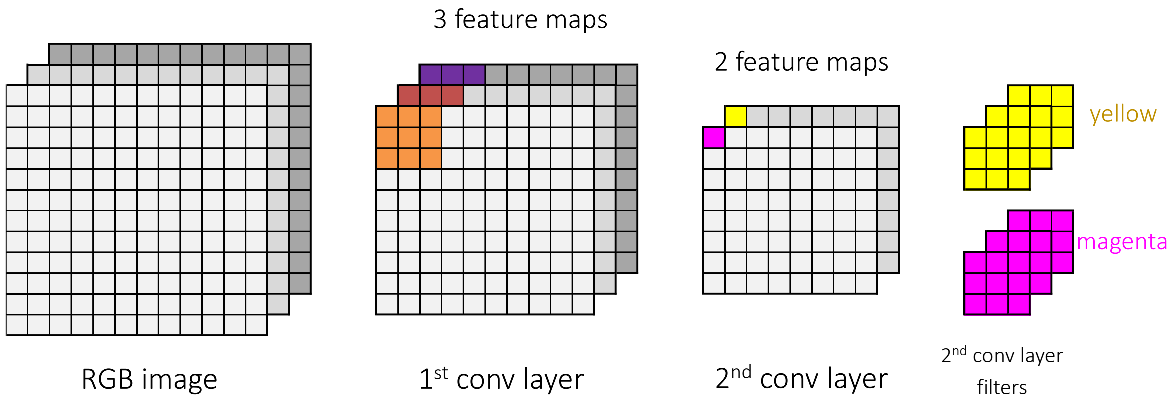
How are features combined in higher-level ones?



Remember: each filter/feature map corresponds to one feature

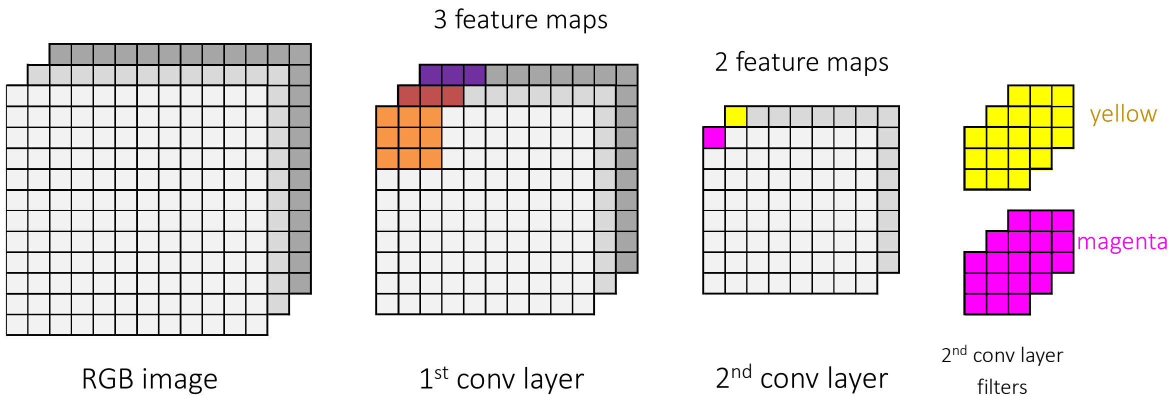
Note: in this example the first conv layer has 3 feature maps but it could have more. Indeed, the conv layers usually have much more than three feature maps. Be aware that if, for example, the first conv layer has 32 feature maps, the filters of the second conv layer will be 32 deep, and so on.

How are features combined in higher-level ones?



It may happen that the network learns a magenta filter that "fires" if the orange and purple features are present in the image

How are features combined in higher-level ones?



Or/and it may happen that the network learns a yellow filter that "fires" if the purple and brown features are present in the image

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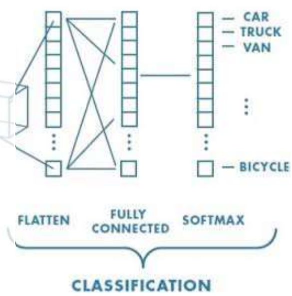
Classification in CNNs

- Convolutional + Pooling layers output high level features
- Fully connected layers use these features for classifying the input image
- They output the probability that the image belongs to each class
- This is done using the softmax function, if we have several classes, or the sigmoid function, if we have a binary classification problem



64

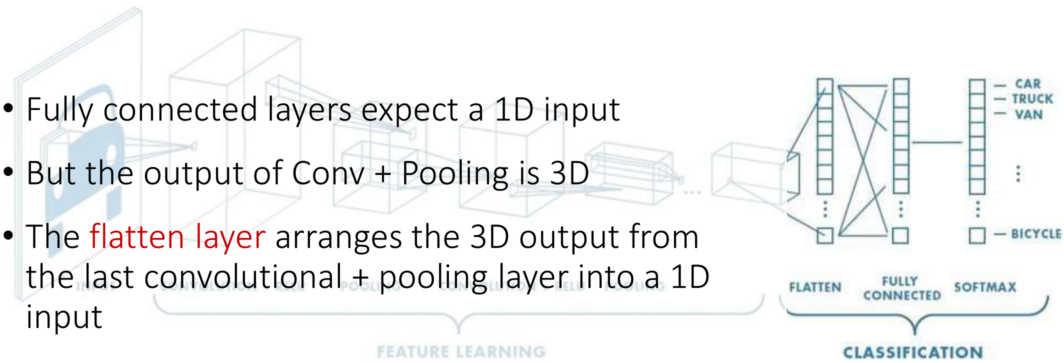
So, Convolutional + Pooling layers output high level features

After the convolution + pooling layers we have a couple of fully connected layers that are responsible for the classification task

This is the same fully connected ANN architecture we talked about in Chapter 2

The dense layer outputs a probability distribution over the image membership in different categories

Classification in CNNs



- Fully connected layers expect a 1D input
- But the output of Conv + Pooling is 3D
- The flatten layer arranges the 3D output from the last convolutional + pooling layer into a 1D input

65

Remember that the output of both convolution and pooling layers are 3D volumes, but a fully connected layer expects a 1D vector of numbers

So, we *flatten* the final pooling layer to a vector and that becomes the input to the fully connected layer

Flattening is simply arranging the 3D volume of numbers into a 1D vector, so nothing fancy happens here

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