Convolutional Neural Networks
CASA course
(09/11/2018)

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Plan for TS4

- Deep Learning
- Convolutional Operation
- Understanding border effects
- Max-pooling operation
- Fully Connected Layer
- What is happening?
- Where to use CNN?

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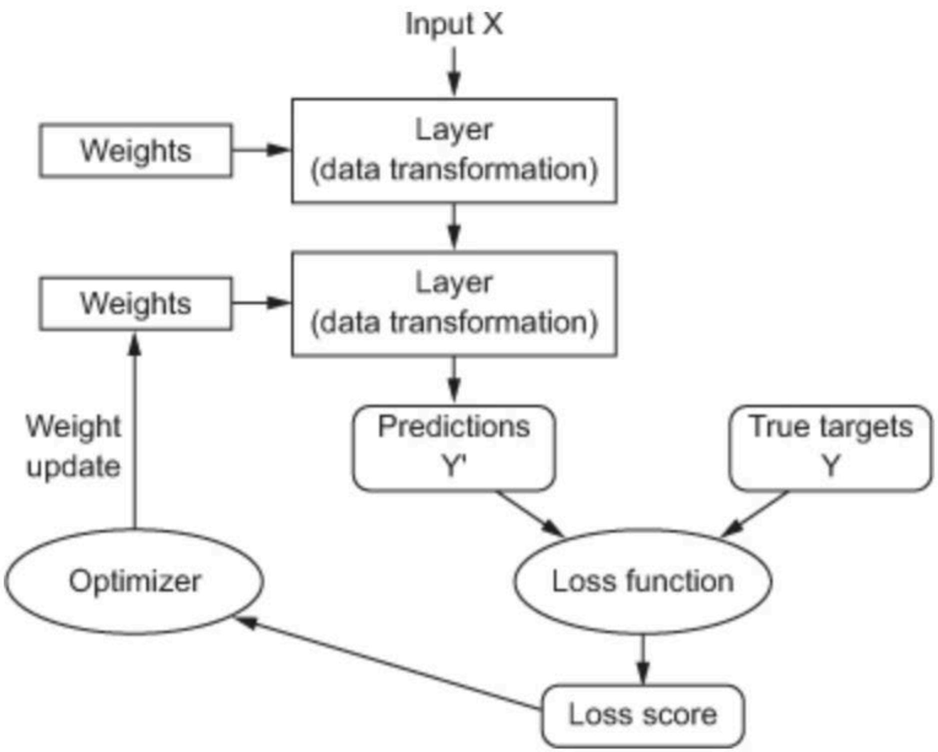
Deep Learning

Does this scheme change? No!



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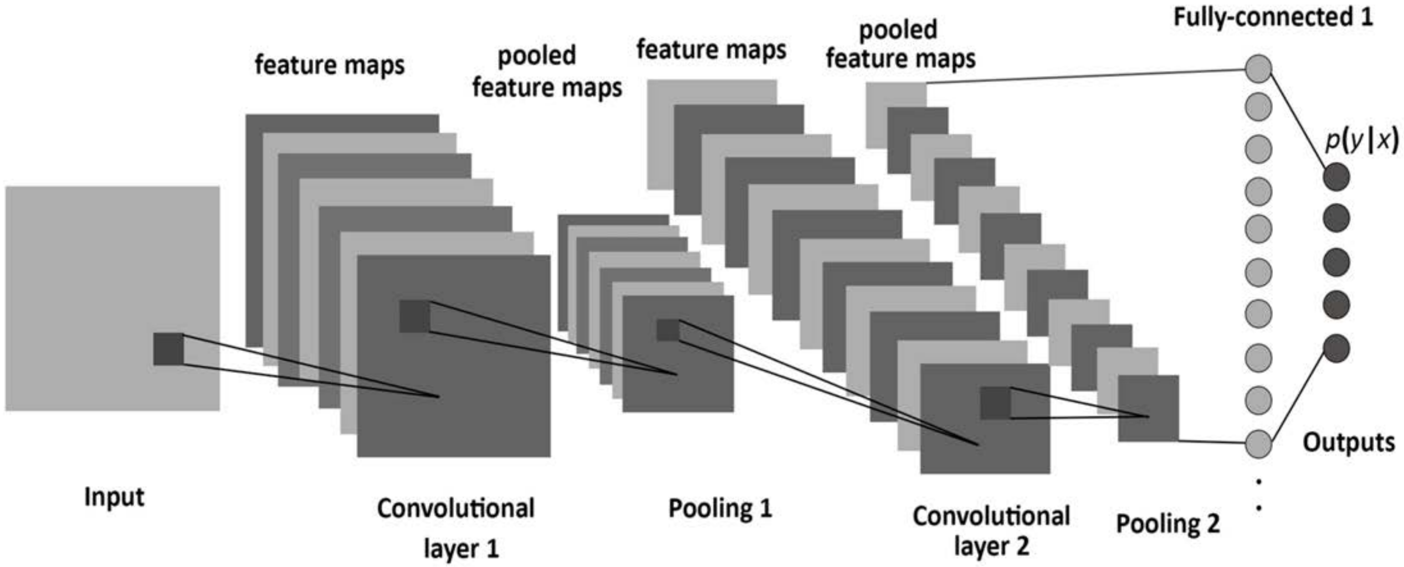
Deep Learning



Convolutional Operation

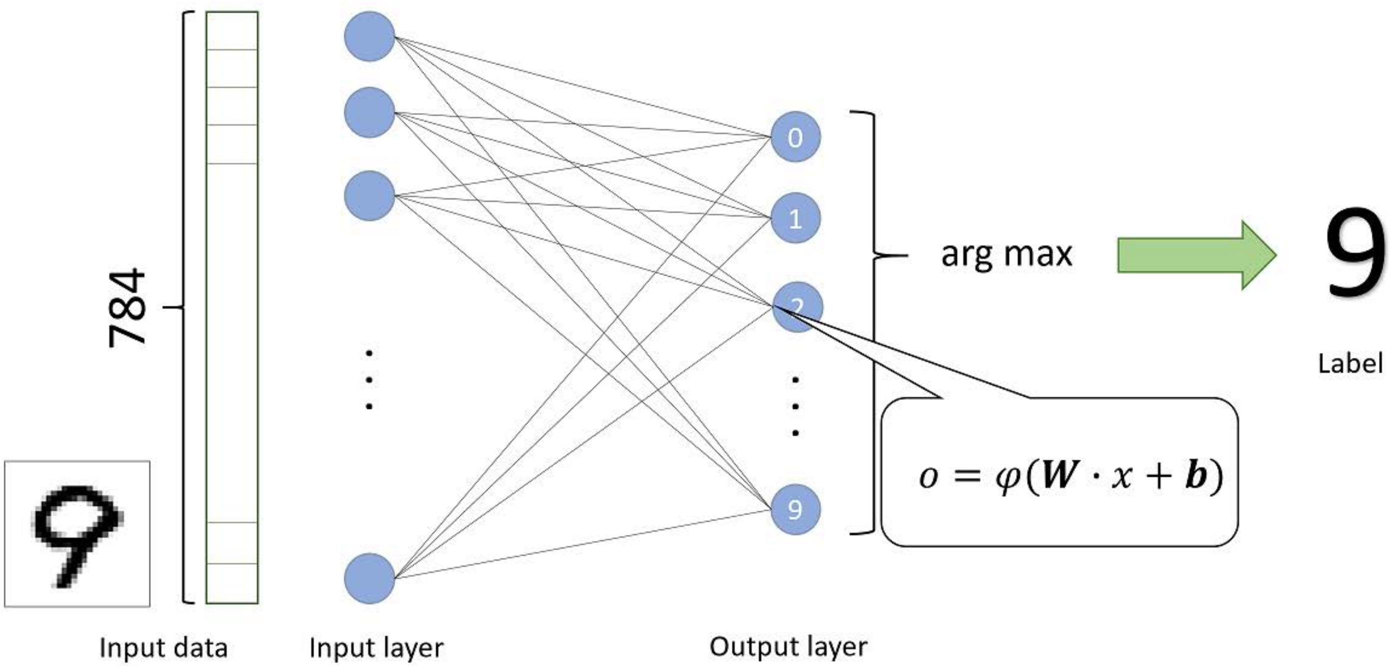
What is the difference between a densely connected layer and a convolution layer?

•Dense layers → Learn global patterns in their input space.

•Convolutional layers → Learn local patterns

Convolutional Operation

Dense layers:



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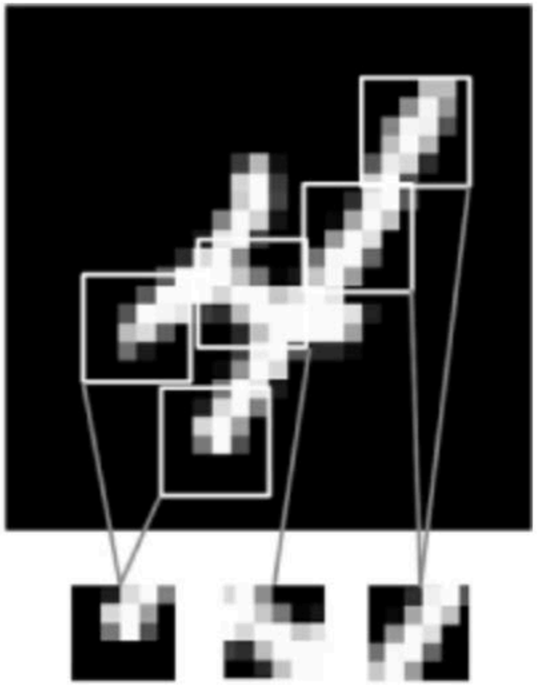
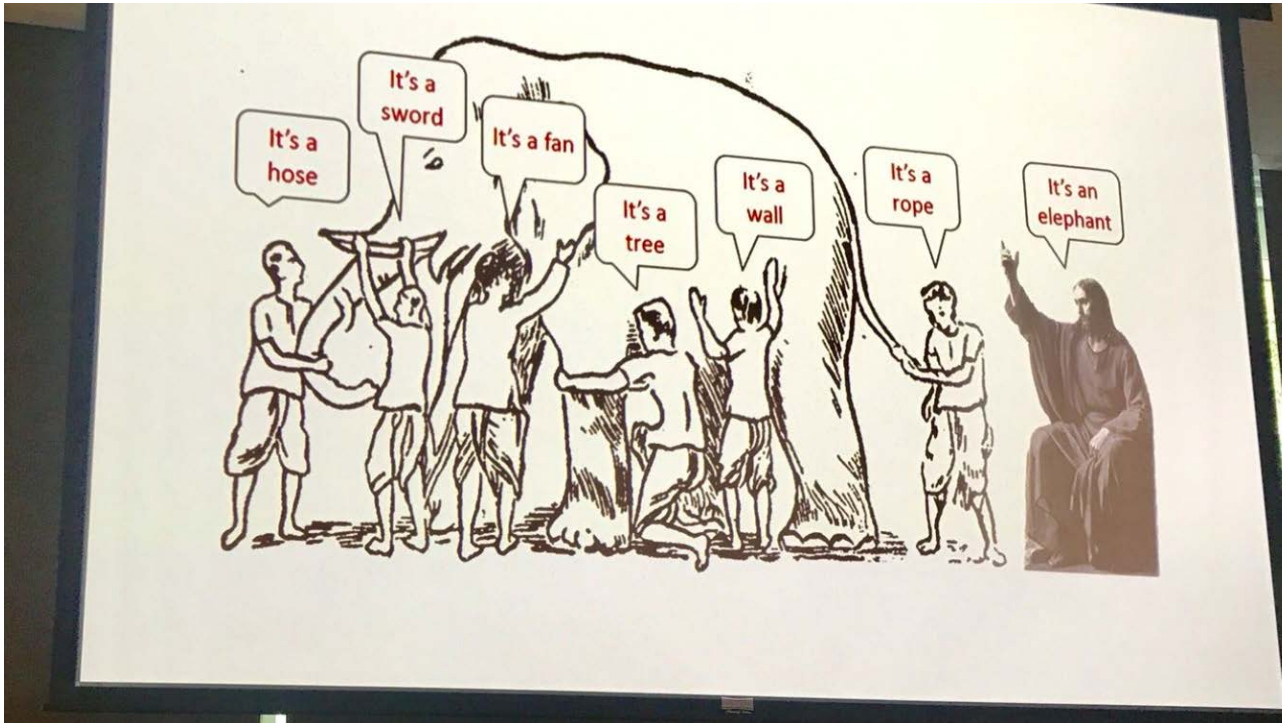
Convolutional Operation

Images can be broken into local patterns:
Edges, textures, etc…



Convolutional Operation

Convolutional layers:



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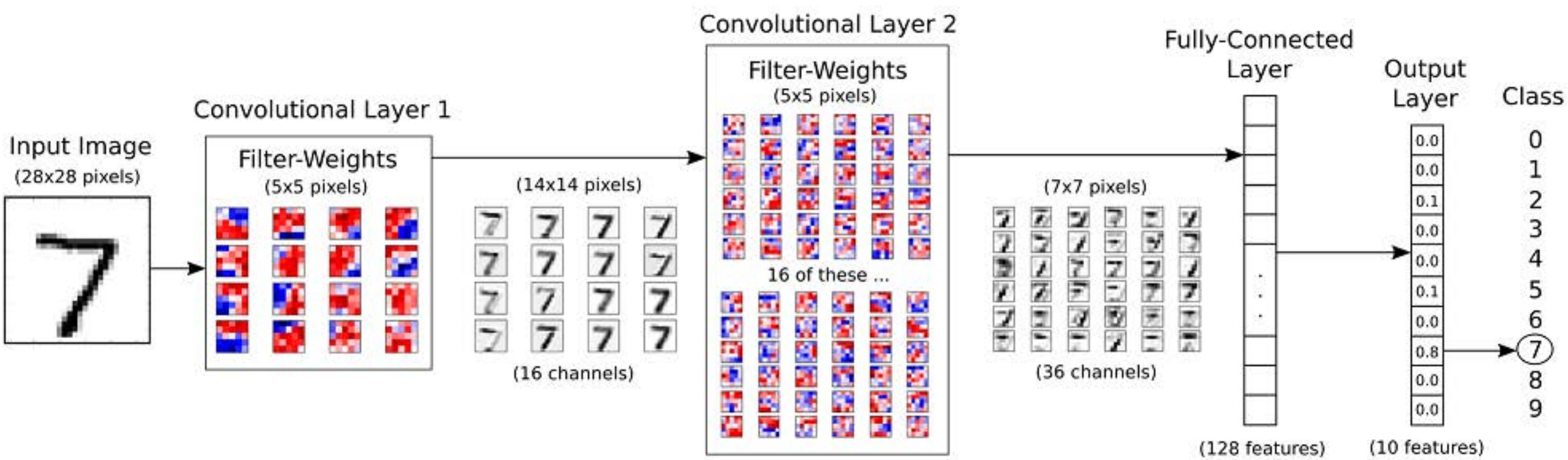
Convolutional Operation

Convolutional layers:



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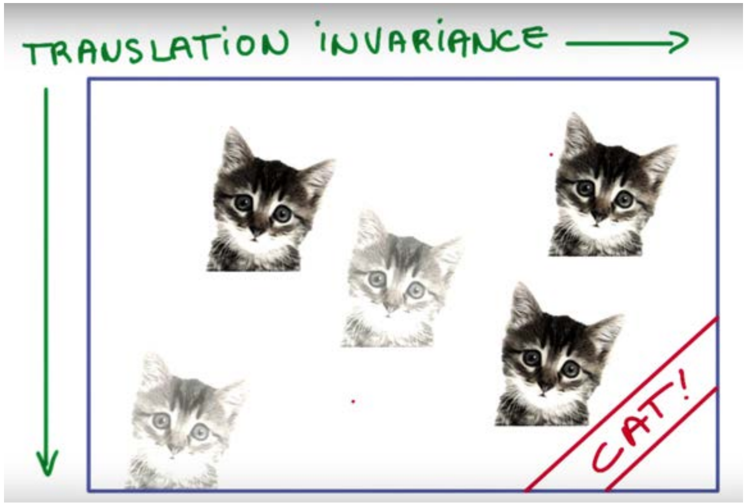
Convolutional Operation

The hability to break the image into local patterns gives convnets two properties:

1. The learned patterns are translation invariant → After learning a certain pattern in the top-left corner of the picture, a convnet can recognize it anywhere (p.e. Lower-right corner)

    The visual world is fundamentally translation invariant:



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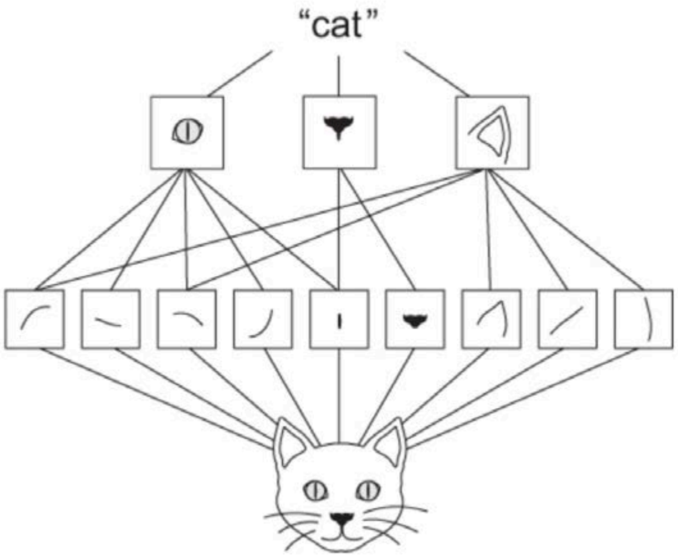
Convolutional Operation

The hability to break the image into local patterns gives convnets two properties:

2. They can learn spatial hierarchies of patterns. A first Conv. Layer will learn a small local patterns such as edges, then a second Conv. Layer will learn larger patterns made of the features of the first layer, and so on.

The visual world is fundamentally spatially hierarchical:



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Convolutional Operation

Operates over 3D tensors known as → Featured maps (height x width x depth)

For RGB image → depth = 3 at the first feature map (input)

The convolutional operation:

1. extracts patches from its input feature map.
2. Applies the same transformation to all this patches
3. Generates an output feature map (height x width x depth)

   depth → no longer RGB colors, now number of filters.

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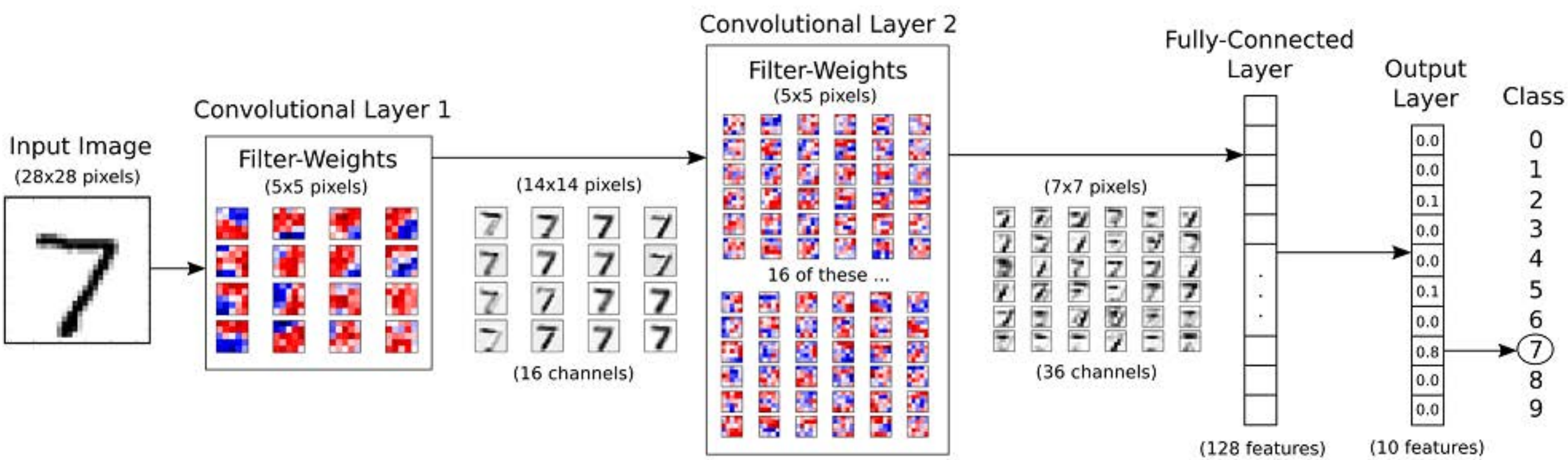
Convolutional Operation

Convolutional layers:



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Convolutional Operation

MNIST example:

...

model = models.sequential()

model.add(layers.Conv2D(32, (3,3), activation='relu', input_shape=(28,28,1)))

...

The first convolutional layer takes a feature map of (28, 28, 1)

And outputs a feature map of size (26, 26, 32):

It computes 32 filters over the input.

Each feature map contains a 26x26 grid of values.

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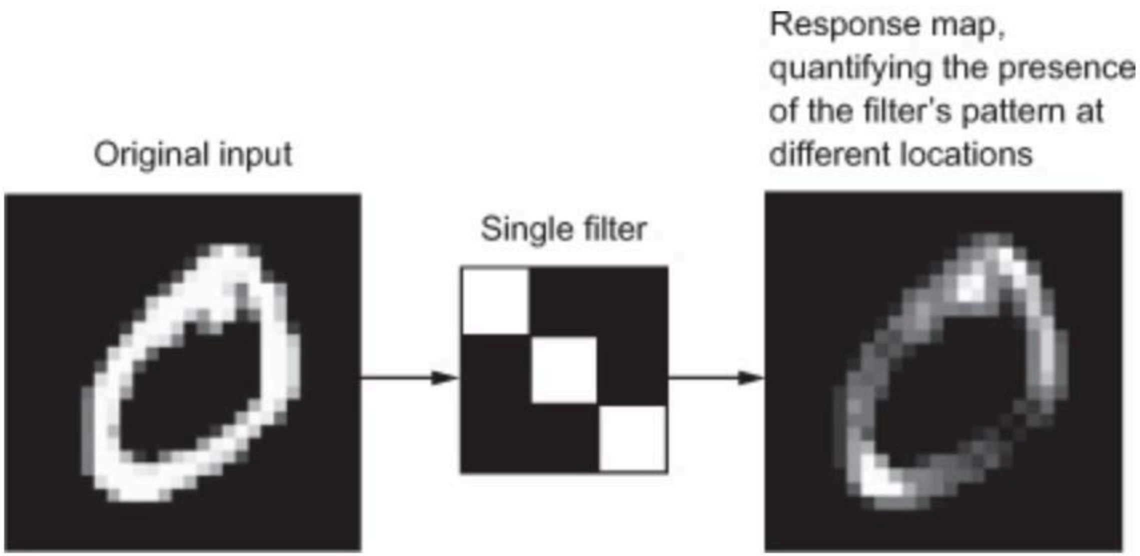
Convolutional Operation

Feature map → is the 2D map of the response of this filter over the input.



Convolutional Operation

Convolutions are defined by two keys parameters:

1. Size of the patches extracted from the inputs → Typically 3x3 or 5x5.

2. Depth of the output feature map → Number of filters computed by the convolution. It is a very dynamic value, usually you start with a depth at the first layers and end with another depth at the final layers.

These parameters can be specified in Keras Conv2D function:

Conv2D(output_depth, (height, width))

Must *read: http://cs231n.github.io/convolutional-networks/*

Convolutional Operation

MNIST example:

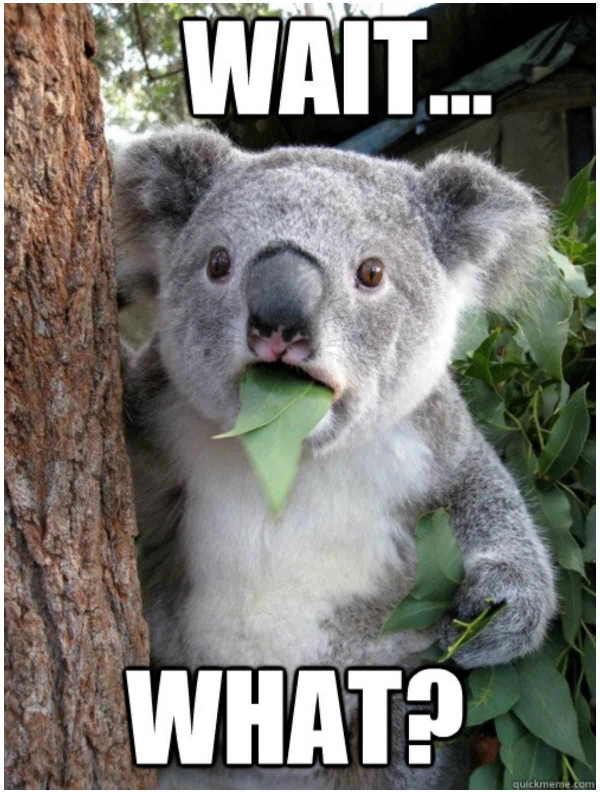
...

model = models.sequential()
model.add(layers.Conv2D(32, (3,3), activation='relu',
input_shape=(28,28,1)))

...

The first convolutional layer takes a feature map of (**28**, **28**, 1)
And outputs a feature map of size (26, 26, 32):

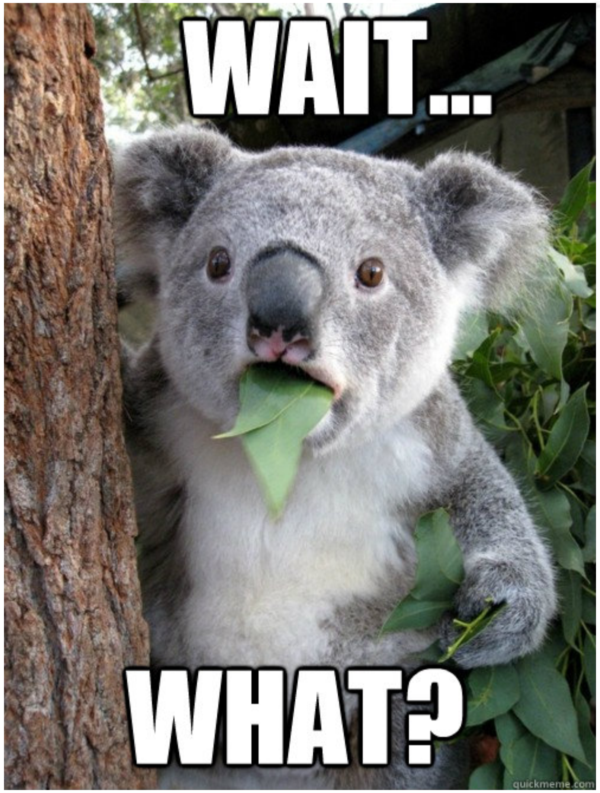
26x26???



Convolutional Operation

```
cnn_model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
conv2d_1 (Conv2D)            (None, 26, 26, 32)        320       
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 13, 13, 32)        0         
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 11, 11, 64)        18496     
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 5, 5, 64)          0         
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 3, 3, 64)          36928     
_________________________________________________________________
flatten_1 (Flatten)          (None, 576)               0         
_________________________________________________________________
dense_3 (Dense)              (None, 64)                36928     
_________________________________________________________________
dense_4 (Dense)              (None, 10)                650       
=================================================================
Total params: 93,322
Trainable params: 93,322
Non-trainable params: 0
_________________________________________________________________
```



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Understanding border effects

Note that the output width and height may differ from the input width and height.

Two possible reasons:

1. Border effects due to the padding of the input feature map.
2. The use of strides

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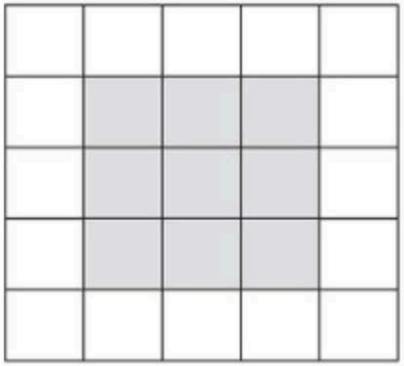
Understanding border effects: Padding

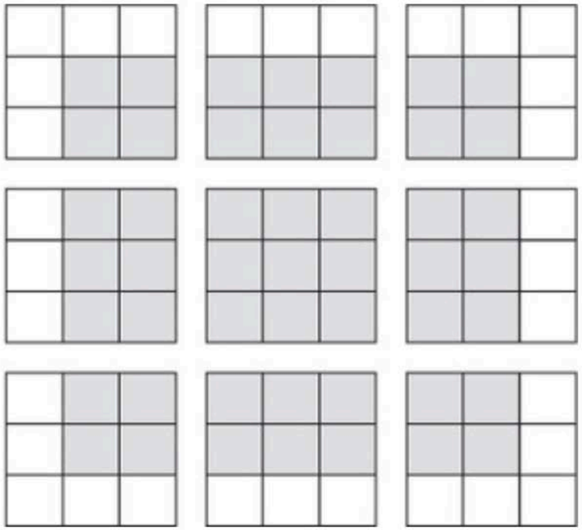
Let's consider:

A 5x5 feature map (25 pixels)

A 3x3 window

Then → There are only 9 possibilities to center the window.





The output feature map shrinks a little (2 pixels x dim)

Same for our 28x28 previous example → 26x26 output dim.

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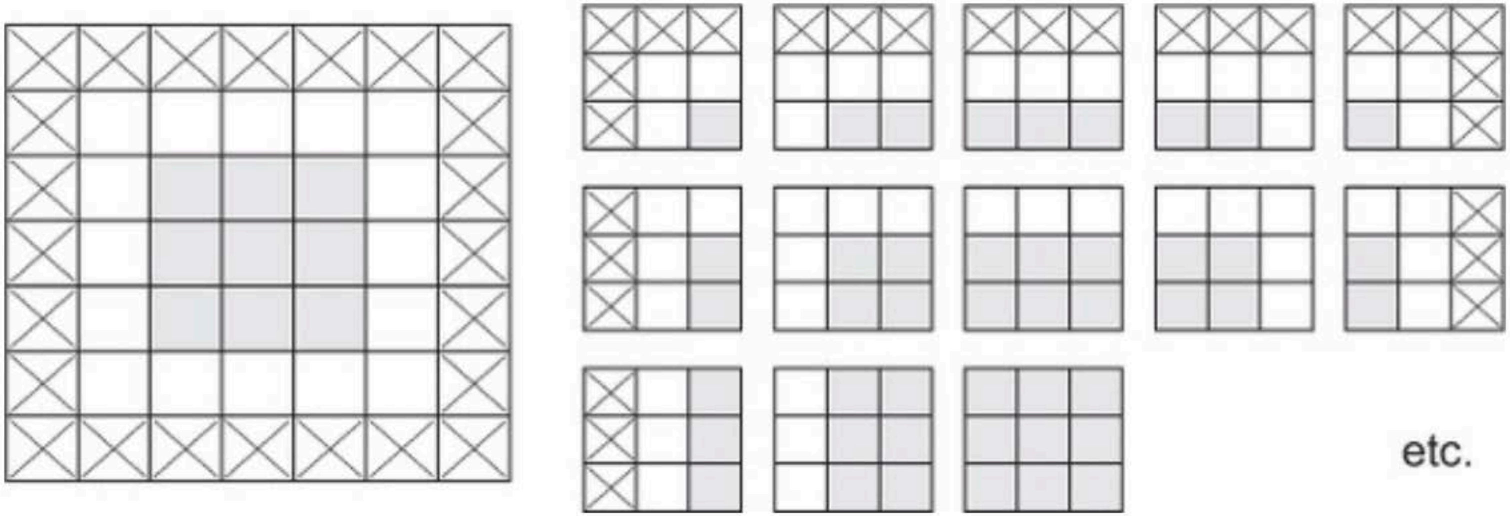
Understanding border effects: Padding

But, let's assume that you want to generate an output feature map with the same spatial dimension as the input → use the parameter *padding*.

Padding consists of adding an appropiate number of rows&columns each side of the input feature map in order to be able to centre perfectly the convolution window.



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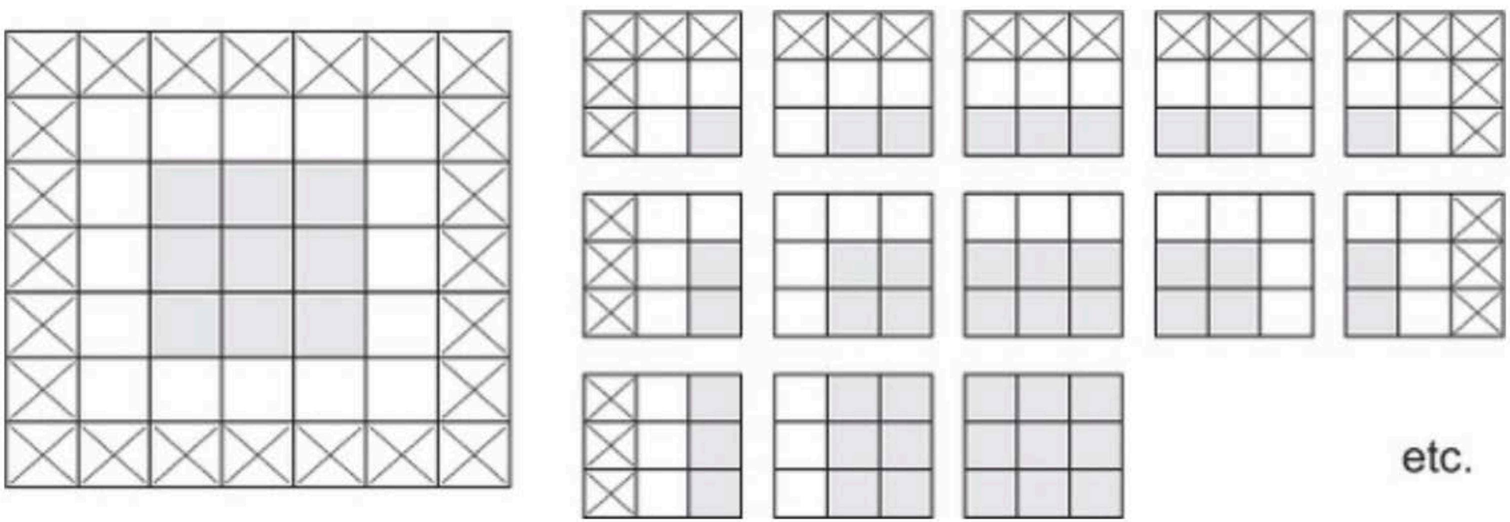
Understanding border effects: Padding

In Keras → Conv2D layers are padding configurable through the padding argument, that takes two values:

‘valid’ → Means no padding (by default)

‘same’ → Means “pad in such way as to have the same width&height as the input



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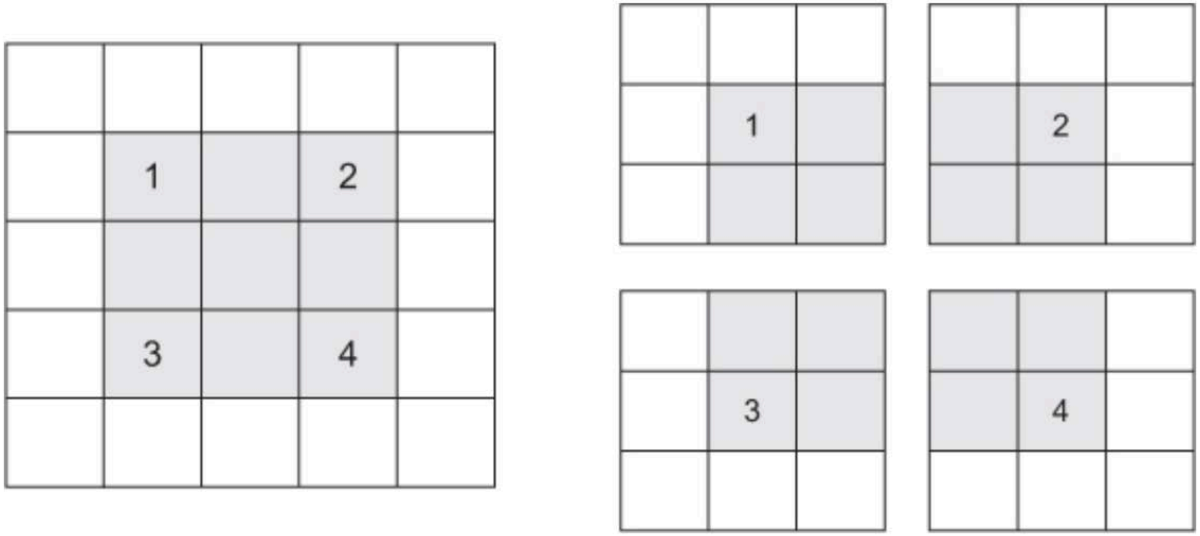
Understanding border effects: Strides

A factor that can influence the output size.

The description of convolution so far has assumed that the filters move in a contiguous way.

But the distance between two succesive windows is a Conv2D parameter → *strides*



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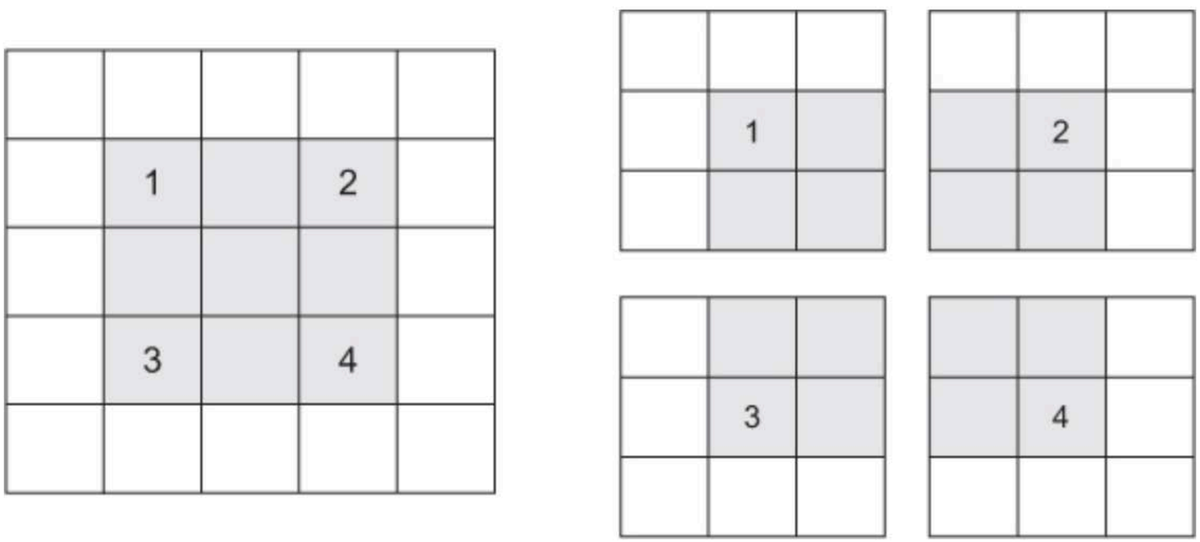
Understanding border effects: Strides

It is possible to have convolutions with a stride higher than 1.

P.e. Using stride 2 means the width&height of the feature map are downsampled by 2.

This is rarely used in practice → instead of strides, we tend to use max-pooling operation.



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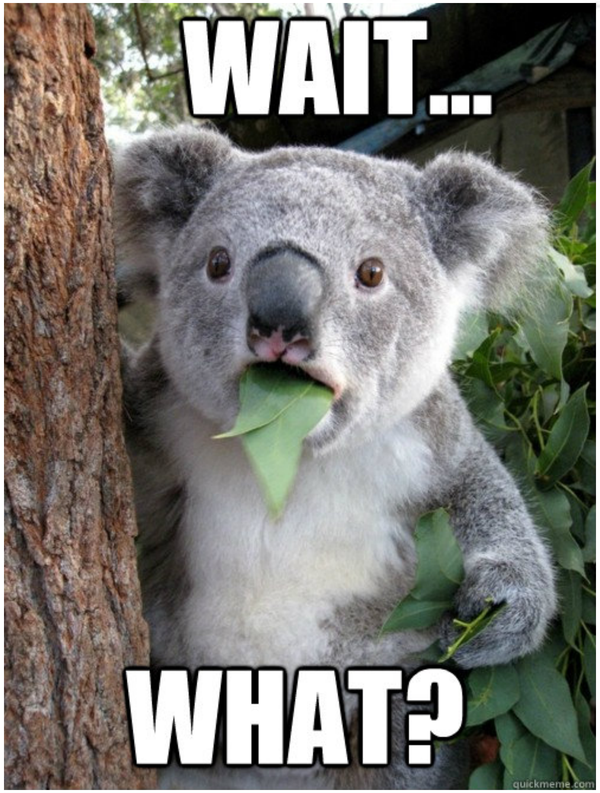
Max-pooling operation

```
cnn_model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_1 (Conv2D)            (None, 26, 26, 32)        320
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 13, 13, 32)        0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 11, 11, 64)        18496
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 5, 5, 64)          0
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 3, 3, 64)          36928
_________________________________________________________________
flatten_1 (Flatten)          (None, 576)               0
_________________________________________________________________
dense_3 (Dense)              (None, 64)                36928
_________________________________________________________________
dense_4 (Dense)              (None, 10)                650
=================================================================
Total params: 93,322
Trainable params: 93,322
Non-trainable params: 0
_________________________________________________________________
```



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Max-pooling operation

MNIST example:

…

model = models.sequential()

model.add(layers.Conv2D(32, (3,3), activation='relu', input_shape=(28,28,1)))

model.add(layers.MaxPooling2D((2, 2)))

…

Max pooling → Aggressively downsample the feature maps (like strided convolutions)

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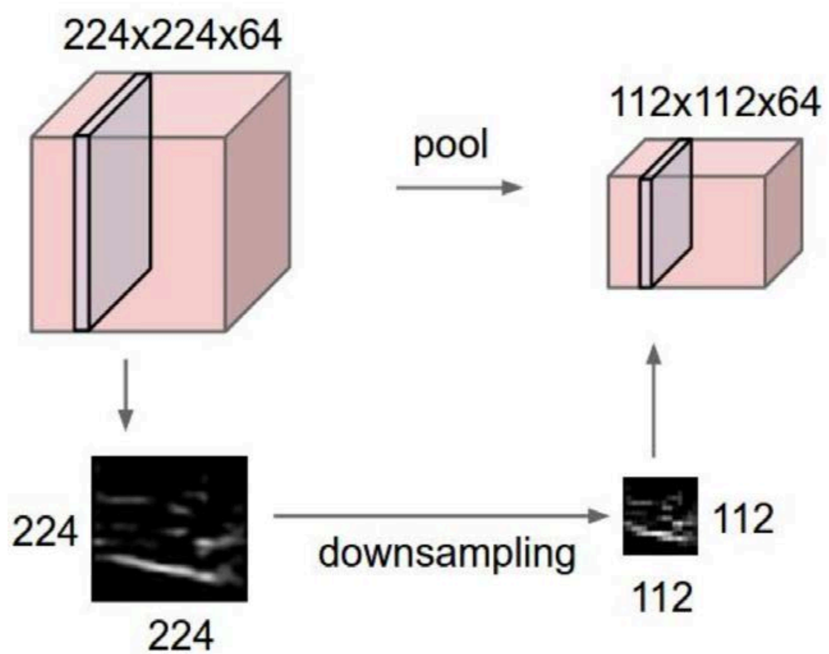
Max-pooling operation

Makes the representation smaller and more manageable
Operates over each feature map independently:



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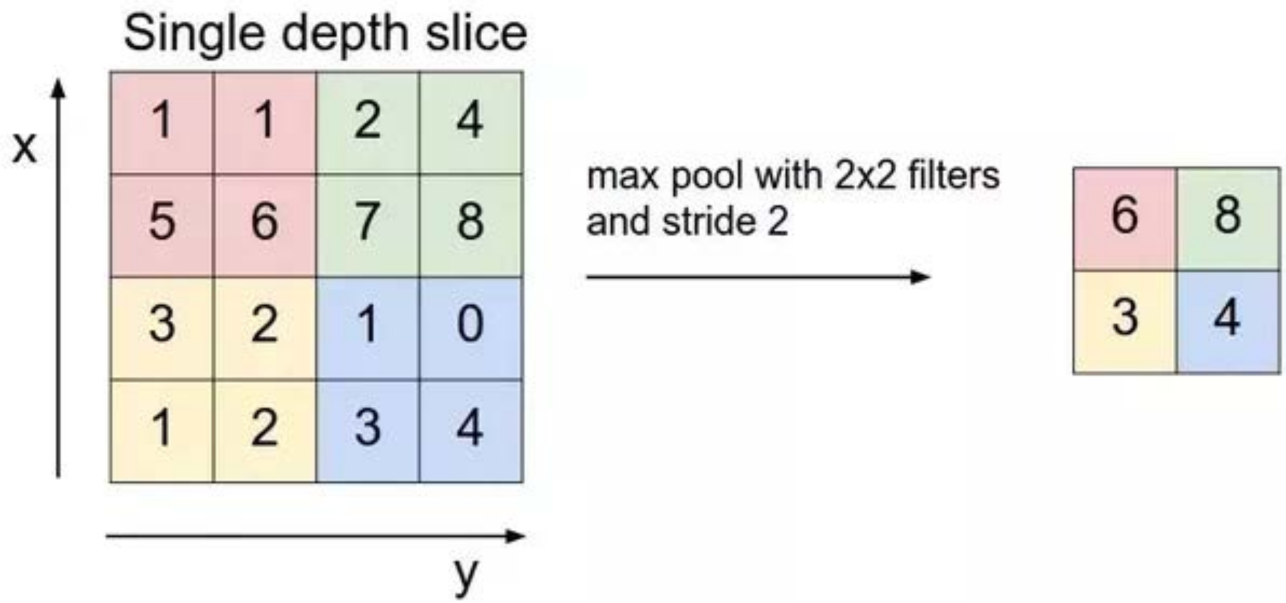
Max-pooling operation



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Max-pooling operation

Why downsample feature maps?

Why don't we remove the max-pooling layers and keep large feature maps all the way up?

```
model_no_max_pool = models.Sequential()
model_no_maxpool.add(layers.Conv2D(32, (3, 3), activation='relu',input_shape=(28, 28, 1)))
model_no_max_pool.add(layers.Conv2D(64, (3, 3), activation='relu'))
model_no_max_pool.add(layers.Conv2D(64, (3, 3), activation='relu'))
```

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Max-pooling operation

Why downsample feature maps?

Why don't we remove the max-pooling layers and keep large feature maps all the way up?

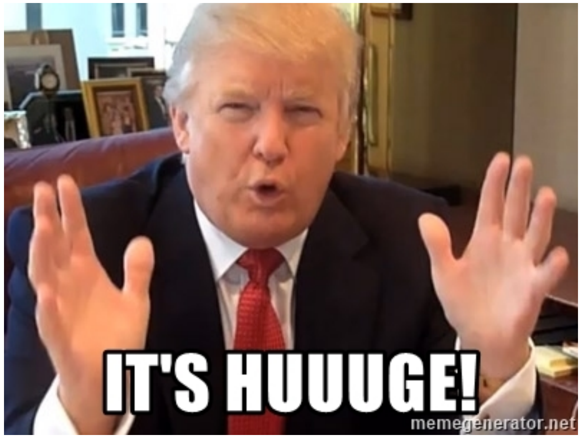
```
>>> model_no_max_pool.summary()

Layer (type)                     Output Shape          Param #
================================================================
conv2d_4 (Conv2D)                (None, 26, 26, 32)    320
________________________________________________________________
conv2d_5 (Conv2D)                (None, 24, 24, 64)    18496
________________________________________________________________
conv2d_6 (Conv2D)                (None, 22, 22, 64)    36928
================================================================
Total params: 55,744
Trainable params: 55,744
Non-trainable params: 0
```

Max-pooling operation

What is wrong with that setup?

The final feature map is 22 x 22 x 64 = 30,976 total coefficients per sample!!
That is huge!

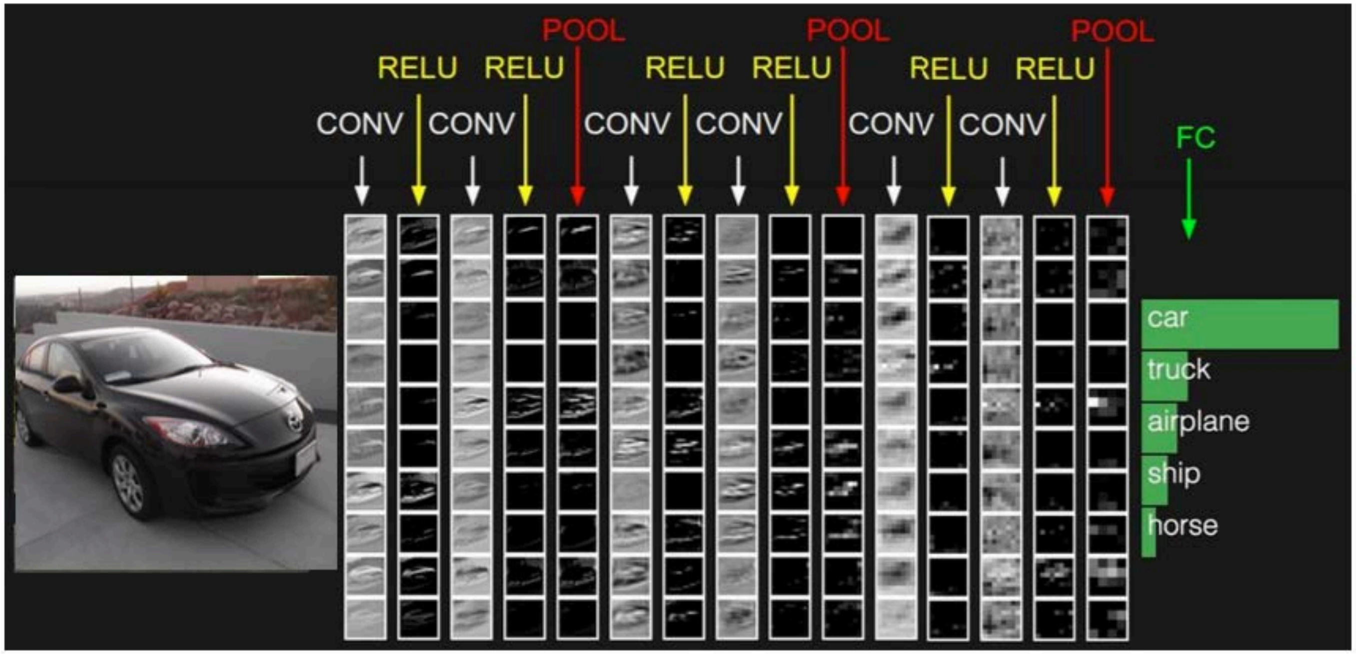
If we want to flatten it to stick a Dense layer of 512 units,



we would have **15.800.000** parameters

Fully Connected Layer

Contains neurons that connect to the entire input volume, as an ordinary NN.



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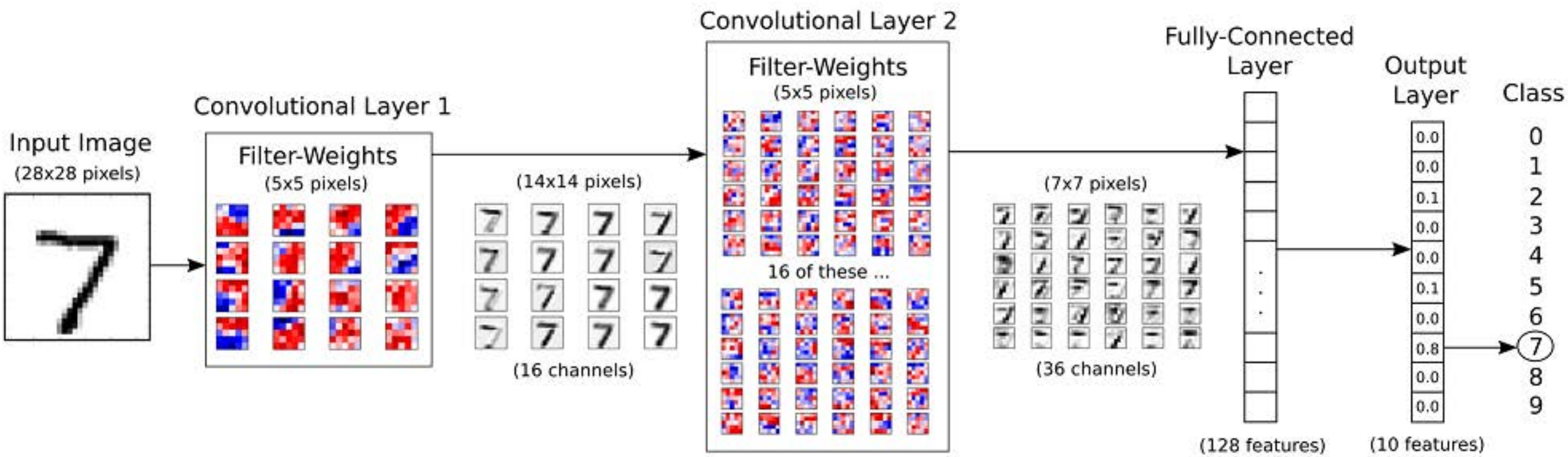
What is happening?

Convolutional layers:



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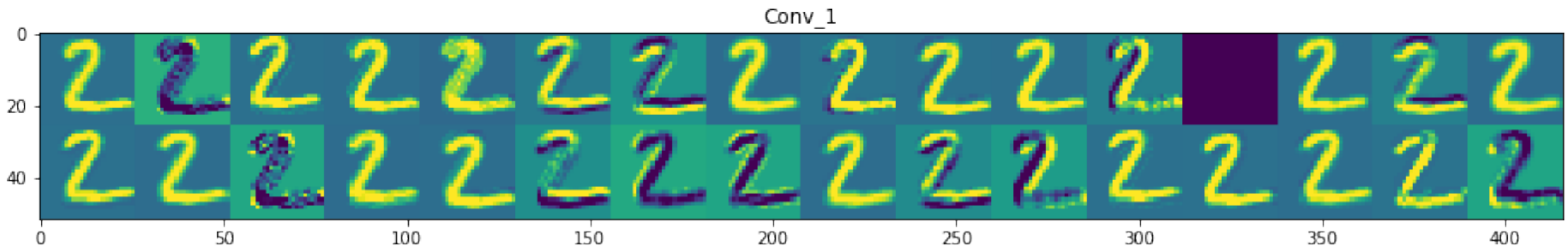
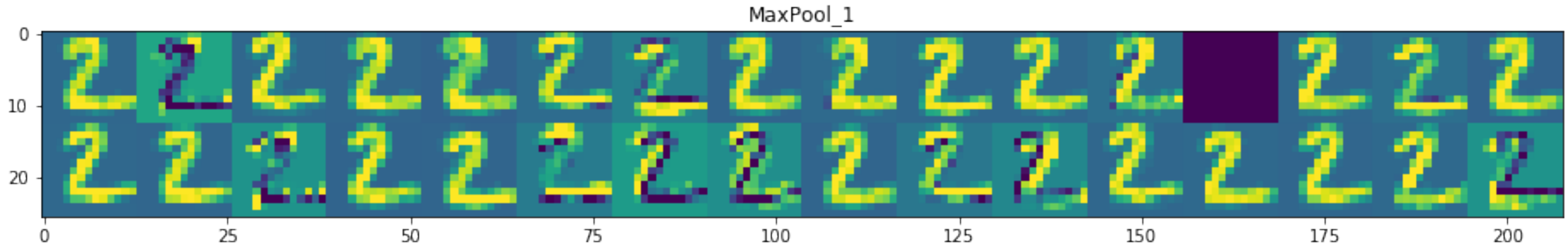
What is happening?
Feature Maps





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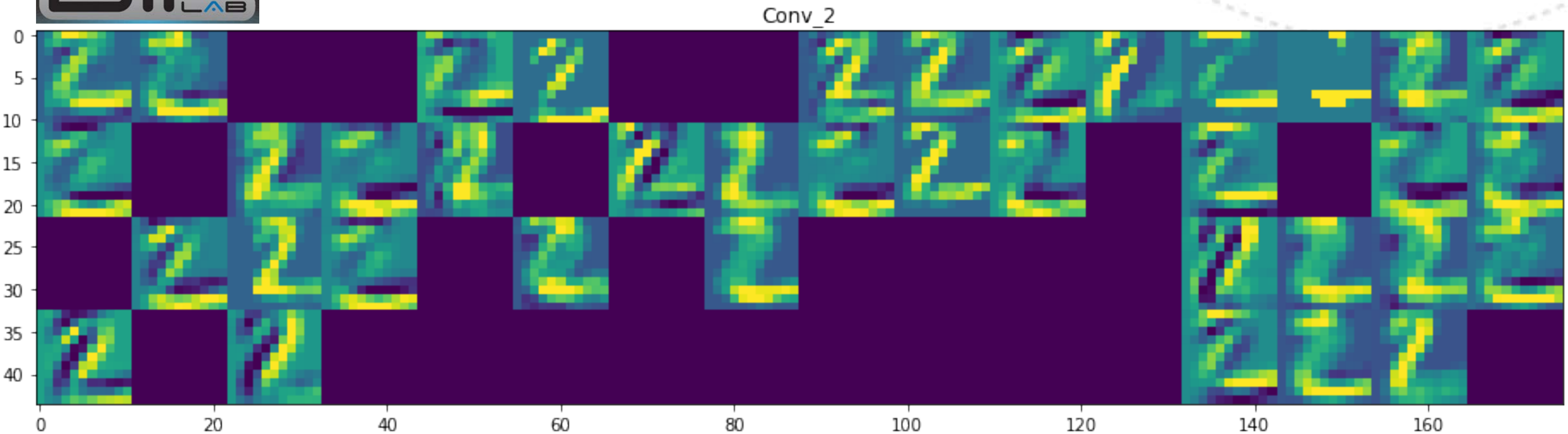
What is happening?
Feature Maps



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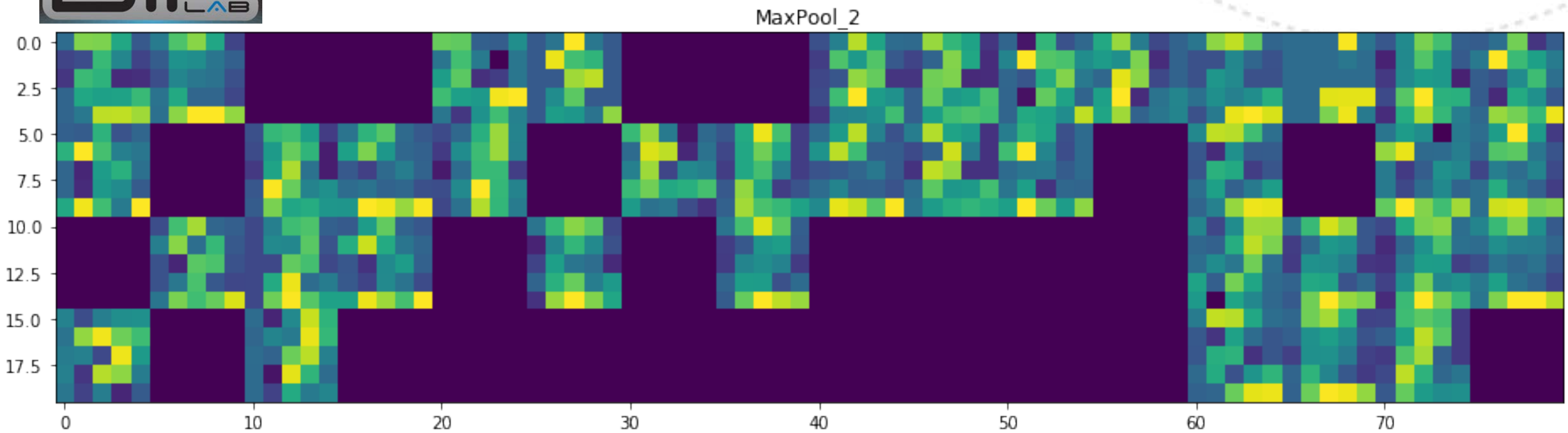
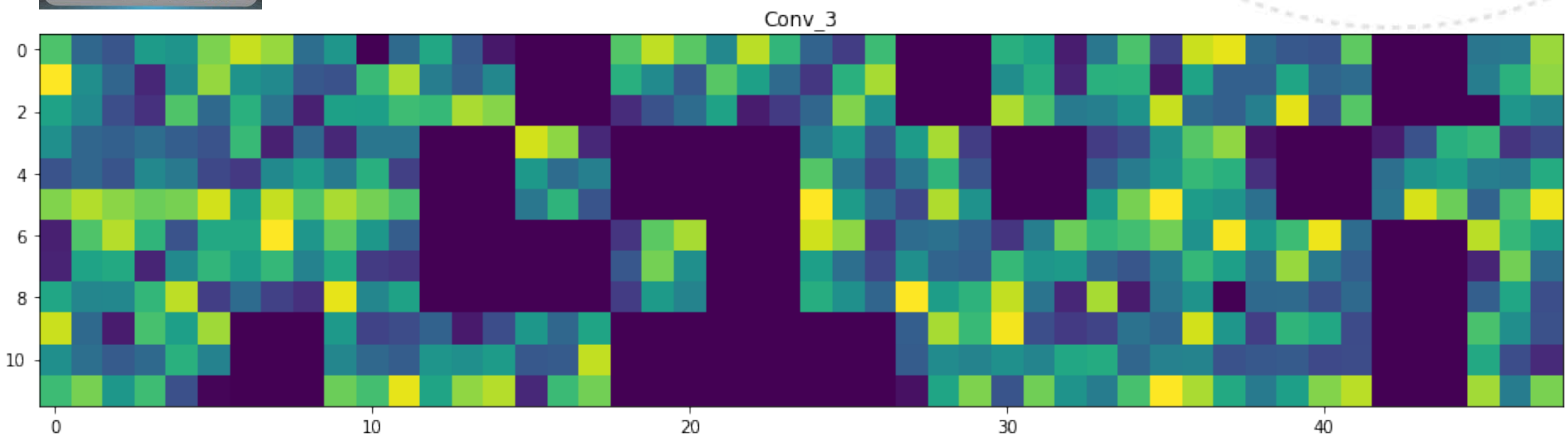
What is happening?
Feature Maps



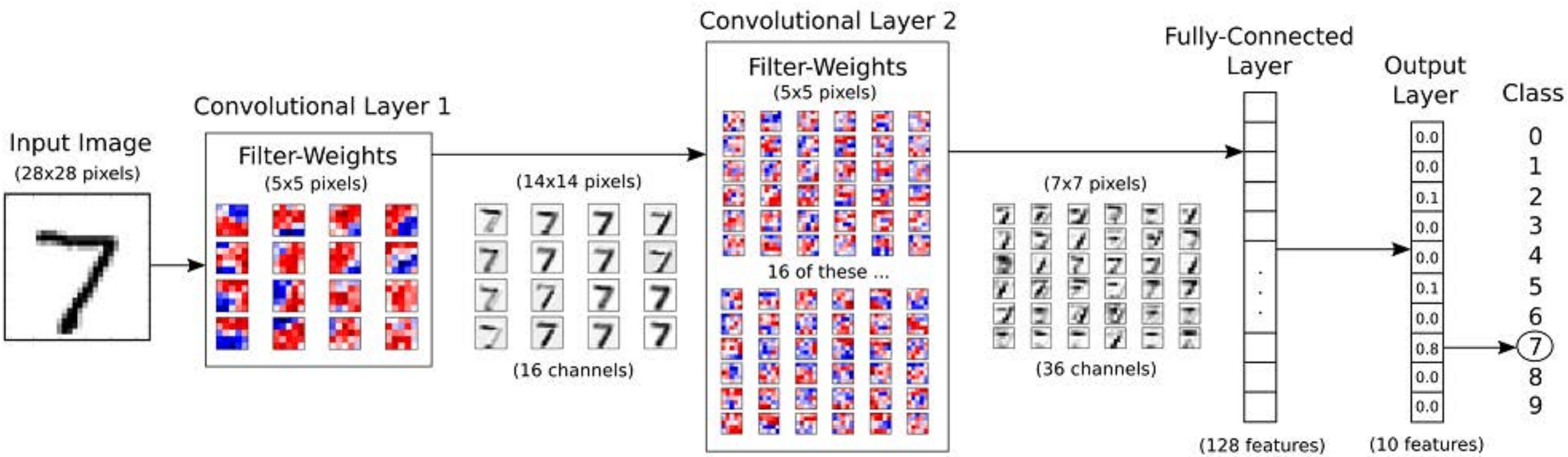
What is happening?
Feature Maps



These feature maps are flattened and stick into the Fully Connected layer!!

What is happening?

Convolutional layers:



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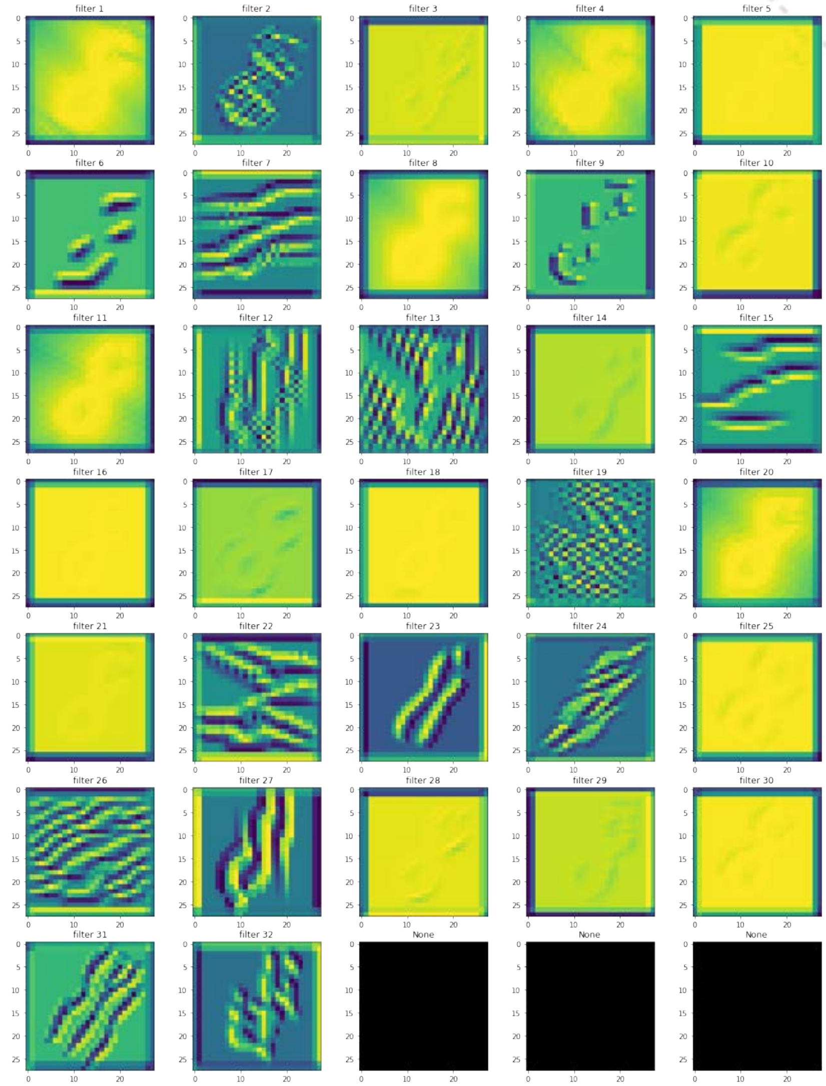
What is happening?
Filters Conv1



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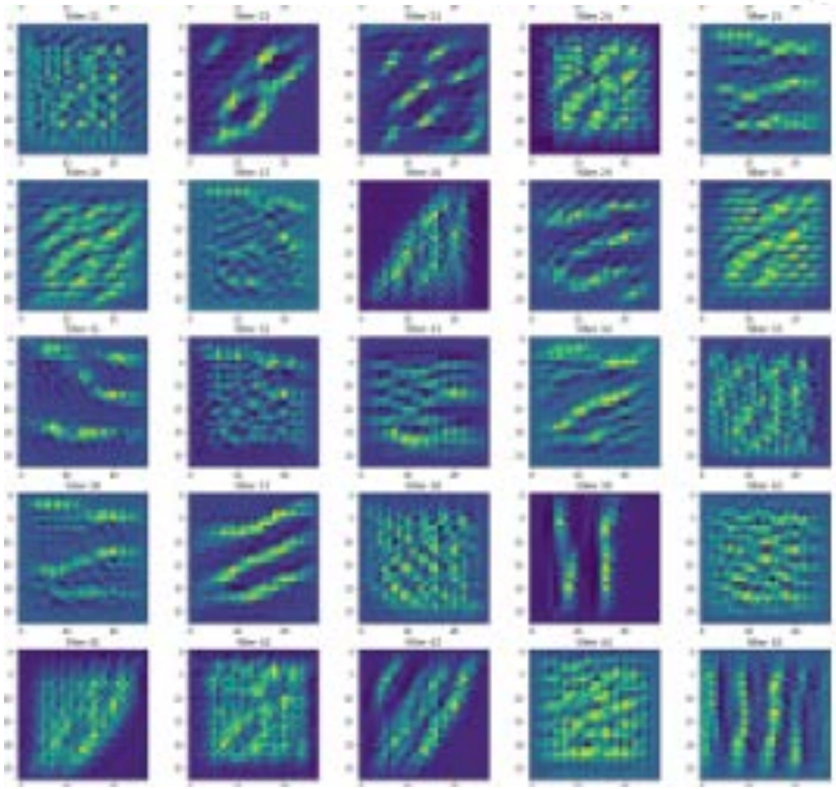
What is happening?
Filters Conv2



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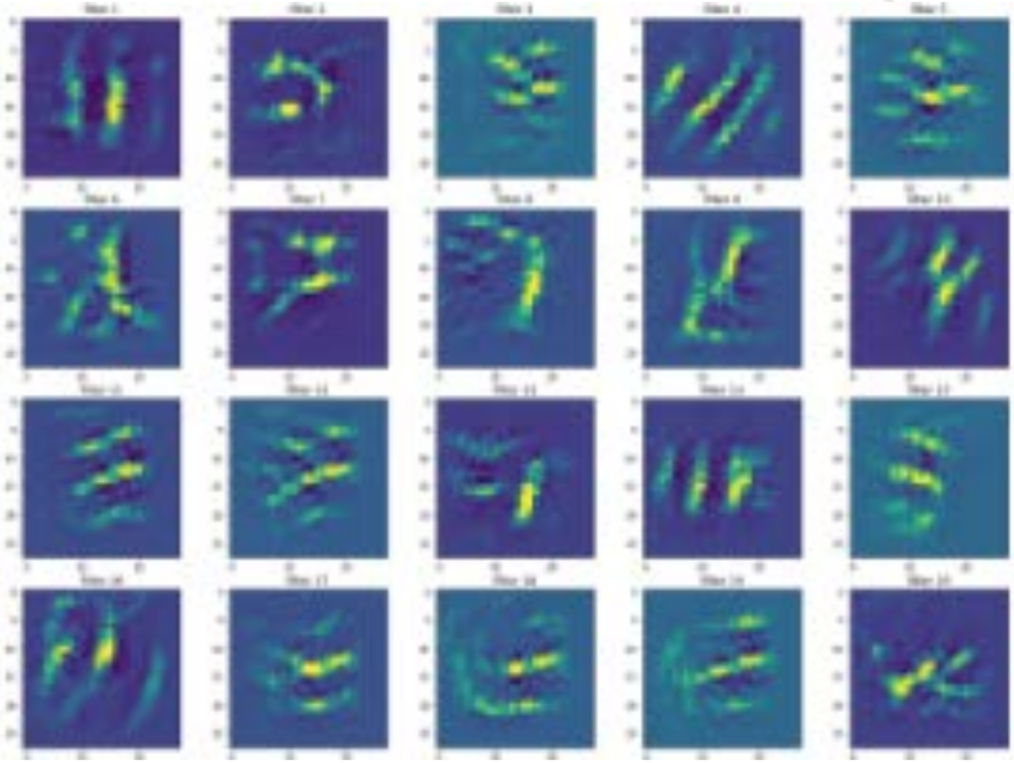
What is happening?
Filters Conv3



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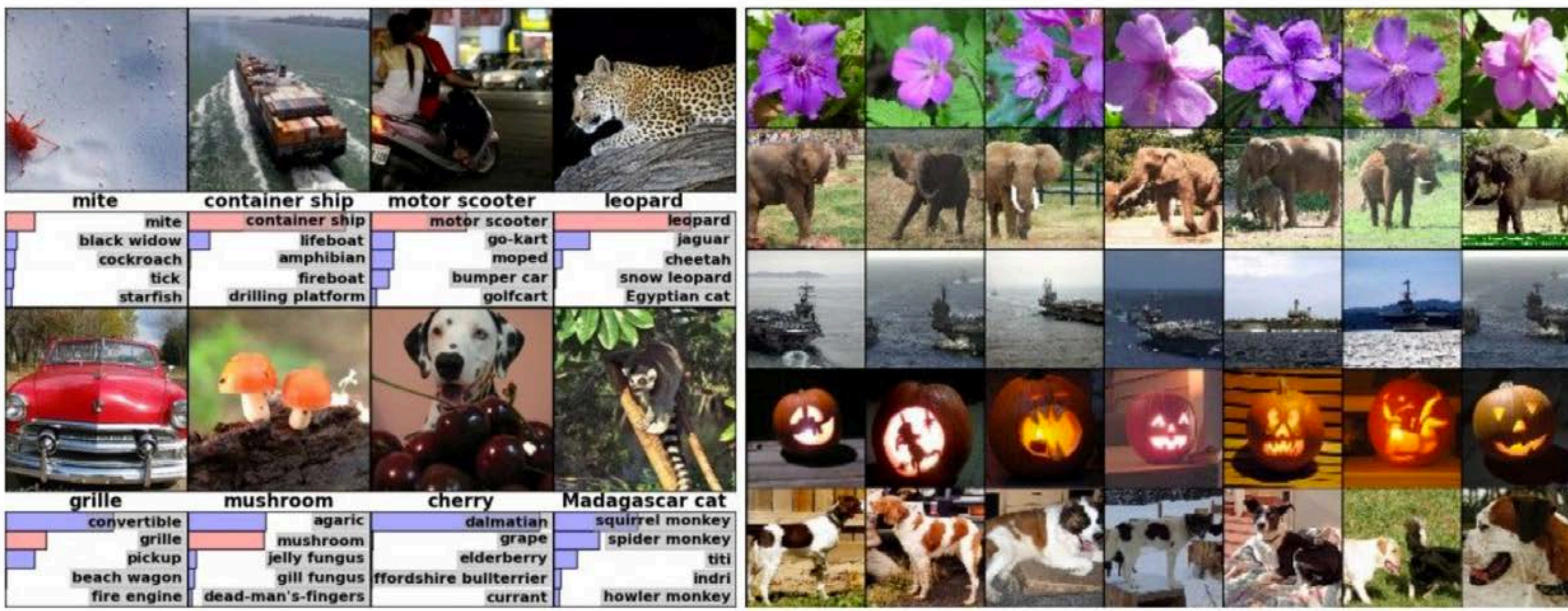
Where to use CNN?

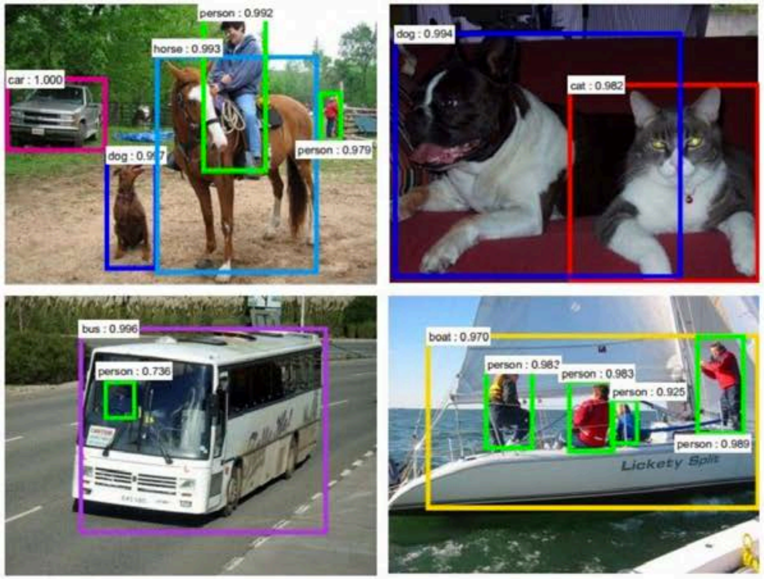
Classification

Retrieval



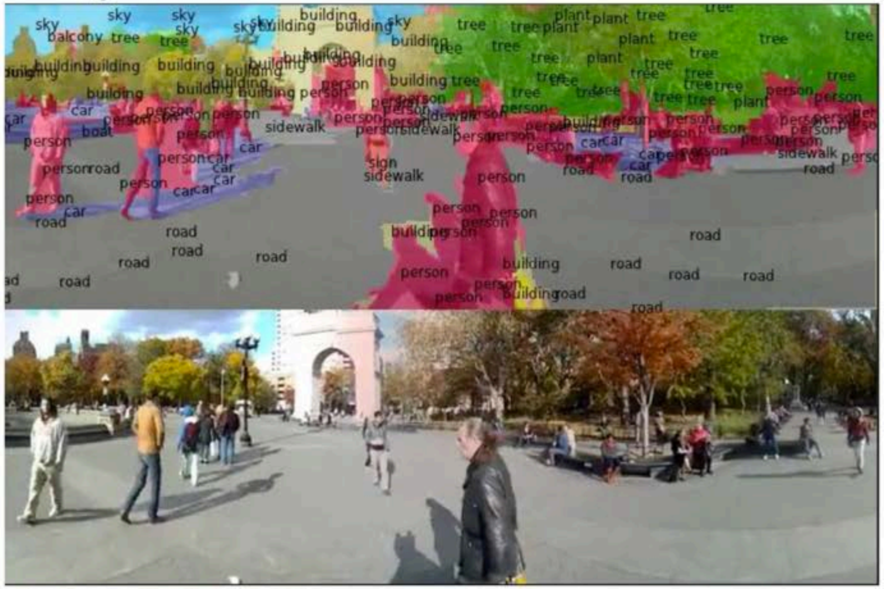
Where to use CNN?

Detection



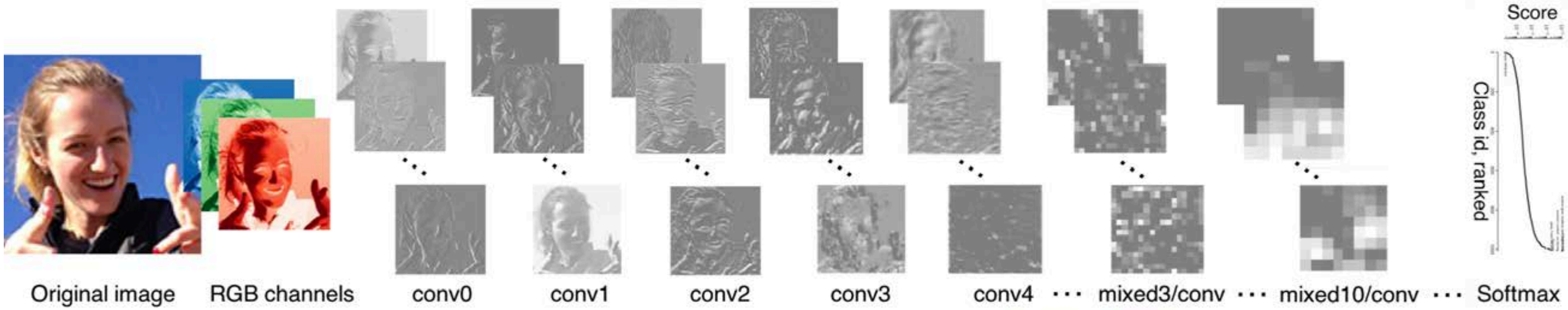
[Faster R-CNN: Ren, He, Girshick, Sun 2015]

Segmentation



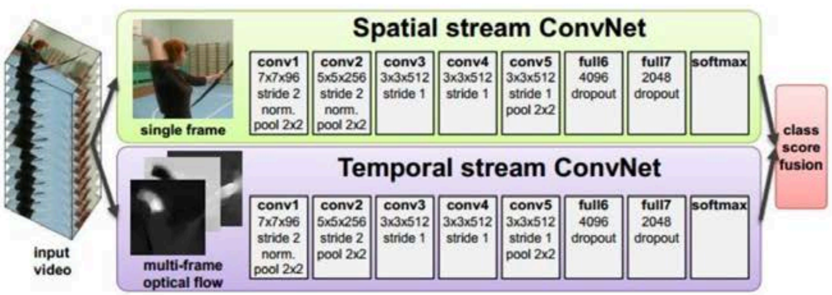
[Farabet et al., 2012]

Where to use CNN?



[Taigman et al. 2014]

Activations of inception-v3 architecture [Szegedy et al. 2015] to image of Emma McIntosh, used with permission. Figure and architecture not from Taigman et al. 2014.



[Simonyan et al. 2014]

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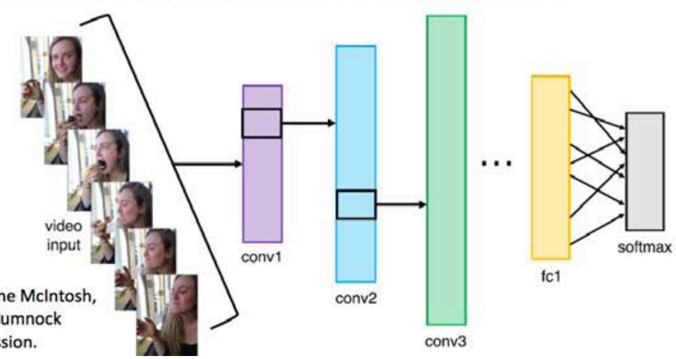

Illustration by Lane McIntosh, photos of Katie Cumnock used with permission.

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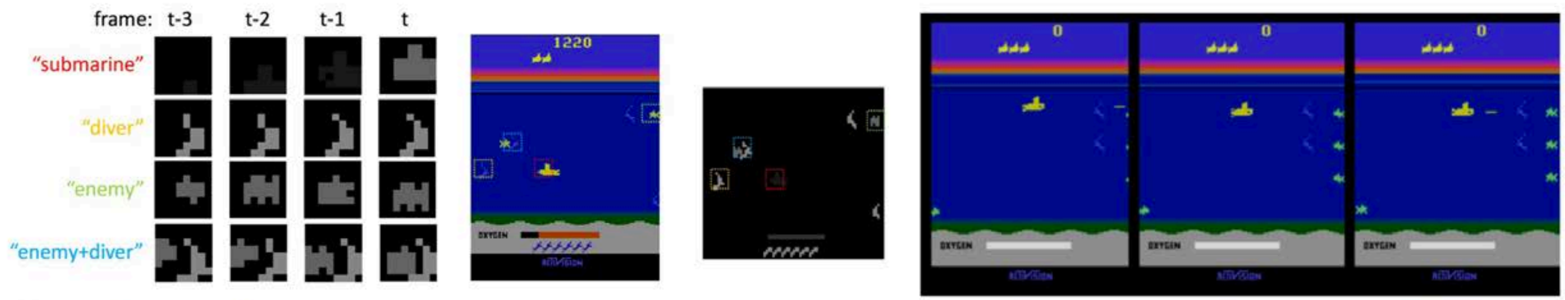
Images are examples of pose estimation, not actually from Toshev & Szegedy 2014. Copyright Lane McIntosh.

[Toshev, Szegedy 2014]



[Guo et al. 2014]

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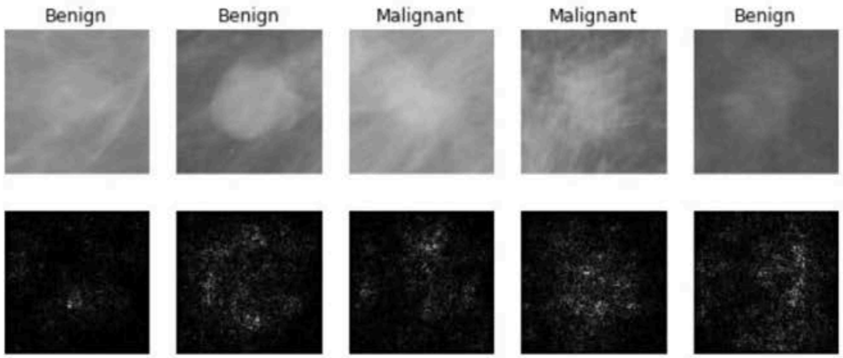

[Levy et al. 2016]

Figure copyright Levy et al. 2016. Reproduced with permission.

[Dieleman et al. 2014]

From left to right: public domain by NASA, usage permitted by ESA/Hubble, public domain by NASA, and public domain.

[Sermanet et al. 2011]
[Ciresan et al.]

Photos by Lane McIntosh. Copyright CS231n 2017.

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Applications

https://www.youtube.com/watch?v=kkha3sPoU70

https://www.youtube.com/watch?v=U1vb-NI9sKE

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Credits

The 'Where to use CNN?' section is partially based on the Lecture 5: Convolutional Neural Networks. By Fei-Fei, Johnson and Yeung. April 18, 2017

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