Applied Machine Learning
Lecture 8-1: Convolutional neural networks

Selpi (selpi@chalmers.se)

The slides are further development of Richard Johansson's slides

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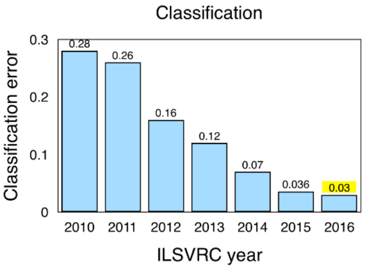
CNNs: motivation

- the introduction of **convolutional neural network** (CNN) models has led to dramatic improvements in image processing

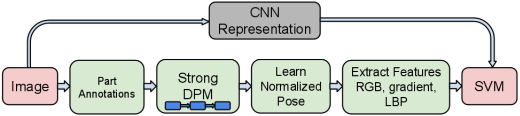


[source]

- they are the default solution today
- plan for this lecture: introduce the typical building blocks and show how they can be used in Keras

reducing the amount of feature engineering

- neural networks (NNs) are systems that learn to form useful abstractions automatically
  - learn to form larger units from small pieces



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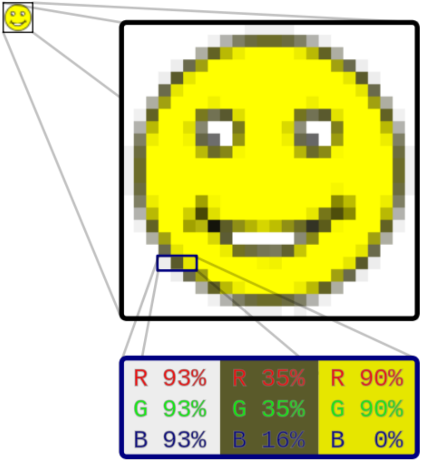
- appealing because of reduction in feature engineering effort

representing image data



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representing image data (2)

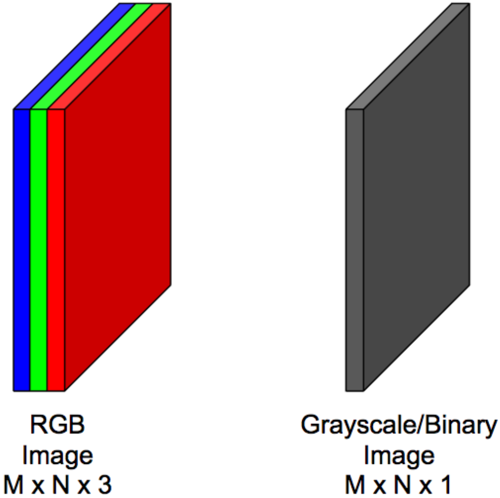
What We See

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

[source]

representing image data (3)

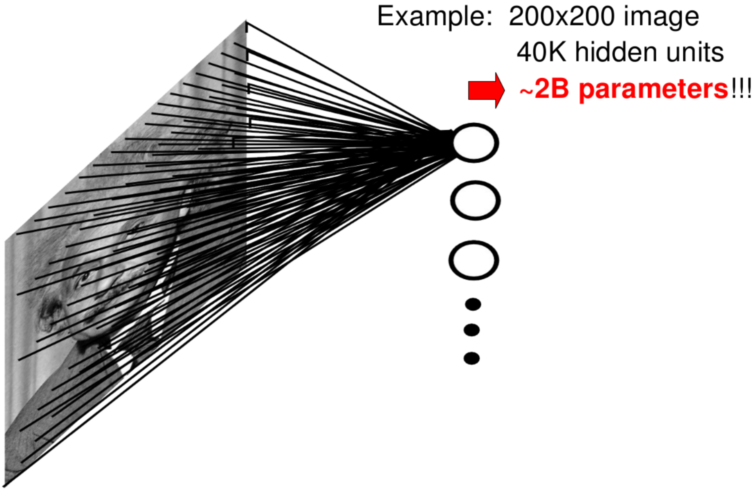


[source]

example: displaying an image stored as a NumPy matrix

```
plt.imshow(some_matrix)
```

Drawback of using feedforward network for image processing (1)



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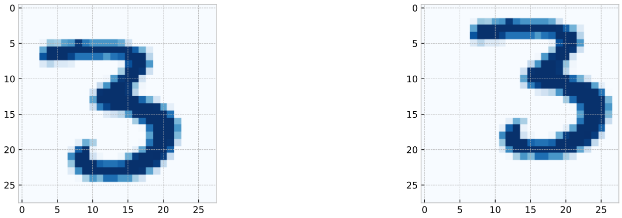
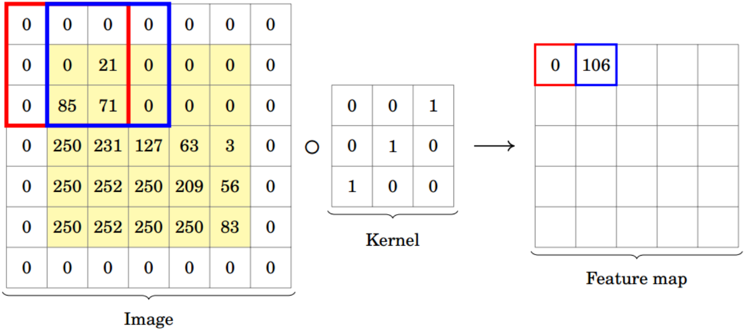
Drawback of using feedforward network for image processing (2)



convolutions (or convolutional filters)

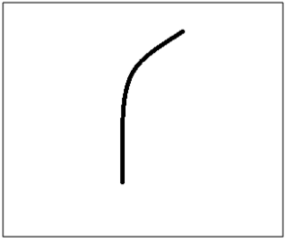


[source]

example of a convolution (1)

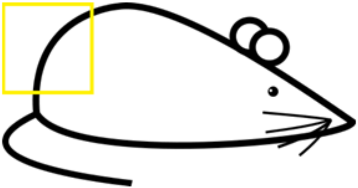
0	0	0	0	0	30	0
0	0	0	0	30	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	0	0	0	0

Pixel representation of filter



Visualization of a curve detector filter

example of a convolution (2)



Visualization of the filter on the image

example of a convolution (3)

0	0	0	0	0	0	30
0	0	0	0	50	50	50
0	0	0	20	50	0	0
0	0	0	50	50	0	0
0	0	0	50	50	0	0
0	0	0	50	50	0	0
0	0	0	50	50	0	0

$*$

0	0	0	0	0	30	0
0	0	0	0	30	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	0	0	0	0

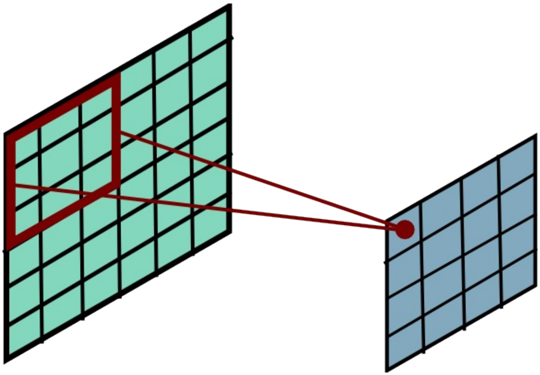
example of a convolution (4)

0	0	0	0	0	0	0
0	40	0	0	0	0	0
40	0	40	0	0	0	0
40	20	0	0	0	0	0
0	50	0	0	0	0	0
0	0	50	0	0	0	0
25	25	0	50	0	0	0

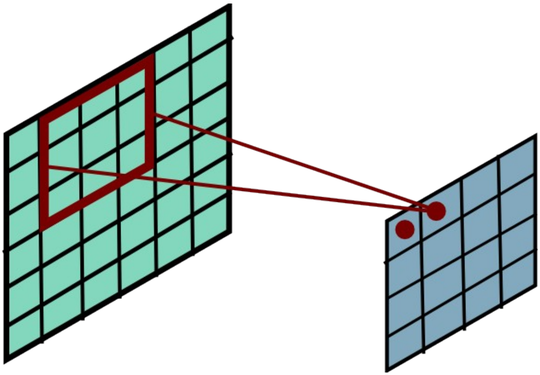
$*$

0	0	0	0	0	30	0
0	0	0	0	30	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	0	0	0	0

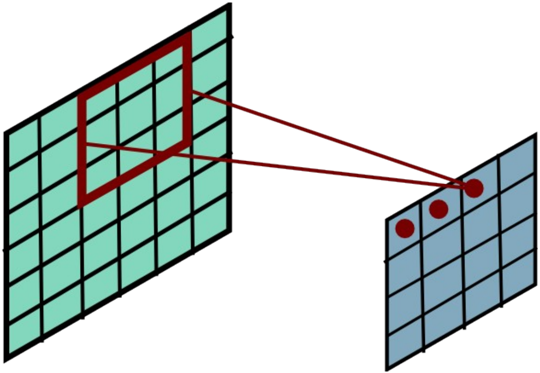
Convolutional Layer



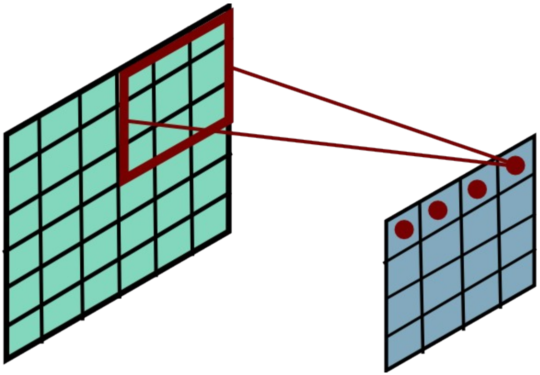
Convolutional Layer



Convolutional Layer

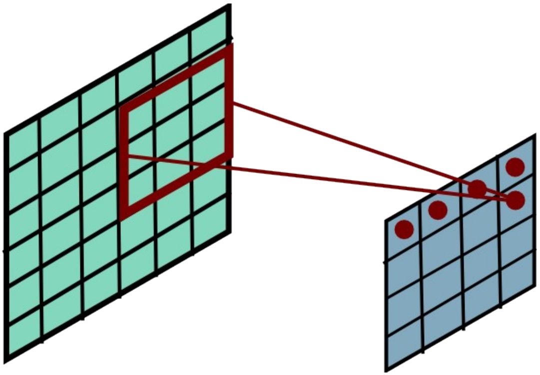


Convolutional Layer

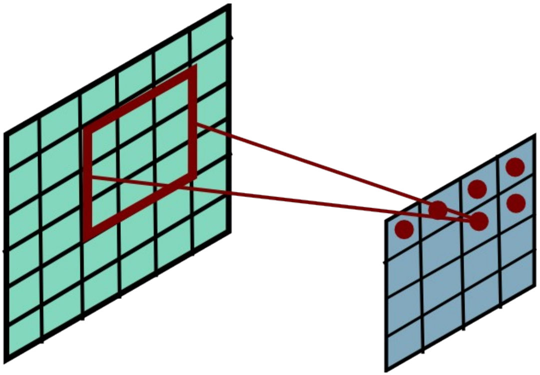


Ranzato

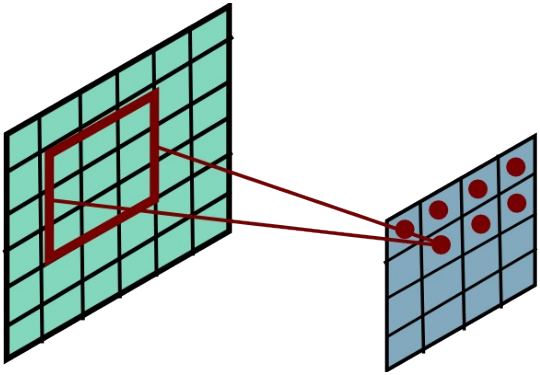
Convolutional Layer



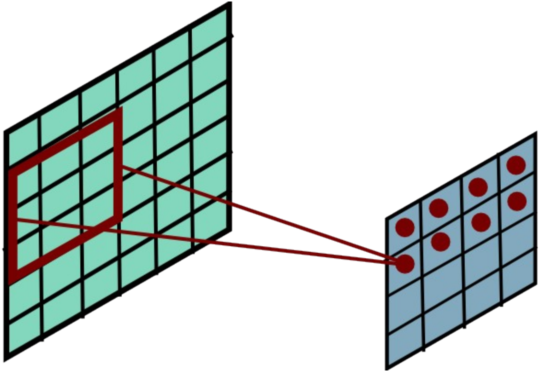
Convolutional Layer



Convolutional Layer

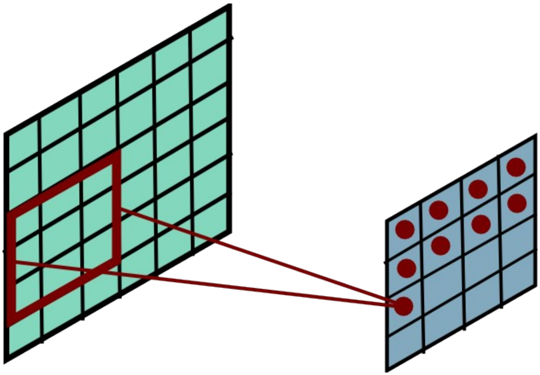


Convolutional Layer

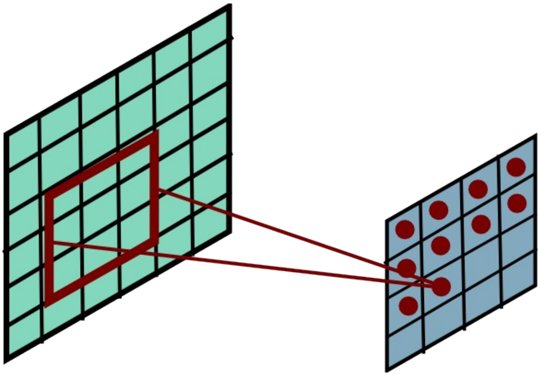


Ranzato

Convolutional Layer

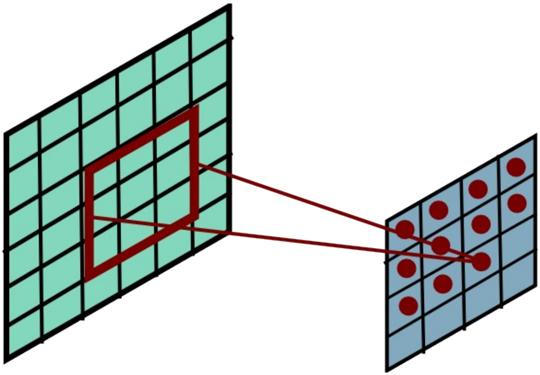


Convolutional Layer

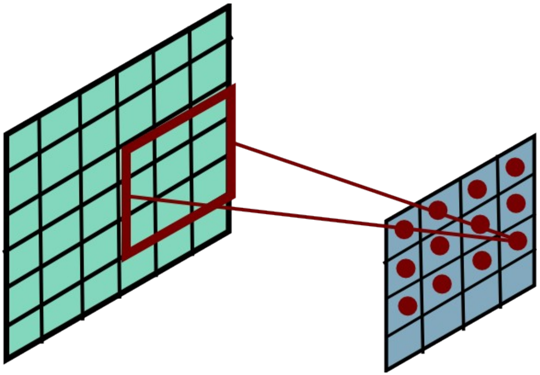


Ranzato

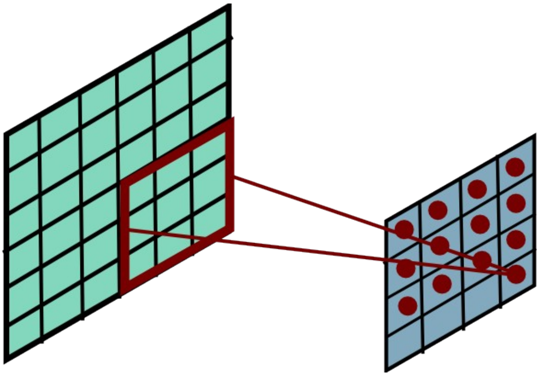
Convolutional Layer



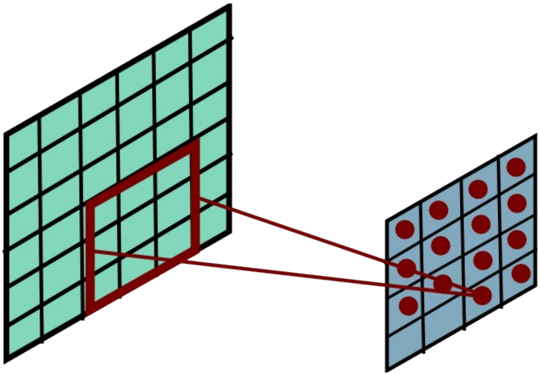
Convolutional Layer



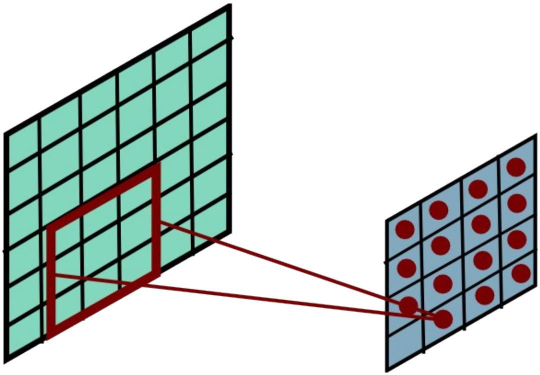
Convolutional Layer



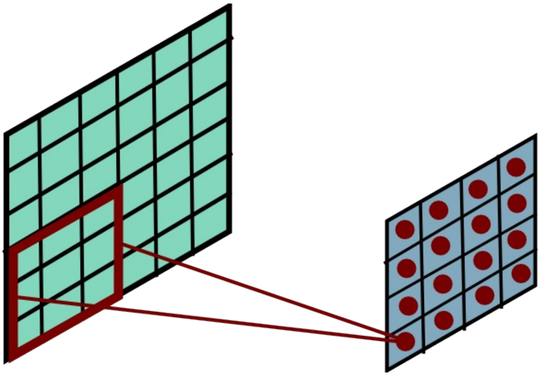
Convolutional Layer



Convolutional Layer

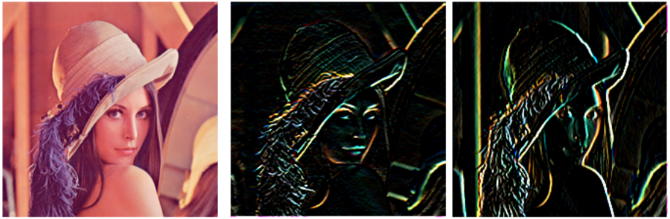


Convolutional Layer



Mathieu et al. "Fast training of CNNs through FFTs" ICLR 2014

example: detecting horizontal and vertical edges



(a) Lenna (b) Horizontal edge (c) Vertical edge

Figure 4: The Lenna image and the effect of different convolution kernels.

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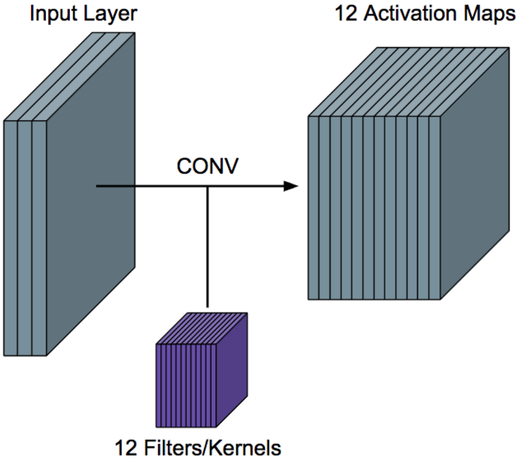
number of dimensions in the convolution

- the convolutions we have seen are called **two-dimensional** convolutions
- alternatives:
  - **1D** convolutions over a sequence (e.g. a speech signal)
  - **3D** convolutions over a volume (e.g. a brain scan)

convolutional neural networks

- a **convolutional neural network** consists of convolutional filters applied sequentially
- after each convolutional layer, an activation is applied (typically ReLU)
- top layers are normal feedforward layers

applying several filters



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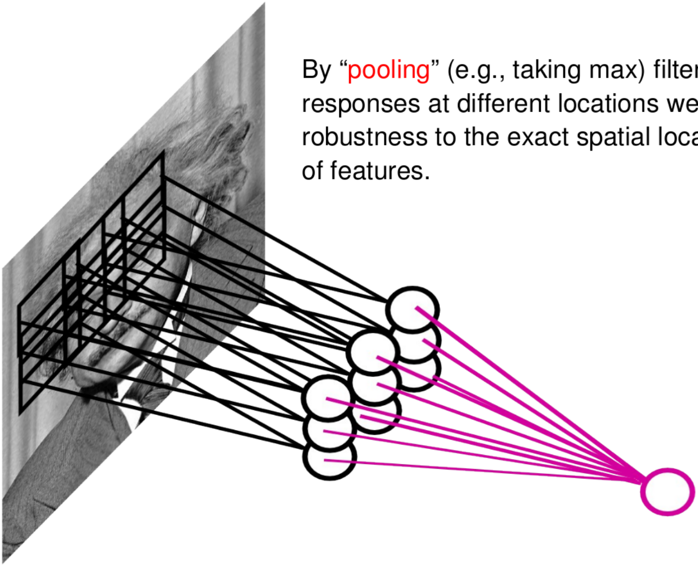
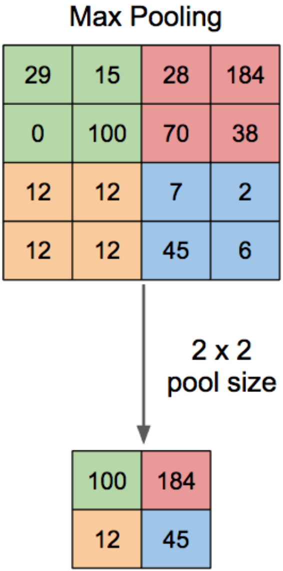
pooling or subsampling



By "pooling" (e.g., taking max) filter responses at different locations we gain robustness to the exact spatial location of features.

max pooling



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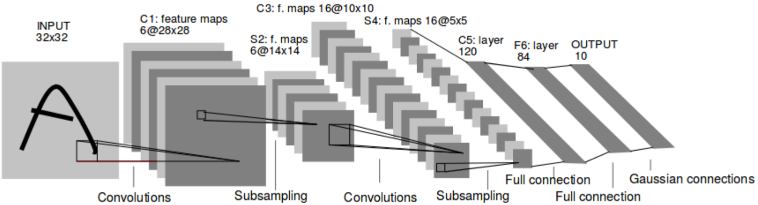
example: LeNet

- LeCun et al. (1998) *Gradient-Based Learning Applied to Document Recognition*

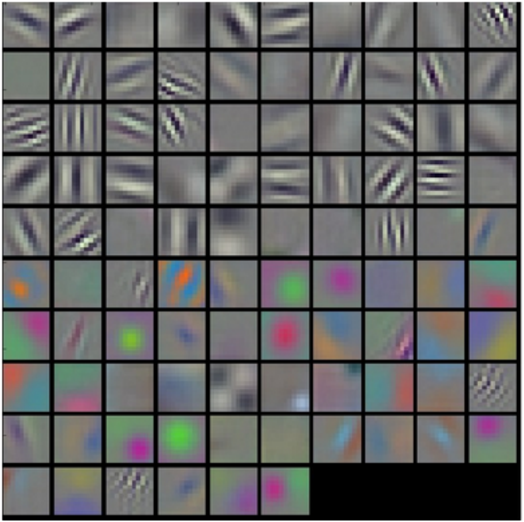


CNNs in Keras

```
model = Sequential()
model.add(Conv2D(32, kernel_size=(5, 5), strides=(1, 1),
                 activation='relu',
                 input_shape=input_shape))
model.add(MaxPooling2D(pool_size=(2, 2), strides=(2, 2)))
model.add(Conv2D(64, (5, 5), activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Flatten())
model.add(Dense(1000, activation='relu'))
model.add(Dense(num_classes, activation='softmax'))
```

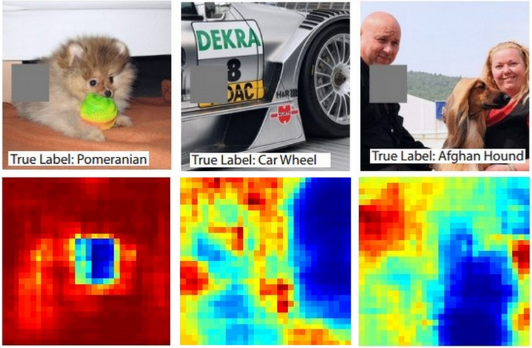
interpreting CNNs: drawing the filters

- see *Visualizing what ConvNets learn*



interpreting CNNs (2): occluding

- see *Visualizing what ConvNets learn*

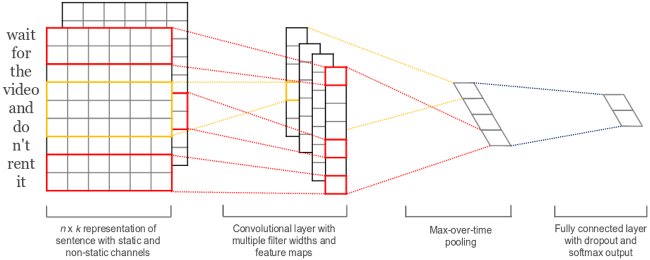


applications of CNNs in medicine (small sample)

- finding skin tumors by classifying images [Esteva et al., 2017]
- finding brain tumors by classifying brain scans [Yi et al., 2016]
- detecting the locations of organs in the body [Larsson et al., 2016]

CNNs for categorizing texts

- Kim (2014) *Convolutional Neural Networks for Sentence Classification*



Other applications

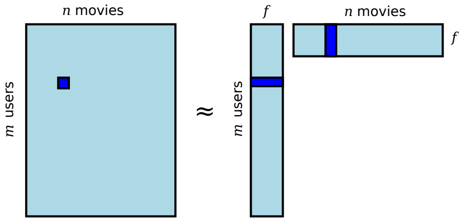
- Traffic sign recognitions (see implications on euroNCAP)
- Face recognitions, emotion recognitions

Review for CNN

- What are the building blocks of CNN and how do we arrange these to make a convolutional neural network?
- What are the drawbacks of feed forward NN compared to CNN for image classification tasks?
- What are the purposes of doing pooling in CNN?
- Describe the hyperparameters of CNN (e.g., kernel size, stride, number of filters, number of layers, pooling size, type of pooling)

next lecture

- dimensionality reduction
- word embeddings
- recommender systems



references I

- Esteva, A., Kuprel, B., and et al., R. N. (2017). Dermatologist-level classification of skin cancer with deep neural networks. *Nature*.
- Kim, Y. (2014). CNNs for sentence classification. In *Proc. EMNLP*.
- Larsson, M., Zhang, Y., and Kahl, F. (2016). Deepseg: Abdominal organ segmentation using deep convolutional neural networks. In *SSBA*.
- Yi, D., Zhou, M., Chen, Z., and Gevaert, O. (2016). 3-d convolutional neural networks for glioblastoma segmentation. In *Arxiv*.