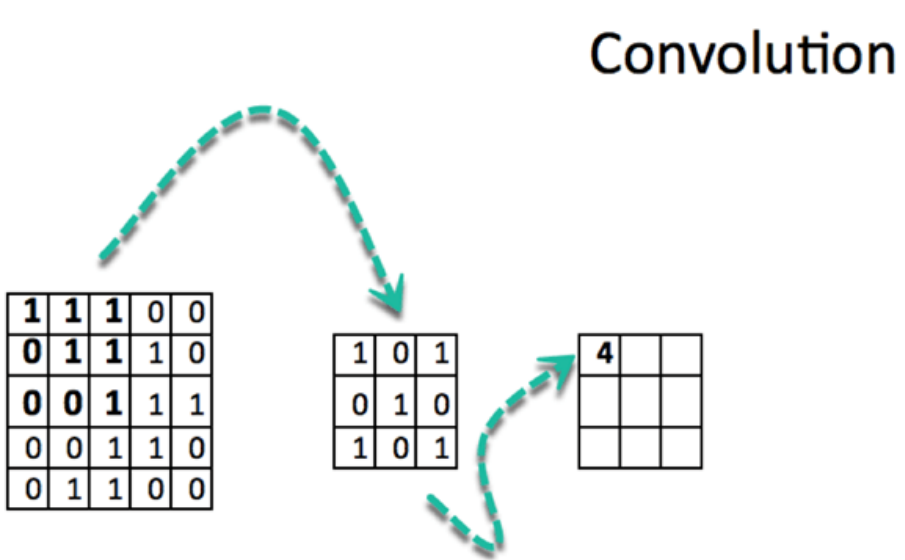
Convolutional Neural Network

Classification of images

171	183	181	171	165	167	164	148	150	154	161	163	160	173	176	182	184	179	180	182	184
166	159	149	144	146	148	142	129	120	115	127	138	150	152	163	178	189	183	187	192	198
155	134	124	130	136	141	130	113	101	107	117	133	141	153	159	179	189	184	183	191	200
134	114	105	114	122	124	107	95	98	103	120	129	144	161	174	183	176	177	181	190	202
128	106	91	94	99	92	79	76	86	96	117	130	145	161	167	161	152	171	190	200	213
113	93	75	71	73	76	72	70	63	72	98	133	144	128	134	144	157	171	186	193	205
86	79	66	62	65	72	78	74	68	75	95	126	121	117	124	155	189	189	199	205	212
72	75	68	63	66	74	74	62	69	75	94	111	108	117	130	166	198	193	204	210	211
67	70	67	65	68	68	62	60	70	78	89	96	103	127	150	181	191	190	190	192	197
69	69	73	79	85	85	73	79	75	80	86	97	123	148	165	175	169	189	186	183	190
76	72	80	86	90	90	86	89	88	87	87	100	108	110	118	125	142	164	170	173	186
84	81	86	87	88	84	78	88	80	76	76	93	91	81	83	97	126	140	148	157	171
88	87	92	91	88	83	78	88	74	70	74	95	85	70	68	89	129	135	142	150	163
85	85	89	87	84	80	78	85	74	74	81	94	84	72	73	99	139	148	152	156	164
97	90	88	80	75	78	83	89	93	101	110	113	110	111	118	139	166	181	183	183	185
130	115	104	91	84	80	86	87	97	108	119	121	127	134	143	155	168	185	191	192	194
162	147	132	116	107	103	101	98	99	100	108	117	128	127	133	141	156	170	179	185	193
176	162	148	131	124	115	109	110	106	103	108	126	134	135	138	143	163	166	176	181	192
187	175	162	152	144	131	124	125	119	117	120	127	147	154	160	172	184	176	180	186	192
189	178	166	157	150	137	122	120	121	122	120	122	139	168	184	203	210	203	203	202	200
189	178	169	161	155	144	127	121	124	128	128	134	155	175	192	208	213	217	216	213	206

Filters



Vertical edge detection

$\longrightarrow$

-1	0	1
-2	0	2
-1	0	1

$\longrightarrow$

Vertical edge detection

$$\begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}$$

$$*$$

$$\begin{bmatrix} 0 & 0 & 0 & 1 & 1 & 1 \\ 0 & 0 & 0 & 1 & 1 & 1 \\ 0 & 0 & 0 & 1 & 1 & 1 \end{bmatrix}$$

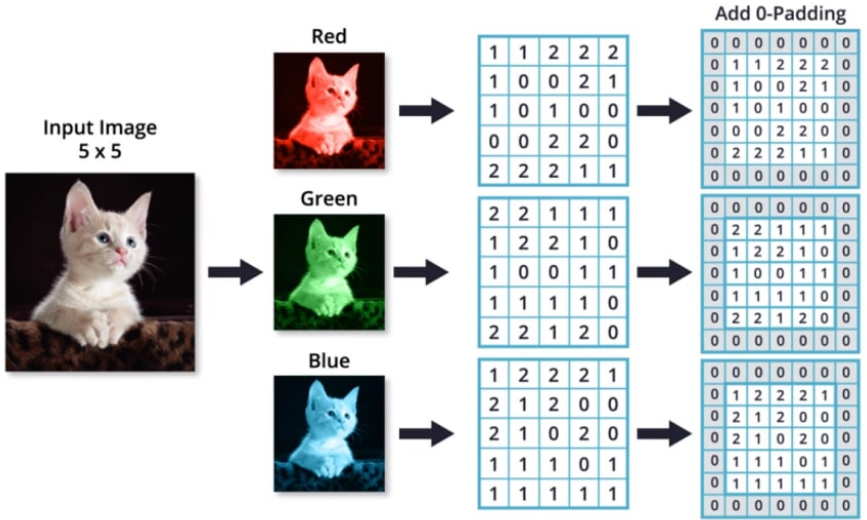
Horizontal edge detection

$\longrightarrow$

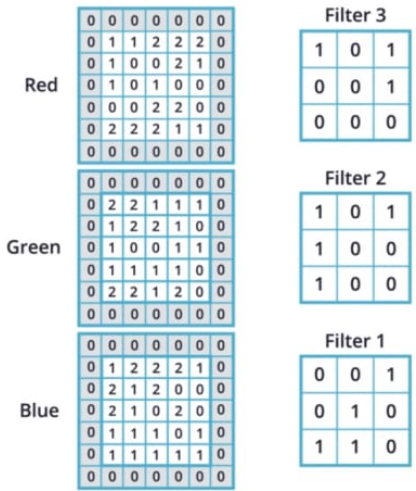
-1	-2	-1
0	0	0
1	2	1

$\longrightarrow$

RGB images



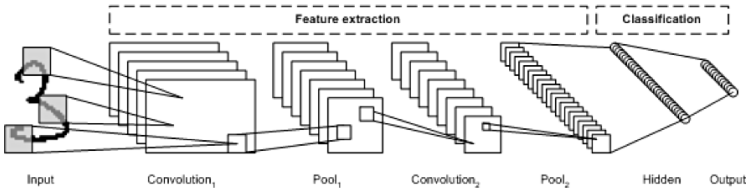
RGB filters



Convoluted Output

ZIP Code reading

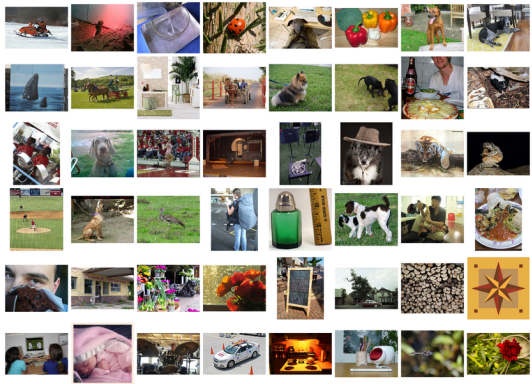
Yann Lecun



LeNet

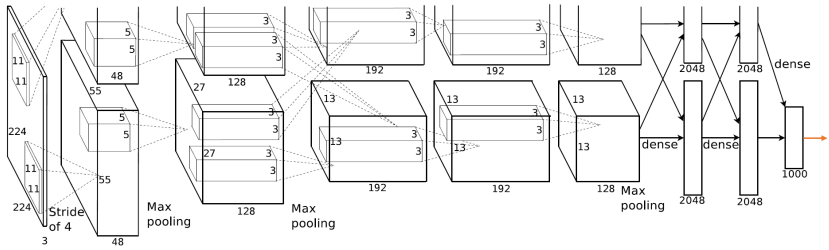
- Lecun et al. (1989) used Convolutional Neural Network - 95% accuracy

Imagenet challenge (2012)



- 1.2 labeled training images: 1000+ images in each of 1000 categories
- 150,000 nonlabeled testing images

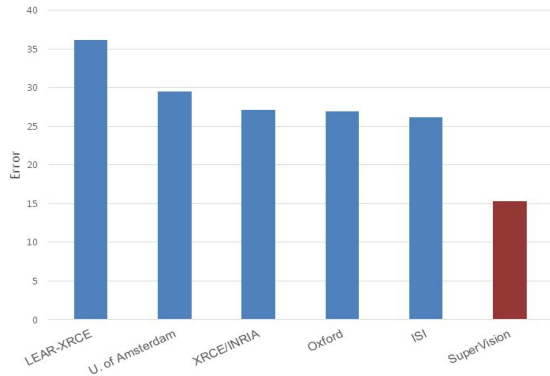
AlexNet



- Geoff Hinton, Alex Krizhevsky and Ilya Sutskever, under the name of *SuperVision*, trained ImageNet with an 8-layer CNN which has 60 million parameters.
- These parameters could be trained with the help of two GTX 580 GPUs.

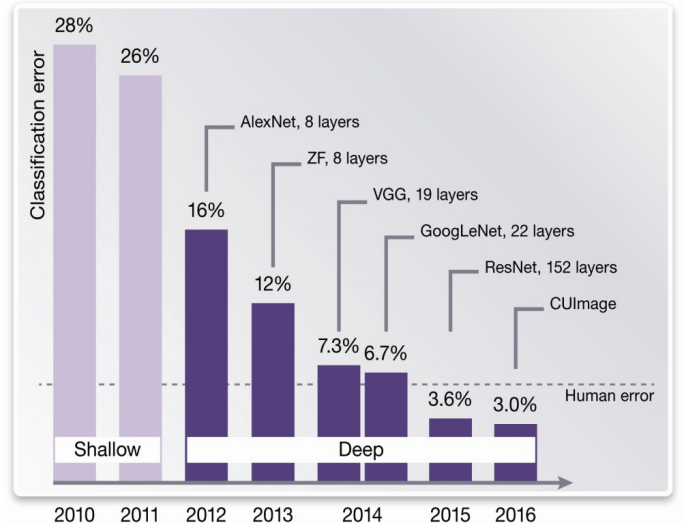
ImageNet 1K Competition

(Fall 2012)



- SuperVision won the competition with 15.3% test error rate compared to 26.2% achieved by the second-best entry.

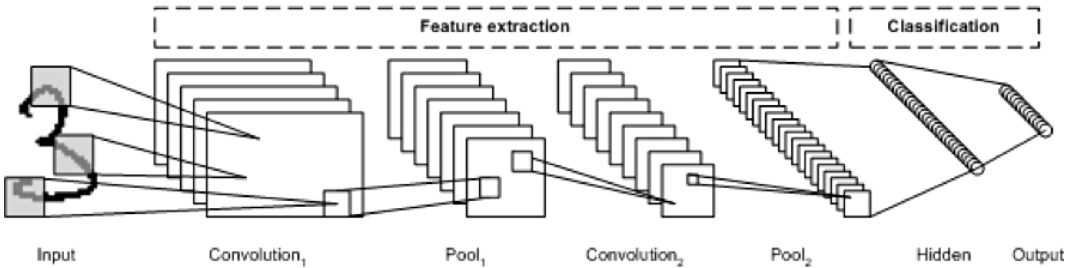
Imagenet results (2010-2016)



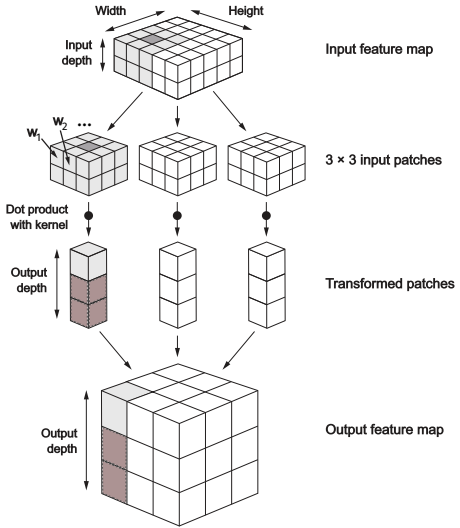
Main layers

There are three main layers in a CNN:

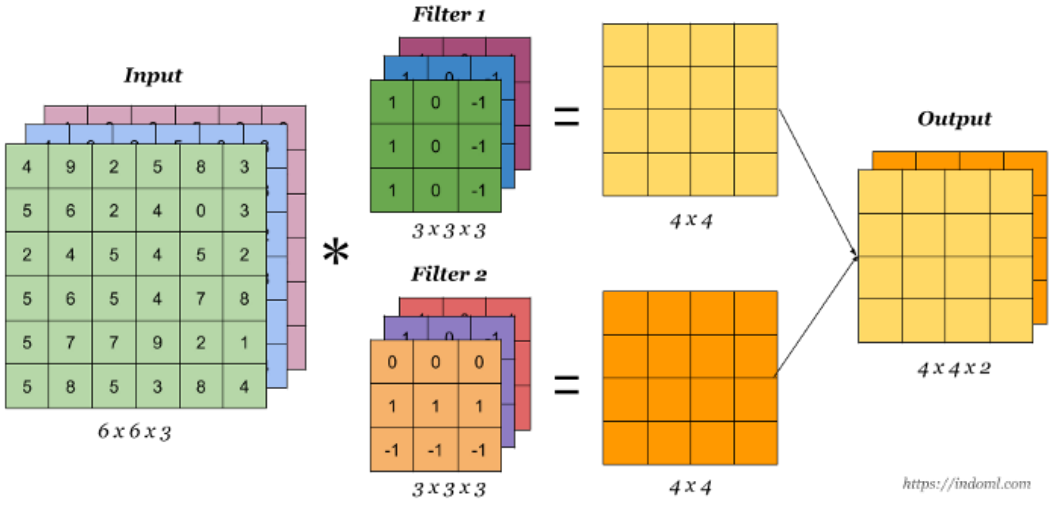
1. Convolutional layers
2. Pooling layers
3. Flatten layers.



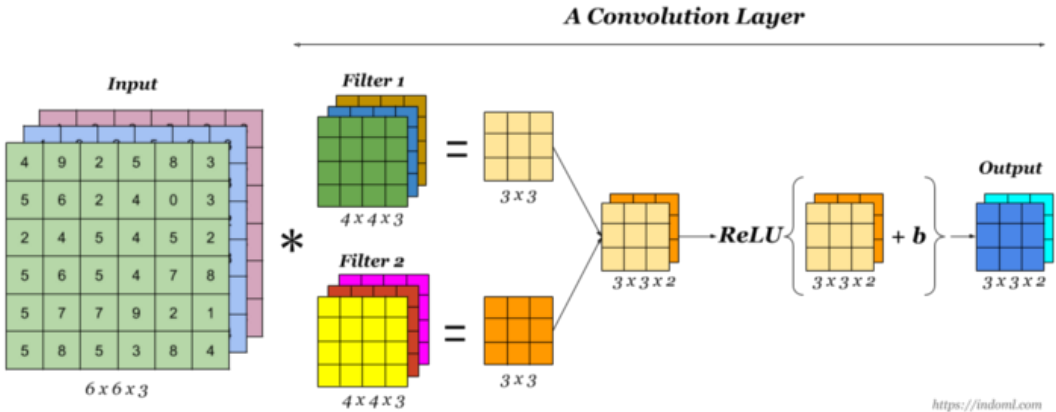
Convolution layers



Multiple filters

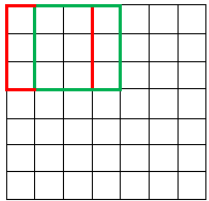


A simple CNN

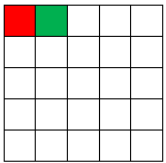

A Convolution Layer
Input
4 9 2 5 8 3
5 6 2 4 0 3
2 4 5 4 5 2
5 6 5 4 7 8
5 7 7 9 2 1
5 8 5 3 8 4
6 x 6 x 3
*
Filter 1
4 x 4 x 3
=
3 x 3
Filter 2
4 x 4 x 3
=
3 x 3
3 x 3 x 2
ReLU
3 x 3 x 2
+ b
Output
3 x 3 x 2
https://indoml.com

Stride

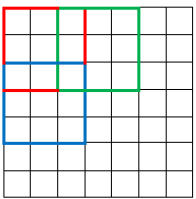
7 x 7 Input Volume



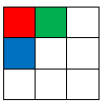
5 x 5 Output Volume



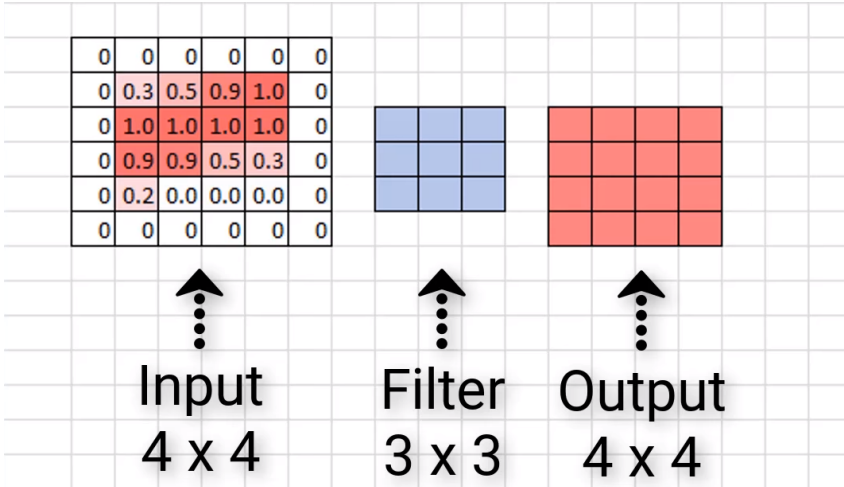
7 x 7 Input Volume



3 x 3 Output Volume



Padding



- In case you want the output to be bigger

Computing the dimension of output

Computing the dimension of output

Example:

- Input $227 \times 227 \times 3$
- 96 Filters of size $11 \times 11 \times 3$
- Stride $= 2$
- Padding $= 1$ on each side

What is the output size?

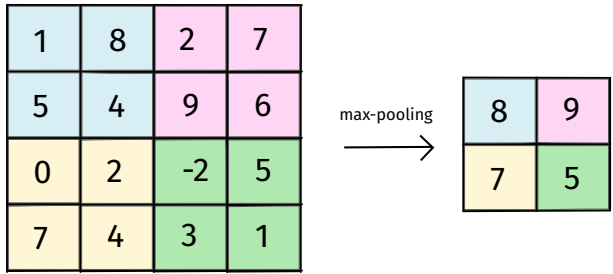
Computing the dimension of output

Example:

- Input $25 \times 25 \times 3$
- 96 Filters of size $3 \times 3 \times 3$
- Stride $= 2$

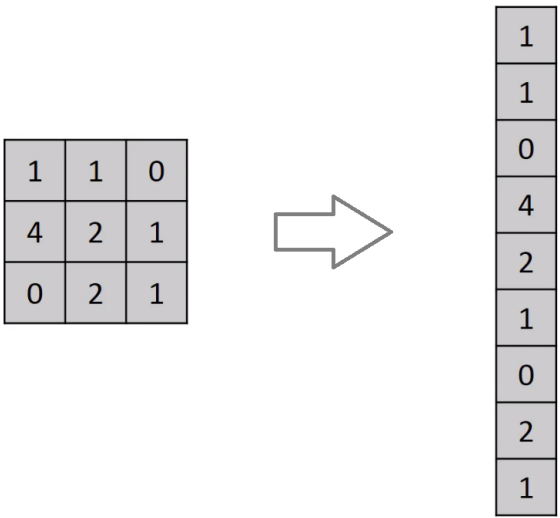
Padding size so that output size = input size?

Max-poolings



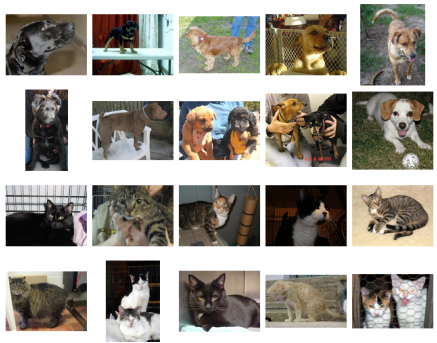
- helps reduce dimensions $\Rightarrow$ less layers to train

Flatten layer

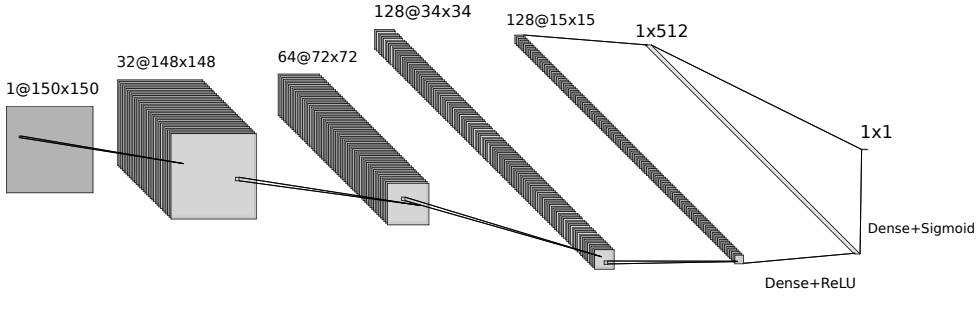


Convolutional Neural Network: Example

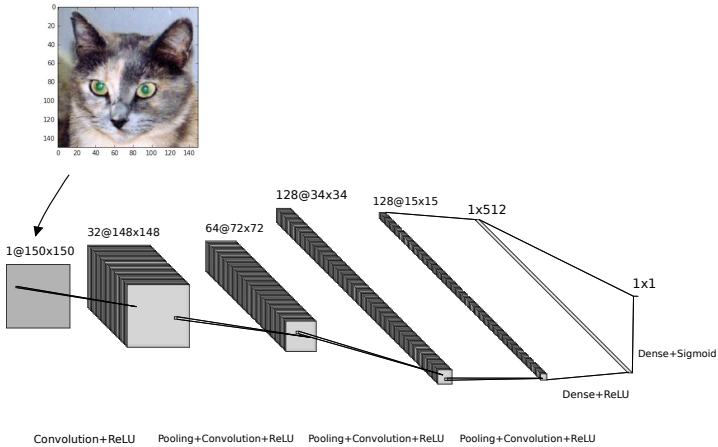
Dogs vs. Cats dataset (https://www.kaggle.com/c/dogs-vs-cats/data)



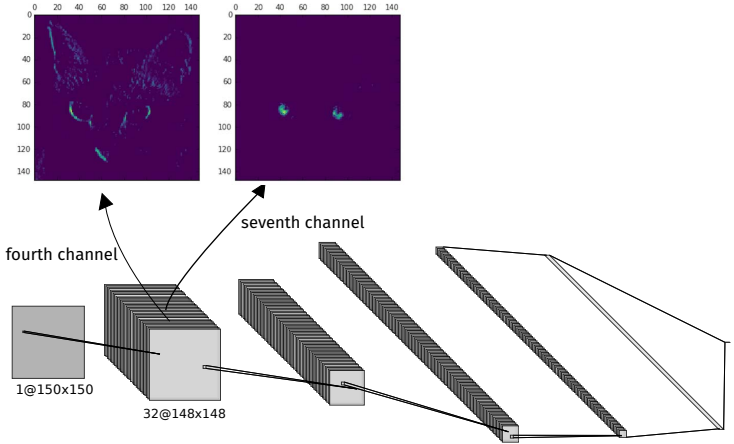
- Training images: 2000 images
- Testing images: 1000 images



- Result: around 70% accuracy on the test set
- Notice the ReLU activations after all hidden layers
- sigmoid at the end for binary classification

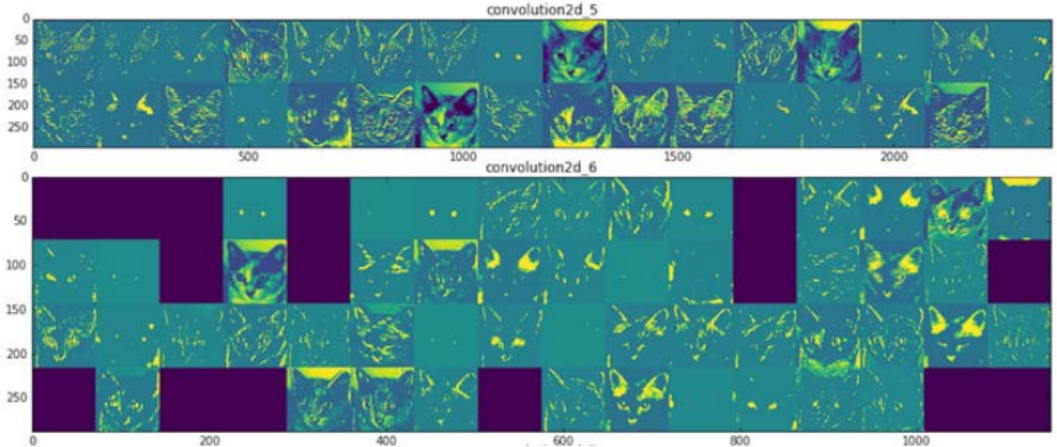


- Let’s see what will happen to this image after the first convolutional layer.

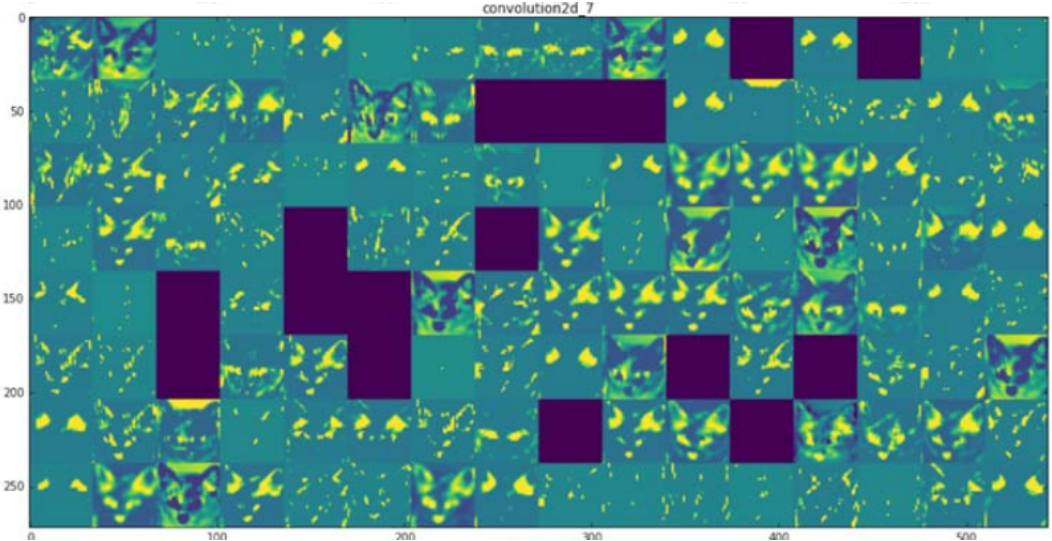


- It looks like the fourth layer detects diagonal edges and the seventh layer detects green pixels.

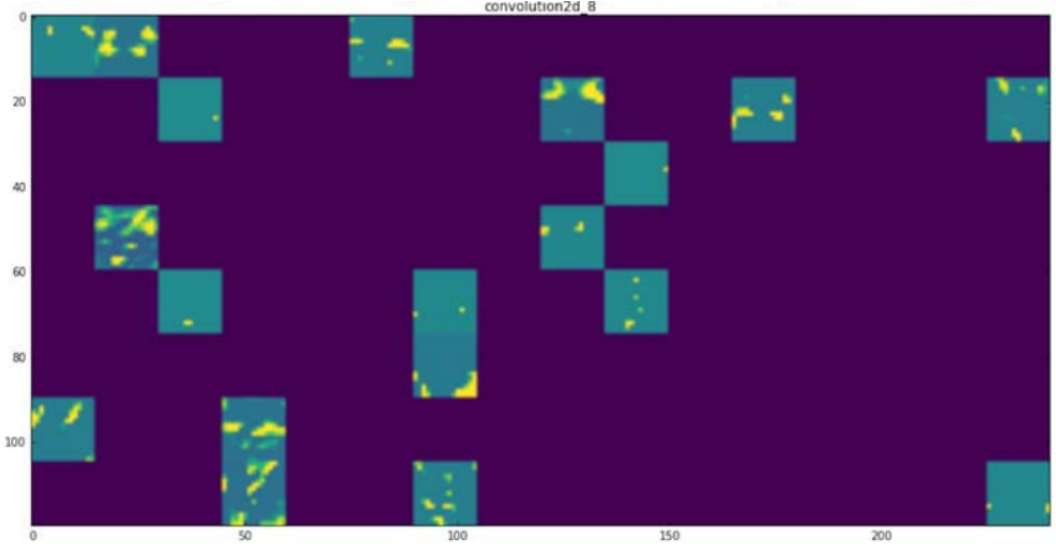
Filtered images from the first two convolutional layers:



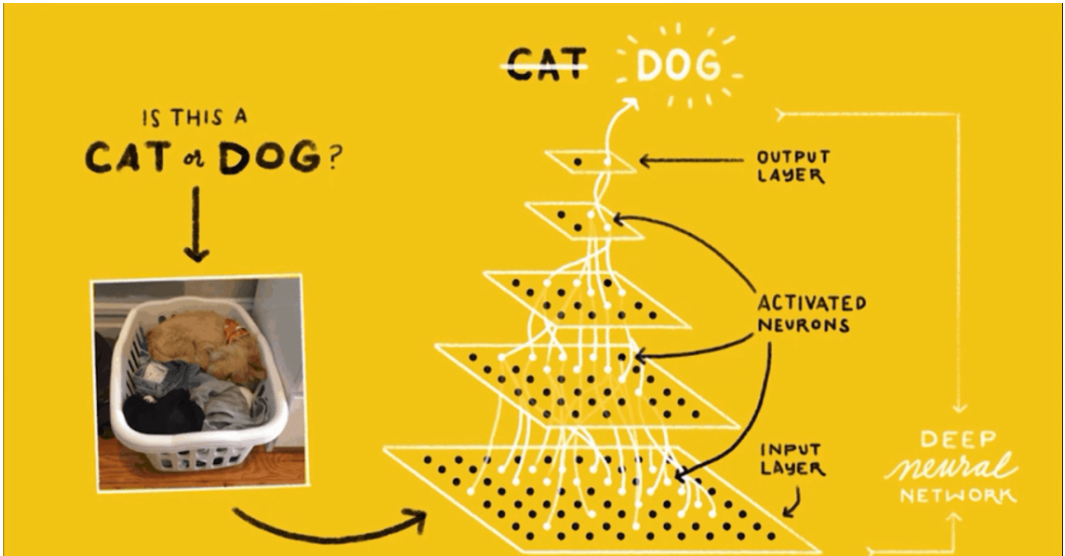
after the third layers:



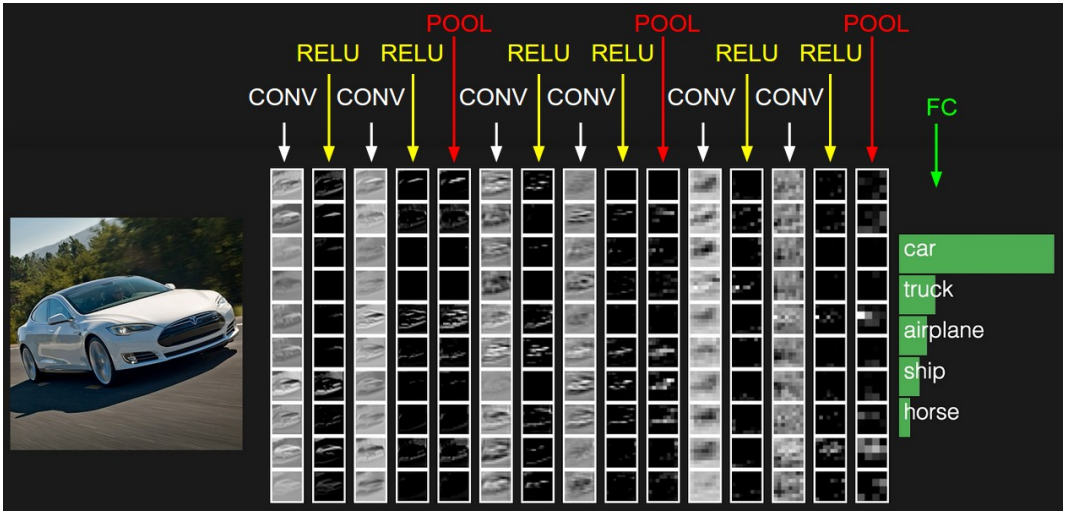
after the fourth layers:



Another simplified picture of CNN



Multiclass classification



Positives

- gives best performance on computer vision tasks
- incremental construction, meaning that one can add or modify existing layers to suit a specific task

Negatives

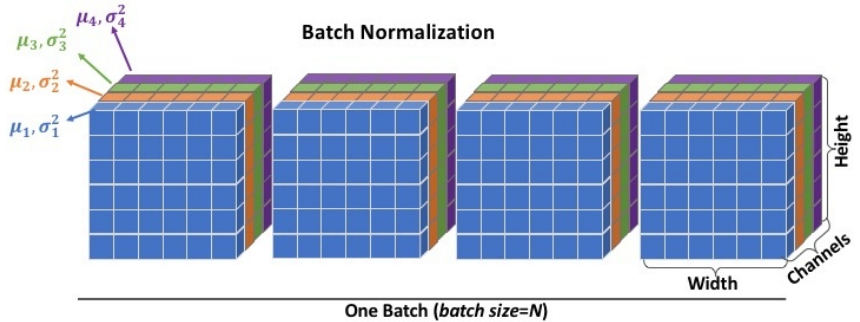
- computational intensive: training millions of parameters requires GPUs
- no unified theoretical support

Other techniques

Data augmentation

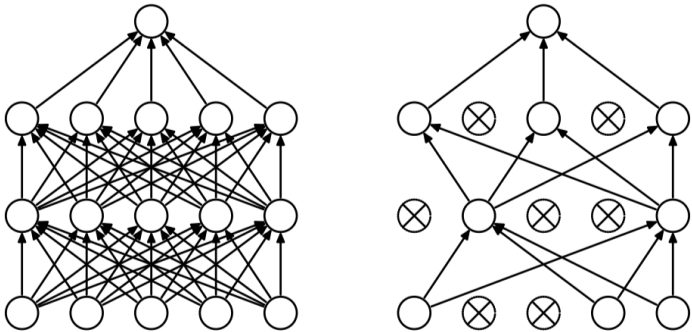
- Translation, rotation, flipping, cropping, color adjustment etc.
- More data to train $\rightarrow$ better predictions.

Batch normalization



- Cells with the same color are subtracted by the same mean and divided by the same variance.
- Prevents the cell values from becoming too large. It also makes the training faster.

Dropouts

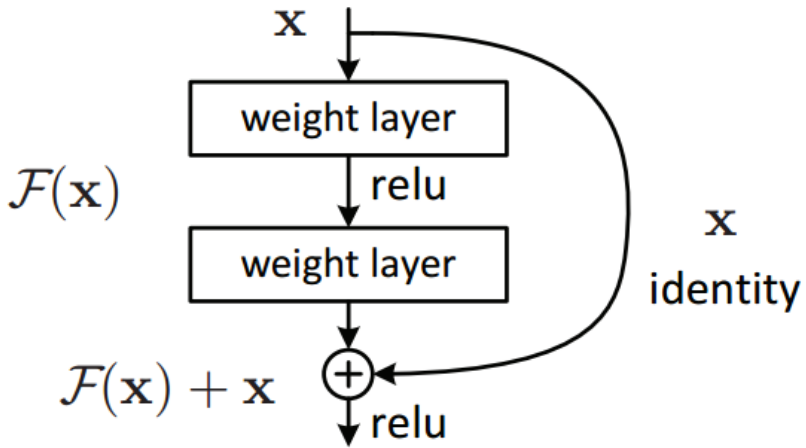


(a) Standard Neural Net

(b) After applying dropout.

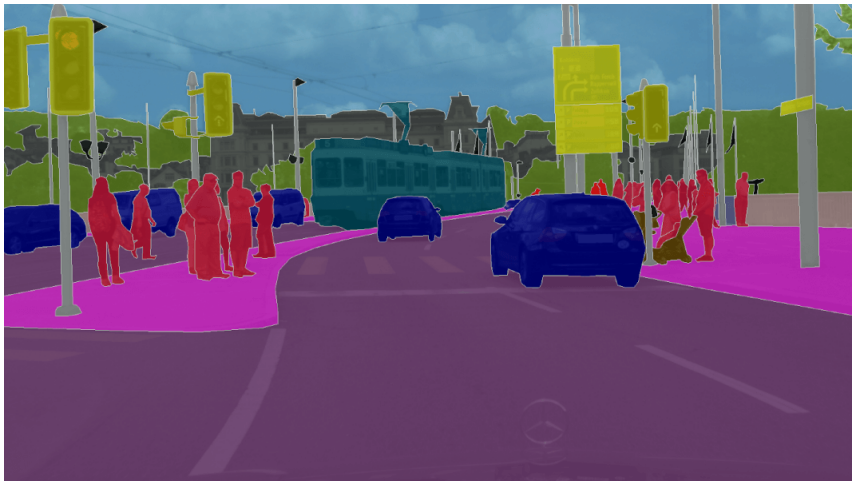
- Some of the nodes are randomly deactivated during each iteration.
- Prevents overfitting on training data. Improves model generalization.

Skip connection



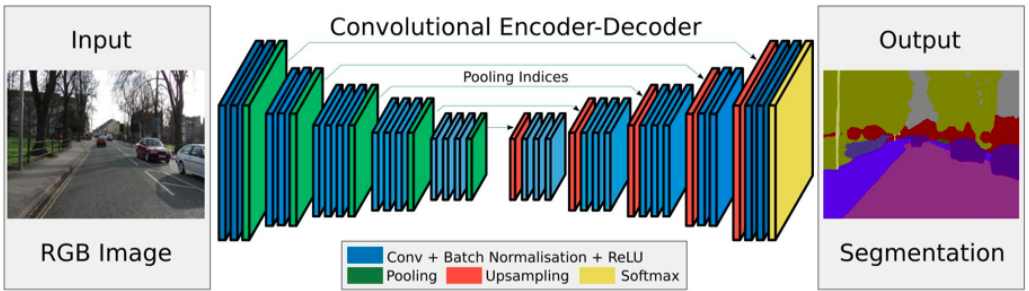
- Prevents the outputs of each layers from becoming zero.

Segmentation



- Road segmentation for self-driving car.

U-Net


Input
RGB Image
Convolutional Encoder-Decoder
Pooling Indices
Conv + Batch Normalisation + ReLU
Pooling
Upsampling
Softmax
Output
Segmentation