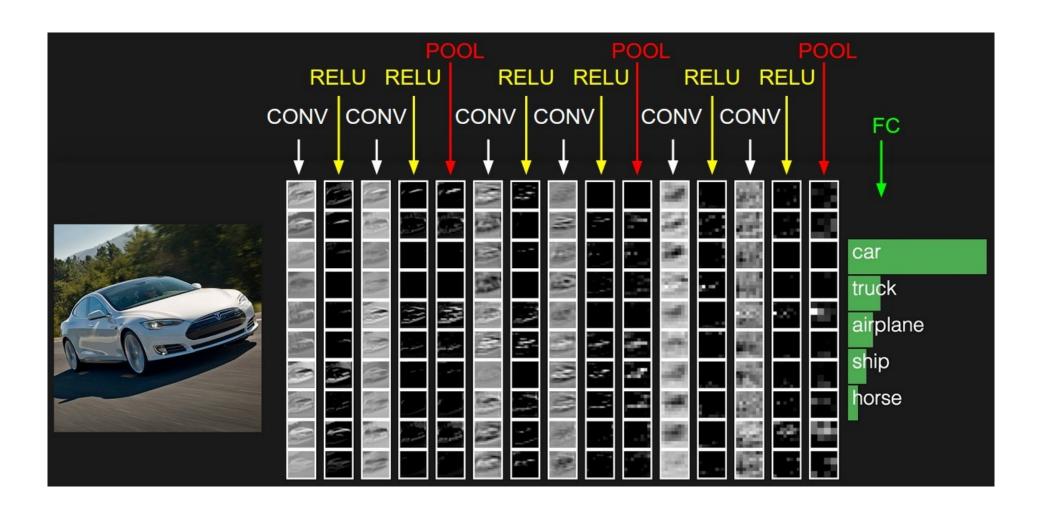
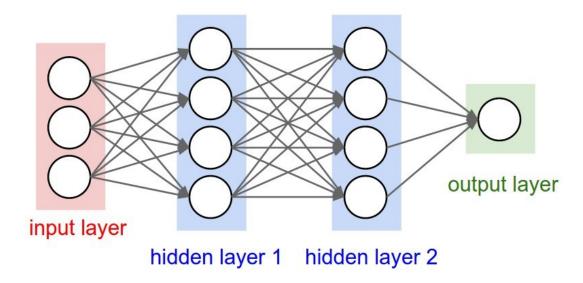
Introduction to Convolutional Networks

Zhengjia Huang 06-07-2017, UAH, Spain

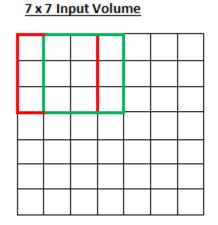


Convolutional layer

Fully connected



Local receptive field & Shared weight

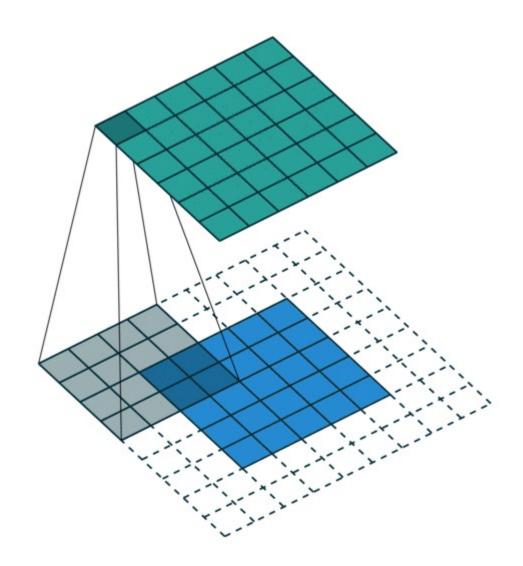


5 x 5 Output Volume

Normal Network

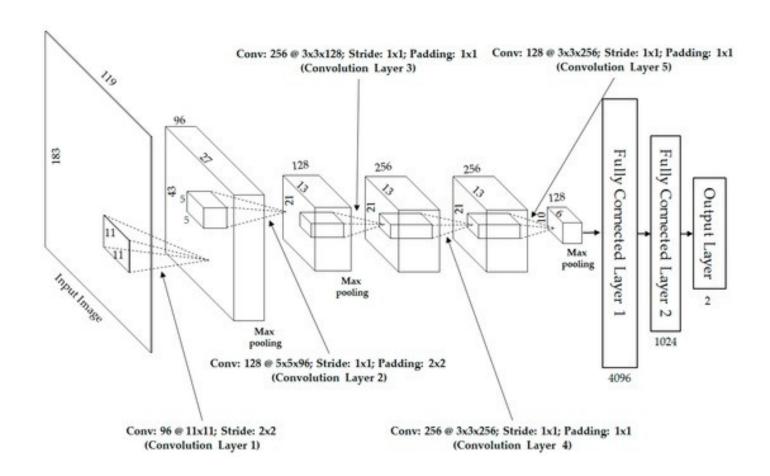
Convolutional Network

Convolutional layer



Padding and stride help us to control the output size.

Convolutional layer

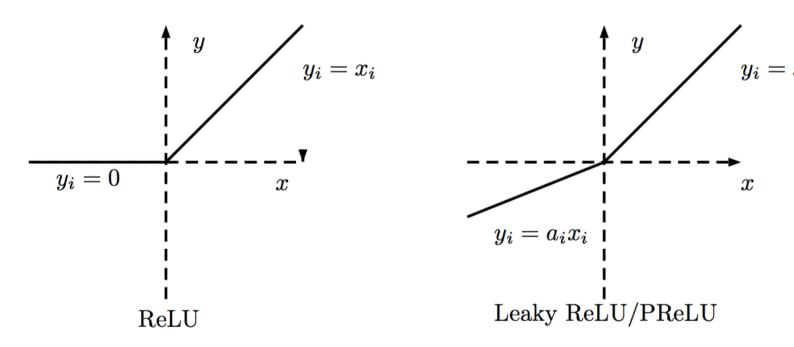


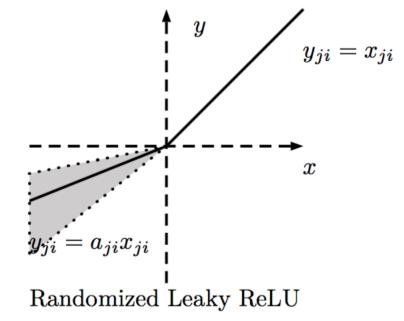
Each convolutional kernel is a 3D structure with depth equal to number of input channel (depth of input).

Each convolutional layer contains many kernels, the number of kernels equals to number of output channels (depth of output).

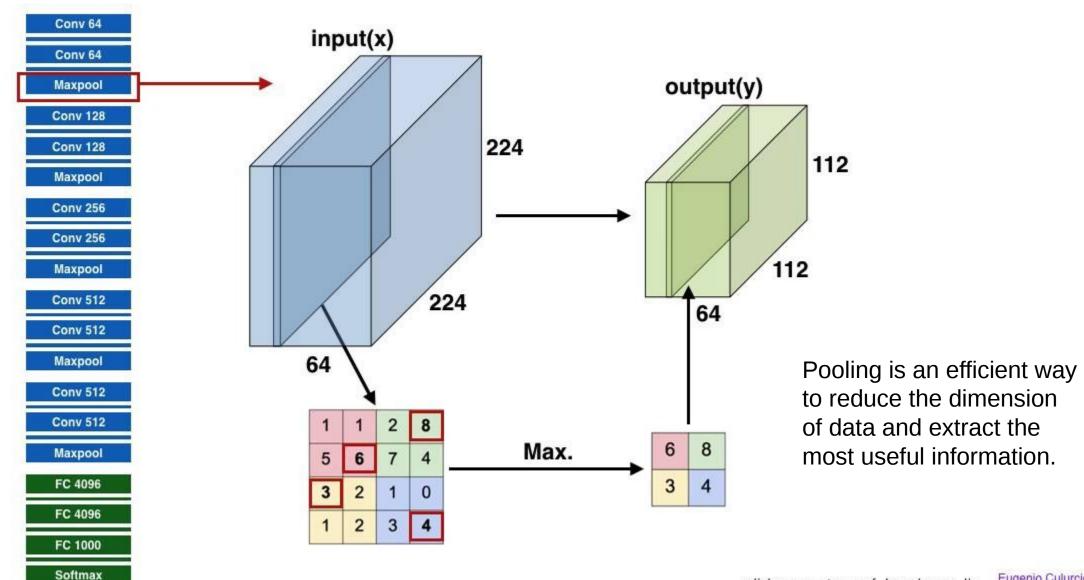
Nonlinearity

Each convolution is a linear operation. In order to represent the nonlinearities of the data, we introduce simple non-linear layers into CNN.

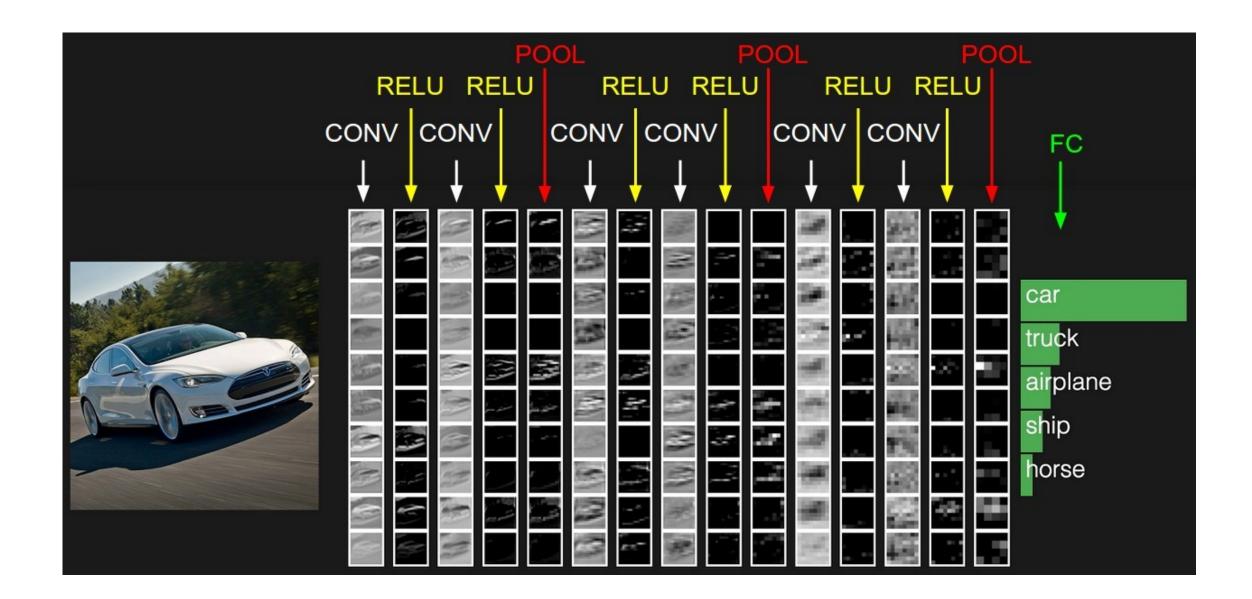




Pooling layer

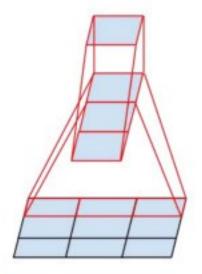


A complete CNN



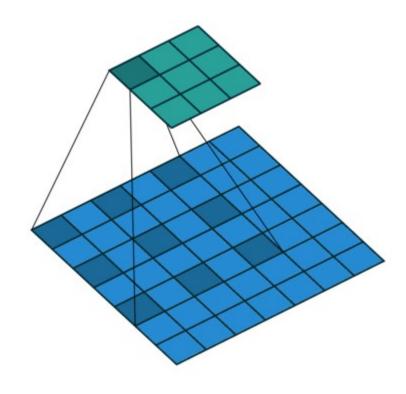
Some tricks

To save time and space



A symmetric convolution

To increase receptive field



Dilated convolution

Some tricks

Faster convergence

Input: Values of
$$x$$
 over a mini-batch: $\mathcal{B} = \{x_{1...m}\}$;

Parameters to be learned: γ , β

Output: $\{y_i = \mathrm{BN}_{\gamma,\beta}(x_i)\}$

$$\mu_{\mathcal{B}} \leftarrow \frac{1}{m} \sum_{i=1}^m x_i \qquad \text{// mini-batch mean}$$

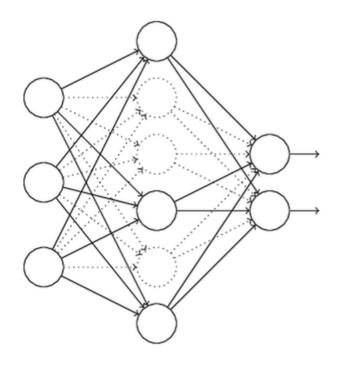
$$\sigma_{\mathcal{B}}^2 \leftarrow \frac{1}{m} \sum_{i=1}^m (x_i - \mu_{\mathcal{B}})^2 \qquad \text{// mini-batch variance}$$

$$\widehat{x}_i \leftarrow \frac{x_i - \mu_{\mathcal{B}}}{\sqrt{\sigma_{\mathcal{B}}^2 + \epsilon}} \qquad \text{// normalize}$$

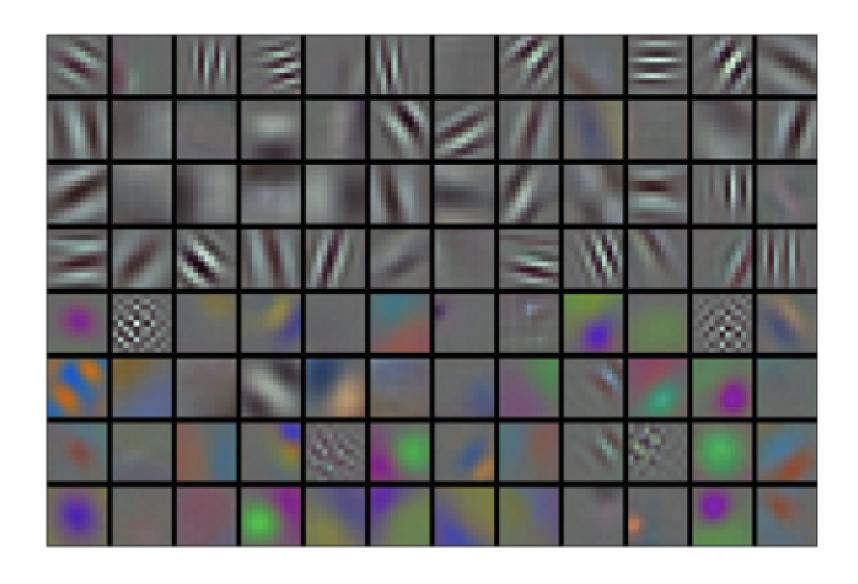
$$y_i \leftarrow \gamma \widehat{x}_i + \beta \equiv \mathrm{BN}_{\gamma,\beta}(x_i) \qquad \text{// scale and shift}$$

Batch normalization

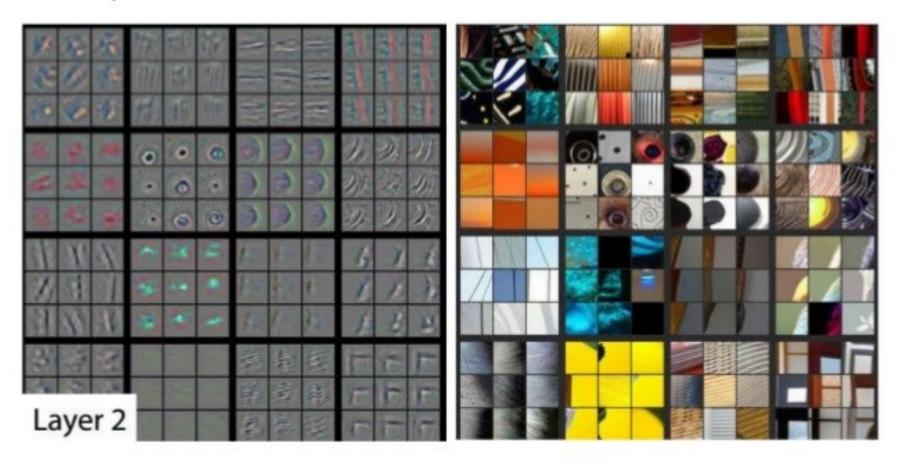
Prevent overfit problem



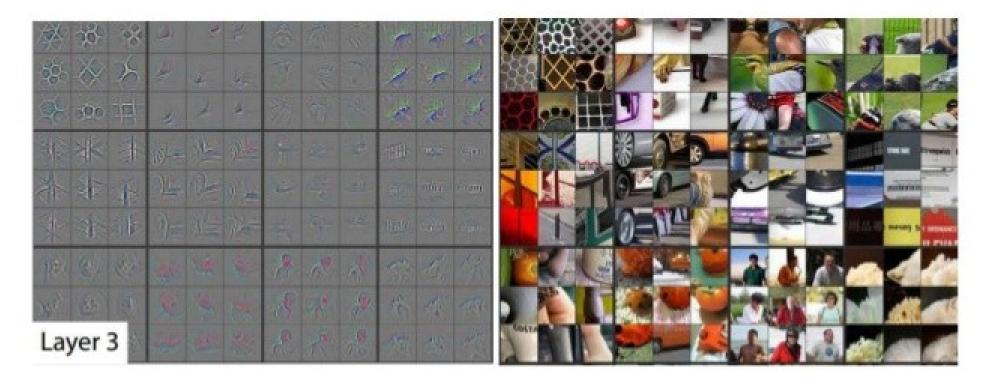
Dropout



Layer 2



Layer 3



Layer 4 and 5

