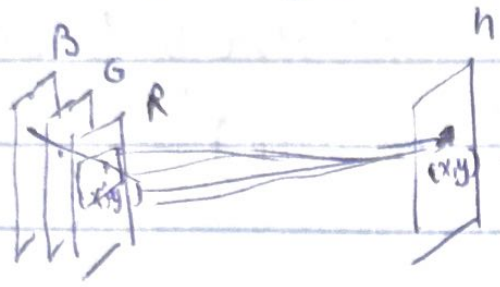
Convolution

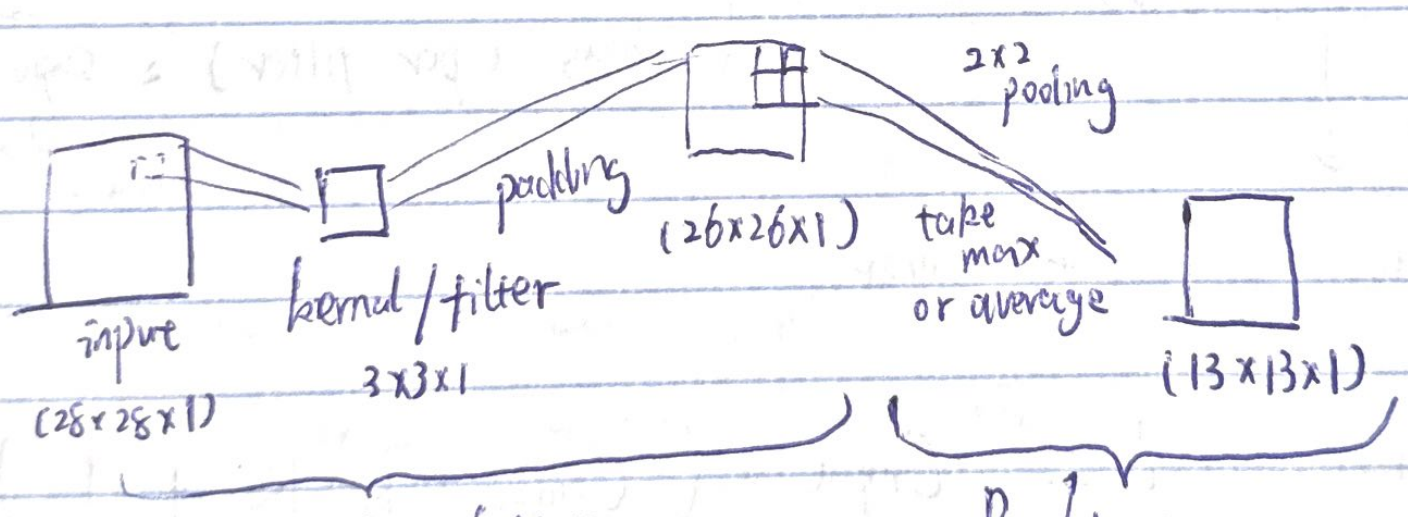
in math. $(f * g)(t) = \int_{-\infty}^{\infty} f(\tau)\, g(t-\tau)\, d\tau$

In Convolutional NN:

3 channels rgb



$$h(x,y) = \sum_{x'=x-1}^{x+1} \sum_{y'=y-1}^{y+1} I^R(x',y')\, W_h^R(x'y' \leftrightarrow xy)$$
$$+ \sum_{x'=x-1}^{x+1} \sum_{y'=y-1}^{y+1} I^G(x',y')\, W_h^G(x'y' \leftrightarrow xy)$$
$$+ \sum_{x'=x-1}^{x+1} \sum_{y'=y-1}^{y+1} I^B(x',y')\, W_h^B(x'y' \leftrightarrow xy)$$



Output Dimensions After Convolution

$$= \left[\frac{(W - F + 2P)}{S}\right] + 1$$

W : input width / height

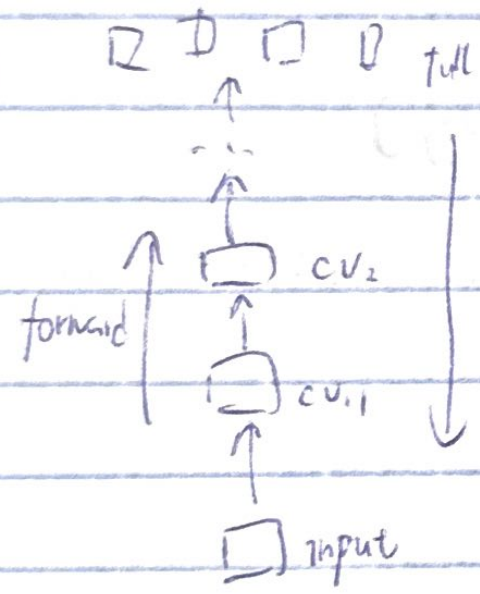
F : kernel / filter size

P : padding (0 for "valid" padding) add extra pixels outside existing input

S : stride (move the kernel by S each time)

Output Dimension After ~~convolution~~ pooling

$$= \left[\frac{(W - F)}{S}\right] + 1 \qquad \text{typically } S = F$$



back propagation : train

- weight (per filters) : matrix # param : ~~filter~~ $(\text{Cinput} \cdot (K)^2)$
- bias (per filter) : single value to shift result to allow network fit better
  # param : 1 (per filter)

Conv: # params trained $= \text{Cinput} \cdot (\text{Coutput} \cdot K \cdot K + 1)$

Cinput: channel; Coutput · K · K: kernel size; 1: bias term

Full Connect: # params trained $= N_{input} \cdot N_{output} + 1 \cdot N_{output}$

N_{input}: # parameter in input; N_{output}: # parameter in output; weights