

## CNNs

- Images generally have a high dimensionality.
- Think of an image - say 1080p image.  
e.g. 1080p =  $1920 \times 1080 \times 3$   
 $\approx$  6 million features
- If you treat each pixel as an independent input variable, the input dimensionality will blow up. (weights)

### Equivariance

- A fn.  $f(\cdot)$  is equivariant if for a transformation  $T$ :  
 $f(T(x)) = T(f(x))$
- In CNNs, we see this principle.

### Invariance

- A fn.  $f(\cdot)$  is invariant to a transformation  $T$  if:  
 $f(T(x)) = f(x)$

We have the output to a particular receptive field as:

$$y = \text{ReLU}(w^T x + w_0)$$

### Lagrangian

$$\begin{aligned} l(x) &= w^T x \\ g(x) &= x^T x - c = 0 \\ l(x, \lambda) &= w^T x - \lambda(x^T x - c) \\ \nabla_x l &= w - 2\lambda x = 0 \\ \Rightarrow x &= \frac{1}{2\lambda} w \\ x &= \alpha w \quad (\alpha = \frac{1}{2\lambda}) \end{aligned}$$

We define Convolution as:

- $I(j, k) \rightarrow$  Image pixels
  - $K(l, m) \rightarrow$  Filter pixels
- $$C(j, k) = \sum_l \sum_m I(j+l, k+m) K(l, m)$$
- Also  $C = I \otimes K$  (notation)

### Padding

- The convolution map is smaller than the original image.

$$\begin{array}{l} \text{Image} \rightarrow J \times K \\ \text{Kernel} \rightarrow M \times M \end{array} \Rightarrow \begin{array}{l} (J-M+1) \times (K-M+1) \\ \text{Feature-Map} \end{array}$$



$$\begin{aligned} J - M + 1 + 2P &= J \\ 2P + 1 &= M \\ P &= \frac{(M-1)}{2} \end{aligned}$$

$$\begin{aligned} K - M + 1 + 2P &= K \\ 2P + 1 &= M \\ P &= \frac{(M-1)}{2} \end{aligned}$$

- $P = 0$  is no-padding. called valid padding.
- As seen above to achieve the same dimension of the feature map as of the image we need  $[P = \frac{m-1}{2}]$ . This is called same padding.

## Strides

- Input :  $J$
- Kernel :  $M$
- Padding :  $P$  (total len =  $J+2P$ )
- Index : 0 to  $J+2P-1$ 
  - First valid start index = 0
  - Last valid start index =  $J+2P-M$
- with stride  $S$ , kernel start positions are :
  - $0, S, 2S, 3S, \dots, kS \leq J+2P-M$
  - $k = J+2P-M$ . The largest  $k$  is  $\lfloor \frac{J+2P-M}{S} \rfloor$ .

## 10.2.5 Multi-dimensional convolution

- Input Tensor =  $J \times K \times C \nearrow$  no. of channels
- Kernel =  $M \times M \times C$
- (This will have  $M^2 C$  weights, regardless of the input size).
- To build more flexible models, we can include multiple such filters.
- Kernel (multidimensional) =  $M \times M \times C_{in} \times C_{out}$   
(This will have  $(M^2 C_{in} + 1) C_{out}$  weights)



## 10.2.6 Pooling

- Max Pooling
- Average Pooling

