

NN

(\Rightarrow No of filter)

\Rightarrow Convolution layer (Conv2D), \Rightarrow filter (f_y), stride (ΔY)

$$Z^{(L)} = \left(1 + \frac{H^{(L-1)} - f_y}{\Delta Y} \right) \times \left(1 + \frac{W^{(L-1)} - f_x}{\Delta X} \right) \times C^{(L)}$$

\Rightarrow Maxpooling \Rightarrow Kernel
(H_k, W_k, c)

① CNN layers

Conv2D (filter, kernel, activation, input)

Maxpooling (pool-size)

Dense (Size, activation) \rightarrow Can be ReLU, Softmax

② Probability

$$P(A|B) = \frac{P(x=A, y=B)}{P(B)} = \frac{\#(x=A, y=B)}{\#(y=B)}$$

$$P(A=x) = \frac{\#(\#=x)}{N}$$

DNN

\Rightarrow Derivative

$$\frac{d}{dx} \cos(x) = -\sin(x)$$

$$\frac{d}{dx} \sin(x) = \cos(x)$$

$$A = xw + \vec{b}^T$$

In general

$$A^{(i)} = A^{(i-1)} \cdot w^{(i)} + \vec{b}^{(i)T}$$

softmax

① Binary classification

true negative: $t_n = \#(y=1, t=1)$

false positive: $f_p = \#(y=2, t=1)$

true positive: $t_p = \#(y=2, t=2)$

false negative: $f_n = \#(y=1, t=2)$

true negative rate (t_{nr})

$$t_{nr} = p(y=1 | t=1)$$

false positive rate (f_{pr})

$$f_{pr} = p(y=2 | t=1)$$

true positive rate (t_{pr})

$$t_{pr} = p(y=2 | t=2)$$

false negative rate (f_{nr})

$$f_{nr} = p(y=1 | t=2)$$

\Rightarrow Sensitivity / recall = t_{pr} (true positive rate)

\Rightarrow Specificity / selectivity = t_{nr} (~~false~~ ^{True} negative rate)

$$\Rightarrow \text{Precision} : p = \frac{t_p}{f_p + t_p} = \frac{t_{pr}}{f_{pr} \cdot \frac{P_m}{P_p} + t_{pr}}$$

$$C = \begin{pmatrix} t_n & f_p \\ f_n & t_p \end{pmatrix} \xrightarrow{t=1} \begin{pmatrix} y=1 & y=2 \\ t_n & f_p \end{pmatrix} \quad \xrightarrow{t=2} \begin{pmatrix} y=1 & y=2 \\ f_n & t_p \end{pmatrix}$$

\Rightarrow negatives: $\#(t=1)$

\Rightarrow positives: $\#(t=2)$

\Rightarrow negative rate:

$$P_m = p(t=1) = \frac{n}{N}$$

\Rightarrow positive rate:

$$P_p = p(t=2) = \frac{m}{N}$$

$$t_{nr} + f_{pr} = 1$$

$$f_{nr} + t_{pr} = 1$$

\Rightarrow Error (E)

$$E = f_{nr} * P_p + f_{pr} * P_m$$

$$\Rightarrow \text{Softmax} = \frac{\exp(x_i)}{\sum_k \exp(x_k)}$$

Partial derivatives: $\frac{\partial s_i}{\partial x_j} = \delta_{ij} s_i - s_i s_j$

\Rightarrow Entropy

$$L = - \sum_k t_k \cdot \log y_k$$

$$\Rightarrow \text{MSE} = \frac{\sum_i (\text{pred} - \text{Actual})^2}{N}$$

\Rightarrow Derivation (define rule, decomposition, Applying rule)

$$\begin{aligned} \text{Chain Rule} &= h(f(g(x))) \\ &= h'(f(g(x))) \cdot f'(g(x)) \cdot g'(x) \end{aligned}$$

$$\begin{aligned} \text{M1H1. Rule} &= f(x) \cdot g(x) \\ &= f'(x) \cdot g(x) + g'(x) \cdot f(x) \end{aligned}$$

\Rightarrow Gradient

$$\vec{x}_{(i+1)} = \vec{x}_{(i)} \oplus \varepsilon \cdot \vec{\Delta}_k \Big|_{\vec{x}_{(i)}}$$

Numpy
⇒ generating nD array ⇒ np. random. uniform (low, high, shape)

Mat
⇒ np.linspace (low, high, ~~step~~ ^{Count})

DNN