

P₁

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Sift finds keypoint locations as parameter scales and assign orientations to them. By ~~using~~ giving each keypoint one or more orientations based on local gradient directions, Sift achieves invariance

P₂

So we have:

$$\frac{\partial L}{\partial y_i} = \frac{\partial L}{\partial p_{gt}} \cdot \frac{\partial p_i}{\partial y_i}$$

$$L = -\log(p_{gt})$$

$$p_{gt} = \frac{e^{y_{gt}}}{\sum_i e^{y_i}}$$

if $i = gt$

$$p_{gt} = p_i$$

$$\frac{\partial L}{\partial y_i} = -\frac{1}{p_{gt}} \cdot \frac{\partial p_i}{\partial y_i}$$

$$\frac{\partial p_i}{\partial y_i} = \frac{\partial \left(\frac{e^{y_i}}{\sum_j e^{y_j}} \right)}{\partial y_i}$$

$$= \frac{\sum_j \frac{\partial e^{y_j}}{\partial y_i} - e^{y_i} \frac{\partial \sum_j e^{y_j}}{\partial y_i}}{\sum_j e^{y_j}^2}$$

$$= \frac{e^{y_i} (\sum_j e^{y_j} - e^{y_i})}{\sum_j e^{y_j}^2} = \frac{e^{y_i}}{\sum_j e^{y_j}} \cdot \frac{(\sum_j e^{y_j} - e^{y_i})}{\sum_j e^{y_j}}$$

$$\frac{\partial p_i}{\partial y_i} \cdot \frac{\partial L}{\partial p_i} = \frac{e^{y_i} (\sum_j e^{y_j} - e^{y_i})}{\sum_j e^{y_j}^2} \cdot -\frac{1}{p_{gt}}$$

$$= \frac{e^{y_i} (\sum_j e^{y_j} - e^{y_i})}{\sum_j e^{y_j}^2} \cdot -\frac{1}{p_{gt}}$$

$$= p_{gt} \cdot (1 - p_{gt}) \cdot -\frac{1}{p_{gt}}$$

$$= p_{gt} - 1$$

$$= p_i - 1$$

if $i \neq gt$

$$\frac{\partial p_{gt}}{\partial y_i} = \frac{\partial \left(\frac{e^{y_{gt}}}{\sum_j e^{y_j}} \right)}{\partial y_i}$$

$$= \frac{\sum_j \frac{\partial e^{y_j}}{\partial y_i} - e^{y_{gt}} \frac{\partial \sum_j e^{y_j}}{\partial y_i}}{\sum_j e^{y_j}^2}$$

$$= 0 - \frac{e^{y_{gt}}}{\sum_j e^{y_j}^2} \cdot e^{y_i}$$

$$= -\frac{e^{y_{gt}}}{\sum_j e^{y_j}} \cdot \frac{e^{y_i}}{\sum_j e^{y_j}}$$

$$= -p_{gt} \cdot p_i$$

$$\therefore \frac{\partial p_i}{\partial y_i} \cdot \frac{\partial L}{\partial p_i} = p_i$$



P3. BP of FC

$$\begin{aligned}
 \frac{\partial L}{\partial w} &= \frac{\partial L}{\partial y} \cdot \frac{\partial y}{\partial w} = \frac{\partial L}{\partial y} \cdot \frac{\partial (wx+b)}{\partial w} = \frac{\partial L}{\partial y} \cdot x^T \\
 \frac{\partial L}{\partial b} &= \frac{\partial L}{\partial y} \cdot \frac{\partial y}{\partial b} = \frac{\partial L}{\partial y} \cdot \frac{\partial (wx+b)}{\partial b} = \frac{\partial L}{\partial y} \cdot 1 \\
 \frac{\partial L}{\partial x} &= \frac{\partial L}{\partial y} \cdot \frac{\partial y}{\partial x} = \frac{\partial L}{\partial y} \cdot \frac{\partial (wx+b)}{\partial x} = \frac{\partial L}{\partial y} \cdot w
 \end{aligned}$$

$R^{0 \times L}$ $R^{0 \times 1}$ $R^{L \times 1}$
 $\frac{\partial L}{\partial y} \sim R^{0 \times 1}$
 $w \sim 0 \times L$
 $x \sim R^{L \times 1}$
 $\frac{\partial L}{\partial y} \cdot x^T$
 $\frac{\partial L}{\partial y} \cdot 1$
 $\frac{\partial L}{\partial y} \cdot w$, adjust to $w^T \cdot \frac{\partial L}{\partial y}$
 $w^T \cdot \frac{\partial L}{\partial y}$

P4.

$$\frac{\partial L}{\partial w_k(t, m, n)} = \frac{\partial L}{\partial y} \cdot \frac{\partial y}{\partial w_k(t, m, n)} = \frac{\partial L}{\partial y} \cdot \frac{\partial}{\partial w_k(t, m, n)} \sum_{t=0}^{T-1} \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} x(t, i, s_{tm}) \cdot j x_{stn} w_k(t, m, n) + b_k$$

$$\frac{\partial L}{\partial w_k(t, m, n)} = \frac{\partial L}{\partial y} \cdot \frac{\partial}{\partial w_k(t, m, n)} \sum_{t=0}^{T-1} \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} x(t, i, s_{tm}) \cdot j x_{stn} w_k(t, m, n) + b_k$$

$$\frac{\partial L}{\partial b(k)} = \sum_{m=0}^K \sum_{i=0}^{H-M} \sum_{j=0}^{W-N} \frac{\partial L}{\partial y(k, i, j)}$$

$$\frac{\partial L}{\partial x(t, m, n)} = \sum_{m=0}^K \sum_{i=0}^{H-M} \sum_{j=0}^{W-N} \frac{\partial L}{\partial y} \cdot w_k(t, m-i, n-j)$$



P5. Max 2D

$$\frac{\partial L}{\partial x(t_{m,n})} = \frac{\partial L}{\partial y} \cdot \frac{\partial y}{\partial x}$$

$$= \begin{cases} \frac{\partial L}{\partial y} & \text{where } x(t, m, n) = x(e', ixstm', jxstm') \\ 0 & \text{otherwise.} \end{cases}$$

