

# Do Lessons from Metric Learning Generalize to Image-Caption Retrieval?

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## A Derivative of the gradient of SmoothAP w.r.t. $\mathbf{q}$

In this section, we give an analyses and derivation of the gradient of SmoothAP [1] w.r.t. query  $\mathbf{q}$ . We start with Eq. 1, the definition of SmoothAP:

$$AP_{\mathbf{q}} = \frac{1}{|\mathcal{S}_{\mathcal{P}}^{\mathbf{q}}|} \sum_{i \in \mathcal{S}_{\mathcal{P}}^{\mathbf{q}}} \frac{1 + \sum_{j \in \mathcal{S}_{\mathcal{P}}^{\mathbf{q}}, j \neq i} \mathcal{G}(D_{ij}; \tau)}{1 + \sum_{j \in \mathcal{S}_{\mathcal{P}}^{\mathbf{q}}, j \neq i} \mathcal{G}(D_{ij}; \tau) + \sum_{j \in \mathcal{S}_{\mathcal{N}}^{\mathbf{q}}} \mathcal{G}(D_{ij}; \tau)}. \quad (1)$$

Here,  $\mathcal{G}$  is a smooth approximation of an indicator/step function:

$$\mathcal{G}(f(x); \tau) = \frac{1}{1 + e^{-\frac{f(x)}{\tau}}}. \quad (2)$$

The derivative of  $\mathcal{G}$  w.r.t. a function  $f(x)$  has the following form:

$$\frac{\partial \mathcal{G}(f(x); \tau)}{\partial x} = \mathcal{G}(f(x); \tau)(1 - \mathcal{G}(f(x); \tau)) \frac{1}{\tau} \frac{\partial f(x)}{\partial x}. \quad (3)$$

Note that  $f(x)$  in the case of SmoothAP is  $D_{ij}$ :

$$D_{ij} = s_i - s_j = \mathbf{q}\mathbf{v}_i - \mathbf{q}\mathbf{v}_j, \quad (4)$$

where both  $\mathbf{v}_i$ ,  $\mathbf{v}_j$  and  $\mathbf{q}$  are normalized on the unit-sphere. The gradient of  $D_{ij}$  w.r.t. query  $\mathbf{q}$  has the following form:

$$\frac{\partial D_{ij}}{\partial \mathbf{q}} = \mathbf{v}_i - \mathbf{v}_j. \quad (5)$$

If we plug in  $D_{ij}$  into Eq. 3 and take the gradient w.r.t. query  $\mathbf{q}$ , we get

$$\begin{aligned} \frac{\partial \mathcal{G}(D_{ij}; \tau)}{\partial \mathbf{q}} &= \mathcal{G}(D_{ij}; \tau)(1 - \mathcal{G}(D_{ij}; \tau)) \frac{1}{\tau} (\mathbf{v}_i - \mathbf{v}_j) \\ &= \text{sim}(D_{ij}, \tau)(\mathbf{v}_i - \mathbf{v}_j), \end{aligned} \quad (6)$$

where  $\text{sim}(D_{ij}, \tau)$  is a function that gives an indication of how close the similarity scores are of candidate  $i$  and  $j$  are w.r.t. query  $\mathbf{q}$ , scaled by  $\tau$ :

$$\text{sim}(D_{ij}, \tau) = \mathcal{G}(D_{ij}; \tau)(1 - \mathcal{G}(D_{ij}; \tau)) \frac{1}{\tau}. \quad (7)$$

Now we define  $\mathcal{R}(i, \mathcal{S}_{\Omega}^{\mathbf{q}})$  and  $\mathcal{R}(i, \mathcal{S}_{\mathcal{P}}^{\mathbf{q}})$ .  $\mathcal{R}(i, \mathcal{S}_{\Omega}^{\mathbf{q}})$  gives the ranking of candidate  $i$  within the full candidate set  $\mathcal{S}_{\Omega}^{\mathbf{q}}$ .  $\mathcal{R}(i, \mathcal{S}_{\mathcal{P}}^{\mathbf{q}})$  gives the rank of candidate  $i$  within the positive candidate set  $\mathcal{S}_{\mathcal{P}}^{\mathbf{q}}$ .

$$\mathcal{R}(i, \mathcal{S}_{\Omega}^{\mathbf{q}}) = \left( \overbrace{1 + \sum_{j \in \mathcal{S}_{\mathcal{P}}^{\mathbf{q}}, j \neq i} \mathcal{G}(D_{ij}; \tau)}^A + \overbrace{\sum_{j \in \mathcal{S}_{\mathcal{N}}^{\mathbf{q}}} \mathcal{G}(D_{ij}; \tau)}^C \right) \quad (8)$$

$$\mathcal{R}(i, \mathcal{S}_P^q) = \left( 1 + \overbrace{\sum_{j \in \mathcal{S}_P^q, j \neq i}^A \mathcal{G}(D_{ij}; \tau)} \right) \quad (9)$$

The gradient of  $\mathcal{R}(i, \mathcal{S}_\Omega^q)$  w.r.t. to  $\mathbf{q}$  has the following form.

$$\frac{\partial \mathcal{R}(i, \mathcal{S}_\Omega^q)}{\partial \mathbf{q}} = \left( \overbrace{\sum_{j \in \mathcal{S}_P^q, j \neq i}^B \text{sim}(D_{ij})(\mathbf{v}_i - \mathbf{v}_j)} + \overbrace{\sum_{j \in \mathcal{S}_N^q}^D \text{sim}(D_{ij})(\mathbf{v}_i - \mathbf{v}_j)} \right). \quad (10)$$

Using all the detentions above, we can write the full gradient of  $AP_{\mathbf{q}}$  w.r.t.  $\mathbf{q}$ :

$$\frac{\partial AP_{\mathbf{q}}}{\partial \mathbf{q}} = \frac{1}{|\mathcal{S}_P^q|} \sum_{i \in \mathcal{S}_P^q} \frac{\mathcal{R}(i, \mathcal{S}_P^q) \frac{\partial \mathcal{R}(i, \mathcal{S}_\Omega^q)}{\partial \mathbf{q}} - \mathcal{R}(i, \mathcal{S}_\Omega^q) \left( \sum_{j \in \mathcal{S}_P^q, j \neq i} \text{sim}(D_{ij})(\mathbf{v}_i - \mathbf{v}_j) \right)}{\mathcal{R}(i, \mathcal{S}_\Omega^q)^2} \quad (11)$$

$$= \frac{1}{|\mathcal{S}_P^q|} \sum_{i \in \mathcal{S}_P^q} \frac{1}{\mathcal{R}(i, \mathcal{S}_\Omega^q)^2} \left( \left( \overbrace{\mathcal{R}(i, \mathcal{S}_P^q)}^A \overbrace{\frac{\partial \mathcal{R}(i, \mathcal{S}_\Omega^q)}{\partial \mathbf{q}}}^{B+D} \right) - \left( \overbrace{\mathcal{R}(i, \mathcal{S}_\Omega^q)}^{A+C} \left( \overbrace{\sum_{j \in \mathcal{S}_P^q, j \neq i}^D \text{sim}(D_{ij})(\mathbf{v}_i - \mathbf{v}_j)} \right) \right) \right). \quad (12)$$

When looking at eq. 12 it becomes clear that we have a function in the following form  $A(B+D) - (A+C)B$ . This can be rewritten to:  $AB + AD - AB - CB = AD - CB$ . If we apply this to Eq. 12, we end up with the following form.

$$\frac{\partial AP_{\mathbf{q}}}{\partial \mathbf{q}} = \frac{1}{|\mathcal{S}_P^q|} \sum_{i \in \mathcal{S}_P^q} \frac{1}{\mathcal{R}(i, \mathcal{S}_\Omega^q)^2} \left( \overbrace{\mathcal{R}(i, \mathcal{S}_P^q)}^A \left( \overbrace{\sum_{j \in \mathcal{S}_N^q}^D \text{sim}(D_{ij})(\mathbf{v}_i - \mathbf{v}_j)} \right) - \overbrace{\sum_{j \in \mathcal{S}_N^q}^C \mathcal{G}(D_{ij}; \tau)} \left( \overbrace{\sum_{j \in \mathcal{S}_P^q, j \neq i}^B \text{sim}(D_{ij})(\mathbf{v}_i - \mathbf{v}_j)} \right) \right) \quad (13)$$

$$= \frac{1}{|\mathcal{S}_P^q|} \sum_{i \in \mathcal{S}_P^q} \frac{1}{\mathcal{R}(i, \mathcal{S}_\Omega^q)^2} \left( \mathcal{R}(i, \mathcal{S}_P^q) \left( \sum_{j \in \mathcal{S}_N^q} \text{sim}(D_{ij})(\mathbf{v}_i - \mathbf{v}_j) \right) - (\mathcal{R}(i, \mathcal{S}_N^q) - 1) \left( \sum_{j \in \mathcal{S}_P^q, j \neq i} \text{sim}(D_{ij})(\mathbf{v}_i - \mathbf{v}_j) \right) \right) \quad (14)$$

## Bibliography

- [1] Brown A, Xie W, Kalogeiton V, Zisserman A (2020) Smooth-AP: Smoothing the path towards large-scale image retrieval. In: European Conference on Computer Vision (ECCV), Springer, pp 677–694