

Calculating the gradient of a cosine similarity loss function

With v, w vectors, the cosine similarity is defined as

$$\text{sim}(x, y) = \frac{v \cdot w}{\sqrt{v \cdot v * w \cdot w}}$$

Now with a matrix transformation $v = Mx$, $w = My$, we have a cosine similarity of

$$\text{sim}(x, y, M) = \frac{My \cdot Mx}{\sqrt{Mx \cdot Mx * My \cdot My}}$$

We want to calculate the derivatives wrt M . First we note

$$\begin{aligned} \frac{\partial v_k}{\partial M_{ij}} &= \delta_{ik} x_j \\ \frac{\partial w_k}{\partial M_{ij}} &= \delta_{ik} y_j \end{aligned}$$

$$\frac{\partial (a \cdot z)}{\partial M_{ij}} = \sum_k \frac{\partial a_k}{\partial M_{ij}} z_k + a_k \frac{\partial z_k}{\partial M_{ij}}$$

Applying this, we have

$$\begin{aligned} \frac{\partial \left(\frac{v \cdot w}{\sqrt{v \cdot v * w \cdot w}} \right)}{\partial M_{ij}} &= \frac{\frac{\partial (v \cdot w)}{\partial M_{ij}}}{\sqrt{v \cdot v * w \cdot w}} - \frac{v \cdot w}{2 (v \cdot v * w \cdot w)^{\frac{3}{2}}} \frac{\partial (v \cdot v * w \cdot w)}{\partial M_{ij}} \\ &= \frac{\sum_k \delta_{ik} x_j w_k + v_k \delta_{ik} y_j}{\sqrt{v \cdot v * w \cdot w}} - \frac{v \cdot w}{2 (v \cdot v * w \cdot w)^{\frac{3}{2}}} \left(\sum_k 2 \delta_{ik} x_j v_k * w \cdot w + v \cdot v * \sum_k 2 \delta_{ik} y_j w_k \right) \\ &= \frac{x_j w_i + v_i y_j}{\sqrt{v \cdot v * w \cdot w}} - \frac{v \cdot w}{(v \cdot v * w \cdot w)^{\frac{3}{2}}} (x_j v_i * w \cdot w + v \cdot v * y_j w_i) \\ &= \frac{x_j w_i + v_i y_j}{(v \cdot v * w \cdot w)^{3/2}} (v \cdot v * w \cdot w) - \frac{v \cdot w}{(v \cdot v * w \cdot w)^{\frac{3}{2}}} (x_j v_i * w \cdot w + v \cdot v * y_j w_i) \\ &= \frac{(x_j w_i + v_i y_j) v \cdot v * w \cdot w - v \cdot w (x_j v_i * w \cdot w + v \cdot v * y_j w_i)}{(v \cdot v * w \cdot w)^{3/2}} \end{aligned}$$

This last formula is the one that is coded

With Normalized vectors

If we normalize x and y before computation, we note this does not change the cosine similarity of the original vectors or the transformed vectors

As a Hermitian Inner Product

We note that

$$\frac{My \cdot Mx}{\sqrt{Mx \cdot Mx * My \cdot My}} = \frac{y^T M^T Mx}{\sqrt{x^T M^T Mx * y^T M^T My}}$$

We note that M only shows up in the form $M^T M$. So we actually don't need to treat M as a transformation, but a normal inner product $A = M^T M$. We note that $M^T M$ will be symmetric for any M . Thus instead of optimizing over M as an arbitrary matrix, we optimize over A as a symmetric matrix, reducing the number of parameters by half. Thus the similarity measure is

$$sim(x, y, A) = \frac{y^T Ax}{\sqrt{x^T Ax * y^T Ay}}$$

To optimize over A , we need to calculate the derivative of sim wrt the components of A . First we note

$$\frac{\partial a^T Ab}{\partial A_{ij}} = a_i b_j$$

$$\begin{aligned} \frac{\partial sim}{\partial A_{ij}} &= \frac{y_i x_j}{\sqrt{x^T Ax * y^T Ay}} - \frac{y^T Ax}{2(x^T Ax * y^T Ay)^{\frac{3}{2}}} (x_i x_j y^T Ay + x^T Axy_i y_j) \\ &= \frac{2y_i x_j (x^T Ax * y^T Ay) - y^T Ax (x_i x_j y^T Ay + x^T Axy_i y_j)}{2(x^T Ax * y^T Ay)^{\frac{3}{2}}} \\ &= \frac{2y_i x_j (x^T Ax * y^T Ay) - y^T Ax (x_i x_j y^T Ay + x^T Axy_i y_j)}{2(x^T Ax * y^T Ay)^{\frac{3}{2}}} \end{aligned}$$

We can simplify this calculation by defining $n = x^T Ax$, $m = y^T Ay$, $l = x^T Ay$. Yielding

$$sim(x, y, A) = \frac{l}{\sqrt{nm}}$$

$$\frac{\partial sim}{\partial A_{ij}} = \frac{2y_i x_j nm - l m x_i x_j - l n y_i y_j}{2(nm)^{\frac{3}{2}}}$$

If we consider the fact that the parameters A_{ij} and A_{ji} are tied together, we can calculate a total gradient for the off-diagonal elements of

$$\frac{dsim}{dA_{ij}} = \frac{2(y_i x_j + y_j x_i) nm - 2l m x_i x_j - 2l n y_i y_j}{2(nm)^{\frac{3}{2}}} = \frac{nm(y_i x_j + y_j x_i) - l m x_i x_j - l n y_i y_j}{(nm)^{\frac{3}{2}}}$$

And for the on-diagonal elements, we get

$$\frac{dsim}{dA_{ii}} = \frac{nmy_ix_i - \frac{1}{2}lmx_i^2 - \frac{1}{2}lmy_i^2}{(nm)^{\left(\frac{3}{2}\right)}}$$