# Derivative of Gromov-Wasserstein 

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Computation of Gromov-Wasserstein (GW) distances alternates between two steps, as specified in Algorithm 1. The algorithm is adjusted to our purpose by fixing the number of GW iterations and constraining $v, w$. The first step is a closed-form exponential formula applied independently to every element of the matrix variable. The other is projection onto the cone of doubly-stochastic matrices. We differentiate the result of GW distance computation by providing derivatives of the two steps independently and composing the formulas during alternation. The exponential is differentiable using formulaic techniques; we work out the derivative of doubly-stochastic projection below.

```
function Gromov-Wasserstein \(\left(\mu_{0}, D_{0}, \mu, D, \alpha, \eta, \Gamma^{0}\right)\)
    \(/ /\) Computes a local minimizer \(\Gamma\) of \(G W\) distance
    for \(i=1,2, \ldots, I\)
        \(K^{i} \leftarrow \exp \left(D_{0} \llbracket \mu_{0} \rrbracket \Gamma^{i-1} \llbracket \mu \rrbracket D^{\top} \eta / \alpha\right) \otimes\left(\Gamma^{i}\right)^{\wedge(1-\eta)}\)
        \(\Gamma^{i}, v^{i}, w^{i} \leftarrow\) Sinkhorn-PROJECTION \(\left(K^{i} ; \mu_{0}, \mu\right)\)
    return \(\Gamma^{I}\),
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function $\operatorname{Sinkhorn-Projection}\left(K ; \mu_{0}, \mu\right)$
$/ /$ Finds $\Gamma$ minimizing $K L(\Gamma \mid K)$ subject to $\Gamma \in \mathscr{M}\left(\mu_{0}, \mu\right)$
$v, w \leftarrow \mathbf{1}$
for $j=1,2,3, \ldots$
$v \leftarrow \mathbf{1} \oslash K(w \otimes \mu)$
$w \leftarrow \mathbf{1} \oslash K^{\top}\left(v \otimes \mu_{0}\right)$
$v \leftarrow v / \sqrt{\frac{\mathbf{1}^{\top} v}{\mathbf{1}^{\top} w}}$
$w \leftarrow w \sqrt{\frac{{\frac{1}{}{ }^{\top} v}_{1^{\top} w}}{}}$
return $\llbracket v \rrbracket K \llbracket w \rrbracket, v, w$

Algorithm 1: Iteration for finding regularized Gromov-Wasserstein distances. $\otimes, \oslash$ denote elementwise multiplication and division.

## 1 Derivative with respect to $K_{i j}$

Suppose we wish to rescale a kernel matrix $K$ to be doubly stochastic (Sinkhorn projection step). We can think of this as solving the following quadratic system of equations for $\Gamma$ and dual vectors $v, w$ (we don't use superscript here for simplicity, we assume all the variables were computed at the same iteration):

$$
\begin{align*}
\Gamma & =\llbracket v \rrbracket K \llbracket w \rrbracket  \tag{1}\\
\Gamma \mu & =\llbracket v \rrbracket K(w \otimes \mu)=\mathbf{1}  \tag{2}\\
\Gamma^{\top} \mu_{0} & =\llbracket w \rrbracket K^{\top}\left(v \otimes \mu_{0}\right)=\mathbf{1}  \tag{3}\\
\mathbf{1}^{\top} v & =\mathbf{1}^{\top} w \tag{4}
\end{align*}
$$

We differentiate these expressions with respect to an element $K_{i j}$. Then,

$$
\begin{align*}
\frac{d \Gamma}{d K_{i j}} & =\llbracket \frac{d v}{d K_{i j}} \rrbracket K \llbracket w \rrbracket+v_{i} w_{j}\left(e_{i} e_{j}^{\top}\right)+\llbracket v \rrbracket K \llbracket \frac{d w}{d K_{i j}} \rrbracket  \tag{5}\\
0 & =\frac{d v}{d K_{i j}} \otimes[K(w \otimes \mu)]+\left(v_{i} w_{j} \mu_{j}\right) e_{i}+\llbracket v \rrbracket K \llbracket \mu \rrbracket \frac{d w}{d K_{i j}}  \tag{6}\\
0 & =\frac{d w}{d K_{i j}} \otimes\left[K^{\top}\left(v \otimes \mu_{0}\right)\right]+\left(v_{i} w_{j} \mu_{0 i}\right) e_{j}+\llbracket w \rrbracket K^{\top} \llbracket \mu_{0} \rrbracket \frac{d v}{d K_{i j}}  \tag{7}\\
\mathbf{1}^{\top} \frac{d v}{d K_{i j}} & =\mathbf{1}^{\top} \frac{d w}{d K_{i j}} \tag{8}
\end{align*}
$$

Let's organize the second two relationships as a matrix equation:

$$
\left(\begin{array}{cc}
\llbracket K(w \otimes \mu) \rrbracket & \llbracket v \rrbracket K \llbracket \mu \rrbracket  \tag{9}\\
\llbracket w \rrbracket K^{\top} \llbracket \mu_{0} \rrbracket & \llbracket K^{\top}\left(v \otimes \mu_{0}\right) \rrbracket \\
\mathbf{1}^{\top} & -\mathbf{1}^{\top}
\end{array}\right)\binom{d v / d K_{i j}}{d w / d K_{i j}}=\left(\begin{array}{c}
-v_{i} w_{j} \mu_{j} e_{i} \\
-v_{i} w_{j} \mu_{0 i} e_{j} \\
0
\end{array}\right)
$$

We can simplify this by leveraging the fact that the diagonal elements of this block $2 \times 2$ matrix appear in the Sinkhorn conditions. In particular, $K(w \otimes \mu)=\mathbf{1} \oslash v$ and $K^{\top}\left(v \otimes \mu_{0}\right)=\mathbf{1} \oslash w$. Hence, we can write the expression as:

$$
\left(\begin{array}{cc}
\llbracket v \rrbracket^{-1} & \llbracket v \rrbracket K \llbracket \mu \rrbracket  \tag{10}\\
\llbracket w \rrbracket K^{\top} \llbracket \mu_{0} \rrbracket & \llbracket w \rrbracket^{-1} \\
\mathbf{1}^{\top} & -\mathbf{1}^{\top}
\end{array}\right)\binom{d v / d K_{i j}}{d w / d K_{i j}}=\left(\begin{array}{c}
-v_{i} w_{j} \mu_{j} e_{i} \\
-v_{i} w_{j} \mu_{0 i} e_{j} \\
0
\end{array}\right)
$$

We factor to make it look symmetric:

$$
\left(\begin{array}{ccc}
\llbracket v \rrbracket & 0 & 0  \tag{11}\\
0 & \llbracket w \rrbracket & 0 \\
0 & 0 & 1
\end{array}\right)\left(\begin{array}{cc}
\llbracket v \otimes v \otimes \mu_{0} \rrbracket^{-1} & K \\
K^{\top} & \llbracket w \otimes w \otimes \mu \rrbracket^{-1} \\
(\mathbf{1} \oslash \mu 0)^{\top} & -(\mathbf{1} \oslash \mu)^{\top}
\end{array}\right)\left(\begin{array}{cc}
\llbracket \mu_{0} \rrbracket & 0 \\
0 & \llbracket \mu \rrbracket
\end{array}\right)\binom{d v / d K_{i j}}{d w / d K_{i j}}=\left(\begin{array}{c}
-v_{i} w_{j} \mu_{j} e_{i} \\
-v_{i} w_{j} \mu_{0 i} e_{j} \\
0
\end{array}\right)
$$

The two vectors on the right-hand side are sparse except element $i$ in the first half and element $j$ in the second half. So, we can invert the first matrix and put the diagonal matrix into the unknowns:

$$
\left(\begin{array}{cc}
\llbracket v \otimes v \otimes \mu_{0} \rrbracket^{-1} & K  \tag{12}\\
K^{\top} & \llbracket w \otimes w \otimes \mu \rrbracket^{-1} \\
(\mathbf{1} \oslash \mu 0)^{\top} & -(\mathbf{1} \oslash \mu)^{\top}
\end{array}\right)\binom{\llbracket \mu_{0} \rrbracket d v / d K_{i j}}{\llbracket \mu \rrbracket d w / d K_{i j}}=\binom{-w_{j} \mu_{j} e_{i}}{-v_{i} \mu_{0 i} e_{j}}
$$

Denote the left inverse of the left matrix as

$$
\left(\begin{array}{cc}
\llbracket v \otimes v \otimes \mu_{0} \rrbracket^{-1} & K  \tag{13}\\
K^{\top} & \llbracket w \otimes w \otimes \mu \rrbracket^{-1} \\
(\mathbf{1} \oslash \mu 0)^{\top} & -(\mathbf{1} \oslash \mu)^{\top}
\end{array}\right)^{+}:=\left(\begin{array}{cc}
A & B \\
C & E
\end{array}\right)
$$

Then,

$$
\begin{align*}
\binom{d v / d K_{i j}}{d w / d K_{i j}} & =\left(\begin{array}{cc}
\llbracket \mathbf{1} \oslash \mu_{0} \rrbracket & 0 \\
0 & \llbracket \mathbf{1} \oslash \mu \rrbracket
\end{array}\right)\left(\begin{array}{cc}
A & B \\
C & E
\end{array}\right)\binom{-w_{j} \mu_{j} e_{i}}{-v_{i} \mu_{0 i} e_{j}}  \tag{14}\\
& =\left(\begin{array}{cc}
\llbracket \mathbf{1} \oslash \mu_{0} \rrbracket & 0 \\
0 & \llbracket \mathbf{1} \oslash \mu \rrbracket
\end{array}\right)\binom{-w_{j} \mu_{j} A_{\text {column } i}-v_{i} \mu_{0 i} B_{\text {column } j}}{-w_{j} \mu_{j} C_{\text {column } i}-v_{i} \mu_{0 i} E_{\text {column } j}} \tag{15}
\end{align*}
$$

## 2 Gradient with respect to $K$

Returning to our original derivative, we extract a single element

$$
\begin{equation*}
\frac{d \Gamma_{k \ell}}{d K_{i j}}=\frac{d v_{k}}{d K_{i j}} K_{k \ell} w_{\ell}+v_{i} w_{j} \delta_{i k} \delta_{j \ell}+v_{k} K_{k \ell} \frac{d w_{\ell}}{d K_{i j}} \tag{16}
\end{equation*}
$$

In the end, we know $\frac{d L}{d \Gamma_{k \ell}}$ for some function $L$ and want $\frac{d L}{d K_{i j}}$. Write the gradient of $L$ with respect to $\Gamma$ as $\nabla_{\Gamma} L$. We start computing

$$
\begin{aligned}
\frac{d L}{d K_{i j}} & =\sum_{k \ell}\left(\nabla_{\Gamma} L\right)_{k \ell} \frac{d \Gamma_{k \ell}}{d K_{i j}} \\
& =\sum_{k \ell}\left(\nabla_{\Gamma} L\right)_{k \ell}\left[\frac{d v_{k}}{d K_{i j}} K_{k \ell} w_{\ell}+v_{i} w_{j} \delta_{i k} \delta_{j \ell}+v_{k} K_{k \ell} \frac{d w_{\ell}}{d K_{i j}}\right]
\end{aligned}
$$

Breaking this down term by term,

$$
\begin{aligned}
\sum_{k \ell}\left(\nabla_{\Gamma} L\right)_{k \ell} \frac{d v_{k}}{d K_{i j}} K_{k \ell} w_{\ell} & =\left(\frac{d v}{d K_{i j}}\right)^{\top}\left(K \otimes \nabla_{\Gamma} L\right) w \\
& =\left(-w_{j} \mu_{j} A_{\text {column } i}-v_{i} \mu_{0 i} B_{\text {column } j}\right)^{\top} \llbracket \mathbf{1} \oslash \mu_{0} \rrbracket\left(K \otimes \nabla_{\Gamma} L\right) w \\
\sum_{k \ell}\left(\nabla_{\Gamma} L\right)_{k \ell} v_{i} w_{j} \delta_{i k} \delta_{j \ell} & =\left(\nabla_{\Gamma} L\right)_{i j} v_{i} w_{j}
\end{aligned}
$$

$$
\begin{aligned}
\sum_{k \ell}\left(\nabla_{\Gamma} L\right)_{k \ell} v_{k} K_{k \ell} \frac{d w_{\ell}}{d K_{i j}} & =v^{\top}\left(K \otimes \nabla_{\Gamma} L\right) \frac{d w}{K_{i j}} \\
& =v^{\top}\left(K \otimes \nabla_{\Gamma} L\right) \llbracket \mathbf{1} \oslash \mu \rrbracket\left(-w_{j} \mu_{j} C_{\text {column } i}-v_{i} \mu_{0 i} E_{\text {column } j}\right)
\end{aligned}
$$

Getting rid of the $i j$ index (and applying symmetry of $A$ and $C$ ) shows

$$
\begin{align*}
\nabla_{K} L= & -A \llbracket \mathbf{1} \oslash \mu_{0} \rrbracket\left(K \otimes \nabla_{\Gamma} L\right) w(w \otimes \mu)^{\top}-\left(v \otimes \mu_{0}\right)\left[\left(C \llbracket \mathbf{1} \oslash \mu_{0} \rrbracket\left(K \otimes \nabla_{\Gamma} L\right) w\right]^{\top}\right. \\
& +\llbracket v \rrbracket \nabla_{\Gamma} L \llbracket w \rrbracket  \tag{17}\\
& -B \llbracket \mathbf{1} \oslash \mu \rrbracket\left(K \otimes \nabla_{\Gamma} L\right)^{\top} v(w \otimes \mu)^{\top}-\left(v \otimes \mu_{0}\right)\left[E \llbracket \mathbf{1} \oslash \mu \rrbracket\left(K \otimes \nabla_{\Gamma} L\right)^{\top} v\right]^{\top}
\end{align*}
$$

## 3 Exponential formula

Given $\nabla_{K^{i}} L$ we would like to compute $\nabla_{\Gamma^{i-1}} L$, the derivatives with respect to $\Gamma$ from the previous iteration. In the rest of this section $K$ will be used for $K^{i}$ and $\Gamma$ for $\Gamma^{i-1}$.

$$
\begin{gather*}
K=\exp \left(D_{0} \llbracket \mu_{0} \rrbracket \Gamma \llbracket \mu \rrbracket D^{\top} \cdot \eta / \alpha\right) \otimes \Gamma^{\wedge 1-\eta}  \tag{18}\\
\frac{d L}{d \Gamma_{i j}}=\sum_{k l} \frac{d L}{d K_{k l}} \frac{d K_{k l}}{d \Gamma_{i j}}  \tag{19}\\
\frac{d K_{k l}}{d \Gamma_{i j}}=\delta_{i==k} \delta_{j==l}(1-\eta)(\Gamma)_{k l}^{-\eta} \exp \left(D_{0} \llbracket \mu_{0} \rrbracket \Gamma \llbracket \mu \rrbracket D^{\top} \cdot \eta / \alpha\right)_{k l}+  \tag{20}\\
\left.\exp \left(D_{0} \llbracket \mu_{0} \rrbracket \Gamma \llbracket \mu \rrbracket D^{\top} \cdot \eta / \alpha\right)_{k l} \frac{\eta}{\alpha}\left[D_{0} \llbracket \mu_{0} \rrbracket\right]_{k i} \llbracket \llbracket \mu \rrbracket D^{\top}\right]_{j l} \Gamma^{\wedge 1-\eta} \\
\nabla_{\Gamma} L=(1-\eta) \nabla_{K} L \otimes(\Gamma)^{\wedge-\eta} \otimes \exp \left(D_{0} \llbracket \mu_{0} \rrbracket \Gamma \llbracket \mu \rrbracket D^{\top} \cdot \eta / \alpha\right)+  \tag{21}\\
\frac{\eta}{\alpha} \nabla_{K} L \otimes\left(\llbracket \mu_{0} \rrbracket D_{0}^{\top}\left(\Gamma^{\wedge 1-\eta} \otimes \exp \left(D_{0} \llbracket \mu_{0} \rrbracket \Gamma \llbracket \mu \rrbracket D^{\top} \cdot \eta / \alpha\right)\right) D \llbracket \mu \rrbracket\right)
\end{gather*}
$$

## 4 Gradient with respect to $D$

Given $\nabla_{K^{i}} L$, we can compute $\nabla_{D} L$ by cumulating the following gradients throughout the iterations:

$$
\begin{gather*}
\frac{d K_{k l}}{d D_{i j}}=\Gamma_{k l}^{1-\eta} \exp \left(D_{0} \llbracket \mu_{0} \rrbracket \Gamma \llbracket \mu \rrbracket D^{\top} \cdot \eta / \alpha\right)_{k l} \delta_{i==l} \frac{\eta}{\alpha}\left[D_{0} \llbracket \mu_{0} \rrbracket \Gamma \llbracket \mu \rrbracket\right]_{k j}  \tag{22}\\
\frac{d L}{d D_{i j}}=\sum_{k} \frac{d L}{d K_{k i}} \frac{\eta}{\alpha} \Gamma_{k i}^{1-\eta} \exp \left(D_{0} \llbracket \mu_{0} \rrbracket \Gamma \llbracket \mu \rrbracket D^{\top} \cdot \eta / \alpha\right)_{k i}\left[D_{0} \llbracket \mu_{0} \rrbracket \Gamma \llbracket \mu \rrbracket\right]_{k j}  \tag{23}\\
\nabla_{D} L=\frac{\eta}{\alpha}\left(\nabla_{K} L \otimes \Gamma^{\wedge 1-\eta} \otimes \exp \left(D_{0} \llbracket \mu_{0} \rrbracket \Gamma \llbracket \mu \rrbracket D^{\top} \cdot \eta / \alpha\right)\right)^{\top} D_{0} \llbracket \mu_{0} \rrbracket \Gamma \llbracket \mu \rrbracket \tag{24}
\end{gather*}
$$

We also add the transposed matrix of derivatives to enforce symmetry.

