## **Fisher information metric on the space of Gaussians**

Consider the space of univariate Gaussian distributions parametrised by  $(\mu, \sigma) \in \mathbb{R} \times (0, \infty)$ . The <u>Gaussian Kullback–Leibler divergence</u> from  $(\mu, \sigma)$  to  $(\mu_1, \sigma_1)$  is:

$$
K(\mu_1, \sigma_1) \coloneqq \mathrm{KL}\big(\mathcal{N}\big(\mu, \sigma^2\big) : \mathcal{N}\big(\mu_1, \sigma_1^2\big)\big) = \log \frac{\sigma_1}{\sigma} + \frac{\big(\mu-\mu_1\big)^2 + \sigma^2 - \sigma_1^2}{2\sigma_1^2}
$$

This has a global minimum when the points  $(\mu, \sigma)$  and  $(\mu_1, \sigma_1)$  coincide,  $K(\mu, \sigma) = 0$ . We can show this because, at this point, the gradient vanishes:

$$
\nabla K(\mu, \sigma) = \begin{bmatrix} \frac{\partial K}{\partial \mu} \\ \frac{\partial K}{\partial \sigma} \end{bmatrix}_{(\sigma, \mu)} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}
$$

and the Hessian (matrix of second derivatives) is positive definite:

$$
\nabla^2 K(\mu, \sigma) = \begin{bmatrix} \frac{\partial^2 K}{\partial \mu^2} & \frac{\partial^2 K}{\partial \mu \partial \sigma} \\ \frac{\partial^2 K}{\partial \sigma \partial \mu} & \frac{\partial^2 K}{\partial \sigma^2} \end{bmatrix} \Bigg|_{(\mu, \sigma)} = \begin{bmatrix} \frac{1}{\sigma^2} & 0 \\ 0 & \frac{2}{\sigma^2} \end{bmatrix}
$$

An equivalent way to write this is as a metric tensor

$$
g = \frac{\mathrm{d}\mu^2 + 2\,\mathrm{d}\sigma^2}{\sigma^2}
$$

so that  $g(\vec{u},\vec{v}) = \vec{u}^T(\nabla^2 K) \vec{v}$  for any vectors  $\vec{u},\vec{v} \in \mathbb{R}^2.$ 

Under a change of coordinates  $\mu =$ √  $2x, \sigma = y$ , the metric g is (twice) the metric of the [Poincaré](https://jollywatt.github.io/notes/poincare-half-plane) [half-plane](https://jollywatt.github.io/notes/poincare-half-plane) model of hyperbolic space.