

Recursive computation of the normalization constant of a multivariate Gaussian distribution truncated on a simplex

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I. PROBLEM STATEMENT

Let \mathbb{S} denote the following simplex:

$$\mathbb{S} = \left\{ \boldsymbol{\alpha} \mid \alpha_r \geq 0, \forall r = 1, \dots, R-1, \sum_{r=1}^{R-1} \alpha_r \leq 1 \right\}, \quad (1)$$

Let $\mathcal{N}_{\mathbb{S}}(\mathbf{A}, \mathbf{B})$ denote the truncated multivariate normal distribution defined on the simplex \mathbb{S} with mean vector \mathbf{A} and covariance matrix \mathbf{B} . The probability density function (pdf) of this truncated multivariate normal distribution denoted as $\phi_{\mathbb{S}}(\cdot \mid \mathbf{A}, \mathbf{B})$ satisfies the following relation:

$$\phi_{\mathbb{S}}(\boldsymbol{\alpha} \mid \mathbf{A}, \mathbf{B}) \propto \phi(\boldsymbol{\alpha} \mid \mathbf{A}, \mathbf{B}) \mathbf{1}_{\mathbb{S}}(\boldsymbol{\alpha}), \quad (2)$$

where

- $\phi(\cdot \mid \mathbf{A}, \mathbf{B})$ is the standard Gaussian pdf with mean vector \mathbf{A} and covariance matrix Σ ,
- $\mathbf{1}_{\mathbb{S}}(\cdot)$ is the indicator function defined on \mathbb{S} ,
- \propto stands for “proportional to”.

This report proposes to evaluate the normalization constant of the multivariate truncated normal distribution $\mathcal{N}_{\mathbb{S}}(\mathbf{u}, \sigma_0^2 \mathbf{I}_{R-1})$, \mathbf{I}_{R-1} is the $(R-1) \times (R-1)$ identity matrix. This normalization constant, denoted $K_{\mathbb{S}}(\mathbf{u}, \sigma_0^2)$, can be derived directly from the definition of $\phi_{\mathbb{S}}(\boldsymbol{\alpha} \mid \mathbf{A}, \mathbf{B})$:

$$\phi_{\mathbb{S}}(\boldsymbol{\alpha} \mid \mathbf{A}, \mathbf{B}) = \frac{1}{K_{\mathbb{S}}(\mathbf{u}, \sigma_0^2)} \exp \left[-\frac{\|\boldsymbol{\alpha} - \mathbf{u}\|^2}{2\sigma_0^2} \right]. \quad (3)$$

Consequently, it can be written:

$$K_{\mathbb{S}}(\mathbf{u}, \sigma_0^2) = \int_{\mathbb{S}} f_{\mathbf{u}, \sigma_0^2}(\boldsymbol{\alpha}) d\boldsymbol{\alpha}, \quad (4)$$

with

$$\begin{cases} \boldsymbol{\alpha} = [\alpha_1, \dots, \alpha_{R-1}]^\top, \\ f_{\mathbf{u}, \sigma_0^2}(\boldsymbol{\alpha}) = \exp \left[-\frac{\sum_{r=1}^{R-1} (\alpha_r - u_r)^2}{2\sigma_0^2} \right]. \end{cases} \quad (5)$$

II. CASE $R = 2$

For $R = 2$, the pdf of the Gaussian distribution truncated on the simplex $\mathbb{S} = \{\alpha_1 | 0 \leq \alpha_1 \leq 1\}$ reduces to the two-sided truncated normal distribution. As an example, the pdf of such distribution with $\sigma_0^2 = 0.2$ and $u = 0$ is depicted in Figure 1.

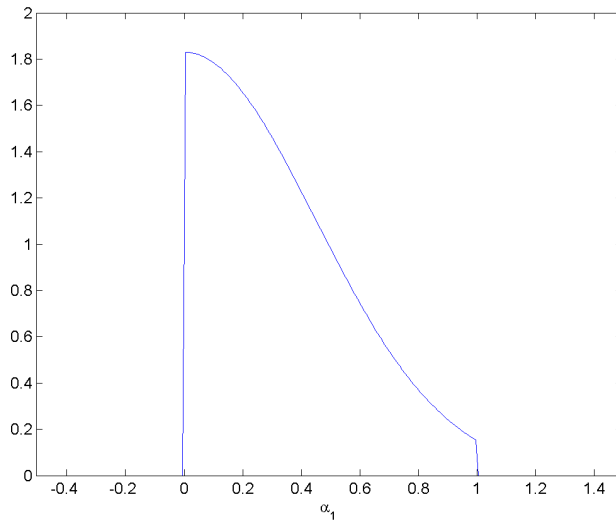


Fig. 1. Pdf of the normal distribution for $\sigma_0^2 = 0.2$ truncated on the simplex \mathbb{S} ($R = 2$).

Consequently, the case $R = 2$ consists in computing the integral of the function $f_{\mathbf{u}, \sigma_0^2}(\alpha_1) = \exp \left[-\frac{(\alpha_1 - u_1)^2}{2\sigma_0^2} \right]$ on the set $\mathbb{S} = \{\alpha_1 | 0 \leq \alpha_1 \leq 1\}$:

$$K_{\mathbb{S}}(u, \sigma_0^2) = \int_0^1 \exp \left[-\frac{(\alpha_1 - u_1)^2}{2\sigma_0^2} \right] d\alpha_1. \quad (6)$$

Let $t = \frac{\alpha_1 - u_1}{\sqrt{2\sigma_0^2}}$,

$$K_{\mathbb{S}}(u, \sigma_0^2) = \sqrt{2\sigma_0^2} \int_{-\frac{u_1}{\sqrt{2\sigma_0^2}}}^{\frac{1-u_1}{\sqrt{2\sigma_0^2}}} \exp[-t^2] dt. \quad (7)$$

Finally,

$$K_{\mathbb{S}}(u, \sigma_0^2) = \frac{\sqrt{2\pi\sigma_0^2}}{2} \left[\operatorname{erf} \left(\frac{1-u_1}{\sqrt{2\sigma_0^2}} \right) + \operatorname{erf} \left(\frac{u_1}{\sqrt{2\sigma_0^2}} \right) \right]. \quad (8)$$

III. GENERAL CASE

The problem consists in computing the following quantity:

$$K_{\mathbb{S}}(\mathbf{u}, \sigma_0^2) = \int_0^1 \int_0^{1-\alpha_1} \int_0^{1-\alpha_1-\alpha_2} \dots \int_0^{1-\sum_{r=1}^{R-2} \alpha_r} \exp \left[-\frac{(\alpha_1 - u_1)^2 + \dots + (\alpha_{R-1} - u_{R-1})^2}{2\sigma_0^2} \right] d\alpha_{R-1} d\alpha_{R-2} \dots d\alpha_1, \quad (9)$$

that can be rewritten as:

$$K_{\mathbb{S}}(\mathbf{u}, \sigma_0^2) = \int_0^1 \exp \left[-\frac{(\alpha_1 - u_1)^2}{2\sigma_0^2} \right] \int_0^{1-\alpha_1} \exp \left[-\frac{(\alpha_2 - u_2)^2}{2\sigma_0^2} \right] \int_0^{1-\alpha_1-\alpha_2} \dots \dots \exp \left[-\frac{(\alpha_{R-2} - u_{R-2})^2}{2\sigma_0^2} \right] \int_0^{1-\sum_{r=1}^{R-2} \alpha_r} \exp \left[-\frac{(\alpha_{R-1} - u_{R-1})^2}{2\sigma_0^2} \right] d\alpha_{R-1} d\alpha_{R-2} \dots d\alpha_1. \quad (10)$$

Inspired by [1], we introduce $\forall x \in \mathbb{R}, \forall \mathbf{y} \in \mathbb{R}^{R-1}, \forall s^2 \in \mathbb{R}_+$:

$$\begin{aligned} g_{R-1}(x, \mathbf{y}, s^2) &= \int_0^x \exp \left[-\frac{(t - y_{R-1})^2}{2s^2} \right] dt \\ &= \frac{\sqrt{2\pi s^2}}{2} \left[\operatorname{erf} \left(\frac{x - y_{R-1}}{\sqrt{2}s} \right) + \operatorname{erf} \left(\frac{y_{R-1}}{\sqrt{2}s} \right) \right]. \end{aligned} \quad (11)$$

Then the following sequence of functions is defined as follows, $r = 1, \dots, R-2$:

$$g_r(x, \mathbf{y}, s^2) = \int_0^x \exp \left[-\frac{(t - y_r)^2}{2s^2} \right] g_{r+1}(x - t, \mathbf{y}, s^2) dt. \quad (12)$$

Therefore, the normalization constant for the multivariate truncated Gaussian distribution $\mathcal{N}_{\mathbb{S}}(\mathbf{u}, \sigma_0^2 \mathbf{I}_{R-1})$ is:

$$\boxed{K_{\mathbb{S}}(\mathbf{u}, \sigma_0^2) = g_1(1, \mathbf{u}, \sigma_0^2)}. \quad (13)$$

REFERENCES

- [1] A. Genz and P. Joyce, "Computation of the normalization constant for exponentially weighted dirichlet distribution integrals," *Computing Science and Statistics*, vol. 35, pp. 557–563, 2003.