

Checking the correctness of the implementation of the variational lower bound of Bayesian GP-LVM in GPflow

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Here I verify that the right-hand side of Eq. 14 in [Titsias and Lawrence \(2010\)](#) (reproduced here as Eq 1) is correctly implemented in the file `gplvm.py` of GPflow (Listing 1).

$$\begin{aligned} \tilde{F}_d(q) \geq & \log \left[\frac{(\beta)^{\frac{N}{2}} |K_{MM}|^{\frac{1}{2}}}{(2\pi)^{\frac{N}{2}} |\beta\Psi_2 + K_{MM}|^{\frac{1}{2}}} e^{-\frac{1}{2}\mathbf{y}_d^T W \mathbf{y}_d} \right] \\ & - \frac{\beta\psi_0}{2} + \frac{\beta}{2} \text{Tr}(K_{MM}^{-1}\Psi_2) \end{aligned} \quad (1)$$

where

$$W = \beta I_N - \beta^2 \Psi_1 (\beta \Psi_2 + K_{MM})^{-1} \Psi_1^T \quad (2)$$

Listing 1: Calculation of the variational lower bound in GPflow’s `gplvm.py`

```
1 cov_uu = covariances.Kuu(self.inducing_variable, self.kernel, jitter=default_jitter())
2 L = tf.linalg.cholesky(cov_uu)
3 sigma2 = self.likelihood.variance
4 sigma = tf.sqrt(sigma2)
5
6 # Compute intermediate matrices
7 A = tf.linalg.triangular_solve(L, tf.transpose(psi1), lower=True) / sigma
8 tmp = tf.linalg.triangular_solve(L, psi2, lower=True)
9 AAT = tf.linalg.triangular_solve(L, tf.transpose(tmp), lower=True) / sigma2
10 B = AAT + tf.eye(num_inducing, dtype=default_float())
11 LB = tf.linalg.cholesky(B)
12 log_det_B = 2.0 * tf.reduce_sum(tf.math.log(tf.linalg.diag_part(LB)))
13 c = tf.linalg.triangular_solve(LB, tf.linalg.matmul(A, Y_data), lower=True) / sigma
14
15 # compute log marginal bound
16 ND = to_default_float(tf.size(Y_data))
17 bound = -0.5 * ND * tf.math.log(2 * np.pi * sigma2)
18 bound += -0.5 * D * log_det_B
19 bound += -0.5 * tf.reduce_sum(tf.square(Y_data)) / sigma2
20 bound += 0.5 * tf.reduce_sum(tf.square(c))
21 bound += -0.5 * D * (tf.reduce_sum(psi0) / sigma2 -
22 tf.reduce_sum(tf.linalg.diag_part(AAT)))
```

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Expanding the logarithm and grouping terms, Eq. 1 can be rewritten as:

$$\begin{aligned}
\tilde{F}(q) \geq & -\frac{ND}{2} \log 2\pi\beta^{-1} \\
& -\frac{D}{2} (\log |\beta\Psi_2 + K_{MM}| - \log |K_{MM}|) \\
& -\frac{1}{2} \sum_{d=1}^D \mathbf{y}_d^\top W \mathbf{y}_d \\
& +\frac{D}{2} \frac{1}{\beta^{-1}} \text{Tr}(K_{MM}^{-1} \Psi_2) \\
& -\frac{D}{2} \frac{\Psi_0}{\beta^{-1}}
\end{aligned}$$

and replacing W (Eq. 2) we obtain:

$$\begin{aligned}
\tilde{F}(q) \geq & -\frac{ND}{2} \log 2\pi\beta^{-1} \\
& -\frac{D}{2} (\log |\frac{\Psi_2}{\beta^{-1}} + K_{MM}| - \log |K_{MM}|) \\
& -\frac{1}{2} \frac{1}{\beta^{-1}} \sum_{d=1}^D \|\mathbf{y}_d\|_2^2 \\
& +\frac{1}{2} \frac{1}{\beta^{-2}} \sum_{d=1}^D \mathbf{y}_d^\top \Psi_1 \left(\frac{\Psi_2}{\beta^{-1}} + K_{MM} \right)^{-1} \Psi_1^\top \mathbf{y}_d \\
& +\frac{D}{2} \frac{1}{\beta^{-1}} \text{Tr}(K_{MM}^{-1} \Psi_2) \\
& -\frac{D}{2} \frac{\Psi_0}{\beta^{-1}}
\end{aligned} \tag{3}$$

Define:

$$\tilde{B} \doteq \frac{\Psi_2}{\beta^{-1}} + K_{MM}$$

and replace it in Eq. 3

$$\begin{aligned}
\tilde{F}(q) \geq & -\frac{ND}{2} \log 2\pi\beta^{-1} \\
& -\frac{D}{2}(\log |\tilde{B}| - \log |K_{MM}|) \\
& -\frac{1}{2} \frac{1}{\beta^{-1}} \sum_{d=1}^D \|\mathbf{y}_d\|_2^2 \\
& +\frac{1}{2} \frac{1}{\beta^{-2}} \sum_{d=1}^D \mathbf{y}_d^\top \Psi_1 \tilde{B}^{-1} \Psi_1^\top \mathbf{y}_d \\
& +\frac{D}{2} \frac{1}{\beta^{-1}} \text{Tr}\left(\frac{\Psi_2}{\beta^{-1}} K_{MM}^{-1}\right) \\
& -\frac{D}{2} \frac{\Psi_0}{\beta^{-1}}
\end{aligned} \tag{4}$$

As outlined in Rasmussen and Williams (2006, Section 3.4.3), to invert $\tilde{B}$ more reliably, we re-write it in the following form (using the Cholesky decomposition $K_{MM} = LL^\top$):

$$\begin{aligned}
\tilde{B} & \doteq \frac{\Psi_2}{\beta^{-1}} + K_{MM} \\
& = \frac{\Psi_2}{\beta^{-1}} + LL^\top \\
& = LL^{-1} \left(\frac{\Psi_2}{\beta^{-1}} + LL^\top \right) (L^\top)^{-1} L^\top \\
& = L \left(L^{-1} \frac{\Psi_2}{\beta^{-1}} (L^\top)^{-1} + I \right) L^\top \\
& = L (\text{AAT} + I) L^\top \\
& = LBL^\top
\end{aligned} \tag{5}$$

$$\tag{6}$$

where AAT and B in Eqs. 5 and 6 are defined as:

$$\text{AAT} \doteq \frac{1}{\beta^{-1}} L^{-1} \Psi_2 (L^\top)^{-1} \tag{7}$$

$$B \doteq \text{AAT} + I \tag{8}$$

Calling L_B the Cholesky factor of B (i.e., $B = L_B L_B^\top$) we have

$$\begin{aligned} \frac{1}{\beta^{-2}} \mathbf{y}_d^\top \Psi_1 \tilde{B}^{-1} \Psi_1^T \mathbf{y}_d &= \frac{1}{\beta^{-2}} \mathbf{y}_d^\top \Psi_1 (L^\top)^{-1} B^{-1} L^{-1} \Psi_1^T \mathbf{y}_d \\ &= \frac{1}{\beta^{-2}} \mathbf{y}_d^\top \Psi_1 (L^\top)^{-1} (L_B^\top)^{-1} L_B^{-1} L^{-1} \Psi_1^T \mathbf{y}_d \\ &= \mathbf{c}_d^\top \mathbf{c}_d \end{aligned} \quad (9)$$

$$\text{with } \mathbf{c}_d = \frac{1}{\beta^{-1}} L_B^{-1} L^{-1} \Psi_1^T \mathbf{y}_d \quad (10)$$

Then

$$\begin{aligned} \log |B| &= \log \left| \frac{1}{\beta^{-1}} L^{-1} \Psi_2 (L^\top)^{-1} + I \right| \\ &= \log \left| \frac{1}{\beta^{-1}} L^{-1} \Psi_2 (L^\top)^{-1} + L^{-1} L \right| \\ &= \log |L^{-1} \left(\frac{\Psi_2}{\beta^{-1}} (L^\top)^{-1} + L \right)| \\ &= \log |L^{-1} \left(\frac{\Psi_2}{\beta^{-1}} + L L^\top \right) (L^\top)^{-1}| \\ &= \log (|L^{-1}| \left| \frac{\Psi_2}{\beta^{-1}} + L L^\top \right| |(L^\top)^{-1}|) \\ &= \log (|L^{-1}| |(L^\top)^{-1}| \left| \frac{\Psi_2}{\beta^{-1}} + L L^\top \right|) \\ &= \log (|L^{-1} (L^\top)^{-1}| \left| \frac{\Psi_2}{\beta^{-1}} + L L^\top \right|) \\ &= \log (|K_{MM}^{-1}| |\tilde{B}|) \\ &= \log |\tilde{B}| + \log |K_{MM}^{-1}| \\ &= \log |\tilde{B}| - \log |K_{MM}| \end{aligned} \quad (11)$$

and

$$\begin{aligned} \text{Tr}(\text{AAT}) &= \text{Tr} \left(\frac{1}{\beta^{-1}} L^{-1} \Psi_2 (L^\top)^{-1} \right) \\ &= \text{Tr} \left(\frac{\Psi_2}{\beta^{-1}} (L^\top)^{-1} L^{-1} \right) \\ &= \text{Tr} \left(\frac{\Psi_2}{\beta^{-1}} K_{MM}^{-1} \right) \end{aligned} \quad (12)$$

Replacing Eqs. 9, 11 and 12 in Eq. 4 we obtain

$$\begin{aligned}
\tilde{F}(q) \geq & -\frac{ND}{2} \log 2\pi\beta^{-1} \\
& -\frac{D}{2} \log |B| \\
& -\frac{1}{2} \frac{1}{\beta^{-1}} \sum_{d=1}^D \|\mathbf{y}_d\|_2^2 \\
& +\frac{1}{2} \sum_{d=1}^D \|\mathbf{c}_d\|_2^2 \\
& +\frac{D}{2} \frac{1}{\beta^{-1}} \text{Tr}(\mathbf{A}\mathbf{A}^T) \\
& -\frac{D}{2} \frac{\Psi_0}{\beta^{-1}}
\end{aligned} \tag{13}$$

Lines 1-6 in Eq. 13 corresponds to lines 17-22 in Listing 1, taking $\beta^{-1} = \sigma^2$.
From line 8 in Listing 1:

$$\begin{aligned}
L \text{ tmp} &= \Psi_2 \\
\text{tmp} &= L^{-1} \Psi_2 \\
\text{tmp}^T &= \Psi_2 (L^{-1})^T
\end{aligned}$$

and from line 9 in Listing 1:

$$\begin{aligned}
\beta^{-1} L \mathbf{A}\mathbf{A}^T &= \text{tmp}^T \\
\mathbf{A}\mathbf{A}^T &= \frac{1}{\beta^{-1}} L^{-1} \Psi_2 (L^{-1})^T
\end{aligned} \tag{14}$$

Eq. 14 agrees with Eq. 7.
From line 7 in Listing 1:

$$\begin{aligned}
\sqrt{\beta^{-1}} L A &= \Psi_1^T \\
A &= \frac{1}{\sqrt{\beta^{-1}}} L^{-1} \Psi_1^T
\end{aligned}$$

and from line 13 in Listing 1

$$\sqrt{\beta^{-1}}L_B \mathbf{c} = A\mathbf{y} = \frac{1}{\sqrt{\beta^{-1}}}L^{-1}\Psi_1^\top\mathbf{y} \quad (15)$$

$$\mathbf{c} = \frac{1}{\beta^{-1}}L_B^{-1}L^{-1}\Psi_1^\top\mathbf{y} \quad (16)$$

Eq. 16 agrees with Eq. 10.

To compute $\log |B|$, line 12 in Listing 1 uses the fact that if $C = LL^\top$ then $\log |C| = 2 \operatorname{Tr}(\log(L))$.

References

- Rasmussen, C. E. and Williams, C. K. (2006). *Gaussian processes for machine learning*. MIT press Cambridge, MA.
- Titsias, M. and Lawrence, N. D. (2010). Bayesian gaussian process latent variable model. In *Proceedings of the Thirteenth International Conference on Artificial Intelligence and Statistics*, pages 844–851. JMLR Workshop and Conference Proceedings.