1. Select a starting prior $\Pi_0 = \mathcal{N}(\overline{\boldsymbol{v}}_0, G_0^{-2})$; Set $k = 0$;

2. Draw an independent sample $\boldsymbol{v}_1^{(k)}, \ldots, \boldsymbol{v}_M^{(k)}$ from the prior $\mathcal{N}\left(\overline{\boldsymbol{v}}_k, G_k^{-2}\right)$. For each $\boldsymbol{v}_m^{(k)}$, compute the corresponding weight

$$w_m^{(k)} = \exp L(\boldsymbol{v}_m^{(k)}).$$

3. Use the collection $(\boldsymbol{v}_m^{(k)}, w_m^{(k)})$ for $m \le M$ (posterior) to build the next prior distribution $\Pi_{k+1} = \mathcal{N}(\overline{\boldsymbol{v}}_{k+1}, G_{k+1}^{-2})$.
4. Increase $k \to k + 1$ and repeat pp. 2 and 3 until convergence.

A prior is called conjugated if the corresponding posterior belongs to the same family of measures as prior. This reduces the step of computing the posterior to parameter update.

Our main result claims that the Gaussian prior for a regular parametric family yields a nearly Gaussian posterior (nearly conjugated). Therefore, it suffices to recompute the parameters of normal law.

It is natural and standard to use the posterior mean

$$\overline{\boldsymbol{\upsilon}}_{k+1} = \widehat{\boldsymbol{\upsilon}}_k = \frac{1}{N_k} \sum_m w_m^{(k)} \boldsymbol{\upsilon}_m^{(k)} , \qquad N_k = \sum_m w_m^{(k)} .$$

Alternatively, a robust (trimmed) mean could be used.