Parameter priors for Ising models

research notes

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Study of uniform priors in parameter space and in constraint space for Ising models

'Flat priors do not exist'
(anonymous)

1 A two-unit model with sufficient statistics

Consider a population of two binary units $\boldsymbol{s} := (s_1, s_2)$ with values in $\{0, 1\}$. One observation of this population can thus give four results: $\boldsymbol{s} \in \{00, 01, 10, 11\}$.

Assume that we have m observations $(\boldsymbol{s}^{(1)}, \dots, \boldsymbol{s}^{(m)})$ of this or other populations prepared in similar conditions, so that knowledge of these observations is relevant for our forecast of a new observation $\boldsymbol{s}$, again in similar conditions. Also assume that only the number, the mean, and the second moments of these past observations are relevant to forecast the new one; that is,

$$m, \qquad \tfrac{1}{m}\big(\boldsymbol{s}^{(1)} + \dots + \boldsymbol{s}^{(m)}\big) =: \boldsymbol{a}, \qquad \tfrac{1}{m}\big(s_1^{(1)} s_2^{(1)} + \dots + s_1^{(m)} s_2^{(m)}\big) =: c \quad (1)$$

are sufficient statistics; note that the second sum contains the first as its diagonal. These assumptions are collectively denoted I. Then the Koopman-Pitman theorem says that our probabilistic forecasts must assume this general form:

$$\mathrm{p}(\boldsymbol{s}^{(1)}, \dots, \boldsymbol{s}^{(n)} \,|\, I) =$$
$$\int \Bigg[\prod_{i=1}^{n} g(\boldsymbol{s}^{(i)})\, \frac{\exp\big(\mu_1 s_1^{(i)} + \mu_2 s_2^{(i)} + \lambda s_1^{(i)} s_2^{(i)}\big)}{Z(\mu_1, \mu_2, \lambda)}\Bigg] \mathrm{p}(\mu_1, \mu_2, \lambda \,|\, I)\, \mathrm{d}\mu_1\, \mathrm{d}\mu_2\, \mathrm{d}\lambda,$$
$$\text{with} \quad Z(\mu_1, \mu_2, \lambda) := 1 + \exp(\mu_1) + \exp(\mu_2) + \exp(\mu_1 + \mu_2 + \lambda). \quad (2)$$

For later convenience, denote $\boldsymbol{\theta} \coloneqq (\mu_1, \mu_2, \lambda)$.

The distribution $g(\boldsymbol{s})$ and the density $\mathrm{p}(\mu_1, \mu_2, \lambda \mid I)$ in the formula above are not determined by the theorem: they need to be determined by additional assumptions. The distribution g is often determined by symmetry or combinatorial properties of the system. In the present study we assume it to be unity: $g(\boldsymbol{s}) = 1$. The density $\mathrm{p}(\boldsymbol{\theta} \mid I)$ is called *prior parameter density*.

Geometrically, the formula above says that our probability distribution is the convex combination of probability distributions from a three-dimensional family parameterized by $\boldsymbol{\theta}$, with weights $\mathrm{p}(\boldsymbol{\theta} \mid I)\,\mathrm{d}\boldsymbol{\theta}$. The parameters $\boldsymbol{\theta}$ are just coordinates of this three-dimensional manifold, and we can choose other coordinates $\boldsymbol{t}$, the weights then being given by $\mathrm{p}(\boldsymbol{t} \mid I)\,\mathrm{d}\boldsymbol{t}$, with the densities for $\boldsymbol{\theta}$ and for $\boldsymbol{t}$ related by a Jacobian determinant:

$$\mathrm{p}(\boldsymbol{\theta} \mid I) = \mathrm{p}[\boldsymbol{t}(\boldsymbol{\theta}) \mid I]\, \det\!\left(\frac{\partial \boldsymbol{t}}{\partial \boldsymbol{\theta}}\right). \tag{3}$$

Using Bayes's theorem with the probabilities (2) we find our forecast for a new observation $\boldsymbol{s}$ conditional on observations $\bigl(\boldsymbol{s}^{(1)}, \dots, \boldsymbol{s}^{(m)}\bigr)$:

$$\begin{aligned}
&\mathrm{p}(\boldsymbol{s} \mid \boldsymbol{s}^{(1)}, \dots, \boldsymbol{s}^{(m)}, I) = \\
&\qquad \int \frac{\exp\bigl(\mu_1 s_1 + \mu_2 s_2 + \lambda s_1 s_2\bigr)}{Z(\boldsymbol{\theta})}\, \mathrm{p}(\boldsymbol{\theta} \mid \boldsymbol{s}^{(1)}, \dots, \boldsymbol{s}^{(m)} I)\,\mathrm{d}\boldsymbol{\theta}
\end{aligned} \tag{4a}$$

with

$$\begin{aligned}
\mathrm{p}(\boldsymbol{\theta} \mid \boldsymbol{s}^{(1)}, \dots, \boldsymbol{s}^{(m)} I) &\propto \left[\prod_{i=1}^{m} \frac{\exp\bigl(\mu_1 s_1^{(i)} + \mu_2 s_2^{(i)} + \lambda s_1^{(i)} s_2^{(i)}\bigr)}{Z(\boldsymbol{\theta})}\right] \mathrm{p}(\boldsymbol{\theta} \mid I) = \\
&\qquad \exp\{m\,[\mu_1 a_1 + \mu_2 a_2 + \lambda c - \ln Z(\boldsymbol{\theta})]\}\, \mathrm{p}(\boldsymbol{\theta} \mid I).
\end{aligned} \tag{4b}$$

The density $\mathrm{p}(\boldsymbol{\theta} \mid \boldsymbol{s}^{(1)}, \dots, \boldsymbol{s}^{(m)} I)$ is called *posterior parameter density*.

The last expression shows that the m observations affect our forecast only through the averages $\boldsymbol{a}$ and c, eq. (1), as we assumed.

The proportionality relation of the last formula reminds us that we must perform an integral over $\boldsymbol{\theta}$ to calculate the posterior parameter density. We must also perform an integral over $\boldsymbol{\theta}$ to calculate the conditional probability for $\boldsymbol{s}$. These integrals are difficult when we consider populations with many units. When the number m of known observations is large, the posterior parameter density is often approximated by a

Dirac delta centred on the maximum of the argument of the exponential, $\mu_1 a_1 + \mu_2 a_2 + \lambda c$.