

Variational Inference for Inverse Reinforcement Learning with Gaussian Processes: Supplementary Material

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16th November 2018

1 Derivatives of the Evidence Lower Bound

1.1 $\partial/\partial \mathbf{m}$

We begin by removing terms independent of \mathbf{m} :

$$\begin{aligned} \frac{\partial \mathcal{L}}{\partial \mathbf{m}} = & -\frac{1}{2} \frac{\partial}{\partial \mathbf{m}} [\mathbf{m}^\top \mathbb{E}[\mathbf{K}_{\mathbf{u}, \mathbf{u}}^{-1}] \mathbf{m}] + \frac{\partial}{\partial \mathbf{m}} [\mathbf{t}^\top \mathbb{E}[\mathbf{K}_{\mathbf{r}, \mathbf{u}}^\top \mathbf{K}_{\mathbf{u}, \mathbf{u}}^{-1}] \mathbf{m}] \\ & - \sum_{i=1}^N \sum_{t=1}^T \frac{\partial}{\partial \mathbf{m}} \mathbb{E}[V_r(s_{i,t})] - \gamma \sum_{s' \in \mathcal{S}} \mathcal{T}(s_{i,t}, a_{i,t}, s') \frac{\partial}{\partial \mathbf{m}} \mathbb{E}[V_r(s')]. \end{aligned}$$

Here

$$\begin{aligned} \frac{\partial}{\partial \mathbf{m}} [\mathbf{m}^\top \mathbb{E}[\mathbf{K}_{\mathbf{u}, \mathbf{u}}^{-1}] \mathbf{m}] &= (\mathbb{E}[\mathbf{K}_{\mathbf{u}, \mathbf{u}}^{-1}] + \mathbb{E}[\mathbf{K}_{\mathbf{u}, \mathbf{u}}^{-1}]^\top) \mathbf{m}, \\ \frac{\partial}{\partial \mathbf{m}} [\mathbf{t}^\top \mathbb{E}[\mathbf{K}_{\mathbf{r}, \mathbf{u}}^\top \mathbf{K}_{\mathbf{u}, \mathbf{u}}^{-1}] \mathbf{m}] &= \mathbf{t}^\top \mathbb{E}[\mathbf{K}_{\mathbf{r}, \mathbf{u}}^\top \mathbf{K}_{\mathbf{u}, \mathbf{u}}^{-1}], \end{aligned}$$

and

$$\begin{aligned} \frac{\partial}{\partial \mathbf{m}} \mathbb{E}[V_r(s)] &= \frac{\partial}{\partial \mathbf{m}} \iiint V_r(s) p(\mathbf{r} | \boldsymbol{\lambda}, \mathbf{X}_{\mathbf{u}}, \mathbf{u}) \mathcal{N}(\mathbf{u}; \mathbf{m}, \mathbf{S}) q(\boldsymbol{\lambda}) d\mathbf{r} d\mathbf{u} d\boldsymbol{\lambda} \\ &= \iiint V_r(s) p(\mathbf{r} | \boldsymbol{\lambda}, \mathbf{X}_{\mathbf{u}}, \mathbf{u}) \frac{\partial}{\partial \mathbf{m}} \mathcal{N}(\mathbf{u}; \mathbf{m}, \mathbf{S}) q(\boldsymbol{\lambda}) d\mathbf{r} d\mathbf{u} d\boldsymbol{\lambda}, \end{aligned} \tag{1}$$

where

$$\begin{aligned} \frac{\partial}{\partial \mathbf{m}} \mathcal{N}(\mathbf{u}; \mathbf{m}, \mathbf{S}) &= \mathcal{N}(\mathbf{u}; \mathbf{m}, \mathbf{S}) \frac{\partial}{\partial \mathbf{m}} \left[-\frac{1}{2} (\mathbf{u} - \mathbf{m})^\top \mathbf{S}^{-1} (\mathbf{u} - \mathbf{m}) \right] \\ &= \mathcal{N}(\mathbf{u}; \mathbf{m}, \mathbf{S}) \left(-\frac{1}{2} \right) (\mathbf{S}^{-1} + \mathbf{S}^{-\top}) (\mathbf{u} - \mathbf{m}) \frac{\partial}{\partial \mathbf{m}} [\mathbf{u} - \mathbf{m}] \\ &= \mathcal{N}(\mathbf{u}; \mathbf{m}, \mathbf{S}) \frac{1}{2} (\mathbf{S}^{-1} + \mathbf{S}^{-\top}) (\mathbf{u} - \mathbf{m}). \end{aligned}$$

Substituting it back into (1) gives

$$\begin{aligned} \frac{\partial}{\partial \mathbf{m}} \mathbb{E}[V_r(s)] &= \frac{1}{2} \iiint V_r(s) (\mathbf{S}^{-1} + \mathbf{S}^{-\top}) (\mathbf{u} - \mathbf{m}) p(\mathbf{r} | \boldsymbol{\lambda}, \mathbf{X}_{\mathbf{u}}, \mathbf{u}) \mathcal{N}(\mathbf{u}; \mathbf{m}, \mathbf{S}) q(\boldsymbol{\lambda}) d\mathbf{r} d\mathbf{u} d\boldsymbol{\lambda} \\ &= \frac{1}{2} \mathbb{E}[V_r(s) (\mathbf{S}^{-1} + \mathbf{S}^{-\top}) (\mathbf{u} - \mathbf{m})]. \end{aligned}$$

Hence

$$\begin{aligned}\frac{\partial \mathcal{L}}{\partial \mathbf{m}} = & -\frac{1}{2}(\mathbb{E}[\mathbf{K}_{\mathbf{u}, \mathbf{u}}^{-1}] + \mathbb{E}[\mathbf{K}_{\mathbf{u}, \mathbf{u}}^{-1}]^\top) \mathbf{m} + \mathbf{t}^\top \mathbb{E}[\mathbf{K}_{\mathbf{r}, \mathbf{u}}^\top \mathbf{K}_{\mathbf{u}, \mathbf{u}}^{-1}] \\ & - \frac{1}{2} \sum_{i=1}^N \sum_{t=1}^T \mathbb{E}[V_r(s_{i,t}) (\mathbf{S}^{-1} + \mathbf{S}^{-\top}) (\mathbf{u} - \mathbf{m})] \\ & - \gamma \sum_{s' \in \mathcal{S}} \mathcal{T}(s_{i,t}, a_{i,t}, s') \mathbb{E}[V_r(s') (\mathbf{S}^{-1} + \mathbf{S}^{-\top}) (\mathbf{u} - \mathbf{m})].\end{aligned}$$

1.2 $\partial/\partial \mathbf{S}$

Similarly to the previous section,

$$\begin{aligned}\frac{\partial \mathcal{L}}{\partial \mathbf{S}} = & \frac{1}{2} \frac{\partial}{\partial \mathbf{S}} \log |\mathbf{S}| - \frac{1}{2} \frac{\partial}{\partial \mathbf{S}} \text{Tr}[\mathbb{E}[\mathbf{K}_{\mathbf{u}, \mathbf{u}}^{-1}] \mathbf{S}] \\ & - \sum_{i=1}^N \sum_{t=1}^T \frac{\partial}{\partial \mathbf{S}} \mathbb{E}[V_r(s_{i,t})] - \gamma \sum_{s' \in \mathcal{S}} \mathcal{T}(s_{i,t}, a_{i,t}, s') \frac{\partial}{\partial \mathbf{S}} \mathbb{E}[V_r(s')],\end{aligned}$$

where

$$\frac{\partial}{\partial \mathbf{S}} \log |\mathbf{S}| = \mathbf{S}^{-\top},$$

and

$$\frac{\partial}{\partial \mathbf{S}} \text{Tr}[\mathbb{E}[\mathbf{K}_{\mathbf{u}, \mathbf{u}}^{-1}] \mathbf{S}] = \mathbb{E}[\mathbf{K}_{\mathbf{u}, \mathbf{u}}^{-1}]^\top$$

by *The Matrix Cookbook* [1]. Then

$$\frac{\partial}{\partial \mathbf{S}} \mathbb{E}[V_r(s)] = \iiint V_r(s) q(\mathbf{r}) \frac{\partial}{\partial \mathbf{S}} \mathcal{N}(\mathbf{u}; \mathbf{m}, \mathbf{S}) q(\boldsymbol{\lambda}) d\mathbf{r} d\mathbf{u} d\boldsymbol{\lambda},$$

where

$$\begin{aligned}\frac{\partial}{\partial \mathbf{S}} \mathcal{N}(\mathbf{u}; \mathbf{m}, \mathbf{S}) = & \frac{\partial}{\partial \mathbf{S}} \left[\frac{1}{(2\pi)^{m/2} |\mathbf{S}|^{1/2}} \exp \left(-\frac{1}{2} (\mathbf{u} - \mathbf{m})^\top \mathbf{S}^{-1} (\mathbf{u} - \mathbf{m}) \right) \right] \\ = & \frac{\partial}{\partial \mathbf{S}} \left[\frac{1}{(2\pi)^{m/2} |\mathbf{S}|^{1/2}} \right] \exp \left(-\frac{1}{2} (\mathbf{u} - \mathbf{m})^\top \mathbf{S}^{-1} (\mathbf{u} - \mathbf{m}) \right) \\ & + \frac{1}{(2\pi)^{m/2} |\mathbf{S}|^{1/2}} \frac{\partial}{\partial \mathbf{S}} \left[\exp \left(-\frac{1}{2} (\mathbf{u} - \mathbf{m})^\top \mathbf{S}^{-1} (\mathbf{u} - \mathbf{m}) \right) \right] \\ = & \frac{1}{(2\pi)^{m/2}} \frac{\partial}{\partial \mathbf{S}} \left[\frac{1}{|\mathbf{S}|^{1/2}} \right] \exp \left(-\frac{1}{2} (\mathbf{u} - \mathbf{m})^\top \mathbf{S}^{-1} (\mathbf{u} - \mathbf{m}) \right) \\ & - \frac{1}{2} \mathcal{N}(\mathbf{u}; \mathbf{m}, \mathbf{S}) \frac{\partial}{\partial \mathbf{S}} [(\mathbf{u} - \mathbf{m})^\top \mathbf{S}^{-1} (\mathbf{u} - \mathbf{m})].\end{aligned}$$

The two remaining derivatives can be taken with the help of *The Matrix Cookbook* [1]:

$$\begin{aligned}\frac{\partial}{\partial \mathbf{S}} \left[\frac{1}{|\mathbf{S}|^{1/2}} \right] = & -\frac{1}{2} |\mathbf{S}|^{-3/2} \frac{\partial |\mathbf{S}|}{\partial \mathbf{S}} = -\frac{1}{2} |\mathbf{S}|^{-3/2} |\mathbf{S}| \mathbf{S}^{-\top} = -\frac{1}{2 |\mathbf{S}|^{1/2}} \mathbf{S}^{-\top}, \\ \frac{\partial}{\partial \mathbf{S}} [(\mathbf{u} - \mathbf{m})^\top \mathbf{S}^{-1} (\mathbf{u} - \mathbf{m})] = & -\mathbf{S}^{-\top} (\mathbf{u} - \mathbf{m}) (\mathbf{u} - \mathbf{m})^\top \mathbf{S}^{-\top}.\end{aligned}$$

Plugging them back in gives

$$\frac{\partial}{\partial \mathbf{S}} \mathcal{N}(\mathbf{u}; \mathbf{m}, \mathbf{S}) = -\frac{1}{2} \mathbf{S}^{-\top} \mathcal{N}(\mathbf{u}; \mathbf{m}, \mathbf{S}) + \frac{1}{2} \mathcal{N}(\mathbf{u}; \mathbf{m}, \mathbf{S}) \mathbf{S}^{-\top} (\mathbf{u} - \mathbf{m}) (\mathbf{u} - \mathbf{m})^\top \mathbf{S}^{-\top},$$

and

$$\begin{aligned}\frac{\partial}{\partial \mathbf{S}} \mathbb{E}[V_r(s)] &= \frac{1}{2} \iiint V_r(s) (\mathbf{S}^{-\top} (\mathbf{u} - \mathbf{m})(\mathbf{u} - \mathbf{m})^\top \mathbf{S}^{-\top} - \mathbf{S}^{-\top}) q(\mathbf{r}) \mathcal{N}(\mathbf{u}; \mathbf{m}, \mathbf{S}) q(\boldsymbol{\lambda}) d\mathbf{r} d\mathbf{u} d\boldsymbol{\lambda} \\ &= \frac{1}{2} \mathbb{E}[V_r(s) (\mathbf{S}^{-\top} (\mathbf{u} - \mathbf{m})(\mathbf{u} - \mathbf{m})^\top \mathbf{S}^{-\top} - \mathbf{S}^{-\top})].\end{aligned}$$

Therefore

$$\begin{aligned}\frac{\partial \mathcal{L}}{\partial \mathbf{S}} &= \frac{1}{2} \mathbf{S}^{-\top} - \frac{1}{2} \mathbb{E}[\mathbf{K}_{\mathbf{u}, \mathbf{u}}^{-1}]^\top - \frac{1}{2} \sum_{i=1}^N \sum_{t=1}^T \mathbb{E}[V_r(s_{i,t}) (\mathbf{S}^{-\top} (\mathbf{u} - \mathbf{m})(\mathbf{u} - \mathbf{m})^\top \mathbf{S}^{-\top} - \mathbf{S}^{-\top})] \\ &\quad - \gamma \sum_{s' \in \mathcal{S}} \mathcal{T}(s_{i,t}, a_{i,t}, s') \mathbb{E}[V_r(s') (\mathbf{S}^{-\top} (\mathbf{u} - \mathbf{m})(\mathbf{u} - \mathbf{m})^\top \mathbf{S}^{-\top} - \mathbf{S}^{-\top})].\end{aligned}$$

1.3 $\partial/\partial \alpha_j$

We begin in the usual way:

$$\begin{aligned}\frac{\partial \mathcal{L}}{\partial \alpha_j} &= -\frac{1}{2} \frac{\partial}{\partial \alpha_j} \mathbb{E}[\text{Tr}[\mathbf{K}_{\mathbf{u}, \mathbf{u}}^{-2}]] - \frac{1}{2} \frac{\partial}{\partial \alpha_j} \mathbb{E}[\text{Tr}[\mathbf{K}_{\mathbf{u}, \mathbf{u}}^{-1} \mathbf{S}]] - \frac{1}{2} \frac{\partial}{\partial \alpha_j} \mathbb{E}[\mathbf{m}^\top \mathbf{K}_{\mathbf{u}, \mathbf{u}}^{-1} \mathbf{m}] - \frac{1}{2} \frac{\partial}{\partial \alpha_j} \mathbb{E}[\log |\mathbf{K}_{\mathbf{u}, \mathbf{u}}|] \\ &\quad + \frac{\partial}{\partial \alpha_j} \mathbb{E}[\mathbf{t}^\top \mathbf{K}_{\mathbf{r}, \mathbf{u}}^\top \mathbf{K}_{\mathbf{u}, \mathbf{u}}^{-1} \mathbf{m}] + \frac{\partial}{\partial \alpha_j} [\alpha_j + \log \Gamma(\alpha_j) + (1 - \alpha_j) \psi(\alpha_j)] \\ &\quad - \sum_{i=1}^N \sum_{t=1}^T \frac{\partial}{\partial \alpha_j} \mathbb{E}[V_r(s_{i,t})] - \gamma \sum_{s' \in \mathcal{S}} \mathcal{T}(s_{i,t}, a_{i,t}, s') \frac{\partial}{\partial \alpha_j} \mathbb{E}[V_r(s')].\end{aligned}$$

First,

$$\frac{\partial}{\partial \alpha_j} [\alpha_j + \log \Gamma(\alpha_j) + (1 - \alpha_j) \psi(\alpha_j)] = 1 + \psi(\alpha_j) - \psi(\alpha_j) + (1 - \alpha_j) \psi'(\alpha_j) = 1 + (1 - \alpha_j) \psi'(\alpha_j)$$

by the definition of ψ . The remaining terms can all be treated in the same way, as they all contain expectations of scalar functions that are independent of α_j , and α_j only occurs in $\Gamma(\lambda_j; \alpha_j, \beta_j)$. Thus we can work with an abstract function as follows:

$$\begin{aligned}\frac{\partial}{\partial \alpha_j} \mathbb{E}[f(k_{\boldsymbol{\lambda}}, \mathbf{r})] &= \frac{\partial}{\partial \alpha_j} \iiint f(k_{\boldsymbol{\lambda}}, \mathbf{r}) q(\boldsymbol{\lambda}) q(\mathbf{r}) q(\mathbf{u}) d\boldsymbol{\lambda} d\mathbf{r} d\mathbf{u} \\ &= \iiint f(k_{\boldsymbol{\lambda}}, \mathbf{r}) q(\lambda_0) \cdots q(\lambda_{j-1}) \frac{\partial}{\partial \alpha_j} \left[\frac{\beta_j^{\alpha_j}}{\Gamma(\alpha_j)} \lambda_j^{\alpha_j-1} \right] e^{-\beta_j \lambda_j} \\ &\quad q(\lambda_{j+1}) \cdots q(\lambda_d) q(\mathbf{r}) q(\mathbf{u}) d\boldsymbol{\lambda} d\mathbf{r} d\mathbf{u}.\end{aligned}$$

Then

$$\begin{aligned}\frac{\partial}{\partial \alpha_j} \left[\frac{\beta_j^{\alpha_j}}{\Gamma(\alpha_j)} \lambda_j^{\alpha_j-1} \right] &= \frac{\frac{\partial}{\partial \alpha_j} [\beta_j^{\alpha_j} \lambda_j^{\alpha_j-1}] \Gamma(\alpha_j) - \beta_j^{\alpha_j} \lambda_j^{\alpha_j-1} \Gamma'(\alpha_j)}{(\Gamma(\alpha_j))^2} \\ &= \frac{\beta_j^{\alpha_j} \lambda_j^{\alpha_j-1} \frac{\partial}{\partial \alpha_j} [\alpha_j \log \beta_j + (\alpha_j - 1) \log \lambda_j] \Gamma(\alpha_j) - \beta_j^{\alpha_j} \lambda_j^{\alpha_j-1} \Gamma'(\alpha_j)}{(\Gamma(\alpha_j))^2} \\ &= \frac{\beta_j^{\alpha_j} \lambda_j^{\alpha_j-1} (\log \beta_j + \log \lambda_j) \Gamma(\alpha_j) - \beta_j^{\alpha_j} \lambda_j^{\alpha_j-1} \Gamma'(\alpha_j)}{(\Gamma(\alpha_j))^2} \\ &= \frac{\beta_j^{\alpha_j} \lambda_j^{\alpha_j-1}}{\Gamma(\alpha_j)} \left(\log \beta_j + \log \lambda_j - \frac{\Gamma'(\alpha_j)}{\Gamma(\alpha_j)} \right),\end{aligned}$$

which means that

$$\begin{aligned}
\frac{\partial}{\partial \alpha_j} \mathbb{E}[f(k_{\boldsymbol{\lambda}}, \mathbf{r})] &= \iiint f(k_{\boldsymbol{\lambda}}, \mathbf{r}) q(\lambda_0) \cdots q(\lambda_{j-1}) \frac{\beta_j^{\alpha_j}}{\Gamma(\alpha_j)} \lambda_j^{\alpha_j-1} e^{-\beta_j \lambda_j} \left(\log \beta_j + \log \lambda_j - \frac{\Gamma'(\alpha_j)}{\Gamma(\alpha_j)} \right) \\
&\quad q(\lambda_{j+1}) \cdots q(\lambda_d) q(\mathbf{r}) q(\mathbf{u}) d\boldsymbol{\lambda} d\mathbf{r} d\mathbf{u} \\
&= \iiint f(k_{\boldsymbol{\lambda}}, \mathbf{r}) \left(\log \beta_j + \log \lambda_j - \frac{\Gamma'(\alpha_j)}{\Gamma(\alpha_j)} \right) q(\boldsymbol{\lambda}) q(\mathbf{r}) q(\mathbf{u}) d\boldsymbol{\lambda} d\mathbf{r} d\mathbf{u} \\
&= \mathbb{E} \left[f(k_{\boldsymbol{\lambda}}, \mathbf{r}) \left(\log \beta_j + \log \lambda_j - \frac{\Gamma'(\alpha_j)}{\Gamma(\alpha_j)} \right) \right] \\
&= \left(\log \beta_j - \frac{\Gamma'(\alpha_j)}{\Gamma(\alpha_j)} \right) \mathbb{E}[f(k_{\boldsymbol{\lambda}}, \mathbf{r})] + \mathbb{E}[f(k_{\boldsymbol{\lambda}}, \mathbf{r}) \log \lambda_j].
\end{aligned}$$

With these results in mind, we can simplify the initial expression to

$$\begin{aligned}
\frac{\partial \mathcal{L}}{\partial \alpha_j} &= 1 + (1 - \alpha_j) \psi'(\alpha_j) + \left(\log \beta_j - \frac{\Gamma'(\alpha_j)}{\Gamma(\alpha_j)} \right) \left(-\frac{1}{2} \mathbb{E}[\text{Tr}[\mathbf{K}_{\mathbf{u}, \mathbf{u}}^{-2}]] - \frac{1}{2} \mathbb{E}[\text{Tr}[\mathbf{K}_{\mathbf{u}, \mathbf{u}}^{-1} \mathbf{S}]] \right. \\
&\quad - \frac{1}{2} \mathbb{E}[\mathbf{m}^\top \mathbf{K}_{\mathbf{u}, \mathbf{u}}^{-1} \mathbf{m}] - \frac{1}{2} \mathbb{E}[\log |\mathbf{K}_{\mathbf{u}, \mathbf{u}}|] + \mathbb{E}[\mathbf{t}^\top \mathbf{K}_{\mathbf{r}, \mathbf{u}}^\top \mathbf{K}_{\mathbf{u}, \mathbf{u}}^{-1} \mathbf{m}] \\
&\quad \left. - \sum_{i=1}^N \sum_{t=1}^T \mathbb{E}[V_r(s_{i,t})] - \gamma \sum_{s' \in \mathcal{S}} \mathcal{T}(s_{i,t}, a_{i,t}, s') \mathbb{E}[V_r(s')] \right) \\
&\quad - \frac{1}{2} \mathbb{E}[\text{Tr}[\mathbf{K}_{\mathbf{u}, \mathbf{u}}^{-2}] \log \lambda_j] - \frac{1}{2} \mathbb{E}[\text{Tr}[\mathbf{K}_{\mathbf{u}, \mathbf{u}}^{-1} \mathbf{S}] \log \lambda_j] - \frac{1}{2} \mathbb{E}[\mathbf{m}^\top \mathbf{K}_{\mathbf{u}, \mathbf{u}}^{-1} \mathbf{m} \log \lambda_j] \\
&\quad - \frac{1}{2} \mathbb{E}[\log |\mathbf{K}_{\mathbf{u}, \mathbf{u}}| \log \lambda_j] + \mathbb{E}[\mathbf{t}^\top \mathbf{K}_{\mathbf{r}, \mathbf{u}}^\top \mathbf{K}_{\mathbf{u}, \mathbf{u}}^{-1} \mathbf{m} \log \lambda_j] \\
&\quad - \sum_{i=1}^N \sum_{t=1}^T \mathbb{E}[V_r(s_{i,t}) \log \lambda_j] - \gamma \sum_{s' \in \mathcal{S}} \mathcal{T}(s_{i,t}, a_{i,t}, s') \mathbb{E}[V_r(s') \log \lambda_j].
\end{aligned}$$

1.4 $\partial/\partial \beta_j$

Finally,

$$\begin{aligned}
\frac{\partial \mathcal{L}}{\partial \beta_j} &= -\frac{1}{2} \frac{\partial}{\partial \beta_j} \mathbb{E}[\text{Tr}[\mathbf{K}_{\mathbf{u}, \mathbf{u}}^{-2}]] - \frac{1}{2} \frac{\partial}{\partial \beta_j} \mathbb{E}[\text{Tr}[\mathbf{K}_{\mathbf{u}, \mathbf{u}}^{-1} \mathbf{S}]] - \frac{1}{2} \frac{\partial}{\partial \beta_j} \mathbb{E}[\mathbf{m}^\top \mathbf{K}_{\mathbf{u}, \mathbf{u}}^{-1} \mathbf{m}] \\
&\quad - \frac{1}{2} \frac{\partial}{\partial \beta_j} \mathbb{E}[\log |\mathbf{K}_{\mathbf{u}, \mathbf{u}}|] + \frac{\partial}{\partial \beta_j} \mathbb{E}[\mathbf{t}^\top \mathbf{K}_{\mathbf{r}, \mathbf{u}}^\top \mathbf{K}_{\mathbf{u}, \mathbf{u}}^{-1} \mathbf{m}] - \frac{\partial}{\partial \beta_j} [\log \beta_j] \\
&\quad - \sum_{i=1}^N \sum_{t=1}^T \frac{\partial}{\partial \beta_j} \mathbb{E}[V_r(s_{i,t})] - \gamma \sum_{s' \in \mathcal{S}} \mathcal{T}(s_{i,t}, a_{i,t}, s') \frac{\partial}{\partial \beta_j} \mathbb{E}[V_r(s')].
\end{aligned}$$

Similarly to the previous section, we can handle all derivatives of expectations in the same way:

$$\begin{aligned}
\frac{\partial}{\partial \beta_j} \mathbb{E}[f(k_{\boldsymbol{\lambda}}, \mathbf{r})] &= \frac{\partial}{\partial \beta_j} \iiint f(k_{\boldsymbol{\lambda}}, \mathbf{r}) q(\boldsymbol{\lambda}) q(\mathbf{r}) q(\mathbf{u}) d\boldsymbol{\lambda} d\mathbf{r} d\mathbf{u} \\
&= \iiint f(k_{\boldsymbol{\lambda}}, \mathbf{r}) q(\lambda_0) \cdots q(\lambda_{j-1}) \frac{\lambda_j^{\alpha_j-1}}{\Gamma(\alpha_j)} \frac{\partial}{\partial \beta_j} [\beta_j^{\alpha_j} e^{-\beta_j \lambda_j}] \\
&\quad q(\lambda_{j+1}) \cdots q(\lambda_d) q(\mathbf{r}) q(\mathbf{u}) d\boldsymbol{\lambda} d\mathbf{r} d\mathbf{u}.
\end{aligned}$$

Since

$$\frac{\partial}{\partial \beta_j} [\beta_j^{\alpha_j} e^{-\beta_j \lambda_j}] = \alpha_j \beta_j^{\alpha_j-1} e^{-\beta_j \lambda_j} - \beta_j^{\alpha_j} e^{-\beta_j \lambda_j} \lambda_j = \beta_j^{\alpha_j} e^{-\beta_j \lambda_j} \left(\frac{\alpha_j}{\beta_j} - \lambda_j \right),$$

we have that

$$\begin{aligned}
\frac{\partial}{\partial \beta_j} \mathbb{E}[f(k_{\boldsymbol{\lambda}}, \mathbf{r})] &= \iiint f(k_{\boldsymbol{\lambda}}, \mathbf{r}) q(\lambda_0) \cdots q(\lambda_{j-1}) \frac{\beta_j^{\alpha_j}}{\Gamma(\alpha_j)} \lambda_j^{\alpha_j-1} e^{-\beta_j \lambda_j} \left(\frac{\alpha_j}{\beta_j} - \lambda_j \right) \\
&\quad q(\lambda_{j+1}) \cdots q(\lambda_d) q(\mathbf{r}) q(\mathbf{u}) d\boldsymbol{\lambda} d\mathbf{r} d\mathbf{u} \\
&= \iiint f(k_{\boldsymbol{\lambda}}, \mathbf{r}) \left(\frac{\alpha_j}{\beta_j} - \lambda_j \right) q(\boldsymbol{\lambda}) q(\mathbf{r}) q(\mathbf{u}) d\boldsymbol{\lambda} d\mathbf{r} d\mathbf{u} \\
&= \mathbb{E} \left[f(k_{\boldsymbol{\lambda}}, \mathbf{r}) \left(\frac{\alpha_j}{\beta_j} - \lambda_j \right) \right] = \frac{\alpha_j}{\beta_j} \mathbb{E}[f(k_{\boldsymbol{\lambda}}, \mathbf{r})] - \mathbb{E}[f(k_{\boldsymbol{\lambda}}, \mathbf{r}) \lambda_j].
\end{aligned}$$

This gives us the final expression of $\frac{\partial \mathcal{L}}{\partial \beta_j}$:

$$\begin{aligned}
\frac{\partial \mathcal{L}}{\partial \beta_j} &= -\frac{1}{\beta_j} - \frac{1}{2} \mathbb{E} \left[\text{Tr}[\mathbf{K}_{\mathbf{u}, \mathbf{u}}^{-2}] \left(\frac{\alpha_j}{\beta_j} - \lambda_j \right) \right] - \frac{1}{2} \mathbb{E} \left[\text{Tr}[\mathbf{K}_{\mathbf{u}, \mathbf{u}}^{-1} \mathbf{S}] \left(\frac{\alpha_j}{\beta_j} - \lambda_j \right) \right] \\
&\quad - \frac{1}{2} \mathbb{E} \left[\mathbf{m}^\top \mathbf{K}_{\mathbf{u}, \mathbf{u}}^{-1} \mathbf{m} \left(\frac{\alpha_j}{\beta_j} - \lambda_j \right) \right] - \frac{1}{2} \mathbb{E} \left[\log |\mathbf{K}_{\mathbf{u}, \mathbf{u}}| \left(\frac{\alpha_j}{\beta_j} - \lambda_j \right) \right] \\
&\quad + \mathbb{E} \left[\mathbf{t}^\top \mathbf{K}_{\mathbf{r}, \mathbf{u}}^\top \mathbf{K}_{\mathbf{u}, \mathbf{u}}^{-1} \mathbf{m} \left(\frac{\alpha_j}{\beta_j} - \lambda_j \right) \right] \\
&\quad - \sum_{i=1}^N \sum_{t=1}^T \mathbb{E} \left[V_r(s_{i,t}) \left(\frac{\alpha_j}{\beta_j} - \lambda_j \right) \right] - \gamma \sum_{s' \in \mathcal{S}} \mathcal{T}(s_{i,t}, a_{i,t}, s') \mathbb{E} \left[V_r(s') \left(\frac{\alpha_j}{\beta_j} - \lambda_j \right) \right].
\end{aligned}$$

2 Proofs

Theorem 1 (Differentiating under the integral sign). *Assume $f : R \times R \rightarrow R$ is such that $x \mapsto f(x, t)$ is measurable for each $t \in R$, that $f(x, t_0)$ is integrable for some $t_0 \in R$ and $\frac{\partial f(x, t)}{\partial t}$ exists for each (x, t) . Assume also that there is an integrable $g : R \rightarrow R$ with $\left| \frac{\partial f(x, t)}{\partial t} \right| \leq g(x)$ for each $x, t \in R$. Then the function $x \mapsto f(x, t)$ is integrable for each t and the function $F : R \rightarrow R$ defined by*

$$F(t) = \int_R f_t d\mu = \int_R f(x, t) d\mu(x)$$

is differentiable with derivative

$$F'(t) = \frac{d}{dt} \int_R f(x, t) d\mu(x) = \int_R \frac{\partial}{\partial t} f(x, t) d\mu(x).$$

Proof. Applying the mean value theorem to the function $t \mapsto f(x, t)$, for each $t = t_0$ we have to have some c between t_0 and t so that

$$f(x, t) - f(x, t_0) = \left. \frac{\partial f}{\partial t} \right|_{(x, c)} (t - t_0).$$

It follows that

$$|f(x, t) - f(x, t_0)| \leq g(x) |t - t_0|$$

and so

$$|f(x, t)| \leq |f(x, t_0)| + g(x) |t - t_0|.$$

Thus

$$\int_R |f(x, t)| d\mu(x) \leq \int (|f(x, t_0)| + g(x) |t - t_0|) d\mu(x) = \int_R |f(x, t_0)| d\mu(x) + |t - t_0| \int_R g d\mu < \infty,$$

which establishes that the function $x \mapsto f(x, t)$ is integrable for each t .

To prove the formula for $F(t)$ consider any sequence $(t_n)_{n=1}^\infty$ so that $\lim_{n \rightarrow \infty} t_n = t$ but $t_n \neq t$ for each t . We claim that

$$\lim_{n \rightarrow \infty} \frac{F(t_n) - F(t)}{t_n - t} = \int_R \frac{\partial f(x, t)}{\partial t} d\mu(x). \quad (2)$$

We have

$$\frac{F(t_n) - F(t)}{t_n - t} = \int_R \frac{f(x, t_n) - f(x, t)}{t_n - t} d\mu(x) = \int_R f_n(x) d\mu(x)$$

where

$$f_n(x) = \frac{f(x, t_n) - f(x, t)}{t_n - t}.$$

Notice that, for each x we know

$$\lim_{n \rightarrow \infty} f_n(x) = \left. \frac{\partial f}{\partial t} \right|_{(x, t)}$$

and so (2) will follow from the dominated convergence theorem once we show that $|f_n(x)| \leq g(x)$ for each x .

That follows from the mean value theorem again because there is c between t and t_0 (with c depending on x) so that

$$f_n(x) = \frac{f(x, t_n) - f(x, t)}{t_n - t} = \left. \frac{\partial f}{\partial t} \right|_{(x, c)}.$$

So $|f_n(x)| \leq g(x)$ for each x . □

References

- [1] K. B. Petersen, M. S. Pedersen, et al. The matrix cookbook. *Technical University of Denmark*, 7(15):510, 2008.